LOCATION RECOMMENDATION FOR GROUPS ON LOCATION-BASED SOCIAL NETWORKS

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

HÜSEYIN ALPER TEOMAN

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
COMPUTER ENGINEERING

JANUARY 2022

Approval of the thesis:

LOCATION RECOMMENDATION FOR GROUPS ON LOCATION-BASED SOCIAL NETWORKS

submitted by **HÜSEYIN ALPER TEOMAN** in partial fulfillment of the requirements for the degree of **Master of Science in Computer Engineering Department, Middle East Technical University** by,

Prof. Dr. Halil Kalıpçılar
Dean, Graduate School of **Natural and Applied Sciences** ________________

Prof. Dr. Halit Oğuztüzün
Head of Department, **Computer Engineering** ________________

Prof. Dr. Pınar Karagöz
Supervisor, **Computer Engineering, METU** ________________

Examining Committee Members:

Prof. Dr. İsmail Hakkı Toroslu
Computer Engineering, METU ________________

Prof. Dr. Pınar Karagöz
Computer Engineering, METU ________________

Prof. Dr. Suat Özdemir
Computer Engineering, Hacettepe University ________________

Date: 31.01.2022

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Surname: Hüseyin Alper Teoman

Signature :

ABSTRACT

LOCATION RECOMMENDATION FOR GROUPS ON LOCATION-BASED SOCIAL NETWORKS

Teoman, Hüseyin Alper
M.S., Department of Computer Engineering
Supervisor: Prof. Dr. Pınar Karagöz

January 2022, 52 pages

In research and business areas, location-based services have become a trending subject. With the increasing popularity of social networks and online communities, group recommendation systems arise in order to support users to interact with those having similar interests, and to provide recommendations for joint activities, such as eating out as a group or seeing a movie with friends. However, the techniques and approaches to provide recommendations to groups are limited, as most of the available studies focus on individual recommendations. In this study, the problem of recommending venues to a group of users is addressed by employing Random Walk with Restart (RWR) algorithm to generate recommendations based on the current location of group members, experts and trusted users visiting the same venues. A new approach is proposed by including the trust factor of users in location-based social networks (LBSNs). The first one aggregates the location recommendations that are generated with the Random Walk algorithm for each member in the group, taking the preferences and objectivity scores of the individuals into account. The second one is based on creating a group profile by blending preferences and venue category types, and using this group profile to run the Random Walk algorithm once. Comprehensive experiments have been performed on different group sizes, and including trust factor of users. The analysis is conducted on the data collected from the location based social network platform Foursquare. The experiments have shown that the trust factor of users improves the performance of group recommendation system and the proposed algorithm provides recommendations to groups with high accuracy compared to the baselines.

Keywords: Group-oriented recommender system, Location-based social networks (LBSNs), Trust-aware recommendation, Random walk

ÖZ

KONUM TABANLI SOSYAL AĞLARDA GRUPLAR İÇİN KONUM ÖNERİSİ

Teoman, Hüseyin Alper
Yüksek Lisans, Bilgisayar Mühendisliği Bölümü
Tez Yöneticisi: Prof. Dr. Pınar Karagöz

Ocak 2022 , 52 sayfa

Araştırma ve iş alanlarında, konuma dayalı hizmetler trend olan bir konu haline geldi. Sosyal ağların ve çevrimiçi toplulukların artan popülaritesi ile birlikte, kullanıcıların benzer ilgi alanlarına sahip diğer kullanıcılar ile etkileşime girmesini desteklemek ve grup olarak dışarıda yemek yemek veya arkadaşlarla bir film izlemek gibi ortak etkinlikler için öneriler sağlamak adına grup öneri sistemleri ortaya çıktı. Fakat, mevcut çalışmaların çoğu bireysel önerilere odaklandığından, gruplara önerilerde bulunma teknikleri ve yaklaşımları sınırlı kalmıştır. Bu çalışmada, aynı mekanları ziyaret eden grup üyelerinin, uzmanların (fenomenlerin) ve güvenilir kullanıcıların mevcut konumlarına dayalı öneriler oluşturmak için Yeniden Başlatmalı Rastgele Yürüyüş (RWR) algoritmasını kullanarak bir grup kullanıcıya etkinlik/mekan önerme sorunu ele alınmıştır. Konum tabanlı sosyal ağlarda (LBSN) kullanıcıların güven faktörünü dahil ederek yeni bir yaklaşım öneriliyor. İlki, gruptaki her üye için Rastgele Yürüyüş algoritması ile oluşturulan konum önerilerini, bireylerin tercihlerini ve objektiflik puanlarını dikkate alarak ortak bir paydada toplar. İkincisi, tercihleri ve mekan kategori türlerini harmanlayarak bir grup profili oluşturmaya ve bu grup profilini Random Walk algoritmasını bir kez çalıştırarak öneriler sunmaya dayanmaktadır. Farklı grup büyüklükleri üzerinde ve kullanıcıların güven faktörünü de içeren kapsamlı deneyler yapılmıştır. İnceleme, konum tabanlı sosyal ağ platformu Foursquare veritabanından toplanan veriler üzerinde gerçekleştirilmiştir. Deneyler, kullanıcıların güven faktörünün grup öneri sisteminin performansını geliştirdiğini ve önerilen algoritmanın, temel metodlara kıyasla gruplara yüksek doğrulukta önerilerde bulunduğunu göstermiştir.

Anahtar Kelimeler: Grup odaklı öneri sistemi, Konum tabanlı sosyal ağlar (LBSN'ler), Güvene dayalı öneri, Rastgele yürüyüş

To my supervisor, my fiance, my mother and my sister...

Thank you for all of your support along the way.

ACKNOWLEDGMENTS

I would like to thank the Scientific and Technological Research Council of Turkey (TUBITAK) for its financial support for this project. This work is supported by TUBITAK with grant number 118E356 and my study is supported by 2210-A scholarship program.

TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

LIST OF ABBREVIATIONS

DTM	Direct Trust Model
GoTaRW	Group-oriented Trust-aware Location recommendation with Random Walk
LBSN	Location Based Social Network
RW	Random Walk
RWR	Random Walk with Restart

CHAPTER 1

INTRODUCTION

1.1 Motivation and Problem Definition

Studies on social networks and recommendation systems have evolved at a fast pace in recent years and a variety of recommendation systems have emerged to answer various needs. However, most of the currently developed systems are designed for individuals only. Social network platforms support the users to contact those who have similar tastes and to perform daily activities such as traveling, watching movies, eating out to be held in groups. Since the group members' preferences may differ, it is the key problem to gather group members in a common denominator to enable them to do an activity together [1, 2]. Both the strong relationship between the group members [3, 4] and the effect of social network information on each group member [5, 6] is taken into consideration by the existing social network group recommendation systems and group recommendations are ultimately generated by aggregation strategies [7]. However, the concepts including users' objectivity scores and trust among them have been mostly ignored by current group recommendation systems.

In this study, the problem of recommending a list of venues to a group of users in a Location based social network (LBSN) is challenged, and Group-oriented Trust-aware Location Recommendation system with Random Walk *(GoTaRW)* is introduced. The proposed solution is based on employing Random Walk with Restart (RWR) algorithm on group members' visit data to generate recommendations according to a given location context. Another novelty of the algorithm is that it includes trusted users and experts as well. Given history data of an LBSN, the employed graph model includes the group members, friends and the locations visited as vertices and the relations of location check-ins and friendships as edges. Additionally, trust values are assigned to group members and other LBSN users. Random walk with restart algorithm is performed on the generated subgraph where the recommendation value of each location is calculated.

1.2 Proposed Methods and Models

In this work, two different approaches are proposed for group recommendations. These two proposed systems are compared in detail with four basic methods to show the efficiency of proposed recommendation systems. The first one aggregates the location recommendations that are generated with the asynchronously employed Random Walk algorithm for each member in the group, taking into account the preferences and objectivity scores of the group members. The second one is based on creating a group profile by blending preferences and venue category types, and to evaluate this group profile as if it were an individual and run the RWR algorithm only once on this profile.

1.3 Contributions and Novelties

The main contributions of this study are as follows:

- The group LBSN subgraph model with trusted user nodes is extended. By using the preferences and objectivity scores of the group members, the group recommendations are enhanced by taking the most trusted users into consideration while scoring the recommended locations (as a weighted approach).
- Two methods to construct graph based group profiles is devised and a Random Walk based solution is used on the group profile.
- In order to analyse the recommendation accuracy performance of the proposed model, extensive experiments are performed on real-life dataset (Foursquare).
- Several baseline methods used in group recommendation systems are also compared with the proposed recommendation systems in terms of accuracy and time

performance.

In parallel, this study has been partially presented in the conference [8].

1.4 The Outline of the Thesis

In the rest of the paper, in Section 2, related studies in the literature on group oriented recommendations systems are reviewed. In Section 3, the proposed method, Group-oriented Trust-aware Location Recommendation System with Random Walk (GoTaRW) is presented and the system framework is described in detail. In Section 4, experiments conducted on the real-world dataset and the obtained results are reported. In Section 5, the paper is summarized with an overview and concluded.

CHAPTER 2

RELATED WORK

In this section, firstly, related studies on group oriented recommendation systems in LBSNs are outlined. Secondly, aggregation methods used in the literature for group recommendation are summarized.

2.0.1 Group Recommender Systems

A group recommendation system offers items that could be relevant for a group of people, such as venues, movies and series etc. Group recommendation systems focus on two main issues: recommendation system mechanism and group decision aggregation mechanism [9, 10, 11]. Basically there are two different recommendation approaches. The first is to recommend items for each users within the group and aggregate the results. The second is to create a group profile by gathering the group on a common denominator and to recommend an item for this collected profile as an *abstract* user.

In [9], Chang et al. present a recommendation mechanism that takes individual preferences, context and social influence into account. They start the approach by creating a list of candidates for the group. Then, the relevance of each item is determined for each group member, and then they use the group consensus function, which they define by combining social influence and conditions.

In [12], Khazaei et al. propose a context-aware group recommendation system, CLGRW, with two phases. They use RWR as the main algorithm for recommendations including aggregating individual recommendations and extending RWR to predict group preferences. The first phase is offline modeling in which a group structure and group formation is constructed and a graph model is derived. The second phase is the context-aware group recommendation in which the locations are rated and recommended to the group profile according to their scores to the group profile. According to their evaluations, creating an ideal subgraph for groups facilitate computations and hence is more time-efficient.

In [13], Zhiyun et al. propose a travel group recommender system based on social influence and user trust. Their model defines the user's direct and indirect trust and calculates the user global trust by combining the two trusts. The social influence of users are calculated by using the PageRank algorithm based on their interaction relationship history. The proposed framework is mainly composed of three parts: a data acquisition module, preference modeling module, and group recommendation algorithm design module which is using Collaborative filtering technology. Our work differs from this study by including directly trusted users in the group graph model and using their visit data in the recommendation subgraph.

Ayala-Gómez et al. propose a method, namely Geo Group Recommender (GGR) [14], to recommend locations for a group of users in the vicinity. GGR is a hybrid recommending system which combines geographical preferences of group members, category, location characteristics and group visits. They use group data in LBSNs to detect groups without any prior assumptions. Results have shown that GGR exceeds the performance of most other recommendation methods.

In [15], McCarthy offers a content-based group recommendation system. His approach recommends restaurants for groups of users based on the foodie characteristics of the restaurant and the location. In particular, McCarthy's system uses information such as distance, planned facilities, preferred food and planned budgets to recommend restaurants in a more accurate way. In this system, the group members should explicitly express the features they prefer individually when requesting restaurant recommendations, and they also assign priority levels to the features. The system calculates the recommendations by aggregating the preferences of group members about features and recommends restaurants according to the preferences of the group.

Purushotham et al. observe the group activities and behaviors, and recommend locations to groups in LBSNs [16]. They propose a Hierarchical Bayesian model that learns group preferences by using topic models, and perform group recommendation using collaborative filtering.

The proposed approach in this study also employs RWR algorithm as in [12] to generate context-aware location recommendations. However a new mechanism is proposed by including the trust factor of users in the LBSN. The basic component of our mechanism includes visit histories, preferences, social influence and trust factor of users.

2.0.2 Aggregation Methods

Group recommender systems use several common aggregation strategies [17, 18, 19]: consensus-based strategies, majority based strategies and the least and most pleasure strategies.

Consensus based strategies consider the preferences of all group members. It calculates the average of the preferences of all group members under equal weight. This strategy is used in MusicFX [20] such that by using a group profile calculated by adding the squares of individual preferences, the most relevant music station is recommended for to people in a gym.

Majority based strategies use the most popular items or categories among group members. For example, each member votes for their preferred item or category, and the most preferred item is selected. Then, this method is applied continuously to obtain an ordered list of items to be recommended. In [21], GroupCast recommender displays content that fits with the intersection of user profiles when people are close to a public screen.

The Least Misery strategy and **the Most Pleasure strategy** keep the minimum and maximum level of interest among group members for each preference respectively. These are the methods where the happiness level of a group is determined by the least or most pleased person in that group. PolyLens [22] uses the Least Misery strategy to recommend movies for a group of people. Their analysis shows that 77% of the users found group recommendations more useful than individual ones.

In the proposed system, **The Weighted Aggregation Method** is used. In this method each group member's score, which is the number of venues they visited, is considered as the user's weight. If a member visits more locations than the other group members, this member would have the highest weight within the group.

CHAPTER 3

PROPOSED METHOD: GOTARW

In this section, the details of the proposed method, Group-oriented Trust-aware Location recommendation with Random Walk (GoTaRW), is described. Firstly, graph structure used for representing LBSNs is illustrated. Then, the trust model which is used for LBSN users's trust scores is described. Afterwards the Random Walk with Restart algorithm, the main algorithm used in generating the location recommendation lists, is presented. Finally the proposed group-oriented trust-aware recommendation algorithm and the aggregation method that is used to recommend top-n locations to the groups are described in detail.

3.1 Social Network Model

The employed LBSN model includes the relation between group members, locations, experts, friends and trusted users in a set of users. A sample subgraph is illustrated in Figure 3.2. This graph (G), is a tuple including nodes (V) and edges (E). V consists of **user nodes** (group members), **location nodes** representing the locations visited by users in vicinity, **friend nodes** representing friends of the user, **expert nodes** representing the location experts in vicinity, **trusted user nodes** representing the trustworthy users in vicinity.

3.2 Trust Model

Trust is an essential notion in social relationships. In order to integrate the trust notion with group recommendation, a trust model is used to generate a *trust score* for

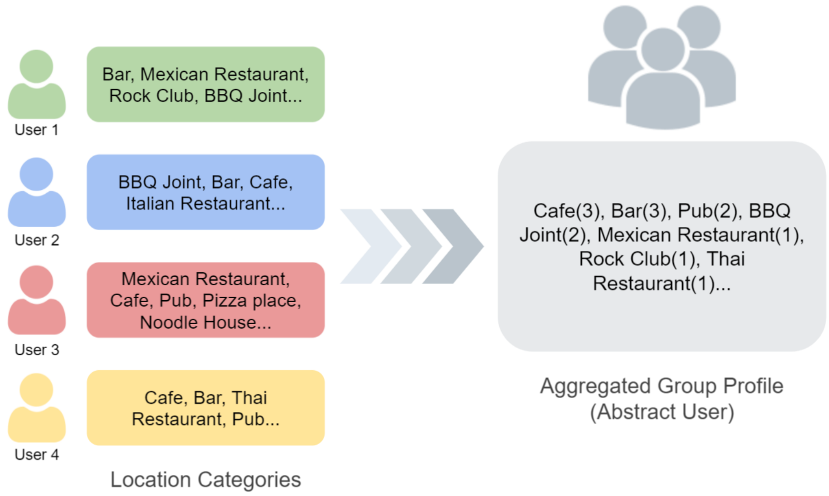


Figure 3.1: Creation of a Group Profile based on the category of visited locations by group members

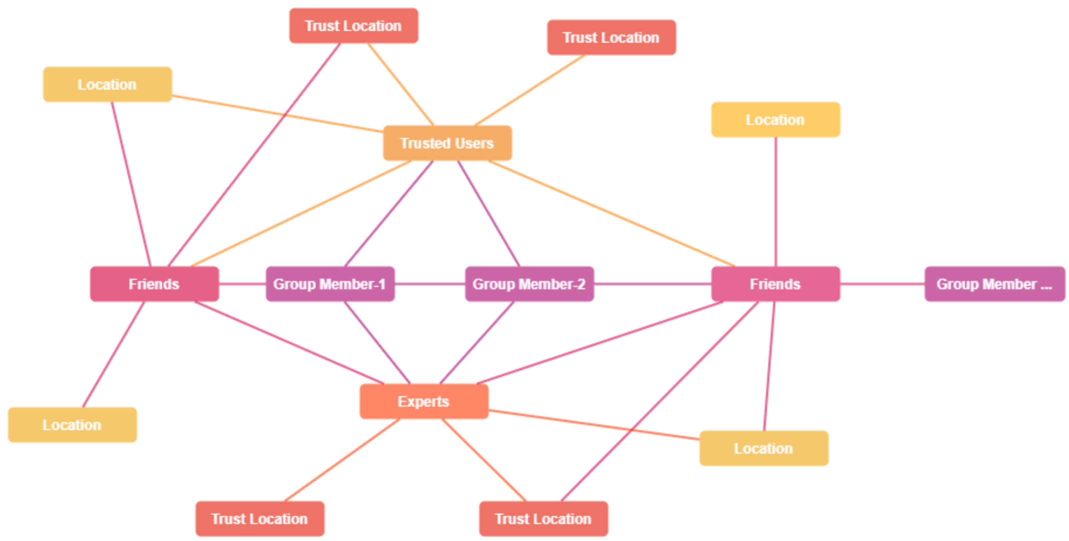


Figure 3.2: Sample group-oriented graph for location recommendation

each LBSN user. The employed model is based on two concepts within the context of LBSN: *objectivity* and *consistency* [23] [24]. A user's objectivity is equal to the normalized average of the objectivity scores of the visits by that user. The visit objectivity score is calculated based on whether the user has visited that location before, and the rank of the location. Consistency is also calculated from the average of the objectivity scores of all users.

The **objectivity** score of a visit depends on the U_{l_u}, which is *1 if the user has visited* *l, otherwise 0*. The calculation of objectivity of a visit is given in *Equation 3.1*.

$$O_{l_u} = |\frac{U_{l_u} - r_l}{s_l}| \tag{3.1}$$

O_{l_u} is calculated based on the average rating of location, denoted by r_l, and the standard deviation of the rating for the location, denoted by s_l in *Equation 3.1*.

The objectivity of a user, O_u, is the average of the objectivity scores of the visit of the user. L represents the set of locations in the data set, illustrated in *Equation 3.2*. As the objectivity value gets closer to 0, the user is considered more objective.

$$O_u = \frac{1}{|L|} \sum_{l \in L} O_{l_u} \tag{3.2}$$

The **consistency** score is calculated as shown in *Equation 3.3*.

$$C_u = \frac{1}{|L|} \sum (O_{avg} - O_u)^2 \tag{3.3}$$

In the equation, O_{avg} represents the average objectivity of all users. C_u represents the consistency of user u. If C_u is closer to 0, this means that the user is more consistent.

In our trust model, *consistency* is considered as the key indicator for a trustable user, and *consistency score* is used as the *trust score* of an LBSN user.

3.3 Random Walk with Restart

In order to recommend locations to users, we run the RWR algorithm on the subgraph of the LBSN [25]. Random walk is performed on a subgraph including the user nodes of group members and their friends, locations in the vicinity as well as experts and popular locations in the vicinity of the location context. The random walk starts from a group member and in every transition, there is a constant probability to jump back to the initial group member node. After the RWR terminates, the locations are sorted by visit counts. Based on the results of the random walks, the algorithm recommends a set of ranked locations.

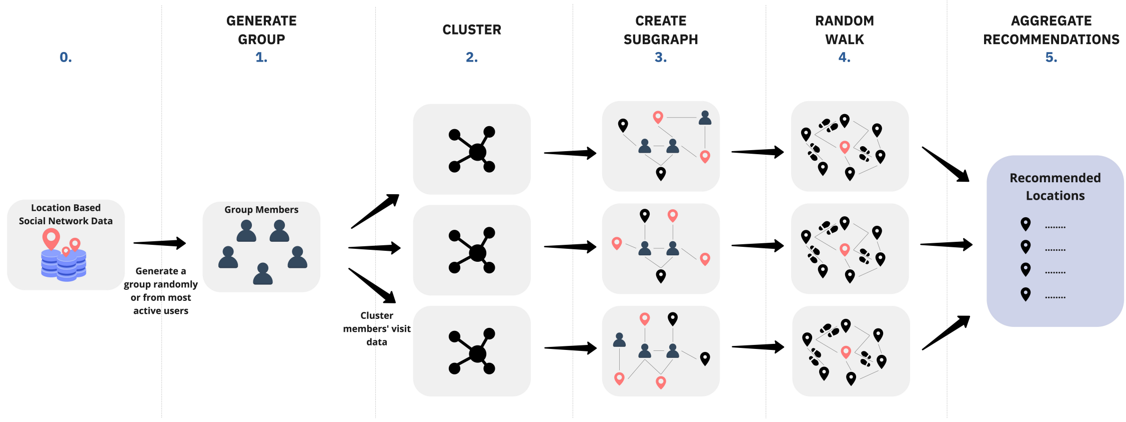


Figure 3.3: Group-oriented Recommendation Flow

3.4 Group-oriented Recommendation Algorithm

In this work, two different approaches are proposed for group recommendations. The first one aggregates the location recommendations that are generated with the asynchronously employed Random Walk algorithm for each member in the group, taking into account the preferences and objectivity scores of the group members. This approach is denoted as GTL. The second one is based on creating a group profile by blending preferences and venue category types, and to evaluate this group profile as if it were an individual and run the RWR algorithm only once on this profile. The second approach is denoted as $GroupProfile$.

The structure describing the general flow of the proposed system is shown above in Figure 3.3. In the first step of the flow, **(1. Generate Group)**, group members are chosen randomly or from among the most active users in LBSN. Algorithm operations are started to suggest a place for this group with size n.

For the analysis, in order to determine location context for the group, the visits data is clustered **(2. Cluster)**. Note that in the practical use, the location context can be explicitly given by the user group. As the clustering algorithm, DBSCAN is used as it does not require the number of clusters in advance, and has proven to provide accurate clustering performance for a variety of problems. DBSCAN has two parameters to define: the radius and the minimum number of points in the neighborhood. The parameter settings used for DBSCAN are explained in detail in Section 4.

Recommending locations to a group member at a given location starts with constructing a subgraph for the current group member by using the locations in the visit history of the group member for the vicinity of the location context and the visit history of Experts, Friends and Trusted users in the vicinity **(3. Create Subgraph)**. Experts in LBSN is determined by applying HITS algorithm on the LBSN graph including only users and visited locations. For Experts and Trusted users' visits in the vicinity, top-n users are selected according to their related scores. After the subgraph is constructed, RWR starts to run to obtain the given recommendation count **(4. Random Walk)**. All location nodes in each RW iteration have the same transition probabilities due to unweighted graph structure. Once the RWR iterations are completed, the locations are sorted on the basis of their scores. The scoring schema applied to locations is the same for both of the proposed approaches **(5. Aggregate Recommendations)**. The details of the two proposed group profiling approaches, GTL and GroupProfile are described in Section 3.5.1 and Section 3.5.2, respectively.

3.5 Proposed Aggregation Approaches: Pre-aggregation & Post-aggregation

3.5.1 Group-oriented Aggregation of Individual Recommendations (GAIR)

In GTL approach, the subgraph of each group member is processed separately to obtain the individual recommendation lists. After the RWR algorithm is run and the recommended locations list for each group member is received, scores are assigned to the locations by using the weighted objectivity values of the group members. This weighted score is calculated as shown in *Equation 3.4*.

$$Score_l = \sum_{u \in G} O_u \times f_{ul} + r_l \tag{3.4}$$

The location score $Score_l$ is calculated by multiplying the frequency of visits the group member makes to the suggested location and the user's objectivity score. This value is calculated for each group member and the final score is obtained by adding the rating of the location, denoted by r_l. In this equation G represents the group, O_u represents the objectivity score of user u, and f_{ul} represents the frequency of visits to the location l by the user u. Top-N recommended locations are obtained by sorting the locations according to this score.

3.5.2 Aggregated Group Profile Approach (GroupProfile)

This second proposed method focuses on the group itself rather than the individuals. In *Aggregated Group Profile* approach, a group profile is constructed by combining preferences and venue category types. RWR algorithm runs on this profile as if it were an individual.

The proposed method generates a weight for each location category for the group profile by considering each group member's preferences in the category of location. Each member's visited location category represents the user's interests in the area. The creation of the Group Profile is demonstrated in Figure 3.1.

The final category weights in the constructed group profile is calculated as given in *Equation 3.5*.

$$C_w = \frac{R_g(c)}{|L|} \times 100 \tag{3.5}$$

In this equation, C_w denotes the category weight in the group profile, which is used in the calculation of the score of locations below in *Equation 3.6*. Here, $R_g(c)$ represents the repetition count of category c in the group profile.

The category with higher repetition weight in the group profile reflects that the preferences (categories of the most visited locations) of the members are of interest for that location. Following this, an abstract user subgraph is created (representing the group profile) and the RWR algorithm is employed on this abstract user graph by collecting all locations in the vicinity from each of the group members. This approach differs from the first one by running the RWR only once for the group recommendation.

In this approach, the score of a location is calculated by considering the category preferences of the group, as given in *Equation 3.6*.

$$Score_l = (O_{gp} \times f_{gpl} + r_l) \times C_w \tag{3.6}$$

In the equation, $Score_l$, denoting the final location score, is calculated by considering the category weighted score (C_w). O_{gp} denotes the average objectivity score of all members in the group. Top-N locations to recommend are obtained by sorting the locations according to this score.

CHAPTER 4

EXPERIMENTS AND RESULTS

In this section, dataset statistics, evaluation methods and metrics, and the results of the proposed approach compared to the different approaches in terms of accuracy, effect of trust factor and running time are provided.

4.1 Dataset

The dataset used in the analysis was collected from Foursquare which is one of the most popular LBSNs [26]. The dataset consists of 6150945 check-ins made by 143618 users over 778202 venues/locations. Each check-in data instance includes venue id, user id, longitude and latitude, venue category, date-time and tagged users in this visits. The friendships are extracted using the tagged information in visits, meaning that tagged users in a visit are assumed to be friends with each other.

In order to evaluate the proposed approaches, data is filtered for the check-ins made in 5 important locations with big data: Istanbul, Izmir, New York, London and Mexico City. The dataset statistics for the filtered subset are shown in Table 4.1.

4.2 Evaluation Methods and Metrics

In the experiments, for DBSCAN algorithm that is used for determining the location context, the neighborhood radius is set as 3 km, and the minimum number of points as 1. Regarding the random walk settings, the restart probability is set (α value) as 0.05 and, random walk iteration count as 1000.

Table 4.1: Foursquare Dataset Statistics

Dataset Statistics					
	Istanbul	**Izmir**	**New York**	**London**	**Mexico City**
# of Locations	31401	13446	2952	1598	10153
# of Users	36916	22954	714	821	5063
# of Check-ins	553824	328922	8118	6156	71802
# of Friendships	241862	180738	2004	768	18676
# of Check-ins per User	15.002	14.330	11.369	7.498	14.182
# of Friends per User	3.168	3.549	2.892	2.048	2.711

In order to evaluate baseline methods and approaches, 5-fold cross validation is applied by randomly dividing the data consisting of group members' check-ins into five equal parts. 1/5 of the check-ins data is used as the test data and the rest is used as training data. Test data includes a subset of the check-ins belonging to group members. Training set is used for constructing group's subgraph and RWR is applied on this training set to obtain recommendations.

For recommendation quality evaluation, the following three metrics are used: AP@N (Average Precision for N recommendations), F-Measure@N (F-Measure for N recommendations) and HR@N (Hit Rate for N recommendations). In the equations, **precision** is the ratio of the number of relevant locations within N recommended locations to N, and **recall** is the ratio of the number of relevant locations within N recommended locations to the total number of relevant locations.

AP@N. The average precision is calculated without paying attention to the order of the locations in the test data. Precision is calculated as the ratio of the number of relevant locations in N recommended locations to N.

F-Measure@N. The F-Measure metric shown in *Equation 4.1*, is the weighted harmonic mean of the well-known metrics of precision and recall. It denotes the lowest performance at 0.

$$F - Measure@N = 2 \times \frac{precision@N \times recall@N}{precision@N + recall@N} \tag{4.1}$$

HR@N. Hit Rate metric given in *Equation 4.2*, indicates the ratio of group members who have a hit for recommended locations.

$$HR@N = \frac{hit(l)}{len(G)} \tag{4.2}$$

where $hit(l)$ is the number of group members who has a relevant location (a location the member visited in the test set) in the Top-N recommended location list and $len(G)$ is the group size.

4.3 Baseline Methods

- **B1. Member with least friends**: It runs RWR on the visits of the member with the least number of friends, and generated recommendations accordingly.
- **B2. Member with most friends**: It runs RWR on the visits of the member with the highest number of friends.
- **B3. Most active member**: It recommends places based on the visits of the most active member.
- **B4. Two most active members**: It runs RWR on the subgraphs of the two most active members, and recommends places based on generated location lists.

4.4 Recommendation Performance Analysis

In this section, the accuracy performance of the methods are compared under varying group sizes, varying group content, and the effect of the trust factor. As mentioned in Section 4, the approach and baselines have been tested on five different cities, Istanbul, Izmir, New York, London and Mexico City. In the evaluation, group members were selected in two ways: from the most active users and randomly generated

Table 4.2: Performance of baseline approaches and proposed approaches in terms of AP@K **with the trust factor** on different **group sizes (2-10)**: Groups of **randomly** selected members, on **Izmir** data set

	AP@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	0.0	**0.02**	0.0	0.0	0.0	0.0
#4	0.0	0.02	0.0	**0.08**	0.04	0.04
#6	0.0	0.0	0.04	0.08	0.20	**0.25**
#8	0.0	0.0	**0.08**	0.0	**0.08**	**0.08**
#10	0.0	0.0	0.04	0.06	**0.20**	**0.20**

Table 4.3: Performance of baseline approaches and proposed approaches in terms of F-Measure@K **with the trust factor** on different **group sizes (2-10)**: Groups of **randomly** selected members, on **Izmir** data set

	F1@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	0.0	**0.034**	0.0	0.0	0.0	0.0
#4	0.0	0.014	0.0	0.059	**0.073**	**0.073**
#6	0.0	0.0	0.029	0.029	**0.084**	0.060
#8	0.0	0.0	0.032	0.0	0.100	**0.120**
#10	0.0	0.0	0.027	0.024	0.077	**0.100**

group. In Figure 4.1 and Figure 4.3, recommendation evaluation results are illustrated for randomly generated groups in Istanbul and Izmir, respectively. Recommendation evaluation results for groups with the most active users are showed in Figure 4.2 and Figure 4.4.

According to the results, it obviously can be seen that the group profile and GTL approaches provide better results than the baselines on all evaluation metrics. In terms of running time, GTL takes longer than the other approaches when the most active users are selected as group members. When group members are selected randomly,

Table 4.4: Performance of baseline approaches and proposed approaches in terms of AP@K **with the trust factor** on different **group sizes (2-10)**: Groups of the **most active members**, on **Izmir** data set

	AP@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	0.08	0.12	0.04	0.12	**0.18**	0.16
#4	0.06	0.04	0.08	0.12	**0.20**	**0.20**
#6	0.10	0.06	0.10	0.12	0.20	**0.22**
#8	0.12	0.06	0.08	0.12	**0.20**	**0.20**
#10	0.10	0.06	0.10	0.12	0.20	**0.22**

Table 4.5: Performance of baseline approaches and proposed approaches in terms of F-Measure@K **with the trust factor** on different **group sizes (2-10)**: Groups of the **most active members**, on **Izmir** data set

	F1@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	0.015	0.022	0.007	0.022	**0.033**	**0.033**
#4	0.006	0.004	0.008	0.012	0.019	**0.020**
#6	0.007	0.004	0.007	0.008	0.028	**0.033**
#8	0.006	0.003	0.004	0.006	**0.043**	0.038
#10	0.004	0.0025	0.004	0.005	0.026	**0.028**

depending on the group size, other methods can take less time than GTL. With GTL's ability to run asynchronously, it can be said that the running time is up to par with others.

In Table 4.2, Table 4.3, Table 4.4 and Table 4.5, the recommendation accuracy results are presented more closely in terms of AP@10 and F-Measure@10 for random groups and groups with the most active users, respectively. For all metrics, GTL and Group profile methods achieve better performance and they bring 50-125% improvements for AP@10, 42-100% improvements for HR@10 and 50-125% improvements for

Table 4.6: Performance of baseline approaches and proposed approaches in terms of AP@K **without the trust factor** on different **group sizes (2-10)**: Groups of the **most active members**, on **Izmir** data set

	AP@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	0.0	0.0	0.02	**0.04**	0.0	0.0
#4	0.0	0.0	0.01	**0.04**	0.01	0.01
#6	0.0	**0.04**	0.02	0.0	0.01	0.02
#8	0.02	0.0	**0.10**	0.02	**0.10**	**0.10**
#10	0.0	0.04	0.0	0.0	0.04	**0.08**

Table 4.7: Performance of baseline approaches and proposed approaches in terms of F-Measure@K **without the trust factor** on different **group sizes (2-10)**: Groups of the **most active members**, on **Izmir** data set

	F1@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	0.0	0.0	0.017	**0.030**	0.0	0.0
#4	0.0	0.0	0.0	**0.028**	0.010	0.020
#6	0.0	0.013	0.007	0.0	**0.020**	0.010
#8	0.006	0.0	**0.038**	0.014	0.032	**0.038**
#10	0.0	0.015	0.0	0.0	**0.019**	**0.019**

F-Measure@10 in comparison to the baselines.

The results show that running RWR for a group of people provides more accurate recommendations. However, generating the recommendations over the aggregated group profile brings limited improvement for accuracy.

In terms of the effects of the trust factor, in Table 4.6 and Table 4.7, recommendation accuracy results are presented for GTL, Group Profile and the Baseline methods, with groups of the most active members, on Izmir dataset, this time not including the trust factor. In case the trust factor is not enabled, all trusted user nodes and

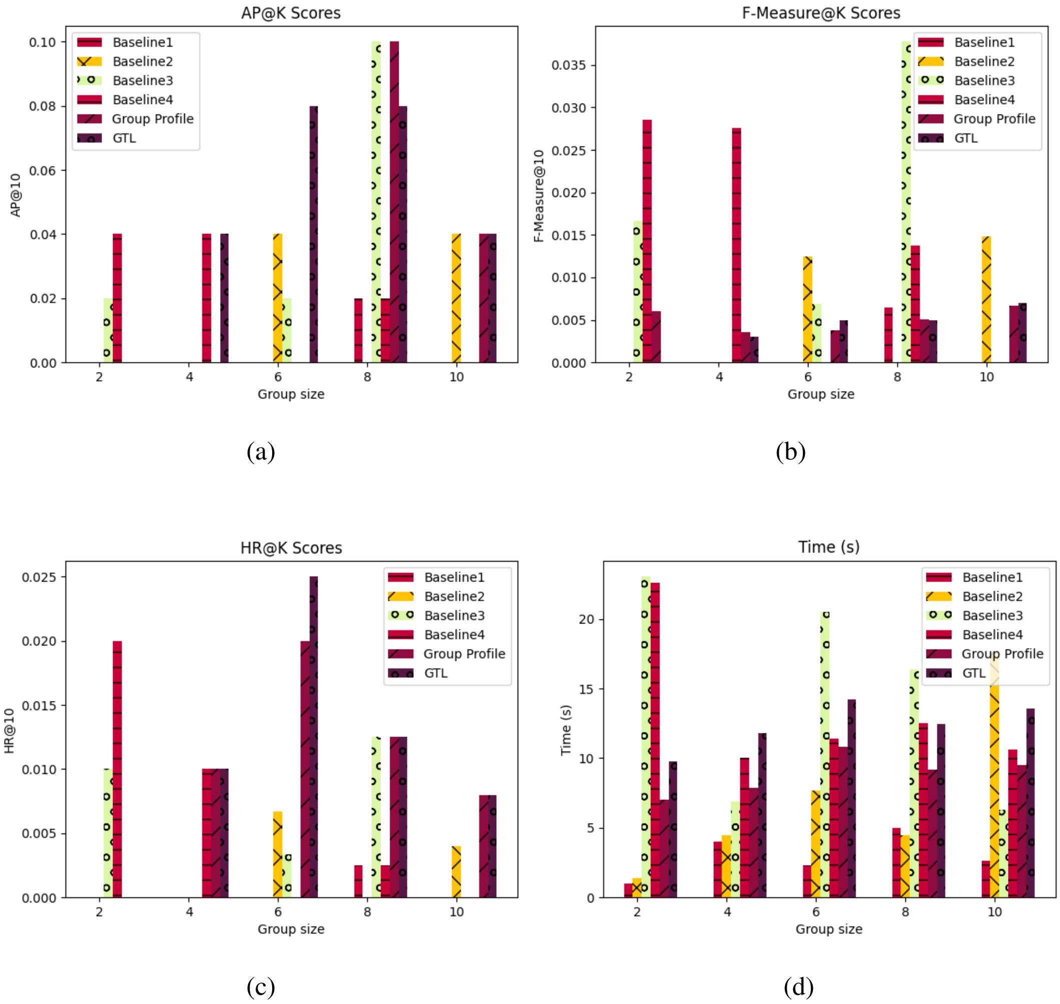
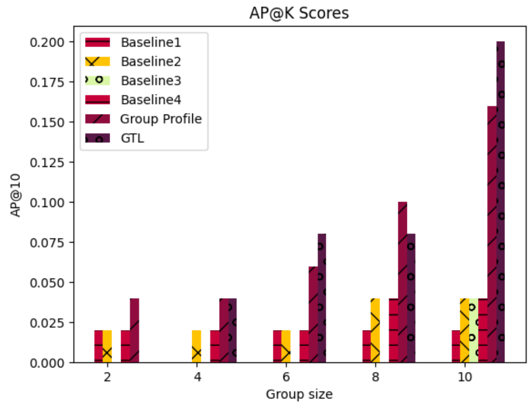


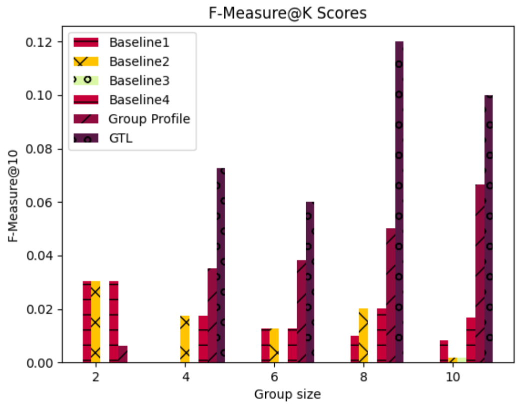
Figure 4.1: **Istanbul** - **Randomly** generated group - Performance of baseline methods and the group profile approach in terms of **(a)** AP@K Score, **(b)** F-Measure@K Score, **(c)** HR@K Score, **(d)** Running time with with different **group sizes (2-10)**

their visit data are also removed from the subgraph where RWR is run. As given in the results, trust factor (objectivity) highly improves the performance of baseline approaches for all metrics by 33-200%. For group sizes 2, 4 and 6, there is a sharp increase in all methods for all metrics and there is no sharp change for group size 8. Whereas it brings up to 900% improvement for GTL for group size 4, and for Group Profile 1900% improvement is obtained. For the group size 10, GTL increases the performance by 47% for F-Measure metric and 225% for AP metric.

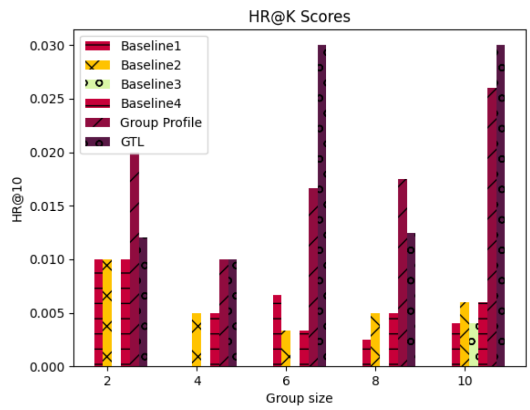
The results show that including trust factor provides significant improvements on all



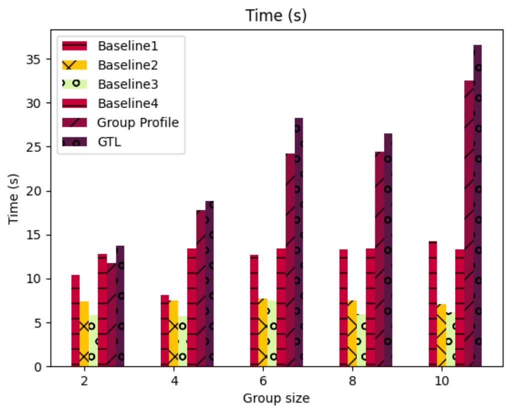
(a)



(b)



(c)



(d)

Figure 4.2: **Istanbul** - Group created with the **most active members** - Performance of baseline methods and the group profile approach in terms of **(a)** AP@K Score, **(b)** F-Measure@K Score, **(c)** HR@K Score, **(d)** Running time with with different **group sizes (2-10)**

performance metrics for the baseline methods and on the proposed approaches. As the GTL and Group Profile already suggested places with higher scores, with the contribution of the trust score, the recommendation results in these two approaches were greatly boosted. Despite a significant improvement over the baseline methods, the GTL and Group Profile methods continue to achieve better recommendation performance on all three metrics.

According to the evaluation results, the most striking point is that the results of the

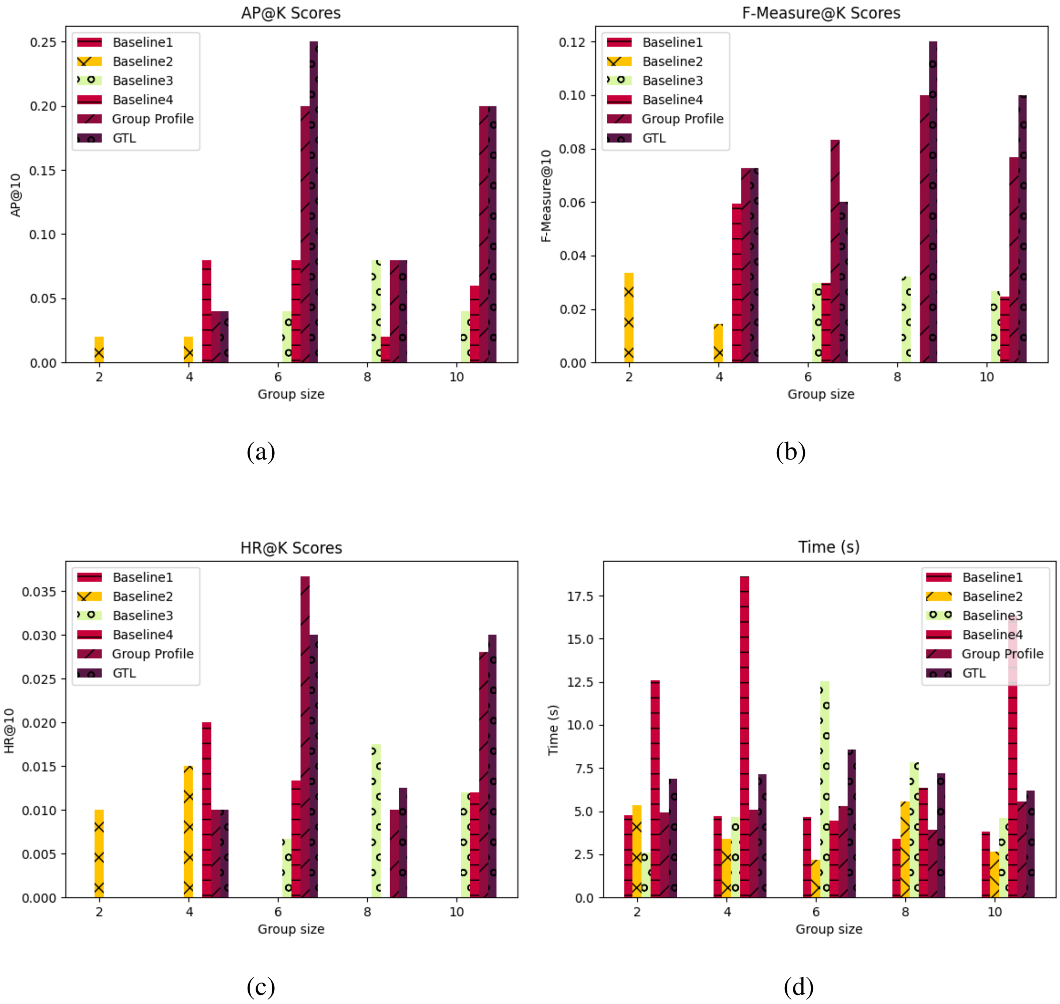
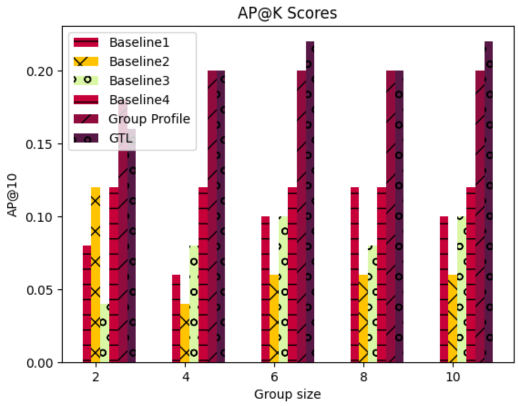
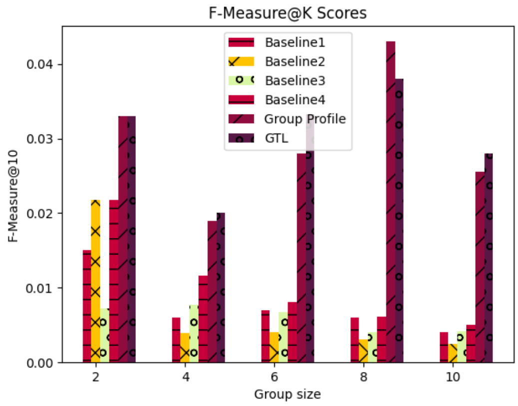


Figure 4.3: **Izmir** - **Randomly** generated group - Performance of baseline methods and the group profile approach in terms of **(a)** AP@K Score, **(b)** F-Measure@K Score, **(c)** HR@K Score, **(d)** Running time with different **group sizes (2-10)**

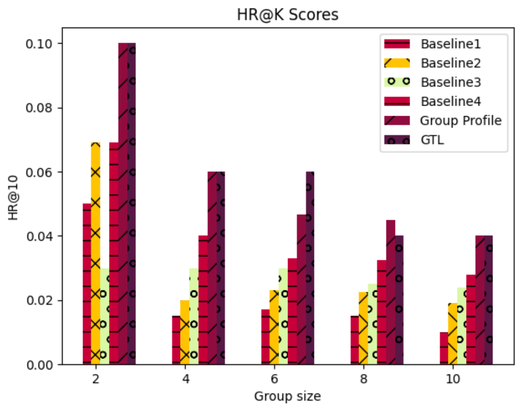
recommendations made to the randomly selected group with the trust factor and the recommendations made to the most active users without the trust factor are very close to each other. As the reason for this, it can be said that there is no trusted user visit data that can be counted as close to the randomly selected group members. This subgraph in the same neighborhood shows that there are few trusted users.



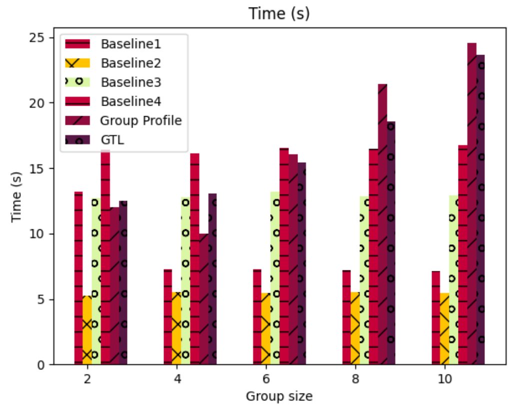
(a)



(b)



(c)

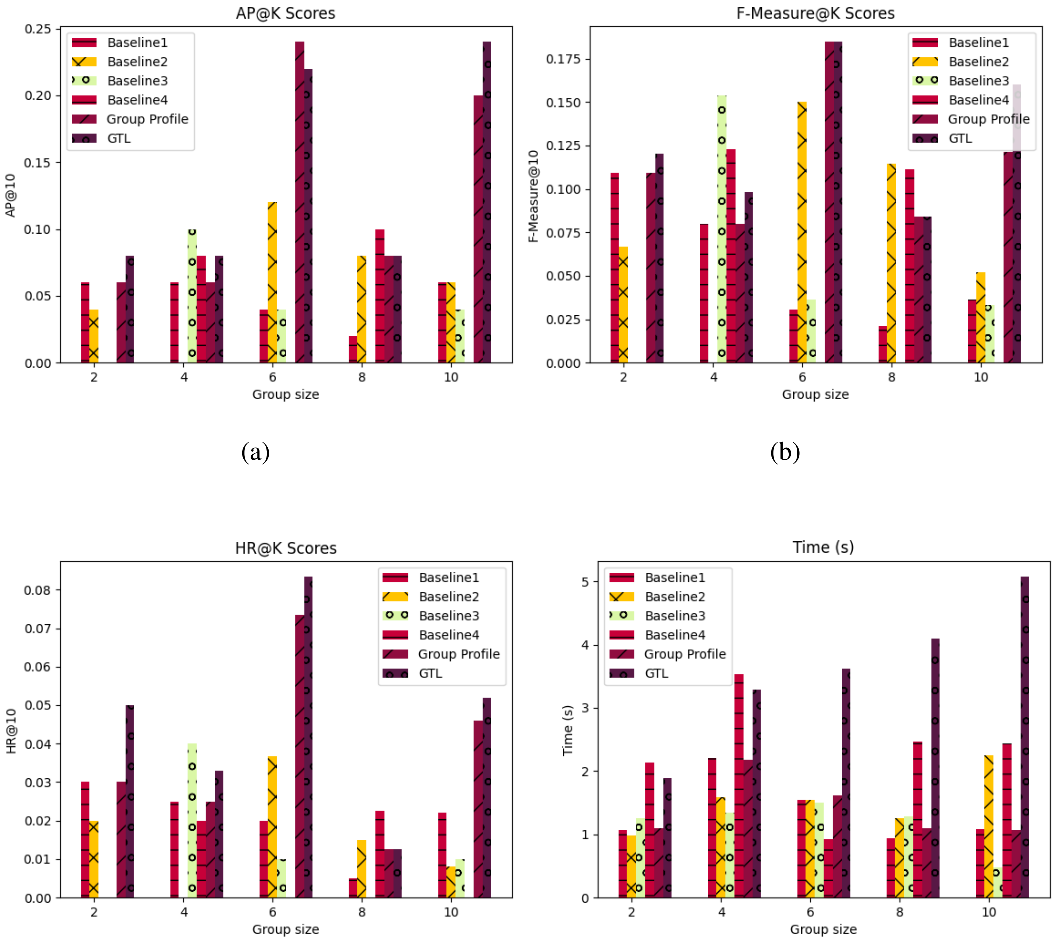


(d)

Figure 4.4: **Izmir** - Group created with the **most active members** - Performance of baseline methods and the group profile approach in terms of **(a)** AP@K Score, **(b)** F-Measure@K Score, **(c)** HR@K Score, **(d)** Running time with different **group sizes (2-10)**

4.5 Comparative Analysis with Related Work

The accuracy of the GTL and Group profile approaches and running time performances against the Direct Trust Model (DTM) which is introduced by Zhiyun et al. in [13] are also compared in Table 4.8 and in Table 4.9. Direct trust is defined as the presence of common rating items and consistent ratings among users. Rating consistency denotes the division of the rating into two parts based on the rating level. If a



(a) (b)

(c) (d)

Figure 4.5: **London** - **Randomly** generated group - Performance of baseline methods and the group profile approach in terms of **(a)** AP@K Score, **(b)** F-Measure@K Score, **(c)** HR@K Score, **(d)** Running time with different **group sizes (2-10)**

user's rating is higher than the median, the rating is positive; otherwise, the rating is negative. There is no rating data in the dataset (Foursquare) used in this study, so the direct trust in the study was tried to be implemented by taking into account the number of likes in the check-in posts. These check-in likes are grouped into the category types of the venues, yielding a category-by-category trust score. A user's trust score in different venue categories is different from each other.

This trust model is put into the GTL algorithm and compared with our own trust model. RWR is also run for the recommendation system. The results are shown in

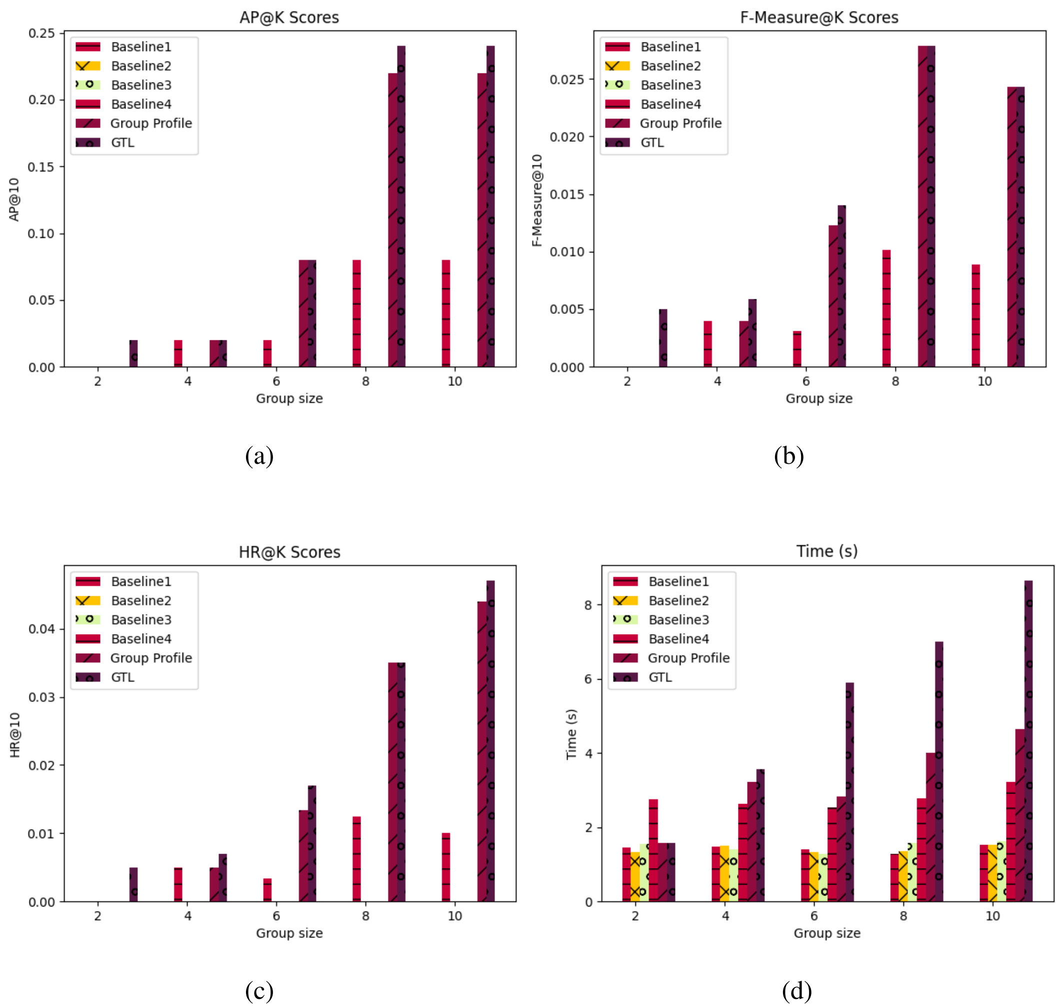
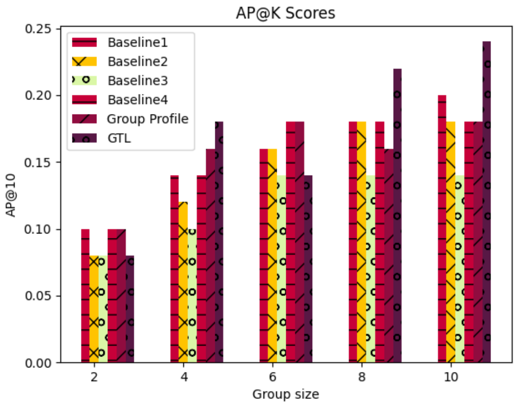
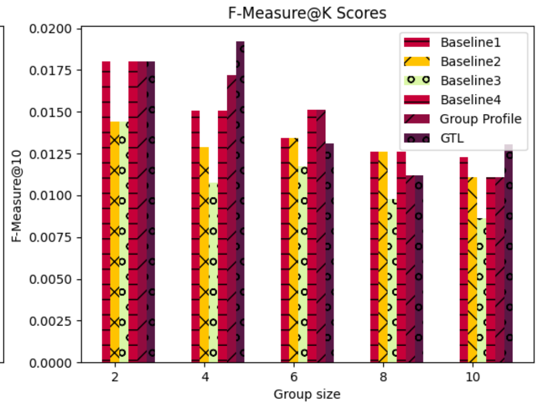


Figure 4.6: **London** - Group created with the **most active members** - Performance of baseline methods and the group profile approach in terms of **(a)** AP@K Score, **(b)** F-Measure@K Score, **(c)** HR@K Score, **(d)** Running time with different **group sizes (2-10)**

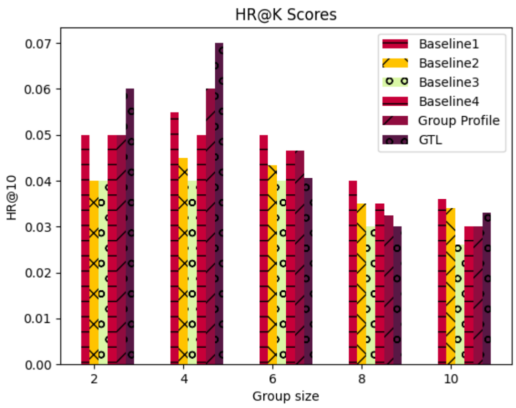
Figure 4.9 and in Figure 4.10. Comparison with the DTM is carried out on the all cities' dataset. As can be seen in Tables 4.8 and 4.9, the DTM surpasses GTL in 2-member groups. But with more than 2 group members, GTL and GP are ahead, and even, GTL gives better results as the number of group members increases. This can be attributed to the category-based trust score. In this case, it can be inferred that Direct Trust becomes less important as the number of group members increases. The proposed trust model yielded better results than DTM for more than two group



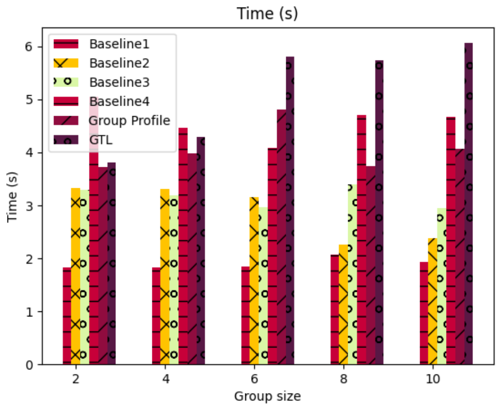
(a)



(b)



(c)



(d)

Figure 4.7: **New York** - Group created with the **most active members** - Performance of baseline methods and the group profile approach in terms of **(a)** AP@K Score, **(b)** F-Measure@K Score, **(c)** HR@K Score, **(d)** Running time with different **group sizes (2-10)**

members.

In order to measure the performance of the proposed approach in different recommendation configurations, recommendations @3, @5 and @10 were made in the same experiments. In the experiments, baseline-4 (which gives the best results among baselines), DTM and proposed approaches GP and GTL were compared. The results of these experiments on Istanbul, Izmir, London, New York and Mexico City data are as shown in the figures respectively Figure 4.11, 4.12, 4.13, 4.14 and 4.15 and

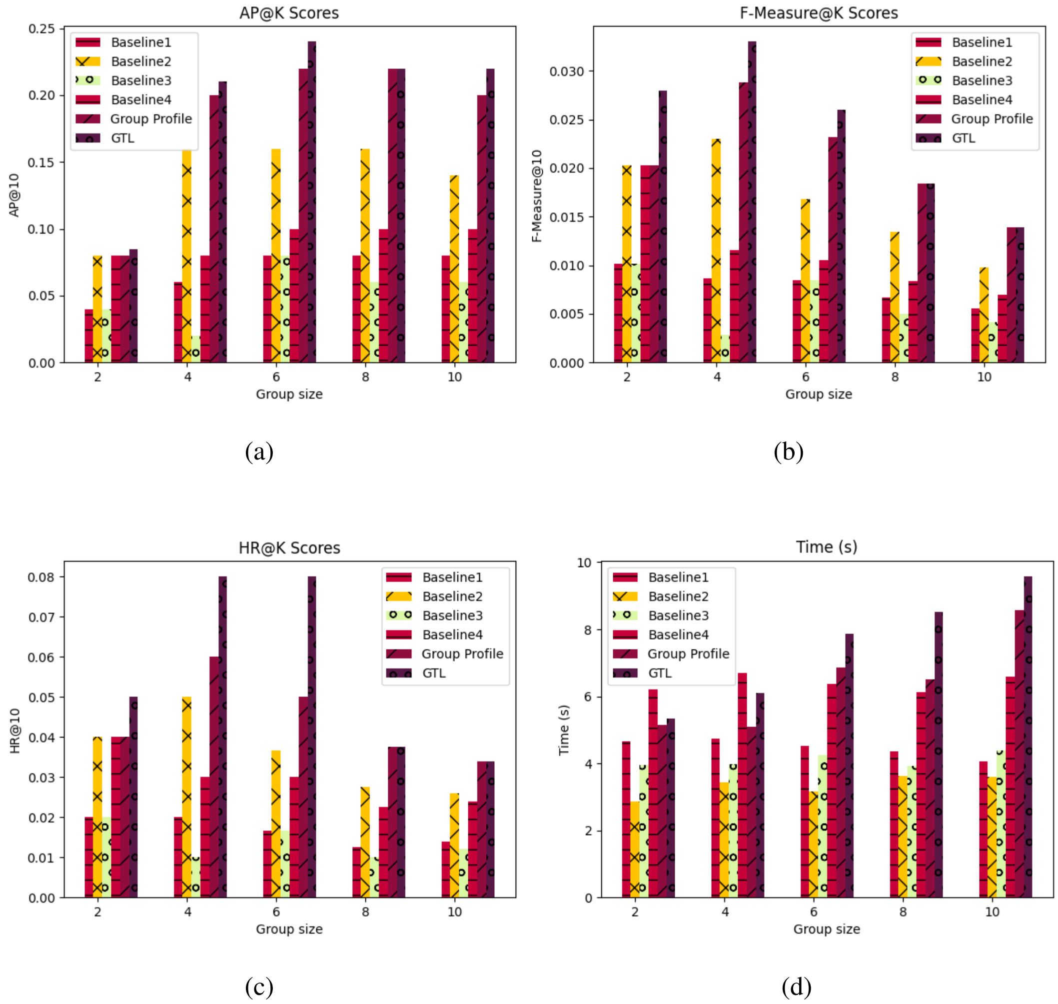
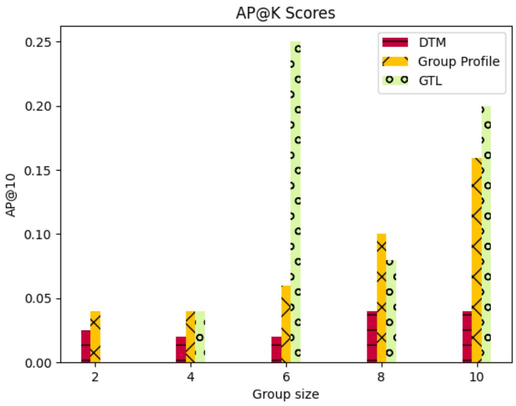
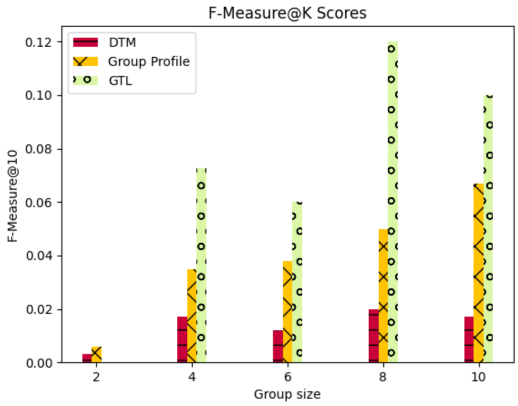


Figure 4.8: **Mexico City** - Group created with the **most active members** - Performance of baseline methods and the group profile approach in terms of **(a)** AP@K Score, **(b)** F-Measure@K Score, **(c)** HR@K Score, **(d)** Running time with different **group sizes (2-10)**

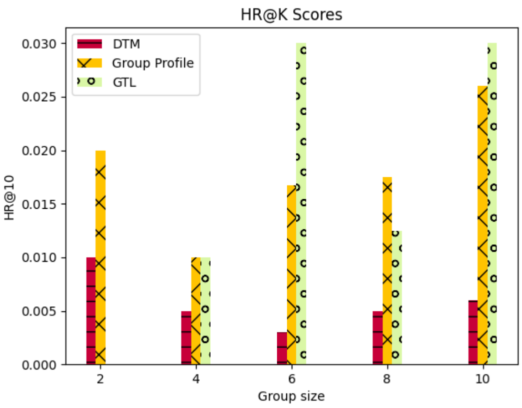
Tables 4.10, 4.11, 4.12, 4.13 and 4.14. As can be seen from the figures and tables, the proposed system gave better results as the number of suggestions decreased. @5 recommendations gave better results than @3 recommendations. From the results, it can be deduced that the average recommendation provides better accuracy. If a performance order is made, a result @5 > @3 > @10 is obtained for all group sizes. It is observed that the rate of deviation from accuracy increases as the number of suggestions increases. The suggested approach yielded the best results when the @5



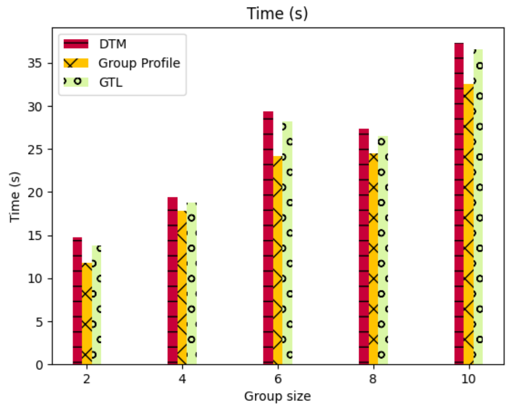
(a)



(b)



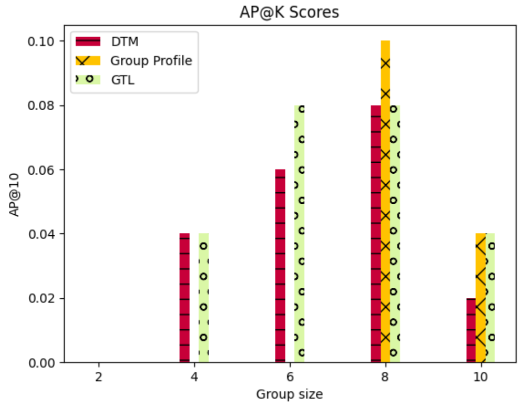
(c)



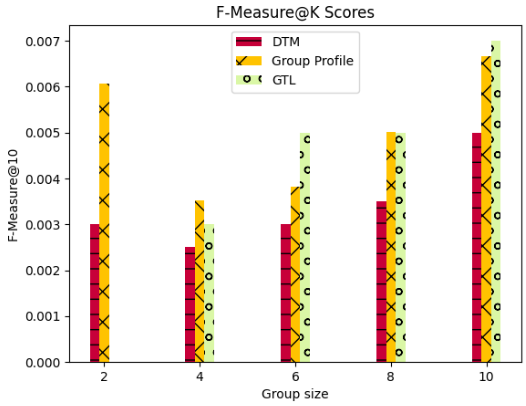
(d)

Figure 4.9: **Istanbul** - Group created with the **most active members** - Performance of proposed approach against the DTM in terms of **(a)** AP@K Score, **(b)** F-Measure@K Score, **(c)** HR@K Score, **(d)** Running time with different **group sizes (2-10)**

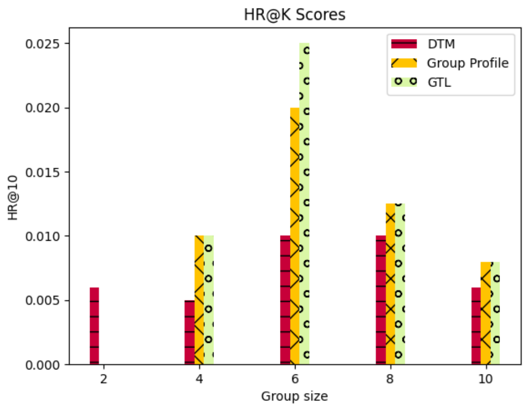
recommendation was made. @5 recommendations, compared to @10 recommendations; it has brought improvement 400% for #2 - #4 group sizes, 50% for #6 group size, and 10% for #8 - #10 group sizes.



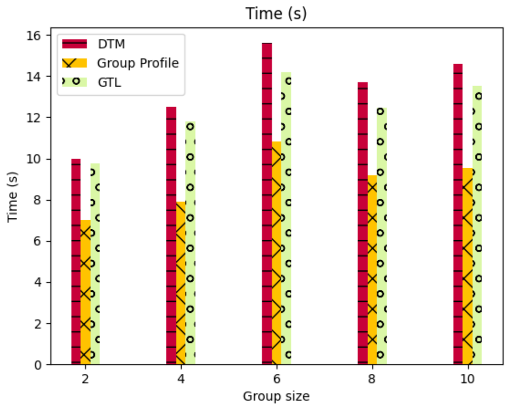
(a)



(b)



(c)



(d)

Figure 4.10: **Istanbul** - **Randomly** generated group - Performance of proposed approach against the DTM in terms of **(a)** AP@K Score, **(b)** F-Measure@K Score, **(c)** HR@K Score, **(d)** Running time with different **group sizes (2-10)**

Table 4.8: Performance of proposed approach against the **DTM** in terms of AP@K and F-Measure@K **with the trust factor** on different **group sizes (2-10)**: Groups of the **most active members**, on **Istanbul** data set

	AP@10			F1@10		
Group Size	DTM	GP	GTL	DTM	GP	GTL
#2	0.025	**0.040**	0	0.030	**0.060**	0
#4	0.020	**0.040**	**0.040**	0.017	0.035	**0.073**
#6	0.020	0.060	**0.250**	0.012	0.038	**0.060**
#8	0.040	**0.100**	0.080	0.020	0.050	**0.120**
#10	0.040	0.159	**0.200**	0.017	0.067	**0.100**

Table 4.9: Performance of proposed approach against the **DTM** in terms of AP@K and F-Measure@K **with the trust factor** on different **group sizes (2-10)**: **Randomly** generated group, on **Istanbul** data set

	AP@10			F1@10		
Group Size	DTM	GP	GTL	DTM	GP	GTL
#2	0	0	0	0.003	**0.006**	0
#4	**0.040**	0	**0.040**	0.002	**0.004**	0.003
#6	0.060	0	**0.080**	0.003	0.004	**0.005**
#8	0.080	**0.100**	0.080	0.004	**0.005**	**0.005**
#10	0.020	**0.040**	**0.040**	0.005	0.006	**0.007**

Table 4.10: Performance of proposed approach against the **Baseline 4** and **DTM** on different recommendation numbers, in terms of AP@K and F-Measure@K with the trust factor on **group size 6**: Group of the **most active members**, on **Istanbul** data set

	AP@K				F1@K			
# of Rec	B4	DTM	GP	GTL	B4	DTM	GP	GTL
@3	0.025	0.020	0.080	**0.267**	0.020	0.016	0.042	**0.067**
@5	0.030	0.024	0.100	**0.315**	0.032	0.018	0.051	**0.072**
@10	0.025	0.020	0.060	**0.250**	0.020	0.012	0.038	**0.060**

Table 4.11: Performance of proposed approach against the **Baseline 4** and **DTM** on different recommendation numbers, in terms of AP@K and F-Measure@K with the trust factor on **group size 6**: Group of the **most active members**, on **Izmir** data set

	AP@K				F1@K			
# of Rec	B4	DTM	GP	GTL	B4	DTM	GP	GTL
@3	0.120	0.216	0.220	**0.247**	0.010	0.022	**0.033**	**0.033**
@5	0.180	0.228	**0.325**	0.316	0.012	0.028	**0.044**	0.041
@10	0.120	0.168	0.200	**0.222**	0.008	0.016	0.028	**0.033**

Table 4.12: Performance of proposed approach against the **Baseline 4** and **DTM** on different recommendation numbers, in terms of AP@K and F-Measure@K with the trust factor on **group size 6**: Group of the **most active members**, on **London** data set

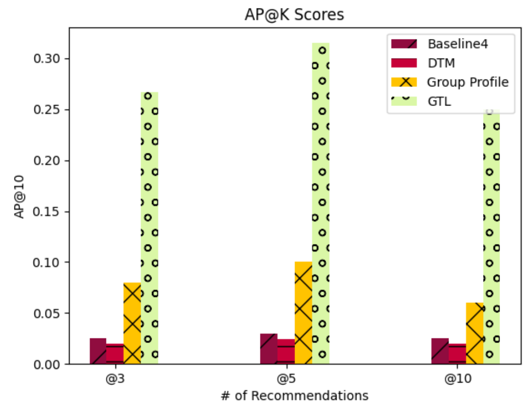
	AP@K				F1@K			
# of Rec	B4	DTM	GP	GTL	B4	DTM	GP	GTL
@3	0.040	0.060	0.080	**0.090**	0.006	**0.016**	0.012	**0.016**
@5	0.030	0.100	**0.120**	**0.120**	**0.032**	0.018	0.018	**0.032**
@10	0.0	0.060	**0.080**	**0.080**	0.0	0.009	0.012	**0.014**

Table 4.13: Performance of proposed approach against the **Baseline 4** and **DTM** on different recommendation numbers, in terms of AP@K and F-Measure@K with the trust factor on **group size 6**: Group of the **most active members**, on **New York** data set

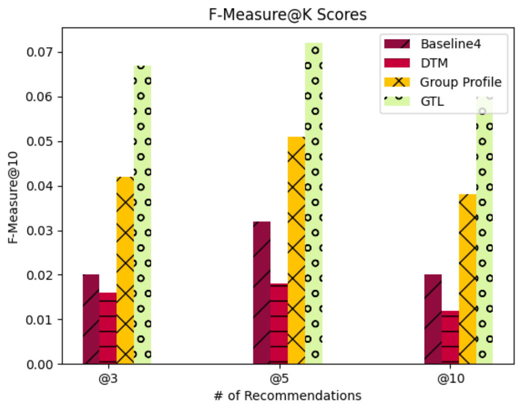
	AP@K				F1@K			
# of Rec	B4	DTM	GP	GTL	B4	DTM	GP	GTL
@3	**0.022**	0.018	**0.022**	0.018	**0.020**	0.016	**0.020**	**0.020**
@5	0.022	0.020	**0.024**	0.022	0.026	0.027	**0.038**	0.027
@10	**0.018**	0.012	**0.018**	0.014	**0.015**	0.012	**0.015**	0.013

Table 4.14: Performance of proposed approach against the **Baseline 4** and **DTM** on different recommendation numbers, in terms of AP@K and F-Measure@K with the trust factor on **group size 6**: Group of the **most active members**, on **Mexico City** data set

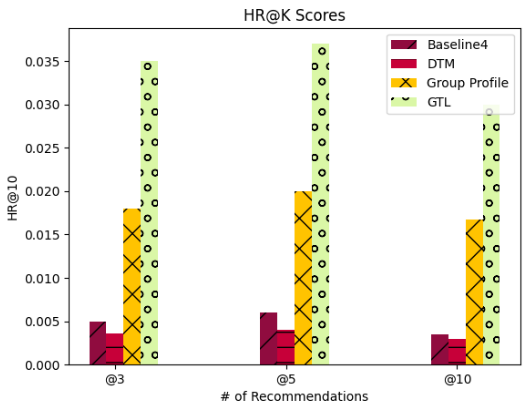
	AP@K				F1@K			
# of Rec	B4	DTM	GP	GTL	B4	DTM	GP	GTL
@3	0.120	0.232	0.256	**0.260**	0.014	0.027	**0.028**	**0.028**
@5	0.180	0.310	0.300	**0.320**	0.019	0.034	0.033	**0.037**
@10	0.100	0.220	0.219	**0.240**	0.010	0.025	0.023	**0.026**



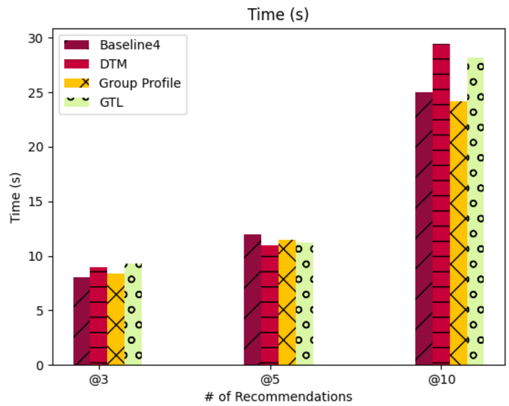
(a)



(b)

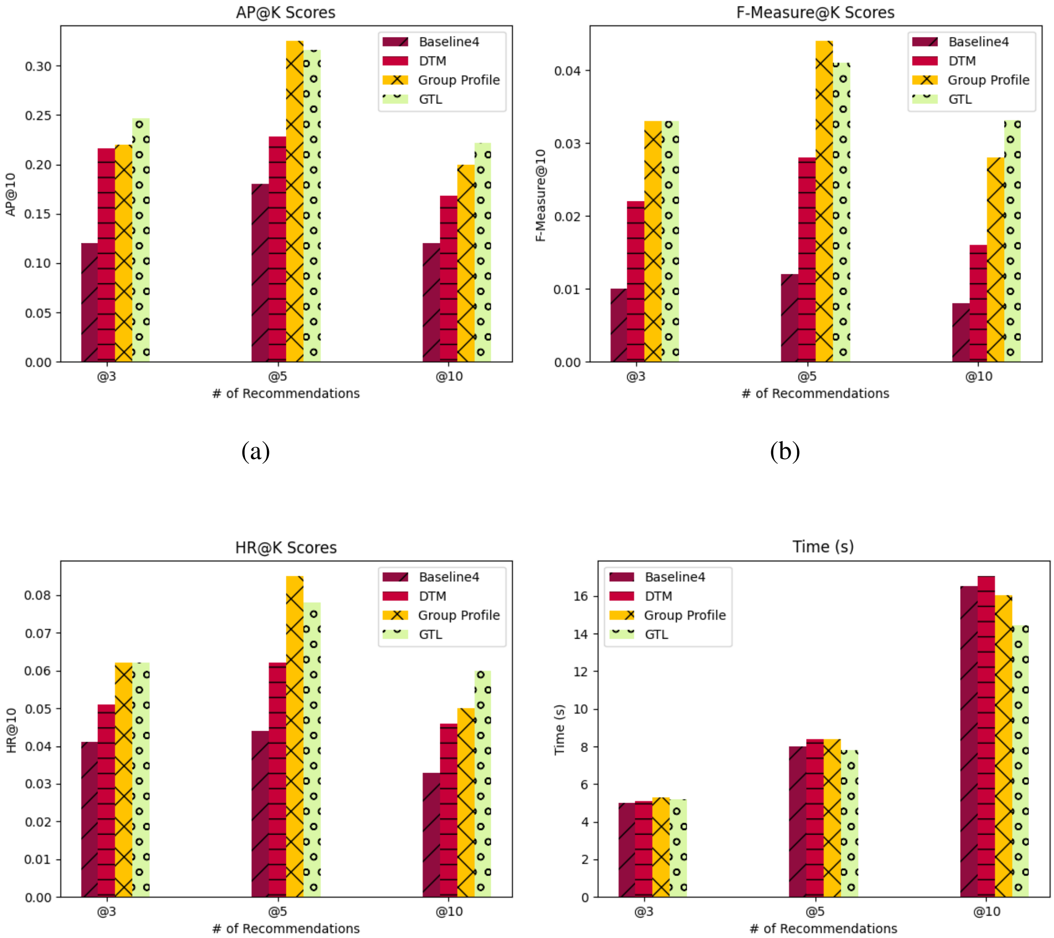


(c)



(d)

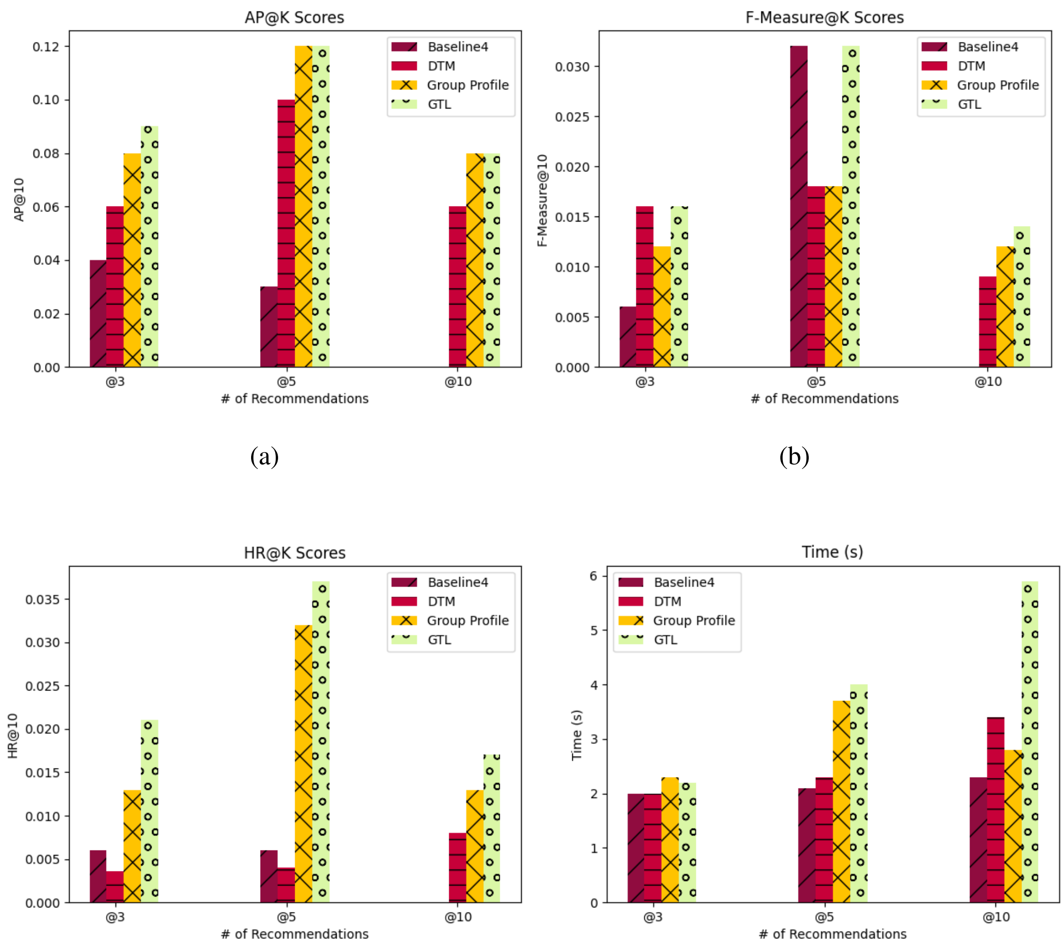
Figure 4.11: **Istanbul** - Group created with the **most active members** - Performance of proposed approach against the **Baseline 4** and **DTM** on different recommendation numbers, in terms of **(a)** AP@K Score, **(b)** F-Measure@K Score, **(c)** HR@K Score, **(d)** Running time with **group size 6**



(a) (b)

(c) (d)

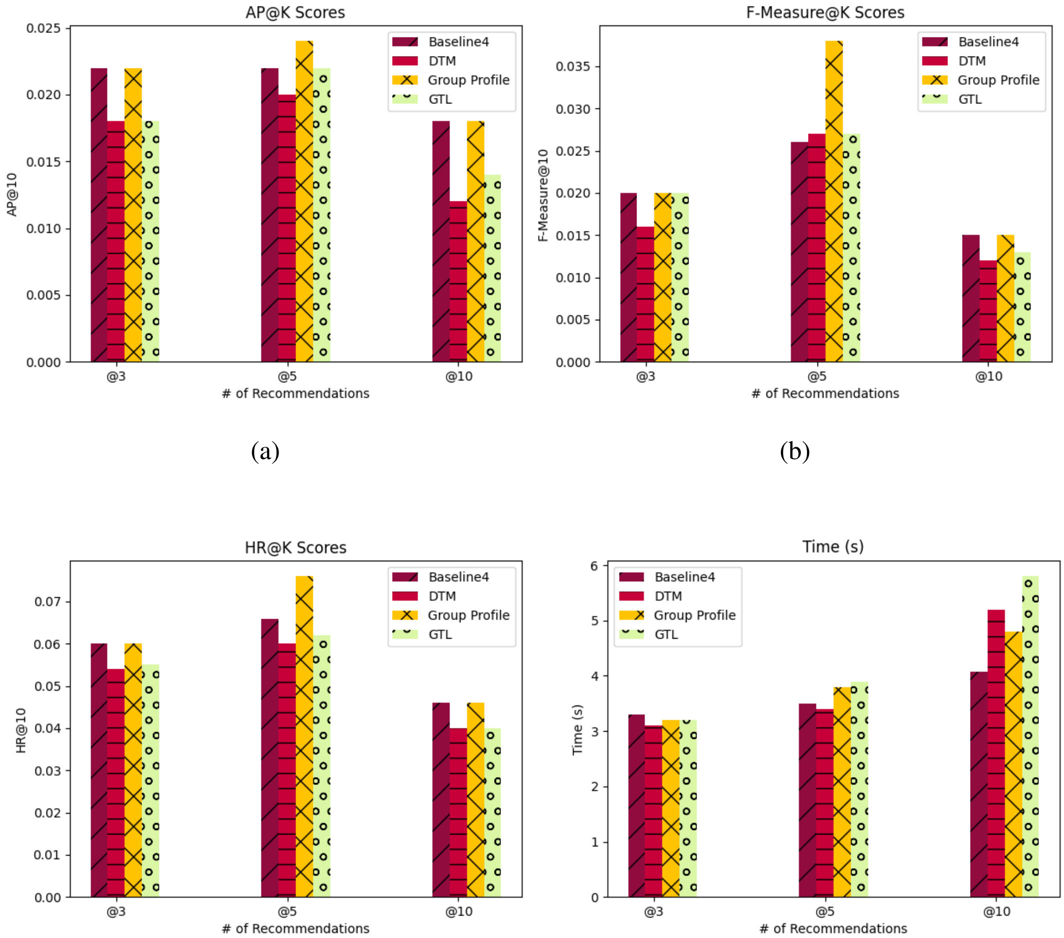
Figure 4.12: **Izmir** - Group created with the **most active members** - Performance of proposed approach against the **Baseline 4** and **DTM** on different recommendation numbers, in terms of **(a)** AP@K Score, **(b)** F-Measure@K Score, **(c)** HR@K Score, **(d)** Running time with **group size 6**



(a) (b)

(c) (d)

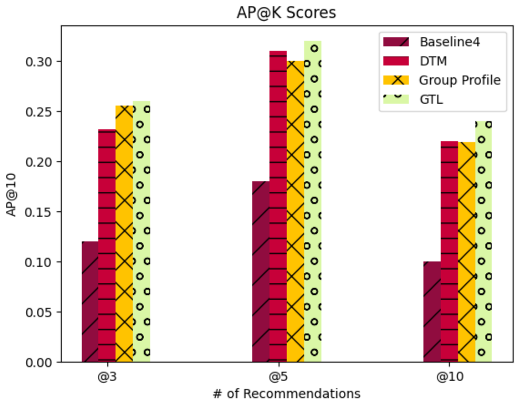
Figure 4.13: **London** - Group created with the **most active members** - Performance of proposed approach against the **Baseline 4** and **DTM** on different recommendation numbers, in terms of **(a)** AP@K Score, **(b)** F-Measure@K Score, **(c)** HR@K Score, **(d)** Running time with **group size 6**



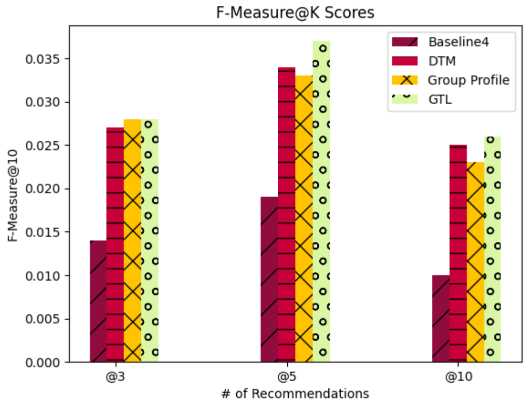
(a) (b)

(c) (d)

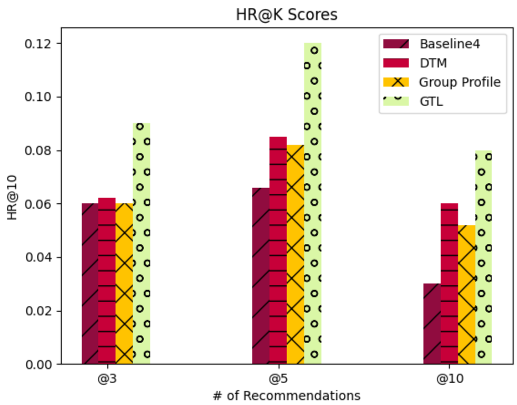
Figure 4.14: **New York** - Group created with the **most active members** - Performance of proposed approach against the **Baseline 4** and **DTM** on different recommendation numbers, in terms of **(a)** AP@K Score, **(b)** F-Measure@K Score, **(c)** HR@K Score, **(d)** Running time with **group size 6**



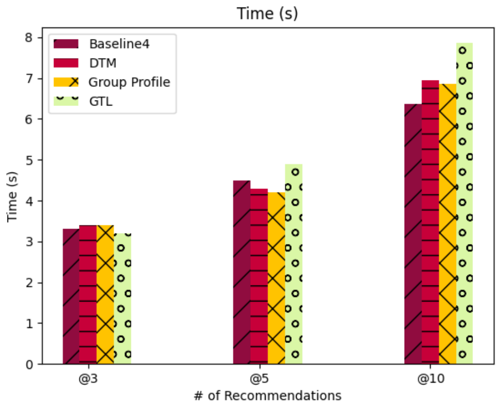
(a)



(b)



(c)



(d)

Figure 4.15: **Mexico City** - Group created with the **most active members** - Performance of proposed approach against the **Baseline 4** and **DTM** on different recommendation numbers, in terms of **(a)** AP@K Score, **(b)** F-Measure@K Score, **(c)** HR@K Score, **(d)** Running time with **group size 6**

CHAPTER 5

CONCLUSION

In this work, a RWR based location recommendation method for groups is presented. The proposed algorithm, GoTaRW, introduces a new recommendation mechanism by including the trust factor of users in the group-oriented location recommendation in LBSNs. The proposed method includes two approaches for generating and scoring the recommendation items. In the first one, GTL, recommendations are obtained for each group member individually and the locations are rescored and sorted. The second one involves creating a group profile by blending preferences and venue category types, called Group Profile approach.

A series of experiments were conducted to analyse the accuracy performance of the models against four baseline methods under varying group sizes and the effect of trust factor. Experiments are conducted on a dataset obtained from Foursquare. Results indicate that the proposed approaches performs better in comparison to the baseline approach.

As seen in the analysis results, trust factor (objectivity) highly improves the performance of all approaches for all metrics. The findings demonstrate that the trust factor consistently adds value to evaluation outcomes. For both the baseline methods and the proposed approaches, including the trust factor improves all performance indicators significantly. For all metrics, GTL and Group profile methods achieve better performance and they bring 50-125% improvements for AP@K, 42-100% improvements for HR@K and 50-125% improvements for F-Measure@K in comparison to the baselines. With the addition of the trust score, the recommendation results in these two techniques were substantially enhanced, since the GTL and Group Profile already indicated venues with higher scores. While the baseline approach is considerably improved with the trust effect, GTL and Group Profile methods still provide higher performance at all metrics.

The running time of the methods increases expectedly, as the group size gets larger. Group Profile approach mostly has lower running times compared to GTL. However this depends on the nature of the generated group profile. If the visited locations of the members have little overlap, a large subgraph may lead to higher processing time. In terms of group formation, groups with most active members, have larger subgraphs due to variety in the visits. This causes higher running times.

The scoring method used in aggregating the ranked recommendations for each group members can be differentiated according to the preferences of group members. Moreover, different trust factors can be applied within the LBSNs in order to model the objectivity and consistency of group members more accurately and to define a trust score belonging to the group when creating a group profile. Moreover, recommendations can be enhanced by taking into account the time information of the visits.

REFERENCES

[1] A. Jameson, "More than the sum of its members: challenges for group recommender systems," *Proceedings of the working conference on Advanced visual interfaces - AVI 04*, 2004.

[2] M. Kompan and M. Bielikova, "Group recommendations: Survey and perspectives," *Computing and Informatics*, vol. 33, pp. 1–31, 01 2014.

[3] L. Quijano-Sanchez, J. A. Recio-Garcia, and B. Diaz-Agudo, "Personality and social trust in group recommendations," *2010 22nd IEEE International Conference on Tools with Artificial Intelligence*, 2010.

[4] L. Quijano-Sánchez, B. Díaz-Agudo, and J. A. Recio-García, "Development of a group recommender application in a social network," *Knowledge-Based Systems*, vol. 71, p. 72–85, 2014.

[5] M. Gartrell, X. Xing, Q. Lv, A. Beach, R. Han, S. Mishra, and K. Seada, "Enhancing group recommendation by incorporating social relationship interactions," *Proceedings of the 16th ACM international conference on Supporting group work - GROUP 10*, 2010.

[6] I. A. Christensen and S. Schiaffino, "Social influence in group recommender systems," *Online Information Review*, vol. 38, no. 4, p. 524–542, 2014.

[7] L. Ravi and S. Vairavasundaram, "A collaborative location based travel recommendation system through enhanced rating prediction for the group of users," *Computational Intelligence and Neuroscience*, vol. 2016, p. 1–28, 2016.

[8] H. A. Teoman and P. Karagöz, "Group oriented trust-aware location recommendation for location-based social networks," *The 37th ACM/SIGAPP Symposium on Applied Computing (SAC'22), April 25–29, 2022, Virtual Event*, 2022.

[9] A. Chang, T.-K. Hwang, Y.-M. Li, and L.-F. Lin, "A contextual group recommender mechanism for location-based service," AMCIS, 2015.

[10] H. Yin, Q. Wang, K. Zheng, Z. Li, J. Yang, and X. Zhou, "Social influence-based group representation learning for group recommendation," in *2019 IEEE 35th International Conference on Data Engineering (ICDE)*, pp. 566–577, 2019.

[11] Z. Bahari Sojahrood and M. Taleai, "A poi group recommendation method in location-based social networks based on user influence," *Expert Systems with Applications*, vol. 171, p. 114593, 2021.

[12] Khazaei and Alimohammadi, "Context-aware group-oriented location recommendation in location-based social networks," *ISPRS International Journal of Geo-Information*, vol. 8, no. 9, p. 406, 2019.

[13] Z. Xu, X. Zheng, H. Zhang, and Y. Luo, "A novel travel group recommendation model based on user trust and social influence," *Mobile Information Systems*, vol. 2021, p. 1–10, 2021.

[14] F. Ayala-Gómez, B. Daróczy, M. Mathioudakis, A. Benczúr, and A. Gionis, "Where could we go?: Recommendations for groups in location-based social networks," *Proceedings of the 2017 ACM on Web Science Conference*, 2017.

[15] J. F. Mccarthy, "Pocket restaurantfinder: A situated recommender system for groups," 2002.

[16] S. Purushotham, C.-C. J. Kuo, J. Shahabdeen, and L. Nachman, "Collaborative group-activity recommendation in location-based social networks," *Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Crowdsourced and Volunteered Geographic Information*, 2014.

[17] J. Masthoff, "Group recommender systems: Combining individual models," *Recommender Systems Handbook*, p. 677–702, 2010.

[18] S. Feng and J. Cao, "Improving group recommendations via detecting comprehensive correlative information," *Multimedia Tools and Applications*, vol. 76, no. 1, p. 1355–1377, 2017.

[19] C. Senot, D. Kostadinov, M. Bouzid, J. Picault, A. Aghasaryan, and C. Bernier, "Analysis of strategies for building group profiles," *User Modeling, Adaptation, and Personalization Lecture Notes in Computer Science*, p. 40–51, 2010.

[20] J. F. Mccarthy and T. D. Anagnost, “Musicfx: an arbiter of group preferences for computer supported collaborative workouts,” *Proceedings of the 1998 ACM conference on Computer supported cooperative work - CSCW 98*, 1998.

[21] J. F. Mccarthy, T. J. Costa, and E. S. Liongosari, “Unicast, outcast groupcast: Three steps toward ubiquitous, peripheral displays,” *Ubicomp 2001: Ubiquitous Computing Lecture Notes in Computer Science*, p. 332–345, 2001.

[22] M. O’Connor, D. Cosley, J. A. Konstan, and J. Riedl, “Polylens: A recommender system for groups of users,” *Ecscw 2001*, p. 199–218.

[23] D. Cantürk, *Trust-aware Location Recommendation in Location-based Social Networks*. PhD thesis, Middle East Technical University, 2021.

[24] H.-K. Oh and S.-W. K. and, “Identifying and exploiting trustable users with robust features in online rating systems,” *KSII Transactions on Internet and Information Systems*, vol. 11, pp. 2171–2195, April 2017.

[25] H. Bagci and P. Karagoz, “Context-aware location recommendation by using a random walk-based approach,” *Knowledge and Information Systems*, vol. 47, no. 2, p. 241–260, 2015.

[26] F. Ayala-Gómez, B. Keniş, P. Karagöz, and A. Benczúr, “Top-k context-aware tour recommendations for groups,” *Advances in Computational Intelligence Lecture Notes in Computer Science*, p. 176–193, 2018.

APPENDIX A

TABLES OF EXPERIMENT RESULTS

Table A.1: Performance of baseline approaches and proposed approaches in terms of AP@K **with the trust factor** on different **group sizes (2-10)**: Groups of the **most active members**, on **Istanbul** data set

	AP@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	0.020	0.020	0.0	0.020	**0.040**	0.0
#4	0.0	0.020	0.0	0.020	**0.040**	**0.040**
#6	0.020	0.020	0.0	0.020	0.060	**0.250**
#8	0.020	0.040	0.0	0.040	**0.100**	0.080
#10	0.020	0.040	0.040	0.040	0.160	**0.200**

Table A.2: Performance of baseline approaches and proposed approaches in terms of F-Measure@K **with the trust factor** on different **group sizes (2-10)**: Groups of the **most active members**, on **Istanbul** data set

	F1@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	0.003	0.003	0.0	0.003	**0.006**	0.0
#4	0.0	0.002	0.0	0.018	0.035	**0.073**
#6	0.001	0.001	0.0	0.013	0.038	**0.060**
#8	0.001	0.002	0.0	0.020	0.050	**0.120**
#10	0.001	0.002	0.002	0.017	0.067	**0.100**

Table A.3: Performance of baseline approaches and proposed approaches in terms of AP@K **with the trust factor** on different **group sizes (2-10)**: Groups of **randomly** selected members, on **Istanbul** data set

	AP@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	0.0	0.0	0.020	**0.040**	0.0	0.0
#4	0.0	0.0	0.0	**0.040**	0.0	**0.040**
#6	0.0	0.040	0.020	0.0	0.0	**0.080**
#8	0.020	0.0	**0.100**	0.020	**0.100**	0.080
#10	0.0	**0.040**	0.0	0.0	**0.040**	**0.040**

Table A.4: Performance of baseline approaches and proposed approaches in terms of F-Measure@K **with the trust factor** on different **group sizes (2-10)**: Groups of **randomly** selected members, on **Istanbul** data set

	F1@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	0.0	0.0	0.017	**0.029**	0.006	0.0
#4	0.0	0.0	0.0	**0.028**	0.004	0.003
#6	0.0	**0.013**	0.007	0.0	0.004	0.005
#8	0.006	0.0	**0.038**	0.014	0.005	0.005
#10	0.0	**0.015**	0.0	0.0	0.007	0.007

Table A.5: Performance of baseline approaches and proposed approaches in terms of AP@K **with the trust factor** on different **group sizes (2-10)**: Groups of the **most active members**, on **London** data set

	AP@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	0.0	0.0	0.0	0.0	0.0	**0.020**
#4	**0.020**	0.0	0.0	0.0	**0.020**	**0.020**
#6	0.020	0.0	0.0	0.0	**0.080**	**0.080**
#8	0.080	0.0	0.0	0.0	0.220	**0.240**
#10	0.080	0.0	0.0	0.0	0.220	**0.240**

Table A.6: Performance of baseline approaches and proposed approaches in terms of F-Measure@K **with the trust factor** on different **group sizes (2-10)**: Groups of the **most active members**, on **London** data set

	F1@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	0.0	0.0	0.0	0.0	0.0	**0.005**
#4	0.004	0.0	0.0	0.0	0.004	**0.006**
#6	0.003	0.0	0.0	0.0	0.012	**0.014**
#8	0.010	0.0	0.0	0.0	**0.028**	**0.028**
#10	0.009	0.0	0.0	0.0	**0.024**	**0.024**

Table A.7: Performance of baseline approaches and proposed approaches in terms of AP@K **with the trust factor** on different **group sizes (2-10)**: Groups of **randomly** selected members, on **London** data set

	AP@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	0.060	0.040	0.0	0.0	0.060	**0.080**
#4	0.060	0.0	**0.100**	0.080	0.060	0.080
#6	0.040	0.120	0.040	0.0	**0.240**	0.220
#8	0.020	0.080	0.0	**0.100**	0.080	0.080
#10	0.060	0.060	0.040	0.0	0.200	**0.240**

Table A.8: Performance of baseline approaches and proposed approaches in terms of F-Measure@K **with the trust factor** on different **group sizes (2-10)**: Groups of **randomly** selected members, on **London** data set

	F1@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	0.109	0.067	0.0	0.0	0.109	**0.120**
#4	0.080	0.0	**0.154**	0.123	0.080	0.098
#6	0.031	0.15	0.036	0.0	**0.185**	**0.185**
#8	0.021	**0.114**	0.0	0.111	0.084	0.084
#10	0.036	0.052	0.033	0.0	0.121	**0.160**

Table A.9: Performance of baseline approaches and proposed approaches in terms of AP@K **with the trust factor** on different **group sizes (2-10)**: Groups of the **most active members**, on **New York** data set

	AP@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	**0.100**	0.080	0.080	**0.100**	**0.100**	0.080
#4	0.140	0.120	0.100	0.140	0.160	**0.180**
#6	0.160	0.160	0.140	**0.180**	**0.180**	0.140
#8	0.180	0.180	0.140	0.180	0.160	**0.220**
#10	0.200	0.180	0.140	0.180	0.180	**0.240**

Table A.10: Performance of baseline approaches and proposed approaches in terms of F-Measure@K **with the trust factor** on different **group sizes (2-10)**: Groups of the **most active members**, on **New York** data set

	F1@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	**0.018**	0.014	0.014	**0.018**	**0.018**	**0.018**
#4	0.015	0.013	0.011	0.015	0.017	**0.019**
#6	0.013	0.013	0.012	**0.015**	**0.015**	0.013
#8	**0.013**	**0.013**	0.010	**0.013**	0.011	0.011
#10	0.012	0.011	0.009	0.011	0.011	**0.013**

Table A.11: Performance of baseline approaches and proposed approaches in terms of AP@K **with the trust factor** on different **group sizes (2-10)**: Groups of the **most active members**, on **Mexico City** data set

	AP@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	0.040	0.080	0.040	0.080	0.080	**0.085**
#4	0.060	0.160	0.020	0.080	0.200	**0.210**
#6	0.080	0.160	0.080	0.100	0.220	**0.240**
#8	0.080	0.160	0.060	0.100	**0.220**	**0.220**
#10	0.080	0.140	0.060	0.100	0.200	**0.220**

Table A.12: Performance of baseline approaches and proposed approaches in terms of F-Measure@K **with the trust factor** on different **group sizes (2-10)**: Groups of the **most active members**, on **Mexico City** data set

	F1@10					
Group Size	Baseline 1	Baseline 2	Baseline 3	Baseline 4	GP	GTL
#2	0.010	0.020	0.010	0.020	0.020	**0.028**
#4	0.009	0.023	0.003	0.012	0.029	**0.033**
#6	0.008	0.017	0.008	0.011	0.023	**0.026**
#8	0.007	0.013	0.005	0.008	**0.018**	**0.018**
#10	0.006	0.010	0.004	0.007	**0.014**	**0.014**