Web Data Mining

Lecture 4: Text Mining

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Summer semester 2019/2020 Humla v0.3

Overview

- Introduction
- Text Processing
- Named Entity Recognition
- Relation Extraction

Introduction

• What is Text Mining

- Extracting information and knowledge from text
- Information and knowledge previously unknown to the user

• Unknown information

- Information not known even for the writer
- Rediscover (extract) information encoded in the text

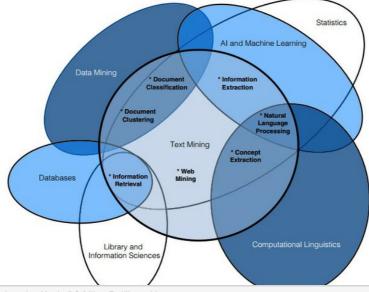
- Text Mining Process
 assembling large corpora of documents
 - performing preprocessing of documents
 - text transformation and feature generation
 - dimensions reduction feature selection
 - pattern discovery (data mining)
 - results interpretation

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Text Mining Overview

- S. M. Weiss, N. Indurkhya, T. Zhang, and F. Damerau, Text mining: predictive methods for analyzing unstructured information. Springer Science and Business Media, 2010.



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Main Challenges

- Text Mining is not easy!
- Main issues:
 - High dimensionality
 - Different terms of same concepts
 - \rightarrow e.g. car, vehicle, auto, automobile, ...
 - Ambiguity same term can identify one or more concepts
 - → e.g. player (sportsman, musician, performer, reproducing device, ...)
 - Lack of structure
 - \rightarrow The data (text) is not structured
 - → Compared to: spreadsheets, database tables, etc.
 - → Rows, columns, headings identify the meaning (semantics) of the content
- But The data is highly redundant!

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Text Mining Applications

- General applications
 - Information retrieval (recommendation systems)
 - Information extraction
- Social and Business
 - Customer profile analysis
 - Social media data analysis
 - Trend analysis & Event tracking
- Data Mining
 - Document classification
 - Document clustering
- Security and Crime
 - Spam filtering
 - Fraud detection

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Overview

- Introduction
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Preprocessing

- Text needs to be preprocessed to be machine understandable
- Converting a raw text file into a well-defined sequence of linguistically-meaningful units
 - Identifying words (tokens)
 - Special symbols dots, commas, whitespaces
 - Identifying sentences
- Needed for further text processing stages
 Part-Of-Speech tagging

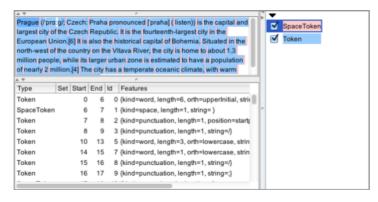
 - Noun phrase chunking
 - Morphological analyzers
 - Named entity recognition

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Tokenization

- Grouping sequences of characters into logical elements called tokens (symbols, words, numbers)
 - tokens are usually separated by whitespace characters of punctuation
- Tokenizer
 - system component performing the process of tokenization



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Tokenization (cont.)

- Trivial for a person familiar with the language structure
- More complicated for a computer program
 - characters are sometimes token delimiters and sometimes not
- Main groups
 - white spaces
 - \rightarrow space, tabs, new lines
 - → acting as delimiters and not as tokens
 - **-** ()<>!?"
 - → delimiters and sometimes tokens
 - **一** .,:-'
 - → delimiters only in specific situations

Tokenization (cont.)

Main situations

```
- .;;

→ not delimiter in numbers

→ e.g. 100,000.5 , 12:45:37, ...

- .

→ part of abbreviations and other constructs

→ e.g. P.S., D.I.Y, Dr., ...

- '

→ part of the token

→ e.g. isn't

→ terminator

→ e.g. Tess'

→ quoting

- .

→ part of a phone number, accounts, ...

→ e.g. 123-456-789
```

• Generally language-dependent

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Tokenization Example

• NLTK code:

```
import nltk
text = """Mr. Speaker, Mr. Vice President, Members of Congress,
the First Lady of the United States, and Citizens of America:
...
In 9 years, the United States will celebrate the 250th annivers
of our founding -- 250 years since the day we declared
our Independence.
...
In Chicago, more than 4,000 people were ...
"""
tokens = nltk.word_tokenize(text)
print(tokens)
```

• Output:

```
['Mr.', 'Speaker', ',', 'Mr.', 'Vice', 'President', ',', 'Members',
'of', 'Congress', ',', 'the', 'First', 'Lady', 'of', 'the', 'United',
'States', ',', 'and', 'Citizens', 'of', 'America', ':', '...', 'In',
'9', 'years', ',', 'the', 'United', 'States', 'will', 'celebrate',
'the', '250th', 'anniversary', 'of', 'our', 'founding', '--',
'250', 'years', 'since', 'the', 'day', 'we', 'declared', 'our', 'Independen
'4,000', 'people', 'were', '...']
```

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Frequency Analysis

- Basic analysis of textual data
- Term frequency
 - compute frequency distributions as ranked lists of terms
- Lexical diversity
 - diversity of an individual's or group's vocabulary

```
import nltk
       from collections import Counter
       text = None
       with open('speech.txt', 'r') as f:
           text = f.read()
      tokens = nltk.word_tokenize(text)
      c = Counter(tokens)
      print(c.most common()[:10])
       print(1.0*len(set(tokens))/len(tokens))
       [(',', 261), ('.', 253), ('the', 215), ('and', 176), ('to', 142), ('of', 142
       0.28324761204996324
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```

Stemming and Lematization

- The goal Reduce the dimensionality!
 - Convert each of the tokens to a standard form.
 - Decreases the number of tokens and increases its frequency.
- Lemmatization
 - Finding lemma (canonical form) for a given word
 - words: are, is, was, were; lemma: be
- Stemming
 - Finding stem for a given word
 - Stem: root form of a word to which suffixes can be attached
 - word: waiting; stem: wait

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Stemming

Part rule-based and part dictionary-based - If token in dictionary return from dictionary - It token ends with s strip s - If token ends with ies replace by y word = "printing" regexp = r'^(.*?) (ing|ly|ed|ious|ies|ive|es|s|ment)?\$' stem, suffix = re.findall(regexp, word)[0] stem # print import nltk from nltk.stem.porter import PorterStemmer text = """Mr. Speaker, Mr. Vice President, Members of Congress, the First Lady of the United States, and Citizens of America: 6 stemmer = PorterStemmer() tokens = nltk.word tokenize(text) 8 stems = {token:stemmer.stem(token) for token in tokens} print(stems) {'the': 'the', 'Citizens': 'Citizen', 'President': 'Presid', 'Congress': 'Congress', 'of': 'of', 'Members': 'Member', 'and': 'and', 'Mr.': 'Mr.', 'First': 'First', ',': ',', 'United': 'Unit', 'Lady': 'Ladi', 'America': 'America', ':': ':', 'Speaker': 'Speaker', 'Vice': 'Vice', 'States': 'State'} Lecture 4: Text Mining - Jaroslav Kuchař & Milan Dojčinovski - 15 -

Lemmatization

```
import nltk
      from nltk.corpus.reader.wordnet import NOUN, VERB
      from nltk.stem import WordNetLemmatizer
      text = """Mr. Speaker, Mr. Vice President, Members of Congress,
      the First Lady of the United States, and Citizens of America:
      In 9 years, the United States will celebrate the 250th anniversary of our fo
   8
      -- 250 years since the day we declared our Independence.
      In Chicago, more than 4,000 people were ...
      lemmatizer = WordNetLemmatizer()
      tokens = nltk.word tokenize(text)
      lemmas = {token:lemmatizer.lemmatize(token, pos=VERB) for token in tokens}
      print(lemmas)
     4
   6
       '...': '...', 'years': 'years', 'Vice': 'Vice', 'States': 'States',
      'more': 'more', 'founding': 'found', 'than': 'than'}
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```

Other Dimensionality Reductions

Stop words

- almost never provide any interesting information
 - \rightarrow articles a and the
 - → pronouns such as it and they

```
from nltk.corpus import stopwords

stops = stopwords.words('english')

text = """In Chicago, more than 4,000 people were ..."""

tokens = nltk.word_tokenize(text)

filtered_tokens = [token for token in tokens if token not in stops]

filtered_tokens

['In', 'Chicago', ',', '4,000', 'people', '...']
```

Frequency information

- most frequent words are often stopwords and can be deleted
- rare words are often typos and can also be dismissed
- tf-idf

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Other Dimensionality Reductions (cont.)

Synonyms vs Antonyms

```
from nltk.corpus import wordnet
   token = "lady"
    synonyms = []
   antonyms = []
   syns = wordnet.synsets(token)
6 for syn in syns:
       print("%s - %s " % (syn.lemmas()[0].name(), syn.definition()))
8
        for 1 in syn.lemmas():
9
            synonyms.append(l.name())
            if l.antonyms():
                 antonyms.append(l.antonyms()[0].name())
12  print(set(synonyms))
13 print(set(antonyms))
   lady - a polite name for any woman
   dame - a woman of refinement
Lady - a woman of the peerage in Britain
    {'peeress', "ma'am", 'madam', 'dame', 'gentlewoman', 'Lady', 'lady',
5 {'Lord', 'nobleman'}
```

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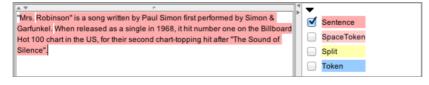
Frequency Analysis 2

```
import nltk
         from nltk.corpus import stopwords
        from string import punctuation
        stops = stopwords.words('english')
        from collections import Counter
        text = None
    8
        with open('speech.txt', 'r') as f:
             text = f.read()
        tokens = nltk.word tokenize(text)
        filtered tokens = [token for token in tokens if token not in stops]
        nopunc tokens = [token for token in filtered tokens if token not in punctuat
        c = Counter(nopunc_tokens)
       print(c.most_common()[:10])
print(1.0*len(set(nopunc_tokens))/len(nopunc_tokens))
       [('--', 67), ('I', 38), ('We', 35), ('America', 30), ('American', 30), ('must', 20), ("'s", 20), ('new', 19), ('us', 18), ('country', 18)] 0.5049261083743842
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```

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Sentence Splitting

- Process of identifying sentences in text
- Not a trivial process
 - Dot can have also other uses then sentence splitting symbol, for example, Mrs. Smith is ...
- Heuristics can be used to improve the sentence splitting
- Maintain a list of patterns containing dot or write
 - Mrs. | Mr. | Dr. | Ph.D. | Ing. | Bc.



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Sentence Splitting (cont.)

```
import nltk
text = """Mr. Speaker, Mr. Vice President, Members of Congress,
the First Lady of the United States, and Citizens of America:
...
In 9 years, the United States will celebrate the 250th anniversary of
-- 250 years since the day we declared our Independence.
...
In Chicago, more than 4,000 people were ...
"""
sentences = nltk.sent_tokenize(text)
print(sentences)

[ 'Mr. Speaker, Mr. Vice President, Members of Congress, \nthe First La
'In 9 years, the United States will celebrate the 250th anniversary o
'...',
In Chicago, more than 4,000 people were ...\n'
] 'In Chicago, more than 4,000 people were ...\n'
]
```

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N-Grams

- Set of co-occurring words within a given window
 - Bigrams for N=2
 - Trigrams for N=3
- Number of N-grams
 - #NG = X-(N-1) where X is a number of tokens in the text.

```
import nltk
text = """
In 9 years, the United States will celebrate the 250th anniversary of
-- 250 years since the day we declared our Independence.
"""

from nltk.util import ngrams

for ng in ngrams(nltk.word_tokenize(text),3):
    print(ng)

('In', '9', 'years')
('9', 'years', ',')
('years', ',', 'the')
(',', 'the', 'United')
('the', 'United', 'States')
...
```

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N-Grams application

Collocations

- Expressions of multiple words which commonly co-occur

```
import nltk
from nltk.collocations import BigramCollocationFinder
from nltk.metrics import BigramAssocMeasures
text = None
with open('speech.txt', 'r') as f:
    text = f.read()
bigram_finder = BigramCollocationFinder.from_words(
    nltk.word_tokenize(text))
bigram_finder.apply_freq_filter(2)
bigrams = bigram_finder.nbest(BigramAssocMeasures.chi_sq, 10)
bigrams

[('Homeland', 'Security'), ('Middle', 'East'), ('United', 'States'),
('middle', 'class'), ('43', 'million'), ('Rare', 'Disease'),
('Republican', 'President'), ('civil', 'rights'),
('illegal', 'immigrant'), ('inner', 'cities')]
```

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N-Grams application (cont.)

• Generating text using N-Grams

```
import nltk
    import random
    text = None
   with open('speech.txt', 'r') as f:
       text = f.read()
   ng = ngrams(nltk.word tokenize(text),2)
   fd = nltk.ConditionalFreqDist(ng)
8
9
   word = "the"
   output = []
   for i in range(15):
       output.append(word)
       word = random.choice(list(fd[word].keys()))
   print(" ".join(output))
14
15
   the courage to make childcare accessible and reaffirmed our uniform.
    the Bible teaches us harm . So I 've saved
    the day we focus on becoming lobbyists for drugs from
```

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Part-of-Speech Tagging

- Linguistic analysis
- Assigning linguistic categories to words in a text *Number of categories is not fixed (from 6 or 7 to tens)*

 - Difficulties:
 - \rightarrow bore could be a noun, a present tense verb, or a past tense verb
 - can also take into consideration the context the words appear

Title	Abbreviation	Example
Noun	NN	computer
Proper Noun	PNP	Africa
Adjective	JJ	nice
Pronoun	PRP	he
Verb	VB	work
Adverb	RB	word "fast" in "He runs fast."
Proposition	IN	in
Conjunction	CC	and

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Part-of-Speech Tagging

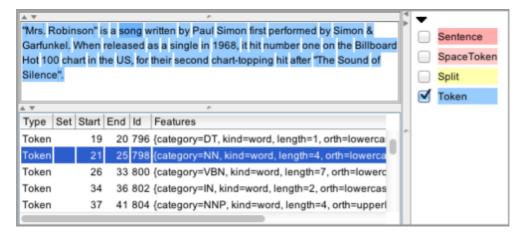
```
1 | nltk.help.upenn_tagset()
    CC: conjunction, coordinating
        & 'n and both but either et for less minus neither nor or plus so
        therefore times v. versus vs. whether yet
    IN: preposition or conjunction, subordinating
        astride among uppon whether out inside pro despite on by throughout below within {f for} towards near behind atop around {f if} like until below
        next into if beside ...
    JJ: adjective or numeral, ordinal
        third ill-mannered pre-war regrettable oiled calamitous first separable
        ectoplasmic battery-powered participatory fourth still-to-be-named
        multilingual multi-disciplinary ...
    NN: noun, common, singular or mass
        common-carrier cabbage knuckle-duster Casino afghan shed thermostat
        investment slide humour falloff slick wind hyena override subhumanity
        machinist ...
    PRP: pronoun, personal
        hers herself him himself hisself it itself me myself one oneself ours
        ourselves ownself self she thee theirs them themselves they thou thy us
        occasionally unabatingly maddeningly adventurously professedly stirringly prominently technologically magisterially predominately
        swiftly fiscally pitilessly \dots
    UH: interjection
        Goodbye Goody Gosh Wow Jeepers Jee-sus Hubba Hey Kee-reist Oops amen
        huh howdy uh dammit whammo shucks heck anyways whodunnit honey golly
        man baby diddle hush sonuvabitch ...
    VB: verb, base form
         sek assambla assass assign assuma atona attantion awoid haka halkaniza
```

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Part-Of-Speech Tagging Example

• Performing POS using the GATE framework



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Simple POS Tagger

- Using large already tagged corpora and perform a mapping/classification task (with default to 'NN') e.g. ('the', 'DT'), ('day', 'NN'), ('celebrate', 'VB'), ...
- Regular expressions

- Rules based approaches
 e.g. VB if the tag of the preceding word is 'TO'
- N-grams
- ...
- → Combinations of all existing approaches

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Part-Of-Speech Tagging Example

```
import nltk
text = """
In 9 years, the United States will celebrate the 250th annivers
-- 250 years since the day we declared our Independence.
"""

print(nltk.pos_tag(nltk.word_tokenize(text)))

[('In', 'In'), ('9', 'CD'), ('years', 'NNS'), (',', ','),
    ('the', 'DT'), ('United', 'NNP'), ('States', 'NNPS'),
    ('will', 'MD'), ('celebrate', 'VB'), ('the', 'DT'),
    ('250th', 'JJ'), ('anniversary', 'NN'), ('of', 'IN'),
    ('our', 'PRP$'), ('founding', 'NN'), ('--', ':'),
    ('250', 'CD'), ('years', 'NNS'), ('since', 'IN'),
    ('the', 'DT'), ('day', 'NN'), ('we', 'PRP'),
    ('declared', 'VBD'), ('our', 'PRP$'),
    ('Independence', 'NN'), ('.', '.')]
```

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Phrase Detection

- Grouping tokens into units
 - Also known as chunking
 - Utilizes grammar categories identified within the POS tagging task
 - Can be a prerequisite for Named Entity Recognition tasks
- Using pattern-based classifications
- Noun Phrase Chunking (NP-chunking)
 - Based on a chunk grammar
 - → set of rules that indicate how sentences should be chunked
 - → e.g. determiner followed by a number/adjective and terminated by a noun

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Phrase Detection (cont.)

```
import nltk
    2
        text = """
        the first lady of the united states.
        text_pos = nltk.pos_tag(nltk.word_tokenize(text))
       grammar = "NP: {<DT>?<JJ>*<NN|NNS>}"
       cp = nltk.RegexpParser(grammar)
       result = cp.parse(text pos)
        print(result)
       result.draw()
           (NP the/DT first/JJ lady/NN)
           of/IN
    4
           (NP the/DT united/JJ states/NNS)
                                           S
                             lady NN
                                        the DT
                                              united JJ
                                                      states NNS
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```

Overview

- Introduction
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Named Entity Recognition

- Entity identification in free texts, and their classification
 - turning verbose text data into a more compact structural form
 - special kind on phrase detection
 → proper noun phrases
- NER sub-tasks
 - recognition
 - → spotting text fragments with entity mentions
 - classification
 - → assigning class to an entity mention
 - disambiguation via linking
 - → assigning URI (e.g., Wikipedia URI) describing the entity
 - → also known as Entity Linking/Disambiguation task
- NER systems are usually trained on a large corpus
 using methods such as Conditional Random Fields
- NER based on previously defined rules (grammars) or gazetteers
 - Gazetteers list of countries, persons, geo locations

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Named Entity Recognition

- Results utilization
 - dimension reduction
 - content enrichment
- Various NER tools/APIs available
 - Entityclassifier.eu
 - AlchemyAPI
 - OpenCalais
 - Wikimeta
 - DBpedia Spotlight
 - NERD
 - and many others

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Entity Recognition using Entity classifier.eu Extraction, Disambiguation and Classification of Entities and Named Entities Input text The Charles Bridge is a famous historic bridge that crosses the Vltava river in Request timeout (in seconds): Prague, Czech Republic. Language of the input text ✓ English ☐ German ☐ Dutch Provenance of types ✓THD ✓DBpedia ✓Yago **Detailed results for entity: Charles Bridge** THD types Knowledge base (THD) ✓ Linked Hypernyms Dataset 1. Bridge for entity disambiguated as Charles Bridge ACC: 0.85 +- 2.5% Local Wikipedia mirror 2. route of transportation for entity disambiguated as Charles Bridge ACC: >= 0.85 +- 2.5% Live Wikipedia 3. infrastructure for entity disambiguated as Charles Bridge ACC: >= 0.85 +- 2.5% Types of entities to extract ✓ Named Entities ☐ Common Entities ☐ Both 1. Place for entity disambiguated as Charles Bridge 2. ArchitecturalStructure for entity disambiguated as Charles Bridge 1. e 102898711 for entity disambiguated as Charles Bridge 2. Bridges completed in 1402 for entity disambiguated as Charles Bridge The Charles Bridge is a famous historic bridge that crosses the Vltava river in Prague, Czech Republic. Results processed in 0.407 seconds.

Entities Recognition Task

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- First and main NER task
- Find entity mentions in text
- Detect start and end offset for each entity mention in a text
- Example:
 - "The Charles Bridge is a famous historic bridge that crosses the Vltava river in Prague, Czech Republic."
- Mentions:
 - substring "Charles Bridge", start: 4, end: 18
 - substring "Vltava", start: 64, end: 70
 - substring "Prague", start: 80, end: 86
 - substring "Czech Republic", start: 88, end: 102

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Entity Recognition using NLTK

```
import nltk
        text = """Mr. Speaker, Mr. Vice President, Members of Congress,
        the First Lady of the United States, and Citizens of America:
    4
        In 9 years, the United States will celebrate the 250th anniversary of our fo
    6
        -- 250 years since the day we declared our Independence.
    8
        In Chicago, more than 4,000 people were ...
       tokens = nltk.word tokenize(text)
       tagged = nltk.pos tag(tokens)
       ne_chunked = nltk.ne_chunk(tagged, binary=True)
        def extractEntities(ne_chunked):
            data = {}
            for entity in ne chunked:
                if isinstance(entity, nltk.tree.Tree):
                     text = " ".join([word for word, tag in entity.leaves()])
                     ent = entity.label()
                     data[text] = ent
                 else:
                     continue
            return data
        extractEntities(ne chunked)
        {'America': 'NE', 'Chicago': 'NE', 'Citizens': 'NE', 'Congress': 'NE', 'Members': 'NE', 'Mr. Speaker': 'NE', 'Mr. Vice': 'NE', 'United States': 'NE
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```

Custom NER Implementation

```
import nltk
text = """Mr. Speaker, Mr. Vice President, Members of Congress,
the First Lady of the United States, and Citizens of America:
In 9 years, the United States will celebrate the 250th anniversary of our founding
 -- 250 years since the day we declared our Independence.
In Chicago, more than 4,000 people were ...
tokens = nltk.word tokenize(text)
tagged = nltk.pos_tag(tokens)
 for tagged_entry in tagged:
   if(tagged_entry[1].startswith("NN") or (entity and tagged_entry[1].startswith("IN"))):
         entity.append(tagged entry)
         if(entity) and entity[-1][1].startswith("IN"):
          entity.pop()
if(entity and " ".join(e[0] for e in entity)[0].isupper()):
    print(" ".join(e[0] for e in entity))
         entity = []
Mr. Speaker
Mr. Vice President
Members of Congress
First Lady
United States
Citizens of America
United States
Independence
Chicago
```

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Entites Classification Task

- Task:
 - for each mention assign a class (type)
- The set of classes can be pre-defined (fixed) or be dynamically created
- Example:
 - "The Charles Bridge is a famous historic bridge that crosses the Vltava river in Prague, Czech Republic."
- Mentions:
 - Mention: "Charles Bridge", class: LOC
 - Mention: "Vltava", class: LOC
 - Mention: "Prague", class: LOC
 - Mention: "Czech Republic", class: GPE

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Classification Set of Classes

- Possible fixed set of classes:
 - LOC (location), GPE (Geo-political entity), ORG (organization), PER (person), MISC (miscellaneous entity, anything else)
- The set of classes can be also defined using an ontology
 - Advantages: each class is identified with an unique URI
 - → Example: DBpedia Ontology
 - → see DBpedia Ontology 3.9
 - → covers 529 classes
 - → used to describe articles in Wikipedia (DBpedia)
 - \rightarrow e.g., http://dbpedia.org/resource/Capital_city

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Entity Classification using NLTK

```
import nltk
       text = """Mr. Speaker, Mr. Vice President, Members of Congress, the First Lady of the United States, and Citizens of America:
       In 9 years, the United States will celebrate the 250th anniversary of our fo
       -- 250 years since the day we declared our Independence.
       In Chicago, more than 4,000 people were ... """
    8
       tokens = nltk.word tokenize(text)
       tagged = nltk.pos tag(tokens)
       ne_chunked = nltk.ne_chunk(tagged, binary=False)
   14
       def extractEntities(ne chunked):
           data = {}
            for entity in ne chunked:
                if isinstance(entity, nltk.tree.Tree):
                    text = " ".join([word for word, tag in entity.leaves()])
   18
                     ent = entity.label()
                     data[text] = ent
                else:
                     continue
            return data
       extractEntities(ne chunked)
        {'America': 'GPE', 'Chicago': 'GPE', 'Citizens': 'ORGANIZATION', 'Congress':
        'First Lady': 'ORGANIZATION', 'Members': 'ORGANIZATION', 'Mr. Speaker': 'PER
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```

Entities Disambiguation Task

- Human language is not exact
 - Same text can refer to totally different entities
- Example: the entity "Maradona" can refer to the football player "Diego Maradona"
 - or, to the football coach and former player "Hugo Maradona"
 - or, to the movie about the football player "Diego Maradona"
- Classification does not help with the ambiguity
 - there can exist two different entities of same type
 - "Diego Maradona" and "Hugo Maradona", type: PER
- Solution: use unique URIs to solve the ambiguity - perform Entity Linking

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Entity Linking Task

- Task:
 - identifying entities using URIs (unique)
- We can use knowledge base URIs to uniquely identify each entity
 - e.g., Wikipedia or ĎBpedia or YAGO knowledge base URIs
- Solution for the "Maradona" ambiguity:
 - the football player "Diego Maradona"
 - → URI: http://dbpedia.org/resource/Diego_Maradona
 - the football coach and former player "Hugo Maradona"
 → URI: http://dbpedia.org/resource/Hugo Maradona
 - the movie about the football player "Diego Maradona"
 → URI:

http://dbpedia.org/resource/Maradona_by_Kusturica

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Coreference Resolution

- In text, different text fragments can refer to same entity
- Main objective
 - mentioned subjects, pronouns and other referring expressions must be connected to the right individuals
 - match proper names and their variants in a document
- Example:
 - Mary Smith and Mrs. Smith
 - → should be matched as same person
 - International Business Machines Ltd. and IBM
 - → should be matched as same company
- State of the art algorithms have accuracy of around 75%

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Overview

- Introduction
- Text Processing
- Named Entity Recognition
- Relation Extraction

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Relation Extraction

- Extracting semantic relation between entities
- Examples
 - PERSON works for ORGANIZATION
 - PERSON attends EVENT
 - PERSON lives in LOCATION
- Using domain-specific patterns
- Naive approach:

 - fixed patterns $\rightarrow X(Subject)$ works for Y(Object)
 - does not scale
- Approaches based on linguistic analysis based on linguistic features (e.g. POS tagging)

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Pattern based Relation Extraction

```
import nltk
        import re
        from nltk.sem import extract rels,rtuple
        with open('speech.txt', 'r') as f:
            text = f.read()
        sentences = nltk.sent_tokenize(text)
        tokenized_sentences = [nltk.word_tokenize(sentence) for sentence in sentences]
        tagged_sentences = [nltk.pos_tag(sentence) for sentence in tokenized_sentences]
       OF = re.compile(r'.*\bof\b.*')
        for i, sent in enumerate(tagged sentences):
            sent = nltk.ne_chunk(sent)
          rels = extract_rels('PERSON', 'GPE', sent, corpus='ace', pattern=OF, window=5)
            for rel in rels:
    print('{0:<5}{1}'.format(i, rtuple(rel)))</pre>
            [PER: 'Jewish/NNP Community/NNP Centers/NNPS']
        'and/CC vandalism/NN of/IN' [GPE: 'Jewish/JJ']

123 [PER: 'Matt/NNP Bevin/NNP'] 'of/IN' [GPE: 'Kentucky/NNP']
        198 [PER: 'Carryn/NNP Owens/NNP'] ',/, the/DT widow/NN of/IN a/DT' [GPE: 'U.S./NNP']
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                                                                                                         - 47 -
```

Pattern based Relation Extraction 2

• https://en.wikipedia.org/wiki/Donald Trump

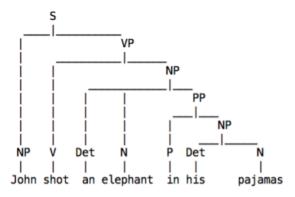
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```
import nltk
import re
from nltk.sem import extract_rels,rtuple
import wikipedia
p = wikipedia.page("Donald Trump")
text = p.content
sentences = nltk.sent_tokenize(text)
tokenized_sentences = [nltk.word_tokenize(sentence) for sentence in sentences]
tagged_sentences = [nltk.pos_tag(sentence) for sentence in tokenized_sentences]
BORN = re.compile(r'.*\bborn\b.*')
for i, sent in enumerate(tagged sentences):
     sent = nltk.ne chunk(sent)
  rels = extract rels('PERSON', 'GPE', sent, corpus='ace', pattern=BORN, window=5)
     for rel in rels:
         print('{0:<5}{1}'.format(i, rtuple(rel)))</pre>
28 [PER: 'Fred/NNP'] 'was/VBD born/VBN in/IN the/DT' [GPE: 'Bronx/NNP']
[PER: 'Donald/NNP'] 'was/VBD born/VBN in/IN the/DT' [GPE: 'Donald/NNP'] '(/( born/VBN in/IN the/DT' [GPE: 'United/NNP States/NNPS'] 'United/NNP States/NNPS'] 'United/NNP'] 'was/VBD born/VBN in/IN the/DT' [GPE: 'U.S./NNP']
```

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Relation Extraction based on Linguistic Analysis

- Identify the subject, predicate and object of the sentence
 - the relation is the predicate
 - the subject is the source entity
 - the object is the target entity
- Perform dependency parsing of the sentence



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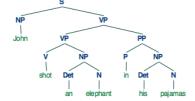
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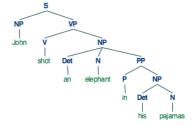
Parsing

Allows to analyze a sentence structure

- Dealing with the ambiguity of the natural language

```
import nltk
grammar = nltk.CFG.fromstring("""
S -> NP VP
PP -> P NP
NP -> Det N | Det N PP | 'John'
VP -> V NP | VP PP
Det -> 'an' | 'his'
N -> 'elephant' | 'pajamas'
V -> 'shot'
P -> 'in'
""")
sentence = ['John', 'shot', 'an', 'elephant', 'in', 'his', 'pajamas']
parser = nltk.ChartParser(grammar)
for tree in parser.parse(sentence):
    print(tree)
tree.draw()
```

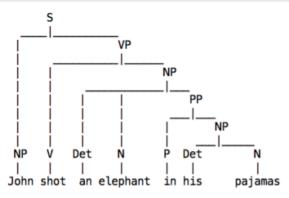




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Identification of a subject in parsed English tree

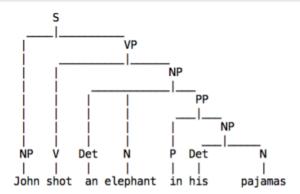


- Identification of a subject for English
 - S indicates the sentence
 - NP is noun phrase
 - VP is verb phrase
 - subject is NP that is the child of S and the sibling of VP

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Relation extraction from parsed trees



- The subject is the NP
 - John
- The relation is the verb (V) in the verb phrase (VP)
 shot
- The object is the noun (N) in the noun phrase (NP) in the verb phrase (VP)
 - elephant

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