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LSGDM Two Stage Consensus Reaching Process for Autocratic Decision Making using Group Recommendations

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Abstract: The decision making is a general and significant action in day-to-day life. In some cases, experts cannot express their preferences using precise value due to inherent unreliability. The utilization of linguistic labels creates expert judgement more informative and consistent for decision making. The group recommendation is considered as a significant factors of e-commerce domain due to their direct impact on profit. The personalized experiments improve the engagement and the count of purchases of the customer when the recommended products are matched to the current interest.In this paper, the Large-Scale Group Decision Making (LSGDM) two stage consensus reaching process is proposed by using three various Amazon real world dataset.This proposed method permits an autocratic decision maker to utilize a different group recommendation for a sequence of decisions at highest level of consensus. The performance of the model is estimated by applying parameters like Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Precision and Recall. The obtained result shows that proposed methodology provides better result while comparing various other methods.

Keywords: Amazon real world dataset, Autocratic, Consensus reaching process, Group recommendation, LSGDM, Power structures.

I. Introduction

The increasing complication of decision-making environment, it is unsuitable for decision makers to examine entirefeatures of decision-making problems that grades in the presence of group decision making [1]. The decision making is applied in several areas of our day-to-day life and for the real-world problem it is difficult and it is impossible to spread the probable decisions with one effective conditions [2].Due to the difficulty in the ordinary schemes, decision makers face several uncertainties in deciding with imperfect and inaccurate data. Decision making involves two steps when dealing with the systematic problems [3]. The first step is to establish the decision informations like criteria weights, the second is to gather criteria information and grades the alternatives based on this information [4]. A group recommendation (GR) is an accumulation approach to the item ratings by several people for providing recommendations. This approach is determined by the group of people, which can cause the impoverished group recommendation [5].

There are various real-time applications in GRsuch as people always choosing recommendations for a movie to watch with their families and friends rather than alone. The same thing to a passenger in a car who wants to listen to music while driving, etc [6]. The GR is focused on the clustering approach; it is a necessary factor and takes a huge time for processing. This clustering method is used to maximize the clustering effectiveness and minimize cost in group recommendation [7]. The content-based algorithm is mostly used due to the efficiency, effectiveness, and simplicity of some recommendation system starting times. Various profits are gained from this algorithm compared with various collaborative filtering such as transparency, and independence [8, 9]. The GR is based on preferences given by the users, utilizing the social aspect of group members to produce recommendations that improve the content quality. Additionally, it addresses the cold start problems and it cause by an Individual recommendation [10].

The rest of the portion present in the manuscript is organised as following: Section 2 illustrates the Literature review. The block diagram of proposed model is presented in Section 3. Experimental result of this proposed model is illustrated in Section 4. Section 5 describes the conclusion of this paper and lastly this paper finish with the references.

II. Literature Review

Shu-ping Wan*et al.* [11] introduced an integrated trapezoidal interval type-2 fuzzy (TrIT2F) technique for

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democratic-autocratic multi criteria decision making basedVIKOR andBest Worst Method (BWM). In this method, the weight normalization is utilized to normalize the weight and the reliability ratio is used to verify the consistency of the attained weights. This method is flexible to handle various decision situations and efficientlymaintains the inherent fuzzy information.This method has heavy computational workload, unsuitable and time consuming for serious emergency decision making.

Ahmad A. Alzahrani *et al.* [12] implemented an efficient group recommender system based on a Fuzzy Content-based Recommended System with dynamic selection of the aggregation functions. In this method, the innermost dynamic selection element is done as a supervised classification using classification rules. These rules are obtained by the fuzzy classification using ID3 algorithm. The benefit of using this model is to provide high response time in real-time application. After attaching the new things to the system this model required to train again.

Zahra Bahari Sojahrood and Mohammad Taleai [13] developed a group recommendation model by usingPOI in Location Based Social Networks (LBSNs).In this method, clustering algorithms like fuzzy c-means and k-means are used to group the users and solve the problems. By using the clustering algorithms, those who are performing in decision-making actively have a huge number of visits than they are alone. In various criteria, the user influence is not measured through the efficiency of the user in several factors.

Ziyu Lyu *et al.* [14] suggested a framework in Multi-view Group Representation Learning (MGPL) for group recommendation. This framework has been supported in different types of information for the representation of deep learning to capture the mobility of selection. The neural networks are used for solving the key problems in recommendation. In the objective function, the target scores and the prediction scores are used for optimization and the learning parameter are gained in the neural collaborative framework. This method only uses simple combination feature methods like a sequence of feature vectors.

Enrique Herrera-Viedma et al. [15] presented a personality aware group recommendation system based pairwise preferences. In this method, three various pairwise scoring methods such as Multiple Pairwise Ranking (MPR), Bayesian Personalized Ranking (BPR)and Matrix Factorization pair-score Prediction (MFP) are utilized to predict the item values. This method is more accurate and gives good predictionbecause of their pairwise comparison. This model not applicable for large scale applications whereas this model working well on the several group size.

III. Proposed Method

The recommendation system is considered as a significant factors of e-commerce domain due to their direct impact on profit. The personalized experiments improve the engagement and the count of purchases of the customer when the recommended products are matched to the current interest. Also, the text information is important for the customer to make the decision on purchase. The text informations like product title, description and this informations are written by the seller of the product. But, most of the platforms are allow customer to share their product reviews. This proposed method permits an autocratic decision maker to utilize a different group recommendation for a sequence of decisions athighest level of consensus. The workflow of proposed methodology is presented in Figure 1.

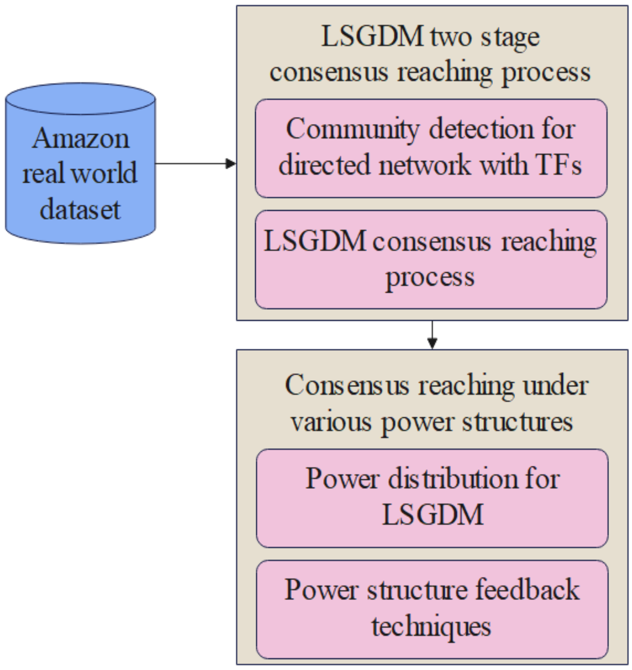

Figure 1. Block Diagram of the Proposed Methodology

3.1 Dataset

The autocratic decision-making using group recommendation is attained from three various real-world dataset from Amazon. Every dataset is from various categories such as TV & Movies, Beauty

and Games. In this Amazon dataset, there are no information about the user like which user buys which product. For that, if a user writes a review about the product, they accept that the user interest with this product. The interaction between user-product is called as action. For every action, they have a review.

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3.2 The Large-Scale Group Decision Making (LSGDM) two stage consensus reaching process

In network the individual'sbehaviors and their interrelation replicates the communitybelongs to them.Certainly, the community of knowledge is used to recognize the structure and overall network function, predict the communication among components of whole network.

1. Community detection for directed network with TFs

This method is used to find the communities in the directed network with the TFs by applying Leicht and Newman's modularity-based algorithm that is one part of Louvain algorithm.

a) Modularity for community structure in directed networks

The connection from $e_p\ to e_q$, presented as r_{pq} which is utilized to calculate the directed strength $w_{pq} = TS(r_{pq})$ where, the TS is represented in eq. (1)

$$TS(r) \quad = \frac{t-d+1}{2} \quad (1)$$

Where TS is the trust score, $t$and d is the trust and distrust degree. The trust value is equal to or greater than the distrust value $TS(r_{pq}) >= 0.5$ is extricated due to it represents the presence trust than the distrust. The directed weighted network modularity function is represented in eq. (2),

$$Q = \frac{1}{w}\sum_{p,q\in G}\left(w_{pq} - \frac{w_p^{out}w_q^{in}}{w}\right)\delta(c_p, c_q) \ (2)$$

Where, $w_p^{out} = \sum_{q\in G} w_{pq}$ is the trust strength out-degree of e_p, $w_q^{in} = \sum_{p\in G} w_{pq}$ is thetrust strength in-degree of e_q, w= $\sum_{q\in G} w_{pq}$ is the trust strength network, $\delta(c_p, c_q)$ is the Kronecker delta signemployed for communities to experts $e_p\ and\ e_q$ are allocated asc_p and c_q respectively. Barthelemy and Fortunato altered the aforementioned modularity formula with accumulation of a determination parameter γ is represented in eq. (3),

$$Q(\gamma) = \frac{1}{w}\sum_{p,q\in G}\left(w_{pq} - \gamma\frac{w_p^{out}w_q^{in}}{w}\right)\delta(c_p, c_q) \quad (3)$$

When the $\gamma < 1$ minimum community can be determined while the $\gamma > 1$permits to reduce the maximum communities.

b) Louvain Algorithm in directed networks with TFs

This algorithm contains different stages. In first stage same nodes are categorized and noticeable corresponding to certain improvement in the modularity is shown in eq. (4). Beginning to early partition with numerous community nodes are in network, every node is allocated tocommunity where every one of its neighbors is localized. The node continuesits unique communitywhich enlarge certain improvement in modularity when the node is allocated to it. This procedurereplicated upto community which entire nodes remains unaffected. The next stage creates latest network which nodes are communities establish through stage one. The latest network modularity is calculated and current iteration of bothstages is performing there is no improvement in modularity.

$$\Delta Q_{i(\gamma)} = \frac{w_{i,\ in}^C}{w}\gamma\frac{w_C^{out}w_i^{in} + w_C^{in}w_i^{out}}{w^2} \ (4)$$

Where, $w_{i,\ in}^C = \sum_{p,i\in C} w_{pi} + w_{ip}$ represents thenode $i$trust strength when allocated to community$C$. $w\ in\ C$ and $w\ out\ C$ are indegree and outdegree trust strength of community C , $w\ ini$ and $w\ out\ i$ are the indegree and outdegree trust strength of $i$correspondingly.

2. LSGDM consensus reaching process

This consensus reaching process is at various phases such as internal and external consensus level computation.

a) The two-phase consensus level computation

By employing the similarity degree, the consensus among every network SMs pair, e_p and e_q on alternative set is achieved as the resemblance of Fuzzy Preference Relation, F_p and F_q is represented in eq. (5),

$$CLI_{pq} = SD(F_p, F_q) \ (5)$$

Where, SD represents the similarity degree, F_p, F_q is the similarity degree two $FPRs$.

i) Internal consensus level computation

Every DM is belonging to community inside the community ς then internal consensus of separate $ep \in \varsigma$ is represented in eq. (6) and the community of internal consensus ς is represent in eq. (7),

$$ACLI_p^\varsigma = \frac{1}{\#\varsigma - 1}\sum_{q\in\varsigma, q\neq p} CLI_{pq} \ (6)$$

$$CLIS^\varsigma = \frac{1}{\#\varsigma}\sum_{p\in\varsigma} ACLI_p^\varsigma \ (7)$$

Where, $\#\varsigma$ represents amount of DM in communityς.

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ii) External consensus level computation

The nonappearance DMs weight in the community belong to collaborative FPR ofcommunity ς is calculated as mean of FPRs of its person is represented as $\bar{F}^{\varsigma} = \frac{1}{\#\varsigma}\sum_{p\in\varsigma} F_p$ or else, the according weighed mean is utilized to descent the collaborative FPR of the community. By employing similarity degree, the consensus among every network pair community, ς *and* k on the replacement set is achieved as parallel of the FPRs, $\bar{F}^{\varsigma}$ *and* $\bar{F}^{k}$ is represented in eq. (8) and external consensus community ς is represented in eq. (9),

$$CLS^{\varsigma\to k} = SD(\bar{F}^{\varsigma}, \bar{F}^{k}) \quad (8)$$

$$CLES^{\varsigma} = \frac{1}{\#C-1}\sum_{k\neq\varsigma} CLS^{\varsigma\to k} \quad (9)$$

Where, $\#C$ represents amount of network in communities.

b) Recognition of inconsistence communities

The inconsistence communities are identified by joining the internal and external consensus community level computation.

c) Personalized feedback technique for inconsistent communities

This technique provides alteration suggestions for inconsistent communities that encourage collection of consensuses.The existing research, represents one of the famous models in the personalized feedback technique with the lowest cost. This paper generates bi-level personalized feedback technique for inconsistent communities and individuals. The personalized suggestion for a recognized inconsistent individual $e_p \in ICI$ is belong to the community ς is represented in eq. (10),

$$rf_{ij}^{p(\varsigma)} = (1-\lambda^p)\cdot f_{ij}^{p(\varsigma)} + \lambda^p \cdot \bar{f}_{ij}^{\varsigma} \quad (10)$$

Where, $f_{ij}^{p(\varsigma)}$ and $\bar{f}_{ij}^{\varsigma}$represents preference degree ofalternate x_i over x_j of individual e_p and community ς. The alteration rate related to inconsistent individual e_p is represented in eq. (11),

$$\sum_{i,j}\left|f_{ij}^{p(\varsigma)} - rf_{ij}^{p(\varsigma)}\right| = \sum_{i,j}\lambda^p\cdot\left|f_{ij}^{p(\varsigma)} - \bar{f}_{ij}^{\varsigma}\right| \quad (11)$$

The personalized acceptance coefficients of inconsistent individuals $\lambda^p$is attainedby resolvingrate optimization represented in eq. (12),

$$\min \sum_{e_p\in ICI}\sum_{i,j}\lambda^p\cdot\left|f_{ij}^{p(\varsigma)} - f_{ij}^{\varsigma}\right| \quad (12)$$

This equation is descent to produce personalized feedback for inconsistent communities. The collaborative consensus on the power structures is used to capture the actual optimal consensus and communities weight distributionapproach clearly.

3.3 Consensus reaching under the various power structures

The various decision-making power impacts the result of decision-making process additionally, it causes the various consensus reaching processes. To identify these problems, various three power structures are generated and thepersonalized feedback techniques are recommended in this section.

1. LSGDM Power distribution

Thestraightappearance of subcategory power is its weight. In consensus reaching structure, the companies trust the fairness to the allocatestockholder weight, maximum consensus community level, the additional weight is specified to community. Additionally, the method based on usage of consistent maximizing the monotonouslogical quantifier$Q(x) = x^{\alpha} (\alpha \in [0,1])$ is proposed to assign the weight is represented in eq. (13),

$$\varpi^{\varsigma} = Q\left(\frac{\varsigma}{\#C}\right) - Q\left(\frac{\varsigma-1}{\#C}\right) (13)$$

The community $\sigma(\varsigma)$ being σ the variationvalidating$CLES^{\sigma(\varsigma)} \geq CLES^{\sigma(\varsigma+1)}$ is to observed as power structure operator to generate the below various three power structures and their parameters are represented in Table 1.

Table 1. Various power structures and its parameters

Power Structures	Power weight (maximum)	Limit of α
Absolute power	$\frac{2}{3} < \varpi_1 \leq 1$	$0 \leq \alpha < \log_{\frac{1}{\#C}}\frac{2}{3}$
Relative power	$\frac{1}{2} < \varpi_1 \leq \frac{2}{3}$	$\log_{\frac{1}{\#C}}\frac{2}{3} \leq \alpha < \log_{\frac{1}{\#C}}\frac{1}{2}$
Democratic power	$0 < \varpi_1 \leq \frac{1}{2}$	$\log_{\frac{1}{\#C}}\frac{1}{2} \leq \alpha < 1$

2. Power structure feedback techniques

This section introduced a feedback technique that responds to various power structures requirements. The personalized recommendation for the recognized inconsistent community $v \in ICS$ is represented in eq. (14),

$$r\bar{f}_{ij}^{v} = (1-\delta^v)\cdot\bar{f}_{ij}^{v} + \delta^v\cdot f_{ij}^{G} \quad (14)$$

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Where, $\bar{f}_{ij}^{v}$ and f_{ij}^{G} are the present community v and the collaborative preference values of alternate x_i over x_j respectively. Collaborative preference calculated as a weighed mean of the community preferences as represented in eq. (15),

$$f_{ij}^{G} = \sum_{\varsigma=1}^{\#C} \varpi^{\varsigma} \cdot \bar{f}_{ij}^{\sigma(\varsigma)} \quad (15)$$

The personalized acceptance constants of inconsistent individuals δ^{v} are attained by resolving the below power structure rate optimization represented in eq. (16),

$$\min \sum_{v \in ICS} \sum_{i,j \in v} \delta^{v} \times \left| \bar{f}_{ij}^{v} - f_{ij}^{v} \right| \quad (16)$$

This equation with a parameter α as per Table 1 generate power structure feedback techniques for three various power structures are recognized.

IV. Result

The Amazon real world dataset is rated in the range of [1 to 5], so the rating prediction in recommendation systems theRMSE, MAE, Precision and Recallare used to estimate the performance of the model. The calculation of the RMSE, MAE, Precision and Recallisrepresented in eq. (17) to (20) respectively,

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(r_{ui} - \hat{r}_{ui})^2} \quad (17)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |r_{ui} - \hat{r}_{ui}| \quad (18)$$

Where, r_{ui} and $\hat{r}_{ui}$ represents the actual and predicted value from the user u for item i respectively. n is the number of ratings from the user-item pairs.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (19)$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (20)$$

Where,

- True Positives (TP) – classifies the positive classes.
- False Positives (FP) – misclassification the predicted outcome is “yes” but the actual Outcome is “no”
- False Negatives (FN) – misclassification the predicted outcome is “no” but the actual Outcome is “yes”.

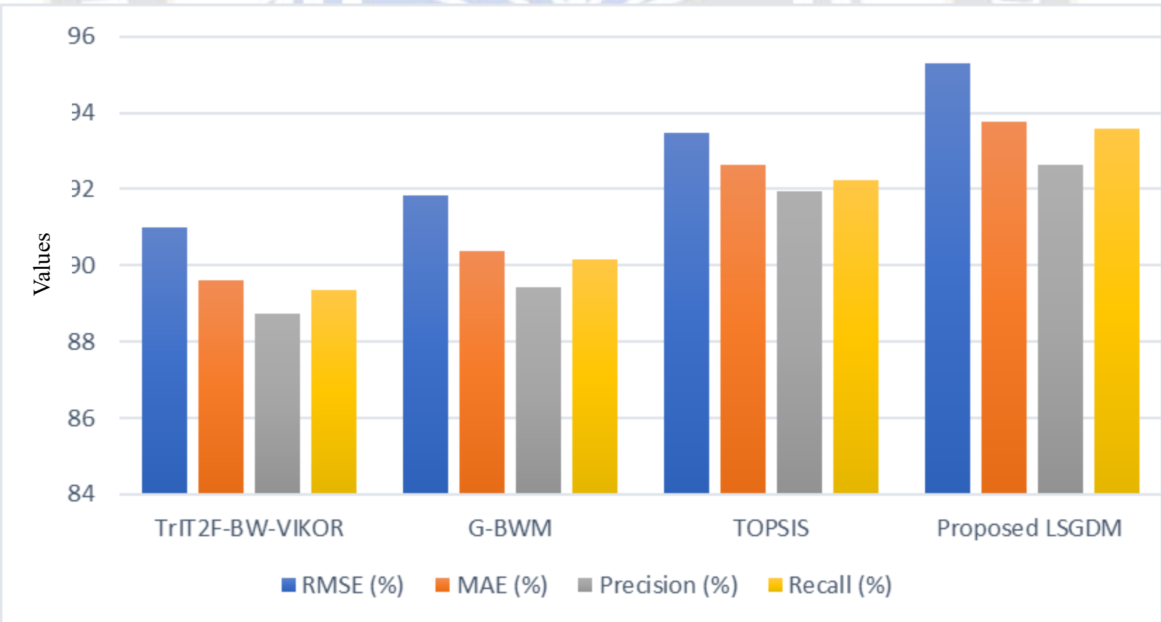

Figure 1. Performance of Amazon real world dataset

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Table 2. Performance comparison with various other algorithms on Amazon real world dataset

Method	RMSE (%)	MAE (%)	Precision (%)	Recall (%)
TrIT2F-BW-VIKOR	90.98	89.61	88.73	89.36
G-BWM	91.85	90.37	89.42	90.14
TOPSIS	93.49	92.64	91.93	92.25
Proposed LSGDM	95.31	93.78	92.64	93.59

Table 2 compares the performance of the proposed LSGDM method with various other algorithms on the Amazon real world dataset. The RMSE, MAE, Precision and Recall of TrIT2F-BW-VIKOR, G-BWM and TOPSIS are measured and matched with the proposed LSGDM method. In this dataset the proposed method has achieved 95.31% of RMSE, 93.78% of MAE, 92.64% of precision and 93.59% of recall. A graphical representation of this proposed method performance is represented in Figure 2.

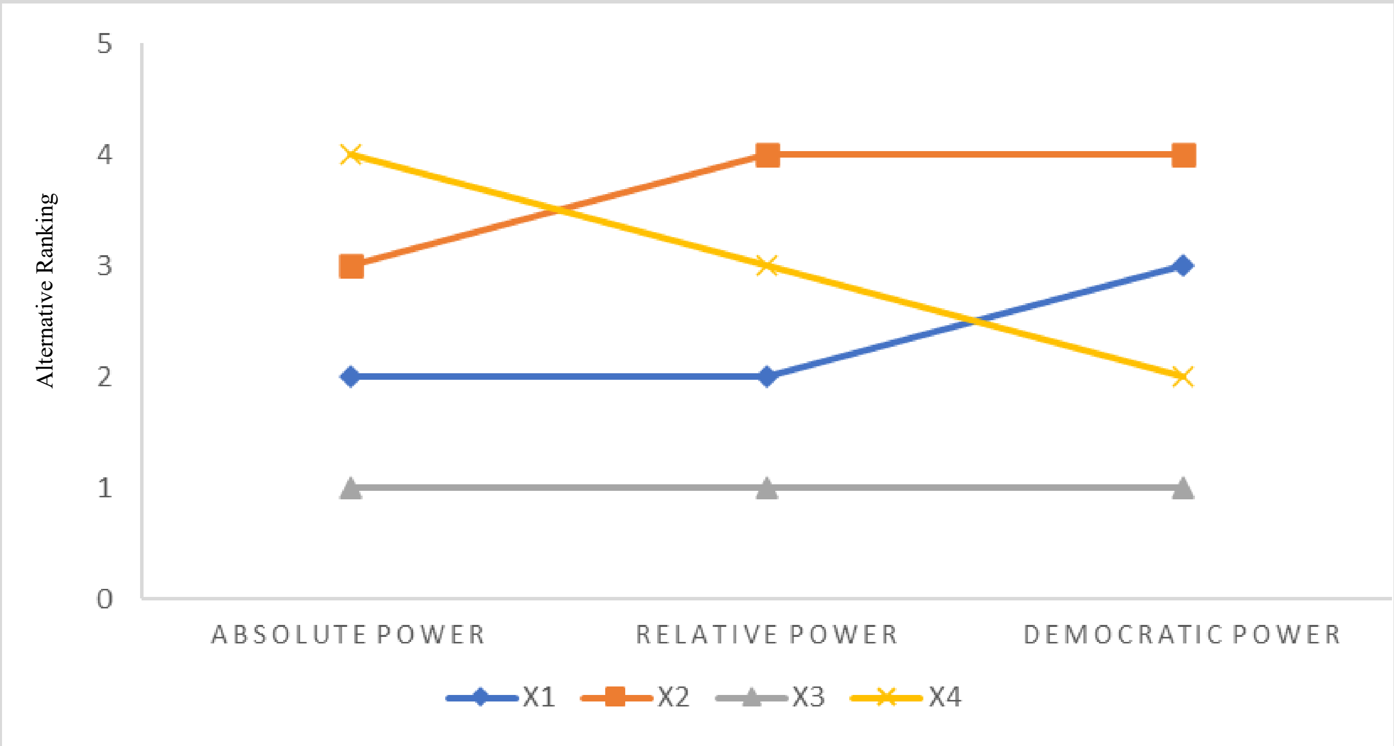

Figure 2. alternative consensus rankingunder three various power structures

Table 3. Alternative consensus ranking under three various power structures

Consensus Ranking	Absolute Power	Relative Power	Democratic Power
X1	2	2	3
X2	3	4	4
X3	1	1	1
X4	4	3	2

Table 3 represents the alternative consensus rankingunder various three power structures cause various group preferences. The one alternative manages its ranking is alternative X3 whereas alternative X4 modify position from 4th to 3rd to 2nd under absolute, relative, democratic power structures correspondingly.

4.1 Comparative Analysis

This section shows the comparative analysis of proposed LSGDM method with various other methods are represented in Table 4. The comparison results of LSGDM method and the existing methods in terms of statistical parameters like RMSE, precision and recall. The existing research such as [10] and [14] are used for evaluating the efficiency of this model. The proposed LSGDM method achieved better performance compared to other existing models.

Table 4. Comparative analysis of proposed method with existing methods

Author	Dataset	RMSE	Precision	Recall
Pengyu Wang *et al.* [10]	MovieLens	1.022	-	-
Ziyu Lyu *et al.* [14]	Foursquare	-	13.79	57.37
Proposed method	Amazon real world dataset	95.31	92.64	93.59

V. Conclusion

The recommendation system is considered as a significant factors of e-commerce domain due to their direct impact on profit. The personalized experiments improve the engagement and the count of purchases of the customer when the recommended products are matched to the current interest. Also, the text information is important for the customer to make the decision on purchase. The proposed method permits an autocratic decision maker to utilize a different group recommendation for a sequence of decisions at highest level of consensus. This manuscript analysis a LSGDM two-stage consensus feedback technique with three various power structures. This paper contains two major contributions, first one is provision bi-level feedback technique is proposed by observingcommunity of internal and external consensus levels. The second one isexecution of power structure to assign the weight to communities.The performance of the model is estimated by applying parameters likeRMSE, MAE, Precision and Recall. The obtained result shows that proposed methodology provides better result while comparing various other methods. In future, the dynamic power structures for decision making and social networks are used for enhancing the model performance.

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