Predicting Fake online Reviews using Machine Learning Models

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ABSTRACT: Online reviews are very important in decision making of customer whether to purchase a product or service. These are main source of information getting from the past customer experience about the features of that service which we are going to purchase. Now a days' Internet is no longer use only for communication purpose. Its use is spread over wide variety of applications' and E-Commerce is one of them. The most important part in e-commerce, from consumer perspective is, the reviews associated with products. Most of the people do their decision making, based on these online reviews about products or services. These reviews not only help user to know the product or service thoroughly but also affect user's decision making ability to a great extent and also divert the sentiments about the product positively or negatively. As a result, there have been attempts made, to change the product sentiments positively or negatively by manipulating the online reviews artificially to gain the business benefits. Ultimately, affect the genuine business experience of the user. Therefore in this paper, we have dealt with this particular problem of ecommerce field, specifically online reviews' in particular and sentiment analysis domain as a whole, in general. This paper introduces some machine learning techniques like Support Vector Machine and Random Forests for sentiment classification of reviews and to detect fake online reviews using the data set of a Hotel reviews. Sentiment Analysis has become most interesting in analysis of text. Using sentiment analysis we can separate negative and positive reviews as well. This paper introduces some semi-supervised and supervised text mining models to detect fake online reviews as well as compares the efficiency of both techniques on dataset containing hotel reviews.

KEYWORDS*:* Fake Online reviews, Semi- supervised learning, supervised learning, Expectation Maximization algorithm, Random Forests, Support Vector Machine classifier.

I. INTRODUCTION

The social Web and the increasing popularity of social media have led to the spread of multiple kinds of content (i.e., textual, acoustic, visual) generated directly by users, the so called user-generated content (UGC). By means of Web 2.0 technologies, it is possible for every individual to diffuse contents on social media, almost without any form of trusted external control. This implies that there are no means to verify, a priori, the reliability of the sources and the believability of the content generated. In this context, the issue of assessing the credibility of the information diffused by means of social media platforms is receiving increasing attention from researchers.

In particular, this issue has been deeply investigated in review sites, where the spread of misinformation in the form of opinion spam, and the negative consequences that it brings, are particularly harmful for both businesses and users. In this context, opinion spam detection aims at identifying fake reviews, fake comments, fake blogs, fake social network postings, deceptions, and deceptive messages [1], and to make them readily recognizable. Detection techniques to identify fake reviews have been proposed in particular for specific review sites such as TripAdvisor1 or Yelp, 2 where users' reviews have a powerful effect on people visiting the Website for advice. Therefore, a recommendation of a product or a service such as a restaurant or a hotel based on false information can have detrimental consequences.

Most approaches that have been proposed so far to detect fake reviews in these social media platforms rely on supervised machine learning techniques and on distinct characteristics, i.e., features, connected to the reviews and/or the reviewers who generated them. It has been shown in the literature that their usage can lead to an effective identification of suspicious contents and/or reviewers 'behaviors, and consequently of misinformation [2].

Recent approaches have suggested the additional use of features that consider the social structure of the network underlying the considered review site. These approaches, which are often based on unsupervised graph based methods[2], usually provide worse performance with respect to supervised solutions. On the other hand, supervised approaches too present some issues. First, available solutions have often considered a small set of features, or distinct classes of features separately; second, they have been evaluated on small datasets extracted from the well-known review sites previously cited. Thus, the proposed solutions are in most of the cases partial, or review-site-dependent.

Considering the variety of features that have been proposed and used separately by supervised approaches, the goal of this article is to provide a feature analysis illustrating the most suited and general review- and reviewer-centric features that can be employed in the review site context to detect fake reviews. Among these features, some are well-known and taken from the literature, others are new and constitute a further contribution of the paper[3]. To evaluate the utility of this set of features in classifying genuine and fake reviews, a supervised classifier based on a well-known machine learning technique has been implemented. With respect to the literature, a publicly available large-scale and general dataset from the Yelp.com review site has been considered. This allows to provide more significant results with respect to the contribution of each feature taken singularly and of groups of features. In particular, the important contribution of a specific group of features in analyzing the credibility of the so called singleton reviews has emerged. The promising results obtained show the effectiveness and the possible utility of the feature analysis illustrated in this article[4]

In machine learning based techniques, there are many algorithms can be applied for the classification and prediction. Here we used Support Vector Machine (SVM) and Random Forest for predicting the reviews. We detect fake positive, fake negative, True positive and True negative reviews. And finally we compare the accuracy of each algorithm. Main objective of this paper is to classify the dataset or reviews into true and fake reviews using machine learning techniques

II. RELATED WORK

In the last few years, depending on the context, researchers have proposed many different approaches to tackle the issue of the assessment of the credibility of the information diffused through social media [2]. Historically, the concept of credibility has been in turn associated with believability, trustworthiness, perceived reliability, expertise, accuracy, and with numerous other concepts or combinations of them [3].

According to Fogg and Tseng [4], credibility is a perceived quality of the information receiver, and it is composed of multiple dimensions. Different characteristics can be connected to:

(i) the source of information,

(ii) the information itself, i.e., its structure and its content, and

(iii) The media used to disseminate information [5].

It has been demonstrated that, when considering these characteristics in terms of credibility, the impact of the delivery medium can change the perception that people have about sources of information and information itself [3], [5]. For this reason, one important question to be tackled nowadays is whether new media in the digital realm introduce new factors that may concur to credibility assessment [6], [7].

In the Social Web, evaluating information credibility deals with the analysis of the user-generated content [8], the authors' characteristics, and the intrinsic nature of social media platforms, i.e., the social relationships connecting the involved entities. These characteristics, namely features, can be simple linguistic features associated with the text, they can be additional meta-data features associated for example with the content of a review or a tweet, they can also be extracted from the behaviour of the users in social media, i.e., behavioural features, or they can be connected to the user profile (if available). Furthermore, different approaches have taken into consideration product-based features, in the case of review sites where products and/or services are reviewed, or have considered social features, which exploit the network structure and the relationships connecting entities in social media platforms [9], [10].

In the last years, several approaches have been proposed to assess in an automatic or semi-automatic way the credibility of information in the Social Web; in particular, the most investigated tasks have been the identification of: (i) opinion spam in review sites [9], (ii) fake news in microblogging sites [11], and (iii) potentially harmful/inaccurate online health information [12]. In general, the majority of these approaches focus on data-driven techniques, which classify with respect to credibility by employing different models.

With regard to opinion spam detection, and in particular to fake review detection, which is the focus of this paper, the approaches that have produced the best results are generally based on supervised or semi-supervised machine learning techniques that take into account both review- and reviewer centric features. The first approaches were purely linguistic, in the sense that they employed simple textual features extracted from the text of reviews, often in the form of unigrams and/or bigrams [13], [14], [15], [16]. Other linguistic approaches have proposed generative classifiers based on language models [17], [18]. It has been demonstrated by Mukherjee et al. in [19] that focusing only on linguistic features is not effective to detect fake reviews from real datasets, since it is practically impossible for a human reader to distinguish between credible and not credible information by simply reading it, especially in an era where the skills in writing false reviews are constantly improving [20].

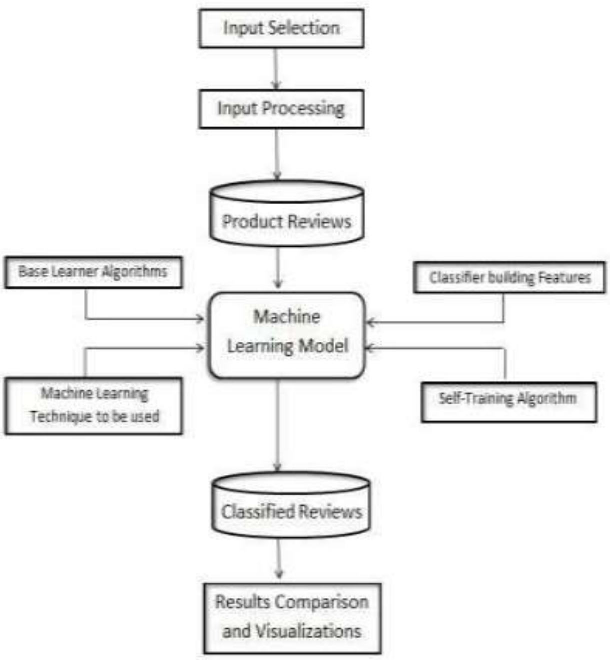
For this reason, more effective multi-feature-based approaches have been proposed, which employ several features of different nature in addition to simple linguistic ones, either by applying supervised or semi-supervised machine learning [1], [19], [21], or by implementing the Multi-Criteria Decision Making (MCDM) paradigm [22]. These approaches usually focus on small labelled datasets for evaluation purposes, constituted in most of the cases by 'near ground truth' data [9].

They usually avoid to consider features that are extracted from the social ties constituting the network of entities (e.g., users, products, reviews) considered by the review site. On the contrary, this kind of features is often utilized (together with the other features previously described) by graph-based approaches [23], [24]. These latter approaches are in most of the cases unsupervised, even if sometimes they can be coupled with a supervised learning phase on a limited number of classification labels [25]. With respect to supervised approaches, totally unsupervised solutions generally provide slightly worst results [2], [9], [20].

This paper, by considering the effectiveness of supervised solutions, discusses and analyses on a general level the most appropriate review- and reviewer-centric features that have been proposed so far in the literature to detect fake reviews; moreover, it proposes some new features suitable for this aim, in particular to detect singleton fake reviews, an issue that has not yet received the attention it deserves. To avoid the problem of the limited size of the labelled datasets considered up to now by the literature, two large-scale publicly-available datasets presented in [25] have been employed for evaluation purposes

III. PROPOSED WORK

As briefly introduced in Section II, many and different are the features that have been considered so far in the review site context to identify fake reviews. In some cases, features belonging to different classes have been considered separately by distinct approaches. In other cases, the employed features constitute a subset of the entire set of features that could be taken into account; furthermore, new additional features can be proposed and analyzed to tackle open issues not yet considered, for example the detection of singleton fake reviews. For these reasons, in this section we provide a global overview of the various features that can be employed to detect fake reviews. Both significant features taken from the literature and new features proposed in this article are considered. Since the most effective approaches discussed in the literature are in general supervised and consider review-and reviewer-centric features, these two classes will be presented in the following sections. The choices behind the selection of the features belonging to the above mentioned classes will be detailed along each section. When the features are taken from the literature, they will be directly referred to the original paper where they have been initially proposed. The absence of the reference will denote those features that have been widely used by almost every proposed technique.



Finally, the presence of the label denoted by [new] will indicate a feature proposed for the first time in this article. A. Review centric Features the first class of features that have been considered, is constituted by those related to a review. They can be extracted both from the text constituting the review, i.e., textual features, and from meta-data connected to a review, i.e., metadata features. In every review site, the time information regarding the publication of the review, and the rating (within some numerical interval) about the reviewed business are metadata, are always provided. In addition, in relation to metadata features, those connected to the cardinality of the reviews written by a given user must be carefully studied. In fact, a large part of reviews are singletons, i.e., there is only one review written by a given reviewer in a certain period of time (this means that in the user account there is only one review at the time of the analysis). For this kind of reviews, specific features must be designed. In fact, as it will be illustrated in the following, many of the features that have been proposed in the literature are based on some statistics over several reviews written by the same reviewer. In the case of singletons, these features lose their relevance in assessing credibility. Therefore, the definition of suitable features that are effective for detecting also singleton fake reviews becomes crucial.

To test this hypothesis, we implemented the self-training algorithm using Support Vector Machine (SVM) and Random Forest as base learners and compared their performance. We will be using two different supervised learning methods Support Vector Machine (SVM) and Random Forest as base learners. We would then be comparing the accuracy of each of the semi-supervised learning methods with its respective base learner. The base learners would be using both behavioral and linguistic features

Decision tree is the most powerful and popular tool for classification and prediction. A Decision tree is a flowchart like tree structure, where each internal node denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node (terminal node) holds a class label

The k-nearest neighbors (KNN) algorithm is a simple, easy-to-implement supervised machine learning algorithm that can be used to solve both classification and regression problems

K-Nearest Neighbours (KNN) algorithm for classification and regression. After reading this post you will know.

- The model representation used by KNN.
- How a model is learned using KNN (hint, it's not).
- How to make predictions using KNN
- The many names for KNN including how different fields refer to it.
- How to prepare your data to get the most from KNN.
- Where to look to learn more about the KNN algorithm

A. Collection of Data

We built a Python crawler to collect restaurant reviews from Yelp. Reviews were collected for all restaurants in a particular zip code in New York. We collected both the recommended and non-recommended reviews as classified by Yelp. The dataset consists of approximately 40k unique reviews, 30k users and 140 restaurants.

B. Pre-processing of Data

We carried out the following steps during preprocessing:

1. Cleaning of Data:

The data that we collected had lots of duplicate records and the first step was to remove these. Following this, we modified the date field of all the records to ensure that the formatting was consistent.

2. Processing of Text Reviews'

The first step here was to remove all the Stop Words. Stop Words are words which do not contain important significance to be used in search queries. These words are filtered out because they return vast amount of unnecessary information [8]. Then we converted the text to lower case and removed punctuations, special characters, white spaces, numbers and common word endings. Finally, we created the Term Document Matrix to find similarity between the text reviews.

C. TEXTUAL FEATURES

As briefly illustrated in Section II, it is practically impossible to distinguish between fake and genuine reviews by only reading their content. The analysis provided by Mukherjee et al. in [19] has shown that the KL-divergence between the languages employed by spammers and non-spammers in Yelp is very subtle. However, the good results obtained in [26] by using linguistic features on a domain specific dataset (i.e., a Yelp‛s dataset containing only New York Japanese restaurants), show that at least on a domain specific level, textual features can be useful. It is possible to use Natural Language Processing techniques to extract simple features from the text, and to use as features some statistics and some sentiment estimations connected to the use of the words.

D. META-DATA FEATURES

these kinds of features are extracted from the meta-data connected to reviews, or they can be generated by reasoning on the reviews‛ cardinality with respect to the reviewer and the entity reviewed.

Basic features: –Rating, i.e., the rating attributed in the review to the entity, in the form of some numerical value belonging to a given interval (e.g., 1-5 ‗stars‛); –Rating deviation [27], i.e., the deviation of the evaluation provided in the review with respect to the entity‛s average rating; –Singleton [25], i.e., it indicates the fact that the review is the only one provided by a reviewer in a given period of time (e.g., a day). These basic features rely on some simple and intuitive heuristics. A fake review tends to contain a more ‗extreme‛ rating with respect to genuine reviews, thus implying that the rating deviation from the entity‘s average rating is higher; furthermore, a singleton review provided by a user could indicate that s/he is not particularly involved in the review site community, which constitutes a possible indication of unreliability.

Burst features: it is said that reviews for an entity are ‗burst' when there is a sudden concentration of reviews in a time period. These review bursts can be either due to sudden popularity of the entities reviewed or to spam attacks. Since it has been proven that reviews in the same burst tend to have the same nature [28], it is possible to easily identify groups of fake reviews by analyzing the nature of the burst.

IV. MACHINE LEARNING ALGORITHM

In our project we focus on using semi-supervised learning with self-training –a widely used method in many domains and perhaps the oldest approach to semi-supervised learning. We chose to evaluate our classifiers using self-training because it follows an intuitive and heuristic approach. Additionally, the usage of Self-Training allowed us to implement multiple classifiers as base learners (for e.g. Support Vector Machine (SVM) and Random Forest etc.) and compare their performance. For the choice of base learners, we had various options. We chose Support Vector Machine (SVM) and Random Forest as our three base learners for the Self-Training algorithm. We chose these options because of the fact that Self-Training requires a probabilistic classifier as input to it. We didn't use non-probabilistic classifiers like Support Vector Machines (SVM-POLY) and K-nearest neighbor (k-NN) because of this reason. We were also considering using co-training as one of our semi-supervised learning approaches. However, Co-Training requires the presence of redundant features so that we can train two classifiers using different features before we finally ensure that these two classifiers agree on the classification for each unlabeled example

SEMI-SUPERVISED LEARNING

In semi-supervised learning there is a small set of labeled data and a large pool of unlabeled data. We assume that labeled and unlabeled data are drawn independently from the same data distribution. In our project, we consider datasets for which nl << nu where nl and nu are the number of labeled and unlabeled data respectively [5].First, we use SVM as a base learner to train a small number of labeled data. The classifier is then used to predict labels for unlabeled data based on the classification confidence. Then, we take a subset of the unlabeled data, together with their prediction labels and train a new classifier. The subset usually consists of unlabeled examples with high-confidence predictions above a specific threshold value [4].In addition to using SVM we are also planning to use RF as base learners. The performance of each of the semi-supervised learning models would then be compared with its respective base learner.

V. RESULTS AND PERFOMANCE ANALYSIS

RESULTS

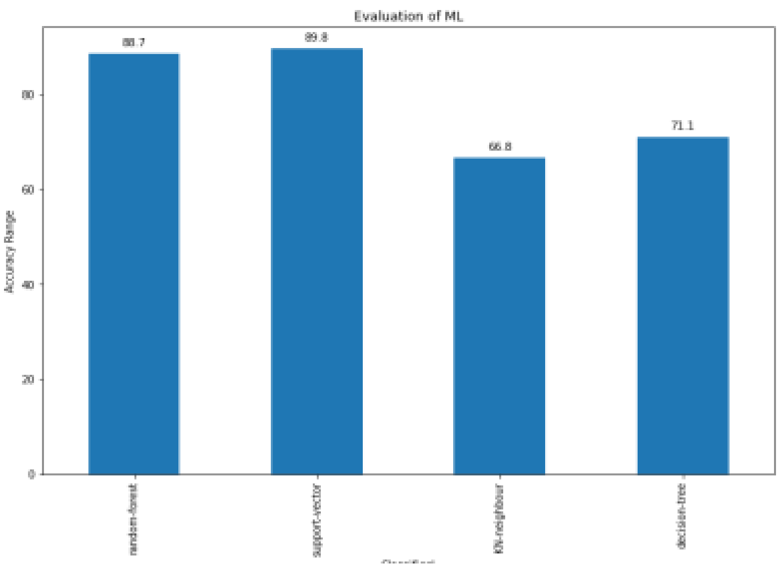
We have used support vector machine (SVM) and random forest classifiers to classify the reviews dataset. We have divided the dataset of 1600 rows with 3 columns with column names reviews, polarity and spamity for each classification process. The data split into train and test in the ratio 80:20. SVM has given accuracy of 83.75 % using random forest algorithm we got the accuracy of 66.56 %. Comparing each of the algorithms, we found that SVM is giving highest accuracy than other classifier has given the least accuracy

Accuracy Comparison

SVM	RFC
83.75 %	66.56%

PERFORMANCE ANALYSIS

The Performances of Our Implemented Techniques Are shown using the Histogram below We can choose Random Forest Classifier as well as SVM as our model since both are giving highest accuracy. By SVM, we could improve the performance accuracy up to 92.7 It is the highest accuracy compared to the other techniques. By importing metric from skleaarn package we can have the confusion metric for the same predictions. Confusion metrics has given the perfect accuracy for each algorithm.



ROC CURVE

The true positive rate is calculated as the number of true positives divided by the sum of the number of true positives and the number of false negatives. It describes how good the model is at predicting the positive class when the actual outcome is positive. The true positive rate is also referred to as Sensitivity The ROC curve is a graph with: The x axis showing 1 – specificity (= false positive fraction = FP/(FP+TN)) The y sensitivity (= true positive fraction = TP/(TP+FN))

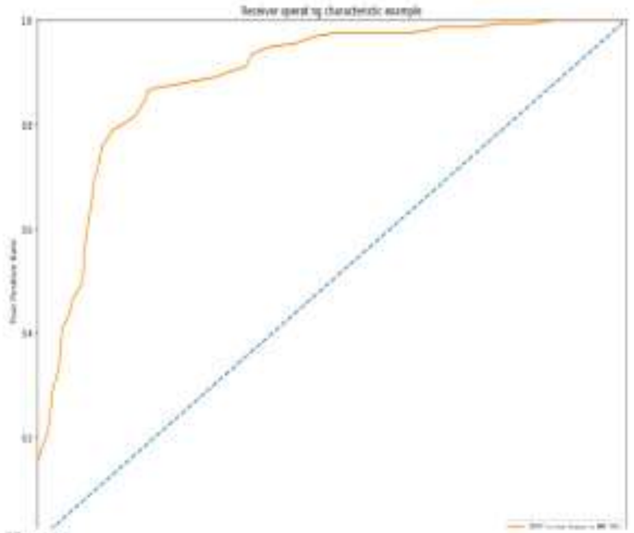


Fig 3

In a Receiver Operating Characteristic (ROC) curve the true positive rate (Sensitivity) is plotted in function of the false positive rate (100-Specificity) for different cut-off points. Each point on the ROC curve represents a sensitivity/specificity pair corresponding particular decision threshold curve (AUC) is a summary measure of the accuracy of a quantitative diagnostic test. It is 89.01

IX. CONCLUSION

In this paper, we proposed several methods to analyze a dataset of hotel reviews. We also presented sentiment classification algorithms to apply a supervised learning of the hotel reviews. We have shown several semi-supervised and supervised text mining techniques for detecting fake online reviews in this research. We have combined features from several research works to create a better feature set. Also we have tried some other classifier that were not used on the previous work. Thus, we have been able to increase the accuracy of previous semi supervised techniques done. We have also found out that supervised SVM classifier gives the highest accuracy. This ensures that our dataset is labeled well as we know semi-supervised model works well when reliable labeling is not available. User behavior can also be combined with texts to have a better model for classification. The evaluation of the effectiveness of the proposed methodology can be done for a larger data set. Supervised classifiers are in general more effective, and usually employ review and reviewer-centric features. Unsupervised classifiers are in most of cases based on graph-based models, and focuses on the social ties underlying the review site in exam (together with other kinds of features). Unsupervised solutions are in general less effective, but have the advantage that they do not need labeled datasets for training. Supervised solutions, on the contrary, have proven their effectiveness with respect to too small or review-site-dependent labeled datasets, and with respect to small subsets of features among the ones that have been proposed in general in the literature. In this article, focusing on the effectiveness of supervised classification, a feature analysis has been performed, in order to summarize the main review- and reviewer-centric features that are suited for fake review detection, and to propose new features that can be particularly useful to detect singleton reviews. To evaluate the impact of these features, a supervised classifier based on Random Forests has been developed.

FUTURE SCOPE

We would like to extend this study to use other datasets such as Amazon dataset or eBay dataset and use different feature selection methods. Furthermore, we may apply sentiment classification algorithms to detect fake reviews using various tools such as Python and R or R studio, Statistical Analysis System (SAS), and Stata; then we will evaluate the performance of our work with some of these tools. To avoid the issues connected to the limited volume of available ground truths, a publicly available large-scale and general labeled dataset has been employed for evaluation purposes. The promising results obtained witness the utility of the proposed study.

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