Distributional Semantic Models

Part 3: Evaluation of distributional similarity

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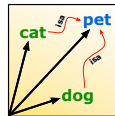[1]Friedrich-Alexander-Universität Erlangen-Nürnberg, Germany
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[3]University of Trento, Italy
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http://wordspace.collocations.de/doku.php/course:start

Outline

What is semantic similarity?
Semantic similarity and relatedness
Attributional similarity

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

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What is semantic similarity?
Semantic similarity and relatedness
Attributional similarity

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Methodology for DSM Evaluation
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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

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

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, allowing categorization, generalization, inheritance

Evaluation of attributional similarity

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

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
    - ⋆ $\lambda y : \text{FOOD } \lambda x : \text{ANIMATE} \left[eat(x, y) \right]$
- "Chicken-and-egg" problem for relationship of categorization and similarity (cf. Goodman 1972, Medin et al. 1993)

## 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 and noun categorization
- categorization can be operationalized 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, …)

Noun categorization: example

Word space clustering of concrete nouns (V−Obj from BNC)
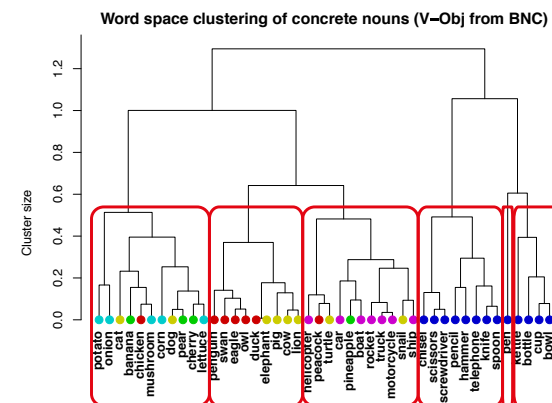
- majority labels: greens, birds, vehicles, tools, tools, tools
- correct: 5/11, 5/9, 7/11, 8/8, 1/1, 4/4
- purity = 30 correct out of 44 = 68.2%

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

model	6-way		3-way		2-way		global
	P	E	P	E	P	E	
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)

Semantic priming

- Hearing/reading a "related" prime facilitates access to a target in various lexical 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 ($\approx$ 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*)
  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

DSM evaluation in published studies

- ▶ One model, many tasks (Padó and Lapata 2007; Baroni and Lenci 2010)
    - ▶ 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


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

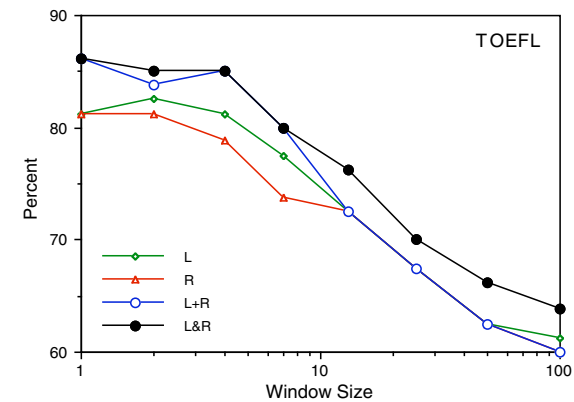## TOEFL results: feature weighting & distance measure
(Bullinaria and Levy 2007, p. 516, Fig. 1)
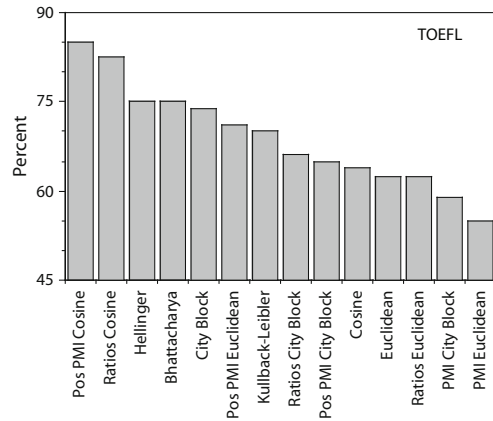
British National Corpus (BNC). Vectors not L2-normalized (frequency is L1-normalized). All other parameters optimized for each setting.
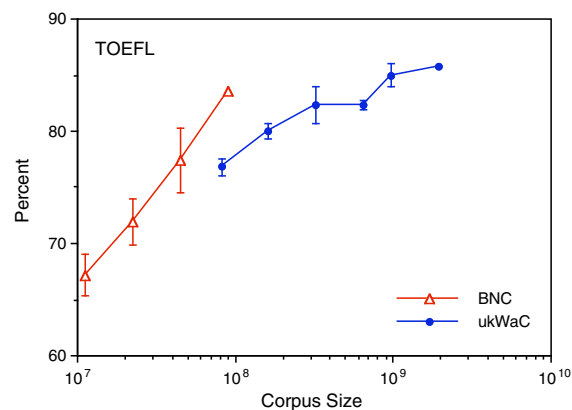
TOEFL results: size & type of co-occurrence window
(Bullinaria and Levy 2012, p. 893, Fig. 1)

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).
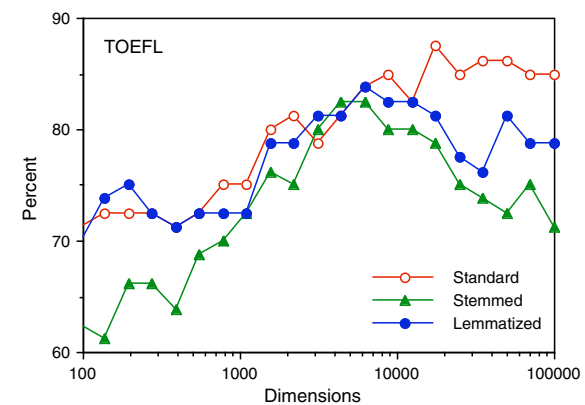
TOEFL results: corpus type & size
(Bullinaria and Levy 2012, p. 894, Fig. 2)

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

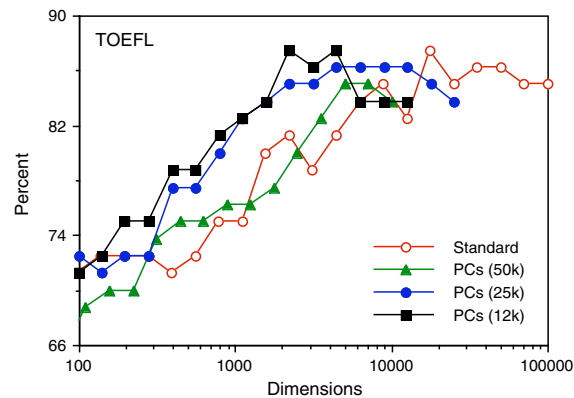## TOEFL results: feature dimensions & pre-processing
(Bullinaria and Levy 2012, p. 895, Fig. 4)

ukWaC corpus. L+R context of size 1. Other parameters presumably as above.
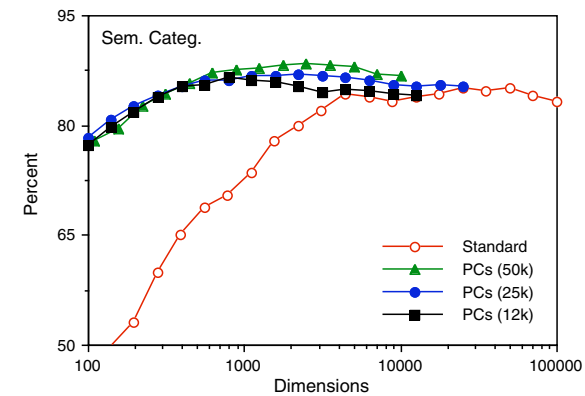
TOEFL results: dimensionality reduction
(Bullinaria and Levy 2012, p. 898, Fig. 5)

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.

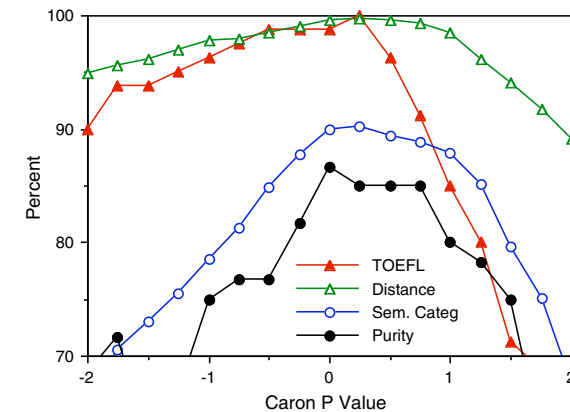## Combined results: skipping first latent dimensions
(Bullinaria and Levy 2012, p. 900, Fig. 7)
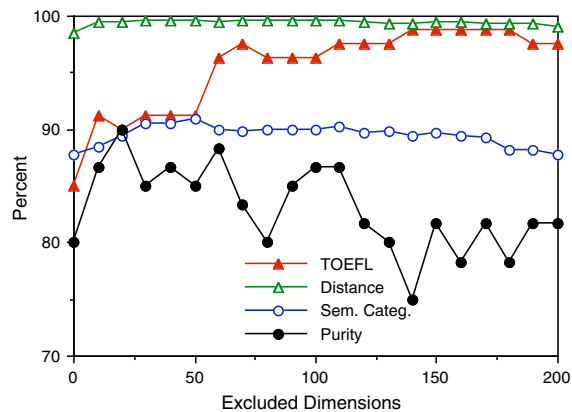
ukWaC corpus with standard settings. 50k feature dimensions reduced to 5000 latent
dimensions.

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

Based on research by Gabriella Lapesa.

Outline

Tasks

1. **Classification**
   - TOEFL 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**
   - Battig: 83 nouns, 10 classes (Van Overschelde *et al.* 2004)
   - AP: 402 nouns, 21 classes (Almuhareb 2006)
   - ESSLLI 2008: 44 nouns, 6 classes[1]
   - Mitchell: 60 nouns, 12 classes (Mitchell *et al.* 2008)

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[1] http://wordspace.collocations.de/doku.php/data:esslli2008: concrete_nouns_categorization

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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[2], the UCS toolkit[3] and the wordspace package[4] for R.

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[2] http://cwb.sf.net/
[3] http://www.collocations.de/software.html
[4] http://wordspace.r-forge.r-project.org/

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**
   - **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-ll, 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. $\bigl(\log \text{rank}(a, b) + \log \text{rank}(b, a)\bigr)/2$

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

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

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

*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 exlains 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:

- ▶ Ablation(corpus) = R^2(corpus) + R^2(corpus: window size) + R^2(corpus: window direction)
- ▶ Ablation(window size) = R^2(window size) + R^2(corpus: window size) + R^2(window size: window direction)
- ▶ Ablation(window direction) = R^2(window direction) + R^2(corpus: window direction) + R^2(window size: window direction)

Outline

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
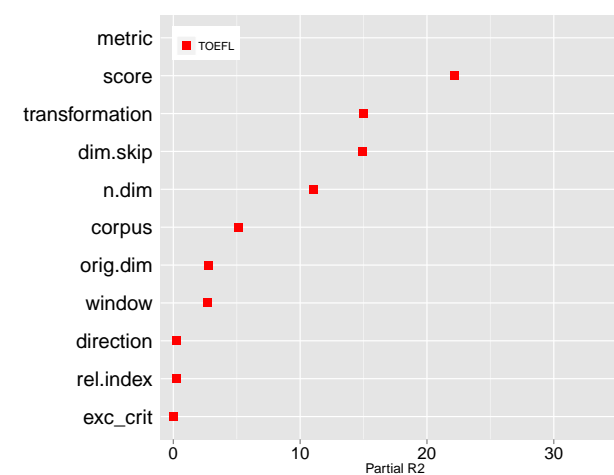### Unreduced versus Reduced Experiments
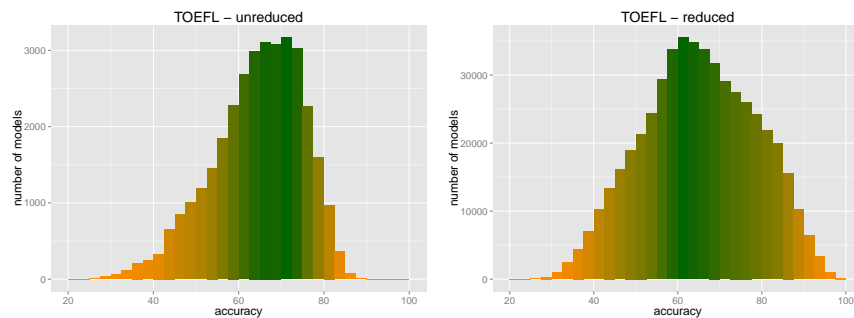
Min: 25 ; Max: 87.5 ; Mean: 63.9

Min: 18.7; Max: 97.4; Mean: 64.4

TOEFL task: parameters and explained variance
Reduced setting: feature Ablation (model R^2: 89%)
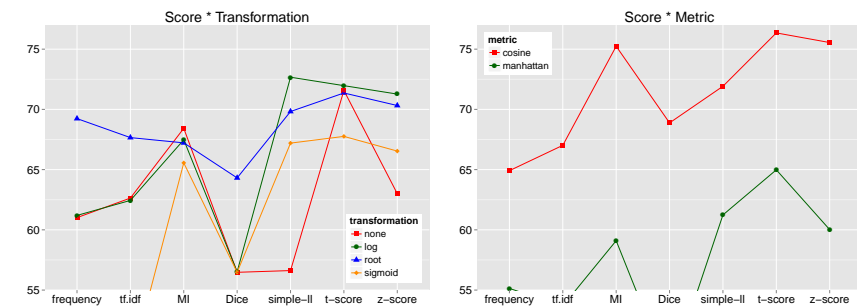
TOEFL task: interactions
Reduced setting ($R^2 > 0.5$)

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
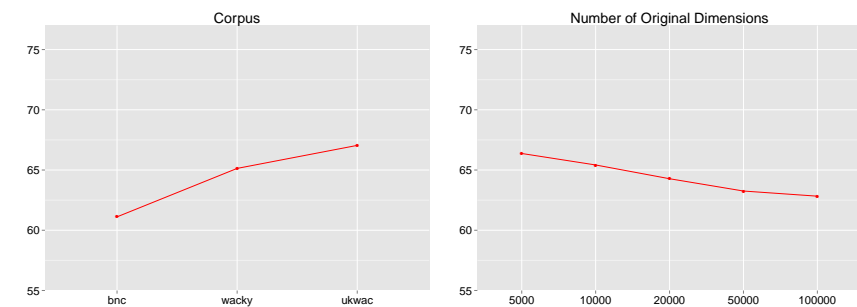Partial effect displays (Fox 2003)

TOEFL task: Dimensionality Reduction
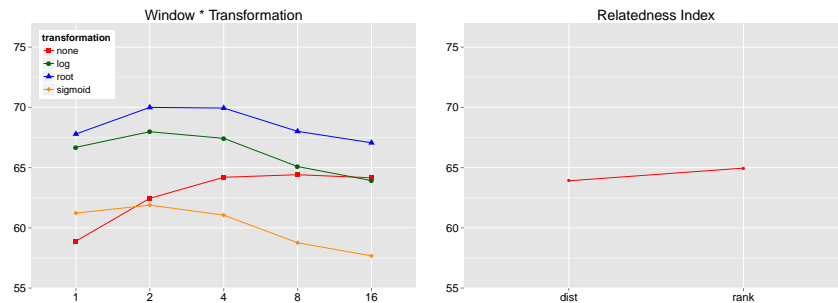Partial effect displays (Fox 2003)
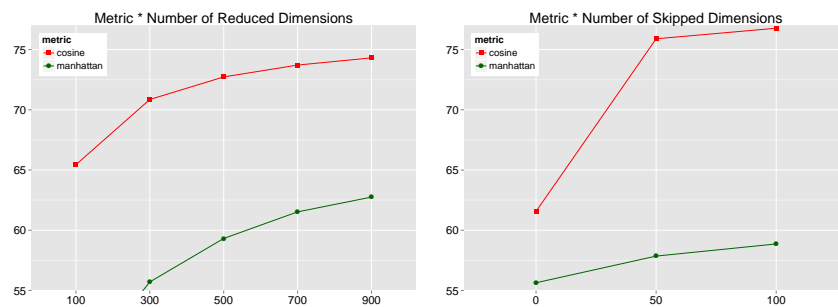
TOEFL task: Corpus and Number of Feature Dimensions
Partial effect displays (Fox 2003)

TOEFL task: Window and Relatedness Index
Partial effect displays (Fox 2003)

TOEFL task: 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
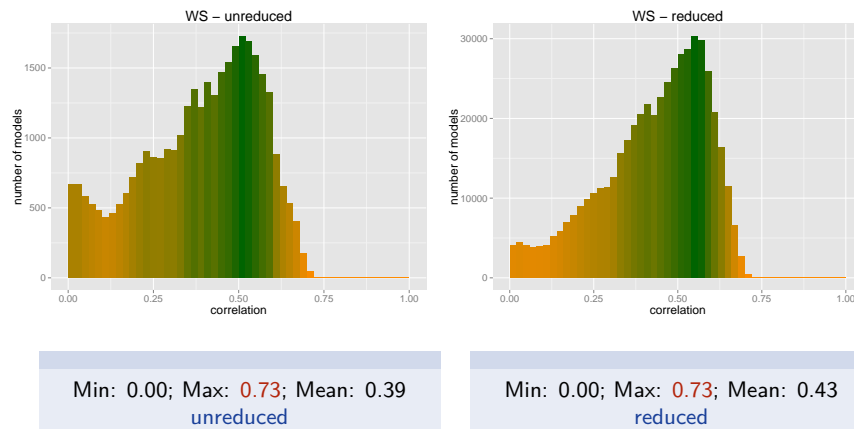- ▶ Performance: **Pearson correlation** r

Similarity ratings: performance on RG65
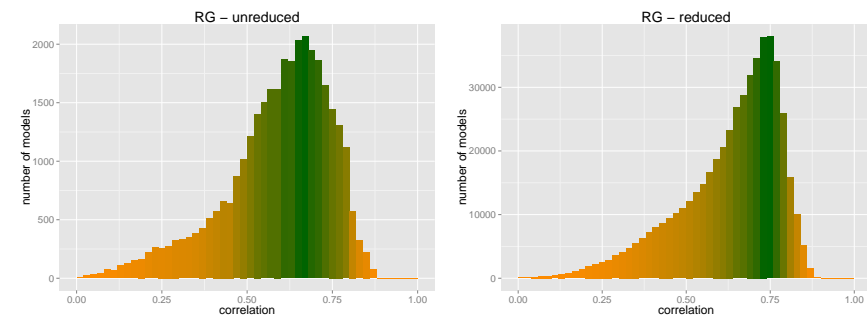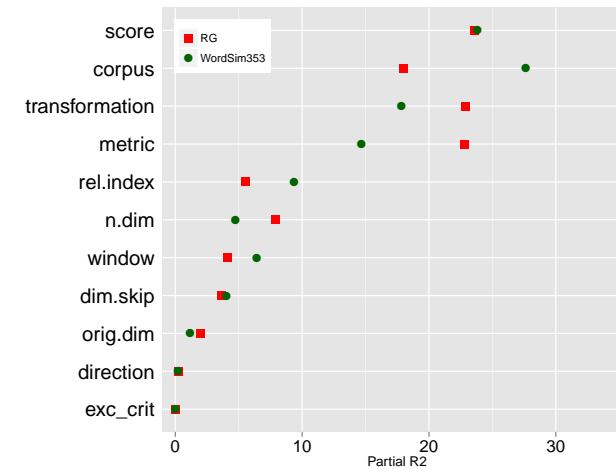

Min: 0.01; Max: 0.88; Mean 0.59
unreduced

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

Similarity ratings: performance on WordSim353

WS – unreduced

WS – reduced

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

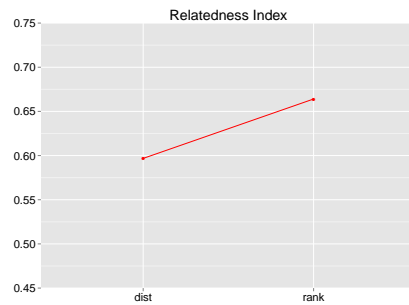Partial effect displays (Fox 2003)
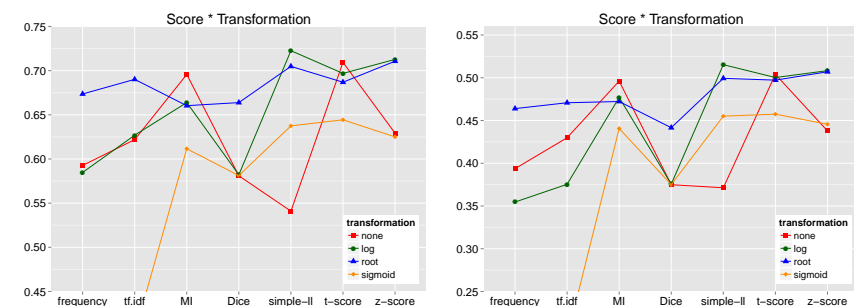
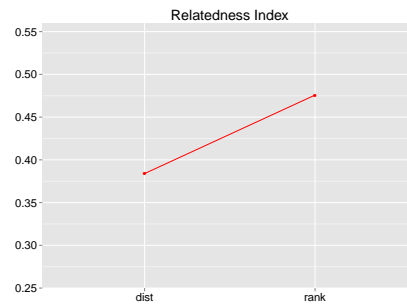

Rubenstein & Goodenough   WordSim-353

Similarity ratings: Relatedness Index
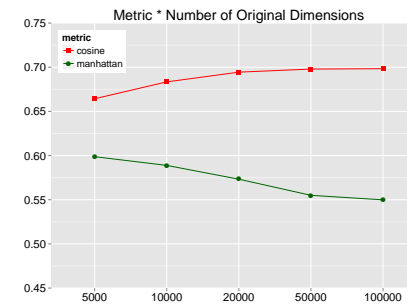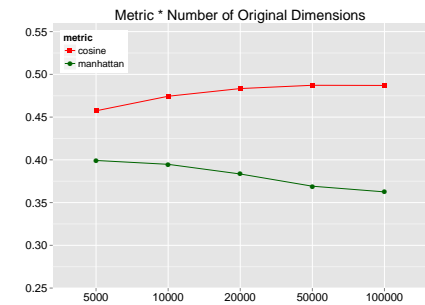Partial effect displays (Fox 2003)

Rubenstein & Goodenough

WordSim-353

Similarity ratings: Metric, Number of Feature Dimensions
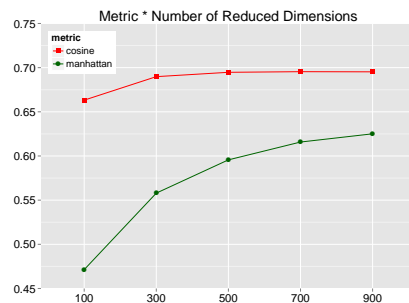Partial effect displays (Fox 2003)
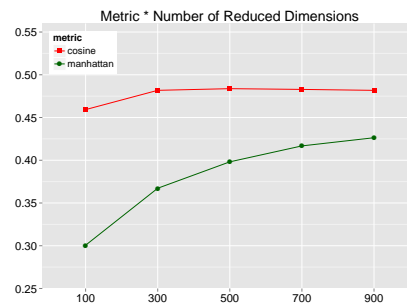

Rubenstein & Goodenough

WordSim-353

Similarity ratings: Number of Latent Dimensions
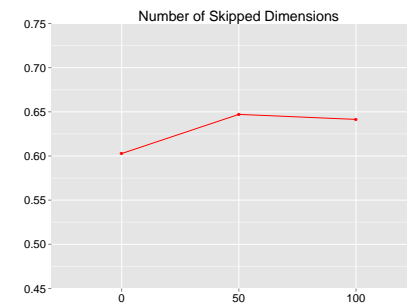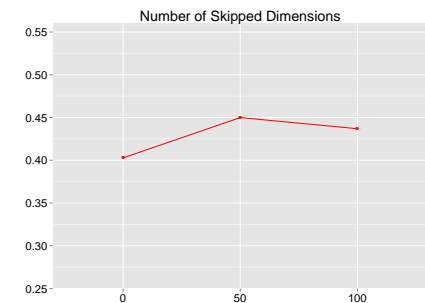Partial effect displays (Fox 2003)

Rubenstein & Goodenough

WordSim-353

Similarity ratings: Number of Skipped Dimensions
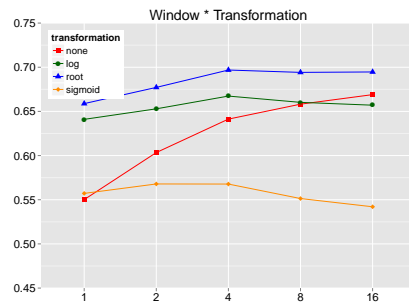Partial effect displays (Fox 2003)

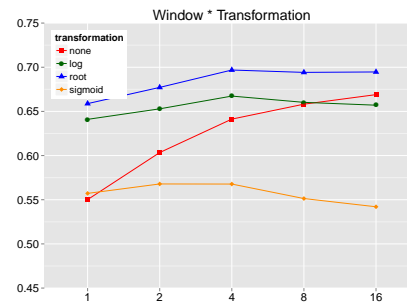
Rubenstein & Goodenough

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: 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
$day \Longrightarrow$ TIME
$kiwi \Longrightarrow$ FRUIT
$kitten \Longrightarrow$ ANIMAL
$volleyball \Longrightarrow$ GAME

BATTIG set

83 nouns, 10 classes
$chicken \Longrightarrow$ BIRD
$bear \Longrightarrow$ LAND_MAMMAL
$pot \Longrightarrow$ KITCHENWARE
$oak \Longrightarrow$ TREE

ESSLLI categorization task

44 nouns, 6 classes
$potato \Longrightarrow$ GREEN
$hammer \Longrightarrow$ TOOL
$car \Longrightarrow$ VEHICLE
$peacock \Longrightarrow$ BIRD

MITCHELL set

60 nouns, 12 classes
$ant \Longrightarrow$ INSECT
$carrot \Longrightarrow$ VEGETABLE
$train \Longrightarrow$ VEHICLE
$cat \Longrightarrow$ 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
- ▶ 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
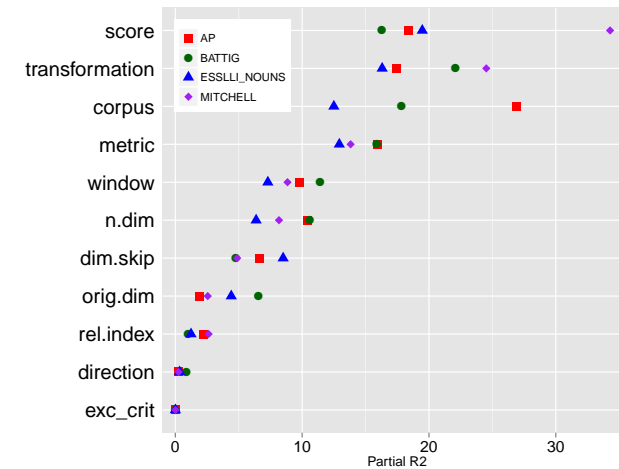
Semantic clustering: performance
Overview: unreduced versus reduced experiments

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)
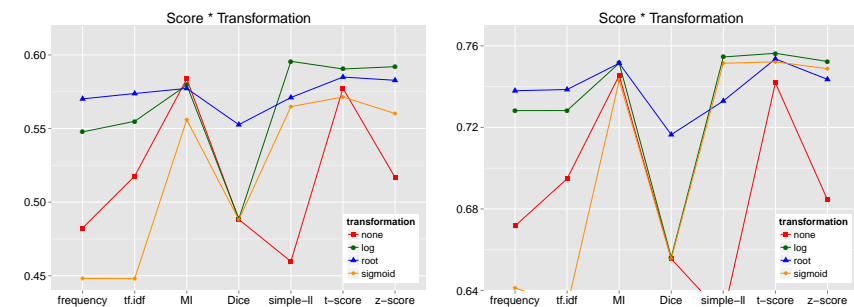
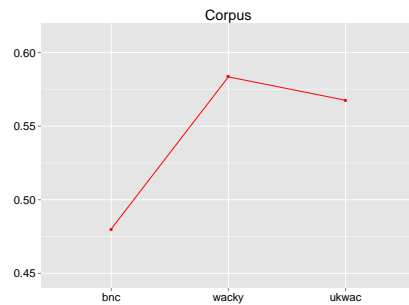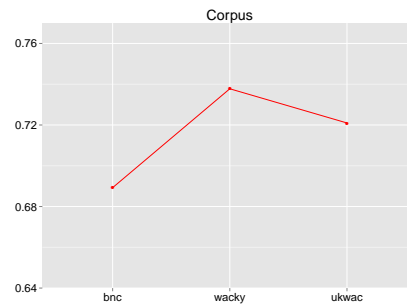

Almuhareb & Poesio   ESSLLI 2008

Semantic clustering: Corpus
Partial effect displays (Fox 2003)

Almuhareb & Poesio

ESSLLI 2008

Semantic clustering: Window Size, Metric
Partial effect displays (Fox 2003)

Almuhareb & Poesio

ESSLLI 2008

Semantic clustering: Metric, Number of Latent Dimensions
Partial effect displays (Fox 2003)

Almuhareb & Poesio

ESSLLI 2008

Semantic clustering: Number of Skipped Dimensions
Partial effect displays (Fox 2003)
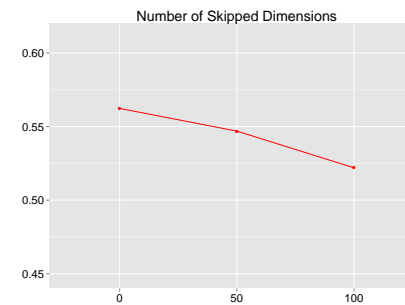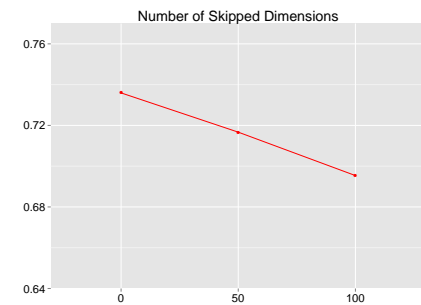
Almuhareb & Poesio

ESSLLI 2008

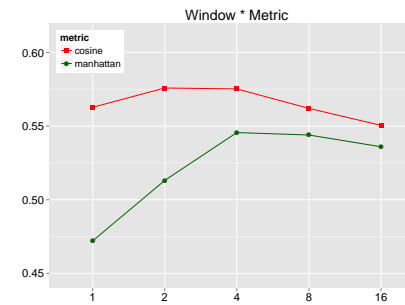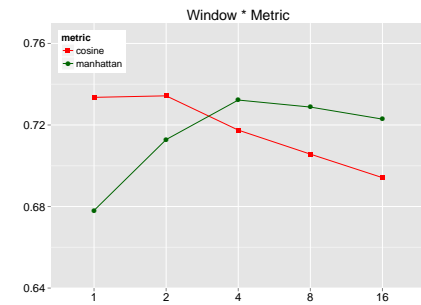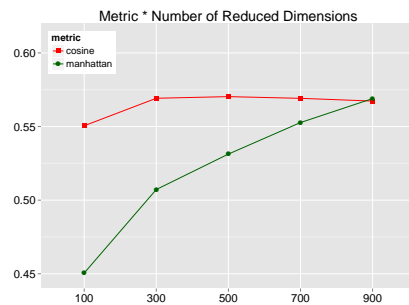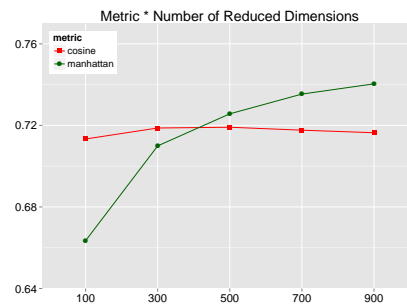# Semantic clustering: Relatedness Index
Partial effect displays (Fox 2003)
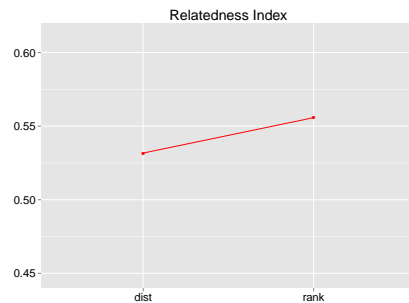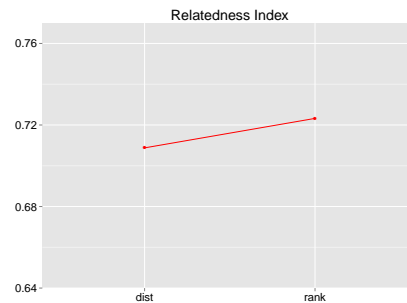
Almuhareb & Poesio   ESSLLI 2008

Semantic clustering: Number of Feature Dimensions
Partial effect displays (Fox 2003)
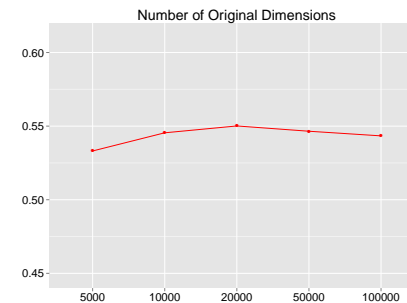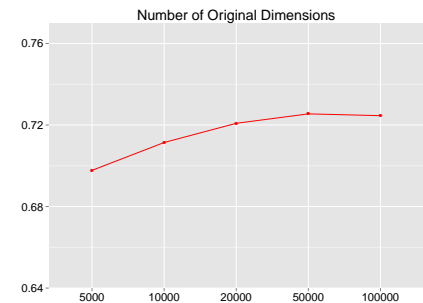
Almuhareb & Poesio   ESSLLI 2008

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

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
- ▶ 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

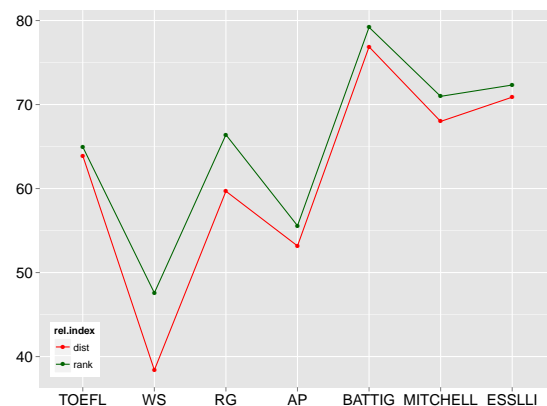| dataset	corpus	w	o.dim	sc	tr	m	rel.ind	n.dim	d.sk	best.s	best.m
TOEFL	ukwac	2	5k	s-ll	log	cos	rank	900	100	92.5	98.75
WS	wacky	4	50k	s-ll	log	cos	rank	300	50	0.67	0.73
RG	wacky	4	50k	s-ll	log	cos	rank	300	50	0.86	0.89
AP	wacky	4	20k	s-ll	log	cos	rank	300	0	0.69	0.76
BATTIG	wacky	8	50k	s-ll	log	cos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

Task	TOEFL	RATINGS	CLUSTERING	GENERAL
TOEFL	92.5	85.0	75.0	90.0
WS	0.60	0.67	0.64	0.68
RG	0.85	0.86	0.84	0.87
AP	0.60	0.66	0.67	0.67
BATTIG	0.85	0.91	0.98	0.90
ESSLLI	0.70	0.77	0.80	0.77
MITCHELL	0.73	0.83	0.88	0.83

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-ll * 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

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