Lecture 6: Word Embeddings (contd.)

Instructor: Swabha Swayamdipta

USC CSCI 544 Applied NLP

Sep 12, Fall 2024

Some slides adapted from Dan Jurafsky and Chris Manning and Xuezhe Ma

Announcements + Logistics

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- Quiz 1 grades released, regrade requests can be made within a week of grade release date
  - We will have opportunities later in class for you to make up your grade
- Group selection deadline
  - TAs have now been assigned to your groups - your TA advisors for your projects
  - 47 teams - check your team / TA assignments
  - Project Proposal Date is coming up (9/26)
- Next week:
  - HW1 due
  - HW2 release
  - Quiz 2

Lecture Outline

- Announcements
- Recap: Multinomial LR
- Recap: Lexical Semantics
- word2vec
- GloVe
- Properties and Evaluation of Word Embeddings

Recap: Multinomial LR

Multinomial Logistic Regression

The probability of everything must still sum to 1

$K > 2$ classes

$$P(y_1 \mid x) + P(y_2 \mid x) + \ldots + P(y_K \mid x) = 1$$

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Softmax

- Generalize the sigmoid function: softmax
  - Input: a vector $\mathbf{z} = [z_1, z_2, \ldots, z_K]$ of K arbitrary values
    - each z_i corresponds to weighted sum of features for the Kth class
  - Outputs a probability distribution

$$\textbf{softmax}(z_i) = \frac{\exp(z_i)}{\sum_{j=1}^{K} \exp(z_j)} \qquad 1 \leq i \leq K$$

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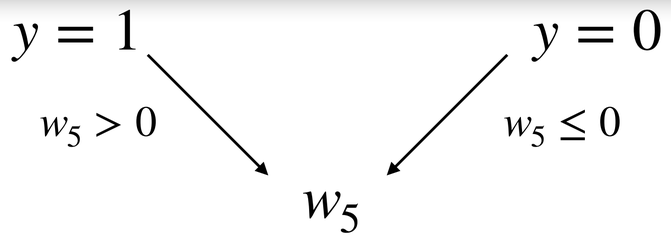
The denominator $\sum_{i=1}^{K} \exp(z_i)$ is used to normalize all the values into probabilities.

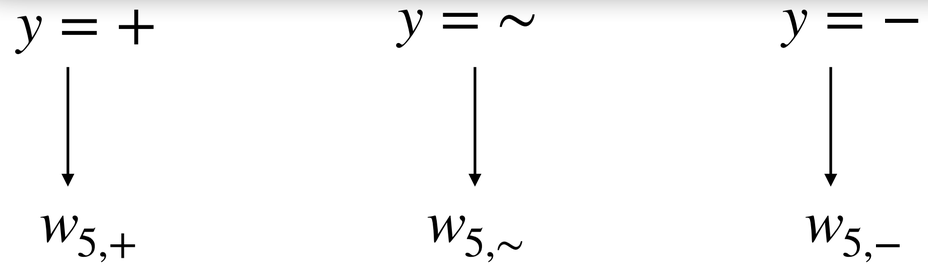
Binary versus Multinomial

Binary Logistic Regression



$$x_5 = \begin{cases} 1 & \text{if } \text{“!”} \in \text{doc} \\ 0 & \text{otherwise} \end{cases} \qquad w_5 = 3.0$$

Multinomial Logistic Regression



Separate weights for each class

Feature	Definition	$w_{5,+}$	$w_{5,-}$	$w_{5,0}$
$f_5(x)$	$\begin{cases} 1 & \text{if } \text{“!”} \in \text{doc} \\ 0 & \text{otherwise} \end{cases}$	3.5	3.1	−5.3

Words, words, words

~~Words, words, words~~

Types, types, types

What do words mean?

A sense or "concept" is the meaning component of a word

"breaking"

Lemmas

- Canonical form
- For example,
  break, breaks, broke, broken a
  nd breaking all share the
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Can be polysemous (have multiple senses)

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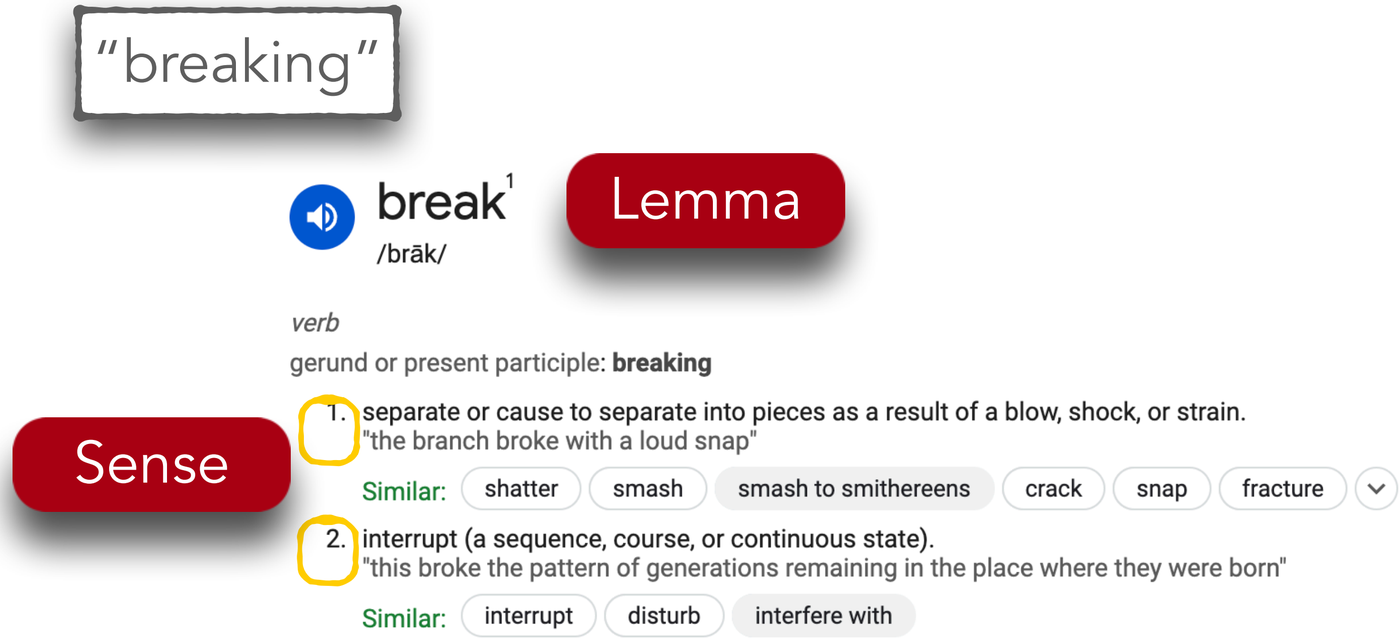

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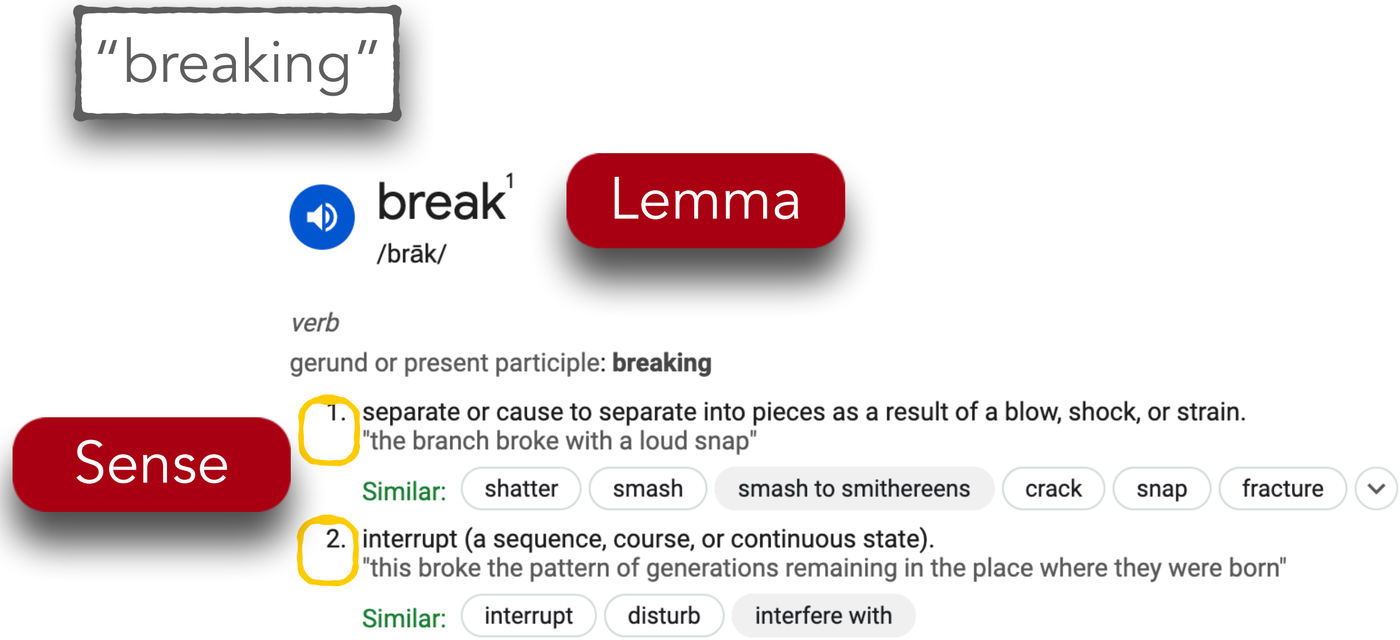

Synonyms: words that have the same meaning in some or all contexts
- e.g. couch / sofa

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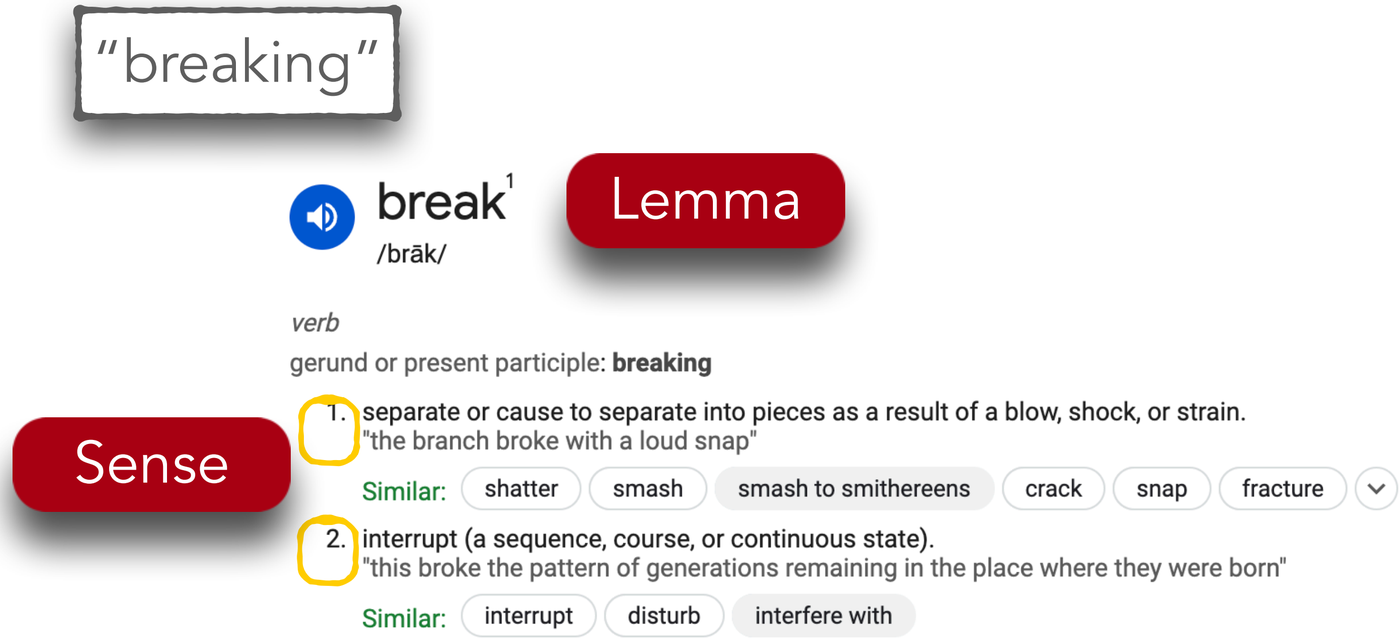

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Is perfect synonymy possible

Similarity

Words with similar meanings. Not synonyms, but sharing some element of meaning

word1	word2
vanish	disappear
behave	obey
belief	impression
muscle	bone
modest	flexible
hole	agreement

Similarity

Words with similar meanings. Not synonyms, but sharing some element of meaning

word1	word2	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

Human assessment of word similarity

Simlex-999 dataset (Hill et al., 2015)

WordNet


PRINCETON UNIVERSITY
WordNet
A Lexical Database for English

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    - chair has legs

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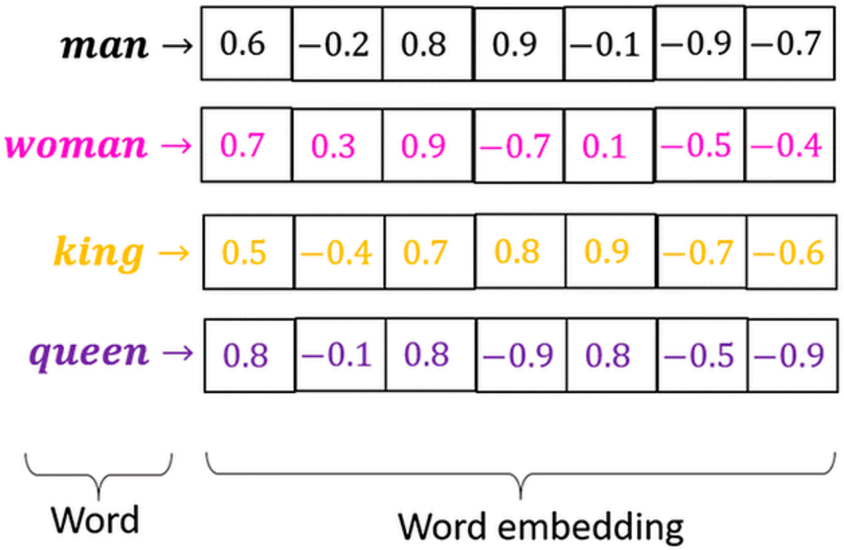
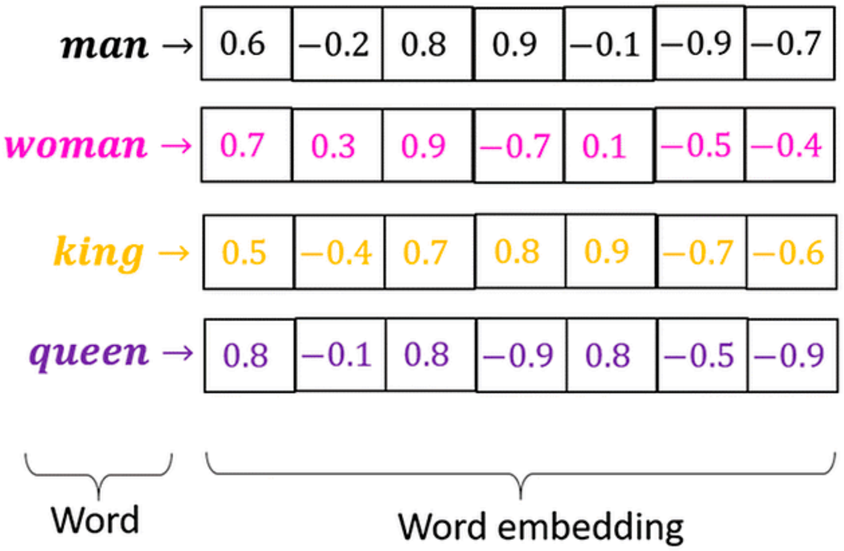
  - Antonymy

Words as Vectors



Words as Vectors

In NLP, we commonly represent word types with vectors!



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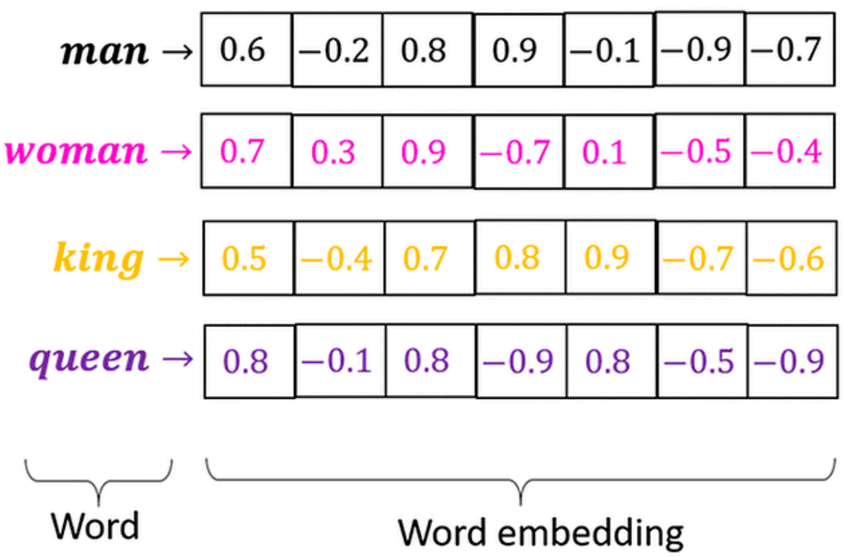
- Very useful in capturing similarity between words, and other forms of lexical semantics (e.g. synonymy, hypernyms, antonymy)

Why?

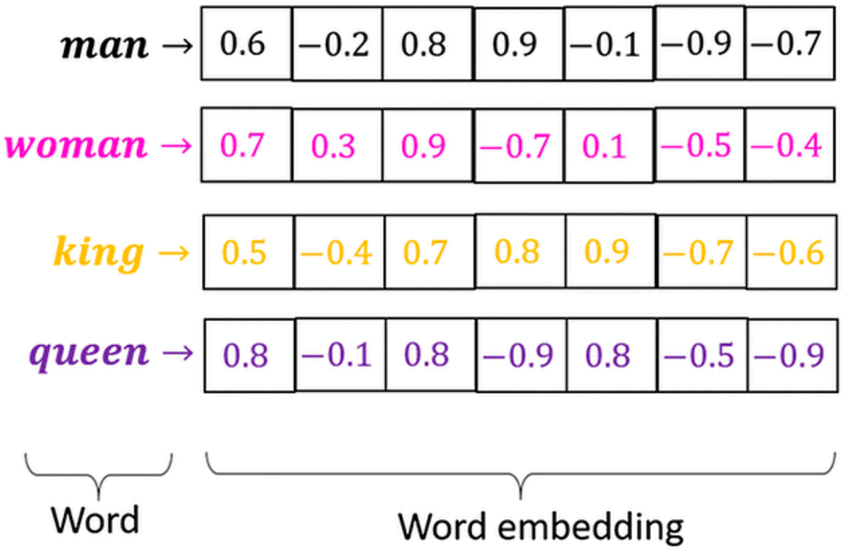


Words as Vectors

In NLP, we commonly represent word types with vectors!

- Very useful in capturing similarity between words, and other forms of lexical semantics (e.g. synonymy, hypernyms, antonymy)
- Computing the similarity between two words (or phrases, or documents) is extremely useful for many NLP tasks
  - Q: How **tall** is Mount Everest?
  - A: The official **height** of Mount Everest is 29029 ft

Why?



"You shall know a word by the company it keeps."

- Firth (1957)

Word Meaning via Language Use

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A bottle of tesgüino is on the table
Everybody likes tesgüino
Tesgüino makes you drunk
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Two words are similar if they have similar word contexts


You think you just fell
out of a coconut tree?


YOU THINK YOU JUST FELL OUT
OF A
COCONUT
TREE?
YOU EXIST IN THE CONTEXT OF ALL IN WHICH
YOU LIVE AND WHAT CAME BEFORE YOU.

Words exist in the context of all that came before…


"In Springfield,
they're eating the dogs,
the people that came in,
they're eating the cats...
They're eating...
they're eating the pets of
the people that live there"
Trump 09/10/2024


FOX NEWS channel
FOX NEWS DEMOCRACY '24
LIVE abc NEWS
2024 PRESIDENTIAL DEBATE

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Conspiracy Theories Warning

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Word Embeddings

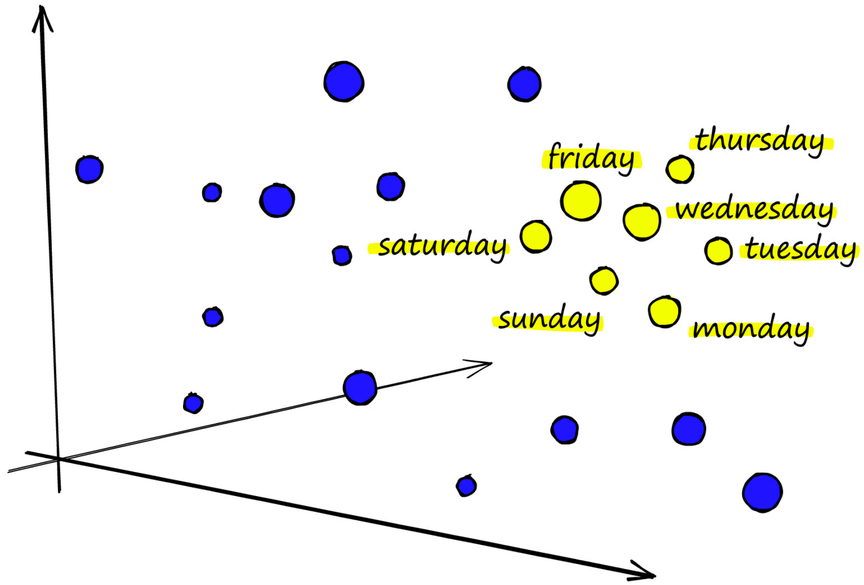
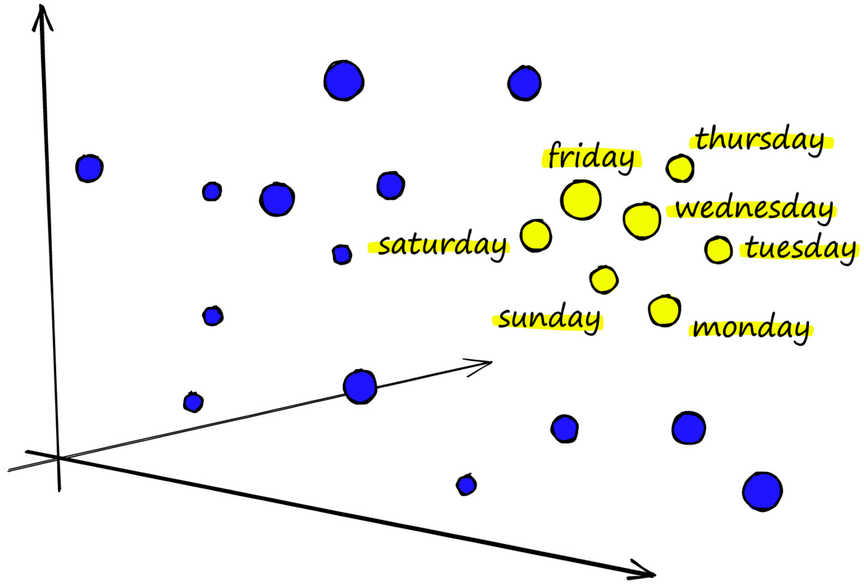


Image Credit: Pinecone

Word Embeddings

- Represent a word as a point in a multidimensional semantic space



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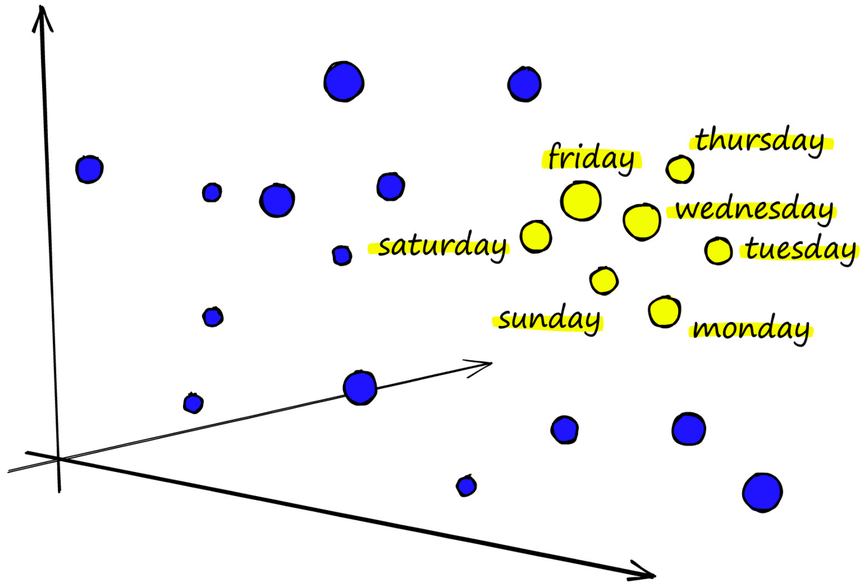

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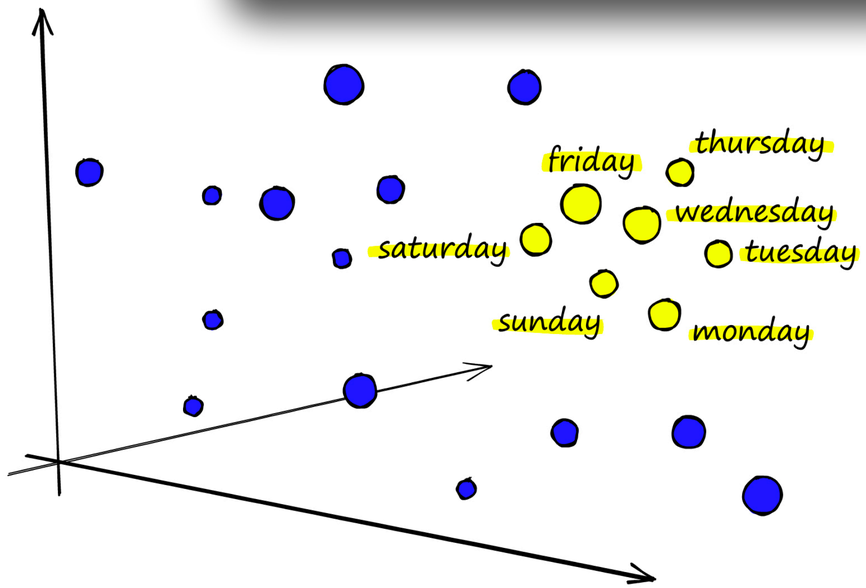

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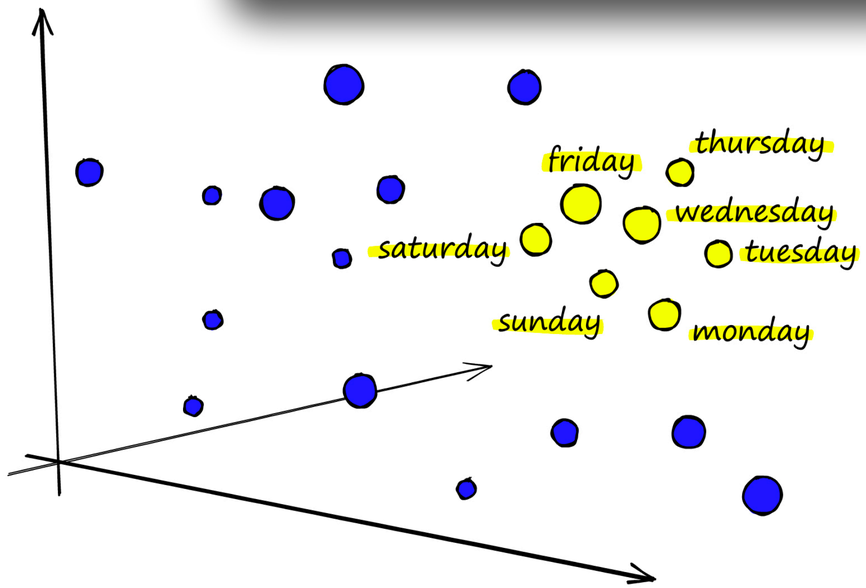

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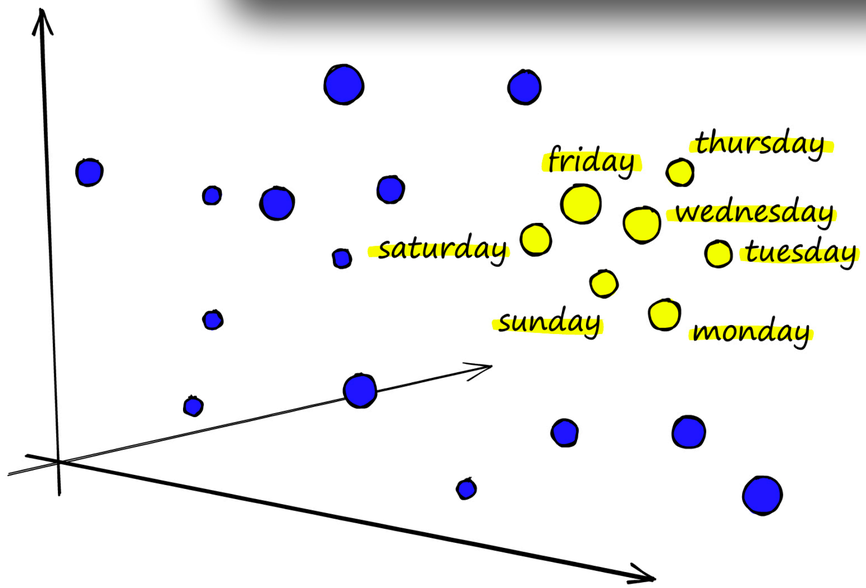

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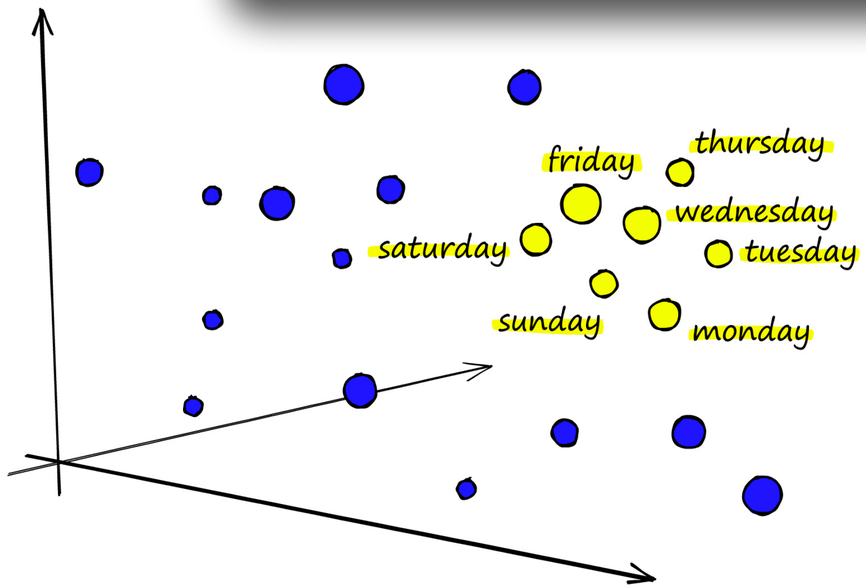

Every modern NLP algorithm uses embeddings as the representation of word meaning

Image Credit: Pinecone

荃者所以在鱼，得鱼而忘荃

言者所以在意，得意而忘言

"Nets are for fish; Once you get the fish, you can forget the net.

Words are for meaning; Once you get the meaning, you can forget the words"

– *Zhuangzi*

庄子

Cosine Similarity for Word Similarity

Cosine similarity of two vectors $$\cos(\vec{v}, \vec{w}) = \frac{\vec{v} \cdot \vec{w}}{|\vec{v}||\vec{w}|} = \frac{\sum_{i=1}^{N} v_i w_i}{\sqrt{\sum_{i=1}^{N} v_i^2}\sqrt{\sum_{i=1}^{N} w_i^2}}$$

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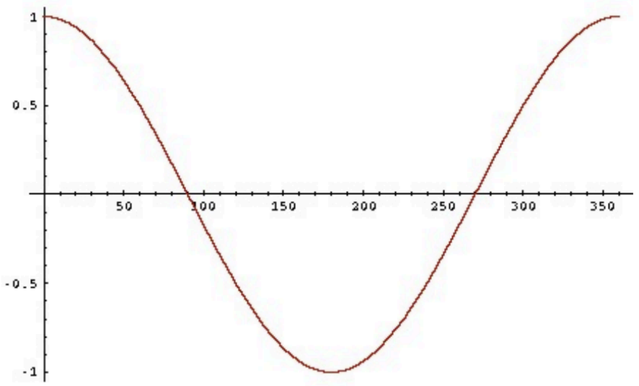
+1: vectors point in same directions

0: vectors are orthogonal



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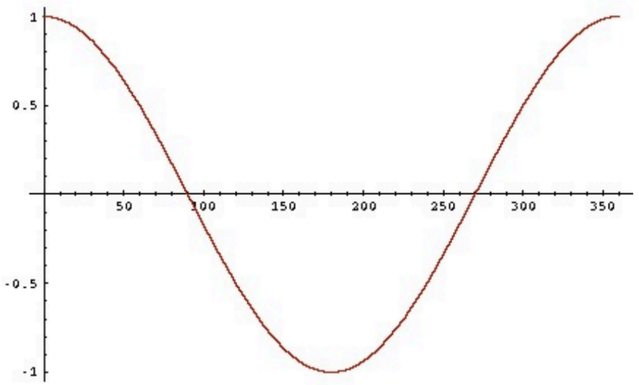

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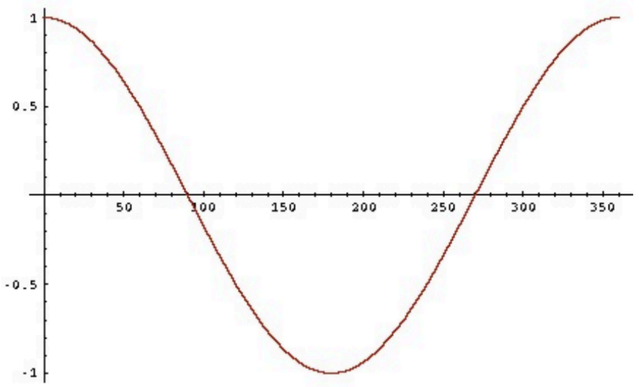

We do not care about the magnitude of the embeddings, just the angle between them

Greater the cosine, more similar the words

n-grams as One-hot Vectors

Unigram Vectors: Represent each word as a vector of zeros with a single 1 identifying the index of the word

n-grams as One-hot Vectors

vocabulary
i
hate
love
the
movie
film

movie = <0, 0, 0, 0, 1, 0>
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How can we compute a vector representation such that the dot product correlates with word similarity?

Dot product is zero! These vectors are orthogonal

Let us consider a collection of documents and count how frequently a word (**term**) appears in each. A document could be a play or a Wikipedia article. In general, documents can be anything; we often call each paragraph a document!

Term-document matrix

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battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

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Each **document** is represented by a vector of words

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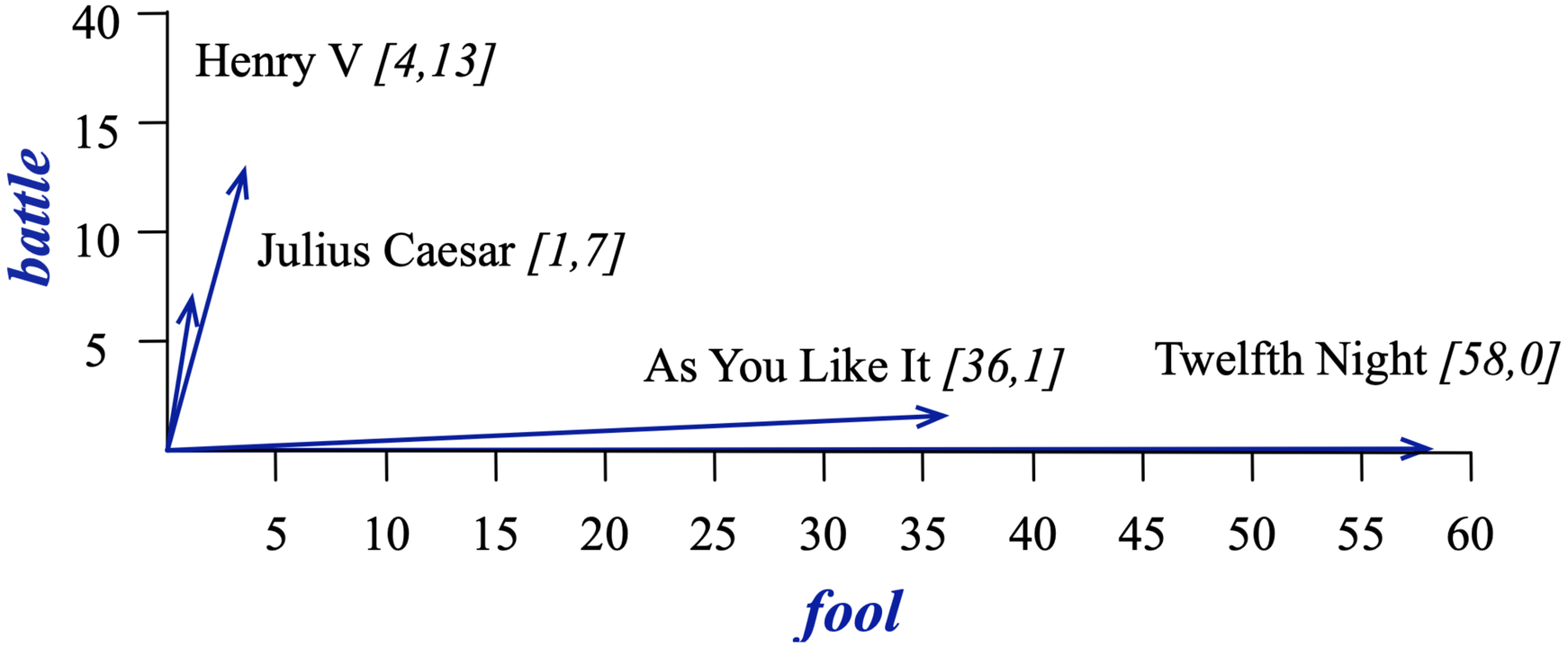

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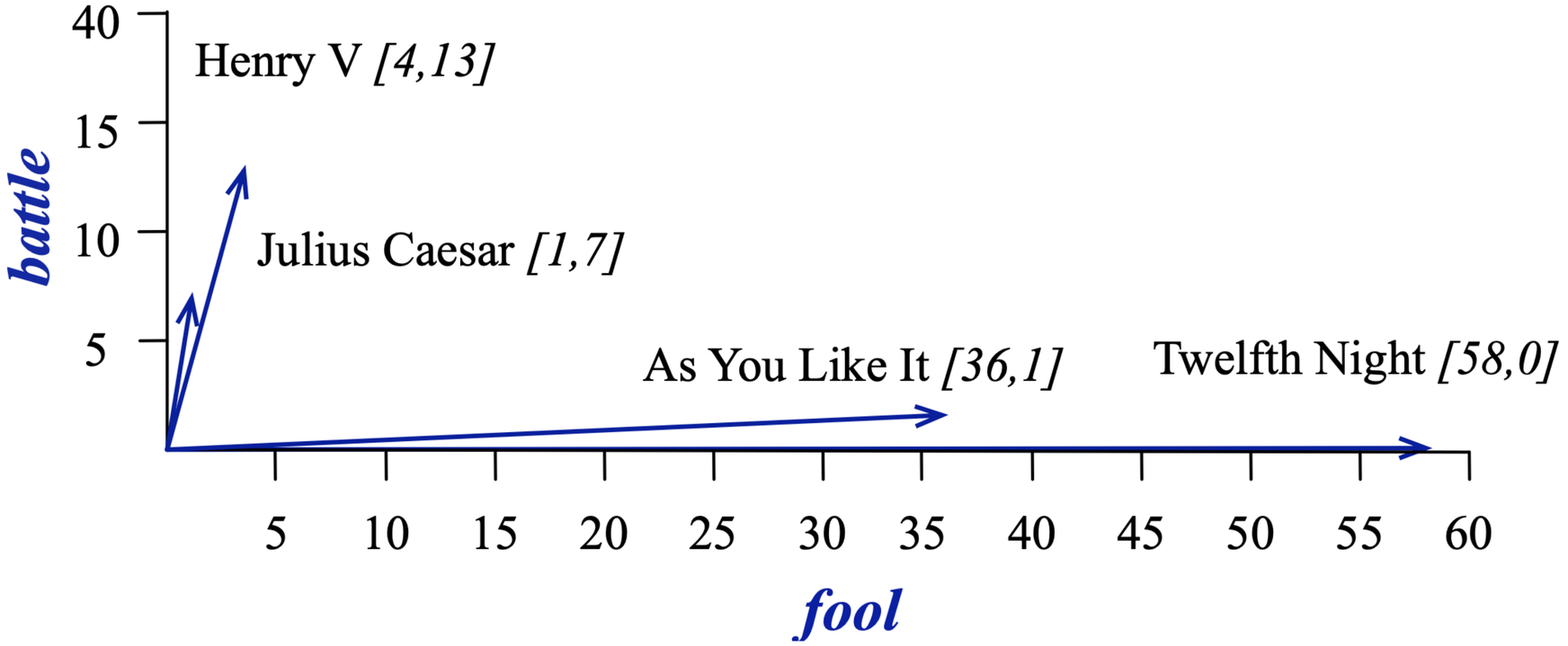

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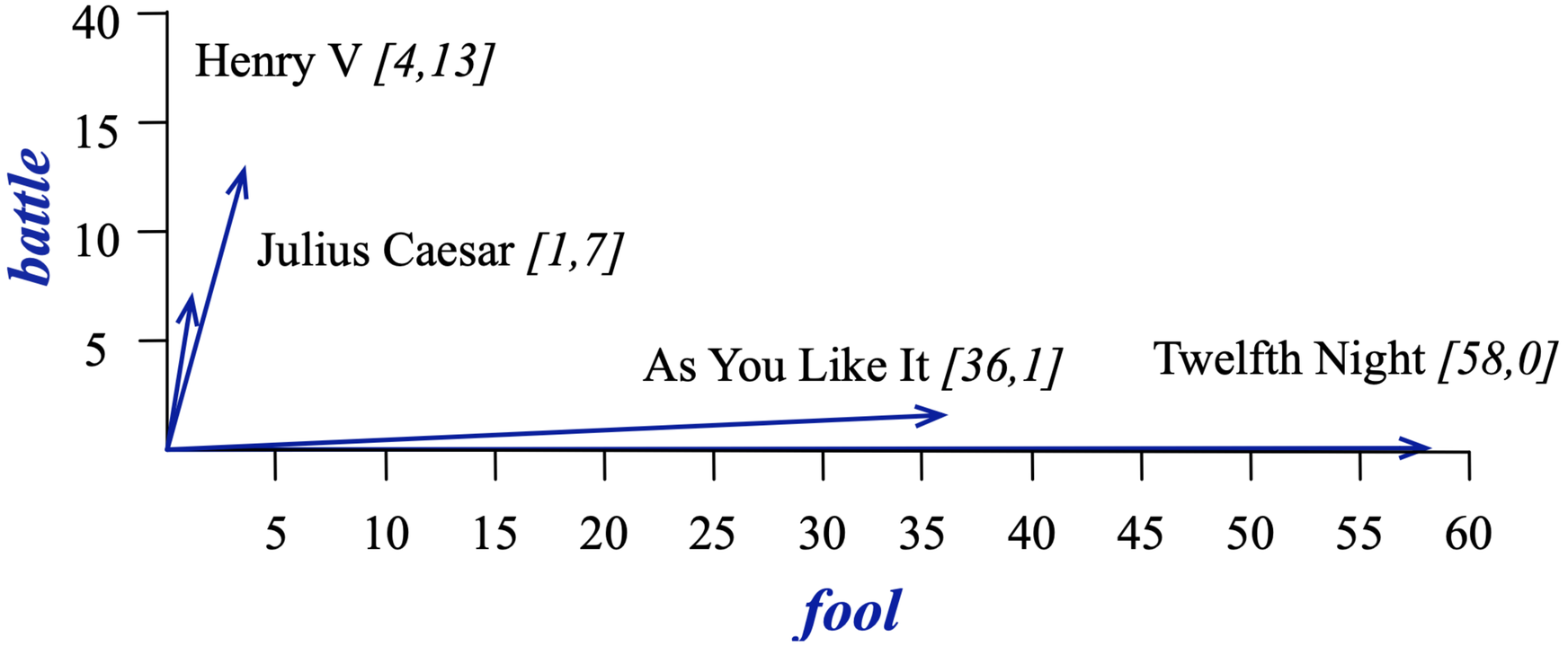

- Vectors are similar for the two comedies
- Comedies are different from the other two (tragedies)
  - More fools, less battle

Words as vectors in a co-occurrence matrix

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Number of dimensions?

Word-word co-occurrence matrix

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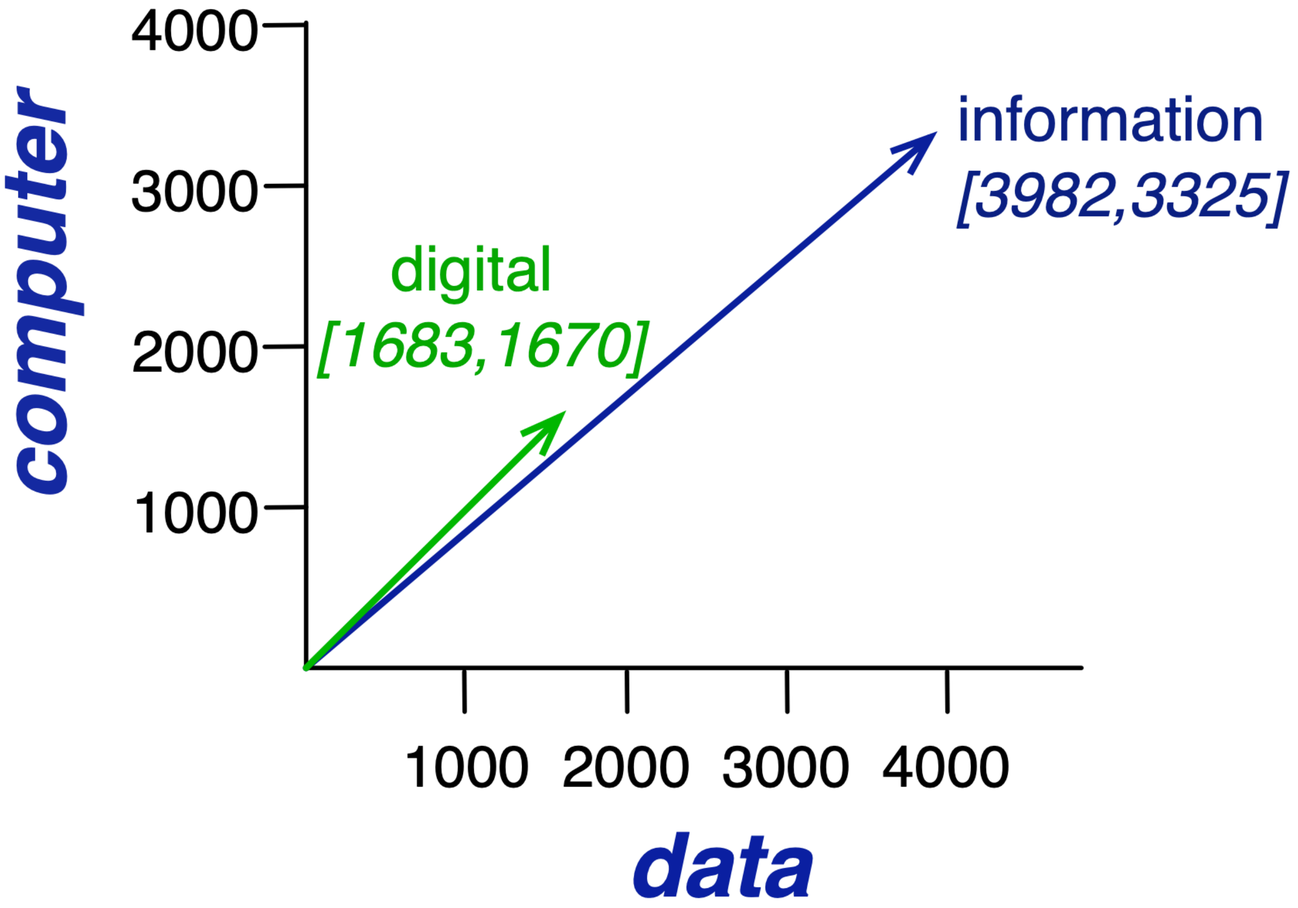

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Need some form of weighting!

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Computing PPMI on a term-context matrix

Context c

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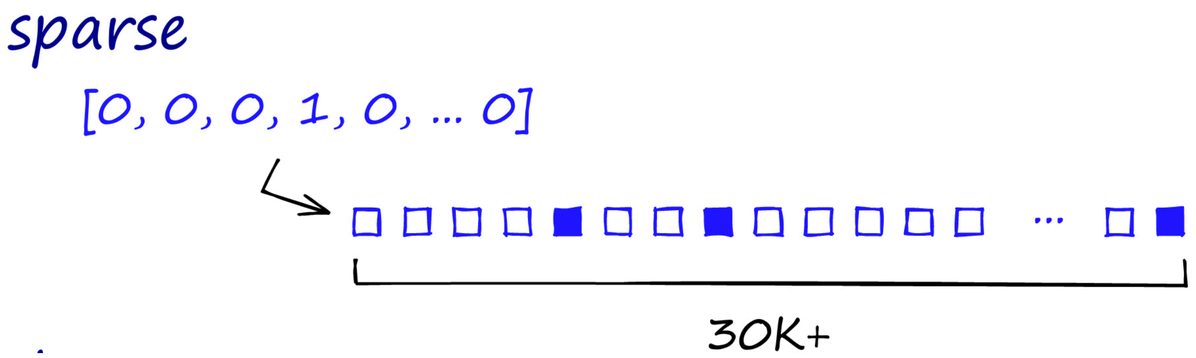
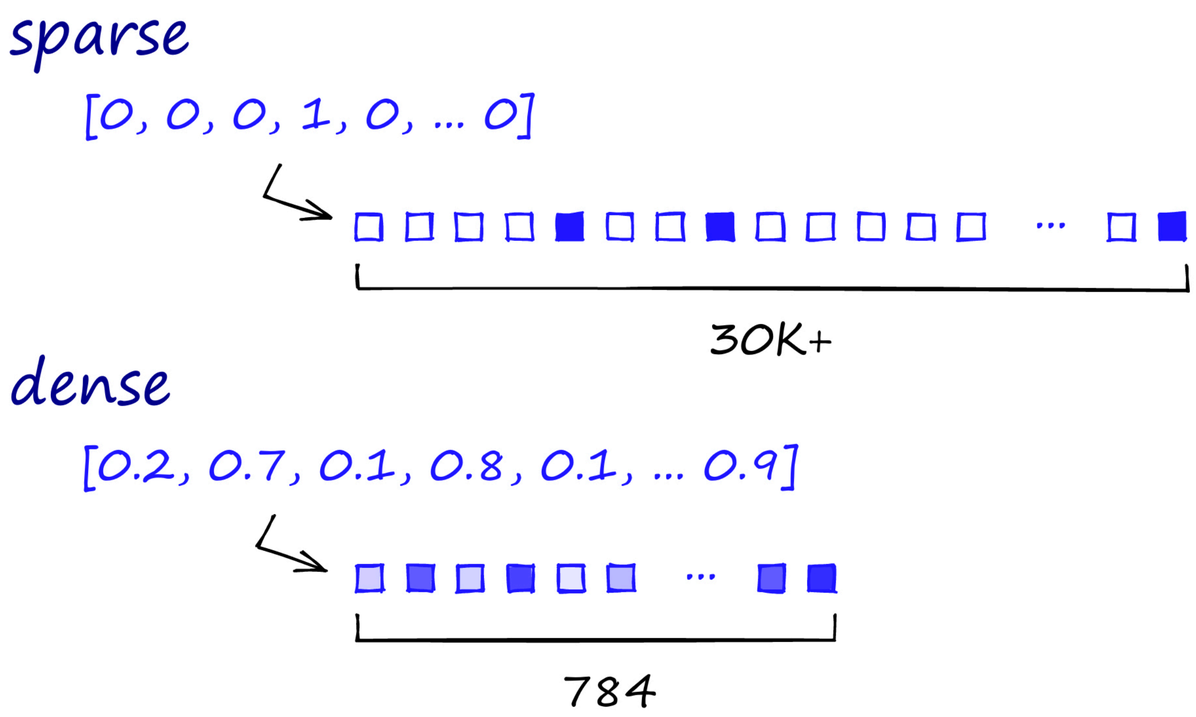


Image Credit: Pinecone

The problem…

- PMI vectors are
  - long (length |V|= 20,000 to 50,000)
  - sparse (most elements are zero)

- Alternative: learn vectors which are
  - short (length 50-1000)
  - dense (most elements are non-zero)



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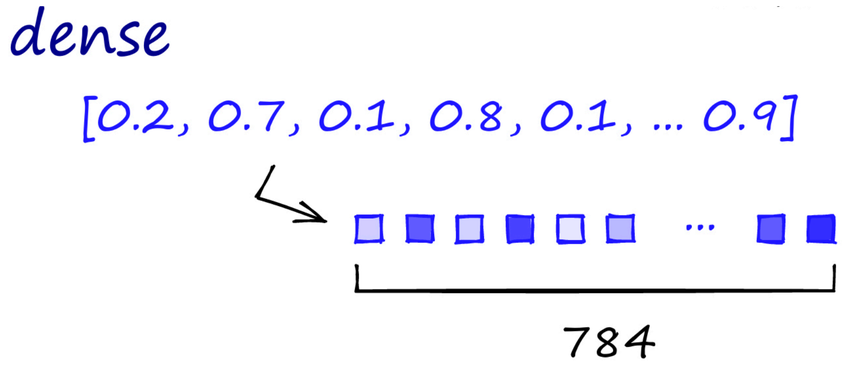
  - In practice, they work better

How to obtain dense vectors?



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"Neural Language Model"-inspired models

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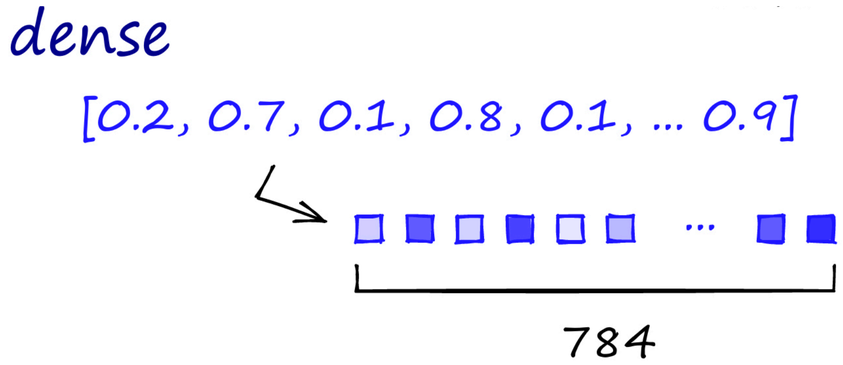

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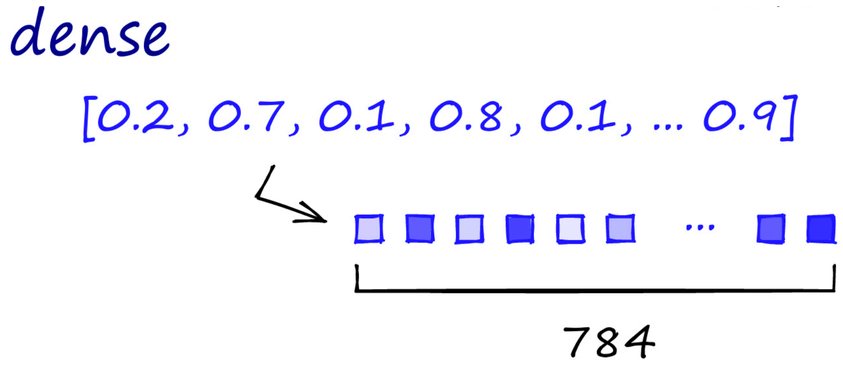

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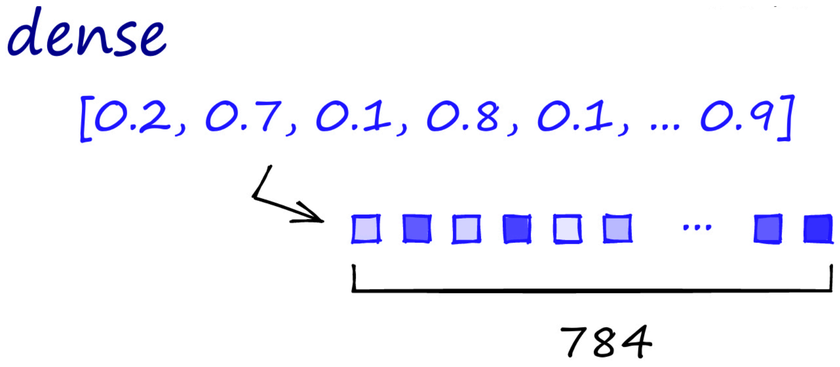

Alternatives to "static word type embeddings":

- Contextual Embeddings (LLM word embeddings)
  - Compute distinct embeddings for a word in its context
  - Separate embeddings for each token of a word

Image Credit: Pinecone

Lecture Outline

- Announcements
- Recap: Multinomial LR
- Recap: Lexical Semantics
- word2vec
  - Classification
  - Learning
- GloVe
- Properties and Evaluation of Word Embeddings

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  - But we'll take the learned classifier weights as the word embeddings

What is $\mathbf{x}$? What is y?

word2vec : Intuition

is traditionally followed by	**cherry**	pie, a traditional dessert
often mixed, such as	**strawberry**	rhubarb pie. Apple pie
computer peripherals and personal	**digital**	assistants. These devices usually
a computer. This includes	**information**	available on the internet

Instead of counting how often each word w occurs near another, e.g. "cherry"

- Train a classifier on a binary prediction task:
  - Is w likely to show up near "cherry"?
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What is $\mathbf{x}$? What is y?

Word embedding itself is the learned parameter!

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What about incorrect labels?

Bengio et al. (2003); Collobert et al. (2011)

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Assume a +/- 2 word window, given training sentence:

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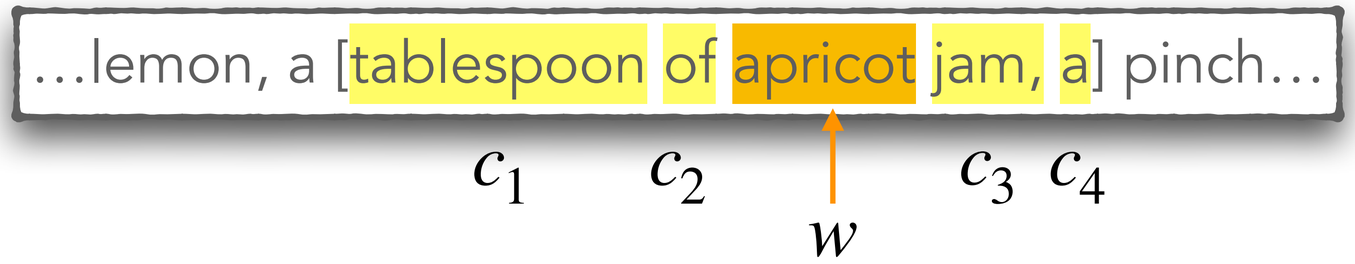

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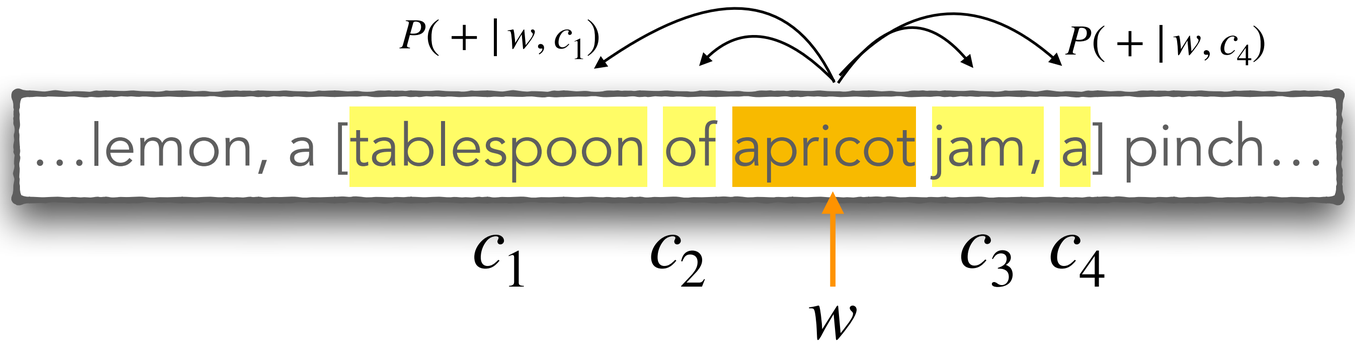

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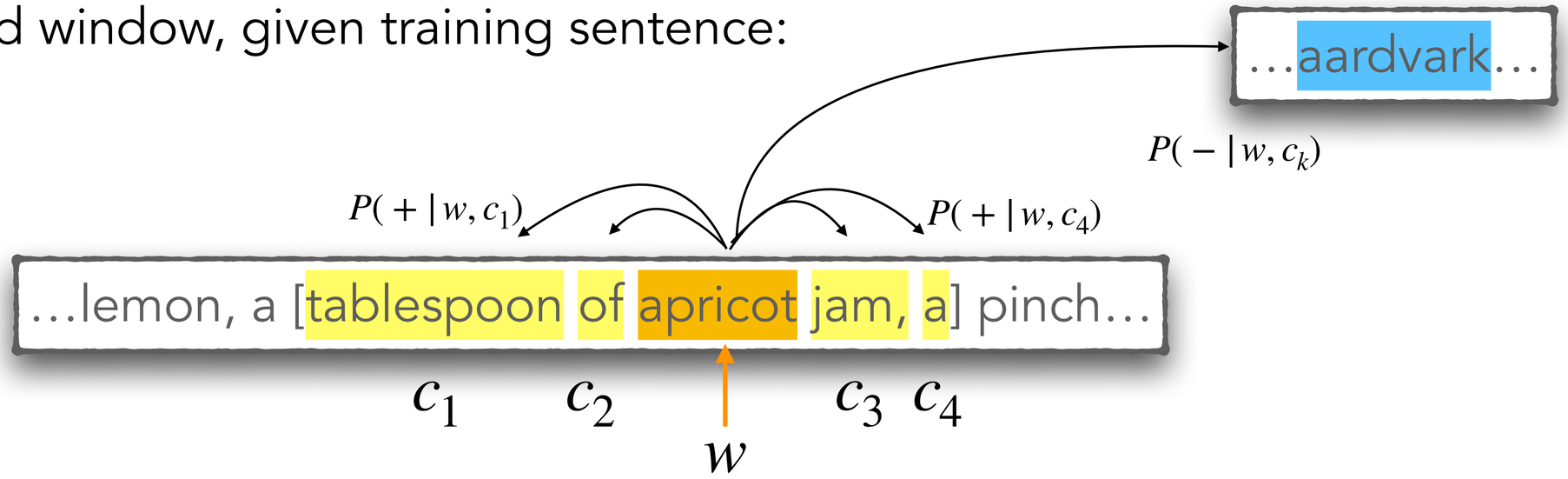

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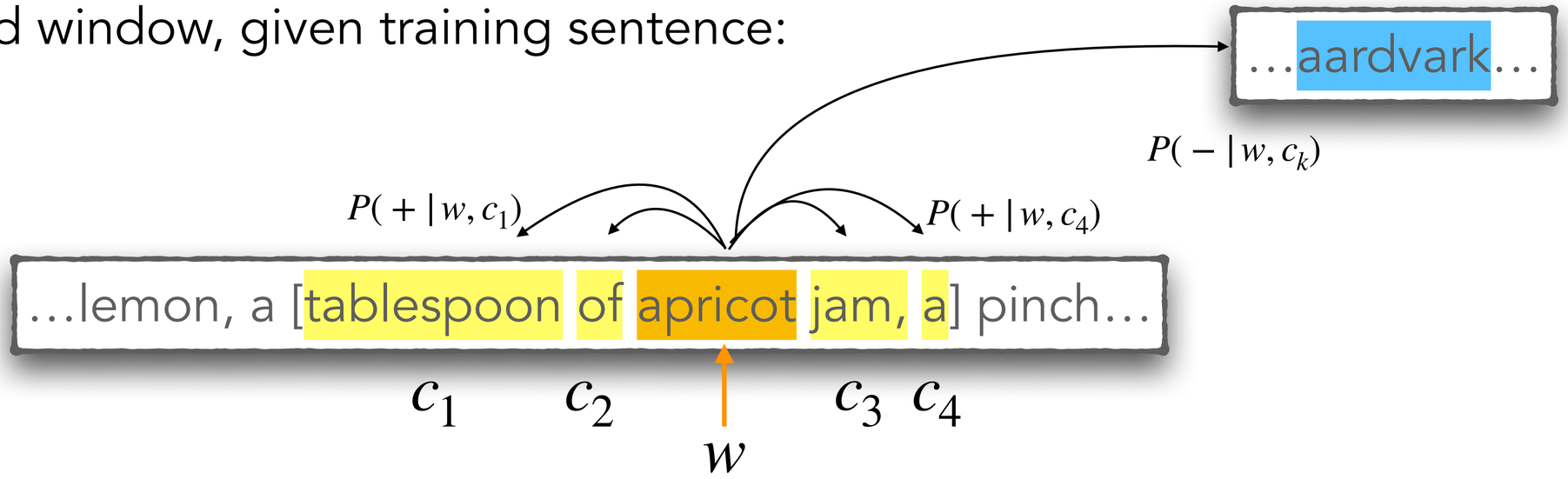

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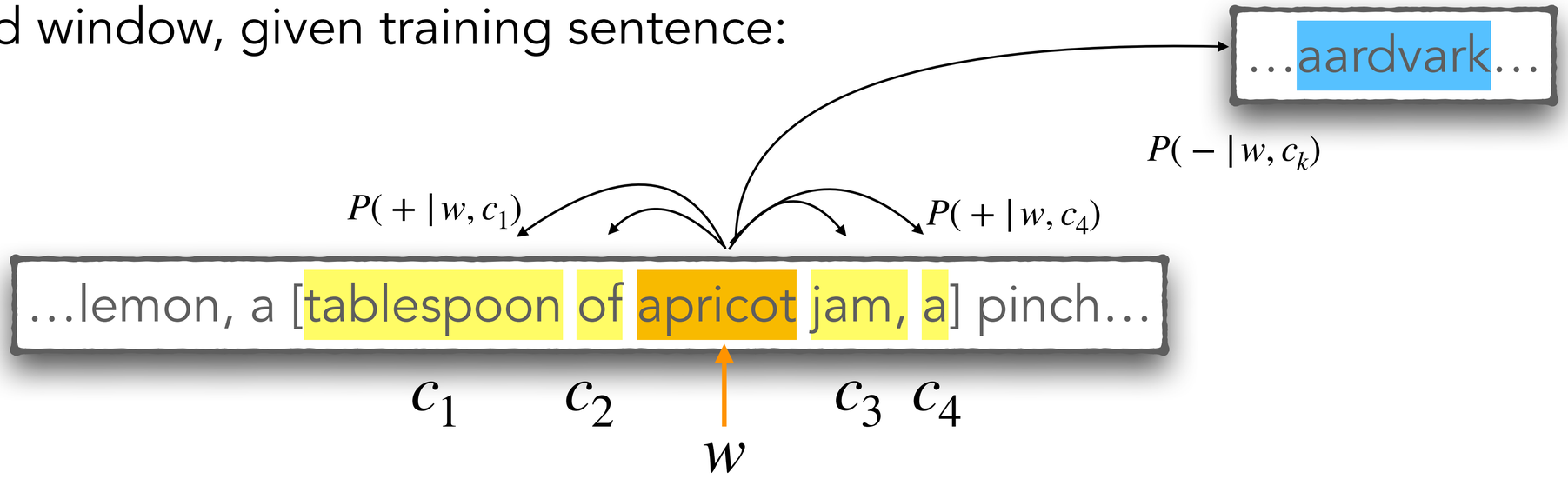

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And assigns each pair a probability:

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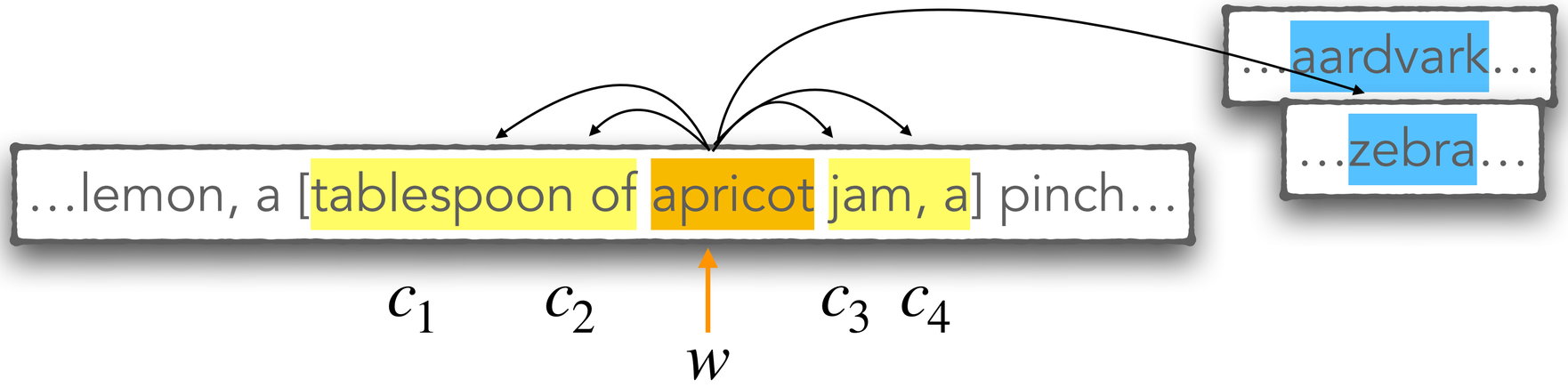
word2vec: Pseudocode



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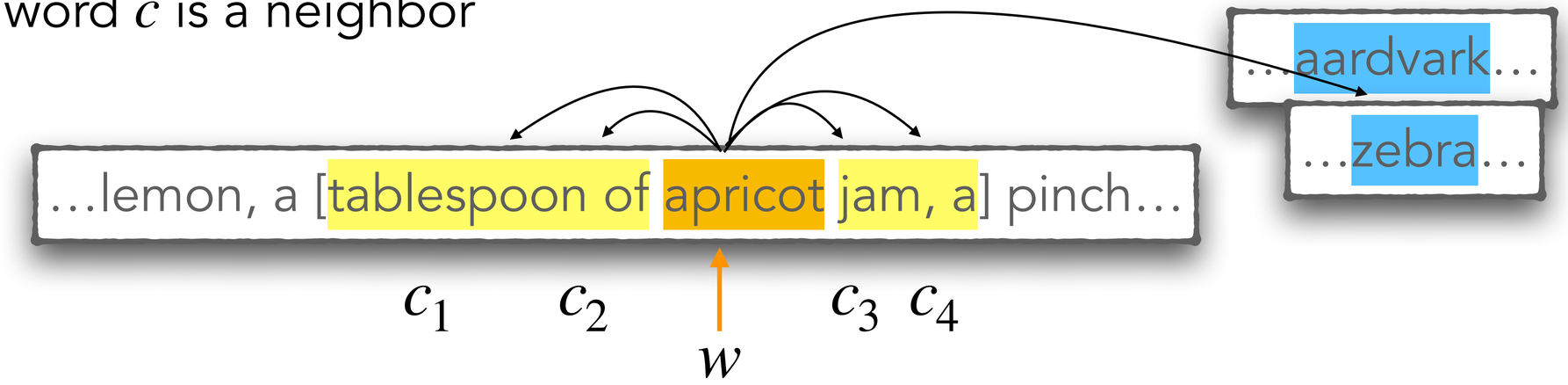
Predict if candidate word c is a neighbor



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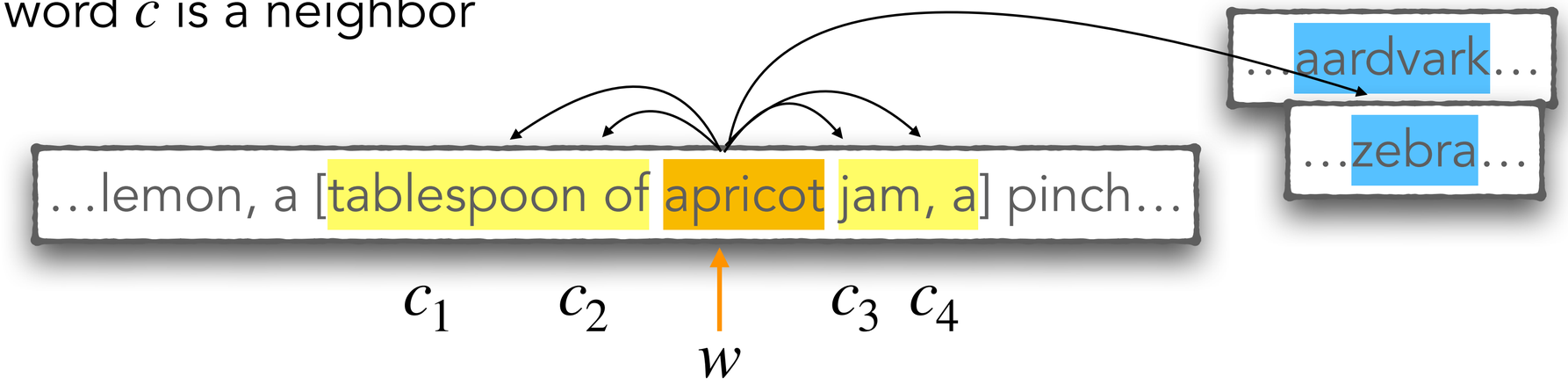

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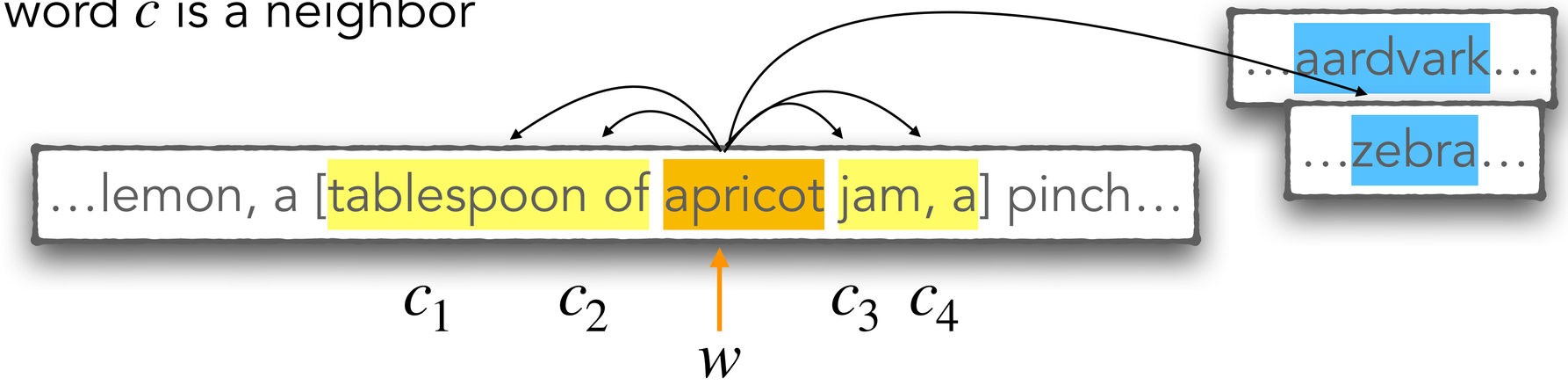

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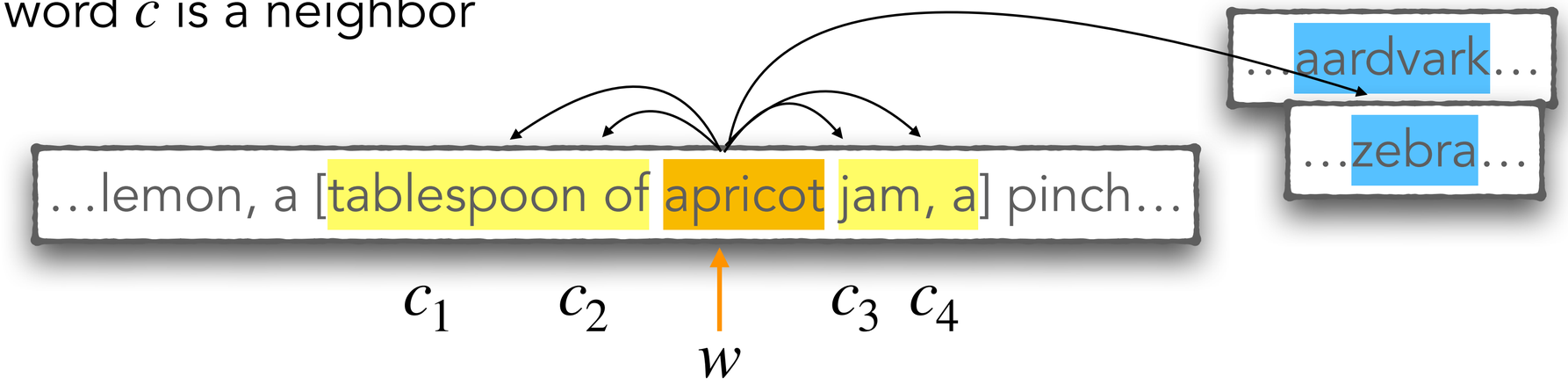

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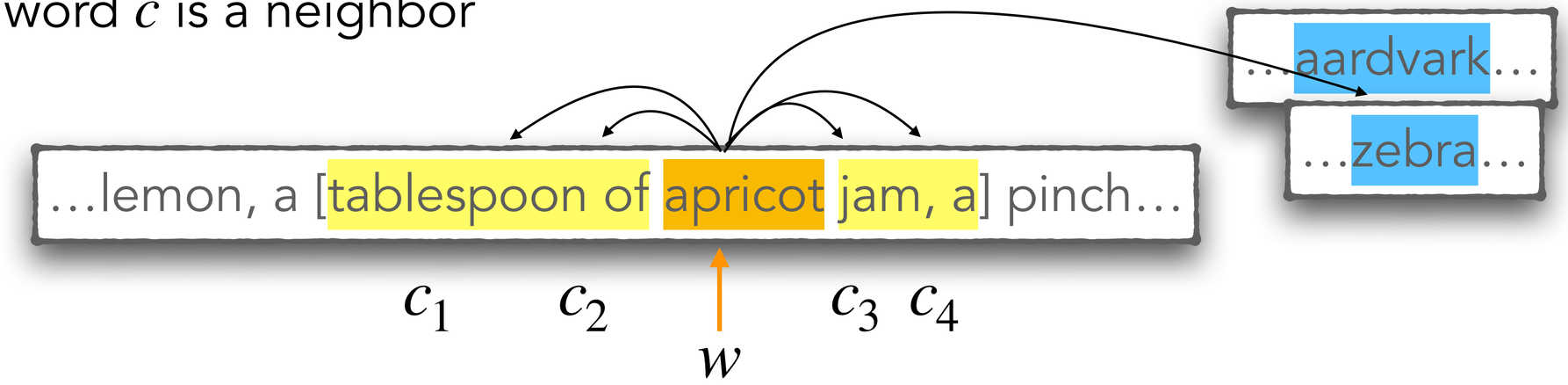

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Similarity:

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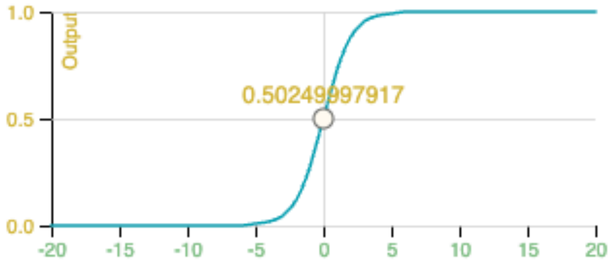

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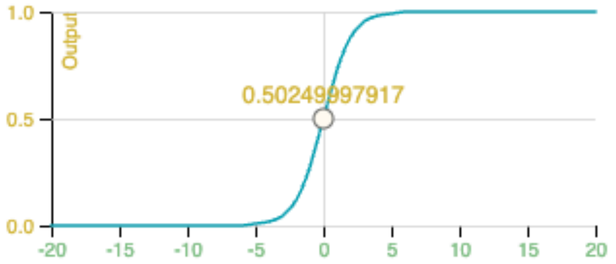

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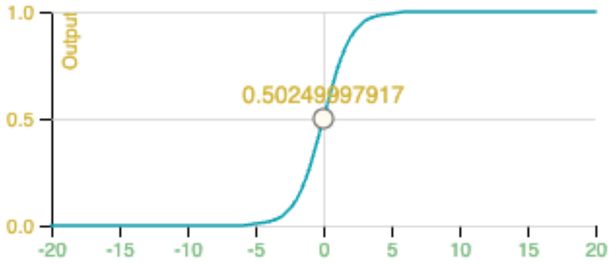

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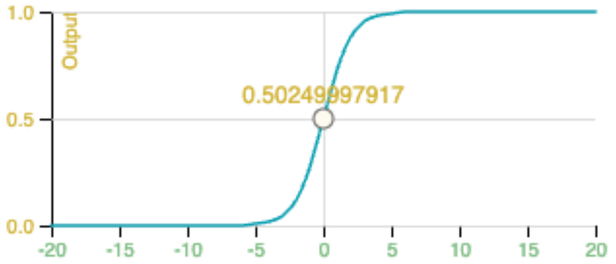

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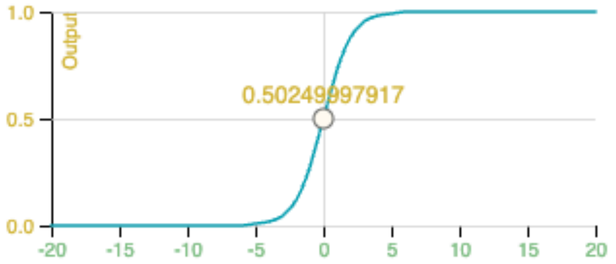

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Logistic Regression!

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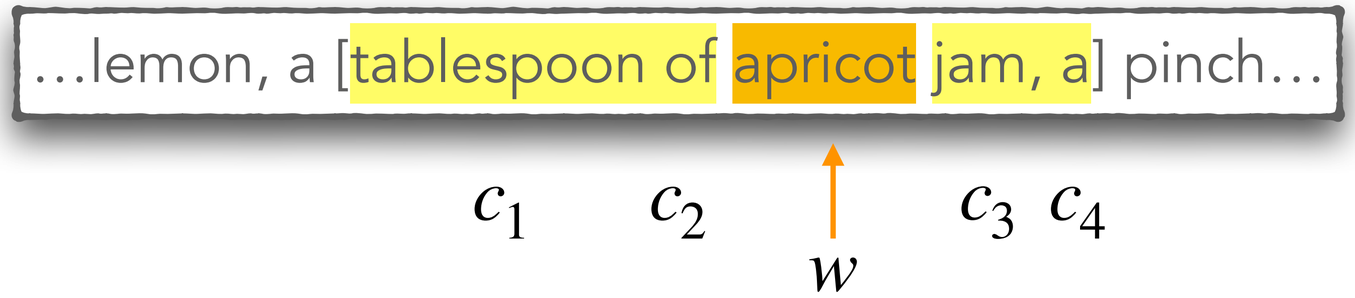

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c_{neg} { …aardvark… …zebra…

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Same with negative context words!

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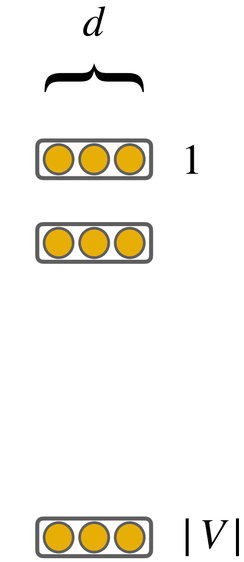

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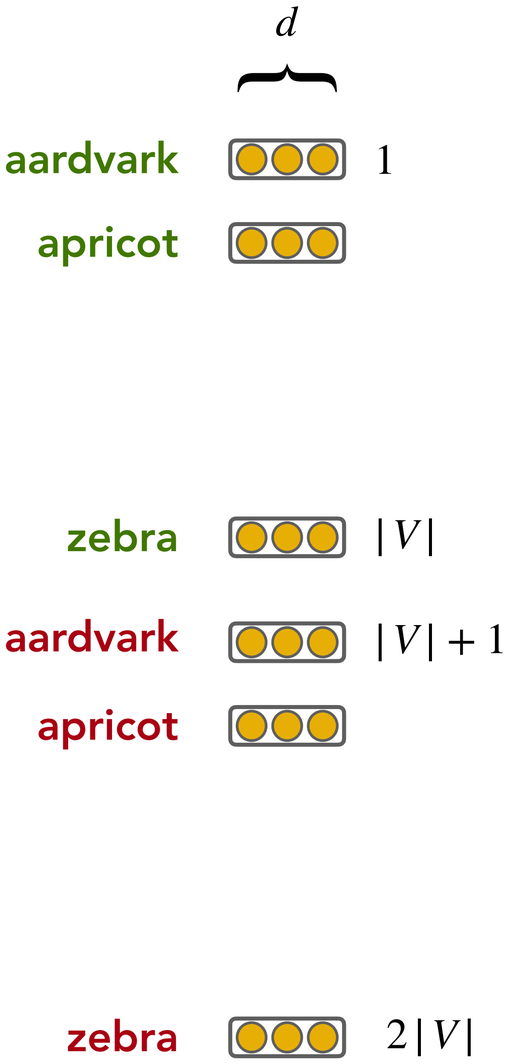

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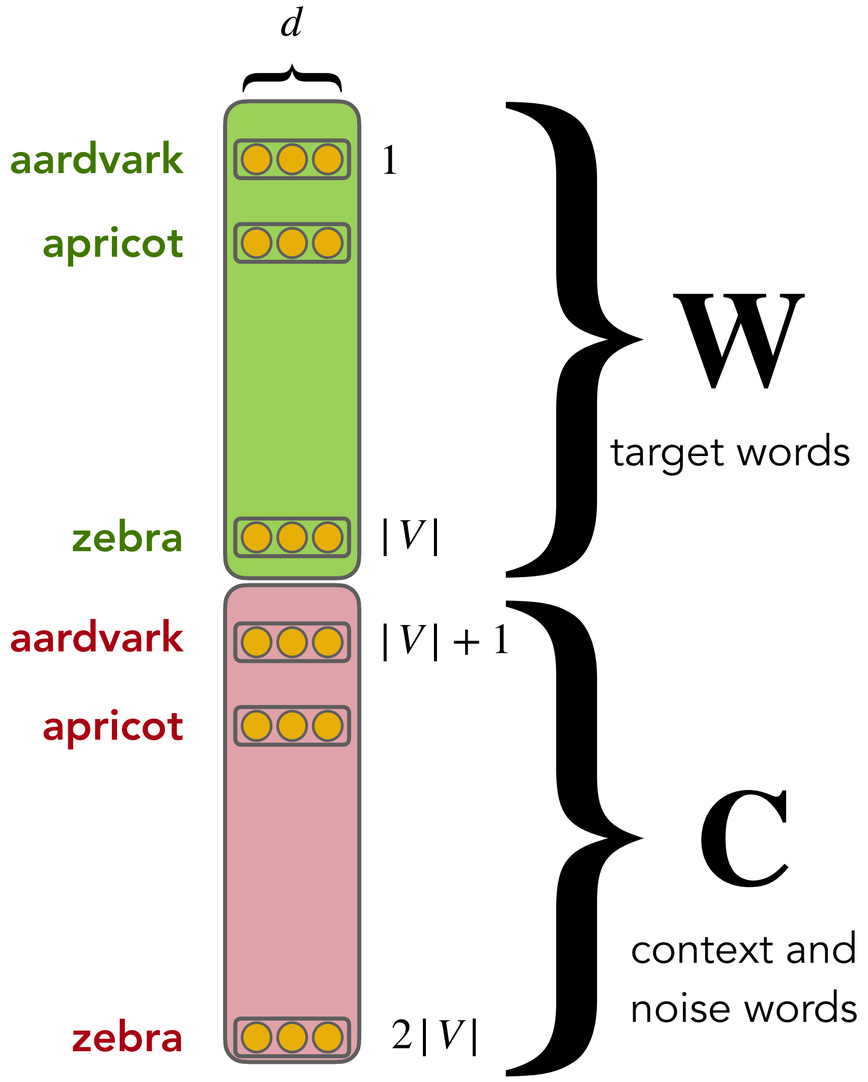

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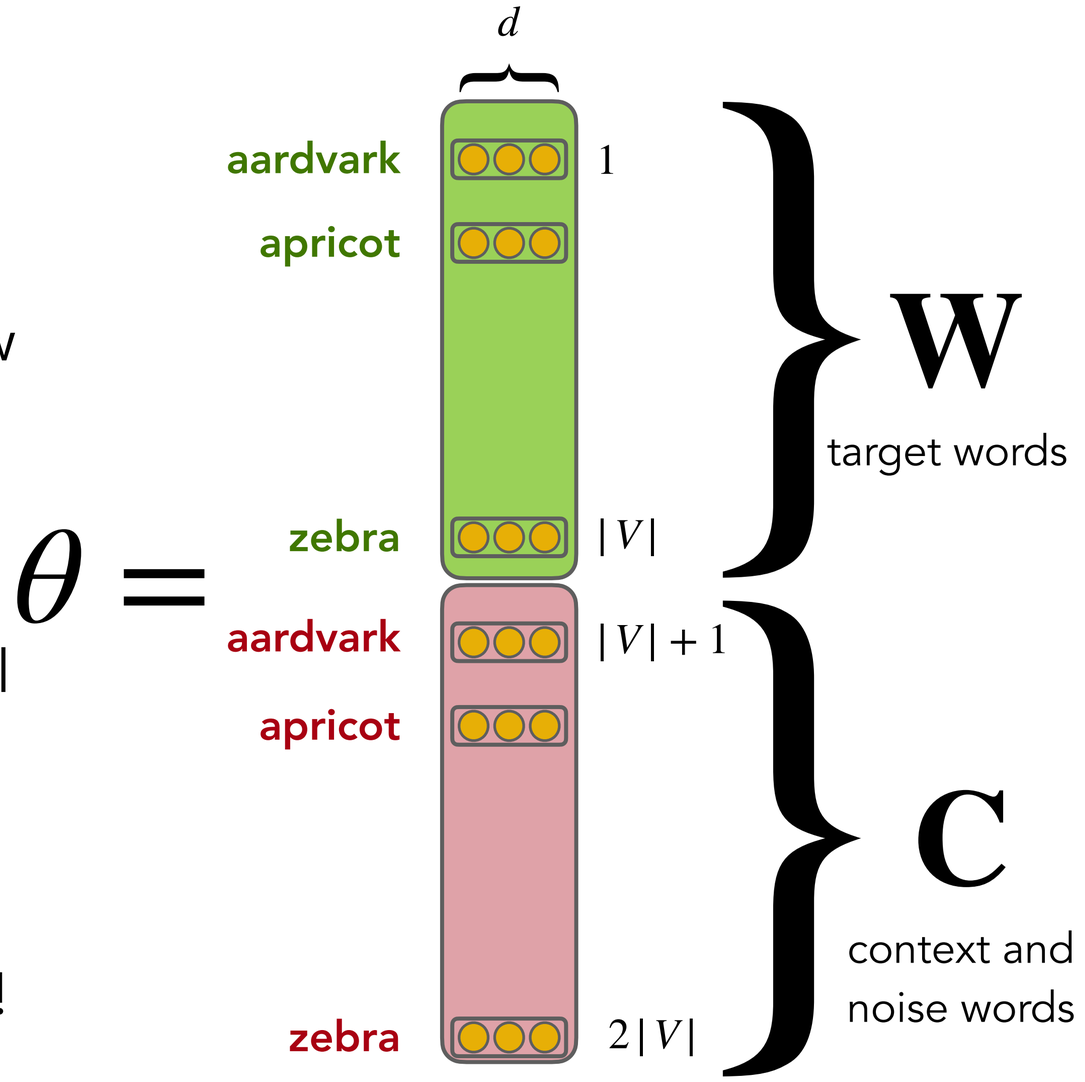
  - Same as the parameters we need to estimate!



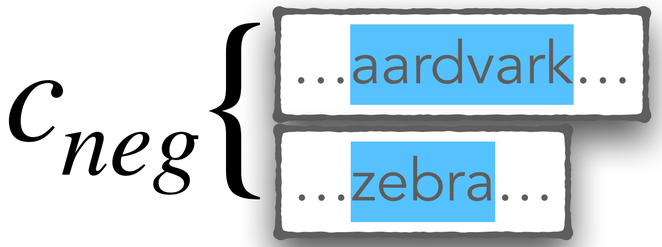
Lecture Outline

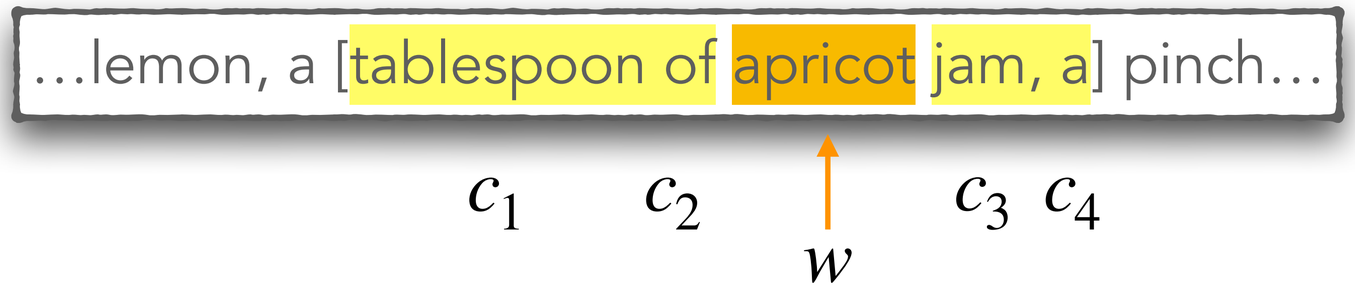
- Announcements
- Recap: Multinomial LR
- Recap: Lexical Semantics
- word2vec
  - Classification
  - Learning
- GloVe
- Properties and Evaluation of Word Embeddings

Learning word2vec embeddings

Word2vec: Training Data

For each positive example we'll grab a set of negative examples, sampling by weighted unigram frequency





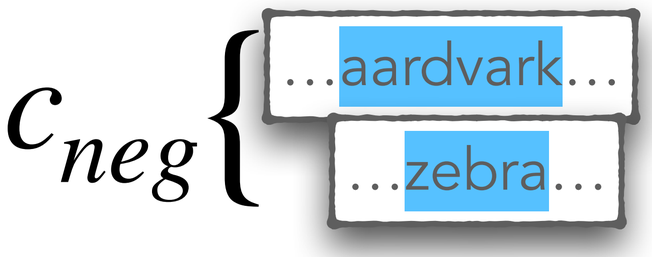
Negative examples

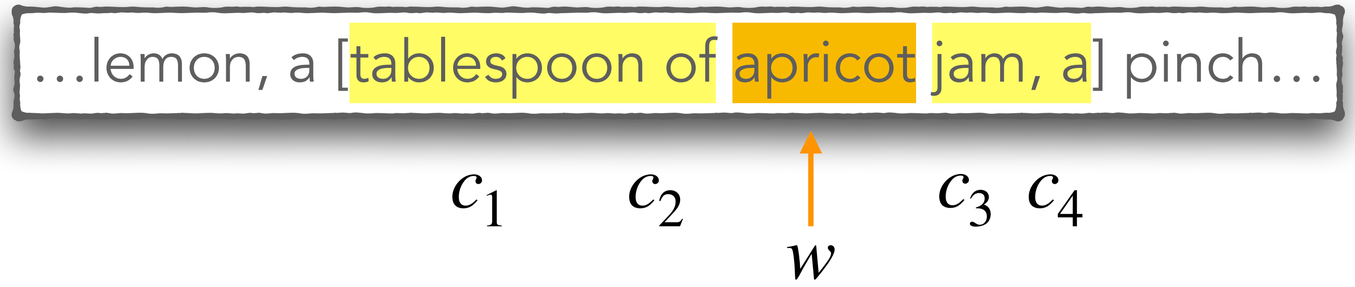
w	c_{neg}
apricot	aardvark
apricot	zebra
apricot	where
apricot	adversarial

Positive examples

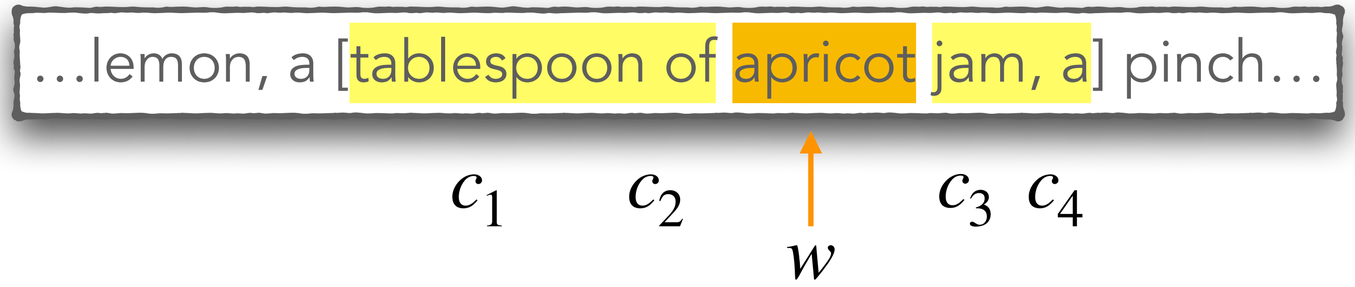
w	c
apricot	tablespoon
apricot	of
apricot	jam
apricot	a

Word2vec: Learning Problem

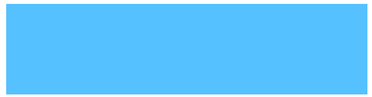




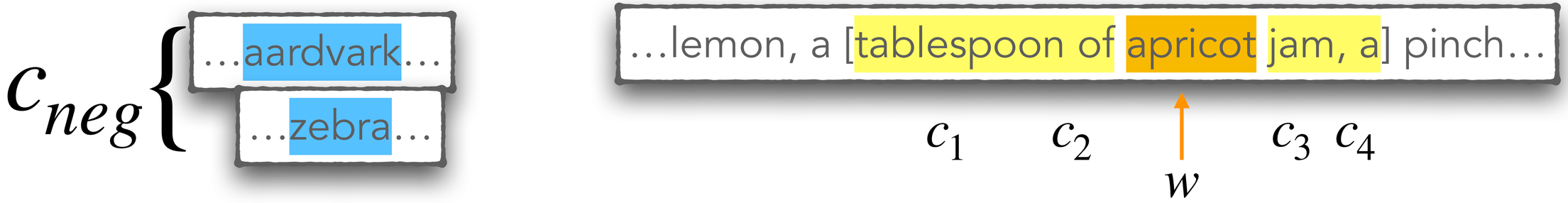
Word2vec: Learning Problem



Given



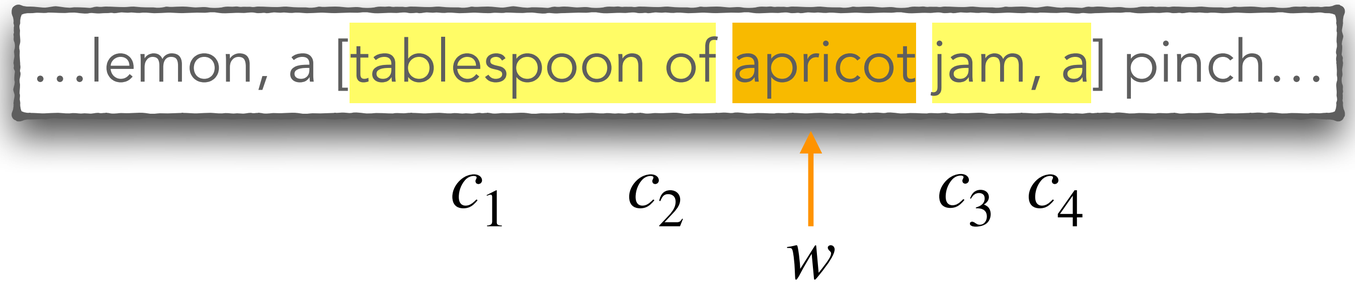
Word2vec: Learning Problem



Given

- the set of positive and negative training instances, and

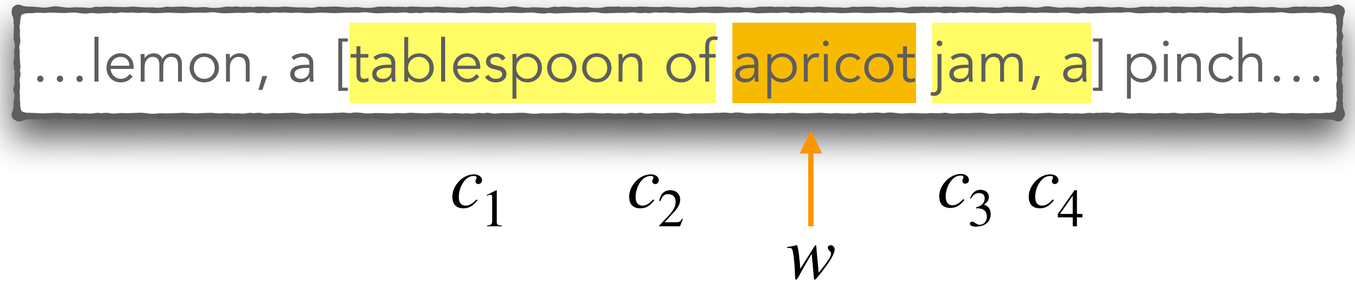
Word2vec: Learning Problem



Given

- the set of positive and negative training instances, and
- a set of randomly initialized embedding vectors of size $2|V|$,

Word2vec: Learning Problem



Given

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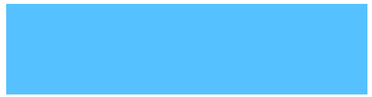
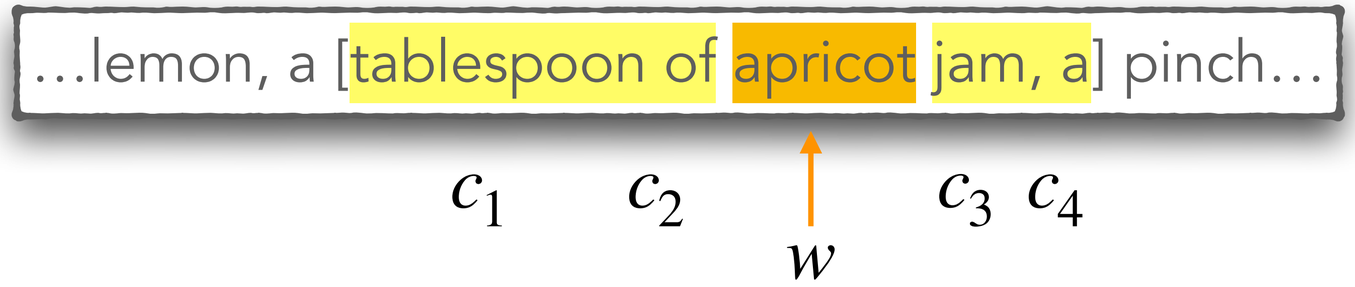
the goal of learning is to adjust those word vectors such that we:



Word2vec: Learning Problem



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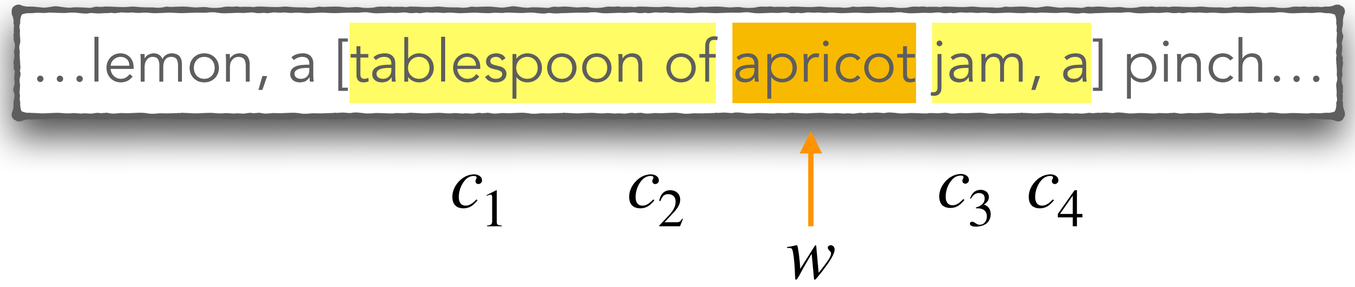
- **Maximize** the similarity of the target word, context word pairs $(w, c_{1:L})$ drawn from the positive data

Word2vec: Learning Problem



Given

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- a set of randomly initialized embedding vectors of size $2|V|$,

the goal of learning is to adjust those word vectors such that we:

- **Maximize** the similarity of the target word, context word pairs $(w, c_{1:L})$ drawn from the positive data
- **Minimize** the similarity of the (w, c_{neg}) pairs drawn from the negative data

Loss function

Maximize the similarity of the target with the actual context words in a window of size L, and minimize the similarity of the target with the $K > L$ negative sampled non-neighbor words

Loss function

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For every word,
context pair…

Loss function

Maximize the similarity of the target with the actual context words in a window of size L, and minimize the similarity of the target with the $K > L$ negative sampled non-neighbor words

For every word, context pair…

$$L_{CE} = -\log[P(+|\mathbf{w}, \mathbf{c}_{pos})P(-|\mathbf{w}, \mathbf{c}_{neg})]$$

Loss function

Maximize the similarity of the target with the actual context words in a window of size L, and minimize the similarity of the target with the $K > L$ negative sampled non-neighbor words

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Cross Entropy

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$$= -\left[\log P(+|\mathbf{w}, \mathbf{c}_{pos}) + \sum_{j=1}^{K} \log P(-|\mathbf{w}, \mathbf{c}_{neg_j})\right]$$

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Maximize the similarity of the target with the actual context words in a window of size L, and minimize the similarity of the target with the $K > L$ negative sampled non-neighbor words

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$$= -\left[\log \sigma(\mathbf{w} \cdot \mathbf{c}_{pos}) + \sum_{j=1}^{K} \log \sigma(-\mathbf{w} \cdot \mathbf{c}_{neg_j})\right]$$

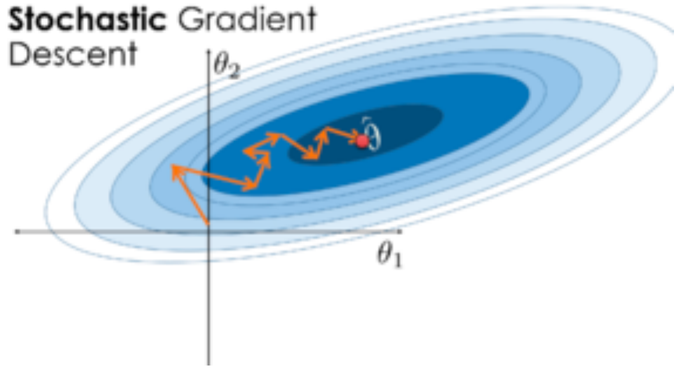
Learning the classifier

Learning the classifier

- How to learn?

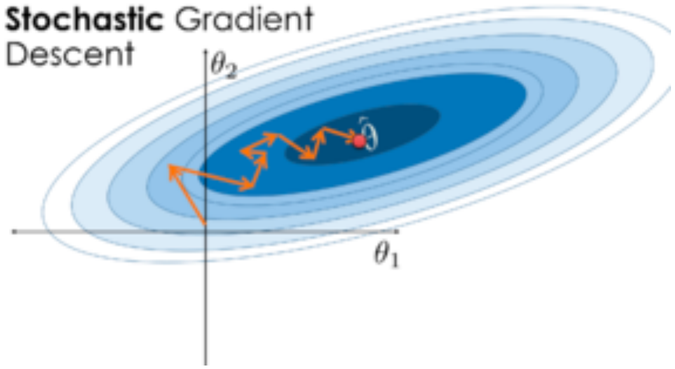
Learning the classifier

- How to learn?
  - Stochastic gradient descent!



Learning the classifier

- How to learn?
  - Stochastic gradient descent!
  - Iterative process



Learning the classifier

- How to learn?
  - Stochastic gradient descent!
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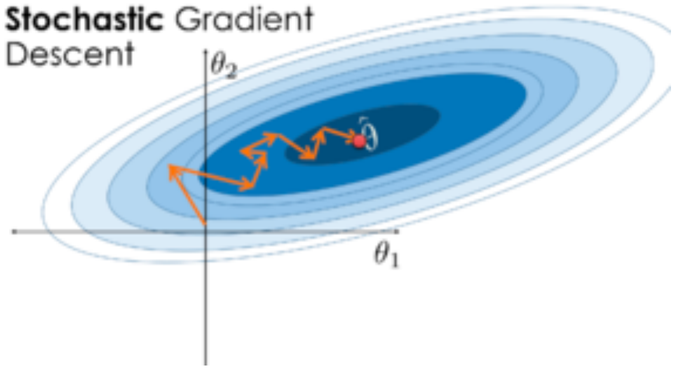
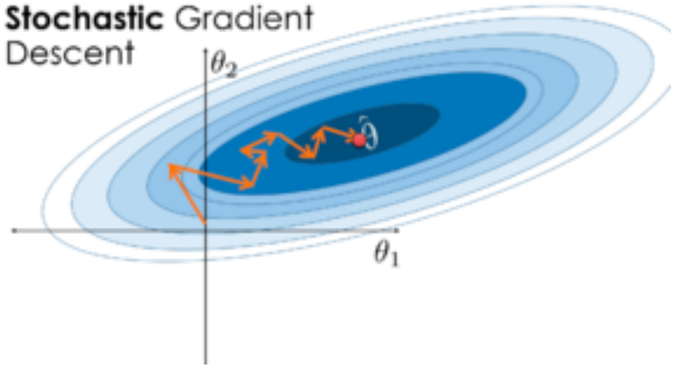
  - Start with randomly initialized weights
    - Update the parameters by computing gradients of the loss w.r..t. parameters

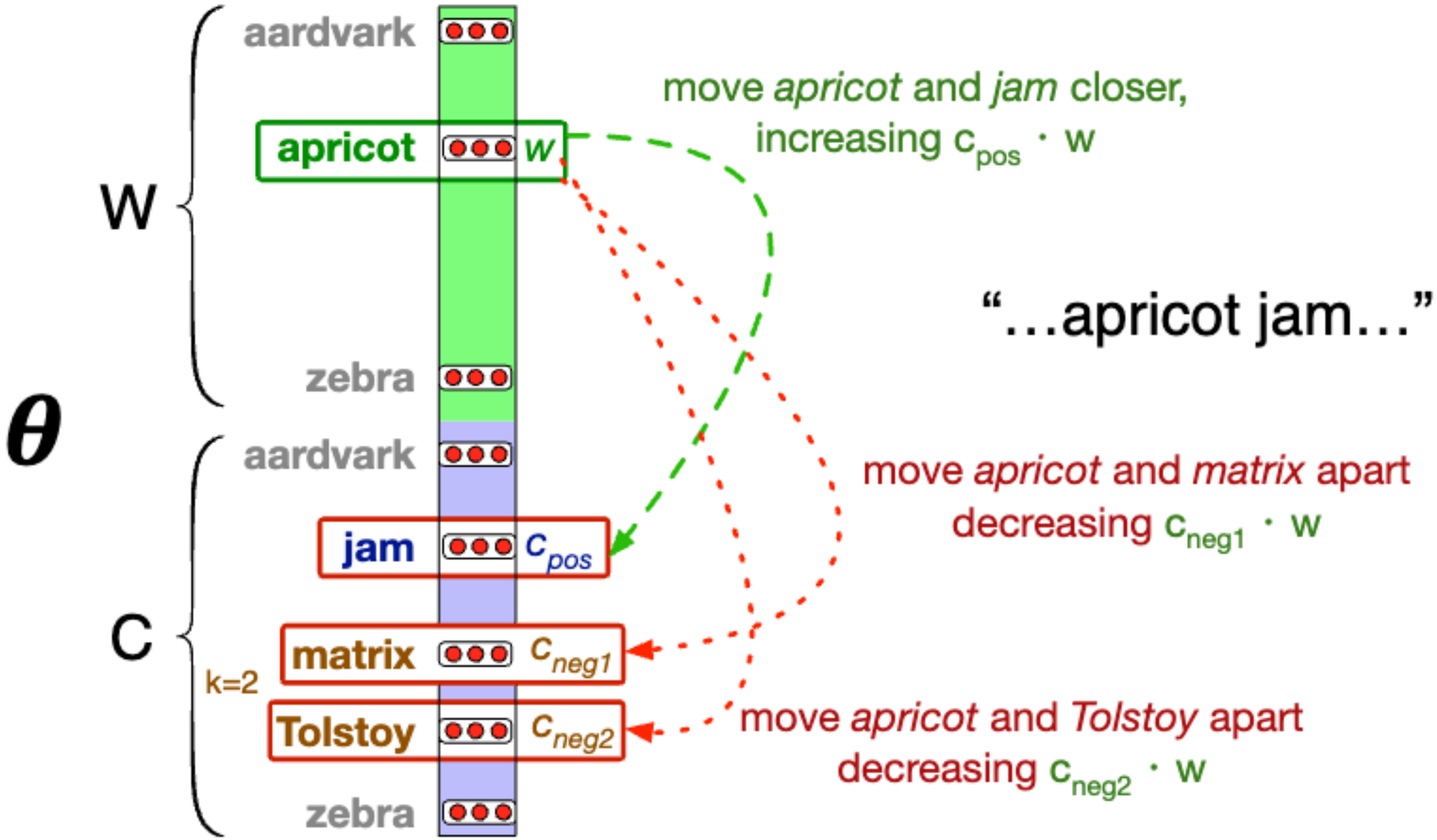


Learning the classifier

- How to learn?
  - Stochastic gradient descent!
  - Iterative process
  - Start with randomly initialized weights
    - Update the parameters by computing gradients of the loss w.r..t. parameters
    - Stop when the parameters (or, the loss) do not change much…
- We'll adjust the word weights to
  - make the positive pairs more likely
  - and the negative pairs less likely,
  - over the entire training set.



Intuition of one step of gradient descent



SGD: Derivates

$$L_{CE} = -\left[\log \sigma(\mathbf{w} \cdot \mathbf{c}_{pos}) + \sum_{j=1}^{K} \log \sigma(-\mathbf{w} \cdot \mathbf{c}_{neg_j})\right]$$

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3 different parameters

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3 different parameters

$$\frac{\partial L_{CE}}{\partial \mathbf{c}_{pos}} = [\sigma(\mathbf{c}_{pos} \cdot \mathbf{w}) - 1]\mathbf{w}$$

SGD: Derivates

$$L_{CE} = -\left[\log \sigma(\mathbf{w} \cdot \mathbf{c}_{pos}) + \sum_{j=1}^{K} \log \sigma(-\mathbf{w} \cdot \mathbf{c}_{neg_j})\right]$$

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SGD: Derivates

$$L_{CE} = -\left[\log \sigma(\mathbf{w} \cdot \mathbf{c}_{pos}) + \sum_{j=1}^{K} \log \sigma(-\mathbf{w} \cdot \mathbf{c}_{neg_j})\right]$$

3 different parameters

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$$\frac{\partial L_{CE}}{\partial \mathbf{c}_{neg_j}} = [\sigma(\mathbf{c}_{neg_j} \cdot \mathbf{w})]\mathbf{w}$$

$$\frac{\partial L_{CE}}{\partial w} = [\sigma(\mathbf{c}_{pos} \cdot \mathbf{w}) - 1]\mathbf{c}_{pos} + \sum_{j=1}^{K} [\sigma(\mathbf{c}_{neg_j} \cdot \mathbf{w})]\mathbf{c}_{neg_j}$$

SGD: Derivates

$$L_{CE} = -\left[\log \sigma(\mathbf{w} \cdot \mathbf{c}_{pos}) + \sum_{j=1}^{K} \log \sigma(-\mathbf{w} \cdot \mathbf{c}_{neg_j})\right]$$

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Update the parameters by subtracting respective η-weighted gradients