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Multi-Dimensional Characterizations of Fine-Grained Features for Identifying Fake Reviews

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ABSTRACT

Information has spread at a rate never previously seen in human history because to the proliferation of the Internet and social media sites like Facebook and Twitter. Consumers are producing and disseminating more content than ever before because to the widespread adoption of social media platforms, some of it is false and has no basis in reality. There is a significant challenge in developing an automated system to determine if a given text article contains false information. If you're an expert in a certain field, you still need to look into a lot of different things before you can make a decision on the reliability of an article[1]. The goal of this study is to develop methods for identifying "fake reviews," often known as knowingly false or misleading news pieces disseminated by dubious media outlets, via the use of Natural Language Processing (NLP) tools. With a count vectorizer (word counts) or a (Term Frequency Inverse Document Frequency) TFIDF matrix, the model can only be taken so far (word counts relative to how often they occur in other articles in your dataset). However, many models fail to account for key aspects or information. Articles might be the same length yet convey entirely distinct messages due to variations in word choice. Data scientists have taken action to address the issue. Facebook uses AI to weed out false news stories from users' feeds, and Kaggle hosts a "Fake News Challenge" for anyone with an interest in the topic. While it's not easy to develop a fake news detector, we suggest creating a model by combining actual and false news stories into a dataset, and then using a Naive Bayes classifier and Logistic Regression to determine whether or not a review is authentic based on its wording and context. Our suggested model has been experimentally shown to outperform state-of-the-art text categorization methods.

Keywords -Fake reviews detection, NLP, TFIDF, SVM.

INTRODUCTION

The problems caused by false reviews these days range from satirical pieces to completely made-up stories to deliberate government propaganda. Misinformation and declining public faith in the reviews media are major social issues. Although it's always been clear that a narrative that deliberately misleads its audience is "fake reviews," the meaning of the term is shifting in the current climate of social media babble. Some of them have taken to using the word to discount evidence that runs opposed to their biases. Particularly after the 2016 U.S. presidential election, the role of misinformation in political discourse received a lot of attention. The phrase "fake reviews" quickly gained popularity as a catch-all for deceptive and inaccurate reviews stories written with the primary goal of increasing page views and advertising revenue. In this work, we want to develop a model that can reliably estimate how likely it is that a particular piece of content is in fact propaganda. After receiving a lot of press, Facebook became the target of many complaints. They have a system in place to alert administrators whenever a user encounters suspicious content, and they have publicly said that they are working on a system to automatically identify false reviews stories. That's not to say it's a simple process. Given that there are false reviews sources on both sides of the political spectrum, any given algorithm must treat all sides of the reviews equally. And then there's the sticky issue of validity. To get to the bottom of this issue, however, you need to know what "Fake Reviews" is. In the future, we need to investigate how methods from machine learning and natural language processing aid in the identification of false reviews.

2. LITERATURE REVIEW

Nidhi A. Patel, Rakesh Patel **A Survey on Fake Review Detection using Machine Learning Techniques**

Internet marketing and usage are rising[2]. The online marketplace provides millions of things and services, creating vast data. Identifying the best services or commodities for a need may be difficult. Consumers depend greatly on others' views, which are generally based on personal experiences. Anyone may post anything online, leading to more fake reviews in a competitive market. Many firms pay people to submit fake, positive ratings of their products and services online and unfair, negative ones of competitors. Because this approach misleads prospective purchasers, we need a way to detect and eradicate fake product reviews. In this study, we apply supervised, unsupervised, and semi-supervised data mining methods to detect fake reviews

Jingdong Wang, Haitao Kan **Fake Review Detection Based on Multiple Feature Fusion and Rolling Collaborative Training**

Customers may be misled by false reviews[3]. Massive property losses and public opinion catastrophes may result from fake reviews. It's vital to detect and remove fake testimonials. Existing techniques depend mainly on single features and a lack of labelled experimental data, reducing their accuracy in spotting fake reviews. We describe an innovative strategy to identifying fraudulent reviews based on numerous criteria and rolling collaborative training. First, the approach requires an index system containing text features, review sentiment features, and reviewer behaviour data. To use the process, you need a training set of examples. To obtain all the important information from a review, we created matching algorithms. Hand categorization is done last. Seven classifiers are trained using the original sample set, and the most accurate classifier is used to categorise new reviews. Newsamples with the attributes and classication labels of newreviews will be added to the current sample. Thus, the sample size will expand. Experiments on the yelp shopping website showed that the recommended methodology was 3.5% more accurate than the baseline approaches. The baseline accuracy is 5.3% greater than the most current deep learning model. Support vector machine (SVM) and random forest (RF) classifiers are the best based on the Friedman test. This means our technique, which uses several traits, outperforms traditional models. In the meanwhile, it solves the lack of labelled training data to spot fake reviews.

Daojing He, Menghan Pan **Fake Review Detection Based on PU Learning and Behavior Density**

The app store's rating system makes it easy to find high-quality applications[4].We describe an approach based on Positive and Unlabeled (PU) learning and behaviour density to detect fraudulent reviews, which may be exploited to smear apps or influence app store rankings. The classifier is trained using Biased-SVM to select which negative samples to trust. Finally, fraudulent review detection combines early screening results with user behaviour density. In fully supervised detection, the quality of tagged data affects the trained classifier. When there are few tagged instances and numerous unlabeled ones, our technique may help.

Tests and case studies indicate our method's excellent accuracy[3].

Julien Fontanarava, Gabriella Pasi **Feature Analysis for Fake Review Detection through Supervised Classification**

Disinformation, or opinion spam, aims to promote or hurt firms by fooling human readers or automated opinion mining and sentiment analysis systems[5]. In recent years, data-driven strategies have been developed to analyse social media user-generated content. Various methodologies analyse reviews and reviewers' qualities and the test review site's network structure. This article analyses review- and reviewer-centric criteria recommended to detect fake reviews, particularly utilising supervised machine learning.These methods outperform unsupervised, graph-based algorithms that utilise review site connections. This research also analyses innovative ways to spot fake reviews. Using well-known and new characteristics and a large-scale labelled dataset, a supervised Random Forests classifier was created. Good results show how new factors may detect singleton fake reviews and the significance of this study[4].

Guohou Shan, Lina Zhou **From conflicts and confusion to doubts: Examining review inconsistency for fake review detection**

Inconsistent online customer reviews (OCRs) may induce buying doubt and confusion[6]. However, there is no comprehensive and empirical study of review inconsistency. This study describes review inconsistency from rating-sentiment, content, and language and presents predictions concerning their implications on fake OCR identification using deception and attitude-behavior consistency theories. We assess review inconsistency with 22 characteristics and test hypotheses using fake OCR machine learning models. Our empirical assessment findings using genuine OCRs corroborate review inconsistencies and show it improves false OCR detection. The results improve customer decision making and OCR credibility[5].

3. WORKING METHOD

1. Multinomial Navies Bayes
2. Passive Aggressive Classifier

MULTINOMIAL NAVIES BAYES

Naive Bayes is a class of algorithms for classifying samples based on their features, where the central (naive) assumption is that no two features are related to one another. These classifiers are probabilistic, therefore they will use Bayes' theorem to determine the likelihood of each category before returning the one with the greatest likelihood as the output. In numerous fields, including Natural Language Processing, Naive Bayes classifiers have proven effective (NLP). When dealing with NLP issues, we also have additional tools at our disposal, such Support Vector Machine (SVM) and neural networks. However, Naive Bayes classifiers are extremely appealing for such classifiers because to their straightforward architecture. They have also been shown to be quick, trustworthy, and accurate in a variety of NLP uses.

4. PASSIVE AGGRESSIVE CLASSIFIER

Step 1

Suppose you have only one data point, didi, and you want to do a regression. To determine the optimal line, you need more than a single data point. Both the yellow and blue lines will be able to go through the centre of the circle without any problems.

Step 2

On the other hand, we can provide an exact description of every line that will pass through it. It is feasible to provide a line description of all potential perfect fits by plotting the weight space of the linear regression (where w0w0 is the constant and w1w1 is the slope). The blue dot represents the blue line, while the yellow dot represents the yellow line.

Step 3

According to Didi, each given location along the line is equivalent. How about we compare it to the values the model was using before it found this outlier? We'll refer to these kilos as worigworig. Therefore, the blue regression seems to be the better option than the yellow one, but is this really the case?

Step 4

To locate the point on the line where our initial weights were closest to worigworig, we may apply mathematics. While linear algebra may suffice in a highly linear system, maintaining a consistent updating strategy in other systems may need ever more complex mathematics.

Step 5

To avoid numerical instability, we may alternatively opt to impose a restriction on the maximum allowable step size (no larger than CC). In this method, we may avoid the problem of grossly overfitting to extreme cases. In addition, we should probably only update our model if our algorithm makes a substantial error. In this way, we may release a somewhat forceful upgrade, while maintaining our quiet stance in other situations. As a result, we have a name for it! While the specifics may vary, the concept of passive aggressive updating can still be applied to systems that do linear classification.

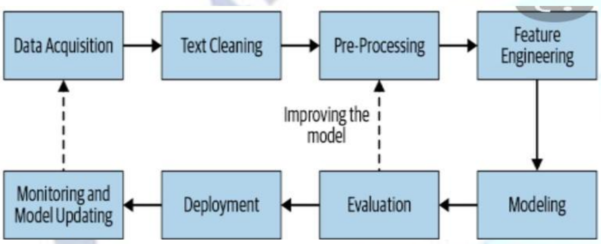

Fig1: System Architecture

5. CONCLUSION

There are two main findings from this study, which come as the identification of internet disinformation becomes a hot topic among both academics and professionals. To start, computational linguistics can help with the automatic identification of bogus reviews at a rate far higher than chance. The suggested linguistics-driven strategy recommends analysing the lexical, syntactic, and semantic level of a reviews item in issue to determine if it is false or authentic. Up to 76% accuracy is achieved by the devised system, which is on par with that of people for this job. Despite the promise of linguistics features, we argue that future work on misinformation detection should expand to incorporate meta features (such as the number of links to and from an article, comments on the article), features from different modalities (such as the visual makeup of a website using computer vision approaches), and the growing potential of computational approaches to fact verification (Thorne et al., 2018). Therefore, 3400 potential future study may desire to investigate the integration of fact verification and data-driven machine learning judgements in hybrid decision models. Our results also shown that a hybrid strategy combining manual and crowdsourced annotation techniques may be used to successfully construct resources for the false reviews detection challenge. Our research detailed the use of these methods in the creation of two datasets, demonstrating that both datasets share certain linguistic aspects relevant to the presentation of false information. Additionally, our dataset is unique in that it consists of genuine reviews snippets as opposed to brief statements containing false reviews content, like the majority of other accessible fake reviews datasets. Last but not least, we hope that the present study and dataset will inspire researchers and practitioners to take on the task of combating disinformation.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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