Data Mining 2

Topic 07 — Text Mining

Lecture 02 — Introduction to Text Mining

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RESOURCE OUTLINE LABEL

- Natural Language Processing (NLP)
- NLTK

Outline

1. Introduction 2

2. NLP Fundmental Concepts 7

3. Part of Speech (POS) Tagging 20

4. TF-IDF 25

What is Natural Language Processing?

Any computation, manipulation of natural language

Tasks

- Classify text documents
- Search for relevant text documents
- Sentiment analysis
- Topic modeling
- Counting words, counting frequency of words
- Finding sentence boundaries
- Part of speech tagging
- Parsing the sentence structure
- Identifying semantic roles
- Identifying entities in a sentence
- Finding which pronoun refers to which entity

Natural languages evolve

- New words get added .... selfe
- Old words lose popularity .... thou
- Meanings of words change .... netflix and chil
- Language rules themselves may change .... position of verbs in sentences

Text Mining Dimensions

- Estimated to be 2.5 Exabytes (2.5 million TB) a day
  - Grow to 40 Zettabytes (40 billion TB) by 2020 (50-times that of 2010)
- Approximately 80% of all data is estimated to be unstructured, text-rich data
  - >40 million articles (5 million in English) in Wikipedia
  - >4.5 billion Web pages
  - >500 million tweets a day, 200 billion a year
  - >1.5 trillion queries on Google a year

- Non-binary
  - Weakly Structured

    few structural cues to text based on layout or markups — research papers, . . .
  - Semi-structured

    extensive format elements, metadata, field labels research papers, . . .

Why is Text Mining Hard?

- Language is ambiguous
- Context is needed to clarify
- The same words can mean different things (**homographs**)
  - Bear (verb) — to support or carry
  - Bear (noun) — a large animal
- Different words can mean the same thing (**synonyms**) — but synonyms can have differing connotations ...
  - Mary became a kind of big sister to Ben.
  - Mary became a kind of large sister to Ben.
- Language is subtle
- Concept / Word extraction usually results in huge number of "dimensions"
  - Thousands of new attributes/features
  - Each features typically has low information content (sparse)
- Mispellings, abbreviations, spelling variants
  - Renders search engines, SQL queries, Regex, ... ineffective

- For example, see order of adjectives in English

Quantity, Quality, Size, Age, Shape, Colour, Proper adjective, Purpose

Python NLP Libraries

Core

- Natural Language Tool Kit (NLTK) www.nltk.org
  - De facto standard NLP library in Python.
  - Large collection of examples (data and models)
- Fuzzywuzzy github.com/seatgeek/fuzzywuzzy
  - Minimal, easy to use, module for fuzzy string matching, using the Levenshtein Distance.
  - Ideal for pre-cleaning incorrect text — e.g., miss-spelling of months.

Of Interest

- spaCy spacy.io
  - A relatively new project, currently very popular on github.
  - The library provides most of the standard functionality (tokenisation, PoS tagging, parsing, named entity recognition, . . .) and is built to be lightning fast.
- TextBlob textblob.readthedocs.io/en/dev/
  - Based on NLTK and Pattern and provides an more uniform/consistent interface to the NLP algorithms.

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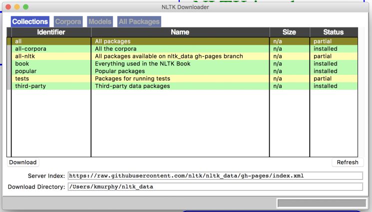
NTK — Import and Download of Datasets

The NLTK library is very mature (started 2001) with a rich API that is well documented.*

```
import nltk
```



The NLTK contains a huge amount of (example) data, corpora and pre-trained models, which are not all installed by default.
To download (uncomment) and run

NLTK.ipynb In[2]:

```
# nltk.download()
```

Access the NLTK book examples …

```
from nltk.book import *
```

```
*** Introductory Examples for the NLTK Book ***
Loading text1, ..., text9 and sent1, ..., sent9
Type the name of the text or sentence to view it.
Type: 'texts()' or 'sents()' to list the materials.
text1: Moby Dick by Herman Melville 1851
text2: Sense and Sensibility by Jane Austen 1811
text3: The Book of Genesis
text4: Inaugural Address Corpus
text5: Chat Corpus
text6: Monty Python and the Holy Grail
text7: Wall Street Journal
text8: Personals Corpus
text9: The Man Who Was Thursday by G . K . Chesterton 1908
```

Natural Language Processing with Python by Bird, Klein, and Loper, www.nltk.org/book.

Accessing the Examples

Text Level

NLTK.ipynb In[4]:

```
texts()
```

```
text1: Moby Dick by Herman Melville 1851
text2: Sense and Sensibility by Jane Austen 1811
text3: The Book of Genesis
text4: Inaugural Address Corpus
text5: Chat Corpus
text6: Monty Python and the Holy Grail
text7: Wall Street Journal
text8: Personals Corpus
text9: The Man Who Was Thursday by G . K . Chesterton 1908
```

NLTK.ipynb In[5]:

```
text1
```

```
<Text: Moby Dick by Herman Melville 1851>
```

Sentence Level

NLTK.ipynb In[6]:

```
sents()
```

```
sent1: Call me Ishmael .
sent2: The family of Dashwood had long been settled in Sussex .
sent3: In the beginning God created the heaven and the earth .
sent4: Fellow - Citizens of the Senate and of the House of Repr
sent5: I have a problem with people PMing me to lol JOIN
sent6: SCENE 1 : [ wind ] [ clop clop clop ] KING ARTHUR : Whoa
sent7: Pierre Vinken , 61 years old , will join the board as a n
sent8: 25 SEXY MALE , seeks attrac older single lady , for discr
sent9: THE suburb of Saffron Park lay on the sunset side of Lon
```

NLTK.ipynb In[7]:

```
sent1
```

```
['Call', 'me', 'Ishmael', '.']
```

Simple NLP Tasks — Counting Vocabulary of Words

We can access/manipulate NLTK texts (type `nltk.text.Text`) and sentences (type `list`) using our usual python constructs …

NLTK.ipynb In[8]:

```
print(text7)
print("Number of words %s" % len(text7))
print("Number of distinct words %s" % len(set(text7)))
```

```
<Text: Wall Street Journal>
Number of words 100676
Number of distinct words 12408
```

NLTK.ipynb In[10]:

```
print(sent1)
print("Number of words %s" % len(sent1))
print("Number of distinct words %s" % len(set(sent1)))
```

Note that punctation is counted!

```
['Call', 'me', 'Ishmael', '.']
Number of words 4
Number of distinct words 4
```

Simple NLP Tasks — Frequency of Words

Given a collection, use NLTK's FreqDist function to construct a dictionary of the frequency of each word ...

```
dist = FreqDist(text7)
print(type(dist))
print("Number of distinct words %s" % len(dist))
```

```
<class 'nltk.probability.FreqDist'>
Number of distinct words 12408
```

Comparable to standard dictionary ... usual methods apply ...

NLTK.ipynb In[12]:

```
vocab1 = dist.keys()
list(vocab1)[:10]
```

```
['Pierre', 'Vinken', ',', '61', 'years', 'old', 'will'
```

Q: How many times did word "four" appear?

NLTK.ipynb In[13]:

```
dist["four"]
```

```
20
```

Q: What are the frequent words?

NLTK.ipynb In[14]:

```
freqwords = [w for w in vocab1 if len(w) > 5 and dist[w] > 100]
print(freqwords)
```

```
['billion', 'company', 'president', 'because', 'market', 'million', 'shares', 'tradi
```

NLTK — Searching Text

A **concordanc view** shows every occurrence of a given word, with some context.

NLTK.ipynb In[15]:

```
text1.concordance("monstrous")
```

```
Displaying 11 of 11 matches:
ong the former , one was of a most monstrous size . ... This came towards us ,
ON OF THE PSALMS . " Touching that monstrous bulk of the whale or ork we have r
ll over with a heathenish array of monstrous clubs and spears . Some were thick
d as you gazed , and wondered what monstrous cannibal and savage could ever hav
that has survived the flood ; most monstrous and most mountainous ! That Himmal
they might scout at Moby Dick as a monstrous fable , or still worse and more de
th of Radney .'" CHAPTER 55 Of the Monstrous Pictures of Whales . I shall ere l
ing Scenes . In connexion with the monstrous pictures of whales , I am strongly
ere to enter upon those still more monstrous stories of them which are to be fo
ght have been rummaged out of this monstrous cabinet there is no telling . But
of Whale - Bones ; for Whales of a monstrous size are oftentimes cast up dead u
```

Find what other words have appeared in a similar range of contexts:

NLTK.ipynb In[16]:

```
text1.similar("monstrous")
```

```
true contemptible christian abundant few part mean careful puzzled
mystifying passing curious loving wise doleful gamesome singular
delightfully perilous fearless
```

Normalization and Stemming I

Normalization

A process that converts a list of words to a more uniform sequence.

- ✔ Useful in preparing text for later processing.
  - Converting to lowercase
  - Removing stopwords
  - Stemming, ...
- ✔ A standard format, will simplify later other operations — "separation of concerns".
- ✔ Can improve text matching. For example, the term "modem router" can be expressed, such as modem and router, modem & router, modem/router, and modem-router.
- ✘ But can also compromise an NLP task — converting to lowercase letters can decrease the reliability of searches when the case is important.

NLTK.ipynb In[17]:

```
input1 = "List listed lists listing listings"

words1 = input1.lower().split()
words1
```

```
['list', 'listed', 'lists', 'listing', 'listings']
```

Normalization and Stemming II

Stemming

A (crude heuristic) process that chops off the ends of words to get a common root.

- Language dependent. For English Porter's algorithm (1980) has repeatedly been shown to be empirically very effective:
  - consists of 5 phases of word reductions,
  - within each phase there are conventions to select rules,

Rule			Example		
SSES	→	SS	caresses	→	caress
IES	→	I	ponies	→	poni
SS	→	SS	caress	→	caress
S	→		cats	→	cat

NLTK.ipynb In[18]:

```
porter = nltk.PorterStemmer()
[porter.stem(t) for t in words1]
```

```
['list', 'list', 'list', 'list', 'list']
```

But

NLTK.ipynb In[19]:

```
[porter.stem(t) for t in ["see", "saw", "seeing","to see"]]
```

```
['see', 'saw', 'see', 'to se']
```

Comparison of Stemming Algorithms

Sample text: Such an analysis can reveal features that are not easily visible from the variations in the individual genes and can lead to a picture of expression that is more biologically transparent and accessible to interpretation

Lovins stemmer: such an analys can reve featur that ar not eas vis from th vari in th individu gen and can lead to a pictur of expres that is mor biolog transpar and acces to interpres

Porter stemmer: such an analysi can reveal featur that ar not easili visibl from the variat in the individu gene and can lead to a pictur of express that is more biolog transpar and access to interpret

Paice stemmer: such an analys can rev feat that are not easy vis from the vary in the individ gen and can lead to a pict of express that is mor biolog transp and access to interpret

Lemmatisation

Lemmatisation

A process that determines the **lemma** of a word. A lemma can be thought of as the dictionary form of a word. For example, the lemma of “was” is “be”.

- ✘ Computational much more expensive than stemming.
- ✔ But will always return a valid word.
- Empericaly:
  - Stemming increases recall while harming precision.
  - Benefit of lemmatisation can be modest — especially for retrieval in Engligh.

Steaming vs Lemmatisation

NLTK.ipynb In[21]:

```
WNlemma = nltk.WordNetLemmatizer()
udhr = nltk.corpus.udhr.words('English-Latin1')
print(udhr[:20])
```

```
['Universal', 'Declaration', 'of', 'Human', 'Rights', 'Preamble', 'Whereas', 'recognit
```

Applying stemming and lemmatisation to the first 20 words . . .

NLTK.ipynb In[22]:

```
[porter.stem(t) for t in udhr[:20]]
```

```
['univers',
 'declar',
 'of',
 'human',
 'right',
 'preambl',
 'wherea',
 'recognit',
 'of',
 'the',
 'inher',
 'digniti',
 'and',
 'of',
 'the',
 'equal',
 'and',
```

NLTK.ipynb In[23]:

```
[WNlemma.lemmatize(t) for t in udhr[
```

```
['Universal',
 'Declaration',
 'of',
 'Human',
 'Rights',
 'Preamble',
 'Whereas',
 'recognition',
 'of',
 'the',
 'inherent',
 'dignity',
 'and',
 'of',
 'the',
 'equal',
 'and',
```

Tokenisation

Tokenisation

Splitting a sentence into words / tokens.

Surly, this is easy … could just use the string split method ?

NLTK.ipynb In[24]:

```
text11 = "Children shouldn't drink a sugary drink before bed."
text11.split()
```

```
['Children', "shouldn't", 'drink', 'a', 'sugary', 'drink', 'before', 'bed.']
```

However, NLTK provides a better (semantics wise) split …

NLTK.ipynb In[25]:

```
print(nltk.word_tokenize(text11))
```

```
['Children', 'should', "n't", 'drink', 'a', 'sugary', 'drink', 'before', 'bed', '.']
```

(i.e., separated punctation and “shouldn’t”)

Sentence Splitting

Sentence Splitting

Splitting a body of text into sentences.

This is harder again … using the string `split(".")` method is optimistic at best.

Example

"This is the first sentence. After Brexit milk in the U.K. will cost 9.99. Is this the third sentence? Yes, it is!"

NLTK.ipynb In[27]:

```python
for s in text12.split("."):
    print(s)
```

```
This is the first sentence
 After Brexit milk in the U
K
 will cost 9
99
 Is this the third sentence? Yes, it is!
```

NLTK.ipynb In[28]:

```python
sentences = nltk.sent_tokenize(text12
for s in sentences:
    print(s)
```

```
This is the first sentence.
After Brexit milk in the U.K. will cost 9.99.
Is this the third sentence?
Yes, it is!
```

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Part of Speech (POS) Tagging

Part of Speech (POS)

Is a special label assigned to each token (word) in a text corpus to indicate the part of speech and often also other grammatical categories such as tense, number (plural/singular), case etc.

Number	Tag	Description
1	CC	Coordinating conjunction
2	CD	Cardinal number
3	DT	Determiner
4	EX	Existential *there*
5	FW	Foreign word
6	IN	Preposition or subordinating conjunction
7	JJ	Adjective
8	JJR	Adjective, comparative
9	JJS	Adjective, superlative
10	LS	List item marker
11	MD	Modal
12	NN	Noun, singular or mass
13	NNS	Noun, plural
14	NNP	Proper noun, singular
15	NNPS	Proper noun, plural
16	PDT	Predeterminer
17	POS	Possessive ending
18	PRP	Personal pronoun
19	PRP$	Possessive pronoun
20	RB	Adverb
21	RBR	Adverb, comparative
22	RBS	Adverb, superlative
23	RP	Particle
24	SYM	Symbol
25	TO	*to*
26	UH	Interjection
27	VB	Verb, base form
28	VBD	Verb, past tense
29	VBG	Verb, gerund or present participle
30	VBN	Verb, past participle
31	VBP	Verb, non-3rd person singular present
32	VBZ	Verb, 3rd person singular present
33	WDT	Wh-determiner
34	WP	Wh-pronoun
35	WP$	Possessive wh-pronoun
36	WRB	Wh-adverb

Fig: POS Tags from Penn Tree Bank.

Example

Tag	Meaning	English Examples
ADJ	adjective	*new, good, high, special, big, local*
ADP	adposition	*on, of, at, with, by, into, under*
ADV	adverb	*really, already, still, early, now*
CONJ	conjunction	*and, or, but, if, while, although*
DET	determiner, article	*the, a, some, most, every, no, which*
NOUN	noun	*year, home, costs, time, Africa*
NUM	numeral	*twenty-four, fourth, 1991, 14:24*
PRT	particle	*at, on, out, over per, that, up, with*
PRON	pronoun	*he, their, her, its, my, I, us*
VERB	verb	*is, say, told, given, playing, would*
.	punctuation marks	*. , ; !*
X	other	*ersatz, esprit, dunno, gr8, univeristy*

```
text = "Children shouldn't drink a sugary drink before bed."
text2 = nltk.word_tokenize(text)
nltk.pos_tag(text2)
```

```
[('Children', 'NNP'),
 ('should', 'MD'),
 ("n't", 'RB'),
 ('drink', 'VB'),
 ('a', 'DT'),
 ('sugary', 'JJ'),
 ('drink', 'NN'),
 ('before', 'IN'),
 ('bed', 'NN'),
 ('.', '.')]
```

proper noun
/MD
Modal
/RB
Adverb
/VB
Base verb
/DT
Determiner
/JJ
Adjective
/NN
Noun, singular or mass
/IN
Preposition

POS Tagging — How hard is it?

- $\approx 89\%$ of English words have only one part of speech (unambiguous).
  - However, many common words in English are ambiguous.
  - But even these can largely be disambiguated by rules or probabilistically.
- Taggers can be rule-based, stochastic (training on a labelled set of words using Hidden Markov Models (HMMs)), or a combination (most popular combination is the “Brill” tagger).

Example of stochastic tagging

The sentence

“Secretariat is expected to race tomorrow”

has POS tagging:

NNP	**VBZ**	**VBN**	**TO**	**VB**	**NR**
Secretariat	is	expected	to	race	tomorrow

NNP	**VBZ**	**VBN**	**TO**	**NN**	**NR**
Secretariat	is	expected	to	race	tomorrow

/NNP
proper noun
/VB
Base verb
/VBN
verb, past participle
/VBZ
verb, 3rd prsn
/TO
to

Looking at transition probabilities (going from **TO** to a **VB** or a **NN**) we have

$$\left.\begin{array}{l}\Pr(\mathbf{NN}|\mathbf{TO}) = 0.0047\\ \Pr(\mathbf{VB}|\mathbf{TO}) = 0.83\end{array}\right\} \Longrightarrow \text{“race” is most likely a verb}$$

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NNP	VBZ	VBN	TO	VB	NR
Secretariat	is	expected	to	race	tomorrow

NNP	VBZ	VBN	TO	NN	NR
Secretariat	is	expected	to	race	tomorrow

/NNP
proper noun
/VB
Base verb
/VBN
verb, past participle
/VBZ
verb, 3rd prsn
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to

Looking at transition probabilities (going from **TO** to a **VB** or a **NN**) we have

$$\left.\begin{array}{l} \Pr(\mathbf{NN}|\mathbf{TO}) = 0.0047 \\ \Pr(\mathbf{VB}|\mathbf{TO}) = 0.83 \end{array}\right\} \implies \text{“race” is most likely a verb}$$

What about "The old man the boat"?

Making Sense of Sentences

Making sense of sentences is easy if they follow a well-defined grammatical structure.

NLTK.ipynb In[32]:

```
text14 = nltk.word_tokenize("Alice␣loves␣Bob")
nltk.pos_tag(text14)
```

```
[('Alice', 'NNP'), ('loves', 'VBZ'), ('Bob', 'NNP')]
```

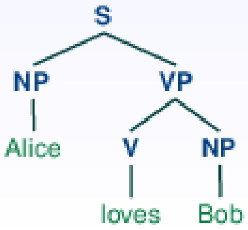
NLTK.ipynb In[33]:

```
grammar = nltk.CFG.fromstring("""
␣S␣->␣NP␣VP
␣VP␣->␣V␣NP
␣NP␣->␣'Alice'␣|␣'Bob'
␣V␣->␣'loves'
␣""")
parser = nltk.ChartParser(grammar)

trees = parser.parse_all(text14)
for tree in trees:
    print(tree)

trees[0]
```

```
(S (NP Alice) (VP (V loves) (NP Bob)))
```



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Term Frequency (TF)

Term Frequency (TF)
Number of times the term occurs in a document

Assumption

- If term occurs more often, it measures something important.
- $2\times$ as many occurrences is $2\times$ as important
  - This can be mitigated if need be — common “fix” is to transform using log transform: (“plus 1” to avoid NaN)

$$\log 10(1 + TF)$$

- Each occurrence is an independent event (not a replicate). Is it true?
  - Information retrieval: probably “yes”
  - Fraud detection, notes, log files: maybe “no”

Since documents vary in length, it is possible that a term would appear much more times in long documents than shorter ones.

- Normalise by dividing by total number of terms in document.

$$\mathrm{TF}(t) = \frac{\text{Number of times term } t \text{ appears in a document}}{\text{Total number of terms in the document}}$$

Document Frequency (DF)

Document Frequency (DF)

Number of documents the term occurs in

Assumption

- Terms that occur in fewer documents are more specified to a document and more descriptive of the content: rarity matters.
- Terms that occur in most documents are common words, not as descriptive. Is it true?
  - Sometimes "yes"
  - Sometimes just reflect textual variants (synonyms), regional differences, personal style.

Again, normalise with respect to number of documents

$$\mathrm{DF}(t) = \frac{\text{Number of document term } t \text{ appears in}}{\text{Total number of documents}}$$

Inverse Document Frequency (IDF)

- For DF, smaller is better — we often want a larger number to be "better".
- Possible transforms:
  - The reciprocal is too severe:

$$\mathrm{IDF}(t) = \frac{1}{\mathrm{DF(t)}}$$

  - Better, more popular definition

$$\mathrm{IDF}(t) = \log_{10}\left(1 + \frac{1}{\mathrm{DF(t)}}\right)$$

    - Again, use of log to "compress" (slows growth rate) an interval $[1, \infty)$.
    - Don't have to use base 10 logs – natural logs are same up to constant factor.

TF-IDF

TD-IDF

Term frequency–inverse document frequency.

- Separately, DF and IDF can be good features
- Together, they represent a good idea

$$\text{TF-IDF} = \text{TF} \times \text{IDF}$$

- Assumption: Higher frequency of terms that are rare may indicate a very important concept
- Why multiply? Are these “independent”?
  - No, but multiplying seems to work just fine
- TF-IDF can be successfully used for stop-words filtering in various subject fields including text summarisation and classification.
- Variations of the TF-IDF weighting scheme are often used by search engines as a central tool in scoring and ranking a document’s relevance given a user query.