Intrinsic Subspace Evaluation of Word Embedding Representations

December 2015

LMU Munich
CIS

Outline

Word Embeddings Evaluation

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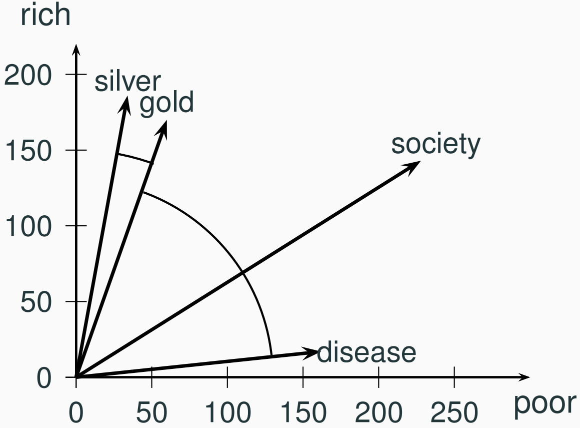
Representation of Words in Vector space model



Word Embeddings

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- Evaluation: how much of these facets are represented accurately and consistently.
- Current methods of evaluation:
    - Extrinsic tasks
    - Intrinsic similarity-based datasets
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- Our proposed method:
  - Identifying generic and fundamental criteria for embedding models that are important to represent facets of words accurately and consistently.
  - Developing corpus-based tests to asses the criteria using PCFG generated datasets
  - Evaluating embedding models by supervised classification that needs to look at subspaces

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Robustness against ambiguity

- Most words are ambiguous.

Robustness against ambiguity

- Important question:
    - for a word with k senses, Should we have k vectors? Or just 1 vector?

*1*vector-$k$senses: 1 embedding to represent two senses?

1 vector-k senses: 1 embedding to represent two senses?

- Two senses of “suit”: litigation vs. clothing

*1*vector-*k*senses: 1 embedding to represent two senses?

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legal-case

apparel

litigation

lawsuit

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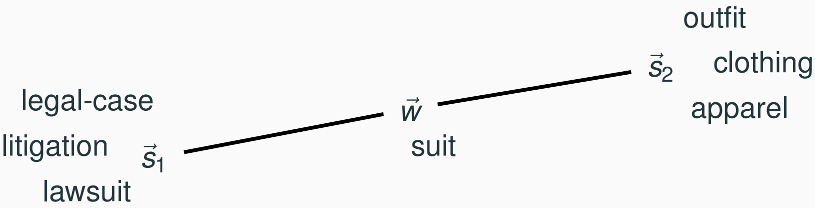

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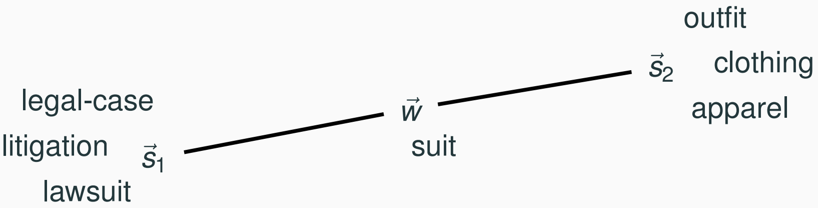

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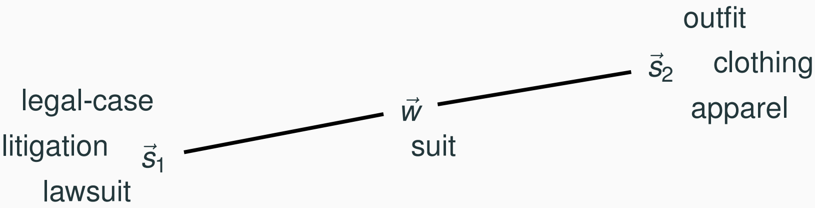

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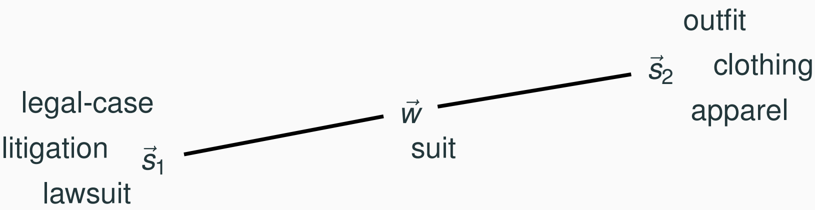

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- Similarity evaluation datasets
  (MEN, WordSim, Stanford Rare Words etc)
  evaluate performance on this objective.

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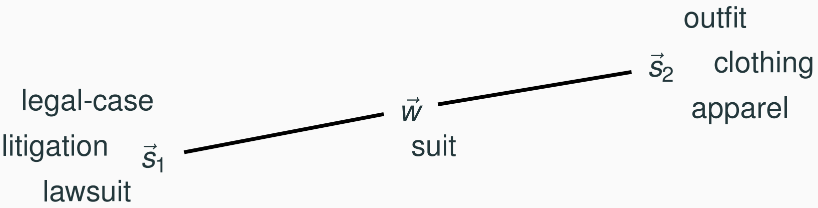

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Embeddings: Remember our objective

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- Word embeddings should represent the facets of words accurately and consistently
- If we adopt this alternative objective,
  then maybe there is no problem with *1*vector-*k*senses?

Setup for ambiguity experiment

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- Train embedding models on corpus:
  each will give us its trained word embeddings

Ambiguity grammar

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P(CW_1D|S) & = & 9/20 & \\
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Two types of contexts: A-B contexts and C-D contexts.

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Unambiguous: $w_5 \ldots w_{49}$ only occur in C-D contexts.

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Ambiguous: $w_0 \ldots w_4$ occur in A-B and C-D contexts.

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Skewedness of ambiguity controlled by β.

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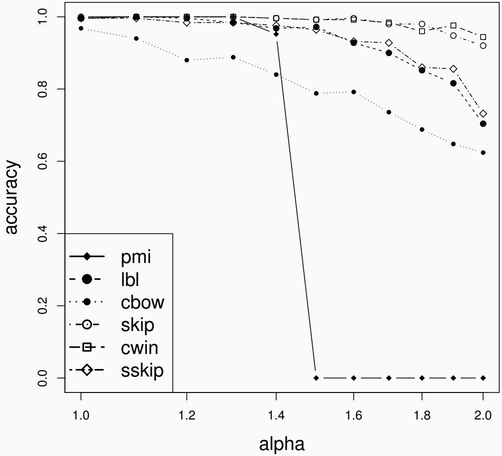
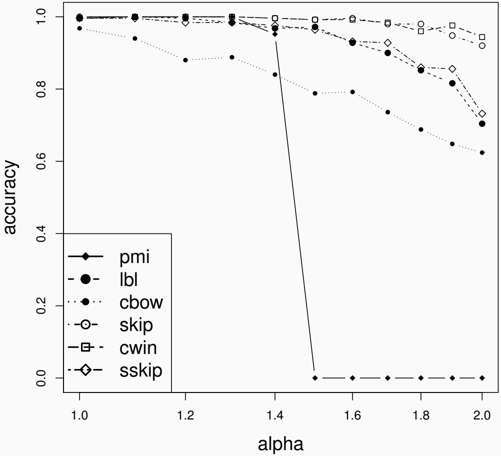
- One SVM for embeddings of each model
- The test set consists of the five ambiguous words $w_0 \ldots w_4$.
- 50 trials of this experiment were run for each of eleven values of β: $\beta = 2^{-\alpha}$ where $\alpha \in \{1.0, 1.1, 1.2, \ldots, 2.0\}$.

Ambiguity: Results





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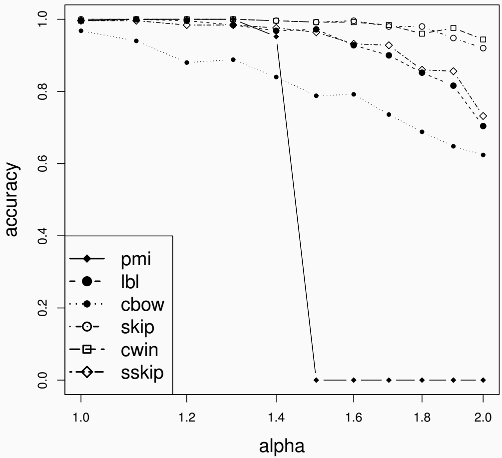

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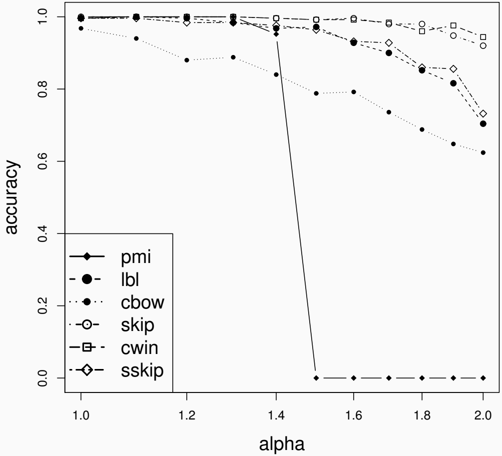

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- PPMI accuracy is 0 for *beta* $\geq$ 1.5.

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- A single embedding will not fare well on analogy/similarity.
- But it is not the word embedding objective.

Accurate and consistent representation of multifacetedness

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- Words have a large number of facets
- Each facet constitutes a small part of the overall information that a representation should capture about a word.

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This grammar generates nouns ($x_i^{\mathrm{n}\cdot}$) and adjectives ($x_i^{\mathrm{a}\cdot}$)

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14	$P(m \mid U_i^{\mathrm{nm}})$	$= 1/2$	
15	$P(\mu(U_i^{\mathrm{nm}}) \mid U_i^{\mathrm{nm}})$	$= 1/2$	
16	$P(x_i^{\mathrm{am}} U_i^{\mathrm{am}} \mid M_f)$	$= 1/5$	$0 \leq i \leq 4$
17	$P(m \mid U_i^{\mathrm{am}})$	$= 1/2$	
18	$P(\mu(U_i^{\mathrm{am}}) \mid U_i^{\mathrm{am}})$	$= 1/2$	

with masculine (x_i^{m}) and feminine (x_i^{f}) gender.

Multifacetedness grammar

1	$P(NF_n\|S)$	$=1/4$	
2	$P(AF_a\|S)$	$=1/4$	
3	$P(NM_n\|S)$	$=1/4$	
4	$P(AM_f\|S)$	$=1/4$	
5	$P(n_i\|N)$	$=1/5$	$0 \leq i \leq 4$
6	$P(a_i\|A)$	$=1/5$	$0 \leq i \leq 4$
7	$P(x_i^{\text{nf}} U_i^{\text{nf}}\|F_n)$	$=1/5$	$0 \leq i \leq 4$
8	$P(f\|U_i^{\text{nf}})$	$=1/2$	
9	$P(\mu(U_i^{\text{nf}})\|U_i^{\text{nf}})$	$=1/2$	
10	$P(x_i^{\text{af}} U_i^{\text{af}}\|F_a)$	$=1/5$	$0 \leq i \leq 4$
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3	$P(NM_n \mid S)$	$=1/4$	
4	$P(AM_f \mid S)$	$=1/4$	
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6	$P(a_i \mid A)$	$=1/5$	$0 \leq i \leq 4$
7	$P(x_i^{\text{nf}} U_i^{\text{nf}} \mid F_n)$	$=1/5$	$0 \leq i \leq 4$
8	$P(f \mid U_i^{\text{nf}})$	$=1/2$	
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Function μ maps each U to one of the paradigms $\{u_0 \ldots u_4\}$

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- Full-space similarity cannot determine the presence of a low entropy facet accurately and consistently.