





# / Text Data



# / Free text features

---

Some tabular datasets contains free text variables. In this lesson we are going to see how to process it.



Remember: If you data consists on solely text data you should consider stronger methods like **RNNs** or **Transformers**.

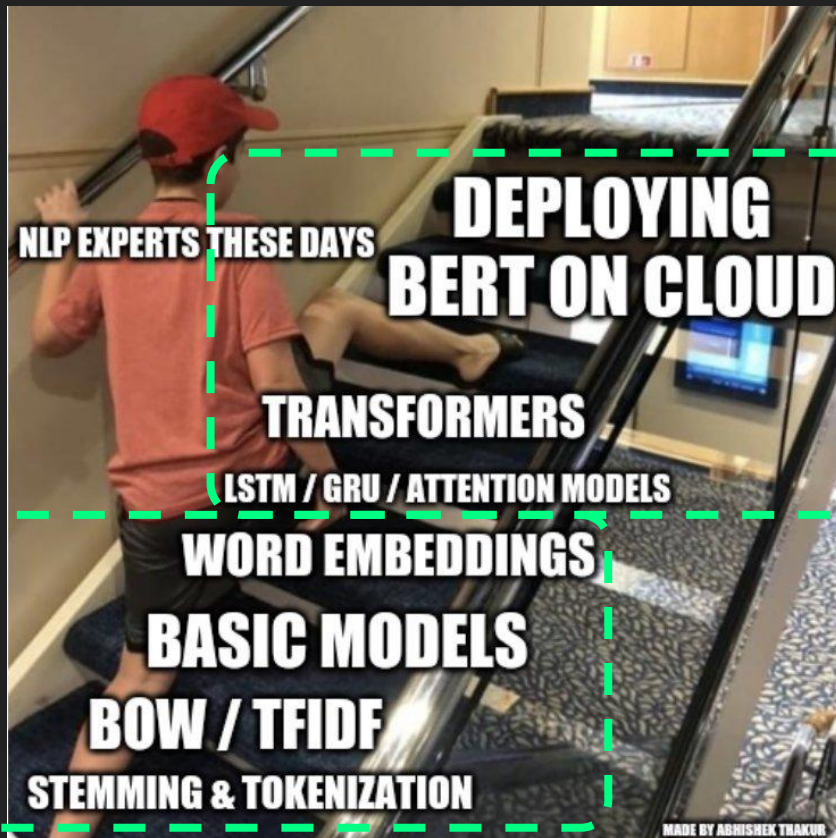


# Many options for NLP





# Many options for NLP



NLP  
Deep Learning  
Session

Today



# Free Text Features

## / Common text features

- **Name** and **surname** (like Titanic dataset)
- House **Direction** (Geoposition encoding)
- **Item** (ad, car, house, 2nd hand product)
  - Title
  - Subtitle
  - Description

name
Braund, Mr. Owen Harris
Cumings, Mrs. John Bradley (Florence Briggs Thayer)
Heikkinen, Miss. Laina
Futrelle, Mrs. Jacques Heath (Lily May Peel)
Allen, Mr. William Henry
Moran, Mr. James
McCarthy, Mr. Timothy J
Palsson, Master. Gosta Leonard
Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)
Nasser, Mrs. Nicholas (Adele Achem)
Sandstrom, Miss. Marguerite Rut
Bonnell, Miss. Elizabeth



# Part 1:

# BoW and TF-IDF



## Bag of Words (BoW)

/ One simple method is **Bag of Words**. You can consider this method as a N-Hot Encoding where we put a 1 if the word appears and 0 otherwise.

The dog is on the table

0	0	1	1	0	1	1	1
are	cat	dog	is	now	on	table	the

/ In sklearn there is a similar method called **Count Vectorizer** where we count the number of occurrences of a word.

```
from sklearn.feature_extraction.text import CountVectorizer
```



# CountVectorizer

/ With **CountVectorizer** where we count the number of occurrences of a word.

(excited) Hi everyone!	I'm so excited about this course!	So excited. SO EXCITED. EXCITED, I AM!
---------------------------	---	--



hi	every one	I'm	so	excited	about	this	course
1	1			1			
		1	1	1	1	1	1
		1	2	3			



# TF-IDF

## Term Frequency (TF)

```
tf = 1 / x.sum(axis=1)[:,None]  
x = x * tf
```

## Inverse Document Frequency (IDF)

```
idf = np.log(x.shape[0] / (x > 0).sum(0))  
x = x * idf
```

```
from sklearn.feature_extraction.text import TfidfVectorizer
```



## Term Frequency (TF)

/ With `TfidfVectorizer(use_idf = False)` we count the percentage of occurrences of a word in a sentence.

(excited) Hi everyone!	I'm so excited about this course!	So excited. SO EXCITED. EXCITED, I AM!
---------------------------	---	--



hi	every one	I'm	so	excited	about	this	course
0.33	0.33			0.33			
		0.16	0.16	0.16	0.16	0.16	0.16
		0.16	0.33	0.5			

*Summation of  
each row  
is equal to 1*

# Term Frequency - Inverse Document Frequency

/ With `TfidfVectorizer(use_idf = True)` we count the percentage of occurrences of a word in a sentence versus the other rows.

*Useful for **boost most unique words** and **ignore most frequent word** (like “excited”)*

(excited) Hi everyone!	I’m so excited about this course!	So excited. SO EXCITED. EXCITED, I AM!
---------------------------	---	--



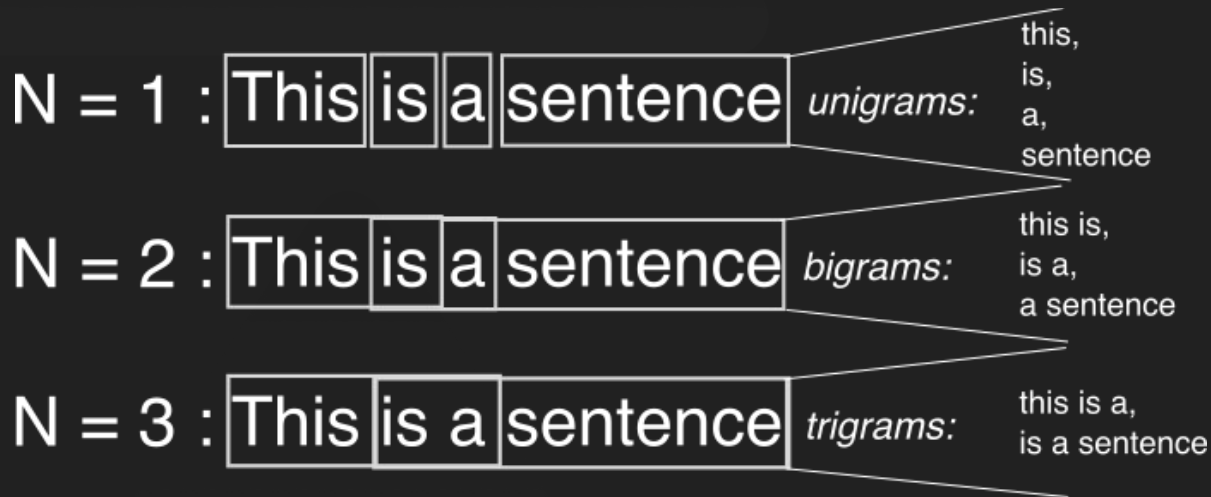
*Technically we postprocess TF matrix by normalizing data column-wise*

hi	every one	I’m	so	excited	about	this	course
0.36	0.36			0			
		0.06	0.06	0	0.18	0.18	0.18
		0.06	0.13	0			



## Parameter: N-Grams

/ Helps to to use local context. Specially words starting with “no” or “not”.



**ngram\_range : tuple (min\_n, max\_n), default=(1, 1)**

The lower and upper boundary of the range of n-values for different n-grams to be extracted. All values of n such that  $\text{min\_n} \leq n \leq \text{max\_n}$  will be used. For example an ngram\_range of (1, 1) means only unigrams, (1, 2) means unigrams and bigrams, and (2, 2) means only bigrams. Only applies if analyzer is not callable.



## Parameter: LowerCase

Very, very  
sunny.

Sunny... Sunny!



Very	very	Sunny	sunny
1	1	0	1
0	0	2	0

**lowercase : *bool*, default=True**

Convert all characters to lowercase before tokenizing.

*We don't want this.*

*So we need to*

*lowercase.*



# Stemming and Lemmatization

I had a car

We have cars



I have car

We have car

## Stemming

democracy, democratic, and democratization → democr  
see, saw → s

## Lemmatization

democracy, democratic, and democratization → democracy  
see, saw → see or saw (depending on context)



## Parameters: Min and Max Frequency

**max\_df : float or int, default=1.0**

When building the vocabulary ignore terms that have a document frequency strictly higher than the given threshold (corpus-specific stop words). If float in range [0.0, 1.0], the parameter represents a proportion of documents, integer absolute counts. This parameter is ignored if vocabulary is not None.

*Useful for ignore common words: "a", "and", "the", ...*

**min\_df : float or int, default=1**    *Also known as Stopwords*

When building the vocabulary ignore terms that have a document frequency strictly lower than the given threshold. This value is also called cut-off in the literature. If float in range of [0.0, 1.0], the parameter represents a proportion of documents, integer absolute counts. This parameter is ignored if vocabulary is not None.

*Useful for ignore too specific or rare words*





## Conclusion BoW & TF-iDF

- Lowercase with: `lowercase`
- stemming/lemmatization
- Remove common words and stopwords: `min_df`
- Remove too specific and rare words: `max_df`
- Ngrams can help to use local context: `ngram_range`
- TFiDF
  - TF helps to normalize in frequencies
  - IDF helps to ignore most frequent word.

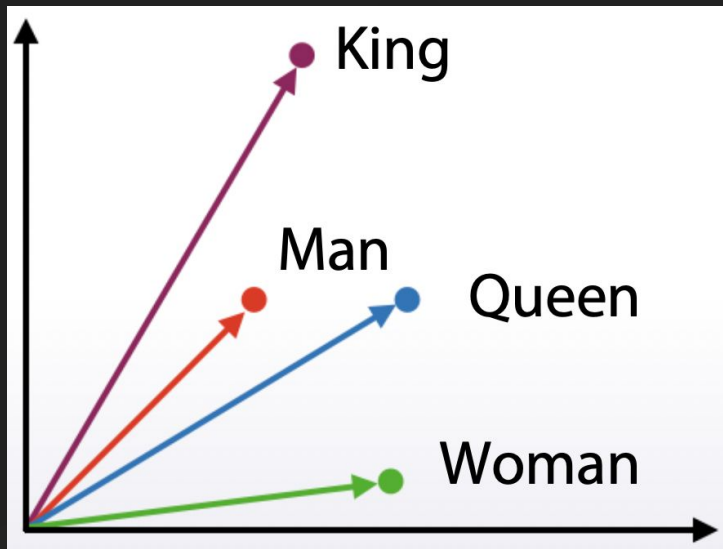


## Part 2:

# Vector representations

# Vector representations

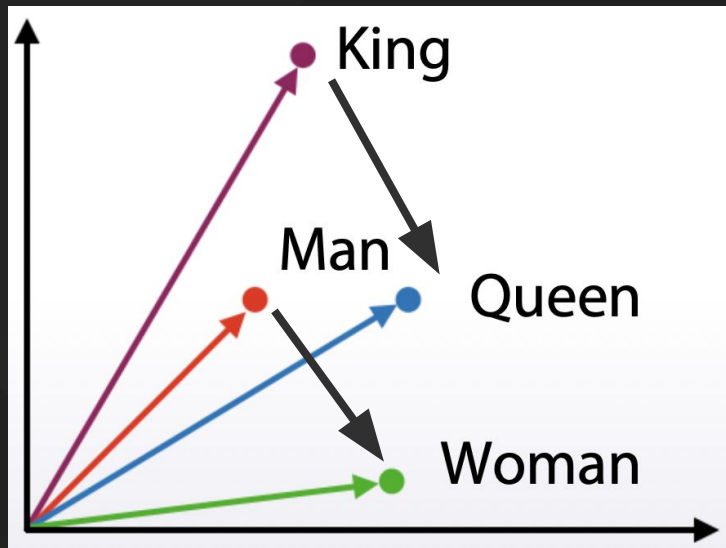
Words (and also sentences) can be represented with **vectors** also known as **embeddings** or **word2vec**.



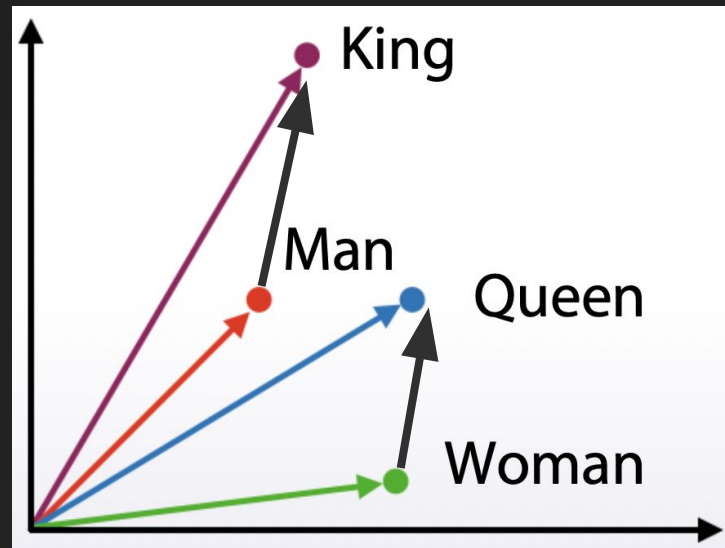
# Vector representations

Vectors have semantic meaning encoded.  $\text{King} + \text{woman} - \text{man} \approx \text{Queen}$

*Male-Female dimension*



*Man-King dimension*





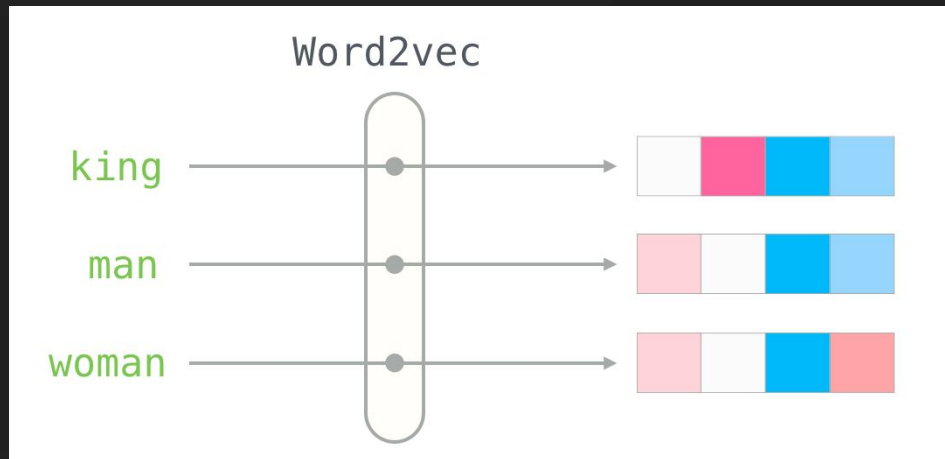
# Pretrained models

## Words

- Word2vec
- Glove
- FastText
- Etc.

## Sentences

- Doc2vec
- Manually: Taking the mean() or sum() of all word vectors.





# Word vectors VS BoW/TF-IDF

## BoW/TF-IDF

- Very large vectors (size of vocabulary dictionary).
  - Super very large vectors if we do NGrams.
- Meaning of each value in vector is known

*Very different but  
your solution can  
have both methods!*

## Word vectors

- Relatively small vectors (sizes typically from 64 to 1024).
- Values in vector can be interpreted only in some cases.
- The words with similar meaning often have similar vectors.



# / Q&A

---

What are your doubts?

