Lecture 9:
Introduction to texts

Ivan Provilkov

Plan

- NLP tasks
- Text classification overview
- Word representations
- LSA
- TFIDF

Based on
https://github.com/yandexdataschool/nlp_course & https://github.com/neychev/harbour_dlia2019

Natural Language Processing (NLP)

This is a subfield of computer science about how to program computers to deal with natural languages (English, Russian...).

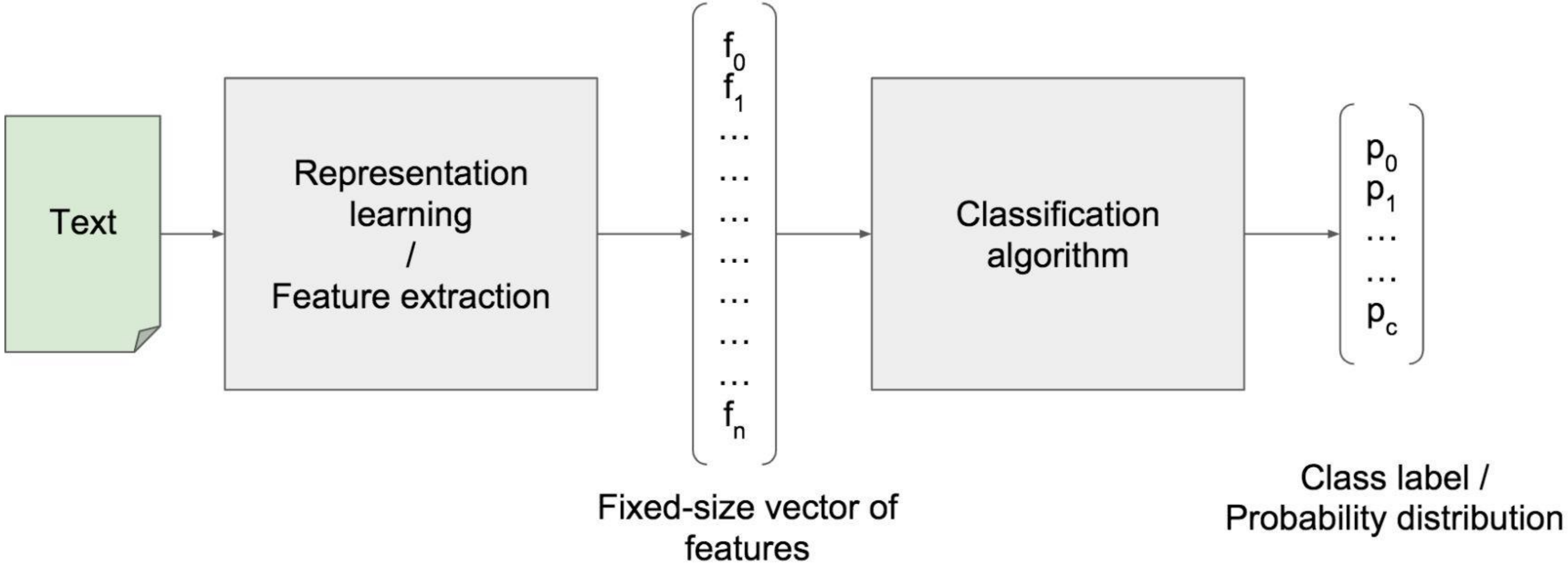
NLP tasks (1)

- Machine Translation
  Between different languages
- Language modeling
  Model which can predict probability of sentence, or word, given context
- Part of speech tagging
  Determine part of speech for each word
- Parsing
  Determine parse tree for sentence which shows relations between words

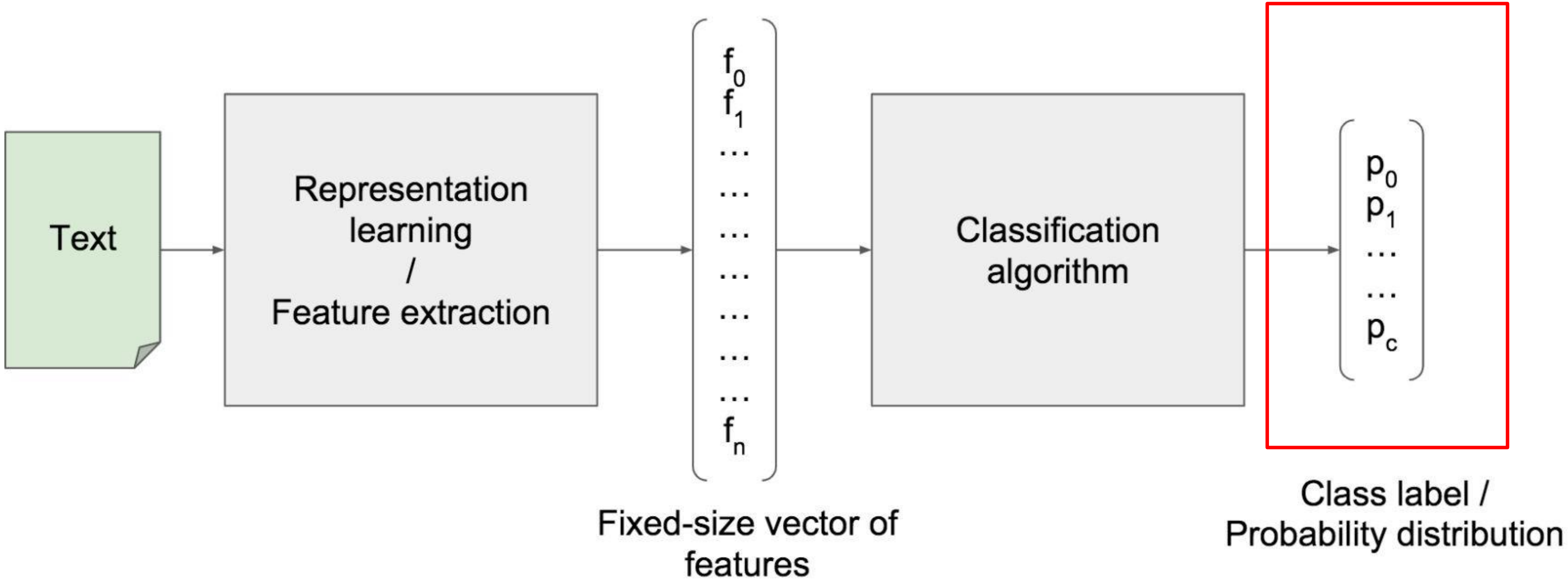
NLP tasks (2)

- Natural language generation
  Convert some information (images, digits) into human readable way
- Named entity recognition
  Determine which items in text map to proper classes. For example, people or organizations
- Question answering
  Given a human language question, determine its answer
- Topic modeling
  Extract topics and determine which relate to text
- ...

Text classification



Text classification



Text labels

- Discrete labels:
  - Binary: spam filtering, sentiment analysis

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  - Multi-class: categorization of items by its description

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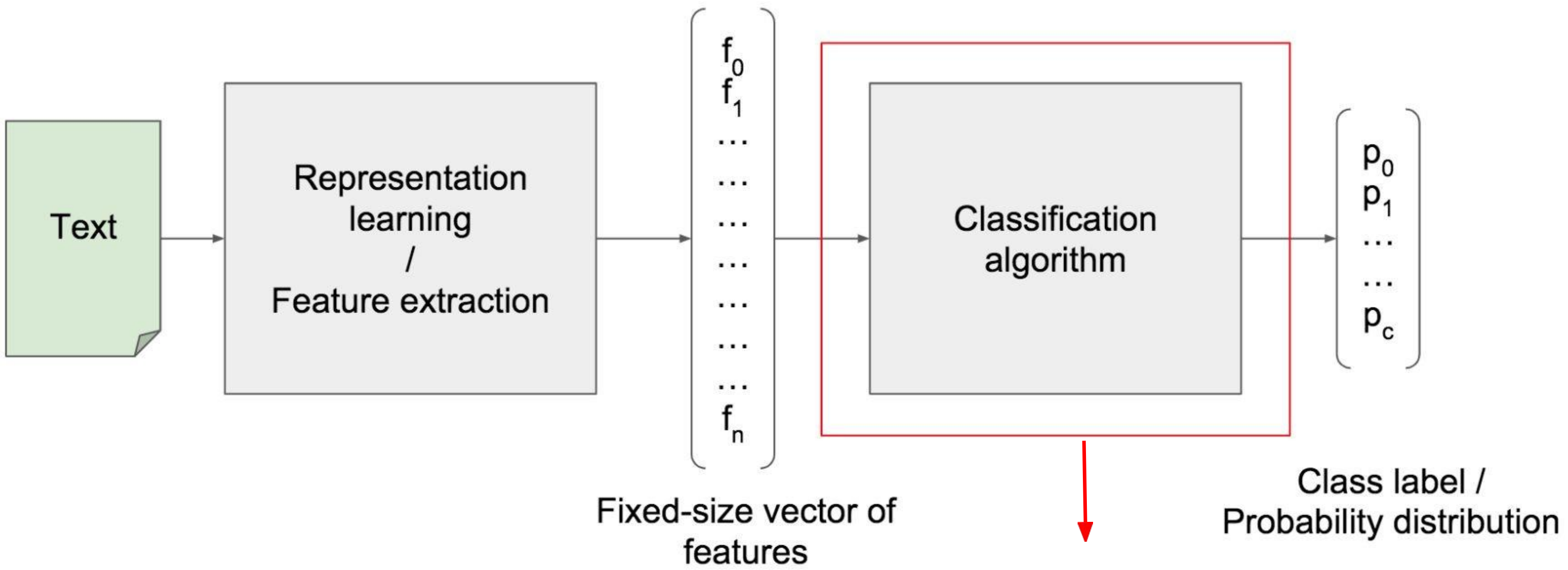
  - Multi-label: #hashtag prediction

Text labels

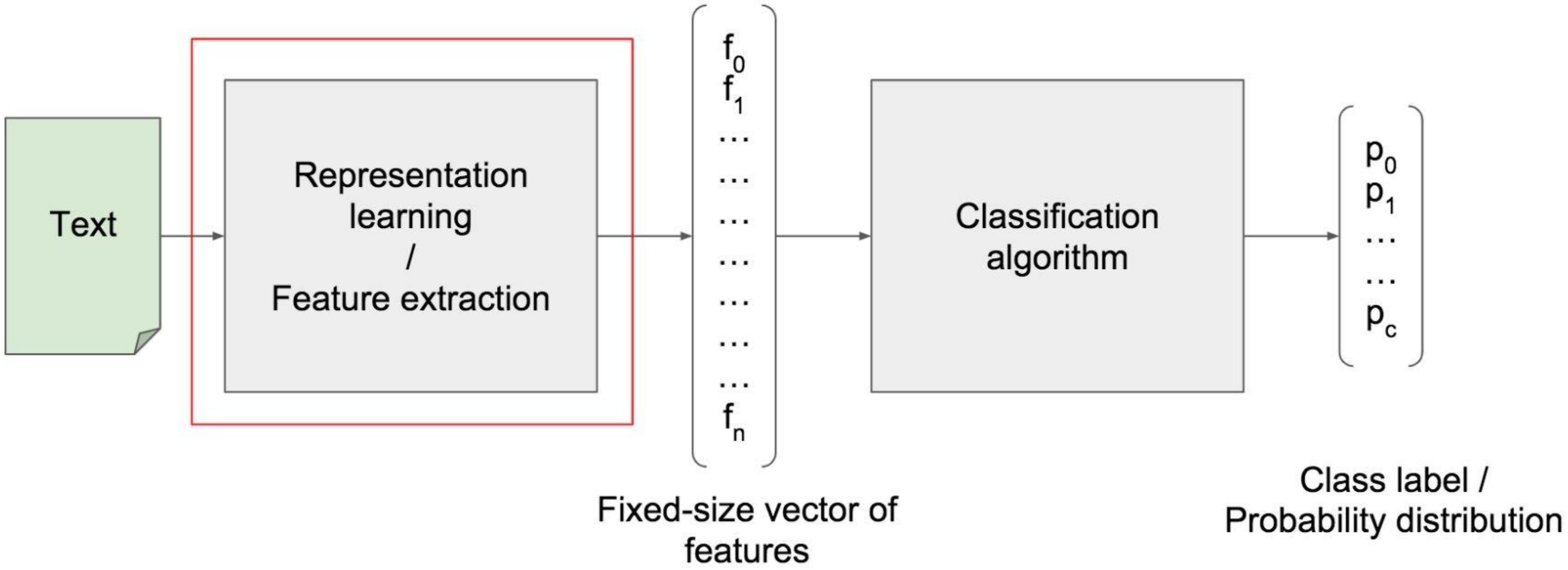
- Discrete labels:
  - Binary: spam filtering, sentiment analysis
  - Multi-class: categorization of items by its description
  - Multi-label: #hashtag prediction
- Continuous labels:
  - Predict product price by its description

Text classification



- Linear Classifier
- Logistic Regression
- etc.

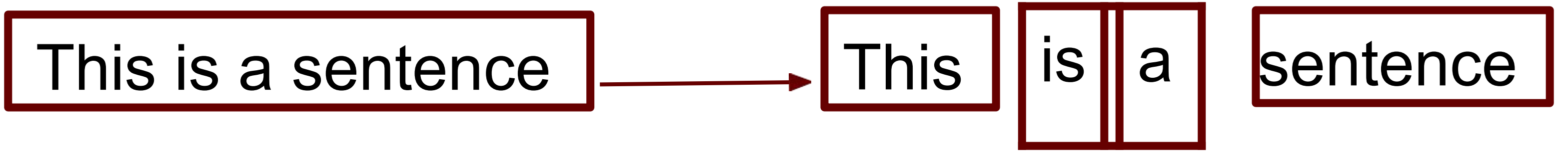
Text classification



Text Preprocessing

Text preprocessing

- Tokenization: split the input into tokens



Text preprocessing

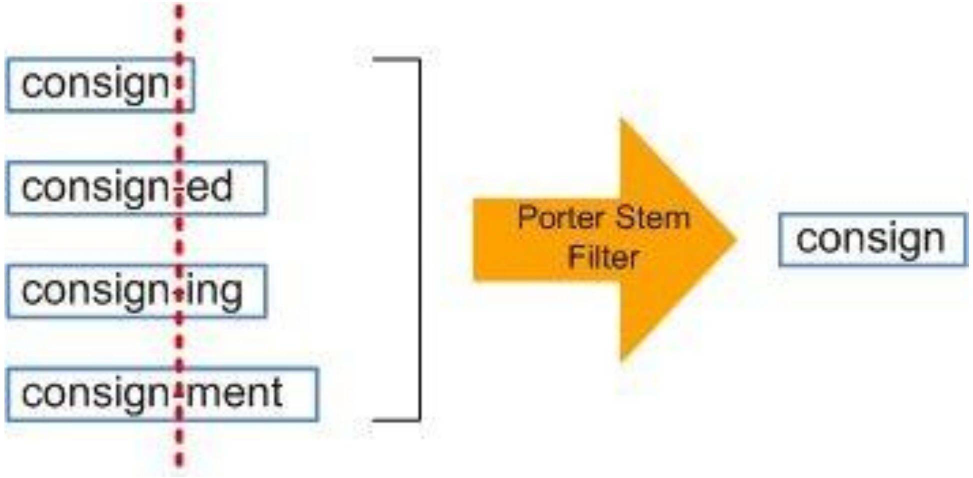
- Token normalization:

Dog, dogs → dog

Bark, barks → bark

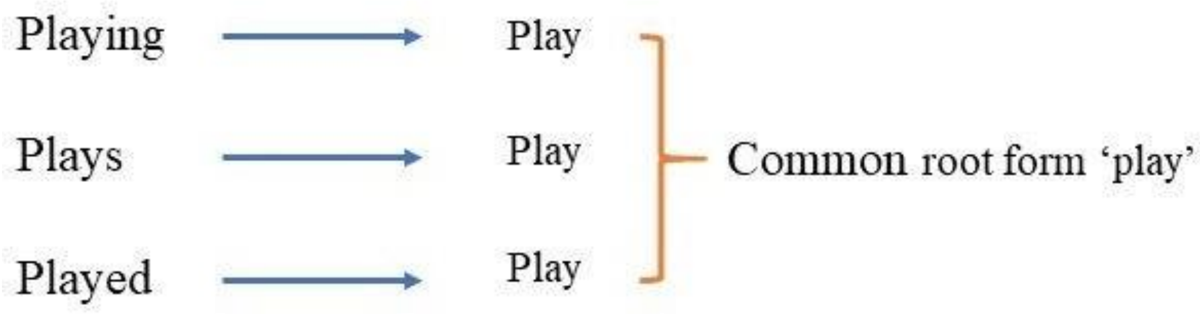
Text preprocessing

- Token normalization:
  - **Stemming**: removing and replacing suffixes to get to the root of the word (**stem**)



Text preprocessing

- Token normalization:
  - **Stemming**: removing and replacing suffixes to get to the root of the word (**stem**)
  - **Lemmatization**: to get base or dictionary form of a word (**lemma**)



Lemmatization

- Lemmatizer:
  - Tries to resolve word to its dictionary form
  - Based on **WordNet** database
  - For the best results feed part-of-speech tagger

Handful tools for preprocessing

- NLTK
  - nltk.stem.SnowballStemmer
  - nltk.stem.PorterStemmer
  - nltk.stem.WordNetLemmatizer
  - nltk.corpus.stopwords
- BeautifulSoup (for parsing HTML)
- Regular Expressions (import re)

Also need to worry about

- Capital Letters
- Punctuation
- Contractions (e.g, etc.)
- Numbers (dates, ids, page numbers)
- Stop-words (“the”, “is”, etc.)
- Tags

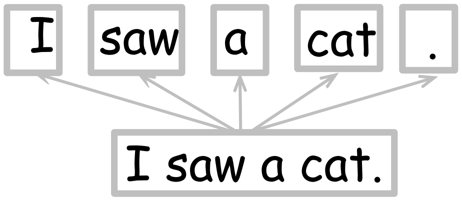
Feature extraction

Why do we need word representations?

I saw a cat.

Text (your input)

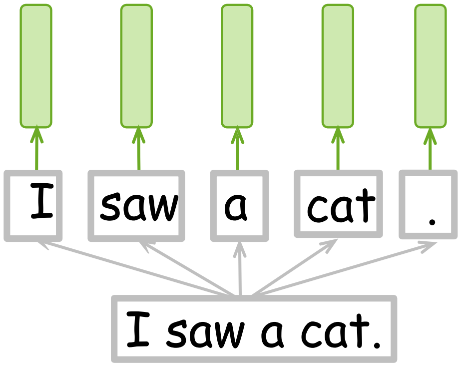
Why do we need word representations?



Sequence of tokens

Text (your input)

Why do we need word representations?

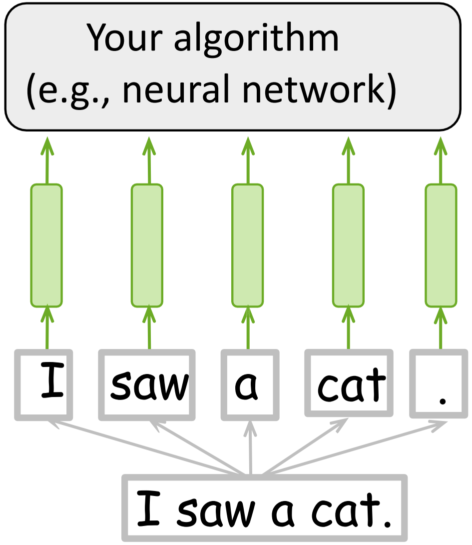


Word representation - vector (input for your model/algorithm)

Sequence of tokens

Text (your input)

Why do we need word representations?



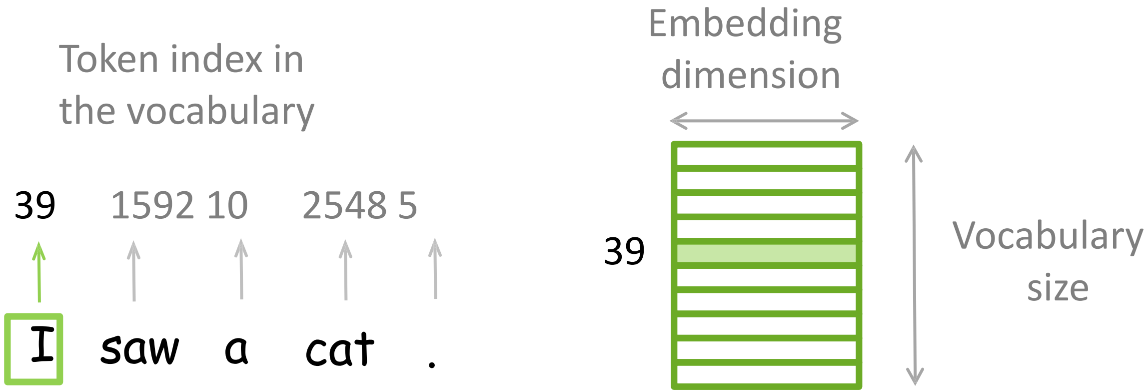
Any algorithm for solving a task

Word representation - vector (input for your model/algorithm)

Sequence of tokens

Text (your input)

How it works: Look-up Table



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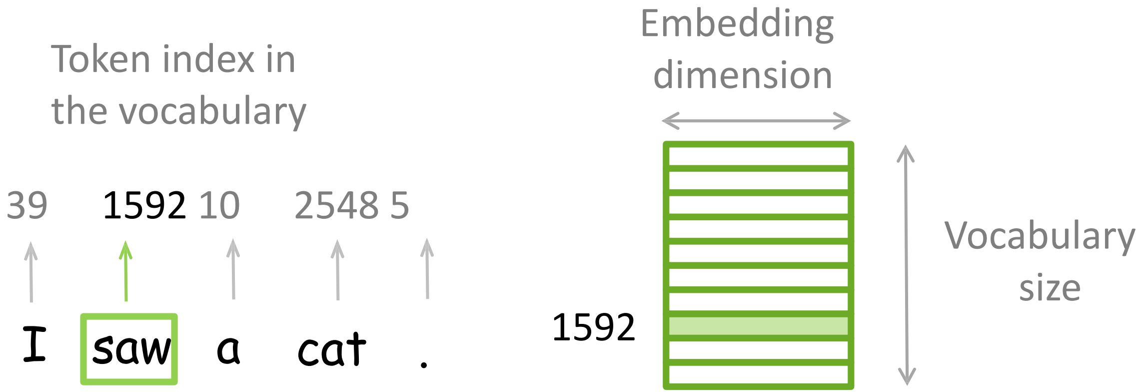

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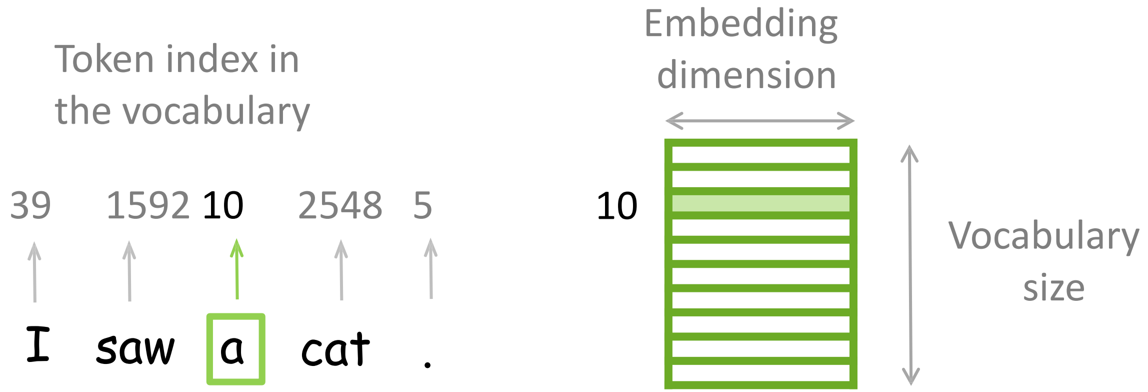

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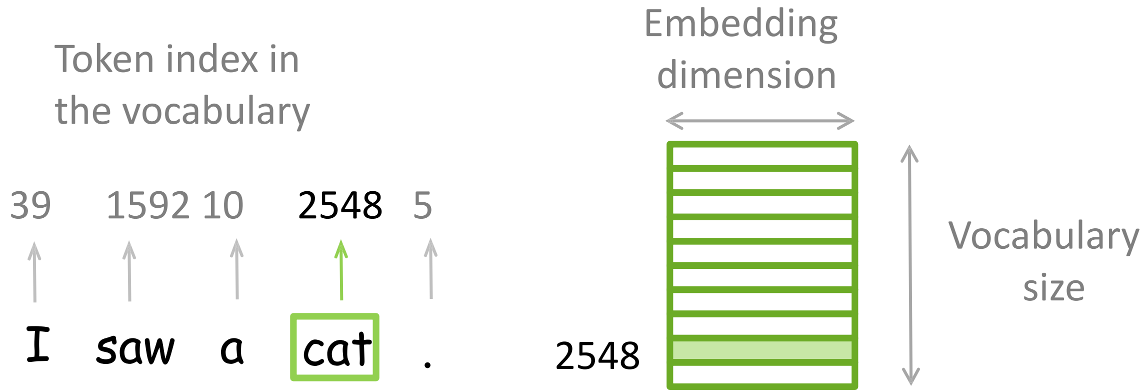

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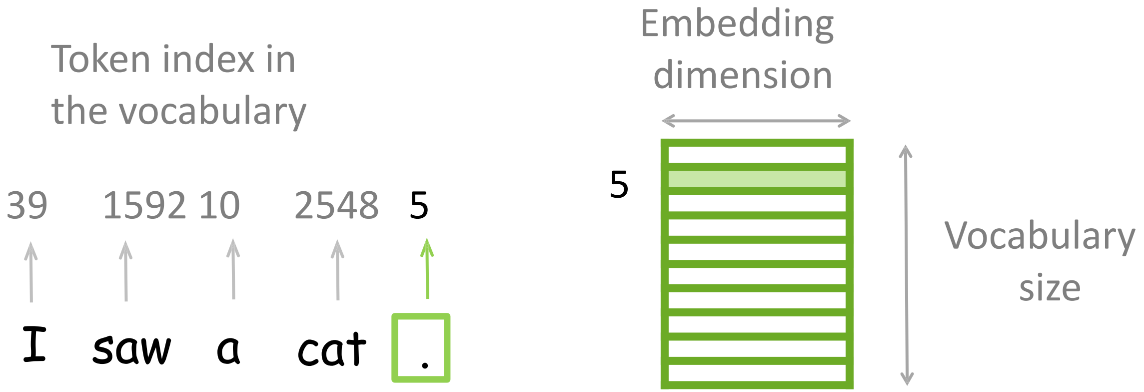

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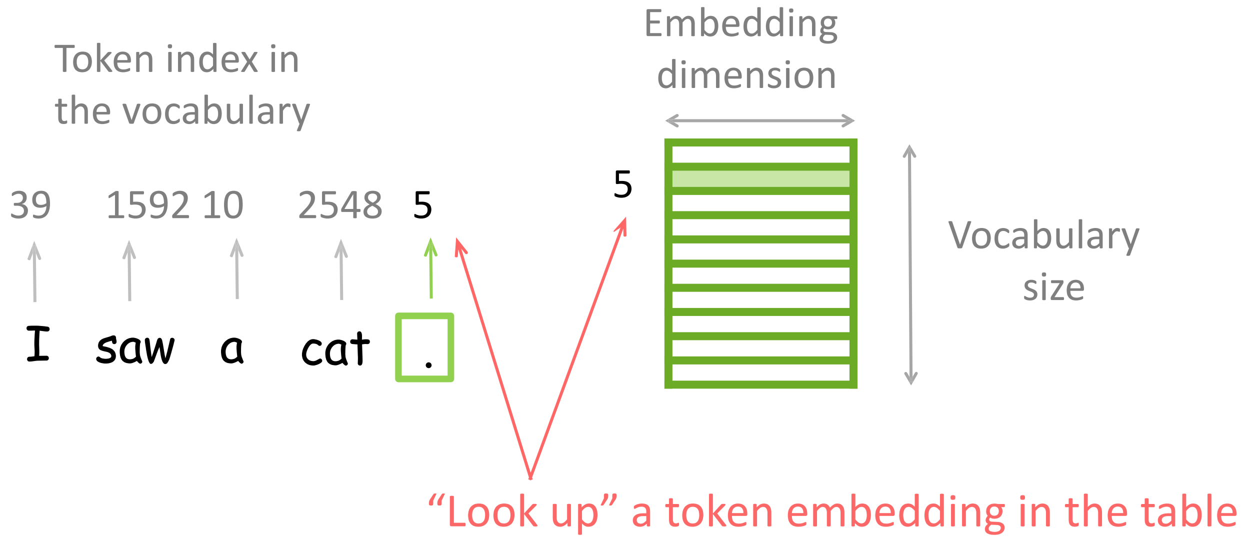
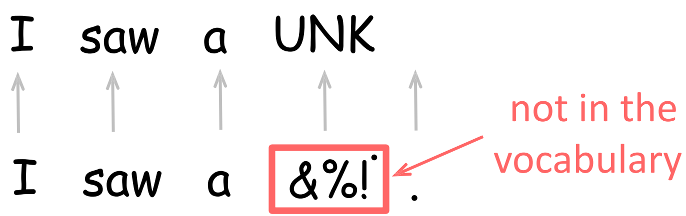


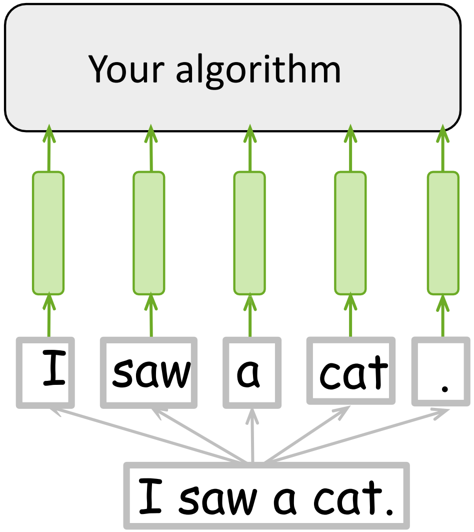
Note UNKs: Out-of-Vocabulary Tokens



Vocabulary is chosen in advance

Therefore, some tokens may be "unknown" – you can use a special token for them

How can we get word representations?



<u>In the following</u>:

How can we get these representations?

One-Hot Vectors: Represent Words as Discrete Symbols

One is 1, the rest are 0

dog 0…0…0 1 0….0…0

cat 0…0 1 0…0….0…0

table 0…0…0….00 1 0…0

Embedding dimension = vocabulary size

One-Hot Vectors: Represent Words as Discrete Symbols

One is 1, the rest are 0

dog	0…0…0 1 0….0…0
cat	0…0 1 0…0….0…0
table	0…0…0….00 1 0…0

Embedding dimension = vocabulary size

Problems:

- Vector size is too large
- Vectors know nothing about meaning

e.g., cat is as close to

dog as it is to table!

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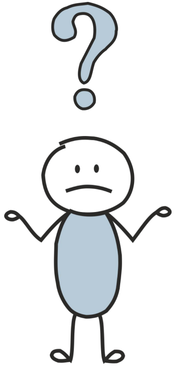
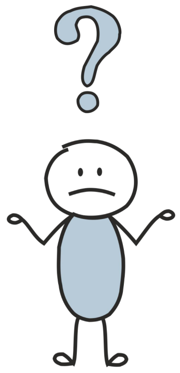


What is meaning?

What is meaning?

Do you know what the word tezgüino means ?

(We hope you do not)



What is meaning?

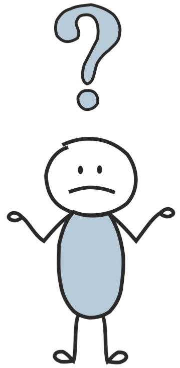
Now look how this word is used in different contexts:

A bottle of tezgüino is on the table. Everyone likes tezgüino.

Tezgüino makes you drunk.

We make tezgüino out of corn.

Can you understand what tezgüino means ?



What is meaning?

Now look how this word is used in different contexts:

A bottle of tezgüino is on the table.

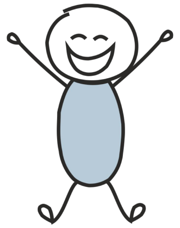
Everyone likes tezgüino.

Tezgüino makes you drunk.

We make tezgüino out of corn.

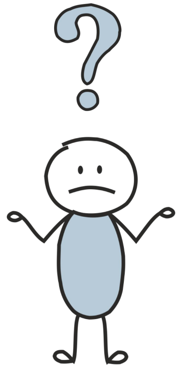
Tezgüino is a kind of alcoholic beverage made from corn.

With context, you can understand the meaning!



What is meaning?

How did you do this?



What is meaning?

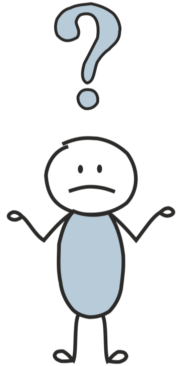
(1) A bottle of ______ is on the table.

(2) Everyone likes ______

(3) ______ makes you drunk.

(4) We make ______ out of corn.

What other words fit into these contexts ?



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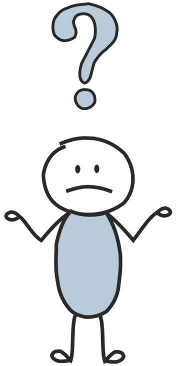

	(1)	(2)	(3)	(4)
tezgüino	1	1	1	1
loud 0	0	0	0	
motor oil	1	0	0	1
tortillas	0	1	0	1
wine 1	1	1	0	

← contexts

← rows show contextual properties: 1 if a word can appear in the context, 0 if not

What is meaning?

(1) A bottle of ______ is on the table.

(2) Everyone likes ______

(3) ______ makes you drunk.

(4) We make ______ out of corn.

	(1)	(2)	(3)	(4)
tezgüino	1	1	1	1
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wine 1	1	1	0	

This is the distributional hypothesis

rows are similar $\Rightarrow$ meanings of the words are similar

Distributional Hypothesis

Words which frequently appear in similar contexts have similar meaning.

(Harris 1954, Firth 1957)

Main idea:

We have to put information about contexts into word vectors.

Count-Based Methods

Idea: co-occurrence counts

Corpus sentences

He also found five fish swimming in murky water in an old **bathtub**.
We do abhor dust and dirt, and stains on the **bathtub**, and any kind of filth.
Above At the far end of the garden room a **bathtub** has been planted with herbs for the winter.
They had been drinking Cisco, a fruity, wine-based fluid that smells and tastes like a mixture of cough syrup and **bathtub** gin.
Science finds that a surface tension on the water can draw the boats together, like toy boats in a **bathtub**.
In fact, the godfather of gloom comes up with a plot that takes in Windsor Davies (the ghost of sitcoms past), a **bathtub** and a big box of concentrated jelly.
'I'll tell him,' said the Dean from the bathroom above the sound of bathwater falling from a great height into the ample Edwardian **bathtub**.

Co-occurrence counts

the	12
a	9
of	7
and	6
in	5
...	...
like	2
water	2
boat	2
from	2
stain	1
toy	1
god-father	1
Cisco	1
...	...

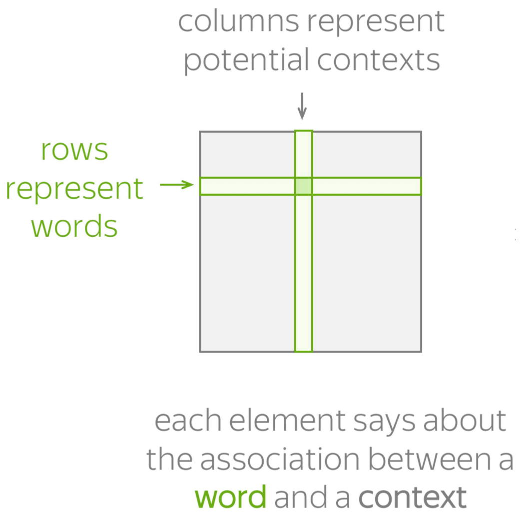
vector

$$\begin{pmatrix} 12 \\ 9 \\ 7 \\ 6 \\ 5 \\ \vdots \\ 2 \\ 2 \\ 2 \\ 2 \\ 1 \\ 1 \\ 1 \\ 1 \\ \vdots \end{pmatrix}$$

Dimensionality reduction

small vector

Count-Based Methods: The General Pipeline



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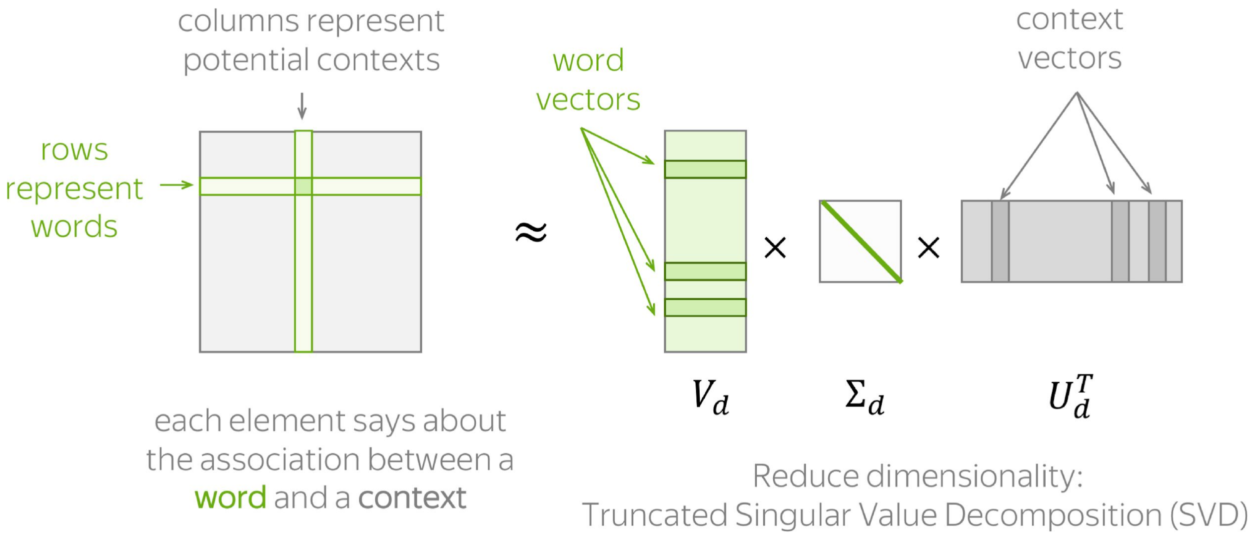

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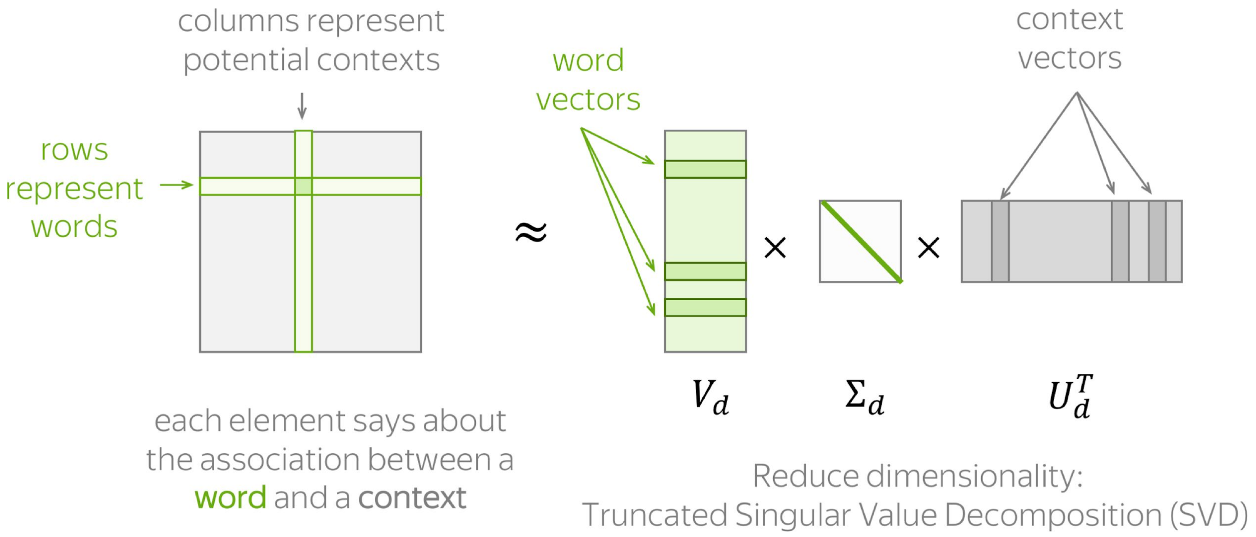


<u>Need to define:</u>

- what is context
- how to compute matrix elements

Simple: Co-Occurrence Counts

2-sized window for cat

… I saw a cute grey cat playing in the garden …

contexts for cat

<u>Context:</u>

- surrounding words
  in a L-sized window

<u>Matrix element:</u>

- number of times word w
  appears in context c

Singular Value Decomposition (SVD)

SVD: $M = U\Sigma V^T \qquad U^T U = I$

- M (m x n) - real matrix
- U (m x m) - orthogonal matrix
- $\sum$ (m x n)- diagonal matrix with non-negative real numbers on the diagonal (singular values)
- V (m x m) - orthogonal matrix

Latent Semantic Analysis (LSA)

Let X be the matrix where t_i is i-th term (word) and d_j is j-th document.

X (vocab_size x corpus_size)

$$
\begin{array}{cc}
 & \begin{array}{ccccc} \phantom{x_{1,1}} & & \mathbf{d}_j & & \phantom{x_{1,n}} \\ & & \downarrow & & \end{array} \\
\begin{array}{c} \\ \\ \mathbf{t}_i^T \rightarrow \\ \\ \\ \end{array} & \begin{bmatrix} x_{1,1} & \dots & x_{1,j} & \dots & x_{1,n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & \dots & x_{i,j} & \dots & x_{i,n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m,1} & \dots & x_{m,j} & \dots & x_{m,n} \end{bmatrix}
\end{array}
$$

Latent Semantic Analysis (LSA)

Dot product $t_i^T t_p$ gives correlation between two terms in the corpus, analogically with documents.

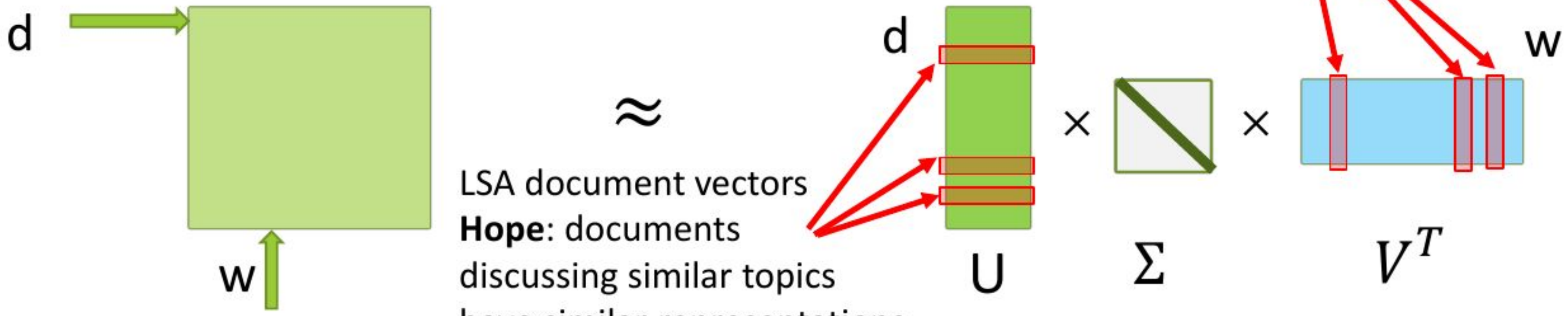
- Let's use SVD $$X = U \Sigma V^T$$
- If you take k biggest singular vectors you will get
  the rank k approximation to X with the smallest error (Frobenius norm)
- Now we can treat terms and documents as semantic space
- Finally we have small representations for terms and documents with meaning
  We can compute similarity with cosine metric.

Latent semantic analysis (LSA)

X - document-term co-occurrence matrix

$$X \approx \hat{X} = U\,\Sigma\,V^T$$

LSA term vectors
Hope: term having common meaning are mapped to the same direction



LSA document vectors
Hope: documents discussing similar topics have similar representations

TF-IDF

Term frequency–inverse document frequency.

We want to represent sentence or document with a vector, based on words we see in this document (also n-grams)

TF-IDF

Term frequency: $$tf(t,d) = \frac{f_{t,d}}{\sum_l f_{l,d}}$$

- $f_{t,d}$ is number of times term t occurs in document d

Another way: $$\mathrm{tf}(t,d) = 0.5 + 0.5 \cdot \frac{f_{t,d}}{\max\{f_{t',d} : t' \in d\}}$$

- Such view is needed to prevent a bias towards long documents

TF-IDF

Inverse document frequency: $$\mathrm{idf}(t, D) = \log \frac{N}{|\{d \in D : t \in d\}|}$$

- N - total number of documents in corpus
- Denominator is the number of documents where t appears

TF-IDF

$$\mathrm{tfidf}(t, d, D) = \mathrm{tf}(t, d) \cdot \mathrm{idf}(t, D)$$

$$\mathrm{tf}(t, d) = 0.5 + 0.5 \cdot \frac{f_{t,d}}{\max\{f_{t',d} : t' \in d\}}$$

$$\mathrm{idf}(t, D) = \log \frac{N}{|\{d \in D : t \in d\}|}$$

Probabilities

$$tf(t,d) = \frac{f_{t,d}}{\sum_l f_{l,d}}$$

$$tf(t,d) \sim P(t)$$

$$\mathrm{idf}(t,D) = \log \frac{N}{|\{d \in D : t \in d\}|}$$

$$idf(t,D) \sim \log \frac{1}{P(t|d)}$$

$$tfidf(t,d) \sim -P(t)\log(P(t|d))$$

Bag-of-words

Bag-of-words is a model where a text is represented as as bag (multiset) of its words.

We do not consider word order here.

```
Sentence: "John","likes","to","watch","movies","Mary","likes","movies","too"
BoW = {"John":1,"likes":2,"to":1,"watch":1,"movies":2,"Mary":1,"too":1}
```

N-gram Bag-of-words

Instead of words we do the same with n-grams:

```
[
    "John likes",
    "likes to",
    "to watch",
    "watch movies",
    "Mary likes",
    "likes movies",
    "movies too",
]
```