ONLINE CONSUMER REVIEW FRAUD DETECTION

Shivaprasad S. More [1], Mirajkar Anirudhha Dilip [2], Dodmani Nikhil Suresh [3], Kulkarni Makrand Ashok [4], Surve Sumit [5], Magdum Elhan [6]

[1] Assistant Professor, Computer Science and Engineering Department Sanjay Ghodawat Group of Institutions, Atigre, Kolhapur, India.

[2,3,4,5,6] UG Scholars, Computer Science and Engineering Department Sanjay Ghodawat Group of Institutions, Atigre, Kolhapur, India.

Abstract

Online consumer reviews have become a baseline for new consumers to try out a business or a new product. The reviews provide a quick look into the application and experience of the business/product and market it to new customers. However, some businesses or reviewers use these reviews to spread fake information about the business/product. The fake information can be used to promote a relatively average product/business or can be used to malign their competition. This activity is known as reviewer fraud or opinion spam. The paper proposes a feature set, capturing the user social interaction behavior to identify fraud. The problem being solved is one of the characteristics that lead to fraud rather than detecting fraud.

Keywords: Crawling, Transformation, Cleaning, Fraud detection, Online reviewers

1. Introduction

The main objective of our project is to build classifiers using Semi-Supervised learning methods. **We will then use this classifier to identify "fake" restaurant reviews posted on** Yelp. Yelp is a website which publishes crowd -sourced reviews about local businesses including restaurants [7]. **Yelp uses its own proprietary algorithm for filtering "fake"** reviews. For the purpose of this project, we would be assuming Yelp classification as pseudo ground truth. Semi-supervised learning is a class of supervised learning tasks and techniques that also make use of unlabeled data for training - typically a small amount of with a large amount of unlabeled data. Supervised learning methods are effective when there are sufficient labeled instances to construct classifiers. Labeled instances are often difficult, expensive, or time consuming to obtain, because they require empirical research. When it comes to restaurant reviews, we have a large supply of unlabeled data. Often semi supervised learning achieves a better accuracy than supervised learning which is only trained on the labeled data.

There are various approaches that can be used for semi-supervised learning. These include Expectation Maximization, Graph Based Mixture Models, Self-Training and Co-Training methods. In our project, we will be focusing on applying the Self-Training **approach to Yelp's** reviews. In self-training, the learning process employs its own predictions to teach itself. An advantage of self-training is that it can be easily combined with any supervised learning algorithm as base learner. We will be using three different supervised learning methods - Naïve Bayes, Decision Trees and Logistic

Regression 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.

2. Existing Work

Extensive studies have been done on determining the effectiveness of existing research methods in detecting real -life fake reviews on a commercial website like Yelp and in trying to emulate Yelp's fake review filtering algorithm. Apart from this, proposed a novel model to detect opinion spamming in a Bayesian framework and model the spamicity of reviewers by identifying certain behavioral features. The key motivation is based on the hypothesis that opinion spammers differ from others on behavioral dimensions.

Research has also been done in the application of semi supervised learning to a pool of unlabeled data and augmenting performance of supervised learning algorithm. They have studied the semi-supervised self-training algorithm with decision trees as base learners. Extensive studies) have been done on determining the effectiveness of existing research methods in detecting real -life fake reviews on a commercial website like Yelp and in trying to emulate Yelp's fake review filtering algorithm.

Apart from this, proposed a novel model to detect opinion spamming in a Bayesian framework and model the spam city of reviewers by identifying certain behavioral features. The key motivation is based on the hypothesis that opinion spammers differ from others on behavioral dimensions. Research has also been done in the application of semi supervised learning to a pool of unlabeled data and augmenting performance of supervised learning algorithm. They have studied the semi-supervised self-training algorithm with decision trees as base learners.

3. Methodologies

3.1 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. The following attributes were extracted:

- Restaurant Name
- Average Rating
- User Name
- Review Text
- Rating
- Date of Review
- Classification by Yelp (Recommended / Not Recommended)

3.2 Preprocessing of Data

We carried out the following steps during preprocessing:

- **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.

- **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.

Calculating Behavioral Dimensions

Variable/description	**Description**
a; A; r; r; ra(a,r)	Author a;set of all authors; a review, review by author a;
F(a)	Minimal number of reviews by authors a
maxRev(a)	Minimal number of reviews posted in a day by an author a
F	Length of the review
F(ra)	Recciever daviation for a review r by auther a
*(ra, p(ra))	The *rating of r on product p(r) on tne 5* rating scale
f	Maximum contain similarity for an author
Consine(r1,r2)	Cosine similarity between review I and j

Table 1: List of Notations

3.3 Sampling

Using random sampling, we split our data set into training and testing sets in the ratio of 70:30 respectively. Then we divided the training set such that approximately 60 % of the records were unlabeled and the remaining were labeled. Following this, we used subsets of increasing sizes from the labeled data to train the base learner (Naïve Bayes). To generate the subsets of labeled data, we used both simple random sampling and stratified sampling approaches. The results of these approaches are discussed in the Experiment and Results' section.

3.4 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. Naïve Bayes, Decision Trees, Logistic Regression etc.) and compare their performance. For the choice of base learners, we had various options. We chose Naïve Bayes, Decision Trees and Logistic regression 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) 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. For the data-set that we were using, we didn't have redundant features and hence we decided against using Co-Training.

3.4.1 Semi-supervised setting

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 $n_l << n_u$ where n_l and n_u are the number of labeled and unlabeled data respectively.

First, we use Naïve Bayes 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

4 Experiment and Results

Stratified Sampling and Simple Random Sampling

While performing Stratified sampling, we have maintained the same ratio of class labels (recommended vs not recommended) in the labeled dataset as the original dataset. Following graphs show the results of individual base learners vs. the semi-supervised self-training method for varying labeled data sets:

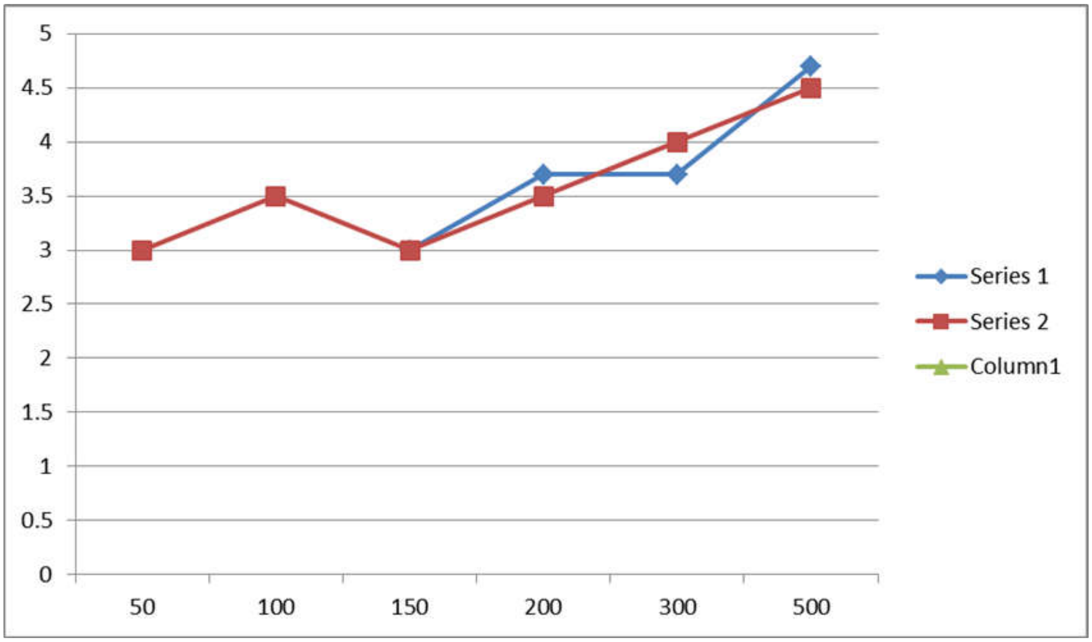
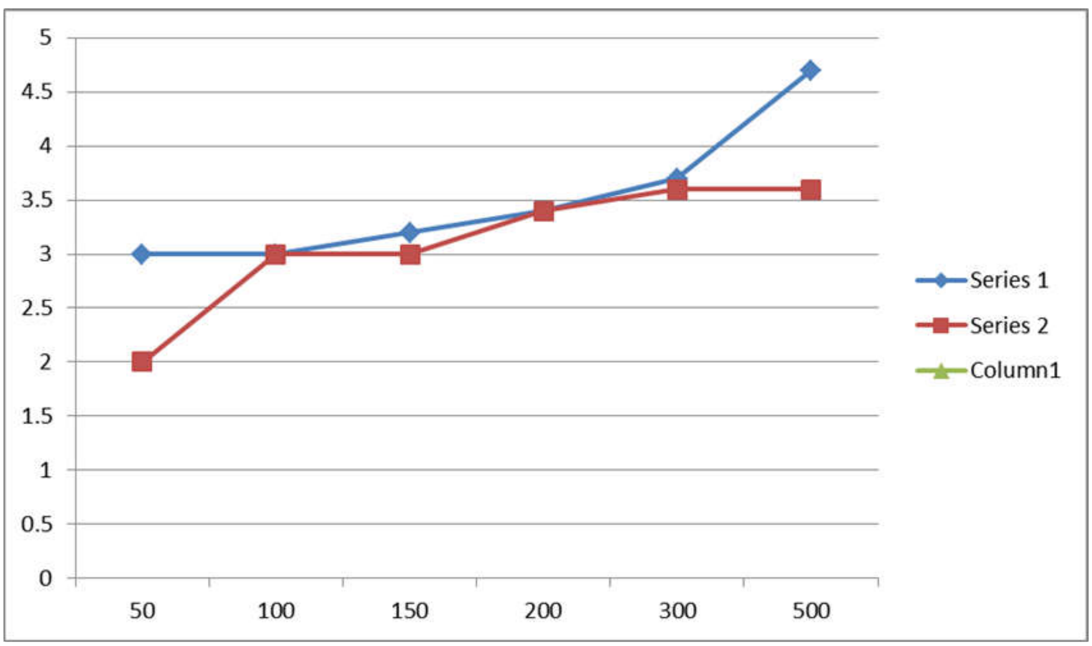


Figure 1: Semi-supervised vs Supervised using Naïve Bayes (Stratified Sampling on the left and Simple Random Sampling on the right.)



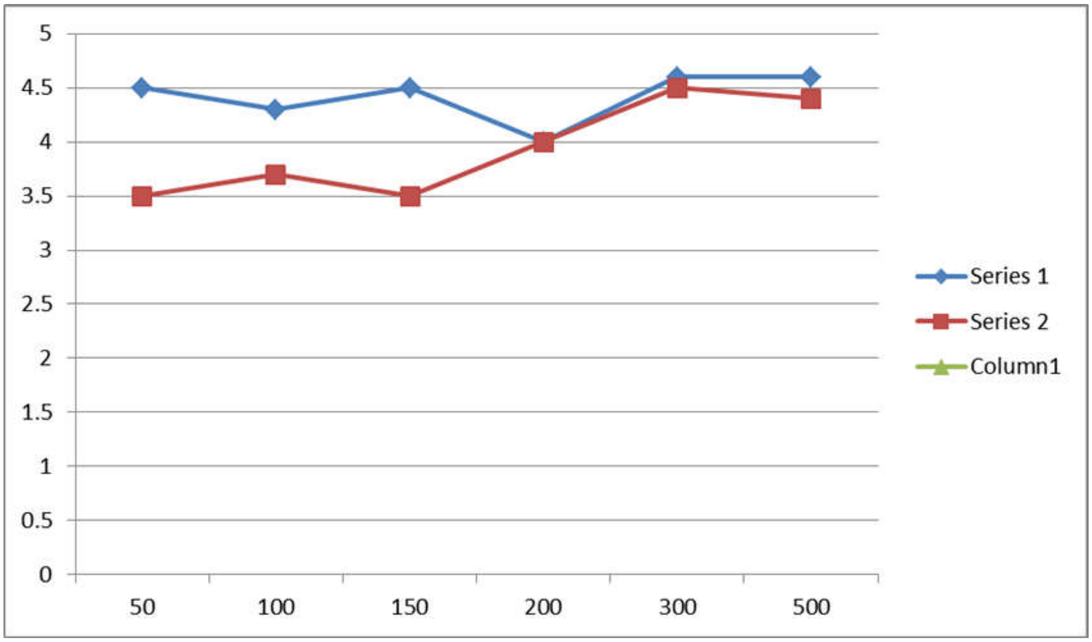
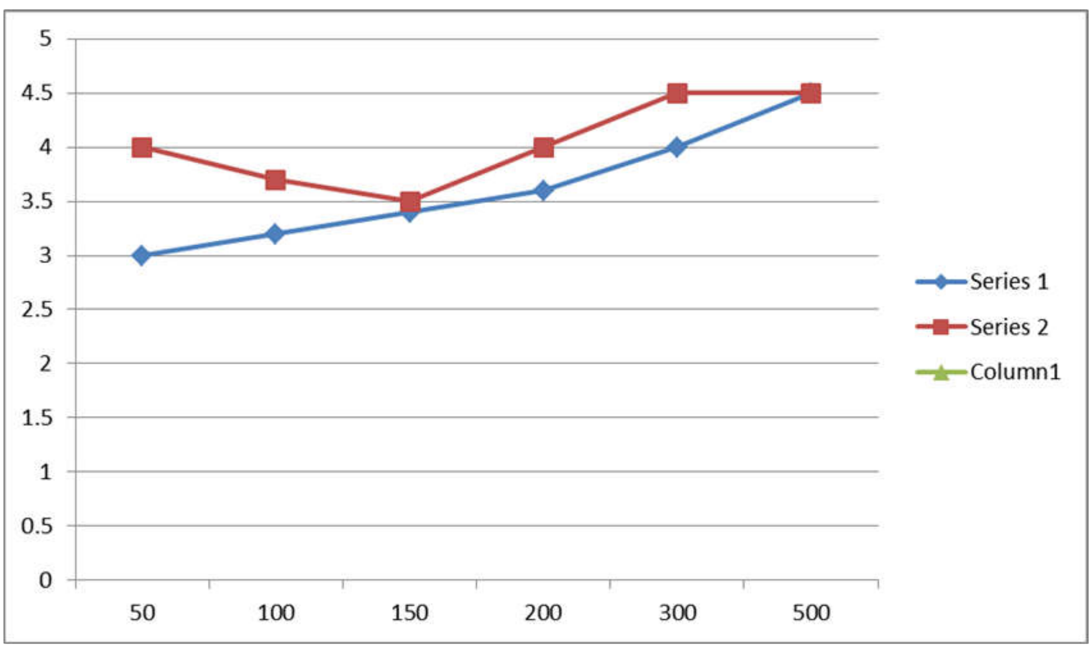


Figure 2**:** Semi-supervised vs Supervised using Naïve Bayes (Stratified Sampling on the left and Simple Random Sampling on the right.)



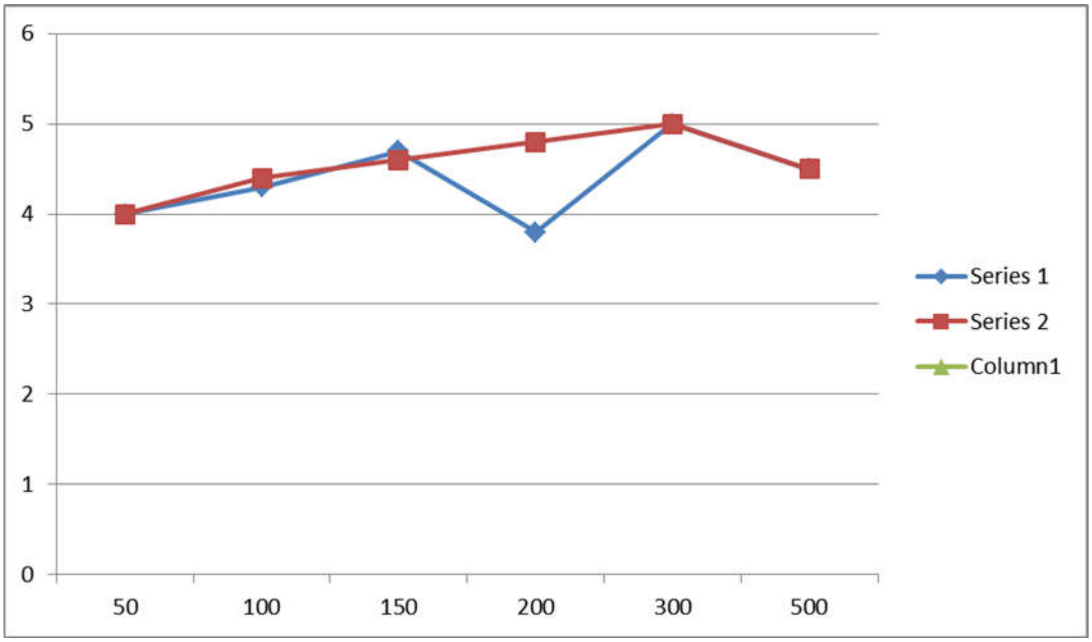


Figure 3: Semi-supervised vs Supervised using Decision Tree (Stratified Sampling on the left and Simple Random Sampling on the right.

4.1 Result Evaluation

4.1.1 Critical evaluation of the Naïve Bayes experiment

- As the size of the labeled data set increases, accuracy of both the models converged to a stable value (Approximately 86%). Thus, Naïve Bayes performed well for both the supervised and semi-supervised training model.

- When number of labeled data was low, Naïve Bayes with simple random sampling performed better with the semi-supervised model than the supervised approach. For stratified sampling, both the models gave similar accuracy. This is in agreement to our initial hypothesis.

- As we increased the number of labeled data, accuracy for the semi-supervised approach was not always better than the supervised approach. This is a deviation from our initial hypothesis. This might be because Naïve Bayes has the strong assumption that the features are conditionally independent. For our project, it is difficult to interpret the interdependencies between behavioral footprints of the reviewers [3].

4.1.2 Critical evaluation of the Decision Tree experiment

- As the size of the labeled data set increases, accuracy of both the models converged to a stable value (Approximately 89%). Thus, Decision Tree performed well for both the supervised and semi-supervised training model.

- For both simple random and stratified sampling, Decision Tree performed better with the semi-supervised model than the supervised approach. This is in agreement to our initial hypothesis.

4.1.3 Critical evaluation of the Logistic Regression experiment

- As the size of the labeled data set increases, accuracy of both the models converged to a stable value (Approximately 88%). Thus, Logistic Regression performed well for both the supervised and semi-supervised training model.

- For both simple random and stratified sampling using Logistic Regression, accuracy for the semi-supervised approach was not always better than the supervised approach. This is a deviation from our initial hypothesis. This might be because of the fact that the self-**training algorithm that we're using doesn't work** well when the base learner does not produce reliable probability estimates to its predictions [5].

5. Conclusion

Through this project, we learnt that self-training works well when the base learner is able to predict the class probabilities of unlabeled data with high confidence. Based on the experiments that we performed, we found that in general semi-supervised learning using self-training does improve the performance of supervised learning methods in the presence of unlabeled data.From the approaches that we tried, we found that semi-supervised self-training using Decision Tree as classifier leads to better selection metric for the self-training algorithm than the Naïve Bayes and Logistic Regression base learners. Thus, Decision tree works as a better classification model for our project.Since the Decision Tree worked well, we had the idea of implementing Naïve Bayes Tree which is a hybrid of Decision Tree and Naïve Bayes on our data set. Tanha et al., (2015) have conducted a series of experiments which show that Naïve Bayes trees produce better probability estimation in tree classifiers and hence would work well with the self-training algorithm [5].

6. References

[1] Mukherjee, A., Venkataraman, V., Liu, B. and Glance, N. 2013. What Yelp Fake Review Filter might be Doing? ICWSM. (2013).

[2]Mukherjee, A., Liu, B. and Glance, N. 2012. Spotting fake reviewer groups in consumer reviews. WWW.

[3]Mukherjee, A., Kumar, A., Liu, B., Wang, J., Hsu, M., Castellanos, M., and Ghosh, R. 2013a. Spotting opinion spammers using behavioral footprints. In Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining, ACM.

[4]Nigam, K., McCallum, A., Thrun, S., and Mitchell, T. Text classification from labeled and unlabeled documents using EM., 2000.

[5] Tanha, J., Someren, M., and Afsarmanesh, H. "Semi-Supervised Self-Training for Decision Tree Classifiers". Int. J. Mach. Learn. & Cyber. (2015): n. pag. Web.

[6]Tanha, J., Someren, M., and Afsarmanesh, H. “Semi-Supervised Self-Training with Decision Trees: An Empirical Study”. In proceeding of: 3rd IEEE International Conference on Intelligent Computing and Intelligent System, (2011)

[7]"Yelp". Wikipedia. N.p., 2016. Web. 10 Apr. 2016.

[8]"List of English Stop Words - XPO6". XPO6. N.p., 2009. Web. 10 Apr. 2016.