

# Data Mining 2

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## RESOURCE OUTLINE LABEL

- Natural Language Processing (NLP)
- NLTK

# Outline

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1. Introduction	2
2. NLP Fundamental 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

The image shows a Twitter profile for 'UN Spokesperson' (@UNSpokesperson). The profile header includes a blue banner with the text 'Data hidden in plain sight' and a photo of a man speaking. Below the banner is the UN logo and the text 'UN Spokesperson'. The profile bio states: 'Official Twitter account of the Office of the Spokesperson for United Nations Secretary-General Ban Ki-moon'. The location is 'New York, USA' and the website is 'un.org/en/spokesperson/'. The profile has 14,656 tweets, 694 followers, 301K following, and 49 lists. The profile is annotated with several green boxes and arrows pointing to specific elements:

- Social network**: Points to the Twitter profile header.
- Author**: Points to the 'UN Spokesperson' name and bio.
- Description**: Points to the bio text.
- Location**: Points to the 'New York, USA' location field.
- Tweet**: Points to a tweet in the timeline.
- Topic**: Points to the text 'Ethics are built right into the ideals and objectives of the United Nations' #UNSG @ NY Society for Ethical Culture bit.ly/2guVeiR'.
- Time**: Points to the timestamp '17h'.
- Popularity**: Points to the retweet and reply counts (4, 6, 15, 37).

- 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)
- Misspellings, 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](http://www.nltk.org)
  - De facto standard NLP library in Python.
  - Large collection of examples (data and models)
- Fuzzywuzzy [github.com/seatgeek/fuzzywuzzy](https://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](http://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/](http://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.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
```

NTK invnh In[11]

NLTK Downloader

Collections	Corpora	Models	All Packages		
Identifier	Name	Size	Status		
all	All packages	n/a	partial		
all-corpora	All the corpora	n/a	installed		
all-nltk	All packages available on nltk_data gh-pages branch	n/a	partial		
book	Everything used in the NLTK Book	n/a	installed		
popular	Popular packages	n/a	installed		
tests	Packages for running tests	n/a	partial		
third-party	Third-party data packages	n/a	installed		

Download Refresh

Server Index: [https://raw.githubusercontent.com/nltk/nltk\\_data/gh-pages/index.xml](https://raw.githubusercontent.com/nltk/nltk_data/gh-pages/index.xml)

Download Directory: [/Users/kmcrpy/nltk\\_data](#)

NLTK.ipynb In[2]:

\* *Natural Language Processing with Python* by Bird, Klein, and Loper, [www.nltk.org/book](http://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 Repre
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 m
sent8: 25 SEXY MALE , seeks attrac older single lady , for disc
sent9: THE suburb of Saffron Park lay on the sunset side of Lone
```

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 punctuation 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 ...

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

NLTK.ipynb In[12]:

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

**Q:** How many times did word “four” appear?

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

NLTK.ipynb In[13]:

```
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 **concordance 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  
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

## 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

## 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	
SSES	→ SS
IES	→ I
SS	→ SS
S	→

Example	
caresses	→ caress
ponies	→ poni
caress	→ caress
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 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

**Porter stemmer:** 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

**Paice stemmer:** 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

# 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.
- Emperically:
  - Stemming increases recall while harming precision.
  - Benefit of lemmatisation can be modest — especially for retrieval in English.



# 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[:20]]
```

```
['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 punctuation 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]:

```
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]:

```
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 <i>there</i>
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

Number	Tag	Description
19	PRP\$	Possessive pronoun
20	RB	Adverb
21	RBR	Adverb, comparative
22	RBS	Adverb, superlative
23	RP	Particle
24	SYM	Symbol
25	TO	<i>to</i>
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

# Example

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

/NNP

proper noun

/MD

Modal

/RB

Adverb

/VB

Base verb

/DT

Determiner

/JJ

Adjective

/NN

Noun, singular or mass

/IN

Preposition

```

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'),
 ('.', '.', '.')]

```

# 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

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

# POS Tagging — How hard is it?

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## Example of stochastic tagging

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**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

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

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')]
```

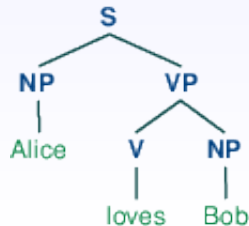
NLTK.ipynb In[33]:

```
grammar = nltk.CFG.fromstring("""
_S->_NP_VP
_VP->_V_NP
_NP->_'Alice'_|_'Bob'
_V->_'loves'
_""")
parser = nltk.ChartParser(grammar)
```

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

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

trees[0]
```



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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.

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

# 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

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

# 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:

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

- Better, more popular definition

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

- 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.