Fake Review Detection Using
Behavioral and Contextual Features

By
Jay Kumar

Department of Computer Science
Quaid-i-Azam University
Islamabad, Pakistan

February, 2018
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Supervised by
Dr. Akmal Saeed Khattak

Department of Computer Science
Quaid-i-Azam University
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A Dissertation Submitted in Partial Fulfillment for the

Degree of

MASTER OF PHILOSOPHY

IN

COMPUTER SCIENCE

Department of Computer Science

Quaid-i-Azam University

Islamabad, Pakistan

February, 2018
DEDICATION

To my beloved mother

To my beloved father

To my beloved brother

To my best friends
Declaration

I hereby declare that this dissertation is the presentation of my original research work. Wherever contributions of others are involved, every effort is made to indicate this clearly with due reference to the literature and acknowledgment of collaborative research and discussions.

This work was done under the guidance of Dr. Akmal Saeed Khattak, Department of Computer Sciences, Quaid-i-Azam University, Islamabad (Pakistan).

Date: 23rd February, 2018

Jay Kumar
Abstract

User reviews reflect significant value of product in the world of e-market. Many firms or product providers hire spammers for misleading new customers by posting spam reviews. There are three types of fake reviews, untruthful reviews, brand reviews and non-reviews. All three types mislead the new customers. A multinomial organization "Yelp" is separating fake reviews from non-fake reviews since last decade. However, there are many e-commerce sites which do not filter fake and non-fake reviews separately. Automatic fake review detection is focused by researcher for last ten years. Many approaches and feature set are proposed for improving classification model of fake review detection. There are two types of dataset commonly used in this research area: psuedo fake and real life reviews. Literature reports low performance of classification model real life dataset if compared with pseudo fake reviews. After investigation behavioral and contextual features are proved important for fake review detection

Our research has exploited important behavioral feature of reviewer named as "reviewer deviation". Our study comprises of investigating reviewer deviation with other contextual and behavioral features. We empirically proved importance of selected feature set for classification model to identify fake reviews. We ranked features in selected feature set where reviewer deviation achieved ninth rank. To assess the viability of selected feature set we scaled dataset and concluded that scaling dataset can improve recall as well as accuracy. Our selected feature set contains a contextual feature which capture text similarity between reviews of a reviewer. We experimented on NNC, LTC and BM25 term weighting schemes for calculating text similarity of reviews. We report that BM25 outperformed other term weighting scheme.
Acknowledgment

Praise is to God, the Almighty who have been giving everything to me and guiding me at every stage of my life. Bundle of thanks and gratefulness go to my supervisor Dr. Akmal Saeed Khattak, without his guidance and follow-up; this research would never have been. In addition, I would like to extend my thanks to Dr. Khalid Saleem, who supported me during my degree period. Additionally, I want to thank Dr. Onaiza Maqbool, Dr. Ghazanfar Farooq, Dr. Muddassar Azam Sindhu, and Dr. Shuaib Kareem who shared useful knowledge in different courses. I would like to thank Dr. Muhammad Usman and non-academic staff who provided all needed facilities and support. I would also like to thank Dr. Bing Liu for providing dataset.

I would like to thank Maryam Javed, Nouman Khan, Naveed Tariq, Aqib Rehman, Muhammad Awais Amjad, Farooq Zaman, Anjum Ara, Muhammad Usman, Qamar Munir, Muhammad Islam, Zaffar Saeed, Khwaja Bilal, Umer Naeem, Younis Iqbal, Aftab Rashid, classmates and junior fellows for making my study a great experience, motivational, useful, enjoyable, and full of joyful atmosphere. Last but not least, I am greatly indebted to my mother, father and brother for motivation, encouragement and always supporting me on every part of life.

Jay Kumar
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Chapter 1

Introduction

Reviews are statements which express suggestion, opinion or experience of someone about any market product. On the online e-commerce websites, users place their reviews on product form to give suggestion or share experience with product providers / sellers / producers and new purchasers. The provided user experience can help any business to grow for improvement by analyzing the suggestions. Polarity of reviews causes certain financial gain or loss to any product provider. On other side, reviews influence new purchasers while taking decision of purchasing any particular product. It can be concluded that effects of reviews target both business and users in different ways. Keeping this point of view, many firms / product providers hire agents to forge fake opinions for growing their business and market reputation. As a result, users take wrong product selection decision.

The pattern of web based shopping is developing day by day. Online e-commerce websites opened channel for selling or purchasing products. E-commerce sites facilitates users to purchase product (e.g. motor bike, headphones, laptop, etc) or avail any service (i.e. hotel reservation, airline ticket booking, etc). Users often give suggestion/opinion/review/comment on e-commerce sites to share their experience after using any product or availing service. Including e-commerce sites, there exist many blogs created by users which contain user experience of product or service. The posted reviews/opinions/suggestions provide useful information to new customers and product providers. Before purchasing any product, people often use to take suggestion from surrounded people. Those suggestions help people to decide
whether the product is worth purchasing or not. Our decision of purchasing or not purchasing a product entirely based on the opinions of people who had used certain product.

For example, if a person want to buy a smart phone of *samsung*, he would take opinion from his friends or family relatives who had used smart phone of *samsung*. Purchasing that smart phone will totally depends on opinions of friends and family relatives. Opinions or suggestions of people effect decision making of other people for product selection. Physically, there are limited persons around us from whom we can take suggestions while choosing a daily life product. However, it seems very difficult while purchasing a product if there is no one around us who have used that particular product. Where as, there are huge number of opinions available on e-commerce sites and people take their purchasing decision by reading reviews and product experience of different people. It is nature of human that more the people favor for purchasing any product more we can rely on that product. That is why, online reviews can influence purchasers in a good or bad way. Companies of product hire agents to distract new customers by placing false opinions about their product or competent product. The task of identifying fake reviews is very important for the betterment of new purchasers and good quality product companies.

This chapter gives an introduction about our research work. It gives a brief discussion on trend of purchasing from outdoor to online shopping. It also discusses about importance of user reviews on a business for helping new customers and business development. The later part of this chapter discusses positive and negative effects of fake opinions. We have also discussed about fake review and their categories. In addition, an overview of contextual and behavioral features of reviews and reviewer are discussed. In last, different problems for detecting fake opinions/reviews and research objectives are defined.

1.1 Importance of User Reviews

Online purchasers on e-commerce sites are increasing day by day. Online purchasers often post reviews/opinions about certain product they have used. In other words, opinions are content created by users on e-commerce websites to express experience of users about any service or
product. Importance of user reviews can be viewed from user and business perspective. From user perspective, these reviews can influence new customers/users for purchasing decision of certain product in a good or bad way. Decision of new purchasers is influenced by reviews of users. Good of bad features in accordance with user experience are described in reviews which help other users for taking the decision of purchasing the product. For purchasing online, user often visit e-commerce sites rich with user experience about products. So quality and number of user experience can effect user traffic on site.

By looking importance of reviews from business perspective, mining of user reviews help product providers for improving the business strategies and product quality. Reviews help product providers for revealing features demanded by customers which can build the stability of product in current market. User reviews can impact any company with certain financial gains or loss. Negative reviews of users can financially harm the company because new purchasers may divert the purchasing decision after reading the negative reviews. Positive reviews on any product influence the purchasing decision of new customers.

1.2 What is Fake Review

Opinion spamming is an immoral activity of posting fake reviews. The goal of opinion spamming is to misguide the review readers. Users involved in spamming activity are called “spammers”. The task of a spammer is to build fake reputation (either good or bad) of a business by placing fake reviews. There exist some businesses who pay spammers to promote the company to attract new customers or to demote competent company of same type of business. A fake review either belong to positive or negative polarity. Review containing praising statement about the product fall in “positive polarity”. And review containing loathing statements about the product fall in “negative polarity”.

It is reported by (C. Sun, Du, & Tian, 2016; Jindal & Liu, 2007a) after analyzing reviews on different e-commerce sites that more than ten percent reviews on e-commerce websites are fake. It was also reported that more than seventy five percent of fake reviews belong to positive polarity. Increasing need for identifying fake reviews has captured the attention of
researchers for solving the problem. Fake reviews not only mislead new customer for taking product purchasing decision but also affects business of good quality product. And due to false and misleading reviews on particular e-commerce site, users will avoid to visit that particular e-commerce site. It is concluded that identifying fake reviews will tackle three loses at one time.

Fake reviews or spam opinions are classified into three categories (Jindal & Liu, 2007a, 2008): untruthful reviews, brand reviews and non-reviews. Untruthful reviews are involved in promoting or demoting false reputation of the particular target product. The content of untruthful reviews may contain statement about different features of product. Brand reviews are posted to assault the product provider, manufacturer or distributor. Content of non-reviews is irrelevant to product on which the review is posted. Content of non-reviews may contain question-answers or advertisements.

1.3 Fake Review Detection

It is also called spam opinion detection, fake opinion detection and spam review detection. The problem of spam opinion detection is classification problem which separate fake reviews from non-fake reviews. In the field of machine learning, one of the popular task in supervised learning is classification. The task of classification is to categorize unknown objects from pre-defined number of groups/classes/ labels based on certain properties or features. It is a very difficult to identify fake reviews by reading huge number of online reviews. With the help of classification and its variety of techniques we are able to classify fake reviews from non-fake reviews. The research area of opinion spam is divided into three tasks: identifying fake reviews, individual spammers and spammer groups. The focus of our research work is to identify spam opinions by exploiting different types of features related to reviewer and review content. Features are characteristics related to business, reviewer and review. Important information can be extracted by analyzing these attributes from different perspectives and that information can reveal the false reviews from huge number of online reviews. Generally, we classify these extracted features in two categories: contextual features and behavioral features.
1.4 Contextual and Behavioral Features

It is reported by researchers that the task of identifying untruthful reviews is more challenging task than identifying brand reviews and non-reviews (Zhang, Zhou, Kehoe, & Kilic, 2016). Commonly, two types of features are used to identifying fake reviews: Contextual and Behavioral features. Both type of features are extracted from three types of attributes: review centric attributes, product centric attributes and reviewer centric attributes (Jindal & Liu, 2007a). A set of attributes of review centric attributes from Yelp can be seen in Figure 1.1. Review centric attributes consist of review content, rating, photos, review post date, different types of votes and others (Tag 1 and 2 of Figure 1.1). Reviewer centric attributes consist of information about reviewer (e.g. name, location, review count, friend count etc) as shown in Figure 1.4. Product centric attributes contain information of the product or service (e.g. name, price, brand, description, etc). Figure 1.2 and 1.3 shows product centric attributes. Detailed discussion of all three types of attributes used in our experimentation is done in Chapter 4.

Contextual features are also called verbal features (Zhang et al., 2016) are extracted from review centric feature. Contextual features represent different perspective of review content of review. Non-verbal extracted features are also referred as “Behavioral features”.

1https://www.yelp.com/sf
CHAPTER 1

INTRODUCTION

Behavioral features capture unusual behavior of reviewer and content of review for fake review detection. Extraction of behavioral features is done from attributes of review, reviewer and product. Exploited contextual and behavioral features in this research are discussed in detail in Chapter 4. Here the main focus of this thesis is to investigate and exploit those contextual and behavioral features which improves fake review classification / detection accuracy and reduce chances of assigning a non-fake review as fake.

1.5 Motivation and Objectives

The usage of web platform is expanding and covering every type of business. The projection of purchasers and sellers is increasing towards online e-market. The availability of e-market/e-commerce websites have increased boundary of users for product selection. Whereas, business of merchants/sellers on e-commerce websites is also growing. It is natural that people use to ask suggestions from their near ones before purchasing any daily life product. Physically there are limited people around whom people can ask but on online platform there are thousands of reviews/opinion/suggestions of users around world. The decision of a purchaser totally depends on reviews of users which effects product provider with certain financial gain or loss. A review is always true in perception of a purchaser however a common purchaser does not know that reviews can be faked. Users are unbound to give review on any product because there is no check

Figure 1.2: Product Information on Yelp

https://www.yelp.com/sf
Figure 1.3: Information about a Restaurant on Yelp
to see either reviewer has used that particular product or not. It gives incentives to businesses to increase their fake reputation by posting fake reviews to attract new customers. To create fake reputation for increase product sale in e-market, businesses pay spammers to post fake reviews. Some businesses pay spammers to harm competitor’s reputation in e-market. Many e-market/e-commerce websites are facing the problem of fake/spam reviews. Harmfulness of fake reviews spread in three direction including misleading user decision, loss of good quality product company and due to misleading reviews risk of losing visitor for e-commerce site. So there is need to identify fake reviews to help both user and business. Our goal is to identify fake reviews, however researchers are exploring this area since 2007 but still there are set of unexplored features which can help to classify fake reviews from non-fake reviews. Main objective of this report is exploitation of such features which can bring improvement in accuracy of classification of fake reviews.

The focus of our research work is to identify untruthful fake reviews. Real life reviews and pseudo fake reviews datasets are commonly used in experimentation for spam review detection (Heydari, Tavakoli, Salim, & Heydari, 2015). The real life dataset contains reviews extracted from Amazon, Yelp etc. The pseudo fake dataset consist of reviews which are created by researcher through variety of sources. One of the way researchers has followed to built dataset pseudo fake reviews is annotating fake and non-fake reviews with the help of annotators(S. P. Algur, Patil, Hiremath, & Shivashankar, 2010). Many researchers also adopted methodology of hiring AMT Turkers for constructing pseudo fake review dataset (Ott, Choi, Cardie, & Hancock, 2011; Myle Ott, n.d.; Istiaq Ahsan, Nahian, All Kafi, Ismail Hossain, &

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**Figure 1.4: User Profile on Yelp**

https://www.yelp.com/sf
AMT is a crowdsourcing platform where businesses (clients) hire turkers (freelancers) for intelligent tasks.

It is more difficult to identify fake reviews from real review dataset than pseudo fake review dataset because real dataset have less accuracy than pseudo fake reviews. So main objective of this thesis is to exploit behavioral and contextual features extracted from three type of attributes to identify fake reviews in real reviews dataset extracted from Yelp.

1.6 Research Questions

Our focus is to investigate the effect of behavioral and contextual features of fake review detection. In this thesis mainly following research questions were thoroughly investigated.

- What is effect of “reviewer deviation” with other contextual and behavioral features to identify fake reviews on Yelp dataset.

- What is the importance of “reviewer deviation” compared with other behavioral features for fake review detection model training?

- Is selected feature set perform well on scaled dataset to identify fake reviews.

- What is effect of different weighting schemes calculating the “Reviewer Content Similarity” feature of reviewer?

1.7 Research Scope and Limitation

This work exploited contextual and behavioral of reviews and reviewers for identifying the fake opinions/reviews. This research work relies on some suppositions and limitations such as:

1. This research work is limited to identifying fake reviews written in English.

2. Research contribution include exploiting contextual and behavioral features in real life Yelp restaurant and hotel reviews.
3. Some extracted behavioral features relies on attributes available in Yelp database (e.g. funny count, friend count etc). It is possible that these attributes may not available on other e-commerce websites.

4. The evaluation of classification model for identifying fake reviews depends on the labeled database of Yelp reviews. Reviews are labeled by Yelp spam filtering algorithm.
Chapter 2

Background Knowledge

Fake review detection task is one of the challenging classification task in the field of knowledge discovery. Multiple angles of capturing deception in reviews data have been focused by researchers for a decade. Focus of our research work is to investigate the techniques and classification model to identify individual fake reviews by analyzing different perspective of review data.

This chapter focuses on background knowledge essential to understand this research work. Section 2.1 gives a brief overview about knowledge discovery. Reviews offer representing unrevealed hidden knowledge that can be helpful to both consumers and businesses. Each step in knowledge discovery process has been discussed. We discuss classification and number of classification algorithms. In last section, we discuss data distribution problem for evaluating classification results.

2.1 Knowledge Discovery

Knowledge discovery is used to extract undiscovered, useful and implicit information from a large amount of data. The main objective of knowledge discovery is recognizing patterns in large amount of data. This area was brought out first by Frawley et al (Frawley, Piatetsky-Shapiro, & Matheus, 1992) and now it has become one of the most popular research field in computer science (Anand, Bell, & Hughes, 1995). Access of vast amount of
information for specific application field (like e-commerce, data of genes in bioinformatics and marketing financial investments) has nourished the enthusiasm for knowledge discovery greatly. Knowledge discovery in reviews has also become very important to discover the user interest and requirement to increase the customer satisfaction and financial gain. An example of knowledge discovery in reviews is exhibited in Figure 2.1. Figure 2.1 shows that Goole PlayStore\(^1\) has categorized the user reviews into different groups by mining the content and rating of reviews. Iterative process of finding the meaningful information from raw data is known as process of knowledge discovery. Stages of the process in database is exhibited in Figure 2.2.

Data might be gathered from divergent types of sources. There are commonly two types of data; structured and unstructured. Our selected dataset contains both structured and unstructured data. The collected data needs to be cleaned before mining process. Next data cleansing step requires the existence of noisy, missing and erroneous data values. It also includes important pre-requisite steps of data reduction like handling outliers and data type reductions. Subset of data is chosen based on significance of general information in definite outcome. Data reduction

\(^1\)https://play.google.com/store
speed up the data mining algorithms to satisfactory execution levels especially where large number of attributes are found in dataset.

After pre-processing next stage is to mine data. Data mining tasks are based selected discovery goal. Likewise, exploratory examination the data gives advance bits of knowledge about the nature of data. Different patterns are explored in data as a result of data mining process. Recognized patterns are then interpreted and evaluated to reveal the hidden knowledge of data. This hidden knowledge can be useful for businesses (Anand et al., 1995; U. Fayyad, Piatetsky-Shapiro, & Smyth, 1996).

2.2 Knowledge Discovery Disciplines

On the basis of diverse formats of data, the research of knowledge discovery is further divided into different disciplines including graph mining, image mining, web mining and data mining. (U. Fayyad et al., 1996; Heydari et al., 2015; Crawford, Khoshgoftaar, Prusa, Richter, & Al Najada, 2015).

Data represented in the form of graphs are specifically handled by graph mining. Task of graph mining is to extract patterns of significance from any graph. Graph mining is introduced by Yoshida et.al (Yoshida, Motoda, & Indurkhya, 1994). Transaction graph mining (TGM) and single graph mining (SGM) are categories of data mining. When you are dealing with finding patterns in single graph, you have to use SGM however, TGM is used when set of graphs are dealt(Washio, Kok, & de Raedt, 2005). Graph mining has large number of applications
in different fields like web data, biological networks. Graph mining techniques are used by various researchers to identify the group spammers based on collaboration of spammer activities. Further usage of graph mining in review data is discussed in Section 3.3.

Image data that is specifically represented in binary form is dealt by Image mining and also Image mining focuses on image classification, image mining and image comparison. Satellite, digital images and medical are some of the examples of binary image data. (Wynne, Mong, & Zhang, 2002). It also focuses on image classification, image mining and image comparison.

Recognition of hidden information from web data is focused by Web Mining. Site page substance, client’s information (server logs) and site page substance are three distinguished types of web data.

Recognition of hidden information from web data is focused in Web mining. Site page substance, client’s information (server logs) and web hyperlink structures are three types of web data. Three further subgroups are formed in research of web data mining which are web content mining, usage mining and web pages structure mining. Since web pages contain most of the text content so web content mining is strongly associated with content mining. (Cios, Pedrycz, & Swiniarsk, 1998).

Data mining is an important step in the knowledge discovery process for revealing significant hidden knowledge. This process extracts the previously unknown information from huge amount of raw data. The learning must have the capacity to be utilized by someone having capability to utilize it, it must be new and non self-evident. Data Mining (DM) is “a multidisciplinary field, drawing work from areas including: database technology, machine learning, statistics, pattern recognition, neural networks, knowledge-based system, artificial intelligence, high performance computing, and data visualization” (Bramer, 2007). Data mining techniques can be applied on a wide range of domains e.g. e-commerce, business financial studies and bio-informatics due to their adaptive and versatile nature on different types of data.
2.3 Data Mining Techniques

Generally, DM tasks can be divided into two groups: Descriptive mining and Predictive mining (U. Fayyad et al., 1996; Heydari et al., 2015; Crawford et al., 2015). Descriptive mining involves describing the general characteristics of the information in the database i.e. clustering and association rules whereas predictive mining involves forecasting values on the basis of available current data i.e. regression, classification and analysis of outlier (Berry & Linoff, 1997; J. Han, Pei, & Kamber, 2011). We define some of general techniques of data mining.

2.3.1 Clustering

Clustering is an unsupervised learning technique used to group the similar type of objects. Unlike classification, we do not need to train the model in clustering, beside that it’s quite similar to classification. Clustering algorithm is all about discovering the unknown similar groups. There are many clustering algorithms which are based on calculating similarity among objects in data collection (H. Han & Mao, 2010) e.g. K-mean clustering, Self Organizing Maps, Fuzzy C-means, Hierarchical clustering. Clustering is used for many applications in different domains such as book ordering libraries, city planning, bioinformatics, image analysis. In the domain of user reviews mining, clustering algorithms help us to create the clusters of fake and non-fake reviews based on different identified features of reviews and reviewers. Exploitation of clustering in identifying deceptive reviews and reviewer by different researchers is discussed in Section 3.1 and 3.2.

2.3.2 Association rules

An association rule is an if/then statement that defines the uncovered relationship between seemingly unrelated data in the data collection. These rules are extracted from the data collection based on how many times objects appear with each other. The ‘if’ part contains a single item whereas ‘then’ part may contain multiple items. There are two threshold set on the basis of which association rules are extracted; one of them is support, support defines the extracted frequency contribution in the data set whereas the second threshold is Confidence,
which defines the reliability of the extracted rule. There are many association rules extraction
techniques e.g. Apriori algorithm, Eclat algorithm, FP-growth algorithm. Association rule
mining examines the association analysis of items in market basket. (Zaiane, 1999; J. Han et
al., 2011).

### 2.3.3 Outlier analysis

Another name for outliers is unusual or special cases or astonishment, they are frequently critical
to distinguish. Very often, there exist data objects that do not comply with general behavior
or model of data. The significance of the outlier analysis depends on domain to domain.
Sometimes outliers are considered as noise in some domains or it reveals some important
information in other one (Bramer, 2007). Outlier analysis has many applications in different
domains, such as the financial industry, quality control, fault diagnosis, intrusion detection, Web
analytics, and medical diagnosis (Aggarwal, 2017). Using outlier analysis, various researchers
have analyzed behavior of reviewer to identify spammers (Z. Zhang & Varadarajan, 2006; Jindal
& Liu, 2007a; Ott et al., 2011; Jindal & Liu, 2008; Debarr & Wechsler, 2009), because textual
or behavioral features of spammers are somehow different from true ones.

### 2.4 Classification

The task of assigning labels to the objects from predefined labels is known as classification.
Classification is a supervised learning approach that used labeled data to train classification
model (Bramer, 2007). Classification model is able to classify the new objects on the basis of
trained data (U. Fayyad et al., 1996; Zaiane, 1999; Dunham, 2006). There are three type of
classification problem: binomial, multinomial and multi-label. Binomial classification problem
is assigning one label to unknown object from two classes e.g. Identifying fake and non-fake
reviews. Multinomial classification problem is assigning one label to unknown object from more
than two classes, e.g. reviews are classified into more than one classes in Figure 2.1. Multi-
label classification problem is assigning more than one label to unknown object from multiple
classes e.g. scientific document classification. The fake review detection is classification
task to label the reviews in two classes: *fake and non-fake*. Different approaches are used by classification algorithm to deal with diverse types of data collection. Two main areas are included by classification to reveal the different type of hidden information; text classification and text mining, which are both central tasks of our research contribution.

### 2.4.1 Data Classification

Data classification is the field that intersects Information Retrieval (IR) and Machine Learning (ML) and this field has received a great enthusiasm in last decade from researchers (Hotho, Nürnberger, & PaaB, n.d.; Osimo & Mureddu, 2012). Assigning at-least one precalculated classes of documents having textual data is the task of data classification. Data classification is applied in many versatile domains and is an important technique being used in real life world e.g. Weather forecast, fraud detection, genes classification and disease diagnosis (Dunham, 2006; Feldman & Sanger, 2007; J. Han et al., 2011). Apart from these, another important application of data classification is spam email filtering and review filtering. Different classification algorithms are proposed to classify object but we are going discuss some of data classification algorithms related with our research work.

### 2.4.2 Text Classification

Text Mining(TM) or Text Data Mining is an area of knowledge discovery which is hot in research as it aims to apply data mining algorithm to textual datasets. “It aims at disclosing the concealed information by means of methods which on the one hand are able to cope with the large number of words and structures in natural language and on the other hand allow to handle vagueness, uncertainty and fuzziness” (Feldman & Sanger, 2007; Hotho et al., n.d.). Sub-tasks like effort regarding important portion of text document, text clustering, opinion mining and document summarization also use text mining for decision making. (Liu, 2006). Reviews content are in form of text and extracting different features from reviews fall in the text mining task.
2.5 Classifiers

There are many classifiers, some of the include Naive Bayes (NB), Logistic Regression (LR), K-Nearest Neighbor (KNN), Decision Tree (DT), Neural Network (NN), Support Vector Machine (SVM), Random Forest (RF). In this section, classification algorithms are discussed for building theoretical background so that our proposed approach and contribution can be understood. Due to best classification results attained by researchers for out dataset, SVM and RF classifiers are focused in this section (D. Zhang et al., 2016; Mukherjee, Venkataraman, Liu, & Glance, 2013b). Working of RF is based on DT due to this reason we are also going to discuss DT.

2.5.1 Support Vector Machine

In support vector machine (SVM), we arrange related supervised learning techniques utilized for regression and classification. Given a set of training examples, we can say that each set is distant as having place with one of two classifications, a model is assembled by the SVM preparing calculation which predicts if another object falls into same classification or the other. Intuitively, with the motive to find possible wide space between cluster of points, SVM places object in the space as a point. Mapping of new objects is placed on same space. Predicted objects to have a place with a classification in view of which side of the separated space they fall on (Duda, Hart, & Stork, 1973; Witten, Frank, Hall, & Pal, 2016). In SVM, dimensions in the space refer to the attributes of the object. SVM is used to create a hyper-plane in the multidimensional space exhibiting all the attributes of the object. Instinctively, The more is the space between two classes , the lesser chances in generalization error of the classifier.

To specify the pattern of constructing space between classed, three kernel functions are used, Linear, RBF and Polynomial as exhibited in Figure 2.3\(^2\). Sometimes, object-points are not linearly seperable, in these cases, the RBF and polynomial are particularly used. Linear SVM uses the Equation 2.1, where vector of feature of document is represented by ’x’ , weight of ’x’ is represted by ’w’ , and tunning parameter represented by ’b’. An example of linear kernel SVM is shown in Figure 2.4, there are two dimensional data objects. Two type of classes on

\(^2\)http://scikit-learn.org/stable/auto_examples/svm/plot_svm_kernels.html
space are separated by hyper-plane.

\[ y = w^T X - b \]  

(2.1)

The classification of SVM is effective on high dimensional spaces. Also, SVM performs well on the clear margin of separation. Classification is also effective when number of dimensions is greater than number of samples. However, the performance of SVM is not good when data is noisy. Many researchers have also used SVM in text classification for fake review detection. Text classification tasks having unbalanced training examples have also used SVM classifier. Hence, we have chosen this to be used in our research experiments.

### 2.5.2 Decision Trees

At the start when artificial intelligence field was emerging, a large set of rules were used to process a large scale dataset on the machine. As the data set size grew larger, Designing the number of rules in accordance with data became difficult. This is when decision tree were invented to solve the problem by creating a tree of rules from which new instances can be assigned predefined class (Safavian & Landgrebe, 1991). To improve the efficiency and to make the diverse data more accurate, decision trees are designed. (Dattatreya & Kanal, 1985; Chang & Pavlidis, 1977).

Working of a decision tree goes like this; each node is the data feature whereas conditions are represented by diamond (i.e. value greater than , less than or equals to 6) over feature of

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http://scikit-learn.org/stable/autoexamples/svm/plot-svm-kernels.html
node. New instances are assigned to the ending node known as leaves. Decision trees are used in a variety of domains to classify data and to create rules for large data set and complex feature rules are broken down into simple ones. For example, disease diagnosis, speech recognition, expert systems, radar signal classification and many more.

Order of the nodes is assigned according to the importance score of the data features while designing the tree. Multiple algorithms is proposed to split a node for constructing decision tree. Decision tree splits the nodes on all available attributes and then selects the split which results in most homogeneous sub-nodes. Algorithm for construction tree is also based on type of data. Here, we are going to discuss only 'Gini Index'. This algorithm is used inside selected library in experimentation.

**Gini Index**

It says that if we randomly select two items from a population then both items must be of same class and if population is pure then probability for this case is 1. There are two steps to calculate Gini (U. M. Fayyad & Irani, 1992) for split:

1. Calculate $Gini$ for sub-nodes using Equation 2.2.
2. Calculate \textit{Gini} for split using weighted \textit{Gini} score of each node of that split.

\[ w = p^2 + q^2 \]  
(2.2)

2.5.3 Random Forest

Random forest is the collection of decision trees or we can say it makes the forest of decision trees. It can be utilized for both classification and regression. To achieve high robustness and accuracy, more trees in the forests are required. Random forests are constructed using the same method of constructing decision trees. Multiple trees are constructed independently and parallel. All the training instances examined with substitution are utilized while constructing each tree. Parameters at every node of tree is enhanced by constructing the forest of decision trees.

To enhance the parameters at every node of tree, the forest of decision trees is constructed. A random subset of the set of features is approached by every node of the tree while training on independent tree as exhibited in the Figure 2.5\textsuperscript{3}. Only one randomly chosen subset of the entire set of features is accessible to each node of the tree. (Schapire, Freund, Bartlett, Lee, & Others, 1998; Liaw, Wiener, & Others, 2002).

It can handle large dataset with high dimensional. It also perform well if there are missing values in dataset. It can be used for outlier detection and extended for unsupervised learning. We can apply random forest to classification as well as regression as it performs well at highly dimensional data set. The usefulness of Random forest allow them to apply it in various domains like for example banking domain for fraud detection, stock exchange market to analyze behavior, disease diagnosis, medicine component composition, recommendation in e-commerce etc. Having versatile nature and pros, there are still some cons of random forest. It does not perform well for regression compared with classification as it does not give precise continuous nature predictions. Random Forest behave like a black box approach for statistical modelers.

\begin{footnote}
\textsuperscript{3}https://www.analyticsvidhya.com/blog/2016/04/complete-tutorial-tree-based-modeling-scratch-in-python/
\end{footnote}
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2.6 Classifier Evaluation

Measures for Classification Performance is basic part in directing the training classifiers. Assessment techniques and measures are important as classification algorithm and are the main key stage to an effective data mining. There are various criteria for evaluating classifiers and criteria is set based on selected goal. This research focuses on accuracy of classification algorithms. Many evaluation measures are used in fake review detection research area. We define some evaluation measure used in this research include Precision, Recall, F1 – measure and Accuracy (Banker & Datar, 1989). In literature, these four measures are commonly used for assessing classification model (D. Zhang et al., 2016; Mukherjee, Venkataraman, Liu, & Glance, 2013a) (defined in Equations 2.3-2.6). We have evaluated our trained classifiers with defined four evaluation measures. Number of fake and non-fake reviews correctly classified are denoted by $t_{fake}$ and $t_{non-fake}$ respectively. Whereas, incorrectly classified fake and non-fake reviews are denoted by $f_{fake}$ and $f_{non-fake}$. Values of these evaluation measures range from 0 to 1.

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https://www.analyticsvidhya.com/blog/2016/04/complete-tutorial-tree-based-modeling-scratch-in-python
2.7 Imbalance Class Distribution Problem and Its Solution

Commonly, the performance of classification algorithms is well when the training data contain an equal number of instances of each class in the dataset. But many real-life datasets contain an unequal number of instances in classes. The outcomes of classifiers may be inaccurate in certain situations (Phung, Bouzerdoum, & Nguyen, 2009). This problem of data distribution is known as “Imbalance Class Distribution Problem” (Chen, Chen, Hsu, & Zeng, 2008; He & Garcia, 2009). This problem happens when a class (majority class) contains a very high number of instances compared with another class (minority class) in the dataset. A classifier typically has a tendency to decide on the majority class and ignore the minority class for this situation. Figure 2.6 illustrates this problem where 97% of instances relate to the majority class and 3% instances of the minority class.

The issue of imbalance class distribution is unavoidable. In current days, many domains are facing class imbalanced data nature. Imbalance class distribution create hurdles to classifiers in learning. In our domain of fake review detection, the number of true reviews is immensely high than fake reviews as reported by (Jindal & Liu, 2007a; C. Sun et al., 2016) that e-commerce sites contain around 10% of fake reviews. One of the popular techniques to solve this problem is “sample technique” which is defined below.
2.7.1 Sampling Techniques

Sampling technique is a popular approach to tackle imbalance class distribution problem. Distribution of minority and majority class are altered for training. It follows equal number of instances in both majority and minority class (Phung et al., 2009). There are two techniques to overcome imbalance class distribution: under-sampling and over-sampling.

2.7.1.1 Under-Sampling

This technique decrease the number of majority class samples. Those samples are selected randomly (He & Garcia, 2009). The aim of under-sampling approach is to reduce the skewed distribution of minority and majority class by downsizing of majority class (Yen & Lee, 2009).
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This approach is appropriate in huge dataset where instances of minority class is very less than majority class (Hu, Liang, Ma, & He, 2009). Process of under-sampling approach is illustrated in Figure 2.7. The figure shows three types of classes occur in dataset and after under-sampling each class contain equal size of instances for training. In our domain of reviews we follow this approach to select randomly same number of reviews from both fake and non-fake labeled reviews.

2.7.1.2 Over-Sampling

Unlike under-sampling, the examples of minority class are increased in this approach. Increasing the samples include replication of random examples of minority class. Applying under-sampling posits the chance of losing information about data but this approach would not compromise information losing. However, computational cost is increased in this technique. Figure 2.8 shows working of this technique, where size of minority class is increased by replicating the training examples.

Figure 2.8: Over-sampling Approach
Chapter 3

Related Work

The research area of opinion spam detection is a challenging task since ten years. First investigation on analyzing spamming activities in reviews was studied by Jindal (Jindal & Liu, 2007a). Three research areas in fake/spam review detection were discussed which include: identification of fake reviews, Individual Spammer and Spammer Group.

First and most common investigation research area is to identify individual fake reviews. Second type of investigation reveals the user accounts that are involved in the deception activity of posting fake reviews called “spammer detection”. Third type of investigation identify the groups of users that involved in having activity of posting fake reviews to achieve single goal called “Spammer Group Detection”. Sixty two percent of publications have focused on detection fake reviews. Thirty one and 7 percentage of research work was on individual spammer and spammer group detection, respectively. Our research work targeted on identifying fake reviews using classification method. Mainly two types of datasets are used for experimentation in identifying fake reviews: real life and pseudo fake as shown in Table 3.1. Two types of features are reported in classifying fake reviews: contextual and behavioral. Our research work focuses on identifying spam reviews using real life dataset on contextual and behavioral features. This chapter gives a brief overview of research work carried out in identifying spam reviews, individual spammers and group spammer.
3.1 Identifying Spam Reviews

A quick overview of literature related to identifying fake reviews can be seen in Table 3.1. Jindal et.al reported a preliminary investigation on spam opinion detection (Jindal & Liu, 2007a). In their next publications, detailed analysis of fake reviews on Amazon were reported (Jindal & Liu, 2008, 2007b). They considered 5.8 million reviews from Amazon and used feature from product and reviewer meta-data on four categories of product to identify fake reviews. The research work comprises identification of untruthful reviews, brand reviews, non-reviews and spammer groups. They discovered spamming activities including identifying duplicate or near duplicate reviews using shingle method. Untruthful reviews were identified by calculating content similarity between all reviews of a reviewer to highlight duplicate reviews. For identifying brand reviews and non-reviews, dissimilarity between product meta data and review content were used. Spammer groups were identified by calculating content similarity of reviews of different reviewers. Logistic Regression was adopted for training on duplicate reviews which achieved 78% on AUC (Area Under ROC curve).

In (S. P. Algur et al., 2010), two annotators were hired to construct pseudo fake reviews dataset containing 960 reviews. The proposed research work comprises identifying duplicate and near duplicate reviews using humming distance. Fifty seven percent accuracy was reported in proposed technique. However, reported accuracy was not significant but their feature extracted from reviews was novel.

Reviews from Epinions was annotated to build dataset by (F. Li, Huang, Yang, & Zhu, 2011). Several features similar to (Jindal & Liu, 2008) are proposed with other features including authority score calculated using PageRank, positive and negative polarity of reviews. They trained SVM, LR and NB to classify fake reviews. Reported results showed that NB achieved best F-Score (58.30%).

(Ott et al., 2011) hired AMT turkers to create dataset of hotel reviews. Annotated dataset of reviews contained 400 fake and 400 non-fake reviews. SVM and NB were trained on three

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1https://www.amazon.com/
2http://www.epinions.com/
3https://www.mturk.com/mturk/welcome
| Year | Author | Dataset Type/Source | Classifier | Feature Type | Evaluation Measures |
|------|--------|---------------------|------------|--------------|---------------------|
| 2007 | Nitin Jindal et. al | Pseudo Fake/Amazon | LR | Contextual | AUC |
| 2008 | Nitin Jindal et. al | Pseudo Fake/Amazon | LR | Contextual | AUC |
| 2010 | C. Lai et. al | Pseudo Fake/Amazon | SVM | Contextual | AUC, Recall, Precision |
| 2010 | Siddu Algur et. al | Pseudo Fake/ Web Page | - | Contextual | Accuracy |
| 2011 | Fangtao Li et. al | Pseudo Fake/Epinions | LR, SVM, NB | Contextual | Precision, Recall, F1 |
| 2013 | Mukherjee Arjun et. al | Real life/Yelp | SVM | Contextual, Behavioral | Precision, Recall, F1, Accuracy |
| 2014 | H. Li et. al | Real life/Diaping | SVM | Contextual, Behavioral | Precision, Recall, F1 |
| 2014 | Yuming Lin et. al | Pseudo Fake/ Amazon | LR, SVM | Contextual, Behavioral | Precision, Recall, F1 |
| 2016 | Istiaq Ahsan et. al | Pseudo Fake, Real Life/ AMT+Yelp | NB, SVM | Contextual | Precision, Recall, F1, Accuracy |
| 2016 | Dongsong Zhang et. al | Real life/Yelp | SVM, DT, RF, NB | Contextual, Behavioral | Precision, Recall, F1, Accuracy |

Table 3.1: Research Work Reported in Identifying Fake Reviews

types of features. First, Parts of Speech (POS) tagger, n-gram, and features from Linguistic Inquiry and Word Count (LIWC) were used. Four approaches were adopted to classify spam reviews. SVM trained on bigrams and LIWC extracted features achieved 89.8% accuracy.

(Wu, Greene, Smyth, & Cunningham, 2010) forged fake reviews for TripAdvisor\(^4\). An unsupervised learning approach based on ranking of product was proposed to identify spam reviews. Fake reviews may damage product ranking on TripAdvisor. It was reported that proposed approach based on product ranking is effective for identifying fake reviews.

(Lai, Xu, Lau, Li, & Jing, 2010) proposed feature set to identify untruthful and non-reviews category of fake reviews. Feature set for identifying non-reviews includes lexical, syntactical and stylistic features. For identifying untruthful reviews, dataset was build containing reviews

\(^4\)https://www.tripadvisor.com/
from Amazon. Two annotators were hired to annotate subset of crawled reviews. SVM acquired 96% recall in classifying non-reviews. Reported results showed improvement in AUC including recall. Using three types of contextual features with KL-divergence, untruthful reviews were identified on hyper-plane.

(H. Li, Liu, Mukherjee, & Shao, 2014) used dataset of Chinese reviews from “Diaping”. On basis of behavioral feature “Diaping” is filtering fake reviews. SVM and Positive-Unlabeled (PU) learning are used to improve classification model. Positive refers to fake reviews and unlabeled refers to unclassified fake and non-fake reviews. In PU learning, model can be trained only on fake reviews. The classification results reported improvement in recall value upto 89%.

Based on three features of review text similarity and two features of reviewer’s posting rate (Lin, Zhu, Wang, Zhang, & Zhou, 2014) proposed accumulative formula to separate fake and non-fake reviews. To calculate the similarity between all reviews, reviewer’s reviews and reviews of a product Jaccard-Similarity was computed. Reported results shows that SVM outperformed LR on dataset adopted by (Jindal & Liu, 2008, 2007a). The trained SVM classification model achieved 85% F1-score.

Real life review dataset or pseudo fake review dataset are used for experimentation. (Istiaq Ahsan et al., 2016) construct dataset by combining real life reviews and pseudo fake reviews. Unlabeled dataset contains reviews from Yelp and Labeled dataset of (Ott, Cardie, & Hancock, 2013) were used. Significant results were reported by using hybrid dataset. The basic novelty of proposed word was applying active learning with supervised learning. Duplicate reviews were identified from unlabeled dataset using KL-JS distance. SVM was trained on duplicate reviews to label reviews of real life dataset. SVM placed reviews on hyper-plan to separate reviews. Manual classification of reviews (close to hyper-plane) by user was done. The accuracy of 88% was reported using NB.

(Mukherjee, Venkataraman, et al., 2013b) exploited contextual and behavioral feature to train classification model. Four unexploited behavioral features were explored for fake review detection. It was empirically proved that using only contextual features can obtain 68.1% accuracy for pseudo fake reviews. Classification model trained on contextual features do not achieve significant accuracy for real life fake reviews. (Mukherjee, Venkataraman, et al., 2013b)
justified that AMT Turkers are not good at faking a review. The reason is that AMT Turkers have limited knowledge about the domain. Word distribution of posted reviews by AMT turkers’ is different from true reviewer. This was the reason (Ott et al., 2011) reported high accuracy of classification model trained on contextual features. (Mukherjee, Venkataraman, et al., 2013b) trained classification model on real life reviews (from Yelp) using combined contextual and behavioral features. The selected feature set consist of “reviewer deviation”, “positive ratio”, “maximum posting rate”, “review length”, “average content similarity” and n-grams features. Reported results showed 86% accuracy on restaurant reviews. It was also reported that 75% of spammers post atleast 6 reviews in a day. Their analysis reported that 80% of spammer are hired for promoting the reputation of business. Third finding of the analysis reported that 70 out of 100 spammers have text similarity between their posted reviews.

Various behavioral features related with reviews and reviewer were exploited by (D. Zhang et al., 2016). The importance of selected features were also investigated for identification of fake reviews. They exploited features including 24 behavioral and 16 contextual features. Exploration of behavioral features were based on Interpersonal Deception Theory (IDT) which posits that “deceivers display both strategic behaviors (e.g., information manipulation) and nonstrategic behaviors during deception” (Buller & Burgoon, 1996). Experiments were conducted on review dataset of Yelp. Reported classification results show 87.8% accuracy using all features. Highly correlated features were identified using Pearson Correlation before feature pruning. Twelve most important features were identified after feature pruning to achieve 90% accuracy by training RF classifier. Moreover, accuracy of SVM, NB, Decision Tree and RF were also compared.

We have discussed both supervised and unsupervised learning approaches used to identify the fake reviews. To the best of our knowledge, supervised learning approaches acquired better results than unsupervised. Therefore, supervised learning is dominant over unsupervised in this research area. It can also analyzed from literature that limited research work is done on real life review dataset. And combining contextual and behavioral features can improve classification model for identifying fake reviews. (Mukherjee, Venkataraman, et al., 2013b) and (D. Zhang et al., 2016) exploited both contextual and behavioral features for classifying fake and non-fake
reviews. However, selected feature set by (D. Zhang et al., 2016) is different from (Mukherjee, Venkataraman, et al., 2013b). Here, we find that combining both feature set (with feature pruning) is worth investigating to improve the classification model.

3.2 Identifying Individual Spammer

A graph based approach was proposed by (Wang, Xie, Liu, & Yu, 2011). Reviewers, reviews, and products were considered as nodes. Based on various features, the edges between reviewer, review and product were placed. Proposed technique captured relationship between nodes “trustworthiness”, “product reliability” and “honest polarity”. The “trustworthiness” of reviewer is based on “honest polarity” of posted reviews. The “honest polarity” is accumulative score of “product reliability” and “review deviation” within a specific time frame. A product is considered as reliable if certain number of posted reviews (positive) belong to trustworthy reviewers. Based on these scores, an iterative algorithm was proposed to assign score to reviewer in range from 1 to -1.

Many researchers assumed that spammers usually allocate a particular time interval to place fake reviews. This assumption was used to identify spammers account (Xie, Wang, Lin, & Yu, 2012). The capturing of unusual events and numbers of reviews rise dramatically in that interval. The behavior of the reviewer was analyzed in spam attacks, casual purchasing and promotion. It was analyzed that spammers start posting reviews as soon as they are hired. Dividing the reviewing duration into time frames may help to detect these type of spam attacks. Three algorithms were used which include: i) Bayes change point detection algorithm ii) template matching algorithm for finding burst patterns and iii) a sliding window to detect blocks in time series matched with a joint burst in all dimensions of the time series.

The review burst is also focused by (Fei et al., 2013) which included other behaviors of the reviewer. Reviews from Amazon were considered for the study that included behavior of reviewer like rating deviation, ratio of Amazon verified purchasers, content similarity between reviews of a reviewer and burst review ratio. The Loopy Belief Propagation Algorithm Loopy was used to process these features in the network of reviewers. The overall 57.5% accuracy was
reported with the followed experimentation.

(Akoglu, Chandy, & Faloutsos, 2013) proposed framework “FRAUDEAGLE” based on graph to identify spammers and false ratings. Unsupervised learning approach was adopted in proposed framework. Signed bipartite graphs were used to classify the network of spammer and non-spammer. The proposed framework “FRAUDEAGLE” focused on connectivity between review content. Proposed framework also analyzed sentiment orientation of review text on a product.

### 3.3 Identifying Spammer Group

So far research on two areas of fake review detection has been discussed in previous sections (Section 3.1 and Section 3.2). However, identifying spammer group is different task. Here, the focus will be on research reported in identifying spammer group.

Different firms may utilize various spammers in a group to promote or demote a product. An interesting research in this regard is carried out by (Liu, 2012). It is discussed that the activity of group spamming can be carried out in two ways. First, an isolated spammer use more than one account to post fake reviews. Second, more than one spammers are hired by a business to promote or demote any target item (Q. Zhang, Zhang, Cai, Qian, & Zhou, 2015; Ye & Akoglu, 2015).

Many spammers might be hired independently for assaulting any target product. By following this manner, capacities of spamming can be expanded. First labeled dataset for spammer group detection was constructed by (Mukherjee, Liu, & Glance, 2012). The dataset contained labeled 2412 non-spammer and spammer groups. Feature used by (Mukherjee et al., 2011) were improved to identify spammer groups. The selected Feature set consist of “group content similarity”, “reviewer burstiness”, “group deviation”, “average content similarity” and others. Spam score of identified groups is calculated by combing all features using frequent-pattern mining. Relational model based GRank was used to to rank all groups to identify spammer groups.
Chapter 4

Research Methodology

This chapter discusses our research methodology. Figure 4.1 gives a brief overview of our research methodology. This chapter focuses on source and attributes of dataset used in this research. It also focuses on contextual and behavioral features. In later part of this chapter, some classification model and evaluation measures is briefly discussed. Our research methodology includes following steps:

**Dataset selection:** Different domains of review data are analyzed. Selection of data include restaurant and hotel reviews from Yelp\(^1\).

**Preprocessing:** Preprocessing techniques are used to handle noisy and inconsistent data. Main preprocessing techniques that were applied include tokenization, lemmatization and others.

**Feature Extraction:** After preprocessing contextual and behavioral features are extracted from available attributes in review database to make feature set for classification model.

**Model Training:** Different classification models are then trained for experimentation related to our research. Main focus was on SVM and RF.

**Evaluation and Analysis:** All outcomes from different classification model are then evaluated using different evaluation measures.

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\(^1\)https://www.yelp.com/sf
Supervised and unsupervised learning approaches for identification of fake reviews are discussed in related work (Chapter 3). To the best of our knowledge, supervised learning approaches acquired better results than unsupervised learning (Heydari et al., 2015; Mukherjee, Venkataraman, et al., 2013a). Therefore, supervised learning is dominant over unsupervised that’s supervised learning is used. For fake review detection, proposed research work include analyzing contextual and behavioral features of reviews and reviewers. We used reviews data from Yelp for experimentation. Contextual and behavioral features are extracted from review dataset.

Twelve features (including contextual and behavioral) were selected by (D. Zhang et al., 2016). More than 30 features including contextual and behavioral features were explored on real life dataset (D. Zhang et al., 2016) but selected twelve features obtain high importance score and classification accuracy. We combine “Reviewer Deviation” explored by (Mukherjee, Venkataraman, et al., 2013b) with feature set of (D. Zhang et al., 2016) for training classification model to identify fake reviews. To the best of our knowledge, selected feature set is not exploited in literature for fake review detection. Therefore, the effect of this feature is explored with other behavioral and contextual features.

Entities and attributes in real life dataset considered for experimentation in Section 4.1 in this chapter. Section 4.2 discussed preprocessing techniques used for experimentation purpose. Different types of features extracted from available attributes are discussed in Section 4.3. Classifiers and some evaluation measures used in this research are briefly discussed in Section 4.4 and Section 4.5.
4.1 Dataset

Most e-commerce sites (e.g. Yelp.com, Epinions.com and Amazon.com) allow users to place suggestion/comment/opinion/reviews about product or services. There are three types of data commonly found in each e-commerce site: Review Content, Reviewer and Product Information.

Discussion on review, reviewer and product related attributes regarding our selected dataset can be seen in Section 4.1.1. From the beginning of fake review detection area, building a dataset for experimentation is a challenging task. Many researchers forged reviews using different types of sources to build review dataset (S. P. Algur et al., 2010; F. Li et al., 2011; Ott et al., 2011; Wu et al., 2010). Using forged review dataset (pseudo fake review) is not recommended by the researchers (Mukherjee, Venkataraman, et al., 2013a). The reason is low classification accuracy on real life dataset as compared to forged review dataset. Reviews from real life dataset is considered this research. Real life dataset is crawled from Yelp (Mukherjee, Venkataraman, et al., 2013b; D. Zhang et al., 2016; Mukherjee, Venkataraman, et al., 2013a).

Yelp was founded in 2004 and the official launch of website in 2005. The website is source for running businesses where users purchase products or services and post opinions/reviews/comments on product and services. In the current position Yelp have more than 1 million business information, 135+ million reviews and 150+ million distinct visitor on mobile and web platform. Users can read and post reviews on businesses. In order to write a review and place a rating (1-5 star), a user must sign in by creating a free account on Yelp that requires a valid email address. Yelp contains businesses information of hotels, restaurants, doctor, shopping, automotive (vehicle booking), beauty parlors, home services, sports and others. Yelp is popular online review site through which many businesses are getting clients. Yelp is filtering fake reviews since last decade. Yelp is using filtering algorithm to detect fake reviews. These techniques are not known to researchers. Yelp provide filtered dataset that

| Table 4.1: Description of Dataset |
|----------------------------------|
|                                | Reviews | Reviewers | Non-Fake | Fake  | Filtered | Not-Filtered | Other Reviews |
| Hotel                           | 688096  | 5132      | 5078     | 780   | 266719   | 415519       | 233           |
| Restaurant                      | 780800  | 35430     | 58716    | 8303  | 317254   | 396527       | 7671          |

35
is available to academic researchers.

Same review dataset is used by (Mukherjee, Venkataraman, et al., 2013b; D. Zhang et al., 2016) for experimentation. The dataset used is provided by Dr. Bing Lui. Table 4.1 shows number of reviews, reviewers with respect to hotels and restaurants. Fake reviews are labeled with “Y” and non-fake reviews are labeled with “N”. Whereas “NR” and “YR” denote filtered and unfiltered reviews.

4.1.1 Entities and Attributes

Two SQLite database is provided that contains crawled review data. First database contains review data of restaurant and second contains of hotel. Both database contains three entities in which two are common: review and reviewer. Restaurant database contains three entities: review, reviewer and restaurant. Whereas, hotel database contains: review, reviewer and hotel. Each entity and related attributes are defined below:

4.1.1.1 Restaurant Entity

This entity is contained by restaurant database which consist of metadata about the restaurant. It contains thirty attributes which contain details about restaurant. A snapshot of restaurant entity along with related attributes is shown in Figure 4.2. We define some attributes of restaurant entity. However, only “reviewCount” is used in the experimentation. Unique key for identification is stored in “restaurantID”. The attribute “name” contains name of restaurant and “location” contains city and state of restaurant. Attribute “reviewCount” contains number of posted reviews on restaurant. Assigned rating of restaurant by Yelp is stored in “rating”. The attribute “categories” contains information about available food items (i.e. Grill Fish, B.B.Q). In the “address”, full address of restaurant is given. Opening hours of restaurant are defined in “Hours”. Suitability of restaurant environment for kids is defined in “GoodforKids”. The attribute “AcceptsCreditCards” contains ’Yes’ if credit card is accepted for paying bill otherwise ’No’. Parking facility in restaurant is notified by “Parking” attribute. The attribute “Attire” contains recommended outfit for customer by restaurant. Attribute “GoodforGroups” contains
information that if the environment of restaurant is good for group meal (e.g. family dinner). The attribute “PriceRange” contains food item rate range. Facility of reservation and food delivery are defined in “TakesReservation” and “Delivery”, respectively.

![Restaurant Entity](image)

**Figure 4.2: Restaurant Entity**

### 4.1.1.2 Hotel Entity

This entity is contained by hotel database which contains thirteen attributes having details about hotel. A snapshot from database of hotel entity along with related attributes is shown in Figure 4.3. We define some attributes of hotel entity. However, only “reviewCount” is used in the experimentation. Unique key for identification is stored in “hotelID”. The attribute “name” contains name of the hotel and “location” contains city and state of hotel. Attribute
“reviewCount” contains number of posted reviews on a hotel. Assigned rating of hotel by Yelp is stored in “rating”. The attribute “categories” contains information about service availability (e.g. event planning, nightlife, bars, etc). The attribute “address” contains full address including street, area, city and state of hotel.

### 4.1.1.3 Reviewer Entity

This entity contains metadata about reviewer and present in restaurant as well as hotel database. It contains thirteen attributes which contain details about reviewer profile. Reviewer entity including the following attributes as shown in Figure 4.4. We define some attributes in reviewer entity used in this research. Unique key for identification is stored in “reviewerID”. Account name of reviewer is stored in “name” attribute. The attribute “location” contain residing city of reviewer. Date of creating account is stored in “yelpJoinDate”. Number of friends as reviewers are defined in “friendCount”. The attribute “reviewCount” contains number of posted reviews by a reviewer. Total number of useful, cool and funny vote count on posted reviews of reviewer is defined in “usefulCount”, “coolCount” and “funnyCount” respectively.
4.1.1.4 Review Entity

This entity contains metadata about reviewer and present in both restaurant and hotel database. It contains ten attributes which contain details about posted reviews. Attributes of review entity in restaurant database can be seen in Figure 4.5.

We define each attribute of review entity. The only difference between review entity of restaurant and hotel database is that instead of “restaurantID” hotel database contains “restaurantID”. Unique key for identification of review is stored in “reviewID”. The attribute “date” contains posted review date. Reviewer entity and restaurant entity are linked with this entity using “reviewerID” and “restaurantID”. The textual content of review is stored in...
“reviewContent”. Number of useful, cool and funny vote count over a review are defined in “usefulCount”, “coolCount” and “funnyCount” respectively. Points (rating) on restaurant/hotel given by reviewer is stored in “rating”. The attribute “flagged” contains “Y” if review is fake otherwise “N”.

4.2 Preprocessing

In many databases of real world contain conflicting and noise data. The reason is that data is often collected from numerous and heterogeneous sources. Inconsistency in data results inaccurate outcomes in data mining process. One of the vital step is preprocessing of data before initiating process of data mining. There are various preprocessing methods (Y. Sun, Kamel, Wong, & Wang, 2007) to handle variety of data ( cleansing, attribute reduction, tokenization, stopwords removing, lemmatization, and stemming). Two types of preprocessing techniques are used for this research work: text and data preprocessing.

4.2.1 Text Preprocessing

Text preprocessing include data mining techniques used to transform unstructured text. Few text preprocessing techniques on our selected dataset are defined as follows:

- **Tokenization**: Tokenization is task of splitting-up the review text into words (tokens). i.e. Review content is tokenized into tokens. For calculating RCS and capital diversity, tokenization is vital step to separate each word in review.

- **Lemmatization**: The task of lemmatizer is to transform word with respect to morphological root word e.g. ’bought’ lemmatized into ’buy’.

4.2.2 Data Preprocessing

It is data mining technique to transform raw data into an understandable data. Data is often noisy, incomplete and/or inconsistent, and may contain errors. Data preprocessing is a method to resolve such type of issues.
Table 4.2: List of Associated Notations

| Notation  | Definition |
|-----------|------------|
| $f(a)$    | function of calculating feature score of reviewer ’a’ |
| $f(r)$    | function of calculating feature score of review ’r’ |
| $\text{rating}_r$ | rating given in review ’r’ |
| $\text{rating}_r(p)$ | rating of review ’r’ on restaurant ’p’ |
| $\text{rating}_r(a)$ | rating of review ’r’ of reviewer ’a’ |
| $N_r(a)$  | number of reviews posted by reviewer ’a’ |
| $N_p(r)$  | number of reviews on a restaurant ’p’ |
| $r_a$     | review of reviewer ’a’ |
| $D_f(a)$  | date of first review posted by reviewer ’a’ |
| $D_l(a)$  | date of last review posted by reviewer ’a’ |
| $\text{similarity}(r_i,r_j)$ | cosine similarity between review $r_i$ and $r_j$ |

It removes unnecessary attributes from review database. In the attribute “date” in review entity, the word “Update” is concatenated with date (e.g. “Update - 02-10-2015”) to identify the review that are updated. The term “Update” is removed and attribute data type string is converted into data type date.

4.3 Features Used For Fake Review Detection

In the projection of this research, two types of features are used: contextual and behavioral features. For training classification model contextual and behavioral features are discussed. Our selected predictive feature set is extracted from Yelp review dataset. However, attributes used for behavioral features extraction in Yelp dataset may or may not be available in review data of other e-market sites.

Contextual and behavioral features are formalized via notations (explained in Table 4.2). Each feature either belong to a review or reviewer denoted by $f(r)$ and $f(a)$ respectively.

4.3.1 Contextual Features

Contextual features are also called verbal features are extracted from review centric feature. Contextual features represent different perspective of review content of review (D. Zhang et al., 2016). Many contextual features are explored which include review length, average review
length, noun ratio, subjectivity, lexical validity, lexical diversity, capital diversity, sentiment orientation, average content similarity and others. Average content similarity is adopted in selected feature set. The reason of selecting average content similarity is that importance of other contextual features are very less compared with average content similarity. Average content similarity is also referred as Reviewer Content Similarity (RCS). RCS is one of the important contextual feature in this research. It shows average text similarity of all posted reviews of a reviewer as defined in Equation 4.1. In RCS, cosine similarity is used to measure similarity of reviews (defined in Equation 4.2). Currently researchers are using TFIDF (term frequency and inverse document frequency) weighting scheme to weight terms in reviews. TF.IDF is denoted by LTC in smart notations as defined in Equation 4.4 (Salton & Buckley, 1988). Different variation of TF.IDF is used to compute RCS. These variation include BM25 and NNC(natural term frequency, no document frequency and cosine) (Walker, 1997; Paltoglou & Thelwall, 2010). Equation 4.3 and 4.5 define formula of NNC and BM25. In defined equations, \( c(t,r) \) represent numbers of terms “t” in review content “r”. Here, “M” denotes number of posted reviews of reviewer and \( df(t) \) denotes number of reviews in which occurrence of term “t” is found.

\[
RCS(a) = \frac{\sum_n \max\left(\int_t \text{similarity}(r_i, r_j)\right)}{n} \quad (4.1)
\]

\[
\text{cosineSimilarity}(r_i, r_j) = \sum_k r_{ik} \cdot r_{jk} \quad (4.2)
\]

\[
NNC = \frac{c(t,r)}{\sqrt{(c(t_1,r))^2 + (c(t_2,r))^2 \ldots (c(t_n,r))^2}} \quad (4.3)
\]

\[
LTC = \frac{(1+ \log(c(t,r))). \left( \log \left( \frac{N}{df(t)} \right) \right)}{\sqrt{(c(t_1,r))^2 + (c(t_2,r))^2 \ldots (c(t_n,r))^2}} \quad (4.4)
\]

\[
BM25 = \frac{c(t,r). \left( \frac{(k+1).c(t,r)}{c(t,r)+k} \right). \log \left( \frac{M+1}{df(t)} \right)}{\sqrt{(c(t_1,r))^2 + (c(t_2,r))^2 \ldots (c(t_n,r))^2}} \quad (4.5)
\]

Another contextual feature named as “Capital Diversity” is used in feature set for hotel
dataset. It is the number of capital words (words starting with capital alphabet) divided by the total number of token in a review.

### 4.3.2 Behavioral Features

Behavioral features are also referred as non-verbal features. These features capture different behavior of reviewer and its posted reviews. Many behavioral features are explored by (D. Zhang et al., 2016) for improving fake review detection model. We define following behavioral feature used in this research:

1. **Membership Length**: It is defined as number of days between today and date on which reviewer account was created (see Equation 4.6).

   \[ M(a) = \text{today} - \text{yelpJoinDate}(a) \]  
   \[ (4.6) \]

2. **Review Count**: It shows the number of reviews posted by a reviewer.

3. **Average Posting Rate**: It shows the ratio of total reviews of a reviewer to number of reviewer active days (see Equation ). An active day is that on which reviewer has posted at least one review.

   \[ \text{APR}(a) = \frac{N_r(a)}{N(\text{posting days})} \]  
   \[ (4.7) \]

4. **Positive ratio**: It shows reviews having more than or equal to 4 as rating value rating divided by total number of reviews of a reviewer (see Equation 4.8)

   \[ R_{\text{pos}}(a) = \frac{N(\{r_a|\text{rating} \geq 4\})}{N_r(a)} \]  
   \[ (4.8) \]

5. **Positive-to-negative ratio**: It shows the ratio of a reviewer having more than or equal to 4 reviews rating value to the reviews having less than or equal to 2 rating value (see Equation 4.9).

   \[ R_{\text{pn}}(a) = \frac{N(\{r_a|\text{rating} \geq 4\})}{N(\{r_a|\text{rating} \leq 2\})} \]  
   \[ (4.9) \]
6. **Maximum Posting Rate**: It is the number of maximum posted reviews in a day (see Equation 4.10).

\[ \text{MPR}(a) = \text{Max} \left( \int n \ \text{number of review}() \right) \]  

(4.10)

7. **Review Duration**: Difference of first posted review and last posted review of reviewer (see Equation 4.11).

\[ \text{RD}(a) = D_f(a) - D_l(a) \]  

(4.11)

8. **Reviewer Deviation**: It captures variation in review rating on a restaurant. It is computed by subtracting review rating with absolute deviation of all ratings on a restaurant (see Equation 4.12).

\[ \text{RevDev}(r) = \left| \text{rating} - \frac{\sum \text{rating}_r(p)}{N_r(p)} \right| \]  

(4.12)

### 4.4 Classifiers Adopted

On the real life dataset many experiments using various classifiers is reported including NB, RF, CART, SVM, KNN and others (D. Zhang et al., 2016; Mukherjee, Venkataraman, et al., 2013b; Kaghazgaran, Caverlee, & Alfifi, 2015; Mukherjee, Kumar, et al., 2013). We considered SVM and RF classifiers because highest results are reported using these classifiers on Yelp dataset by (Mukherjee, Venkataraman, et al., 2013b; D. Zhang et al., 2016). SMV and RF classifiers are discussed in Section 2.5.1 and Section 2.5.3. The effect of “reviewer deviation” is explored. The feature “reviewer deviation” is combined with feature set of (D. Zhang et al., 2016). Review dataset is scaled for investigating the vitality of new feature set.

### 4.5 Evaluation Measures

In the research area of fake review detection many different evaluation measures are used to measure accuracy of constructed classification model. We adopted four predictive accuracy measure for assessing trained classification model: \textit{Precision}, \textit{Recall}, \textit{F1 – measure} and \textit{Accuracy}. Formula of these four features are discussed in Section 2.6. We adopted 10-fold
cross validation in evaluation process. The average performance of ten classification results for each classifier is reported. Most of previous research work on training classifier for fake review detection adopted 10-fold cross validation.
Chapter 5

Experimental Results and Analysis

This chapter discusses a complete experimental setup. This includes selection of reviews and related attributes from real life Yelp database. Furthermore, extracted contextual and behavioral features from available attributes of Yelp database is discussed. Main focus was to investigate behavioral feature “reviewer deviation” with other behavioral and contextual features. Further, a contextual feature “reviewer content similarity” was explored using different schemes of term weighting. After preprocessing and computing features, reviews were classified using RF and SVM classifiers. At last classification models are evaluated using different evaluation measures. For evaluation 10-fold cross validation is used. We compare classification results with three perspectives including classifiers, feature sets and term weighting schemes.

5.1 Dataset and Experimental Setup

First of all, SQLite database of reviews was provided upon making request to Dr. Bing Liu. Dataset was extracted from these reviews of Yelp. Further, details of reviews dataset is discussed. Three SQLite entities are used which are named as “restaurant/hotel”, “reviewer” and “review”. Each entity consist of several attributes. These attributes are used in computing contextual and behavioral features. Twelve contextual and behavioral features are explored including “reviewer deviation”. Java is used to extract features from attributes, selecting dataset based on random reviews, generating CSV files and normalize data. These extracted features
are given to two classifiers RF and SVM. Both classifiers are implemented in Python. Python provides rich packages for machine learning. Two popular packages for machine learning tasks named as ‘SKLEARN’ and ‘PANDAS’. The result of classification model is evaluated using precision, recall, F1-measure and accuracy using 10-fold cross validation.

Our experimentation consist of a dataset of hotel reviews and two different sized dataset of restaurant reviews from Yelp database. Two reviews dataset from restaurant review database were extracted as shown in Table 4.1, we conducted experimentation on two dataset out of 780800 restaurant reviews. The dataset of hotel reviews for experimentation can be seen in Table 5.2 in which 1550 random reviews were selected out of 688096 reviews. The selection of reviews for experiments is based on previously followed pattern. Dataset 1 consist of randomly selected 2060 reviews. In Dataset 1, 1964 reviewers posted 2060 reviews. The second dataset (Dataset 2) is scaled upto 12000 reviews. In Dataset 2, 9754 reviewers posted on 92 restaurants as shown in Table 4.1. All datasets contain equal number of fake and non-fake reviews. We selected equal size of fake and non-fake reviews to avoid imbalance class distribution problem as discussed in section 2.7. The reason behind scaling the review data size is: i) to prove the vitality of selected feature set, and ii) to report the improvement in results of evaluation measures.

Three different combination of contextual and behavioral features are used in experiments for restaurant datasets. Feature set FS1 and FS4 consist of eleven features used by (D. Zhang et al., 2016) for restaurant and hotel reviews respectively. The feature set FS3 consists of features used by (Mukherjee, Venkataraman, et al., 2013b). More than thirty features including both contextual and behavioral features were exploited by (D. Zhang et al., 2016), but best results were reported using twelve features after feature pruning. Ten features are common between feature set for hotel reviews and restaurant reviews. We selected eleven features from feature set used for restaurant and hotel reviews and added “Reviewer Deviation” in each feature set. Our

|        | Restaurants | Reviews | Reviewers | Non-Fake | Fake |
|--------|-------------|---------|-----------|----------|------|
| Dataset 1 | 31          | 2060    | 1964      | 1030     | 1030 |
| Dataset 2 | 92          | 12000   | 9754      | 6000     | 6000 |
selected dataset for restaurant reviews and hotel reviews can be seen in Table 5.4 and Table 5.7 respectively. The feature set consists of a behavioral feature “Reviewer Deviation” along with feature used by (D. Zhang et al., 2016) for restaurant reviews and referred as FS2. A feature set consists of a behavioral feature “Reviewer Deviation” along with eleven feature used by (D. Zhang et al., 2016) for hotel reviews and referred as FS5. Our feature set consist of twelve feature including one contextual and eleven behavioral features for restaurant reviews as shown in Table 5.4. Second feature set for hotel reviews include two contextual and ten behavioral features as shown in Table 5.7. Another feature set used by (Mukherjee, Venkataraman, et al., 2013b) consist of six features including four behavioral features, a contextual feature and unigram (shown in Table 5.5).

A snapshot of a dataset is shown in Figure 5.1 where each row represents a review. Each column in Figure 5.1 represent a feature. RCS is one of the important contextual feature. RCS shows average text similarity of all posted reviews of a reviewer. RCS is discussed in Section 4.3.2. In RCS, cosine similarity is used to measure similarity of reviews. Currently researchers are using cosine similarity based on TF.IDF weighting scheme to weight terms in reviews. Different variation of TF.IDF is used to compute RCS. These variation include BM25
Table 5.4: Feature Set of Reviewer Deviation and Other Features used by Zhang et.al for restaurant reviews

| Features (FS2)                          |
|----------------------------------------|
| 1. Useful Count                        |
| 2. Cool Count                          |
| 3. Funny Count                         |
| 4. Friend Count                        |
| 5. Review Count                        |
| 6. Average Posting Rate                |
| 7. Positive Ratio                      |
| 8. Reviewer Content Similarity         |
| 9. Membership Length                   |
| 10. Review Duration                    |
| 11. Positive to Negative Ratio         |
| 12. Reviewer Deviation                 |

Table 5.5: Feature Set Used by Mukherjee et.al for Yelp reviews

| Features (FS3)                          |
|----------------------------------------|
| 1. Content Length                      |
| 2. Positive Ratio                      |
| 3. Reviewer Content Similarity         |
| 4. Reviewer Deviation                  |
| 5. Maximum Number of Reviews           |
| 6. Unigrams                            |

Table 5.6: Feature Used by Zhang et.al for hotel reviews

| Features (FS4)                          |
|----------------------------------------|
| 1. Useful Count                        |
| 2. Cool Count                          |
| 3. Funny Count                         |
| 4. Friend Count                        |
| 5. Review Count                        |
| 6. Average Posting Rate                |
| 7. Tips Count                          |
| 8. Reviewer Content Similarity         |
| 9. Membership Length                   |
| 10. Review Duration                    |
| 11. Capital Diversity                  |
Table 5.7: Feature Set of Reviewer Deviation and Other Features used by Zhang et.al for hotel reviews

| Features (FS5)                  |
|-------------------------------|
| 1. Useful Count               |
| 2. Cool Count                 |
| 3. Funny Count                |
| 4. Friend Count               |
| 5. Review Count               |
| 6. Average Posting Rate       |
| 7. Tips Count                 |
| 8. Reviewer Content Similarity|
| 9. Membership Length          |
| 10. Review Duration           |
| 11. Capital Diversity         |
| 12. Reviewer Deviation        |

In short, one of the focus was to extract data from real life dataset. Three datasets as mentioned earlier were extracted from Yelp database to investigate the effect of behavioral feature “reviewer deviation” combined with other contextual and behavioral features on classification of fake reviews. Another focus was to explore a contextual feature RCS using different variations of weighting terms in reviews for computation of text similarity. SVM and RF is used for classification. Ten fold cross validation is used for evaluation. Different evaluation measures accuracy, precision, recall and F1-measure are used.

| reviewtext | rating | usefulCount | friendCount | review_count | avg_posts | review_sentiment | review_group | membership_length | review_duration | capital_diversity | reviewer_deviation |
|------------|--------|-------------|-------------|--------------|-----------|------------------|--------------|-------------------|-----------------|-------------------|-------------------|
| This place is great to my previous favorite. | 4      | 0           | 0           | 6            | 1.022323  | 50               | 0.877721     | 0.919             | 61              | 61                | 3                 | 0.312 Y          |
| AMAZING FOOD! The food is on (3) good. | 4      | 0           | 0           | 6            | 1.022323  | 50               | 0.877721     | 0.919             | 61              | 61                | 3                 | 0.312 Y          |
| I love Tha food. I crave it like a first class train. | 3      | 0           | 0           | 5            | 1.022323  | 40               | 0.877721     | 0.919             | 61              | 1                 | 1                 | 0.292 Y          |
| We have been to Opal Thai four times. The food has been excellent every time. | 4      | 0           | 0           | 6            | 1.233333  | 25               | 0.877721     | 0.919             | 61              | 64                | 1                 | 0.135 Y          |
| We've really enjoyed Opal Thai House many times. | 4      | 0           | 0           | 6            | 1.233333  | 25               | 0.877721     | 0.919             | 61              | 64                | 1                 | 0.135 Y          |
| This place was recommended to me by a friend. | 4      | 0           | 0           | 7            | 3.333333  | 25               | 0.877721     | 0.919             | 61              | 64                | 1                 | 0.135 Y          |
| Opal Thai House is a restaurant that is near me. | 4      | 0           | 0           | 7            | 3.333333  | 25               | 0.877721     | 0.919             | 61              | 64                | 1                 | 0.135 Y          |
| This is my favorite restaurant to go to for Thai food. | 5      | 0           | 0           | 6            | 1.000000  | 100              | 0.954244     | 0.980             | 79              | 116               | 6                 | 0.445 Y          |
| After being to so many and a wonderful place. | 5      | 0           | 0           | 6            | 1.000000  | 100              | 0.954244     | 0.980             | 79              | 116               | 6                 | 0.445 Y          |
| This is my favorite out Thai food. & Com. | 4      | 0           | 0           | 6            | 1.000000  | 100              | 0.954244     | 0.980             | 79              | 116               | 6                 | 0.445 Y          |
| My friend and I eat a lot of Thai food and Opal Thai is wonderful. | 4      | 0           | 0           | 6            | 1.000000  | 100              | 0.954244     | 0.980             | 79              | 116               | 6                 | 0.445 Y          |
| I don't know why everyone loves about this place. | 3      | 0           | 0           | 6            | 1.000000  | 100              | 0.954244     | 0.980             | 79              | 116               | 6                 | 0.445 Y          |
| Best Thai in Orange! This tell on quality. | 5      | 0           | 0           | 6            | 1.000000  | 100              | 0.954244     | 0.980             | 79              | 116               | 6                 | 0.445 Y          |
| This place has a great environment & delicious food. | 5      | 0           | 0           | 6            | 1.000000  | 100              | 0.954244     | 0.980             | 79              | 116               | 6                 | 0.445 Y          |
| I have been going to Opal Thai that | 5      | 0           | 0           | 6            | 1.000000  | 100              | 0.954244     | 0.980             | 79              | 116               | 6                 | 0.445 Y          |

Figure 5.1: Snapshot of dataset
5.2 Importance of Reviewer Deviation

Experiments were made on three datasets, two dataset consist of 2060 and 12000 reviews on restaurants and third dataset consist of 1550 reviews on hotels. Datasets were extracted from Yelp dataset which considered to be real life dataset. Three different feature sets were used for restaurant reviews and two feature sets for hotel reviews. Three of these feature sets for restaurant and hotel reviews are used by (D. Zhang et al., 2016) and (Mukherjee, Venkataraman, et al., 2013a). One of the feature set comprises of a behavioral feature named as “Reviewer Deviation” and eleven features used by (D. Zhang et al., 2016) for restaurant and hotel reviews. One of the focus of this research was to investigate the importance of “Reviewer Deviation” along with contextual and behavioral feature used by (D. Zhang et al., 2016). Interestingly, it was found after computing importance score that the importance score of “Reviewer Deviation” is ranked in top ten contextual and behavioral features. Results on using “Reviewer Deviation” along with other contextual and behavioral features used by (D. Zhang et al., 2016) and (Mukherjee, Venkataraman, et al., 2013a), shows improvement in terms of precision and accuracy. Detailed analysis is made on following section.

5.2.1 Importance Score of Contextual and Behavioral Features

The importance score of each contextual and behavioral features on dataset 1 with FS2 and dataset 3 with FS5 are computed. Behavioral feature “reviewer deviation” is ranked among top ten features according to computation of importance score for “reviewer deviation” using RF as shown in Table 5.8 and Table 5.9. The reason for using RF for computation of importance score of each feature is that it outperform SVM.

Dataset 1 contains reviews from Yelp restaurant database. Feature ranking on Dataset 1 shows that useful, cool, funny votes are most important features for restaurant reviews. Whereas number of posted reviews and friend of reviewer acquired low ranking as to the above mentioned features. Usefulness of votes count show that other users also support review content. Another behavior of spammer is identified by fifth feature which defines that total number of posted reviews by spammer is much greater than a true reviewer. “Average posting rate” ranked
sixth proves that considering posting frequency of a reviewer is also a vital perspective for fake review detection. It is analyzed by many researchers that 80% of reviews by spammers deviates towards positive polarity (F. Li et al., 2011; S. Algur, Hiremath, Patil, & Shivashankar, 2010). Our observations also support previous reported results about positive ratio which is on seventh rank. Initial study on fake review detection by (Jindal & Liu, 2007a, 2007b) were based on content similarity of reviews and similarity of 90% reviews with content of other reviews were considered as fake. Likewise top eighth feature which relates to contextual feature is proved important which support observation that reviews of spammer have textual resemblance with each other (Jindal & Liu, 2007a; D. Zhang et al., 2016; Mukherjee, Venkataraman, et al., 2013a; Myle Ott, n.d.; Ott et al., 2011; Lin et al., 2014). Deviation of rating of a review from other reviews on a restaurant increase the change of “spamicity”. That is why “reviewer deviation” is observed on ninth rank which support the research investigation objective for empirically proving vitality of this behavioral feature. “Membership Length” is investigated due to assumption in literature that more old the reviewer’s account is more reliable it is. In some cases spammer create account to place false reviews for a little time period. This behavior of spammer is captured with ’Review Duration’ which is ranked eleventh. The last behavior is the ratio between positive and negative rating of reviews by reviewer. It is interpreted that variation in the ratio of positive reviews compared with negative reviews of fake reviewer is different than true reviewer (D. Zhang et al., 2016).

Dataset 2 contains reviews from Yelp hotel database and feature ranking for classification can be seen in Table 5.9. Feature ranking on Dataset 2 shows that “Review Duration”, “Tips Count” and “Useful Count” obtained highest score among all features. Whereas, “Capital Diversity”, “Cool Count” and “Funny Count” obtained lowest importance score in classification. The contextual feature “Reviewer Content Similarity” is more effective for classifying hotel reviews hence it gained fifth ranking. The feature under consideration “reviewer deviation” is observed on eighth rank which support the research investigation objective for empirically proving vitality of this behavioral feature.

The focus was to investigate the importance of “Reviewer deviation” in combination with contextual and behavioral features used by (D. Zhang et al., 2016) and (Mukherjee,
Venkataraman, et al., 2013a). This feature was compared with feature sets used by (D. Zhang et al., 2016) and (Mukherjee, Venkataraman, et al., 2013a). (D. Zhang et al., 2016) and (Mukherjee, Venkataraman, et al., 2013a) used a contextual feature “Reviewer Content Similarity” based on TF.IDF (LTC). Experiments were made using RF and SVM. For evaluation 10-fold cross validation is used. Three datasets were used that include restaurant and hotel reviews. Dataset 1 and Dataset 2 consist of 2060 and 12000 restaurant reviews respectively as shown in Table 5.1. Dataset 3 consists of 1550 hotel reviews as shown in Table 5.2.

Table 5.8: Importance Score of Selected Set of Features on Restaurant Reviews

| Rank | Features               | Importance Score |
|------|------------------------|------------------|
| 1    | Useful Count           | 24.668           |
| 2    | Cool Count             | 18.649           |
| 3    | Funny Count            | 14.638           |
| 4    | Friend Count           | 12.239           |
| 5    | Review Count           | 9.017            |
| 6    | Average Posting Rate   | 5.031            |
| 7    | Positive Ratio         | 4.222            |
| 8    | Reviewer Content Similarity | 3.408          |
| 9    | Reviewer Deviation     | 2.993            |
| 10   | Membership Length      | 2.504            |
| 11   | Review Duration        | 1.787            |
| 12   | Positive Negative Ratio| 0.843            |

Table 5.9: Importance Score of Selected Set of Features on Hotel Reviews

| Rank | Features              | Importance Score |
|------|-----------------------|------------------|
| 1    | Review Duration       | 23.934           |
| 2    | Tips Count            | 21.082           |
| 3    | Useful Count          | 13.545           |
| 4    | Review Count          | 12.323           |
| 5    | Reviewer Content Similarity | 10.871          |
| 6    | Average Posting Rate  | 4.260            |
| 7    | Membership Length     | 3.432            |
| 8    | Reviewer Deviation    | 2.940            |
| 9    | Friend Count          | 2.593            |
| 10   | Capital Diversity     | 2.353            |
| 11   | Cool Count            | 1.668            |
| 12   | Funny Count           | 0.993            |
CHAPTER 5 EXPERIMENTAL RESULTS AND ANALYSIS

5.2.2 Results and Analysis on Dataset 1

FS3 achieved precision, recall, f1-score and accuracy of 71.96%, 77.96%, 74.84% and 73.17% respectively on Dataset 1 using RF classifier as shown in Table 5.10. Whereas FS2 achieved precision, recall, f1-score and accuracy of 89.07%, 92.13%, 90.57% and 90.23% respectively. The improvement here in accuracy, precision, recall and f2-score is 17.06%, 17.1%, 14.17% and 15.73% respectively. This improvement is quite significant. Similarity, using SVM the accuracy, precision, recall and f1-measure on FS3 is 70.43%, 70.64%, 73.88% and 72.22% respectively. Whereas FS2 gives accuracy, precision, recall and f1-measure of 87.86%, 87%, 89.22% and 88.09% respectively. It gives improvement of 17.42%, 16.36%, 15.34% and 15.87% in terms of accuracy, precision, recall and f1-measure respectively which is quite significant. The visualization of FS2 and FS3 can be seen in Figure 5.3.

FS1 achieved accuracy, precision, recall and f1-measure of 90.09%, 88.6%, 92.33%, 90.42% respectively using RF on dataset1 as shown in Table 5.10. The improvement of FS2 compared with FS1 is 0.47%, 0.15%, 0.13% in terms of precision, recall, f1-measure and accuracy respectively using RF. Whereas improvement using SVM is 0.63%, 0.32%, 0.38% in terms of precision, f1-measure and accuracy respectively. Improvements using both classifiers are quite significant. The visualization of FS1 and FS2 can be seen in Figure 5.2.

Table 5.10: Results on Dataset 1 Using LTC

| Classifier | Feature Set | Precision | Recall | F1   | Accuracy |
|------------|-------------|-----------|--------|------|----------|
| RF         | FS1         | 88.600    | 92.330 | 90.426 | 90.097   |
|            | FS2         | 89.073    | 92.135 | 90.578 | **90.231** |
|            | FS3         | 71.967    | 77.961 | 74.844 | 73.170   |
| SVM        | FS1         | 86.370    | 89.223 | 87.773 | 87.475   |
|            | FS2         | 87.002    | 89.223 | 88.098 | 87.864   |
|            | FS3         | 70.641    | 73.883 | 72.226 | 70.439   |

5.2.3 Results and Analysis on Dataset 2

FS3 achieved precision, recall, f1-score and accuracy of 74.86%, 76.29%, 75.57% and 75.18% respectively on Dataset 2 using RF classifier as shown in Table 5.11. Whereas FS2 achieved precision, recall, f1-score and accuracy of 90.01%, 93.03%, 91.49% and 91.24% respectively.

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The significant improvement here in precision, recall, f1-measure and accuracy is 15.15%, 16.73%, 15.92% and 16.06% respectively. Similarity, using SVM the precision, recall, f1-measure and accuracy on FS3 is 75.95%, 83.59%, 79.58% and 78.37% respectively. Whereas FS2 gives precision, recall, f1-measure and accuracy of 85.90%, 89.21%, 87.52% and 87.22% respectively. It gives improvement of 9.95%, 5.62%, 7.94%, 8.85% in terms of precision, recall, f1-measure and accuracy respectively which is quite significant. Comparison between FS2 and FS3 is visualized in Figure 5.4.

FS1 achieved precision, recall, f1-measure and accuracy of 90.54%, 92.98%, 91.74% and 91.17% respectively using RF on dataset1 as shown in Table 5.10. The improvement of FS2 compared with FS1 is 0.05% and 0.07% in terms of recall and accuracy respectively using RF. Whereas improvement using SVM is 0.26%, 0.48%, 0.37% and 0.36% in terms of precision, recall, f1-measure and accuracy respectively. In comparison with Dataset 1 improvement of 1%
### Table 5.11: Results on Dataset 2 Using LTC

| Classifier | Feature Set | Precision | Recall  | F1      | Accuracy |
|------------|-------------|-----------|---------|---------|----------|
| RF         | FS1         | 90.545    | 92.983  | 91.748  | 91.172   |
|            | FS2         | 90.015    | 93.032  | 91.499  | 91.244   |
|            | FS3         | 74.862    | 76.295  | 75.572  | 75.184   |
| SVM        | FS1         | 85.643    | 88.737  | 87.163  | 86.868   |
|            | FS2         | 85.907    | 89.213  | 87.529  | 87.229   |
|            | FS3         | 75.951    | 83.590  | 79.588  | 78.375   |

in accuracy and F1 is observed. The results of FS1 and FS2 are visualized in Figure 5.5.

![Figure 5.4: Comparison of FS2 and FS3 on Dataset 2](image)

5.2.4 Results and Analysis on Dataset 3

The results of RF on Dataset 3 using FS5 acquired highest accuracy of 91.096% which is observed due to increase in recall as shown in Table 5.12. Whereas, FS4 obtained 90.967% accuracy which is the little difference between the accuracy with FS5. Similarity, using SVM the precision, recall, f1-measure and accuracy on FS5 is 85.15%, 89.84%, 87.28% and 86.83% respectively. This difference between both classification on FS4 and FS5 shows small increase in recall. The comparison between results of both feature set with classification results can be visualized in Figure 5.6.
Figure 5.5: Comparison of FS1 and FS2 on Dataset 2

Table 5.12: Results on Dataset 3 Using LTC

| Classifier | Feature Set | Precision | Recall | F1    | Accuracy |
|------------|-------------|-----------|--------|-------|----------|
| RF         | FS4         | 91.226    | 92.782 | 91.102| 90.967   |
|            | FS5         | 91.155    | 92.925 | 91.269| 91.096   |
| SVM        | FS4         | 85.301    | 89.696 | 87.129| 86.774   |
|            | FS5         | 85.153    | 89.840 | 87.287| 86.838   |

5.3 RCS Based on Different Weighting Schemes

The most important contextual feature “Reviewer Content Similarity” (RCS) which calculates similarity between reviews of a reviewer to identify duplicates or partial duplicates reviews. This contextual feature RCS is used along with other behavioral features. Focus was to investigate RCS using different term weighting schemes. In literature LTC (TF.IDF) term weighting scheme is used in calculating cosine similarity between two reviews. Two term weighting schemes are explored: NNC and BM25. Formal representation of these weighting schemes are discussed in Section 4.3.1. Main focus was to investigate the effect of these weighting schemes on RCS. Experiments were carried out to explore if RCS based on these weighting schemes have any effect on fake review detection. Experiments were carried out to detect fake reviews based on RCS (using different term weighting schemes) along with other behavioral features. RF and SVM were used as classifiers and 10-fold cross validation is used for evaluation. Experiments were carried out on two datasets. Detailed analysis on results is given in the following section.
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Figure 5.6: Comparison of FS4 and FS5 on Dataset 3

Table 5.13: Results of Dataset 1 Using NNC

| Classifier | Feature Set | Precision | Recall  | F1       | Accuracy | Weighting Scheme |
|------------|-------------|-----------|---------|----------|----------|------------------|
| RF         | FS1         | 88.600    | 92.330  | 90.426   | 90.097   | LTC              |
|            | FS2         | 89.559    | 92.135  | 90.829   | 90.194   | NNC              |
|            | FS3         | 71.967    | 77.961  | 74.844   | 73.170   | LTC              |
| SVM        | FS1         | 86.370    | 89.223  | 87.773   | 87.475   | LTC              |
|            | FS2         | 83.727    | 87.378  | 85.513   | 85.097   | NNC              |
|            | FS3         | 70.641    | 73.883  | 72.226   | 70.439   | LTC              |

5.3.1 Results and Analysis on Dataset 1

The results of RCS based on NNC along with other behavioral features can be seen in Table 5.13. FS2 achieved precision, recall, f1-measure and accuracy of 89.55%, 92.13%, 90.82% and 90.19% respectively using RF on Dataset 1. The improvement of FS2 compared with FS3 is 17.59%, 14.17%, 15.98% and 17.02% in terms of precision, recall, f1-measure and accuracy respectively. Whereas comparing with FS1 shows improvement of precision, f1-measure and accuracy of 0.96%, 0.40% and 0.1% respectively. Similarly using SVM, FS2 achieved precision, recall, f1-measure and accuracy of 83.72%, 87.37%, 85.51% and 85.09% respectively which shows improvement of 13.08%, 13.49%, 13.28% and 14.65% in terms of precision, recall, f1-measure and accuracy compared with FS1.

The results of RCS based on BM25 along with other behavioral features can be seen in Table 5.14. FS2 achieved precision, recall, f1-measure and accuracy of 89.55%, 92.13%, 90.82% and 90.19% respectively using RF. Compared with FS3, the improvement of 17.59%, 14.17%, 15.98% and 17.02% in terms of precision, recall, f1-measure and accuracy respectively.

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**Figure 5.7:** Results of NNC, LTC and BM25 Schemes of FS2 on Dataset 1

Whereas improvement of 0.96%, 0.40%, 0.1% in precision, f1-measure and accuracy respectively is observed. Similarity using SVM, FS2 achieved precision, recall, f1-measure and accuracy of 83.72%, 87.37%, 85.51% and 85.09% respectively. The improvement compared with FS3 is 13.086%, 13.495, 13.28% and 14.65% in terms of precision, recall, F1-measure and accuracy respectively.

**Table 5.14:** Results of Dataset 1 Using BM25

| Classifier | Feature Set | Precision | Recall | F1  | Accuracy | Weighting Scheme |
|------------|-------------|-----------|--------|-----|----------|------------------|
| RF         | FS1         | 88.600    | 92.330 | 90.426 | 90.097   | LTC              |
|            | FS2         | 90.033    | 92.233 | 91.119 | 90.776   | BM25             |
|            | FS3         | 71.967    | 77.961 | 74.844 | 73.170   | LTC              |
| SVM        | FS1         | 86.370    | 89.223 | 87.773 | 87.475   | LTC              |
|            | FS2         | 86.978    | 89.611 | 88.275 | 88.009   | BM25             |
|            | FS3         | 70.641    | 73.883 | 72.226 | 70.439   | LTC              |

The result comparison of all three term weighting schemes of FS2 using RF are visualized in Figure 5.7 of Dataset 1 from which we can justify that BM25 weighting scheme improves precision, f1-score and accuracy.

### 5.3.2 Results and Analysis on Dataset 2

The results of RCS based on NNC along with other behavioral features can be seen in Table 5.15. FS2 achieved precision, recall, f1-measure and accuracy of 89.32%, 92.81%, 91.03% and
Table 5.15: Results of Dataset 2 with NNC

| Classifier | Feature Set | Precision | Recall | F1   | Accuracy | Weighting Scheme |
|------------|-------------|-----------|--------|------|----------|-----------------|
| RF         | FS1         | 90.545    | 92.983 | 91.748 | 91.172   | LTC             |
|            | FS2         | 89.322    | 92.819 | 91.037 | 91.081   | NNC             |
|            | FS3         | 74.862    | 76.295 | 75.572 | 75.184   | LTC             |
| SVM        | FS1         | 85.643    | 88.737 | 87.163 | 86.868   | LTC             |
|            | FS2         | 84.806    | 90.049 | 87.349 | 86.860   | NNC             |
|            | FS3         | 75.951    | 83.590 | 79.588 | 78.375   | LTC             |

Table 5.16: Results of Dataset 2 Using BM25

| Classifier | Feature Set | Precision | Recall | F1   | Accuracy | Weighting Scheme |
|------------|-------------|-----------|--------|------|----------|-----------------|
| RF         | FS1         | 90.545    | 92.983 | 91.748 | 91.172   | LTC             |
|            | FS2         | 90.673    | 92.950 | 91.861 | 91.396   | BM25            |
|            | FS3         | 74.862    | 76.295 | 75.572 | 75.184   | LTC             |
| SVM        | FS1         | 85.643    | 88.737 | 87.163 | 86.868   | LTC             |
|            | FS2         | 85.901    | 89.196 | 87.518 | 87.221   | BM25            |
|            | FS3         | 75.951    | 83.590 | 79.588 | 78.375   | LTC             |

91.08% respectively using RF on Dataset 1. This results does not show improvement compared with FS1. However, the improvement of FS2 compared with FS3 is 14.46%, 16.52%, 15.46% and 15.89% in terms of precision, recall, f1-measure and accuracy respectively. Similarly using SVM, FS2 achieved precision, recall, f1-measure and accuracy of 84.80%, 90.04%, 87.34% and 86.86% respectively which shows improvement of 8.85%, 6.459%, 7.7% and 8.48% in terms of precision, recall, f1-measure and accuracy compared with FS3.

The results of RCS based on BM25 along with other behavioral features can be seen in Table 5.16. FS2 achieved precision, recall, f1-measure and accuracy of 90.67%, 92.95%, 91.86% and 91.39% respectively using RF. Compared with FS3, the improvement of 15.81%, 16.65%, 16.29% and 16.21% in terms of precision, recall, f1-measure and accuracy respectively. Whereas improvement of 0.13%, 0.11% and 0.22% in precision, f1-measure and accuracy respectively is observed. Similarity using SVM with FS2 achieved precision, recall, f1-measure and accuracy of 85.90%, 89.19%, 87.51% and 87.22% respectively. The improvement compared with FS1 is 0.26%, 0.46%, 0.36% and 0.35% in terms of precision, recall, F1-measure and accuracy respectively.

The result comparison of all three term weighting schemes of FS2 using RF are visualized
5.3.3 Results and Analysis on Dataset 3

The comparative results of FS2, FS4 and FS5 based on variation of RCS on Dataset 3 can be seen in Table 5.17. The feature set FS5 achieved highest precision and accuracy of 91.27% and 91.09% respectively. The improvement of our selected feature set with BM25 weighting scheme is less than improvement for restaurant reviews. The less improvement can be justified due to size of hotel reviews dataset is less than the restaurant reviews dataset. The visualization of the comparison can be seen in Figure 5.9. It clearly shows the slight improvement in precision which effects the overall accuracy of the classification results.

| Classifier | Feature Set | Precision | Recall  | F1     | Accuracy | Weighting Scheme |
|------------|-------------|-----------|---------|--------|----------|-----------------|
| RF         | FS4         | 91.226    | 92.782  | 91.102 | 90.967   | LTC             |
|            | FS2         | 90.453    | 92.910  | 90.943 | 90.838   | BM25            |
|            | FS5         | 91.274    | 92.668  | 91.252 | 91.096   | BM25            |
| SVM        | FS4         | 85.301    | 89.696  | 87.129 | 86.774   | LTC             |
|            | FS2         | 84.936    | 89.821  | 87.117 | 86.709   | BM25            |
|            | FS5         | 85.153    | 89.965  | 87.215 | 86.838   | BM25            |
5.4 Performance of Classifiers on Fake Review Detection

Two classifiers were selected for experimentation which include SVM and RF. The reason of selecting SVM and RF is that both classifiers are appreciated in literature for fake review detection. SVM and RF generated best results on Yelp dataset. We conducted experiments with three different feature sets. We also computed RCS based on three different weighting schemes and combined with other behavioral features. All outcomes of classification supports the statement that RF outperformed SVM in every evaluation measure. To check the performance of classifiers we initially conducted the experiments and the results are shown in Table 5.10. Results show that SVM did not perform well in comparison with RF. The difference of precision, recall, f1 and accuracy on FS2 in Dataset 1 is visualized in Figure 5.10. The improvement of 2.6%, 3.1%, 2.2% and 2.6% in terms of accuracy, recall, precision and in f1-measure respectively was observed. Including the improvement of 4.1%, 3.97%, 3.8% and 4.1% in terms of in accuracy, f1-measure, recall and precision with FS2 using LTC. The comparison is shown in Figure 5.11. Above mentioned result tables support that RF outperformed SVM on Dataset 1 and Dataset 2 including all three term weighting schemes.
5.5 Result Analysis

Experiments conducted with variation of behavioral and contextual feature sets explored importance of selected features for training fake review detection model. We compared results of different feature sets including three different term weighting schemes on SVM and RF. From initial experiments for exploring importance of “Review Deviation” with other behavioral and contextual features we analyze that by new feature improves accuracy. Where as the finding based on our experimental results shows that by scaling dataset can improve the classification
accuracy and f1-score. Literature on classifier comparison by (D. Zhang et al., 2016) also reports that RF outperformed other classifiers. The worthy considerable finding of the conducted experimentation on variety of feature set and dataset size is that by adopting term weighting scheme $BM25$ to calculate similarity of two vectors of reviews can improve the evaluation score.
Chapter 6

Conclusion and Future Directions

This chapter discusses a brief summary of this research work and gives future direction. It discusses the conclusion drawn on exploring contextual and behavioral features for fake review detection. Some of the major contribution is also discussed. It also gives future research direction.

6.1 Summary

The impact of online user reviews heavily influence the customer decisions and businesses. Reviews help in decision making of a customer for purchasing of particular product or service. Fake reviews can mislead customer in terms of decision making. Fake reviews are use to promote or demote product or services on e-commerce sites. It can harm the reputation of a good service or product provider and thus can cause financial loss a firm. In some cases fake reviews can falsely cause financial gain to a company or firm. Fake reviews are damaging for both customers and businesses. Researchers have focused pm fake review detection since 2007. There are three main research areas: identifying fake reviews, identifying individual spammer and spammer group. The focus of this research was to detect fake reviews using contextual and behavioral features. Researchers have used two types of dataset: pseudo fake reviews and real life reviews. Using only contextual features researchers reported high classification results on pseudo fake review dataset but same classification model failed to acquire high accuracy on real
life review dataset. Our findings reveal some unexplored angle of fake review detection area for exploitation of behavioral and contextual features to improve the classification model for identification of fake reviews in real life dataset.

6.2 Conclusion

In this research, dataset of real life reviews extracted from Yelp was used. The main focus was to investigate the effect of a behavioral feature “reviewer deviation” with other contextual and behavioral features on classifying fake reviews. This feature set shows improvement in classifying fake reviews as compared to the feature sets used by (Mukherjee, Venkataraman, et al., 2013a) and (D. Zhang et al., 2016). Another focus was to explore a contextual feature “reviewer content similarity” (RCS) using different weightings. Researchers have used RCS based on TF.IDF (Jindal & Liu, 2007a; D. Zhang et al., 2016; S. Algur et al., 2010; Banerjee & Chua, 2014; Lin et al., 2014; Ott et al., 2013). RCS based on NNC and BM25 along with other contextual and behavioral features shows improvement in real life review dataset. Our findings reveal some unexplored angle of fake review detection area. It was observed that RF outperforms SVM in detecting fake reviews on real life dataset and this fact is reported by several researchers (D. Zhang et al., 2016; Mukherjee, Venkataraman, et al., 2013a).

6.3 Contributions

A set of predictive features containing behavioral and contextual features to identify fake reviews was investigated. A behavioral feature “reviewer deviation” was not explored in any of the feature set used to identify fake reviews. The perspective of “reviewer deviation” is to capture different behavior of reviewer by calculating deviation of given ratings with other ratings on same restaurant/hotel. The proposed idea to combine “reviewer deviation” with other contextual and behavioral feature for fake review classification shows improvement. The importance of “reviewer deviation” with other predictive features was investigated. The result shows that “reviewer deviation” is among top ten most important feature in terms of importance
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score. Another contribution was to investigate a contextual feature “reviewer content similarity” (RCS) based on different weightings: NNC and BM25. Results on RCS based on NNC and BM25 shows improvement in classifying fake reviews.

6.4 Future Work

There are three research areas associated with fake review detection: identifying fake reviews, identifying individual spammer and spammer group. Identifying group spammer can be explored in future using social network analysis techniques. Further feature selection can be pruned using deep learning techniques. RCS can be explored further using text processing techniques.
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