ITEC874 — Big Data Technologies

Week 9 Lecture 1: Analysing Unstructured Data

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ITEC874 2019H2

Programme

1. Analysing Unstructured Data
2. Analysing Text Data

Reading

- Lecture notes.
- Text Analytics — Microsoft Azure Machine Learning Studio.

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1. Analysing Unstructured Data
2. Analysing Text Data

Why Analyse Unstructured Data

It's about Variety

- Probably the biggest impact of Big Data in companies is the possibility to analyse unstructured data.
- Unstructured data contains information that can potentially be very useful.
- It opens up the possibility to access yet untapped information from multiple sources.

Sources of Unstructured Data

Video: surveillance cameras, videos in social media.

Images: Web images, images in social media, satellite images.

Sound: Call centre recordings.

Text: Documents, reports, webpages, social media posts.

Motivating Example: United Healthcare

- Have recorded voice files from customer calls to call centres.
- The voice data was converted to text using speech-to-text conversion tools.
- The text was then analysed using natural language processing software.
- Their analysis focused on identifying customers who use terms suggesting strong dissatisfaction.
- A United representative can then make some sort of intervention.

Use Cases of Image Analytics

https://www.zencos.com/blog/5-amazing-use-cases-of-image-analytics/

1. Identify bags at airports.
2. Analyse social media images for missing persons.
3. Real-time vehicle damage assessment.
4. Detect pneumonia from chest x-rays.

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Why Analysing Text?

Information Overload

- A lot of information is available as free text.
- The most natural form to write information is through free text.
- A great deal of digital information is available as free text.
- People can read and understand free text easily.
- But it's very hard for machines!

Examples of Using Text for Big Data

Analysis of social media posts

- What do people think about us?
- What do people think about our product?
- What do people think about our competitors?
- What are the most common topics mentioned in media?
- What are the common trends?

Analysis of text documents

- Is this patent claim related to other patents?
- Evidence based medicine: What treatment has best clinical evidence?
- Is this message spam?
- Who is the best person to forward this user request?

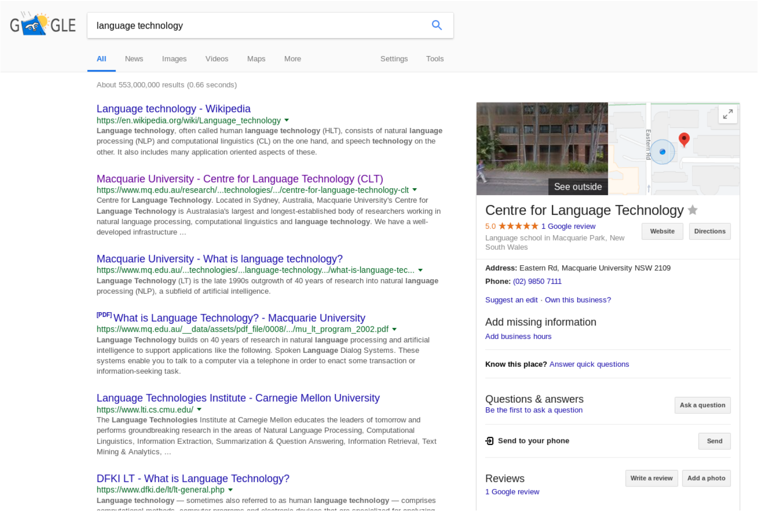
Integrating Natural Language Processing and Data Mining

Results to queries asked in current search engines may be enriched with information mined from:

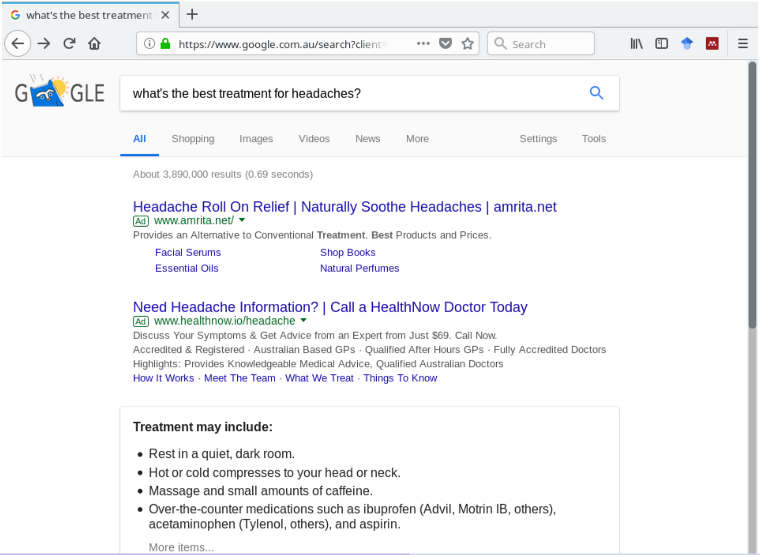
- Knowledge sources such as Google's Knowledge Graph.
- Text mining based on the characteristics of the query.

https://www.google.com/intl/bn/insidesearch/features/search/knowledge.html

Google Search (13 Feb 2018)



Google Search (13 Feb 2018)



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   - Characteristics of Text
   - Common Building Blocks for Text Analytics
   - Some APIs for Text Analytics

Text as Arbitrary Symbols

- Words are encoded as arbitrary symbols.
- Different languages use different representations to represent the same word.
- Even within one language there is no clear correspondence between a word symbol and its meaning.

https://www.linguisticsociety.org/content/how-many-languages-are-there-world

Ambiguity everywhere I

Language features ambiguity at multiple levels.

Lexical

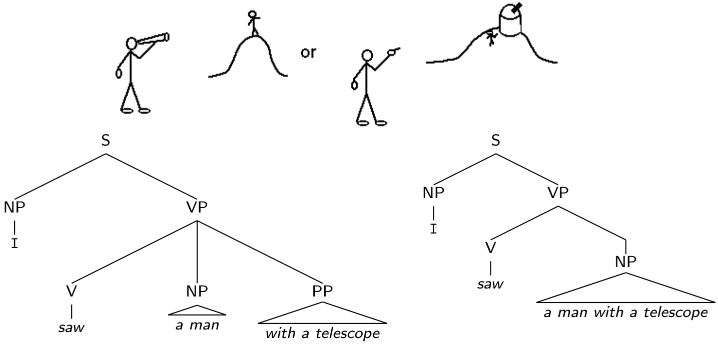
Example from Google's dictionary:

- bank (n): the land alongside or sloping down a river or lake.
- bank (n): financial establishment that uses money deposited by customers for investment, ...
- bank (v): form in to a mass or mound.
- bank (v): build (a road, railway, or sports track) higher at the outer edge of a bend to facilitate fast cornering.
- ...

Ambiguity everywhere II

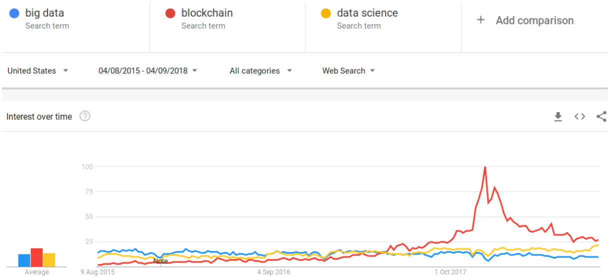
Syntactic

- "I saw a man with a telescope" ... who has the telescope?



So many words!

- Any language features a large number of distinct words.
- New words are coined.
- Words change their use in time.
- There are also names, numbers, dates... the possibilities are infinite.



https://trends.google.com

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Tokenisation

- Tokenisation: Break down the input into words and other kinds of tokens.
- Sentence Segmentation: Break down the input into sentences.
- Tokenisation needs to be done as a first step in other applications.
- Same process as identifying separate units in programming languages, but harder.
- Tokenisation in space-delimited languages is fairly easy but some languages have no clear-cut way to separate words, or even sentences.

Keyword Extraction and Word Clouds

- Keyword extraction: Extract the most important words in a document or collection of documents.
- Word cloud: a graphical interface that displays words according to their importance.

How to Select and Score words?

- Remove stop words.
- Select words by frequency.
- Use tf.idf
- ...

Removing Stop Words

- Many packages offer lists of stop words.
- These lists include words that usually are not important.
- There is no universal list of stop words.

Stop words in the Python NLTK package

```
>>> from nltk.corpus import stopwords
>>> stopwords.words('english')
['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're",
 "you've", "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he',
 'him', 'his', 'himself', 'she', "she's", 'her', 'hers', 'herself', 'it', "it's",
 'its', 'itself', 'they', 'them', 'their', 'theirs', 'themselves', 'what', 'which',
 'who', 'whom', 'this', 'that', "that'll", 'these', 'those', 'am', 'is', 'are',
 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having', 'do',
 'does', 'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because',
 'as', 'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about', 'against',
 'between', 'into', 'through', 'during', 'before', 'after', 'above', 'below',
 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'again',
 'further', 'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all',
 'any', 'both', 'each', 'few', 'more', 'most', 'other', 'some', 'such', 'no',
 'nor', 'not', 'only', 'own', 'same', 'so', 'than', 'too', 'very', 's', 't',
 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll',
 'm', 'o', 're', 've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn',
 "didn't", 'doesn', "doesn't", 'hadn', "hadn't", 'hasn', "hasn't", 'haven',
 "haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't", 'mustn', "mustn't",
```

Selecting Words by Frequency

- If you want to find words that discriminate between different documents ...
  - Very frequent words are not useful (because they are in most documents).
  - Very rare words are not useful (because they are in too few documents).
  - The right solution is somewhere in the middle.
- A practical solution is to apply this sequence:
  1. Remove stop words.
  2. Select the most frequent remaining words.

Selecting Words by tf.idf

- tf.idf strikes a balance between words that are frequent but are not too frequent.
- tf: Term frequency. Words that are very frequent are more important.

$$tf(w,d) = \text{number of times word } w \text{ occurs in document } d$$

- idf: Inverse document frequency. Words that occur in many documents are less important.

$$idf(w) = 1 + \log\left(\frac{\text{number of documents}}{\text{number of documents containing word } w}\right)$$

- $tf.idf(w,d) = tf(w,d) \times idf(w)$
- We select words from document d with high $tf.idf$, possibly after removing stop words.

Stemming and Lemmatisation

- Words in many languages (e.g. English) have inflections.
  - Singular, plural, verb-ing, etc.
- Stemming and lemmatisation allow to group words that are different only because of their inflections.
- Stemming: Remove the part of a word that has the inflection to produce the stem.
- Lemmatisation: Convert an inflected word into a word without inflections to produce the lemma or base form.
- Stemming is easier and requires less knowledge of the language. Often stemming is all you need.
- Lemmatisation is useful when you want to produce real words.
  - E.g. if you want to display keywords.

Part of Speech Tagging

- Words with the same part of speech have similar grammatical properties.
- In general, one can replace a word with another of the same part of speech and the sentence is still grammatical.
- Most words belong to open class types: nouns, verbs, adjectives, adverbs.
  - These words usually determine the topic of the sentence.
  - For example, keywords would normally be words in open class types.
- Words in the closed class types are useful to connect other words: prepositions, determiners, pronouns, conjunctions, ...
  - These words are usually removed by some text applications.
  - For example, stop words are normally words from closed class types.

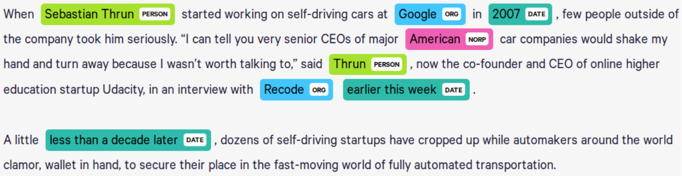
Parts of Speech in the Penn Treebank

CC	Coordinating conjunction
CD	Cardinal number
DT	Determiner
EX	Existential there
FW	Foreign word
IN	Preposition or subordinating conjunction
JJ	Adjective
JJR	Adjective, comparative
JJS	Adjective, superlative
LS	List item marker
MD	Modal
NN	Noun, singular or mass
NNS	Noun, plural
NNP	Proper noun, singular
NNPS	Proper noun, plural
PDT	Predeterminer
POS	Possessive ending
PRP	Personal pronoun

PRP$	Possessive pronoun
RB	Adverb
RBR	Adverb, comparative
RBS	Adverb, superlative
RP	Particle
SYM	Symbol
TO	to
UH	Interjection
VB	Verb, base form
VBD	Verb, past tense
VBG	Verb, gerund or present participle
VBN	Verb, past participle
VBP	Verb, non-3rd person singular present
VBZ	Verb, 3rd person singular present
WDT	Wh-determiner
WP	Wh-pronoun
WP$	Possessive wh-pronoun
WRB	Wh-adverb

Named Entity Recognition

- Named entities are (often multi-word) expressions that refer to proper names of specific types.
    - Persons, organisations, locations, artifacts, dates, ...
- Named entity recognition is one of the most common tasks in text analytics.



https://explosion.ai/demos/displacy-ent

Entities in the Message Understanding Conference

- Named Entities
  - Organization
  - Person
  - Location
- Temporal Expressions
  - Date
  - Time
- Number Expressions
  - Money
  - Percent

MUC

- Initiated and financed by DARPA (Defense Advanced Research Projects Agency).
- From 1987 to 1997.
- The goal was to advance methods for information extraction from text.
- MUC-6 (1995) introduced the task of named entity recognition.
- The MUC named entities have been used by many systems since then.

Text Classification

Many different tasks can be seen as text classification.

- E-mail filtering, spam detection, sentiment analysis . . .

To classify text it needs to be converted into a vector of features.

Feature Selection

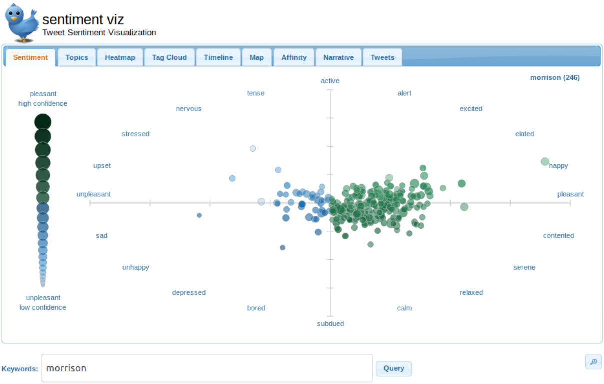
- Extract key words and use them to build document vectors for classification.
- For example, remove stop words and/or select words with high tf.idf.

Feature Extraction

- Generate document vectors based on mathematical and statistical combinations of the entire information of the text.
- Latent Semantic Analysis (LSA), Singular Value Decomposition (SVD) and Principal Component Analysis (PCA) are traditionally used for feature extraction.
- More recent approaches use neural networks and word embeddings.

Sentiment Analysis

- Sentiment analysis is a popular example of text classification.
- Often needed for market analysis.
- A well known approach to analyse social media posts.



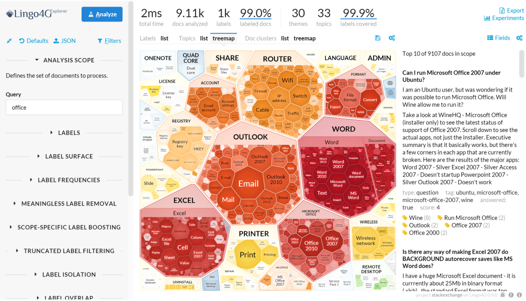
https://www.csc2.ncsu.edu/faculty/healey/tweet_viz/tweet_app/

Text Retrieval / Filtering

- Often needed to find specific information in large volumes of text.
- Search engines are the first popular applications of text retrieval.
- A common step before doing other processing tasks such as sentiment analysis.

Text Clustering

- Nothing to do with computer clusters . . .
- Useful when we have large volumes of text but no labels.
- Can help characterise types of customers, common views of opinion, etc.



https://get.carrotsearch.com/lingo4g/1.4.0/doc/

Topic Modelling

- Topic modelling is a more complex form of unsupervised text processing.
- The task is to find the common topics in a collection of texts (e.g. tweets).
- Implementations such as Latent Dirichlet Allocation (LDA) return keywords that are most characteristic of each topic.

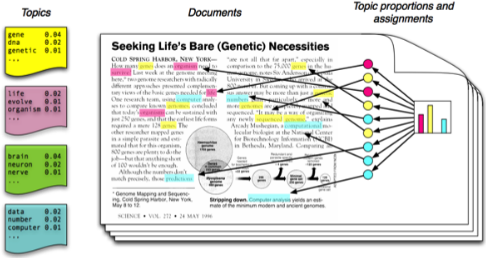


Figure source: Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM*, 55(4), 77-84.

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Web Demos

- https://explosion.ai/demos/
- https://www.csc2.ncsu.edu/faculty/healey/tweet_viz/tweet_app/
- https://developer.aylien.com/text-api-demo
- http://text-processing.com/demo/
- ...

Programming Libraries

- Spacy https://spacy.io/
- Natural Language Toolkit (NLTK) https://www.nltk.org/
- Scikit-Learn http://scikit-learn.org/stable/
- Keras https://keras.io/
- ...

Graphical Interfaces

Usually integrated in general machine learning tools

- RapidMiner
- Weka
- SAS Enterprise Miner, SAS Viya
- ...

Cloud Services

- Azure Machine Learning Studio https://docs.microsoft.com/en-us/azure/machine-learning/studio-module-reference/text-analytics
- Aylien https://aylien.com/text-api/
- ...

Comparison for Named Entity Recognition

Text APIs compared in these two posts:

- https://medium.com/@boab.dale/text-analytics-apis-part-1-the-bigger-players-3ce8a93577bd
- https://becominghuman.ai/text-analytics-apis-part-2-the-smaller-players-c9e608cf7810

Table 2. *Results on the CoNLL shared task data; all values are percentages*

	Amazon comprehend			Google NL			IBM NL		
	Prec'n	Recall	$F_{\beta=1}$	Prec'n	Recall	$F_{\beta=1}$	Prec'n	Recall	$F_{\beta=1}$
LOC	**76.13**	72.66	74.36	58.81	**86.45**	70.00	70.17	86.15	**77.34**
MISC	**58.40**	10.40	17.65	36.76	**19.37**	**25.37**	2.08	0.14	0.27
ORG	**74.72**	**59.24**	**66.08**	68.03	48.16	56.40	69.86	27.63	39.60
PER	**87.14**	82.99	**85.02**	82.45	**83.36**	82.90	73.13	76.07	74.57
Overall	**78.95**	63.93	**70.65**	66.15	**65.97**	66.06	70.51	55.36	62.03

https://medium.com/@boab.dale/text-analytics-apis-part-1-the-bigger-players-3ce8a93577bd

Take-home Messages

- Sources of unstructured data.
- Impact of unstructured data.
- Characteristics of text.
- Common building blocks for text analytics.

What's Next

Week 10

- Visual Analytics.