Are community-built ontologies robust enough to build maintainable NLG systems?

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NLG Needs Ontological Resources

• Traditionally, NLG needs ontological resources

• Large scale ⇒ expensive

• Community-built ⇒ unreliable?
Example: Simple NLG Task

• **Build the full name of a person**
  - Only given names and last name?

• **However:**
  - Some cultures use paternal last name then maternal last name
  - Others use maternal last name then paternal
  - Others do gender agreement with the paternal last name

• **Data needs:**
  - Given names
  - Paternal last name
  - Maternal last name
  - Region of origin
  - Gender
Wikipedia to the Rescue

- Some of that info can be scrapped from Wikipedia
  - Such scrapping effort is facilitated by the Infoboxes, the boxes at the top of a page

- A large scale effort to achieve this is DBpedia

- But each triple extracted involves 4 people working somewhat independently:
  - Page editor/author
  - Infobox editor/author
  - DBpedia mapping editor/author
  - DBpedia extractor programmer
This talk

- Community driven resources change dangerously

- Ontological resources might be at the cross-roads
  - Compared to, for example, lexical resources

- Do we need robust ontology-driven systems?
  - Yes.

- Some DBpedia anecdotes and three papers
About the Speaker

- Columbia University – NLG

- IBM Research Watson – Question Answering
  - Deep QA - Watson: ML component used in the show

- Montreal (Canada) – Consulting
  - Collaboration with Université de Montreal: 1-Click Search
  - Free Software and consulting for Startups and SMBs

- White Plains (NY) – Research sabbatical
  - Personal sabbatical focusing in Research & Free Software
  - Launching a NLG venture in Vancouver

- Robust NLG through human-understandable ML
DBpedia

- DBpedia [Bizer et al., 2009] is an ontology curated from Wikipedia infoboxes
  - Infoboxes are the small tables containing structured information at the top of most Wikipedia pages.
  - The mappings between the infoboxes labels to the ontology is done in a wiki itself: http://mappings.dbpedia.org/.
  - The source code of the scrapping scripts is also available with all its development history.

- Not to be confused with a new project targeting to provide structured information to Wikipedia, wikidata.
George W. Bush

- **almaMater**: dbr:Yale_College, dbr:Harvard_Business_School
- **award**: dbr:United_States_Aviator_Badge, dbr:National_Defense_Service_Med, dbr:Air_Force_Outstanding_Unit_Aw, dbr:Marksmanship_Ribbon
- **birthDate**: 1946-07-06 (xsd:date)
- **birthPlace**: dbr:New_Haven_Connecticut
- **child**: dbr:Jenna_Bush_Hager, dbr:Barbara_Pierce_Bush
- **country**: dbr:United_States
- **lieutenant**: dbr:Rick_Perry, dbr:Bob_Bullock

Bush was the 43rd President of the United States and the father of the 41st President, George H. W. Bush. He served as President from 2001 to 2009. Bush left office in 2009, and has written a memoir, Decision Points. He purchased a home in a suburban area of Dallas.
Infobox ↔ Mappings

Mapping en:Infobox president

This is the mapping for the Wikipedia template Infobox president. Find usages of this Wikipedia template here.

Test this mapping (or in namespace File or Creator) with some example Wikipedia pages.
Check which properties are not mapped yet!

Read more about mapping Wikipedia templates.

Template Mapping (help)

| map to class | President |

Mappings

Property Mapping (help)

<table>
<thead>
<tr>
<th>template property</th>
<th>otherparty</th>
</tr>
</thead>
<tbody>
<tr>
<td>ontology property</td>
<td>otherParty</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>template property</th>
<th>name</th>
</tr>
</thead>
<tbody>
<tr>
<td>ontology property</td>
<td>foaf:name</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>template property</th>
<th>birth_date</th>
</tr>
</thead>
<tbody>
<tr>
<td>ontology property</td>
<td>birthDate</td>
</tr>
</tbody>
</table>
### Type files analysis

<table>
<thead>
<tr>
<th>Property</th>
<th>3.6</th>
<th>2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of triples</td>
<td>6,173,940</td>
<td>28,031,852</td>
</tr>
<tr>
<td>Unique subjects (entities)</td>
<td>1,668,503</td>
<td>4,218,628</td>
</tr>
<tr>
<td>Unique objects (types)</td>
<td>250</td>
<td>547</td>
</tr>
<tr>
<td>Max objects per subject</td>
<td>6</td>
<td>16</td>
</tr>
</tbody>
</table>

### Mapping files analysis

<table>
<thead>
<tr>
<th>Property</th>
<th>3.6</th>
<th>2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of verbs</td>
<td>1,100</td>
<td>1,370</td>
</tr>
<tr>
<td>Number of triples</td>
<td>13,795,664</td>
<td>33,449,633</td>
</tr>
</tbody>
</table>

- However, many entities lost their types
  - From 20,693 Politicians in 3.6, 4,542 are gone (20%-25%).
  - However, the total Politicians in 2014 is 40,343.
DBpedia Details

- **Changelogs**: http://oldwiki.dbpedia.org/Changelog
  - DBpedia 2014 (09/2014)
  - DBpedia 3.9 (09/2013)
  - DBpedia 3.8 (08/2012)
  - DBpedia 3.7 (08/2011)
  - DBpedia 3.6 (01/2011)

- **DBpedia 3.9 (09/2013): Changelog**
  - Core Framework: refined rules for URIs of sub-resources, e.g., for Wikipedia pages having multiple infoboxes
  - These are the type of disruptive changes that you can expect

- **But there’s more!**
  - Current infobox for GWB is president
  - 2011 was president: https://en.wikipedia.org/w/index.php?title=George_W._Bush&action=edit&oldid=411168563
What Might Mean to NLG Practitioners

- Either take a version and freeze it in time
  - Losing the ability to cope with large amount of up-to-date entities

- Be ready to adapt resources for each new version
  - Extra resources built on top might become stale

- For example:
  - A system that has a generation lexicon for Politician will need to be updated for OfficeHolder
  - Some entities will be Politician, some will be OfficeHolder
  - This level of resilience is unusual for NLG
Three Papers

- **NAACL 2012**
  - DBpedia is useful enough for referring expressions

- **MICAI2015/WebNLG2016**
  - Using two versions of DBpedia allows studying impact of errors in referring expression generation

- **Iberamia 2016**
  - Robustness helps to learn Preference Ordering for properties for the Incremental Algorithm
  - Conference is next week!
Collaborators

Martin Dominguez  Paula Estrella  Fabian Pacheco
Referring Expression Generation (REG)

- **Classic NLG problem**
  - **Input:** set of entities (with a distinguished element), set of triples pertaining to the entities.
  - **Output:** a Definite Description, i.e., a set of *positive triples* and *negative triples*.
  - Focus on running time **efficiency** and generating **succint** and **easily understandable** expressions.

- **Example output**

<table>
<thead>
<tr>
<th>Referent</th>
<th>Incremental Algorithm</th>
<th>Gardent</th>
</tr>
</thead>
<tbody>
<tr>
<td>EB</td>
<td>{ (EB occupation Software_Freedom_Law_Center) }</td>
<td>{ (EB occupation Software_Freedom_Law_Center) }</td>
</tr>
<tr>
<td>LL</td>
<td>{ (LL birthPlace United_States), (LL, occupation Harvard_Law_School) }</td>
<td>{ (LL birthPlace Rapid_City_South_Dakota) }</td>
</tr>
<tr>
<td>LT</td>
<td>{ (LT occupation Software_engineer) }</td>
<td>{ (LT nationality Finnish_American) }</td>
</tr>
</tbody>
</table>
Incremental Algorithm (IA) – an established REG algo

- Introduced in [Dale and Reiter, 1995]
  - Greedy approach, use a **default ordering**: Preference Order (PO)
  - Iterates over PO and selects a type
  - Adds a triple of the given type one at a time
  - Removes from the confusor set $C$ all entities ruled out by the new triple
  - Triples that do not eliminate any new entity from $C$ are ignored
  - The algorithm terminates when $C$ is empty.

- Many other algorithms
  - Graph
  - Full Brevity
  - Gardent’s
Possible Application To Multi-document Summarization

Use REG to fix anaphoric references drafted from different documents (similar to [Siddharthan et al., 2011])

- Excerpt from Columbia Newsblaster:

_Thousands of cheering, flag-waving Palestinians gave Palestinian Authority President Mahmoud Abbas an enthusiastic welcome in Ramallah on Sunday, as he told them triumphantly that a “Palestinian spring” had been born following his speech to the United Nations last week. The **president** pressed Israel, in unusually frank terms, to reach a final peace agreement with the Palestinians, citing the boundaries in place on the eve of the June 1967 Arab-Israeli War as the starting point for negotiation about borders._
Can REG Help Summarization?


- **Do we have data for the relevant entities?**
  - Yes, roughly 50% of the time.
  - We used anaphora training data and looked it up on DBpedia by hand.

- **Do we have discriminant data for relevant entities?**
  - Yes, roughly 80% of the time.
  - Measured on Wikinews, Cohen’s $\kappa$ of 79%.

- **Are classic REG algorithms enough?**
  - *Maybe not,* they either fail to produce an output or return a poor description in 60%+ of the cases.
Experiments With Wikinews-derived REG Tasks

- Wikinews, a news service operated as a wiki
  - Entities disambiguated by *interwiki* links.

  Former [[New Mexico] | {{w|Governor of New Mexico|governor}} | {{w|Gary Johnson}}] ended his campaign for the {{w|Republican Party (United States)|Republican Party}}

- Human-written Property Ordering:

  TYPE orderInOffice nationality country profession birthPlace leaderName−1 keyPerson−1 author−1 commander−1 occupation knownFor instrument successor monarch successor−1 primeMinister−1 activeYearsEndDate party deathDate deathPlace child almaMater activeYearsStartDate religion spouse president−1 notableCommander−1 vicePresident president primeMinister award militaryRank child−1 militaryCommand serviceStartDate office battle spouse−1 knownFor−1 predecessor foundationPerson−1 monarch−1 predecessor−1 activeYearsStartDate activeYearsEndDate starring−1 lieutenant parent governor−1 homepage residence appointer−1 . . .
Using Change to Simulate Errors


- Three algorithms of REG on anachronistic input.
  - On old data, produce a referring expression, check whether holds on new data.

- We found poor results with marginal differences among the algorithms.
  - Gardent’s algorithm might be ahead but using closed world assumptions.
  - Nice task and problem, worth extending.
WebNLG 2016 results

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Execution Errors</th>
<th>Dice</th>
<th>Omission Errors</th>
<th>Inclusion Errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>People – Entity has “birth date”? ⇒ person (3,051 tasks)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incremental</td>
<td>232 (5%)</td>
<td>0.48</td>
<td>1,406 (50%)</td>
<td>145 (5%)</td>
</tr>
<tr>
<td>Gardent</td>
<td>0 (0%)</td>
<td>0.58</td>
<td>1,089 (36%)</td>
<td>554 (18%)</td>
</tr>
<tr>
<td>Graph</td>
<td>15 (0%)</td>
<td>0.38</td>
<td>1,870 (62%)</td>
<td>20 (0%)</td>
</tr>
<tr>
<td>Organizations – Entity has “creation date”? ⇒ organization (2,370 tasks)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incremental</td>
<td>1,386 (45%)</td>
<td>0.69</td>
<td>305 (31%)</td>
<td>3 (0%)</td>
</tr>
<tr>
<td>Gardent</td>
<td>829 (27%)</td>
<td>0.70</td>
<td>338 (22%)</td>
<td>357 (23%)</td>
</tr>
<tr>
<td>Graph</td>
<td>934 (31%)</td>
<td>0.06</td>
<td>1,347 (94%)</td>
<td>2 (0%)</td>
</tr>
</tbody>
</table>

- **Alusivo**: Open Source implementation of REG algos
  - (MPL) [https://github.com/DrDub/Alusivo](https://github.com/DrDub/Alusivo)
  - Java, Maven, RDF-based
  - CSP-based algorithms, Graph isomorphism-based algorithms, etc
Using Robustness to Learn the Property Ordering


- We tried to learn the PO using errors on generated referring expressions as a metric

- Intuitions
  - A good referring expression should refer to stable properties

- Results
  - Robustness helps to learn orderings
  - But popularity on DBpedia is a stronger signal
Iberamia Metrics

- Measure learned POs against the hand-written PO
  - Kendall’s $\tau$ [Lebanon and Lafferty, 2002]:
    \[
    \tau = 1 - \frac{2(\text{number of inversion})}{N(N - 1)/2}
    \]
    * too strict, moved to a metric that considers the REs being generated rather than the exact ordering
  - Dice over selected properties.
    * Seemingly very different POs produce comparable results
    * Metric of choice

- Do observable variables change similarly to target?
  - Spearman’s rho
First Experiments

- **Experiment: Correlations over People**

<table>
<thead>
<tr>
<th>Exp/metric</th>
<th>length</th>
<th>Dice</th>
<th>exclusion errors</th>
<th>inclusion errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hand-written</td>
<td>-0.018</td>
<td>-0.215</td>
<td>0.185</td>
<td>0.397</td>
</tr>
<tr>
<td>Popularity</td>
<td>-0.226</td>
<td>0.232</td>
<td>-0.258</td>
<td>0.394</td>
</tr>
</tbody>
</table>

- **Experiment: overfit fitness function**
  - A function that approximates the Dice for the hand-picked PO using the observable variables. Linear regression:
    
    \[
    target = -1.608 \times \text{length} + 15.5279 \times \text{inclusion} + 0.8787 \times \text{exclusion} + 1.9403
    \]
  - Pearson’s correlation coefficient of 0.872

- **Experiment: Can the GA learn?**
Main Experiments

- Experiment: Genetic Algorithm over organizations using fitness trained on peopled
  - Disappointment: after 50 generations, we get a Dice property overlap of only 0.435
  - When popularity PO achieves 0.93.

- This is our main negative result
Closing Experiments

- **Experiment: Correlations over Organizations**
  - Strong Spearman’s rho, but very different from people’s numbers.

<table>
<thead>
<tr>
<th>Exp/metric</th>
<th>length</th>
<th>Dice</th>
<th>exclusion errors</th>
<th>inclusion errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hand-written</td>
<td>0.059</td>
<td>0.832</td>
<td>-0.834</td>
<td>0.840</td>
</tr>
<tr>
<td>Popularity</td>
<td>-0.064</td>
<td>0.864</td>
<td>-0.866</td>
<td>0.841</td>
</tr>
</tbody>
</table>

- **Experiment: Only length & inclusion errors**
  - Preliminary result, insight obtained from looking at both tables (test set)
  - Trained on people, Dice on organizations of 0.906
  - Trained on organizations, Dice on people of 0.608
  - Below the popularity PO but more generalization strength

- **Experiment: GA using only inclusion errors**
  - Dice of 0.272 (people) and 0.361 (organizations)
  - Robustness alone is not enough, combining it with length is key.
Learning PO Discussion

- Main result: correlation between hand-written PO and robustness
- Lack of generalization: organizations change differently from people (hypothesis)

![Graphs showing correlation between length and robustness for people and organizations.](image)
Other Work

- Radialpoint Reveal / Canadian AI
- Thoughtland / EWNLG
- Hybrid IE Systems / IE4OpenData
Radialpoint Reveal

• In Montreal I was part of a multi-year effort to build an enhanced search engine experience for tech support agents: Radialpoint Reveal
• We worked on multiple fronts, including
  – Better search by pooling results across agents
  – Identifying tech support rich pages vs. other device-related pages
  – Identifying solutions to problems within a page and matching problem statements to search terms, devices and models
Neto, Desaulniers, Duboue, Smirnov. *Filtering Personal Queries from Mixed-Use Query Logs.* (Best Paper Award) Canadian AI 2014.

- Similar to Google Trends but for work searches
- We filter out 78.7% of private queries losing only 9.3% of the business queries
  - Kappa 0.87 for annotating them
Thoughtland / EWNLG


- Cross-validation: cloud of error points
- Cluster with mixture of Dirichlet models: \( n \)-balls
- Determine overall size, density, distances to others
- Source code (AGPL): [https://github.com/DrDub/thoughtland](https://github.com/DrDub/thoughtland)

There are six components and three dimensions. Component One is big, components Two, Three and Four are small and component Five is giant. Component Five is sparse and components Two, Three and Four are very dense. Components One and Two are at a good distance from each other. The rest are all far from each other.
Duboue. *Automatic Reports from Spreadsheets: Data Analysis for the Rest of Us.* (Demo) INLG 2016.

- Domain independent tabular data verbalization
- Conduit for domain-dependent customization through consulting engagements
Hybrid IE Systems

- Last summer I taught a 15hs winter school on Hybrid IE Systems.
  - In Universidad de Buenos Aires
  - Generalities of IE systems
  - Rule-based systems using Apache RuTA
  - CRFs using Mallet
  - Underlining framework Apache UIMA

- Slides: (in English, CC-BY-SA)
  https://github.com/IE4OpenData/ECI2016T2

- Code: (Apache Licenced)
  https://github.com/IE4OpenData/Octroy
The course spawned a project on using Information Extraction over Open Data

– Better transparency in democracy

http://ie4opendata.org
Conclusions

- DBpedia/Wikinews is a suitable source for doing research on robust REG algorithms.

- DBpedia is fine as a one time NLG resource
  - Usage over time requires better algorithms

- Links
  - http://duboue.net
  - https://twitter.com/pabloduboue
  - https://github.com/DrDub
  - https://scholar.google.com/citations?user=Exngg_MAAAAJ&hl=en
Backup Slides

References


