Text Analytics

- Sources of Text
- Applications of Text Analytics
- Text Analytics Concepts & Terminology
- Text EDA
- Vector Space Modeling
  - Set-of-Words: Binary word occurrences
  - Bag-of-Words: Word occurrences
  - TF-IDF
  - Word embedding

Imdad ullah Khan

Text Analytics

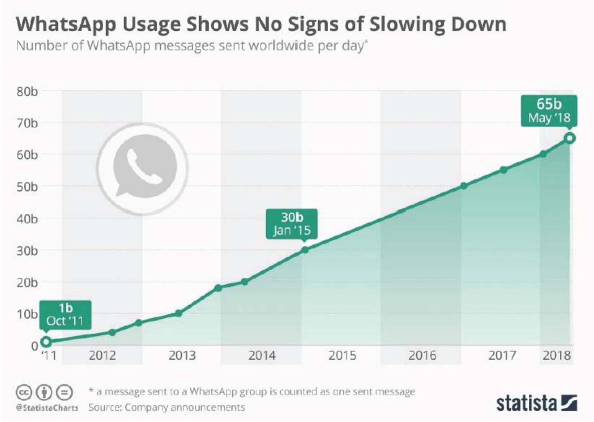
Applying data analytics to derive knowledge from text

Huge amount of textual data is available in the form of

- Social media posts
- Tweets
- Question answer forums
- Blogs
- YouTube video comments
- SMS
- Product reviews
- News articles

How much textual data is produced?

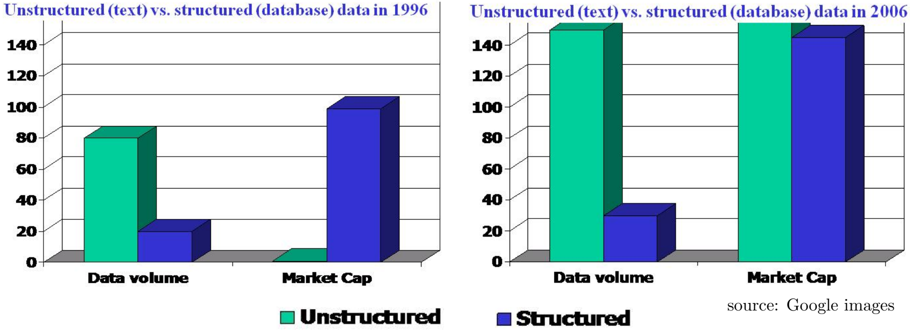
- 2.5 quintillion bytes of data created each day (Forbes)
- More than 65 billion messages sent on WhatsApp every day (Statista)
- 500 million tweets per day



Stakeholders of text analytics

- Government
  - What is the response of people towards a particular policy?
- Advertisers
  - What is trending that could be used for advertisement?
  - Careem used **LUMSU** as promo code
- Movie Makers
  - What people disliked about a movie?
  - This information is used to deliver in future what people want
- Brand Managers
  - What value added services people want in a brand?
  - How people respond to social responsibility campaigns of a brand?
- Academia
  - Is this document plagiarized?
  - Retrieve similar documents

Structured Vs Unstructured Data



source: Google images

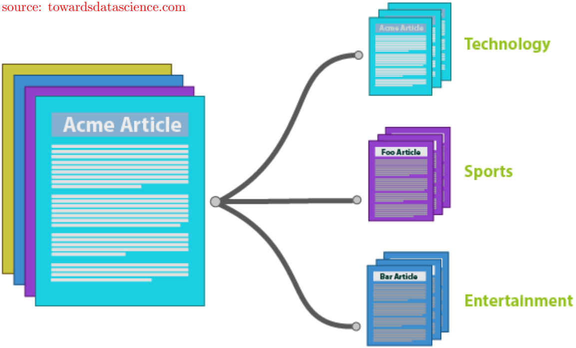
- Unstructured (text) vs. structured (database) data in 1996 (left) and 2006 (right)
- Market cap of unstructured data has grown massively
- Need better techniques to handle queries/search on unstructured data

Text Analytics: Applications

Document Classification: Classify texts into fixed categories

Apply classification after text analytics

source: towardsdatascience.com

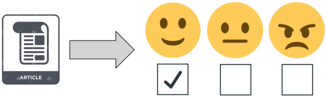


Sentiment Analysis and Emotion Mining

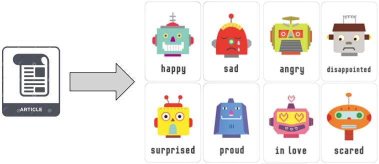
Determine if the sentiment in the text is **positive** or **negative**

▷ Emotion Mining is fine-grained Sentiment Analysis

Sentiment Analysis



Emotion Mining

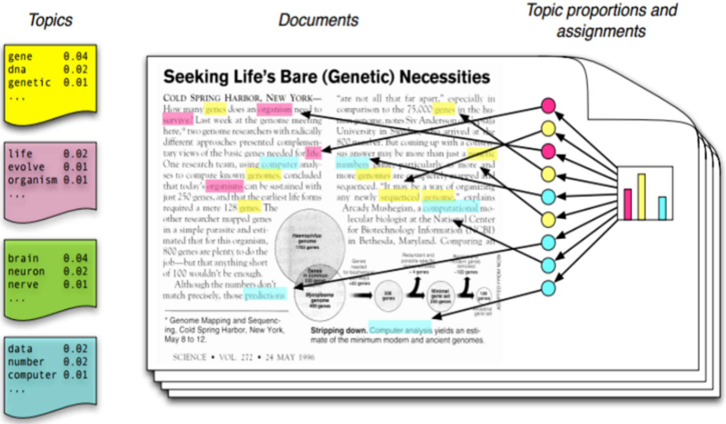


- Determine how the product is perceived by public from reviews
- The Obama administration used it to gauge public opinion on policies and campaign messages ahead of 2012 election
- Given news headlines for last n days, would the stock market go up?

Text Analytics: Tasks

Topic Modeling: Determine the topics and subject of documents

- Document clustering, information retrieval, reviewer assignment



Text Analytics: Tasks

Author profiling: Determine author attributes (age, gender, name etc.)

- Security: Who is behind anonymous threat message?
- Sales and marketing: Determine the demographic of the people behind online reviews who liked or disliked the products

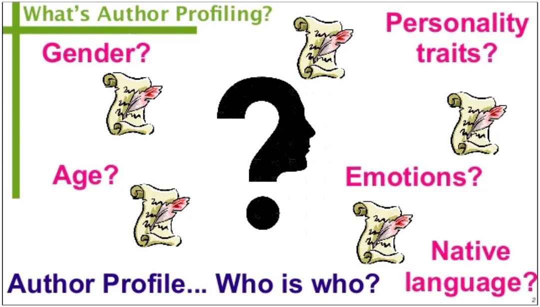


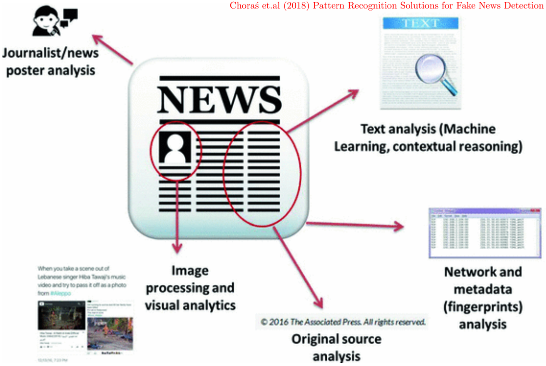
Figure credit: Francisco Rangel & Paolo Rosso [Universitat Politècnica de València]

Text Analytics: Tasks

Fake News Identification: Determine if a news item is fake

- Filtering and blocking of misleading information
- Identify trustworthy news sources

Choraś et.al (2018) Pattern Recognition Solutions for Fake News Detection

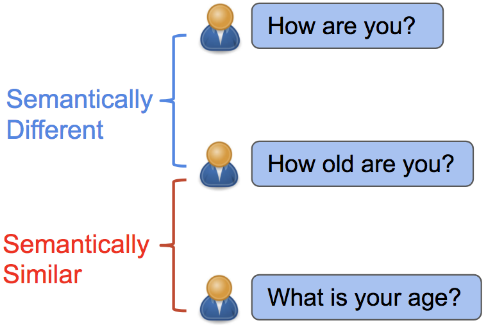


Text Analytics: Tasks

Paraphrase Identification: Find paraphrases or duplicates texts

- Used for document clustering, information retrieval, plagiarism
- Useful for question-answer forums, where an answer could be retrieved if a question has already been asked and answered

source: Google AI blog

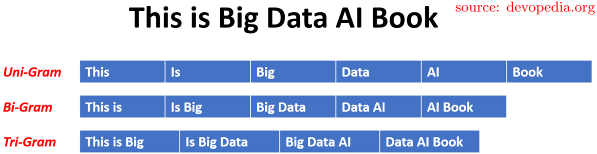


Text Analytics: Basic Concepts

Vocabulary (language lexicon): Unique words that may appear in texts

***n*-gram**: a (sub)sequence of n contiguous words in text (aka shingle)

Texts considered as sequences of n-grams, large n captures more context



source: devopedia.org

- In computational biology, they are called k-mers

Tokenization: Break a character sequence into predefined units

- Can be character level or word level, n-gram tokens

Text Analytics: Basic Concepts

Text Analytics: Text Normalization

Text Normalization

- Initial Pre-procesing of text dataset
- The goals is to standardize sentence structure and vocabulary
- Helps reduce number of variables (dimensionality)

Exact preprocessing steps depends on application, they include

- Remove duplicate whitespaces, punctuations, accents, capital letters, special characters
- Substitute word numerals by numbers (thirty $\rightarrow$ 30), values by type ($100 $\rightarrow$ currency/money), contractions by phrases (I've $\rightarrow$ I have)
- Standardize formats (e.g. dates), replace abbreviation (e.g. USA)
- Stopwords removal
- Stemming
- Lemmatization

Stop words

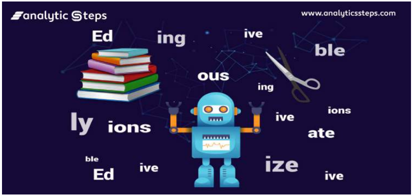
- Common words not providing useful information the, it, is, are, an, a
- Often removed (filtered out) during pre-processing
- No universally good list of stop words
- Reduces time/space complexity, can improve analytics quality

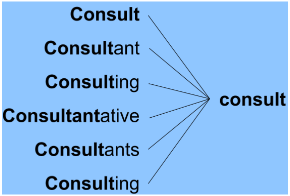
Sr.No	Tokenized sentences	SWR sentences
1	I have been on this medicine for 2 years	Medicine 2 years.
2	It has no side effects except for gaining of weight.	Side effects except gaining weight.
3	It also helps me sleep at night.	Also helps sleep night.
4	I was extremely suicidal and depressed	Extremely suicidal depressed.
5	completely did the opposite effect of what it is meant for	Completely opposite effect meant.

M Qasim (2018) Mining health reviews from online blogs and news

Stemming and Lemmatization

- Convert different variations of a word to a common root form





- **Stemming**: crude heuristic way of chopping off ends of words
- **Lemmatization**: grammatically sound words replacing
- am, are, is $\longrightarrow$
- car, cars, car's, cars' $\longrightarrow$ car
- "the boy's cars are different colors" $\longrightarrow$ "the boy car be differ color"

Text EDA

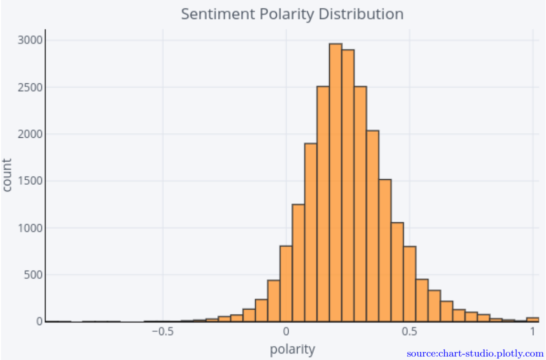
Text Analytics: Where to start?

First step in text analytics is Exploratory Data Analysis **(EDA)**

- Gives insight about the data such as:
  - Class distribution
  - Top occurring words in the dataset
  - Distribution of words per document
- These insights help in formulating solution strategies for the task
  - What preprocessing should be used?
  - What classifier should be used?

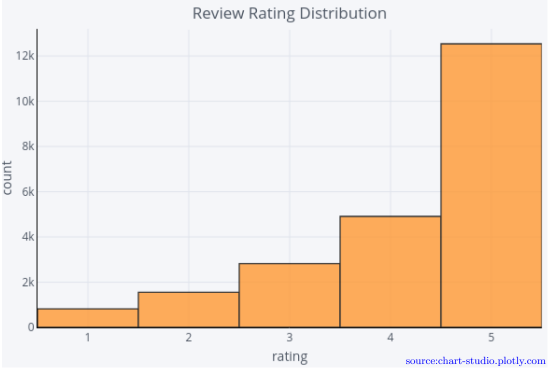
Sentiment Polarity Detection Dataset

- Clothing products review text, Reviewer info, rating and sentiment
- Sentiment labels $\in \{-1, 0, 1\} = \{\text{Negative, Neutral, Positive}\}$
- The problem is treated as Regression



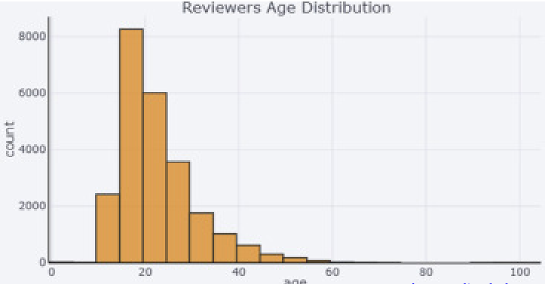
Text Exploratory Data Analysis

- Rating distribution



Text Exploratory Data Analysis

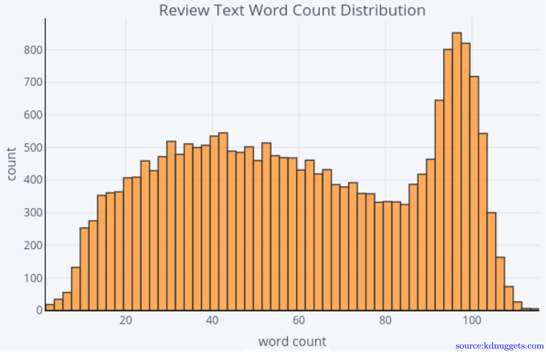
- Distribution of age of the reviewers



source:chart-studio.plotly.com

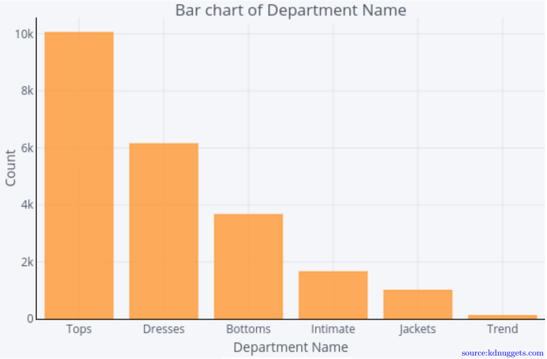
Text Exploratory Data Analysis

- Distribution of the text length of the reviews



Text Exploratory Data Analysis

- Reviews per department



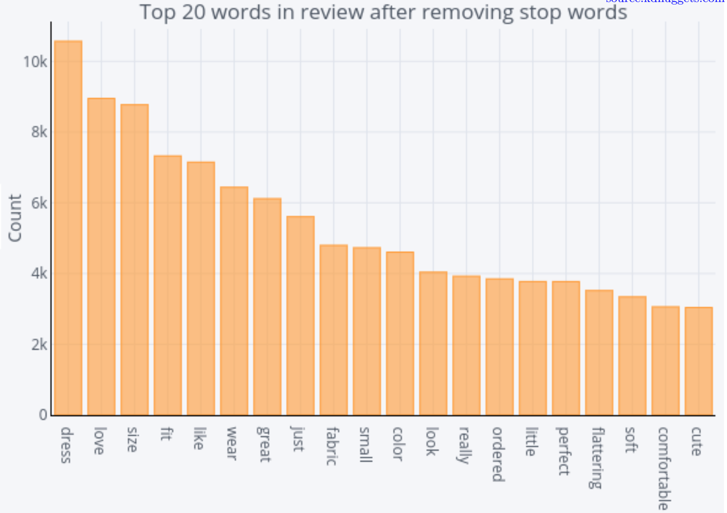
Text Exploratory Data Analysis

- Frequency of top unigrams **before** removing stopwords

Text Exploratory Data Analysis

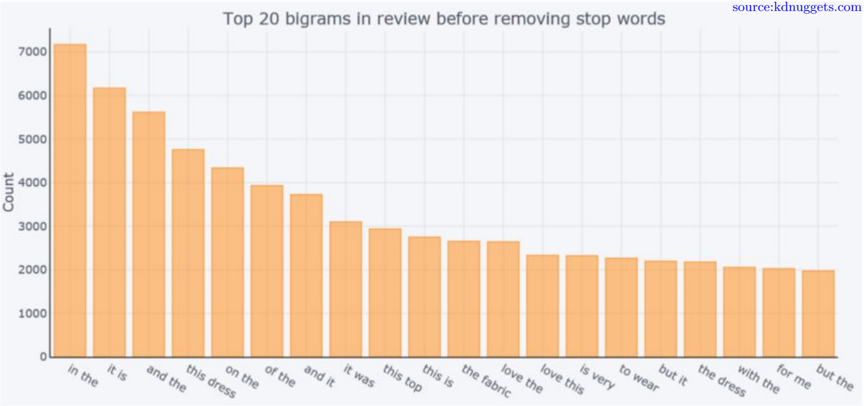
- Frequency of top unigrams **after** removing stopwords

source:kdnuggets.com



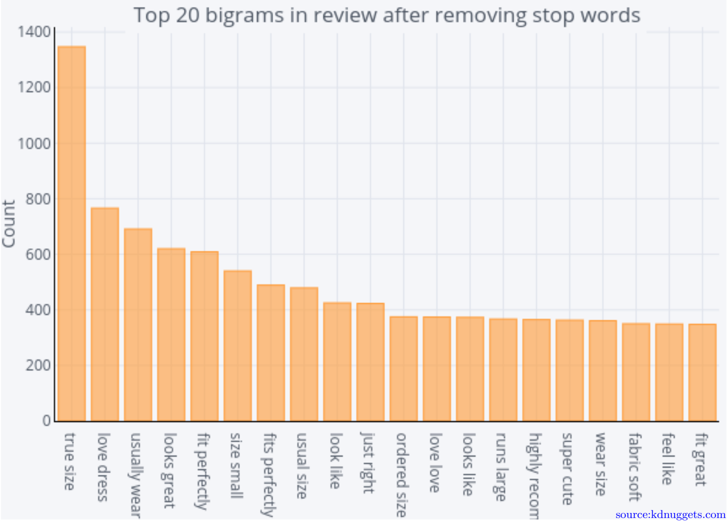
Text Exploratory Data Analysis

- Frequency of top bigrams **before** removing stopwords



Text Exploratory Data Analysis

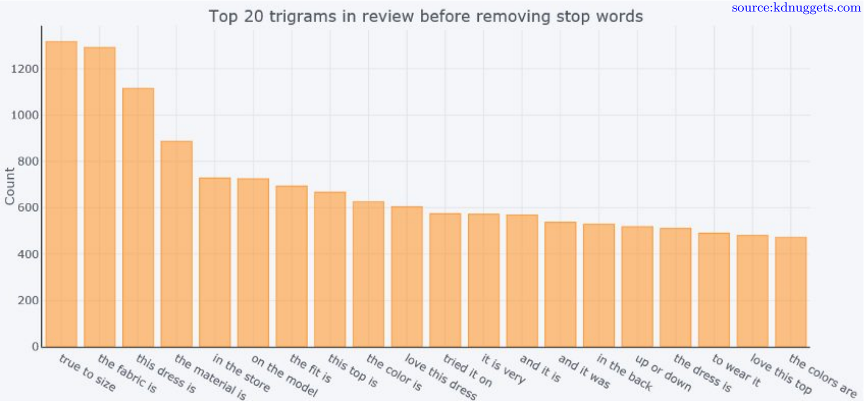
- Frequency of top bigrams **after** removing stopwords



source:kdnuggets.com

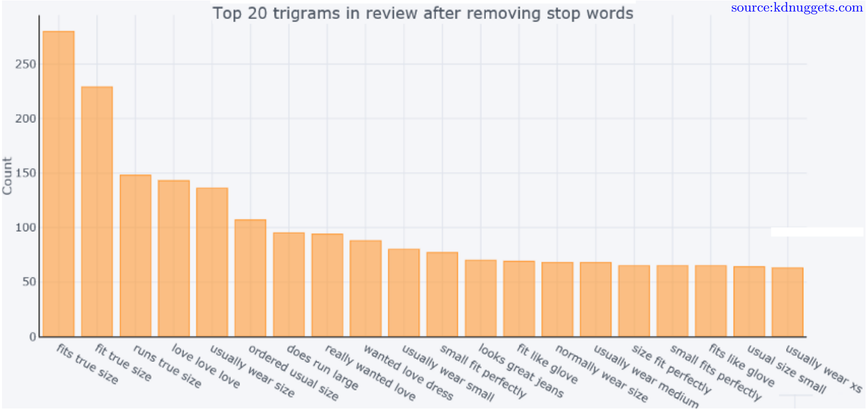
Text Exploratory Data Analysis

- Frequency of top trigrams **before** removing stopwords



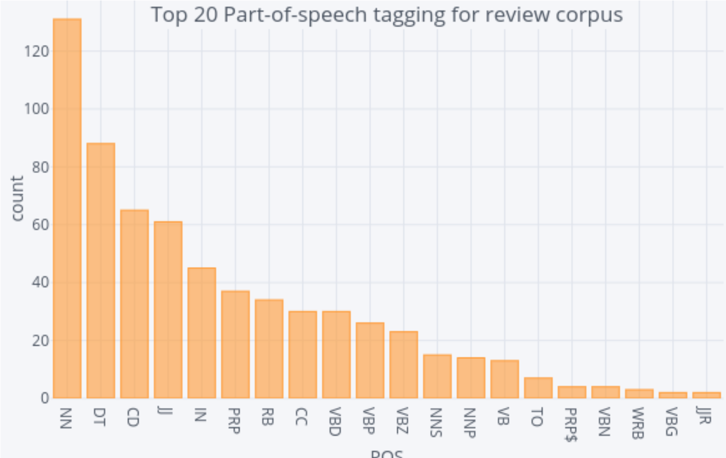
Text Exploratory Data Analysis

- Frequency of top trigrams **after** removing stopwords



Text Exploratory Data Analysis

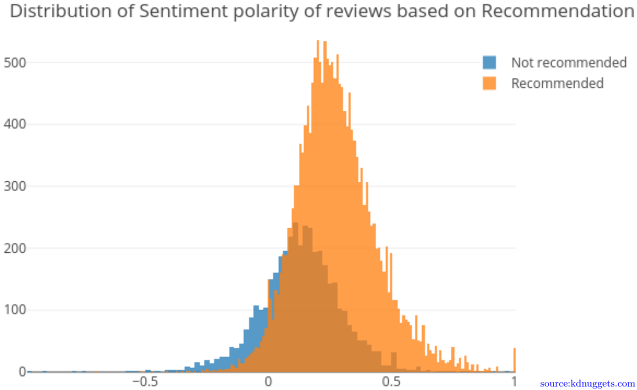
Part-Of-Speech Tagging (POS) is a process of assigning parts of speech to each word, such as noun, verb, adjective, etc



source:kdnuggets.com

Text Exploratory Data Analysis

- Visualizing class-wise polarity distribution
- Shows the threshold of sentiment score after which people tend to recommend clothing



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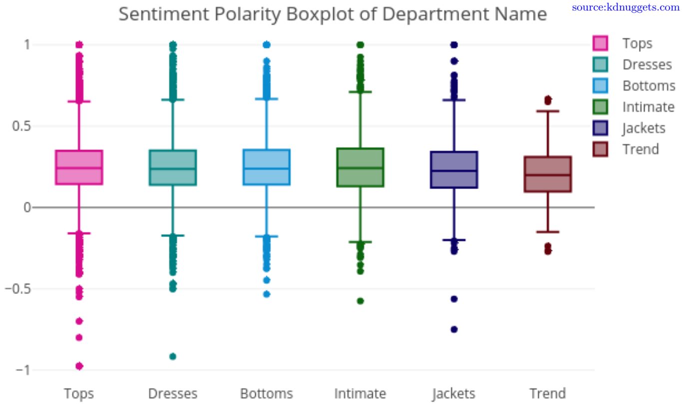
Text Exploratory Data Analysis

- Visualizing department wise sentiment polarity via boxplot
- Shows the statistical summary of the values



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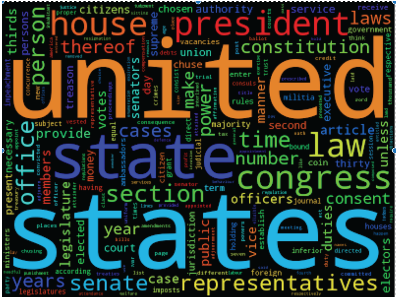
Text Exploratory Data Analysis

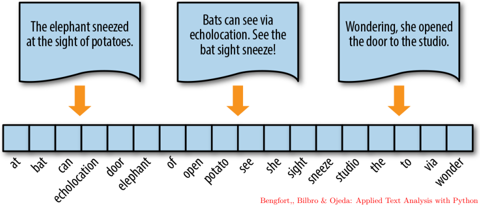
- An integral tool for text EDA is **Word Cloud**
- What could be said about the texts by looking at below examples?



Vector Space Models

Vector Space Models

- Algorithms cannot work with raw texts directly
- Calculate similarity/difference between two documents?
- Convert texts to vectors. Vector Space Modeling

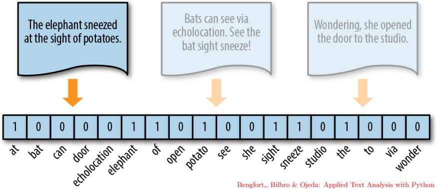


Bengfort,, Bilbro & Ojeda: Applied Text Analysis with Python

- Extract features from texts to reflect linguistic properties of the text
- Popular feature extraction methods (VSM variations) are
  - Set-of-Words: Binary word occurrences
  - Bag-of-Words: Word occurrences
  - TF-IDF
  - Word embedding

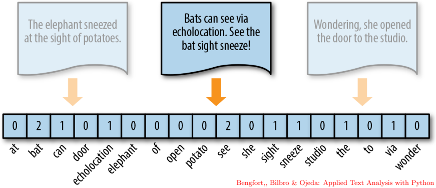
Set and Bag of Words Models

- Text represented as a set or a bag (multiset) of words it contains
- Disregard grammar and word order
- Binary Word Occurrences (Set of Words)



Bengfort,, Bilbro & Ojeda: Applied Text Analysis with Python

- Word Occurrences (aka Term Frequency) (Bag of Words)
- Bag-of-Words model is Set-of-Words but it accounts for frequencies



Bengfort,, Bilbro & Ojeda: Applied Text Analysis with Python

The Set-of-Words Model

Set-of-Words: Documents represented by vectors $\in \{0,1\}^{|\Sigma|}$

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
ANTHONY	1	1	0	0	0	1	
BRUTUS	1	1	0	1	0	0	
CAESAR	1	1	0	1	1	1	
CALPURNIA	0	1	0	0	0	0	
CLEOPATRA	1	0	0	0	0	0	
MERCY	1	0	1	1	1	1	
WORSER	1	0	1	1	1	0	
...							

The Bag of words Model

Bag-of-Words: Documents represented by term-frequency vectors $\in \mathbb{N}^{|\Sigma|}$

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
ANTHONY	157	73	0	0	0	1	
BRUTUS	4	157	0	2	0	0	
CAESAR	232	227	0	2	1	0	
CALPURNIA	0	10	0	0	0	0	
CLEOPATRA	57	0	0	0	0	0	
MERCY	2	0	3	8	5	8	
WORSER	2	0	1	1	1	5	
...							

Bag of Words

Issues with Sets and Bag of Words

- Set representation has associated high computational complexity
- Dimensionality blow up, $|\Sigma|$ could be very large
- (SoW) treats mere appearance of words as feature of document (Word appearing 1000 times versus one appearing once only)

TF-IDF is more refined model to select features to represent texts

- Key idea is to find special words characterizing the document
- Reflect how significant a word is to a "document" in a "collection"
- **Frequency:** Most frequent words implies most significant in doc
- Actually exactly the opposite is true
- Most frequent words ("the", "are", "and") help English structure and build ideas but not significant in characterizing documents
- **Rarity:** Indicator of topics are rare words
- rare words overall but concentrated in a few docs "batsman", "prime-minister"
- ball, bat, pitch, catch, run $\implies$ cricket related doc
- An indicator word is likely to be repeated if it appear once

TF-IDF

- TF-IDF value increases proportionally to the number of times a word appears in a document
- Offset by the number of documents in corpus containing that word
- Best known weighting scheme in IR. Value for a term increases with
  - Number of occurrences within a document
  - Rarity of the term in collection
- Helps to adjust for the fact that some words appear more frequently in general (frequent words are less meaningful than the rare ones)
- Involve two characteristics of words (terms: bigram, trigram)
  - Term frequency
  - Inverse document frequency

TF-IDF: Term Frequency

Documents: $D_1, \ldots D_N$. Terms (Σ): $t_1, \ldots, t_m$

- **Frequency, f_{ij}:** frequency of term t_i in document D_j
- Find a parameter to measure importance of t_i to D_j
- f_{ij} is not good, (very high for stop words in all documents)
- It is also possible that large docs D_j (books) have larger f_{ij}, than $f_{ij'}$ of short document $D_{j'}$ even if t_i is more important for $D_{j'}$ than D_j
- Recall normalization and scaling
- **Term Frequency:** $\text{TF}_{ij} := \dfrac{f_{ij}}{max_i f_{ij}}$
- Most frequent term t_i in D_j gets $\text{TF}_{ij} = 1$ others are < 1

TF-IDF: Inverse Document Frequency

Documents: $D_1, \dots D_N$. Terms (Σ): $t_1, \dots, t_m$

- Term frequency considers all t_i equally important
- Stop words appear frequently but have little importance
- Need to weigh down the frequent terms while scale up the rare ones
- Some terms are rare but appear in many documents a few times
- Weigh TF_{ij} (inversely) by the term's overall popularity in collection
- Suppose the term t_i appears in n_i out of N documents. Then
- **Inverse Document Frequency:** $\text{IDF}_i := \log\left(\frac{N}{n_i + 1}\right)$
- $+1$ in denominator avoids dividing by 0 if t_i doesn't appear in any doc

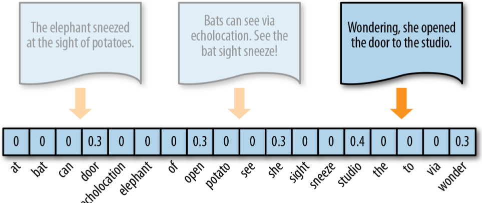
TF-IDF: Term frequency-inverse document frequency

Documents: $D_1, \ldots D_N$.   Terms (Σ): $t_1, \ldots, t_m$

- Finally, weight or importance of a term t_i in document D_j is given as

$$\text{TF-IDF}(i,j) = \text{TF}_{ij} \times \text{IDF}_i$$

- Check the extreme cases
- If t_i appears in all the documents, then $\text{TF-IDF}(i,j) = 0$ in all D_j
- Many stop words would get score close to 0
- A term frequently appearing in some docs gets higher score there



Bengfort,, Bilbro & Ojeda: Applied Text Analysis with Python

TF-IDF: Example

- D_1: "The car is driven on the road"
- D_2: "The truck is driven on the highway"

Word	TF		IDF	TF*IDF	
	A	B		A	B
The	1/7	1/7	log(2/2) = 0	0	0
Car	1/7	0	log(2/1) = 0.3	0.043	0
Truck	0	1/7	log(2/1) = 0.3	0	0.043
Is	1/7	1/7	log(2/2) = 0	0	0
Driven	1/7	1/7	log(2/2) = 0	0	0
On	1/7	1/7	log(2/2) = 0	0	0
The	1/7	1/7	log(2/2) = 0	0	0
Road	1/7	0	log(2/1) = 0.3	0.043	0
Highway	0	1/7	log(2/1) = 0.3	0	0.043

- Common words score is zero (not significant)
- Score of "car", "truck", "road", and "highway" are non-zero (significant words)

The TF-IDF Model

Each document is represented by a real vector of TF-IDF weights $\in \mathbb{R}^{|\Sigma|}$

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
ANTHONY	5.25	3.18	0.0	0.0	0.0	0.35	
BRUTUS	1.21	6.10	0.0	1.0	0.0	0.0	
CAESAR	8.59	2.54	0.0	1.51	0.25	0.0	
CALPURNIA	0.0	1.54	0.0	0.0	0.0	0.0	
CLEOPATRA	2.85	0.0	0.0	0.0	0.0	0.0	
MERCY	1.51	0.0	1.90	0.12	5.25	0.88	
WORSER	1.37	0.0	0.11	4.15	0.25	1.95	
...							

Vector Space Models

- *"worst acting, worst plot, worst movie ever"*
- *"best acting, best movie ever"*
- Set of Words

Row No.	acting	best	ever	movie	plot	worst
1	1	0	1	1	1	1
2	1	1	1	1	0	0

- Bag of Words

Row No.	acting	best	ever	movie	plot	worst
1	1	0	1	1	1	3
2	1	2	1	1	0	0

- TF–IDF

Row No.	acting	best	ever	movie	plot	worst
1	0	0	0	0	0.316	0.949
2	0	1	0	0	0	0

Vector Space Models

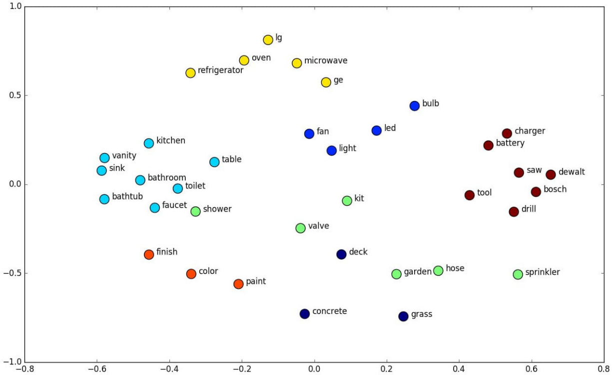
Problems with previous 3 VSM models

- Dimensionality blow up, $|\Sigma|$ could be very large
- None preserve words order, which carries contextual information
- Following two documents produce identical vectors (in all 3 models), although the context and meaning is very different
  - *Mary is faster than John*
  - *John is faster than Mary*
- They ignore synonyms ("old bike" vs "used bike") and homonyms
- *n*-gram model of vocabulary takes care of context to some extent

Solution: Word embedding

Vector Space Models: Word embedding

- Represent each word with n dimensional **dense** vector ▷ WORD2VEC
- Words appearing in similar context mapped to close-by points in $\mathbb{R}^n$
- Neural networks are used to learn these mappings ▷ See SVD



Vector Space Models: Document embedding

- Can be extended to learn document level embeddings
- Following is a 2-D representation of n-D document embeddings. (Can convert n-D vectors to 2-D vectors by tSNE or PCA)