OMCR: An Opinion-Based Multi-Criteria Ranking Approach

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Abstract. Due to proliferation of competitive online Business-to-Consumer (B2C) models, it is becoming a challenging task for new users to choose best products, based on existing users' reviews residing on different e-commerce websites. On analysis, it is found that the opinions of the existing customers play an important role for new customers in making appropriate purchase decisions. Though there are some online websites that provide aggregation of basic product information from multiple sources, there is a negligible research effort in the direction of opinion-based product ranking. In this paper, we propose an Opinion-based Multi-Criteria Ranking (OMCR) approach, which amalgamates structural and content-based features of review documents to rank different alternatives of the online products. It uses a total number of five features based on reviews' meta-data and contents to rank different alternatives using multi-criteria decision making approaches. OMCR also incorporates a sentiment analysis and visualization approach to determine sentiment polarity values and visualize them in a comprehendible manner. Experiments are conducted over two different real datasets, and efficacy of OMCR is assessed using *set intersection* method, which is generally used to compare two ranked lists in terms of their overlapping score.

Keywords: Text mining, Sentiment analysis, Multi-criteria ranking, Multi-criteria decision making, Opinion-based ranking

1. Introduction

Due to easy accessibility and availability of Business-to-Consumer (B2C) websites, customers are shifting from traditional interactive shopping to online shopping to save time and get products at a competitive price. B2C websites allow customers to directly purchase goods or services from manufacturers online, without involving any third party sellers, which reduces the overall costs of the products. The online shopping also enhances consumers' ability to access product details and prices from different online shopping sites and compare them easily to take an informed decision. However, generally it is very difficult for customers to take purchase decision based on only product descriptions provided by the B2C websites. Rather, they are very much curious to know the opinion of existing customers and competitive price offered by different B2C websites before making any purchase decision.

Since most of the B2C websites facilitate their customers to write reviews of the purchased products, opinions of the existing customers have become an important and reliable source of information to help new customers for making an appropriate purchase decision. Moreover, the opinions of the existing customers may be helpful for the manufacturers to know the sentiments of the users, so that the positive features could be used for marketing and the negative features could be improved for better customer satisfaction. However, due to unstructured and distributed nature of the reviews of same product across multiple B2C sites, their manual analysis is not feasible. Though some of the existing websites such as *naaptol.com*, *mysmartprice.com*, etc. provide comparison of similar products based on their basic features and price, none of them

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provides a holistic ranking of the products. Moreover, none of such websites provides comparison of products based on the opinions of the existing users. Therefore, curating review documents from different B2C websites in a common format and analyzing them using different meta-data and content-based features to generate rank scores for different alternative of a product category seems useful for both new customers and manufacturers.

1.1. Our Contributions

Though a good amount of research efforts have been directed towards opinion mining and sentiment analysis [9,14,28], relatively little attention has been directed towards the opinion-based product ranking. In this paper, we present an Opinion-based Multi-Criteria Ranking (OMCR) approach to rank different alternatives of online products using Multi-Criteria Decision Making (MCDM) techniques. The MCDM is an area of operation research which is generally used to find best alternatives by evaluating multiple conflicting criteria. We have identified a set of five features, such as *star rating*, *user verification status*, *review title*, *review content*, and *review usefulness* based on meta-data and contents of the review documents to rank different alternatives of online products. We have also shown how features identified from review documents can be ranked using AHP (Analytic Hierarchy Process), and how decision matrix can be generated from review documents to rank different alternatives of a product using TOPSIS (Technique for Order Preference by Similarity to Ideal Solution). The proposed OMCR also incorporates a sentiment analysis and visualization technique to determine sentiment polarity values and visualize them in a comprehendible manner.

In short, the key contributions of this paper can be summarized as follows:

- Development of an opinion-based multi-criteria ranking approach to rank different alternatives of online products using meta-data and content-based features of review documents.
- Feature identification from review documents and their ranking using AHP.
- An approach for decision matrix generation from review documents and ranking different alternatives of a product using TOPSIS.
- A sentiment aggregation and visualization scheme to determine sentiment polarity values and visualize them in a comprehendible manner.

For experimental evaluation of the OMCR, we have generated two real datasets using import.io from three different e-commerce websites – *Amazon*, *Flipkart*, and *Snapdeal*. The first dataset consists of 5623 reviews of smartphones, whereas the second dataset consists of 32014 reviews of hard disk drives. The efficacy of the OMCR is assessed using *set intersection* method, which is generally used to compare two ranked lists in terms of their overlapping score.

The rest of the paper is organized as follows. Section 2 presents a brief review of the existing works on different product ranking approaches. Section 3 presents some basic concepts related to MCDM. The functioning details of our proposed OMCR approach is presented in section 4. Sections 5 and 6 presents experimental and evaluation results. Finally, section 7 concludes the paper with future directions of research.

2. Related Works

This section presents a brief review of the state-of-the-art techniques in product ranking. The authors in [13] presented an estimation of the finest mobile phones based on users preferences using multi-criteria decision making. They considered three mobile phones of same price-range and ranked them using AHP and TOPSIS. In [31], the authors proposed a product ranking technique using the product features extracted from review documents. They modelled review documents as a weighted and directed graph and applied graph-theoretic approaches for product ranking.

In order to identify the relationship between mobile phone preferences of different users, a number of researchers have worked in this direction [3,6,8,10]. Chen et al. [4] argued that success level of a new product is highly dependent on the customers requirements. In this work, they proposed a system prototype using neural networks for multi-cultural factors evaluation and customer requirements acquisition. The authors in [17] showed direct relationship between users satisfaction and product design, and proposed a relationship model to predict users satisfaction.

In [30], the authors proposed an approach to rank e-commerce websites using MCDM techniques based on different criteria, such as *appearance*, *easy to use*, and *price*. They applied AHP technique for criteria weighting and evaluating the structure of a ranking problem. Thereafter, they used Fuzzy Sets to represent uncertainty, and applied TOPSIS for final rank genera-

tion. The authors in [11] proposed a ranking system using linguistic features and support vector regression model to rank review documents. They generated a corpus containing 3730 Chinese reviews of eight different product categories, such as cell phones, toys, books, etc. to evaluate the proposed ranking system using different confidence measures.

Though a numer of literatures exist in the doamin of recommendar system (e.g., [2,19]), the authors in [16] proposed a hybrid framework, which combines multi-criteria decision analysis technique with collaborative filtering for recommendations. In [27], the authors proposed different categories of MCDM problems, including an evidential reasoning method, which is one of the recent advances in managing mixed MCDM problems. They also presented a comparison of the evidential reasoning method with AHP technique. A feedback-based diagnosis system using MCDM techniques is presented in [7] to assist the advertising group of an e-commerce organization.

Opinion-based multi-criteria ranking of online products comes under the category of MCDM, which is a branch of operation research. It is defined as the ranking of alternate products based on multiple but conflicting criteria [20]. The MCDM methods assist in decision making process through organizing, resolving decisions, and planning difficulties in terms of multiple criteria, and they have been used in various application domains [5,23,24,29]. The MCDM methods can be used to recognize preferred measures amongst a set of alternatives through which strengths and weaknesses of several adaptation choices can be calculated using multiple criteria.

To the best of our knowledge, none of the works mentioned above has considered the amalgamation of reviews-based features and MCDM techniques to rank different alternatives of the online products. Our proposed work is in line to the work presented in [13], but instead of product- and customer-related features, we have used reviews-based features to rank different alternatives of the online products.

3. Preliminaries

In this section, we present technical details about two popular MCDM techniques – AHP and TOPSIS that are mainly used for feature and product ranking, respectively in our proposed OMCR method.
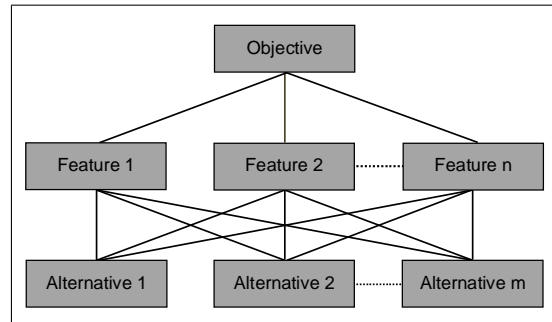

Fig. 1. Hierarchical structure used in AHP to represent the decomposition of a complex condition into criteria, sub-criteria, and alternatives

3.1. Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) was developed by Thomas L. Saaty in the year 1980 [22]. It is one of the widely used methods to rank different criteria. It decomposes a complex and unstructured condition into its constituent parts and arranges the criteria, sub-criteria, and alternatives into a hierarchical structure, as shown in figure 1.

One of the appealing features of AHP is the pair-wise comparison of criteria to assign them numeric weights for comparing different alternatives. It relies on the experts' judgement to gain knowledge on a priority scale. AHP is a non-linear approach, and it has a special concern to determine whether pair-wise criteria weights assigned by the experts are consistent or not. As pointed out in [1], the general form of AHP is susceptible to rank reversal problem, i.e., AHP may change the ranking of alternatives on addition of a new alternative [25]. However, despite the controversies and problems faced by AHP, it is one of the most widely used MCDM models for decision making problems. A detailed discussion including limitations, pitfalls, and practical difficulties associated with the multi-criteria decision analysis techniques can be seen in [15]. A brief descriptions of the steps used in AHP to rank a given list of alternatives are given in the following paragraphs.

Step 1: Hierarchical representation of the problem

AHP represents a decision-making problem as a tree-like hierarchy, in which *objective* is represented by root node, *criteria* and *sub-criteria* are represented by middle-level nodes, and *alternatives* are represented by leaf nodes.

Step 2: Feature score-vector generation

After hierarchical representation of the problem, a relative criteria score matrix ($\mathcal{C}$), as defined in equation 1, is generated. $\mathcal{C}$ is a positive reciprocal real matrix of order $n \times n$, where n is the total number of criteria, and c_{ij} represents the importance of ith criteria over j^{th} criteria. Since in comparison to assigning weights to individual criteria, it is easier to determine relative importance between a pair of criteria, $\mathcal{C}$ matrix is generated using the values assigned by a domain expert using the Saaty's nine-point scale given in table 1. For n criteria, expert needs to assign only $n(n-1)/2$ relative values. The elements above the diagonal of $\mathcal{C}$ (i.e. c_{ij} for $i > j$) are determined using expert's feedback, the diagonal elements (i.e. c_{ii}) are kept as 1, and the elements below the diagonal are determined using the reciprocal property, i.e., $c_{ij} = 1/c_{ji}$.

$$\mathcal{C} = \begin{pmatrix} c_{11} & c_{12} & \ldots & c_{1n} \\ c_{21} & c_{22} & \ldots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \ldots & c_{nn} \end{pmatrix} \tag{1}$$

In order to rank criteria, principal eigenvector of $\mathcal{C}$ is calculated. Though there are various approaches to calculate principal eigenvector, an approximate principle eigenvector of a matrix can be obtained by normalizing the elements in each column and then taking the average of each row [21]. Therefore, we normalize $\mathcal{C}$ by dividing each element of a column with the respective column-sum. Equation 2 presents the normalized matrix $\hat{\mathcal{C}}$, in which $\hat{c}_{ij} = \frac{c_{ij}}{\sum_{i=1}^{n} c_{ij}}$. In order to compute a numeric score for each criterion, a criteria score vector $\mathcal{S} = (s_1, s_2, ..., s_n)^T$ in the vector space $\Re^n$ is calculated using normalized criteria matrix $\hat{\mathcal{C}}$, in which s_i represents the score of the ith criteria and calculated as $s_i = \frac{\sum_{j=1}^{n} \hat{c}_{ij}}{n}$, i.e., as an average of the ith row of $\hat{\mathcal{C}}$.

$$\hat{\mathcal{C}} = \begin{pmatrix} \hat{c}_{11} & \hat{c}_{12} & \ldots & \hat{c}_{1n} \\ \hat{c}_{21} & \hat{c}_{22} & \ldots & \hat{c}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{c}_{n1} & \hat{c}_{n2} & \ldots & \hat{c}_{nn} \end{pmatrix} \tag{2}$$

Step 3: Consistency checking

Inconsistency may arise due to assigning incorrect scores to different criteria-pairs by the expert. Therefore, AHP provides a mechanism to check whether the scores provided by the expert are consistent or not. To this end, a *consistency ratio* (r) is calculated as the ra-

Table 1

Saaty's [22] nine-point scale for pair-wise scoring between criteria c_1 and c_2

Numeric value	Linguistic meaning
1	Both c_1 and c_2 are equally important
3	c_1 is slightly more important than c_2
5	c_1 is more important than c_2
7	c_1 is strongly more important than c_2
9	c_1 is extremely more important than c_2
2, 4, 6, 8	intermediate value of importance

tio of *consistency index* (CI) to the *random consistency index* (RI), and a judgement is considered as consistent, if $r < 0.1$, otherwise it is considered as inconsistent. In order to calculate CI, first we calculate a weight vector $\mathcal{D} = (d_1, d_2, \ldots, d_n)^T$ as a product of relative criteria score matrix $\mathcal{C}$ and *criteria score vector* $\mathcal{S}$, i.e., $\mathcal{D} = \mathcal{C} \times \mathcal{S}$. Thereafter, a consistency vector $\mathcal{D}' = (d'_1, d'_2, \ldots, d'_n)^T$ is obtained by dividing the elements of vector $\mathcal{D}$ by the respective elements of vector $\mathcal{S}$, i.e., $d'_i = \frac{d_i}{s_i}$. The value of CI is calculated using equation 3, where λ is the average of the consistency vector $\mathcal{D}'$ and n is the number of criteria. An appropriate RI value is chosen from the list of RI values derived by the authors of [21]. Table 2 presents some sampler RI values corresponding to different values of n.

$$CI = \frac{(\lambda - n)}{(n - 1)} \tag{3}$$

Table 2

Sampler *random consistency index* (RI) values [21]

n	2	3	4	5	6	7	8	9	10
RI	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Step 4: Decision matrix generation and alternatives ranking

The final step of AHP is to generate a decision matrix $\mathcal{D}$ of order $m \times n$, where m and n represent the number of *alternatives* and *criteria*, respectively. The values of $\mathcal{D}$ can be generated either from a dataset or from expert's judgement. In expert judgement method, a relative score matrix $\mathcal{A}$ of order $m \times m$ is generated by pair-wise comparison of alternatives for each criteria, explained in step 2. Thereafter, corresponding to each criteria, a score vector for each alternative is calculated using the process explained in step 2, and all

score vectors are arranged together to generate the decision matrix $\mathcal{D}$. Finally, $\mathcal{D}$ is multiplied with the criteria score vector $\mathcal{S}$ to get rank vector $\mathcal{R}$, in which i^{th} element represents the rank score of the ith alternative.

3.2. Technique for Order Preference by Similarity to Ideal Solution

The technique for order preference by similarity to ideal solution (TOPSIS) was developed by Hwang and Yoon [12] in 1980, and since then it is considered as one of the most widely used alternatives ranking methods. It categorizes criteria into two different classes – one includes all those criteria that have positive impact on the goal, and the other includes all those criteria that have negative impact on the goal. Accordingly, it calculates two different ideal solutions, namely *best* and *worst* ideal solutions. The *best ideal* solution is taken as the maximum of the positive criteria values and minimum of the negative criteria values, whereas *worst ideal* solution is taken as the minimum of the positive criteria values and maximum of the negative criteria values. Finally, TOPSIS uses Euclidean distance to measure the relative closeness of the alternatives to the ideal solutions and determines their ranks.

One of the advantages of TOPSIS lies in its easy to use, simple and programmable process [25]. However, it suffers with a major disadvantage due to using Euclidean distance, which does not consider criteria correlation. A brief description of the steps involved in TOPSIS process to rank alternatives are given in the following paragraphs.

Step 1: Decision matrix generation

The first step in the TOPSIS process is to generate a decision matrix $\mathcal{D}$ of order $m \times n$ (equation 4), where m and n represent the number of alternatives and criteria, respectively. The d_{ij} entry of $\mathcal{D}$ represents the score of the ith alternative with respect to the jth criteria.

$$\mathcal{D} = \begin{pmatrix} d_{11} & d_{12} & \ldots & d_{1n} \\ d_{21} & d_{22} & \ldots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \ldots & d_{mn} \end{pmatrix} \tag{4}$$

Step 2: Decision matrix normalization

The next step followed by TOPSIS is to normalize the decision matrix $\mathcal{D}$ in such a way that the length of each column vector becomes 1, which is achieved by dividing each element of a column by the length of the respective column-vector. The normalized deci-

sion matrix $\hat{\mathcal{D}}$ corresponding to $\mathcal{D}$ is shown in equation 5, where $\hat{d}_{ij} = \frac{d_{ij}}{\sqrt{\sum_{i=1}^{m} d_{ij}^2}}, i = 1, 2, \ldots, m; j = 1, 2, \ldots, n.$

$$\hat{\mathcal{D}} = \begin{pmatrix} \hat{d}_{11} & \hat{d}_{12} & \ldots & \hat{d}_{1n} \\ \hat{d}_{21} & \hat{d}_{22} & \ldots & \hat{d}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{d}_{m1} & \hat{d}_{m2} & \ldots & \hat{d}_{mn} \end{pmatrix} \tag{5}$$

Step 3: Weighted normalized decision matrix calculation

The weighted normalized decision matrix $\mathcal{T}$ is obtained by multiplying each column of $\hat{\mathcal{D}}$ with the corresponding criteria rank score, which can be calculated using any criteria ranking technique. A weighted normalized decision matrix $\mathcal{T}$ is shown in equation 6, where $t_{ij} = \hat{d}_{ij} \times s_j$ and s_j is the rank score of the jth criteria.

$$\mathcal{T} = \begin{pmatrix} t_{11} & t_{12} & \ldots & t_{1n} \\ t_{21} & t_{22} & \ldots & t_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ t_{m1} & t_{m2} & \ldots & t_{mn} \end{pmatrix} \tag{6}$$

Step 4: Ideal solutions determination

The criteria set $\mathcal{F}$ is partitioned into two subsets $F^{(+)}$ and $F^{(-)}$, where $F^{(+)}$ includes all criteria that have positive impact on the goal, and $F^{(-)}$ includes all those criteria that have negative impact on the goal. The best and worst ideal solutions are denoted by row vectors $\mathcal{B} = (b_1, b_2, \ldots, b_n)$ and $\mathcal{W} = (w_1, w_2, \ldots, w_n)$ and defined using equations 7 and 8, respectively.

$$b_j = \begin{cases} \max\limits_{i=1}^{m} \{t_{ij}\} & \text{if } \mathcal{F}[j] \in F^{(+)} \\ \min\limits_{i=1}^{m} \{t_{ij}\} & \text{if } \mathcal{F}[j] \in F^{(-)} \end{cases} \tag{7}$$

$$w_j = \begin{cases} \min\limits_{i=1}^{m} \{t_{ij}\} & \text{if } F[j] \in F^{(+)} \\ \max\limits_{i=1}^{m} \{t_{ij}\} & \text{if } F[j] \in F^{(-)} \end{cases} \tag{8}$$

Step 5: Alternatives ranking

In order to rank different alternatives, Euclidean distance of each alternatives with the ideal solutions $\mathcal{B}$ and $\mathcal{W}$ is calculated. For i^{th} alternative, distance from best and worst ideal solutions is denoted by $\delta_b[i]$ and

$\delta_w[i]$ and calculated using equations 9 and 10, respectively.

$$\delta_b[i] = \sqrt{\sum_{j=1}^{n}(t_{ij} - b_j)^2} \tag{9}$$

$$\delta_w[i] = \sqrt{\sum_{j=1}^{n}(t_{ij} - w_j)^2} \tag{10}$$

After calculating distance from ideal solutions, the rank score $\mathcal{R}[i]$ $(i = 1, 2, \ldots, m)$ of ith alternative is calculated using equation 11. The value of $\mathcal{R}[i]$ is always between 0 and 1, and it is 0 when $\delta_w[i] = 0$, showing worst condition for the alternative (i.e., its distance from worst ideal solution is 0). Similarly, the value of $\mathcal{R}[i]$ is 1 when $\delta_b[i] = 0$, showing best condition for the alternative (i.e., its distance from best ideal solution is 0).

$$\mathcal{R}[i] = \frac{\delta_w[i]}{\delta_w[i] + \delta_b[i]} \tag{11}$$

4. Proposed Opinion-Based Multi-Criteria Ranking Approach

In this section, we present the functioning details of the proposed opinion-based multi-criteria ranking (OMCR) approach. Figure 2 presents the work-flow of the OMCR, which mainly performs five different but related functionalities, such as *data crawling and pre-processing*, *feature identification and data matrix generation*, *feature ranking*, *product ranking*, and *rank and sentiment visualization*. Further details about these functionalities are presented in the following sub-sections.

4.1. Data Crawling and Pre-processing

This section present a brief detail of the data retrieval and pre-processing processes. We have used import.io, which is a web-based tool to fetch customer reviews from e-commerce websites and store them in a tabular form. We have considered three popular e-commerce websites, such as *Amazon*, *Flipkart*, and *Snapdeal* for data crawling. For a particular product category, import.io is able to retrieve various review-related information, such as price, launch date, total number of reviews, reviewer id, user name, post date, star rating, user verification status, review title, review content, review usefulness, etc. Out of these, OMCR uses only five attributes like *star rating*, *review title*, *review content*, *user verification status*, and *review usefulness* that are significant in online products ranking. Table 3 presents a small set of customer reviews of *iPhone 7* and *Google Pixel* smartphones retrieved from the e-commerce websites mentioned above.

4.2. Feature Identification and Data Matrix Generation

The task of this module is to identify different reviews-related information components, such as *star rating*, *review title*, *review content*, *user verification status*, and *review usefulness* to generate data matrix from the review documents. Out of total five features, the values of three features (*star rating*, *user verification status*, and *review usefulness*) are numeric, whereas the values of the remaining two features (*review title* and *review content*) are textual, that are subjected to a sentiment analysis system to assign numeric scores representing the sentiment polarity of the users expressed in the review title and contents. We have used the NLTK TextBlob for sentiment analysis purpose. The TextBlob identifies statistical and linguistic features from a review document and classifies them as positive, negative, or neutral, depending on the sentiment score calculated using the SentiWordNet dictionary. SentiWordNet is a lexical resource in which each word is associated with a positive, negative, and objective scores, representing the respective degree of sentiment. The sentiment score of a review title and content (body) is determined as an aggregation of the sentiment scores of the opinionated words contained within them. Table 4 shows sentiment scores of the review titles and contents given in table 3.

The data matrix is generated as a data cube in which X-axis represents features, Y-axis represents review documents, and Z-axis represents products. Each cell of the data matrix stores a numeric value, representing the feature value extracted from the review document of a particular product. Table 5 shows the data matrix corresponding to the sample reviews given in table 3.

4.3. Feature Ranking

The feature ranking task aims to determine the relative importance of the features [18]. To this end, the
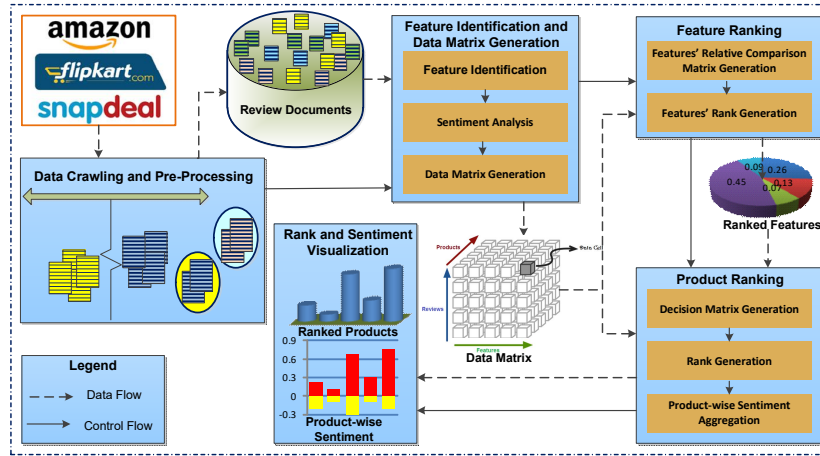
Fig. 2. Work-flow of the proposed OMCR approach

Table 3

Exemplar reviews of *iPhone 7* and *Google Pixel* smartphones

Smartphones	Source	SR*	Review title	Review content	UVS*	RU*
iPhone 7	*Amazan*	5	Five Stars	It's nice to see IPhone 7 ... it's like butter in stomach. Very excellent .. working as expected	1	0
		1	Defective phone	Although the product is great hardly 4 days old the sounds and ringtone isn't working. Checked all the settings but no use. Bad experience.	1	1
	Flipkart	5	NYC experience	good delivery speed by Flipkart and my new iPhone is awesome.	1	10
	Snapdeal	5	Super product	Awesome product, super fast and amazing UX.	1	6
Google pixel	*Amazan*	3	Heat problem	Gets heated in compact box. When it came it was already heated	1	1
	Flipkart	5	Brilliant	Great phone. Camera is too good.	1	76
	Snapdeal	4	Excellent product	Just love it	1	1

* *SR: star rating; UVS: user verification status; RU: review usefulness*

Table 4

Sentiment scores extracted from the reviews of table 3 using `TextBlob`

SN	Review Title	Score	Review Content	Score
1.	Five Stars	0.99	It's nice to see IPhone 7 ... it's like butter in stomach. Very excellent .. working as expected	0.84
2.	Defective phone	-0.89	Although the product is great hardly 4 days old the sounds and ringtone isn't working. Checked all the settings but no use. Bad experience.	-0.66
3.	NYC experience	0.82	good delivery speed by Flipkart and my new iPhone is awesome.	0.94
4.	Super product	0.64	Awesome product, super fast and amazing UX.	0.91
5.	Heat problem	-0.68	Gets heated in compact box. When it came it was already heated	-0.52
6.	Brilliant	0.88	Great phone. Camera is too good.	0.86
7.	Excellent product	0.96	Just love it	0.99

Table 5

Data matrix corresponding to reviews given in table 3

Product	SR*	Review title	Review content	UVS*	RU*
iPhone 7	5	0.99	0.84	1	0
	1	-0.89	-0.66	1	1
	5	0.82	0.82	1	10
	5	0.64	0.91	1	6
Google pixel	3	-0.68	-0.52	1	1
	5	0.88	0.86	1	76
	4	0.96	0.99	1	1

* *SR: star rating; UVS: user verification status; RU: review usefulness*

feature ranking module of OMCR generates features relative score matrix using the expert's inputs for each feature pairs. Algorithm 1 presents the feature ranking and consistency checking processes formally. Table 6 presents the expert's inputs for relative scores of all possible feature pairs. Table 7 presents step-wise de-

tails, showing intermediate results of the features ranking and consistent checking processes using AHP. It can be seen in this table that the value of the consistency ratio (r) is 0.05, which is less than 0.1, and thereby features relative score matrix generated using expert's inputs is consistent. The final rank scores of the features are shown in table 8. It can be seen in this table that *user verification status* is ranked first with score 0.5, followed by the *star rating* feature with

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Algorithm 1: **FeatureRank** $(\mathcal{F}, RI)$: Feature ranks calculation using AHP

Input : A feature list $(\mathcal{F})$ and random consistency index (RI) parameter
Output: Numeric scores of the features
1   $n \leftarrow length(\mathcal{F})$;   // n is the number of features
2   consistent $\leftarrow$ FALSE;
3   **repeat**
     // generating $n \times n$ features relative score matrix.
4   **for** $i \leftarrow 1$ **to** n **do**
5   **for** $j \leftarrow 1$ **to** n **do**
6   **if** *(i <j)* **then**
           // read expert's preference of $\mathcal{F}[i]$ over $\mathcal{F}[j]$
7            $C[i][j] \leftarrow$ readExpertInput();
8   **else if** *(i == j)* **then**
9            $C[i][j] \leftarrow 1$;
10   **else**
11            $C[i][j] \leftarrow 1/C[j][i]$;
12   **end**
13   **end**
14   **end**
     // generating a normalized matrix $\hat{C}$ from C
15      $\hat{C}[i][j] \leftarrow \frac{C[i][j]}{\Sigma_{i=1}^{n} C[i][j]}$, for $i, j = 1, 2, \ldots, n$;
     // calculating feature scores as average of individual rows of $\hat{C}$
16      $\mathcal{S}[i] \leftarrow \frac{\Sigma_{j=1}^{n} \hat{C}[i][j]}{n}$ for $i = 1, 2, \ldots, n$;
17      $\mathcal{D} \leftarrow C \times \mathcal{S}$;   // $\mathcal{D}$ is a weight vector
18      $\mathcal{D}'[i] \leftarrow \frac{\mathcal{D}[i]}{\mathcal{S}[i]}$, for $i = 1, 2, \ldots, n$;   // $\mathcal{D}'$ is a consistency vector
19      $\lambda \leftarrow mean(\mathcal{D}')$;
20      $CI \leftarrow \frac{(\lambda - n)}{(n-1)}$;   // CI is consistency index
21      $r \leftarrow \frac{CI}{RI}$;
22   **if** *(r< 0.1)* **then**
23   consistent $\leftarrow$ TRUE;
24   **end**
25   **until** *(consistent)*;
26   return $\mathcal{S}$;

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score 0.26, and *review usefulness* feature received lowest position with score 0.03.

Table 6

Features relative score matrix

Preferences of pair-wise criteria	Score
Preference of *star rating* over *review title*	3
Preference of *star rating* over *review content*	5
Preference of *star rating* over *user verification status*	1/3
Preference of *star rating* over *review usefulness*	7
Preference of *review title* over *review content*	3
Preference of *review title* over *user verification status*	1/5
Preference of *review title* over *review usefulness*	5
Preference of *review content* over *user verification status*	1/7
Preference of *review content* over *review usefulness*	3
Preference of *user verification status* over *review usefulness*	9

4.4. Product Ranking

This section presents the product ranking process, which uses feature rank scores and data matrix as inputs to rank different alternatives of a product. Initially, a decision matrix $\mathcal{D}$ of order $m \times n$ is generated using the data matrix, where m and n represent the num-

Table 7

Step-wise details of the features ranking process using AHP

$$C = \begin{pmatrix} 1 & 3 & 5 & 1/3 & 7 \\ 1/3 & 1 & 3 & 1/5 & 5 \\ 1/5 & 1/3 & 1 & 1/7 & 3 \\ 3 & 5 & 7 & 1 & 9 \\ 1/7 & 1/5 & 1/3 & 1/9 & 1 \end{pmatrix} ; \hat{C} = \begin{pmatrix} 0.21 & 0.31 & 0.31 & 0.19 & 0.28 \\ 0.07 & 0.10 & 0.18 & 0.11 & 0.20 \\ 0.04 & 0.03 & 0.06 & 0.08 & 0.12 \\ 0.64 & 0.52 & 0.43 & 0.56 & 0.36 \\ 0.03 & 0.02 & 0.02 & 0.06 & 0.04 \end{pmatrix} ; \qquad \mathcal{S} = \begin{pmatrix} 0.26 \\ 0.13 \\ 0.07 \\ 0.50 \\ 0.03 \end{pmatrix}$$

$$\mathcal{D} = C \times \mathcal{S} = \begin{pmatrix} 1 & 3 & 5 & 1/3 & 7 \\ 1/3 & 1 & 3 & 1/5 & 5 \\ 1/5 & 1/3 & 1 & 1/7 & 3 \\ 3 & 5 & 7 & 1 & 9 \\ 1/7 & 1/5 & 1/3 & 1/9 & 1 \end{pmatrix} \cdot \begin{pmatrix} 0.26 \\ 0.13 \\ 0.07 \\ 0.50 \\ 0.03 \end{pmatrix} = \begin{pmatrix} 1.41 \\ 0.70 \\ 0.34 \\ 2.74 \\ 0.18 \end{pmatrix} ; \mathcal{D}' = \begin{pmatrix} 5.43 \\ 5.20 \\ 5.03 \\ 5.46 \\ 5.09 \end{pmatrix} ; \quad \lambda = 5.24$$

$$CI = \frac{(\lambda - n)}{(n-1)} = \frac{5.24 - 5}{4} = 0.06; \ RI(5) = 1.12; \ r = \frac{CI}{RI} = \frac{0.06}{1.12} = 0.05 \text{ (consistent)}$$

Table 8

Features and their rank scores generated using AHP

Feature	Rank	Rank score
star rating	2	0.26
review title	3	0.13
review content	4	0.07
user verification status	1	0.50
review usefulness	5	0.03

ber of alternatives (of a product) and features, respectively. $\mathcal{D}$ is a real-valued matrix, in which an entry represents the preference of an alternative over other alternatives, with respect to the corresponding feature. $\mathcal{D}$ is generated by taking the average of each features for each alternatives. In case of review title and review content features, averaging is done after normalization of their values in the scale of [0, 1] using *min-max* normalization. Equation 12 shows an exemplar decision matrix for two alternatives of smartphones (*iPhone 7* and *Google Pixel*) and five features corresponding to the sample reviews given in table 3. Finally, the decision matrix is used to rank the alternatives of a given product using TOPSIS.

$$\mathcal{D} = \begin{pmatrix} 4.33 & 0.74 & 0.79 & 1.00 & 5.50 \\ 4.00 & 0.68 & 0.66 & 1.00 & 26.00 \end{pmatrix} \tag{12}$$

The TOPSIS considers features rank score and decision matrix as inputs and ranks the alternatives using the procedure discussed in section 3.2. Algorithm 2 presents the product ranking process using TOPSIS formally. Table 9 shows the intermediate results of ranking different alternatives of smartphone using TOPSIS with respect to the reviews given in table 3.

It may be noted that OMCR provides sentiment-based review aggregation for each alternatives of a product, in addition to the product ranking. To this end, it determines the percentage of positive, negative, and neutral reviews based on their sentiment scores recorded in the data matrix, which provides an abstraction of the

Algorithm 2: **ProductRank**($\mathcal{D}, \mathcal{S}, \mathcal{F}^{(+)}, \mathcal{F}^{(-)}$): rank the products using TOP-SIS

Input : An $m \times n$ decision matrix $\mathcal{D}$, feature score vector $\mathcal{S}$, lists of positive features $\mathcal{F}^{(+)}$ and negative features $\mathcal{F}^{(-)}$.

Output: Rank scores of the products.

```
1  m ← rows(D) ;                          // m is the number of products
2  n ← columns(D) ;                       // n is the number of features
3  F ← F⁽⁺⁾ ∪ F⁽⁻⁾;                      // F is the feature list.
   // generating a normalized decision matrix D̂ from D
4  for i ← 1 to m do
5      for j ← 1 to n do
6          D̂[i][j] ← D[i][j]/√(Σᵢ₌₁ᵐ(D[i][j])²) ;
7      end
8  end
   // generating a weighted normalized decision matrix T using D̂
   // and S
9  for i ← 1 to m do
10     for j ← 1 to n do
11         T[i][j] ← D̂[i][j] × S[j];
12     end
13 end
   // calculating best (B) and worst (W) ideal solution vectors
14 for j ← 1 to n do
15     if (F[j] ∈ F⁽⁺⁾) then
16         B[j] ← maxᵢ₌₁ᵐ{T[i][j]};
17         W[j] ← minᵢ₌₁ᵐ{T[i][j]};
18     else if (F[j] ∈ F⁽⁻⁾) then
19         B[j] ← minᵢ₌₁ᵐ{T[i][j]};
20         W[j] ← maxᵢ₌₁ᵐ{T[i][j]};
21     end
22 end
23 for i ← 1 to m do
24     δ_b ← √(Σⱼ₌₁ⁿ(T[i][j] − B[j])²) ;    // distance between the feature
                                            vector of iᵗʰ product and best ideal solution vector.
25     δ_w ← √(Σⱼ₌₁ⁿ(T[i][j] − W[j])²) ;    // distance between the feature
                                            vector of iᵗʰ product and worst ideal solution vector.
26     R[i] ← δ_w/(δ_w+δ_b) ;               // rank score of iᵗʰ product.
27 end
28 return R;
```

Table 9

Step-wise results of ranking smartphone alternatives with respect to the sample reviews given in table 3

$$\mathcal{D} = \begin{pmatrix} 4.33 & 0.74 & 0.79 & 1.00 & 5.50 \\ 4.00 & 0.68 & 0.66 & 1.00 & 26.00 \end{pmatrix}; \hat{\mathcal{D}} = \begin{pmatrix} 0.73 & 0.74 & 0.77 & 0.71 & 0.21 \\ 0.68 & 0.68 & 0.64 & 0.71 & 0.98 \end{pmatrix};$$

$$\mathcal{T} = \begin{pmatrix} 0.19 & 0.10 & 0.05 & 0.36 & 0.01 \\ 0.18 & 0.09 & 0.04 & 0.36 & 0.03 \end{pmatrix}; \mathcal{B} = \begin{pmatrix} 0.19 & 0.10 & 0.05 & 0.36 & 0.03 \end{pmatrix};$$

$$\mathcal{W} = \begin{pmatrix} 0.18 & 0.09 & 0.04 & 0.36 & 0.01 \end{pmatrix}; \delta_b = \begin{pmatrix} 0.03 \\ 0.02 \end{pmatrix}; \delta_w = \begin{pmatrix} 0.02 \\ 0.03 \end{pmatrix}; \mathcal{S} = \begin{pmatrix} 0.41 \\ 0.59 \end{pmatrix}$$

alternatives, before going to the finer details to take an appropriate purchase decision. Table 10 presents sentiment aggregation for different alternatives of smartphone with respect to the sample reviews given in table 3.

Table 10

Sentiment aggregation for different alternatives of smartphone with respect to the sample reviews given in table 3

Smartphones	Number of reviews			Percentage of reviews		
	Positive	Negative	Neutral	Positive	Negative	Neutral
iPhone 7	3	1	0	75%	25%	0%
Google Pixel	2	1	0	67%	33%	0%

4.5. Rank and Sentiment Visualization

Bar charts spanning only in the first quadrant of the Cartesian coordinate system are used for alternatives' rank visualization, in which the height of a bar corresponds to the rank score of the respective alternative. On the other hand, the sentiment polarity values of the alternatives are visualized using the bar charts spanning in both first and fourth quadrants of the Cartesian coordinate system, in which the portions of the bar lying in the first quadrant represents the percentage of positive reviews and that the portion lying in the fourth quadrant represents the percentage of the negative reviews of an alternative.

5. Experimental Setup and Results

This section presents experimental results obtained from two real datasets related to electronic products – *smartphone* and *hard disk drive*. Review documents were crawled from three popular e-commerce websites *Amazon*, *Flipkart*, and *Snapdeal* using *import.io* tool. After pre-processing of the reviews, features values were extracted and stored in a data matrix. Thereafter, features relative score matrix was generated using expert's input and analyzed using `FeatureRank` algorithm (Algorithm 1) for features rank generation. Table 8 presents the rank scores of all five features considered in our experiment. Finally, the features rank vector and data matrix were processed using `ProductRank` algorithm (Algorithm 2) to rank different alternatives of the electronic products.

For smartphone, we have considered five different alternatives namely *Google Pixel*, *HTC Desire 10 Pro*, *iPhone 7*, *Lenovo Z2 Plus*, and *Samsung Galaxy S7 Edge*, and downloaded reviews from all three websites mentioned above. Table 11 shows the statistics of the smartphone dataset. Table 12 presents the decision matrix generated from the smartphone dataset, and table 13 presents the rank of the various alternatives of the smartphone obtained by `ProductRank` algorithm. It can be observed from this table that *Samsung Galaxy*

S7 Edge is ranked at first with score 0.75, followed by *iPhone 7* with score 0.67, and rest of the alternatives have received lower ranks. Figure 3 presents a visualization of the ranks of the various smartphone alternatives. Table 14 presents the sentiment aggregation of the smartphone alternatives and figure 4 presents its visualization.

Table 11

Statistics of the smartphone dataset

Smartphones	Number of reviews			Total #reviews
	Amazan	Flipkart	Snapdeal	
Google Pixel	113	180	9	302
HTC Desire 10 Pro	100	120	4	224
iPhone 7	702	1116	121	1939
Lenovo Z2 Plus	2179	310	224	2713
Samsung Galaxy S7 Edge	307	135	3	445
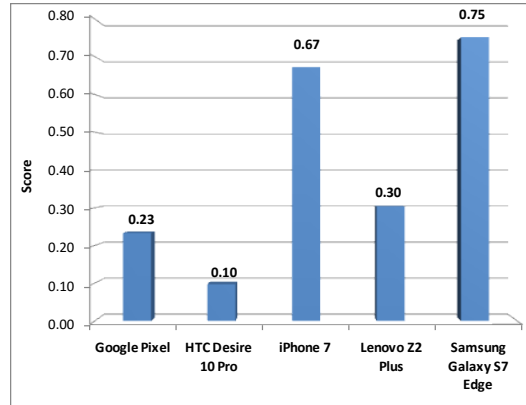
Table 12

Decision matrix generated from the smartphone dataset

Smartphones	Star rating	Review title	Review content	User verification status	Review usefulness
Google Pixel	3.9330	0.6686	0.6803	0.7168	21.3375
HTC Desire 10 Pro	3.9611	0.7208	0.6747	0.6739	4.4278
iPhone 7	4.3583	0.7226	0.7286	0.9036	6.0267
Lenovo Z2 Plus	3.7679	0.6294	0.6194	1.0000	4.0877
Samsung Galaxy S7 Edge	4.4526	0.6710	0.7329	0.7360	18.9450

Table 13

Ranks of different alternatives of the smartphone

Smartphone	Rank	Rank score
Google Pixel	4	0.23
HTC Desire 10 Pro	5	0.10
iPhone 7	2	0.67
Lenovo Z2 Plus	3	0.30
Samsung Galaxy S7 Edge	1	0.75

Table 14

Sentiment aggregation of different alternatives of the smartphone

Smartphones	Number of reviews			Percentage of reviews		
	Positive	Negative	Neutral	Positive	Negative	Neutral
Google Pixel	204	87	11	67.55%	28.81%	3.64%
HTC Desire 10 Pro	158	60	6	70.54%	26.79%	2.68%
iPhone 7	1469	400	70	75.76%	20.63%	3.61%
Lenovo Z2 Plus	1517	924	272	55.92%	34.06%	10.03%
Samsung Galaxy S7 Edge	319	98	28	71.69%	22.02%	6.29%

For hard disk drive too, we considered five different alternatives manufactured by different companies

Fig. 3. Visualization of different alternatives of the smartphone

Fig. 4. Visualization of sentiment aggregation for different alternatives of the samrtphone

namely *Samsung M3 HDD*, *Seagate*, *Toshiba Canvio Basics*, *Transcend Storejet 25H3*, and *WD elements*, and downloaded reviews from all three websites mentioned above. Table 15 shows the statistics of the hard disk drive dataset. Table 16 presents the decision matrix generated from the hard disk drive dataset, and table 17 presents the rank of the various alternatives of hard disk drive obtained by `ProductRank` algorithm. It can be observed from this table that *WD elements* is ranked first with score 0.81, followed by *Seagate* with score 0.76, and rest of the alternatives have received lower ranks. Figure 5 presents a visualization of the ranks of the various alternatives of hard disk drive. Table 18 presents the sentiment aggregation of hard disk drive alternatives, and figure 6 presents its visualization.

Table 15

Statistics of the hard disk drive dataset

Hard disks drives	Number of reviews			Total #reviews
	Amazan	Flipkart	Snapdeal	
Samsung M3 HDD	378	130	281	789
Seagate	11769	350	3672	15791
Toshiba Canvio Basics	1415	250	1861	3526
Transcend Storejet 25H3	430	192	329	951
WD elements	6671	450	3836	10957

Table 16

Decision matrix generated from the hard disk drive dataset

Hard disk drives	Star rating	Review title	Review content	User verification status	Review usefulness
Samsung M3 HDD	4.5229	0.7753	0.7504	0.8831	0.4417
Seagate	4.2729	0.7317	0.7296	0.9670	2.4685
Toshiba Canvio Basics	4.4397	0.7849	0.7684	0.9693	0.6081
Transcend Storejet 25H3	4.4224	0.7672	0.7244	0.9482	0.5666
WD elements	4.3761	0.7648	0.7544	0.9881	1.9459

Table 17

Ranks of different alternatives of the hard disk drive

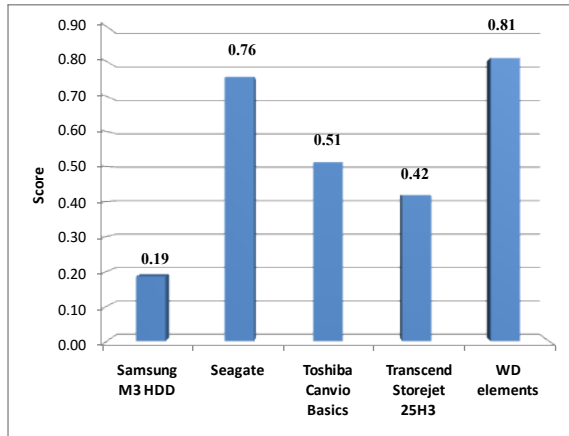| Hard disk drives	Rank	Rank score
Samsung M3 HDD	5	0.19
Seagate	2	0.76
Toshiba Canvio Basics	3	0.51
Transcend Storejet 25H3	4	0.42
WD elements	1	0.81

Fig. 5. Visualization of different alternatives of the hard disk drive

6. Evaluation Results

Since there is no standard benchmark showing the relative ranks of various smartphone and hard disk drive alternatives, we have taken the opinions of three domain experts for each product. All three experts

Table 18

Sentiment aggregation of different alternatives of the hard disk drive

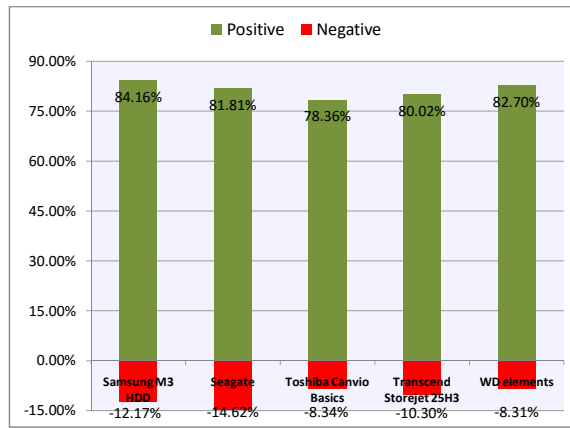| Hard disk drives	Number of reviews			Percentage of reviews		
	Positive	Negative	Neutral	Positive	Negative	Neutral
Samsung M3 HDD	664	96	29	84.16%	12.17%	3.68%
Seagate	12919	2309	563	81.81%	14.62%	3.57%
Toshiba Canvio Basics	2763	294	469	78.36%	8.34%	13.30%
Transcend Storejet 25H3	761	98	92	80.02%	10.30%	9.67%
WD elements	9061	910	986	82.70%	8.31%	9.00%

Fig. 6. Visualization of the sentiment aggregation of different alternatives of hard disk drive

were given the review documents and requested to provide a rank to each alternative in the range of 1 to 5, based on the reviews. Table 19 presents the ranks of different smartphone alternatives assigned by all three domain experts. It also shows the ranks of the alternatives determined by the OMCR approach. Similarly, table 20 presents the ranks of different hard disk drive alternatives assigned by all three domain experts. It also shows the ranks of the alternatives determined by the OMCR approach.

Table 19

Ranks of smartphone alternatives generated by OMCR and assigned by domain experts

ID	Smartphones	System generated rank (L)	Experts' rank		
			L_1	L_2	L_3
M1	*Google Pixel*	4	4	3	5
M2	*HTC Desire 10 Pro*	5	3	4	4
M3	*iPhone 7*	2	2	1	2
M4	*Lenovo Z2 Plus*	3	5	5	3
M5	*Samsung Galaxy S7 Edge*	1	1	2	1

Thereafter, in order to compare different ranks, we have used *set intersection* method, which is generally

Table 20

Ranks of hard disk drive alternatives generated by OMCR and assigned by domain experts

ID	Hard disk drives	System generated rank (L)	Experts' rank		
			L_1	L_2	L_3
D1	*Samsung M3 HDD*	5	4	5	4
D2	*Seagate*	2	1	2	3
D3	*Toshiba Canvio Basics*	3	3	4	2
D4	*Transcend Storejet 25H3*	4	5	3	5
D5	*WD elements*	1	2	1	1

used to compare two ranked lists in terms of their overlapping score [26]. The *set intersection* method calculates the fraction of content overlapping at different depths, and its novelty lies in the fact that unlike Kendall's Tau method, it generates different overlapping scores for change in rank order at different positions.

Table 21 presents the calculation of the overlapping score of the ranked list generated by the OMCR with the ranked lists given by the experts for smartphone alternatives. It also provides average overlap score and aggregated average overlap score. Similarly, table 22 presents the calculation of the overlapping score of the ranked list generated by the OMCR with the ranked lists given by the experts for hard disk drive alternatives. It also provides average overlap score and aggregated average overlap score. It can be seen from these tables that the aggregated average overlap score for smartphone and hard disk drive are 83.67% and 84.33%, respectively, which reflects that the ranks determined by the OMCR method is closer to the experts' rank, and it can be used to rank various alternatives of products based on their multiple features automatically.

7. Conclusion and Future Work

In this paper, we have presented the development of an opinion-based multi-criteria product ranking (OMCR) approach to rank different alternatives of the online products, based on their reviews. The proposed approach seems very useful for online customers to make informed purchase decisions based on the concerns expressed by the existing customers in their reviews. The core functioning of the OMCR is based one `FeatureRank` and `ProductRank` algorithms. The `FeatureRank` algorithm aims to rank different features identified from meta-data and contents of the reviews, whereas `ProductRank` algorithm is used to rank different alternatives of the products using the

features rank scores generated by the previous algorithm. The OMCR is also integrated with a visualization module to display both rank and sentiment polarity of different alternatives of the products. Though the evaluation results of the OMCR on *smartphone* and *hard disk drive* datasets are 83.67% and 84.33%, respectively, it can be further improved through introducing more appropriate review- and structure-based features. Review and user reliability is another important criteria that can be quantified and integrated with the OMCR to enhance its effectiveness.

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Table 21

Overlapping score calculation for smartphone ranks generated by
OMCR with the ranks given by the experts

Depth (k)	A={L@k}	Overlap score with L_1		Overlap score with L_2		Overlap score with L_3	
		B = {L_1@**k**}	$\lvert A \cap B \rvert / k$	**C** = {L_2@**k**}	$\lvert A \cap C \rvert / k$	**D** = {L_3@**k**}	$\lvert A \cap D \rvert / k$
1	{M5}	{M5}	$1/1 = 1.00$	{M3}	$0/1 = 0.00$	{M5}	$1/1 = 1.00$
2	{M5,M3}	{M5,M3}	$2/2 = 1.00$	{M3,M5}	$2/2 = 1.00$	{M5,M3}	$2/2 = 1.00$
3	{M5,M3,M4}	{M5,M3,M2}	$2/3 = 0.67$	{M3,M5,M1}	$2/3 = 0.67$	{M5,M3,M4}	$3/3 = 1.00$
4	{M5,M3,M4,M1}	{M5,M3,M2,M1}	$3/4 = 0.75$	{M3,M5,M1,M2}	$3/4 = 0.75$	{M5,M3,M4,M2}	$3/4 = 0.75$
5	{M5,M3,M4,M1,M2}	{M5,M3,M2,M1,M4}	$5/5 = 1.00$	{M3,M5,M1,M2,M4}	$5/5 = 1.00$	{M5,M3,M4,M2,M1}	$5/5 = 1.00$
Average overlap score		$(1 + 1 + 0.67 + 0.75 + 1)/5 = 0.88$		$(0 + 1 + 0.67 + 0.75 + 1)/5 = 0.68$		$(1 + 1 + 1 + 0.75 + 1)/5 = 0.95$	
Aggregated average overlap score =		$(0.88 + 0.68 + 0.95)/3 = 0.8367 = 83.67\%$					

Table 22

Overlapping score calculation for hard disk drives ranks generated by OMCR with the ranks given by the experts

Depth (k)	A={L@k}	Overlap score with L_1		Overlap score with L_2		Overlap score with L_3	
		B = {L_1@**k**}	$\lvert A \cap B \rvert / k$	**C** = {L_2@**k**}	$\lvert A \cap C \rvert / k$	**D** = {L_3@**k**}	$\lvert A \cap D \rvert / k$
1	{D5}	{D2}	$0/1 = 0.00$	{D5}	$1/1 = 1.00$	{D5}	$1/1 = 1.00$
2	{D5,D2}	{D2,D5}	$2/2 = 1.00$	{D5,D2}	$2/2 = 1.00$	{D5,D3}	$1/2 = 0.50$
3	{D5,D2,D3}	{D2,D5,D3}	$3/3 = 1.00$	{D5,D2,D4}	$2/3 = 0.67$	{D5,D3,D2}	$3/3 = 1.00$
4	{D5,D2,D3,D4}	{D2,D5,D3,D1}	$3/4 = 0.75$	{D5,D2,D4,D3}	$4/4 = 1.00$	{D5,D3,D2,D1}	$3/4 = 0.75$
5	{D5,D2,D3,D4,D1}	{D2,D5,D3,D1,D4}	$5/5 = 1.00$	{D5,D2,D4,D3,D1}	$5/5 = 1.00$	{D5,D3,D2,D1,D4}	$5/5 = 1.00$
Average overlap score		$(0 + 1 + 1 + 0.75 + 1)/5 = 0.75$		$(1 + 1 + 0.67 + 1 + 1)/5 = 0.93$		$(1 + 0.50 + 1 + 0.75 + 1)/5 = 0.85$	
Aggregated average overlap score =		$(0.75 + 0.93 + 0.85)/3 = 0.8433 = 84.33\%$					

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