Natural Language Processing

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Contents

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- Popular NLP packages
    - spaCy
    - NLTK
    - Gensim
- Clustering
- Classification

Preprocessing

- Tokenization:
    - Process of breaking a stream of text up into (key)words, symbols, or other meaningful elements called tokens
    - Tokens are small units of (meaningful) text, such that a comparison between a token in the query and a token in a document can take place
    - Usually tokenization based on whitespace, but we will see that that doesn't always work very well
    - Removing punctuation may or may not be useful depending on further transformations, good for TF-IDF but may lose information for 2Vec models
- The quick brown fox jumps over the lazy dog = the, quick, brown, fox, …

Preprocessing

- Stopword removal:
  - Stopwords are words that are too frequent in a language or document collection and have very little semantic meaning
  - Removing them reduces the feature space
- The quick brown fox jumps over the lazy dog = quick, brown, fox, …

Preprocessing

- Stemming:
  - Different word forms may have similar meaning e.g. jumps, jumping
  - Therefore, create a “standard” representation for them by removing the endings
- The quick brown fox jumps over the lazy dog = quick, brown, fox, jump, …

Feature Representations

- TF-IDF:
  - Term Frequency *tf* = number of times term *t* occurs in document *d*
  - Document Frequency *df* = number of documents a term *t* occurs in
  - Inverse Document Frequency *idf* = $\log_2$(total number of documents/*df*)
  - TF-IDF = *tf* * *idf*
- Word2Vec, Sentence2Vec, Doc2Vec, …
  - Each word, sentence, document, etc is represented as an n-dimensional real vector that encapsules the semantic and syntactic properties of the object
  - These vectors can in turn be used for finding similar words, clustering or classification

Word2Vec

- We can get these vectors by training an artificial neural network on a large corpus to predict the semantic and syntactic meaning of words
- TensorFlow has a nice tutorial for that: https://www.tensorflow.org/tutorials/text/word2vec
- But usually we use pre-trained models for that task since there are plenty good ones out there already e.g. fastText by Facebook AI Research
- We will use the pre-trained models by spaCy

Popular NLP Packages

spaCy, NLTK, Gensim

spaCy

- https://spacy.io/
- spaCy is a natural language processing library that comes with many built-in features that solve core linguistic tasks like tokenization, lemmatization, POS-tagging and NER

Exercise 1:
https://github.com/michabirklbauer/hgb_dse_text_mining/blob/master/spaCy.ipynb
https://colab.research.google.com/github/michabirklbauer/hgb_dse_text_mining/blob/master/spaCy.ipynb

NLTK

- https://www.nltk.org/
- NLTK - short for Natural Language Toolkit - is a leading platform for building Python programs to work with human language data
- It provides easy-to-use tokenization, stemming, and much more
- I mostly use NLTK for preprocessing tasks because it is more light-weight and straightforward than spaCy in my opinion

Gensim

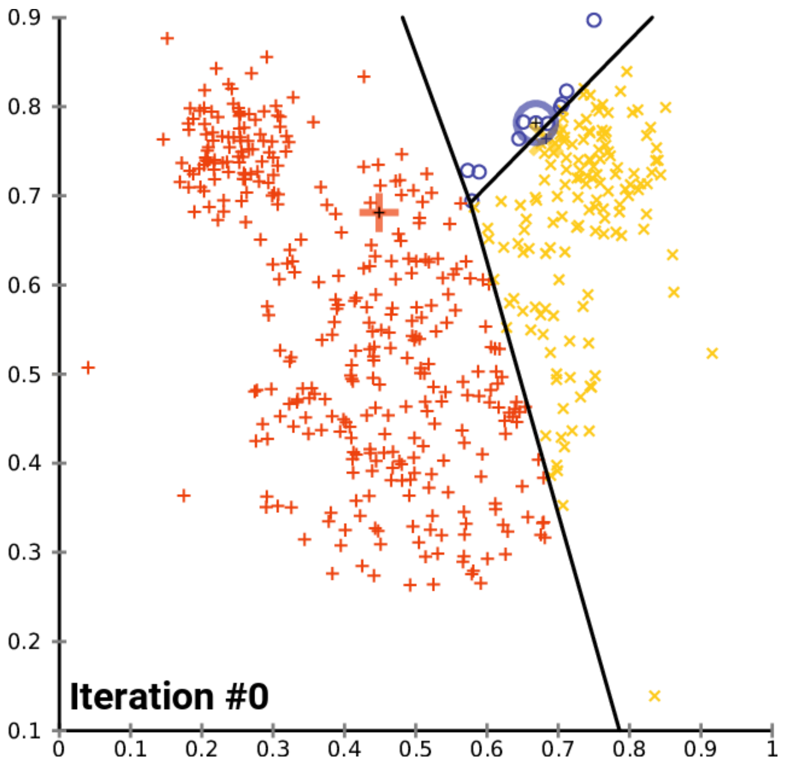
- https://radimrehurek.com/gensim/
- Gensim “Topic Modelling for Humans” is another NLP library in Python
- Gensim offers easy-to-use implementations for TF-IDF and text/document queries

Exercise 2:

https://github.com/michabirklbauer/hgb_dse_text_mining/blob/master/NLTK_Gensim.ipynb

https://colab.research.google.com/github/michabirklbauer/hgb_dse_text_mining/blob/master/NLTK_Gensim.ipynb

Clustering



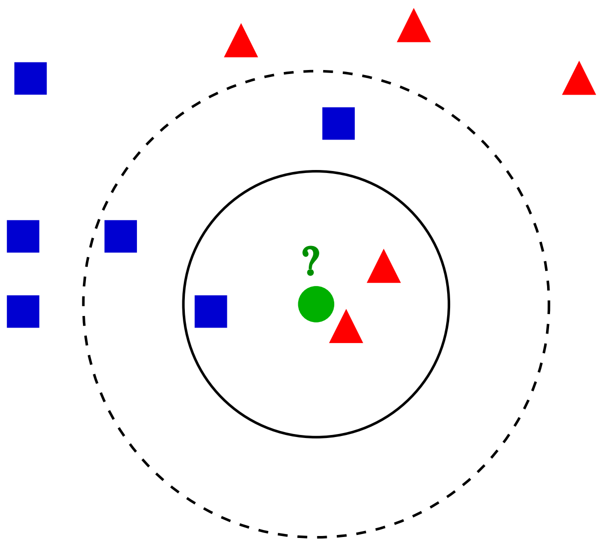
kMeans

kMeans Clustering

1. Initially select *k* random datapoints (documents) as cluster centroids
2. Assign each document in the corpus to the nearest centroid
3. Calculate new cluster centroids
4. Repeat 2. and 3. until convergence or maximum iteration (or other stopping criterion) is met

Exercise 3:
https://github.com/michabirklbauer/hgb_dse_text_mining/blob/master/Features_Clustering.ipynb
https://colab.research.google.com/github/michabirklbauer/hgb_dse_text_mining/blob/master/Features_Clustering.ipynb

Classification



kNN, naiveBayes

kNN

- Predict the class that is most frequent among the *k* closest datapoints (documents)
- (That's it…)

naiveBayes

- The probability of class *C* given feature *F* is according to Bayes Theorem given as:

$$p(C \mid F) = \frac{p(F \mid C)\,p(C)}{p(F)}$$

- We want to predict the Class C_{MAP} that has the highest probability given *F*, we call that the class with the maximum a-posteriori probability

$$C_{MAP} = \underset{C \in H}{\arg\max}\; p(C \mid F)$$

$$C_{MAP} = \underset{C \in H}{\arg\max}\; \frac{p(F \mid C)\,p(C)}{p(F)}$$

naiveBayes

- For a finite set of features $F_1, \ldots, F_n$ we can write this down as:

$$C_{MAP} = \arg\max_{C \in H} \frac{p(C)p(F_1,\ldots,F_n \mid C)}{p(F_1,\ldots,F_n)}$$

- The denominator is not dependent on C and therefore constant and we can eliminate it:

$$C_{MAP} \sim \arg\max_{C \in H} p(C)p(F_1,\ldots\ldots,F_n \mid C)$$

- If we can assume that all features $F_1, \ldots, F_n$ are independent we can decompose the last part into:

$$p(C,F_1,\ldots,F_n) = p(C)p(F_1 \mid C)p(F_2 \mid C)\ldots p(F_n \mid C) = p(C)\prod_i p(F_i \mid C)$$

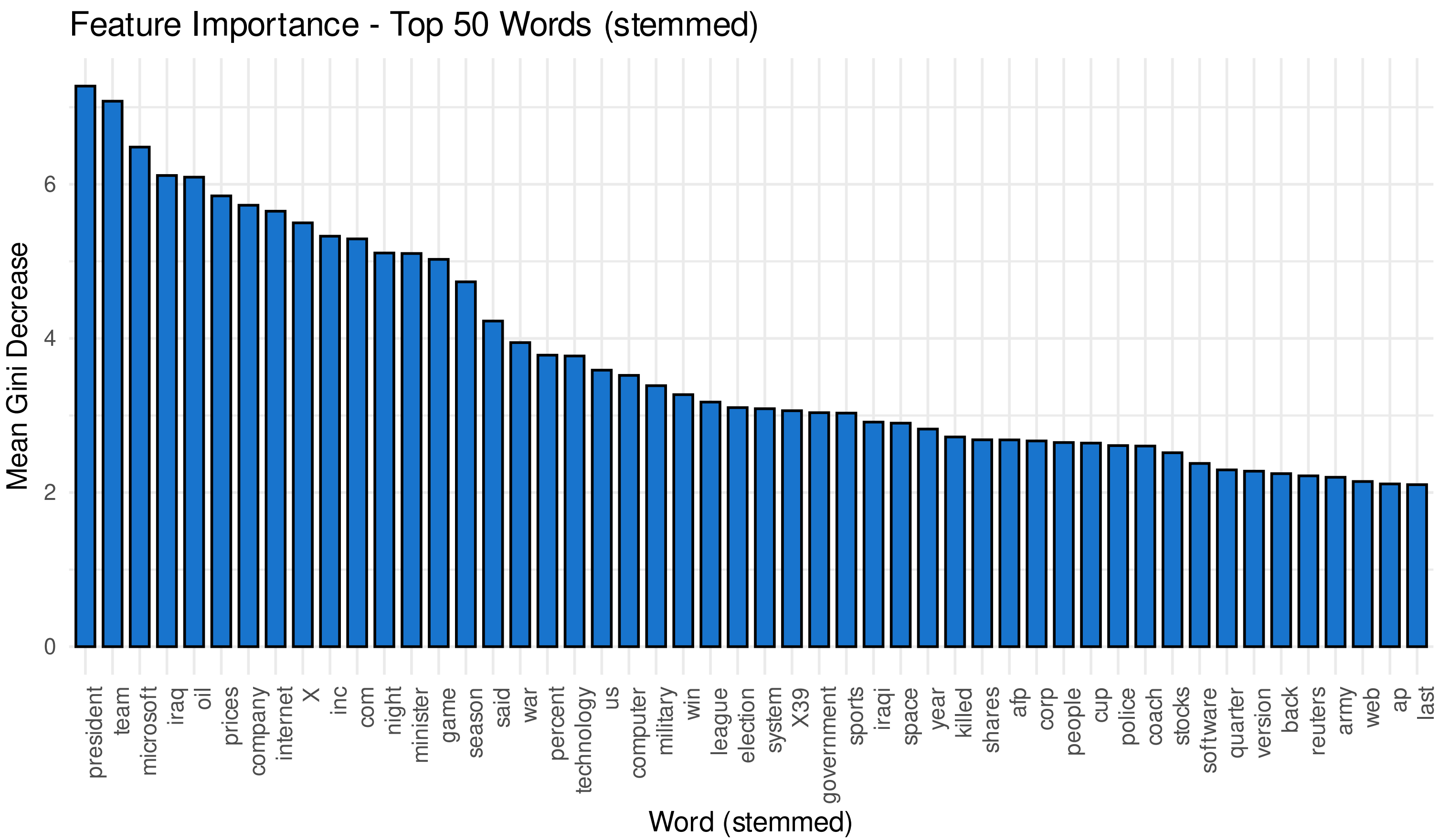
naiveBayes

- Our final classifier is therefore:

$$C_{NB} = \arg\max_{C_j \in H} p(C_j) \prod_i p(F_i \mid C_j)$$

Exercise 4:
https://github.com/michabirklbauer/hgb_dse_text_mining/blob/master/Classification.ipynb
https://colab.research.google.com/github/michabirklbauer/hgb_dse_text_mining/blob/master/Classification.ipynb

Feature Importance



Homework

Exercise 1:

Select an english or german wikipedia article of your choice and analyze it with spaCy analogous to what we did in the lecture.

Tasks:

- You may directly load the article with python or just copy-and-paste a paragraph into your jupyter notebook.
- You should select a random sentence and pre-process it as the following:
    - Tokenize it and print the tokens (1 pt.)
    - Lemmatize it and print the lemmas (1 pt.)
    - Carry out POS-tagging and visualize them as a dependency plot (2 pt.)
    - Carry out NER and visualize it with displacy (2 pt.)

You are expected to hand in a jupyter notebook with at least minimal comments in either .ipynb or .html format!

Hand-in is due 9th of January 2023, 23:59;

2. Block – Outlook:

- Artificial Neural Networks
- Generative Models
- Hands-on: Sentiment Analysis
- Hands-on: Show-and-Tell models

Feedback & Questions:

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