INTRODUCTION TO TEXT ANALYTICS

DxU Methods Workshop

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OUTLINE

- Introduction
    - What is text mining/text analytics?
- Natural Language Processing
    - From text to numbers
- Text analysis
    - From numbers to insight

WHAT IS TEXT MINING?

Text mining is an umbrella term for a variety of techniques

- combining methods from:
  - linguistics,
  - statistics,
  - machine learning,
  - computer science.
- Common goal of deriving useful information from text data

TEXT MINING, TEXT ANALYTICS, NLP

Is text analytics something else?

- The two work interchangeably
- Usage might depend on application
  - text **mining** provides qualitative answers,
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Then what is Natural Language Processing?

- Unstructured text is just a long string of characters?
- We need to express it in a way that allows analysis.
- This is the goal of NLP
  - Process the texts
  - to capture the meaning/content
  - in a form that allows further analysis

The **choice of methods** used in text mining depend on the **questions that need to be answered**

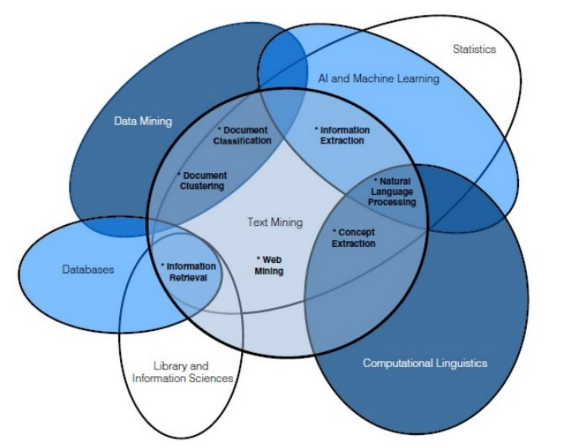

Figure: Miner et al. (2012), Practical text mining and statistical analysis for non-structured text data applications.

TYPES OF APPLICATIONS - INFORMATION RETRIEVAL/EXTRACTION

Information retrieval

- "I've got a question, **where** is the answer?"
- The granddaddy of text mining: library science (1940's-...)
- Nowadays: search engines

Information extraction

- "I've got a question, **what** is the answer?"
- First "real" text mining - military application (1980's-...)
- Nowadays: knowledge bases (Google, Siri etc.)
- Some economic research applications:
    - Analysis of patent applications, tax statements

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Generally, building a whole, domain specific system such that

- Ask questions $\rightarrow$ get answers (or at least the location).
- Usually, and **answer is based on one text** (or just a few).

TYPES OF APPLICATIONS - SUMMARIZING TEXTS

Many applications in economic research:

- **Single question** known upfront (or just a few)
- **Many texts** that are informative
- We want to consider all/most of them
- We therefore want to summarize the information
- Usually in a quantitative manner.

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Document classification and clustering:

- Generally, rather simple questions and answers
  - "Are those text optimistic or pessimistic?"
  - "What issues do those texts mention?"
- Either **predefined** (classification) or **learned** (clustering) labels
- Hard or soft (degree/score instead of label)
- Per-document, not 100% accurate, but useful when aggregated.

EXAMPLES OF APPLICATIONS IN ECONOMIC RESEARCH

- Economic Policy Uncertainty index (Baker et al., 2016)
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- How much does the news drive the economy (Larsen and Thorsrud, 2019)
  - Identifies the news topics that have impact on the stock market and macroeconomic aggregates.
- The economic impact of statements by Fed (Hansen and McMahon, 2016) and other policymakers
  - Identifying news about tax changes from U.S. presidential speeches (Jassem et al., 2021)

NATURAL LANGUAGE PROCESSING

WHY DO WE NEED NATURAL LANGUAGE PROCESSING?

Main goal: Make the computer "understand" the texts

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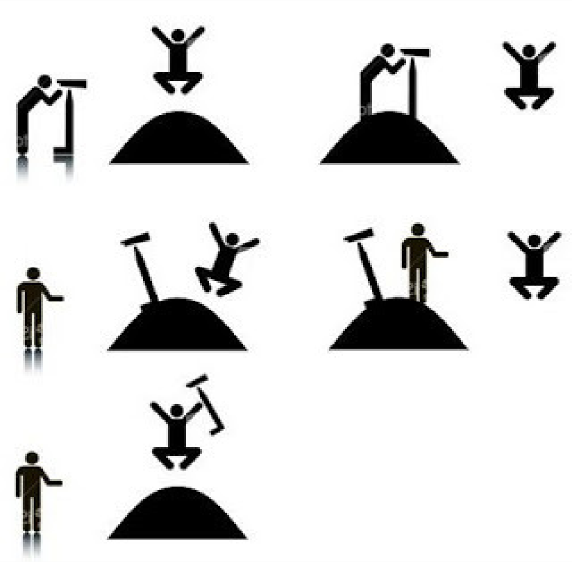
“I saw a man on a hill with a telescope.”

I SAW A MAN ON A HILL WITH A TELESCOPE



Feature selection

- What information am I interested in? (application dependent)
- What features of the text carry that information?
- What amount of detail do I need to consider?
    - What words are used in the text?
    - Do I need to consider the syntax?
    - Or punctuation (e.g. ?!@#) ?
    - Or the context (e.g. named entities)?
- Trade-off: simplicity vs complexity

We want to process the texts to express them in terms of the relevant features.

For analysis, we usually want to quantify the features.

- Often as simple as counting how many times each feature appears in a text

Basic approach: Bag-of-words approach

- If the meaning is carried by the words used
- just count how many times each word was used in each text.

1. We have D documents $\boldsymbol{w}_d$

   $\boldsymbol{w_1} =$ "Thank you. Wow. Well, you know..."

   $\boldsymbol{w_2} =$ "We meet here at a moment of unlimited potential..."

   $\vdots$

1. We have D documents $\boldsymbol{w}_d$
2. We break them up into individual words $\boldsymbol{w}_d = (w_{d,1}, \ldots, w_{d,N_d})$ (tokenization), identify the vocabulary $\mathcal{V} = \{v_1, \ldots, v_V\}$
   $\mathcal{V} = \{\text{`aardvark'}, \text{`abbreviate'}, \ldots, \text{`zymotic'}\}$
   $\boldsymbol{w_1} = (\text{`thank'}, \text{`you'}, \text{`wow'}, \text{`well'}, \text{`you'}, \text{`know'}, \ldots)$
   $\boldsymbol{w_2} = (\text{`we'}, \text{`meet'}, \text{`here'}, \text{`at'}, \text{`a'}, \text{`moment'}, \text{`of'}, \text{`unlimited'}, \ldots)$
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2. We break them up into individual words $\boldsymbol{w}_d = (w_{d,1}, \ldots, w_{d,N_d})$ (tokenization), identify the vocabulary $\mathcal{V} = \{v_1, \ldots, v_V\}$
3. We count how many times each word appears in each document (vectorization),

$$f_{d,i} = \sum_{n=1}^{N_d} \mathbb{1}(w_{d,n} = v_i), \quad \boldsymbol{f}_d = (f_{d,1}, \ldots, f_{d,V}$$

End result - a document-term counts matrix:.

$$F = \begin{bmatrix} f_{1,1} & \cdots & f_{1,V} \\ \vdots & \ddots & \vdots \\ f_{D,1} & \cdots & f_{D,V} \end{bmatrix}$$

IMPROVING ON THE *BAG-OF-WORDS*

Basic ways to improve a bag-of-words approach:

- Cleaning the vocabulary - removing stopwords ('a', 'the', 'and'...), rare words (e.g. typos), common words.
- Stemming/lemmatization - 'dogs' $\rightarrow$ 'dog', 'running' $\rightarrow$ 'run'

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- Stemming/lemmatization - ‘dogs’ $\rightarrow$ ‘dog’, ‘running’ $\rightarrow$ ‘run’
- Not all words are equally informative.
  - Term frequency - inverse document frequency (TF-IDF) score
  - Scale down the score of the terms that appear in many texts, e.g.:

$$\mathrm{tfidf}_{d,i} = \mathrm{tf}_{d,i} \times \mathrm{idf}_i$$

$$\mathrm{tf}_{d,i} = \frac{f_{d,i}}{N_d}$$

$$\mathrm{idf}_i = \log\left(\frac{D}{\sum_{d=1}^{D} \mathbb{1}(f_{d,i} > 0) + 1}\right)$$

GOING PAST *BAG-OF-WORDS*

By considering only individual words we lose a lot of information.

- n-grams - Meaningful phrases consisting of more than one word.
  - Identify combinations of consecutive words that appear "abnormally" often, e.g. bigrams:

$$P(w_{d,n} = v_i, w_{d,n+1} = v_j) > P(w_{d,n} = v_i)P(w_{d,n} = v_j)$$

- Part-of-speech tagging - the meaning of the word can depend on whether it's a noun, verb etc.
- Chunking (shallow parsing)
  - Based on the POS tags we can define certain syntax structures we're interested in
  - For example, noun-phrases: $<\text{PREP}>?<\text{ADJ}>*<\text{NOUN}>+$ (potential preposition, any number of adjectives, one or more nouns)

ANALYSIS OF THE TEXTS

Example:

Consumer reviews: predict rating based on features of the text

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Example:
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$$\texttt{rating}_d = \alpha + \sum_{i=1}^{V} \beta_i f_{d,i} + \varepsilon_d$$

This might be **thousands or even millions of variables.**

- OLS likely is not going to cut it

Some methods are better suited for the high-dimensional setting:

- Penalized regression (LASSO, Ridge etc.)
- Support-Vector Machines, Naive Bayes classifier, …

Those methods don't really tell us much about the underlying meaning of the texts.

- For this, we might want to perform dimensionality reduction
  - Represent the features/texts using smaller number of dimensions
- Semantic space, such that the dimensions that have some meaningful interpretation

General idea:

- Simple neural network
- Predicting word usage using the rest of the text
- Hidden layer has lower dimensionality.
  - It creates a **lower-dimensional representation** of a word

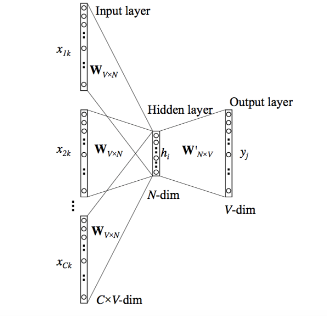

Figure: Rong (2014)

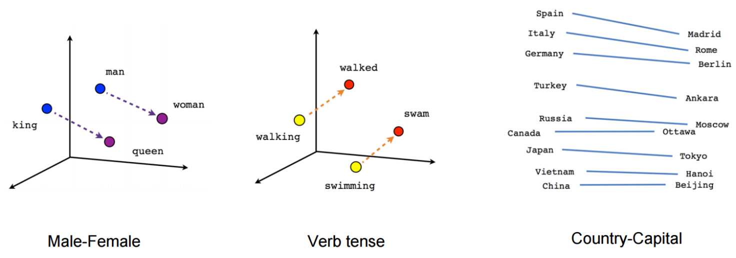

Figure: Visualisation of word2vec

RULES- AND LEXICON-BASED APPROACH

RULES-BASED APPROACH

General idea:
We know a priori that some words convey some particular meaning.
Let's just look for those.

Example: Economic Policy Uncertainty Index (Baker et al., 2016)
For each news article check if it contains at least one word that's:

1. related to economy - {`'economy'`, `'economic'`, ...}
2. related to policy - {`'policy'`, `'congress'`, ...}
3. related to uncertainty - {`'uncertain'`, `'uncertainty'`, ...}

It does? Then it is about economic policy uncertainty.

Count how many of those in a quarter - there's your EPU index.
(almost 7000 citations)

For each meaning of interest we can make a list of related words, so called lexicon.
Then we might ask - how much of a given document is within each lexicon?

- D documents $\boldsymbol{w}_d = (w_{d,1}, \ldots, w_{d,N_d}), \quad w_{d,n} \in \mathcal{V}$.
- K categories, each with a lexicon $L_k \subset \mathcal{V}, \quad k = 1, \ldots, K$

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Then we can simply express the documents as $\boldsymbol{p}_d = (p_{d,1}, \dots, p_{d,K})$ where:

$$p_{d,k} = \frac{\sum_{n=1}^{N_d} \mathbb{1}(w_{d,n} \in L_k)}{N_d}$$

(or any alternative aggregation scheme)

Lexicon based approach is commonly used in sentiment analysis, answering questions such as:

- Is the consumer review positive or negative?
- Is the news article optimistic or pessimistic?
- What emotions do the policymakers convey?

Based on pre-defined lexicons for each sentiment

- Those can be “all-purpose” or domain-specific

Common extension: valence/intensity $v(\text{term})$

- How strong is the sentiment of the word, e.g.:

$$0 < v(\text{`okay'}) < v(\text{`good'}) < v(\text{`great'}) < v(\text{`perfect'}) \leq 1$$

TOPIC MODELLING

FROM SUPERVISED TO UNSUPERVISED METHODS

Let's say instead of sentiments, we want to identify news topics.

- How would we specify a lexicon for every possible topic?
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However, we see that certain terms tend to co-occur in the documents.

- For each topic, certain words are used more often
- Can we learn from the data which words are indicative of which topics?

We observe the data: $D \times V$ document-term counts matrix.

We want to explain is using $K \ll V$ topics:

- a $D \times K$ document-term matrix - what are the documents about
- and $K \times V$ topic-term matrix - what terms are the topics using,

To achieve this, we are going to perform clustering. We are effectively clustering:

- terms based on their co-occurance in documents,
- at the same time, documents based on what terms they use.

We are expressing both the terms and the documents in a lower-dimensional (semantic) space.

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Let's take a step back: consider the simplest probabilistic model - unigram model.

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Each token $w_{d,n}$ is assumed to be a draw from a categorical distribution over the vocabulary, given by a probability vector $\boldsymbol{\phi} = (\phi_1, \ldots, \phi_V)$:

$$w_{d,n} \sim \mathsf{Cat}(\boldsymbol{\phi})$$

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Those probabilities doesn't depend on anything, it's the same for all the words in all the documents. Not very informative.

Instead, assume there are K such distributions, one for each topic

$$\boldsymbol{\phi}_k = (\phi_{k,1}, \ldots, \phi_{k,V}), \quad k = 1, \ldots, K$$

- This is the basis for the LDA model proposed by Blei et al. (2003)

The key assumption of LDA is that each token $w_{d,n}$ has a latent topic assignment $z_{d,n}$

$$w_{d,n} | z_{d,n} \sim \mathsf{Cat}(\boldsymbol{\phi}_{z_{d,n}})$$

$$\mathbb{P}(w_{d,n} = v_i | z_{d,n}) = \phi_{z_{d,n},i}$$

Which terms are used depends on what the token is about.

For each document we can consider:
What is the proportion of tokens that are about a particular topic?

We can express this with a probability vector:

$$\boldsymbol{\theta}_d = (\theta_{d,1}, \ldots, \theta_{d,K}), \quad d = 1, \ldots, D$$

such that:

$$z_{d,n} \sim \mathsf{Cat}(\boldsymbol{\theta}_d)$$

$$\mathbb{P}(z_{d,n} = k) = \theta_{d,k}$$

LATENT DIRICHLET ALLOCATION MODEL, CONT.

Using Bayesian methods we can find $\boldsymbol{\phi}_1, \ldots, \boldsymbol{\phi}_K$ and $\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_D$ that best explain the actual data we see.

- $\boldsymbol{\phi}_1, \ldots, \boldsymbol{\phi}_K$ tell us how each of the topics is discussed
    - We don't really know which distribution is about what
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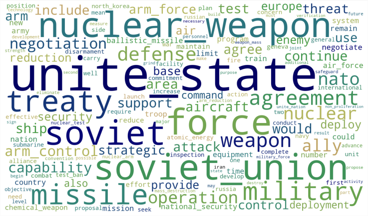
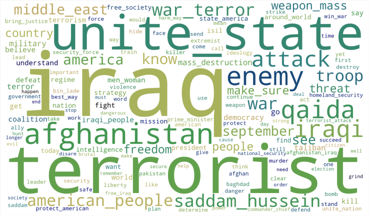
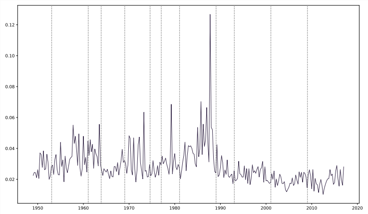
Let's consider the example of U.S. presidential speeches.

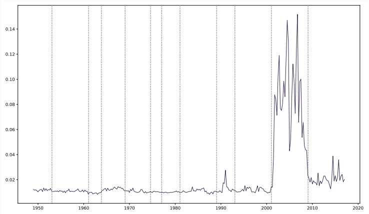
- We might even want to aggregate the per-document proportion into per-quarter measures.

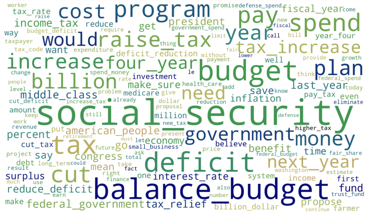
U.S. PRESIDENTIAL SPEECHES







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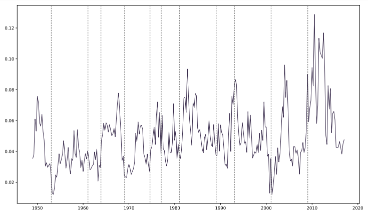
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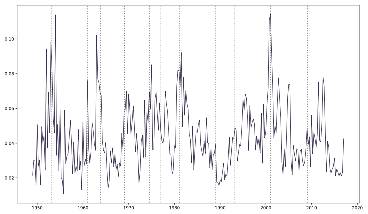
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QUESTIONS?

PLAN FOR THE SECOND SESSION

Hand-on experience using `python` (jupyter)

- `colab` - an online service for running `python` code
  - https://colab.research.google.com/
  - No need to install python/packages
- Notebook from GitHub > amjassem > DxU > **Book Reviews**
  - Basics of NLP
  - Sentiment analysis
  - Basic statistical models
  - Topic modelling
- ... > **Trump Tweets**

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