

**On The Feasibility of
Open Domain Referring Expression Generation
Using Large Scale Folksonomies**

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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 (among other things) on running time **efficiency**.
- Question: does efficiency matters nowadays?
 - Yes, it does.
 - We used a large scale *folksonomy* (DBpedia) and a set of naturally occurring entities (from Wikinews).

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 κ of 79% (small evaluation size, though).
- Are classic REG algorithms enough?
 - *Maybe not*, they either fail to produce an output or return a poor description in 60%+ of the cases.
 - But there is hope and our evaluation needs to be extended.

About The Authors



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.***

Three Single Referent REG Algorithms

- DR [Dale and Reiter, 1995]
 - A classic algorithm.
 - Greedy approach, use a **default ordering**.
- Gardent [Gardent, 2002]
 - An algorithm generating negations.
 - Constraint satisfaction programming.
- Full Brevity (FB) [Bohnet, 2007]
 - More exhaustive search of the solution space

Data: 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.
 - We used “Ontology Infobox Properties” which contains 1,7520,158 triples (for English).
 - *We missed Ontology Infobox **Types**.*

Experiments With Anaphora Resolution Training Data

- Hand-annotated corpus [Hasler et al., 2006]
 - 74 documents, 239 coreference chains.
 - 44% in DBpedia
 - 16 documents usable for REG eval (40 REG tasks).
- Failure rate
 - DR: 12 (30%), Gardent: none (0%), FB: 23 (57.5%).
 - * Lack of unique differentiating triples.
 - * FB ran out of memory multiple times.
- Execution timings
 - DR and Gardent, comparable; FB 16x slower.
- Discard FB

Experiments With Wikinews-derived REG Tasks

- Wikinews, a news service operated as a wiki
 - News articles interspersed with *interwiki* links.
 - * Entities disambiguated.

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

- Finding people and organizations
 - Entity has “birth date”? \Rightarrow person
 - Entity has “creation date”? \Rightarrow organization.
 - 4,230 tasks (17,814 runs) for people and 12,998 (44,080) for organizations.

Wikinews Timings And Failure Rates

- Failure Rates

- People

- * DR: 2.8%, Gardent 2% (negations on 14%).

- Organizations

- * DR: 30.8%, Gardent 0% (negations on 12%).

- Execution Timings

- For people, Gardent was 46x slower.

- For organizations, Gardent was 29x slower.

- DR took 3' for the 44,080 runs for organizations.

Wikinews Human Evaluation

- Evaluating referring expressions is hard.
 - Open Domain: the judges need to be acquainted with all entities in the training set.
- Inter-annotator agreement
 - Random sample of 20 runs, two annotators.
 - Cohen's κ of 60% for annotating DD results.
 - κ of 79% for determining whether the folksonomy had enough information to build a satisfactory DD.
- Final evaluation
 - Extended to 60 runs (one annotator).
 - DR: 41.6% accuracy; Gardent: 43.4% accuracy.
 - Folksonomy contained enough information: 81.6%.

Issues

- DR algorithm issues
 - Default ordering strategy not stable across different subtypes (e.g., politicians vs. musicians).
 - Recent paper might help (Koolen et al. at INLG'12).
- Gardent's algorithm issues
 - Sometimes it selects a bad triple (an obscure fact).
 - A negative piece of information could just be a missing piece of information.
 - Example: **China** vs. { Peru and Taiwan }
 - * “the place where they do not speak Chinese”
- Robust NLG for noisy (ontological) inputs.

Conclusions

- A folksonomy can enable traditional NLG referring expression generation for Open Domain tasks.
- Three tasks remain:
 - Dealing with missing information.
 - * *smart default values*, ontological siblings.
 - Estimating salience for ontological information.
 - * Search engine salience.
 - Transform the extracted triples into actual text
 - * Custom-made grammar.

Backup Slides

Efforts to automate this task in NLG [Gatt et al., 2007] have taken an approach similar to machine translation BLEU scores [Papinini et al., 2001], for example, by asking multiple judges to produce referring expressions for a given scenario. These settings usually involve images of physical objects and relate to small ontologies. While such an approach could be adapted to the

Intro

- What is Referring Expression Generation (REG)
 - Input: (generation from **data**), ontological information about the referents
 - Output: Definite Descriptions (DD), set of *positive triples* and a set of *negative triples*,
 - Lot of attention in NLG
 - * early work: using custom-tailored ontologies
 - * recent years: [Belz et al., 2010] “Open Domain Referring Expression Generation,” (OD REG), properties come from a *folksonomy*, a large-scale volunteer-built ontology.
- Two sets of experiments:
 - one with anaphora resolution training information

- roughly half of the entities annotated in the documents were present in the folksonomy
- sets of distractors from Wikinews
- 40k referring expression tasks.

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