Summary

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Outline

NLP tasks

In most NLP tasks, we are searching for a specific answer to given questions:

- **Sentiment Analysis:** Is this context positive or rather negative?
- **Text Classification:** is the task of assigning predefined categories to the text documents.
- **Language Identification:** is the task of automatically detecting the language present in a document.
- **Word Sense Disambiguation (WSD):** What is the meaning of the word in this context?
- **POS tagging:** What is the POS tag of the current word?

The two camps: Rule-based and Machine Learning

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- **Language Identification:** if the document contains umlaut, then the language present in a document is German
- **WSD:** compare the tokens of all possible definitions of the word with its context tokens and pick the meaning with highest overlap (**Lesk algorithm**)
- **POS tagging:** if the word ends in *ed*, label it as a past tense verb

The two camps: Rule-based and ML

However, NLP tasks can be solved without having to apply a predefined set of rules. We used a **machine learning approach**.

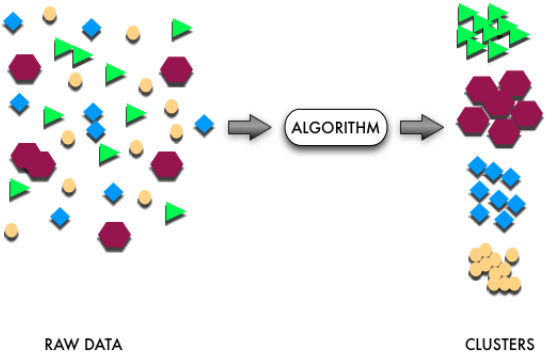
Machine Learning

Machine learning is tightly connected to artificial intelligence:

- to understand, design and improve the algorithms that can be used to build a system that is capable of learning from big amounts of data $\rightarrow$ to develop models
- making autonomous decisions about new/unseen data using these models

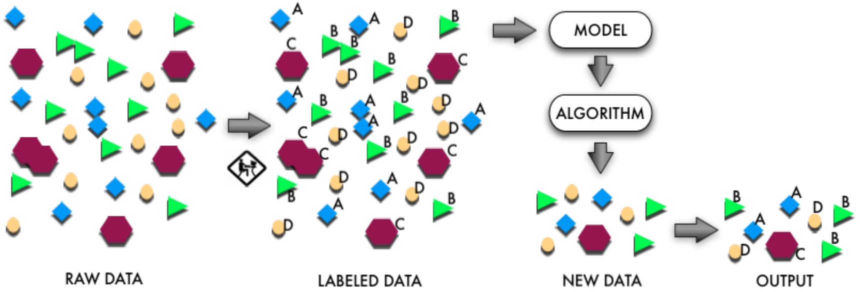
Unsupervised ML: Clustering

no label given, purely based on the given raw data → find common structure in data



Supervised ML: Classification

data labeled with the correct answers to learn from



Classification

Classification:

- choose the correct label (class)
- select the class from a predefined set
- base the decision on specific information collected for each example (so called features)

Classification. Example

Text Classification:

- choose the correct category of the document
- the category is selected from a given set of categories
- base the decision on the features for this document
- features are numerical statistics (TF-IDF) from document

TF-IDF statistics

```
Document Set:
d1: The sky is blue.
d2: The sun is bright, the bright sky

#ignore stopwords and create vocabulary
```

$$\mathrm{E}(t) = \begin{cases} \text{"blue"} \\ \text{"sun"} \\ \text{"bright"} \\ \text{"sky"} \end{cases}$$

TF-IDF statistics

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```

$$\mathrm{E}(t) = \begin{cases} ''\mathit{blue}'' \\ ''\mathit{sun}'' \\ ''\mathit{bright}'' \\ ''\mathit{sky}'' \end{cases}$$

$$\mathrm{tf}(t,d) = \frac{\sum\limits_{x \in d} \mathrm{fr}(x,t)}{max_{t' \in d} tf(t',d)}, \qquad \mathrm{fr}(x,t) = \begin{cases} 1, & \text{if } x = t \\ 0, & \text{otherwise} \end{cases}$$

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Vocabulary $\mathrm{E}(t)$ contains {blue,sun,bright,sky}

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$$\vec{v_{d_n}} = (\mathrm{tf}(t_1,d_n), \mathrm{tf}(t_2,d_n), \mathrm{tf}(t_3,d_n), \ldots, \mathrm{tf}(t_n,d_n))$$
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???

$$\vec{v_{d_2}} = (???)$$

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???

$\vec{v_{d_2}} = (0\ 0.5\ 1\ 0.5)$

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$$\vec{v_{d_1}} = (\mathrm{tf}(t_1,d_1), \mathrm{tf}(t_2,d_1), \mathrm{tf}(t_3,d_1), \ldots, \mathrm{tf}(t_n,d_1))$$

tf

$\vec{v_{d_1}} = (???)$

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d1: The sky is blue.
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```

Vocabulary $\mathrm{E}(t)$ contains {blue,sun,bright,sky}

$$\mathrm{idf}(t) = \log_{10}\frac{|D|}{df_t}, \mathrm{tf\text{-}idf}(t) = \mathrm{tf}(t,d) \times \mathrm{idf}(t)$$

$$\mathrm{idf}(t = blue) = \log_{10}\frac{|D|}{df_t} = \log_{10}\frac{2}{1} \sim 0.3$$

$$\mathrm{idf}(t = sun) = \log_{10}\frac{|D|}{df_t} = \log_{10}\frac{2}{1} \sim 0.3$$

$$\mathrm{idf}(t = bright) = \log_{10}\frac{|D|}{df_t} = \log_{10}\frac{2}{1} \sim 0.3$$

$$\mathrm{idf}(t = sky) = \log_{10}\frac{|D|}{df_t} = \log_{10}\frac{2}{2} = 0$$

tf-idf

$\vec{v_{d_2}} =$ (0*0.3 0.5*0.3 1*0.3 0.5*0) = (0 0.15 0.3 0)

TF-IDF statistics

- **tf** $\rightarrow$ the weight how import the term in the document
- **idf** $\rightarrow$ diminishes the weight of terms that occur very frequently in the document set and increases the weight of terms that occur rarely
- **tf-idf** $\rightarrow$ the product of two statistics

K Nearest Neighbors Classification

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- **Cosine similarity** can be used to measure similarity between objects

$$cos(\vec{q},\vec{d}) = \frac{\vec{q}*\vec{d}}{|\vec{q}|*|\vec{d}|} = \frac{\sum_{i=1}^{V} q_i*d_i}{|\vec{q}|*|\vec{d}|}$$

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- Objects are represented by vectors (feature vectors)
- Feature vectors of documents are TF-IDF statistics and cosine similarity is an indicator how close the documents are in the semantics of their content

Cosine similarity

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```
import math
def dot_product(v1, v2):
    return sum([value1*value2 for value1, value2
                in zip(v1,v2)])

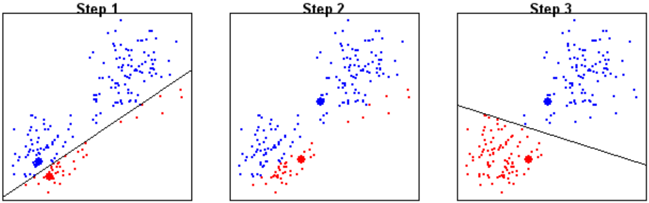
def cosin_sim(v1, v2):
    prod = dot_product(v1, v2)
    len1 = math.sqrt(dot_product(v1, v1))
    len2 = math.sqrt(dot_product(v2, v2))
    return prod / (len1 * len2)

cosin_sim([1,2],[3,4])
>>> 0.9838699100999074
```

K-Means Clustering

Goal: find similarities in the data points and group similar data points together

- randomly initialize cluster centroids
- assign each point to the centroid to which it is closest
- recompute cluster centroids
- go back to 2 until nothing changes (or it takes too long)



K-nearest neighbors vs. K-Means

- K-means is a **clustering** algorithm → partitions points into K clusters: points in each cluster tend to be near each other
- K-means is a **unsupervised** algorithm → points have no external classification
- K-nearest neighbors is a **classification** algorithm → determines the classification of a new point
- K-nearest neighbors is a **supervised** algorithm → classifies a point based on the known classification of other points.

Basic Text Statistics

- `len(text)` – extract the number of **tokens** (the technical name for a sequence of characters. It can be a word but also punctuation symbol or smiles from chat corpus) in text
- `len(set(text))` – extract the number of unique tokens (**types**) in text (**vocabulary of text**). You can also use `nltk.text.Text.vocab()`.
- `sorted(set(text))` – extract the number of item types in text in sorted order
- `len(text) / len(set(text))` – lexical diversity of the text
- `sum([len(w) for w in text])/len(text)` – average word length

Brown Corpus Statsistics

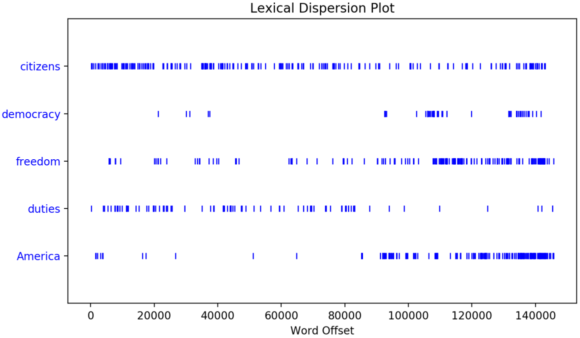
- **hapaxes**: words that only occur once in the text
- hapaxes in the Brown Corpus: `...'Ashley', 'Ashikaga', 'Asher', ...`

Lexical Dispersion Plots

- Location of a word in the text can be displayed using a **dispersion plot**
- Dispersion plots are good for **diachronic language studies** (the exploration of natural language when time is considered as a factor)

Diachronic Language Studies

```
>>> from nltk.book import *
text4.dispersion_plot(["citizens", "democracy", "freedom",
    "duties","America"])
```



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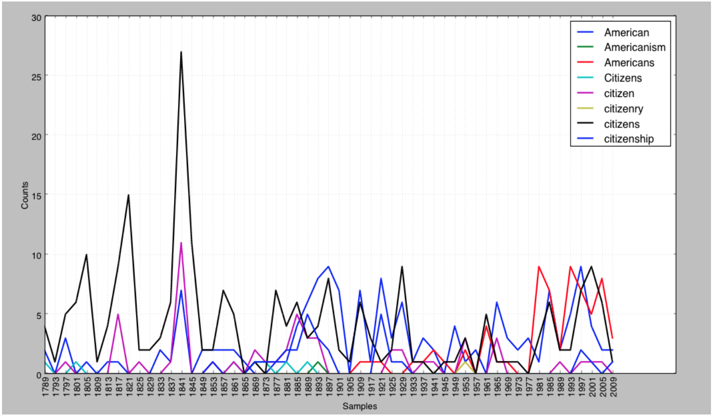


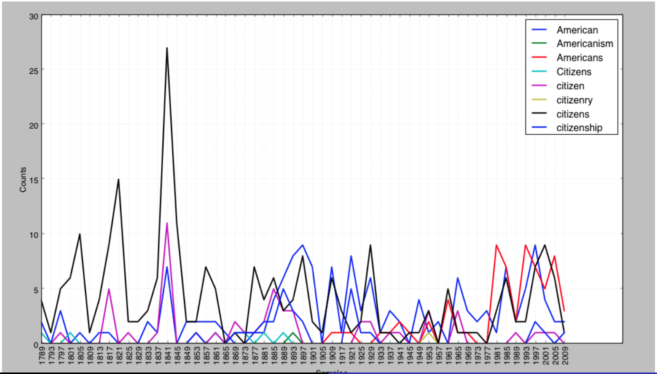
Diachronic Language Studies. Conditional Frequency Distributions (CFD)

```
import nltk
from nltk.corpus import inaugural

cfd = nltk.ConditionalFreqDist((w, fileid[:4])
    for fileid in inaugural.fileids()
    for w in inaugural.words(fileid)
    for target in ["american", "citizen"]
    if w.lower().startswith(target))
print(cfd.plot())
```

Diachronic Language Studies

- 8 conditions: "American","Americanism","Americans",...
- for each condition we create a frequency distribution over the years



Diachronic Language Studies

How many conditions will be generated here?

```
import nltk
from nltk.corpus import inaugural
print(inaugural.fileids())
>>>['1789-Washington.txt', '1793-Washington.txt','1797-
    Adams.txt', ...
cfd = nltk.ConditionalFreqDist((w, fileid[:4])
                for fileid in inaugural.fileids()
                for w in inaugural.words(fileid)
                for target in ["american" , "free", "power"]
                if w == target)
print(cfd.conditions())
>>> ???
```

CFD: Generating Random Text

```
import nltk

text = nltk.corpus.genesis.words("english-kjv.txt")
bigrams = nltk.bigrams(text)
cfd = nltk.ConditionalFreqDist(bigrams)

print(cfd.conditions())
>>> ['In', 'the', 'beginning', 'God', 'created', ... ]
```

We treat each word as a condition, and for each one we create a frequency distribution over the following words

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print(list(cfd["living"]))
>>>['creature', 'thing', 'soul', '.', 'substance', ',']

print(list(cfd["living"].values()))
>>> [7, 4, 1, 1, 2, 1]

print(cfd["living"].max())
>>> creature
```

Most likely token in that context is "creature"

CFD: Language Identification

```
import nltk
from nltk.corpus import udhr

def build_language_models(list_param, dict_param):
    return nltk.ConditionalFreqDist((language, char_bigram)
                for language in list_param
                for word in dict_param[language]
                for char_bigram in nltk.bigrams(word.lower()))

languages = ['English', 'German_Deutsch']
language_base = dict((list_item, udhr.words(list_item + '-Latin1'))
    for list_item in languages)
language_model_cfd = build_language_models(languages,
    language_base)
text1 = "Peter had been to the office before they arrived."
text2 = "Das ist ein schon recht langes deutsches Beispiel."
print(guess_lang(language_model_cfd, text1))
print(guess_lang(language_model_cfd, text2))
```

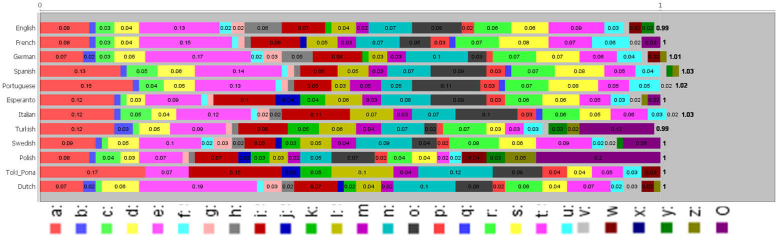
CFD: Language Identification

```
def guess_lang(cfd_param, string_param):
    max_score = 0
    for condition in cfd_param.conditions():
        counter = 0
        for word in string_param.split():
            word = word.lower()
            for char_bigram in nltk.bigrams(word):
                counter = counter + cfd_param[condition].freq(
                    char_bigram)
        if counter > max_score:
            max_language = condition
            max_score = counter
    return max_language
```

Language Guesser Task

- The distribution of characters in a languages of the same language family is usually not very different.
- Thus, it is difficult to differentiate between those languages using a unigram character model $\rightarrow$ use bigram models.

Letters Frequencies in Different Latin Languages



Collocations and Bigrams

- Bigrams are a list of word pairs extracted from a text

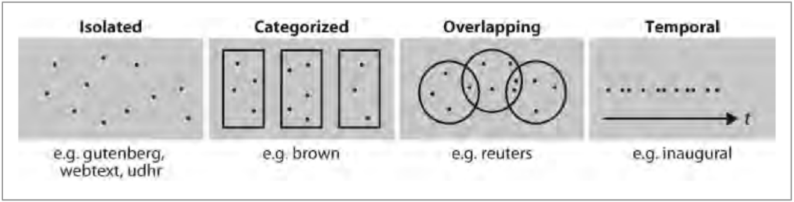
```
>>> from nltk import bigrams
>>>list(bigrams(["more","is","said","than","done"]))
>>>[('more', 'is'), ('is', 'said'), ('said', 'than'),
    ('than', 'done')]
```

- A **collocation** is a sequence of words that occur together unusually often: essentially just frequent bigrams (*red wine*, *United States*)

Corpora Structure

Corpora are designed to achieve specific goal in NLP:

- **Brown Corpus:** resource for studying systematic differences between genres (*stylistics*) → `type of categorized structure`
- **Inaugural Adress Corpus**: used for *diachronic language studies* → `type of temporal structure`



Lexical Resources (Lexicon)

Lexical resource, or lexicon, is a collection of words and/or phrases along with associated information (part-of-speech, sense definitions):

- *vocab = sorted(set(my_text))* – builds the vocabulary of *my_text*

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  - *nltk.corpus.names* → **Anaphora Resolution**

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    - *nltk.corpus.names* → **Anaphora Resolution**
    - *nltk.corpus.words* → to find unusual or misspelt words in a text

WordNet

WordNet is semantically-oriented lexical database of English where words (nouns, verbs, adjectives, etc.) are grouped into sets of synonyms (synsets), each expressing a distinct concept.

WordNet Relations

- **synonymy**

```
>>> wn.synset("car.n.01").lemma_names()
["car", "auto", "automobile", "machine", "
    motorcar"]
```

- **super-subordinate relation** (hyperonymy/hyponymy or is-a relation) → links general synsets like `car` to specific ones like `ambulance` or `bus`

```
>>> wn.synset("car.n.01").hyponyms()
[Synset('ambulance.n.01'), Synset('beach_wagon.n.
    01'), Synset('bus.n.04'), ...
```

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- **super-subordinate relation** (hyperonymy/hyponymy or is-a relation) $\rightarrow$ links general synsets like `car` to specific ones like `ambulance` or `bus`
- **meronymy** $\rightarrow$ the part-whole relation holds between synsets like `tree` and `trunk, crown, limb`
- relationships between verbs $\rightarrow$ `walk` **entails** `step`
- **antonymy** $\rightarrow$ `supply` vs `demand`

Lesk Algorithm

- classical algorithm for Word Sense Disambiguation (WSD) introduced by Michael E. Lesk in 1986
- idea: word's dictionary definitions are likely to be good indicators for the senses they define

```
>>> wn.synset("car.n.01").definition()
"a motor vehicle with four wheels; usually
    propelled by an internal combustion engine"
```

Lesk Algorithm: Example

Sense	Definition
s1: tree	a tree of the olive family
s2: burned stuff	the solid residue left when combustible material is burned

Table: Two senses of **ash**

Score = number of (stemmed) words that are shared by sense definition and context

Scores	Context
s1 s2	The ash is one of the last trees
1 0	to come into leaf

Semantic Similarity

You can use similarity measures defined over the collection of WordNet

- `path_similarity()` assigns a score in the range 0-1 based on the shortest path that connects the concepts in the hypernym hierarchy

```
>>> right.path_similarity(minke)
0.25
>>> right.path_similarity(orca)
0.16666666666666666
>>> right.path_similarity(tortoise)
0.07692307692307693
>>> right.path_similarity(novel)
0.043478260869565216
```

WordNet

WordNet is a large lexical database where nouns, verbs, adjectives and adverbs are grouped into sets of synonyms:

- word sense disambiguation - **Lesk Algorithm** (also implemented in **NLTK**)
- find hypernyms and hyponyms

Preprocessing Steps

- **Tokeniziation** → breaking raw text into its building parts: words, phrases, symbols, or other meaningful elements called tokens
- **Punctuation removal**
- **Lowecasing**
- **Stemming** → removing morphological affixes from words, leaving only the word stem (may not be a real word)
- **Lemmatization** → removing morphological affixes from words, leaving only lemmas (**lemma** is a canonical form of the word)

```
import nltk
print(nltk.LancasterStemmer().stem("colors"))
# prints col
print(nltk.WordNetLemmatizer().lemmatize("colors"))
# prints color
```

- **Stopword removal**

Web Crawling

- **Urllib** $\rightarrow$ a high-level interface for fetching data across the World Wide Web
- **Beautiful Soup** $\rightarrow$ Python library for pulling data out of HTML and XML files

```
import nltk
import urllib
import bs4

def get_text(url):
    html = urllib.request.urlopen(url).read().decode("utf-8")
    return bs4.BeautifulSoup(html).get_text()

raw=get_raw("http://www.bbc.com/news/world-middle-east-42412729")
```

POS Tagging Overview

- **parts-of-speech (POS)** $\rightarrow$ word class, lexical categorys e.g. verb, noun, adjective, etc.
- **part-of-speech tagger** $\rightarrow$ labels words according to their POS
- **tagset** – the collection of tags used for a particular task

POS Tagging

POS Tagging allows

1. find likely words for a given tag
2. extract most ambiguous words across the word classes

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4. Count those sentences, which contain at least one word with lemma "have” and pos-tag "verb”.

ML Application Development

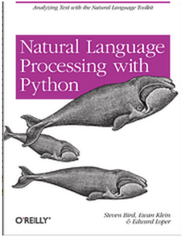
1. Implement a base version (baseline)
2. Train using training data (80% of all data)
3. Evaluate using development data (10% of all data)
4. Analyze errors (e.g. using confusion matrix)
5. Implement improvements – optimize
6. Go back to step 2
7. ...
8. Evaluate optimized version using test data (10% of all data)
9. Store the model

spaCy

spaCy is open-source library for advanced Natural Language Processing (NLP) in Python

- use pre-trained models (e.g. **en_core_web_sm**)
- use the models to preprocess the text: e.g. tokenization, pos-tagging and lemmatization
- customize tokenizer
- use the models for information extraction: named entities, dependency labels (use both for relation extraction)

References

- 

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