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Ontology based sentiment analysis for fake review detection

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ABSTRACT

Majority of customers and manufacturers who tend to purchase and trade via e-commerce websites primarily rely on reviews before making purchasing decisions and product improvements. Deceptive reviewers consider this opportunity to write fake reviews to mislead customers and manufacturers. This calls for the necessity of identifying fake reviews before making them available for decision making. Accordingly, this research focuses on a fake review detection method that incorporates review-related features including linguistic features, Part-of-Speech (POS) features, and sentiment analysis features. A domain feature ontology is used in the feature-level sentiment analysis and all the review-related features are extracted and integrated into the ontology. The fake review detection is enhanced through a rule-based classifier by inferencing the ontology. Due to the lack of a labeled dataset for model training, the Mahalanobis distance method was used to detect outliers from an unlabeled dataset where the outliers were selected as fake reviews for model training. The performance measures of the rule-based classifier were improved by integrating linguistic features, POS features, and sentiment analysis features, in spite of considering them separately.

1. Introduction

With the vast expansions of the Internet, people tend to engage in online shopping. The fact that there is no limitation over the Internet encourages anyone to buy and sell via e-commerce websites and write ideas about the products themselves. These opinions emphasize positive or negative attributes of online products which in turn influence prospective purchasing decisions and product enhancement decisions. However, due to the rapid increase of reviews, it is quite tedious and time-consuming to read reviews one by one, and to comprehend the customer sentiment and product features highlighted therein. Most of the time, people hardly read the whole review, yet assess the individual rating, overall rating, or feature-level summaries of a particular product. Hence, people are highly interested in the regular analysis of reviews through sentiment analysis rather than manual reading.

Sentiment analysis or opinion mining is an area of Natural Language Processing (NLP), computer linguistics, and text mining (Ganeshbhai & Shah, 2015). An opinion is a personal view on a specific product or a specific product feature thereof, which is expressed as positive, negative, or neutral. Sentiment analysis is the process of identifying the polarity/sentiment or sentiment orientation of the expressed opinions (Ganeshbhai & Shah, 2015). Sentiment analysis evaluates people's opinions, evaluations, sentiments, attitudes, appraisals, and emotions on what they are commented on (Liu, 2010). The primary aim of the sentiment analysis on customer reviews is to identify the polarity of review content (Sasikala & Mary Immaculate Sheela, 2020). It determines the subjectivity, polarity (positive/negative), and polarity strength (weakly positive, mildly positive, or strong positive) of an opinion text (Alonso et al., 2021; Mars & Gouider, 2017).

The basic task of sentiment analysis is to classify the polarity of the review as positive, negative, or neutral. There are three different stages for performing sentiment analysis at sentence-level, document-level, or product feature-level (Pawar, 2015). The sentence-level sentiment analysis classifies a sentence as neutral, positive, or negative. Document-level sentiment analysis classifies the entire document which consists of many neutral, positive, or negative sentences. The feature-level sentiment analysis considers the related product features of each sentence and determines the overall polarity of the review and is thus considered a product feature-wise opinion of the reviewer. Such feature-level sentiment analysis is quite essential for manufacturers as it monitors the reviews regarding numerous product features which enables them to enhance product quality. Feature-level sentiment analysis aims to extract product features from reviews and then determine associated opinions of each feature (Quan & Ren, 2016). Compared to all stages of performing sentiment analysis, feature-level sentiment analysis is able to provide accurate sentiment on certain opinion targets (Hu & Liu, 2004).

Feature-level sentiment analysis involves product feature extraction and feature-level opinion determination (Quan & Ren, 2016). Although

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several methods were proposed to deal with feature extraction and opinion identification in feature-level sentiment analysis, they either rely on labeled datasets or failed to extract features in different domains. As well, the extracted features may be different based on the domain. As a result, this research used a domain ontology-based approach for feature extraction and opinion determination in feature-level sentiment analysis.

Reviewers who tend to write reviews with the purpose of misleading customers are considered fraudulent reviewers. Such fake reviews affect the overall sentiment generated by reviews in general. These reviewers may write fake positive reviews to promote or fake negative reviews to demote products' reputation (Vidanagama et al., 2021a). Customers may get a bad impression of products if they are deceived by spam reviews. Accordingly, fake reviews have the potential to deceive customers and create a negative impression on products, thereby destroying the customer base of any producer. Always, polarity and excitement are used by reviewers to misdirect readers (Alonso et al., 2021). Consequently, sentiment analysis provides details on the review content related to its trustfulness or fake (Alonso et al., 2021). Therefore, sentiment analysis is a powerful and useful tool which can be used in fake review content identification.

Research used different review-related features for fake review identification such as Part-Of-Speech (POS) features, linguistic features, and metadata features (Abri et al., 2020; Fontanarava et al., 2017; Mushtaq et al., 2016; Sun et al., 2016). The major contribution of this paper is to incorporate feature-level sentiment analysis along with POS features and linguistic features for fake review detection. The ontology-based approach is used for feature-level sentiment analysis. Thus, it is of vital importance to find the sentiment preference and overall sentiment of the reviews using the feature-level sentiment analysis method. Most specifically, the opinion targets are extracted while calculating the sentiment orientation and overall sentiment using domain feature ontology. The proposed system can be used by a broader user base including the customers who wish to make purchasing decisions and manufacturers who wish to analyze the customer reviews on a particular product. The system automatically classifies the customer reviews as truthful or fake when the user requests to analyze the reviews on a particular product in the domain. The users no need to have expert knowledge on incorporated technologies although they can view results.

The remainder of the paper is organized as follows: Section 2 discusses the related research work in the area of fake review detection. Section 3 discusses the proposed approach of integrating ontology-based feature-level sentiment analysis for fake review detection. Section 4 includes the experiment and evaluation of the fake review detection method using the Amazon unlocked mobile phone review dataset. Finally, Section 5 concludes the paper with the conclusion and future research directions.

2. Related work

Since anyone can write reviews over a product with the identity or anonymously, some people write fraud reviews to deceive customers or organizational decision-makers to achieve significant monetary benefits or business advantages (2X ECommerc, 2014). The opinions written to downgrade or promote the reputation of any product are called 'spam reviews' or 'fake reviews' (Jindal & Liu, 2008). Jindal and Liu (2007) categorized spam reviews into three types, including false opinions (type 1), brand-only reviews (type 2), and non-reviews (type 3). Type 1 reviews contain hyper-spam and defaming spam reviews. Hyper reviews are positive spam reviews used for promoting products, and defaming reviews are negative spam reviews used for demoting the products. Type 1 reviews are considered deceptive reviews, which are very harmful and difficult to detect. Type 2 reviews do not comment on the product but comment only on the brand. Type 3 reviews do not contain any opinion and do not serve the purpose of reviews such as advertisements, questions or answers, and comments or random text (Jindal & Liu, 2007). These kinds of reviews are considered destructive reviews. These types of reviews may change the aggregate ratings of the product as the ratings for reviews are randomly assigned. Therefore, detection of fake reviews has become a big concern nowadays to authenticate online reviews and increase consumer belief.

Existing approaches of type 1 (fake reviews) review detection methods can be classified into three major categories such as machine learning approaches, network-based approaches, pattern-mining approaches, and rule-based approaches (Vidanagama et al., 2020). The machine learning approach consists of supervised learning which requires labeled training data, unsupervised learning which requires for which a set of unlabeled data is necessary and semi-supervised learning which requires a relatively small set of labeled data supplemented with a large amount of unlabeled data (Vidanagama et al., 2020). Generally, the review content, author behavior, and combinations of these two are considered when applying machine learning techniques.

In terms of unsupervised learning methods, Mukherjee et al. (2013) used the Bayesian clustering method in which their model considered the degree of spamming of authors and reviews using the Latent Spam Model (LSM). In addition, Lin et al. (2014) calculated a score value using weight parameters which turn the contributions of the feature set and identify untruthful reviews using a threshold value. Further, Singh (2015) utilized the unsupervised K-Nearest Neighbor (KNN) method to detect the outliers of reviews based on the review, reviewer, and product-centric features. While, Wang et al. (2011) incorporated a review graph-based approach to capture relationships among reviewers, reviews, stores, items, and group reviewers to identify the fake reviews, Xie et al. (2012) introduced an approach that maps the singleton review spam detection problem to an abnormally correlated temporal pattern-detection problem. Further, Li et al. (2014) also considered meta-data patterns, both temporal and spatial patterns when detecting untruthful reviews and certain other authors used outlier detection methods to categorize the reviews as spam or truthful (Liu et al., 2019; Rout et al., 2017; You et al., 2020). Outlier detection is a prominent data analysis concern that focuses on identifying anomalies in datasets (Chatterjee et al., 2021). Also, it was used in a wide range of applications in fraud detection, fault detection, and intrusion detection (Afzal et al., 2021). It helps recognize an entity that prominently differs from most of the samples in a dataset. Such entities may represent frauds, spam, defects, and errors in a dataset (Chatterjee et al., 2021).

The existing techniques for outlier detection are broadly categorized into four approaches including statistical distribution-based approaches, distance-based approaches, density-based approaches, and subspace-learning based approaches (Afzal et al., 2021). Statistical distribution-based approaches consider a distribution or probability model for the given dataset whereas most of such approaches are designed for univariate datasets. These statistical parameters may influence the results of outlier detection. Density-based approaches have high computational complexity whereas subspace-learning based approaches can be used for massive high-dimensional datasets (Afzal et al., 2021). The distance-based approaches compute distances from the largely available data points to mean value, and is useful for multivariate datasets with massive data points (Afzal et al., 2021).

You et al. (2020) proposed an aspect-rating local outlier factor model (AR-LOF) to identify the spam reviews. They used the LOF algorithms in Sklearn which is an unsupervised anomaly detection algorithm. Also, Liu et al. (2019) detected the outlier reviews of products based on the reviewing records of reviews and comments using an isolation forest algorithm. Similarly, Algur et al. (2016) used an outlier detection technique GARCH (1, 1) is to find review spamicity.

The classical Mahalanobis distance is a common distance-based method for detecting outliers. It is calculated on the sample mean vector and sample covariance matrix. Since the classical mean vector and covariance matrix algorithms are sensitive to outliers, the classical Mahalanobis distance is also sensitive to outliers (Li et al., 2019). Therefore, this research is also selected the Mahalanobis distance method to prepare the testing dataset with outliers as fake reviews.

According to the literature on the subject, various limitations were identified among supervised and semi-supervised approaches used for fake review detection (Saumya & Singh, 2018). Firstly, the manually labeled dataset of fake and non-fake reviews can often be inaccurate. Secondly, the labeled spam review data for model training is scarce. In addition, it was proved that fake reviews dataset generated through crowdsourcing mechanisms may not be valid training data because the models do not generalize well on real-life test data (Lin et al., 2014). Therefore, this research is focused on a fake review detection mechanism without using labeled datasets.

The effectiveness and accuracy of any fake detecting algorithm depend on the input features provided to that algorithm (Rastogi & Mehrotra, 2017). Therefore, most of the researchers focused on correctly identifying diverse kinds of features when deciding on fake reviews. They often consider different characteristics (features) of fake reviews related to reviews and reviewers who generate them. The literature showed that the usage of features can lead to effective identification of fake contents and/or fake reviewers' behaviors (Fontanarava et al., 2017). Based on the features studied, the existing research can be divided into content-based spam filtering, behavior-based spam filtering, product information-related spam filtering, and spammer groups-based spam detection methods (Cardoso et al., 2018). Most of the research focused on content-based spam filtering approaches (Harris, 2012; Jindal & Liu, 2007; Ott et al., 2011; Vidanagama et al., 2021a). Therefore, this research focuses on review-related features combining content-related features and review meta-data for fake review detection.

Considering content-related features, Newman et al. (2003) investigated the linguistic style features which distinguished between true and false content. He argued that the deceptive communications were characterized by a less number of first-person singular pronouns (I, my, me), third-person pronouns (she, their, them, he) and exclusive words, yet higher frequencies of negative emotion words and motion verbs (walk, move, go). Concerning identifying fake content, Li et al. (2014) argued that POS features of the content can be used to distinguish between fake and truthful content since genuine content comprises more nouns, adjectives, prepositions, conjunctions, and determiners, whereas fake content tends to have more verbs, adverbs and pronouns. Moreover, verbose content which comprises more questions, negative emotion words, pronouns, and fewer first-person singular nouns, exclusive words, negation terms, and causation words (because, hence, effect) may lead to being fake (Hancock et al., 2007). In the same vein, Ong et al. (2014) showed that genuine reviews are highly readable, less complex, and use more subjective statements to express personal opinion by using more pronouns, while deceptive reviewers use more objective sentences. By employing readability as a measurement for writing style, Harris (2012) proposed a lower readability index for fake reviews in comparison with truthful ones. He found that honest reviewers write descriptive reviews, whereas spam reviewers write generic reviews to be able to reuse their text. These researchers analyzed different writing styles and linguistic features used by fraudulent reviewers and those can be incorporated into this proposed fake review detection method.

Apart from these writing patterns, the reviewers can express their opinions in the content of the review and provide a rating on the product based on the overall sentiment. Review rating is the sentiment orientation representation of a review. Sometimes, the rating does not sufficiently represent the sentiment orientation of reviews, for, at times, there may be certain negative sentiment-oriented reviews with higher ratings and positive sentiment-oriented reviews with lower ratings. Therefore, the sentiment of the review and the assigned rating does not always seem to be clear and consistent each other (Maks & Vossen, 2013). Although the ratings and sentiments are highly correlated, the inconsistency between them is more significant in fake reviews (Shan et al., 2018).

Further, there could also be two reviews with the same ratings, yet different sentiment orientations. It is argued that the rating of the review may be consistent with the sentiment of review text published by the same user (Zhang, Cheng, et al., 2011). According to the observations regarding the rating score and the content of the reviews, there can be many reviews in which the rating and the sentiment score are inconsistent with each other (Ganeshbhai & Shah, 2015; Peng & Zhong, 2014). Consequently, it can be argued that both the content of a review and the rating is highly important when analyzing fake reviews. Thus, Heydari et al. (2016) proposed a spam detection method by incorporating content similarity, rating deviation, and activeness of reviewers in a specific period and assigning a spam score value. Furthermore, sentiment analysis techniques are incorporated in spam detection by computing the sentiment score and then combining the discriminate rules from the abnormal time windows (Peng & Zhong, 2014).

The sentiment-related features can be extracted through sentiment analysis. The user-generated content over a product expresses the reviewers' opinion, the analysis of which is a significant task of sentiment analysis. Sentiment analysis aims to determine the attitude of the reviewer concerning a certain product feature or overall polarity of the review. Accordingly, the basic task of sentiment analysis is to categorize the polarity of the review at sentence-level, document-level, or product-feature-level into positive, negative, or neutral (Pawar, 2015). In contrast to feature-level sentiment analysis, both document-level and sentence-level analysis are not significantly discover exact opinions on product features (Joshi & Itkat, 2014).

Therefore, the feature-level sentiment analysis is important, when analyzing the opinions expressed on the product features. A critical aspect involved in feature-level sentiment analysis is product feature extraction (Zhang, Yu, et al., 2011). In earlier research, association rule mining (Hu & Liu, 2004), pair-wise mutual information (Popescu & Etzioni, 2005), language model approach (Scaffidi et al., 2007), pattern mining (Li et al., 2015), and bootstrapping iterative learning strategy (Wang & Wang, 2008) were used in product feature extraction in feature-level sentiment analysis. Recently, double propagation method, Conditional Random Fields (CRF), Maximum Entropy Models (ME), topic modeling, and clustering (Zhang, Cheng, et al., 2011). On the other hand, most of the researchers (Alkadri & Elkorany, 2016; Freitas & Vieira, 2019; Vidanagama et al., 2021b; Wang et al., 2003) used domain ontology-based method to capture the features in reviews. The ontology-based approach does not require a training dataset for feature extraction (Vidanagama et al., 2021a). Freitas and Vieira (2019) used the domain ontology for feature identification and sentiment lexicons and linguistic rules for polarity identification. Aboelela et al. (2021) extracted the product features using semantic similarity and WordNet ontology and uses the SentiWordNet dictionary to classify the users' comments as positive and negative. Vidanagama et al. (2021b) also used an ontology-based feature extraction method and utilized SentiWordNet and PMI value to find the sentiment orientation of each opinion word. Taking into consideration the above mentioned findings, the authors of this paper suggest incorporating the ontology-based feature-level sentiment analysis method for fake review identification, without using a manual labeling dataset for model training.

3. Proposed methodology

Due to the complexity of the problem of fake review identification, the overall system process is broken down into smaller manageable modules. Initially, the reviews are pre-processed for cleaning and further processing. Later, product feature and opinion extraction, Sentiment analysis, and content-based feature extraction are performed with the support of ontology. Finally, the fake reviews are detected based on the extracted features. The proposed methodology for detecting fake

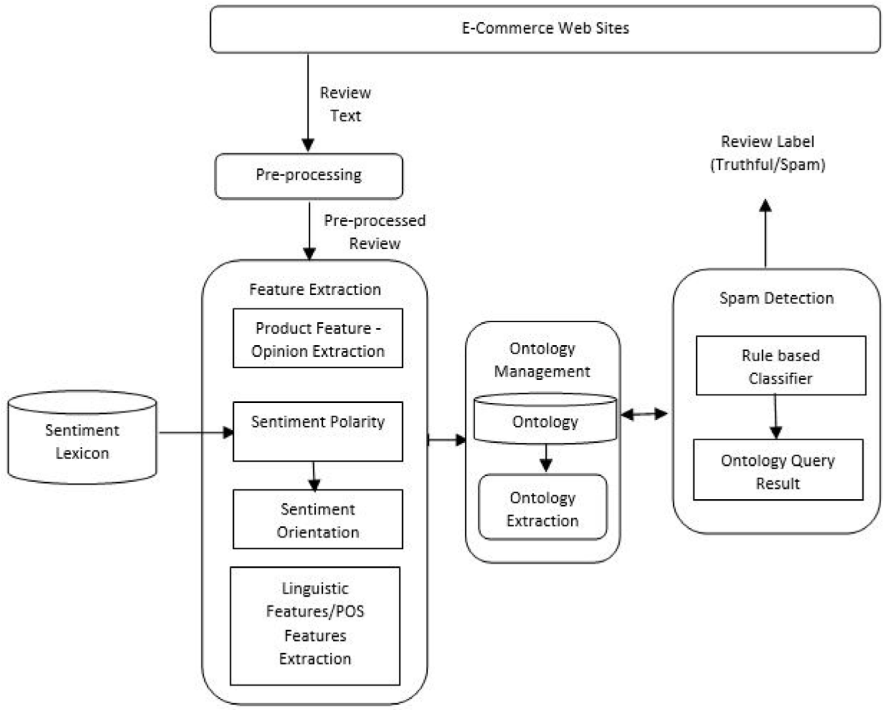


Fig. 1. Proposed Fake Review Detection Model.

reviews, shown in (Fig. 1), consists of four main modules: (1) Pre-Processing (2) Feature Extraction, (3) Ontology Management, and (4) Spam Detection. This can ideally be used by any e-commerce related website to detect fake reviews. The following sub-sections illustrate each module in brief.

3.1. Pre-processing module

Reviews may contain numerous irrelevant characters as well as unwanted and incorrect wordings. The proposed module is responsible for eliminating unnecessary words and characters, sentence splitting, spell correction, stop word elimination, tokenization, POS tagging, lemmatization, and dependency parsing (Fig. 2). The dependency parsed sentence which is the output of this module is used when extracting relevant product features and opinions in the extraction module. These pre-processing tasks have been implemented in Python language using Python libraries.[1]

- Sentence splitting: Generally reviews consist of many sentences. The product feature–opinion pairs are extracted sentence-wise. Therefore, initially, the reviews are split into multiple sentences using delimiters.
- Tokenization : Tokenization breaks up the sentences into words by removing white spaces and other symbols.
- Lemmatization : Mapping the words into their original form or to a single meaningful term. This is vital when identifying the words as opinions or product features.
- POS tagging : After the tokenization, a lexical is assigned to each word such as noun, verb, adjective, and adverb. POS tagging is quite essential to determine product features and opinion pairs.
- Dependency Parsing: Finally, a lexical category is assigned to each word based on the relationship between the words. This is used to identify the opinion words associated with each product feature.

3.2. Ontology management module

Ontology is a common vocabulary of relations among concepts of a specific domain. The product feature extraction process is accelerated by mapping the extracted product features with the feature words related to ontological concepts. Extraction of sentiment analysis features and filtering of fake reviews are done through the ontology. Fake reviews on different domains can be filtered through the replacement of domain ontology. Although there are various tools available for developing ontologies like Hozo, DOML, AltovaSemantic Works, etc (Jain & Singh, 2013), the widely used ontology development editor Protégé[2] is used to develop the proposed ontology. This ontology consists of concepts such as Feature, OpinionWords, Review, Product, and Sentence (Fig. 3(a)). While the feature class consists of sub-classes of specific features of the respective product, the domain-specific product features and synonyms of features are incorporated into it. Further, each product feature has a data property on sentiment expectation which contains an integer of either −1 or 1. OpinionWords class, on the other hand, contains the instances of opinion words extracted by SentiWordNet mapping (Baccianella et al., 2010). While the Review class contains the ontological instances of reviews, th Sentence class comprises the ontological instances of sentences in the reviews. All the concepts are associated with object properties (Fig. 3(b)) and data properties (Fig. 3(c)) which can be used for diverse purposes. The ontology can be renewed with recently identified features to accurately perform sentiment analysis and fake review detection. The ontological instances and related properties are updated according to the addition of new reviews.

3.3. Feature extraction module

This module plays a major role in the extraction of appropriate features which finally effect the accuracy of the result in fake review detection. Among all of the identified review-related features discussed

[1] https://www.nltk.org/

[2] https://protege.stanford.edu/

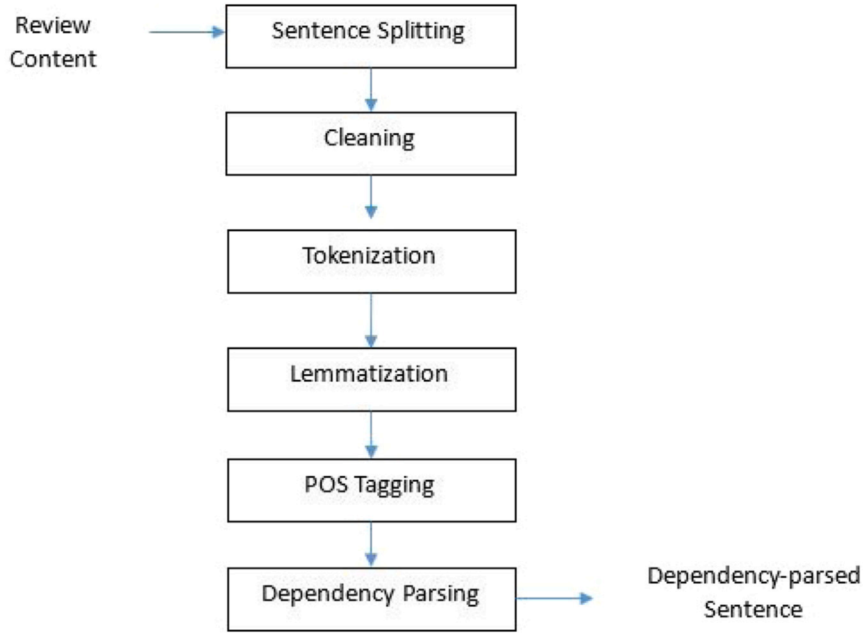


Fig. 2. Pre-processing module.

(a) Ontology Concepts (b) Object Properties

(c) Data Properties

Fig. 3. Mobile Phone Ontology.

in Section 2, along with some new features constitute a further contribution of the paper. Feature Extraction module comprises of three processes: Product feature and opinion extraction, Sentiment analysis, and Content-based feature extraction.

3.3.1. Product features and opinion extraction

In each review, customers express their view on a product, based on different features of the particular product. The product features and the opinions are extracted during this process and, usually, each product feature is a noun or a noun phrase. The features and opinions on the candidate product can be easily extracted by following a rule-based strategy. The rules are derived using dependency parsing and POS tag patterns (Vidanagama et al., 2021a). Even though all the extracted candidate product features are nouns/noun phrases, most of the extracted candidate nouns/noun phrases may not be related to the domain. Therefore, a feature score value is calculated (Eq. (1)) to reduce the number of candidate product features which will then be mapped with the ontology (Vidanagama et al., 2021b).

The $product\ feature\ score$ value is calculated using an existing domain-specific corpus of reviews. Here, x is the candidate product feature y_i is the existing product feature of the ontology, $f(x, y_i)$ is the number of times the feature x and y_i co-occur in each sentence, $f(x)$ is the number of sentences in the corpus where x appears and N is the total number of sentences in the corpus.

$$Product\ Feature\ Score = \sum_i \frac{f(x, y_i)}{f(x)f(y_i)} N \tag{1}$$

Candidate product features possessing a product feature score value greater than 1 can be selected as eligible features, failing which, the candidate product feature is disregarded. Firstly, the selected candidate product features are mapped with the product feature concepts of the ontology. Secondly, if such a product feature cannot be mapped with the ontology concept, all possible synonyms are to be extracted from the WordNet database (Fellbaum, 1998) and the synonyms will be mapped with the ontological concept. Thirdly, in a case where any eligible product feature cannot be mapped to an ontology concept directly or via synonyms, that particular product feature is required to be added under a selected subcategory that has gained the highest PMI value among all the subcategories (Eq. (2)) (Vidanagama et al., 2021a). Here x is the candidate product feature, S_i is the ith subcategory among the features of the ontology and N is the number of review sentences. $GoogleHitsCount(x, S_i)$ is used to calculate the co-occurrence hit count of the candidate product feature and the ontology feature sub category within the Google search engine. While $GoogleHitsCount(x)$ is used to calculate the Google search engine hit count of the candidate product feature while $GoogleHitsCount(S_i)$ is to calculate the Google search engine hit count of the feature sub category.

$$PMI(x, S_i) = \log_2 \frac{GoogleHitsCount(x, S_i)}{GoogleHitsCount(x) \times GoogleHitsCount(S_i)} \times N \tag{2}$$

Reviewers express opinions against the features of products. The opinion extraction process is following a rule-based strategy, based on the POS tag pattern and the type of dependency relation which is identified from Stanford Dependency Parser (Klein & Manning, 2003). Mostly the opinion may be an adjective, verb, or adverb (Vidanagama et al., 2021b). Then the extracted candidate opinions are compared with the SentiWordNet opinion words extract the real opinions. If the candidate opinion word exists in SentiWordNet, then it is selected as an eligible opinion word associated with the product feature. These opinion words may sometimes be combined with adverbs (ex: very, quickly, extremely, slowly, etc.) or negation words (ex: no, never, nothing, without, etc.) or conjunction words (ex: but, and, or etc.) which may change the sentiment of the opinion (Vidanagama et al., 2021a). These kinds of adverbs, negation words, or conjunction words modify the sentiment of a sentence. The next process of the extraction module then calculates the sentiment value of each extracted feature opinion pair and aggregates them to generate the overall sentiment of each review.

3.3.2. Sentiment analysis

The sentiment value of each product feature–opinion pair is calculated using the proposed algorithm shown in Fig. 4. The Sentiment Lexicon database, SentiWordNet Baccianella et al., 2010) provides the sentiment-score of opinion word. There are three score values for each synset of SentiWordNet, objective, positive, and negative score values. The maximum out of the positive or negative score is retrieved as the sentiment of opinion word. Although the reviews may contain many sentences, the sentiment-score values of all pairs of a review are considered when deciding the overall sentiment of the review. The overall positive sentiment score is calculated using (Eq. (3)) by considering the positive feature–opinion pairs. Whereas the overall negative sentiment-score is calculated by considering the feature–opinion negative pairs (Eq. (4)). Finally, the overall sentiment score of the review is calculated using Eq. (5).

$$Sentiment_{\text{Positive}}(review) = min\left[1, \sum_i^n SS_i(A-O)\right] \tag{3}$$

$$Sentiment_{\text{Negative}}(review) = max\left[-1, \sum_j^m SS_j(A-O)\right] \tag{4}$$

$$Sentiment(review) = Sentiment_{\text{Positive}}(review) + Sentiment_{\text{Negative}}(review) \tag{5}$$

Generally, the reviewers use a 5-point polarity scale for review rating. This value was normalized into a scale of [−1,1] representing −1 as extreme negative and +1 as extreme positive.

3.3.3. Review-related feature extraction

This process generates a set of review-related features which is used to distinguish between fake reviews and genuine reviews. Table 1 demonstrates the description of the extracted review-related features (Vidanagama et al., 2021b). Sentiment analysis-related features should be extracted from the previous process in Section 3.3.2.

3.4. Spam detection module

This module incorporates a rule-based classifier which uses previously extracted review-related features to classify a review as truthful or spam. The rule-based classifier uses a set of rules generated from review-related features extracted in Section 3.3.3. Some of the features (F_i) for which the threshold values are defined are compared with the threshold values (T_i) to determine the final decision. Based on the comparisons over the review-related features, the review can be classified as truthful or fake. The following classification rules illustrate how the classification is conducted.

$$\begin{aligned} R_{\text{Label}} &= Truthful;\ if\ F_1 < T_1\ and\ F_4 < T_4\ and\ F_{19} > T_{19}\ and\ F_{20} < T_{20} \\ &and\ F_5 >= T_5\ and\ F_6 >= T_6\ and\ F_7 >= T_7\ and\ F_8 < T_8\ and \\ &F_9 < T_9\ and\ F_{10} < T_{10}\ and\ F_{11} < T_{11}\ and\ F_{21} > 0\ and\ F_{22} > 0\ and \\ &F_{23} >= T_{23}\ and\ F_{24} < T_{24}\ and\ F_{25}\ =\ False\ and\ F_{26} < 0.7 \end{aligned}$$

$$\begin{aligned} R_{\text{Label}} &= Fake;\ if\ F_1 >= T_1\ and\ F_4 >= T_4\ and\ F_{19} < T_{19}\ and\ F_{20} >= T_{20} \\ &and\ F_5 < T_5\ and\ F_6 < T_6\ and\ F_7 < T_7\ and\ F_8 >= T_8\ and \\ &F_9 >= T_9\ and\ F_{10} >= T_{10}\ and\ F_{11} >= T_{11}\ and\ F_{21} = 0\ and\ F_{22} = 0\ and \\ &F_{23} < T_{23}\ and\ F_{24} >= T_{24}\ and\ F_{25}\ =\ True\ and\ F_{26} >= 0.7 \end{aligned}$$

The system which is to be implemented using the proposed methodology can be accessed by both customers and manufacturers who require to analyze product reviews of a specific product. After crawling the reviews on a specific product on e-commerce websites, the values of

Input: For each aspect-opinion pair - Aspect (A), Opinion (O), Adverb (adv), number of negation words (n), Sentiment Score of opinion word - SC(O)
Output: Sentiment score of aspect – opinion pair – SS(A-O)
If adv does not exist, Then
 $SS(A\text{-}O) = (-1)^n * SS(O) * SE(A)$
Else
 If SS (adv) > 0, then
  $SS(A\text{-}O) = (-1)^n * \min\{1, SS(adv)+SS(O)\} * SE(A)$

 If SS (adv)< 0, then
  $SS(A\text{-}O) = (-1)^n * \max\{-1, SS(adv)+SS(O)\} * SE(A)$
End If

Fig. 4. Proposed algorithm of sentiment-score calculation for product feature–opinion pairs.

Table 1
Descriptions of review-related features.

Dimension	Review-related feature	Description
Linguistic features	Word Count Total (F1)	Total number of words in the review
	Word Count Average (F2)	Average number of words per sentence
	Ratio of Numeral Word Count (F3)	Total number of words containing numerical values/ Word Count Total
	Ratio of exclusive words (F4)	Total number of exclusive words/ Word Count Total
	Ratio of negation words (F5)	Total number of negation words/ Word Count Total
	Ratio of causation words (F6)	Total number of causation words/ Word Count Total
	Ratio of capital letters (F7)	Total number of words containing capital letters/Word Count Total
	Ratio of all Caps Word (F8)	Total number of all caps words/ Word Count Total
	Content Similarity (CS) (F9)	Content similarity percentage
	Ratio of exclamation marks (F10)	Total number of words with exclamation marks/Word Count Total
	Ratio of question marks (F11)	Total number of words with question marks /Word Count Total
	Ratio of naming entities (F12)	Total number of named entities/ Word Count Total
POS features	Ratio of nouns (F13) /adjectives (F14)/prepositions (F15)/determiners (F16)/verbs (F17)/ adverbs (F18)/ connector words (F19)/first person pronouns (F20)/ pronouns (F21)	Total number of POS words/ Word Count Total
Sentiment features	Ratio of product feature related words (F22)	Total of number of product features/Word Count Total
	Ratio of opinion words(F23)	Total number of opinions/ Word Count Total
	Ratio of positive (F24) /negative (F25) opinion terms	Number of positive/negative opinion terms/Total opinion count
	Sentiment Deviation (SD) (F26)	Difference between the calculated sentiment value and user rating

the review-related features of the reviews are automatically calculated and added into the ontology. Once inference, the reviews are automatically classified into the ‘Spam’ or ‘Truthful’ class according to the feature values based on classification rules. By querying, the users can see all the available spam reviews amidst the crawled reviews (Fig. 5). Content of fake reviews and truthful reviews categorized by inferencing is shown in Figs. 6 and 7. Moreover, the users can query the ontology and assess the fakeness or truthfulness of a particular review among the crawled reviews by providing the review’s unique identity (Fig. 8). Users will be provided with user-friendly interfaces for inferencing and querying through the ontology, even if they lack the technical knowledge on tools used to develop this proposed methodology.

As revealed by the literature review, due to the issues with labeled datasets, this research has suggested an ontology-based inference method for fake review classification without relying on labeled datasets. Linguistic, POS tagging, and semantic related features are considered for the classification. All the extracted content features are stored in the ontology and the inference results may provide the classification output by following a rule-based strategy.

4. Experiment and evaluation

This research utilized an unlabeled dataset of Amazon Unlocked Mobile Reviews provided by Kaggle.[3] This a widely used dataset in customer review analysis (Aljuhani & Saleh, 2019; Alqahtani, 2021; Guia et al., 2019). It contained 400000 unlabeled reviews comprising the review content and rating. 5000 reviews were selected from the downloaded dataset for model training. Then, the dataset was pre-processed and extracted features. The samples of extracted linguistic

[3] https://www.kaggle.com/PromptCloudHQ/amazon-reviews-unlocked-mobile-phones

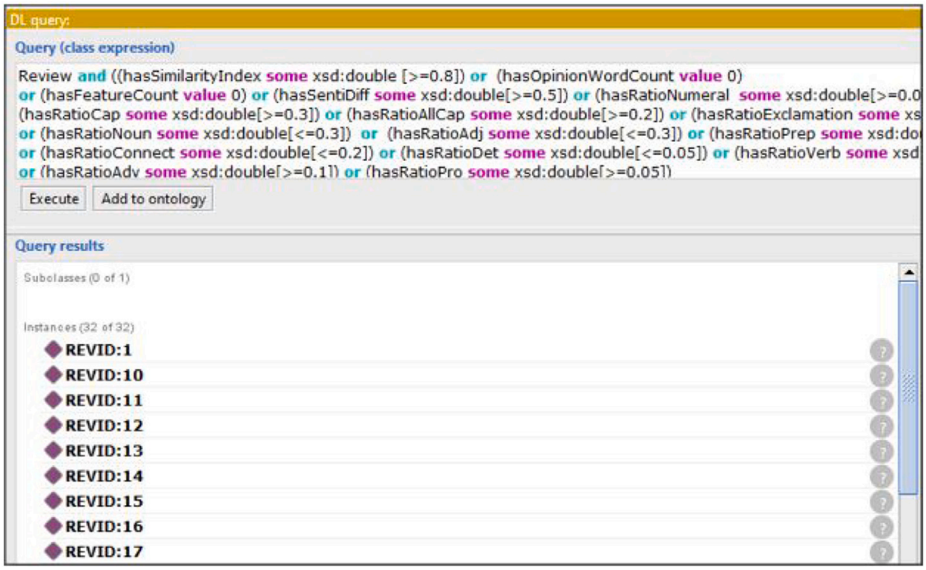
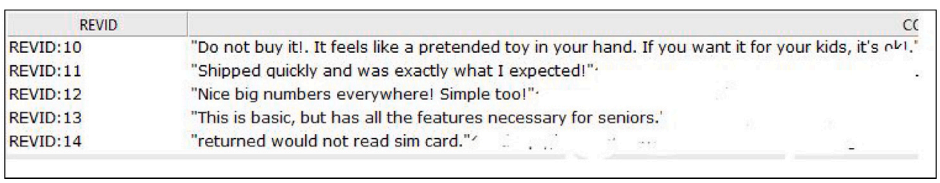
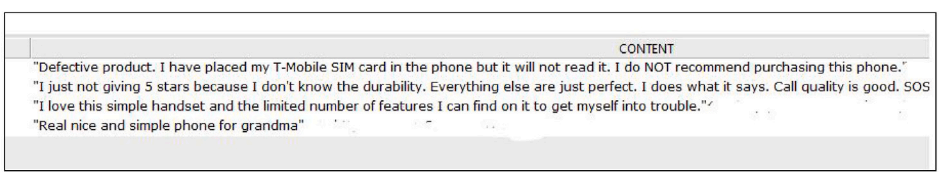


Fig. 5. Query result of available fake reviews in ontology.



REVID	CC
REVID:10	"Do not buy it!. It feels like a pretended toy in your hand. If you want it for your kids, it's ok!."
REVID:11	"Shipped quickly and was exactly what I expected!"
REVID:12	"Nice big numbers everywhere! Simple too!"
REVID:13	"This is basic, but has all the features necessary for seniors."
REVID:14	"returned would not read sim card."

Fig. 6. Examples for Fake Reviews.



CONTENT
"Defective product. I have placed my T-Mobile SIM card in the phone but it will not read it. I do NOT recommend purchasing this phone."
"I just not giving 5 stars because I don't know the durability. Everything else are just perfect. I does what it says. Call quality is good. SOS
"I love this simple handset and the limited number of features I can find on it to get myself into trouble."
"Real nice and simple phone for grandma"

Fig. 7. Examples for Truthful Reviews.

features, POS features, and sentiment features are shown in Fig. 10, Fig. 11, and Fig. 12 respectively.

The outliers may be deviated and not consistent with general reviews. Hence, this argument is used to generate labeled spam reviews and truthful reviews using outliers. Because of not being able to find a labeled dataset with spam reviews, the outliers were considered spam reviews while others were considered truthful reviews for model training. Moreover, the Mahalanobis distance (IBM Corp, 2016) was used to detect the outliers of the multivariate dataset where the multivariate outliers were a combination of unusual scores of different features.

The difference between the customer-given rating and the calculated sentiment polarity of the reviews are shown in Fig. 9. The deviation value of zero indicates no deviation among the customer given rating and the calculated sentiment polarity, whereas higher deviation values indicate significant deviations among the customer given rating and the calculated sentiment polarity. And so on, the outlier distribution of reviews over the percentage of opinion word occurrence is shown in Fig. 13. Similarly, all features listed in Table 1 were considered when detecting outliers.

The calculated review-related features were used to cluster the dataset for identifying the spam and truthful datasets derived from the Mahalanobis distance method. The reviews which were clustered as outliers were taken as spam reviews, while the rest was considered to be truthful reviews. Out of the clusters, the labeled dataset was selected with 1500 spam reviews and 1500 truthful reviews, where 70% and 15% from the dataset were used as a training sample and for testing respectively, while the rest was used for validation. This training dataset is then used to find each feature's threshold value. The threshold values were determined by iteratively processing the rules over the training dataset. Finally, the rules were included in the Protege rule engine as Semantic Web Rule Language(SWRL) rules. In this manner, with the arrival of each new review, it will be stored in the ontology as a review instance and the review-related feature values will thus be calculated. After inferencing, the SPARQL query result will provide the classification result on a review, stating whether it is fake or truthful, based on rules incorporated in the rule engine of the ontology.

Also worth noting is the use of a rule-based classifier to evaluate the effect of linguistic features, POS features, and sentiment analysis features. The extracted features were evaluated against the classification rules. Three models were created with different combinations of review-related features and the model performances were evaluated with performance metrics. Table 2 shows the experimental results of classifiers. The classification performance of model 1 which is modeled only with the linguistic features, reached the accuracy of 64.1% while model 2 with the combination of linguistic features and POS features, reached the accuracy of 73.3%. Nonetheless, when considering model 3 with linguistic features, POS features, and sentiment-related features as a combination, the classifier reached high values of precision, recall, accuracy, and F1 score.

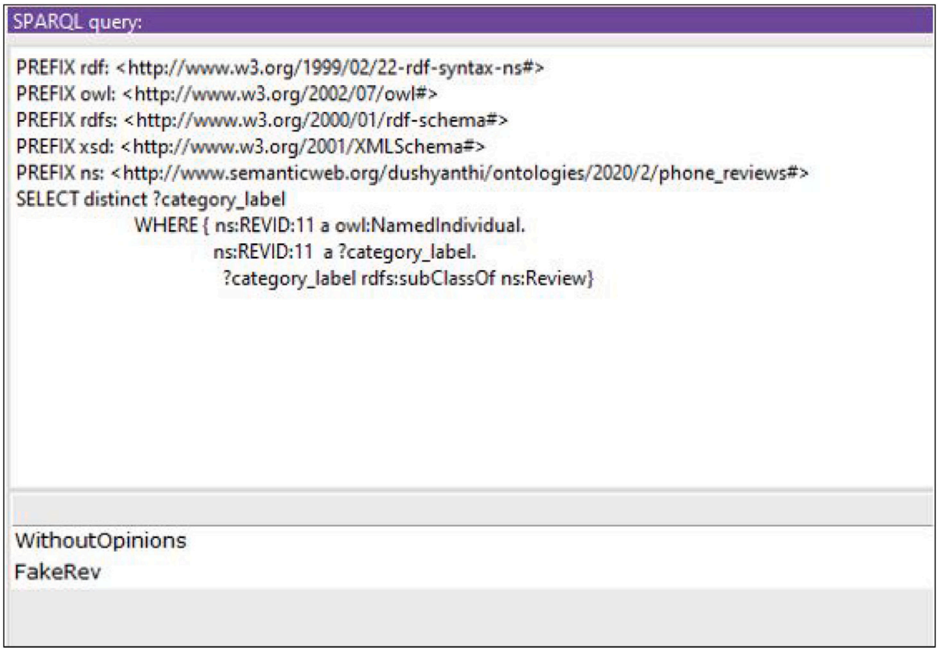


Fig. 8. Query result of the category of Review.

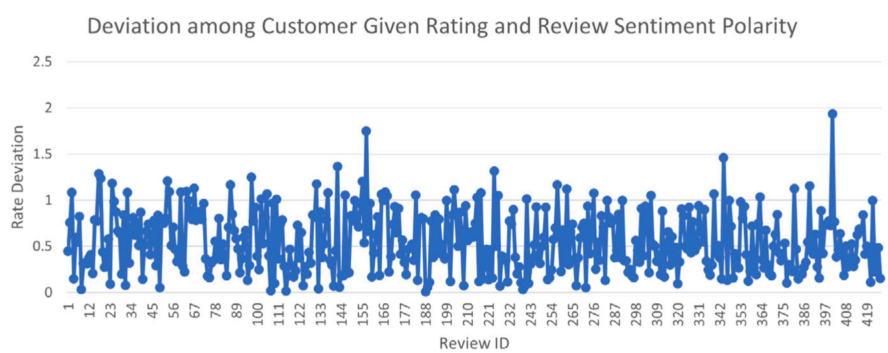


Fig. 9. Deviation among customer given rating and review sentiment polarity.

F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
40	10	0.05	0	0.025	0	0.275	0	0.58	0	0.025	0.05
38	19	0	0	0	0	0.052632	0	0.72	0	0	0
162	10.8	0.006173	0.006173	0	0	0.12963	0.030864	0.59	0.006173	0	0.006173
337	24.07143	0.005935	0.020772	0.002967	0	0.109792	0.050445	0.85	0	0	0.017804
49	24.5	0.020408	0	0	0	0.489796	0.122449	0.71	0.020408	0.020408	0.040816
25	12.5	0	0	0	0	0.12	0	0.75	0	0	0
20	10	0	0	0.05	0	0.25	0.05	0.76	0.1	0	0
7	7	0.142857	0	0	0	0.142857	0	0.83	0	0	0
5	5	0	0	0	0	0.4	0.2	0.83	0	0	0
28	9.333333	0	0	0	0	0.107143	0	0.73	0	0	0
22	22	0	0	0.045455	0	0.045455	0	0.7	0	0	0
22	7.333333	0	0	0	0	0.136364	0.090909	0.41	0	0	0
27	9	0.074074	0	0.037037	0	0.259259	0.074074	0.83	0	0	0.037037
43	43	0	0	0	0	0.093023	0.023256	0.76	0	0	0
33	16.5	0	0.030303	0	0	0.060606	0.030303	0.83	0.030303	0	0
21	21	0.047619	0	0	0	0.142857	0	0.65	0	0	0.047619

Fig. 10. Sample of extracted Linguistic Features.

Table 2
Performance metrics of classification results.

Model	Features of model	Precision	Recall	Accuracy	F1 Score
Model 1	Linguistic	61.11%	71.6%	64.1%	65.9%
Model 2	Linguistic +POS	68%	70.2%	73.3%	69.1%
Model 3	Linguistic + POS + Sentiment	88.69%	90.90%	88.98%	89.79%

F13	F14	F15	F16	F17	F18	F19	F20	F21
0.35	0.075	0.1	0.025	0.225	0.075	0.025	0	0
0.210526	0.157895	0.078947	0.105263	0.236842	0.052632	0.026316	0	0.052632
0.240741	0.08642	0.104938	0.098765	0.191358	0.080247	0.049383	0.049383	0.055556
0.216617	0.086053	0.118694	0.115727	0.219585	0.089021	0.032641	0.032641	0.059347
0.22449	0.061224	0.081633	0.122449	0.22449	0.102041	0.040816	0.020408	0.040816
0.16	0.12	0.08	0.08	0.12	0.08	0.08	0.04	0.2
0.25	0.15	0.05	0.05	0.25	0.05	0	0.05	0.05
0.142857	0.142857	0.285714	0.142857	0.142857	0	0	0	0
0.2	0	0	0	0.4	0.2	0	0	0
0.25	0.142857	0.035714	0.071429	0.178571	0.071429	0.071429	0.035714	0.071429
0.181818	0.181818	0.136364	0.045455	0.181818	0.090909	0.045455	0	0.045455
0.318182	0.090909	0.181818	0.045455	0.136364	0.136364	0	0.090909	0.045455
0.259259	0.074074	0.037037	0.111111	0.222222	0.074074	0.074074	0.074074	0.037037
0.162791	0.116279	0.023256	0.046512	0.302326	0.069767	0.046512	0.023256	0
0.272727	0.181818	0.121212	0.121212	0.181818	0	0.060606	0.030303	0
0.285714	0.285714	0.047619	0.095238	0.190476	0	0	0.047619	0.047619

Fig. 11. Sample of extracted POS Features.

F22	F23	F24	F25	F26
0.025	0.075	13.33333	26.66667	0.066667
0.052632	0.052632	38	0	0.05625
0.030864	0.067901	117.8182	44.18182	0.425
0.011869	0.059347	286.45	50.55	0.174691
0.020408	0.020408	49	0	1.10098
0.04	0.2	25	0	0.185969
0.05	0.05	0	20	0.2375
0.142857	0.142857	0	7	0.233333
0	0	0	0	0.05
0.071429	0.142857	21	7	0.2
0.045455	0.136364	22	0	1.7
0	0.090909	22	0	1.1375
0	0.037037	27	0	0.8
0.023256	0.093023	43	0	0
0.030303	0.060606	33	0	0.15
0.047619	0.142857	21	0	0.383333

Fig. 12. Sample of extracted Sentiment Features.

5. Conclusion and future work

This paper investigated a fake review classification method by incorporating the review-related features, without considering a labeled dataset for model training. Previous research revealed the scarcity and drawbacks of utilizing a labeled dataset for model training. Also, the importance of utilizing the review-related features for fake review classification was highlighted. Therefore, while classification was fundamentally performed utilizing a rule-based classifier, the review-related features such as linguistic features, POS tagging features, and sentiment analysis features were also taken into account. The linguistic features consist of semantic patterns of a review while POS tagging features include the grammatical structures of a review. Sentiment analysis features include the sentiment-related features of a review. Though there are different ways to explore the sentiment features of a review, this research highlighted the importance of feature-level sentiment analysis using domain-related product features characterized by a domain feature ontology. Accordingly, all the features were extracted for each new review and stored within the ontology. Due to the issues related to the manually labeled dataset for model training, the outliers of an unlabeled dataset were considered as spam reviews and the rest of the reviews were used as truthful reviews. The outliers were calculated using the Mahalanobis distance method which is a widely used distance-based outlier detection method. The training dataset is used to calculate the threshold values of the rules. When inferencing, the classification result will be generated according to the SWRL rules of the ontology. The accuracy, recall, precision and F1 score values of the rule-based classifier were slightly increased when incorporating linguistic features, POS tagging features and sentiment analysis features all together in spite of considering them individually. Therefore, this research emphasizes the value of incorporating linguistic features, POS tagging features, and sentiment analysis features when classifying the fake reviews and truthful reviews as well as the worth of utilizing ontology-based sentiment analysis. A direction for future research is available for checking the possibility of increasing the classification accuracy by incorporating more review-related features, and by incorporating reviewer-related features along with the product-related features of reviews. Moreover, this research used a rule-based classifier when classifying reviews as fake or truthful. The authors will

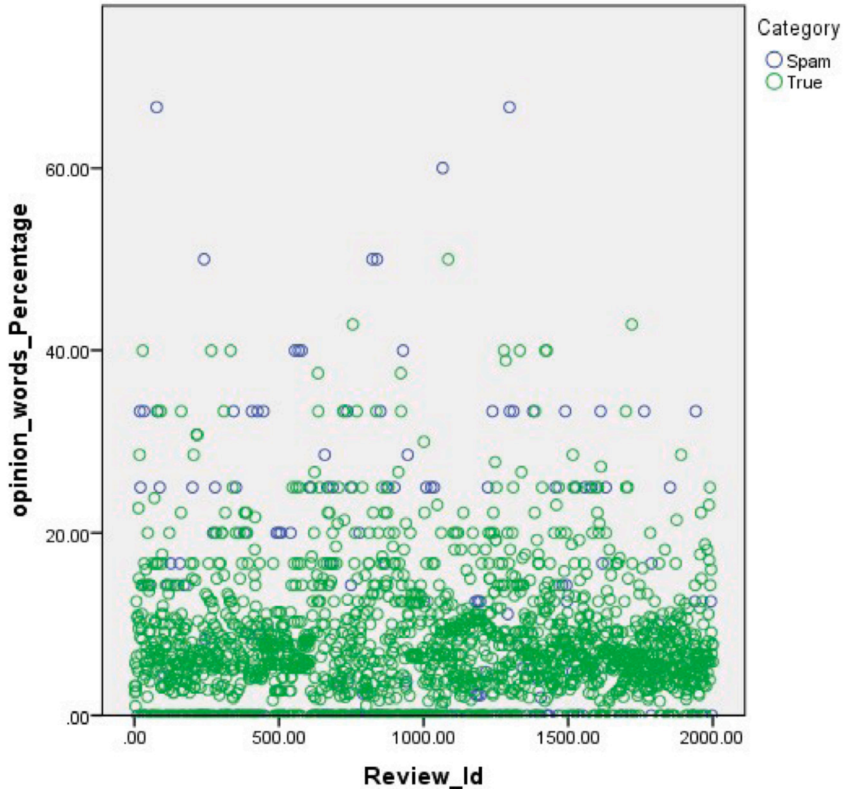


Fig. 13. Outlier Distribution over ratio of opinion words.

plan to explore the performance of different classifiers over the rule-based classifier. Furthermore, future research directions are available to identify the credibility level of reviews and reviewers, without precisely classifying the reviews into fake or truthful groups.

CRediT authorship contribution statement

D.U. Vidanagama: Conceptualization, Methodology, Data Preparation, Implementation, Testing, Validation, Writing. **A.T.P. Silva:** Supervision, Reviewing, Editing. **A.S. Karunananda:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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