MINING ONLINE REVIEWS TO SUPPORT CUSTOMERS' DECISION-MAKING PROCESS IN E-COMMERCE PLATFORMS: A NARRATIVE LITERATURE REVIEW

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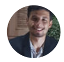
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Mining Online Reviews to Support Customers' Decision-Making Process in E-Commerce Platforms: a Narrative Literature Review

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Abstract: By dint of the massive daily production of user-generated content (textual reviews) in E-commerce platforms, the need to automatically process it and extract different types of knowledge from it becomes a necessity. In this work, an attempt has been made to summarize some studies that aim to propose systems which automatically mine textual reviews expressed in natural languages for the purpose of supporting customers' decision-making process in E-commerce (buying, renting, and booking). The given review is the first work of this type and it includes 44 studies (30 aspect/feature based summarizers and 14 reputation systems) published from 2004 to 2021. First, it investigates aspect and feature based summarizers that aim to help customers in making an informed decision toward online entities (products, movies, hotels, services . . .). Second, it introduces reputation generation systems that seek to provide valuable information about online items. Finally, it provides recommendations for future research directions and open problems.

Keywords: E-Commerce, Decision-Making, Opinion mining, Reputation generation, Feature-based Summarization

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1 Introduction

Nowadays, the amount of unstructured text data that online users produce on E-commerce websites has grown dramatically. The quantity of the collected data may be very large especially for trendy items (products, movies, TV shows, hotels, services . . .), where the number of available users and customers' opinions could easily surpass thousands (Pecar, 2018) (Fig. 1). In fact, while, a good number of reviews could indeed give a hint about the quality of an item, a potential customer may not have the time or effort to read all reviews for the purpose of making an informed decision (buying, renting, booking . . .). Thus, the need for the right tools and technologies to help in such a task becomes a necessity for the buyer as for the seller.

During the last twenty years, Natural Language Processing (NLP) techniques have been applied to support customers during their decision-making process in E-commerce by mining online textual reviews as they carry the subjective preferences and attitudes of humans toward various online items (Hulisi and Bedri, 2012; Reinstein and Snyder, 2005; Chintagunta et al., 2010; Yan et al., 2018; Amblee et al., 2017; Kim et al., 2018; Kapoor and Piramuthu, 2009).

Sentiment analysis and automatic text summarization techniques have been widely used to mine customer reviews. The main task of sentiment analysis is to determine the polarity expressed in a review (positive, negative, or neutral). In the last twenty years, many sentiment analysis approaches have been applied in various domains: automobiles (Turney, 2002), tourism (Shi and Li, 2011; Valdivia et al., 2017), movies (Pang et al., 2002; Ghorbel and Jacot, 2011; Kennedy and Inkpen, 2006), banks (Turney, 2002) and products (Yang et al., 2020; Cernian et al., 2015; Haque et al., 2018). Backing to automatic text summarization, the main objective of these summarizers is to produce a summary that includes the main ideas in the input document (El-Kassas et al., 2021) in less space (Radev et al., 2002) and to keep repetition to a minimum (Moratanch and Chitrakala, 2017).

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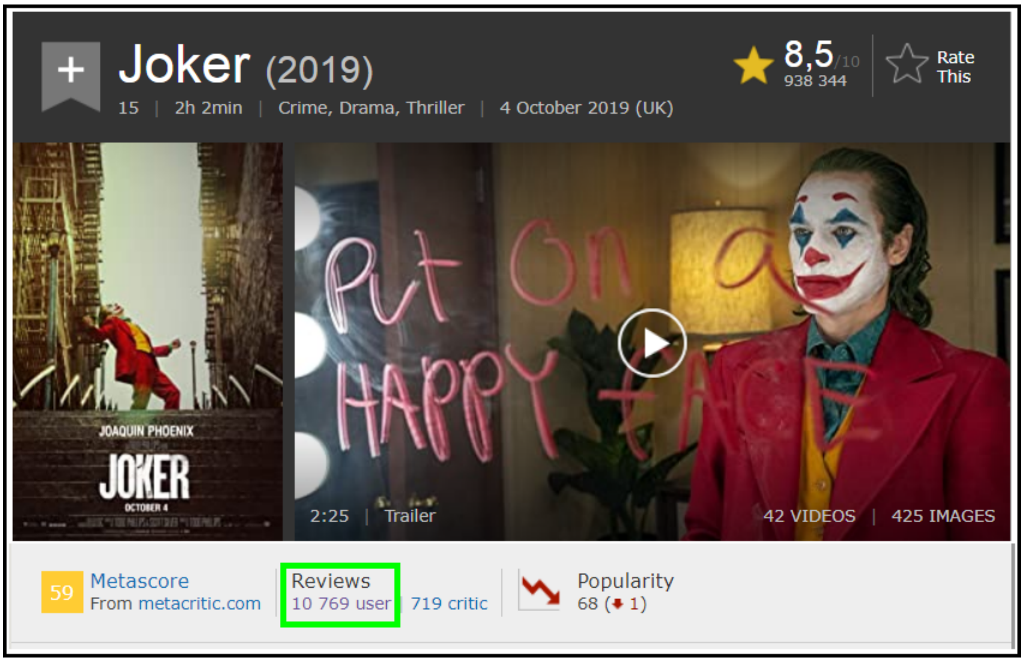

Fig. 1: Number of reviews attached to the movie **Joker**

Over the last two decades, few summarizers have been proposed to perform text summarization of customers' reviews. The summarizers are applied in various domains: tourism (Raut and Londhe, 2014; Hu et al., 2017; Lovinger et al., 2019; Tsai et al., 2020), movies (Xiong and Litman, 2014) and products (Xiong and Litman, 2014; Lovinger et al., 2019; Alsaaran et al., 2020), however, these two approaches don't provide potential customers with sufficient information that can help them make up their mind toward online items (buying, renting, booking).

1.1 Focus of this Review

We can find in the literature several review papers that survey the state of the art of aspect-based opinion mining (Do et al., 2019; Maitama et al., 2020; Tubishat et al., 2018; Moussa et al., 2018; Rana and Cheah, 2016; Zhou et al., 2019; Nazir et al., 2020; Schouten and Frasincar, 2016; Wang et al., 2019). However, none of them has covered Natural Language Processing (NLP) techniques that have been used to support customers during their online decision-making process in E-commerce platforms.

In this paper, we present a short narrative literature review of Natural Language Processing (NLP) techniques that have been used for the purpose of supporting customers' decision-making process in E-commerce. The paper focuses on aspect/feature summarizers and reputation systems since they provide potential customers with valuable information that helps them make an informed decision (whether to buy/rent/book or not). This review doesn't cover research papers that propose aspect/feature extraction techniques or sentiment analysis techniques (Mukherjee and Liu, 2012; Poria et al., 2014; Chen et al., 2014; Poria et al., 2016; Wang et al., 2014; Tubishat et al., 2018; Luo et al., 2019; Dragoni et al., 2019; Li et al., 2015; Aydin and Güngör, 2020; Meng et al., 2019; Sun et al., 2020; Jing et al., 2015; He et al., 2018; Li et al., 2020a; Su et al., 2020; Ishaq et al., 2020; Li et al., 2020b; Lin et al., 2021; Zhao et al., 2021), and only focuses on aspect/feature based summarizers since they integrate both aspect extraction and sentiment identification tools to generate feature-based summaries (Fig. 3).

This paper reviews 30 aspect/feature based summarizers and 14 reputation systems that were published during the last two decades (Fig. 2).

The reason behind reviewing only 14 reputation systems resides in the fact that there is particularly a lack of studies that handle the task of reputation generation based on mining online reviews expressed in natural languages. In fact, previous studies on reputation generation of online products have primarily focused on exploiting user ratings (Paul and Richard, 2002; Schneider et al., 2000; Garcin et al., 2009; Resnick et al., 2000; Leberknight et al., 2012; Cho et al., 2009; Jøsang et al., 2007) or prefabricated textual feedback (Rahimi and El Bakkali, 2013) to generate a score toward

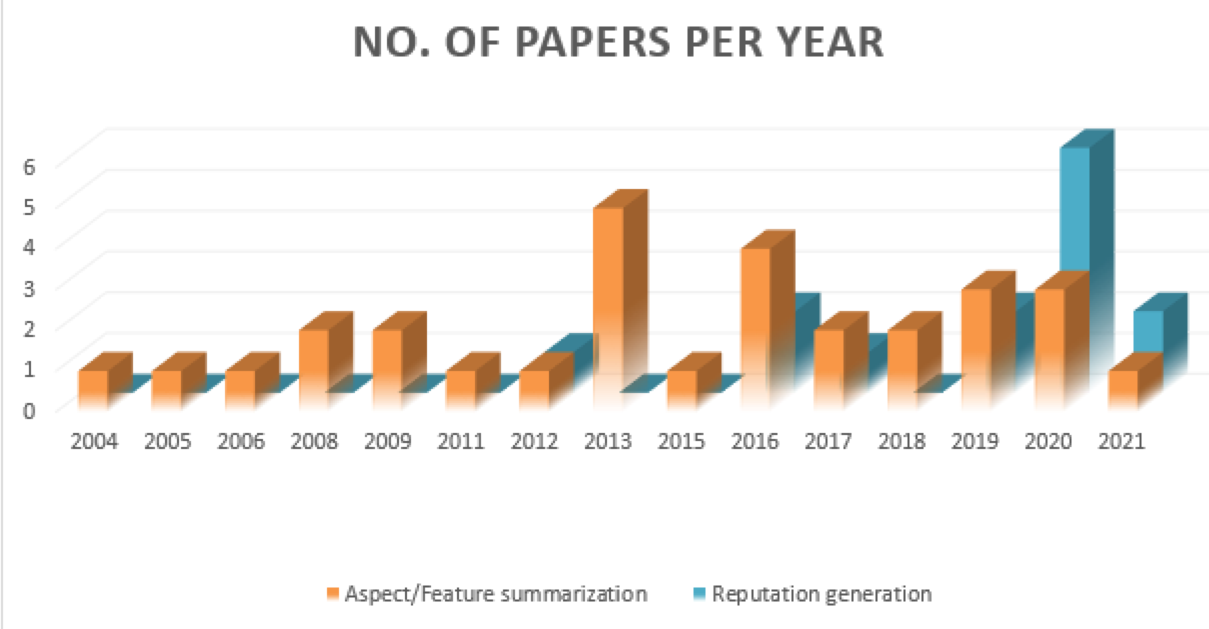

Fig. 2: The number of published papers per year (reviewed papers)

online products. Surprisingly, textual data (reviews), which constitute a significant part of customer information, have been somewhat ignored until 2012 when Abdel-Hafez et al. (2012) designed a product reputation model that uses text reviews rather than users' ratings for the purpose of generating a more realistic reputation value.

1.2 Motivation of this Review

To the best of our knowledge, this is the first work that reviews Natural Language Processing (NLP) techniques that have been used to help E-commerce customers in making an informed decision toward various online items (products, movies, hotels, services . . .).

We have written this paper in order to provide readers and researchers with a comprehensive understanding of the key aspects of Natural Language Processing (NLP) techniques that have been employed to support customers during their online decision-making process in E-commerce platforms by clarifying the most notable advancements and by shedding some light on future studies and open problems. In this manner, this paper addressed the following research questions:

- Which Natural Language Processing (NLP) techniques have been used to help E-commerce customers in making informed decisions toward online items?
- What are the different techniques that have been employed to perform feature-based summarization (aspect extraction and sentiment orientation identification)?
- What are the main limitations and disadvantages of the reviewed feature-based summarization approaches?
- What are the different techniques and features that have been adopted to perform reputation generation?
- What are the main limitations and disadvantages of the reviewed reputation generation systems?
- What are the main challenges for feature-based summarization and reputation generation?

1.3 Methodology of this Review

We used Google Scholar to find research papers that focus on these keywords (reputation generation and text or opinion mining, feature or aspect based summarization and customer reviews) during the last 20 years. We filtered many papers that mainly concentrate on aspect extraction and sentiment identification. We also filtered papers that exploited redundant techniques and approaches in both aspect/feature based summarization and reputation generation in order to preserve the diversity of this review. Furthermore, we have eliminated reputation systems that support buyers (providers and manufacturers) and only kept those that help customers during their decision-making process.

1.4 Organization of this Review

The rest of the paper is organized in the following way, we present a summary of some existing systems for aspect/feature based summarization and we highlight their disadvantages and limitations in the second section . The third section introduces reputation systems that apply opinion mining techniques to perform reputation generation and visualization. Finally, we conclude the paper after discussing future researches and open problems for both feature-based summarization and reputation generation.

2 Aspect/Feature based Summarization

2.1 Summaries of the previous research works

Feature-based opinion summarization is: *"one of the opinion summarization techniques which provide brief yet most important information containing summary about different aspects related to the target product. Since it focuses on different features instead of giving the general details about a product, it has become more significant and demanded form of summarization. This technique is also known as Aspect-based Opinion Summarization. It is actually a way of generating summaries for a set of aspects or features of a specific product."* (Makadia, 2016). Fig. 3 depicts the general three steps of aspect-based opinion summarization (Moussa et al., 2018).

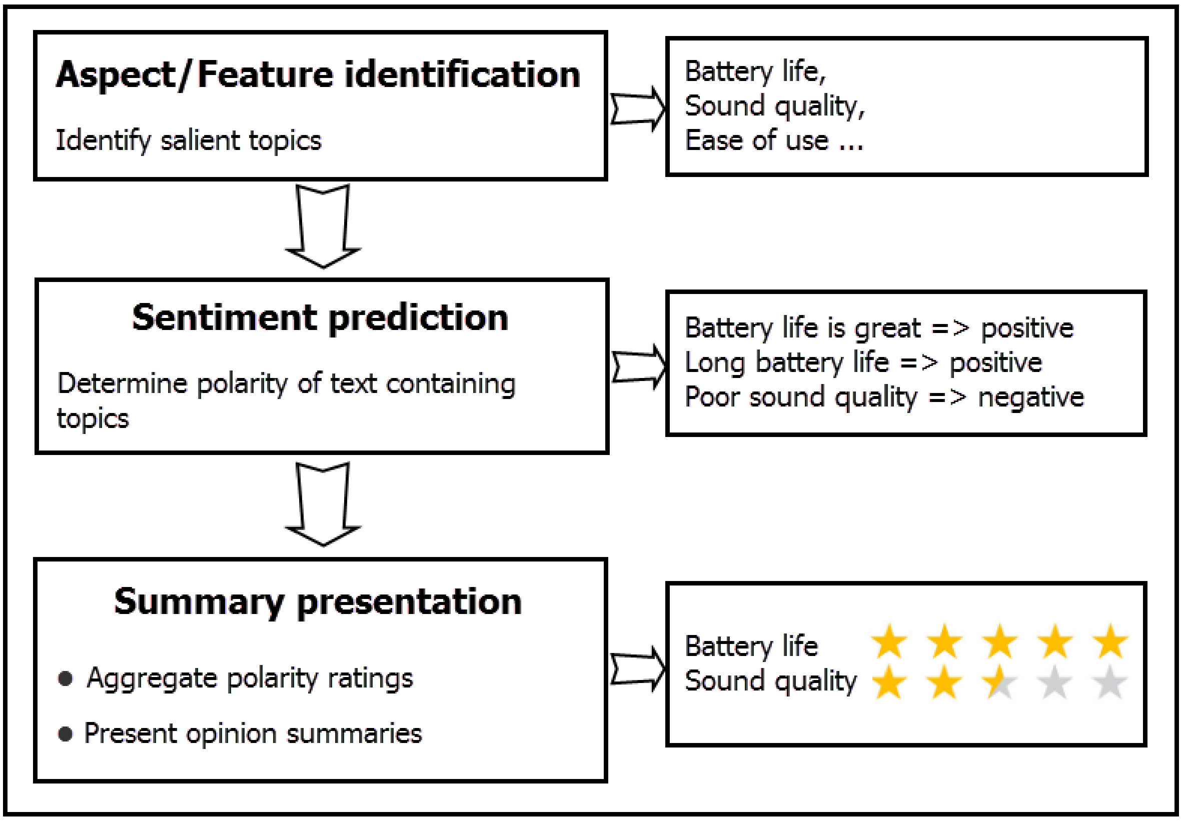

Fig. 3: General three steps of aspect-based opinion summarization (Moussa et al., 2018)

The pioneer work on feature-based opinion summarization of online product reviews was proposed by Hu and Liu (2004b). First, the authors extract explicit product features from reviews by using association rule mining (Agrawal and Srikant, 1994), then, they apply two pruning techniques (Compactness pruning and Redundancy pruning) to reduce unlikely features. Second, they identify opinion sentences in each review and determine their polarity (positive or negative) by using a set of adjective words called *opinion words*. Besides, they propose an algorithm to predict the semantic orientation of each adjective by utilizing the adjective synonym set and antonym set in WordNet (Miller, 1995; Fellbaum, 1998), and they propose another algorithm to determine the orientation of opinion sentences based on the dominant orientation of their opinion words. Finally, they provide a structured feature-based review summary by (1) counting the number of positive/negative opinions toward a target feature, and (2) ranking the extracted features according to the frequency of their appearances in the customer reviews.

Popescu and Etzioni (2005) introduced *OPINE*, a review-mining system of product features that extract the product features with the use of the web as a corpus, and determine the semantic orientation of opinion words by applying relaxation labeling strategy (Hummel and Zucker, 1983). The system achieves 22% higher precision and 3% lower recall compared to Hu and Liu (2004b) work in extracting explicit features. The authors found that a third of their system precision increase over Hu and Liu (2004b) system comes from using Pointwise Mutual Information (PMI) (Turney and Littman, 2003) assessment on reviews and the other two-thirds from the use of the Web PMI (Turney, 2001) statistics.

Zhuang et al. (2006) investigated the similarities and differences between movie reviews and product reviews and found that mining movie reviews is more challenging due to the diversity of their features (movie elements and movie-related people). They also built a multi-knowledge based approach for summarizing movie reviews by initially identifying features and opinions with the use of a keyword list generated from labeled training data, movie casts of IMDb[1] (Internet Movie Database) and WordNet. Two movie feature class groups were defined: ELEMENT and PEOPLE. Furthermore, they applied grammatical rules to mine valid *feature-opinion pairs*. Lastly, they produced a summary by counting positive/negative opinions toward a target feature.

Sasha et al. (2008) proposed an aspect-based summarizer of local service reviews (restaurants and hotels). First, they split review text into sentences with the help of a text extractor. Second, they identify the polarity (positive, negative and neutral) of each extracted sentence by applying a hybrid approach that uses sentiment lexicon (Hu and Liu, 2004b), label propagation algorithm (adjacency matrix) (Xiaojin and Zoubin, 2002) and maximum entropy classifier (Berger et al., 1996; Malouf, 2002). Third, they combine a dynamic aspect extraction (Hu and Liu, 2004b) and a static aspect extraction to identify service aspects with efficiency. Finally, they generate an aspect-based summary that provides both quantitative and qualitative information. Quantitatively, the summarizer translates the aggregated sentences that describe a given feature into a five-star rating. Qualitatively, the system depicts a set of reviews related to a given aspect along with their sentiment polarities. In the same year, Titov and McDonald (2008b) presented a joint model of text and aspect ratings for extracting text to be displayed in sentiment summaries.

Since association rule mining algorithms suffer from several major drawbacks including uselessness in large-scale problems (time/resource consuming) and inefficiency to extract features by confusing common frequent descriptive phrases with feature candidates, Homoceanu et al. (2011) proposed a multi-stage language model approach to extract features and to generate summaries of positive and negative aspects mentioned in movie reviews. The approach relies on the assumption that each domain (electronic product, movie, hotel, service . . .) has phrases that occur more frequently in online customer reviews than in common English language. During the phase of features extraction, a list of candidate features is built by extracting all nouns with the help of POS and sentence chunking from all available reviews. Then a probabilistic approach is adopted to eliminate irrelevant candidates. The lexical resource SentiWordNet (Esuli and Sebastiani, 2006; Baccianella et al., 2010) is adopted to determine the semantic polarity of each adjective before mining feature-adjective pairs by computing the distance between them (*each adjective is assigned to the closest feature in the sentence*.) After the above steps, a feature-based summary is generated by either applying a simple or a weighted aggregation of review polarity profiles (Fig. 4).

Kushal and Durga (2013) proposed a dynamic (daily/hourly) system called *FBS* (Feature-Based Summarization) to mine and summarize product reviews by updating Hu and Liu (2004b) work. The major updates were: (1) applying an *expectation-maximization* (EM) algorithm (Nigam et al., 2000; Zhai et al., 2011) based on Naïve Bayesian (Maron, 1961) classification to cluster domain synonyms words and phrases under the same feature group, (2) combining association rule mining and probabilistic approach for feature extraction, (3) using opinion lexicon[2] and SentiWordNet to determine the polarity of opinion words. Experiment results depict high effectiveness and efficiency

[1] www.imdb.com

[2] http://www.alias-i.com

Fig. 4: Homoceanu et al. (2011) feature-based summary

in extracting product features and determining opinion sentences polarity compared to Hu and Liu (2004b) and Homoceanu et al. (2011) works.

Dalal and Zaveri (2013) discussed the challenges of analyzing reviews expressed in natural language since they are generally unstructured and noisy, which justify the need for extensive preprocessing (Dey and Haque, 2008). Also, they proposed a *semi-supervised* multistep approach that mines online reviews in order to produce comparative feature-based statistical summaries (Fig. 5). The first step is to preprocess reviews by correcting spelling mistakes and detecting sentence boundaries (Dey and Haque, 2008). Then the Link Grammar Parser (Sleator and Temperley, 1993) is used to perform parts of speech (POS) tagging on the preprocessed reviews, and features are extracted by applying the multiword approach (Church and Hanks, 1990; Wen Zhang et al., 2007; Dalal and Zaveri, 2012; Zhang et al., 2008), for example, "front camera" and "wireless connectivity." The decomposition strategy (Wen Zhang et al., 2007) is adopted to keep shorter feature and to eliminate longer ones. For instance, if "Nexus 7 front camera" and "front camera" have been extracted as frequent features, the decomposition strategy would have to keep "front camera" and to discard "Nexus 7 front camera" as feature. Similar features are manually grouped together such as "cost/price" and WordNet is used to enhance the *"final feature set."* Finally, the sentiment polarity of adjectives describing features is identified with the use of SentiWordNet, and the orientation of user opinion is determined based on the dominant orientation of their features polarity. The authors compared their work with Apriori based approach (Hu and Liu, 2004b; Shaoning Shi and Yu Wang, 2011; Chih-Ping et al., 2010; Haiping Zhang et al., 2011; Hu and Liu, 2004a) and the seed set expansion approach (Zhao and Li, 2009; Dey and Haque, 2008) and found that their semi-supervised approach outperforms the two others in extracting product features.

Wang et al. (2013) designed and built a system called *SumView* that aims to generate a feature-based summary of customer reviews. The proposed system puts more efforts to perform summarization and ignores sentiment analysis. The contribution of *SumView* is fourfold. First, the customer reviews are gathered from Amazon using a web crawler. the extracted reviews are then preprocessed (stop words removal, text segmentation, parts of speech tagging (POST)), meanwhile, the *term-sentence matrix (TSM)* is constructed. Second, A similar approach to Hu and Liu (2004b) is used to extract product features from reviews: the primary set of candidate opinion features contains nouns and noun phrases, then, the number is reduced to 20 candidates that hold the highest term frequency-inverse sentence frequency (tf-isf) (Allan et al., 2003) scores, finally, the top 5 frequent features are picked and recommended to users (The users can select any combination of selected opinion features and can also input their desired features). Third, the review sentences are grouped into different feature-relevant clusters by applying (feature-based weighted non-negative matrix factorization) algorithm (FNMF). Finally, the review summary is formed from the most representative sentence in each cluster. The authors compared *SumView* with four widely used document summarization systems: *Centroid-based* (Radev et al., 2004), *Graph-based* (Erkan and Radev, 2004; Mihalcea and Tarau, 2004; Wan and Yang, 2008), *Non-negative matrix factorization (NMF)* (Li and Ding,

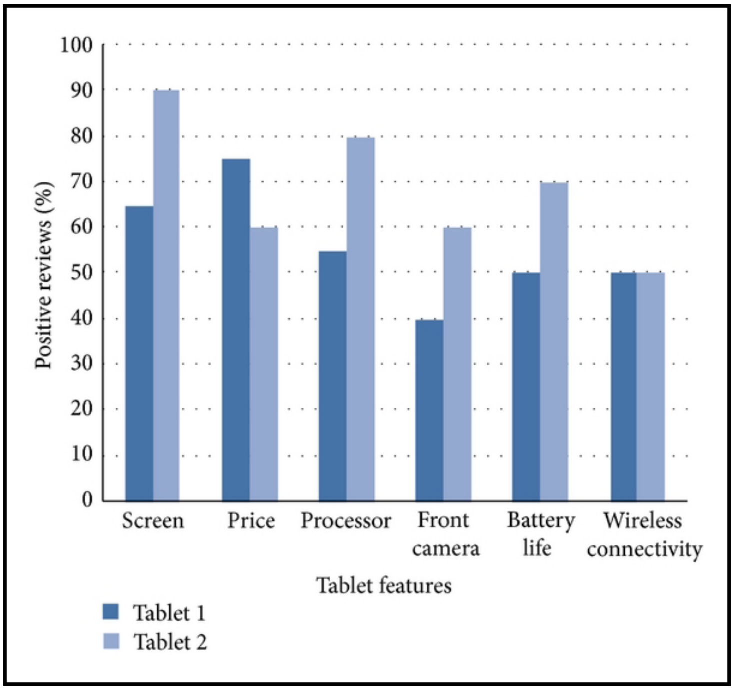

Fig. 5: Dalal and Zaveri (2013) comparative feature summary

2006) and *Corpernic*[3]. Experiment results show that *SumView* outperforms the other four systems in generating a representative feature-based summary for 173 reviews of a rice cooker. They also invited 25 students to assign a score of one to five for five product summaries generated by eight document summarization systems: *SumView*, *Corpernic*, *Centroid*, *Graph*, *NMF*, *Latent semantic analysis (LSA)* (Gong and Liu, 2001), *Term-RS* and *ListAll* ,and found that *SumView* obtained the highest score.

Ge et al. (2015) described and built a Chinese feature-based summarizer and applied it on Tan et al. (2005) corpus that contains 2000 Chinese reviews of hotels, notebooks, and books. The summarizer applies three steps to extract features, (1) frequent features are extracted based on the association rule mining method by setting 0.5% as the minimum support threshold for the frequency of nouns/noun phrases in the selected reviews, (2) infrequent features are identified by applying a similar approach to the Double Propagation algorithm (Qiu et al., 2009), a set of rules are applied to remove redundant and useless features. After extracting explicit and implicit features, the Naïve Bayes classifier is used to determine the sentiment orientation of opinion words.

Deep learning approaches have emerged as a prospect for performing feature/aspect based opinion summarization. Wu et al. (2016) and D et al. (2016) have respectively applied Convolutional Neural Network (CNN) and Recurrent neural network (RNN) which contain aspect mappers/taggers and sentiment classifiers to produce aspect/feature based summaries for smartphone and restaurant reviews.

An important issue that was neglected in previous studies on feature/aspect based summarization is spam detection. In fact, filtering irrelevant 'spam' reviews will reduce the computation cost and will improve the accuracy of opinion mining (summary generation) (Yan et al., 2017). Therefore, Kangale et al. (2016) took review spam detection into account and developed a system that generates a feature-based review summary of product reviews which includes a numerical rating for each individual feature (Fig. 6). The proposed system firstly identifies fake reviewers based on their social media account behaviors and patterns by applying Naïve Bayes classifier (He et al., 2012). The same classifier is used to detect spam reviews by training it with a manually annotated corpus of reviews ('spam' and 'genuine'). Beautiful Soup[4] python library is used to collect smartphone and digital camera reviews. Then, POS tagging and association rule mining are applied to extract frequent features and their opinion words. To remove unwanted features, a feature trimming is performed using two types of pruning proposed by Hu and Liu (2004b) (*compactness pruning* and *redundancy pruning*) and an extra type of pruning called miscellaneous pruning that improves this task. A set of

[3]http://www.copernic.com/en/products/summarizer
[4]https://www.crummy.com/software/BeautifulSoup/bs4/doc/

sixty adjectives with manually annotated semantic orientation is adopted to determine the orientation of opinion words with the help of a database-based algorithm that expands the seed list using an online database of synonyms and antonyms. The orientation of a sentence is the dominant orientation of its opinion words. Finally, a feature-based graphical summary is produced (Fig. 6). The summary depicts (1) the overall 5-star rating toward the targeted product, (2) a 5-star rating for every product feature, and (3) the proportion of positive and negative sentences that describe the targeted feature.

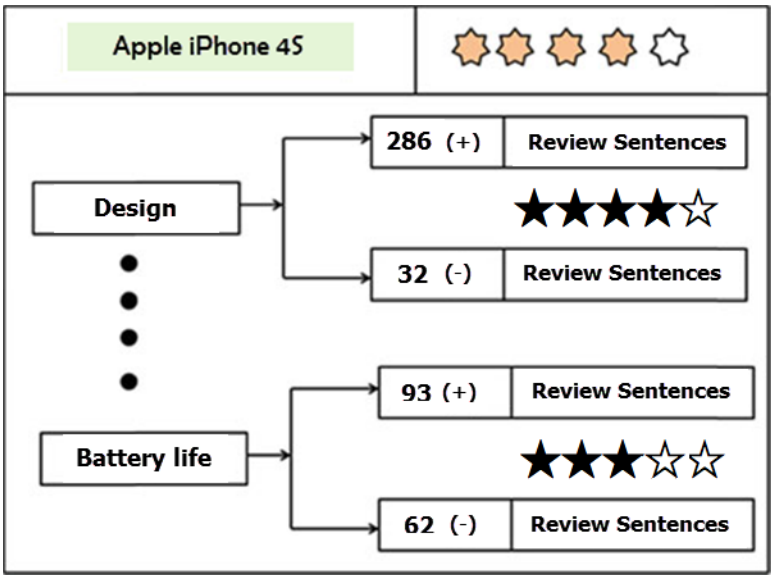

Fig. 6: Kangale et al. (2016) overall summary

El-Halees and Salah (2018) proposed the first Arabic feature-based opinion summarizer and applied it on 2860 hotel reviews extracted from TripAdvisor[5]. The feature extraction process (Siqueira and Barros, 2010) is performed in three steps: step one to identify frequent nouns; step two to identify relevant nouns by discarding prepositions, irrelevant words, and stop words; step three to remove unrelated nouns using the Pointwise Mutual Information - Information Retrieval (PMI-IR) (Turney, 2002) semantic similarity measure. The Arabic Sentiment and Emotion Lexicon (ArSenL)[6] is used to determine the sentiment orientation of feature opinion. The proposed system achieves an accuracy of 81.48% for the feature identification step by extracting 22 features from 27 features.

Differently from existing works on feature-based opinion summarization, Gupta et al. (2019) constructed an aspect vector that contains mobile's aspect categories and their aspects terms for the purpose of identifying different aspects from mobile reviews. The aspect categories are extracted from GSMArena[7] website that provides metadata/ specification of mobiles, and the aspects terms are extracted from 1000 Amazon's mobile reviews. In order to determine the sentiment orientation of each aspect, the authors exploited Thet et al. (2010) lexicon and SentiWordNet. Finally, a graphical aspect level summary is produced as shown in Fig. 7.

Coavoux et al. (2019) associated the popularity of unsupervised opinion summarization approaches with the lack of opinion summarization corpora and proposed an unsupervised abstractive review summarizer that (1) encodes review sentences into vectors using the recurrent neural network (RNN) (Rumelhart et al., 1986; Jordan, 1997) language model long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997); (2) clusters review sentences that represent the same aspect into the same group by applying a supervised aspect classifier; (3) aggregates review sentence representations by computing a single representation vector for each cluster; (4) decodes the single vector representation of each cluster by applying the top-k sampling decoding (Fan et al., 2018) method in order to generate the summary. The proposed approach is compared to the publicly available TextRank algorithm implementation[8] (Barrios et al., 2016) applied to the Oposum dataset[9] (Angelidis and Lapata, 2018).

[5]https://www.tripadvisor.com
[6]http://oma-project.com/ArSenL/download_intro
[7]https://www.gsmarena.com/
[8]https://github.com/summanlp/textrank
[9]https://github.com/stangelid/oposum

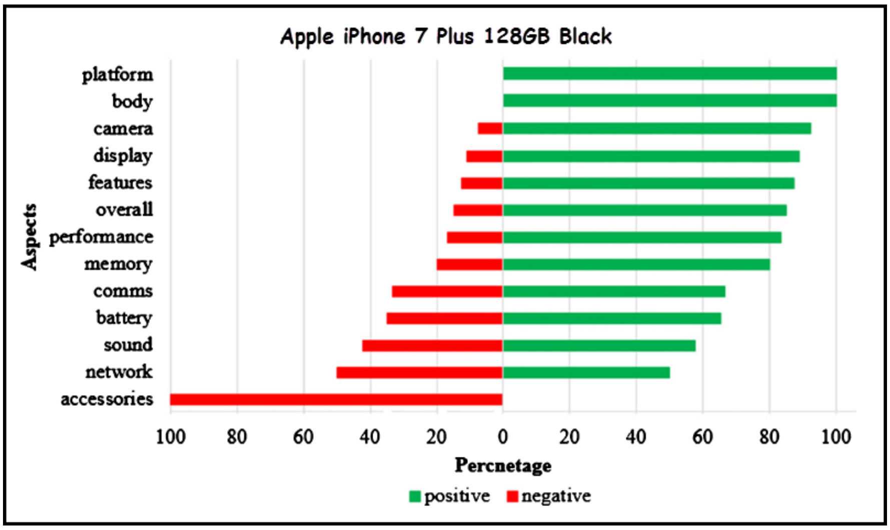

Fig. 7: Gupta et al. (2019) Gupta et al. (2019) graphical aspect level summary

The results show that their proposed summarizer outperforms TextRank algorithm on all ROUGE[10] (Lin, 2004) metrics (ROUGE-1, ROUGE-2 and ROUGE-L).

Recently, optimization techniques have been adopted to handle the task of feature-based summarisation (Nenkova and McKeown, 2012), though, they suffer from major drawbacks including the incapability to address the scaling of the large volume of data and redundancy. Therefore, Priya and Umamaheswari (2020) incorporated distributed clustering with simple-objective optimization (modified genetic algorithm) for feature-based summarisation in order to address the scaling of large datasets and to avoid redundancy. LSA model is applied to extract features from reviews and Naïve Bayes classifier is used to detect the polarity of opinion words associated with the extracted features. A combination of K-means clustering algorithm and MapReduce (Dean and Ghemawat, 2008) framework is adopted to generate feature-based summaries.

Mabrouk et al. (2021) proposed SEOpinion, the first summarizer that considers both template information provided by manufacturers and customer reviews to produce a hierarchical feature-based summary (Fig. 8) for laptops by performing three tasks: web scraping, hierarchical aspect extraction, and hierarchical aspect-based opinion summarization. The authors investigated the effectiveness of contextualized word embeddings from BERT with RNN and CNN for both hierarchical aspect extraction and hierarchical aspect-based opinion summarization (sentiment analysis) and reported that RNN+BERT outperforms CNN+BERT on the two tasks.

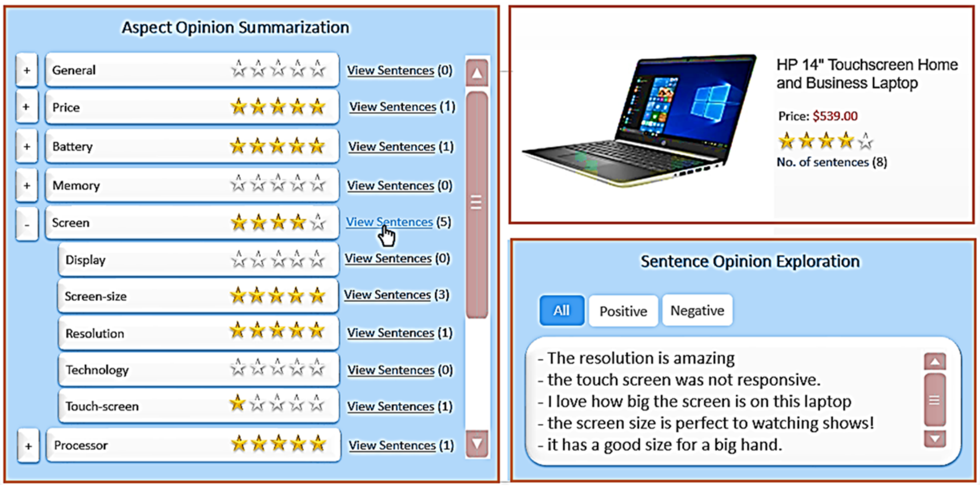

Fig. 8: Screenshot of SEOpinion system summary Mabrouk et al. (2021)

Tables 1 and 2 summarize the reported performance and the exploited techniques of presented systems for feature-based summarization.

[10] https://github.com/Diego999/py-rouge

Tab. 1: Approaches for aspect/feature based summarization

Work	Language	Domain	Evaluation task	Performance
Hu and Liu (2004b)	English	Electronic products	Frequent / Infrequent feature identification	Precision: 0.56 - 0.72 Recall: 0.68 - 0.80
Popescu and Etzioni (2005)	English	Electronic products	Explicit feature identification	Precision: 0.94 Recall: 0.77
Zhuang et al. (2006)	English	Movies	Feature-opinion pair identification	Precision: 0.483 Recall: 0.585 F-score: 0.529
Titov and McDonald (2008b)	English	Hotels	Aspect extraction	N/A
Sasha et al. (2008)	English	Local services	Static aspect identification	Precision: 0.705 - 0.946 Recall: 0.471 - 0.822 F-score: 0.565 - 0.859
Abulaish et al. (2009)	English	Electronic products	Feature-opinion extraction	Precision: 0.9112 Recall: 0.5097 F-score: 0.6490 Accuracy: 0.8887
Lu et al. (2009)	English	Products	Aspect discovery and clustering	Accuracy: 0.52
Homoceanu et al. (2011)	English	Movies Electronic products	Feature identification Feature identification	N/A Accuracy: 0.873
Liu et al. (2012)	Chinese	Movies	Feature identification	Precision: 0.8301 Recall: 0.8363 F-score: 0.8332
Kushal and Durga (2013)	English	Electronic products	Feature identification	Accuracy: 0.92
Dalal and Zaveri (2013)	English	Electronic products	Feature identification	Precision: 0.9160 Recall: 0.7826 F-score: 0.8441
Wang et al. (2013)	English	Electronic products	Feature identification	N/A
Marrese-Taylor et al. (2013)	English	Tourism	Aspect extraction	Precision: 0.38 Recall: 0.33 F-score: 0.36
Jmal and Faiz (2013)	English	Electronic products	Feature identification	Precision: 0.641 Recall: 0.671 F-score: 0.655
Ge et al. (2015)	Chinese	Hotels Books & Notebooks	Frequent / Infrequent feature extraction Frequent / Infrequent feature extraction	Precision: 0.674 - 0.745 Recall: 0.766 - 0.794 F-score: 0.717 - 0.769 Precision: 0.5885 - 0.7345 Recall: 0.706 - 0.761 F-score: 0.6415 - 0.7465
Kangale et al. (2016)	English	Electronic products	Feature identification	N/A
Hanni et al. (2016)	English	Products	Feature extraction	N/A
D et al. (2016)	English	Restaurants	Aspect category detection	Precision: 0.886 Recall: 0.824 F-score: 0.854
Wu et al. (2016)	English	Electronic products	Aspect mapping.	Precision: 0.761 - 0.871 Recall: 0.635 - 0.797 F-score: 0.696 - 0.812
Akhtar et al. (2017)	English	Hotels	Feature identification	N/A
Yauris and Khodra (2017)	English	Video games	Aspect extraction	Precision: 0.6010 Recall: 0.6748 F-score: 0.6239
El-Halees and Salah (2018)	Arabic	Hotels	Feature identification	Accuracy: 0.8148
Penubaka et al. (2018)	English	Electronic products	Feature Extraction	Accuracy: 0.90 - 0.94
Gupta et al. (2019)	English	Electronic products	Feature identification	Precision: 0.78 Recall: 0.77 F-score: 0.80
Panagiotopoulos et al. (2019)	English	Video games	Aspect extraction	N/A
Coavoux et al. (2019)	English	Electronic products	Feature extraction	N/A
Priya and Umamaheswari (2020)	English	Hotels Movies Electronic products	Feature extraction Feature extraction Feature extraction	N/A N/A N/A
Mukherjee et al. (2020)	English	Tourism	Aspect identification	N/A
Jerripothula et al. (2020)	English	Electronic products	Feature identification	N/A
Mabrouk et al. (2021)	English	Electronic products	Hierarchical aspect extraction	Precision: 0.7726 Recall: 0.7754 F-score: 0.7734

Tab. 2: Approaches for aspect/feature based summarization

Work	Aspect extraction/mapping	Sentiment/Semantic orientation identification
Hu and Liu (2004b)	Association rule mining	• WordNet • Seed adjectives • Extraction rules
Popescu and Etzioni (2005)	• Association rule mining • PMI • Web PMI	Relaxation labelling
Zhuang et al. (2006)	• Feature keyword list • Dependency relation templates	• Opinion keyword list • WordNet
Titov and McDonald (2008b)	• Multi-Grain LDA (MG-LDA) (Titov and McDonald, 2008a)	—
Sasha et al. (2008)	• Dynamic aspect extractor (Hu and Liu, 2004b) • Binary Maximum Entropy Classifier	• Seed lexicon • WordNet
Abulaish et al. (2009)	Rule-based system	SentiWordNet
Lu et al. (2009)	• K-Means • Unstructured probabilistic latent semantic analysis (PLSA) (Hofmann, 1999) • Structured PLSA	—
Homoceanu et al. (2011)	• Multi-stage language model approach (Kageura and Umino, 1996) • Probabilistic approach	• SentiWordNet • System's users or administrators
Liu et al. (2012)	Latent Semantic Analysis (LSA)	Support Vector Machines (SVM)
Wang et al. (2013)	Co-occurrence based approach	—
Kushal and Durga (2013)	• Association rule mining • Probabilistic model	• Opinion lexicon[11] • SentiWordNet
Dalal and Zaveri (2013)	• Multiword approach • WordNet	SentiWordNet
Marrese-Taylor et al. (2013)	Association rule mining	• WordNet • Seed adjectives • Extraction rules
Jmal and Faiz (2013)	Co-occurrence based approach	• SentiWordNet • Twitter
Ge et al. (2015)	• Association rule mining • Double Propagation • Extraction rules	Naïve Bayes classifier
D et al. (2016)	Recurrent neural network (RNN)	Convolutional Neural Network
Kangale et al. (2016)	Association rule mining	• Seed adjectives • Database-based algorithm
Wu et al. (2016)	Convolutional Neural Network (CNN) (LeCun et al., 2015)	Convolutional Neural Network (CNN)
Hanni et al. (2016)	Association rule mining	• VADER lexicon (Hutto and Gilbert, 2014) • Stanford CoreNLP[12] • Naïve Bayes classifier
Akhtar et al. (2017)	Latent Dirichlet allocation (LDA) (Blei et al., 2003)	SentiWordNet
Yauris and Khodra (2017)	Double Propagation	Opinion Lexicon[13]
El-Halees and Salah (2018)	WhatMatter System (Siqueira and Barros, 2010)	ArSenL Lexicon[14]
Penubaka et al. (2018)	• Association rule mining • Probabilistic approach	• Opinion lexicon[15] • SentiWordNet
Gupta et al. (2019)	• Mobile metadata • Aspect vector	• Generic lexicon (Thet et al., 2010) • SentiWordNet
Panagiotopoulos et al. (2019)	K-means	VADER lexicon
Priya and Umamaheswari (2020)	Latent Semantic Analysis (LSA)	Naïve Bayes classifier
Mukherjee et al. (2020)	Attention-based Aspect Extraction (ABAE) (He et al., 2017)	CoreNLP SentimentAnnotator Manning et al. (2014)
Jerripothula et al. (2020)	Co-occurrence based approach	VADER lexicon
Mabrouk et al. (2021)	RNN+BERT	RNN+BERT

2.2 Limitations and disadvantages of the previous research works

It is very crucial to highlight the limitations and disadvantages of the previous research works on aspect/feature based summarization, which would assist the research community in their selection of the methods. Based on our analysis of the previous research works conducted on aspect/feature based summarizers, we are able to produce a list of 10 disadvantages of these systems:

- Issue 1: the system doesn't deal with opinion sentences that need pronoun resolutions (Tetreault, 1999).
- Issue 2: the system only considers adjectives as indicators to determine the sentiment orientation of sentences, disregarding the use of verbs and nouns.
- Issue 3: the system is incapable of extracting implicit features.
- Issue 4: the system considers some frequently occurring noun phrases as features.
- Issue 5: the system doesn't integer a spelling correction component during the preprocessing phase.
- Issue 6: the system doesn't consider the context information during the identification of the semantic orientation of opinion words.
- Issue 7: the system is highly dependant on the training data.
- Issue 8: the system achieved very poor performances during the aspect detection phase.
- Issue 9: the system doesn't handle ironical reviews.
- Issue 10: the system doesn't filter reviews that are not related to the underlying entity (opinion spam and unrelated opinions).

Table 3 summarizes the limitations and disadvantages of the reviewed aspect/feature based summarizers. The Check Mark Symbol ✓ means that the work suffers from the target issue and the Ballot X Symbol ✗ means that the work doesn't suffer from the target issue.

Tab. 3: Limitations and disadvantages of the previous research works for aspect/feature based summarization

Work	Issue 1	Issue 2	Issue 3	Issue 4	Issue 5	Issue 6	Issue 7	Issue 8	Issue 9	Issue 10
Hu and Liu (2004b)	✓	✓	✓	✓	✗	✗	✗	✗	✓	✓
Popescu and Etzioni (2005)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
Zhuang et al. (2006)	✗	✗	✗	✗	✓	✓	✓	✗	✓	✓
Titov and McDonald (2008b)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
Sasha et al. (2008)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
Abulaish et al. (2009)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
Lu et al. (2009)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
Homoceanu et al. (2011)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
Liu et al. (2012)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
Wang et al. (2013)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
Kushal and Durga (2013)	✗	✗	✓	✗	✗	✗	✗	✗	✓	✓
Dalal and Zaveri (2013)	✗	✗	✓	✗	✗	✗	✗	✗	✓	✓
Marrese-Taylor et al. (2013)	✗	✗	✓	✗	✗	✗	✗	✓	✓	✓
Jmal and Faiz (2013)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
Ge et al. (2015)	✗	✗	✗	✗	✓	✗	✗	✗	✓	✓
Kangale et al. (2016)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✗
Hanni et al. (2016)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
D et al. (2016)	✗	✗	✓	✗	✓	✗	✓	✗	✓	✓
Wu et al. (2016)	✗	✗	✗	✗	✓	✗	✓	✗	✓	✓
Akhtar et al. (2017)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
Yauris and Khodra (2017)	✓	✓	✓	✗	✓	✗	✗	✗	✓	✓
El-Halees and Salah (2018)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
Penubaka et al. (2018)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
Gupta et al. (2019)	✗	✗	✗	✗	✓	✗	✓	✗	✓	✓
Panagiotopoulos et al. (2019)	✗	✗	✗	✗	✓	✗	✓	✗	✓	✓
Coavoux et al. (2019)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
Priya and Umamaheswari (2020)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
Mukherjee et al. (2020)	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓
Jerripothula et al. (2020)	✗	✗	✓	✗	✗	✗	✗	✗	✓	✓
Mabrouk et al. (2021)	✗	✗	✓	✗	✗	✗	✓	✗	✓	✓

3 Reputation Generation

3.1 Summaries of the previous research works

The Cambridge Dictionary [16] defines reputation as *"the opinion that people in general have about someone or something, or how much respect or admiration someone or something receives, based on past behaviour or character."*

Previous studies on reputation generation of online products have primarily focused on exploiting user ratings (Paul and Richard, 2002; Schneider et al., 2000; Garcin et al., 2009; Resnick et al., 2000; Leberknight et al., 2012; Cho et al., 2009; Jøsang et al., 2007) to generate a score toward online products. Surprisingly, textual data (reviews), which constitute a significant part of customer information, have been somewhat ignored until 2012 when Abdel-Hafez et al. (2012) designed a product reputation model that uses text reviews rather than users' ratings for the purpose of generating a more realistic reputation value for every feature of the product and the product itself by incorporating opinion orientation and opinion strength (sentiment analysis), though, there was no evidence to support the efficiency of the proposed reputation system since the authors **assumed** that the product features and the opinion orientation and strength to the features in each product review have been determined by using existing opinion mining techniques without actually applying them.

Farooq et al. (2016b) represented a review as an octuple $< g, Nr, Tr, rt, t, a, \alpha, \beta >$ in which g is the product name, Nr is the numeric rating (1-5 or 1-10), Tr is the textual rating (textual comment), rt is the review title, t is the review date, a is the author id, α is the positive review helpful votes, β is the negative review helpful votes, and proposed a reputation system that took both numeric and textual ratings into account during the reputation generation phase toward products. During the first phase, the system extracts products' reviews from eBay[17], CNET[18] and Amazon. In the second phase, the association rule mining approach is adopted to extract features and SentiWordNet sentiment lexicon is used to determine the sentiment orientation of the extracted and preprocessed reviews. In the third phase, a reputation value is computed toward each rating in order to rank its reputability before considering it for computing reputations. In the fourth and last phase, five aggregation methods are proposed to compute five different reputations. **Feature reputation**: which represents a numerical reputation value toward each feature associated with the target product. **Features based product reputation**: which represents a numerical reputation value that depends on the **feature reputation**. **Aggregating general opinions**: this value is computed without considering features. **Product reputation**: this value represents the overall product reputation, and it's computed by considering both numeric and textual ratings. **Product reputation based on review titles**: this value is computed based on the result of opinion mining (sentiment analysis) of review titles and rating reputation. Although the system is very efficient in terms of reputation generation since it considers a lot of features including source reliability, reviewer expertise, rating trustworthiness, and ageing factor, it doesn't offer any form of reputation visualization to help customers making an informed decision toward the target products.

Yan et al. (2017) were the first to propose an approach for generating a single reputation value toward a target product based on fusing and mining customer reviews and their attached ratings. First, they develop a web spider to collect 5424 product information (product descriptions, customer reviews, and review ratings) from Amazon China [19] and Amazon English [20], then, they remove word segmentation and stop words in the collected reviews. Second, they filter untruthful and irrelevant reviews based on opinion pertinence (Wang et al., 2015). Third, they fuse the remaining similar reviews into a number of principal opinion sets based on their similarity (cosine similarity and Latent Semantic Analysis model (Landauer and Dutnais, 1997; Landauer et al., 1998). Finally, they design a new formula to generate a single reputation value toward the target product. However, the major issue of their work is the reliance on LSA model to group similar opinions together (Benlahbib and Nfaoui, 2020c). The same approach has been adopted in Benlahbib and Nfaoui (2019) by applying

[16]https://dictionary.cambridge.org/fr/dictionnaire/anglais/reputation
[17]https://www.ebay.com/
[18]https://www.cnet.com/
[19]https://www.amazon.cn
[20]https://www.amazon.com

LSA model and K-means (Lloyd, 1982) algorithm to group semantically similar reviews into the same cluster.

Benlahbib and Nfaoui (2020c) focused on building a reputation generation method that overcomes the weakness of Yan et al. (2017) approach by applying document-level sentiment classification and opinion fusion techniques. The authors gather manually 1000 movie reviews and their ratings[21] from the IMDb website. Then, they use Naïve Bayes and Linear Support Vector Machine (Cortes and Vapnik, 1995) classifiers to separate reviews into positive and negative. After, they fuse and group separately positive reviews and negative reviews into different opinion sets based on semantic relations. Later, they compute a custom reputation value separately for positive opinion sets and negative opinion sets. Lastly, they compute the final reputation value toward the target movie using Weighted Arithmetic Mean. The authors compared their work to Yan et al. (2017) approach and found that their reputation generation method performs well in generating accurate reputation values.

The same authors designed and built a new reputation system (Benlahbib and Nfaoui, 2020a) that considers review time, review helpfulness votes, and review sentiment orientation for the purpose of generating reputation toward online entities (products, movies, hotels, and services). They fine-tuned Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019) model to determine the sentiment orientation probability of the collected reviews. The system also provides a new form of reputation visualization by depicting the numerical reputation value, the distribution of sentiment over the reviews, the top positive review, and the top negative review (Fig. 9).

Elmurngi and Gherbi (2020) proposed a system that computes reputation scores from users' feedback based on a sentiment analysis model (SAM). The reputation score of a product is the ratio of the number of positive reviews over the total number of reviews toward this product. The same approach was adopted by Boumhidi and Nfaoui (2020); Boumhidi et al. (2021) to generate reputation scores for movies.

Recently, Benlahbib and Nfaoui (2021) incorporated fine-grained opinion mining and semantic analysis for the purpose of generating and visualizing reputation toward movies and TV shows (MTVRep). The authors trained the Multinomial Naïve Bayes classifier on the SST-5 dataset (Manning et al., 2014) to group reviews into five emotion classes: strongly negative, weakly negative, neutral, weakly positive, and strongly positive, then, Embeddings from Language Models (ELMo) (Peters et al., 2018) and cosine similarity were applied to extract the semantic similarity between reviews and to compute a custom score for each emotion class. Finally, the weighted arithmetic mean is used to compute the movie or TV show reputation value. The authors compared the performance of MTVRep in generating accurate reputation values to Yan et al. (2017) reputation system on 20 datasets and found that MTVRep outperforms it on 19 datasets.

A legitimate question may nevertheless come to mind: *"What is the difference between feature-based summarizers and feature-based reputation systems."* While feature-based summarizers aim at extracting the features of a target entity, then computing a score toward each aspect based on the number of positive/negative opinions, and finally calculating an overall score toward the entity by averaging their aspects' scores, feature-based reputation systems exploit various factors that could be extracted from customer reviews including review time, review helpfulness, user credibility, sentiment strength, etc., in order to compute accurate and reliable scores toward the extracted aspects and the entity itself.

Tables 4, 5, 6 summarize the opinion mining techniques, the depicted elements, and the exploited features during the reputation generation and visualization for the reviewed reputation systems.

[21] https://data.mendeley.com/datasets/38j8b6s2mx/1

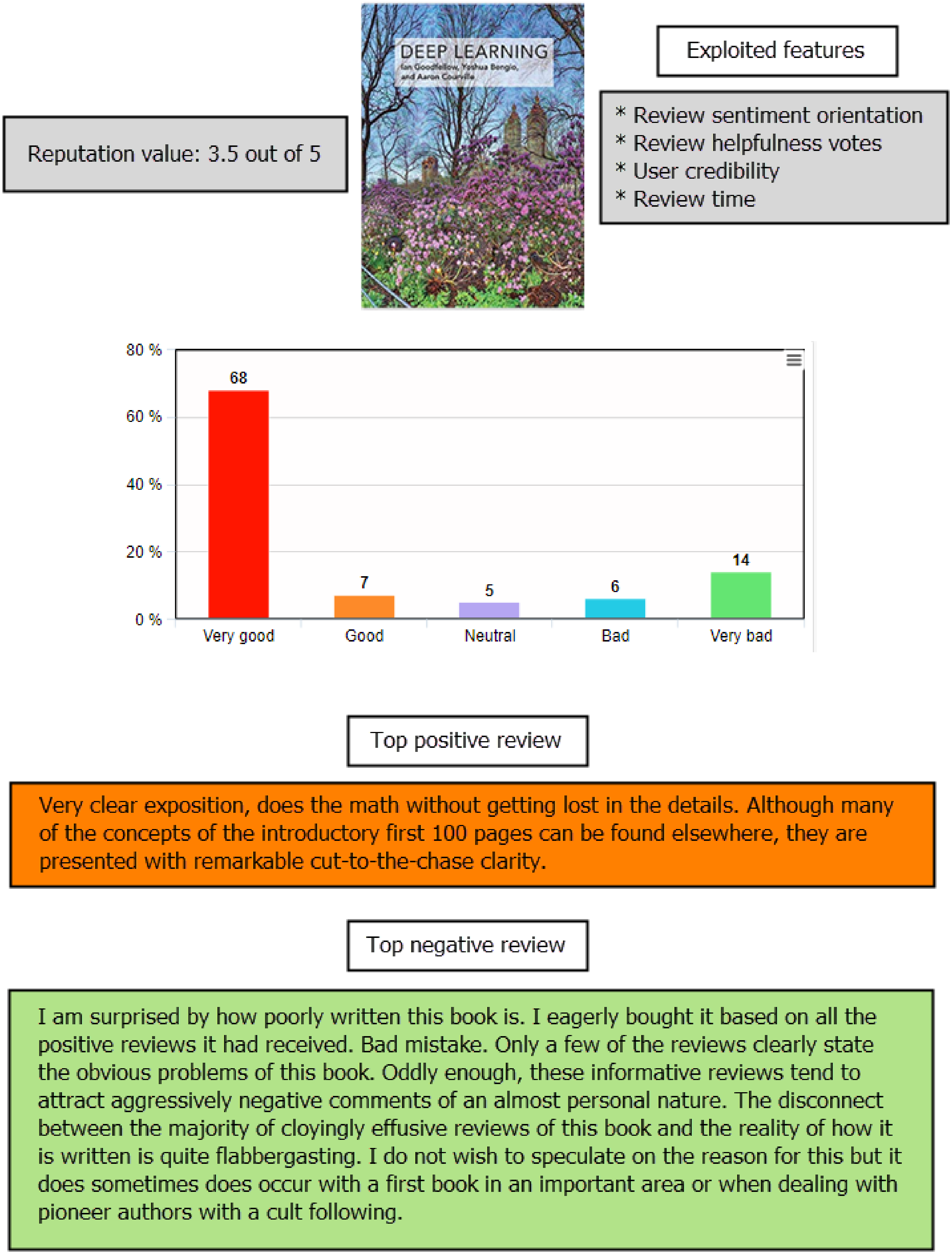

Fig. 9: Benlahbib and Nfaoui (2020b) reputation visualization

Tab. 4: Approaches for reputation generation

Work	Language	Domain	Semantic analysis	Sentiment analysis
Abdel-Hafez et al. (2012)	N/A	N/A	N/A	N/A
Farooq et al. (2016b)	English	Products	N/A	SentiWordNet
Farooq et al. (2016a)	English	Products	N/A	N/A
Yan et al. (2017)	• English • Chinese	Products	Latent Semantic Analysis (LSA)	N/A
Benlahbib and Nfaoui (2019)	English	Movies	Latent Semantic Analysis (LSA)	N/A
Benlahbib et al. (2019)	English	Movies	Latent Semantic Analysis (LSA)	Logistic Regression
Benlahbib and Nfaoui (2020c)	English	Movies	Latent Semantic Analysis (LSA)	• Naïve Bayes • Linear Support Vector Machine
Elmurngi and Gherbi (2020)	English	Products	N/A	Logistic Regression
Benlahbib and Nfaoui (2020a)	English	• Products • Movies & TV Shows • Hotels	N/A	Bidirectional Encoder Representations from Transformers (BERT)
Benlahbib and Nfaoui (2020b)	English	Products	N/A	Bidirectional Gated Recurrent Unit (Bi-GRU)
Boumhidi and Nfaoui (2020)	English	• Movies • Restaurants	N/A	Bidirectional Gated Recurrent Unit (Bi-GRU)
Gupta et al. (2020)	English	• Movies • Books	N/A	• Bidirectional Encoder Representations from Transformers (BERT) • Naïve Bayes • Support Vector Machine
Boumhidi et al. (2021)	English	Movies	N/A	Bidirectional Long Short-Term Memory (BI-LSTM)
Benlahbib and Nfaoui (2021)	English	Movies & TV Shows	Embeddings from Language Models (ELMo)	Multinomial Naïve Bayes

Tab. 5: Approaches for reputation generation: depicted elements during reputation visualization

Work	Reputation value	Distribution of user reviews sentiment polarity	Top-k positive/negative reviews
Abdel-Hafez et al. (2012)	✓	✗	✗
Farooq et al. (2016b)	✓	✗	✗
Farooq et al. (2016a)	✓	✗	✗
Yan et al. (2017)	✓	✓	✗
Benlahbib and Nfaoui (2019)	✓	✗	✗
Benlahbib et al. (2019)	✓	✗	✗
Benlahbib and Nfaoui (2020c)	✓	✓	✗
Elmurngi and Gherbi (2020)	✓	✓	✗
Benlahbib and Nfaoui (2020a)	✓	✓	✓
Benlahbib and Nfaoui (2020b)	✓	✓	✓
Boumhidi and Nfaoui (2020)	✓	✓	✗
Gupta et al. (2020)	✓	✗	✗
Boumhidi et al. (2021)	✓	✓	✗
Benlahbib and Nfaoui (2021)	✓	✓	✗

Tab. 6: Approaches for reputation generation: features exploited by recent reputation systems

Work	Semantic	Sentiment	Rating	Review helpfulness	Review time	User credibility
Abdel-Hafez et al. (2012)	✗	✓	✗	✗	✗	✗
Farooq et al. (2016b)	✗	✓	✓	✓	✓	✓
Farooq et al. (2016a)	✗	✗	✓	✓	✓	✓
Yan et al. (2017)	✓	✗	✓	✗	✗	✗
Benlahbib and Nfaoui (2019)	✓	✗	✓	✗	✗	✗
Benlahbib et al. (2019)	✓	✓	✓	✗	✗	✗
Benlahbib and Nfaoui (2020c)	✓	✓	✓	✗	✗	✗
Elmurngi and Gherbi (2020)	✗	✓	✗	✗	✗	✗
Benlahbib and Nfaoui (2020a)	✗	✓	✓	✓	✓	✗
Benlahbib and Nfaoui (2020b)	✗	✓	✓	✓	✓	✓
Boumhidi and Nfaoui (2020)	✗	✓	✗	✗	✗	✗
Gupta et al. (2020)	✗	✓	✓	✓	✗	✗
Boumhidi et al. (2021)	✗	✓	✓	✗	✗	✗
Benlahbib and Nfaoui (2021)	✓	✓	✓	✗	✗	✗

3.2 Limitations and disadvantages of the previous research works

It is very crucial to highlight the limitations and disadvantages of the previous research works on reputation generation based on mining online reviews, which would assist the research community in their selection of the methods. Based on our analysis of the previous research works conducted on reputation generation, we are able to produce a list of 4 disadvantages of these systems:

- Issue 1: the system doesn't handle ironical reviews.
- Issue 2: the system doesn't filter reviews that are not related to the underlying entity (opinion spam and unrelated opinions).
- Issue 3: the system doesn't provide customers with valuable information to make an informed decision toward the target online product.
- Issue 4: the system doesn't consider review time, review helpfulness or user credibility during the reputation generation and visualization.

Table 7 summarizes the limitations and disadvantages of the reviewed reputation generation systems. The Check Mark Symbol ✓ means that the work suffers from the target issue and the Ballot X Symbol ✗ means that the work doesn't suffer from the target issue.

Tab. 7: Limitations and disadvantages of the previous research works for reputation generation

Work	Issue 1	Issue 2	Issue 3	Issue 4
Abdel-Hafez et al. (2012)	✓	✓	✓	✓
Farooq et al. (2016b)	✓	✓	✓	✗
Farooq et al. (2016a)	✓	✓	✓	✗
Yan et al. (2017)	✓	✗	✓	✓
Benlahbib and Nfaoui (2019)	✓	✓	✓	✓
Benlahbib et al. (2019)	✓	✓	✓	✓
Benlahbib and Nfaoui (2020c)	✓	✓	✓	✓
Elmurngi and Gherbi (2020)	✓	✓	✓	✓
Benlahbib and Nfaoui (2020a)	✓	✓	✗	✗
Benlahbib and Nfaoui (2020b)	✓	✓	✗	✗
Boumhidi and Nfaoui (2020)	✓	✓	✓	✓
Gupta et al. (2020)	✓	✓	✓	✗
Boumhidi et al. (2021)	✓	✓	✓	✓
Benlahbib and Nfaoui (2021)	✓	✓	✓	✓

4 Future researches and open problems

There are many areas that still need further investigations and solutions

4.1 Common challenges for feature-based summarization and reputation generation

- **Opinion spam detection**: due to the openness of the Internet, many malicious users post fake reviews (false positive/false negative) aiming to impact the popularity and credibility of online products. Thus, it is very important to detect and remove fake and irrelevant reviews by applying a filtering phase and therefore reducing the processing time and increasing the efficiency of the systems at once since only relevant and useful reviews will be taken into account.
- **Sarcastic reviews**: sarcasm is when someone speaks contradictory to the true intention. In fact, understanding sarcasm and irony is hard since it requires not just language proficiency, but also knowledge of common sense, cultural knowledge, and context. Actually, none of the reviewed works for both feature-based summarization and reputation generation dealt with sarcastic reviews. Thus, future studies should focus on improving the opinion mining task by handling sarcasm and irony in online customer reviews.
- **Language problems**: most of the conducted works are in English and Chinese languages. Other languages are still unemployed in aspect extraction and reputation generation.
- **Dataset problems**: there is no standard dataset available for use in both implicit aspect extraction and reputation generation.

4.2 Challenges for feature-based summarizaiton

- **Implicit aspects/features detection**: the majority of aspect identification techniques fail to extract implicit features from reviews. For example, *"While light, it will not easily fit in pockets."* This review is talking about the size of the phone, but the word size does not appear in the sentence.
- **Domain adaptation**: it is obvious that the polarity of a word can only be determined given its domain or context. For example, “small” contains a positive sentiment in the electronics domain in “the phone is small and convenient” but it has negative sentiment in a restaurant review when it states, “the portion is small” (Do et al., 2019).

4.3 Challenges for reputation generation

- **Evaluation measure**: for the time being, there are no standard evaluation measures to assess the accuracy of reputation systems in generating reputation. Therefore, it is very crucial to determine a suitable evaluation measure for the purpose of evaluating the effectiveness and robustness of reputation systems.
- **Reputation visualization**: reputation systems should provide customers with valuable information to help them make an informed decision toward the target online products. Therefore, future studies should focus on incorporating aspect-based opinion mining since it will enhance and improve the reputation visualization form. Indeed, the system will depict more useful information toward the target entity such as the reputation value toward each feature, the number of positive reviews toward each feature, the number of negative reviews toward each feature . . .

5 Conclusions

To the best of our knowledge, this is the first work that reviews Natural Language Processing (NLP) techniques that have been used to help E-commerce customers in making an informed decision toward various online items (products, movies, hotels, services . . .).

There are some significant findings obtained from this review. Studies on feature-based summarization and reputation generation used datasets that were created by the researchers themselves since there are no publicly available benchmark datasets for those tasks. Therefore, future researchers can build new standard datasets for feature-based summarization or reputation generation. Our review also shows that the major works in feature-based summarization and reputation generation don't filter reviews that are not related to the underlying entity (opinion spam and unrelated opinions). We also found that the majority of studies on feature-based summarization and reputation generation were conducted only for some major languages such as English and Chinese. However, other languages such as Arabic, French, Spanish, German, Italian, and Hindi are still not being explored. Besides, none of the reviewed works for both feature-based summarization and reputation generation dealt with sarcastic reviews. Thus, future studies should focus on improving the opinion mining task by handling sarcasm and irony in online customer reviews.

From the previous studies, we also found that the majority of aspect identification techniques fail to extract implicit features from reviews. Thus, it is another possible future research area for aspect/feature based summarizers.

Another issue identified in this paper is the inexistence of any standard evaluation measures to assess the accuracy of reputation systems in generating reputation. Therefore, it is very crucial to determine a suitable evaluation measure to evaluate the effectiveness and robustness of reputation systems.

We hope this paper can provide readers and researchers with a comprehensive understanding of the key aspects of Natural Language Processing (NLP) techniques that have been used to support customers during their online decision-making process in E-commerce platforms by clarifying the most notable advancements and by shedding some light on future studies and open problems.

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