Intrinsic Subspace Evaluation of Word Embedding Representations

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ACL 2016

CIS - LMU Munich

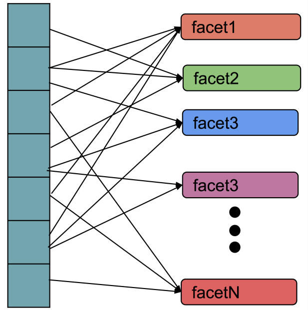
Outline

1. Background
2. Intrinsic Subspace Evaluation
3. Extrinsic Evaluation: Entity Typing

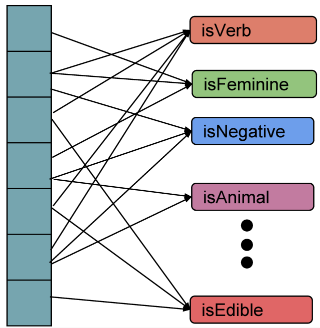
Background

Word Embeddings

... represent generic word properties (facets) in real valued vectors

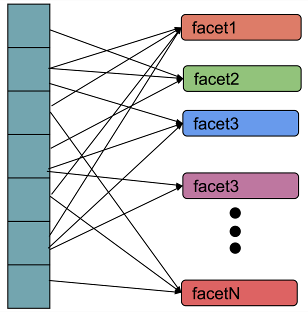


Word Embeddings: Example Facets

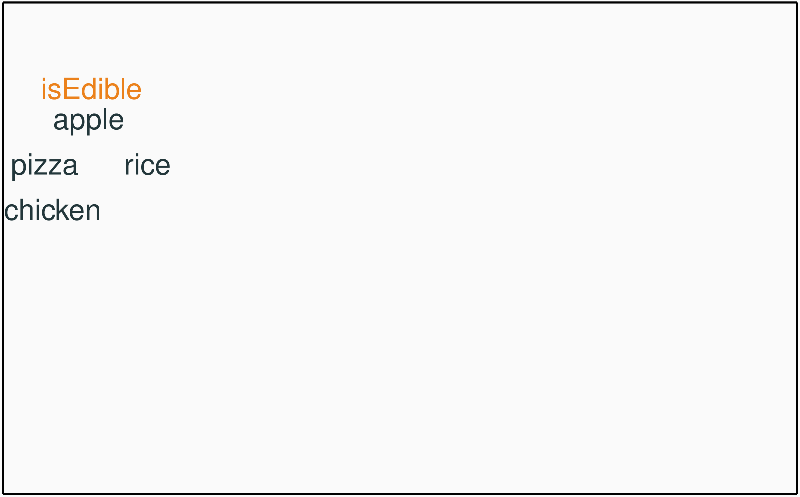


Fullspace vs. Subspace Similarity of Words

- Fullspace similarity: similarity on all facets
- Subspace similarity: similarity on a subset of facets



What embeddings should ideally represent



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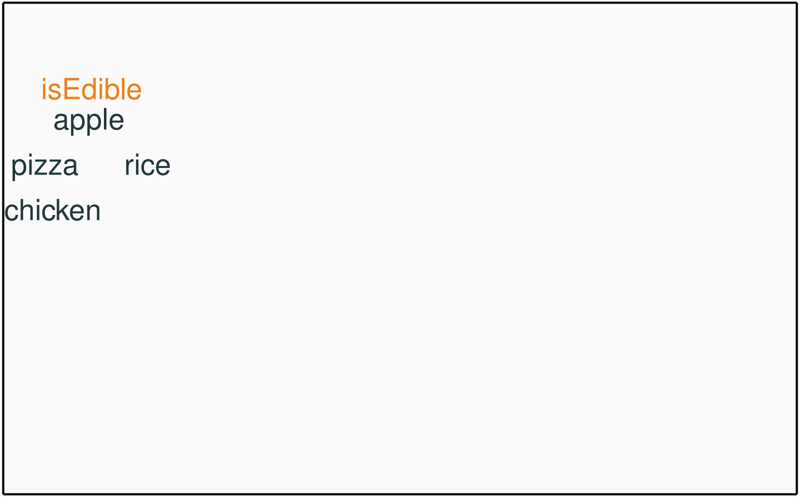

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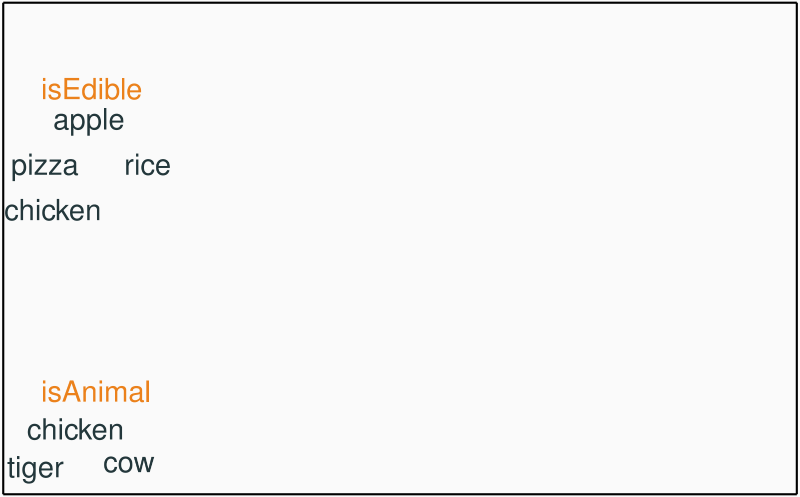

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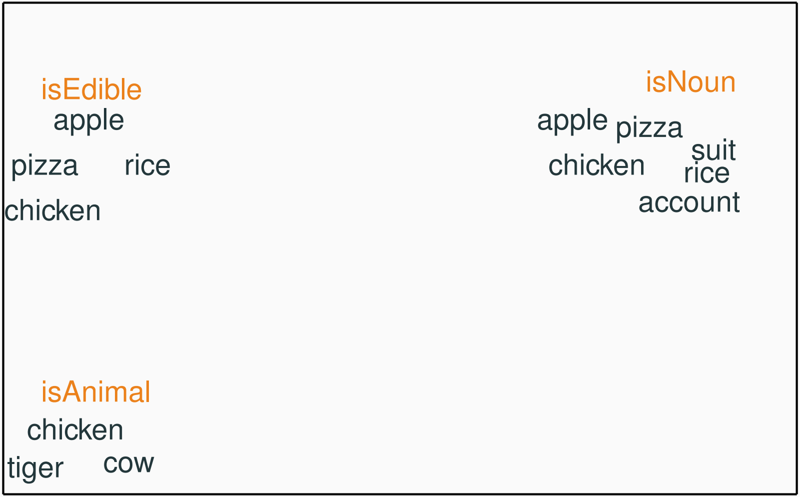

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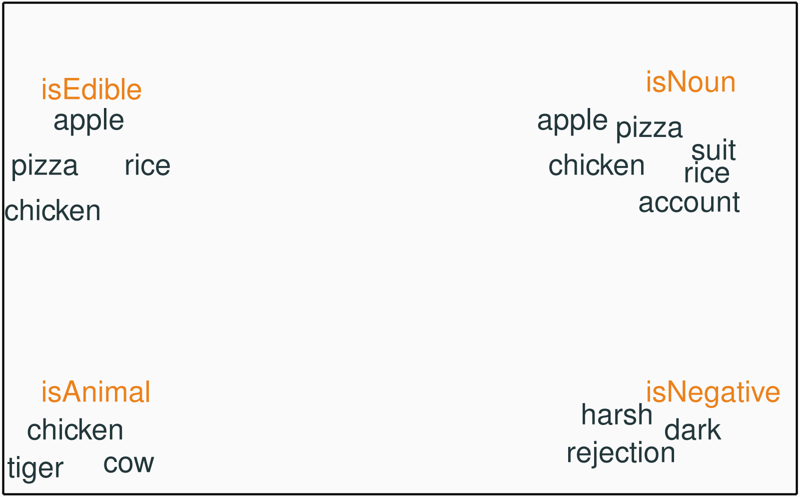

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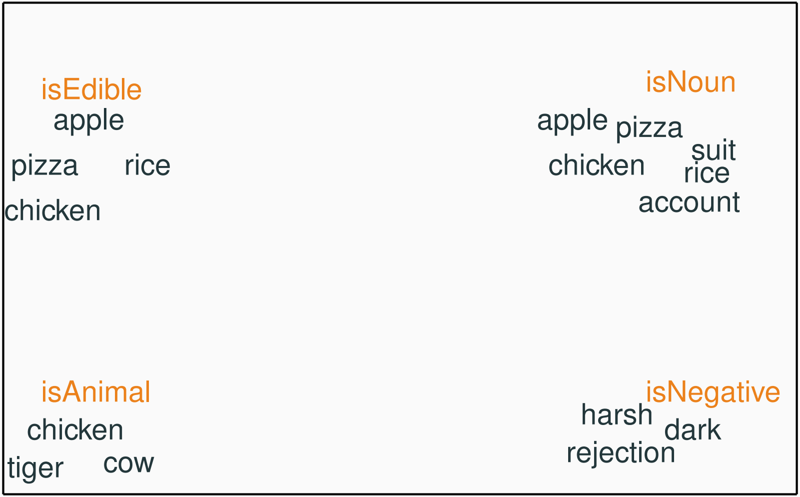

- Ideally, words with similar facets should be close.
- But they are not on fullspace sim, only on subspace sim!

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  - Expensive evaluation
  - Hard to analyze the results

What Should We Do Then?

We need an intrinsic evaluation that explores subspaces!

Intrinsic Subspace Evaluation

Word Embedding Challenges?!

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We can evaluate word embeddings with respect to these challenges!

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- Generate a corpus using the PCFG
- Train embedding models on corpus
- Evaluate embeddings using a supervised task

Challenge 1: Ambiguity

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\begin{array}{lcll}
P(AV_1B|S) & = & 9/20 & \\
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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: $v_0 \ldots v_{49}$ only occur in A-B contexts.

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Ambiguity level controlled by β

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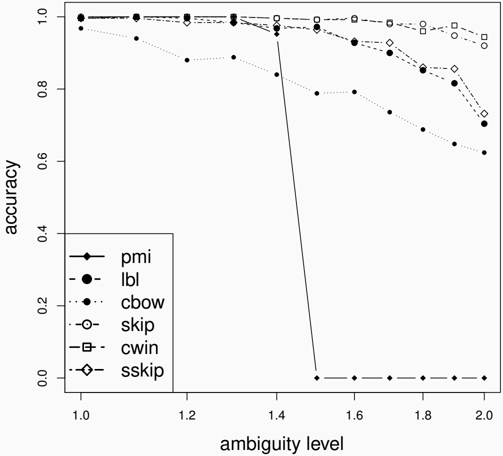
- 50 trials of this experiment for different ambiguity levels

Ambiguity: Comparison of Six Embedding Models



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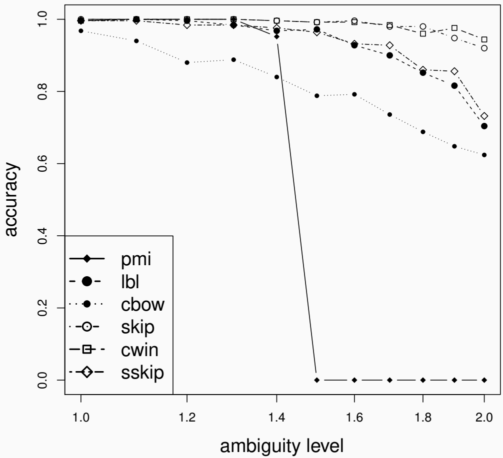

- Accuracy
  - ∼100% for ambiguity level 1.0 (two senses equal)
  - much lower for ambiguity level 2.0 (one sense three times more frequent)

Discussion: Common Premise for Ambiguity

We need k vectors for a word with k senses

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Why?

Why Some People Are Against single-embedding-per-word

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

Why Some People Are Against single-embedding-per-word

outfit

$\vec{s}_2$ clothing

legal-case

apparel

litigation $\vec{s}_1$

lawsuit

- Two senses of “suit”: litigation vs. clothing
- Let’s represent these two senses using the embeddings $\vec{s}_1$, $\vec{s}_2$.

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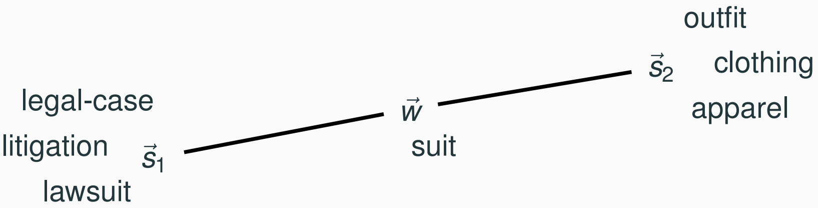

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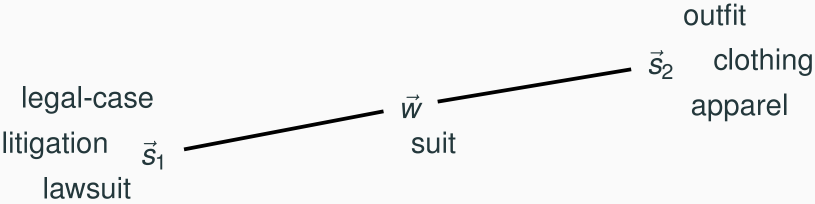

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- But $\vec{w}$ is not close to either senses (“litigation” / “clothing”)!

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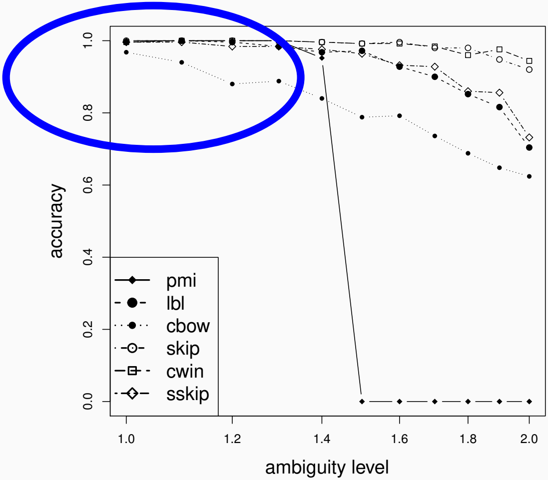

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- Our experiment shows:
  one-embedding-per-word is robust to some level of ambiguity
- Similar conclusion in (Li and Jurafsky (2015)): increasing word embedding dimensionality can do the job of multi sense embeddings
- However for skewed sense distributions, one-embedding-per-word is challenging

Challenge 2: Multifacetedness

- Words have large number of facets

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- Words have large number of facets
- Embedding should accurately represent all of them

Multifacetedness Grammar

1	$P(NF_n\|S)$	$=1/4$	
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This grammar generates nouns ($x_i^{\text{n}\cdot}$) and adjectives ($x_i^{\text{a}\cdot}$)

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

Multifacetedness Grammar

1	$P(NF_n \mid S)$	$= 1/4$	
2	$P(AF_a \mid S)$	$= 1/4$	
3	$P(NM_n \mid S)$	$= 1/4$	
4	$P(AM_f \mid S)$	$= 1/4$	
5	$P(n_i \mid N)$	$= 1/5$	$0 \leq i \leq 4$
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	$P(f \mid U_i^{\text{nf}})$	$= 1/2$	
9	$P(\mu(U_i^{\text{nf}}) \mid U_i^{\text{nf}})$	$= 1/2$	
10	$P(x_i^{\text{af}} U_i^{\text{af}} \mid F_a)$	$= 1/5$	$0 \leq i \leq 4$
11	$P(f \mid U_i^{\text{af}})$	$= 1/2$	
12	$P(\mu(U_i^{\text{af}}) \mid U_i^{\text{af}})$	$= 1/2$	
13	$P(x_i^{\text{nm}} U_i^{\text{nm}} \mid M_n)$	$= 1/5$	$0 \leq i \leq 4$
14	$P(m \mid U_i^{\text{nm}})$	$= 1/2$	
15	$P(\mu(U_i^{\text{nm}}) \mid U_i^{\text{nm}})$	$= 1/2$	
16	$P(x_i^{\text{am}} U_i^{\text{am}} \mid M_f)$	$= 1/5$	$0 \leq i \leq 4$
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Function μ maps each U to one of the morphological paradigms $\{u_0 \ldots u_4\}$

Multifacetedness: Example Sentences

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$a_1\ x_0^{\mathrm{af}}\ u_1$ $a_0\ x_0^{\mathrm{af}}\ f$	x_0^{af} : a feminine adjective with paradigm u_1
$a_4\ x_1^{\mathrm{af}}\ u_2$ $a_3\ x_1^{\mathrm{af}}\ f$	x_1^{af} : a feminine adjective with paradigm u_2
$n_3\ x_3^{\mathrm{nf}}\ u_3$ $n_1\ x_3^{\mathrm{nf}}\ f$	x_3^{nf} : a feminine noun with paradigm u_3
$n_3\ x_2^{\mathrm{nm}}\ u_1$ $n_2\ x_2^{\mathrm{nm}}\ m$	x_2^{nm} : a masculine noun with paradigm u_1

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  "is this word feminine or masculine?"
- Training on the "nouns", predict the gender of "adjectives"
- 10 trials of experiments with different paradigm assignments

Multifacetedness: Results

- No single error in the classification
- Representation of gender facet by all six embedding models is perfect

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Multifacetedness: Results

- No single error in the classification
- Representation of gender facet by all six embedding models is perfect
- But what if we used fullspace similarity?

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  - classification: 0%

Evaluation of Multifacetedness: Summary

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- Fullspace similarity is misleading

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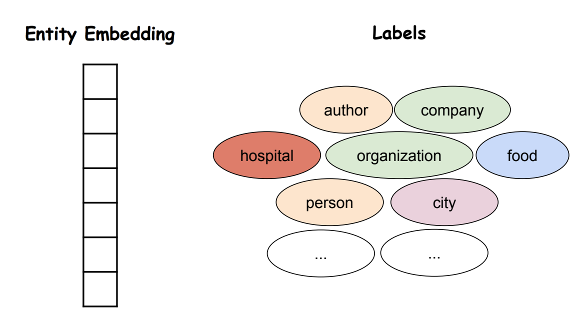
- Fullspace similarity is misleading
- Subspace similarity works well

Extrinsic Evaluation: Entity Typing

Task


Entity Embedding
Labels
author
company
hospital
organization
food
person
city
...
...

Entity Typing: Experiment

Entity Typing: Experiment

- Two types of classifiers:
  - fullspace similarity based: KNN
  - subspace similarity based: MLP

Results

	MLP	KNN
PPMI	61.6	44.0
LBL	63.5	51.7
CBOW	63.0	53.5
CWIN	66.1	53.0
SKIP	64.5	57.1
SSKIP	66.2	52.8

- MLP $>>$ KNN (i.e., subspace sim $>>$ fullspace sim)

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- MLP $>>$ KNN
  (i.e., subspace sim $>>$ fullspace sim)
- Fullspace sim is misleading:
  - fullspace sim incorrectly suggests:
    SSKIP is worse than SKIP
  - subspace sim shows that in reality:
    SSKIP is better than SKIP

Entity Typing: Results (2)

	all entities		frequent entities		rare entities	
	MLP	KNN	MLP	KNN	MLP	KNN
PPMI	61.6	44.0	69.2	63.8	43.0	28.5
LBL	63.5	51.7	72.7	66.4	44.1	32.8
CBOW	63.0	53.5	71.7	69.4	39.1	29.9
CWIN	66.1	53.0	73.5	68.6	46.8	31.4
SKIP	64.5	57.1	69.9	71.5	49.8	34.0
SSKIP	66.2	52.8	73.9	68.5	45.5	31.4

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- Spearman's rho between subspace sim (MLP) and fullspace sim (KNN) is: 0.03 for frequent and 0.75 for rare

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- Spearman's rho between subspace sim (MLP) and fullspace sim (KNN) is: 0.03 for frequent and 0.75 for rare
- What does the correlation difference in frequent and rare entities tell us?

Summary

- Intrinsic evaluation is needed
- Fullspace similarity is limited and misleading
- Subspace similarity is necessary for a good evaluation
- Artificial corpora can help to evaluate and understand

Thank you!

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