Derivational Smoothing for Syntactic Distributional Semantics

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The 51st Annual Meeting of the Association for Computational Linguistics
August 6, 2013
Distributional Semantics

- Representation of word meaning as vectors
  - Vector components: co-occurrences with context features
  - Firth (1957): *You shall know a word by the company it keeps*

Peter convinced himself to write reports

\[
\begin{array}{c|c}
\text{report} & 1 \\
\text{Peter} & 1 \\
\text{convince} & 1 \\
\text{write} & 1 \\
\end{array}
\]

- Vector similarity approximates semantic similarity
  - Simple, unsupervised induction of word meaning
  - Used in variety of tasks (Turney and Pantel, 2010)
Lexical (word) context captures topical similarity
Syntactic (word-relation) context captures relational similarity

- Can model fine-grained information (Baroni and Lenci, 2010)
- More appropriate for free word order languages
Syntactic vector spaces are very *sparse*
- Even if constructed from very large corpora
- Reason: Less cooccurrences

Many word pairs receive semantic similarities of zero
- Real dissimilarity or missing data?

\[
\begin{align*}
\text{Peter convinced himself to write reports} & \quad \Rightarrow \\
\text{report} & \quad \text{write} \quad 1
\end{align*}
\]
The question

Where can we get semantic relatedness information to smooth distributional similarity?

The answer: Derivational morphology

- Consider derivational families:

  - Words that are derived from one another have similar meaning
  - Available from resources like CatVar (Habash and Dorr, 2003)
If vectors are sparse, do not compute semantic similarity directly.

Instead, back off to less sparse members of derivational families.

\[ \text{smoothed-sim}(\text{arguably, debatably}) = f(\text{arguably, debatably}) \]

(Similar to back-off to less sparse \( n-1 \) grams in LMs)
Derivational parameters: Two parameters

1. **Smoothing trigger:** When is a vector considered too sparse?
   - Smooth always
   - Smooth only if $sim(l_1, l_2) = 0$ (or undefined)

2. **Smoothing scheme:** How to bring in derivational family
   - maxSim: Consider most similar pair between families
   - avgSim: Consider average similarity of all pairs
   - centSim: Consider similarity of family centroids
Experiments

Language choice: German

- Resource situation comparable to English, but not quite as good
- Derivation important process of word formation

Distributional models

- Base Model: German Distributional Memory DM.DE (Padó and Utt, 2012)
  - 900M-token SDEWAC web corpus (Faaß et al., 2010)
  - DERIVBASE derivational families (Zeller et al., 2013)
    - Rule-based resource for German, focus on precision
    - 18,000 non-singleton families covering 60,000 lemmas
- Baseline: Bag-of-words models (same corpus)
Evaluation

**Task 1: Synonym choice**
- 980 targets with four candidates each (Reader’s Digest)
  “Which term is *antiquated* most similar to?
  (a) venerable, (b) old, (c) unusable, (d) outdated?”
- Prediction: candidate with max cosine similarity to target
- Evaluation: Accuracy (%) + Coverage (%)

**Task 2: Word similarity prediction**
- 350 pairwise judgments on 5-point scale (Zesch *et al.*, 2007)
  
  \[
  (monkey, macaque) \Rightarrow 4 \\
  (office, tiger) \Rightarrow 1
  \]
- Prediction: Cosine similarity
- Evaluation: Correlation (Pearson’s *r*) + Coverage (%)

Padó, Šnajder, Zeller (ACL 2013)
## Results: Synonym choice

| Model                                      | Acc. % | Cov. % |
|--------------------------------------------|--------|--------|
| DM.DE, unsmoothed                          | 53.7   | 80.8   |
| avgSim                                     | 46.0   | 86.6   |
| maxSim                                     | 50.3   | 86.6   |
| centSim                                    | 49.1   | 86.6   |
| DM.DE, smooth always                       |        |        |
| avgSim                                     | 52.6   | 86.6   |
| maxSim                                     | 51.2   | 86.6   |
| centSim                                    | 51.3   | 86.6   |
| DM.DE, smooth if sim = 0                   |        |        |
| avgSim                                     | 52.6   | 86.6   |
| maxSim                                     | 51.2   | 86.6   |
| centSim                                    | 51.3   | 86.6   |
| BoW “baseline”                             | 56.9   | 98.5   |

- Gain in coverage (+6%), but small loss in accuracy (-1%)
  - BoW “baseline” performs best
- Conservative trigger (smooth if necessary) works best
Results: Semantic similarity

| Model                               | \( r \) | Cov. % |
|-------------------------------------|---------|--------|
| DM.DE, unsmoothed                   | .44     | 58.9   |
| DM.DE, smooth always                | avgSim  | .30    | 88.0   |
|                                     | maxSim  | .43    | 88.0   |
|                                     | centSim | .44    | 88.0   |
| DM.DE, smooth if \( sim = 0 \)      | avgSim  | .43    | 88.0   |
|                                     | maxSim  | .42    | 88.0   |
|                                     | centSim | .47    | 88.0   |
| BoW baseline                        | .36     | 94.9   |

- Again, conservative trigger works best
- Big increase in coverage (+30%), small increase in correlation
Task Comparison

Result change through smoothing

| Task                | Quality          | Coverage |
|---------------------|------------------|----------|
| Synonym choice      | -0.09 % Acc.     | +6%      |
| Semantic similarity | +0.03 Corr.      | +30%     |

- Semantic similarity benefits more from derivational smoothing than synonym choice
  - Derivational families contain *related words*, not *synonyms*
Sparsity is a problem for syntax-based distributional models
  “Derivational smoothing”: Back off from rare word to derivational family
Initial experiments
  Conservative trigger (smooth only when sim=0) works best
  Jury still out on smoothing scheme (combination method)
Future work
  More experiments on smoothing schemes
  Use richer information about derivational families
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