Natural Language Processing

Romain Benassi

Course 1

Spring 2024

Romain Benassi

Data Scientist (PhD) with specialty in Deep Learning, **NLP**, Energy and Bayesian methods

- **Since 2020**: Consultant at ***Publicis Sapient France***, mainly in **NLP** field

publicis
sapient

- **2013-2019** : Data Scientist in the field of energy (in several start-ups)
- **2013** : PhD on Bayesian statistics (***Centrale-Supélec***)

CentraleSupélec

- **2009** : Engineer’s degree (***IMT Atlantique***) with specialization in signal processing

IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

Romain Benassi

Experience in Natural Language Processing (NLP)

Since 2019, three projects on this field

- **Vidal**: work on deep learning algorithms for automatic indexation of medical documents
- **Enedis**: Automatic classification, and topic extraction, from strategic text documents
- **Tamalou** project: development of a supervised clustering algorithm and automatic reply association for medical texts from internet forums

Co-speaker in Devoxx France 2022 : *l'IA pour le bon usage du médicament* (Vidal & Publicis Sapient)

https://www.youtube.com/watch?v=1qeiou8GGj8

One blog article (in French)

https://blog.engineering.publicissapient.fr/2021/03/17/nlp-concepts-cles-et-etat-de-lart/

Online formation certifications (as student)

- Natural Language Processing Specialization (4-course specialization)
- Introduction to TensorFlow for Artificial Intelligence, Machine Learning, and Deep Learning
- Natural Language Processing in TensorFlow

Course Schedule

- **Course 1**: NLP introduction
- **Course 2**: Word embedding
- **Course 3**: LSTM (Long Short-Term Memory) principle
- **Course 4**: “Attention” Mechanism and Transformer Architectures
- **Course 5**: Large Language Models and Generative AI

Evaluation

1. **A graded exam will be used as evaluation and will be done at the beginning of the last course (Course 5)**

   This exercise will contain

   - multiple-choice-questions (MCQ)
   - theoretical questions
   - Coding questions

2. **A graded project (details given in the following Courses)**

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- **Course 1**: NLP introduction
- **Course 2**: Word embedding
- **Course 3**: LSTM (Long Short-Term Memory) principle
- **Course 4**: “Attention” mechanism and Transformer architectures
- **Course 5**: Large Language Models and Generative AI

Course Schedule

- **Course 1**: **NLP introduction**
  - **NLP use cases**
  - **Preprocessing** (tokenization, stemming, lemmatization…)
  - **NLP libraries** (spaCy and NLTK)
  - **Text Mining** (Bag of words, TF-IDF)
  - **Topic Modeling** (NMF, LDA)

This Week

- **Course 2**: Word embeddings

- **Course 3**: Long Short-Term Memory (LSTM) architecture

- **Course 4**: “Attention” mechanism and Transformer architectures

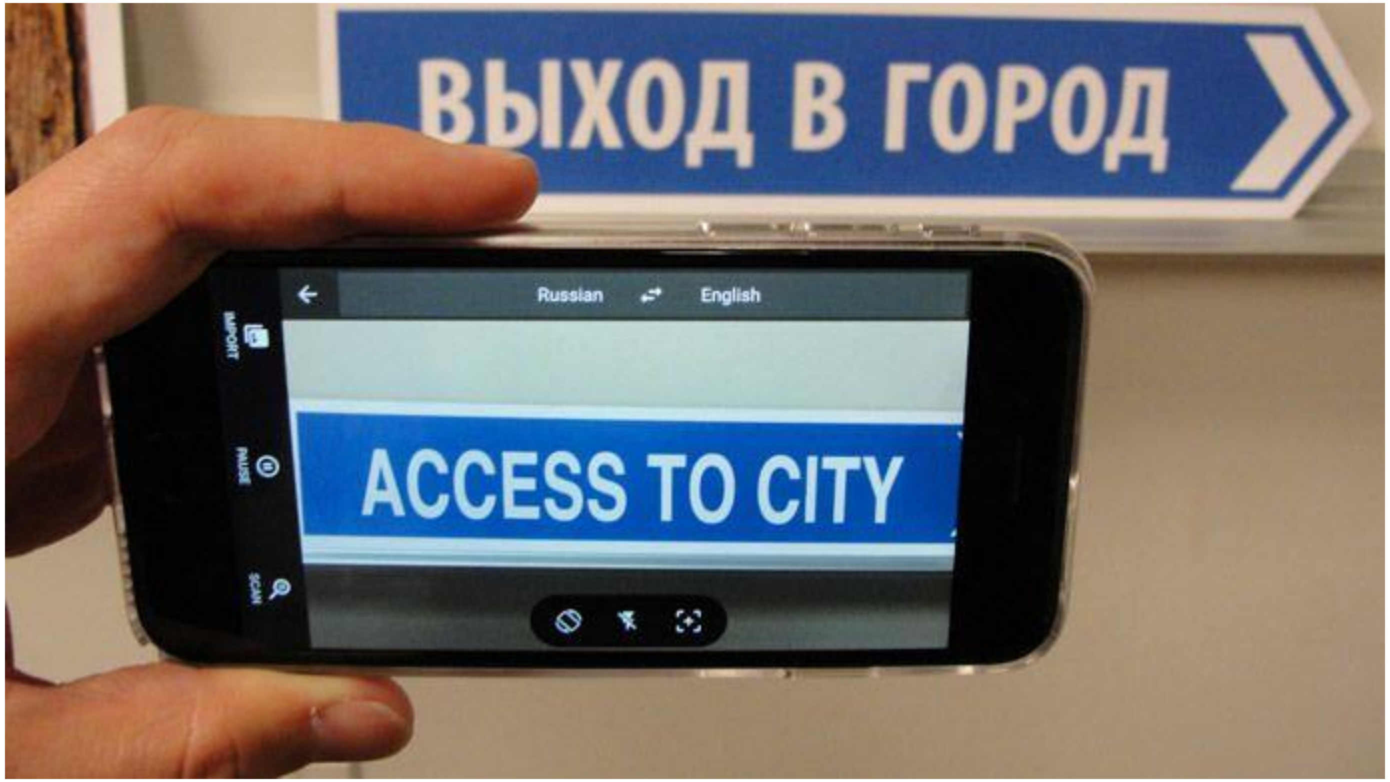
- **Course 5**: Large Language Models and Generative AI

Course 1: NLP Introduction

NLP use cases

NLP use cases

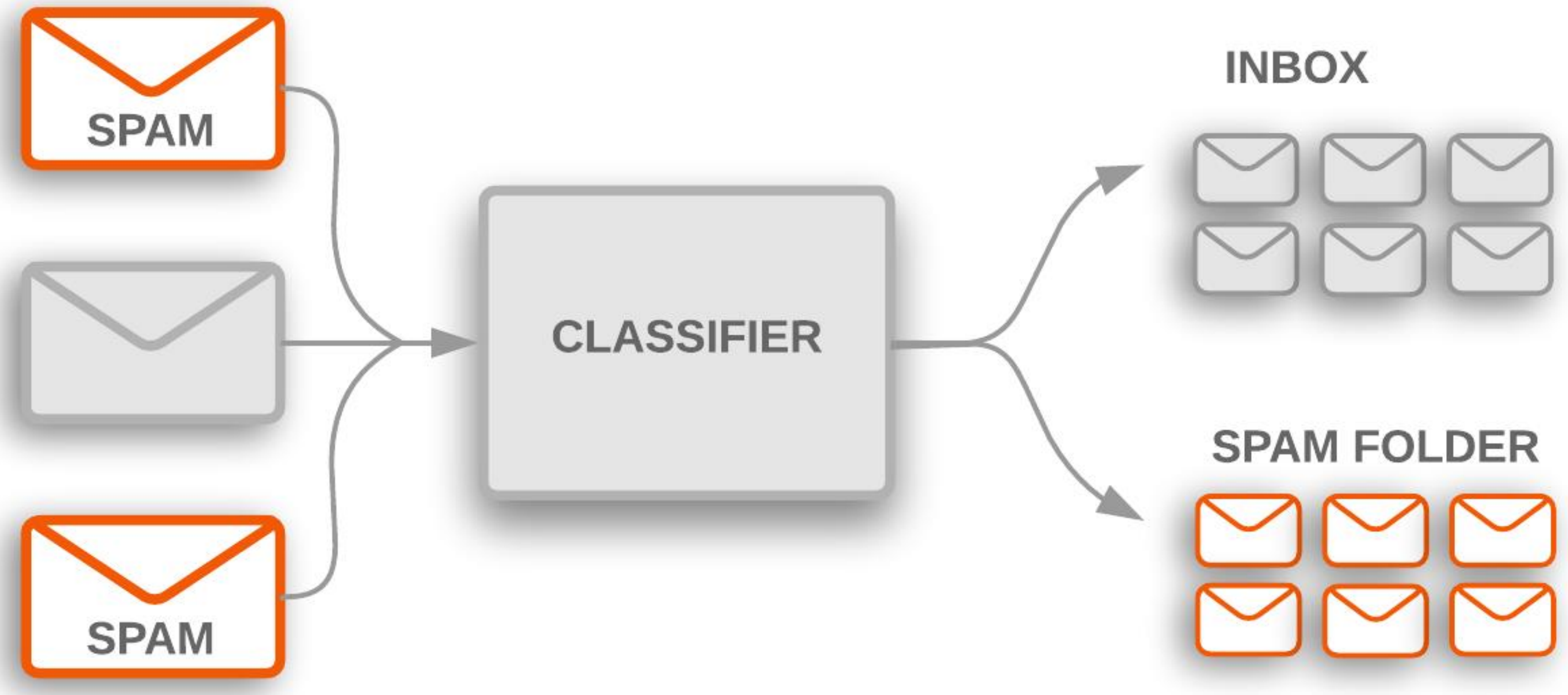
Translation



https://marmelab.com/blog/2017/05/05/dotai.html

NLP use cases

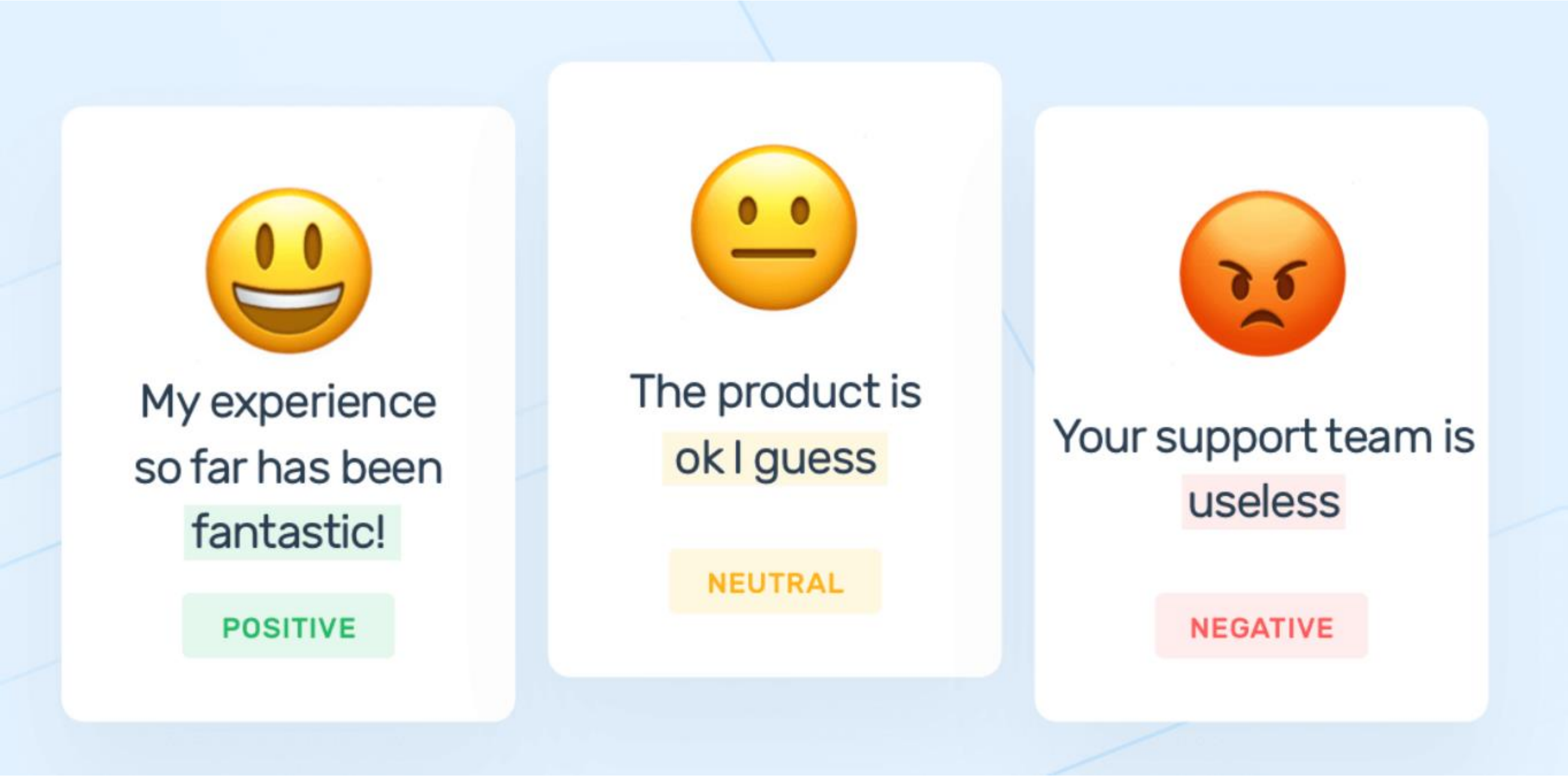
Spam detection



https://medium.com/@naveeen.kumar.k/naive-bayes-spam-detection-7d087cc96d9d

NLP use cases

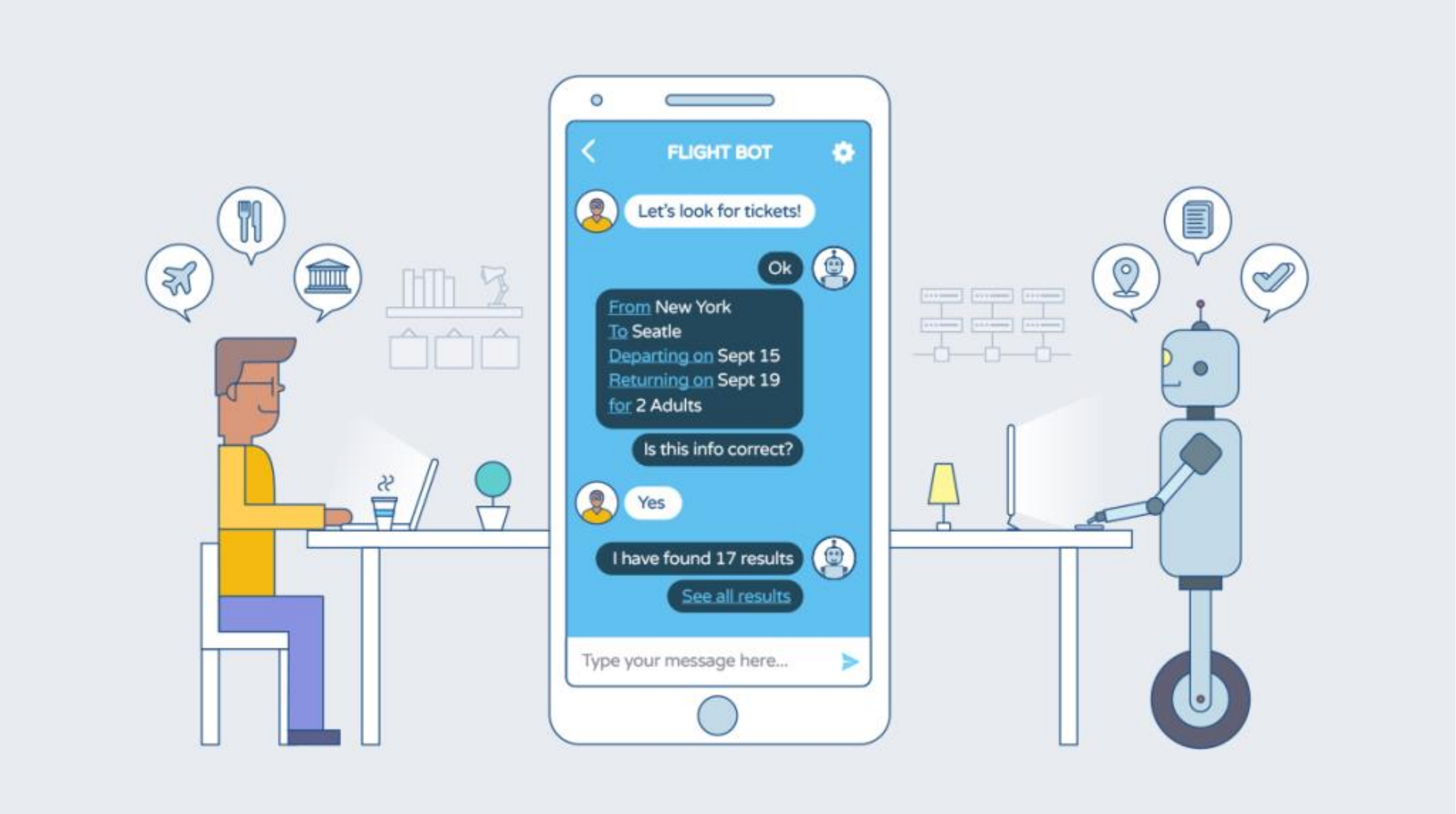
Sentiment analysis



https://monkeylearn.com/sentiment-analysis/

NLP use cases

Chatbot



https://tendancecom.com/les-avantages-marketing-du-chatbot

NLP use cases

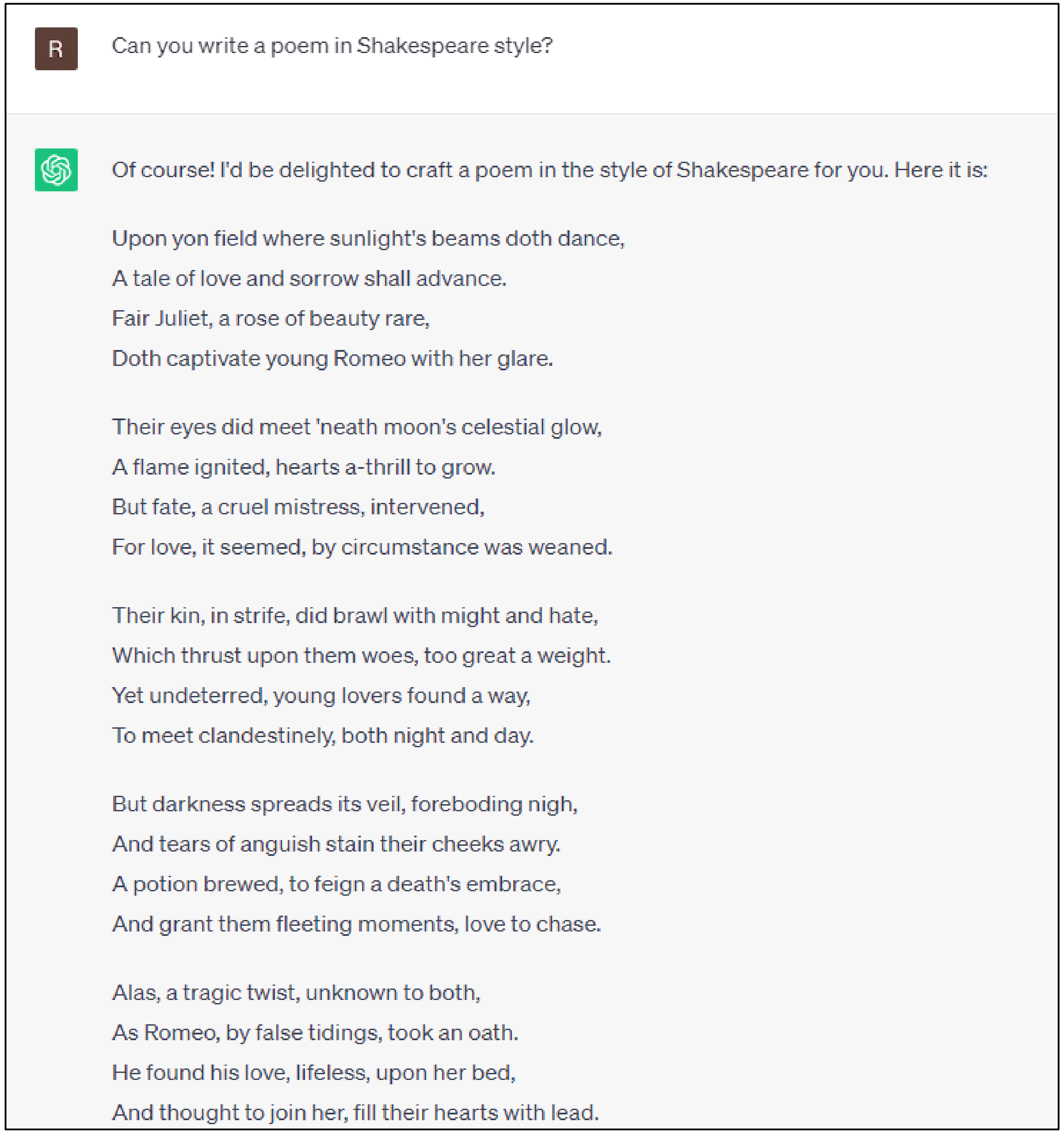
Image generation : DALL-E 2, Midjourney, Imagen…

Spider-Man from ancient Rome

https://labs.openai.com/s/MEWyqzcI8X85dIaMyNo5OEgy

NLP use cases

Text generation : Chat-GPT



R

Can you write a poem in Shakespeare style?

Of course! I'd be delighted to craft a poem in the style of Shakespeare for you. Here it is:

Upon yon field where sunlight's beams doth dance,
A tale of love and sorrow shall advance.
Fair Juliet, a rose of beauty rare,
Doth captivate young Romeo with her glare.

Their eyes did meet 'neath moon's celestial glow,
A flame ignited, hearts a-thrill to grow.
But fate, a cruel mistress, intervened,
For love, it seemed, by circumstance was weaned.

Their kin, in strife, did brawl with might and hate,
Which thrust upon them woes, too great a weight.
Yet undeterred, young lovers found a way,
To meet clandestinely, both night and day.

But darkness spreads its veil, foreboding nigh,
And tears of anguish stain their cheeks awry.
A potion brewed, to feign a death's embrace,
And grant them fleeting moments, love to chase.

Alas, a tragic twist, unknown to both,
As Romeo, by false tidings, took an oath.
He found his love, lifeless, upon her bed,
And thought to join her, fill their hearts with lead.

NLP main issue

Computers are known to be good at handling numerical data

⇨ **What can we do with text data?!**

https://www.tes.com/teaching-resource/data-representation-texts-images-and-sound-compression-and-file-types-computer-science-igcse-12193121

Preprocessing

Common NLP tasks

- Tokenization
- Stemming
- Lemmatization
- Removal of stop words

Tokenization

Tokenization is the breaking up of raw text into smaller relevant parts (tokens). These parts can be words or groups of successive letters.

<u>Example of word tokenization:</u>

Raw text : *My son's friend, however, plays a high-risk game.*

Tokenized : [*My*] [*son*] [*'s*] [*friend*] [,] [*however*] [,] [*plays*] [*a*] [*high*] [-] [*risk*] [*game*] [.]

Stemming

Stemming is the process of reducing a word to its root form (word stem).

Most of the time, it consists to drop the last letters of the word until the stem is reached.

Example of stemming:

fishing, fished or fisher => fish

Stemming

- Porter’s algorithm (1980) is one of the most well-know stemming procedure used for English language
- Five reduction phases used in order to get the stem of the word
- Different variants of the original Porter’s stemming procedure exists like Snowball or the English Stemmer (Porter2 stemmer)

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First phase

S1		S2	word		stem
SSES	→	SS	caresses	→	caress
IES	→	I	ponies	→	poni
			ties	→	ti
SS	→	SS	caress	→	caress
S	→		cats	→	cat

More sophisticated rules

S1		S2	word		stem
(m>0) ATIONAL	→	ATE	relational	→	relate
			national	→	national
(m>0) EED	→	EE	agreed	→	agree
			feed	→	feed

https://www.udemy.com/course/nlp-natural-language-processing-with-python

Stemming

Porter Stemmer (NLTK) example

```
run----->run
runner----->runner
ran----->ran
runs----->run
easily----->easili
fairly----->fairli
fairness----->fair
```

https://www.udemy.com/course/nlp-natural-language-processing-with-python

Stemming

Snowball Stemmer (NLTK) was developed as well by Porter and offers a slight improvement both in logic and speed.

```
run  ------> run
runner  ------> runner
ran  ------> ran
runs  ------> run
easily  ------> easili
fairly  ------> fair
fairness  ------> fair
```

https://www.udemy.com/course/nlp-natural-language-processing-with-python

Lemmatization

Lemmatization is the algorithmic process of determining the canonical form (lemma) of a word.

Unlike stemming, it is not only a word reduction but depends on the meaning of the word in a sentence and needs to consider a language’s full vocabulary.

<u>Example of lemmatization:</u>

was -> *be*

meeting -> *meet* or *meeting* (depending on the context)

walking -> *walk* (identical to stemming)

Lemmatization

- Lemmatization gives a more informative result than stemming
- It looks at surrounding text to correctly identify the part of speech and meaning of the word
- For theses reasons, a lemmatization procedure exists directly in spaCy whereas this is not the case for stemming, considered as a less efficient preprocessing step
- Stemming procedures (including both Porter and Snowball) can be found in NLTK if needed

Removal of stop-words

- A stop-word is a word so frequent that it makes it not relevant to take it into account during an analysis
- Most of the time, there are filtered out before any NLP processing
- Obviously, each language has its own specific set of stop-words
- <u>Examples</u>
  - In English: *the*, *is*, *at*, *which*, *on*…
  - In French: *le*, *la*, *du*, *ce*…
- spaCy has a list of 305 English stop-words

NLP Libraries

spaCy and NLTK

- spaCy (2015) and NLTK (2001) are both popular NLP libraries
- spaCy implements generally only one algorithm for each task, but the most efficient one currently available
- NLTK provides generally several algorithms for each tasks, but with less efficient implementations

spaCy gives more efficient implementations but offers less possibilities than NLTK

The choice between both should be made depending on the applications

spaCy and NLTK

	ABSOLUTE (MS PER DOC)			RELATIVE (TO SPACY)		
SYSTEM	TOKENIZE	TAG	PARSE	TOKENIZE	TAG	PARSE
spaCy	0.2ms	1ms	19ms	1x	1x	1x
CoreNLP	0.18ms	10ms	49ms	0.9x	10x	2.6x
ZPar	1ms	8ms	850ms	5x	8x	44.7x
NLTK	4ms	443ms	*n/a*	20x	443x	*n/a*

https://www.udemy.com/course/nlp-natural-language-processing-with-python

spaCy and NLTK

	SPACY	SYNTAXNET	NLTK	CORENLP
Programming language	Python	C++	Python	Java
Neural network models	✓	✓	✗	✓
Integrated word vectors	✓	✗	✗	✗
Multi-language support	✓	✓	✓	✓
Tokenization	✓	✓	✓	✓
Part-of-speech tagging	✓	✓	✓	✓
Sentence segmentation	✓	✓	✓	✓
Dependency parsing	✓	✓	✗	✓
Entity recognition	✓	✗	✓	✓
Coreference resolution	✗	✗	✗	✓

https://www.udemy.com/course/nlp-natural-language-processing-with-python

NLP Basics: Tutorial

course1_basics_NLP.ipynb

Goal: Get used to classic NLP preprocessing operations (lemmatization, stemming, entity detection…) using both spaCy and NLTK library

Text Mining

Text Mining

- Examining of document collection (*corpus*) to discover new information
- This can be used as a first step for lots of different applications (topic modeling, spam detection, sentiment analysis, security…)
- We will focus on two of the most famous text mining approaches
  - Bag-of-words (BoW) model
  - TF-IDF

Bag-of-words (BoW) model

In this model, a document *d* is represented as a set of tuples

{*w*: nb of occurrences of *w* in *d* | for all word *w* in *d*}

Example

For the (short) document:

"Xavier likes to play football. Eric likes football too."

The bag-of-word representation is:

{*Xavier*: 1, *likes*: 2, *to*: 1, *play*: 1, *football*: 2, *Eric*: 1, *too*: 1}

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{*Xavier*: 1, *likes*: 2, *to*: 1, *play*: 1, *football*: 2, *Eric*: 1, *too*: 1}

It is equivalent to a word-frequency histogram representation

Bag-of-words (BoW) model

If we have several texts:

Document1: *"Xavier likes to play football. Eric likes football too."*
Document2: *"Eric prefers tennis to football."*

We have the representation below:

	Xavier	likes	to	play	football	Eric	too	prefers	tennis
Document1	1	2	1	1	2	1	1	0	0
Document2	0	0	1	0	1	1	0	1	1

This representation can be used to characterize texts (e-g in spam filtering)

Bag-of-words (BoW) model

If we have several texts:

Document1: *"Xavier likes to play football. Eric likes football too."*
Document2: *"Eric prefers tennis to football."*

The documents are transformed into numerical representations

We have the representation below:

	Xavier	likes	to	play	football	Eric	too	prefers	tennis
Document1	1	2	1	1	2	1	1	0	0
Document2	0	0	1	0	1	1	0	1	1

This representation can be used to characterize texts (e-g in spam filtering)

Bag-of-words (BoW) model

This simple model has some drawbacks

- Term frequencies are not necessarily the best representation of a text
- Each time of new word appears, the length of the vector increases as well
- Most of the time, text representations are sparse (many zeros)
- No information about grammar or about the original word ordering is kept

TF-IDF

- TF-IDF means term frequency-inverse document frequency
- This is a ponderation method used in information retrieval.
- This statistical measure gives **an evaluation of how important is a word to a document**, depending on the corpus considered
- The weight increase proportionally to the occurrences of a word in a text
- This weight is **also** offset by the number of documents in the corpus containing the word

TF-IDF

TF-IDF is calculated as : $\mathrm{tfidf}(t, d, D) = \mathrm{tf}(t, d) \cdot \mathrm{idf}(t, D)$

TF-IDF: tf(t,d)

TF-IDF is calculated as : $\mathrm{tfidf}(t, d, D) = \boxed{\mathrm{tf}(t, d)} \cdot \mathrm{idf}(t, D)$

Term frequency tf(t,d)

$$\mathrm{tf}(t, d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}},$$

With $f_{t,d}$ the number of times term *t* appears in document *d*

TF-IDF: tf(t,d)

Term frequency tf(t,d) variants :

Variants of term frequency (tf) weight

weighting scheme	tf weight
binary	$0, 1$
raw count	$f_{t,d}$
term frequency	$f_{t,d} \Bigg/ \sum_{t' \in d} f_{t',d}$
log normalization	$\log(1 + f_{t,d})$
double normalization 0.5	$0.5 + 0.5 \cdot \frac{f_{t,d}}{\max_{\{t' \in d\}} f_{t',d}}$
double normalization K	$K + (1 - K)\frac{f_{t,d}}{\max_{\{t' \in d\}} f_{t',d}}$

https://en.wikipedia.org/wiki/Tf%E2%80%93idf

TF-IDF: idf(t,d)

TF-IDF is calculated as : $\mathrm{tfidf}(t,d,D) = \mathrm{tf}(t,d) \cdot \boxed{\mathrm{idf}(t,D)}$

Inverse document frequency idf(t,D)

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

With *N* the number of documents in corpus *D*

TF-IDF: idf(t,d)

Inverse document frequency idf(t,D) variants :

Variants of inverse document frequency (idf) weight

weighting scheme	idf weight ($n_t = \|\{d \in D : t \in d\}\|$)
unary	1
inverse document frequency	$\log \frac{N}{n_t} = -\log \frac{n_t}{N}$
inverse document frequency smooth	$\log \left(\frac{N}{1 + n_t} \right) + 1$
inverse document frequency max	$\log \left(\frac{\max_{\{t' \in d\}} n_{t'}}{1 + n_t} \right)$
probabilistic inverse document frequency	$\log \frac{N - n_t}{n_t}$

https://en.wikipedia.org/wiki/Tf%E2%80%93idf

TF-IDF

TF-IDF is calculated as : $\mathrm{tfidf}(t, d, D) = \mathrm{tf}(t, d) \cdot \mathrm{idf}(t, D)$

$$\Rightarrow \quad \boxed{\frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}} \cdot \log \frac{N}{|\{d \in D : t \in d\}|}}$$

TF-IDF

Document1: *"Xavier likes to play football. Eric likes football too."*

Document2: *"Eric prefers tennis to football."*

	Xavier	likes	to	play	football	Eric	too	prefers	tennis
Document1	1	2	1	1	2	1	1	0	0
Document2	0	0	1	0	1	1	0	1	1
idf	Log(2)	Log(2)	0	Log(2)	0	0	Log(2)	Log(2)	Log(2)
tf_doc1	1/9	2/9	1/9	1/9	2/9	1/9	1/9	0	0
tf_doc2	0	0	1/5	0	1/5	1/5	0	1/5	1/5
tf-idf_doc1	0,033	0,067	0	0,033	0	0	0,033	0	0
tf-idf_doc2	0	0	0	0	0	0	0	0,06	0,06

TF-IDF

Document1: *"Xavier likes to play football. Eric likes football too."*

Document2: *"Eric prefers tennis to football."*

	Xavier	likes	to	play	football	Eric	too	prefers	tennis
Document1	1	2	1	1	2	1	1	0	0
Document2	0	0	1	0	1	1	0	1	1
idf	Log(2)	Log(2)	0	Log(2)	0	0	Log(2)	Log(2)	Log(2)
tf_doc1	1/9	2/9	1/9	1/9	2/9	1/9	1/9	0	0
tf_doc2	0	0	1/5	0	1/5	1/5	0	1/5	1/5
tf-idf_doc1	0,033	0,067	0	0,033	0	0	0,033	0	0
tf-idf_doc2	0	0	0	0	0	0	0	0,06	0,06

Again, the documents are transformed into numerical representations

TF-IDF: Exercise

course1_tfidf_ex.ipynb

Goal: Illustration of TF-IDF on a very simple corpus

Remarks:

- We compute the TF-IDF twice on the same corpus (directly from the formula and with *sklearn* library)
- The results may be different depending on the settings used with the *sklearn* function

Topic Modeling

Topic modeling

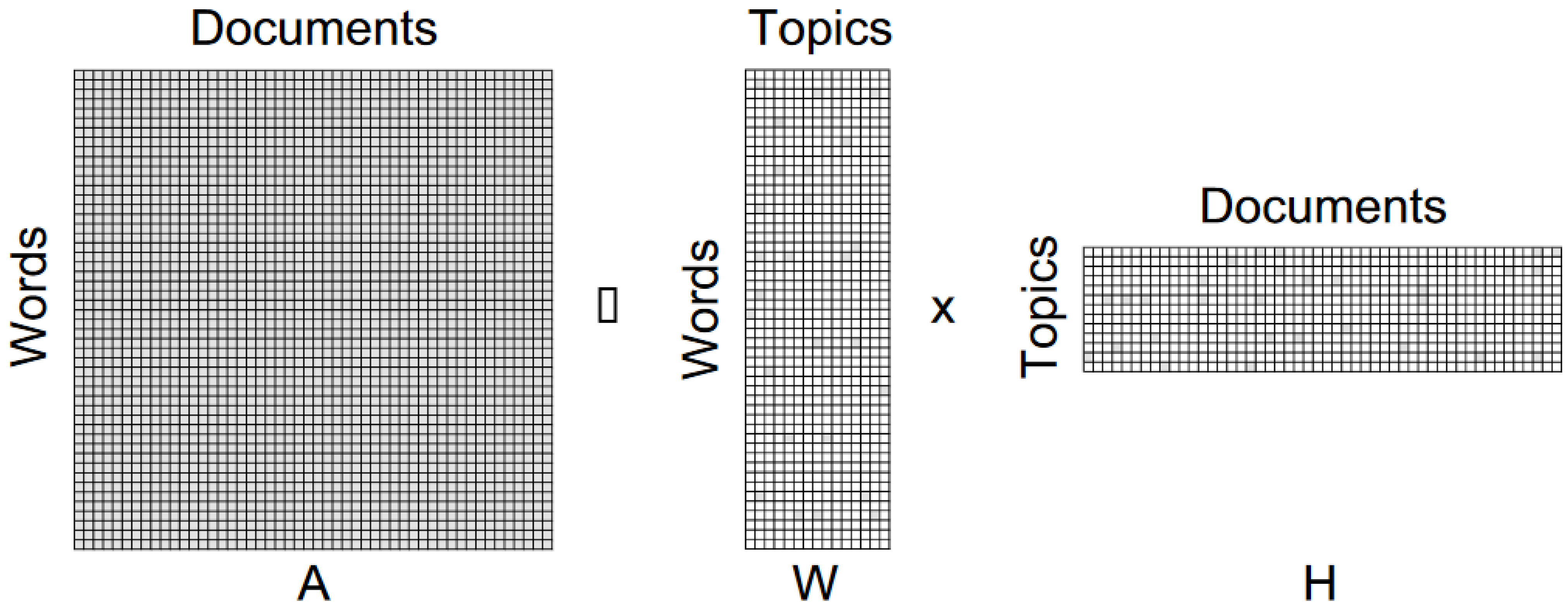
- Unsupervised algorithms
- Use to analyze text by clustering document into topics
- The idea is for the documents in the same cluster to correspond to a common topic
- Can be used to analyze large volumes of text

Non-negative Matrix factorization (NMF)

- Non-negative Matrix Factorization is an unsupervised topic modeling algorithm
- The number of clusters must be defined by the user
- It allows both clustering and dimensionality reduction
- Generally, it is used from a **TF-IDF procedure** performed on all the documents of the corpus

Non-negative Matrix factorization (NMF)

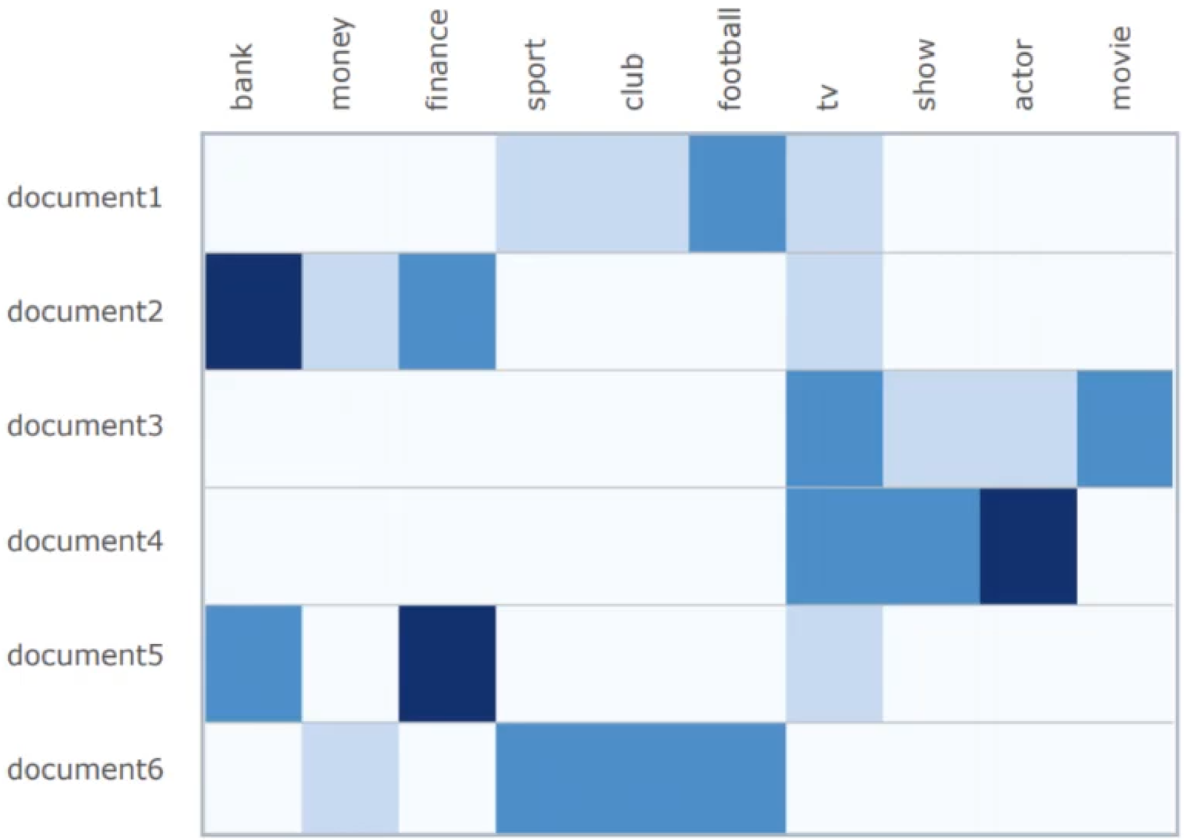
The procedure involves the decomposition of matrix A as the product of two other matrices W and H. All three matrices are non-negative



https://www.researchgate.net/publication/312157184_Crime_Topic_Modeling/download

Non-negative Matrix factorization (NMF)

The A’ matrix comes from a TF-IDF vectorization



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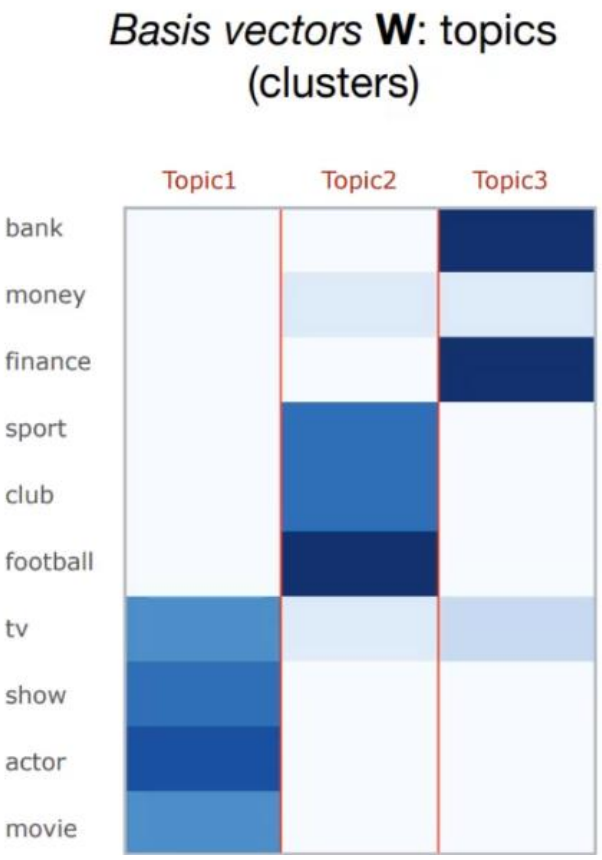
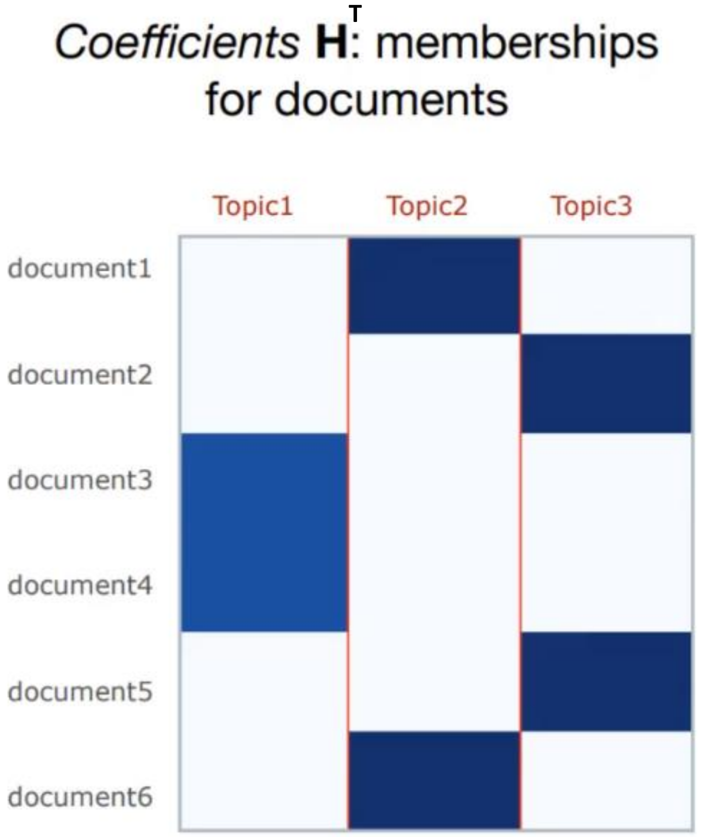
Non-negative Matrix factorization (NMF)





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Non-negative Matrix factorization (NMF)

Procedure

- **Inputs**: Matrix A, a number *k*, matrices W and H randomly generated
- **Objective function**: the reconstruction error between A and WH

$$\frac{1}{2}||\mathbf{A}-\mathbf{WH}||_{\mathsf{F}}^{2}=\sum_{i=1}^{n}\sum_{j=1}^{m}(A_{ij}-(WH)_{ij})^{2}$$

- The computation of W and H are performed sequentially with an **Expected-Maximization** (EM) procedure until convergence

1. Update **H**

$$H_{cj} \leftarrow H_{cj}\frac{(W\mathbf{A})_{cj}}{(W\mathbf{WH})_{cj}}$$

2. Update **W**

$$W_{ic} \leftarrow W_{ic}\frac{(\mathbf{A}H)_{ic}}{(\mathbf{WH}H)_{ic}}$$

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Latent Dirichlet Allocation (LDA)

- Dirichlet was a German mathematician (1805-1859)
- The Dirichlet Distribution was named after him
- LDA is a statistical model based on this specific distribution
- It was first presented in 2002 (Blei, Ng and Jordan) for document topic detection
- Since then, this model has been used in many applications (data mining, NLP…)

Latent Dirichlet Allocation (LDA)

LDA principles

- Documents with similar topics use similar groups of words
- Latent topics correspond to groups of word frequently occurring together in the corpus documents

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- Each word's presence is attributable to a topic (considered here as a probability distribution over words)

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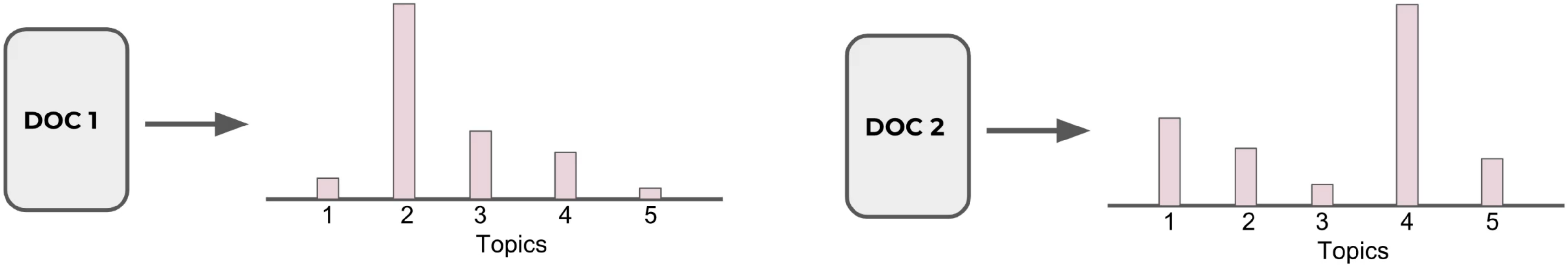

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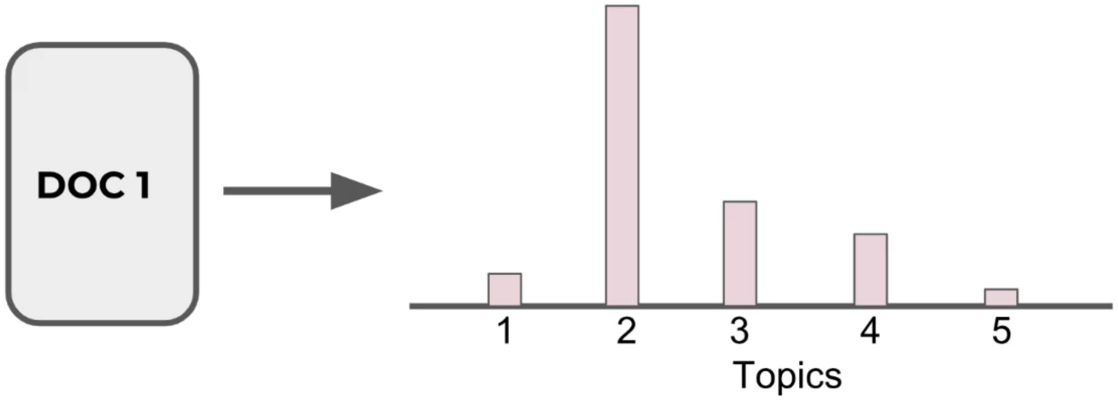
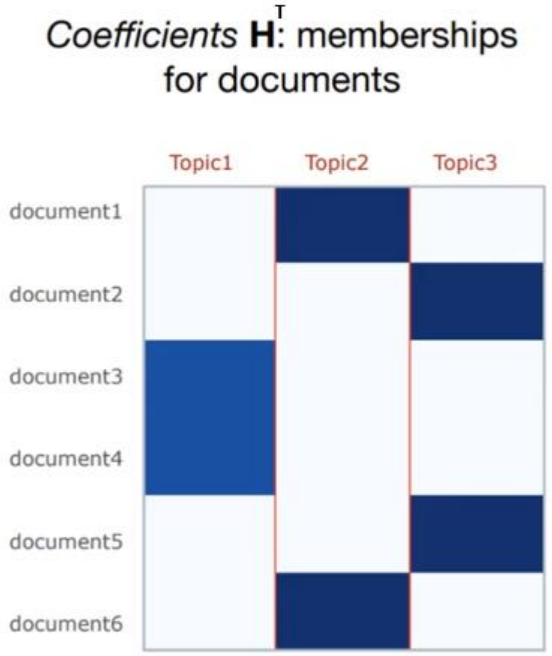
Latent Dirichlet Allocation (LDA)

Comparison with NMF: weights of topics for each document



LDA



NMF

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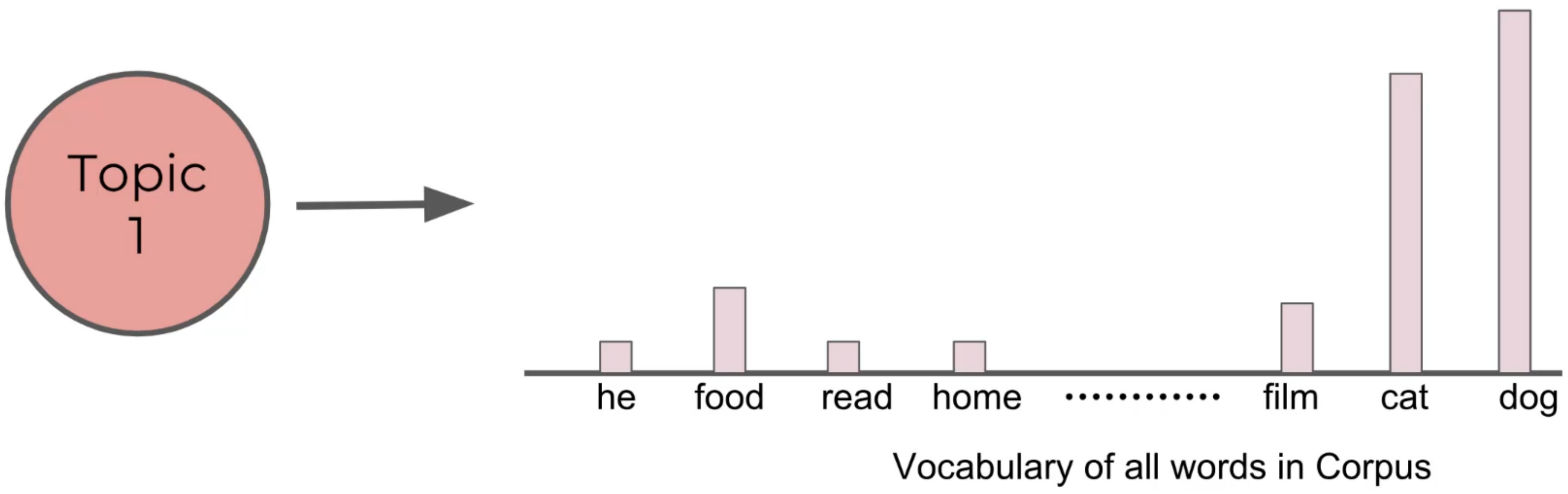

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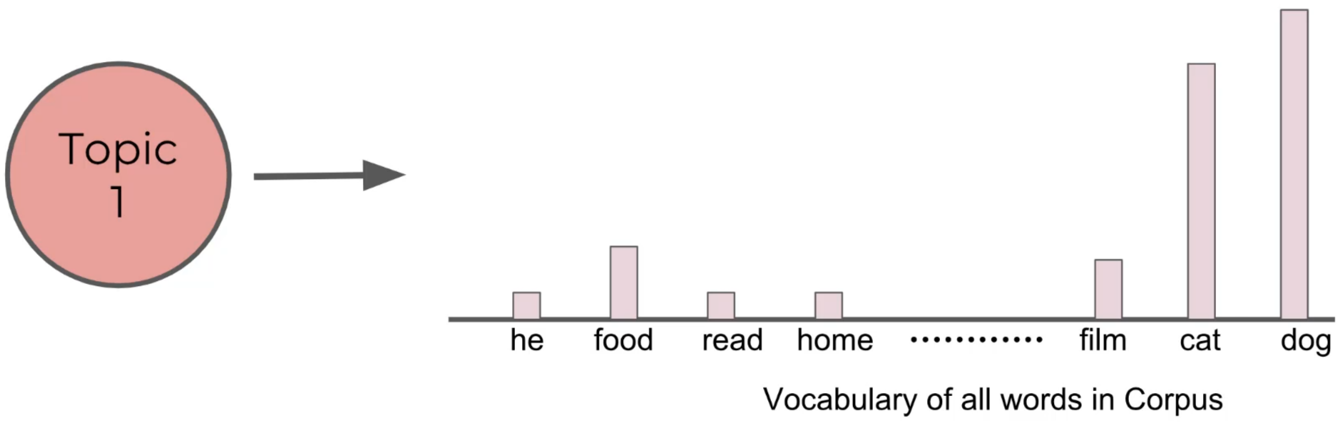
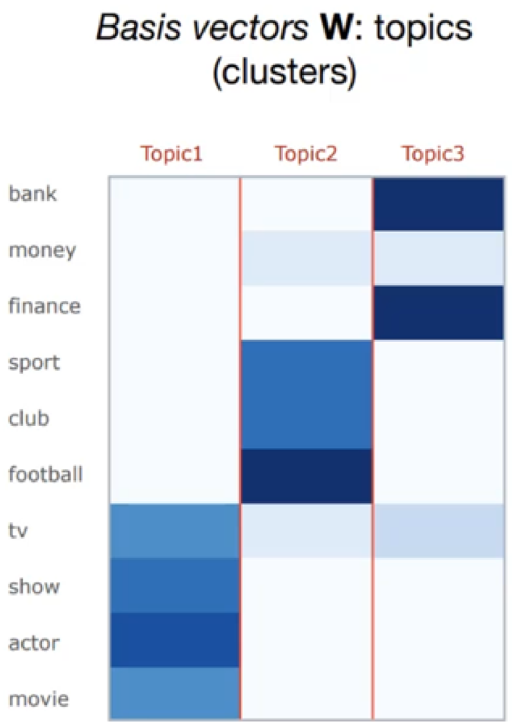
Comparison with NMF: weights of words on each topic



LDA



NMF

https://www.udemy.com/course/nlp-natural-language-processing-with-python

Latent Dirichlet Allocation (LDA)

A document can be seen as

- A chosen N number of words
- A specific mixture of topic (selected according to a Dirichlet distribution over the set of topics)-e.g.: 50% cinema, 30% sport, 20% animals

Each word in the document are generated by the following procedure

- Chose a topic (according to the topics multinomial distribution) and generate from it a word

This is the generative model use to create a set of documents

Latent Dirichlet Allocation (LDA)

Let’s go back to the topic modelling objective

- We have a set of documents
- We chose a number *k* of topics to discover
- We use LDA for topic modelling, and to determine the topic representation of each document and the words associated to each topic

Latent Dirichlet Allocation (LDA)

Procedure

1. Randomly assign, according to a Dirichlet distribution, each word of each document to one of the *k* topics
2. You have a first (but meaningless) representation of the word and document distribution of the topics
3. We iterate over every word and every document in the following way. For each topic *t*, document *d* and word *w* we calculate:

   P(t|d) = proportion of words in *d* currently assigned to *t*

   P(w|t) = proportion of assignments to *t* over all documents containing *w*
4. Reassign each word *w* a new topic *t*, according the probability *p(w|t) . p(t|d)*
5. Repeat the previous steps enough times to converge to acceptable topic assignments

Latent Dirichlet Allocation (LDA)

- In the end of the procedure, we can assign document to topics
- However, we do not have relevant labels to associate topics with
- It is up to the user, in a next step, to find a way to identify these topics found

LDA & NLM: Exercise

course1_LDA_NMF_ex.ipynb

Goal: Learn how to use **LDA** and **NMF** to address **Topic Modeling** on a **real dataset**

Remarks:

- We use *scikit-learn* implementation for **LDA** and **NMF**
- The dataset is composed of **real** questions taken from the internet forum ***Quora***

Take-away from Course 1

- One of the main issues of NLP is finding a **relevant numerical representation for texts**
- Before converting texts into numerical vectors, some **preprocessing steps** (tokenization, lemmatization, stemming, stop word removal…) exist and can prove **very useful**
- Bag-of-words (BoW) and TF-IDF can transform a corpus of texts into an **array of numerical vectors**
- These numerical vectors **can be used as input data** for classical ML procedures (e.g., topic modeling with LDA and NMF algorithms which rely respectively on BoW and TF-IDF)

References

Online formations

- https://www.udemy.com/course/nlp-natural-language-processing-with-python
- https://www.coursera.org/specializations/natural-language-processing

Book

Koehn, Statistical Machine Translation, Cambridge University Press (2009)