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An enhanced hybridized approach for group recommendation via reliable ratings

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ABSTRACT

A group recommender system aim's to provide relevant information to all members of the group. To determine group preferences, the majority of existing studies use aggregation approaches. An aggregation method is a strategy for recommending products to a group by combining the individual preferences of group members. So far, a slew of different types of aggregation algorithms has been discovered. However, they only aggregate one component of the offered ratings (e.g., counts, rankings, high averages), which limits their ability to capture group members' proclivities. This study proposes a novel aggregation method called weighted count that aggregates ratings by providing weights equal to the number of users who provide ratings to an item (location). In addition, the study proposes combining additive utilitarian and weighted count approaches to highlight popular locations on which group members agreed. Experiments on a benchmark check-in dataset demonstrated that the proposed blended technique surpasses the existing methods significantly.

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1. INTRODUCTION

The explosive growth in technology and tourism has led to the development of location based social networks (LBSNs) and point of interest (POI) recommendation systems. POI, a location based service in LBSNs takes advantage of the location dimension to support social networking [1]. The POI recommendation system recommends places to users based on their behavior or activities. Generally, these POIs may be public places that people often visit, for instance, tourist attractions, hotels, parks, or restaurants, and exclude private locations like homes, and offices.

Most recommender systems recommend items to users individually; however, many times activities like going to a restaurant for dinner, organizing a trip with friends, watching movies, and other similar activities, are performed in a group. For such group pleasures, preferences, priorities, and interests of different group members should be considered. So, group recommendation is an important problem to be focused on for POI recommendation. Moreover, the recommendation task for social groups is more complicated, as it involves a large number of people [2], [3], their relationships [4], and each member's weighted contribution [5]. The first objective of any group recommender system (GRS) is to detect groups based on user choices. Then, the group preferences can be computed either by consolidating the choices of members in a group or by merging individual recommendations as indicated by the organization. In either case, various aggregation methods like summation, and average. Can be utilized to aggregate individual preferences [6]. Group aggregation techniques are broadly categorized as: i) consensus based techniques, ii) majority based techniques, ii) borderline techniques, and iv) dictatorship techniques. Consensus based techniques are the aggregating techniques that employ basic arithmetic calculations such as addition, multiplication, and average, and the popular techniques under this cadre are additive utilitarian (AU) [7]-[10], and multiplicative (Mul) [11], average (Avg) [11]-[17] and average without misery (AwM) [18]. Additive utilitarian totals the individual item ratings to determine group preference, while the multiplicative technique multiplies all the users' ratings to have group ratings. On the other hand, average computes group ratings by averaging individual ratings. Average without misery is a modified version of average in which ratings below a user-defined threshold are not taken into account while calculating the average. These techniques then rank the items and recommend an item that has received the highest ratings. Assuming a group of three users and seven items and let the user-item rating matrix be as defined in Table 1, Consensus Based techniques are illustrated in Table 2.

The consensus techniques are simple to implement and effective. However, they do not always guarantee a group's true taste. The same applies to AU and Mul techniques also. These techniques provide high ratings for items, which have been rated low by most of the members, resulting in the GRS endorsing the item. Furthermore, the overflow problem entails in Mul in case a large number of group members rate an item, then the group rating determined by Mul for the relevant item converges to infinity.

Majority based techniques generate group estimates by applying aggregation strategies to the most popular items. Popular majority based techniques are approval voting [6], [9], borda count [9], [19], plurality voting [18], [20], Copeland rule [18], [21]. Approval voting counts the number of times an item is rated beyond a user-defined threshold value. This helps to avoid the items receiving negative ratings. In BC, items rated by the members are ranked in increasing order for each member, with the lowest rated item receiving a rank of 0. After then, BC adds up all of the rankings for each item. This technique is criticized because of the sorting involved and if the items receiving the same ratings are large, breaking ties is an inevitable process. Another technique to regard the highest rating is the PV method. In the PV technique, the products with the highest ratings for each user are chosen first. As a result, the item with the highest rating from the majority of the group members is chosen as the most favored item. The Copeland rule (CR) is an aggregation technique that recovers the most favored things by taking into account the relative importance of the items based on the group members' evaluations. Tables 3-5 demonstrate BC, PV, and CR approaches respectively.

Table 1. User-item rating matrix

	i_1	i_2	i_3	i_4	i_5	i_6	i_7
Amit	3	1	5	4	-	4	2
Sumit	-	2	4	4	5	3	-
Kushal	4	5	2	2	4	3	3

Table 2. Group aggregation score using consensus based techniques

	i_1	i_2	i_3	i_4	i_5	i_6	i_7
AU	7	8	11	10	9	10	5
Mul	12	10	40	32	20	36	6
Avg	3.5	2.67	3.67	3.3	3	3.3	1.67
AwM	3.5	1.67	3	4	3	4	0
AV	1	1	2	2	2	1	0

Table 3. Group aggregation score using BC aggregation technique

	i_1	i_2	i_3	i_4	i_5	i_6	i_7
Amit	2	0	5	3.5	-	3.5	1
Sumit	-	0	2.5	2.5	4	1	-
Kushal	4.5	6	0.5	0.5	4.5	2.5	2.5
BC	6.5	6	8	6.5	8.5	7	3.5

Table 4. Group aggregation score using PV aggregation technique

	1	2	3	4	5	6	7
Amit	i_3	i_4,i_6	i_6	i_1	i_7		
Sumit	i_5	i_4	i_6				
Kushal	i_2	i_1	i_1	i_1	i_7		
PV		i_4	i_6	i_1	i_7		

Table 5. Group aggregation score using CR aggregation technique

	i_1	i_2	i_3	i_4	i_5	i_6	i_7
i_1	-	1	1	1	0	1	-2
i_2	-1	-	1	1	-1	1	-1
i_3	-1	-1	-	-1	1	-1	-1
i_4	-1	-1	1	-	1	0	-1
i_5	0	1	-1	-1	-	-1	-1
i_6	-1	-1	1	0	1	-	-1
i_7	2	1	1	1	1	1	-
CR	-2	0	+4	+1	+3	+1	-7

Most pleasure [22], [23] and least misery [14], [24] are two prominent examples of borderline strategy. The highest rating given to an item by group members is chosen as the group rating in the MP technique, whereas the lowest rating is selected in the LM technique. A group's choice can also be based on the preferences of a powerful member, for instance, most respected person (MRP) [25] creates a group profile by leveraging the ratings of the group's most important members. Depending on the opinions of a single user while dismissing the opinions of the others in the group is rarely the best aggregation strategy, especially when dealing with larger groups. Moreover, it is debatable which member should be chosen as the esteemed member of a group. Even though multiple GRSs in various domains have been established so far, the best aggregation technique and group size for each scenario are different. To put it another way, there is no single best aggregation technique or group size for all cases.

UL technique proposed by Seo *et al.* [6] is an upgraded aggregation approach that takes into account the distribution of group members' preferences throughout the aggregating process. It accomplishes this by calculating deviations from preferences for an item, then combining them with group scores computed using Avg and AV approaches to estimate ultimate group ratings for the associated item. Logesh *et al.* [26] proposed a novel hybridization strategy for combining recommendations from many recommendation systems to improve recommendation effectiveness, which they tested on Yelp and TripAdvisor's real-time large-scale datasets. The results outperformed both standalone and baseline hybrid techniques.

IBGR as devised by Nozari and Koohi [27] is a new method for recommending movies to groups that takes into account the social interactions between group members throughout the aggregate process. This method calculates the similarity and trust among users to determine the influence of group members on one another. The Avg approach is then used to weight the preferences of the people.

ECOagg is a new aggregation approach proposed by Ismailoglu [28] for GRSs. They devised a crowdsourcing-based aggregation method for estimating group members' expertise levels. By introducing a new concept called users' spatial ratio in a group vectors and using a 2D kernel density estimate approach, Sojahrood and Taleai [29] constructed a new geographical model based on the check-in behavior of the group in location-based social networks to improve group recommendations.

As suggested by Yalcin *et al.* [30] to hybridize aggregation techniques, base techniques should be chosen keeping in view the expectations from the aggregation strategy to be constructed [30]. Focused on achieving group consensus and suggesting items that are popular among the majority of the members. As a result, they combined AU and AV. Every member having an opinion on a subject can participate in the group's decision on that subject through AU. The number of times an item is rated beyond a user-defined threshold value is counted in approval voting. This reduces the likelihood of negative feedback on the items.

Different authors have suggested various ways of hybridization and aggregation [31] and have utilized multiple aggregation strategies like Avg, AV, AU. However, each of these has its own limitations. AU and Avg do not always guarantee a group's true taste. In AV excluding all ratings below a threshold, on the other hand, makes it difficult to discern the true sentiment about a product.

Therefore, to overcome the shortcomings of previous aggregation techniques for group recommendation, weighted count (WC) has been proposed. The proposed WC technique differs from AV in the sense that it revolves around all the ratings provided by the users to different items and utilizes a weighted approach to identity popular items among a group of users. AV, however, ignores the poor rating provided by users.

A new variant of aggregation strategy, with AU and WC as the foundation techniques is also proposed. Theproposed hybridized technique enables featuring popular items where a consensus is reached and to achieve synergy in overcoming flaws of mentioned aggregation strategy. The main contributions of this paper are:

a) The limitations of the classic aggregation approaches used for group recommendation tasks are examined while aggregating individual preferences.
b) A novel hybridized aggregation technique is presented that effectively combines weighted count and additive utilitarian method to provide more reliable group recommendations.
c) The proposed technique is applied to a vast LBSN Dataset and empirically evaluated.

2. MATERIAL AND METHOD

This section describes our group recommendation scheme, which consists of two basic processes, as shown in Figure 1. The first process creates user groups from individual user preferences. The later process presents a unique aggregation that determines the rating for a group, to recommend top-N items.

Recent researches show a drift towards the identification of similar user groups automatically [32]. Recognizing groups automatically is advantageous as it reflects changing user interests over time, and is also easier to implement rather than manual group identification. Proposed work has adopted clustering methods like k-means [3], [9] and hierarchical algorithms [33], as these are simple and efficient methods. The goodness of created clusters is measured using silhouette analysis, and the appropriate number of clusters is determined using the silhouette score. Silhouette score can be computed as shown in (1)

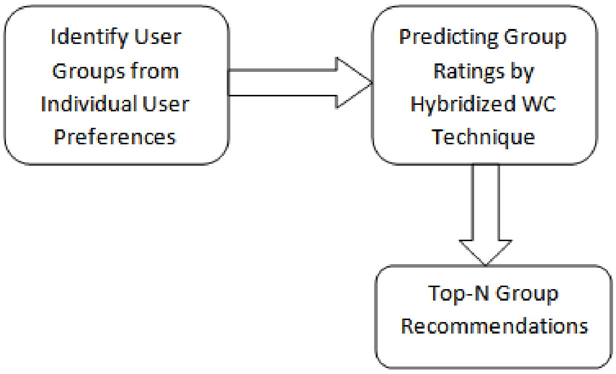

Figure 1. Group recommendation process

$$silhouette\ score = (p - q)/\max(p, q) \tag{1}$$

Where, p denotes mean distance to the points in the nearest cluster and q is mean intra-cluster distance to all the points. The silhouette score varies from -1 to +1, with:
- 1 indicating that clusters are well separated and distinct.
- 0 denoting unrelated clusters or that the distance between them is insignificant.
- -1: clusters were wrongly assigned.

Silhouette score values for our experiment were ranging from0.5 to 6.5 for 6 clusters formed using k-means clustering and 0.7 to 6.3 for 3 clusters formed using hierarchical clustering, implying the suitable number of clusters would be 6 for k-means and 3 for hierarchical clustering. In weighted count (WC) the popular items among a group of members are identified by counting the number of times an item is rated j by n number of users and then applying the weighted concept for finding the actual count. Here, weights are the number of users n providing rating value j to item i. Let us elaborate using an example. The weights are positive for a rating above a defined threshold, otherwise, weights are negative. WC of item i4 is (4*2+2*(-1))/3, where for rating value 4 weight is 2 equal to the number of users who have provided rating 4 and for rating 2 weight is -1 as 1 user voted below or equal to the threshold (3 in this case). Mathematically, it is shown in (2). Table 6 shows the group aggregation score generated using WC aggregation technique.

$$\mathrm{WCg,i} = \sum_{i=i}^{n}(w_r * r_{u,i}) / \Sigma i \tag{2}$$

Where, w_r is the weight of the rating r, $r_{u,i}$ is the rating value provided by user u to item i.

Table 6. Group aggregation score using WC aggregation technique

	i_1	i_2	i_3	i_4	i_5	i_6	i_7
Amit	3	1	5	4	-	4	2
Sumit	-	2	4	4	5	3	-
Kushal	4	5	2	2	4	3	3
WC	0.5	0.66	2.33	2	4.5	-0.66	-2.5

Group ratings are computed by taking into consideration (i) the sum of group members' preferences (achieved through AU) and (ii) the score of popular items (achieved by employing WC). The hybridized technique comprises AU as propelling force, and WC is an added factor to determine final group ratings, as defined in (3) and pseudocode is described as psuedocode1.

$$R_{g,i}^{AUWC} = AUg,i + (AUg,i * WCg,i) \tag{3}$$

Where, $AU_{g,I}$ and $WC_{g,i}$ represent rating for group g on item i estimated by AU and WC methods, respectively.

Pseudocode1: Generation of Group Aggregation score using hybridized AU_{WC} Aggregation
Input: User-Item rating matrix
Output: Group Aggregation score

```
FOR each item i in {1,2,3,4,…..N}
        FOR each unique rating ru,i
                count number of users providing rating r to item i
                IF  ru,i>3:
                        wr=count(ru,i).
                ELSE
                        wr=-count(ru,i)
                ENDIF
        ENDFOR
ENDFOR
Compute Group score WCg,i  using (1).
Compute Group score AUg,i by adding all ratings of item i.
Compute R_{g,i}^{AU_wc} using (3).
```

3. RESULTS AND DISCUSSION

In this section, we examine the accuracy, fairness, and satisfaction of the proposed aggregation approaches on the acquired LBSN dataset, and important observations that are deduced from the empirical results. The experiment has been performed on the New York City (NYC) dataset published by [34] containing 227,428 check-ins in New York City is utilized. The dataset consists of user preferences on venues denoted as check-ins. The dataset statistics are described in Table 7.

Table 7. NYC dataset statistics

Attributes	Count(nos)
Users	824
Venues	38,336
check-ins	227,428
Average number of activity categories per user	38.37

Five-fold cross-validation has been used to assess the performance of the proposed group recommendation mechanism. To do this, the set of locations was partitioned into five subsets at random, with each subset containing roughly 20% of the total locations. To create groups, we used the k-means and hierarchical clustering algorithms, and the silhouette measure has been applied to perform cluster analysis. Six groups were produced using k-means and three groups were formed using hierarchical clustering, according to the silhouette coefficient. The proposed technique has been compared with popular methods of group recommendation on metrics like nDCG and scores have been computed as defined in (4).

$$nDCG_N^u = \frac{DCG_N^u}{IDCG_N^u} \tag{4}$$

Fairness difficulties in group recommendation have been addressed by various researchers [35], [36]. Given that the proposed aggregation strategy attempts to satisfy all group members equally, their fairness performance must be assessed. We use m-proportionality [37] as defined in (5). In (6) defines the computation of GSM for a group g.

$$fairnessm - prop(g) = |gN|/|g| \tag{5}$$

$$\text{GSMg} = \sum_{u \epsilon g} \left| \frac{I_u \cap N}{|g|X|N|} \right| \tag{6}$$

3.1. Evaluation of AU_{WC}

A broad set of experiments have been conducted with created user clusters and different sizes of recommendation list (N) to see how well the proposed hybridized aggregation AU_{WC} technique predicts group ratings. Tables 8 and 9 present the cluster information formed using k-means and the hierarchical clustering technique. In addition, the result of these trials to ten baseline aggregation procedures for the NYC dataset has been shown in Table 10. Based on the nDCG results derived from the NYC dataset. It has been demonstrated that the WC, AU, and AV, BC approaches perform relatively better than the other baseline techniques.

Table 8. K-means clusters

Cluster	No of users/Cluster
0	26,530
1	11,345
2	21,600
3	24,798
4	123,650
5	5,640
6	13,865

Table 9. Hierarchical clusters

Cluster	No of users/Cluster
0	41,460
1	155,324
2	30,644

Table 10. *n*DCG scores (NYC dataset)

Top-N	Aggregation technique	Clustering technique	
		K-means	Hierarchical clustering
1	AU	0.773	0.769
	Mul	0.736	0.730
	AV	0.784	0.781
	Avg	0.742	0.740
	AwM	0.734	0.731
	BC	0.785	0.780
	CR	0.763	0.757
	LM	0.736	0.729
	SC	0.738	0.732
	MP	0.736	0.731
	AU_{AV}	0.797	0.794
	AV_{AU}	0.784	0.779
	WC	0.812	0.795
	AU_{WC}	0.817	0.813
3	AU	0.768	0.765
	Mul	0.734	0.729
	AV	0.773	0.773
	Avg	0.740	0.737
	AwM	0.734	0.734
	BC	0.782	0.779
	CR	0.759	0.753
	LM	0.734	0.730
	SC	0.740	0.737
	MP	0.739	0.735
	AU_{AV}	0.795	0.793
	AV_{AU}	0.777	0.774
	WC	0.799	0.795
	AU_{WC}	0.817	0.812
5	AU	0.764	0.763
	Mul	0.728	0.727
	AV	0.769	0.764
	Avg	0.744	0.741
	AwM	0.730	0.729
	BC	0.778	0.776
	CR	0.757	0.752
	LM	0.726	0.721
	SC	0.737	0.734
	MP	0.741	0.738
	AU_{AV}	0.796	0.791
	AV_{AU}	0.781	0.785
	WC	0.798	0.799
	AU_{WC}	0.810	0.806
10	AU	0.761	0.760
	Mul	0.731	0.731
	AV	0.769	0.764
	Avg	0.745	0.745
	AwM	0.730	0.727
	BC	0.775	0.773
	CR	0.755	0.749
	LM	0.727	0.722
	SC	0.739	0.736
	MP	0.745	0.742
	AU_{AV}	0.797	0.794
	AV_{AU}	0.780	0.778
	WC	0.799	0.795
	AU_{WC}	0.812	0.810

Experiments on datasets also show that AU, AV, BC, CR, AU_{AV}, AV_{AU}, WC, AU_{WC}, and SC approaches perform better for K-means clusters. Furthermore, practically all aggregation strategies appear to be less significant as N (recommended items) expands, owing to diminishing nDCG scores. Table 11 shows the comparison of the proposed technique wrt *n*DCG scores with benchmark group aggregation techniques such as IBGR, and UL.

Table 11. Comparison of *n*DCG scores (NYC dataset) of AU_{WC} against benchmarks IBGR, UL

Top-N	Aggregation Technique	No. of Clusters	
		3	6
1	AU_{WC}	0.839	0.831
	IBGR	0.819	0.808
	UL	0.828	0.824
3	AU_{WC}	0.839	0.830
	IBGR	0.811	0.803
	UL	0.820	0.812
5	AU_{WC}	0.833	0.830
	IBGR	0.801	0.799
	UL	0.809	0.805
10	AU_{WC}	0.834	0.827
	IBGR	0.729	0.719
	UL	0.801	0.728

3.2. Investigation of fairness score

Additional trials have been conducted to provide a thorough inspection of the proposed AU_{WC} technique's performance in terms of fairness and satisfaction. We compared its performance to state-of-the-art techniques such as AU, AV, AwU. We investigate groups created using k-means and hierarchical clustering. Finally, we experiment with m values ranging from 1 to 5 to see how these values affect the fairness score.

The fairness and GSM scores of the proposed approach and compared techniques on the NYC dataset are presented in Tables 12 and 13. The tables show scores for the top-5 locations for group recommendation. Based on the findings, it can be concluded that the suggested hybridized AU_{WC} methodology generates group suggestions with a higher level of fairness than baseline methods. The results also show that when the value of m increases, the fairness scores of all strategies fall. According to the findings, AU_{WC} technique considerably improves group member satisfaction, especially when groups are large or medium in size.

Table 12. Fairness scores of top-5 group recommendations for NYC dataset

	K-means clustering M					Hierarchical Clustering M				
Aggregation Method	1	2	3	4	5	1	2	3	4	5
AU	0.872	0.742	0.601	0.428	0.198	0.756	0.731	0.578	0.422	0.196
AV	0.875	0.758	0.613	0.436	0.220	0.866	0.737	0.572	0.420	0.223
IBGR	0.881	0.762	0.612	0.449	0.227	0.869	0.736	0.578	0.423	0.221
UL	0.879	0.762	0.609	0.442	0.226	0.864	0.736	0.574	0.421	0.222
AwU	0.904	0.779	0.631	0.460	0.242	0.871	0.732	0.600	0.415	0.219
AU_{WC}	0.906	0.795	0.656	0.471	0.247	0.872	0.736	0.605	0.423	0.242

Table 13. GSM scores of top-5 group recommendations

Aggregation technique	Groups	
	K-means clusters (6)	Hierarchical clusters (3)
AU	0.777	0.767
AV	0.793	0.784
IBGR	0.795	0.789
UL	0.792	0.782
AwU	0.827	0.820
AU_{WC}	0.833	0.825

3.3. Analysis and discussions

In the study, it has been observed that hybridized aggregation approaches, AU_{WC}, AV_{AU}, AU_{AV}, and AwU, produced the greatest nDCG scores when compared to the other baseline procedures, as predicted.

This is due to the fact that using several aggregation approaches helps to overcome the drawbacks of the basic procedures and solves the challenge of aggregating people's preferences from numerous perspectives. AU_{WC}, in particular, outperforms the other two hybridized techniques, AU_{AV} and AV_{AU}. Experiments on the NYC dataset revealed that AU_{WC} is the most effective aggregating approach, even for huge groups. The proposed approach is robust and is independent of group size and the range of items to be recommended.

4. CONCLUSION

Aggregation techniques are mathematical methodologies that aggregate individual group members' preferences or approximated forecasts to recommend products to a group. We propose in this paper to use a combination of aggregation strategies to solve the POI recommendation problem for a group of users. To this goal, we propose the weighted count aggregation technique that counts the popularity score of items among a group of members by associating weights (+ve or –ve) to the items based on the number of users' that rate an item above or below a defined threshold. We employ a combination of additive utilitarian and weighted count to give items on which group members established a consensus.

Experiments on popular LBSN dataset has been conducted on groups formed by employing popular clustering strategies. The results revealed that the proposed AU_{WC} beat popular baseline and benchmark aggregation strategies in terms of item appropriateness when recommending groups. Although the proposed technique outperforms other techniques, it can be strengthened by considering the social relations and trust factor in the future.

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