Computer Forensics Uncovered: A Holistic Overview of Techniques, Tools, Challenges, and Future Prospects

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ABSTRACT

People produce a deluge of product evaluations and comments due to the proliferation of Internet-based applications like social networks and e-commerce websites. Therefore, processing them automatically becomes very important. There have been a lot of proposals for systems that can produce and display reputation by mining numerical and textual evaluations in the last decade. But they have overlooked the possibility that bad actors may write evaluations online with the express purpose of damaging the target product's reputation. Beyond that, these systems only care about the entity's reputation value and don't bother to generate reputation ratings for the product's individual features. In order to provide trustworthy reputation values, we built a system that uses spam filtering, review popularity, review posting time, and aspect-based sentiment analysis. With the use of user reviews gathered from several sources, the suggested model assigns numerical reputation ratings to entities and their attributes. Additionally, our suggested system provides a high-tech visualization tool that shows comprehensive data on its output. Experimental findings comparing the proposed approach to state-of-the-art reputation generating methods demonstrate its efficacy on several datasets obtained from diverse platforms (e.g., Twitter, Facebook, Amazon, etc.).

E-commerce, opinion mining, decision-making, aspect-based sentiment analysis, and index terms.

I. INTRODUCTION

The way consumers engage with companies and their goods has been transformed by the widespread availability of the internet. People are quick to express their thoughts and evaluations on anything from real goods to internet services on different online platforms. Customers are more likely to write a review if their experience makes them feel something, according to a new study1. This holds true regardless of whether the review is good or negative. By sifting through this mountain of customer feedback, we may learn valuable information about the product's quality and use it to guide our purchasing decisions. An emerging subfield of NLP known as reputation creation has garnered significant attention in recent years.

The primary goal of reputation generating systems is to assign a numerical value to an entity by mining numerical ratings and reviews from customers. In order to create and display the reputation of online goods and services by combining and mining numerical and textual evaluations, several reputation creation methods have been suggested in the last ten years [1]_[8]. But these systems haven't thought of things like (1) gathering reviews from different sources and processing them, (2) screening out reviews that could be spam, (3) assigning a numerical reputation value to each part of the product in question, and (4) offering a sophisticated visualization tool for reputations to help with decision-making. In order to reliably calculate and display an entity's reputation (be it a product, movie, hotel, restaurant, or service), we devised and implemented an improved reputation generation model that addresses the drawbacks of the prior methods.

The suggested method is able to gather and analyze information from social media and online stores. The next step is to use a spam filtering system to remove any spam reviews. After that, the cleaned output is ready to be used in aspect-based sentiment analysis (ABSA), which involves extracting aspects of the target object from the reviews based on their sentiment polarity. After that, we use the popularity and time characteristics of the reviews in conjunction with the ASBA findings to calculate the overall reputation value and the reputation value of each attribute of the target entity. Additionally, the technology suggests an analytical dashboard that provides comprehensive data on the target entity's reputation.

This study seeks to answer the following research question: can the suggested reputation model outperform state-of-the-art (SOTA) systems in terms of reputation generation and visualization while taking review popularity, review time, spam filtering, and ABSA into account?

The structure of this article is as follows. The relevant work on the ABSA models and earlier reputation generating systems is detailed in Section 2. In Section 3, we cover the groundwork. We lay forth our plan in Section 4.

Learn everything about the experiments in Section 5. The topic is presented in Section 6. Finally, this study is concluded in Section 7.

II. RELATED WORK

Here we take a look back at what the field of ABSA and NLP-based reputation management systems have accomplished.

A. Feelings Based on Observations

The field of study known as sentiment analysis (SA), often called opinion mining, has been expanding at a fast pace in recent years [9] with the goal of determining an entity's polarity. Document-level [10], sentence-level [11], and aspect-level [12] are the three most common levels at which SA may occur. Given its significance to the paper's content, ABSA will be the primary topic of this subsection. ABSA finds the parts of the provided textual evaluation about the product or service and assigns them to the appropriate emotion class. Aspect polarity classification (APC) and aspect extraction (AE) are the two primary processing steps that classify ABSA. Aspects, either explicit (defined as "aspect terms"), implicit (defined as "aspects"), or both are extracted in the first step. The second step involves emotionally labeling the previously determined features as either favorable, bad, or neutral. The writers pioneered a suite of natural language processing (NLP) methods for mining and summarizing product reviews in [16]. Providing a feature-based overview of several web product evaluations was their primary goal. First, they used the association rule mining method to mine customer-expressed product characteristics [17]. The next step was to find the opinion sentences in each review and then identify their polarity. After compiling all of the data, they drafted a summary. Additionally, the first deep learning method for the AE problem in opinion mining was reported by Poria et al. in [18]. To classify the textual thoughts as either aspect or non-aspect, the writers used a 7-layer deep convolutional neural network. In addition to the deep learning classifier, the authors suggested a series of heuristic language patterns that, when combined, significantly outperform prior SOTA approaches in terms of accuracy. For aspect-level sentiment classification, the authors of [19] suggested an LSTM [20] that is attention-based. The basic premise is to educate aspects on how to compute attention weights by learning their embeddings. To make them more competitive for aspect-level classification, the suggested model may shift their emphasis to various portions of a phrase when given different aspects. On the SemEval 2014 Task 4 dataset, the suggested model outperformed the conventional LSTM [21]. Using convolutional neural networks [23] and a model based on gating mechanisms (GCAE), which has been shown to be more accurate and efficient, Wei and Toi enhanced the de_ciencies of the earlier LSTM techniques in [22].

The innovative Gated Tanh-ReLU Units may output the sentiment characteristics selectively according on the aspect or object that is presented.

Compared to the attention layer utilized by earlier models, the suggested model's design is far more straightforward.

In comparison to LSTM-based models, experimental results on SemEval datasets demonstrate an increase in performance. In their proposal, the authors of [24] created an INN that could learn many related tasks at the token-level and the document-level concurrently. In order to make greater use of the correlation, the IMN implements a message transmission system that permits informative interactions across jobs. By a wide margin, IMN beats alternative baselines in experiments conducted on three benchmark datasets derived from SemEval 2014 and SemEval 2015 [25]. A hierarchical attention-based position-aware network (HAPN) was suggested by the authors of [26] as a solution to the problem of existing methods ignoring aspect position information when encoding sentences. This network uses position embeddings to learn position-aware sentence representations and then generates target-specific contextual word representations. When compared to earlier approaches, HAPN attained SOTA performance on the SemEval 2014 dataset. The review reading comprehension (RRC) task was introduced by Xu et al. [27]. They used BERT [28] as their foundation model and suggested a combined post-training and netuning method for ATE, APC. The suggested post-training method seems to be very successful based on the experimental findings.

To use adversarial training for AE and APC, the authors later suggested a new architecture in [29] called BERT Adversarial Training (BAT). This design generates artificial data and is executed in the embedding space. When it comes to AE and APC tasks, the suggested model is superior to both the regular BERT and the in-domain post-trained BERT. Using the SemEval 2014 Task 4 restaurants dataset, the authors of [30] achieve improved SOTA performance by combining domain-specific BERT language model training with supervised task-specific tuning.

Developing a Reputation

Reputation is defined as "the opinion that people have about what someone or something is like, based on what has happened in the past" according to the Oxford Learner's Dictionaries3, entry 3.

Movies, TV programs, hotels, and goods are just some of the many online commodities that have been the subject of several reputation systems that aim to calculate a satisfaction score [36]_[42]. Until 2012, when Abdel-Hafez et al. [1] developed a reputation model that incorporates opinion orientation and opinion strength (opinion mining) to calculate a realistic reputation value for each product feature and the product itself, these systems relied solely on numerical reviews (ratings) for reputation computation and ignored the use of textual reviews. However, no evidence has been presented to support the efficacy of their product reputation system. The first method to create and display reputation for Amazon's items was suggested by Yan et al. [3]. It mixes opinion fusion with semantic analysis. A recent improvement to this method was made in [4] by prefacing the opinion fusion and grouping phase with a binary sentiment classification step. In their reputation model, Benlahbib and Nfaoui [6] took into account review duration, review usefulness, and review sentiment intensity when visualizing and computing reputation. A method that calculates reputation ratings from user comments using a SA model was proposed by Elmurngi and Gherbi [5]. A product's reputation score is calculated by dividing the total number of reviews for the product by the number of favorable reviews. Both [43] and [44] used the same concept.

III. PROPOSED APPROACH

Sections 1–8 detail the proposed system's architecture, data gathering and processing, opinion spam detection, aspect extraction and classification, popularity score calculation, time score calculation, reputation generation, and finally, reputation visualization.

Part A: System Overview

Using textual and numerical data gathered from various sources, this system computes a satisfaction score for each feature of the target item and generates a reputation value for online entities (e.g., movies, hotels, restaurants, services, etc.). Its design is shown in FIGURE 1. The first step is to collect customer reviews from various sources like Twitter, Amazon, YouTube, etc.

Afterwards, a spam filtering mechanism is used automatically to identify and remove spam reviews. Next, we utilize a SOTA ABSA model to analyze user evaluations and derive a score according to the sentiment orientation of the retrieved characteristics. In addition, using the statistical elements derived from the textual evaluations, we compute a popularity score and a time score. We conclude by calculating a reputation value using the scores that were previously computed, and we suggest a new visualization interface that is easy for users to understand and use, which provides detailed information on the target entity's reputation.

Section B: Information Gathering and Preprocessing

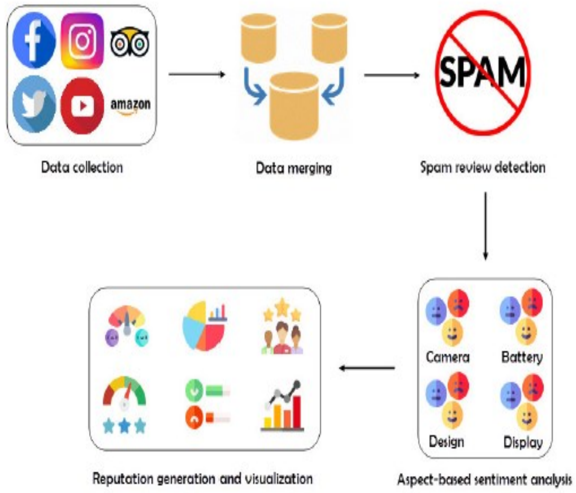
The capacity to gather and handle data from several platforms is a key component of the suggested system.

In the past, reputation generating systems would get their data from social networking sites like Facebook and Twitter or from online retailers like Amazon and TripAdvisor. Based on our classification of online platforms into two groups, we were able to standardize their features and create a single combined dataset. One group includes platforms like Amazon and YouTube, where users can easily access reviews along with the number of likes they've received. The second type allows users to access textual reviews along with the number of likes and shares they have received from networks like Twitter and Facebook. This is in contrast to the first type platforms, which only provide the number of likes.

By using natural language processing methods such as text normalization, lower-casing, noise reduction, etc., the textual reviews are cleaned.

Table 1: Overview of Natural Language Processing (NLP)-based Reputation Systems.

Work	Language	Domain	Semantic Analysis	Document-Level Sentiment Analysis	Aspect-Based Sentiment Analysis
Abdel-Hafez et al. (2012) [1]	N/A	N/A	N/A	N/A	N/A
Farooq et al. (2016) [2]	English	Products	N/A	N/A	• Association rule mining • SentiWordNet [48], [49]
Yan et al. (2017) [3]	• English • Chinese	Products	Latent Semantic Analysis (LSA)	N/A	N/A
Benlahbib and Nfaoui (2019) [50]	English	Movies	Latent Semantic Analysis (LSA)	N/A	N/A
Benlahbib et al. (2019) [51]	English	Movies	Latent Semantic Analysis (LSA)	Logistic Regression	N/A
Benlahbib and Nfaoui (2020) [4]	English	Movies	Latent Semantic Analysis (LSA)	• Naïve Bayes • Linear Support Vector Machine	N/A
Elmurngi and Gherbi (2020) [5]	English	Products	N/A	Logistic Regression	N/A
Benlahbib and Nfaoui (2020) [6]	English	• Products • Movies & TV Shows • Hotels	N/A	Bidirectional Encoder Representations from Transformers (BERT)	N/A
Benlahbib and Nfaoui (2020) [52]	English	Products	N/A	Bidirectional Gated Recurrent Unit (Bi-GRU)	N/A
Boumhidi and Nfaoui (2020) [43]	English	• Movies • Restaurants	N/A	Bidirectional Gated Recurrent Unit (Bi-GRU)	N/A
Gupta et al. (2020) [7]	English	• Movies • Books	N/A	• Bidirectional Encoder Representations from Transformers (BERT) • Naïve Bayes • Support Vector Machine	N/A
Boumhidi et al. (2021) [44]	English	Movies	N/A	Bidirectional Long Short-Term Memory (BI-LSTM)	N/A
Benlahbib and Nfaoui (2021) [45]	English	Movies & TV Shows	Embeddings from Language Models (ELMo)	Multinomial Naïve Bayes	N/A
Boumhidi and Nfaoui (2021) [8]	English	• Products • Services • Hotels • Movies	N/A	Bidirectional Encoder Representations from Transformers (BERT)	N/A
This study	English	• Products • Services • Hotels • Movies	N/A	N/A	LCF-ATEPC



C. OPINION SPAM DETECTION

The fact that everyone, regardless of location, may publish evaluations about any product or service is one major downside of opinion-sharing sites. By falsely elevating or lowering the target's reputation, opinion spammers want to sway customers' views in their favor [53]. For our reputation system to provide a trustworthy and dependable reputation value—which in turn helps consumers make safe decisions—filtering and removing spam reviews is of the utmost importance. There has been tremendous advancement in the detection of spam reviews on commercial review hosting sites like Yelp and Amazon [54]. On the other hand, we've decided to use two normalized spammer behavioral traits to identify spam reviews [55] as we're gathering people's opinions from numerous platforms. Referring to TABLE 2, the notations used in this subsection are catalogued.

Subsection: Opinion spam detection uses the concepts given in Table 2.

Variable	Description
E_j	Target entity j
R'_{jk}	Set of reviews for an entity j posted by author k before spam filtering
N_j	Total number of reviews toward entity j
N_{jk}	Total number of reviews posted by author k for an entity j.
$CP(R'jk)$	Set of pair-combination generated from the R'_{jk} set

$$F_1(u_{jk}) = \frac{\sum Cosine(CP(R'_{jk}))}{N_{jk}} \times 10 \qquad (1)$$

$$F_2(u_{jk}) = \frac{N_{jk}}{N_j} \times 10 \qquad (2)$$

Equation (3) is used to determine the spammer score, which is based on the two previously proposed spammer behavioral traits. By comparing the spammer score with a predefined threshold, as mentioned in section 5, each author is given a label from the set L D{normal, spammer}. People that evaluate content on a regular basis are called "normal" reviewers, whereas those who review content that contains spam are called "spammer" reviewers. We assign labels to each user using Equation (4).

$$Score(u_{jk}) = \frac{F_1(u_{jk}) + F_2(u_{jk})}{2} \qquad (3)$$

$$L(a_i) = \begin{cases} Spammer, & \text{if } Score(u_{jk}) > \tau \\ Normal, & \text{if } Score(u_{jk}) < \tau \end{cases} \qquad (4)$$

If a person is found to be a spammer, all of their reviews will be removed from the dataset. The next phase of the reputation system proposal may now begin with the cleaned dataset, which is devoid of spammers.

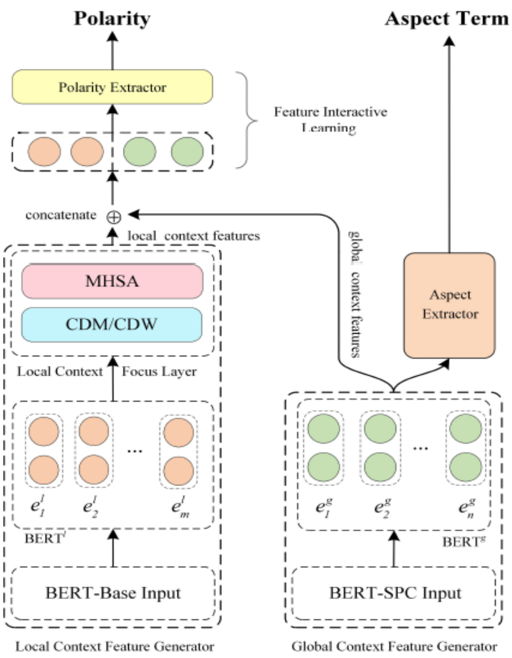


FIGURE 2. Network architecture of LCF-ATEPC model [34] for ABSA.

$$psr_{ij} = \frac{l_{ij} \times 0.5}{max(L_j)} + \frac{s_{ij} \times 0.5}{max(S_j)} \qquad (5)$$

The end result is a popularity score for each review, which might be anywhere from 0 to 1. The more popular the review is, the more influential it is.

To determine the target entity's reputation, those popularity ratings will be used.

Review popularity score is one of the concepts utilized in this subsection (see Table 3).

Variable	Description
psr_{ij}	Popularity score of review i expressed for an entity j
l_{ij}	Number of likes received for a review i expressed for an entity j
s_{ij}	Number of shares received for a review i expressed for an entity j
$max(L_j)$	Max number of likes received by a review toward entity j
$max(S_j)$	Max number of shares received by a review toward entity j

Time, however, does not have an effect on all products in all fields. Even if it's from a long time ago, an online review of a product like cheese or a classic film may have contemporary relevance. Therefore, the review's date is irrelevant here. Here we presented Equation (6) as a means of determining a review time score.

According to the suggested equation, the most up-to-date reviews will have a score around 1 while older reviews would have a value closer to 0. Table 4 lists the notations used in this subsection. In the proposed reputation system, we indicated that this functionality would be optional.

If the user doesn't want time to be considered, they may disable the review time score that is used to determine a product's reputation.

$$tsr_{ij} = 1 - (y - rt_{ij}) \times 0.03 \tag{6}$$

TABLE 4. Notions used in sub-section: Review time score.

Variable	Description
tsr_{ij}	Time score of a review i expressed for an entity j
y	Current year
rt_{ij}	Posting year of a review r_{ijk}

TABLE 5. Notions used in sub-section: Review sentiment analysis.

Variable	Description
asp_{ij}	Aspect i for entity j
p_{ij}	Total number of positive reviews toward asp_{ij}
n_{ij}	Total number of negative reviews toward asp_{ij}
$ssasp_{ij}$	Sentiment score toward aspect asp_{ij}

TABLE 6. Examples of the results obtained from the employment of the LCF-ATEPC on a sample of reviews.

Review	Aspect	Sentiment polarity	popularity score
The camera is good but the design is bad.	camera	Positive	0.4
	design	Negative	0.4
I love the camera and the design is so cool, but i have no opinion on the screen quality.	camera	Positive	0.2
	design	Positive	0.2
	screen	Neutral	0.2

$$ssasp_{ij} = \frac{p_{ij}}{p_{ij} + n_{ij}} \tag{7}$$

The suggested method uses Equation (8) to determine a reputation value for each component based on the attributes that have already been computed. The sentiment score ssaspij and the average time scores sum (Tij) mij are multiplied by 9 to get a number that can be anywhere from 0 to 9. Then, we combine this with a customized average of negative and positive popularity scores PPposij and PP negegij Lij, which can be anywhere from 0 to 1. The reputation of an aspect aspij is represented by a numerical number between 0 and 10, which is the final outcome. In Table 8 you can see all the notations that are used in this part.

$$Rep(asp_{ij}) = \max\left[1, \left(ssasp_{ij} \times \frac{sum(T_{ij})}{m_{ij}} \times 9\right) + \frac{\sum PS_{pos_{ij}} - \sum PS_{neg_{ij}}}{L_{ij}}\right] \tag{8}$$

where

$$L_{ij} = \begin{cases} p_{ij}, & \text{if } \sum PS_{pos_{ij}} - \sum PS_{neg_{ij}} \geq 0 \\ n_{ij}, & \text{if } \sum PS_{pos_{ij}} - \sum PS_{neg_{ij}} \leq 0 \end{cases}$$

In order to generate the overall reputation for an entity, the system calculates the average of all aspects' reputation values using Equation (9).

$$FinalRep(E_j) = \frac{\sum_{i=0}^{n} Rep(asp_{ij})}{n} \tag{9}$$

The review score is a value calculated based on the popularity and time scores using Equation (10), and it is used to determine the most in_uential review. This score is not considered in the reputation value computation, and it is only employed during reputation visualisation in order to determine the most in_uential posting review.

$$rs_{ij} = \frac{psr_{ij} + tsr_{ij}}{2} \tag{10}$$

IV. EXPERIMENT RESULTS

A. EXPERIMENTAL DATA COLLECTION AND PREPROCESSING

Each of the four experimental review datasets—product, movie, hotel, and restaurant—belongs to a separate domain. Each dataset is a compilation of reviews from different social media and e-commerce sites; each review comprises the following information: the host of the platform, the number of likes and shares, the year the review was posted, the user's actual opinion, and the review's body. To manually label the four datasets, we recruited four human annotators who extracted and identified the polarity of each aspect in the reviews.

Table 10 displays review samples from one of the datasets, while Table 9 displays statistical information about the evaluation dataset. After the dataset's textual evaluations are cleaned and pre-processed, any URLs, punctuations, or special characters are removed. Slang terms are replaced with more professional ones. Lastly, we cleanse the textual reviews and get them ready for the LCF-ATEPC model by tokenizing them and adding some particular tokens.

Part B: Identifying Opinion Spam

A thousand reviews were hand-picked from several online sites to make up the assessment dataset, because there were no available spam review datasets. Based on their review posting habits, we manually classified each user as either "Normal" or "Spammer" using annotators.

Our assessment dataset contains 682 legitimate reviews and 318 spam reviews, as a consequence of this method. There are two stages to spam review identification utilizing spammer behavioral features: (1) using two spammer behavioral characteristics, CS and MNR, to get the spammer score, Score(a). Using accuracy, precision, and recall as metrics, we will test the suggested spam review detection model by changing the threshold value from 0:50 to 0:68 in a step of 0:01.

The optimal accuracy performance is shown by TABLE 7 as having a threshold value of _ D 0:57.

FIGURE 3. Reputation visualisation dashboard.

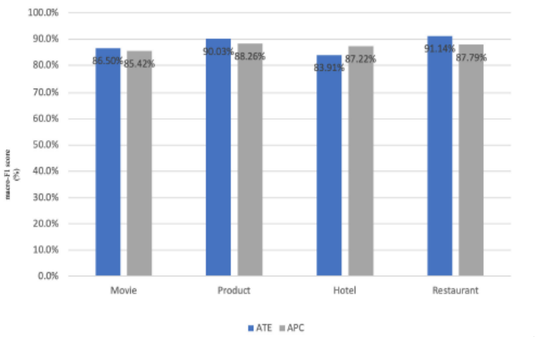


FIGURE 4. F1-score results for the ATE & APC tasks on the evaluation datasets.

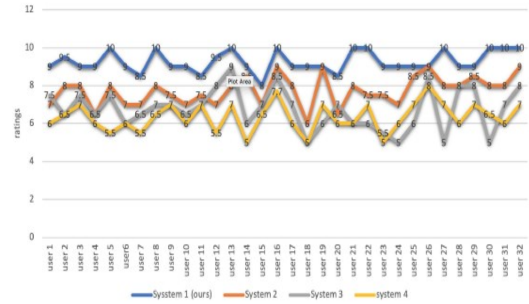


FIGURE 5. Comparison of users' ratings on SOTA reputation generation systems.

$$CV = \frac{\sigma}{\mu} 100\% \quad (11)$$

where

$$\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - \mu)^2}$$

V. DISCUSSION

An sophisticated decision-making tool, the method suggested in this study may extract numerical values representing an entity's reputation from online reviews and comments; this includes items, services, movies, hotels, and more. Because of its exceptional flexibility in processing characteristics from diverse platforms, the suggested system is the first of its kind to handle opinions from several platforms.

Our system is more safe against assaults by spammers and generates more trustworthy reputation values because the proposed reputation system is the first to include an opinion spam filter. This filter identifies and removes spam opinions based on the characteristics of spammers' activities. In addition, it has SOTA aspect-based sentiment-analysis tools for extracting and analyzing target entity aspects, which is a key component. To further enhance its reliability and trustworthiness, the system includes variables such as popularity and the time of opinion publishing to generate reputation. Online decision-making will be made easier for both normal users and company owners with the help of a visualization tool that displays the comprehensive output results of the full reputation generating operation in an interactive user-friendly interface.

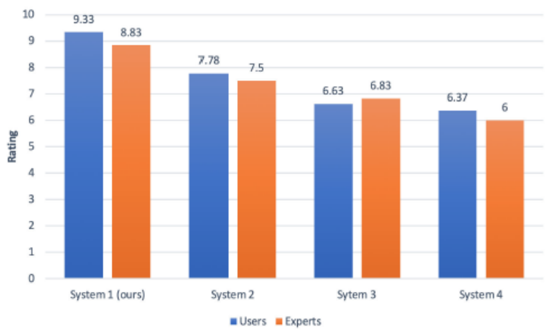


FIGURE 6. Comparison between users' and experts' average ratings on SOTA reputation generation systems.

VI. CONCLUSION

Based on internet evaluations and comments, our reputation system may assign numerical ratings to many characteristics of a certain object (such as a product, movie, service, hotel, etc.). This work's contribution is centered on four features that were underutilized in earlier systems. In the first, we have cross-platform compatibility, which means that the suggested system can manage and standardize the characteristics of many platforms while simultaneously collecting and processing opinions from various platforms (e.g., Facebook, Amazon, Twitter, TripAdvisor, etc.). The second one is opinion spam filtering, which uses characteristics of spammers' behavior to identify and remove spam views while preserving genuine ones. The third one uses an LCF-ATEPC model, which is based on SOTA aspects, to extract and evaluate the aspects inside the textual views. Finally, we used the aforementioned data in conjunction with mathematical formulae to determine the target entity's reputation value and the reputation values of its aspects, by calculating the review time score and the review popularity score. Furthermore, the system offers a comprehensive reputation visualization that shows the exact outcomes of the reputation generating process. We polled 32 users and 3 experts on their opinions of four different SOTA reputation systems, asking them to rank each one by numerical satisfaction ratings, so we could see how well our system performed. Among both users and experts, our reputation system received the best average satisfaction rates. We want to test our system's efficacy in the future by adding features that make it possible to automatically provide a written summary of the pros and cons of the targeted entity, in addition to numerical reputation values. Additionally, we want to enhance this system so it can handle information in several languages.

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