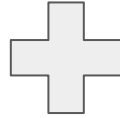


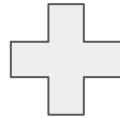
# Natural language processing

обзор задач и некоторых эмбеддингов

Computer science



Artificial intelligence



Linguistics



# More Deeper Application of NLP

Group 1	Group 2	Group 3
Cleanup, Tokenization	Information Retrieval and Extraction (IR)	Machine Translation
Stemming	Relationship Extraction	Automatic Summarization/ Paraphrasing
Lemmatization	Named Entity Recognition (NER)	Natural Language Generation
Part of Speech Tagging	Sentiment Analysis/Sentence Boundary Disambiguation	Reasoning over Knowledge Based
Query Expansion	World sense and Disambiguation	Quation Answering System
Parsing	Text Similarity	Dialog System
Topic Segmentationand Recognition	Coreference Resolution	Image Captioning & other Multimodel Tasks
Morphological Degmentation (Word/Sentences)	Discourse Analysis	

# Named entity recognition

## Stanford Named Entity Tagger

Classifier:

Output Format:

Preserve Spacing:

Please enter your text here:

Partial invoice (€100,000, so roughly 40%) for the consignment C27655 we shipped on 15th August to London from the Make Believe Town depot. INV2345 is for the balance.. Customer contact (Sigourney) says they will pay this on the usual credit terms (30 days).

Partial invoice (€100,000, so roughly 40%) for the consignment C27655 we shipped on 15th August to London from the Make Believe Town depot. INV2345 is for the balance.. Customer contact (Sigourney) says they will pay this on the usual credit terms (30 days).

Potential tags:

LOCATION

TIME

PERSON

ORGANIZATION

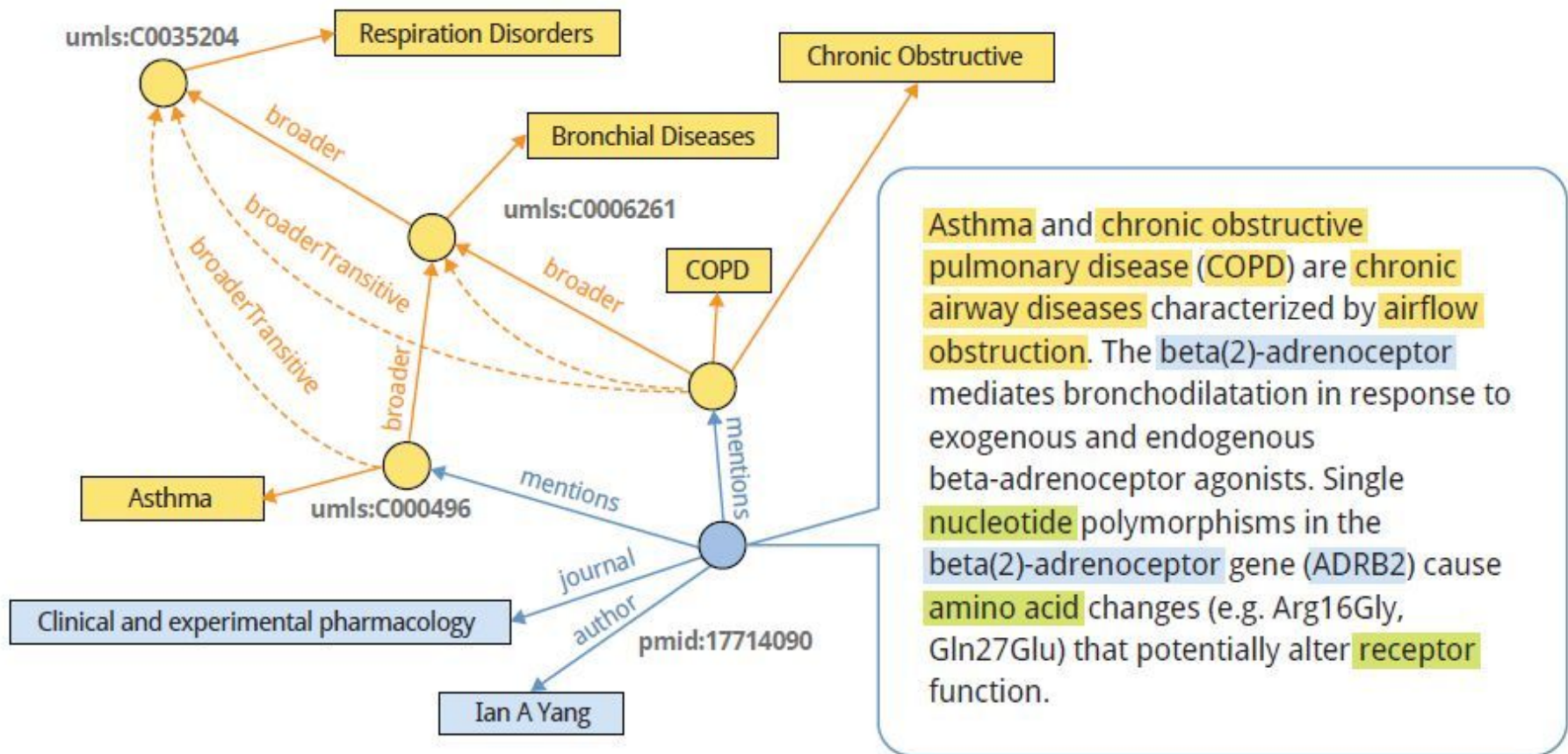
MONEY

PERCENT

DATE

atomic elements in text

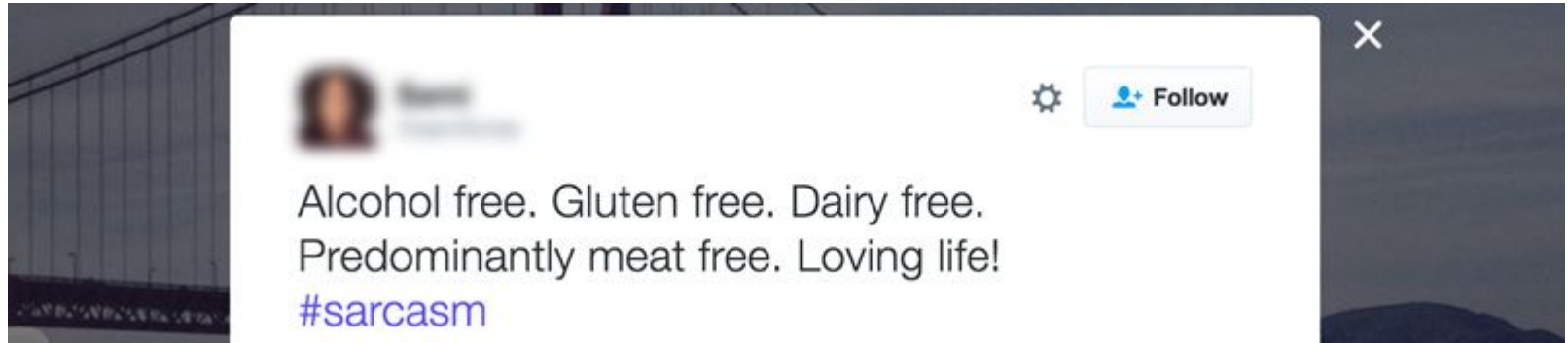
predefined categories

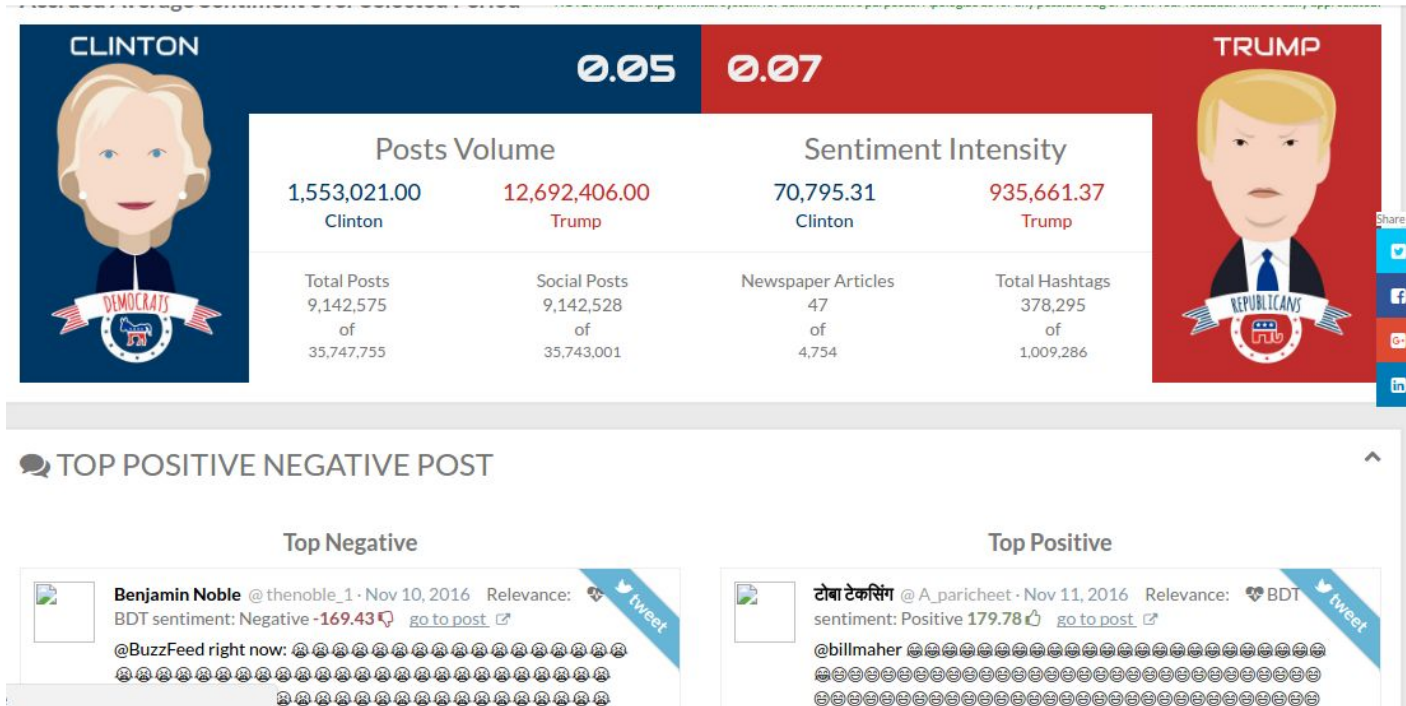


# Sentiment analysis

I like my life!

I do not dislike my life.

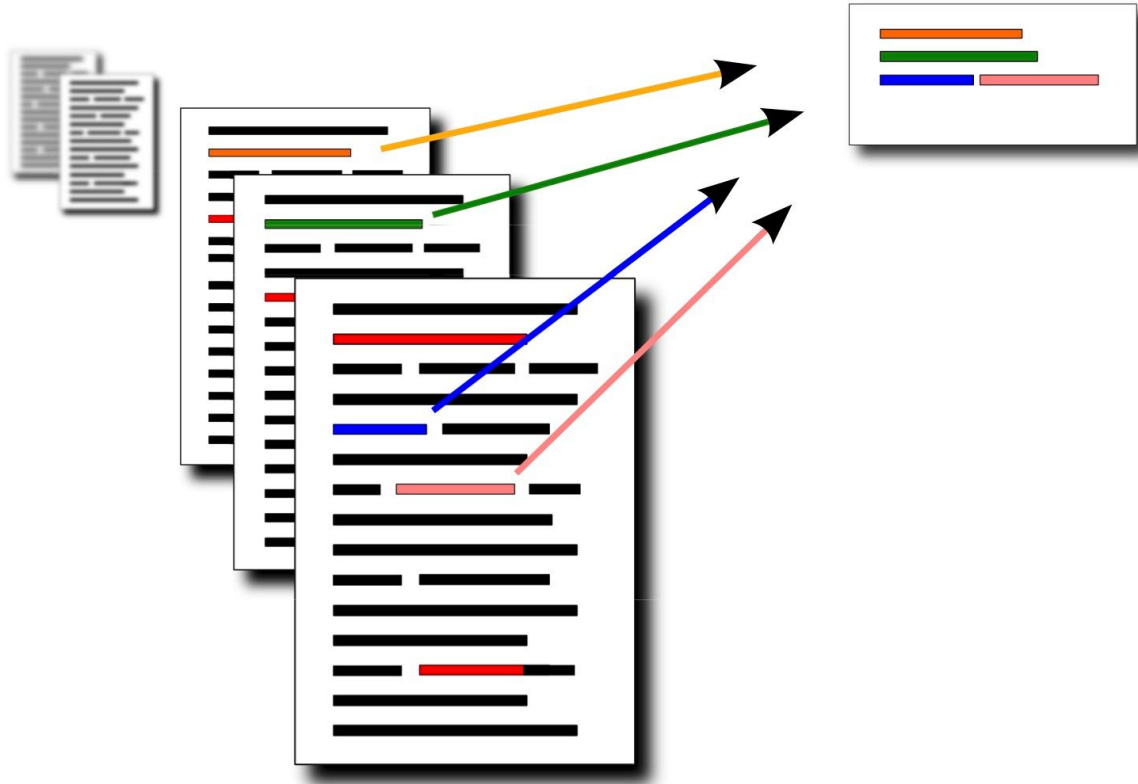




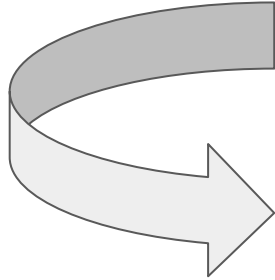
<http://elections.bdt.systems/#/how/introductory>



# Automatic summarization



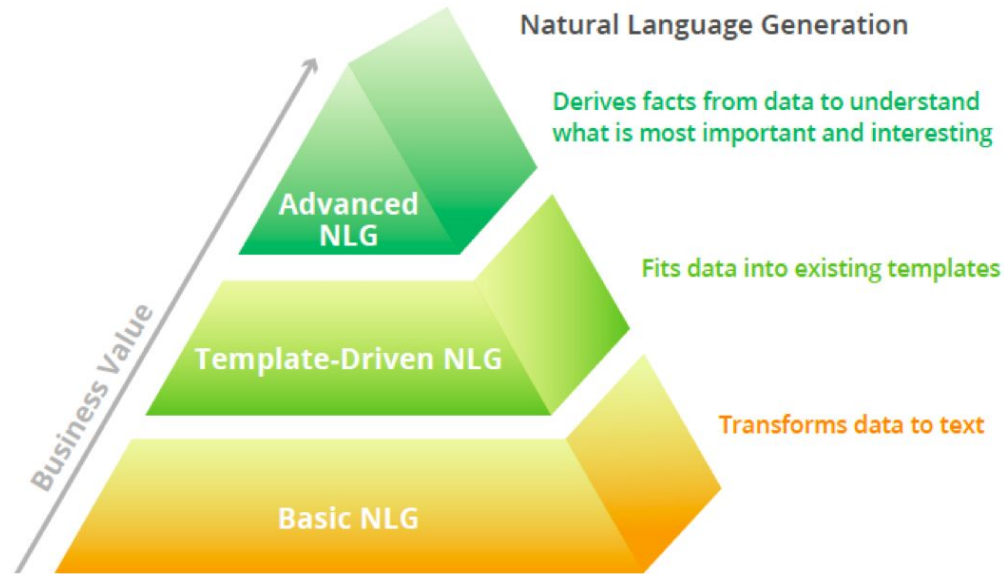
Sifting through lots of documents can be difficult and time consuming.



By extracting important sentences and creating comprehensive summaries, it's possible to quickly assess whether or not a document is worth reading.

- calculating the word frequencies for the entire text document;
- the N most common words are stored and sorted;
- each sentence is then scored based on how many high frequency words it contains, with higher frequency words being worth more;
- the top X sentences are then taken, and sorted based on their position in the original text.

# Natural language generation



[the Associated Press uses NLG](#) to create its corporate earnings reports.

# word2vec

“words which are similar in meaning occur in similar contexts”  
(Rubenstein & Goodenough, 1965)

“words with similar meanings will occur with similar neighbors if  
enough text material is available” (Schutze & Pedersen, 1995)

# Skip-gram

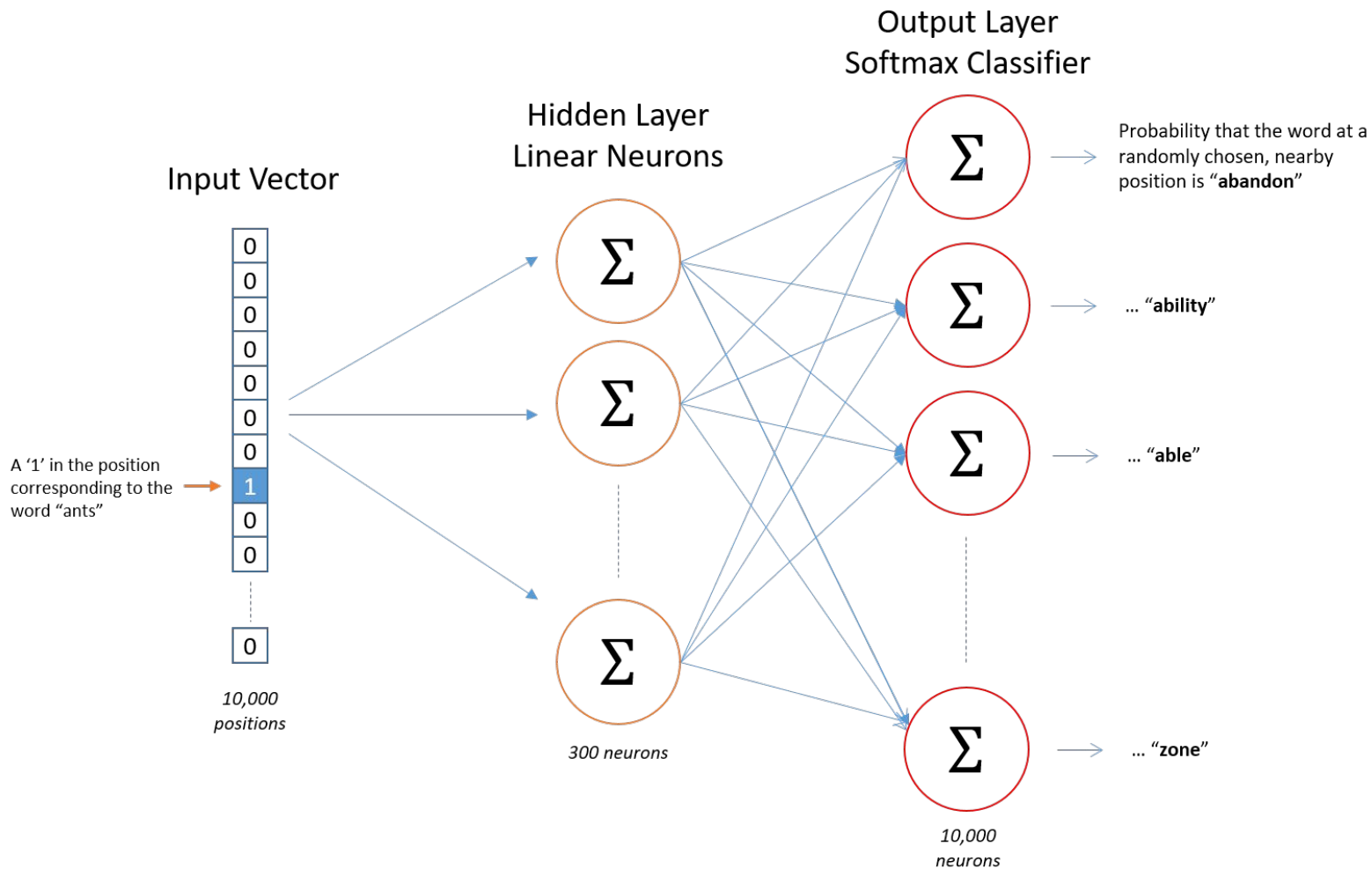
Given a specific word in the middle of a sentence (the input word), look at the words nearby and pick one at random. The network is going to tell us the probability for every word in our vocabulary of being the “nearby word” that we chose.

“nearby”  parameter “window size”

## Source Text

## Training Samples

The quick brown fox jumps over the lazy dog. ➡	(the, quick) (the, brown)
The quick brown fox jumps over the lazy dog. ➡	(quick, the) (quick, brown) (quick, fox)
The quick brown fox jumps over the lazy dog. ➡	(brown, the) (brown, quick) (brown, fox) (brown, jumps)
The quick brown fox jumps over the lazy dog. ➡	(fox, quick) (fox, brown) (fox, jumps) (fox, over)

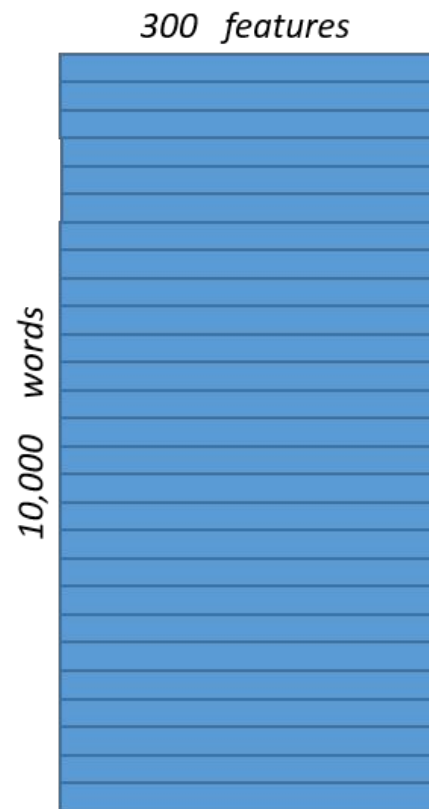
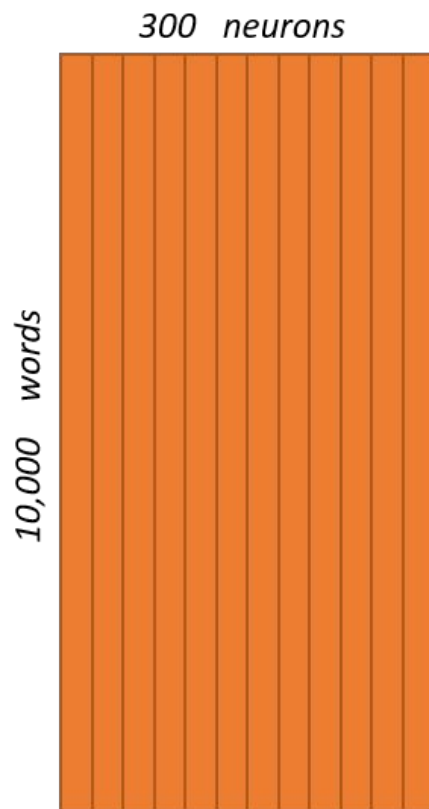


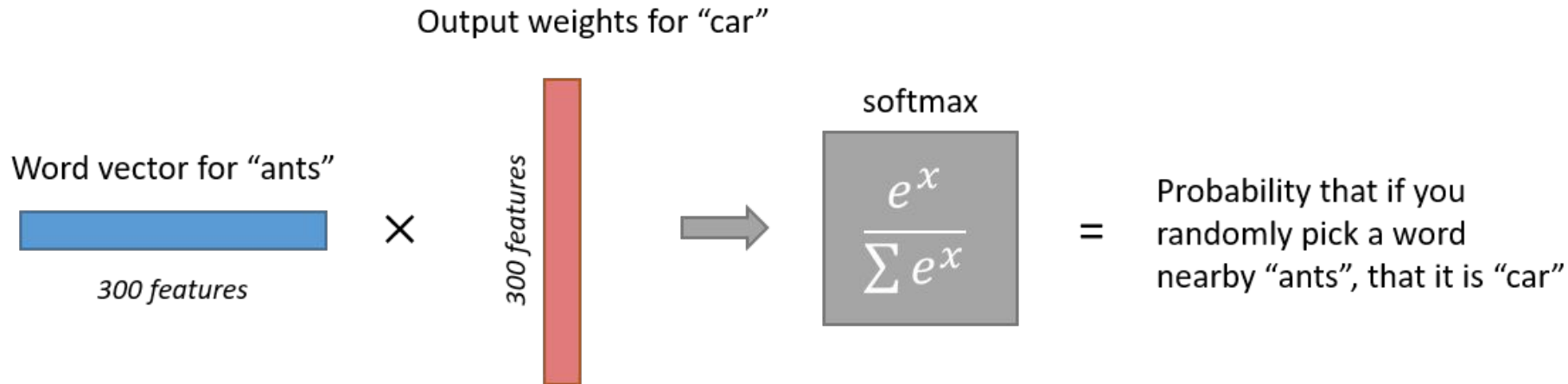


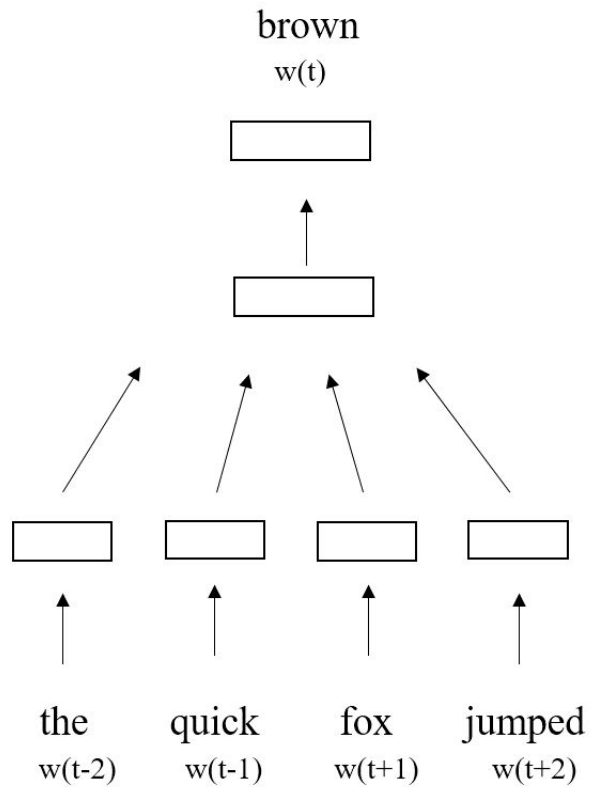
Hidden Layer  
Weight Matrix



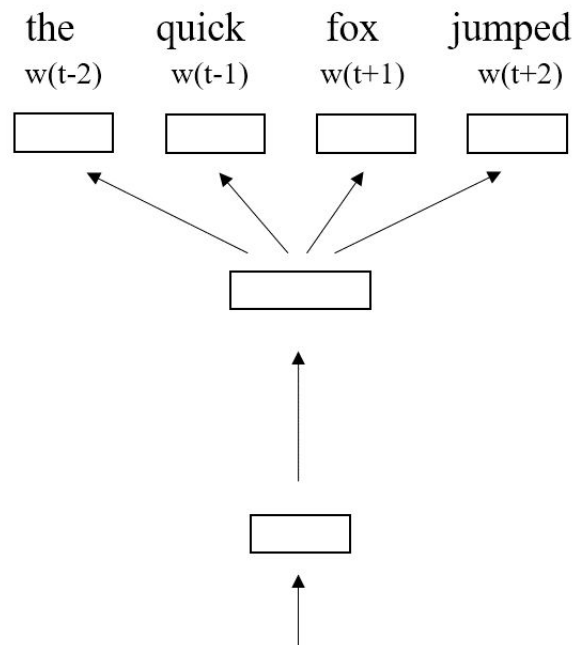
*Word Vector  
Lookup Table!*







CBOW



Skip-gram

# Continuous Bag of Words (CBOW)

[OBJ]

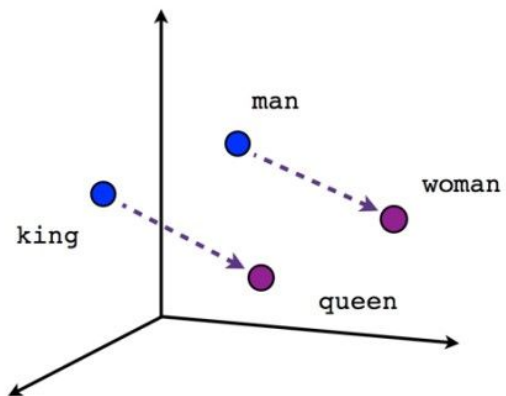
target word (vector)

scoring function

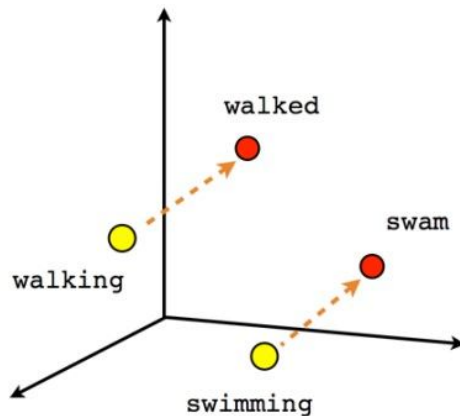
$$P(w_o | w_c) = \frac{e^{s(w_o, w_c)}}{\sum_{w_i \in V} e^{s(w_i, w_c)}}$$

context vector

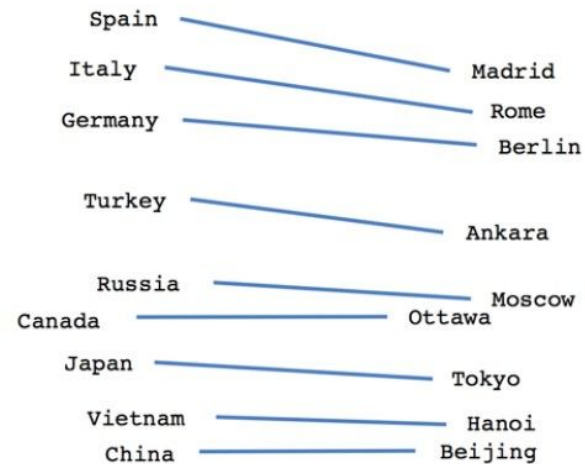
The diagram illustrates the Continuous Bag of Words (CBOW) model's probability formula. It features three annotations with arrows: 'target word (vector)' points to the output variable  $w_o$  in the numerator; 'scoring function' points to the  $s(\cdot)$  function in the exponent of the numerator; and 'context vector' points to the input variable  $w_c$  in both the numerator and denominator. The formula itself is  $P(w_o | w_c) = \frac{e^{s(w_o, w_c)}}{\sum_{w_i \in V} e^{s(w_i, w_c)}}$ .



Male-Female



Verb tense



Country-Capital

# Enriching Word Vectors with Subword Information

Each word  $w$  is represented as a bag of character  $n$ -gram. We also include the word  $w$  itself in the set of its  $n$ -grams, to learn a representation for each word (in addition to character  $n$ -grams).

In practice, we extract all the  $n$ -grams for  $n$  greater or equal to 3 and smaller or equal to 6

We represent a word by the sum of the vector representations of its  $n$ -grams

# Why?

Popular models that learn such representations ignore the morphology of words, by assigning a distinct vector to each word. This is a limitation, especially for languages with large vocabularies and many rare words

<https://www.upwork.com/hiring/for-clients/artificial-intelligence-and-natural-language-processing-in-big-data/>

<http://www.informit.com/articles/article.aspx?p=2265404>

<https://arxiv.org/pdf/1301.3781.pdf>

<https://arxiv.org/pdf/1607.04606.pdf>

<http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/>

<https://blog.algorithmia.com/introduction-automatic-text-summarization/>