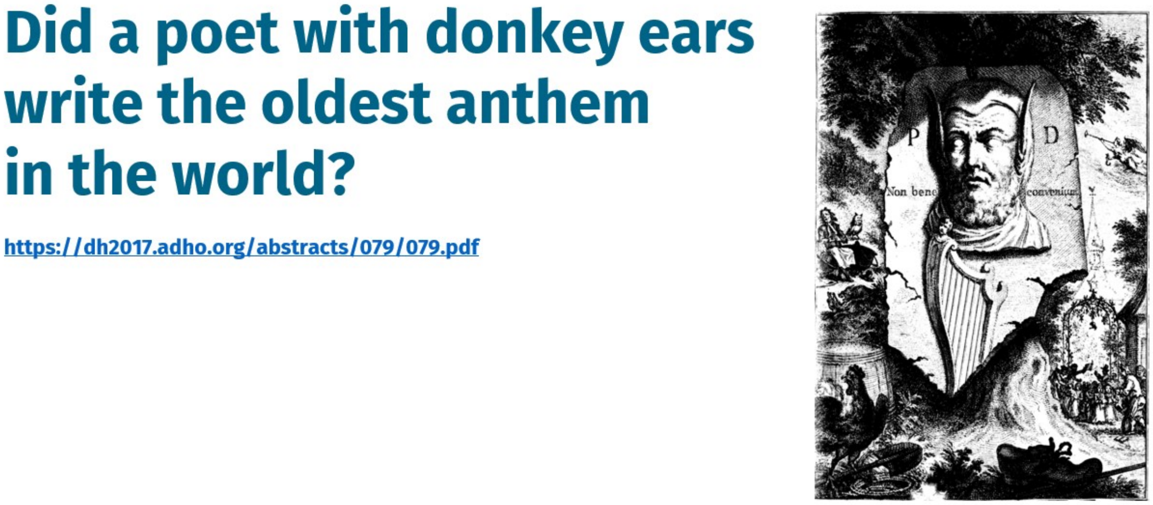
Introduction

Applied Text Mining

Ayoub Bagheri



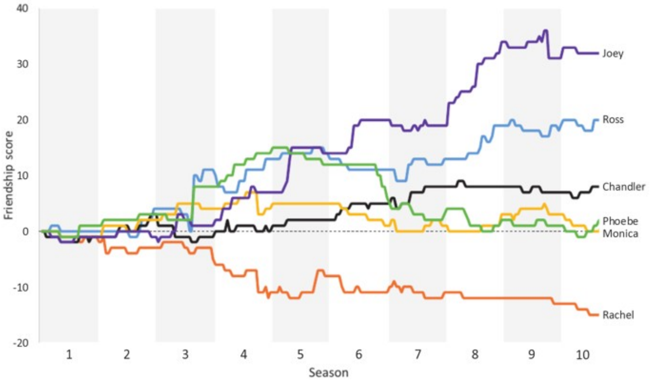
Did a poet with donkey ears write the oldest anthem in the world?

https://dh2017.adho.org/abstracts/079/079.pdf

P
D
Non bene
convenium

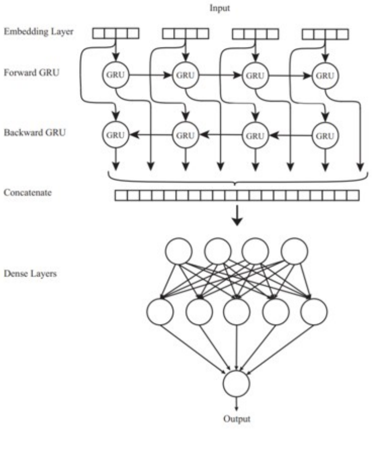
Who was the best Friend?

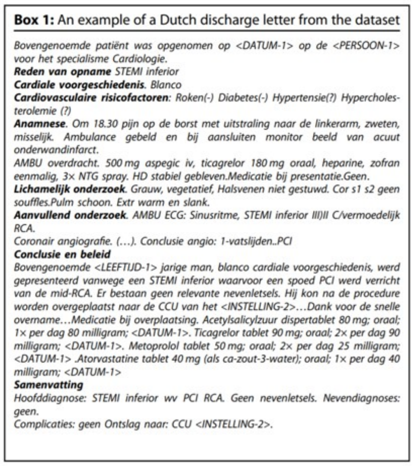
https://rss.onlinelibrary.wiley.com/doi/epdf/10.1111/1740-9713.01574



Automatic detection of ICD10 codes in cardiology discharge letters

https://www.nature.com/articles/s41746-021-00404-9





Box 1: An example of a Dutch discharge letter from the dataset

Bovengenoemde patiënt was opgenomen op <DATUM-1> op de <PERSOON-1> voor het specialisme Cardiologie.
***Reden van opname** STEMI inferior*
***Cardiale voorgeschiedenis**. Blanco*
***Cardiovasculaire risicofactoren**: Roken(-) Diabetes(-) Hypertensie(?) Hypercholesterolemie (?)*
***Anamnese**. Om 18.30 pijn op de borst met uitstraling naar de linkerarm, zweten, misselijk. Ambulance gebeld en bij aansluiten monitor beeld van acuut onderwandinfarct.*
AMBU overdracht. 500 mg aspegic iv, ticagrelor 180 mg oraal, heparine, zofran eenmalig, 3× NTG spray. HD stabiel gebleven.Medicatie bij presentatie.Geen.
***Lichamelijk onderzoek**. Grauw, vegetatief, Halsvenen niet gestuwd. Cor s1 s2 geen souffles.Pulm schoon. Extr warm en slank.*
***Aanvullend onderzoek**. AMBU ECG: Sinusritme, STEMI inferior III)II C/vermoedelijk RCA.*
Coronair angiografie. (…). Conclusie angio: 1-vatslijden..PCI
Conclusie en beleid
Bovengenoemde <LEEFTIJD-1> jarige man, blanco cardiale voorgeschiedenis, werd gepresenteerd vanwege een STEMI inferior waarvoor een spoed PCI werd verricht van de mid-RCA. Er bestaan geen relevante nevenletsels. Hij kon na de procedure worden overgeplaatst naar de CCU van het <INSTELLING-2>…Dank voor de snelle overname…Medicatie bij overplaatsing. Acetylsalicylzuur dispertablet 80 mg; oraal; 1× per dag 80 milligram; <DATUM-1>. Ticagrelor tablet 90 mg; oraal; 2× per dag 90 milligram; <DATUM-1>. Metoprolol tablet 50 mg; oraal; 2× per dag 25 milligram; <DATUM-1> .Atorvastatine tablet 40 mg (als ca-zout-3-water); oraal; 1× per dag 40 milligram; <DATUM-1>
Samenvatting
Hoofddiagnose: STEMI inferior wv PCI RCA. Geen nevenletsels. Nevendiagnoses: geen.
Complicaties: geen Ontslag naar: CCU <INSTELLING-2>.

Course Logistics

Course materials

You can access the course materials quickly from

https://ayoubbagheri.nl/applied_tm/

Teachers

Anastasia

Janke

Luka

Berit

Dong

Javier

Program

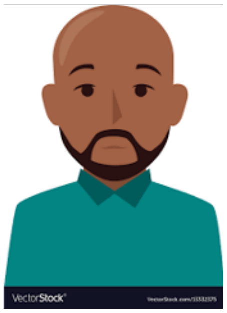
Time	Monday	Tuesday	Wednesday	Thursday	Friday
9:00 - 10:30	**Lecture 1**	**Lecture 3**	**Lecture 5**	**Lecture 7**	**Lecture 9**
	Break	Break	Break	Break	Break
10:45 – 11:45	Practical 1	Practical 3	Practical 5	Practical 7	Practical 9
11:45 – 12:15	Discussion 1	Discussion 3	Discussion 5	Discussion 7	Discussion 9
	Lunch	Lunch	Lunch	Lunch	Lunch
13:45 – 15:15	**Lecture 2**	**Lecture 4**	**Lecture 6**	**Lecture 8**	**Lecture 10**
	Break	Break	Break	Break	Break
15:30 – 16:30	Practical 2	Practical 4	Practical 6	Practical 8	Practical 10
16:30 – 17:00	Discussion 2	Discussion 4	Discussion 6	Discussion 8	Discussion 10

Goal of the course

- Text data are everywhere!
- A lot of world's data are in the format of unstructured text
- This course teaches
  - text mining techniques
  - using Python
  - on a variety of applications
  - in many domains.

What is Text Mining?

Text mining in an example



- This is **Garry**!
- **Garry** works at Bol.com (a webshop in the Netherlands)
- He works in the dep of **Customer relationship management**.
- He uses Excel to read and search customers' reviews, extract aspects they wrote their reviews on, and identify their sentiments.
- Curious about his job? See two examples!

This is a nice book for both young and old. It gives beautiful life lessons in a fun way. Definitely worth the money!

+ Educational

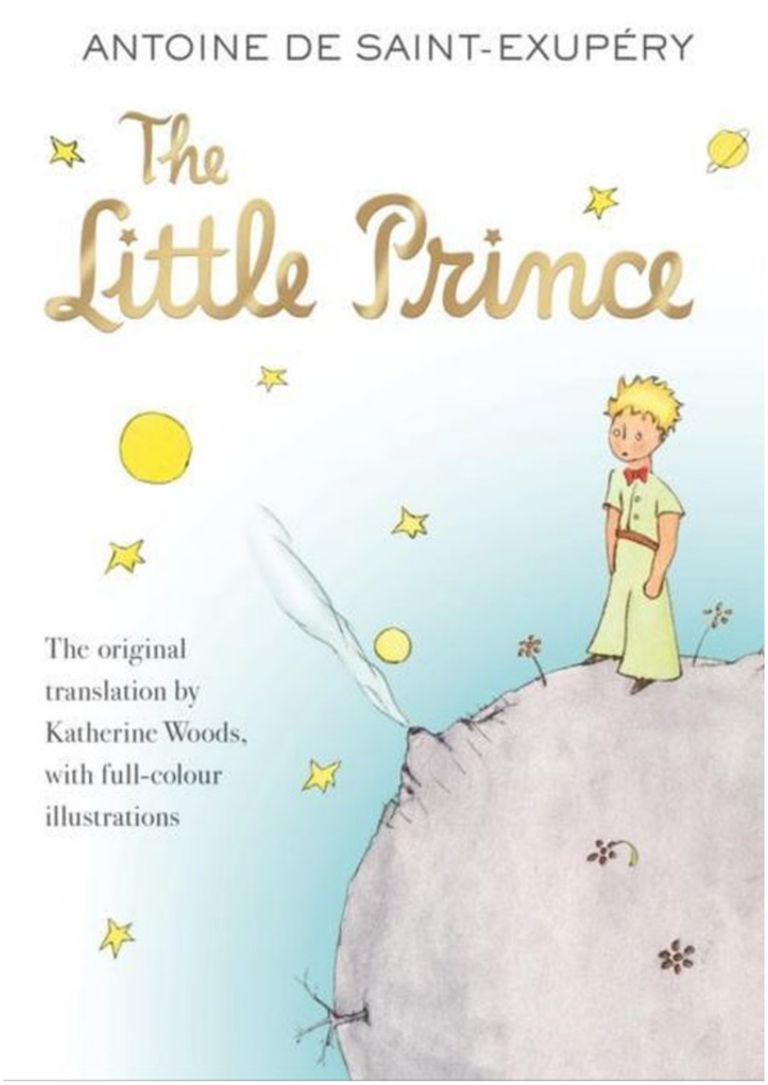
+ Funny

+ Price

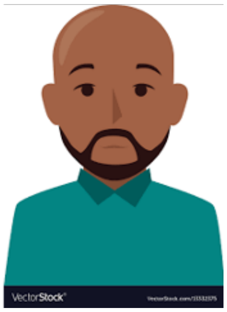
Nice story for older children.

+ Funny

- Readability

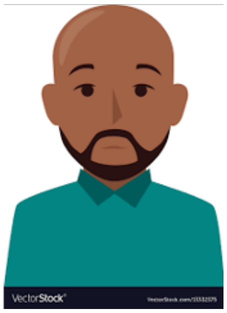

ANTOINE DE SAINT-EXUPÉRY
The Little Prince
The original translation by Katherine Woods, with full-colour illustrations

Example



- Garry likes his job a lot, but sometimes it is frustrating!
- This is mainly because their company is expanding quickly!
- Garry decides to hire **Larry** as his assistant.

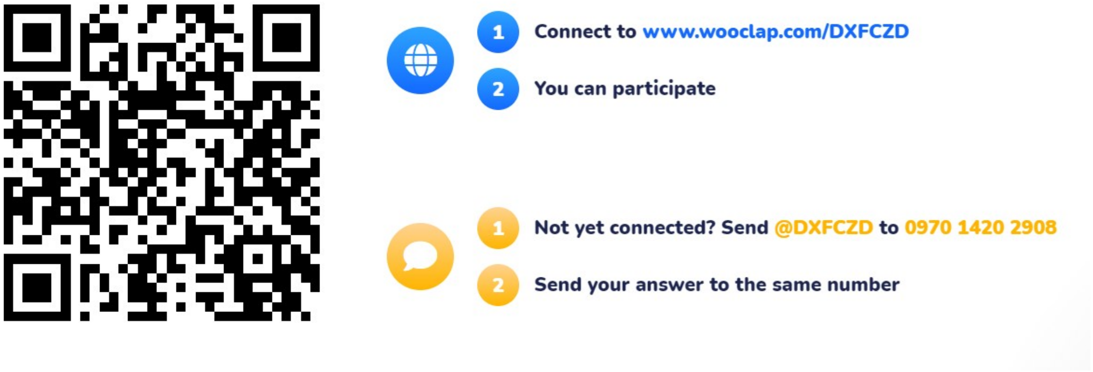
Example



- Still, a lot to do for two people!
- Garry has some budget left to hire another assistant for couple of years!
- He decides to hire **Harry** too!
- Still, manual labeling using Excel is labor-intensive!

Challenges?

- What are the challenges they encounter in working with text?



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2. You can participate

1. Not yet connected? Send @DXFCZD to 0970 1420 2908
2. Send your answer to the same number

Language is hard!

- Different things can mean more or less the same (“data science” vs. “statistics”)
- Context dependency (“You have very nice shoes”);
- Same words with different meanings (“to sanction”, “bank”);
- Lexical ambiguity (“we saw her duck”)
- Irony, sarcasm (“That’s just what I needed today!”, “Great!”, “Well, what a surprise.”)
- Figurative language (“He has a heart of stone”)
- Negation (“not good” vs. “good”), spelling variations, jargon, abbreviations
- All the above are different over languages, 99% of work is on English!

Text Mining to the Rescue!

Text mining

- “the discovery by computer of new, previously unknown information, by automatically extracting information from different written resources” Hearst (1999)

- Text mining is about looking for patterns in text, in a similar way that data mining can be loosely described as looking for patterns in data.

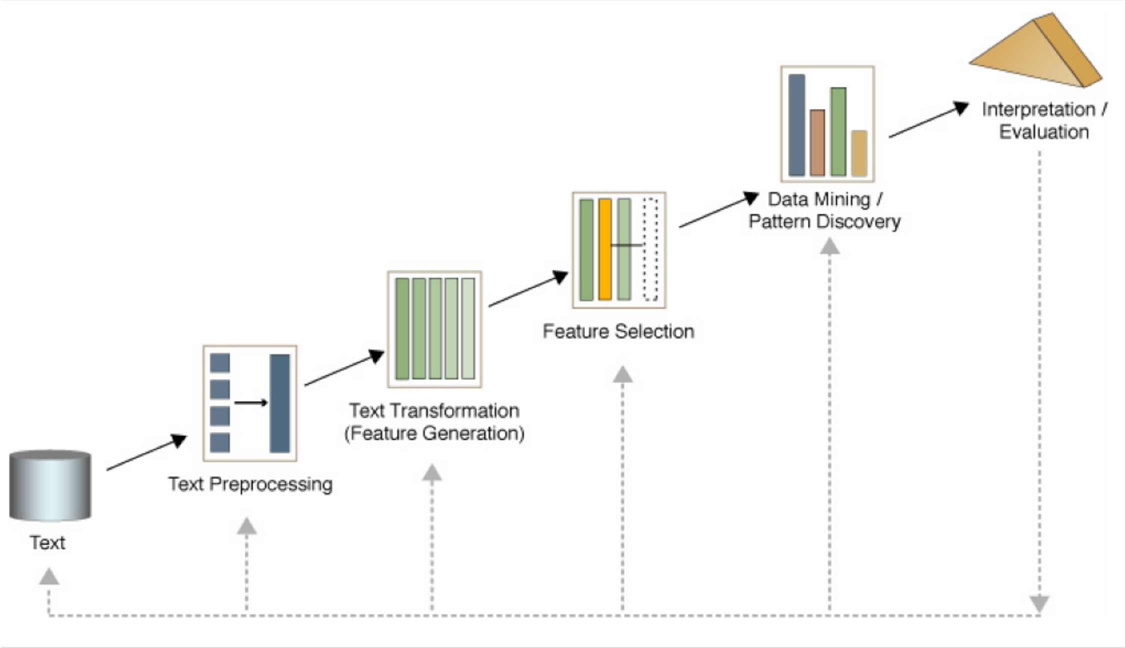
- Text mining describes a set of linguistic, statistical, and machine learning techniques that model and structure the information content of textual sources. (Wikipedia)

Language is hard!

- We won’t solve linguistics …
- In spite of the problems, text mining can be quite effective!

Process & Tasks

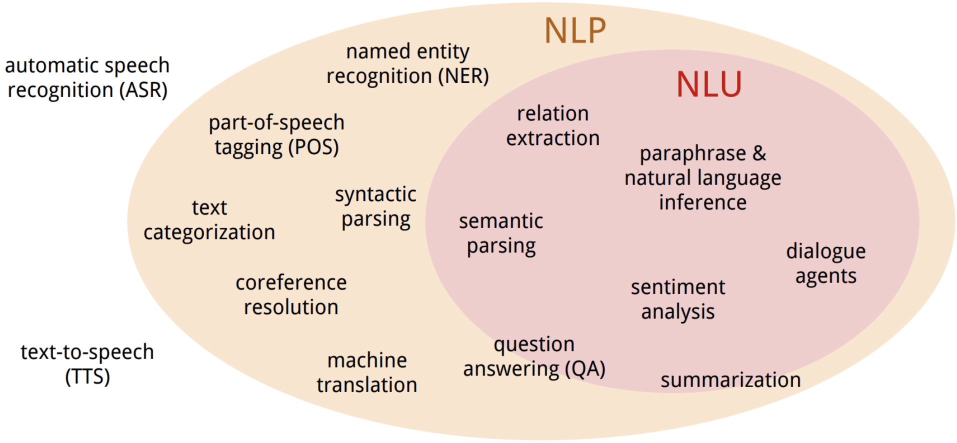
Text mining process


Text
Text Preprocessing
Text Transformation (Feature Generation)
Feature Selection
Data Mining / Pattern Discovery
Interpretation / Evaluation

Text mining tasks

- Text classification
- Text clustering
- Sentiment analysis
- Feature selection
- Topic modelling
- Responsible text mining
- Text summarization

And more in NLP



source: https://nlp.stanford.edu/~wcmac/papers/20140716-UNLU.pdf

Text Preprocessing

Text preprocessing

- is an approach for cleaning and noise removal of text data.
- brings your text into a form that is analyzable for your task.
- transforms text into a more digestible form so that machine learning algorithms can perform better.

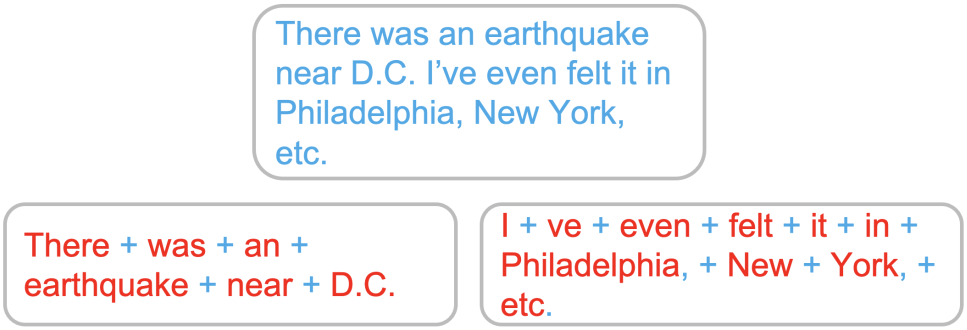
Typical steps

- Tokenization (“text”, “ming”, “is”, “the”, “best” , “!”)
- Stemming (“lungs”→“lung”) or Lemmatization (“were”→“is”)
- Lowercasing (“Disease”→“disease”)
- Stopword removal (“text ming is best!”)
- Punctuation removal (“text ming is the best”)
- Number removal (“I42”→“I”)
- Spell correction (“hart”→“heart”)

Not all of these are appropriate at all times!

Tokenization/Segmentation

- Split text into words and sentences



There was an earthquake near D.C. I've even felt it in Philadelphia, New York, etc.

There + was + an + earthquake + near + D.C.

I + ve + even + felt + it + in + Philadelphia, + New + York, + etc.

N-grams

- N-grams: a contiguous sequence of N tokens from a given piece of text
  - E.g., *'Text mining is to identify useful information.'*
  - Bigrams: *'text_mining'*, *'mining_is'*, *'is_to'*, *'to_identify'*, *'identify_useful'*, *'useful_information'*, *'information_.'*

  - Pros: capture local dependency and order

  - Cons: increase the vocabulary size

Part Of Speech (POS) tagging

- Annotate each word in a sentence with a part-of-speech.

I ate the spaghetti with meatballs.
Pro V Det N Prep N

John saw the saw and decided to take it to the table.
PN V Det N Con V Part V Pro Prep Det N

- Useful for subsequent syntactic parsing and word sense disambiguation.

Vector Space Model

Basic idea

- Text is "unstructured data"
- How do we get to something structured that we can compute with?
- **Text must be represented somehow**
- Represent the text as something that makes sense to a computer

How to represent a document

- Represent by a string?
  - No semantic meaning
- Represent by a list of sentences?
  - Sentence is just like a short document (recursive definition)
- Represent by a vector?
  - A vector is an ordered finite list of numbers.

Vector space model

- A vector space is a collection of vectors
- Represent documents by concept vectors
  - Each concept defines one dimension
  - k concepts define a high-dimensional space
  - Element of vector corresponds to concept weight

Vector space model

- Distance between the vectors in this concept space
  - Relationship among documents
- The process of converting text into numbers is called Vectorization

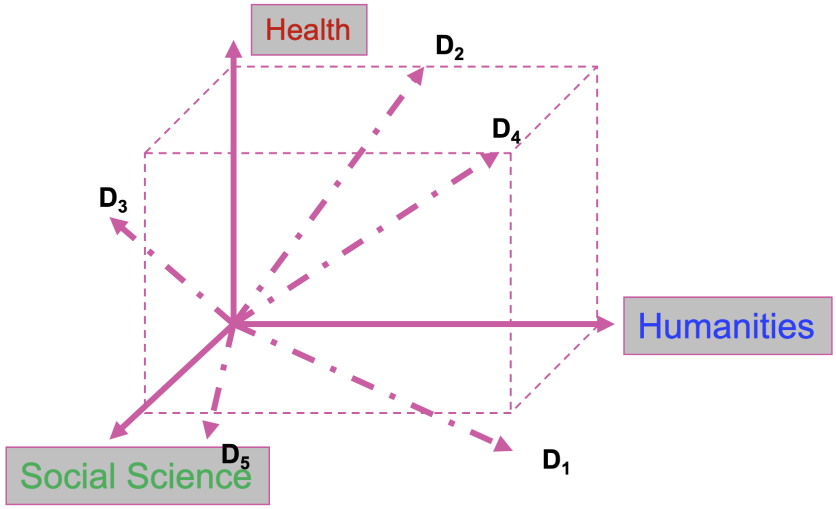
Vector space model

- Terms are generic features that can be extracted from text
- Typically, terms are single words, keywords, n-grams, or phrases
- Documents are represented as vectors of terms
- Each dimension (concept) corresponds to a separate term

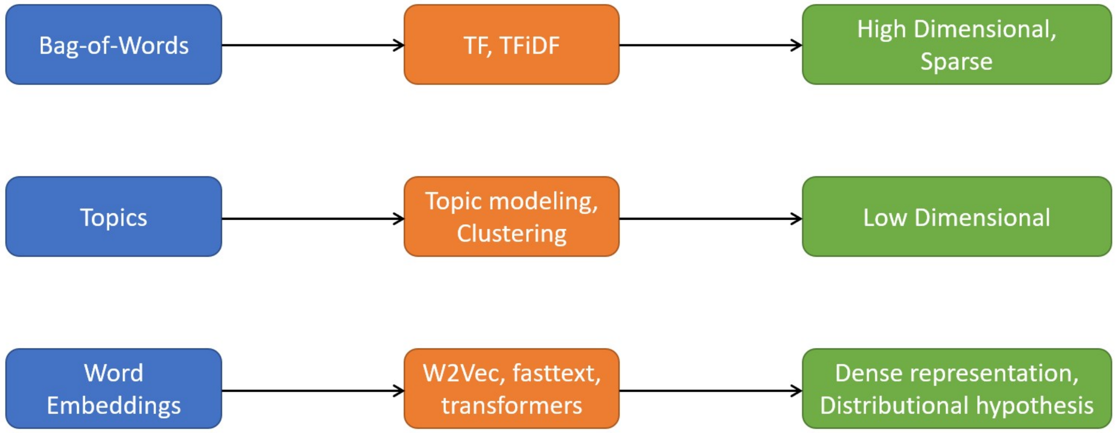
$$d = (w_1, ..., w_n)$$

An illustration of VS model

- All documents are projected into this concept space



VSM: How do we represent vectors?



Bag-of-Words → TF, TFiDF → High Dimensional, Sparse

Topics → Topic modeling, Clustering → Low Dimensional

Word Embeddings → W2Vec, fasttext, transformers → Dense representation, Distributional hypothesis

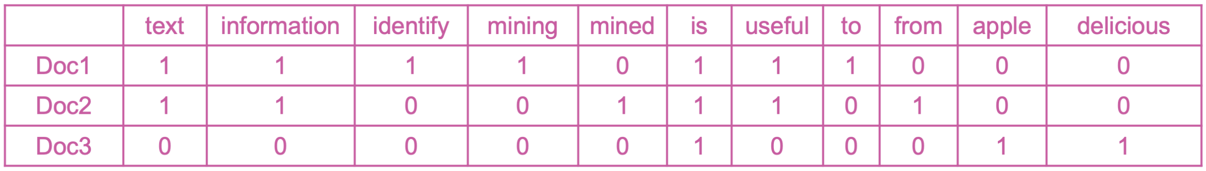
Bag of Words (BOW)

- *Terms* are words (more generally we can use n-grams)
- *Weights* are number of occurrences of the terms in the document
  - Binary
  - Term Frequency (TF)
  - Term Frequency inverse Document Frequency (TFiDF)

Binary

- Doc1: Text mining is to identify useful information.

- Doc2: Useful information is mined from text.
- Doc3: Apple is delicious.

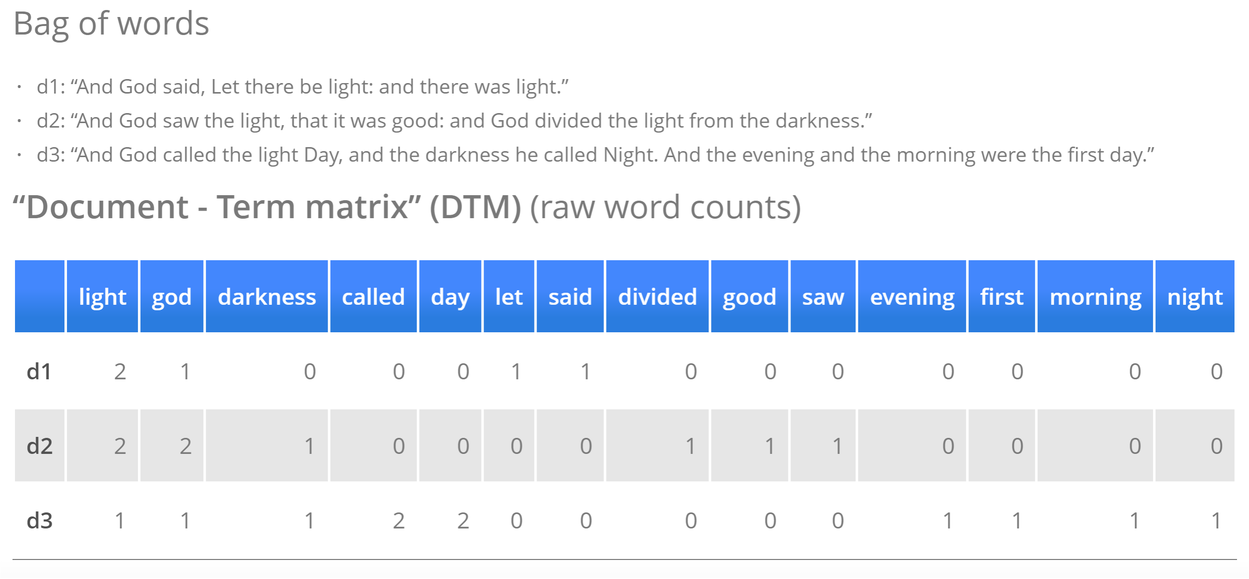


	text	information	identify	mining	mined	is	useful	to	from	apple	delicious
Doc1	1	1	1	1	0	1	1	1	0	0	0
Doc2	1	1	0	0	1	1	1	0	1	0	0
Doc3	0	0	0	0	0	1	0	0	0	1	1

Term Frequency

- Idea: a term is more important if it occurs more frequently in a document
- TF formulas
  - Let $t(c, d)$ be the frequency count of term t in doc d
  - Raw TF: $tf(t, d) = c(t, d)$

TF: Document - Term Matrix (DTM)



Bag of words

- d1: “And God said, Let there be light: and there was light.”
- d2: “And God saw the light, that it was good: and God divided the light from the darkness.”
- d3: “And God called the light Day, and the darkness he called Night. And the evening and the morning were the first day.”

“Document - Term matrix” (DTM) (raw word counts)

	light	god	darkness	called	day	let	said	divided	good	saw	evening	first	morning	night
d1	2	1	0	0	0	1	1	0	0	0	0	0	0	0
d2	2	2	1	0	0	0	0	1	1	1	0	0	0	0
d3	1	1	1	2	2	0	0	0	0	0	1	1	1	1

TFiDF

- Idea: a term is more discriminative if it occurs a lot but only in fewer documents

Let $n_{d,t}$ denote the number of times the t-th term appears in the d-th document.

$$TF_{d,t} = \frac{n_{d,t}}{\sum_i n_{d,i}}$$

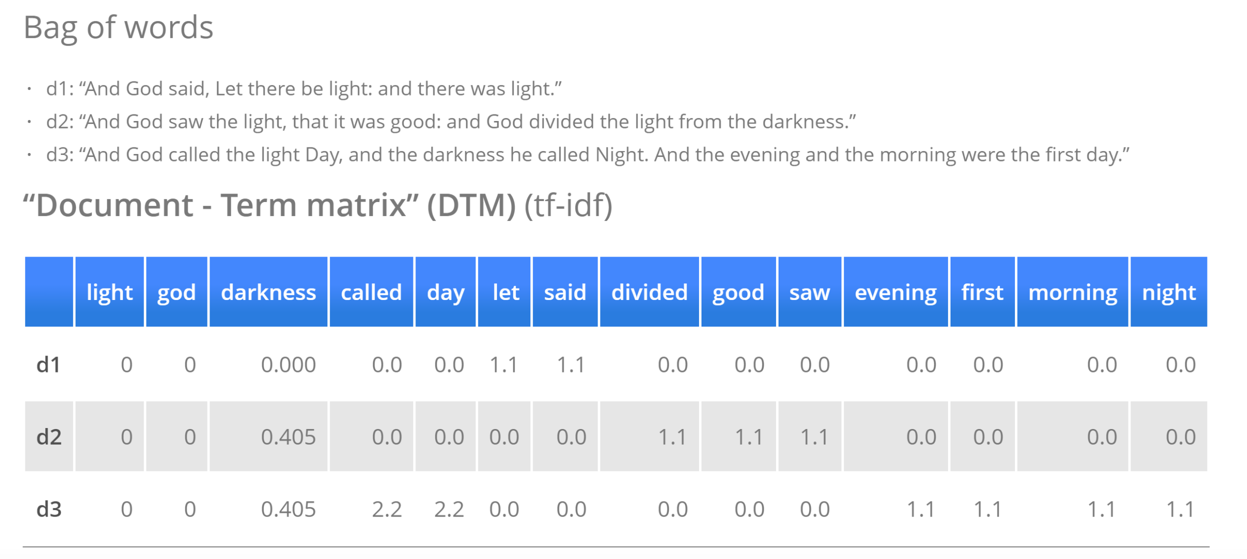
Let N denote the number of documents annd N_t denote the number of documents containing the t-th term.

$$IDF_t = log(\frac{N}{N_t})$$

TFiDF weight:

$$w_{d,t} = TF_{d,t} \cdot IDF_t$$

TFiDF: Document - Term matrix (DTM)



Bag of words

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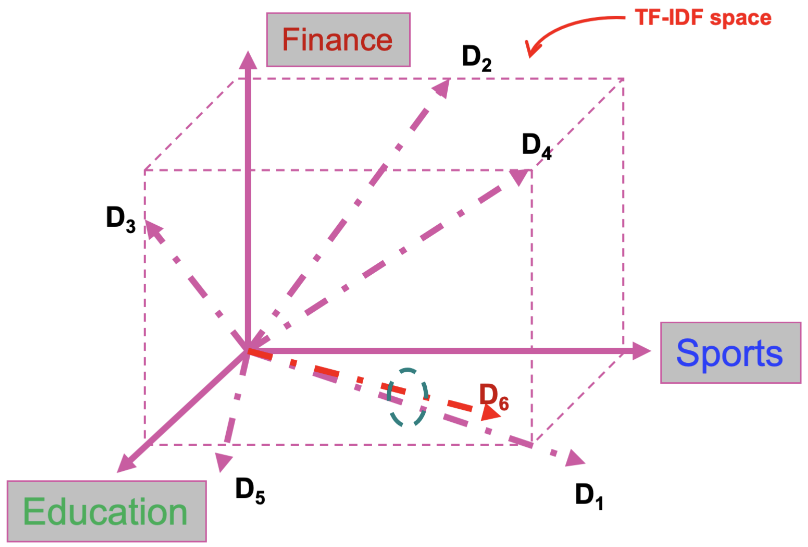
“Document - Term matrix” (DTM) (tf-idf)

	light	god	darkness	called	day	let	said	divided	good	saw	evening	first	morning	night
d1	0	0	0.000	0.0	0.0	1.1	1.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
d2	0	0	0.405	0.0	0.0	0.0	0.0	1.1	1.1	1.1	0.0	0.0	0.0	0.0
d3	0	0	0.405	2.2	2.2	0.0	0.0	0.0	0.0	0.0	1.1	1.1	1.1	1.1

How to define a good similarity metric?



How to define a good similarity metric?

- Euclidean distance
  $dist(d_i, d_j) = \sqrt{\sum_{t \in V} [tf(t, d_i)idf(t) - tf(t, d_j)idf(t)]^2}$
  - Longer documents will be penalized by the extra words
  - We care more about how these two vectors are overlapped
- Cosine similarity
  - Angle between two vectors:
    $cosine(d_i, d_j) = \frac{V_{d_i}^T V_{d_j}}{|V_{d_i}|_2 \times |V_{d_j}|_2} \leftarrow$ TF-IDF vector
  - Documents are normalized by length

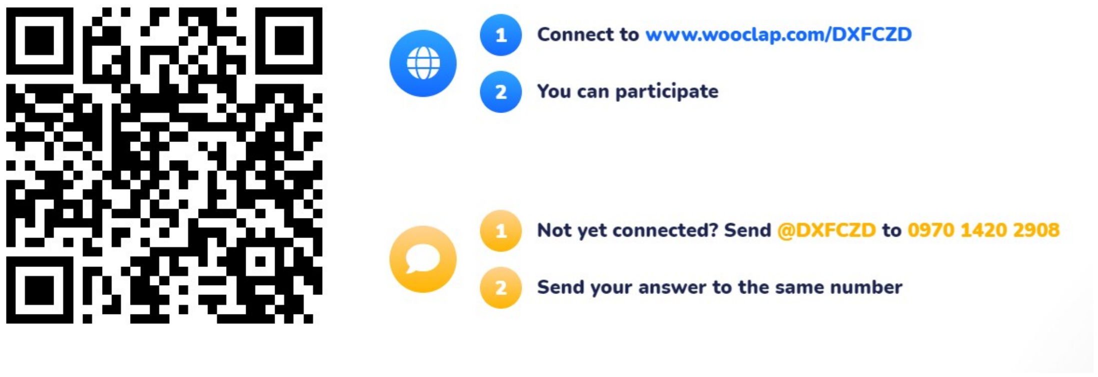
Next

- Text classification

Python Questionnare

How familiar are you with Python?

- What is your experience level with Python?



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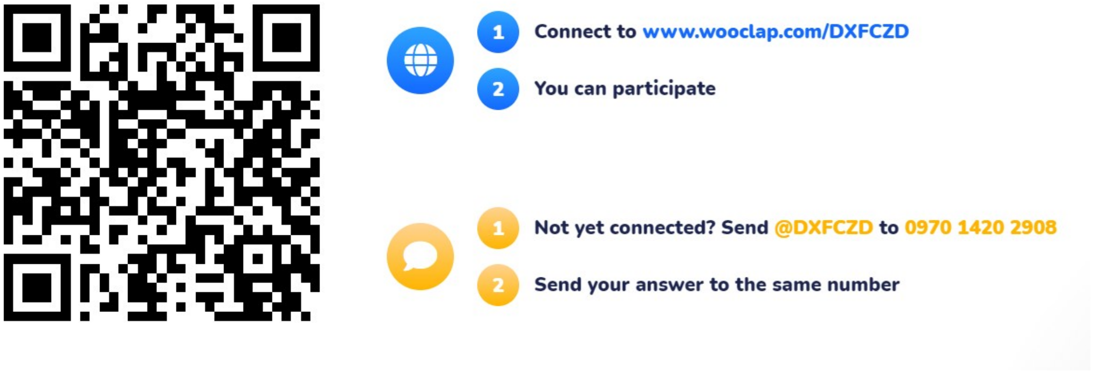
Python IDE?

- Which Python IDE do you mostly use? If you use more than one environment fill in the other text boxes.



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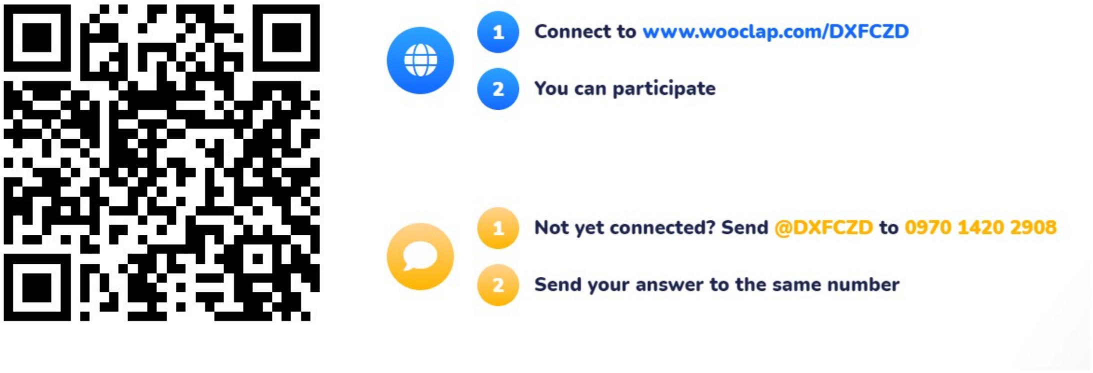
Google Colab?

- How familiar are you with Google Colab? (1: limited to 5: expert)



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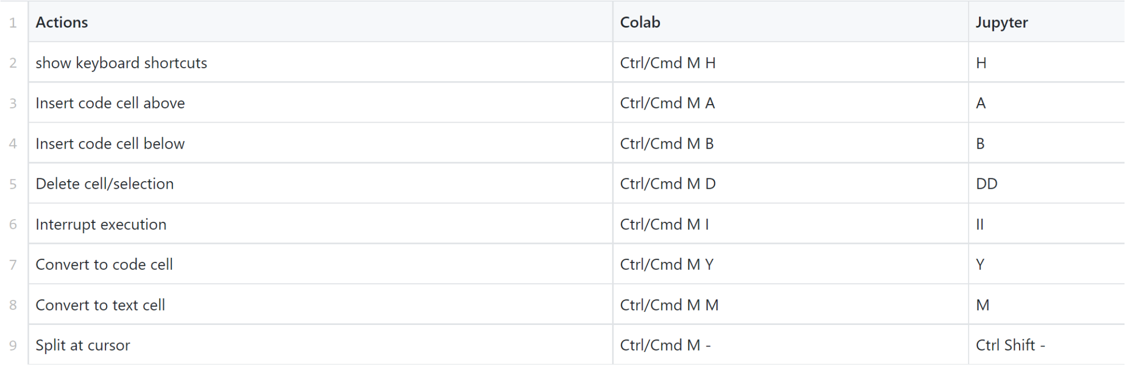
Python

- Latest: Python 3.10
- Follow the tutorial on Python in Google Colab for the Applied Text Mining course: link
- Python For Beginners
  - https://www.python.org/about/gettingstarted/
- The Python Language Reference
  - https://docs.python.org/3/reference/
- Python 3.9.1 documentation
  - https://docs.python.org/3/

Google Colab

- Colaboratory, or “Colab” for short, allows you to write and execute Python in your browser, with
  - Zero configuration required
  - Free access to GPUs
  - Easy sharing
- [Intro](https://colab.research.google.com/notebooks/intro.ipynb)
- Cheat-sheet for Google Colab
- Keyboard shortcuts:



Actions	Colab	Jupyter
show keyboard shortcuts	Ctrl/Cmd M H	H
Insert code cell above	Ctrl/Cmd M A	A
Insert code cell below	Ctrl/Cmd M B	B
Delete cell/selection	Ctrl/Cmd M D	DD
Interrupt execution	Ctrl/Cmd M I	II
Convert to code cell	Ctrl/Cmd M Y	Y
Convert to text cell	Ctrl/Cmd M M	M
Split at cursor	Ctrl/Cmd M -	Ctrl Shift -

Summary

Summary

- Text data are everywhere!
- Language is hard!
- The basic problem of text mining is that text is not a neat data set
- Solution: text pre-processing & VSM

Practical 1