

# Natural Language Processing 1

## Lecture 5: Lexical semantics and word embeddings

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# Outline.

Introduction to lexical semantics

Distributional semantics

Semantics with dense vectors

# Semantics

## Compositional semantics:

- ▶ studies how meanings of phrases are constructed out of the meaning of individual words
- ▶ principle of compositionality: meaning of each whole phrase derivable from meaning of its parts
- ▶ sentence structure conveys some meaning: obtained by syntactic representation

## Lexical semantics:

- ▶ studies how the meanings of individual words can be represented and induced

## What is lexical meaning?

- ▶ recent results in psychology and cognitive neuroscience give us some clues
- ▶ but we don't have the whole picture yet
- ▶ different representations proposed, e.g.
  - ▶ formal semantic representations based on logic,
  - ▶ *or* taxonomies relating words to each other,
  - ▶ *or* distributional representations in statistical NLP
- ▶ but none of the representations gives us a complete account of lexical meaning

## How to approach lexical meaning?

- ▶ **Formal semantics**: set-theoretic approach  
e.g.,  $\text{cat}'$ : the set of all cats;  $\text{bird}'$ : the set of all birds.
- ▶ meaning postulates, e.g.  
$$\forall x[\text{bachelor}'(x) \rightarrow \text{man}'(x) \wedge \text{unmarried}'(x)]$$
- ▶ Limitations, e.g. *is the Pope a bachelor?*
- ▶ Defining concepts through enumeration of all of their features in practice is highly problematic
- ▶ How would you define e.g. *chair, tomato, thought, democracy*? – impossible for most concepts
- ▶ **Prototype theory** offers an alternative to set-theoretic approaches

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- ▶ Defining concepts through enumeration of all of their features in practice is highly problematic
- ▶ How would you define e.g. *chair, tomato, thought, democracy*? – impossible for most concepts
- ▶ **Prototype theory** offers an alternative to set-theoretic approaches

# How to approach lexical meaning?

## Prototype theory

- ▶ introduced the notion of **graded semantic categories**
- ▶ no clear boundaries; no requirement that a property be shared by all members
- ▶ certain members of a category are more central or **prototypical** (i.e. instantiate the prototype)

*furniture*: *chair* is more prototypical than *stool*

- ▶ Categories form around prototypes; new members added on basis of resemblance to prototype

Eleanor Rosch 1975. *Cognitive Representation of Semantic Categories* (J Experimental Psychology)

# How to approach lexical meaning?

## Semantic relations

### Hyponymy: IS-A

*dog* is a **hyponym** of *animal*  
*animal* is a **hypernym** of *dog*

- ▶ hyponymy relationships form a **taxonomy**
- ▶ works best for concrete nouns

## How to approach lexical meaning?

### Semantic relations

Meronymy: PART-OF e.g., *arm* is a **meronym** of *body*, *steering wheel* is a meronym of *car*

Synonymy e.g., *aubergine/eggplant*.

Antonymy e.g., *big/little*

Also:

Near-synonymy/similarity e.g., *exciting/thrilling*  
e.g., *slim/slender/thin/skinny*

**WordNet**: a large-scale lexical resource linking words by their semantic relations.

## Polysemy and word senses

The children **ran** to the store

If you see this man, **run**!

Service **runs** all the way to Cranbury

She is **running** a relief operation in Sudan

the story or argument **runs** as follows

Does this old car still **run** well?

Interest rates **run** from 5 to 10 percent

Who's **running** for treasurer this year?

They **ran** the tapes over and over again

These dresses **run** small

# Outline.

Introduction to lexical semantics

Distributional semantics

Semantics with dense vectors

## Distributional hypothesis

*You shall know a word by the company it keeps* (Firth)

*The meaning of a word is defined by the way it is used*  
(Wittgenstein).

it was authentic scrumpy, rather sharp and very strong

we could taste a famous local product — scrumpy

spending hours in the pub drinking scrumpy

Cornish Scrumpy Medium Dry. £19.28 - Case

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# Scrumpy



## Distributional hypothesis

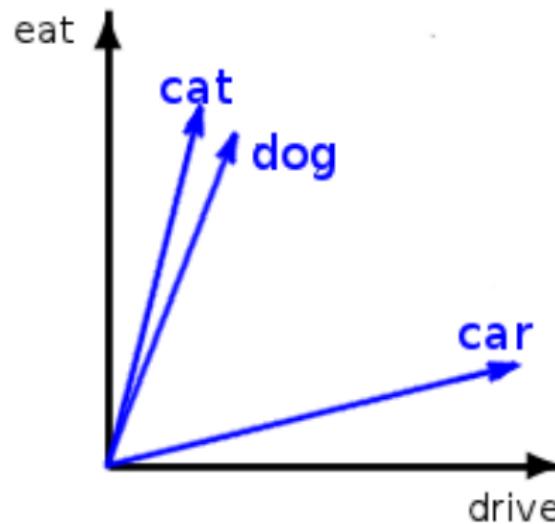
This leads to the **distributional hypothesis** about word meaning:

- ▶ the context surrounding a given word provides information about its meaning;
- ▶ words are similar if they share similar linguistic contexts;
- ▶ semantic similarity  $\approx$  distributional similarity.

## The general intuition

- ▶ **Distributions** are vectors in a multidimensional semantic space.
- ▶ The **semantic space** has dimensions which correspond to possible contexts – **features**.
- ▶ For our purposes, a distribution can be seen as a point in that space (the vector being defined with respect to the origin of that space).
- ▶ *scrumpy* [...pub 0.8, drink 0.7, strong 0.4, joke 0.2, mansion 0.02, zebra 0.1...]

# Vectors



## The notion of context

- 1 Word windows:  $n$  words on either side of the lexical item.

**Example:**  $n=2$  (5 words window):

*/ The prime **minister** acknowledged the /  
question.*

*minister* [ the 2, prime 1, acknowledged 1, question 0 ]

## Context

2 Lexeme window: as above but using stems.

**Example:** n=2 (5 words window):

*/ The prime **minister** acknowledged the / question.*

*minister* [ the 2, prime 1, acknowledge 1, question 0 ]

# Context

3 Syntactic relations (dependencies). Context for a lexical item is the syntactic dependency structure it belongs to.

## Example:

*The prime **minister** acknowledged the question.*

*minister* [ prime 1, acknowledge 1]

*minister* [ prime\_mod 1, acknowledge\_subj 1]

## Context weighting

1. **Binary model:** if context  $c$  co-occurs with word  $w$ , value of vector  $\vec{w}$  for dimension  $c$  is 1, 0 otherwise.
2. **Basic frequency model:** the value of vector  $\vec{w}$  for dimension  $c$  is the number of times that  $c$  co-occurs with  $w$ .
3. **Characteristic model:** Weights given to the vector components express how *characteristic* a given context is for word  $w$ .

## Characteristic model

- ▶ Weights given to the vector components express how *characteristic* a given context is for word  $w$ .
- ▶ Pointwise Mutual Information (PMI)

$$PMI(w, c) = \log \frac{P(w, c)}{P(w)P(c)} = \log \frac{P(w)P(c|w)}{P(w)P(c)} = \log \frac{P(c|w)}{P(c)}$$

$$P(c) = \frac{f(c)}{\sum_k f(c_k)}, \quad P(c|w) = \frac{f(w, c)}{f(w)},$$

$$PMI(w, c) = \log \frac{f(w, c) \sum_k f(c_k)}{f(w)f(c)}$$

$f(w, c)$ : frequency of word  $w$  in context  $c$

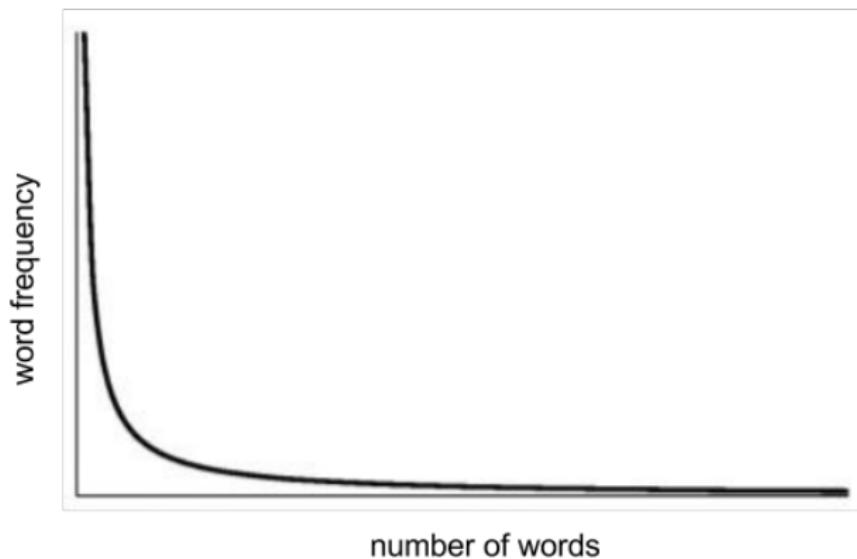
$f(w)$ : frequency of word  $w$  in all contexts

$f(c)$ : frequency of context  $c$

## What semantic space?

- ▶ Entire vocabulary.
  - ▶ + All information included – even rare contexts
  - ▶ - Inefficient (100,000s dimensions). Noisy (e.g. `002.png/thumb/right/200px/graph`). **Sparse**
- ▶ Top  $n$  words with highest frequencies.
  - ▶ + More efficient (2000-10000 dimensions). Only 'real' words included.
  - ▶ - May miss out on infrequent but relevant contexts.
- ▶ Dimensionality reduction using matrix factorization
  - ▶ + Very efficient (200-500 dimensions). Captures generalisations in the data.
  - ▶ - The resulting matrices are not interpretable.

## Word frequency: Zipfian distribution



# What semantic space?

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## An example noun

- ▶ *language*:

0.54::other+than+English	0.44::of+instruction
0.53::English+as	0.44::speaker+of
0.52::English+be	0.42::pron+speak
0.49::english	0.42::colon+English
0.48::and+literature	0.42::be+English
0.48::people+speak	0.42::language+be
0.47::French+be	0.42::and+culture
0.46::Spanish+be	0.41::arabic
0.46::and+dialects	0.41::dialects+of
0.45::grammar+of	0.40::percent+speak
0.45::foreign	0.39::spanish
0.45::germanic	0.39::welsh
0.44::German+be	0.39::tonal

## An example adjective

- ▶ *academic*:

0.52::Decathlon	0.36::reputation+for
0.51::excellence	0.35::regalia
0.45::dishonesty	0.35::program
0.45::rigor	0.35::freedom
0.43::achievement	0.35::student+with
0.42::discipline	0.35::curriculum
0.40::viceresident+for	0.34::standard
0.39::institution	0.34::at+institution
0.39::credentials	0.34::career
0.38::journal	0.34::Career
0.37::journal+be	0.33::dress
0.37::vocational	0.33::scholarship
0.37::student+achieve	0.33::prepare+student
0.36::athletic	0.33::qualification

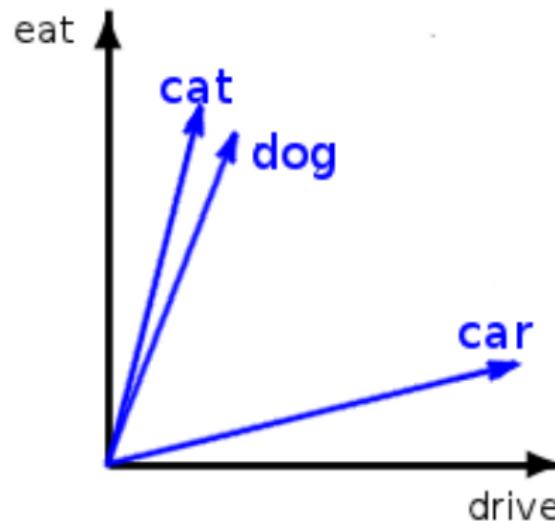
# Polysemy

- ▶ Distribution for *pot*, as obtained from Wikipedia.

0.57::melt	0.32::boil
0.44::pron+smoke	0.31::bowl+and
0.43::of+gold	0.31::ingredient+in
0.41::porous	0.30::plant+in
0.40::of+tea	0.30::simmer
0.39::player+win	0.29::pot+and
0.39::money+in	0.28::bottom+of
0.38::of+coffee	0.28::of+flower
0.33::amount+in	0.28::of+water
0.33::ceramic	0.28::food+in
0.33::hot	

## Calculating similarity in a distributional space

- ▶ Distributions are vectors, so distance can be calculated.



## Measuring similarity

- ▶ Cosine:

$$\cos(\theta) = \frac{\sum v1_k * v2_k}{\sqrt{\sum v1_k^2} * \sqrt{\sum v2_k^2}} \quad (1)$$

- ▶ The cosine measure calculates the angle between two vectors and is therefore length-independent.
- ▶ Other measures include Euclidean distance etc.

## The scale of similarity: some examples

house – building 0.43

gem – jewel 0.31

capitalism – communism 0.29

motorcycle – bike 0.29

test – exam 0.27

school – student 0.25

singer – academic 0.17

horse – farm 0.13

man – accident 0.09

tree – auction 0.02

cat – county 0.007

## Words most similar to *cat*

as chosen from the 5000 most frequent nouns in Wikipedia.

1 cat	0.29 human	0.25 woman	0.22 monster
0.45 dog	0.29 goat	0.25 fish	0.22 people
0.36 animal	0.28 snake	0.24 squirrel	0.22 tiger
0.34 rat	0.28 bear	0.24 dragon	0.22 mammal
0.33 rabbit	0.28 man	0.24 frog	0.21 bat
0.33 pig	0.28 cow	0.23 baby	0.21 duck
0.31 monkey	0.26 fox	0.23 child	0.21 cattle
0.31 bird	0.26 girl	0.23 lion	0.21 dinosaur
0.30 horse	0.26 sheep	0.23 person	0.21 character
0.29 mouse	0.26 boy	0.23 pet	0.21 kid
0.29 wolf	0.26 elephant	0.23 lizard	0.21 turtle
0.29 creature	0.25 deer	0.23 chicken	0.20 robot

## But what is similarity?

- ▶ In distributional semantics, very broad notion: synonyms, near-synonyms, hyponyms, taxonomical siblings, **antonyms**, etc.
- ▶ Correlates with a psychological reality.
- ▶ Test via correlation with human judgments on a test set:
  - ▶ Miller & Charles (1991)
  - ▶ WordSim
  - ▶ MEN
  - ▶ SimLex
- ▶ Correlation of 0.8 or more.

## Distributional methods are a usage representation

- ▶ Distributions are a good conceptual representation if you believe that ‘the meaning of a word is given by its usage’.
- ▶ Corpus-dependent, culture-dependent, register-dependent.  
Example: similarity between *policeman* and *cop*: 0.23

## Distribution for *policeman*

### **policeman**

0.59::ball+poss	0.28::incompetent
0.48::and+civilian	0.28::pron+shoot
0.42::soldier+and	0.28::hat+poss
0.41::and+soldier	0.28::terrorist+and
0.38::secret	0.27::and+crowd
0.37::people+include	0.27::military
0.37::corrupt	0.27::helmet+poss
0.36::uniformed	0.27::father+be
0.35::uniform+poss	0.26::on+duty
0.35::civilian+and	0.25::salary+poss
0.31::iraqi	0.25::on+horseback
0.31::lot+poss	0.25::armed
0.31::chechen	0.24::and+nurse
0.30::laugh	0.24::job+as
0.29::and+criminal	0.24::open+fire

# Distribution for *cop*

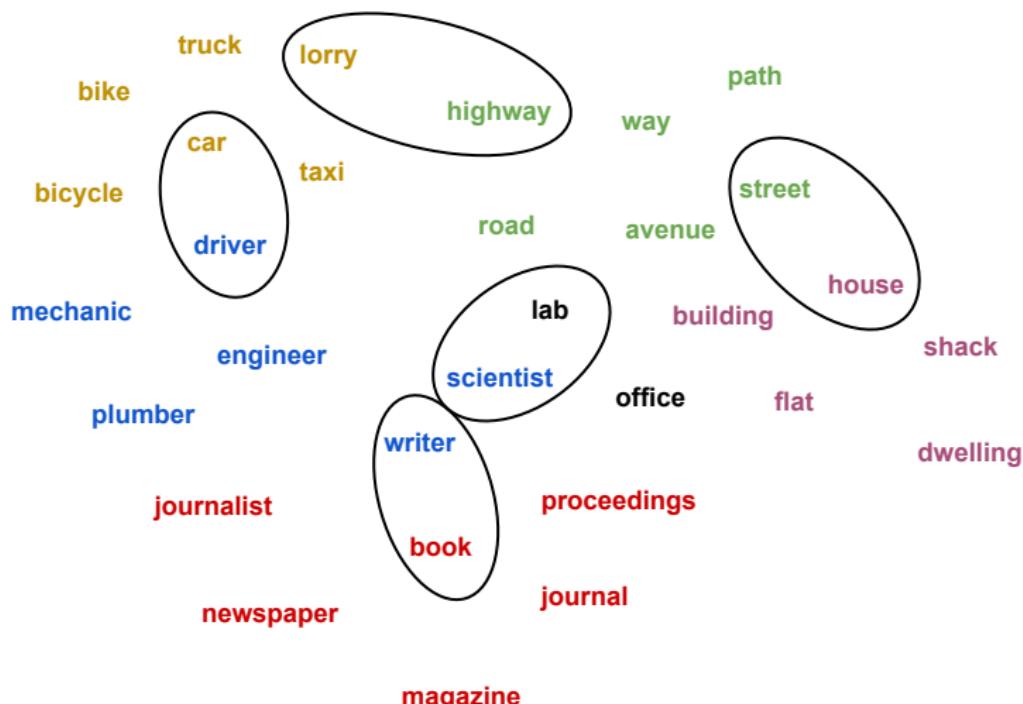
## **cop**

0.45::crooked	0.27::investigate+murder
0.45::corrupt	0.26::on+force
0.44::maniac	0.25::parody+of
0.38::dirty	0.25::Mason+and
0.37::honest	0.25::pron+kill
0.36::uniformed	0.25::racist
0.35::tough	0.24::addicted
0.33::pron+call	0.23::gritty
0.32::funky	0.23::and+interference
0.32::bad	0.23::arrive
0.29::veteran	0.23::and+detective
0.29::and+robot	0.22::look+way
0.28::and+criminal	0.22::dead
0.28::bogus	0.22::pron+stab
0.28::talk+to+pron	0.21::pron+evade

# Clustering nouns



# Clustering nouns



# Outline.

Introduction to lexical semantics

Distributional semantics

Semantics with dense vectors

# Distributional semantic models

## 1. Count-based models:

- ▶ Explicit vectors: dimensions are elements in the context
- ▶ **long sparse** vectors with **interpretable** dimensions

## 2. Prediction-based models:

- ▶ Train a model to predict plausible contexts for a word
- ▶ learn word representations in the process
- ▶ **short dense** vectors with **latent** dimensions

# Sparse vs. dense vectors

## Why dense vectors?

- ▶ easier to use as features in machine learning (less weights to tune)
- ▶ may generalize better than storing explicit counts
- ▶ may do better at capturing synonymy:
  - ▶ e.g. *car* and *automobile* are distinct dimensions in count-based models
  - ▶ will not capture similarity between a word with *car* as a neighbour and a word with *automobile* as a neighbour

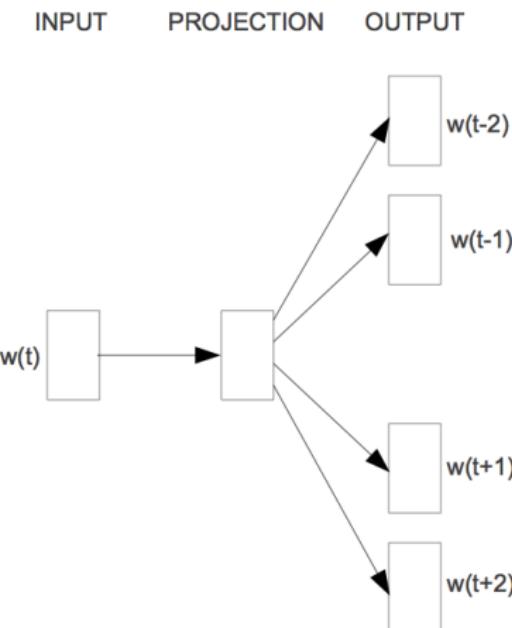
## Prediction-based distributional models

Mikolov et. al. 2013. *Efficient Estimation of Word Representations in Vector Space.*

**word2vec**: **Skip-gram** model

- ▶ inspired by work on neural language models
- ▶ train a neural network to predict neighboring words
- ▶ learn dense embeddings for the words in the training corpus in the process

# Skip-gram



## Skip-gram

**Intuition:** words with similar meanings often occur near each other in texts

Given a word  $w(t)$ :

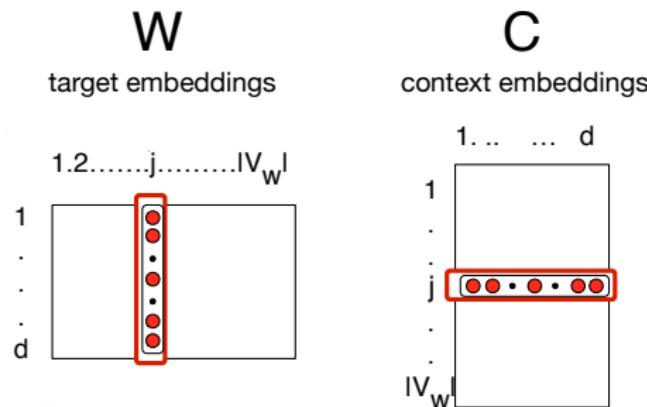
- ▶ Predict each neighbouring word
  - ▶ in a context window of  $2L$  words
  - ▶ from the current word.
- ▶ For  $L = 2$ , we predict its 4 neighbouring words:

$$[w(t-2), w(t-1), w(t+1), w(t+2)]$$

## Skip-gram: Parameter matrices

Learn 2 embeddings for each word  $w_j \in V_w$ :

- ▶ **word embedding**  $v$ , in word matrix  $W$
- ▶ **context embedding**  $c$ , in context matrix  $C$



## Skip-gram: Setup

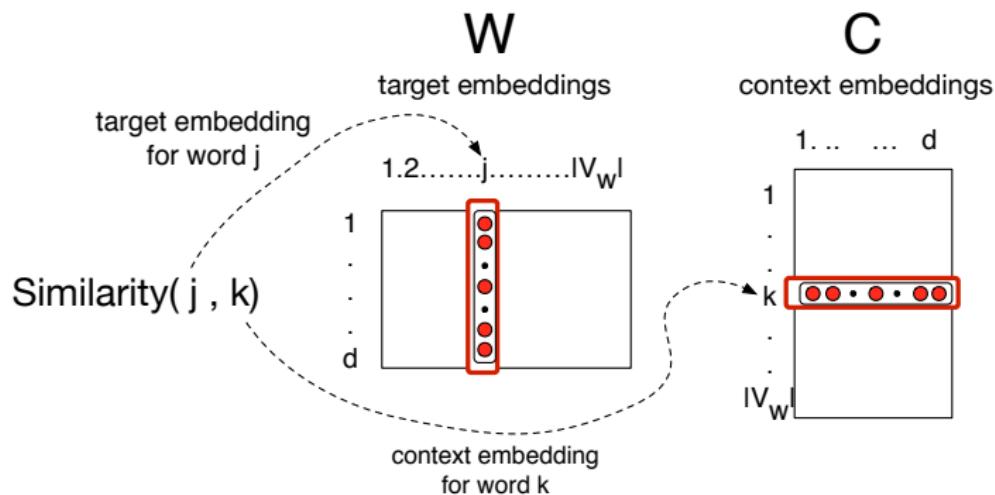
- ▶ Walk through the corpus pointing at word  $w(t)$ , whose index in the vocabulary is  $j$  — we will call it  $w_j$
- ▶ our goal is to predict  $w(t + 1)$ , whose index in the vocabulary is  $k$  — we will call it  $w_k$
- ▶ to do this, we need to compute

$$p(w_k | w_j)$$

- ▶ **Intuition** behind skip-gram: to compute this probability we need to compute similarity between  $w_j$  and  $w_k$

## Skip-gram: Computing similarity

Similarity as dot-product between the target vector and context vector



Slide credit: Dan Jurafsky

## Skip-gram: Similarity as dot product

- ▶ Remember cosine similarity?

$$\cos(v1, v2) = \frac{\sum v1_k * v2_k}{\sqrt{\sum v1_k^2} * \sqrt{\sum v2_k^2}} = \frac{v1 \cdot v2}{\|v1\| \|v2\|}$$

It's just a normalised dot product.

- ▶ Skip-gram: Similar vectors have a high dot product

$$\text{Similarity}(c_k, v_j) \propto c_k \cdot v_j$$

## Skip-gram: Compute probabilities

- ▶ Compute similarity as a dot product

$$\text{Similarity}(c_k, v_j) \propto c_k \cdot v_j$$

- ▶ Normalise to turn this into a probability
- ▶ by passing through a softmax function:

$$p(w_k | w_j) = \frac{e^{c_k \cdot v_j}}{\sum_{i \in V} e^{c_i \cdot v_j}}$$

## Skip-gram: Learning

- ▶ Start with some initial embeddings (usually random)
- ▶ At training time, walk through the corpus
- ▶ iteratively make the embeddings for each word
  - ▶ more like the embeddings of its neighbors
  - ▶ less like the embeddings of other words.

## Skip-gram: Objective

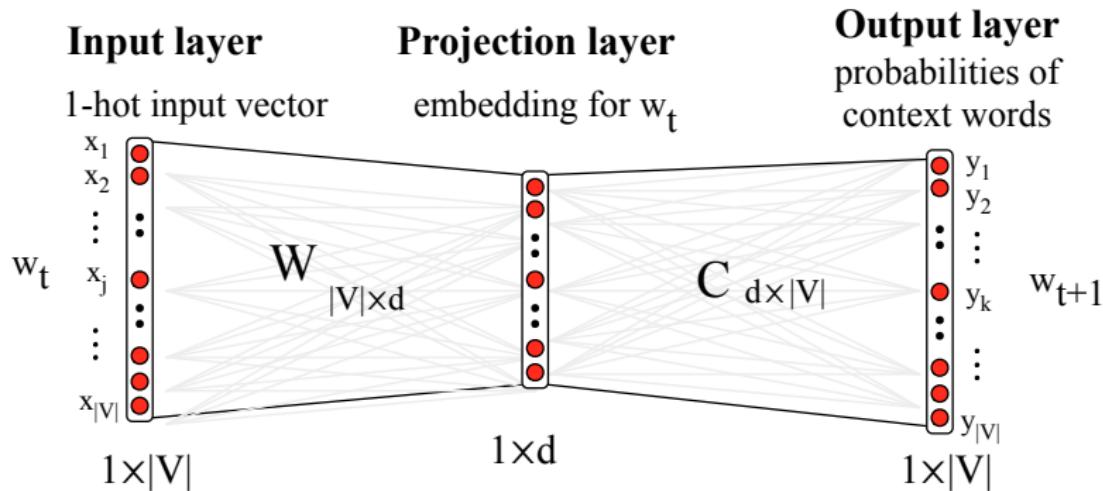
Learn parameters  $C$  and  $W$  that maximize the overall corpus probability:

$$\arg \max \prod_{(w_j, w_k) \in D} p(w_k | w_j)$$

$$p(w_k | w_j) = \frac{e^{c_k \cdot v_j}}{\sum_{i \in V} e^{c_i \cdot v_j}}$$

$$\arg \max \prod_{(w_j, w_k) \in D} p(w_k | w_j) = \prod_{(w_j, w_k) \in D} \frac{e^{c_k \cdot v_j}}{\sum_{i \in V} e^{c_i \cdot v_j}}$$

## Visualising skip-gram as a network

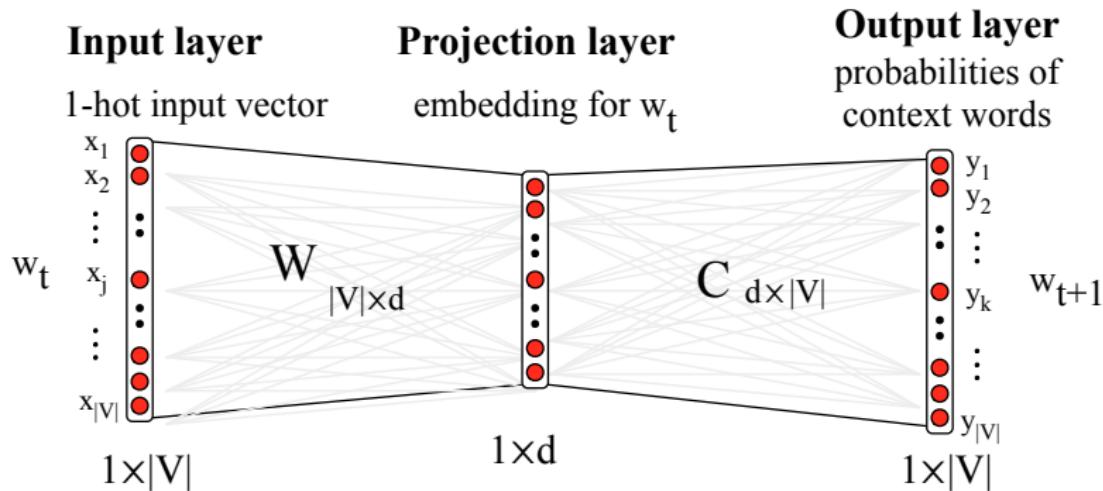


Slide credit: Dan Jurafsky

## One hot vectors

$$w_0 \ w_1 \ \dots \ w_j \ \dots \ w_{|V|}$$

## Visualising skip-gram as a network



Slide credit: Dan Jurafsky

## Skip-gram with negative sampling

Problem with softmax: expensive to compute the denominator for the whole vocabulary

$$p(w_k | w_j) = \frac{e^{c_k \cdot v_j}}{\sum_{i \in V} e^{c_i \cdot v_j}}$$

Approximate the denominator: **negative sampling**

- ▶ At training time, walk through the corpus
- ▶ for each target word and positive context
- ▶ sample  $k$  noise samples or negative samples, i.e. other words

## Skip-gram with negative sampling

- ▶ Objective in training:
  - ▶ Make the word like the context words  
lemon, a [tablespoon of apricot preserves or] jam.

$c_1 \quad c_2 \quad w \quad c_3 \quad c_4$

- ▶ And not like the  $k$  negative examples

[cement idle dear coaxial apricot attendant whence forever puddle]

$n_1 \quad n_2 \quad n_3 \quad n_4 \quad w \quad n_5 \quad n_6 \quad n_7 \quad n_8$

## Skip-gram with negative sampling: Training examples

Convert the dataset into word pairs:

- ▶ **Positive (+)**

- (apricot, tablespoon)
- (apricot, of)
- (apricot, jam)
- (apricot, or)

- ▶ **Negative (-)**

- (apricot, cement)
- (apricot, idle)
- (apricot, attendant)
- (apricot, dear)

...

## Skip-gram with negative sampling

- ▶ instead of treating it as a **multi-class problem** (and returning a probability distribution over the whole vocabulary)
- ▶ **return a probability** that word  $w_k$  is a valid context for word  $w_j$

$$P(+|w_j, w_k)$$

$$P(-|w_j, w_k) = 1 - P(+|w_j, w_k)$$

## Skip-gram with negative sampling

- ▶ model similarity as dot product

$$\text{Similarity}(c_k, v_j) \propto c_k \cdot v_j$$

- ▶ turn this into a probability using the **sigmoid function**:

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

$$P(+|w_j, w_k) = \frac{1}{1 + e^{-c_k \cdot v_j}}$$

$$P(-|w_j, w_k) = 1 - P(+|w_j, w_k) = 1 - \frac{1}{1 + e^{-c_k \cdot v_j}} = \frac{1}{1 + e^{c_k \cdot v_j}}$$

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## Skip-gram with negative sampling: Objective

- ▶ make the word like the context words
- ▶ and not like the negative examples

$$\arg \max \prod_{(w_j, w_k) \in D_+} p(+|w_k, w_j) \prod_{(w_j, w_k) \in D_-} p(-|w_k, w_j)$$

$$\arg \max \sum_{(w_j, w_k) \in D_+} \log p(+|w_k, w_j) + \sum_{(w_j, w_k) \in D_-} \log p(-|w_k, w_j) =$$

$$\arg \max \sum_{(w_j, w_k) \in D_+} \log \frac{1}{1 + e^{-c_k \cdot v_j}} + \sum_{(w_j, w_k) \in D_-} \log \frac{1}{1 + e^{c_k \cdot v_j}}$$

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- ▶ and not like the negative examples

$$\arg \max \prod_{(w_j, w_k) \in D_+} p(+|w_k, w_j) \prod_{(w_j, w_k) \in D_-} p(-|w_k, w_j)$$

$$\arg \max \sum_{(w_j, w_k) \in D_+} \log p(+|w_k, w_j) + \sum_{(w_j, w_k) \in D_-} \log p(-|w_k, w_j) =$$

$$\arg \max \sum_{(w_j, w_k) \in D_+} \log \frac{1}{1 + e^{-c_k \cdot v_j}} + \sum_{(w_j, w_k) \in D_-} \log \frac{1}{1 + e^{c_k \cdot v_j}}$$

## Skip-gram with negative sampling: Objective

- ▶ make the word like the context words
- ▶ and not like the negative examples

$$\arg \max \prod_{(w_j, w_k) \in D_+} p(+|w_k, w_j) \prod_{(w_j, w_k) \in D_-} p(-|w_k, w_j)$$

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# Properties of embeddings

They capture similarity

FRANCE	JESUS	XBOX	REDDISH	SCRATCHED	MEGABITS
454	1973	6909	11724	29869	87025
AUSTRIA	GOD	AMIGA	GREENISH	NAILED	OCTETS
BELGIUM	SATI	PLAYSTATION	BLUISH	SMASHED	MB/S
GERMANY	CHRIST	MSX	PINKISH	PUNCHED	BIT/S
ITALY	SATAN	IPOD	PURPLISH	POPPED	BAUD
GREECE	KALI	SEGA	BROWNISH	CRIMPED	CARATS
SWEDEN	INDRA	PSNUMBER	GREYISH	SCRAPED	KBIT/S
NORWAY	VISHNU	HD	GRAYISH	SCREWED	MEGAHERTZ
EUROPE	ANANDA	DREAMCAST	WHITISH	SECTIONED	MEGAPIXELS
HUNGARY	PARVATI	GEFORCE	SILVERY	SLASHED	GBIT/S
SWITZERLAND	GRACE	CAPCOM	YELLOWISH	RIPPED	AMPERES

Slide credit: Ronan Collobert

## Properties of embeddings

They capture **analogy**

**Analogy task:**  $a$  is to  $b$  as  $c$  is to  $d$

The system is given words  $a, b, c$ , and it needs to find  $d$ .

“apple” is to “apples” as “car” is to ?

“man” is to “woman” as “king” is to ?

**Solution:** capture analogy via vector offsets

$$a - b \approx c - d$$

$$man - woman \approx king - queen$$

$$d_w = \underset{d'_w \in V}{\operatorname{argmax}} \cos(a - b, c - d')$$

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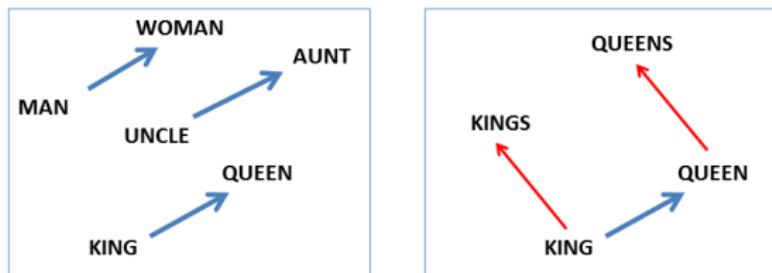
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## Properties of embeddings

Capture analogy via vector offsets

$$man - woman \approx king - queen$$



Mikolov et al. 2013. *Linguistic Regularities in Continuous Space Word Representations*

# Properties of embeddings

They capture a range of semantic relations

Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

Mikolov et al. 2013. *Efficient Estimation of Word Representations in Vector Space*

## Word embeddings in practice

Word2vec is often used for pretraining in other tasks.

- ▶ It will help your models start from an **informed** position
- ▶ Requires only **plain text** - which we have a lot of
- ▶ Is very **fast** and easy to use
- ▶ Already **pretrained** vectors also available (trained on 100B words)

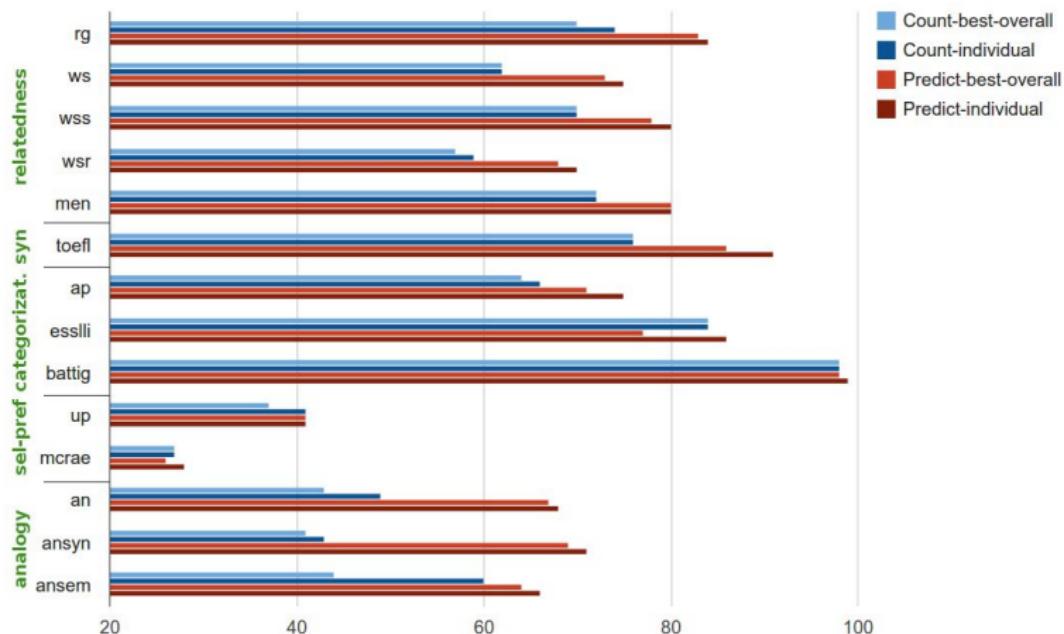
However, for best performance it is important to continue training, fine-tuning the embeddings for a specific task.

## Count-based models vs. skip-gram word embeddings

Baroni et. al. 2014. *Don't count, predict! A systematic comparison of context-counting vs. context-predicting semantic vectors.*

- ▶ Comparison of count-based and neural word vectors on 5 types of tasks and 14 different datasets:
  1. Semantic relatedness
  2. Synonym detection
  3. Concept categorization
  4. Selectional preferences
  5. Analogy recovery

## Count-based models vs. skip-gram word embeddings



Some of these findings were later disputed by Levy et. al. 2015. *Improving Distributional Similarity with Lessons Learned from Word Embeddings*

## Acknowledgement

*Some slides were adapted from Ann Copestake, Dan Jurafsky and Marek Rei*