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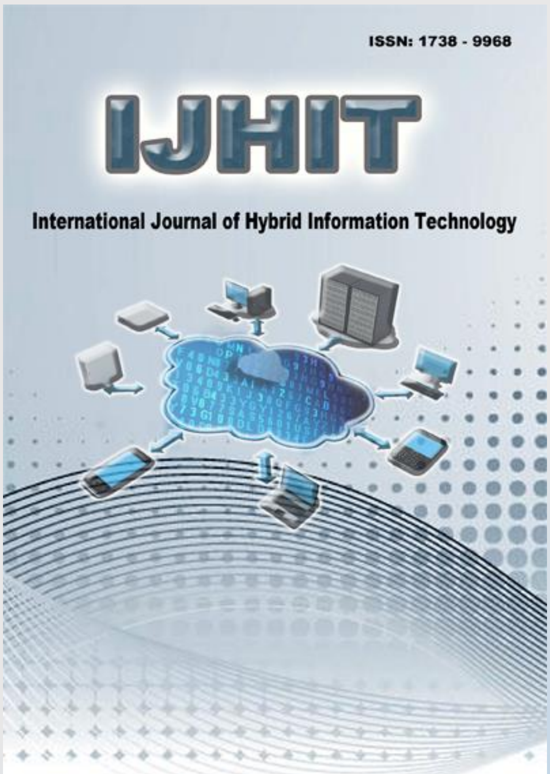

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Identifying Deceptive Opinion Spam using Aspect-based Emotions and Human Behavior Modeling

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Abstract

Online product reviews have become the major source of information for the end users to make purchasing decisions. Companies/individuals often hire people for writing fake reviews to increase the sale of their products. These individuals are known as opinion spammers and their activities are known as opinion spamming. Manually it is difficult for a human being to detect these deceptive reviews. Features play a major role to build effective deceptive reviews detection classifiers. We have observed human behavior through reviews, blogs datasets, and transferred these observations into features.Towards the end, we have built automated deceptive reviews classifiers using document level and aspect level domain independent features. We have performed our experiments in hotels domain. We achieved around 93 percent accuracy on Myle Ott's gold standard dataset [1] *and up to 86 percent accuracy on the self-crawled Yelp[1] dataset.*

Keywords*: opinion spamming, machine learning, subjectivity, linguistic, review based features, parts of speech*

1. Introduction

Opinion mining has been a growing field of research in the last decade. In this field, most of the research done was based on the assumption that all the reviews are authentic. While, not all online reviews are written by genuine users of products, so the outcome of opinion mining research may drift from the reality. Reviews and ratings have a direct monetary impact on products, organizations and companies. One study shows that one-star increase in Yelp rating leads to a 5-9 percent increase in revenue in hotels domain [2]. That's why Companies with malicious intentions are often indulged in hiring people to post fake opinions to promote or discredit target products, services or organizations.

This paper has mainly focused upon:

- Establishing a relation between opinion spam detection and various review-related behavioral features.
- Identifying several new features such as aspect-based emotion, formality and informality, authenticity and tone analysis. In our knowledge, no preliminary study has been reported on the application of these measures in opinion spamming domain.
- Showing a comparative study and analysis of different supervised methods and features on commercial dataset of spam reviews along with crowdsourced dataset.

The rest of the paper is organized as follows. The second section focuses on various works related to opinion spamming in consideration with different approaches. Section 3 explains the framework for automatic deceptive review classification. This section justifies the use of various features with their logical significance to detect deceptive opinions. This section also contains brief introduction of various supervised learning methods and the datasets that we have used in this paper. In the penultimate section *i.e.* Section 4, experimental details and results analysis have been done. The last section comprises of the conclusion along with the future work.

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2. Related Work

Opinion spam detection techniques mainly rely on three information source to extract the features: review text, reviewer characteristics and product information. Review text is a foremost source for information as other information is not available in most of the related datasets. In this area, the key challenges are a lack of proper review spam dataset and no access to spammers' identity to the analyst.

Initially opinion spam problem has been treated as duplicate review identification problem [3]. However, this assumption is not appropriate. Previous attempts for spam/spammer detection used reviewer's behaviors [4], text similarity and linguistics features [1] [5], review helpfulness, rating patterns, graph-based method [6], and temporal activity-based method [4].

One of the finest works in the field of deceptive opinion spam identification has been done by integrating psychology and computational linguistics by Ott *et al.* [1]. The author claimed that best performance was achieved by using psychological features along with unigrams by using linear support vector machine. Linear SVM yielded an F-measure of 86.1% and 89.3% respectively under 5-fold cross-validation framework. They have also contributed a large-scale publicly available gold standard data set for deceptive opinion spam research. This dataset contains 800 truthful and 800 deceptive reviews. Truthful reviews are crawled from TripAdviser[2]. While, to solicit deceptive reviews, they used anonyms online workers (knowns as turkers). These turkers were told to assume themselves as an employee in the marketing department of the company. They were paid one dollar to write each fake review for the hotels. We have also used this same crowdsourced dataset to perform our experiments.

As earlier studies suggest, ratings have a high influence on revenue. Higher rating results in higher revenue. Many companies are indulging in insidious practices to get undue benefits. Unfair and biased rating pattern has been studied in several previous works [7], [8]. In one of the approach author identified several characteristics behavior of review spammer and model this behavior to detect the spammer [4]. They derived an aggregated behavior scoring methods for ranking reviews according to the degree to which they demonstrate the spamming behavior. Their study shows that by removing reviewers with very high spam sources, the highly spammed products and product group has experienced significant changes in aggregate rating compared with removing randomly scored or unrelated reviewers.

Another approach may involve capturing the general difference of language usages between deceptive and truthful reviews [9]. This model tried to include several domain independent features that allow formulating general rules for recognizing deceptive opinion spam. They used part of speech (POS), psychological and some other general linguistic cues of deception with SAGE[10] and SVM model. The dataset used in this work include following domains, namely hotel, restaurant, and doctor. SAGE achieved much better result than SVM and were around 0.65 accurate in the cross-domain task. Another model that integrates some deep linguistic features derived from syntactic dependency parsing tree was proposed to discriminate deceptive opinions from normal ones [11]. They worked on Ott's data set and a Chinese data set and claim to produce a state of art results on both of the topics.

Opinion spamming can be done individually or may involve a group [12]. If it involves a group then it can be even more damaging as they can take total control of the sentiment on the target product due to its size. Their work was based on the assumption that a group of reviewers works together to demote or promote a product. The author has used frequent pattern mining to find a candidate spammer group and used several behavioral models derived from the collusion phenomenon among fake reviews and relation models.

Other interesting findings include rating behaviors [13], network-based analysis of reviews [13], topic models based approach [14], review burstiness and time-series analysis [15] [16] and reviewers with multiple user id's or accounts [17]. Apart from these techniques, some other recently proposed studies include machine learning based approaches [18]–[20] and hybrid approaches [21].

3. Automated Deceptive Review Classification

This section explains basic elements for deceptive spam classification framework which include feature identification, classification methods and datasets.

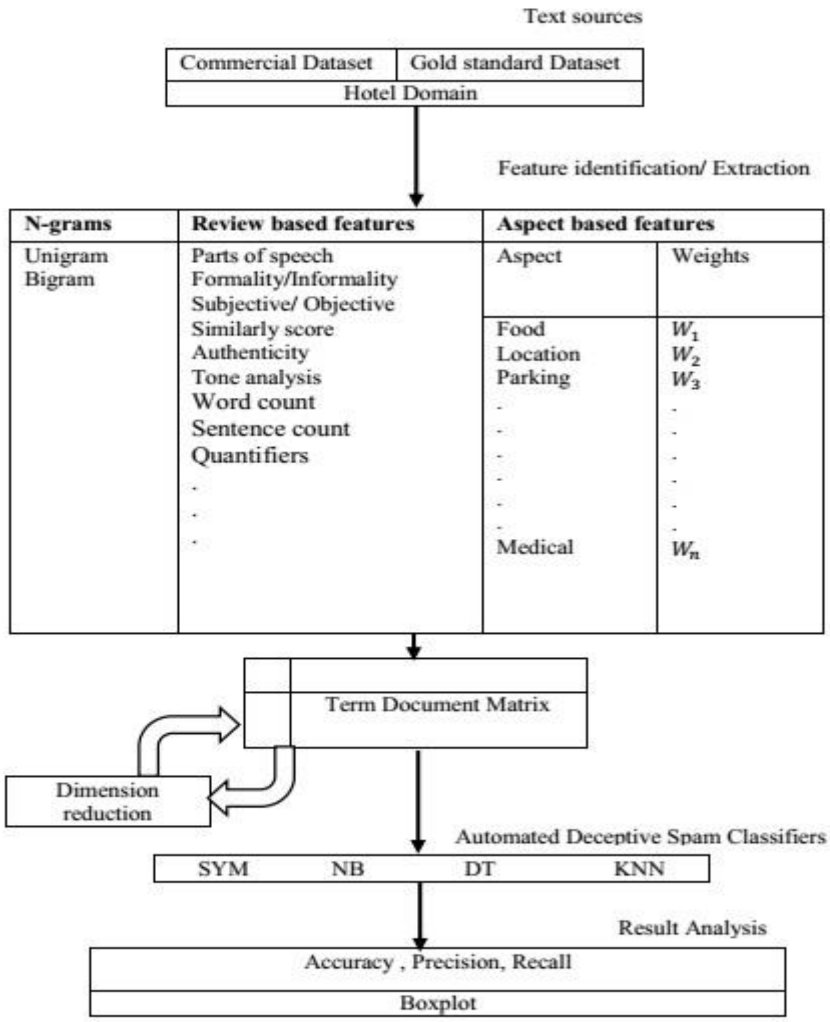

Figure 1. Framework for Automated Deceptive Review Classification

3.1 Feature Identification

Features play a vital role in opinion spam identification. In this work, we have used N-grams, various text-based characteristics and aspect based emotion score. These characteristic measures have been used as features of the review. All of these features is extracted using R packages (RtextTools, qdap, tm *etc*.) , internet slang dictionaries and Linguistic Inquiry and Word Count (LIWC)[22]. LIWC is a transparent text analysis program that counts words in psychologically meaningful categories.

3.1.1. N-grams (NG)

Unigrams (UG) and bigrams (BG) have been used to get the context of the review. Some generic preprocessing like removing stop words, extra white spaces have been done before generating DTM (Document-Term Matrix). Top UG and BG were filtered based on their term frequency and inverse document frequency score. Jointly we have referred UG and BG as N-gram(NG) in this paper.

3.1.2. Review Based Features (RBF)

Common Parts of speech: A different genre of text has a difference in POS distribution. To utilize this fact we have used common parts of speech such as noun, personal pronouns, impersonal pronoun, comparative and superlative adjectives, adverbs, articles *etc*. to differentiate between the deceptive and truthful reviews.

Quantitative Feature: A review with more factual numbers and fewer emotion words have higher chances of being truthful. Word count, sentence count, numbers (thousand, third) and quantifiers (many, few, much) is calculated and used as a quantitative text feature.

Formality and Informality score:

The concept of formality and informality can be used as a most important dimension of variation between linguistic expressions to distinguish between spam and non-spam reviews. Formal communication conveys information explicitly, through the linguistic expression itself, whereas informal communication conveys information implicitly. For example, the contextual expression "It is better than that" can be rephrased more formally as "Apple iPhone is better than Samsung Grand".

Nouns, adjectives, articles and prepositions are more frequent in formal styles; pronouns, adverbs, verbs and interjections are more frequent in informal/contextual styles.Formality score is calculated using part of speech tags of reviews. Informality score is calculated based on the internet words (lol, omg, ohh...), swear words (damm, shit, fuck), non-fluencies words(umm, hmm…) and filler words(uknow,imean…).

Subjectivity and Objectivity score: A subjective sentence expresses some personal feelings, views, judgments, or beliefs. Whereas an objective sentence states some factual information. The concepts of subjectivity and sentiment are not equivalent, although they have a large intersection.

Similarity score Cosine similarity score is calculated for each review with others. Highest cosine score is assigned as a similarity score for that review. Higher similarity value is often associated with high chances of spam review.

$$Similarity\ Score(r) = max\{Cosine(r, R_d)\} \tag{1}$$

$subject\ to\ 1 \leq d \leq n, where\ n\ is\ a\ positive\ integer.$

$$cosine(r, R) = \frac{\sum_{i=1}^{|V|} W_{ir} \times W_{iR}}{\sqrt{\sum_{|1|}^{|V|} W_{ir}^2} \times \sqrt{\sum_{i=1}^{|V|} W_{iR}^2}} \tag{2}$$

$$W_{ir} = TF_{ij} \times IRF_i \tag{3}$$

R_d is the set of reviews
W_{ir} is weight of i^{th} term in r^{th} review.
W_{iR} is weight of i^{th} term in R^{th} review.
TF_{ij} is the frequency of i^{th} term in j^{th} review.

$$IRF_i = \log(\frac{N}{rf_i}) \tag{4}$$

IRF_i is inverse Review frequency.
N is total number of reviews
rf_i is the number of reviews in which i^{th} term is present

Authenticity and Tone analysis Authenticity[23], and emotional tone [24] is calculated for each review and used as a review feature.

3.1.3. Aspect-based Emotions (ABE)

Products, organization and services have different aspects (features) for example in the case of hotels it may have aspects such as food, location, parking *etc*. Some aspects have a higher weight (importance) than others. By analyzing various reviews and blogs datasets, we have observed that opinion spammer goes extremely positive on highly weighted aspects to make an impact. But on the other hand go slightly negative on fewer significant aspects to sound authentic. We have extracted more than four hundred aspects and categorized them into different aspect categories. The polarity of each review in each aspect category is calculated and used as a feature. Table 1 shows few example of aspects and their respective category.

Table 1. List of Few Examples of Aspects and their Categories

Aspect Category	Aspects
Food	Breakfast, Lunch, Dinner, Snacks, Buffet, cuisines’
Location	Locality Place, View, Location, distance, sunset
Spacious	Spacious rooms, Comfortable bed
Internet	Internet, Wi-Fi, LAN
TV	LED, LCD, TV, Flat screen
Parking	Free Parking, Parking, Valet Service
Medical	Doctor on Call, Wheelchair Access
Car Wash	Car Service, Car Wash
Wake up Service	Wake-up Service
Fitness	Gym, Fitness Centre, therapies
Hygiene	Clean, Room Freshener, Hygiene
Pool	Indoor Pool, Outdoor Pool, Swimming
Currency	Currency Exchange, Money Exchange
Housekeeping	Staff, Housekeeping, ,
Reception	Front Desk, Customer Service, Desk Staff
Pets	Dogs, Cats, Pets
Casino	Casino
Meeting Room	Business service, Meeting room, Business, auditorium
Bath	Jacuzzi, Steam Bath, Sauna, Spa

3.2 Methods

We have used several supervised learning methods. Out of them support vector machine (SVM), NB (Naive Bayes), k-nearest neighbor (k-NN) and Decision Tree (DT) have performed better than the rest. Here we have given a very brief introduction to each of them.

SVM [25] is among the most powerful supervised technique for non-linear data classification. It tries to find optimal separating hyperplane between the classes. It uses kernel methods to map the data into higher dimensions using some non-linear mapping.

$$k(x,x^{'}) = (exp(-\|x-x_i\|^2 /2\sigma^2) \tag{5}$$

$$F(x) = \sum_{i=1}^{N} \alpha_i y_i (exp(-\| x - x_i \|^2 / 2\sigma^2) + b \qquad (6)$$

Subject to $0 \le \alpha_i \le c; i = 1,2...l$

Naïve Bayesian (NB) classifier is a probabilistic classifier based on Bayes rule. It relates the conditional probability to the inverse conditional probability. NB is based on the strong assumption of conditional independence in features given the review class.

k-NN is a supervised learning algorithm. The algorithm utilizes the distance metric (Euclidian, Manhattan distance *etc*.) to identify the k most similar reviews from a given review. Assuming k is an odd number, it then calculates the majority class (spam or non-spam) and assigns that class to that review.

C4.5 is used to implement DT. At each node of the tree, C4.5 chooses one attribute of the data that most effectively splits its set of samples into subsets enriched in one class or the other. It uses information gain to split the data at each node. Information gain is calculated for remaining attributes and then attribute with highest normalized information gain is used for node splitting.

3.3. Datasets

In this work we have used two datasets. One is a publicly available gold standard corpus of deceptive opinion spam given by Myle Ott [1]. This data set is generated through crowdsourcing and domain expert as discussed earlier. Another dataset we have crawled from Yelp. Yelp is a review hosting commercial site which publicly filters the fake reviews. Yelp's filtering algorithm has evolved over the time to filter deceptive and fake reviews. Yelp's filter has also been claimed to be highly accurate by a study in BusinessWeek [26] We have crawled 2600 truthful and 2600 deceptive/filtered reviews and both of these consist of 1300 positive and 1300 negative reviews. We have treated five-star rated review as a positive review and one star as a negative review. We have collected these reviews from hundred Chicago hotels. To maintain the class balance we have selected the same number of filtered and non-filtered reviews from each hotel.

4. Experiments and Results Analysis

We have simulated our experiments using R software. As all our methods are supervised in nature so dataset is divided into training and testing sets. We have used 5-fold nested cross-validation for evaluating classifiers. Micro-average precision and recall are computed as micro-averaging gives equal weight to each per-document classification decision.

We have taken SVM accuracy of unigrams and psychological features as baseline [1]. Table 2 has shown the result for the gold standard dataset in hotel domain and Table 3 is showing the results for Yelp dataset. Clearly the experiments show that SVM and NB are performing better than other methods. Quite surprisingly even though the assumption for independent features doesn't hold but still NB is giving very competitive results. We got our best results by using review related features and aspect based emotions with n-grams on SVM. We got comparatively poor results if we didn't consider n-grams which clearly shows the need for considering the context of the review.

Table 2. Automated Classifiers 5-Fold Cross-Validation Accuracy Averaged Over Ten Runs For The Gold Standard Dataset. Boldface Indicates the Highest Value In Respective Rows

Strategy	Feature set	SVM	NB	KNN	TREE
Baseline	NG, LIWC	89.64			
Text Classification	UG	**88.40**	87.58	82.23	83.14
	UG, RBF	90.67	**90.81**	86.23	85.14
	UG, RBF,ABE	**92.17**	91.43	88.22	87.13
	NG	**89.33**	88.21	83.89	84.64
	NG, RBF	91.31	**91.67**	87.44	86.04
	NG, RBF,ABE	**93.04**	92.69	90.09	89.59

The highest individual accuracy is achieved by all the classifiers using N-grams, Review based features and aspects based emotions. Two tail t-test has failed to find any significant difference in baseline accuracy and KNN, DT best accuracies on the gold standard dataset (two-tailed t-test p=0.045). But on Yelp we have noticed a significant improvement by both of these classifiers (two-tailed t-test p=0.012) in compare to baseline accuracy.

To analyze the result better we have to check the impact of the individual features set. Deceptive spammers have more emphasis on emotions rather than facts compare to truthful reviewers. That's why we can clearly observe the difference in facts, numbers and subjectivity scores. In the case of the similarity score the difference was quite significant in Yelp dataset but not much in the gold standard dataset. The reason might be that, every reviewer was told to write only one review in Ott's dataset, while in Yelp dataset we have reviewers who have written more than one review.

Deceptive opinion detection problem can also be treated as genre identification task. Various linguistic studies have shown a difference in POS distribution and formality/informality scores to distinguish different genre. POS along with Formality and informality score alone has secured 75.30 % accuracy for Ott's dataset and 69.55 % accuracy for Yelp dataset.

Table 3. Automated Classifiers 5-Fold Cross-Validation Accuracy Averaged Over Ten Runs For Yelp Dataset. Boldface Indicates The Highest Value In Respective Rows

Strategy	Feature set	SVM	NB	KNN	TREE
Baseline	NG, LIWC	78.82			
Text Classification	UG	**73.87**	72.18	68.23	70.88
	UG, RBF	**79.58**	79.09	74.23	73.90
	UG, RBF,ABE	**83.84**	82.16	79.22	78.55
	NG	**75.13**	74.88	70.19	71.12
	NG, RBF	**82.11**	81.17	75.44	74.41
	NG, RBF,ABE	**85.84**	84.64	82.49	80.29

We can see in Table 4 that in the case of using aspect based emotions, both precision and recall are higher for positive reviews compare to negative once. It shows the general behavior of deceptive spammer that Spammers who target the different aspects of the product, generally write to promote the product rather than demoting it. As we can see in Table 5 also the same behavior follows even for Yelp dataset.

Table 4. Micro-Averaged Precision, Recall and F-Score For Top Performing Classifier For Each Strategy and Corresponding Feature Set On Gold Standard Dataset

			Positive		Negative	
Feature set	Classifier	Accuracy	Precision	Recall	Precision	Recall
UG	SVM	88.40	89.20	87.50	87.80	85.30
UG, RBF	NB	90.81	91.19	89.17	89.44	87.80
UG, RBF, ABE	SVM	92.17	95.13	94.70	89.60	89.23
NG	SVM	89.33	90.16	91.56	88.50	84.83
NG, RBF	NB	91.67	92.21	90.8	90.80	88.05
NG, RBF,ABE	SVM	93.04	95.76	92.65	89.90	89.82

Table 5. Micro-Averaged Precision, Recall and F-Score For Top Performing Classifier For Each Strategy and Corresponding Feature Set On Yelp Dataset

			Positive		Negative	
Feature set	Classifier	Accuracy	Precision	Recall	Precision	Recall
UG	SVM	73.87	74.90	73.22	72.73	70.32
UG, RBF	SVM	79.58	81.90	79.71	77.21	75.15
UG, RBF, ABE	SVM	83.84	88.33	83.46	77.83	74.13
NG	SVM	75.13	77.26	77.16	72.90	70.93
NG, RBF	SVM	82.11	83.21	83.10	81.10	80.55
NG, RBF,ABE	SVM	85.84	90.16	91.15	81.10	76.52

Boxplots below are showing a comparative analysis of all classification models for gold standard and yelp dataset respectively. A significant difference has been noticed in SVM (two-tailed t-test p=0.0045), NB (two-tailed t-test p=0.03) compare to baseline accuracy as shown in Figure 1. While two tail t-test couldn't be able to find any significant difference in KNN and DT compare to baseline accuracy for Ott's dataset. In the case of Yelp dataset we have seen a significant difference for all the classifiers SVM (two-tailed t-test p=0.001), NB (two-tailed t-test p=0.004), KNN (two-tailed t-test p=0.0045) and DT (two-tailed t-test p=0.06) compared to baseline accuracy as shown in Figure 2.

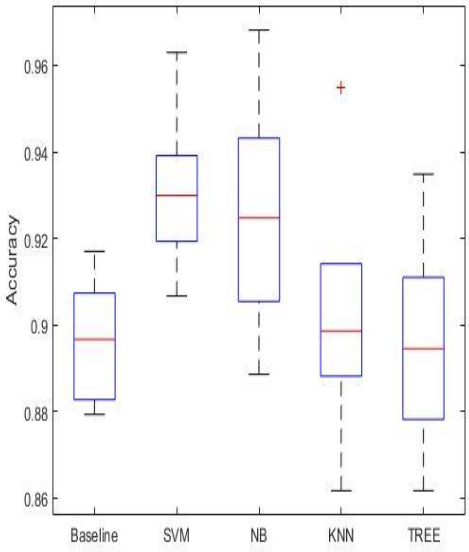

Figure 2. 10-Fold Cross-Validation Accuracy For Each Classifier On Gold Standard Dataset

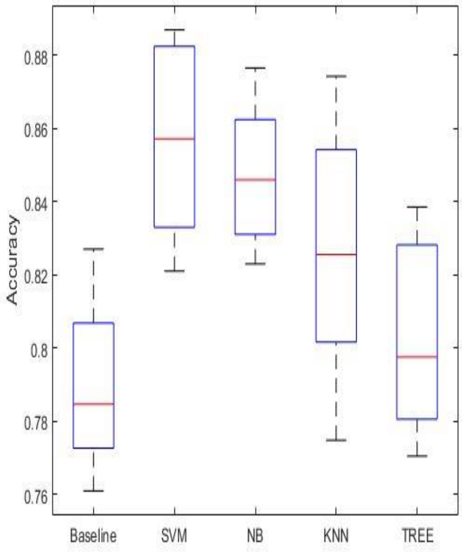

Figure 3. 10-Fold Cross-Validation Accuracy For Each Classifier on Yelp Dataset

5. Conclusion and future work

In this paper, we have trained automated classifiers using review related domain-independent features. To the best of our knowledge many features such as aspect based emotions, formality and informality score have never been used before for finding opinion spams. We have shown a comparative study of machine-learning algorithms with respective feature sets.This paper made many theoretical contributions and contrasted some deceptive assumptions and also strengthen many.

Spammers are getting smart every day that's why for future, both domain specific and independent deceptive clues needed to be discovered. One of the possible future direction to evaluate these deception clues to other domains.

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