# Effect of Normalization Techniques in VIKOR Approach for Mining Product Aspects in Customer Reviews

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**Summary**

Product aspect ranking becomes an important field of research as the tremendous number of aspects discussed on the retail Websites disallows the probable customers to focus on specific product aspects to compare among the presented products. Frequency-based, opinion-based, and aspect relevancy are common criteria for ranking the extracted product aspects from customer reviews. The multi criteria nature of the aforementioned problem makes Multi-Criteria Decision Making (MCDM) approach provide promising solution of product aspect ranking. However, one of the most important problems of MCDM is the ranking abnormality. Thus, the focus of this research is to analyze the performance of VIKOR approach with various normalization techniques in addressing the product aspect ranking problem. The experimental results on different product reviews demonstrate that Vector normalization approach is more efficient in prioritizing important product aspects using VIKOR approach.

***Key words:***

*MCDM, Aspect ranking, Normalization, VIKOR, NDCG*

## 1. Introduction

Customer reviews are considered great reference for both probable customers as well as for businesses. Probable customers can use the freely available product reviews to compare among the presented products or services to make a wise purchase. a considerable study by Deloitte Touché´ USA affirmed that 62% of American customers read the opinions on social networks, 98% of them believe that these opinions are reliable, and 80% of those customers said that online opinions affected their buying intensions [1]. On the other hand, businesses consider customers feedback as a valuable resource for enhancing their products and keeps track of their reputation. A recent study, made by Internet Retailor on top 100 companies in US, pointed that the majority of these companies have a profile on Facebook (79%), Twitter (69%) or both (59%) [2], so these companies can easily get the feedback from their customers regarding their products and services. Accordingly, it may be no longer needed for organizations to manage surveys to (and) collect the customers' opinions about their products in order to measure the degree of customer satisfaction, because such information is already available on the Web with an explosive growth of social networks [3], [4]. However, the tremendous number of online reviews on the Web is maximized rapidly, which makes it impossible task to be tracked manually. Moreover, some of the products have different aspects mentioned in customer reviews which are vary in their number and importance [5] , which creates a real obstacle for the potential customer to focus on the key aspects that mainly used to make a wise comparison among the products. Hence, there is a need to rank the extracted product aspects in customer reviews to highlight and prioritize the key aspects.

In sum, finding key aspects that best support a wise comparison among the products and purchasing decision present a challenge in such a multidimensional problem that have tremendous number of online reviews, about several product aspects, with varying importance degree.

In the literature, various "Opinion Mining" [6] approaches have been proposed to address two main problems with Online reviews: aspect extraction and sentiment classification regarding these aspects. The focus of this paper is ranking the extracted product aspects from customer reviews in order to support the customers and businesses with the key aspects in such a way that maximizes the usability of Web reviews.

Aspect ranking problem have been studied previously in several studies as a Multi-Criteria Decision Making (MCDM) problem because of the multiple extraction criteria used to identify product aspects [7], [8]. Among numerous MCDM approaches, VIKOR approach has been utilized with various normalization techniques to investigate the impact of these techniques on aspect ranking.

## 2. Related Works

Aspect ranking problem has been investigated in the literature with different criteria; the first criterion ranks the extracted product aspects based on their occurrences in customer reviews, such as the approach in [9], while other research studies, like [10], considered the criterion of opinionated aspects, where important product aspects should be associated with customer opinions (positively or negatively) to express the customer satisfaction regarding these product aspects. A recent studies investigated the

Manuscript received December 5, 2019
Manuscript revised December 20, 2019

problem of aspect ranking as a decision making problem using MCDM [7], [8]. These studies argued that the multi-criteria nature of product aspect ranking problem is more suitable to be addressed using MCDM approaches because the ability of MCDM to consider several criteria simultaneously. Moreover, these research studies proposed additional criterion to be considered in aspect ranking process called "Aspect relevancy" in order to prioritize relevant product aspects to a specific domain product. Thus, two MCDM approaches (TOPSIS and VIKOR) have been re-contextualized in [7] to enhance the aspect ranking problem.

Generally, MCDM is a significant tool for addressing the problem of decision-making when there are several criteria. The distinguishing characteristic of MCDM is its ability to rank multiple alternatives by considering several criteria [11]. MCDM approaches are mainly based on two phases to address any decision making problem; first one is criteria weighting and the second phase is normalization. To the best of our knowledge, no research has previously investigated the performance of MCDM methods with various normalization techniques in addressing the problem of product aspect ranking. Therefore, this research analysed the performance of VIKOR in the domain of product aspect ranking with a set of normalization techniques.

## 3. Normalization methods in MCDM

The first step in the procedure of every MCDM method is to calculate the normalized decision matrix. Nnormalization process of the performance scores of the alternatives in the decision matrix is essential to be standard and comparable. It has been acknowledged that normalization procedures have a great impact on the final MCDM result [12].

Commonly, the problem of MCDM is framed as a decision matrix $\boldsymbol{D^k}$, where $k=1,\ldots,K$, for each decision-maker as shown in Fig. 1, Where $A_i$ is the alternative and $X_j$ is the criterion. About $x^k_{ij}$ represents the performance score of $A_i$ based on criterion $X_j$ which is assigned by decision-maker $k$.

$$\boldsymbol{D}^k = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccccc} X_1 & X_2 & \cdots & X_j & \cdots & X_n \end{array} \\ \begin{bmatrix} x^k_{11} & x^k_{12} & \cdots & x^k_{1j} & \cdots & x^k_{1n} \\ x^k_{21} & x^k_{22} & \cdots & x^k_{2j} & \cdots & x^k_{2n} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ x^k_{i1} & x^k_{i2} & \cdots & x^k_{ij} & \cdots & x^k_{in} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ x^k_{m1} & x^k_{m2} & \cdots & x^k_{mj} & \cdots & x^k_{mn} \end{bmatrix} \end{array}$$

Fig. 1 Decision matrix for any MCDM problem

Each MCDM method uses one normalization technique. For example, Simple Additive Weighting (SAW) method uses MAX normalization method to normalize all the alternatives to be comparable. Similarly TOPSIS method uses Euclidean normalization of all the alternatives. Then, decision-maker assigns weights to each criterion which indicates to its relative importance to be treated as weighted normalized decision matrix.

Multiple normalization techniques have been used with different MCDM methods as follows:

1) Vector normalization: this method is mainly used in TOPSIS approach [11]. In this method, each performance score in the decision matrix is divided by the sum of squares of the performance scores of a specific attribute as given in Eq.1

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \qquad (1)$$

2) MAX normalization: it is applied in SAW approach. In this method, normalized value of any alternative is generated by dividing it by maximum value for benefit criterion, and dividing minimum value in the corresponding column by that alternative in case of cost criterion. The relation of MAX method is given in Eq.2

$$r_{ij} = \frac{x_{ij}}{x_j^{max}} \qquad (2)$$

3) Max-Min normalization: This is mainly used in VIKOR method [13]. This method is expressed as shown in Eq.3

$$r_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \qquad (3)$$

4) Sum normalization: the simplest normalization method which is used in some MCDM methods like AHP. The normalized value for each attribute is given in Eq. 4.

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \qquad (4)$$

## 4. VIKOR method

VIKOR approach is formerly developed in the research study of [13] as an MCDM approach to find a compromise solution if the problem has various evaluating criteria. The main idea of VIKOR method is to use a multi criteria ranking index to select the compromise solution based on its closeness to the ideal solution [14]. The ranking index in VIKOR is derived by considering both the maximum group utility and minimum individual regret of the opponent [14] in order to determine the closeness of each alternative to the feasible solution.

## 5. Product aspect ranking using VIKOR

The overall framework for product aspect ranking (see Fig. 2) has two stages [7]: aspect extraction and aspect ranking. we used the same approach of our previous study of [15] for product aspect extraction stage, whereas, this research deploys relatively the same approach of [7] in the product aspect ranking stage . The approach used in this research to analyse the performance of normalization techniques on VIKOR in product aspect ranking. Briefly, the two stages of product aspect ranking have been discussed in the next subsections.

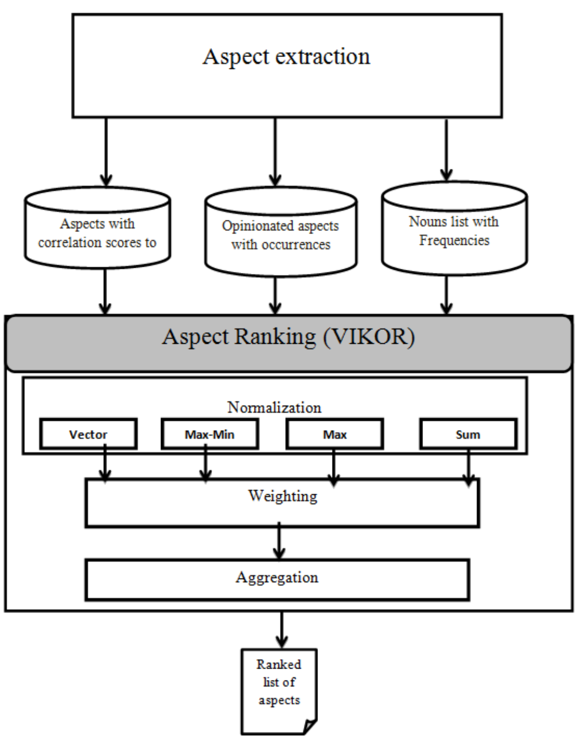


Fig. 2 High level framework for Product aspect ranking using VIKOR with various normalization methods

1) Product aspect extraction

In this stage, three different extraction criteria have been applied in order to identify product aspects. The result of this stage is three different lists of aspects that will be used to formulate the problem of aspect ranking as a decision matrix as shown in Fig.3.

| Candidate Product Aspects | Extraction Criteria | | |
|---|---|---|---|
| | $freq(A)$ | $OS(A)$ | $Aspect\ Relevancy(A,P)$ |
| $Aspect_1$ | $X_{11}$ | $X_{12}$ | $X_{13}$ |
| $Aspect_2$ | $X_{21}$ | $X_{22}$ | $X_{23}$ |
| .... | .... | .... | .... |
| $Aspect_i$ | $X_{i1}$ | $X_{i2}$ | $X_{i3}$ |
| .... | .... | .... | .... |
| $Aspect_m$ | $X_{m1}$ | $X_{m2}$ | $X_{m3}$ |

Fig. 2The structure of decision matrix for product aspect ranking

The following are the extraction criteria:

a) Frequent product aspects (freq(A)): product reviews are tagged using Stanford tagger( http://nlp.stanford.edu), which determines the grammatical structure of the sentences by assigning PoS tags to every word in a sentence based on the context [16]. Noun patterns (NN) are considered as the candidate product aspects. Further processing is applied on the extracted nouns to remove useless characters, such as the hyphen character (-) in noun words like ‘auto-focus’. Moreover, stop word removal is accomplished using a word list in (http://www3.nd.edu/~mcdonald/Word_Lists.html). The benefit of using stop word elimination in this stage is to verify that the extracted nouns from online reviews do not belong to the stop word list. The lemmatization process has an important role in this stage; Specifically, to extract product aspects correctly, it is important to unify different forms of a single word to its base form like ‘cameras→camera’, ‘qualities→quality’. By the end of lemmatization process, one main list of all words that have been identified as nouns will be generated as $N = \{n_1, n_2, \dots, n_m\}$ . This stage ends by extracting the frequency $f_n$ for each $n \in N$ to generate updated version of N list, where this list is sorted in ascending order based on the frequency. The final list contains only the nouns words that have been discussed in the customer reviews many times as follow:

$N = \{(n_1, f_{n1}), (n_2, f_{n2}), \ldots, (n_m, f_{nm})\}$ , where each n is associated with its frequency $f_n > 1$ in the customer reviews.

b) Opinionated product aspects (OS(A)): In this task, for each customer review, sequence of lexical analysis processes (like tokenization, lower casing, and punctuation removal) in addition to stop word elimination are applied for noise reduction. In contrast to most of previous research studies which started the aspect extraction process by locating the nouns in the customer reviews [17], in this task we started by identifying the opinion words firstly in each review and then the surrounded nouns for each opinion word are considered as candidate opinionated aspects. To identify the opinion words in each customer review, we exploits the sentiment lexicon SentiStrength [18], which has been designed using many linguistic resources such as Bing Liu and MPQA lexicons [19]. The identification of candidate opinionated aspects is accomplished using N_gram analysis. To emphasize, for every opinion word in the review, trigram analysis has been applied on both sides of the opinion word (forward and backward), or on one side, based on its position in the review, to find the candidate product aspects (nouns only). Once the candidate aspect(s) was found at any side of the opinion word, then a numerical score called aspect score (as) for each aspect is increased by 1. This step is repeated until the last opinion word in the review has been reached.
After we apply this process on all of the customer reviews, a list of candidate opinionated aspects (OA) will be generated as follows:
$OA = \{(n_1, as_1), (n_2, as_2), \ldots, (n_m, as_m)\}$ , $n_i \in N \text{ and } as_i > 0$,
where this list will be the input to the last task in this stage.

c) Aspect relevancy: lexicographer files in WordNet have been used in this task to quantify the relationship between the domain product term (like camera, phone) and all the extracted opinionated aspects in the previous task. Lexicographer files are one of the most important components in WordNet lexicon. WordNet synsets are categorized into these files based on the syntactic category (noun, adj, verb, or adv). noun lexicographer files have been considered only as most of candidate product aspects are nouns. To sum up, firstly, we extract the domain(s) of the product name from the lexicographer files, then the correlation between the product name and all the opinionated aspects are calculated based on the number of shared synsets that belong to the same domain(s). The correlation relationship between the domain product term (P) and each aspect (A) has been formulated as given in Eq 5.

$$C(A, P) = \frac{|A(synsets) \cap P(synsets)|}{|A(synsets)|} \quad (5)$$

Finally, all aspects will be assigned a $C(A, P)$ score, where these scores are in the range [0,1], each score indicates to what extents that a specific aspect is correlated to the domain of the product. The resulted lists of candidate product aspects from these criteria will be used in the stage of aspect ranking.

### 2) Aspect ranking

For this stage, the decision matrix presented in Fig.3 has been constructed which contains the performance values for each extraction criterion regarding each aspect. Then, the following steps have been applied:

a) Normalization of decision matrix values: the performance scores in the decision matrix should be normalized to be comparable. This task is considered the main focus of this research, where various normalization processes have been applied. These normalization techniques are presented in the equations of Eq1, Eq1, Eq3, and Eq4 respectively.
b) Weighting of Criteria: the evaluative criteria are weighted subjectively in VIKOR method based on DM evaluation [14]. In this study, the weights are assigned as follow: W( $freq(A)$) = $\alpha$,W($OS(A)$)=$\beta$, and W( Aspect Relevancy) = $\gamma$, where $\alpha > \beta > \gamma$ and $\sum_{i=1}^{n} w_i = 1$.

These steps are applied generally in VIKOR. The remaining steps for VIKOR are discussed below.

### **3)** VIKOR procedure

- Determine the best $r_j^+$ and the worst $r_j^-$ value for each evaluation criterion *j*. where $r_j^+ = max(r_{ij})$ and $r_j^- = min(r_{ij})$.
- Compute the $S_i$, which represent the distance of the aspect to the positive ideal solution, and the value of $R_i$ which express the distance of $i^{th}$

aspect from the negative ideal solution as given in Eq.6 and Eq. 7 respectively [20]:

$$S_i = \sum_{j=1}^{n} w_j(r_j^+ - r_{ij})/(r_j^+ - r_j^-) \qquad (6)$$

$$R_i = \max[w_j(r_j^+ - r_{ij})/(r_j^+ - r_j^-)] \qquad (7)$$

- Compute the value of $Q_i$, which represent the rating value for each alternative as the following relation as given in Eq. 8:

$$Q_i = \frac{v(S_i - S^-)}{S^+ - S^-} + \frac{(1-v)(R_i - R^-)}{R^+ - R^-} \qquad (8)$$

Where $S^- = \min(S_i)$ , $S^+ = \max(S_i)$ , $R^- = \min(R_i)$, $R^+ = \max(R_i)$, and $v$ is the weight of the maximum group utility, and $(1-v)$ is the weight of the minimum individual regret. The value of $v$ is usually set to 0.5 [14]

Finally, the alternatives are ranked based on $Q_i$, the lesser the value of $Q_i$ , the better the alternative is.

## 6. Evaluation

In this research , VIKOR method has been used for ranking the extracted product aspects from online reviews, and its performance has been analysed with different normalization techniques to find the best normalization method to be used with VIKOR to prioritize important product aspects. For our experiments, we used the benchmark datasets of customer reviews of four electronic products that have been introduced by Bing Liu [21] as shown in Table 1.

Table 1: Description of reviews datasets

| Product description | Total review sentences | Total opinionated aspects |
|---|---|---|
| Digital camera 1: Nikon Coolpix 4300 | 148 | 59 |
| Digital camera 2: Canon G3 | 172 | 69 |
| Cell phone: Nokia 6610 | 261 | 76 |
| Mp3 player: Creative Labs Nomad Jukebox Zen Xtra 40GB | 721 | 117 |

The performance of VIKOR method with various normalization techniques has been demonstrated using Normalized Discounted Cumulative Gain at top k (NDCG@k), which is considered as one of the most important measures for ranking quality compared to many ranking measures [22], [23]. The importance of NDCG ranking measure comes from its ability to handle multiple levels of relevance judgments by using a graded relevance as a measure of usefulness, whereas other ranking measures like Mean Average Precision (MAP) can only handle cases with binary relevance ("relevant" or "irrelevant") [24] where the measure of *NDCG* accumulated at a particular rank k is defined as the relation given in Eq. 9.

$$NDCG@k = \frac{1}{Z}\sum_{i=1}^{k} \frac{2^{t(i)}-1}{\log(1+i)} \qquad (9)$$

Where $t(i)$ indicates to the relative importance of the candidate product aspect at position $i$ , and $Z$ is a normalization term that has been derived from the perfect ranking at the top-k aspects. To determine the importance of each aspect, the evaluation approach introduced in the research study of [5] has been relatively adopted. The aspect importance is mainly based on the human judgments by inviting three annotators to judge the importance of each aspect using three levels of importance: "Un-important", "Ordinary", and "Important", these levels of importance are represented mathematically by "1", "2", and "3" respectively. Figures 4-6 show the comparison among the performances of various normalization techniques used with VIKOR approach in prioritizing the most important product aspects. The comparisons are presented in terms of NDCG@5, NDCG@10, and NDCG@15 respectively.

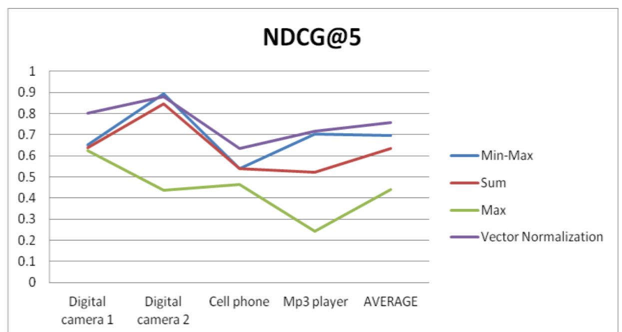


Fig. 4 Performance of VIKOR with normalization methods in terms of NDCG@5

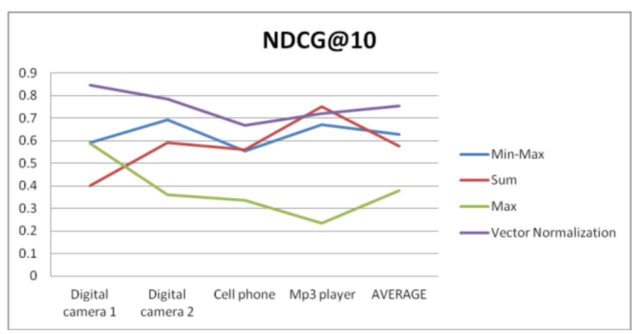


Fig. 5 Performance of VIKOR with normalization methods in terms of NDCG@10

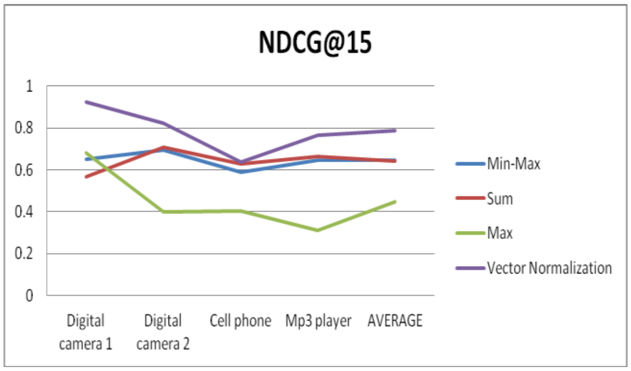


Fig. 6 Performance of VIKOR with normalization methods in terms of NDCG@15

## 7. Conclusion and Future Work

Effective normalization technique can remarkably improve the performance of any MCDM method. In this research, the performance of VIKOR approach has been analysed with various normalization techniques. The motive behind this research is to test which of normalization techniques is more suitable with VIKOR to enhance the results of product aspect ranking problem. Four normalization techniques have been used in this study; Sum, Max, Min-Max, and Vector normalization methods. The results showed that Vector normalization method was more efficient to be used with VIKOR approach to prioritize most important product aspect mentioned in customer reviews. The performance of VIKOR with Vector normalization on average outperforms the remaining normalization methods. However, more comparative studies using other MCDM approaches should be conducted in order to investigate the performance of MCDM approaches in addressing the product aspect ranking problem.

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