

Distributional Semantic Models

Part 3: Evaluation of distributional similarity

Stefan Evert¹

with Alessandro Lenci², Marco Baroni³ and Gabriella Lapesa⁴

¹Friedrich-Alexander-Universität Erlangen-Nürnberg, Germany

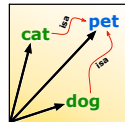
²University of Pisa, Italy

³University of Trento, Italy

⁴University of Stuttgart, Germany

<http://wordspace.collocations.de/doku.php/course:start>

Copyright © 2009–2016 Evert, Lenci, Baroni & Lapesa | Licensed under CC-by-sa version 3.0



Outline

What is semantic similarity?

- Semantic similarity and relatedness

- Attributional similarity & quantitative evaluation

Parameter evaluation

- Evaluation strategies

- An example (Bullinaria & Levy 2007, 2012)

A large scale evaluation study

- Tasks & parameters

- Methodology for DSM Evaluation

- Evaluation on Standard Tasks

- Summary & conclusion

Outline

What is semantic similarity?

- Semantic similarity and relatedness

- Attributional similarity & quantitative evaluation

Parameter evaluation

- Evaluation strategies

- An example (Bullinaria & Levy 2007, 2012)

A large scale evaluation study

- Tasks & parameters

- Methodology for DSM Evaluation

- Evaluation on Standard Tasks

- Summary & conclusion

Distributional similarity as semantic similarity

- ▶ DSMs interpret semantic similarity as a **quantitative notion**
 - ▶ if **a** is closer to **b** than to **c** in the distributional vector space, then *a* is more semantically similar to *b* than to *c*

| rhino | fall | rock |
|------------|-------------|---------|
| woodpecker | rise | lava |
| rhinoceros | increase | sand |
| swan | fluctuation | boulder |
| whale | drop | ice |
| ivory | decrease | jazz |
| plover | reduction | slab |
| elephant | logarithm | cliff |
| bear | decline | pop |
| satin | cut | basalt |
| sweatshirt | hike | crevice |

Types of semantic relations in DSMs

Nearest DSM neighbors have different types of **semantic relations**.

car (InfomapNLP on BNC; n = 2)

- ▶ van **co-hyponym**
- ▶ vehicle **hyperonym**
- ▶ truck **co-hyponym**
- ▶ motorcycle **co-hyponym**
- ▶ driver **related entity**
- ▶ motor **part**
- ▶ lorry **co-hyponym**
- ▶ motorist **related entity**
- ▶ cavalier **hyponym**
- ▶ bike **co-hyponym**

car (InfomapNLP on BNC; n = 30)

- ▶ drive **function**
- ▶ park **typical action**
- ▶ bonnet **part**
- ▶ windscreen **part**
- ▶ hatchback **part**
- ▶ headlight **part**
- ▶ jaguar **hyponym**
- ▶ garage **location**
- ▶ cavalier **hyponym**
- ▶ tyre **part**

Manual analysis of semantic relations

for 44 concrete English nouns (Baroni and Lenci 2008)

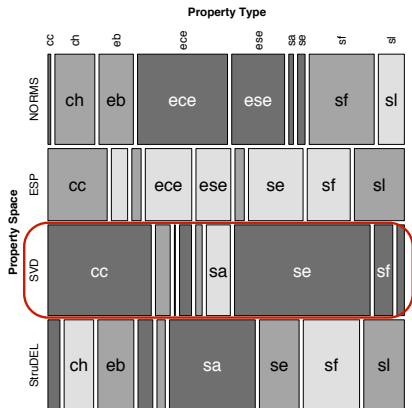


Figure 1: Distribution of property types across property spaces.

Taxonomic category:

cc (co-)hyponym

ch hypernym

Properties of entity:

eb typical behaviour

ece external component

ese surface property

Situationally associated:

sa action

se other entity

sf function

sl location

Distribution of semantic relations among DSM neighbours (**SVD**), pattern collocations (**StruDEL**) and human-generated properties (**NORMS**).

Semantic similarity and relatedness

- ▶ **Attributional similarity** – two words sharing a large number of salient features (attributes)
 - ▶ synonymy (*car/automobile*)
 - ▶ hyperonymy (*car/vehicle*)
 - ▶ co-hyponymy (*car/van/truck*)

Semantic similarity and relatedness

- ▶ **Attributional similarity** – two words sharing a large number of salient features (attributes)
 - ▶ synonymy (*car/automobile*)
 - ▶ hyperonymy (*car/vehicle*)
 - ▶ co-hyponymy (*car/van/truck*)
- ▶ **Semantic relatedness** (Budanitsky and Hirst 2006) – two words semantically associated without necessarily being similar
 - ▶ function (*car/drive*)
 - ▶ meronymy (*car/tyre*)
 - ▶ location (*car/road*)
 - ▶ attribute (*car/fast*)

Semantic similarity and relatedness

- ▶ **Attributional similarity** – two words sharing a large number of salient features (attributes)
 - ▶ synonymy (*car/automobile*)
 - ▶ hyperonymy (*car/vehicle*)
 - ▶ co-hyponymy (*car/van/truck*)
- ▶ **Semantic relatedness** (Budanitsky and Hirst 2006) – two words semantically associated without necessarily being similar
 - ▶ function (*car/drive*)
 - ▶ meronymy (*car/tyre*)
 - ▶ location (*car/road*)
 - ▶ attribute (*car/fast*)
- ▶ **Relational similarity** (Turney 2006) – similar relation between pairs of words (analogy)
 - ▶ *policeman:gun :: teacher:book*
 - ▶ *mason:stone :: carpenter:wood*
 - ▶ *traffic:street :: water:riverbed*

Outline

What is semantic similarity?

Semantic similarity and relatedness

Attributional similarity & quantitative evaluation

Parameter evaluation

Evaluation strategies

An example (Bullinaria & Levy 2007, 2012)

A large scale evaluation study

Tasks & parameters

Methodology for DSM Evaluation

Evaluation on Standard Tasks

Summary & conclusion

DSMs and semantic similarity

- ▶ DSMs are thought to represent **paradigmatic** similarity
 - ▶ words that tend to occur in the same contexts
- ▶ Words that share many contexts will correspond to concepts that share many attributes (**attributional similarity**), i.e. concepts that are **taxonomically/ontologically similar**
 - ▶ synonyms (*rhino/rhinoceros*)
 - ▶ antonyms and values on a scale (*good/bad*)
 - ▶ co-hyponyms (*rock/jazz*)
 - ▶ hyper- and hyponyms (*rock/basalt*)
- ▶ Taxonomic similarity is seen as the **fundamental semantic relation** organising the vocabulary of a language, allowing categorization, generalization and inheritance

Evaluation of attributional similarity

- ▶ **Synonym identification**
 - ▶ TOEFL test
- ▶ **Modeling semantic similarity judgments**
 - ▶ Rubenstein/Goodenough norms
 - ▶ WordSim-353
- ▶ **Noun categorization**
 - ▶ ESSLI 2008 dataset
 - ▶ Almuhareb & Poesio dataset (AP)
 - ▶ ...
- ▶ **Semantic priming**
 - ▶ Hodgson dataset
 - ▶ Semantic Priming Project

Give it a try ...

- ▶ The wordspace package contains pre-compiled DSM vectors
 - ▶ based on a large Web corpus (9 billion words)
 - ▶ L4/R4 surface span, log-transformed G^2 , SVD dim. red.
 - ▶ targets = lemma + POS code (e.g. `white_J`)
 - ▶ compatible with evaluation tasks included in package

```
library(wordspace)
```

```
M <- DSM_Vectors
```

```
nearest.neighbours(M, "walk_V")
```

| | | | | |
|------------------------|-----------------------|------------------------|--------------------------|------------------------|
| <code>amble_V</code> | <code>stroll_V</code> | <code>traipse_V</code> | <code>potter_V</code> | <code>tramp_V</code> |
| 19.4 | 21.8 | 21.8 | 22.6 | 22.9 |
| <code>saunter_V</code> | <code>wander_V</code> | <code>trudge_V</code> | <code>leisurely_R</code> | <code>saunter_N</code> |
| 23.5 | 23.7 | 23.8 | 26.2 | 26.4 |

you can also try white, apple and kindness

The TOEFL synonym task

- ▶ The TOEFL dataset (80 items)
 - ▶ Target: *levied*
Candidates: *believed, correlated, imposed, requested*

```
# ask your course instructor for non-public data package  
> library(wordspaceEval)  
> head(TOEFL80)
```

The TOEFL synonym task

- ▶ The TOEFL dataset (80 items)
 - ▶ Target: *levied*
Candidates: *believed, correlated, imposed, requested*

```
# ask your course instructor for non-public data package  
> library(wordspaceEval)  
> head(TOEFL80)
```

The TOEFL synonym task

- ▶ The TOEFL dataset (80 items)
 - ▶ Target: *levied*
Candidates: *believed, correlated, imposed, requested*
 - ▶ Target *fashion*
Candidates: *craze, fathom, manner, ration*

```
# ask your course instructor for non-public data package  
> library(wordspaceEval)  
> head(TOEFL80)
```


The TOEFL synonym task

- ▶ The TOEFL dataset (80 items)
 - ▶ Target: *levied*
Candidates: *believed, correlated, imposed, requested*
 - ▶ Target *fashion*
Candidates: *craze, fathom, manner, ration*

```
# ask your course instructor for non-public data package  
> library(wordspaceEval)  
> head(TOEFL80)
```

The TOEFL synonym task

- ▶ The TOEFL dataset (80 items)
 - ▶ Target: *levied*
Candidates: *believed, correlated, imposed, requested*
 - ▶ Target *fashion*
Candidates: *craze, fathom, manner, ration*
- ▶ DSMs and TOEFL
 1. take vectors of the target (**t**) and of the candidates (**c**₁ ... **c**_n)
 2. measure the distance between **t** and **c**_i, with $1 \leq i \leq n$
 3. select **c**_i with the shortest distance in space from **t**

ask your course instructor for non-public data package

```
> library(wordspaceEval)
```

```
> head(TOEFL80)
```

Humans vs. machines on the TOEFL task

- ▶ Average foreign test taker: 64.5%

And you?

```
> eval.multiple.choice(TOEFL80, M)
```

Humans vs. machines on the TOEFL task

- ▶ Average foreign test taker: 64.5%
- ▶ Macquarie University staff (Rapp 2004):
 - ▶ Average of 5 non-natives: 86.75%
 - ▶ Average of 5 natives: 97.75%

And you?

```
> eval.multiple.choice(TOEFL80, M)
```

Humans vs. machines on the TOEFL task

- ▶ Average foreign test taker: 64.5%
- ▶ Macquarie University staff (Rapp 2004):
 - ▶ Average of 5 non-natives: 86.75%
 - ▶ Average of 5 natives: 97.75%
- ▶ Distributional semantics
 - ▶ Classic LSA (Landauer and Dumais 1997): 64.4%
 - ▶ Padó and Lapata's (2007) dependency-based model: 73.0%
 - ▶ Distributional memory (Baroni and Lenci 2010): 76.9%
 - ▶ Rapp's (2004) SVD-based model, lemmatized BNC: 92.5%
 - ▶ Bullinaria and Levy (2012) carry out aggressive parameter optimization: 100.0%

And you?

```
> eval.multiple.choice(TOEFL80, M)
```

Semantic similarity judgments

- ▶ Rubenstein and Goodenough (1965) collected similarity ratings for 65 noun pairs from 51 subjects on a 0–4 scale

| w_1 | w_2 | avg. rating |
|-------------|-------------------|-------------|
| <i>car</i> | <i>automobile</i> | 3.9 |
| <i>food</i> | <i>fruit</i> | 2.7 |
| <i>cord</i> | <i>smile</i> | 0.0 |

```
> RG65[seq(0,65,5), ]  
> head(WordSim353) # extension of Rubenstein-Goodenough
```

Semantic similarity judgments

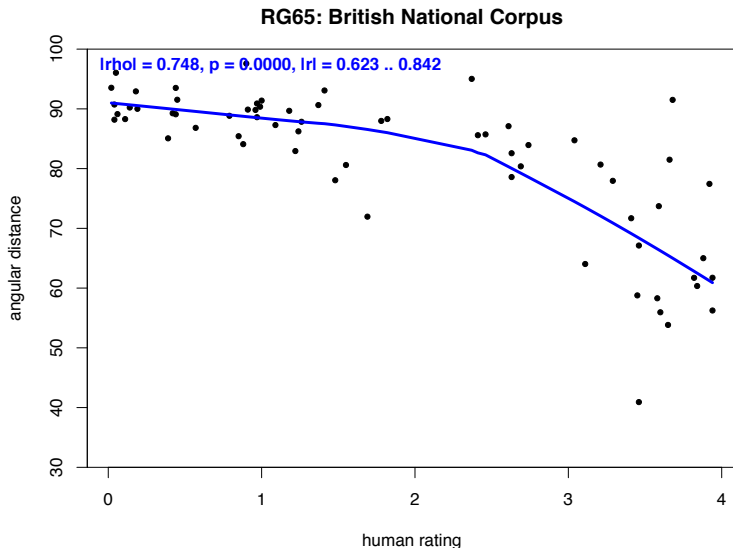
- ▶ Rubenstein and Goodenough (1965) collected similarity ratings for 65 noun pairs from 51 subjects on a 0–4 scale

| w_1 | w_2 | avg. rating |
|-------------|-------------------|-------------|
| <i>car</i> | <i>automobile</i> | 3.9 |
| <i>food</i> | <i>fruit</i> | 2.7 |
| <i>cord</i> | <i>smile</i> | 0.0 |

- ▶ DSMs *vs.* Rubenstein & Goodenough
 1. for each test pair (w_1, w_2) , take vectors \mathbf{w}_1 and \mathbf{w}_2
 2. measure the distance (e.g. cosine) between \mathbf{w}_1 and \mathbf{w}_2
 3. measure (Pearson) correlation between vector distances and R&G average judgments (Padó and Lapata 2007)

```
> RG65[seq(0,65,5), ]
> head(WordSim353) # extension of Rubenstein-Goodenough
```

Semantic similarity judgments: example



Semantic similarity judgments: results

Results on RG65 task:

- ▶ Padó and Lapata's (2007) dependency-based model: 0.62
- ▶ Dependency-based on Web corpus (Herdağdelen *et al.* 2009)
 - ▶ without SVD reduction: 0.69
 - ▶ with SVD reduction: 0.80
- ▶ Distributional memory (Baroni and Lenci 2010): 0.82
- ▶ Salient Semantic Analysis (Hassan and Mihalcea 2011): 0.86

And you?

```
> eval.similarity.correlation(RG65, M, convert=FALSE)
      rho  p.value missing      r r.lower r.upper
RG65 0.687 2.61e-10      0 0.678  0.52  0.791
> plot(eval.similarity.correlation( # cosine similarity
      RG65, M, convert=FALSE, details=TRUE))
```

Noun categorization

- ▶ In **categorization tasks**, subjects are typically asked to assign experimental items – objects, images, words – to a given category or group items belonging to the same category
 - ▶ categorization requires an understanding of the relationship between the items in a category
- ▶ Categorization is a basic cognitive operation presupposed by further semantic tasks
 - ▶ **inference**
 - ★ if X is a CAR then X is a VEHICLE
 - ▶ **compositionality**
 - ★ $\lambda y : \text{FOOD } \lambda x : \text{ANIMATE } [\text{eat}(x, y)]$
- ▶ “Chicken-and-egg” problem for relationship of categorization and similarity (cf. Goodman 1972, Medin et al. 1993)

Noun categorization: the ESSLI 2008 dataset

Dataset of 44 concrete nouns (ESSLI 2008 Shared Task)

- ▶ 24 natural entities
 - ▶ 15 animals: 7 birds (*eagle*), 8 ground animals (*lion*)
 - ▶ 9 plants: 4 fruits (*banana*), 5 greens (*onion*)
- ▶ 20 artifacts
 - ▶ 13 tools (*hammer*), 7 vehicles (*car*)

```
> ESSLI08_Nouns[seq(1,40,5), ]
```

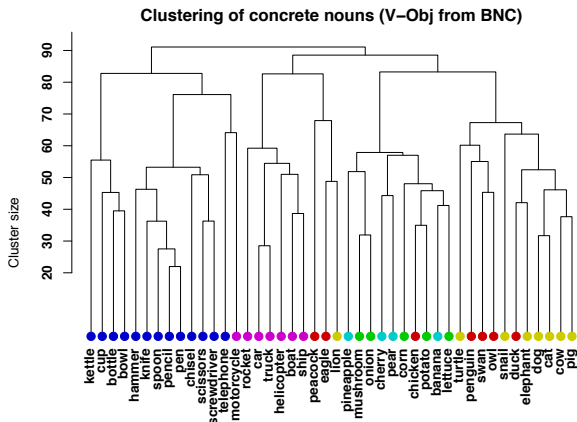
Noun categorization: the ESSLLI 2008 dataset

Dataset of 44 concrete nouns (ESSLLI 2008 Shared Task)

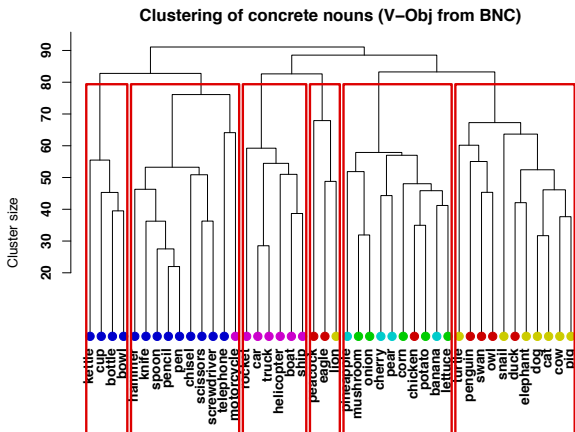
- ▶ 24 natural entities
 - ▶ 15 animals: 7 birds (*eagle*), 8 ground animals (*lion*)
 - ▶ 9 plants: 4 fruits (*banana*), 5 greens (*onion*)
- ▶ 20 artifacts
 - ▶ 13 tools (*hammer*), 7 vehicles (*car*)
- ▶ DSMs operationalize categorization as a **clustering task**
 1. for each noun w_i in the dataset, take its vector \mathbf{w}_i
 2. use a **clustering method** to group similar vectors \mathbf{w}_i
 3. evaluate whether clusters correspond to gold-standard semantic classes (purity, entropy, ...)

```
> ESSLLI08_Nouns[seq(1,40,5), ]
```

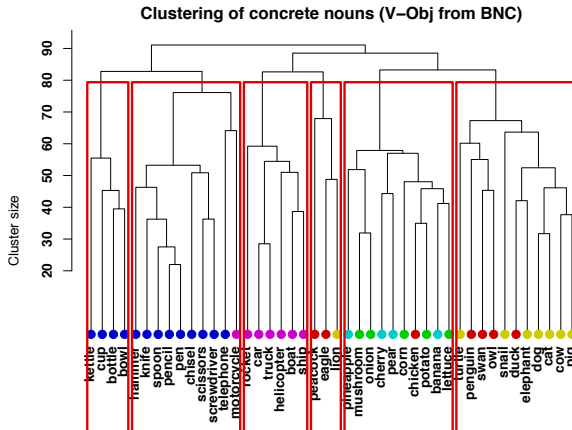
Noun categorization: example



Noun categorization: example

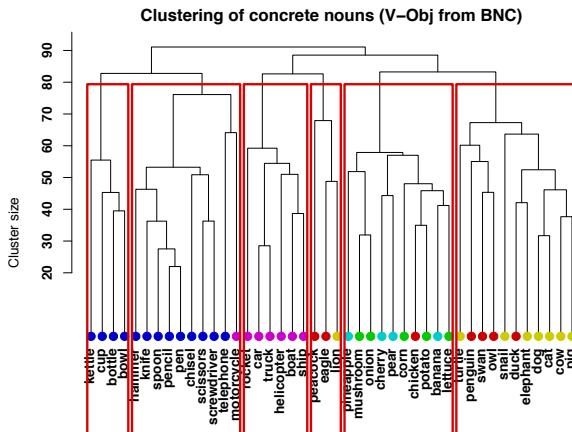


Noun categorization: example



- majority labels: tools, tools, vehicles, birds, greens, animals
- correct: 4/4, 9/10, 6/6, 2/3, 5/10, 7/11

Noun categorization: example



- ▶ majority labels: tools, tools, vehicles, birds, greens, animals
- ▶ correct: 4/4, 9/10, 6/6, 2/3, 5/10, 7/11
- ▶ purity = 33 correct out of 44 = 75.0%

ESSLLI 2008 shared task

- ▶ Clustering experiments with CLUTO (Karypis 2003)
 - ▶ repeated bisection algorithm
 - ▶ 6-way (birds, ground animals, fruits, greens, tools and vehicles), 3-way (animals, plants and artifacts) and 2-way (natural and artificial entities) clusterings

ESSLLI 2008 shared task

- ▶ Clustering experiments with CLUTO (Karypis 2003)
 - ▶ repeated bisection algorithm
 - ▶ 6-way (birds, ground animals, fruits, greens, tools and vehicles), 3-way (animals, plants and artifacts) and 2-way (natural and artificial entities) clusterings
- ▶ Quantitative evaluation
 - ▶ **entropy** – whether words from different classes are represented in the same cluster (**best = 0**)
 - ▶ **purity** – degree to which a cluster contains words from one class only (**best = 1**)
 - ▶ **global score** across the three clustering experiments

$$\sum_{i=1}^3 \text{Purity}_i - \sum_{i=1}^3 \text{Entropy}_i$$

ESSLLI 2008 shared task

| <i>model</i> | <i>6-way</i> | | <i>3-way</i> | | <i>2-way</i> | | <i>global</i> |
|-------------------|--------------|----------|--------------|----------|--------------|----------|---------------|
| | <i>P</i> | <i>E</i> | <i>P</i> | <i>E</i> | <i>P</i> | <i>E</i> | |
| Katrenko | 89 | 13 | 100 | 0 | 80 | 59 | 197 |
| Peirsman+ | 82 | 23 | 84 | 34 | 86 | 55 | 140 |
| dep-typed (DM) | 77 | 24 | 79 | 38 | 59 | 97 | 56 |
| dep-filtered (DM) | 80 | 28 | 75 | 51 | 61 | 95 | 42 |
| window (DM) | 75 | 27 | 68 | 51 | 68 | 89 | 44 |
| Peirsman− | 73 | 28 | 71 | 54 | 61 | 96 | 27 |
| Shaoul | 41 | 77 | 52 | 84 | 55 | 93 | -106 |

Katrenko, Peirsman+/-, Shaoul: ESSLLI 2008 Shared Task
DM: Baroni & Lenci (2009)

And you?

```
> eval.clustering(ESSLLI08_Nouns, M) # uses PAM clustering
```

Semantic priming

- ▶ Hearing/reading a “related” prime facilitates access to a target in various psycholing. tasks (naming, lexical decision, reading)
 - ▶ the word *pear* is recognized faster if heard/read after *apple*

Semantic priming

- ▶ Hearing/reading a “related” prime facilitates access to a target in various psycholing. tasks (naming, lexical decision, reading)
 - ▶ the word *pear* is recognized faster if heard/read after *apple*

- ▶ Hodgson (1991) single word lexical decision task, 136 prime-target pairs (cf. Padó and Lapata 2007)
 - ▶ similar amounts of priming found for different semantic relations between primes and targets (≈ 23 pairs per relation)
 - ★ synonyms (synonym): *to dread/to fear*
 - ★ antonyms (antonym): *short/tall*
 - ★ coordinates (coord): *train/truck*
 - ★ super- and subordinate pairs (supersub): *container/bottle*
 - ★ free association pairs (freeass): *dove/peace*
 - ★ phrasal associates (phrasacc): *vacant/building*

Simulating semantic priming

McDonald and Brew (2004); Padó and Lapata (2007)

- ▶ DSMs and semantic priming
 1. for each related prime-target pair, measure cosine-based similarity between items (e.g., *to dread* / *to fear*)

Simulating semantic priming

McDonald and Brew (2004); Padó and Lapata (2007)

- ▶ DSMs and semantic priming
 1. for each related prime-target pair, measure cosine-based similarity between items (e.g., *to dread* / *to fear*)
 2. to estimate **unrelated primes**, take average of cosine-based similarity of target with other primes from same semantic relation (e.g., *to value* / *to fear*)

Simulating semantic priming

McDonald and Brew (2004); Padó and Lapata (2007)

- ▶ DSMs and semantic priming
 1. for each related prime-target pair, measure cosine-based similarity between items (e.g., *to dread* / *to fear*)
 2. to estimate **unrelated primes**, take average of cosine-based similarity of target with other primes from same semantic relation (e.g., *to value* / *to fear*)
 3. similarity between related items should be significantly higher than average similarity between unrelated items

Simulating semantic priming

McDonald and Brew (2004); Padó and Lapata (2007)

- ▶ DSMs and semantic priming
 1. for each related prime-target pair, measure cosine-based similarity between items (e.g., *to dread* / *to fear*)
 2. to estimate **unrelated primes**, take average of cosine-based similarity of target with other primes from same semantic relation (e.g., *to value* / *to fear*)
 3. similarity between related items should be significantly higher than average similarity between unrelated items
- ▶ Significant effects ($p < .01$) for all semantic relations
 - ▶ strongest effects for synonyms, antonyms & coordinates

Simulating semantic priming

McDonald and Brew (2004); Padó and Lapata (2007)

- ▶ DSMs and semantic priming
 1. for each related prime-target pair, measure cosine-based similarity between items (e.g., *to dread* / *to fear*)
 2. to estimate **unrelated primes**, take average of cosine-based similarity of target with other primes from same semantic relation (e.g., *to value* / *to fear*)
 3. similarity between related items should be significantly higher than average similarity between unrelated items
- ▶ Significant effects ($p < .01$) for all semantic relations
 - ▶ strongest effects for synonyms, antonyms & coordinates
- ▶ Alternative: **classification** task
 - ▶ given target and two primes, identify related prime (→ multiple choice like TOEFL)

Outline

What is semantic similarity?

Semantic similarity and relatedness

Attributional similarity & quantitative evaluation

Parameter evaluation

Evaluation strategies

An example (Bullinaria & Levy 2007, 2012)

A large scale evaluation study

Tasks & parameters

Methodology for DSM Evaluation

Evaluation on Standard Tasks

Summary & conclusion

DSM evaluation in published studies

- ▶ **One model, many tasks** (Padó and Lapata 2007; Baroni and Lenci 2010; Pennington *et al.* 2014)
 - ▶ A novel DSM is proposed, with specific features & parameters
 - ▶ This DSM is tested on a range of different tasks (e.g. TOEFL, priming, semantic clustering)

DSM evaluation in published studies

- ▶ **One model, many tasks** (Padó and Lapata 2007; Baroni and Lenci 2010; Pennington *et al.* 2014)
 - ▶ A novel DSM is proposed, with specific features & parameters
 - ▶ This DSM is tested on a range of different tasks (e.g. TOEFL, priming, semantic clustering)
- ▶ **Incremental tuning of parameters** (Bullinaria and Levy 2007, 2012; Kiela and Clark 2014; Polajnar and Clark 2014)
 - ▶ Several parameters (e.g., scoring measure, distance metric, dimensionality reduction)
 - ▶ Many tasks (e.g. TOEFL, semantic & syntactic clustering)
 - ▶ Varying granularity of parameter settings
 - ▶ One parameter (sometimes two) varied at a time, with all other parameters set to fixed values or optimized for each setting
 - ▶ Optimal parameter values are determined sequentially

Outline

What is semantic similarity?

Semantic similarity and relatedness

Attributional similarity & quantitative evaluation

Parameter evaluation

Evaluation strategies

An example (Bullinaria & Levy 2007, 2012)

A large scale evaluation study

Tasks & parameters

Methodology for DSM Evaluation

Evaluation on Standard Tasks

Summary & conclusion

Bullinaria & Levy (2007, 2012)

- ▶ One of the first systematic evaluation studies
- ▶ Test influence of many standard parameter settings
 - ▶ frequency weighting + distance measure
 - ▶ co-occurrence window, structured *vs.* unstructured
 - ▶ corpus type & size, number of feature dimensions
 - ▶ dimensionality reduction (SVD), number of latent dimension

Bullinaria & Levy (2007, 2012)

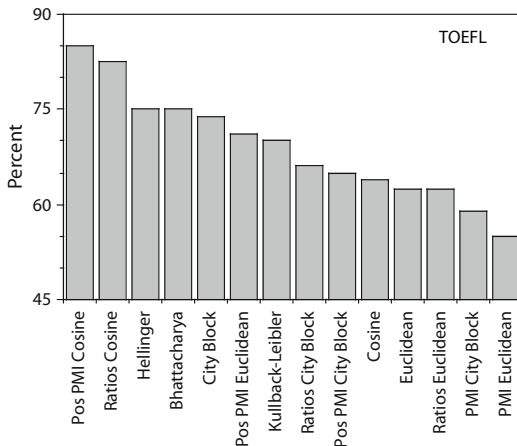
- ▶ One of the first systematic evaluation studies
- ▶ Test influence of many standard parameter settings
 - ▶ frequency weighting + distance measure
 - ▶ co-occurrence window, structured *vs.* unstructured
 - ▶ corpus type & size, number of feature dimensions
 - ▶ dimensionality reduction (SVD), number of latent dimension
- ▶ In four different evaluation tasks
 - ▶ TOEFL
 - ▶ distance comparison: related word *vs.* 10 random words
 - ▶ semantic categorization: nearest-centroid classifier
 - ▶ syntactic categorization (2007)
 - ▶ semantic clustering of nouns (2012)

Bullinaria & Levy (2007, 2012)

- ▶ One of the first systematic evaluation studies
- ▶ Test influence of many standard parameter settings
 - ▶ frequency weighting + distance measure
 - ▶ co-occurrence window, structured *vs.* unstructured
 - ▶ corpus type & size, number of feature dimensions
 - ▶ dimensionality reduction (SVD), number of latent dimension
- ▶ In four different evaluation tasks
 - ▶ TOEFL
 - ▶ distance comparison: related word *vs.* 10 random words
 - ▶ semantic categorization: nearest-centroid classifier
 - ▶ syntactic categorization (2007)
 - ▶ semantic clustering of nouns (2012)
- ▶ Novel parameters
 - ▶ skipping of first latent dimensions (with highest variance)
 - ▶ Caron's (2001) P : power-scaling of singular values

TOEFL results: feature weighting & distance measure

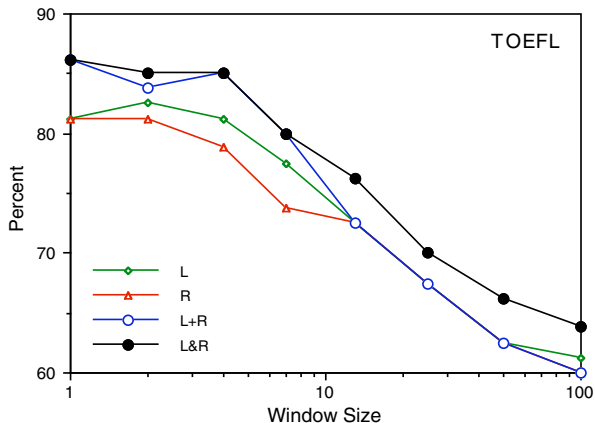
(Bullinaria and Levy 2007, p. 516, Fig. 1)



British National Corpus (BNC). Vectors not L2-normalized (frequency is L1-normalized). All other parameters optimized for each setting.

TOEFL results: size & type of co-occurrence window

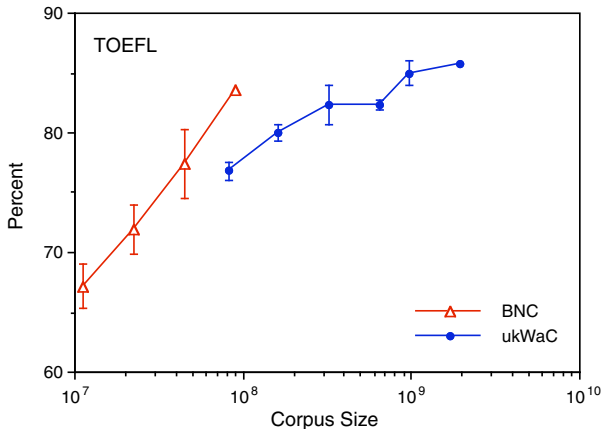
(Bullinaria and Levy 2012, p. 893, Fig. 1)



ukWaC Web corpus. Positive PMI + cosine (Bullinaria and Levy 2007). Number of feature dimensions optimized for each window size & task. No dimensionality reduction. L&R = structured surface context (left/right).

TOEFL results: corpus type & size

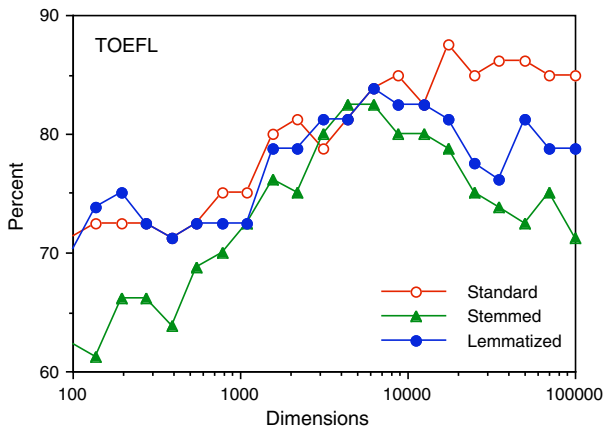
(Bullinaria and Levy 2012, p. 894, Fig. 2)



L+R context of size 1. Average + standard error over equally-sized corpus slices.
Other parameter settings unclear.

TOEFL results: feature dimensions & pre-processing

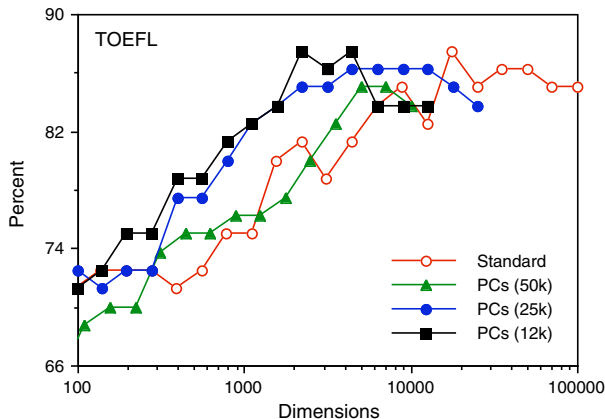
(Bullinaria and Levy 2012, p. 895, Fig. 4)



ukWaC corpus. L+R context of size 1. Other parameters presumably as above.

TOEFL results: dimensionality reduction

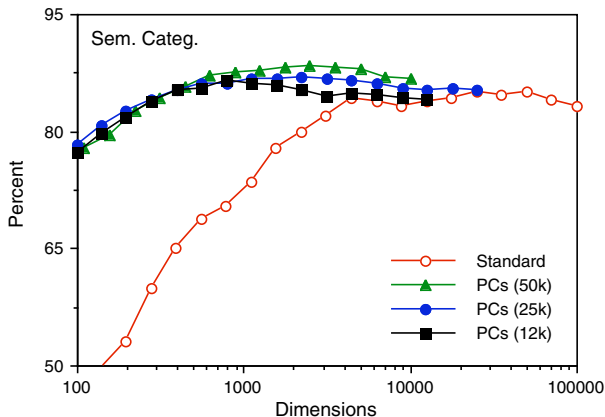
(Bullinaria and Levy 2012, p. 898, Fig. 5)



ukWaC corpus. Positive PMI + cosine. Standard = no dimensionality reduction.
Other: number of latent dimensions for 12k, 25k and 50k original feature dimensions.

Semantic categorization: dimensionality reduction

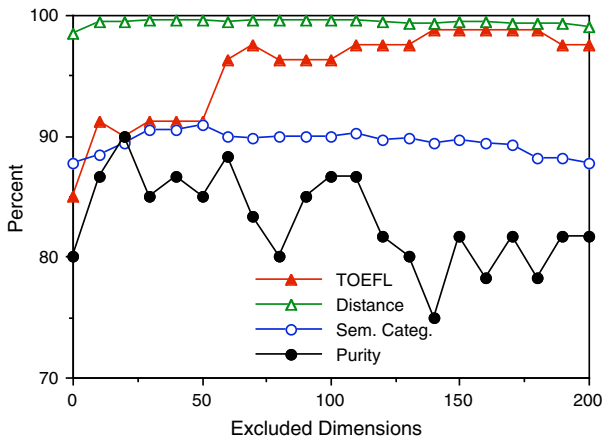
(Bullinaria and Levy 2012, p. 898, Fig. 5)



ukWaC corpus. Positive PMI + cosine. Standard = no dimensionality reduction.
 Other: number of latent dimensions for 12k, 25k and 50k original feature dimensions.

Combined results: skipping first latent dimensions

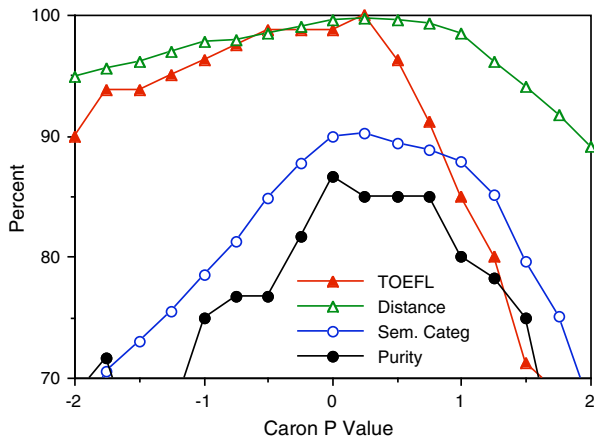
(Bullinaria and Levy 2012, p. 900, Fig. 7)



ukWaC corpus with standard settings. 50k feature dimensions reduced to 5000 latent dimensions.

TOEFL results: power scaling (Caron's P)

(Bullinaria and Levy 2012, p. 900, Fig. 7)



ukWaC corpus with standard settings. 50k feature dimensions reduced to 5000 latent dimensions. Neutral value is $P = 1$.

A (very) large-scale evaluation study

(Lapesa and Evert 2014)

Outline

What is semantic similarity?

Semantic similarity and relatedness

Attributional similarity & quantitative evaluation

Parameter evaluation

Evaluation strategies

An example (Bullinaria & Levy 2007, 2012)

A large scale evaluation study

Tasks & parameters

Methodology for DSM Evaluation

Evaluation on Standard Tasks

Summary & conclusion

Tasks

1. Classification

- ▶ **TOEFL80**: multiple-choice classification task (Landauer and Dumais 1997)

2. Correlation to Similarity Ratings

- ▶ **RG65**: 65 noun pairs (Rubenstein and Goodenough 1965)
- ▶ **WordSim353**: 351 noun pairs (Finkelstein *et al.* 2002)

3. Semantic Clustering

- ▶ **Battig82**: 82 nouns, 10 classes (Van Overschelde *et al.* 2004)
- ▶ **AP402**: 402 nouns, 21 classes (Almuhareb 2006)
- ▶ **ESSLLI08_Nouns**: 44 nouns, 6 classes
- ▶ **Mitchell**: 60 nouns, 12 classes (Mitchell *et al.* 2008)

Distributional models: general features

- ▶ **Term-term** distributional semantic models (bag-of-words)
- ▶ **Target** terms (rows)
 - ▶ vocabulary from Distributional Memory (Baroni and Lenci 2010) + terms from evaluation datasets
 - ▶ 27522 lemma types
- ▶ **Feature** terms (columns)
 - ▶ filtered by part-of-speech (nouns, verbs, adjectives, adverbs)
 - ▶ further context selection determined by two model parameters

Distributional models were compiled and evaluated using the IMS **Corpus Workbench**¹, the **UCS toolkit**² and the **wordspace package** for R.

¹<http://cwb.sf.net/>

²<http://www.collocations.de/software.html>

Evaluated parameters

Building the co-occurrence matrix

1. **Source corpus:** BNC, Wackypedia, UkWac

Our source corpora – standard choices in distributional semantics – differ in both size and quality. Is there a quantity/quality trade-off?

2. **Window** (= surface span)

- ▶ **Direction:** directed (= structured), undirected
- ▶ **Size:** 1, 2, 4, 8, 16 words

We expect those parameters to be crucial as they determine the granularity (direction) and amount (size) of shared context involved in the computation of similarity.

Evaluated parameters

Selecting dimensions from the co-occurrence matrix

3. Feature selection:

- ▶ **Criterion:** frequency, number of non-zero entries
- ▶ **Threshold:** top n dimensions ($n = 5000, 10000, 20000, 50000, 100000$)

How many context dimensions (words) are needed for DSMs to perform well in specific tasks? Are too many context dimensions detrimental? What is the best selection criterion?

Evaluated parameters

Weighting and scaling co-occurrence counts

4. **Feature scoring**: frequency, simple-II, MI, Dice, t-score, z-score, tf.idf

Association measures represent an interpretation of co-occurrence frequency, and they emphasize different types of collocations (Evert 2008). Does this have an effect on DSM performance?

5. **Transformation**: none, logarithmic, square root, sigmoid

Transformations reduce the skewness of feature scores.

Evaluated parameters

Dimensionality reduction

6. Dimensionality reduction with randomized SVD:

- ▶ **number of reduced dimensions**: 100, 300, 500, 700, 900
- ▶ **number of skipped dimensions**: 0, 50, 100

Dimensionality reduction is expected to improve semantic representation and make computations more efficient. How does SVD interact with the other parameters? Bullinaria and Levy (2012) report improvements in some tasks (e.g. TOEFL) when the first latent dimensions (with highest variance) are discarded. Does this result generalize to our tasks/datasets?

Evaluated parameters

Computation and usage of distances

7. **Distance metric:** cosine (angular distance), manhattan

Both are symmetric, while cognitive processes are often asymmetric

8. **Index of distributional relatedness**

- ▶ **distance:** $\text{dist}(a, b)$
- ▶ **neighbor rank**, calculated differently for different tasks:
 - ★ TOEFL: backward rank, i.e. $\text{rank}(b, a)$
 - ★ Ratings and Clustering: average of logarithmic forward and backward rank, i.e. $(\log \text{rank}(a, b) + \log \text{rank}(b, a)) / 2$

This parameter allows us to account for asymmetries: $\text{rank}(b, a)$ is different from $\text{rank}(a, b)$. While cognitively plausible, neighbor rank is computationally expensive: does it improve the performance of DSMs?

Outline

What is semantic similarity?

Semantic similarity and relatedness

Attributional similarity & quantitative evaluation

Parameter evaluation

Evaluation strategies

An example (Bullinaria & Levy 2007, 2012)

A large scale evaluation study

Tasks & parameters

Methodology for DSM Evaluation

Evaluation on Standard Tasks

Summary & conclusion

How many models did we end up with?

... and how do we make sense of all those results?

- ▶ We tested all the possible parameter combinations (we will see later that this is crucial for our evaluation methodology)
- ▶ **537600 model runs** (33600 in the unreduced setting, 504000 in the reduced setting)
- ▶ The models were generated and evaluated on a large HPC cluster at FAU Erlangen-Nürnberg as well as servers at the University of Stuttgart, within approximately 5 weeks

Evaluation methodology: linear regression

Our proposal for a robust evaluation of DSM parameters

- ▶ Attempts to predict the values of a “dependent” variable from one or more “independent” variables and their combinations
- ▶ Is used to understand **which independent variables are closely related to the dependent variable**, and to **explore the forms of these relationships**

Example

Dependent variable: income

Independent variables: gender, age, ethnicity, education level, first letter of the surname (hopefully not significant)

Evaluation methodology: linear regression

Our proposal for a robust evaluation of DSM parameters

We use linear models to analyze the influence of different DSM parameters and their combinations on DSM performance

- ▶ dependent variable = **performance**
(accuracy, correlation coefficient, purity)
- ▶ independent variables = model **parameters**
(e.g., source corpus, window size, window direction)

We want to understand which of the parameters are related to the dependent variable, i.e., we want to find the parameters whose manipulation has the strongest effect on DSM performance.

DSM evaluation and linear regression

Toy example: a $2 \times 2 \times 2$ design

| Corpus | Window size | Window direction | Accuracy |
|--------|-------------|------------------|----------|
| ukWaC | 1 | directed | 88 |
| ukWaC | 16 | undirected | 92 |
| ukWaC | 1 | directed | 91 |
| ukWaC | 16 | undirected | 93 |
| BNC | 1 | undirected | 80 |
| BNC | 16 | undirected | 53 |
| BNC | 1 | directed | 72 |
| BNC | 16 | directed | 71 |

$$\begin{aligned}
 \text{Accuracy} = & \beta_0 + \beta_1(\text{corpus}) + \beta_2(\text{window size}) + \beta_3(\text{window direction}) \\
 & + \beta_4(\text{corpus: window size}) + \beta_5(\text{corpus: window direction}) + \\
 & + \beta_6(\text{window size: window direction}) + \epsilon
 \end{aligned}$$

*we're aware that this regression model is almost saturated ...

DSM evaluation and linear regression

Analysis of variance

Goal: quantify the impact of a specific parameter (or interaction) on DSM performance, in terms of the proportion of variance explained by the parameter

Key notions:

- ▶ R^2 (R squared)
 - ▶ proportion of explained variance, i.e.

$$1 - \frac{\text{residual variance of } \epsilon}{\text{variance of dependent variable}}$$

- ▶ calculated (i) for the full model (→ how well the model explains the experimental results) as well as (ii) for specific parameters and interactions (quantifying how much they contribute to predictions)
- ▶ Feature ablation

DSM evaluation and linear regression

Analysis of variance: feature ablation

Feature ablation

Proportion of variance explained by a parameter together with all its interactions, corresponding to the reduction in R^2 of the linear model fit if this parameter is left out.

In our toy model with 3 parameters and all two-way interactions:

- ▶ $\text{Ablation}(\text{corpus}) = R^2(\text{corpus}) + R^2(\text{corpus: window size}) + R^2(\text{corpus: window direction})$
- ▶ $\text{Ablation}(\text{window size}) = R^2(\text{window size}) + R^2(\text{corpus: window size}) + R^2(\text{window size: window direction})$
- ▶ $\text{Ablation}(\text{window direction}) = R^2(\text{window direction}) + R^2(\text{corpus: window direction}) + R^2(\text{window size: window direction})$

Outline

What is semantic similarity?

Semantic similarity and relatedness

Attributional similarity & quantitative evaluation

Parameter evaluation

Evaluation strategies

An example (Bullinaria & Levy 2007, 2012)

A large scale evaluation study

Tasks & parameters

Methodology for DSM Evaluation

Evaluation on Standard Tasks

Summary & conclusion

TOEFL multiple-choice classification task

Introducing the task

A collection of 80 multiple-choice questions from a synonym task in the Test Of English as a Foreign Language (TOEFL)

TOEFL dataset

Target: *consume* – Choices: *breed*, *catch*, *eat*, *supply*

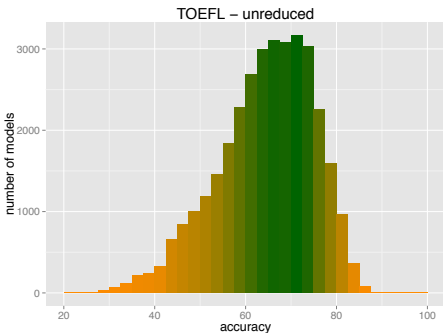
Target: *constant* – Choices: *accidental*, *continuing*, *instant*, *rapid*

Target: *concise* – Choices: *free*, *positive*, *powerful*, *succinct*

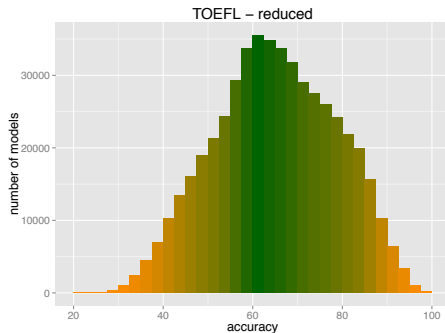
- ▶ A **classification** task
- ▶ If DSMs capture synonymy relations, we expect that **the distance between the target and the correct choice will be smaller than to the wrong choices**
- ▶ Performance: **% accuracy**

TOEFL task: performance

Unreduced versus Reduced Experiments



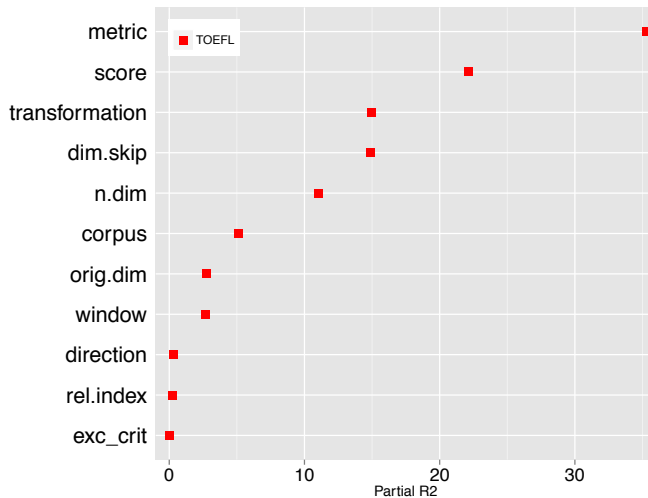
Min: 25 ; Max: 87.5 ; Mean: 63.9



Min: 18.7; Max: 97.4; Mean: 64.4

TOEFL task: parameters and explained variance

Reduced setting: feature Ablation (model R^2 : 89%)



TOEFL task: interactions

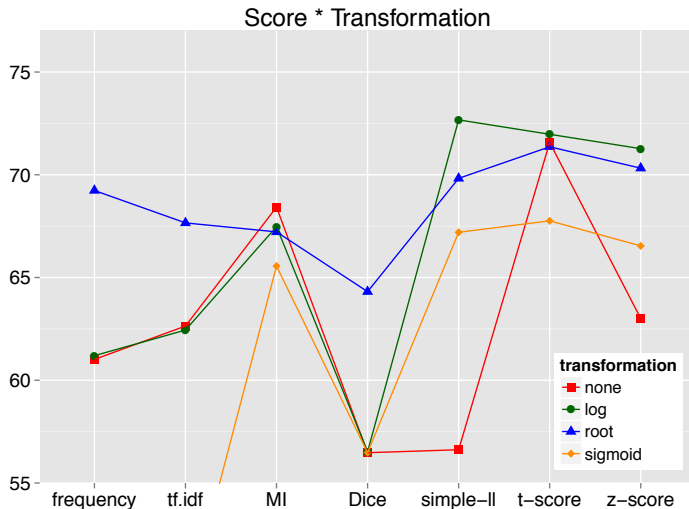
Reduced setting ($R^2 > 0.5$)

| Interaction | Df | R^2 |
|-----------------------|----|-------|
| score:transformation | 18 | 7.42 |
| metric:dim.skip | 2 | 4.44 |
| score:metric | 6 | 1.77 |
| metric:orig.dim | 4 | 0.98 |
| window:transformation | 12 | 0.91 |
| corpus:score | 12 | 0.84 |
| score:orig.dim | 24 | 0.64 |
| metric:n.dim | 4 | 0.63 |

TOEFL task: interactions, R^2

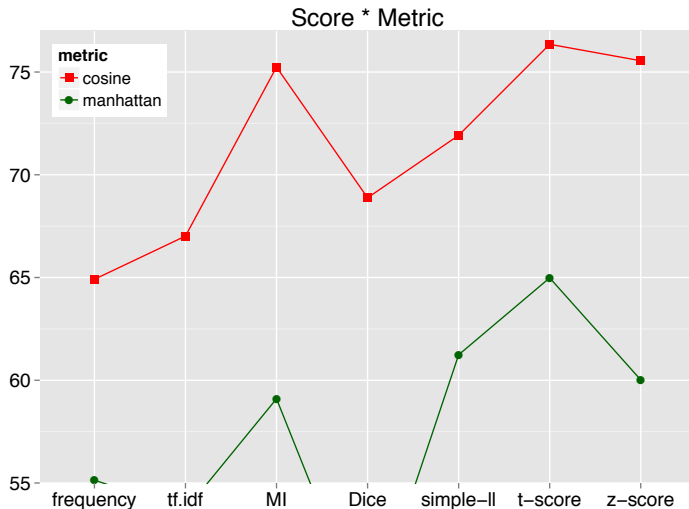
TOEFL task: Metric, Score, Transformation

Partial effect displays (Fox 2003)



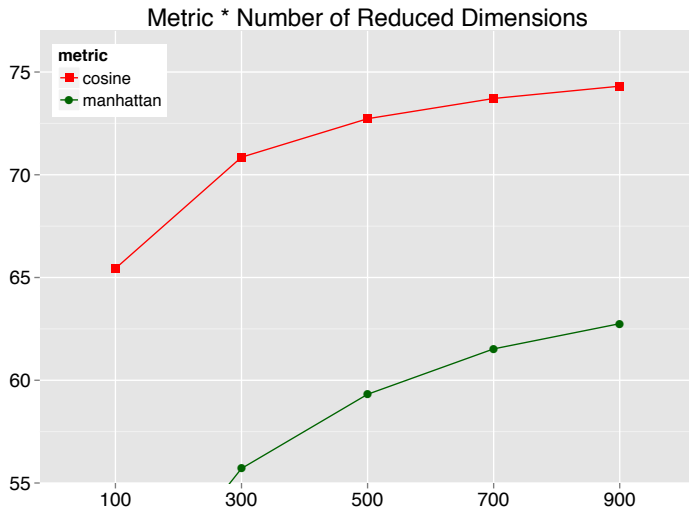
TOEFL task: Metric, Score, Transformation

Partial effect displays (Fox 2003)



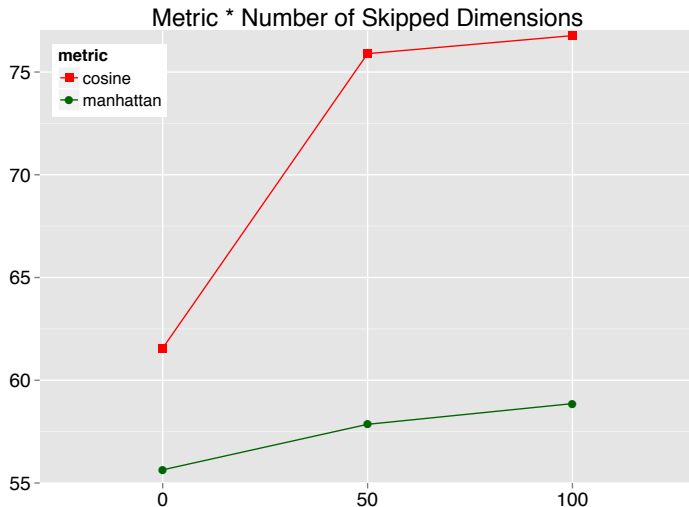
TOEFL task: Dimensionality Reduction

Partial effect displays (Fox 2003)



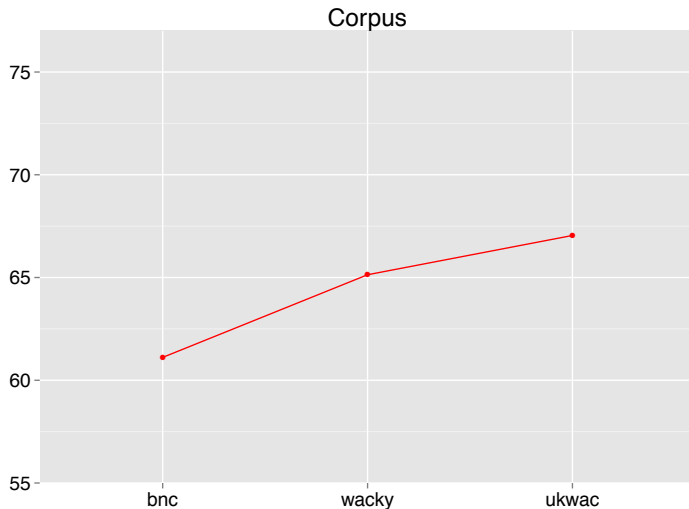
TOEFL task: Dimensionality Reduction

Partial effect displays (Fox 2003)



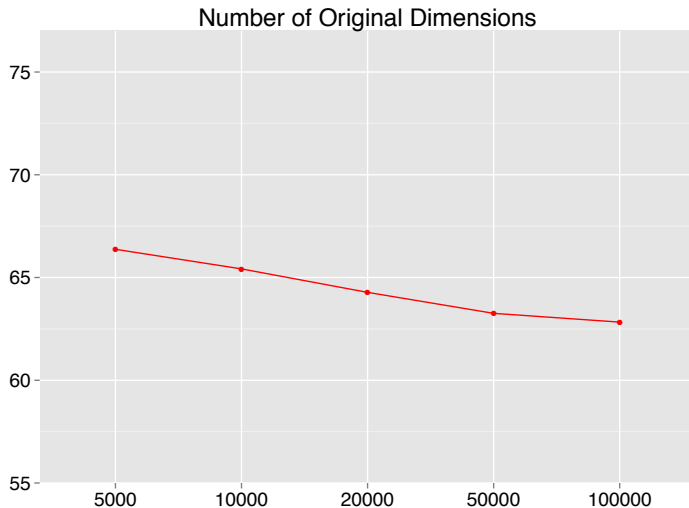
TOEFL task: Corpus and Number of Feature Dimensions

Partial effect displays (Fox 2003)



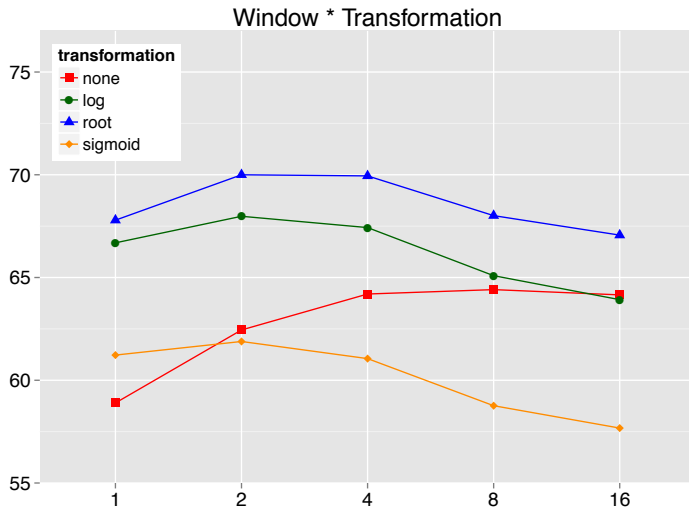
TOEFL task: Corpus and Number of Feature Dimensions

Partial effect displays (Fox 2003)



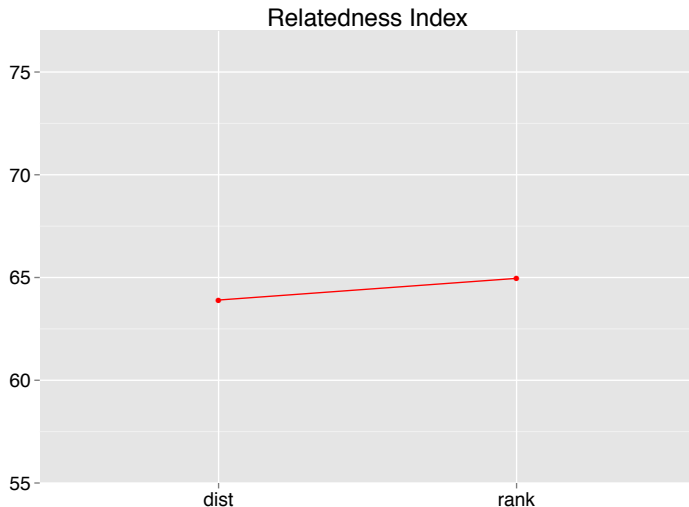
TOEFL task: Window and Relatedness Index

Partial effect displays (Fox 2003)



TOEFL task: Window and Relatedness Index

Partial effect displays (Fox 2003)



TOEFL task: summary

TOEFL: best setting

- ▶ Corpus: ukWac
- ▶ Window: undirected, 2 words
- ▶ Feature selection: top 5000/10000 dimensions, based on frequency
- ▶ Score * Transformation: simple-ll * log
- ▶ Dimensionality Reduction: 900 latent dimensions, skipping the first 100
- ▶ Distance Metric: cosine
- ▶ Index of Distributional Relatedness: neighbor rank

DSMs and similarity ratings

Introducing the task

RG65

65 pairs, rated from 0 to 4

gem – *jewel*: 3.94

grin – *smile*: 3.46

fruit – *furnace*: 0.05

WordSim353

353 pairs, rated from 1 to 10

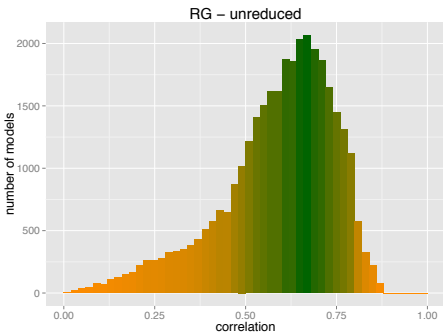
announcement – *news*: 7.56

weapon – *secret*: 6.06

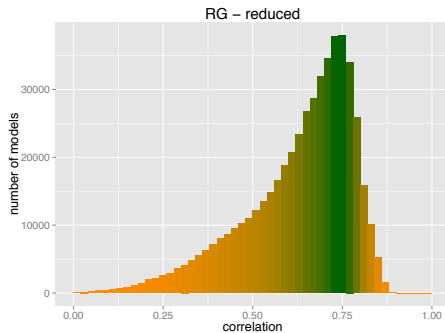
travel – *activity*: 5.00

- ▶ A **prediction** task
- ▶ If distributional representation are close to speakers' conceptual representations, we expect to find some **correlation** between distance in the semantic space and speaker's judgments concerning semantic similarity
- ▶ Performance: **Pearson correlation** r

Similarity ratings: performance on RG65

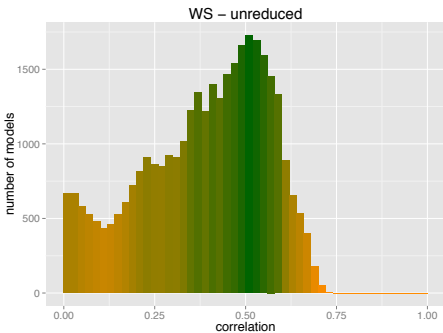


Min: 0.01; Max: 0.88; Mean 0.59
unreduced

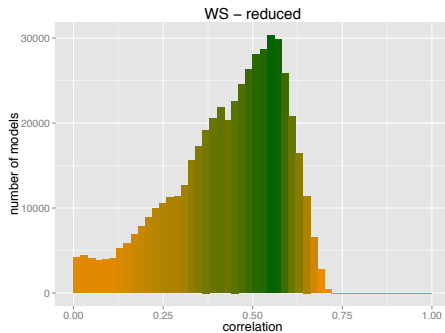


Min: 0.00; Max: 0.89; Mean: 0.63
reduced

Similarity ratings: performance on WordSim353



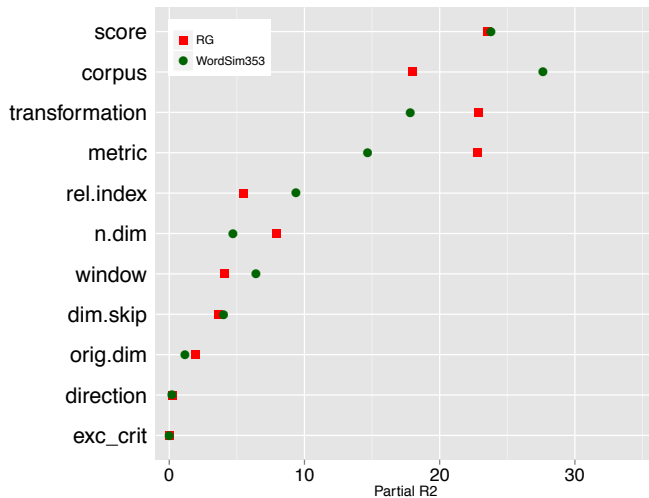
Min: 0.00; Max: 0.73; Mean: 0.39
unreduced



Min: 0.00; Max: 0.73; Mean: 0.43
reduced

Similarity ratings: parameters and explained variance

Reduced setting: feature ablation (full model R^2 : RG65 86%; WS353 90%)



Similarity ratings: interactions

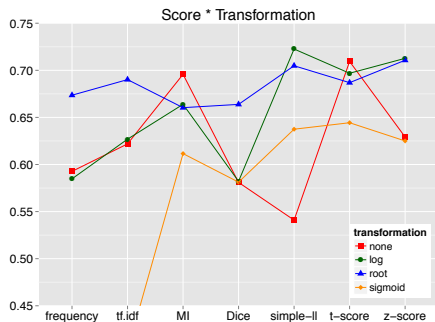
Reduced setting ($R^2 > 0.5$)

| Interaction | Df | RG65 | WordSim353 |
|-----------------|----|-------|------------|
| score:transf | 18 | 10.28 | 8.66 |
| metric:n.dim | 4 | 2.18 | 1.42 |
| window:transf | 12 | 1.43 | 1.01 |
| corpus:metric | 2 | 1.83 | 0.51 |
| score:metric | 6 | 1.91 | 0.59 |
| metric:orig.dim | 4 | 1.08 | 0.62 |
| corpus:score | 12 | 0.77 | 0.82 |
| window:score | 24 | 0.77 | 0.69 |
| score:dim.skip | 12 | 0.58 | 0.85 |

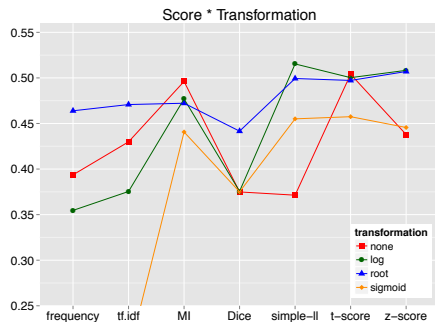
Similarity ratings: interactions, R^2

Similarity ratings: Score, Transformation

Partial effect displays (Fox 2003)



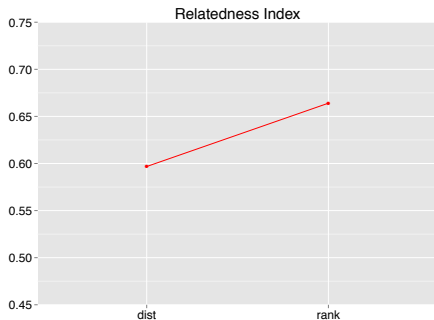
Rubenstein & Goodenough



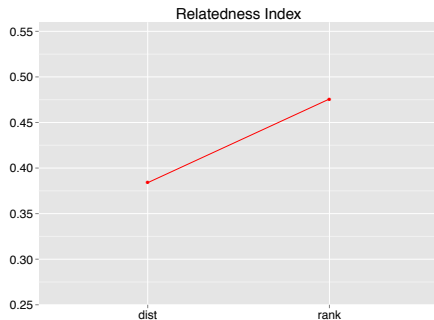
WordSim-353

Similarity ratings: Relatedness Index

Partial effect displays (Fox 2003)



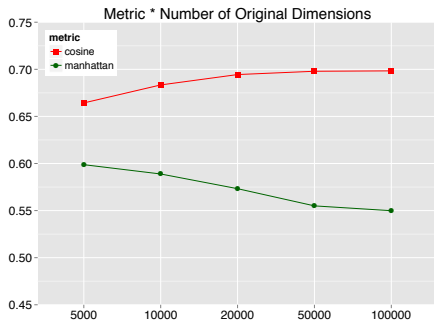
Rubenstein & Goodenough



WordSim-353

Similarity ratings: Metric, Number of Feature Dimensions

Partial effect displays (Fox 2003)



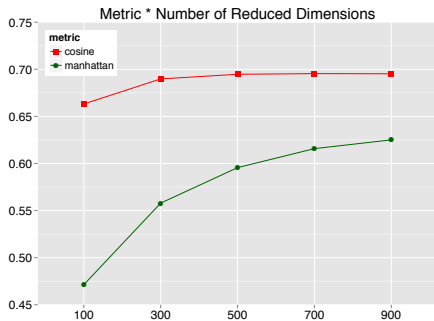
Rubenstein & Goodenough



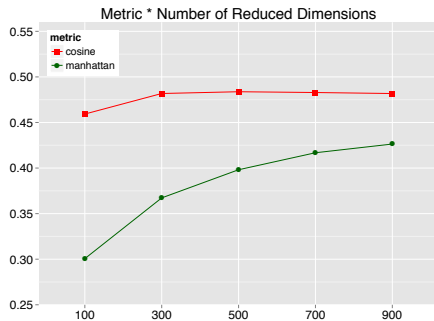
WordSim-353

Similarity ratings: Number of Latent Dimensions

Partial effect displays (Fox 2003)



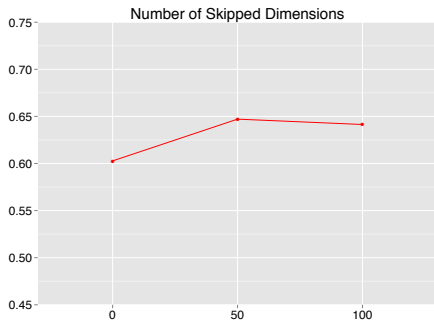
Rubenstein & Goodenough



WordSim-353

Similarity ratings: Number of Skipped Dimensions

Partial effect displays (Fox 2003)



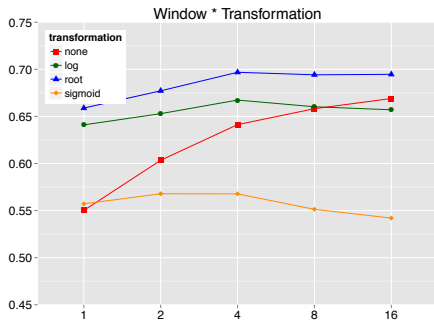
Rubenstein & Goodenough



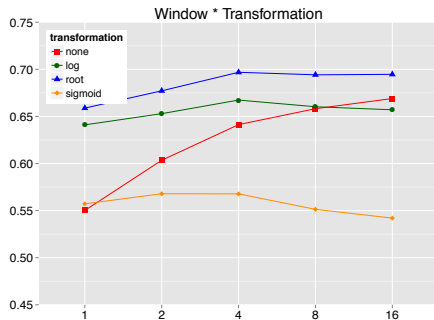
WordSim-353

Similarity ratings: Window Size, Transformation

Partial effect displays (Fox 2003)



Rubenstein & Goodenough



WordSim-353

Summing up: Ratings

Ratings: best setting

- ▶ Corpus: wacky
- ▶ Window: undirected, 4 words
- ▶ Feature selection: top 20000/50000 dimensions, based on frequency
- ▶ Score * Transformation: $\text{simple-ll} * \log$
- ▶ Dimensionality Reduction: 300 latent dimensions, skipping the first 50
- ▶ Distance Metric: cosine
- ▶ Index of Distributional Relatedness: neighbor rank

DSMs and semantic clustering

Introducing the task

Almuhareb & Poesio

402 nouns, 21 classes

day \Rightarrow TIME

kiwi \Rightarrow FRUIT

kitten \Rightarrow ANIMAL

volleyball \Rightarrow GAME

BATTIG set

82 nouns, 10 classes

chicken \Rightarrow BIRD

bear \Rightarrow LAND_MAMMAL

pot \Rightarrow KITCHENWARE

oak \Rightarrow TREE

ESSLLI categorization task

44 nouns, 6 classes

potato \Rightarrow GREEN

hammer \Rightarrow TOOL

car \Rightarrow VEHICLE

peacock \Rightarrow BIRD

MITCHELL set

60 nouns, 12 classes

ant \Rightarrow INSECT

carrot \Rightarrow VEGETABLE

train \Rightarrow VEHICLE

cat \Rightarrow ANIMAL

DSMs and semantic clustering

Introducing the task

- ▶ A **categorization** task
- ▶ If distributional representations approximate human conceptual representations, we expect word categorization based on distributional features to produce concept clusters similar to those in the gold standard datasets
- ▶ Performance: **cluster purity**
 - ▶ classification accuracy for optimal cluster labelling
 - ▶ percentage of nouns that belong to the majority category within their cluster

DSMs and semantic clustering

Introducing the task

- ▶ A **categorization** task
- ▶ If distributional representations approximate human conceptual representations, we expect word categorization based on distributional features to produce concept clusters similar to those in the gold standard datasets
- ▶ Performance: **cluster purity**
 - ▶ classification accuracy for optimal cluster labelling
 - ▶ percentage of nouns that belong to the majority category within their cluster
- ▶ **Partitioning around medoids** (Kaufman and Rousseeuw 1990)
 - ▶ implemented as `pam()` in R standard library
 - ▶ direct comparison → equal to or even better than CLUTO
 - ▶ works with arbitrary dissimilarity matrix

Semantic clustering: performance

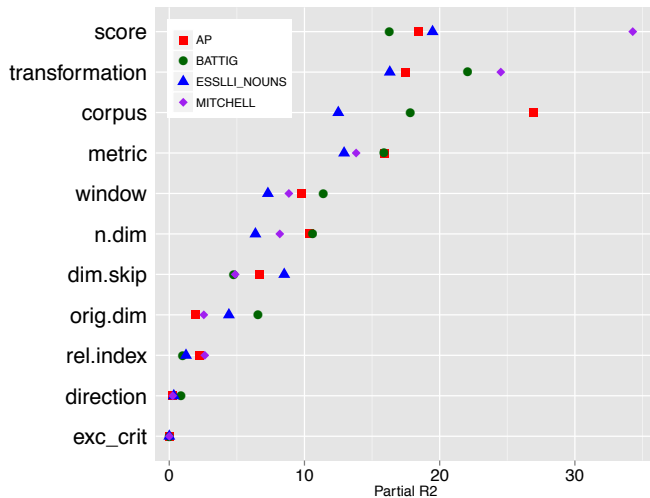
Overview: unreduced versus reduced experiments

| Dataset | Unreduced | | | Reduced | | |
|----------|-----------|------|------|---------|------|------|
| | Min | Max | Mean | Min | Max | Mean |
| AP | 0.15 | 0.73 | 0.56 | 0.13 | 0.76 | 0.54 |
| BATTIG | 0.28 | 0.99 | 0.77 | 0.23 | 0.99 | 0.78 |
| ESSLLI | 0.32 | 0.93 | 0.72 | 0.32 | 0.98 | 0.72 |
| MITCHELL | 0.26 | 0.97 | 0.68 | 0.27 | 0.97 | 0.69 |

Semantic clustering: summary of performance (purity)

Semantic clustering: parameters and explained variance

Feature ablation (model R^2 – AP: 82%; BATTIG: 77%; ESSLLI 58%; MITCHELL 73%)



Semantic clustering: interactions

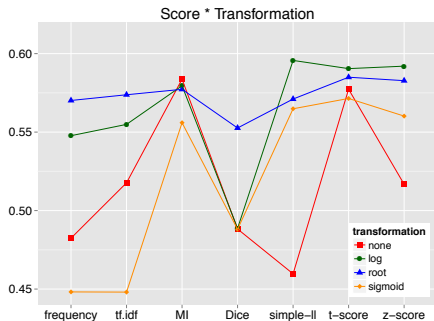
Reduced setting ($R^2 > 0.5$)

| Interaction | Df | AP | BATTIG | ESSLLI | MITCHELL |
|-----------------------|----|------|--------|--------|----------|
| score:transformation | 18 | 7.10 | 7.95 | 7.56 | 11.42 |
| window:metric | 4 | 2.22 | 1.26 | 2.97 | 2.72 |
| metric:n.dim | 4 | 3.29 | 3.16 | 2.03 | 0.58 |
| metric:dim.skip | 2 | 2.25 | 1.54 | 2.77 | 0.86 |
| window:transformation | 12 | 2.00 | 2.95 | 0.88 | 2.66 |
| corpus:metric | 2 | 1.42 | 2.91 | 2.79 | 1.11 |
| corpus>window | 8 | 2.36 | 1.18 | 1.49 | 1.23 |
| score:dim.skip | 12 | 0.56 | 1.15 | 0.99 | 1.39 |
| window:score | 24 | 0.74 | 0.77 | 0.54 | 0.65 |

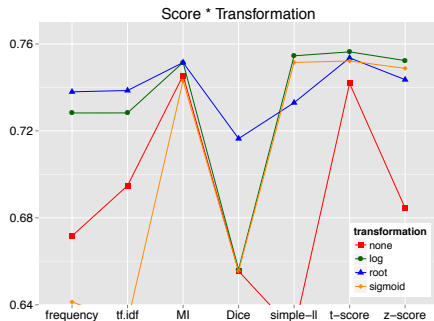
Clustering datasets: interactions, R^2

Semantic clustering: Score, Transformation

Partial effect displays (Fox 2003)



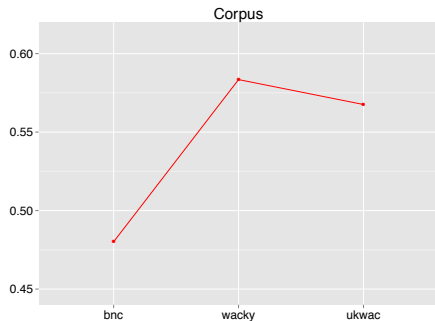
Almuhareb & Poesio



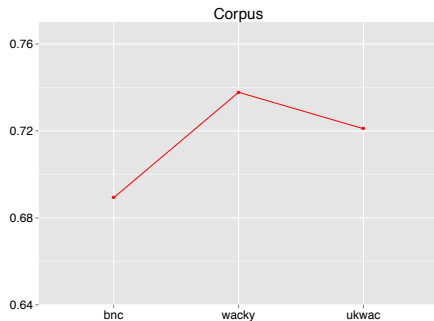
ESSLI 2008

Semantic clustering: Corpus

Partial effect displays (Fox 2003)



Almuhareb & Poesio

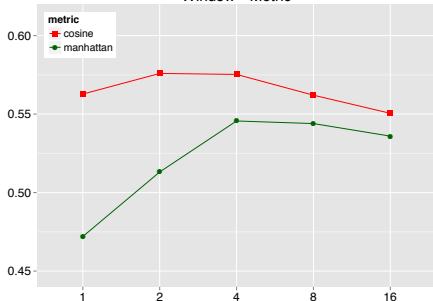


ESSLI 2008

Semantic clustering: Window Size, Metric

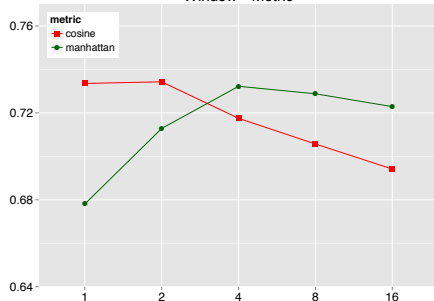
Partial effect displays (Fox 2003)

Window * Metric



Almuhareb & Poesio

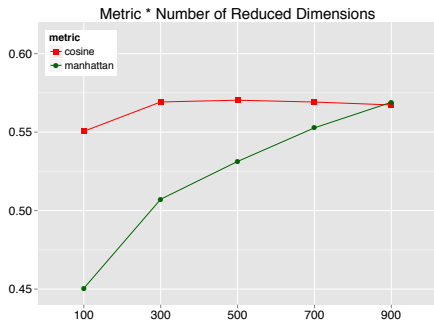
Window * Metric



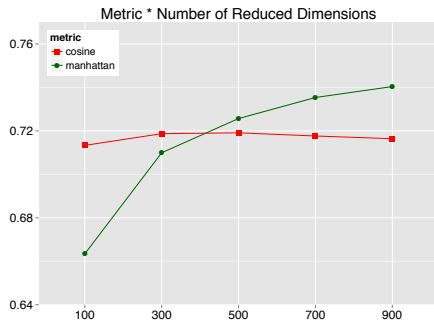
ESSLI 2008

Semantic clustering: Metric, Number of Latent Dimensions

Partial effect displays (Fox 2003)



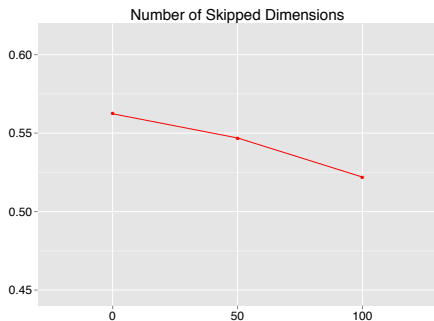
Almuhareb & Poesio



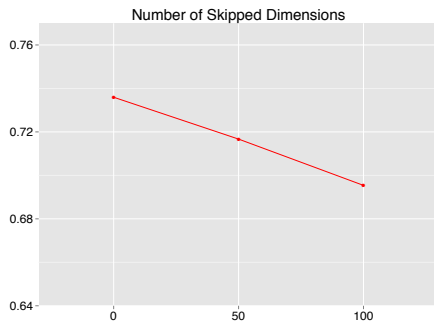
ESSLI 2008

Semantic clustering: Number of Skipped Dimensions

Partial effect displays (Fox 2003)



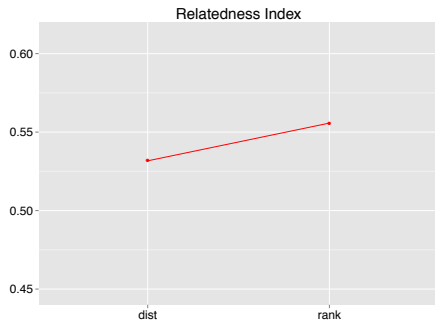
Almuhareb & Poesio



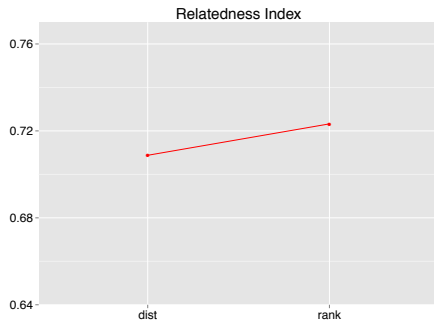
ESSLI 2008

Semantic clustering: Relatedness Index

Partial effect displays (Fox 2003)



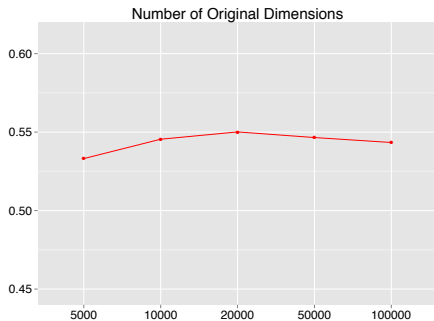
Almuhareb & Poesio



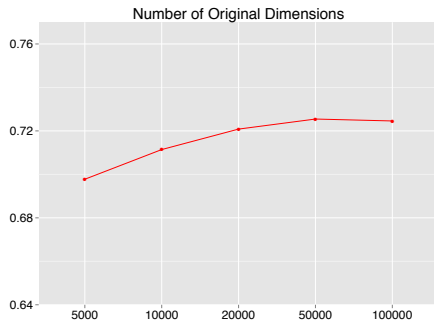
ESSLI 2008

Semantic clustering: Number of Feature Dimensions

Partial effect displays (Fox 2003)



Almuhareb & Poesio



ESSLI 2008

Summing up: Semantic Clustering

Clustering: best setting

- ▶ Corpus: wacky
- ▶ Window: undirected, 4 words
- ▶ Feature selection: top 50000 dimensions, based on frequency
- ▶ Score * Transformation: simple-ll * log (or t-score * log)
- ▶ Dimensionality Reduction: 300/500 latent dimensions, no skipping necessary
- ▶ Distance Metric: cosine
- ▶ Index of Distributional Relatedness: neighbor rank

Outline

What is semantic similarity?

Semantic similarity and relatedness

Attributional similarity & quantitative evaluation

Parameter evaluation

Evaluation strategies

An example (Bullinaria & Levy 2007, 2012)

A large scale evaluation study

Tasks & parameters

Methodology for DSM Evaluation

Evaluation on Standard Tasks

Summary & conclusion

Does our evaluation methodology work?

1. What are the most explanatory parameters?
2. By inspecting the effect plots, we identified best settings for every dataset: what is the performance of such best settings? Are they close to the best runs in the experiment?
3. Is it possible to identify a general best setting that performs reasonably well across all tasks?

Summary: parameters

- ▶ Parameters with strong effect on DSM performance and homogeneous behavior across tasks and datasets
 - ▶ score
 - ▶ transformation
 - ▶ distance metric

Summary: parameters

- ▶ Parameters with strong effect on DSM performance and homogeneous behavior across tasks and datasets
 - ▶ score
 - ▶ transformation
 - ▶ distance metric
- ▶ Parameters with strong effect on DSM performance, but differences across tasks
 - ▶ dimensionality reduction parameters
 - ▶ window
 - ▶ corpus (to a lesser extent)

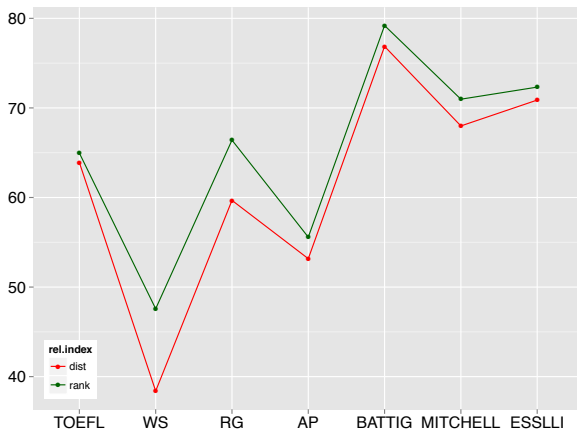
Summary: parameters

- ▶ Parameters with strong effect on DSM performance and homogeneous behavior across tasks and datasets
 - ▶ score
 - ▶ transformation
 - ▶ distance metric
- ▶ Parameters with strong effect on DSM performance, but differences across tasks
 - ▶ dimensionality reduction parameters
 - ▶ window
 - ▶ corpus (to a lesser extent)
- ▶ A less crucial parameter with homogeneous behavior
 - ▶ number of context dimensions

Summary: parameters

- ▶ Parameters with strong effect on DSM performance and homogeneous behavior across tasks and datasets
 - ▶ score
 - ▶ transformation
 - ▶ distance metric
- ▶ Parameters with strong effect on DSM performance, but differences across tasks
 - ▶ dimensionality reduction parameters
 - ▶ window
 - ▶ corpus (to a lesser extent)
- ▶ A less crucial parameter with homogeneous behavior
 - ▶ number of context dimensions
- ▶ Parameters that have no or little effect on DSM performance
 - ▶ criterion for context selection
 - ▶ direction of the context window

How about the index of distributional relatedness?



Best settings and their performance

| dataset | corpus | w | o.dim | sc | tr | m | rel.ind | n.dim | d.sk | best.s | best.m |
|----------|--------|---|-------|------|-----|-----|---------|-------|------|--------|--------|
| TOEFL | ukwac | 2 | 5k | s-ll | log | cos | rank | 900 | 100 | 92.5 | 98.75 |
| WS | wacky | 4 | 50k | s-ll | log | cos | rank | 300 | 50 | 0.67 | 0.73 |
| RG | wacky | 4 | 50k | s-ll | log | cos | rank | 300 | 50 | 0.86 | 0.89 |
| AP | wacky | 4 | 20k | s-ll | log | cos | rank | 300 | 0 | 0.69 | 0.76 |
| BATTIG | wacky | 8 | 50k | s-ll | log | cos | rank | 500 | 0 | 0.98 | 0.99 |
| ESSLLI | wacky | 2 | 20k | t-sc | log | cos | rank | 300 | 0 | 0.77 | 0.98 |
| MITCHELL | wacky | 4 | 50k | s-ll | log | cos | rank | 500 | 0 | 0.88 | 0.97 |

Best settings for each dataset

w = window size, o.dim = number of feature dimensions, sc = scoring function, tr = transformation, m = metric, d.sk = number of skipped dimensions, best.s = performance of best setting for this dataset, best.m = performance of best run for this dataset

General settings

| task | corpus | w | o.dim | sc | tr. | m | rel.ind | n.dim | d.sk |
|------------|--------|---|-------|------|-----|-----|---------|-------|------|
| TOEFL | ukwac | 2 | 5k | s-ll | log | cos | rank | 900 | 100 |
| Rating | wacky | 4 | 50k | s-ll | log | cos | rank | 300 | 50 |
| Clustering | wacky | 4 | 50k | s-ll | log | cos | rank | 500 | 0 |
| General | wacky | 4 | 50k | s-ll | log | cos | rank | 500 | 50 |

General best settings

General settings

| task | corpus | w | o.dim | sc | tr. | m | rel.ind | n.dim | d.sk |
|------------|--------|---|-------|------|-----|-----|---------|-------|------|
| TOEFL | ukwac | 2 | 5k | s-ll | log | cos | rank | 900 | 100 |
| Rating | wacky | 4 | 50k | s-ll | log | cos | rank | 300 | 50 |
| Clustering | wacky | 4 | 50k | s-ll | log | cos | rank | 500 | 0 |
| General | wacky | 4 | 50k | s-ll | log | cos | rank | 500 | 50 |

General best settings

| Task | TOEFL | RATINGS | CLUSTERING | GENERAL | SoA |
|----------|-------|---------|------------|---------|-------|
| TOEFL | 92.5 | 85.0 | 75.0 | 90.0 | 100.0 |
| RG | 0.85 | 0.86 | 0.84 | 0.87 | 0.86 |
| WS | 0.60 | 0.67 | 0.64 | 0.68 | 0.81 |
| AP402 | 0.60 | 0.66 | 0.67 | 0.67 | 0.79 |
| BATTIG | 0.85 | 0.91 | 0.98 | 0.90 | 0.96 |
| ESSLLI | 0.70 | 0.77 | 0.80 | 0.77 | 0.91 |
| MITCHELL | 0.73 | 0.83 | 0.88 | 0.83 | 0.94 |

General best settings – Performance

Conclusion

- ▶ Our results show that it is possible to find a single DSM configuration that performs relatively well on every task
- ▶ The most explanatory parameters show similar behavior across all tasks and datasets
 - ▶ Simple-II * Logarithmic Transformation
 - ▶ Cosine Distance
- ▶ Parameters that show variation determine the amount and nature of the shared context
 - ▶ Context window: 4 is a good compromise solution
 - ▶ Dimensionality reduction: skipping the first dimensions (but not too many) generally helps
 - ▶ Number of Feature Terms (to a lesser extent)

Conclusion

- ▶ Among the source corpora, WaCkypedia appears to be a better option than UkWaC for all tasks but TOEFL
 - ▶ A good trade-off between quantity and quality?
- ▶ As an index of distributional relatedness, neighbor rank is always better than distance, even if its contribution to model performance varies across tasks
 - ▶ Perhaps some tasks/datasets are less asymmetric than others?
 - ▶ may need to exploit directionality in a more granular way

References I

- Almuhareb, Abdulrahman (2006). *Attributes in Lexical Acquisition*. Ph.D. thesis, University of Essex.
- Baroni, Marco and Lenci, Alessandro (2008). Concepts and properties in word spaces. *Italian Journal of Linguistics*, **20**(1).
- Baroni, Marco and Lenci, Alessandro (2010). Distributional Memory: A general framework for corpus-based semantics. *Computational Linguistics*, **36**(4), 673–712.
- Budanitsky, Alexander and Hirst, Graeme (2006). Evaluating WordNet-based measures of lexical semantic relatedness. *Computational Linguistics*, **32**(1), 13–47.
- Bullinaria, John A. and Levy, Joseph P. (2007). Extracting semantic representations from word co-occurrence statistics: A computational study. *Behavior Research Methods*, **39**(3), 510–526.
- Bullinaria, John A. and Levy, Joseph P. (2012). Extracting semantic representations from word co-occurrence statistics: Stop-lists, stemming and SVD. *Behavior Research Methods*, **44**(3), 890–907.
- Caron, John (2001). Experiments with LSA scoring: Optimal rank and basis. In M. W. Berry (ed.), *Computational Information Retrieval*, pages 157–169. Society for Industrial and Applied Mathematics, Philadelphia, PA, USA.

References II

- Evert, Stefan (2008). Corpora and collocations. In A. Lüdeling and M. Kytö (eds.), *Corpus Linguistics. An International Handbook*, chapter 58, pages 1212–1248. Mouton de Gruyter, Berlin, New York.
- Finkelstein, Lev; Gabrilovich, Evgeniy; Matias, Yossi; Rivlin, Ehud; Solan, Zach; Wolfman, Gadi; Ruppín, Eytan (2002). Placing search in context: The concept revisited. *ACM Transactions on Information Systems*, **20**(1), 116–131.
- Fox, John (2003). Effect displays in r for generalised linear models. *Journal of Statistical Software*, **8**(15), 1–27.
- Hassan, Samer and Mihalcea, Rada (2011). Semantic relatedness using salient semantic analysis. In *Proceedings of the Twenty-fifth AAAI Conference on Artificial Intelligence*.
- Herdağdelen, Amaç; Erk, Katrin; Baroni, Marco (2009). Measuring semantic relatedness with vector space models and random walks. In *Proceedings of the 2009 Workshop on Graph-based Methods for Natural Language Processing (TextGraphs-4)*, pages 50–53, Suntec, Singapore.
- Hodgson, James M. (1991). Informational constraints on pre-lexical priming. *Language and Cognitive Processes*, **6**(3), 169–205.
- Kaufman, Leonard and Rousseeuw, Peter J. (1990). *Finding Groups in Data: An Introduction to Cluster Analysis*. John Wiley and Sons, New York.

References III

- Kiela, Douwe and Clark, Stephen (2014). A systematic study of semantic vector space model parameters. In *Proceedings of the 2nd Workshop on Continuous Vector Space Models and their Compositionality (CVSC)*, pages 21–30, Gothenburg, Sweden.
- Landauer, Thomas K. and Dumais, Susan T. (1997). A solution to Plato's problem: The latent semantic analysis theory of acquisition, induction and representation of knowledge. *Psychological Review*, **104**(2), 211–240.
- Lapesa, Gabriella and Evert, Stefan (2014). A large scale evaluation of distributional semantic models: Parameters, interactions and model selection. *Transactions of the Association for Computational Linguistics*, **2**, 531–545.
- McDonald, Scott and Brew, Chris (2004). A distributional model of semantic context effects in lexical processing. In *Proceedings of the 42nd Meeting of the Association for Computational Linguistics (ACL '04)*, pages 17–24, Barcelona, Spain.
- Mitchell, Tom M.; Shinkareva, Svetlana V.; Carlson, Andrew; Chang, Kai-Min; Malave, Vicente L.; Mason, Robert A.; Just, Marcel Adam (2008). Predicting human brain activity associated with the meanings of nouns. *Science*, **320**, 1191–1195.
- Padó, Sebastian and Lapata, Mirella (2007). Dependency-based construction of semantic space models. *Computational Linguistics*, **33**(2), 161–199.

References IV

- Pennington, Jeffrey; Socher, Richard; Manning, Christopher D. (2014). GloVe: Global vectors for word representation. In *Proceedings of EMNLP 2014*.
- Polajnar, Tamara and Clark, Stephen (2014). Improving distributional semantic vectors through context selection and normalisation. In *Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics*, pages 230–238, Gothenburg, Sweden.
- Rapp, Reinhard (2004). A freely available automatically generated thesaurus of related words. In *Proceedings of the 4th International Conference on Language Resources and Evaluation (LREC 2004)*, pages 395–398.
- Rubenstein, Herbert and Goodenough, John B. (1965). Contextual correlates of synonymy. *Communications of the ACM*, **8**(10), 627–633.
- Turney, Peter D. (2006). Similarity of semantic relations. *Computational Linguistics*, **32**(3), 379–416.
- Van Overschelde, James; Rawson, Katherine; Dunlosky, John (2004). Category norms: An updated and expanded version of the Battig and Montague (1969) norms. *Journal of Memory and Language*, **50**, 289–335.