

Product Recommendation System Using Opinion Mining on Vietnamese Reviews



Quoc-Dinh Truong, Trinh Diem Thi Bui, and Hai Thanh Nguyen

Abstract Opinion mining (also known as sentiment analysis) through customers' reviews or feedbacks which can identify the user opinion about different product features has received a lot of attention exhibited in numerous studies. The majority of recommender systems have recommended products based only on overall evaluation and primarily based on expert's evaluation. In this work, we propose a method to explore Vietnamese reviews extracted from e-commerce websites in Vietnam to provide suggestions in products selection based on products' features/functions. The proposed approach introduces a topic-based model to identify products' features which are mentioned in customer comments/reviews. The proposed system is implemented with the integration combining the VietSentiWordnet to calculate the importance scores for the features of each product. We also construct a product recommendation database which can store customers preference and purchases history. The work is analysed on more than 2,000 Vietnamese comments/reviews about laptop products and is expected to be feasible to apply in practical cases.

1 Introduction

E-commerce in recent years has been developing strongly, bringing many benefits to the global economy. It is not easy to support users choose a product that they like on e-commerce websites because there are too many products in same price range, similarly displayed and promoted. Numerous organizations and companies have successfully applied the recommendation systems to their e-commerce pages such as amazon.com, movielens.org, youtube.com, etc. In Vietnam, there are also

Q.-D. Truong (✉) · H. T. Nguyen
College of Information and Communication Technology, Can Tho University, Can Tho, Vietnam
e-mail: tqdinh@cit.ctu.edu.vn

H. T. Nguyen
e-mail: nthai@cit.ctu.edu.vn

T. D. Thi Bui
Nam Can Tho University, Can Tho, Vietnam

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N. H. Phuong and V. Kreinovich (eds.), *Soft Computing: Biomedical and Related Applications*, Studies in Computational Intelligence 981,
https://doi.org/10.1007/978-3-030-76620-7_27

ing techniques, Content-based Filtering, hybrid grouping, and non-personalization technical group. Many studies based on previous user behaviors such as transaction history to find rules of interaction between users and items have proposed. Therefore, suggestion systems based on this approach are not interested in the attributes of the item, it is capable of exploiting information outside the scope of the item attributes. The models can be built based on the behavior of one user, or more effectively, it can be conducted from many different users with the same characteristics. When the models consider other users' behavior, collaborative filtering uses group knowledge to generate recommendations based on similar users. More clearer, it provides suggestion based on users with the same interests, or those with similar behaviors, who clicked like, and gave points for the same item. Also, numerous works have explored neighbor-based methods: numerous authors introduced methods based on past data of "similar" users or based on past data of "similar" items. The author in [1] proposed a recommender system for online sales based on explicit feedbacks from users through reviews for products. The author built an online sales system and deploy the recommendation system to advise customers on products they might like. The author in [2] introduced a solution to build a recommender system for online sales using potential feedback from users. The authors proposed the methods to collect potential feedbacks, then a model is used to learn the appropriate suggestion methods. The authors combined predictive models to increase accuracy. The author in [3] introduced an improved method of collaborative filtering clustering and optimal collaborative repetition using PSO algorithm. The accuracy is significantly improved compared to the traditional collaborative filtering method while the method also solved the problem of sparse data that collaborative filtering methods often encounter. The work in [4] introduced to use latent feedback from users (such as the ratio of the length of time that the user has listened to over the total length of the song) to use the ranking algorithm to build the "Song Suggestion System". Trieu Vinh Viem et al. [5] also proposed to build a film suggestion system. This model can improve the accuracy on par with the latent factor model. It not only maintained the advantages of the neighborhood model, but also immediately solved the problem of new users when ranking for the first time without having to retrain. The authors [6, 7] proposed the application of collaborative filtering in the context of an e-learning system to predict the likelihood that a student may complete a certain learning task or not. The work in [8] proposed a solution in building a contextual suggestion system, applied to tourism suggestions to suggest the most suitable tourist destinations for tourists. This system combines methods such as integrated input context-based suggestion with matrix decomposition technique and output context processing to increase the system's accuracy. Some similar studies can be found in [9, 10, 12, 13].

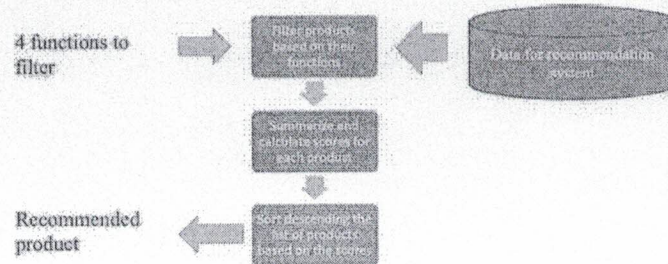


Fig. 2 The proposed architecture for product recommendation system based on features/functions of the products

analysis of customer opinion in the comments/reviews related to the characteristics of each particular product. In order to make product recommendations according to features that users are interested in, the system needs to build a suggestion database, in which the most important information to have is the rating score on each feature of the product group. In the scope of this study, a product's interest score is aggregated through the determination of the user's views on certain features of a product expressed by users in their comments. Therefore, the system needs to collect customers' comments/reviews related to products in the product group that need to make suggestions. Sources for comments/reviews are from e-commerce websites that sell laptop products and allow customers to make comments on a particular product. The user views about a certain product feature will be extracted and synthesized by the system to build the suggested database. By using this recommendation database products with features of products, the method is expected to provide a match between the suggested products and the user's needs.

3.1 Data Collection

Collected data include comments/reviews from e-commerce websites that provide rating pages such as fptshop.com, www.thegioididong.com and so on, related to the considered product group (notebook). The data collected for a product group are divided into 2 datasets. The first dataset contains all the comments on all products and has been feature-labeled that is used to build the topic-based model (the set of keywords is often used to refer to a feature) for product features. The second dataset which consists of comments but is not labeled feature is used to calculate the feature score for each product and to build a suggestion database.

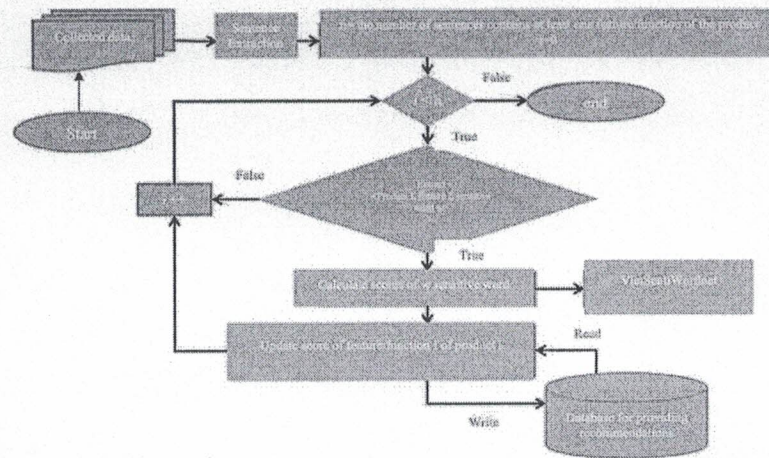


Fig. 4 The steps for building a database for supporting to provide recommendations

word. Keywords labelled as generic are retained for consideration as keywords representing product features.

- Synthesize the list of keywords returned, in which each keyword has more information that is the number of occurrences corresponding to each feature.
- Select a keyword with the highest number of impressions than K and the largest number of impressions of all features, which is a keyword that represents each product feature.

For instance, the keyword “money” appears 10 times with the “price” feature and appears with the “design” feature 9 times. With the K of 5, the keyword “money” is selected as the representative for “price”.

Figure 4 includes steps to build a dataset for supporting to provide the features’ product-based recommendations. Exploring the set of collected reviews/comments from social network sites, e-commerce websites, for each comment, the system performs the steps of separating words, retaining nouns, adjectives, and verbs. The feature thread model is used to validate which feature a comment is referring to. The result of the analysis step includes the trio of: <Product>, <features>, <emotion word>. Emotional dictionary is used to determine the rating for the commented feature. This rating is calculated into the total score of the performance of the corresponding product in the suggestion database.

The system makes suggestions to the user in two ways: by the list of selected features and without the list of selected features. In case the user is not interested in a particular feature, the system calculates the score for the product according to the total score of the features. The overall rating for a product is calculated by the formula 1.

Table 1 An illustration on the products with the highest and lowest scores for recommendations

No	Features or functions	Product name	
		The highest score	The lowest score
1	Pin (battery)	FX503VD_E4082T	X510UQ_i5_8250U_BR632T
		15_bs572TU_i3_6006U_2JQ69PA	15_bs555TU_Core_i3_6006U
		Inspiron_5570_i5_8250U	ThinkPad_E570
2	Màn hình (Monitor)	A315_51_364W	Inspiron_5570_i5_8250U
		Vivobook_A510UF_EJ182T	Inspiron_5567_i5_7200U
		Vivobook_X407MA_BV043T	Inspiron_5567_i5_7200U_M515384W

at least 1 emotional word. Feature points for the features of one product will be accumulated according to the formula of 1 and 2. For each product, there are several of features that the user has rated and the system calculates the score for that feature as illustrated in Table 1.

4.2 Scenarios

In this section, we present the results of product recommendations in 2 scenarios. In the first scenario, we select features/functions of the product (maximum 4 features) for generating recommendations; The second case, no feature is selected in advance. The database is used for the system to calculate scores of the suggestion for each product corresponding to 2 cases with or without a list of features of interest.

When the user does not choose any features, the system suggests the products with the largest total feature points in the database (Fig. 5). The following table shows detailed configurations of the 3 products with the highest total score.

Figure 6 shows a list of recommended products when the user selected the list of features of interest in order of priority: battery, ram, price and quality of the integrated webcam. When a user selects a row on the result, the score information for each feature of the respective product displayed as Fig. 7.

4.3 Discussion

Collected reviews include more than 2000 comments with more than 4000 sentences. 3300 sentences were related to product features and more than 764 sentences did not mention product features. Such sentences which do not comment on product features can be questions that the user asked on the sites (for getting more information) or contains special characters, or the questions that contain unsigned Vietnamese such as “man hinh, gia, thiet ke” (monitor, price, design, etc.),

No.	Product name	Score
1	FX503VD_E4082T	0.8999999
2	15_86572TU_13_8006U_2KD89PA	0.7726874
3	Inspiron_5570_i5_4250U	0.7083333
4	GL82M_7RDX_i5_7300HQ	0.65625
5	Pavilion_x360_14_ba066TU	0.6111111
6	Pavilion_x360_99026TU_13_7100U	0.5804347
7	A315_51_394W	0.55
8	X441NA_IJ4200	0.5221491

#pin	1.578125
#màn_hình	0.0
#wifi	0.0625
#game	0.0
#thiết_kế	0.375
#giá	-0.0825

Fig. 7 A list of suggested products in the case the user does not select any feature a, a detailed feature score of the selected product

unorthodox young people's language abbreviations ("ok, đc" (okay, right/fine)), or sentences which do have meaning but not related to the product (for example, "Cám ơn bạn nhân viên tên Ngân đã hỗ trợ nhiệt tình" ("Thank you, your staff named Ngan who gave us an enthusiastic support"))).

Due to the human subjective factors in making reviews and depending on the needs of the user, reviews made on the products are also different. For example, with the same of time for the battery for 3h, normal users who only use the laptop for surfing the internet or use normal office software give a good review of the battery. However, people who usually implement heavy software such as Photoshop, processing video, etc. can give a bad review on battery. It seems more appropriate with the reality that users only choose the products that suit their needs. When they give reviews, they only consider features/function which they are interested in.

Some sentences satisfy the requirements that contain features but they do not have emotional words, then such sentences are removed. For example: "should add the ssd drive". Although that sentence belongs to the feature of the hard drive it does not contain the emotional word. This is one of the limitations that the system has not solved yet. Some products are rated well by experts (eg., Apple products) but are they were not recommended by the system because there are too few comments regarding the Apple product group. The main reason is the price level, so it is not suitable for the majority of ordinary users. Product recommendation results based on customer comment analysis are also consistent with user reviews on sales pages. For example, the rating of some famous websites such as thegioididong.com and fptshop.com about the products that the system has suggested is the best when the user does not choose any feature, all have quite high scores respectively: 3.6, 4.8 and 4.5.

5 Conclusion

In this study, we propose a feature-based product recommendation system mining from customer comments. The system collects automatically the dataset from customers' reviews and comments about laptop products on the online sales system of FPT enterprises and Mobile World. We deployed a topic-based model for building a

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11. Ho, T.T.: Phân tích Mạng xã hội dựa theo Mô hình Chủ đề và Ứng dụng (social media analytics based on subject matter model and application). Ph.D. thesis. Ho Chi Minh Information Technology University (2015)
12. Tagliabue, J., Yu, B., Bianchi, F.: The embeddings that came in from the cold: improving vectors for new and rare products with content-based inference. In: RecSys 2020: Fourteenth ACM Conference on Recommender Systems, September 2020, pp. 577–578 (2020). <https://doi.org/10.1145/3383313.3411477>
13. Dadouchi, C., Agard, B.: Recommender systems as an agility enabler in supply chain management. *J. Intell. Manuf.* **31**, 2020 (2020). <https://doi.org/10.1007/s10845-020-01619-5>

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College of Information and Communication Technology, Can Tho University, Can Tho, Vietnam
e-mail: tqdinh@cit.ctu.edu.vn

H. T. Nguyen
e-mail: nthai@cit.ctu.edu.vn

T. D. Thi Bui
Nam Can Tho University, Can Tho, Vietnam

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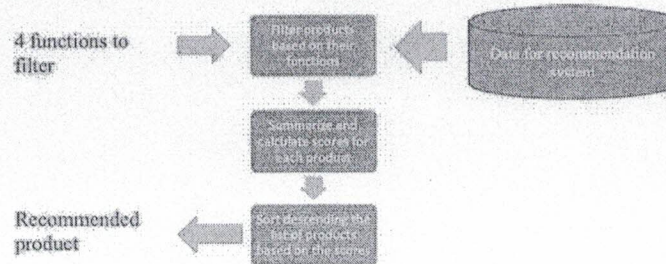


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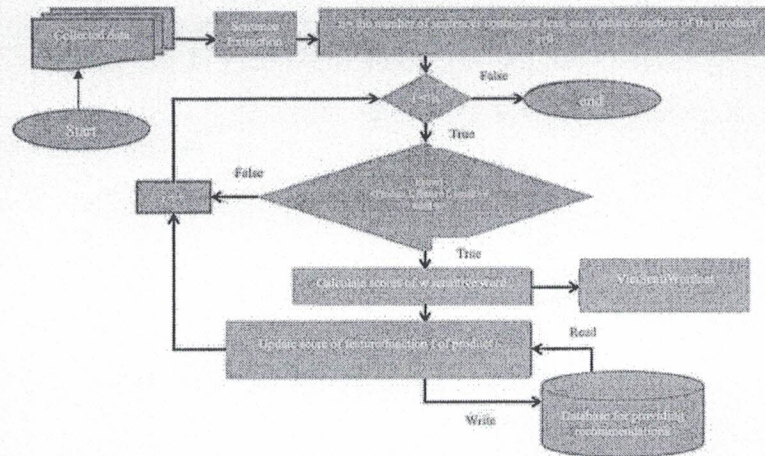


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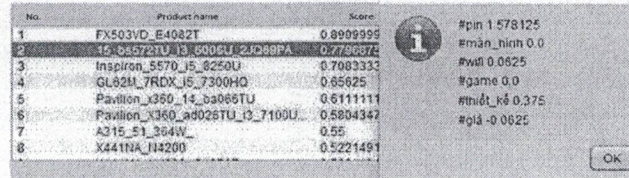
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4	GL82M_7RDX_I5_7300HQ	0.65625
5	Pavilion_x350_14_ba086TU	0.6111111
6	Pavilion_x360_a3026TU_I3_7100U	0.5804347
7	A315_51_364W	0.55
8	X441NA_I4200	0.5221491

Additional information on the right side of the interface:

- #pin 1 578125
- #man_hinh 0.0
- #wifi 0.0625
- #game 0.0
- #niet_kh 0.375
- #gia -0.0625

An "OK" button is located at the bottom right of the interface.

Fig. 7 A list of suggested products in the case the user does not select any feature *a*, a detailed feature score of the selected product

unorthodox young people's language abbreviations ("ok, đc" (okay, right/fine)), or sentences which do have meaning but not related to the product (for example, "Cảm ơn bạn nhân viên tên Ngân đã hỗ trợ nhiệt tình" ("Thank you, your staff named Ngan who gave us an enthusiastic support"))).

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