International Journal of Advanced Technology and Engineering Exploration, Vol 9(93)
ISSN (Print): 2394-5443 ISSN (Online): 2394-7454
http://dx.doi.org/10.19101/IJATEE.2021.875768

Research Article

Entropy for item inclination in sub-community based recommender system

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Received: 09-April-2022; Revised: 22-August-2022; Accepted: 25-August-2022

Abstract
To overcome the new user cold-start problems in collaborative filtering, an innovative framework has been propsed that used entropy for item inclination in sub-community-based recommender system (EISR). It administered demographic filtering on user and item attributes for finding similar users and applied collaborative filtering on rating preferences. The proposed framework leveraged the advantages of traditional group aggregation strategies for delivering good quality recommendations using item preferences of the members of a refined group detected using two-tier approach. At Tier-I, user communities were detected using demographic attributes, which were decomposed into discernible sub-communities by exploiting the item preferences of users. A novel entropy-based hybrid group aggregation method called pragmatic propensity was used to combine the item preferences of members of these sub-communities. Also, experiments conducted using the MovieLens and Book-crossing datasets revealed the better quality of recommendations and the comparison with other algorithms confirmed the effectiveness of the proposed framework.

Keywords
Group recommender systems, Cold start problem, Community detection, Social network, Entropy, Item inclination, collaborative filtering, Demographic filtering, Group aggregation strategies.

1.Introduction
Machine learning (ML) entails self-learning via data usage and experience [1]. It requires no human intervention to uncover patterns in data [2]. Recent work in this area includes classification of liver tumours [3]; extraction of clinical attributes from the breast cancer dataset [4]; prediction of student performance [5]; accurate recognition of complex physical human activity acquired using body-worn sensors [6]. Recommender system (RS) is also an exciting application of ML for suggesting relevant items to a user [7]. ML driven recommendation engines [8] have become ubiquitous in the last few decades. Intelligent web engines have crept in everywhere, recommending everything from movies, songs, food, social media posts to anything conceivable. Unconsciously, everybody is following these recommendations. The apparent reasons are convenience and satisfaction; else, dealing with a profusion of information on the web is quite cumbersome.

Famous online service providers like Facebook, Netflix, Spotify, Amazon, and LinkedIn use recommendation engines to boost sales and enhance customer satisfaction by utilising data filtering techniques of underlying RS [9].

RS uses traditional filtering techniques [10, 11] viz. collaborative filtering (CF), content-based filtering (CbF), demographic filtering (DF), and knowledge-based filtering (KF), along with hybrid filtering techniques that combine the benefits of former techniques [12]. Liao et al. have found that users trust systems that use CF for recommendation over those using CbF or DF and have given pointers for solving cold-start problems [13]. CF is the most sought-after technique that collects users' preferences and predicts their interests. However, unfortunately it suffers from cold-start problems (non-availability of preference information for the new user/item). Recent research points towards the inclusion of user demographic attributes (age, gender and location) to abate these problems [14]. Recently, González et al. have also utilized demographic information to evaluate the bias and unfairness of recommendations given to the minority groups [15].

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In light of this, an innovative hybrid approach has been proposed using DF on user and item attributes for finding similar users and subsequently, applying CF on rating preferences to generate recommendations.

1.1Objective

People have an innate gregarious instinct; therefore, providing recommendations based on the choice of like-minded users of a group makes more sense. A group recommender system (GRS) identifies groups of similar-taste users (neighbours or mentors), estimates the most agreeable group for a new user, and generates appropriate recommendations from the cumulative preferences of the group members [16]. The framework of a GRS consists of two components viz. online group identifier (On-GI) and offline group recommender (Off-GR) as shown in *Figure 1*. Component Off-GR runs offline and is composed of two sub-components, viz. group constructor (GC) and group aggregator (GA) to pre-compute the group recommendations for the new user. Component On-GI delivers top-N group recommendations to the new user in consultation with component Off-GR based on demographic attributes gathered from the registration data of the new user. Finally, On-GI displays the aggregated group recommendations for the new user. Following are the three crucial steps performed by a GRS:

a. Clustering of users with similar taste into groups by GC. Users'taste is defined by rating preferences, user attributes, and/or item attributes. Each group represents the nearest neighbour group (NNgp) of users.
b. Aggregation of user preferences in NNgp by the GA to compute group recommendations for the new user.
c. Identification of promising nearest neighbour group (PNNgp) by online component On-GI for item recommendation.

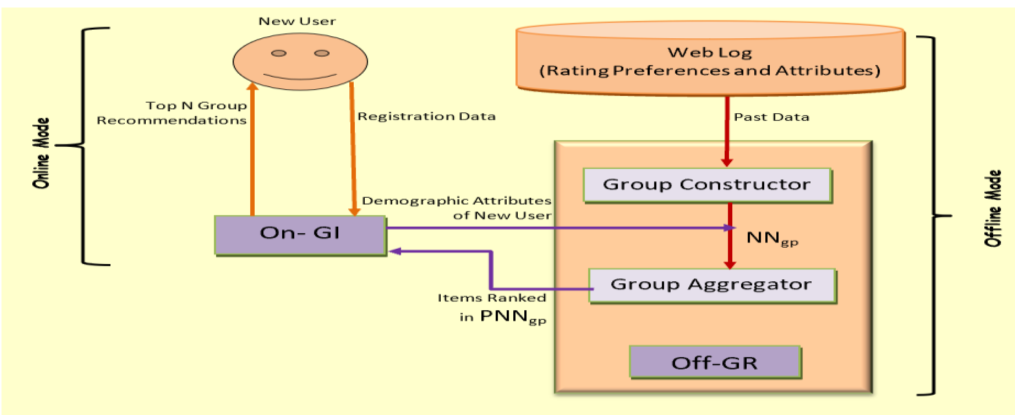

Figure 1 Framework of a group recommender system (GRS)

1.2Motivation

Most often, a GRS suffers from scalability, sparsity, and cold-start issues [17, 18]. The main aim of the proposed paper is to deliver practical recommendations to the new user while finding an optimal solution for the said problems. Quality of group recommendations depends on two factors, viz. formation of NNgp and aggregation of rating preferences of members in NNgp. A social network is an excellent tool to capture close interactions between users/items. Recently, researchers have also utilized location-based social networks for suggesting tourist spots [19]. Bedi et al. [20] have leveraged the ability of social networks to identify similar users in the group construction phase using a community detection (CD) algorithm. Gorripati et al. [17] have also used a community-based CF approach for group formation. The first goal of this paper is to devise a way for GC to further split a community into sub-communities based on the rating preferences of the members to deliver quality item recommendations. Afterwards, GA uses traditional preference group aggregation techniques (majority-based, consensus-based, and borderline strategy) to identify an item that satisfies the individual preferences of most of the group members. The second goal of this paper is to devise a novel group aggregation technique using item entropy on rating preferences for GA to ascertain the inclination of the group members on existing items.

After forming the communities, the component On-GI detects the most relevant community using his/her demographic attributes. Since GC and GA work offline, pre-detection of sub-communities and aggregation of preferences within the sub-community leads to fast, scalable group recommendations. Hence, Off-GR handles scalability issues by performing offline computations and GC solves sparsity issue, i.e., presence of a large number of null values in the rating preferences. In this work, an innovative framework has been proposed, '*Entropy for Item inclination in Sub-community-based Recommender system (EISR)*' that exploits entropy in the refined community structures to generate group recommendations using a hybrid filtering approach to tackle user cold-start problem.

Section 2 reviews the literature on GRS emphasising the user cold-start problem, group formation and group aggregation. Section 3 describes the proposed framework *'EISR'*. Section 4 elaborates on design of experiments conducted. Section 5 describes the results of experimentation and section 6 discusses the final outcome achieved by using the EISR framework along with the insights gained. Finally, section 7 concludes the study.

2.Literature review

This section discussed recent work on user cold start problem, followed by research on group formation techniques and group aggregation strategies used in GRS.

2.1User cold-start problem in GRS

The cold start issue significantly hinders the accuracy of recommendations generated for a new user. Gasparetti et al. collect historical data of a new user from social platforms to initiate the recommendation engine [21]. Xinchang et al. and Vilakone et al. exploit social network analysis to tackle the cold-start problem [14, 22]; Gonzalez-Camacho et al. identify influential friends using social networking data and propose a model utilizing the strength of friendship and degree of influence among people [23]; Bedi et al. and Cao et al. explore the weighted bipartite graph-based CF techniques to mitigate the cold-start issue [20, 24]. Anwaar et al. found that the addition of item content features to CF alleviates the cold-start problem. They generate user profiles from the features using a word embedding model, which helps in interpreting user liking [25]. Hawashin et al. identify appropriate groups for the new user to deliver effective recommendations by finding hidden interests and behavioural motives of the group members [26].

2.2Group formation in GRS

Finding a group of like-minded users with similar tastes for a new user is challenge for GRS. Mushrooming of multiple social networks allows individuals to connect by messaging and sharing ideas related to personal and business needs. Such networks are the primary source of personal information related to individuals, their family, friends, occupation, likeness, and many more. Such handy details of users are leveraged to build a network wherein two users sharing similar interests and demographic details are connected [27]. The topological structure of the network aids in creating suitable groups aka communities for recommendation using CD algorithms where each group represents an integration of users' collective behaviour in terms of their similar interests, preferences and activities [14, 21]. Gorripati et al. propose a community-based CF approach and leverage high correlation between likeminded neighbours in the community for recommending new items to a user with a pre-requisite of user-consultation data [17].

Xinchang et al. utilise readily available demographic details, e.g., age, occupation, etc., of all the registered users to build a network and place likeminded users into clusters [14]. A new user is mapped to the most similar community to give recommendations. In a recent survey on social RS, Gasparetti et al. have suggested multiple CD methods for revealing users collective behaviour and leveraged them to recommend items [21]. Two paradigms for recommendations viz. single domain and multi-domain are described where single-domain works with recommendations from a single community. In contrast, multi-domain recommendations are from the secondary partitions [21]. Multi-domain network-based RS uses overlapping CD algorithms wherein a user may be affiliated to multiple communities. This strategy improves recommendation by incorporating the preferences of many users but at the cost of high computational complexity.

2.3 Group aggregation in GRS

Suggesting recommendations to an individual using preference of all of the members of a group is a tedious task as members may have varied interests. Many traditional techniques have been proposed in literature for preference group aggregation. Ceh-Varela et al. found out that average aggregation function gives best results for group recommendations on ephemeral groups [28]. In this paper, authors are describing three prominent techniques viz. majority-based (aggregates most favoured items), consensus-based (aggregates preferences of all the group members) and borderline strategy (aggregates preferences of only a subset of users).

Majority-based strategy counts the frequency of ratings to gauge the interest of the community (group of users) to capture the popularity of items. A trivial approach, approval voting (AV) counts the ratings above the approval threshold [29] as per Equation 1.

$$AV_x^i = \frac{P_x^i}{N_x^i} \qquad (1)$$

where N_x^i is the count of members of C_i community who have rated item x and P_x^i is the count of those community members who have rated item x above the threshold.

Other approaches include Borda count, copeland rule and plurality voting [30−32]. Borda count checks the item ratings given by users, gives zero points to the last item in the preference list, and subsequently increases the points for the following item in the list. Finally, it reports the item with the maximum points. Copeland rule, a ranked voting method, selects the item with the most votes in pairwise contests, and plurality voting chooses items that get the best ratings from most members.

However, all these techniques have some shortcomings. Excluding ratings below a threshold value in AV strategy may lead to delusive opinions. Borda count and plurality voting strategies require sorting, which demands high computation time. Comparing item pairs in copeland rule strategy leads to high computational cost, especially for a large number of items.

Consensus-based strategy aggregates the opinion of all the community members to generate community rating [33]. One popular aggregation technique is Average, which calculates the mean of member ratings [34]. It considers the view of all members of the community (C_i) for generating aggregate rating (AR_x^i) of item x, as shown in Equation 2.

$$AR_x^i = \frac{\sum_{m=1}^{n} R_x^m}{N_x^i} \qquad (2)$$

where R_x^m is the rating value of item x given by m^{th} member of the community C_i .

Masthoff [35] describe other popular consensus-based techniques: the average without misery technique excludes item ratings below a threshold while aggregating the rating values; the additive utilitarian technique chooses the items with highest sum of ratings; the fairness technique allows users to choose items in an order and generates rankings accordingly; and the multiplicative technique calculates the group rating for an item by multiplying ratings of all users in the group. These consensus-based techniques are straightforward, but they may not always reveal the genuine taste of the group and may end up in a contradictory result.

Borderline strategy is different from both consensus-based and majority-based strategy as it considers a subset of ratings [29, 36]. Three distinguished techniques under this category are the least misery strategy that considers the lowest rating of an item as the group rating; the most pleasure strategy makes the highest rating of an item as the group rating; and the most respected person or dictatorship strategy takes the rating of the most influential person of the group and makes it the group choice. Most pleasure strategy and least misery strategy pick up highest and lowest ratings respectively of the existing items and thus, fail to highlight preferred items of the group. The most respected person strategy, on the other hand, is biased towards one influential person and may not yield good results, especially for large groups. Also, finding such a person is a tedious task in itself.

Many researchers have hybridised these three techniques to generate better quality recommendations. For example, Agarwal et al. apply a hybrid aggregation technique, which uses modified least misery with priority resulting in enhanced group satisfaction [37]. Seo et al. claim that hybridising standard deviation (SD) with traditional preference aggregation techniques results in better results [31]. They demonstrate that for uni-modal rated distributed items (items having only one peak in the distribution, signifying that majority of the members have a similar taste for that item), their technique generates good quality group recommendations.

Hybridisation of traditional techniques and rating distribution-based preference aggregation techniques helps in satisfying the majority of the group members [31, 32]. Rating distribution is also directly affected by the size of a group. With increase in the group size, the chances of having multi-modal rated distributed items over uni-modal also increases. This weakens SD in analysing disagreements among group members due to removal of items with high SD values from the recommendation list. This problem increases many-fold for large group size and also with growth in the heterogeneity of item taste among group members in terms of nil or multiple ratings for the same item by the members of group. Hence, Item Entropy (H) has been employed in multi-modal distributions in order to detect and eliminate evenly distributed items for which group members reach little or no consensus [32].

Entropy, a measure of uncertainty, has proved to be more robust than SD in analysing distribution on discrete rating preferences [38]. Shannon was the first to introduce entropy in information theory to measure the amount of uncertainty inherent in the system and represents the average information [39]. If there are n possible events associated with an item x and each event E_i characterised by (w_i, p_i); i = 1, . . . n; $\sum_{i=1}^{n} p_i = 1$, $w_i \geq 0$, where p_i is the probability of the event E_i for an item x and w_i is the weight quantifying qualitative aspect of E_i, then weighted item entropy $H_w(x)$ is computed as Equation 3.

$$H_w(x) = H_w\big(E_1(w_1, p_1), \ldots, E_i(w_i, p_i), \ldots, E_1(w_n, p_{1n})\big) = \sum_{i=1}^{n} w_i . p_i \; log \; p_i \quad (3)$$

In GRS, weighted item entropy is used to find users inclination on existing items. Both positive and negative rating preferences by group members are leveraged to compute entropy in order to get a clearer inclination of users for the items [40, 32]. Relevance of negative preference ratings for generating quality recommendations has been proved by Xinchang et al. [14]. They propose Adaptive Radio for a shared environment that uses negative preferences to determine songs of sub-standard taste for each group member to determine recommendations pleasing to the entire group.

This study proposed a novel preference aggregation technique by hybridising a consensus-based strategy with a majority-based strategy. The proposed hybrid strategy enhances traditional aggregation strategies by incorporating information entropy on positive and negative multi-modal rating distribution of items to generate Top-N community recommendations for the new user.

3.Methods

The proposed framework tackled cold start issues by segregating existing users on their demography and rating preferences into communities, and subsequently identified inclination of underlying members using hybrid aggregation strategy. Following are the two components of the proposed framework that exploited EISR for giving recommendations to a new user.

I. Offline Entropy based Sub-Community Recommender (Off-EbSC Recommender): It has following two sub-components

a. Demographic Sub-Community Detector (DSC Detector)

b. Item Entropy Inclinator (IE Inclinator)

II. Online Sub-Community Identifier (On-SC Identifier)

To ease the decision making in a community activity like viewing a web series with cousins, travelling to a destination with a spouse, etc., the proposed framework EISR recommended a set of Top-N relevant items to a new user U while placing irrelevant items at the lower ranks in the list of recommended items. *Figure 2* delineates the important steps followed in the framework. The offline component, Off-EbSC Recommender, identifies preference ratings of items within a sub-community. It has two sub-components, viz., DSC Detector and IE Inclinator. The first subcomponent, DSC detector (analogous to GC in *Figure 1*) uses a novel group formation technique to identify sub-communities (SC) based on item attributes from the communities formed on user attributes. This component exploits DF to generate sub-communities. The second component, IE Inclinator, capitalizes entropy on user preferences on existing items for determining their inclination by hybridizing the advantages of consensus-based strategy and majority-based strategy. IE Inclinator uses CF to generate Top-N recommendations for userU. These two components work offline, thereby managing scalability issues in the proposed GRS.

The second online component, On-SC Identifier (*Figure 2*), works online to assign U to a promising sub-community (PSC). On-SC Identifier selects PSC from the pool of the sub-communities formed by DSC Detector using demographic attributes of U. On-SC Identifier is analogous to online group identification marked as On-GI in *Figure 1*. The detailed working of two offline sub-components of Off-EbSc recommender and the functionality of the On-SC Identifier are given in the following subsections.

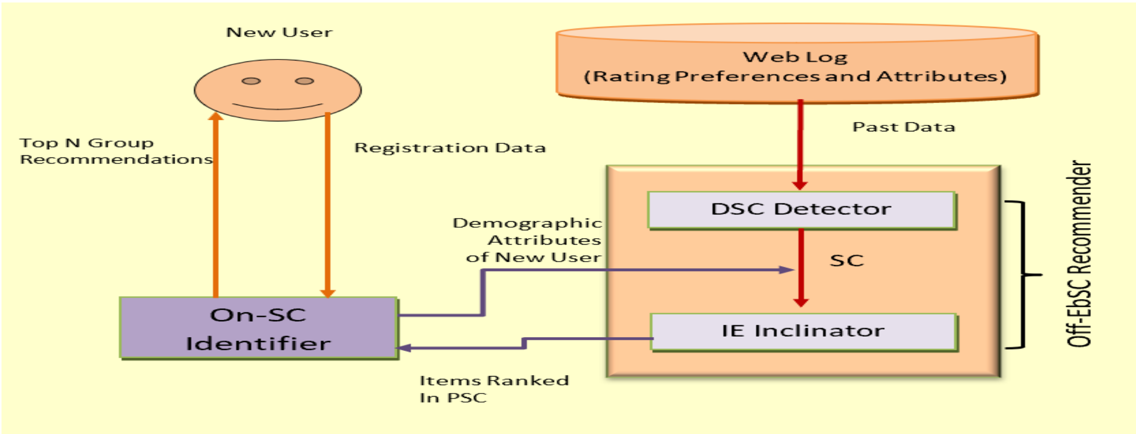

Figure 2 Framework using entropy for item inclination in sub-community-based recommender system (EISR)

3.1Demographic sub-community detector (DSC detector)

We proposed a 2-tier approach for sub-CD where tier-I detected communities using user's demographic attributes and Tier-II revealed nested sub-communities using demographic attributes of items rated by underlying members for each community detected at tier-I. Detail description of each component follows. Note that terms 'user' and 'member' are used interchangeably in the paper.

Tier-I: Community detection using user's demographic attributes

Social interactions among users are indicators of their similarity and helpful in underpinning the groups of users with similar tastes. Social ties may be explicit or implicit where explicit ties are captured during data collections e.g., thru social media like Facebook, Twitter etc. [21]. In the absence of explicit social relationship among user, implicit social relations may be built by using available demographic user information such as age, gender, occupation, and place of leaving to deliver a network which are referred as profile-based similarity [21]. Alternatively, rating-based similarity is defined based on their behavior, likeness captured through rating of items, frequency of using any item, genre of the item etc. Constructed network of user relationships is further explored to reveal a users' group aka community with similar profiles by using a CD algorithm. To target the cold-start problem of a newly registered user U with no prior item rating history, at Tier-I we identified communities of users in a network constructed using profile-based similarity. Consider a set U of N users such that for each user $u_i \in$ U, k profile features $F = \{a_1, \cdot \cdot \cdot, a_k\}$ are known. Construct a network $G(U, E)$ such that $\exists$ an edge $e_{ij} \in$ E between two users u_i, u_j if $D(\vec{f_i}, \vec{f_j}) > \delta$ where D is a similarity metric, $\vec{f_i}$ is the feature vector of user u_i and δ is the user-specified threshold. Application of a CD algorithm on G delivered non-overlapping community structure $C = \{C_1, \cdot \cdot \cdot, C_k\}$ s.t. $U_i \in C_i$ where U_i is the set of users that are part of community C_i and K is the total number of communities. Example 1 gives the overview of method adopted at Tier-I.

Example 1: Let us consider fourteen users (*Figure 3*) where users with similar demographic attributes and item preferences are represented using same color. Applying CD algorithm in the first step revealed two communities C_1 and C_2 formed on the basis of user demographic features F. Users marked with purple and orange color are placed in one community C_1 whereas users marked as pink, green and blue color are placed in second community C_2 because of their similarity on user's demographic attributes. Note that for simplicity, only two communities are considered.

Subsequently, community with maximum profile-based similarity with new user U is examined for recommending items based on group preferences. However, such recommendations may be generic to a group and need exploration at finer granularity level to deliver good quality recommendations to user U. We targeted this problem by constructing a second level (Tier-II) of communities as detailed in the following section.

Tier-II: Nested sub-communities using item's preferences of the members in a community

In order to fine tune the recommendations, users in each community were further split into sub-communities based on their item preferences (signifying item likeness) which were available in their history of item usage. For each community C_i

with users U_i, we further constructed a network G_i exploiting their item preferences such that social interactions represented item similarity between two users. Application of CD algorithm on G_i was expected to reveal set of finer subgroups in terms of sub-communities. Assume that the application of CD algorithm resulted in n_i sub-communities named SC_{ij} with $j \in (1, n_i)$ in the network G_i such that users within each sub-community are similar to each other on their item preferences compared to the rest of the users in G_i. Note that the objective of sub-community was to get a refined set of like-minded members for generating recommendations. The steps followed in this stage are briefly explained using Example 2, which is in continuation to Example 1.

Example 2: *Figure 3* shows the decomposition of first community C_1 into two sub-communities SC_{11} and SC_{12} whereas second community C_2 is decomposed into three sub-communities($SC_{21}, SC_{22}, SC_{23}$), where member of each sub-community is represented by a unique color. Revealed sub-communities represent users with similar item preferences and retain their association based on user's demographic attributes because of their parent community. Despite the fact that purple colored and orange-colored users have similar user demographic attributes (members of community C_1 at Tier-I), they are divided into two different sub-communities (SC_{11}, SC_{12}) at Tier-II based on their item attribute preferences. Likewise, community C_2 is split into three sub-communities, with each consisting of pink, green and blue colored users. Note that DSC detector maintains a list of all refined communities as $S = SC_{11}, SC_{12}, \cdot\cdot\cdot, SC_{1n_1}, \cdot\cdot\cdot, SC_{k1}, SC_{k2} \cdot\cdot\cdot, SC_{kn_k}$) to be used further by component On-SC Identifier. The authors claim that the Top-N recommendations generated by the refined communities aka sub-communities at Tier-II serve the interest of U better in comparison to the recommendations generated by using communities at Tier-I (See experiment Section 5.2).

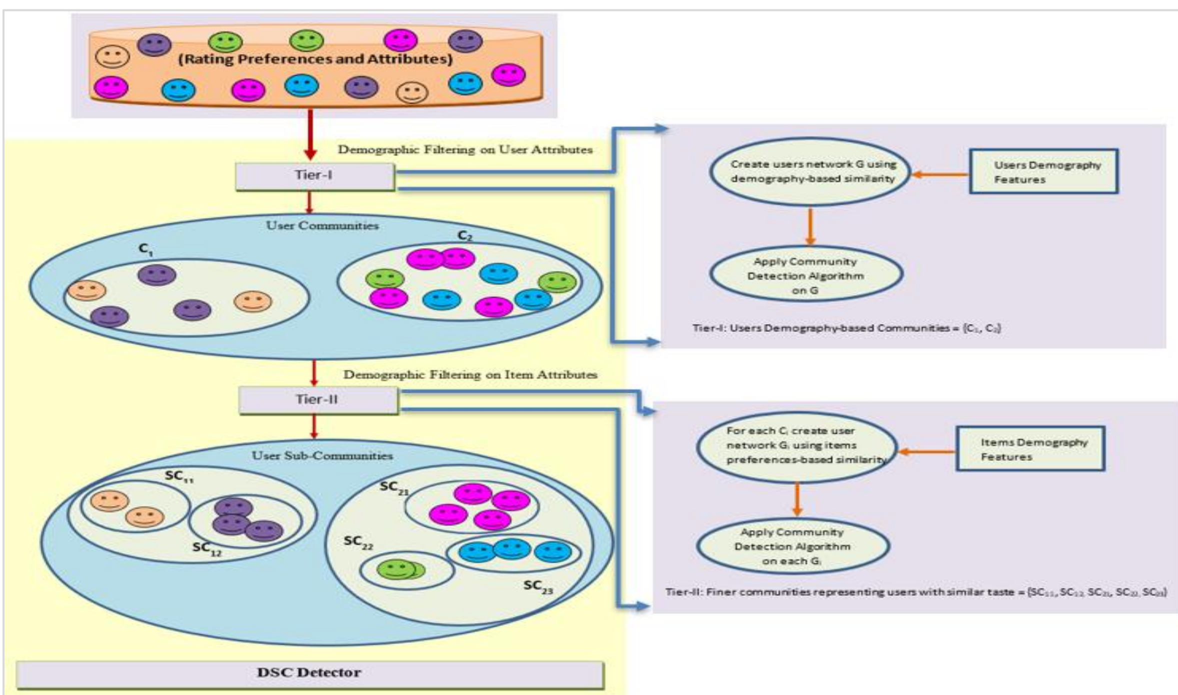

Figure 3 Demographic sub-community detector (DSC Detector)

3.2Item entropy inclinator (IE Inclinator)

The objective of IE Inclinator was to aggregate the rating preferences of sub-community members into single recommendation list that satisfies most of the members. Hence, consensus-based strategy was hybridized with majority-based strategy to enhance traditional aggregation strategies by incorporating weighted item entropy. Note that in traditional approach of AV strategy exclusion of ratings below threshold may lead to delusive opinion. To overcome this limitation, we have proposed an intuitive aggregation approach, which considered both positive and negative ratings given by the underlying members. We leveraged the advantages of traditional strategies viz. AV and average rating (AR) for computing item inclination using positive and negative item preferences of sub-community members. IE Inclinator used a novel hybrid group aggregation technique that exploited weighted item entropy of existing items to generate good quality group recommendations.

Item entropy is usually computed using positive ratings given by group members [32]. Item with low entropy on AV indicates high inclination because of collective attraction of the group members for the item. Precisely, the resulting inclination of the group on an item indicates only the probable attraction towards it. We conjecture that including entropy of negative ratings, that indicate the probable repulsion from an item, will represent a truer picture of member preferences. Therefore, IE Inclinator used positive as well as negative rating preferences to generate net item inclination. Further, IE Inclinator analysed uni-modal/multimodal distribution of item ratings that captured consensus and dissension among the members on item preferences respectively. Uni-modal distribution indicating a consensus among the vast majority of sub-community members suffices the use of average strategy on positive and negative ratings. Multimodal distribution in item preferences demands the use of hybrid strategy using a combination of AV and AR techniques for computing weighted item entropy of existing items.

The proposed unit, IE Inclinator, revealed discernible inclination of the sub-community SC_{ij} for an existing item x considering both positive and negative ratings. This group level inclination for an item x is referred as p*ragmatic propensity (PP)* I_{ij}^{x}. It was computed using a novel weighted item entropy-based group preference aggregation technique, which hybridized the advantages of majority-based AV and consensus-based AR to deliver good quality item recommendations.

IE Inclinator categorized rating preferences as pleasure rating and dejection rating on the basis of a user-specified rating threshold. A rating was categorized as *pleasure rating* if it was equal to or above the threshold; else it was considered as *dejection rating*. The motivation for proposing a novel group aggregation strategy was the fact that both pleasure and dejection shown in the rating preferences for an item governed its inclusion in the recommendation list. Hence, it necessitated categorization of items considering opinion of all members of a sub-community SC_{ij} as one of the following:

1. *Pleasure consistent item (PCI)*: An item x which is assigned pleasure rating by all those members who have rated it.
2. *Dejection consistent item (DCI)*: An item x which is given dejection rating by all the members who have rated it.
3. *Assorted inconsistent item (AII)*: An item x which is given pleasure ratings by some members and dejection rating by the rest of the members who have rated it.

Computing pragmatic propensity

PP of an item x (I_{ij}^{x}) captured the inclination of a sub-community towards it. Let there be m_{ij} members in a sub-community SC_{ij}, consider following three computations of PP based on the rating preference consistency of an item within a group.

1. *PP of PCI* (α_{ij}^{x}): It reveals the overall inclination aka *Net Attraction* of members of SC_{ij} towards PCI and is computed as shown in Equation 4.

$$\alpha_{ij}^{x} = N\left(\frac{\sum_{u=1}^{m_{ij}} PR_{u}^{x}}{P_{ij}^{x}}\right) \quad (4)$$

where N is a normalization function, PR_{u}^{x} is the pleasure rating value given by uth member of sub-community SC_{ij} for item x and P_{ij}^{x} is the count of such members in the sub-community.

PP of DCI (β_{ij}^{x}): It captures the overall inclination aka *Net Repulsion* of members of SC_{ij} for DCI. It quantifies the dejection of item x and is computed as shown in Equation 5.

$$\beta_{ij}^{x} = N\left(\frac{\sum_{u=1}^{m_{ij}} DR_{u}^{x}}{D_{ij}^{x}}\right) \quad (5)$$

where N is a normalization function, DR_{u}^{x} is the dejection rating value given by uth member of sub-community SC_{ij} for item x and D_{ij}^{x} is the count of such members in the sub-community.

PP of AII (I_{ij}^{x}): AII having multi-modal rating distribution capture the amalgamation of rating preferences among the underlying members of the sub-community SC_{ij}. Consensus-based strategies that use Item Entropy on AV to measure consensus on preference rating among members are not sufficient to measure I_{ij}^{x}.

The authors introduced two variants of AV for AII viz. Approval Pleasure Voting (PV_{ij}^{x}) and Approval Dejection Voting (DV_{ij}^{x}) within the sub-community SC_{ij} and the computations are as shown in Equations 6 and 7 respectively where N_{ij}^{x} is the count of members of the sub-community SC_{ij} who have rated an item x.

$$PV_{ij}^{x} = \frac{P_{ij}^{x}}{N_{ij}^{x}} \quad (6)$$

$$DV_{ij}^{x} = \frac{D_{ij}^{x}}{N_{ij}^{x}} \quad (7)$$

Unweighted item entropy on P_{ij}^{x} and D_{ij}^{x} represents the dispersion of approval pleasure voting and approval dejection voting respectively amongst the members of the sub-community SC_{ij} on an item x. It captures the uncertainty by which members of a sub-community do not meet the rating consensus of the item.

In general, unweighted item entropy measures uncertainty as the function of the probability with which an item is voted. It reflects quantitative value only. Precisely, high entropy value indicates no agreement has arrived on the item's rating preference amongst the members. Lower the entropy value, higher the level of confidence that the sub-community members have attained on the item's rating preferences.

Note that in Equations 4 and 5, α_{ij}^{x} and β_{ij}^{x} captures net attraction and net repulsion respectively within the sub-community SC_{ij} for an item x. In order to reveal qualitative information instead of quantitative information α_{ij}^{x} and β_{ij}^{x} within the sub-community SC_{ij} may be used as weight of the item x along with the probability distribution on pleasure AV and dejection AV respectively to get weighted item entropy. We reiterate that traditional RS uses only positive rating preferences given to an existing item within a group, whereas the proposed EISR framework exploits positive as well as negative rating preferences to improve the recommendation quality.

Uncertainty and information are associated to each other such that reduction in uncertainty among the member preferences enhances the information revealed by the IE Inclinator. Hence, subtracting the normalized value of weighted item entropy (uncertainty) revealed the net consensus among the sub-community members for the item's rating preferences. We computed degree of attraction (DA) (A_{ij}^{x}) and degree of repulsion (R_{ij}^{x}) for item x in the sub-community SC_{ij} as given in Equations 8 and 9 respectively.

$$A_{ij}^{x} = 1 - \mathcal{N}\left(-\sum_{m=1}^{n} \alpha_{ij}^{x}\left(PV_{ij}^{x}\right) \log_2 PV_{ij}^{x}\right) \quad (8)$$

$$R_{ij}^{x} = 1 - \mathcal{N}\left(-\sum_{m=1}^{n} \beta_{ij}^{x}\left(DV_{ij}^{x}\right) \log_2 DV_{ij}^{x}\right) \quad (9)$$

where $\mathcal{N}$ is a normalization function.

The DA and repulsion of an item depicts incomplete interest of the sub-community members towards it. PP of AII is based not only on DA but also on degree of repulsion. In order to get PP i.e., aggregated preference of an item within a sub-community, the preferences of all the members need to be integrated. Therefore, we used harmonic mean of the DA and repulsion to compute I_{ij}^{x} as shown in Equation 10.

$$I_{ij}^{x} = \frac{A_{ij}^{x} * R_{ij}^{x}}{A_{ij}^{x} + R_{ij}^{x}} \quad (10)$$

Once, the PP was computed for all the items categorized as PCI, DCI or AII using Equations (4), (5) and (10) respectively; the existing items were ranked in descending order of their computed values. Finally, top-N items were presented to user U who was assigned to the sub-community SC_{ij} by On-SC Identifier.

Figure 4 shows the working of IE Inclinator that takes the sub-communities revealed by DSC Detector as input and outputs the existing items sorted in decreasing order of their PP. For each sub-community, IE Inclinator categorizes items as PCI, DCI and AII, which are shown in red, green and pink colors respectively in the figure and computes their PP as detailed earlier.

All members vs Influential members

Once sub-communities are identified, the next question arises: Whether to use rating preferences of all members [41] or rely on the most influential (respected) person in the group [35]. In case the group is very large, aggregating individual's preferences will be computationally expensive and time consuming. On the other hand, strategy using preferences of most influential person may not yield good results especially for large groups. Hence, we proposed an alternate strategy that considers user specified number of influential persons having similar topological characteristics for generating recommendations.

Recent works have demonstrated that nodes in the top-most core/truss identified through k-core/k-truss decomposition are the most influential in terms of their ability to spread information [42, 43]. Hence, we used these two strategies for identifying top-K influential persons leveraging network hierarchy in each identified group (Community/Sub-community) and describe them briefly.

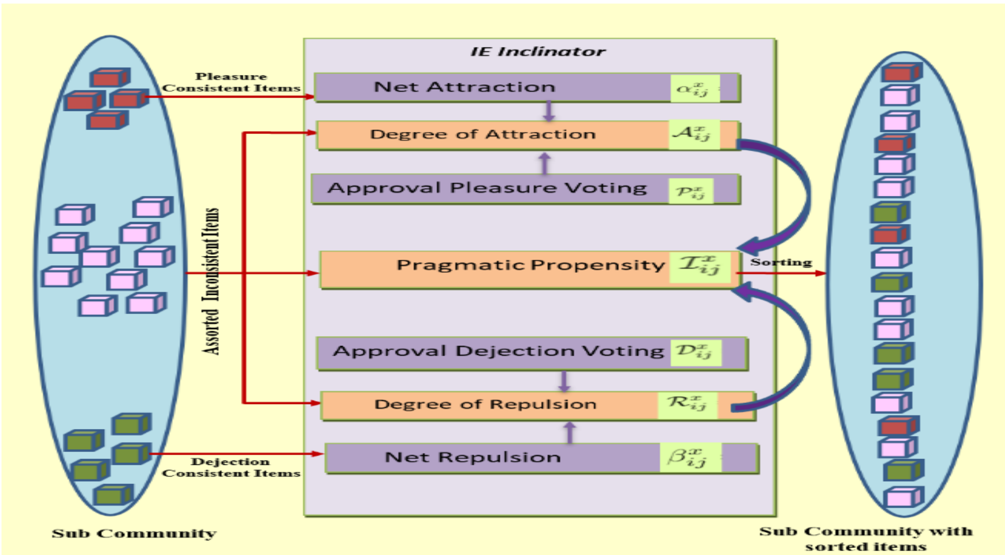

Figure 4 Item entropy inclinator

Core-based influencers: In first strategy, we identified influencers as those who were in the innermost core of the network and thereby had more influence over others compared to individuals with lesser connections. We used node coreness revealed using k-core decomposition to identify whether the node belonged to a very densely connected part of the network referred as core or to its periphery [44]. Higher the coreness, denser is the group.

Truss-based influencers: In this strategy, influencers were detected using k-truss decomposition method that found nested, dense subgraphs composed of closed triads in a graph to reveal edge trussness [45]. Node trussness was determined using trussness of edges that were directly linked to the node and revealed its position in hierarchy in the network. Higher the level more influential the node is.

We used k-core decomposition because it is a fast $O(|E|)$ algorithm for such decomposition [44]. Reason for using k-truss decomposition lies within its finer hierarchy over k-cores, however, it is much slower algorithm of complexity $O(|E|^{1.5})$.

3.3 Online sub-community identifier (On-SC Identifier)

Whenever recommendations are sought for a new user U, On-SC identifier finds the most similar sub-community using demographic attributes from S and recommends Top-N items of the group to the user. Recall that IE Inclinator has maintained all items preferred by each community in descending order of their PP value. In order to compare similarity of a user with a sub-community different approaches are feasible. We used the simplest and popular method based on centroid aka central node of a community to compute similarity.

Assume a sub-community SC had m members where each user had a feature vector $\vec{f}$ for k profile features $F = \{a_1, \cdot\cdot\cdot, a_k\}$. Note that to keep the notation simple, subscripts have not been used with SC. Centroid $\vec{C}$ of SC was computed as shown in Equation 11.

$$\vec{C} = \frac{\sum_{i=1}^{m} \vec{f_i}}{m} \quad (11)$$

To detect most similar community, On-SC identifier computed similarity of a new user U with each community using similarity metric $D\,(\vec{C}, \overrightarrow{f_U})$ and recommended Top-N items of the most similar community. Alternatively, single linkage could also have been used where U is assigned to a group on the basis of maximum similarity with any member of that group for providing group recommendations, but with additional computation time for identifying the most similar user of a group.

4.Experimental design

This section presents the specific settings of our experiments, data pre-processing done for network construction and metrics employed for performance evaluation followed by result discussion.

4.1Dataset description and experimental setting

The proposed EISR framework was tested using two datasets whose descriptions follow:

MovieLens dataset [46] contains 100k ratings given by 943 users on 1682 movies, with at least 20 movies rated by each user. It consists of three data files viz. user information, rating information and movie information. The rating scale ranges from 1 (dislike) to 5 (like). Book-crossing dataset [47] has 1,157,112 ratings provided by 278, 858 users on 271, 379 distinct books. It has 3 datafiles viz. BX-Users containing user's demographic attributes, BX-Book having books details and BX-Book-Ratings consisting of the book rating information with scale range 1 (dislike) to 10 (like).

We used 80% of the data for training the proposed framework EISR and remaining 20% for evaluating the accuracy. We implemented algorithm EISR in Python 3.6.9 [https://www.python.org/] and igraph-0.9.8 and executed it on Intel Core i7-6700 CPU @3.40GHz dual core with 16GB RAM.

4.1.1Data pre-processing and user/item attribute vector construction

We pre-processed both datasets to remove anomalous records and those with missing values. Next, for each user, we create a vector consisting of user demography attributes $(\overrightarrow{\boldsymbol{U}})$. We also constructed item attribute vector $(\overrightarrow{\boldsymbol{I}})$ for each user by analysing the attributes of items that users have rated. We explain in detail the construction of these vectors for both datasets below.

MovieLens dataset: The user information file in the MovieLens dataset consists of records having four user demography attributes (age, gender, occupation and zip code) per user. We dropped two occupation types (none, other) out of 22 occupations due to their vague interpretation. The attribute zip Code was converted into categorical state code using Python library *uszipcode* (https://pypi.org/project/uszipcode/). Age, being a numeric attribute, was binned into five levels (teenager, youth, middle age, senior and super senior). Dummy coding was employed to convert categorical attributes viz. gender to two gender levels (M/F), occupation to twenty (20) occupation levels, and State Code to 51 state levels. Thus, each user was associated with a user attribute feature vector $(\overrightarrow{\boldsymbol{U}})$ of cardinality 78.

For the item attributes, we used the genre information of movies. The movie information file contains 18 binary columns corresponding to genres to which movies belong to (such as Comedy, Drama, Documentary, and so on). Rating Information file has three columns corresponding to user, movie, and rating indicating the rating given by a user to a movie. Both files were used to construct the item attribute feature vector $(\overrightarrow{\boldsymbol{I}})$ for each user representing the per genre frequency of movies reviewed and the per genre average rating given by the user.

We show the Pearson correlation coefficient between the computed Item attribute features in *Figure 5*. It can be seen from the figure that, users who reviewed Action movies also reviewed Adventure, Thriller and Crime movies. This is also reflected in the high correlation of the ratings given to these genres by users. The frequency and rating attributes corresponding to the Comedy and Children Genre also exhibit similar high correlation. These conclusions are in accordance with real life intuition.

Book-crossing dataset: The BX-Users file in the book-crossing dataset consists of anonymized records having two user demography attributes Age and Location. The location column was parsed to determine the country of the user. Records with invalid or no country names were manually filtered and dropped. Dummy coding was employed to convert country to 167 binary levels. Age, being a numeric attribute, was binned into five levels (teenager, youth, middle age, senior and super senior). Thus, each user was associated with a user attribute feature vector $(\overrightarrow{U})$ of cardinality 182. For the item attributes, the genre information pertaining to books was not available. Hence, we mapped book titles to book genre using 'spaCy' (https://spacy.io/), a free open-source library for Natural Language Processing in Python and its module "en_core_web_lg" for English language. We provided a list of book titles along with a pre-specified list of 24 genres taken from BISAC subject headings list [48] and the module predicted the most appropriate label from the provided list. The top 3 predicted genres were assigned to each book. The book information data was then augmented with 24 binary columns corresponding to genres to which books belong (such as fiction, poetry, folklore, romance and so on). For experimentation purposes we used 1000 users randomly selected from the original file. BX-Rating file has three columns corresponding to user, book, and rating indicating the rating given by a user to a book. Both files were used to construct item attribute feature vector $\overrightarrow{(I)}$ per user representing the per genre frequency of books reviewed and the per genre average rating given by the user. The Pearson correlation coefficient between the computed Item attributes features is shown in *Figure 6*. Being a very sparse data, no semantic information pertaining to real-life scenario could be retrieved directly from the correlation matrix shown in the figure.

4.1.2Construction of Tier-I and Tier-II communities of users

In Tier-I, the network of users (User Graph), was constructed. For this, the cosine similarity between user attribute vectors $\overrightarrow{(U)}$ was computed. An edge was added between users u_i and u_j if the cosine similarity $D(\overrightarrow{u_i}, \overrightarrow{u_j}) > 0.5$.

We detected groups of similar users in the constructed network by applying Multilevel CD [49] algorithm and got seven communities at Tier-I. Note that we experimented with several CD algorithms available in the Python igraph library; as the modularity of community structure detected by Multilevel CD algorithm was maximum, we used this algorithm for reporting results. The size and order of Tier-I communities of the MovieLens and Book-crossing datasets are shown in *Tables 1(a)* and *1(b)* respectively.

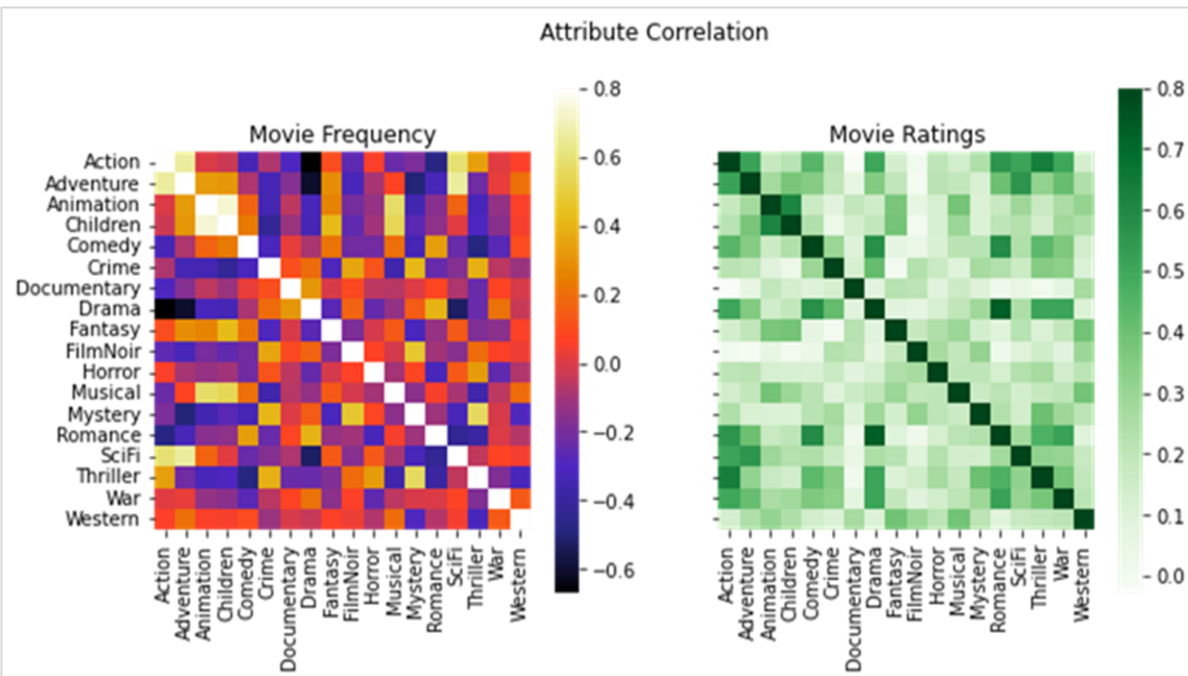

Figure 5 Correlation between the frequency and ratings of item attributes of users for the MovieLens dataset

To further refine Tier-I communities, we used item attributes, namely, the genre preference of users. Like before, cosine similarity $D(\overrightarrow{I_i}, \overrightarrow{I_j}) > 0.5$ between item feature vectors of users u_i and u_j was used to build a network for members of each community. Application of Multilevel CD algorithm on the newly constructed graph of the members of a community resulted in 13 sub-communities at Tier-II. Sub-communities with less than five members were dropped while generating recommendations. The size and order of Tier-II communities of the MovieLens and Book-crossing datasets are shown in *Tables 2(a)* and *2(b)* respectively.

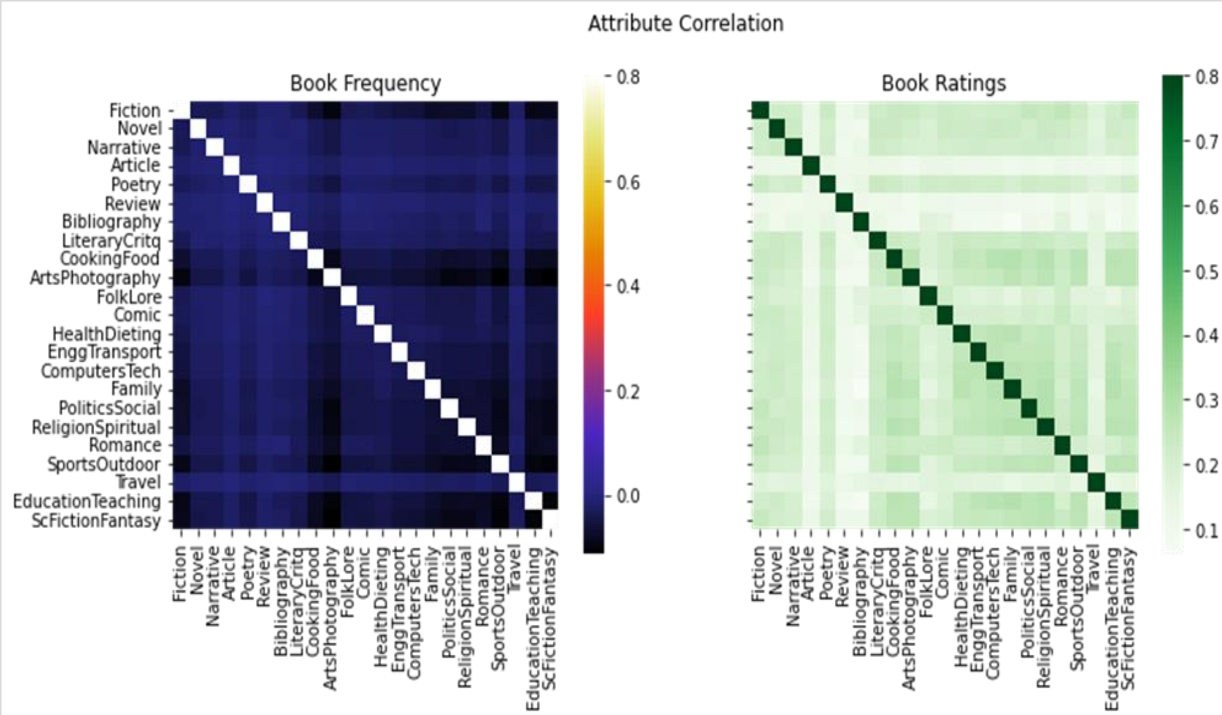

Figure 6 Correlation between the frequency and ratings of item attributes of users for the book-crossing dataset

Table 1(a) Size (no of vertices), Order (no of edges) and assortativity coefficient of user attributes for Tier-I Communities of the MovieLens dataset

Tier-1 community	Size	Order	Assortativity coefficient			
			Gender	Occupation	Age	State Code
C_1	117	1285	1.0	0.776	0.031	0.161
C_2	265	5316	1.0	0.722	0.148	0.206
C_3	217	2096	0.152	0.502	0187	0.250
C_4	138	9209	1.0	0.032	0.007	-0.01
C_5	69	2346	1.0	1.0	0.014	-0.02
C_6	66	1517	0.332	0.706	0.019	0.014
C_7	71	2350	1.0	0.399	0.014	0.014

Table 1(b) Size (No of Vertices), Order (No of Edges) and assortativity coefficient of user attributes for tier-I communities of the book-crossing dataset

Tier-1 community	Size	Order	Assortativity coefficient	
			Age	Country
C_1	471	110685	0.021	0.426
C_2	529	78109	0.022	0.513

Table 2(a) Size, order and genres with positive assortativity coefficient on item attributes for tier-II Communities of the MovieLens dataset

Tier-2 Community	Size	Order	Genres with Positive Assortativity Coefficient
SC_{00}	31	463	Drama
SC_{01}	82	3275	Documentary, Thriller, Western
SC_{10}	92	3677	Documentary, Drama, FilmNoir, Horror
SC_{11}	130	8206	SciFi
SC_{12}	43	822	Documentary
SC_{20}	42	820	Crime

SC_{21}	69	2260	Action, Animation, Drama, Thriller
SC_{22}	106	5201	Animation, Comedy
SC_{30}	59	1639	Thriller
SC_{31}	79	2882	Documentary, FilmNoir
SC_{40}	55	1479	Drama, Fantasy
SC_{41}	14	79	Horror, Musical, SciFi
SC_{50}	64	1990	Animation, War
SC_{60}	24	267	Mystery, Romance, Thriller
SC_{61}	43	882	Drama, Mystery

Table 2(b) Size, order and genres with positive assortativity coefficient on item attributes for Tier-II communities of the book-crossing dataset

Tier-2 Community	Size	Order	Genres with positive assortativity coefficient
SC_{00}	106	5565	Novel
SC_{01}	186	6549	Bibliography, Review,
SC_{02}	70	1939	Education and Teaching, Parenting and Relationships
SC_{03}	60	1770	Science Fiction and Fantasy
SC_{04}	49	1176	Folklore
SC_{10}	103	3945	Religion and Spirituality
SC_{11}	43	581	Poetry, Narrative
SC_{12}	87	1153	Cookbooks Food and Wine
SC_{13}	51	1058	Comic, Romance
SC_{14}	53	1378	Travel, Narrative
SC_{15}	86	2325	Review, Bibliography
SC_{16}	69	2346	Romance, Poetry, Fiction
SC_{17}	37	667	Fiction, Politics and Social Sciences

4.2 Design of experiments

It is well understood that the quality of group recommendations depends on two factors viz. group formation and aggregation of rating preferences of members in a group. In the following section, we detail the experiments that were conducted to determine whether the presence of DSC Detector and IE Inclinator in the proposed EISR framework improved the quality of group recommendations in comparison to traditional methods.

Specifically, we designed the experiments to answer the following six questions:

a) Do the communities detected at Tier-I and Tier-II by DSC detector exhibit homophily (Sec. 5.1)?
b) Is the quality of the Top-N group recommendations generated at Tier-II better compared to recommendations generated at Tier-I (Sec. 5.2)?
c) Does the PP used by IE Inclinator deliver superior outputs compared to traditional aggregation strategies (Sec. 5.3)?
d) How do members selected for recommendations impact the quality of recommendations (Sec. 5.4)?
e) Are the recommendations generated by the EISR framework more effective compared to competitive methods (Sec. 5.5)?
f) Which method of group identification is effective for On-SC Identifier (Sec. 5.6)?

To answer the above questions, top-N recommendations were computed using 80% of used dataset (training set) and accuracy of prediction was computed using remaining 20% (testing set).

5. Results

This section provides detailed analysis of results of experiments conducted to answer the six questions mentioned in section 4.2.

5.1 Homophily of communities detected by DSC detector

We evaluated the quality of community structures discovered by DSC detector via their homophily. In sociology, the homophily principle states that similar people connect with each other at a higher rate than dissimilar people [50]. One of the most accepted and popular metrics to detect homophily in networks is the assortativity coefficient [51] that measures the propensity of similar vertices in networks to be connected to each other. A positive assortativity coefficient (ρ) for a vertex attribute implies that vertices with that attribute have a high tendency to be connected. Formally, assortativity coefficient (ρ) for categorical attribute values is computed using Equation 12.

$$\rho = \frac{\sum_x e_{xx} - \sum_x a_x b_x}{1 - \sum_x a_x b_x} \quad (12)$$

where $a_x = \sum_y e_{xy}$ and $b_y = \sum_x e_{xy}$

Here, e_{xy} is the fraction of edges connecting vertices with attribute value x and value y at each edge end respectively. For the communities revealed by DSC detector, we evaluated homophily of user demography attributes for Tier-I communities and of item demography attributes for Tier-II sub-communities.

We report assortative coefficient values for the MovieLens and Book-crossing datasets to support our hypothesis of like-minded users belonging to the same communities. Assortative coefficient value for user demography attributes is reported for Tier-I communities of the MovieLens and the Book-crossing dataset in *Tables 1(a)* and *1(b)* respectively. In case of the MovieLens data, it is evident that Tier-I communities show significant homophily with respect to gender followed by occupation being the most significant factor causing the grouping of users. For the book-crossing dataset, homophily is evident with respect to country rather than age. For Tier-II sub-communities, we report genres with positive assortativity coefficient in *Tables 2(a)* and *2(b)* respectively. It is vindicated from the table that refined communities have like-minded users with preferences for the genres specified in the tables.

5.2Evaluation of quality of group recommendations

In order to show that the quality of results improve by refining communities at Tier-I, we compared Top-N group recommendations computed for communities at Tier-I and sub-communities at Tier-II for both datasets. We exploited root mean square error (RMSE) and mean absolute error (MAE) to find the accuracy of top-N recommendations because of their popularity and ability to detect errors in the predictions accurately.

We used metrics MAE and RMSE to find the accuracy of group recommendations produced at Tier-I and Tier-II for varying number of recommendations (Top-N) and report the results in *Figure 7* and *8* respectively for both datasets. Figures show that MAE and RMSE are lower for recommendations generated using sub-communities at the Tier-II approach compared to that of communities at Tier-I for both the MovieLens as well as the Book-crossing dataset.

Thus, it is established that the quality of group recommendations depends on the sub-community formation by DSC Detector. As more attention was paid to selecting like-minded members to form each sub-community, better was the Top-N group recommendation quality. Recall that at Tier-I, like-minded members in communities were found using user attributes, whereas, at Tier-II, like-minded members in sub-communities were found using user attributes along with item attributes. Hence, the selection of attributes in group formations is crucial for revealing good recommendations.

5.3Effectiveness of pragmatic propensity used by IE inclinator

In order to prove the effectiveness of the proposed IE Inclinator, we compared the quality of recommendations generated at Tier-II using PP versus those generated using traditional aggregation strategies viz. AV shown in Equation (1) and AR shown in Equation (2). We also compared recommendations delivered by IE Inclinator using PP with the recommendations obtained using a DA only shown in Equation (8) to show the net impact of the DA and DR on the quality of recommendations generated using PP shown in Equation (10). We computed MAE and RMSE for the output delivered using each of these four methods on both datasets to prove the effectiveness of the proposed PP used by IE inclinator and show the plots in *Figures 9* and *10* respectively.

From the results in the figures, it is evident that both MAE and RMSE are least when PP is used than when consensus-based or majority-based aggregation strategies are employed for predicting recommendations in case of both datasets. Also, it is apparent that the quality of group recommendations generated using both pleasure as well as dejection ratings results in reduced errors in prediction versus use of only pleasure rating (DA) (see the orange line in *Figure 9* and *10* (respectively). Hence, the proposed hybrid strategy using weighted item entropy on positive and negative preferences is better than consensus-based and majority-based strategies.

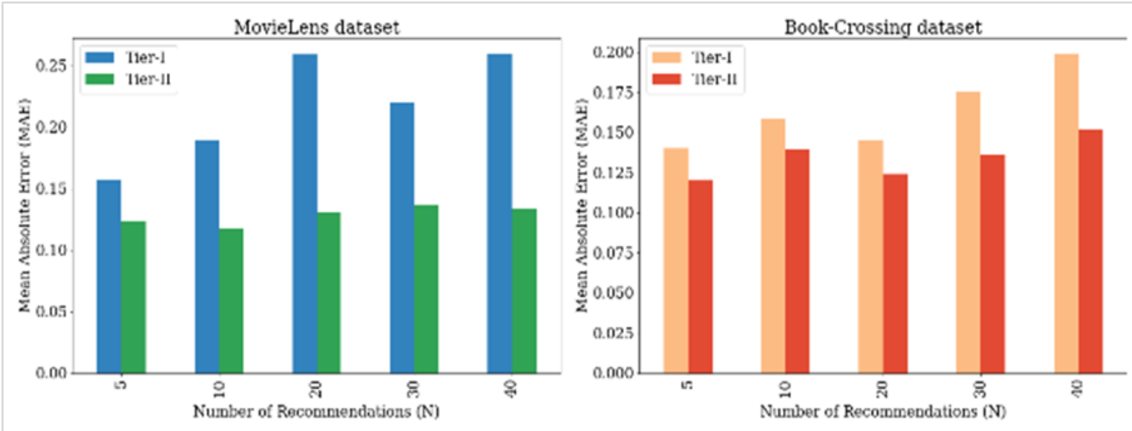

Figure 7 MAE with varying Top-N item recommendations using groups at Tier-I and Tier-II

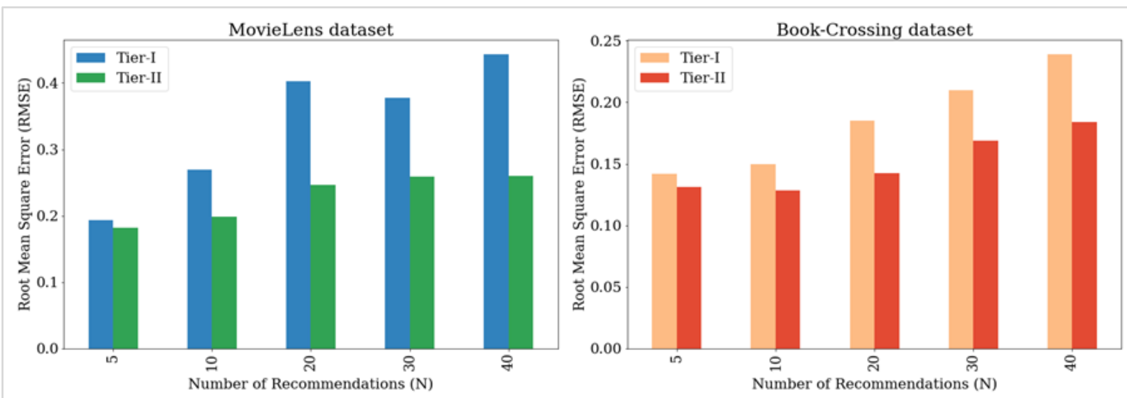

Figure 8 RMSE with varying Top-N item recommendations using groups at Tier-I and Tier-II

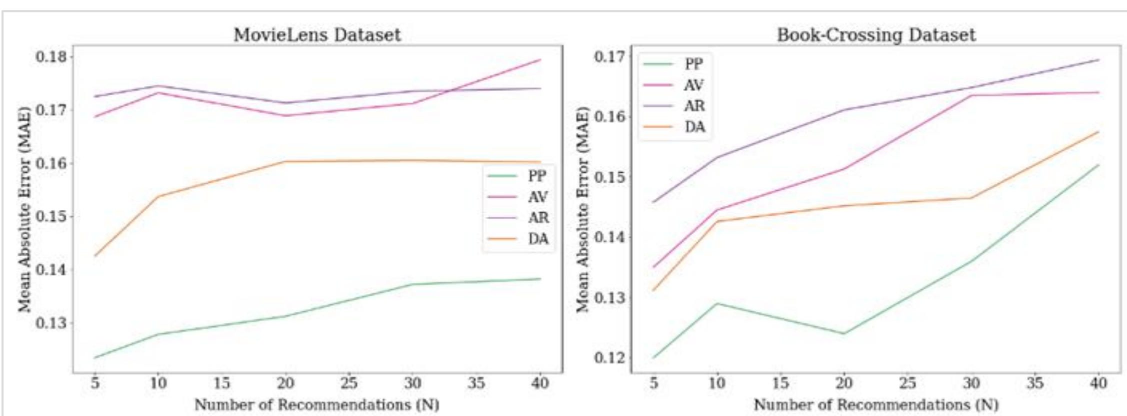

Figure 9 MAE with varying Top-N item recommendations using pragmatic propensity (PP), approval voting (AV), average rating (AR), and degree of attraction (DA)

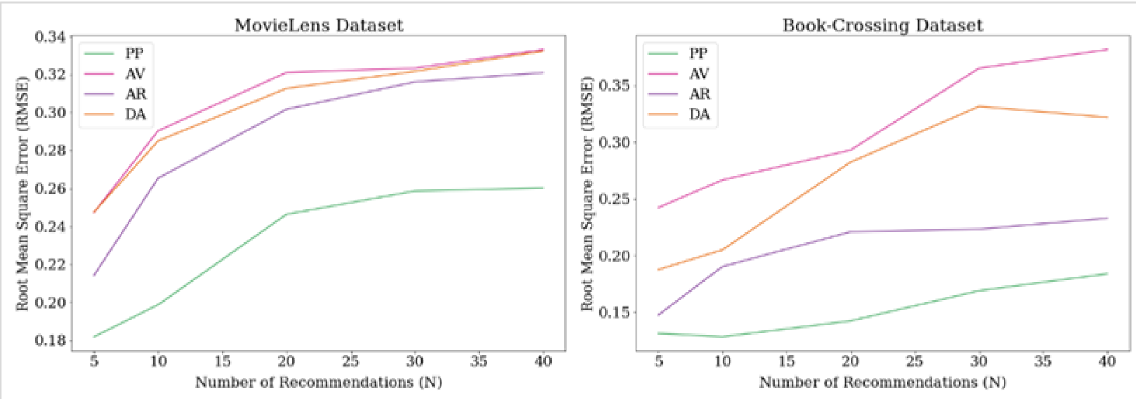

Figure 10 RMSE with varying Top-N item recommendations using pragmatic propensity (PP), approval voting (AV), average rating (AR), and degree of attraction (DA)

5.4Effect of All vs influential members for group recommendations

The objective of this experiment was to capture the difference in the quality of item recommendations using the preferences of all members and those of the most influential persons. Recall that most influential persons are captured in two ways k-core and k-truss. Authors intended to show the variation in PP with respect to the number of users. Instead of all the members of a group, the most influential person strategy selects user-specified influential users as per the community and/or sub-community. Top-N recommendations were obtained from the set of items rated by the selected influential users in a community/sub-community.

We computed Top-N group recommendations using top-10 influential members' detected using k-Core and k-Truss at Tier-II with varying N. These results were compared with Top-N group recommendations produced using PP of all members of the group found at Tier-II. *Figures 11* and *12* show the results of MAE and RMSE at varying values of a number of items (Top-N) recommended on both datasets. It clearly indicates that using the most influential person strategy on PP does not make the quality of group recommendations further better. Thus, it can be concluded that the PP used by IE-Inclinator diligently aggregates the preferences of a large set of members for recommending items compared to a selected set of influential users.

To further validate the results, each of these methods was employed for Tier-I communities as well. The results are shown in *Figures 13* and *14.* It is confirmed that recommendations incorporating all members' preferences deliver better results compared to the selected influential individuals even when communities are not refined. Thus, it is concluded that the quality of group recommendations depends not only on the method used for aggregation of rating preferences of the members in a group but also on the user set used in aggregation. Hence, both rating preferences along with users involved in rating play an important role in the CF.

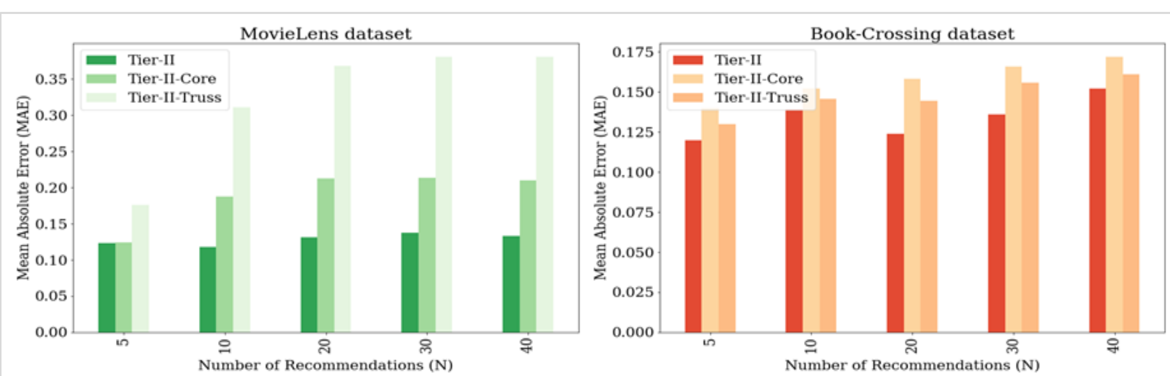

Figure 11 MAE with varying Top-N Recommendations generated using all members vs. most influential members of sub-communities revealed at Tier-II

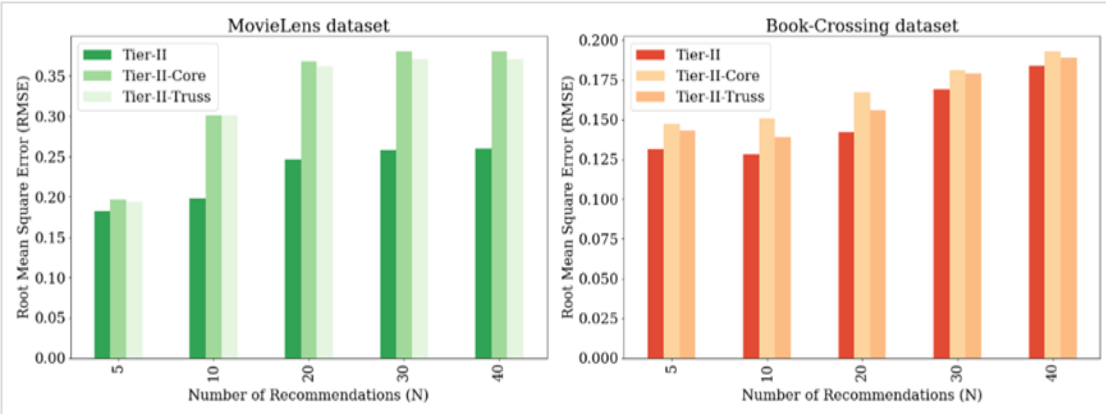

Figure 12 RMSE with varying Top-N recommendations generated using all members vs. most influential members of sub-communities revealed at Tier-II

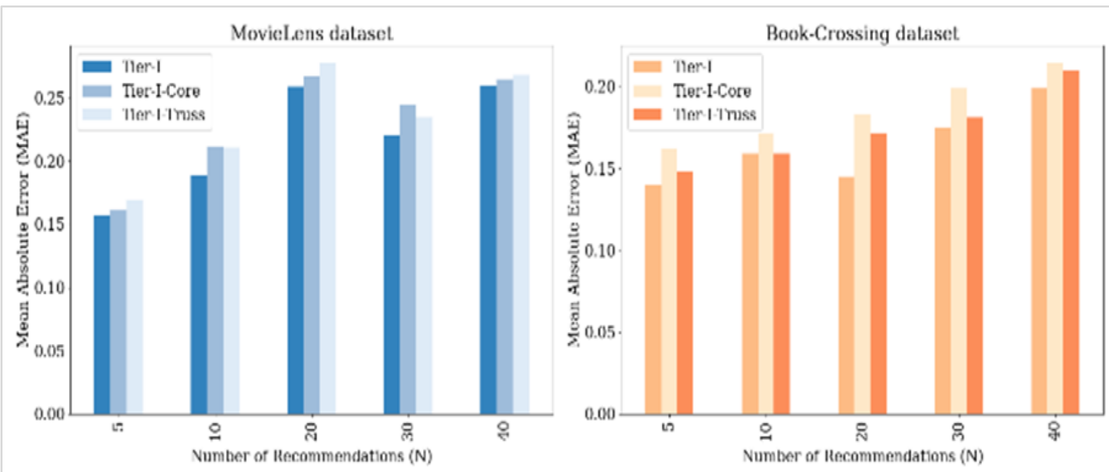

Figure 13 MAE with varying Top-N Recommendations generated using all members vs. most influential members of sub-communities revealed at Tier-I

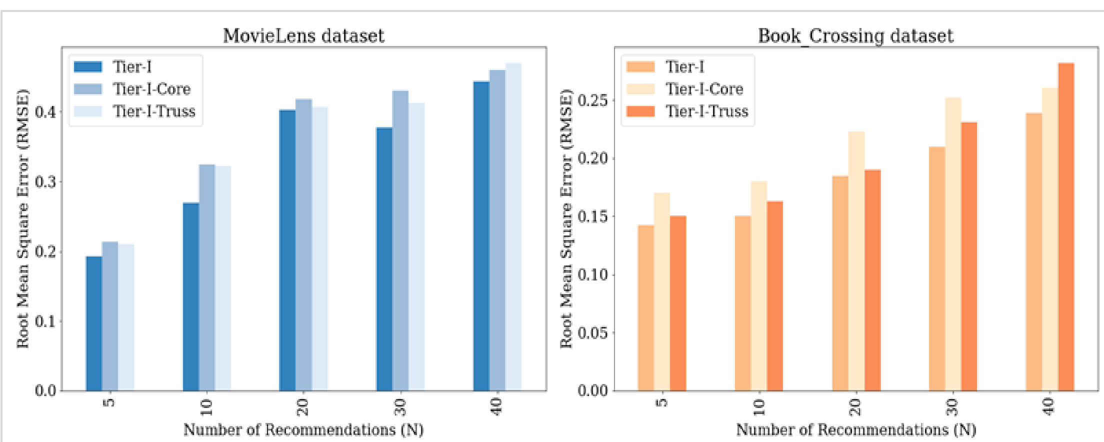

Figure 14 RMSE with varying Top-N Recommendations generated using all members vs. most influential members of sub-communities revealed at Tier-I

5.5Comparison with competitive methods

We also compared the results of EISR with two well know recommendation algorithms viz. UserKNN [52] and ItemKNN [53] considering top-10 and top-20 recommendations using MovieLens dataset. We computed mean average precision for Top-10 recommendations and Top-20 recommendations (*Figure 15*). Reduced error in Top-20 case is accredited to the larger number of rightly captured recommendations by EISR. It is vindicated from the figure that EISR performs better for large number of recommendations in contrast to KNN in both cases. Similar conclusion was drawn for Top-10 recommendations but difference is marginal. Hence, inclusion of refined communities to identify most similar users in Tier-II for recommending most relevant items increases the performance of the proposed model.

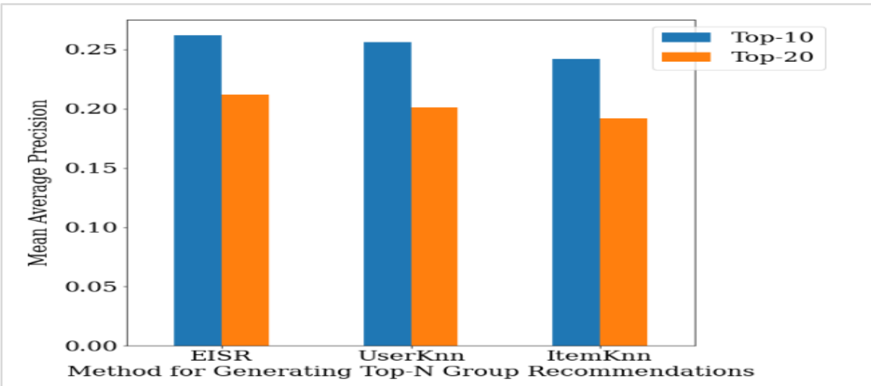

Figure 15 Mean Average Precision for Top-10 and Top-20 recommendations produced by various methods on MovieLens dataset

5.6Effectiveness of component On-SC identifier

As discussed in Section 3.3, component On-SC Identifier identifies the most similar community for new user using demographic features in two ways viz. centroid-based (M1) and single linkage (M2).

We designed an experiment to test which method among the two has better applicability for our approach. We used sub-communities detected at Tier-II because of their effectiveness as revealed in earlier experiments. Treating data in the testing set as of as new users, their target (most similar) community was predicted using both methods. *Table 3* shows the Precision and Recall between the actual community of new user and the predicted community. Results of this experiment indicate that both methods are capable of detecting most similar sub-community for the new user. However, centroid-based method (M1) shows marginally better performance and is preferable for online group detection due to lower computation time compared to the second method M2.

Table 3 Comparing performance of sub-community identification methods using MovieLens data

Methods used by On-SC identifier	Precision	Recall
M1	0.997	0.998
M2	0.982	0.987

6.Discussion

We introduced a novel EISR framework that attempts to solve the cold start problem by providing recommendations inferred from communities of users with similar demography and similar preferences for items. CD was used at two levels to form groups. A novel hybrid group aggregation strategy named PP was also introduced to reveal item inclinations of the members. Use of refined communities resulted in finer sets of similar users which helped to predict more effective recommendations for new users.

Experiments conducted using the MovieLens and Book-crossing datasets showed that EISR delivered superior quality Top-N group recommendations compared to traditional group aggregation strategies viz. AV and AR. Further, the sub-communities detected at Tier-II improved the quality of recommendations in comparison to that of communities at Tier-I. Comparison done with other methods also confirmed its efficacy in improved recommendations.

Though the analysis of the experimental study vindicated the efficacy of the proposed framework compared to other methods, there are still some unresolved challenges. The proposed framework handles cold start issues using user's demographic attributes. In the absence of demographic attributes, Tier-I processing will be skipped and only communities generated using item attributes at Tier-II will be used for recommendations. This will not only increase computational complexity of generating communities with large number of viewed items but will be unable to deliver effective recommendations to new users with no history of item usage. The most trivial solution that may be adopted in such a scenario would be to give the top most recommendations of each community formed to the new user. We intend to solve this problem by extracting user's interests from their social networking profile.

A complete list of abbreviations is shown in *Appendix I.*

7.Conclusion and future work

This paper proposed a novel EISR framework that formed homophilic sub-communities of similar users based on DF on user attributes at Tier-I and item attributes at Tier-II. PP, a hybrid preference group aggregation strategy that leverages item entropy on rating preferences, was exploited to capture the item inclination of sub-community members. Thus, entropy-based item inclinations computed from refined communities enable EISR framework to resolve cold-start problem.

Although, the proposed framework has shown promising results, unavailability of user's demographical details may impact its performance while giving recommendations. We intend to filter out users' interests from their social networking profile to improve the quality of recommendations in the absence of users' demographic attributes. In future, authors plan to modify truss-based method for member selection within the sub-communities based on item viewing and apply ML models for predictions.

Acknowledgment

None.

Conflicts of interest

The authors have no conflicts of interest to declare.

Author's contribution statement

Harita Ahuja, Sunita Narang, Sharanjit Kaur and Rakhi Saxena: Wrote the manuscript text and equally contributed towards the research ideas and their implementation. **Harita Ahuja and Sunita Narang:** prepared figures 1 through 4, writing and reviewing. **Sharanjit Kaur and Rakhi Saxena:** Prepared figures 5 through 15, writing and reviewing.

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Appendix I

S. No.	Abbreviation	Description
1	AII	Assorted Inconsistent Item
2	AR	Average Rating
3	AV	Approval Voting
4	CbF	Content-Based Filtering
5	CD	Community Detection
6	CF	Collaborative Filtering
7	DA	Degree of Attraction
8	DCI	Dejection Consistent Item
9	DF	Demographic Filtering
10	DSC Detector	Demographic Sub-Community Detector
11	EISR	Entropy for Item Inclination In Sub-Community-Based Recommender System
12	GA	Group Aggregator
13	GC	Group Constructor
14	GRS	Group Recommender System
15	IE Inclinator	Item Entropy Inclinator
16	KF	Knowledge-Based Filtering
17	MAE	Mean Absolute Error
18	ML	Machine Learning
19	NNgp	Nearest neighbour Group
20	Off-EbSC Recommender	Offline Entropy Based Sub-Community Recommender
21	Off-GR	Offline Group Recommender
22	On-GI	Online Group Identifier
23	On-SC Identifier	Online sub-Community Identifier
24	PCI	Pleasure Consistent Item
25	PNNgp	Promising Nearest Neighbour Group
26	PP	Pragmatic Propensity
27	PSC	Promising Sub-Community
28	RMSE	Root mean Square Error
29	RS	Recommender System
30	SD	Standard Deviation