MODULE 05

Text Mining

Text mining is the art and science of discovering knowledge, insights and patterns from an organized collection of textual databases. Textual mining can help with frequency analysis of important terms, and their semantic relationships.

Text is an important part of the growing data in the world. Social media technologies have enabled users to become producers of text and images and other kinds of information. Text mining can be applied to large-scale social media data for gathering preferences, and measuring emotional sentiments. It can also be applied to societal, organizational and individual scales.

Text Mining Applications

Text mining is a useful tool in the hands of chief knowledge officers to extract knowledge relevant to an organization. Text mining can be used across industry sectors and application areas, including decision support, sentiment analysis, fraud detection, survey analysis, and many more.

1. Marketing: The voice of the customer can be captured in its native and raw format and then analyzed for customer preferences and complaints.

1. Social personas are a clustering technique to develop customer segments of interest. Consumer input from social media sources, such as reviews, blogs, and tweets, contain numerous leading indicators that can be used towards anticipating and predicting consumer behaviour.

2. A ‘listening platform’ is a text mining application, that in real time, gathers social media, blogs, and other textual feedback, and filters out the chatter to extract true consumer sentiment. The insights can lead to more effective product marketing and better customer service.

3. The customer call center conversations and records can be analyzed for patterns of customer complaints. Decision trees can organize this data to create decision choices that could help with product management activities and to become proactive in avoiding those complaints.

2. Business operations: Many aspects of business functioning can be accurately gauged from analyzing text./

1. Social network analysis and text mining can be applied to emails, blogs, social media and other data to measure the emotional states and the mood of employee populations. Sentiment analysis can reveal early signs of employee dissatisfaction which can then can be proactively managed.

2. Studying people as emotional investors and using text analysis of the social Internet to measure mass psychology can help in obtaining superior investment returns.

3. Legal: In legal applications, lawyers and paralegals can more easily search case histories and laws for relevant documents in a particular case to improve their chances of winning.

1. Text mining is also embedded in e-discovery platforms that help in minimizing risk in the process of sharing legally mandated documents.

2. Case histories, testimonies, and client meeting notes can reveal additional information, such as morbidities in a healthcare situation that can help better predict high-cost injuries and prevent costs.

4. Governance and Politics: Governments can be overturned based on a tweet originating from a self-immolating fruit-vendor in Tunisia.

1. Social network analysis and text mining of large-scale social media data can be used for measuring the emotional states and the mood of constituent populations. Micro-targeting constituents with specific messages gleaned from social media analysis can be a more efficient use of resources when fighting democratic elections.

2. In geopolitical security, internet chatter can be processed for realtime information and to connect the dots on any emerging threats.

3. In academic, research streams could be meta-analyzed for underlying research trends.

Text Mining Process

Text Mining is a rapidly evolving area of research. As the amount of social media and other text data grows, there is need for efficient abstraction and categorization of meaningful information from the text.

The first level of analysis is identifying frequent words. This creates a bag of important words. Texts – documents or smaller messages – can then be ranked on how they match to a particular bag-of-words. However, there are challenges with this approach. For example, the words may be spelled a little differently. Or there may be different words with similar meanings.

The next level is at the level of identifying meaningful phrases from words. Thus 'ice' and 'cream' will be two different key words that often come together. However, there is a more meaningful phrase by combining the two words into 'ice cream'. There might be similarly meaningful phrases like 'Apple Pie'.

The next higher level is that of Topics. Multiple phrases could be combined into Topic area. Thus the two phrases above could be put into a common basket, and this bucket could be called 'Desserts'. Text mining is a semi-automated process. Text data needs to be gathered, structured, and then mined, in a 3-step process (Figure 11.1)

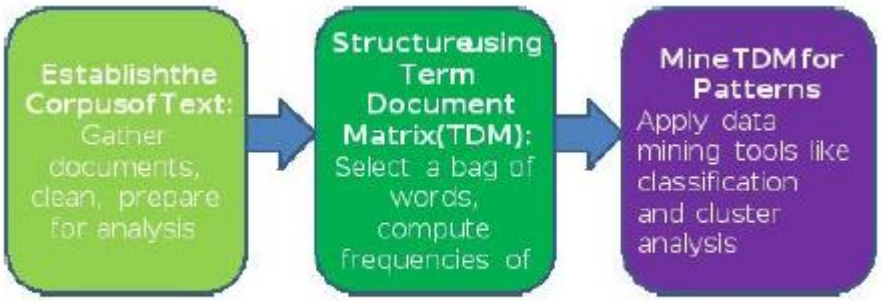


Figure 11.1: Text Mining Architecture

1. The text and documents are first gathered into a corpus, and organized.

2. The corpus is then analyzed for structure. The result is a matrix mapping important terms to source documents.
3. The structured data is then analyzed for word structures, sequences, and frequency.

Term Document Matrix

This is the heart of the structuring process. Free flowing text can be transformed into numeric data in a TDM, which can then be mined using regular data mining techniques.

1. There are several efficient techniques for identifying key terms from a text. There are less efficient techniques available for creating topics out of them. For the purpose of this discussion, one could call key words, phrases or topics as a term of interest. This approach measures the frequencies of select important terms occurring in each document. This creates a t x d Term–by–Document Matrix (TDM) where t is the number of terms and d is the number of documents (Table 11.1).
2. Creating a TDM requires making choices of which terms to include. The terms chosen should reflect the stated purpose of the text mining exercise. The list of terms should be as extensive as needed, but should not include unnecessary stuff that will serve to confuse the analysis, or slow the computation.

	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		
…					

Table 11.1: Term-Document Matrix

Here are some considerations in creating a TDM.

1. A large collection of documents mapped to a large bag of words will likely lead to a very sparse matrix if they have few common words. Reducing dimensionality of data will help improve the speed of analysis and meaningfulness of the results. Synonyms, or terms will similar meaning, should be combined and should be counted together, as a common term. This would help reduce the number of distinct terms of words or ‘tokens’.

2. Data should be cleaned for spelling errors. Common spelling errors should be ignored and the terms should be combined. Uppercaselowercase terms should also be combined.

3. When many variants of the same term are used, just the stem of the word would be used to reduce the number of terms. For instance, terms like customer order, ordering, order data, should be combined into a single token word, called ‘Order’.

4. On the other side, homonyms (terms with the same spelling but different meanings) should be counted separately. This would enhance the quality of analysis. For example, the term

order can mean a customer order, or the ranking of certain choices. These two should be treated separately. "The boss ordered that the customer orders data analysis be presented in chronological order'. This statement shows three different meanings for the word 'order'. Thus, there will be a need for a manual review of the TD matrix.

5. Terms with very few occurrences in very few documents should be eliminated from the matrix. This would help increase the density of the matrix and the quality of analysis.

6. The measures in each cell of the matrix could be one of several possibilities. It could be a simple count of the number of occurrences of each term in a document. It could also be the log of that number. It could be the fraction number computed by dividing the frequency count by the total number of words in the document. Or there may be binary values in the matrix to represent whether a term is mentioned or not. The choice of value in the cells will depend upon the purpose of the text analysis. At the end of this analysis and cleansing, a well-formed, densely populated, rectangular, TDM will be ready for analysis. The TDM could be mined using all the available data mining techniques.

Mining the TDM

The TDM can be mined to extract patterns/knowledge. A variety of techniques could be applied to the TDM to extract new knowledge. Predictors of desirable terms could be discovered through predictive techniques, such as regression analysis. Suppose the word profit is a desirable word in a document. The number of occurrences of the word profit in a document could be regressed against many other terms in the TDM. The relative strengths of the coefficients of various predictor variables would show the relative impact of those terms on creating a profit discussion. Predicting the chances of a document being liked is another form of analysis.

For example, important speeches made by the CEO or the CFO to investors could be evaluated for quality. If the classification of those documents (such as good or poor speeches) was available, then the terms of TDM could be used to predict the speech class. A decision tree could be constructed that makes a simple tree with a few decision points that predicts the success of a speech 80 percent of the time. This tree could be trained with more data to become better over time.

Clustering techniques can help categorize documents by common profile. For example, documents containing the words investment and profit more often could be bundled together. Similarly, documents containing the words, customer orders and marketing, more often could be bundled together. Thus, a few strongly demarcated bundles could capture the essence of the entire TDM. These bundles could thus help with further processing, such as handing over select documents to others for legal discovery. Association rule analysis could show relationships of coexistence. Thus, one could say that the words, tasty and sweet, occur together often (say 5 percent of the time); and further, when these two words are present, 70 percent of the time, the word happy, is also present in the document.

Comparing Text Mining and Data Mining

Text Mining is a form of data mining. There are many common elements between Text and Data Mining. However, there are some key differences (Table 11.2). The key difference is that text mining requires conversion of text data into frequency data, before data mining techniques can be applied.

Dimension	Text Mining	Data Mining
Nature of data	Unstructured data: Words, phrases, sentences	Numbers; alphabetical and logical values
Language used	Many languages and dialects used in the world; many languages are extinct, new documents are discovered	Similar numerical systems across the world
Clarity and precision	Sentences can be ambiguous; sentiment may contradict the words	Numbers are precise.
Consistency	Different parts of the text can contradict each other	Different parts of data can be inconsistent, thus, requiring statistical significance analysis
Sentiment	Text may present a clear and consistent or mixed sentiment, across a continuum. Spoken words adds further sentiment	Not applicable
Quality	Spelling errors. Differing values of proper nouns such as names. Varying quality of language translation	Issues with missing values, outliers, etc
Nature of	Keyword based search; co-existence of themes; Sentiment	A full wide range of statistical and machine learning analysis for
	mining;	relationships and differences

Table 11.2: Comparing Text Mining and Data Mining

Text Mining Best Practices

Many of the best practices that apply to the use of data mining techniques will also apply to text mining.

1. The first and most important practice is to ask the right question. A good question is one which gives an answer and would lead to large payoffs for the organization. The purpose and the key question will define how and at what levels of granularity the TDM would be made. For example, TDM defined for simpler searches would be different from those used for complex semantic analysis or network analysis.

2. A second important practice is to be creative and open in proposing imaginative hypotheses for the solution. Thinking outside the box is important, both in the quality of the proposed solution as well as in finding the high quality data sets required to test the hypothesized solution. For example, a TDM of consumer sentiment data should be combined with customer order data in order to develop a comprehensive view of customer behavior. It's important to assemble a team that has a healthy mix of technical and business skills.

3. Another important element is to pursue the problem iteratively. Too much data can overwhelm the infrastructure and also befuddle the mind. It is better to divide and conquer the problem with a simpler TDM, with fewer terms and fewer documents and data sources. Expand as needed, in an iterative sequence of steps. In the future, add new terms to help improve predictive accuracy.

4. A variety of data mining tools should be used to test the relationships in the TDM. Different decision tree algorithms could be run alongside cluster analysis and other techniques. Triangulating the findings with multiple techniques, and many what-if scenarios, helps build confidence in the solution. Test the solution in many ways before committing to deploy it.

Web Mining

Web mining is the art and science of discovering patterns and insights from the World-wide web so as to improve it. The world-wide web is at the heart of the digital revolution. More data is posted on the web every day than was there on the whole web just 20 years ago. Billions of users are using it every day for a variety of purposes. The web is used for electronic commerce, business communication, and many other applications. Web mining analyzes data from the web and helps find insights that could optimize the web content and

improve the user experience. Data for web mining is collected via Web crawlers, web logs, and other means.

Here are some characteristics of optimized websites:

1. Appearance: Aesthetic design. Well-formatted content, easy to scan and navigate. Good color contrasts.

2. Content: Well planned information architecture with useful content. Fresh content. Search-engine optimized. Links to other good sites.

3. Functionality: Accessible to all authorized users. Fast loading times. Usable forms. Mobile enabled. This type of content and its structure is of interest to ensure the web is easy to use.

The analysis of web usage provides feedback on the web content, and also the consumer's browsing habits. This data can be of immense use for commercial advertising, and even for social engineering.

The web could be analyzed for its structure as well as content. The usage pattern of web pages could also be analyzed. Depending upon objectives, web mining can be divided into three different types: Web usage mining, Web content mining and Web structure mining (Figure 12.1).

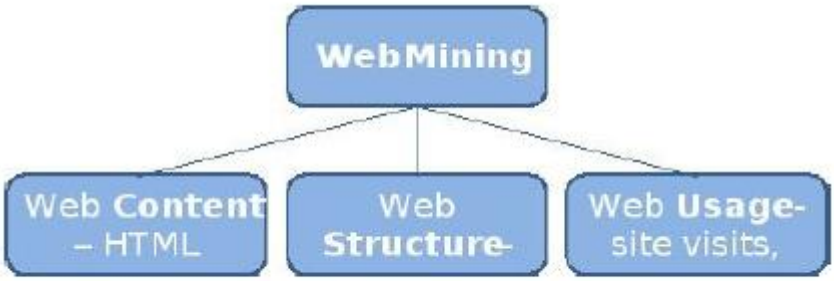


Figure: 12.1 Web Mining structure

Web content mining

A website is designed in the form of pages with a distinct URL (universal resource locator). A large website may contain thousands of pages. These pages and their content is managed using specialized software systems called Content Management Systems. Every page can

have text, graphics, audio, video, forms, applications, and more kinds of content including user generated content.

The websites keep a record of all requests received for its page/URLs, including the requester information using 'cookies'. The log of these requests could be analyzed to gauge the popularity of those pages among different segments of the population. The text and application content on the pages could be analyzed for its usage by visit counts. The pages on a website themselves could be analyzed for quality of content that attracts most users.

Thus the unwanted or unpopular pages could be weeded out, or they can be transformed with different content and style. Similarly, more resources could be assigned to keep the more popular pages more fresh and inviting.

Web structure mining

The Web works through a system of hyperlinks using the hypertext protocol (http). Any page can create a hyperlink to any other page, it can be linked to by another page. The intertwined or self-referral nature of web lends itself to some unique network analytical algorithms. The structure of Web pages could also be analyzed to examine the pattern of hyperlinks among pages. There are two basic strategic models for successful websites: Hubs and Authorities.

1. Hubs: These are pages with a large number of interesting links. They serve as a hub, or a gathering point, where people visit to access a variety of information. Media sites like Yahoo.com, or government sites would serve that purpose. More focused sites like Traveladvisor.com and yelp.com could aspire to becoming hubs for new emerging areas.

2. Authorities: Ultimately, people would gravitate towards pages that provide the most complete and authoritative information on a particular subject. This could be factual information, news, advice, user reviews etc. These websites would have the most number of inbound links from other websites. Thus Mayoclinic.com would serve as an authoritative page for expert medical opinion. NYtimes.com would serve as an authoritative page for daily news.

Web usage mining

As a user clicks anywhere on a webpage or application, the action is recorded by many entities in many locations. The browser at the client machine will record the click, and the web server providing the content would also make a record of the pages served and the user activity on those pages. The entities between the client and the server, such as the router, proxy server, or ad server, too would record that click.

The goal of web usage mining is to extract useful information and patterns from data generated through Web page visits and transactions. The activity data comes from data stored in server access logs, referrer logs, agent logs, and client-side cookies. The user characteristics and usage profiles are also gathered directly, or indirectly, through syndicated data. Further, metadata, such as page attributes, content attributes, and usage data are also gathered. The web content could be analyzed at multiple levels (Figure 12.2).

1. The server side analysis would show the relative popularity of the web pages accessed. Those websites could be hubs and authorities.

2. The client side analysis could focus on the usage pattern or the actual content consumed and created by users.

1. Usage pattern could be analyzed using ‘clickstream’ analysis, i.e. analyzing web activity for patterns of sequence of clicks, and the location and duration of visits on websites. Clickstream analysis can be useful for web activity analysis, software testing, market research, and analyzing employee productivity.

2. Textual information accessed on the pages retrieved by users could be analyzed using text mining techniques. The text would be gathered and structured using the bag-of-words technique to build a Term-document matrix. This matrix could then be mined using cluster analysis and association rules for patterns such as popular topics, user segmentation, and sentiment analysis.

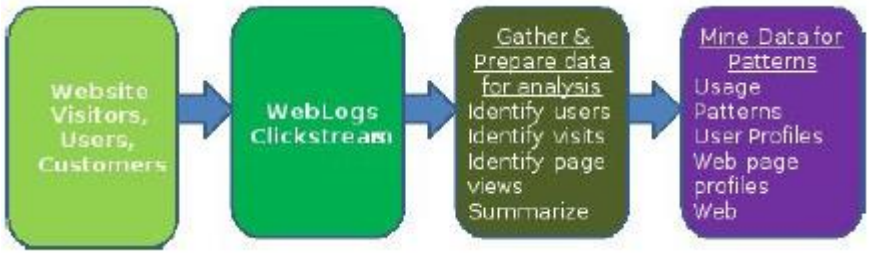


Figure: 12.2 Web Usage Mining architecture

Web usage mining has many business applications. It can help predict user behavior based on previously learned rules and users' profiles, and can help determine lifetime value of clients. It can also help design cross-marketing strategies across products, by observing association rules among the pages on the website. Web usage can help evaluate promotional campaigns and see if the users were attracted to the website and used the pages relevant to the campaign. Web usage mining could be used to present dynamic information to users based on their interests and profiles. This includes targeted online ads and coupons at user groups based on user access patterns.

Web Mining Algorithms

Hyperlink-Induced Topic Search (HITS) is a link analysis algorithm that rates web pages as being hubs or authorities. Many other HITS-based algorithms have also been published. The most famous and powerful of these algorithms is the PageRank algorithm. Invented by Google co-founder Larry Page, this algorithm is used by Google to organize the results of its search function. This algorithm helps determine the relative importance of any particular web page by counting the number and quality of links to a page. The websites with more number of links, and/or more links from higher-quality websites, will be ranked higher. It works in a similar way as determining the status of a person in a society of people. Those with relations to more people and/or relations to people of higher status will be accorded a higher status.

PageRank is the algorithm that helps determine the order of pages listed upon a Google Search query. The original Page Rank algorithm formuation has been updated in many ways and the latest algorithm is kept a secret so other websites cannot take advantage of the algorithm and manipulate their website according to it. However, there are many standard elements that remain unchanged. These elements lead to the principles for a good website. This process is also called Search Engine Optimization (SEO).

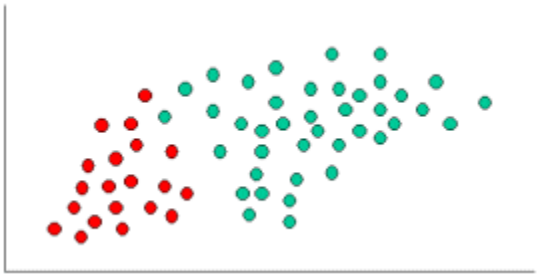
Naïve Bayes Analysis

NB algorithm is easy to understand and works fast. It also performs well in multi class prediction, such as when the target class has multiple options beyond binary yes/ no classification. NB can perform well even in case of categorical input variables compared to numerical variable(s).

compute prior probability. Suppose the data gathered for the last one year showed that during that period there were 2500 customers for R, and 1500 customers for M. Thus the default (or prior) probability for the next customer to be for R is 2500/ 4000 or 5/ 8.

Naive Bayes Classifier Introductory Overview

The Naive Bayes Classifier technique is based on the so-called Bayesian theorem and is particularly suited when the dimensionality of the inputs is high. Despite its simplicity, Naive Bayes can often outperform more sophisticated classification methods.



To demonstrate the concept of Naïve Bayes Classification, consider the example displayed in the illustration above. As indicated, the objects can be classified as either GREEN or RED. Our task is to classify new cases as they arrive, i.e., decide to which class label they belong, based on the currently exiting objects.

Since there are twice as many GREEN objects as RED, it is reasonable to believe that a new case (which hasn't been observed yet) is twice as likely to have membership GREEN rather than RED. In the Bayesian analysis, this belief is known as the prior probability. Prior probabilities are based on previous experience, in this case the percentage of GREEN and RED objects, and often used to predict outcomes before they actually happen.

Thus, we can write:

$$Prior\ probability\ for\ GREEN \propto \frac{Number\ of\ GREEN\ objects}{Total\ number\ of\ objects}$$

$$Prior\ probability\ for\ RED \propto \frac{Number\ of\ RED\ objects}{Total\ number\ of\ objects}$$

Since there is a total of 60 objects, 40 of which are GREEN and 20 RED, our prior probabilities for class membership are:

$$Prior\ probability\ for\ GREEN \propto \frac{40}{60}$$

$$Prior\ probability\ for\ RED \propto \frac{20}{60}$$

Probability

Probability is the likelihood or chance of an event occurring. Probability = the number of ways of achieving success. the total number of possible outcomes.

In math, probability is the likelihood that an event will happen. It is the ratio of the number of ways an event can occur to the number of possible outcomes.Probability is expressed as a fraction or decimal from 0 to 1.

Meaning and Importance Probability is the study of random events. It is used in analyzing games of chance, genetics, weather prediction, and a myriad of other everyday events. Statistics is the mathematics we use to collect, organize , and interpret numerical data.

For example, theprobability of flipping a coin and it being heads is ½, because there is 1 way of getting a head and the total number of possible outcomes is 2 (a head or tail). ... The probability of something which is certain to happen is 1.

What are the rules of probability?

Addition Rule 1: When two events, A and B, are mutually exclusive, the probability that A or B will occur is the sum of the probability of each event. Addition Rule 2: When two events, A and B, are non-mutually exclusive, there is some overlap between these events.

It is a classification technique based on Bayes' Theorem with an assumption of independence among predictors. In simple terms, a Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature.

Social Network Analysis

There are two major levels of social network analysis: discovering sub- networks within the network, and ranking the nodes to find more important nodes or hubs.

Computing the relative influence of each node is done on the basis of an input- output matrix of flows of influence among the nodes.