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# VIDEO ADVERTISEMENT MINING FOR PREDICTING REVENUE USING RANDOM FOREST

A Thesis

Submitted to the Faculty

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by

Yuan Hsin Huang

In Partial Fulfillment of the

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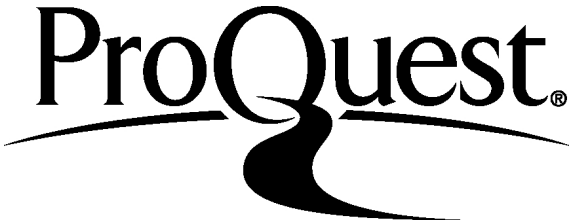

This work is devoted to my husband Wei-Chung Hsu, my family members Chung-Tong Huang, Shu-Yu Su, Yu-Chen Huang, Hung-Rai Huang, my lovely grandmother, and my best friend Yin-Yu Huang.

All their loves and supports prompt me to persist what I always pursued for.

Hope Grandmother and Yin-Yu also feel proud and happy for me in Heaven.

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Several terms are required to define within this document. The definition of those terms are indicated as below:

| | |
|---|---|
| API | Application Programming Interface |
| CART | Classification and Regression Tree |
| JJ | Adjective |
| LSP | Lexical Syntactic Pattern |
| NN | Noun |
| NP | Noun Phrase |
| OOB | Out of Bag Error |
| ORF | Offline Random Forest |
| POS | Part Of Speech |
| RFM | Recency, Frequency, Monetary Value |
| ROC | Receiver Operating Characteristic Curve |
| ROLEX-SP classifier | Rules of Lexical Syntactic Patterns |
| UGC | User Generated Content |
| VB | Verb |
| WOM | Word Of Mouth |

# GLOSSARY

Several terms are required definition as follows:

- API: Application program interface is a group of routines for creating software applications that indicates how software components should interact and are utilizing when programming graphical user interface components.
- Bagging: This method is also called Bootstrap Aggregation. It is an ensemble machine learning algorithm that creates bootstrap samples of a training set using sampling with replacement. Its classification is accomplished by plurality voting.
- CART: Classification and regression trees are machine learning methods for constructing forecasting models showed as decision trees which are achieved by recursively partitioning the data space and fitting a simple prediction model within each partition.
- Confusion Matrix: A table visualizes the performance of a machine learning algorithm. Each column of the matrix stands for the instances in a predicted class, while each row indicates the instances in an actual class. Through the comparison, it is clear whether two classes are confused or not.
- Logical Negation: A preposition role in reversing the meaning of opinions.
- Mean Decrease Accuracy: It is determined by the normalized difference of the classification accuracy for the out-of-bag data, which was randomly permuted. The bootstrap iterations of Mean Decrease Accuracy make its estimate unduly optimistic.
- Mean Decrease Gini: A measure of variable relevance to the classification dependent on the Gini impurity index, averaging the sum of overall weighted impurity decreases for all trees in the forest.

- Out-of-Bag Error Rate: It indicates the estimate of generalization error, averaging all the internal errors of forests. It had a similar multiple training process of leave-one-out cross-validation without additional computational workload.
- Proximity Measure: An anomaly detection method that adopts proximities between pairs of classes to investigate the similarity between individuals and identifies the outliers.
- Random Forest: A schema for building a classification ensemble with a set of decision trees grows in the different bootstrapped aggregation of the training set on the basis of CART (Classification and Regression Tree) and the Bagging techniques.
- Receiver Operating Characteristic Curve: It is constructed to diagnose the accuracy of the model. The region under the ROC curve referred to the percentage of randomly determining which is true on the basis of the uninformative test; the greater area represents the better test.
- ROLEX-SP Classifier: Rules of Lexical Syntactic Patterns is an approach for automatic induction of rules to build text classifiers that depends on lexical syntactic patterns as a set of features to classify text documents.
- Sentiment Analysis: Opinion mining is the domain of the computational study that analyzes people’s opinions, sentiments and emotions expressed in the text.

# ABSTRACT

Yuan-Hsin, Huang. M.S., Purdue University, May 2015. Video Advertisement Mining for Predicting Revenue Using Random Forest. Major Professor: John A. Springer.

Shaken by the threat of financial crisis in 2008, industries began to work on the topic of predictive analytics to efficiently control inventory levels and minimize revenue risks. In this third-generation age of web-connected data, organizations emphasized the importance of data science and leveraged the data mining techniques for gaining a competitive edge. Consider the features of Web 3.0, where semantic-oriented interaction between humans and computers can offer a tailored service or product to meet consumers' needs by means of learning their preferences. In this study, we concentrate on the area of marketing science to demonstrate the correlation between TV commercial advertisements and sales achievement. Through different data mining and machine-learning methods, this research will come up with one concrete and complete predictive framework to clarify the effects of word of mouth by using open data sources from YouTube. The uniqueness of this predictive model is that we adopt the sentiment analysis as one of our predictors. This research offers a preliminary study on unstructured marketing data for further business use.

# CHAPTER 1. INTRODUCTION

With the maturity of social media websites, the resulting word of mouth effects (WOM) have already deeply impacted not only an individual's psychological state but also an organization's performance. Thus, a large amount of contextual data is increasingly arising without a concrete and complete adoption in marketing science. Essentially, from the perspective of marketing strategy, companies have begun to shift their emphasis from merely managing product line mixes to optimizing customer lifetime value. In other words, the prior focus on suitable product line management to maximize per concept contribution has evolved into developing diverse customer-oriented plans to strengthen and further expand their market share. TV commercial advertisements are the typical communication platform to deliver brand value and introduce new products to consumers.

Moreover, as a vast number of viewers increasingly shift to digital media to watch videos online, the radical changes of target audience behaviors caused by the rapid development of the social media ecosystem will offer not only a suitable platform to study viewer data but also paint a comprehensive picture of the pool involved in social media. Therefore, all the contextual sentiments derived from real customers' feedback and related quantitative variables- such as the amount of feedback evaluation- can be integrated into one forecasting model to generate corresponding trustworthy sales prediction by a random forest algorithm. Through the split among a random subset of the

predictors, this forecasting mechanism provides an estimate of what predictors are important in the classification when generating an internal unbiased estimate of the generalization error as the forest building progresses—rather than directly deleting the predictors.

## 1.1 Scope

Aimed at TV commercial advertisements put on YouTube by official company owners, the proposed study will explore one specific consumer product: Coca-Cola. Regarding the two advertisement types, one is brand advertising for delivering brand value and the other is product advertising for the new product launch. This research will explore both types of advertisement. Based on the time period of 2009 to 2014 and limited to the North America region, the search space for this study will focus on quarterly advertisements and their corresponding sales data from official earnings release reports.

The main reason why this research focused on the TV commercial advertisements created by the Coca-Cola Company is its excellent reputation for advertising and marketing manipulation. Generally speaking, the earnings report always consists of all brands of product lines; thus, the performance evaluation for one single brand is very hard to specify. Undoubtedly, the product portfolio belonging to the Coca-Cola brands is more purely representative of the sales achievement. Apart from Coca-Cola's consistent 40% plus market share in the U.S.-its related product lines account for a significant portion of total net operating revenue between all brands of the Coca-Cola Company. Therefore, this case study focuses on the TV commercial advertisements from all Coca-Cola Company’s accounts on YouTube to proceed with relevant video mining.

In terms of the model's predictors, the textual comments in English left on TV commercial advertisements on YouTube will be defined as one of the key factors for building up the forecasting system. The subscribed channels from users who left opinions can be used to categorize user preferences and can be also deemed as one influential factor to integrate with their social shares for further viewer segmentation. Moreover, the related numerical indices covering viewer traffic and video evaluation, e.g., number of likes and dislikes and length of video, will be elaborated in this proposed forecasting model.

After conducting the processes of data collection and features classification, the implementation of this predictive schema is to adopt random forest as the ensemble learning approach. This is in order to simulate the possible association between video advertisements and corresponding quarterly net operating revenue.

## 1.2 Significance

Generally speaking, pre-campaign sales prediction through early orders is an extremely important component for both marketing and supply chain teams to achieve their key performance indexes. This prediction mechanism can be regarded as a warning signal for detecting and preventing any further revenue risk. However, there are still several restrictions on this pre-campaign forecasting. Firstly, this predictive model is dependent on the volume of early orders. For example, a short campaign decreases the number of early orders, which will lead to an inaccurate estimation. Moreover, there is limited time to create corresponding plans. Hence, this method always causes either a heavy workload for team members or unsurprisingly poor performance due to lack of flexibility.

Additionally, TV commercial and video advertisements always account for a heavy portion of the marketing budget, even only for the promotion of key products or the intent of brand awareness. Compared with other types of advertisements, video advertisements can easily employ word-of-mouth effects and leave further impressions on a consumer's mind. Nevertheless, traditional approaches for assessing the performance of video advertisements cannot effectively link the causal relationship between customer perception and sales.

Thus, from the perspective of organizational performance, the accuracy of sales prediction through the proposed advertisement mining will offer more flexible space and time to adjust marketing plans. Before early-order pre-forecasting for campaigns, this prediction method can strengthen risk control of both inventory and sales. Furthermore, one can obtain critical successful rules for advertisement design and marketing plan. Another advantage is to infer if the heavy budget allocation on advertisements is appropriate or if any other improvement is needed.

## 1.3 Research Questions

From the perspective of marketing science, the main research questions of this study were:

1. How can advertisement mining be leveraged to assist in sales prediction?
2. How can marketers take advantage of user preferences and their socially influential powers to categorize viewer segmentation? What are the main clusters of preferences for viewers who watched Coca-Cola advertisements on YouTube?
3. Do the predictors related with traffic concept have a significant impact on sales performance?

4. How can one efficiently classify sentiment to improve ROLEX-SP performance?
5. What is the predictive effect of sentiment analysis, including the feature-scoring and degree of polarity?

## 1.4 Assumptions

Subsequent research was dependent on the following assumptions:

- The coverage of advertisements adopted in this paper can be considered as typical of advertisement types produced by the Coca-Cola Company.
- The comments on a TV commercial advertisement were voluntarily left by active YouTube users, and they can be regarded as general viewpoints that are representative of the target audience.
- The subscribed-to channels or videos of these YouTube who left comments on a TV commercial advertisement can be utilized to categorize their preferences.
- The highest frequency of channel subscriptions can be taken for granted as a viewer's major preference.
- The preferences of viewers who never subscribed to any channels, can be disregarded; instead, those preferences can be simulated by others who have complete subscription data for the same video.
- The possibility of external economic factors that influenced quarterly revenue has been excluded in this study. This study only focused on the cause and effect between an advertisement and, accordingly, the quarterly report of earnings.

## 1.5 Limitations

This research was restricted by the following boundaries:

- The collection of sentiment was only derived from the official communities created by the Coca-Cola Company, which included the following user accounts: Coca-Cola, Coca-Cola Light, Coca-Cola Zero and CocaColaCo.
- The quantity of sentiment for further classification in each video did not exist at the same scale; it was limited by the maximum number of comments we can extract.
- We cannot acquire exact revenues generated from the relevant advertisement; therefore, only the official earning release can be simulated as the reasonable outcome variable in this study.

## 1.6 Delimitations

The admitted delimitations for this research were as follows:

- The scope was limited to Coca-Cola brands (Coca-Cola, Coca-Cola Zero, Diet Coke) and two types of advertisements (product advertisements and brand advertisements). Other types were not taken into consideration in this study.
- This study only concentrated on the integration of sentiment analysis, user preference and associated quantitative variables—including the length of video, feedback evaluation and viewer counts—to build up a random forest without considering any other possible predictors.

## 1.7 Summary

This chapter explained why this was an imperative research topic and what the research expected to demonstrate from the specific experimental design. In addition, this section also pointed out a list of assumptions, limitations and delimitations to specify the studying scope. The next chapter presented a brief summary of relevant literature covering advertisement evaluation, the practice of video mining, the characteristic and application of two step clustering method, the classification of sentiment analysis, the principle of the random forest-learning algorithm.

# CHAPTER 2. LITERATURE REVIEW

Researchers persistently pursue ways to leverage the effective analytical models on predicting future possible scenarios. Due to the ever-increasing surge of accessible textual information in all types of web documents nowadays, researchers can aggressively decipher the mining rule of unstructured data. They adopt statistical natural language processing methods and machine learning algorithms to develop extensive unsupervised applications such as the forecasting mechanism (Manning & Schütze, 2002). Accordingly, scholars can utilize a hybrid recommender engine based on mixed data-mining techniques to elaborate a predictive support system.

The main focus of this study is to build up a sound sales forecasting module by integrating a sentiment-oriented video advertisement analysis based on the modified ROLEX-SP classifier (Rules of Lexical Syntactic Patterns) and the clusters of viewer segmentation. Consequently, this literature review serves as a guideline to provide a broad, holistic coverage and summation of specific data-mining domains for the purposes of future research.

The opening section presents an overview of advertisement effects involving the impact by the emergence of interactive advertisement. The levels of audience involvement in the advertisement are subsequently mentioned, and we will further discuss the evolutionary methods of advertisement evaluation. The next part stresses the research results from recent studies of video-mining, and summarizes the contributions to

media exploration. Moreover, the third section accounts for the principle and application of a two-step clustering algorithm and illustrates the practicality with related hybrid design from historical studies. Then, the fourth section outlines current approaches of semantic classification and derives the utilization of sentiment analysis. Finally, the random forest method, applied to bridge content-based predictors with sales generation, is explained in detail. Along with the clear description of the principal algorithm, several predictive mechanisms relying on the random forest approach are demonstrated.

## 2.1 Interactive Advertisement

With gaining widespread popularity of adopting web 2.0 nowadays, the video sharing Websites can represent as one of the typically online UGC (user generated content) paradigms. They permit the audience to upload, share, distribute or store video content on the internet and simultaneously comment on the content posted by the peers. In recent years, most video sharing services are regarded as an optimal interactive platform to embed in advertisement mechanism including banner ads and mid-roll video ads (Saito & Murayama, 2010). The most representative website, YouTube, makes users stream their video content, and over 6 billion hours of video are watched each month (YouTube Statistics, 2014). In addition, the incredible scalability of website traffic, more than 1 billion unique users visiting YouTube each month, witnesses the prosperity of interactive video-sharing platform. According to the study of Fen and Florian (2014), four variables "Search", "Category", "Best Rating" and "Popular" can be granted as the key indicators to perform the data mining prototype on YouTube. Therefore, this study will adopt the most active interactive video-sharing platform YouTube to examine the

relationship between contextual feedback on commercial TV advertisement and corresponding financial performance by means of comprehensive mining techniques.

### 2.1.1 Advertisement Involvement

The value delivery of advertisement has great influence on the achievement of sales target. Generally speaking, the concept of involvement plays an imperative role in the field of consumer behavior and closely relates with variations in marketing performance. In the light of audience involvement in advertising, references show that individuals under high advertising involvement would generate more message attention and further perform a brand evaluation (Laczniak, Muehling & Grossbart, 1989). Based on this assumption, more belief strength and attitude towards ads would be elicited as well (Laczniak & Muehling, 1993). Andrews, Durvasula and Akhter (1990) identified that a consumer under high advertising involvement has more search and shopping behavior and more complexity of decision-making. Additionally, he needs more time to examine alternatives and easily perceived product attribute differences. Even though low-involved consumers might not show much impact of advertising communications on beliefs, they might be induced more easily than highly involved consumers to try a new product or brand (Robertson, 1976). Accordingly, comments left behind and embedded on interactive video sharing platform-YouTube can be deemed a kind of advertising involvement. Regardless of the level of viewer involvement in advertising, the sentiment mining undoubtedly offers a pretest of subsequent revenue generation.

### 2.1.2 Advertisement Evaluation

Researchers came up with many theories to execute the evaluation of advertising effectiveness; in other words, to verify whether an advertisement campaign achieved

prospective effects through evaluating the process after the implementation of activities. From the perspective of psychology research, Lewis (1989) put forward the influential advertising psychological model of AIDA. It demonstrated the effectiveness of an advertising activity by measuring whether or to what extent can the advertising cause the consumers' attention, arousing their interest, stimulating their desire, and changing their action. Colley (1961) defined advertising goals for measured advertising results that mainly represented the audience's psychological change before and after the advertising campaign intuitively, unknown - known - understand - be convinced - action. In other words, the role of emotional factors in decision-making was extremely emphasized in this model. Furthermore, Lang (1980) explored the relationships with attitude, cognitive, brand interest, purchase intention, and finally formed the evaluation system based on joy attention value - influence. With respect to the evaluation structure of AC Nielsen, through a simulated environment of advertisements, it conducted an emulation test to examine four aspects of advertisement: appetency, persuasion, infectivity and communication effect. To summarize, most evaluation structures concerned with consumer's psychological process don't take the role of consumer's initiative demand and response into consideration. In this study, more emphasis will be concentrated on transforming advertisement effectiveness into real sales report. Through analyzing lexical messages left by viewers to consider their psychological cognition, the researcher will assess the numerical value generated from TV advertisement.

## 2.2 Video Mining

With the widespread adoption of video sharing websites, scholars transfer their attention to digital videos mining. The video can be defined as one kind of content-based

multimedia data which is typically analyzed from the viewpoint of specific video semantic annotation- text, audio and visual information. Zhang (2012) proposed one efficient video mining schema that combined object recognition, continuous speech recognition and video caption text recognition. He applied the dense sub graph finding approach to explore the semantic relationship between two neighboring words that only reserved the noun and verb words.

Additionally, in terms of feature-based video mining approach, it can be categorized as video clustering mining, video classification mining and video association mining. The video clustering mining leverages the clustering algorithms such as k-means method on organizing the videos based on their homogeneous feature objects (Latecki & Wild, 2002). As for the video classification mining, it emphasized to dig out the implicit patterns among video objects like the semantic descriptions. In practice, Saravanan and Srinivasan (2010) also focused on the attribute extraction- fields of image processing, segmentation, edge detection, pattern recognition to design one efficient video frame-based retrieval system. After grouping all the extracted features from videos, this structured data can be examined if there exists any associated patterns by the association rule (Xie & Chang et al., 2003). Apart from using low-level features with little meanings for naïve users, researchers (Zhu, Wu, A.K. & Wu, 2005) designed a knowledge-based video indexing and content management framework for sports domain specific videos. They took advantage of multilevel sequential association rule to explore the relationship between the audio and visual cues.

In terms of the interactive characteristic of videos, majority of the studies concentrate on analyzing the components of the video itself rather than the subjective

facts provided from the viewers. However, the audience is the most significant key to determine the influential effect of the videos. Hence, instead of studying the video's elements, the true experience of viewers is the main focus of this study, involving the classification of viewers' preference and their attitudes toward this video.

## 2.3 Two Step Clustering Analysis

Customer segmentation is the primary marketing emphasis for effectively positioning the right role of portfolio strategies. Consider the scalability and complexity of data, researchers (Chiu, Fang, Chen, Wang & Jeris, 2001) demonstrated the design of two step clustering algorithm that performed well for mixed type attributes in large database environment. The fundamental procedures of this two-stage approach is to execute a pre-clustering step by the decrease in log-likelihood distance measure at first and then conduct a modified hierarchical agglomerative clustering algorithm to categorize the dense regions sequentially into homogenous clusters (Mooi & Sarstedt, 2011). In general, the number of clusters is automatically assessed by calculating measures of fit such as Akaike Information Criterion or Bayesian information criterion (Schwarz, 1978).

Literatures showed many successful applications of the two stage clustering method that contribute to the gain of competitive edge. In terms of customer segmentation in one Pakistan mobile telecommunication company, researchers (Salar, Moaz, Faryal, Ali, Aatif & Ahsan, 2013) adopted customers' daily call and SMS usage as well as revenue generation data, discretized via binning method, to do the classification and uncover the usage behaviors.

Moreover, some scholars also took advantage of data mining technology to develop the new type of two-step clustering approach. Namver, Gholamian & KhakAbi (2010) leveraged RFM (Recency, Frequency, Monetary Value), demographic and customer lifetime value data to construct one new customer segmentation model. The mechanism they developed is to leverage k-means technique on the construction of intelligent customer segmentation based on the two-phase clustering schema. This study aimed at customer data in banking industry and grouped the existing customers according to their shared transactional behavior and characteristics. Through the analysis, this research help marketers establish better customer relationship management strategies, reduce the churn and find the good opportunities for up and cross selling.

In practice, the two step clustering algorithm is not merely useful for marketing use but also for the behavior prediction. The study of Higgs and Abbas (2013) revealed that each driver showed a unique distribution of behavior, but some of the behaviors existed in more than one driver but at different frequencies through the two-stage clustering method. Regarding the adoption of this methodology in this research, it is definitely necessary for the process of variable transformation. In this study, the number of segmentation, categorized by users' subjective preferences and their social influence-total upload views and subscription counts, is examined by means of the two-step clustering algorithm, proposed by Chiu et al. (2001).

## 2.4 Sentiment Analysis

Researchers started to study sentiments and opinions earlier (Das & Chen, 2001; Morinaga et al., 2002; Pang, Lee & Vaithyanathan, 2002; Tong, 2001; Turney, 2002; Wiebe, 2000) than the term sentiment analysis first appeared in (Nasukawa & Yi, 2003).

Bing (2012) elucidated that sentiment analysis, also called opinion mining, is the domain of the computational study that analyzes people's opinions, sentiments and emotions expressed in the text. With the explosive growth of social media, individuals and organizations are increasingly using the content in these media for decision making. Therefore, many studies attempt to dig out the potential for a number of applications, for example: Xujuan, Xiaohui and Jianming (2013) proposed a Tweets Sentiment Analysis Model to spot the societal interest and general people's opinions in regard to a social event. They took Australian federal election 2010 event as an example of sentiment analysis experiments to demonstrate the effectiveness of the system.

References show that sentiment classification is the significant focus to extensively study (Pang & Lee, 2008), which organize user opinions and classify opinion comments into positive, negative and neutral categories by means of scaling system. Essentially, the general classification methods can be fallen into two categories, semantic-based and learning-based. Hatzivassiloglou and Wiebe used four different levels to do sentiment analysis including word level, phrase level, sentence level, and document level (2000). Therefore, in terms of semantic-oriented classification, the sentiment dictionary or a large-scale knowledge database (Hugo, Henry & Ted, 2003) helps to organize sentiments to assign to individual documents (Tetsuya & Jeonghee, 2003; Pero & Alison, 2001). Three representative methods are correspondingly generated to establish it including manual construction (Das & Chen, 2001), semi-automatic construction (Hu & Liu, 2004) and automatic construction (Kamps & Marx, 2002).

Through the bag-of-words approach, Turney (2002) regarded a document as a mere collection of words without considering the association between individual words

that is called term-counting approach. This method clarified all words' sentiment and then combined their value to judge the real meaning behind the overall sentiment with aggregation functions. Besides, Bunescu (2003) was applied to classify positive and negative sentiments for whether a sentence is subjective or objective. However, phrase level categorization can't effectively identify the true sentiment once multiple sentiments within one sentence.

Aimed at developing the new classifier from different domains of knowledge, one modified version of ROLEX-SP classifier (Rules of Lexical Syntactic Patterns) was proposed by Mohammed and Samer (2014). In fact, it was very suitable to this social networking generation. Essentially, the principle of ROLEX-SP is to construct the specific textual classifier to enhance the possibility of accurate judgment for the semantic classifier. Consequently, the modified framework has three layers to divide the data collection into domain-specific collections and further assign the classification task. The first homogeneous data layer minimizes ambiguity among heterogeneous data collected from a specific domain of knowledge and simultaneously contributes to accurate retrieval of relevant information. And the second layer offers the logic of classifying data to transform the first layer data into the given domain. Lastly, the access layer at the top controls semantic connections among different knowledge sources and facilitates modularity. In this rule, multi-class classification feature assumes that some information might be related to other knowledge database and good for better performance and less ambiguity.

Nevertheless, semantic classification is too complicated to establish a systematic database; accordingly researchers leveraged the machine-aided methods on getting better

performance for sentiment categorization. By means of machine learning approaches, Pang and Lee (2004) redefined the semantic classification problem as a kind of statistical classification task. Regarding learning-oriented approach, Barbosa and Feng (2010) did a two-step automatic sentiment analysis for tweets classification. In case more labeling effort in developing classifiers, a noisy training set was adopted, and tweets were grouped into subjective and objective category. After that, subjective tweets are assigned to either positive or negative group.

As a matter of fact, traditional learning techniques such as Naive Bayes, Maximum Entropy and Support Vector Machines are typically applied to do opinion classification. On the other hand, features of each comment can be simple words (Durant & Smith, 2007), n-grams (Kushal, Lawrence and David, 2003), and syntactic relations (Nasukawa, Bunescu & Niblack, 2003), which are used to define the semantic orientation. Nirmala and Murali (2012) utilized SVM model to build up their discriminate function to predict the hotspots based on sentiment analysis in online forums. Accuracy of this polarity classification is low in sentiment analysis due to the dimension of feature space is quite large in text classification tasks. In other words, the classification issue is quite linearly separable and therefore linear kernel is commonly used (Theresa, Janyce & Paul, 2005). Wu and Ren (2011) generated an influence probability model to do the twitter sentiment analysis. Any tweet beginning with @username is the retweet and mainly correlated with influenced probability. Hence, the probability and association rule play the imperative role in opinion classification that logic of syntax highly correlates with the order of phrases.

## 2.5 Random Forest

Random Forest is a schema for building a classification ensemble with a set of decision trees that grow in the different bootstrapped aggregation of the training set on the basis of CART (Classification and Regression Tree) and the Bagging techniques (Breiman, 2001). Instead of exploring the optimal split predictor among all controlled variables, this learning algorithm determines the best parameter at each node in one decision tree by randomly selecting a number of features. Unquestionably, this process not only ensures the model scale well when each feature vector owns many features, but also lessons the interdependence between the features. In other words, from the viewpoint of Random Forest, the attributes with low correlation are less vulnerable to inherent noise in the data (Criminisi, Shotton & Konukoglu, 2012). On the other hand, the diversity in each tree effectively restrains the possibility of an overfitting issue. The classification decision is yielded by averaging the mode of the class output by individual trees.

In view of Random Forest's classification performance, Breiman (2001) regarded the Out-of-Bag (OOB) error rate as a signal of how well a forest classifier works on the data. The estimate of out-of-bag error rate can replace cross validation approach to examine the explanation ratio of Random Forest model through the average of misclassification results over all trees made from the bootstrap sample. Theoretically, the classification strength of each individual tree and the correlation between trees affect the error rate of the Random Forest classifier. Therefore, to increase selected features improves both the correlation between the trees and the strength of each tree.

Compared with CART approach, Random Forest method fits a multitude of CARTs into bootstrap sets resampled from the training set. Moreover, it precedes the

forecasting work through the mode of the predictions iterated by the fitted CARTs. In order to avoid disadvantages of CART- high variance, the modification of the Random Forest method not only adds the Bagging method but also adopts randomized node optimization to further reduce the CART variance (Mei, He, T., & Qu, 2014). In other words, single decision trees often lead to high variance or high bias.

Theoretically, Random Forest approach can produce a reasonable predictive model to form the highly accurate prediction by getting a natural balance between the two extremes: high variance or high bias. Many researches have demonstrated that Random Forest classifiers can achieve high accuracy in classifying data in domains of high dimensions with many classes (Banfield, Hall, Bowyer, & Kegelmeyer, 2007). Moreover, studies- the real time key point recognition (Parkour, 2013) and semantic segmentation (Shotton, Johnson & Cipolla, 2008) adopting Random Forest algorithm, are also the evidences to illustrate the better or comparable performance to other classification methods. Generally, the practice of Random Forest is realized on different design of forecasting framework. One instance is that scholars (Georga, Protopappas, Polyzos & Fotiadis, 2012) employed the Random Forests regression technique to solve the problem of subcutaneous glucose concentration prediction in type 1 diabetes on the basis of a multivariate dataset obtained under free-living conditions.

Theoretically, Random Forest approach can produce a reasonable predictive model to form the highly accurate prediction by getting a natural balance between the two extremes: high variance or high bias. Many researches have demonstrated that Random Forest classifiers can achieve high accuracy in classifying data in domains of high dimensions with many classes (Banfield, Hall, Bowyer, & Kegelmeyer, 2007). Moreover,

studies- the real time key point recognition (Parkour, 2013) and semantic segmentation (Shotton, Johnson & Cipolla, 2008) adopting Random Forest algorithm, are also the evidences to illustrate the better or comparable performance to other classification methods. Generally, the practice of Random Forest is realized on different design of forecasting framework. One instance is that scholars (Georga, Protopappas, Polyzos & Fotiadis, 2012) employed the Random Forests regression technique to solve the problem of subcutaneous glucose concentration prediction in type 1 diabetes on the basis of a multivariate dataset obtained under free-living conditions.

Regarding the methodology of this study, original Random Forest is the only option to bridge the association between advertisement video and revenue generation in place of any advanced Random Forest models.

## 2.6 Summary

This chapter has provided an overview of pertinent literature for the advertisement mining and predictive system including sentiment analysis, two step clustering approach and random forest algorithm. Unlike traditional methods of evaluating advertisement performance, more emphases are put on opinion mining of interactive advertisement and the subsequent transforming linkage between textual data and quantitative sales report in this paper. From this literature review, we can conclude, although many researchers worked on topics of sentiment classification and application of customer segmentation, there is a noticeable shortage of predictive model for the effect of word of mouth. Therefore, this research firstly adopts the random forest algorithm to examine the ensemble effect of TV commercial advertisement.

# CHAPTER 3. FRAMEWORK AND METHOGOLOGY

The purpose of this study was to propose a new sales prediction approach based on adopting data-mining discovery knowledge rules for video advertisements. The main benefit of this forecasting mechanism was to build up more solid pre-campaign predictive mechanisms that offered abundant time- and customer-driven information to adjust subsequent marketing campaign plans. Another benefit was the ability to extract the influential factors on the success of the advertisement campaigns.

Essentially, this predictive framework aimed to exploit the random forest approach to identify the importance of the predictors without removing any independent variables. In other words, through this ensemble method, all the key factors in the advertising model were fully taken into consideration without over-fitting and sensitiveness to noisy data. Therefore, the effect of customer opinions and the number of viewer segmentations were completely evaluated if there existed any relationship with revenue performance. This mechanism was further refined by multiple tool kits including Python, MySQL, R programming language and SPSS Statistics.

## 3.1 Research Hypothesis

The major purpose of this study was to examine the associated strength and feasibility of our hypotheses as below:

1. Most industries can adopt TV commercial advertisements to quantify customer satisfaction, as demonstrated by a sales prediction system.

2. The viewer segmentation can be grouped by the viewers' preference and their socially influential power. The analysis of viewer clusters can offer comprehensive guidelines regarding viewer behaviors, including their subjective preference boundaries and influential shares of social networking, to improve the company's advertising strategy. Consequently, the number of viewer clusters helped build the revenue prediction model.
3. The polarity of each comment was influenced by prior comments regarding the same advertising video, but was not be influenced by other similar advertising comments. In other words, each advertising video can be regarded as having independent data. We can make use of the lexicon compiled by partial advertising videos to effectively study the dependent sentiment data within one advertising video.

## 3.2 Data Collection

With respect to data sources for this research, input and output datasets both must be retrieved from an open and reliable database system to test if the association between each other was significant.

### 3.2.1 Raw Data Extraction

In terms of input-data comments of video advertisements, the process of extracting raw data was to exploit Google API and YouTube Data API version2 and version3 (Application Programming Interface) with the Python programming language. The process was used to gather comments left on TV commercial advertisements shown on YouTube along with the corresponding profile data of each distinct user who left messages, including the user's subscribed channels, total upload views and subscription

counts. This programming language package also can help retrieve all related video data, e.g., the length of the video and the video's traffic evaluation (viewer counts, the number of comments, and the number of thumbs-up and thumbs-down). After cleaning these data, a complete database for establishing a subsequent predictive model was built by means of MySQL. Moreover, the dependent variable of net operating revenues was obtained from the official quarterly earning release reports disclosed on the Coca-Cola Company's official website.

### 3.2.2 Limitation of the Data

This research mainly leveraged YouTube Data API (v2, v3) to fetch the search results of specific videos. Though its full-fledged functionality can fulfill the needs of discovering online videos, there were still several execution limitations in manipulating YouTube API to retrieve video data in practice. With regard to the quota limitation, the problem of execution was that 500 write requests per video constituted the upper limit for requesting data; beyond that, the server disconnected. That is to say, when one video attracted over 500 records of comments, it was necessary to repeat the request and tackle the inevitable issue of data overlapping. Therefore, the time of cleaning data exponentially increased along with the increase of data. On the other hand, another general daily quota limit was that only 50,000 requests per project per day were allowed to be retrieved. Considering the above common overlapping scenarios, the lead time for preparing the dataset costs became much longer with regard to the YouTube Data API quota limitations.

Additionally, this study focused on the video advertisements on YouTube uploaded by the Coca-Cola Company; therefore, the accessible quantity of video data

was restricted. The official communities owned by the Coca-Cola Company were composed of the following accounts: Coca-Cola, Coca-Cola Light, Coca-Cola Zero, and CocaColaCo. Furthermore, considering the specified research boundary, only the video advertisements played in North America are used for this research. All the limitations for enhancing research validity set the boundary on the available data volume.

## 3.3 Data Transformation for Variables

This forecasting mechanism utilized eight predictors to explore the video advertisements. Seven of these independent variables were quantitative, including: video lengths, viewer counts, thumbs up, thumbs down, all comments, the cluster number of viewer segmentation and feature scoring of sentiment. The mere qualitative predictor was the degree of the polarity generated by the sentiment analysis. Unquestionably, three of the predictors—the cluster number of viewer segmentation, feature scoring and degree of polarity produced by sentiment analysis—must be re-processed for further predictive analysis; they were discussed in the following sections.

### 3.3.1 The Cluster Number of Viewer Segmentation

The complexity of this predictor lied in its two analytic layers. The first stage was to identify the principal preferences of individual viewers—who left opinions on one video advertisement from their lists of subscribed channels—and the social influential indexes, including total upload views and subscription counts. Subsequently, the next step was to execute the statistical approach/two-step clustering method to obtain the ideal grouping numbers for each video.

With reference to the concrete procedure of the first stage, the goal was to recognize whether the viewer account has channel subscriptions and whether or not we can narrow the research scope. This was based on the assumption that people with high involvement in any functionality of social media reflected the true experience to the videos. It implied that the user accounts were active and worthy of learning on. After reserving the viewer information regarding who has subscribed to channels, the other non-subscribing viewers were temporarily omitted; their preferences were not included in this predictor's component. In light of the remaining viewers, the rule was to adopt the category with the maximum frequency from their subscribed channels as their representations of preference.

Accordingly, the second stage was to deploy the segmentation setting for carrying out the two-step clustering method. In the first step, this research undertook a modified hierarchical agglomerative clustering procedure that combines the objects sequentially to construct homogenous clusters on the basis of log-likelihood distance measure. The calculation formula for this probability-based distance between clusters $C_i$ and $C_j$ can be defined as follows:

$$d(i, j) = \xi_i + \xi_j - \xi_{(i, j)} \tag{1}$$

Where

$$\xi_v = -N_V \left( \sum_{K=1}^{K^A} \tfrac{1}{2} \log(\hat{\delta}_k^2 + \hat{\delta}_{vk}^2) + \sum_{K=1}^{K^B} \hat{E}_{VK}^2 \right) \tag{2}$$

and

$$\hat{E}_{VK}^{2} = -\sum_{l=1}^{L_K} \frac{N_{VKl}}{N_V} \log \frac{N_{VKl}}{N_V} \quad (3)$$

ξv was similar as a variance within cluster v (v = i, j, (i, j) ). The first formula $-N_V \sum_{K=1}^{K^A}$ ½ log( $\hat{\delta}_k^2 + \hat{\delta}_{vk}^2$ ) measured the dispersion of the continuous variables $X_j$ within cluster v. If $\hat{\delta}_k^2$ was ignored in the expression for ξv, the distance between clusters i and j was exactly the decrease in the log-likelihood function after integrating cluster i with j.

In terms of the second entropy part $-N_V$ ($\sum_{K=1}^{K^B}$ $\hat{E}_{VK}^2$), it was used to evaluate the dispersion of the categorical variable ( Bacher, Wenzig & Vogler , 2004).

As for the second stage, this study allowed the technique to automatically determine how many clusters were retained by calculating the measure of fit-Bayesian Information Criterion of Schwarz (1978). There was no doubt the procedure returned the best number of clusters for further use. Narinc (2010) defined the Bayesian Information Criterion as the math formula below:

$$BIC = n * \ln(\frac{SSN}{n}) + p * \ln(n) \quad (4)$$

Where

n = number of observations in the model fitting

SSR = Sum of squares of residuals of the model

p = number of model parameters

Regarding this independent variable's processing, it was necessary to make use of Python programming language to identify the individual viewer's preference. Moreover, SPSS Statistics was utilized to do the two-step clustering analysis as follows.

### 3.3.2 Sentiment Analysis

Another significant analytic point of this study was to assess the strength of the WOM on sales achievement. The principal component of sentiment can be divided into two predictors: feature-scoring and degree of polarity for forecasting use.

In terms of feature-scoring, it can be interpreted as the normalized weighting of a feature's orientation by means of statistical evaluation. On the other hand, the majority of viewers' attitudes toward the video advertisement experience can be defined as the degree of polarity. Additionally, the pre-processing work for producing both independent variables from opinions was to compile the lexicon, which involves the feature indexes and terms of polarity (positive, negative, neutral), along with logical words, to automatically identify the semantic location and further work on the classification. All the procedures for generating both predictors were clarified accordingly.

#### 3.3.2.1 Lexical Syntactic Pattern Generator

Based on the ROLEX-SP (Mohammed & Aysu, 2011) schema, this research added additional neutral and logical terms to strengthen the capability of classification rather than merely judging by positive and negative semantic patterns. The lexical syntactic patterns were extracted in accordance with the existence of a category's lexicon. Hence the compilation of the lexicon had a critical influence on the performance of classification. In this study, the lexicon not only comprised the distinguished feature

indexes to the specific Coca-Cola advertising eyestops but also the set of polarity terms. All the synonyms, antonyms, and co-existing concepts of these entries were categorized in this exclusive dictionary, which covered all the expressions of advertisement experience.

Subsequently, the lexical-based classifiers automatically parsed the corpus and applied the statistical scoring function to obtain the feature-weighting as its score, and conducted the inference of polarity at the same time. Figure 3.1 indicated the procedure for how lexical syntactic pattern generators were derived from the sentiment data. This process split the corpus of video data into three disjointed parts: training set, validation set and test set. All these sets were randomly selected from the corpus in the ratio 50% : 25% : 25% with replacement.

In terms of the 25 videos sampled as the training set, the most important task was to categorize the sentiment into two groups of classification: feature indexes and tendency LSP. The feature indexes contained 9 groups: Brand, Icon, Image, Music, Story_Festival, Story_Theme, Design, Issue, and Competitor. The purpose of identifying features was to analyze the core message, which implied the subjects the viewer cared about most.

Moreover, the tendency of lexical syntactic patterns comprised categories including positive, negative, neutral and logical words. In particular, the logic of using neutral patterns was that the tendency terms following the neutral phrases determined the polarity of a sentence. It can exclude any possibility of mistaken judgement. Take, for example, “feel like” as one of the illustrations; without the involvement of neutral

patterns, the phrase was identified as positive due to the word “like”. Furthermore, the logical patterns were interpreted as the words that can thoroughly reverse the tendency of opinions, such as the word “not” and phrase “devoid of”. How the statistical algorithm converted these patterns into a classification rule to produce two predictors—feature-scoring and degree of polarity—was discussed in the next section.

LSP Generator

•Goal: to extract positive, negative, logical and neutral lexical syntactic patterns from training set

•Input: Lexicon, 25 videos

- Lexicon: Feature Index and Tendency LSP

(1)Feature Index($C^f$): Brand, Icon, Image, Music, Story_Festival, Story_Theme, Design, Issue, Competitor

(2)Tendency LSP: Positive($C^+$), Negative($C^-$), Neutral($C^n$), Logical($C^l$)

- 25 videos(TS): randomly select 50% videos as traning set

total 2571 comments: Y2009 2 videos, Y2011 3 videos, Y2012 3 videos, Y2013 5 videos, Y2014 11 videos

•Output: Positive $P^+$, Negative $P^-$, Neutral $P^n$, Logical $P^l$

•Method: Apply below instructions

Begin

1. $P^+=\{\}$, $P^-=\{\}$, $P^n=\{\}$, $P^l=\{\}$
2. For each video($vid_i$) from TS, each $vid_i$ consists of one sentiment document($d_i$).
   Therefore, $p_i$=Parse($d_i$,Lexicon($C^f$,$C^+$,$C^-$,$C^n$,$C^l \in C_i$)).
3. Each $p_i$ can be grouped into P ($p_i \in P$).
4. accuracy($p_i$,$C_i$)=$N_{correct}$($p_i$,$C_i$)/$N_{cover}$($p_i$) Ncover(pi)>0
   if $N_{cover}$(pi)=0, accuracy(pi,Ci)=0
5. If accuracy($p_i$,$C_i$)>=threshold then, $p_{ci}^+ = p_{ci}^+ \cap p$ ; $p_{ci}^- = p_{ci}^- \cap p$ ; $p_{ci}^n = p_{ci}^n \cap p$; $p_{ci}^l = p_{ci}^l \cap p$
6. Return ( P+={}, P-={}, Pn={}, Pl={} )

End

*Figure 3.1* Lexical Syntactic Pattern Generator

### 3.3.2.2 The Conversion of Two Predictors

After recognizing all the terms from the lexicon, an individual comment set left by one viewer was independently diagnosed if his or her experience toward that specific video advertisement was good, bad or can’t be determined. With regard to the coverage

of each video, the separate sentiment set can be judged from two dimensions—its emphasized feature and polarity. Additionally, the chi-square statistical test was adopted to grade all the sentiment sets of one video by means of a contingency table. The scores can stand for the strength of the striking feature and the polarity on the video. Through the transformation of the scoring function, this study leveraged the chi-square scores as the feature scores and determined the degree of polarity. Below was the chi-square formula:

$$X^2 = \sum \frac{(OBSERVED\_FREQUENCY - EXPECTED\_FREQUENCY)^2}{(EXPECTED\_FREQUENCY)}$$

## 3.4 Modeling Procedures

This model involved four phases. The first stage entailed collecting data and creating one database to store that data. The second stage entailed processing the data, especially in terms of viewer segmentation and sentiment classification. The third stage applied statistical methods such as Random Forest to build up the predictive system. The final stage was to verify the predictive performance. After the implementation of this predictive model, we adopted some validation approaches to examine its performance. There were more explanations to account for the major tasks in each phase, as described below.

Phase 1. Database Setup

After collecting all the data by means of API (Application Programming Interface), the infrastructure of the database was established to create tables to store data and subsequently clean the noisy data. There were four tables:

(1) *Comment table*. Each video had its own VID. For each advertisement

video, this database used its VID as the table name.

(2) *Subscription table*. This table contained all the subscription channels.

(3) *User table*. This table contained all the user information who posted the comments.

(4) *Video table*. This table contained all the video information, including targeting advertisement videos and favorite videos.

Phase 2. Data Processing

In this stage, the transformation of two separate variables was constructed and then combined into one predictive schema. This model put more emphasis on content-based filtering. In light of the content-based filtering variable, sentiment analysis was the imperative predictor to adopt in this model.

The proposed framework to develop semantics and syntactic classification was the modification of Rules of Lexical Syntactic Patterns (ROLEX-SP classifier). The idea was to construct more layers for connecting classifiers from different series of advertisements semantically in the specific domain. That was, this modified ROLEX-SP classification put more emphasis on the lexicon compilation and subsequently leveraged one of the statistical methods on assessing the feature scoring and the degree of polarity. The goal was to identify the tendency of the viewing experience and the features that people highlighted more significantly in their opinions, for deriving an association with sales performance.

In terms of a predictive system, aside from unstructured data analysis, user preference was regarded as one of the factors that impacted sales generation and was categorized by what channel to which the user had subscribed. Dimensionality reduction

promptly created the correct forecasting engine bridge between input- and output-sales generation. Therefore, all the classifications in each factor of this hybrid forecasting framework concentrated on minimal but proper groupings to represent the real viewers' experience.

Phase 3. Predictive System Modeling

Through R programming language, the proposed forecasting model followed the principle of a Random Forest algorithm to construct trees. Each tree in the ensemble was built from a sample drawn with a replacement from the training set. Furthermore, when splitting a node during the construction of the tree, the split that was picked was the best split among a random subset of the features. Because this algorithm combined classifiers by averaging their probabilistic prediction instead of letting each classifier vote for a single class, this predictive schema yielded an overall better model. Additionally, regarding the output, a data-earning release report was retrieved from the official website of the Coca-Cola Company, which made all the financial reports public for investors.

Phase 4. Validation

The study examined the case study and inferred if it was suitable to leverage video advertisements on predictive tasks via the execution of forecasting. Based on my proposed forecasting framework, it can verify which variable mix contributed to higher accuracy for the aforementioned consumer product company.

## 3.5 Summary

This chapter had depicted the methodology used in this study. It provided a detailed description of predictors, how they were obtained and classified, and how we used them to build the forecasting mechanism.

# CHAPTER 4. RESULTS

## 4.1 Introduction

Results from the parametric research outlined in the previous chapter were presented in this section. The findings included the overview of data and the data analysis generated from the two-step clustering approach for viewer segmentation, along with the performance evaluation of this predictive schema developed by the random forest algorithm. Through the exploration of video advertisement and its target audience behavior, the knowledge base was created to assess the value of word-of-mouth and make the utilization of social media transparent. Ultimately, these results were applied to determine the forecasting effect if the video advertisement played on social media followed a consistent trend with the subsequent sales achievement. If so, it can be regarded as a predictive signal for the adjustment of a future marketing strategy.

## 4.2 Data Summary

In consideration of the aforementioned search criteria, 49 videos were gathered from the official Coca-Cola communities on YouTube. Among these videos, the quantity of each yearly video advertisement distributed in an unbalanced fashion: 3 from year 2009, 1 from year 2010, 4 from year 2011, 6 from year 2012, 12 from year 2013 and 23 from year 2014. In addition, the total records of sentiment sets were 36,464, based on each viewer who left comments below the video. No one opinion necessarily stood for one independent user account, which meant an overlapping phenomenon exists. The data

showed that the total number of distinct user accounts was 12,427. It can be inferred that the viewers probably tended to leave multiple comments on the same or other videos. On the other hand, one record of a sentiment set commonly consists of more than one. However, the overlapping was not serious enough to impact the study of viewer preference. An overview of the retrieved data was shown in Table 4.1.

Table 4.1 *Summary of Data Collection*

| Year | Quarter | Number of Ad Videos | Records of Sentiment | Net Operating Revenues |
|---|---|---|---|---|
| 2009 | 2 | 3 | 215 | 3,655 |
| 2010 | 1 | 1 | 1,011 | 1,932 |
| 2011 | 1 | 2 | 893 | 4,687 |
| 2011 | 2 | 2 | 432 | 5,504 |
| 2011 | 4 | 1 | 3 | 4,993 |
| 2012 | 1 | 2 | 651 | 4,921 |
| 2012 | 3 | 1 | 132 | 5,670 |
| 2012 | 4 | 2 | 10,520 | 5,292 |
| 2013 | 1 | 6 | 2,287 | 4,887 |
| 2013 | 2 | 1 | 189 | 5,713 |
| 2013 | 3 | 2 | 1,593 | 5,719 |
| 2013 | 4 | 3 | 420 | 5,271 |
| 2014 | 1 | 6 | 14,770 | 4,793 |
| 2014 | 2 | 9 | 1,070 | 5,717 |
| 2014 | 3 | 1 | 99 | 5,599 |
| 2014 | 4 | 7 | 2,179 | 5,370 |
| Grand Total | | 49 | 36,464 | |

## 4.3 Two Step Clustering Analysis for Viewer Segmentation

Results showed the average percentage of viewers who posted reviews on video advertisements and also subscribed to channels on YouTube. This average was 50% per video. According to the analysis of these viewer data, the number of channels viewers subscribed to on average is approximately 20. Accordingly, it implied that a group

participating in the discussion of experience-sharing generally had a high level of involvement in the social media platform.

This study followed the definition of video category created by YouTube. In light of YouTube's requirements, the user must choose the appropriate category from its predefined categories for the video the viewer uploaded. Therefore, leveraging this function and data on automatic classification efficiently reduced the error of diagnosis and the execution time. The coverage of this research involved 17 categories: Music, Games, Film, Entertainment, Sports, How-to, People, Animals, Autos, Comedy, Education, Nonprofit, Shows, Tech, News, Travel, and Others. Among these categories, the analysis revealed that Music, Entertainment and Games were the main viewing preferences of users who watched and commented on the Coca-Cola video advertisements. Thus, future advertising design can take these three user preferences into consideration, although it was difficult to indicate if there existed any preference difference between viewers who watched the advertisements on a social video-sharing platform or on cable television.

After integrating two indexes of social network influential power—total upload views and subscription counts—the two-step clustering method was adopted to determine the optimal number of viewer segmentation for each videos. According to the principle of likelihood distance measure and Schwarz's Bayesian criterion, when the cluster quality was between 0.2 and 0.5, it can be judged as an acceptable classification quality. Once the cluster quality was greater than 0.5, the quality was judged as good. As seen in Figure 4.1, the cluster quality mainly lied in fair and good conditions on the basis of the silhouette measure of cohesion and separation in this study. Most video data can be

partitioned among 2 to 3 groups of viewers. With the increase of viewer volume, data apparently showed the growth of segmentation numbers. In this study, 7 groups were the maximum number of clusters for categorizing the video's viewer pool.

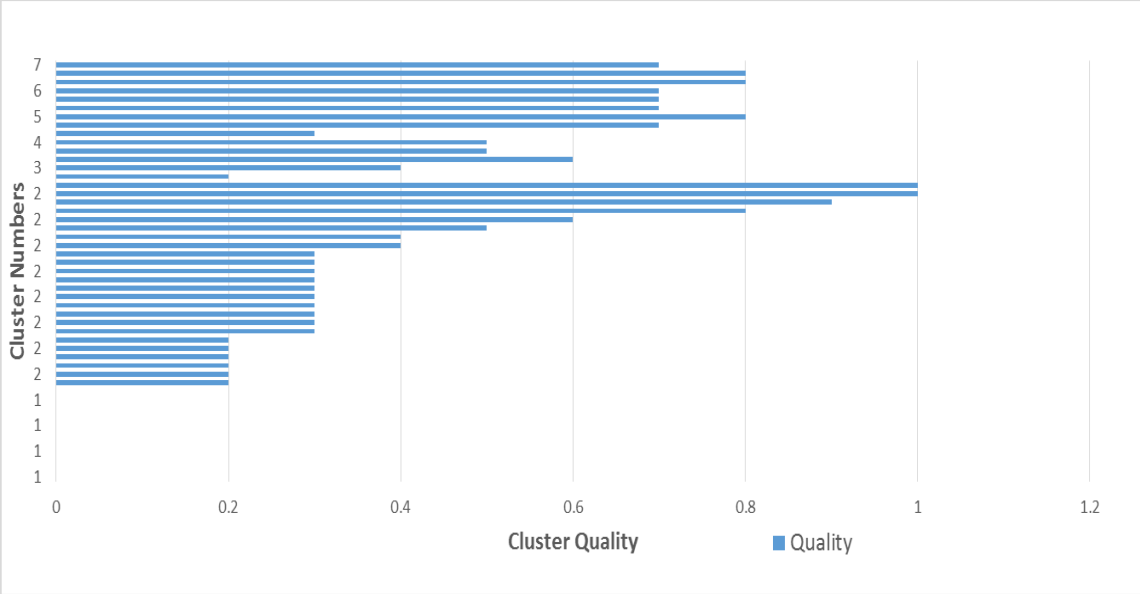


*Figure 4.1* Sihouette Measure of Cohesion and Separation

## 4.4 Sentiment Analysis

The lexicon was compiled as 5 tag categories—feature, positive, negative, logical, and neutral—by gathering the keywords from the training set of 25 videos. The total number of word count was 46,051. Regarding the word count distribution of each index, Table 4.2 presented all the ratios; the positive section apparently occupied the highest portion (41%). Notably, the negative part only accounted for 4%; however, 16% of word counts fell in the logical section, which was used to convert the inclination of opinions.

Table 4.2 *Distribution of Sentiment Data*

| Index | Feature | Positive | Negative | Logical | Neutral | Total |
|---|---|---|---|---|---|---|
| Word Counts | 17,301 | 18,962 | 1,957 | 7,179 | 652 | 46,051 |
| Ratio | 38% | 41% | 4% | 16% | 1% | 100% |

From the viewpoint of feature tags, Table 4.3 pinpointed that “Brand” and “Music” were the top two attributes viewers used to describe their advertisement experience. Additionally, it was clear that the size of word groups was irrelevant to the number of word counts, such as attribute-brand. Data in Table 4.3 showed that the brand of Coca-Cola and its advertisement audio were the most impressive characteristics of the Coca-Cola video advertisements.

Table 4.3 *Summary of Feature Tag*

| Feature | Category | Word Counts | Ratio |
|---|---|---|---|
| Brand | 8 | 8,801 | 51% |
| Music | 19 | 5,580 | 32% |
| Issue | 10 | 916 | 5% |
| Theme | 12 | 583 | 3% |
| Image | 25 | 463 | 3% |
| Competitor | 1 | 279 | 2% |
| Festival | 4 | 278 | 2% |
| Design | 2 | 241 | 1% |
| Icon | 11 | 160 | 1% |
| Total | 92 | 17,301 | 100% |

With regard to the individual word category of separate feature dimensions, Figure 4.2 illustrated the results of word classification by means of k-fold cross-validation method in validation set. From this graph, one of the word categories, “Song,”

was a relatively better classifier to identify the feature of Music compared to the other two categories of “Music” and “Version”. Furthermore, Figure 4.3 showed that the word category of “Song” had the dominant classification effect for identifying the feature of music in the test set; the accuracy of feature classification in all word coverage of documents was fairly strong as well.

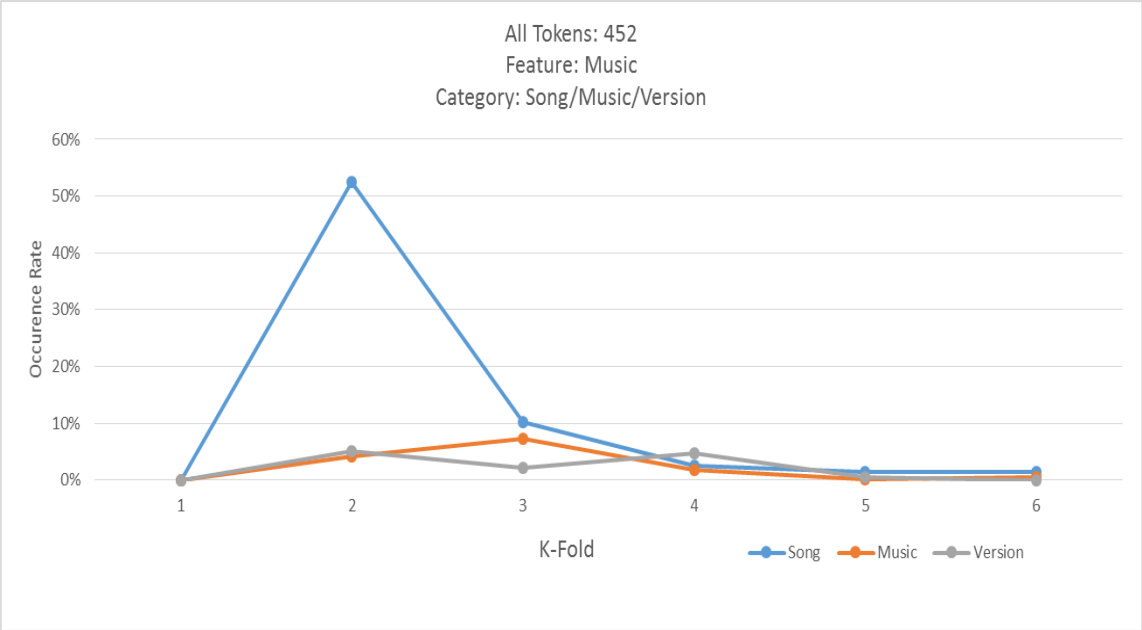


*Figure 4.2* Cross-Validation for the Feature Classification (K=6)

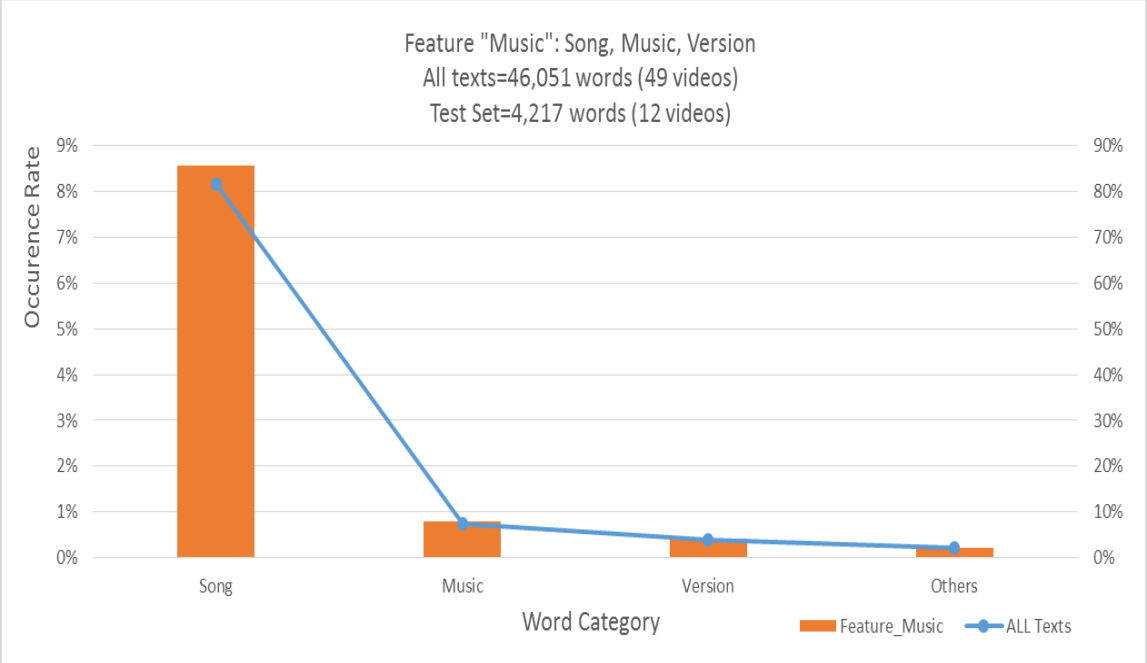


*Figure 4.3* Test Set for the Examination of Classification Effect

Moreover, tables 4.4 and 4.5 showed the JJ (adjective) and VB (verb) were the most common part-of-speech (POS) tags for viewers to express their feelings of experience. All these tags went through the process of k-fold cross-validation and subsequently verified their classification performance in the test set. Figure 4.4 utilized the words “Beautiful”, “Good” and “Wonderful” to examine the implementation of classification. Obviously, the word “Good” represented a normal adjective to describe the viewing experience, but the word “Beautiful” can clearly reflect the attitude toward some specific characteristics in the advertisement. In addition, the graph also pointed out that the word “Wonderful” was not a powerful positivity.

Table 4.4 *Summary of Positive Sentiment*

| POS tags | Category | Word Counts | Most Frequent Term |
|---|---|---|---|
| JJ | 54 | 9,875 | Beautiful |
| VB | 18 | 8,113 | LOVE, Like |
| NP | 7 | 526 | IN LOVE |
| NN | 10 | 448 | HAPPINESS |
| Total | 89 | 18,962 | |

Table 4.5 *Summary of Negative Sentiment*

| POS tags | Category | Word Counts | Most Frequent Term |
|---|---|---|---|
| JJ | 24 | 833 | Stupid, Dumb |
| VB | 22 | 514 | Dislike, Suck |
| NN | 15 | 416 | Hell, Crap |
| VP | 1 | 194 | Make no sense |
| Total | 62 | 1,957 | |

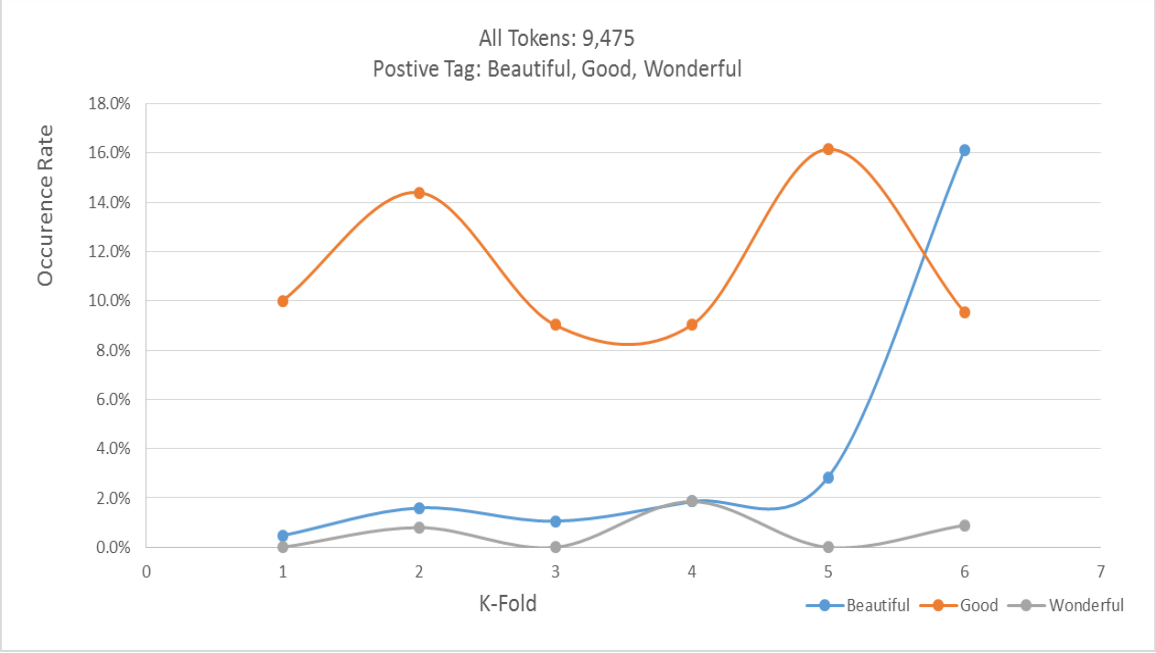


*Figure 4.4* Cross-Validation for the Positivity in Positive Sentiment (K=6)

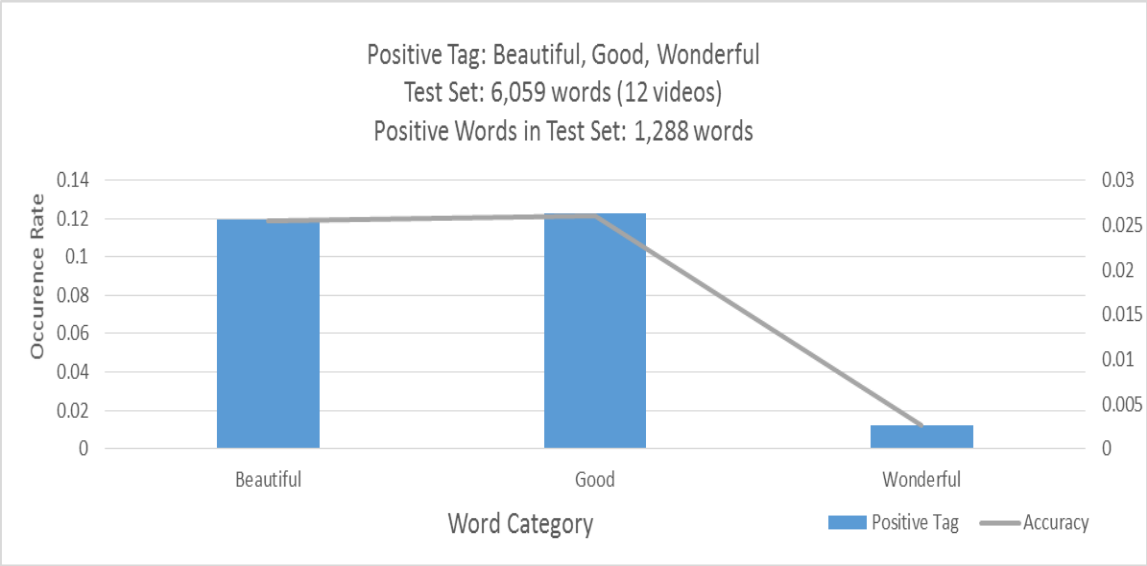


*Figure 4.5* Test Set for the Examination of Positivity Classification

Similarly, figures 4.6 and 4.7 presented the classification effect of negativity in negation. Word categories such as “Stupid” and “Fake” were more prevalent annotations with great classification effects for how viewers responded to the video advertisements, than “Terrible”. Furthermore, Figure 4.8 illustrated the word category “Stupid” in overall negation to explore the effects of distinct word components. The plot validated that the classification effect of the word ”Stupid” dominated all other synonyms, including “Silly” and “Dumb”. Hence, it can be concluded that negative tags categorized from the training set had a healthy classification performance in the test set as well.

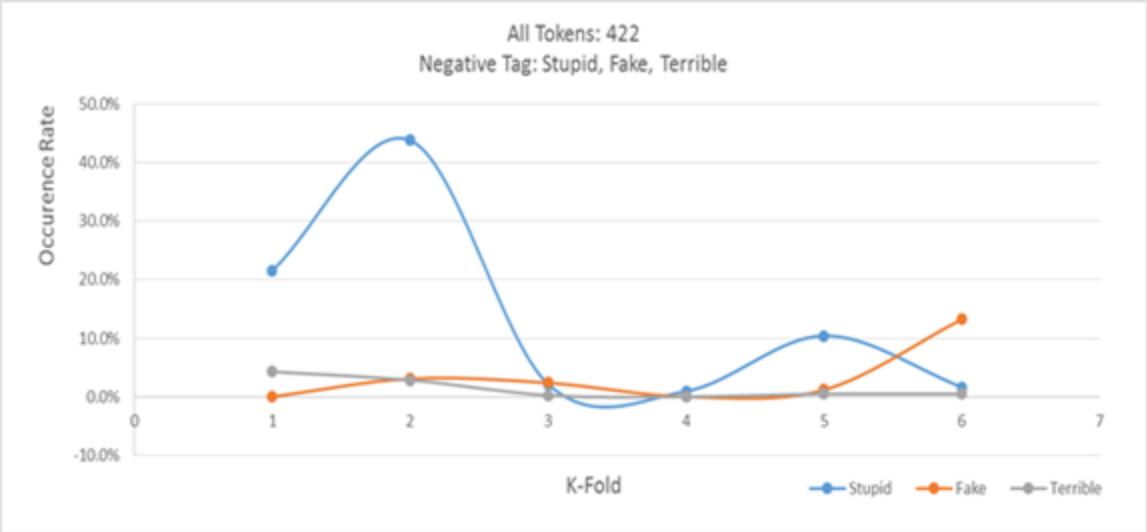


*Figure 4.6* Cross-Validation for the Negativity in Negation (K=6)

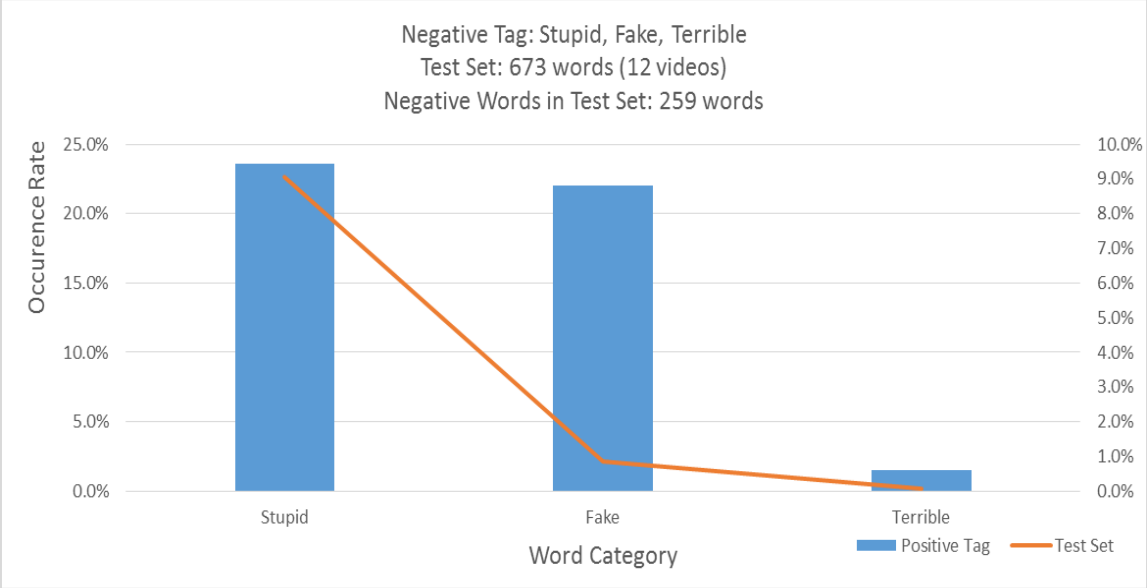


*Figure 4.7* Test Set for the Examination of Negativity Classification

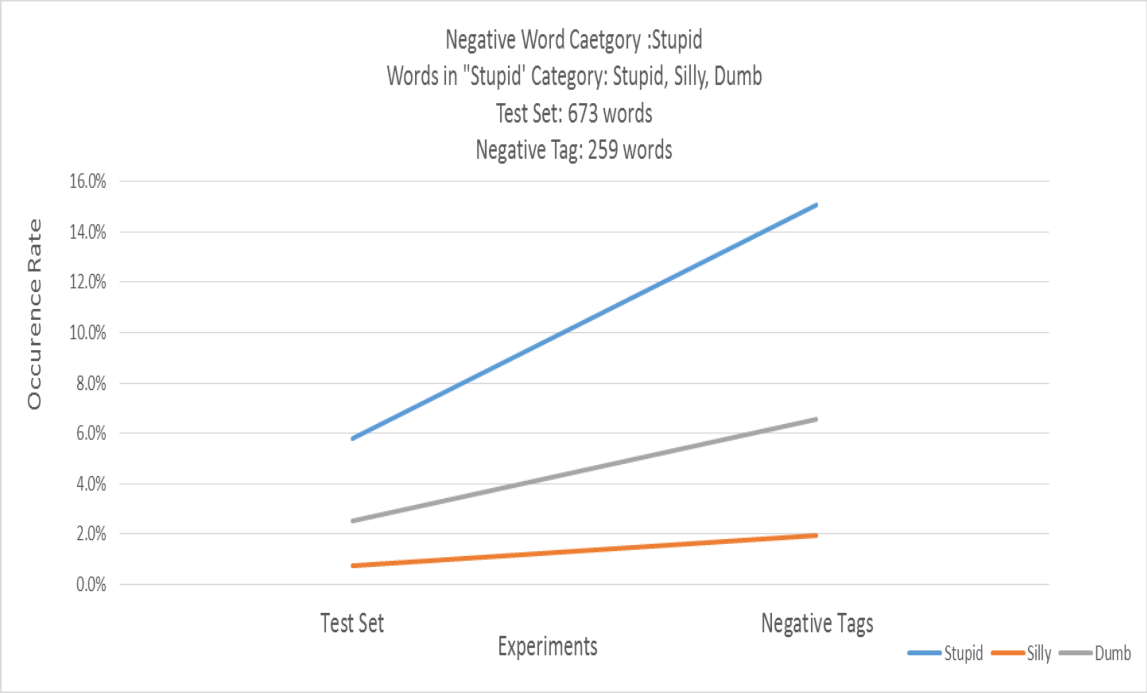


*Figure 4.8* Effect of Different Negativity in Negation

Moreover, the logical negation played a preposition role in reversing the meaning of opinions. In Figure 4.9, the validation experiment adopted 6 folds to verify the contrasts between logical negation and negative tags. Apparently, logical negation empowered the linguistic structure more powerfully to identify the classification of polarity.

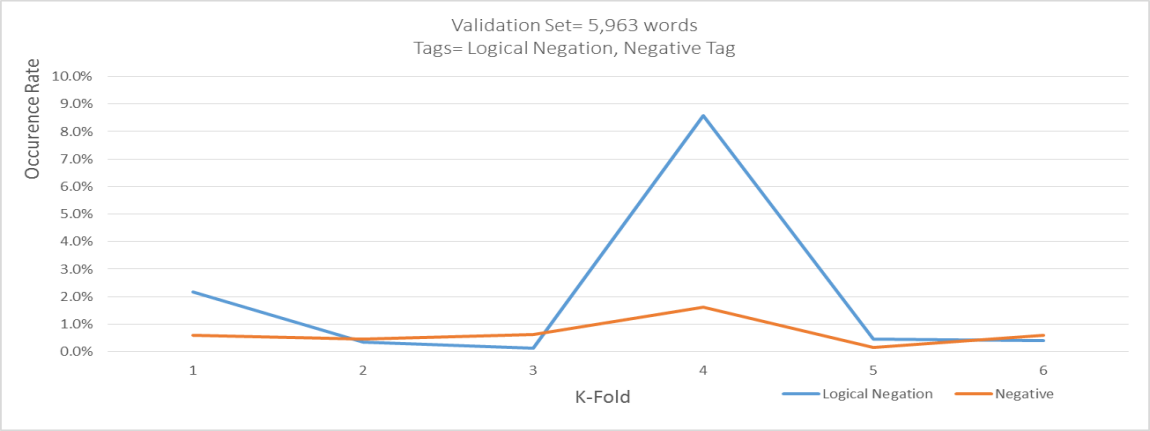


*Figure 4.9* Comparison between Logical Negation and Negative Tags

Regarding the neutral tags, Figure 4.10 exhibited less confusion caused by the neural terms in this corpus through the cross-validation method. To take the word group "Look Like" as an example, it didn't have enough strength to impact the inclinations of opinion as compared to the strength of the word group "Like". Thus, it can be inferred that a strong influence from positive tags overwhelms the impact from neutral tags. Subsequently, Figure 4.11 also leveraged the most frequently used neutral term "Can Not Stand" to compare with the intensity of negative tags such as "Not". Evidence demonstrated that both positive and negative POS tags mainly determined the attitudes toward the video advertisement.

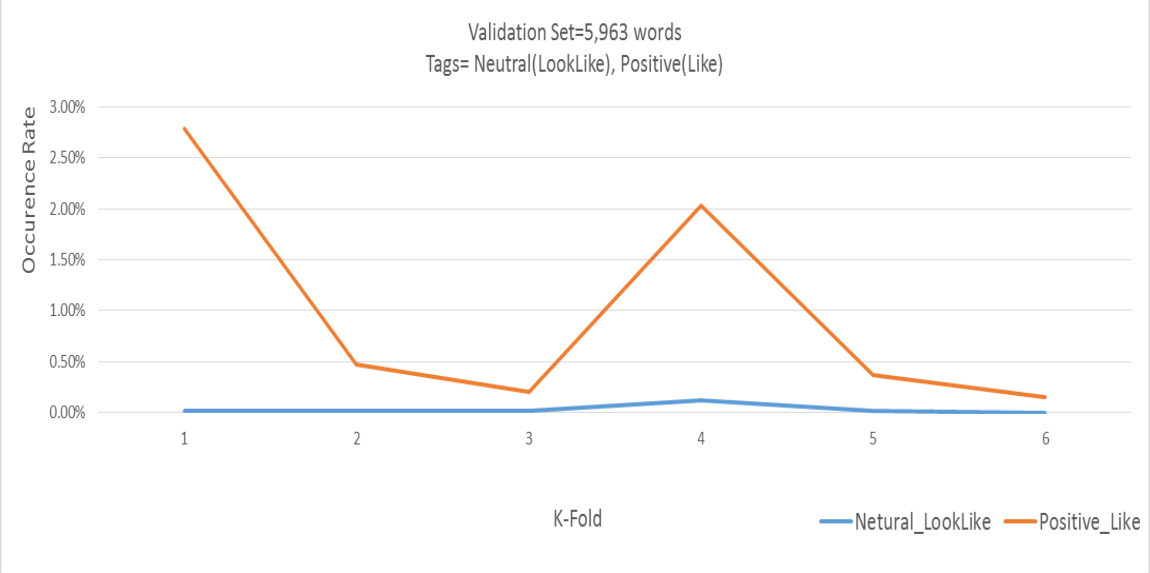


*Figure 4.10* Distinction between Neutral Tags and Positive Tags

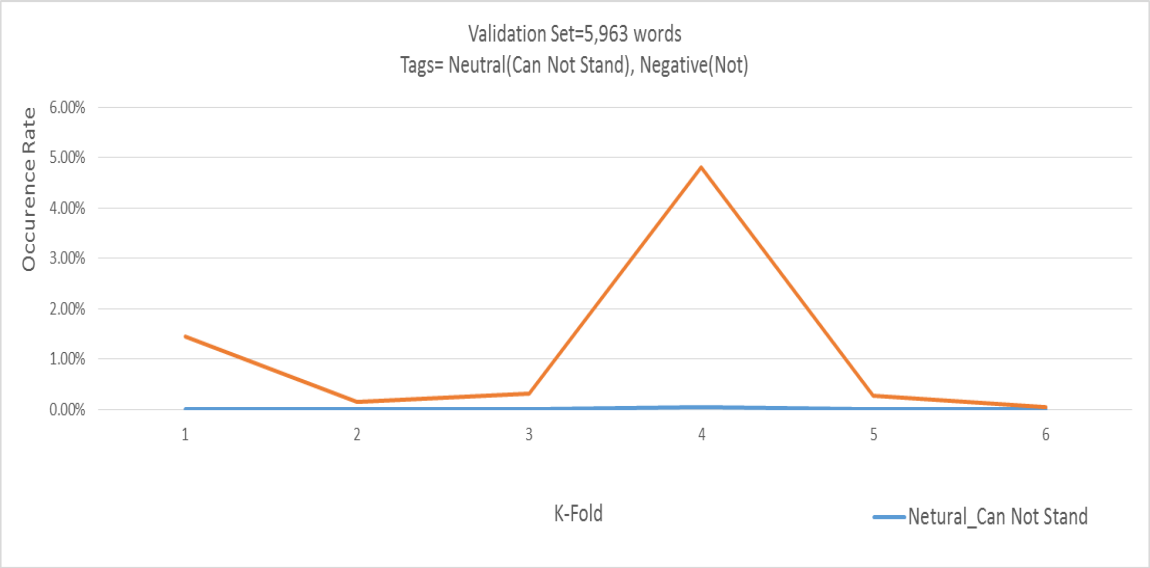


*Figure 4.11* Distinction between Neutral Tags and Negative Tags

As for the determination of polarity, this study followed the ROLEX-SP classifier approach to locate all part-of-speech tags through above LSPs at first, and exploited the chi-square scoring function to return its feature scores as degree of polarity and the polarity itself.

From the experimentation, neutral tendency accounted for a major portion of polarity (75%, 35 videos) in this sentiment text, and positive responses occupied the second-largest proportion (20%, 10 videos). Only 4 videos returned the negative feedback (8%). In Figure 4.12, the distribution took advantage of the quartile to transform the chi-square scores as three degrees of polarity—Low, Medium, High—to investigate the strength of each polarity. Evidence revealed that neutrality with medium power was the mainstream in this data. Even in the positivity or negation, there was no significant influence that reinforced or weakened the inclination of polarity. To sum up, a majority of the Coca-Cola video advertisements offered viewers a neutral or good experience.

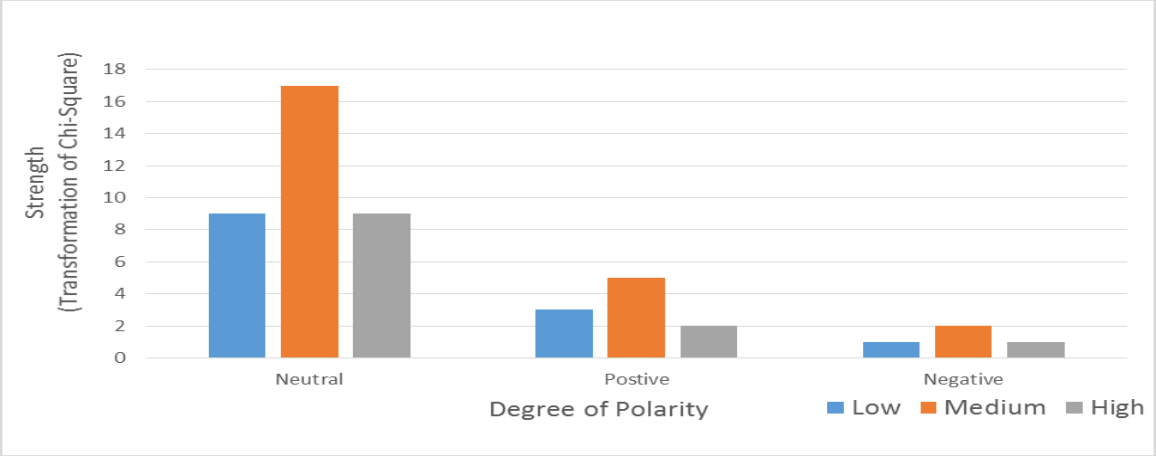


*Figure 4.12* Distribution for Degree of Polarity (49 videos)

## 4.5 Random Forest Model

This study adopted Classification Random Forest to examine the achievement of this predictive framework. Hence, the response variable of net operating revenue was transformed into a multiclass categorical predictor: high, medium and low. The revenue categorization was judged by the quartile of the net operating revenue; if the revenue was greater or equal than the third quartile of overall data, it was identified as the high level revenue. If the revenue lied between first quartile and third quartile, then it was recognized as the medium level and the remainder was low level. In addition, this research separated the dataset into a 75% training set and 25% test set that relied on the sampling without replacement to verify the model's predictive effect.

In this section, all the parameters and the tree simulation generated by the Random Forest algorithm were further discussed as follows: the out-of-bag error, variable importance indices, proximity measure, and tree structure. Moreover, the evaluation of predictive performance was demonstrated by Receiver Operating Characteristic Curves (ROC) as well.

### 4.5.1 The Out-of-Bag Error Estimate

In terms of the out-of-bag error, this estimate of generalization error had a similar multiple training process of leave-one-out cross-validation without additional computational workload. From the experimentation, the output of this Random Forest model showed that the estimate of out-of-bag error rate was 55.56% on the basis of 500 trees in the forest, and the 3 predictors sampled at each split. Additionally, the confusion matrix revealed that the misclassification rates were generally high among three dependent variables. Table 4.6 showed that only medium-level revenue had relatively less classification error (25%). However, there was no significant classification boundary for high and low levels of revenue.

Table 4.6 *Confusion Matrix of Response Variable*

| Dependent Variable: Revenue | H | L | M | Class.Error |
|---|---|---|---|---|
| H | 0 | 0 | 9 | 100% |
| L | 0 | 4 | 7 | 63% |
| M | 1 | 3 | 12 | 25% |

* H: High level  L: Low level  M: Medium level

Consider the impact of one tuning parameter—the number of trees in building random forests. Both Table 4.7 and Figure 4.13 implied that the research should reduce the size of trees down to 400 and gain relatively little loss in the increase of error. Nevertheless, Table 4.7 also showed that a small number of trees (ntree=100) apparently had large error rates (66.67%). Therefore, this research used 400 random trees as the optimal tree size to build up the forecasting forest.

Table 4.7 *OOB Error Rate in Different Tree Size*

| ntree | OOB | 1 | 2 | 3 |
|---|---|---|---|---|
| 100 | 66.67% | 88.89% | 63.64% | 56.25% |
| 200 | 61.11% | 100.00% | 72.73% | 31.25% |
| 300 | 55.56% | 100.00% | 72.73% | 18.75% |
| 400 | 50.00% | 100.00% | 63.64% | 12.50% |
| 500 | 55.56% | 100.00% | 63.64% | 25.00% |

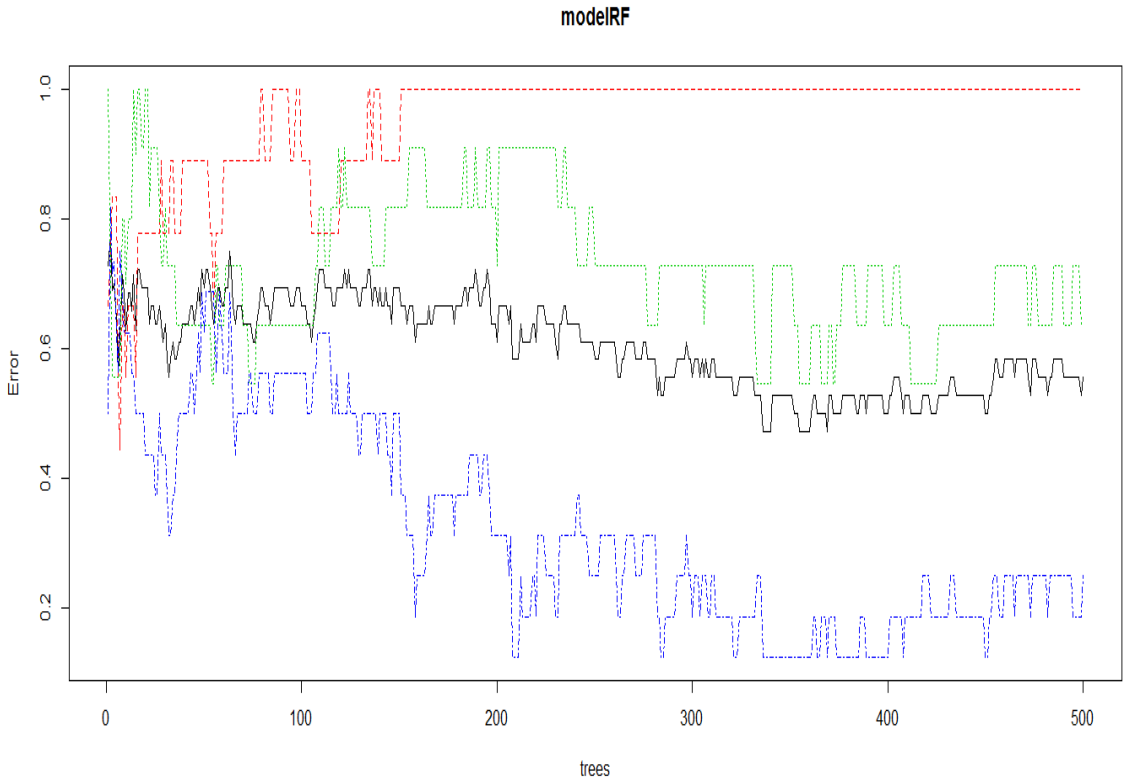


*Figure 4.13* OOB Error Rate in Different Tree Size

### 4.5.2 The Evaluation of Variable Importance

Regarding the assessment of variable significance, the feature selection based on the Gini impurity index manipulated a regularized linear classification to reduce the dimensionality of this optimal subset of features and exclude the noise from the classification work. In the Random Forest algorithm, Mean Decrease Gini represented a measure of variable relevance to the classification dependent on the Gini impurity index, averaging the sum of overall weighted impurity decreases for all trees in the forest. Figure 4.14 displayed that three of the attributes in this model were obviously significant to assist the classification: the number of all comments, the number of thumbs up and the viewer counts. Evidently, the features related with traffic concept played a pivotal role in segmenting distinct characteristics of individual explanatory variables; however, the predictors—feature scores, the number of viewer segmentation and the polarity—did not present conspicuous effects of classification.

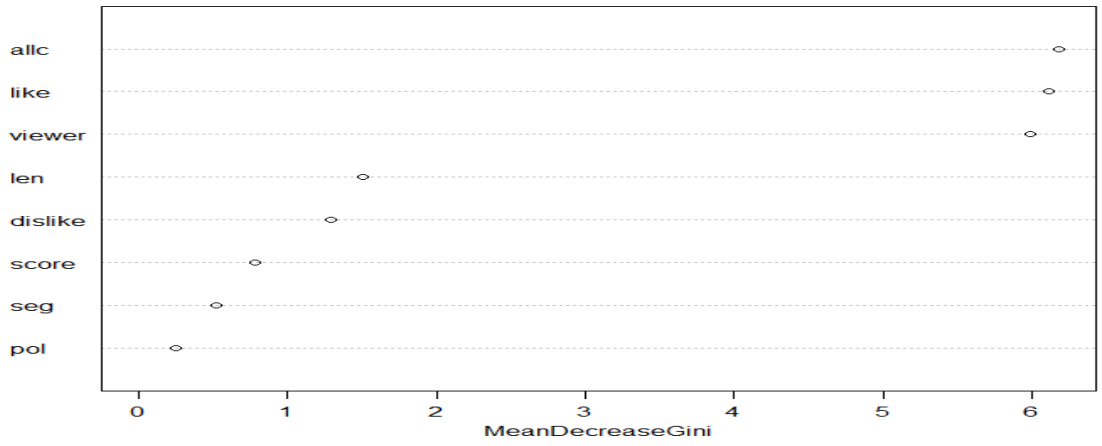


*Figure 4.14* Mean Decrease of Gini impurity index

Regarding the permutation measure of impact on accuracy, Figure 4.15 pinpointed that the features with higher values of mean decrease in accuracy—video length, viewer

counts and the number of thumbs up and down—were more imperative to the classification of prediction. Nevertheless, the independent variables—the number of viewer segmentation, feature scores, polarity and the number of comments—showed less importance to the accuracy of output.

Essentially, the main difference between Mean Decrease Accuracy and Mean Decrease Gini was whether the calculation is based on the out-of-bag data or not. In other words, Mean Decrease Accuracy was determined by the normalized difference of the classification accuracy for the out-of-bag data, which was randomly permuted. The bootstrap iterations of Mean Decrease Accuracy made its estimate unduly optimistic, but Mean Decrease Gini was immune to this issue due to its manipulation that relied on the data used to fit trees. In Table 4.8, the feature of the number of comments was useful to differentiate the feature space, but did nothing to strengthen the output of forecasting.

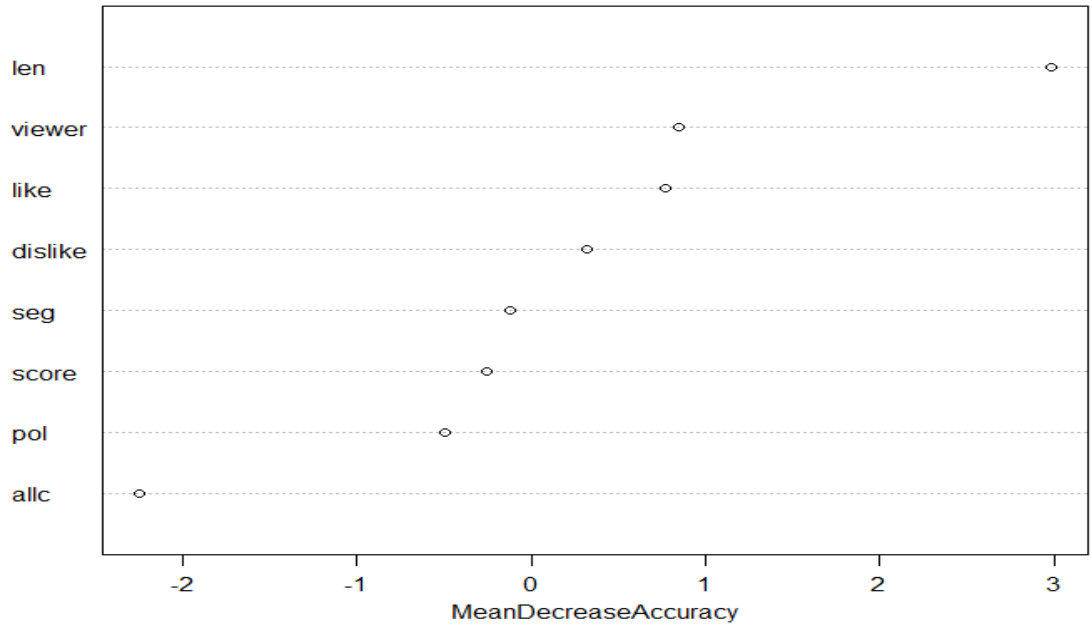


*Figure 4.15* Mean Decrease of Accurace

Table 4.8 *Summary of Variable Importance*

| | High | Low | Medium | MeanDecreaseAccuracy | MeanDecreaseGini |
|---|---|---|---|---|---|
| len | 4.310541 | 3.333754 | -2.02161 | 2.98779 | 1.500544 |
| like | 1.182817 | -0.22512 | 0.916229 | 0.7733121 | 6.109954 |
| dislike | -1.26247 | 1.542705 | 0.081146 | 0.3241799 | 1.291617 |
| viewer | -0.08671 | 1.352347 | 0.719293 | 0.8485249 | 5.988672 |
| allc | -1.50358 | -1.09983 | -2.00338 | -2.2456001 | 6.188275 |
| seg | 1.838202 | 1.921321 | -2.27885 | -0.119943 | 0.52006 |
| score | -0.76538 | -0.17701 | 0.089373 | -0.2524489 | 0.776212 |
| pol | -0.84609 | 0.364208 | -1.02507 | -0.4951433 | 0.246888 |

### 4.5.3 Proximity Measure

Apart from providing high-fidelity data, the anomaly detection was typically tightly concerned with the exploration of novelty. In the Random Forest algorithm, proximities between pairs of classes helped investigate the similarity between individuals. Figure 4.16 presented the analysis of proximity measure to highlight three video outliers from the training set. Although the Random Forest method was theoretically robust against irrelevant outliers in training data, summarizing the distinct characteristics of these three video advertisements was conducive to future advertisement design.

According to Figure 4.16, video 35, video 32 and video7 were specified as the outlying observations with dissimilarity between others. In terms of video 35, its aim was to gather all Coke fans' originality to express the indescribable feeling from enjoying Coke. From prior sentiment analysis, brand was the core feature viewers emphasized on video 35, and its overall evaluation of opinions was positive. The advertisement style of video 35 focused on the creative ideas derived from an individual's brand and drinking experience, which was quite different from other advertisement ideas. Moreover, consider

the principal schema of video 32, which was on a mission to convert Coca-Cola Light's likers to lovers. Unwavering passion was the theme pursued in this advertisement, rather than an emphasis on the sub-brand of Coca-Cola Light. Thus, music was the most frequent feature viewers mentioned via their comments, instead of the brand.

Finally, the theme of video 7 was to present the concept of "open happiness," which meant that Coca-Cola brought happiness to human beings. This topic was representative of one of the classical Coca-Cola advertisement themes and features; music was significantly reflected in the opinion-mining. All of these three videos should be studied to investigate the reasons why the diversity existed for further development of advertising strategy.

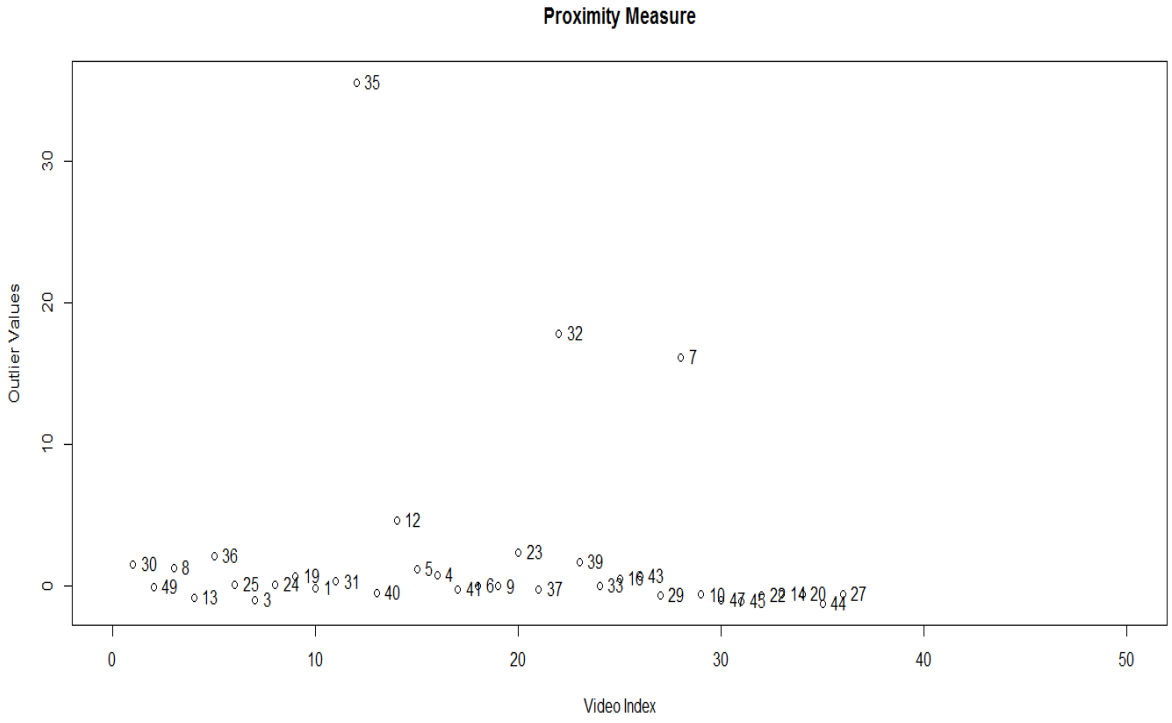


*Figure 4.16* Measure of Similarity

### 4.5.4 Receiver Operating Characteristic Curve

The receiver operating characteristic curve (ROC) was typically constructed to diagnose the accuracy of the model. The dimensions between the diagonal line revealed the measure of discrimination, which indicated the ability of the experiment to correctly classify the results. The region under the ROC curve referred to the percentage of randomly determining which was true on the basis of the uninformative test. Consequently, the area under the ROC curve reflected how good the model was at distinguishing. In other words, the greater area represented the better test.

Figure 4.17 exhibited that the classification probability of this predictive framework fell under the area of the ROC curve. This evidence demonstrated an unsound model that had insensitivity to the revenue classification; the accuracy of predicted classification was mere 30.77%.

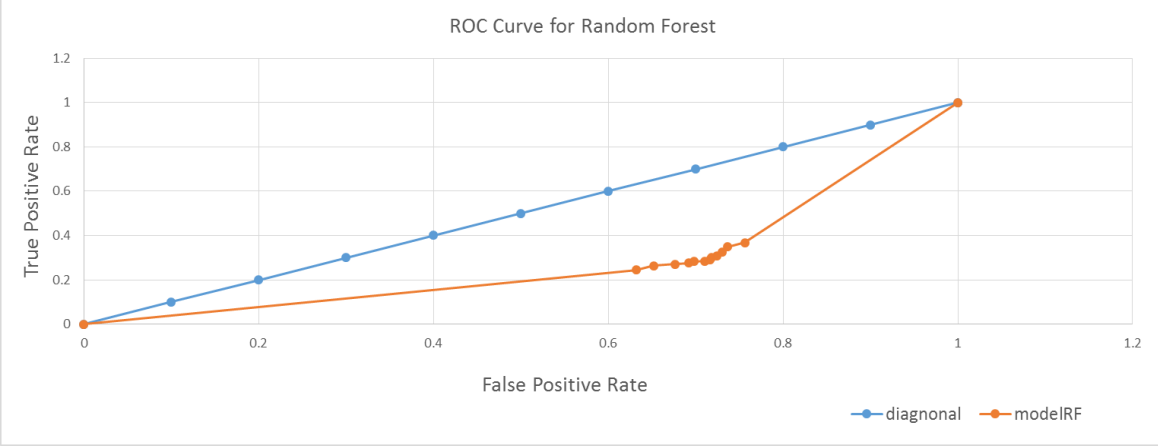


*Figure 4.17* ROC Curve for Random Forest Model

# CHAPTER 5. CONCLUSIONS AND RECOMMENDATIONS

The overriding purpose of this chapter was to outline overall research and provide some imperative recommendations as guidelines for future research. The first section of the chapter explained the aim of this research and discussed the design of this predictive schema used to explore the association between video advertisement and earning generation. Subsequently, the second section summarized the major findings along with the examination of forecasting performance. Finally, the implications of mining the video advertisements on YouTube and further suggestions for improving the predictive model were discussed.

## 5.1 Summary

Undoubtedly, social video-sharing media has subverted the ecology of the advertising media, as demonstrated by the explosive growth of traffic on YouTube during recent years. Through this new type of media, the uniqueness of advertisement mining begins to concentrate on the extended application of the true target audience's experience. Consequently, this study attempted to employ several marketing factors obtained from YouTube to establish classification random forests for the value discovery of video advertisements.

Apart from objective factual variables—e.g., the length of video and predictors related with traffic-viewer counts, the number of comments viewers left, the number of

thumbs up and down—both sentiment analysis and the number of viewer segmentation were the spotlight in this research. Hence the process of variable transformation was necessary for the deployment of this predictive framework. Simultaneously, we can identify some prominent inferences from the perspective of viewers.

In practice, the number of viewer segmentation was determined by the viewers' preferences, i.e., subscribed channels on YouTube; and their socially influential powers, i.e., subscription counts and total upload views. The differentiation of viewer clusters was implemented by the two-step clustering algorithm that adopted Schwarz' log-likelihood distance measure and Bayesian information criterion to automatically return the ideal number of clusters.

Moreover, in terms of sentiment analysis, feature scores and its polarity were regarded as two separate predictors in this study, even though typical research generally regarded feature scores as the degree of polarity. All the lexical syntactical patterns attested to their classification effects by the k-fold cross-validation approach. The attitude detection was subsequently allowed to be acquired by means of modified ROLEX-SP approach, involving the neutral and logical negation POS tags.

To provide real-world practice, this study retrieved video advertisements on YouTube from the Coca-Cola Company to realize the predictive structure and verify its feasibility of measuring the value of word-of-mouth. Unfortunately, the forecasting performance was not reliable enough to bridge the connection between video advertisements and revenue generation. However, there were still many distinct findings from the process of building this predictive model regarding either the analysis of viewer

segmentation or opinion-mining, and even model improvement. All of these discoveries were generalized in the next section.

## 5.2 Conclusions

In light of the viewer segmentation, viewers with high involvement in the Coca-Cola video advertisements on YouTube mainly fell into three preference categories: “Music”, “Entertainment” and “Games” as defined by their most frequently subscribed-to channels on YouTube. The variables relevant to the traffic concept, i.e., total upload views and subscription views, cooperated well with the user preference to determine the optimal number of segmentations. Moreover, evidence also demonstrated that no relationship existed between the number of segmentation and viewer counts.

Additionally, from the angle of opinion-mining, a majority of viewer perceptions of the Coca-Cola Company’s video advertisements were neutral or slightly positive with mild strength. In the advertising domain, the positive, negative and logical negation part-of-speech tags dominated the expression of feelings, instead of the unobvious classification effect from neutral tags. On the other hand, positive tags and logical negation tags had the absolutely significant classification effects on attitude detection in the advertising area as well.

Regarding the whole random forests, the ideal out-of-bag error rate was 50% on the basis of 400 trees. In addition, the confusion matrix clarified that the optimal classification paradigm of this model was merely realized on the medium-level revenue. As far as the variable importance was concerned, features associated with the traffic—i.e., the number of all comments, the number of thumbs up and the viewer counts—had

significant feature spaces different from the attributes with unmarked feature boundaries, i.e., feature scores, the number of viewer segmentation and the polarity.

Separately, the important features for the accuracy of prediction were input variables- video length, viewer counts and the number of thumbs up and down. In particular, although the feature of the number of comments had a distinct classification effect on feature differentiation, it cannot consolidate the predictive results. Moreover, we must consider that the anomalies in these video advertisements, the creativity from sharing the Coca-Cola experience and the background music piquing viewers' interests rendered the advertisements unique.

In summary, the predictive performance in this classification of random forests was not perfectly good; it was only 30.77%. Rather than the word-of-mouth effect and viewer clusters, the traffic factors and the time investment for the video advertisements were conducive to revenue achievement. However, the poor result did not indicate that word-of-mouth and customer segmentation were inappropriate for forecasting. The inference of this frustrating output was discussed in the following section for further reforms and exploration.

## 5.3 Recommendations

The conclusion of this research resulted in several recommendations from two perspectives. Firstly, regarding the implementation of this predictive model, the variable transformation should be reviewed and strengthened. That is to say, in terms of the segmentation clusters, almost half of viewers who joined the discussion didn't subscribe to any channels. This study ignored this significant percentage of viewer preferences,

which possibly resulted in a less-representative result of viewer segmentation. Therefore, adoption of other relevant behaviors regarding the preference of this group, such as uploaded videos, can reasonably consolidate the reliability of this predictor.

Furthermore, the lexicon compilation should be extended to cover missing words, including misspelled words and new word categories. For example, the word "awesoooome" expressed the same meaning of the word "awesome" but was not included in this dictionary. We must keep in mind that the comments left on social media often have grammar and spelling errors. Thus, expanding the coverage of the word categories will be helpful to enhance the accuracy of opinion classification.

The second recommendation for further studies was to extend this preliminary work by adding new predictors, testing other models to fit or changing the independent variable.

With regard to involving new predictors, variables related to the traffic concept were worthy to add in this model; this also corresponded to the external trend. Aside from the random forests algorithm, many other classification learning methods can be leveraged on this measurement, such as SVM (Support Vector Machine), based on this precursory research. Finally, the target variable of this study was classified by the net operating revenues from the earning release reports as different levels of revenue indexes. Nevertheless, it only reflected the quarterly performance rather than the monthly base. Hence, the ambiguous differentiation between each definite timeline probably leaded to poor classification of predictions. Any other data with more concrete presentation of performance will reinforce this forecasting framework.

The adoption of social video-sharing sites is a prevalent trend in this generation. Effective leverage of the data generated from this kind of social media is becoming a vital analytic task. Typically, companies have viewed this challenge in a profit-making light; therefore, enterprises are eager for optimal mining solutions to explore the connection between revenue generation and social goods data. This research provided a complete paradigm of one social-goods mining practice and outlined the behavior analytics for future extensions.

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