CS 4650/7650
Distributional Lexical Semantics

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[1]Some slides borrowed from Marco Baroni and Michael Collins

The Semantics Roadmap

- **Compositional semantics**
  - assemble the meaning of a sentence from its components
  - What state borders Texas? $\rightarrow$
    $\lambda x.\textsc{state}(x) \wedge \textsc{borders}(x, \textsc{Texas})$

The Semantics Roadmap

- **Compositional semantics**
  - assemble the meaning of a sentence from its components
  - What state borders Texas? $\rightarrow$
    $\lambda x.\textsc{state}(x) \wedge \textsc{borders}(x, \textsc{Texas})$
- **Shallow semantics**
  - identify the key predicates and arguments in sentences
  - [$_{agent}$ Doris] gave [$_{goal}$ Cary] [$_{theme}$ the book].

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- **Compositional semantics**
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  - What state borders Texas? $\rightarrow$ $\lambda x.\textsc{state}(x) \wedge \textsc{borders}(x, \textsc{Texas})$
- **Shallow semantics**
  - identify the key predicates and arguments in sentences
  - $[_{agent}$ Doris$]$ gave $[_{goal}$ Cary$]$ $[_{theme}$ the book$]$.
- **Today: lexical semantics**
  vector-space models for the meaning of individual words

New words

How do we do semantic analysis of words that we've never seen before?

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- A bottle of tezgüino is on the table.
- Everybody likes tezgüino.
- Tezgüino makes you drunk.
- We make tezgüino out of corn.

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How do we do semantic analysis of words that we've never seen before?

- A bottle of __________ is on the table.
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New words

How do we do semantic analysis of words that we've never seen before?

- A bottle of __________ is on the table.
- Everybody likes __________.
- __________ makes you drunk.
- We make __________ out of corn.

How well do other words fit into these contexts?

- Loud, motor oil, tortillas, choices, wine

The vector-space model

Key idea: each word (type) is represented by a vector of contexts.

- C1: A bottle of __________ is on the table.
- C2: Everybody likes __________.
- C3: __________ makes you drunk.
- C4: We make __________ out of corn.
- ...

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- C1: A bottle of ________ is on the table.
- C2: Everybody likes ________.
- C3: ________ makes you drunk.
- C4: We make ________ out of corn.
- ...

	C1	C2	C3	C4	...
tezgüino	1	1	1	1	
loud	0	0	0	0	
motor oil	1	0	0	1	
tortillas	0	1	0	1	
choices	0	1	0	0	
wine	1	1	1	1	

The Vector-space model

- The "meaning" of tezgüino is represented by the vector $\{1, 1, 1, 1, \ldots\}$.
- Wine has a similar vector and therefore a similar meaning.
- The vector-space model is used in a huge range of NLP and information retrieval applications.
- Key technical questions:
  - How kinds of context should we consider?
  - How do we measure similarity?
  - How do we distinguish frequent and infrequent events?

What is “context”?

The silhouette of the sun beyond a wide-open bay on the lake; the sun still glitters although evening has arrived in Kuhmo. It’s midsummer; the living room has its instruments and other objects in each of its corners.

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What is “context”?

The silhouette-n of the sun beyond a wide-open-a bay-n on the lake-n; the sun still glitter-v although evening-n has arrive-v in Kuhmo. It’s midsummer; the living room has its instruments and other objects in each of its corners.

What is “context”?

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What is “context”?

The silhouette-n_ppdep of the sun beyond a wide-open bay on the lake; the sun still glitter-v_subj although evening- has arrived in Kuhmo. It’s midsummer; the living room has its instruments and other objects in each of its corners.

Same corpus (BNC), different contexts (window sizes)

Nearest neighbours of *dog*

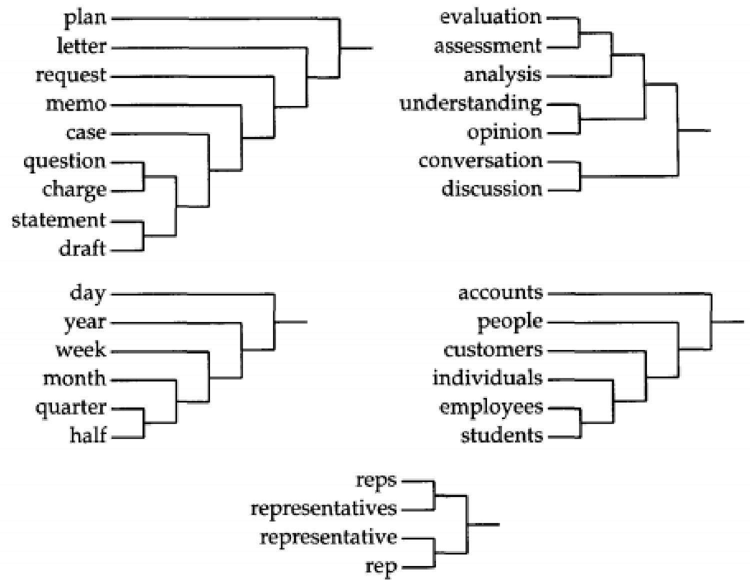
2-word window

- cat
- horse
- fox
- pet
- rabbit
- pig
- animal
- mongrel
- sheep
- pigeon

30-word window

- kennel
- puppy
- pet
- bitch
- terrier
- rottweiler
- canine
- cat
- to bark
- Alsatian

Mutual information trees



Bit strings

- Equivalently, each word can be described by a **bit string** of branchings in the induced hierarchy.
- From Miller et al (2004):

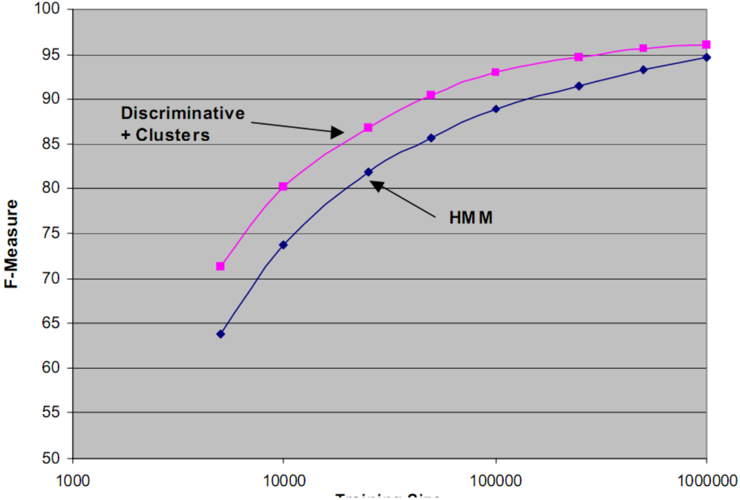
lawyer	1000001101000
newspaperman	100000110100100
stewardess	100000110100101
toxicologist	10000011010011
slang	1000001101010
babysitter	100000110101100
conspirator	1000001101011010
womanizer	1000001101011011
mailman	10000011010111
salesman	100000110110000
bookkeeper	1000001101100010

Nike	1011011100100101011100
Maytag	10110111001001010111010
Generali	10110111001001010111011
Gap	1011011100100101011110
Harley-Davidson	10110111001001010111110
Enfield	101101110010010101111110
genus	101101110010010101111111
Microsoft	10110111001001011000
Ventritex	101101110010010110010
Tractebel	1011011100100101100110
Synopsys	1011011100100101100111
WordPerfect	1011011100100101101000

John	1011100100000000000
Consuelo	1011100100000000001
Jeffrey	1011100100000000010
Kenneth	101110010000000001100
Phillip	1011100100000000011010
WILLIAM	1011100100000000011011
Timothy	101110010000000001110
Terrence	1011100100000000011110
Jerald	1011100100000000011111
Harold	1011100100000000100
Frederic	1011100100000000101
Wendell	101110010000000011

- Bit strings can easily be converted into features for supervised learning.
  - Named entity tagging (Miller et al, 2004)
  - Dependency parsing (Koo et al, 2008)

Brown clusters in NER



Lin (1998): qualitative evaluation

Pairs of words which are each others respective nearest neighbors

Nouns		
Rank	Respective Nearest Neighbors	Similarity
1	earnings profit	0.572525
11	plan proposal	0.47475
21	employee worker	0.413936
31	battle fight	0.389776
41	airline carrier	0.370589
51	share stock	0.351294
61	rumor speculation	0.327266
71	outlay spending	0.320535
81	accident incident	0.310121
91	facility plant	0.284845
101	charge count	0.278339
111	baby infant	0.268093
121	actor actress	0.255098
131	chance likelihood	0.248942
141	catastrophe disaster	0.241986
151	fine penalty	0.237606
161	legislature parliament	0.231528
171	oil petroleum	0.227277
181	strength weakness	0.218027
191	radio television	0.215043
201	coupe sedan	0.209631

Adjective/Adverbs		
Rank	Respective Nearest Neighbors	Similarity
1	high low	0.580408
11	bad good	0.376744
21	extremely very	0.357606
31	deteriorating improving	0.332664
41	alleged suspected	0.317163
51	clerical salaried	0.305448
61	often sometimes	0.281444
71	bleak gloomy	0.275557
81	adequate inadequate	0.263136
91	affiliated merged	0.257666
101	stormy turbulent	0.252846
111	paramilitary uniformed	0.246638
121	sharp steep	0.240788
131	communist leftist	0.232518
141	indoor outdoor	0.224183
151	changed changing	0.219697
161	defensive offensive	0.211062
171	sad tragic	0.206688
181	enormously tremendously	0.199936
191	defective faulty	0.193863
201	concerned worried	0.186899

Lin (1998): quantitative evaluation

This method can be used to induce thesauri, which can then be compared with manually-crafted resources like WordNet and Roget's thesaurus.

	WordNet	
	average	σ_{avg}
Roget	0.178397	0.001636
sim	0.212199	0.001484
Hindle	0.204179	0.001424
Hindle$_r$	0.164716	0.001200
cosine	0.199402	0.001352

	Roget	
	average	σ_{avg}
WordNet	0.178397	0.001636
sim	0.149045	0.001429
Hindle	0.14663	0.001383
Hindle$_r$	0.115489	0.001140
cosine	0.135697	0.001275

Outline

Latent semantic analysis (LSA)

In **latent semantic analysis** (Deerwester et al., 1990), "contexts" are just the documents in which words appear.

Example of text data: Titles of Some Technical Memos

c1:	*Human* machine *interface* for ABC *computer* applications
c2:	A *survey* of *user* opinion of *computer system response time*
c3:	The *EPS user interface* management *system*
c4:	*System* and *human system* engineering testing of *EPS*
c5:	Relation of *user* perceived *response time* to error measurement
m1:	The generation of random, binary, ordered *trees*
m2:	The intersection *graph* of paths in *trees*
m3:	*Graph minors* IV: Widths of *trees* and well-quasi-ordering
m4:	*Graph minors*: A *survey*

Latent semantic analysis (LSA)

In **latent semantic analysis** (Deerwester et al., 1990), "contexts" are just the documents in which words appear.

	c1	c2	c3	c4	c5	m1	m2	m3	m4
human	1	0	0	1	0	0	0	0	0
interface	1	0	1	0	0	0	0	0	0
computer	1	1	0	0	0	0	0	0	0
user	0	1	1	0	1	0	0	0	0
system	0	1	1	2	0	0	0	0	0
response	0	1	0	0	1	0	0	0	0
time	0	1	0	0	1	0	0	0	0
EPS	0	0	1	1	0	0	0	0	0
survey	0	1	0	0	0	0	0	0	1
trees	0	0	0	0	0	1	1	1	0
graph	0	0	0	0	0	0	1	1	1
minors	0	0	0	0	0	0	0	1	1

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	c1	c2	c3	c4	c5	m1	m2	m3	m4
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interface	1	0	1	0	0	0	0	0	0
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system	0	1	1	2	0	0	0	0	0
response	0	1	0	0	1	0	0	0	0
time	0	1	0	0	1	0	0	0	0
EPS	0	0	1	1	0	0	0	0	0
survey	0	1	0	0	0	0	0	0	1
trees	0	0	0	0	0	1	1	1	0
graph	0	0	0	0	0	0	1	1	1
minors	0	0	0	0	0	0	0	1	1

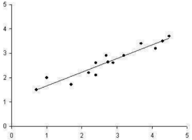
- correlation(human,user) = -.38
- correlation(human,minors) = -.29

Transforming the count matrix

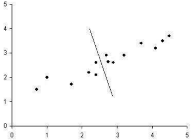
- The count matrix $\mathbf{X}$ can be huge
- In this space, similarity will be sensitive to noise.
- We'd prefer to measure similarity in a more compact space.
- Singular value decomposition (SVD): $\mathbf{X} \approx \mathbf{U}\mathbf{S}\mathbf{V}^\top$
  - $\mathbf{U}\mathbf{U}^\top = \mathbf{I}$, $\mathbf{V}\mathbf{V}^\top = \mathbf{I}$ (they are orthonormal)
  - The columns of $\mathbf{U}$ are the eigenvectors of $\mathbf{X}\mathbf{X}^\top$.
  - The columns of $\mathbf{V}$ are the eigenvectors of $\mathbf{X}^\top\mathbf{X}$.
  - $\mathbf{S}$ is a diagonal matrix containing the square roots of the eigenvalues in descending order.

Singular value decomposition (SVD)

- SVD as repeated regression on residuals:
  - fit a line to your data



  - compute residuals
  - fit a line to the residuals



  - repeat

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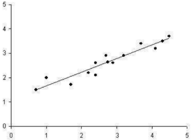

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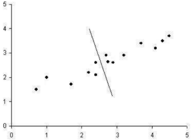

  - repeat

- If we fit as many lines as the smaller dimension of $\mathbf{X}$, SVD can reconstruct it exactly.
- If not, SVD forms a least-squares approximation $\hat{\mathbf{X}}$

Singular value decomposition (SVD)

$$\mathbf{X} = \mathbf{U}\mathbf{S}\mathbf{V}^\top$$

Intuitively,

- **U** describes the rows (words).

0.20	0.61	0.46	0.54	0.28	0.00	0.01	0.02	0.08
-0.06	0.17	-0.13	-0.23	0.11	0.19	0.44	0.62	0.53
0.11	-0.50	0.21	0.57	-0.51	0.10	0.19	0.25	0.08
-0.95	-0.03	0.04	0.27	0.15	0.02	0.02	0.01	-0.03
0.05	-0.21	0.38	-0.21	0.33	0.39	0.35	0.15	-0.60
-0.08	-0.26	0.72	-0.37	0.03	-0.30	-0.21	0.00	0.36
0.18	-0.43	-0.24	0.26	0.67	-0.34	-0.15	0.25	0.04
-0.01	0.05	0.01	-0.02	-0.06	0.45	-0.76	0.45	-0.07
-0.06	0.24	0.02	-0.08	-0.26	-0.62	0.02	0.52	-0.45

Singular value decomposition (SVD)

$$\mathbf{X} = \mathbf{U}\mathbf{S}\mathbf{V}^\top$$

Intuitively,

- $\mathbf{U}$ describes the rows (words).
- $\mathbf{V}^\top$ describes the columns (documents).

0.22	-0.11	0.29	-0.41	-0.11	-0.34	0.52	-0.06	-0.41
0.20	-0.07	0.14	-0.55	0.28	0.50	-0.07	-0.01	-0.11
0.24	0.04	-0.16	-0.59	-0.11	-0.25	-0.30	0.06	0.49
0.40	0.06	-0.34	0.10	0.33	0.38	0.00	0.00	0.01
0.64	-0.17	0.36	0.33	-0.16	-0.21	-0.17	0.03	0.27
0.27	0.11	-0.43	0.07	0.08	-0.17	0.28	-0.02	-0.05
0.27	0.11	-0.43	0.07	0.08	-0.17	0.28	-0.02	-0.05
0.30	-0.14	0.33	0.19	0.11	0.27	0.03	-0.02	-0.17
0.21	0.27	-0.18	-0.03	-0.54	0.08	-0.47	-0.04	-0.58
0.01	0.49	0.23	0.03	0.59	-0.39	-0.29	0.25	-0.23
0.04	0.62	0.22	0.00	-0.07	0.11	0.16	-0.68	0.23
0.03	0.45	0.14	-0.01	-0.30	0.28	0.34	0.68	0.18

Singular value decomposition (SVD)

$$\mathbf{X} = \mathbf{U}\mathbf{S}\mathbf{V}^\top$$

Intuitively,

- $\mathbf{U}$ describes the rows (words).
- $\mathbf{V}^\top$ describes the columns (documents).
- $\mathbf{S}$ gives the importance of each dimension in $\mathbf{U}$ and $\mathbf{V}$.

3.34
2.54
2.35
1.64
1.50
1.31
0.85
0.56
0.36

Correlation in the reconstructed counts

With only two singular values, we obtain a *reduced-rank* approximation:
$\mathbf{X} \approx \hat{\mathbf{X}} = \mathbf{USV}^\top$

	c1	c2	c3	c4	c5	m1	m2	m3	m4
human	0.16	0.40	0.38	0.47	0.18	-0.05	-0.12	-0.16	-0.09
interface	0.14	0.37	0.33	0.40	0.16	-0.03	-0.07	-0.10	-0.04
computer	0.15	0.51	0.36	0.41	0.24	0.02	0.06	0.09	0.12
user	0.26	0.84	0.61	0.70	0.39	0.03	0.08	0.12	0.19
system	0.45	1.23	1.05	1.27	0.56	-0.07	-0.15	-0.21	-0.05
response	0.16	0.58	0.38	0.42	0.28	0.06	0.13	0.19	0.22
time	0.16	0.58	0.38	0.42	0.28	0.06	0.13	0.19	0.22
EPS	0.22	0.55	0.51	0.63	0.24	-0.07	-0.14	-0.20	-0.11
survey	0.10	0.53	0.23	0.21	0.27	0.14	0.31	0.44	0.42
trees	-0.06	0.23	-0.14	-0.27	0.14	0.24	0.55	0.77	0.66
graph	-0.06	0.34	-0.15	-0.30	0.20	0.31	0.69	0.98	0.85
minors	-0.04	0.25	-0.10	-0.21	0.15	0.22	0.50	0.71	0.62

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computer	0.15	0.51	0.36	0.41	0.24	0.02	0.06	0.09	0.12
user	0.26	0.84	0.61	0.70	0.39	0.03	0.08	0.12	0.19
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minors	-0.04	0.25	-0.10	-0.21	0.15	0.22	0.50	0.71	0.62

- correlation(human,user) $=$ .94
- correlation(human,minors) $=$ -.83
- SVD has identified a low-dimensional basis for $\mathbf{X}$, in which correlations are much more robust.

Title correlations

Similarly, correlation of titles in the raw counts was not informative:

Correlations between titles in raw data:

	c1	c2	c3	c4	c5	m1	m2	m3
c2	-0.19							
c3	0.00	0.00						
c4	0.00	0.00	0.47					
c5	-0.33	0.58	0.00	-0.31				
m1	-0.17	-0.30	-0.21	-0.16	-0.17			
m2	-0.26	-0.45	-0.32	-0.24	-0.26	0.67		
m3	-0.33	-0.58	-0.41	-0.31	-0.33	0.52	0.77	
m4	-0.33	-0.19	-0.41	-0.31	-0.33	-0.17	0.26	0.56

	c1	c2	c3
		0.02	
		-0.30	0.44

Title correlations

But correlation in the reduced-rank approximation reveals the underlying structure:

Correlations in two dimensional space:

c2	0.91							
c3	1.00	0.91						
c4	1.00	0.88	1.00					
c5	0.85	0.99	0.85	0.81				
m1	-0.85	-0.56	-0.85	-0.88	-0.45			
m2	-0.85	-0.56	-0.85	-0.88	-0.44	1.00		
m3	-0.85	-0.56	-0.85	-0.88	-0.44	1.00	1.00	
m4	-0.81	-0.50	-0.81	-0.84	-0.37	1.00	1.00	1.00

0.92		
-0.72	1.00	

LSA for expanding sentiment dictionaries

Turney and Littman (2004) use LSA to expand a small sentiment dictionary.

$$\text{Semantic-orientation}(i) = \sum_{j \in \text{pos-words}} \text{sim}(u_i, u_j) - \sum_{j \in \text{neg-words}} \text{sim}(u_i, u_j)$$

- u_i is the row in the matrix $\mathbf{U}$ corresponding to word i

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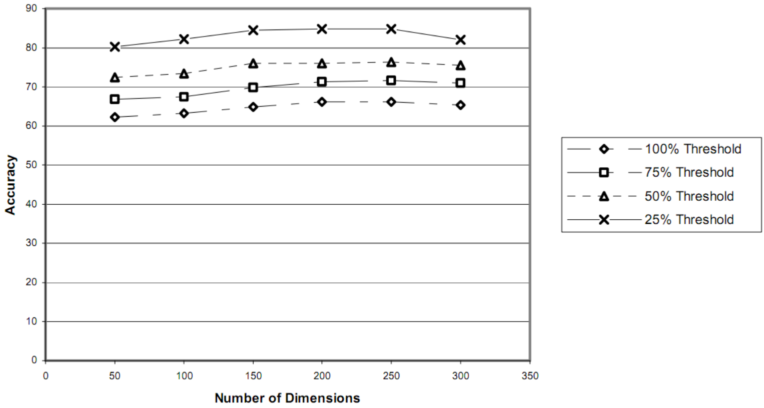
- u_i is the row in the matrix $\mathbf{U}$ corresponding to word i
- The similarity function $\text{sim}(u_i, u_j)$ is the *cosine* similarity:

$$\text{cosine}(\boldsymbol{x}, \boldsymbol{y}) = \frac{\boldsymbol{x}^\top \boldsymbol{y}}{\sqrt{\sum_i x_i^2}\sqrt{\sum_i y_i^2}}$$

LSA for expanding sentiment dictionaries



- Dimensionality tradeoff: expressiveness for robustness
- Turney and Littman find that the ideal number of dimensions is around 250 (for this task and corpus).

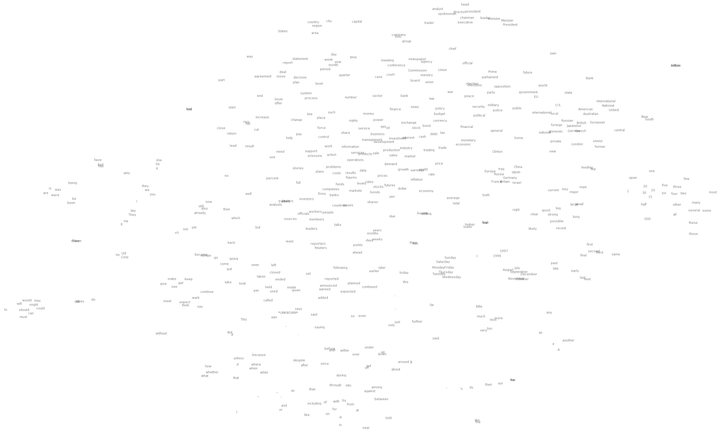
LSA for automatic essay grading

- Latent semantic analysis can be used to automatically grade test essays (Landauer et al., 1998).
- Ungraded essays are compared via cosine similarity to graded essays.
- LSA agrees with expert raters about as often as they agree with each other!
- The educational testing service (ETS) uses a combination of LSA with other features such as grammar, spelling, and repeated words (Burnstein 2003).

“Neural” word embeddings, $K = 25$

“Neural” word embeddings, $K = 50$

“Neural” word embeddings, $K = 200$



Word2vec

A very popular recent neural approach is **word2vec**.
It encompasses two models:

- **Skipgrams** predict each element in the context, conditioned on the word.
- **Continuous bag-of-words (CBOW)** predict each word conditioned on its context.

These methods were made practical by a new estimation heuristic called *negative sampling*.

Semantic similarity tasks

See http://www-nlp.stanford.edu/projects/glove/

Summary of lexical semantics

- Distributional similarity is a powerful tool for understanding the relationships between words.
- The vector space model describes each word by a vector of contextual information.
- Latent semantic analysis (LSA) operates on the term-document matrix to identify a low-rank representation for both word **and** document semantics.
- Today we examined only synonymy, but there are many other lexical relations, such as *antonyms*, *part-of*, *type-of*...