

# A Systematic Literature Review on the Product Ranking Methods

Achmad Choirun Najib, Nur Aini Rakhmawati

Information Systems Department  
Institut Teknologi Sepuluh Noverember  
ahmadchoirunnajib@gmail.com

**Abstract**-The vast amount of online products data such as product properties, or product reviews plays an essential role in providing better information to the consumers to make a purchase decision. Thus, product ranking is a valuable research topic while many methods proposed by researchers in different approaches and case studies. This paper aims to develop a Systematic Literature Review (SLR) to summarise existing research and finding new gaps in product ranking research. We develop SLR by defining inclusion criteria, initiating preliminary findings, selecting primary studies and summarizing the outcome of results. We proposed three dimensions as research questions. It consists of ranking item types of product ranking, approaches of product ranking and dataset characteristics of each study. First, we found three ranking item types of product ranking that indicate what will be ranked in the studies. It consists of product ranking, aspect ranking, and review ranking. Second, there are four approaches, namely: collaborative filtering, content-based recommendation, hybrid-based and knowledge-based. Third, datasets characteristics summarise the information of datasets like the type of data and statistics. Also, we found new gaps by identifying each dimension to positioning for further research in the future.

**Keywords:** a systematic review, aspect ranking, product ranking, ranking methods, review ranking

## 1. Introduction

Online shopping is becoming increasingly popular and important that used by seller and buyer to make transactions over the Internet. The huge of users increase the amount of online products data include product properties or product reviews. It plays an essential role in providing better information to a consumer to make a purchase decision. Usually, consumers using sales history, numeric rating, product reviews, and product aspects as a consideration before making a purchase decision. However, it is difficult for consumers to read all product reviews and find product aspects in text reviews. Hence, product ranking plays a vital role to make better and faster consumers purchase decision to buy a desirable product.

Product ranking provides benefits for both consumers and firms. At the consumer's side, good product ranking improves the consumers shopping experience. On the other hand, firms can perform analysis to get customer perception and improvements regarding their products based on product reviews or market feedback. Sorokina et al. [1] improving relevance ranking influence the shopping experience of millions of consumers and significantly impact revenue at Amazon e-commerce.

Many studies perform product ranking using various approach and case studies. Huang et al., Alengadan et al., Liu et al., Kumar et al., Najmi et al. [2]–[6] employ product reviews (e.g., numeric rating, text reviews) using sentiment analysis to perform product ranking. Alengadan et al. [3] perform product ranking using product aspects to gear up faster decision-making. Krestel et al. [7] employ numeric rating, sentiment analysis, language model, topic model to perform review ranking. Sangeetha et al. employs aspect extraction using pos tagging and ranking the aspects using sentiment score which uses sentiment dictionaries. Usually, every different case study implies a different approach to present appropriate product ranking. It may cause new gaps for particular domain or case study.

For a specific area, e.g., graph, knowledge base, and semantic web require a different approach to serving appropriate product ranking. Scholz et al. [8] perform product ranking using a graph model with product centrality ranking algorithm (PCRA), which solves some problems of existing default ranking algorithms. The PCRA uses the PageRank centrality of products in a product domination graph to determine their ranks.

Although many studies had developed on product ranking research, to the best of our knowledge, no one

develops a systematic literature review to summarise existing product ranking methods and find new gaps for positioning further research in the future. Therefore, we perform systematic literature. Our main contribution can be listed as follows:

- Presents summaries of product ranking methods
- Finding new gaps in positioning for further research in the future

We present research method in section 2. Section 3 describes our results. Section 4 describes discussion and close with conclusions in Section 5.

## 2. Research Methods

### a. Research Questions

A systematic literature review is a method for identifying, evaluating and interpreting all available researches relevant to a particular research question, or topic area, or phenomenon of interest. It can be used to summarise existing research, finding new gaps in a specific topic of study and positioning for new research [9].

In this paper, we present the results of a systematic literature review on the product ranking methods. The position of this paper is in the *Information Retrieval* field. We study the following research questions :

1. What are the existing ranking items for product ranking?
2. What are the current approaches for product ranking?
3. What are datasets characteristics for ranking a list of products?

At first, we define existing ranking items as a research question to know the parameters that may contribute to perform product ranking. These parameters can be accumulated as a weight to present the better ranking result at product ranking approach. Second, the current approaches show how to conduct product ranking. For each product ranking approach has a different method to rank the items at the dataset. Third, the characteristics of the datasets show how appropriate method performs at the right dataset characteristic. Finally, these research questions aim to produce a summary of product ranking methods that can be used to perform and present better product ranking approaches and results in future research.

### b. Research Process

The research process consisted of three main steps. The first step is defining inclusion criteria, the second step is preliminary searches, and the third step is to study selection.

#### 1) Defining Inclusion Criteria

Based on the focus topic of research, we set four types of inclusion criteria to align our inclusion/exclusion

criteria related to product ranking: *product ranking*, *aspect ranking*, *review ranking* and *empirical*. Table 1 lists the types and detail the examples of the relevant or non-relevant topic.

#### 2) Preliminary Findings

We were initially selecting and identifying primary studies. We make an initial search to select, develop and evaluate strings or keywords. We use “product ranking”, “product ranking methods”, “aspect ranking” and “review ranking” strings, to find the relevant papers. The results show many studies for this topic, only the relevant papers selected by criteria as candidate studies. We identified from the title and keywords.

#### 3) Study Selection

The set of relevant papers as primary studies candidate identified by filtering based on abstract and full text. Abstract filtering was performed by ensuring candidates must be specified standard abstract sections such as background, purpose, methods, and results. Full-text filtering was performed by evaluating the text of each candidate against the four types of inclusion criteria.

### c. Finding Results

At the preliminary findings, we found eight candidate studies at Elsevier, 16 at IEEE, four at Springer, one at ACM and three at other publishers. After study selection, we eliminated by evaluating abstract and ensuring the full text satisfy to our inclusion criteria. Only seven studies at Elsevier, nine studies at IEEE, four studies at Springer, one study at ACM, and one study at another publisher were selected as primary studies. Total we found 22 primary studies. We summarise each primary studies based on year, publishers, publication types and brief aim. Year, publishers and publication types fields figured in Fig. 1-3. Table 2 summarises title, author, year, publisher, publication type and brief aim of each primary study.

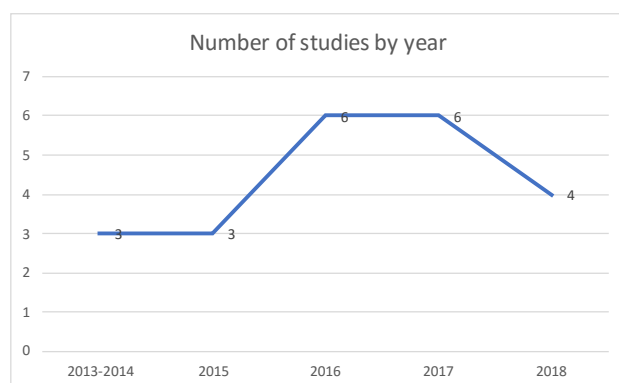


Figure 1. Number of studies by year

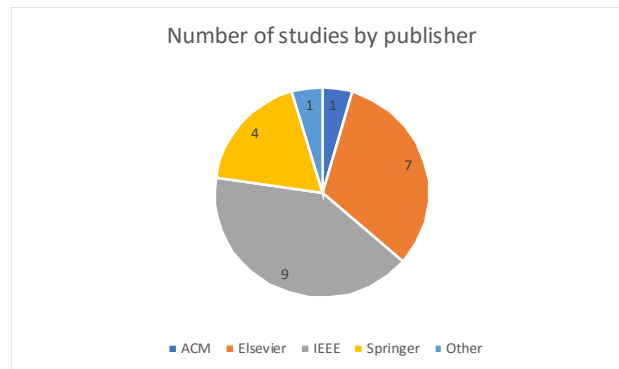


Figure 2. Number of studies by the publisher

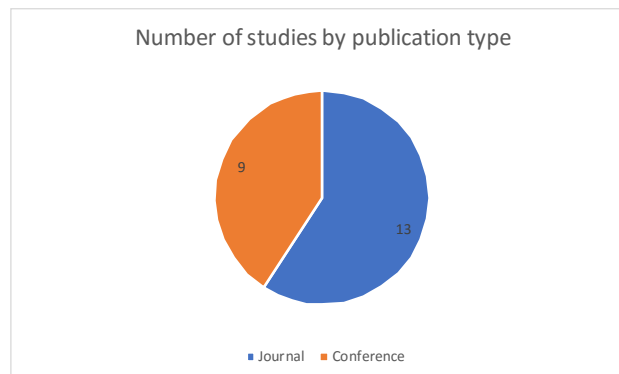


Figure 3. Number of studies by publication type

Table 1. List of Types and Detail Examples of Relevant and Non-relevant Topic

Type	Relevant	Non-relevant Examples
Product Ranking	Presents methods to rank products based on specific criteria; product ranking on search or recommendation list	Ranking model for product name extraction; brand ranking
Aspect Ranking	Presents methods to find aspects of a product and rank these aspects	Presents methods to find aspects of a product only
Review Ranking	Presents methods to rank reviews of a product based on specific criteria	Review classification
Empirical	Based on the case study, experimental reports, research article	Systematic review, textbooks, student experiments, theory papers

Table 2. Summary of Primary Studies

Code	Author, Year	Publisher, Publication type	Title	Brief aim
P1	Sorokina, et al. , 2016 [1]	ACM, Conference	Amazon Search: The Joy of Ranking Products	Explain several algorithms used in Amazon Search today
P2	Zhang et al., 2015 [10]	Elsevier, Journal	Prediction uncertainty in collaborative filtering: Enhancing personalized online product ranking	Propose RPU (Ranking with Prediction Uncertainty) methods to improve the accuracy of personalized product ranking through incorporating the uncertainty information

<i>Code</i>	<i>Author, Year</i>	<i>Publisher, Publication type</i>	<i>Title</i>	<i>Brief aim</i>
P3	Krestel et al., 2015 [11]	Elsevier, Journal	Diversifying customer review rankings	Present a framework to rank product reviews by optimizing the coverage of the ranking concerning sentiment or aspects, or by summarizing all reviews with the top-K reviews in the ranking
P4	Yang et al., 2016 [12]	Elsevier, Journal	Integrating rich and heterogeneous information to design a ranking system for multiple products	Propose a method to integrate heterogeneous information (descriptive and comparative information). Help consumers to compare multiple products and make appropriate purchase decisions effortlessly
P5	Liu et al., 2017 [4]	Elsevier, Journal	Ranking products through online reviews: A method based on sentiment analysis technique and intuitionistic fuzzy set theory	Propose an approach based on the sentiment analysis technique and the intuitionistic fuzzy set theory to rank the products through online reviews.
P6	Scholz et al., 2017 [8]	Elsevier, Journal	Using PageRank for non-personalized default rankings in dynamic markets	Propose a method utilizing the product centrality ranking algorithm (PCRA), which solves some problems of existing default ranking algorithms. The PCRA uses the PageRank centrality of products in a product domination graph to determine their ranks
P7	Sabharwal et al., 2017 [13]	Elsevier, Journal	An SVD-Entropy and Bilinearity based product ranking algorithm using heterogeneous data	Review some of the prevalent review classification techniques and present a hybrid approach, involving Singular Value Decomposition (SVD), Entropy and Bilinear Similarity measures, that uses heterogeneous product data and simultaneously analyze and rank products for customers
P8	Kumar et al., 2018 [5]	Elsevier, Journal	Aspect-based opinion ranking framework for product reviews using a Spearman's rank correlation coefficient method	Propose a new framework for ranking products based on product aspects using Spearman's rank correlation coefficient
P9	Kaur et al., 2016 [14]	FCS (Foundation of Computer Science), Journal	Semantic Product Ranking Model (SePRaM) using PNN over the Heuristic Product Data	Propose a model based upon the hybridized approach using dual-stage rank preparation. First stage using content-based ranking and the second is collaborative filtering
P10	Huang et al., 2013 [2]	IEEE, Conference	Web Product Ranking Using Opinion Mining	Presents a product ranking system using opinion mining techniques
P11	Zha et al., 2014 [15]	IEEE, Journal	Product Aspect Ranking and Its Applications	Propose product aspect ranking framework, which automatically identifies the important aspects of products from online consumer reviews, aiming at improving the usability of the numerous reviews
P12	Raja et al., 2014 [16]	IEEE, Conference	ProRankSys: Ranking consumer products by predicting opinion's weight on reviews	Propose a method to calculate individual opinion's weight by predicting the strength of each review and assessing the overall rank of the product by consolidating the predicted review strength
P13	Bhamre et al., 2016 [17]	IEEE, Conference	Aspect Rating Analysis Based Product Ranking	Propose a system use of aspect rating to improve the performance of important aspect identification and ranking
P14	Alrababah et al., 2016 [18]	IEEE, Conference	Product aspect ranking using sentiment analysis and TOPSIS	Propose aspect ranking framework using sentiment analysis and TOPSIS (Technique for Order Performance by Similarity to Ideal Solution)
P15	Sangeetha et al., 2017 [19]	IEEE, Conference	Aspects based Opinion Mining from Online Reviews for Product Recommendation	Propose a method for identifying and prioritizing the aspects of products based on the online reviews given by the customers using aspect extraction and scoring aspects using sentiment dictionaries



<i>Code</i>	<i>Author, Year</i>	<i>Publisher, Publication type</i>	<i>Title</i>	<i>Brief aim</i>
P16	Shahbazi et al., 2017 [20]	IEEE, Conference	IRanker: Query-Specific Ranking of Reviewed Items	Presents efficient top-k algorithms to rank items, by weighing each review's rating by its relevance to the user query.
P17	Kuo et al., 2018 [21]	IEEE, Conference	Feature Learning with Rank-Based Candidate Selection for Product Search	Propose a method to rank product by attributes, image pairs, categories with deep convolutional neural networks (CNNs) for solving cross-domain image retrieval and product search
P18	Alengadan et al., 2018 [3]	IEEE, Conference	Modified Aspect/Feature-Based Opinion Mining for a Product Ranking System	Propose a method to rank the products and its essential aspects which to gear up faster decision-making.
P19	Najmi et al., 2015 [6]	Springer, Journal	CAPRA: a comprehensive approach to product ranking using customer reviews	Propose a product ranking system that facilitates the online shopping experience by analyzing the reviews for sentiments, evaluating their usefulness, extracting and weighing different product features and aspects, ranking it among similar comparable products, and finally creating a unified rank for each product
P20	Zhang et al., 2015 [22]	Springer, Journal	Learning user credibility for product ranking	Present a twin-bipartite graph model to catch the review and ranking relationship among users, products, and shops.
P21	Li et al., 2017 [23]	Springer, Journal	Product ranking using hierarchical aspect structures	Present a novel hierarchical aspect-based product ranking approach.
P22	Fan et al., 2018 [24]	Springer, Journal	Supporting consumer's purchase decision: a method for ranking products based on online multi-attribute product ratings	Proposes a method for ranking products based on online multi-attribute product ratings

#### 4. Results

In this section, we present our findings. We discuss the findings organized according to our research questions.

##### a. Ranking Items

In this section, we answer our first research question, RQ1. *What are the existing ranking items for product ranking?* Primary studies generally proposed product ranking method to rank three ranking items consist of product ranking, review ranking and aspect ranking. We found 17 studies propose methods to perform product ranking, one study proposes a method to perform review ranking, four studies propose methods to perform aspect ranking. We organized the found primary studies based on three ranking items in Table 3.

**Table 3. Primary studies categorized by ranking items**

<i>Ranking item</i>	<i>Primary studies</i>	<i>Total</i>
Product	P1, P2, P4, P5, P6, P7, P8, P9, P10, P12, P16, P17, P18, P19, P20, P21, P22	17
Review	P3	1
Aspect	P11, P13, P14, P15	4

##### 1) Product Ranking

Product ranking performs the comparison between the list of product items to specify the position of the item. It aims to serve appropriate product ranking to improve consumers experience and to expedite consumers purchase decision. It was done by various ranking approaches based on a custom algorithm or specific criteria in a ranking system. Huang et al., Alengadan et al., Liu et al., Kumar et al., Najmi et al. [2]–[6] employ product reviews (e.g., numeric rating, text reviews) using sentiment analysis to perform product ranking. Alengadan et al. [3] using product aspects to perform product ranking to gear up faster decision-making. Thus, review ranking and aspect ranking becoming part of product ranking.

##### 2) Review Ranking

Product reviews must be ranked based on the importance of each text review to serve a better purchase decision to the consumers. The importance of a review frequently indicated by the recency and helpfulness of the review and calculated by specific ranking criteria. Krestel et al. [7] employ numeric rating, sentiment analysis, language model, topic model to perform review ranking. This study proposes three review ranking strategies consist of summary-focused ranking, sentiment-focused

ranking, and topic-focused ranking. Summary-focused summarises the opinions about a product present in all reviews. Sentiment-focused summarise only one particular class of ratings, for example, negative aspects as represented by the topic-rating model with score one. Topic-focused focus the review ranking on a specific latent topic and allows to get all opinions – positive, neutral, and negative – about a particular aspect

### 3) *Aspect Ranking*

Consumers frequently consider the aspects of a product before purchasing a product. It aims to find the importance of aspects. The importance of aspects may consist of quality, performance, durability or other measurements. Hence, it is essential to rank aspects of a product to identify the critical aspects of products from online consumer reviews, aiming at improving the usability of the numerous reviews. Commonly, aspect ranking was done by extracting aspects and ranked these aspects using sentiment analysis based on text reviews. Sangeetha et al. [19] employ aspect extraction using pos tagging and rank the aspects using sentiment score which utilizes sentiment dictionaries.

## b. Ranking Approaches

In this section, we answer our second research question, RQ2. *What are the current approaches for product ranking?* We classified the found primary study approaches to four ranking approach types consist of collaborative filtering, content-based, hybrid-based, knowledge-based [14]. We found one study conduct collaborative filtering approach, 20 studies conduct a content-based approach, and one study conduct hybrid and knowledge approach to perform product ranking. We organized primary studies based on the ranking method in Table 4.

**Table 4. Primary studies classified by ranking approach**

<i>Ranking item</i>	<i>Primary studies</i>	<i>Total</i>
Collaborative filtering	P2	1
Content-based	P3, P4, P5, P6, P7, P8, P9, P10, P11, P12, P13, P14, P15, P16, P17, P18, P19, P20, P21, P22	20
Hybrid based	P1	1
Knowledge-based	P1	1

### 1) *Collaborative filtering approach*

Collaborative filtering approach ranking conducted by using a collaborative filtering algorithm. Collaborative filtering is a method to perform automatic predictions based on information or preferences gathered from many users data [25]. A typical example is movie recommendation might be like for a new user. Zhang et al. [10] conduct product ranking using a collaborative filtering approach in MovieLens dataset. This study proposes a method called RPU (Ranking with Prediction Uncertainly)

to improve the accuracy of personalized product ranking through incorporating the uncertainty information. This study utilizes historical data, e.g., consumer, item and rating to perform collaborative filtering and product ranking.

### 2) *Content-based approach*

Content-based approach ranking conducted by using the concepts of information retrieval and information filtering, e.g., string similarity, document similarity, TF-IDF measurement [14]. In majority, products ranked by utilizing the product data, e.g., product title, description, sales history, or product reviews. Twenty primary studies use a content-based approach to perform ranking by utilizing text information such as text review, numeric rating, number of voting, product images and product history data. They ranked by various methods, e.g., custom weighting, graph weighting, sentiment analysis, and PageRank. Except in one study, Kuo et al. [21] using an image as a query to present similar images as product ranking results. It was done by using convolutional neural networks. Table 5 summarises the content-based approach studies ranking methods.

### 3) *Hybrid-based approach*

Hybrid-based approach ranking used a combination of two or more techniques. It aims to generate a better and appropriate ranking. Combine collaborative filtering, and content-based approach produces more accurate recommendation and ranking [14]. Sorokina et al. [1] perform product ranking on Amazon e-commerce using various methods, e.g., general machine learning within categories, blending separate rankings in All Product Search, NLP techniques used for matching queries and products.

### 4) *Knowledge-based approach*

Knowledge-based approach ranking typically conducted for a specific domain and may be involving experts to determine the rules to present more appropriate and accurate ranking results. Sorokina et al. [1] perform product ranking on Amazon e-commerce especially ranking in Fashion Store. The challenge is a discrepancy between what the majority of customers buy and what they want to see on top of the page. Assume consumers search “diamond ring” product. Commonly consumers bought cheap zirconium ring. However, if the search results show the zirconium ring as a first result, search results will be perceived as broken. The Fashion Store would look like a flea market, instead of a classic department store where the latest collections meet consumers at the entrance. This study set rules to solve this problem by identifying strategic categories of fashionable customers, customers who bought or added to cart fashion brand products significantly amplify their influence while designing the training set.

### c. Dataset Characteristics

In this section, we answer our third research question, RQ3. *What are datasets characteristics for ranking a list of products?* We identify the dataset of each primary studies by identifying the type of data and statistics, e.g., the number of domain and records.

We categorize the type of data to four categories: structured, e.g., relational; semi-structured, e.g., JSON, XML; unstructured and graph. We found four studies

using structured, four studies using semi-structured, ten studies using unstructured and three studies using graph type of data. We classify the number of the domain by the number of categories or product types in the dataset while the number of records shows the aggregate number of reviews, products, or other items presented in the dataset. Table 6 classifies primary studies by type of data and statistics of the dataset.

**Table 5. Content-based Approach Studies Ranking Methods**

<i>Code</i>	<i>Ranking item</i>	<i>Ranking summary</i>	<i>Ranking methods</i>	<i>Features used</i>
P3	Review ranking	Reviews and ratings are used to extract topic distributions using LDA or word distributions using LM. The ranking was computed by minimizing Kullback–Leibler Divergence (KLD) with task-specific target distributions.	LDA/LM, summarization-based, topic-based, rating-based	Reviews, numeric ratings
P4	Product ranking	Product ranked by using descriptive and comparative information, descriptive using numeric rating and text sentiment, comparative using online votes and comparative sentences	Weighting Graph Building	Numeric rating, reviews, votes, comparative sentences
P5	Product ranking	The ranking method based on the sentiment analysis technique (HowNet dictionary) and the intuitionistic fuzzy set theory to rank the products through online reviews	Sentiment Analysis, Fuzzy set theory	Reviews
P6	Product ranking	The ranking method based on PageRank centrality of products in a product domination graph. The product domination graph model products as nodes and the dominance relations between the products' attribute levels as edges.	PageRank	Product attributes
P7	Product ranking	Ranking products by combining weighted Q&A rank, weighted text-based review rank, and normalized rank.	SVD-entropy, Bilinearity	Reviews, Q&A data, rating of the reviews
P8	Product ranking	Spearman's rank correlation coefficient-based opinion ranking method is applied to rank the products based on positive and negative ranks.	Spearman's rank correlation	Reviews
P9	Product ranking	Ranking products by using similarity between the search query arguments and the product ranking data (product popularity)	Content similarity, Product popularity	Product data
P10	Product ranking	Product ranked by author formula. Multiply of $APR_i$ is the Average Polarity of Reviews, $PW_i$ is the Popularity Weight, and $WPRM_i$ is the Weight of Product Release Month.	Reviews polarity (positive or negative), product popularity using several reviews, current release month	Reviews, product release month
P11	Aspect ranking	Ranking aspect by exploiting the pros and cons of reviews to improve aspect identification in free text reviews. Then split the sentences and classify them to the aspects of the product, then analyze using sentiment classifier, then compute weight score for each aspect to measure the importance and rank of these aspects.	Sentiment analysis	Reviews
P12	Product ranking	Ranking product by reviews' weight-based ranking algorithm	Sentiment analysis	Reviews
P13	Aspect ranking	Ranking aspect by combining sentiment classification, aspect frequency, importance score, and the rating score	Sentiment analysis	Reviews
P14	Aspect ranking	Ranking aspect by employing aspect extraction using sentiment analysis and aspect ranking using the TOPSIS method	Sentiment analysis	Reviews

<i>Code</i>	<i>Ranking item</i>	<i>Ranking summary</i>	<i>Ranking methods</i>	<i>Features used</i>
P15	Aspect ranking	Aspect ranking employs aspect extractor: POS Tagging, Non-Aspect Removal, and sentiment score predictor: Sentiment Dictionary (SD), Sentiment Degree Dictionary (SDD), Negation Dictionary (ND)	Sentiment analysis	Reviews
P16	Product ranking	Product ranking employs efficient top-k algorithms to rank items, by weighing each review's rating by its relevance to the user query.	NRA-IRanker	Reviews
P17	Product ranking	Ranking product by attributes, image pairs, and categories with deep convolutional neural networks (CNNs)	Convolutional Neural Networks	Product image
P18	Product ranking	Ranking product by aspect polarity identification	Sentiment Analysis	Reviews
P19	Product ranking	Ranking product by combining review ranking, aspect weighting, and brand ranking to produce unified product ranking	Sentiment Analysis, aspect weighting, brand ranking, review usefulness	Reviews
P20	Product ranking	Product ranking conducted by using twin-bipartite graph model to catch the review and ranking relationship among users, products, and shops.	Custom formulation	Reviews, ratings
P21	Product ranking	Ranking by using Graph-based ordering algorithms to present a novel hierarchical aspect-based product ranking approach	Graph-based ordering algorithm	Reviews
P22	Product ranking	Ranking by calculating stochastic dominance degrees and ranking the candidate products using the PROMETHEE-II method.	Stochastic dominance rules, PROMETHEE-II method	Product attributes

**Table 6. Primary Studies Classified by Type of Data and Statistics of The Dataset**

<i>Code</i>	<i>Source</i>	<i>Type of data</i>	<i>Number of categories</i>	<i>Number of items in the dataset</i>
P1	Amazon	Unspecified	Whole Amazon categories	Unspecified
P2	MovieLens	Unstructured	1 (Movies)	1,000,209 movie ratings from 6,040 users on 3,706 movie items
P3	Epinions	Unstructured	4 (America West Airlines, Pokemon Snap for Nintendo 64, Starbucks, Microsoft Windows ME)	More than 300 products, with over 200,000 reviews
P4	zol.com.cn	Unstructured	3 (Mobile phones, laptops, digital camera)	500 product reviews
P5	Automobile Home, PCAuto	Unstructured	1 (Automobile products)	1679 reviews
P6	Amazon	Graph	3 (Energy-saving Lamp, Hotel Room, Washing Machine)	140 products
P7	Amazon	Semi-structured	3 (Musical Instruments, Electronics, Health, and Personal Care)	1500 products
P8	OpinRank	Semi-structured	1 (Car)	611 reviews
P9	Unspecified	Unspecified	Unspecified	Unspecified
P10	Doctors, Amazon	Semi-structured	Unspecified	Unspecified
P11	cnet.com, viewpoints.com, reevoo.com, gsmarena.com, and pricegrabber.com	Unstructured	8 (Camera, Laptop, MP3, Phone, Camcorder, TV, GPS, Printer)	94,560 consumer reviews on 21 products
P12	Unspecified	Semi-structured	1 (Digital Camera)	8746 products
P13	Amazon and Cnet	Structured	6 (Camera, Mobile, Router, Antivirus, MP3 Player, DVD Player)	14 products reviews
P14	Bing Liu	Unstructured	3 (Digital Camera, Cell Phone, MP3 Player)	1302 reviews
P15	Amazon.in	Unstructured	1 (Mobile Phone)	3000 reviews

Code	Source	Type of data	Number of categories	Number of items in the dataset
P16	Doctors and Amazon	Unstructured	4 (Healthcare, Books, Clothing, Movies)	Doctors 248580 items 726996 reviews Amazon 9743974 items 82037337 reviews
P17	DeepFashion, Alibaba	Unstructured	5 (Fashion, Clothes, Snacks, Beauty, Furniture)	DeepFashion 8,471 items Alibaba 400 items
P18	review.net	Structured	Unspecified	Unspecified
P19	Amazon	Structured	2 (HDTVs and Cameras)	197 products and 56,368 Reviews
P20	Taobao	Graph	15 (Clothes and Shoes, Books, etc.)	553,000 customers, 300,000 products, 10,000 shops and 924,000 reviews
P21	CNet, Amazon, Reevo, Gsmarena	Graph	2 (Mobile Phone, MP3 Players)	Six mobile phone reviews, five mp3 players reviews
P22	Autohome (autohome.com.cn)	Unstructured	1 (Automobile)	7322 reviews

## 5. Discussion

In this section, we discuss our general observation to find open issues or new gaps in the literature. We start finding issues or new gaps by identifying our findings based on our research question answers.

As the answer to RQ1: “*What are the existing ranking items for product ranking?*”, We identify the majority of the existing ranking item is “product ranking”, followed by “aspect ranking”. But only one study perform “review ranking”. It indicates the “review ranking” is a valuable research topic area. Besides, Electronic Word of Mouth (e-WOM) products massive data in product reviews, not only in the form of text reviews and numeric ratings but also pictures of the product. This plays an essential role to determine how to rank the reviews better, such as usefulness, recency or relevancy for a particular aspect or whole aspects.

As the answer to RQ2: “*What are the current approaches for product ranking?*”, We identify the majority of ranking approach is the content-based approach, followed by one study of each collaborative filtering, hybrid-based and knowledge-based approach. Although content-based is a majority, combining other methods may result in the better product ranking. Thus, different approaches are valuable research topic area for a specific case study. For example, by adding a knowledge-based and hybrid-based approach may provide more relevant product ranking in a particular area, e.g., halal product ranking [26]. It is crucial to add a knowledge-based approach such as make higher ranking to the product which has a halal certificate to indicate the safe product guarantee for Muslim.

As the answer to RQ3: “*What are datasets characteristics for ranking a list of products?*”, We identify the majority type of data is unstructured, followed by semi-structured, structured and graph. In the majority, the studies conduct product ranking using sentiment analysis, except the study which uses a graph. Commonly, the graph uses different approaches to rank the products such as product centrality to calculate the product score

to indicate product popularity. Also, product attributes and connection strength of edges also contribute to producing a higher score. Example of the type data as a semi-structured and able to model as a graph is Resource Description Framework (RDF). RDF contains a subject, predicate, and object to present a fact. Based on all of the studies, no one conduct product ranking use RDF as a source of the type of data and model as a graph. Thus, it is a valuable research topic area.

## 6. Conclusion

We presented a systematic literature review of empirical studies on product ranking methods. We present 22 studies describing various product ranking methods in various case studies.

The identified primary studies are research articles which experiment certain case studies. More than half published in the journal and the rest at the conference.

The ranking items of product ranking are classified into three of ranking item types: product ranking, aspect ranking, and review ranking. The existing approaches for product ranking classified into four categories: collaborative filtering, content-based, hybrid-based, and knowledge-based. The dataset characteristics type of data in the majority are unstructured, followed by semi-structured, structured and graph.

As future research topics, we suggest conducting product ranking in case studies of product ranking or review ranking. Then perform a knowledge-based or hybrid-based approach for a better product ranking. Then do product ranking using a semi-structured type of data and modeling as a graph.

## 7. Acknowledgment

This research is being conducted and was supported by funding from Lembaga Penelitian dan Pengabdian kepada Masyarakat, Institut Teknologi Sepuluh Nopember (LPPM - ITS) and Kementerian Riset, Teknologi, dan



Pendidikan Tinggi (or Ministry of Higher Education Indonesia) with the scheme of Postgraduate Research number 1168/PKS/ITS/2019.

## References

- [1] D. Sorokina and E. Cantú-paz, "Amazon Search : The Joy of Ranking Products," *Proc. 39th Int. ACM SIGIR Conf. Res. Dev. Inf. Retr.*, 2016.
- [2] Yin-Fu Huang and Heng Lin, "Web product ranking using opinion mining," in *2013 IEEE Symposium on Computational Intelligence and Data Mining (CIDM)*, 2013, pp. 184–190.
- [3] B. B. Alengadan and S. S. Khan, "Modified aspect/feature based opinion mining for a product ranking system," in *2018 IEEE International Conference on Current Trends in Advanced Computing (ICCTAC)*, 2018, pp. 1–5.
- [4] Y. Liu, J. W. Bi, and Z. P. Fan, "Ranking products through online reviews: A method based on sentiment analysis technique and intuitionistic fuzzy set theory," *Inf. Fusion*, 2017.
- [5] A. K. J and S. Abirami, "Aspect-based opinion ranking framework for product reviews using a Spearman's rank correlation coefficient method," *Inf. Sci. (Nijl.)*, 2018.
- [6] E. Najmi, K. Hashmi, Z. Malik, A. Rezgui, and H. U. Khan, "CAPRA: a comprehensive approach to product ranking using customer reviews," *Computing*, 2015.
- [7] R. Krestel and N. Dokoohaki, "Diversifying customer review rankings," *Neural Networks*, vol. 66, pp. 36–45, Jun. 2015.
- [8] M. Scholz, J. Pfeiffer, and F. Rothlauf, "Using PageRank for non-personalized default rankings in dynamic markets," *Eur. J. Oper. Res.*, 2017.
- [9] B. Kitchenham and S. Charters, "Guidelines for performing Systematic Literature reviews in Software Engineering Version 2.3," *Engineering*, 2007.
- [10] M. Zhang, X. Guo, and G. Chen, "Prediction uncertainty in collaborative filtering: Enhancing personalized online product ranking," *Decis. Support Syst.*, 2016.
- [11] R. Krestel and N. Dokoohaki, "Diversifying customer review rankings," *Neural Networks*, 2015.
- [12] X. Yang, G. Yang, and J. Wu, "Integrating rich and heterogeneous information to design a ranking system for multiple products," *Decis. Support Syst.*, 2016.
- [13] C. L. Sabharwal and B. Anjum, "An SVD-Entropy and bilinearity based product ranking algorithm using heterogeneous data," *J. Vis. Lang. Comput.*, 2017.
- [14] G. Kaur and R. Bhatia, "Semantic Product Ranking Model (SePRaM) using PNN over the Heuristic Product Data," *Int. J. Comput. Appl.*, 2016.
- [15] Zheng-Jun Zha, Jianxing Yu, Jinhui Tang, Meng Wang, and Tat-Seng Chua, "Product Aspect Ranking and Its Applications," *IEEE Trans. Knowl. Data Eng.*, vol. 26, no. 5, pp. 1211–1224, May 2014.
- [16] M. Arun Manicka Raja, S. G. Winster, R. Saravanan, and S. Swamynathan, "ProRankSys: Ranking consumer products by predicting opinion's weight on reviews," in *Proceedings of IEEE International Conference on Computer Communication and Systems ICCCS14*, 2014, pp. 033–038.
- [17] N. R. Bhamre and N. N. Patil, "Aspect rating analysis based product ranking," in *2016 International Conference on Global Trends in Signal Processing, Information Computing and Communication (ICGTSPICC)*, 2016, pp. 197–202.
- [18] S. A. A. A. Alrababah, K. H. Gan, and T-P. Tan, "Product aspect ranking using sentiment analysis and TOPSIS," in *2016 Third International Conference on Information Retrieval and Knowledge Management (CAMP)*, 2016, pp. 13–19.
- [19] T. Sangeetha, N. Balaganesh, and K. Muneeswaran, "Aspects based opinion mining from online reviews for product recommendation," in *2017 International Conference on Computational Intelligence in Data Science (ICCIDS)*, 2017, pp. 1–6.
- [20] M. Shahbazi, M. Wiley, and V. Hristidis, "IRanker: Query-specific ranking of reviewed items," in *Proceedings - International Conference on Data Engineering*, 2017.
- [21] Y. H. Kuo and W. H. Hsu, "Feature Learning with Rank-Based Candidate Selection for Product Search," in *Proceedings - 2017 IEEE International Conference on Computer Vision Workshops, ICCVW 2017*, 2018.
- [22] R. Zhang, M. Gao, X. He, and A. Zhou, "Learning user credibility for product ranking," *Knowl. Inf. Syst.*, 2016.
- [23] S. Li, Z. Ming, Y. Leng, and J. Guo, "Product ranking using hierarchical aspect structures," *J. Intell. Inf. Syst.*, 2017.
- [24] Z. P. Fan, Y. Xi, and Y. Liu, "Supporting consumer's purchase decision: a method for ranking products



- based on online multi-attribute product ratings,” *Soft Comput.*, 2018.
- [25] J. S. J. Breese, D. Heckerman, and C. Kadie, “Empirical analysis of predictive algorithms for collaborative filtering,” *Proc. 14th Conf. Uncertain. Artif. Intell.*, 1998.
- [26] N. A. Rakhmawati, J. Fatawi, A. C. Najib, and A. A. Firmansyah, “Linked open data for halal food products,” *J. King Saud Univ. - Comput. Inf. Sci.*, 2019.