ChoseAmobile: A Web-based Recommendation System for Mobile Phone Products

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Abstract

Information and communication technologies brought-in tools and technologies in the field of electronic commerce that introduced new modes of shopping. With the emergence of e-commerce platforms, the user base is shifting from the traditional mode of shopping towards online e-commerce sites. A large number of e-commerce sites share multiple brands and products that make it difficult for the user to decide which site is presenting genuine specifications as well as the best price offerings. In this work, we present a recommendation system choseAmobile that uses specific metrics and product reviews as side information and provides suitable recommendations to the user. The system continuously monitors and analyzes the data sources to see and incorporate the updates in order to present up to date and accurate results. The experimentation results show that the system is proved to be feasible and effective, thus resulting in better recommendations for mobile phone selection, especially for novice users.

Keywords: Artificial intelligence, Electronic commerce, Machine learning, Recommender system, Semantic web

1 Introduction

The technological advancements in the telecommunication industry has paved the way for the exponential growth of cell phone technology. The number and usage of cell phone devices is increasing day by day. The recent evolution of smartphones changed the shape of cell phone demand and the market. It is predicted that by 2019, there will be approximately 5.6 billion smartphone users, which will produce 10 Exabyte (1018 bits) of data flow [1]. In recent years, the demand for smartphones devices increased based upon the factors which include the features and functions of smartphones, multitasking support, as a means of an entertainment device, communication aspects, ease of use, lightweight can carry it around. There are multiple vendors offering a variety of cell phones not only in terms of shape and design alone but also in terms of features and specifications.

The smartphone market has grown not only conventionally but also in the online market. There are several online e-commerce websites and portals that provide a way to search for cell phones based upon search criteria. The search results of these systems are usually generalized and contain a long list of items that are of no interest to users. As the cell phone market is so huge and diverse, not all smartphones have good quality in terms of specifications and features to fulfill customer needs. Customers usually tend to know the user's opinion about the specification and features of a specific smartphone before going to buy. This information can only be learned through customer reviews and opinions posted on online platforms. The presence of a large number of e-commerce platforms means a large volume of data containing customer reviews related to mobile phones. For an intended customer, this information is very crucial and supporting in decision making but on the other hand, it is time-consuming and is not possible for the customer to read and understand each and every review. In this paper, we present a web-based tool choseAmobile [2] that uses web scraping and automatic sentiment classification. Web scrapping [3] technique is used to extract and preprocess data from multiple e-commerce platforms in order to analyze the reviews and to provide more precise results. Sentiment classification aims to classify user reviews to positive and negative opinions. Classification techniques commonly used for sentiment analysis. The tool will help users to get quick useful insights from reviews data which can save time, money and efforts. Thus makes it easier for users to choose smartphone best in terms of specification and features from a large market. The important highlights

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of the paper are:

- The proposed work implies techniques such as web scraping, web mining and sentiment analysis.
- Users' reviews are scrapped from different sources and are used as side information.
- Performed sentiment analysis on overall specifications as well as individual features.
- Provide useful insights about mobile phones in the form of sentiment analytics.
- It helps the buyer to get quick and real-time information for the selection of mobile phones.
- Finally, the tool is proved to be efficient and effective by simulation experiments.

The rest of the paper is organized as follows: Section 2 presents the literature review. Section 3 describes the proposed approach and evaluation of our study are reported in Section 4. Lastly, Section 5 concludes the paper.

2 Literature Review

E-Commerce is known as electronic commerce, involves the trading of products or services over the internet using web-based applications. With the rapid development of the internet and the number of goods sold online, e-commerce plays an important role in the present trend. In the current business market, e-commerce is playing a role in services, retails, finance, telecommunications, and information technology services. E-commerce provides an easy way to search for any particular product efficiently using the web. It also deals with context-aware services which can be based on a provided context i.e. location, time of the day or user preferences.

Today, the internet is the most widely used communication medium in modern enterprises. Many companies are redefining their business strategy to increase business output and productivity. Internet-based business provides the opportunity in terms of a business hub where customers and partners can find their products and specific businesses, and also an interaction platform [4-6]. Nowadays, online business crosses the barriers of time and space compared with traditional physical offices. Big companies all over the world realize that e-commerce not only purchases and sells through the internet, but also increases the efficiency of competition with other giants in the global market. Due to this reason, data mining is sometimes referred to as knowledge discovery. Web mining is a data mining technique applied to the World Wide Web. There is a lot of information on the internet [7].

E-commerce websites are now one of the most important sources for buying various products. Many strategies have been developed to analyze the behavior of customers to attract more business and people's participation [8]. Since there are many e-commerce websites available, it is difficult for users to choose the best deal for the desired product in these websites. E-commerce product comparison using web mining enables users to analyze prices and obtain desired products at the lowest price. Users can also choose multiple products that belong to the same category to compare their functionality. To get the best price from e-commerce sites, web crawlers and web scrapping technology are used to obtain detailed information [9].

A large amount of data related to customer reviews/comments is rather difficult to analyze and requires existing methods to obtain a broad summary of opinions. Various web resources, news reports, e-commerce websites, social networks, blogs, and forums help express opinions that can be used to understand the public and consumers about social events, political campaigns, corporate strategies, marketing campaigns, product preferences, and monitor reputation. Research groups, scholars, and industrialists have been conducting thorough research on sentiment analysis for the past few years to accomplish these tasks [10-11].

Sentiment analysis is a computer domain in which machines analyze and classify human emotions, emoticons, and views on any topic expressed in text or speech form. It can be referred to as computational identification and categorization [12]. Sentiment analysis is broadly categorized into lexicon-based and machine-learning based approaches [13]. Most of these methods are performed in a two-phase retrieval model. First, one of the standard information retrieval methods is applied to the localization of local related documents; secondly, various opinion mining/sentiment analysis algorithms are used to find and identify opinionated texts in documents [14].

In the comments, emotions about specific products are seldom explicitly positive or negative; instead, people tend to have different opinions on various features, some are positive and some are negative. Therefore, feature-specific opinions are more important than overall opinions. Consider reviewing "*Multimedia features of Oppo are best but battery life is terrible*". This sentence has a complex sentiment. The sentiments about multimedia are positive, and the sentiments about battery life are negative. Therefore, it is important to extract only opinions related to specific functions (such as battery life or multimedia) and categorize them instead of using complete sentences and overall emotions [15].

Feature extraction is an important part of feature-based sentiment analysis. Most researchers use Natural Language Processing (NLP) techniques to extract product features from customer reviews. At the same time, researchers also use different topic modeling and monitoring techniques for this purpose but require users to provide some training data. A lot of research on feature extraction is available, especially on explicit feature extraction. However, in the area of feature-based sentiment analysis, we observed relatively little work on implicit feature extraction and feature clustering [16].

Different features techniques like unigrams, bigrams, unigrams + bigrams, unigrams + POS tagging, position, and unigrams + position are used and then machine learning techniques like Support Vector Machine (SVM), Maximum Entropy and Naïve Bayes classification algorithms are applied on the preprocessed dataset. Classification algorithms perform better than human-based classifier. WordNet synset is used to increases the accuracy of a classification algorithm. Machine learning methods are supervised learning methods because classifiers are trained on a dataset and semantic methods are unsupervised because it measures the degree to which a word is positively or negatively related. Both methods have advantages and disadvantages. In this article, monitoring machine learning methods is more accurate than a semantic direction, but training models are a time-consuming process. The semantic positioning method is not very accurate, but it is very efficient [17].

Analyzing expressions and contextual texts and machine learning classifiers produces better accuracy than existing methods. There are fewer studies on expression and situation-based analysis, which will bring more problems and challenges to industry and scholars. Improvements in emoticon and contextual dictionaries will lead to better results [10].

Recommendation systems have been introduced in many application areas to assist users in finding the desired information. Amato et al. [18] proposed a multimedia recommender system that uses users' context information to generate recommendations in social media networks. Many recommender systems that use predictive feedback employ subject modeling techniques for modeling consumers or products [19]. User feedback is an important feature and can be used to mine product's aspects to specifically state user preferences [20-21]. Aspect-oriented sentiment analysis provides more insights about products and helps in the generation of better rating predictions. Chen et al. [22] suggested a perception-based model for the consumer. This model takes into account aspect-based sentiment analysis for the prediction process from user reviews of products. Tutubalina et al. [23] proposed an aspect-based recommender system that analyzes aspects from a given dataset of user reviews for video/gaming applications and produces good quality recommendations with illustratable aspects.

In another approach, Hernández-Rubio et al. [24] proposed a recommender system that focuses on identifying the references to product characteristics in user reviews, classification of the emotion orientations in reviews, and then the use of information associated with these features. These approaches try to avoid the problem of starting at cold by assuming that information to qualify the user exists and are available. Certain approaches suggested to employ hybrid techniques for recommender systems to improve the suggestions and accuracy of recommendations. In order to improve prediction accuracy, Logesh and Subramaniyaswamy suggested the customized context-aware hybrid travel recommender system based on the consumer contextual information and opinion mining methodology [25]. By combining the user interaction knowledge for a wide number of users, Qian et al. [26] significantly increased the accuracy of the recommendation system by evaluating the consumer preference for products and social networks comprehensively. Vall et al. [27] in their research gives an example of how different types of knowledge can be used to enhance playlist production in music recommender system. In generating the recommendations, explanation styles are also important as this aspect highlights the ease of satisfaction towards explanation styles. Kouki et al. [28] analyzed different explanation styles in the context of the recommender system and introduced a custom hybrid music recommender system that combines multiple information sources and creates suggestions with a range of explanation styles.

Yang and Huang [29] have developed a gaming recommendation system to propose personality-based games to players that are learned by chatting with other users. Reference [30] proposed a deep neural network to discover the knowledge about the relationship between the higher-level features of input data within the context of the video game recommendation system. The deep neural network model generated interaction knowledge was more than what the FM model had provided.

Besides e-commerce, recommender systems are also being adopted in the tourism sector for tourist attractions to recommend [31-33]. Mettouris and Papadopoulos [34] proposed a framework UbiRS4Tourism based upon domain-specific modeling language, for the design and development of tourist recommender system. The system acquires the user preferences from several resources within the social network of a user and helps to learn the user behavior and points of interest which help to generate more accurate recommendations.

3 Proposed Framework

In this section, we present the proposed system and describe its internal processes and working. The motivation behind building such a system is to provide a mobile phone selection system based on reviews analytics. The architecture of the proposed system is presented in Figure 1.

The proposed system on one end analyses the reviews data and on the other end by using data visualization provides useful insights on overall specifications as well as individual features of mobile phones.

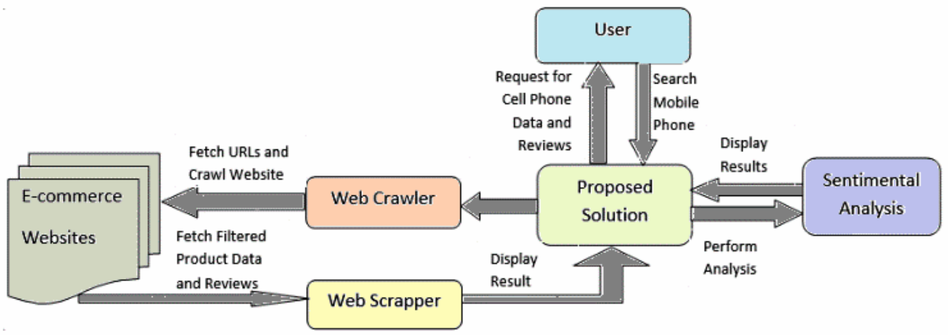

Figure 1. The architecture of the proposed system

3.1 Components

The proposed system is implemented as a web-based application that helps in searching for mobile phones by use of user reviews as side information. Python scraping framework Beautiful Soup [35] is used to scrape real-time data on click events and Urllib2 [36] is used to perform crawling of source pages in real-time. The search results contain mobile phone specifications, as well as ratings based upon user reviews, are returned to the user. The goal is to provide search results according to users' requirements; it may be price, brand, specification or features. The system extracts data including mobile specifications, reviews, and prices from different e-commerce sites. The user can only enter a keyword or use filters (brand filter, price range filter, and specification filter) and get results supported by review polarity rating. By incorporating the reviews analytics in the search results, the objective is to facilitate the user in mobile selection.

The user base for e-commerce websites is growing day by day. These e-commerce websites stores a large volume of users' data that can be helpful in business strategies as well as for individual users to determine trends and reputation. The main benefit of this proposed framework is that it helps the customer to know what people think about the mobile phone (company, service, etc.), how positive or negative are people about a particular mobile phone. The likeness and preference of people about mobile phones also much contribute. It provides an easy way to search for cell phones and see their specifications supported by sentiment ratings which makes it easier for the customer to decide in a quick time without reading a large number of reviews.

For the sentiment analysis part, rule-based polarity classifier subjectivity lexicon and Word-Net is used for calculating accuracy. The subjective phrases are separated first and then further features are extracted. The polarity classification is performed on those subjective sentences to train SVM. According to the topic and feature, the feature level sentimental analysis is also performed. The objective sentences are considered as neutral. It increases accuracy and efficiency both at a time.

3.2 Working Pattern for Sentiment Analysis

The sentiment analysis and classification approach used in the proposed system is illustrated in Figure 2.

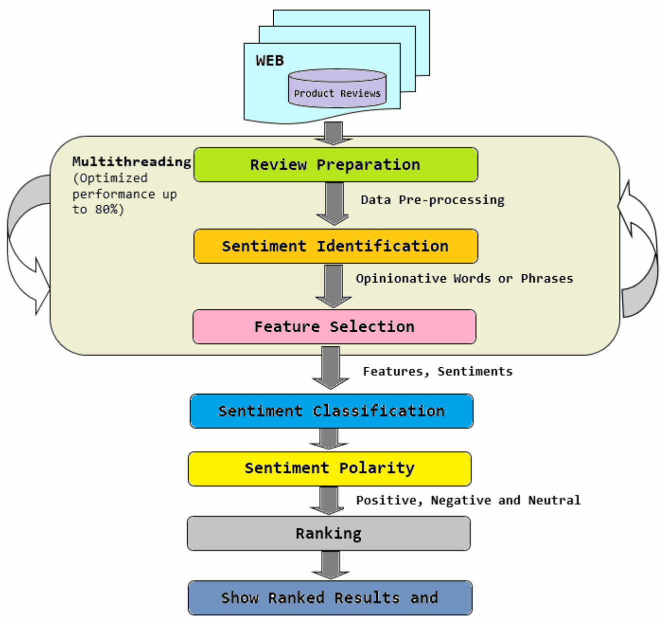

Figure 2. Sentiment analysis and classification approach

Steps of the algorithm for sentiment analysis and classification are as follows:

Step 1. Multithreading – Pre-processing a large number of reviews data from different sources requires a lot of computational resources and affects the system performance. Thus by introducing the concept of multithreading, system performance is optimized as multiple threads execute in parallel and perform tasks of review preparation, sentiment identification, and feature selection so that classification can be performed in lesser time.

Step 2. Review Preparation - Extracting reviews from different web sources and storing it locally for data pre-processing. In data pre-processing, stemming and POS (part of speech) tagging is performed.

Step 3. Sentiment Identification – After getting pre-processed data, sentiment identification is performed in which sentiment containing sentences, words or phrases are extracted.

Step 4. Feature Selection – Sentiment phrases contain some target entities. These entities are extracted and termed as features e.g. Camera is not good but has good battery timing. In this sentence, two features are targeted “Camera” and “Battery”.

Step 5. Sentiment Classification – After identifying features the sentiment is classified with respect to targeted feature using the SVM classifier.

Step 6. Sentiment Polarity – After classification, the sentiment polarity is determined as positive, negative or neutral sentiment.

Step 7. Ranking – In the end ranking is done based on best to worst product based on sentiment result score.

4 Results and Discussion

In order to demonstrate the effectiveness of our proposed web-based tool, we experimented with several mobile phone models as search keywords and then provide our observations as well as corresponding results.

The system choseAmobile (http://www.choseamobile.com/) has been developed and deployed by the authors as per the proposed framework. The tools and technologies used in the development of choseAmobile include PHP, CSS, HTML and MySQL database. All data analyzed and the information supporting the findings of this study are generated through the proposed system.

The overall efficiency in terms of performance of system and reviews analysis is examined. Table 1 shows the overall percentage sentiment polarity of representative mobile phones. The results presented here are for a few representative mobile phones but the same results can be obtained for every mobile using this system in real-time.

Table 1. Overall percentage sentiment polarity of products

Mobile phone	Total Reviews	Positive Ratio	Negative Ratio	Neutral Ratio
Samsung Galaxy S7	815	24%	13%	62%
Apple iPhone 6	1098	25%	10%	64%
LG G5	30001	26%	9%	63%
Nokia 9	465	31%	9%	60%

Table 2, Table 3, Table 4 and Table 5 shows feature-level sentiment polarity percentage of respective cell phones.

Table 2. Feature level percentage sentiment polarity of Samsung Galaxy S7

Samsung Galaxy S7				
Features	Total Reviews	Positive Ratio	Negative Ratio	Neutral Ratio
Ram	116	23%	6%	69%
Storage	67	28%	16%	55%
Battery	291	21%	13%	64%
Heating	137	29%	15%	55%
Camera	204	24%	14%	61%

Table 3. Feature level percentage sentiment polarity of iPhone 6

Apple iPhone 6				
Features	Total Reviews	Positive Ratio	Negative Ratio	Neutral Ratio
Ram	227	26%	11%	61%
Storage	84	20%	11%	68%
Battery	394	22%	11%	65%
Heating	66	29%	5%	64%
Camera	327	28%	8%	63%

Table 4. Feature level percentage sentiment polarity of LG G5

LG G5				
Features	Total Reviews	Positive Ratio	Negative Ratio	Neutral Ratio
Ram	165	27%	4%	68%
Storage	149	18%	6%	74%
Battery	1614	26%	11%	62%
Heating	265	22%	12%	65%
Camera	808	29%	8%	62%

Table 5. Feature level percentage sentiment polarity of Nokia 9

Nokia 9				
Features	Total Reviews	Positive Ratio	Negative Ratio	Neutral Ratio
Ram	58	35%	6%	57%
Storage	25	26%	11%	61%
Battery	183	34%	9%	56%
Heating	28	27%	10%	62%
Camera	162	26%	10%	63%

To further validate the results, Chi-Square has been applied. The data is categorical so divided the data into two groups. Chi-Square test gives us a probability, called the p-value. If $p < 0.05$ then it means both groups are dependent. If $p > 0.05$ then both groups are independent.

Table 6 shows the T-Test values for individual features of representative mobile phone products.

Table 6. T-Test (probability) of the product's features

Mobile phone	RAM	Storage	Battery	Heating	Camera
Samsung Galaxy S7	0.88	0.15	0.13	0.20	0.57
Apple iPhone 6	0.65	0.05	0.30	0.08	0.56
LG G5	0.50	0.49	0.53	0.93	0.32
Nokia 9	0.84	0.61	0.17	0.81	0.20

Further, we conducted an evaluation of T-Test for individual products. The results are presented in Table 7.

Table 7. T-Test (probability) of products

Samsung Galaxy S7	Apple iPhone 6	LG G5	Nokia 9
0.74	0.86	0.39	0.32

From Table 6 and Table 7, it is evident that p values are large, so both groups are independent as well as all data is independent.

The search results are also presented in graphical representation for quick analysis and recognition. The results shown in Figure 3 indicate the overall specification analysis and feature analysis for Samsung Galaxy S7 mobile phone.

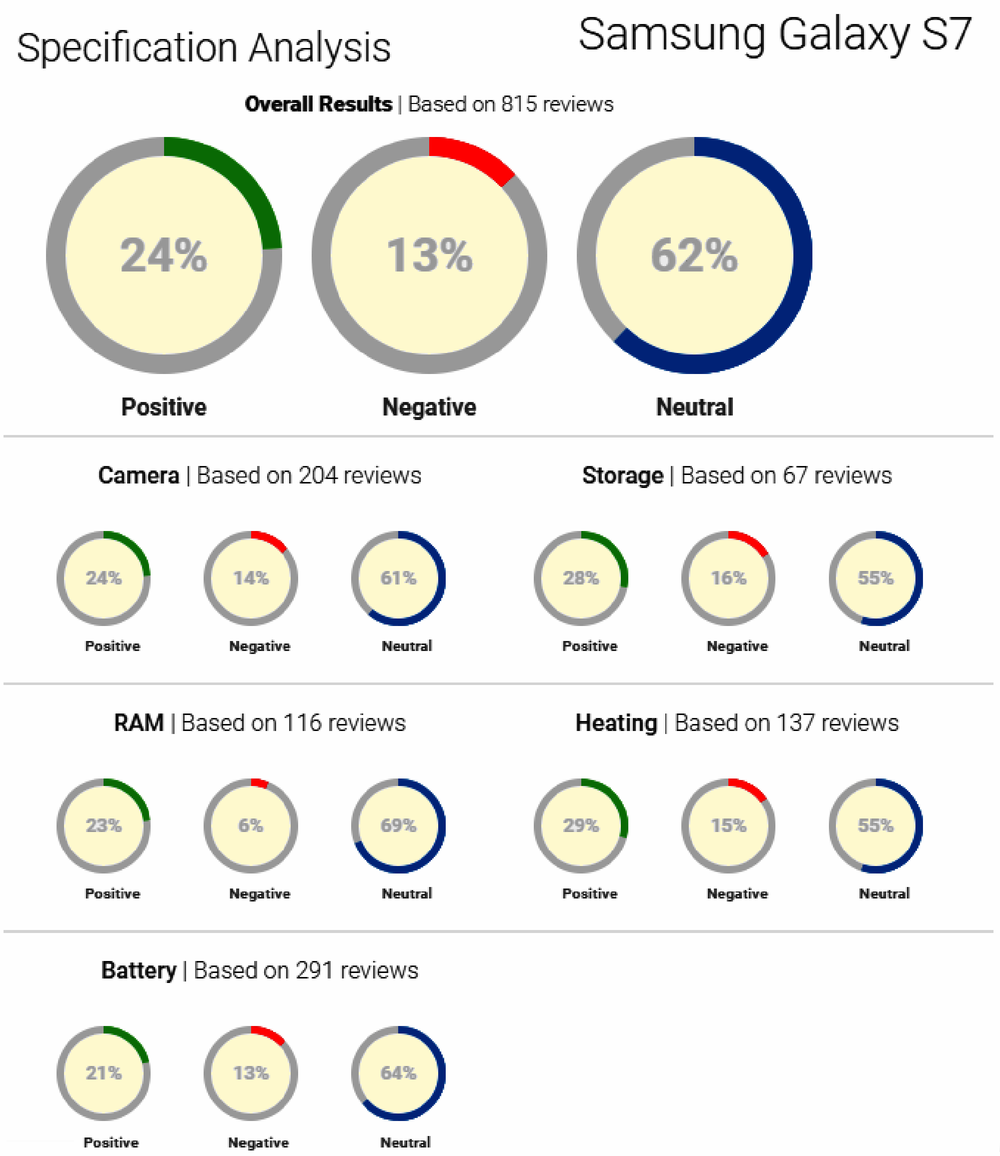

Figure 3. Search results for Samsung Galaxy S7

5 Conclusion

With the emergence of e-commerce platforms, availability of product information like daily prices, specifications, speculations, trends and review based ratings using web mining present at a single platform helps users making good decisions while buying the product. The proposed system facilitates users to analyze prices, product and feature reviews, trends and specifications based rating, through a single platform. The proposed system also provides specification based sentimental analysis on reviews in real-time on every product to save the time and effort of the user. Ultimately, combining techniques of web crawling, web scraping, and machine learning, presented a recommendation system that provides reviews analytics from leading online stores and helps the buyer to make decision easily and shop online. The findings of the experiments showed that our method is successful and prompted further work in this direction. For future work, we want to add an analysis of reviews timeline as priorities can change over time. Further, the current location of the user must be carefully considered in comparison to prior location history and the user interests related to them. This will help in designing a user-satisfiable recommender system.

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