Similarity based Aggregation Strategy for Group Recommendations

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Abstract: Internet has so much information and become a data source for us. If a user desires to go looking for data on the web, he just gets information from internet sources and search engines like Google but that contains both desirable and non-desirable information, so for that purpose a Recommender System was created to solve that problem of searching. It considers user requirements, interests and explores information that targeted user looks for. The Recommender System has become famous topic of research for past few years. At first all the studies have mainly concentrated only one user suggestions. Recently the Group Recommender Systems have paid attention to suggestions of a group of users as in few cases the products to be suggested are not only for one user but for a group of users. For example, a DVD could be visually examined by different users in a group of family members. The current research has labeled the query of initializing advises of different members of a group and that is to satisfy the distinct preferences of all the group members as much as possible. This paper we discuss at Existing Aggregation strategies favors the opinion of that group member who gets extreme rating (either very high or very low). For Example, a group has three members, two of them have given 3 rating on a particular item and one of them has given 1 rating than according to the average aggregation strategy the group rating will be approximately 2 which means group members dislike the item however if we consider their individual rating than two members from the group of 3 members actually like the item but only for one member the low rating is considered as dislike. Finally, if we consider the problem of ratings or recommendations, it requires more extension and needs to be improved for that here we use RMSE as evaluation matric One characteristic of the RMSE is that it tends to disproportionately penalize large errors because of the squared term within the summation in result it will be get appropriate results.

Keywords: *Recommender system; Group recommendation; Collaborative filtering; Aaggregation strategy*.

1. Introduction

Recommender Systems are software tools implemented for user suggestions as we learnt that every software must have some sort of input and output. And in order to gain output something going to be processed between input and output, i.e. so in recommender system input is user and output is different recommendations that recommend by any recommender system. Different algorithms and aggregation strategies are going to be processed between that user and recommendations. These are the systems that help select out similar things or items whenever you select something online.

As the Internet has so much information that was overloaded, so if a user wants to search information on the internet, he just gets information from internet sources like google.com so for that purpose a Recommender system was created to solve that problem of searching. It considers user requirements, interest and explores information that targeted user looks for. The information can be in form of activities, products and contents. In e-commerce applications recommender system technology is vastly utilized, such as by Amazon as a practical business implement [1]. Furthermore, explaining in real life social examples like Netflix will recommends other movies that user might want to watch. Pandora will recommend different songs that user might want to listen.Amazon.com will recommends what kind of another products user want to buy. Facebook will even suggest some of other friends that a user want to add. Each of these systems operates using the same kind of algorithm. Basically, these algorithms are surprisingly big business in the world of user recommendation suggestions.

There are three basic kinds of algorithms that are at play when we talk about generating recommendations. In recommender systems the widely used technique is collaborative filtering. It gives recommendation based on the items relished by other users possessing homogeneous taste to that of the target user [1,3].

Second frequently used technique in recommender system is Content-based filtering which gives suggestions of another item that has similar contents of that item liked by user previously.

Third most widely used technique in recommender system is called hybrid approach which is combination of both aforementioned techniques and is commonly used in actual applications [1,2].

The Recommendation system has become famous topic for research at the past few years. So, at that time all the studies have mainly concentrated only one user suggestions. Recently the group recommender systems have paid attention to suggestions of a group of users. However, in few cases the products to be suggested are not only for use of the one user but for a group of users. For example, a DVD could be visually examined by different users in a group of family members. The current research

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has labeled the query of initializing advices of different members of a group and that is to satisfy the distinct preferences of all the group members as much as possible. Group recommendation approaches based on collaborative filtering algorithms and aggregation strategies. Aggregation strategies are basically aggregation of every group members in a group. Group recommendation techniques are based on aggregation strategies and approaches. Here two approaches can be take place while make recommendations of any particular group.

(i) Aggregating the both user preference as well as the individual user of the group and then making different recommendations with the help of single group recommendation.

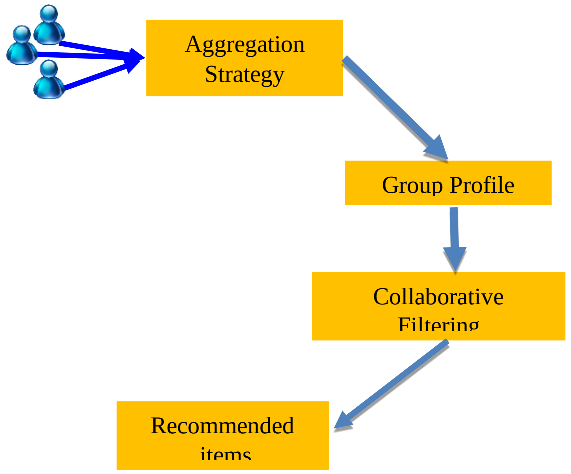

Figure.1. *Aggregation Preferences of Group Members*

(ii) It makes a recommendation list of all group members, and then it aggregates user recommendation obtained by gathering the recommendations of each group member which is made by the system itself [1-8].

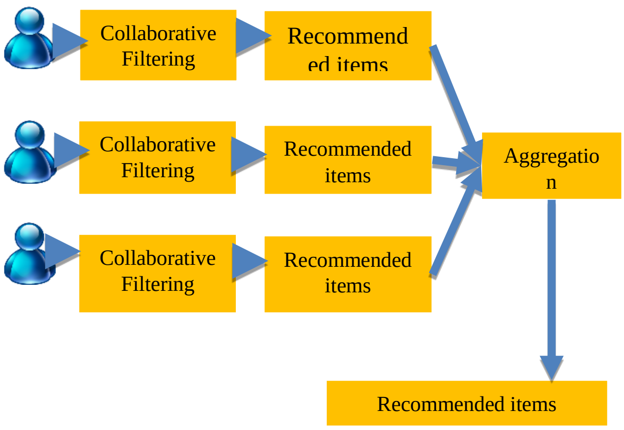

Figure.2. *Aggregating Recommendations Lists of Group Members*

Our research manly focuses on aggregation strategies. Aggregation strategies favor only one extreme rating (either very high or very low). Every group member has their individual expectations for that there are Four Aggregation Strategies:

(i) **Least Miserly**: Group rating is computed by taking the minimum of individuals' member's ratings

(ii) **Most Pleasure**: Group rating is calculated by preceding the maximum of individuals members ratings

(iii) **Average**: Group rating is computed by taking the average of individual members rating.

(iv) **Weighted Average**: It has same concept like average strategy only difference is that each member is assigned a weight.

1.1 Aggregation Strategies Examples

When presenting each strategy, we have to use following example:

3 users (u1, u2, u3)

3 items (i1, i2, i3)

Each element of the table represents a rating (1 to 5)

Table.1. Aggregation Strategies

Group Members	i1	i2	i3
u1	5	5	4
u2	4	5	3
u3	1	1	2

❖ G=(U_1, U_2, U_3); r_{G,I_1}=??

Least Miserly

G=(U_1, U_2, U_3); r_{G,I_1}=2

Most Pleasure

G=(U_1, U_2, U_3); r_{G,I_1}=4

Average

G=(U_1, U_2, U_3); r_{G,I_1}=3

Weighted Average

G=(U_1, U_2, U_3); r_{G,I_1}=3

2. Related Work

An outstanding and magnificent quantity of work in the field of group recommendation system has been done. The research work in this field of study is actually based on collaborative filtering by considering some accumulated strategies and traditional approaches has been additionally focused by evaluation studies. Relating to the current period of time, group recommendation approaches in consequence of substantial experiments, in order to examine their performance and to have knowledge of the positive and negative effects of each approach.[6]

Here, Author represent a novel approach through these effective recommendations of a group with group sizes are computed. They first represented a model that describes relationship between number of users and number of items using a bipartite graph from particular ratings in a group. And they analysis various aggregation strategies and found that average perform better than others.[1]

Gediminas Adomavicious with others discussed many new limitations and extensions of recommender system that help to get more accurate results.[2]

Fernando Ortega and other proposed a method uses matrix factorization based on collaborative filtering to compute different group recommendations and map a set of users of a particular group and compare their proposed methods by three approaches and sizes of a group using small, medium and large they done analyses through group sizes and matrix factorization based on collaborative filtering to get best recommendations.[13]

Reference [11] proposes a new system called Item-network-based on user collaborative filtering they present four types of steps to compute different recommendation, first they make to implement that system named item-network-based-user that construct different items individually based on users feasibility that what user actually going to purchase second that system has an option to auto calculating users history that what he purchased and in third step that system uses closeness and degree some centralized point of users secured items previously and in last step that system item-network-based-users generates different recommendations based on prediction score.

3. Methodology

In this section the methodology is described briefly into four steps.

- Proposed approach
- Implement that proposed approach
- Perform experiments on real world data set
- Compare with comparatives analysis

3.1 Proposed Approach

In this section here describing that how algorithm work and proposed an Aggregation Strategy that aggregate all user rating and make one. The main purpose of this approach is to make accurate recommendations as much as possible. These are the symbols used in proposed approach.

A group recommendation approach aims to make group recommendations as accurate as possible for most of the group members. The accuracy of group recommendation approach depends on the aggregation strategy.

Aggregation strategy either aggregates group members' given ratings or the predicted ratings on unrated items. All the users in a group rate the items individually.

Table.2. *Symbols*

Symbol	Description
R	Sparse rating matrix of size m×n
m	Number of users
n	Number of items
U	Set of User IDs
I	Set of item IDs
$r_{u,i}$	Rating of user *u* on item *i*
$\bar{r_u}$	Average rating of u.
$\hat{r_{G,i}}$	Predicted rating of group *G* on item *I*
$\|G\|$	Total numbers of group members
sim(u,v)	Similarity score between two users *u* and *v*
Sim(G,u)	Average similarity score of user *u* with users in group *G*

In this paper we propose that if a user is highly similar (in terms of preferences) to other group members. Those users' ratings should be given more weightage for the aggregation of ratings.

Example, recommendations need to be made for a group that contains four members. Three of them like comedy movies (i.e., they provide high ratings on comedy movies). One of them does not like comedy movie (i.e he/she provides low rating on comedy movie)

Mathematically,

$$\hat{r_{G,i}} = \sum_{u \in G} \frac{\boldsymbol{sim(G,u).r_{u,i}}}{|\boldsymbol{G}|}$$

3.2 Implement that proposed approach

Here similarity score $\boldsymbol{sim(G,u)}$ is average similarity of all group members. Similarity scored measured individually of all users. Similarity score between two users $\boldsymbol{sim(u,v)}$is computed by using PCC Pearson correlation coefficient. Similarity score between two users' (i.e., between their ratings) is computed using PCC.

$$\boldsymbol{sim(u,v)}= \frac{\sum(\mathbf{r_{u,i}} - \bar{\mathbf{r_u}})(\mathbf{r_{v,i}} - \bar{\mathbf{r_v}})}{\sqrt{\sum(\mathbf{r_{u,i}} - \bar{\mathbf{r_u}})^2} \times \sqrt{\sum(\mathbf{r_{v,i}} - \bar{\mathbf{r_v}})^2}}$$

When we have to calculate $sim(u,v)$ And then all weighted values computed in $sim(G,u)$ Here Pearson correlation coefficient is used for computation. As Pearson correlation coefficient has summation of $\boldsymbol{r_{u,i}}$ rating of user *u* on item *I* minus Average rating of u multiplied by other users rating minus average rating after this both users' summation divided by their square roots.

Here Pearson correlation coefficient PCC computed average strategy but we have to compute simavg, so an evaluating matrix is used for that purpose that is RMSE (root-mean-square-error) through RMSE we get actual ratings.

The *RMSE* is in units of ratings, rather than in units of squared ratings. The *RMSE* was used as the standard metric for the Netflix Prize contest.

One characteristic of the *RMSE* is that it tends to disproportionately penalize large errors because of the squared term within the summation.

$$\boldsymbol{RMSE} = \sqrt{\frac{\sum_{u,i \in E}(\widehat{r_{ui}} - r_{ui})^2_{ui}}{|\boldsymbol{E}|}}$$

RMSE used to implement the approach that was $\hat{r_{G,i}}$

RMSE computed errors. Our approach get more accurate results when RMSE is less.

3.3 Perform experiments on real world data set

Here we use a data set "Movie Pilot dataset, released in 2011" it consists of two sets one is training set other is testing set. They both has data that contain numbers of users, numbers of user groups, numbers of ratings and numbers of items. Here we use only three groups for getting results because our dataset contains only three groups that are group size 2, group size 3 and group size 4. group size 2 a group contain two users, group size 3 a group contain three users etc.

3.4 Compare with comparatives analysis

Here we compare our proposed approach with other competitors that are four aggregation strategies described previous section. Least miserly and Most pleasure take extreme rating either very high or very low is not good for user to get results, whereas the Average and Weighted average is better for measuring actual accuracy but just better not good as desired.

Our proposed approach $SimAvg$ consider good one because it consists likeness and dislikeness of users. It uses group members Similarity if Similarity score is high then ratings also high if Similarity score is low then ratings also low.

4. Results and Discussion

Before discussing Results firstly here again describing Group recommendations approaches:

(i) Aggregating all user's preference as well as the individual user of the group and then making different recommendations with the help of single group recommendation and

(ii) It makes a recommendation list of all group members, and then it aggregates user recommendation obtained by gathering the recommendations of each group member which is made by the system itself.

Our results are satisfying these both approaches.

4.1 Aggregating preferences of group members

Here in this Figure.3. at x-axis there are four aggregation strategies least miserly LM, most pleasure MP, average AVG and weighted average Wavg including SimAvg that is proposed approach. At y-axis represents RMSE root mean square error values and at z-axis represents three groups group size 2, group size 3 and group size 4. Only these three groups we use to apply experiments because our data set contain only these three groups.
Here if we consider to RMSE values, if RMSE value increased then rating accuracy decreased, so here it is clear that RMSE value basically inversely proportional to our rating accuracy that we are going to compute that's why we consider low RMSE value. Consider SimAvg this approach has low RMSE value for that we got accurate recommendations of all three groups.

4.2 Aggregating recommendations lists of group members

Here aggregation strategy aggregates the recommendation list of group members that's why if we consider here, we get highest RMSE values, all aggregating strategies least miserly, most pleasure, average, weighted average and proposed one we get highest RMSE value here. SimAvg also has highest value but when comparing their competitors SimAvg is better from all other four strategies. (Figure.4.)

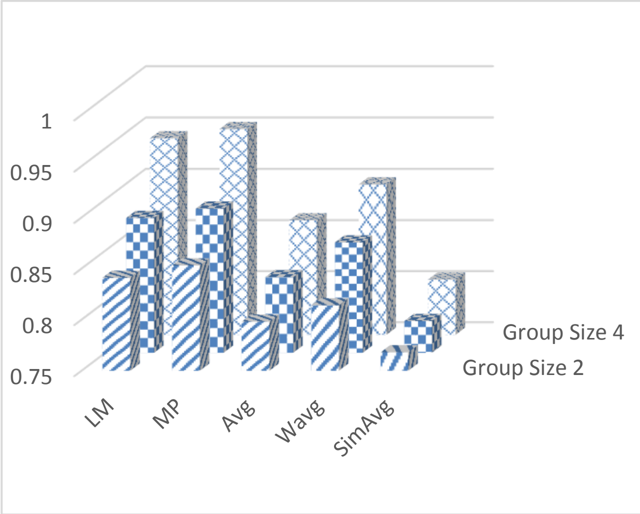

Figure.3. Aggregating preferences of group members

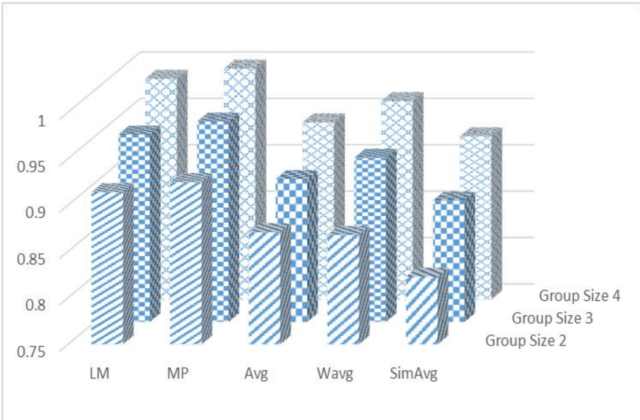

Figure.4. Aggregating recommendations lists of group members

5. Conclusion

This paper proposed an aggregation strategy as form of proposed approach that computes similarity score to get accurate results. Here we discuss that both approaches of group recommendations are firstly preference of aggregating group members then applying user based collaborative filtering and make recommendations and secondly aggregation recommendations lists of all users and individually applying user based collaborative filtering then make recommendations so from these both approaches here experimentally described that first one has getting more accurate results as compare second one. So, it's clear that first aggregate all users then applying user based collaborative filter is much clearer results, because it uses group member's similarity first likeness and dis-likeness of user preference. Here also comparing all aggregation strategies that average aggregation strategy also has better results previously research relies on average strategy but here through this research SimAvg get clear accuracy of all recommendations for you to begin to format your paper, first write and save the content as a separate text file. Keep your text and graphic files separate until after the text has been formatted and styled. Do not use hard tabs, and limit use of hard returns to only one return at the end of a paragraph. Do not add any kind of pagination anywhere in the paper.

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