Hybrid Multi-Criteria Decision Making Approach for Product Ranking Using Customers Reviews

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ABSTRACT: *Consumer's reviews provided with the product descriptions play a great role in the popularity of E-commerce Web sites. However, there are various products, which have thousands of user generated reviews. Mining this enormous online reviews and tuning these abundant individual consumers view into collective consumer's choice became a challenging task. These collective reviews aid in product improvement processes, ranking of various products, and many other such operations. This paper proposes a hybrid Multi-Criteria Decision Making (MCDM) approach for product ranking. The proposed approach consists of two steps: 1) Buckley Analytic Hierarchy Process (AHP) to find out the relative weights of evaluation criteria and, 2) Ranked Voting Method (RVM) to determine rank of cell phone alternatives. Experiment is carried on real dataset collected from Amazon web sites. We have also compared our AHP-RVM approach with Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method.*

Keywords: Product Ranking, Reviews Rating, Ranked Voting Method, Analytical Hierarchy Process

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1. Introduction

In current competitive market, goals of a seller are maximization of revenue and maximization of customer's satisfaction. Sellers always need to identify opinions of public regarding their respective products and services to achieve their goals. Customers always wish to know the reviews of regular customers or users before buying a product to decide whether to buy the product or not. Expansion of the internet has been made this an easy task by making web the most popular information source for the consumers. Users freely share their reviews of the products on the web site, web forum, BBS and blog. Sharing of the opinions and sentiments about particular product or services with other people through posting online reviews has become a popular scheme. Lots of consumers decide whether to buy a product or not on the basis of the products' reviews. Many e-commerce websites such as Amazon (www.amazon.com) commonly provide venues sites and facilities for the users to share their reviews. Social networking websites, blog posts, and many dedicated review websites such as Epinions are also providing platforms for providing the reviews. (www.epinions.com)

A plenty of adequate information can be presented by these online reviews on various products and services. This information can help sellers by providing valuable network and social intelligence for the betterment of their respective businesses. Availability of numerous online reviews would facilitate different business person and other interested parties to avail useful information that could be economically beneficial for them. As a result of above scenario opinion review mining has recently gained the interest of various researchers working in the field of text analysis and opinion mining. What about current market scenario? Opinion mining, also called Sentiment analysis, is defined by [1] as the field of study that analyzes people‘s opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes”. It represents a wide problem space?. This online word-of-mouth represents new and measurable sources of information with many practical applications.

Today, it has become a regular process among the both on-line and off-line consumers to keep them self updated about the reviews of any particular product from online web sites before going to purchase. On-line customers spend a lot of time in analyzing different textual reviews. However, there are various products, which have thousands of user’s generated reviews. Enormously increasing volume of reviews has led to another problem of information overload. Mining these enormous online reviews and tuning these abundant individual consumer’s view into collective consumer‘s choice became a challenging task. These collective reviews aid in product improvement processes, ranking of various products, and many other such operations.

To deal with these problems, we have proposed a ranking product approach using reviews rating, which can help customers in choosing best products. Proposed framework for ranking product is based on AHP-RVM, which aims to automatically identify important products using consumer reviews rating. Our main contribution in this framework is product ranking approach, which takes input as reviews rating and ranks the products on the basis of reviews rating. In this framework, for ranking products we have proposed a hybrid (AHP-RVM) approach. This hybrid approach works in two steps. In first step, AHP method is used to find out the relative weights of evaluation attributes. In second step, RVM technique is conducted to determine the rank of the products. we have compared our approach with another well-known ranking approach “TOPSIS”. The experimental study shows that the proposed approach is effective than TOPSIS method.

The rest of the paper is organized as follows: Section 2 explains the basic methodology used in this paper. In section 3 we present the general framework for sentiment classification of reviews. In next Section 4, we propose the framework for ranking the products based on AHP-RVM approach. Section 5, illustrates of our method through experiments on cell phone dataset. Finally, we conclude the paper with a summary and directions for future work in Section 6.

2. Multi Criteria Decision Making (MCDM)

Multi-Criteria Decision Analysis, or MCDA, is a valuable tool that we can apply to many complex decisions. It is most applicable to solving problems that are characterized as a choice among alternatives. In this section we briefly explain two important approaches for MCDM : TOPSIS and AHP.

2.1 TOPSIS Method

Among numerous MCDA/MCDM methods developed to solve real-world decision problems, TOPSIS continues to work satisfactorily in diverse application areas. Hwang and Yoon (1981)[4] originally proposed TOPSIS to help select the best alternative with a finite number of criteria. TOPSIS method is based on choosing the best alternative, which has the shortest distance from the positive-ideal solution and the longest distance from the negative-ideal solution. The positive ideal solution maximizes the benefit criteria and minimizes the cost criteria, whereas the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria[3].

2.2 AHP Method

AHP is a method for Multi Criteria Decision Making (MCDM). It was developed by saaty [2] and is well-known and widely accepted in research decision making for selection, comparison and ranking of multiple available alternatives with multiple attributes. AHP as a tool has been successfully used in various fields such as business, government etc. Various steps involved in AHP as discussed in [3] are presented below:

Step 1: AHP follows a hierarchal structure i.e. complex problem is represented as collection of sub-problems in a hierarchal structure. Goal of problem is placed at the top and criteria to reach the goal, is decomposed in sub-criteria and represented by

Stepwise procedure for TOPSIS methodology is given below :-

Step 1 : Calculate normalized decision matrix

$$n_{ij} = a_{ij} / \sqrt{\sum a_{ij}^2} \; for \; i = 1, \ldots m; j = 1, \ldots n$$

Where a_{ij} and n_{ij} are original and normalized score of decision matrix

Step 2 : Calculate the weighted normalized decision matrix

$$y_{ij} = w_j \; n_{ij}$$

Where w_j is the weight for j criterion

Step 3 : Find the positive ideal and negative ideal solution

$X^* = \{y^*_{1, \ldots} y^*_n\}$ positive ideal solution.

where $y^*_j = \{\max(y_{ij}) \text{ if } j \in \text{J}; \; \min(y_{ij}) \text{ if } j \in J'\}$

$X' = \{y'_{1, \ldots} y'_n\}$, negative ideal solution.

where $y'_j = \{min(y_{ij}) \text{ if } j \in \text{J}; \; max(y_{ij}) \text{ if } j \in J'\}$

Step 4 : Find the separation measure for each alternatives

The separation from positive ideal alternative is:

$$S_i^* = [\sum (y_j^* - y_{ij})^2]^{1/2} \quad i=1,\ldots,m$$

level. Sub-criteria is further decomposed into sub-criteria and represented by sub-level and so on as per the requirement. Overall hierarchy is shown in Figure 1.

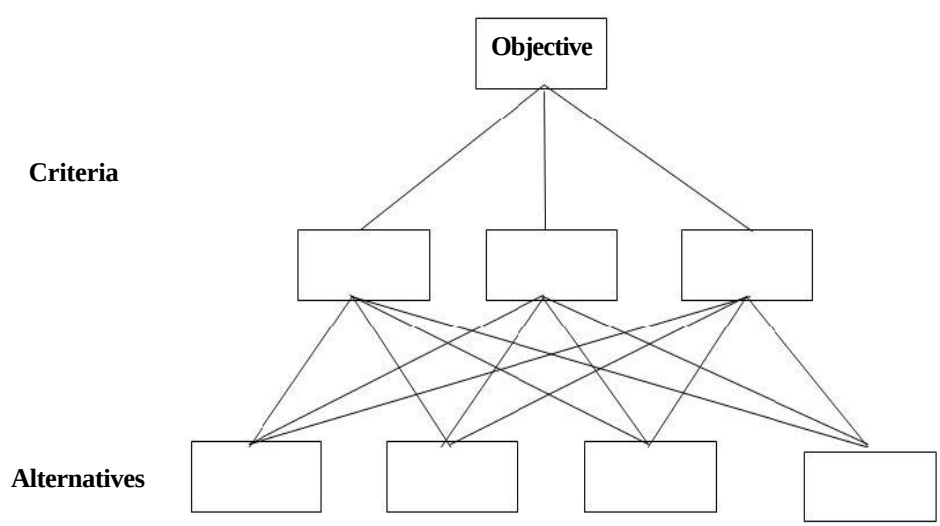

Figure 1. The hierarchical structure of the decision making problem [3]

Step 2: In this step a decision matrix is constructed for assessment of each alternative in respect to decision criteria on the basis of saaty nine point scale. In saaty scale, used for pair wise comparison, 1-9 numbers are used for scaling where 1 represents equal importance, 3 represents moderately more importance, 5 represents strong or essential importance, 7 represents demonstrated importance, 9 represents extremely important while 2, 4, 6, 8 represent compromised value of importance. Let *m* be the number of alternatives and *n* be the number of criteria, then decision matrix is represented as :

$$D = \begin{bmatrix} d_{11} & d_{12} & . & d_{1n} \\ d_{21} & d_{22} & & d_{2n} \\ . & & & \\ d_{m1} & d_{m2} & & d_{mn} \end{bmatrix} \tag{1}$$

The element $\{d_{ij}\}$ signifies the rating of the ith alternative in respect to the jth criteria.

Numerical assessment	**Linguistic meaning**
1	Equal important
3	Moderately more important
5	Strongly more important
7	Very strongly important
9	Extremely more important
2, 4, 6, 8	Intermediate values of importance

Table 2. The numerical assessments and their linguistic meanings[3]

Step 3: In this step the elements of the obtained hierarchy are compared with each others. After this comparison relative priorities are assigned to each elements based on saaty's 1-9 scale.

$$\begin{bmatrix} b_{11} & b_{12} & . & b_{1n} \\ b_{21} & b_{22} & & b_{2n} \\ . & & & \\ b_{n1} & b_{n2} & & b_{nn} \end{bmatrix} = \begin{bmatrix} w_1/w_1 & w_1/w_2 & . & w_1/w_n \\ w_2/w_1 & w_2/w_2 & & w_2/w_n \\ . & & & \\ w_n/w_1 & w_n/w_2 & & w_n/w_n \end{bmatrix} \tag{2}$$

Here *n* is the number of criteria and the elements $\{b_{ij}\}$ will satisfy the following conditions: $b_{ij} = w_i/w_j = 1/b_{ji}$ and $b_{ii} = 1$ with $i, j, k = 1, 2, \ldots n$.

In the matrix, b_{ij} is the degree of preference of ith criteria over j^{th} criteria. Obtaining the weight of the criteria is more suitable with pairwise comparison than getting them directly because the comparison of two attribute is easier than assigning the overall weight.

Step 4: This method calculates inconsistency coefficient for the decision matrix and pairwise comparison matrix to show the consistency of decision maker's judgments.

$$CI = \frac{\lambda_{\max} - N}{N - 1} \quad (3)$$

This calculated inconsistency index should be near to zero to represent greater consistency. If $b_{ij} \bullet b_{jk} = b_{ik}$ is true for all criteria, assessment ensures consistency. Generally, if value is less than 0.10, results are considered consistent otherwise procedure starts again from step 2.

Step 5: The comparison matrix is to be normalized before calculation of vector of priorities. To normalize the matrix, each element of column of matrix is divided by sum of the value of each element in corresponding column.

Step 6: In this step, relative weights of criteria are calculated which are basically Eigen value of matrix. The relative weights obtained in the third step should verify.

$$B \cdot W = \lambda_{\max} \cdot W \quad (4)$$

Where B is pairwise comparison matrix and $\lambda_{\max}$ is the highest eigenvalue. In case of presence of elements at higher level, obtained weight vector is multiplied by higher level elements' weight coefficients until the top of hierarchy is not reached. The alternative with highest weight coefficient should be taken as best alternative using AHP.

3. General Framework for Review Classification

This section presents the general framework used for sentiment classification as shown in Figure 2. This framework is used to classify the reviews into different classes on the basses of their strength. The various steps used in this framework are discussed below in detail.

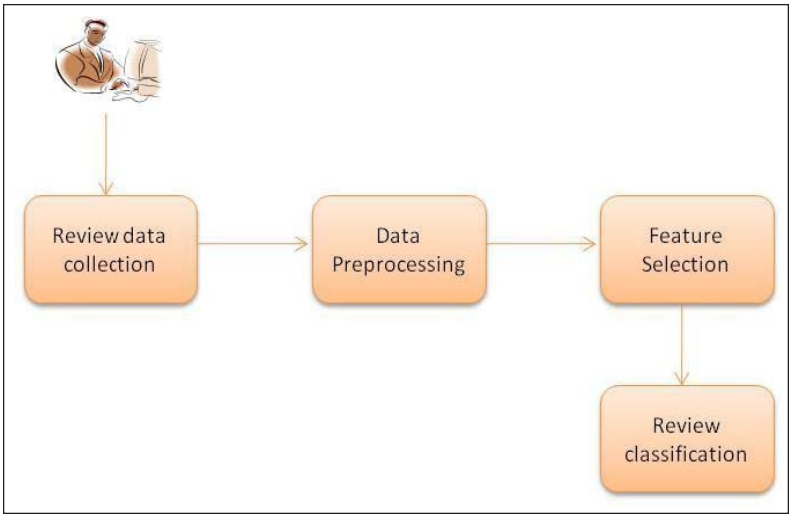

Figure 2. General Framework for Review Classification [5]

3.1 Review Dataset Collection

Reviews are general opinion about various product, movie, books etc. given by the users. These reviews are used to find out the opinion of users about that product. Consumer reviews are composed in different formats on various forum Websites. The Websites such as CNet.com requires consumers to give an overall rating on the product, describe concise positive and negative opinions (i.e. Pros and Cons) on some product aspects, as well as write a paragraph of detailed review in free text. Some Websites, e.g., Viewpoints.com, only ask for an overall rating and a paragraph of free-text review. The others such as Reevoo.com just require an overall rating and some concise positive and negative opinions on certain aspects. In summary, besides an overall rating, a consumer review consists of Pros and Cons reviews, free text review, or both. There are various review datasets available online.

3.2 Data Preprocessing

Data pre-processing is the process of cleaning the data in order to prepare it for classification. Online raw text usually contains plenty of noise and many irrelevant things such as advertisements, HTML tags, scripts etc. In addition, whenever we go for words level processing, each word is treated as one dimension in the text. However, there are many words in the text like stopwords, which do not have a major impact on the general orientation of the text [6]. Keeping such irrelevant words in the experimental dataset increases the dimensionality of the problem and hence makes the process of classification more difficult. It is the hypothesis that if the working data is properly pre-processed then it can reduce the noise in the text which in terns, speeds up the classification process and helps in improving the classifier performance. The process of data pre-processing includes stop words removal like prepositions and articles, expanding abbreviation, white space removal, stemming that is to reduce term variations to a single representation etc.

3.3 Feature Selection

Feature selection is a process in which unnecessary information is removed from the corpus before the training of the classifier. This allows the classifier to fit a model to the problem set more quickly since there is less information to consider, and thus facilitates faster classification[7]. The main goal of the feature selection is to reduce the dimensionality of the feature space and thus improve the computational cost. Feature selection also reduces the over-fitting of the learning scheme to the training data.

In text mining, feature selection methods can be divided into lexicon-based methods which need human annotation, and statistical methods which are more frequently used. Lexicon-based approaches usually begin with a small set of seed‘ words. Then bootstrapping is applied to this set through synonym detection or on-line resources to obtain a larger lexicon. This process has many difficulties as reported by Whitelaw et al. [8].

3.4 Review Classification

Sentiment Classification techniques can be roughly divided into machine learning approach, lexicon based approach and hybrid approach [9].The Machine Learning Approach (ML) applies any ML algorithms and uses linguistic and statistical features to train the classifiers.

The Lexicon-based Approach relies on a sentiment lexicon, a collection of known and precompiled sentiment terms. It is divided into dictionary-based approach and corpus-based approach which uses statistical or semantic methods to find sentiment polarity. The hybrid Approach combines both approaches and it is very common with sentiment lexicons playing a key role in the majority of methods. The text classification methods using ML approach can be roughly divided into supervised and unsupervised learning methods. The supervised methods make use of a large number of labeled training documents. The unsupervised methods are used when it is difficult to find these labeled training documents. The lexicon-based approach depends on finding the opinion lexicon which is used to analyze the text. There are two methods in this approach[10]. The dictionary-based approach which depends on finding opinion seed words, and then searches the dictionary of their synonyms and antonyms. The corpus based approach begins with a seed list of opinion words, and then finds other opinion words in a large corpus to help in finding opinion words with context specific orientations. This could be done by using statistical or semantic methods.

Classifiers use appropriate machine learning algorithm to classify document into various classes. The classification could be binary or multiclass. In case of sentiment classification we can have a binary classifier predicting the negative or positive class for a classifier. On the other hand, we can also have a classifier that predicts the strength of the sentiments for a review document. In such case a star rating from 1 to k (Generally $k = 5$) is predicted to indicate the strength of sentiment. Given the classified output for different review data, the information can be utilized to rank the product based on strength of reviews for that product. Our system captures this idea to extend the functionality of existing system. The detail of proposed system are presented in next section.

4. Framework for Proposed System

The main contribution of this paper is to suggest a product ranking mechanism based on the strength of reviews of the product. In our proposed ranking mechanism we have considered similar types of products. The proposed framework is the extension of the general framework of sentiment classification as discussed in previous section. Here, the rating of the review corresponds to the class of the review. The proposed framework is simple and effective, which ensures good product selection as well as

returns top-k efficient product to the customers. The input to our system is the set of reviews and their corresponding ratings. Output is top-k efferent products based on the efficiency of the review. To assign a rank to the product through reviews, one has to follow some general steps that are presented below :

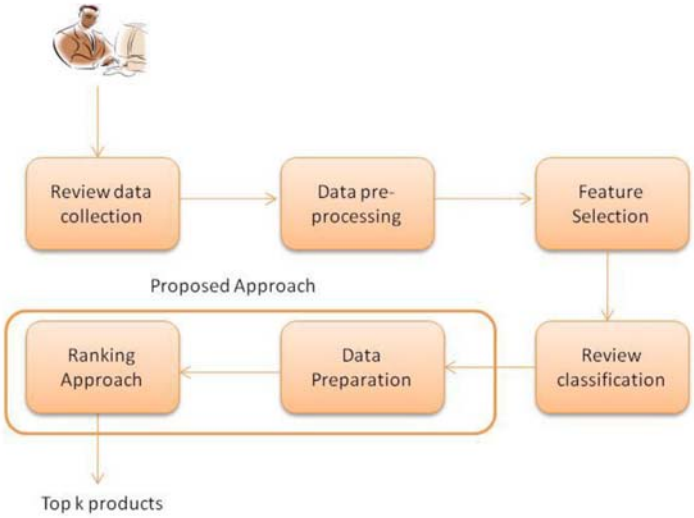

Figure 3. Framework for Product Ranking

4.1 Data Preparation

From the classified reviews, rating data set is prepared for AHP-RVM approach. The format of the dataset is shown below (Table 1). Let m be the numbers of products in market and $k(k \leq m)$ dbe the number of numerical rating from the numbers 1 to k (here $k = 5$). Let r_{ij} be the number of jth place numerical rating of the product in i^{th} place where $i = 1 \ldots m$ and $j = 1 \ldots k$. Now our data set is prepared for our AHP-RVM approach. In next step, we can apply AHP-RVM approach.

Product ID	$rating_1$	$rating_2$	$rating_3$	.	$rating_k$
$prod_1$	r_{11}	r_{12}	r_{13}		r_{1k}
$prod_2$	r_{21}	r_{22}	r_{23}		r_{2k}
$prod_3$	r_{31}	r_{32}	r_{33}		r_{3k}
.					
$prod_m$	r_{m1}	r_{m2}	r_{m3}		r_{mk}

Table 1. Data Representation

4.2 Ranking Approach

After data preparation, the proposed AHP-RVM approach can be applied to rank the products.

The proposed approach work in two steps:

(1) In first step, the AHP method is applied to determine the relative weights of evaluation attribute.

(2) In second step, RVM method is used to find out the rank the product alternatives.

4.2.1 AHP Approach

In this work to find a criterion weight, AHP is used. It was developed by saaty [2] and is well-known and widely accepted in

research decision making for selection, comparison and ranking of multiple available alternatives with multiple attributes. After calculate the criteria weight, multiply the column of rating dataset by its associated weight. AHP is discussed in Section 2.The resultant weighted rating dataset are then passed to RVM method.

4.2.2 RVM Approach

In this work, to find a best product for a user, ranked voting method is used [11]. In ranked voting system, voter ranks alternatives in order of preference. In our case the review rating corresponds to the order of preference. There is a long list of reviews to find an efficient product. Each review act as a voter, where products are candidates. Thus, a ranked voting data set is prepared. In research, some method has been proposed to analyze ranked voting data such as Data Envelopment Analysis (DEA) introduced by Cook and Kress [12]. But DEA often suggests more than one efficient candidate. Some methods are proposed to discriminate these efficient candidates. But order of preference may be changed because of existence of an inefficient candidate. Tsuneshi Obata and Hiroaki Ishii introduced [11] a novel method which does not use information of inefficient candidate to discriminate efficient candidates given by DEA. Recently Gaurav et al. [13] have used ranked voting method (RVM) for the selection of best cloud service provider.

The ranked voting method is applied in two steps:-

a) Find Efficient Products

Let *m* be the numbers of products in market and $k(k \leq m)$ $k(k \leq m)$ be the number of numerical rating i.e. a user has to select one product and assign a numerical rating to the product from the numbers 1 to *k*. Let r_{ij} be the number of jth place numerical ratings of the ith product, where $i = 1 \ldots m$ and $j = 1 \ldots k$. Now preference score z_i should be calculated for each product *i* as a weighted sum of numerical ratings with certain weight w_i, i.e.

$$z_i = \sum_{j=1}^{k} w_j r_{ij} \tag{5}$$

By using data envelopment analysis (DEA), Cook and Kress [12] have proposed a method for estimating preference scores without imposing any fixed weights from outset. Each candidates score is calculated with their most favorable weights. Their formulation is the following:

$$z_o^* = \text{maximize} \sum_{j=1}^{k} w_j r_{ij} \tag{6}$$

subject to

$$\sum_{j=1}^{k} w_j r_{ij} \leq 1, \; i = 1, \ldots, m, \tag{7}$$

$$w_{j+1} - w_j \geq d(j, \in), \; j = 1, \ldots, k-1, \tag{8}$$

$$w_k \geq d(k, \in), \tag{9}$$

where $d(\cdot, \in)$, called the discrimination intensity function, is nonnegative and non-decreasing in $\in$, and satisfies $d(\cdot, \in) = 0$. Parameter $\in$ is nonnegative.

After applying DEA, value of z_i will be 1 for all efficient products. After the problems are solved for all products, several (not only one) products often achieve the maximum attainable score 1. We call these products efficient products. We can judge that the set of efficient products is the top group of products, but cannot single out only one best among them.

b) Discriminate Efficient Products :

Let $\hat{z}_o$ be the normalized preference score of efficient products $(z_i = 1)$. Model for ranked voting method with discrimination of efficient products is as follows.

$$1/_{Z_o^*} = minimize\|w\|, \tag{10}$$

subject to

$$\sum_{j=1}^{k} w_j r_{oj} = 1, \tag{11}$$

$$\sum_{j=1}^{k} w_j r_{ij} \leq 1, i \neq o \tag{12}$$

$$w_{j+1} - w_j \geq d(k, \in), j = 1, \dots, k-1, \tag{13}$$

$$w_k \geq d(k, \in), \tag{14}$$

where $d(\cdot, \in)$ called discrimination intensity function, is non-negative and non-decreasing in $\in \in \geq 0$ and satisfies $d(\cdot, 0) = 0$. Constraint (11) is for efficient products, constraint (12) is for products which are not efficient and constraint (13) means review of higher place may have greater importance than that of the lower place.

The normalized preference score Z_o^* is obtained as a reciprocal of the optimal value. Product with highest normalized preference score will be winner. i.e. best Product for user.

Our method does not use any information about inefficient products and the problem of changing the order of efficient products does not occur. Because there is no existence of an inefficient product.

5. Experimental Results and Analysis

To evaluate the effectiveness of proposed AHP-RVM approach the experiments were performed on the 2 different samples. In this section, first we describe the dataset used in our experiment in subsection 5.1. After that we explain the implementation procedure of our AHP-RVM approach in 5.2. In sub section 5.3, the comparisons of proposed AHP-RVM method with TOPSIS method is presented.

5.1 Dataset Description

In order to evaluate the effectiveness of the AHP-RVM method, the experiments have been performed on Cell Phone dataset which is publicly available dataset on the website *https://snap.stanford.edu/data/web-Amazon.html*. Each product is accompanied by a set of reviews, each on a scale of 1-5 rating. These ratings are provided by consumers who wrote original reviews. This dataset contains incomplete data points since all the reviews available on this website contain both a review text and the ratings for all the reviews of products. This dataset contains 7,438 products and 78,930 reviews.

5.2 Implementation Procedure

We empirically evaluate our AHP-RVM method, described in Section4.2 by calculating the rank of cell phones products collected from the website *https://snap.stanford.edu/data/web-Amazon.html*. Below, we describe the procedure of our AHP-RVM method.

Step 1. Prepare the Rating Dataset

From the classified reviews, rating data set is prepared. Here, rating is considered to be the class of the reviews. The format of the dataset is shown in Table 1. Let *m* be the numbers of products in market and $k(k \leq m)$ be the number of numerical ratings from the numbers 1 to *k* (here *k* = 5). Let r_{ij} be the number of j_{th} place numerical ratings of the product in i_{th} place where $i = 1 \dots m$ and $j = 1 \dots k$.. Now our data set is prepared for ranking algorithm.

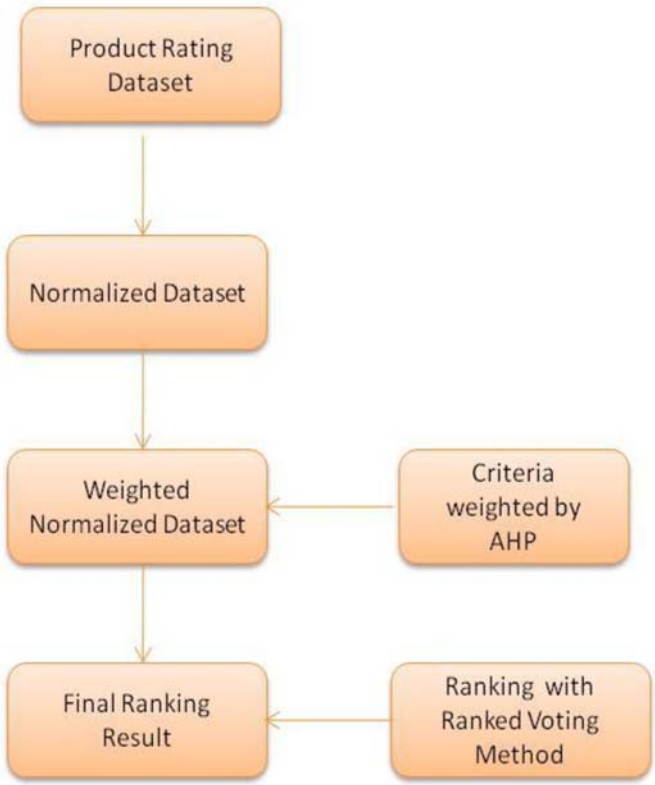

Figure 4. The Proposed work procedure

Step 2: Normalize the Rating Dataset

After rating dataset prepared, we have to normalized the rating dataset. For normalizing, Each column of rating dataset, is divided by root of sum of square of respective columns.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum x_{ij}^2}} \text{for i=1,...,m; j=1,...,n} \quad (15)$$

Where x_{ij} and r_{ij} are original and normalized score of rating dataset.

Step 3: Calculate the Weights of Criteria through Applying AHP Method
In this step we have constructed weighted standardized rating dataset by multiplying attributes weight to each rating.

Here, we have used AHP to find the attributes weight. Assume we have a set of weights for each criteria w_j for $j = 1,\ldots n$. Multiply each column of the normalized rating dataset by its associated weight. An element of the new matrix is:

$$v_{ij} = w_j r_{ij} \quad (16)$$

Where w_j is the weight for j criteria.

Step 4: Conducting RVM to Achieve the Final Ranking Results
In this step, we have used the Ranked Voting Method to find the rank of the products.

5.3 Design of Experiments

The experiments were performed on two samples in which each sample contains 50 products and each product contains first 50 reviews. In each sample, First column shows the product id and next five column shows the rating attributes of the sample. In our experiment, we considered the rating attributes in decreasing order.

Rating 5 is assigned highest priority and Rating 1 has lowest priority. Ratings of each sample were normalized and on normalized rating, weighted standardized ratings were calculated by multiplying attributes weight to each rating. To calculate the attributes weight to each rating, AHP was applied. The weighted vector after AHP is {0.436070657289994, 0.284899496096129,0.166288277313251, 0.0815659781826236, 0.0311755911180021 }. We have used same weight for each sample. Now, after preparing weighted standardized rating dataset, we applied RVM to calculate the rank of the products.

5.3.1 Result and Analysis on Sample 1

Table 3 shows the result of proposed AHP-RVM approach and Table 4 show the results of TOPSIS method on sample 1. It can be observed that both the methods assign the highest score to product id B000E7YSWK and B000CQVMYK. From the given data it can be observed these two products should get highest ranking, therefore both methods have performed equally well for them.

In next observations, we can observe that our method assigns rank 3 to product B000H7GVA4, whereas TOPSIS assigns third rank to product B0002W2H2K. In the given data set, the frequency of rating 5 for product id B000H7GVA4 is 36 and for rating 4 it is 9, so from general observations it should be at rank 3. Our approach assigns rank 3 to product id B000H7GVA4, the TOPSIS method does not assign rank 3 to product B000H7GVA4 but it is assigned fifth rank. Thus our approach follows general observation more properly.

To explain this case through graphically we have used kiviat graph (Figure 5). From the graph it can be observed that that the product id B000H7GVA4 gets more preference in rating 5 criteria but on the rating 4 product id B0002W2H2K gets more preference than product id B000H7GVA4. As the rating 5 has higher priority than rating 4, our method correctly assigns rank 3 to product id B000H7GVA4.

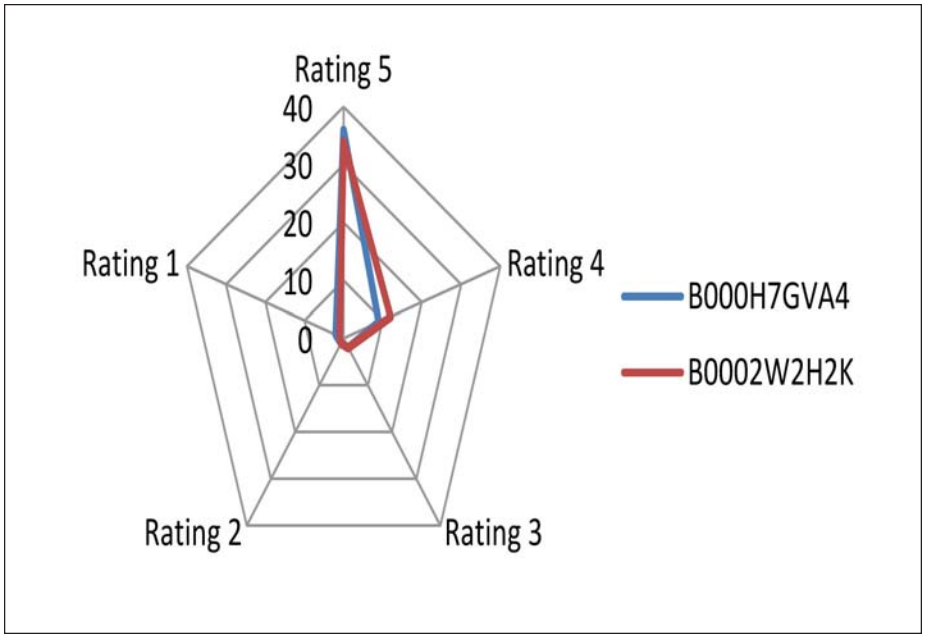

Figure 5. Kiviat graph between product id B000H7GVA4 and B0002W2H2K

5.3.2 Result and Analysis on Sample 2

This subsection presents result of experiments on sample 2. Table 5 shows the result of proposed AHP-RVM approach for sample 2. The experimental results of TOPSIS method are shown in Table 6. It can be observed that (Table 5 and Table 6) both methods

Product_id	Rating 5	Rating 4	Rating 3	Rating 2	Rating 1	Score
B000E7YSWK	38	11	0	1	0	1
B000CQVMYK	38	11	0	1	0	1
B000H7GVA4	36	9	2	1	2	0.947773
B000IVEQYW	36	7	0	2	5	0.947368
B0002W2H2K	34	12	2	1	1	0.944626
B0006HP7NC	34	12	2	1	1	0.944626
B000EBHW4W	32	14	2	1	1	0.929346
B0009MYS9S	32	11	2	1	4	0.890876
B000JL4Y3Y	28	17	1	1	3	0.879133
B0000SX3BK	31	11	3	1	4	0.877241
B000C1CHVC	33	7	4	2	4	0.87625
B000DLAMPO	30	12	3	1	4	0.869601
B000JHKU72	28	12	4	3	3	0.840596
B0007NP8PW	22	20	4	2	2	0.817854
B000RZFNN2	23	17	6	2	2	0.813505
B000P9I6B6	24	14	6	3	3	0.798045
B00063DKVC	30	7	2	0	11	0.796109
B000HD79J0	25	11	3	5	6	0.764647
B0002NM98Q	27	8	0	3	12	0.741524
B000ID10JE	19	16	4	5	6	0.71281
B000I8FL0S	23	8	6	4	9	0.703189
B000I8C68S	20	11	8	7	4	0.701566
B000FL2DMC	18	17	2	6	7	0.69406
B000J6FWTO	16	19	4	4	7	0.687343
B000PYJ4NK	20	10	5	11	4	0.678443
B000G2TLIO	15	18	6	5	6	0.67026
B0000SX2U2	15	17	5	12	1	0.668435
B000EM8REU	21	9	4	6	10	0.666521
B000F9LRYO	16	12	9	4	9	0.631723
B000J2FOF0	17	10	8	8	7	0.629898
B000BBCTJ8	22	4	2	1	21	0.596477
B000067BEY	13	15	6	7	9	0.595957
B00081GX8O	19	6	6	3	16	0.593141
B000FJ20CM	13	11	12	7	7	0.585635
B000BPR2SW	17	7	6	5	15	0.570131
B0009SHMUY	12	12	8	8	10	0.553227
B0006I3L7K	14	9	5	12	10	0.545385
B000PB8CQI	20	3	2	2	23	0.545273
B0000DZG40	9	15	7	13	6	0.536211
B000E14G7S	8	16	11	5	10	0.535512
B000HBMP82	15	7	5	6	17	0.524922
B000ROGDNM	9	12	8	9	12	0.494383
B0000CEPC8	12	7	7	10	14	0.487375
B000FL9QGI	7	13	7	11	12	0.464544
B000LGE1LW	11	7	9	2	21	0.460195
B00009WCAP	12	6	4	8	20	0.448973
B000ELOPZ6	10	6	11	5	18	0.448206
B000RZCI80	12	7	3	5	23	0.447327
B000E84CQQ	9	9	4	9	19	0.428599
B000GUKT9Q	3	6	5	9	27	0.274176

Table 3. AHP-RVM Result on Sample 1

Product_id	Rating 5	Rating 4	Rating 3	Rating 2	Rating 1	Score
B000E7YSWK	38	11	0	1	0	0.815293
B000CQVMYK	38	11	0	1	0	0.815293
B0002W2H2K	34	12	2	1	1	0.794861
B0006HP7NC	34	12	2	1	1	0.794861
B000H7GVA4	36	9	2	1	2	0.789639
B000EBHW4W	32	14	2	1	1	0.776035
B000IVEQYW	36	7	0	2	5	0.764696
B0009MYS9S	32	11	2	1	4	0.753645
B000C1CHVC	33	7	4	2	4	0.739044
B0000SX3BK	31	11	3	1	4	0.737378
B000DLAMPO	30	12	3	1	4	0.724302
B000JL4Y3Y	28	17	1	1	3	0.700635
B000P9I6B6	30	7	2	0	11	0.683593
B000JHKU72	28	12	4	3	3	0.682692
B0002NM98Q	27	8	0	3	12	0.626967
B000HD79J0	25	11	3	5	6	0.604522
B00063DKVC	24	14	6	3	3	0.599135
B000RZFNN2	23	17	6	2	2	0.587295
B0007NP8PW	22	20	4	2	2	0.571928
B000I8FL0S	23	8	6	4	9	0.542621
B000EM8REU	21	9	4	6	10	0.496525
B000BBCTJ8	22	4	2	1	21	0.49308
B000I8C68S	20	11	8	7	4	0.486468
B000ID10JE	19	16	4	5	6	0.482413
B000PYJ4NK	20	10	5	11	4	0.478801
B000FL2DMC	18	17	2	6	7	0.461782
B0006I3L7K	20	3	2	2	23	0.441958
B00081GX8O	19	6	6	3	16	0.433889
B000J6FWTO	16	19	4	4	7	0.428981
B000J2FOF0	17	10	8	8	7	0.406156
B000G2TLIO	15	18	6	5	6	0.403033
B0000SX2U2	15	17	5	12	1	0.397393
B000F9LRYO	16	12	9	4	9	0.392757
B000BPR2SW	17	7	6	5	15	0.388305
B000067BEY	13	15	6	7	9	0.338661
B000HBMP82	15	7	5	6	17	0.336626
B000PB8CQI	14	9	5	12	10	0.323538
B000FJ20CM	13	11	12	7	7	0.322515
B0009SHMUY	12	12	8	8	10	0.29804
B0000CEPC8	12	7	7	10	14	0.26656
B0000DZG40	9	15	7	13	6	0.264309
B000E14G7S	8	16	11	5	10	0.263123
B000ELOPZ6	12	7	3	5	23	0.258582
B00009WCAP	12	6	4	8	20	0.256288
B000LGE1LW	11	7	9	2	21	0.245041
B000ROGDNM	9	12	8	9	12	0.236229
B000RZCI80	10	6	11	5	18	0.224522
B000FL9QGI	7	13	7	11	12	0.211239
B000E84CQQ	9	9	4	9	19	0.202724
B000GUKT9Q	3	6	5	9	27	0.093599

Table 4. TOPSIS Result on Sample 1

assign rank 1 to product id B0001NJFVQ. So by observation it can be said that both methods behave according to property of data sets.

Our proposed method assigns rank 2 to product id B000M8TTA2 and rank 3 to product id B000KIHEQ0. The frequency of product id B000M8TTA2 for rating 5 is 26, 15 for rating 4 and 3 frequency for rating 3. The product id B000KIHEQ0 has 27 frequency for rating 5, 13 for rating 4 and 1 for rating 3. According to the rating 5 the product id B000KIHEQ0 should get more preference than product id B000M8TTA2, but with inclusion of rating 4 and rating 3, the product id B000M8TTA2 should get higher rank than product id B000KIHEQ0. Our method assigns same rating as general behavior of the data sets.

Product_id	Rating 5	Rating 4	Rating 3	Rating 2	Rating 1	Score
B0001NJFVQ	35	5	0	3	7	1
B000M8TTA2	26	15	3	1	5	0.986384
B000KIHEQ0	27	13	1	5	4	0.956248
B0006I2HN4	23	18	3	2	4	0.952909
B0006J27C4	24	13	8	3	2	0.943936
B000FSJYQ8	28	10	2	0	10	0.933893
B000ELUXIO	29	8	3	2	8	0.925856
B000I8ACMU	28	8	2	0	12	0.891931
B000MSDKHA	19	20	4	1	6	0.891615
B000FL60P8	23	15	2	2	8	0.877453
B00001W0ET	18	20	2	7	3	0.86275
B000C12GH2	22	11	7	5	5	0.847372
B0006HP7NW	21	15	3	4	7	0.84399
B000KJS8CI	19	16	6	4	5	0.839432
B000G7LWRM	23	10	6	2	9	0.834994
B000FAQ6S0	16	17	9	5	3	0.818939
B0004OPNTA	14	21	7	5	3	0.815009
B00022NE6I	19	16	2	5	8	0.806626
B000FYU4SO	20	12	5	7	6	0.800568
B000HZZIGO	27	3	1	6	13	0.798231
B000DZXIRY	20	13	3	5	9	0.79373
B000246XQE	22	8	7	3	10	0.792612
B000HBPMV4	21	9	7	3	10	0.783798
B000FYUYT8	19	10	8	5	8	0.765129
B000J4HCBM	14	16	11	4	5	0.758025
B0006B088W	15	16	8	3	8	0.753582
B00009PGN0	16	15	4	8	7	0.745575
B0000C1HLG	16	13	7	6	8	0.733744
B000KNNKVS	15	16	4	4	11	0.725007
B000BNOCMS	17	12	3	6	12	0.711046
B000FL4GBI	12	17	7	8	6	0.704362
B000LNOFH0	14	11	11	6	8	0.68845
B000JP8P0I	17	7	8	5	13	0.673527
B000982UY2	12	15	8	3	12	0.66796
B0003RA29O	13	13	7	5	12	0.659979
B00074JWIK	11	13	11	7	8	0.65015
B000LMBJMA	10	16	7	10	7	0.648226
B00006Z95D	10	14	10	10	6	0.642272
B0007WY0AW	11	13	7	9	10	0.624513
B000AA7KZI	12	11	4	6	17	0.586084
B000BF109O	13	9	3	6	19	0.572226
B000AZ1LIK	11	6	12	9	12	0.560344
B00066MA9W	10	11	3	12	14	0.548616
B000M92GLK	10	7	11	8	14	0.540712
B000KNJEV8	9	11	6	3	21	0.522198
B000BBAKWQ	10	9	4	2	25	0.497523
B0008F6QE6	9	8	4	12	17	0.488502
B000FDZLZQ	8	9	5	12	16	0.487566
B000BK1QSE	8	7	8	12	15	0.481612
B000JDY0U4	5	14	3	12	16	0.474954

Table 5. AHP-RVM Result for Sample 2

Product_id	Rating 5	Rating 4	Rating 3	Rating 2	Rating 1	Score
B0001NJFVQ	35	5	0	3	7	0.721288
B000ELUXIO	29	8	3	2	8	0.68458
B000KIHEQ0	27	13	1	5	4	0.683763
B000FSJYQ8	28	10	2	0	10	0.68054
B000M8TTA2	26	15	3	1	5	0.677257
B000I8ACMU	28	8	2	0	12	0.661516
B0006J27C4	24	13	8	3	2	0.619301
B0006I2HN4	23	18	3	2	4	0.614867
B000FAQ6S0	27	3	1	6	13	0.596774
B000FL60P8	23	15	2	2	8	0.595086
B000KJS8CI	23	10	6	2	9	0.566246
B000C12GH2	22	11	7	5	5	0.548898
B0006HP7NW	21	15	3	4	7	0.542585
B000246XQE	22	8	7	3	10	0.526451
B000MSDKHA	19	20	4	1	6	0.521091
B000HBPMV4	21	9	7	3	10	0.506455
B000DZXIRY	20	13	3	5	9	0.501395
B000HZZIGO	19	16	6	4	5	0.498995
B000G7LWRM	20	12	5	7	6	0.497935
B00022NE6I	18	20	2	7	3	0.494743
B00001W0ET	19	16	2	5	8	0.4934
B000FYUYT8	19	10	8	5	8	0.460017
B0004OPNTA	16	17	9	5	3	0.432774
B000BNOCMS	14	21	7	5	3	0.415767
B000FYU4SO	17	12	3	6	12	0.411193
B00009PGN0	16	15	4	8	7	0.4099
B0000C1HLG	16	13	7	6	8	0.397817
B000J4HCBM	15	16	8	3	8	0.397697
B000KNNKVS	15	16	4	4	11	0.391669
B000JP8P0I	17	7	8	5	13	0.384997
B0006B088W	14	16	11	4	5	0.380002
B000LNOFH0	12	17	7	8	6	0.338672
B000FL4GBI	14	11	11	6	8	0.338454
B0003RA29O	13	13	7	5	12	0.320556
B000982UY2	12	15	8	3	12	0.318846
B000LMBJMA	10	16	7	10	7	0.290894
B000BF109O	11	13	11	7	8	0.287021
B00074JWIK	13	9	3	6	19	0.278704
B0007WY0AW	11	13	7	9	10	0.276623
B000AA7KZI	10	14	10	10	6	0.27656
B00006Z95D	12	11	4	6	17	0.271669
B000AZ1LIK	11	6	12	9	12	0.235843
B00066MA9W	10	11	3	12	14	0.228121
B000M92GLK	10	7	11	8	14	0.213632
B000KNJEV8	9	11	6	3	21	0.208951
B000BBAKWQ	10	9	4	2	25	0.203306
B000JDY0U4	5	14	3	12	16	0.200926
B0008F6QE6	9	8	4	12	17	0.177283
B000FDZLZQ	8	9	5	12	16	0.171183
B000BK1QSE	8	7	8	12	15	0.163243

Table 6. TOPSIS Result for Sample 2

Again to justify this case graphically we use kiviat graph (Fig 6). From graph it has been observed that the product id B000KIHEQ0 gets more preference in rating 5 criteria but on the rating 4 and rating 3 product id B000M8TTA2 gets more preference than product id B000KIHEQ0. On the basis of rating 4 and rating 3 our method have assigns rank 2 to product id B000M8TTA2.

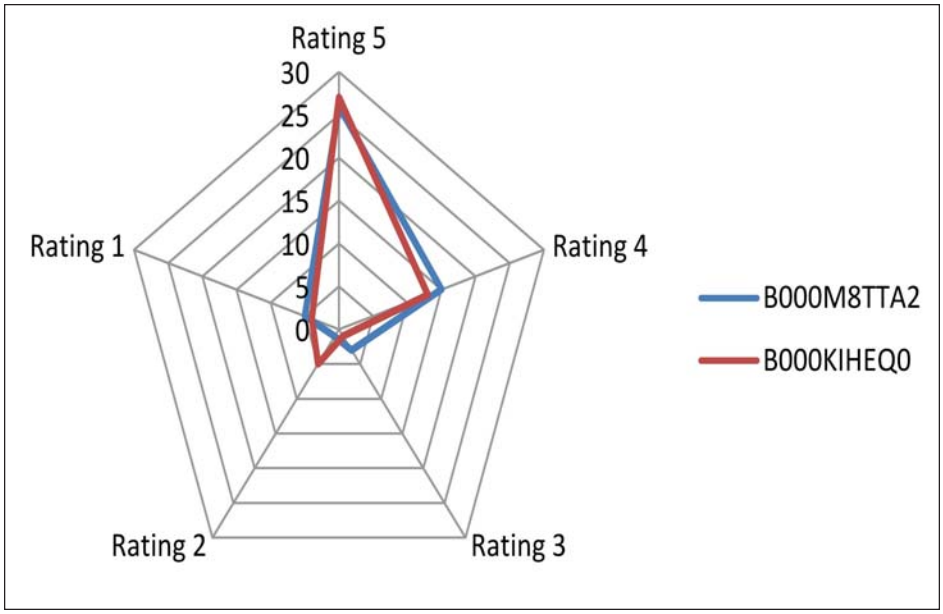

Figure 6. Kiviat graph between Product id B000M8TTA2 and B000KIHEQ0

6. Conclusion and Future Work

Due to the enormous increase in online reviews there are various products with thousands of user‘s generated reviews. Mining these enormous online reviews and tuning these abundant individual consumers view into collective consumer‘s choice becomes a challenging task. To solve this problem we have proposed a ranking mechanism which can be efficiently used to rank different products in accordance to their reviews rating. Hybrid approach using AHP and RVM has been used to rank the products. The effectiveness of our approach has been shown through an experiment on 2 samples. Proposed approach does not use inefficient product’s information to discriminate efficient products therefore order of efficient product never changes if inefficient products are added or removed.

In future, this framework may also be applied for recommendation of the top-k products on the basis of product reviews rating. Further this proposed approach can be generalized and applied to any different sector, considering similar decision-making problems.

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