Online Product Review sentiment analysis using Machine Learning Approaches

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Abstract:
Reviews are a common kind of opinion spam in online markets. People are frequently employed to write extremely good or bad reviews for particular brands in an effort to promote or hinder them. This is frequently carried out in groups. Few studies have looked into identifying and analysing opinion spam groups that target a brand as a whole rather than just its products, despite some earlier attempts to do so. In this post, a set of 923 possible reviewer groups was manually classified using the reviews we gathered from the Amazon product review website. In order to cluster users who have mutually reviewed a large number of brands' products together, frequent item set mining over brand similarities is used to extract the groups. We postulate that eight characteristics unique to a (group, brand) pair determine the makeup of the reviewer groups. To categorize prospective groups as extremist entities, we create a supervised model based on features. For the job of classifying a group based on user ratings, we run various classifiers to see if the group exhibits extremity manifestations. The best classifier is found to be a three-layer perceptron-based classifier. To better understand the dynamics of brand-level opinion fraud, we continue to examine the actions of these groups in greater detail. Consistency in ratings, review sentiment, confirmed purchases, review dates, and helpful votes earned on reviews are examples of these characteristics. Surprisingly, we find that many certified reviewers exhibit strong sentiment, which, upon closer examination, reveals ways to get beyond the current safeguards against unauthorized incentives on Amazon.

Keywords: Online Product, Machine Learning, Naïve Bayes, Websites, Sentiment Analysis.

INTRODUCTION

"A website that facilitates meeting people, finding like minds, communicating and sharing content, and developing community" is the definition of a social media website. These websites permit or promote a variety of activities, including social, commercial, and a mix of the two. Digital libraries, e-commerce, entertainment, forums, geolocation, social bookmarks, social reviews, social games, and social networks are some examples of social media categories. Social media, which is the social structure of people who are connected by shared interests, has a subcategory called social networks. Social media refers to social channels of communication that use desktop computers, mobile devices, and web-based technology. Through the creation of highly interactive platforms, these technologies enable people, groups, and organizations to exchange information, engage in discussions, rate, and comment on, and alter online and user-generated material. Communication between companies, groups, communities, and individuals is made possible by these developments. Social media technologies, which are always evolving, alter how people and big businesses communicate. Sentiment analysis has a wide range of purposes in public policy and business. Nowadays, sentiment analysis is applied to anything from the promotion of particular products to the identification of antisocial behaviour. The public's perception of businesses and organizations has always been a concern. A number of factors, such as public relations and marketing, contribute to this worry. Before the Internet, an organization could only monitor its media reputation by hiring someone to read newspapers and manually compile lists of references to the organization that were neutral, positive, and negative. They could also conduct costly surveys with questionable validity. Nowadays, a lot of newspapers are released online. While some distribute their print edition's pages in PDF format, others publish specialized online editions. Opinionated articles can be found online via blogs and other social media platforms, in addition to newspapers. This makes it possible to automatically identify whether an organization is mentioned favourably or unfavourably in internet articles, which would significantly cut down on the amount of work needed to gather this kind of data. In light of this, organizations are showing a growing interest in learning more about the mood of news items. Because opinions can be communicated in so many different ways, fine-grained sentiment analysis is a very difficult problem. Because news items typically conceal overt signs of attitudes, they provide an even bigger issue. However, news items that depict objectively positive or negative occurrences can nonetheless be polarizing even when they appear to be neutral. A lot of sentiment analysis techniques are naïve and rely on identifying specific keywords that indicate the speaker's or author's feelings. To categorize statements as neutral, negative, or positive, we employ naïve sentiment analysis, which is a fine-grained approach.

OBJECTIVE

Research from academia and the news event computing community has welcomed the development of the social media big data mining field, which seeks to identify key components of the news event sentiment computing task.

RELATED WORK

Online product reviews using machine learning techniques because sentiment analysis can transform large volumes of client comments into useful information, it has become very popular. Businesses can accurately assess customer sentiment thanks to machine learning algorithms, which may then directly affect marketing and product development. In a work by m. a. shafin et al., m. m. hasan et al., m. r. alamet et al., m. a. mithuet et al., a. u. nur, and m. o. faruk et al. [2020], Product Review Sentiment Analysis is conducted in Bengali utilizing NLP and Machine Learning. The paper examines several supervised and unsupervised classification methods, including Logistic Regression [2023], SVM [2021], Naive Bayes [2020], Decision Trees [2021], and deep learning models like RNN [2022,] to assess their effectiveness in sentiment analysis. Among the feature extraction techniques we look at in our research are Bag of Words (BoW) [2020], Term Frequency-Inverse Document Frequency (TF-IDF) [2021], and word embedding's such as Word2Vec [2022] and GloVe [2019]. The effectiveness of the Naive Bayes and SVM algorithms [2020; 2021] in categorizing sentiment as neutral, negative, or positive was assessed in our work. Within the context of the product evaluation, this comparison highlights the advantages and disadvantages of each strategy. One important strategy is to pre-process text data using Natural Language Processing (NLP) methods including tokenization [2021], stemming [2022), and lemmatization [2020]. These first processing stages greatly enhance the quality of the input data, which is essential for increasing the accuracy of machine learning models. Our experiments showed that combining these pre-processing techniques with feature extraction improved the classification accuracy of different models, especially with standard SVM implementations [2021]. The suggested models were evaluated using data gathered from well-known e-commerce websites [2020], and the results demonstrated improvements in recall, accuracy, and precision.

EXISTING SYSTEM

Labelling a group of reviewers is significantly simpler than labelling individual reviews, as demonstrated by Mukherjee et al. There are more intriguing research that use metadata to describe various entities in e-commerce sites that concurrently classify people, reviews, and products. Kakhki et al. and Fei et al. demonstrated the importance of synchrony as a group behaviour. Together with a number of other metrics, Xu and Zhang also employed this signal as a temporal indicator and put forth a fully unsupervised model for identifying group collusion. Additionally, a number of graph-based methods have demonstrated the ability to simultaneously identify spam reviewers and spam reviews.

Disadvantages of Existing System

The phenomena of groups engaging in brand-based opinion spamming is still mostly unstudied. According to earlier research, 10% to 15% of reviews are merely restating the original reviews, which is deceptive.

PROPOSED SYSYTEM

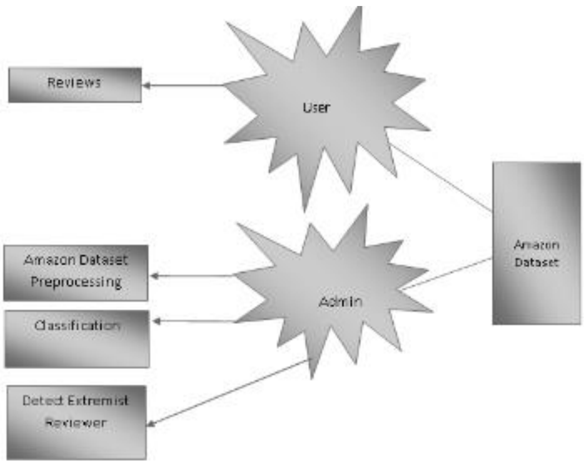
We identify and investigate the behavioural traits of radical reviewer groups in this project. Additionally, in order to detect extremist organizations in the Amazon India marketplace, we develop a feature-based classifier based on the brand-specific actions of reviewer groups. We next compare and examine the general trend of these groups in relation to their actions, as well as further examine our methods to uncover behaviours that most accurately represent such activities.

Advantages of Proposed System

Given that extremism eventually influences "brand attitudes," no research has been done on the phenomenon of extremism at the group level, particularly in relation to a brand. We present the issue at the brand level, which none of the other studies took into account. Here, we concentrate on extremist reviewer detection, which may not be phony, in contrast to other research that primarily focus on fake review/reviewer detection. Furthermore, rather than looking for "individual users," we try to find "groups." We discovered a sizable percentage of spam organizations exhibiting extremist behaviour during the labelling and categorization process. This supports our theory that extremism is pervasive at the brand level, with organizations seeking to elevate or devalue brands for a variety of reasons, some of which may involve financial incentives offered by the brand directly or indirectly.

ARCHITECTURE DIAGRAM

It is a simple graphical system used to symbolize a gadget in phrases of facts input into a computer, various methods performed on that data, and data generated through the machine. Modelling gadget additives. These additives are the method of the gadget, the facts utilized by the manner, the outside entity related to the gadget, and the facts flowing into the gadget. Shows how statistics moves in a gadget and how it undergoes a chain of adjustments. It is a graphical method of depicting facts flow and the changes used even as taking facts from enter to output.



MODULES

- Data Collection
- Dataset
- Data Preparation
- Model Selection
- Analyze and Prediction
- Accuracy on test set
- Saving the Trained Model

1. Data Collection:

The process of gathering data is the first actual step in creating a machine learning model. This crucial stage will have a cascading effect on the model's performance; the more and better data we collect, the better the model will function. Data can be gathered using a variety of methods, including physical interventions, web scraping, and more. Kagle and other sources provided the dataset utilized in this Detecting and Characterizing Extremist Reviewer.

2. Dataset:
There are 2133 distinct data points in the dataset. The dataset contains three columns, which are explained below. Id: distinct id Labels: Product review labels that can be classified as moderate or suicide extreme 1. Extremist 0: moderate Text: evaluation of the product.
3. Data Preparation:
We will change the data. By eliminating certain columns and missing data. We will start by compiling a list of the column names that we wish to preserve. After that, we eliminate or drop every column save for the ones we choose to keep. Lastly, we eliminate from the data set the rows that have missing values. Actions to take: Eliminating unnecessary symbols eliminating punctuation taking the Stop words Out Tokenization by Stemming Extraction of features TF-IDF vectorizer utilizing a TF-IDF transformer, the counter vectorizer.
4. Model Selection:
We used Naïve BAYES algorithms.
5. Analyse and Prediction:
In the actual dataset, we chose only 1features: Text: product review Labels: Labels of product review which can be either suicide extremist or moderate 1: extremist 0: moderate.
6. Accuracy on test set:
We got an accuracy of 90.02% on test set.

PROPOSED ALGORITHM

Machine Learning:
The utilization of measurements and calculations to mimic the manner in which artificial intelligence follows human examination and steadily builds its exactness is the focal point of the AI (ML) part of man-made intelligence and PC innovation. Method of Decision-Making Algorithms for computer learning are typically used to make predictions and classifications. Your calculation evaluates the example in the records using a variety of information measurements that can be referred to. A blunder characteristic that assesses the model gauge is called a mistake capability. Correlations can be used to examine the issue portrayal model's precision using models. Model improvement procedure expecting the model best matches the real factors tended to in the planning dataset, the heaps are adjusted to restrict the qualification between the known event and the expected version.

This "assessment and advancement" procedure is repeated by the calculation, which keeps refreshing the loads until an exactness edge is reached. Since significant learning and computer-based intelligence are by and large used on the other hand, it's very huge the nuances between the two. Subsets of computerized reasoning incorporate brain organizations, profound learning, and AI. However, deep learning is a subset of brain organizations, and brain networks are a subset of AI. AI and profound learning differ in how each calculation learns. "Significant" computational learning, generally called coordinated learning, can use named enlightening records to enlighten its rules, but not exactly a portrayed educational file. From raw data, such as text or images, a deep learning strategy is able to consistently identify a set of consistent features that differentiate one type of information from another. This eliminates the need for human intervention and makes it possible to utilize a large amount of data. As Lex Friedman raises in this MIT talk, you can think about significant learning "at the contraption learning level" (associate is external to IBM.com).

CONCLUSION

This study has important limitations even though it contributes valuable information on how consumers respond to mobile phone assessments to the theoretical and empirical literature. Ten good and ten negative reviews per cell phone is a small sample size that may not fully capture the complexities of consumer decision. Future studies should aim for a dynamic experimental design that can handle more comments to give a more complete understanding of how reviews influence purchase decisions.

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