Natural Language Processing

AIS

Romain Benassi

Spring 2022

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**: Chatbot

Evaluation

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

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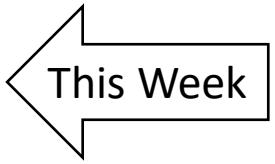
- **Course 2**: Word embedding
- **Course 3**: LSTM (Long Short-Term Memory) principle
- **Course 4**: “Attention” mechanism and Transformer architectures
- **Course 5**: Chatbot

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)



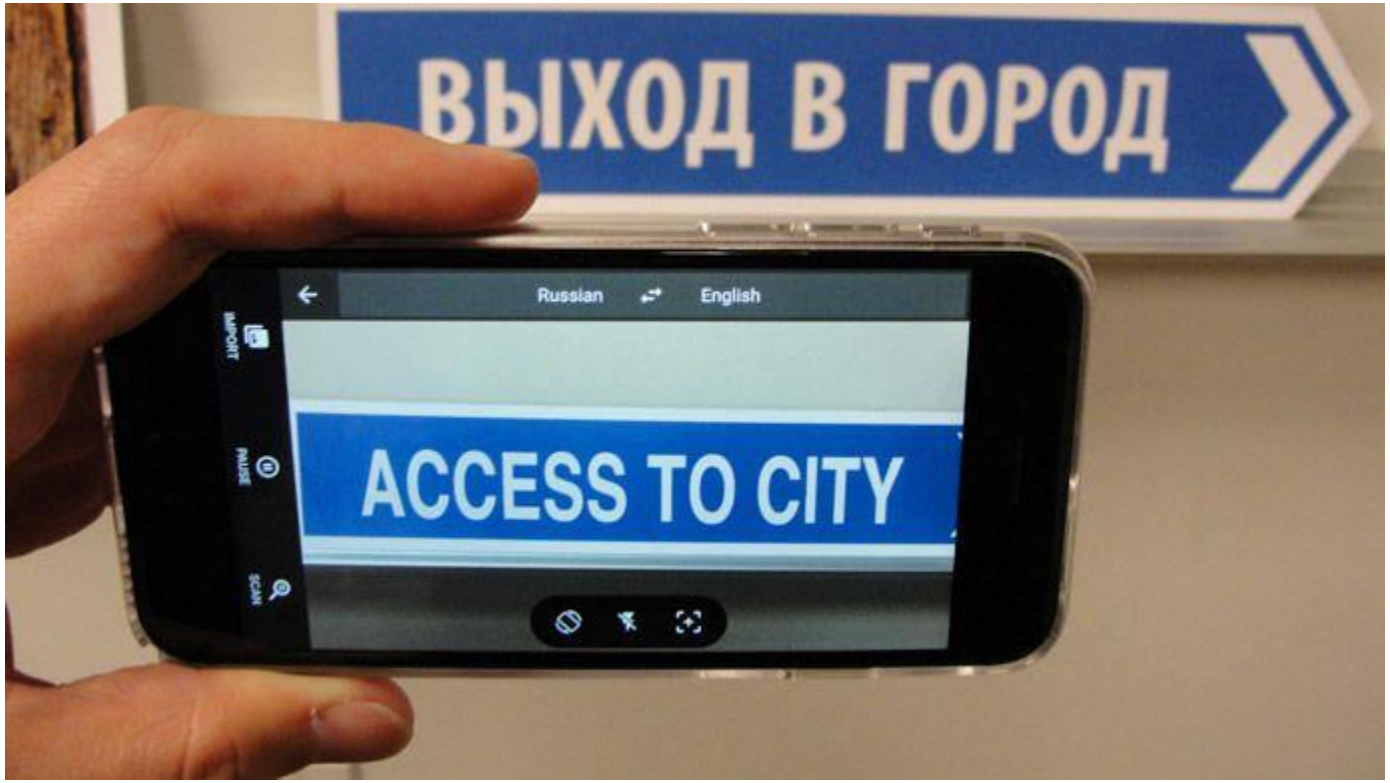
- **Course 2**: Word embeddings
- **Course 3**: Long Short-Term Memory (LSTM) architecture
- **Course 4**: “Attention” mechanism and Transformer architectures
- **Course 5**: Chatbot

Course 1: NLP Introduction

NLP use cases

NLP use cases

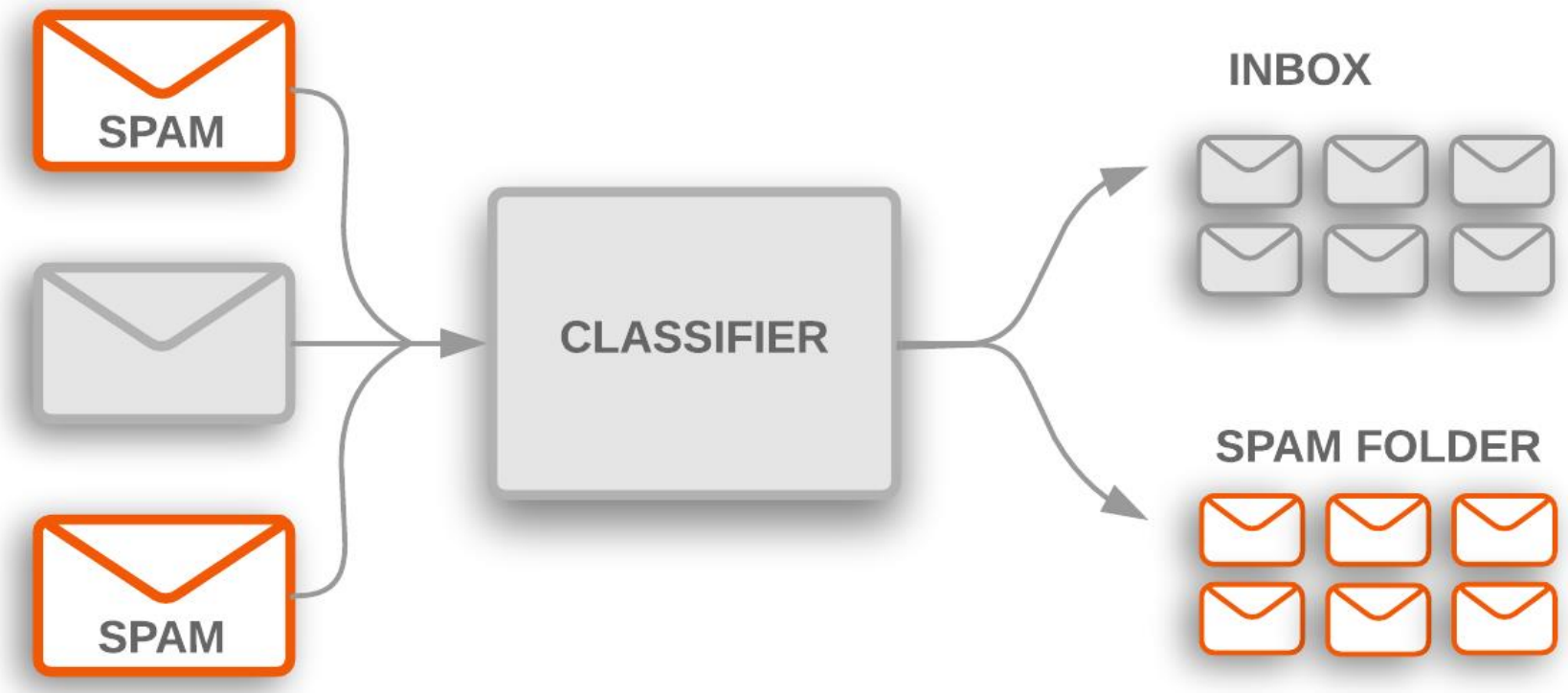
Translation



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

NLP use cases

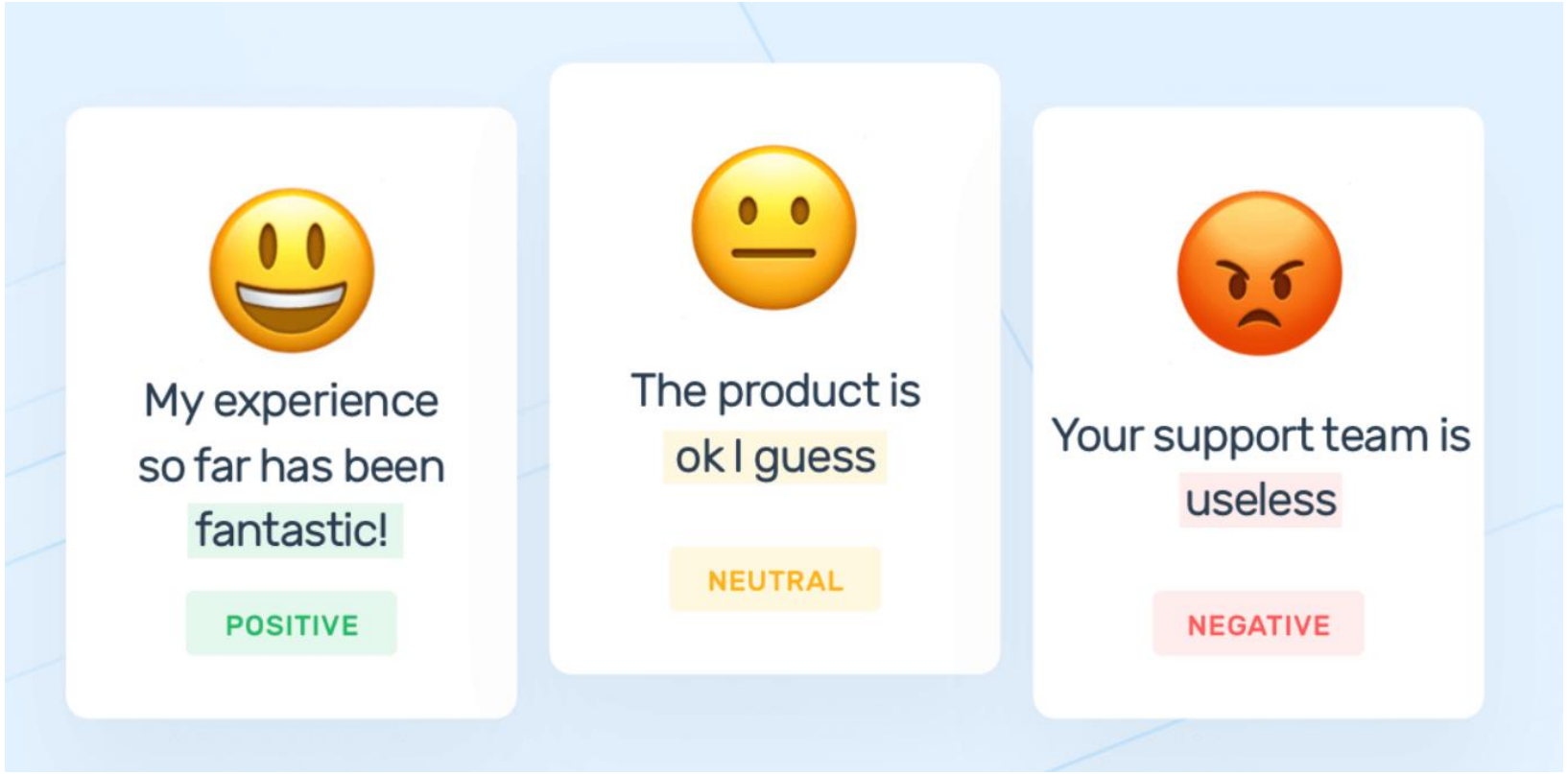
Spam detection



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

NLP use cases

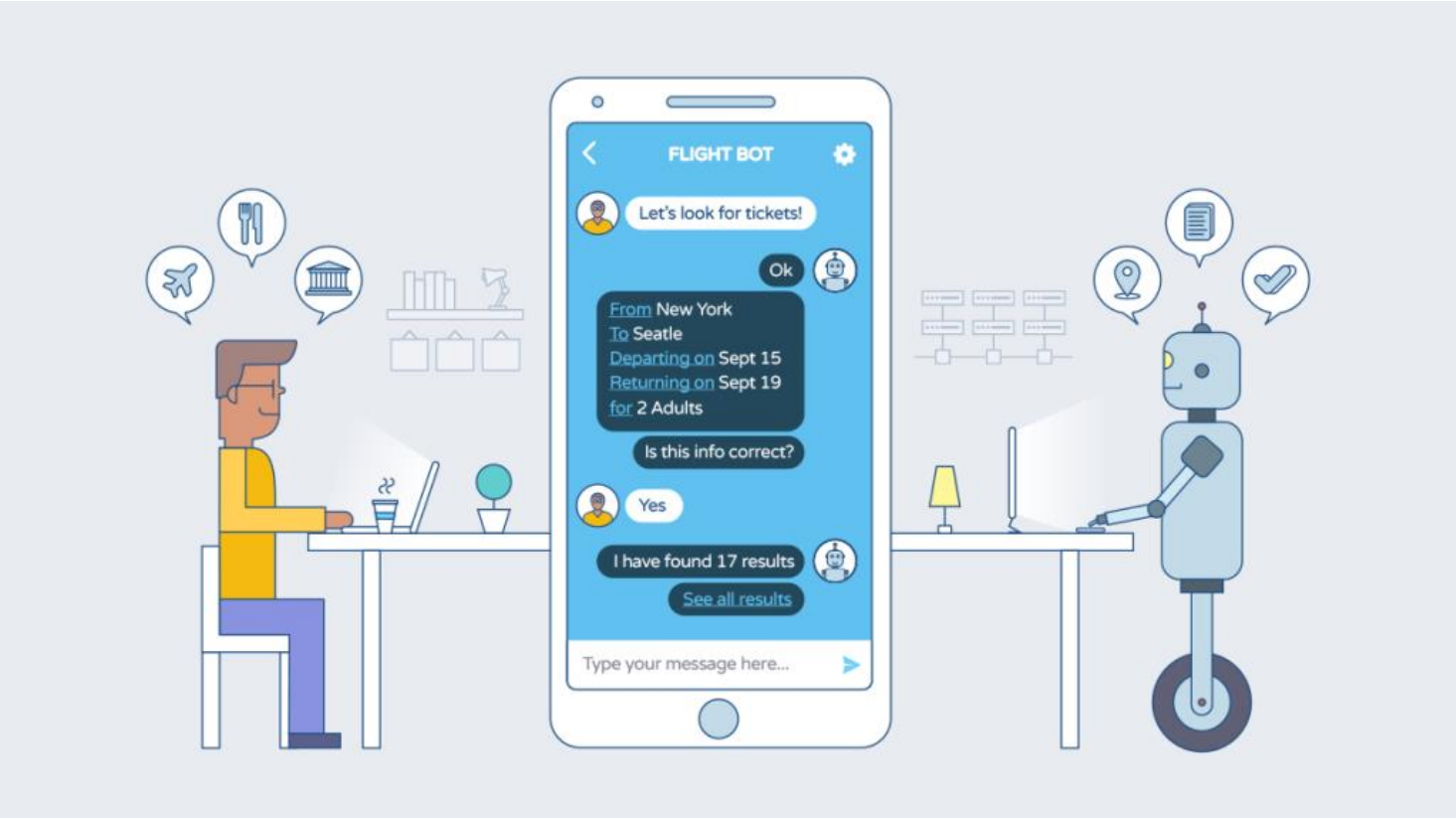
Sentiment analysis



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

NLP use cases

Chatbot



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

NLP main issue

Computers are known to be good at handling numerical data

⇨ **What can we do with text data?!**

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.

Example of word tokenization:

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.

Example of lemmatization:

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
- Examples
  - 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	✗	✗	✗	✓

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NLP Basics: Tutorial

course1_basics_NLP.ipynb

Goal: Get used to classic NLP prepocessing 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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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 representation

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	Xavier	likes	to	play	football	Eric	too	prefers	tennis
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This representation can be used to characterize texts (e-g in spam filtering)

Bag-of-words (BoW) model

This simple model have 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)

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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	$f_{t,d} \Big/ \sum_{t' \in d} f_{t',d}$
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 : $\mathrm{tfidf}(t, d, D) = \mathrm{tf}(t, d) \cdot \mathrm{idf}(t, D)$

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 :

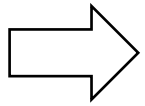
Variants of inverse document frequency (idf) weight

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



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

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."*

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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 representation

TF-IDF: Exercise

course1_tfidf_ex.ipynb

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

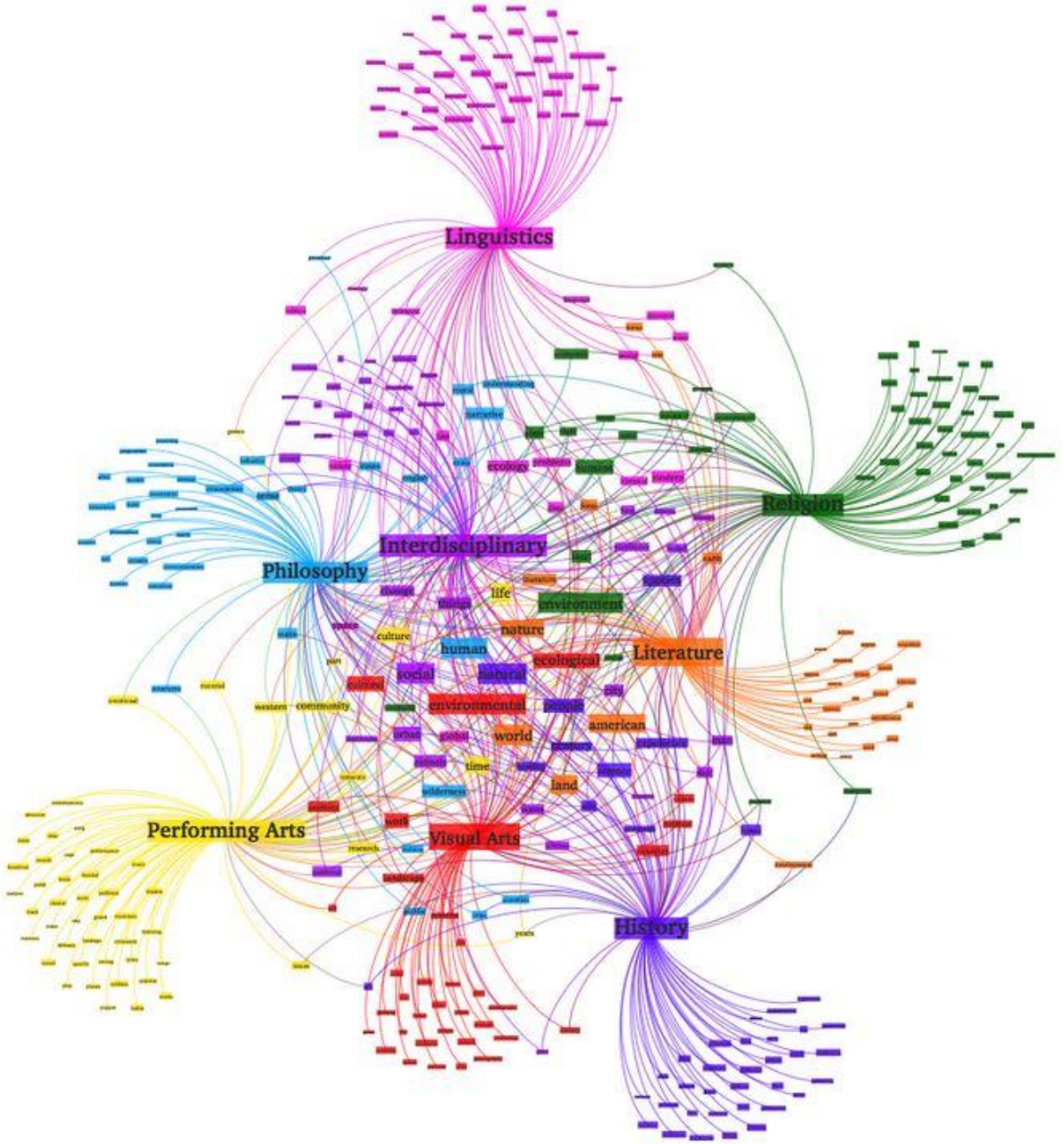
Remarks:

- 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

Clustering document into topics



https://medium.com/nanonets/topic-modeling-with-lsa-psla-lda-and-lda2vec-555ff65b0b05

Topic modeling

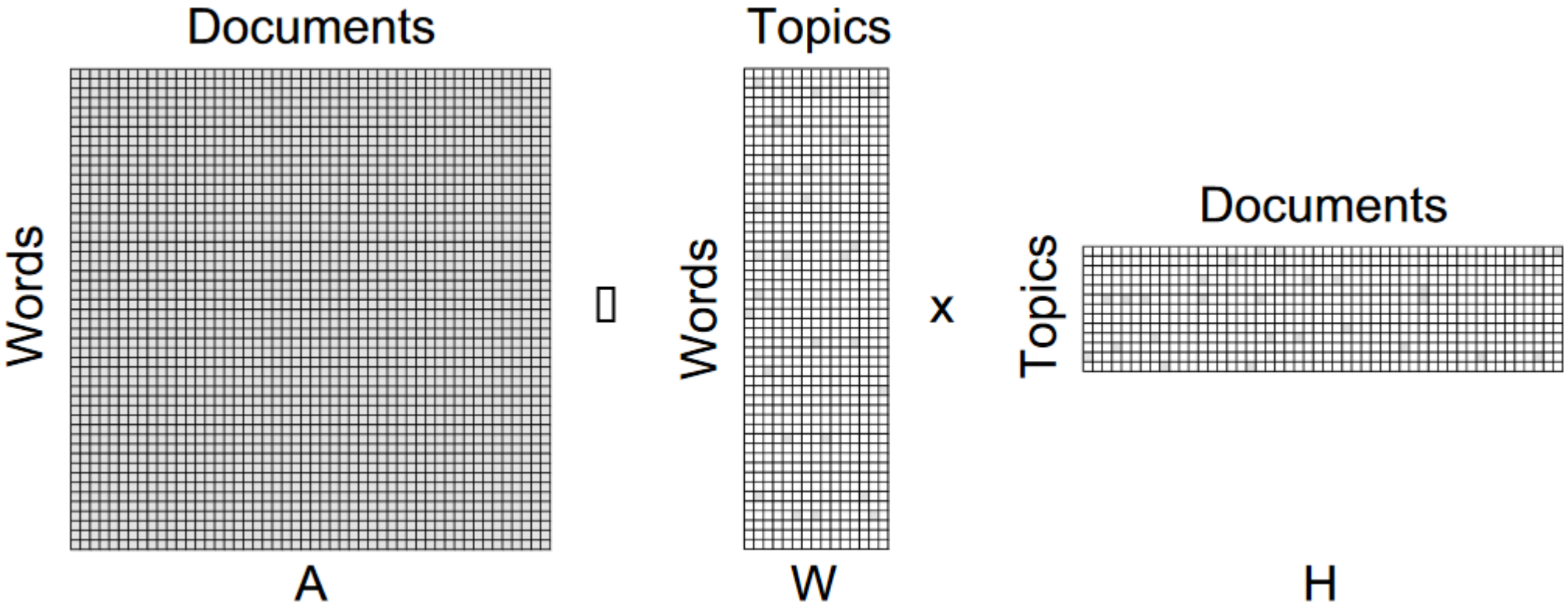
- Unsupervised algorithms
- Use to analyze text by clustering document into topics
- The idea is for the documents in the same cluster to correspond to a common topic
- Can be used to analyze large volumes of text

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)

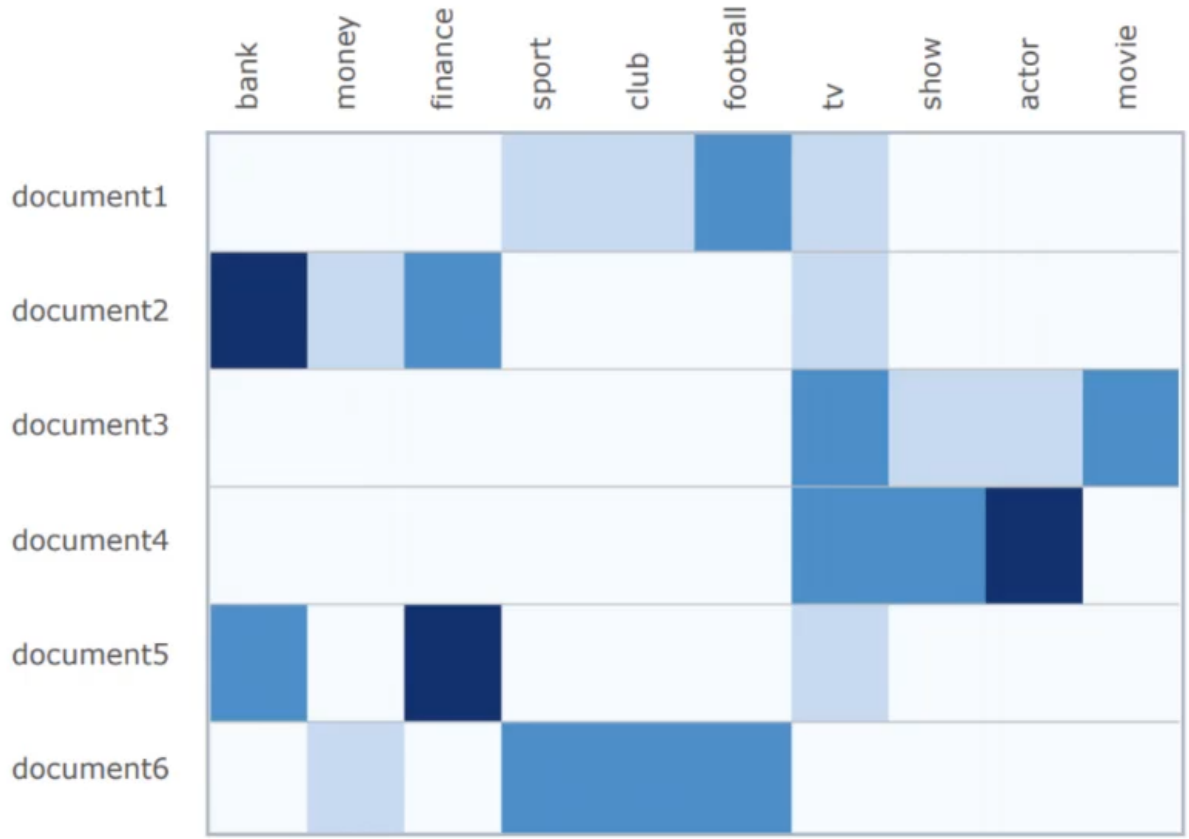
The procedure involves the decomposition of matrix A in the product of two other matrices W and H. All three matrices are non-negative



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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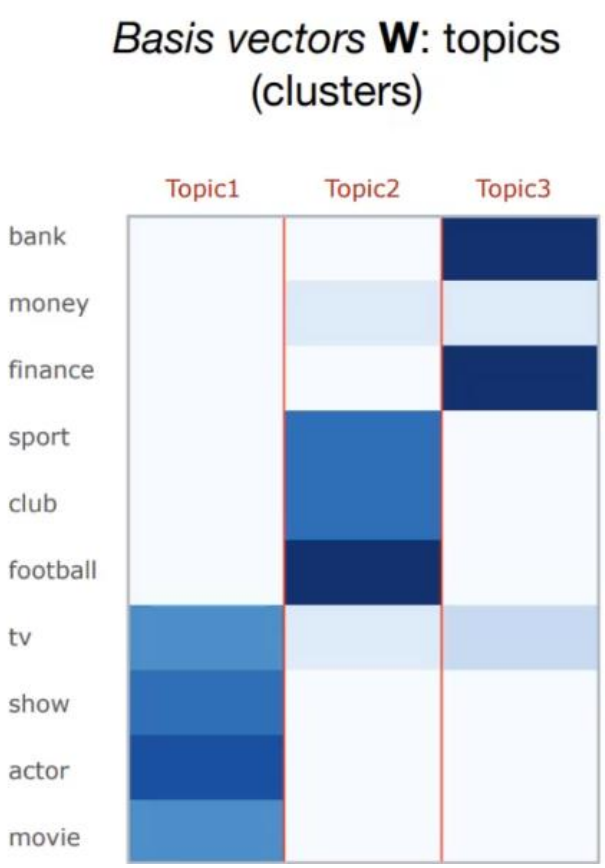

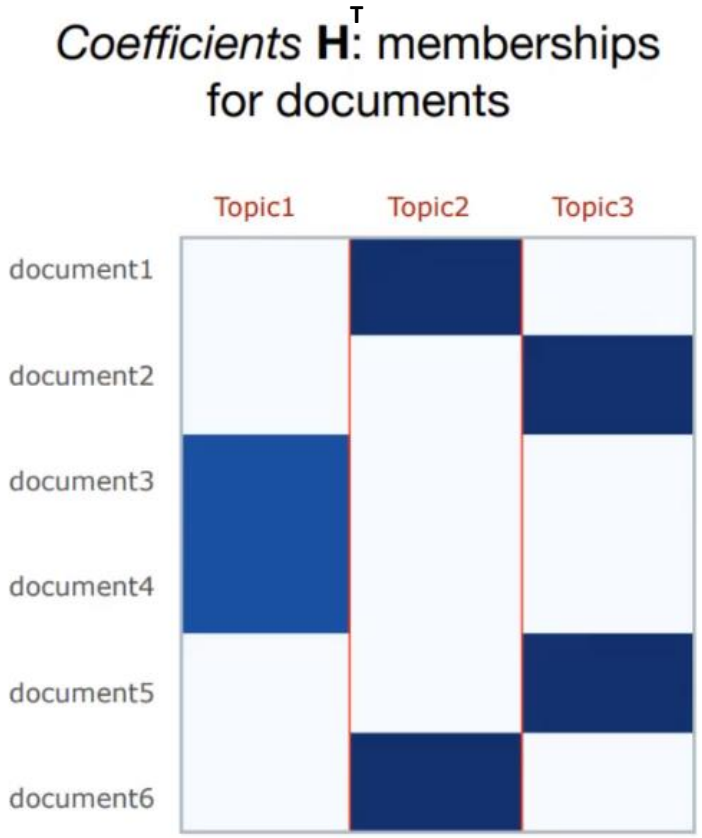

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Non-negative Matrix factorization (NMF)

Procedure

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

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

- 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**

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

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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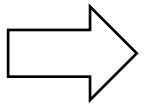

- Each document is a mixture of a small number of topics
- Each word’s presence is attributable to a topic (considered here as a probability distribution over words)

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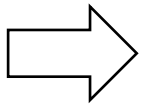

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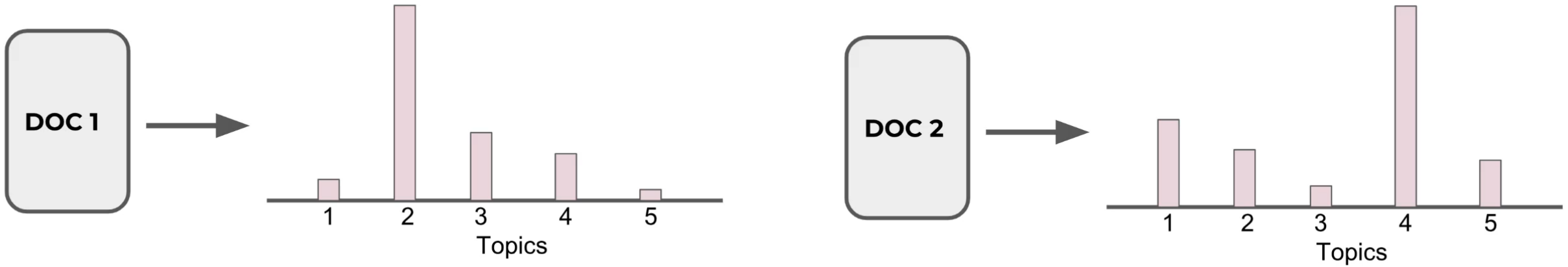

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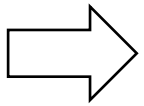
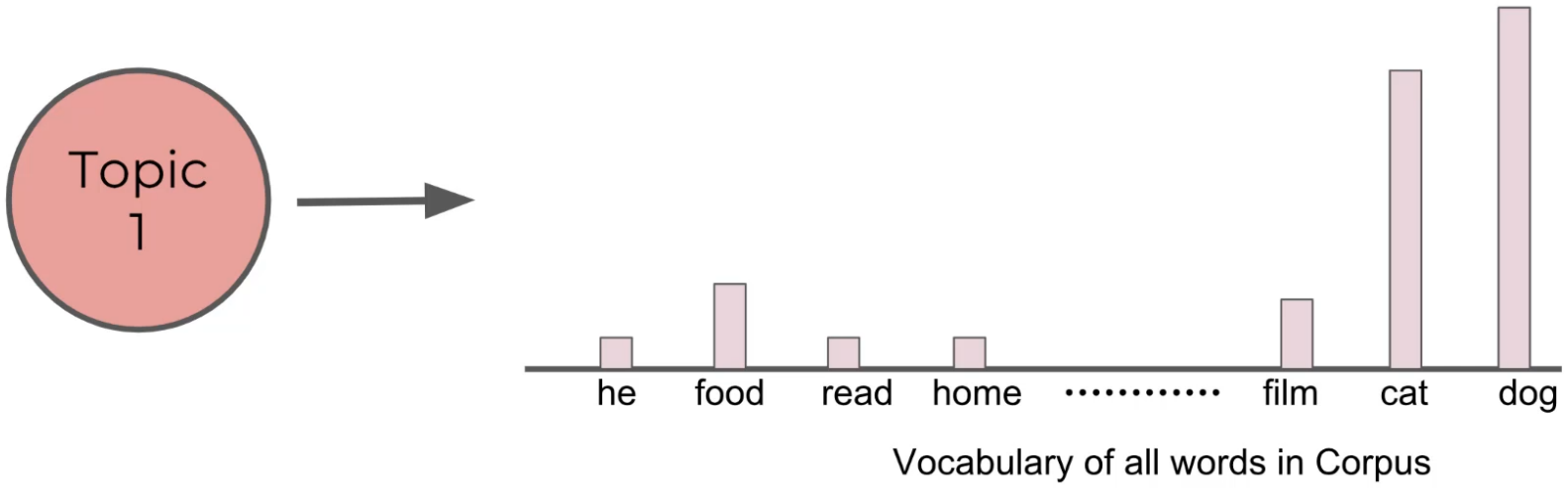


- Each document is a mixture of a small number of topics
- **Each word's presence is attributable to a topic (considered here as a probability distribution over words)**

Latent Dirichlet Allocation (LDA)

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



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 theses 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:

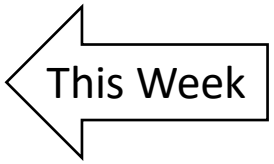
- We use *scikit-learn* implementation for **LDA** and **NMF**
- The dataset is composed of **real** questions taken from the internet forum ***Quora***

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)

Course Schedule

- **Course 1**: NLP introduction
- **Course 2**: **Word embedding**
  - Word embedding introduction
  - Cosine similarity distance
  - Text embedding
  - Sentiment analysis



- **Course 3**: Long Short-Term Memory (LSTM) architecture
- **Course 4**: “Attention” mechanism and Transformer architectures
- **Course 5**: Chatbot implementation

Course 2: Word embedding

Word embedding introduction

Tokenization and one-hot encoding steps

Principle

To be or not to be

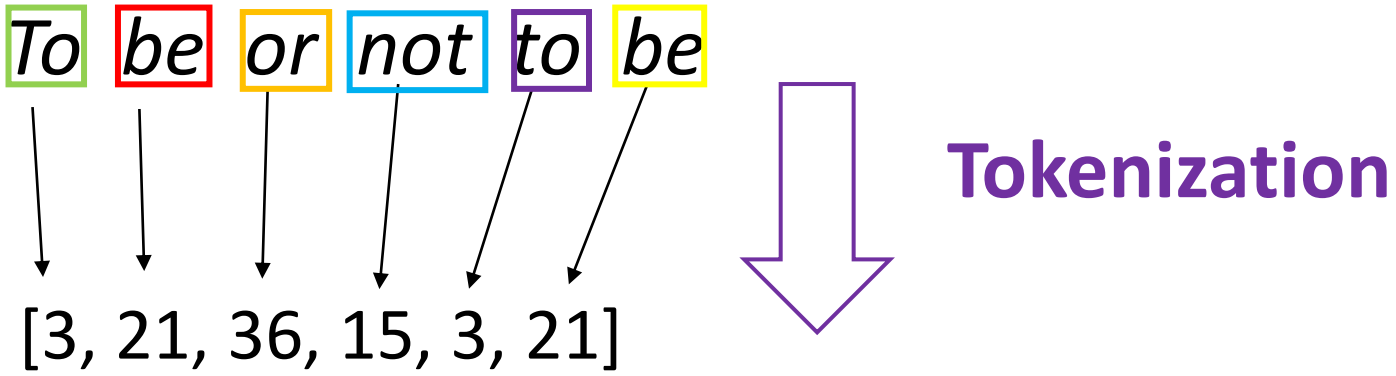
Tokenization and one-hot encoding steps

Principle

Tokenization

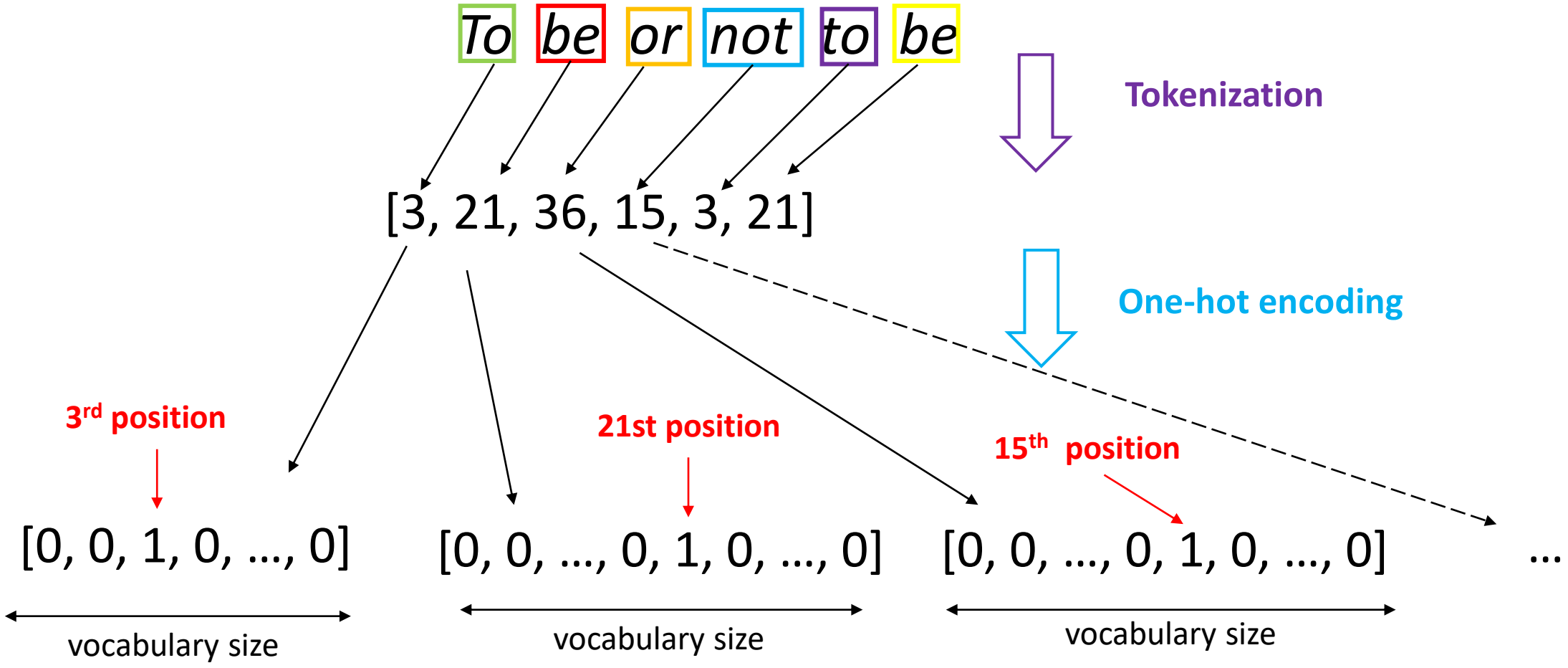
Tokenization and one-hot encoding steps

Principle



Each token is associated to its **number** in the **vocabulary** considered

Tokenization and one-hot encoding steps

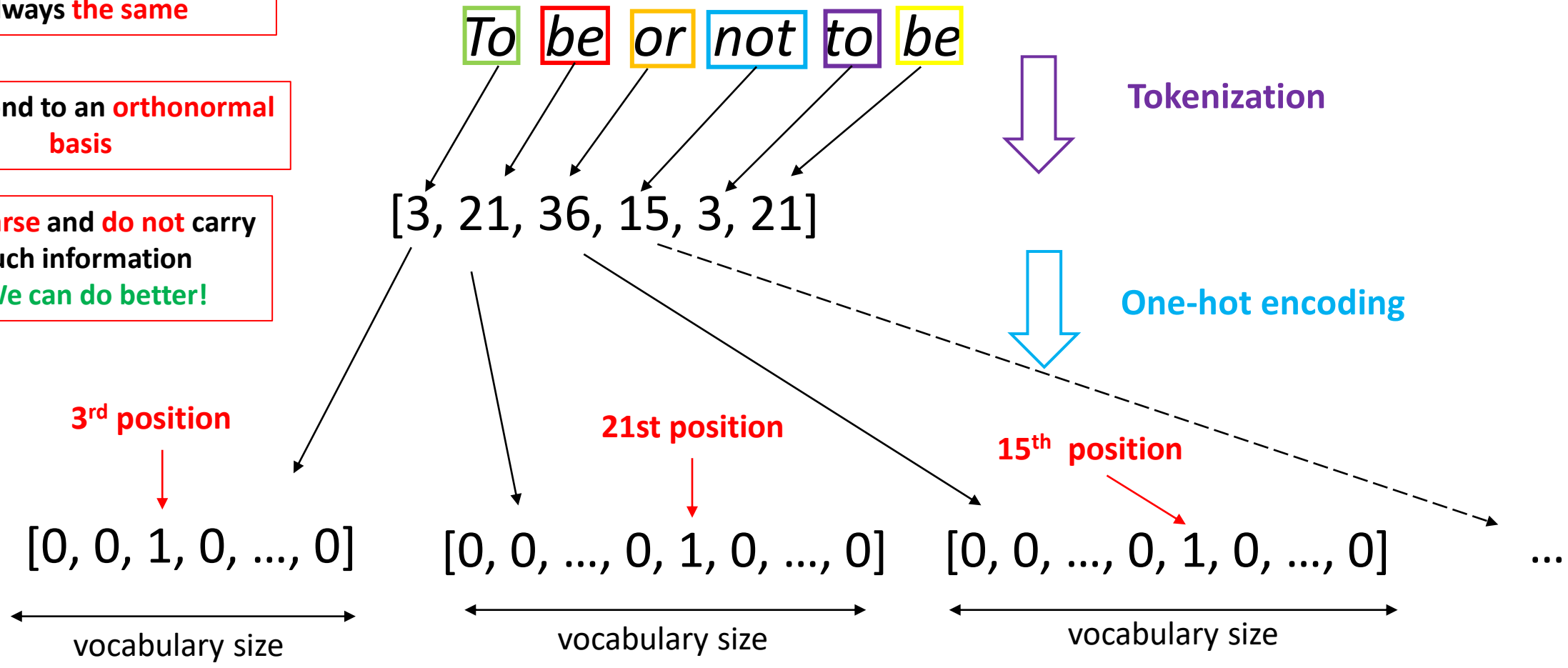


Tokenization and one-hot encoding steps

The distance between two different one-hot vectors is always the same

Correspond to an orthonormal basis

Very sparse and do not carry much information
=> We can do better!



Word embeddings

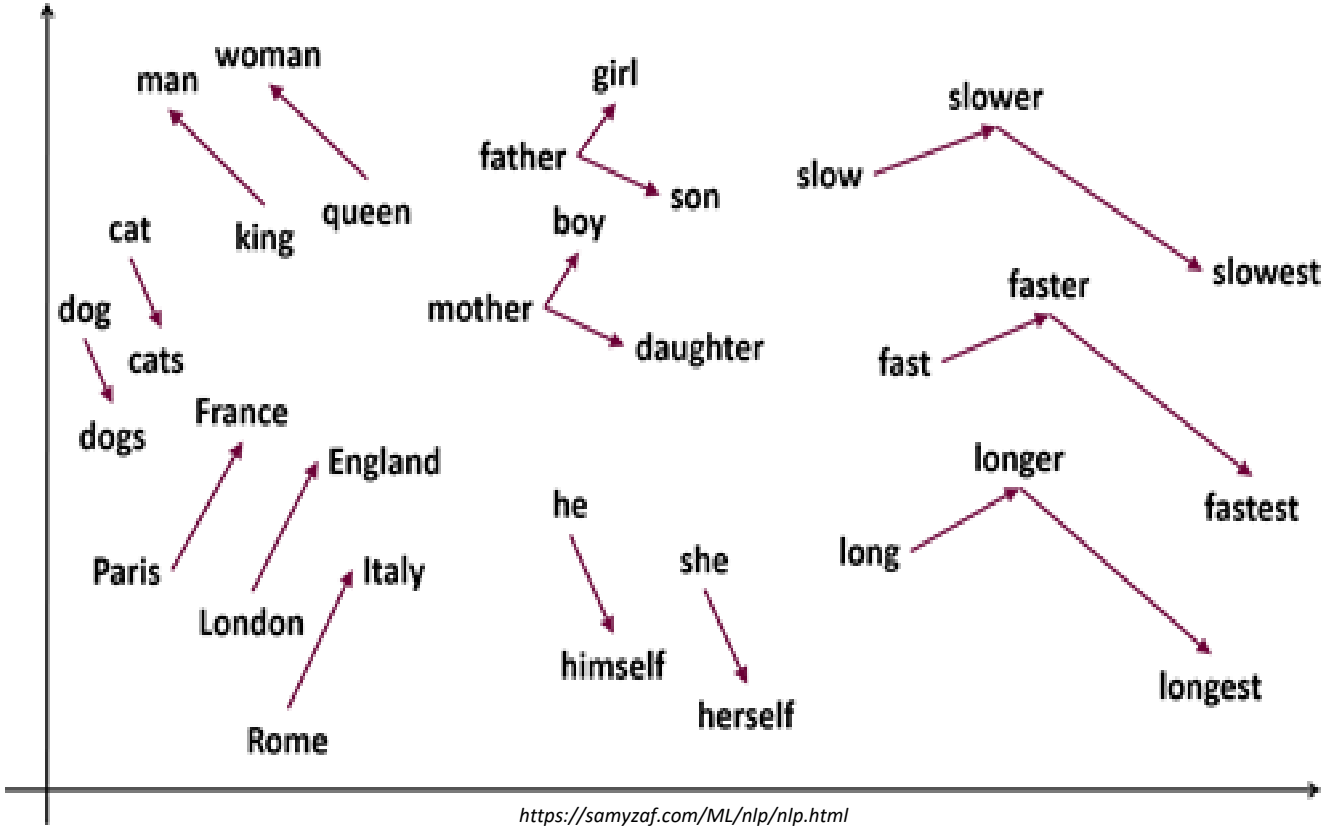
Principles

- To get numerical vectors as representation of words
- **Goal** : **two words with closed meaning should be represented by closed vectors as well**
- This is a different approach from the classical *one hot encoding*, no need to consider vectors with a size equals to the number of words in the vocabulary

Theoritically, a word embedding should consider a vector space in which that kind of relationship between vectors should be verified

king – man + woman ≈ queen

Word embedding: Illustration



https://samyzaf.com/ML/nlp/nlp.html

king – man + woman ≈ queen

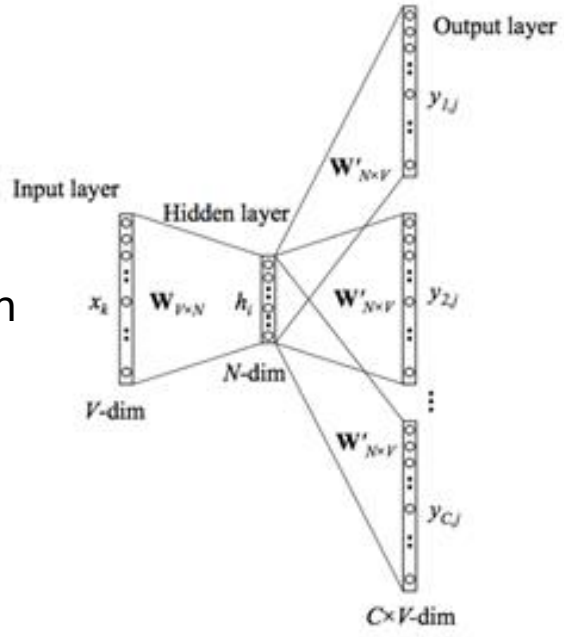
France – Paris + London ≈ England

Word embeddings: Principle

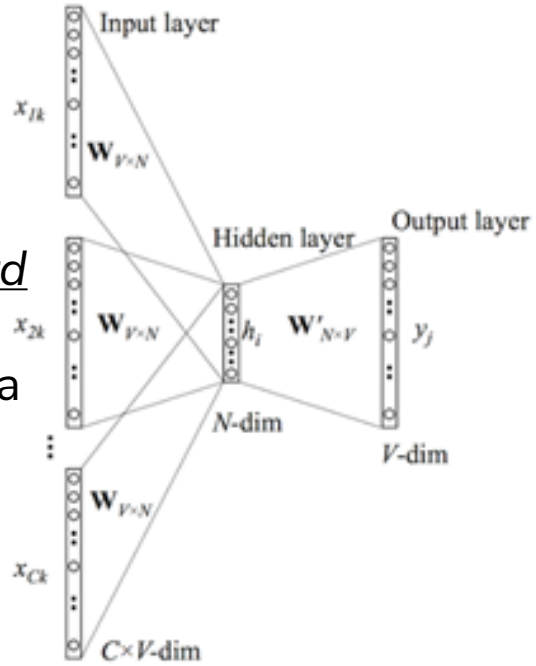
How are generated word embeddings?

- By training a neural network on **huge** corpus
- **Two main approaches** are generally used for that

Skip-gram model:
Context prediction from a word



Continous Bag of Word (CBOW) model:
Word prediction from a context



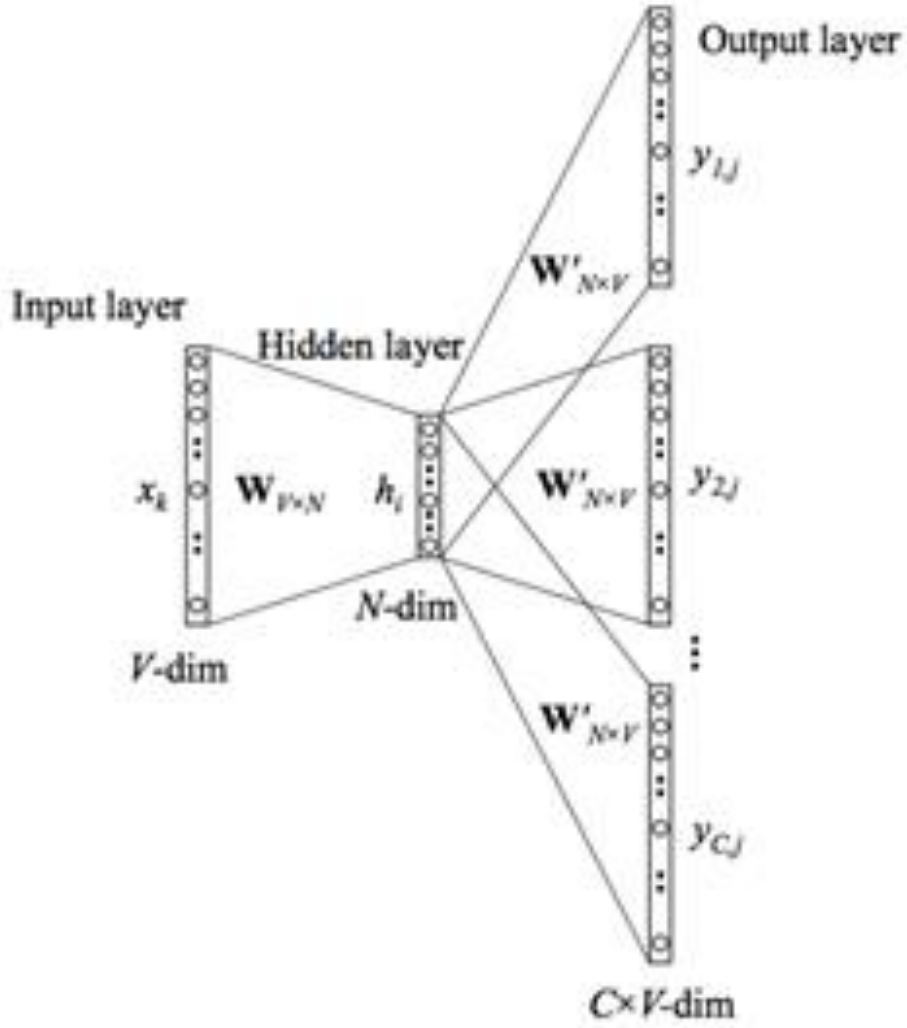
Word embedding: Skip-gram model

Train to predict the **context** from
a given **word**

Example:

*The cat **sat** on the mat*

The word ***sat*** is given as an input and we try to predict ***cat*** and ***mat*** at position -1 and 3 (stop words are generally not predicted)



https://fr.wikipedia.org/wiki/Word_embedding

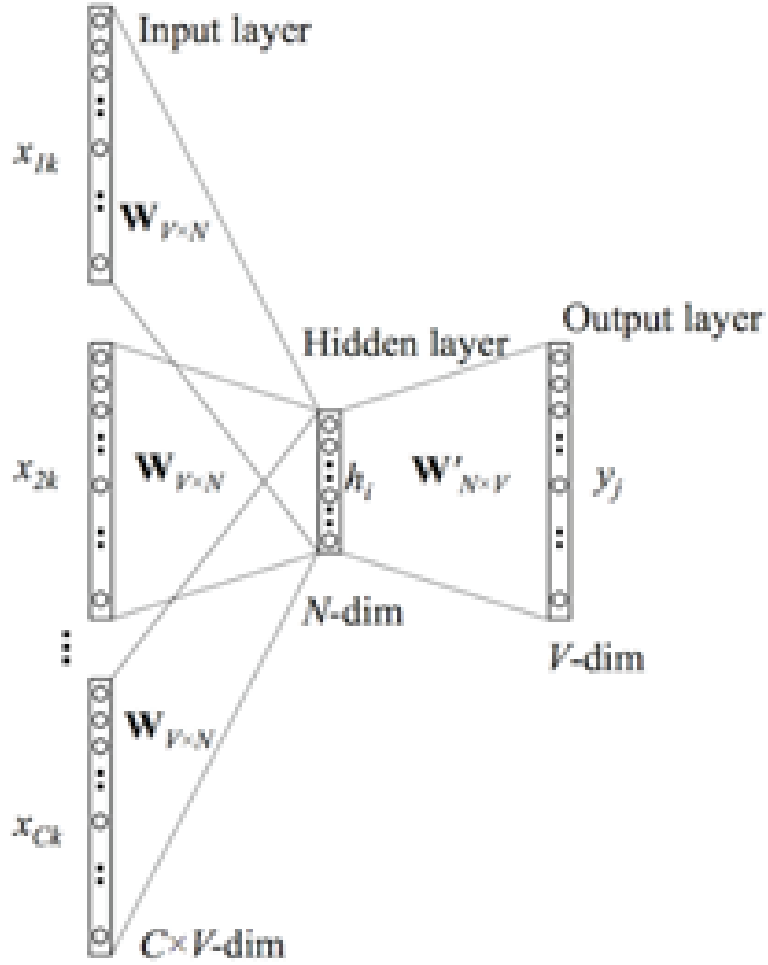
Word embedding: CBOW model

Train to predict a **word** from
a given **context**

Example:

The cat** sat **on the mat

The words [***The***] [***cat***] [***on***] [***the***] [***mat***]
are given as inputs and we try
to predict the word ***sat***



https://fr.wikipedia.org/wiki/Word_embedding

Embedding: word2vec

- **word2vec** is a tool providing an **efficient** implementation for word embedding generation
- It allows you to choose between the **two main** algorithms
  - The continuous bag-of-words (CBOW) model
  - The skip-gram model
- It needs a (**huge**) text corpus as input in order to produce an efficient word embedding model as output
- The learning step can be **avoided** in loading pre-trained models
  - **Google News** model has been trained on about 100 billion (!) words and gives a 300-dimension embedding

Embedding: spaCy

- **spaCy** allows to load models with **pre-trained embeddings**
- **For example**, both '***en_core_web_md***' or '***en_core_web_lg***' models (respectively *medium* and *large*) contain **300-dimension vector** for each **token** in the vocabulary
- E.g.,

```
nlp = spacy.load('en_core_web_md')
nlp.vocab['king'].vector
```

gives the **300-dimension vector** representation of the token "king"

Embedding: fastText

- ***fastText*** is an open-source library allowing to use **pre-trained word embeddings** (and text classifiers) for almost 300 languages

- It has been developed by Facebook's AI Research (FAIR) lab

- Unlike most of other embeddings, dependent of a vocabulary, fastText treats each word as composed of **N-grams** (subsequences of characters)

  ⇨ ***fastText* can generate vectors for word not even in the training corpus**

- This gives some **advantages** of *fastText* over more classical embedding models

- However, a drawback of this model is a **high memory requirement** to load and use it

Cosine similarity distance

Cosine similarity distance

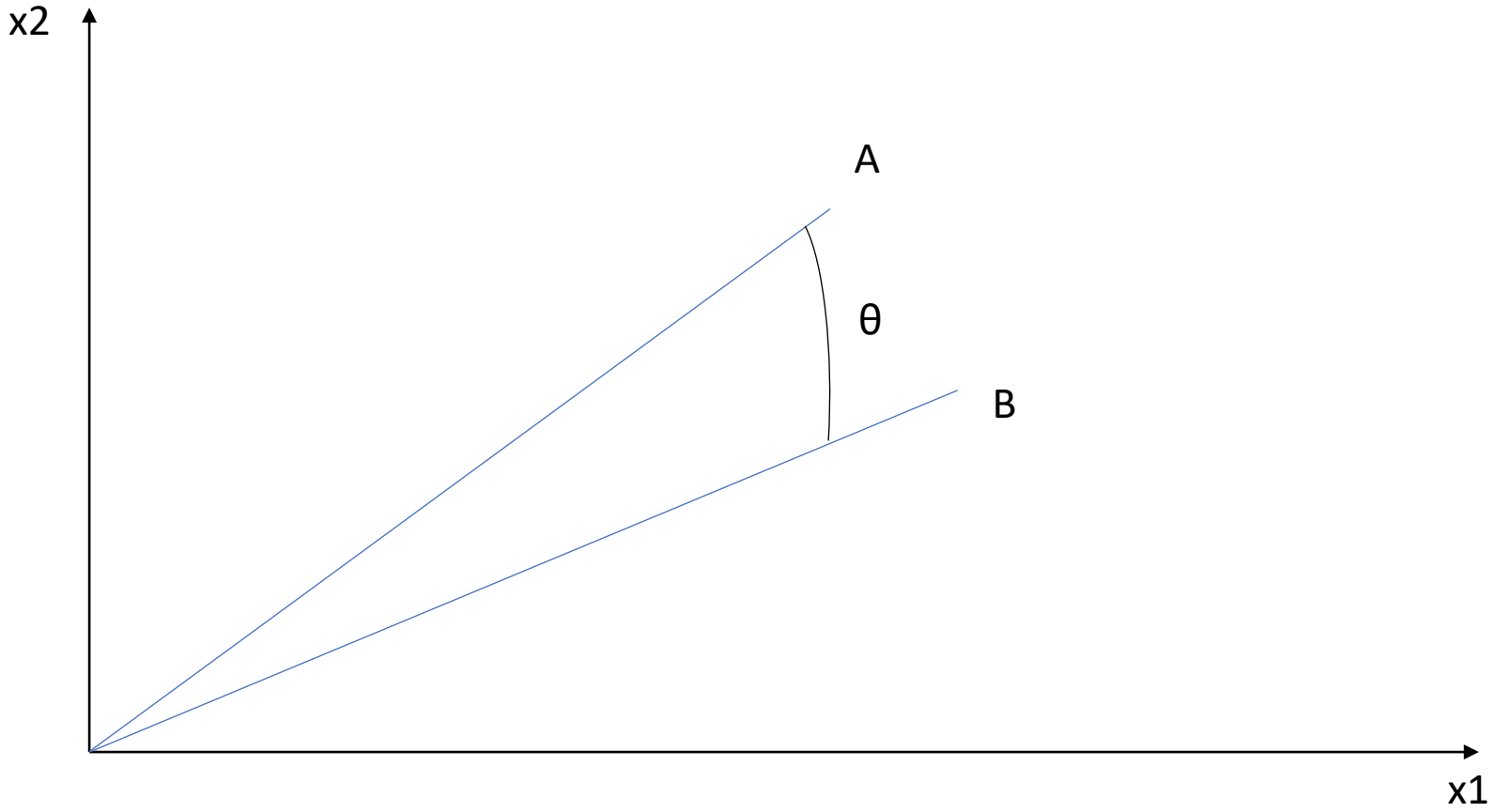
- The **cosine similarity** is a measure of similarity between two vectors which relies on the **cosine of their angle**

- This is the distance generally used to compare **two documents**

- Most of the time, the text embeddings have very **high dimensions**, so all texts are far from each others with a Euclidean distance

- To consider a distance **based only on the angle is more relevant** to determine similarity between vectors in that kind of space

Cosine similarity distance



Cosine similarity distance

For two vectors A and B, the cosine similarity distance is the value

$$D(A,B) = 1 - SC(A,B)$$

with **SC(A,B)** the **cosine similarity**

$$\frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

The **smallest** the angle between A and B is, the **closest** they are.

Embedding: Exercise

Course2_embedding_illustration_ex.ipynb

Goal: Check the validity of the relationship: ***king – man + woman ≈ queen***

from three libraries with pre-trained embedding models:

- ***spaCy***
- ***Glove***
- ***fastTest***

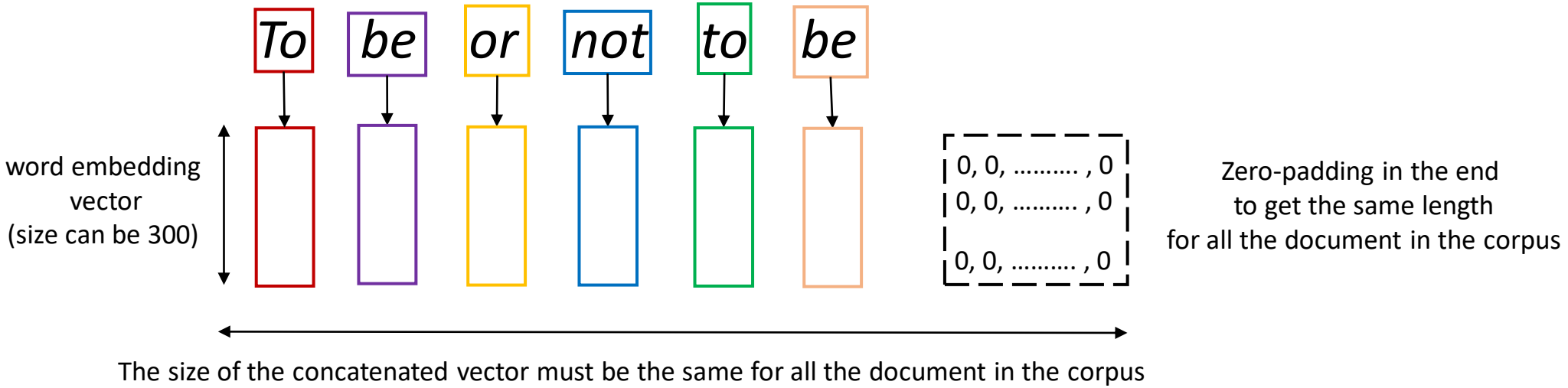
Text embedding

Embedding: Text embedding

- Word embedding allows to transform **tokens** into numerical representation
- For some applications, it may be useful to get numerical representation for **entire texts**
- **Different solutions** can be used in order to get that result

Embedding: Sequence embedding

One solution is to concatenate the embedding vectors of all the tokens of the text

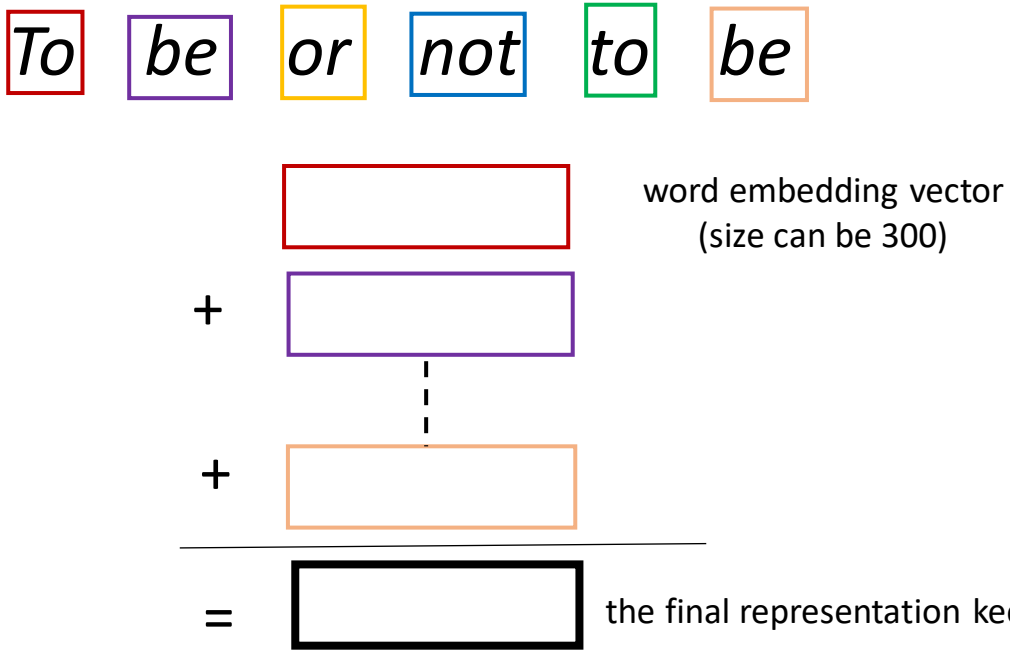


Remarks

- to keep **the same dimensions** for each text of a corpus, there is a need to **truncate** the number of tokens or to **add padding** (depending on the number of tokens)
- The dimension of each text representation can be very **high** (e.g., several thousands)

Embedding: Text embedding

Another solution is to average the embedding vectors of all the tokens in the text



Remarks

- There is **no need** to use **padding** or **truncation** to **keep the same dimension**
- The dimension of the text embedding remains quite **low**
- There is a significant **loss of information** in comparison with the previous method

Embedding: Text embedding

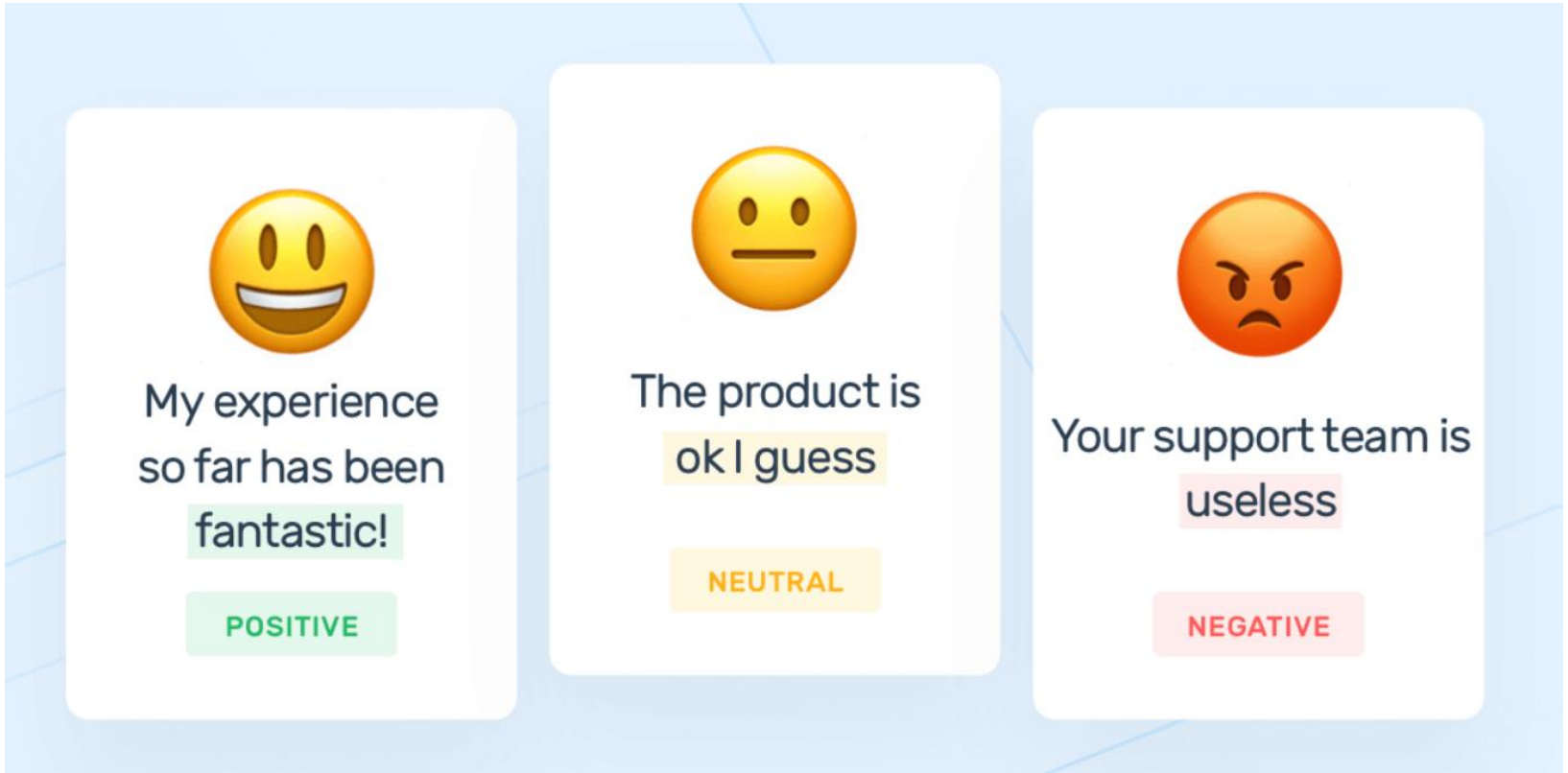
Some libraries offers to deal directly with **text** embeddings

- **spaCy** can compute directly text embedding (with averaging method)
- The model ***doc2vec***, based on the ***word2vec*** logic, allows to build text embedding
- Some models directly available from ***tensorFlow Hub***

Sentiment Analysis

Sentiment Analysis

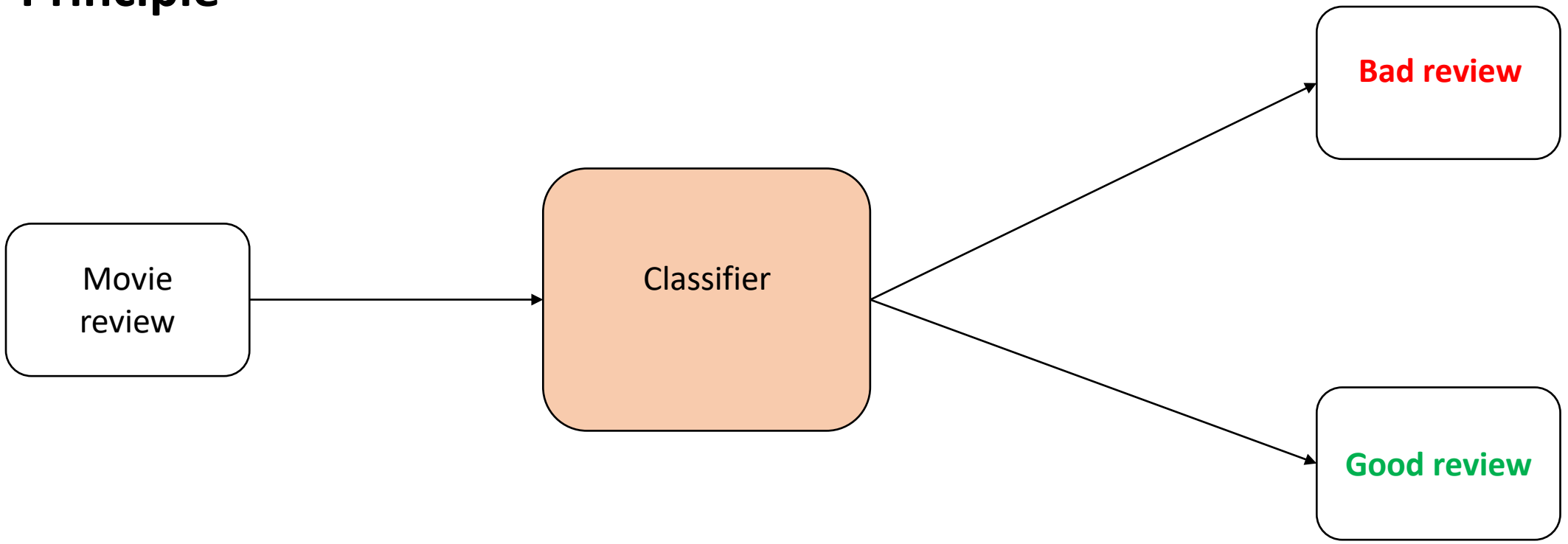
What is sentiment analysis ?



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

Sentiment Analysis

Principle



The **IMDB dataset**, from the famous internet site of the same name and containing numerous **real movie reviews**, is a very useful and famous dataset to train **sentiment analysis** classifier

Sentiment Analysis: Principle

- Sentiment analysis is a specific task consisting in characterizing the **presence of a sentiment** inside a text
- The difficulty may depend on the sentiment searched for
- The most famous example of sentiment analysis consists in categorizing a text into **positive** (“love”) or **negative** (“hate”) feeling
- This kind of positive-negative application can make sense for reviews (movies…), reactions to a specific event (Twitter…)

Sentiment Analysis: Embeddings

To train a sentiment analysis classifier, **numerical representation** of texts are **needed** as inputs

Text embeddings are generally **good** options as such inputs

- **All supervised classification** algorithms can be used
- **Deep learning** and **neural network** can be good options as well

Embedding: Exercise

Course2_spacy_svm_ex.ipynb

Goal: Use of spaCy **text embedding** model to train a Support Vector Machine (**SVM**) for a **sentiment analysis** application on **IMDB dataset**

Remarks:

- The computation of text embedding can be **time consuming**
- To avoid this issue, the notebook allows you to load text embeddings **already computed**

Sentiment Analysis: Vader model

- Some **pre-trained** sentiment analysis **models** are available
- One of them is **Vader** (**V**alence **A**ware **D**ictionary for s**E**ntiment **R**easoning) and can be found in the **NLTK** package
- Vader is a model allowing positive/negative sentiment text **classification** and characterize also the **intensity** of the emotion
- It is specifically train to analyze **social media text** (e.g., it can analyze smileys)

```
# Create a SentimentIntensityAnalyzer object.
sid_obj = SentimentIntensityAnalyzer()
```

```
sid_obj.polarity_scores(":)")
```

```
{'neg': 0.0, 'neu': 0.0, 'pos': 1.0, 'compound': 0.4588}
```

```
sid_obj.polarity_scores(" :(")
```

```
{'neg': 1.0, 'neu': 0.0, 'pos': 0.0, 'compound': -0.4404}
```

Embedding: Exercise

Course2_sentiment_analysis_vader_ex.ipynb

Goal: Use of Vader model for **sentiment analysis** application on **IMDB dataset**

Remarks:

- The Vader model is pre-trained and be directly used without training
- This model was pre-trained specifically for sentiment analysis

Sentiment Analysis: Neural Network (NN)

Implementing a neural network with **Keras**

- Keras provides functions to load some common datasets such as **IMDB dataset**
- A NN can be created using Keras Sequential API
- NN can be created by adding **layers** to a model
- **Deep Learning** corresponds to chaining together several layers in order to build complex structures

Sentiment Analysis: Neural Network (NN)

Data Preprocessing

```
import tensorflow_datasets as tfds

datasets, info = tfds.load("imdb_reviews", as_supervised=True, with_info=True)

train_size = info.splits["train"].num_examples
batch_size = 32

train_set = datasets["train"].shuffle(10000).repeat().batch(batch_size).prefetch(tf.data.AUTOTUNE)

test_size = info.splits["test"].num_examples
test_set = datasets["test"].repeat().batch(batch_size).prefetch(tf.data.AUTOTUNE)
```

Sentiment Analysis: Neural Network (NN)

Data Preprocessing

The tensorflow_datasets API allows to load easily common datasets (here *imdb_reviews*)

```
import tensorflow_datasets as tfds

datasets, info = tfds.load("imdb_reviews", as_supervised=True, with_info=True)

train_size = info.splits["train"].num_examples
batch_size = 32

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test_set = datasets["test"].repeat().batch(batch_size).prefetch(tf.data.AUTOTUNE)
```

Sentiment Analysis: Neural Network (NN)

Data Preprocessing

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train_set = datasets["train"].shuffle(10000).repeat().batch(batch_size).prefetch(tf.data.AUTOTUNE)

test_size = info.splits["test"].num_examples
test_set = datasets["test"].repeat().batch(batch_size).prefetch(tf.data.AUTOTUNE)
```

A split between “train” and “test” dataset is already done

Sentiment Analysis: Neural Network (NN)

Data Preprocessing

```
import tensorflow_datasets as tfds

datasets, info = tfds.load("imdb_reviews", as_supervised=True, with_info=True)

train_size = info.splits["train"].num_examples
batch_size = 32

train_set = datasets["train"].shuffle(10000).repeat().batch(batch_size).prefetch(tf.data.AUTOTUNE)

test_size = info.splits["test"].num_examples
test_set = datasets["test"].repeat().batch(batch_size).prefetch(tf.data.AUTOTUNE)
```

Ensure the training data are well distributed

Sentiment Analysis: Neural Network (NN)

Data Preprocessing

```
import tensorflow_datasets as tfds

datasets, info = tfds.load("imdb_reviews", as_supervised=True, with_info=True)

train_size = info.splits["train"].num_examples
batch_size = 32

train_set = datasets["train"].shuffle(10000).repeat().batch(batch_size).prefetch(tf.data.AUTOTUNE)

test_size = info.splits["test"].num_examples
test_set = datasets["test"].repeat().batch(batch_size).prefetch(tf.data.AUTOTUNE)
```

Used to repeat the initial dataset, possibly forever

Sentiment Analysis: Neural Network (NN)

Data Preprocessing

```
import tensorflow_datasets as tfds

datasets, info = tfds.load("imdb_reviews", as_supervised=True, with_info=True)

train_size = info.splits["train"].num_examples
batch_size = 32

train_set = datasets["train"].shuffle(10000).repeat().batch(batch_size).prefetch(tf.data.AUTOTUNE)

test_size = info.splits["test"].num_examples
test_set = datasets["test"].repeat().batch(batch_size).prefetch(tf.data.AUTOTUNE)
```

Return a dataset consisting of groups of items

Sentiment Analysis: Neural Network (NN)

Data Preprocessing

```
import tensorflow_datasets as tfds

datasets, info = tfds.load("imdb_reviews", as_supervised=True, with_info=True)

train_size = info.splits["train"].num_examples
batch_size = 32

train_set = datasets["train"].shuffle(10000).repeat().batch(batch_size).prefetch(tf.data.AUTOTUNE)

test_size = info.splits["test"].num_examples
test_set = datasets["test"].repeat().batch(batch_size).prefetch(tf.data.AUTOTUNE)
```

Used to improve the performance by optimizing some data reading (setting to tf.data.AUTOTUNE allows an automatic dynamic choice)

Embedding: Exercise

Course2_sentiment_analysis_nn_training_ex.ipynb

and/or

Course2_sentiment_analysis_nn_training_spacy_ex.ipynb

Goal: train a neural network for **sentiment analysis** application on **IMDB dataset**

Remarks:

- The first notebook **load IMDB dataset** and a **text embedding** model **directly** from **tensorflow API**
- The second notebook train the network from **spaCy text embedding computer before** (you can compare the results with those got from the SVM model from a previous exercise)
- If you have time, try to train both, but you can start with the **first one**

Sentiment Analysis: Neural Network (NN)

- The use of tf.keras, instead of just Keras, allows for a better integration with other TensorFlow components
- We can create a model using the **Sequential API** of Keras by **adding layers to the stack**
- We must define the **number of layers**, the **kind of layers**, the **dimensions** and the **activation function**

```
model = tf.keras.models.Sequential([
    hub.KerasLayer(embed,
                   dtype=tf.string, input_shape=[], output_shape=[50]),
    Dense(128, activation="relu"),
    Dense(300, activation="relu"),
    Dense(1, activation="sigmoid")
])
```

Sentiment Analysis: Neural Network (NN)

The summary method displays all model's information

- The ones defined previously
- The total number of trainable and non-trainable parameters

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
keras_layer (KerasLayer)     (None, 50)                48190600
_________________________________________________________________
dense (Dense)                (None, 128)               6528
_________________________________________________________________
dense_1 (Dense)              (None, 300)               38700
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 301
=================================================================
Total params: 48,236,129
Trainable params: 45,529
Non-trainable params: 48,190,600
_________________________________________________________________
```

Sentiment Analysis: Neural Network (NN)

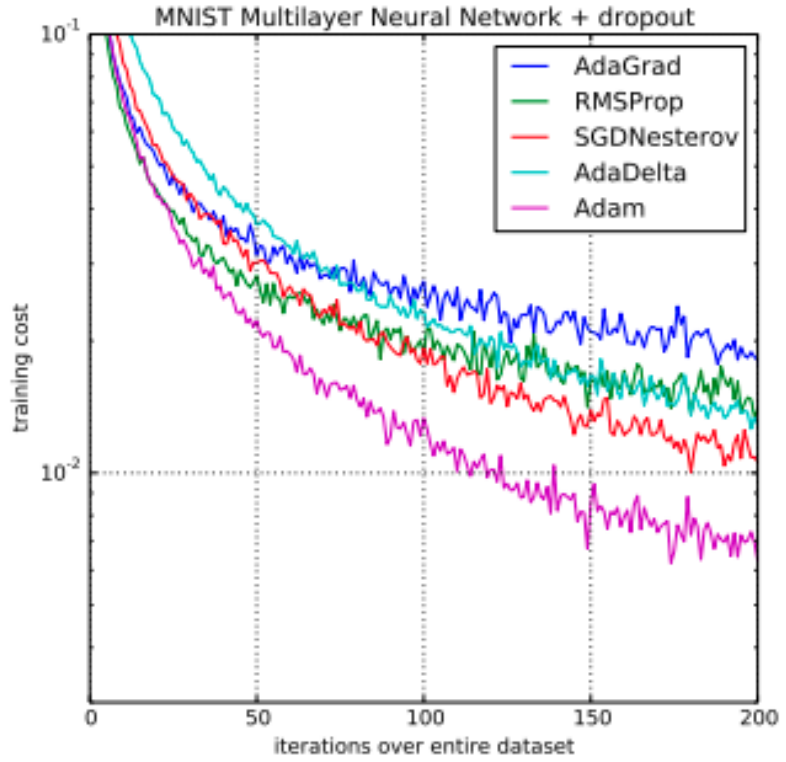
Optimizers Variants

- Most optimizers are **implemented** in Tensorflow

```
optimizer = tf.keras.optimizers.SGD(lr=0.001, momentum=0.9)
optimizer = keras.optimizers.SGD(lr=0.001, momentum=0.9, nesterov=True)
optimizer = tf.keras.optimizers.Adagrad(lr=0.001)
optimizer = tf.keras.optimizers.RMSprop(lr=0.001, rho=0.9)
optimizer = tf.keras.optimizers.Adam(lr=0.001, beta_1=0.9, beta_2=0.999)
optimizer = tf.keras.optimizers.Nadam(lr=0.001, beta_1=0.9, beta_2=0.999)
```

- Both optimizer and loss function must be entered during the **compilation** step

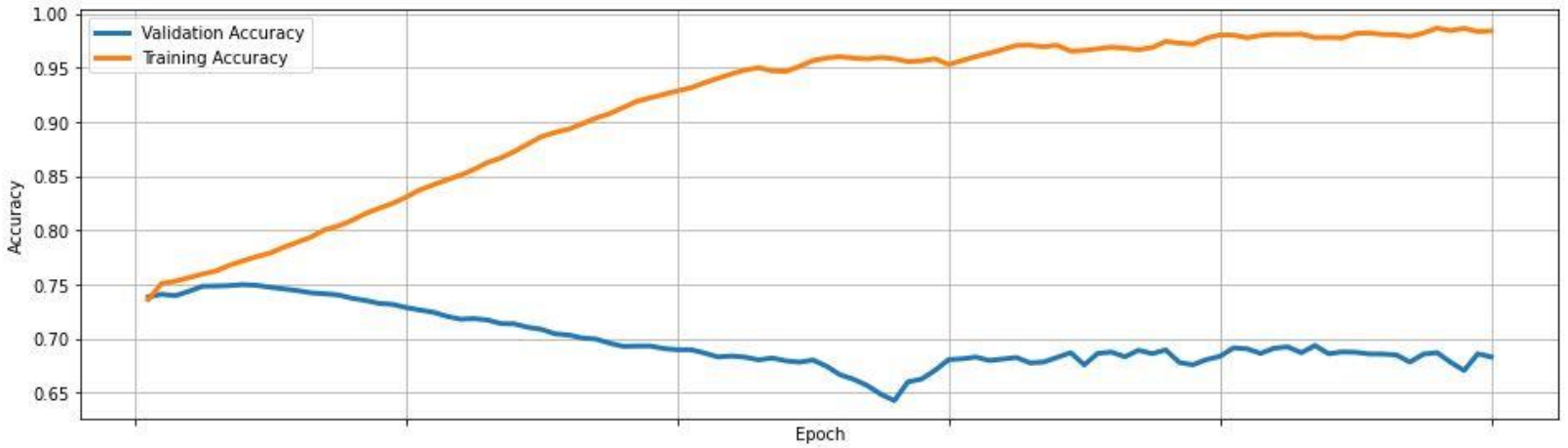
```
model.compile(loss="binary_crossentropy", optimizer=optimizer)
```

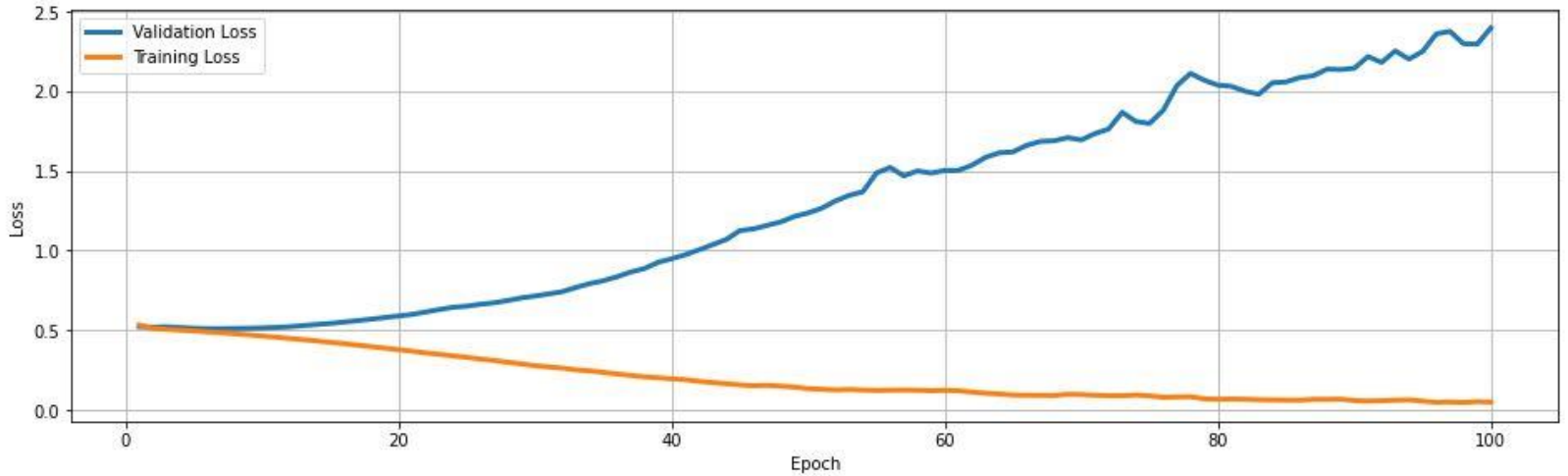


Comparison of Adam to Other Optimization Algorithms Training a Multilayer Perceptron
Taken from Adam: A Method for Stochastic Optimization, 2015.

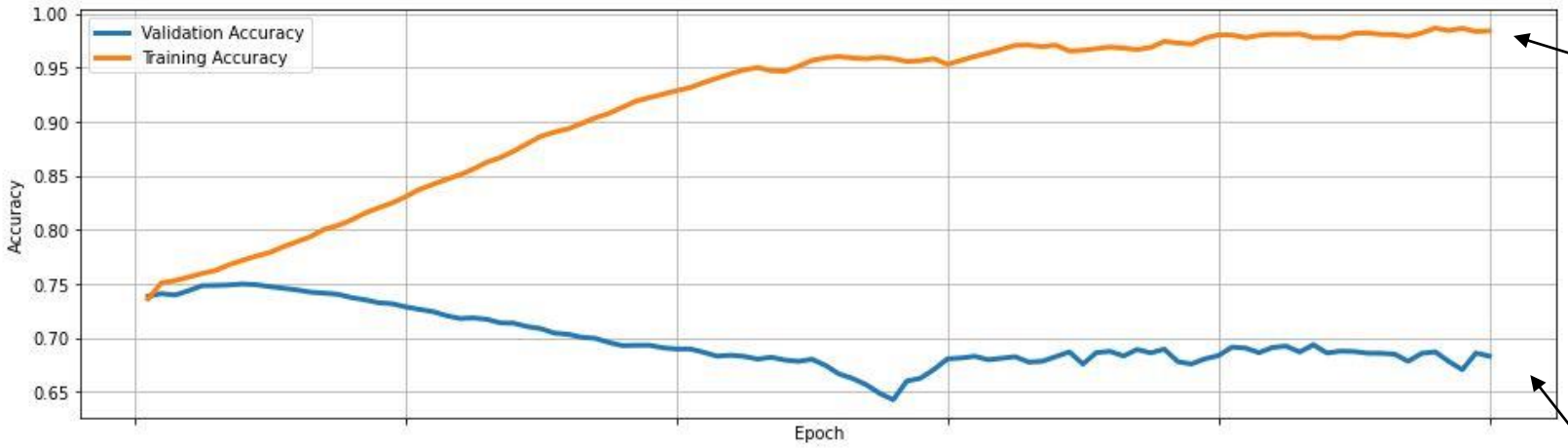
Inspired by Publicis Sapient's *Deep Learning with Tensorflow* formation

Sentiment Analysis: Neural Network (NN)



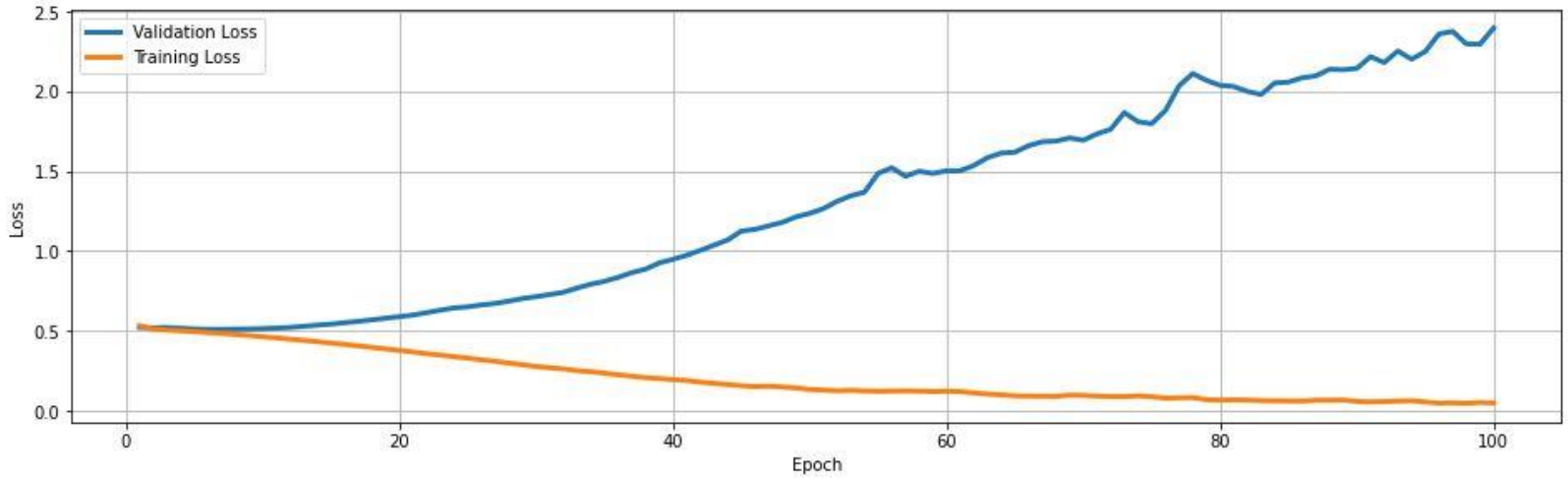


Sentiment Analysis: Neural Network (NN)

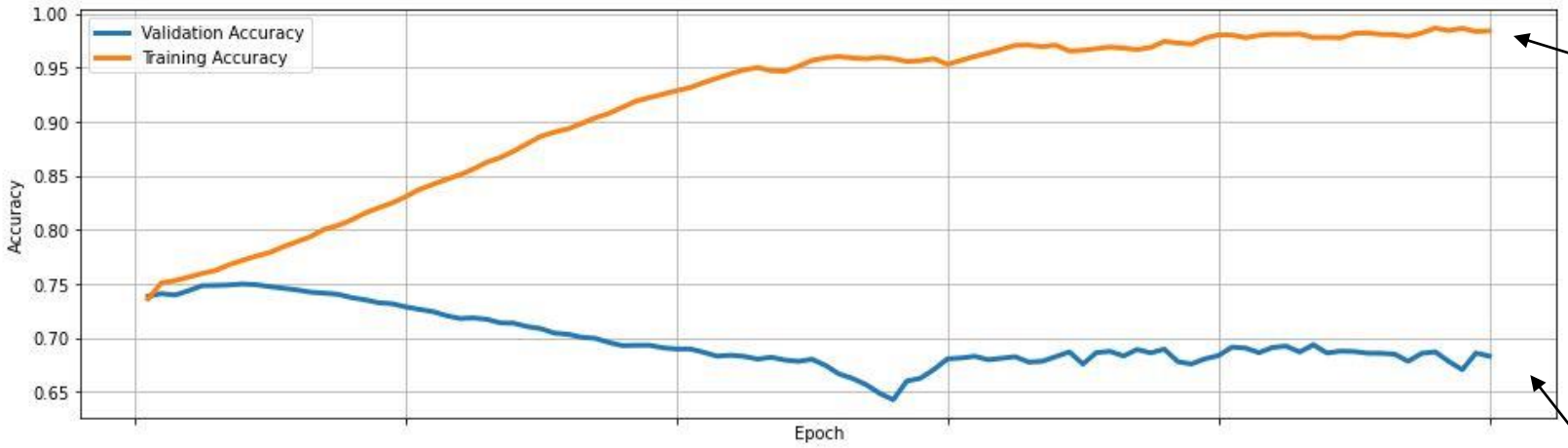


The results seem good on the train set…

… but there are significantly less good on the test set



Sentiment Analysis: Neural Network (NN)



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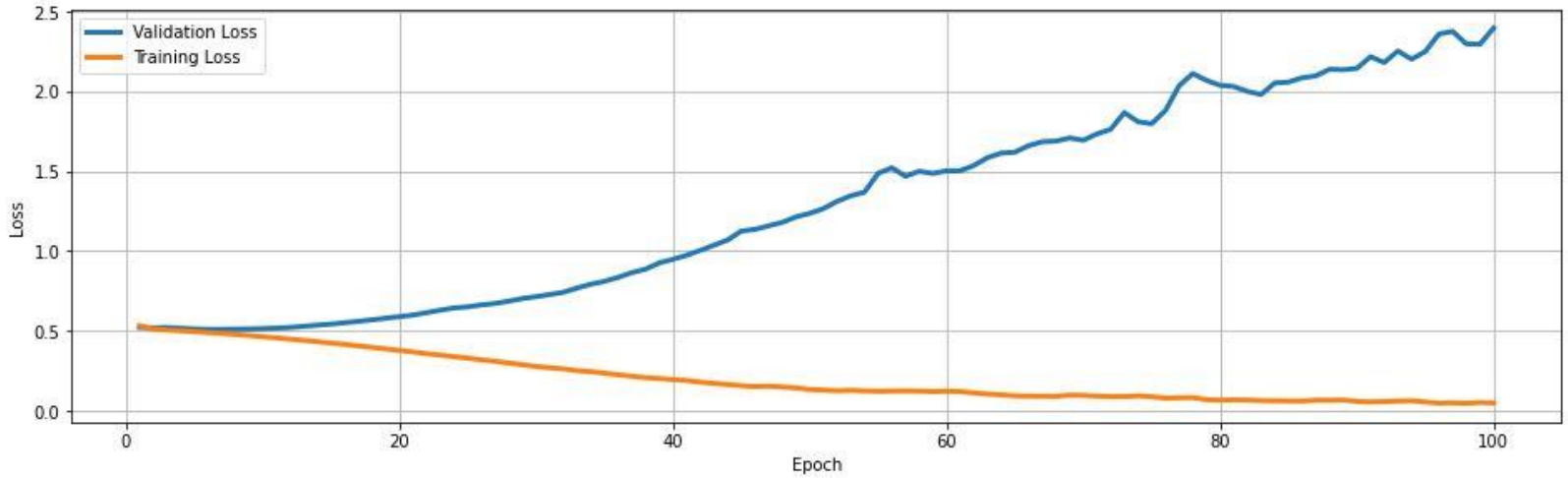
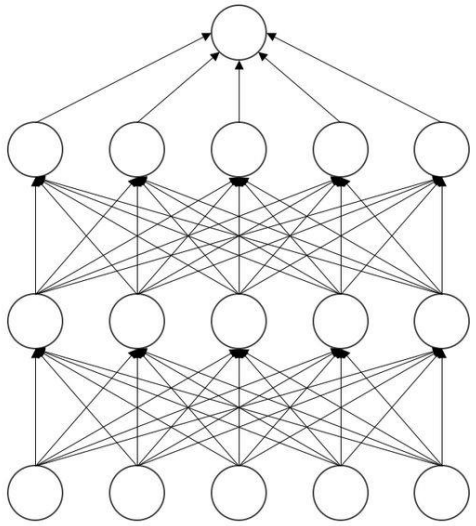


Overfitting !!!

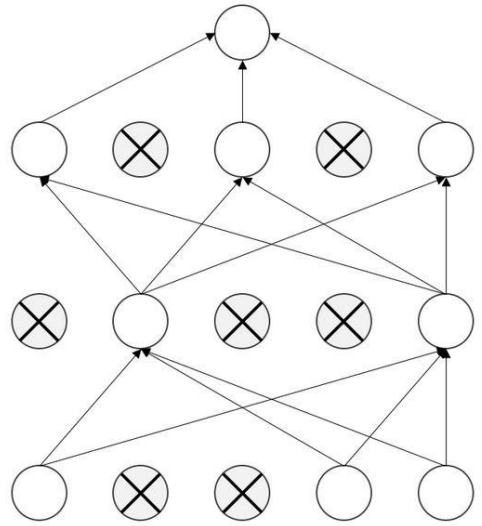
Sentiment Analysis: Neural Network (NN)

- To solve **overfitting** issues in a Neural Network, a powerful tool is to add **Dropout** layers
- **Dropout** : randomly dropping out (setting to 0) some of output features of a given layer
- It adds noise inside the network in order to prevent the neurons from being too sensitive to variations

```
model = tf.keras.models.Sequential([
    hub.KerasLayer(embed,
                   dtype=tf.string, input_shape=[], output_shape=[50]),
    Dense(128, activation="relu"),
    Dropout(rate=0.8),
    Dense(300, activation="relu"),
    Dropout(rate=0.8),
    Dense(1, activation="sigmoid")
])
```



Standard Neural Net



After applying dropout

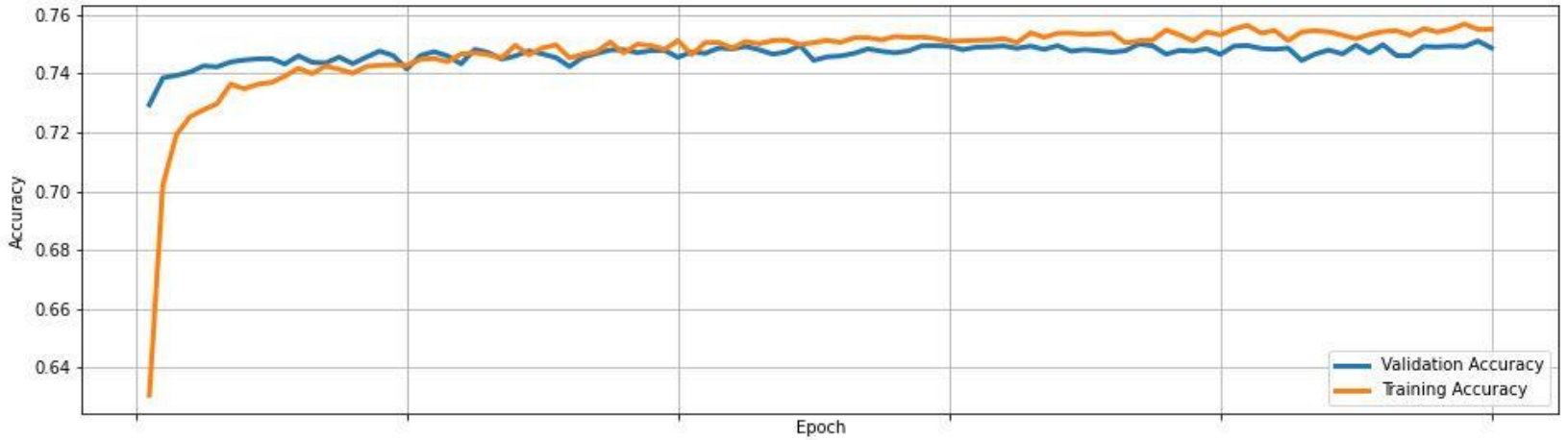
https://www.oreilly.com/library/view/deep-learning-for/9781788295628/a22e6b18-79e3-4875-b003-2f4c6080bf54.xhtml

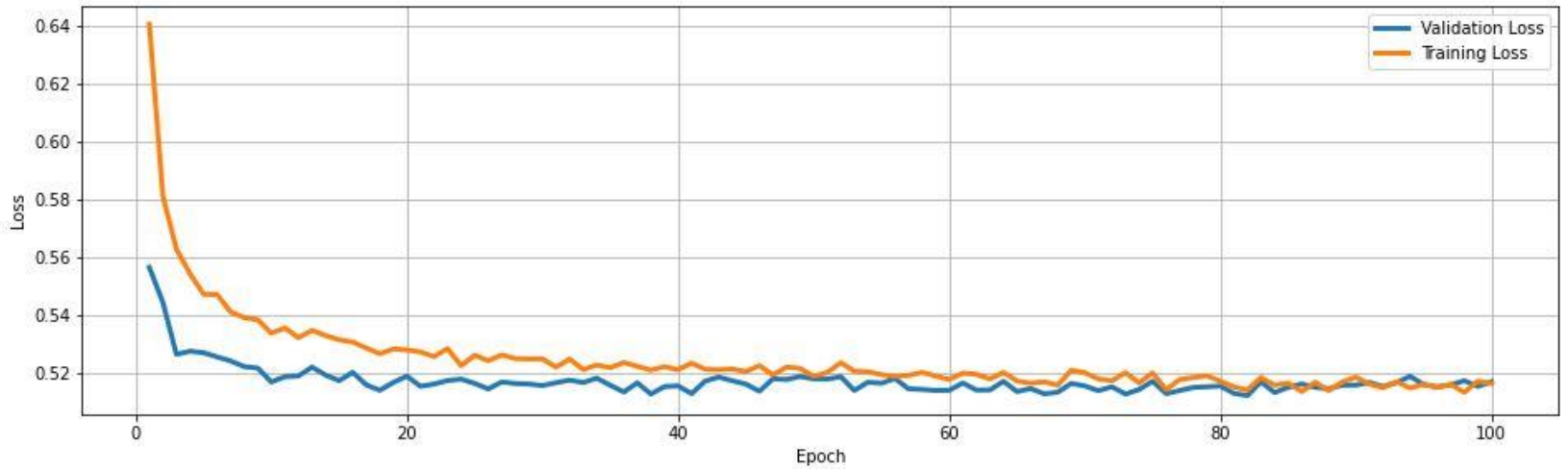
Sentiment Analysis: Neural Network (NN)

```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
keras_layer_2 (KerasLayer)   (None, 50)                48190600
_________________________________________________________________
dense_6 (Dense)              (None, 128)               6528
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_7 (Dense)              (None, 300)               38700
_________________________________________________________________
dropout_3 (Dropout)          (None, 300)               0
_________________________________________________________________
dense_8 (Dense)              (None, 1)                 301
=================================================================
Total params: 48,236,129
Trainable params: 45,529
Non-trainable params: 48,190,600
_________________________________________________________________
```

Sentiment Analysis: Neural Network (NN)





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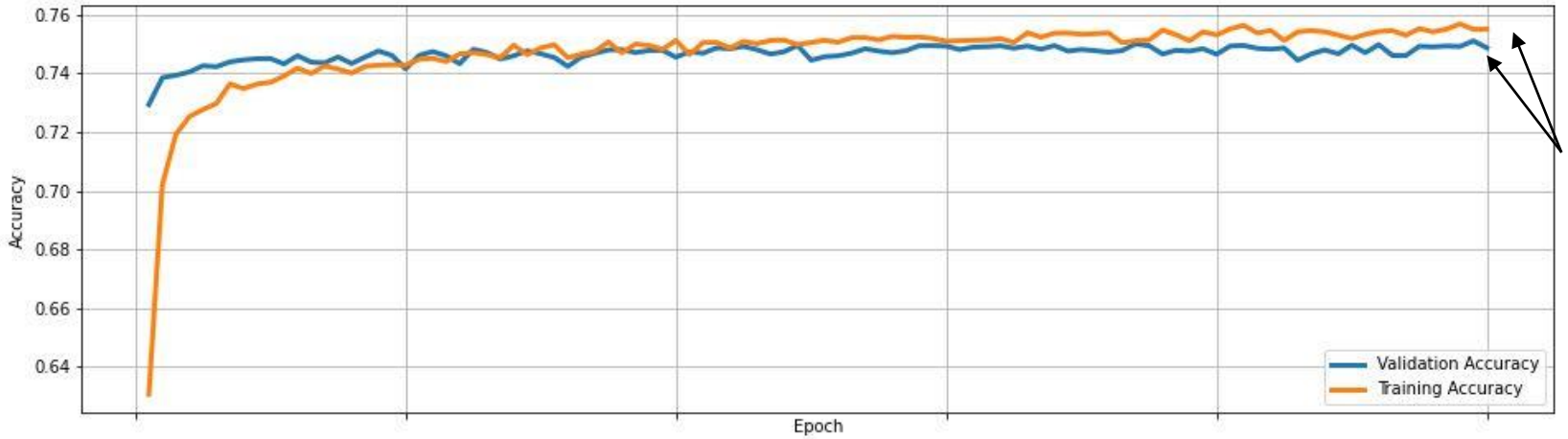
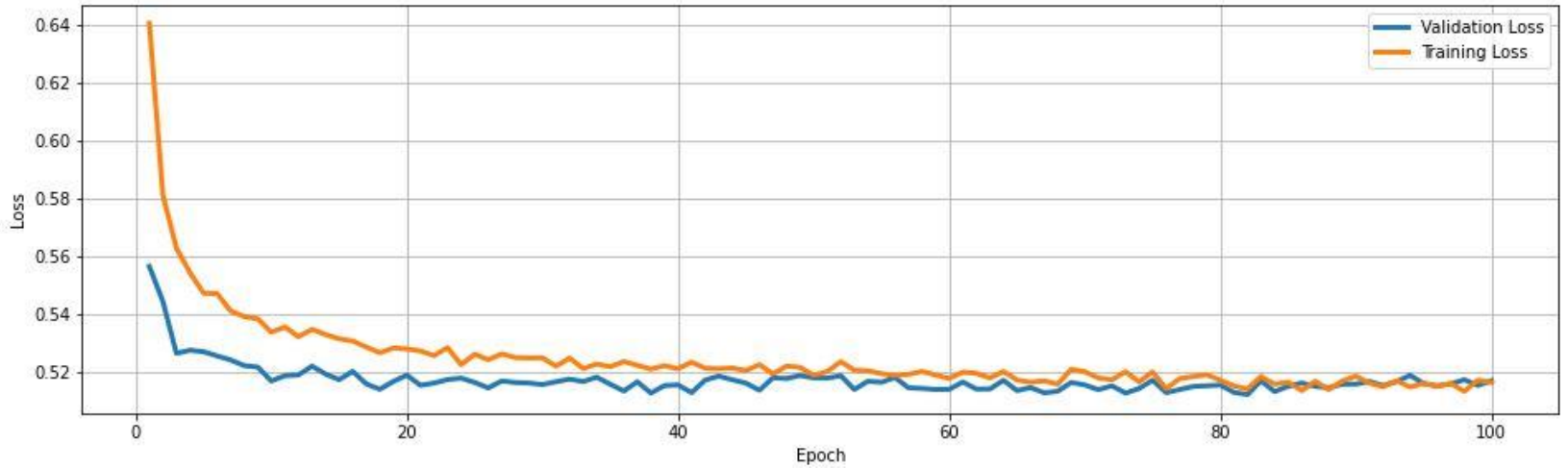
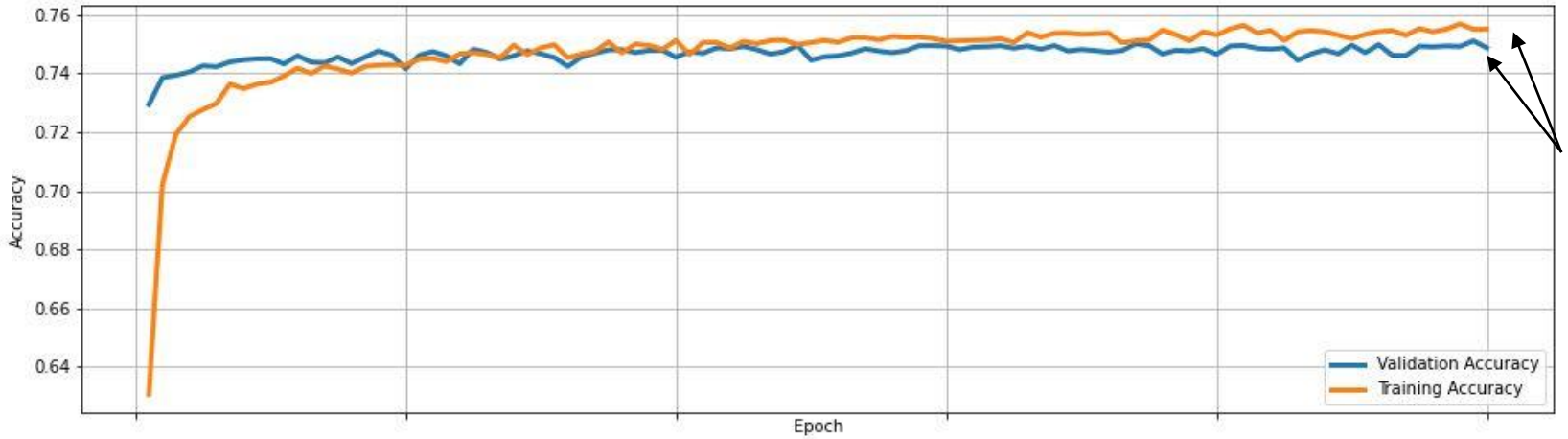


The results are similar for both train and test set



Sentiment Analysis: Neural Network (NN)



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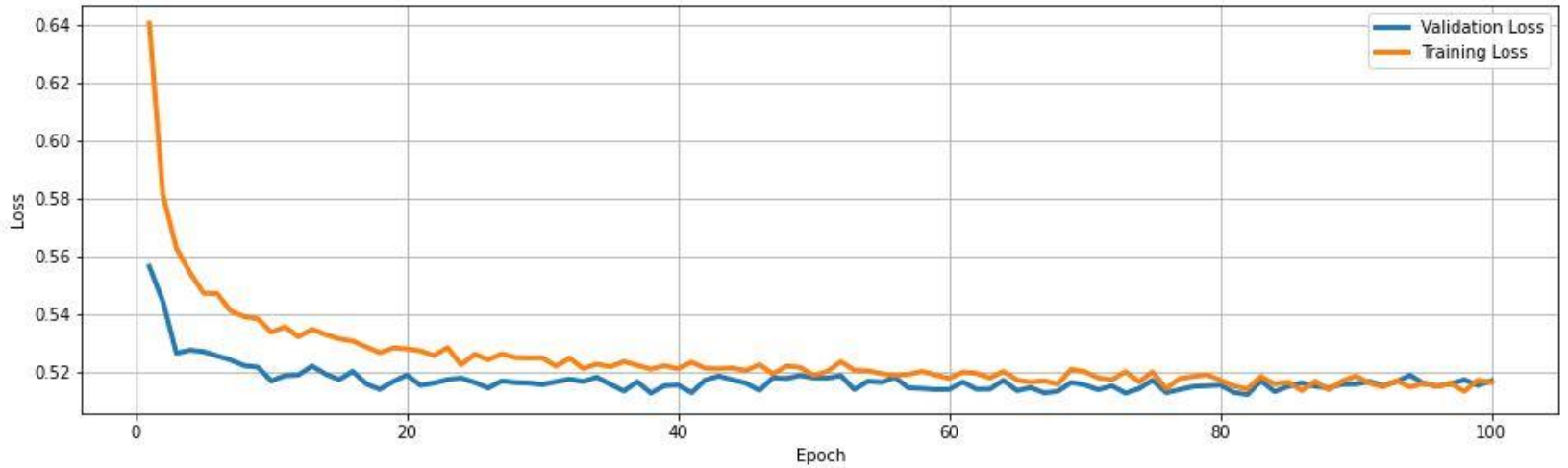


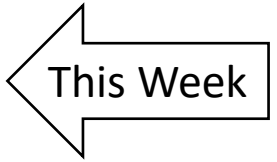
Overfitting prevented !

Take-away from Course 2

- **Word embedding** is a powerful way to convert text into **numerical value vector**
- **Solves** the problems of **sparsity** and **very high dimension** met with basics methods like Bag of words and TF_IDF (see Course 1)
- Allows as well a better **representativity of the language** : **words are close in the vector space if their meaning is similar**
- Word embeddings come from neural network training on **HUGE** datasets: need to use **pre-trained libraries** for general use cases
- To compare the distance between two word-vectors, the **cosine similarity distance** is generally the best choice
- Word embeddings can be used as **inputs for NLP use cases** (such as sentiment analysis), and are often used as **neural network first layer inputs**

Course Schedule

- **Course 1**: NLP introduction
- **Course 2**: Word embedding
- **Course 3**: **Long Short Term Memory (LSTM) architecture**
  - Recurrent Neural Network (RNN)
  - LSTM principle and architecture
  - Text preprocessing (to feed an LSTM)
  - Use case studies
    - Sentiment analysis
    - Translation
    - Text generation

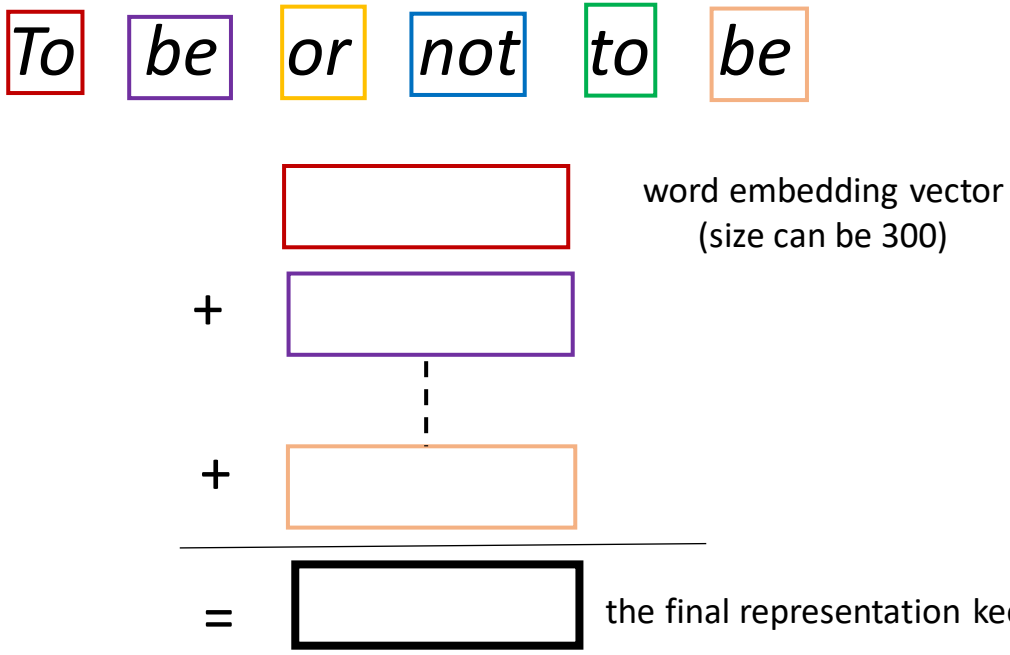


- **Course 4**: “Attention” mechanism and Transformer architectures
- **Course 5**: Chatbot implementation

Previously in Course 2

Embedding: Text embedding

One can get a **text embedding** in **averaging** the embedding vectors of all the tokens in the text

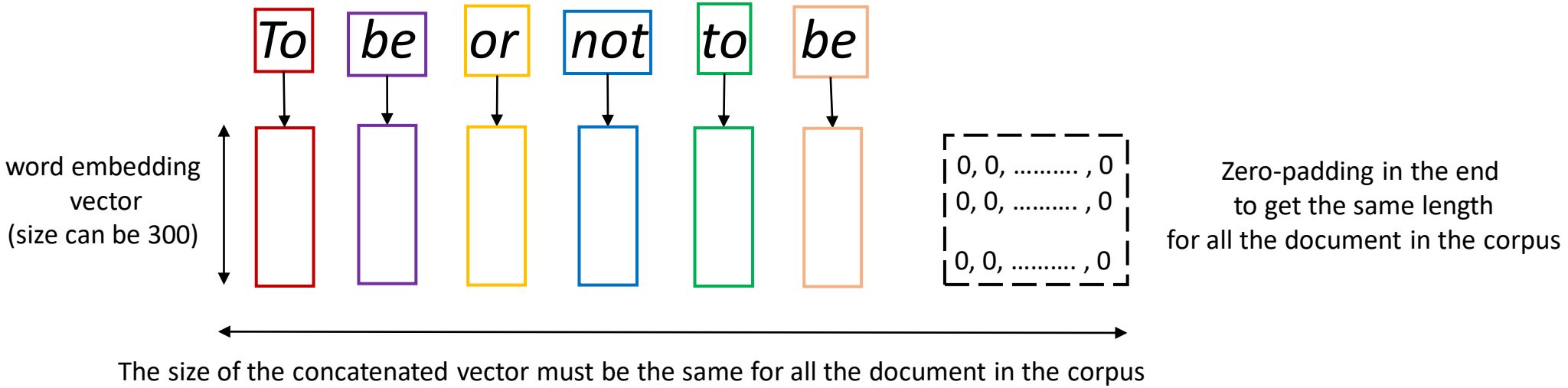


Remarks

- The dimension of the text embedding remains quite **low**
- There is a significant **loss of information** in comparison with the previous method

Embedding: Sequence embedding

One solution is to concatenate the embedding vectors of all the tokens of the text



Remarks

- to keep **the same dimensions** for each text of a corpus, there is a need to **truncate** the number of tokens or to **add padding** (depending on the number of tokens)
- The dimension of each text representation can be very **high** (e.g., several thousands)

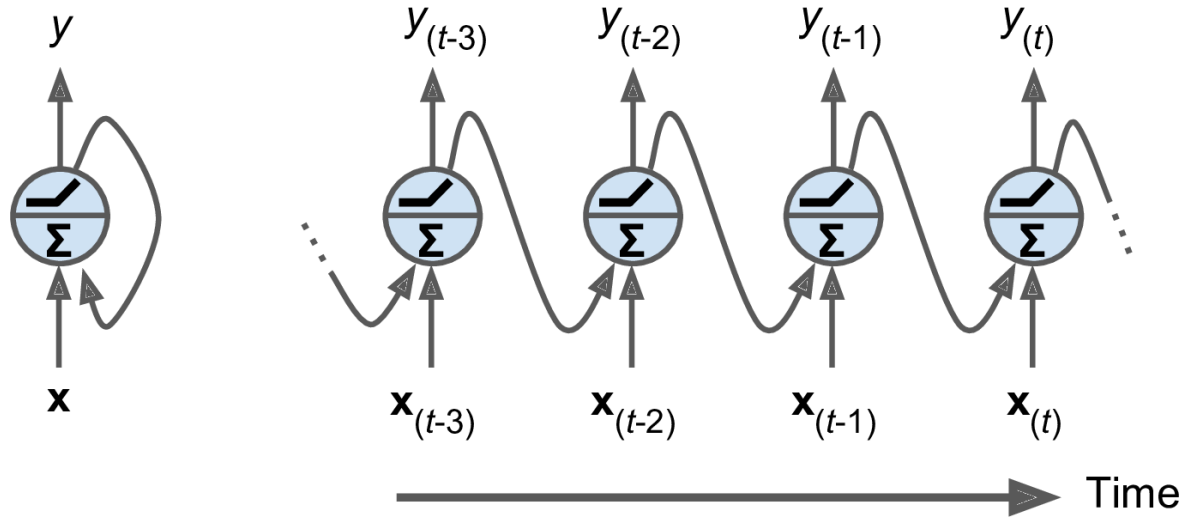
Course 3: Long Short Term Memory (LSTM)

Recurrent Neural Network (RNN)

Recurrent Neural Network (RNN): Definition

- A **RNN** is a kind of neural network dealing with **recurrent** connection
- Allows to deal with **temporal sequences**
- E.g., on the figure below, a sequence **X** is given as **input**, and we get a sequence **Y** as **output**

A simple RNN



Hands-On Machine Learning with Scikit-Learn, Keras, and Tensorflow: Concepts, Tools, and Techniques to Build Intelligent Systems, 2019

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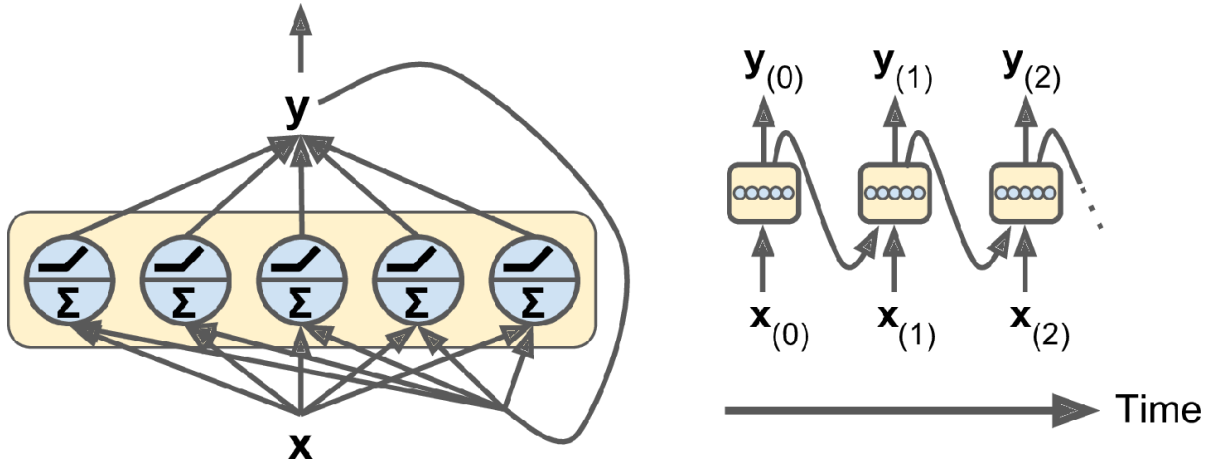
A multi-neuron RNN



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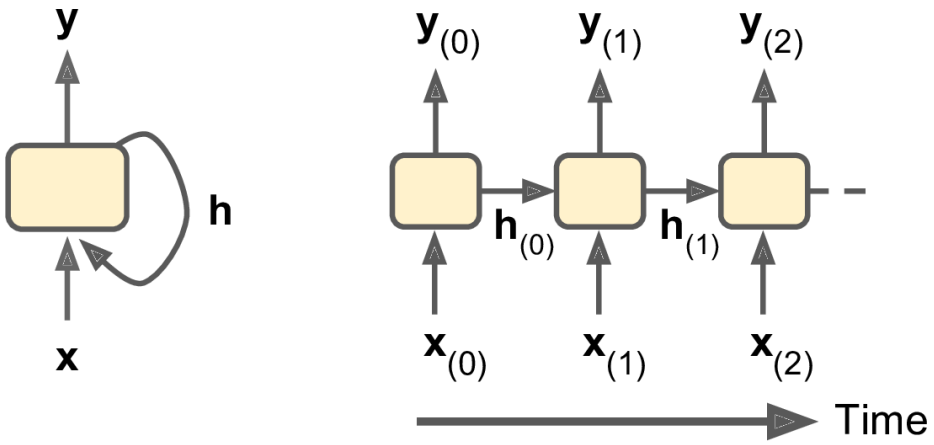
- E.g., on the figure below, a sequence **X** is given as **input**, and we get a sequence **Y** as **output**
- **A cell hidden state h and the output y may be different**

A hidden state RNN



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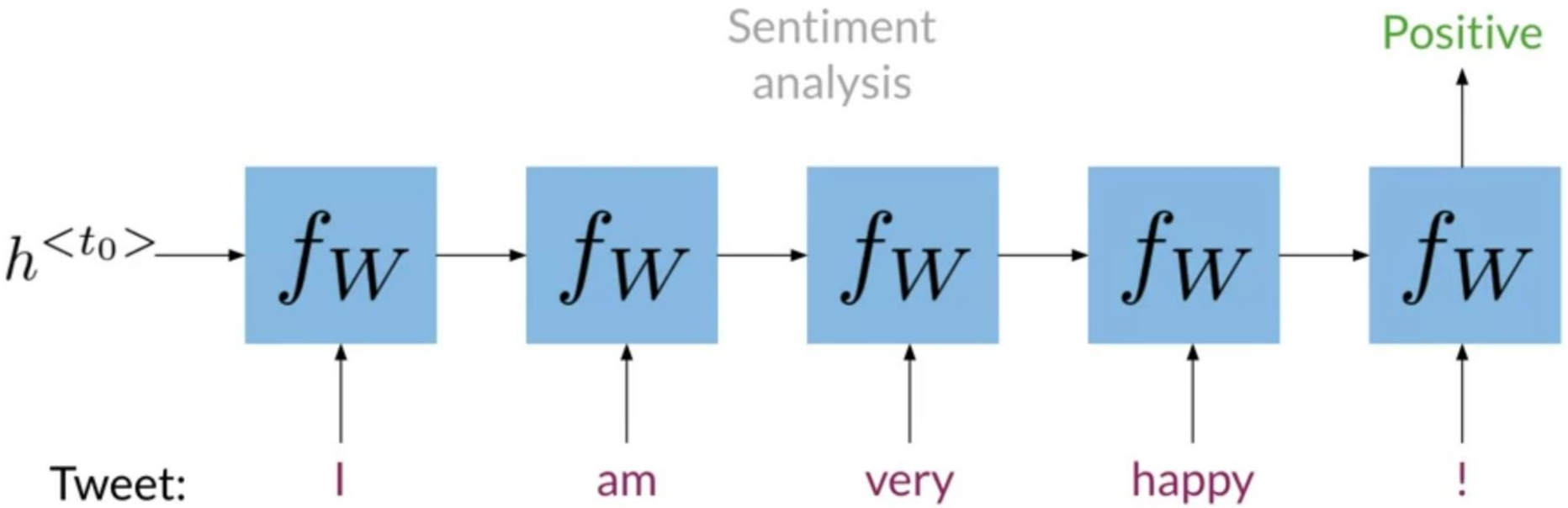
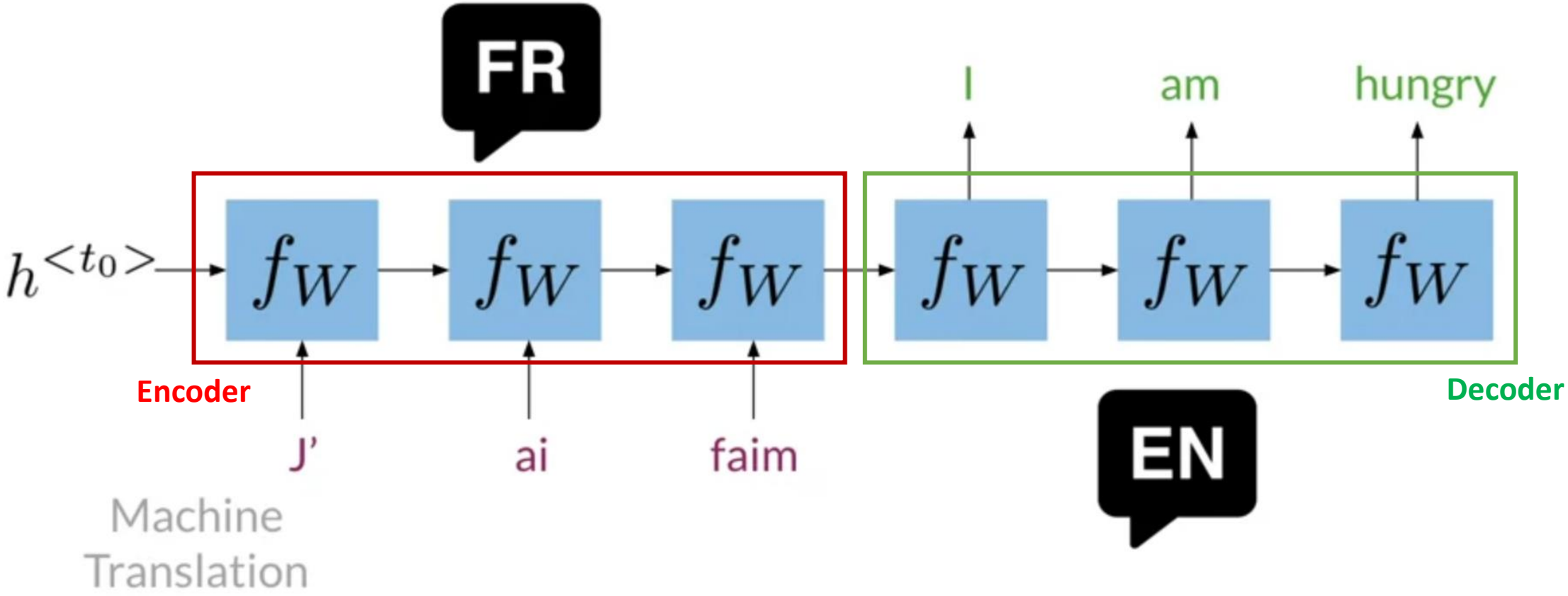
RNN Applications : Many to one



https://www.coursera.org/learn/sequence-models-in-nlp/lecture/VLEGc/applications-of-rnns

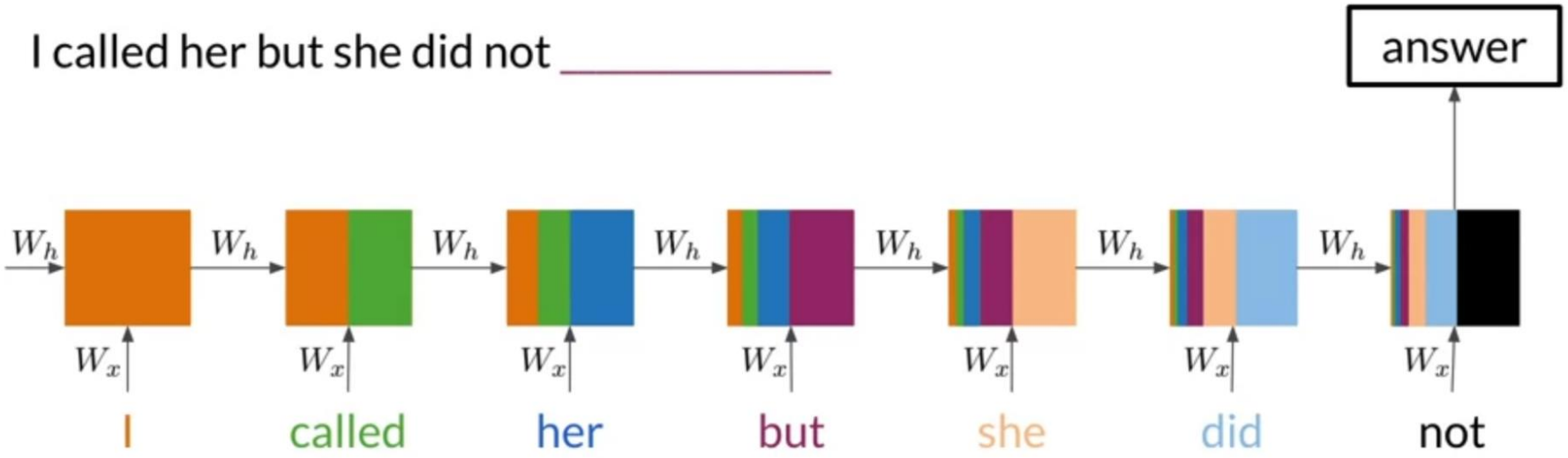
RNN Applications : Many to many



https://www.coursera.org/learn/sequence-models-in-nlp/lecture/VLEGc/applications-of-rnns

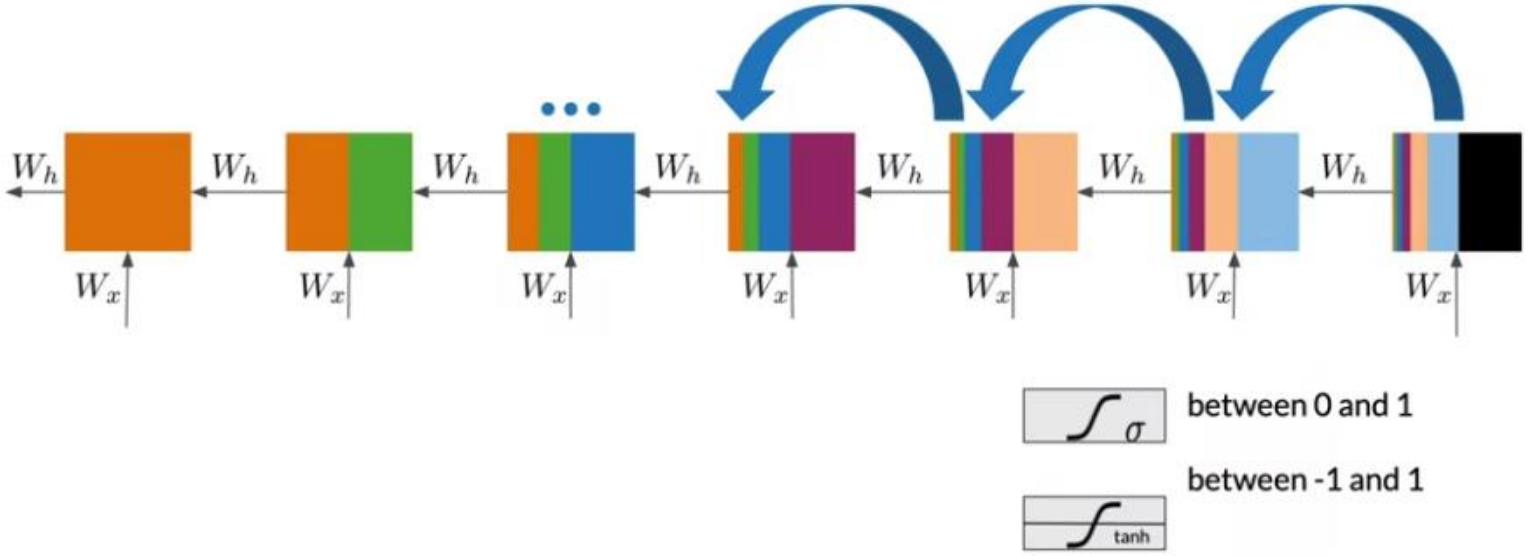
RNN : Long sequence issue

- As shown in the illustration, **RNN** can be used for **text generation**
- However, we can see that, after a **few** cells only, the **impact** of each word almost **disappear**



RNN : Vanishing gradient

- **Vanishing gradient** is another common problem with RNN especially for very long sequences => **makes training non efficient**
- Having a close look at **gradient backpropagation equations** shows that the gradient issues are due to the **derivative of the *tanh*** activation function (<1)



LSTM principle and architecture

LSTM (Long Short Term Memory)

Principle

- The classical deep neural network (e.g., **RNN**) cannot avoid both **vanishing gradient problem** and **loss of early information**

- **LSTM networks** were invented by **Hochreiter** and **Schmidhuber** in 1997

    1. To deal with the **vanishing gradient problem**

    2. To proceed **entire sequences** of data **without forgetting** the meaning of the **early information** proceeded

LSTM (Long Short Term Memory)

Example

I used to live in France, I speak French fluently

The word ***French*** can describe both a language or a nationality. Here the **context** help us to know it corresponds to the language.

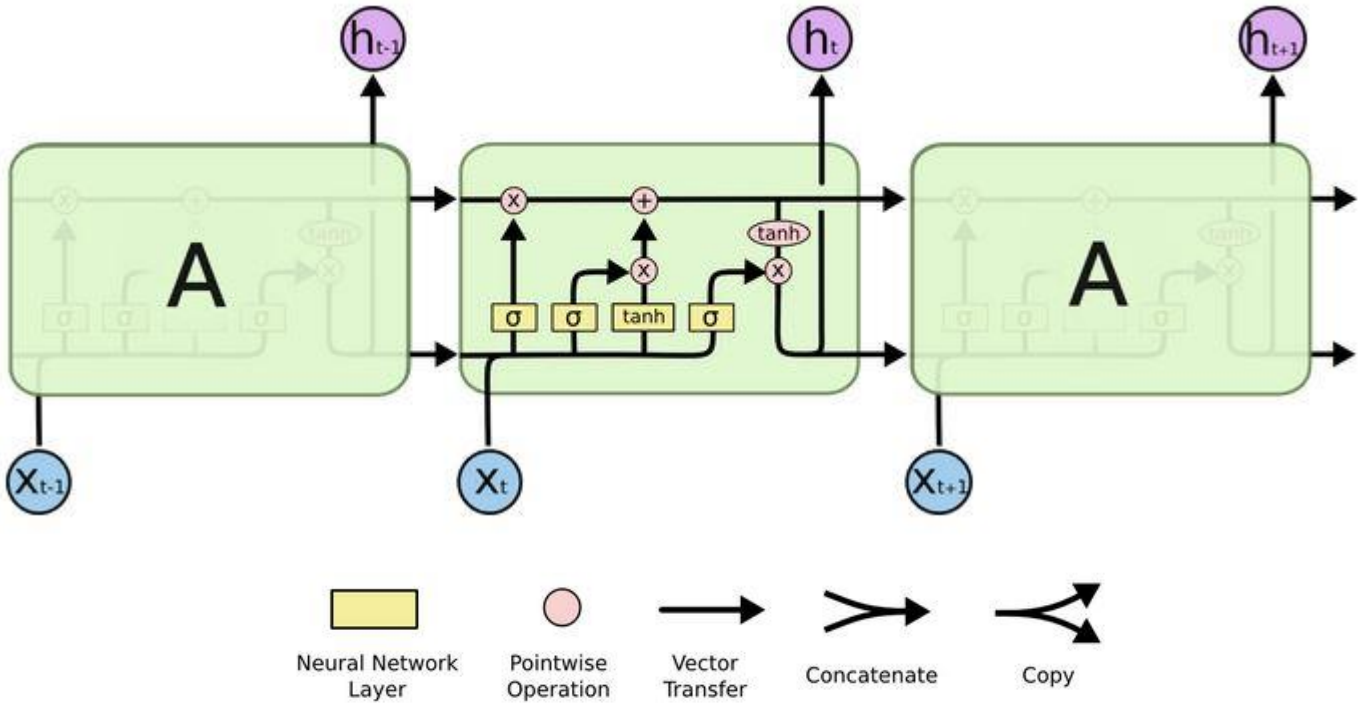
LSTM aims to make good use of the context to determine the meaning of the analyzed words

LSTM (Long Short Term Memory)

A **LSTM architecture** is composed of a set of cells, each of those containing **three gates**

- **An input gate**: decides what to add
- **An output gate**: decides what the next hidden state will be
- **A forget gate**: decides what to keep

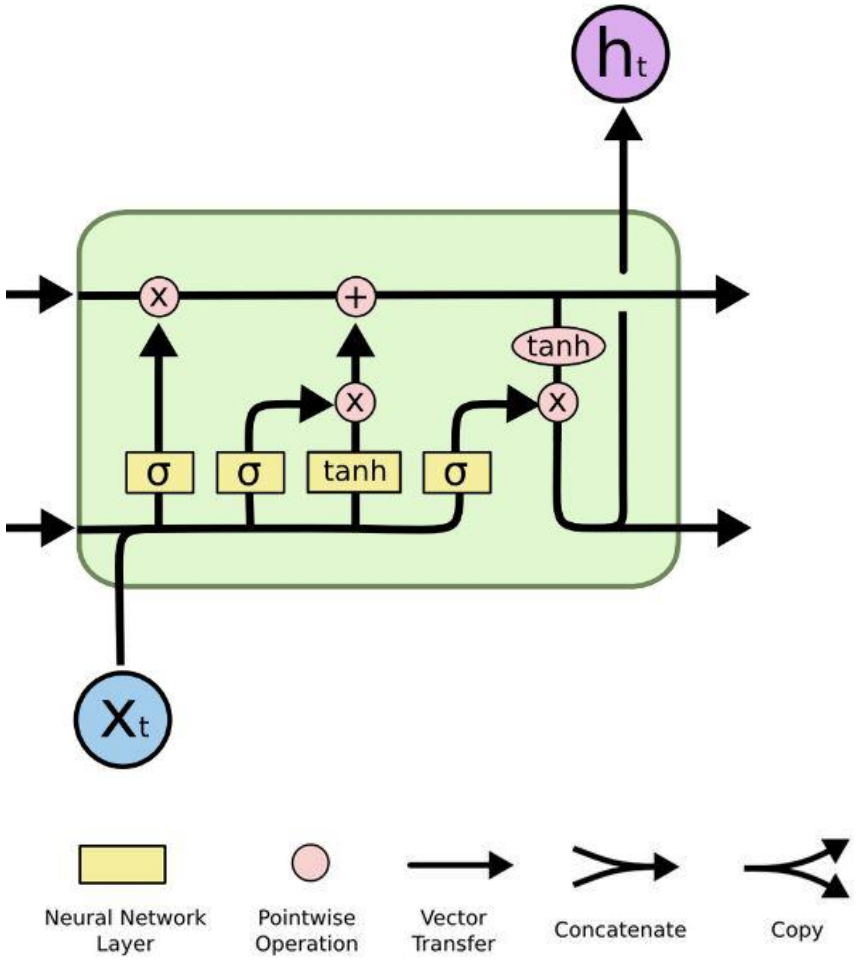
Repeated LSTM modules
(each of them containing four layers)



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM (Long Short Term Memory)

LSTM module



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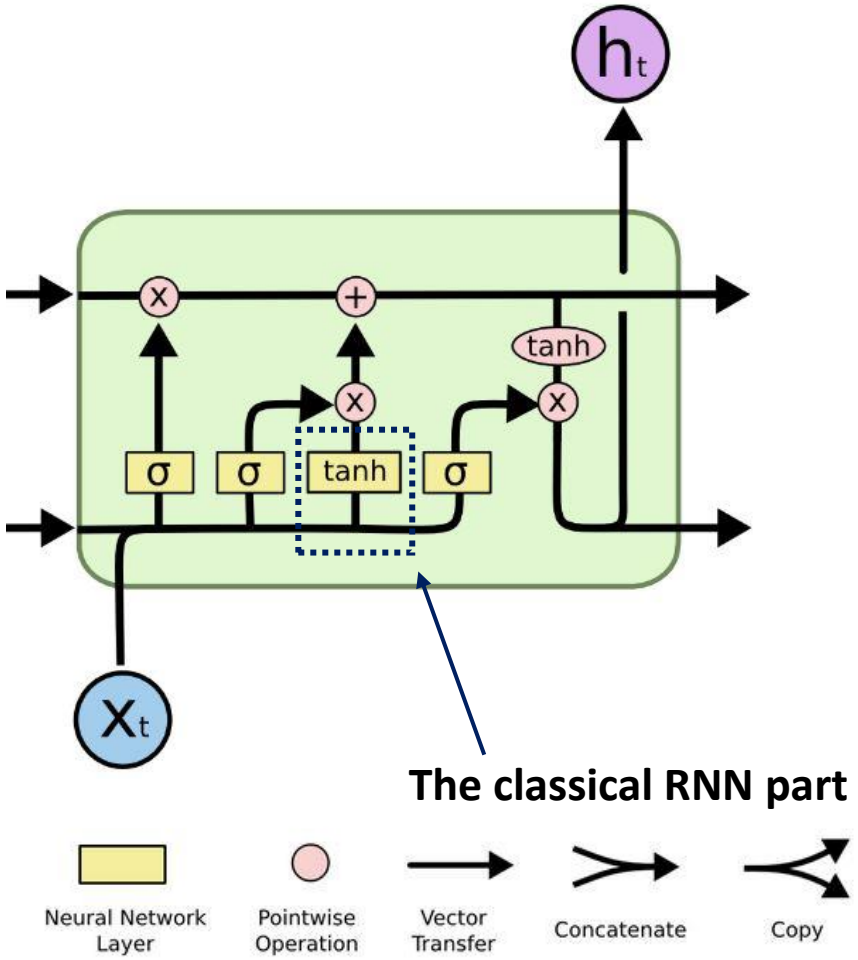
LSTM (Long Short Term Memory)

LSTM module



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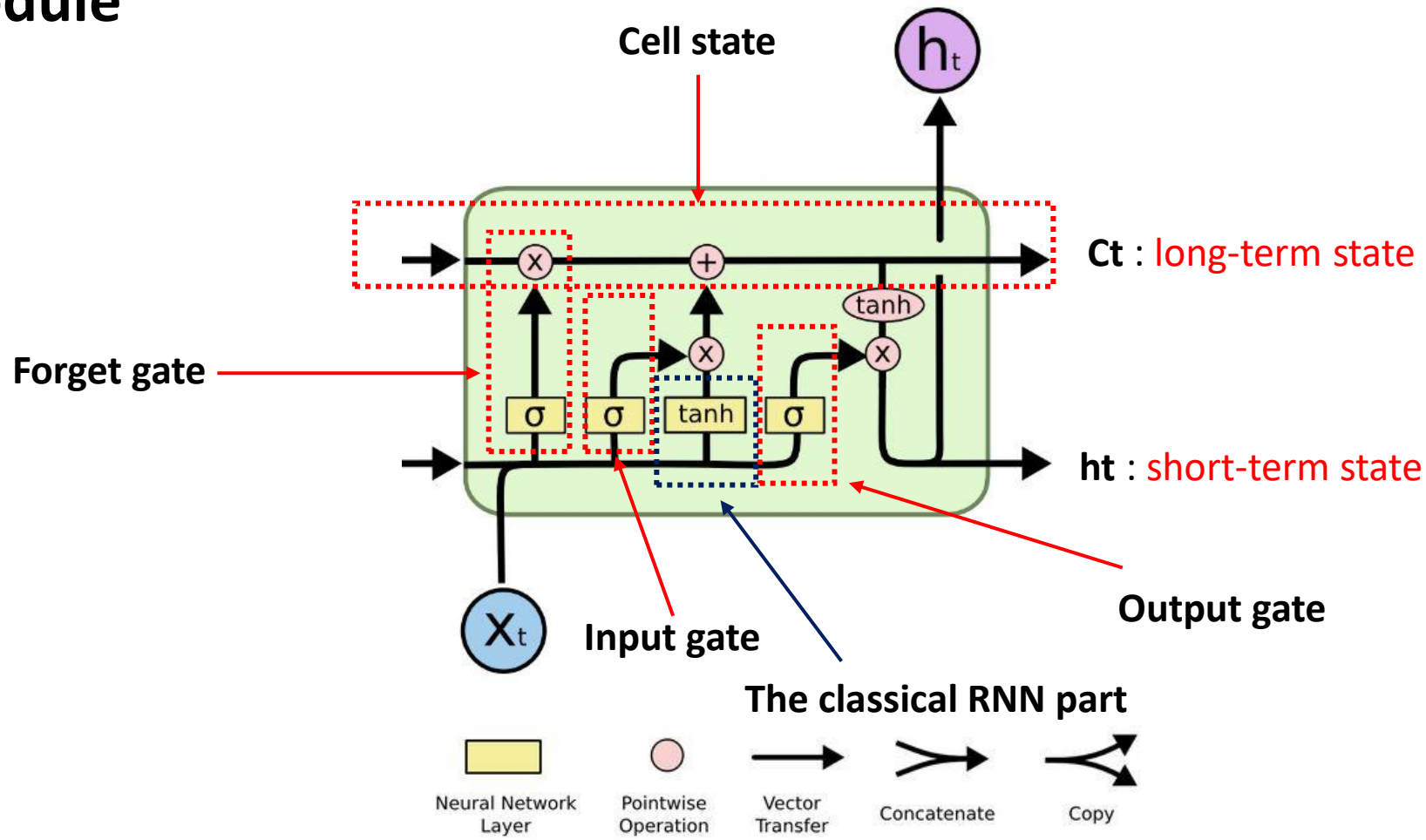
LSTM (Long Short Term Memory)

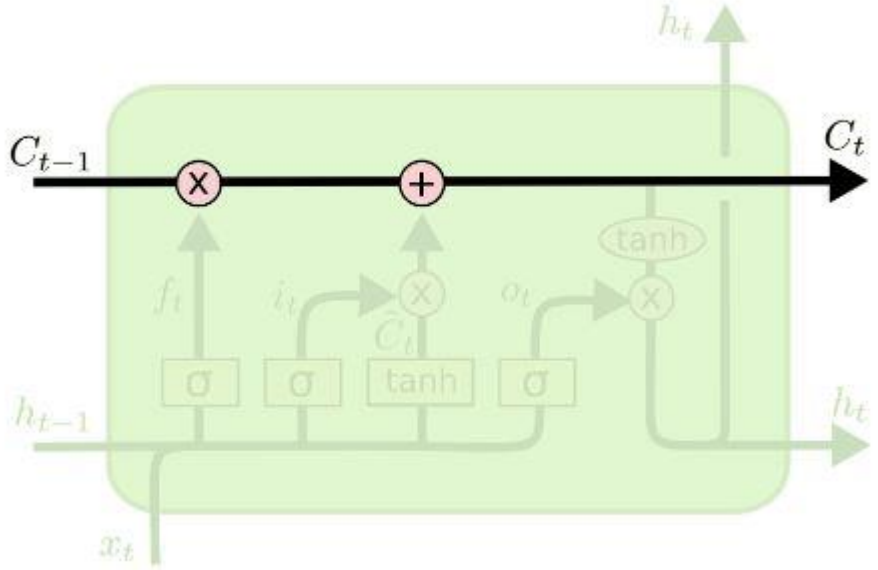
LSTM module



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM (Long Short Term Memory)

Cell state: C_t



The cell state runs down the entire chain with some linear interactions through each LSTM module met down the way

Gates allow LSTM to optionally remove or add information to the cell state

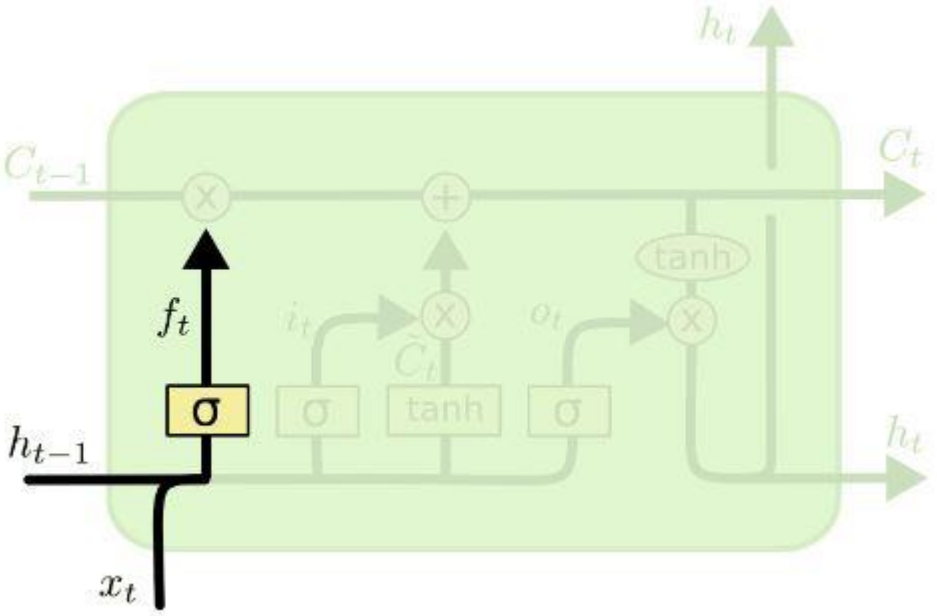
http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM (Long Short Term Memory)

Forget gate: decide what information we drop from the cell state

The sigmoid output a number between 0 and 1 for each number in the cell state C_{t-1}

Example: the cell state might include the gender of a present subject.
If a new subject is seen => forget the previous one



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

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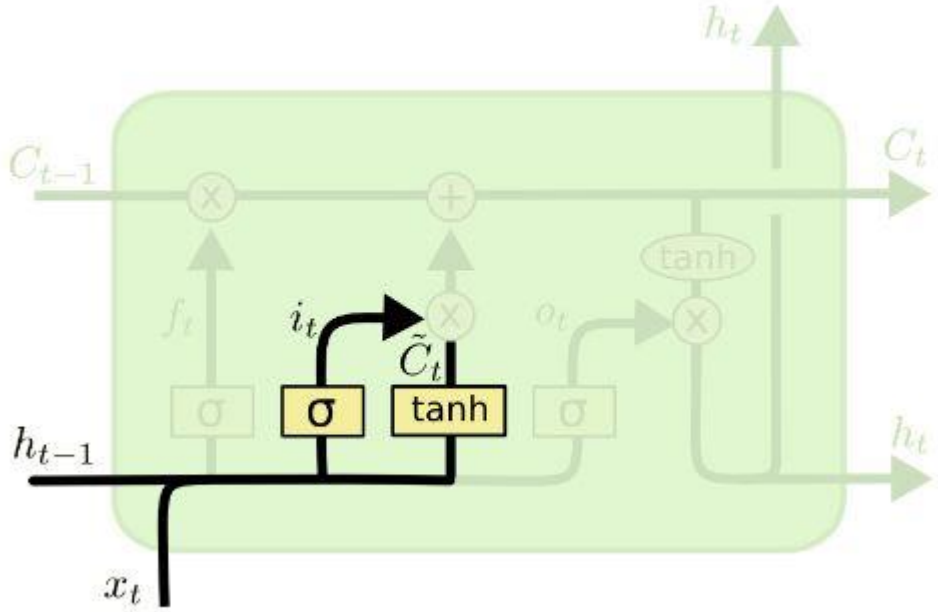
LSTM (Long Short Term Memory)

Input gate: decide what new information we store in the cell state



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Two parts:

- **A sigmoid layer to decide which values we update**
- **A tanh layer to create a vector of new candidate values for C_t**

Example: we add the gender of the new subject to replace the previous one which has been forgotten

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

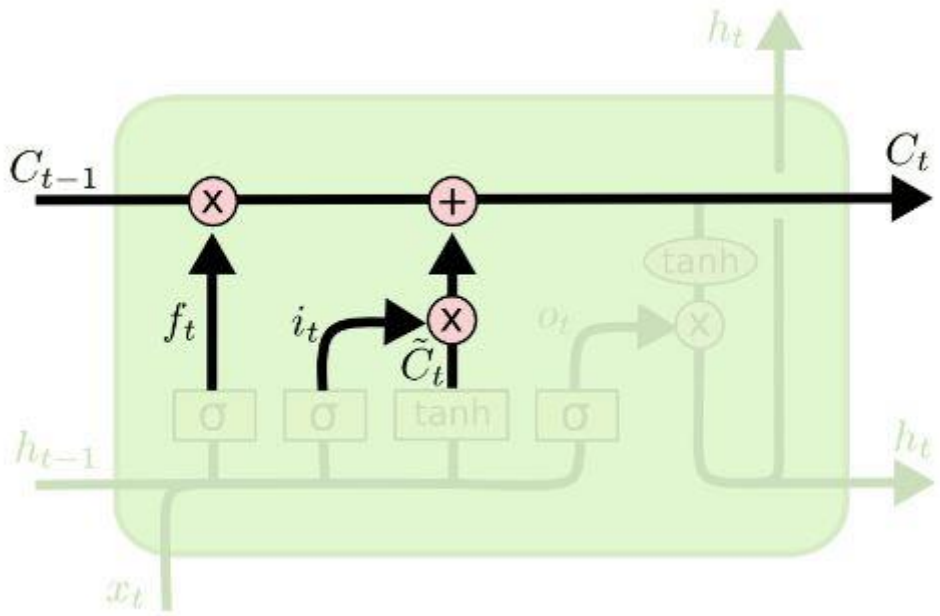
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

LSTM (Long Short Term Memory)

Cell state update: $C_{t-1} \Rightarrow C_t$

- **The previous state is multiplied by *ft*, to forget the things we decided earlier**
- **We add the new candidate values, scaled by how much we decided to update earlier**

Example: we drop the information about the old gender and add the information related to the new one



$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

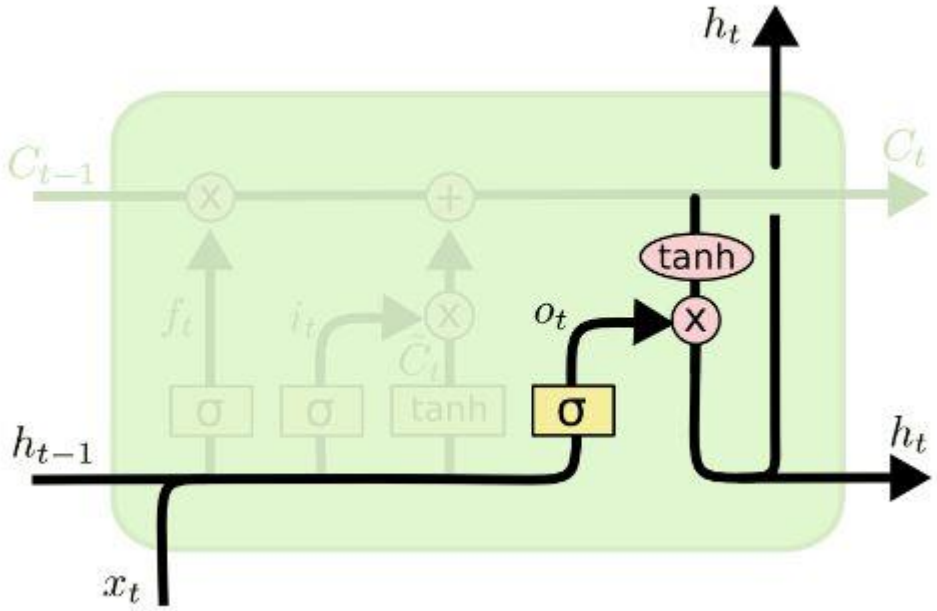
http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM (Long Short Term Memory)

Output gate: decide what information to output

The output is a filtered version of the cell state

- **First, we run a sigmoid layer to decide what part of the cell state to output**
- **Then, we rescale the cell state (using a tanh layer) and multiply it by the result of the output gate**



http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Example: it might output whether the subject is singular or plural, in order to know how to conjugate the following verb

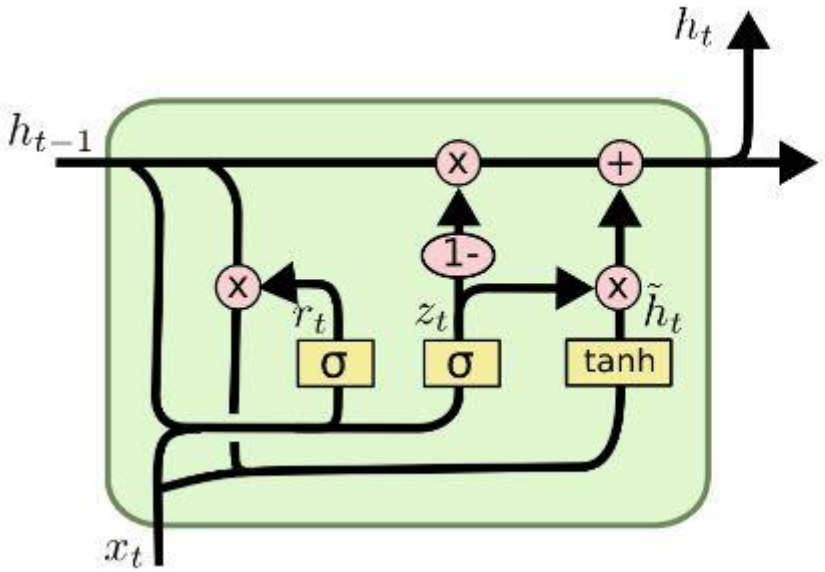
$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

Gated Recurrent Unit (GRU)

Introduced in 2014, it corresponds to a simplified LSTM variant with only two gates

- The **forget** and **input** gates are combined into a single **update** gate which defines how much information to keep
- A **reset** gate is defined to determine how much information to forget
- Both LSTM and GRU can be useful depending on the specific application



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

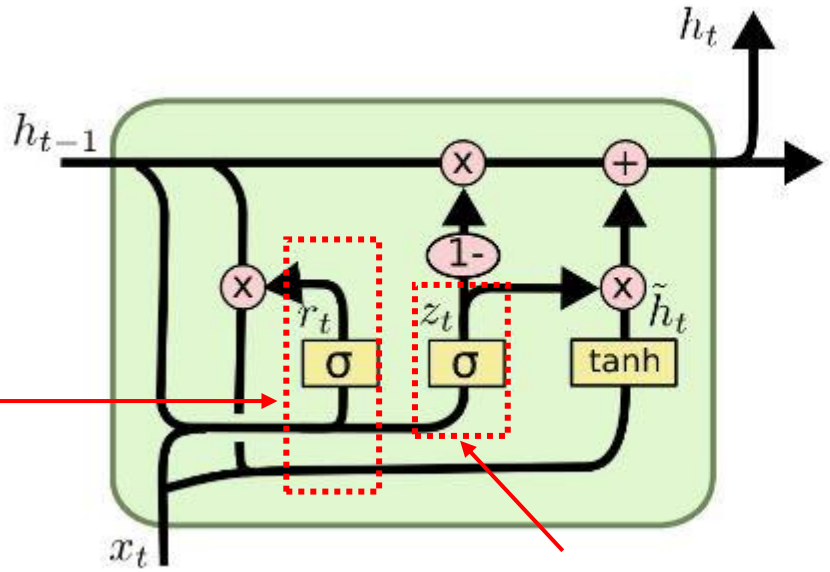
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Gated Recurrent Unit (GRU)

Introduced in 2014, it corresponds to a simplified LSTM variant with only two gates

- The **forget** and **input** gates are combined into a single **update** gate which defines how much information to keep
- A **reset** gate is defined to determine how much information to forget
- Both LSTM and GRU can be useful depending on the specific application



Reset gate

Update gate

$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

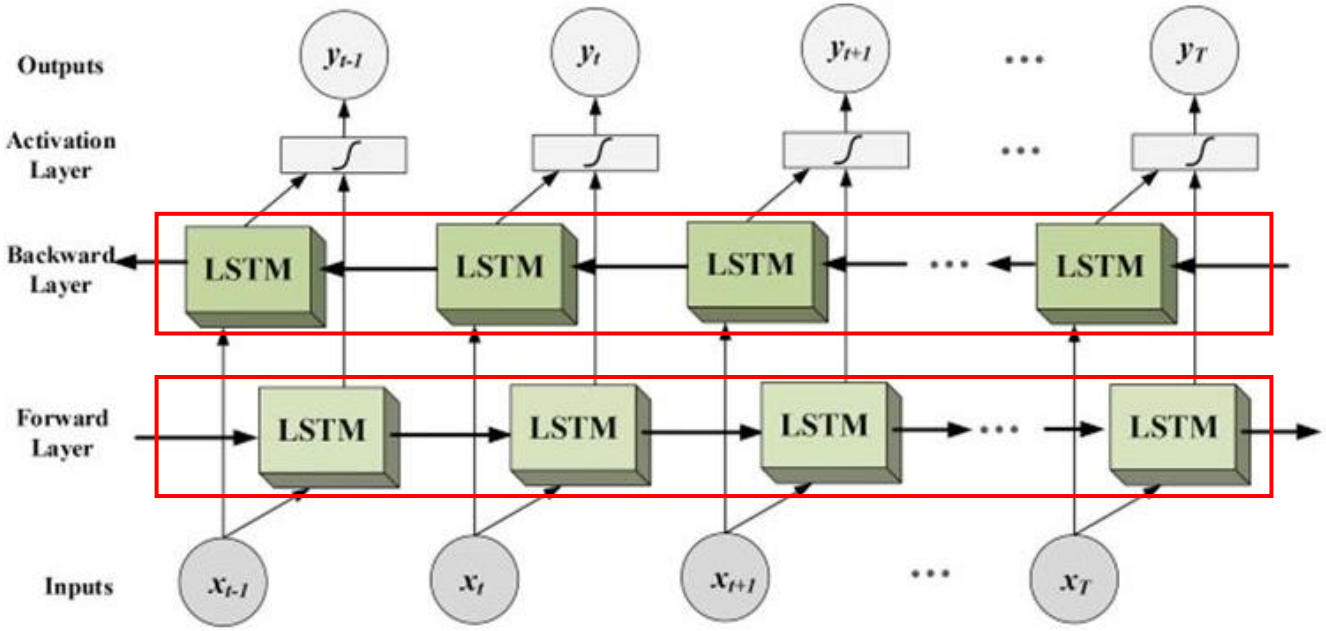
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Bidirectional LSTM

In a **classic LSTM** architecture, the sentence/sequence is processed only in **one direction** (generally from the past to the present or future)

The **bidirectional** structure process the data in **both directions** => can be useful for some applications



https://medium.com/the-official-integrate-ai-blog/what-you-need-to-know-about-natural-language-processing-2c8240e6c38e

The **Queen** of the United Kingdom ←

The **queen** of hearts ←

The **queen** of bees ←

Here, the word queen will be encode differently
if read in reverse order

Hands-On Machine Learning with Scikit-Learn, Keras, and Tensorflow: Concepts, Tools, and Techniques to Build Intelligent Systems, 2019

LSTM (Long Short Term Memory)

Applications

- **Text analysis**
- **Text translation**
- **Next-word prediction**
- Chatbots
- Music composition
- Image captioning
- Speech recognition

Text preprocessing (to feed an LSTM)

Text preprocessing

The **LSTM architecture** was conceived to process **long sequences** without any **long-term dependency issues**

We train an **LSTM** Network with **chunks of text**:

1. Each chunk of text must be split into sequences => **Tokenization**
2. Each sequence must have the same length => **Padding**
3. Each element in a sequence should be converted into numerical values => **Embedding**

Text preprocessing

The **LSTM architecture** was conceived to process **long sequences** without any **long-term dependency issues**

We train an **LSTM** Network with **chunks of text**:

1. **Each chunk of text must be split into sequences => Tokenization**
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Tokenization

Principle

To be or not to be

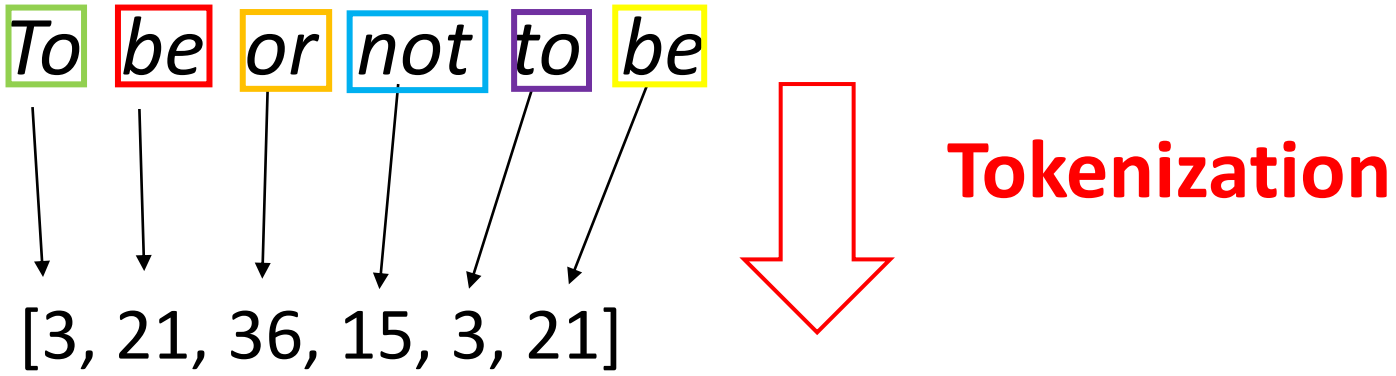
Tokenization

Principle

Tokenization

Tokenization

Principle



Each token is associated to its **number** in the **vocabulary** considered

Text preprocessing

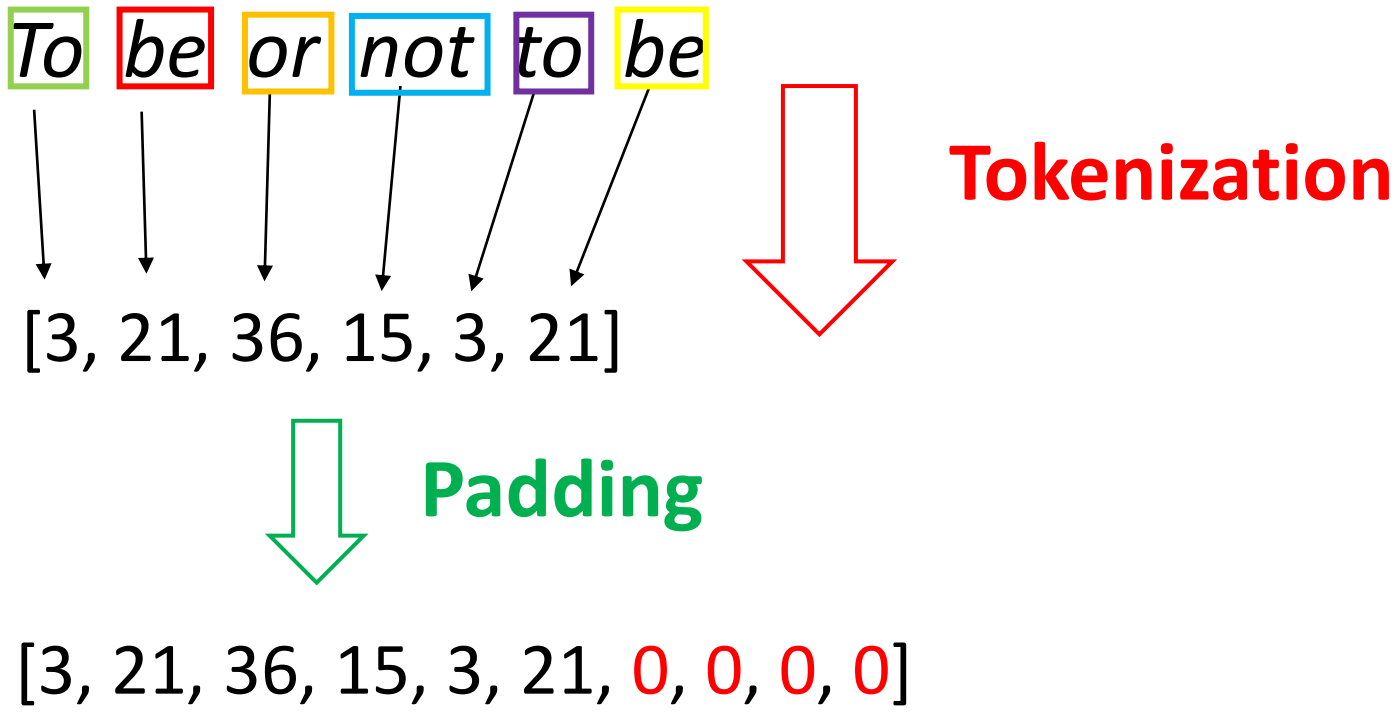
The **LSTM architecture** was conceived to process **long sequences** without any **long-term dependency issues**

We train an **LSTM** Network with **chunks of text**:

1. Each chunk of text must be split into sequences => **Tokenization**
2. **Each sequence must have the same length => Padding**
3. Each element in a sequence should be converted into numerical values => **Embedding**

Padding

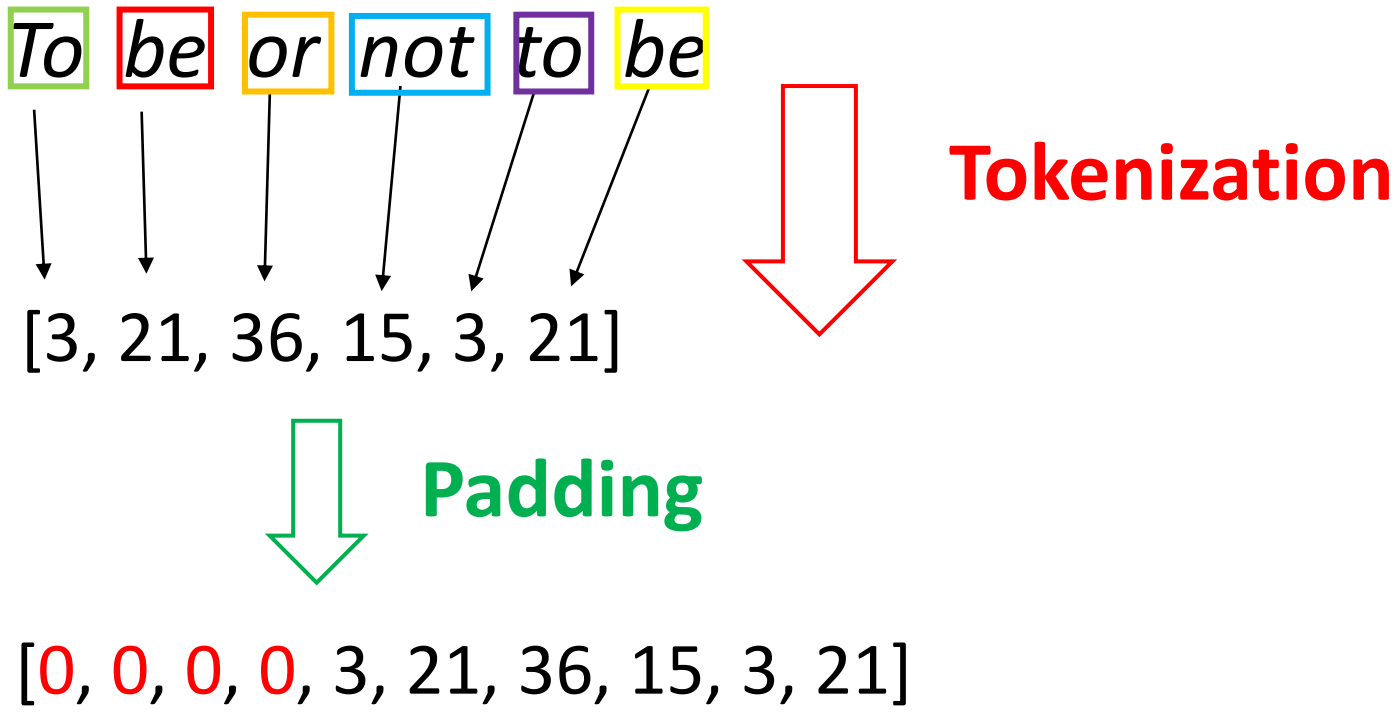
Principle



We add **additional zeros** in the **end** in order to consider a **fixed length** for every sequence

Padding (Variant)

Principle



We can as well add the **additional zeros** in the **beginning** instead

The choice may depend on the application

Text preprocessing

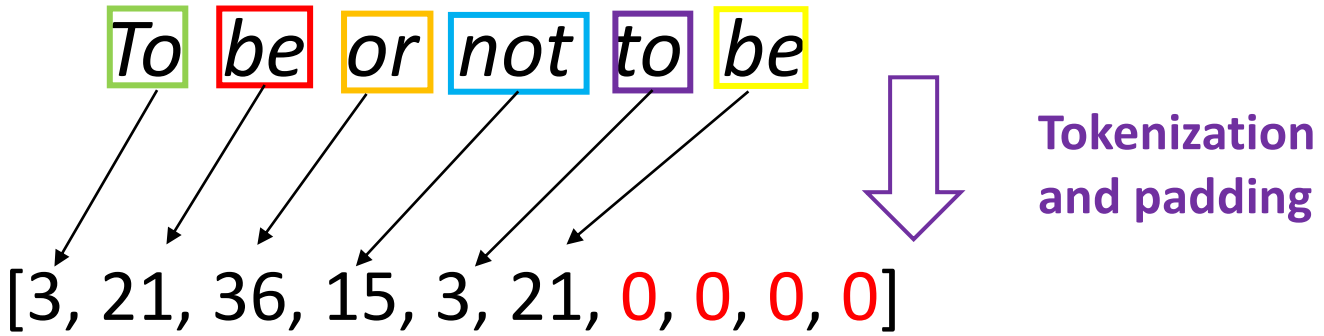
The **LSTM architecture** was conceived to process **long sequences** without any **long-term dependency issues**

We train an **LSTM** Network with **chunks of text**:

1. Each chunk of text must be split into sequences => **Tokenization**
2. Each sequence must have the same length => **Padding**
3. **Each element in a sequence should be converted into numerical values => Embedding**

Embedding

Once we get the padded sequence



two possibilities concerning the next step

1. Use of a pre-trained embedding (see **Course 2**)
2. **Learn a new embedding from scratch (use of an Embedding layer in Keras)**

Embedding

As we saw during last **Course**:

*Word embeddings come from neural network training on **HUGE** datasets: need to use **pre-trained libraries** for general use cases*

BUT in some cases, we are not interested by a model with a good representation of a language **in general** but only for a **specific** application.

In that case, and if the training data set is **big enough**, we can learn from scratch a new embedding for **the specific task** we are interested in.

(Another possibility is to **fine-tune** a pre-trained model – let's see that later in **Course 4**!)

Embedding: One-hot encoding step

To feed an embedding training network, we must use a relevant format for the input

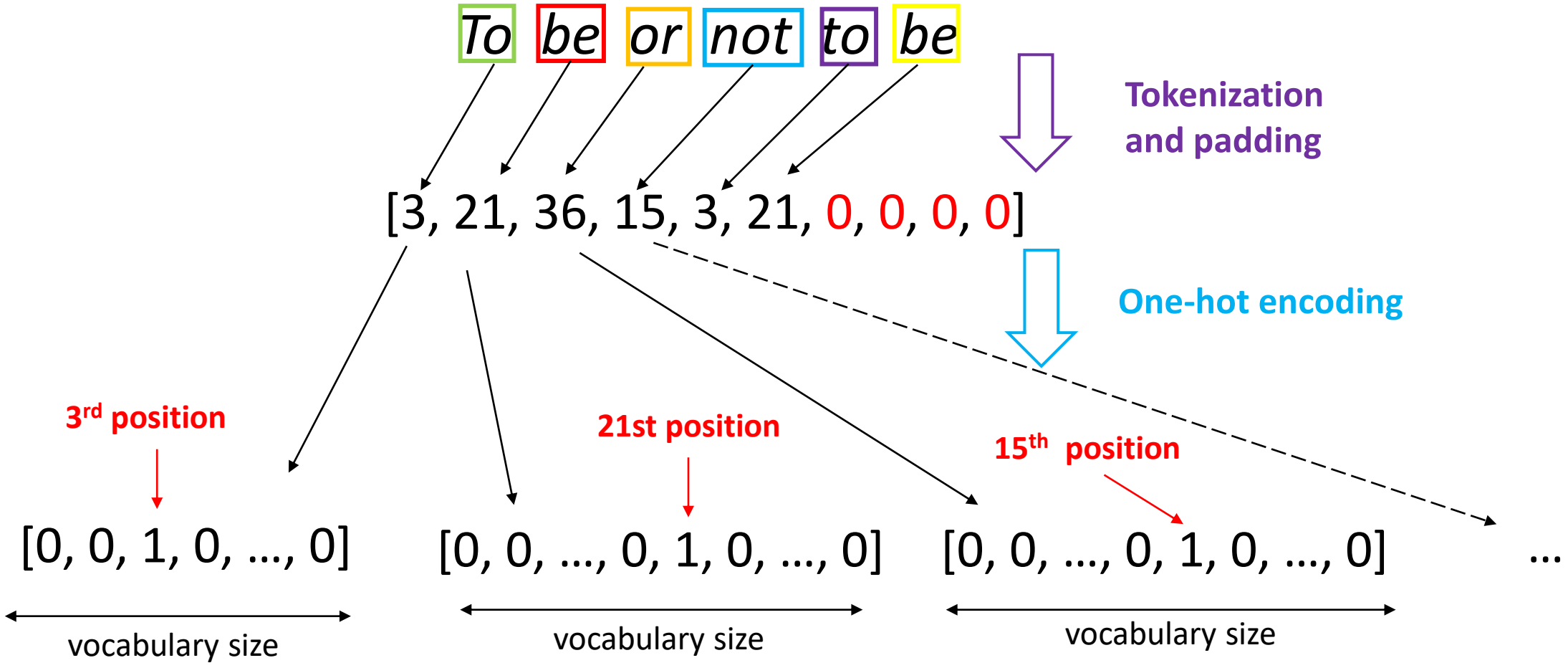
Normally, we cannot use the token sequence directly as inputs of the neural network because the numerical values are misleading

[3, 21, 36, 15, 3, 21, 0, 0, 0, 0]

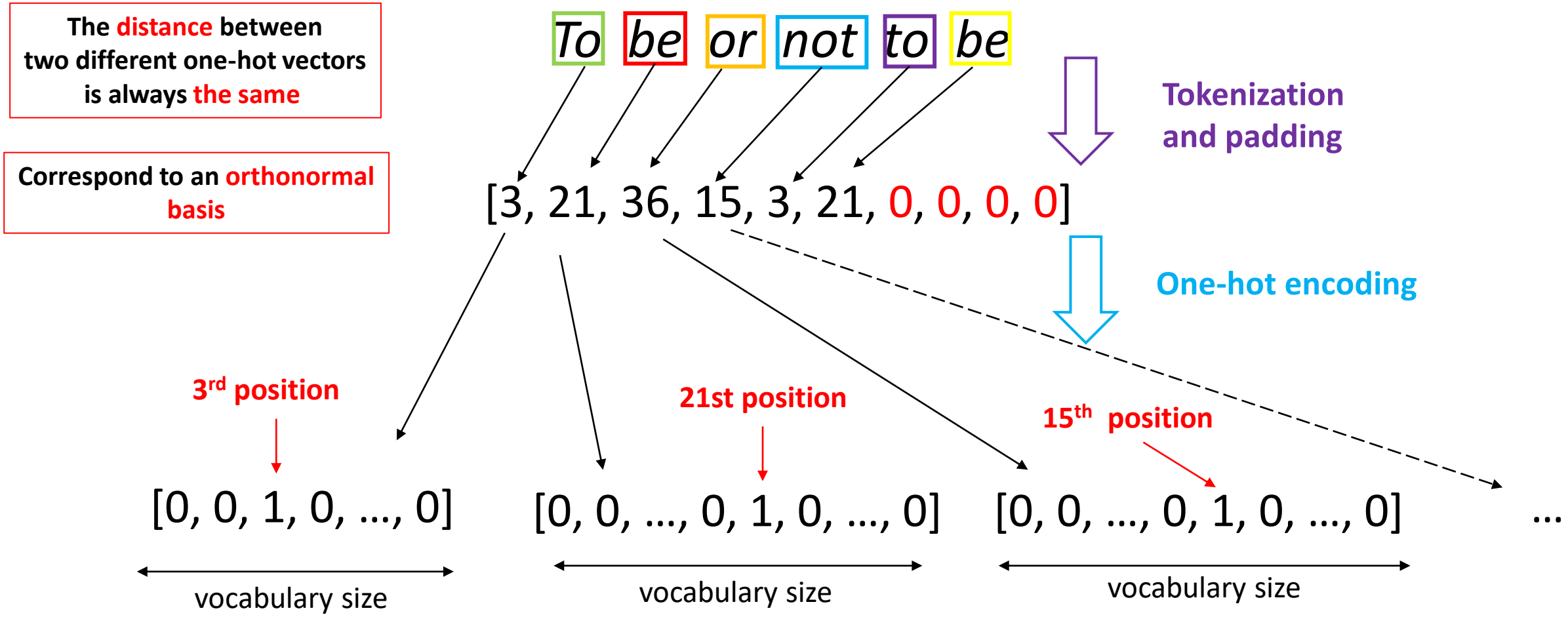
Indeed, all tokens are **independent**, the network should **NOT** consider that tokens “2” and “3” are closer than, let’s say, tokens “2” and “3000”

Because of that, a **more neutral** numerical representation is **needed** => **One-hot encoding**

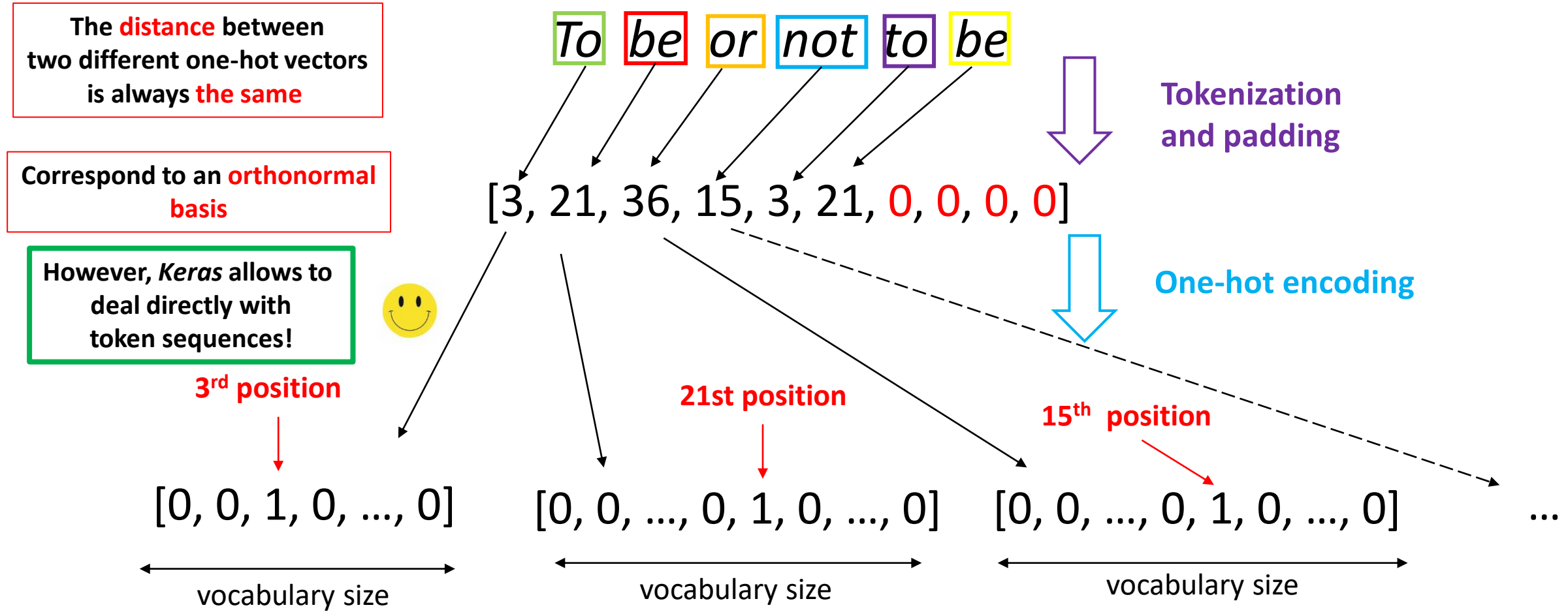
Embedding: One-hot encoding step



Embedding: One-hot encoding step



Embedding: One-hot encoding step



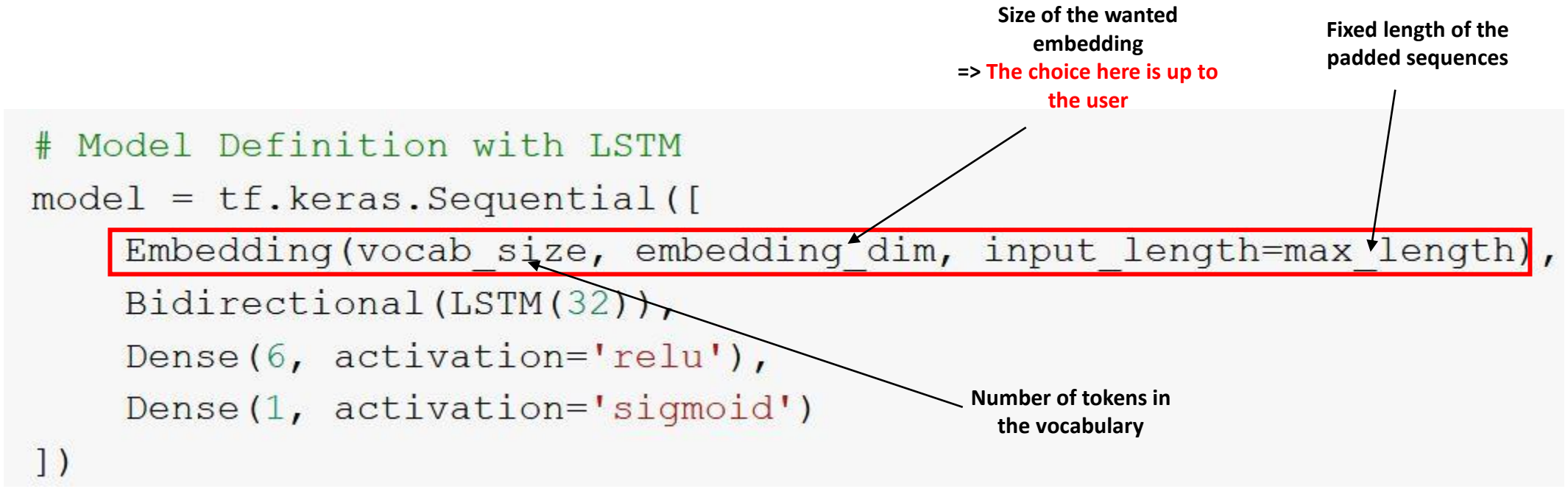
Embedding: *Embedding* Keras layer

In order to **train an embedding from scratch** (using **directly** the **token** sequences), one can use the ***Embedding* Keras layer**

```
# Model Definition with LSTM
model = tf.keras.Sequential([
    Embedding(vocab_size, embedding_dim, input_length=max_length),
    Bidirectional(LSTM(32)),
    Dense(6, activation='relu'),
    Dense(1, activation='sigmoid')
])
```

Embedding: *Embedding* Keras layer

In order to **train an embedding from scratch** (using **directly** the **token** sequences), one can use the ***Embedding*** **Keras layer**




```
# Model Definition with LSTM
model = tf.keras.Sequential([
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    Bidirectional(LSTM(32)),
    Dense(6, activation='relu'),
    Dense(1, activation='sigmoid')
])
```

Text sequence preprocessing: Exercise

course3_text_sequence_prepocessing_ex.ipynb

Goal: Get used to the basics of text sequence preprocessing before feeding an RNN/LSTM network **IMDB dataset**

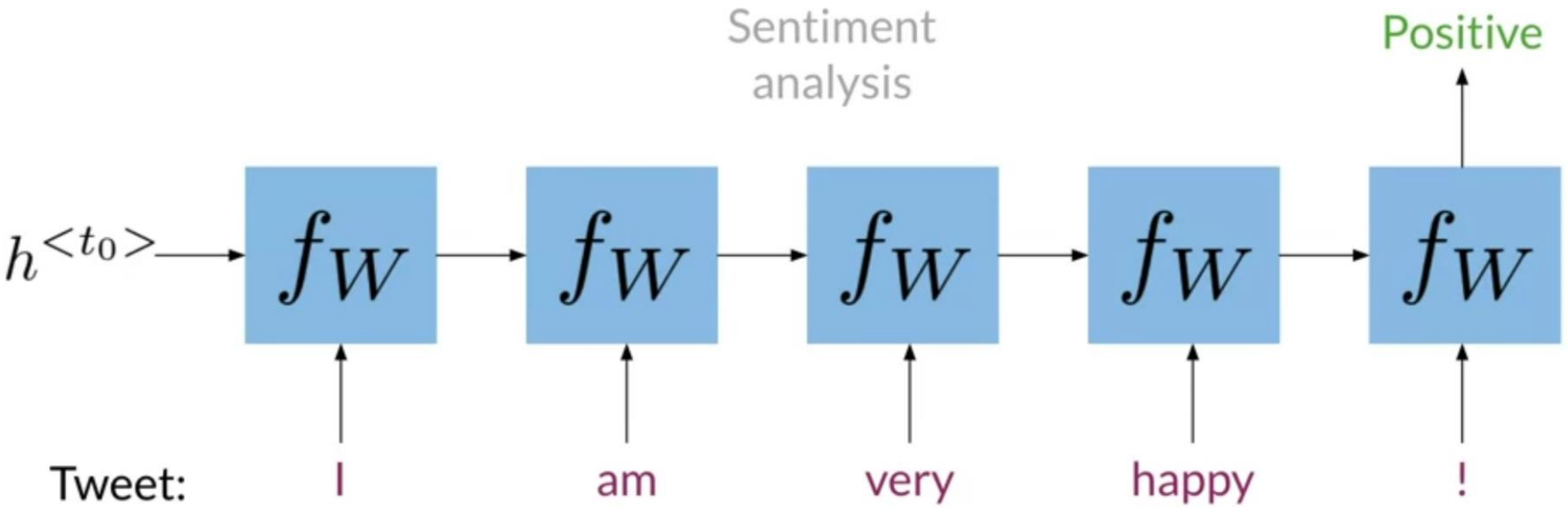
Remarks:

- We will see how to compute **tokenization**, **padding** and **one-hot encoding** from the **Keras** API
- We use (again) **IMDB reviews dataset** for this exercise

Use cases

Use cases: Sentiment analysis

Sentiment analysis: Illustration



https://www.coursera.org/learn/sequence-models-in-nlp/lecture/VLEGc/applications-of-rnns

Sentiment analysis: Exercise

course3_sentiment_analysis_LSTM_ex.ipynb

Goal: Use of **text sequences** to feed neural networks such as **LSTM** for a **sentiment analysis** use case

Remarks:

- The **main difference** with last **Course** sentiment analysis exercises is that we do not use **an average text embedding** as input any longer, but the **concatenated token embedding vector sequences**
- Another difference is that we do not use a pre-trained embedding model but **learn it from the dataset itself**

Sentiment analysis : LSTM model

Use of a Bidirectional LSTM model

```
# Model Definition with LSTM
model = tf.keras.Sequential([
    Embedding(vocab_size, embedding_dim, input_length=max_length),
    Bidirectional(LSTM(32)),
    Dense(6, activation='relu'),
    Dense(1, activation='sigmoid')
])
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
model.summary()
```

Sentiment analysis : GRU model

Use of a Bidirectional GRU model

```
# Model definition with GRU
model = tf.keras.Sequential([
    Embedding(vocab_size, embedding_dim, input_length=max_length),
    Bidirectional(GRU(32)),
    Dense(6, activation='relu'),
    Dense(1, activation='sigmoid')
])
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
model.summary()
```

Sentiment analysis : LSTM vs GRU

LSTM

```
# Model Definition with LSTM
model = tf.keras.Sequential([
    Embedding(vocab_size, embedding_dim, input_length=max_length),
    Bidirectional(LSTM(32)),
    Dense(6, activation='relu'),
    Dense(1, activation='sigmoid')
])
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 120, 16)           160000
_________________________________________________________________
bidirectional_1 (Bidirection (None, 64)                12544
_________________________________________________________________
dense_2 (Dense)              (None, 6)                 390
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 7
=================================================================
Total params: 172,941
Trainable params: 172,941
Non-trainable params: 0
_________________________________________________________________
```

172, 941

GRU

```
# Model definition with GRU
model = tf.keras.Sequential([
    Embedding(vocab_size, embedding_dim, input_length=max_length),
    Bidirectional(GRU(32)),
    Dense(6, activation='relu'),
    Dense(1, activation='sigmoid')
])
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 120, 16)           160000
_________________________________________________________________
bidirectional (Bidirectional (None, 64)                9600
_________________________________________________________________
dense (Dense)                (None, 6)                 390
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 7
=================================================================
Total params: 169,997
Trainable params: 169,997
Non-trainable params: 0
_________________________________________________________________
```

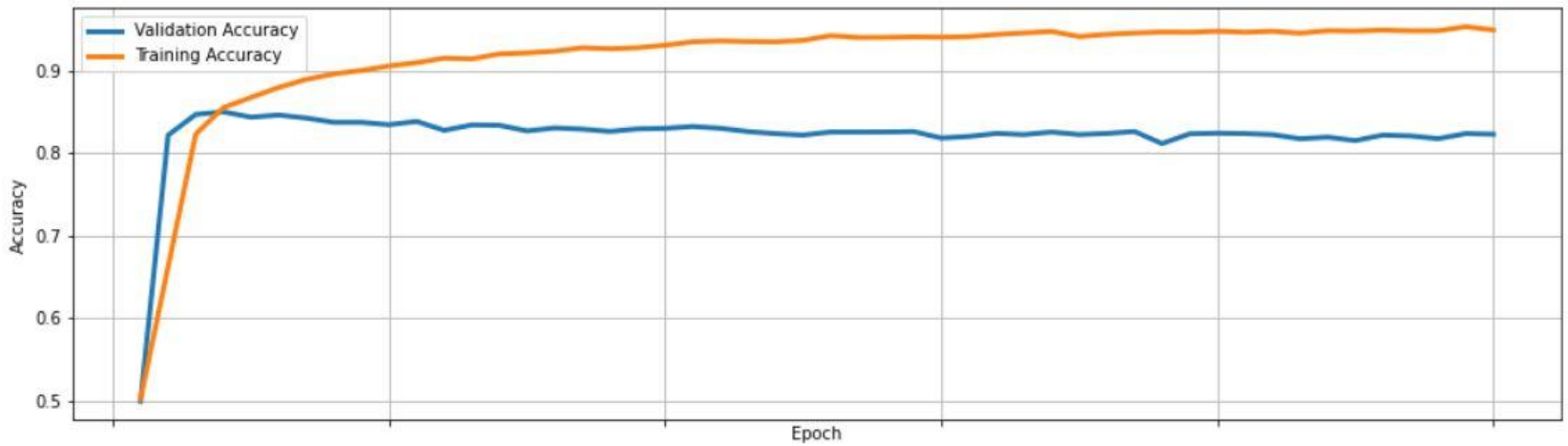
169, 997

A (little) less trainable parameters for the GRU model

Sentiment analysis : Results

- **Using a GRU model (with Dropout)**
- **50 epochs**

```
# Model definition with GRU
model = tf.keras.Sequential([
    Embedding(vocab_size, embedding_dim, input_length=max_length),
    Dropout(0.5),
    Bidirectional(GRU(32)),
    Dense(6, activation='relu'),
    Dropout(0.5),
    Dense(1, activation='sigmoid')
])
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
model.summary()
```



Sentiment analysis : Results

- **Using a GRU model (with Dropout)**
- **50 epochs**

```
# Model definition with GRU
model = tf.keras.Sequential([
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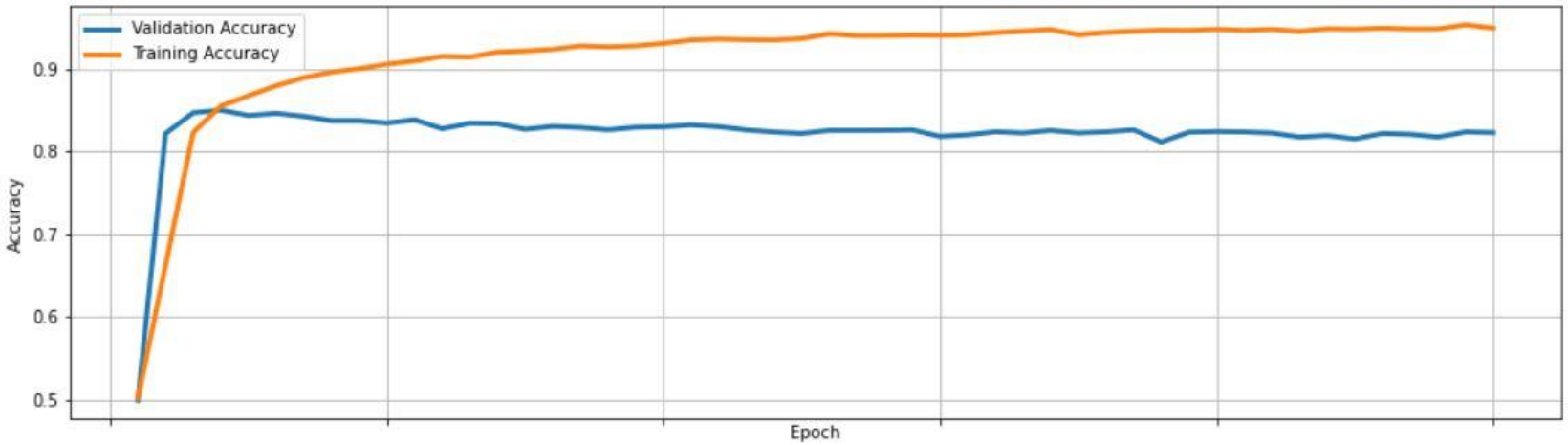
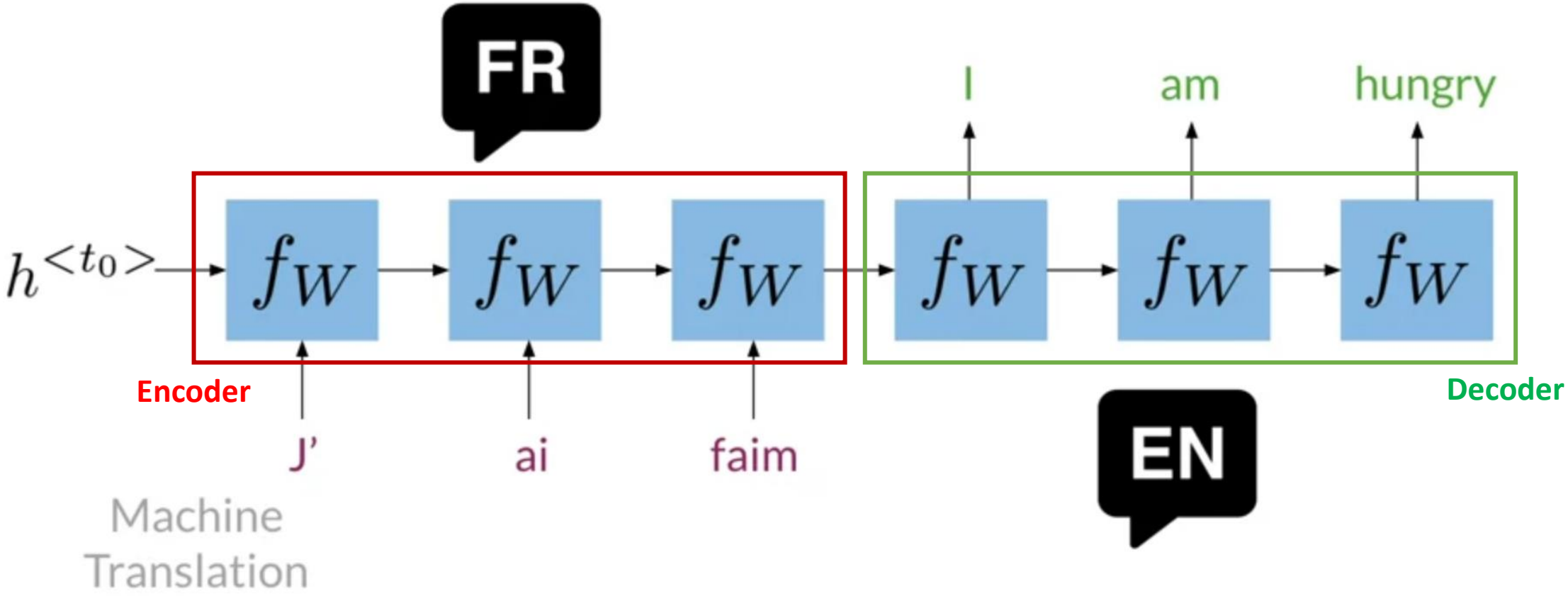
    Bidirectional(GRU(32)),
    Dense(6, activation='relu'),
    Dropout(0.5),
    Dense(1, activation='sigmoid')
])
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
model.summary()
```



You can definitively achieve better results by tweaking the model a little!

Use cases: Translation

Translation: Illustration



https://www.coursera.org/learn/sequence-models-in-nlp/lecture/VLEGc/applications-of-rnns

Translation: Exercise

course3_translation_LSTM.ipynb

Goal: Have a look at how an English-French translation LSTM model can be trained

Remarks:

- The model is an **adaptation** of some **articles** found on the internet (the references are given inside the notebook)
- The students **do not have to complete anything**, the model would be **too long to train** to work on it during the class
- The results obtain in the current notebook comes from a model which has **not converged yet**, so the results are currently quite **low**

Translation : A closer look at the model

```
model = Sequential()
model.add(Embedding(eng_vocab_size, 512, input_length=eng_length, mask_zero=True))
model.add(LSTM(512))
#------------------------- Choose either the RepeatVector of the Bidirectional
model.add(RepeatVector(fren_length))
#model.add(Bidirectional(LSTM(fren_length), return_sequences = True))
#---------------------------
model.add(LSTM(512, return_sequences=True))
model.add(Dense(fren_vocab_size, activation='softmax'))
```

Translation : A closer look at the model

```
model = Sequential()
model.add(Embedding(eng_vocab_size, 512, input_length=eng_length, mask_zero=True))
model.add(LSTM(512))
#------------------------- Choose either the RepeatVector of the Bidirectional
model.add(RepeatVector(fren_length))
#model.add(Bidirectional(LSTM(fren_length), return_sequences = True))
#---------------------------
model.add(LSTM(512, return_sequences=True))
model.add(Dense(fren_vocab_size, activation='softmax'))
```

Be careful, this option is needed to feed the LSTM layer coming just after

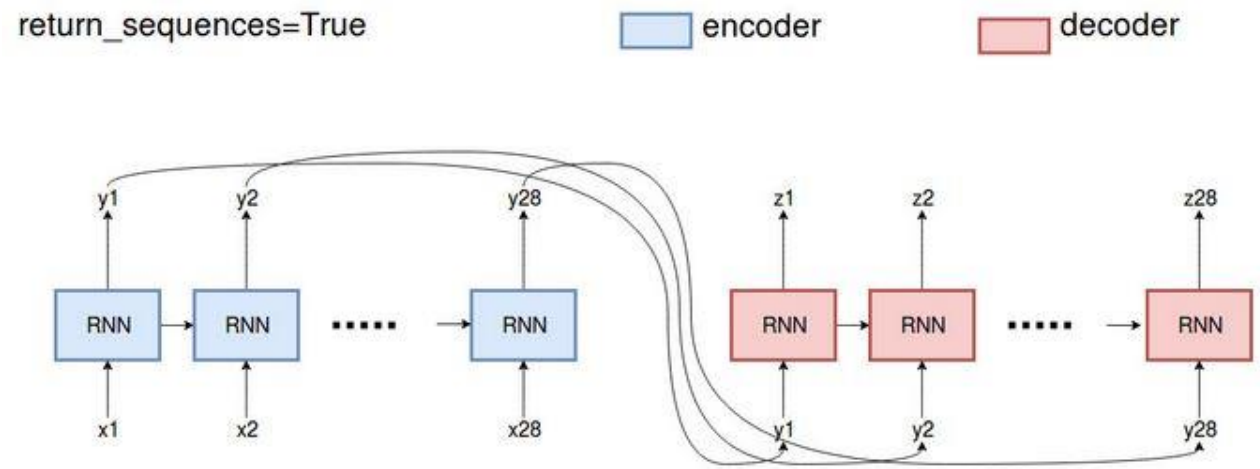
Two possibilities on this **specific layer** between **RepeatVector** and **Bidirectional(LSTM)**

The goal is to feed the **LSTM layer** coming next after

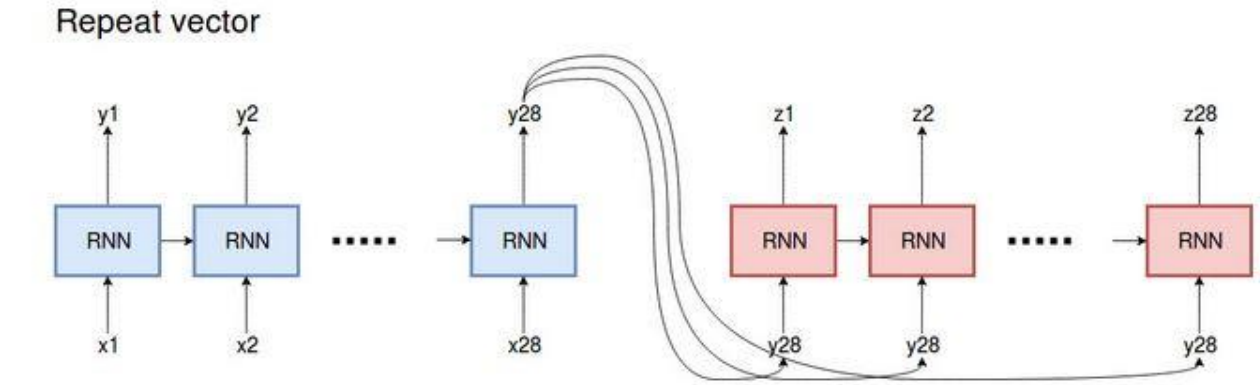
Translation: ReturnSequence vs RepeatVector

LSTM

with **return_sequences=True**



RepeatVector

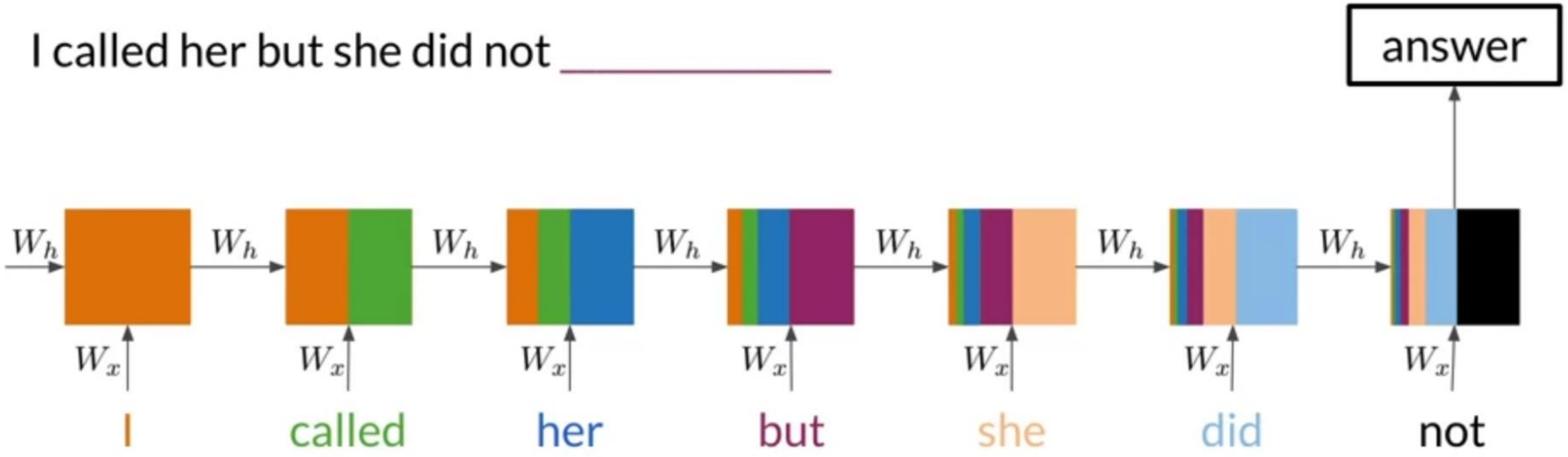


https://stackoverflow.com/questions/51749404/how-to-connect-lstm-layers-in-keras-repeatvector-or-return-sequence-true

RepeatVector will only return the **last value** of the output sequence to the next layer

Use cases: Text generation

Text generation: Illustration



Text generation: Shakespeare sonnets

- We want to train a model able to generate text with the **same writing style as Shakespeare**
- For that, we use as database a compilation of his sonnets
- To train the model, we use sequences from the sonnet corpus
- As input, we give the **beginning of a sentence** and, as label, the word coming just after

Text generation: Shakespeare sonnets

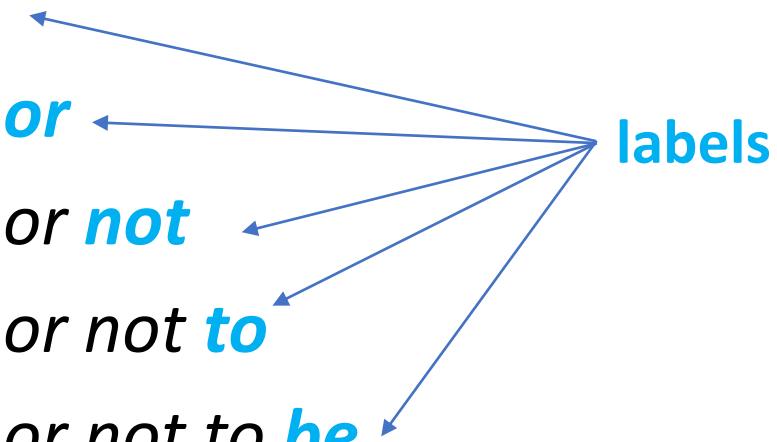
Example: the sentence ***To be or not to be*** gives **5 training sequences** to feed the model*:*

1. *To **be***
2. *To be **or***
3. *To be or **not***
4. *To be or not **to***
5. *To be or not to **be***

Text generation: Shakespeare sonnets

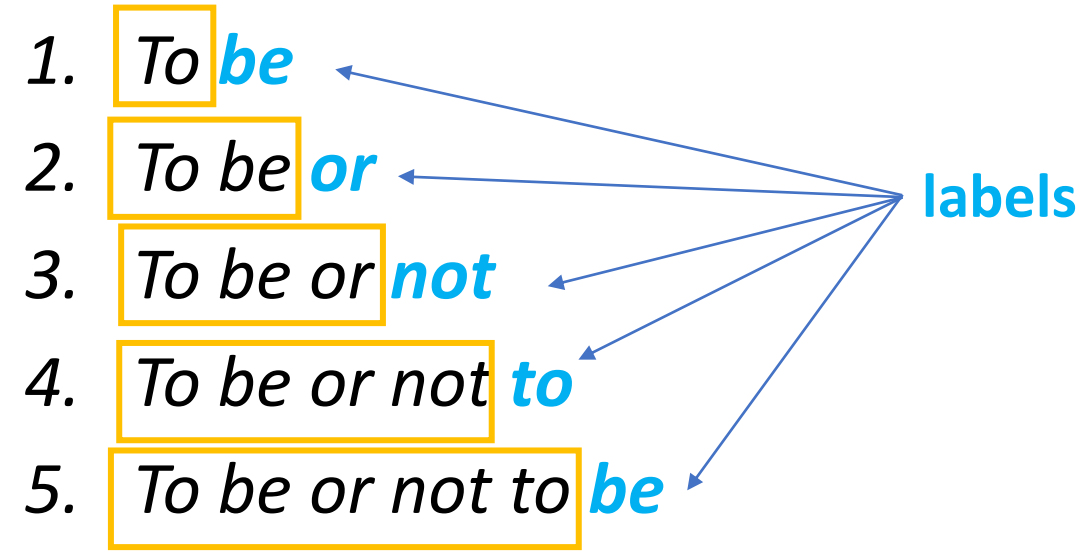
Example: the sentence ***To be or not to be*** gives **5 training sequences** to feed the model*:*

1. *To* ***be***
2. *To be* ***or***
3. *To be or* ***not***
4. *To be or not* ***to***
5. *To be or not to* ***be***



Text generation: Shakespeare sonnets

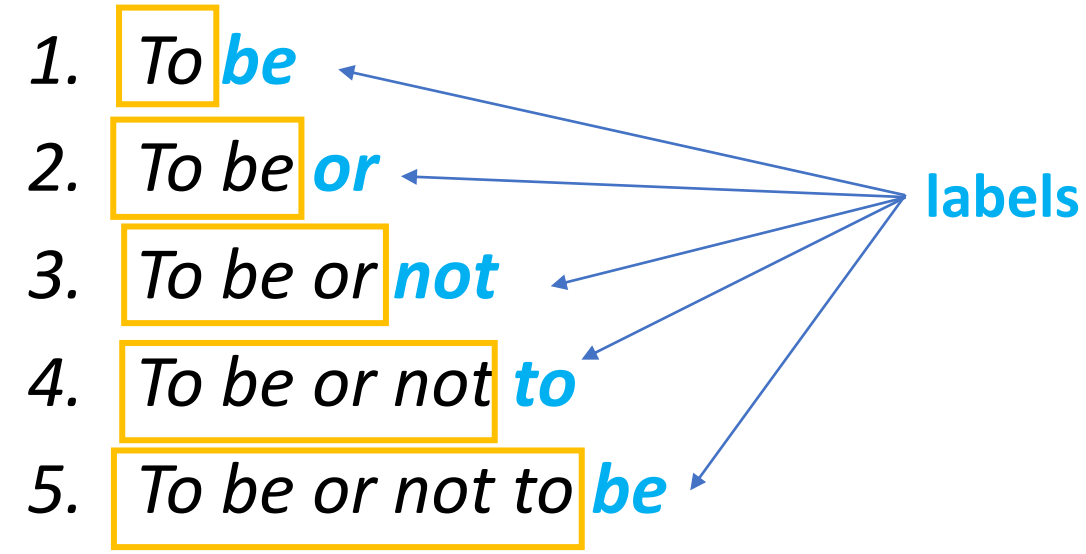
Example: the sentence ***To be or not to be*** gives **5 training sequences** to feed the model*:*



Input sequences for training the model

Text generation: Shakespeare sonnets

Example: the sentence ***To be or not to be*** gives **5 training sequences** to feed the model*:*



A n-token sequence in the corpus gives n-1 input sequences for training

Text generation: Exercise

course3_text_generation_LSTM_ex.ipynb

Goal: To solve a complex NLP problem from the text processing to model tuning. In the end, we should get a model able of generating text with Shakespeare characteristic style!

Remark:

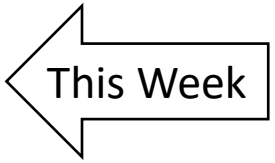
- We are not looking for especially good predictions, we only want the model being able to generate text looking like Shakespeare
- If the generated text is not too repetitive and looks like Shakespeare, even if it does not make much sense, you can consider it being good enough

Take-away from Course 3

- For some **complex NLP** applications (**translation**, **text generation**…), it is needed to use **text** as temporal **sequences**
- The **Recurrent Neural Network** (**RNN**) are designed to process such data
- However, **RNN** have some **limitations** such as **loss of information for long sequences** as well as **vanishing gradient issues**
- A **good alternative** are the **LSTM** and their variants (**GRU**)
- Some **specific preprocessing steps** must be performed in order to use texts as sequences able to **train** that kind of model
- If the **train dataset** is **big enough** and the **task specific enough**, Keras allows to easily **train from scratch embeddings** (see ***Embedding* layer**)

Course Schedule

- **Course 1**: NLP introduction
- **Course 2**: Word embedding
- **Course 3**: Long Short Term Memory (LSTM) architecture
- **Course 4**: **“Attention” mechanism and Transformer architectures**
  - Encoder-decoder
  - Attention Mechanism
  - Transformer architectures
  - BERT model
  - Current state-of-the-art
  - Fine tuning use case on GPT-2



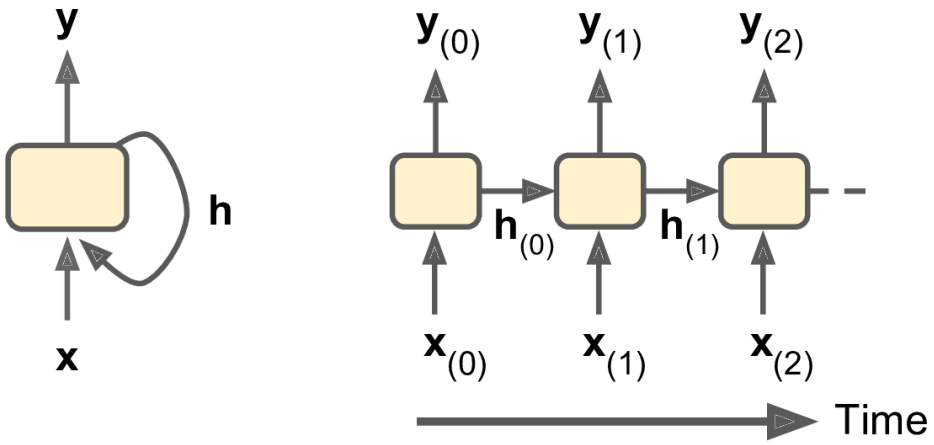
- **Course 5**: Chatbot introduction

Previously in Course 3

Recurrent Neural Network (RNN): Definition

- A **RNN** is a kind of neural network dealing with **recurrent** connection
- Allows to deal with **temporal sequences**
- E.g., on the figure below, a sequence **X** is given as **input**, and we get a sequence **Y** as **output**
- **A cell hidden state h and the output y may be different**

A hidden state RNN



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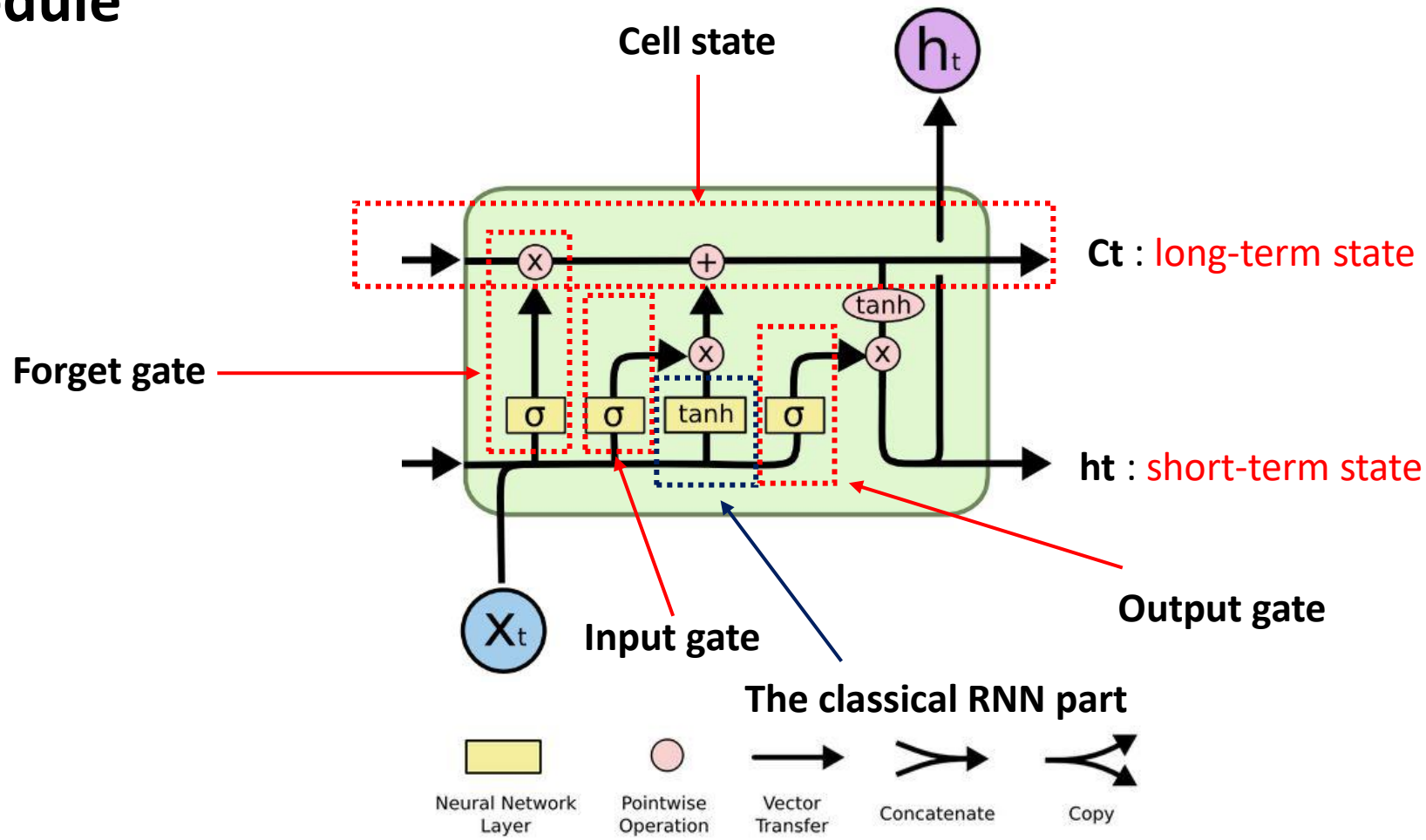
LSTM (Long Short Term Memory)

LSTM module

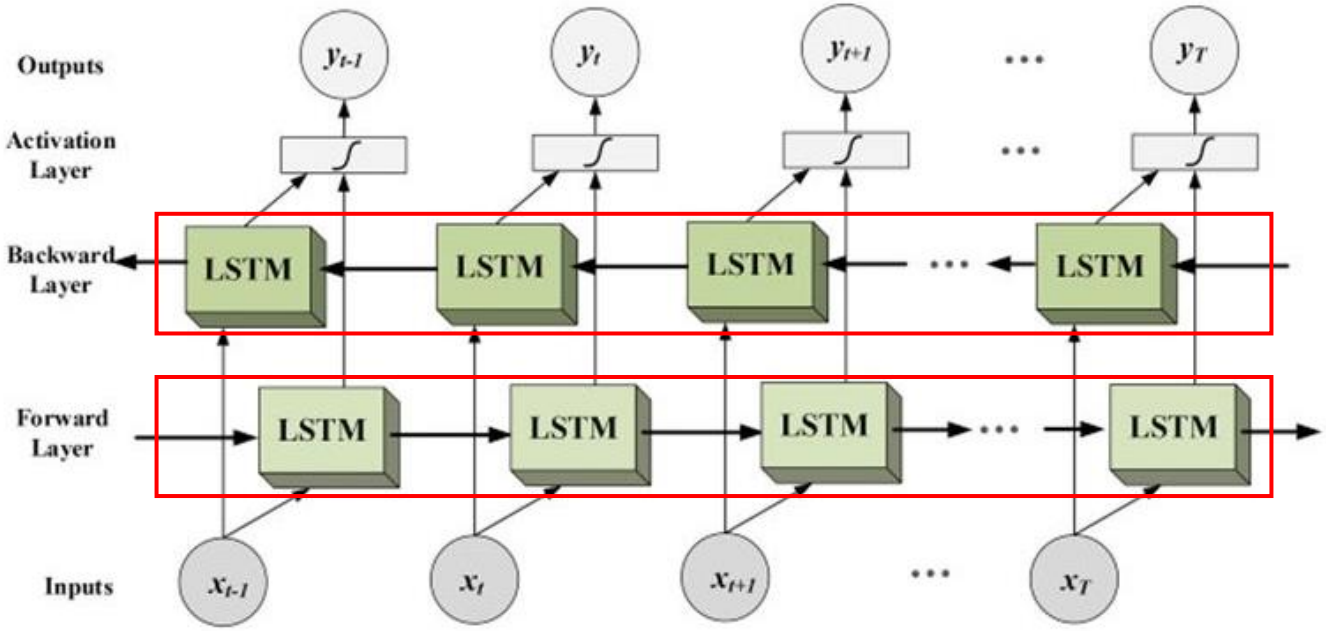


http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Bidirectional LSTM

In a **classic LSTM** architecture, the sentence/sequence is processed only in **one direction** (generally from the past to the present or future)

The **bidirectional** structure process the data in **both directions** => can be useful for some applications



https://medium.com/the-official-integrate-ai-blog/what-you-need-to-know-about-natural-language-processing-2c8240e6c38e

The **Queen** of the United Kingdom ←

The **queen** of hearts ←

The **queen** of bees ←

Here, the word queen will be encode differently
if read in reverse order

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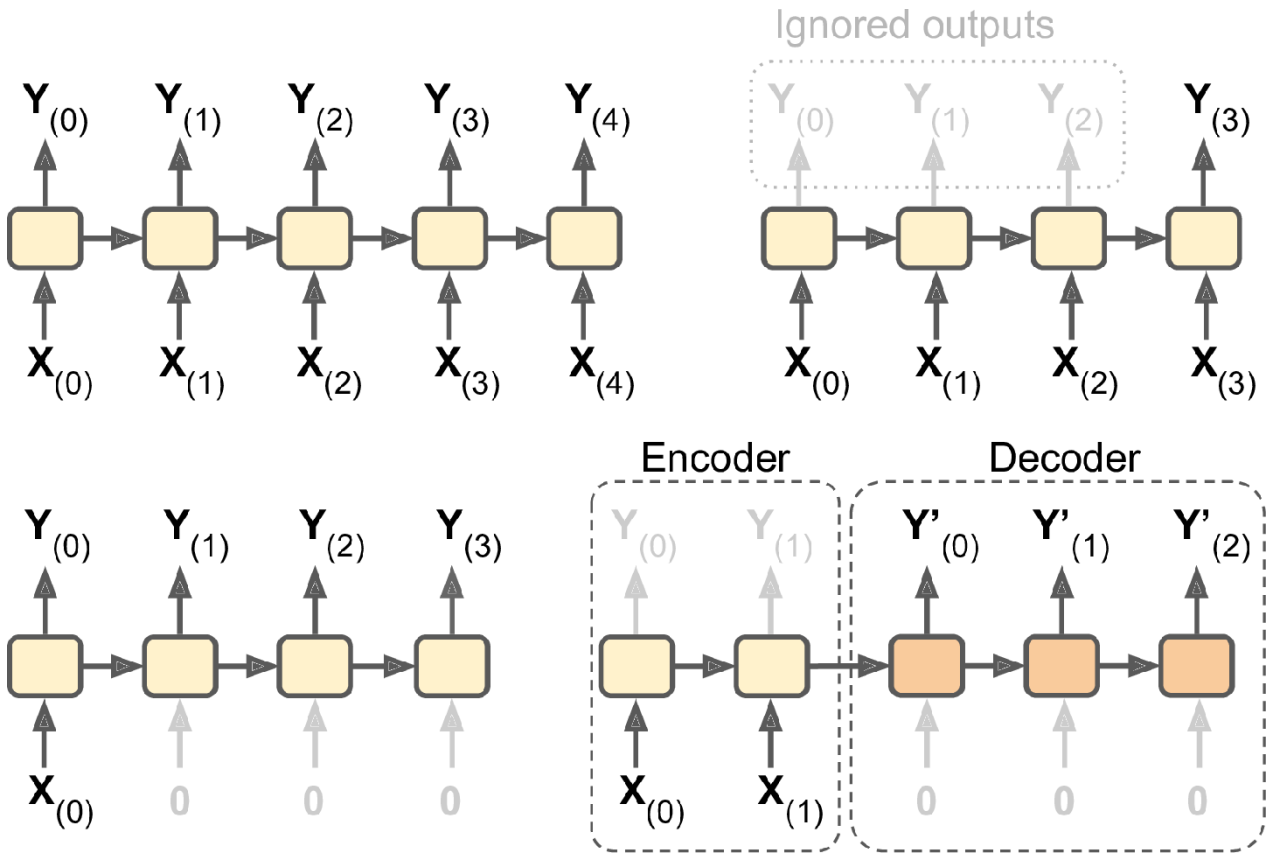
Recurrent Neural Network (RNN): Use cases



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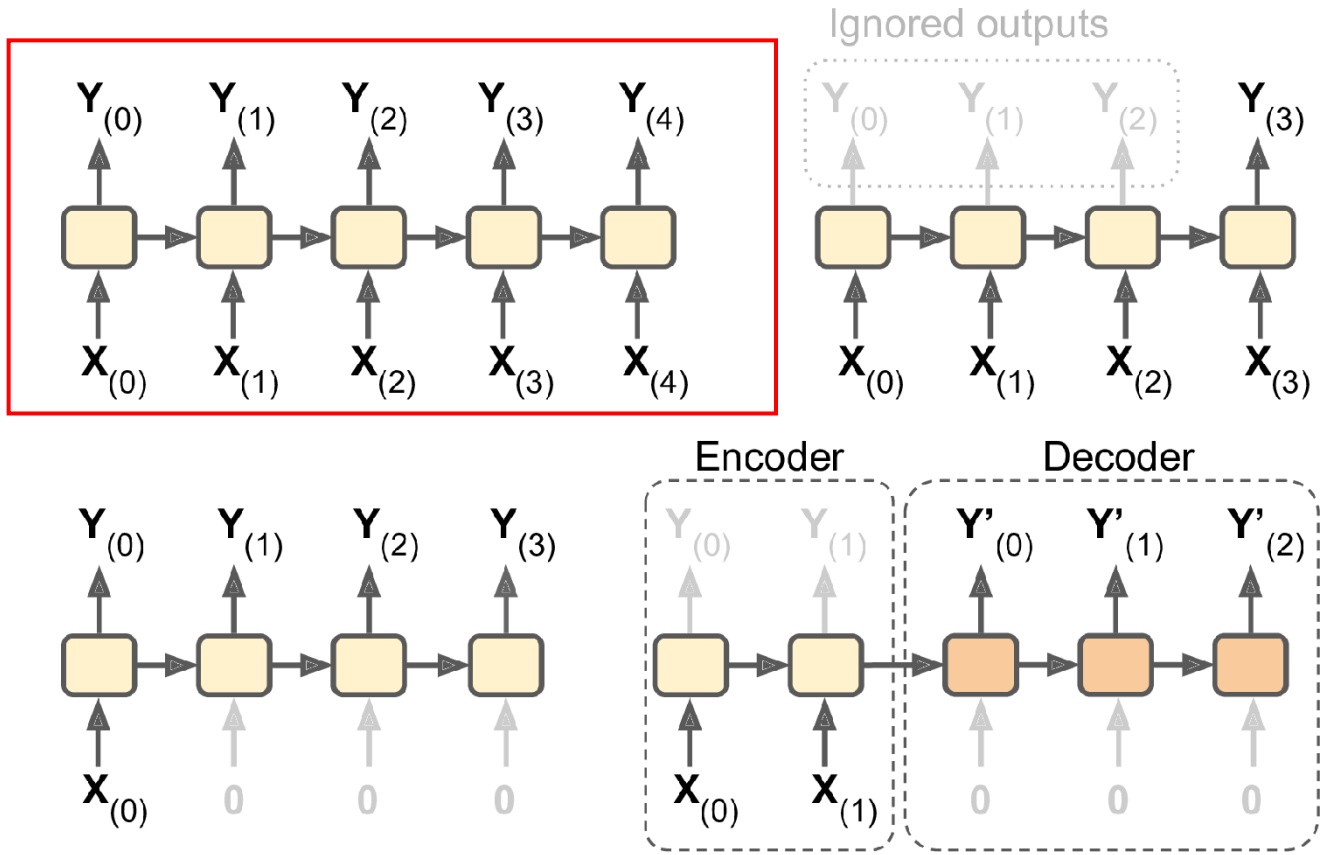
Recurrent Neural Network (RNN): Use cases

sequence-to-sequence

e.g. predicting time series



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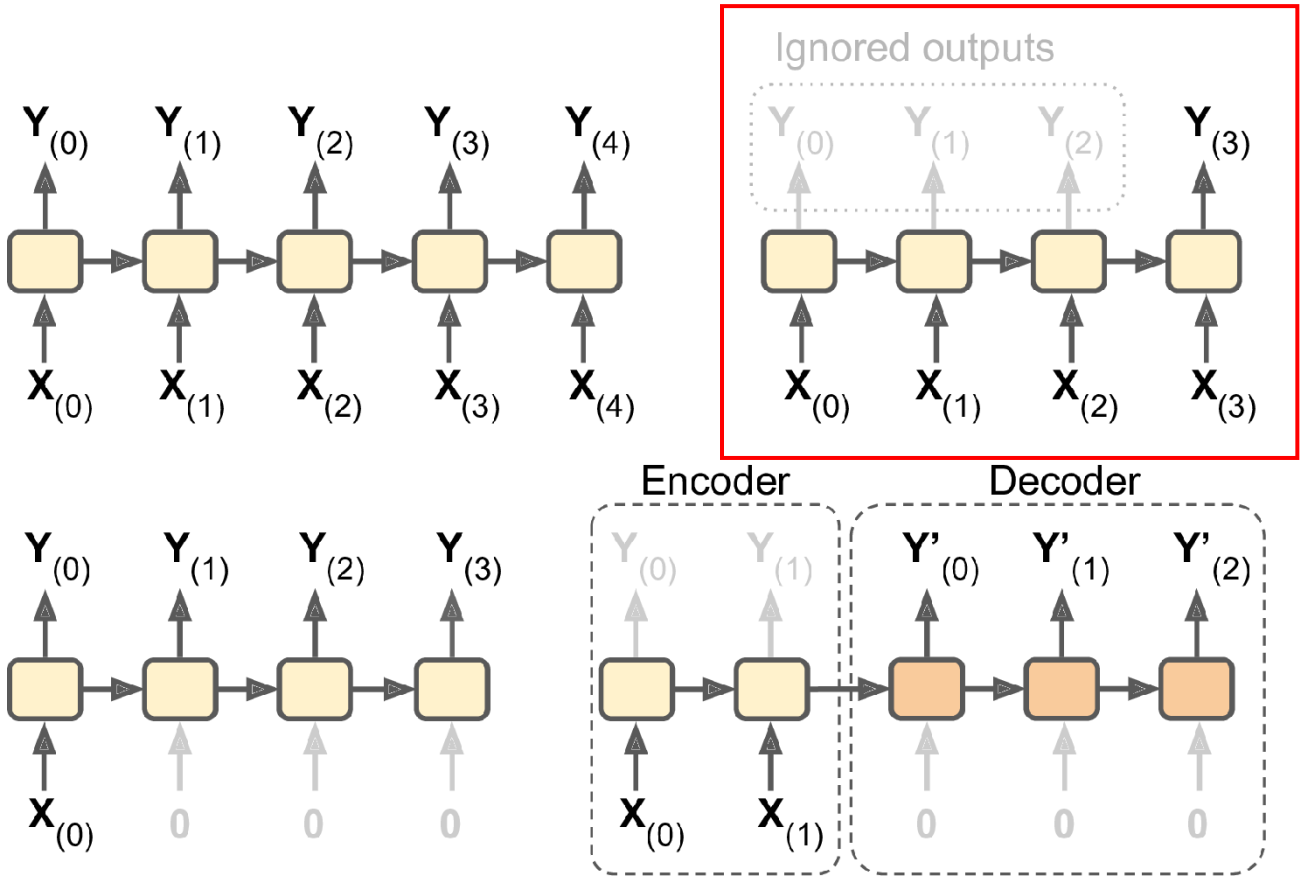
Recurrent Neural Network (RNN): Use cases



sequence-to-vector

e.g. sentiment analysis

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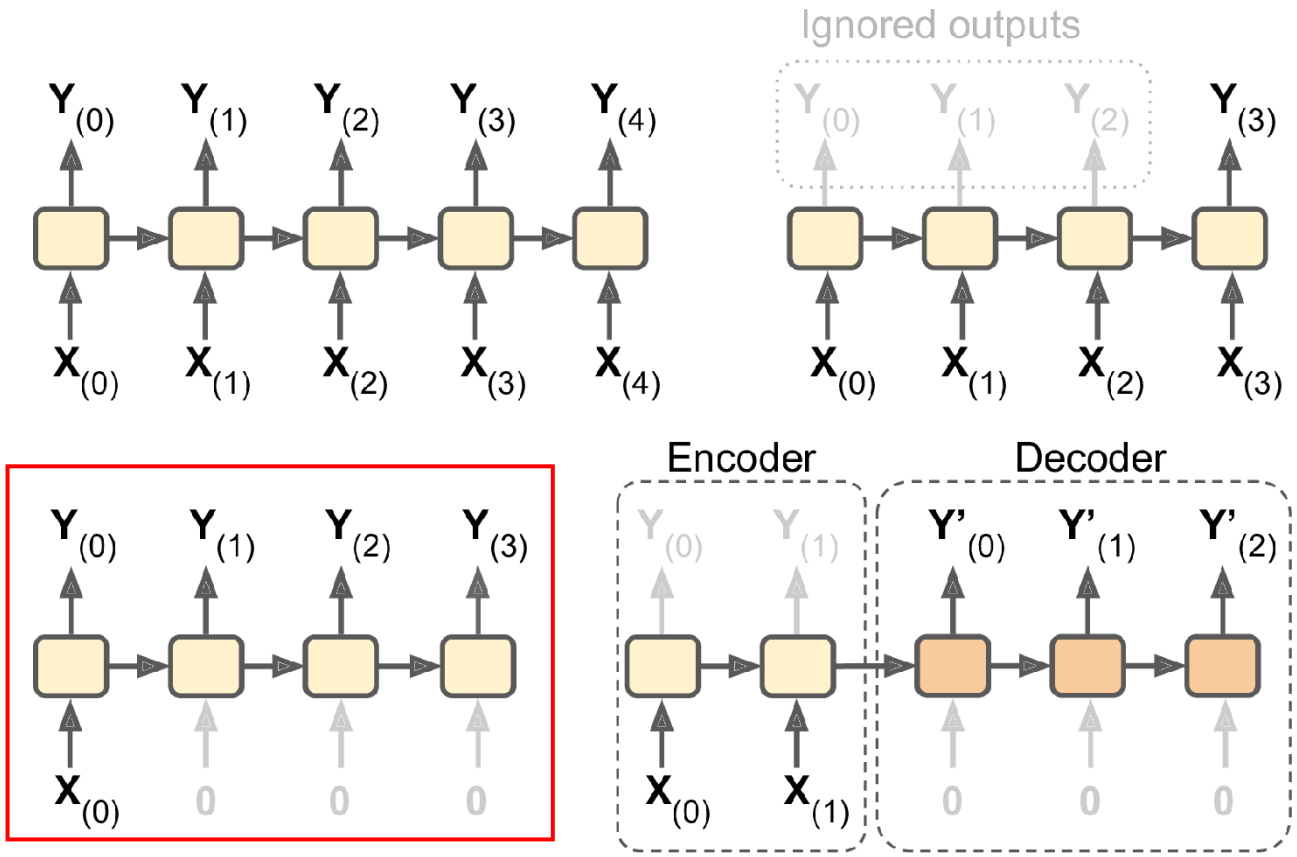
Recurrent Neural Network (RNN): Use cases



vector-to-sequence

e.g. image caption generation

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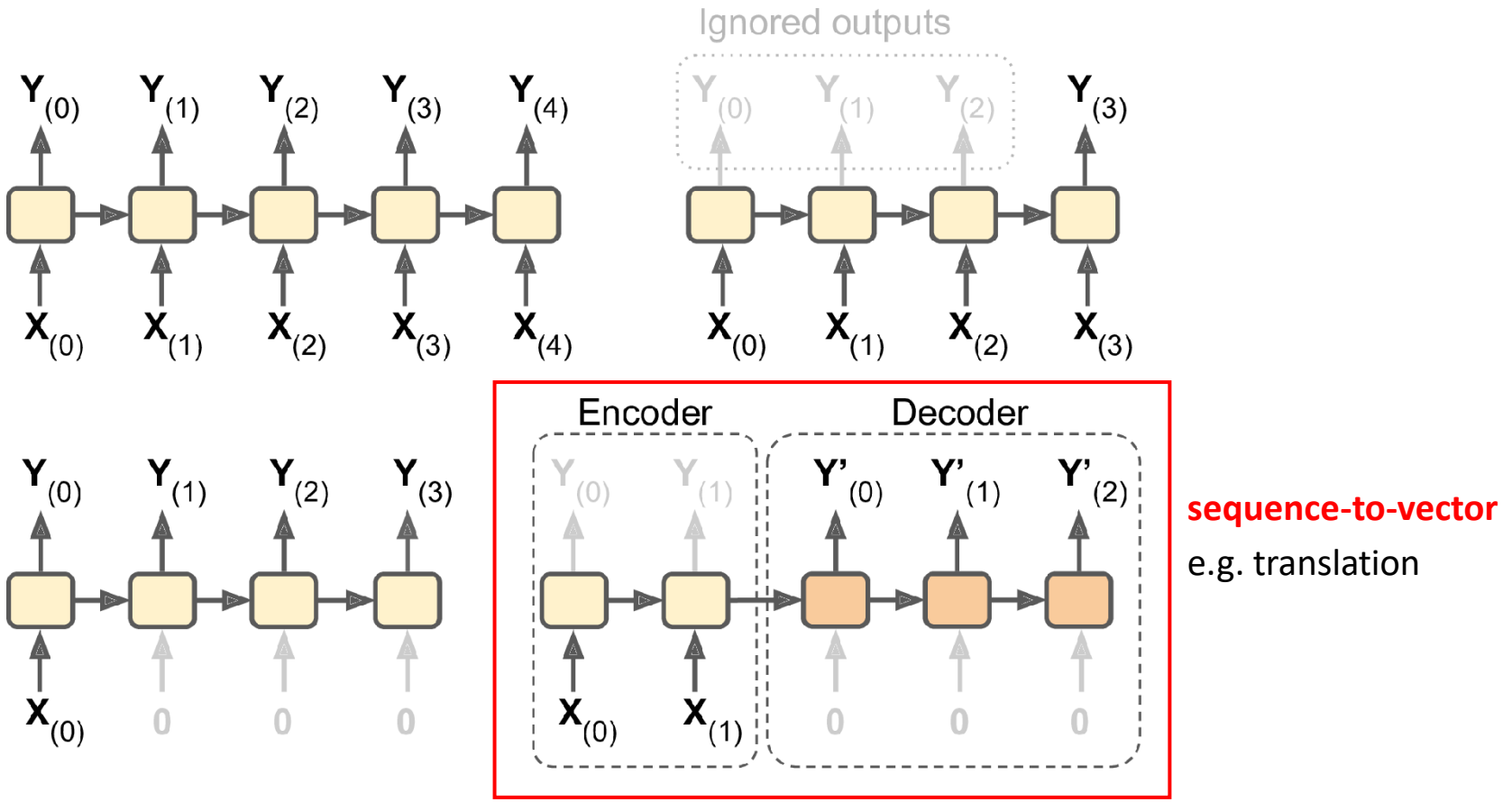
Recurrent Neural Network (RNN): Use cases



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Course 4: Attention Mechanism and Transformer Architectures

Encoder-decoder

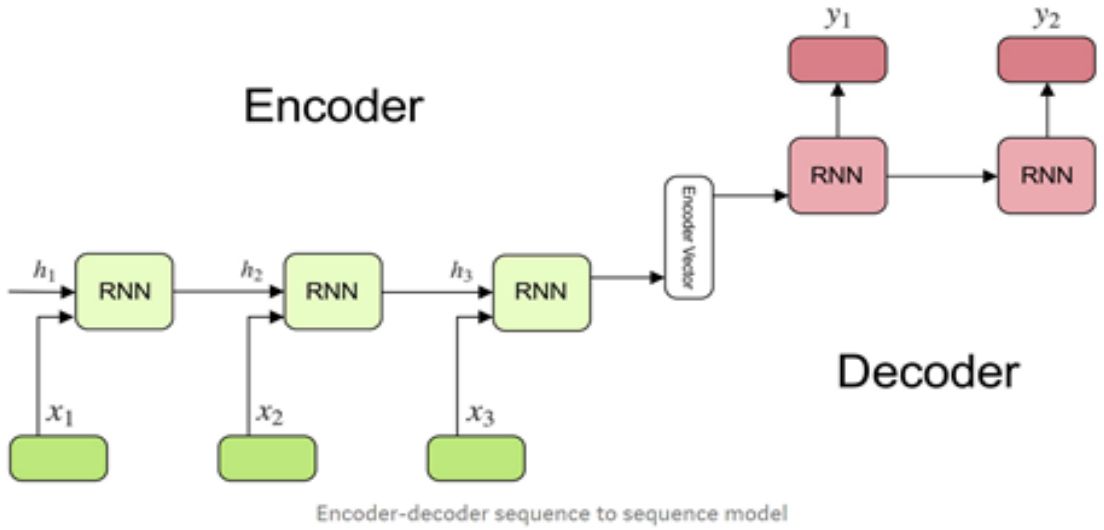
Encoder-decoder: A core concept

Principle

The goal is to project the input values into a smaller vector space before returning into the larger vector space expected

Architecture

- An encoder
- An encoded vector
- A decoder



Encoder-decoder sequence to sequence model

https://towardsdatascience.com/understanding-encoder-decoder-sequence-to-sequence-model-679e04af4346

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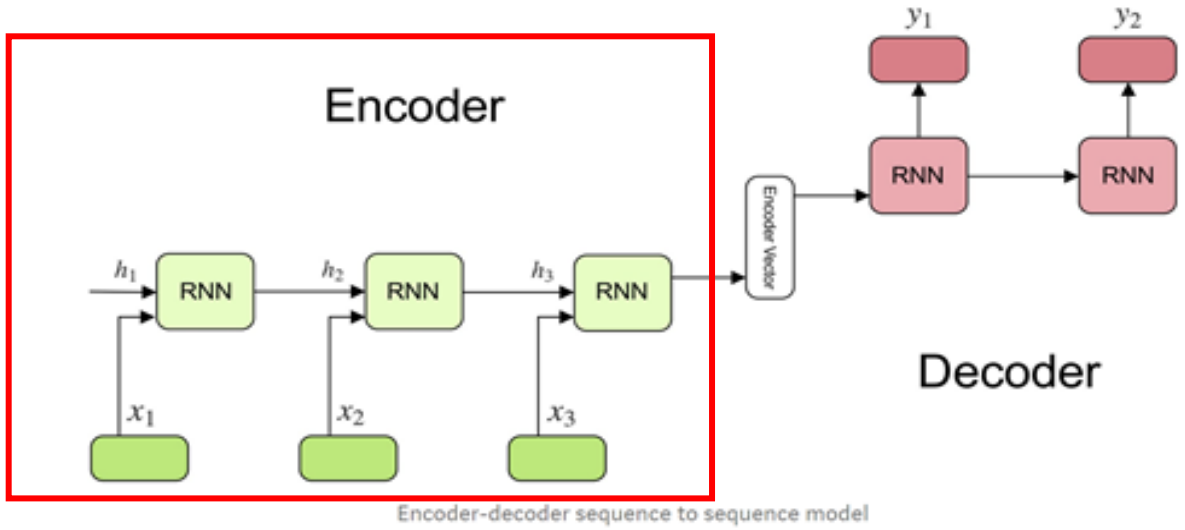

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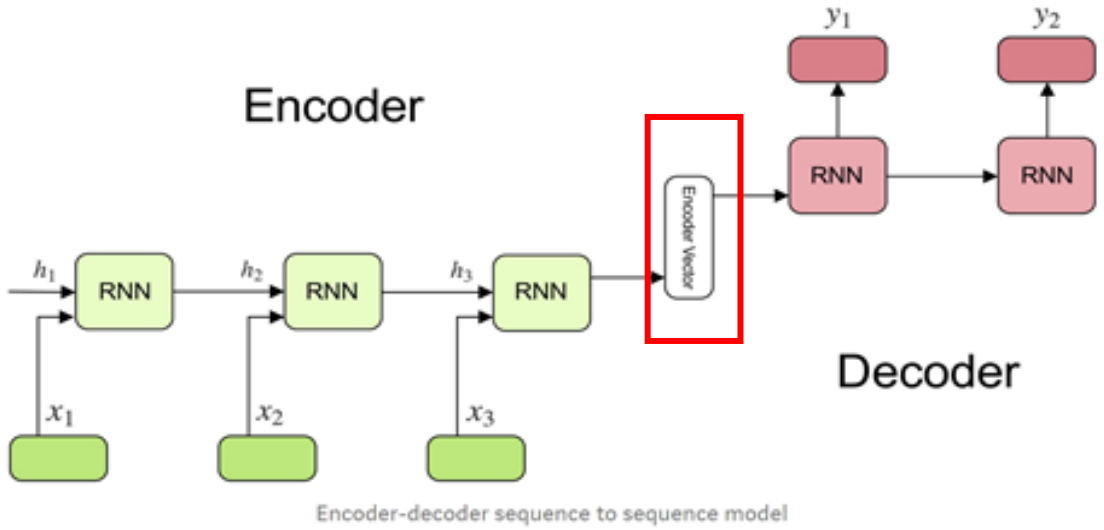

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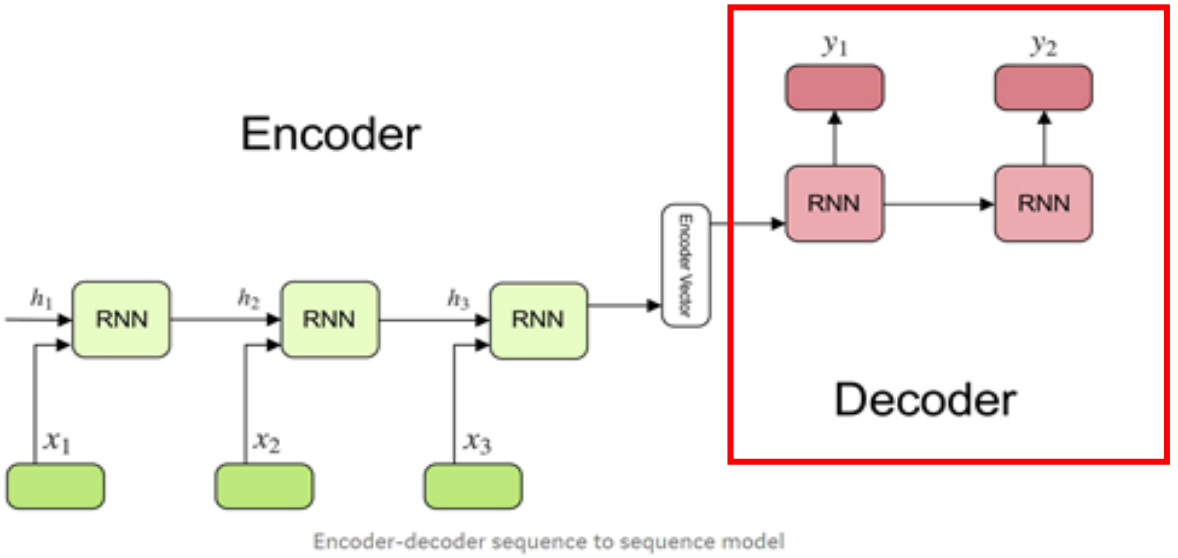
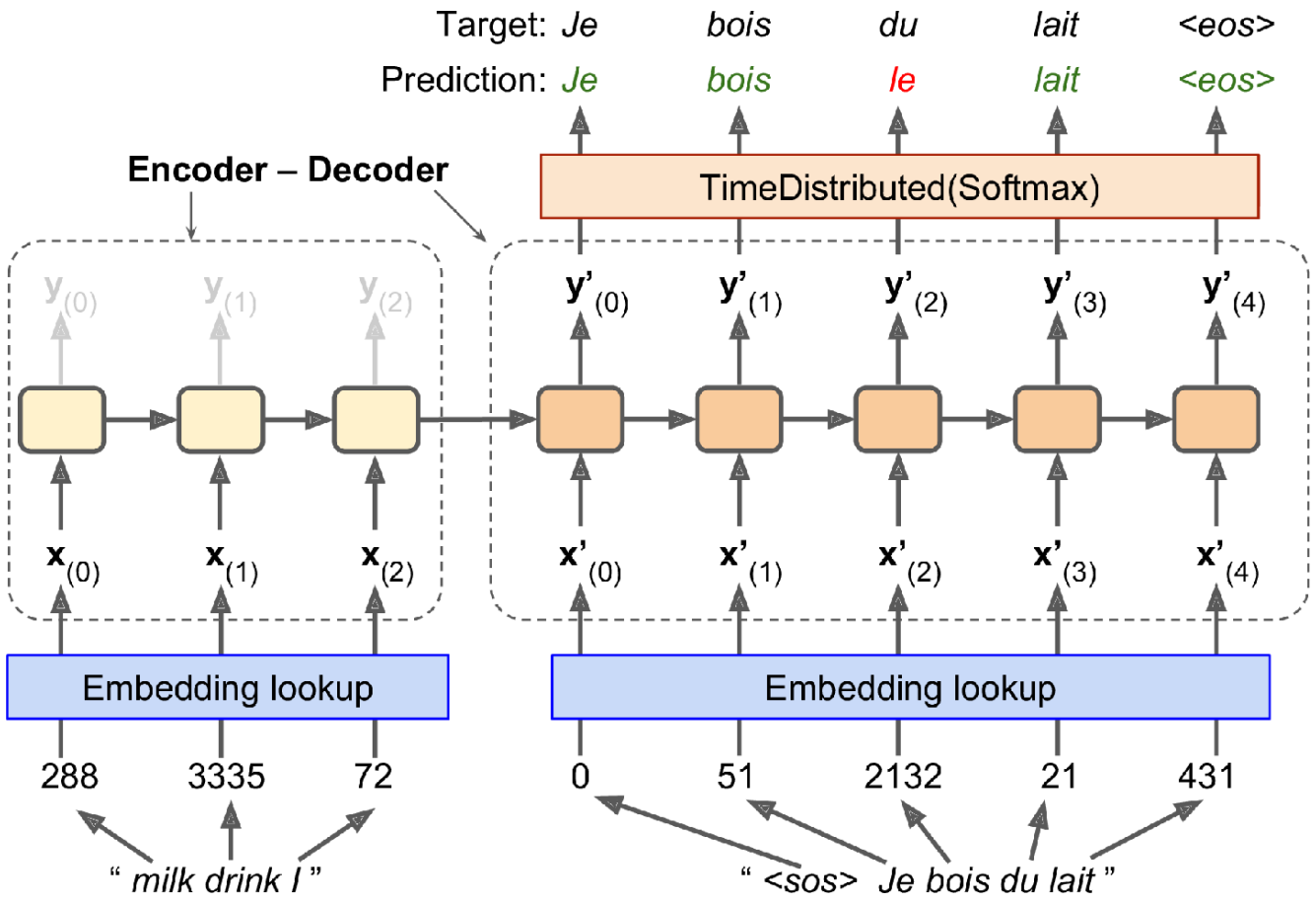


Encoder-decoder sequence to sequence model

https://towardsdatascience.com/understanding-encoder-decoder-sequence-to-sequence-model-679e04af4346

Encoder-decoder: Translation example



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Encoder-decoder: Keras

```
import tensorflow_addons as tfa

encoder_inputs = keras.layers.Input(shape=[None], dtype=np.int32)
decoder_inputs = keras.layers.Input(shape=[None], dtype=np.int32)
sequence_lengths = keras.layers.Input(shape=[], dtype=np.int32)

embeddings = keras.layers.Embedding(vocab_size, embed_size)
encoder_embeddings = embeddings(encoder_inputs)
decoder_embeddings = embeddings(decoder_inputs)

encoder = keras.layers.LSTM(512, return_state=True)
encoder_outputs, state_h, state_c = encoder(encoder_embeddings)
encoder_state = [state_h, state_c]

sampler = tfa.seq2seq.sampler.TrainingSampler()

decoder_cell = keras.layers.LSTMCell(512)
output_layer = keras.layers.Dense(vocab_size)
decoder = tfa.seq2seq.basic_decoder.BasicDecoder(decoder_cell, sampler,
                                                 output_layer=output_layer)
final_outputs, final_state, final_sequence_lengths = decoder(
    decoder_embeddings, initial_state=encoder_state,
    sequence_length=sequence_lengths)
Y_proba = tf.nn.softmax(final_outputs.rnn_output)

model = keras.Model(inputs=[encoder_inputs, decoder_inputs, sequence_lengths],
                    outputs=[Y_proba])
```

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encoder_embeddings = embeddings(encoder_inputs)
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```

encoder

```
encoder = keras.layers.LSTM(512, return_state=True)
encoder_outputs, state_h, state_c = encoder(encoder_embeddings)
encoder_state = [state_h, state_c]
```

allow to get both ht and Ct

```
sampler = tfa.seq2seq.sampler.TrainingSampler()
```

to tell the decoder at each step what was the previous output

decoder

```
decoder_cell = keras.layers.LSTMCell(512)
output_layer = keras.layers.Dense(vocab_size)
decoder = tfa.seq2seq.basic_decoder.BasicDecoder(decoder_cell, sampler,
                                                 output_layer=output_layer)
final_outputs, final_state, final_sequence_lengths = decoder(
    decoder_embeddings, initial_state=encoder_state,
    sequence_length=sequence_lengths)
Y_proba = tf.nn.softmax(final_outputs.rnn_output)
```

model construction

```
model = keras.Model(inputs=[encoder_inputs, decoder_inputs, sequence_lengths],
                    outputs=[Y_proba])
```

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Attention Mechanism

Attention Mechanism: Introduction

Problem to solve

- Even with a LSTM architecture, it can be difficult to characterize long sentences in an efficient way

Attention mechanism principle

- To put more weight on specific word positions of the sentence depending **both** on the **context** and the **relative positions of words**

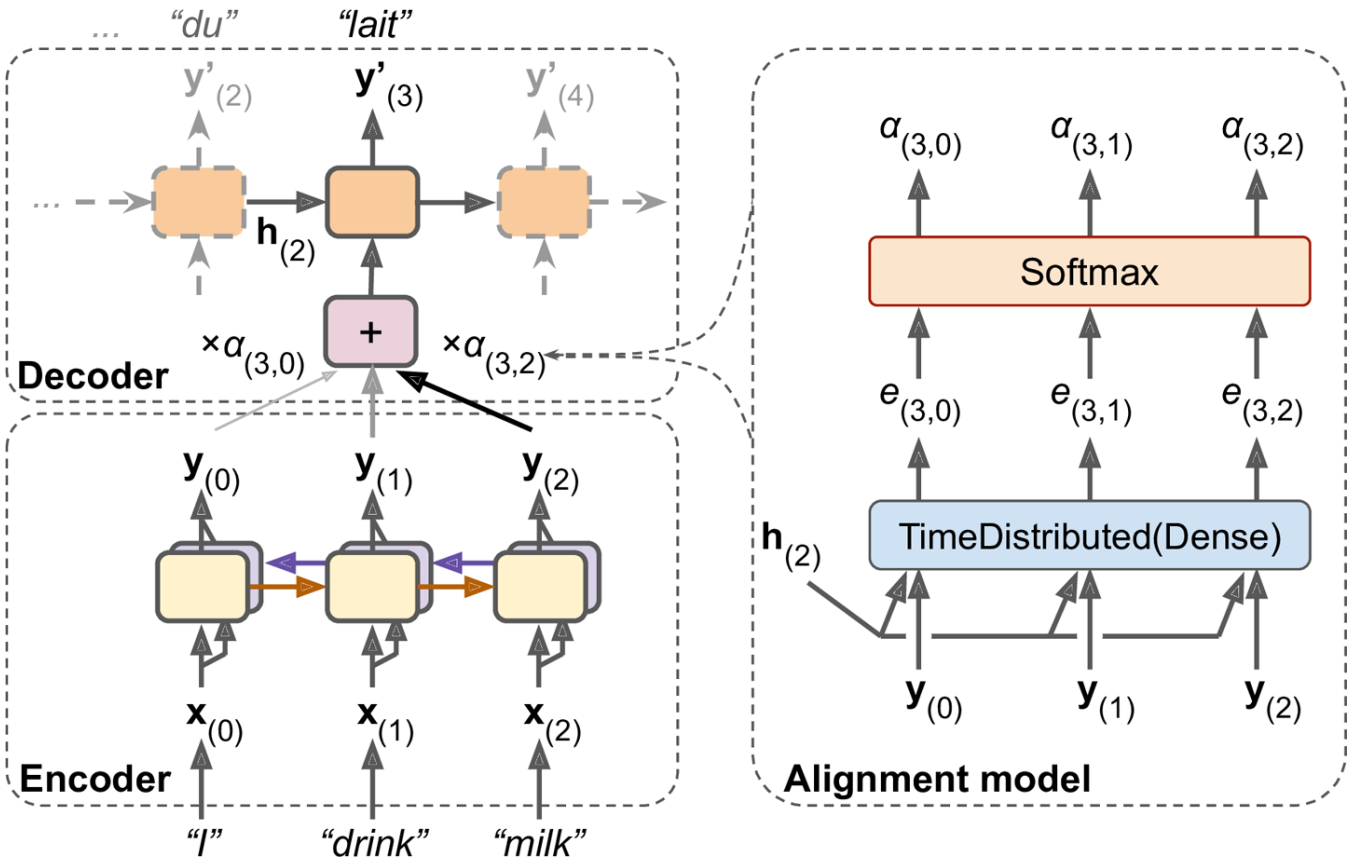
Example

Despite being from Uttar Pradesh, as he was brought up in Bengal, he is more comfortable in Bengali.

To predict the word *Bengali*, the expressions *brought up* and *Bengal* must be associated to higher weights.

https://www.analyticsvidhya.com/blog/2019/11/comprehensive-guide-attention-mechanism-deep-learning/

Attention Mechanism: Translation illustration



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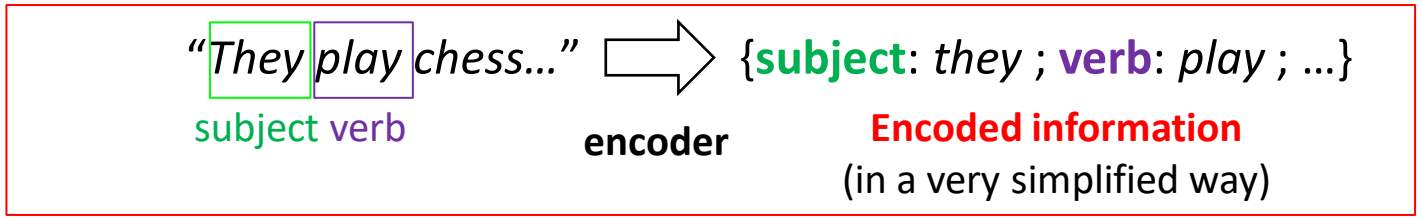
Attention Mechanism: Get the intuition

Imagine you want to translate the sentence using an **encoder-decoder**:

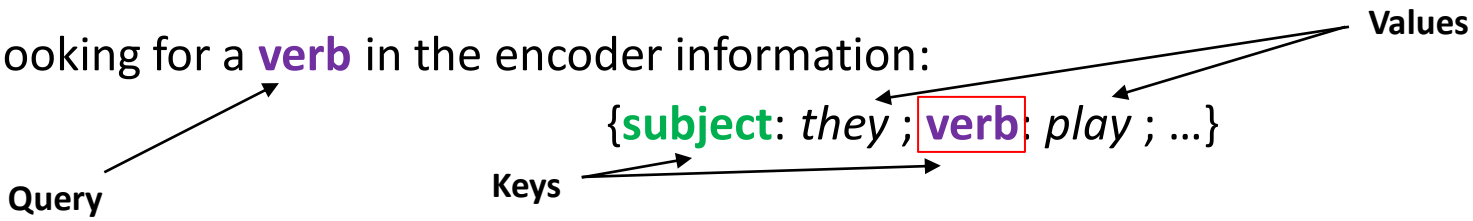
"They play chess…"

Actually, you expect the encoder to deal with it that way:



Just imagine you already translated the **first word** and are looking for the **next one**:

You are looking for a **verb** in the encoder information:



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Attention Mechanism: Get the intuition

Imagine you want to translate the sentence using an **encoder-decoder**:

"They play chess…"

Actually, you expect the encoder to deal with it that way:

"They play chess…" ⇨ {**subject**: *they* ; **verb**: *play* ; …}

subject verb

encoder

Encoded information
(in a very simplified way)

Just imagine you already translated the **first word** and are looking for the **next one**:

Ils ???

subject verb?

You are looking for a **verb** in the encoder information:

Query

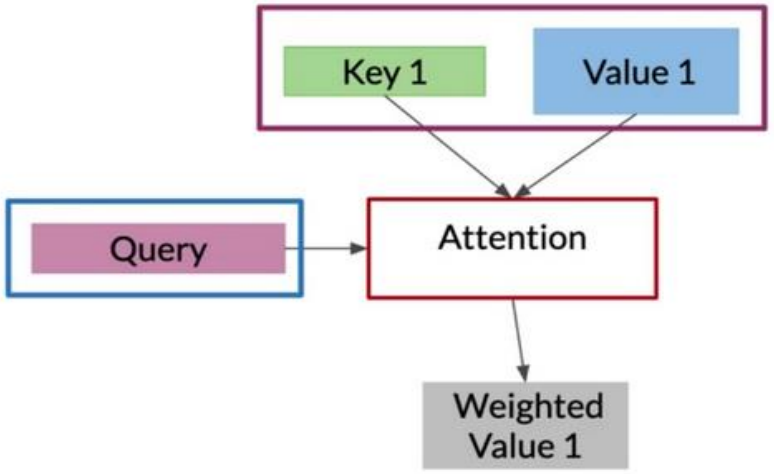
{**subject**: *they* ; **verb**: *play* ; …}

Keys and Values are oftenly fused together in the encoder vector, so you take Keys = Values

Attention Mechanism: Principle

Formalism

- To associate a ***query*** and a set of (***key-value***) tuples with an ***output***
- The **query**, the (**key-value**) set and the **ouput** are all vectors
- The output corresponds to the **weighted sum** of values, with weights determined from a **compatibility function** between the query and the corresponding key



https://www.coursera.org/specializations/natural-language-processing

Attention Mechanism: Formula

Formula

The mathematical expression generally used to compute the attention function is

$$softmax(QK^T)V$$

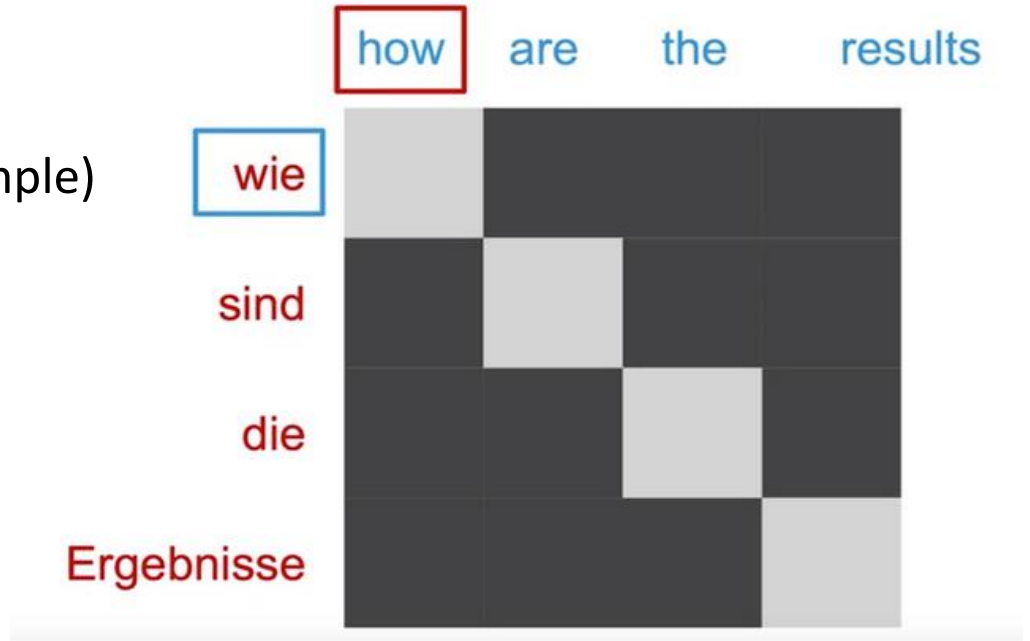
*With **Q**, **K*** and ***V*** respectively the *query*, *key* and *value*, matrices.

The ***softmax*** function gives normalized values between 0 and 1

Attention Mechanism: Illustration 1

Example for the case of English-German translation

- The bright squares show where the algorithm « **look** » to translate a word
- Here, words in English and German **share the same order**
- So, the match is only on the **diagonal**
- No need to look other word positions (on this specific example)

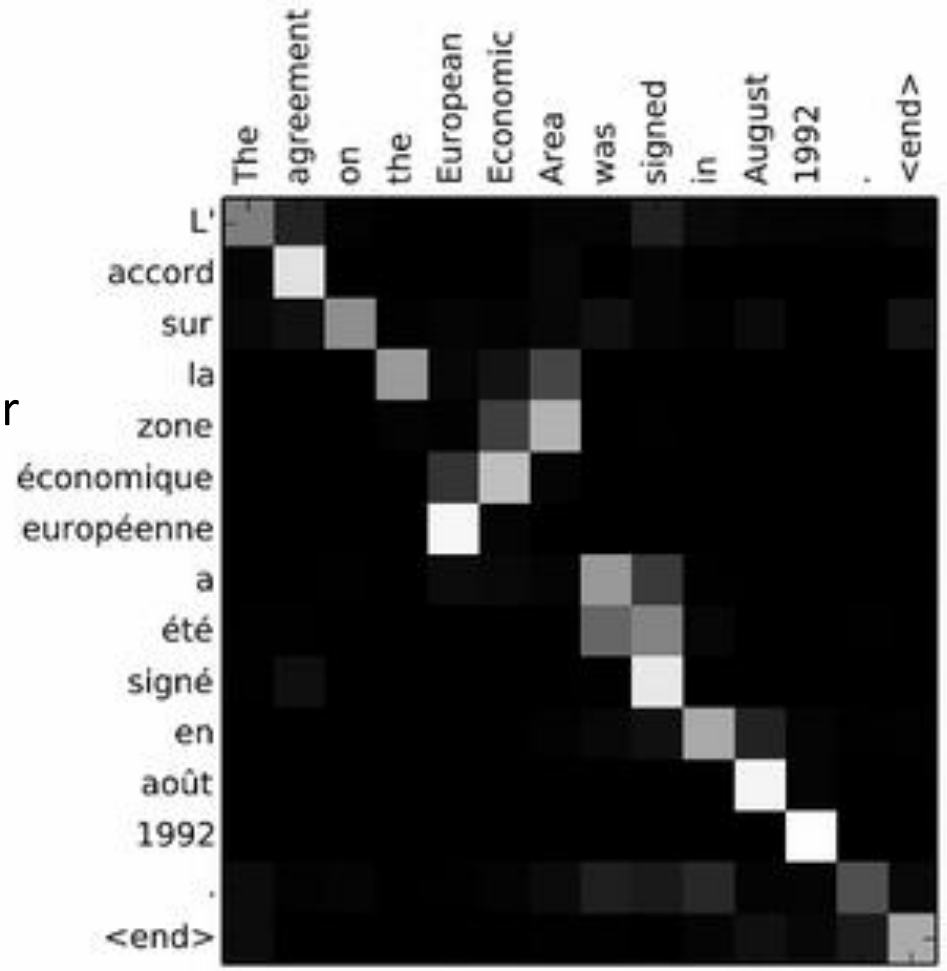


https://www.coursera.org/specializations/natural-language-processing

Attention Mechanism: Illustration 2

Example for the case of English-French translation

- Here, the match is **not on a specific word only**
- The figure shows the contribution of each word
- **Several words** can contribute to the translation of another



https://www.coursera.org/specializations/natural-language-processing

Attention Mechanism: Examples

Intuition behind query and (key, value) concepts

Depends on the application

In NLP, usually, the **key** and **value** correspond to the **same vectors**:

- **Translation**: the **query** can be the encoded sentence vector in **one language** and both **key** and **value** can be the **encoded** sentence vector in the **other language**
- **Text similarity**: the **query** can be the sequence embedding of the **first piece of text** and both **key** and **value** can be the sequence embedding of the **second piece of text**

However, in some cases, the concepts key and value **can be different**:

- if you are looking for a video in *Youtube*, the **query** can be derived from the **text you entered**, the **keys** can correspond to **the video descriptions** and the **values** can be **the videos themselves**

Attention Mechanism: Keras Layer

An Attention Layer is available in Keras

Here we can see an illustration for translation

```
# Attention layer
attention_layer = AttentionLayer(name='attention_layer')
attention_out, attention_states = attention_layer({"values": encoded_en,
                                                   "query": encoded_fr})
```

Attention Mechanism: Keras Layer

An Attention Layer is available in Keras

Here we can see an illustration for translation

```
# Attention layer
attention_layer = AttentionLayer(name='attention_layer')
attention_out, attention_states = attention_layer({"values": encoded_en,
                                                   "query": encoded_fr})
```

Here, the **values** correspond to the encoded **English** sentences

As usual in that kind of context, the **keys** are implicitly the same as the **values** (the encoded English sentences)

Here, the **queries** correspond to the encoded **French** sentences

Visual Attention: Illustration

Goal: Generate automatically the caption of a picture with an attention mechanism

"A woman is throwing a frisbee in a park"

Kelvin Xu et al., "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention," *Proceedings of the 32nd International Conference on Machine Learning* (2015): 2048–2057.

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Goal: Generate automatically the caption of a picture with an attention mechanism

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Kelvin Xu et al., "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention," *Proceedings of the 32nd International Conference on Machine Learning* (2015): 2048–2057.

Transformer architecture

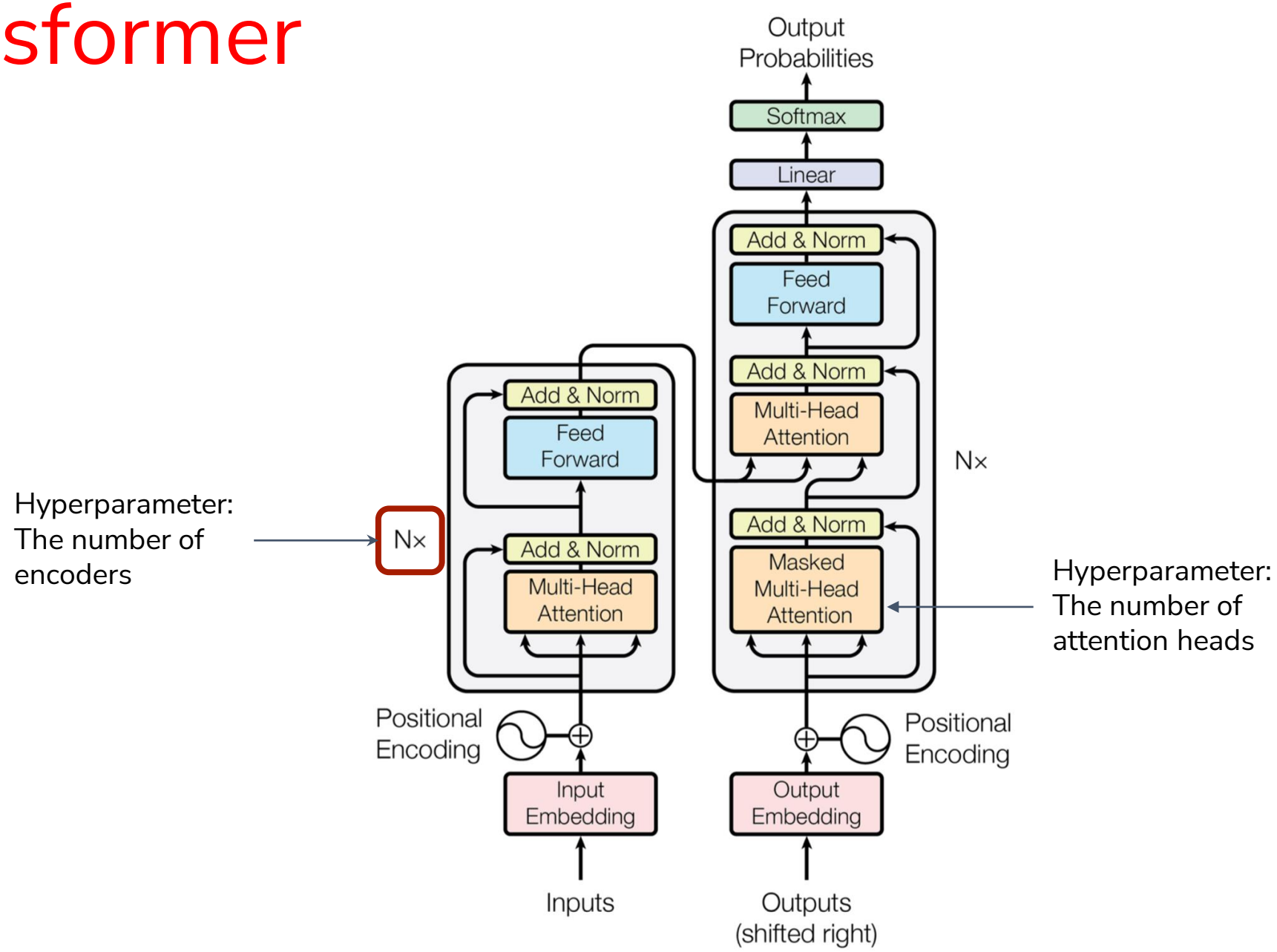
Transformer: Introduction

Principle

- A quite new deep learning model (2017), introduced in the **game changing** article *Attention is all you need*
- Relies heavily on the **Attention mechanism**
- **Does not need to process a sequence in a specific order**
- Solves the issue of keeping into memory the information related to distant words (and that even **without LSTM**)
- Makes possible a significant use of **parallelization** computing
- At every moment, the algorithm can access the complete set of the successive states visited during the procedure

The main idea is that the Attention mechanism alone, without any recurrent sequential procedure, is powerful enough to reach the state of the art

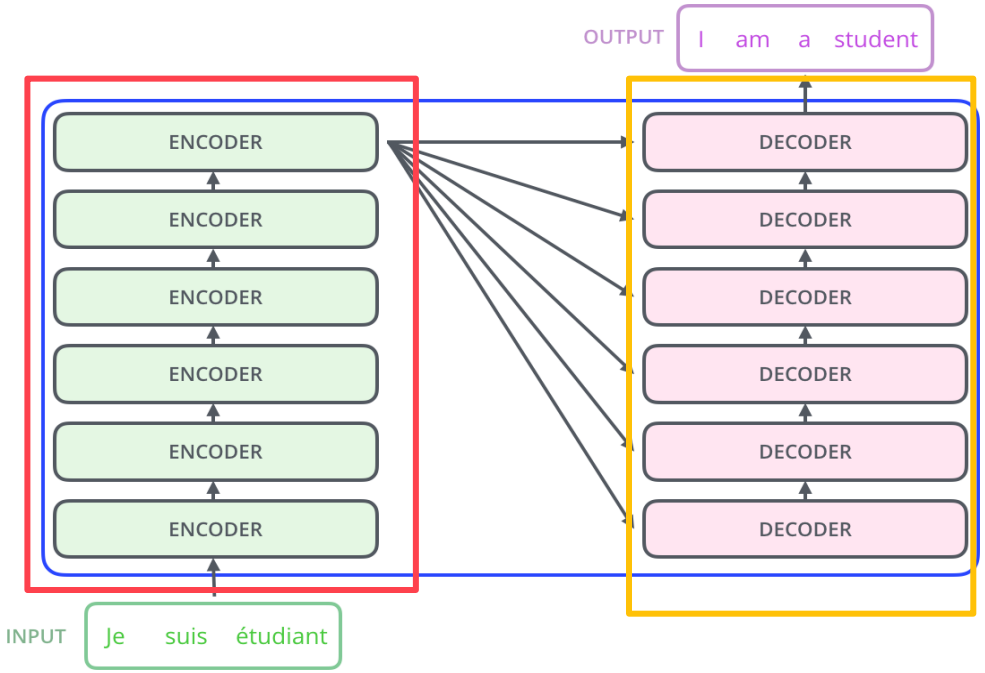
Transformer

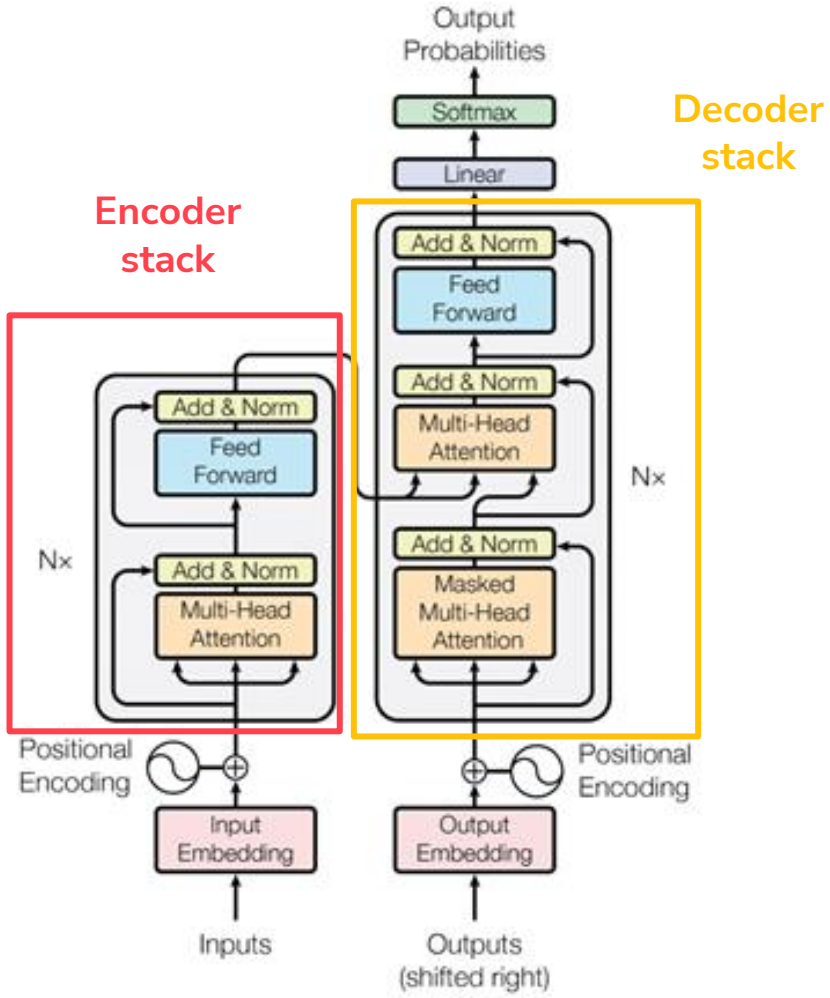


Transformer: Architecture

The Transformer is made of two main components:

- A stack of **identical encoders** (independents form each other)
- Followed by a stack of ***identical decoders*** (independents form each other)



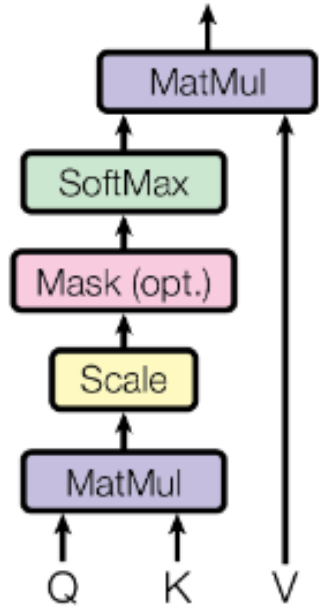


Transformer: Scaled Dot-Product Attention

Formula

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

dk corresponds to the query and key dimension



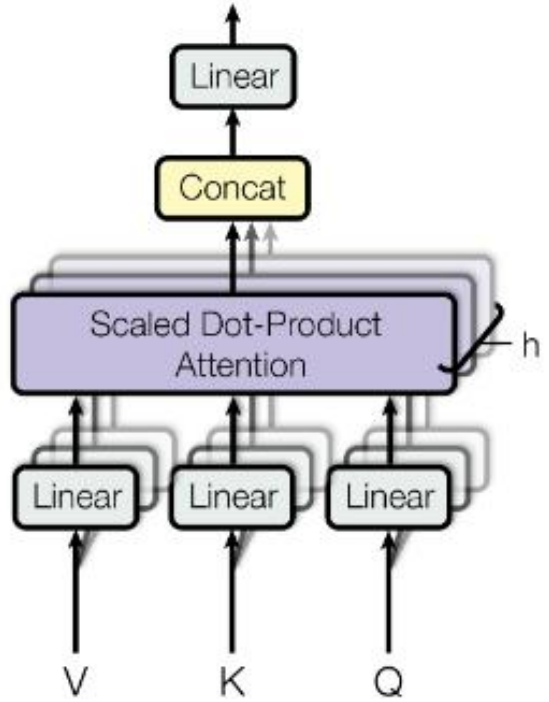
- The **normalization** prevents the result of the dot-product to reach high values and, doing so, **prevents the gradient to vanish** into small values
- An **additive** variant of the attention function exists, but the dot-product version is preferred here for the efficiency of the matrix calculations it allows

Transformer: Multi-Head Attention

Principle

- **Several Attention** layers computed in parrallel
  - the *queries*, *keys* and *values* are projeted *h* times
  - the h results are concatenated
  - then projeted one last time
- Enable the use of different sub-space information
- The mathematical expression is the following

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_\text{h})W^O$$
$$\text{where head}_\text{i} = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

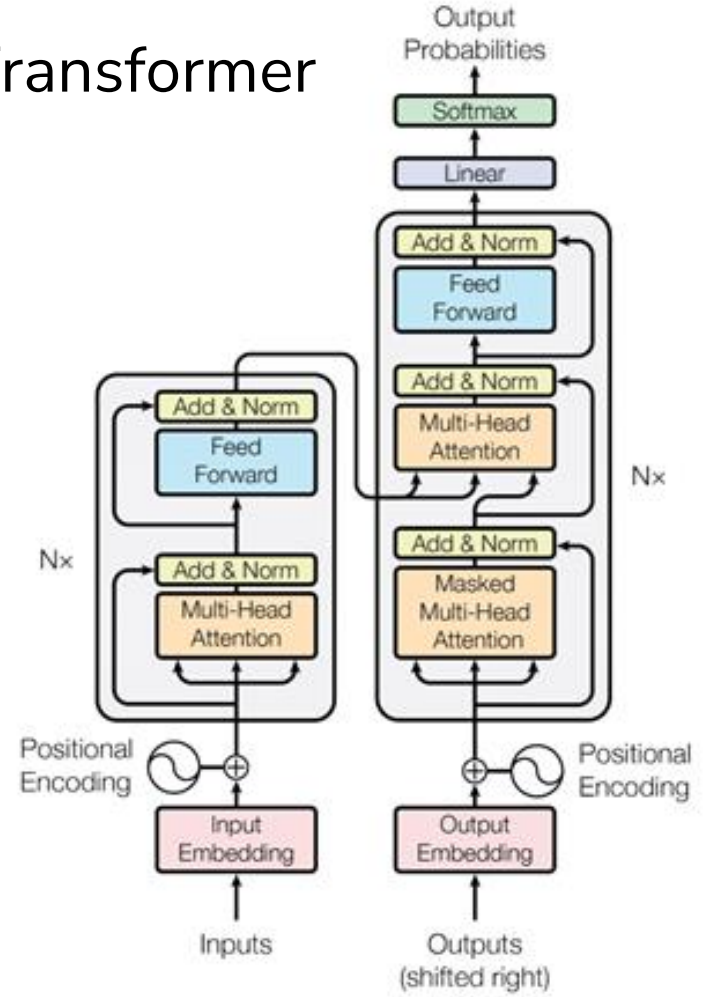


Where the Wi* corresponds to the respective projection matrices

Transformer: Multi-Head Attention

The **Multi-Head Attention** is used three times in the Transformer

- Inside the encoder
- Inside the decoder
- At the encoder-decoder interface

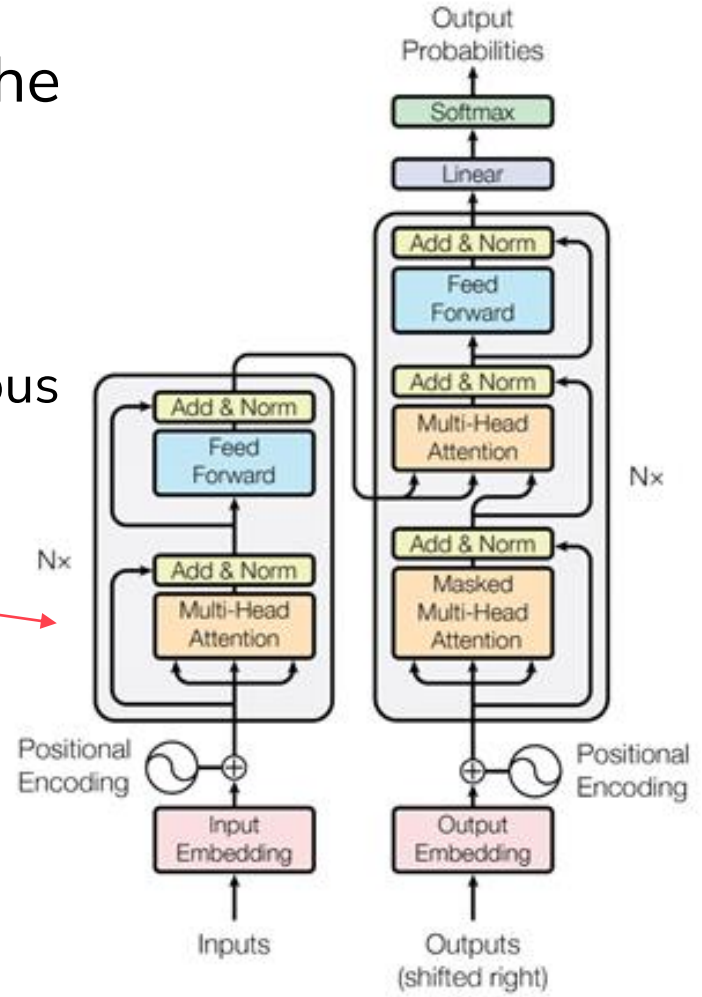


Transformer: Multi-Head Attention

The **Multi-Head Attention** is used three times in the Transformer

- **Inside the encoder**
  - the queries, keys and values all come from the previous encoder output
- Inside the decoder
- At the encoder-decoder interface

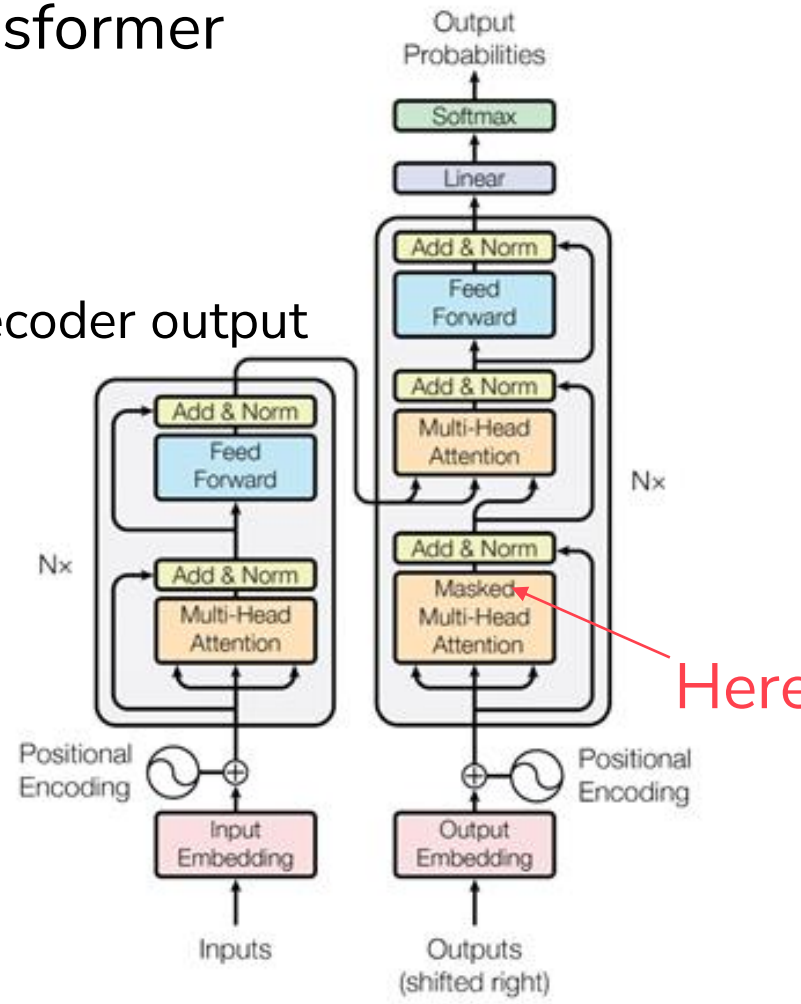
Here



Transformer: Multi-Head Attention

The **Multi-Head Attention** is used three times in the Transformer

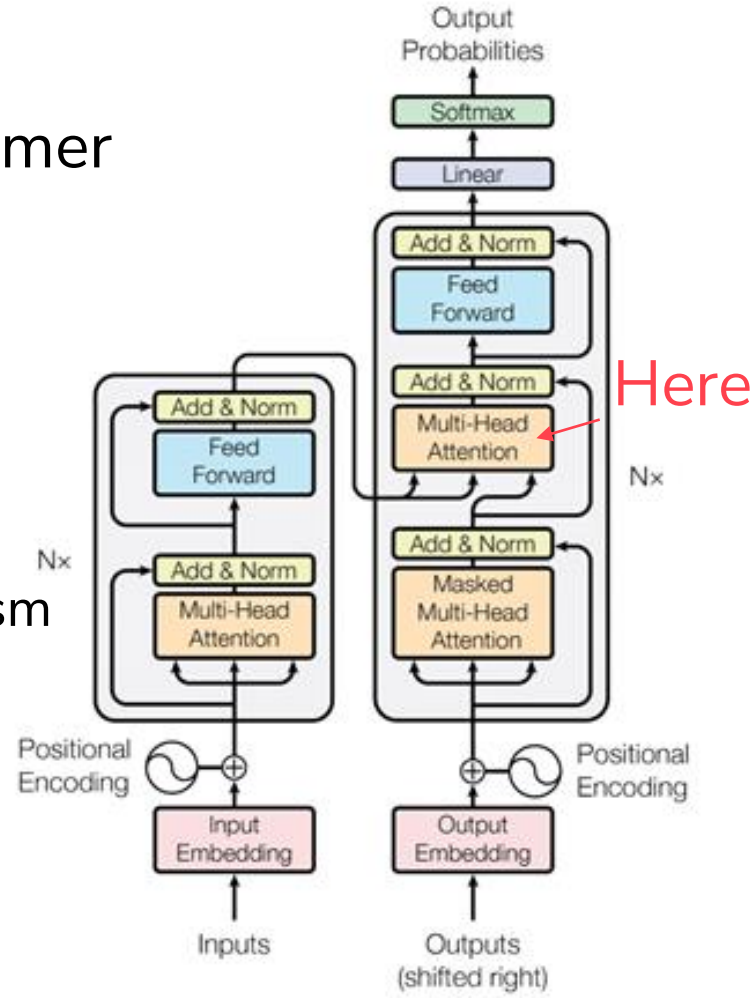
- Inside the encoder
- **Inside the decoder**
  - the queries, keys and values all come from the previous decoder output
  - use of a « mask » to decode only from known elements
- At the encoder-decoder interface



Transformer: Multi-Head Attention

The **Multi-Head Attention** is used three times in the Transformer

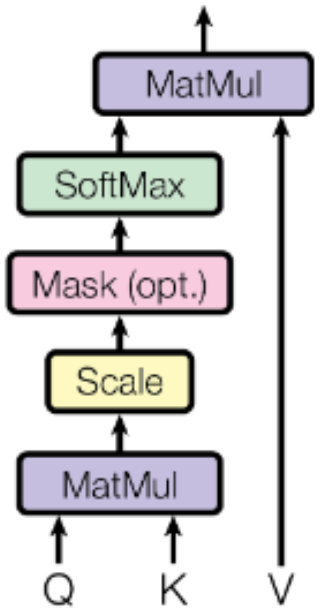
- Inside the encoder
- Inside the decoder
- **At the encoder-decoder interface**
  - the queries come from the previous decoder layer
  - the keys and values come from the encoder outputs
  - identical to the classical “encoder-decoder” Attention mechanism



Transformer: Attention

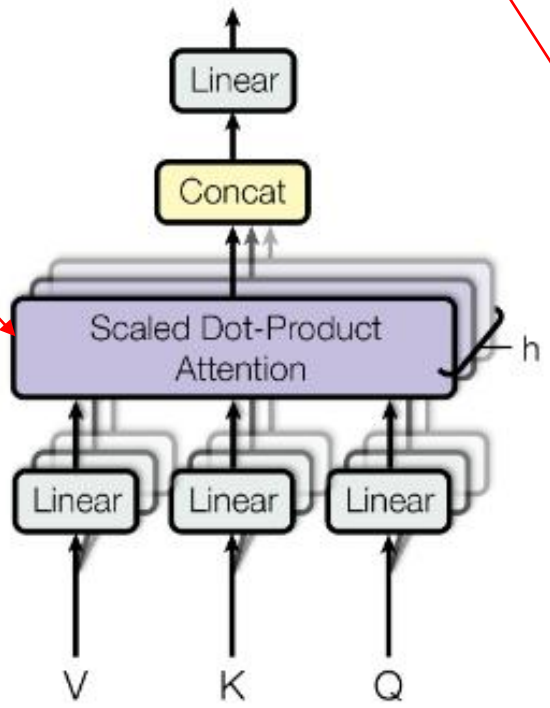
Transformer

Attention



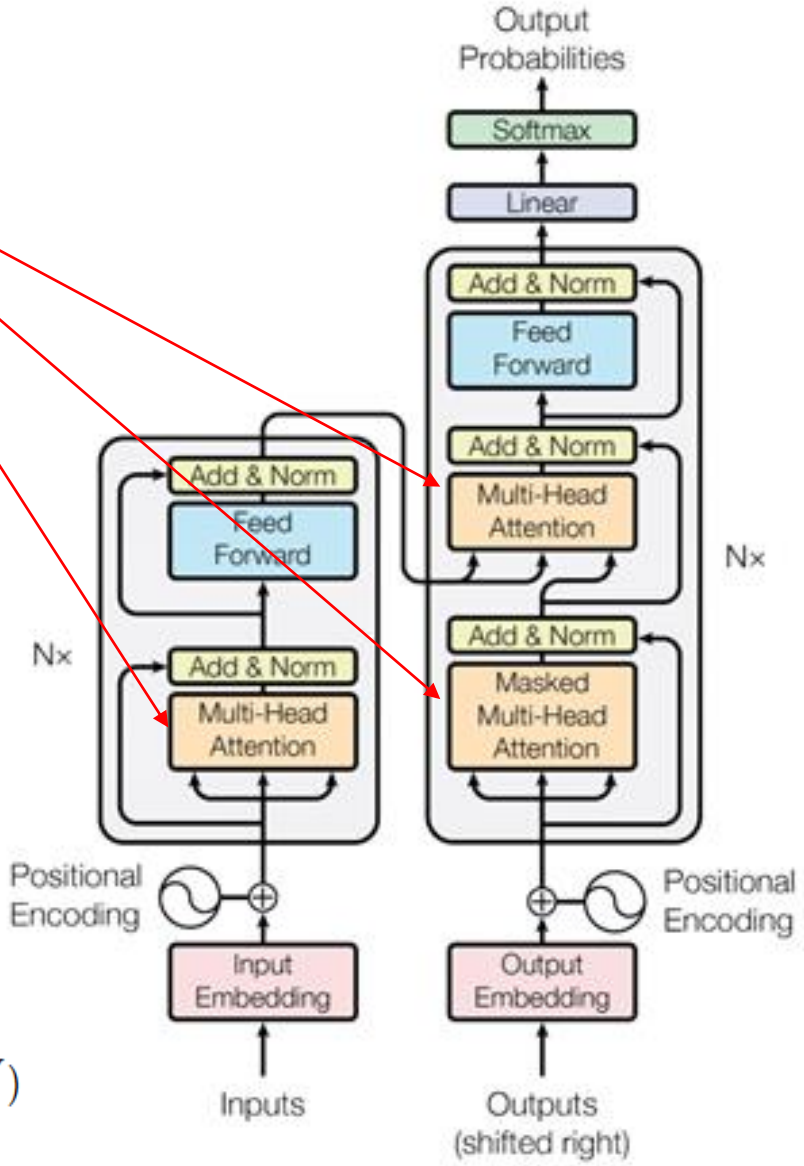
$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

multi-head Attention



$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_\text{h})W^O$$

$$\text{where head}_\text{i} = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$



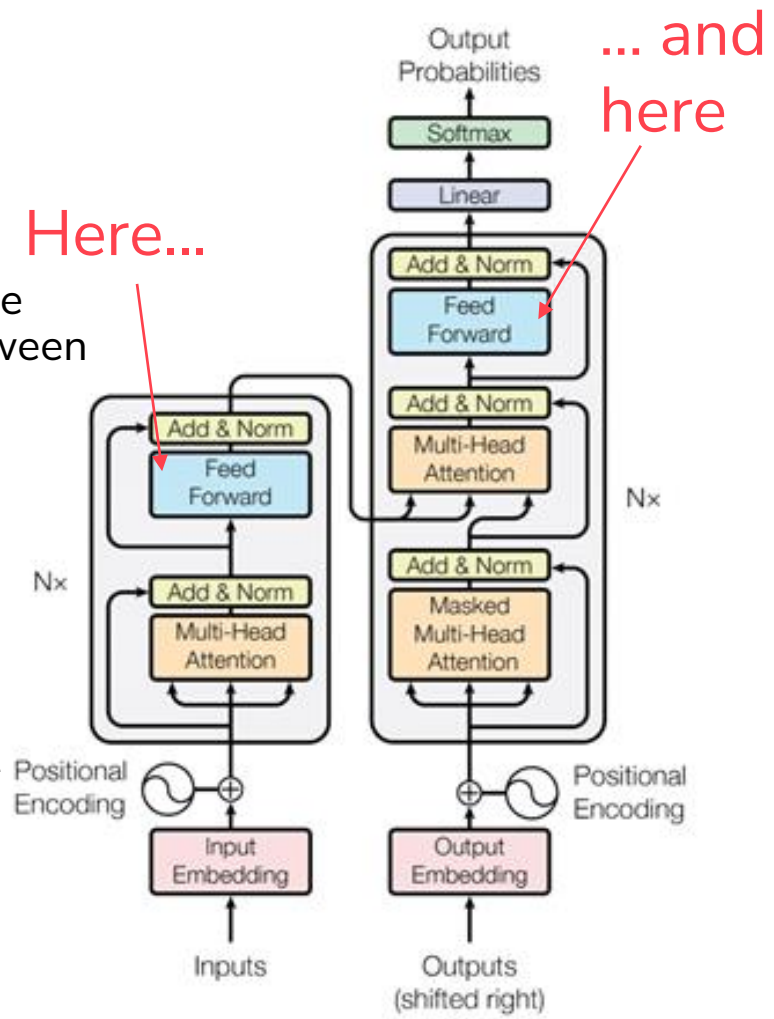
Transformer: Feed-Forward Networks

Principle

- **Feed-Forward network** in each **encoder** and each **decoder** layer
- Each of these Feed-Forward network is completly connected
- Applied in an independent and identical way to each element in the sequence
- Consist in two linear transformations, with the use of a ReLu fonction in between

$$\mathrm{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

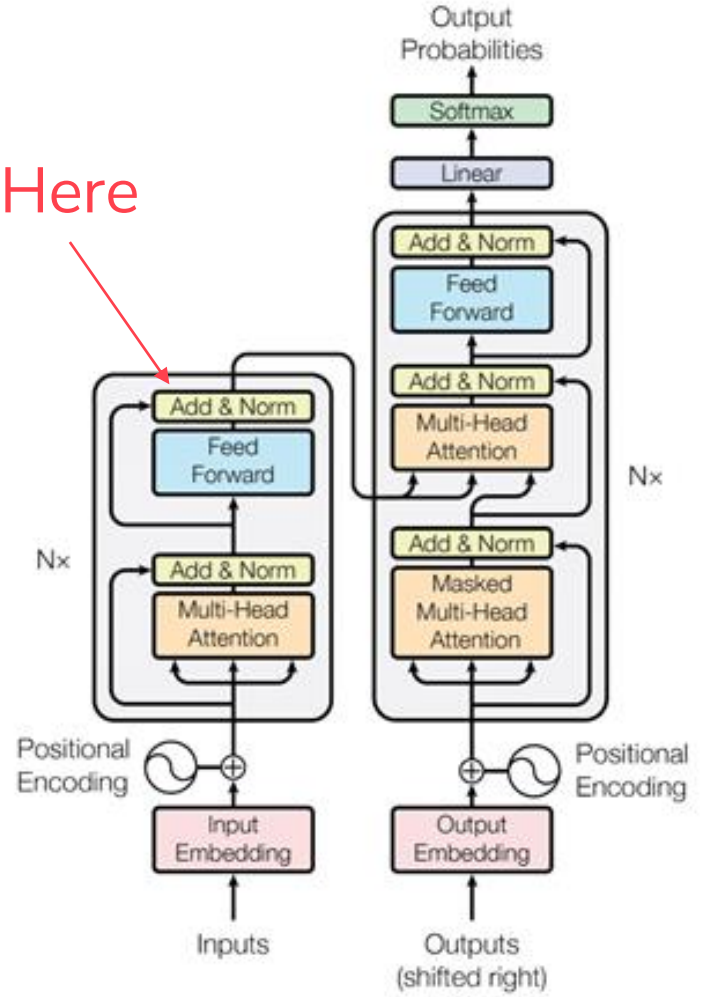
- The linear transformations are identical for each element in the sequence...
- ... but are different for each layer
- Its role is to process the output from one attention layer to better fit the next



Transformer: The residual connection

Principle

- **Add**: To strengthens the Transformer memory.
- **Normalisation**: To reduce the needed steps to optimize the network.



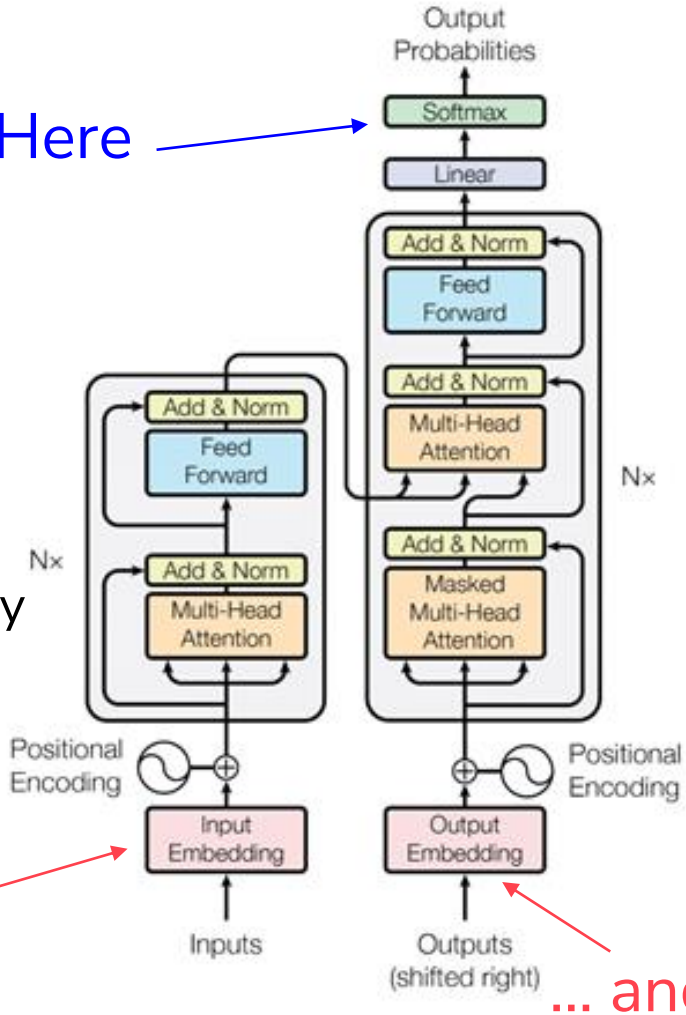
Transformer: Embeddings et Softmax

Embedding learning in order to convert

- The input *tokens*
- The output *tokens*

Use of a *Softmax* layer

- Convert the *decoder* output into the next token prediction probability



Transformer: Positional Encoding

Principle

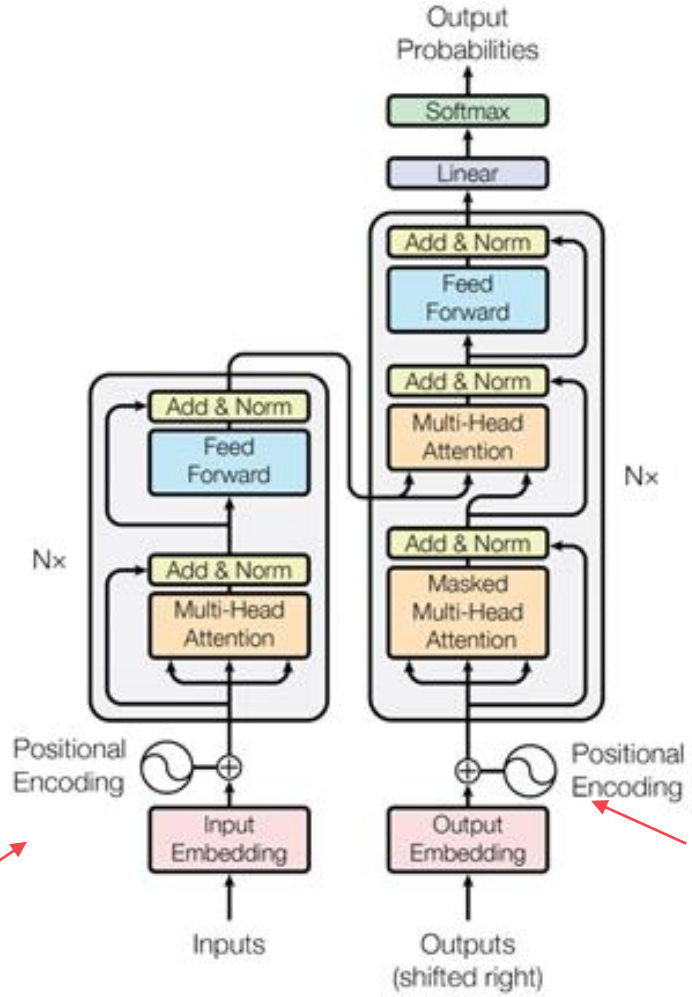
- Keep in memory the *token* positions in the sequence
- Add of "*positional encodings*" to the input *embeddings*
- Used just before the *encoder-decoder* stacks

Formulas

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$

$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

- with *pos* the position and *i* the dimension
- Each dimension corresponds to a sinusoïd
- For each *k*, *PEpos+k* is a linear function of *PEpos*



Here...

... and here

Transformer: Results on the Benchmark *BLEU*

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet	23.75			
Deep-Att + PosUnk		39.2		$1.0 \cdot 10^{20}$
GNMT + RL	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	**$3.3 \cdot 10^{18}$**	
Transformer (big)	**28.4**	**41.8**	$2.3 \cdot 10^{19}$	

https://papers.nips.cc/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf

Transformer: Tutorial notebook

course4_transformer_tutorial.ipynb

Goal: Illustration of how a Transformer can be build step by step in Python

Remarks:

- This notebook comes from a **tutorial notebook** **freely accessible** (the original reference is given at the very beginning, in the first cell)

BERT model

BERT: Introduction

BERT (2018) is for ***B**idirectional **E**ncoder **R**epresentations from **T**ransformers*

- A Transformer variant with a **Bidirectional** specificity
- Thanks to it, there is no need for the end sequence token masking constraint anymore (into the decoders Attention mechanism)
- Build an efficient and generic language representation

The two main BERT steps

- A **pre-training** step on non-labelled data
- A **specialization** step ("***fine tuning***") for a specialized task, from pre-trained parameters
  - There is only need to train **the « last » layers** of the model to get such a specialization

French versions of BERT exists, the most famous one being probably **CamemBERT**

BERT: Architecture

The initial **BERT** architecture (2018) is the following:

- Length of the processed sequences: **512** (Limitation to contain a quadratic explosion)
- Stack of **Nx = 12 blocks** of encoders and decoders (a 24-blocks variant exists)
- **h = 12** attention heads
- It means there are h x Nx = 12 x 12 = **144** distinct attention mechanisms
- Each head gives an output vector of size: **64**
- A hidden layer of h x 64 = **768** dimensions
- Roughly **110 millions** of parameters for the basic version (12 encoders) and **340 millions** for the large version (24 encoders)

Reminder, the initial Transformer architecture (2017)

- Length of the processed sequences: **512** as well
- Stack of **Nx = 6 blocks** of encoders and decoders
- **h = 8** attention heads

BERT: Pre-training

BERT is pre-trained from two unsupervised tasks:

Masked Language Modeling (MLM)

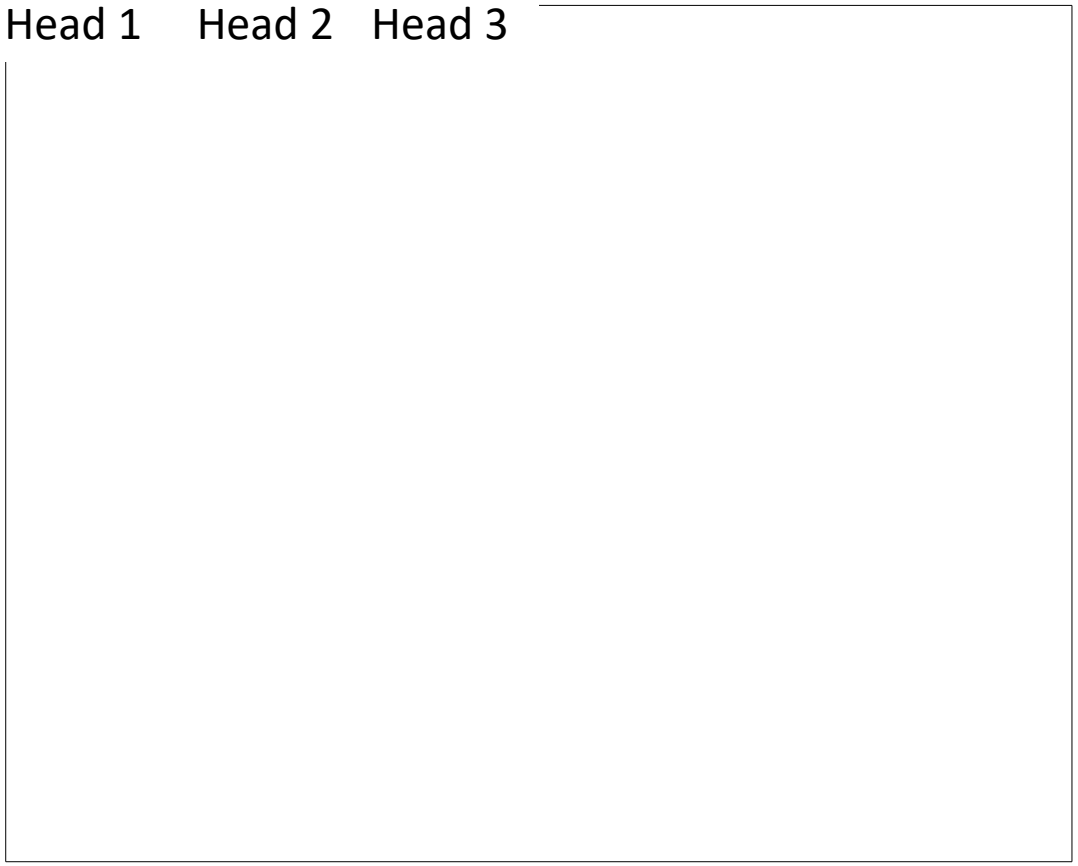
- The model is pre-trained from sequences decomposed into *tokens*
- The goal is to predict some of these tokens (15%) randomly masked in the text

Next Sentence Prediction (NSP)

- The goal is to understand the relationship between two successive sentences
- To do that, the algorithm is trained in order to predict the sentence following a given sentence
- The training set is composed of sentence tuples (A,B)
  - In 50% of the cases, B is the **sentence following** the sentence A (the tuple is then labelled *IsNext*)
  - In 50% of the cases, B is a sentence **randomly** chosen in the corpus (*NotNext* label)

CamemBERT and Attention mechanism

Attention level, for each head, relativly to the french word “ils” (« they »). Each head “see” **different** things from others (**complementarity**)



CamemBERT and Attention mechanism

On the first 6 layers (out of 12), attention mechanism visualization example over the 12 heads

BERT: Fine-tuning

The initial pre-training step needs:

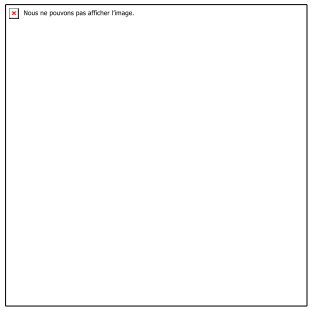
- A **huge** corpus of **generic** texts
- Very **high** computational resources

The fine-tuning step relies on the already pre-trained algorithm, so it only needs :

- A **reduce** and **specialized** corpus
- Significantly **reduces** resources

The aim is obviously to move from a **generic language** modelization to a **task specific one**

Hugging Face



- Hugging Face is an open-source provider of NLP technologies for Python
- A Hugging Face **Transformer** package is available and quite popular
- It gives access to pretrained models such as BERT but also to modules to perform fine-tuning
- It previously supported only **Pytorch**, but now **Tensorflow** is more and more supported as well

BERT implementation: Tutorial notebook

course4_transformer_model_libraries.ipynb

Goal: Illustration of how pre-trained Transformer can be loaded and used from open-source libraries such as Hugging Face

Remarks:

- This notebook comes from a **tutorial notebook** **freely accessible** (the original reference is given at the very beginning, in the first cell)

Current state-of-the-art

GPT

- **OpenAI** is an AI research laboratory founded in 2015 by Elon Musk, Sam Altman and others
- The **GPT** model (2018) was designed by OpenAI researchers (Altman et al.)
- Its architecture is composed of a stack of 12 transformers modules (using only Masked Multi-Head Attention layers) and was train on a large dataset
- It is fine-tuned on tasks such as text classification, similarity and question answering…

GPT-2

- **GPT-2** (2019) was developed few months later, with a similar architecture but larger (1.5 billion parameters!)
- It can be good on many tasks even without fine-tuning
- A **smaller version** of the GPT-2 model is available (“only” 117 million parameters)
- We will see a GPT-2 fine-tuning application later in this **Course**

GPT-3

- **GPT-3** is a language model developed by the Californian start-up OpenAI, it succeeds GPT and GPT-2 in **July 2020**
- GPT-3 has much more parameters than GPT-2 (175 billions VS 1.5 billion!)
- GPT-3 has been trained on a larger dataset than GPT-2 (50 times bigger)
- Unlike BERT, GPT-3 does not need to be fine-tuned for a specific task, it achieves high performance from the pre-trained model only (**zero-shot learning**)

GPT-3

Applications

- Text generation
- Chatbot
- Sum-up information
- Code generation
- Translation…

All classical NLP tasks can be virtually addressed by GPT-3

GPT-3

Limits

- Cannot be trained on a personal computer…
- … and would need close to **5 million dollars** for training only
- The results can be “**unsafe**” (different kind of bias)
- Microsoft announced in September 2020 that it had **licensed exclusive** use of GPT-3
- **Not open-source**, can be used with an API only (after application)
- Some organizations are working on their own version of GPT-style architecture in order to offer an open-source alternative

Volume comparison

Model	Corpus (Giga words)	Parameters (Giga)	Cost (Tera flops)
BERTLARGE	250	0.36	5.33 x 10^8
CamemBERT	138	0.11	
RoBERTa Large	2 000	0.36	4.26 x 10^9
GPT-3	300	174.00	3.14 x 10^11

Reference: LE MAGAZINE DE L'INTELLIGENCE ARTIFICIELLE

Take-away from Course 4

- **LSTM** architectures are **historically important** but there **are not** the state-of-the-art **any more**
- The **"Attention" mechanism** allowed a **significant performance improvement** than using LSTM only
- It has been demonstrated in the seminal paper ***Attention is all you need* (2017)**, thanks to the **Transformer architecture** introduced in it, that "Attention" **alone** is enough to reach the state-of-the-art (no LSTM needed and no need to process a sequence in a specific order)
- **BERT** is an example of such **pre-trained Transformer models**, and it can be **fined-tuned** for specific tasks
- **Hugging Face** offers quite convenient tools **for using and fine-tuning BERT**
- The best models available (like **GPT-3**) can achieve very impressive results on a lot of tasks, but **are not open source**
- However, some **fine-tuning can be done** and sometimes quite **easily** (see **GPT-2**) for interesting results

References Course 1

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)

References Course 2

Online formations

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

Internet site

- https://towardsdatascience.com/skip-gram-nlp-context-words-prediction-algorithm-5bbf34f84e0c

Book

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

Formation (for the *Optimizers* part)

Deep Learning with Tensorflow, *Publicis Sapient France*

References Course 3

Book

A. Géron, *Hands-On Machine Learning with Scikit-Learn, Keras, and Tensorflow: Concepts, Tools, and Techniques to Build Intelligent Systems* (2019)

Online formations

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

Internet sites

- http://colah.github.io/posts/2015-08-Understanding-LSTMs/
- https://blog.engineering.publicissapient.fr/2020/09/23/long-short-term-memory-lstm-networks-for-time-series-forecasting/
- https://medium.datadriveninvestor.com/how-do-lstm-networks-solve-the-problem-of-vanishing-gradients-a6784971a577

References Course 4

Book

A. Géron, *Hands-On Machine Learning with Scikit-Learn, Keras, and Tensorflow: Concepts, Tools, and Techniques to Build Intelligent Systems* (2019)

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- https://www.coursera.org/specializations/natural-language-processing
- https://www.coursera.org/learn/natural-language-processing-tensorflow

Internet sites

- https://arxiv.org/abs/1706.03762 *(Attention is al you need)*
- https://www.youtube.com/watch?reload=9&v=OyFJWRnt_AY
- http://jalammar.github.io/illustrated-transformer/
- https://medium.com/dissecting-bert/dissecting-bert-part-1-d3c3d495cdb3
- https://camembert-model.fr/
- https://huggingface.co/
- https://lesdieuxducode.com/blog/2019/4/bert--le-transformer-model-qui-sentraine-et-qui-represente
- https://www.youtube.com/watch?v=S0zQoTkX_YQ (github copilot)

Online notebooks

- https://colab.research.google.com/github/tensorflow/text/blob/master/docs/tutorials/transformer.ipynb
- https://colab.research.google.com/github/sarthakmalik/GPT2.Training.Google.Colaboratory/blob/master/Train_a_GPT_2_Text_Generating_Model_w_GPU.ipynb
- https://colab.research.google.com/github/ziadloo/attention_keras/blob/master/examples/colab/LSTM.ipynb