Comparing SVM and Naïve Bayes Classifiers for Online Reviews Based on Aspect-Based Sentiment Analysis

Pimpa Cheewaprakobkit
Faculty of Business Administration
Asia-Pacific International University
E-mail: pimpa@apiu.edu

ABSTRACT

Nowadays, opinions on products and services on social networking sites are increasing rapidly and continuously. These web texts are an incredibly rich knowledge base, and the marketing industry is beginning to recognize the value of web texts as a source of information about their customers. Consequently, it would be very helpful for businesses to know customer needs while responding to them efficiently and effectively in a timely manner. However there is a problem, what is the effective method for analyze these data to reflect the customer's opinion? Therefore, this study proposes a text mining technique to extract meaningful information from an unstructured text. To do this, initially 1,285 customers review were collected from yelp.com, twitter.com and tripadvisor.com, and the reviews were evaluated based on their degree of positivity or negativity with respect to the whole document by comparing the classifications through performances of Support Vector Machine (SVM) and Naïve Bayer algorithm approached. In this study, the results were validated with a 10-fold cross validation coefficient. Nevertheless, in this level of analysis, the results do not provide the necessary detailed information. To obtain more fine grained analysis, we used the Aspect-Based Sentiment Analysis, which requires deeper Natural Language Processing, while showing opinions in difference aspects (e.g. food, staff, value, drink, menu, dessert, cleanliness ambience, and location). The results showed that SVM with polynomial kernel is better than Naïve Bayer in term of Precision, Recall and Accuracy, with the percentage of 86.01, 74.89, and 80.42, respectively.

KEYWORDS: Sentiment Analysis, Aspect-Based Sentiment Analysis, Opinion Mining, Support Vector Machine, Naïve Bayer

Introduction

With the rapid expansion of e-commerce, there is a growing availability and popular source to acquire public opinions towards entities such as products, services, brands and events. These customer reviews, whether they be positive remarks or negative criticisms, have a significant influence on the image of those who have received such reviews. Therefore, businesses should keep track of their consumers' opinions and feedbacks regularly, as the above information could be used to improve the businesses performances and services. However, due to the vast number of social networking sites online, monitoring and analyzing can be complicated and information may not be as extensive. In addition, posts and entries on the Internet are written in lingo that is not the usual spoken language. With incorrect grammatical structured sentences that make analysis more difficult, Opinion Mining and Sentiment Analysis Techniques are means of analyzing the above information.

Opinion in sentiment analysis refers to analyzing feeling, emotion, or opinion of people expressed through social media. There are three main classification types, namely feature level, sentence level, and document level (Cardie, 2014). The feature level classification extracts, the important feature from the document and then classifies whether it is a positive or negative opinion. The sentence level classification considers classification of reviews at an individual sentence. The document level sentiment classification aims to classify document positively or negatively by considering the whole document. The Machines learning algorithms are applied to classify a document whether it expresses positive or negative opinion. Supervised classification algorithms have proved effectively and widely used in sentiment classification (Pang, Lee, & Vaithyanathan, 2002). In this task, there is also a concern to Aspect Based Sentiment Analysis (ABSA), where the goal is to identify the aspects of given target entities and the sentiment expressed towards each aspect. Datasets consisting of customer reviews with human-authored annotations identify the mentioned aspects of the target entities.

Purposes

The aim of this research is to compare the classifications performances of Support Vector Machine Algorithm and Naïve Bayer algorithms, as well as the analysis customer review based on the Syndicate Public Company Limited (S&P) as a case study using Aspect Based Sentiment Analysis (ABSA) technique. This is to show the opinions in difference aspects such as services, facilities, drinks, and food.

Benefit of Research

Opinion mining or sentiment analysis is a new research field at the present, and it plays an important role for researchers as well as businesses too. In business, opinion surveys have been used in advertisement and marketing. For example, Pang and Lee (2004) have analyzed customers' movies reviews through weblogs. The results showed that sentiment could be used to predict ticket sales of a movie. Tumasjan, Sprenger, Sandner, and Welpe (2010) used comments from Twitter to predict election results. These results were compared with the actual electoral votes, and showed a Mean Absolute Error (MAE) of only 1.65%. Mostafa (2013) applied text mining techniques to investigate consumer attitudes towards global brands and they reported that Twitter could be used as a reliable method in analyzing attitudes toward global brands. Therefore, in this study was collected data from Twitter, Yelp and Tripadvisor for analysis.

To extract meaningful information of customer's reviews and evaluate its positivity or negativity with respect to the whole document, the sentiment classification of reviews has been the focus of recent research. It has been attempted in different domains such as movie reviews, product reviews, and customer feedback reviews (Gamon, 2004). Much of the research up to this point has focused on training machine learning algorithms such as Support Vector Machine (SVM) to classify reviews. Kalaivani and Shunmuganathan (2013) applied Support Vector Machine, Naïve Bayer and K-Nearest Neighbors algorithm for sentiment classification using movie reviews. They used 3-fold cross validation and obtained accuracy of 81.45% by using a SVM classifier.

This study is comparing the classifications performances of Support Vector Machine and Naïve Bayer algorithm for finding the appropriate algorithm. Joachims (1998) tested the efficiency of the message classification model by comparing the classifications performances of Support Vector Machine and Naïve Bayer algorithm. He found that the Support Vector Machine algorithm was better than Naïve Bayer algorithm but Sukhum, Nitsuwat, and Haruechaiyasak (2011) proposed a classification of opinions from the facts of the news with Support Vector Machine and Naïve Bayer algorithm. The result showed that Naïve Bayer was better than the Support Vector Machine algorithm. Therefore, in this study we wanted to examine the classifications performances again. In this study we selected these two algorithms for several reasons. First, they are popular with data analysis, machine learning, and statisticians. Second, the Naïve Bayers and Support Vector Machine are generative and discriminative. Third, they are often applied to handle higher dimension data, for instance, text data (Shi & Liu, 2011).

To obtain more fine grained analysis, this study will use Aspect Based Sentiment Analysis which requires deeper Natural Language Processing to show opinion in difference aspects, such as food, staff, value, drink, menu, dessert, cleanliness ambience, and location. Schutze (1992) distributed vector representations and associated similar vectors with similar words and phrases.

These vectors provided useful information for the learning algorithms to achieve better performance in Natural Language Processing tasks. Most approaches to computing vector representations use the observation that similar words appear in similar contexts. Several ABSA methods have been proposed for various domains, like consumer electronics (Hu & Liu, 2004), restaurants (Ganu, Elhadad, & Marian, 2009) and movies (Thet, Na, & Khoo, 2010). The most common approaches (Carrdie, 2014) are to aggregate only synonyms or near synonyms, using WordNet (Liu, Hu, & Cheng, 2005), statistics from Corpora (Chen, Lin, & Wei, 2006) or semi-supervised learning (Zhai, Liu, Xu, & Jia, 2011), cluster the aspect terms using latent and topic models (Jo & Oh, 2011). Topic models do not perform better than other methods (Zhai et al., 2010) in aspect aggregation, and their clusters may overlap.

Research Process

Data Pre-processing: There are 4 main processes of Text pre-processing that are as the follows:

1) Tokenization: This is the process of splitting a text into individual words or sequences of words.

2) Steaming: This is the process of conflating the variant forms of a word into a common representation, the stem. For example, the words "presentation", "presented", and "presenting" could be all reduced to a common representation "present" (Kannan & Gurusamy, 2014).

3) Stop word removal: This is the process of filtering out tokens that contain non-letter characters such as numbers and punctuation, using a regular expression ([A-Za-z]*) and finally, tokens shorter than 3 characters will be discarded.

4) Case folding: This process consists of converting all the characters to the same kind of letter case, either upper case or lower case (Gupta & Lehal, 2009).

Classifications of Support Vector Machine and Naïve Bayer algorithm: After pre-processing step, we performed text representation. This is a process of rearranging and formatting text into the right sentence structure. A commonly used technique is called Vector Space Model (Nuntiyagul, 2006), in which reformatting text may be completed in different ways, such as Bag-of-Word, Term Frequency and Term Frequency Inverse Document Frequency (TF-IDF). This study used the TF-IDF method, which is the most effective and popular method (Salton & Buckley, 1988). The tool that was used in this paper was Rapid Miner program to compare the classifications performances of Support Vector Machine and Naïve Bayer algorithm. In step of Support Vector Machine method with polynomial kernel, this study validated results with 10-fold cross validation.

Aspect Based Sentiment Analysis: The next step was to use the Aspect Based Sentiment Analysis. The sentiment analysis required more than just positive or negative categorization. From a business point of view, sentiment analysis becomes more effective when considering a specific view. In this paper, the Aspect Based Sentiment Analysis (ABSA) technique was used to show opinions for difference aspects. The Correlation Matrix show the correlation coefficients between sets of variables by analyzing words which are most commonly used to express a certain sentiment (positive or negative) towards a certain aspect (e.g. food, staff, value, drink, menu, cleanliness, dessert, ambience, and location).

Confusion Matrix: A confusion matrix is a table used to describe the performances of a classifications model on a set of test data for which the true values are known.

Table 1 A Confusion Matrix

		Predicted Class	
		Positive	**Negative**
Actual Class	**Positive**	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

True positive and true negative are the observations that are correctly predicted and therefore shown in green color. We want to minimize false positives and false negatives so they are shown in red color.

True Positive (TP) - These are the correctly predicted positive values which means that the value of actual class is “yes”, and the value of predicted class is also “yes”.

True Negative (TN) - These are the correctly predicted negative values which means that the value of actual class is “no”, and value of predicted class is also “no”.

False positive and false negative, these values occur when your actual class contradicts with the predicted class.

False Positive (FP) – When actual class is “no” and predicted class is “yes”.

False Negative (FN) – When actual class is “yes” but predicted class is “no”.

Precision - Precision is the ratio of correctly predicted positive observations to the total predicted positive observations.

Recall - Recall is the ratio of correctly predicted positive values to the actual positive values.

Accuracy - Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations. These terms are define as follows:

$$P = \frac{TP}{TP+FP},\ R = \frac{TP}{TP+FN},$$

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN}$$

Population and Sample

In the experiment, 1,285 customer reviews about the Syndicate Public Company Limited was collected from crawl website and reviews for landmark, accommodation and restaurants such as yelp.com, twitter.com, and tripadvisor.com. Then the data was manually annotated to two levels: positive and negative.

Instruments

Machine Learning: Data scientists use many different kinds of machine learning algorithms to discover patterns in big data that lead to actionable insights. At a high level, these different algorithms can be classified into two groups based on the way they learn about data to make predictions: supervised and unsupervised learning. The Support vector machine and Naïve Bayer algorithms represent supervised machine learning which are powerful for classification and predictive modeling (Castle, 2017).

Support Vector Machine (SVM): Support Vector Machine are supervised learning models with associated learning algorithms that analyze data and recognize patterns. It is also used for classification and regression analysis. The basic SVM takes a set of input data as the training set. Then, for each given test input predicts which of two possible classes forms the input, making it a non-probabilistic binary linear classifier. A set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on (Vanjari & Thombre, 2015).

Naïve Bayes: The Naïve Bayes algorithm is a simple probabilistic classifier that calculates a set of probabilities by counting the frequency and combinations of values in a given data set. The algorithm uses Bayes theorem and assumes all attributes to be independent given the value of the class variable. This conditional independent assumption rarely holds true in real world applications, hence the characterization of the approach as Naïve. The algorithm tends to perform well and learns rapidly in various supervised classification problems (Dimitoglou, Adams, & Jim, 2012).

Aspect Based Sentiment Analysis: Classifying opinionated texts at a document level or at a sentence level is useful, but this type of classification does not provide necessary details needed for many applications. A positive opinionated document about a particular entity does not mean that the author has an entirely positive opinion about all the features of the entity. Likewise, a negative opinionated document does not mean that the author does not like every feature of the entity. In a typical opinionated text, the authors write both positive and negative opinions with respect to entities and their attributes. The majority of current approaches, however, attempt to identify the overall polarity of a document, sentence, paragraph or text, irrespective of the entities involved. To obtain the hidden details, an Aspect Based Sentiment Analysis (Hercig, Brychcin, Svoboda, Konkol, & Steinberger, 2016).

Aspect Based Sentiment Analysis aims to identify the aspects of entities being used in expressing sentiments. It is also used to determine the sentiment that is expressed by the author towards each aspect of the entity. Aspect Based Sentiment Analysis is critical in mining and summarizing opinions from any kinds of datasets. It consists of four subtasks (SemEval-2014 Task 4, 2017):

1) Aspect Term Extraction (ATE): Given a set of sentences with pre-identified entities (for example, restaurants), the task is to identify the aspect terms present in the sentence and return a list containing all the distinctive aspect terms. For example, "I liked the service and the staff, but not the food”⟶{service, staff, food}

2) Aspect Term Polarity (ATP): For a given set of aspect terms within a sentence, the task is to determine the polarity of each aspect term: positive, negative or neutral. For example, “I hated their breads, but their salads were great” ⟶ {breads: negative, salads: positive}

3) Aspect Category Detection (ACD): Given a pre-defined set of aspect categories, the task is to identify the aspect categories discussed in a given sentence. Aspect categories are typically coarser than the aspect terms of Subtask 1, and they do not necessarily occur as terms in the given sentence. In the analyzed domain of ‘restaurants’, the categories include food, staff, value, drink, menu, cleanliness, dessert, ambience and location as the following examples:

“The chicken was not fresh and lemon tea was horrible” ⟶ {food, drink}

“The waiters were not attentive, but the juice food was great” ⟶ {staff, food}

4) Aspect Category Polarity (ACP): Given a set of pre-identified aspect, the task is to determine the polarity (positive, negative or neutral) of each aspect category as the following examples:

“The chicken was not fresh and lemon tea was horrible” ⟶ {food: negative, drink: negative}

“The waiters were not attentive, but the food was great” ⟶ {staff: negative, food: positive}

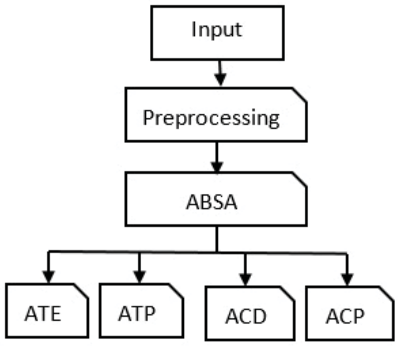

Figure 1: Aspect Based Sentiment Analysis Tasks

Data Analysis

The results are given in Table 2 and Table 3. They show that SVM, with a polynomial kernel and 10-fold cross validation, is better than Naïve Bayer. The Precision, Recall and Accuracy of SVM equal 86.01%, 74.89%, and 80.42%, respectively.

Table 2 The results of testing data with the SVM method

Accuracy: 80.42% +/- 2.53% (mikro: 80.42%)			
	True Positive	True Negative	Class Precision
Predict Positive	504	82	86.01%
Predict Negative	169	527	75.72%
Class Recall	74.89%	86.54%	

Table 3 The results of testing data with the Naïve Bayer method

Accuracy: 72.39% +/- 3.69% (mikro: 72.39%)			
	True Positive	True Negative	Class Precision
Predict Positive	400	81	83.16%
Predict Negative	273	528	65.92%
Class Recall	59.44%	86.70%	

Aspect Based Sentiment Analysis (ABSA)

The result of ABSA showed the opinions in different aspects. In this study, we will see which words are most commonly used to express a certain sentiment (positive or negative) towards a certain aspect (food, staff, value, drink, menu, cleanliness, dessert, ambience, and location). The results are given in Figure 2.

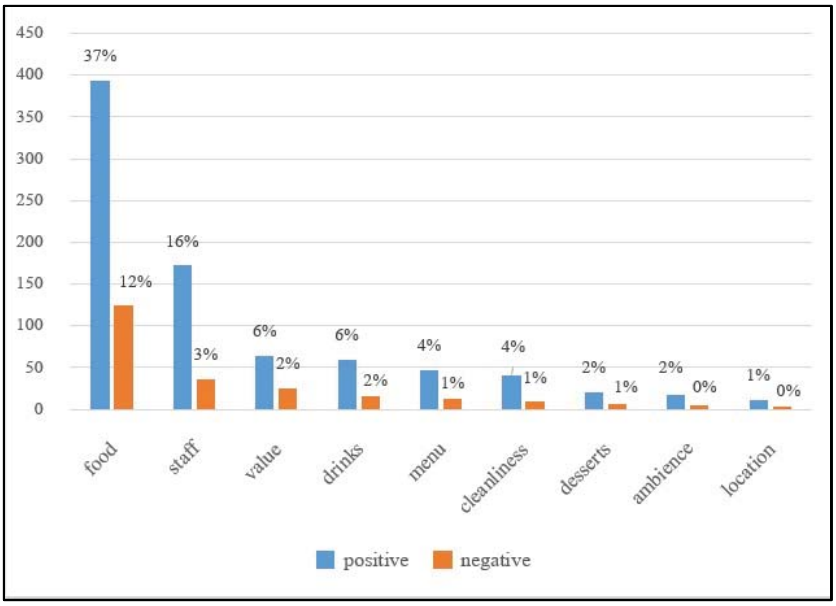

Figure 2: The chart of aspects mentioned

Figure 2 indicates that most of the customer opinions mentioned food in a positive sentiment, which is 37% and in a negative sentiment 12%, and staff is mentioned in a positive sentiment, which is 16% and in a negative sentiment 3%, and so on.

Table 4 Examples of raw data

Sentiment	Text
NEGATIVE	atmosphere was lacking
NEGATIVE	awful service.
NEGATIVE	bad service
NEGATIVE	bakery is not good as i expected.
NEGATIVE	cake it's so hard i do not like.
NEGATIVE	chicken strips and onion rings are not good quality
NEGATIVE	coffee was bad
NEGATIVE	disappointing.
NEGATIVE	do not like the decoration of the shop.
NEGATIVE	don't come here if you want a decent meal, terrible experience.
NEGATIVE	expensive
NEGATIVE	food not lots of choices
NEGATIVE	for thais this is a bit expensive
NEGATIVE	fried pork with rice the taste was bad

Table 4 Examples of raw data (Continued)

Sentiment	Text
NEGATIVE	green tea ice cream not very good.
NEGATIVE	heavy price tag
POSITIVE	excellent service and courteous staff.
POSITIVE	extensive menu, affordable price for all
POSITIVE	fast food service and friendly waiter
POSITIVE	first time i been here the staff are very friendly and helpful they recommend a good food for me and i like it
POSITIVE	flawless food, duck is delicious and well priced as is everything else they serve, bit of a trek from the main tourist area but worth it.
POSITIVE	food always delicious and staff very friendly.
POSITIVE	food and drinks are good
POSITIVE	food is amazing and delivery was fast.

Table 5 Examples of Aspect Based Sentiment Analysis from experiment

Aspect	Reviews
menu: negative	Menus are not attractive.
food: negative, value: negative	Fried rice was flavorless and overpriced.
staff: negative	Poor customer service and a bad attitude.
value: positive	Price are not cheap but amount is bit less I felt so.
value: negative	Price was unreasonable.
food: negative	Seafood salad was not delicious.
staff: positive	Service has not been great for me.
staff: negative	Unfriendly services
cleanliness: negative	Whole place is completely run down and dirty.
dessert: negative	Cakes are terrible.
dessert: negative	Cake was flavorless.
drink: negative	Too much sugar was added.
ambience: positive	S&P has good air conditioning and we relaxed in the cool atmosphere.
cleanliness: positive, staff: positive	Service was very good and the restaurant was clean and tidy.
ambience: positive, menu: positive	Great atmosphere and big enough to bring a large group. Good selection.
drink: positive	Juices are great.

The Table 4 displays the examples of raw data before classification process. The Table 5 displays the examples of Aspect Based Sentiment Analysis of sentences which determined the polarity (positive or negative) of each aspect category. Table 6 and Table 7 show the examples of Correlation Matrix in each aspect and each word.

The processes of interpreted data in each sentence are as follow: First, we do the Data Pre-processing. In this process the text was split into individual words then the word was transformed into a common representation or root word. For example, the words "juices", "relaxed" could be reduced to common representation "juice" and "relax". The stop word in the sentence was removed and all the characters was converted to the lower case. Second, the system attempt to detect the main aspects of the texts (e.g. food, staff, value, drink, menu, cleanliness, dessert, ambience, and location) and to estimate the average sentiment of the texts per aspect (e.g., how positive or negative opinions are on average for each aspect) by using Correlation Matrix.

Table 6 Examples of Correlation Matrix in aspect

Attributes	ambience: negative	ambience: positive	cleanlines: negative	cleanlines: positive	drink: negative	drink: positive	food: negative	food: positive
ambience: negative	1.000							
ambience: positive	-0.005	1.000						
cleanlines: negative	-0.005	-0.014	1.000					
cleanlines: positive	-0.005	-0.015	-0.016	1.000				
drink: negative	-0.006	-0.018	-0.019	-0.020	1.000			
drink: positive	-0.008	0.012	-0.025	-0.026	-0.032	1.000		
food: negative	-0.019	-0.055	0.110	-0.060	0.021	-0.095	1.000	
food: positive	-0.021	0.104	-0.065	0.147	-0.083	0.196	-0.250	1.000

Table 7 Examples of Correlation Matrix in words

Attributes	delicious	food	friendly	good	menu	price	service	staff	taste
delicious	1.000								
food	-0.022	1.000							
friendly	-0.018	-0.022	1.000						
good	-0.059	0.062	-0.015	1.000					
menu	0.014	-0.058	-0.001	-0.023	1.000				
price	-0.034	-0.044	-0.002	-0.045	-0.014	1.000			
service	-0.014	-0.058	0.056	0.047	-0.059	-0.050	1.000		
staff	-0.029	-0.088	0.171	-0.041	-0.040	-0.035	0.005	1.000	
taste	0.005	-0.053	0.008	0.015	-0.034	-0.028	-0.059	-0.051	1.000

Conclusion

This study has performed experiments and compared learning algorithms of SVM and Naive Bayes. The results were found that SVM performance was better than Naïve Bayer, and the result corresponded to those of Joachims (1998) and Yang and Pedersen (1997). The accuracy of Naive Bayes was slightly lower than SVM. The Aspect Based Sentiment Analysis technique is very useful for businesses they ideally need to know the customer's opinion for positive and negative in different aspects (services, drink, location, food), so whether they can respond to them efficiently.

Discussion

For the comparison of classification models, we selected a dataset of 1,285 recordswhich consists of sentiment (positive/negative) and Text (customer's reviews). Calculation preformed for the Accuracy, Recall, and Precision showed that the performance of SVM with a polynomial kernel and 10-fold cross validation was better than Naïve Bayer method in terms of the proportion of correctly classified, with the percentage of 80.42%, 74.89%, and 86.01%, respectively. Actually, literature indicates that there is no better classification method. SVM and Naive Bayes Classifier have different options including the choice of kernel function for each that are sensitive parameter for optimization. Different dataset and parameter selection can significantly change their output. As a limited amount of data was used for training the model, the performance will be better if have more data for training. For Aspect Based Sentiment Analysis, this study shows that ambiguous terms are also present in the reviews. The polarity of the ambiguous terms depends on the context so that the same word can act positive in one domain and negative in another domain. In the future, to improve the accuracy of the Aspect Based Sentiment Analysis for customer's reviews using context aware learning whereby context has more relevant aspects.

Limitation and Implication

During the experiment, a limited amount of data was chosen to train these models. A larger training data set will produce different models, which might be better. The Aspect Based Sentiment Analysis of the customer's views may not be thorough enough. In the future, we can do an in-depth analysis of each aspect of the feedback and briefly summarize the comments in order to be more useful.

References

Cardie, C. 2014. [Review of the book Sentiment Analysis and Opinion Mining: Synthesis Lectures on Human Language Technologies, by B. Liu]. **Computational Linguistics,** 40(2): 511-513.

Castle, N. July 13, 2017. **Supervised vs. Unsupervised Machine Learning.** Retrieved September 20, 2017, from https://www.datascience.com/blog/supervised-and-unsupervised-machine-learning-algorithms

Chen, H., Lin, M., & Wei, Y. 2006. Novel association measures using web search with double checking. **The 21st International Conference on Computational Linguistics and the 44th annual meeting of the Association for Computational Linguistics** (pp. 1009–1016). Sydney, Australia.

Dimitoglou, G., Adams, J. A., & Jim, C. M. 2012. Comparison of the C4.5 and a Naive Bayes Classifier for the Prediction of Lung Cancer Survivability. **Journal of Computing,** 4(8): 1-9.

Gamon, M. 2004. Sentiment Classification on Customer Feedback Data: Noisy Data, Large Feature Vectors, and the Role of Linguistic Analysis. **The 20th International Conference on Computational Linguistics** (pp. 841-847). Geneva, Switzerland.

Ganu, G., Elhadad, N., & Marian, A. 2009. Beyond the stars: Improving rating predictions using review text content. **The 12th International Workshop on the Web and Databases (WebDB 2009),** Providence, Rhode Island, USA.

Gupta, D. K., & Ekbal, A. 2014. IITP: Supervised machine learning for aspect based sentiment analysis. **The 8th International Workshop on Semantic Evaluation (SemEval 2014)** (pp. 319-323). Dublin, Ireland. Retrieved September 24, 2017, from http://www.aclweb.org/anthology/S14-2053

Gupta, V., & Lehal, G. S. 2009. A survey of text mining techniques and applications. **Journal of Emerging Technologies in Web Intelligence,** 1(1): 60-76.

Hercig, T., Brychcin, T., Svoboda, L., Konkol, M., & Steinberger, J. 2016. Unsupervised methods to improve aspect-based sentiment analysis in Czech. **Computación y Sistemas,** 20(3): 365-375.

Hu, M., & Liu, B. 2004. Mining and summarizing customer reviews. **The tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining** (pp. 168–177). Seattle, USA

Jo, Y., & Oh, A. H. 2011. Aspect and sentiment unification model for online review analysis. **The 4th ACM International Conference on Web Search and Data Mining** (pp. 815–824). Hong Kong, China.

Joachims, T. 1998. Text categorization with Support Vector Machines: Learning with many relevant features. **The 10th European Conference on Machine Learning (ECML'98)** (pp. 137-142). Chemnitz, Germany.

Kalaivani, P., & Shunmuganathan, K. L. 2013. Sentiment classification of movie reviews by supervised machine learning approaches. **Indian Journal of Computer Science and Engineering,** 4(4): 285-292.

Kannan, S., & Gurusamy, V. 2014. **Preprocessing techniques for text mining.** Retrieved October 5, 2017, from https://www.researchgate.net/publication/273127322_Preprocessing_Techniques_for_Text_Mining

Laskari, N. K., & Sanampudi, S. K. 2016. Aspect based sentiment analysis survey. **IOSR Journal of Computer Engineering,** 18(2): 24-28.

Liu, B., Hu, M., & Cheng, J. 2005. Opinion observer: Analyzing and comparing opinions on the Web. **The 14th international conference on World Wide Web** (pp. 342–351). Chiba, Japan.

Mostafa, M. M. 2013. More than words: Social networks' text mining for consumer brand sentiment. **Expert Systems with Applications,** 40(10): 4241-4251.

Nuntiyagul, A. 2006. **Text categorization & retrieval for Thai item bank using patterned keyword in phrase (PKIP).** (Doctoral Dissertation, Mahidol University).

Pang, B., & Lee, L. 2004. A Sentimental Education: Sentiment Analysis Using Subjectivity Summarization Based on Minimum Cuts. **The 42nd Annual Meeting on Association for Computational Linguistics.** Barcelona, Spain.

Pang, B., Lee, L., & Vaithyanathan, S. 2002. Thumbs Up? Sentiment Classification using Machine Learning Techniques. **The Conference on Empirical Methods in Natural Language Processing** (pp. 79-86). Philadelphia, USA.

Patil, T. R., & Sherekar, S. S. 2013. Performance analysis of Naive Bayes and J48 classification algorithm for data classification. **International Journal of Computer Science and Applications,** 6(2): 256-261.

Salton, G. & Buckley, C. 1988. Term-Weighting Approaches in Automatic Text. **Information Processing & Management,** 24(5): 513-523. Retrieved October 2, 2017, from https://doi.org/10.1016/0306-4573(88)90021-0

Schutze, H. 1992. Dimensions of meaning. **The 1992 ACM/IEEE Conference on Supercomputing** (pp. 787–796). Minneapolis, USA.

SemEval-2014 Task 4. 2014. **Task description: Aspect Based Sentiment Analysis (ABSA).** Retrieved September 5, 2017, from http://alt.qcri.org/semeval2014/task4

Shi, H., & Liu, Y. 2011. Naïve Bayers vs. Support Vector Machine: Resilience to missing data. In H. Deng., D. Miao., J. Lei., & F.L. Wang. (Eds.) **The 3rd International Conference on Artificial Intelligence and Computational Intelligence** (pp. 680-687). Berlin, Heidelberg, Germany.

Staelin, C. 2002. **Parameter selection for Support Vector Machines.** Retrieved October 30, 2017, from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.4.2355&rep=rep1&type=pdf

Sukhum, K., Nitsuwat, S., & Haruechaiyasak, C. 2011. Opinion detection in Thai political news columns based on subjectivity analysis. **Information Technology Journal,** 7(14): 32-37.

Thet, T. T., Na, J. C., & Khoo, C. S. G. 2010. Aspect-based sentiment analysis of movie reviews on discussion boards. **Journal of Information Science,** 36(6): 823–848.

Tripathi, G., & Naganna, S. 2015. Feature Selection and Classification Approach for Sentiment Analysis. **Machine Learning and Applications: An International Journal,** 2(2): 1-16.

Tumasjan, A., Sprenger, T., Sandner, P., & Welpe, I. 2010. Predicting elections with Twitter: what 140 characters reveal about political sentiment. **The Fourth International AAAI Conference on Weblogs and Social Media** (pp. 178-185). Munich, Germany.

Vanjari, P. S., & Thombre, V. D. 2015. An experiential study of SVM and Naïve Bayes for gender recognization. **International Journal on Recent and Innovation Trends in Computing and Communication,** 3(9): 5456-5460.

Yang, Y., & Pedersen, J. O. 1997. A comparative study on feature selection in test categorization. In D. H. Fisher (Ed.), **The International Conference on Machine Learning** (pp. 412-420). Nashville, USA.

Zhai, Z., Liu, B., Xu, H., & Jia, P. 2010. Grouping product features using semi supervised learning with soft-constraints. **The 23rd International Conference on Computational Linguistics** (pp. 1272–1280). Beijing, China.

Zhai, Z., Liu, B., Xu, H., & Jia, P. 2011. Clustering product features for opinion mining. **The Fourth ACM International Conference on Web Search and Data Mining** (pp. 347–354). HongKong, China.