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Incentivized comment detection with sentiment analysis on hotel reviews

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Abstract

With the enormous platforms currently available, consumers communicate and interconnect online frequently with web users all around the world to share their experiences. Thus, online platforms have become a major source of reviews and opinions about different entities. People travel frequently around the world for different purposes. Seeking good hotels for accommodation is a prime concern. Reviews on hotels from customers help future customers to make decisions about their accommodation and help hotel owners to think about designing customer facilities. However, many online reviews are biased due to different factors. Many hotel owners often come up with attractions like referral rewards, coupons, bonus points, etc. for the reviewers to motivate them to write biased reviews. We have looked at reviews on 100 hotels in the US and found 952 incentivized reviews among 19175 reviews, which is 4.96% of the total number of reviews. A categorization of incentivized reviews is performed as well. Furthermore, hotels are distinguished based on real and incentivized reviews about them. The results are verified using machine learning algorithms. The Random Forest, K-Nearest Neighbor and Support Vector Machine machine learning algorithms are applied to validate the accuracy of our model, and their prediction results are compared. Random Forest outperforms the others with 94.4% prediction accuracy.

Keywords: Incentivized reviews, Sentiment analysis, Text mining, Machine learning

1. Introduction

Today, the significance of social media sites has been raised in people's day-to-day lives. People share their feelings via social media through posting reviews [1]. As a result, a wide range of information is available to customers while they are making decisions like booking a hotel room. Consumers get adequate knowledge about other consumers' satisfaction or regret levels with a hotel by reading their posted reviews [2]. Besides reading about other customers' experiences, consumers can check the star rating as well. There are several ways that consumers can access online reviews, for example, blogs, social media, forum discussions, etc. [3]. The frustrating thing is that this enormous source is being polluted by dishonest people. More and more incentivized comments are being posted on social media, and they are usually influenced by companies, retailers or owners of hotels. They offer various incentives to people to post comments in favor of them [4]. These dishonest practices have negative consequences for customers who are seeking accommodation or will seek it in the future. As there is no way of getting physical experience in advance while booking a remote hotel, customers rely solely on online information.

Researchers have found that, instead of relying on company provided information, consumers rely more on information given by other consumers. Thus, after family and friends, online reviews have become the second most trusted source of information [5]. However, biased reviews mislead future customers. As a result, consumers often do not get their expected services and they become disappointed. The objective of this study is to differentiate between proper reviews and incentivized reviews. This study might help people who make their decisions based on online reviews. Firstly, public reviews on 100 hotels in the USA are extracted. Then, necessary pre-processing tasks are carried out to represent the reviews in a meaningful way. A sentiment analysis technique is applied to measure the sentiment polarities of reviews. By different computational and statistical means, incentivized comments are identified. Moreover, a comparative analysis is shown on incentivized reviews among different hotels. Finally, the model is validated using three well-known machine learning algorithms—K Nearest Neighbor (KNN), Random Forest and Support Vector Machine (SVM).

2. Materials and methods

2.1 Natural language processing

The main aim of Natural Language Processing (NLP) is to understand human level languages. NLP methods are perceptive and effective. Indicative software engineering processes provide the grounds for applying natural language processing. The increasing adoption of outcomes from the NLP community in software engineering research provides opportunities for processing large amounts of data efficiently. Examples of research topics include the identification of textual characteristics, assessment of the quality of any product, detection and classification of different types of emotions, etc. [6]. Language is a proxy for human behavior and a strong signal with individual characteristics. People use this signal consciously to portray themselves in a certain way, but they can also be identified as members of specific groups by their use of subconscious traits [7]. NLP often relies on statistical techniques, specially to formulate the words in texts. The scope of NLP is enormous and increasing rapidly day by day. NLP applications include semantic analysis, question answering, chatbots, automatic summarization, market intelligence, opinion mining, language translation, etc. Opinion mining is a branch of NLP that provides a methodology to computationally process the unstructured data to extract opinions and identify their sentiments [8]. Firstly, using formal grammar and a lexicon, the text is parsed syntactically. Then, NLP techniques are applied to interpret it semantically in order to understand what the text is actually saying. NLP is comprised of techniques like tokenization, part-of-speech tagging, word stemming, lemmatization, multiword phrase grouping, synonym normalization, word-sense disambiguation, anaphora resolution, role determination, etc.

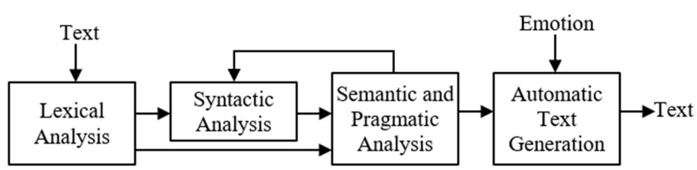

Figure 1 The steps of processing natural language.

Figure 1 shows the natural language processing steps. At the lexical analysis step, individual words are interpreted with their associative meaning. Then, a series of processing steps are followed. Each word is tied up with its corresponding POS tag. In the syntactic phase, words are analyzed to understand a sentence and its grammatical structure. A parser along with a specific grammar is needed for syntactic analysis. The output of the syntactic analysis shows the inter-relationships between the words.

2.2 Sentiment analysis

Sentiment analysis measures the polarity of the sentiment for a given text or opinion. It detects the subjectivity of text as well. Sentiment analysis has been applied to various software engineering (SE) tasks, such as evaluating app reviews, analyzing developers' emotions and many more [9]. In this work, subjective opinions on specific products (hotels) belonging to customers are recognized using sentiment analysis in order to understand customer perception. Sentiment analysis identifies a person’s attitude towards products or services by recognizing the polarity of the opinion that he or she has given. Today, a text classification task starts from designing the best feature extractors and choosing the best possible classifiers [10]. Unstructured text data produced on the internet is growing rapidly, and performing sentiment analysis on texts is becoming a challenge because of the limit of the contextual information they usually contain.

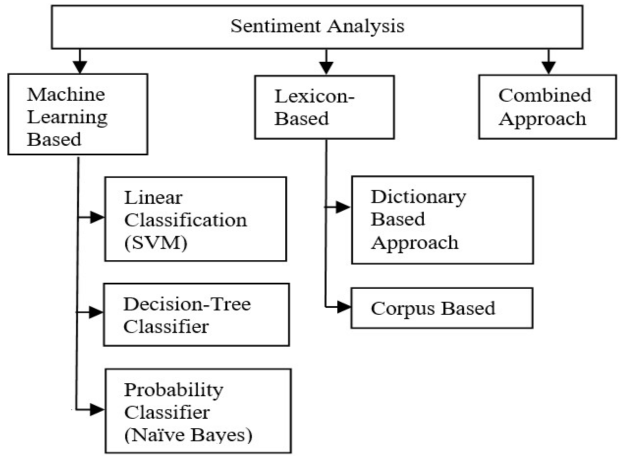

Figure 2 Sentiment analysis approaches.

Figure 2 shows different analysis methods for sentiment scoring. Lexicon-based approaches measure the sentiment of a text or opinion and classify the polarity as positive, negative or neutral by utilizing the sentiment lexicon. This approach is more understandable and can be easily implemented. There are two types of lexicon-based approaches—the corpus-based approach and the dictionary-based approach. The Twitter messaging service has become a platform for customers and news consumers to express sentiments that can be identified with both the dictionary-based approach and supervised machine learning tools for sentiment classification [11].

In this work, we have used the dictionary-based approach for lexicon analysis. In machine learning-based algorithms, the quality and volume of the training data affect the prediction performance of the classifier. A large database is required to get good results.

Several systems have been experimented with for text analysis or detecting spam, such as the Naive Bayes classifier, TF-IDF (term frequency–inverse document frequency), etc. However, the drawback of those systems is that they do not extract the semantic information of the phrases and spam words. Analyzing the text of public comments has the significance of retrieving semantic information from the words. For that, sentiment analysis algorithms called SVM, KNN, VADER Lexicon, Decision Tree and Random Forest have been compared. Comparing all of the algorithms' work efficiencies, advantages and disadvantages, the VADER algorithm is found to be appropriate for this research because it is found to perform better with tweets. The algorithm considers several important factors, like capitalization and access to punctuation, which lead to a better performance compared to other approaches that ignore them. There are several tools for analysing sentiment (Table 1). For measuring the sentiment polarity, we have used VADER, since it is efficient and simple.

Table 1 Tools for analyzing sentiment.

Tools	Work
Feelings Polarity	It works on reviews or emoticons.
Linguistic Inquiry and Word Count	By using a dictionary, it recognizes the emotional, cognitive and structural components of the context besides identifying the polarity.
Happiness Index	It gives the happiness index of the analyzed text between 1 and 9 using the Affective Norms for English Words (ANEW).
SentiStrength	It gives a polarity score to phrases in the text (how positive or negative they are) using a sentiment lexicon.
SentiWordNet	It recognizes the sentiment using WordNet, where nouns, adjectives and verbs are assigned a numerical score indicating positive and negative information.
VADER	VADER classifies sentences using a sentiment lexicon. All the necessary words are stored in the lexicon with an associated score indicating polarity. Along with recognizing polarity, VADER identifies the intensity of the positivity or negativity of a sentiment.

2.3 Text mining

The majority of today's online data are unstructured. So, it is often difficult for a computer system to process such an unstructured text. To extract meaningful information from an unstructured text, some useful techniques are needed. The meaningful texts derived using these techniques are then stored in the text database. The source of these texts can be emails, SMSs, chats, journal articles, newspapers or product or service reviews. Most of the data of different organizations, institutions and industries are stored in electronic form. Text data mining can be viewed as a knowledge discovery that extracts precious information from unorganized text [12]. Using different techniques, unstructured data are interpreted into a machine-readable form. Text mining is concerned with text analysis, information extraction, clustering and visualization. That is why it is called a multidisciplinary field.

2.4 Incentivized review

The rise of the internet has enhanced the way that people communicate. E-commerce is one of the major inventions in the marketing sector. Businesses have now been developing globally on a large scale with much less effort compared to the strategies used twenty or thirty years back. Consumers do not need to visit markets or shops physically; instead, they can choose their products from among a large collection of products from home. Purchasing a desired product is just a matter of clicking a mouse or pressing the enter key on a keyboard. Nevertheless, the fundamental concept of commerce has not yet changed [13]. There are still a large number of buyers and sellers, and product-related issues and issues like being satisfied or disappointed with a product are present. Presently, people often rely on online reviews while making a decision to purchase a product, thinking that the reviews are unbiased and real. Customer reviews generate more sales, affect consumers' trust and create a word-of-mouth spill over effect [14]. The shocking thing is that most often, the customers are disappointed, because the reviews that are not real. The spreading of fake and biased reviews is a great threat for consumers [15]. Different government and private agencies are trying to protect customers from being deceived. These economic hazards are threatening billions of dollars in e-commerce revenue. Some businesses are even trying to remove their names from review websites or take actions against the trend of fake reviews by encouraging their customers to post funny, unfavourable reviews for them. Hence, filtering out the fake reviews is of prime importance. So, it is necessary to detect biased reviews on hotels, because day by day, the use of hotels is increasing.

2.5 Related works

Researchers have been working for the last few years on text and online review processing to determine the
Researchers have been working for the last few years on text and online review processing to determine the
sentiment polarity, which helps consumers with comparisons of products and services. Very few studies have been conducted to detect fraudulent online reviews. This work aims to understand and analyze the characteristics of fake news, especially related to sentiments, for the automatic detection of fake news and rumours [16]. Salehan and Kim analyzed the forecasting of readership and the usefulness of online customer reviews using a sentiment mining approach [17]. They found that titles consisting of highly positive reviews have more readership. Wang et al. proposed a model that enables the detection of aspect ranking from online reviews [18]. They measured the influence of user opinions by information gain theory rather than on the sentiment strength alone.

Kostyra et al. applied a choice-based conjoint experiment in analysing consumer reviews [14]. They combined all relevant levels of online consumer reviews and identified the effects of online reviews on customer choice. They found that consumers' choices are not influenced by the volume or variance. They tried to moderate the impact of valence on consumers' choices. Costa et al. experimented with a data mining technique to predict incentivized reviews based on some selected features, such as the lengths of the reviews, how helpful they are, etc. [9]. Ruchansky et al. used a text-based approach for fake news detection but considered the test, response and clustering of user features determined by support vector decomposition and integrated into a hybrid model [5].

A number of works have been conducted on the analysis of online customer reviews and determining their impact on a customer's choice. However, incentivized or biased reviews can mislead customers. Identifying the fraud that is frequently occurring in online platforms is a new concept. In this research, we analyzed this perspective.

2.6 Dataset

The dataset in this experiment is a collection of public reviews in text format on different hotels in the United States. Public reviews on a list of 100 hotels in different towns in the USA are extracted from Datafiniti's Business Database [19]. Each hotel has more than 500 reviews. From the dataset, we used only four columns, and the rest of the columns have been removed for the simplicity of our work. A sample of our dataset is given in Table 2.

Table 2 Data set.

Hotel Name	Review	Country	Town
Rancho Valencia Resort Spa	Our experience at Rancho Valencia was absolutely perfect from beginning to end!!!! We felt special and very happy during our stayed.	USA	Rancho Santa Fe
Days Inn and Suites Albany	In my line of work, I use meeting space in hotels often.	USA	New York
Hotel Phillips	Old hotel with many remaining architectural charms and most modern amenities. The staff is exceptional friendly.	USA	Kansas

2.7 Methodology

The VADER algorithm is used to measure sentiment; it uses subjectivity and the polarity concept. The polarity concept differentiates between positive and negative words as well as defining the range of the polarity, which is in between -1 and 1. Polarity, also known as orientation, is the emotion expressed in the sentence. Subjectivity indicates when a text is an explanatory article that must be analyzed in context. Previous experiments on VADER showed remarkable and precise results. In the field of public comment analysis, where the text is complex, with a mixture of a variety of texts, VADER is found to perform well. Based on a sentiment lexicon and grammar, VADER analyzes the sentiment polarity of a sentence or opinion. The words in the lexicon are rated as negative or positive, and how negative or positive they are is given as well, based on a given public score. To determine the positivity or negativity of words, the developers of these approaches need to get a bunch of people to manually rate them. VADER generates four sentiment metrics from these word ratings. The first three metrics represent the proportion of negative, neutral and positive associations of the word, and the fourth metric shows the compound score calculated from the sum of the ratings. The compound score is normalized between -1 (most negative) and +1 (most positive). Sentiments are categorized as
Positive sentiment (compound score >= 0.05)
Neutral sentiment (compound score in between [-0.05, 0.05])
Negative sentiment (compound score <= -0.05)

Table 3 Sentiment score.

Compound	Positive	Negative	Neutral
0.431	0.192	0	0.808
0.848	0.199	0.098	0.703
-0.296	0	0.355	0.645

Table 3 shows how VADER scored three random sentences. The scores in the columns positive, negative and neutral indicate how much a sentence is positive, negative and neutral, respectively. The compund column indicates the compound polarity score of a sentence based on the positive, negative and neutral components.

Algorithm
- Import the dataset.
- Select the required column, discard the others.
- For each hotel:
  Calculate the sentiment score for each review.
  Calculate the mean, median using compound values.
  Calculate standard deviation from mean and median.
  Select either mean or median as final compound score for each hotel based on smaller standard deviation.
- For each review:
  Calculate the variance between sentiment score of that review and final sentiment score for the hotel.
  Mark as incentivized comment if difference greater than threshold value.
- Show the output.
- Validate the model using KNN, SVM and Random Forest algorithms.

The sentiment analyzer gives one sentiment compound score for each of the reviews. After calculating the sentiment compound score for each comment on a hotel, we calculated the mean sentiment score for each of the hotels, which is the mean of all of the compound scores for the hotel. The median sentiment score is also calculated for each hotel, which is the median value of all compound scores for that hotel. Then, the standard deviation from the mean and standard deviation from the median are calculated separately and compared with each other. Finally, the sentiment score for each hotel is identified based on the computed standard deviation. If the standard deviation from the mean is smaller, the mean sentiment score is selected as the final sentiment score; otherwise, the median sentiment score is selected. We always tried to find the optimal value, so that the variance is kept low.

Table 4 Mean, median and standard deviation values.

Mean	Median	STD from Mean	STD from Median
0.225	0.401	0.639	0.663
0.431	0.494	0.735	0.524

Table 4 shows the mean, median and standard deviation scores for two reviews of two hotels. The first one indicates that the standard deviation from the mean is less than the standard deviation from the median. So, in this case, the mean score should be selected to minimize the variance.

With respect to the final sentiment score for a hotel, the variance for each of the reviews is calculated considering the polarity score of that review and the final sentiment score of the hotel. A threshold value of 0.6 is chosen. For choosing the threshold value, a quantitative approach has been followed. A set of known good quality products and a set of known bad quality products are picked. Several individuals are asked to put true reviews for those products. Sentiment polarity scores are measured for each individual product and their standard deviations are calculated as well. The maximum standard deviaton found is 0.6. Hence, 0.6 is chosen as a threshold value. A review is marked as incentivized whose variance is more than the threshold value. This process continues for all of the individual hotel reviews.

Finally, the model is evaluated using three well-known machine learning approaches-K Nearest Neighbor (KNN), Random Forest and Support Vector Machine (SVM). These approaches are applied to investigate the results (review status) given by our model. The dataset has been developed with the hotel reviews as the attribute and the review status, given by the model, as the class value. Hence, there are two possible values for the class-incentivized or real. The three approaches measure the prediction accuracy and precision of our model. Thus, they validate the model. We attempted to discover better results by changing the number of folds. We applied 5-fold and 10-fold validation and compared the results given by each algorithm for individual folding.

3. Results and discussion

In this research, natural language processing techniques are experimented with to analyze sentiment. Since the data are in an unstructured format, instead of transforming it into numeric values, we recognized the semantic and contextual meaning. Python is used as a programming language. For mining text, the Natural Language Toolkit (NLTK) package is implemented, and for manipulating data, other packages like pandas and NumPy are included. The VADER algorithm is used to measure the sentiment score. We have used some statistical functions, the mean, median and standard deviation, for analyzing sentiment scores.

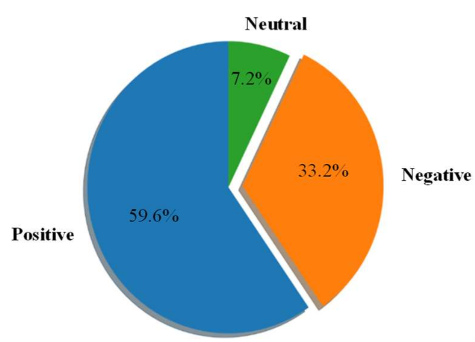

Figure 3 Polarity of reviews on Americas Best Value Inn hotel.

Figure 3 shows the proportion of negative, positive and neutral reviews for one hotel (Americas Best Value Inn). The polarities of the reviews are measured for all of the individual hotels. For example, the above figure shows that the Americas Best Value Inn hotel has 59.6% positive reviews, 33.2% negative reviews and 7.2% neutral reviews.

Table 5 shows the output results for some of the reviews on 40 Berkeley Hostel. The columns are described below:

Table 5 Outputs of reviews.

Name of the hotel	Reviews of the hotel	Com pound	Mean_ Com pound	Med_ Com pound	STD_ Mean	STD_ Med	Small_ Dev	Difference	Out-put
40 Berkeley Hostel	If you just make a little conversation with Paula then she isn't that bad.	0.431	0.2852	0.3561	0.103	0.053	0.053	0.0749	Real
40 Berkeley Hostel	The staff here was brilliant - so attentive and friendly - they were more than happy to assist with any queries. The place seems to be partially used as a shelter or temporary accommodation so there are people living there semi-permanently.	0.9682	0.2852	0.3561	0.483	0.4328	0.4328	0.6121	Incenti vized
40 Berkeley Hostel	Avoid at all costs	-0.096	0.2852	0.3561	0.27	0.3197	0.27	0.3812	Real
40 Berkeley Hostel	As an American, hosteling is a bit intimidating. Personal space and privacy are a big deal. But after one look at hotel prices in Boston, I ran away screaming. Why is everything on the East Coast so expensive Well, not 40 Berkeley. Staying here was the best choice! The hostel front desk was especially helpful, and the private room.	0.4735	0.2852	0.3561	0.133	0.083	0.083	0.1174	Real
40 Berkeley Hostel	My roommate and I did not make use of the movie room or free coffee simply because we were not in the hostel all that much, but we did take nights to study in the many spots available. Although I have stayed at hostels in Asia that were much nicer this one was great for its location and price.	0.7127	0.2852	0.3561	0.302	0.2522	0.2522	0.3566	Real
40 Berkeley Hostel	I love this place - clean, cheap, and in the center of town. One note: they no longer offer a complimentary breakfast. You can't beat the prices, and the staff is professional and friendly. Free wife abounds, and there's ample space to work.	0.3337	0.2852	0.3561	0.034	0.0158	0.0158	0.0224	Real
40 Berkeley Hostel	We stayed for 3 nights. Rooms are very basic, and without air conditioning it was pretty warm in the room. But for the price we expected and tolerated that. Shared bathrooms were finding and regularly cleaned. Free Wi-Fi was a godsend. All in all just what I expected for a traveler type hostel.	0.746	0.2852	0.3561	0.326	0.2757	0.2757	0.3899	Real
40 Berkeley Hostel	Don't let the fact that this is a hostel; it is good, clean, affordable accommodation in the trendy Back Bay area. If you take the communal shower option they are spotlessly clean and well maintained. It is within a short walk from Back Bay station and Copley Square. The staff is great and very helpful. There is a small 7/11.	0.5312	0.2852	0.3561	0.174	0.1238	0.1238	0.1751	Real
40 Berkeley Hostel	I stayed in Berkeley 40 just for one day and although I really wanted to write a great review unfortunately I cannot do it. First the good things: The desk staff was super friendly and helpful, I cannot say enough positive things about them. The location is superb, 8 minutes' walk to Cobley Plaza. My room has a big window.	0.1491	0.2852	0.3561	0.096	0.1464	0.096	0.1361	Real
40 Berkeley Hostel	Walking distance to historic area and attractions. Only reason that you want this place is budget. no air-condition and small room but it is expensive to stay in hotels in Boston. It is college dormitory style.	0.1154	0.2852	0.3561	0.12	0.1702	0.12	0.2407	Real

Compound: Compound polarity of each review.
Mean_compound: Calculated mean compound score of all the reviews for each hotel.
Med_compound: Calculated median compound score of all the reviews for each hotel.
STD_mean: Standard deviation of Compound from Mean_compound.
STD_med: Standard deviation of Compound from Med_compound.
Small_Dev: Smaller value between STD_mean and STD_med.
Difference: Unsigned difference between Compound and Mean_compound or Med_compound based on Small_Dev.
Output: Status of the review.

For each review, there is an entry in the table. All the numeric values are rounded to three decimal points. The polarity of the first review on 40 Berkeley Hostel is 0.431 approx. So, it is a positive review but not too positive. Here, the standard deviation from the mean (0.103 approx.) is less than that of the median (0.053 approx.). As the standard deviation from the median is smaller than that of the mean, the final sentiment score for that hotel will be the median compound score. So, the difference is calculated between the polarity of that review (0.431 approx.) and the median compound score (0.3561 approx.). The review is real, as the difference is less than the threshold value (0.6 approx.). The second review is incentivized because the difference (0.6121 approx.) is greater than the threshold value.

Figure 4 shows the total number of reviews, real reviews and incentivized reviews. Out of 19175 total reviews, we found 952 incentivized reviews and 18058 real reviews. That is, 4.96% of total reviews are marked as incentivized, which is a significant proportion.

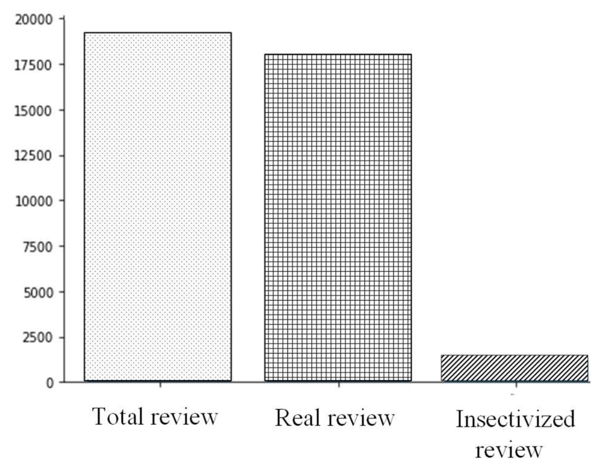

Figure 4 Summary of reviews.

Experimenting with K Nearest Neighbor, Random Forest and the Support Vector Machine, the prediction accuracy and precision given by the model are measured. Hence, these three approaches are used to validate the model.

Table 6 Accuracy given by algorithms.

Algorithm	Folding	Accuracy (%)	Precision
KNN	5 Fold	91.2	0.93
	10 Fold	92.8	0.95
SVM	5 Fold	92.8	0.93
	10 Fold	93.2	0.94
Random Forest	5 Fold	93.1	0.94
	10 Fold	94.4	0.97

Table 6 shows the evaluation of the three chosen algorithms for different folds of the dataset. All three algorithms show better results with 10-fold validation compared to 5-fold validation. Random Forest gives the best results, in terms of both the accuracy (94.4%) and precision (0.97), when 10-fold validation is applied.

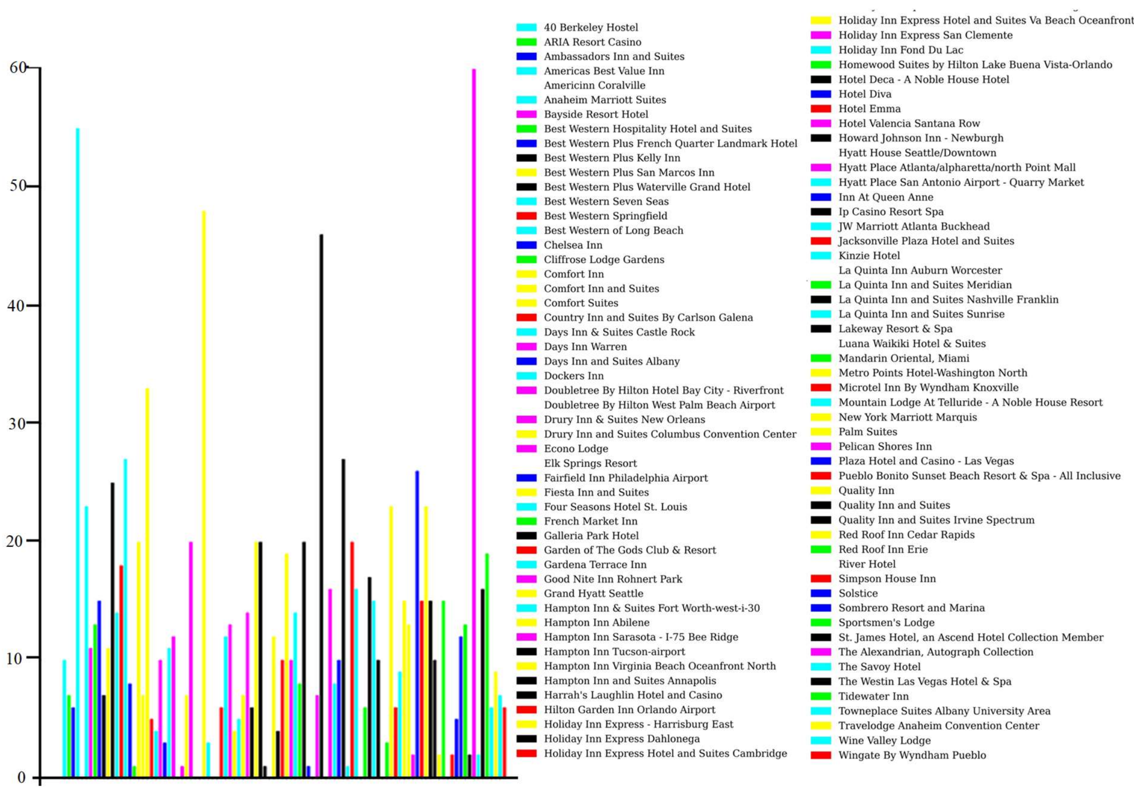

Figure 5 Incentivized reviews for individual hotels.

While looking at the results closely, the number of incentivized reviews for individual hotels is monitored. It is found that some hotels have a high number of incentivized reviews, while some have no incentivized reviews at all (Figure 5). The Alexandrian Autograph Collection hotel has the highest number of incentivized reviews 63, while Americas Best Value Inn is in second place with 53 incentivized reviews. Hotels like the Days Inn and Suites Albany, Galleria Park Hotel, French Market Inn, Hilton Garden Inn Orlando Airport, Hotel Diva, etc. have no incentivized reviews.

The variance graph shows how the number of total reviews and incentivized reviews for each hotel varied in our experiment (Figure 6).

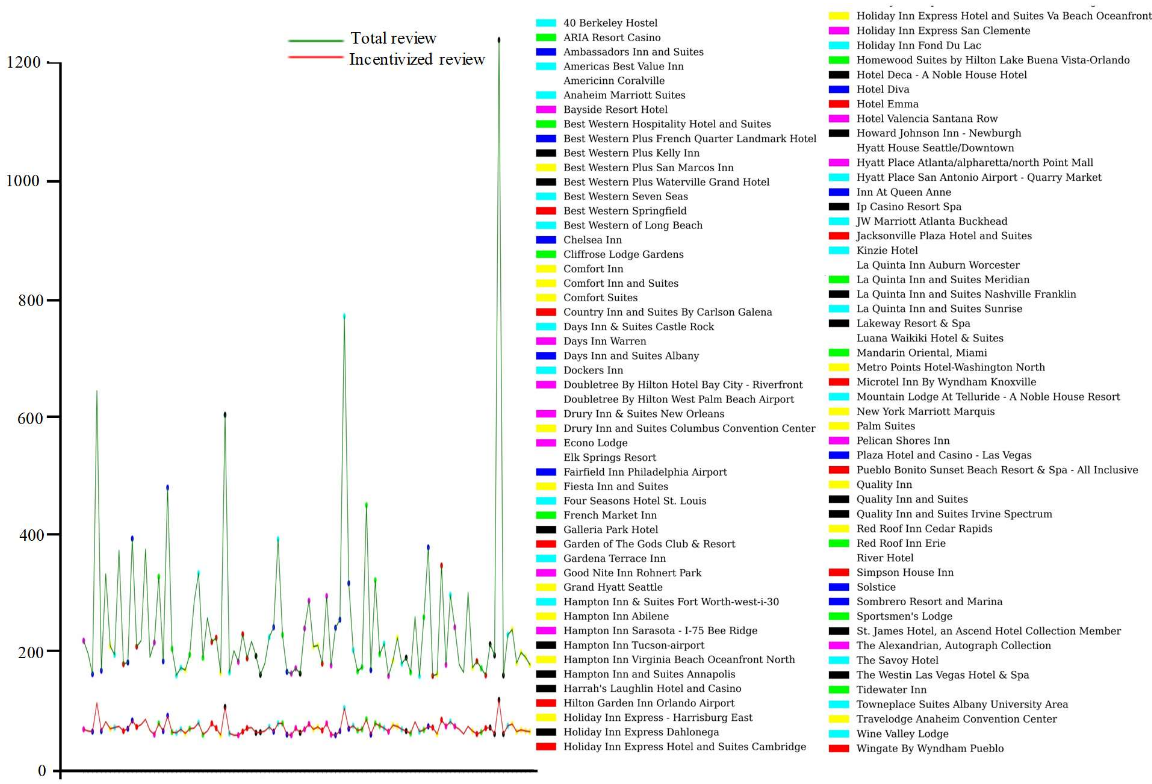

Figure 6 Incentivized reviews with respect to total reviews.

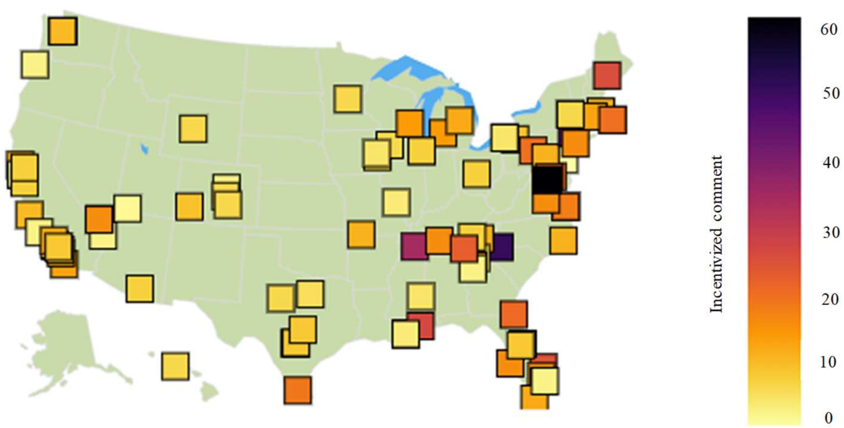

Figure 7 US map with incentivized comments.

Figure 7 shows incentivized comments in different locations of the US. The way that incentivized comments vary between different cities in the US is shown in the figure.

4. Conclusion

When booking a hotel online, reviews are crucial for most customers in making decisions regarding purchases. Since customers have no physical interaction with the products, they fully rely on reviews, thinking that they resemble the true experiences of consumers. However, incentivized or biased reviews often mislead customers who are going to book a hotel. This paper analyzes the online reviews of US hotels to identify incentivized reviews. The statistics of biased reviews in terms of individual hotels and different cities in the US are shown. This paper renders a clear view on the presence of online fake reviews. People should be more aware of online fraud when booking hotels or purchasing other services or products.

5. Acknowledgements

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