Distributional Semantics

COMP90042

Natural Language Processing

Lecture 10

Semester 1 Week 5
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Lexical Databases - Problems

- Manually constructed
  - Expensive
  - Human annotation can be biased and noisy
- Language is dynamic
  - New words: slang, terminology, etc.
  - New senses
- The Internet provides us with massive amounts of text. Can we use that to obtain word meanings?

Distributional Hypothesis

- *You shall know a word by the company it keeps*
  — Firth, 1957

- Document co-occurrence indicative of topic (**document** as context)
  - E.g. *voting* and *politics*

- Local context reflects its meaning (**word window** as context)
  - E.g. *eat a pizza* vs. *eat a burger*

Guessing Meaning from Context

- Learn unknown word from its usage
  - *tezgüino*

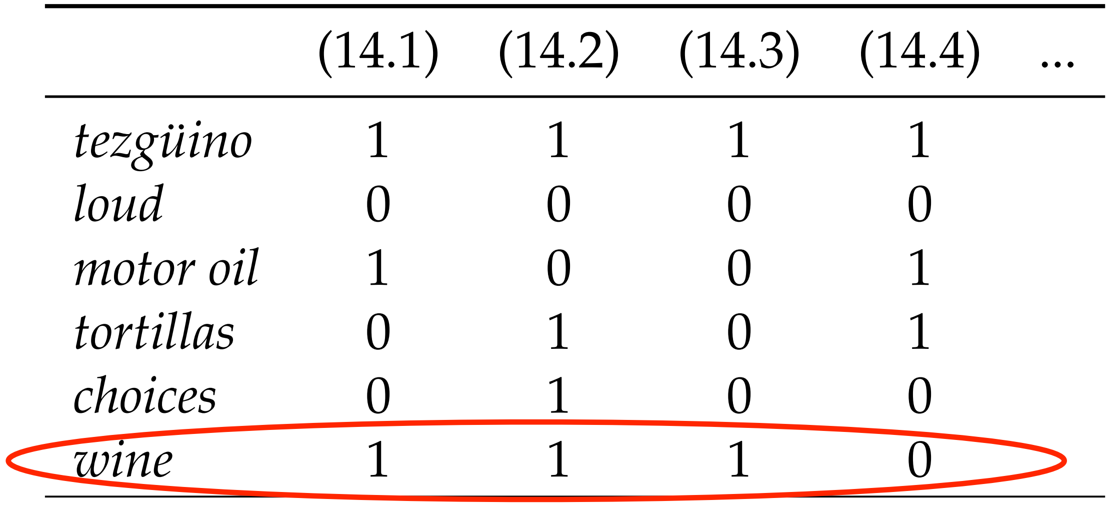
(14.1) A bottle of _____ is on the table.

(14.2) Everybody likes _____.

(14.3) Don't have _____ before you drive.

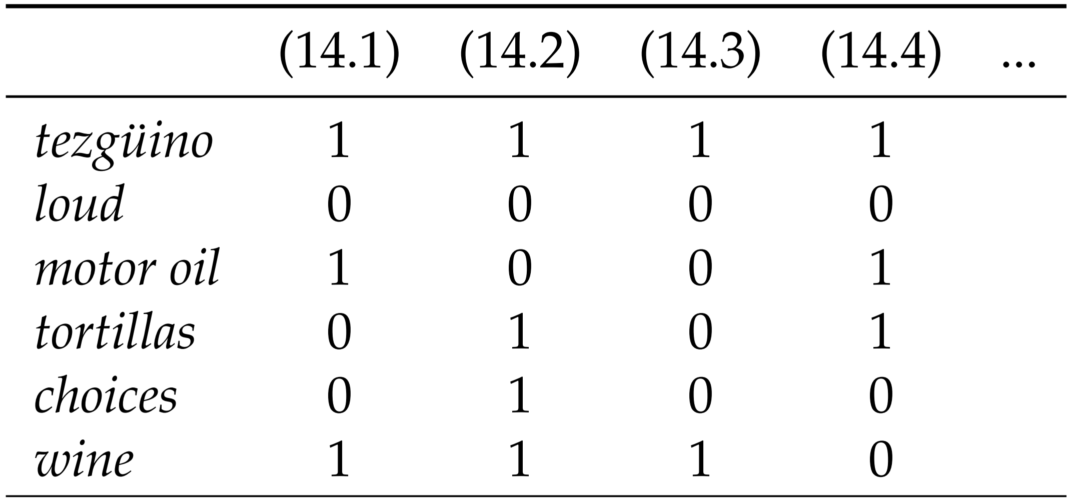
(14.4) We make _____ out of corn.

- Another way: look at words that share similar contexts!



	(14.1)	(14.2)	(14.3)	(14.4)	...
tezgüino	1	1	1	1	
loud	0	0	0	0	
motor oil	1	0	0	1	
tortillas	0	1	0	1	
choices	0	1	0	0	
wine	1	1	1	0	

Word Vectors



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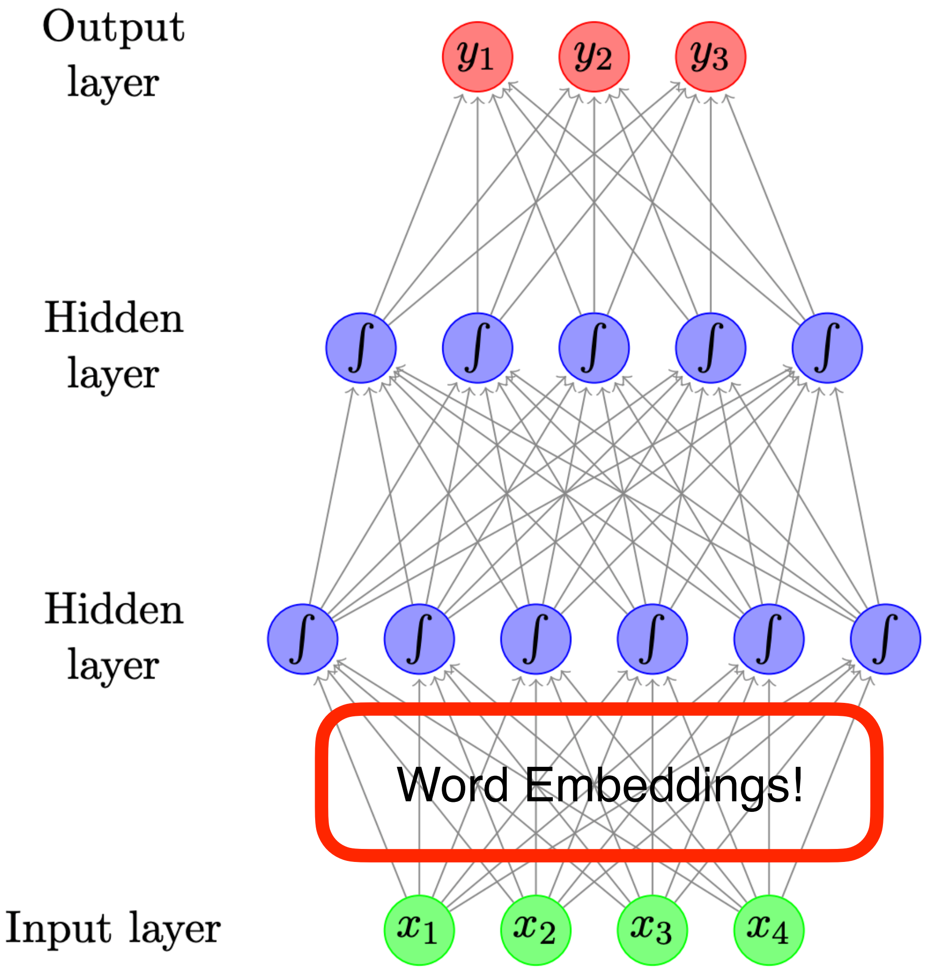
wine	1	1	1	0	

- Each row can be thought of a **word vector**
- It describes the distributional properties of a word
  - i.e. encodes information about its context words
- Capture all sorts of semantic relationships (synonymy, analogy, etc)

Word Embeddings?

- We’ve seen word vectors before: word embeddings!
- Here we will learn other ways to produce word vectors
  - Count-based methods
  - More efficient neural methods designed just for learning word vectors



Outline

- Count-based methods
- Neural methods
- Evaluation

Count-Based Methods

Learning Count-Based Word Vectors

- Generally two flavours
  - Use document as context
  - Use neighbouring words as context

Document as Context: The Vector Space Model

- Core idea: represent word meaning as a vector
- Consider documents as context
- One matrix, two viewpoints
    - Documents represented by their words
    - Words represented by their documents

	…	state	fun	heaven	…
…					
425		0	1	0	
426		3	0	0	
427		0	0	0	
……					

Manipulating the VSM

- Weighting the values (beyond frequency)
- Creating low-dimensional dense vectors

Tf-idf

- Standard weighting scheme for information retrieval
- Discounts common words!

$$idf_w = \log \frac{|D|}{df_w}$$

total #docs

#docs that has w

	…	the	country	hell	…
…					
425		43	5	1	
426		24	1	0	
427		37	0	3	
…					
df		500	14	7	

tf matrix

	…	the	country	hell	…
…					
425		0	26.0	6.2	
426		0	5.2	0	
427		0	0	18.6	
…					

tf-idf matrix

Dimensionality Reduction

- Term-document matrices are very **sparse**
- Dimensionality reduction: create shorter, denser vectors
- More practical (less features)
- Remove noise (less overfitting)

Singular Value Decomposition

$$\begin{array}{cc} & |D| \\ |V| & \begin{bmatrix} 0 & 1 & 0 & & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & & 0 \\ & \vdots & & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 0 \end{bmatrix} \end{array}$$

A
(term-document matrix)

$$A = U \Sigma V^T$$

U
(new term matrix)

$$\begin{array}{cc} & m \\ |V| & \begin{bmatrix} 2.2 & 0.3 & & 8.7 \\ 5.5 & -2.8 & \cdots & 0.1 \\ -1.3 & 3.7 & & 3.5 \\ \vdots & & \ddots & \vdots \\ 2.9 & -2.1 & \cdots & -1.9 \end{bmatrix} \end{array}$$

Σ
(singular values)

$$\begin{array}{cc} & m \\ m & \begin{bmatrix} 9.1 & 0 & 0 & & 0 \\ 0 & 4.4 & 0 & \cdots & 0 \\ 0 & 0 & 2.3 & & 0 \\ & \vdots & & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 0.1 \end{bmatrix} \end{array}$$

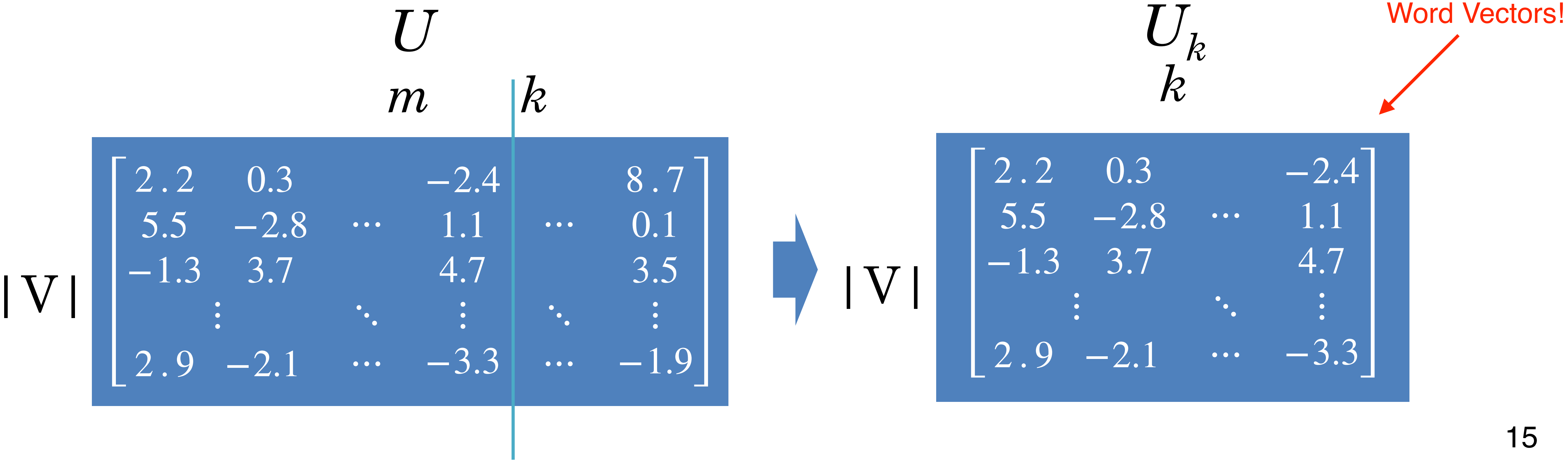
V^T
(new document matrix)

$$\begin{array}{cc} & |D| \\ m & \begin{bmatrix} -0.2 & 4.0 & & -1.3 \\ -4.1 & 0.6 & \cdots & -0.2 \\ 2.6 & 6.1 & & 1.4 \\ \vdots & & \ddots & \vdots \\ -1.9 & -1.8 & \cdots & 0.3 \end{bmatrix} \end{array}$$

$m = Rank(A)$

Truncating – Latent Semantic Analysis

- Truncating *U, Σ,* and *V* to *k* dimensions produces best possible *k* rank approximation of original matrix
- U_k is a new low dimensional representation of words
- Typical values for *k* are 100-5000



$$U \qquad\qquad\qquad U_k$$

$$\begin{array}{cc} & m \quad | \quad k \\ |V| & \begin{bmatrix} 2.2 & 0.3 & & -2.4 & & 8.7 \\ 5.5 & -2.8 & \cdots & 1.1 & \cdots & 0.1 \\ -1.3 & 3.7 & & 4.7 & & 3.5 \\ \vdots & & \ddots & \vdots & \ddots & \vdots \\ 2.9 & -2.1 & \cdots & -3.3 & \cdots & -1.9 \end{bmatrix} \end{array} \Rightarrow \begin{array}{cc} & k \\ |V| & \begin{bmatrix} 2.2 & 0.3 & & -2.4 \\ 5.5 & -2.8 & \cdots & 1.1 \\ -1.3 & 3.7 & & 4.7 \\ \vdots & & \ddots & \vdots \\ 2.9 & -2.1 & \cdots & -3.3 \end{bmatrix} \end{array}$$

Word Vectors!

Words as Context

- Lists how often words appear with other words
  - In some predefined context (e.g. a window of N words)
- The obvious problem with raw frequency: dominated by common words
  - But we can't use tf-idf!

	…	the	country	hell	…
…					
state		1973	10	1	
fun		54	2	0	
heaven		55	1	3	
……					

Pointwise Mutual Information

- For two events *x* and *y*, PMI computes the discrepancy between:
  - Their joint distribution = $P(x, y)$
  - Their individual distributions (assuming independence) = $P(x)P(y)$

$$\text{PMI}(x, y) = \log_2 \frac{P(x, y)}{P(x)P(y)}$$

Calculating PMI

	…	the	country	hell	…		Σ
…							
state		1973	10	1			12786
fun		54	2	0			633
heaven		55	1	3			627
…							
Σ		1047519	3617	780			15871304

$$\text{PMI}(x, y) = \log_2 \frac{P(x, y)}{P(x)P(y)}$$

$$P(x, y) = \frac{\text{count}(x, y)}{\Sigma}$$

$$P(x) = \frac{\Sigma_x}{\Sigma}$$

$$P(y) = \frac{\Sigma_y}{\Sigma}$$

x = state, y = country

$$P(x, y) = \frac{10}{15871304} = 6.3 \times 10^{-7}$$

$$P(x) = \frac{12786}{15871304} = 8.0 \times 10^{-4}$$

$$P(y) = \frac{3617}{15871304} = 2.3 \times 10^{-4}$$

$$\text{PMI}(x, y) = \log_2 \frac{6.3 \times 10^{-7}}{(8.0 \times 10^{-4})(2.3 \times 10^{-4})} = 1.78$$

PMI(heaven, hell)?

	…	the	country	hell	…		Σ
…							
state		1973	10	1			12786
fun		54	2	0			633
heaven		55	1	3			627
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PollEv.com/jeyhanlau569

PMI(heaven, hell)?

	…	the	country	hell	…		Σ
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$$\mathrm{PMI}(x, y) = \log_2 \frac{P(x, y)}{P(x)P(y)}$$

$$P(x, y) = \frac{\mathrm{count}(x, y)}{\Sigma}$$

$$P(x) = \frac{\Sigma_x}{\Sigma}$$

$$P(y) = \frac{\Sigma_y}{\Sigma}$$

$$\mathrm{PMI}(x, y) = \log_2 \left(\frac{\frac{3}{15871304}}{\frac{627}{15871304} \times \frac{780}{15871304}} \right) = 6.61$$

higher than PMI(state, country) = 1.78

PMI Matrix

- PMI does a better job of capturing semantics
  - E.g. *heaven* and *hell*
- But very biased towards rare word pairs
- And doesn’t handle zeros well

	…	the	country	hell	…
…					
state		1.22	1.78	0.63	
fun		0.37	3.79	-inf	
heaven		0.41	2.80	6.61	
……					

PMI Tricks

- Zero all negative values (Positive PMI)
  - Avoid –inf and unreliable negative values
- Counter bias towards rare events

Normalised PMI $$\left(\frac{\mathrm{PMI}(x, y)}{-\log P(x, y)} \right)$$

SVD ($A = U\Sigma V^T$)

	…	the	country	hell	…
…					
425		0	26.0	6.2	
426		0	5.2	0	
427		0	0	18.6	
…					

tf-idf matrix

	…	the	country	hell	…
…					
state		1.22	1.78	0.63	
fun		0.37	3.79	0	
heaven		0.41	2.80	6.60	
……					

PPMI matrix

- Regardless of whether we use document or word as context, SVD can be applied to create dense vectors

Neural Methods

Word Embeddings

- We’ve seen word embeddings used in neural networks (lecture 7 and 8)
- But these models are designed for other tasks:
  - Classification
  - Language modelling
- Word embeddings are just a **by-product**

Neural Models for Embeddings

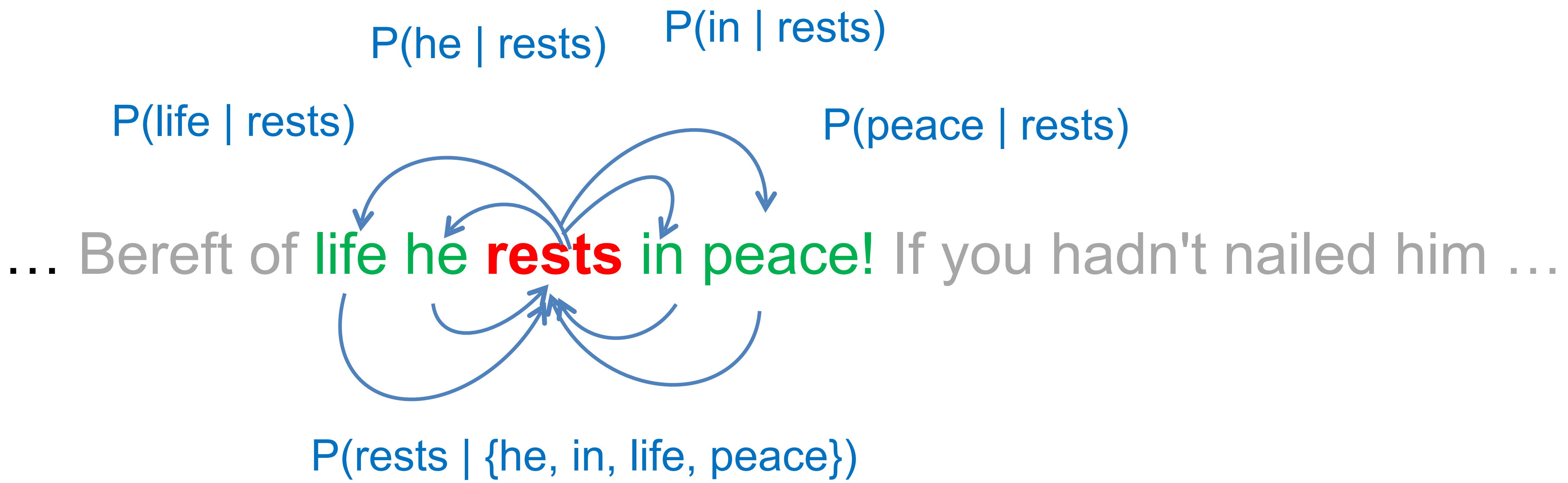
- Can we design neural networks whose goal is to purely learn word embeddings?
- Desiderata:
  - Unsupervised
  - Efficient

Word2Vec

- Core idea
  - *You shall know a word by the company it keeps*
  - Predict a word using context words

Word2Vec

- Framed as learning a classifier
  - **Skip-gram**: predict surrounding words of target word



P(he | rests) P(in | rests)

P(life | rests) P(peace | rests)

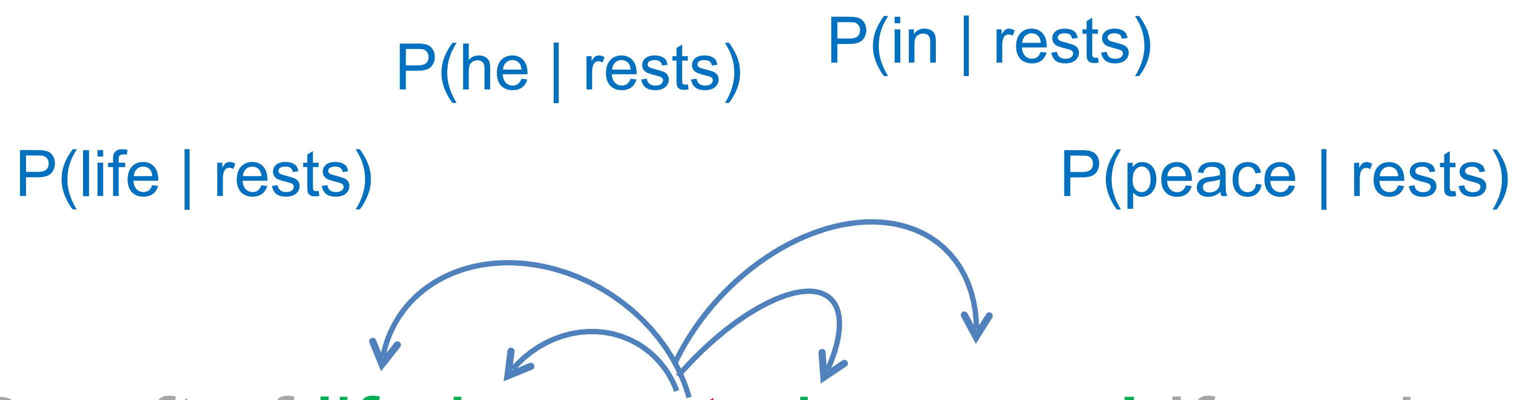
… Bereft of life he **rests** in peace! If you hadn't nailed him …

P(rests | {he, in, life, peace})

  - **CBOW**: predict target word using surrounding words
- Use surrounding words within L positions, L=2 above

Skip-gram Model

- Predicts each neighbouring word given target word



P(he | rests) P(in | rests)

P(life | rests) P(peace | rests)

… Bereft of life he **rests** in peace! If you hadn't nailed him …

- Total probability defined as

$$\prod_{l \in -L,\ldots,-1,1,\ldots,L} P(w_{t+l} \mid w_t)$$

- Using a (multinomial) logistic regression model with softmax

$$P(\text{life} \mid \text{rests}) = \frac{\exp(W_{\text{rests}} \cdot C_{\text{life}})}{\sum_{u \in V} \exp(W_{\text{rests}} \cdot C_u)}$$

word embedding of *rests*

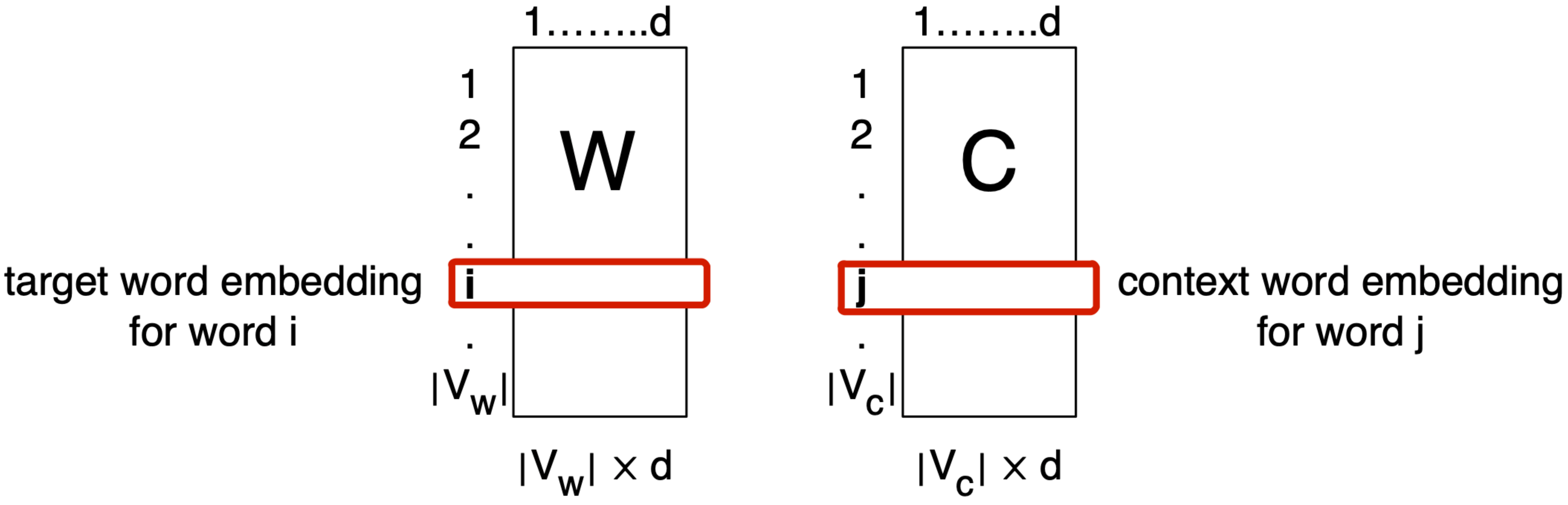
word embedding of *life*

dot product

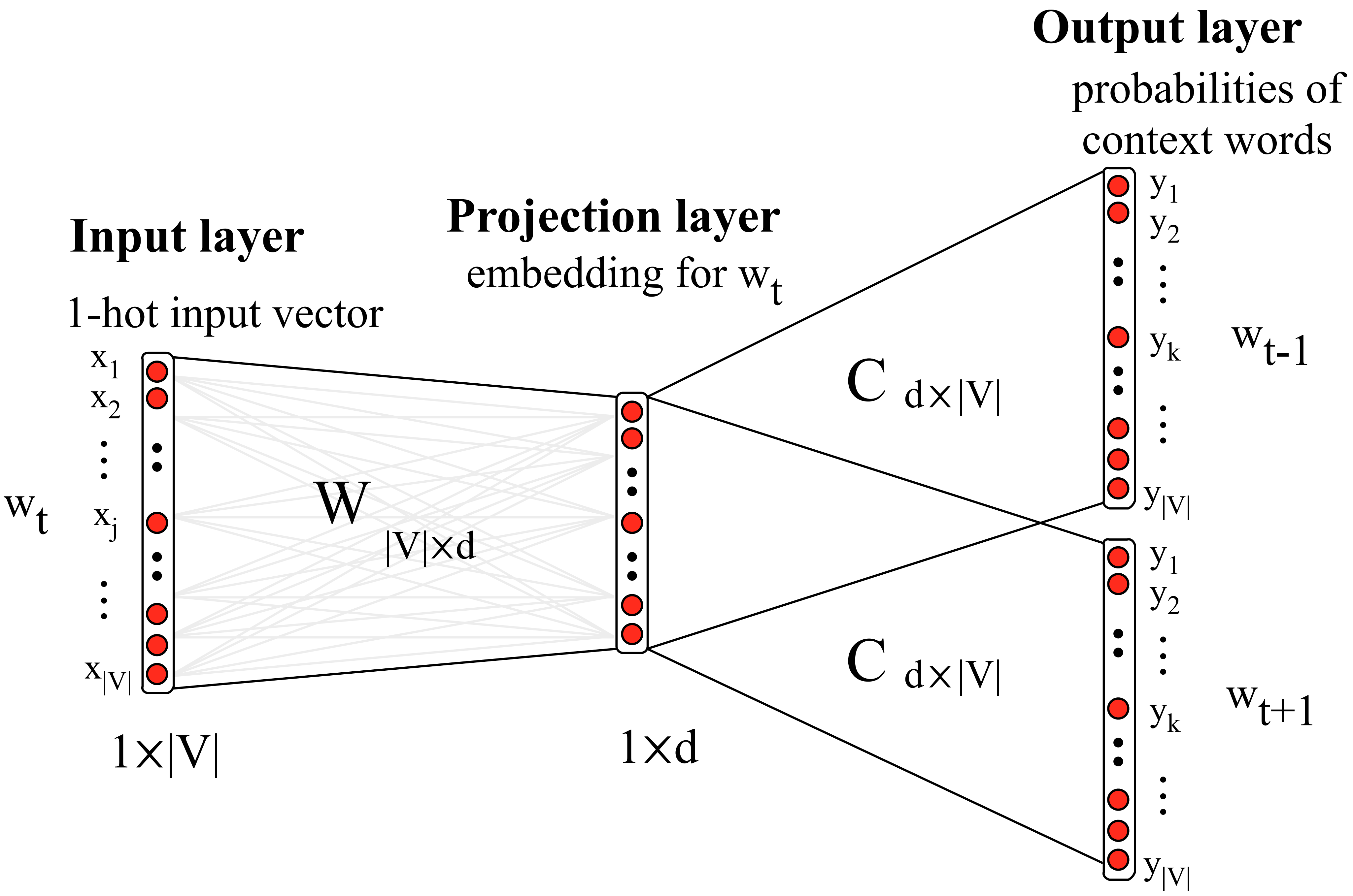
Embedding parameterisation

$$P(\text{life} \mid \text{rests}) = \frac{\exp(W_{\text{rests}} \cdot C_{\text{life}})}{\sum_{u \in V} \exp(W_{\text{rests}} \cdot C_u)}$$

- Two word embedding matrices (W and C)!


1……..d
1
2
.
.
i
.
|Vw|
W
target word embedding for word i
|Vw| × d
1……..d
1
2
.
.
j
.
|Vc|
C
context word embedding for word j
|Vc| × d

Skip-gram model



Training the skip-gram model

- Train to maximise likelihood of **raw text**
- Too slow in practice, due to normalisation over |V|

$$P(\text{life} \mid \text{rests}) = \frac{\exp(W_{\text{rests}} \cdot C_{\text{life}})}{\boxed{\sum_{u \in V} \exp(W_{\text{rests}} \cdot C_u)}}$$

- Reduce problem to binary classification
  - (*rests*, *life*) → real context word
  - (*rests*, *aardvark*) → non-context word
  - How to draw non-context word or **negative samples**?
  - Randomly from V

Negative Sampling

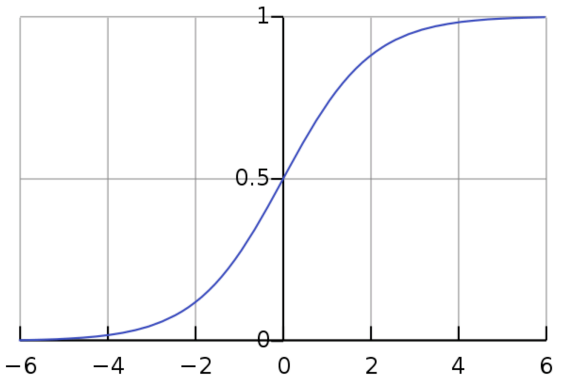
```
... lemon,  a [tablespoon of apricot jam,     a] pinch ...
               c1         c2     t     c3     c4
```

positive examples +

t	c
apricot	tablespoon
apricot	of
apricot	jam
apricot	a

negative examples -

t	c	t	c
apricot	aardvark	apricot	seven
apricot	my	apricot	forever
apricot	where	apricot	dear
apricot	coaxial	apricot	if



$$\frac{1}{1+e^{-x}}$$

$$P(+|t,c) = \frac{1}{1+e^{-t \cdot c}}$$

maximise similarity between target word and real context words

$$P(-|t,c) = 1 - \frac{1}{1+e^{-t \cdot c}}$$

minimise similarity between target word and non-context words

Skip-gram Loss

$$L(\theta) = \sum_{(t,c)\in+} \log P(+|t,c) + \sum_{(t,c)\in-} \log P(-|t,c)$$

- In practice, use *k* negative examples

$$L(\theta) \ = \ \log P(+|t,c) + \sum_{i=1}^{k} \log P(-|t,n_i)$$

Desiderata

- Unsupervised
  - Unlabelled corpus
- Efficient
  - Negative sampling (avoid softmax over full vocabulary)
  - Scales to very very large corpus

Evaluation

Word Similarity

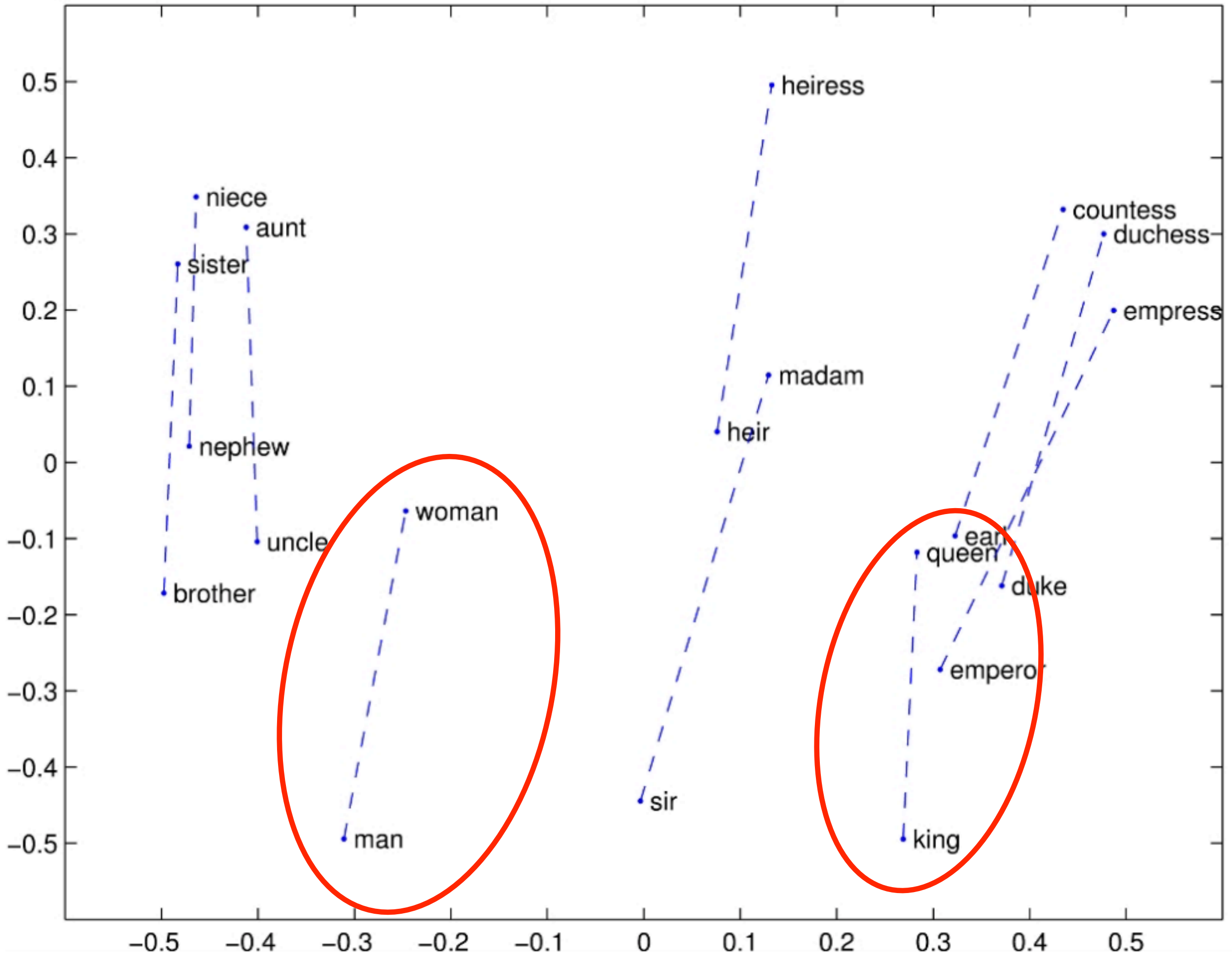
- Measure similarity of two words using cosine similarity
- Compare predicted similarity with human intuition
- Datasets
  - *WordSim-353* are pairs of nouns with judged relatedness
  - *SimLex-999* also covers verbs and adjectives

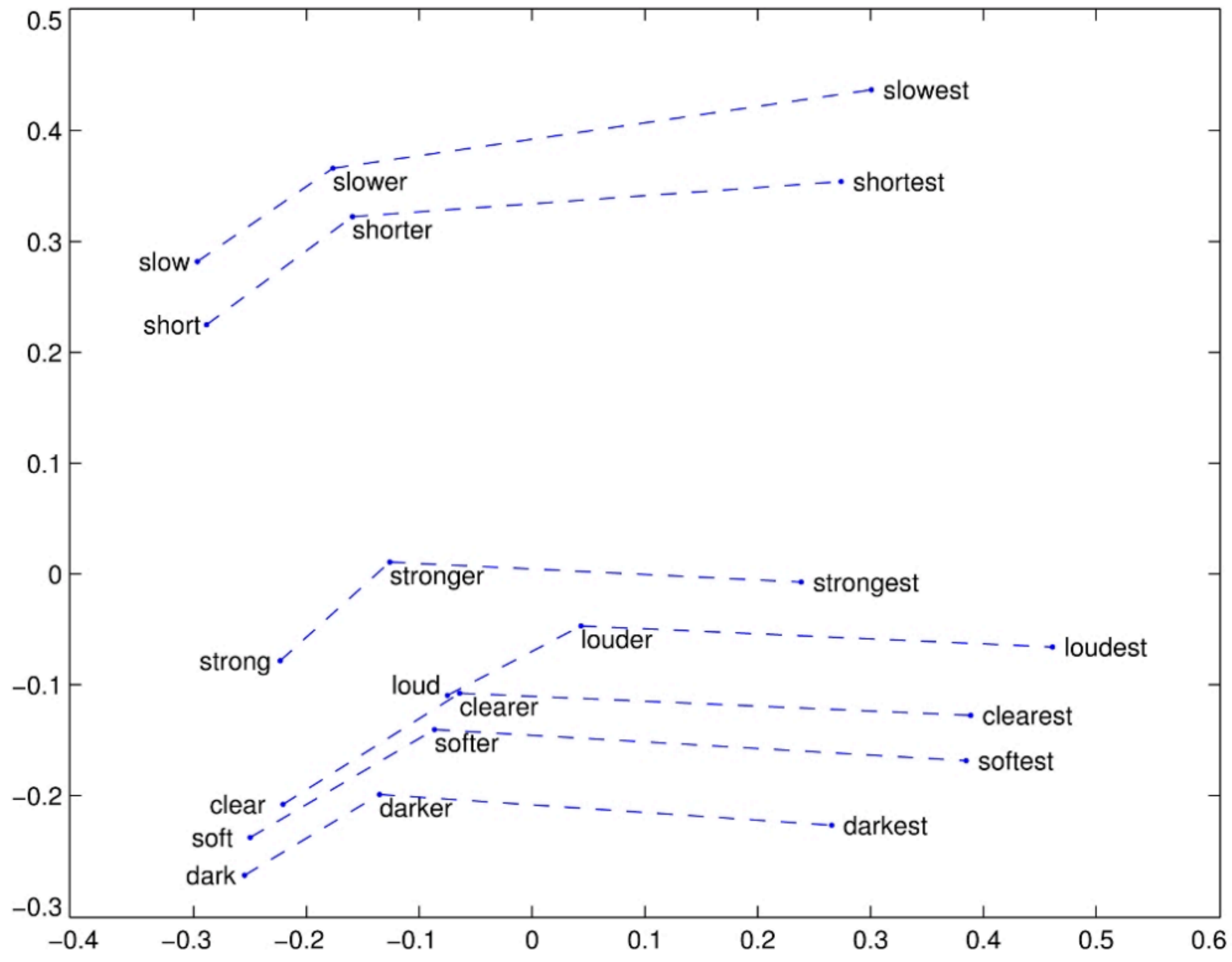
Word Analogy

- Man is to King as Woman is to ???
- v(Man) - v(King) = v(Woman) - v(???)
- v(???) = v(Woman) - v(Man) + v(King)
- Find word whose embedding is closest to v(Woman) - v(Man) + v(King)

Embedding Space

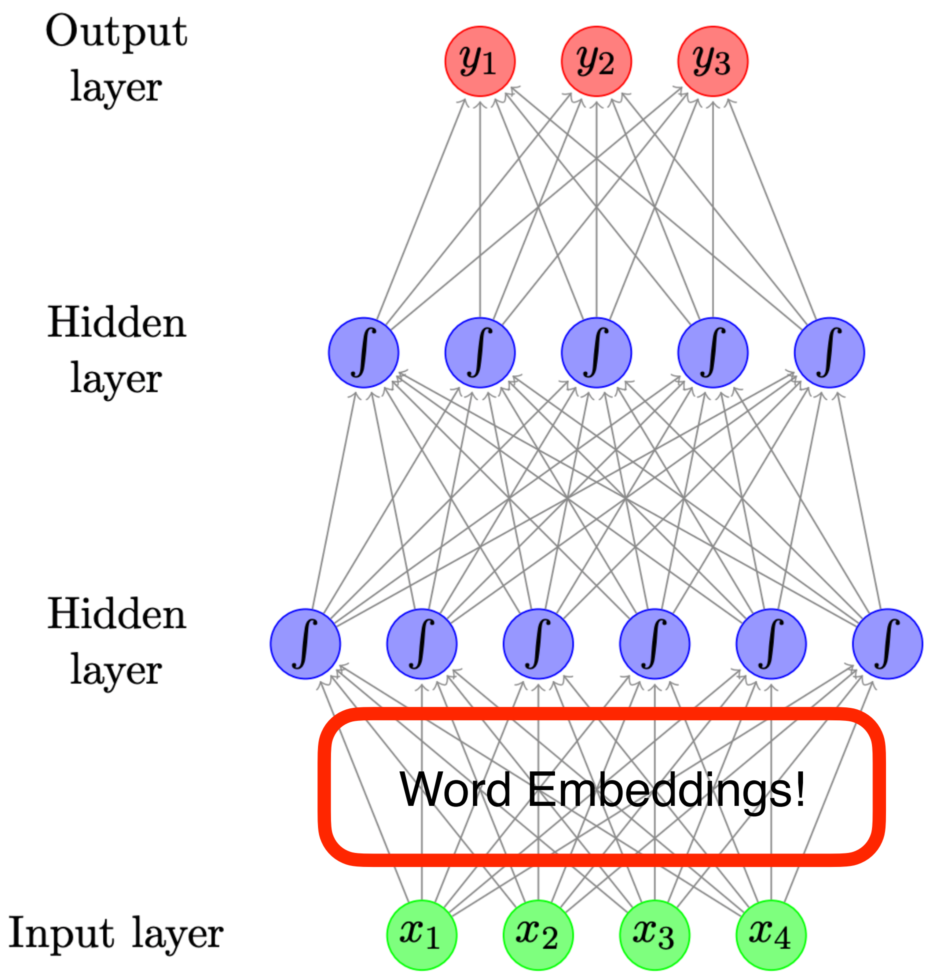
- Word2Vec embeddings show interesting geometry
- Explains why they are good in word analogy task





Downstream Tasks

- Best evaluation is in other downstream tasks
    - Use bag-of-word embeddings as a feature representation in a classifier
    - First layer of most deep learning models is to embed input text
    - Initialise them with pretrained word vectors!



General Findings

- neural $>$ count
- **Contextual word representation** is shown to work even better
- Dynamic word vectors that change depending on context!
- ELMO & BERT (next lecture!)

Pointers to Software

- Word2Vec
  - C implementation of Skip-gram and CBOW https://code.google.com/archive/p/word2vec/
- GenSim
  - Python library with many methods include LSI, topic models and Skip-gram/CBOW https://radimrehurek.com/gensim/index.html
- GLOVE
  - http://nlp.stanford.edu/projects/glove/

Further Reading

- JM3, Ch 6