

# Exploring Lexical Semantics with Word Embeddings

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`img/QR_slides.png`

- ▶ What is a word meaning?

- ▶ What is a word meaning?

## Example: Dictionary Approach

### **dog**

- ▶ is a **mammal**,
- ▶ descended from **wolf**,
- ▶ is commonly a **pet**,
- ▶ subtypes are **poodle**, **bulldog**, ...
- ▶ has **fur**,
- ▶ ...

The screenshot shows a web browser window with the title "WordNet Search - 3.1". The address bar shows the URL "wordnetweb.princeton.edu/perl/webwn?c=0&sub=Change&o2=&o0=". The browser's taskbar at the bottom includes icons for "Apps", "Blackboard", "Oracle | PeopleSo...", "Faculty of Langua...", and "Convertitore da Y...".

The main content area has an orange header with the text "WordNet Search - 3.1" and links for "- [WordNet home page](#) - [Glossary](#) - [Help](#)".

Below the header, there is a search section with the text "Word to search for:" followed by a text input field containing the word "dog" and a "Search WordNet" button.

Underneath the search field, there is a "Display Options:" section with a dropdown menu set to "(Select option to change)" and a "Change" button.

A key is provided: "Key: 'S:' = Show Synset (semantic) relations, 'W:' = Show Word (lexical) relations".

Below the key, it says "Display options for sense: (gloss)".

The word "dog" is categorized under the "Noun" section. It lists several synsets, each starting with "S: (n)" and followed by a list of related words and a brief definition:

- 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)
- S: (n) [frump](#), [dog](#) (a dull unattractive unpleasant girl or woman)
- S: (n) [dog](#) (informal term for a man)
- S: (n) [cad](#), [bounder](#), [blackguard](#), [dog](#), [hound](#), [heel](#) (someone who is morally reprehensible)
- 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 word "dog" is also categorized under the "Verb" section. It lists one synset:

- S: (v) [chase](#), [chase after](#), [trail](#), [tail](#), [tag](#), [give chase](#), [dog](#), [go after](#), [track](#) (go after with the intent to catch)

# Why the Dictionary Approach is Problematic

- ▶ Such dictionaries have been tried for computers.  
e.g. WordNet
- ▶ They must be created by hand, which is a big problem:
  - ▶ expensive
  - ▶ only available for some languages
  - ▶ many new words missing
- ▶ We need dictionaries that can be generated automatically.

# Meaning as Word Use

- ▶ The philosopher **Ludwig Wittgenstein** said that a word's meaning is its use.

## Computational Counterpart

A word's meaning is given by how often it occurs together with other words.



# Counting Tokens for Word Meaning

**Step 1:** Record in how many sentences words **occur together**

## Example

*The dog barked at the cat. The cat ran away. The dog ran after the cat. The dog kept barking. He also kept running.*

	dog	cat	bark	run
dog	-			
cat		-		
bark			-	
run				-

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bark	2	1	-	0
run				-



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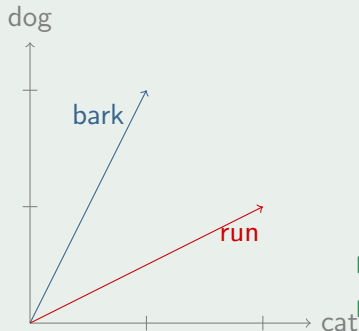
	dog	cat	bark	run
dog	-	2	2	1
cat	2	-	1	2
bark	2	1	-	0
run	1	2	0	-

# From Vectors to Vector Spaces

**Step 2:** Construct an  $n$ -dimensional vector space.

$n$  is given by the number of word types in the text

## 2-Dimensional Vector Space with *dog* and *cat*



	dog	cat	bark	run
dog	-	2	2	1
cat	2	-	1	2
bark	2	1	-	0
run	1	2	0	-

► *bark* more closely related to *dog*

► *run* more closely related to *cat*

# Problems?

- ▶ **Conceptual Concerns**

- ▶ Is word meaning really just a bunch of numbers?

- ▶ **(More) Practical Concerns**

- ▶ In a real-word model, the vector space will have thousands of dimensions (thousands of unique words)
  - ▶ most of the words in the vocabulary will not co-occur in the same sentence (or document!)
    - ⇒ results in vectors with mostly empty (zeros) slots.
  - ▶ Will similar words have similar vectors?

# Word Embedding Methods

Method	Paper
LSA	Landauer & Dumais (1997)
Word2Vec	Mikolov et al. (2013)
ELMo	Peters et al. (2018)
BERT	Devlin et al. (2019, arxiv)

## Word2Vec

- ▶ Word2Vec is **predictive model** for learning word embeddings from raw text
- ▶ a shallow, two-layer neural networks trained to reconstruct linguistic contexts of words
- ▶ words that share common contexts in the corpus are located in close proximity to one another in the space

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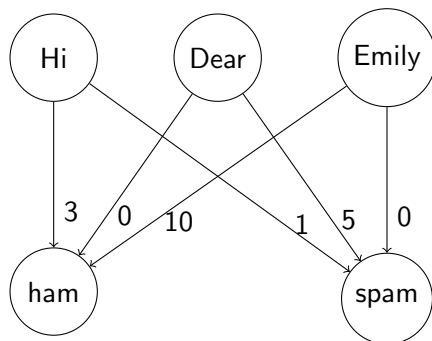
## Word2Vec

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# A Quick Excursus: The Perceptron

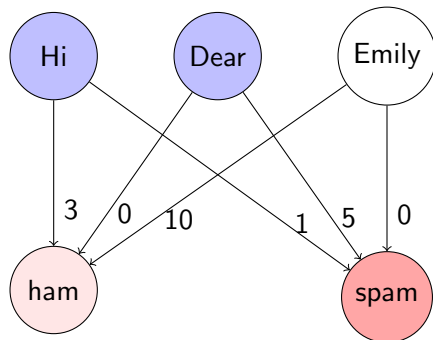
## The Perceptron: A Mini-Version of a Neural Network

- ▶ **input layer:** neurons that are sensitive to input
- ▶ **output layer:** neurons that represent output values
- ▶ **connections:** weighted links between input and output layer
- ▶ most activated output neuron represents decision

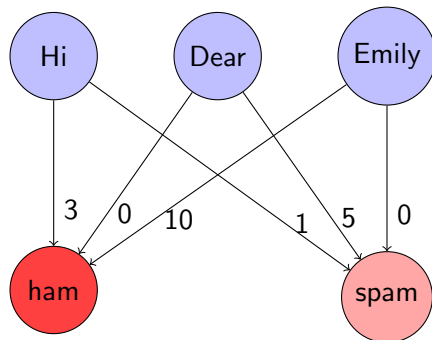




## Perceptron Activation for *Hi Dear*

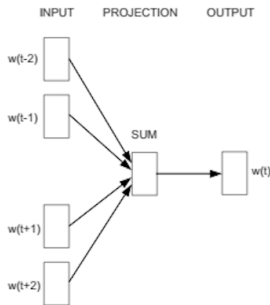


## Perceptron Activation for *Hi Dear Emily*

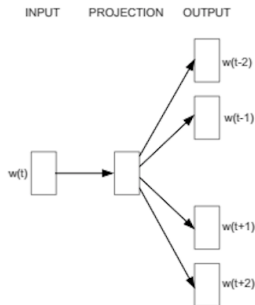


# Back to Word2Vec

- ▶ A NN trained to reconstruct linguistic contexts of words
- ▶ Two learning algorithms:
  - ▶ the Continuous Bag-of-Words (CBOW)
  - ▶ the Skip-Gram model



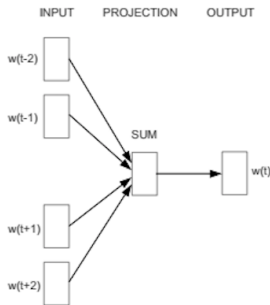
CBOW



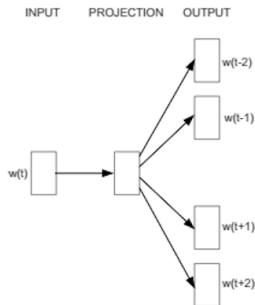
Skip-gram

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CBOW



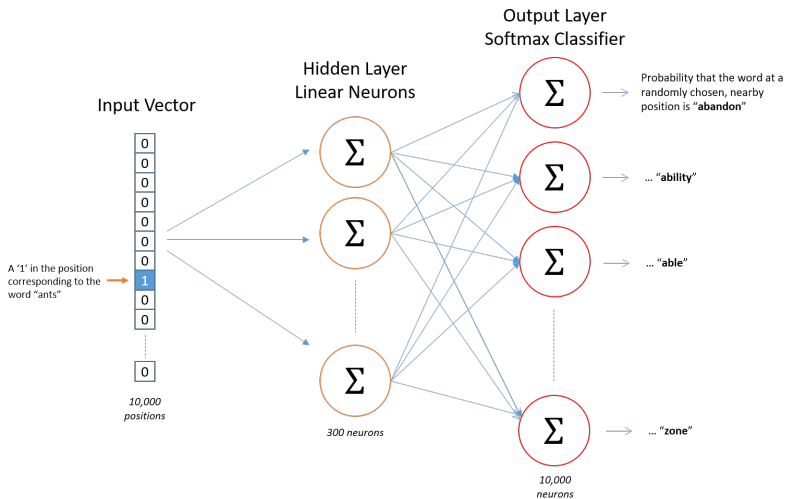
Skip-gram

# The Skip-Gram Model: Intuition

- Skip-Gram: predict **context** based on **target** word.

Source Text	Training Samples						
<table><tr><td>The</td><td>quick</td><td>brown</td></tr></table> fox jumps over the lazy dog. ➡	The	quick	brown	(the, quick) (the, brown)			
The	quick	brown					
<table><tr><td>The</td><td>quick</td><td>brown</td><td>fox</td></tr></table> jumps over the lazy dog. ➡	The	quick	brown	fox	(quick, the) (quick, brown) (quick, fox)		
The	quick	brown	fox				
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The	quick	brown	fox	jumps			
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The	quick	brown	fox	jumps	over		

# The Skip-Gram Model: Architecture



0.3	0.1	0.38	0.22	0.05	0.09	...	0.98	0.13	0.2
-----	-----	------	------	------	------	-----	------	------	-----

**Let's try it together!**

# Some Recent Applications

## ▶ **Web Search**

- ▶ construct meaning vector for every website
- ▶ rank websites by vector similarity

## ▶ **Ad Sense**

- ▶ associate every ad with a vector
- ▶ pick ad that most closely matches website vector

## Possible Concerns

- ▶ Watch out for **intrinsic biases!**



# The Danger of Corpora

THE VERGE

TECH

REVIEWS

SCIENCE

CREATORS

ENTERTAINMENT

VIDEO

MORE



MICROSOFT / WEB / TL;DR

## Twitter taught Microsoft's AI chatbot to be a racist asshole in less than a day

68

By James Vincent | Mar 24, 2016, 6:43am EDT

Via [The Guardian](#) | Source [TayandYou \(Twitter\)](#)



SHARE



### GOOD DEALS



Save on Amazon's 4K Fire TV devices, the Pixel 4, and more



# Is This Realistic?

- ▶ **Possible Concerns**

- ▶ Is word meaning really just a bunch of numbers?
- ▶ But this might actually capture something psychologically real!

## Psycholinguistic Experiments

- ▶ Word association tasks (Rubinstein et al. 2015)
- ▶ ERP measures of context appropriateness (Broderik et al. 2018, Ettinger et al. 2016)
- ▶ Priming effects (Gunther et al. 2016)
  - ▶ Check it out: **Masked priming effects!**

## Is This Realistic? [cont.]

- ▶ For word meaning, the approach seems to work.
- ▶ But what about sentence/text meaning?

### Example

The following two sentences receive the same vector:

- (1) a. Dog bites man!  
b. Man bites dog!

# Is This Realistic? [cont.]

- ▶ Meaning is not just about lexical representations.



# Is This Realistic? [cont.]

- ▶ Meaning is not just about lexical representations.

You can't:

- ▶ [eat a dumpling] [wearing a tuxedo]
- ▶ eat a [dumpling wearing a tuxedo]



## Word embeddings

- ▶ A computational implementation of a **distributional semantics**!
- ▶ useful in a variety of applications
  - ▶ Ad-sense, stylistic analysis
  - ▶ parsing
- ▶ source of theoretical insights
  - ▶ diachronic change, semantic shifts, etc.
  - ▶ control for semantic similarity in psycholinguistic experiments
- ▶ cognitive parallels?

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**But: Meaning is more complex than simple distributional information!**

# Further Readings

- 1 Distributed Representations of Words and Phrases and their Compositionality
- 2 Efficient Estimation of Word Representations in Vector Space
- 3 A Neural Probabilistic Language Model
- 4 A nice series of blog posts by Chris McCormick
- 5 Evaluating distributional models of compositional semantics
- 6 A semi-technical tutorial (some of the pictures in this presentation are from there)
- 7 Exploring the Implications of Biases in Word2Vec
- 8 Debiasing Word Embeddings



# Appendix

# Word Embeddings

We saw sparse vectors:

0	1	0	0	0	0	...	0	0	0
---	---	---	---	---	---	-----	---	---	---

- ▶ But word vectors can be dense:  
real numbers in a small number of dimensions
- ▶ Compress sparse matrices into smaller ones

0.3	0.1	0.38	0.22	0.05	0.09	...	0.98	0.13	0.2
-----	-----	------	------	------	------	-----	------	------	-----

# Word Embeddings

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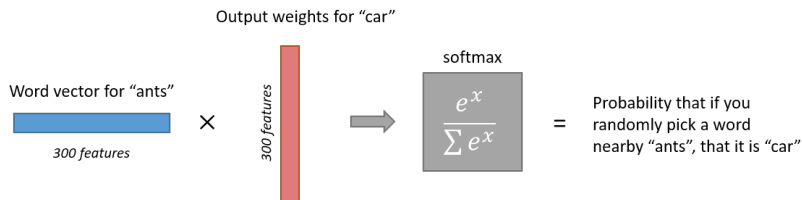
0.3	0.1	0.38	0.22	0.05	0.09	...	0.98	0.13	0.2
-----	-----	------	------	------	------	-----	------	------	-----

# The Skip-Gram Model: Some Details

- ▶ some math:

$$[0 \quad 0 \quad 0 \quad 1 \quad 0] \times \begin{bmatrix} 17 & 24 & 1 \\ 23 & 5 & 7 \\ 4 & 6 & 13 \\ 10 & 12 & 19 \\ 11 & 18 & 25 \end{bmatrix} = [10 \quad 12 \quad 19]$$

- ▶ a high-level illustration of the architecture:



Source: A nice technical tutorial

## Will similar words have similar vectors?

- ▶ Consider the following sentences:
  - 1 I like watching movies.
  - 2 I enjoy watching movies.
  - 3 I hate watching movie.
- ▶ What is the distance between *like*, *enjoy*, and *hate*?

## Will similar words have similar vectors?

- ▶ Consider the following sentences:
  - 1 I like watching movies.
  - 2 I enjoy watching movies.
  - 3 I hate watching movie.
- ▶ What is the distance between *like*, *enjoy*, and *hate*?
- ▶ How similar are the following sentences?
  - 1 I like pancakes.
  - 2 Steven enjoys cookies.

# An Observation on Frequencies: Zipf's Law

- ▶ Word models care about word frequency.
- ▶ But there is a problem...

## Zipf's Law

The frequency of a type is inversely proportional to its rank.



## In Plain English

The most frequent word is

- ▶ 2 times as common as the 2nd most frequent word,
- ▶ 3 times as common as the 3rd most frequent word,
- ▶ and so on.

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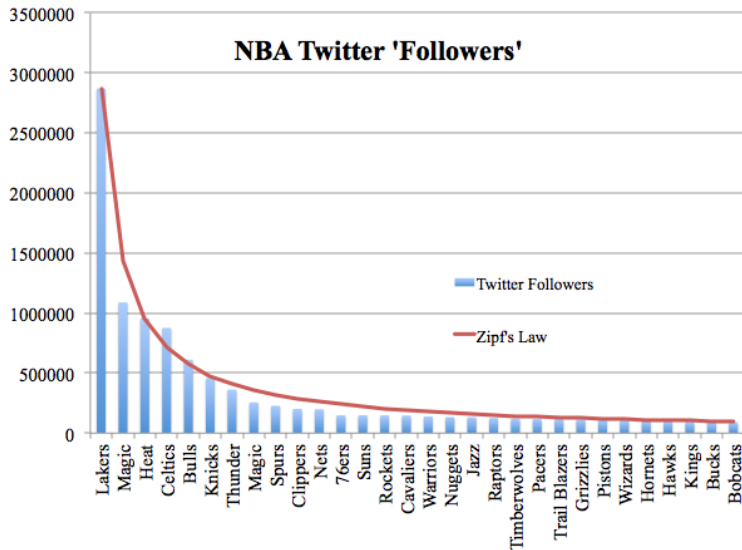
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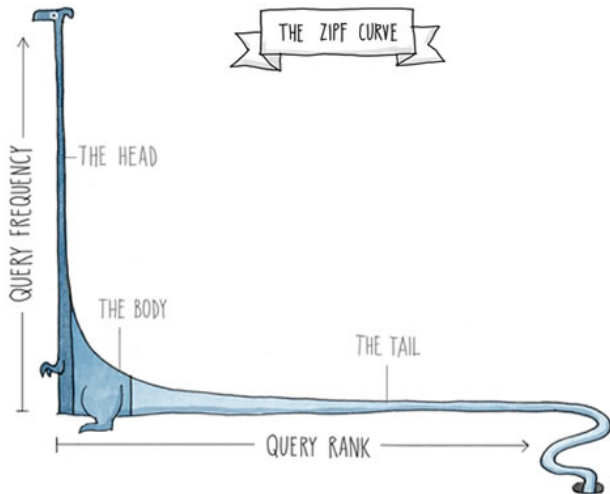
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# An Example from...the NBA?



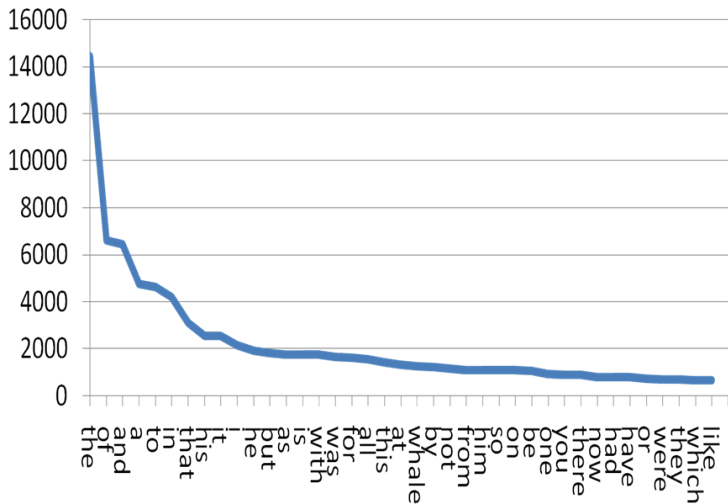
# Visualizing Zipf Distributions



# Zipf's Law is Everywhere. . .

- ▶ A distribution is probably Zipfian if
  - ▶ there is a **long neck**:  
a few types make up the majority of tokens,
  - ▶ there is a **long tail**:  
most types only have 1 token (**hapax legomenon**)
- ▶ Surprisingly, Zipf's Law shows up in tons of places:
  - ▶ size of large cities in a country
  - ▶ citations for academic papers
  - ▶ frequencies of last names
  - ▶ frequencies of weekdays in text

## ... Even in Language!



# Stop Words

- ▶ About 150 words make up 50% of all English texts:  
*the, of, and, a, ...*
- ▶ These are called **stop words**.
- ▶ Stop words are not very informative for many applications.
- ▶ So they are usually discarded after the tokenization step.
- ▶ Failure to do so can greatly reduce the model's performance.

## Steps of Word Counting Model (Revised)

- 1 collect corpus
- 2 remove stop words
- 3 tokenize strings
- 4 count tokens for each type

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## Example: A Text Without (Non)-Stop Words

- ▶ Stop words are much less informative than non-stop words.
- ▶ Just check the example below.

### **Stop Words only**

The                    having no                    on the

## Example: A Text Without (Non)-Stop Words

- ▶ Stop words are much less informative than non-stop words.
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### **Stop Words and Non-Stop Words**

The sun shone having no alternative on the nothing new



## Example: A Text Without (Non)-Stop Words

- ▶ Stop words are much less informative than non-stop words.
- ▶ Just check the example below.

### **Non-Stop Words only**

sun shone

alternative

nothing new

# An Important Consequence of Zipf's Law

- ▶ Texts mostly consist of stop words.
- ▶ Hence it can be difficult to get representative counts for non-stop words.

## Sparse Data Problem

- ▶ Most of the data is not informative.
- ▶ You need tons of data to have enough useful data.

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- ▶ Most of the data is not informative.
- ▶ You need tons of data to have enough useful data.

## Example

- ▶ Most models require corpora with at least a few million sentences.
- ▶ Really good models (e.g. Google translate) use billions of data points.