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Institut für Maschinelle Sprachverarbeitung

Integrating Distributional Lexical Contrast into Word Embeddings for Antonym–Synonym Distinction

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Overview

1. Introduction
   1.1. Word Vector Representations
   1.2. Antonym-Synonym Distinction Task

2. Contributions
   2.1. Improving Weights of Feature Vectors
   2.2. Distributional Lexical Contrast Embeddings Model

3. Experiments

4. Conclusion

1.1. Word Vector Representations

1.1.1. Distributional Semantic Model (DSM)

- A means to represent meaning vectors of words.
- DSM rely on the *distributional hypothesis.* (Harris, 1954)
- Words with similar distributions have related meanings.
- Each weighted feature can be:
  - Co-occurrence frequency.
  - Association measure: local mutual information (LMI) (Evert, 2005)

1.1.2. Word Embeddings

- Representing words as low-dimensional dense vectors.
- Words with similar distributions have similar vectors.

1.2. Antonym-Synonym Distinction Task

- Goal
  - Distinguishing antonyms from synonyms.
- Problems
  - DSM tend to capture both antonyms (`formal-informal`) and synonyms (`formal-conventional`).
  - Word embeddings represent vectors of both antonyms and synonyms as similar vectors.
- Causes
  - Antonymy and synonymy are paradigmatic relations.
  - Antonyms and synonyms often occur in similar contexts.

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2.1. Improving Weights of Feature Vectors

- Goal:
  - Improving the quality of weighted feature vectors.
- Solution:
  - Strengthening most salient features in the vectors.
  - Using the lexical contrast information of the target words and their contexts.
  - Proposing the new weight for feature vectors.
- Representing words based on DSM with positive LMI.
- For each target word w:
  - Determining the sets of antonyms $A(w)$ and synonyms $S(w)$.
  - Determining the set of shared words $W(f)$ for each feature f.
- Computing the new weight (called $weight^{SA}$) as follows:

2.1. Improving Weights of Feature Vectors

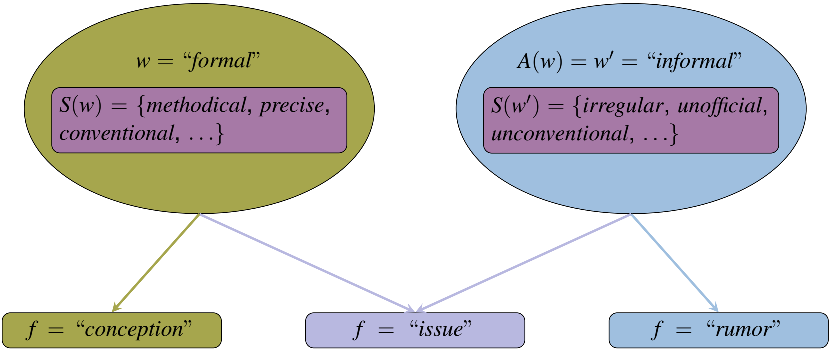
Average similarity to synonyms

$$weight^{SA}(w,f) = \frac{1}{\#(w,u)} \sum_{u \in W(f) \cap S(w)} sim(w,u)$$

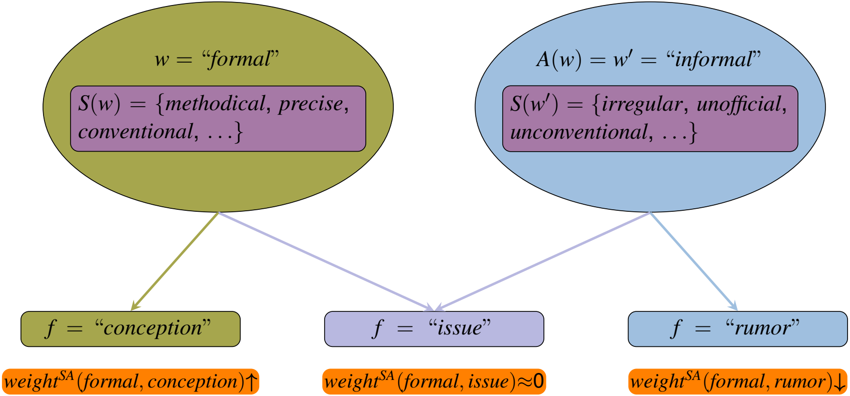
$$- \frac{1}{\#(w',v)} \sum_{w' \in A(w)} \sum_{v \in W(f) \cap S(w')} sim(w',v)$$

Average similarity to antonyms

2.1. Improving Weights of Feature Vectors



2.1. Improving Weights of Feature Vectors



$$weight^{SA}(w,f) = \frac{1}{\#(w,u)} \sum_{u \in W(f) \cap S(w)} sim(w,u) - \frac{1}{\#(w',v)} \sum_{w' \in A(w)} \sum_{v \in W(f) \cap S(w')} sim(w',v)$$

2.2. Distributional Lexical Contrast Embeddings Model (dLCE)

- Aims:
  - Learning word embeddings.
  - Moving synonyms closer to each other in space.
  - Moving antonyms further away from each other in space.
- Solution:
  - Integrating distributional lexical contrast into the transformation of Skip-gram model (Mikolov et al. 2013, Levy et al., 2014).
  - Applying lexical contrast to every single context of the target word.
- The proposed objective function as follows:

2.2. Distributional Lexical Contrast Embeddings Model (dLCE)

Distribution of target word and contexts

Distribution of negative contexts

$$\sum_{w \in V} \sum_{c \in V} \{ \boxed{ \left(\#(w,c) \log \sigma(sim(w,c)) + k\#(w) P_0(c) \log \sigma(-sim(w,c)) \right) }$$

$$\boxed{ + \left(\frac{1}{\#(w,u)} \sum_{u \in W(c) \cap S(w)} sim(w,u) - \frac{1}{\#(w,v)} \sum_{v \in W(c) \cap A(w)} sim(w,v) \right) } \}$$

Distribution of synonymous pairs

Distribution of antonymous pairs

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3. Experiments

- Evaluating $weight^{SA}$ on Antonym-Syntonym distinction task.
- Evaluating effects of dLCE model:
  - Antonym-Syntonym distinction task.
  - Similarity task.

3.1. Antonym–Synonym Distinction

- Corpus: ENCOW14A (Schäfer and Bildhauer, 2012) contains 14.5 billion tokens.
- Dataset: a gold standard resource of paradigmatic relation pairs (Roth and Schulte im Walde, 2014)

Word Class	Ant-pairs	Syn-pairs	Total
Adjective	300	300	600
Noun	350	350	700
Verb	400	400	800

- Using average precision (AP) to evaluate.
- Using box-plots to compare the cosine medians of antonymous *vs.* synonymous pairs.

3.1. Antonym–Synonym Distinction

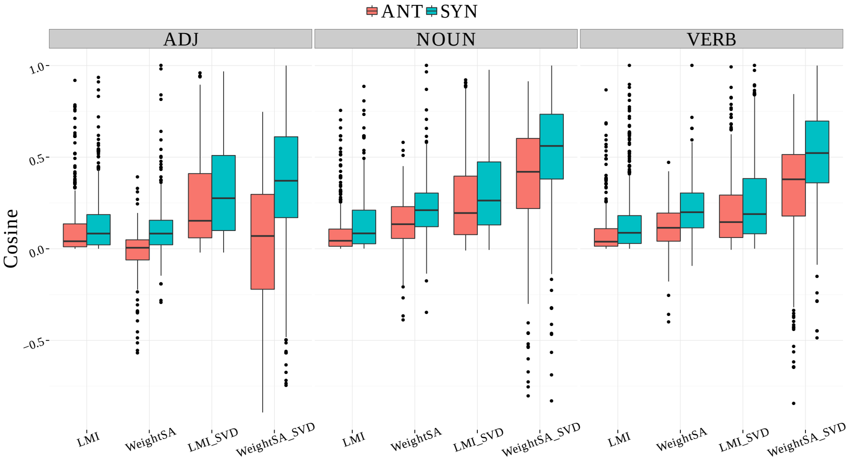
- AP evaluation results[1]:

	Adjectives		Nouns		Verbs	
	ANT	SYN	ANT	SYN	ANT	SYN
LMI	0.46	0.56	0.42	0.60	0.42	0.62
$weight^{SA}$	**0.36****	**0.75****	**0.40**	**0.66**	**0.38***	**0.71***
LMI + SVD	0.46	0.55	0.46	0.55	0.44	0.58
$weight^{SA}$ + SVD	**0.36*****	**0.76*****	**0.40***	**0.66***	**0.38*****	**0.70*****

[1] $\chi^2, {}^{***}p < .001, {}^{**}p < .005, {}^{*}p < .05$

3.1. Antonym–Synonym Distinction

- Results in box-plots:



3.2. Effects of dLCE model

3.2.1. Antonym-Synonym Distinction:

- Dataset: the gold standard resource of paradigmatic relation pairs (Roth and Schulte im Walde, 2014).
- Using area under curve (AUC) to identify antonyms.
- Comparison Models: Skip-gram (SGNS), mLCM (Pham et al., 2015)
- Results:

	Adjectives	Nouns	Verbs
SGNS	0.64	0.66	0.65
mLCM	0.85	0.69	0.71
dLCE	**0.90**	**0.72**	**0.81**

3.2. Effects of dLCE model

3.2.2. Similarity Task:

- Dataset: SimLex-999 (Hill et al., 2015)
- Using Spearman correlation coefficient ρ to evaluate.
- Comparison Models: SGNS, mLCM.
- Results:

SGNS	mLCM	dLCE
0.38	0.51	**0.59**

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- We have presented two methods to address the task of antonym-synonym distinction:
  - Improving the quality of weighted feature vectors.
  - Integrating distributional lexical contrast into word embeddings.
- The results from the experiments show that our approaches can model semantic similarity and distinguish between antonyms and synonyms.

Thank you!