Discovering Factions in the Computational Linguistics Community

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Related work

• “Macroscopic”
  – Citation networks and collaboration graphs (Small, 1973; White & Griffith, 1981)

  – Analyzing text in articles using topic models (Blei et al, 2003; McCallum et al, 2006; Dietz et al, 2007; Hall et al, 2008; Gerrish & Blei, 2010)

  – Analyze authorships (Rosen-Zvi et al, 2004; Johri et al, 2011)
Our work

• “Microscopic” investigations of interactions
  – Individual sentences that author use in citations

“To model these different effects on language, we use a sparse additive generative (SAGE) model (Eisenstein et al., 2011).”

“We use the gradient-based optimization routine OWL-QN (Andrew and Gao, 2007) to maximize the above objective function with respect to $\eta$ for each pair of factions $g$ and $h$. “
Goals

• An exploratory data analysis.
  – To *discover meaningful factions* in the ACL community
  – Illustrate the use of a *probabilistic model* for such discovery
Factions in ACL?

• Groups of individuals within a larger community whom we expect to
  –collaborate closely within factions
  –cite within the faction using distinct language from that without
Our approach

• Probabilistic model over
  – co-authorship relations
  – citation sentences

“To model these different effects on language, we use a sparse additive generative (SAGE) model (Eisenstein et al., 2011).”

“We use the gradient-based optimization routine OWL-QN (Andrew and Gao, 2007) to maximize the above objective function with respect to \( \eta \) for each pair of factions \( g \) and \( h \).”
Probabilistic graphical model

co-authorship relations

faction memberships

SAGE language model
Sparse Additive Generative models


\[
\beta_{v}^{(g,h)} = \frac{\exp(\eta_{v}^{(g,h)} + m_{v})}{\sum_{v'} \exp(\eta_{v'}^{(g,h)} + m_{v'})}
\]
Learning and Inference (EM)

• E-step
  – Collapsed Gibbs sampling

\[ p(a^{(i)} = g \mid a^{(-i)}, w, \eta, \alpha, \gamma) \propto p(a^{(i)} = g, a^{(-i)}, w \mid \eta, \alpha, \gamma) \]

• M-step
  – Gradient-based optimization routine (with L1-regularizer) for SAGE vectors

\[ \langle c^{(g,h)} \rangle^T \eta^{(g,h)} - \langle C^{(g,h)} \rangle \log \sum_v \exp(\eta_v^{(g,h)} + m_v) - \lambda \left\| \eta^{(g,h)} \right\|_1 \]
Dataset

• Preprocessing
  – 500 most cited authors who published at least 5 papers
  – Extracted sentences containing citations (with regular expressions)

• Data
  – 8,144 papers
  – 80,766 citation sentences
  – 391,711 words and 3,037 word types
Factions

Top 5 authors with the largest expected incoming citations, i.e. $p(\text{faction} \mid \text{author}) \times \text{incoming citations}$

Manual labels for factions

<table>
<thead>
<tr>
<th>Parsing (20)</th>
</tr>
</thead>
</table>
| **Self cites:**
| **In cites:**
| **Out cites:**

- Self cites: parser, parsing, model, perceptron, parsers, dependency
- In cites: parser, perceptron, supersense, parsing, dependency, results, hmm, models
- Out cites: parsing, forest, treebank, model, coreference, stochastic, grammar, task

How they cite themselves

How others cite them

How they cite others
## Our factions

| Machine Translation (MT1) (9) | *Kevin Knight, Michel Galley, Jonathan Graehl, Wei Wang, Sanjeev P. Khudanpur*
<table>
<thead>
<tr>
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<tbody>
<tr>
<td><strong>Self cites:</strong></td>
<td>inference, scalable, model</td>
</tr>
<tr>
<td><strong>In cites:</strong></td>
<td>scalable, inference, machine, training, generation, translation, model, syntaxbased phrasebased, hierarchical, inversion, forest, transduction, translation, ibm, discourse</td>
</tr>
<tr>
<td><strong>Out cites:</strong></td>
<td>sense, preferences, wordnet, acquired, semcor, word, semantic, calle sense, subcategorization, acquisition, automatic, corpora, lexical, processing, wordnet</td>
</tr>
<tr>
<td><strong>Word Sense Disambiguation (WSD) (42)</strong></td>
<td><em>David Yurowsky, Rada Mihalcea, Eneko Agirre, Ted Pedersen, Yorick Wilks</em></td>
</tr>
<tr>
<td><strong>Self cites:</strong></td>
<td>parser, parsing, model, perceptron, parsers, dependency parser, perceptron, supersense, parsing, dependency, results, hmm, models parsing, forest, treebank, model, coreference, stochastic, grammar, task</td>
</tr>
<tr>
<td><strong>In cites:</strong></td>
<td>discourse, structure, centering discourse, phrasebased, centering, tag, focus, rhetorical, tags, lexicalized discourse, rhetorical, framenet, realizer, tags, resolution, grammars, synonyms</td>
</tr>
<tr>
<td><strong>Discourse (29)</strong></td>
<td><em>Daniel Marcu, Aravind K. Joshi, Barbara J. Grosz, Marilyn A. Walker, Bonnie Lynn Webber</em></td>
</tr>
<tr>
<td><strong>Self cites:</strong></td>
<td>training, error error, giza, rate, alignment, training, minimum, translation, phrasebased forest, subcategorization, arabic, model, translation, machine, models, heuristic</td>
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</tbody>
</table>
Comparisons to Graph Clustering

<table>
<thead>
<tr>
<th>Our Model</th>
<th>Collaboration Network</th>
<th>Co-citation Network</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daniel Marcu, Aravind K. Joshi, Barbara J. Grosz, Marilyn A. Walker, Bonnie Lynn Webber</td>
<td>Daniel Marcu, Kevin Knight, Daniel Gildea, David Chiang, Liang Huang</td>
<td>Franz Josef Och, Hermann Ney, Vincent J. Della Pietra, Daniel Marcu, Robert L. Mercer</td>
</tr>
<tr>
<td>discourse, phrasebased, centering, tag, focus</td>
<td>phrasebased, forest, cube, spmt, hiero</td>
<td>giza, bleu, phrasebased, alignment, mert</td>
</tr>
</tbody>
</table>
Inter-faction relationships

Discourse → alignment, giza, training → MT 2
  ← phrase, model, joint, translation, probability

MT 2 ← alignment, giza, using, model
  ← parsing, parser, perception, hmm, dependency

Semantics ← using, alignment, giza, translation, model
  ← memory, judges, voice, allow, sequences

Formalisms ← tags, lexicalized, grammars, adjoining, trees
  ← tags, grammars, lexicalized, synchronous, formalism

Parsing ← parsing

Word Sense Disambiguation

Preferences, sense, wordnet, acquired, sensor
Factions over time

• Multiple “incarnations” of author, one for each time period
  – i.e. (Marcu, 1990), (Marcu, 2000) and (Marcu, 2006)

Factions over time

Eugene Charniak

1.0
0.8
0.6
0.4
0.2
0
1970-1989
1990-1999
2000-2005
2006-2011

building, annotated, discourse, treebank, kappa

parser, parsing, stylistic

Daniel Marcu

1.0
0.8
0.6
0.4
0.2
0
1990-1999
2000-2005
2006-2011

building, annotated, discourse, treebank, kappa

phrasebased, forest, joint, hierarchical, kbest

Cotraining, scalable, moses, open, implementen
Future work

• More continuous representation of time

• Accounting for birth and death of factions

• Nonparametric extension to the model

• Evaluation
Summary

• Defined factions in terms of how authors talk about each other’s work

• Computationally modeling faction formation

• Faction alignments changes over time
Thank you