



DETECTING FAKE ONLINE REVIEWS USING SUPERVISED AND SEMI-SUPERVISED LEARNING

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ABSTRACT - *Online reviews have a great impact on today's business and commerce. Decision making for purchase of online products mostly depends on reviews given by the users. Hence, opportunistic individuals or groups try to manipulate product reviews for their own interests. It introduces some semi-supervised and supervised text mining models to detect fake online reviews as well as compares the efficiency of both techniques on a dataset containing hotel reviews.*

KEYWORDS : *Reviews,*

1. INTRODUCTION

Using social network are growing day by day, to communicate with their peers so that they can share their personal feeling everyday and views are created on large scale. Social Media Monitoring or tracking is most important topic in today's current scenario. In today many companies have been using Social Media Marketing to advertise their products or brands, so it becomes essential for them that they can be able to calculate the success and usefulness of Nowadays, Social media is becoming more and more popular since mobile devices can access social network easily from anywhere. Therefore, Social media is becoming an important topic for research in many fields. As number of people each product .

For Constructing a Social Media Monitoring, various tool has been required which involves two components: one to evaluate how many user of their brand are attracted due to their promotion and second to find out what people thinks about the particular brand. To evaluate the opinion of the users is not as easy as it seems to all users. For evaluating their attitude may requires to perform Sentiment Analysis, which is defined as to identify the polarity of customer behavior, the subjective and the emotions of particular document or sentence.

1.1. Machine Learning:

Supervised Learning, Unsupervised Learning, and Reinforcement are three types of machine learning. The training dataset can be thought of as a teacher teaching his students because of supervised learning. Machine learning is about extracting knowledge from data. It is a research field at the intersection of statistics, artificial intelligence, and computer science and is also known as predictive analytics or statistical learning. The application of machine learning methods has in recent years become ubiquitous in everyday life. Supervised learning is the process where you have input variables (X) and an output variable (Y) and you use an algorithm to learn the mapping function from the

input to the output. The goal is to approximate the mapping function so well that when you have new input data (X) that you can predict the output variables (Y) for that data. It is called supervised learning because the process of an algorithm learning from the training dataset can be thought of as a teacher supervising the learning process.

Unsupervised machine learning algorithms, on the other hand, are trained on unlabeled data and must determine feature importance on their own based on inherent patterns in the data. The most basic disadvantage of any Unsupervised Learning is that its application spectrum is limited.

1.2. Algorithm Used:

For semi supervised learning, we use Expectation-maximization algorithm. Statistical Naive Bayes classifier and Support Vector Machines (SVM) are used as classifiers in our research work to improve the performance of classification.

We have mainly focused on the content of the review based approaches. As feature we have used word frequency count, sentiment polarity and length of review.

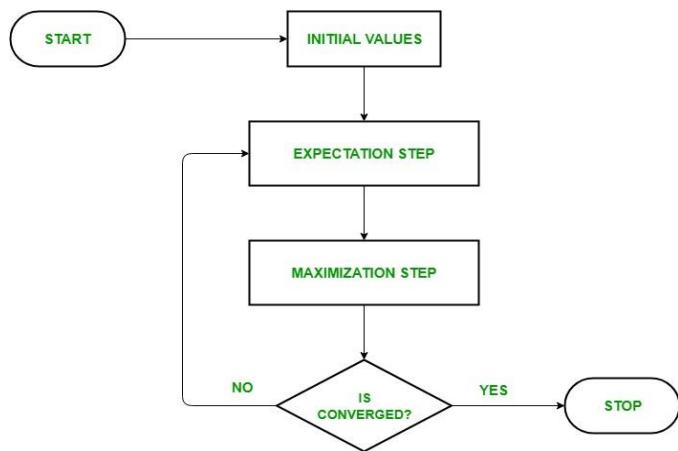


Fig.1 Expectation- Maximization Algorithm

2. SYSTEM ARCHITECTURE

A system architecture can consist of system

components and the sub-systems developed, that will work together to implement the overall system. There have been efforts to formalize languages to describe system architecture, collectively these are called architecture description languages.

System architecture conveys the informational content of the elements consisting of a system, the relationships among those elements, and the rules governing those relationships.

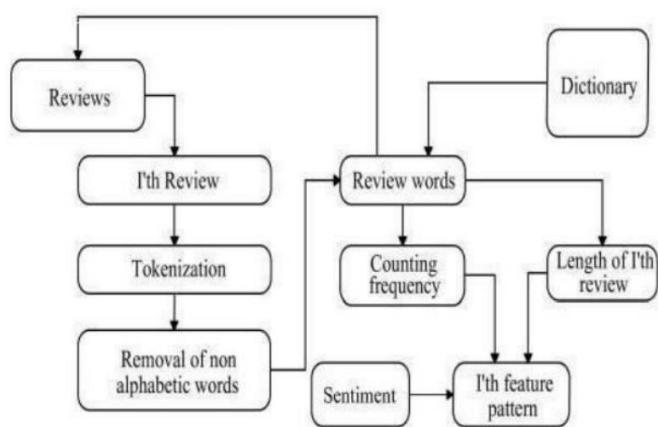


Fig.2 Architectural Diagram

The architectural components and set of relationships between these components that an architecture description may consist of hardware, software, documentation, facilities, manual procedures, or roles played by organizations or people. A system architecture primarily concentrates on the internal interfaces among the system's components or subsystems, and on the interface(s) between the system and its external environment, especially the user.

2.1 Block Diagram

Block diagrams are typically used for higher level, less detailed descriptions that are intended to clarify overall concepts without concern for the details of implementation. Contrast this with the schematic diagrams and layout diagrams used in electrical engineering, which show the implementation details of electrical components and physical construction.

A Block Diagram is a fundamental way that

hardware and software developers utilize to describe these systems while illustrating their workflows and processes. Electricians, on another hand, need them to represent systems and their shifting, for example, the mechatronic systems in the trucking industry.

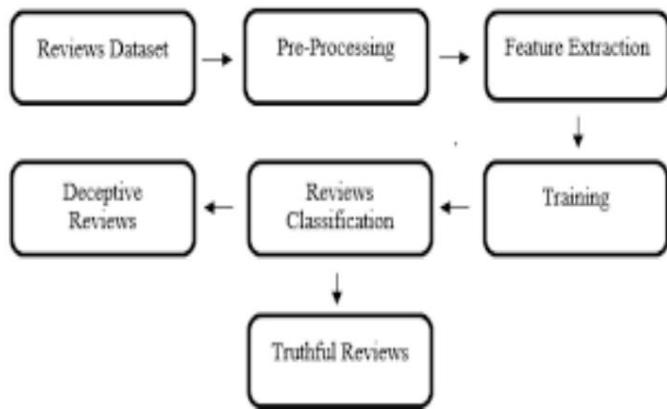


Fig.2.1 Block Diagram

More often than not, block diagrams are of great assistance when a clear picture of information or control flows is required, besides when a project has a myriad of processes.

3.EXISTING SYSTEM

Sun et al. proposed a method that offers classification results through a bagging model which bags three classifiers. They introduced a product word composition classifier to predict the polarity of the review. The model was used to map the words of a review into the continuous representation while concurrently integrating the product-review relations

To build the document model, they took the product word composition vectors as input and used Convolutional Neural Network CNN to build the representation model. Jitendra et al. proposed semi-supervised method where labeled and unlabeled data both are trained together.

3.1 Limitations of Existing System

The existing systems have the following disadvantages:

1. Assuring of the quality of the reviews is difficult.
2. A labeled data point to train the classifier is difficult to obtain.
3. Human are poor in labeling reviews as fake or genuine.

4. PROPOSED SYSTEM

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.

4.1 Advantages of Proposed System

- We have chosen our features carefully to reduce over fitting. We have not taken derived features like bigrams or trigrams. We have taken review length as a feature as it has well significance.
- We have chosen Naive Bayes as our classifier considering properties of our dataset. By doing these we have been able to increase the accuracy of semi-supervised classification to 85.21% where Jiten et al. were able to get the highest accuracy of 83.75%.
- We have also found the highest accuracy of 86.32% by using supervised classification with Naive Bayes classifier.

5. RESULT

The implementation is done with the help of Python 3.7. This is divided into polarity,source and hotels.

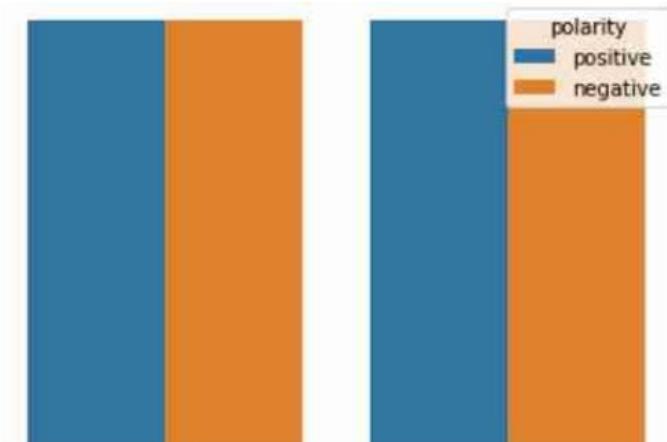


Fig.5.1 Polarity

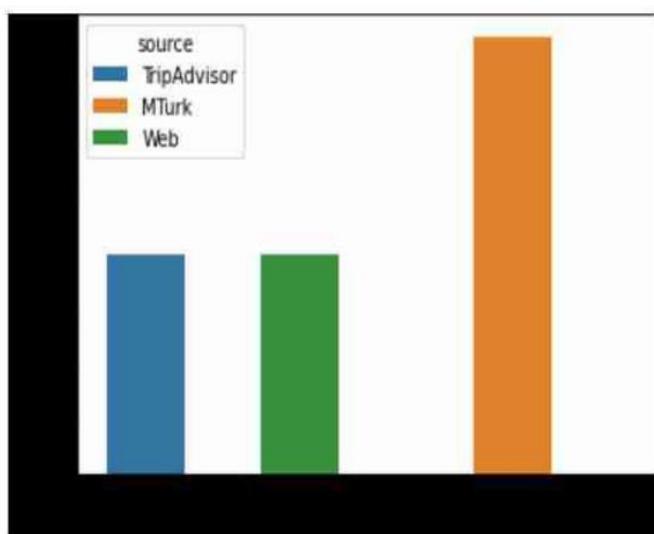


Fig.5.2 Source

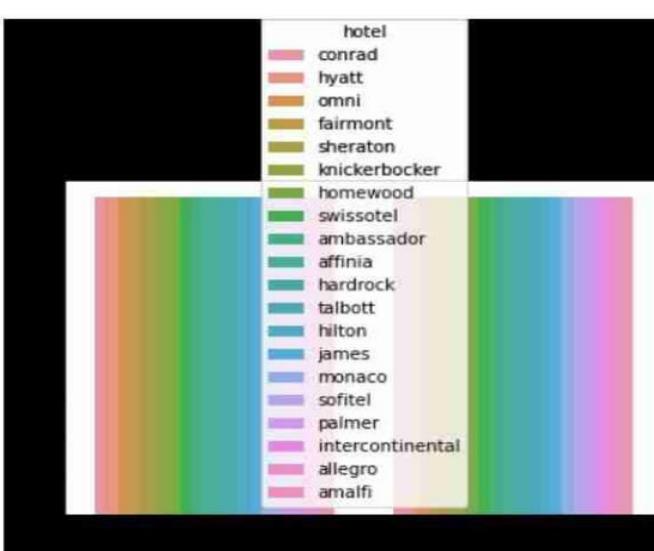


Fig.5.3 Hotels

	deceptive	hotel	polarity	source	text
0	truthful	conrad	positive	TripAdvisor	We stayed for a one night getaway with family ...
1	truthful	hyatt	positive	TripAdvisor	Triple A rate with upgrade to view room was le...
2	truthful	hyatt	positive	TripAdvisor	This comes a little late as I'm finally catchi...
3	truthful	omni	positive	TripAdvisor	The Omni Chicago really delivers on all fronts...
4	truthful	hyatt	positive	TripAdvisor	I asked for a high floor away from the elevato...
...
1595	deceptive	intercontinental	negative	MTurk	Problems started when I booked the InterConti...
1596	deceptive	amalfi	negative	MTurk	The Amalfi Hotel has a beautiful website and i...
1597	deceptive	intercontinental	negative	MTurk	The Intercontinental Chicago Magnificent Mile ...
1598	deceptive	palmer	negative	MTurk	The Palmer House Hilton, while it looks good i...

Fig.5.4 Output screen of real and fake reviews

6.CONCLUSION

Determining and classifying a review into a fake or truthful one is an important and challenging problem. In this paper, we have used linguistic features like unigram presence, unigram frequency, bigram presence, bigram frequency and review length to build a model and find fake reviews. After implementing the above model we have come to the conclusion that, detecting fake reviews requires both linguistic features and behavioral features.

7.Future Scope

In future, user behaviors can be combined with texts to construct a better model for classification. Advanced preprocessing tools for tokenization can be used to make the dataset more precise. Evaluation of the effectiveness of the proposed methodology can be done for a larger data set. This research work is being done only for English reviews. It can be done for Bangla and several other languages.

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