Text Mining

Quite different from previous data mining tasks where variables or features are numeric, categorical and well-defined. Text mining can be hard, but also exciting and extremely useful

Sample applications

- Spam filtering
- Natural Language Processing,
- Sentiment Analysis
- Basis for chat bot
- Law (previous case studies)
- Finance (market sentiments)
- Fraud and Deception detection

Numerous Data Sources :

- Tweets
- Blogs
- Books
- News Feeds

Data Mining versus Text Mining

- Both seek for novel and useful patterns
  - Both are semi-automated processes
- Difference is the nature of the data:
  - Data Mining works on structured data stored in databases
  - Text Mining works on unstructured data in Word documents, PDF files, XML files, etc
- Text mining – first, impose structure to the data, then mine the structured data

Text Mining Fundamental Concepts

- Text mining Objective
  - A semi-automated process of extracting knowledge from unstructured data sources i.e. knowledge discovery in textual databases
- Structuring a collection of text
  - Traditional approach: bag-of-words
  - New approach: natural language processing for understanding nuances of spoken words
- Sentiment Analysis
  - A technique used to detect favorable and unfavorable opinions toward specific products and services

Text Mining Process – three steps

Establish the Corpus of Text:

Gather documents, clean, prepare for analysis

Structure using Term Document Matrix (TDM):

Select a bag of words, compute frequencies of occurrence

Mine TDM for Patterns

-Apply data mining tools like classification and cluster analysis

Text Mining Process

Step 1: Establish the corpus (corpus defined on slide 10)

- Collect all relevant unstructured data
  e.g., textual documents, XML files, emails, Web pages, short notes, voice recordings…
- Digitize, standardize the collection
  e.g., all in ASCII text files
- Place the collection in a common place
  e.g., in a flat file, or in a directory as separate files

Text Mining Process

Step 2: Create the Term–by–Document Matrix

	Term Document Matrix				
Document / Terms	investment	Profit	happy	Success	…
Doc 1	10	4	3	4	
Doc 2	7	2	2		
Doc 3			2	6	
Doc 4	1	5	3		
Doc 5		6		2	
Doc 6	4		2		
…					

Text Mining Process

Step 2: Create the Term–by–Document Matrix (TDM), cont.

- Should all terms be included?
  - Stop words, include words
  - Synonyms, homonyms
  - Stemming
- What is the best representation of the indices (values in cells)?
  - Row counts; binary frequencies; log frequencies;
  - Inverse document frequency

stop words = like, a, the (check slide 10)

= words that from the same root (give, gave, given) should be counted as same word (check slide 10)

Text Mining Process

Step 2: Create the Term–by–Document Matrix (TDM), cont.

- TDM is a sparse matrix. How can we reduce the dimensionality of the TDM? **Ways to Reduce Dimensionality:**
  - Manual - a domain expert goes through it
  - Eliminate terms with very few occurrences in very few documents
  - Transform the matrix using singular value decomposition (SVD)
  - SVD is similar to principle component analysis
  - Phrase-Mining and Term-Mining

If we have 30,000 unique words we would have 30,000. HUGE matrix (so we want to reduce the dimensionality)

PCA (a dimensionality-reduction method that is often used to reduce the dimensionality of large data sets) is a technique for dimension reduction.
EX: 100 variables in a dataset, PCA to reduce the dataset into only 10 variables

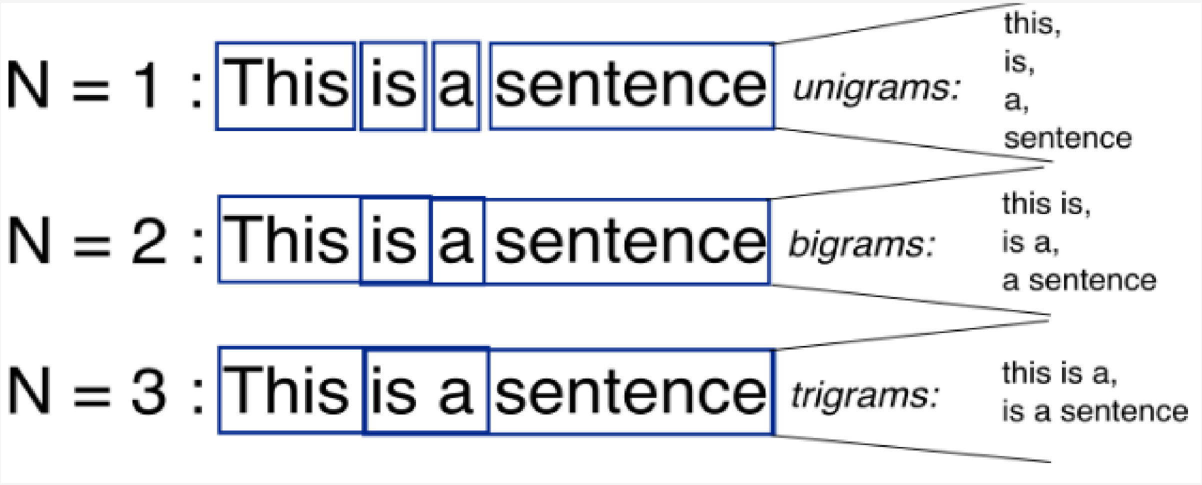
Text Mining Process

Step 3: Extract patterns/knowledge

- Classification (text categorization)
- Clustering (natural groupings of text)
  - Improve search recall & precision
  - Scatter/gather
  - Query-specific clustering
- Association rules among the documents
- Trend Analysis

Now, let’s be more specific on the terminology

- Document: the unit that contains the text (Books, individual tweets, one emails)
- Corpus: a collection of documents (books in a library, tweets feeds, emails received in a company)
- Stop words: relatively useless words in text mining (a, an, the, she, he, why, ….)
- Tokenizer: function to split the text into individual words
- Stemming / Lemmatization: utility to group similar words (e.g wait, waiting, waited into wait)
- Bag of words: a bag of words
- N-grams: instead of consider a single word, it may be more meaningful to consider combination of words.



EX: “is a” —> this is a bi-gram (2 word combo)
“this is a” —> this is a tri-gram (3 word combo)

Terminology cont'd (Term Frequency (TF), Inverse Document Frequency (IDF))

Imagine you are a librarian to find the most relevant book from a search query "Book for Analytics newbie"

	Word Frequency								
Book Number	The	Big-Data	Analytics	Tree	newbie	book	for	Girl	honest
1	120	80	60	20	1	5	120	0	0
2	110	0	0	100	10	20	100	40	10
3	130	0	0	10	11	30	110	20	10
4	100	0	0	2	20	40	100	10	100
5	90	0	0	10	30	20	100	100	40

<u>Term Frequency</u> is just the frequency of a word in the document. The only thing is if a word X occurs in document A 1 time and in B 10 times, its generally not true that the word X is 10 times more relevant in B than in A. The difference is generally lesser as compared to the actual ratio. Hence we TF is defined as

TF = 1 + log(TF) if TF > 0
    = 0   if TF = 0

1 + log (# of words aka raw frequency)
EX: 1 + log (80) = 2.9

	TF								
Book Number	The	Big-Data	Analytics	Tree	newbie	book	for	Girl	honest
1	3.1	2.9	2.8	2.3	1.0	1.7	3.1	0.0	0.0
2	3.0	0.0	0.0	3.0	2.0	2.3	3.0	2.6	2.0
3	3.1	0.0	0.0	2.0	2.0	2.5	3.0	2.3	2.0
4	3.0	0.0	0.0	1.3	2.3	2.6	3.0	2.0	3.0
5	3.0	0.0	0.0	2.0	2.5	2.3	3.0	3.0	2.6

TF-IDF Matrix

EX:
N = 5 (aka 5 total documents)
DF = Big-Data = 1 (appears in 1 document)

Log (N / DF) = Log (5 / 1) = 0.70

- **Inverse Document Frequency (IDF)** is based on the principle that less frequent words are generally more informative.

  IDF = log (N / DF) where

  N = number of documents

  DF = number of documents that has the word

- **TF-IDF Matrix** is simply the multiplication of the TF and IDF

- Document 1 is the most relevant to a search query of "Book for Analytics newbie"

IDF	The	Big-Data	Analytics	Tree	newbie	book	for	Girl	honest
N	5	5	5	5	5	5	5	5	5
DF	5	1	1	5	5	5	5	4	4
N/DF	1	5	5	1	1	1	1	1.25	1.25
Log(N/DF)	0.00	0.70	0.70	0.00	0.00	0.00	0.00	0.10	0.10

	TF-IDF								
Book Numbe	The	Big-Data	Analytics	Tree	newbie	book	for	Girl	honest
1	0.0	2.0	1.9	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.2
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.2
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.3
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.3

Spam Mail Classification as NLP showcase

- **SMS Spam Collection Data Set from UCI**
  https://archive.ics.uci.edu/ml/datasets/SMS+Spam+Collection

- pip install nltk
- pip install wordcloud
- Pip install TextBlob

Text Mining

Learning by doing

Some online tutorials

https://www.analyticsvidhya.com/blog/2015/04/information-retrieval-system-explained/

https://www.analyticsvidhya.com/blog/2018/02/the-different-methods-deal-text-data-predictive-python/

https://medium.com/towards-artificial-intelligence/text-mining-in-python-steps-and-examples-78b3f8fd913b

https://towardsdatascience.com/spam-classifier-in-python-from-scratch-27a98ddd8e73

https://jakevdp.github.io/PythonDataScienceHandbook/05.05-naive-bayes.html