Hybrid Approach for User Reviews' Text Analysis and Visualization: A Case Study of Amazon User Reviews

https://doi.org/10.3991/ijim.v16i08.30169

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Abstract—Nowadays, many people prefer to purchase through online websites. Usually, those people start with reading user reviews and comments before making a purchase decision. The user reviews are considered powerful sources of information about products, in which users share opinions and previous experiences on using these products. However, these reviews are mostly textual and uncategorized. Thus, new customers need to read a massive amount of reviews, one by one, to make a decision. This study attempts to bridge this gap and proposes a hybrid approach of topic modeling that combines supervised and unsupervised learning. In particular, the study collected a massive amount of Amazon user reviews, analyzed the reviews' texts, and combined two approaches of topic modeling, which are unsupervised and supervised learning, i.e., semi-supervised learning. Besides, the study makes classification on reviews based on sentiment analysis. The resulting reviews' topics and their sentiment classifications are displayed on a visual dashboard. The proposed hybrid approach showed better performance in terms of text analysis and clearer representation of review topics. The outcome of this study helps customers make their decision on purchase products in a more effortless and clearer way.

Keywords—user reviews, sentiment analysis, topic modeling, visualization

1 Introduction

In the past, people used to rely on other people around them, such as friends, family, and colleagues, to purchase products through word of mouth. Over the past few decades, that has changed to the digital market, which has grown dramatically, so people's thinking and perspective have changed to emphasize online reviews. With the increasing number of online shoppers, users post reviews on their favorite websites and items that give them the power of opinion. Customers provide their opinions on products that help other customers to decide. With the growth of the online shopping market, more problems have come up to the surface, such as:

- The reviews have not been classified into topics, which caused an overload of reviews and confusion for customers.
- Often behind a perfect score rating or reviews, there may be conflicting results with the rest of them. As an example, and as shown in Figure 1, the rating of a selected product is high, i.e., 4.5 stars based on 427 reviews; however, many customers, i.e., 981 people, agreed with a negative review about the product.
- Although some existing studies and systems of user reviews provide visualization of user reviews, these visualizations are not very easy for a typical user to understand. e.g., [1] and [2] (refer to related work section).

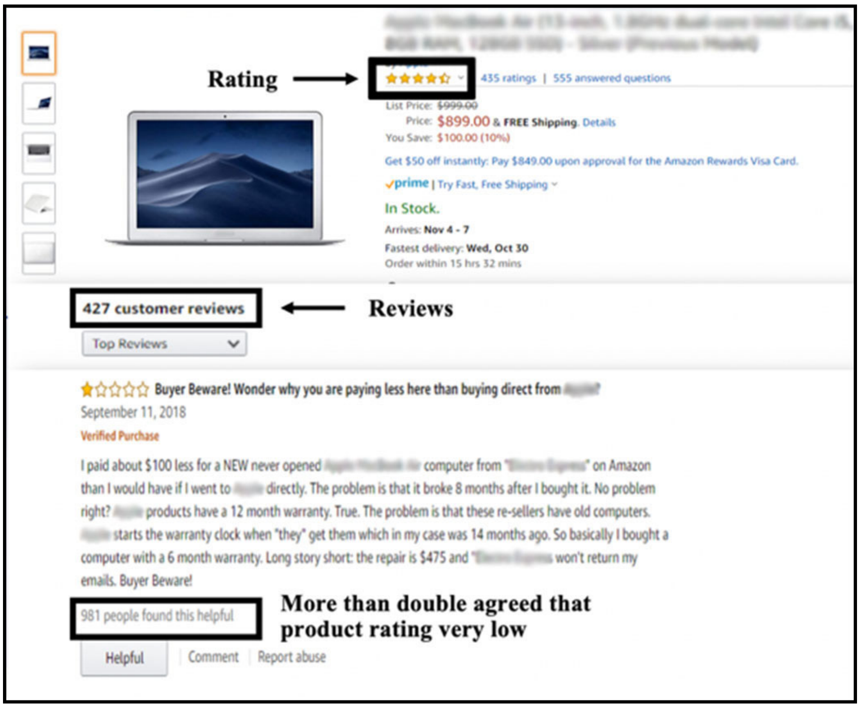


Fig. 1. An example of conflicting reviews and ratings of products

This study collects user reviews, categorizes the reviews based on a hybrid approach of topic modeling, and visualizes the topics and reviews with their sentiment classification on a developed dashboard. This way, customers can use previous user reviews more flexibly. The main contributions of this study are:

1. A hybrid topic model that applies both supervised and unsupervised learning to the user reviews.
2. A sentiment analysis of the user reviews.
3. A dashboard of user reviews' topic modelling as well as sentiment analysis.

This paper is organized as follows: Section 2 presents the works related to the present study. Section 3 introduces our method. Section 4 presents the results based on our method. Finally, Section 6 concludes the paper.

2 Related work

In literature, several studies have applied topic modeling to analyze user reviews text, e.g., [3]. In topic modeling studies, topics are created along with the most likely words to happen frequently [4]. A survey of several models found that successful topic models could be established by analyzing the content of comprehensive text collections [5]. A common method used for topic modeling in previous studies such as [6], [7], and [8], is Latent Dirichlet Allocation, or in short (LDA). LDA is an unsupervised method that has been widely applied in the field of natural language processing. This method is helpful to organize the text, but it does not always produce good results. Many studies, such as [7] and [9], used unsupervised LDA to classify the text. Texts of user reviews have also been analyzed in terms of sentiment. Multiple methods have been applied to classify the text into positive, negative, and neutral based on polarity (See Table 1.). These include Naive Bayes (NB), e.g., [3], [8], [10], and [11], Random Forest (RF) [10], support vector machine (SVM) [10], [11], decision tree (DT) [11], K-Nearest Neighbours algorithm (KNN) [11], Skyttle [12], and SentiText [13]. The study [Hani, 20], applies the sentiment scores, which the scores will be generated for the data, then they will be scaled to fit specific characteristics, after that return the text as positive, neutral, or negative. In the study of L. Lin et al. [14], the authors focused on sentiment categorizations to summarize opinions using the Apriori algorithm. In another study [10], the authors suggest two sentiment categorization methods: sentence-level categorization and review-level categorization. The goal of sentence-level categorization is to classify into positive and negative. The second type is generated from reviews that have 4-star ratings are labeled as positive and negative ones are generated from 1-star and 2-star reviews. In study of [15] the authors proposes semi-supervised learning targeted sentiment classification by using both labelled and unlabeled data. The analysis of text [16] on the web can also be unsupervised where unorganized groups of data, and by using artificial intelligence, the models are trained in order to understand them in a comprehensive way. Examples include the work of C. Sindhu et al. [11] and S. Brody and N. Elhadad [16]. In addition, the study of Y. Chen et al. [17] provided an interactive system for visual processing natural language and sentiment lexicon of the reviews using the Natural Language Toolkit (NLTK) library. LDA classified the main topic of the dataset and visuals them in the interactive system.

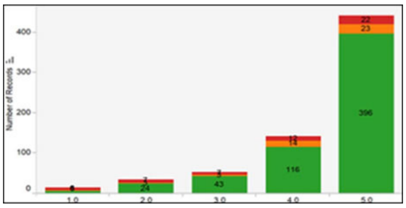
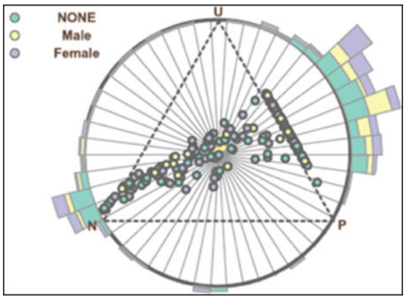
Table 1. Sentiment analysis methods

Method	Definition
Naive Bayes [1], [8], [10], [11]	Naive Bayes is a machine learning algorithm that is written for the classification of probability.
SVM [10], [11]	An algorithm that analyzes the data based on supervised learning models.
Random Forest [10]	The random forest is an algorithm that classifies statements as a tree structure.
LDA [11]	Latent Dirichlet Allocation (LDA) a statistical model method that groups data based on similarity.
Skyttle [12]	A web-based service that performs a phrase-level sentiment on up to 10,000 characters of text per API call.
SentiText [13]	Corpus oriented towards the polarity of opinions.
Unsupervised Sentiment Model [16]	An unsupervised model that analyzes data based on sentiment analysis.

In terms of user review visualization, several studies have been found. A summary of these studies is shown in Table 2.

The authors in [18] developed a system that helps visualize the customer's reviews using sentiment analysis, which can be positive, negative, or neutral. The system visualizes the reviews as stacked bars, word cloud, packed bubbles, and linear chart in a single dashboard to help any customer get a faster evaluation of a product based on other customer's reviews. In another study [19], the authors have created novel visual methods that analyze most customer feedback using feature-based term associations and sentence-based term association algorithms and give sentiment values. They have visualized the results in several ways: pixel-based sentiment, geo map, association map, and key term geo map. Also, the authors of A study by E. Guzman et al. [20] proposed an approach to visualize user reviews based on four different abstraction levels: general, review-based, feature-based, and feature-topic based.

Table 2. Visualization analysis method

<table>
<tr><th>Method</th><th>Sample</th></tr>
<tr><td>Word Cloud [1], [18]</td><td>
</td></tr>
<tr><td>Bar Charts [1], [2], [18]</td><td></td></tr>
<tr><td>Opinion-Wheel [1]</td><td>
</td></tr>
<tr><td>Geo Map [19]</td><td></td></tr>
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3 Methods

This paper is to proposes and hybrid approach for user review analysis and visualization. The user reviews' text is to be categorized into topics and analyzed in terms of sentiment and visualized on a dashboard. The proposed approach is shown in Figure 2.

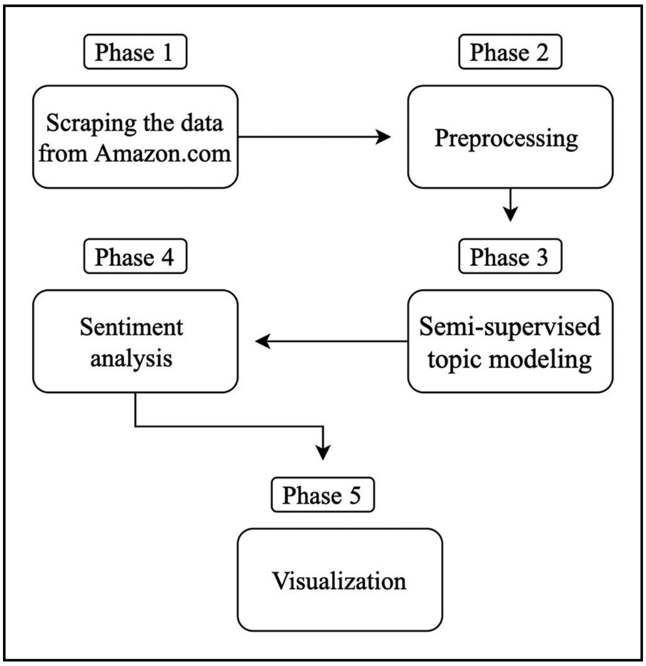


Fig. 2. The proposed approach

3.1 Data collection method

The method that has been chosen for data collection is web scraping. Web scraping is a method of extracting information from website pages and is sometimes referred to as web data extraction [21]. Unlike the tedious method of manually collecting data, web scraping uses smart technology to gather massive data points. Scraping is more appropriate for collecting Amazon data as Amazon.com API mainly supports advertisers but not for public use.

3.2 Data pre-processing

In this phase, data will be clean and formatted through several processes such as removing unnecessary data punctuation and processing other data, such as reducing the vocabulary size of the textual data, and lemmatization which converts a word to its root form. [22]

3.3 User reviews' text analysis

This phase includes two sub-stages, namely: topic modeling and sentiment analysis.

Topic modeling. Topic modeling is a simple way to analyze unclassified text [5] and is aimed at extracting certain groups of important words from the reviews. These groups of words are the topics that would help to determine what consumers are talking about in the reviews. For topic modeling, we propose the use of a hybrid approach to integrating the analysis of unlabeled data, unsupervised learning as well as labeled data, i.e., supervised learning. Some references such as [23] refer to this approach as semi-supervised learning.

In this work, the hybrid semi-supervised learning was applied through a technique called the principle of correlation explanation (CorEx) [24]. CorEx has recently been introduced as a way to build rich representations that are informative about relationships in data. CorEx is an information-theoretic principle for learning abstract representations that are maximally informative about the data and an alternative approach to topic modeling that does not assume an underlying generative model.

The first step in the proposed hybrid approach applies unsupervised learning to the review text. Using a technique, namely Term Frequency-Inverse Document Frequency (TF-IDF). TF-IDF measures the word's frequency in a document based on how often it appears in that document and a given collection of the dataset. The word is given a high score if it has a high frequency in the document. The TF-IDF is based on IDF and TF. The equations of the three measures are shown below:

$$TFIDF\ (w, d, D) = TF\ (w, d) * IDF\ (w, D) \tag{1}$$

$$IDF(w, D) = ln\left(\frac{Number\ of\ Documents\ (N)\ in\ Corpus\ D}{Number\ of\ Documents\ Containing\ w}\right) \tag{2}$$

$$TF(w, d) = \frac{Occurences\ of\ w\ in\ Document\ d}{Total\ Number\ of\ Words\ in\ Document\ d} \tag{3}$$

Where (w) is the words in a document (d), and (D) is the corpus.

After that, supervised learning is applied. Models become supervised by requiring training the data. With the gained knowledge, it can predict answers for future instances. The model is trained using a labeled dataset. When an out of sample data is given to the system, it can predict the result. Anchors are used to guide the learning process. Anchored data are composed of a combination of correlation explanations in a topic. Anchors can be presented as a single set of words to a single topic, single sets of words to multiple topics. Sample anchors are shown in Table 3.

Table 3. Sample anchors and their related words

Anchor Topics	Related Words
Price	"price", "money", "buying", "budget", "purchased"
Size	"size", "storage", "weight", "light", "lightweight"
Using	"work", "run", "speed", "slow", "delay"

Sentiment analysis. Sentiment analysis is the process of automatically extracting subjective information from the digital text and classifying it as positive, neutral, or negative. sentiment analysis or opinion mining is the computational study of people's thoughts, sentiments, evaluations, behaviors, and emotions from comments on social media, product reviews, and making decisions based on data. [25]

3.4 User reviews' visualization

Information visualization uses graphic approaches to help in the comprehension and analysis of data. [26] People can see, examine, and understand massive amounts of information at once using visual representations and interaction approaches. The user review topics, and their sentiments are to be visualized on a dashboard. The dashboard contains pie charts for the topics and their sentiments.

4 Results and discussions

This section represents the results based on our method presented in the previous section.

4.1 Description of dataset

Figure 3 shows a sample of data collected. As shown in the figure, the rows represent reviews of a certain product. The attributes that have been scrapped were as follows:

1. Products: the name of the product.
2. Price: The price of the product.
3. Total Rating: The total number of ratings.
4. Rating: The rating of the product from one to five stars.
5. Review: The customer's opinion of the product.

	A	B	C	D	E
1	Products	Price	Total Rating	Rating	Review
2	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	Item weight of 3.9lbs in the "technical descriptio
3	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	I compared this machine with several offerings.
4	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	Was not expecting much from this when purcha
5	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	This is a really good computer for the price. Dor
6	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	Got this laptop because mines broke and didn't
7	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	It is a pleasure to buy an inexpensive item and f
8	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	Bought this laptop for movies only . But I found i
9	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	At first I was skeptical about buying a laptop onl
10	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	It is smaller than I usually get, but the screen is
11	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	This Jumper laptop is far better than it's price wo
12	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	I love this laptop! This is a basic laptop that func
13	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	The EZ book has a great screen - sharp, with ric
14	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	This laptop computer is a deal price for me; how
15	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	The manufacturers got most things right on this.
16	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	We're all familiar with the adage "You get what y
17	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	This laptop is easy for even a beginner to use. I
18	Jumper EZbook X3 Windows 10 Laptop, Laptop compute	$219.00	161 ratings	4.1 out of	Crazy cool it's very fast and battery efficient and

Fig. 3. Snapshot of data collection

4.2 Results of user reviews' text analysis

In user reviews' text analysis shows both results of the hybrid approach of topic modelling and sentiment analysis.

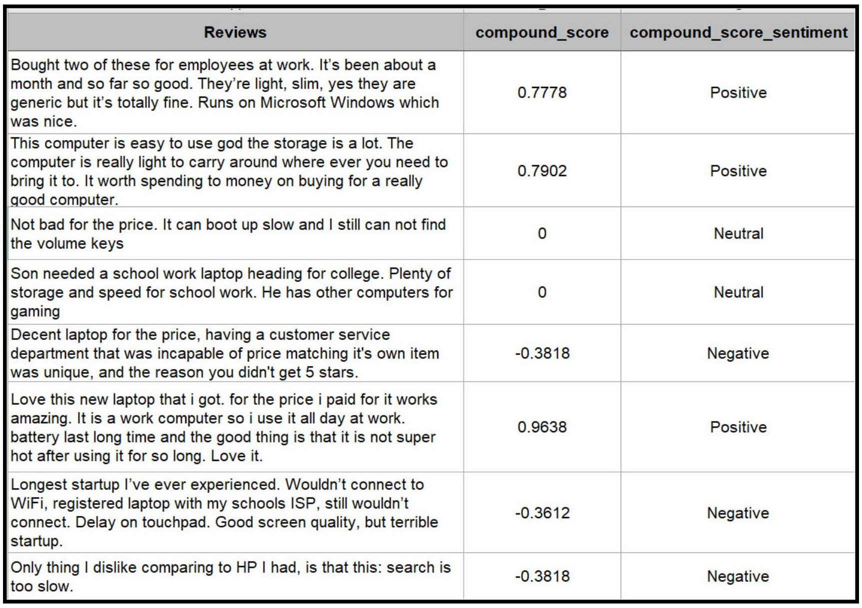
Topic Modeling Results. Figure 4 shows our result of topic modeling, which assigns each review to a specific topic. In the figure, topic 1 represents the price, topic 2 represents the shipping, topic 3 represents the quality, topic 4 represents the size, and topic 5 represents the warranty. As shown in the figure, some reviews may contain multiple topics; for example, the first review mixes among the five topics.

Reviews	Price	Shipping	Quality	Size	Warranty
This is a really good computer for the price. Don't let the chinese/japanese characters scare you. It boots up pretty fast, maybe 10 seconds at most. It's made out of aluminum and feels sturdy while staying light. The bottom heats up but wouldn't burn your legs, maybe sweat. There's some bloatware but it's easy to uninstall. One of the things I don't like is the coloring, the WHOLE computer is the same material and color except for the trackpad (which is also nice). The fact that its 6gb of ram and 64gb of memory should make you buy it considering the price. It lags sometimes, but its bearable, you won't have programs crashing though. I'm using this mostly for watching youtube and school, so it works for that. I haven't played any games with it but I wouldn't recommend it because there's only 64 gb and the processor isn't the strongest. 4.5/5	1	0	1	1	1
Got this laptop because mines broke and didn't really want to spend the money for a new one..So I went the cheaper route..I've never heard of the brand so I was a little nervous about buying it, but took the chance anyway..So far so good.. it moves faster than my last laptop which was an HP.. it's supper light weight, hold an battery for an extremely long time	1	0	0	1	0
Bought this laptop for movies only . But I found it running fast. It's full HD screen . The battery can running long times . The sound is good. Value for this low price. I recommend to many friends .	1	0	1	0	0
At first I was skeptical about buying a laptop online, but my friend bought one online and it turned out pretty well so I decided to follow suit. The 1 GHZ of storage is really nice, more than my previous laptop. The screen is pretty fluent, HD screen doesn't disappoint at all. It's not pixelated at all, and the settings were really easy to set up. The speakers are also very solid, exceeded beyond that my skeptical expectations, not to mention it is way faster than my previous laptop. All my worries went out the window when I received this, and I love it!	1	1	1	1	0
It is smaller than I usually get, but the screen is so clear that I have no problem seeing the screen. It is really a great computer at a great price. I'm really glad that I decided to take a chance on it. I absolutely love it.	1	0	1	0	0

Fig. 4. Result of topic modeling

Sentiment Analysis Results. Our sentiment analysis results depend on VADER (Valence Aware Dictionary for Sentiment Reasoning) Sentiment Analyzer, a lexicon and rule-based resource for evaluating sentiments. It has over 9,000 lexical features and contains required sentiment scores associated with terms, emoticons, and slang [27], e.g., words that are usually classified as either positive or negative according to their semantic orientation. The results are shown in Figure 5.

The compound score is a metric that measures the total of all the normalized lexicon scores between –1 (most extreme negative) and +1 (most extreme positive). That is, the positive sentiment has a compound score > = 0.5, neutral sentiment has a compound score > –0.5 and < 0.5, and negative sentiment has a compound score <= –0.5. [28]



Reviews	compound_score	compound_score_sentiment
Bought two of these for employees at work. It's been about a month and so far so good. They're light, slim, yes they are generic but it's totally fine. Runs on Microsoft Windows which was nice.	0.7778	Positive
This computer is easy to use god the storage is a lot. The computer is really light to carry around where ever you need to bring it to. It worth spending to money on buying for a really good computer.	0.7902	Positive
Not bad for the price. It can boot up slow and I still can not find the volume keys	0	Neutral
Son needed a school work laptop heading for college. Plenty of storage and speed for school work. He has other computers for gaming	0	Neutral
Decent laptop for the price, having a customer service department that was incapable of price matching it's own item was unique, and the reason you didn't get 5 stars.	-0.3818	Negative
Love this new laptop that i got. for the price i paid for it works amazing. It is a work computer so i use it all day at work. battery last long time and the good thing is that it is not super hot after using it for so long. Love it.	0.9638	Positive
Longest startup I've ever experienced. Wouldn't connect to WiFi, registered laptop with my schools ISP, still wouldn't connect. Delay on touchpad. Good screen quality, but terrible startup.	-0.3612	Negative
Only thing I dislike comparing to HP I had, is that this: search is too slow.	-0.3818	Negative

Fig. 5. Results of sentiment analysis

4.3 The dashboard of the user reviews topics and sentiment

Our dashboard is shown in Figure 6. The visualization technique relies on viewing the topics as interactive pie charts and viewing review sentiment as bar charts. In the pie chart, the topics are shown together with the reviews making up this topic and the reviews' sentiment (See Figure 7). Pie charts that have a big green section contain many positive reviews. On the other hand, pie charts that have a big red section show the corresponding topic contains many negative reviews. Figure 8 shows the sentiment of a selected topic represented as bar charts.

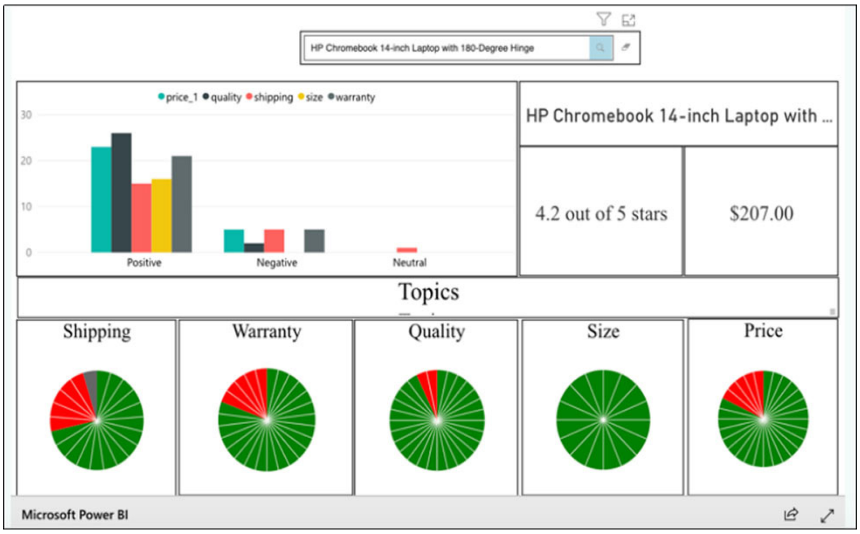


Fig. 6. The proposed dashboard

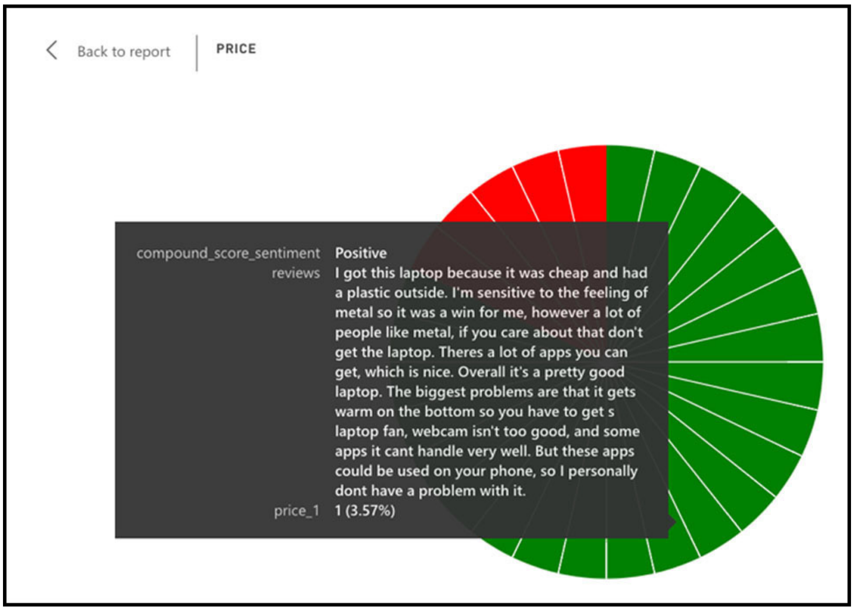


Fig. 7. Interactive pie chart for the user review topics

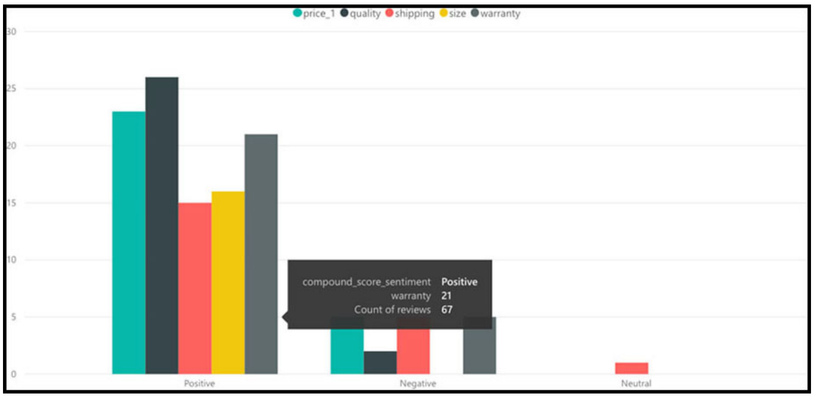


Fig. 8. Interactive bar chart for the sentiment of the user review topics

4.4 Evaluation

Our hybrid model used for topic modeling applied the CorEx technique. To evaluate it, we create another model for topic modeling based on the LDA technique, which is an unsupervised method, and then compared the topics resulted from our hybrid model, i.e., a semi-supervised model with the topics resulted from the LDA-based model. The results of both models are shown. Table 4 shows the results. As shown in the table, the results of the hybrid approach are more accurate. For example, the "price" topic in resulted from the LDA-base model contains non-related terms such as "great", "fast," and "nice".

Table 4. The final results of topic modeling in LDA and CorEx

Topic	Results of the LDA-based Model (Unsupervised)	Results of CorEx-based Model (Hybrid)
Price	good, 'price', great, fast, quality, nice, light, easy, deal, pretty	'price', 'buy', 'cheap', jumper, computer, problem, thing, one, happy, recommend, long
Size	great, love, perfect, 'small', school, 'size', daughter, 'lightweight', son, kid	'light', 'storage', 'size', 'weight', laptop, 'carry', enough, 'memory', issue, bit, Size set, 'small', 'lot', everything

As a sort of evaluation and to explore whether people like to have the user reviews in the form of topics shown on a dashboard, we created a simple survey. The survey responses were collected from 242 people. The people were shown the dashboard, and they were asked if they prefer it over the existing method of viewing user reviews on Amazon. The results were as follows: 58.3% of the respondents agreed with our dashboard, 28.9% disagreed, and 12.8% did not find a difference.

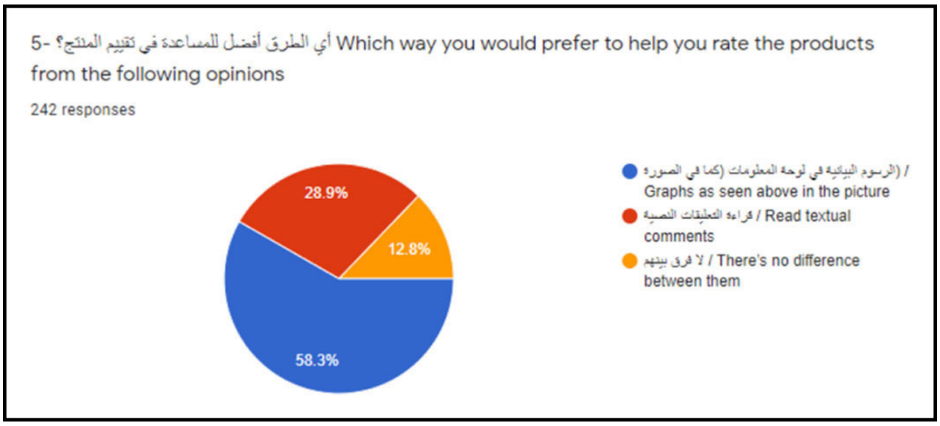


Fig. 9. People opinion on the proposed dashboard

5 Conclusion

This paper proposed the analysis of one of the most popular sources of information, which is user reviews of products. These reviews are mostly textual and unclassified which consumers need to read all reviews to make a decision. This paper handled this problem using both unsupervised and supervised learning, i.e., the hybrid approach, for classifying the reviews into main topics based on the reviews collected from Amazon.com. The study also applied sentiment analysis for the reviews of each topic. Besides, the study proposed visualizing reviews' topics and their sentiments on a dashboard. The dashboard's content is the selected product details such as price and rating, and two types of charts, which are the pie chart and the bar chart for the reviews topics and sentiment. The outcome of this study will assist both industry and general users. The industry such as Amazon can benefit from which products have weak points, so it can help to enhance or make some discounts on them. The general users can take a short time and less effort to decide to purchase products.

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Article submitted 2022-02-12. Resubmitted 2022-03-01. Final acceptance 2022-03-04. Final version published as submitted by the authors.