Natural Language Processing

DSA

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Course 2

Fall 2023

Course Schedule

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

Evaluation

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

   This exercise will contain
   - multiple-choice-questions (MCQ)
   - theoretical questions
   - Coding questions

2. **A graded project (starts now; see details given in the pdf)**

Evaluation

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2. **A graded project (starts now; see details given in the pdf)** This Week

Course Schedule

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

This Week

- **Course 3**: Long Short-Term Memory (LSTM) architecture
- **Course 4**: “Attention” mechanism and Transformer architectures
- **Course 5**: Large Language Models and Generative AI

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

To *be* *or* *not* *to* *be*

Tokenization

Tokenization and one-hot encoding steps

Principle

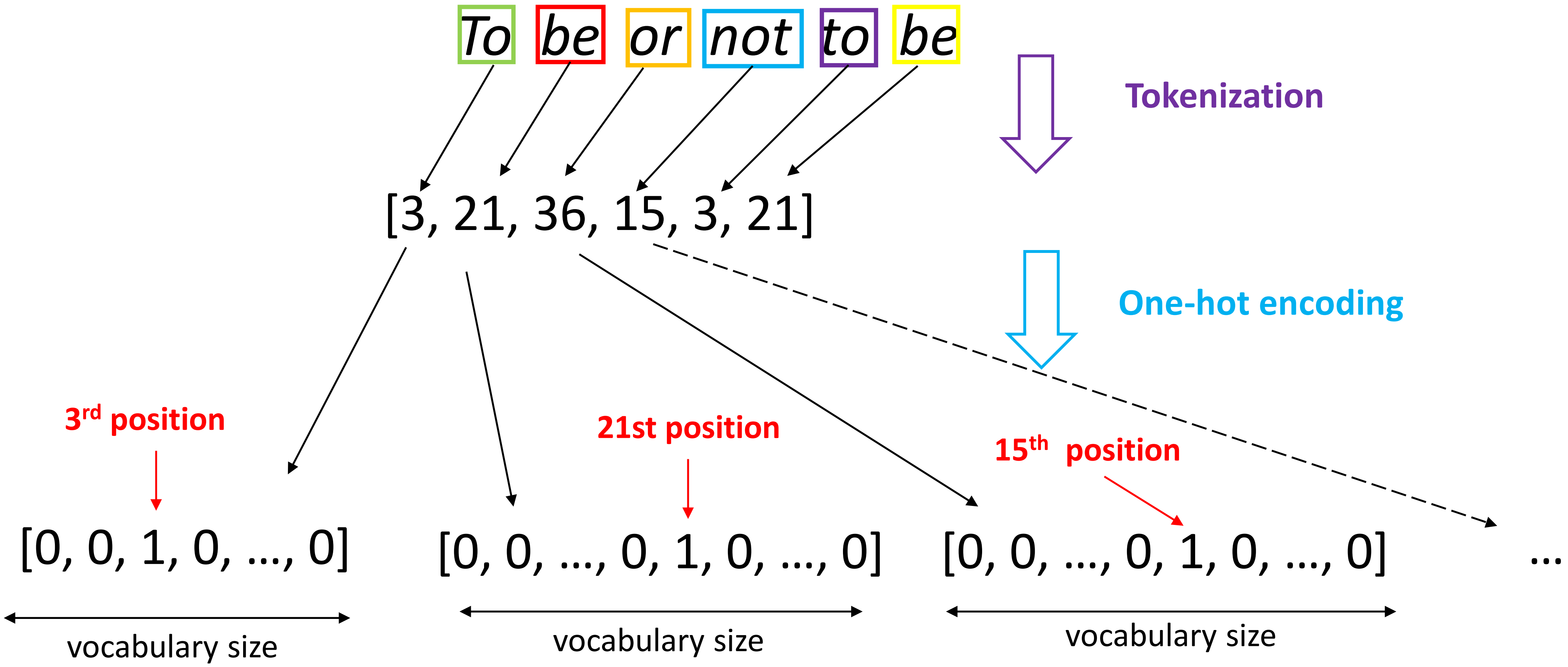
To be or not to be

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

Tokenization

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

Tokenization and one-hot encoding steps

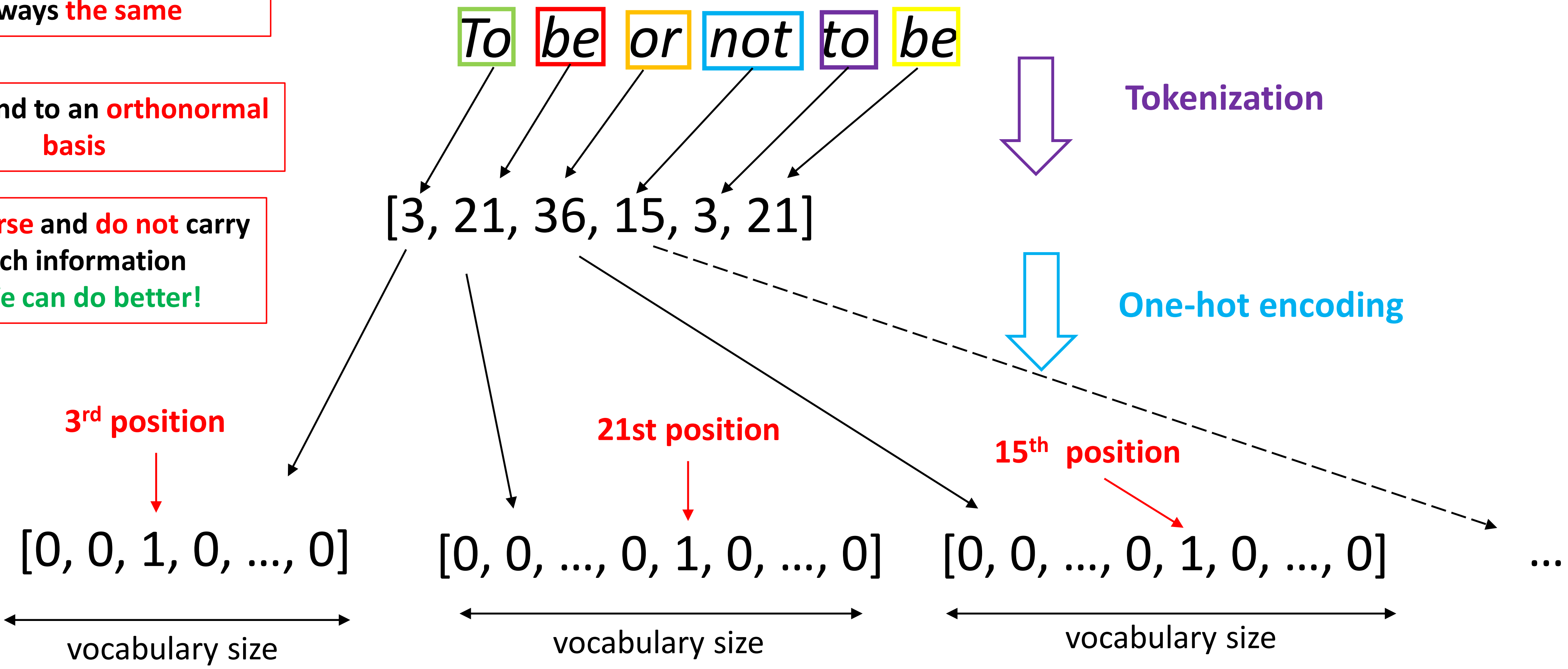


Tokenization and one-hot encoding steps

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

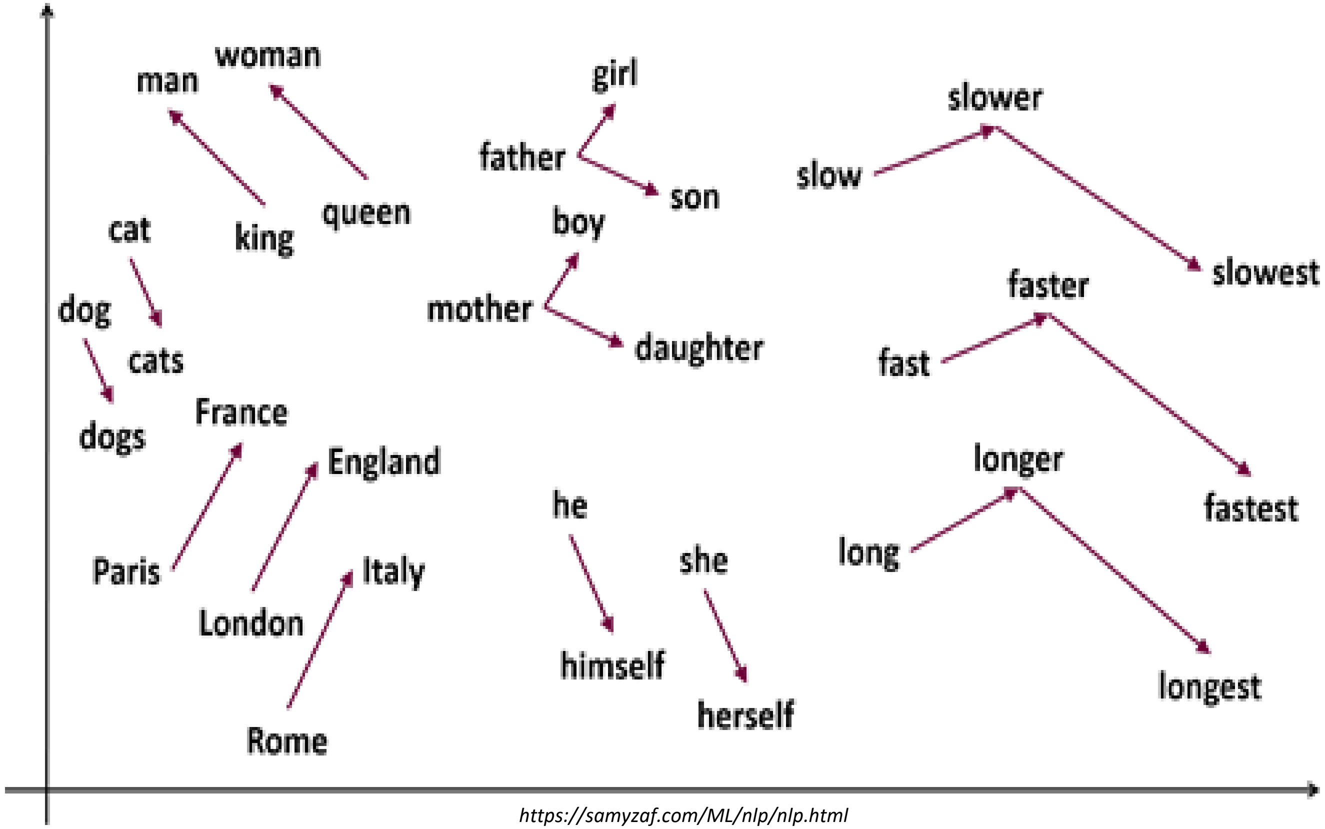
- Goal : **two words with closed meaning should be represented by closed vectors as well**

- 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

$$\boxed{\textit{king} - \textit{man} + \textit{woman} \approx \textit{queen}}$$

Word embedding: Illustration



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

$$\text{king} - \text{man} + \text{woman} \approx \text{queen}$$

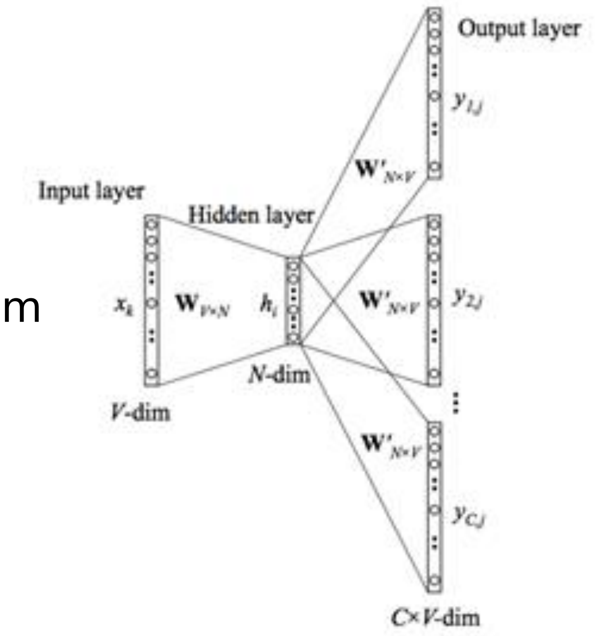
$$\text{France} - \text{Paris} + \text{London} \approx \text{England}$$

Word embeddings: Principle

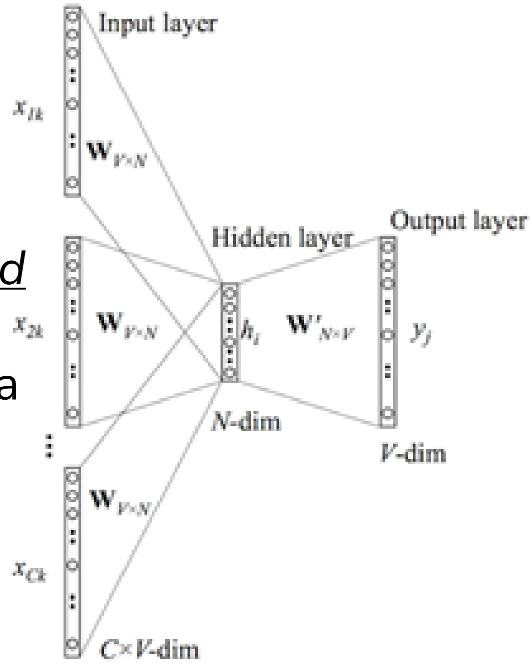
How are generated word embeddings?

- 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



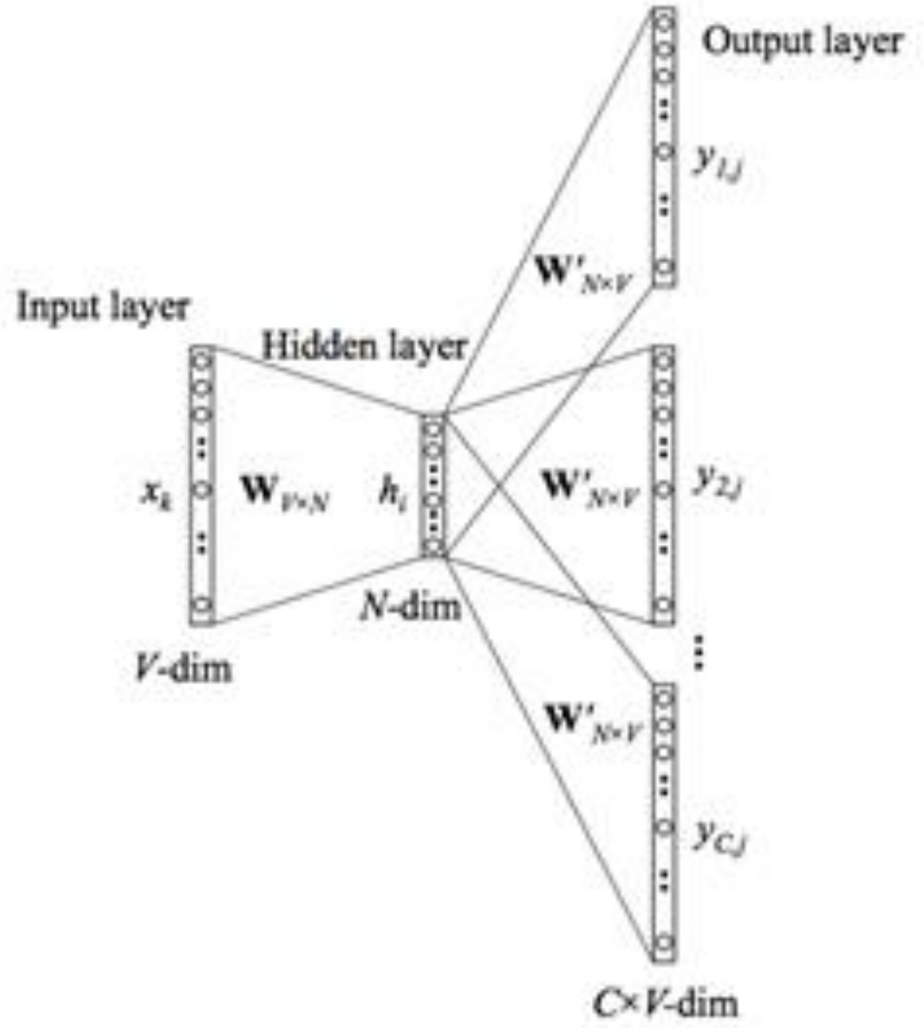
Word embedding: Skip-gram model

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

<u>Example</u>:

*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

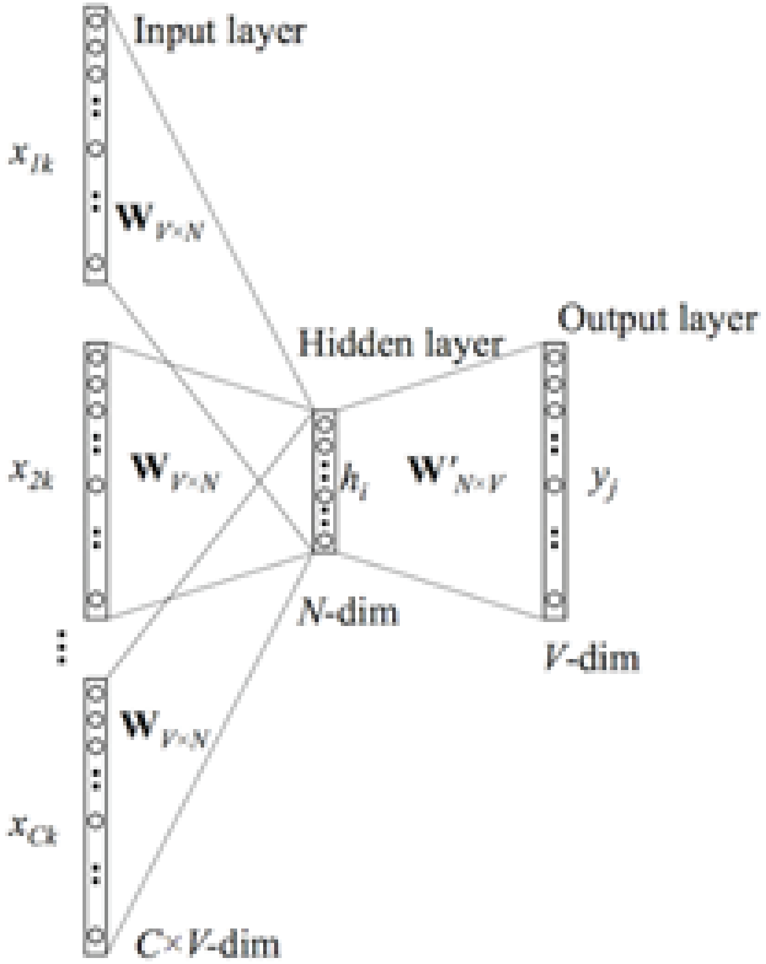
Word embedding: CBOW model

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)
  $\Rightarrow$ ***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

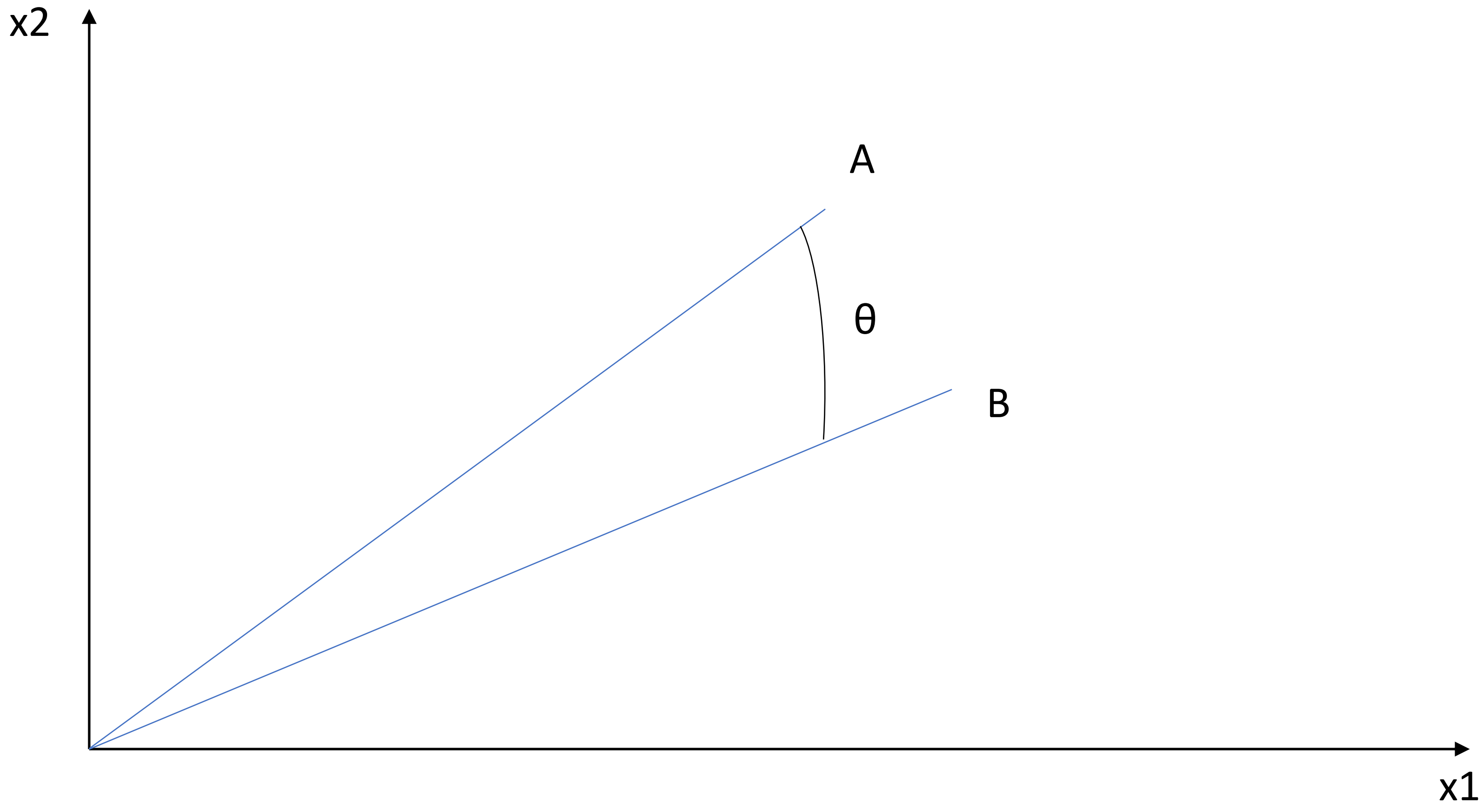
- The **cosine similarity** is a measure of similarity between two vectors which relies on the **cosine of their angle**

- 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

<u>Goal</u>: Check the validity of the relationship: $\boxed{\textit{king} - \textit{man} + \textit{woman} \approx \textit{queen}}$

from three libraries with pre-trained embedding models:

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

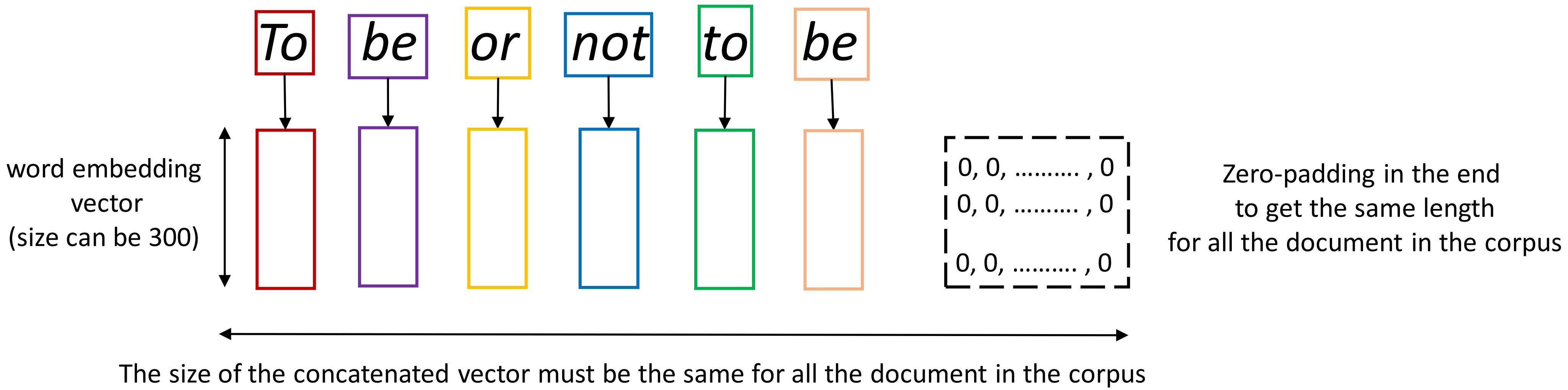
Text embedding

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

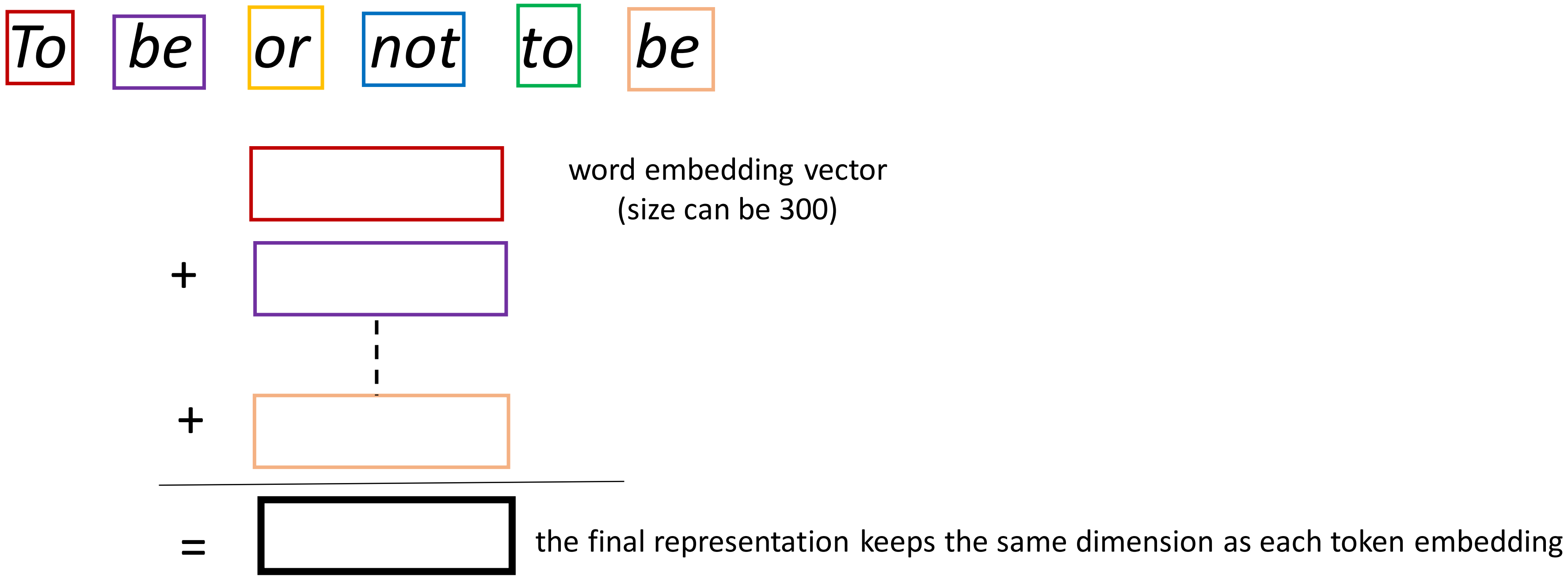


Remarks

- 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

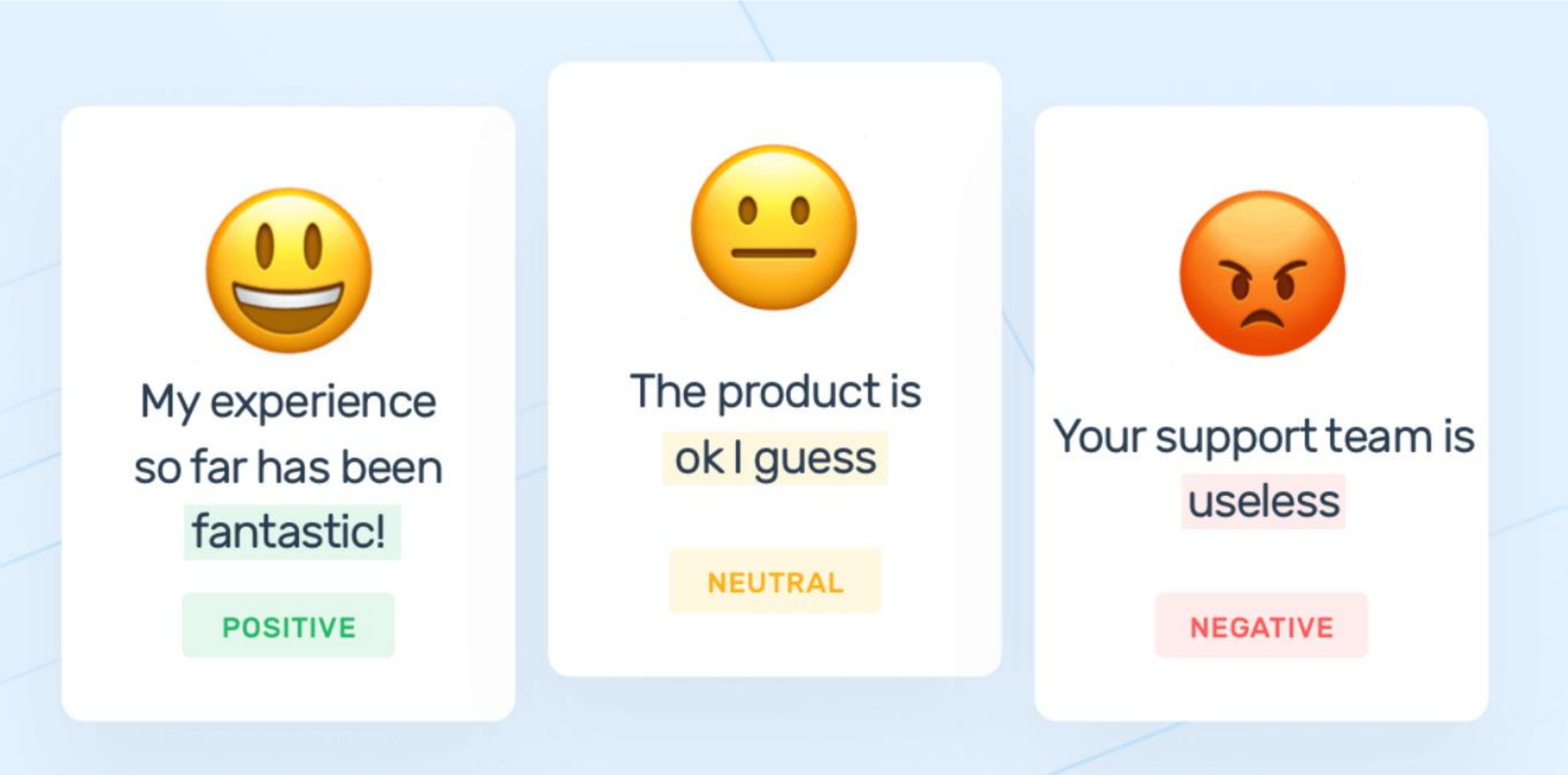
Some libraries offers to deal directly with **text** embeddings

- **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

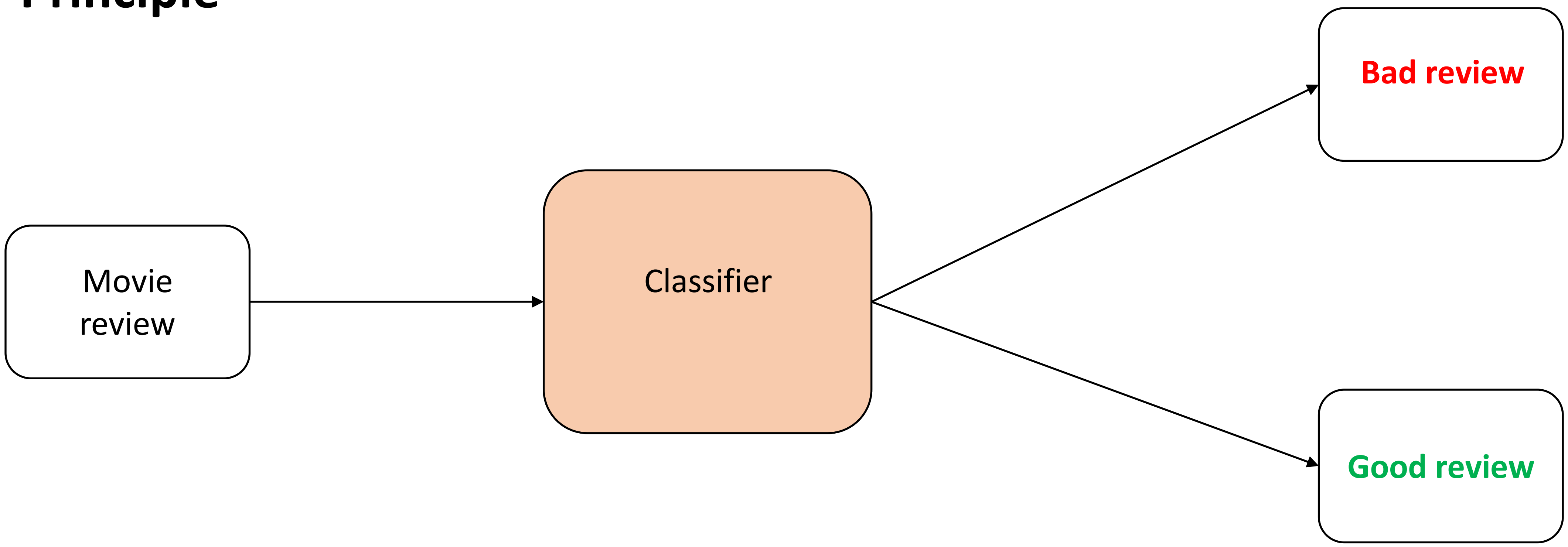
What is sentiment analysis ?



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

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_spacy_svm_vader_ex.ipynb

<u>Goal</u>: a **sentiment analysis** application on **IMDB dataset**

- Use of spaCy **text embedding** model to train a Support Vector Machine (**SVM**)
- Use of Vader model

<u>**Remarks:**</u>

- The computation of text embedding can be **time consuming**
- To avoid this issue, the notebook allows you to load text embeddings **already computed**
- The **Vader** model is pre-trained and be directly used without training

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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Sentiment Analysis: Neural Network (NN)

Data Preprocessing

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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

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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

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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

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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

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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)

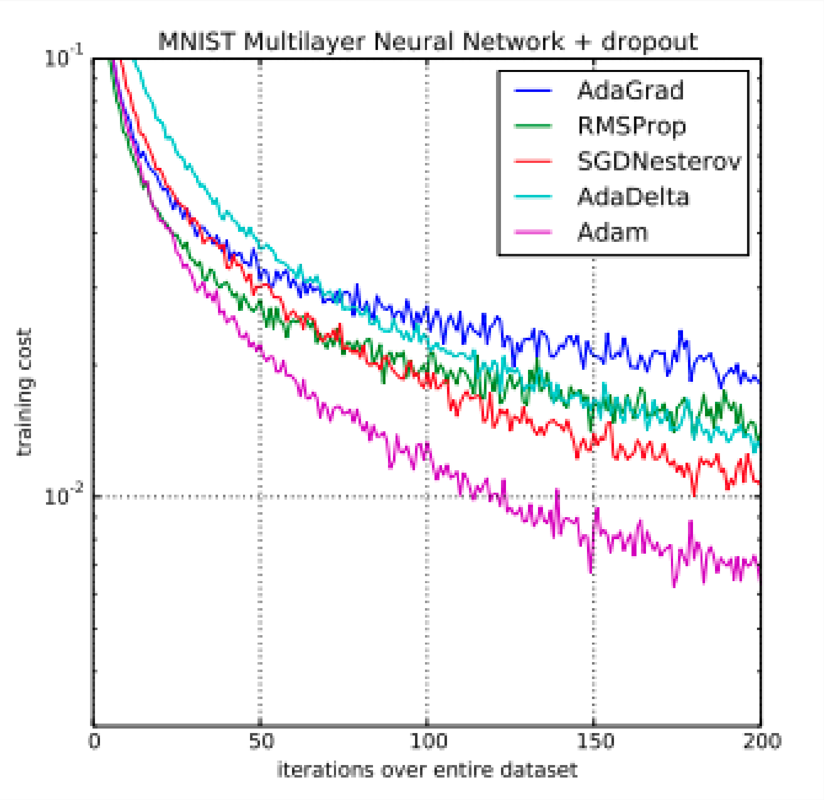
Optimizers Variants

- 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)
```

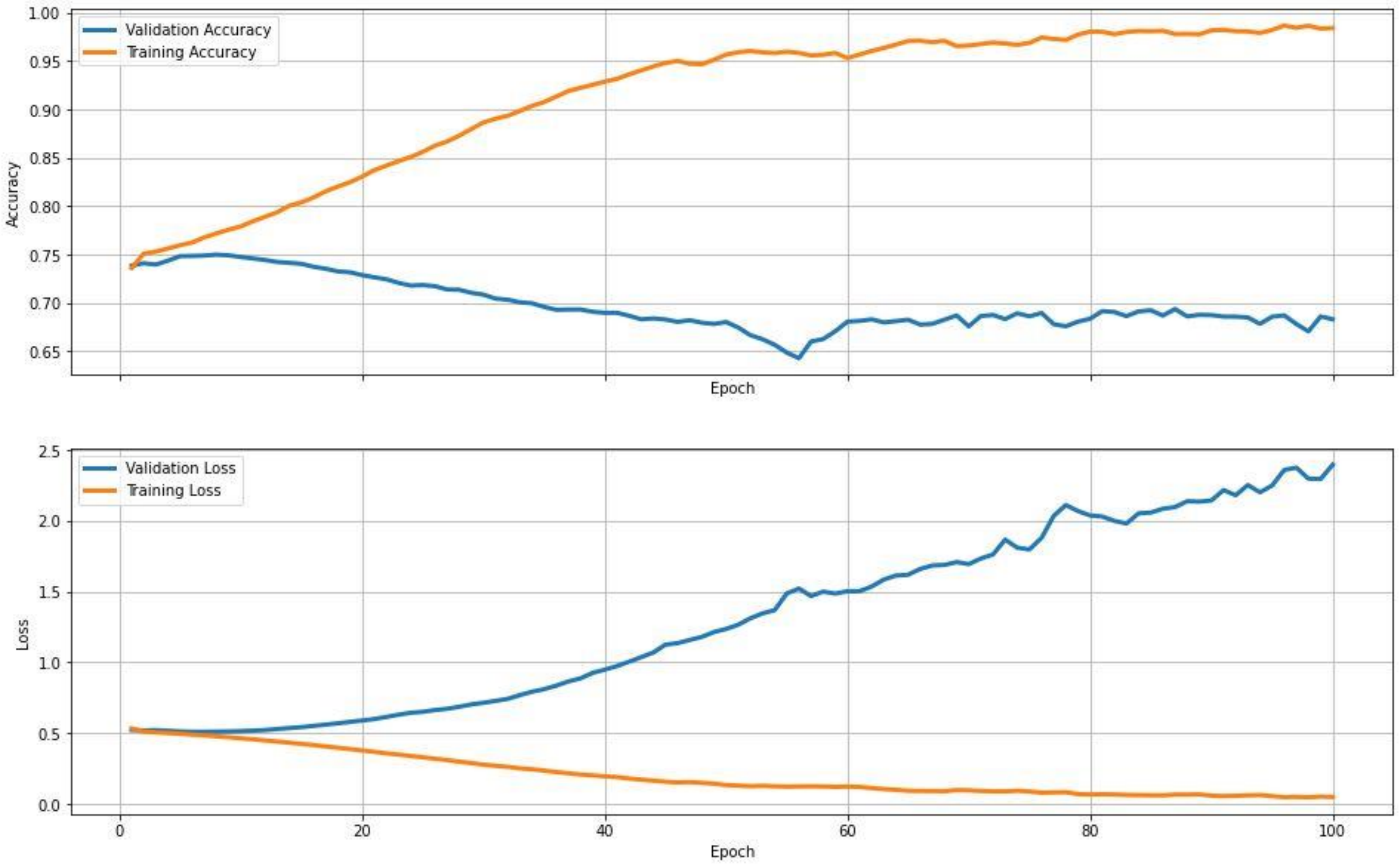
- Both optimizer and loss function must be entered during the **compilation** step

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

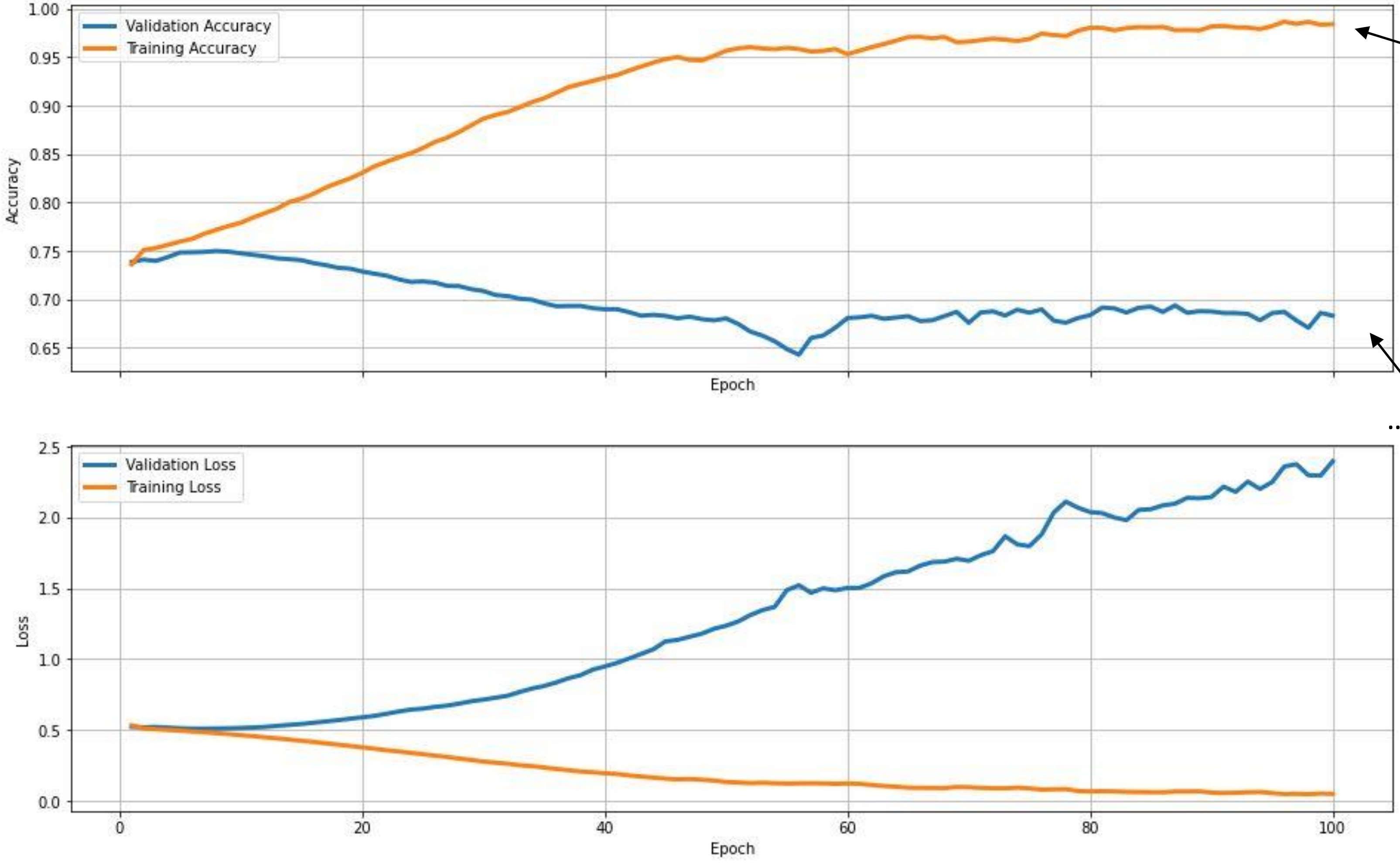


Comparison of Adam to Other Optimization Algorithms Training a Multilayer Perceptron
Taken from Adam: A Method for Stochastic Optimization, 2015.

Sentiment Analysis: Neural Network (NN)



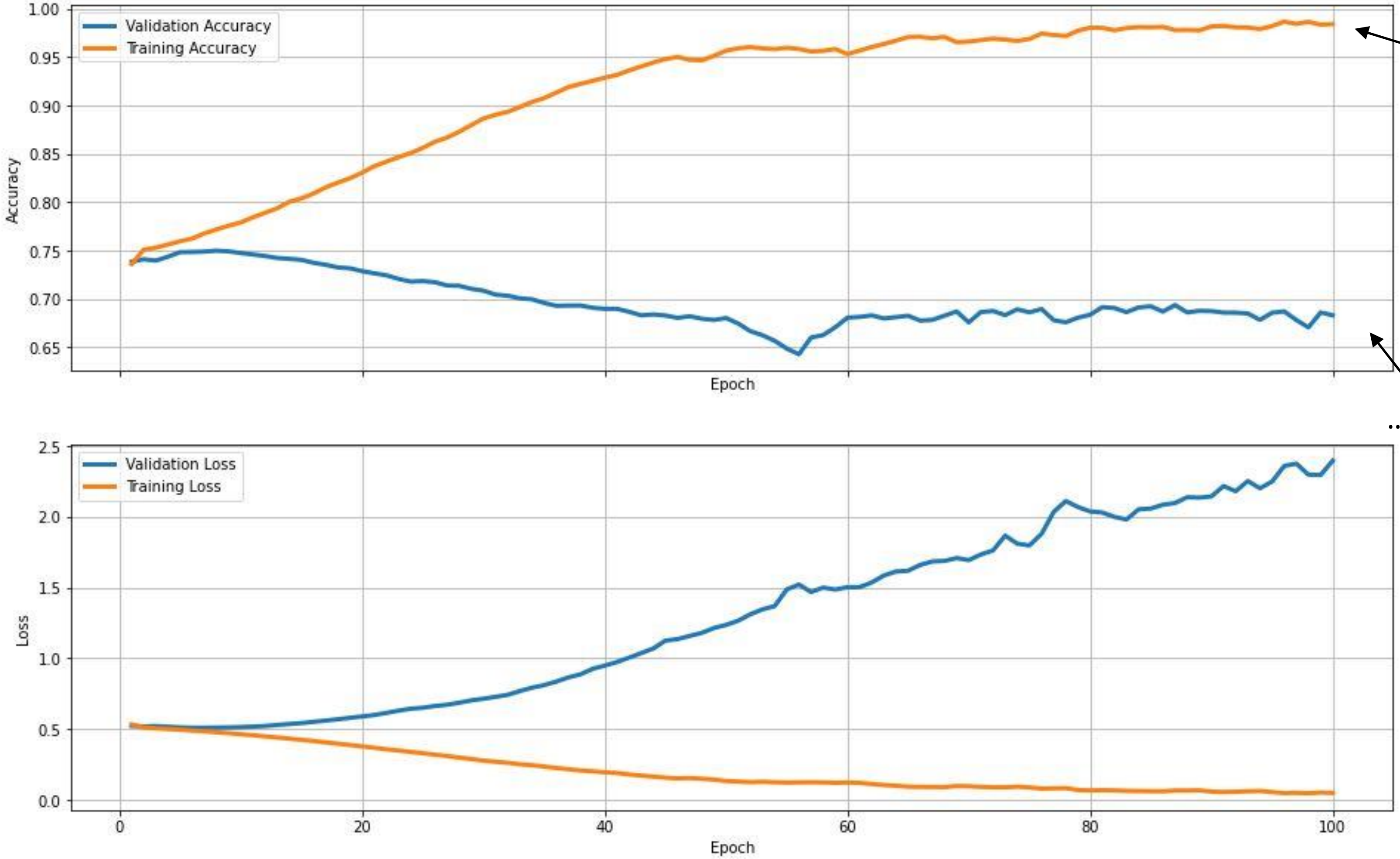
Sentiment Analysis: Neural Network (NN)



The results seem good on the train set…

… but there are significantly less good on the test set

Sentiment Analysis: Neural Network (NN)



The results seem good on the train set…

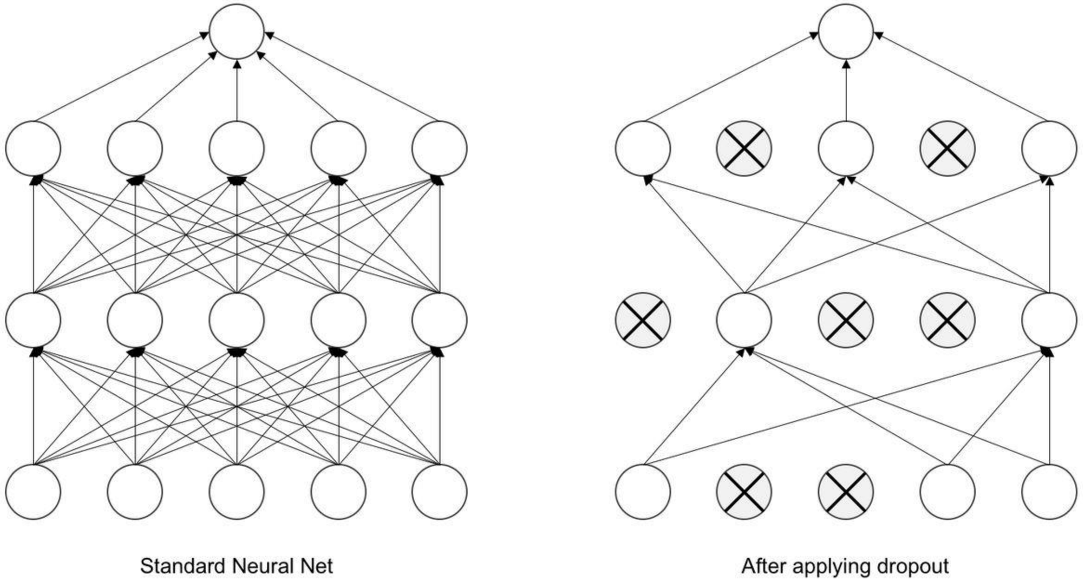
… but there are significantly less good on the test set

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")
])
```



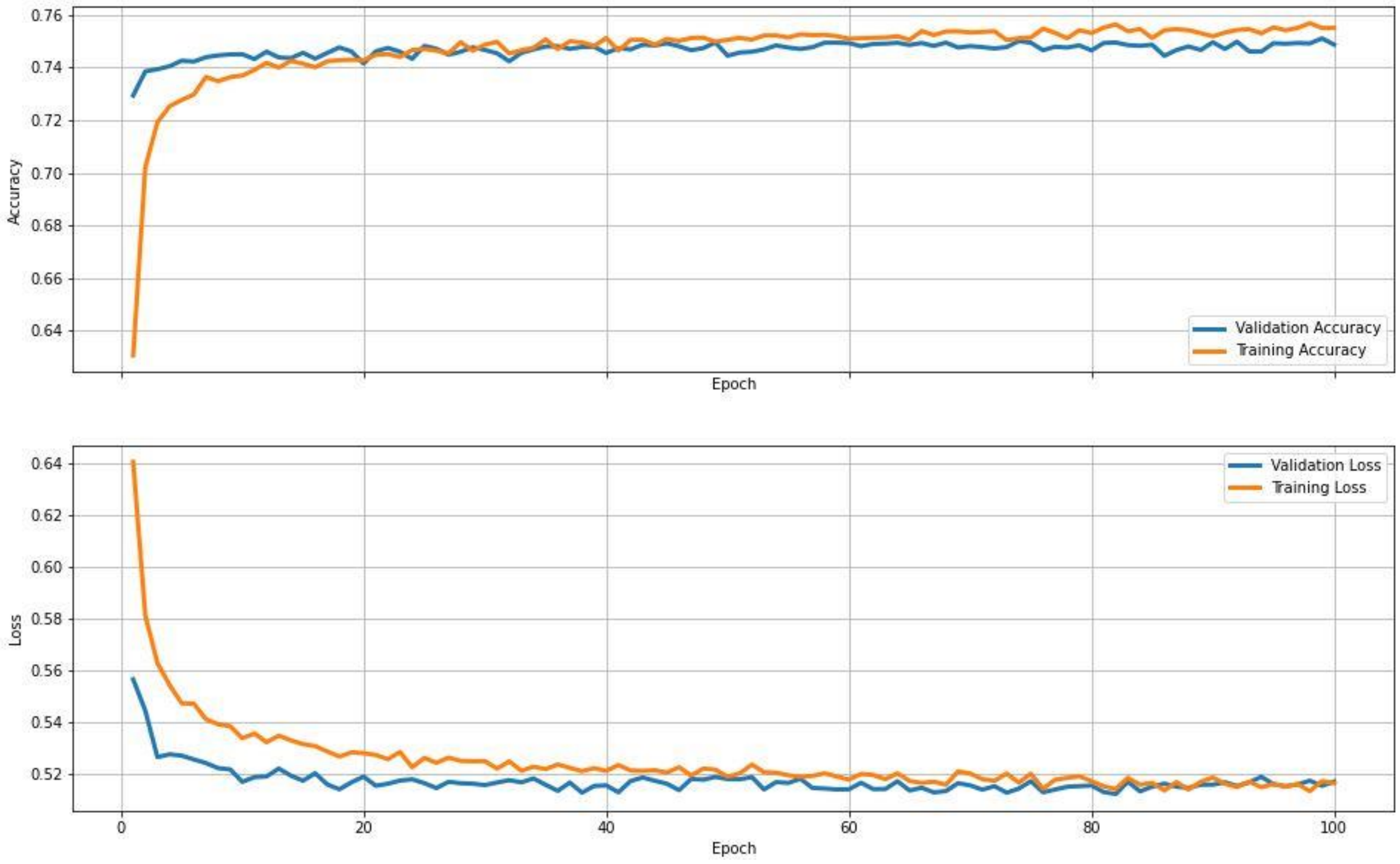
https://www.oreilly.com/library/view/deep-learning-for/9781788295628/a22e6b18-79e3-4875-b003-2f4c6080bf54.xhtml

Sentiment Analysis: Neural Network (NN)

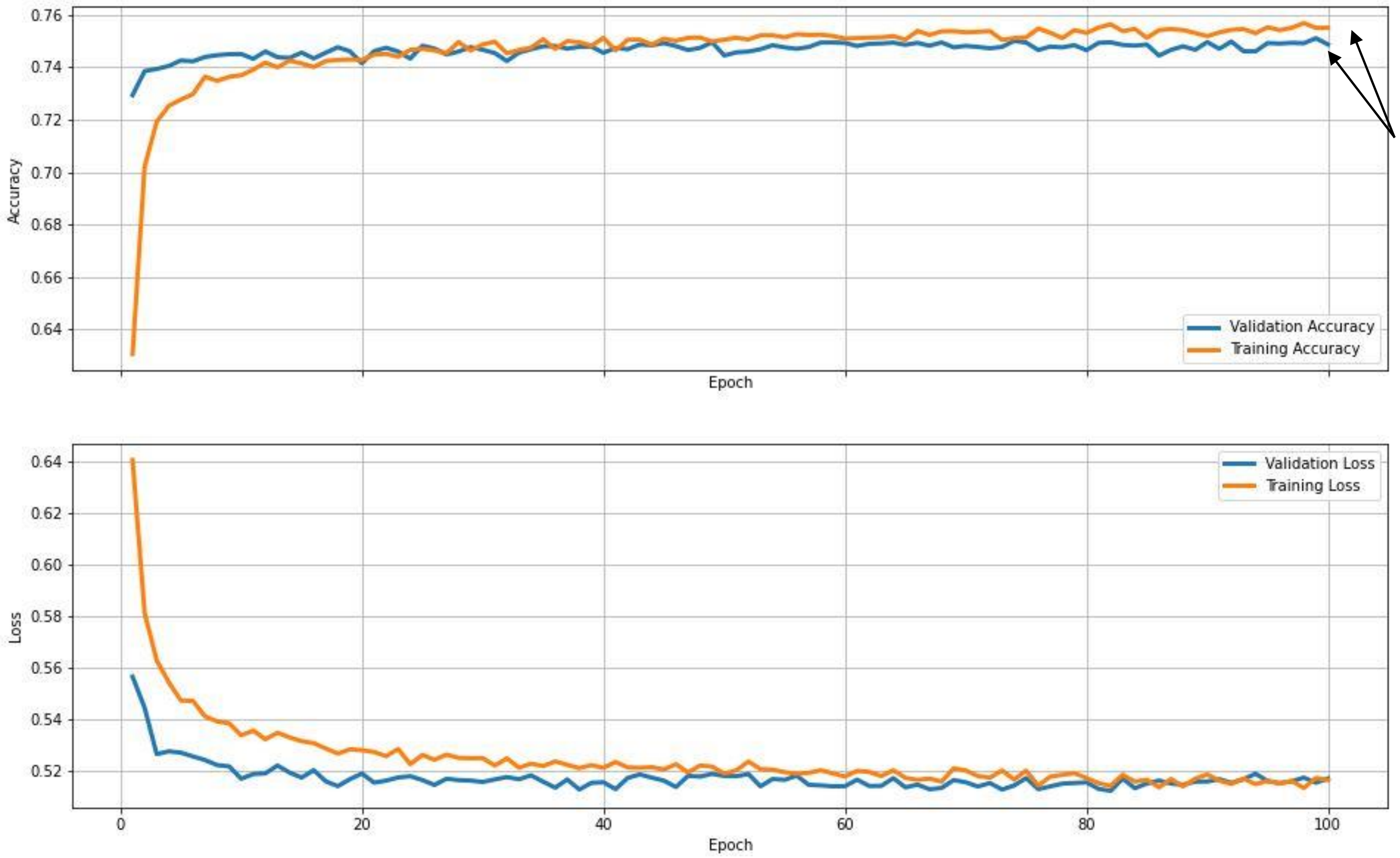
```
model.summary()
```

```
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)

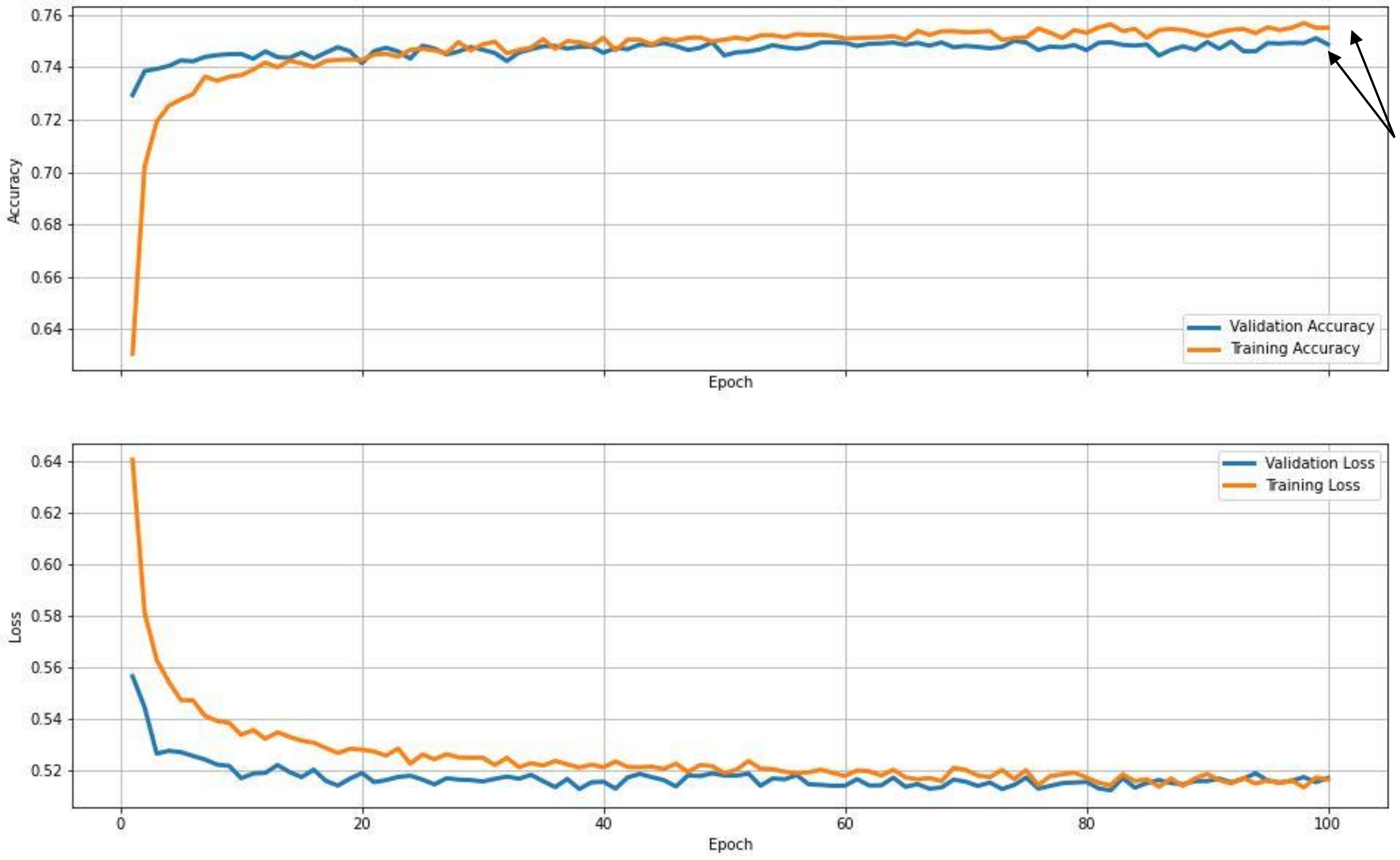


Sentiment Analysis: Neural Network (NN)



The results are similar for both train and test set

Sentiment Analysis: Neural Network (NN)



The results are similar for both train and test set

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**

References

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 *Optimizer* part)

Deep Learning with Tensorflow, *Publicis Sapient France*