Indirect Supervised Learning of Strategic Generation Logic

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Submitted in partial fulfillment of the

requirements for the degree

of Doctor of Philosophy

in the Graduate School of Arts and Sciences

COLUMBIA UNIVERSITY

2005

Abstract

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The Strategic Component in a Natural Language Generation (NLG) system is responsible for determining content and structure of the generated output. It takes a knowledge base and communicative goals as input and provides a *document plan* as output. The Strategic Generation process is normally divided into two subtasks: Content Selection and Document Structuring. An implementation for the Strategic Component uses Content Selection rules to select the relevant knowledge and Document Structuring schemata to guide the construction of the *document plan*. This implementation is better suited for descriptive texts with a strong topical structure and little intentional content. In such domains, special communicative knowledge is required to structure the text, a type of knowledge referred as Domain Communicative Knowledge. Therefore, the task of building such rules and schemata is normally recognized as tightly coupled with the semantics and idiosyncrasies of each particular domain. In this thesis, I investigate the automatic acquisition of Content Selection rules and the automatic construction of Document Structuring schemata from an aligned Text-Knowledge corpus. These corpora are a collection of human-produced texts together with the knowledge data a generation system is expected to use to construct texts that fulfill the same communicative goals as the human texts. They are increasingly popular in learning for NLG because they are readily available and do not require expensive hand labelling. To facilitate learning I further focus on domains where texts are also abundant in anchors (pieces of information directly copied from the input knowledge base). In two such domains, medical reports and biographical descriptions, I have found aligned Text-Knowledge corpus for my learning task. While aligned Text-Knowledge corpora are relatively easy to find, they only provide indirect information about the selected or omitted status of each piece of knowledge and their relative placement. My methods, therefore, involve Indirect Supervised Learning (ISL), as my solution to this problem, a solution common to other learning from Text-Knowledge corpora problems in NLG. ISL has two steps; in the first step, the Text-Knowledge corpus is transformed into a dataset for supervised learning, in the form of *matched texts*. In the second step, supervised learning machinery acquires

the CS rules and schemata from this dataset. My main contribution is to define empirical metrics over rulesets or schemata based on the training material. These metrics enable learning Strategic Generation logic from positive examples only (where each example contains indirect evidence for the task).

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Acknowledgments

This thesis has been possible with the continuous support of many, many friends and colleagues. Sometimes just a word of encouragement, a smile in the corridor was all what it takes to keep the flow of effort through the days.

First and foremost, I would like to thank my family, in special my parents Ariel and Patricia, and my sister Carolina for their continuous support all through the years. I dedicate this thesis to them. To my extended family, in particular to Jaime, Mema, Victor, Ana, Vicky, Conri, Marina, Gusti, also my deepest thanks.

This thesis has been possible through the continuous guidance and support of my advisor, Prof. Dr. Kathleen R. McKeown. I have been blessed of having Kathy as my advisor. She is not only extremely knowledgeable in the subject matter of this dissertation, but I do believe she as also able to let out the best in each of her students. When Kathy speaks, she is the voice of the community speaking. Every time I had to change something in a paper following her advice, I find out later at conferences that her advice was well motivated. For all these years, thanks Kathy.

My thesis committee contained an unusual rainbow of skills that evaluated and contributed criticism to this thesis from different, varied perspectives. The committee chair, Prof. Dr. Julia Hirschberg has asked me some of the toughest research questions I have been asked in my life. Questions that kept me thinking for months. Questions for which I may spend years after having finished this thesis still looking for answers. I am most thankful to Julia for sharing her continuous scientific curiosity with me. My external committee members Prof. Dr. Dan Jurafsky and Dr. Owen Rambow both offered different perspectives over the subjects dealt in this dissertation. Dan made a many comments about the indirect supervised part. His comments helped me shape the problem in the way it is presented today. Owen was the other NLG person in the committee (aside from Kathy). I have admired Owen's work since my candidacy exam and it has been a pleasure to have him in my committee. Finally, Prof. Dr. Tony Jebara contributed his deep knowledge in Machine Learning in several, different ways. I have learned a lot from Tony, both in the technical aspects of Machine Learning and in the inter-personal issues related to communicating with researchers in that community. I just wish I have had started interacting with Tony earlier in this dissertation. The machine learning part would be definitely better.

Special thanks go for Smara, Michel and Tita. This thesis wouldn't be here without their continuous support through the years. Seriously. You know that very well. Thanks, thanks, thanks.

To my friends at the CU NLP Group: Michel Galley, Smaranda Muresan, Min-

Yen Kan, Noemie Elhadad, Sasha Blair-Goldensohn, Gabriel Illouz, Simone Teufel, Hong Yu, Nizar Habash, Elena Filatova, Ani Nenkova, Carl Sable, Dave Evans, Barry Schiffman, James Shaw, Shimei Pan, Hongyan Jing, Regina Barzilay, Judith Klavans, Owen Rambow, Vassielios Hatzivassiloglou, David Elson, Brian Whitman, Dragomir Radev, Melissa Holcombe, Greg Whalen, Rebecca Passonneau, Sameer Maskey, Aaron Harnly, John Chen, Peter Davis, Melania Degeratu, Jackson Liscombe and Eric Siegel. To the GENIES Team, in special to Andrey Rzhetsky. To the MAGIC Team, in special to Dr. Desmond Jordan. To the Columbia and Colorado AQUAINT team for creating the environment where half of this thesis flourished, in particular to James Martin, Wayne Ward and Sameer Pradham.

To my friends at the Computer Science Department: Amélie Marian (et Cyril!), Sinem Guven, Guarav Kc, Panos (Panagiotis Ipeirotis), Liz Chen, Kathy Dunn, Alpa Shah, Gautam Nair, Anurag Singla, Tian Tian Zhou, Blaine Bell, Rahul Swaminathan, Vanessa Frias, Maria Papadopouli, Phil Gross, Katherine Heller, Jennifer Estaris, Eugene Agichtein and Gabor Blasko thanks for their friendship and support. My deepest thanks to Martha Ruth Zadok, Anamika Singh, Twinkle Edwards, Remiko Moss and Patricia Hervey. To my officemates: Liu Yan, Lijun Tang, dajia xiexie. Special thanks to the professors Luis Gravano, David Sturman, Bernie Yee, Bill Noble, and Sal Stolfo. Finally, to to my former students Howard Chu, Yolanda Washington, Min San Tan Co, Ido Rosen and Mahshid Ehsani, from which I learned much than what they might learned from me, most certainly.

To the many friends at Columbia University that keep me away from screens and keyboards and let me regain some of my lost sanity. Special thanks to Fabi (Fabiola Brusciotti), Sato (Satoko Shimazaki), Cari (Carimer Ortiz), Al (Alberto Lopez-Toledo), Steve (Steven Ngalo), Sila Konur, Daniel Villela, Ana Belén Benítez Jiménez, Gerardo Hernández Del Valle, Victoria Dobrinova Tzotzkova, Raúl Rodríguez Esteban. Also to: Tarun Kapoor, Hui Cao, Tammy Hsiang, Maria Rusanda Muresan, Priya Sangameswaran, Shamim Ara Mollah, Ivan Iossifov, Su-Jean Hwang, Enhua Zhang, Kwan Tong, Barnali Choudhury, Manuel Jesus Reyes Gomez, Isabelle Sionniere.

To the CRF staff, specially Daisy, Mark and Dennis, for allowing me to terrorize their computer facilities and cleaning after my mess.

I would like also to thank also my friends in Argentina, for their many years of support. In particular, special thanks to Maximal (Maximiliano Chacón), Alvarus (Álvaro De La Rua), Juancho (Juan Lipari), Juanjo (Juan José Gana), Erne (Ernesto Cerrate) and El Unca (Nicolás Heredia), for standing my continuous rantings over non-issues and always receiving me with an open container of unspecified beverages. Also thanks to my friends Diego Pruneda, Martin Lobo, Victoria de Marchi, Paola Allamandri, Andrea

Molas, Carlos Abaca, Virginia Depiante, Dolores Table, Alejandra Villalba, Shunko Rojas, Eugenia Rivero, Andriana Quiroga, Clarita Ciuffoli, Maximiliano Oroná, Mariana Cerrate, Gustavo Gutierrez, Facundo Chacón, Paula Asis and Hernán Cohen for being my friends in spite of the distances.

To my friends at Fa.M.A.F.: Gabriel Infante López, Sergio Urinovksy, Nicolás Wolovick, Guillermo Delgadino, Tamara Rezk, Mirta Luján, Pedro Sánchez Terraf and Martin Dominguez, for making me feel I never left. To the professors Javier Blanco, Daniel Fridlender, Francisco Tamarit, Pedro D'Argenio and Oscar Bustos, for their friendship over the years. To my former students: Paula Estrella and Jimena Costa, may the luck of the draw with their next advisors be more favorable to them.

To my friends at UES21: Daniel Blank, Alejandra Jewsbury, Cristina Álamo and to my former students José Norte, Rolando Rizzardi, Federico Gomez, Liliana Novoa and Manuel Diomeda.

To my Argentinian friends in or around NYC: Matt (Matias Cuenca Acuña) and Cecilia Martinez for their continuous support even if I tend to disappear well too often, Alejandro Troccoli, Agus (Agustín Gravano), Quique (Sebastián Enrique), Nicolás Bruno, Guadalupe Cabido, Miguel Mosteiro, Paola Cyment, Marcelo Mydlarz, Tincho (Martín Petrella) and Nacho (Ignacio Miró).

To my Argentinian friends around the world: Patricia Scaraffia and Walter Suarez for being part of my extended family, Horacio Saggion, Fernando Cuchietti and Soledad Búcalo, Paula Sapone, Silvia Seiro, and family, Rainiero Rainoldi, and Alejandra González-Beltrán.

To Tita, Coco and Marina, for being my family away from home.

To my friends from the Association for Computational Linguistics: Anja Belz, Maria Lapata, Nikiforos Karamanis, Roger Evans, Michael White, Gideon Mann, Tomasz Marciniak, Roxana Girju, Maarika Traat, Francesca Carota, Stephen Wan, John Atkinson, Paul Piwek, David Reitter, Nicolas Nicolov, Karin Verspoor, Monica Rogati, Dan Melamed, Clare Voss, Roy Byrd, Srinivas Bangalore, Satoshi Sekine, Aggeliki Dimitromanolaki, Farah Benamara, Mila Ramos-Santacruz, Aline Villavicencio, Sonja Niessen, Rada Mihalcea, Ingrid Zukerman, Mona Diab, Rui Pedro Chaves, Nawal Nassr, Esther Sena, Sara Mendes. Many of you helped directly or indirectly to the completion of this dissertation. I look forward further collaboration in the years to come.

To my friends: Annie, Ellen, Xiao Ma, Raúl, Claudio, Sylvia, Marcos, Gimena, Bella, Grace. Maringela, Marylu, Flavia, Aparna, for being my friends in unusual circumstances.

For helping me go through this ordeal at different moments in my life: Lily, Kaming, Carolinita, Niina, Viara, Anushik, Jessica, Alba, Tiantian, Chihiro, Roxy, Keunyoung, Jael, Annie, Sepide, Ale, Patty, Vika, Patty, Luisa, and Cyd. My fondest memories are with each of you.

To my former suite-mates: Lillian, Yen, Majid, Stephen, Onur, Sakura, Miho, Susie, Ansel, Victoria, Arnaud, Gurol, Chihiro, Ramiro, Vikren, Heather, Muhammad, Veronica, Liz, and Melina. You guys taught me how to make the life in New York City a thrilling experience. May God brightens your path in life.

To my new colleagues at IBM: Jennifer Chu-Carroll, John Prager, Kryzsztof Czuba, Bill Murdock and Chris Welty, thanks for bearing the deposit frenzy. I look forward working with you. Also thanks to Glenny and Annie for a daily smile at the workplace (and pocky!).

A mis padres, Ariel y Patricia.

A mi hermana preferida, Carolina.

Chapter 1

Introduction

In a standard generation pipeline, any non-trivial multi-sentential/multi-paragraph generator will require a complex STRATEGIC COMPONENT,[1] responsible for the distribution of information among the different paragraphs, bulleted lists, and other textual elements. Information-rich inputs require drastic filtering, resulting in a small amount of the available data being conveyed in the output. Moreover, building a strategic component is normally tightly coupled with the semantics and this depends on the idiosyncrasies of each particular domain.

Traditionally, Strategic Generation is divided into two subtasks: CONTENT SELECTION, i.e., choosing the right bits of information to include in the final output, and DOCUMENT STRUCTURING, i.e., organizing the data in some sensible way. The overall goals of Strategic Generation are to produce text that is at the same time **coherent** (marked by an orderly, logical, and aesthetically consistent relation of parts; this measure relates to the structuring subtask), **concise** (expressing much in few words; this measure arguably relates to both subtasks, and it is not always a requirement) and **appropriate** (meant or adapted for an occasion or use; this measure relates to the selection subtask).

Figure 1.1, an example of the strategic generation task, shows the two main elements of input to a generation system: the input knowledge base (a set of facts, e.g., `ex-spouse(person-1, person-2)`) and the communicative goal (e.g., *"Who is Sean Connery,"*[2] or *"Convince the Hearer that Sean loves Micheline,"*[3]). The two example text excerpts differ at the content level (as opposed to differences at the word level, for example). Both of the aforementioned subtasks of the strategic component can

[1] Also known as content planner, e.g., (McKeown, 1985), macro planner, e.g., (Vander Linden, 1995) or text structurer, e.g., (Moore and Paris, 1988); in RAGS (Cahill et al., 2000) nomenclature, it includes the *Conceptual, Rhetorical,* and, to a certain extent, *Document* representation levels.

[2] INFORM(`person-1`).

[3] CONVINCE(H, `loves(person-1,person-3)`).

be seen in this example. The first text is not only wrongly structured, but also contains facts that are irrelevant for the given communicative goal (e.g., `eye-color`) while failing to mention important ones (e.g., `occupation`). In contrast, the second text presents a much more felicitous selection of content, in addition to linking the facts in a reasonable and natural way.

The example also illustrates some related concepts in the strategic generation literature. For instance, there is a **rhetorical relation** of CAUSE between the facts `award(person-1,oscar-1)` and `work(person-1,bond-1)`. The **cue phrase** *"because"* makes this relation explicit. The output of the Content Selection step is the **relevant knowledge pool** that in the example does not contain `eye-color`. The *document plan* is a sequence of **messages,** where each message is the instantiation of a **rhetorical predicate** using the input knowledge as arguments. In the example, `intro-person(..)` is a predicate with arguments `first-name`, `last-name`, `occupation`.[4] On the other hand, `intro-person(person-1)` is a message —verbalized as *"Sean Connery is an actor and a producer."*

The difficulty of the strategic generation task resides in the fact that, without prior knowledge, any ordering in a subset of the input is a possible *document plan*. Since the planner can select any number k of facts between 1 and n (in $\binom{k}{n}$ ways) and then reorder each such set in $k!$ ways, there are $\sum_{k=2}^{n} \frac{n!}{(n-k)!}$ possible plans. This large number of possibilities makes for a very challenging task, that needs to be approximated with strong domain heuristics.

These domain heuristics depend on the type of the target texts. Of particular importance to this dissertation are texts that exhibit a fixed structure that can be explained by tracking the evolution of discourse in a field over time, but can not be explained with the information the text contains nor with domain knowledge itself. That is the case, for example, in discourse reporting or summarizing factual information. In such cases, the extra knowledge required to structure documents in these domains has been named **Domain Communicative Knowledge** or DCK (Kittredge, Korelsky, and Rambow, 1991). In the medical domain, therefore, we can distinguish domain independent knowledge (e.g., people have diseases that can be treated with surgery), domain specific knowledge (e.g., a surgery patient needs to be anesthetized), from DCK (e.g., in medical reports about bypass surgeries, the anesthestetics information should start the description of the surgery, right after the description of the patient). It is clear that DCK helps reduce the large number of orderings that can be expected *a priori* to a manageable set of feasible possibilities.

Even though there are general tools and techniques to deal with surface realization

[4] Abbreviated `intro-person(person)` in the figure.

Communicative Goal:

Who is Sean Connery? INFORM(person-1)

Knowledge Base:

```
name-first(person-1,'Sean')          name-last(person-1,'Connery')
occupation(person-1,c-actor)         occupation(person-1,c-producer)
ex-spouse(person-1,person-2)         spouse(person-1,person-4)
name-first(person-2,'Diane')         name-last(person-2, 'Cilento')
occupation(person-2,c-actress)       name-first(person-4,'Micheline')
name-last(person-4,'Roquebrune')     relative(person-1,c-son,person-3)
occupation(person-4,c-painter)       relative(person-2,c-son,person-3)
name-first(person-3,'Jason')         name-last(person-3,'Connery')
work(person-1,bond-1)                title(bond-1,'James Bond')
work(person-1,movie-2)               title(movie-2,'operation warhead')
award(person-1,oscar-1)              title(oscar-1,'Oscar')
sub-title(oscar-1,'Best Actor')      reason(oscar-1,bond-1)
eye-color(person-1,c-green)          accent(person-1,c-scottish)
```

Compare:

- *Diane Cilento is the mother of Jason. The movie 'James Bond' received an Oscar. Micheline Roquebrune is the wife of Sean Connery and has green eyes. Jason Connery is son of Sean Connery. Diane Cilento is an* ***ex-wife*** *of Sean Connery. The movie 'James Bond' is starred by Sean Connery.*

- *Sean Connery is an actor and producer. He* ***married and later divorced*** *the actress Diane Cilento and they have a child, Jason. He also married Micheline Roquebrune, a painter. Because he starred in the movie 'James Bond', he received an Oscar for Best Actor.*

Document Plan (Message Sequence):

```
 [ intro-person(person-1), ] [ ex-spouse(person-1,person-2),
intro-person(person-2), spouse(person-1,person-3),
intro-person(person-3), ] [ child(person-1,person-4),
intro-person(person-4), ] [ movie(bond-1,person-1),
intro-award(oscar-1,person-1) ]
```

Possible Schema:

```
intro-person(self), |
(spouse(self,spouse), intro-person(spouse);
     { child(spouse,self,child), intro-person(child) } |
)*
(movie(self,movie), intro-movie(movie);
     { award(movie,self,award), intro-award(award,self)
} | )*
```

Figure 1.1: An example of a content planning task. A small knowledge base is given as input together with a communicative goal. Two example text excerpts are presented. The realization of the atom in bold is also shown in bold in the texts. Also shown: a *document plan* and a possible schema; both for the second text (discussed later in this chapter).

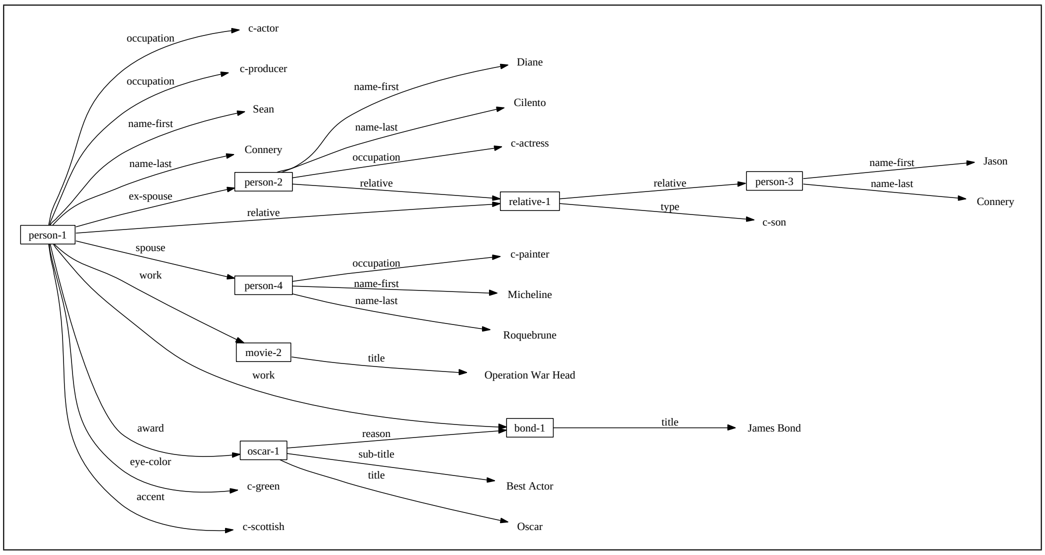


Figure 1.2: Graph Rendering of my Knowledge Representation.

(Elhadad and Robin, 1996; Lavoie and Rambow, 1997) and sentence planning (Shaw, 1998; Dalianis, 1999), the inherent dependency on each domain makes the Strategic Generation problem difficult to deal with in a unified framework. My thesis builds on machine learning in an effort to provide such a tool to deal with Strategic Generation in an unified framework; machine learning techniques can bring a general solution to problems that require customization for every particular instantiation.

The work described in this thesis investigates the automatic acquisition of Strategic Generation logic,[5] in the form of Content Selection rules and Document Structuring schemata, from an aligned Text-Knowledge corpus. A Text-Knowledge corpus is a paired collection of human-written texts and structured information (knowledge), similar to the knowledge base the generator will use to generate a text satisfying the same pragmatic (i.e., communicative) goals being conveyed in the human input text. For example, weather reports for specific dates may be paired with weather prediction data for each of those dates. The construction of such corpora is normal practice during the knowledge acquisition process for the building of NLG systems (Reiter, Robertson, and Osman, 2000). These corpora are increasingly popular in learning for NLG because they are readily available and do not require expensive hand labelling. However, they only provide indirect information about whether each piece of knowledge should be selected or omitted or the actual document structure. Indirect Supervised Learning (ISL) is my pro-

[5] Here the term ‘logic’ is used in the sense of control logic, as an operational variant of the term ‘acquired knowledge.’

posed solution to this problem. ISL has two steps; in the first step, the Text-Knowledge corpus is transformed into *matched texts*, an intermediate structure indicating where in the text each piece of knowledge is appearing (if it appears at all). From the *matched texts*, a training dataset of selected/omitted classification labels or *document plans* can be read out, accordingly. In the second step, Content Selection rules or Document Structuring schemata are learned in a supervised way, from the training dataset constructed in the previous step.

My thesis, therefore, receives as input the **natural datasets** for its learning task, in the form of text and knowledge. Such input is natural for this task, in the sense that this is the same material humans will use to acquire the Strategic Generation logic themselves. This is the type of information a knowledge engineer may use, together with other knowledge sources, to build a Strategic Generation component for a NLG system.

The rest of this chapter will address the definition of my problem in the next section, present my research hypothesis (Section 1.2), summarize my methods (Section 1.3), enumerate my contributions (Section 1.4), and introduce the domains (medical reports, biographical descriptions) where this research is grounded. An overview of each chapter concludes this introduction.

1.1 Problem Definition

My problem is the learning of control logic for particular implementations of the first two modules in a generation system. The acquired logic has to be appropriate to solve the Strategic Generation problem in isolation and within existing NLG systems. I describe the integration of my technique in existing NLG systems first, by examining my assumed NLG architecture, and then go deeper into the internals of the logic being sought.

1.1.1 Assumed NLG Architecture

As I am automatically acquiring the knowledge necessary for two internal processes inside a NLG system, the assumed architecture of the system is of great importance. I need to consider an architecture abstract enough to allow for a broad range of applications of the rules and schemata but grounded enough to be executable.

I expect the input data to be provided in a frame-based knowledge representation formalism. Each frame is a table of attribute-value pairs. Each attribute is unique, but it is possible to have lists as values. As such, the values can be either atomic or list-based. The atomic values I use in my work are NUMERIC (either integer or float); SYMBOLIC (or unquoted string); STRING (or quoted string); and frame references (a distinguished symbolic value, containing the name of another frame in the frameset).[6] The list-based types are lists of atomic values. Each frame has a unique name and a distinguished **TYPE** feature. This feature has a symbolic filler that can be linked to an ontology, if provided.

Because my knowledge representation allows for cycles, the actual knowledge representation can be seen as a directed graph: each frame is represented as a node and there are edges labeled with the attribute names joining the different nodes. Atomic values are also represented as special nodes. From this standpoint, the knowledge base of Figure 1.1 is just a factual rendering of the underlying representation. The actual knowledge base would be as shown in Figure 1.2.

Figure 1.3 shows my assumed two-stage NLG architecture. The Strategic Component is divided into the two modules I am learning. The figure also highlights the interaction between Strategic Generation and both aggregation and lexicalization in the Tactical Component, as they pose challenges to my learning system. The aggregation module will take a list of aggregation chunks (each containing a number of messages) and produce as output a list of sentences (each sentence containing one or more messages). The lexicalization module changes messages into words; it encompasses referring expressions, lexicalization and surface realization. Therefore, aggregation and lexicalization will re-order messages locally; when observing text as evidence of *document plans* the original ordering will be distorted. I will now discuss Content Selection and Document Structuring as they are the focus of this dissertation.

1.1.2 Content Selection Rules

The Content Selection module takes the full knowledge base as input and produces a projection (a subset) as output. This module should also consider the communicative goal when building the output subset. The output of the Content Selection module has been termed the **relevant knowledge pool** (McKeown, 1985), **viewpoints** (Acker and Porter, 1994) or **generic structure potential** (Bateman and Teich, 1995).

A possible implementation of a Content Selection module uses rules to decide whether or not to include a piece of information. This decision is based solely on the semantics of the data (e.g., the relation of the information to other data in the input). These rules take as input a node in the knowledge representation graph and execute a predicate on it ($f : node \rightarrow \{T, F\}$).

The decision of whether to include a given piece of data is done solely on the given data (no text is available during generation, as the generation process is creating

[6] A STRING is a regular English phrase (e.g., "*Gone with the wind*") while a SYMBOLIC field is either a reference to another frame (e.g., `place-of-study-22`) or a value linked to an ontology (e.g., `c-tv-or-radio-anchor`).

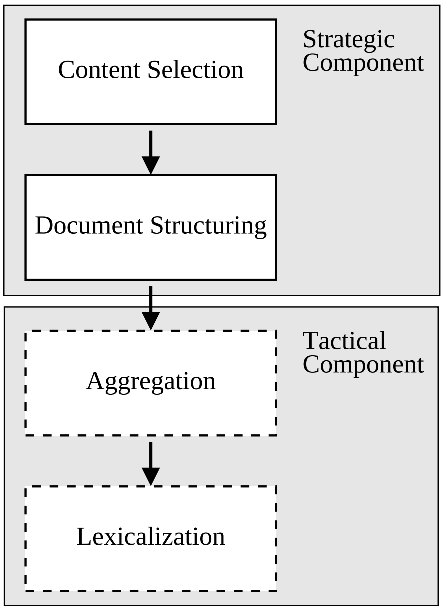


Figure 1.3: Assumed NLG architecture. The Strategic Component is divided into two models, the focus for learning. I have some mild assumptions about the Tactical Component, but they are not a requirement for my techniques. The Lexicalization component subsumes a Surface Realization component, together with a Lexical Chooser and Referring Expression generator.

⟨`person name-first`⟩ (-, -, -). ;SELECT-ALL
Always say the first name of the person being described.

⟨`person eye-color`⟩: (false, -, -). ;SELECT-NONE
Never say the eye color of the person being described.

⟨`person award title`⟩: (value $\in$ {*"Oscar"*, *"Golden Globe"*}, -,-).
Only mention the name of an award if it is whether a Golden Globe or an Oscar.

⟨`person work title`⟩: (-,⟨`-title -reason title`⟩,value $\in$ {*"Oscar"*}).
Only mention the title of a movie if the movie received an Oscar or a Golden Globe.

Figure 1.4: Example Content Selection rules.

the output text).[7] The current node and all surrounding information are useful to decide whether or not to include a piece of data. For example, to decide whether or not to include the name of a movie, whether the movie was the reason behind an award (and the award itself) may be of use. Such a situation can be addressed with the rules defined below.

While I experimented with a number of rule languages, I will describe here the **tri-partite** rule language, a solution that exhibits the right degree of simplicity and expressive power to capture my training material in the biographical profiles domain. Other domains may require a more complex rule language but, in practice, the tri-partite rules are quite expressive and very amenable for learning.

Tri-partite rules select a given node given constraints on the node itself and a second node, at the end of a path rooted on the current node. For the constraints on nodes, I have used two particular type of constraints: whether or not the value of the node belongs to a particular set (e.g., *value* $\in$ {*"Oscar"*, *"Golden Globe"*}) or a special (TRUE) constraint that always selects the item for inclusion (the absence of any rule that selects a node is equivalent to a FALSE rule). Again, more complex constraints are possible, but these types of constraints are easily learnable. Some example rules are detailed in Figure 1.4.

1.1.3 Document Structuring Schemata

A schema is a particular solution to the Document Structuring task, a task that takes as input a subset of the knowledge base (the relevant knowledge pool) and returns a se-

[7] This is obviously a simplification as pragmatics and the user model will also play a role.

```
predicate Education
  variables
     person            :  c-person
     education-event   :  c-education-event
  properties
    education-event ≡ person.education
  output
```

$$\left[\begin{array}{ll} \text{pred} & \texttt{education} \\ \textit{pred}_0 & \texttt{person} \\ \textit{pred}_1 & \texttt{education-event}\rightarrow\texttt{teaching-agent} \\ \textit{pred}_2 & \texttt{education-event}\rightarrow\texttt{subject-matter} \\ \text{mods} & \left[\begin{array}{ll} \text{time} & \left[\begin{array}{ll} \text{start} & \texttt{education-event}\rightarrow\texttt{date-start} \\ \text{end} & \texttt{education-event}\rightarrow\texttt{date-end} \end{array}\right] \\ \text{place} & \texttt{education-event}\rightarrow\texttt{place} \\ \text{reason} & \texttt{education-event}\rightarrow\texttt{reason} \end{array}\right] \end{array}\right]$$

Figure 1.5: Example of a communicative predicate in the biographical descriptions domain. This predicate uses a person and an education event frames such that the education event is among the person's education events (`education-event` ≡ `person.education`). The generated output accesses fields in the education event to fill the output frame, e.g., the subject matter being studied (`education-event`→`subject-matter`).

quence of messages (a *document plan*). These messages are produced by communicative predicates (Figure 1.5) composed of three items: variables, properties and output. Each variable has a type, which further constrains the possible values it can take. The actual number and nature of these predicates varies from domain to domain. A predicate can be considered as a function that takes a number of defined (and maybe undefined) variables and searches the knowledge representation for values of the undefined variables that satisfy the constraints inside the predicate. If none are found (or if the provided variables do not satisfy the constraints), the predicate cannot be instantiated. For each set of values[8] that satisfy its constraints, the predicate produces a **message** (Figure 1.6), a data structure assembled using the variable assignment found during the search. The messages are the nexus between the schema and the rest of the NLG system. A predicate, therefore, can be thought of in this context as a blueprint for making messages.

Given a set of predicates, a schema (shown in Chapter 5, Figure 5.3) is a finite

[8] The predicate returns only one message, if several sets of variable assignments satisfy the constraints, they will be iterated upon invocations of the predicate,when the iteration process is finished —the set of variable assignments is exhausted— the predicate fails to instantiate.

$$\begin{bmatrix} \text{pred} & \texttt{education} \\ \textit{pred}_0 & \texttt{person-32} \\ \textit{pred}_1 & \texttt{"Columbia University"} \\ \textit{pred}_2 & \texttt{"Computer Science"} \\ \text{mods} & \begin{bmatrix} \text{time} & \begin{bmatrix} \text{start} & \texttt{"1999/8/27"} \\ \text{end} & \texttt{"2005/1/17"} \end{bmatrix} \\ \text{place} & \texttt{"New York, NY"} \end{bmatrix} \end{bmatrix}$$

Figure 1.6: Example of an instantiated predicate (message). These messages are later grouped by the aggregation component and verbalized by the lexicalization component.

state machine over the language of predicates with variable references. At each step during schema instantiation, a current node is kept and all the predicates in the edges departing from the current node are instantiated. A focus mechanism will then select the next node (and add the message to the *document plan*). The instantiation process finishes when no new predicate can be instantiated departing from the current node. While the schema itself is simple (an automaton with predicate and variable names on its edges), the instantiation process presents some complexities. Interestingly, my schema induction algorithm is independent of the instantiation process or its internal details. However, this complexity forbids using existing learning techniques for finite state machines to learn the schemata.

Schemata are explained in detail in Chapter 2 (McKeown's original definition, Section 2.2.1) and Chapter 5 (my schemata implementation, Section 5.1).

1.2 Research Hypothesis

My research hypothesis is three-fold. First, I share McKeown (1983)'s original research hypothesis that the text structure is usually different from the knowledge structure.[9] I refer to the structure of the knowledge as *domain orderings*, such as time or space. This type of information controls some of the placement of information in the text, e.g., news articles about a certain event enumerate some events chronologically (Barzilay, Elhadad, and McKeown, 2001). However, these orderings cannot be expected *a priori* for every domain and, in general, text structure is not governed by them.

Second, as this dissertation focuses on learning schemata, my main hypothesis is centered on the feasibility of automatically constructing schemata from indirect obser-

[9] That is, the need for Domain Communicative Knowledge.

vations, using shallow methods. Indirect observations refer to learning schemata from positive examples, contained in a Text-Knowledge corpus. I have this corpus *instead* of a fully supervised training material (in the form of *document plans* or sequences of predicates). Text has a linear structure, defined by the fact that words come one after another. Even though exact word placement is misleading (as it interacts with aggregation and lexicalization), I can match text and knowledge and migrate the text linear structure to the knowledge. In that sense, my hypothesis implies that shallow text analysis methods can be used to acquire Domain Communicative Knowledge (cf. Section 2.2, Chapter 2) for schema construction. That is, to gain information about the domain behavior in general, via Indirect Supervised Learning as described in the next section. This level of analysis lets me gain information about the behavior of the domain in general, but not necessarily solve an understanding task for each particular text.

Finally, part of my research hypothesis is that schemata are useful as a learning representation. Their simplicity, a fact that has been criticized in the literature (Zock, 1986; Hovy, 1993), make them a prime candidate for learning. Moreover, the fact they are learnable should shed more light on their empirical importance (already highlighted by the number of deployed NLG systems employing them (Paris, 1987; Maybury, 1988; Bateman and Teich, 1995; Lester and Porter, 1997; Milosavljevic, 1999)).[10]

1.3 Methods

The input to my learning system is thus knowledge and text. For the task of learning Strategic Generation logic, this is a supervised setting; the learning system is presented with the input to Strategic Generation (knowledge) and text that is determined from the output of the strategic generation component (relevant knowledge and *document plans*). As the text is not the output of the Strategic Generation component, but something that can be derived **from** the output of the strategic component, my solution to this problem is Indirect Supervised Learning, which I explain at length in Chapter 3, Section 3.2.

As mentioned in Section 1.1, the output of the Strategic Generation component is defined as follows: the relevant knowledge pool is a subset of the knowledge base, which I assume is a frame-based knowledge representation. The *document plan* is a sequence of messages (rhetorical predicates instantiated from the relevant knowledge pool), segmented into paragraphs and aggregation sets.[11]

To obtain the relevant knowledge pool and the *document plan*, I build without human intervention an intermediate structure, the *matched text*, by using assumptions on

[10] This hypothesis was only partially validated, see the limitations chapter (Chapter 8).

[11] I did not address this segmentation problem in this thesis.

how knowledge can be verbalized within the text. These *matched texts* are built without any examples of actual *matched texts* (unsupervised learning). For example, the first sentence of the biography in Figure 1.1 will produce the following *matched text*[12] when matched against the knowledge base shown in the figure:

`name-first(person-1,'Sean')` `name-last(person-1,'Connery')` is an
`occupation(person-1,c-actor)` and a `occupation(person-1,c-producer)`

With the *matched text* in hand, it is easy to see which knowledge has been selected for inclusion in the text: any piece of knowledge matched to a text segment is thus assumed to be selected by the human author for inclusion in the text. Having now a task (Content Selection) with training input (KB) and output (KB plus selection labels) pairs, this comprises a well defined learning problem, where Content Selection rules can be learned.

Continuing with the example, let's suppose we have two biographies:

- *Sean Connery is an actor and a producer. He received an Oscar for Best Actor for his acting in the movie 'James Bond'.*
- *Sean Connery is an actor and a producer. He married and later divorced the actress Diane Cilento with whom he had a child, Jason. He also married Micheline Roquebrune, a painter.*

The first biography is a *business-style* biography, while the second one is a *family-style* biography. For each style, the *matched text* provides labels for each fact in the knowledge base. These labels (selected or omitted) are shown in Figure 1.7 for the *business-style* biography.

To choose among the different possible rulesets (e.g., ruleset $\mathscr{R}_1$ and ruleset $\mathscr{R}_2$), I look at the information retrieval task of retrieving the labels (selected, omitted) for each piece of knowledge in the input knowledge base. The F^*-measure from information retrieval (van Rijsbergen, 1979) of this retrieval task can be used as a likelihood for each ruleset. The supervised learning step becomes searching for the ruleset that maximizes this likelihood. Therefore, if the F^*-measure of the labels obtained by applying $\mathscr{R}_1$ to the training set is greater than the F^*-measure of applying $\mathscr{R}_2$, then $\mathscr{R}_1$ should be preferred over $\mathscr{R}_2$.

[12] This is a different representation of the *matched texts* as used thorough this thesis. Here the chunk of text matched is replaced with the knowledge representation matched against it. This representation is used here just to illustrate my methods.

sel	**name-first(person-1,’Sean’)**
sel	**name-last(person-1,’Connery’)**
sel	**occupation(person-1,c-actor)**
sel	**occupation(person-1,c-producer)**
¬*sel*	ex-spouse(person-1,person-2)
¬*sel*	spouse(person-1,person-4)
¬*sel*	name-first(person-2,’Diane’)
¬*sel*	name-last(person-2, ’Cilento’)
¬*sel*	occupation(person-2,c-actress)
¬*sel*	name-first(person-4,’Micheline’)
¬*sel*	name-last(person-4,’Roquebrune)
¬*sel*	occupation(person-4,c-painter)
¬*sel*	relative(person-1,c-son,person-3)
¬*sel*	relative(person-2,c-son,person-3)
¬*sel*	name-first(person-3,’Jason’)
¬*sel*	name-last(person-3,’Connery’)
sel	**work(person-1,bond-1)**
sel	**title(bond-1,’James Bond’)**
sel	**award(person-1,oscar-1)**
sel	**title(oscar-1,’Oscar’)**
sel	**sub-title(oscar-1,’Best Actor’)**
sel	**reason(oscar-1,bond-1)**
¬*sel*	eye-color(person-1,c-green)
¬*sel*	accent(person-1,c-british)

Figure 1.7: A knowledge base showing items that should be selected (*sel*) or should be omitted (¬*sel*). Selected items are also marked in bold, for emphasis. When constructing a *matched text*, these items are linked to bracketed segments inside the text (the brackets resembling named entity tags).

The *matched text* also provides input and output for learning schemata: the input to a schemata-based strategic component is the relevant knowledge pool, extracted in the previous Content Selection step. The output of the schema, the *document plan*, can not directly be extracted from the *matched text*, but the sequence of matched pieces of knowledge can approximate the messages.

That is, the sequence of pieces of knowledge (facts) extracted for the *matched text* of the biography shown in Figure 1.1 will read as follows:

```
[ name-first(person-1) name-last(person-1) occupation(person-1)
occupation(person-1) ] [ ex-spouse(person-1) name-first(person-2)
name-last(person-2,) occupation(person-2) relative(person-2)
name-first(person-3) ] [ spouse(person-1) name-first(person-4)
name-last(person-4) occupation(person-4) ] [ work(person-1)
title(bond-1) reason(oscar-1) award(person-1) title(oscar-1)
sub-title(oscar-1) ]
```

Compare this to the *document plan* shown in Figure 1.1. As *document plans* are at the predicate level, I mine patterns over the placement of atomic pieces of knowledge in the knowledge sequence extracted from the text (in the example above, I find that ⟨`name-first`, `name-last`, `occupation`⟩ is a recurring pattern), mine order constraints over them and use the constraints to evaluate the quality of *document plans* from possible schemata. Finally, to compare sequences of atomic pieces of knowledge to predicates, I defined a dynamic programming-based metric, explained in Chapter 5, Section 5.4.2.

Given a set of relevant knowledge pool–*document plan* pairs, I define the likelihood of a schema by summing up three terms:

- F* of the associated knowledge retrieval task (on-line content selection): disregarding the ordering, see which percentage of the right information appears in the output.
- Number of order constraints the output of the schema satisfies: measures local ordering.
- Alignment distance between the output of the schema and the target sequence of atomic values: measures global ordering.

As with Content Selection, defining means to tell good schemata from bad ones renders the learning problem an optimization one.

1.3.1 Technical Approach

On technical grounds, Figure 1.8 shows a generalized graphical model[13] for my system. There, my observed input (knowledge base) and output (text) are marked in black. The mapping I am interested in learning is “knowledge base” to “relevant knowledge pool” and “relevant knowledge pool” to *document plan*.

Indirect Supervised Learning involves an unsupervised step, based on assumptions on the structure of the model, to elucidate the hidden variables and supervised steps to generalize from the constructed mapping.[14] The assumptions on the model I use are related to the ways knowledge can appear on the text. More specifically, I see the knowledge as a collection of atomic items (the concepts), and I see the text as a collection of phrases. The relation between phrases and concepts is given by a verbalization function $\mathscr{D}$ from concepts to sets of phrases (possible verbalizations). The model I use for the unsupervised part is summarized by the following two tests, where H_0 is the null hypothesis, p and c are particular phrases and concepts, $\mathscr{P}$ is the set of phrases that make a particular text, $\mathscr{C}$ is the set of concepts that make a particular knowledge representation (where $\mathscr{C}$ and $\mathscr{P}$ refer to the same entity) and $\mathscr{D}$ is the verbalization dictionary:

$$\begin{array}{lrl} H_0: & P(p \in \mathscr{P} | c \in \mathscr{C}) = p_0 = P(p \in \mathscr{P}) & \text{if } p \notin \mathscr{D}(c) \\ H_1: & P(p \in \mathscr{P} | c \in \mathscr{C}) = p_1 \gg p_2 = P(p \in \mathscr{P}) & \text{if } p \in \mathscr{D}(c) \end{array}$$

Here, H_0 says that if a given phrase p is not a verbalization of a given concept c, then knowing that c holds will not change the chances of p appearing in the text. On the contrary, H_1 says that is p is a verbalization for c, knowing that c holds makes it much more likely for p to appear in the text.

Supervised Learning. As the experiments in Chapter 3 will attest, the *matched text* construction process is able to identify in an automatic fashion training material with an F^*-measure as high as 0.70 and as low as 0.53. These results imply that learning using the *matched texts* as training material will require a robust machine learning methodology. I will now mention some features common to the supervised learning algorithms presented in Chapter 4 and Chapter 5. Both Content Selection rules and Document Structuring schemata are symbolic and highly structured in nature. In both cases, I have input and output pairs (I,O) to learn them, extracted from the *matched text*. I am interested in finding the object o^* (belonging to the set of all possible Content Selection rules or

[13] The arcs are not stochastic.

[14] The overall process is an instance of supervised learning —therefore the name, ‘indirect *supervised* learning.’ However, no examples of the hidden variable are available to the learner and the mapping between the training data and the hidden variable is non-trivial. This mapping is done in an unsupervised fashion, per the model described here.

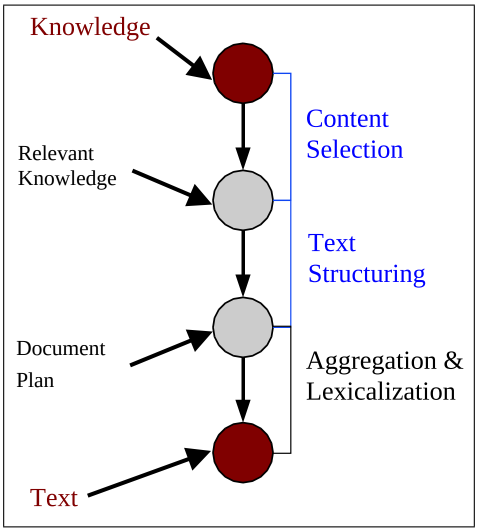


Figure 1.8: Learning Architecture.

Document Structuring schemata, in either case) such that o^* maximizes the posterior probability given the training material:

$$o^* = \underset{o}{argmax} P(o|I,O)$$

Here, instead of computing the probability $P(o|I,O)$, I use the input/output pairs to compute for each putative object o a likelihood $f(o,I,O)$. This likelihood will also allow me to compare among the different o and it is thus a quality function in the representation space. In both cases, I use a similarly defined function: employ the rules or the schemata to generate from the input I a set of outputs O'. The sought quality function becomes the distance between the training output and the produced output, $||O-O'||$, for suitable distances.

Given the quality function, finding o implies a search process on the large space of representations. Several algorithms can be of use here (e.g., A^*, hill-climbing or simulated annealing). However, given the highly structured nature of my representations, I have found it valuable to define a successor instance coming from **two** instances in the search pool, instead of one. This type of approach is known as Genetic Algorithms (GAs). In general, I consider GAs as a meaningful way to perform symbolic learning with statistical methods.

System Architecture. The process described above is sketched in Figure 1.9, using the thresholds and parameters[15] described in Table 1.1. The Text and Knowledge corpus is

[15] See Chapter 8, Section 8.1, for further details on these parameters.

fed into a *matched text* construction process, described in Chapter 3. This process will employ the model with a minimum score on the t-values (thr_t) for concepts that appear in at least thr_{supp} documents. Once some matches have been identified, a disambiguation process using w words around each match will be spanned.

From the *matched text*, a Content Selection dataset will be used to learn Content Selection rules (presented in Chapter 4). This process is centered about a GA with a population of $population_{size}$. This initial population is built using a bread-first search until depth $depth$ in the knowledge graph. The fitness function will weight precision and recall using a weight of α.

Also from the *matched text*, sequences of semantic labels are extracted and used to learn Order Constraints (Chapter 5). For this process, only patterns that appear in a $supportthreshold$ sequences are further considered. The mined constraints are only considered if their associated probability is above thr_{oc}.

Finally, the Content Selection dataset, the Order Constraints, sequences of atomic values extracted from the *matched text* and rhetorical predicates are all used to learn schemata (Chapter 5). A population of $population^{(2)}_{size}$ is used to learn schemata with a maximum of n_v variables per type.

1.4 Contributions

This thesis puts forward contributions at three levels. First, it contributes by devising, implementing and testing a system for the automatic construction of training material for learning Content Selection and Document Structuring logic. The technique described in Chapter 3 is able to process hundreds of text and knowledge pairs and produce Content Selection training material with quality as high as 74% precision and 67% recall. The Document Structuring material (orderings) it produces is also highly correlated to hand annotated material. This *matched texts* construction process emphasizes the use of structured knowledge as a replacement for manual tagging. The Text-Knowledge corpus in the biographies domain assembled as part of this thesis is now a valuable resource, available for further research in the area, together with the machinery to obtain new training material in a number of domains discussed in Chapter 9. The evaluation methodology employed in this thesis is also a contribution: using a number of human written texts for evaluation, dividing them into training and test set and using the test set to evaluate **both** the unsupervised as well as the supervised steps. Alternative approaches will require larger amounts of human-annotated data or will leave the unsupervised part without proper evaluation.

Second, among my contributions are also the proposal and study of techniques

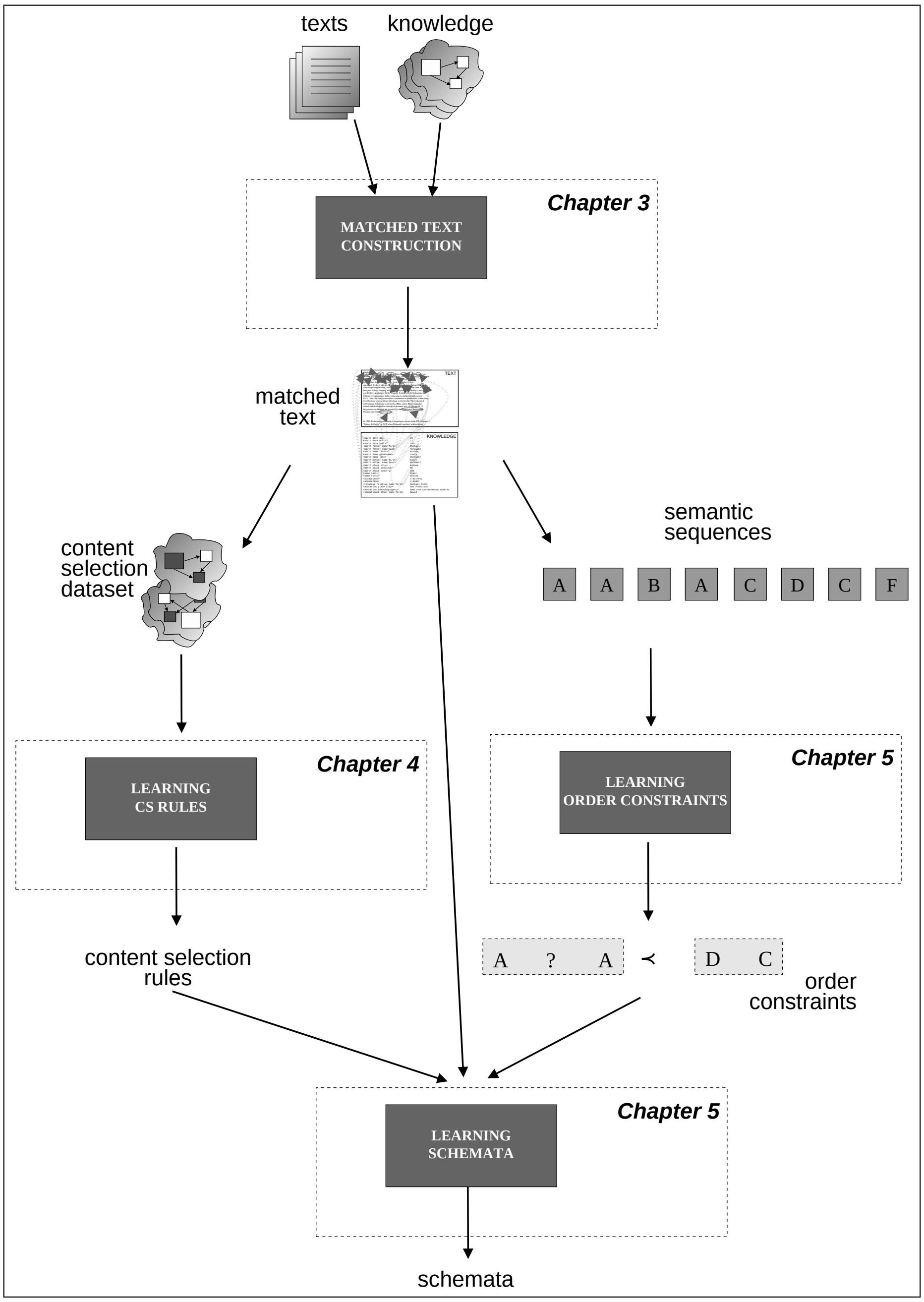


Figure 1.9: System Architecture.

Threshold	Description	Value
Chapter 3		
thr_t	t-test cut-point	9.9
thr_{add}	Percentage of the available number of matches to run the on-line dictionary induction.	20%
thr_{top}	Number of top scoring matches to add in each step (computed as a percentage of the total number of matches).	10%
w	Disambiguation window, in words.	3
thr_{supp}	Concept support, in percentage of the total number of instances.	20%
Chapter 4		
$population_{size}$	Size of the population in the genetic search for Content Selection rules.	1000
$depth$	Depth cut-off for the breath-first search building the population for the rule search.	6
α	F-measure weighting.	2.0
l	Saturation area of the *MDL* sigmoid function.	0.99
Chapter 5		
support threshold	Minimum number of sequences a pattern should match to be further considered (this threshold is expressed as percentage of the total number of sequences).	30%
thr_{oc}	Probability threshold for a given order constraint to be further considered.	0.98
n_v	Number of variables per type.	2
windowsize	How many items are used to build a pattern.	8
relative distance threshold	Clustering parameter when mining order constraints.	0.1
probability cut-point	Minimum probability for accepting a learned constraint.	0.99

Table 1.1: Thresholds and Parameters used in this Thesis.

to learn Content Selection logic from a training material consisting of structured knowledge and selection labels. As the training material is automatically obtained, it contains a high degree of noise. Here, my contribution includes techniques that are robust enough to learn in spite of this noise. I set the problem as a rule optimization of the F^*-measure over the training material. My techniques have elucidated Content Selection rules in four different styles in the biographies domain. Moreover, my experiments in Content Selection contribute to our understanding of the Content Selection phenomenon at several levels. First, it separates nicely the need for off-line (high-level) Content Selection from on-line Content Selection, where the approach described in this thesis could potentially be used to learn Content Selection logic at **both** levels.[16] From a broader perspective, my acquired Content Selection rules provide an empirical metric for *interestingness* of given facts.

Finally, I defined the problem of learning Document Structuring schemata from indirect observations, proposing, implementing and evaluating two different, yet similar techniques in two different domains. The Document Structuring problem is one of the most complex problems in NLG. My techniques are among the first efforts to effectively learn Document Structuring solutions automatically. At a fine grained level of detail, my main contribution is a dynamic-programming metric that compares sequences of values (that can be read out from text) to sequences of messages (that are produced by the schemata). The acquired schemata are written in a declarative formalism, another contribution of this thesis. Previous implementations of schemata had mixed declarative/procedural definitions that impose a high burden for any learning technique.

1.5 Domains

I discuss now my experimental domains (Medical Reports and Person Descriptions). These domains were central to research projects I have been involved with. Other potential domains are discussed in Section 9.3, including Biology, Financial Markets, Geographic Information Systems, and Role Playing Games.

1.5.1 Medical Domain: MAGIC

MAGIC (Dalal et al., 1996; McKeown et al., 2000) is a system designed to produce a briefing of patient status after the patient undergoes a coronary bypass operation. Currently, when a patient is brought to the intensive care unit (ICU) after surgery, one of the residents who was present in the operating room gives a briefing to the ICU nurses and

[16] I did not conduct experiments targeting the validation of this claim.

Input Knowledge

```
(patient-info-12865, c-patient, (a-age,
age-12865), (a-name, name-12865), (a-gender,
gender-12865), (a-procedure, procedure-12865),
(a-birth-date, ...), ...)
(age-12865, c-measurement, (a-value, 58),
(a-unit, "year"))
(gender-12865, c-male)
(ht-12865, c-measurement, (a-value, 175),
(a-unitm "centimeter"))
(name-12865, c-name, (a-first-name, "John"),
(a-last-name, "Doe"))
(procedure-12865, c-procedure, (a-value,
"mitral valve replacement"))

...
```

MAGIC output

John Doe is a 58 year-old male patient of Dr. Smith undergoing mitral valve repair. His weight is 92 kilograms and his height 175 centimeters. Drips in protocol concentrations include Dobutamine, Nitroglycerine and Levophed. He received 1000 mg of Vancomycin and . . .

Figure 1.10: MAGIC domain example (the data excerpt maps to the highlighted text).

residents. The generation system uses data collected from the machine in the operating room to generate such a presentation, avoiding distracting a caregiver at a time when they are critically needed for patient care.

Figure 1.10 shows an example of a data excerpt (a data file in the CLASSIC formalism with 127 facts on average) and presentation. Several of the resident briefings were collected and annotated for a past evaluation. Each transcription was subsequently annotated with semantic tags as shown in Figure 6.2, on page 127.

1.5.2 Person Descriptions: AQUAINT Q&A

As part of the Question Answering project (AQUAINT) taking place jointly at Columbia University and University of Colorado, I have developed PROGENIE, a system that generates biographic descriptions of persons, taking as input information gathered from the WWW. The biographical descriptions domain is central, as it has available larger amounts of data compared to the medical domain. Because of this data availability, I only pursued Content Selection experiments in this domain.

For these experiments, fact-sheet pages and other structured data sources provide the input knowledge base (Duboue and McKeown, 2003b). The texts are the biographies written by professional writers or volunteers, depending on the corpus. Figure 1.11 exemplifies an aligned pair.

This domain is very rich, allowing me to gather multiple biographies for each person I have independently obtained knowledge. Such multi-aligned corpus had also proven useful for mining verbalization templates (Barzilay and Lee, 2002).

Input Knowledge

```
fact(person42,name,’Sean Connery’).
fact(person42,birthname,’Thomas Sean Connery’).
fact(person42,birthdate,month(’August’),day(’25’),
year(’1930’)).
fact(person42,birthplace,’Edinburgh,
Scotland’).
fact(person42,education,’Dropped out of school
at age 13’).
fact(person42,family,Mother,name(’Euphamia
Connery’)).
fact(person42,family,Brother,name(’Neil’)).
fact(person42,family,Son,name(’Jason Joseph
Connery’)).
fact(person42, occupation, "actor").
fact(person42, occupation, "director").
fact(person42, occupation, "model").
fact(person42, occupation, "producer").

...
```

Human-written Text

Actor, born Thomas Connery on August 25, 1930, in Fountainbridge, Edinburgh, Scotland, the son of a truck driver and charwoman. He has a **brother, Neil**, born in 1938. Connery dropped out of school at age fifteen to join the British Navy. Connery is best known for his portrayal of the suave, sophisticated British spy, James Bond, in the 1960s. . . .

Figure 1.11: Biographies domain example (the data excerpt maps to the highlighted text).

1.6 Structure of this Dissertation

This dissertation is divided into the following chapters.

Chapter 2. Relation between this thesis and previous research. The research in Strategic Generation is quite vast, so the focus of the chapter is in document structuring via schemata (although key RST-based papers are also discussed). Other learning approaches in NLG are also discussed.

Chapter 3. Learning approach, focusing on the unsupervised part. The construction of the *matched texts* is the focus of this chapter. It presents the foundation for learning Content Selection rules and Document Structuring schemata. Its experimental results are in the biographical profiles generation.

Chapter 4. Supervised learning of Content Selection rules. This includes a discussion of the rules themselves and different methods to acquire them automatically. Meaningful baselines for comparison are also discussed. It also contains experimental results in the biographies domain.

Chapter 5. Supervised learning of Document Structuring schemata. A new, declarative, version of McKeown (1985) schemata is introduced and its automatic construction through an adaptation of existing methods to learn finite state machines is presented.

Chapter 6. Preliminary Document Structuring experiments performed in medical domain. They show the feasibility of the technique in a different domain.

Chapter 7. Document Structuring experiments in biographical profile generation.

Chapter 8. Limitations of the approach. A succinct description of some limitations I have identified throughout the thesis.

Chapter 9. Conclusions and some possible extensions.

Chapter 2

Related Work

In this chapter, I discuss related work in Strategic Generation and learning in NLG. These topics are very broad; I have decided to focus on a small number of highly relevant papers. I first analyze related work in Content Selection (Section 2.1), in particular, the work on the ILEX (Cox, O'Donnell, and Oberlander, 1999; O'Donnell et al., 2001) and STOP (Reiter et al., 1997) projects. Afterwards, I introduce the Document Structuring task together with schemata and RST, its two most widespread document structuring solutions. I then relate my work to other recent learning efforts in NLG in Section 2.3. To conclude this chapter, I present related work in a number of assorted areas, including the relation between the strategic component and other modules of the NLG pipeline, planning diverse media, summarization and biography generation.

2.1 Related Work in Content Selection

Content Selection, the task of choosing the right information to communicate in the output of a NLG system, has been argued to be the most important task from a user's standpoint; users may tolerate errors in wording, as long as the information being sought is present in the text (Sripada et al., 2001). This task has different levels of complexity, with solutions requiring a full inferential engine in certain cases (Zukerman, Korb, and McConarchy, 1996).

I will present here one of the most recent Content Selection algorithms in the literature, developed as part of the ILEX project and compare it to my two level Content Selection approach. In Section 2.1.2, I will summarize the knowledge acquisition process that the researchers in the STOP project pursued to build their Content Selection module. I will also compare that human acquisition with my the automated one described in Chapter 4. Some remarks regarding integrated or separated Content Selection close this section.

2.1.1 ILEX Content Selection Algorithm

One of the most well-regarded integrated Content Selection algorithms proposed in the literature is the one used in the ILEX project (Cox, O'Donnell, and Oberlander, 1999; O'Donnell et al., 2001), a generation system that provides dynamic labels for exhibits in a Web-based museum gallery. ILEX tries to improve current static (fully pre-written) Web pages by means of Dynamic Hypertext (Dale et al., 1998), the marriage of NLG and hypertext systems. In Dynamic Hypertext, a generator will produce not only text that lives in the nodes of a hyper-linked environment, but also the links between these nodes.

In the ILEX Content Selection algorithm, each tuple coming from a relational database is transformed into an **object** definition where each of the entries in the object must be declared in a **predicate** definition (Figure 2.1). These definitions contain, among other things, a simplified user model composed of three items: **interest** (how appealing is this fact to the user, static), **importance** (contribution of the fact for an overall task, also static) and **assimilation** (level of acquaintance to the fact, dynamically updated). These numbers are hardwired in the predicate definition.

Their algorithm computes a *relevant knowledge pool* with an innovative relevancy metric. They follow the same line of work presented by McKeown (1985) Content Selection (pages 113–121, "Selection of relevant knowledge"), that is, to take the object being described and the entities directly reachable in the *Content Potential*, a graph with objects as nodes. ILEX also collects all entities relevant to the entity being described, with an innovative spreading-activation relevancy metric. In this metric, the relevancy of an object is given by the mathematical combination of the static importance of the object and the relevancy of the object in the path to the object being described. Their relevance calculation allows them to prioritize the top *n* most salient items, while maintaining coherence. Different links preserve relevance in different ways. ILEX authors assigned for each class of links hand-picked relevancy multipliers.

The ILEX Content Selection algorithm is complementary to my approach. For instance, my algorithm could be used to provide ILEX **interest** scores, an appealing topic for further work.

2.1.2 STOP Content Selection Knowledge Acquisition

Reiter et al. (1997)'s work addresses the rarely studied problem of knowledge acquisition for Content Selection in generation. Knowledge acquisition is used for STOP, a

```
(def-predicate Designer
     :Arg1 jewellery
     :Arg2 person
     :importance ((expert 10) (default 1) (child 3))
     :interest ((expert 10) (default 6) (child 6))
     :assimilation ((expert 0) (default 0) (child 0))
     :assim-rate ((expert 1) (default 1) (child 1))
     :expression ( :verb design-verb   :tense past   :voice
passive)
     :comparison ( :variation (string 1)   :scale nominal))
```

Figure 2.1: Definition of an ILEX predicate, (O'Donnell et al., 2001), page 11.

NLG system that generates letters encouraging people to stop smoking. STOP's input is a questionnaire, filled out by a smoker; STOP uses the questionnaire to produce a personalized letter encouraging the smoker to quit. Reiter et al. explored four different knowledge acquisition techniques: directly asking experts for knowledge, creating and analyzing a corpus, structured group discussions and think aloud sessions. I detail each of them below.

The first technique they employed was to directly inquire domain experts for Content Selection knowledge, given that STOP was a multidisciplinary project with motivated experts within reach of the NLG team. This technique proved unsuccessful, as experts would usually provide "textbook style" responses (academic knowledge). Such knowledge differs very much from their actual knowledge as practitioners.

Their next effort focused on creating a small Text-Knowledge corpora (what they call a *conventional* corpus). They collected 11 questionnaire-letter pairs, with letters written by five different experts. Problems arised when comparing letters written by different doctors; the difference in style, length and content make this corpus very difficult to use.

Their final two methods were borrowed from the Knowledge Engineering literature (Buchanan and Wilkins, 1993) and proved to be very useful (structured group discussions and think-aloud sessions).

This research is relevant to my Content Selection work (presented in Chapter 4) where I propose automated mining of Content Selection rules from a Text-Knowledge corpus similar to the one Reiter et al. collected. Interestingly enough, they found the corpus approach insufficient. I find these possible explanations to their problem:

Size of the corpus. Text production has many variables, the natural variability among normally occurring text will make 11 pairs very likely to diverge noticeably just by chance.

Lack of a well defined task. It is possible that, in an effort to avoid biasing the corpus collection effort, the experts were given little or no instructions about the letter cessation writing task. High variability in collected data is usually a signal of this type of problem.

Lack of expertise in the task. The experts in their work were medical experts, but not necessarily smoke cessation letters experts.

Excessive number of experts. As 11 pairs is too small to come up with a model for a single expert, using more experts rendered the whole task unsurmountable (as they concluded).

These problems are not present in my biographies work (neither in a number of domains that I have identified as suitable for application of my technique), where I have found hundreds of biography-knowledge pairs, written by professional biographers that have to adhere to a writing style.

2.1.3 Separated vs. Integrated Content Selection

While most classical approaches (Moore and Swartout, 1991; Moore and Paris, 1993) tend to perform the Content Selection task integrated with the Document Structuring, there seems to exist some momentum in the literature for a two-level Content Selection process (Lester and Porter, 1997; Sripada et al., 2001; Bontcheva and Wilks, 2001). For instance, Lester and Porter (1997) distinguish two levels of content determination: **local** content determination is the *"selection of relatively small knowledge structures, each of which will be used to generate one or two sentences,"* while **global** content determination is *"the process of deciding which of these structures to include in an explanation."* Global content determination makes use of the concept of *viewpoints*, introduced by Acker and Porter (1994), which allow the generation process to be somewhat detached from the knowledge base (KB). My Content Selection rules, then, can be thought of as picking the global Content Selection items.

In the same vein, Bontcheva and Wilks (2001) use a Content Selection algorithm that operates at early stages of the generation process, allowing for further refinement down the pipeline. They present it as an example of techniques to overcome the identified problems in pipelined architectures for generation (they call this a *recursive pipeline architecture,* similar to Reiter (2000)).

Most recently, the interest in automatic, bottom-up content planners has put forth a simplified view where the information is **entirely** selected before the document structuring process begins (Marcu, 1997; Karamanis and Manurung, 2002; Dimitromanolaki and Androutsopoulos, 2003). While this approach is less flexible, it has important ramifications for machine learning, as the resulting algorithm can be made simpler and more amenable to learning. Nevertheless, two-level Content Selection can provide a broad restriction of the information to consider, with more fine grained, hand-built algorithms applied later on to select information in context or with length restrictions.

My work is in the schema tradition, with a two level Content Selection. The first, global level is performed with Content Selection rules and the second level is within the Document Structuring schema.

2.2 Document Structuring

I will now address some generalities to the Document Structuring problem; namely, its output and overall algorithms employed, before introducing schemata and RST-based planners, the two most widely deployed solutions.

The output of the Document Structuring is a *document plan*, normally a tree or a sequence of messages. The relations between these messages usually are rhetorical in nature and employed later on to divide the discourse into textual units, such as paragraphs or bulleted lists (Bouayad-Agha, Power, and Scott, 2000) and sentences (Shaw, 2001; Cheng and Mellish, 2000). Most systems use trees as *document plans*; the RAGS consensus architecture (Cahill et al., 2000) defines the `Rhetoric` representation level as a tree. Sequences, on the other hand, are more restricted than trees, but for several applications present enough expressive power. Examples include the works of Huang (1994) and Mellish et al. (1998). Sequences are important for my work as schemata, as defined originally by McKeown (1985), use sequences as *document plans* (when employed without schemata recursion). Moreover, even if trees have more momentum as *document plans* in the literature, several incompatibility results (Marcu, Carlson, and Watanabe, 2000; Bouayad-Agha, Power, and Scott, 2000), may suggest otherwise. The use of trees seem forced in some cases, for example Mann and Thompson (1988) claim that the rhetorical structure ought to be a tree in *most of the texts.* However, their JOINT rhetorical relation seems to be just an *ad hoc* procedure to keep a tree from becoming a forest (Rambow, 1999). Finally, Danlos, Gaiffe, and Roussarie (2001) analyze cases where trees are not expressive enough. Their solution is to employ equational systems (actually directed acyclic graphs or DAGs) that increase expressivity by reusing rhetorical nodes.

The algorithm normally involves a search on the space of possible *document plans*. That is the case of Schemata-based, RST-based or opportunistic planners, which I discuss later in this section. However, several Document Structuring problems in the literature have been solved with no search, as in a good number of cases, *planning* is just a label for a stage solved by other means, as pointed out by Rambow (1999). Complex planning process examples include Huang (1994), working on automatic verbalization of the output of theorem provers and Ansari and Hirst (1998), working on generating instructional texts. In general, full planning is the most comprehensive solution to the document structuring problem, although it is expensive and requires modeling complex issues such as the intentional status of both hearer and speaker, and the full consequences of all actions that may not be necessary (or even feasible) in all domains of interest to NLG practitioners.

Another question being asked by previous research is the direction of the building of the plan. Normally, speed and ease of understanding motivates building top-down planners, e.g., Young and Moore (1994), which uses the Longbow AI planner (Young, 1996). However, other authors, for example Marcu (1997), see the whole planning process as a linking among facts by means of input-given RST-relations, an approach that is indeed bottom-up (I discuss opportunistic planners in Section 2.2.2). A hybrid approach is taken by Huang (1994), which combines a top-down (planned) approach with a bottom-up opportunistic perspective based on centering.

Several other approaches have been investigated. Besides the approaches I discuss later in this section, Power (2000) poses the problem as a constraint satisfaction and uses CSP techniques (Jaffar and Lassez, 1986) to solve it. Knott et al. (1997) make a stand for the use of defeasible rules as a tool for planning coherent and concise texts. Wolz (1990) models the problems by having different AI-plans compete with each other to come out with a final decision (another mechanism for doing CSP). In my work, I learned schemata from data (a bottom-up approach), where the schemata are a type of planner that involves a local search during instantiation (top-down skeleton planners, as discussed by Lim (1992)).

Traditionally, Strategic Generation problems have been addressed in NLG by means of two techniques: AI planners and Schemata. Reasoning can derive the text structure in some cases. In a scenario (Figure 2.2) borrowed from the work of Rambow (1999), a reasoning process [1] can derive the text shown in the figure, using, for example,

[1] Such as, *"I say S*1 *to accomplish* (3) *but in virtue of* (4), *I want to say S*2 *because it will accomplish it by means of* (5)," and so on.

operators derived from rhetorical relations (Section 2.2.2). Reasoning-based Strategic Generation focuses on domains where the structure can be fully deduced from the input data and the intentions of the speaker.

Not all text can be fully deduced from the input; some text has fixed structure coming from the domain. Even though I consider AI-style content planning a useful and interesting approach, many cases require special domain knowledge. For instance, if I know that an actor won three Oscars, was married twice and is 58 years old, common knowledge about biographies would dictate starting a biography with the age and occupation, leaving the rest of the information for later. Nothing intrinsic to age or awards specifies this ordering (it is not part of the domain knowledge itself). The text structure in formulaic domains presents very little intentional structure and is historically motivated; while its current form has logically evolved over time, there is no rationale behind it that can be used for planning. What is needed in such domains is domain knowledge related to its communicative aspects: Domain Communication Knowledge (DCK). DCK has been defined by Kittredge, Korelsky, and Rambow (1991) as:

> *(. . .) the means of relating domain knowledge to all aspects of verbal communication, including communicative goals and function. DCK is necessarily domain dependent. However, it is not the same as domain knowledge; it is not needed to reason about the domain, it is needed to communicate about the domain.*

This knowledge can be explicitly or implicitly represented in a strategic component, depending on the judgement of the authors and on its importance for the scenario at hand. In most cases it is left implicitly represented. A notable exception is the work of Huang (1994), which defines the notion of proof communicative act (PCAs).

What is happening behind the scenes is that three different structures can be mapped to the discourse: informative, intentional and focus. In certain domains, one structure dominates the production of texts and a formalism based on only one of them can be enough to structure the text. Rambow (1999) proposes an integrated approach to deal with DCK and other issues.

With respect to intention, Moore and Paris (1993) (also Hovy (1988)) present a discussion of how to represent the beliefs of the **Hearer** and the intentions of the **Speaker** in instructional dialogs. Also, the *degree* of belief may be important to model as in the works of Zukerman, Korb, and McConarchy (1996), Walker and Rambow (1994) and Rambow (1999). However, other approaches, e.g., Moore and Paris (1993) and Young and Moore (1994), prefer to consider belief as a binary (believe or disbelieve)

1. I know my interlocutor will believe in Sam’s word.
2. I know Sam saw John without shaving.
3. I want to convince my interlocutor that John overslept.
4. I know my interlocutor will not believe me directly.
5. I know my interlocutor knows that a man doesn’t shave when he oversleeps.

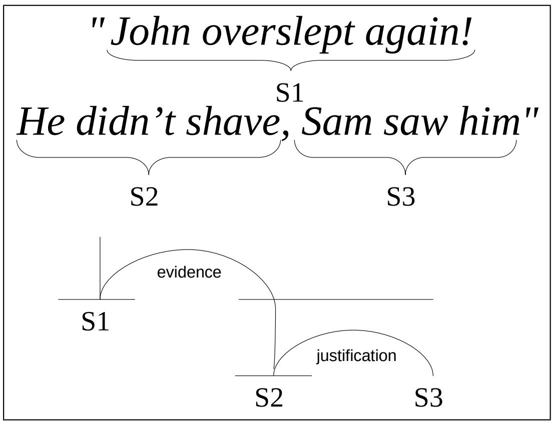


Figure 2.2: Example scenario and rhetorical tree.

datum. In my work, I do not represent nor use intentional structure, beyond the REPORT(FACT) type of intention, as part of simplifying assumptions to make Strategic Generation amenable for learning. An interesting area for future work is to incorporate intentional data coming from text by using current research in opinion identification (Zhou, Burgoon, and Twitchell, 2003; Yu and Hatzivassiloglou, 2003). The matched text can be enriched with opinion and opinion polarity labels by an automatic opinion/polarity tagger. My system can then use this extra information to theorize Content Selection rules that take into account the agent’s stance toward certain facts (that information will need to be modelled outside of the learning system, using traditional cognitive modelling).

I will turn now to schemata-based document structuring.

2.2.1 Schemata-based Document Structuring

In this section, I present McKeown’s original schemata, then discuss KNIGHT, MAGIC and other schema-like systems. McKeown’s schemata are grammars with terminals in a language of **rhetorical predicates**, discussed below. The four schemata identified by McKeown in her work are the **attributive,** (Figure 2.3) **identification, constituency,** and **compare and contrast** schemata. The schemata accept recursion, as some entries inside the schema definition can be fulfilled directly with predicates or by other schemata. They are not fully recursive as only four schemata are proposed and there are 23 predicates, although McKeown expressed her belief that the formalism can be possibly extended to full recursion.

Her predicates are important for my work as they contain a major operational part,

Attributive Schema

Attributive
{Amplification; Restriction}
Particular-illustration*
{Representative}
{Question; Problem; Answer} / {Comparison; Contrast; Adversative}
Amplification/Explanation/Inference/Comparison

Figure 2.3: An example McKeown original schema. The braces mean optionality, the slash separates alternatives, plus and star have their usual one (or zero) or more repetition meanings and the semicolon indicates propositions that cannot be clearly assigned to one predicate or another.

the search for associated knowledge. When the schema reaches a rhetorical predicate such as **attribute**, it fills it with required arguments, e.g., the entity the attribute belongs to. From there, the rhetorical predicate (actually a piece of Lisp code) will perform a search on the relevant knowledge pool for all possible attributes to the given entity. These instantiated predicates (*messages* in this dissertation) will be available for the schema-instantiation mechanism to choose (by virtue of her focus mechanism, explained below) and then build the *document plan.*

Schemata are then structure and predicates. My work focuses in learning the structure but not the predicates (I basically learn only part of the schemata, in a sense). Which predicates to use and how to define them is an important part of the schema that I thus assume to be part of the input to my learning system. This is a point of divergence with McKeown's schemata that used predicates rhetorical in nature. My predicates are domain dependent, what makes creating these predicates a process worth automating. As a step in that direction, I have been able to provide a declarative version of these predicates in a constraint satisfaction formalism (discussed in Chapter 5, Section 5.1).

To implement the schemata, McKeown employed Augmented Transition Networks (ATNs) an extensible declarative formalism where some of her requirements used these extensions. In her system, the rhetorical predicates are executed when traversing different arcs. Both the actions in the arcs and the conditions are arbitrary pieces of Lisp code. An example ATN (Figure 2.4) shows a fair degree of possibilities at each node (seen by the number of arcs leaving each state). One contribution from McKeown's work is to use focus to guide the local decision of which arc to traverse at each moment. I will discuss her focus mechanism now.

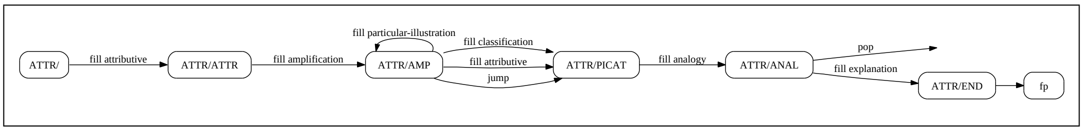


Figure 2.4: McKeown's Attributive Schema (ATN).

Focus

McKeown (1985) contains a full chapter ("Focusing in Discourse," pages 55–81) describing the importance of centering theory and proposing a motivated solution for discourse planning. She built on the works of both Grosz (global focus) and Sidner (local focus) to extend their interpretation theories with decision heuristics for generation. McKeown's work on focus is a major ingredient of her schemata and has been adapted for use in other generation systems (e.g., Paris (1987)'s TAILOR generator). However, few *schema-like* planners mentioned in the literature include this piece of the schema. I find that a major oversight of later followers of McKeown's work.

As pointed out by Kibble and Power (1999), research on focus in understanding is interested in discourse comprehension, mostly solving cases of anaphora, e.g., pronominalization. Most centering theories, therefore, provide tools to cut down the candidate search space for anaphora resolution. Nevertheless, the generation case is different, as these theories lack insights of how to choose among the set of candidates. Understanding does not require these decisions, as they have been taken by the human author in the text already. McKeown complemented centering theories with heuristics suitable for generation. For recent work on centering, Karamanis (2003) presents a learning approach to the problem.

McKeown presents heuristics for two decision problems involving focus. In the first problem, the system has to decide between continuing speaking about the current focus or switching to an entity in the previous potential focus list. Her heuristic in that case is to switch, otherwise the speaker will have to reintroduce the element of the potential focus list at a later point. The next decision arises when deciding whether to continue talking about the current focus or switching back to an item in the focus stack. Here her heuristic was to stick to the current focus, to avoid false implication of a finished topic.

This is, *grosso modo*, McKeown's treatment of focus. The details are more complex but I will skip them as I use McKeown's focus mechanism without any modifications. Her focus mechanism is important because my machine learning mechanism interacts with it and has to learn schemata in spite of the actual focus system.

KNIGHT Explanation Design Packages

Lester and Porter (1997) were interested in robust explanation systems for complex phenomena. When designing their Document Structuring module, they focused on two issues, **expressiveness** (the Document Structuring module should be able to perform its duties), and **Discourse-Knowledge Engineering** (DCK requires expertise to be acquired and represented, see Section 2.2, they were particularly interested in providing tools to support this vision). This last issue arise after working in an non-declarative Explanation Planning module for a period of time. As the module grew larger, adding new functionality or understanding existing ones became an issue as the actual logic was buried under lines and lines of Lisp code.

To solve this problem, Lester and Porter took the most declarative pieces of their approach and moved it to the knowledge representation system, creating the Explanation Design Packages (EDP). EDPs are trees represented as frames in a knowledge representation. The frames encapsulate a good deal of Lisp code, defining local variables, conditions over local and global variables, invoking KB accessors and arbitrary functions. They are as rich as a programming language.

When compared to schemata, it seems that Lester and Porter arrive at a similar solution coming from the opposite direction. McKeown analyzed a number of texts and background work in rhetorical predicates to hypothesize her schemata as a suitable representation of discourse that she later operationalized using ATNs. As ATNs are of a hybrid declarative/procedural nature, extensions can be coded in by means of extra Lisp code. Her schemata required using some of these extensions. McKeown, therefore, arrived at a hybrid declarative/procedural implementation starting from a fully declarative problem. Lester and Porter, on the other hand, started with a fully procedural implementation and further structured and simplified it until they arrived to their hybrid declarative/procedural EDPs.

True to their roots, EDPs have a more procedural flavor, but that does not avoid making a direct comparison with schemata. The frames in EDP correlate roughly to schemata's states. Note, however, that there are no cycles on the EDPs (as they are trees). The loops in the schemata are represented in EDP by an iteration mechanism. More interestingly, the KB accessor functions behave operationally exactly the same as McKeown's predicates. The major difference (and this may be the reason why Lester and Porter did not draw this parallelism) is that McKeown stressed the **rhetorical** nature of her predicates. KNIGHT predicates are not rhetorical, but domain dependent; this is an approach I follow in my work as well. Finally, both approaches allow plugging a sizeable amount of extra Lisp code into their formalisms. EDPs provide more places to do so, while the ATNs concentrated this in the arc transitions.

A key distinction is that, while schemata are skeleton-planners because they contain the skeleton of a plan but they perform a local search (driven by McKeown's focus mechanism) to arrive to the final plan (Lim, 1992), EDPs lack any type of search. Lester and Porter did not mention this fact on their work and it is clear they did not need such a mechanism for their robust generation approach.

EDPs expand schemata by providing a hierarchical organization of the text that is suitable for multi-paragraph texts. Moreover, they include a prioritization model that makes for a bare-bones user model (but does not compare to either the TAILOR (Paris, 1987) or ILEX (O'Donnell et al., 2001) treatment of the issue) and a number of well-defined non-rhetorical predicates for natural entities and processes. However, Lester and Porter followed a more procedural extension of the schemata, which makes them unsuitable for my learning approach.

Other Schema-like Planners

MAGIC. MAGIC took the topic tree approach of Lester and Porter and simplified it until it became fully declarative, with a high toll on its expressive power. Its schema is a tree with topic internal nodes and predicate-leaves. The internal nodes constitute the text organization and structure the output into two levels of chunking (paragraph chunks that contain aggregation chunks). The predicate-leaves fetch from the knowledge base all the values matching the predicate and insert the resulting messages into the output. This is the only iteration process in the MAGIC planner. By being encapsulated into the leaves, it spares the need of cycles as in TEXT or iterators and local variable definitions as in KNIGHT. The MAGIC planner is so simple that it is surprising that it works. A closer look may reveal MAGIC's secret: the repetition-at-the-leaves approach produces highly cohesive lists of related facts, realized in the form of enumerations, with the rest of the information shuffled around inside the aggregation chunks by the MAGIC complex aggregation component, one of the foci of the project. Interestingly enough, this representation was very amenable to my learning techniques (Chapter 5). The representation, however, seems only suitable for planning single-topic discourse (all discourse in MAGIC has the same focus —the patient the surgery was about).

Other schemata implementations. Plenty of other people used schemata, including the work in the TAILOR generator (Paris, 1987) that expands schemata with user model and trace-explanation systems, the work done by Maybury (1988) that attempts to add more rhetorical predicates, the work in the KOMET project (Bateman and Teich, 1995) that expands schemata for text and graphics, and the work in the Peba-II system, that

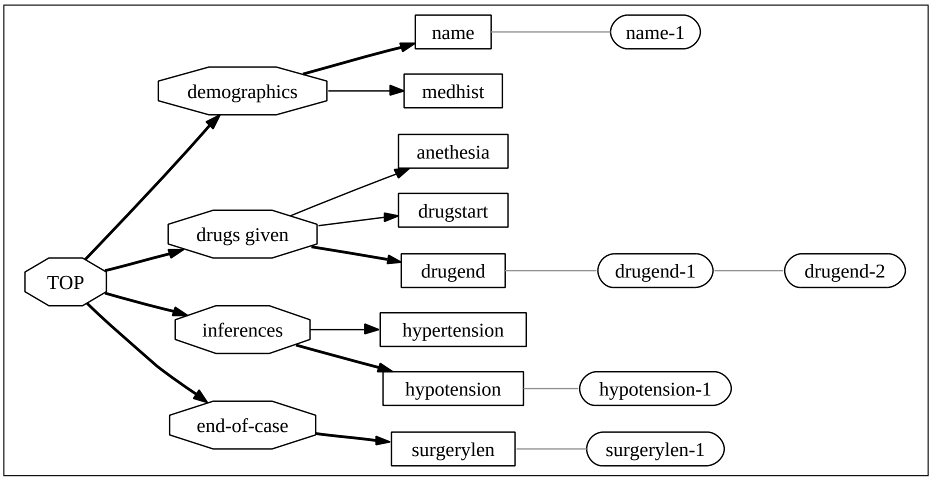


Figure 2.5: An example of MAGIC's schemata-like Document Structuring trees (left, straight edges nodes) and output (right, rounded nodes). The Document Structuring tree is instantiated for the four semantic units (`drugend-1, drugend-2, hypotension-1, name-1, surgerylen-1`). The resulting *document plan* has four leafs, five internal nodes and eight edges (shown in bold).

applies schemata to dynamic multimedia and comparisons (Milosavljevic, 1999). I detail my own declarative implementation of schemata in Chapter 5.

2.2.2 RST-based planning

Continuing with the idea already present in McKeown's work of consolidating and improving rhetorical relations defined previously in the literature, Mann and Thompson (1988) studied a number of texts in different genres and styles and formulated their Rhetorical Structure Theory (RST). RST states that every text has a unique rhetorical structure based on text spans where rhetorical relations hold. They add to the rhetorical treatment of McKeown two key ingredients: hierarchy and asymmetry. Now a text span can be subdivided into sub-relations and a super relation can hold over it. Schema recursion is supposed to capture this fact but McKeown did not investigate schema recursion much herself. Hierarchy is not the only key ingredient added to the picture by Mann and Thompson, as they also realize that a number (almost all) of the rhetorical relations they identified in texts were **asymmetrical**, in the sense that they contained two text spans, one of which (the **nucleus**) was central to the discussion and could not be removed, while the second span (the **satellite**) expands or complements the nucleus.

From their analysis, they propose 23 rhetorical relations, divided into two categories, presentational and informational. The distinction is made depending on whether they hold in the text by virtue of the text flow (presentational) or by virtue of the underlining truth of the given facts (informational). For example, a relation such as JUSTIFY will only hold depending on what has been said before and what we want to say now (that is, it depends on the information selected and how it is placed on the text, in the **intention** of the speaker), while a relation such as VOLITIONAL CAUSE holds statically between two facts in the knowledge base.

RST is a theory designed to capture the structure of texts in general, without particular ties to understanding or generation. Relative early success in understanding (Marcu, 2000) has run into problems defining a set of rhetorical relations (Marcu and Echihabi, 2002). Nowadays, the existence of rhetorical relations that hold between spans of text is an agreed fact and research focuses on the sizes of those spans and the number and nature of the relations. Regarding the size of the spans, Mann and Thompson (1988) work at the clause level but other researchers such as Stent (2000) use variable sizes from words to sentences. Regarding the number of the relations, Knott and Dale (1993) provide a bottom-up perspective on the number of relations issue, postulating that despite the actual relations taxonomy, it should in some way be reflected by the existence of related cue phrases. Marcu and Echihabi (2002) put this idea into practice, in their study using a very large corpus. Other approaches postulate a large number of relations, which Hovy and Maier (1995) organized in a taxonomy. Finally, there is the issue of whether or not the number of rhetorical relations is bounded. On the one hand, Rambow (1999) and Knott and Dale (1993) argue in favor of bounding their number as otherwise the theory will become unsound. On the other hand, Mann and Thompson (1988) and Hovy and Maier (1995) sacrifice soundness on behalf of a further reaching theory (on pragmatic grounds).

From the generation perspective, Hovy (1988) was the first to apply it for building a strategic component (Hovy, 1993). His approach involved reversing the direction of the RST relations defined by Mann and Thompson (so its observed effect is used as a precondition and its applicability constraints as post-conditions) and using them as operators in a planning process. While this approach enjoyed limited success, it has a number of drawbacks. Some problems between this planning approach and intentional structure have been discussed at length by Moore and Pollack (1992) (e.g., how intentional structure will be lost if only rhetorical structure is kept as the output of the planner, complicating follow-up reasoning over the generated text), but more relevant to my dissertation are the operational issues involved in a RST-based planner. Building a RST-based planner requires modelling carefully the intentions of both the speaker and the hearer (cognitive modelling), a problem in purely informative domains, where the only intentional structure that can be associated with the text is the simple REPORT(FACTS). Moreover, purely informative domains are prime candidates for using NLG techniques and therefore of practical importance. As pointed out by Lim (1992), a RST-planner requires additional guidance to be able to plan reasonable text in reasonable amounts of time. In that direction, my work can be adapted to acquire this domain-based information from a Text-Knowledge corpus.

Opportunistic Planning

Another avenue to incorporate rhetorical relations when planning purely informative texts is to rely solely on informative relations, precalculated on the semantic input (considered, therefore as an integrated part of the knowledge representation) and then search for a text that is able to incorporate as many of the rhetorical relations as possible (Marcu, 1997), together with other text structuring operators (Mellish et al., 1998) and most importantly, focus-based constraints (Karamanis and Manurung, 2002). That approach renders the document structuring an optimization process, a search for the text structure that maximizes an evaluation (objective) function. Interestingly enough, the techniques employed to solve this problem involve also genetic algorithms (in particular, Genetic Search (Michalewicz, 1992)). I also use genetic algorithms in my work. While Mellish et al. (1998)'s intention was to push stochastic search as a feasible method for **implementing** a document structurer, I pursue the automatic **construction** of the schema itself. My system, moreover, uses a corpus-based fitness function, while they use a rhetorically-motivated heuristic function with hand-tuned parameters.

Considering rhetorical relations as part of the input has the advantage of avoiding an explicit representation of the intentional state of the **Hearer**. In such settings, a trivial cognitive model, where every fact uttered by the speaker will be immediately assimilated and believed by the hearer, can be employed. While opportunistic planners succeed in incorporating rhetorical relations in their outputs, they seem to be limited to problems lacking any real use of the communicative power of the rhetorical structure. In contrast, most content planners, (Young and Moore, 1994) and architectures (Cahill et al., 2000) find the relations while structuring the document. By doing so, they can find relations that hold as a result of the structure (**presentational** relations). In my case, the input is the relevant knowledge pool, a subset of the KB in the frame-based Knowledge Representation described in Chapter 1, Section 1.1.1 and it contains no rhetorical information.

2.3 Related Work in Learning in NLG

In recent years, there has been a surge of interest in empirical methods applied to natural language generation (Columbia, 2001). One of the first applications of machine learning to NLG systems is a hybrid architecture trained on target text (example outputs) introduced by Knight and Hatzivassiloglou (1995). In this architecture, a first component over-generates a large number of possible solutions, and a second component chooses among them. The first component is quite simple and the second component is the one based on machine learning. For example, a symbolic engine may generate *his success as an actress* and *her success as an actress* but the probabilities in a corpus of related texts will choose the second (correct) output. My system is an example of an alternative architecture that is trained in input/output pairs, in the form of a Text and Knowledge corpus (besides the fact that my system works in learning for the Strategic Generation component and not the syntactic/realization component).

Text-Knowledge corpora, a traditional resource for knowledge acquisition in Natural Language Generation, are recently gaining momentum as a resource for Statistical NLG (Barzilay and Lee, 2002; Duboue and McKeown, 2002; Sripada et al., 2003; Barzilay, Reiter, and Siskind, 2003). They have been employed for learning elements at the strategic level (Duboue and McKeown, 2002; Duboue and McKeown, 2003a), for lexical choice (Barzilay and Lee, 2002; Sripada et al., 2003) and at other levels (Barzilay, Reiter, and Siskind, 2003; Ratnaparkhi, 2000).

Dimitromanolaki and Androutsopoulos (2003) worked also in machine learning applied to Document Structuring. Their training material consisted of sequences of atomic values, an ideal training set, as each atomic value was actually a message and thus the input of the document structurer was compatible with its output. In my case, in contrast, the input are facts and the output are messages assembled over those facts. Because each of these sequences was rather short (about six messages long), the following approach proved fruitful: they trained a cascade of classifiers to decide the exact (absolute) position that each pre-selected fact has to take in the output. It is unclear whether their approach will apply to other (more complex) settings. Absolute and relative positioning are quite similar in sequences of six elements, but in longer sequences, telling between the two allows for a better utilization of the training material. My mining of order constraints described in Chapter 5 is an example of relative orderings.

Shaw and Hatzivassiloglou (1999) work on the probabilistic ordering of premodifiers in complex NPs (e.g., *“a 35-year-old asthmatic male patient of Dr. Smith”*), a task also addressed by a number of authors (Cheng et al., 2001; Malouf, 2000; Poesio, Henschel, and Kibble, 1999). Because this type of ordering information is domain dependent, they designed an algorithm to acquire order constraints from a corpus. This algorithm is important for this thesis, as I have employed an adaptation of it for my Document Structuring work described in Chapter 5. Their algorithm starts by collecting a table of observed ordering behaviors. In this table, the entry at position i, j indicates the number of times in the corpus the object i came before the object j. From the table, they try to reject the null hypothesis that i, j came in any order (equivalent to saying that the probability of i coming before j is 0.5). The following formula will compute the probability of the observed frequencies:

$$\sum_{k=m}^{n} \binom{n}{k} \quad 0.5^n$$

where m is the total number of times i has been seen occurring before j in the corpus and n is total number of times i and j occur in a pair. That equation can be used with a threshold to select “likely enough” constraints or can be piped into more complex, smoothing techniques described at length by Shaw (2001).

NITROGEN (Langkilde and Knight, 1998) is the generation component in a Japanese-English machine translation system. They employ a **language model** like those used in speech recognition (an *n*-gram model, in this case a bigram model) and a symbolic module that uses a grammar to transform the input representation into an intermediate representation (a word lattice) that is scored by the language model. The word lattice has several drawbacks (Langkilde and Knight, 1998). Langkilde (Langkilde, 2000) moves away from the word lattice by replacing it with a packed forest on the same underlying model.

Varges and Mellish (Varges and Mellish, 2001; Varges, 2003) employ instance-based learning to build IGEN, a surface realizer with limited sentence planning capabilities, trained on input/output pairs. An interesting difference from NITROGEN is that the symbolic generator uses a semantic grammar extracted from training data (in an approach similar to Fergus (Bangalore and Rambow, 2000)). The sentence is chosen as a function of the sum of the cosine similarity to a set of instances, and the ratio of input semantic elements covered in the output sentence, a memory-based approach (a technique already employed in surface realization by Neumann (1997), in concept-to-speech by McKeown and Pan (1999) and recently in sentence planning by Pan and Shaw (2004)). Interestingly, his training material is very close to my *matched texts*, although Varges created them by hand.

A system completely trained on input/output pairs is Amalgam, a trainable generation module for Machine Translation, developed at Microsoft Research (Corston-Oliver et al., 2002).

At higher levels in the generation pipeline, SPoT (Walker, Rambow, and Rogati, 2002), a trainable sentence planner, uses a ranking process for the filtering. The ranking methodology is based on experiments that showed that it was easier to train the system based on human preferences than clear cut selection. Candidate sentence plans for a sequence of communicative goals are generated randomly. Then, the chooser component determines which of the candidates is most suitable. This chooser component has been trained by having human subjects rank candidates during the training phase; boosting is used to learn discriminative re-ranking rules. This system is trained on ranked outputs.

Barzilay and Lee (2002) work on the problem of inducing a generation lexicon. Such a lexicon provides words for parametric predicates, in the form of templates where the parameters from the predicate can be plugged in. As input they use data to be verbalized and a variety of human-written verbalizations for such data. This is a multi-aligned Text-Knowledge corpus.

All these systems receive symbolic representations as input, mixing seamlessly with my learned schemata (that contains symbolic representations in the predicates).

2.4 Related Work in Other Areas

I will discuss work in the related areas of summarization and dialog systems.

2.4.1 Related Work in Dialog Systems

Oh and Rudnicky (2000) work on NLG for dialog systems. In such systems *"NLG and TTS synthesis are the only component that users will experience directly. But with limited development resources, NLG has traditionally been overlooked by spoken dialog system developers."* They presented an *n*-gram based system that operates at different levels of the NLG pipeline. As their output is very small for the NLG tradition (one or two sentences), their work is an example of the power of *n*-grams when dealing with short output. While they claim their model to be grounded on Knight and Hatzivassiloglou (1995)'s model (the model later popularized by the NITROGEN generator), they have a major divergence from them, as their system is fully statistical and not hybrid. More important to this dissertation, they perform limited Content Selection by defining a task mixing Content Selection and lexical choice and solving it with statistics computed on text (outputs only). Their approach is very valuable but their simplified task only makes sense when the mapping from concepts to words is as direct as in the case of some dialog systems. In my case, the need for a verbalization dictionary makes more clear the need for training in both input and output pairs and therefore the need for inducing such dictionary if it is not available. At any rate, both approaches are comparable. A synergy between them is interesting for further work, if there is interest in applying my technique to dialog systems.

Also working in dialog systems, Young (2002) presented a theoretical fully trainable system “built” from published trainable components and models. While he does not address any Strategic Generation issues *per se* (dialog systems have very simplified generation needs, as discussed before), he arrives at the Knight and Hatzivassiloglou (1995) model coming from a fully statistical setting, as a corrective term to linearize concepts verbalized from the understanding probabilities. These coefficients are estimated on target texts (example outputs), following NITROGEN’s example. The only reason I can postulate for him not using input/output pairs to train the linearization component (e.g., as it is done in Amalgam (Corston-Oliver et al., 2002) for surface realization and in this thesis for Strategic Generation), is the fact that he based his model in published works, and at that time there were few or no work done on trainable systems on input/output pairs.

2.4.2 Related Work in Summarization

In summarization, the two subtasks of the strategic component in generation get mapped to the task of selecting which sentence or clauses to include in the output and how to order them. For the task of selecting sentences using machine learning approaches, most of the work on the field can be tracked back to the seminal work of Kupiec, Pedersen, and Chen (1995). There, they collected 188 summaries plus the original texts and aligned summary sentences to text (semi-automatic construction of the summarization equivalent of my *matched texts*). From there, they computed a number of features on the original texts (similar to my computation of structural features on the semantic representation) and used them to predict which sentences were more likely to be included in the output. While they were working in a text-to-text environment, both approaches are compatible. The main difference, besides the novel use of shallow knowledge in my work, is that summarization works with a fixed output size as an argument to the task while in my generation task the output size is unconstrained, but has to mimic exactly the information selected in the target texts (that is, some biographies contain one paragraph, while others contains three paragraphs, just because there are more things worth telling about the latter person; the key is not including irrelevant facts).

After the work of Kupiec and colleagues, effort has concentrated on evaluation (Van Halteren and Teufel, 2003; Nenkova and Passonneau, 2004), feature consolidation (Radev et al., 2002), improving the matching between text summary and text source (Jing and McKeown, 1999; Daumé III and Marcu, 2004) or better theoretical frameworks (Filatova and Hatzivassiloglou, 2004). The overall relation between my Content Selection work and summarization is an issue I am particularly interested in following up in further work.

With respect to sentence ordering, this constitutes very little problem in single document summarization, where the order in which the sentences appear in the document normally constitutes a reasonable and appropriate ordering, although there are some exceptions (Jing and McKeown, 2000). The situation changes when confronted with a number of sentences coming from different documents. Barzilay, Elhadad, and McKeown (2002) investigated this problem of re-ordering clusters of sentences (which they call *themes*) for multi-document summarization. They performed a number of experiments with human subjects before proposing a bottom-up algorithm, based on chronological ordering and topical structure. Their first experiment validated the importance of re-ordering and found out that *"if reordering is not, in general, helpful, there is only a 7% chance that doing reordering anyway would produce a result that is different in quality from the original ordering."* That speaks of the importance of ordering for the summarization task. They then compared two naïve algorithms, Chronological Ordering, which presents each theme at the earliest of its publication time and Majority Ordering, that presents each theme according to the relative position in the original texts of most sentences (as possible). For the majority ordering, they employed the greedy approximation proposed by Cohen, Schapire, and Singer (1999). Their experiments showed both strategies to be unsatisfactory so they went on to perform experiments at a larger scale to elucidate the impact of ordering according to human judges. In one experiment, they found out that '*"there are many acceptable orderings given one set of sentences."* This reinforces my using a **population** of schemata as in my GA-based algorithm in Chapter 5, as opposed to finding the one and only best schemata (as in, for example, hill climbing). On the other hand, from 40,320 possible orderings, 50 subjects produced only 21, speaking of a small number of acceptable solutions.

They collected a corpus of ordering preferences among subjects and used them to estimate a preferred ordering. They found out that there is a certain stability on clusters of objects (a phenomenon that re-inforces my use of pattern detection algorithms to preprocess the sequences) and modeled that stability with a coherence constraint that ensures that blocks of sentences on the same topic tend to occur together. This technique results in a bottom-up approach for ordering that opportunistically groups sentences together based on content features. In contrast, my work attempts to automatically learn schemata for generation based on semantic types of the input clause, resulting in a top-down planner for selecting and ordering content. While the learning approach is also bottom-up, the schemata learned are top-down, resulting in efficient execution times.

Kan and McKeown (2002) presented work on sentence reordering trained in a corpus annotated with semantic predicates. The main contribution was to compare different decay functions for modelling the context in an environment where majority orderings were built by search. My approach differs from Kan in two key aspects: first, I have developed techniques to automatically annotate training material, using a Text-Knowledge corpus. The knowledge is used to replace the human annotation. From these, instead of collecting statistics over the training and using them at runtime to order the facts (what I call the "on-line" approach), I use the corpus (sometimes also collecting statistics) to build a schema that will order the facts at runtime more efficiently (the "off-line" approach). My approach, therefore, has the advantage of using structured knowledge instead of hand labelled data and of providing a more efficient and easier to understand document structurer.

A later approach also employed a Markov assumption for text structuring (Lapata, 2003). Lapata's system used a number of computable features (including syntactic and lexical features) to collect statistics of which sentence may follow a previous one. Working only with the previous sentence (i.e., using a very short memory in the Markov process), a necessary constraint to obtain meaningful statistics, she obtained very promising results that speak very well of her election of features. My approach, in contrast, tries to obtain a global (top-down) text structurer from a rich training set (the Text-Knowledge corpus). Her system, however, can be trained directly on text and might be more independent of particular domains.

Very recently, Barzilay and Lee (2004) proposed and evaluated a method for constructing HMM-based content models from text. Their system constructs topical models of text while also constructing models of the ordering between these topics. Their system has never been applied to NLG tasks, but it will require the full verbalization of the text to do so (as it only orders text and not concepts). In a similar situation, Reiter (2000) found such an approach to be very inefficient. Moreover, for their technique to work in NLG, the concepts should be verbalized in a way that is compatible with the training text. For example, if the training text said *"X was born on DATE"*, their system may find the word *"born"* as a strong marker of a topic but if the NLG system decides to verbalize this concept as *"(DATE)"* then the word *"born"* will not appear there to signal it. Compare this with my approach in Chapter 3 where I induce the verbalization dictionary from a Text-Knowledge corpus. Barzilay and Lee's algorithm is also a highly efficient method for sentence selection. Theirs is a method to incorporate the position of the sentences in the text to be summarized as a sentence selection criteria. Such an approach can not be applied easily to knowledge selection, as the knowledge to be selected ("summarized") appears unordered in the knowledge representation. Besides the inherent differences on working with or without a knowledge representation, my technique targets planners that work with smaller spans of text (as small as a single word), allow for cycles and that are very efficient planners and easy to understand by humans. In summary, they present a new solution fully trained in unannotated text with a number of results for summarization. Their approach seems very appealing for NLG and more research in that direction must prove fruitful.

2.4.3 Related Work in Assorted Areas

Requirements on the output of the strategic component. The decisions taken at the planner level may relate issues at levels lower than the actual *document plans*. Two items worth mentioning in this regard are the location inside the generation pipeline where the *connectives* (e.g., cue phrases like *'but'* or *'however'*) should be defined and whether or not the particularities in the realization of given phrases (active/passive, to-inf/gerund) should be synchronized with rhetorical decisions. Dealing with instructional text, Vander Linden (1992) provides a very detailed analysis of the issues concerning the election of syntactical forms given a communicative context. The authors identify different factors, including pragmatic, semantic and user-related constraints, that affect this choice. For example, for the CAUSE relation, the order between nucleus and satellite depends upon whether the consequence is intended or not. Rambow (1999) introduces a framework that allows the content planner to synthesize decisions at different levels of abstractions. Bouayad-Agha, Power, and Scott (2000) analyze possible incompatibilities between the text structure (i.e., paragraphs and sections) and the rhetorical structure. With respect to sentence planning, Shaw (2001) expects the strategic component to provide a *document plan* segmented into aggregation chunks. Information inside each aggregation chunk can be reshuffled by his aggregation component.

Related Work in Artificial Intelligence. The AI Planning community (Minton, 1993) focuses its learning efforts in acquiring information that allows speeding up the control of the planner, e.g., ordering between the rules to speed up the planner or to arrive greedily to a good local solution. My techniques also provide as output skeleton planners with very efficient runtime. Also within AI, Muslea (1997) presents a Genetic Programming (Koza, 1994) based planner. The plans being learned are competitive with the state of the art in AI planning, with impressive running times.

Multimedia/Multilingual/Layout. When planning different type of content, textual and non-textual information can be planned together. There is interest in reusing the results of the planning process across content types, as it impacts the economics of the generation process. In particular, the layout affects the communicative process, and different languages affect the structuring of the message. Dale, Milosavljevic, and Oberlander (1997) try to approach the building of interactive websites with an NLG dialog perspective, with mixed results. Kamps et al. (2001) provide a very comprehensive study of the relation between graphical disposition of textual and non-textual elements on the page, and show that it is possible to plan layout and content altogether. Stent (2000) adapts RST to model dialogs. Marcu, Carlson, and Watanabe (2000) show a negative result on the sharing of rhetorical trees between English and Japanese. Other multilingual generation papers include the work of Rösner and Stede (1992). Bouayad-Agha, Power, and Scott (2000) show another incompatibility result, now between rhetorical structure and text structure. André and Rist (1995) present schema-like coordinated text and graphics system.

With respect to Dynamic Hypertext, O'Donnell et al. (2001) argue that their problem of **prioritization**, **history awareness**, **limited output** and **limited planning** made schemata unsuitable for their task. That is true when considering schemata as originally defined by McKeown (1983), but certain aspects of their problem would have benefited from a schemata-based planner. They seem to imply that a schema is a completely fixed interaction, while ignoring the focus-based decoding process. Their Content Selection algorithm can be used to provide a *relevant knowledge pool* and then a schemata could have been written, rich in choices that would have followed through using focus to produce coherent texts.

Related Work in Biography Generation. Part of the research described in this thesis has been done for the automatic construction of the Content Selection and Document Structuring modules of PROGENIE (Duboue, McKeown, and Hatzivassiloglou, 2003), a biography generator. Biography generation has the advantages of being a constrained domain amenable to current generation approaches, while at the same time offering more possibilities than many constrained domains, given the variety of styles that biographies exhibit, as well as the possibility for ultimately generating relatively long biographies. The need for person descriptions has been addressed in the past by IR, summarization and NLG techniques. IR-based systems (Müller and Kutschekmanesch, 1995) look for existing biographies in a large textual database such as the Internet. Summarization techniques (Radev and McKeown, 1997; Schiffman, Mani, and Concepcion, 2001) produce a new biography by integrating pieces of text from various textual sources. Natural language generation systems for biography generation (Teich and Bateman, 1994; Kim et al., 2002) create text from structured information sources. PROGENIE is a novel approach, which builds on the NLG tradition. It combines a generator with an agent-based infrastructure expecting to ultimately mix textual (like existing biographies and news articles) as well as non-textual (like airline passengers lists and bank records) sources. PROGENIE offers significant advantages, as pure knowledge sources are able to be mixed directly with text sources and numeric databases. It diverges from the NLG tradition, as it uses examples from the domain to automatically construct content plans. Such plans guide the generation of biographies on unseen people. Moreover, the output of the system is able to be personalized; and by the fact that the system learns from examples, it is able to be dynamically personalized.

2.5 Conclusions

The Strategic Generation literature is quite vast. It usually deals with the many ways to model the Strategic Generation phenomenon. For the sake of this dissertation, this literature puts forward different representations to capture such phenomenon in NLG systems. This thesis contributes some empirical answers to the question of which representations might or might not been amenable for learning.

The NLG machine learning literature is more recent than its Strategic Generation counterpart, although it starts gaining ground. Nevertheless, Strategic Generation have not received as much attention in NLG learning as the surface generation and sentence planning areas.

Chapter 3

Indirect Supervised Learning

To address the needs of Strategic Generation, I learn sets of rules and schemata. Even though each of these two representations pose different problems and challenges, I learn both from a Text-Knowledge corpus, using similar methods. In this chapter, I introduce the methods common to both learning tasks.

The evidence available as input to my learning system makes for an indirect source, as my Knowledge and Text pairs are different from the ideal training material to learn Content Selection rules or Document Structuring schemata. In both cases, the ideal training material are input and output pairs. In the case of Content Selection, these pairs are pairs of Knowledge and Relevant Knowledge, while in the case of Document Structuring, they are pairs of Relevant Knowledge and *document plans*. Interestingly, a compound data structure (*matched text*) can be derived in an unsupervised fashion from the Text-Knowledge corpus to solve this lack of ideal training material. A *matched text* is a semantically tagged text where each tag is linked to the knowledge representation conveyed by the piece of text under the tag. The ideal training pairs mentioned above can be easily extracted from the *matched text*. For instance, the Relevant Knowledge can be read out from a *matched text* as all the knowledge that appears matched somewhere in the text. Similarly, the *document plan* can be approximated from the placement clues provided by the *matched text*.

This coupling of an unsupervised technique (construction of the *matched text*) with a supervised one (learning of Content Selection rules or Document Structuring schemata) is what I call *Indirect Supervised Learning* (Section 3.2) and is the focus of this chapter. The next two chapters will then present the specifics of the Indirect Supervised Learning process for each task: extraction of the training material from the *matched text* and supervised learning. While the supervised learning step varies in each case, I conclude this chapter by presenting an unified view of the technique employed to learn both Content Selection rules and Document Structuring schemata. I will now introduce some key definitions.

3.1 Definitions

In this section, I define my knowledge representation, the decomposition of texts into phrases, the *matched texts* and related notions. These definitions are used in the algorithms presented in the next sections.

Knowledge Representation. I expect the input data to be represented in a frame-based knowledge representation formalism, similar to RDF (Lassila and Swick, 1999). Each frame is a table of attribute-value pairs with a unique **NAME** and a distinguished **TYPE** feature (that can be linked to an ontology, if provided). Each attribute is unique, but it is possible to have lists as values. As such, the values can be either atomic or list-based. The atomic values I use in my work are NUMERIC (either integer or float); SYMBOLIC (or unquoted string); and STRING (or quoted string).[1] Non-atomic values are lists and frame references. The list-based types are lists of atomic values or frame references. Because my knowledge representation allows for cycles, the actual knowledge representation can be seen as a graph: each frame is a node on the representation and there are edges labelled with the attribute names joining the different nodes. Atomic values are also represented as special nodes, with no departing edges (Figure 3.1).

Data-classes. Any equivalence class over the nodes of the graph qualifies as a data-class. Data-classes are similar to semantic tags in other contexts. I will describe now the data-classes I use in my work, but other definitions are possible (for example, path plus frame types across the path), a subject I am interested in pursuing in further work (Chapter 9, Section 9.2).

Data-paths. As domain independent data-classes,[2] I employed paths in the knowledge representation (**data-paths**). I need to identify particular pieces of knowledge inside the graph. I thus select a particular frame as the **root** of the graph (the person whose

[1] A STRING is a regular English phrase (e.g., "*Gone with the wind*") while a SYMBOLIC field is either a reference to another frame (e.g., `place-of-study-22`) or a value linked to an ontology (e.g., `tv-or-radio-anchor`).

[2] Other alternatives as domain independent data-classes are possible, but data-paths are easier to conceptualize and to implement. The communicative predicates described in Section 5.1, Chapter 5 can be considered domain dependent data-classes, a subject I have not further investigated.

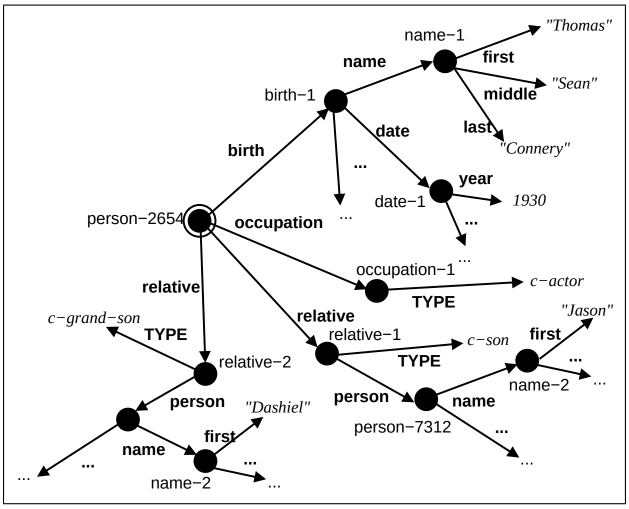


Figure 3.1: A frame-based knowledge representation example, in the biographies domain. Here, “Daniel” and “Dashiel” belong to the same data-class, namely defined by the data-path $\langle\texttt{relative person name first}\rangle$.

biography I am generating, in my case —doubly circled in the figure) and consider the paths in the graph as identifiers for the different pieces of data. Each path will identify a **class** of values, given the fact that some attributes are list-valued (e.g., the **`relative`** attribute in the figure). I use the notation $\langle\texttt{attribute}_1\ \texttt{attribute}_2 \ldots \texttt{attribute}_n\rangle$ to denote these data paths (Figure 3.1 shows an example).

Text. A text is a sequence of words.

Concept. To compute statistics over knowledge representations, I need a means to decompose them into statistical events. A concept is anything that can be asserted to be true or false (false as a negation of true) given a knowledge representation. To avoid data sparseness I employ concepts in the form of a data-path to **an atomic node** and **the value of the atomic node** (e.g., $(\langle\texttt{birth date day}\rangle, 5)$). More complex concepts can include decision logic (e.g., $value > 35$) and mix several atomic nodes, a subject I started some preliminary investigations (Duboue, 2004). To clarify, based on this definition, $(\langle\texttt{birth date day}\rangle, 5)$ and $(\langle\texttt{birth date day}\rangle, 6)$ are **different** concepts. $\langle\texttt{birth date day}\rangle$ is a data-path (a type of data-class), and not a concept.

Phrase. In the same vein, phrases provide a way to decompose a text into statistical events over which statistics can be computed. In my work, I have used uni-grams as phrases (bi-grams in preliminary investigations (Duboue and McKeown, 2003a)). This decision was also taken to avoid data sparseness. In general, patterns over the text (e.g., *"found* X *out"*) would make for ideal phrases.

Verbalization Dictionary. A function that takes a concept as input and returns a set of phrases that can potentially verbalize the given concept.

Matched Text. A *matched text* (an example is shown in Figure 3.2) is a text where selected phrases are linked to concepts.[3] The data-path provide a semantic tag for the piece of *matched text*.

3.2 Indirect Supervised Learning

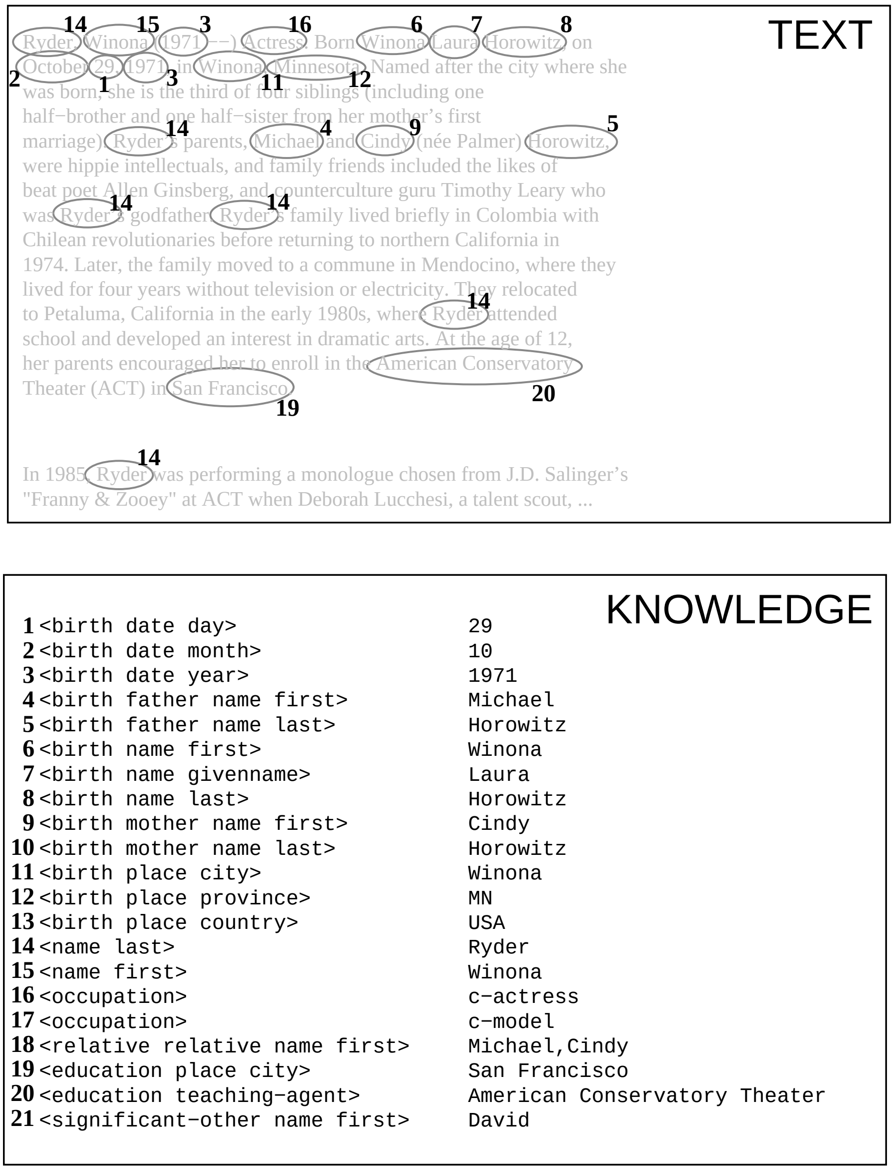
My work can be termed Indirect Supervised Learning[4] because my training material is fully supervised but the input/output pairs do not have the information needed for direct learning. I thus have input (the knowledge representation), output (text) and a hidden class (the *document plans*). I want to learn the mapping from input to the hidden class (how to build *document plans* from a knowledge source, the task of the strategic component in a NLG system) and I have a model of the mapping from the hidden class to the output (from *document plans* to texts, the remainder of the NLG system). The key is that I want to learn the estimator for the hidden class **together** with the estimator for the text to the hidden class. While I could have a classifier that assigns sets of observed outputs to values of the hidden class, I am actually trying to approximate this classifier from some independence assumptions.[5]

My current model assumes that the hidden class (the *document plan*) is the only element needed to determine the wording in the text (an independence assumption). I thus consider the text to be randomly sampled from all the texts that verbalize the *document plan* (Figure 3.3). Therefore, Indirect Supervised Learning has two steps; in the first step, the indirect training material (natural dataset) is transformed into direct training material (the hidden class is elucidated). In the second step, output learning representations

[3] In this thesis, a phrase can only be linked to at most one concept. This is a simplification that fits my data as partially overlapping tags are extremely rare. Completely overlapping tags are dealt with the disambiguation techniques presented later in this chapter.

[4] Indirect Supervised Learning, where the system learns from indirect, teacher provided examples is not to be confused with Semi-Supervised Learning. The latter is a bootstrapping method while the former is related to re-inforcement learning.

[5] Another possibility would be to use EM (Dempster, Laird, and Rubin, 1977), but that will imply learning both a generation **and** an extraction system, something clearly outside the scope of this thesis.



Ryder, Winona (1971−−) Actress. Born Winona Laura Horowitz on October 29, 1971, in Winona, Minnesota. Named after the city where she was born, she is the third of four siblings (including one half−brother and one half−sister from her mother's first marriage). Ryder's parents, Michael and Cindy (née Palmer) Horowitz, were hippie intellectuals, and family friends included the likes of beat poet Allen Ginsberg, and counterculture guru Timothy Leary who was Ryder's godfather. Ryder's family lived briefly in Colombia with Chilean revolutionaries before returning to northern California in 1974. Later, the family moved to a commune in Mendocino, where they lived for four years without television or electricity. They relocated to Petaluma, California in the early 1980s, where Ryder attended school and developed an interest in dramatic arts. At the age of 12, her parents encouraged her to enroll in the American Conservatory Theater (ACT) in San Francisco.

In 1985, Ryder was performing a monologue chosen from J.D. Salinger's "Franny & Zooey" at ACT when Deborah Lucchesi, a talent scout, ...

1	<birth date day>	29
2	<birth date month>	10
3	<birth date year>	1971
4	<birth father name first>	Michael
5	<birth father name last>	Horowitz
6	<birth name first>	Winona
7	<birth name givenname>	Laura
8	<birth name last>	Horowitz
9	<birth mother name first>	Cindy
10	<birth mother name last>	Horowitz
11	<birth place city>	Winona
12	<birth place province>	MN
13	<birth place country>	USA
14	<name last>	Ryder
15	<name first>	Winona
16	<occupation>	c−actress
17	<occupation>	c−model
18	<relative relative name first>	Michael,Cindy
19	<education place city>	San Francisco
20	<education teaching−agent>	American Conservatory Theater
21	<significant−other name first>	David

Figure 3.2: An example of a *matched text* (excerpt). Here, for example, "American Conservatory Theater" is linked to item number 20 (one of the elements at the end of the data-path ⟨`education teaching-agent`⟩) in the knowledge representation.

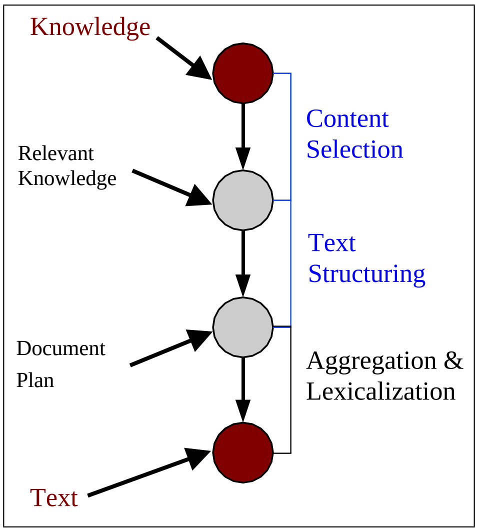


Figure 3.3: Learning Architecture. The full circles represent observed data (text and knowledge in my case). The grayed circles represent hidden variables (relevant knowledge and *document plans* in my case).

are learned in a supervised way, from the training dataset constructed in the previous step.

A different alternative I explore in Chapter 6 is to compute the output of the hidden class, that is, to produce text from the *document plans* and then use text-to-text metrics for learning. However, as I am not learning the transformation from *document plans* to final text, the verbalization becomes a deterministic step where no parameters are estimated, and will therefore be a source of constant noise.[6]

3.2.1 Evaluation

The evaluation process I follow for my Indirect Supervised Learning task is also a contribution of this thesis, as it lets me evaluate both the supervised and unsupervised steps at the same time. Given the training material, I divide it into train (Tr) and test (Te) sets. I then proceed to hand-annotate the test set (Te).

To evaluate the unsupervised part, I join $Tr + Te$ (again, only to evaluate the *unsupervised part*) and induce annotations automatically (by virtue of the unsupervised nature

[6] In Chapter 6, I am already dealing with a very noisy environment. Verbalizing the knowledge lets me gain more information from the training data as the semantic classes are too general. For example, generating the text and comparing it to the target text is necessary to distinguish tachycardia from bradycardia problems (both are mapped to the “intra-op-problems” semantic tag). That is not the case with the *matched texts* presented in this chapter.

of the process) over the whole $Tr + Te$ set. Now, I bring back the human annotations over Te and use them to evaluate the quality of the automatically assigned annotations. This measures the quality of the training material for the supervised part.

To evaluate the supervised system, I execute the unsupervised system again, but now only over Tr alone. I then use the annotations automatically obtained over Tr to train the supervised system and execute it over Te (*that was not available during training at any point*) and compare it to the quality of the human annotations over Te. This measures the generalization power of the technique.

I evaluate the matched texts extrinsically for Content Selection and Document Structuring. The extrinsic evaluation (how good are the *matched texts* with respect to selection and ordering) is motivated by the fact that I do not have a gold standard *matched text* constructed by hand; instead, I have annotated the selection labels on the text set and ordered them by first mention on the text.

As a Content Selection metric, I use precision (P), recall (R) and F^* measure, from information retrieval (van Rijsbergen, 1979). They are defined as:

$$\begin{aligned} P &= \frac{\text{true positives}}{\text{true positives} + \text{false positives}} \\ R &= \frac{\text{true positives}}{\text{true positives} + \text{false negatives}} \\ F^* &= \frac{2PR}{P+R} \end{aligned}$$

Where **true positives** is the number of atoms present in both the hand-tagged test set and the automatically constructed *matched texts*. The number of items wrongly included becomes the number of **false positives**. Finally, the items that should have been included but were missed are the number of **false negatives**.

To evaluate statistical significance of the results, I followed Mitchell (1997), pages 146-147, and divide Tr and Te into three non-overlapping folds. In each fold, I executed different variants of the system and then compare *their differences in error rate on each fold.* This constitutes a case of a paired experiment (every system is trained and tested in the same data). Because each of the sets is non-overlapping, this setting makes for more reliable statistics. For each fold, the **error rate** E defined as

$$E = \frac{\text{false positives} + \text{false negatives}}{\text{total cases}}$$

is computed. Then the error differences δ_i in each fold are computed. Therefore, given three folds (Tr_1, Te_1), (Tr_2, Te_2), (Tr_3, Te_3) and two system variants $\mathcal{V}_A$, $\mathcal{V}_B$, each variant is trained in $(Tr_1 + Te_1)$, $(Tr_2 + Te_2)$, $(Tr_3 + Te_3)$ and tested in Te_1, Te_2, Te_3. Then defining:

$$\begin{aligned} \delta_i &= E_i^{\mathcal{V}_A} - E_i^{\mathcal{V}_B} \\ \overline{\delta} &= \frac{1}{3}\sum_{i=1}^{3}\delta_i \\ S_{\overline{\delta}} &= \sqrt{\frac{1}{3(3-1)}\sum_{i=1}^{3}(\delta_i - \overline{\delta})^2} \end{aligned}$$

The true difference in the two variants lies in the interval

$$\overline{\delta} \pm t_{N,2} S_{\overline{\delta}}$$

Where $\overline{\delta}$ is the mean of the differences and $S_{\overline{\delta}}$ is an estimator for the standard deviation of the differences. The $t_{2,N}$ are the t-values for two degrees of freedom and they depend on the confidence interval (N%). They are given by the following table:

N =	90%	95%	98%	99%
t =	2.92	4.30	6.96	9.92

As a Document Structuring metric, I employ Kendall's τ correlation coefficient (Lebanon and Lafferty, 2002) between the elements common to the hand-tagged test set and the automatically obtained training material:

$$\tau = 1 - \frac{2(\text{number of inversion})}{N(N-1)/2}$$

Where N is the number of atomic values in the intersection and inversions is the number of exchanges on consecutive objects required to put them in the order appearing in the hand tagged reference. This metric ranges over the interval $[-1.0, 1.0]$ with a value of 1.0 meaning perfect correlation, 0.0 no correlation and -1.0 inverse correlation. As explained in Chapter 5, this is an accepted metric for ordering in text structure (Lapata, 2003).

3.3 Unsupervised Construction of Matched Texts

In this section, I detail how general training material, in the form of Text and Knowledge is transformed into a *matched text,* a training material that can be used for both the task of learning Content Selection rules and Document Structuring schemata.

3.3.1 Dictionary Induction

Indirect supervised learning involves an unsupervised step, based on assumptions on the structure of the model, to elucidate the hidden variable and supervised steps to generalize from the constructed mapping. My assumptions are related to the ways knowledge can appear on the text. This model is summarized by the following two tests, where H_0 is the null hypothesis, p and c are particular phrases and concepts, $\mathscr{P}$ is the set of phrases that make a particular text, $\mathscr{C}$ is the set of concepts that make a particular knowledge representation (where $\mathscr{C}$ and $\mathscr{P}$ refer to the same entity) and $\mathscr{D}$ is the verbalization dictionary:

$$\begin{array}{llr} H_0: & P(p \in \mathscr{P} | c \in \mathscr{C}) = p_0 = P(p \in \mathscr{P}) & \text{if } p \notin \mathscr{D}(c) \\ H_1: & P(p \in \mathscr{P} | c \in \mathscr{C}) = p_1 \gg p_2 = P(p \in \mathscr{P}) & \text{if } p \in \mathscr{D}(c) \end{array}$$

The null hypothesis H_0 (an independence equation) can be paraphrased as saying that if a phrase p does not belong to the verbalization dictionary for a given concept c, then, for a given text (decomposed into a set of phrases $\mathscr{P}$), knowing that the concept belongs to the knowledge representation associated with that text[7] does not affect the chances of the phrase p appearing in the text. On the contrary, H_1 says that the chances are much greater if the phrase p **does belong** to the verbalization dictionary of c. This model is inspired by the work of Dunning (1993). It is clear that, given a verbalization dictionary $\mathscr{D}$, the *matched text* construction reduces to a disambiguation task. My experiments, however, use H_0 and H_1 in an attempt to elucidate the $\mathscr{D}$ while constructing the *matched texts.*

In a sense, I am using the existence of a concept in a particular knowledge representation as a way to partition the set of all knowledge representations. For example, I can use the concept of being a comedian $(\langle\texttt{occupation}\rangle, \texttt{c-comedian})$ to put together all the data of comedians vs. non-comedians. I then want to see if I can observe changes on the distribution of phrases over the texts associated with the partitions. This statistical test selects words that are then added to the verbalization dictionary (Figure 3.4). I will now analyze each of the components of the system (Concept Enumeration and Statistical Filtering).[8]

[7] This is not the knowledge representation of the text itself, but the knowledge representation associated with the text in the aligned Text-Knowledge corpus.

[8] This technique will not learn verbalizations for open class values, although in such cases using the actual phrases as verbalizations produces useful result for a number of data-paths.

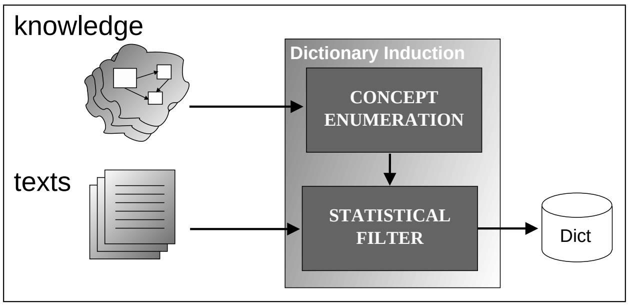


Figure 3.4: Dictionary induction.

Concept Enumeration

The dictionary induction starts by enumerating all possible concepts that can be asserted over a set of knowledge representations. This process starts by enumerating all paths in a composite graph (e.g., $\langle$`birth date day`$\rangle$) and then checking the possible *values* that can be found at the end of each path for each of the input knowledge representations (e.g., $(\langle$`birth date day`$\rangle, 29)$ for Winona Ryder, $(\langle$`birth date day`$\rangle, 2)$ for Pablo Duboue and so on). Concepts found this way make for a large total number (the concept enumeration can generate as many as 20,000 concepts in a given run). Only concepts that are true for a minimum number of knowledge representations (the concept's **support**) are used. More complex concepts can be enumerated via clustering (Duboue and McKeown, 2003b). Thus open class sets are only enumerated for their more common elements (e.g., `first-name`=*"John"*). In my experiments, I use a support value of thr_{supp}, as shown in Table 3.10.

Hypothesis Testing

I then compare the distribution of phrases in the partition of texts associated with the partition in the knowledge representations induced by the concept.[9] That is to say, I want to see if there is a change in the distribution of words between the two sets; for example, if the biographies of people born in 'MI' (a concept) have a higher-than-expected chance of containing the phrase *"Michigan."*

Therefore, I have two sets of texts (Michigan and non-Michigan) and I analyze if they diverge in their associated language models over phrases; if they represent samples coming from two different distributions. To achieve this goal, I collect phrasal counts

[9] In the general case, a concept is anything that can be asserted to be true or false in a given knowledge representation. Therefore, a concept naturally divides a set of knowledge representations into two sets: the set of knowledge representations where the concept holds and the set where it does not.

(uni-grams over words in my case) and analyze whether or not these counts can be considered samples coming from the same probability distribution. I collect counts over all phrases (i.e., words in my case). This process is schematically represented by the pseudo-code shown in Figure 3.5.

Student's t-test. I investigated statistical tests on the counts for each phrase on either partition. In my statistical test, I test the null hypothesis that these words appeared there just by chance. For example, if the partition is induced by the concept *"his or her occupation is to be a comedian,"* I want to conclude that their associated biographies contain the phrases (i.e., words) *"comedian," "stand-up,"* and *"comic"* more than expected by chance on this corpus.

There might be other terms found frequently for a given concept that are not exact verbalizations of that concept. For example, for people born in Michigan, phrases like *"Upper Peninsula"* or *"Detroit"* are to be expected. Therefore, this approach might over-generate.

I compared three statistical tests χ^2, likelihood ratios and Student's t-test. My counts were too small for χ^2, likelihood ratios do not allow for the sampling process described below and therefore only Student's t-test is used as part of the final algorithm.

I have the total number of occurrences of the events (in this case, phrases) and I want to see if a phrase is associated with the partition induced by the concept. Therefore, as shown in the pseudo-code in Figure 3.8, I split the texts into two sets, the texts belonging to the partition, and the texts that do not belong to the partition. If I apply likelihood ratios or similar techniques to the counts associated with the whole clusters, usually the most descriptive phrases for each element in the cluster will prevail (e.g., in the case of biographies, the *names* of the people involved in the cluster will appear).[10] I thus resort to a **sampling** process to avoid this effect. I sample sets of five texts from the partition and five from texts outside and collect phrasal counts. After several samples (100 in my case), I end up with two sequences of numbers, representing the number of times a given phrase appear in each partition; to determine if the two sequences of numbers belong to the same distribution I use the Student's t-test.[11] If the test results are over a threshold thr_t (see Table 3.10), I consider the phrase to be a verbalization adding it to the verbalization dictionary.

[10] The same problem will appear if I use weighted counts, e.g., weighting each word with its TF*IDF weight.

[11] To see how the sampling filters out the name of the person described in each biography, notice that in each sample the names will have a strong difference in counts but that difference will not be carried out across the board —unless the same person appeared in all samples, an unlikely event.

```
$C \leftarrow \emptyset$                      ; *set of all concepts*
$P \leftarrow \emptyset$                      ; *set of all phrases*

FOREACH $(T,K) \in$ *set of all text-knowledge pairs* DO
    $C \leftarrow C \cup$ *set of all concepts in K*
    $P \leftarrow P \cup$ *set of all phrases in T*
DONE

FOREACH concept $c \in C$ DO
    $s \leftarrow \emptyset$              ; *all text-knowledge pairs where c holds*
    $ns \leftarrow \emptyset$             ; *all text-knowledge pairs where c does **not** hold*

    FOREACH $(T,K) \in$ *set of all text-knowledge pairs* DO
        IF *c holds on K* THEN
            $s \leftarrow s \cup \{(T,K)\}$
        ELSE
            $ns \leftarrow s \cup \{(T,K)\}$
        FI
    DONE

    ; *look for words associated with the partition s/ns*

    FOREACH $p \in P$ DO
        $\text{Counts}_s$=ARRAY[100]
        $\text{Counts}_{ns}$=ARRAY[100]
        FOREACH $i = 1..100$ DO
            $\text{Sample}_s$=*select at random 5 texts from s*
            $\text{Sample}_{ns}$=*select at random 5 texts from ns*
            $\text{Counts}_s$[i]=*number of times p appears in* $\textit{Sample}_s$
            $\text{Counts}_{ns}$[i]=*number of times p appears in* $\textit{Sample}_{ns}$
        DONE

        IF $\textit{Counts}_s$ *and* $\textit{Counts}_{ns}$ *are stat. sig. different* THEN
            *Add p to the verbalization dictionary for c*
        FI
    DONE
DONE
```

Figure 3.5: Pseudo-code for the hypothesis testing step of the dictionary induction.

(⟨**birth date month**⟩,3) *March*.

(⟨**birth date day**⟩,17) *17*.

(⟨**birth placecountry**⟩,***England***) *England, Britain, UK, British*.

(⟨**significant-other #TYPE**⟩,***c-fiancee***) *dated, engaged*.

(⟨**occupation #TYPE**⟩,***c-job-comedian***) *comic, stand-up, Comedian, Comedy, comedian, comedy, comedic, Comedians*.

Figure 3.6: Extracted words.

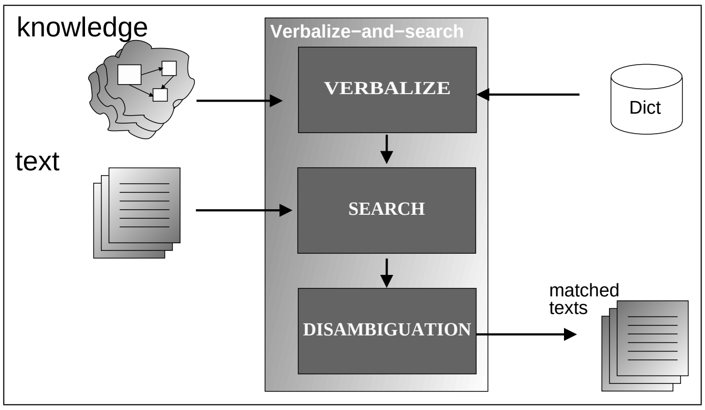


Figure 3.7: Verbalize-and-search.

The output of the dictionary induction process is a verbalization dictionary containing sets of putative verbalizations for each concept. An example of newly added words is shown in Figure 3.6. I only evaluated this dictionary extrinsically, my measuring its impact on the quality of the obtained *matched texts*.

3.3.2 Verbalize-and-search

The *verbalize-and-search* process (Figure 3.7) aims to identify pieces from the input that contain known verbalizations in the target text. It enriches a *matched text* initialized with plain target texts. The verbalization step takes a concept and returns all the phrases associated with the concept in the verbalization dictionary. For example, given a concept such as (⟨name first⟩, *"John"*), I will search for the strings *"John"*,*"J."* and *"JOHN"*. To search for the phrases in the text, any classical search algorithm can be employed, e.g., KMP or Boyer-Moore (Gusfield, 1997).

The overall operation is prone to two type of errors: omission (if the verbalization dictionary misses the exact verbalization, e.g., `c-comedian` appears in the text as *"he performed comedy for several years"* or *"MA"* instead of *"Maryland"*) and overgeneration (if there are several values for it, e.g., *"Smith"* appears in the text and it is simultaneously the name of the father and a brother). The former errors were addressed by the **dictionary induction** technique described in the previous section. The latter errors are addressed by means of **disambiguation** methods explained below.

Disambiguation

The ambiguity problem in the *verbalize-and-search* approach cannot be overlooked. For example, Winona Ryder was born in a city named Winona, in Minnesota. When the phrase *"Winona"* is found in the text whether the previous words are *"born in"* or *"born as"* can provide strong indication for either usage. To acquire the contexts (*"born in"* vs. *"born as"*) for each data-class (⟨`name last`⟩ vs. ⟨`birth place city`⟩), I compute all ambiguous matches across documents and use standard disambiguation techniques (Naïve Bayes) to smooth[12] the evidence and decide for each class against a null model (trained in every word in the document). This is a local disambiguation, using a very small window ($w = 3$, see Table 3.10).

In other words, I accumulate statistics for matching at the data-class level. Each match is delimited by a context and all the contexts are accumulated across all the members of the class. This process works on the assumption that, for example, the words surrounding the name of a relative are the same across names of relatives and different biographies. Therefore, I have my list of verbalizations and the places where they match, some of these matches are spurious matches, but working on the hypothesis that the good matches still outnumber the spurious ones (something that is normally the case), I collect statistics from all these contexts. Figure 3.8 shows pseudo-code for this process.

Moreover, I retrain the disambiguators after some matches have been identified to improve their generalization capabilities. For example, if my system has successfully identified an occurrence of *"Ryder"* in the text *"Winona Ryder is an actress"* as ⟨`name last`⟩, it can use it later to disambiguate *"Winona"* as ⟨`name first`⟩ rather than ⟨`birth place city`⟩.

[12] This is similar to train and execute in the same corpus and thus is used as a smoothing technique. I also performed experiments with leave-one-out generalization, but such approach was much slower and produced slightly lower performance.

```
NullModel$\leftarrow \emptyset$
FOREACH $T \in$ all available texts DO
    FOREACH word in place $w \in T$ DO
        Train NullModel for a small context (window $= 3$) around $w$
    DONE
DONE
$M \leftarrow \emptyset$                ; all matches
FOREACH $(T,K) \in$ set of all text-knowledge pairs DO
    FOREACH concept $c \in K$ DO
        $M \leftarrow M \cup$ set of all matches in $T$ for a verbalization of $c$
    DONE
DONE

PathModel$_{\text{data-paths}} \leftarrow \emptyset$

FOREACH data-path $d \in$ all possible data-paths DO
    FOREACH match $m \in M$ such that path of $m$ equals to $d$ DO
        Train PathModel$_d$ for a small context (window $= 3$) around $m$
    DONE
DONE

MatchesToAdd$\leftarrow \emptyset$

FOREACH match $m \in M$ DO
    IF PathModel$_{\text{path of } m}(m) >$ NullModel$(m)$ THEN
        Add m to MatchesToAdd ordered by the score of PathModel
    FI
DONE
```

Figure 3.8: Pseudo-code for the disambiguation step in the *verbalize-and-search* matched text construction.

Table 3.1: Impact of the different disambiguation methods in the *matched text* Construction.

Disambiguation Method	Precision	Recall	F-measure
Naïve Bayes	0.706± 0.007	0.681± 0.013	0.694± 0.010
Naïve Bayes (Strict)	0.636± 0.028	0.416± 0.007	0.503± 0.013
HMM	0.698± 0.016	0.543± 0.009	0.611± 0.006
HMM (Strict)	0.526± 0.011	0.057± 0.015	0.100± 0.022

While my final system uses Naïve Bayes disambiguation, I also investigated three other variants, shown in Table 3.1 (this experiment was done on the `biography.com` corpus mentioned later in this chapter). In the table, the *strict* variants refer to whether to require that only the left or right context decides in favor of the class (regular variant) or to require that **both** contexts decide in favor of the class (strict variant). My experiments with the strict variant did not confirm the intuition that it should provide a higher precision, therefore I discontinued its use. I also re-implemented a HMM-based disambiguator following the IDENTIFINDER trainable named-entity system (Bikel, Schwartz, and Weischedel, 1999). My implementation, however, did not include the complex class-based smoothing complexities described by Bikel et al., with an inferior performance to the Naïve Bayes approach. I thus decided to focus on the Naïve Bayes technique.

3.4 Data

The Text-Knowledge corpus used in this chapter consists of knowledge extracted from a semi-structured knowledge base, biographical fact-sheets of assorted celebrities. These fact-sheets were crawled from E! on-line[13] in November 2002. In addition to this knowledge source, I also employ an extended knowledge source, also extracted from E! on-line but with a slightly different ontology and with added information about which movies each actor appeared in. This extended knowledge source was incorporated as part of these experiments at the end of this dissertation and was not used during system development (i.e., no parameters were fit on this corpus). Different biographical sites provide the text part, to test the ability of the system to learn from different types of data. The process of constructing this Text-Knowledge corpus is detailed in Chapter 7, Section 7.1, I will just detail here the overall size of each Text-Knowledge corpus. As explained in

[13] `http://eonline.com`.

Section 3.2.1, each corpus was split into a training and test set, with the test set tagged for selection and ordering (ordering only in the last corpus) by the author.

3.4.1 biography.com

The biography.com corpus is the smallest (in number of pairs) corpus of the collection and it was used mostly for development. The biographies are clearly written by professional editors and present the higher level of homogeneity.

biography.com	Total	Average	Train	Test
# pairs	102	-	91	11
# frames	4,956	45.588	4,442	514
# triples	10,628	104.196	9,500	1,128
# words	54,001	529.422 ± 301.15	49,220	4,781
# chars	337,775	3,311.520 ± 1,857.96	307,978	29,797

In the table, *pairs* refer to the number of text and knowledge pairs; *frames* refer to the number of internal nodes in the graph; *triples* refer to the number of triples in the form (frame, link, target), the equivalent of an arrow in Figure 3.1; *words* and *chars* refer to the number of words and characters in the target texts, respectively. The average number of words per biography and its standard deviation speaks of quite lengthy biographies with a stable length (compared to the next two corpora).

The test set contains 334 selected triples, from a total of 744 triples to select from (an F*[14] for the SELECT-ALL strategy of 0.62 —The SELECT-ALL strategy can be thought of as a baseline). The total number of triples is different than the number shown in the table as the table also shows triples that connect internal nodes.

This corpus was a fine development corpus, as its small size allowed me to implement and test different ideas quite quickly. On the other hand, this corpus constitutes a high baseline that makes it difficult to appreciate the relative differences of system variants. For that reason, I introduced the other corpora detailed next, each of which presents a relatively harder *matched text* construction task.

3.4.2 s9.com

The s9.com corpus is the largest corpus (in number of pairs) and the one with the shortest biographies. The biographies are mostly one-liners and it is unclear whether or not they have been written by editorial staff.

[14] I abbreviate the F-measure from Information Retrieval as F* in this dissertation.

s9.com	Total	Average	Train	Test
# pairs	578	-	558	20
# frames	30,709	53.130	29,723	986
# triples	95,032	164.415	92,969	2,063
# words	21,037	36.396 ± 34.04	20,192	845
# chars	138,711	239.984 ± 215.82	133,204	5,507

Because of the small size of each biography, this is a challenging corpus, where out of 1,377 triples to select from, only 170 are selected (an F* for the SELECT-ALL strategy of 0.22). The texts are so small (36 words on average) that one would be hard pressed to call them biographies. The standard deviation is also pretty large.

3.4.3 imdb.com

In previous work (Duboue and McKeown, 2003a; Duboue, 2004), I have used the corpus assembled from `imdb.com` as a test corpus. It is of medium size and has biographies submitted by volunteers over the Web; this made it more challenging than corpora written by an editorial staff.

imdb.com	Total	Average	Train	Test
# pairs	199	-	185	14
# frames	10,123	50.869	9,362	761
# triples	31,676	159.176	29,323	2,353
# words	64,196	322.593 ± 285.63	60,086	4,110
# chars	378,778	1,903.407 ± 1,693.88	354,560	24,218

The test set contains a total of 369 selected triples out of 1,060 (an F* for SELECT-ALL of 0.516). While the size of each biography is around 300 words, so is the standard deviation; and thus, the biographies on this corpus are clearly of diverging sizes.

3.4.4 wikipedia.org

Near the end of this dissertation work, I created an extended knowledge source by adding to the previous knowledge extra information in the form of artistic credits (the movie starred by each actor). This extended knowledge source was paired against biographies from `wikipedia.org`. The site `wikipedia.org` is a collaborative collection of encyclopedic articles embodied in the concept of a Wiki, a page that allows any person with WWW access to edit it. The Wiki approach produces a very dynamic set of pages that pose a more challenging environment than the previous corpora. On the bright side, this corpus contains more pairs than the `imdb.com` and it has a very liberal license that allows for corpus re-distribution. This is the only corpus annotated with ordering information, because the extended knowledge source is the only one compatible with the hand-written communicative predicates presented in Chapter 5. These predicates are a requirement for learning Document Structuring schemata.

`wikipedia.org`	Total	Average	Train	Test
# pairs	361	-	341	20
# frames	58,387	161.737	55,326	3,061
# triples	108,009	299.194	102,297	5,712
# words	68,953	191.006 ± 55.17	64,784	4,169
# chars	418,035	1,157.992 ± 334.01	392,925	25,110

The test set contains 598 selected triples out of 2,906 (an F* for SELECT-ALL of 0.341).

3.5 Experiments

The architecture presented in the previous sections leaves room for a number of variations, some of which I have investigated in this thesis. I investigated the following issues:

Addition of the matches to the *matched text* being constructed. As mentioned in Section 3.3.2, it is advantageous to retrain the disambiguators after a certain number of matches have been identified. I investigated two possibilities for adding matches to the partial *matched text*. I describe them below.

(*Path*$_{add}$) Path-based addition. I have investigated adding all matches in a data-path in order (data-paths with more selected matches first). For each match, the algorithm selects the ones with a score over the null model for that position. I then record the percentage of total matches over selected matches. The data-path with a higher percentage was considered to be of better quality and thus added to the *matched text*. The problem of this approach is that it may incorporate a good deal of noise in one step (and that noise will be carried on afterwards, as the algorithm does not allow for backtracking).

(*Score*$_{add}$) Score-based addition. To avoid the problem of forcing a decision over all elements in a data-path (including some matches over which the system has less than perfect evidence), I investigated adding a percentage of the higher scoring matches (across different data-paths) in each step. Given a set of selected matches (i.e., matches that are higher than the null model), I order them by their predicted belonging to the class. I then add to the *matched text* the top scoring 10% of the matches in the first step (20% in the second step and so on). In general, an EM-based algorithm (Dempster, Laird, and Rubin, 1977) will be the most general solution to this problem, but will imply learning also how to extract the knowledge from the text.

Creation of the verbalization dictionary. While in this thesis I focus on the automatic construction of the verbalization dictionary (Section 3.3.1), this dictionary can be obtained in a number of ways, some of which do not necessarily include learning:

(*Trivial*$_{dict}$) Trivial. The verbalization for (path, *phrase*) is *phrase*, e.g., for a concept such as (⟨`name first`⟩,*John*), the verbalization is *John*. This will obviously not work in the case the value is not phrase, e.g., ⟨`occupation TYPE`,`c-painter`⟩.

(*External*$_{dict}$) External. A small external dictionary with possible verbalizations of states, months and numbers can be provided as a knowledge-based external verbalization dictionary. This problem of small variations in numbers and dates is similar to the problem of telling them apart in Speech Recognition or reading them aloud in Speech Synthesis (Jurafsky and Martin, 2000); I thus employ a small verbalization system based on Finite State Transducers *(shallow generation grammars)*. Examples of these paraphrases include number verbalizations (e.g., *"three"* for '3'), months (e.g., *"September"* for '9') and state names (e.g., *"Michigan"* for 'MI').

(*On-line*$_{dict}$) On-line. The on-line dictionary construction implies executing the dictionary induction only when the number of available matches is low or its quality is below a threshold thr_{add} (see Table 3.10). For example, in the data-path variant, if the ratio of matches accepted by the disambiguator is below 20% (that is 80% of the matches for a data-path are considered spurious by the disambiguator), the dictionary induction is executed. An advantage of this variant is that the dictionary induction is executed over the *matched texts*, where the pieces of text matched to a concept are replaced with semantic tags —the data-path for the concept.

(*Off-line*$_{dict}$) Off-line. This involves executing the dictionary induction algorithm before the *verbalize-and-search* process. Because the partial matches are not available at this point, this dictionary induction may introduce some noise in the process.

I explored these options through the following variants:

Variant 0 (*Path*$_{add}$+ *Trivial*$_{dict}$) Simplest system, with no dictionary induction and no disambiguation; the most popular path is added first, where popular means the path with more matches. Such a system is similar to currently used approaches for bootstrapping information extraction systems (Chieu, Ng, and Lee, 2003).

Variant 1 (*Path*$_{add}$+ *On-line*$_{dict}$) This variant adds matches in a path-based fashion with the dictionary updated after the scores fell under threshold thr_{add} (see Table 3.10).

Variant 2 (*Score*$_{add}$+ *Off-line*$_{dict}$) This variant adds matches to the *matched text* being constructed in a percentage-based fashion, with an off-line computation of the dictionary.

Variant 3 (*Score*$_{add}$+ *External*$_{dict}$) This variant adds matches to the *matched text* being constructed in a percentage-based fashion, using an external verbalization dictionary.

Variant 4 (*Score*$_{add}$+ *External*$_{dict}$+ *Off-line*$_{dict}$) This variant combines Variants 2 and 3; it adds matches in a percentage-based fashion, using both an external verbalization dictionary and an off-line computation of the dictionary.

The results for the Content Selection quality of the learned *matched texts* are shown in Table 3.2.

Variant 1 was computationally too expensive to compute on the larger corpora and only **biography.com** results are included. The relative differences between Variant 1 and Variant 2 can only be seen if we plot precision and recall during the *matched text* construction process (Figure 3.9 and Figure 3.10). The figures are obtained by evaluating the *matched text* being constructed as matches are being added to the matched text. The y-axis measures precision and recall and the x-axis are iterations on the *matched text* construction process. These figures show clearly how Variant 1 starts very well until its curves suddenly drop (around the tenth iteration), most likely because it commits itself to add all matched instances in a wrongly matched data-path. Variant 2, on the other hand, has a much softer curve, where the benefits of re-training the disambiguators on earlier matches can be seen clearly;[15] even precision improves after some matches have been identified.

[15] In Variant 2, the dictionary induction is performed off-line while the disambiguators are re-trained after a percentage thr_{top} (Table 3.10) of the highest scoring concepts are added to the matched text.

In general, Variant 0 has the best precision across all corpora, with Variant 4 presenting the best recall. When considering F^*-measure, Variant 4 has the best F^* overall, although that is not the case in all corpora.

Because of the differences in Table 3.2 are pretty small, I conducted a cross-fold validation experiment to test the differences between the variants. The actual results of these experiments are presented in Appendix A. I will mention here the highlights. For `biography.com`, only Variant 1 has a statistically significant difference with a good level of confidence. For `s9.com` and `imdb.com`, no difference has a good confidence, although the difference between variants 3 and 4 in `imdb.com` is noteworthy. In `wikipedia.org`, the differences between Variant 2 and the Variants 0 and Variants 3 are statistically significant with good confidence.

In this evaluation, the system is trained in $(Tr + Te)$ and tested in Te (as explained in Section 3.2.1). Here Tr is used to provide extra evidence to the dictionary induction and disambiguation methods. This approach begs the question of the importance of the size of Tr for the results reported over Te. Moreover, because the cross-validation experiments that measure statistical significance are trained in one third of Tr each fold, it is also important to understand how different such system may be with respect to the system trained in all Tr. Figure 3.11 and Figure 3.12 show the impact of the size of Tr for Variants 2 and 3 in 10 different random subsets of different size (10,11,..,30, 40, ..., 90) of Tr (plus all Te) and testing the obtained labels on Te. The figures show clearly that Variant 2 requires at least 60 instances to stabilize, while Variant 3 (that does not performs any dictionary induction) profits from the extra training material very slowly (by improving the disambiguators).

Finally, to shed further light on the differences in Table 3.2, I analyzed the error over each data-path. Tables 3.3 and 3.4 show major contributors to the error and success rates, respectively. These contributors perform similarly across all variants. There we can see that the free-text paths (for example, paths that end in `canned-text` in this particular knowledge representation) and the symbolic paths (paths that finish in `#TYPE`, for example) are responsible for a large number of errors. On the other end of the spectrum (more successful paths), there are paths such as ⟨`award title`⟩ or ⟨`award reason`⟩ (movie names and the like) that have higher chances of appearing in the text exactly as they appear in the knowledge representation (they are stronger *anchors*, in the nomenclature of Chapter 1). These are data-paths containing more named-entity alike information and they are better captured by my system.

While my system has no provisions for free-text values, the dictionary induction should deal with the `#TYPE paths`. This can be seen in Tables 3.5-3.8 that show error contribution itemized per variant for data-paths with variant-related differences. In

Table 3.2: Content Selection results. See the text for discussion.

Variant 0 (*Path*$_{add}$+ *Trivial*$_{dict}$)

Corpus	Prec.	Rec.	F*	selected
biography.com	0.7407	0.6432	0.6885	297
s9.com	0.5108	0.5280	0.5193	184
imdb.com	0.7118	0.5303	0.6078	295
wikipedia.org	0.6952	0.4664	0.5583	420

Variant 1 (*Path*$_{add}$+ *On-line*$_{dict}$)

Corpus	Prec.	Rec.	F*	selected
biography.com	0.7112	0.6842	0.6974	329

Variant 2 (*Score*$_{add}$+ *Off-line*$_{dict}$)

Corpus	Prec.	Rec.	F*	selected
biography.com	0.7508	0.6676	0.7068	297
s9.com	0.5000	0.5529	0.5251	188
imdb.com	0.7035	0.5338	0.6070	280
wikipedia.org	0.6190	0.4782	0.5396	462

Variant 3 (*Score*$_{add}$+ *External*$_{dict}$)

Corpus	Prec.	Rec.	F*	selected
biography.com	0.7335	0.6347	0.6805	289
s9.com	0.5026	0.5529	0.5266	187
imdb.com	0.6853	0.5311	0.5984	286
wikipedia.org	0.6280	0.5083	0.5619	484

Variant 4 (*Score*$_{add}$+ *External*$_{dict}$+ *Off-line*$_{dict}$)

Corpus	Prec.	Rec.	F*	selected
biography.com	0.7466	0.6706	0.7066	300
s9.com	0.5193	0.5529	0.5356	181
imdb.com	0.6830	0.5941	0.5941	284
wikipedia.org	0.6451	0.5183	0.5746	481

biography.com corpus, for example the table shows that the variants with dictionary induction (Variants 1 and 2) mildly address the symbolic fields with Variant 1 marginally better than Variant 2. This is to be expected as Variant 1 does a very costly on-line dictionary induction, where the dictionary is re-induced after some matches are identified (improving the quality of the language models). With respect to the differences coming from the use of disambiguation, this can be appreciated in the last name of relatives (⟨relative relative name last⟩). However, the use of disambiguators makes the whole system more wary of places where little evidence across frames supports the match (the system becomes more conservative). This situation slightly increases the number of mismatches in a number of paths.

The error analysis for the s9.com corpus (Table 3.6) shows the same overall behavior of biography.com, although here the disambiguation improves more paths than in biography.com. Interestingly, as the system becomes more conservative, the gains equalize again. This is because I am averaging over all paths. The table shows how the distribution of errors is more uniform thanks to the disambiguated system. This will be particularly important for the ordering behavior in the wikipedia.org corpus.

Table 3.7 contains the misses per data-path in imdb.com, which are also in line with the previous two corpora. Note how ⟨birth place province⟩ benefits from the small external dictionary in Variant 3.

The results for Document Structuring on the wikipedia.org corpus are shown in Table 3.9. While the sequences are similar in length to the text set, according to Table 3.2 only half of the information there appears also in the test set. For these elements in the intersection, there is a near-perfect correlation in the ordering. This implies this data can be used positively to learn Document Structuring schemata.

The sequences evaluated here are sequences of atomic values as they appear in the *matched text*. These sequences are different from sequences of instantiated communicative predicates (such sequences are *document plans*) but they will nevertheless be used in Chapter 5 to evaluate different schemata during learning. The sequences of atomic values will also be used to learn Order Constraints.

3.6 Conclusions

The process presented in this chapter is able to automatically identify training material with an F^*-measure as high as 0.70 and as low as 0.53 and a τ as high as 0.94 and as low as 0.86. These results imply that learning using the *matched texts* as training material will require a robust machine learning methodology as the ones introduced in the next two chapters.

Table 3.3: Major contributor paths to the **error** rate per corpus. Here `education #TYPE` includes c-college-education, c-highschool-education; `significant-other #TYPE` includes c-spouse, c-dated; `relative #TYPE` includes c-mother, c-father; `occupation #TYPE` includes c-actor, c-director, etc. Note that `wikipedia.org` uses a slightly different ontology where `relative #TYPE` is now `family #TYPE` and awards are contained inside work events. In some cases the country of birth is missed because it may appear as an adjective (e.g., “Australian”) instead of the noun in the knowledge representation (e.g., “Australia”).

`biography.com`

education #TYPE
factoids canned-text
birth place city

`imdb.com`

factoids canned-text
claimtofame canned-text
education #TYPE
significant-other #TYPE
occupation #TYPE
relative #TYPE
birth mother name last

`s9.com`

claimtofame canned-text
birth place country
factoids canned-text
significant-other #TYPE
occupation #TYPE
relative #TYPE

`wikipedia.org`

claim-to-fame canned-text
factoid canned-text
education #TYPE
education teaching-agent #TYPE
occupation #TYPE
significant-other #TYPE
family #TYPE
work-event #TYPE
birth place country

Table 3.4: Major contributor paths to the **success** rate per corpus. Most entries are self-contained.

`biography.com`

birth date year
birth date month
birth date day
birth place country
award reason
award title

`imdb.com`

education major canned-text
birth father name first
education teaching-agent name
birth place country
birth mother name first
birth place city
birth date year
birth date month
birth date day
relative relative name givenname
significant-other significant-other name last
award reason
award subtitle
award title
relative relative name first

`s9.com`

birth mother name last
birth father name first
birth mother name first
name last
birth date year
significant-other significant-other name last
significant-other significant-other name first
relative relative name first

`wikipedia.org`

education subject-matter canned-text
education place city
work-event reason key
birth name first-name
birth place city
birth date-instant year
birth date-instant day
education teaching-agent name name
work-event award sub-title
work-event award title

Table 3.5: Analysis of errors for `biography.com` corpus. The system had to select 334 matches; it selected 297, 74 of which were wrong (it missed 111). Here is a an analysis, per data-path, of the major contributors to the errors and success rates. Each column contains the number of misses per variant (from the total to select, presented in the last column).

path	**misses per variant**				**total**
	0	1	2	3	**to select**
claimtofame canned-text	**11**	**10**	**11**	**11**	**11**
occupation #TYPE	**16**	**10**	**13**	**16**	**16**
significant-other #TYPE	15	14	15	15	15
relative #TYPE	17	16	15	17	17
relative relative name last	**9**	**6**	**5**	**5**	**11**
education teaching-agent name	3	3	4	4	7
significant-other significant-other name first	1	1	2	2	15
significant-other significant-other name last	1	1	2	3	13
award subtitle	4	5	4	4	11
award date year	3	3	6	6	21
relative relative name first	1	1	3	5	14

Table 3.6: Analysis of errors for `s9.com` corpus.

path	**variant**			**total**
	0	2	3	**to select**
birth father name last	2	1	1	2
birth name last	11	8	7	13
birth name first	5	5	3	14
name first	0	1	3	16
relative relative name last	3	2	3	5

Table 3.7: Analysis of errors for `imdb.com` corpus. Here, `birth place province` profits from the external verbalization dictionary and `relative relative name last` profits from the disambiguation (although it then hurts `name last`).

path	**variant**			**total**
	0	2	3	**to select**
birth father name last	5	0	1	5
education place country	1	0	0	1
birth place province	**6**	**6**	**0**	**8**
relative relative name last	11	2	4	12
name first	0	5	5	14
name last	0	9	9	14
significant-other significant-other name first	0	0	2	9
award date year	2	5	5	13

Table 3.8: Analysis of errors for the `wikipedia.org` corpus. In this extended knowledge representation #TYPE is the gender of the person whose information is contained in the representation.

path	**variant**			**total**
	0	2	3	**to select**
birth name last-name	6	2	3	6
birth place province	10	10	1	10
birth date-instant month	19	16	1	19
#TYPE	20	15	20	20
education place province	1	1	0	3
name last-name	0	2	4	20
name first-name	0	1	1	20
work-event reason name name	3	3	4	16
family relative name last-name	13	5	4	18
significant-other significant-other name last-name	2	2	3	18
significant-other significant-other name first-name	1	3	2	17
family relative name first-name	0	1	1	26
work-event date-instant year	11	12	12	51
work-event built name name	20	24	21	66

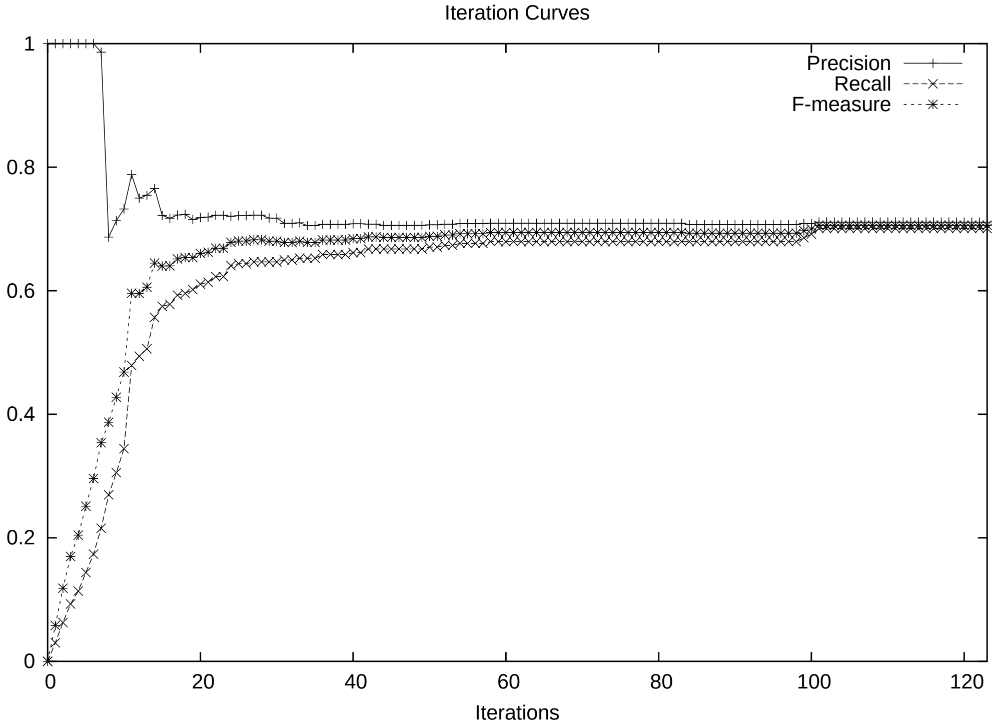


Figure 3.9: Quality of the *matched text* during its construction, for Variant 1 (*Path*$_{add}$+ *On-line*$_{dict}$). The figure shows an evaluation of the quality of the *matched text* being constructed as the number of iterations progresses. It has a clear sudden drop of precision around iteration 10. This drop is due to the mass addition of all matches in a path with a number of wrong matches.

Table 3.9: Document Structuring results. All these figures are computed on the wikipedia corpus, where the average sequence length in test set is 29.8 ± 10.8559.

Variant		avg. length	τ
0	(*Path*$_{add}$+ *Trivial*$_{dict}$)	21.55 ± 7.7083	0.9400 ± 0.0989
2	(*Score*$_{add}$+ *Off-line*$_{dict}$)	23.10 ± 8.3470	0.8686 ± 0.1283
3	(*Score*$_{add}$+ *External*$_{dict}$)	26.50 ± 12.2280	0.9232 ± 0.1004
4	(*Score*$_{add}$+ *External*$_{dict}$+ *Off-line*$_{dict}$)	26.35 ± 11.4260	0.8909 ± 0.1154

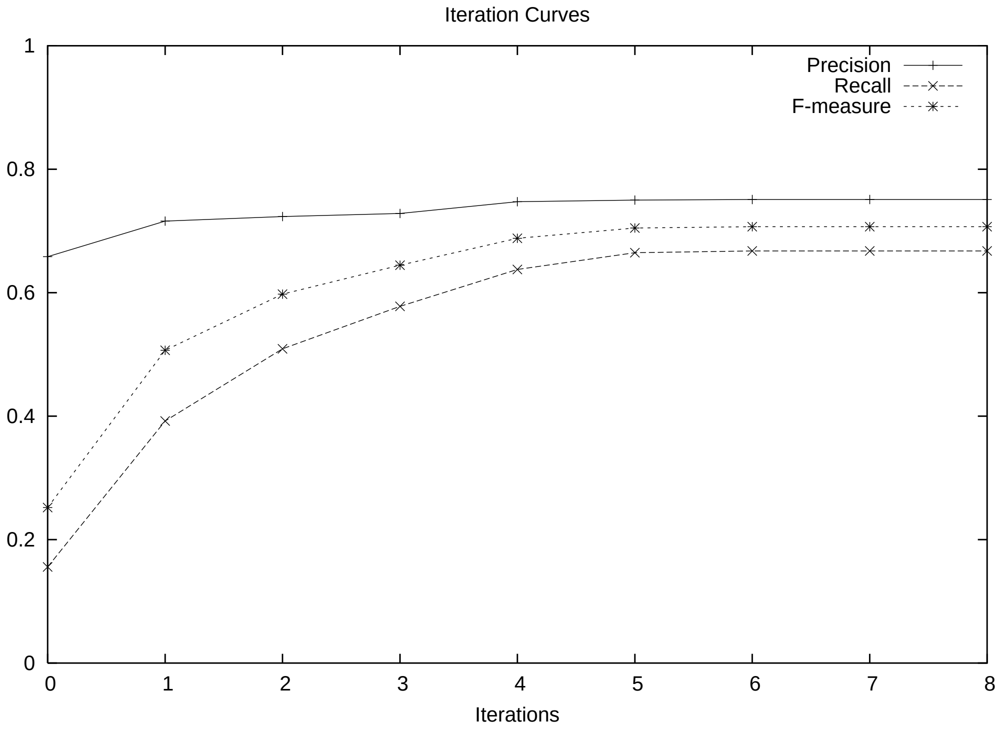


Figure 3.10: Quality of the *matched text* during its construction, for Variant 2 ($Score_{add}$+ $Off\text{-}line_{dict}$). Similar to Figure 3.9, this figure shows an evaluation of the *matched text* as it is being constructed. Compared to Variant 1, Variant 2 produces a much soft curve which makes preferable in the general case.

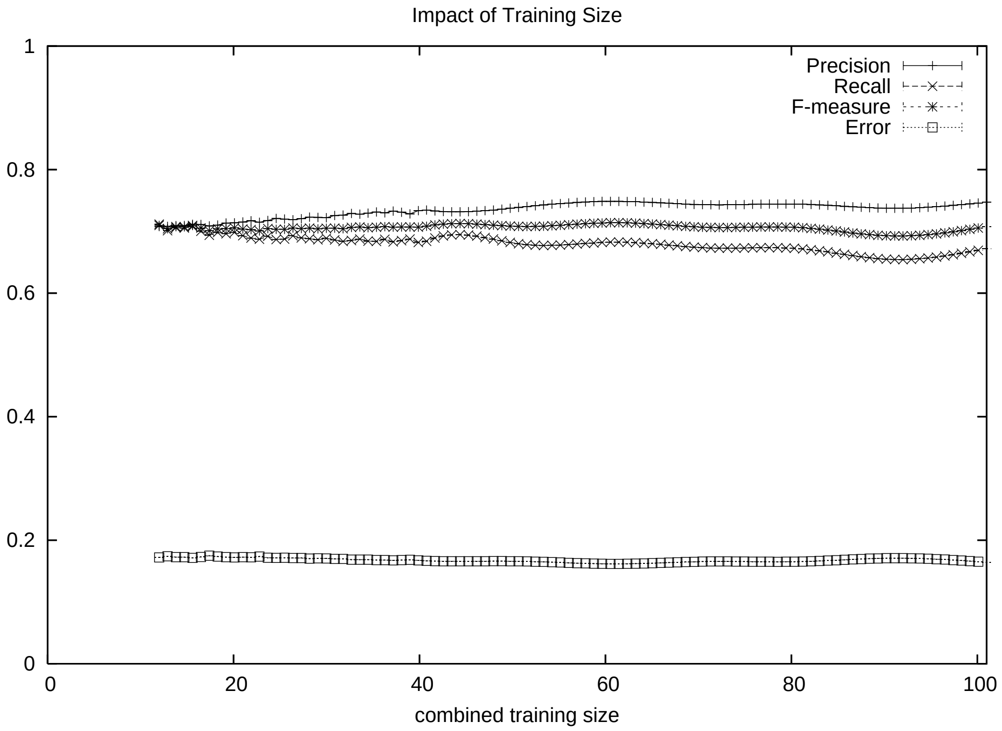


Figure 3.11: Impact of the training size for the *matched text* construction, Variant 2 ($Score_{add}$+ $Off\text{-}line_{dict}$). This variant learns the dictionary from the training material and it gets hurt by a lack of it. The figure shows how at least 60 instances are need to reach stable results.

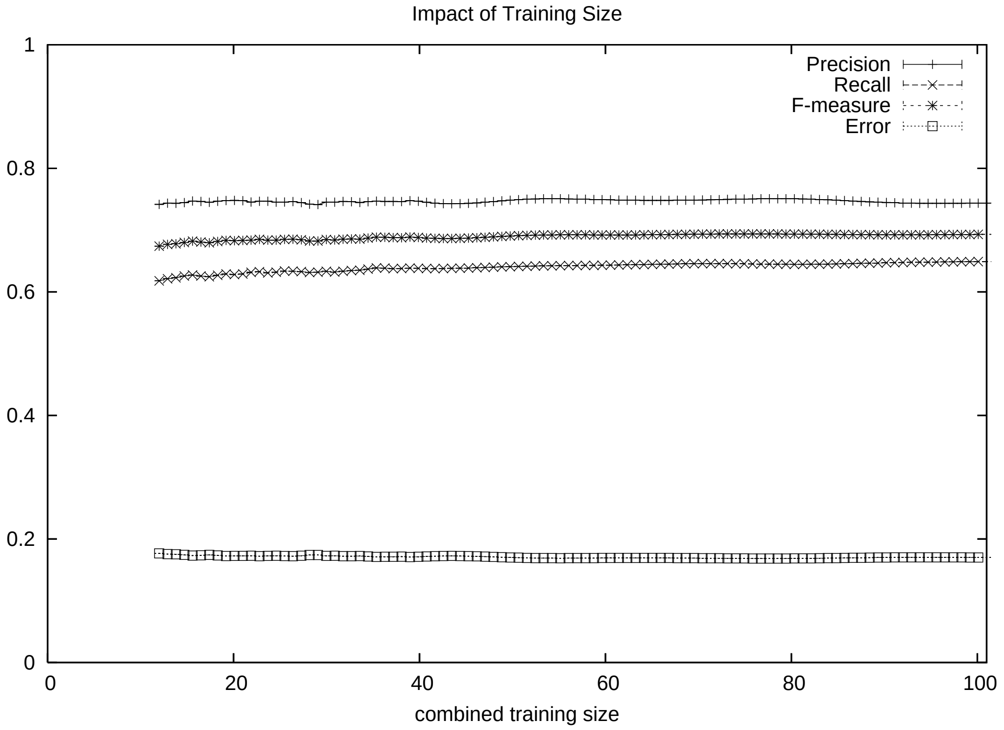


Figure 3.12: Impact of the training size for the *matched text* construction, Variant 3 ($Score_{add}$+ $External_{dict}$). This variant does not learn the dictionary from the training material and it only profits from a larger pool of data to improve the quality of the disambiguators. The impact of the extra training material is positive albeit very small.

Threshold	Description	Value
thr_t	t-test cut-point	9.9
thr_{add}	Percentage of the available number of matches to run the on-line dictionary induction.	20%
thr_{top}	Number of top scoring matches to add in each step (computed as a percentage of the total number of matches).	10%
w	Disambiguation window, in words.	3
thr_{supp}	Concept support, in percentage of the total number of instances.	20%

Table 3.10: Thresholds and Parameters in the *matched text* construction process.

Moreover, as it will be discussed in Chapter 8, the technique presented here cannot learn after a certain point. Particularly, it has problems with free-text fields (e.g., “claim to fame”) or facts included in the text out of being of extraordinary nature.

Chapter 4

Learning of Content Selection Rules

This chapter presents my work on the automatic acquisition of a set of Content Selection rules. These rules provide a particular solution to the Content Selection task (a task defined in the next section). I decided to use these symbolic rules (also described in the next section) as a representation for learning because they capture the requirements of my Content Selection problem. Moreover, they are also easy to understand by humans, allowing the output of the learning system to be further refined for quality, if needed.

The internals of this rule learning process are the focus of this chapter. The rule learning mechanism described here learns from the **ideal dataset** for the task of learning Content Selection rules: knowledge data with select (*sel*) or omit ($\neg$*sel*) labels (Figure 4.1 (b)). Such training material can be considered ideal for learning Content Selection logic as it is the input and output of the Content Selection process. The labels will thus signal, for each piece of data, whether or not the piece of data should be selected for inclusion in the final text. The ideal dataset can be obtained directly by hand-tagging but I am interested in a solution without any human intervention, neither from a knowledge engineer or annotators. Therefore, I learn from a noisy approximation obtained from the natural dataset for the task, in the form of a Text-Knowledge corpus (Figure 4.1 (a)), using the *matched text* from the previous chapter.[1] The Supervised Learning step (Section 4.2) will thus search for rules that better accommodate this training material. The training material from the biographies domain sketched in the previous chapter (Section 3.4, discussed at length in Chapter 7, Section 7.1) will be used to run a number of experiments, presented in Section 4.3.

Learning from a dataset extracted automatically makes for a very challenging task. For instance, my approach of analyzing how variations in the data affect the text

[1] A trivial label extraction step is necessary to read out the labels from the *matched text*, although it will not be discussed here.

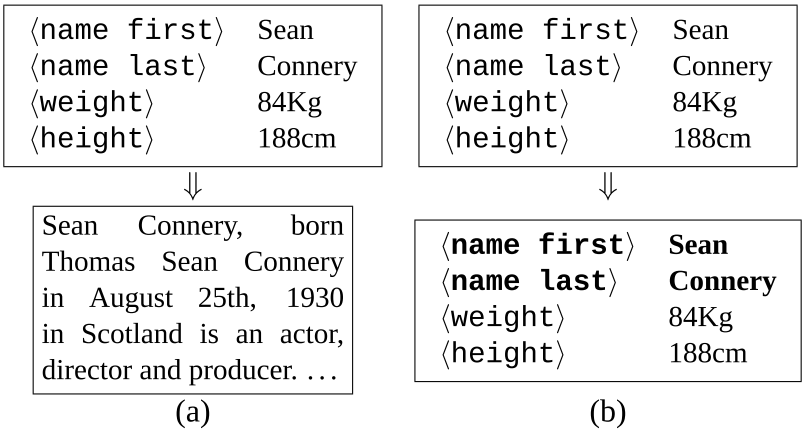


Figure 4.1: Input to the learning system. (a) Actual input, a set of associated knowledge base and text pairs (indirect evidence for learning) (b) Fully supervised input with selected items shown in bold; this is obtained as a byproduct of the processing done by my system.

(used to build the *matched texts* in the previous chapter) is prone to over-generation, as explained in the limitations chapter, Section 8.2. This over-generation implies that the rules learned from this dataset will be likely to have low precision.

4.1 Definitions

I will now introduce some definitions I use in the remainder of this chapter.

Content Selection. This is the action of choosing the right information to communicate in a NLG system, a complex and domain dependent task. Figure 4.2 shows an example; its input is a set of attribute-value pairs, and its output is a subset of the input attribute-value pairs, determined by the selection labels (*sel* or ¬*sel*). The labeled with *sel* subset contains the information that will make up the final, generated text. Content Selection can be thought of as a filtering or as a labelling process. When thought of as a labelling process, the system will choose between two labels: *sel* (i.e., filter accepts) or ¬*sel* (i.e., filter rejects). The labelling approach allows for a generalized Content Selection task, where each piece of data is assigned a **salience score**. In my work, I will consider a labelling task with two classes. My approach can be extended to accommodate generic classes as discussed in the Conclusions chapter (Section 9.2).

label	data-path	value
sel	⟨**name** → **first**⟩	**“Sean”**
sel	⟨**name** → **last**⟩	**“Connery”**
$\neg$*sel*	⟨weight⟩	84Kg
$\neg$*sel*	⟨height⟩	188cm
sel	⟨**award** → **name**⟩	**“Oscar”**
$\neg$*sel*	⟨award → name⟩	“MTV”
sel	⟨**relative** → **type**⟩	**c-grand-son**
sel	⟨**relative** → **name** → **first**⟩	**“Dashiel”**
$\neg$*sel*	⟨relative → type⟩	c-step-cousin
$\neg$*sel*	⟨relative → name → first⟩	“Jason”

(a)

Sean Connery received an Oscar and has a grand-son, Dashiel …

(b)

Figure 4.2: Content Selection Example. (a) The input to the Content Selection module plus its output (selection labels) (b) Verbalization of the selected attribute-value pairs.

Content Selection rules. The output of my learning system are Content Selection rules, which base their decision solely on the available knowledge. All rules are functions from a node to $\{T,F\}$; that is, they take a node in the knowledge representation and return true or false. In this way, my Content Selection rules contain decision logic only for atomic nodes. In this chapter, expressions such as “a piece of data to be selected” are formalized as an atomic node in the knowledge representation graph (of all types but REFERENCE type, see the definitions in the previous chapter). The decision of whether to include a given piece of data is made solely on the given data (no text is available during generation, as the generation process is creating output text). Sometimes it is enough only to analyze the value of the atomic node (e.g., to tell an Oscar from a BAFTA award). In other cases, however, it is also necessary to look at the surrounding information to decide whether or not to include a piece of data. For example, to tell the name of a cousin from the name of a grand-son (Figure 4.3) or to tell a successful movie (movies that received a number of awards) from failures. A simplifying assumption involved in a two level Content Selection approach, as the one presented in this thesis, is that all nodes are processed independently during the first Content Selection level. Therefore, the outcome of the decision about other nodes is not part of a given node decision. This simplifying assumption is clearly wrong (in a extreme case, if a piece of information ap-

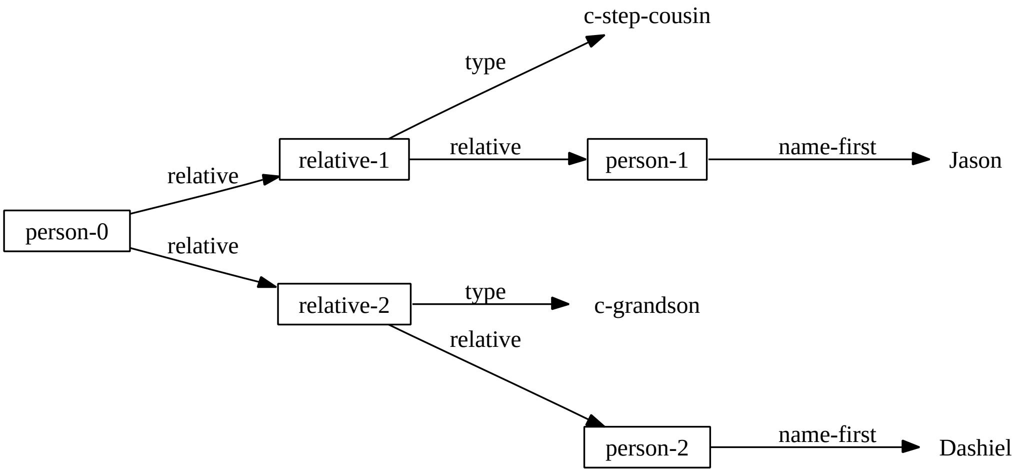


Figure 4.3: The value of nodes outside the node being selected may contain information that governs the selection process. In this example, to decide whether to include "Dashiel" or "Jason," the type of the relative frame is important (in the nomenclature used in this dissertation, that value can be accessed through the path ⟨`-name-first -relative type`⟩.

pears repeated as two different nodes, the inclusion of one node should prevent the other node to be included), but Content Selection in context is attacked by the fitness function presented in the next chapter.

I mine a different set of rules for each data-class (data-path in my case). The impact of the data-class equivalence classes for the quality of Content Selection rules is a subject I am interested in pursuing in further work.

Select-All/Select-None rules. The first type of rules, SELECT-ALL/SELECT-NONE, addresses the first four rows of Figure 4.2. After analyzing a number of target biographies in a hypothetical style, it is easy to see that the first and last names of the person being described should **always** be included in the biography. Conversely, his weight or height should **never** be included. These rules will select or omit each and every instance of a given data-class at the same time (e.g., if ⟨`relative person name-first`⟩ is selected, then *"Dashiel"* and *"Jason"* will both be selected in Figure 4.2).[2]

Tri-partite rules. After careful analysis of my training data and experimentation with different rule languages, I have settled for rules containing three pieces of information

[2] As my rules apply only to atomic values, no rules will be needed for ⟨`relative person`⟩.

(these rules are applied to an atomic node in the graph, the 'current node'):

1. Constraints on the current node.
2. Path to a second node (relative to the current node).
3. Constraints on the second node[3] (the node at the end of the path).

The constraints can be very general (including access to global variables or arithmetic operations on NUMERIC nodes), but in my work I have used two simple constraints. The first constraint, TRUE, always selects the information for inclusion. It is marked as '-' in my representation of the rules. The second type of constraints are constraints saying that the value of the node has to belong to a set of values. They are marked as 'value $\in \{\text{set}\}$'. The tri-partite rules can contain empty paths (denoted as '-'), in which case there should be no constraints on the second node.

This rule language addresses three types of selection needs, all shown in the example knowledge base with selection labels of Figure 4.2. To begin with, it is possible to express SELECT-ALL/SELECT-NONE rules in this language (first two rules in Figure 4.4), successfully addressing the first four rows of Figure 4.2.

The next two rows, regarding different awards the person has received make for a more interesting case, where the information should be included only if it belongs to a certain set of **important** values. In the celebrities domain, important awards include, for example, *Oscars* or the *Golden Globes* (motivating rules such as the third one in Figure 4.4). Obviously, the relative importance of the different awards is clearly domain dependent. The case shown in the figure is paradigmatic: *MTV movie awards* are seldom mentioned in target biographies. This omission is to be expected according to people I consulted who are interested in celebrities issues. Nothing *a priori* in the data prepare you for that result, as *MTV* is a source of authority in the celebrities domain. As the experiments in Section 4.3 show, my system is able to acquire this type of information.

Finally, for the last four rows in Figure 4.2, the information to solve the selection of the name of the relative does not lie on the name itself but in the value of another node that can be reached from the name node: the type of the relation. This fact motivates the path and the constraints in the other node (as part of the tri-partite rule). My final goal has been to be able to express with the rules concepts as complex as *this movie should be selected if it received an Oscar*, as shown in the last rule of Figure 4.4.

[3] Here, "second node" actually denotes a set of nodes, because paths can traverse list-valued attributes.

⟨`person name-first`⟩ (-, -, -). ;SELECT-ALL
Always say the first name of the person being described.

⟨`person eye-color`⟩: (false, -, -). ;SELECT-NONE
Never say the eye color of the person being described.

⟨`person award title`⟩: (value ∈ {*"Oscar"*, *"Golden Globe"*}, -,-).
Only mention the name of an award if it is whether a Golden Globe or an Oscar.

⟨`person work title`⟩: (-,⟨`-title -reason title`⟩,value ∈ {*"Oscar"*}).
Only mention the title of a movie if the movie received an Oscar.

Figure 4.4: Example content selection rules. In the path, `-title` refers to traversing a link `title` in the opposite direction. I employ hard rules instead of soft percentages to allow for a natural integration with hand-written rules. reviewPablosay this also in the text

Complex Content Selection Rules. In preliminary investigations (Duboue, 2004), I presented a variant of my system that targets more complex rules than the tri-partite ones I have just defined. These rules allow for recursion and are summarized in Figure 4.5. While this rules are more expressive than the tri-partite ones, I discontinue their use in favor of the tri-partite rules, as the latter are a more constrained representation that makes better use of the training material.

4.2 Supervised Learning

Figure 4.6 illustrates my two-step indirect supervised learning approach, divided into a number of modules. The first step, Dataset Construction (discussed in the previous chapter), turns the aligned Text-Knowledge corpus into a training dataset consisting of knowledge and selected or omitted labels (the Relevant Knowledge). Once the labels have been elucidated, the Supervised Learning module performs a Genetic Search in the space of possible rulesets, as described in this section.

I have thus a dataset consisting of classification labels (selected, *sel*, or omitted, ¬*sel*) for each piece of input knowledge. I want to learn that mapping (from concept to classification label) and capture that information about the mapping using Content Selection rules. This constitutes a case for Supervised Learning. The information available to the learner is thus the frame knowledge representation (a graph) plus the labels. This implies learning from structural information (as compared to learning from flat feature vectors). To this end, several alternatives are possible, including using memory-based

TRUE() Always select.

IN(list of atomic values) Select if the value is in the list.

TRAVERSE(path in the graph, rule) Select if the node at the of the path are selected by the rule.

TRAVERSE-EQ(path in the graph) Select if the value of the node at the end of the path is equal to the value of the current node.

AND(rules) Select if all the rules select the current node.

OR(rules) Select if any of the rules select the current node.

Figure 4.5: Complex Rule language. All rules are of the form $f : \text{node} \rightarrow \{T, F\}$, that is, they take a node in the knowledge representation and return true or false. These rules are more expressive than their simplified counterpart.

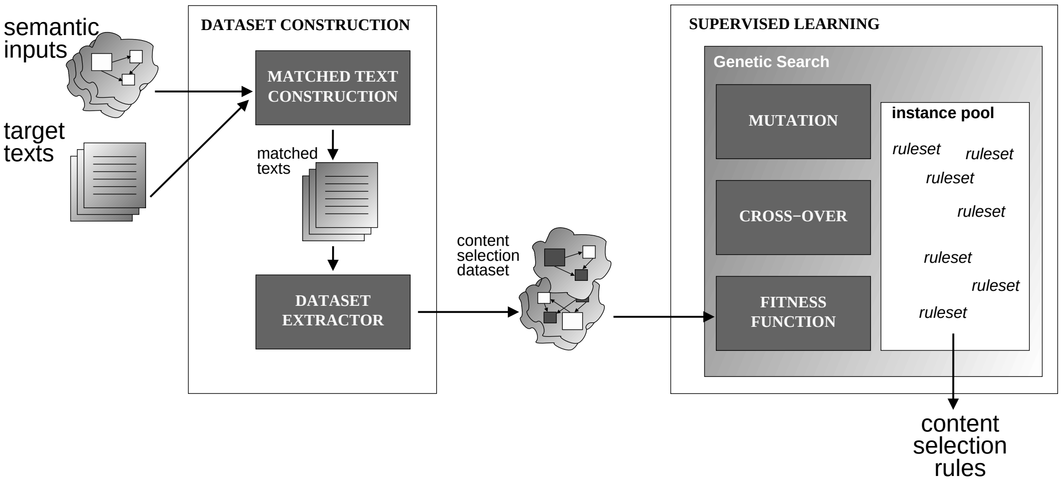


Figure 4.6: The rule induction system. The *matched text* construction is described in the previous chapter.

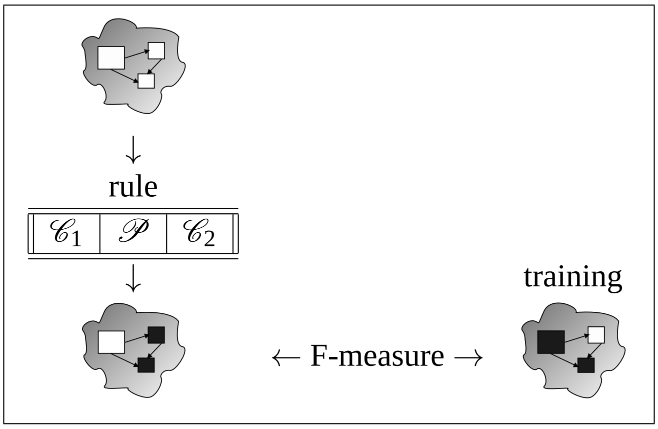


Figure 4.7: Rule evaluation. Each rule is executed and its output compared to the automatically obtained reference.

learning, inductive logic programming, combinatorial algorithms and kernel methods (Washio and Motoda, 2003). Given the high dimensionality of the decision space over graphs, I have found it valuable to be able to define a successor instance coming from **two** instances in the search pool, instead of one. This type of approach is known as Genetic Algorithms (Section 4.2.1). In general, I consider GAs as a meaningful way to perform symbolic learning with statistical methods. To motivate its use I also propose a comparison to ML classification systems in Section 4.2.2 and to some meaningful baselines in Section 4.2.3.

4.2.1 Learning Rules

I have input and output pairs of knowledge and labels (K,L), with labels extracted from the *matched text*. I am interested in finding the rules r^* (belonging to the set of all possible Content Selection rules) such that r^* maximizes the posterior probability given the training material:

$$r^* = \underset{r}{argmax}\ P(r|K,L)$$

instead of computing a probability, I use the input and output pairs to compute for each putative rules r a likelihood $f(r,K,L)$ that allows me to compare among them. This likelihood is thus a quality function in the representation space. I use the rules (r) to generate from the input knowledge K a set of labels L'. The sought quality function becomes the distance between the training output and the produced output, $||L-L'||$. As distance, I use the F-measure from Information Retrieval (IR). This process is sketched in Figure 4.7.

With the quality function in hand, finding the rules r^* implies a search process on the large space of representations. The key ingredients in a Genetic Algorithms solution are the **fitness function** (the quality function mentioned above), the **operators** and the **initial population**. I will describe them shortly.

Fitness Function. The fitness function takes a tri-partite rule r and computes its expected goodness with respect to the training material. One contribution of this thesis is to employ as fitness function the F_α measure (weighted f-measure from IR (van Rijsbergen, 1979)) of the classification task of recovering all selection labels on the training datasets. That is to say, for a given data-class, there are a number of items in the data-class to be selected according to the training material. The tri-partite rule r is applied to the knowledge and the number of correctly selected items becomes the rule's number of **true positives**. The number of items the rule wrongly selects is its number of **false positives**. Finally, the items the rule should have selected but it missed are the rule's number of **false negatives**. The F_α then is defined as follows, where P stands for precision and R stands for recall:

$$\begin{aligned} F_\alpha &= \frac{\left(\alpha^2+1\right)PR}{\alpha^2 P+R} \\ P &= \frac{\text{true positives}}{\text{true positives}+\text{false positives}} \\ R &= \frac{\text{true positives}}{\text{true positives}+\text{false negatives}} \end{aligned}$$

The fitness function is the key to learning using GAs. In earlier versions of my system the fitness function was too biased towards selecting all elements in the data-class. The key ingredient for a successful function in my problem has been to add information about the **priors** for each class (selected or omitted) in each data-class. The function defined above implicitly incorporate these priors (in the counts of false positives and false negatives).

As I wanted to obtain rules with higher recall than precision, I employed $\alpha = 2.0$ (recall is doubly as important as precision), as shown in Table 4.5. I added a minimum description length (MDL) term to the fitness function to avoid over-fitting the data (by memorizing all training instances). The final fitness function is then:

$$F = F_\alpha + MDL$$

MDL term. To avoid overtraining I use a MDL term as part of the fitness function. The type of over-training I try to avoid are, for example, cases where *month-of-birth* is always selected but I only see all months but June in the training material. There a rule like (value $\in \{$*"Jan"*, *"Feb"*, *"Mar"*, *"Abr"*, *"Jul"*, *"Aug"*, *"Sep"*, *"Oct"*, *"Nov"*, *"Dec"*$\}$, -,-) will accomodate the training material, but (-,-,-) (TRUE) will also explain it, and generalize better.

Coming up with this MDL term was much harder that I expected as easy choices were either too strong and dominated the fitness function or were too weak and failed to avoid over-training completely. I defined the final MDL function as:

$$\begin{aligned} \beta &= 1.5\frac{log(\frac{s}{1-s})}{t} \\ MDL &= -\frac{1}{1+e^{-\beta l}} \end{aligned}$$

Where t is the total number of items to be selected in the current data class, s is a user-provided saturation parameter (I used 0.99 in my experiments, see Table 4.5) and l is the length of the rule being evaluated measured in characters.

This MDL term is a heuristic function with the following justification: it is a negative value between 0 and -1.0. When combined with the F_α (that ranges between 0 and 1.0), the resulting fitness function will range between -1.0 and 1.0. The MDL function is a sigmoid with two saturation regions controlled by the s parameter. In one saturation region, the function will evaluate to 0 (no MDL penalty) and in the other it will evaluate to -1.0 (MDL rejects completely). Outside the saturation area, the function is quasi-linear, with its slope depending on the number of selected items to be selected (data classes with more items to be selected tolerate more complex rules).

The use of MDL to increase generalization capabilities is inspired by the tree pruning performed in C4.5 (Quinlan, 1993). The sigmoid function is similar to sigmoid activation functions for neural networks (Hertz, Krogh, and Palmer, 1991).

Operators. I have a cross-over operator (Figure 4.8) that takes the two rules and combines them into a new one, by following these steps: first, the constraints in the node are merged, when merging constraints, there is a 50% chance that the constraints are copied from only one parent (a parent decided proportionally to its fitness value). The other 50% chance goes to 25% chance of picking the union of the constraints and a 25% chance of picking the intersection of the constraints (although an empty intersection is promoted to TRUE). Then it looks at whether the two parents share the same path (the second entry in the tri-partite rule) or not. If they share the same path, the constraints in the second node are merged. Otherwise, one parent is selected (again, fitness-proportional), and its path and constraints copied to the child.

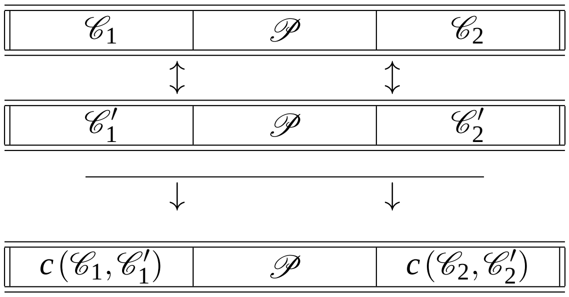


Figure 4.8: Combining two rules. The new rule share some of the constraints of its parents.

While cross-over takes two instances to create the new instance, mutation operations work on an existing instance, producing a new instance with a variation of the original. I investigated three possible variations, detailed below: growing the existing instance, shrinking the existing instance, and shuffling the existing instance.

The grow mutation will, with equal probability, add a new random value to check for in the constraints for the node and the node at the end of the path. The shrink mutation will remove a value from the constraints (if there is any value to remove). Finally, the shuffle mutation will change the path in the rule with a new path taken randomly from the set of all possible paths. The constraint at the end of the path will also be selected randomly.

Initial Population. I do not use the genetic algorithm to explore different paths; it only explores the space of constraints over nodes. The paths are exhaustively enumerated when building the initial population, until a maximum distance from the node (breath-first search, $depth$ in Table 4.5) is reached. To obtain these paths, a composite graph is created from all training instances. Moreover, the selection and distribution of atomic values at each node in the composite graph is also recorded. This distribution is used to create initial constraints for the paths obtained via breath-first search. Other areas of the graph do not contribute to the construction of the initial population.

Stopping Criteria. I considered two stopping criteria for the genetic search. The first one was an overall maximum number of generations. The second criteria has to do with lack of changes in the overall population. When the best instance found so far stays the same for a certain number of generations, the population is considered to have converged to a maximum.

4.2.2 Traditional ML

I use Weka (Witten and Frank, 2000), a framework containing a number of supervised automatic classification algorithms, to provide an alternative solution to the Content Selection task. Weka machine learning algorithms take as input a fixed-size feature-vectors with fixed types representing the relevant information for each instance, together with its target class, in my case select or omit.

My traditional ML module takes the full data for a person, together with the selected labels and transforms this information into training material for the Weka classification system. I trained binary classifiers (selected or omitted) for each data-path. The main problem resolved in this module is how to represent a graph-based knowledge representation using flat feature vectors. My solution to this problem is explained below.

Given the highly structured frame knowledge representation (a DAG, with values in the leaves and attributes in the connecting links), to obtain a flat structure it was necessary to create a structure that encompasses all the possible input structures, and later linearize it. I employed the following algorithm to propositionalize my input graphs: first, I turned the graph into exactly one tree, by taking a spanning tree rooted in the node[4] to be selected or omitted, with maximum depth (normally between 3 to 6). Each of these trees could be traversed to obtain a flat vector. However, I needed to be able to represent all possible (available) trees in a simple vector. In that vector, a fixed coordinate has to have the same meaning across trees. For example, in the celebrities domain each tree represents one person, so I wanted coordinate 89 for Marilyn Monroe to be “name of the third cousin” and coordinate 89 for Warren Beaty to be **also** “name of the third cousin.” As different inputs may have defined different attributes (for example, in the medical domain a patient may have a key `tachycardia-start-time` while other may have `bradycardia-start-time`), and some attributes may be duplicated several times (for example, the patient may have had several drugs administered during the surgery, all of them are values for the `drugs-given` attribute), I needed a means to record and fix the possible attributes appearing at every node, together with the possible number of values (“fan-out”) each of these attributes can take (in the case of multiple-valued keys, like `award` or `relative`). For this purpose, I build a **unifier** tree for all the training trees. The process of building such a tree is summarized in Figure 4.9.

This unifier is built from training examples. Given enough of them, I expect to be able to capture all the possible attributes seen in an arbitrary input with its corresponding fan-outs. In the worst case, there will be data in an input that the Weka classifier will not

[4] This is different from what I did in (Duboue and McKeown, 2003a), where I used an spanning tree rooted in the person the biography was about. That approach deprived the ML from important information and was thus unsuccessful.

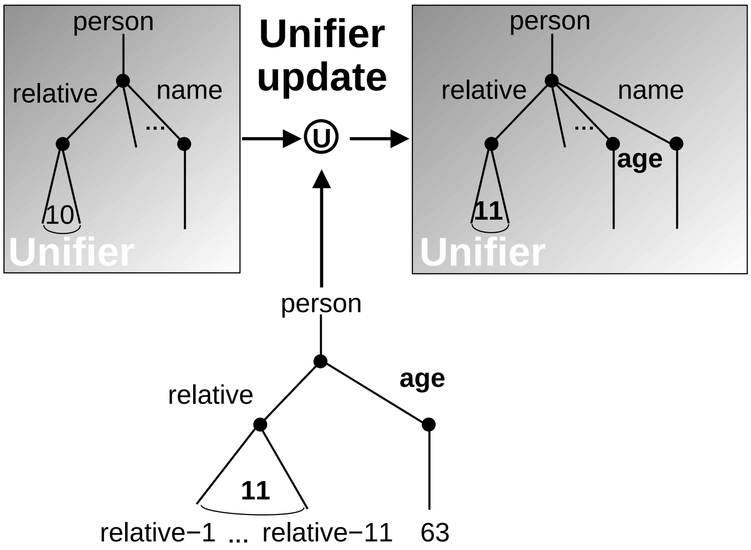


Figure 4.9: Computing the most general unifier for a set of structured inputs. A unifier in the process of being computed is updated with a new tree. The tree contains an unseen attribute (`age`) and more elements (11) in an already seen attribute (`relative`). Both elements get updated in the unifier.

be able to use for classification, providing suboptimal, but possibly adequate, results.

With such a unifier, a flat attribute-vector representation can be obtained by simultaneously traversing both the unifier and the tree at hand, producing default values in the case of non-existent data in the target tree or the occurring value otherwise. Finally, the module automatically assigns types to each coordinate of the output vector. I identify three types: numerical values, strings belonging to a small subset of possible values (Weka nominal type, such a *"mg"*, *"mcg"* and *"g"* for units of measurement) and strings from an open set that receive only one boolean entry representing whether it is defined or not.

This propositionalization process generated a large number of features, e.g., if one person had a grandmother, then there will be a "grandmother" column for every person. This situation gets more complicated when list-valued values are taken into consideration. In the biographies domain, an average-sized 100-triples biography spanned over 500 entries in the feature vector, even after pruning it for entries that are invariant in the training data.

The training vectors can be generated by the procedure described above for both the automatically obtained datasets and the hand-tagged evaluation set. After training on in the automatically obtained training material (one classifier per data-path), the combined system is tested on the unseen test vectors.

In Section 4.3, I compared the following machine learning techniques:

J48. Weka implementation of C4.5 (Quinlan, 1993) decision trees.

NaiveBayes. A naïve Bayesian classifier (John and Langley, 1995).

SMO. A sequential minimal optimization for training a support vector (SVM) using a polynomial kernel (Platt, 1998).

Logistic. Multinomial logistic regression model with a ridge estimator (le Cessie and van Houwelingen, 1992).

Recent additions to Weka allow for set-valued features, in the form of the jRip package (re-implementing the RIPPER algorithm (Cohen, 1996)). Such additions would allow to use parts of paths as features, but they were not available at the time of these experiments.

4.2.3 Baselines

As baseline, I use SELECT-ALL/SELECT-NONE rules over the baseline *matched text* described in the last chapter, Section 3.5 (*matched texts* without dictionary induction nor disambiguation). This solution involves counting how many items in each data-path appear as selected in the training material and then choosing the strategy SELECT-ALL or SELECT-NONE if the F^* for the path is greater than 0.5 (I use the F^* as a way to equally balance precision and recall). This algorithm maximizes the overall F^* for the path-based SELECT-ALL/SELECT-NONE strategy. When mined from *matched texts* obtained through the Variant 0 system in the previous chapter (Section 3.5), they provide a meaningful baseline for comparison. When mined from Variant 4 *matched texts* (Duboue and McKeown, 2003a), they provide a simpler alternative to the rules presented in this chapter, as they are faster to execute and less prone to errors coming from the assemblage of the *matched text*. SELECT-ALL/SELECT-NONE rules, however, still require a good level of post-filtering in later stages (they over-generate quite a bit) and may miss relevant information.

4.3 Experiments

To shed further light on the relative strengths of the methods described in this chapter, I ran a number of experiments. First, I learned SELECT-ALL/SELECT-NONE rules (Table 4.1). I learned the rules from the Variant 0 *matched texts* (Section 3.5) to obtain some

Table 4.1: SELECT-ALL/SELECT-NONE rules results. The 'sel' column contains the number of selected paths. Rules mined over Variant 4 select more paths which means a greater recall across the board with a toll on precision. Nevertheless, their overall F^* is better (the differences are statistically significant, although with low confidence, see Appendix A).

	Variant 0				Variant 4			
Corpus	P	R	F^*	sel	P	R	F^*	sel
`biography.com`	0.6023	0.6077	0.6050	36	0.5785	0.6616	0.6173	55
`s9.com`	0.3542	0.4647	0.4020	11	0.5000	0.4823	0.4910	18
`imdb.com`	0.5841	0.3197	0.4133	22	0.5269	0.3712	0.4356	39
`wikipedia.org`	0.8515	0.1822	0.3002	10	0.5884	0.2892	0.3878	33

baseline rules. I also learned from Variant 4 *matched texts* (*matched texts* with a combination of dictionary induction and external verbalization dictionary). The table shows that, while the differences in intrinsic quality reported in the previous chapter for the two variants was small (less than two percentual points in the F^*), it translates in a major difference in the type of SELECT-ALL/SELECT-NONE rules that can be learned from them (an extrinsic evaluation). Moreover, SELECT-ALL/SELECT-NONE rules mined on Variant 4 are a good competitor to tri-partite rules, as presented next.

Using again the best available *matched texts* (Variant 4), I learned tri-partite rules per Section 4.2.1 (Figure 4.10 illustrates some of the rules learned). The results over the four corpora are shown in Table 4.2. These results improve several points over the baseline, while all but `s9.com` improve over Variant 4 rules. The improvement is more marked in some corpora than others. For example, the improvements over `biography.com` are moderate but note that the rules are six points from the F^* of the training material The `wikipedia.org` corpus presents the higher improvement over the baseline (13 points in F^*-measure). That illustrates how my learning system can profit from a larger knowledge pool. The fact that `Select-All/Select-None` rules on Variant 4 for the `s9.com` corpus perform better than the tri-partite rules over the same corpus supports the hypothesis that SELECT-ALL/SELECT-NONE rules are to be preferred in the presence of high noise.

Appendix A shows that Variant 4 has a high confidence statistically significant difference with the baseline for all corpora but `imdb.com`. In `wikipedia.org`, the rules also present good confidence for the difference between SELECT-ALL/SELECT-NONE rules and the baseline.

Using the `biography.com` Variant 4 training material, traditional ML classifi-

⟨`name first`⟩ (-, -, -) TRUE; ⟨`name last`⟩ (-, -, -) TRUE

Always say first and last names.

⟨`education place country`⟩ (value ∈ {*“Scotland”*, *“England”*}, -, -)

As I used U.S. biographies, the country of education is only mentioned when it is abroad.

⟨`relative #TYPE`⟩ (value ∈ {`c-sister`,`c-step-father`}, -, -)

Mention sisters and step-fathers.

⟨`significant-other #TYPE`⟩ (value ∈ {`c-husband`,`c-wife`}, -, -)

Mention husband and wives (but not necessarily boyfriends, girlfriends or lovers).

Figure 4.10: Learned rules.

Table 4.2: My system results.

Corpus	P	R	F^*	sel
`biography.com`	0.5829	0.7155	0.6424	410
`s9.com`	0.3387	0.4941	0.4019	248
`imdb.com`	0.5029	0.4607	0.4809	338
`wikipedia.org`	0.5150	0.3729	0.4325	433

Table 4.3: Machine Learning results. These results suffer from the relative lack of training material compared to a large number of features.

Metric	j48 (C4.5)	Naïve Bayes	SMO (SVM)	Logistic
Precision	0.6790	0.6226	0.6086	0.6161
Recall	0.4940	0.4940	0.5029	0.5718
F^*	0.5719	0.5509	0.5508	0.5931

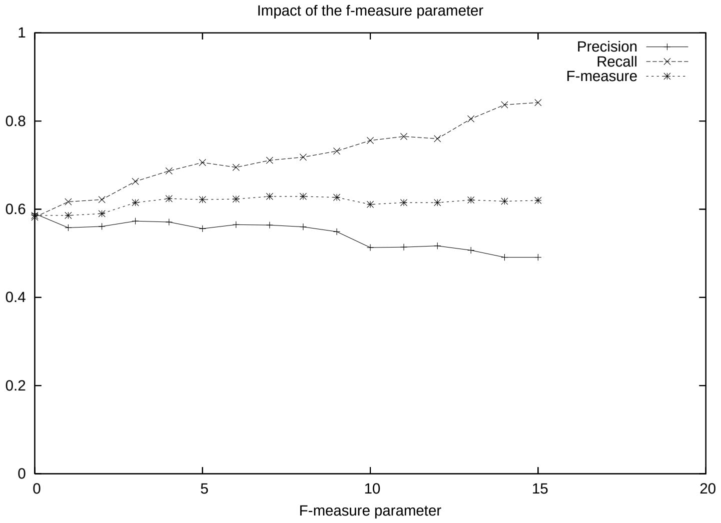


Figure 4.11: Impact of the F-measure weighting parameter for the supervised learning of Content Selection rules.

cation systems were trained and tested, following Section 4.2.2. The results are shown in Table 4.3. Because all the results are below baseline (0.60 in Table 4.1), it may be the case that the unification/spanning-tree approach described in Section 4.2.2 is generating too many features for the small training material available. This hypothesis is supported by the fact that logistic regression is the approach that fares better in Table 4.3.

To further validate my tri-partite rule induction system, I ran the system under different values of the α parameter (Figure 4.11). The figure attests that the α parameter works as expected, producing rules with a stable F^* but varying degrees of precision and recall controlled by the α parameter. The importance of these results cannot be overlooked, as they show how my approach can be tuned to learn broad rules or highly precise rules, from an automatically obtained training material.

Finally, I tested whether the rules being learned were different or not by running

Table 4.4: Cross-corpus results. Precision and recall scores appear next to the F^*-measure. Figures in bold are the best score for that corpus.

Tested on	Trained on					
	`biography.com`		`s9.com`		`imdb.com`	
`biography.com`	$\frac{0.5829}{0.7155}$	**0.6424**	$\frac{0.1683}{0.7941}$	0.2777	$\frac{0.4013}{0.6666}$	0.5010
`s9.com`	$\frac{0.6592}{0.3532}$	**0.4600**	$\frac{0.3387}{0.4941}$	0.4019	$\frac{0.4623}{0.2493}$	0.3239
`imdb.com`	$\frac{0.5565}{0.3682}$	0.4432	$\frac{0.2295}{0.5941}$	0.3311	$\frac{0.5029}{0.4607}$	**0.4809**

them across corpora. Table 4.4 shows a 3×3 grid obtained by training the system in each of the three corpora and testing it in each of the three corpora (`wikipedia.org` is in a different knowledge representation so it could not be used). The figure clearly illustrates how the rules learned are different for each corpus. Interestingly, the rules learned on `biography.com` perform better in `s9.com` than the rules learned on `s9.com` themselves. The *matched texts* for `s9.com` are so noisy that quality rules **for the domain** learned in a higher quality corpus perform better than rules learning in a very noisy approximation to the corpus itself. This result encourages work not now in generating a particular **biography style**, but selecting data that adheres to a **biographical domain**. That is, given information about a person, certain information would be more naturally fit to be included into a biography (it can be selected on the basis of the biographical domain). Categorizing information in this way is different from the task targeted in this thesis, where a particular style of biographies was sought to be mimicked. The domain-related task results in a summarization problem. Adapting my technique to summarization is an issue I am interested in addressing in future work (Chapter 9, Section 9.2).

4.4 Conclusions

The technique targeting learning Content Selection rules presented in this chapter is able to effectively learn rules from the noisy *matched texts*. Moreover, it is noticeable how the differences between the different *matched text* variants get a boost when used to learn

Threshold	Description	Value
$population_{size}$	Size of the population in the genetic search for Content Selection rules.	1000
$depth$	Depth cut-off for the breath-first search building the population for the rule search.	6
α	F-measure weighting.	2.0
l	Saturation area of the *MDL* sigmoid function.	0.99

Table 4.5: Thresholds and Parameters in the learning of Content Selection rules.

Content Selection rules.

An alternative approach using traditional machine learning methods suffers from a data sparsity problem that speaks in favor of techniques specifically designed to target the Content Selection problem.

While the rules mined in this chapter are ready to be used in a generation system, as mentioned in the conclusions of the previous chapter, it is necessary to model free-text fields (e.g., “claim to fame”) or facts included in the text out of being of extraordinary nature to make progress beyond the results presented here.

Chapter 5

Learning of Document Structuring Schemata

This chapter describes my learning technique to acquire Document Structuring schemata from an aligned Text-Knowledge corpus. As mentioned in Chapter 3, my learning has two steps: an unsupervised step and a supervised step. The unsupervised step in this case involves building the *matched texts* (per Chapter 3, Section 3.3); and then mining sequences of atomic values and order constraints (presented here, Section 5.2). For the supervised process of learning Document Structuring schemata (Section 5.4), I use a fitness function based on three items: Content Selection, order constraints and sequence alignment.

This technique is evaluated in two domains: Medical Reports (next chapter), where it enjoyed limited success and Biographical Descriptions (Chapter 7) where some of the problems encountered point to needed improvements discussed in Chapter 8.

I will now introduce some key concepts used in the rest of this chapter.

5.1 Definitions

For learning Document Structuring schemata, I use as input the aligned Text-Knowledge corpus and a set of communicative predicates. The Text-Knowledge corpus has already been introduced in Chapter 3. I will define here the communicative predicates. Moreover, one of the contributions of this dissertation is OpenSchema (Duboue, 2005), a declarative definition of the Document Structuring schemata, also presented in this section. These schemata are compatible with McKeown (1985)'s original definition, discussed in chapter 2, Section 2.2.1.

Document Structuring Task. The Document Structuring task takes as input a subset of the knowledge base (the relevant knowledge pool) and returns a sequence of messages (a *document plan*). These messages are produced by the predicates defined below.

Communicative Predicates. Each predicate (Figure 5.1) is composed of three items: variables, properties and output. Each variable has a type, which further constrains the possible values it can take (an item of that type or subtype, given an ontology). These variables range over frame references. Following KNIGHT, MAGIC and similar systems, I use domain dependent predicates (instead of McKeown (1985) **rhetorical** predicates). I call these predicates **communicative** predicates, as they hold a good deal of Domain Communication Knowledge, DCK (Chapter 2, Section 2.2). The actual number and nature of these predicates varies from domain to domain. In my implementation these predicates are defined in a constraint satisfaction formalism. For the discussion that follows, a predicate can be considered as a function that takes a number of defined (and maybe undefined) variables and searches the knowledge representation for values of the undefined variables that satisfy the constraints inside the predicate. If none are found (or if the provided variables do not satisfy the constraints), the predicate cannot be instantiated. For each set of values[1] that satisfy its constraints, the predicate produces a **message** (Figure 5.2), a data structure assembled using the variable assignment found during the search. The messages are the nexus between the schema and the rest of the NLG system. A predicate, therefore, can be thought of in this context as a blueprint for making messages. In this thesis, I use functional descriptions (FDs) as messages, as I work with a FUF/SURGE (Elhadad and Robin, 1996) based implementation. The details of the messages are important because I will later need a means to compare these messages (the output of the schema) to sequences of atomic values (that I can read out from *matched texts*).

Document Plan. A document plan is a sequence of messages produced by predicates instantiated from variables ranging over frames in the knowledge representation.

My Declarative Schemata. Given a set of predicates, a schema (Figure 5.3) is a finite state machine over the language of predicates with variable references. All the variables in the schema are *global* variables, to distinguish them from the predicate variables (*local*

[1] The predicate returns only one message, if several sets of variable assignments satisfy the constraints, they will be iterated upon invocations of the predicate,when the iteration process is finished —the set of variable assignments is exhausted— the predicate fails to instantiate. The order of iteration follows the order they appear in the knowledge base. The hope is that the facts in the knowledge base are ordered following some natural domain ordering, like time or space.

```
predicate Education
  variables
      person            :  c-person
      education-event   :  c-education-event
  properties
    education-event ≡ person.education
  output
```

$$\begin{bmatrix} \text{pred} & \texttt{education} \\ \textit{pred}_0 & \texttt{person} \\ \textit{pred}_1 & \texttt{education-event}\rightarrow\texttt{teaching-agent} \\ \textit{pred}_2 & \texttt{education-event}\rightarrow\texttt{subject-matter} \\ \text{mods} & \begin{bmatrix} \text{time} & \begin{bmatrix} \text{start} & \texttt{education-event}\rightarrow\texttt{date-start} \\ \text{end} & \texttt{education-event}\rightarrow\texttt{date-end} \end{bmatrix} \\ \text{place} & \texttt{education-event}\rightarrow\texttt{place} \\ \text{reason} & \texttt{education-event}\rightarrow\texttt{reason} \end{bmatrix} \end{bmatrix}$$

Figure 5.1: Example of a communicative predicate in the biographical descriptions domain.

$$\begin{bmatrix} \text{pred} & \texttt{education} \\ \textit{pred}_0 & \texttt{person-32} \\ \textit{pred}_1 & \texttt{"Columbia University"} \\ \textit{pred}_2 & \texttt{"Computer Science"} \\ \text{mods} & \begin{bmatrix} \text{time} & \begin{bmatrix} \text{start} & \texttt{"1999/8/27"} \\ \text{end} & \texttt{"2005/1/17"} \end{bmatrix} \\ \text{place} & \texttt{"New York, NY"} \end{bmatrix} \end{bmatrix}$$

Figure 5.2: Example of an instantiated predicate (message).

variables). At each step during schema instantiation, a current node is kept and all the predicates in the edges departing from the current node are instantiated (via the process sketched in the previous definition). A focus mechanism (coming directly from McKeown (1985) and thus described in Chapter 2, Section 2.2.1) will then select the next node (and add the message to the *document plan*), situations with 12 or more possible continuations during schema instantiation have been found in practice. The instantiation process finishes when no new predicate can be instantiated departing from the current node. While the schema itself is simple (an automaton with predicate and variable names on its edges), the instantiation process is complex because it has to keep track of free (i.e., undefined) and bound variables (predicates bind variables;[2] some variables can also be bound before the instantiation begins —as global arguments of the schema, for example, the person being described in the biography) and focus stacks. Interestingly, my schema induction algorithm makes no assumptions on the instantiation process, being therefore independent of the instantiation process or its internal details (e.g., the local search strategy —focus in my case). This makes for a very knowledge lean approach with a wider range of application. However, this complex instantiation process forbids using existing learning techniques for finite state machines (FSMs) to learn the schemata. This situation arises as a finite state machine will produce all the strings belonging to its language. A schema contains a FSM but will produce a much smaller set of strings, only the ones licensed by the FSM **and** the focus mechanism. This situation cannot be overlooked: if we believe that schemata explain the data we are observing (the human data), then the only strings being observed are the ones valid according to the focus mechanism. Therefore, there will not be enough data to elucidate the original FSM by using only FSM-learning techniques.

5.2 Training Material

To learn Document Structuring schemata, I have *matched texts* and a set of predicates. As mentioned in the previous section, a schemata takes relevant knowledge as input and produces as output *document plans.* Examples of these *document plans* would be needed to supervisedly learn schemata. The *document plans,* however, are not readable from the *matched texts,* as they contain no mention of the rhetorical predicates. For example, assume there are two predicates: **occupation** and **date-of-birth**. Both take two arguments, **occupation** takes a person and an occupation and **date-of-birth** takes a person and a date-of-birth. Then, for the text

[2] Once variables receive a value, it cannot be changed, except in the place where they received the value.

```
schema Biography(self: c-person)
  Person(person↔self)+
  {Birth(person ↔ self)}
  {Alias(person ↔ self)}
  ((Father(self ↔ self,parent ↔ parent)
   ||
   Mother(self ↔ self,parent ↔ parent))
   Person(person ↔ self)+)∗
  Education(person↔self)+


  (Built(person ↔ self,built ↔ built)
   appraisal(reason ↔ built)∗)∗
  Other-Work-Event(person↔self)*


  (Relationship(self ↔ self,partner ↔ partner)
   ((Child-Mother(father ↔ self,mother ↔ partner,child ↔ child)
   ||
   Child-Father(father ↔ partner,mother ↔ self,child ↔ child))
   Person(person ↔ child)∗)∗


  (Relative(self ↔ self,relative ↔ relative)
   Person(person ↔ relative)∗)∗
  {Death(person ↔ self)}
```

Figure 5.3: Example of a biographical description schema. The biography has four parts. The first part introduces the person, including birth date and place, parents and education. The second part summarizes work activities, including awards. The third part talks about relationships on which the person has been involved and children (small family circle). The last part mentions relatives (extended family circle). The braces mean optionality, the vertical double bar separates alternatives, plus and star have their usual one (or zero) or more repetitions meanings and the double arrow imply global to local variable bindings.

"John Doe is an actor. John Doe was born on 1/1/80."

generated from the sequence of two instantiated predicates:

occupation(`person-1`, `occupation-1/type`) **date-of-birth**(`person-1`, `date-1/month`, `date-1/day`, `date-1/year`).

the *matched text* will only contain the eight-item sequence of atomic values:

```
name-1/first name-1/last occupation-1/type name-1/first
name-1/last date-1/month date-1/day date-1/year
```

but no reference to the predicates **occupation** and **date-of-birth**.

Moreover, the *matched text* construction process has no provisions for anaphoric expressions. As a result, only the first mention will be reliably identified. Therefore, if the above example is laid out more naturally as

"John Doe is an actor. He was born on 1/1/80."

The sequence of atomic values will thus be reduced to

```
name-1/first name-1/last occupation-1/type date-1/month
date-1/day date-1/year
```

My system does not resolve *"He"* to *"John Doe,"* so it misses the second mention. That is to say, the *matched text* can reliably provide the placement information for **the first mention** of the atomic value in question (in general, first mentions are always easier to identify (Jansche, 2003)). The sequences mentioned below, extracted from the *matched text* will thus be cleaned for repeated values after the first mention (to ensure compatible results in cases where second mention were not identified).

To learn the schemata I then focus on three items that can be extracted from the *matched texts:*

- Selected knowledge, as employed to learn Content Selection rules.
- Semantic sequences, obtained by looking at the data classes of each of the identified values in the *matched text* (Figure 5.4 (b)).
- Sequences of atomic values, read directly from the *matched texts* (Figure 5.4 (a)).

These three elements will be used to implement a fitness function in the schemata space. This function (described in Section 5.4.2) will not utilize the semantic sequences directly, but will profit from **order constraints** mined over such sequences. These order constraints are also useful to produce a baseline to compare against the learned schemata. They are the focus of the next section.

name-24→first-name	⟨name first-name⟩
name-24→last-name	⟨name last-name⟩
date-24→year	⟨birth date-instant year⟩
date-24→month	⟨birth date-instant month⟩
date-24→day	⟨birth date-instant day⟩
name-30→first-name	⟨family relative name first-name⟩
award-1→title	⟨work-event award title⟩
name-40→first-name	⟨family relative name first-name⟩
sister-relative-1→TYPE	⟨family TYPE⟩
date-7→year	⟨work-event date-instant year⟩
date-30→year	⟨work-event date-instant year⟩
date-2→year	⟨work-event date-instant year⟩
date-26→year	⟨work-event date-instant year⟩
date-36→year	⟨work-event date-instant year⟩
date-27→year	⟨work-event date-instant year⟩
date-34→year	⟨work-event date-instant year⟩
date-35→year	⟨work-event date-instant year⟩
date-14→year	⟨work-event date-instant year⟩
date-23→year	⟨work-event date-instant year⟩
date-16→year	⟨work-event date-instant year⟩
date-1→year	⟨work-event date-instant year⟩
date-12→year	⟨work-event date-instant year⟩
wn-musician-2-1→TYPE	⟨occupation TYPE⟩
name-18→name	⟨work-event built name name⟩
(a)	(b)

Figure 5.4: Example of a sequence of first-mention atomic values (a), as read out from a *matched text* and its corresponding sequence of data-paths (b).

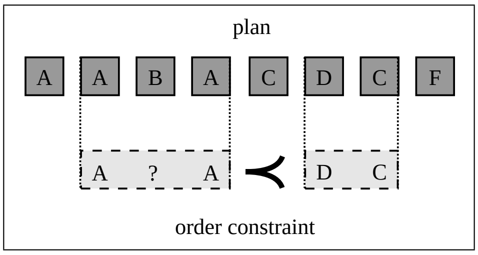


Figure 5.5: Fitness function: Constraints.

5.3 Order Constraints

This section describes the mining and usage of order constraints over the placement of semantic types over text (data-paths as used in this thesis, data-classes in the general case). These sequences can be read directly from the text (after it has been matched against the knowledge representation as in Chapter 3 or it has been hand annotated as will be presented in the next chapter). As such, they can be mined from annotated texts, as described in the next section.

The order constraints can be then used to measure how felicitous a given *document plan* is. For that, a semantic sequence can be read out from the *document plan*. Because the predicates contain no ordering information over the atomic values used to instantiate them, a technique for approximate matching over sequences of sets (each set representing an instantiated predicate) is discussed in Section 5.3.2.

5.3.1 Learning Order Constraints

As mentioned in the previous section, to learn the order constraints, I extract from the *matched text* the sequence of data-classes (data-paths), a sequence that I call a **semantic sequence** (in Figure 5.4, from the sequence of atomic values (a), the semantic sequence is (b)). I base my unsupervised learning algorithm on techniques used in computational genomics (Durbin et al., 1998), where patterns representing meaningful biological features are discovered from large amounts of seemingly unorganized genetic sequences. In my application, I search for patterns that occur repeatedly across multiple semantic sequences. By learning ordering constraints over these elements, I produce constraints that allow later selection of the schema that better explains the training material. My system uses combinatorial pattern matching (Rigoutsos and Floratos, 1998) combined with clustering to learn patterns. Subsequently, it applies statistical procedures to learn ordering constraints among these clusters of patterns.

The algorithm can be sketched as follows: I applied combinatorial pattern discovery (detailed in the next section) to the semantic sequences. The obtained patterns are refined through clustering. Counting procedures are then used to estimate order constraints between the clusters.

Pattern Detection. Pattern discovery techniques are often used for information extraction (e.g., (Riloff, 1993; Fisher et al., 1995)), but most work uses data that contains patterns labelled with the semantic slot the pattern fills. Given the difficulty for humans in finding patterns systematically in my data, I needed unsupervised techniques such as those developed in computational genomics, where patterns of the type I need are called *motifs*.

As explained by Hudak and McClure (1999), motif detection is usually addressed with alignment techniques (as mentioned by Durbin et al. (1998)) or with combinatorial pattern discovery techniques such as the ones I use here. Combinatorial pattern discovery is more appropriate for my task because it allows for matching across patterns with permutations, for representation of wild cards and for use on smaller data sets.

I will now provide a brief explanation of my pattern discovery methodology. The explanation builds on the definitions below:

$\langle L, W \rangle$ **pattern.** Given that Σ represents the data-paths alphabet, a pattern is a string of the form $\Sigma(\Sigma|?)^*\Sigma$, where ? represents a *don't care* (wild-card) position. The $\langle L, W \rangle$ parameters are used to further control the amount and placement of the *don't cares*: in every subsequence of length W, at least L positions must be filled (i.e., they are non-wild-cards characters). This definition entails that $L \leq W$ and also that a $\langle L, W \rangle$ pattern is also a $\langle L, W+1 \rangle$ pattern, etc.

Support. The support of pattern p given a set of sequences S is the number of sequences that contain at least one match of p. It indicates how useful a pattern is in a certain environment.

Specificity. A partial order relation on the pattern space can be defined as follows: a pattern p is said to be more specific than a pattern q if: (1) p is equal to q in the defined positions of q but has fewer undefined (i.e., wild-cards) positions; or (2) q is a substring of p. Specificity provides a notion of complexity of a pattern (more specific patterns are more complex). See Figure 5.6 for an example.

Using the previous definitions, the algorithm reduces to the problem of, given a set of sequences, integers L and W, a minimum window size, and a *support threshold*, finding maximal $\langle L, W \rangle$-patterns with at least a support of *support threshold*. My implementation can be sketched as follows:

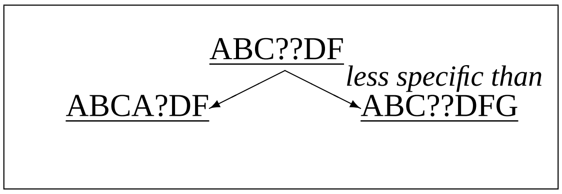


Figure 5.6: The specificity relation among patterns.

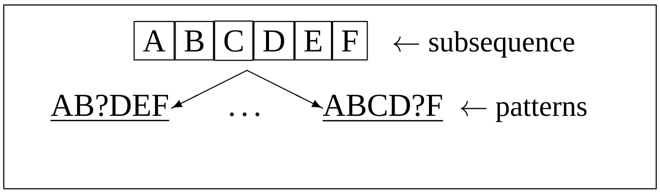


Figure 5.7: The process of generalizing an existing subsequence.

Scanning. For a given window size *n*, I identify all the possible subsequences (i.e., *n*-grams) occurring in the training set. I repeat this process for different window sizes.

Generalizing. For each of the identified subsequences, patterns are created by replacing valid positions (i.e., any place but the first and last positions) with wild-cards. Only $\langle L, W\rangle$ patterns with support greater than *support threshold* (described in Table 5.1 are kept. Figure 5.7 shows an example.

Filtering. The above process is repeated increasing the window size until no patterns with enough support are found. The list of identified patterns is then filtered according to specificity: given two patterns in the list, one of them more specific than the other, if both match in exactly the same positions, I prune the less specific one, as it adds no new information. This gives us the list of **maximal** motifs (i.e. patterns) which are supported by the training data.[3]

Clustering. After the detection of patterns is finished, the number of patterns is relatively large. Moreover, as they have fixed length, they tend to be pretty similar. In fact, many tend to have their support from the same subsequences in the corpus. As I was

[3] See Rigoutsos and Floratos (1998) for details on the optimality of this technique.

interested in similarity in form as well as similarity in context, a convenient solution was to further cluster the patterns, according to an **approximate matching** distance measure among patterns.

An approximate matching measure is defined for a given extended pattern. The extended pattern is represented as a sequence of sets; defined positions have a singleton set, while wild-card positions contain the non-zero probability elements in their *don't care* model. Consider p to be such a pattern, S a sequence and o an offset over S, the approximate matching is defined by

$$\hat{m}(p,o,S) = \frac{\sum_{i=0}^{\text{length}(p)} \text{match}(p[i], S[i+o])}{\text{length}(p)}$$

where the $\text{match}(P,e)$ function is defined as 0 if $e \in P$, 1 otherwise, and where P is the set at position i in the extended pattern p and e is an element of the sequence S. This measure falls in the interval $[0,1]$. Using this function, I defined the approximate matching distance measure (one way) between a pattern p_1 and a pattern p_2 as the sum (averaged over the length of the offset list of p_1) of all the approximate matching measures of p_2 over the offset list of p_1. This is, again, a real number in $[0,1]$. To ensure symmetry, I defined the distance between p_1 and p_2 as the average between the one way distance between p_1 and p_2 and between p_2 and p_1.

This metric provides an approximate measure of how well a given pattern does match in the contexts where other pattern matches, if the original pattern is "forced" to match there. If two patterns are fully compatible, this metric will give a score of 1.0. If they are completely incompatible, it will give a score of 0.0.

I used agglomerative clustering with the distance between clusters defined as the maximum pairwise distance between elements of the two clusters. Clustering stops when no inter-cluster distance falls below a user-defined threshold. An example is shown in Figure 5.8.

Constraints Inference. The last step of my algorithm measures the frequencies of all possible order constraints among pairs of clusters and atomic values, retaining those that occur often enough to be considered important, according to a relevancy measure. The algorithm proceeds as follows: a table counting how many times a pair of patterns belonging to particular clusters or atomic values are matched and appear in a particular order is built. From there, I use Shaw and Hatzivassiloglou (1999) approach (discussed in the Related Work chapter, Section 2.3, repeated here for clarity).

In the table of counts, therefore, the entry at position i,j indicates the number of times in the corpus the object i came before the object j. From the table, I can try to

intraop-problems	**intraop-problems**	{ **operation** 11.11% **drip** 33.33% **intraop-problems** 33.33% **total-meds-anesthetics** 22.22% }	**drip**	
intraop-problems	{ **operation** 14.29% **drip** 14.29% **intraop-problems** 42.86% **total-meds-anesthetics** 28.58% }	**drip**	**drip**	
intraop-problems	**intraop-problems**	{ **operation** 20.00% **drip** 20.00% **intraop-problems** 20.00% **total-meds-anesthetics** 40.00% }	**drip**	**drip**

Figure 5.8: Cluster and patterns example. Each line corresponds to a different pattern. The elements between braces are don't care positions (three patterns conform this cluster: **intraop-problems intraop-problems ? drip**, **intraop-problems ? drip drip** and **intraop-problems intraop-problems drip drip** the don't care model shown in each brace must sum up to 1 but there is a strong overlap between patterns —the main reason for clustering)

reject the null hypothesis that i, j came in any order (equivalent to say that the probability of i coming before j is 0.5). The following formula will compute the probability of the observed frequencies:

$$\sum_{k=m}^{n} \binom{n}{k} \quad 0.5^n$$

where m is the total number of times i has been seen occurring before j in the corpus and n is total number of times i and j occur in a pair. I thus use the above equation with a threshold thr_{oc} (Table 5.1) to select "likely enough" constraints.

5.3.2 Using Order Constraints

I will describe in this section how order constraints can be used to evaluate a schema being constructed or as a stand-alone planning mechanism, but first I will explain how to evaluate the constraints themselves.

Evaluating Order Constraints

I evaluated two items: how effective[4] the patterns and constraints learned were in an unseen test set and how accurate[5] will report the **number of patterns, clusters and constraints learned** during training. These figures are the upper bound for the **number of**

[4] Patterns and constraints that cannot be applied in the unseen test set are of no real use

[5] Constraints that do not hold in the unseen test set are considered wrong.

patterns, clusters and constraints found on unseen, held-out sequences. The number of constraints found is particularly important as only constraints found on the held-out sequences can be evaluated whether they hold or not. If every time a specific constraint is found on a held-out sequence it is the case that the constraint does hold, I will call that constraint a *valid* constraint. I therefore report the **number of valid constraints**. If there are some sequences where the constraint holds and some others where the constraint does not hold, I look at how many times each case happens. If the number of positive sequences is greater than the number of negative sequences, I will call it a *mixed* constraint, otherwise I will call it an *invalid* constraint.[6] I thus report also the **number of mixed** and **invalid constraints**.

Order Constraints as a Schemata Quality (Fitness) Function

Given a *document plan,* a sequence of multi-sets[7] can be extracted from it by recording the data-classes (semantic tags) for each piece of data. Each message, therefore, will correspond to a multi-set. The order of the multi-sets is given by the order of the messages in the *document plan*. Semantic tags coming from repeated atomic values are removed after the first mention (as my technique only works with first mentions) but several semantic tags can appear if they come from different atomic values.

To use these order constraints, therefore, it is necessary to extend the pattern matching to the sequence of sets of atomic values Σ_{set}, by means of the algorithm shown in Figure 5.9. The constraints are then checked by keeping track of whether or not the patterns in the cluster hold over the Σ_{set}. The constraints are counted (or discounted, if they are violated) weighted by the probability mined per Section 5.3. If a constraint does not apply, it is considered it had at least one mismatch (to promote schemata that contain structure similar to the one fostered by the constraints).

Example:

The pattern $AAB?D$ when matched against $[\{A,B,D\},\{A,D,E\}]$ will align $AAB?$ to $\{A,A,B,D\}$ and D to $\{A,D,D\}$.[8]

[6] An alternative way to define invalid constraints is to define them as constraints that never hold, but such definition produced no invalid constraints in my experiments. The definition above is preferred, as it is more informative.

[7] Multi-sets, also known as bags, are sets that allow for repeated elements.

[8] As explained above, the elements extracted from each predicate are multi-sets, that is, sets that accept repeated elements.

```
FUNCTION matches(pattern p, int pos_pattern, seq of sets $\Sigma_{set}$, int pos_setseq):
bool

    IF pos_pattern is the first position in the pattern p THEN

        take the set at pos_setseq
        FOR k FROM 1 TO the size of the set DO

            if the first k elements of p (including don't care po-
            sitions) belong to the set recurse on $pos\_setseq + 1$
            and $pos\_pattern + k$

        DONE
        IF any of these recursive call is successful, THEN RETURN
        true
        ELSE RETURN false

    ELSE IF pos_pattern is not the first position in the pattern p, THEN

        IF the set at position pos_setseq (of size k) matches the first
        k elements of the pattern p (including wild-cards) THEN
        recurse on $pos\_pattern + k$ and $pos_s etseq + 1$ (IF there are
        more elements left in the pattern, ELSE RETURN true).
        ELSE IF the first k elements do not match, THEN RETURN
        false FI


    FI
```

Figure 5.9: Checking a pattern over a sequence of sets of atomic values.

Order Constraints as a Stand-alone Planning Mechanism

The order constraints can be used directly to plan texts by performing a search on the space of *document plans* for some input data and selecting the document plan that scores better for the fitness function described in the previous section. This alternative was not explored in this thesis.

5.4 Supervised Learning

The supervised step for learning Document Structuring schemata follows the guidelines of Chapter 3 and is thus similar to the learning Content Selection rules counterpart presented in the previous chapter. It learns Document Structuring schemata from pairs of relevant knowledge (input to the Document Structuring module) and sequences of atomic values and order constraints (an approximation to the *document plans*, the output of the Document Structuring schemata). Training on examples of input and output pairs made for a supervised learning setting. The algorithm keeps at all times a set of schemata found to be the best solution so far. In each step of the search, a percentage of the less promising solutions is discarded and operators are applied to the remaining schemata to obtain new solutions. Two type of operators are defined: *mutations* (that produce a new schema by modifying an old one) and *cross-over* (that produces a new schema by combining two existing ones, its 'parents').

This process (a particular instantiation of a genetic search) is repeated a number of times with the goal of obtaining a schema that explains the training data well. The key element for this situation to arise is to tell in a sensible way good schemata from bad ones, by means of a fitness function.

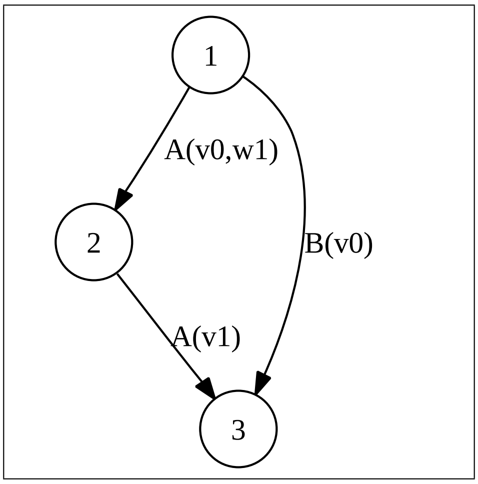
A main contribution of my work is the use of a combination of three corpus-based fitness functions. The schema being evaluated is executed in a set of knowledge and a set of *document plans* are collected and scored using these fitness functions. These functions address the goodness of the schema at the Content Selection level and at coarse and fine structuring levels. The coarse structuring level uses an approximate evaluation function, F_C, which determines whether order constraints (I use the constraints acquired in the previous section) are met in the current *document plans.* These constraints relate sets of patterns by specifying strict restrictions on their relative placements. The fine structuring fitness function will compare the obtained *document plans* to the sequences of atomic values mined from the *matched texts*.

On the outside, my problem is that of learning a finite state automaton. This complex problem has been studied in the past and a number of solutions have been proposed for it (Zhou and Grefenstette, 1986; Dupont, 1994; Belz, 2000). Instead of devising a brand new solution to this problem, an issue outside of the scope of this thesis, I decided to adapt a recently proposed technique, the *Genetic Automaton Learner, GAL,* to my task.

5.4.1 GAL (Genetic Automaton Learner)

GAL (Belz, 2000) targets learning finite-state automata that generalize over a given training set of positive examples. Clearly, the goals of *GAL* are different from schemata induction because schemata instantiation does not focus on determining the language the automaton accepts but instead cares about the steps followed by the automaton (the schema) as these steps provide the structure for the document being created. That is, the schemata add to the automaton the focus mechanism described in Section 5.1. Nevertheless, both problems involve learning a finite-state automaton. I thus adapt *GAL* to my task by using *GAL*'s selection mechanism, an extension of *GAL*'s instance representation (over a language of predicates plus variables), *GAL*'s cross-over and mutation operators, initial population and stopping criteria. My fitness function is then my major contribution (note that, for the differences described before, *GAL*'s fitness function would not apply to my problem).

***GAL*'s instance representation.** GAL instance representation is a linearization of the transition matrix of the automaton. That is, every instance is an array of integers of variable size (each instance can have a different number of states). The first integer is the number of states in the automaton n. GAL assumes that all m symbols in the language are known beforehand (I also assume that communicative predicates and their variables, are given beforehand). The transition matrix is a $n \times m$ matrix with states as rows and symbols (predicates) as columns. The integer at position (s_0, sym) is the state where a link from state s_0 will land while producing *sym* as output, or -1 if there is no link leaving s_0 producing *sym*. To be able to apply GAL, I need to fix the total number of symbols beforehand, which in turn implies fixing the number of variables that can appear in a schema. To this end, I use a global parameter n_v (Table 5.1) that says the number of variables **per type** the system can use in the search. For example, the predicate `Education` shown in Figure 5.1 has two variables, one of type `c-person` and the other of type `c-education-event`. If n_v equals 3, then the automaton can use `c-person-0`, `c-person-1`, `c-person-2`, `c-education-event-0`, `c-education-event-1` and `c-education-event-2` as global variables in the schema. For n_v equal to 2, the predicate `Education` will span 8 symbols:



state	$A_{-1,-1}$	$A_{-1,0}$	$A_{-1,1}$	$A_{0,-1}$	$A_{0,0}$	$A_{0,1}$	$A_{1,-1}$	$A_{1,0}$	$A_{1,1}$	B_{-1}	B_0	B_1
1	-	-	-	-	-	2	-	-	-	-	3	-
2	-	-	-	-	-	-	3	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-	-	-	-

Figure 5.10: Example of GAL's instance representation and my adaptation to the learning schema through the use of predicates plus variables as symbols. In the example, the schema is defined over two predicates. The first one has two variables and the second has one variable. The maximum number of variables per type (n_v) is 2 in this case. A value of -1 indicates the local variable is not bounded to any global variable.

```
Education(),
Education(c-person-0),
Education(c-education-event-0),
Education(c-person-0, c-education-event-0),
Education(c-person-0, c-education-event-1)
Education(c-person-1),
Education(c-person-1, c-education-event-0),
Education(c-person-1, c-education-event-1).
```

An example of the representation is shown in Figure 5.10. Belz (2000) experimentally motivates the states in the rows and symbols in the columns representation (over states on rows and columns, for example) on the basis that more meaningful information can be transfered from parents to children in the GA.

***GAL*'s selection mechanism.** GAL uses a torus to store the instances (a table that wraps around on the borders). In each step of the search, each instance may have a cross-over with randomly selected neighbors (among the eight adjacent neighbors of a cell in the torus). If the fitness of the child is better than the parent, it replaces the parent. Alternatively, the instance can be mutated (instead of the cross-over). Again, only a fitter instance will remain. This selection mechanism slows down the advance of fitter instances into the pool, allowing a search on several parts of the error surface simultaneously, without quickly getting stuck into local minima.

***GAL*'s cross-over operator.** GAL introduces the FPU_cross-over (fitness proportional uniform cross-over) where a percentage (dictated by their relative differences in fitness) of the transition table from each parent is copied into the child. FPU_cross-over is a general GA operator, with a number of experiments justifying its advantages for the learning of automaton case.

***GAL*'s mutation operator.** GAL mutation operator will flip positions in the transition matrix, respecting the number of states and depending on some parameters.

Stopping criteria. I use as stopping criteria reaching a maximum number of generations.

Initial population. The initial population is created by randomly choosing a number of states and variables and mutating every position in both the transition and variables matrices.

5.4.2 Fitness Function

To tell good schema from bad ones implies in this case differentiating how well a proposed schema explains the training data. That is, a function that approximates the conditional probability of the schema S given the text T and knowledge K:

$$P(S|T,K)$$

Actually, as I am searching for the best schema (S^*) that maximizes this probability, I change my definition of the problem to use a likelihood:

$$S^* = \underset{S}{argmax} P(S|T,K) = \underset{S}{argmax} F(S,T,K)$$

From T and K, I can compute the relevant knowledge pool K', a set of order constraints $\mathscr{C}$ and the sequence of atomic values Σ in an unsupervised manner, as described in the previous section. My *fitness function* (similar to a likelihood in the context of a stochastic search) will thus be defined as:

$$S' = \underset{S}{argmax} F(S, K', \mathscr{C}, \Sigma)$$

The hope is that S^* and S' will be the same or very close. To compute the function $F(S, K', \mathscr{C}, \Sigma)$, I use the following heuristic definition, where I divide the fitness function into three additive components, D are the *document plans* and Σ_{set} are the sequences of sets of atomic values derived from D (in a process detailed below):

$$\begin{aligned} D &= instantiate(S, K') \\ \Sigma_{set} &= extract(D) \\ F(S, K', \mathscr{C}, \Sigma) &= \omega_C F_C(K', \Sigma_{set}) + \omega_O F_O(\mathscr{C}, \Sigma_{set}) + \omega_A F_A(\Sigma, \Sigma_{set}) \end{aligned}$$

An important point to note here is that each of these three tiers are data-dependent as they analyze the goodness or badness of *output document plans D*, i.e., sequences of communicative predicates. They require instantiating the schema multiple times for each of the different knowledge sets K'. The *document plans D* are sequences of messages as the ones shown in Figure 5.2. These messages contain atomic values that can be extracted from them. However, the atomic values inside a message are unordered (the order is given later by the surface realizer). The *extract* function will keep them unordered, returning a sequence of sets Σ_{set}, where each set represents all the atomic values contained in a message (as a set so no assumptions are made with respect to their ordering). To make them compatible with sequence of first mentions, every repeated value is removed from the sets (i.e., also contain only first mentions). I combine the three functions with weights ω_i, on the basis that, for example, a schema with great ordering but some mis-selections should not be discarded.

I will now analyze each tier in turn.

First Tier. The function $F_C(K', \Sigma_{set})$ measures the Content Selection in place (as opposed to the previous chapter, where no context was taken into account). The selected atomic values are extracted from the sequence of sets Σ_{set} and the F_C is then the F_α measure described in the previous chapter, using $\alpha = 1$ (precision is now considered as important as recall).

Second Tier. The second tier, F_O, uses the order constraints mined over sequence of atomic values as described in Section 5.3.2.

Third Tier. The last component of the fitness function is its most interesting subfunction and the main contribution of my work. It compares the sequence of atomic values Σ with the sequence of sets of atomic values Σ_{set} (coming from the messages) by means of an alignment-based metric efficiently computed using dynamic programming.

This function scores how well the sequence of a set of atomic values Σ_{set} can be mapped into the sequence of atomic values Σ. This mapping is by virtue of non-crossing alignments between atomic values and sets of atomic values. This non-crossing property penalizes changes in ordering (i.e., when aligning *A*–*B*–*C* and *C*–*B*–*A* they will align both *B*s but neither *A* nor *C*[9]) while enabling the use of dynamic programming, thus making this computation very efficient.

My dynamic programming is similar to global alignment with affine gap penalty, the Needleman–Wunsch algorithm in bioinformatics, as defined by Durbin et al. (1998) (pages 17–28). The dynamic programming is governed by the following recurrences:

$$T(i,j) = max \left\{ \begin{array}{ll} T(i-1,j) \text{ if } T(i-1,j) \text{ was a mismatch} & \textit{(skip)} \\ T(i-1,j-1) & \textit{(match)} \\ T(i,j-1) & \textit{(stay)} \end{array} \right\} + c(i,j)$$

where $c(i,j)$ is the comparison between a set of atomic values s at position i and an atomic value v at position j, it equals to 1 if the value is in the set and -1 otherwise:

$$c(i,j) = \left\{ \begin{array}{cc} 1 & \text{if } v \in s \\ \text{-1} & v \notin s \end{array} \right.$$

These recurrences can be understood as follows: at any given time during the alignment process, the alignment of the set of atomic values at position i (coming from the message) against the atomic value at position j equals the maximum of three possible values. The first value is that of an alignment skipping the previous set of atomic values (a *skip*). This option is only possible if the previous set of atomic values mismatched the atomic value (otherwise an atomic value will be double counted). Another possibility is that the previous atomic value matched successfully to the previous message (a *match*). Finally, several atomic values may be aligned to the same set of atomic values (the *stay*). In either case, the value of the alignment at that point is 1 if the atomic value belongs to the set or -1 otherwise.

Example:

Alignment of $[A,B,C,D,E,F,G]$ against $[\{B,C,D\},\{E,A\},\{C,B\},\{A,F\}]$. The dynamic programming matrix will be:

[9] Another possibility is for they to align only the *A*s or the *C*s. The outcome really depends on the score of aligning correctly any of them.

	A	B	C	D	E	F	G
{B;C;D}	−1	← 0	← 1	← 2	1	0	−1
{E;A}	0	−1	0	1	↖ 3	2	1
{C;B}	−1	1	2	1	↑ 2	↖ 2	1
{A;F}	0	0	1	1	1	↖ 3	← 2

The alignment reads:

A,B,C,D	E	F,G
$\{B,C,D\}$	$\{E,A\}$	$\{A,F\}$

Analysis. This fitness function so defined has a number of advantages. First, the degree of generalization in the schemata can be achieved by restricting the number of nodes available for the automata (to avoid memorizing the training material). Second, the incorporation of a Content Selection tier F_C allows for a two level Content Selection learning where the fine grain Content Selection is performed in-place. That is the case because a complete Content Selection system can only be evaluated over the *document plan*, as a result of the inclusion of intermediate information following cohesion principles. Therefore, while the Content Selection rules mined in the previous chapter are of coarse granularity, fine Content Selection granularity can be adjusted at the schemata level. An important point to note here is that all three functions are data-dependent, as they analyze the goodness or badness of *instantiated* schemata. An advantage of the function F_O is that while an aligned corpus is needed to collect the constraints, I consider the constraints to be valid for any knowledge so the constraints can be checked on a much larger range of semantic inputs,[10] not only the ones used to mine the constraints. While F_C measures content with no ordering and F_A measures ordering in a very strict fashion, F_O is somewhat in between. The contribution of F_O is expected to be greater in earlier stages of the search, where the schema is producing results of too low quality to be fully evaluated using alignments. For example, let's suppose the system is trying to learn *ABCD* and it is currently producing *CDAB*. Non-crossing alignments will be able to see that *AB* is correctly placed or *CD* is correct, but not both. For the sake of discussion, let's say it aligns correctly *CD*:

$$\begin{array}{ccc} AB & CD & -- \\ -- & CD & AB \end{array}$$

This alignment misses the important fact that *AB* is in the right order, that is, it will score *CDAB* the same as *CDBA*. Order constraints remedy that situation, allowing the system to reward differently instances that produce promising sub-sequences.

[10] An approach I didn't implement in the current set of experiments.

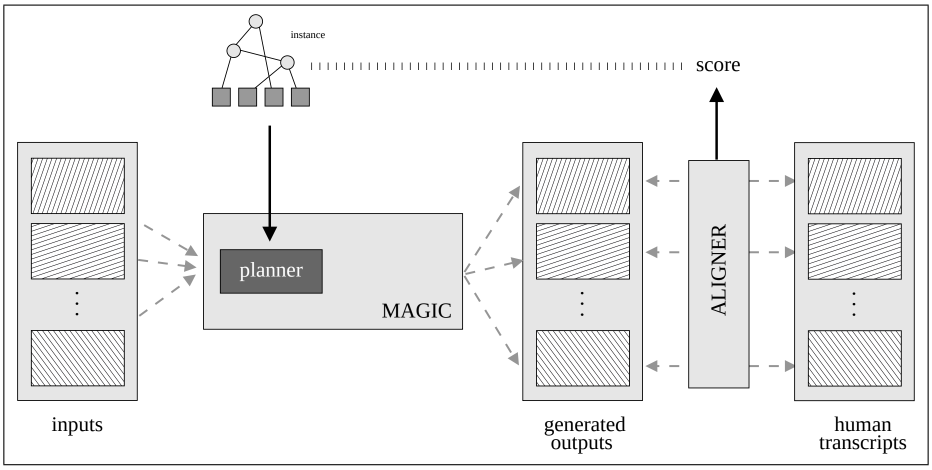


Figure 5.11: Fitness function: Alignment architecture.

Finally, texts governed by DCK are supposed to be **historically motivated**, in the sense that their current shape does not necessarily obey any logic behind it, but there is a history of logically motivated changes that determine its current, accepted shape. Therefore, it may be the case that genetic algorithms can **simulate** that previous history.

5.5 Variants

I have investigated possible variations to the process described in this chapter (Duboue and McKeown, 2002). In particular, for the experiments in the medical domain discussed in the next chapter, I did not have enough data to perform an unsupervised step. Instead, a laborious manual tagging transformed the text side of the Text-Knowledge corpus in a sequence of message-types (semantic tags). However, this process could only be performed for a small number of texts. I succeeded in applying my technique in this different setting, with the following modifications:

Simpler schema. In this context, I targeted learning the schema-like planners discussed in the Related Work chapter, Section 2.2.1. These planners are schemata containing only sequence nodes and where each predicate has a Kleene star node preceding it.

No Content Selection. The data that should appear in the text was already selected. Moreover, the simpler schema did not allow for any Content Selection logic to be added to it. In a sense, it was using no focus decoding (greedy decoding).

Manual mapping of predicates to message types. The tag-set used by the tagging crew was developed by a domain expert and did not correspond directly to the system's ontology, nor the existing schema predicates. I manually mapped one onto the other.

Text-to-text comparison. The most innovative variation was the use of a text-to-text comparison between generated text and the text part of the Text-Knowledge corpora. For computing the fitness function, I introduced the multiple-tiers approach described in this chapter, where the knowledge is used to produce *document plans* that are then scored for goodness. I scored them using order constraints in the same vein of the second tier of the fitness functions described in this chapter. From there, however, it was impossible to continue at the *document plan* level: the tagged texts did not contain information about the parameters that instantiated the predicate, only its type (e.g., I knew that an *anesthesia* predicate has been instantiated, but I lacked the information of which drug was given, and in which quantity —the parameters of the *anesthesia* predicate). The tagging crew did not annotate this information because it was present in the text inside the tag. To solve this problem, I employed the anchors hypothesis of my research[11] and used the existing text generator to produce full verbalizations of the *document plans* (Figure 5.11). I then compare the generated text against the text from the Text-Knowledge corpus using a dynamic programming based function similar to the one described for the third tier of the fitness function presented in this chapter (but operating at the word level instead of the conceptual level). As substitution metric, I employed the information content on a corpus of related discourse.[12]

5.6 Evaluation Methods

I evaluate the learned schemata by using hand tagged reference sequences of atomic values and computing the Kendall's τ (Lebanon and Lafferty, 2002) as employed by Lapata (2003):

$$\tau = 1 - \frac{2(\text{number of inversion})}{N(N-1)/2}$$

Where N is the number of objects (atomic values) and inversions is the number of exchanges on consecutive objects required to put them in the order appearing in the hand tagged reference. Because the sequence being evaluated is a sequence of sets of atomic

[11] From Chapter 1, Research Hypothesis, Section 1.2.

[12] As computed by Pan and McKeown (1999).

Threshold	Description	Value
support threshold	Minimum number of sequences a pattern should match to be further considered (this threshold is expressed as percentage of the total number of sequences).	30%
thr_{oc}	Probability threshold for a given order constraint to be further considered.	0.98
n_v	Number of variables per type.	2
windowsize	How many items are used to build a pattern.	8
relative distance threshold	Clustering parameter when mining order constraints.	0.1
probability cut-point	Minimum probability for accepting a learned constraint.	0.99

Table 5.1: Thresholds and Parameters in the Document Structuring schemata learning.

values, for the sake of evaluation I consider the items inside the set are ordered in the correct order.

5.7 Conclusion

A schema is a highly structured representation, consisting in turn of a finite state machine, a set of rhetorical predicates and a focus decoder. The technique presented in this chapter targets the learning of the finite state machine given a set of rhetorical predicates and McKeown (1985)'s original focus decoding. The next two chapters present the results of applying this technique to two domains, medical and biographical. These chapters stress the contributions of the proposed fitness function and the mining of order constraints.

Chapter 6

Experiments in the Medical Domain

This chapter describes my contributions to the MAGIC project (Dalal et al., 1996; McKeown et al., 2000);[1] this project built a generation system that produced briefings of patient status after a coronary bypass surgery. Normal work-flow in the hospital requires a medical specialist to give a briefing to the Intensive Care Unit nurses and residents before the patient arrives at the ICU. This briefing is given by one of the residents who was present in the operating room. The generation system uses data collected from the machines in the operating room to generate a coordinated speech and graphics replacement presentation for the briefing, avoiding distracting a caregiver at a time when they are critically needed for patient care. Figure 6.1 shows an example of a data excerpt (a CLASSIC data file with 127 facts on average) and generated presentation.

For evaluation purposes, McKeown et al. (2000) collected and transcribed 24 briefings that then were used, along with the admission note (the gold standard), to quantify the quality of MAGIC output (100% precision, 78% recall). Each report transcription was subsequently annotated with semantic tags as shown in Figure 6.2, on page 127.

When comparing the system output and the briefings, it can be seen that there are quite a few differences among them. In particular, the briefings are normally occurring speech. Aside from being much more colorful than the system output, they also include a considerable amount of information not present in our semantic input. And there is also some information present in the system that is not being said by the doctors, for example, because at the time the briefing is given, data such as the name of the patient is available in paper format to the target audience.

The transcripts and the semantic inputs constitute an aligned Text-Knowledge corpus, albeit a very small one. The experiments in this chapter address the Document

[1] MAGIC, Multimedia Abstract Generation for Intensive Care, was a joint project between the Columbia Presbyterian Medical Hospital and the Columbia University Computer Science Department.

Structuring schemata part of this thesis, with modifications to deal with the small amount of data. My task was to learn a tree representing a planner that performs as well as the planner developed manually for MAGIC. To remedy the lack of training material, more human effort was employed. The fitness function discussed in the previous chapter had three components: Content Selection, order constraints and alignments. In MAGIC, the planner makes no Content Selection decisions, therefore the first tier is not used in the MAGIC domain. For the other two tiers, the obvious choice would have been to assemble the *matched texts* by hand. This option, however, was utterly laborious. A simpler task in the form of semantic tagging was preferred.[2] While the semantically tagged texts are a weaker source of information than the *matched texts*, in this case they are of pristine quality, as they were hand-built. The tagged texts provide semantic sequences to mine order constraints as discussed in the previous chapter (Section 5.3).

For the third tier, I had available the full-fledged MAGIC system. I combined the *verbalize-and-search* process from Chapter 3 with an alignment-based metric similar to the one presented in Chapter 5. For this combined metric, the MAGIC system produces a text presentation for the output (*document plan*) of the schemata being evaluated and then the text presentation is fed into an alignment based metric now at the text level.[3] I thus align human text against the generated text.

In this chapter, I first introduce the data (Section 6.1), and then two series of experiments: learning order constraints (Section 6.2) and learning MAGIC schema-like planners (Section 6.3).

6.1 Data

In the aforementioned evaluation,[4] McKeown et al. equipped the resident with a wearable tape recorder to tape the briefings, which they transcribed to provide the base of the empirical data used in this chapter. They subsequently annotated the text with semantic tags as shown in Figure 6.2. The figure shows that each sentence is split into several semantically tagged chunks. They developed the tag-set with the assistance of a domain expert in order to capture the different information types that are important for communication in this domain. Two non-experts did the tagging, after measuring acceptable agreement levels with the domain expert (McKeown et al., 2000). The tag-set totalled

[2] This is a *post-hoc* analysis; the texts were semantically tagged for the said evaluation before I started my experiments.

[3] This metric imposes the requirement of having a generation system able to verbalize *document plans* before being able to learn the planner. That requirement is not present in the technique I present in the next chapter.

[4] I was not part of the evaluation efforts.

```
(patient-info-12865, c-patient, (a-age, age-12865), (a-name,
name-12865), (a-gender, gender-12865), (a-birth-date, ...), ...,
(r-receive-blood-product, received-BloodProduct1-12865), ...)
(age-12865, c-measurement, (a-value, 38), (a-unit, "year")) maps to
sentence 1 (b)
(ht-12865, c-measurement, (a-value, 175), (a-unitm "centimeter"))
maps to sentence 1 (b)
(name-12865, c-name, (a-first-name, "John"), (a-last-name, "Doe"))
maps to sentence 1 (b)
...
(received-BloodProduct1-12865, c-receive-blood-product, (r-arg2,
BloodProcut1-12865), (a-dosage, Measure-BloodProduct1-12865)) maps
to sentence 5 to last (b)
(BloodProduct1-12865, c-blood-product, (a-name, ‘‘Cell Savers’’))
maps to sentence 5 to last (b)
(Measure-BloodProduct1-12865, c-measurement, (a-value, 3.0),
(a-unit, ‘‘unit’’)) maps to sentence 5 to last (b)
...
```

(a)

> John Doe is a 41 year-old male patient of Dr. Smith undergoing mitral valve repair. His weight is 92 kilograms and his height 175 centimeters. Drips in protocol concentrations include Dobutamine, Nitroglycerine and Levophed. He received 1000 mg of Vancomycin and 160 mg of Gentamicin for antibiotics. Around induction, he was anesthetized with 130.0 mg of Rocuronium, 11.0 mg of Etomidate, 500.0 mcg of Fentanyl and 1.0 mg of Midazolam. Before start of bypass , he had hypotension, at start of bypass, alkalosis, before coming off bypass, bradycardia and after coming off bypass, hypotension and relative-anemia. He received three units of cell savers. His total cross clamp time was 2.0 hour 1.0 minute. His total bypass time was 2.0 hour 33.0 minutes. His pre-op cardiac output was 4.13. Cardiac output immediately off was 4.73 .

(b)

Figure 6.1: Example of the MAGIC system. (a) Semantic input excerpt. (b) MAGIC output.

He is $\underset{\text{age}}{\underline{\text{58-year-old}}}$ $\underset{\text{gender}}{\underline{\text{male}}}$. History is significant for $\underset{\text{pmh}}{\underline{\text{Hodgkin's disease}}}$, treated with …to his neck, back and chest. $\underset{\text{pmh}}{\underline{\text{Hyperspadias}}}$, $\underset{\text{pmh}}{\underline{\text{BPH}}}$, $\underset{\text{pmh}}{\underline{\text{hiatal hernia}}}$ and $\underset{\text{pmh}}{\underline{\text{proliferative lymph edema in his right arm}}}$. No IV's or blood pressure down in the left arm. Medications — $\underset{\text{med-preop}}{\underline{\text{Inderal}}}$, $\underset{\text{med-preop}}{\underline{\text{Lopid}}}$, $\underset{\text{med-preop}}{\underline{\text{Pepcid}}}$, $\underset{\text{drip-preop}}{\underline{\text{nitroglycerine}}}$ and $\underset{\text{med-preop}}{\underline{\text{heparin}}}$. $\underset{\text{ekg-preop}}{\underline{\text{EKG has PAC's}}}$. $\underset{\text{echo-preop}}{\underline{\text{His Echo showed AI, MR of 47 cine amps with hypokinetic basal and anterior apical region.}}}$ $\underset{\text{hct-preop}}{\underline{\text{Hematocrit 1.2}}}$, otherwise his labs are unremarkable. Went to OR for what was felt to be $\underset{\text{procedure}}{\underline{\text{2 vessel CABG off pump both mammaries}}}$ ……

Figure 6.2: An annotated transcription of an ICU briefing (after anonymising). A full briefing is shown in Figure 6.11 (b), on page 141.

age, gender, pmh, pmh, pmh, pmh, med-preop, med-preop, med-preop, drip-preop, med-preop, ekg-preop, echo-preop, hct-preop, procedure, …

Figure 6.3: The semantic sequence obtained from the transcript shown in Figure 6.2.

over 200 tags. The domain expert also mapped these 200 tags to 29 categories, which are the ones I used for my experiments.

From these transcripts, I derived the sequences of semantic tags building semantic sequences as the ones mentioned in the previous chapter (Figure 6.3). These sequences constitute the input and working material for my order constraints analysis, they have an average length of 33 tags per transcript (min $= 13$, max $= 66$, $\sigma = 11.6$). A tag-set distribution analysis (Table 6.1) showed that some of the categories dominate the tag counts (this is similar to the effect seen by Varges (2003) when semantically tagging leading sentences in WSJ acquisition articles). Furthermore, some tags occur fairly regularly towards either the beginning (e.g., **date-of-birth**) or the end (e.g., **urine-output**) of the transcript, while others (e.g., **intraop-problems**) are spread more or less evenly throughout.

Obtaining these transcripts was a highly expensive task involving the cooperation and time of nurses and physicians in the busy ICU. My corpus contains a total number of 24 transcripts. Therefore, it was important to develop techniques that can detect patterns without requiring large amounts of data.

Table 6.1: The complete reduced tag-set used in my experiments.

tag name	count	placement†			
allergies	20	40	50	10	
blood-gases	2				100
cardiac-output	30	3	7	30	60
cell-saver	21		5	43	52
cross-clamp-time	10		40	40	20
date-of-birth	13	100			
drip	42		10	60	31
exogenous-red-blood-cell	12			42	58
fluid	33		3	52	45
height	5	100			
h/h	21	5	9	33	52
intubation	34	21	62	12	6
intraop-problems	92	4	25	45	26
labs	17	6	29		65
minute-bypass-time	11		55	27	18
name	6	100			
operation	27	37	44	19	
other-lines	10	20	80		
platelet	2				100
preop-diagnosis	18	94			6
past-medical-history	154	75	16	7	2
preop-med	96	36	59	1	3
sex	9	100			
swan	5	20	80		
temperature-intraop	2		50	50	
total-meds-anesthetics	79		23	59	18
urine-output	17			24	76
weight	5	80			20

†relative distribution of the tags in the sequence, in percentiles, e.g. $[6, 0, 29, 65]$ means that 6% of the occurrences of this tag fell in the first fourth of the sequence, none appeared in the second fourth, 29% in the third fourth and 65% at the end. For the sake of readability, zero values are not printed.

6.2 Learning Order Constraints

As explained in Chapter 5, learning order constraints is a case of unsupervised learning: sets of patterns, clusters of patterns and order constraints over clusters are mined from the sequences of semantic tags without any need of annotated data. To test the quality of the acquired patterns, clusters and constraints, I keep aside a set of held-out semantic sequences and compute how often the patterns identified during training can be identified in the held-out; how often clusters of patterns can be identified, and, more interestingly, how often the order constraints do hold over the held-out sequences, using the metrics introduced in Section 5.3.2. I will present quantitative results using them via cross validation. A comparison against the plan of the MAGIC system for qualitative evaluation closes this section.

Quantitative Evaluation

I used 3-fold cross-validation to compute these metrics averaged over 10 executions of the experiment. The different parameter settings were defined as follows: for the pattern detection algorithm, I set $\langle L, W\rangle$ to $\langle 2, 8\rangle$ (a *window size* of 8) and the *support threshold* to 0.2. The clustering algorithm used a *relative distance threshold* of 0.1. The results at the *probability cut-point* of 0.99 are reported below. This figure was chosen to avoid generating a very large number of constraints.

The system obtained an average of 58.538 (±8.460) patterns,[5] clustered into 19.705 (±3.023) clusters. When tested on the held out fold, all patterns and clusters are found. For the default cut-point of 0.99, an average of 401.938 (±51.226) constraints are found,[6] from which 205.205 (±45.954, a 51.904%) are always correct, 196.605 (±68.134, a 48.072%) sometimes contain errors and 0.138 (±0.350, a 0.037%) contains a large number of errors. Table 6.2 shows other results at different probability cut-points.

Figure 6.4 shows the impact of the support threshold. As we require the patterns to appear in more instances in the training set, less patterns are found, which in turn produce clusters and constraints with higher accuracy. A support threshold of 0.2 seemed a good compromise between the number of patterns and their quality.

Figure 6.5 illustrates the effect of the window size on the different metrics. As the window size grows, better quality is achieved. The curves stabilize at a window size of 8, the number employed in my experiments.

Figure 6.6 shows the impact of the distance threshold for clustering. While fewer

[5] The number between parenthesis represent the standard deviation calculated over the different executions of the experiment.

[6] The constraints are defined not only over clusters, but also over individual elements.

Table 6.2: Evaluation metrics at different probability cut-points. All metrics refer to number of constraints over held-out sequences. Here, a cut-point of 0.99 is chosen as it provides fewer mixed constraints and a reasonable total number of constraints.

cut-point	found	valid	mixed	invalid
1	30.71 ± 7.56	8.55 ± 6.68	22.21 ± 8.62	0.00 ± 0.00
0.99	401.98 ± 51.27	205.25 ± 45.99	196.65 ± 68.17	0.18 ± 0.39
0.98	461.88 ± 59.97	240.35 ± 50.83	221.28 ± 77.44	0.35 ± 0.75
0.97	465.25 ± 60.34	240.35 ± 50.83	224.65 ± 77.66	0.35 ± 0.75
0.9	606.01 ± 74.96	329.91 ± 63.86	274.81 ± 93.31	1.38 ± 1.65
0.8	712.48 ± 82.47	397.58 ± 73.2	311.98 ± 101.48	3.01 ± 2.44
0.7	831.75 ± 93.33	490.51 ± 85.54	336.48 ± 108.81	4.85 ± 300

clusters may arguably produce better results, I settled for a small distance threshold to obtain a greater number of clusters and therefore be able to appreciate the effects of clustering better.

The learning curve (Figure 6.7) shows some of the problems of working with such a small data set: the curves present some peaks and valleys and still shows no sign of stabilizing.

Qualitative Evaluation

The system was executed using all the available information (the 24 transcripts), with similar parametric settings to the ones used in the quantitative evaluation, yielding a set of 29 constraints, out of 23 generated clusters.

These constraints were analyzed by hand and compared to the existing strategic component. We found that most rules that were learned were validated by the existing plan. Moreover, we gained placement constraints for two pieces of semantic information (e.g., medical history) that are currently not represented in the system's plan. In addition, we found minor order variation in relative placement of two different pairs of semantic tags. This leads us to believe that the fixed order on these particular tags can be relaxed to attain greater degrees of variability in the generated plans. The process of creation of the existing content-planner was thorough, informed by multiple domain experts over a three year period. The fact that the obtained constraints mostly occur in the existing plan was very encouraging.

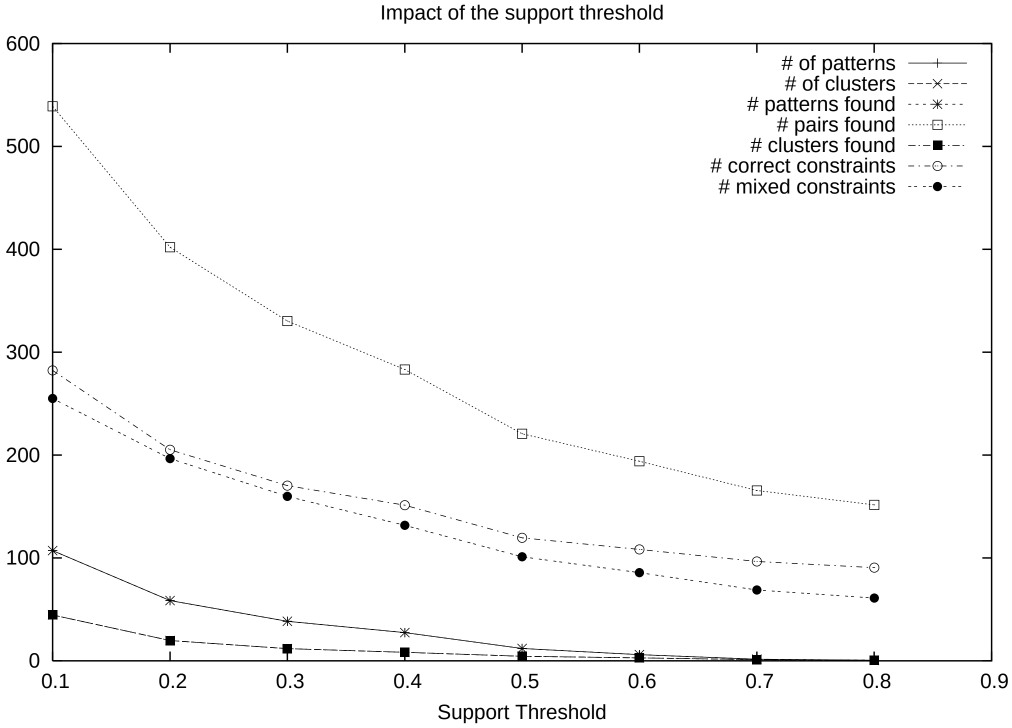


Figure 6.4: Impact of the support threshold.

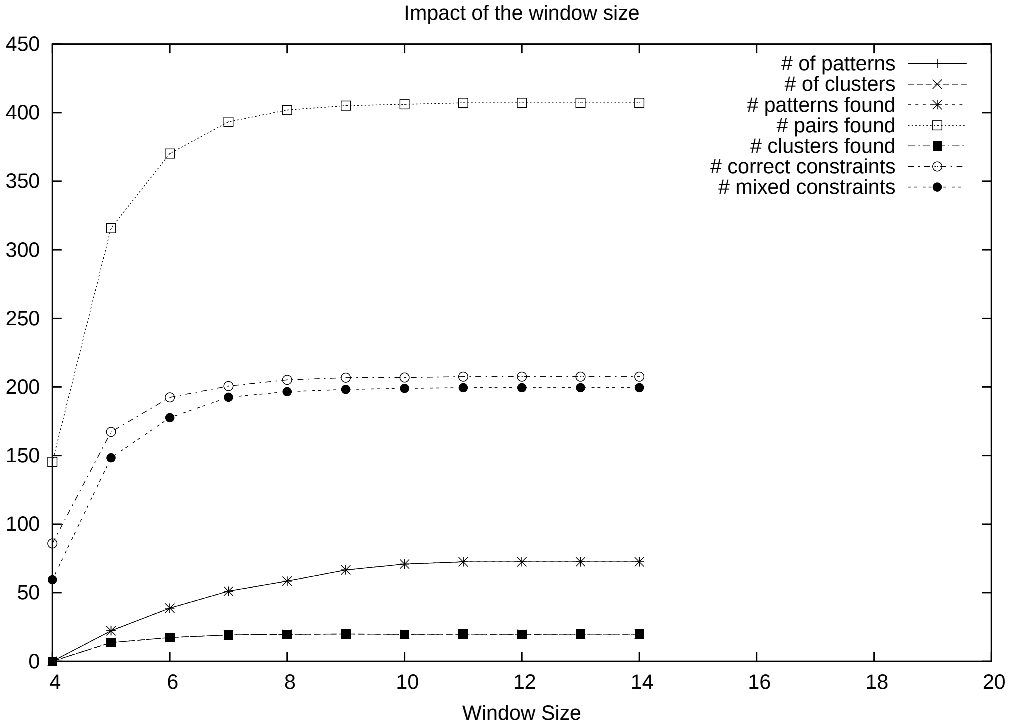


Figure 6.5: Impact of window size. The curves stabilize around window size 8, the one used for the experiments reported here.

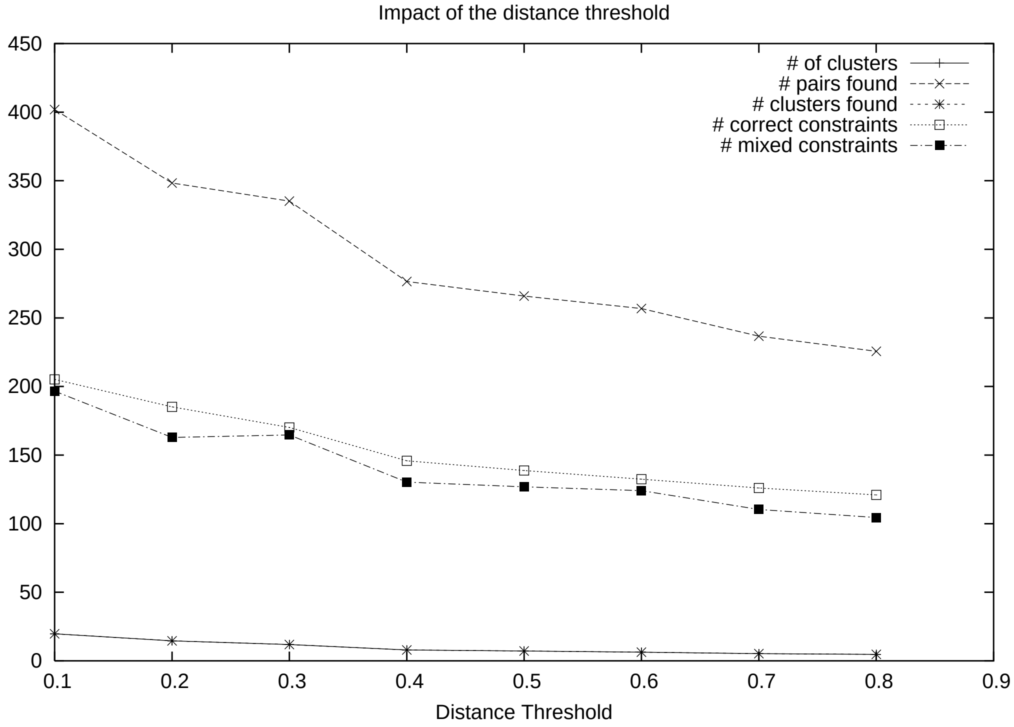


Figure 6.6: Impact of distance threshold. A higher threshold produces a fewer number of constraints.

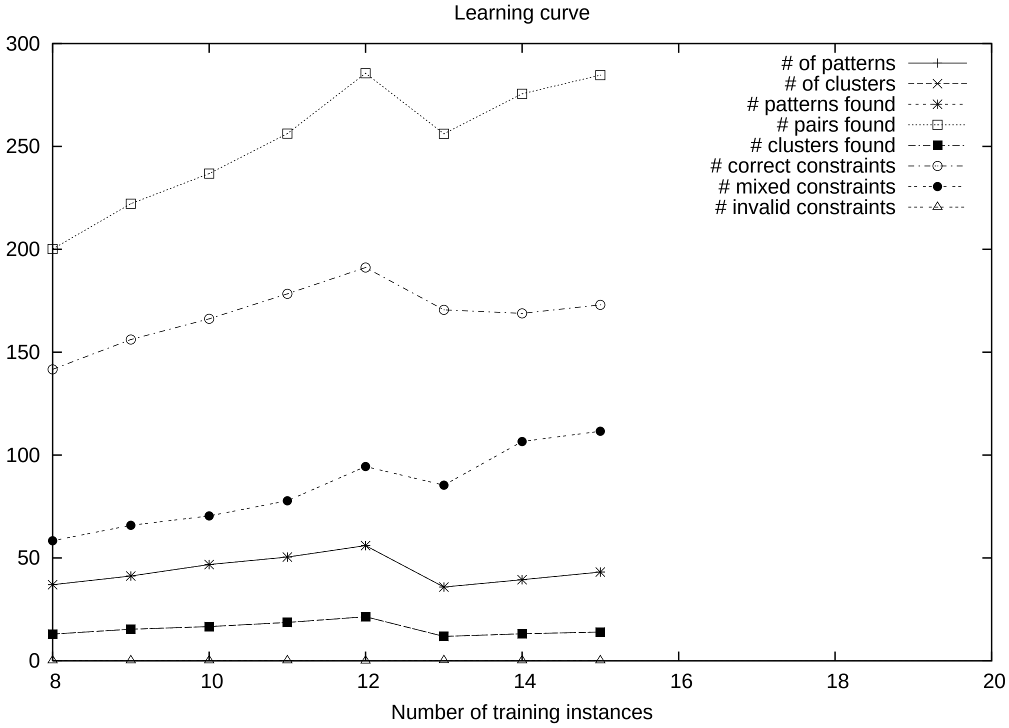


Figure 6.7: Learning curve.

6.3 Learning Document Structuring Schemata

The framework described in Chapter 5 (Section 5.5) was implemented as follows: I employed a population of 2000 chromosomes, discarding 25% of the worse-fitted ones in each cycle. The vacant places were filled with 40% chromosomes generated by mutation and 60% by cross-over. The mutation operator was applied with a 40% probability of performing a node insertion or deletion and 60% chance of choosing a shuffle mutation. The population was started from a chromosome with one root node connected to a random ordering of the 82 operators and then nodes were inserted and shuffled 40 times.[7]

As baseline, I used the initial population of the three runs (6K randomly built planners in total). The MAGIC planner was used as my gold standard, as it has been previously evaluated by domain experts as highly accurate and was not involved in my learning process at any part.

The planner used in the MAGIC system was developed with efficiency in mind, but it lacks flexibility and the plan used is more appropriate for textual output (as opposed to the speech output it was targeted). It has a total of 274 operators, 192 of them being structure-defining (*discourse* or *topic* levels) and 82, data defining (*atomic* level) operators.[8] Figure planner, the input is checked for the existence of the datum specified by the operator. If there is data available, the corresponding semantic structures are inserted in the output.[9] The internal nodes, on the other hand, form a tree representing the discourse plan; they provide a structural frame for the placement of the atomic operators. Thus, the execution of the planner involves a traversal of the tree while querying the input and instantiating the necessary nodes (an example of such trees was presented in Chapter 2, Figure 2.5).

The MAGIC strategic component uses a tree as internal representation because its *document plans* contain text planning information (i.e., top level nodes provide paragraph divisions) and aggregation information (the elements below pre-terminals can all be aggregated together). If it not were for this extra information, a plain sequence of atomic operators would be equally expressive. On the other hand, I expect the genetic algorithm handling of the trees to produce robust structures: only pre-terminals that behave reasonably well under node shuffling mutations will remain in the genetic pool, meaning

[7] I picked this figure to obtain trees with *height* ≈ 4. The other figures where picked following the author's intuitions about the domain.

[8] Equivalent to the notion of **messages** (Reiter and Dale, 2000), pages 61–63. This atomic level operators are similar to my communicative predicates, albeit they do not contain any constraints beyond checking whether there is data avaible for instantiation.

[9] A node can span several nodes in the instantiated plan if its specified data is multi-valued, this is similar to say that the schemata is sequence of nodes with a Kleene star operator over each of them.

that trees with felicitous arranging of the internal nodes will increase their presence in the population.

The MAGIC generator has a special emphasis on its aggregation component, CASPER (Shaw, 2001). One of the original motivations of my proposed architecture was to learn automatically the interaction between the planner and the aggregation component. While my preliminary experiments (Duboue and McKeown, 2002) showed the feasibility of such approach, it had two drawbacks: first, it requires the MAGIC generator to be effectively run for every *document plan*. If aggregation is disable, the caching mechanism described below can be employed to dramatically speed up the approach. The second drawback is more problematic to the experiments presented here; CASPER imposes a number of preconditions on the strategic component. If these preconditions are not satisfied, its behavior is undefined. Because the existing planner satisfies these preconditions, including the aggregation component into the fitness function adds an extra piece of information to the function, biasing the function towards the MAGIC planner. This situation is problematic, as I am interested in analyzing the feasibility of reproducing the existing planner using only the Text and Knowledge corpus.

When the aggregation component is switched off, every atomic operator will ultimately produce a sentence on its own. The quality of the generated text will be then quite low and very repetitive (repeating phrases such as *the patient is* in almost half of the sentences and so on). This repetitive nature should not be a major problem as the text-to-text metric employs the word information content computed over a large corpus of comparable texts to score the relative importance of words.

Metrics

I evaluate using the Kendall's τ described in the previous chapter:

$$\tau = 1 - \frac{2(\text{number of inversion})}{N(N-1)/2}$$

Where N is the number of objects (atomic operators) and inversions is the number of exchanges on consecutive objects required to put them in the order returned by the MAGIC planner.

Experiments

I did a number of experiments to gain further insights on the search process and validate the approach. For the first experiment, I looked to build a characterization of the search process. To that end, I let the search go for 50 iterations, in one run. The fitness of the

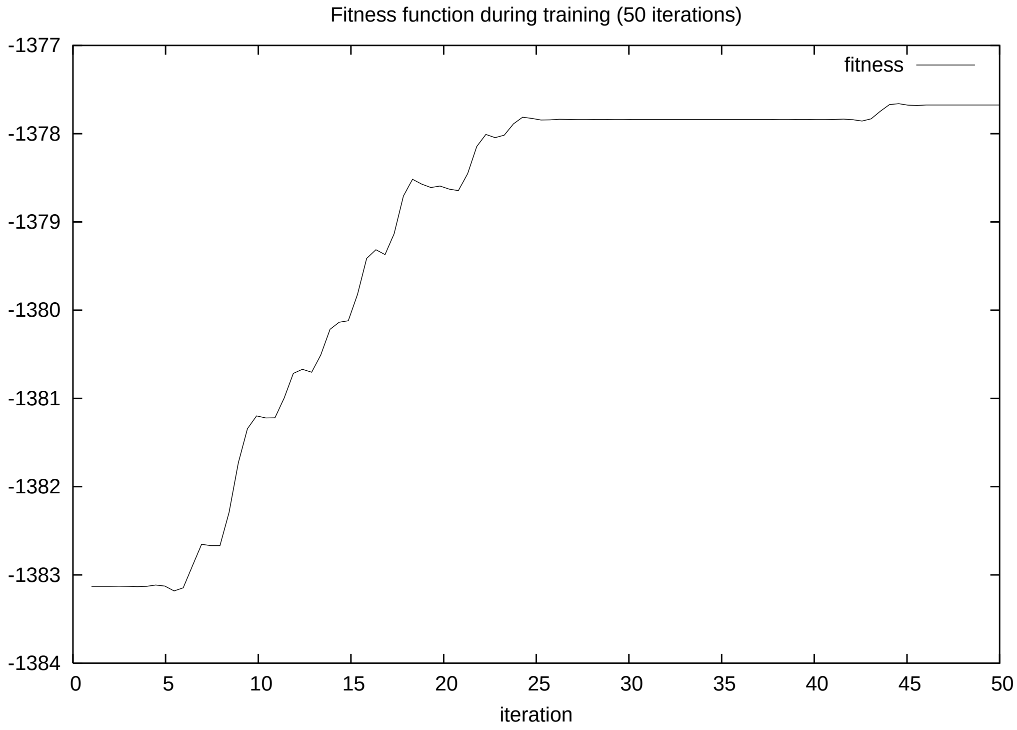


Figure 6.8: Fitness over 50 iterations.

best instance is plotted in Figure 6.8. The search achieves a certain level of stabilization around iteration 25. I thus plot three different runs (together with an interpolated average) until iteration 21 (Figure 6.9) to validate the learning process.

Another way to appreciate the learning process is to take a look at the goodness of the population as a whole, at different generations (Figure 6.10). There we can see that the order constraints are important at early stages of the search.

The second experiment is the actual evaluation of the planners against the MAGIC planner, using Kendall's τ. In this experiment, three independent runs are iterated 21 steps. The best instance for each run at each iteration step is executed over 50, unseen, semantic inputs and the output *document plan* (converted into a sequence of atomic operators) is scored against the sequence obtained from the MAGIC planner. The average over the three runs gave τ of 0.2288 $\pm$ 0.0342.

To provide a baseline, I joined together the first generation of the three runs (a total of 6,000 random instances). When scored using Kendall's τ against the MAGIC planner, they had an average τ of 0.0952 ($\pm$ 0.1144).

These experiments show the feasibility of the approach, although the training material was unsuitable to fully re-create the existing MAGIC planner. It would have

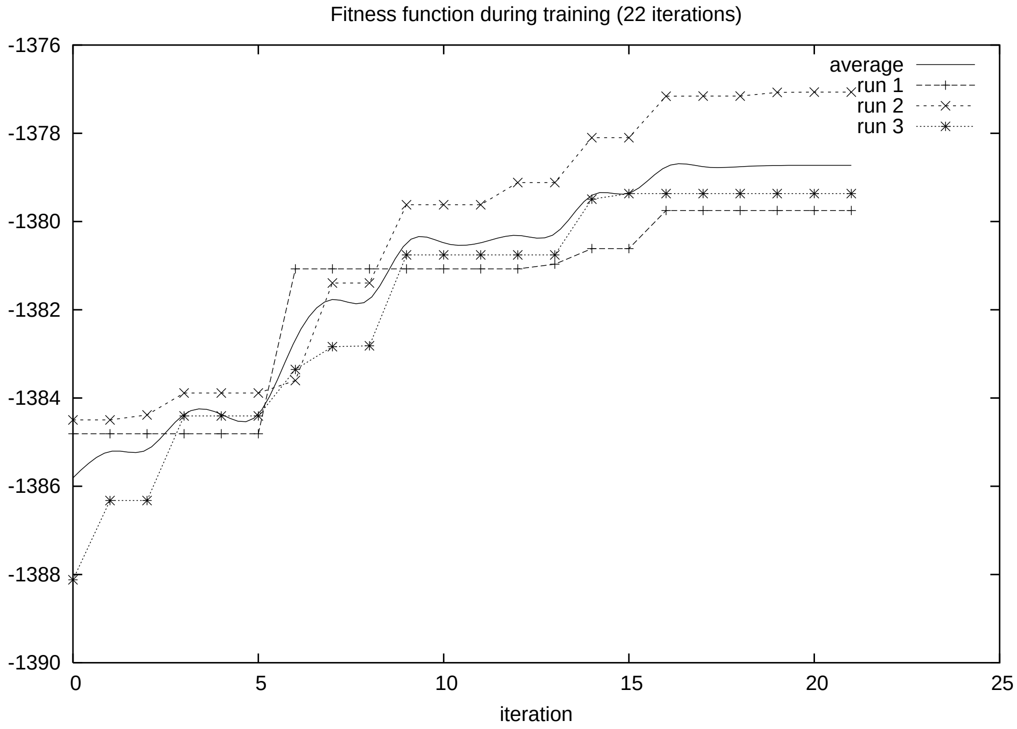


Figure 6.9: Fitness over 21 iterations in three different runs. The y-axis is the fitness value of each run.

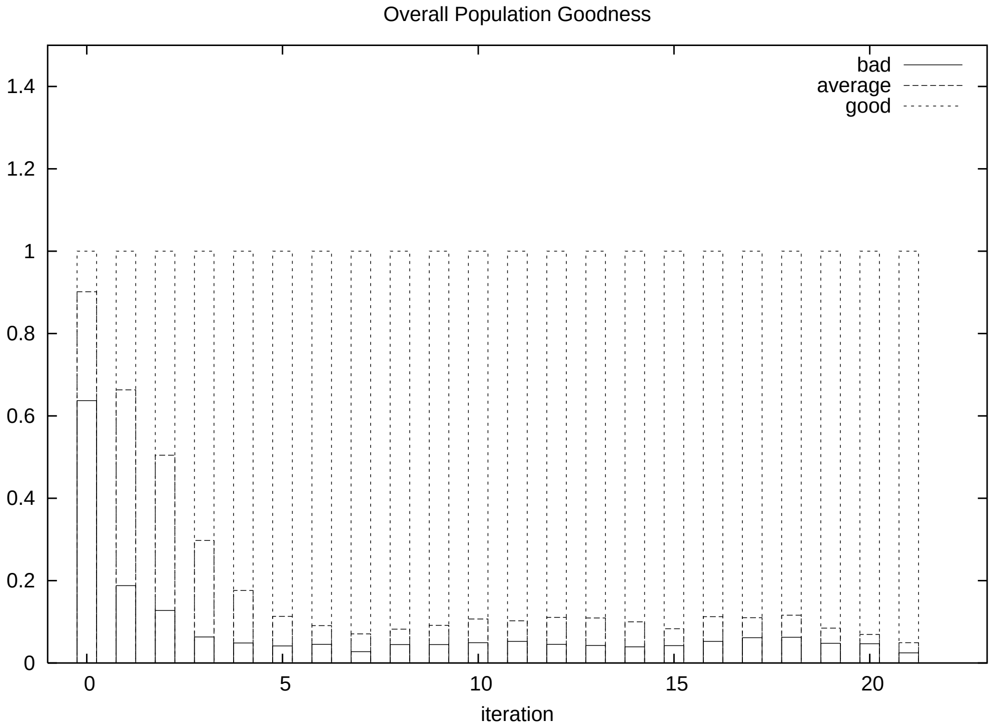


Figure 6.10: Percentage of the new instances that violated all order constraints (marked as ‘bad’), violated some order constraints (marked as ‘average’) or validated all of them and were verbalized (marked as ‘good’). The y-axis is the percentage (from 0 to 100% —marked 1 in the graph) of the population covered by each class. Here we can see that in early stages of the search, bad and average instances dominate the genetic pool. As the search progresses, only good instances remain.

been interesting to see the impact of the technique as a quick prototyping tool during early stages of the development of the project, although that is no longer possible.

6.4 Conclusions

This chapter exemplifies the application of the technique described in the previous chapter to data in the medical domain. This domain has a straightforward rhetorical structure that allows my techniques to positively learn Strategic Generation logic.

From a broader perspective, the results are quite low. A τ of 0.22 shows an improvement over a completely random baseline but it is still a weak correlation with the MAGIC planner. I think the problem in this case is to evaluate the automatically obtained schema against the MAGIC planner. It may be the case that the training material differs to a large extent with the MAGIC planner.[10] Moreover, the reduced training size forbids using cross-validation techniques to analyze how well the learned planners perform when tested against unseen training material.

The approach presented here is definitely CPU-intensive with running times usually expressed in days. Nevertheless, as Figure 6.9 shows, this is a search process that makes positive progress towards its goal. Moreover, the progress is not only in the best instance of the population, but it is a progress across the board, as shown in Figure 6.10, where it is clear that as times progresses, the population contains a larger percentage of really worthy instances. This progress is to be contrasted with the lack of progress when these technique are applied to PROGENIE data, as presented in the next chapter.

Figure 6.10 also shows the impact of the order constraints, as earlier stages of the population use them to distinguish totally wrong instances (the lower part of the bar) with the most promising instances (the upper part of the bar). Other extrinsic evaluations of the value of the order constraints were not attempted.

Contrasting MAGIC and PROGENIE results, it begs the question of which attributes in the MAGIC data makes it amenable for the learning. As mentioned in Chapter 2 (Section 2.2.1), MAGIC schemata are only suitable for planning single-topic discourse, as all discourse in MAGIC has the same focus —the patient the surgery was about. In the PROGENIE data, for the contrary, the focus shifts from the actor being described to her selected movies, and then to major awards each movie itself received.

[10] Sadly, the τ of the training material against the MAGIC planner was not determined.

Approximately 175-cm gentleman. History of rheumatic fever and polio. He is nonambulatory but can move his legs. History of acute renal insufficiency with a hematocrit of 1.4. History of mixed mr/ms lesion, tricuspid regurg and ai. Decreased right and left sided function, 4 chamber dilatation. Tricuspid repair with the ringand mvr with a st. jude's valve. History of pulmonary hypertension with a baseline of 90/40 catheter. He was on heparin nph preop. No allergies. Feed and .... lines were extubated he was on bypass approximately 2.5 hours. His ischemic time was 2 hours and 2 minutes. No problems. He came off on dobutamine because of poor function. No problems post-bypass. Maintained on levo, nitro and dobutamine at 4.5 mcg per kilo. Got vancomycin and gentamicin at 9 o'clock, standard iv anesthetics. He received a liter of albumin, 3 units of cell saver, no exogenous blood. Last po2 was 453, potassium of 4.6, hematocrit of 26, before getting any blood gas. His cardiac output with his chest closed

(a)

The patient is male. He had an easy intubation. Before coming off bypass, he had bradycardia. Drips in protocol concentrations include Dobutamine, Nitroglycerine and Levophed. At start of bypass, he had alkalosis. After coming off bypass, he had relative-anemia. Around induction, he was anesthetized with 130.0 mg of Rocuronium, 11.0 mg of Etomidate, 500.0 mcg of Fentanyl and 1.0 mg of Midazolam. His weight is 92 kilograms and his pre-op cardiac output 4.13.

(b)

Figure 6.11: Examples. (a) Physician briefing. (b) Learned planner output.

Chapter 7

Experiments in the Biographical Domain

This chapter describes the second round of Document Structuring experiments performed in this dissertation. As part of the joint Columbia University—University of Colorado Open Question Answering project (AQUAINT), I developed PROGENIE, a biography generator. The goal of PROGENIE was to provide final users with means to quickly and concisely communicate information about persons of interest. I combined a natural language generator with an information extraction infrastructure leading to ultimately mix textual (such as existing biographies and news articles) as well as non-textual (such as airline passengers lists and bank records) sources. I used the examples from the domain contained in the corpus described in this chapter to automatically construct Document Structuring schemata. These schemata guide the generation of biographies on unseen people.

I gathered an aligned Text-Knowledge corpus in the biography domain, as explained in the next section. More specifically, my corpus is a collection of human-produced texts together with the knowledge base a generation system might use as input for generation. The knowledge base contains many pieces of information related to the person the biography talks about (and that the system will use to generate that type of biography), not all of which necessarily will appear in the biography. That is, the associated knowledge base is not the semantics of the *target text* but the larger set[1] of all things that could possibly be said about the person in question. The ordering of the intersection between the input knowledge base and the semantics of the target text is what I am interested in capturing by means of my statistical techniques.

[1] The semantics of the text normally contain information not present in my semantic input, although for the sake of Content Selection is better to consider it as a "smaller" set.

7.1 Data

The Text-Knowledge corpus used in this chapter consists of knowledge's extracted from a semi-structured knowledge, biographical fact-sheets of assorted celebrities. These fact-sheets were crawled from E! on-line[2] in November 2002. In addition to this knowledge source, I also employ an extended knowledge source, also extracted from E! on-line but with a slightly different ontology and with information about the movies actors appeared in added. This extended knowledge knowledge source was incorporated to these experiments at the end of this dissertation and was not used during system development. Different biographical sites provide the text part, to test the ability of the system to learn from different types of data. As explained in Section 3.2.1, each corpus was split into a training and test set, with the test set tagged for selection and ordering (ordering only in the last corpus) by the author.

The annotation was done by the author, by reading the biographies and checking which triples (in the RDF sense, ⟨frame, slot, value⟩) were actually mentioned in the text (going back and forth to the biography as needed). Two cases required special attention. The first one was *aggregated information*, e.g., the text may say *"he received three Grammys"* while in the semantic input each award was itemized, together with the year it was received, the reason and the type (Best Song of the Year, etc.). In that case, only the **name** of award was selected, for each of the three awards. The second case was factual errors. For example, the biography may say the person was born in MA and raised in WA, but the fact-sheet may say he was born in WA. In those cases, the *original aim* of the human writer was given priority and the place of birth was marked as selected, even though one of the two sources were wrong.

Biographical Descriptions Domain. Biography generation is an exciting field that has attracted practitioners of NLG in the past (see the Related Work chapter, Section 2.4.3). It has the advantages of being a constrained domain amenable to current generation approaches, while at the same time offering more possibilities than many constrained domains, given the variety of styles that biographies exhibit, as well as the possibility for ultimately generating relatively long biographies.

The AQUAINT project focuses mostly on military and intelligence targets. However, there is a lack of publicly available information about such targets. Therefore, I shifted my attention to more popular individuals. As my approach is based on Machine Learning, given enough training data, the particular biographical field chosen is immaterial.

[2] `http://eonline.com`.

By far the most popular domain for biographies and assorted data about people is the *celebrities* domain. Most fans are eager to express their support to their favorite actor, model, singer or director by collecting sizable amounts of trivia or assembling them in very detailed biographies. The availability of information in this domain has lured other researchers into working with it (Pang, Lee, and Vaithyanathan, 2002; Taskar, Segal, and Koller, 2001).

I obtained the semantic input from pages describing itemized factual information about persons: **fact-sheet** pages (Figure 7.1). Such pages are abundant for *celebrities* (singers, movie stars and other famous people).

However, the level of detail of the fact-sheets was too coarse for my needs; I employed a combination of Information Extraction (IE) scripts to break the fact-sheet pages into smaller parts. A full-fledged natural language generation system expects a level of detail in its input that goes beyond the lay person ontological modeling found in the mined fact-sheets. To improve over that scenario, I performed a process I termed *Closed Information Extraction*. In this process, I build scripts without generalization in mind. It can be thought of as over-fitting a regular IE process.

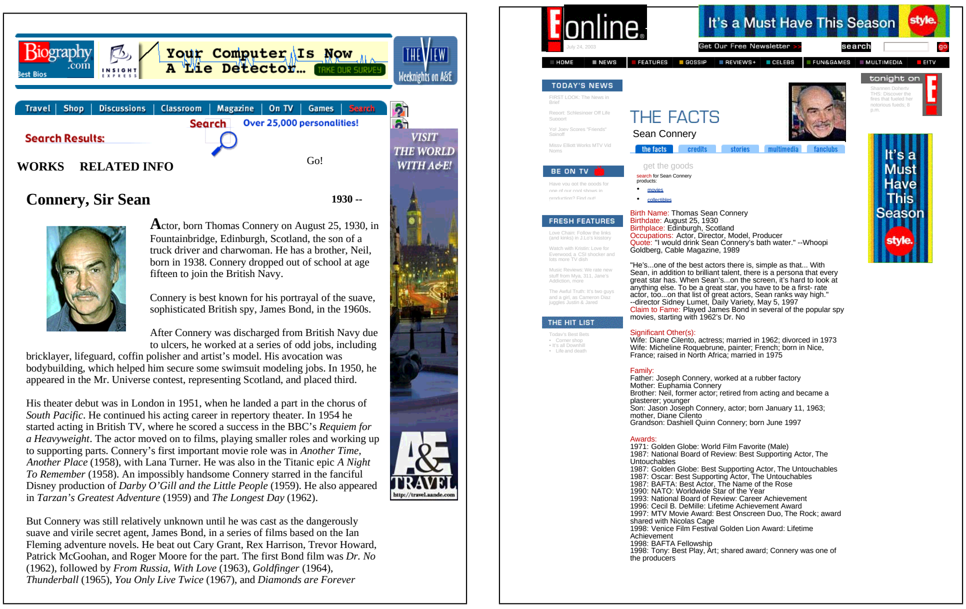
My current corpus contains semantic information for about 1,100 people, together with aligned biographies in four different sub-corpora, linked against 108, 578, 205 and 341 biographies for each of these sub-corpora. The sub-corpora were mined from four different Web sites and contain different writing styles and text structure. Such an environment is ideal for learning and testing content planning related issues.

Acquisition Process

The acquisition process consisted roughly of three steps: crawling, cleaning and linking. The crawling step involved downloading the actual pages. The cleaning step was the most time-consuming step and involved the *Closed Information Extraction* process mentioned above. Finally, I had data about people and biographies about (hopefully the same) people. The last step took care of linking data with biography, when appropriate.

While *E! Online* contains also biographies, chances are the fact-sheets are based on the biographies or vice-versa. To improve the quality of the aligned corpora, I mined different sites for the biographies. While several Web sites offer biographical information repositories, most of them focus in particular type of individuals. The sites I crawled that made up my corpus are: `www.biography.com`, `www.s9.com`, `www.imdb.com`, and `www.wikipedia.org`.

Regarding the cleaning step, it was the most time-consuming step, as already mentioned. This was no surprise, as data cleansing is normally considered among the most time consuming steps in data mining (Rahm and Do, 2000).



Connery, Sir Sean **1930 --**

Actor, born Thomas Connery on August 25, 1930, in Fountainbridge, Edinburgh, Scotland, the son of a truck driver and charwoman. He has a brother, Neil, born in 1938. Connery dropped out of school at age fifteen to join the British Navy.

Connery is best known for his portrayal of the suave, sophisticated British spy, James Bond, in the 1960s.

After Connery was discharged from British Navy due to ulcers, he worked at a series of odd jobs, including bricklayer, lifeguard, coffin polisher and artist's model. His avocation was bodybuilding, which helped him secure some swimsuit modeling jobs. In 1950, he appeared in the Mr. Universe contest, representing Scotland, and placed third.

His theater debut was in London in 1951, when he landed a part in the chorus of *South Pacific*. He continued his acting career in repertory theater. In 1954 he started acting in British TV, where he scored a success in the BBC's *Requiem for a Heavyweight*. The actor moved on to films, playing smaller roles and working up to supporting parts. Connery's first important movie role was in *Another Time, Another Place* (1958), with Lana Turner. He was also in the Titanic epic *A Night To Remember* (1958). An impossibly handsome Connery starred in the fanciful Disney production of *Darby O'Gill and the Little People* (1959). He also appeared in *Tarzan's Greatest Adventure* (1959) and *The Longest Day* (1962).

But Connery was still relatively unknown until he was cast as the dangerously suave and virile secret agent, James Bond, in a series of films based on the Ian Fleming adventure novels. He beat out Cary Grant, Rex Harrison, Trevor Howard, Patrick McGoohan, and Roger Moore for the part. The first Bond film was *Dr. No* (1962), followed by *From Russia, With Love* (1963), *Goldfinger* (1964), *Thunderball* (1965), *You Only Live Twice* (1967), and *Diamonds are Forever*

(a) Biography

THE FACTS

Sean Connery

get the goods

search for Sean Connery products:

- movies
- collectibles

Birth Name: Thomas Sean Connery
Birthdate: August 25, 1930
Birthplace: Edinburgh, Scotland
Occupations: Actor, Director, Model, Producer
Quote: "I would drink Sean Connery's bath water." --Whoopi Goldberg, Cable Magazine, 1989

"He's...one of the best actors there is, simple as that... With Sean, in addition to brilliant talent, there is a persona that every great star has. When Sean's...on the screen, it's hard to look at anything else. To be a great star, you have to be a first- rate actor, too...on that list of great actors, Sean ranks way high." --director Sidney Lumet, Daily Variety, May 5, 1997
Claim to Fame: Played James Bond in several of the popular spy movies, starting with 1962's Dr. No

Significant Other(s):
Wife: Diane Cilento, actress; married in 1962; divorced in 1973
Wife: Micheline Roquebrune, painter; French; born in Nice, France; raised in North Africa; married in 1975

Family:
Father: Joseph Connery, worked at a rubber factory
Mother: Euphamia Connery
Brother: Neil, former actor; retired from acting and became a plasterer; younger
Son: Jason Joseph Connery, actor; born January 11, 1963; mother, Diane Cilento
Grandson: Dashiell Quinn Connery; born June 1997

Awards:
1971: Golden Globe: World Film Favorite (Male)
1987: National Board of Review: Best Supporting Actor, The Untouchables
1987: Golden Globe: Best Supporting Actor, The Untouchables
1987: Oscar: Best Supporting Actor, The Untouchables
1987: BAFTA: Best Actor, The Name of the Rose
1990: NATO: Worldwide Star of the Year
1993: National Board of Review: Career Achievement
1996: Cecil B. DeMille: Lifetime Achievement Award
1997: MTV Movie Award: Best Onscreen Duo, The Rock; award shared with Nicolas Cage
1998: Venice Film Festival Golden Lion Award: Lifetime Achievement
1998: BAFTA Fellowship
1998: Tony: Best Play, Art; shared award; Connery was one of the producers

(b) Fact-sheet

Figure 7.1: Biography and fact-sheet page, from the Web.

Table 7.1: Main categories in my semantic input.

Agency
Awards
Birth date
Birth Name
Birthplace
Claim to Fame
Date of Death
Education
Factoids
Family
Occupations
Person
Quote
Significant Other(s)

award 1996: London Film Critics' Circle: Best British Actor, *Trainspotting*; tied with Ian McKellen (*Richard III*) (E. McGregor)

education Yale University, New Haven, Connecticut; M.A., English Literature, 1987 Worked toward Ph.D.; did not complete thesis (D. Duchovny)

family Mother: Helen Barr, bookkeeper, cashier at Dee's Hamburger Drive-In; appeared with Roseanne on the Lifetime interview tribute special, *Like Mother, Like Daughter* (Roseanne)

significant other(s) Husband: Alan Hamel, producer, manager; met while both worked on *The Anniversary Game*; married 1977 (S. Somers)

Figure 7.2: Examples of the data that make up my frames.

I cleaned the **fact-sheets** by means of a *Closed Information Extraction* process. The fact-sheets originally contained information in 14 categories, shown in Table 7.1. While some categories contained information that could be directly included in my knowledge representation (I use a representation similar to RDF (Lassila and Swick, 1999)), others contained heavily aggregated information (some difficult cases are shown in Figure 7.2).

To cope with these cases, I wrote a series of scripts, with patterns to capture different types of information. As usual, the patterns had errors, most frequently overgenerating.

Having a sizable set of semantic inputs and several sets of biographies as separated resources involved a real problem when it was the time to put them together. While I did not hesitate in spending hours of human labor for the construction of this corpus, aligning 1,100 fact-sheets against 20,000 biographies is truly unfeasible to be done by hand. I thus needed to link the two resources, a step complicated by the fact that names tend to be paraphrased, and are not unique identifiers (e.g., there is a silent-movies era actor also named *Harrison Ford*). I used techniques from *record linkage* in census statistical analysis (Fellegi and Sunter, 1969), a well studied discipline with more than 40 years of practice.

Table 7.2: Relations in my biographical knowledge base.

agency
aka
award
birth
canned-text
city
claimtofame
country
date
day
death
degree
education
end
factoids
father
first
full
givenname
last
major
month
mother
name
occupation
older
place
postmod
premod
province
quote
reason
relative
significant-other
source
start
subtitle
teaching-agent
text
title
xtra
year
younger

This section summarizes major highlights of the constructed corpus. I briefly describe the knowledge representation, and report total figures of frames, relations, words, tokens and links.

I employed a type-based frame structure, with inheritance. The information for each person is kept in a separate file, as a set of frames. Each frame has a unique name, a type (linked to an ontology) and a list of attribute-value pairs. Following RDF nomenclature, I count triples of the form $(\textit{frame name}, \textit{attribute}, \textit{value})$. Attributes can be list-valued, can refer to other frames, or may contain atomic values (currently of types *symbol, string,* or *number*).

The final corpus contains 50,000 frames, with 106K frame-attribute-value triples, for the 1,100 people mentioned in each fact-sheet. The frames are linked through 43 different relations shown in Table 7.2. An example set of frames is shown in Figure 3.1.

The details of the linked resource were detailed in Chapter 3, but I summarize their details in Table 7.3.

Table 7.3: Characteristics of the four different corpora.

biography.com	Total	Average	Train	Test
# pairs	102	-	91	11
# frames	4,956	45.588	4,442	514
# triples	10,628	104.196	9,500	1,128
# words	54,001	529.422 ± 301.15	49,220	4,781
# chars	337,775	3,311.520 ± 1,857.96	307,978	29,797

s9.com	Total	Average	Train	Test
# pairs	578	-	558	20
# frames	30,709	53.130	29,723	986
# triples	95,032	164.415	92,969	2,063
# words	21,037	36.396 ± 34.04	20,192	845
# chars	138,711	239.984 ± 215.82	133,204	5,507

imdb.com	Total	Average	Train	Test
# pairs	199	-	185	14
# frames	10,123	50.869	9,362	761
# triples	31,676	159.176	29,323	2,353
# words	64,196	322.593 ± 285.63	60,086	4,110
# chars	378,778	1,903.407 ± 1,693.88	354,560	24,218

wikipedia.org	Total	Average	Train	Test
# pairs	361	-	341	20
# frames	58,387	161.737	55,326	3,061
# triples	108,009	299.194	102,297	5,712
# words	68,953	191.006 ± 55.17	64,784	4,169
# chars	418,035	1,157.992 ± 334.01	392,925	25,110

Table 7.4: Evaluation metrics at different probability cut-points. All metrics refer to number of constraints over held-out sequences.

cut-point	found	valid	mixed	invalid
1	61.35 ± 3.82	24.85 ± 3.44	36.54 ± 4.58	0.00 ± 0.00
0.99	537.08 ± 18.47	276.68 ± 15.54	260.45 ± 12.42	0.00 ± 0.00
0.98	598.94 ± 20.13	306.01 ± 15.95	292.95 ± 13.78	0.08 ± 0.23
0.97	605.41 ± 20.24	306.01 ± 15.95	299.41 ± 14.44	0.08 ± 0.23
0.9	766.65 ± 27.49	403.41 ± 21.4	363.21 ± 15.11	0.11 ± 0.41
0.8	930.81 ± 30.79	497.81 ± 24.58	432.88 ± 13.98	0.21 ± 0.51
0.7	1134.01 ± 37.61	668.58 ± 30.49	465.14 ± 17.72	0.38 ± 0.65

7.2 Learning Order Constraints

Mimicking the experiments in the previous chapter, the system obtained an average of 14.171 (±1.806) patterns, clustered into 3.838 (±0.384) clusters. When tested on the held out fold, all patterns and clusters are found. For the default cut-point of 0.99, an average of 537.038 (±18.426) constraints are found,[3] from which 276.638 (±15.502, a 51.502%) are always correct, 260.405 (±12.377, a 48.507%) sometimes contain errors and no constraints contains a large number of errors. Table 7.4 shows other results at different probability cut-points. These figures are compatible with the ones presented in the previous chapter.

Figure 7.3 shows the impact of the support threshold. Again, as we require the patterns to appear in more instances in the training set, less patterns are found, which in turn produces clusters and constraints with higher accuracy. Here too, a support threshold of 0.2 seemed a good compromise between the number of patterns and their quality.

Figure 7.4 illustrates the effect of the window size on the different metrics. As the window size grows, better quality is achieved, but the window stabilizes very early in the process.

The learning curve (Figure 7.5) shows that the training material is now enough to produce a smooth curve.

7.3 Learning Document Structuring Schemata

I will discuss here my preliminary results in learning Document Structuring schemata. I fully implemented the approach described in Chapter 5 and performed a number of

[3] The constraints are defined not only over clusters, but also over individual elements.

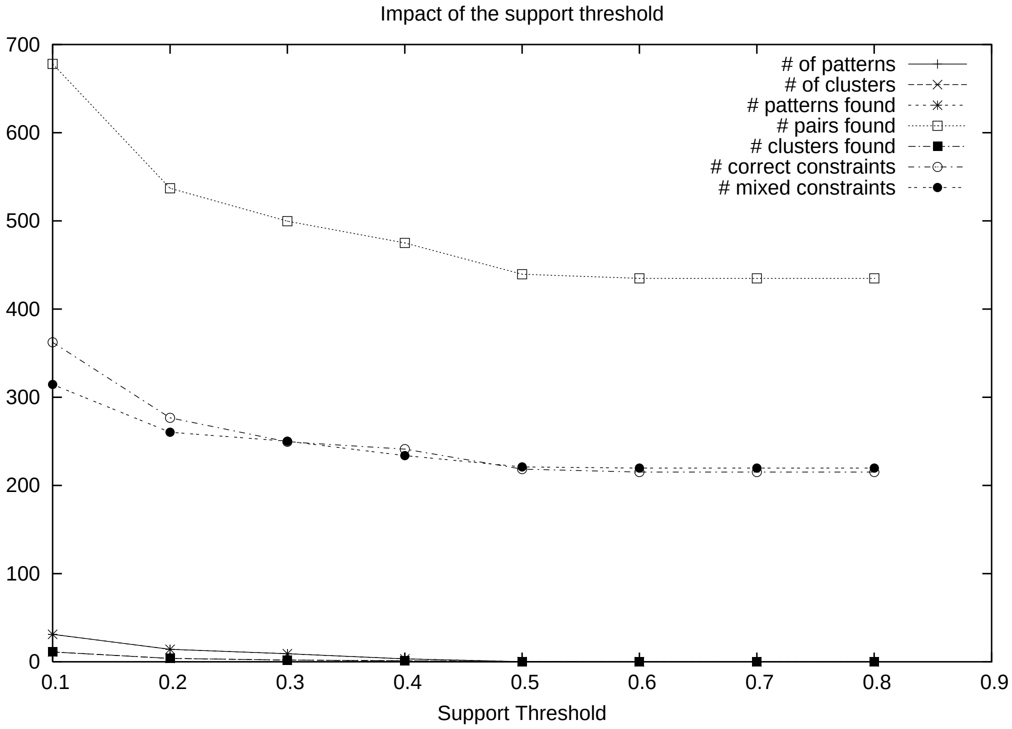


Figure 7.3: Impact of the support threshold. The support threshold is the percentage of the total number of sequences that a pattern has to appear on to be used for learning order constraints. From the figure, a support threshold of 20% represented a good compromise.

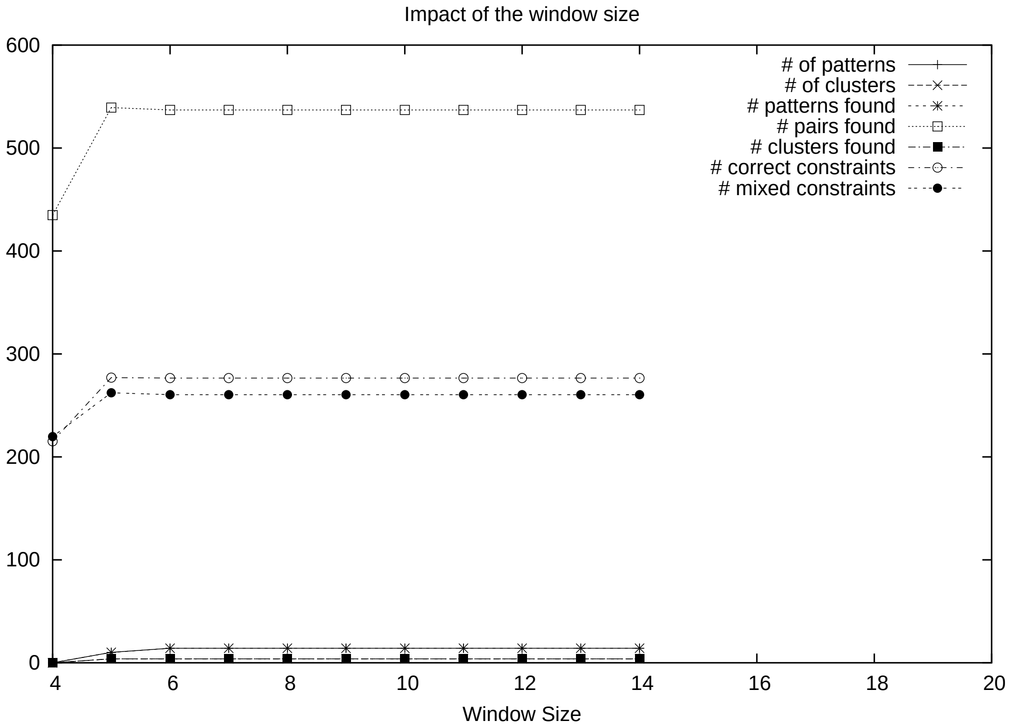


Figure 7.4: Impact of the window size. The window size shows an impact only for small numbers.

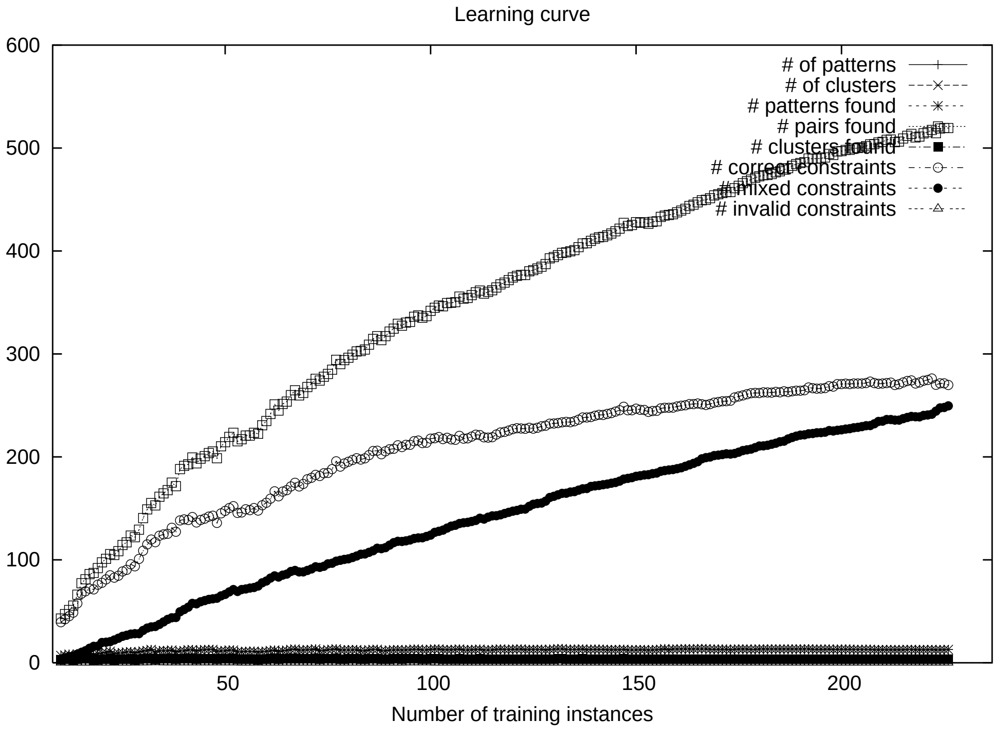


Figure 7.5: Learning curve. As more training is available, the number of constraints found stabilizes.

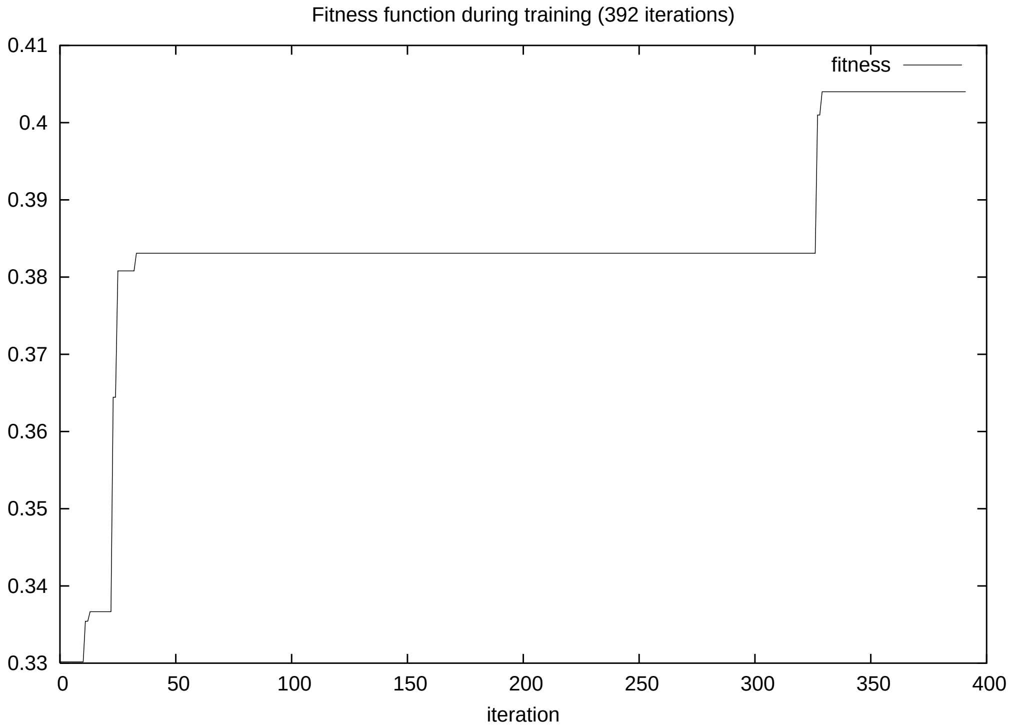


Figure 7.6: Fitness value over 392 iterations. The peak in the figure shows the successful application of an operator to the best schema.

rounds of training with the order sequences obtained from the Variant 4 *matched texts* in the `wikipedia.org` corpus. Figure 7.6 shows one such a run, representative of the experiments I conducted. The figure shows the evolution (or lack of it) of the fitness function. Even though my approach is faster than doing full verbalization, the curve took a good one week to be computed on a dual 3Ghz Pentium 4 machine. The curve shows a certain improvement over time, however (the peak around iteration 300). This very slow rate of convergence can easily be attributed to two factors: the size of the search space and the lack of training-motivated operators. While the fitness function is defined by the training material, the operators just induce random alterations on the instances (schemata). Given the size of the search space this ensures a particularly slow convergence for the search.

A schema at the end of the process is shown in Figure 7.7. This figure may be a piece of evidence for another problem with the approach: the focus mechanism is an integral part of the semantics of the schemata. Without a deep understanding of both the meaning of the communicative predicates (the edges in the graph) and the prioritization made by the focus mechanism, it is very difficult, if not impossible to predict the path over the graph that will result in the *document plans*. I suspect the focus mechanism as defined originally by McKeown (1985) is hurting my learning, because it can result in abrupt changes on the schemata. It seems learning both items together will benefit the composite process.

7.4 Conclusions

The domain of biographical descriptions contains some of the complexities that makes the Strategic Generation problem difficult in a general setting (recursion, branching, etc.). These complexities imply further research is needed to fully acquire a schema from a Text-Knowledge corpus. This subject is further explored in the next chapter.

Continuing with the discussion in the conclusions of the previous chapter, here a complex domain implies a domain that requires to drill down in different entities. The example biography schema, shown in Figure 5.3, contains many such drill downs: for example, after an entity (`built`) of which the person (`Self`) has been involved into the construction has been introduced, the appraisals motivated by that entity are enumerated.

The difference then between the MAGIC data and the ProGenIE data is in the latter's need to capture focus shifts during learning. The hope was that, as the technique described in Chapter 5 was focus agnostic, the GA was going to be able to learn the schema in spite of this focus problem.

Sadly, *post hoc* analysis shows that focus affects the GA too negatively; when a very promising solution is slightly modified, most of the time it will produce a completely invalid offspring. That means that, for the most part no improvements are done in each step of the genetic search. This can be seen by comparing Figure 6.9 in the previous chapter with Figure 7.6. Both figures took comparable amount of time to be computed. We can see that in roughly the same amount of time, the approach without using verbalizations takes an order of magnitude less time to compute. However, in 21 steps the system running in MAGIC data already stabilizes. In 392 steps, the system running in ProGenIE data has managed to make only one successful step. Moreover, it is intuitive that the ProGenIE data will need more than only 21 steps to find a solution. Therefore, if it takes about a week to do each of these steps, it is clear that the current solution runs into computational feasibility problems with this data.

With respect to the order constraints, the lack of results in the overall schema learning forbids an extrinsic evaluation as done in the previous chapter. A feasible alternative would have been to evaluate their use as stand-alone planners, but this approach was not attempted.

Some ways to go around the problems identified in these experiments will be

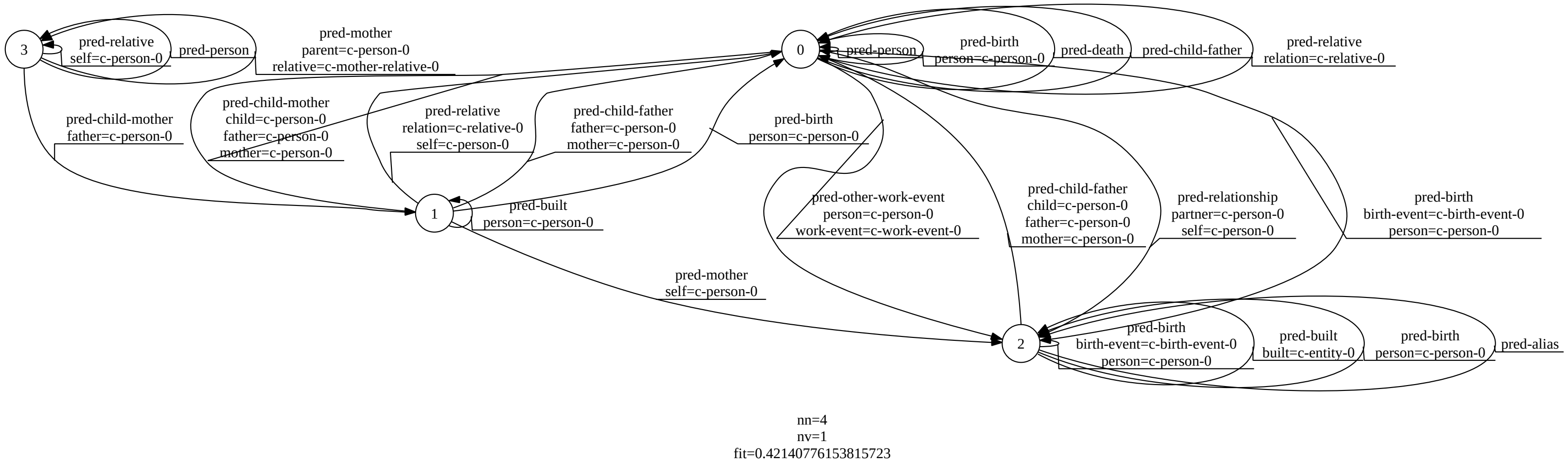


Figure 7.7: A learned schemata. The schema has four states and a maximum of one variable per type.

discussed in the next chapter and in the conclusions chapter. Succinctly, one alternative would be to improve the system with more informed operators that will modify the population according to the training material (data-driven operators). Another promising alternative is learning the focus mechanism together with the finite state automaton. Both approaches are target for future work.

Chapter 8

Limitations

My proposed technique to acquire Content Selection rules and Document Structuring schemata from a Text and Knowledge corpus has a number of drawbacks and limitations. I have identified some of them that I will summarize in this chapter. I will first discuss general limitations of my techniques (Section 8.1), including the need for a Text-Knowledge corpus and domain requirements. The limitations of the matched text construction process are discussed in Section 8.2. Finally, the learning of Content Selection rules and Document Structuring schemata have particular limitations discussed in Section 8.3 and Section 8.4, respectively.

8.1 General Limitations

I will now mention briefly some general limitations of my approach.

Knowledge requirement. The Strategic Generation component in a NLG system operates at a very high level of abstraction; it takes knowledge as input and produces *document plans* as output. It is natural that a system learning Strategic Generation logic will also require knowledge as training material. This requirement obviously restricts the application of the technique to domains where such structured knowledge can be gathered. Luckily, existing efforts such as the W3C Semantic Web (Berners-Lee, Hendler, and Lassila, 2001) or the standardization of XML formats[1] increase the availability of structured knowledge.

[1] `http://www.oasis.org`.

Text-Knowledge corpus requirement. This is a major requirement of my technique. In a sense, my thesis is an exploration of the possibilities of such a formidable learning resource. Working on relaxations to the Text-Knowledge requirement is an attractive follow-up to my work, for example using text alone and extracting knowledge from it by means of information extraction techniques. It would be difficult, if not impossible, to acquire Content Selection knowledge with such an approach. Other researchers have coped with the lack of a perfect Text-Knowledge resource with manual efforts. Barzilay and Lee (2002) had knowledge available and then had people write verbalizations for it. On the contrary, Karamanis and Manurung (2002) had texts available and built associated knowledge.

Domain Requirements. For a more precise description of the domain requirements imposed by my technique, five issues need to be taken into account:

1. An RST analysis of the documents in the domain will contain more that a certain percentage of JOINT. Marcu (2000)'s or Corston-Oliver et al. (2002) rhetorical parsers can be used to measure this figure.

2. There is a large percentage of *hapax* words (word types that appear only once in a document) that can be traced back to the semantic input.

3. There is a bound on the length of the text itself; my system addressed successfully texts in the order of four to six paragraphs. Lengthy texts are outside the capabilities of current generation systems, at any rate.

4. As mentioned before, an aligned Text-Knowledge corpus has to be available. Each domain must supply training data for my system, in the form of a resource consisting of text and an associated knowledge base (a set of *aligned pairs*).

5. There is a lack of intentional structure *per segment of the text*; from the intentional stand-point, the whole text is an atomic INTENTION: REPORT. Measuring this fact is quite complex but I would argue new techniques for opinion detection can be of use here (Taskar, Segal, and Koller, 2001; Pang, Lee, and Vaithyanathan, 2002; Yu and Hatzivassiloglou, 2003).

Computationally Expensive. The methods employed in this thesis normally involve searches in large spaces and other computationally intensive tasks. This type of behavior is to be expected when dealing with large combinatorial problems. More importantly, most of the algorithms described here are parallelizeable with trivial or nearly trivial effort. Some of my experimental chapters also speak of the feasibility of my technique, although some of the problems in the previous chapter can be traced back to this limitation.

Learning for NLG. My work relates to recent uses of Machine Learning techniques for NLG tasks. A word of caution is required, as the type of logic produced will mimic the quality of the material offered to the system. Reiter and Sripada (2002) pointed out that exposing a learning system to poorly written text will learn a robust understanding system. In the NLG case, however, they pointed out that using poor texts will be akin to using poor parse trees in the understanding setting: poor training text means poor output text quality in NLG, not robustness. Moreover, I believe careful study of a domain allows the NLG practitioner to make a system that generates better texts than the average human. Humans do not succeed in producing texts that are consistent, unambiguous and concise at all times. A well tuned NLG system can reach such levels of perfection. By learning a symbolic representation, my thesis fits perfectly in this picture as a quick prototyping tool.

Thresholds and Parameters. The parameter tables in the different chapters (summarized in Table 1.1) point to another limitation of this thesis' techniques: the need for a number of thresholds and parameters. This necessity arises from two sources. First, the use of a unsupervised learning approach in areas of this thesis usually calls for certain parameters to be hand-picked. This is normal practice in other unsupervised settings (e.g., the number of cluster in a clustering application). Second, Genetic Algorithms are usually criticized as having a number of parameters (e.g., population size, mutation rate, etc.) that varies widely from application to application of GAs. My particular deployment of GAs does not escape from this limitation.

The situation described above is a true limitation of the approach described here. Nevertheless, as explained in Chapter 1, I envision a Strategic Generation-learner system as a tool for the NLG practitioner that will assist the practitioner when building a NLG system for a new domain. As such, the parameters of this tool (my system) will have to be dealt intuitively by the NLG practitioner. The parameters I used in my experiments (shown in Table 1.1) are provided as a means to help build these intuitions.

8.2 Limitations of the *matched text* construction process

The *matched text* construction process is a large source of errors but also a major contribution of this thesis. Unsupervised systems derive all their behavior from underlying assumptions on the model. This fact makes them unstable and difficult to deal with in general. My system is no exception to these general issues. To talk of its shortcoming is to talk about the shortcomings of the model itself. I will just point out two major issues I have noticed while experimenting with the approach: the need for large amounts of text and the fact that the system can be easily mislead.

Because of its statistical nature, large quantities of text are needed to identify meaningful verbalizations. Moreover, even if normally the 'default' verbalizations are picked by the system, an even larger amount of text is necessary to select relevant variants. In experiments (unreported in this thesis) I have pursued using a 25M words corpus downloaded from the Web, the system was able to identify 'Johnny', 'J' as possible verbalizations of $(\langle \texttt{name first} \rangle, \textit{'John'})$. With a little more effort, I would expect the system to identify 'Dick' as a verbalization for $(\langle \texttt{name first} \rangle, \textit{'Richard'})$. Now, it would be definitely impossible to pick up a verbalization of 'Pirot' for the concept $(\langle \texttt{name last} \rangle, \textit{'Ipeirotis'})$. However, humans will have no problem telling that (maybe not proposing 'Pirot' as a verbalization of 'Ipeirotis' in abstract, but identifying in a given text that 'Pirot' refers to the last name 'Ipeirotis' —context makes a big difference, usually). However, there is no human intervention during the *matched text* construction (again, it is unsupervised). Therefore, it needs a large number of textual examples and even in that case there will be cases that cannot be captured. Note that this is a problem with the model. The model, however, can be improved to accommodate new cases.[2] More research is needed to propose new models and enrich existing ones. Mine is a simple model to help bootstrap the exploration process.

The *matched text* construction works on the hypothesis that changes in the data are correlated with changes in the text. There are times that the change in data affects the text, while not appearing explicitly. For example, on work on revision-based generation (Robin and McKeown, 1993), it was the case that information that did not appeared in the text was affecting lexical choice: stocks **surge** when they start raising in the morning but they **raise** if they do it in the middle of the day, although the actual time does not appear mentioned in the text.[3] Therefore, keeping these concepts for further processing is of use for a NLG pipeline; as the example show, the data not selected for inclusion has a role in lexicalization. In any case, the overgeneration implies that the statistical rules

[2] For example, expanding the model with the assumption that 'any subsequence of at least 5 letters is a possible verbalization' will accommodate the 'Pirot' example.

[3] Personal communication.

will be prone to have low precision.

8.3 Limitations of the learning of Content Selection rules

Inducing Content Selection logic from a Text-Knowledge corpus will capture paradigmatic, schema-like information that has to be included in the text. Capturing this paradigmatic information has been the objective of my work. However, it is clear that not all the information that makes up a text can be obtained this way: biographies, for example, will usually contain mentions to out-of-the-ordinary facts about a person that are worth being reported. Take again the *MTV Movie Awards* discussed in Chapter 4 as omitted in celebrities biographies. Now, if a person had won the *MTV Movie Awards* every year for the last ten years, such fact will be included in the biography. Techniques that operate exclusively on the knowledge side (being able to infer which facts are out-of-the-ordinary) (Knott et al., 1997) or exclusively on the text side (looking for sentences in biographies with special markers or novelty words) (Schiffman, 2002) will be of use to approach this problem.

At a finer level of detail, my Content Selection mining techniques would profit from additional domain knowledge. In an effort to make the solution as domain independent as possible, the system lacks any type of ontological information. Relatively mild generalizations such as *"entertainers" should include TONY awards* while *"writers" should include Writer's Guild of America awards* will be impossible to be achieved. This is the case, as "entertainers" is split into "actors," "comedians," etc. and writers is split into "writers," "screen-writers," etc. This lack of ontological information obviously hampers the generalization power of my technique.

8.4 Limitations of the learning of Document Structuring schemata

With respect to the learning of Document Structuring schemata, my work in this area speaks the complexity of the task and contributes successful results for simpler domains and preliminary results for complex domains. I can put forward the following reasons behind some of the negative results in the previous chapter:

- Uninformed operators. While the schema-learning process uses a data-driven fitness function, the changes in each schema are performed at random. Using the training material to guide the mutation and cross-over operators may prove, therefore, fruitful.

- Efficiency issues. As a result of the aforementioned uninformed operators and its combinatorial nature, the schema-learning problem seems intractable with current computing technology. This is no surprise, given the combinatorial nature of the problem. Further advances in computational power may bridge the gap to achieve this goal.

- Problems with focus decoding. Applying a FSM-learner like GAL to the problem of learning a FSM "hidden" behind a focus decoder, without allowing the system to adjust the decoding process at any point seemed too much of an ambitious goal, in retrospective. The decoding process should be laid out in a formalism that allows for it to be learned simultaneously with the FSM.

I would like to point out now two intrinsic limitations of the approach. The first limitation is the use of Document Structuring schemata, meaning that my system inherits schemata limitations, well studied and documented in the literature. Second, as explained in Chapter 5, my learning system requires as part of its input the communicative predicates for the domain. I will discuss some of the ramifications of this requirement in this section.

Limitations of Using Document Structuring Schemata. Schemata have a number of well studied and well understood limitations that my work inherits by using them as a learning representation. The first issue that is normally associated with schemata is their lack of intentional structure; no effort is made to model or represent in the schema the reasons behind the text structure (e.g., the existence of a decision or a sequence). This is the case, as schemata represent texts that are rich in Domain Communicative Knowledge (DCK, discussed in the Chapter 2, Section 2.2), where there is no real reason behind the text structure. The lack of intentional structure, however, implies that the generation system will not be able to reason about the text it has produced. This is particularly important for dialog systems that may need to answer follow up questions or justify their answers. My technique, therefore, will be hard pressed to be applied directly to dialog systems. Nevertheless, in dialog systems the problems are different and current work is normally concerned with learning Dialog Managers, as well as Sentence Planners that produce a more concise output, as discussed in the Chapter 2, Section 2.4.

Finally, schemata only capture long distance rhetorical relations by means of schema recursion. As I have not addressed the problem of learning several, recursively related schemata, my system is further limited to local rhetorical structure (specified by the communicative predicates).

In spite of these problems, my decision to use Document Structuring schemata is well motivated. Schemata have been shown as highly applicable and have been used in a number of NLG projects and domains (Paris, 1987; Maybury, 1988; Bateman and Teich, 1995; Dalal et al., 1996; Milosavljevic, 1999). From a scientific standpoint, it is a more sensible solution to learn a well established representation than to learn a representation easy to learn (and then investigate what type of tasks does this representation can be useful for (Filatova and Hatzivassiloglou, 2003; Barzilay and Lee, 2004)). Researchers in NLG have been studying the Strategic Generation problem for almost 30 years now. Coming up with a new solution to this problem is a valuable goal that does not require learning and, more to the point, is not the focus of this dissertation.

Predicates Requirement. Strategic Generation involves a good deal of knowledge engineering that my dissertation seeks to alleviate. At first sight, it is not clear to which degree my system is really taking the burden from the knowledge engineer. It may be argued that greater efforts in knowledge engineering are required to build the ontology and to identify the communicative predicates in the domain. However, this is very difficult to quantify, as both process are normally intertwined. Even in projects in which I have been involved it is difficult to tell predicate construction from building the actual schema. The impact of my technique in the knowledge engineering process performed by NLG practitioners is still to be seen, in some sense.

I would like to discuss two valid points, however. First, requiring the predicates to come from outside the schema induction process is a sensible decision. These predicates encapsulate the symbolic information used by the remaining components of the generation pipeline. Without this solution, my schemata will impose on the NLG practitioner particular solutions to other components in the NLG pipeline. Moreover, learned predicates may impose the need for a fully statistical NLG pipeline, with the obvious impact on the text quality and lack of maintainability. An added benefit of my approach is that these predicates can be reused when generating text on the same domain (e.g., when generating admission notes and surgery reports in a hospital). The schemata, on the other hand, cannot be reused, as it is a major source of DCK, and makes sense to learn them from examples.

The final point has to do with the fact that automatically learning Strategic Generation logic not only improves our existing practices but also enables new exciting possibilities. PROGENIE, for example, can be re-trained for Content Selection of new target biographies by its final users. This type of flexibility is unseen in earlier NLG systems.

8.5 Conclusions

Strategic Generation is a well-studied and complex problem in NLG, as the literature reviewed in Chapter 2 attests. Learning Strategic Generation logic from positive data adds further complexities to it. My techniques enjoy a relative success but have a number of limitations. More research is needed to overcome them, some of which will be introduced in the next chapter as further work.

Chapter 9

Conclusions

I have presented in this thesis a technique to learn **Strategic Generation logic**, in the form of Content Selection rules and Document Structuring schemata. Strategic Generation is a key step in the generation of multi-sentential/multi-paragraph text. In the words of Bontcheva and Wilks (2004) “The main effort in porting a generator to a new domain is in the adaptation of its discourse planning component.” Its difficulty lies in the large number of possible orderings and the domain information needed to solve it.

My learning technique is based on **Indirect Supervised Learning**, a two-stage learning pipeline that combines unsupervised and supervised learning. The unsupervised step uses human texts to supplant an otherwise laborious annotation. The obtained training material is quite noisy and therefore the supervised learning techniques have to be robust enough to learn in spite of this noise. As a robust learning methodology, I use optimization of objective functions over the training material.

Experiments in **two different domains** for Document Structuring schemata and in **four different styles** for Content Selection rules help understand and validate the approach. My Content Selection results are of major practical importance and are ready to be tested in other domains. The Document Structuring experiments show promising results and point the research to future areas that need further development (like corpus-based search operators in the schemata space and the need to learn focus together with the schema structure). These techniques can be applied to new descriptive domains with no strong intentional nor rhetorical structure. Their success depends on a strong topical structure, together with good anchors between the knowledge base and the text. These requisites are accomplished by a broad range of domains, of practical importance.

I will detail now the contributions of this dissertation, including its deliverables. I will then highlight a few of the many extensions opened by the present work. A preliminary list of other domains appropriate for this thesis’ techniques concludes this chapter.

9.1 Contributions

This thesis puts forward a number of contributions. Its main contribution is the learning machinery to induce Strategic Generation logic from a Text-Knowledge corpus. This machinery contributes to the knowledge engineering aspects of the NLG process, as well as shedding light on the learning issues of the problem (empirically addressing questions such as *"can the Strategic Generation logic be automatically acquired?"* or, more interestingly, *"can it be learned from indirect,* ***positive*** *evidence?"*).

It contributes at three levels. First, it contributes by devising, implementing and testing a system for the automatic construction of training material for learning Content Selection and Document Structuring logic. The technique described in Chapter 3 is able to process hundreds of text and knowledge pairs and produce Content Selection training material with quality as high as 74% precision and 67% recall. The Document Structuring material it produces is also highly correlated to hand annotated material. This *matched texts* construction process emphasizes the use of structured knowledge as a replacement for manual tagging. The possibilities for application of such automatically tagged texts are by no means exhausted in this dissertation and open new lines of exciting research. The Text-Knowledge corpus in the biographies domain assembled as part of this thesis (Chapter 7, Section 7.1) is now a valuable resource, available for further research in the area, together with the machinery to obtain new training material in a number of domains discussed in Chapter 9. Resources for learning in NLG that include semantic counterparts are scarce and of small size. In its current form, the PROGENIE corpus is rivaled only by Reiter et al. marine forecast corpus (Sripada and Reiter, 2003), where the semantic input is a table with a dozen values and the text is a few sentences long (his team has collected thousands of these reports). The PROGENIE corpus has hundreds of facts per person and multi-paragraph length biographies. The evaluation methodology employed in this thesis is also a contribution: using a number of human written texts for evaluation, dividing them into training and test set and using the test set to evaluate **both** the unsupervised as well as the supervised steps.

Second, there are also among my contributions the proposal and study of techniques to learn Content Selection logic from a training material consisting of structured knowledge and selection labels. As the training material is automatically obtained, it contains a high degree of noise. Here I contribute with techniques that are robust enough to learn in spite of this noise. I set the problem as an optimization of the F^* over the training material. My techniques have elucidated Content Selection rules in four different styles in the biographies domain. Moreover, my experiments in Content Selection contribute to our understanding of the Content Selection phenomenon at several levels.

First, it separates nicely the need for off-line (high-level) Content Selection from on-line Content Selection, where the approach described in this thesis can potentially learn Content Selection logic at **both** levels. From a broader perspective, my acquired Content Selection rules provide an empirical metric for *interestingness* of given facts. This metric (induced from a Text-Knowledge corpus) can be compared to ontology-based metrics (Basu et al., 2001) or summarization based ones (Van Halteren and Teufel, 2003).

Finally, I defined the problem of learning Document Structuring schemata from indirect observations, proposing, implementing and evaluating two different, yet similar techniques in two different domains. The Document Structuring problem is one of the most complex problems in NLG. My techniques are among the first efforts to effectively learn Document Structuring solutions automatically. At a fine grain of detail, my main contribution is a dynamic-programming metric, presented in Chapter 5, Section 5.4.2, that compares sequences of values (that can be read out from text) against sequences of messages (that are produced by the schemata). This approach is similar to my earlier work in comparing fully verbalized text, which allows text-to-text generation logic to be incorporated into NLG systems (described in Chapter 6). The new method presented here, on the other hand, is far more efficient. The acquired schemata are written in a declarative formalism, another contribution of this thesis. Previous implementations of schemata had mixed declarative/procedural definitions that impose a high burden for any learning technique. Moreover, the learned schemata are ready to be plug into an open source package, OpenSchema,[1] that I have written as part of this thesis. OpenSchema works as a reference implementation, allowing people to enjoy the full advantages of schemata-based document structuring without worrying about its implementation hassles. It is my hope that OpenSchema will reduce the use of schema-like planners on behalf of full-fledged schemata ones.

Aside from my main contributions, my work contributes to the broader linguistics community as a new technique to analyze discourse in particular domains. My induced Document Structuring schemata can be of service to linguists analyzing the discourse of particular domains. In some sense, they could behave, for example as Text Grammars (Zock, 1986).

9.1.1 Deliverables

Part of the contributions of this thesis are the following deliverables:

1. *Matched text* construction programs.

[1] `http://openschema.sf.net/`.

2. Content Selection rule-induction programs.
3. Document Structuring schemata induction programs.
4. Biographies Text-Knowledge corpus.
5. OpenSchema reference implementation.
6. PROGENIE generator.

9.2 Possible Extensions

I describe here some further issues worth investigating in relation to the topic of this dissertation.

Complex Concepts and Phrases. While I have reported my tri-partite rules as expressive enough to capture the needs of my biographies corpus, it is clear that other domains may need a more expressive rule language. The expressivity of the rule language is deeply tied to the expressive power of the concepts and phrases. Further investigation of patterns instead of *n*-grams for the definition of phrases opens exciting new alternatives. Finally, the impact of the equivalence classes used to define the data-classes is an issue worth further investigation.

Learning jointly Information Extraction and Strategic Generation. While this dissertation explored exclusively learning Strategic Generation from a Text-Knowledge corpus, settings as the graphical model presented in Chapter 1 are usually addressed using the Expectation-Maximization (EM) algorithm (Dempster, Laird, and Rubin, 1977). In this context, using EM will imply adjusting an Information Extraction model together with a Strategic Generation model.

Learning jointly Schemata and Focus. Following the discussion in the previous chapter, learning a bottom-up focus function may help overcome the schemata induction problems observed in the more complex domain (biographies).

Summarization. Possible extensions for summarization involve learning generic labels for Content Selection, in the form of salience scores. To shape the Content Selection task into a summarization framework, the labels should be learned not now from a Text-Knowledge corpus with only a single text adhering to some particular style paired against the knowledge, but many different texts, all belonging to the same domain (i.e., all biographies of the person, but written by different authors).

Aggregation and Content Planning. Content Planning and Aggregation interact in complicated ways (Bontcheva and Wilks, 2001). Shaw (2001)'s thesis started pointing out some of the issues, I would be interesting to follow up that line of research. In particular, his work on manual deaggregation is worth automating (following existing work in text simplification (Siddharthan, 2003)), if possible, to improve the overall behavior of my learning pipeline.

Intentions. I would like to start investigating techniques to identify opinions (Pang, Lee, and Vaithyanathan, 2002; Turney, 2002) and incorporate them into my framework. While intention is different from opinion, a text containing a large number of sentences with a negative opinion about a topic could be considered as having the intention of lowering the value of the topic in the hearer's mind. Similarly, a text with plenty of positive opinions could target increasing the value of the topic. These are very simple intentions (compared to the treatment of intentions made by Moore and Paris (1993) or Zukerman, Korb, and McConarchy (1996)), but such model can be used to learn Content Selection rules that should be used when the system wants to generate positive or negative texts, depending on the task at hand.

Different Media. I am interested in the relations between my learning of schemata and speech act detection (Ries, 1999; Porayska-Pomsta, Mellish, and Pain, 2000) and techniques to acquire dialog managers (Levin and Pieraccini, 1997; Singh et al., 2002). It would be also interesting to relate my research to work in layout planning using rhetorical operators, as the work done by Kamps et al. (2001). On that behalf, I have access to the MAGIC system, a multimedia system of coordinated speech and graphics.

9.3 Other Possible Domains

I would like to conclude with a description of additional domains suitable for the application of my technique. Each domain provides input to my system in the form of an aligned Text-Knowledge corpus. All these domains are of descriptive nature and abundant in anchors (phrases copied verbatim from the input knowledge base). These new domains are to added to the two domains used in this thesis (Section 1.5), namely Medical Reports and Person Descriptions. I mention these extra domains as supporting evidence of the broad applicability of my technique.

Input Knowledge

```
1.  use-coins(archaic-period)
2.  creation-period(ex5, archaic-period)
3.  madeof(ex5, silver)
4.  name(ex5, stater)
5.  origin(ex5, croton)
6.  concept-description(croton)
7.  exhibit-depicts(ex5, sides,tripod)
8.  concept-description(tripod)
9.  symbol(tripod, apollo)
10.  dated(ex5, 530-510bc)
```

Human-written Text
Towards the end of the archaic period, coins were used for transactions. This particular coin, which comes from that period, is a silver stater from Croton, **a Greek Colony in South Italy.** On both the obverse and the reverse side there is a tripod (vessel standing on three legs), Apollo's sacred symbol. Dates from between 530-510.

Figure 9.1: Example of museum training data, from Karamanis and Manurung (2002).

9.3.1 Museum Exhibit Descriptions: M-PIRO

A suitable domain for the application of my technique is the automatic generation of exhibit descriptions (e.g., short descriptions of archaeological artefacts), for virtual museums. There is considerable work done along these lines in Europe and Australia, particularly in Edinburgh, as part of the M-PIRO and ILEX projects (Cox, O'Donnell, and Oberlander, 1999; Androutsopoulos et al., 2001). See Figure 9.1 for an example. An exciting possibility for this domain is to provide a means of comparison with recent experiments of statistical methods applied to content planning in generation (Mellish et al., 1998; Karamanis and Manurung, 2002).

Knowledge	database tuples about different museum pieces.
Text	description of pieces written by a domain expert.

9.3.2 Biology: KNIGHT

The focus of this domain is the generation of definitions of biological processes and entities. It deals with structured knowledge in biological domain and uses a broad coverage knowledge base of biological facts built independently from construction of the generator (ensuring separation of input representation and generation structures). During the evaluation of the system reported by Lester and Porter (1997), biology experts where asked to write biology definitions. They were later evaluated against the computer produced ones. It would be feasible to employ such aligned Text-Knowledge corpus as input for my learning machinery. An example is show in Figure 9.2.

Knowledge	a large database of biology facts.
Text	definitions of different biological processes and entities.

9.3.3 Geographic Information Systems: Country Descriptions

Description of countries or other geographical items is also a feasible domain for my approach. From semi-structured repositories of geographic information such as the CIA fact-book (Figure 9.3 (a)) a knowledge base can be mined. Different textual representations can be found for different audiences or needs. See Figure 9.3 (b) for one possible description.

Knowledge	tabular data from geographical/intelligence sources.
Text	country descriptions, fitting different needs.

9.3.4 Financial Market: Stock Reports

Financial news provide an important source of text and tabular data. This rich resource has been employed in the past, e.g., the work done by Kukich (1983) in generating leading paragraphs of the WSJ and by Smadja and McKeown (1990) in extracting and representing collocations for NLG.

Knowledge	tabular data regarding stock trading information.
Text	professional descriptions of the data.

9.3.5 Role Playing Games: Character Descriptions

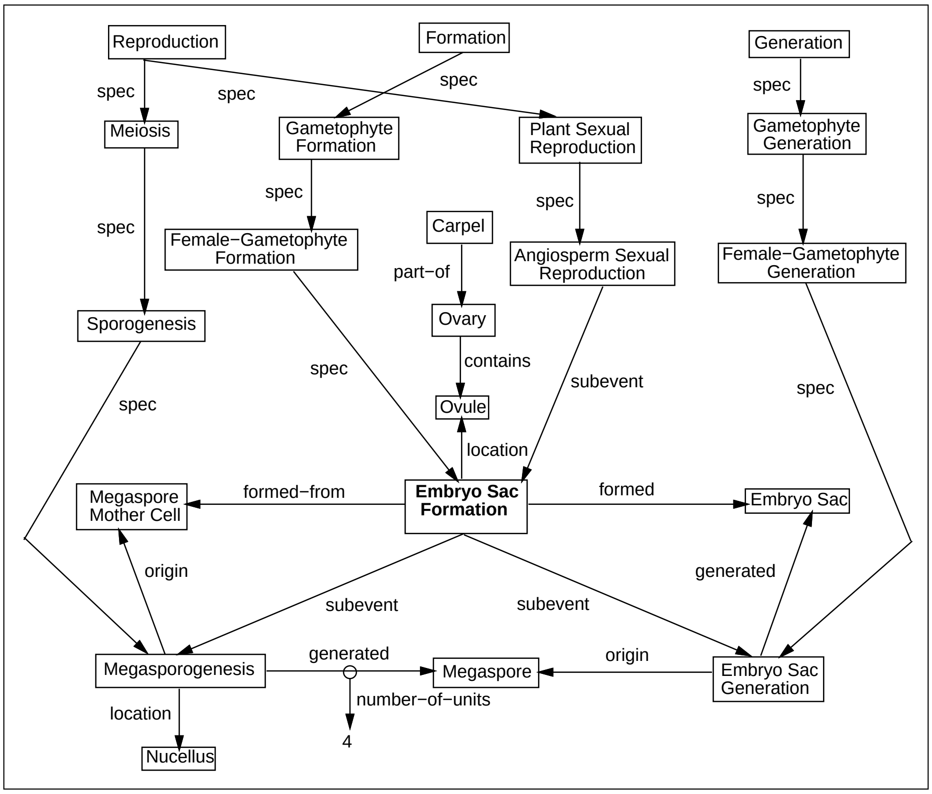
While publicly available sources constitute a good starting point for building person descriptions (i.e., biographies), some of the information being used by biographers requires subjective judgements or information highly inferential in nature. My biography generator is able to perform its task because it can mine text snippets from existing biographies. On the other hand, it would be interesting to produce person descriptions from completely tabular data. A good scenario to achieve this goal is generation associated to Role Playing Games, where a particular character is specified by means of numeric attributes such as DEXTERITY or DODGE-SKILLS. An example is shown in Figure 9.4.

Expert written. The seven celled (eight nuclei) female gametophyte of angiosperms (flowering plants). The embryo sac consists of 1 egg cell surrounded by two companion cells, 3 antipodal cells, and a large central cell which contains 2 polar nuclei. The embryo sac is found inside the ovule of the sporophyte (diploid plant).

(a)

System generated. The embryo sac is a kind of female gametophyte. It is contained in the nucellus. It is generated from the megaspore. It contains the endosperm mother cell, 3 antipodal cells and the egg apparatus.

(b)



(c)

Figure 9.2: Example of training data in a biology domain. (a) Expert written description (b) Generated description (c) Input knowledge. (Adapted from Lester and Porter (1997).)

ARGENTINA

Location Southern South America, bordering the South Atlantic Ocean, between Chile and Uruguay

Map references South America

Area **total area:** 2,766,890 sq km

land area: 2,736,690 sq km

Land boundaries: total 9,665 km, Bolivia 832 km, Brazil 1,224 km, Chile 5,150 km, Paraguay 1,880 km, Uruguay 579 km

Coastline: 4,989 km

Maritime claims: **contiguous zone:** 24 nm

Climate: mostly temperate; arid in southeast; subantarctic in southwest

Terrain: rich plains of the Pampas in northern half, flat to rolling plateau of Patagonia in south, rugged Andes along western border

Natural resources: fertile plains of the pampas, lead, zinc, tin, copper, iron ore, manganese, petroleum, uranium

Land use: **arable land:** 9%

permanent crops: 4%

. . . . . .

(a) Example entry from the World Fact-book (excerpt).

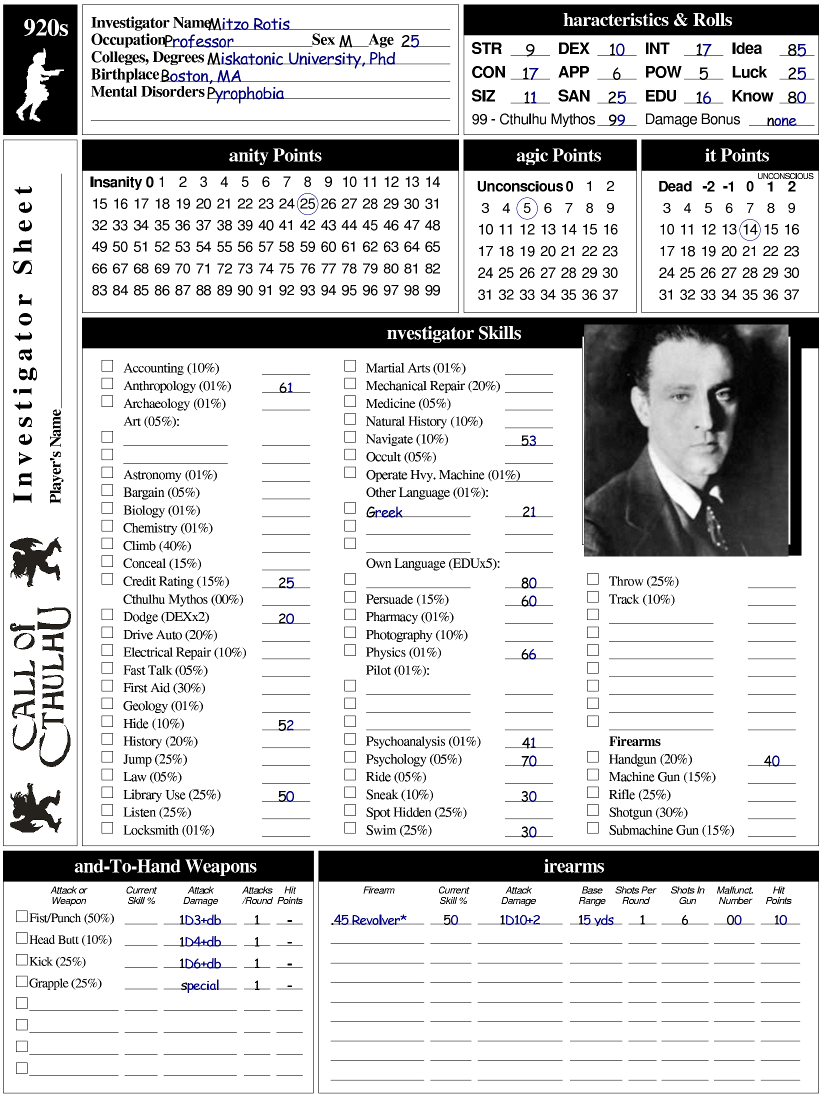
Physical Argentina is located in Southern South America, bordering the South Atlantic Ocean, Chile (west) and Uruguay (east). It covers an area almost three-tenths the size of the US. Argentina has a mostly temperate climate which is arid in the southeast and subantarctic in the southwest. The country's terrain consists of the rich plains of the Pampas in the northern half of the country, a flat to rolling plateau of Patagonia in the south, and rugged Andes Mountains along the western border. Some natural resources prevalent in Argentina include lead, iron ore, copper, manganese, and petroleum.

People More than 36,000,000 people live in Argentina. Spanish is the official language, but English, Italian, German, and French are often spoken as well. Ethnically, the country is 85% white with the remaining 15% being mestizo, Amerindian, or other non-white groups. The religious breakdown of the country is as follows: Roman Catholic (90%-less than 20% practicing), Protestant (2%), Jewish (2%), and other (6%).

Government The country is officially known as the Argentine Republic. Its capital, Buenos Aires, is located on Argentina's eastern coast near Uruguay. Argentina has both a president and vice president elected by popular vote . . .

(b) Country description, from `http://www.elca.org/dgm/-country_packet/packets/latin_america-caribbean/argentina/-desc.html`

Figure 9.3: Example of Country Data and Description.



920s

Investigator Name Mitzo Rotis
Occupation Professor Sex M Age 25
Colleges, Degrees Miskatonic University, Phd
Birthplace Boston, MA
Mental Disorders Pyrophobia

Investigator Sheet
Player's Name

CALL of CTHULHU

haracteristics & Rolls

STR	9	DEX	10	INT	17	Idea	85
CON	17	APP	6	POW	5	Luck	25
SIZ	11	SAN	25	EDU	16	Know	80

99 - Cthulhu Mythos 99 Damage Bonus none

anity Points

Insanity 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14
15 16 17 18 19 20 21 22 23 24 [✓ 25] 26 27 28 29 30 31
32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48
49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65
66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82
83 84 85 86 87 88 89 90 91 92 93 94 95 96 97 98 99

agic Points

Unconscious 0 1 2
3 4 [✓ 5] 6 7 8 9
10 11 12 13 14 15 16
17 18 19 20 21 22 23
24 25 26 27 28 29 30
31 32 33 34 35 36 37

it Points

UNCONSCIOUS
Dead -2 -1 0 1 2
3 4 5 6 7 8 9
10 11 12 13 [✓ 14] 15 16
17 18 19 20 21 22 23
24 25 26 27 28 29 30
31 32 33 34 35 36 37

nvestigator Skills

□ Accounting (10%)
□ Anthropology (01%) 61
□ Archaeology (01%)
Art (05%):
□
□
□ Astronomy (01%)
□ Bargain (05%)
□ Biology (01%)
□ Chemistry (01%)
□ Climb (40%)
□ Conceal (15%)
□ Credit Rating (15%) 25
Cthulhu Mythos (00%)
□ Dodge (DEXx2) 20
□ Drive Auto (20%)
□ Electrical Repair (10%)
□ Fast Talk (05%)
□ First Aid (30%)
□ Geology (01%)
□ Hide (10%) 52
□ History (20%)
□ Jump (25%)
□ Law (05%)
□ Library Use (25%) 50
□ Listen (25%)
□ Locksmith (01%)

□ Martial Arts (01%)
□ Mechanical Repair (20%)
□ Medicine (05%)
□ Natural History (10%)
□ Navigate (10%) 53
□ Occult (05%)
□ Operate Hvy. Machine (01%)
Other Language (01%):
□ Greek 21
□
□
Own Language (EDUx5):
□ 80
□ Persuade (15%) 60
□ Pharmacy (01%)
□ Photography (10%)
□ Physics (01%) 66
Pilot (01%):
□
□
□
□ Psychoanalysis (01%) 41
□ Psychology (05%) 70
□ Ride (05%)
□ Sneak (10%) 30
□ Spot Hidden (25%)
□ Swim (25%) 30

□ Throw (25%)
□ Track (10%)
□
□
□
□
□
□
□

Firearms
□ Handgun (20%) 40
□ Machine Gun (15%)
□ Rifle (25%)
□ Shotgun (30%)
□ Submachine Gun (15%)

and-To-Hand Weapons

Attack or Weapon	Current Skill %	Attack Damage	Attacks /Round	Hit Points
□ Fist/Punch (50%)		1D3+db	1	-
□ Head Butt (10%)		1D4+db	1	-
□ Kick (25%)		1D6+db	1	-
□ Grapple (25%)		special	1	-
□				
□				
□				
□				

irearms

Firearm	Current Skill %	Attack Damage	Base Range	Shots Per Round	Shots In Gun	Malfunct. Number	Hit Points
.45 Revolver*	50	1D10+2	15 yds	1	6	00	10

(a) Character Page

Mitzo Rotis is a prodigious professor. Born in Boston, MA, as young as 25 year-old, he is already an acclaimed anthropologist, well know by his persuasive speeches and psychological set ups. A weak, average sized person, a fire accident early on his life marked his physical appearance and his psyche (he is afraid of fire in all its forms). This is not a problem for the psychoanalytic Dr. Rotis, that is still able to charm any audience with his never ending conversation and most varied knowledge, ranging from Physics to Greek.

(b) Character Description

Figure 9.4: Role-playing games domain example

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Appendix A

Additional Tables

Following Mitchell (1997), pages 146-147, to compute whether the differences observed between two machine learning methods are statistically significant, it is necessary to compute their mean and an estimator for their standard deviation. I will use a three-fold cross-validation to compute these differences. Therefore, given three folds (Tr_1, Te_1), (Tr_2, Te_2), (Tr_3, Te_3) and two system variants $\mathcal{V}_A$, $\mathcal{V}_B$, each variant is trained in $(Tr_1 + Te_1)$, $(Tr_2 + Te_2)$, $(Tr_3 + Te_3)$ and tested in Te_1, Te_2, Te_3:

$$\begin{aligned} \delta_1 &= E_1^{\mathcal{V}_A} - E_1^{\mathcal{V}_B} \\ \delta_2 &= E_2^{\mathcal{V}_A} - E_2^{\mathcal{V}_B} \\ \delta_3 &= E_3^{\mathcal{V}_A} - E_3^{\mathcal{V}_B} \end{aligned}$$

Then we compute the average, defined as

$$\bar{\delta} = \frac{1}{k} \sum_{i=1}^{k} \delta_i$$

$$S_{\bar{\delta}} = \sqrt{\frac{1}{k(k-1)} \sum_{i=1}^{k} (\delta_i - \bar{\delta})^2}$$

The true difference in the two variants lies in the interval

$$\bar{\delta} \pm t_{N,2} S_{\bar{\delta}}$$

where $\bar{\delta}$ is the mean of the differences and $S_{\bar{\delta}}$ is an estimator for the standard deviation defined above and $t_{2,N}$ depends on the confidence interval (N%), and it is given by the following table:

Table A.1: Experiments in `biography.com`.

Variant	Partition 1	Partition 2	Partition 3
	size=439	size=410	size=280
0 (*Path*$_{add}$+ *Trivial*$_{dict}$)	86 | 48 30 | 275 error=0.17	76 | 45 15 | 274 error=0.14	57 | 29 32 | 162 error=0.21
1 (*Path*$_{add}$+ *On-line*$_{dict}$)	100 | 34 49 | 256 error=0.18	90 | 31 39 | 250 error=0.17	60 | 26 41 | 153 error=0.23
2 (*Score*$_{add}$+ *Off-line*$_{dict}$)	94 | 37 41 | 267 error=0.17	79 | 37 21 | 273 error=0.14	56 | 31 27 | 166 error=0.20
3 (*Score*$_{add}$+ *External*$_{dict}$)	88 | 43 29 | 279 error=0.16	69 | 47 15 | 279 error=0.15	56 | 31 25 | 168 error=0.2
4 (*Score*$_{add}$+ *External*$_{dict}$+ *Off-line*$_{dict}$)	94 | 37 40 | 268 error=0.17	79 | 37 21 | 273 error=0.14	59 | 28 27 | 166 error=0.19

N=	90%	95%	98%	99%
t=	2.92	4.30	6.96	9.92

In the following tables, I will consider the difference between two variants to be statistically significant if the interval over $\overline{\delta}$ described above does not includes the zero. Please note these differences are over error rates and in this thesis I have focused in differences on F-measure. I am using these differences to shed light about whether the different variants are performing in a way that can be due purely to chance or not.

Matched Text Construction

`biography.com` corpus. Table A.1.
Baseline stat. signif. different from Variant 4, conf.: 74.658
Baseline stat. signif. different from Variant 3, conf.: 66.476
Baseline stat. signif. different from Variant 2, conf.: 76.322

Table A.2: Experiments in `s9.com`.

Variant	Partition 1	Partition 2	Partition 3
	size=509	size=1031	size=515
0 ($Path_{add}$+ $Trivial_{dict}$)	33 27 11 438 error=0.07	29 27 78 897 error=0.10	33 28 3 451 error=0.06
2 ($Score_{add}$+ $Off\text{-}line_{dict}$)	35 26 10 438 error=0.07	27 25 76 903 error=0.09	30 27 10 448 error=0.07
3 ($Score_{add}$+ $External_{dict}$)	36 25 11 437 error=0.07	26 26 73 906 error=0.09	30 27 5 453 error=0.06
4 ($Score_{add}$+ $External_{dict}$+ $Off\text{-}line_{dict}$)	39 22 12 436 error=0.06	27 25 76 903 error=0.09	30 27 9 449 error=0.06

Variant 2 stat. signif. different from Variant 4, conf.: 68.240
Variant 1 stat. signif. different from Baseline, conf.: 96.969
Variant 1 stat. signif. different from Variant 4, conf.: 93.142
Variant 1 stat. signif. different from Variant 3, conf.: 96.605
Variant 1 stat. signif. different from Variant 2, conf.: 92.958
variant4-variant3, no conclusion could be arrived.
variant3-variant2, no conclusion could be arrived.

`s9.com` corpus. Table A.2.
Baseline stat. signif. different from Variant 3, conf.: 61.629
Variant 2 stat. signif. different from Variant 4, conf.: 77.157
Variant 2 stat. signif. different from Variant 3, conf.: 67.628
baseline-variant4, no conclusion could be arrived.
baseline-variant2, no conclusion could be arrived.
variant4-variant3, no conclusion could be arrived.

Table A.3: Experiments in `imdb.com`.

Variant	Partition 1	Partition 2	Partition 3
	size=685	size=519	size=378
0 ($Path_{add}$+ $Trivial_{dict}$)	91 73 43 478 error=0.16	62 59 25 373 error=0.16	56 54 16 252 error=0.18
2 ($Score_{add}$+ $Off\text{-}line_{dict}$)	80 73 41 491 error=0.16	60 51 33 375 error=0.16	55 50 19 254 error=0.18
3 ($Score_{add}$+ $External_{dict}$)	82 71 43 489 error=0.16	60 51 30 378 error=0.15	52 53 20 253 error=0.19
4 ($Score_{add}$+ $External_{dict}$+ $Off\text{-}line_{dict}$)	82 71 41 491 error=0.16	65 46 29 379 error=0.14	54 51 20 253 error=0.18

`imdb.com` corpus. Table A.3.
Baseline stat. signif. different from Variant 4, conf.: 63.724
Baseline stat. signif. different from Variant 2, conf.: 81.351
Variant 3 stat. signif. different from Variant 4, conf.: 87.437
baseline-variant3, no conclusion could be arrived.
variant4-variant2, no conclusion could be arrived.
variant3-variant2, no conclusion could be arrived.

`wikipedia.org` corpus. Table A.4.
Variant 3 stat. signif. different from Baseline, conf.: 57.515
Variant 2 stat. signif. different from Baseline, conf.: 92.959
Variant 2 stat. signif. different from Variant 4, conf.: 85.757
Variant 2 stat. signif. different from Variant 3, conf.: 91.401
baseline-variant4, no conclusion could be arrived.
variant4-variant3, no conclusion could be arrived.

Table A.4: Experiments in `wikipedia.org`.

Variant	Partition 1	Partition 2	Partition 3
	size=2110	size=2048	size=916
0 $(\mathit{Path}_{add}+$ $\mathit{Trivial}_{dict})$	122 107 63 1818 error=0.08	93 124 47 1784 error=0.08	80 99 29 708 error=0.13
2 $(\mathit{Score}_{add}+$ $\mathit{Off\text{-}line}_{dict})$	111 102 83 1814 error=0.08	84 124 61 1779 error=0.09	86 91 39 700 error=0.14
3 $(\mathit{Score}_{add}+$ $\mathit{External}_{dict})$	113 100 77 1820 error=0.08	89 119 52 1788 error=0.08	92 85 43 696 error=0.13
4 $(\mathit{Score}_{add}+$ $\mathit{External}_{dict}+$ $\mathit{Off\text{-}line}_{dict})$	120 93 81 1816 error=0.08	88 120 63 1777 error=0.08	93 84 39 700 error=0.13

Learning Content Selection Rules

`biography.com` corpus. Table A.5.
Variant 4 stat. signif. different from Baseline, conf.: 96.421
Variant 4 stat. signif. different from Select-All/Select-None, conf.: 89.501
Select-All/Select-None stat. signif. different from Baseline, conf.: 89.539

`s9.com` corpus. Table A.6.
Baseline stat. signif. different from Select-All/Select-None, conf.: 77.382
Variant 4 stat. signif. different from Baseline, conf.: 95.858
Variant 4 stat. signif. different from Select-All/Select-None, conf.: 80.741

`imdb.com` corpus. Table A.7.
Variant 4 stat. signif. different from Baseline, conf.: 75.658
Variant 4 stat. signif. different from Select-All/Select-None, conf.: 64.636

Table A.5: Experiments in `biography.com`.

Variant	Partition 1	Partition 2	Partition 3
	size=439	size=410	size=280
0 (*Path*$_{add}$+ *Trivial*$_{dict}$)	76 55 46 262 error=0.23	64 52 50 244 error=0.24	57 30 32 161 error=0.22
4 (SELECT-ALL / SELECT-NONE)	98 33 73 235 error=0.24	78 38 83 211 error=0.29	60 27 43 150 error=0.25
4 (*Score*$_{add}$+ *External*$_{dict}$+ *Off-line*$_{dict}$)	110 21 108 200 error=0.29	102 14 117 177 error=0.31	78 9 87 106 error=0.34

Table A.6: Experiments in `s9.com`.

Variant	Partition 1	Partition 2	Partition 3
	size=509	size=1031	size=515
0 (*Path*$_{add}$+ *Trivial*$_{dict}$)	28 33 16 432 error=0.09	26 26 112 867 error=0.13	26 31 16 442 error=0.09
4 (SELECT-ALL / SELECT-NONE)	28 33 11 437 error=0.08	26 26 56 923 error=0.07	27 30 11 447 error=0.07
4 (*Score*$_{add}$+ *External*$_{dict}$+ *Off-line*$_{dict}$)	34 27 24 424 error=0.10	30 22 123 856 error=0.14	27 30 19 439 error=0.09

Table A.7: Experiments in `imdb.com`.

Variant	Partition 1	Partition 2	Partition 3
	size=685	size=519	size=378
0 (*Path*$_{add}$+ *Trivial*$_{dict}$)	49 104 37 495 error=0.20	44 67 15 393 error=0.15	33 72 15 258 error=0.23
4 (Select-All / Select-None)	64 89 74 458 error=0.23	51 60 32 376 error=0.17	50 55 33 240 error=0.23
4 (*Score*$_{add}$+ *External*$_{dict}$+ *Off-line*$_{dict}$)	110 43 125 407 error=0.24	69 42 110 298 error=0.29	59 46 45 228 error=0.24

Select-All/Select-None stat. signif. different from Baseline, conf.: 82.845

`wikipedia.org` corpus. Table A.8.
Variant 4 stat. signif. different from Baseline, conf.: 96.205
Variant 4 stat. signif. different from Select-All/Select-None, conf.: 95.816
Select-All/Select-None stat. signif. different from Baseline, conf.: 88.590

Table A.8: Experiments in `wikipedia.org`.

Variant	Partition 1		Partition 2		Partition 3	
	size=2110		size=2048		size=916	
0 ($Path_{add}$+ $Trivial_{dict}$)	43	170	38	170	34	143
	7	1890	7	1833	6	733
	error=0.08		error=0.08		error=0.16	
4 (SELECT-ALL / SELECT-NONE)	65	148	65	143	52	125
	43	1854	48	1792	41	698
	error=0.09		error=0.09		error=0.18	
4 ($Score_{add}$+ $External_{dict}$+ $Off\text{-}line_{dict}$)	95	118	84	124	74	103
	148	1749	102	1738	89	650
	error=0.12		error=0.11		error=0.20	