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A Framework to Categorize Shill and Normal Reviews by Measuring it's Linguistic Features

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Abstract— Shill reviews detection has attracted significant attention from both business and research communities. Shill reviews are increasingly used to influence the reputation of products sold on websites in positive or negative manner. The spammers may create shill reviews which mislead readers to artificially promote or devalue some target products or services. Different methods which work according to *linguistic features* have been adopted and implemented effectively. Surprisingly, review manipulation was found on reputable e-commerce websites also. This is the reason why linguistic-feature based methods have gained more and more popularity. Lingual features of shill reviews are examined in this study and then a tool has been developed for extracting product features from the text used in the product review under analysis. Fake reviews, fake comments, fake blogs, fake social network postings and deceptive texts are some forms of shill reviews. By extracting linguistic features like informativeness, subjectivity and readability, an attempt is made to find difference between shill and normal reviews. On the basis of these three characteristics, hypotheses are formed and generalized. These hypotheses help to compare shill and normal reviews in analytical terms. Proposed work is for based on polarity of the text (positive or negative), as shill reviewer tend to use a definite polarity based on their intention, positive or negative.

Keywords- *Informativeness; Linguistic characteristics; Readability; Reputation manipulation; Shill reviews; Subjectivity*

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I. INTRODUCTION *(HEADING 1)*

As the Internet continues to grow in both size and importance, the quantity and impact of online reviews continually increases. Review websites often feature user-generated opinions. Such review websites may permit a user to provide review for any type of service or product, for example, a restaurant, bar, hotel, Transportation Company (e.g. airline, train), shopping venue, spa and beauty service provider, financial service provider etc. Review websites are generally open for any registered or guest users to submit a review.

Customer generated content is mostly amorphous text, poorer quality, noisy, spam. The product information provided in reviews generally comes from actual users of the product. This knowledge from actual product users helps rest of the consumers to reduce the risks related with buying products they have never used before [17]. However, the positive impact of item for consumption reviews on product sales provides a strong incentive for sellers to manipulate reviews using fake reviews.

Fake reviews are also called as shill reviews. Shill and shilling are the terms used about reputation manipulation. A fake review writer can be the salesperson or someone rewarded by the salesperson for writing a review [1]. Thus, shill review writers can be agents of sellers, distributors, manufacturer and authors who get profit from the sales of a product.

A review may be given for a particular product or service. Full text review is description of a particular product or service. Numerical rating is one form of the review. Numerical rating of predefined aspects of the product or service is one option of expressing opinion. Another option is short phrases summarizing pros and cons of product or service. General buyer seeks opinions from friends and family. Focus groups, opinion polls and surveys are some sources to get consumer feedback for which business spend a lot money.

There is a need to find the differences between shill reviews and normal reviews, as purchaser blindly trust on product reviews. They may fail to identify the shill reviews because spammers have adapted different styles of writing the reviews. This paper will focus on some linguistic features of reviews, and model a framework to classify the fake reviews from authentic ones. Informativeness, Subjectivity and Readability are those linguistic features and accordingly methods are derived in this framework. As an additional work, this framework is applied on negative reviews also are because purchaser don't believe on negative reviews as compared to positive ones.

II. RELATED WORK

This section represents the various approaches for detection of shill reviews.

Spam detection is done in areas like e-mail, Web and SMS. But because of huge response for online shopping, researchers work got significant attraction towards review manipulation on online e-commerce websites. This work will focus on differentiating shill and normal (authentic) reviews by using Description Based Feature Extraction Method (DFEM). DFEM uses 'informativeness', which is one of the linguistic features of text for calculating accuracy of reviews.

Following are some approaches for finding shill reviews.

A. Sentiment Analysis:

Since fake reviews are created to enhance the positivity or negativity of a product or service, it will create a positive or negative sentiment from online review. Therefore, sentiment analysis can be employed as a tool for detecting shill reviews. This is done by computing the sentiment score of a review based on the sentiment scores of the terms used in the review. The sentiment of the review is defined to be equal to the sum of the sentiment scores for each term in the review.

Peng et. al [13] used sentiment analysis to compute sentiment score from the natural language text by a shallow dependency parser. The relationship between sentiment score and spam reviews are discussed in further part.

Xiolong deng et al [16] has done further investigation on fake reviews on 'hype'. By human tagging of sentiment words, they have classified those words into four dimensions - service, overall attitude, taste and environment. The bayes classifier conducts sentiment analysis, and if the analysis result of four dimensions is same, then the review is defined as 'hype review'.

B. Linguistic features of product reviews:

1. Informativeness: An amount or quantum of product information provided in a review can be called as 'informativeness of the review'. Product information can be divided in following categories.

- *Official features:* This is the type of product information, which can be easily seen to the consumers, and especially given by the manufacturer of the said product.
- *Unofficial features:* This is not a part of product description provided by the manufacturer. It can be called as confidential information known only to the users of the product.

II. Readability: Length of review is the count of words in the given review. There are some index measures used to calculate readability of a given text in the review, such as Gunning-Fog Index, Coleman-Liau Index, Automated Readability Index and Flesch-Kincaid Grade Level. For a given text, the arithmetic mean of index measure of all sentences is called as 'Readability' of that text. Hence the general tool to classify a comprehensibility aimed features are number of words used in the text and 'mean readability' of the text.

III. Subjectivity: A subjective sentence gives very personal information about the product and an objective sentence lists the features of the product. After using the product, the normal reviewer will feel free in expressing their feelings about the product. So, normal reviews are likely to include more subjective sentences than shill reviews.

IV. Writing style: To express an opinion about a specific product, reviewer uses a particular style. Writing style consists of the use of sentiment words, deceptive words, tenses as well as punctuations in reviews. Main feature of writing style used by a researcher is 'Stylometry'. This is forensic technique especially for security research as it helps to detect authorship of unknown documents.

Michael P. O'Mahony et.al [11] addressed issues in the perspective of user generated product reviews. For easy purchase, product reviews have become an important asset to users that enables assessments of product quality. In particular, their focus was on features relating to the structure and readability of review texts, and examines the classification performance provided by these features.

Ee-Peng Lim et al [5] tried to find shill reviews generated by consumers. They made use of behaviors of review spammers by identifying their several characteristic. By using web based spammer evaluation software, they made a subset of highly suspicious reviewers for further processing.

Snehasish Banerjee et al [3] showed the difference between genuine and shill reviews in context of three textual features, like comprehensibility, informativeness and writing style. By collaborating multiple classification algorithms through polling, the analysis is done. Results verify that, reviews those are rich in nouns are expected to be genuine, whereas those rich in past tense, pronouns and articles are likely to be shill.

Jo Mackiewicz et al [20] stated that three characteristics of product reviews namely *Credibility, informativeness and readability,* positively affects review quality, and perceptions of quality is strongly influenced by the feature of informativeness, mainly a statement of the amount to which the product met the reviewer's expectations. These results imply that informativeness is the most important component of review quality perceived by users.

C. Machine Learning Techniques

Machine learning techniques were used frequently by past researchers to detect fake reviews [7]. Current research using supervised learning methods has been restricted to three learners: Logistic Regression (LR), Naïve Bayes (NB) and Support Vector Machine (SVM), even if there is a large number of machine learning algorithms (learners) available. Although SVM normally offered the best performance, it is rarely beaten by NB or LR, so it cannot be said as best learner.

Fan et al. [9] derivate a Statistical Opinion Analyzer (SOA) which extracts the polarity of online user reviews using NB classifier and frequency distribution. This framework makes it easy for a new consumer to buy a product and select manufacturer to increase the product's functionality. First, Reviews were crawled then pre-processed by GO tagger and inserted in SOA to find the positive and negative opinion probability with frequency distribution. This application gives promising results.

Tian et al. [10] devised a framework on Vietnamese reviews of mobile phones. By using HAC clustering and semi-SVMkNN classification synonym feature words were grouped. Opinion words along with weights have been used to extract feature words using pre-constructed adjective words and VietSentiWordNet. Then, positive, negative and neutral polarities have been extracted, which is based on the weights and are used for opinion orientation.

Ott et al. [12] conducted a more current study of deceptive opinion spam by using the same data and framework as they used previous; on the other hand, they restricted their scope to n-gram based features and only used the SVM classifier since it outperformed Naïve Bayes in their previous work. An accuracy of approximately 86% is achieved by using unigram and bigram term frequency features when considering only reviews with negative sentiment.

III. IMPLEMENTATION DETAILS

This section, explains the experimental evaluation of the proposed scheme.

To differentiate fake and normal review, it is required to measure the characteristics of shill reviews. There are methods to measure the features of a shill review. Figure 1 shows the block diagram of DFEM which is based in informativeness of a product feature.

A. Description-based feature extraction method :

The count of official and unofficial features in a review defines its Informativeness. Following steps are followed to find Informativeness of a review.

Steps:

1. Collect the target product technical description.
2. Crawl to get all reviews of the target product, the technical description and reviews of all relevant products in the same category as product under study.
3. Pre-process the reviews of the target product for POS tagging.
4. Extract nouns and noun phrases from the reviews of the target product and compare them with those found in product technical description of the target product.
5. If a term used in review is also used in the product description, then it can be identified as an official feature.
6. The terms which do not appear in the product description, go through a filtering process that uses the technological description of other products in the same category to recognize which terms represent unofficial features of the product.

DFEM performance is calculated by following performance measures.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$F = 2 \cdot \frac{precision.recall}{precision + recall} \tag{3}$$

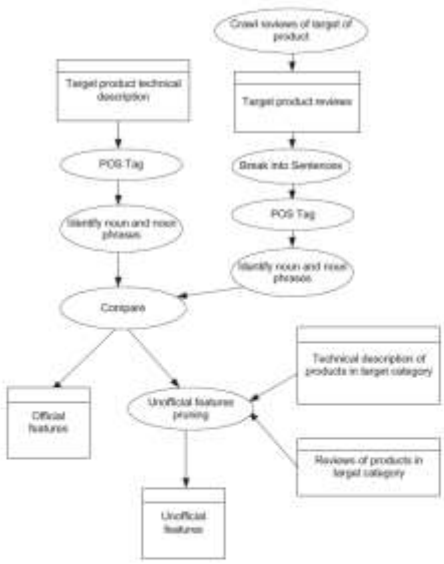

Fig.1: Description based feature extraction method

Readability is measured through following index measures:

1. The Fog Index:

The value range of the Fog Index is from 1 to 12. A lower Fog Index means more readable text. The Fog Index of each review can be calculated as follow:

$$Fog = 0.4 * \left\{ \frac{words}{sentences} + 100 * \left(\frac{complex\_words}{N(words)} \right) \right\} \quad (4)$$

2. The Flesch Kincaid or Flesch Reading Ease Index:

The value of this index is from 0 to 100, smaller scores indicating less readable text.

$$FK = 206.855 - 1.015 * \left(\frac{N(words)}{N(sentences)} \right) + 84.6 * \left(\frac{N(syllables)}{N(words)} \right) \quad (5)$$

3. The Automated Readability Index (ARI):

The value of this index is from 1 to 12, number indicates the grade level education needed to understand the text. For example, ARI = 5 requires the reader to have fifth grade education to understand the text. ARI can be calculated as follow:

$$ARI = 4.71 * \left(\frac{N(characters)}{N(words)} \right) + 0.5 * \left(\frac{N(words)}{N(sentences)} \right) - 21.43 \quad (6)$$

4. The Colemon-Liau Index (CLI)

The CLI ranges from 1 to 16 indicating the grade level education needed to understand the text.

$$CLI = 0.0588L - 0.296S - 15.8 \quad (7)$$

where,

L: number of characters per 100 words.

S: number of sentences per 100 words

5. Simple measure of Gobbledygook (SMOG)

A SMOG result also ranges from 1 to 12. SMOG is calculated as follow:

$$SMOG = 1.043 \sqrt{30 \frac{\text{Quantity of polysyllables}}{\text{Quantity of sentences}}} + 3.1291 \quad (8)$$

B. Dataset:

The dataset taken for this study requested named as Cell Phone reviews. This dataset consists of reviews from Amazon. The data duration is a period of 18 years, including 35 million reviews up to March 2013. Reviews consist of attributes like product and consumer information, ratings, and a plain text review.

C. Results:

From cell phone dataset, first 100 reviews are extracted to evaluate the performance with recall, precision and harmonic mean measures. Another dataset is created which contains negative reviews only with same category and product description.

In figure 2, classification of features is done on positive reviews and negative reviews, results shows that negative reviews contains less no of official features compared to positive reviews. It also specifies that positive reviews contain fewer unofficial features. This concludes that negative reviews are more authentic than positive one for a given dataset.

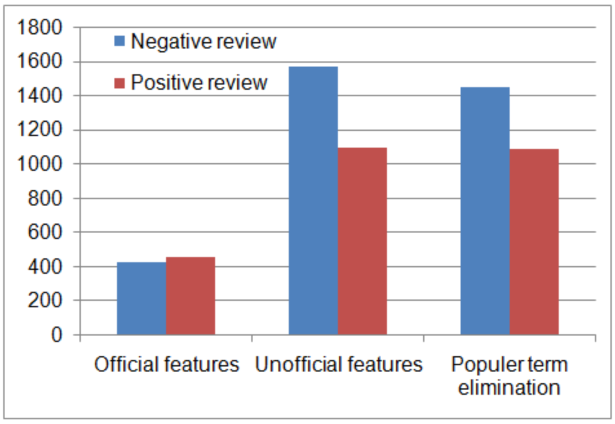

Fig. 2: Performance of DFEM

Readability is one of the effective measures to classify shill and normal reviews. Fog index is performance measure to calculate readability value of reviews. Fig 3 shows the fog index values for various reviews. Readable zone shows the reviews which can be read easily. By calculating fog index values for negative reviews, it shows that, 1 review is more readable than other 4 reviews.

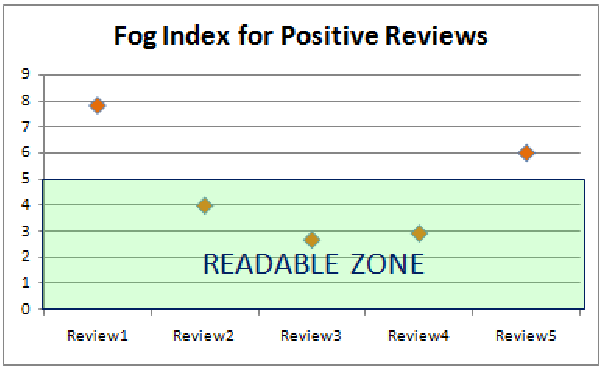

Fig. 3: Readability performance for negative reviews

IV. CONCLUSION AND FUTURE WORK

A general evidence of shill review is that, it is long enough and occurs frequently. Reason being, the spammer wants to grab attention of readers to official features of the target product or service. One can identify a shill review or reviewer based on the content of the review. Shill reviewer tend to use more objective features copied from the product/service specification sheet. On the other hand, a genuine or normal reviewer who also might have used the product/service by himself/herself tends to give more personal opinion hence being more subjective. As negative reviews are more likely to be shill, here for a given dataset, it showed that positive reviews are more fake than negative reviews.

Future work may focus on other methods which will measure other features like credibility, comprehensibility. Further there can some work done on identification of text polarity to identify shill reviews by using more representative dataset

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