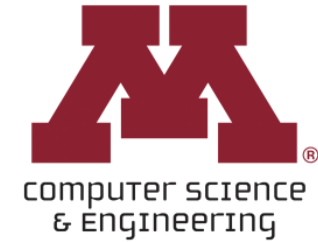


CSCI 5541: Natural Language Processing

Lecture 4: Distributional Semantics and Word Embeddings



Announcement (0916)

- ❑ HW2 is now due 09/21 Sunday
- ❑ Project Team Formation due 09/18
 - A list of team members and the team name
- ❑ Project description out (More detailed guideline on Sep 30)
- ❑ Lectures on Word Embeddings



Outline

- ❑ What is semantics?
- ❑ Three ways of looking at word meaning
 - Decompositional
 - Ontological
 - Distributional
- ❑ Different kinds of encoding “context”
 - Count-based
 - Distributed prediction-based (type) embeddings
 - Distributed contextual (token) embeddings from language models
 - Many more variants



What is semantics?
How do you define meaning?



Define “cup”



Decompositional semantics



Color: blue, black, etc

Shape:



Texture: ceramic, wood, glass, clay, etc

Three ways of looking at word meaning

❑ Decompositional

- What **characteristics/components** of what the word represents

❑ Ontological

- How the meaning of the word **relates** to the meanings of other words

❑ Distributional

- What **contexts** the word is found in, relative to other words

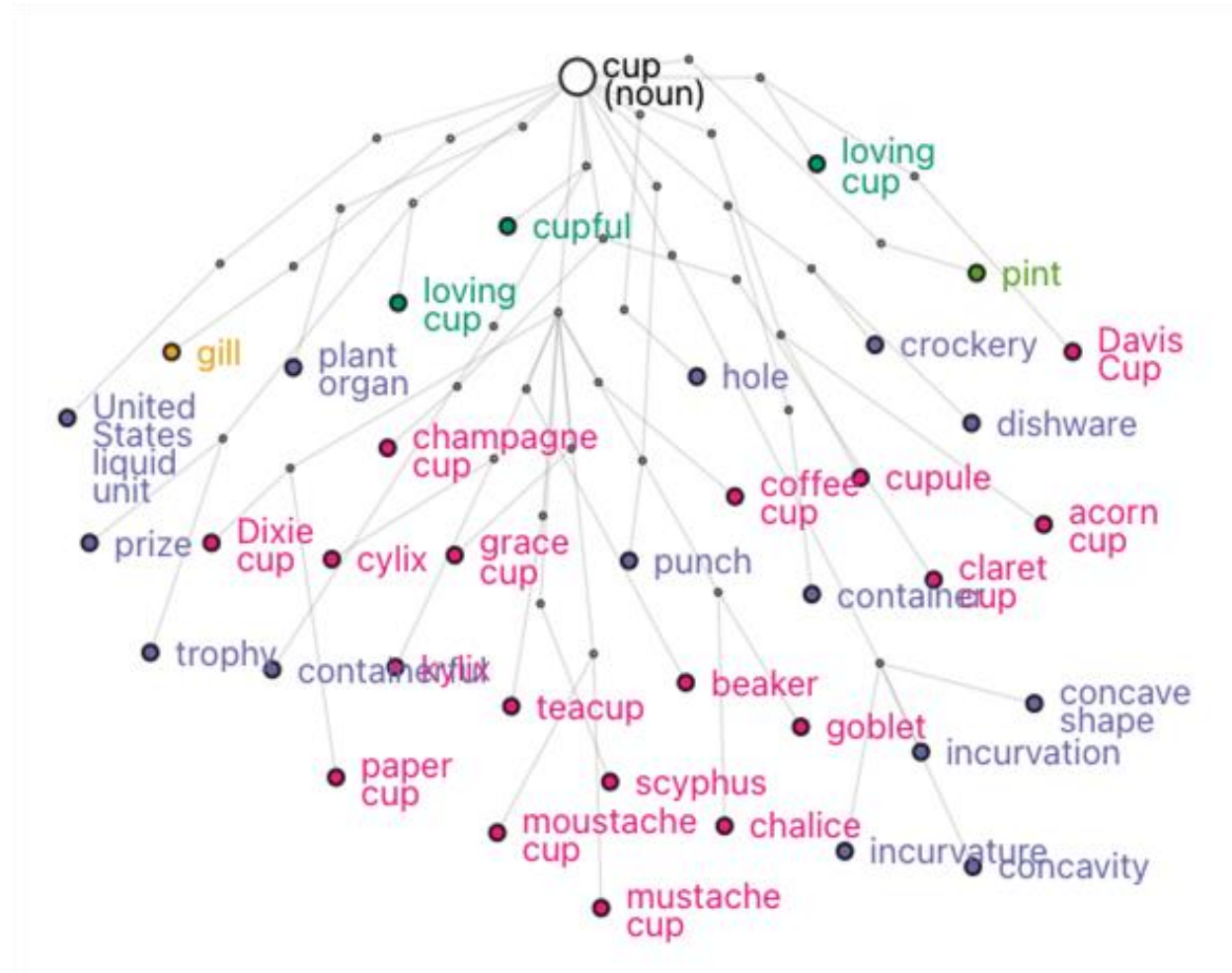


Ontological semantics

☐ synonym
☐ hyponym
☐ attribute

☐ antonym
☒ holonym
☐ entailment

☐ hypernym
☒ meronym
☐ cause

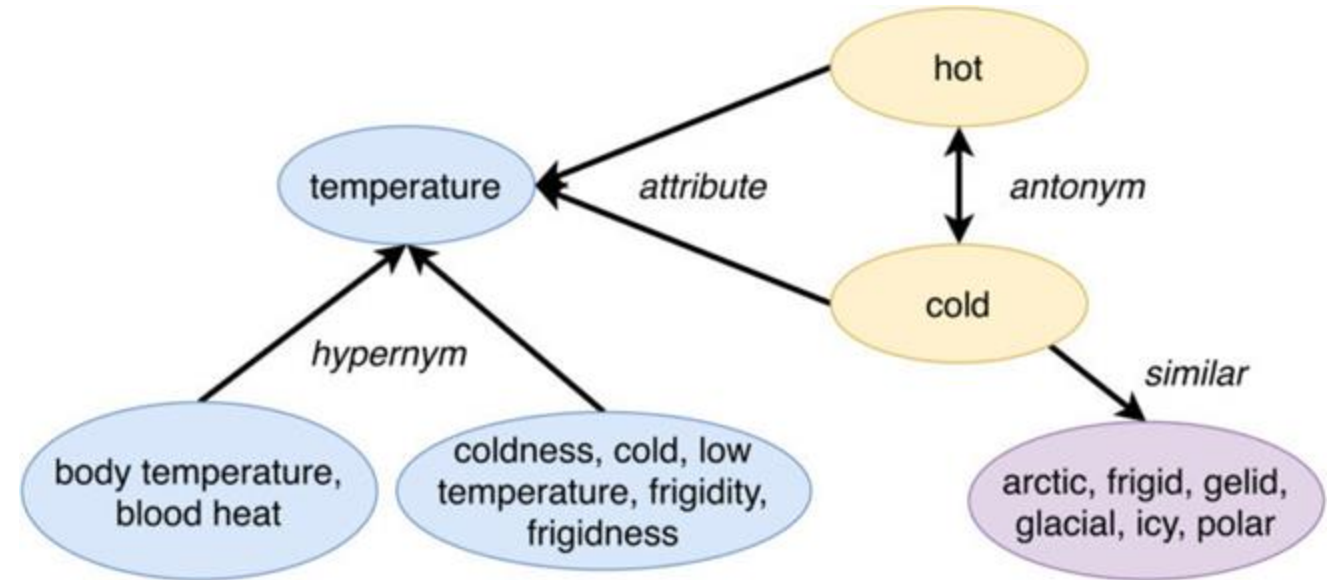


<https://lexical-graph.herokuapp.com/>



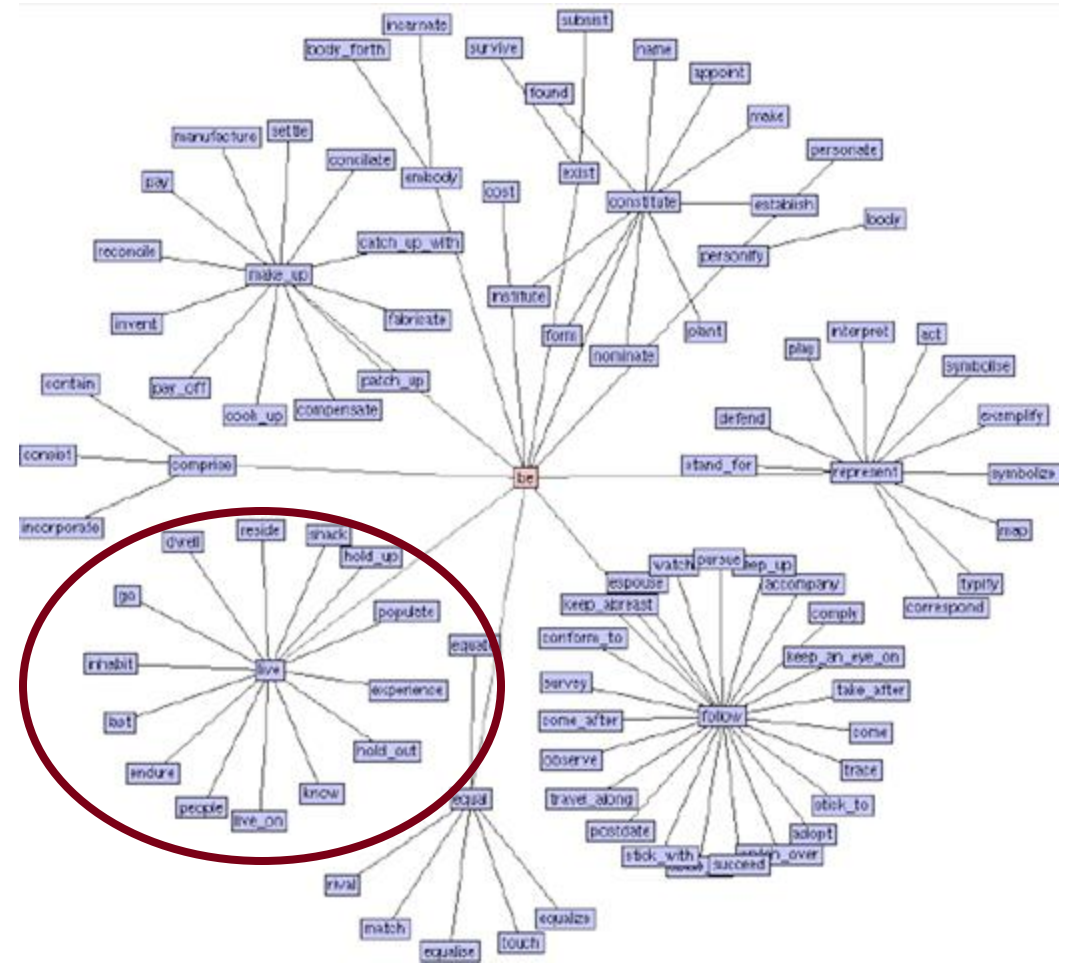
Semantic relations

- ❑ Synonymy — equivalence
 - <small, little>
- ❑ Antonymy — opposition
 - <small, large>
- ❑ Meronymy — part-of relation
 - <liver, body>
- ❑ Holonymy — has-a relation
 - <body, liver>
- ❑ **Hyponymy** — subset; is-a relation
 - <dog, mammal>
- ❑ **Hypernymy** — superset
 - <mammal, dog>

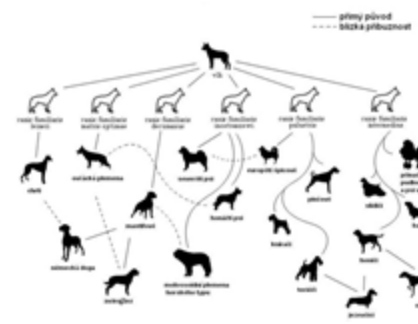


WordNet

- Each sense is associated with a **synset**;
 - a set of words that are roughly synonymous for a particular sense



Synsets for *dog* (n)



English Word Definitions, Terminology, and Jargon

Quora

What is a male dog term, like 'bitch' is a female dog?

[Answer](#) [Follow · 19](#) [Request](#)

1



- ☐ S: (n) **dog, domestic dog, Canis familiaris** (a member of the genus Canis (probably descended from the common wolf) that has been domesticated by man since prehistoric times; occurs in many breeds) "the dog barked all night"
- ☐ S: (n) **dog** (informal term for a man) "you lucky dog"
- ☐ S: (n) **cad, bounder, blackguard, dog, hound, heel** (someone who is morally reprehensible) "you dirty dog"
- ☐ S: (n) **frank, frankfurter, hotdog, hot dog, dog, wiener, wienerwurst, weenie** (a smooth-textured sausage of minced beef or pork usually smoked; often served on a bread roll)
- ☐ S: (n) **pawl, detent, click, dog** (a hinged catch that fits into a notch of a ratchet to move a wheel forward or prevent it from moving backward)
- ☐ S: (n) **andiron, firedog, dog, dog-iron** (metal supports for logs in a fireplace) "the andirons were too hot to touch"
- ☐ S: (n) **dog** (a person who is a member of a particular group or organization)



Tools for WordNet

- ❑ Original English WordNet project:
 - <https://wordnet.princeton.edu/related-projects>
- ❑ WordNets in the World (many languages available):
 - <http://globalwordnet.org/resources/wordnets-in-the-world/>

WordNet Search - 3.1

[WordNet home page](#) - [Glossary](#) - [Help](#)

Word to search for:

Display Options:

Key: "S:" = Show Synset (semantic) relations, "W:" = Show Word (lexical) relations
 Display options for sense: (gloss) "an example sentence"

Noun

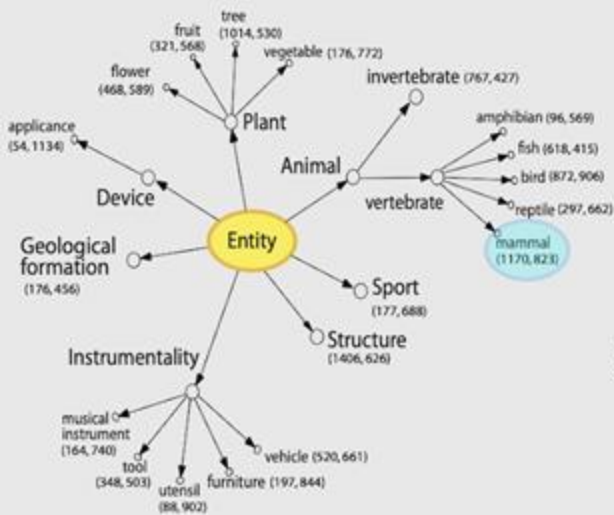
- S: (n) [jump](#), [leap](#) (a sudden and decisive increase) "a jump in attendance"
- S: (n) [leap](#), [jump](#), [saltation](#) (an abrupt transition) "a successful leap from college to the major leagues"
- S: (n) [jump](#) ((film) an abrupt transition from one scene to another)
- S: (n) [startle](#), [jump](#), [start](#) (a sudden involuntary movement) "he awoke with a start"
- S: (n) [jump](#), [parachuting](#) (descent with a parachute) "he had done a lot of parachuting in the army"
- S: (n) [jump](#), [jumping](#) (the act of jumping; propelling yourself off the ground) "he advanced in a series of jumps"; "the jumping was unexpected"

Taxonomy	Synsets		Lemmas		New words	
	Nouns	Verbs	Nouns	Verbs	Nouns	Verbs
WordNet 1.6	66 025	12 127	94 474	10 319	-	-
WordNet 1.7	75 804	13 214	109 195	11 088	11 551	401
WordNet 2.0	79 689	13 508	114 648	11 306	4 036	182
WordNet 2.1	81 426	13 650	117 097	11 488	2 023	158
WordNet 3.0	82 115	13 767	117 798	11 529	678	33

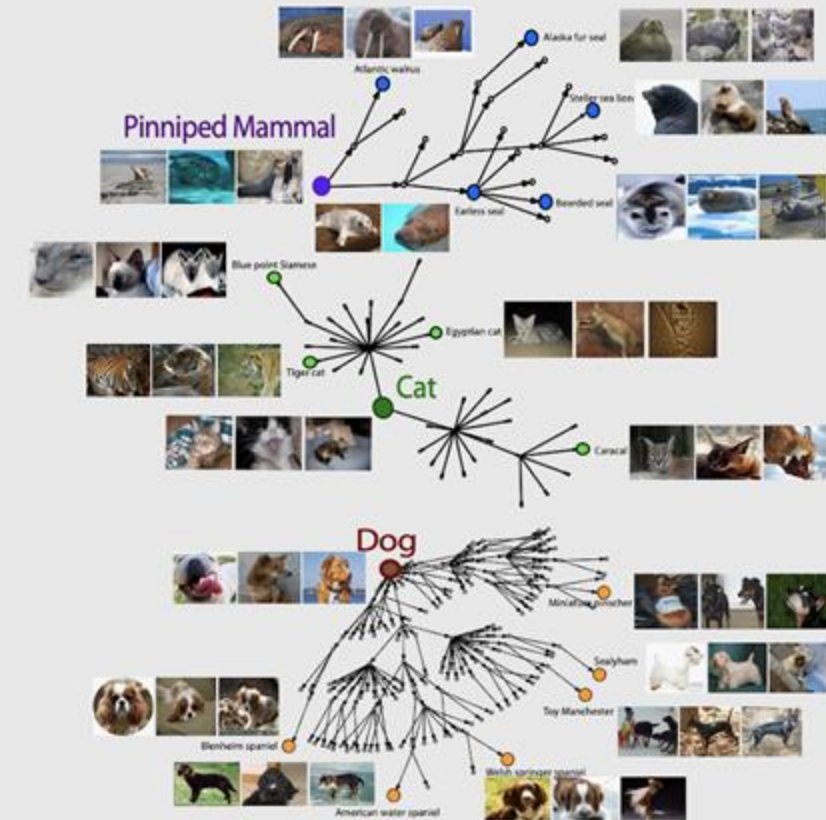
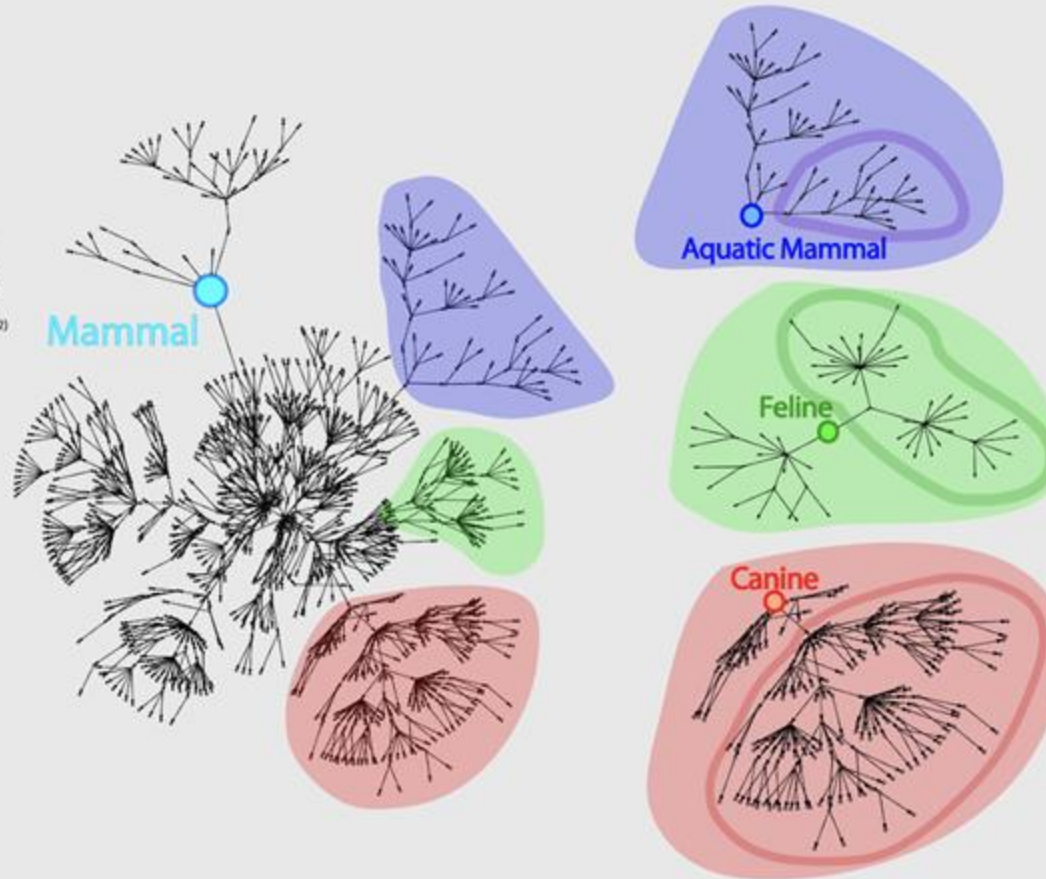


ImageNet based on WordNet

ImageNet Trees



* synset name (# of synsets in the sub tree, average # of images per synset)



L. Fei-Fei and J. Deng. **ImageNet: Where have we been? Where are we going?**, *CVPR Beyond ImageNet Large Scale Visual Recognition Challenge workshop*, 2017, [pdf](#)

Dictionary: A Database for Lexical Semantics

Lemma → **cup** *noun*

Sense →

Definition →

Usage →

1 ★ **A1** [countable] a small container that is like a bowl in shape, usually with a handle, used for drinking tea, coffee, etc.

- He filled the cup with water.
- a coffee cup
- a cup and saucer
- a plastic/paper cup

SEE ALSO **Dixie Cup™**, loving cup, sippy cup

Extra Examples

- Customers don't like drinking out of plastic cups.
- She raised her cup to her lips.
- She was so thirsty that she drained her cup.

2 ★ **A1** [countable] the contents of a cup

- She drank the whole cup.
- **cup of something** Would you like a cup of tea?

Extra Examples

Oxford Collocations Dictionary

3 ★ **A2** [countable] a gold or silver cup on a stem, often with two handles, that is given as a prize in a competition

- She's won several cups for skating.
- He lifted the cup (= won) for the fifth time this year.

Extra Examples

TOPICS **Sports: ball and racket sports** **A2**

Oxford Collocations Dictionary

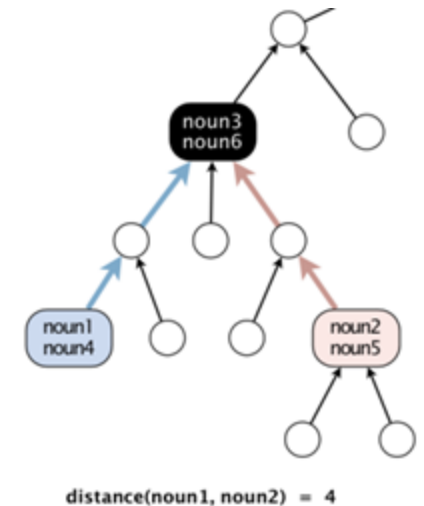
<https://www.oxfordlearnersdictionaries.com/>



Limitations of WordNet and ontological semantics

- ❑ WordNet is a useful resource, but there are intrinsic limits
 - It requires many years of manual effort by experts like skilled lexicographers
 - Some lexicographers are not skilled, and this has led to inconsistencies (<https://en.wikipedia.org/wiki/WordNet>)
 - Ontology is only as good as ontologists; not driven by data
- ❑ Sparse
 - wicked, sick, badass, ninja..
- ❑ Hard to compute word relationships

Let's look into lexical semantics driven by data
and not rely on lexicographers



Three ways of looking at word meaning

❑ Decompositional

- What **characteristics/components** of what the word represents

❑ Ontological

- How the meaning of the word **relates** to the meanings of other words

❑ **Distributional**

- What **contexts** the word is found in, relative to other words



Assumptions in distributional semantics

“The meaning of word is its **use** in the language”

Wittgenstein PI 43

“You shall know a word by the **company** it keeps”

Firth, J. R. 1957:11

“If A and B have almost identical **environments**
we say that they are synonyms.”

Harris 1954



What does “beef” mean?



Beef

001. □ t but of different schools. Cook had discovered a BEEF in his possession a few days earlier and, whe
002. □ ity to available canned pork products. Tests with BEEF have been largely unsuccessful because of the
003. □ ermaster Corps program is to find the reasons for BEEF's low palatability and means of overcoming it
004. □ rads can extend the shelf life (at 35 F) of fresh BEEF from 5 days to 5 or 6 weeks. However, the pro
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009. □ secret employers their money's worth. A good many BEEF-hungry settlers were accepting the death of W
010. □ ogrammes and cost-cutting measures are planned to BEEF up performance. Analysts at Paribas are looki
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013. □ they threw it back at us. "Good gracious, corned BEEF, cheese and bread and butter, they were lucky
014. □ Greece) Ingredients 1 small packet feta cheese 2 BEEF tomatoes ¼ cucumber 1 small jar stoned
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017. □ "Every week or so I'd see them come in for their BEEF ration. And they're allowed to hunt. They can
018. □ ll specialize in steaks, chops, chicken and prime BEEF as well as Tom's favorite dish, stuffed shrim
019. □ close, she said. She had raised a calf, grown it BEEF-fat. She had, with her own work-weary hands,
020. □ and get ready to bear. She was ready to kill the BEEF, dress it out, and with vegetables from her g
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022. □ 12. _HAMBURGER PATTIES WITH NUTS_ 1 pound ground BEEF 2 teaspoons grated onion Dash of pepper 1/2 t
023. □ a highly competitive business more profitable for BEEF, dairy, and sheep men. The target chart quick
024. □ cle assumes that the rations you are feeding your BEEF, dairy cattle, and sheep are adequately balan
025. □ -infective properties of this drug. _HOW TO FEED: BEEF CATTLE (FINISHING RATION)_ - To increase rate
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029. □ oves growth rate and feed efficiency of fattening BEEF animals. _HOW TO FEED:_ At the rate of 2-1/2



Beef

- Suppose you see these sentences:
 - "there was the smell of **roast** **beef**"
 - "I smell **seared** **beef**, and my stomach twists from hunger."

- Suppose you've also seen these:
 - ..a piece of **meat** **roasted** or for roasting..
 - ..So long as the **meat** was **seared**, they gulped down several times their own weight every day, ...



Beef is a **meat** **roasted** or **seared** with smell.

Beef is the culinary name for meat from cattle.

Wikipedia, "beef"

Beef

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Sentences from the brown corpus. Extracted from the concordancer in The Compleat Lexical Tutor, <http://www.lextutor.ca/>



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Beef

0.7
1.3
-4.5

e.g., shape

e.g., color

e.g., smell

Learned latent feature/component:

Learning a vector representation of
 "Beef" from context



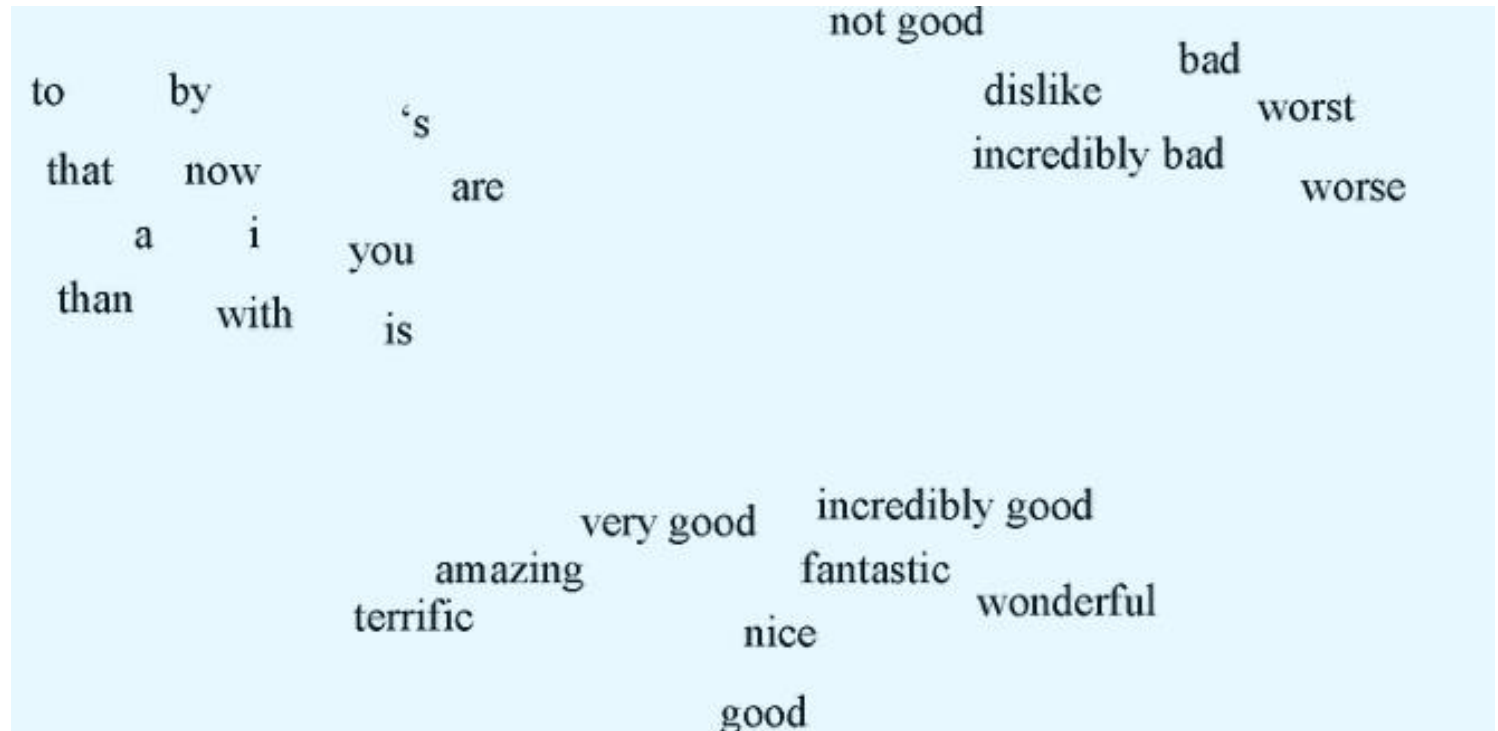
Model of meaning focusing on similarity

❑ Each word = a vector

❑ Not just “word”; Similar words are nearby in space

❑ The standard way to represent meaning in “NLP” these days

0.7
1.3
-4.5



Distributed representation

- ❑ Vector representation that encodes information about the **distribution** of contexts a word appears in
- ❑ Words that appear in similar contexts have similar representations (and similar meanings, by the **distributional hypothesis**).
- ❑ We have several different ways we can encode the notion of "**context**."



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029. [] once growth rate and feed efficiency of fattening BEEF animals. _HOW TO FEED: At the rate of 2-1/2



Another example of polysemy

have a beef with (someone or something)

To have an outstanding or unsettled dispute or disagreement with someone or something

Why does she have a beef with me? I'm always nice to her!

Dad has a real beef with the phone company because they keep raising their rates.

Beef

0.7
1.3
-4.5
0.1
0.4
...

Polysemy should be learned to some extent, assuming that the word vector is trained using ***diverse textual contexts*** and the ***dimensions of the vector*** is large enough



Different kinds of encoding “context”

- ❑ **Count-based**

- PMI, TF-IDF

- ❑ **Distributed prediction-based (type) embeddings**

- Word2vec, GloVe, Fasttext

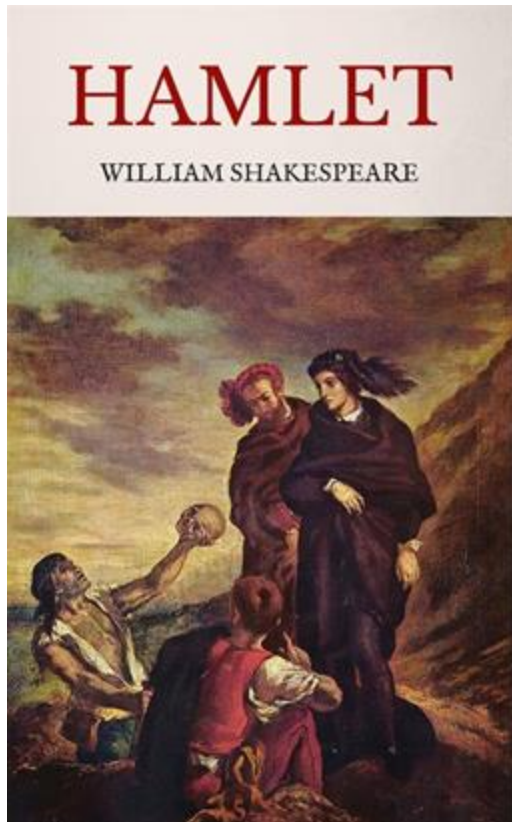
- ❑ **Distributed contextual (token) embeddings from language models**

- ELMo, BERT, GPT

- ❑ **Many more variants**

- Multilingual / multi-sense / syntactic embeddings, etc





Term-document matrix

	Hamlet	Macbeth	Romeo & Juliet	Richard III	Julius Caesar	Tempest
knife	1	1	4	2		2
dog				6	12	2
sword	2	2	7	5		5
love	64		135	63		12
like	75	38	34	36	34	41
...						

Context = appearing in the same document.



Word vectors

		Macbeth				
knife	1	1	4	2		2
sword	2	2	7	5		5
		38				

Vector representation of the **term**;
vector size = **number of documents**

Vector representation of the **document**;
vector size = **number of vocabulary**



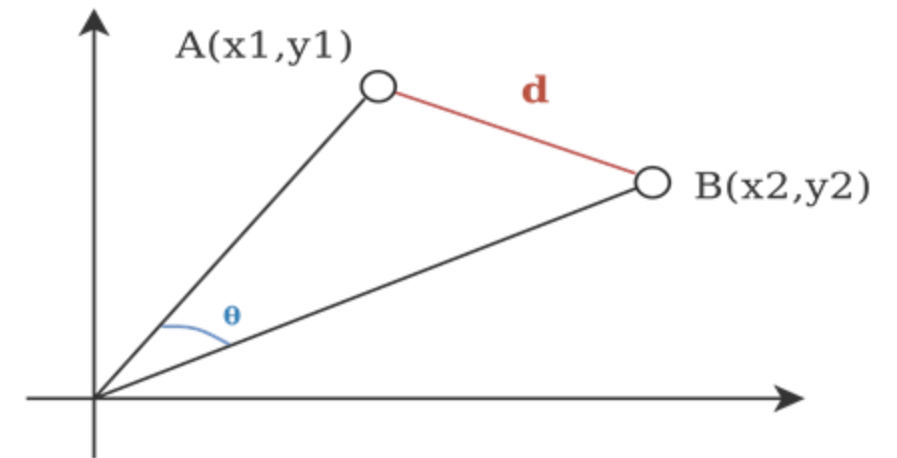
Cosine Similarity

- ❑ Calculate the cosine similarity between the two word vectors, to judge the degree of their similarity [Salton 1971]

Note:

- ❑ Euclidean distance measures the **magnitude** of distance between two points
- ❑ Cosine similarity measures their **orientation**

$$\cos(x, y) = \frac{\sum_{i=1}^F x_i y_i}{\sqrt{\sum_{i=1}^F x_i^2} \sqrt{\sum_{i=1}^F y_i^2}}$$



<https://cmry.github.io/notes/euclidean-v-cosine>



	Hamlet	Macbeth	Romeo & Juliet	Richard III	Julius Caesar	Tempest
knife	1	1	4	2		2
dog				6	12	2
sword	2	2	7	5		5
love	64		135	63		12
like	75	38	34	36	34	41
...						

$\cos(\text{knife}, \text{knife})$ 1.0
 $\cos(\text{knife}, \text{dog})$ 0.11
 $\cos(\text{knife}, \text{sword})$ 0.99
 $\cos(\text{knife}, \text{love})$ 0.65
 $\cos(\text{knife}, \text{like})$ 0.61

Not all dimensions are equally informative.
 Let's weight dimensions!



TF-IDF

- ❑ Term frequency ($TF_{t,d}$) = the number of times terms t occurs in document d
 - Several variants: e.g., passing through log function
- ❑ Inverse document frequency (IDF_d) = inverse function of number of documents containing (D_t) among total number of documents N .

$$tfidf(t, d) = tf_{t,d} \times \log \frac{N}{D_t}$$



	Hamlet	Macbeth	Romeo & Juliet	Richard III	Julius Caesar	Tempest
knife	1	1	4	2		2
dog				6	12	2
sword	2	2	7	5		5
love	64		135	63		12
like	75	38	34	36	34	41
...						

IDF
0.07
0.30
0.07
0.20
0.00

$$tfidf(t, d) = tf_{t,d} \times \log \frac{N}{D_t}$$

IDF indicates the **informativeness** of the terms when comparing documents.



knife	0.07	0.07	0.28	0.14	0	0.14
dog	0	0	0	1.8	3.6	0.6

	Hamlet	Macbeth	Romeo & Juliet	Richard III	Julius Caesar	Tempest
knife	1	1	4	2		2
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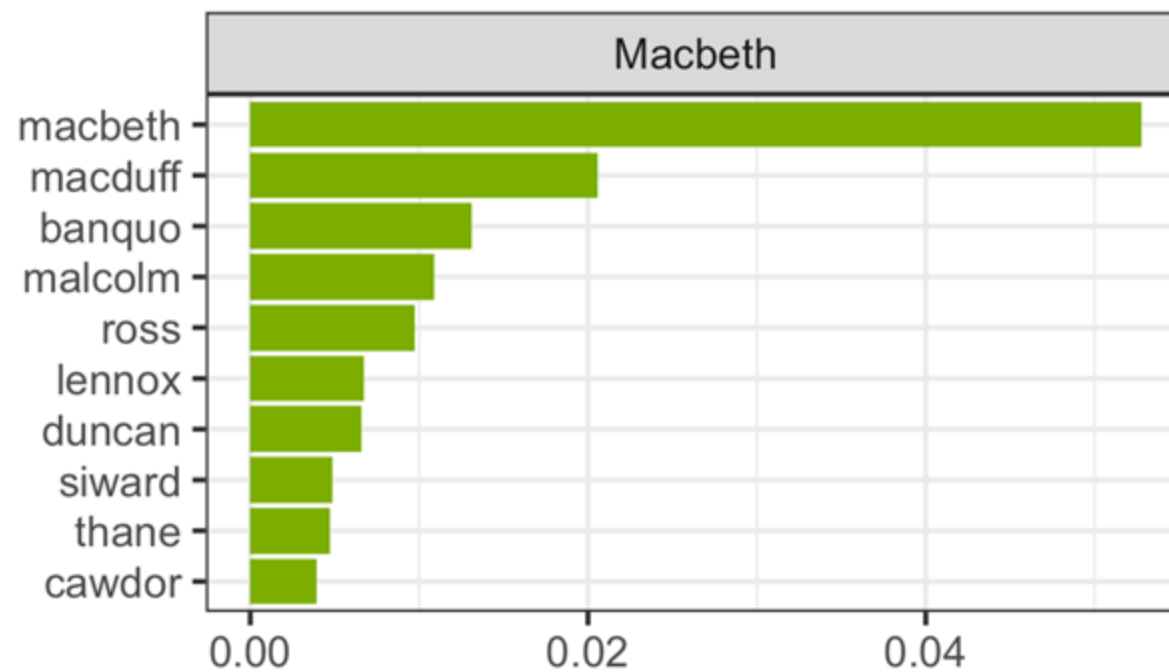
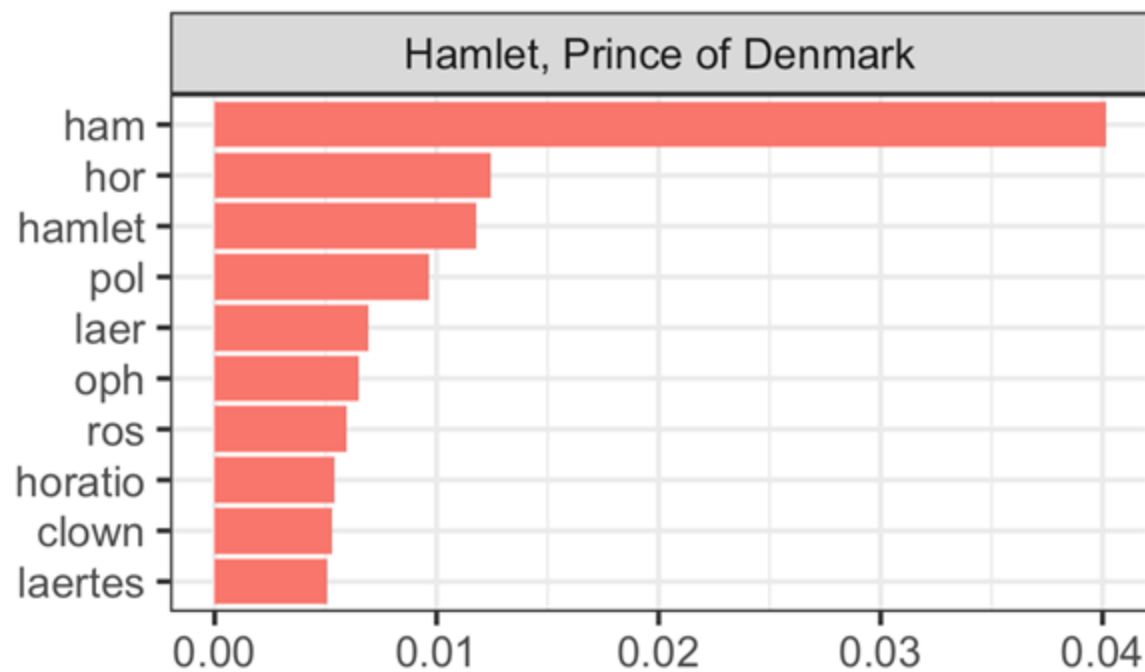
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sword						
love						
like						
...						

$$tfidf(t, d) = tf_{t,d} \times \log \frac{N}{D_t}$$





<https://datavizs21.classes.andrewheiss.com/example/13-example/>



$$\cos(x, y) = \frac{\sum_{i=1}^F x_i y_i}{\sqrt{\sum_{i=1}^F x_i^2} \sqrt{\sum_{i=1}^F y_i^2}}$$

#	Name	Formula
1.	Joint probability	$P(xy)$
2.	Conditional probability	$P(y x)$
3.	Reverse conditional probability	$P(x y)$
4.	Pointwise mutual information	$\log \frac{P(xy)}{P(x)P(y)}$
5.	Mutual dependency (MD)	$\log \frac{P(x,y)^2}{P(x)P(y)}$
6.	Log frequency biased MD	$\log \frac{P(x,y)^2}{P(x)P(y)} + \log P(xy)$
7.	Normalized expectation	$\frac{2f(xy)}{f(x)+f(y)}$
8.	Mutual expectation	$\frac{2f(xy)}{f(x)+f(y)} \cdot P(xy)$
9.	Saliency	$\log \frac{P(xy)}{P(x)P(y)} \cdot \log f(xy)$
10.	Pearson's χ^2 test	$\sum_{i,j} \frac{(f_{ij} - f_{ij}^e)^2}{f_{ij}^e}$
11.	Fisher's exact test	$\frac{f(x,y)!f(x,y)!f(x,y)!}{N!f(x,y)!f(x,y)!f(x,y)!}$
12.	t test	$\frac{f(xy) - f(x,y)}{\sqrt{f(xy)(1 - (f(xy)/N))}}$
13.	z score	$\frac{f(xy) - f(x,y)}{\sqrt{f(xy)(1 - (f(xy)/N))}}$
14.	Poisson significance measure	$\frac{f(xy) - f(x,y) \log f(xy) + \log f(xy)}{\log N}$
15.	Log likelihood ratio	$-2 \sum_{i,j} f_{ij} \log f_{ij} / f_{ij}$
16.	Squared log likelihood ratio	$-2 \sum_{i,j} \log f_{ij}^2 / f_{ij}$
17.	Russel-Rao	$\frac{a}{a+b+c+d}$
18.	Sokal-Michener	$\frac{a+d}{a+b+c+d}$
19.	Rogers-Tanimoto	$\frac{a+d}{a+2b+c+d}$
20.	Hamann	$\frac{(a+d) - (b+c)}{a+b+c+d}$
21.	Third Sokal-Sneath	$\frac{a+d}{a+b+c}$
22.	Jaccard	$\frac{a}{a+b+c}$
23.	First Kulczynsky	$\frac{a}{a+b+c}$
24.	Second Sokal-Sneath	$\frac{a}{a+2(b+c)}$
25.	Second Kulczynsky	$\frac{1}{2} (\frac{a}{a+b} + \frac{a}{a+c})$
26.	Fourth Sokal-Sneath	$\frac{1}{4} (\frac{a}{a+b} + \frac{a}{a+c} + \frac{d}{a+b} + \frac{d}{a+c})$
27.	Odds ratio	$\frac{ad}{bc}$
28.	Yule's ω	$\frac{\sqrt{ad} - \sqrt{bc}}{\sqrt{ad} + \sqrt{bc}}$
29.	Yule's Q	$\frac{ad-bc}{ad+bc}$
30.	Driver-Kroeber	$\frac{a}{\sqrt{(a+b)(a+c)}}$
31.	Fifth Sokal-Sneath	$\frac{ad}{\sqrt{(a+b)(a+c)(d+b)(d+c)}}$
32.	Pearson	$\frac{ad-bc}{\sqrt{(a+b)(a+c)(d+b)(d+c)}}$
33.	Baroni-Urbani	$\frac{a + \sqrt{ad}}{a+b+c + \sqrt{ad}}$
34.	Braun-Blanquet	$\frac{a}{a+b+c + \sqrt{ad}}$
35.	Simpson	$\frac{a}{\max(a+b, a+c)}$
36.	Michael	$\frac{a}{4(ad-bc)}$
37.	Mountford	$\frac{ad}{2bc+ad+ac}$
38.	Fager	$\frac{a}{\sqrt{(a+b)(a+c)}} = \frac{1}{2} \max(b, c)$
39.	Unigram subtuples	$\log \frac{ad}{bc} = 3.29 \sqrt{\frac{1}{a} + \frac{1}{b} + \frac{1}{c} + \frac{1}{d}}$
40.	U cost	$\log(1 + \frac{\min(b,c)+a}{\max(b,c)+a})$
41.	S cost	$\log(1 + \frac{\min(b,c)}{a+1}) - \frac{1}{2}$
42.	R cost	$\log(1 + \frac{a}{a+b}) \cdot \log(1 + \frac{a}{a+c})$
43.	T combined cost	$\sqrt{U \times S \times R}$
44.	Phi	$\frac{P(x,y) - P(x)P(y)}{\sqrt{P(x)P(y)(1-P(x))(1-P(y))}}$
45.	Kappa	$\frac{P(x,y) + P(x)P(y) - P(x)P(y)}{1 - P(x)P(y) - P(x)P(y)}$

#	Name	Formula
46.	J measure	$\max[P(xy) \log \frac{P(x,y)}{P(x)P(y)} + P(xy) \log \frac{P(y,x)}{P(y)P(x)}, P(xy) \log \frac{P(x,y)}{P(x)P(y)} + P(xy) \log \frac{P(y,x)}{P(y)P(x)}]$
47.	Gini index	$\max[P(x,y)(P(y x)^2 + P(x y)^2) - P(x,y)^2, P(x,y)(P(y x)^2 + P(x y)^2) - P(x,y)^2, P(x,y)(P(y x)^2 + P(x y)^2) - P(x,y)^2]$
48.	Confidence	$\max[P(y x), P(x y)]$
49.	Laplace	$\max[\frac{N P(x,y) + 1}{N P(x,y) + 2}, \frac{N P(y,x) + 1}{N P(y,x) + 2}]$
50.	Conviction	$\max[\frac{P(x,y)P(y,x)}{P(x)P(y)}, \frac{P(x,y)P(y,x)}{P(x)P(y)}]$
51.	Platersky-Shapiro	$P(xy) - P(x)P(y)$
52.	Certainty factor	$\max[\frac{P(x,y) - P(x)P(y)}{1 - P(x,y)}, \frac{P(x,y) - P(x)P(y)}{1 - P(x,y)}]$
53.	Added value (AV)	$\max[P(y x) - P(x,y), P(x y) - P(x,y)]$
54.	Collective strength	$\frac{P(x,y) + P(x,y)}{P(x,y) + P(x,y)}, \frac{1 - P(x,y) - P(x,y)}{1 - P(x,y) - P(x,y)}$
55.	Kloggen	$\sqrt{P(xy) \cdot AV}$
56.	Context entropy	$-\sum_w P(w C_x) \log P(w C_x)$
57.	Left context entropy	$-\sum_w P(w C_x) \log P(w C_x)$
58.	Right context entropy	$-\sum_w P(w C_x) \log P(w C_x)$
59.	Left context divergence	$P(x,y) \log P(x,y) - \sum_w P(w C_x) \log P(w C_x)$
60.	Right context divergence	$P(x,y) \log P(x,y) - \sum_w P(w C_x) \log P(w C_x)$
61.	Cross entropy	$-\sum_w P(w C_x) \log P(w C_x)$
62.	Reverse cross entropy	$-\sum_w P(w C_x) \log P(w C_x)$
63.	Intersection measure	$\frac{2 C_x \cap C_y }{ C_x + C_y }$
64.	Euclidean norm	$\sqrt{\sum_w (P(w C_x) - P(w C_y))^2}$
65.	Cosine norm	$\frac{\sum_w P(w C_x)P(w C_y)}{\sqrt{\sum_w P(w C_x)^2} \sqrt{\sum_w P(w C_y)^2}}$
66.	L1 norm	$\sum_w P(w C_x) - P(w C_y) $
67.	Confusion probability	$\sum_w \frac{P(w C_x)P(w C_y)}{P(w C_x) + P(w C_y)}$
68.	Reverse confusion probability	$\sum_w \frac{P(w C_x)P(w C_y)}{P(w C_x) + P(w C_y)}$
69.	Jensen-Shannon divergence	$\frac{1}{2} [D(p(w C_x) \frac{1}{2}(p(w C_x) + p(w C_y))) + D(p(w C_y) \frac{1}{2}(p(w C_x) + p(w C_y)))]$
70.	Cosine of pointwise MI	$\frac{MI(w,x)MI(w,y)}{\sqrt{MI(w,x)^2} \sqrt{MI(w,y)^2}}$
71.	KL divergence	$\sum_w P(w C_x) \log \frac{P(w C_x)}{P(w C_y)}$
72.	Reverse KL divergence	$\sum_w P(w C_y) \log \frac{P(w C_y)}{P(w C_x)}$
73.	Skew divergence	$D(p(w C_x) \alpha p(w C_x) + (1-\alpha)p(w C_y))$
74.	Reverse skew divergence	$D(p(w C_y) \alpha p(w C_x) + (1-\alpha)p(w C_y))$
75.	Phrase word cooccurrence	$\frac{1}{2} (\frac{f(x C_x)}{f(x)} + \frac{f(y C_x)}{f(y)})$
76.	Word association	$\frac{1}{2} (\frac{f(x C_x) - f(x)}{f(x)} + \frac{f(y C_x) - f(y)}{f(y)})$
Cosine context similarity:		$\frac{1}{2} (\cos(e_x, e_y) + \cos(e_x, e_y))$
77. in boolean vector space		$e_x = \{z_i\}; \cos(e_x, e_y) = \frac{\sum z_i z_i}{\sqrt{\sum z_i^2} \sqrt{\sum z_i^2}}$
78. in tf vector space		$z_i = \delta(f(w_i C_x))$
79. in tf · idf vector space		$z_i = f(w_i C_x) \cdot \frac{N}{df(w_i)}; df(w_i) = \{x: w_i \in C_x\} $
Dice context similarity:		$\frac{1}{2} (\text{dico}(e_x, e_y) + \text{dico}(e_x, e_y))$
80. in boolean vector space		$e_x = \{z_i\}; \text{dico}(e_x, e_y) = \frac{2 \sum z_i z_i}{\sum z_i^2 + \sum z_i^2}$
81. in tf vector space		$z_i = f(w_i C_x)$
82. in tf · idf vector space		$z_i = f(w_i C_x) \cdot \frac{N}{df(w_i)}; df(w_i) = \{x: w_i \in C_x\} $

Table 1: Inventory of lexical association measures for collocation extraction. Pecina, P. (2008). Lexical Association Measures: Collocation Extraction.



Different kinds of encoding “context”

☒ ~~Count-based~~

- PMI, TF-IDF

☐ **Distributed prediction-based (type) embeddings**

- Word2vec, GloVe, Fasttext

☐ **Distributed contextual (token) embeddings from language models**

- ELMo, BERT, GPT

☐ **Many more variants**

- Multilingual / multi-sense / syntactic embeddings, etc



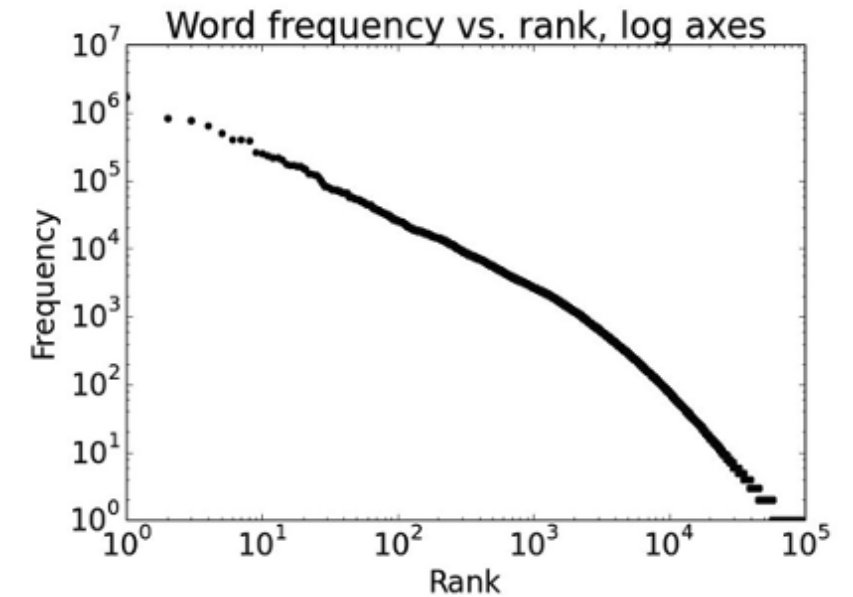
Sparse vectors



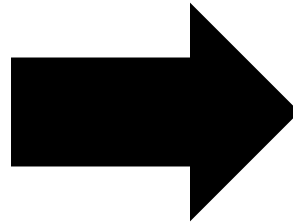
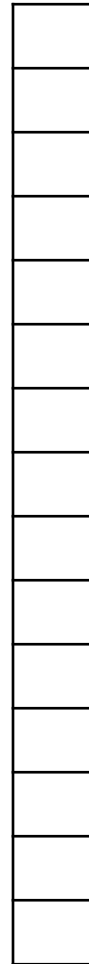
"aardvark"

V-dimensional vector, single 1 for the identity of the element

a	0
a	0
aa	0
aal	0
aalii	0
aam	0
Aani	0
aardvark	1
aardwolf	0
...	
zythem	0
Zythia	0
zythum	0
Zyzomys	0
Zyzzogeton	0



Sparse vectors -> Dense vectors

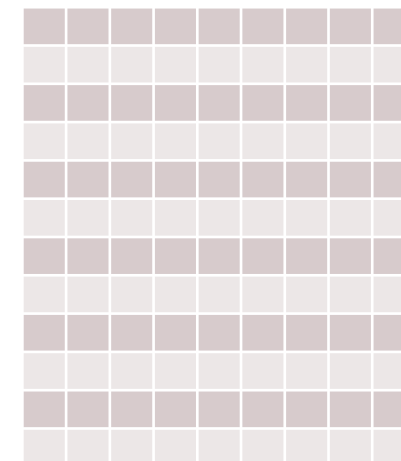


0.7
1.3
-4.5



	Hamlet	Macbeth	Romeo & Juliet	Richard III	Julius Caesar	Tempest
knife	1	1	4	2		2
dog				6	12	2
sword	2	2	7	5		5
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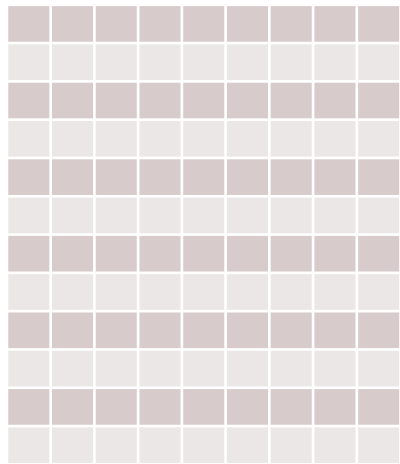
=



$n \times d$

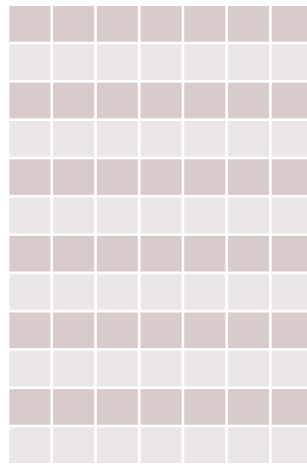
Singular value decomposition (SVD)

- Any $n \times d$ matrix X can be decomposed into the product of three matrices
 - where m is the number of linearly independent rows



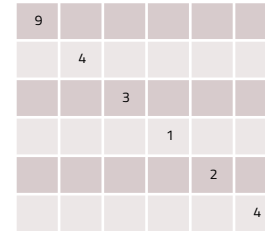
$n \times d$

=



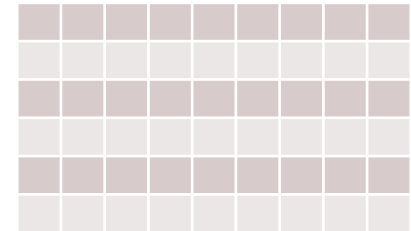
$n \times m$

×



$m \times m$
(diagonal)

×

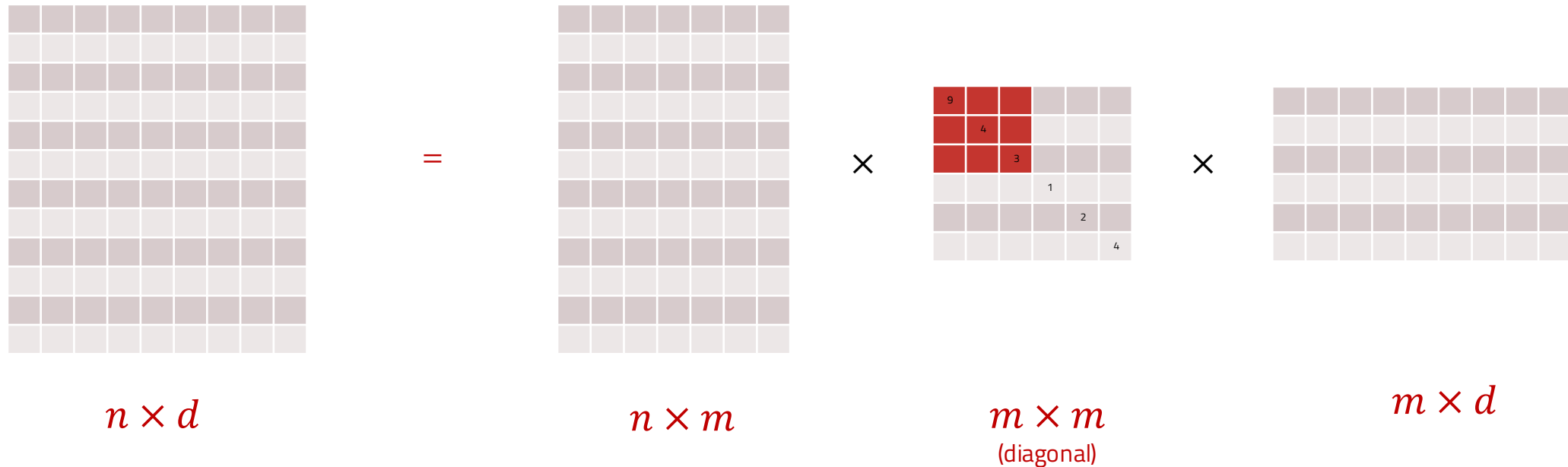


$m \times d$



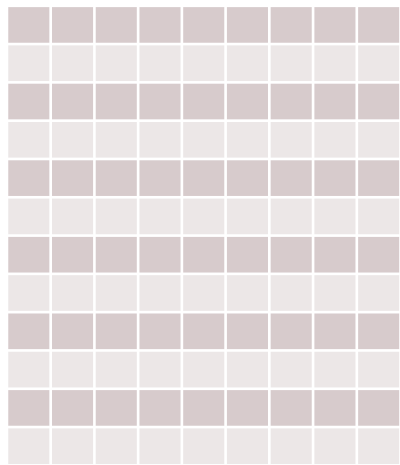
Singular value decomposition (SVD)

- We can approximate the full matrix by only considering the **leftmost k terms** in the diagonal matrix



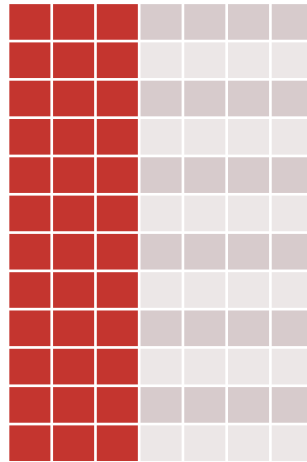
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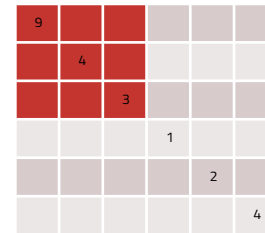
$n \times d$

$\approx$



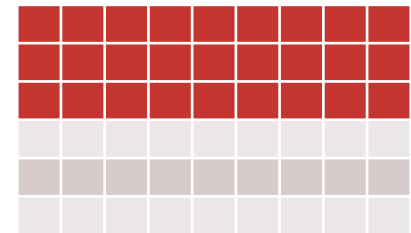
$n \times m$

$\times$



$m \times m$
(diagonal)

$\times$

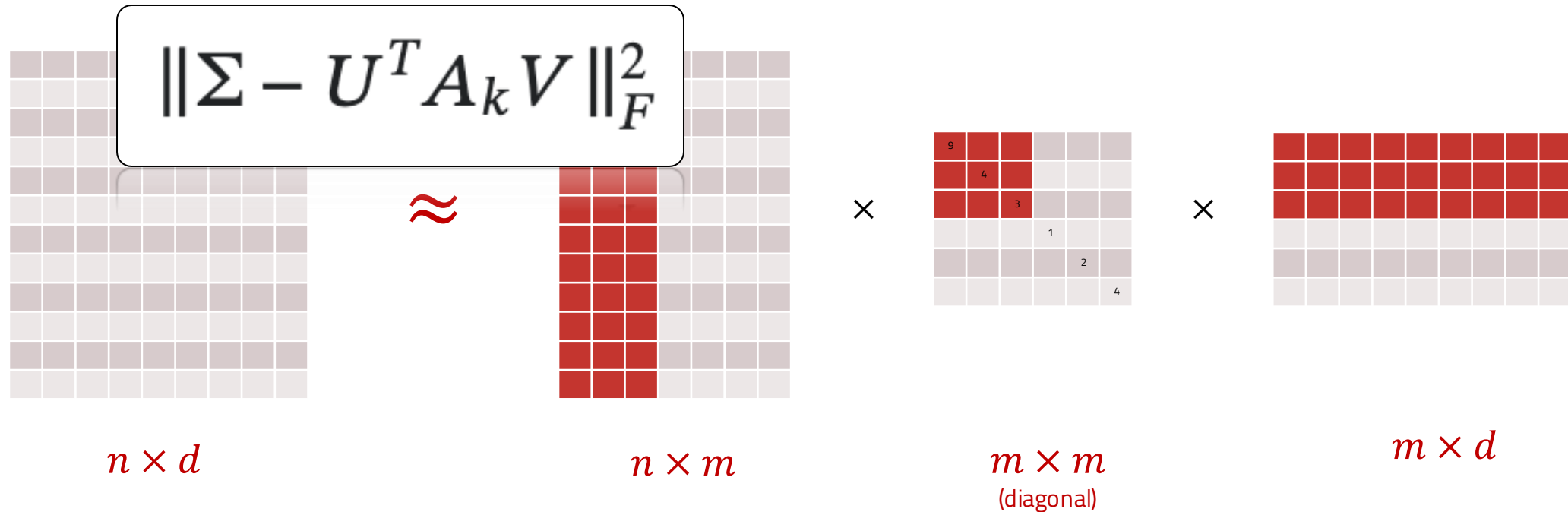


$m \times d$



Singular value decomposition (SVD)

- We can approximate the full matrix by only considering the **leftmost k terms** in the diagonal matrix



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love	64		135	63		12
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knife	0.2	0.42	0.22
dog	0.5	1.2	8.6
sword	-0.2	0.7	-2.2
love	9.3	-0.5	0.5
like	0.2	4.3	0.9

$$n \times m$$

×

0.5		
	0.3	
		2.5

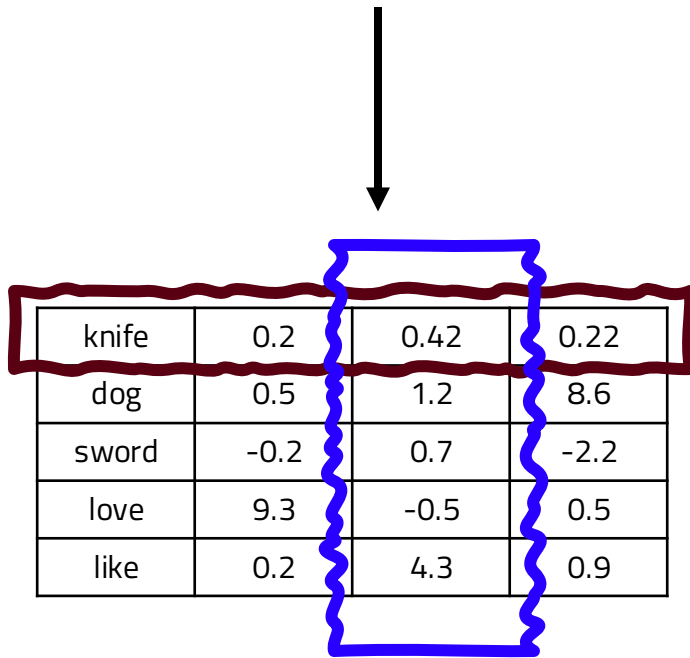
$$m \times m$$

×

Hamlet	Macbeth	Romeo & Juliet	Richard III	Julius Caesar	Tempest
-0.2	0.7	-2.2	-0.2	0.7	-2.2
-0.2	0.7	-2.2	9.3	-0.5	0.5
9.3	-0.5	0.5	-0.5	0.5	9.3

$$m \times d$$

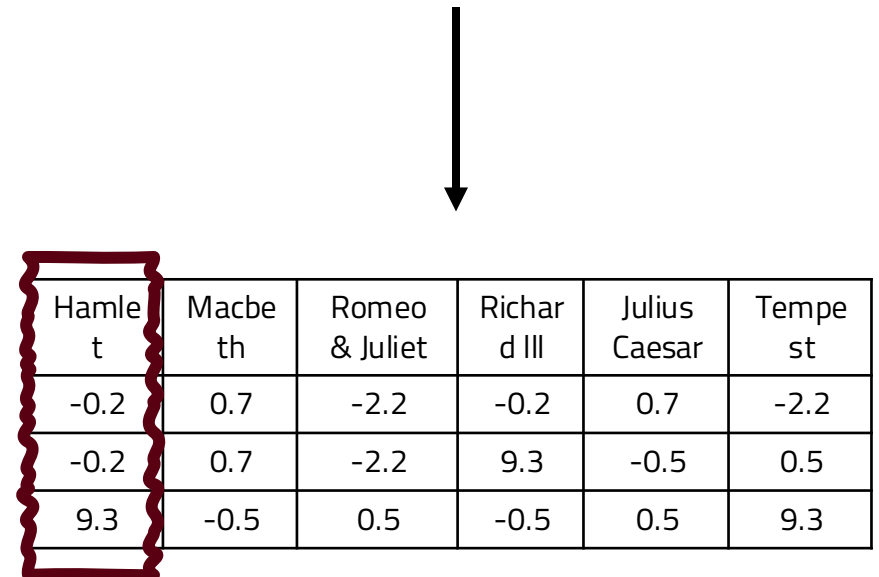
Low-dimensional representation
for **terms** (here 3 dimensions)



knife	0.2	0.42	0.22
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0.5		
	0.3	
		2.5

Low-dimensional representation
for **documents** (here 3 dimensions)



Hamlet	Macbeth	Romeo & Juliet	Richard III	Julius Caesar	Tempest
-0.2	0.7	-2.2	-0.2	0.7	-2.2
-0.2	0.7	-2.2	9.3	-0.5	0.5
9.3	-0.5	0.5	-0.5	0.5	9.3

Latent semantic analysis

- ❑ Latent Semantic Analysis/Indexing is this process of applying SVD to the term-document co-occurrence matrix
 - Terms typically weighted by tf-idf
- ❑ This is a form of dimensionality reduction
 - for terms, from a D-dimensional sparse vector to a K-dimensional dense one where $K \ll D$.
- ❑ Similar kinds:
 - Probabilistic Latent Semantic Indexing (pLSI) (Hofmann, 1999)
 - Nonnegative Matrix Factorization (NMF) (Lee & Seung, 1999)
 - Latent Dirichlet Allocation (LDA) (Blei et al., 2003)

	#1	#2	#3
knife	0.2	0.42	0.22
dog	0.5	1.2	8.6
sword	-0.2	0.7	-2.2
love	9.3	-0.5	0.5
like	0.2	4.3	0.9

Sort by probabilities

#1	#2	#3	#4
music	how	program	10
film	what	project	30
theater	about	russian	11
mr	their	space	12
this	or	russia	15

(Deerwester et al. 1998)

Latent semantic analysis



001. [A box of different schools, Cook had discovered a beef in his possession a few days earlier and, the
002. [try to available cannot pork products, tests with beef have been largely unsuccessful because of the
003. [remember Cook's program is to find the reason for meat's low palatability and means of concealing it.
004. [Cook can extend the shelf life of beef from 5 days to 5 to 6 weeks. However, the pro
005. [rationing bleaching process discards the treated beef and liquid concentrates in prepackaged cuts. C
006. [of liquid concentrates in prepackaged cuts, cooked beef irradiated in the absence of oxygen assumes a
007. [the important sources of health and safety for beef bacteria. There was, of course, no real need a
008. [of the hot source from his was substituted by a beef barrel with wide knotholes out. In this heavy a
009. [would emphasize their meat's worth. A good meat beef-hungry activities were among the death of a
010. [aggressive and cost-cutting measures are planned to beef up performance. Annapolis at Paris are looki
011. [since like animal feed, produce 600,000 tonnes of beef, which alone is worth \$1,000 million at whol
012. [pay on the French market. He moved them up across beef, cheese, pork and hot soups, and they thi
013. [they threw to back at us. "Good question," asked beef, cheese and bread and butter, they were toke
014. [French ingredients I shall avoid like cheese & beef because I should be afraid
015. [for the past twenty minutes? Waiter! Waiter! The beef surprise was lovely, but what's the surprise?
016. [to handle who come for a Mr. Mouton one surprise beef to the refrigerator at at the kitchen. I guess
017. [every week or so I'd see them come in for their beef ration. And they're allowed to buy. They can
018. [is something to make, things, chicken and game beef as well as their favorite dish, stuffed oliv
019. [since, she said, she had raised a calf, grown in beef-fat, the hat, with her own work-wear body,
020. [and get ready to bear, she was ready to kill the beef, down in oil, and with vegetables from her g
021. [I know what to say. He did say she could get her beef and vegetables in case this summer. He did se
022. [it. ANNEBORNE NOTICES WITH MEAT, I found ground beef & sausage spread once both of eggs 1/2 1
023. [a highly competitive business were profitable for beef, dairy, and sheep meat. The target chart quick
024. [for anyone that the various you are feeding your beef, dairy cattle, and sheep are obviously balan
025. [infective properties of this meat. NOW TO PORK: BEEF DIRTIE OFFENDING PARTS. - To increase sale
026. [in the production of liver abundance in feed-on beef cattle, transfection of bacterial pneumonia, an
027. [founder, and in controlling enteric. NOW TO PORK: BEEF AND SAUSY CRISIS. - 0.2 gram Spenser per head
028. [main and improve feed efficiency. NOW TO PORK: BEEF CRISIS. - 10 milligrams of disinfectant/feeding
029. [one growth rate and feed efficiency of fattening beef animals. NOW TO PORK: at the rate of 2-1/2



Beef	
0.7	e.g., shape
1.3	e.g., color
-4.5	e.g., smell

Learned latent feature/component:

Learning a vector representation of "Beef" from context

	#1	#2	#3
knife	0.2	0.42	0.22
dog	0.5	1.2	8.6
sword	-0.2	0.7	-2.2
love	9.3	-0.5	0.5
like	0.2	4.3	0.9

Sort by probabilities

	#1	#2	#3	#4
music	how	program	10	
film	what	project	30	
theater	about	russian	11	
mr	their	space	12	
this	or	russia	15	

(Deerwester et al. 1998)



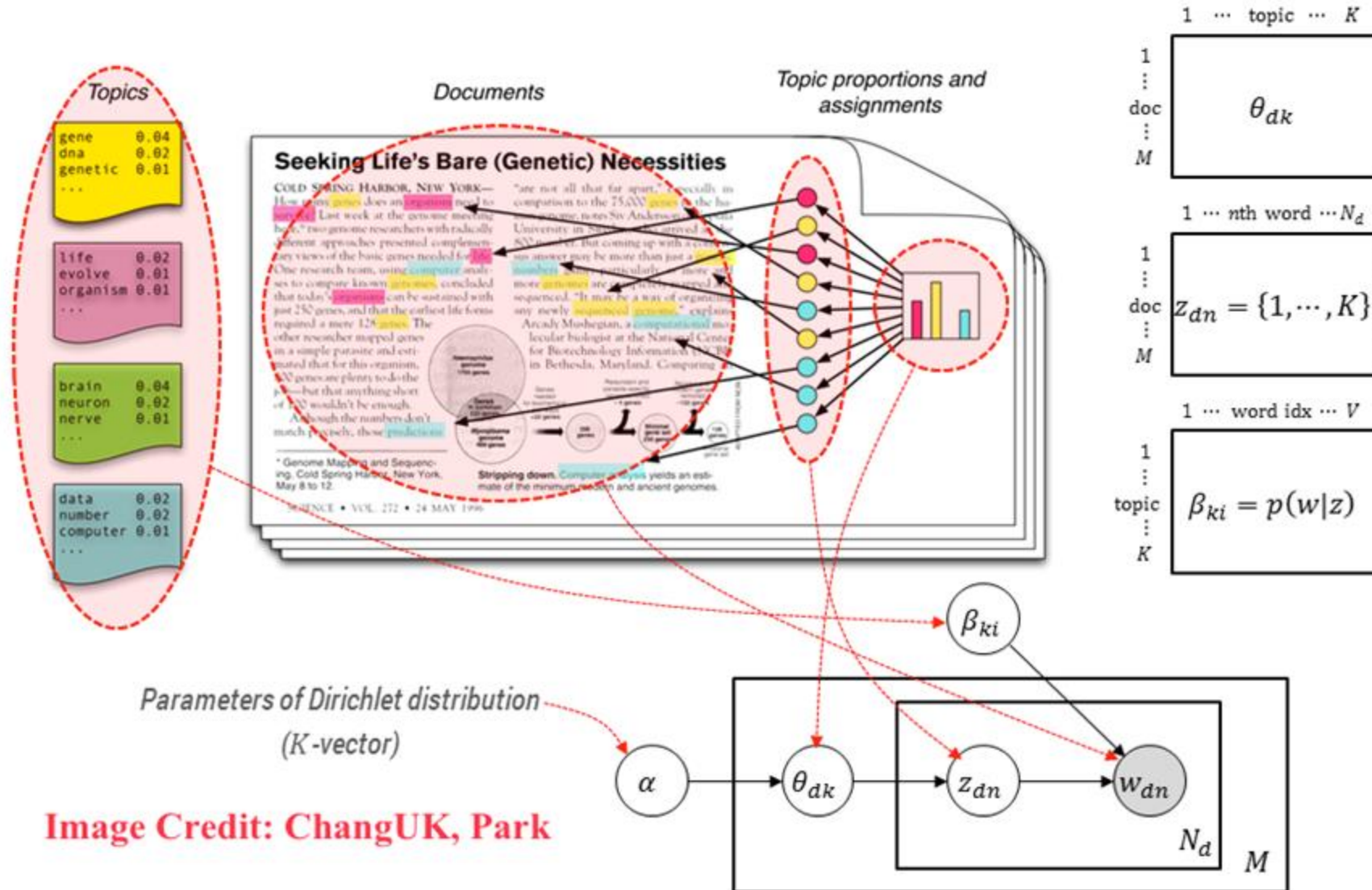
Topic Modeling

- ❑ A probabilistic model for discovering hidden “topics” (groups of **terms** that tend to occur together) in documents.
- ❑ Unsupervised (find *interesting structure* in the data)
- ❑ Clustering **tokens** into **topics**

{album, band, music}	{government, party, election}	{game, team, player}
album	government	game
band	party	team
music	election	player
song	state	win
release	political	play
{god, call, give}	{company, market, business}	{math, number, function}
god	company	math
call	market	number
give	business	function
man	year	code
time	product	set



Topic Modeling



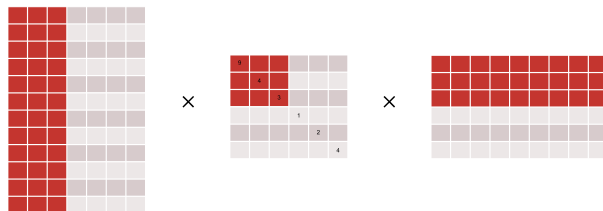
Count-based vs Prediction-based Methods

To obtain good dense representations

LSA, HAL (Lund & Burgess)

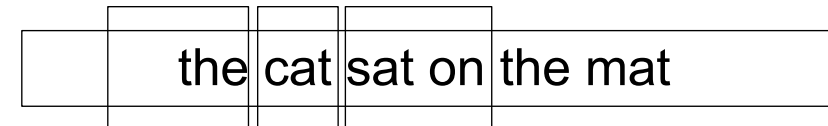
Hellinger-PCA (Rohde et al, Lebrete & Collobert)

	Hamlet	Macbeth
knife	1	1
dog		
sword	2	2
love	64	
like	75	38



Skip-gram/CBOW (Mikolov et al)

NLM, HLBL, RNN (Bengio et al; Collobert & Weston; Huang et al; Mnih & Hinton)



Text Classification Revisited

$x = \text{"Today's weather is great"}$

$$P(y | x)$$

$y = \{\text{positive, negative}\}$

$\hat{y} = \text{positive}$

$$|Y| = 2$$

$x_{<t} = \text{"Today's weather is"}$

$$P(x_t | x_{<t})$$

$x_t = \{\text{a, aa .. apple .. banana .. great .. good .. zebra ..}\}$

$\hat{x} = \text{great}$

$$|X| = V \text{ (vocabulary size)}$$

$x_{<t} = \text{"Today's [] is great"}$

$$P(x_t | x_{t-2, t-1, t+1, t+2})$$

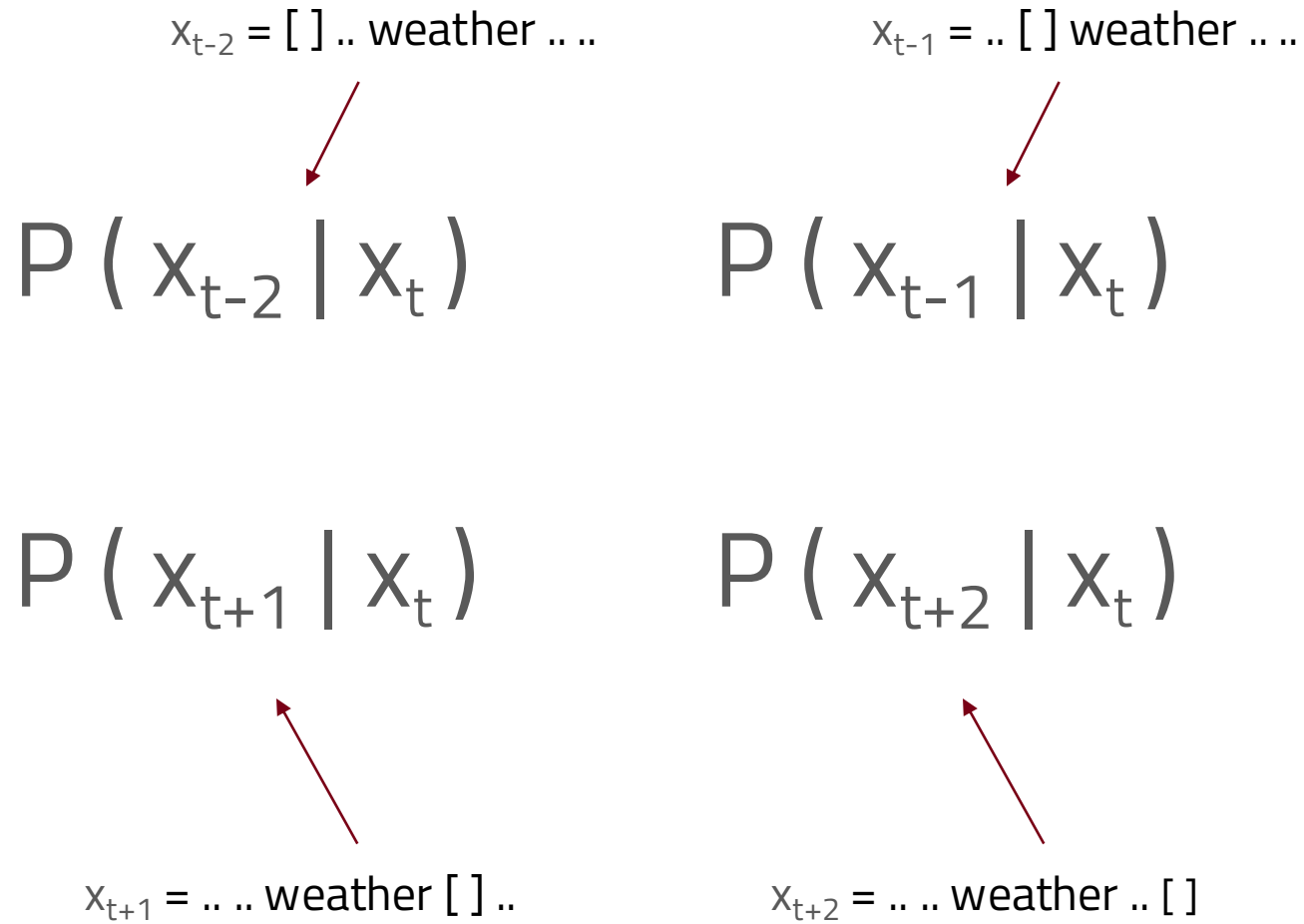
$x_t = \{\text{a, aa .. apple .. banana .. great .. good .. zebra ..}\}$

$\hat{x} = \text{weather}$

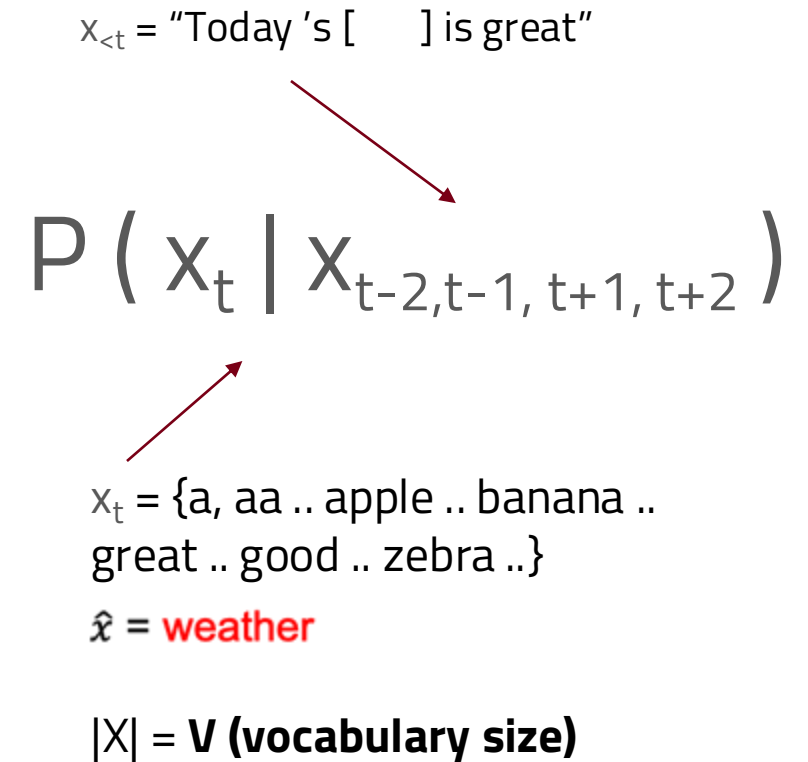
$$|X| = V \text{ (vocabulary size)}$$



Text Classification Revisited



Predict the neighboring word(s) from the middle word



Predict the middle word from neighboring words

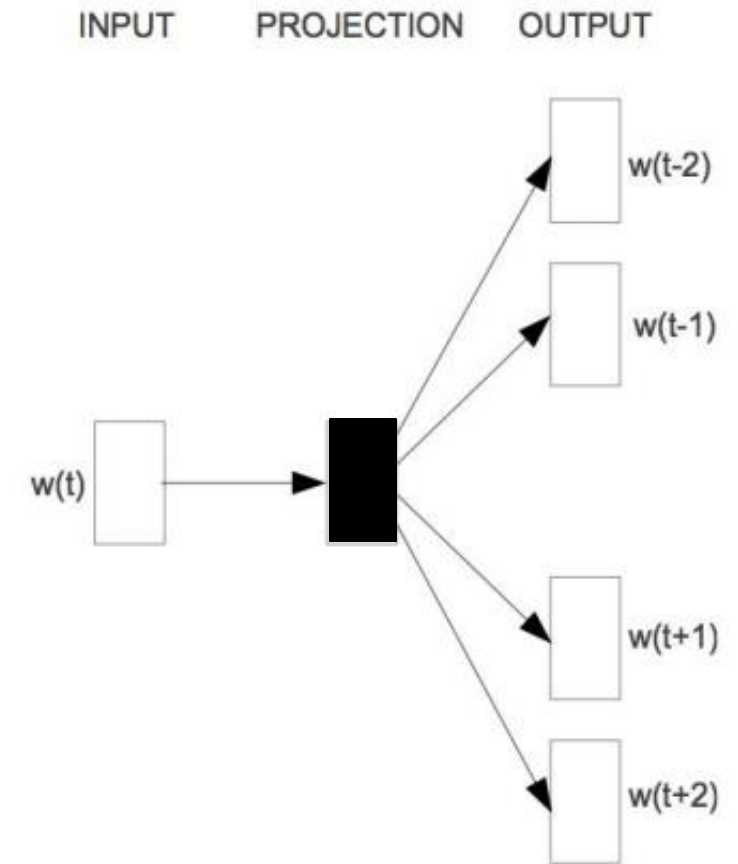


Dense vectors from prediction (not count)

the cat sat on the mat

Skipgram model: given a single word in a sentence, predict the words in a context window around it.

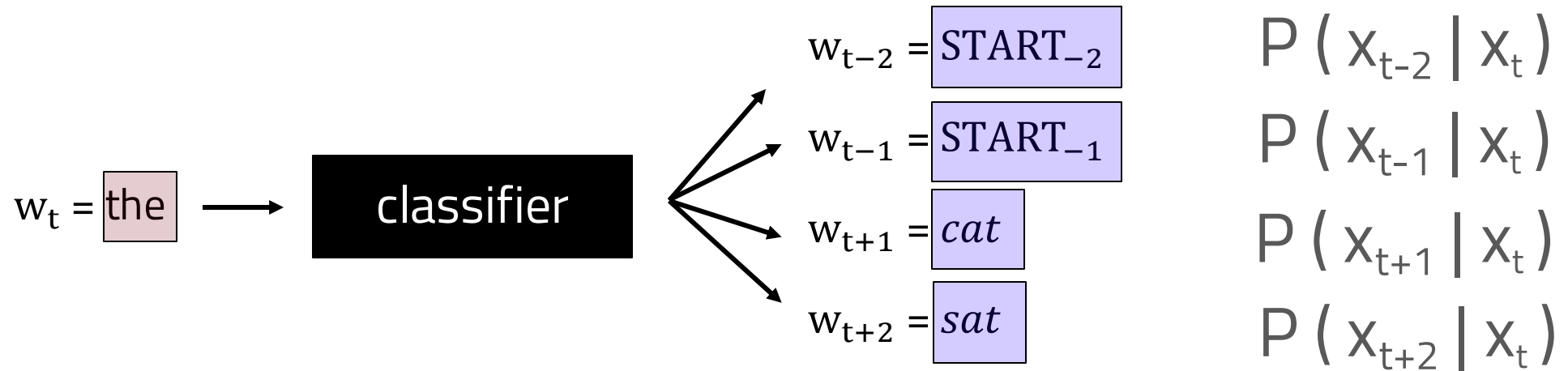
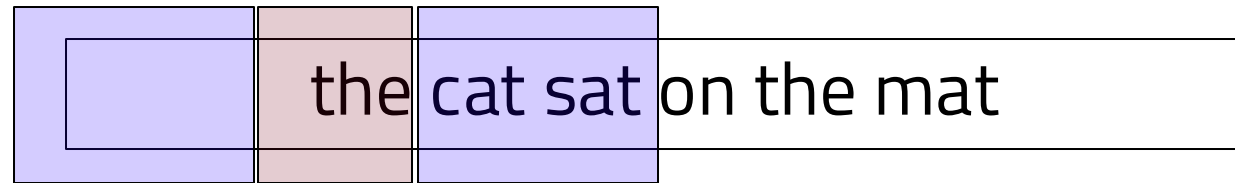
Predict the neighboring word(s) from the middle word



(Mikolove et al., 14)

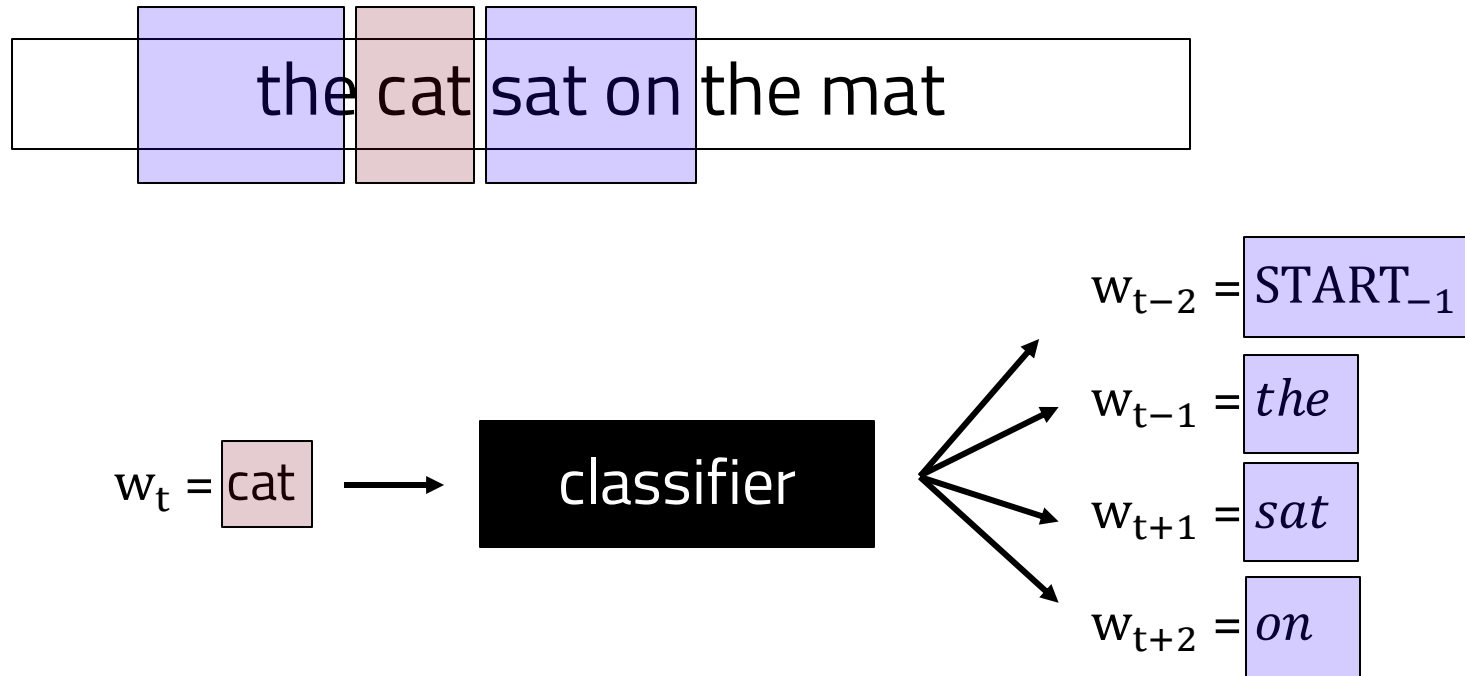


Dense vectors from prediction (not count)



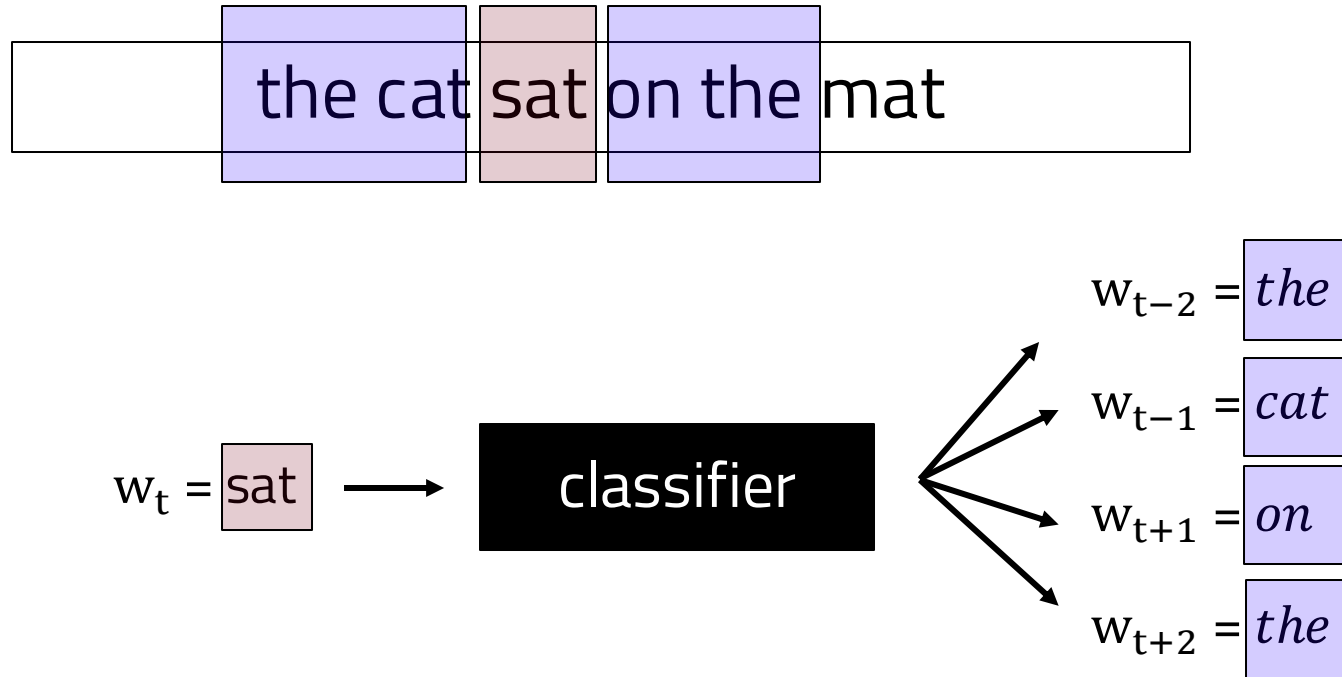
Context window size = 2

Dense vectors from prediction (not count)



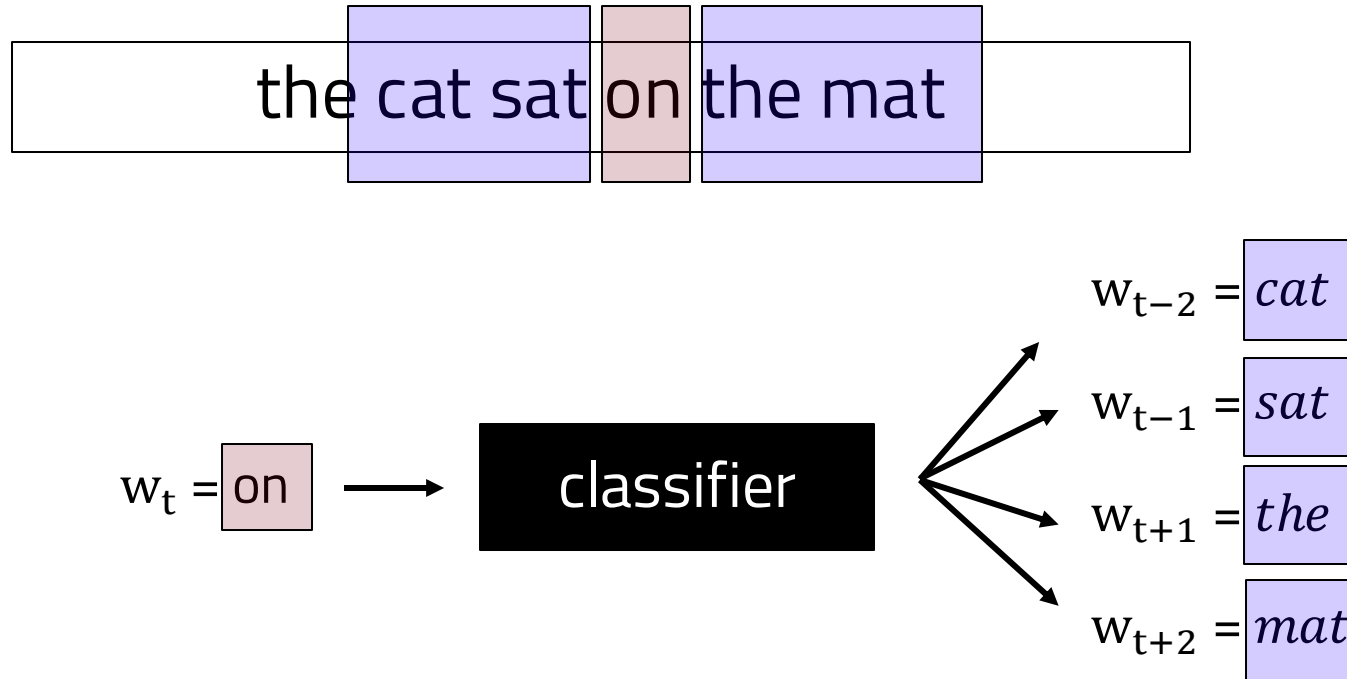
Context window size = 2

Dense vectors from prediction (not count)



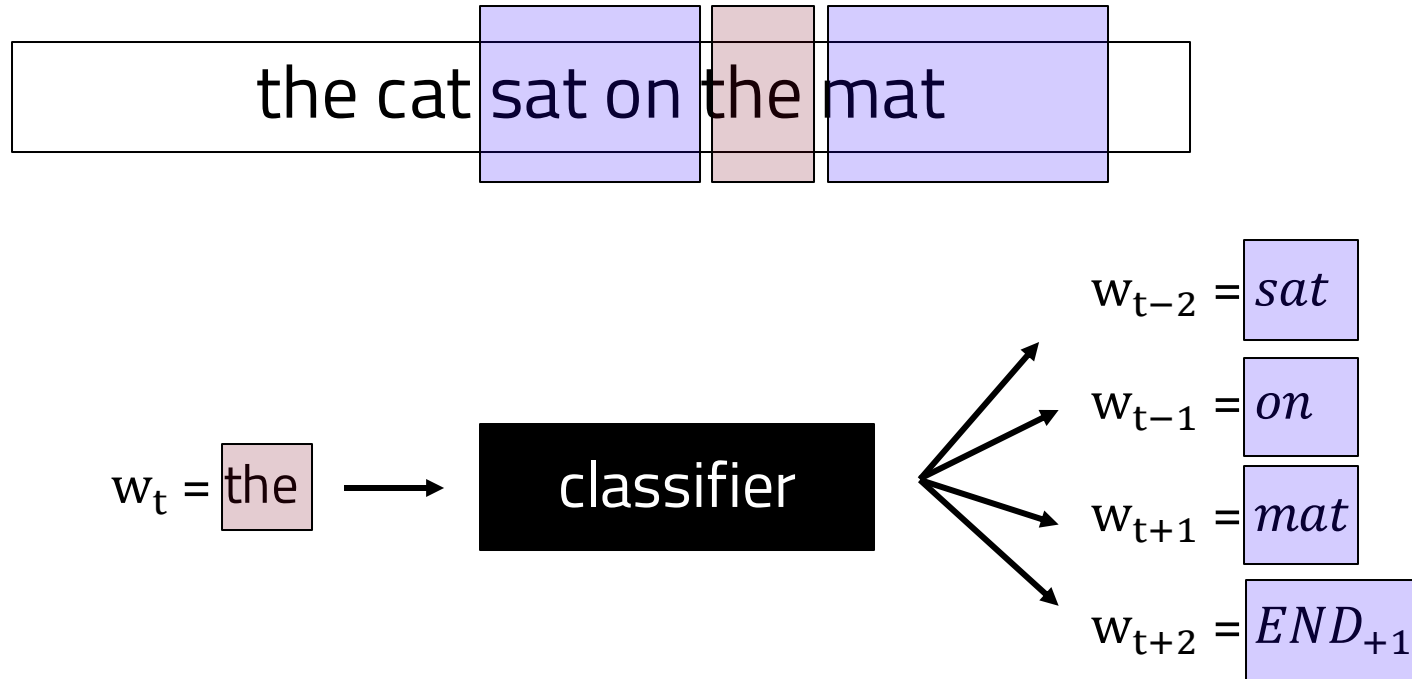
Context window size = 2

Dense vectors from prediction (not count)



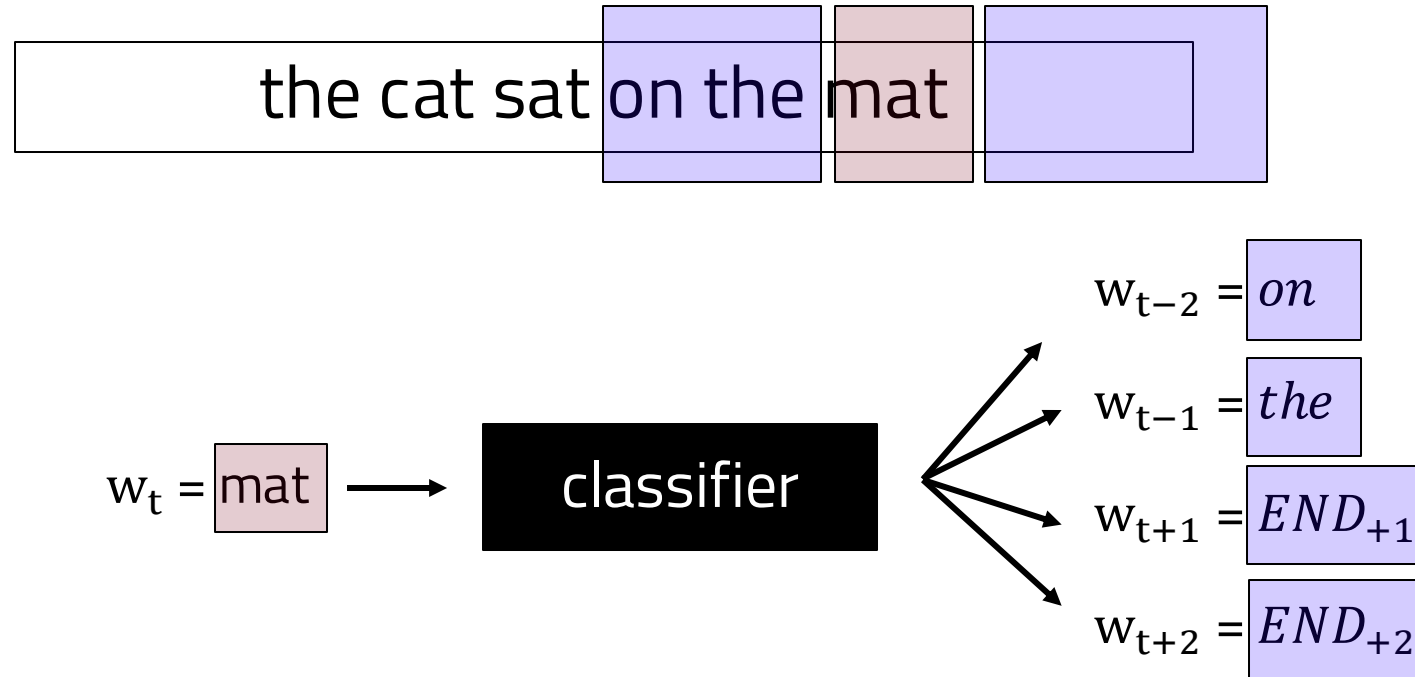
Context window size = 2

Dense vectors from prediction (not count)



Context window size = 2

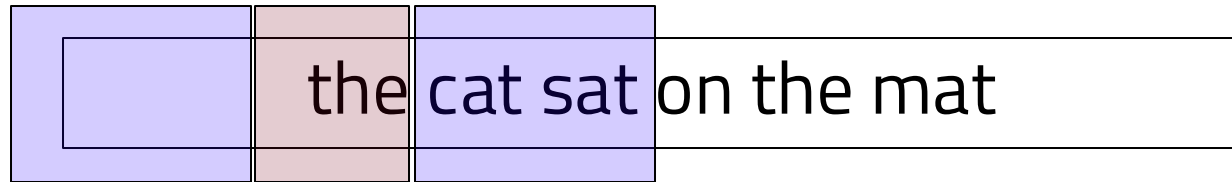
Dense vectors from prediction (not count)



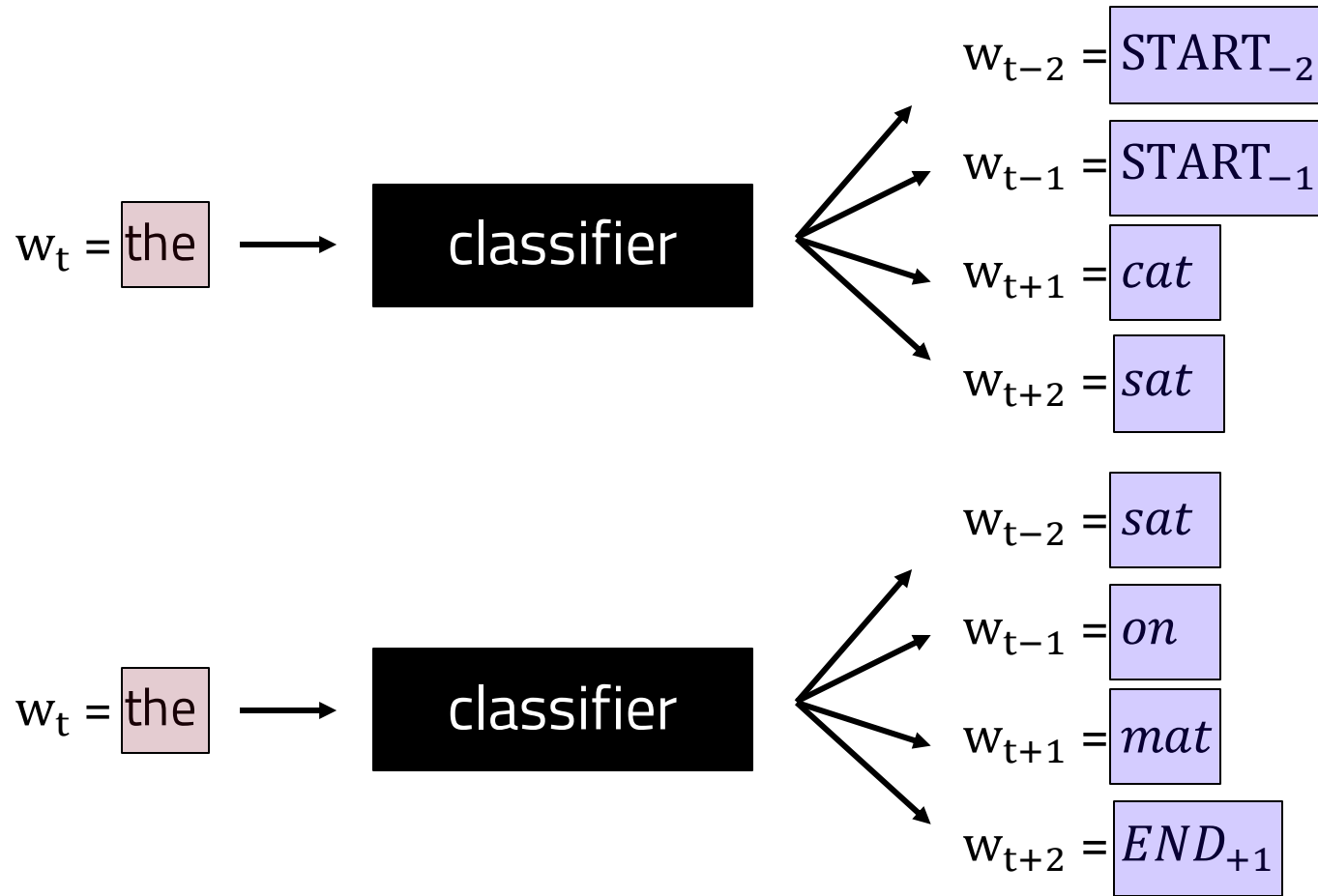
Context window size = 2



Same context but different output?



Same context but different output?



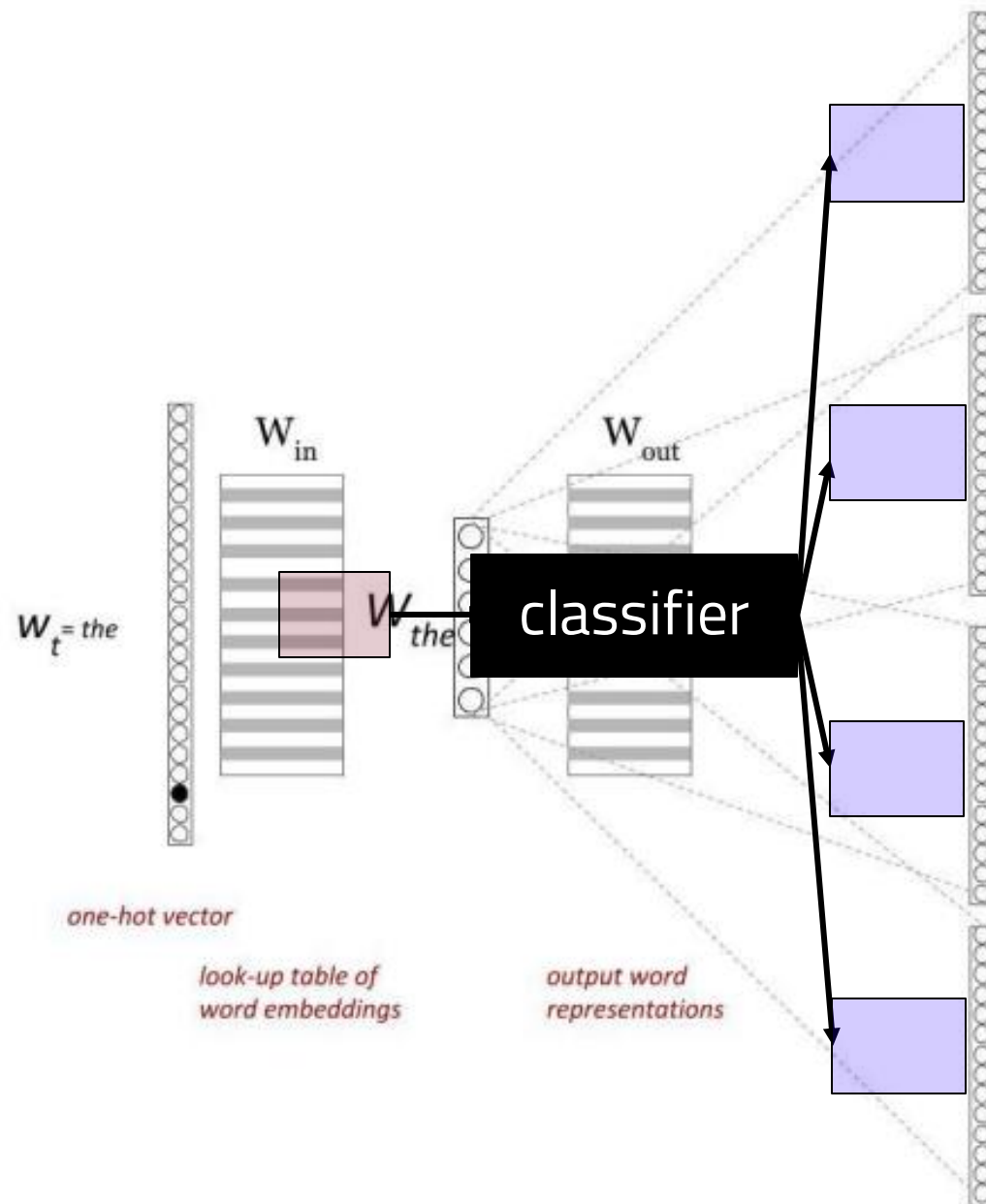
Learning
*multiple
senses/context*

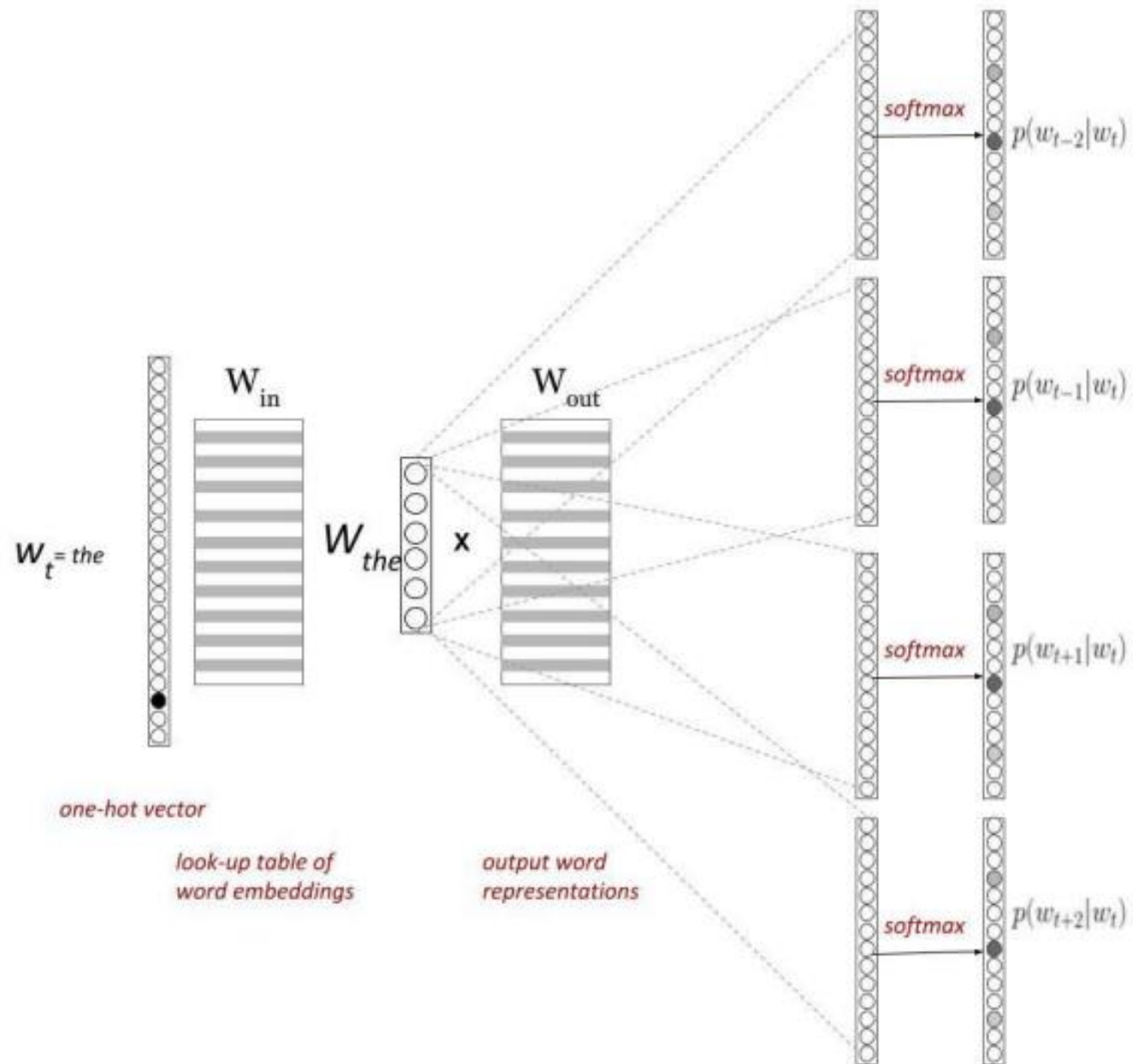
Context window size = 2



Dense vectors from prediction (not count)







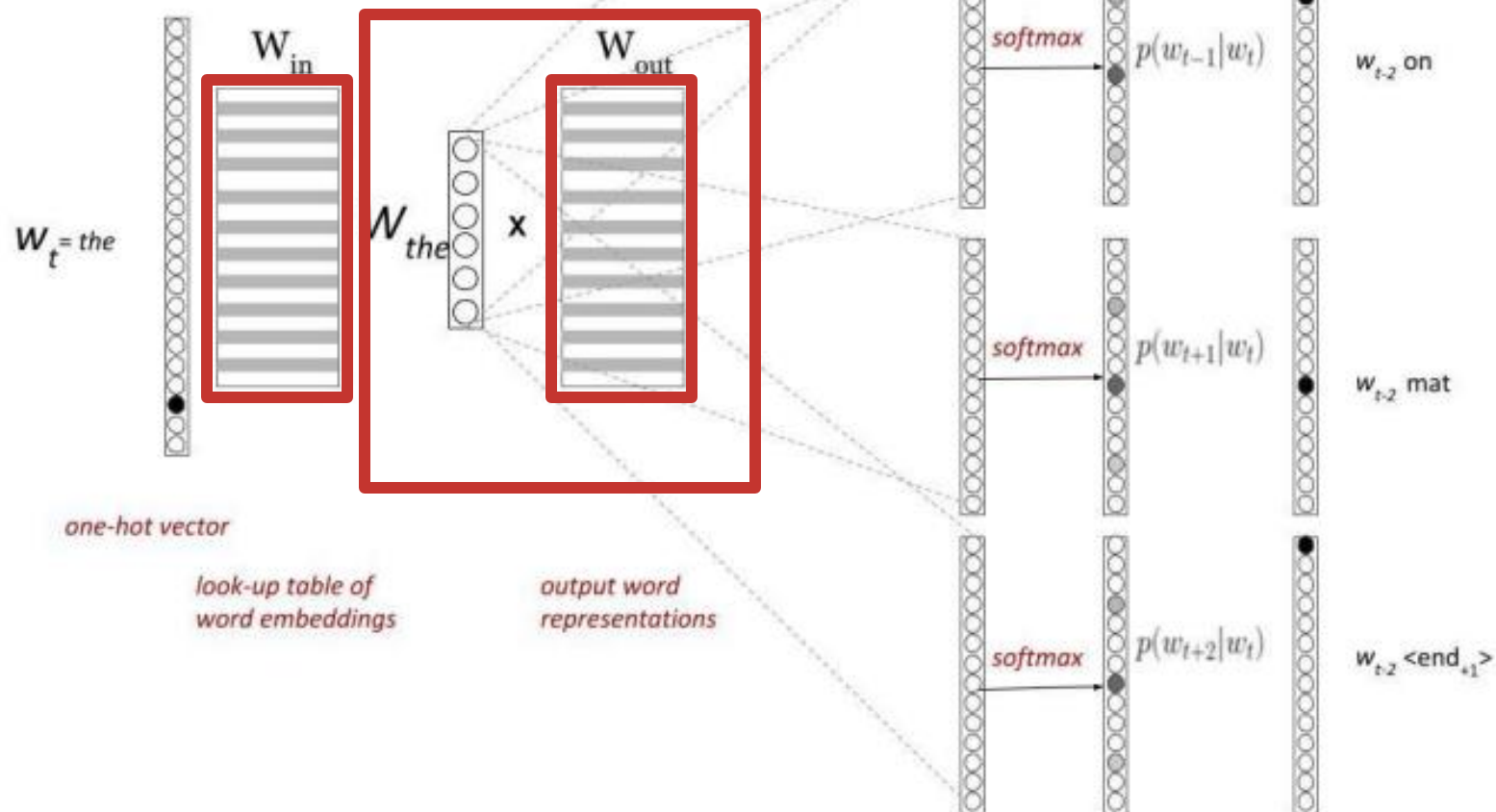
V

the	cat	mat	on	sat	..			
5.2	1.5	...						
0.5	0.4	...						
-6.2	0.6	..						
0.5	-3.4	..						
...								

Word embedding (v_c) for center word (c) "the"

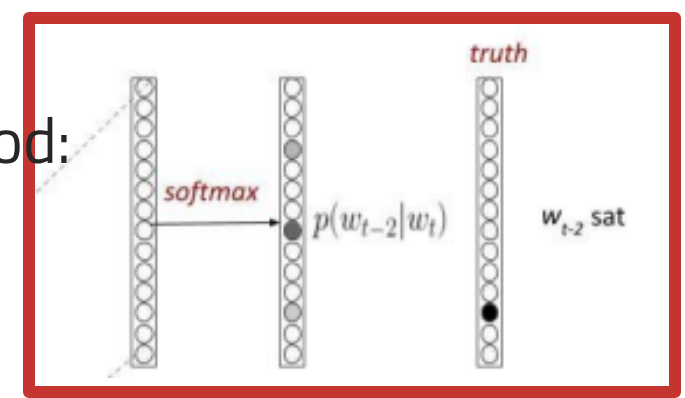
Word embedding (u_o) for output word (o)

$$\frac{\exp(u_o^T v_c)}{\sum_{w \in V} \exp(u_w^T v_c)}$$



The objective function $J(\theta)$ is the average negative log likelihood:

$$J(\theta) = -\frac{1}{T} \sum_{t=1}^T \sum_{-m \leq j \leq m, j \neq 0} \log P(w_{t+j} | w_t; \theta)$$



All word
vectors

the	cat	mat	on	sat	-			
5.2	1.5	...						
0.5	0.4	...						
-5.2	0.6	..						
0.5	-3.4	..						
...								

For a center word c and a context word o :

$$x_i = P(o | c) = -\frac{\exp(u_o^T v_c)}{\sum_{w \in V} \exp(u_w^T v_c)}$$

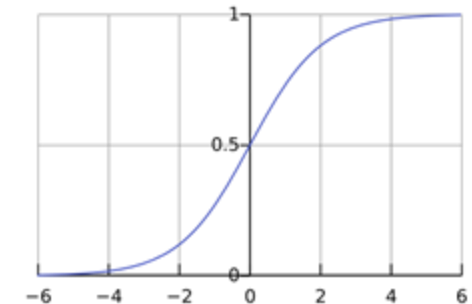
Dot product compares similarity of o and c . $u^T v = u \cdot v = \sum_{i=1}^n u_i v_i$

Normalize over entire vocabulary to give probability distribution

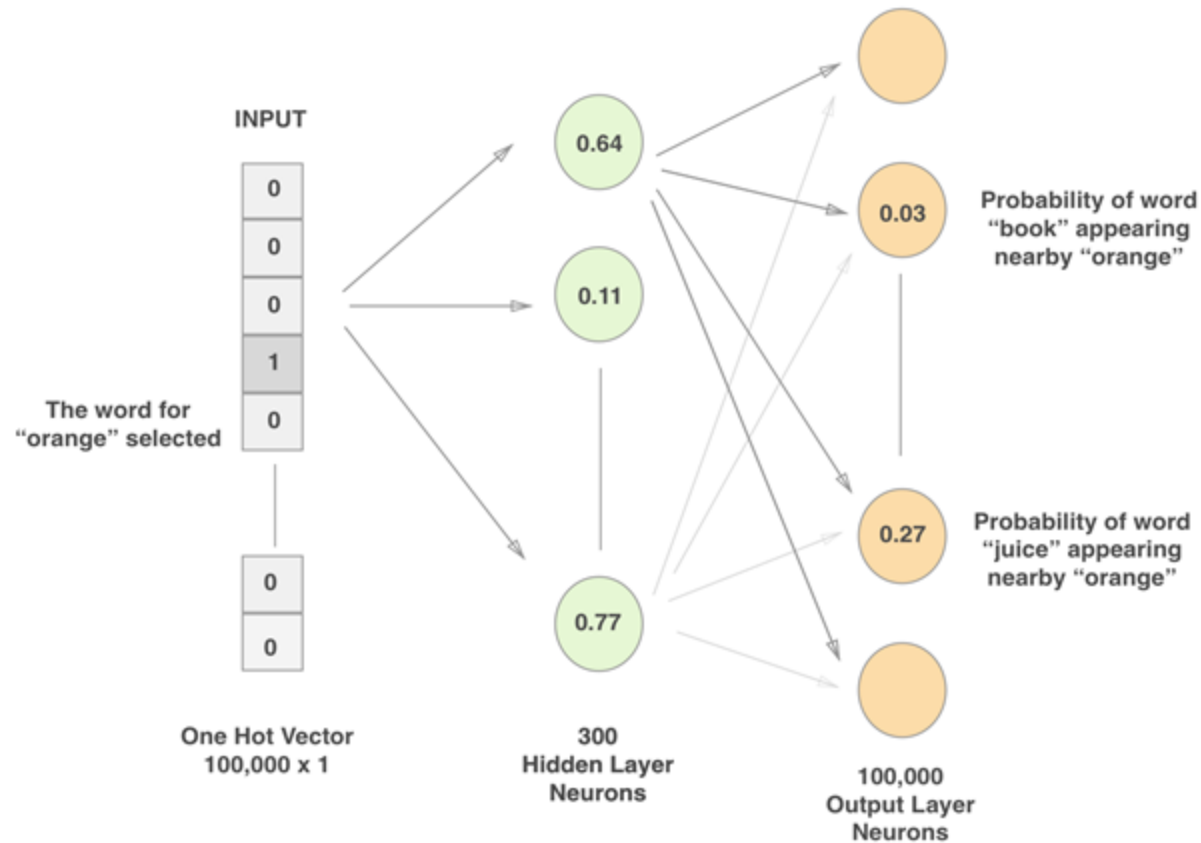
"soft" because still assigns some probability to smaller x_i

"max" because amplifies probability of largest x_i

$$\text{softmax}(x_i) = \frac{\exp(x_i)}{\sum_{j=1} \exp(x_j)} = p_i$$



$$P(x_{t-2} | x_t)$$

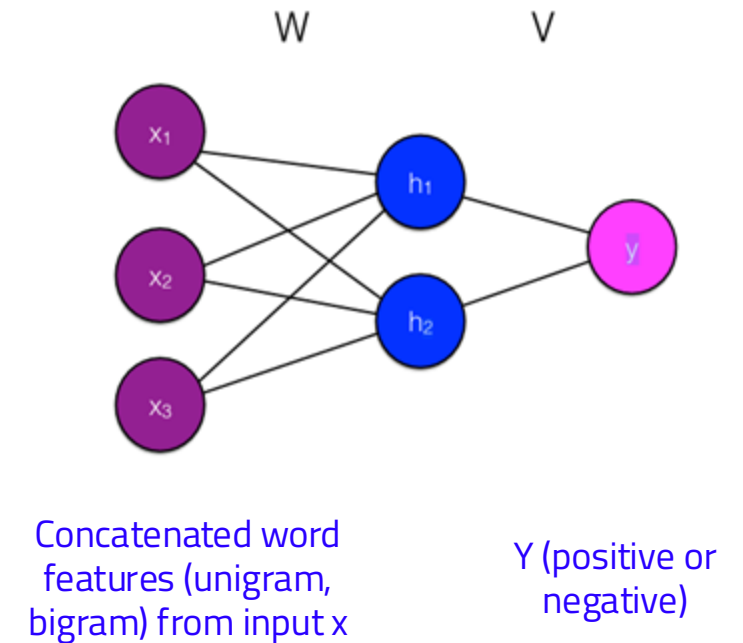


Context word 1-hot vector
(middle word in Skipgram)

Fixed-dimension word
embeddings to learn

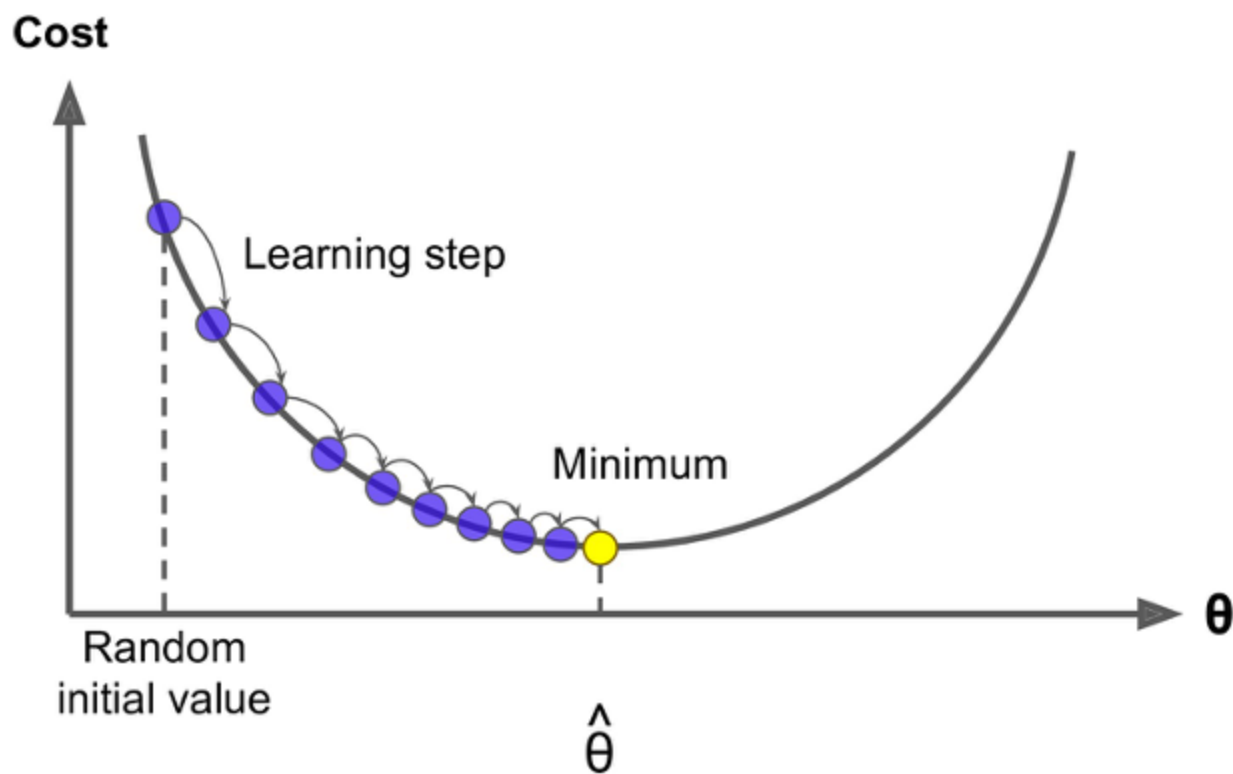
Output word to predict
(neighboring words in Skipgram)

$$P(y | x)$$



Minimize the objective function $J(\theta)$ using *gradient descent*

Idea: for current value of θ , calculate gradient of $J(\theta)$ then take small step in direction of negative gradient. Repeat this until convergence



Two kinds of training data

❑ The labeled data for specific tasks

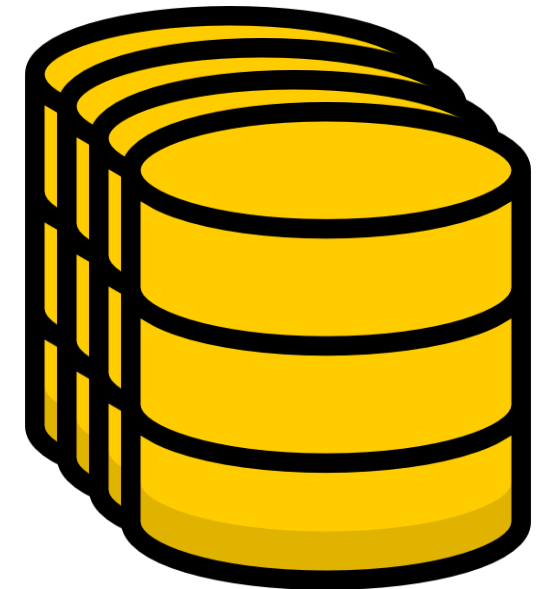
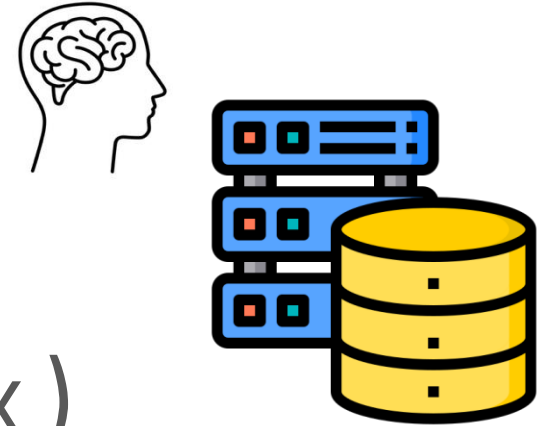
- Labeled sentiment for movie reviews (~2K labels/reviews, ~1.5 words)

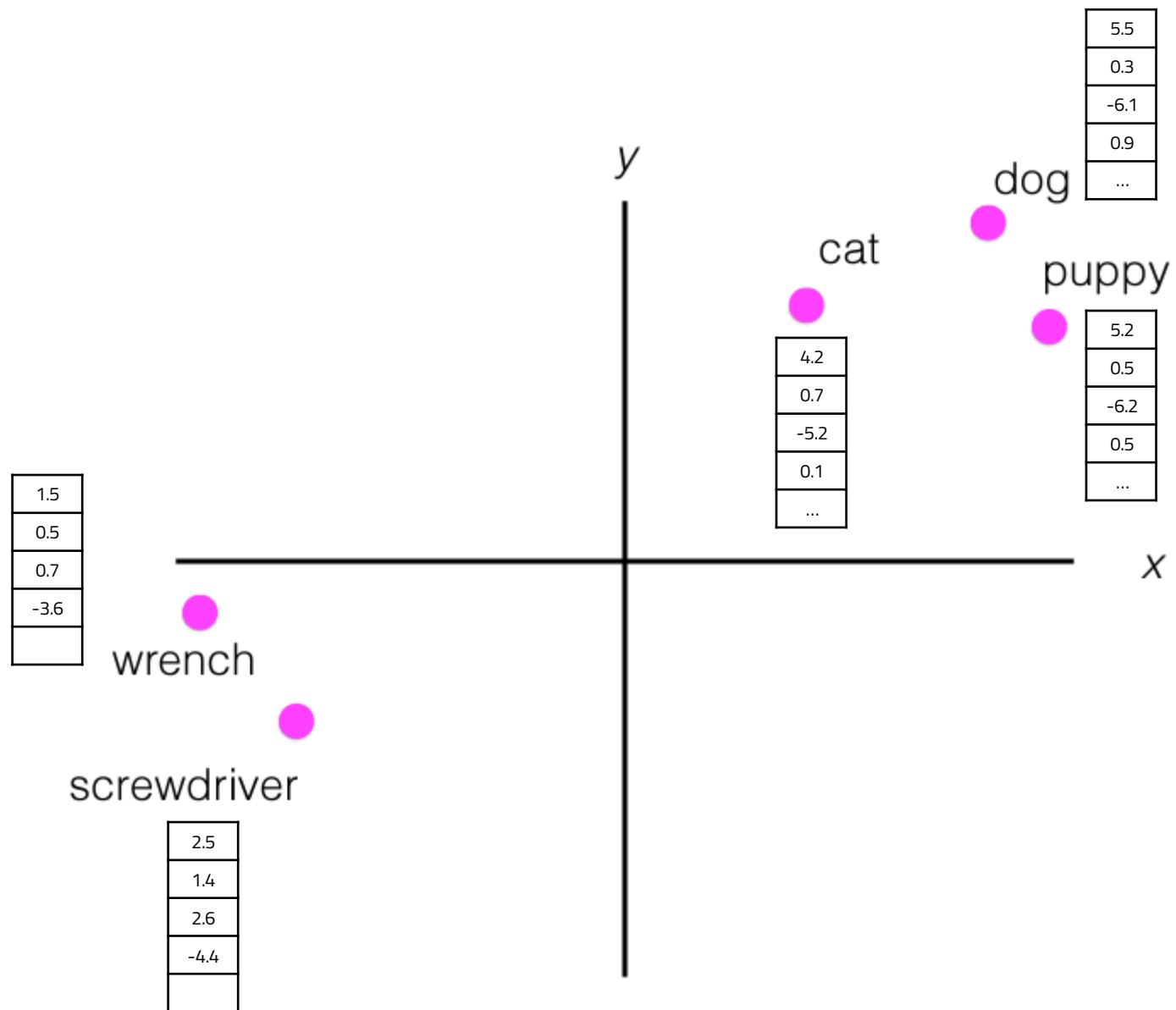
- Used for **supervised** models (text classification) $P(y | x)$

❑ Unlabeled text for representation learning

- Trillions of words (Wikipedia, web text, books, etc)
- Used for **word distributed representations** (skipgram training)

$$P(x_{t-2} | x_t)$$





Why *dog* and *cat* are in similar positions

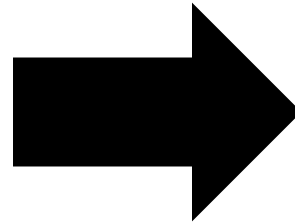
the	black	dog	jumped	on	the	table
the	black	cat	jumped	on	the	table
the	black	puppy	jumped	on	the	table

the	black	wrench	jumped	on	the	table
the	black	shoe	jumped	on	the	table



Dimensionality reduction

"a"	0
"the"	1
"for"	0
"in"	0
"on"	0
...	0
	0
	0
	0
	0
	0
	0



"the"
0.7
1.3
-4.5

V-dimensional space (1-hot)

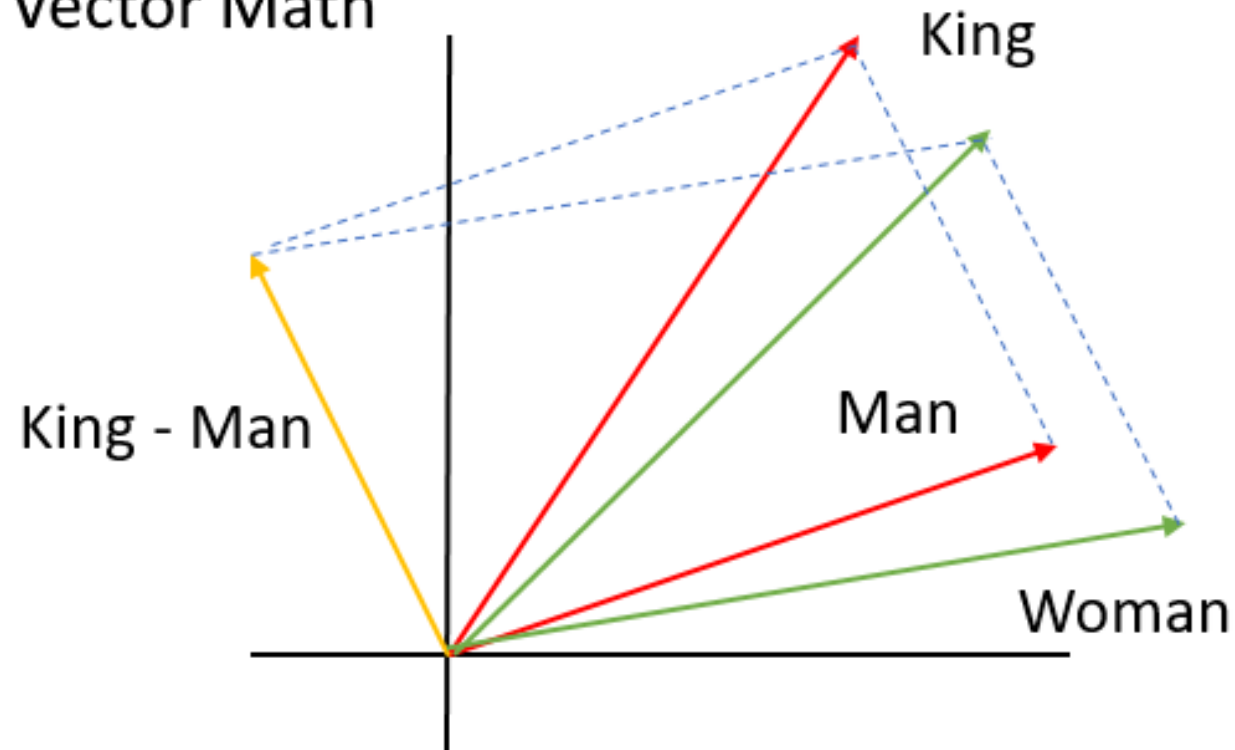
Representations for all words are completely independent

3-dimensional space

Representations are not structured



Vector Math



Mikolov et al. 2013 show that vector representations have some potential for **analogical reasoning** through **vector arithmetic**.

$$v(\text{"King"}) - v(\text{"Man"}) + v(\text{"Woman"}) =$$

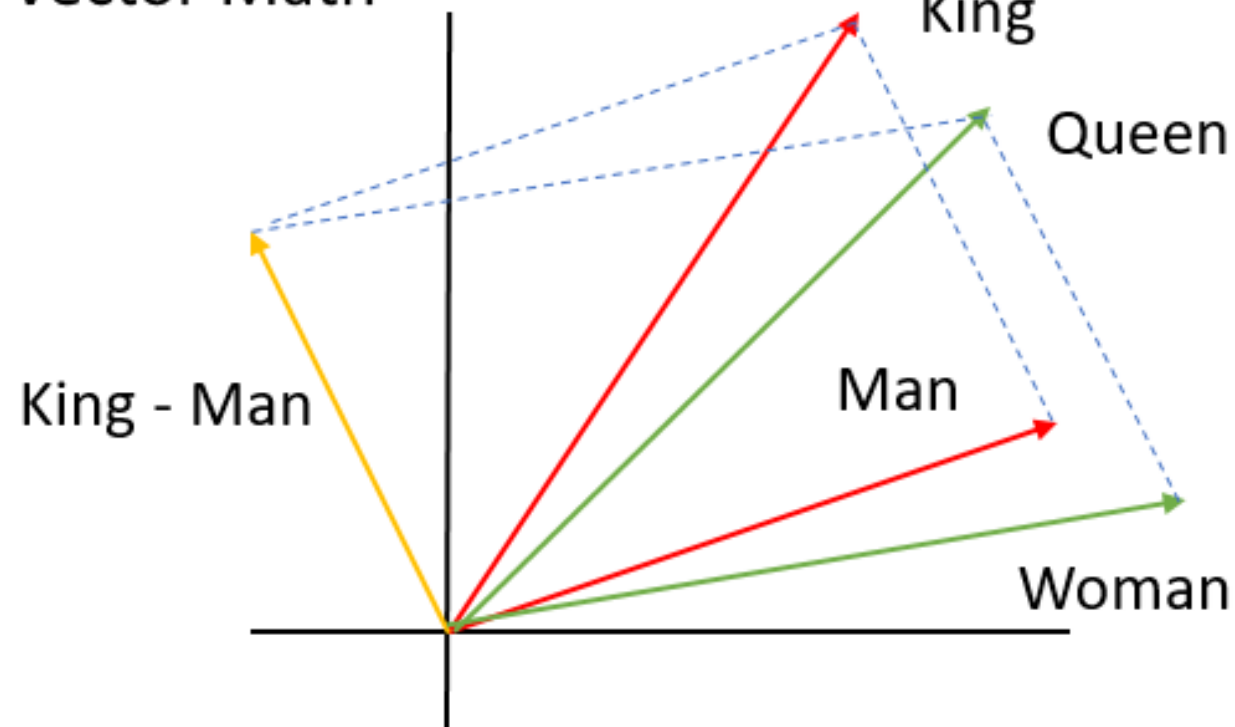
0.7	5.2	4.2	5.2
1.3	0.5	0.7	0.5
-4.5	-6.2	-5.2	-6.2
...	0.5	0.1	0.5
...	...	...	...

Closest vector

the	king	man	on	sat	..			
5.2	1.5	...						
0.5	0.4	...						
-6.2	0.6	..						
0.5	-3.4	..						
...								



Vector Math



Mikolov et al. 2013 show that vector representations have some potential for **analogical reasoning** through **vector arithmetic**.

$$v(\text{"King"}) - v(\text{"Man"}) - v(\text{"Woman"}) =$$

0.7	5.2	4.2	5.2
1.3	0.5	0.7	0.5
-4.5	-6.2	-5.2	-6.2
...	0.5	0.1	0.5
...	...	...	...

Closest vector

the	king	man	on	sat	..	queen		
5.2	1.5	...						
0.5	0.4	...						
-6.2	0.6	..						
0.5	-3.4	..						
...								





Boy



Girl

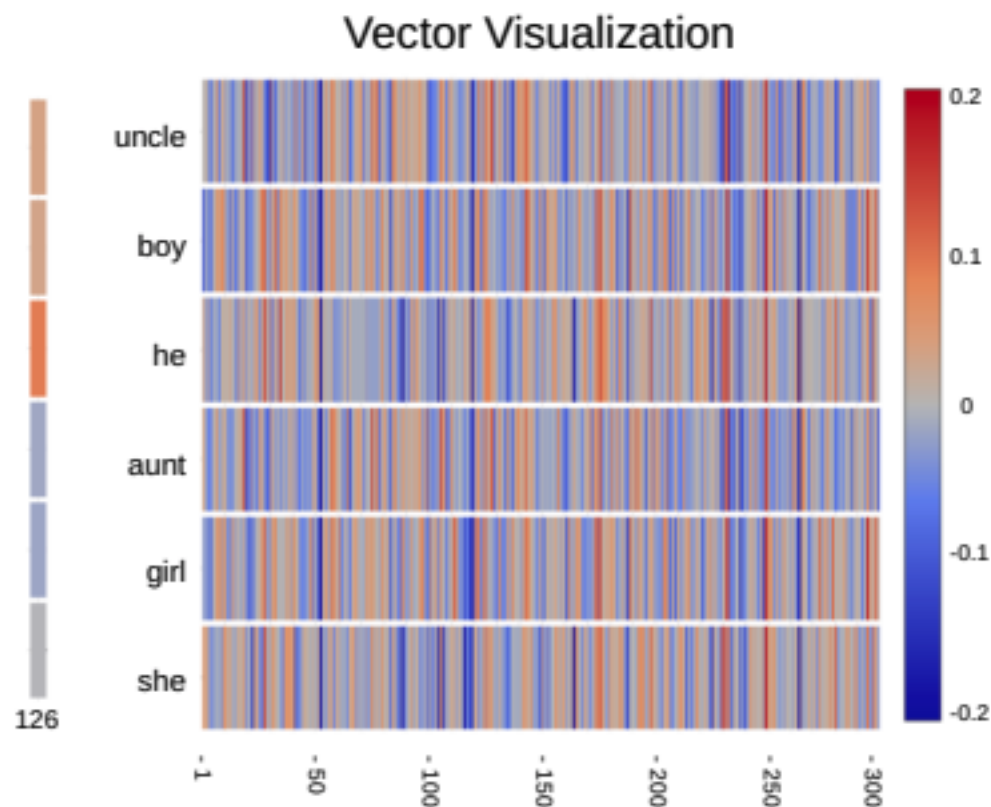


Figure 2: Embedding vectors for three male words (“uncle”, “boy”, “he”) and three female words (“aunt”, “girl”, “she”). Component 126, shown magnified at left, is positive for the male words and negative for the female words.

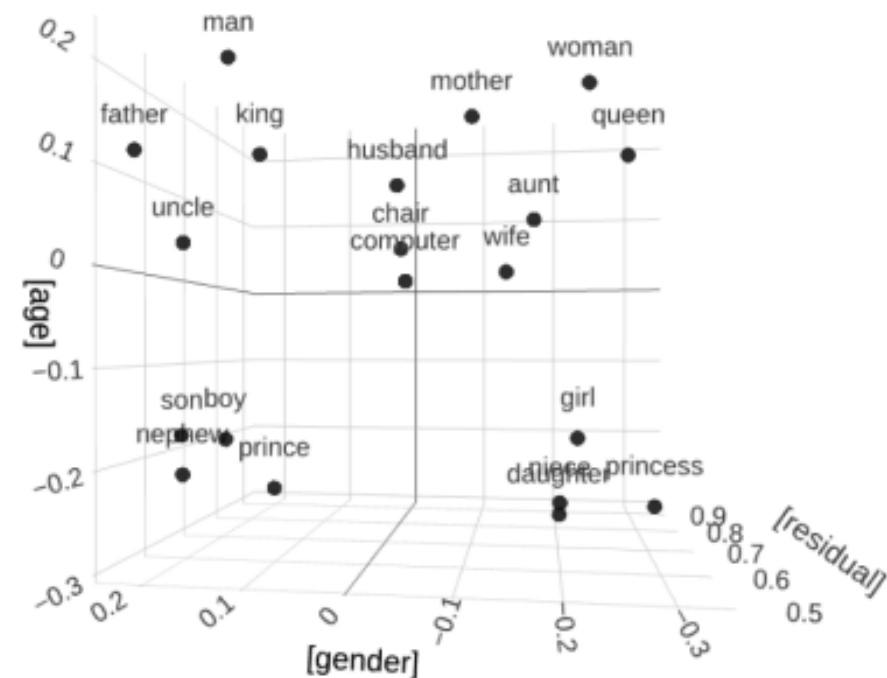


Figure 3: Words plotted in our 3D semantic space. Male words appear in the positive (left) half of the x-axis; female words in the negative (right) half. Adult words are in the positive (top) half of the y-axis; youth words in the negative (bottom) half. The third dimension is the “semantic residual”, explained in the main text.

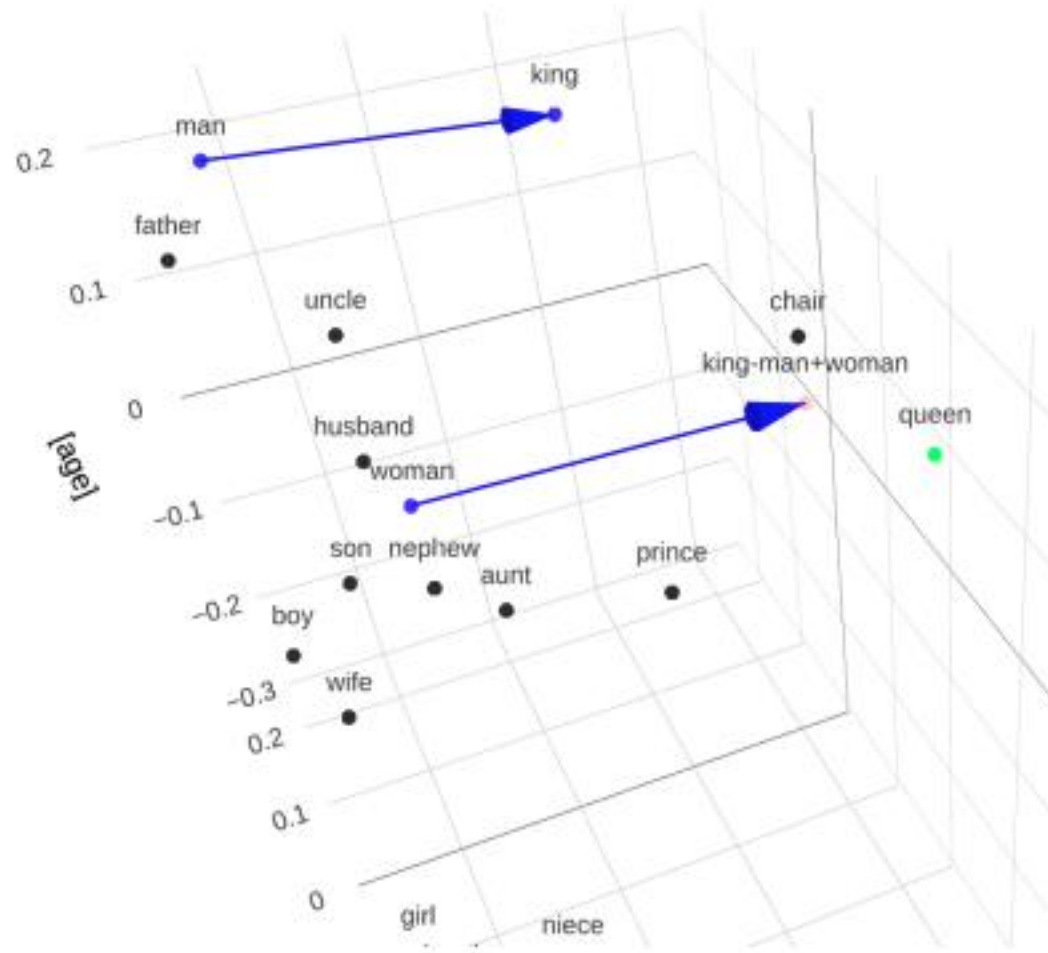


Figure 5: Analogy by vector arithmetic: “man” is to “king” as “woman” is to “king - man + woman” = “queen”.

Low-dimensional, distributed representations

- ❑ Two similar words (e.g., **synonyms** or words under the same **class**) have similar distributional properties
- ❑ In neural models, replace the initial V -dimensional sparse vector with much smaller k -dimensional dense vectors
- ❑ Low-dimensional, dense word representations are extraordinarily powerful and are a large part of why neural network models have been so successful for NLP



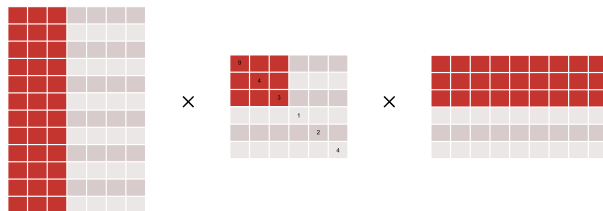
Count-based vs Prediction-based Methods

To obtain good dense representations

LSA, HAL (Lund & Burgess)

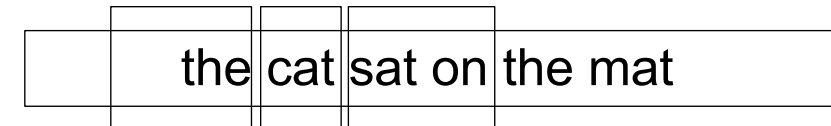
Hellinger-PCA (Rohde et al, Lebrete & Collobert)

	Hamlet	Macbeth
knife	1	1
dog		
sword	2	2
love	64	
like	75	38



Skip-gram/CBOW (Mikolov et al)

NLM, HLBL, RNN (Bengio et al; Collobert & Weston; Huang et al; Mnih & Hinton)



Count-based vs Prediction-based Methods

LSA, HAL (Lund & Burgess)

Hellinger-PCA (Rohde et al, Lebrete & Collobert)

- ☐ Fast training
- ☐ Efficient usage of statistics
- ☐ Primarily used to capture word similarity
- ☐ Disproportionate importance given to large counts

Skip-gram/b (Mikolov et al)

NLM, HLBL, RNN (Bengio et al; Collobert & Weston; Huang et al; Mnih & Hinton)

- ☐ Scales with corpus size
- ☐ Inefficient usage of statistics
- ☐ Generated improved performance on other tasks
- ☐ Can capture complex patterns beyond word similarity

Count-based and Prediction-based Methods

- ❑ Strong connection between count-based methods and prediction-based methods (Levy and Goldberg 2014)
- ❑ Skip-gram objective is equivalent to matrix factorization with PMI and discount for number of samples k

$$M_{w,c} = \text{PMI}(w, c) - \log(k)$$

Neural Word Embedding as Implicit Matrix Factorization, (Levy & Goldberg, 2014)



Other techniques and embeddings not covered

- ❑ Contrastive learning with negative samples

- ❑ Other variants

- ⊖ ~~Word2Vec~~ (Mikolove et al., 14)

- ✓ <https://code.google.com/archive/p/word2vec/>

- GloVe (Pennington et al., 14)

- ✓ <http://nlp.stanford.edu/projects/glove/>

- FastText (Bojanowski et al.' 17)

- ✓ <http://www.fasttext.cc/>



Word2Vec Demo

❑ Pre-trained word2vec models:

- <https://code.google.com/archive/p/word2vec/>

❑ Gensim:

- https://radimrehurek.com/gensim/auto_examples/tutorials/run_word2vec.html

❑ Online demos:

- <http://nlp.polytechnique.fr/word2vec>
- <http://vectors.nlpl.eu/explore/embeddings/en/>
- <https://remykarem.github.io/word2vec-demo/>



Evaluation:

How representative is your learned vector?



Types of Evaluation

❑ Intrinsic vs Extrinsic

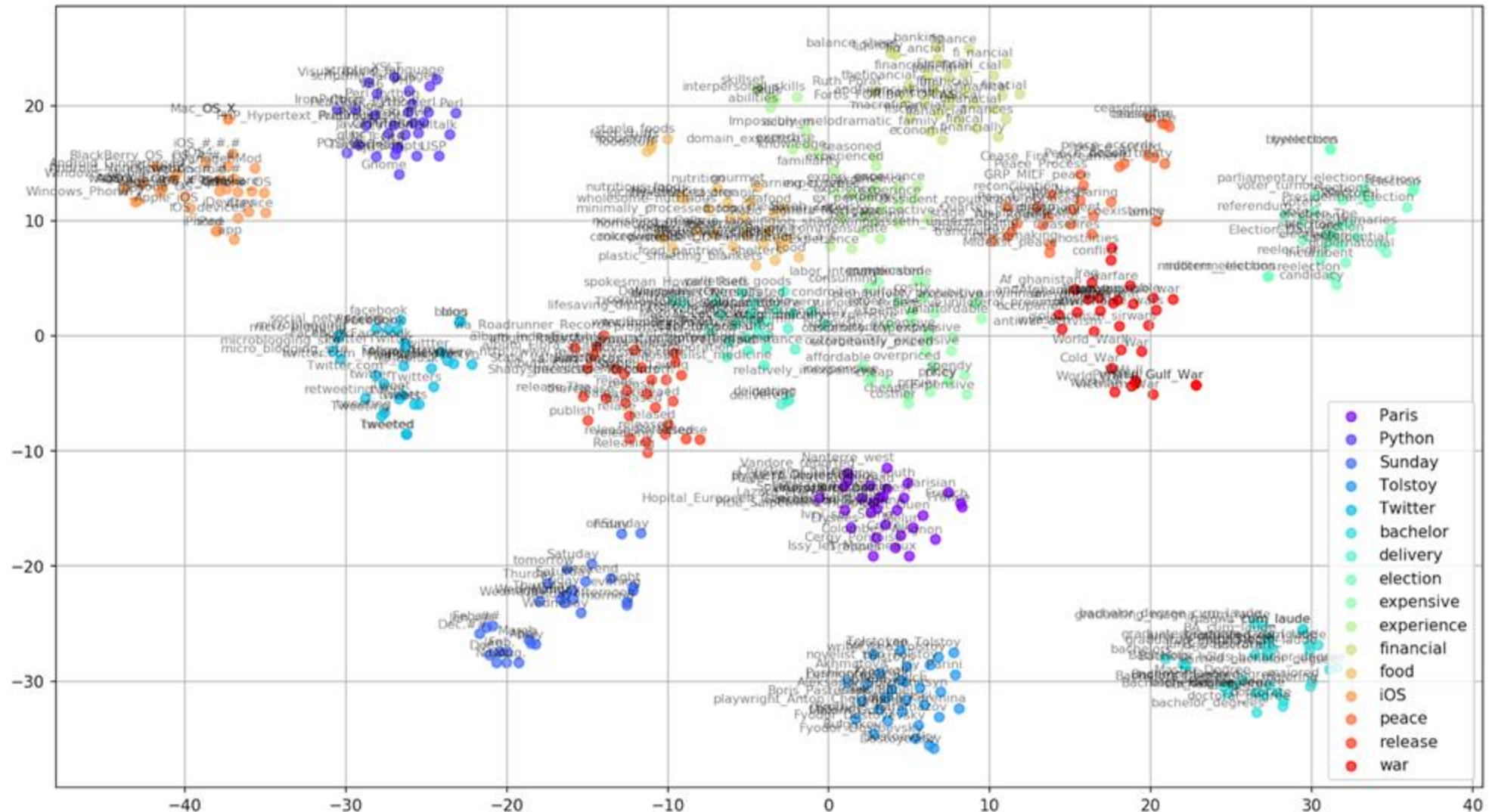
- Intrinsic: How good is it based on its features?
- Extrinsic: How useful is it downstream?

❑ Qualitative vs. Quantitative

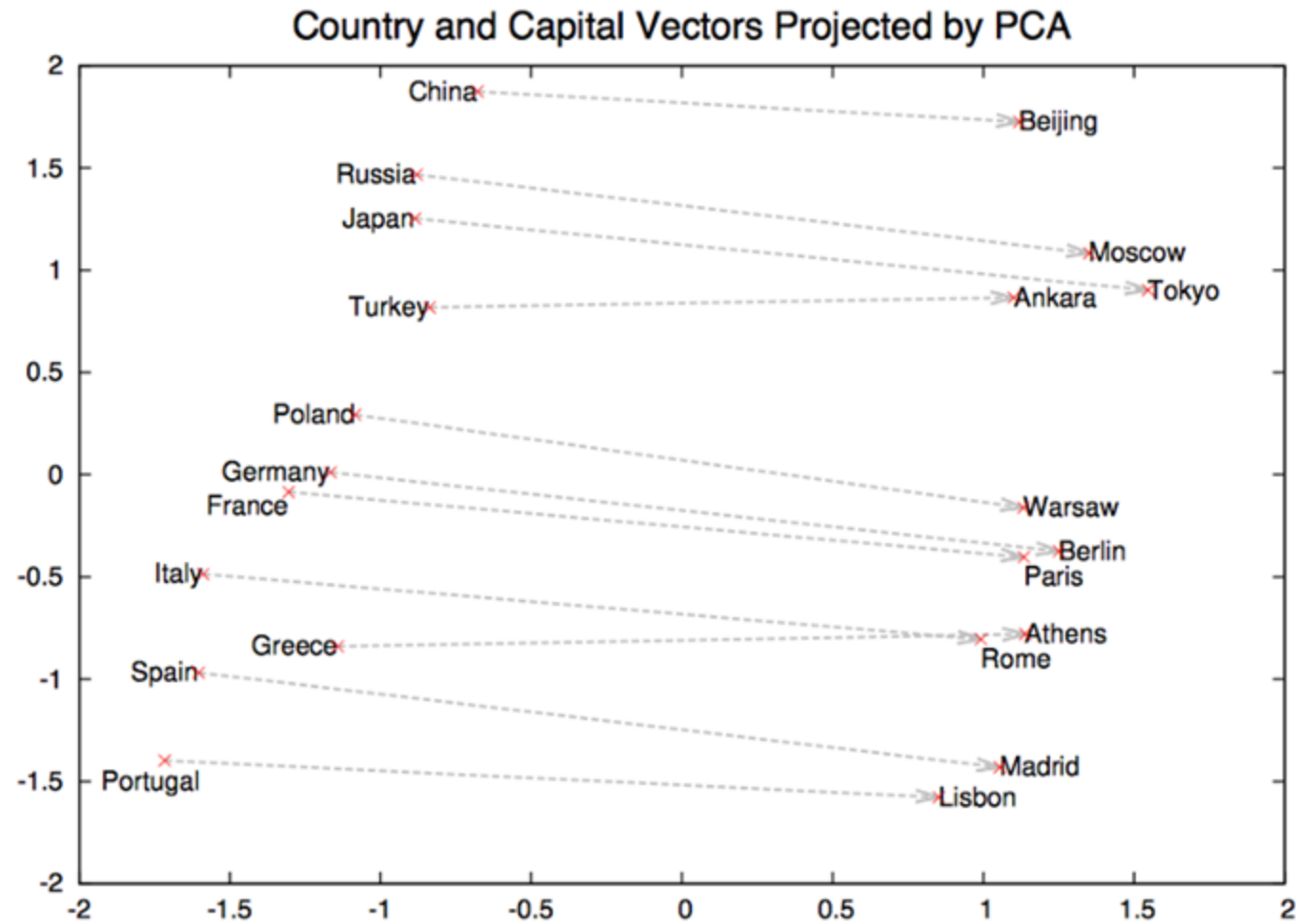
- Qualitative: Examine the characteristics of examples.
- Quantitative: Calculate statistics



Visualization of Embeddings



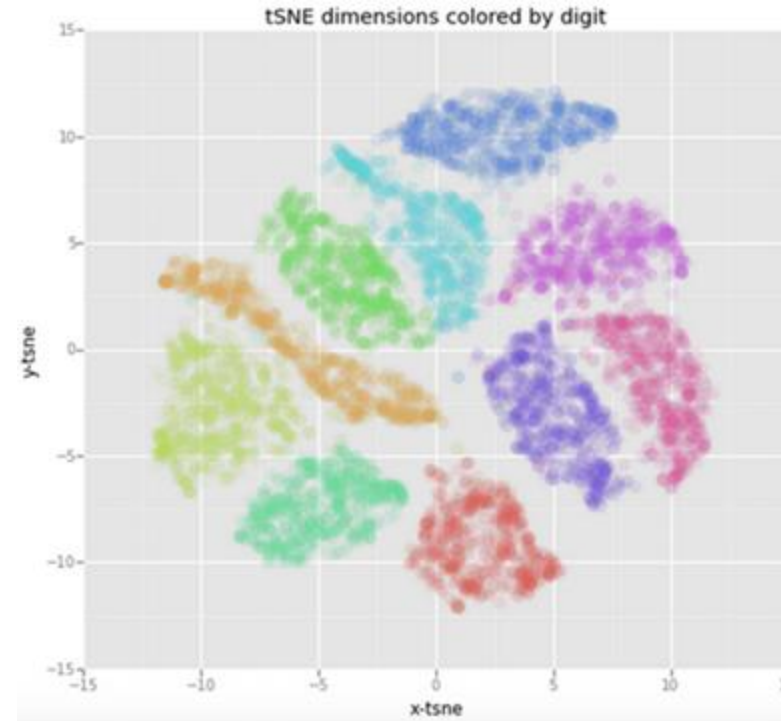
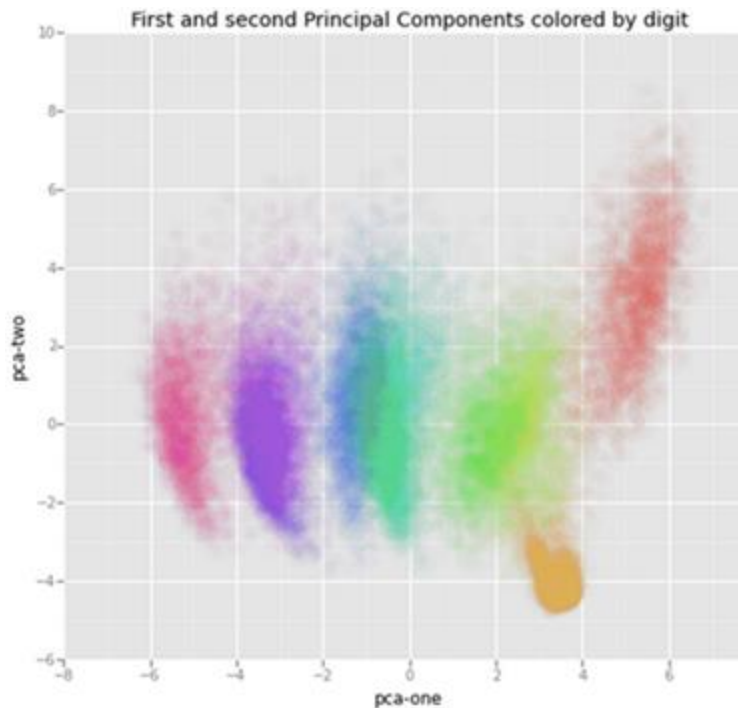
Visualization of Embeddings



Linear and Non-linear Projection

- Non-linear projections group things that are close in high-dimensional space
 - e.g. SNE/t-SNE (van der Maaten and Hinton 2008) group things that give each other a high probability according to a Gaussian

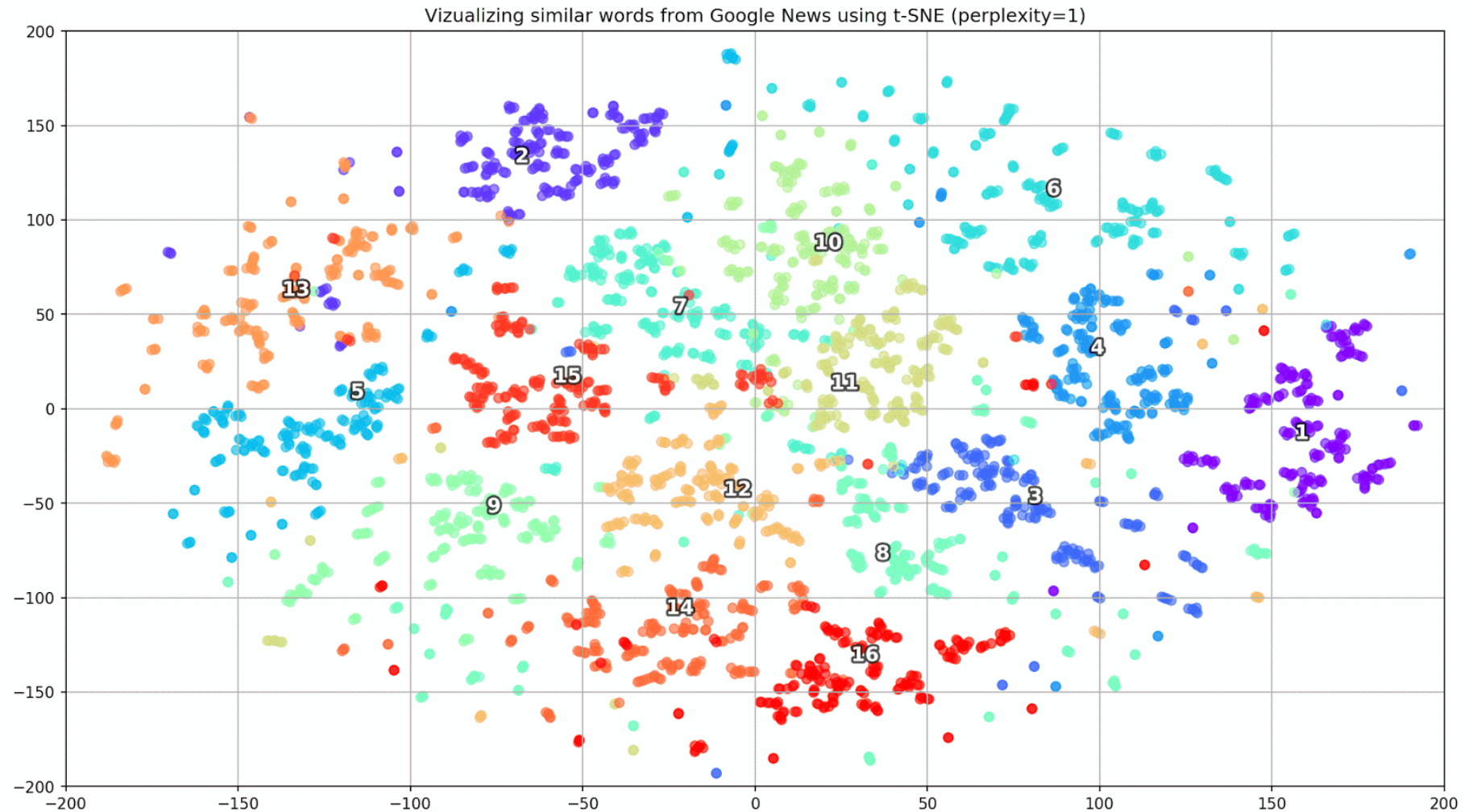
PCA



T-SNE

Image from Derksen (2016)

Hyper-parameters in t-SNE (e.g., perplexity)

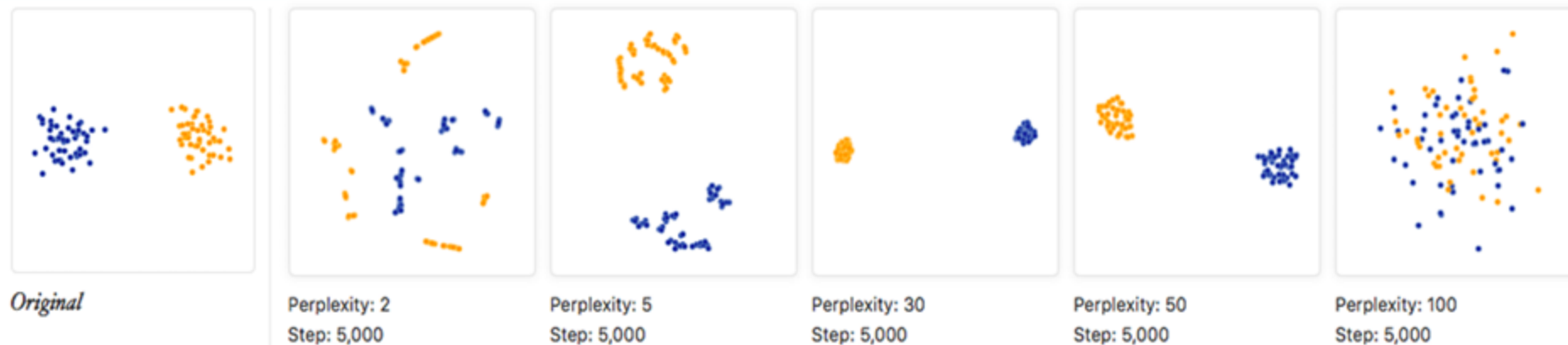


<https://towardsdatascience.com/google-news-and-leo-tolstoy-visualizing-word2vec-word-embeddings-with-t-sne-11558d8bd4d>

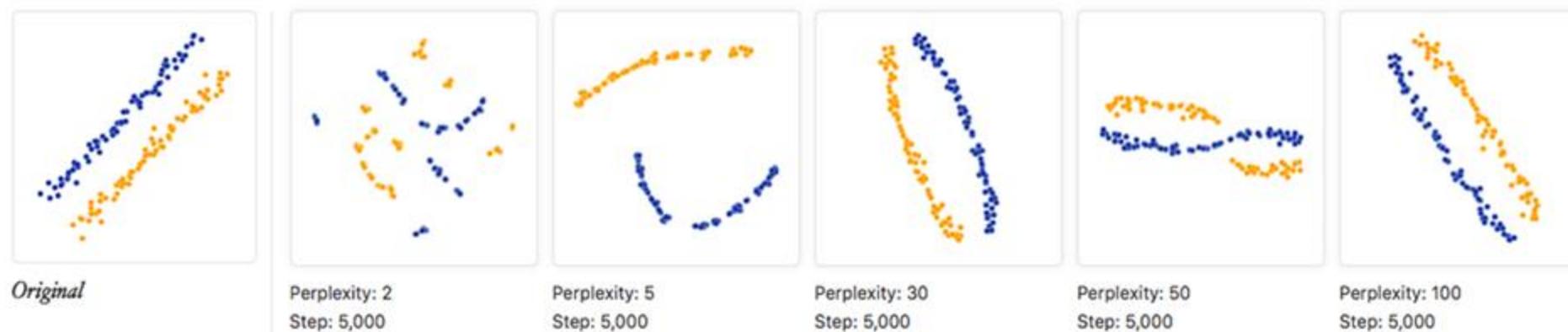


t-SNE Visualization can be Misleading! (Wattenberg et al. 2016)

Settings matter



Linear correlations cannot be interpreted



Intrinsic Evaluation of Embeddings

- ❑ **Relatedness:** The correlation between embedding cosine similarity and human eval of similarity?
- ❑ **Analogy:** Find x for “ a is to b , as x is to y ”.
- ❑ **Categorization:** Create clusters based on the embeddings, and measure purity of clusters.
- ❑ **Selectional Preference:** Determine whether a noun is a typical argument of a verb.

(categorization from Schnabel et al 2015)



Intrinsic evaluation:

Ask humans how similar two words are

Relatedness:

correlation (Spearman/Pearson) between vector similarity of pair of words and human judgments

Word 1	Word 2	similarity
vanish	Disappear	9.8
behave	obey	7.3
belief	Impression	5.95
muscle	Bone	3.65
modest	Flexible	0.98
hole	agreement	0.3

SimLex-999 dataset ([Hill et al., 2015](#))

WordSim-353 dataset ([Finkelstein et al., 2002](#))



Intrinsic evaluation:

Analogical reasoning (Mikolov et al., 2013).

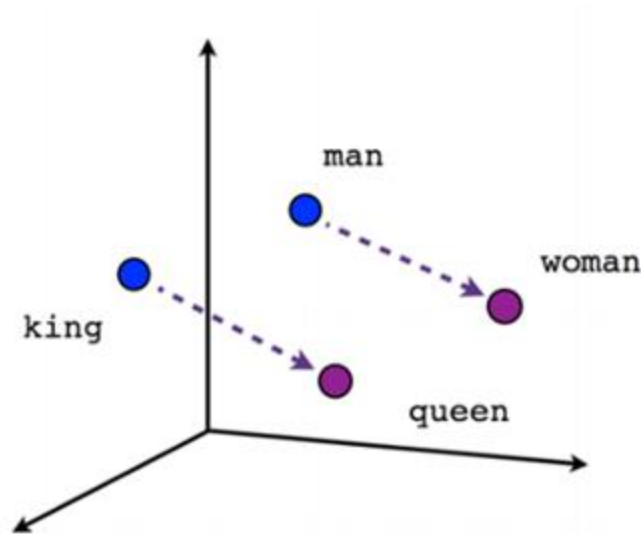
For analogy **Germany : Berlin :: France : ?**,
find closest vector to $v(\text{"Berlin"}) - v(\text{"Germany"}) + v(\text{"France"})$

possibly	impossibly	Certain	Uncertain
generating	generated	Shrinking	Shrank
think	thinking	Look	Looking
Baltimore	Maryland	Minneapolis	Minnesota
shrinking	shrank	Slowing	Slowed
Rabat	Morocco	Astana	Kazakhstan

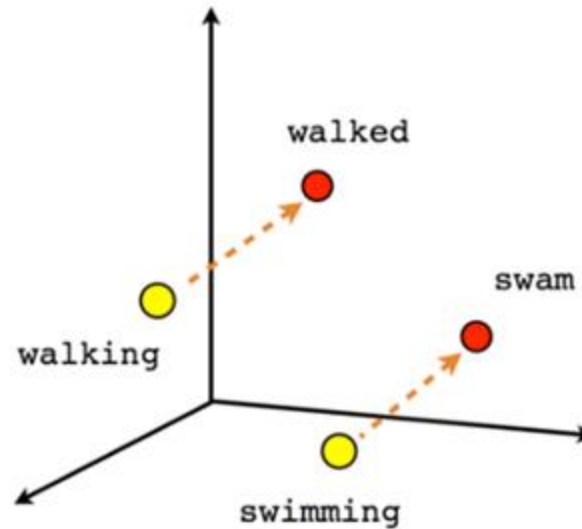


Intrinsic evaluation:

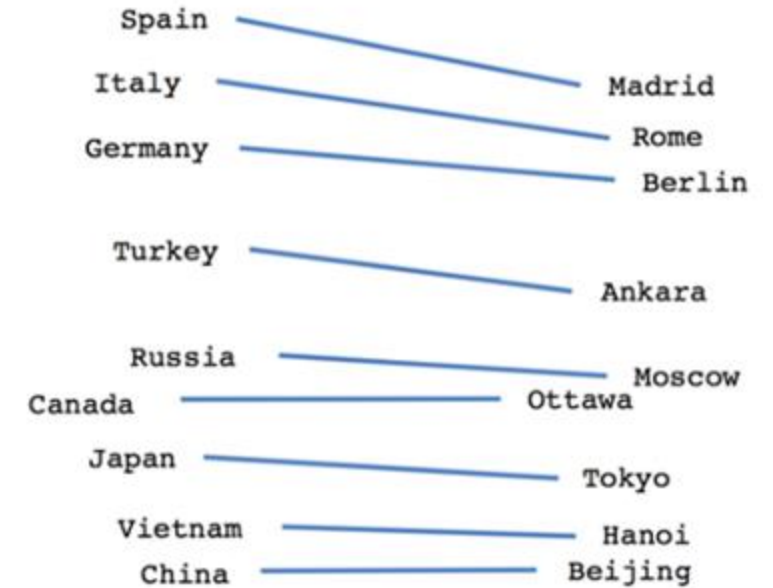
Analogical reasoning (Mikolov et al., 2013).



Male-Female



Verb tense



Country-Capital

Analogical reasoning test

Type of relationship	Word Pair 1		Word Pair 2	
Common capital city	Athens	Greece	Oslo	Norway
All capital cities	Astana	Kazakhstan	Harare	Zimbabwe
Currency	Angola	kwanza	Iran	rial
City-in-state	Chicago	Illinois	Stockton	California
Man-Woman	brother	sister	grandson	granddaughter
Adjective to adverb	apparent	apparently	rapid	rapidly
Opposite	possibly	impossibly	ethical	unethical
Comparative	great	greater	tough	tougher
Superlative	easy	easiest	lucky	luckiest
Present Participle	think	thinking	read	reading
Nationality adjective	Switzerland	Swiss	Cambodia	Cambodian
Past tense	walking	walked	swimming	swam
Plural nouns	mouse	mice	dollar	dollars
Plural verbs	work	works	speak	speaks

Mikolov et al. 2013



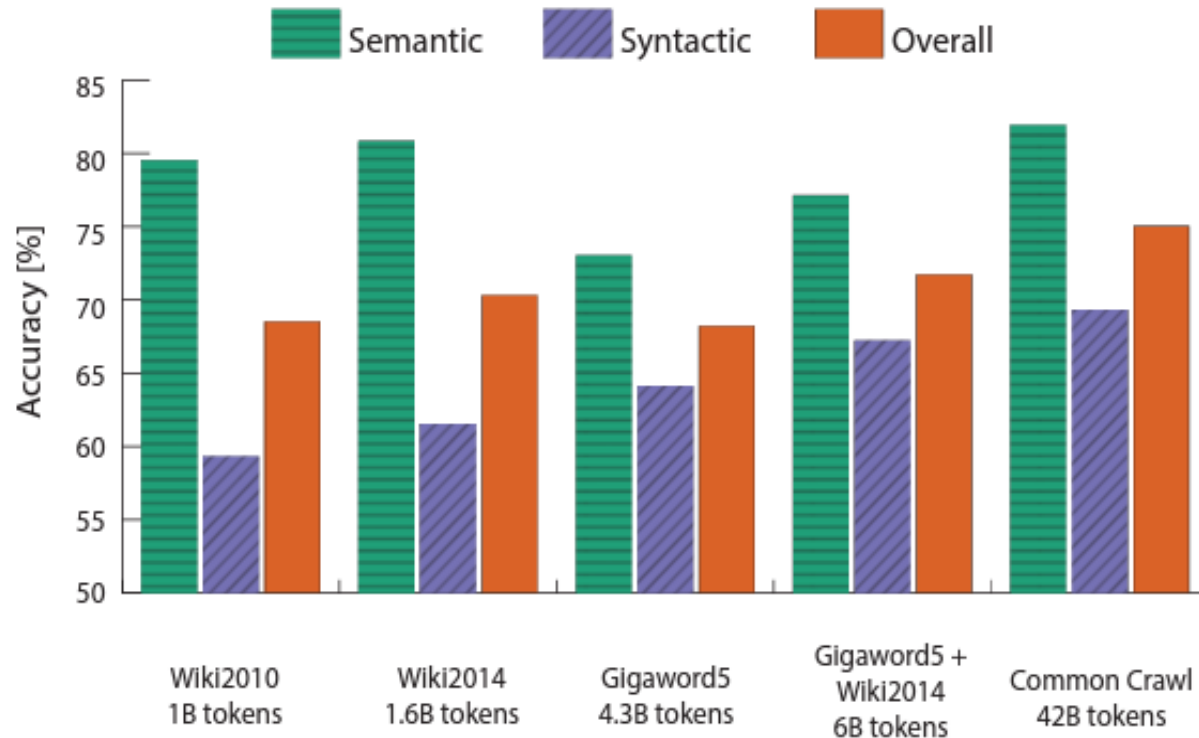
Analogical reasoning test

Model	Vector Dimensionality	Training words	Accuracy [%]		
			Semantic	Syntactic	Total
CBOW	300	783M	15.5	53.1	36.1
Skip-gram	300	783M	50.0	55.9	53.3

Mikolov et al. 2013



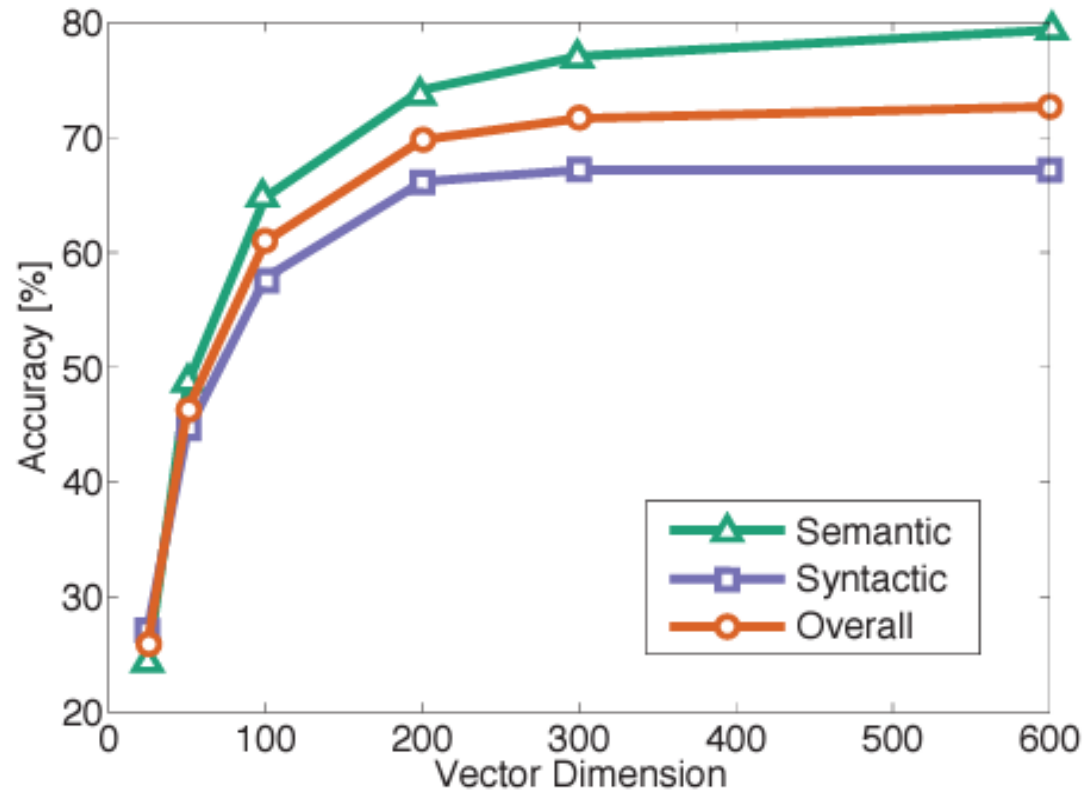
Analogy evaluation and hyper-parameters



- More data helps
- Wikipedia is better than news text



Analogy evaluation and hyper-parameters



- Dimensionality
- Good dimension is ~300

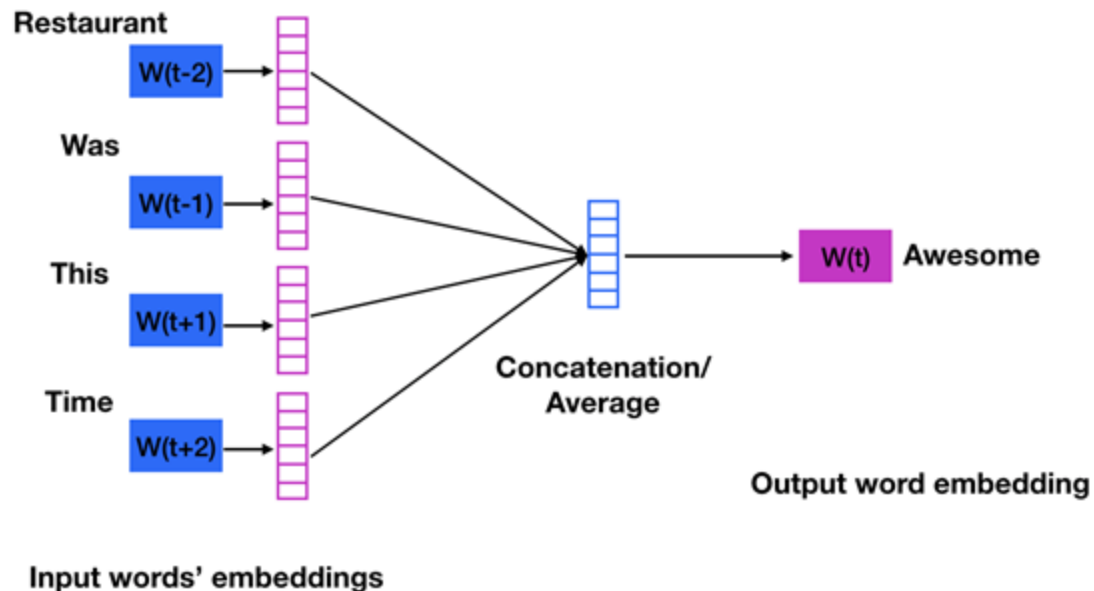


Extrinsic Evaluation

Be aware and use the best one for the task

Method	Fine-grained	Binary
DAN		
- Word2vec	46.2	84.5
- GloVe	46.9	85.7

Sentiment classification



Model	Dev	Test	ACE	MUC7
Discrete	91.0	85.4	77.4	73.4
SVD	90.8	85.7	77.3	73.7
SVD-S	91.0	85.5	77.6	74.3
SVD-L	90.5	84.8	73.6	71.5
HPCA	92.6	88.7	81.7	80.7
HSMN	90.5	85.7	78.7	74.7
CW	92.2	87.4	81.7	80.2
CBOV	93.1	88.2	82.2	81.1
GloVe	93.2	88.3	82.9	82.2

Named Entity Recognition: identifying references to a person, organization or location:

When are Pre-trained Embeddings Useful?

- ❑ Basically, when training data is insufficient
 - E.g. Low-resource languages
- ❑ **Very useful:** tagging, parsing, text classification
- ❑ **Less useful:** machine translation
- ❑ **Basically not useful:** language modeling



Limitations of Word Embeddings

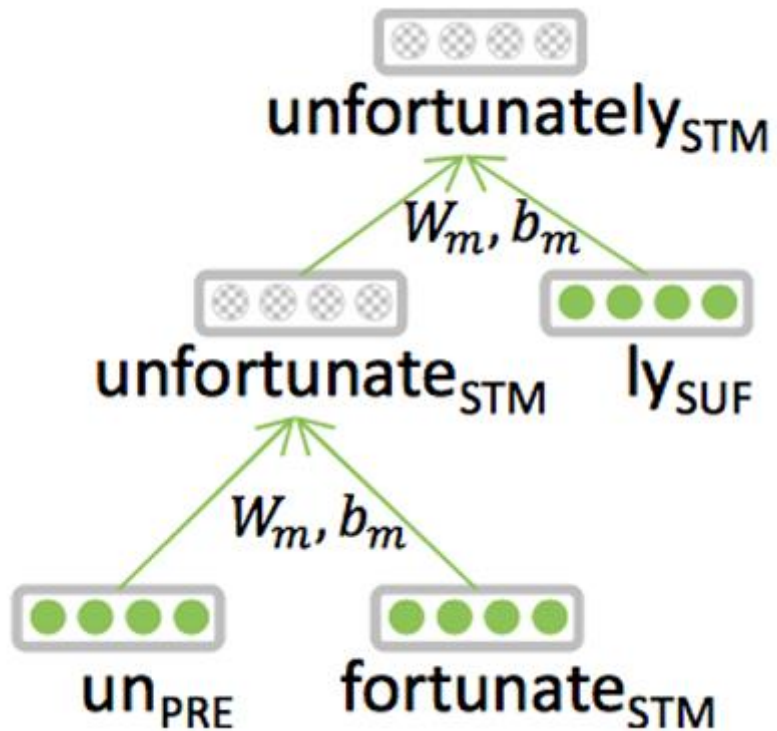


Limitations of Embeddings

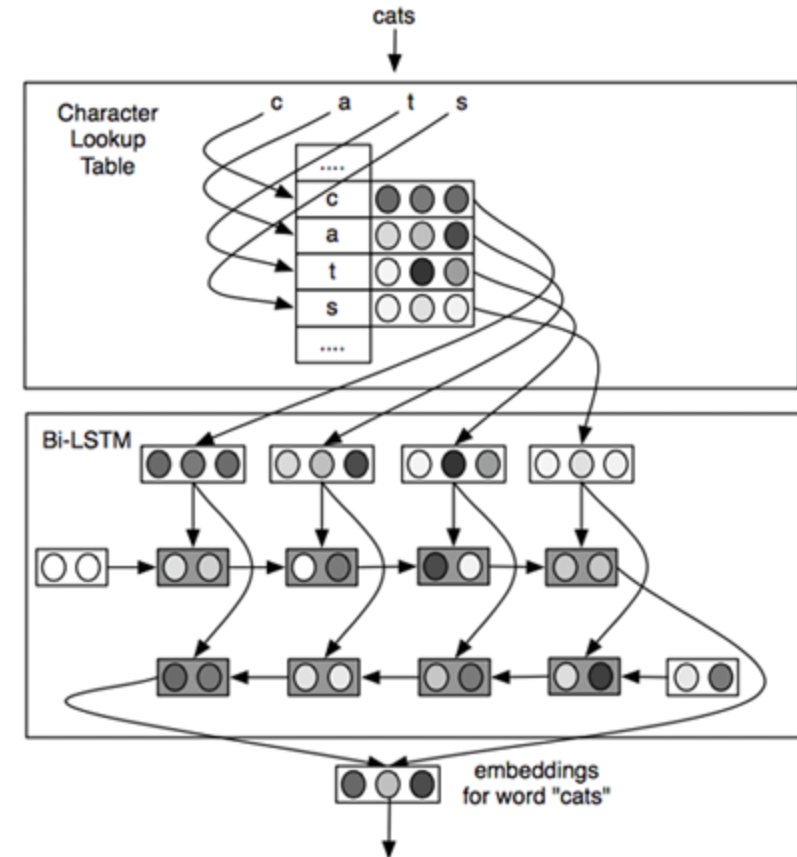
- ❑ Sensitive to **superficial differences** (dog / dogs)
 - E.g. misspellings: “minuscule” → “miniscule”
 - E.g. compounded/prefixed/suffixed words split into “wrong” subwords
“descheduled” ⇒ [“des”, “##ched”, “##uled”]
- ❑ **Not necessarily coordinated** with knowledge or across languages
- ❑ Can encode **bias** (encode stereotypical gender roles, racial biases)



Sub-word Embeddings

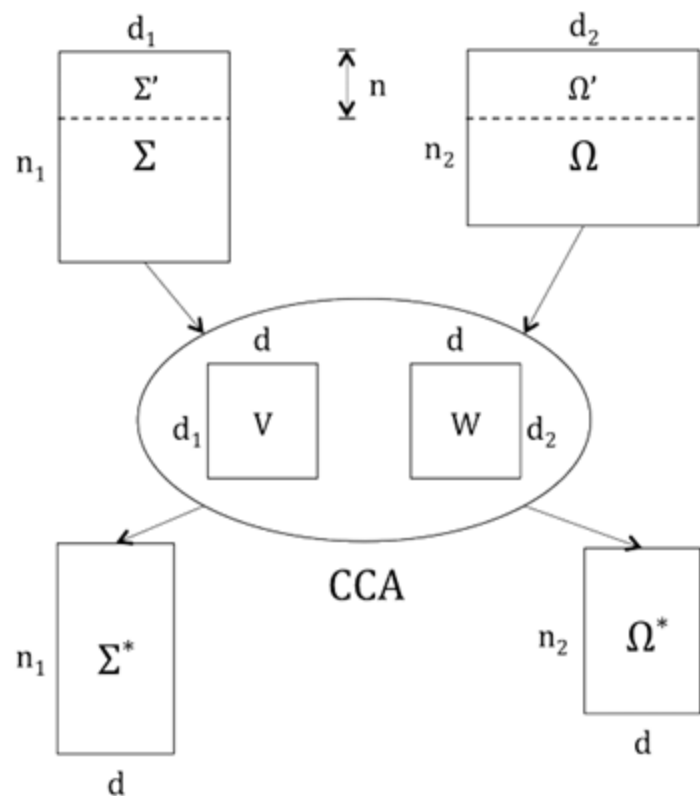


Morpheme-based (Luong et al. 2013)

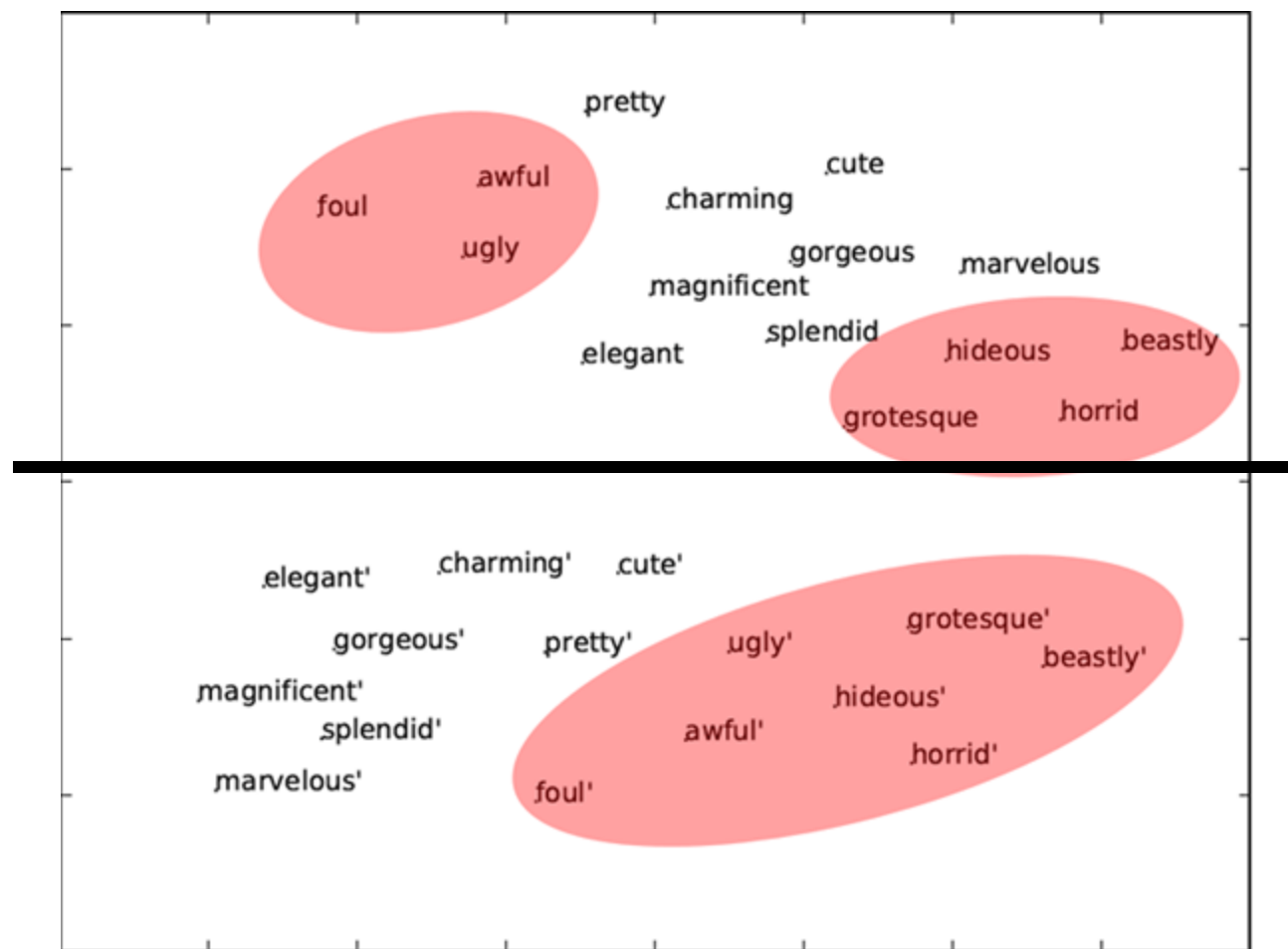


Character-based (Ling et al. 2015)

Multilingual Coordination of Embeddings using dictionaries



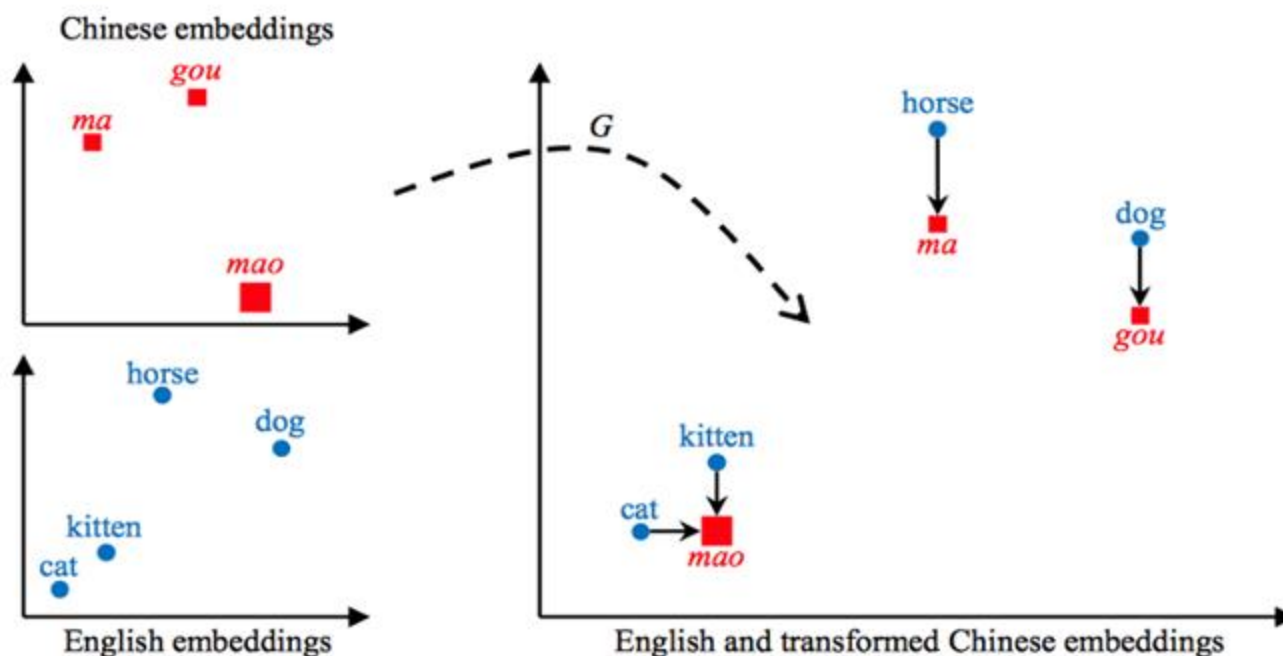
Improving Vector Space Word Representations Using Multilingual Correlation (Faruqui & Dyer, 2014)



Monolingual (top) and multilingual (bottom) word projections of the antonyms (shown in red) and synonyms of "beautiful"

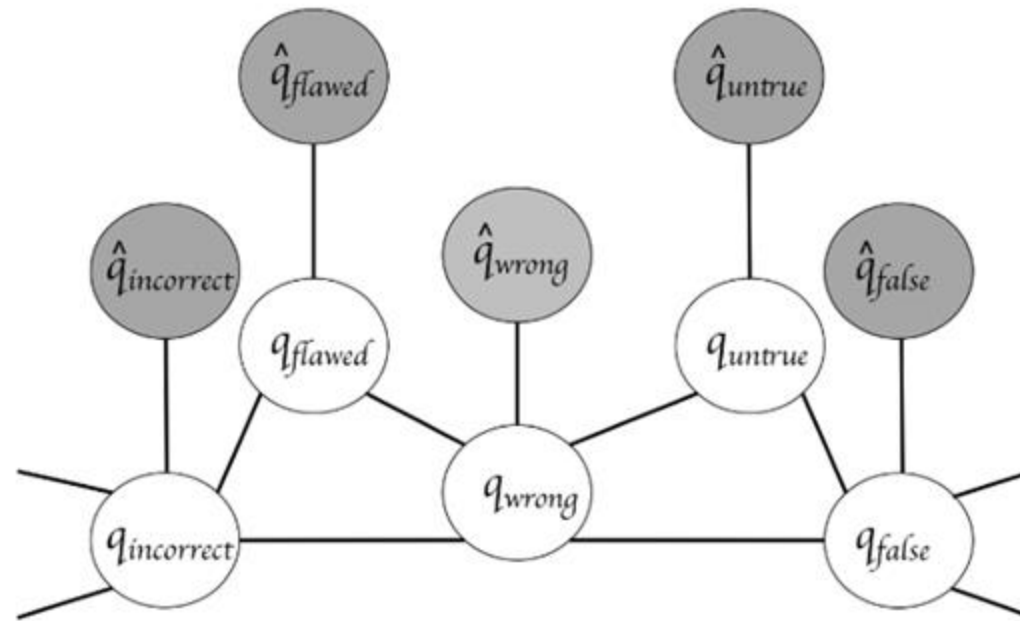
Unsupervised Coordination of Embeddings

- In some cases, we can do it with no dictionary at all!
 - Just use identical words, e.g. the digits (Artexte et al. 2017)
 - Or, just match distributions (Zhang et al. 2017)

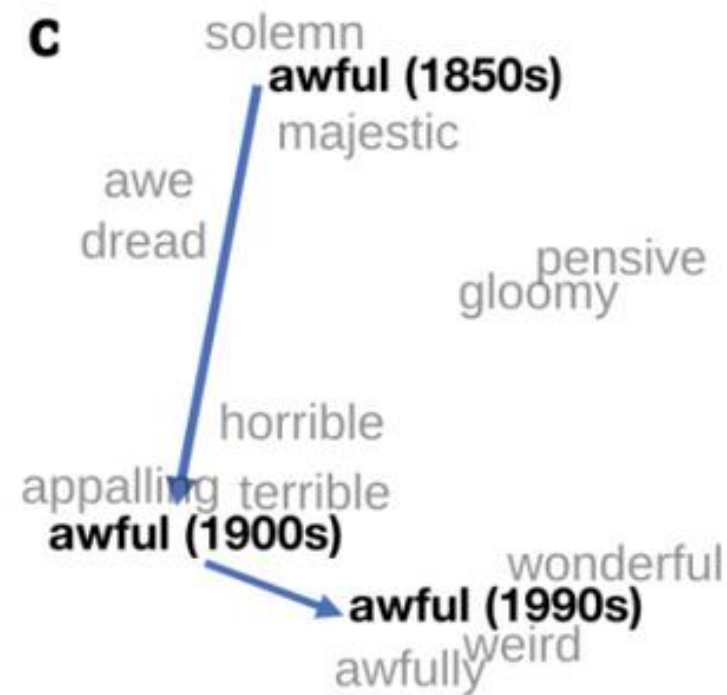
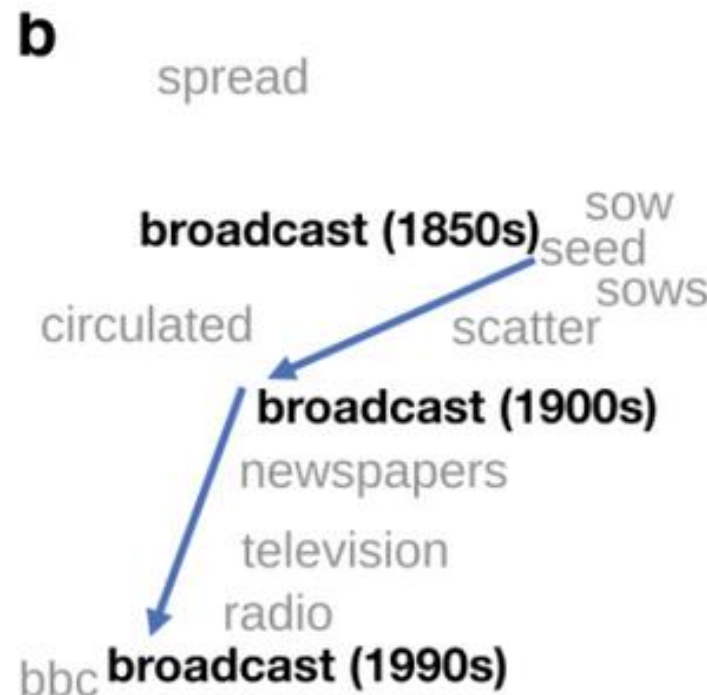
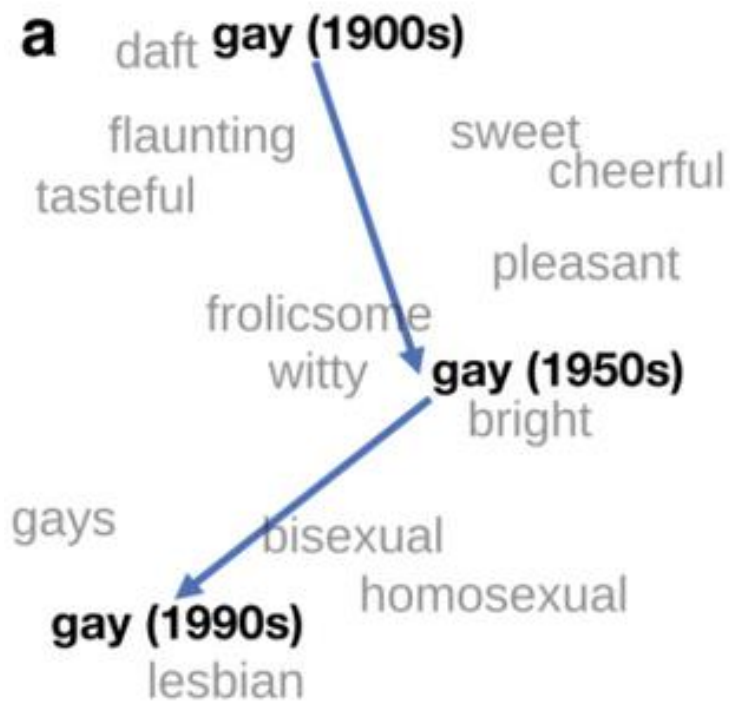


Retrofitting of Embeddings to Existing Lexicons

- Make word vectors to match with existing lexicon like WordNet (Faruqui et al. 2015)



$$\Psi(Q) = \sum_{i=1}^n \left[\alpha_i \|q_i - \hat{q}_i\|^2 + \sum_{(i,j) \in E} \beta_{ij} \|q_i - q_j\|^2 \right]$$



semantic to model temporal word analogy or relatedness (Szymanski, 2017; Rosin et al., 2017) or to capture the dynamics of semantic relations (Kutuzov et al., 2017)

Questions



- ❑ We've just learned how to learn the meaning of "bank" from data as a dense vector. What if meaning of "bank" can be different by context? Can we learn the vectors **dynamically** adaptable by context?
- ❑ How do you interpret the vector? You only know the "relationship" between words but not meaning of word itself. Does each dimension of the vector in distributional semantics correspond to "component" in the compositional semantics?
- ❑ Some words like "war" include various information. Can we quantify the abstract nature of words in distributed representations?

"cup"

0.7	<i>shape</i>
1.3	<i>color</i>
-4.5	<i>texture</i>

