NEW LOCATION RECOMMENDATION TECHNIQUE ON NETWORK

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A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Science Program in Computer Science and Information Technology
Department of Mathematics and Computer Science
Faculty of Science
Chulalongkorn University
Academic Year 2017

เทคนิคการแนะนำสถานที่แบบใหม่บนเครือข่าย

นางสาวสุทธารัตน์ เชิญอักษร

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
สาขาวิชาวิทยาการคอมพิวเตอร์และเทคโนโลยีสารสนเทศ ภาควิชาคณิตศาสตร์และวิทยาการคอมพิวเตอร์
คณะวิทยาศาสตร์ จุฬาลงกรณ์มหาวิทยาลัย
ปีการศึกษา 2560

Thesis Title	NEW LOCATION RECOMMENDATION TECHNIQUE ON NETWORK
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Field of Study	Computer Science and Information Technology
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Accepted by the Faculty of Science, Chulalongkorn University in Partial Fulfillment of the Requirements for the Master's Degree

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สุทธารัตน์ เชิญอักษร : เทคนิคการแนะนำสถานที่แบบใหม่บนเครือข่าย (NEW LOCATION RECOMMENDATION TECHNIQUE ON NETWORK) อ.ที่ปรึกษาวิทยานิพนธ์หลัก: ผศ. ดร. ศรันญา มณีโรจน์, หน้า.

ในปัจจุบันระบบการแนะนำกำลังเข้ามามีบทบาทในชีวิตประจำวันมากขึ้น โดยจะพบเห็นได้ทั่วไปในเวปไซต์ประเภทต่างๆ ซึ่งระบบแนะนำจะทำหน้าที่ในการช่วยแนะนำสิ่งที่น่าสนใจแก่ผู้เข้าชมเวปต์ไซต์ ยกตัวอย่างเช่น lonelyplanet.com, netfliex.com ฯลฯ จากตัวอย่างพบว่าระบบแนะนำนั้นถูกแทรกอยู่ในหลาย Domain เช่น lonelyplanet.com จัดอยู่ในประเภท Location-Domain และ netflex.com จัดอยู่ในประเภท Movie-Domain เป็นต้น การเลือกท่องเที่ยวในสถานที่ที่น่าสนใจ จากเวปต์ไซต์แนะนำสถานที่ท่องเที่ยว หรือตัดสินใจเลือกชมภาพยนต์ที่ชอบ จากเวปต์ไซต์ภาพยนต์ออนไลน์ ฯลฯ ส่วนหนึ่งมาจากคำแนะนำที่ได้จากระบบ โดยระบบแนะนำจะมีเทคนิคที่นิยมใช้กันอย่างแพร่หลาย เพื่อวิเคราะห์หาสิ่งที่ผู้ใช้งานสนใจ ได้แก่ Content-based filtering และ Collaborative filtering แต่ทั้ง 2 วิธีก็มีข้อดีข้อเสียที่แตกต่างกันออกไป ดังนั้นจึงมีการคิดค้น recommender system ที่มีมากกว่า 1 วิธีขึ้น เพื่อที่จะนำข้อดีของวิธีหนึ่งไปแก้ไขข้อเสียของอีกวิธีหนึ่ง นอกจากนี้จากการที่ social network กำลังได้รับความนิยมมากในปัจจุบัน ยังทำให้เกิดเทคนิคใหม่เรียกว่า Social filtering ซึ่งใช้สำหรับการค้นหาผลกระทบของผู้ใช้งานที่มีต่อคนอื่นในสังคมออนไลน์ โดยสำหรับวิทยานิพนธ์เล่มนี้ได้นำเสนอวิธีการใหม่ ซึ่งถูกสร้างอยู่ใน Location-Domain สำหรับการแนะนำสถานที่ท่องเที่ยวให้กับผู้ใช้งาน โดยรวมเทคนิคของระบบคำแนะนำ 3 วิธี คือ Content-based filtering, Collaborative filtering, และ social-filtering ผลการเปรียบเทียบพบว่าวิธีการใหม่ที่เสนอ ให้ผลการใช้งานด้าน Coverage result และด้าน NDCG Average Score ได้ดีกว่าอีก 2 วิธี

ภาควิชา	คณิตศาสตร์และวิทยาการคอมพิวเตอร์	ลายมือชื่อนิสิต	....
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สาขาวิชา	วิทยาการคอมพิวเตอร์และเทคโนโลยีสารสนเทศ		
ปีการศึกษา	2560		

5872625223 : MAJOR COMPUTER SCIENCE AND INFORMATION TECHNOLOGY

KEYWORDS: RECOMMENDER SYSTEM / COLLABORATIVE FILTERING / CONTENT-BASED FILTERING / SOCIAL FILTERING

SUTARAT CHOENAKSORN: NEW LOCATION RECOMMENDATION TECHNIQUE ON NETWORK. ADVISOR: ASST. PROF. SARANYA MANEEROJ, Ph.D., pp.

Nowadays, recommender systems play a crucial role in our daily life as can be seen from numerous websites that utilize the systems to recommend interesting items for their visitors, such as lonelyplanet.com, netfliex.com etc. From operational viewpoint, the recommender system is embedded in several domains by which it is categorized based on their usage. For example, lonelyplanet.com is categorized as a Location-Domain while netflex.com is in a Movie-Domain. In fact, the interesting attractions from traveling websites or movie selections from movie online sites are part of the recommendation outcome. To analyze the user's preferences, many methods have been widely used including Content-based filtering and Collaborative filtering. Nevertheless, both methods have different benefits and drawbacks. As a result, a hybrid recommender system using more than one technique has been proposed to supplement the short-coming of one technique by the strength of the other technique. Additionally, with the popularity of social network, the new social filtering technique has also been deployed to search for the impact among users on the social network. This thesis proposed a novel method to recommend tourist attractions for the visitors implemented on the location-domain with the combination of 3 recommender system techniques: Content-based filtering, Collaborative filtering, and social-filtering. The comparative results show that the proposed method yields better performance of coverage result and NDCG average score than the other two methods.

Department:	Mathematics and Computer Science	Student's Signature	....
		Advisor's Signature	....
Field of Study:	Computer Science and Information Technology		
Academic Year:	2017		

ACKNOWLEDGEMENTS

I would like to say 'Thank you' to all of you and your contributions to making this thesis complete.

Firstly, I would like to thank you Assistant Professor Dr. Saranya Maneeroj for her kindness, which is the part for the success of this thesis by helping me in many ways such as explaining the methods or techniques that I do not understand, advice on the research methodology, and checking and verifying the accuracy of the thesis.

In addition, I must thank Associate Professor Dr. Peraphon Sophatsathit and Assistant Professor Dr.Saichon Jaiyen for your advice and feedback for my thesis.

Finally, I thank my family for being a good supporter and always stay by my side, as well as the SD3 team for their advice about the study throughout the course of my master study. Thank you very much.

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Chapter 1 Introduction

At present, recommender systems are playing an increasingly important role in our daily life. It can be found generally in websites. The recommender systems will suggest interesting content to website's visitors. Sample website are lonelyplanet.com, netfliex.com, etc., and categorized in many domains, such as lonelyplanet.com as Location-Domain and netflex.com as Movie-Domain. Selecting an interesting location to visit from travel websites or selecting an interesting movie from online movie website can be obtained from the recommendation. The recommender systems usually employ popular techniques as their analysis capability such as Content-based filtering (CBF) and Collaborative filtering (CF).

For CBF, it is a technique which predicts the interesting recommendation to users by analyzing user' histories in the system. For CF, it is a technique which predicts the interesting recommendation to users by analyzing behaviors of other users who have the same behavior as the active user.

The Location-Domain recommender system is a well-adopted technique to find interesting locations for users. For example, to find a location, the CF or combination of CF and CBF techniques can be used to find the desired result.

Besides the two techniques, there is social filtering technique which is also used to analyze the relationships among users and the impact of users to others in social network. There are developments of the recommender system in Location-Domain by social filtering technique to find interesting locations, for example, using CF and social-filtering to suggest recommend locations.

However, there is no research which uses all 3 techniques at the same time to find locations. Therefore, this research proposes a new method which is built on Location-Domain incorporating CBF, CF, and social-filtering techniques. In so doing, the proposed method can provide more accurate outcome than systems which use only 2 traditional recommender systems techniques for suggesting locations.

1.1. Objectives

The objectives of this work are as follows:

1. To propose a new method which is based on Location-Domain,
2. To generate accurate outcomes from the combination of 3 RS techniques, i.e., CBF, CF, and social-filtering.

1.2. Scope of the work

This study will use Gowalla dataset which are collected since November 2010 and acquired by Facebook in December 2011. Coverage will include the followings:

1. The number of the users is 407,533.
2. The number of check-ins is 36,001,959 that is collected before June 1, 2011.
3. The number of friendships of user is 4,418,339.
4. The number of location is 15,209.

1.3. Expected Outcomes

The outcome of this research is expected to yield more accurate outcome than the methods that use only 2 RS techniques.

Chapter 2. Related Work

2.1. Theoretical groundwork

At the present time, there are a lot of researches that are based on the domain of Location using the CBF or the CF technique in the creation of the place recommendation system. Some of the researches that are based on the domain of Location use more than 1 technique to create the place recommendation system; such as creating the place recommendation system by combining the CBF and CF techniques or CF and Social Filtering technique together. Therefore, we can divide the main techniques into 4 following main techniques

1. Content-based filtering
2. Collaborative filtering
3. Social filtering
4. Hybrid Recommender System

2.1.1. Content-based filtering

Content-based filtering (CBF) is a popular method to predict the recommended outcomes. The characteristics of recommended items are analyzed whether they are similar to the characteristic of the items which the users have visited, used, and interested in (Figure 1). This technique can effectively predict a good recommendation when the characteristics of items are in the textual format such as movie and books recommenders. On the contrary, the performance of CBF for predicting the recommendation is reduced when the items are unavailable in textual format, for example, video and music, etc.

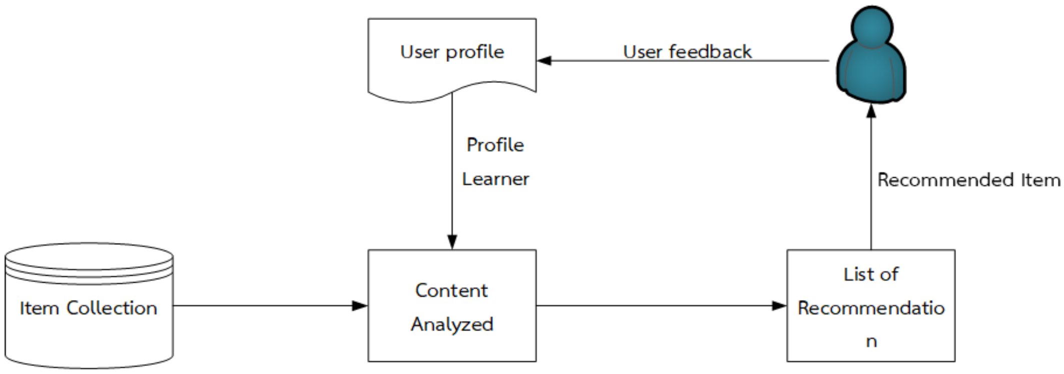

Figure 1 The model of CBF technique

An advantage of CBF is that new items in the system can be recommended to the users immediately after they are added to the system without requiring any other user preference rating. On the other hand, the drawback is that the recommended items from the prediction system are too specific, depending on the similarity between the recommended items and the history of items from the user preference. It turns out that if the system predicts similar item to the item on the user preference history, the recommended item may be similar to the items that users preferred in the past. As a result, the issue of the variety of item might occur.

Table 1 The example of the number of times the users watch a variety of movies (called weights).

No.	User	Movie Genres						
		Action	Adventure	Drama	Sci-Fi	Family	Thriller	Crime
1.	Michel	8	6		2			1
2.	Stephanie			4		2		
3.	Max	4	3		1		1	1
4.	Neo	3	1				3	

Table 2 The movie samples that are defined in different types related to the movie.

No.	Movie	Movie Genres						
		Action	Adventure	Drama	Sci-Fi	Family	Thriller	Crime
1.	The Dark Knight	x	x				x	
2.	The Incredibles	x				x		
3.	Frozen					x		
4.	Prince of Persia	x	x					
5.	8 Mile			x				
6.	Sand Castle	x	x					
7.	Green Lantern	x	x				x	
8.	The Matrix	x			x			
9.	Real Steel				x			
10.	CJ7					x		

For example, a movie online website can create a profile for each user, therefore the movies can be recommended to the user based on the movie type from the user's preference and interest. If a user *u* login and selects the movie to watch, the history of movie types will be recorded in the system database which can be used for analytical and searching process. Consequently, when the user login again, the system can recommend the similar types of movies from the user preference.

Table 1 shows the number of time that a user watches each type of movie (called weights). It can be seen that Michel (called user *u*) has a historical record of watching action movie most with 8 times. Secondly, movie types adventure, Sci-Fi, and Crime, with 6, 2, and 1 times, respectively. In contrast, the movie types drama, family, and thriller, with zero-time visiting means that Michel has never watched these

3 types movie. Table 2 presents the movie samples identified to the types related to the movie. Hence, each movie can have more than one type, for example, a movie 'Sand Castle' can be identified with action, adventure, and drama types. All these all types are related to the movie which can be used for user matching selection.

Table 3 recommended movie prediction results for the user *u* (Michel).

No.	Movie Recommend	Movie Genres						
		Action	Adventure	Drama	Sci-Fi	Family	Thriller	Crime
1.	The Dark Knight	x	x				x	
2.	The Incredibles	x				x		
3.	Prince of Persia	x	x					
4.	Sand Castle	x	x					
5.	Green Lantern	x	x				x	
6.	The Matrix	x			x			

From the historical records, Michel has the highest record to watch action movie type and secondary with adventure type. Therefore, the system can match the movie similar to Michel's preference record in order to predict the recommended movie for her. Table 3 illustrates the outcome after matching movie for the recommendation and it suggests that the all 6 movies are recommended to Michel.

2.1.2. Collaborative filtering

Collaborative filtering (CF) is another popular method for predicting the recommended item from other users who share similar preference items and behavior with the active user. The items must have a high rating from the users and never been used from the active user before (Figure 2).

Food	Tom	Scott	Tiffany	Eve
Pizza	15	11	14	?
Salad	12	-	-	-
Steak	2	2	7	2
spaghetti	-	9	-	5

Figure 2 The CF technique

The benefit of CF is that various new items can be recommended to active users. Nevertheless, CF has one major drawback, sparsity problem, when the numbers of items are much greater than the items used by the users. As a result, the performance of recommended item prediction is reduced, especially active users who used rare items or items that have never been used.

Table 4 The example of the number of times the users watch a variety of movies (called weights).

No.	User	Movie Genres						
		Action	Adventure	Drama	Sci-Fi	Family	Thriller	Crime
1.	Michel	8	6		2			1
2.	Stephanie			4		2		
3.	Max	1	2		1		4	
4.	Neo	2	1				7	

Table 5 The movie samples that are defined in different types related to the movie.

No.	Movie	Movie Genres						
		Action	Adventure	Drama	Sci-Fi	Family	Thriller	Crime
1.	The Dark Knight	x	x				x	
2.	The Incredibles	x				x		
3.	Frozen					x		
4.	Prince of Persia	x	x					
5.	8 Mile			x				
6.	Sand Castle	x	x	x				
7.	Green Lantern	x	x				x	
8.	The Matrix	x			x			
9.	Real Steel				x			
10.	CJ7					x		

For example, a movie online website that the users can rate the interesting movie from their preference. Table 4 shows the number of time that a user watches each type of movie (called weights). It can be seen that Michel (called user *u*) has a historical record of watching move type action the most with 8 times. Secondly, movies types adventure, sci-fi, and crime, with the number of times in 6, 2, and 1, respectively. On the other hand, Stephanie has a record of watching movie type drama the most with 4 times, and secondary movie types family with 2 times. In addition, Max has a record of watching movie type thriller the most with 4 times, and secondary movie types adventure, action, and sci-fi with 2, 1, and 1 times, respectively. Finally, Neo has a record of watching movie type thriller the most with 7 times, and secondary movie types action, and adventure with 2, and 1 times, respectively. From the movie history of Stephanie, Max, and Neo, the results suggest that Max and Neo have more similar interest for the movie with Michel than Stephanie. Table 5 presents the sample movie with the types related to the movie which can be used for matching the recommendation for the users.

Table 6 The results from movie prediction.

No.	Movie Recommend	Movie Genres						
		Action	Adventure	Drama	Sci-Fi	Family	Thriller	Crime
1.	The Dark Knight	x	x				x	
2.	The Incredibles	x				x		
3.	Prince of Persia	x	x					
4.	Sand Castle	x	x	x				
5.	Green Lantern	x	x				x	
6.	The Matrix	x			x			

From Table 6, the prediction outcome after comparing users' behaviors suggests these 6 movies recommended will be recommended to Michel while movie 'CJ7', '8 mile' and other movies won't be recommended to Michel until Max or Neo watch this movie first. In another case, if other users with behavior similar to Michel more than Max or Neo watch this type of movie, then the system will recommend this type of movie to Michel.

2.1.3 Social filtering

Social filtering is a technique to analyze the relationship between social network users in order to find the impact of a user to other users. Commonly, the users who can affect other users on the social network must have a high number of followers or friends, in addition to the trust on social media (Figure 3) to share any information that other users believe, for example, famous persons or celebrities which can cause the imitation behavior in the end.

Figure 3 The social media

For example, if a famous active user who is a movie reviewer has shared the movie experience on social network by reviewing or pressing like button, many friends or followers after learning this information might go to see this movie influenced by this active user.

2.1.4 Hybrid Recommender System

Hybrid Recommender System is a technique combining other techniques mentioned above at least one, in order to predict the interesting items for the users. In fact, one advantage of a technique can address the problem of the other technique, and therefore the system can improve the performance of the recommendation system.

For example, the movie online website which only uses CBF can only predict the same type of movie which might be old or the users might already have watched.

Table 7 The prediction outcomes of the movies that will be recommended for the user *u* (Michel) by using CBF technique.

No.	Movie Recommended	Movie Genres						
		Action	Adventure	Drama	Sci-Fi	Family	Thriller	Crime
1.	The Dark Knight	x	x				x	
2.	The Incredibles	x				x		
3.	Prince of Persia	x	x					
4.	Sand Castle	x	x					
5.	Green Lantern	x	x				x	
6.	The Matrix	x			x			

Table 8 The example of the number of times the users watch a variety of movies (called weights).

No.	User	Movie Genres						
		Action	Adventure	Drama	Sci-Fi	Family	Thriller	Crime
1.	Michel	8	6		2			1
2.	Stephanie			2		2		
3.	Max	1	2		1		4	
4.	Neo	2	1				7	

The process starts by using CBF to predict the movies to be recommended to the users. To address the sparsity problem, the data initiating of CF is performed by using CBF to prepare the movies to recommend for users. The second step begins after the recommended movies are obtained. To address the issue of CBF, the CF is utilized to solve the problem of specific recommended items. Table 7, these 6 movies recommended will be recommended for Michel by using CBF technique. As a result, CF is used to predict the movie in recommendation process by using the behavioral data from other users in Table 8 to analyze for accurate movie prediction.

Table 9 The recommended movie for user *u* (Michel)

No.	Movie Recommend	Movie Genres						
		Action	Adventure	Drama	Sci-Fi	Family	Thriller	Crime
1.	The Dark Knight	x	x				x	
2.	Green Lantern	x	x				x	

From Table 9, the system recommends the movie 'The Dark Knight' and 'Green Lantern' to Michel since the movie preference for Michel is similar to Max and Neo movie preference.

2.2 Related Work

Location recommendation system is popularly used and be studied to increase the accuracy of location recommending to users for the better efficiency. There were many researches which studied the Location domain. The 2 famous techniques are CBF and CF techniques. In addition, social filtering is another technique which calculates relationships among online users. It shows the influence of users which impact other users. The impact may be in the form of imitation behavior and people whose impact have to be famous persons or well-known who have many followers (Table 10).

Table 10. The previous research on RS technique

Year	Title(s)	Research
Only Single Technique		
2014	WhereToGo: Personalized Travel Recommendation for Individuals and Groups [4]	Long Guo, Jie Shao, Kian-Lee Tan, and Yang Yang
2016	Travel Intention-Based Attraction Network for Recommending Travel Destination [5]	Kyo-Joong Oh, Zaemyung Kim, Hyungrai Oh, Chae-Gyun Lim, and Gahgene Gweon
Combination of 2 Techniques		
2013	A Personalized Travel Recommender Model Based on Content-based Prediction and Collaborative Recommendation [6]	Shini Rengith, and Anjali C
2016	Personalized Travel Package with Multi-Point-of-Interest Recommendation Based on Crowdsourced User Footprints [7]	Zhiwen Yu, Huang Xu, Zhe Yang, and Bin Guo
2016	Point of Interest Recommendation with Social and Geographical Influence [8]	Da-Chuan Zhang, Mei Li, and Chang-Dong Wang

2.2.1 single technique recommender system

2.2.1.1. CF technique

In 2014 "WhereToGo: Personalized Travel Recommendation for Individuals and Groups" was presented by Guo, *et al.* [4], their work was the location RS for the individual. In the beginning, their group developed the bi-part graph model (Figure 4) to show the relation between 2 sides of nodes, all user nodes, and all location nodes.

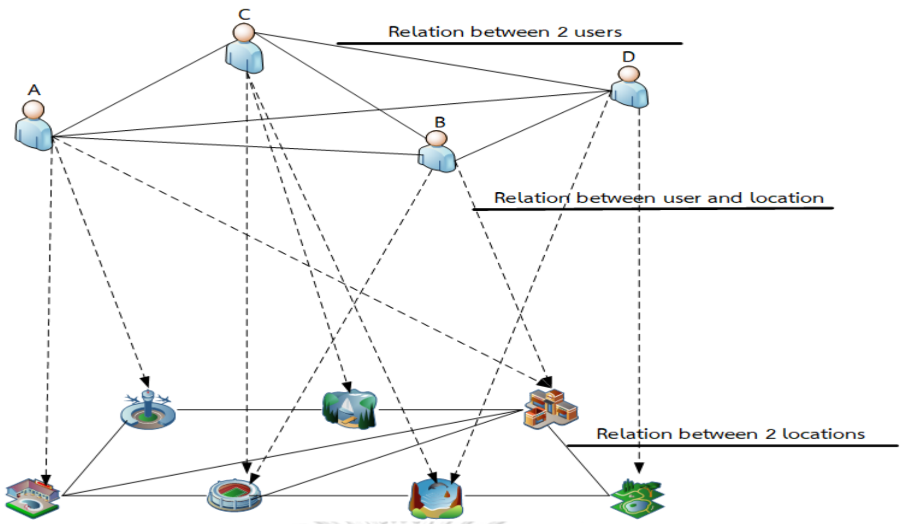

Figure 4. The bi-part graph model shows the relation between 2 sides of nodes, all user nodes, and all location nodes.

The line weight of each link was defined according to the number of user check-in of each location. Therefore, the relationship could be explained by 2-way relationship such as the relationship between users and locations or location popularity, the relationship among users or user similarity, and the relationship among locations or location similarity. These 3 relationships were calculated by CF and demonstrated the relationships as 3 sub-matrixes. Then, these 3 sub-matrixes were combined as a big matrix (Figure 5).

$$\left[\begin{array}{c|c} \text{users-users} & \text{users-locations} \\ \hline \text{users-location}^{T} & \text{Locations-locations} \end{array}\right]$$

Figure 5. The 3 sub-matrixes were combined as a big matrix.

Then, they used location indication which made each relationship between user and location different. After that, analyzing with the matrix. The outcome of the analysis was the probability which users visited each location and sorted ranks to recommend to users.

2.2.1.2. CBF technique

In 2016 "Travel Intention-Based Location Network for Recommending Travel Destination" was presented by Kim, *et al.* [5], they presented the location RS by showing objective information of visiting or doing activities each location as a graph for users to make the decisions. The scope of objectives of each location by users' reviews could be classified as 8 objectives such as Business and professional, Eating out, Education and training, Health and medical care, Holiday, leisure, and recreation, Religion and pilgrimages, Shopping, and Socializing (friends and family). First calculate the intention similarity of each review by CF to show the relationship between review and objective group. Each review was compared with word campus which was a vocabulary center that contained and classified vocabularies according to 8 objectives in terms of vectors. Then, calculate the average of these 8 objectives of each location for every review. Then, normalize the similarity to 0-1. After that, demonstrating the information in the form of weight graph which consisted of node, line, and weight (Figure 6).

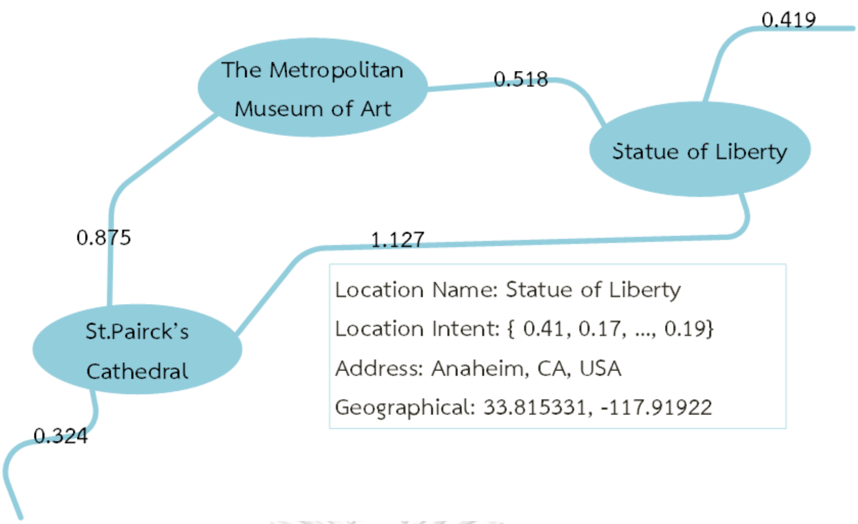

Figure 6. The information in the form of weight graph consisted of node, line, and weight.

Each node denoted one location and showed the average similarity of 8 objectives. Line was the mode of transportation between nodes (locations) such as road, public transportation. Weight was the distance between nodes. This weight graph was used to support the decision making of users that each location was suitable for visiting due to what objective.

2.2.2. Combined techniques recommender system

2.2.2.1. CBF and CF technique

In 2013 "A Personalized Travel Recommender Model Based on Content-based Prediction and Collaborative Recommendation" was present by Rengith, *et al.* [6], their work was an individual RS. First, they used CBF to calculate user preference which reflected preference level of users to each location. Each location had type information which recorded and could be used to compare to find the same type of locations later. Then, used CF to calculate the user preference of each location by using user's scoring and other users' scoring to be calculated by cosine similarity formula. After that, mapped locations from 2 techniques together. Location mapping was done according to types and high user preference location. Last, mapped the outcome locations with near location of users at the specific time to recommend users.

In 2016 "Personalized Travel Package with Multi-Point-of-Interest Recommendation Based on Crowdsourced User Footprints" was presented by Yu, *et al.* [7], their work was a location package RS for users. The period of packages was separated into 6 periods. Each period, users could be recommended for interesting locations. It started from using CBF to calculate user preference which showed the relationship between users and each location. Then, used CF to calculate user similarity which wed the relationship between 2 users by user preference from the previous step. Then, calculated by cosine similarity formula. The next step was calculating the average locations' preference of each month. Then, it was the process of probability calculation of all locations by using user similarity to weight the preference. After that, selected the locations with probability more than 0.3 and mapped those locations with users' location. Then, recommended nearby locations to users at that time and recorded as the package according to the period (Figure 7).

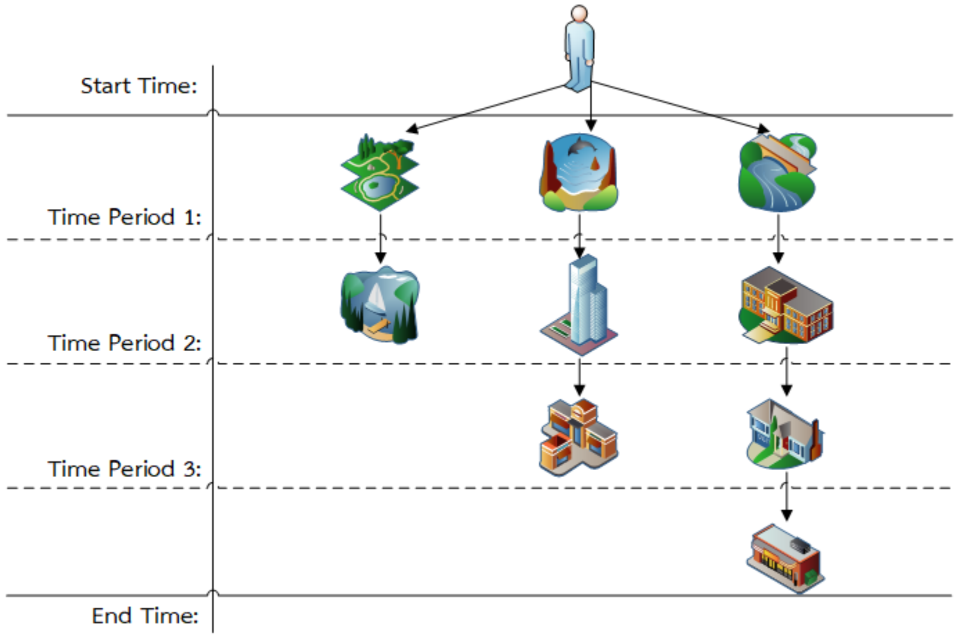

Figure 7. The Travel Route Planning tree

Users could set the start date and the last date of the trip themselves. Then, the system would recommend the package to users.

2.2.2.2. CF and social filtering technique

In 2016 "Point of Interest Recommendation with Social and Geographical Influence" was presented by Zhang, *et al.* [8], their work was the individual location RS. They presented the new framework called Social and Geographical Fusing Model or SGFM for RS. SGFM was the framework from the analysis of social influence and geographical influence together. Social influence was started by using CF to calculate the relationship among users. Then, used social filtering to generate social similarity which showed the close of friend group in the social network. If social similarity closed to 1, that showed there 2 users had the same friend group. If social similarity closed to 0, there 2 users had the different friend group in the social network. Then, used 2 calculated similarities from the previous step to calculate combinative similarity. After that, generated social influence by weighting combinative similarity by indication which showed the relationship between users and locations. The indication would be 1 when users used to check-in that location. On the other hand, the indication would be 0 if users had never check-in that location. For geographical influence, it was calculated by check-in behavior of users. When 2 influences were calculated, they would be input to SGFM framework to analyze the probability of users visited each location and recommended for locations where had top scores to users.

Chapter 3. Proposed Method

3.1. Proposed Method

This study proposes a new method on the Location-Domain by combining 3 techniques which consists of 3 techniques as follows:

1. CBF technique which is used to find the relationship between users and each location.
2. CF technique which is used to find the relationship between a user and other users.
3. Social filtering technique which is used to find the relationship between influence users and other users in the social network.

These technique will be deployed to create better accuracy of location recommendation to users rather than RS in Location-Domain which combines only 2 techniques.

	id	placeid	spot_categories	url	cat_id	sub_cat_id
1	185867	15255	"[{'url': '/categories/1' 'name': 'Coffee Shop'}]"	/categories/1	3	37
2	185867	15641	"[{'url': '/categories/96' 'name': 'Bookstore'}]"	/categories/96	6	93
3	185867	15641	"[{'url': '/categories/96' 'name': 'Bookstore'}]"	/categories/96	6	93
4	185867	15641	"[{'url': '/categories/96' 'name': 'Bookstore'}]"	/categories/96	6	93
5	185867	15641	"[{'url': '/categories/96' 'name': 'Bookstore'}]"	/categories/96	6	93
6	185867	15641	"[{'url': '/categories/96' 'name': 'Bookstore'}]"	/categories/96	6	93
7	185867	15245	"[{'url': '/categories/1' 'name': 'Coffee Shop'}]"	/categories/1	3	37
8	185867	15590	"[{'url': '/categories/106' 'name': 'Grocery'}]"	/categories/106	6	102
9	185867	15590	"[{'url': '/categories/106' 'name': 'Grocery'}]"	/categories/106	6	102
10	185867	15662	"[{'url': '/categories/117' 'name': 'Salon & Bar...	/categories/117	6	115
11	185867	15662	"[{'url': '/categories/117' 'name': 'Salon & Bar...	/categories/117	6	115
12	185867	15662	"[{'url': '/categories/117' 'name': 'Salon & Bar...	/categories/117	6	115
13	185867	11368	"[{'url': '/categories/155' 'name': 'Pizza'}]"	/categories/155	3	50
14	185867	11368	"[{'url': '/categories/155' 'name': 'Pizza'}]"	/categories/155	3	50
15	185867	11438	"[{'url': '/categories/16' 'name': 'American'}]"	/categories/16	3	31
16	185867	16597	"[{'url': '/categories/45' 'name': 'Airport'}]"	/categories/45	7	124
17	185867	16597	"[{'url': '/categories/45' 'name': 'Airport'}]"	/categories/45	7	124
18	185867	11405	"[{'url': '/categories/1' 'name': 'Coffee Shop'}]"	/categories/1	3	37
19	185867	11405	"[{'url': '/categories/1' 'name': 'Coffee Shop'}]"	/categories/1	3	37
20	185867	14470	"[{'url': '/categories/45' 'name': 'Airport'}]"	/categories/45	7	124
21	185867	13339	"[{'url': '/categories/154' 'name': 'Burgers'}]"	/categories/154	3	36
22	185867	21241	"[{'url': '/categories/19' 'name': 'Italian'}]"	/categories/19	3	45
23	185867	14185	"[{'url': '/categories/22' 'name': 'Historic Chur...	/categories/22	1	6

Figure 8. The location check-in history of a user id *185867* who will be called user *u*.

	id	placeid	spot_categories	url	cat_id	sub_cat_id
1	124343	15013	"[{'url': '/categories/28' 'name': 'Dive Bar'}]"	/categories/28	4	63
2	124343	15284	"[{'url': '/categories/100' 'name': 'Steakhouse'}]"	/categories/100	3	55
3	124343	11601	"[{'url': '/categories/79' 'name': 'Stadium'}]"	/categories/79	2	10
4	124343	11601	"[{'url': '/categories/79' 'name': 'Stadium'}]"	/categories/79	2	10
5	124343	13140	"[{'url': '/categories/166' 'name': 'Historic Land...	/categories/166	5	72
6	124343	13981	"[{'url': '/categories/15' 'name': 'Mexican'}]"	/categories/15	3	47
7	124343	14236	"[{'url': '/categories/79' 'name': 'Stadium'}]"	/categories/79	2	10
8	124343	14236	"[{'url': '/categories/79' 'name': 'Stadium'}]"	/categories/79	2	10
9	124343	14236	"[{'url': '/categories/79' 'name': 'Stadium'}]"	/categories/79	2	10
10	124343	13141	"[{'url': '/categories/22' 'name': 'Historic Church...	/categories/22	1	6
11	124343	23511	"[{'url': '/categories/170' 'name': 'Warehouse & ...	/categories/170	1	5
12	124343	23511	"[{'url': '/categories/170' 'name': 'Warehouse & ...	/categories/170	1	5
13	124343	23511	"[{'url': '/categories/170' 'name': 'Warehouse & ...	/categories/170	1	5
14	124343	23511	"[{'url': '/categories/170' 'name': 'Warehouse & ...	/categories/170	1	5
15	124343	23511	"[{'url': '/categories/170' 'name': 'Warehouse & ...	/categories/170	1	5
16	124343	14163	"[{'url': '/categories/101' 'name': 'Sandwich Sh...	/categories/101	3	51
17	124343	14163	"[{'url': '/categories/101' 'name': 'Sandwich Sh...	/categories/101	3	51
18	124343	26845	"[{'url': '/categories/20' 'name': 'Apartment'}]"	/categories/20	1	3
19	124343	35473	"[{'url': '/categories/54' 'name': 'Other - Shoppi...	/categories/54	6	111
20	124343	35473	"[{'url': '/categories/54' 'name': 'Other - Shoppi...	/categories/54	6	111
21	124343	35473	"[{'url': '/categories/54' 'name': 'Other - Shoppi...	/categories/54	6	111
22	124343	35473	"[{'url': '/categories/54' 'name': 'Other - Shoppi...	/categories/54	6	111
23	124343	35473	"[{'url': '/categories/54' 'name': 'Other - Shoppi...	/categories/54	6	111

Figure 9. The location check-in history of a user id *124343* who will be called user v_1.

	id	placeid	spot_categories	url	cat_id	sub_cat_id
1	11365	15700	"[{'url': '/categories/15' 'name': 'Mexican'}]"	/categories/15	3	47
2	11365	15700	"[{'url': '/categories/15' 'name': 'Mexican'}]"	/categories/15	3	47
3	11365	15700	"[{'url': '/categories/15' 'name': 'Mexican'}]"	/categories/15	3	47
4	11365	11943	"[{'url': '/categories/24' 'name': 'Pub'}]"	/categories/24	4	67
5	11365	13104	"[{'url': '/categories/171' 'name': 'Tea Room'}]"	/categories/171	3	57
6	11365	21287	"[{'url': '/categories/123' 'name': 'Breakfast'}]"	/categories/123	3	35
7	11365	22253	"[{'url': '/categories/16' 'name': 'American'}]"	/categories/16	3	31
8	11365	22253	"[{'url': '/categories/16' 'name': 'American'}]"	/categories/16	3	31
9	11365	25389	"[{'url': '/categories/24' 'name': 'Pub'}]"	/categories/24	4	67
10	11365	21351	"[{'url': '/categories/16' 'name': 'American'}]"	/categories/16	3	31
11	11365	21351	"[{'url': '/categories/16' 'name': 'American'}]"	/categories/16	3	31
12	11365	21351	"[{'url': '/categories/16' 'name': 'American'}]"	/categories/16	3	31
13	11365	21351	"[{'url': '/categories/16' 'name': 'American'}]"	/categories/16	3	31
14	11365	22968	"[{'url': '/categories/99' 'name': 'Beach'}]"	/categories/99	5	73
15	11365	23395	"[{'url': '/categories/64' 'name': 'Other - Food '}]"	/categories/64	3	49
16	11365	15599	"[{'url': '/categories/42' 'name': 'Golf Course'}]"	/categories/42	2	17
17	11365	26629	"[{'url': '/categories/101' 'name': 'Sandwich Sh...	/categories/101	3	51
18	11365	36326	"[{'url': '/categories/16' 'name': 'American'}]"	/categories/16	3	31
19	11365	31001	"[{'url': '/categories/24' 'name': 'Pub'}]"	/categories/24	4	67
20	11365	31011	"[{'url': '/categories/124' 'name': 'Diner'}]"	/categories/124	3	39
21	11365	40497	"[{'url': '/categories/24' 'name': 'Pub'}]"	/categories/24	4	67
22	11365	39117	"[{'url': '/categories/154' 'name': 'Burgers'}]"	/categories/154	3	36
23	11365	29041	"[{'url': '/categories/61' 'name': 'Sports & Outdo...	/categories/61	6	116

Figure 10. The location check-in history of a user id *11365* who will be called user v_2.

	id	placeid	spot_categories	url	cat_id	sub_cat_id
1	112942	15653	"[{'url': '/categories/31' 'name': 'Performing Ar...	/categories/31	2	24
2	112942	11568	"[{'url': '/categories/15' 'name': 'Mexican'}]"	/categories/15	3	47
3	112942	12505	"[{'url': '/categories/45' 'name': 'Airport'}]"	/categories/45	7	124
4	112942	14128	"[{'url': '/categories/45' 'name': 'Airport'}]"	/categories/45	7	124
5	112942	12840	"[{'url': '/categories/45' 'name': 'Airport'}]"	/categories/45	7	124
6	112942	12840	"[{'url': '/categories/45' 'name': 'Airport'}]"	/categories/45	7	124
7	112942	12840	"[{'url': '/categories/45' 'name': 'Airport'}]"	/categories/45	7	124
8	112942	13087	"[{'url': '/categories/1' 'name': 'Coffee Shop'}]"	/categories/1	3	37
9	112942	12840	"[{'url': '/categories/45' 'name': 'Airport'}]"	/categories/45	7	124
10	112942	12840	"[{'url': '/categories/45' 'name': 'Airport'}]"	/categories/45	7	124
11	112942	13729	"[{'url': '/categories/15' 'name': 'Mexican'}]"	/categories/15	3	47
12	112942	13729	"[{'url': '/categories/15' 'name': 'Mexican'}]"	/categories/15	3	47
13	112942	13114	"[{'url': '/categories/45' 'name': 'Airport'}]"	/categories/45	7	124
14	112942	14520	"[{'url': '/categories/121' 'name': 'Corporate O...	/categories/121	1	5
15	112942	13022	"[{'url': '/categories/95' 'name': 'Train Station'...	/categories/95	7	133
16	112942	13022	"[{'url': '/categories/95' 'name': 'Train Station'...	/categories/95	7	133
17	112942	14045	"[{'url': '/categories/45' 'name': 'Airport'}]"	/categories/45	7	124
18	112942	23254	"[{'url': '/categories/45' 'name': 'Airport'}]"	/categories/45	7	124
19	112942	25510	"[{'url': '/categories/11' 'name': 'Mall'}]"	/categories/11	6	106
20	112942	24963	"[{'url': '/categories/45' 'name': 'Airport'}]"	/categories/45	7	124
21	112942	9175	"[{'url': '/categories/1' 'name': 'Coffee Shop'}]"	/categories/1	3	37
22	112942	25576	"[{'url': '/categories/15' 'name': 'Mexican'}]"	/categories/15	3	47
23	112942	24458	"[{'url': '/categories/26' 'name': 'Ultra-lounge'}]"	/categories/26	4	70

Figure 11. The location check-in history of a user id *112942* who will be called user V_3.

…

	id	placeid	spot_categories	url	cat_id	sub_cat_id
1	1004273	14944	"[{'url': '/categories/908' 'name': 'Chocolate'}]"	/categories/908	3	38
2	1004273	15184	"[{'url': '/categories/74' 'name': 'Arcade'}]"	/categories/74	2	9
3	1004273	15184	"[{'url': '/categories/74' 'name': 'Arcade'}]"	/categories/74	2	9
4	1004273	14923	"[{'url': '/categories/61' 'name': 'Sports & Outdo...	/categories/61	6	116
5	1004273	14917	"[{'url': '/categories/42' 'name': 'Golf Course'}]"	/categories/42	2	17
6	1004273	14917	"[{'url': '/categories/42' 'name': 'Golf Course'}]"	/categories/42	2	17
7	1004273	14917	"[{'url': '/categories/42' 'name': 'Golf Course'}]"	/categories/42	2	17
8	1004273	14932	"[{'url': '/categories/51' 'name': 'Sculpture'}]"	/categories/51	2	11
9	1004273	14935	"[{'url': '/categories/188' 'name': 'Gallery'}]"	/categories/188	2	11
10	1004273	14935	"[{'url': '/categories/188' 'name': 'Gallery'}]"	/categories/188	2	11
11	1004273	15365	"[{'url': '/categories/58' 'name': 'Other - Entertai...	/categories/58	2	23
12	1004273	15376	"[{'url': '/categories/212' 'name': 'Science Mus...	/categories/212	2	22
13	1004273	15366	"[{'url': '/categories/165' 'name': 'Plaza / Squar...	/categories/165	5	85
14	1004273	14125	"[{'url': '/categories/22' 'name': 'Historic Church...	/categories/22	1	6
15	1004273	13078	"[{'url': '/categories/54' 'name': 'Other - Shoppi...	/categories/54	6	111
16	1004273	26192	"[{'url': '/categories/172' 'name': 'Ferry'}]"	/categories/172	7	127
17	1004273	26192	"[{'url': '/categories/172' 'name': 'Ferry'}]"	/categories/172	7	127
18	1004273	14518	"[{'url': '/categories/64' 'name': 'Other - Food '}]"	/categories/64	3	49
19	1004273	26134	"[{'url': '/categories/48' 'name': 'Resort'}]"	/categories/48	7	131
20	1004273	26134	"[{'url': '/categories/48' 'name': 'Resort'}]"	/categories/48	7	131
21	1004273	26134	"[{'url': '/categories/48' 'name': 'Resort'}]"	/categories/48	7	131
22	1004273	12855	"[{'url': '/categories/79' 'name': 'Stadium'}]"	/categories/79	2	10
23	1004273	26125	"[{'url': '/categories/48' 'name': 'Resort'}]"	/categories/48	7	131

Figure 12. The location check-in history of a user id *1004273* who will be called user V_n.

	userid	in_degree	out_degree
1	100159	4	4
2	100192	1	1
3	100315	14	14
4	1004273	24	24
5	100533	1	1
6	10054	22	22
7	1006167	1	1
8	1006227	8	8
9	101846	271	271
10	103951	226	226
11	106384	85	85
12	108643	63	63
13	111477	113	113
14	112942	123	123
15	11365	67	67
16	1141687	91	91
17	1148785	62	62
18	1180690	66	66
19	120239	75	75
20	124343	436	436
21	133064	121	121
22	134413	72	72
23	139658	271	271

Figure 13. The example of the relationship among users in the social network.

From the above information, they consist of location check-in history of a user id *185867* (Figure 8) who will be called user u, location check-in history of a user id *124343* (Figure 9) who will be called user v_1, location check-in history of a user id *11365* (Figure 10) who will be called user v_2, location check-in history of a user id *112942* (Figure 11) who will be called user v_3, ... , location check-in history of a user id *1004273* (Figure 12) who will be called user v_n and the relationship among users in the social network (Figure 13). This information will be used as the sample calculations for the recommendation of each step. There are 4 steps in recommendation calculation as follows:

3.1.1 Create User Preference

First, we use CBF which a technique to find the relationship between users and locations. In this study, it is the user preference to each location. A pool of check-in histories is recorded and used to predict the preference of each user. The preference can be calculated by counting a number of check-in of each location and divided by the total numbers of check-in of each user (Figure 14).

```
Step 1: Start
Step 2: Declare and Set List of user to all uers and List of place to all places
Step 3: Declare preference property
Step 4: Declare valiables checkinTimes, frequency and userperference

Step 5: Repeat the steps until until 0 < count of List of user
    5.1 Set checkinTimes by a user

    5.2 Repeat the steps until  0 < count of List of place
        5.2.1 Set frequency by user and place
        5.2.2 Set userpreference = frequency/checkinTimes

        5.2.3 Set new preference property
        5.2.4 Set user, place and preference to preference property

        5.2.5 Insert into schedule of UserPreference in databse

Step 6: Stop
```

Figure 14. The algorithm of creating user preference process.

User preference can be calculated by Equation 1.

$$F_o^u = \frac{VC_{(u,o)}}{VC_{(u)}} \qquad (1)$$

F_o^u is the preference of user *u* to visit location *o*.

$VC_{(u,o)}$ is the numbers of check-in at location *o* of user *u*.

$VC_{(u,o)}$ is the total number of check-in of user *u*.

The range of user preference is 0-1. If the preference closes to 1, the user highly prefers to visit that location respectively. On the other hand, if the preference closes to 0, the user rarely prefers to visit that location respectively as well.

```
Step 1: Start
Step 2: Declare and Set List of user to all uers
Step 3: Declare frequency property, List of frequency and List of checkin

Step 3: Repeat the step until 0 < count of List of user
    3.1 Set new List of frequency
    3.2 Declare status to false
    3.3 Set List of checkin by a user

    3.4 Repeat the step until 0 < count of List of checkin

        3.4.1 if count of List of frequency == 0
                Set status to false;
            else
                Set a loop up to the count of List of checkin minus one

                if place of List of frequency is equal with place of List of Checkin
                    count of checkin plus one
                    Set status to true
                else
                    Set status to false

        3.4.2 if status is not true
                Set new frequency property
                Set user , place to frequency property
                Set count of checkin plus one to frequency property
                Add frequency property to List of frequency
                Set status to true

    3.5 Repeat the step until 0 < count of List of frequency
         3.5.1 Insert into schedule of Frequency in databse

Step 4: Stop
```

Figure 15. The algorithm of creating frequency process.

From the information of check-in history of user *u*, user v_1, user v_2, user v_3, ... , and user v_n the numbers of check-in are 230 times, 3,624 times, 141 times, 189 times, ..., and 1,753 times, respectively, as follows the algorithm of creating frequency process (Figure 15).

Table 11. The number of check-in time of each location of user *u*

User *u* (user id *185867*)		
No.	Location ID	Checked-in Times (Frequency)
1.	103988	1
2.	1054735	1
3.	11368	2
4.	11405	2
5.	14470	1
6.	17831	1
7.	15590	2
8.	24587	1
9.	27256	1
10.	9410	3
...	...	...
141.	9789	1
142.	99699	1
Total		230

Table 12. The number of check-in time of each location of user v_1

User v_1 (user id *124343*)		
No.	Location ID	Checked-in Times (Frequency)
1.	1000197	2
2.	1004733	3
3.	10075	1
4.	1027900	4
5.	1103412	1
6.	611400	1
7.	633159	1
8.	1462360	2
9.	1522061	1
10.	9410	1
...	...	...
141.	955754	1
142.	997522	1
Total		3624

Table 13. The number of check-in time of each location of user v_2

User v_2 (user id *11365*)		
No.	Location ID	Checked-in Times (Frequency)
1.	10497	2
2.	15599	1
3.	17831	2
4.	22968	3
5.	239191	1
6.	27256	1
7.	304110	2
8.	40119	1
9.	51865	2
10.	633159	1
...	...	...
105.	89928	4
106.	99209	1
Total		141

Table 14. The number of check-in time of each location of user v_3

User v_3 (user id *112942*)		
No.	Location ID	Checked-in Times (Frequency)
1.	117078	1
2.	12840	5
3.	415137	1
4.	4236342	1
5.	4398577	2
6.	52548	1
7.	599868	2
8.	696911	1
9.	758109	6
10.	793997	1
...	...	...
138	80987	1
139.	9175	2
Total		189

...

Table 15. The number of check-in time of each location of user v_n

User v_n (user id *1004273*)		
No.	Location ID	Checked-in Times (Frequency)
1.	15184	2
2.	1574693	4
3.	16717	1
4.	196283	1
5.	212713	4
6.	213277	8
7.	32913	3
8.	50539	1
9.	661187	1
10.	6756627	1
...	...	...
700.	935572	1
701.	960022	1
Total		1753

Table 11, Table 12, Table 13, Table 14, and Table 15 show the number of check-in time (called frequency) of each location of user u, user v_1, user v_2, user v_3, ... , and user v_n ,respectively.

Table 16. the example of preference calculation of user *u*.

User *u* (userid *185867*)					
No.	Location ID	Checked-in Times ($VC_{(u,o)}$)	Total Checked-in Times ($VC_{(u)}$)	Calculation	User preference (F_o^u)
1.	103988	1	142	1/142	0.0043478
2.	1054735	1	142	1/142	0.0043478
3.	11368	2	142	2/142	0.0086956
4.	11405	2	142	2/142	0.0086956
5.	14470	1	142	1/142	0.0043478
6.	17831	1	142	1/142	0.0043478
7.	15590	2	142	2/142	0.0086956
8.	24587	1	142	1/142	0.0043478
9.	27256	1	142	1/142	0.0043478
10.	9410	3	142	3/142	0.0130435
...	...	...	...	...	...
141.	9789	1	142	1/142	0.0043478
142.	99699	1	142	1/142	0.0043478

Table 17. the example of preference calculation of user v_1.

User v_1 (userid *12343*)					
No.	Location ID	Checked-in Times ($VC_{(v_1,\circ)}$)	Total Checked-in Times ($VC_{(v_1)}$)	Calculation	User preference ($F_{\circ}^{v_1}$)
1.	1000197	2	3624	2/3624	0.0005518
2.	1004733	3	3624	3/3624	0.0008278
3.	10075	1	3624	1/3624	0.0002759
4.	1027900	4	3624	4/3624	0.0011038
5.	1103412	1	3624	1/3624	0.0002759
6.	611400	1	3624	1/3624	0.0002759
7.	633159	1	3624	1/3624	0.0002759
8.	1462360	2	3624	2/3624	0.0005518
9.	1522061	1	3624	1/3624	0.0002759
10.	9410	1	3624	1/3624	0.0002759
...	...	...	...	...	...
2138.	955754	1	3624	1/3624	0.0002759
2139.	997522	1	3624	1/3624	0.0002759

Table 18. the example of preference calculation of user v_2.

User v_2 (user id *11365*)					
No.	Location ID	Checked-in Times ($VC_{(v_2,o)}$)	Total Checked-in Times ($VC_{(v_2)}$)	Calculation	User preference ($F_o^{v_2}$)
1.	10497	2	141	2/141	0.0141844
2.	15599	1	141	1/141	0.0070922
3.	17831	2	141	2/141	0.0141844
4.	22968	1	141	1/141	0.0070922
5.	239191	1	141	1/141	0.0070922
6.	27256	1	141	1/141	0.0070922
7.	304110	2	141	2/141	0.0141844
8.	40119	1	141	1/141	0.0070922
9.	51865	2	141	2/141	0.0141844
10.	633159	1	141	1/141	0.0070922
…	…	…	…	…	…
105.	89928	4	141	4/141	0.0283688
106.	99209	1	141	1/141	0.0070922

Table 19. the example of preference calculation of user v_3

User v_3 (user id *112942*)					
No.	Location ID	Checked-in Times ($VC_{(v_3,o)}$)	Total Checked-in Times ($VC_{(v_3)}$)	Calculation	User preference ($F_o^{v_3}$)
1.	117078	1	189	1/189	0.0052910
2.	12840	5	189	5/189	0.0264550
3.	14470	1	189	1/189	0.0052910
4.	4236342	1	189	1/189	0.0052910
5.	4398577	2	189	2/189	0.0105820
6.	52548	1	189	1/189	0.0052910
7.	599868	2	189	2/189	0.0105820
8.	696911	1	189	1/189	0.0052910
9.	758109	6	189	6/189	0.0317460
10.	793997	1	189	1/189	0.0052910
…	…	…	…	…	…
138	9410	1	189	1/189	0.0052910
139.	99699	2	189	2/189	0.0105820

Table 20. the example of preference calculation of user v_n

User v_n (user id *1004273*)					
No.	Location ID	Checked-in Times ($VC_{(v_n,o)}$)	Total Checked-in Times ($VC_{(v_n)}$)	Calculation	User preference ($F_o^{v_n}$)
1.	15184	2	1753	2/1753	0.0011409
2.	1574693	4	1753	4/1753	0.0022818
3.	16717	1	1753	1/1753	0.0005705
4.	196283	1	1753	1/1753	0.0005705
5.	212713	4	1753	4/1753	0.0022818
6.	213277	8	1753	8/1753	0.0045636
7.	32913	3	1753	3/1753	0.0017114
8.	50539	1	1753	1/1753	0.0005705
9.	661187	1	1753	1/1753	0.0005705
10.	6756627	1	1753	1/1753	0.0005705
…	…	…	…	…	
700.	935572	1	1753	1/1753	0.0005705
701.	960022	1	1753	1/1753	0.0005705

Table 16, Table 17, Table 18, Table 19, and Table 20 show the example of preference calculation of user *u*, user v_1, user v_2, user v_3, and user v_n, all having different preferred locations. User *u* has the highest preference to location id *9410* while user v_1 has the highest preference to location id *1027900*. User v_2 has the highest preference to location *89928,* user v_3 has the highest preference to location *758109, and* user v_n has the highest preference to location *213277*.

After the calculation of user preference of each user in every location, use the calculated information to generate profile vector to show the preference of each user to all locations as in Equation 2.

$$F^{u} = [F^{u}_{o1}, F^{u}_{o2}, \dots, F^{u}_{on}] \tag{2}$$

F^{u} is the vector which shows the preference of user *u* to all locations.

F^{u}_{o} is the preference of user *u* to location *o* which calculated by Equation 1.

1,2, … , *n* is the order of locations from 1 to *n*.

From the tables of preference examples calculation to locations of user *u*, user v_1, user v_2, user v_3, ..., and v_n, we can generate the vectors which show the preference of users to all locations as follows:

Table 21. The vectors which show the preference of users to all locations.

User	The vectors which show the preference of users of all locations
	$[F^{u}_{o1}, F^{u}_{o2}, F^{u}_{o3}, F^{u}_{o4}, \dots, F^{u}_{on}]$
User *u* (F^{u})	[0, 0, 0, 0, 0.0043478, 0, 0.0043478, 0, 0.0086956, 0.0086956, ..., 0.0043478, 0]
User v_1 (F^{v_1})	[0.0005518, 0.0008278, 0.0002759, 0.0011038, 0, 0, 0, 0.0002759, 0, 0, ..., 0, 0.0002759]
User v_2 (F^{v_2})	[0, 0, 0, 0, 0, 0, ..., 0, 0]
User v_3 (F^{v_3})	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ..., 0.0043478, 0]
...	...
User v_n (F^{v_n})	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ..., 0, 0.0002759]

** *n* = 15,209 Locations

3.1.2 Find User Similarity

After the generation of all preference users, step 2 uses CF to find the relationship between a user and other users or similarity between 2 users. The similarity of 2 users can be calculated by cosine similarity equation which is popular in vector calculation (Figure 16).

```
Step 1: Start
Step 2: Declare and Set List of user to all uers and List of place to all places
Step 3: Declare List of user preference of active user and other user
Step 4: Declare similarity property
Step 5: Declare valiables uspfSum, uspfActive, uspfOther and uspfSq
Step 6: Declare valiables sim

Step 7: Repeat the steps until until 0 < count of List of active user
    7.1 Set List of user preference by an active user

    7.2 Repeat the steps until until 0 < count of List of other user
        7.2.1 function clear();
        7.2.2 Set List of user preference by an other user

        7.2.3 Set a loop up to the count of List of place minus one
            7.2.3.1 Set uspfSum += preference by place of active user * preference by place of other user
            7.2.3.2 Set uspfActive += Math.Pow(preference by place of active user,2)
            7.2.3.3 Set uspfother += Math.Pow(preference by place of other user,2)

        7.2.4 Set uspfSq = (Math.Sqrt(uspfActive)*Math.Sqrt(uspfOther))

        7.2.5 if uspfSq > 0
                Set sim = uspfSum/uspfSq
            else
                Set sim = 0

        7.2.6 Set new similarity property
        7.2.7 Set active user, other user to similarity property
        7.2.8 Set similarity = sim to similarity property
        7.2.9 Insert into schedule of UserSimilarity in databse

Step 8: Stop
```

Figure 16. The algorithm of finding user similarity process.

The similarity between users is shown as in Equation 3.

$$Sim_{(u,v)} = \frac{F^{u} * F^{v}}{\sqrt{F^{u^2}} * \sqrt{F^{v^2}}} \quad (3)$$

$Sim_{(u,v)}$ is the similarity between user *u* and user *v*.

F^{u} and F^{v} are the preference vector of user *u* and user *v* to all locations determined by Equation (2), respectively.

The range of the similarity is 0-1. If the similarity closes to 1, both of users prefer and have the same behavior of visiting location. On the other hand, if the similarity closes to 0, both of users differently have different behavior of visiting location.

From the above example, we can use preference vector of user *u* and user *v* to calculate the similarity between user *u*, user v_1, user v_2, user v_3, ..., and user v_n as follows:

Table 22. Calculating the similarity between user *u* and user v_1.

Similarity between user *u* and user v_1			
F^u	F^{v_1}	Calculation	Similarity ($Sim_{(u,v_1)}$)
[0, 0, 0, 0, 0.0043478, 0, 0.0043478, 0, 0.0086956, 0.0086956, …, 0.0043478, 0]	[0.0005518, 0.0008278, 0.0002759, 0.0011038, 0, 0, 0, 0.0002759, 0, 0, …, 0, 0.0002759]	$\frac{F^u * F^{v_1}}{\sqrt{F^{u^2}} * \sqrt{F^{v_1 2}}}$	0.0735931

Table 23. Calculating the similarity between user *u* and user v_2.

Similarity between user *u* and user v_2			
F^u	F^{v_2}	Calculation	Similarity ($Sim_{(u,v_2)}$)
[0, 0, 0, 0, 0.0043478, 0, 0.0043478, 0, 0.0086956, 0.0086956, …, 0.0043478, 0]	[0, 0, 0, 0, 0, 0, …, 0, 0]	$\frac{F^u * F^{v_2}}{\sqrt{F^{u^2}} * \sqrt{F^{v_2 2}}}$	0

Table 24. Calculating the similarity between user *u* and user v_3.

Similarity between user *u* and user v_3			
F^u	F^{v_3}	Calculation	Similarity ($Sim_{(u,v_3)}$)
[0, 0, 0, 0, 0.0043478, 0, 0.0043478, 0, 0.0086956, 0.0086956, …, 0.0043478, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, …, 0.0043478, 0]	$\frac{F^u * F^{v_3}}{\sqrt{F^{u^2}} * \sqrt{F^{v_3 2}}}$	0.0429660

Table 25. Calculating the similarity between user u and user v_n.

Similarity between user u and user v_n			
F^u	F^{v_n}	Calculation	Similarity ($Sim_{(u,v_n)}$)
[0, 0, 0, 0, 0.0043478, 0, 0.0043478, 0, 0.0086956, 0.0086956, ..., 0.0043478, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ..., 0, 0.0002759]	$\frac{F^u * F^{v_n}}{\sqrt{F^{u^2}} * \sqrt{F^{{v_n}^2}}}$	0.0312882

From Table 22, Table 23, Table 24, and Table 25 which show the calculations of user similarities, the similarity between user u and user v_1 is 0.0735931, so both of them have similar behavior of visiting locations. While the similarity between user u and user v_3, user u and user v_n are 0.0429660 and 0.0312882, respectively, that are lower than the similarity between user u and user v_1, so these users have different behavior of visiting locations. The last similarity pair between user u and user v_2 is 0, that means these two have the different behavior of visiting locations.

3.1.3 Find Social Impact of Each User

In this step, we use Social filtering to find the relationship bet ween influence an active user to other users in the social network (called social impact). In this study, the impact is considered by the number of friends or followers in the social network. This means that the influent user of the influent impact the social network at a specific time has to be famous and credible in the social network. A person who has many friends or followers tends to be credible and influent others rather than a person who has few friends or followers. To calculate the impact, the number of friends or followers of users is divided by the highest number of friends or followers of a user who have the most friends in the social network (Figure 17).

```
Step 1: Start
Step 2: Declare List of friendship
Step 3: Declare socialImpact property
Step 4: Declare valiable maxFriendship

Step 5: Set List of friendship to all user

Step 6: Set maxFriendship to max of friendship

Step 7: Repeat the step until 0 < count of List of friendship
    7.1 Set new socialImpact property
    7.2 Set user to socialImpact property
    7.3 Set impact = friendship of user/maxFriendship
    7.4 Insert into schedule of SocialImpact in databse

Step 8: Stop
```

Figure 17. The algorithm of finding social impact of each user process.

The impact of each user can be calculated by Equation 4.

$$IP_u = \frac{|FR_u|}{Max(|FR|)} \tag{4}$$

IP_u is the impact of user *u* to other users in the social network.

$|FR_u|$ is the number of friends or followers of user *u* in the social network.

$Max(|FR|)$ is the highest numbers of friend or followers of a user in the social network.

The range of social impact is 0-1. If the impact of a user closes to 1, that user can highly impact other users in the social network. On the other hand, If the impact of a user closes to 0, that user can rarely impact other users in the social network as well.

Table 26. Finding the social impact of user *u*, user v_1 and user v_n.

User	FR	Max(FR)	Calculation	IP
User *u*	129	781	129/781	0.16517
User v_1	436	781	436/781	0.55826
User v_2	67	781	67/781	0.08579
User v_3	123	781	123/781	0.15749
...	...	...	...	...
User v_n	24	781	24/781	0.03073

Table 26 shows the example of impact calculation. The impact of user v_1 is the one who most impacts other users in the social network that is equal to 0.16517.

3.1.4 Calculate Predicted Rating of Locations

After we calculate the similarity from Equation 3 and social impact of each user to others in the social network from Equation 4, we can find the predicted rating of each user's visiting locations. The calculation can be done by multiplying the similarity of users by social impact then weighting by the numbers of check-in of each user and location. Because each location is differently important for each user so this study uses the number of check-in of each user and location to increase/decrease the importance of each location (Figure 18).

```
Step 1: Start
Step 2: Declare and Set List of active user to all user
Step 3: Declare List of checkin, and List of rating
Step 4: Declare variable ip

Step 5: Repeat the step until 0 < count of List of active user
    5.1 Set ip to socialimpact by a user
    5.2 Set new List of rating
    5.3 Set List of checkin by calling function findplace(userid: string) (For finding the places that active user checked in)

    5.4 Repeat the step until 0 < count of List of active user
        5.4.1 Declare and Set Lis of other user to all user
        5.4.2 Declare rating property
        5.4.3 Declare variables similarity, frequency, sumSimsubFrequency, sumSimsupFrequency, socailImplact and rating

        5.4.4 Repeat the step until 0 < count of List of other user

            5.4.4.1 if active user != other user
                        Set similarity to simialrity by active user and other user
                        Set socialimpact to socialimpact by other user
                        Set frequency to frequency by other user and place

                        Set sumSimsubFrequency += (similarity * socialimpact * frequency)
                        Set sumSimsupFrequency += (similarity * socialimpact)

        5.4.5 if sumSimsupFrequency > 0
                    Set rating = sumSimsubFrequency/sumSimsupFrequency

        5.4.6 Set new rating property
        5.4.7 Set user,place and rating to rating property

        5.4.8 Insert into schedule of Rating in databse

Step 6: Stop
```

Figure 18. The algorithm of creating predicted rating of locations process.

The predicted rating can be calculated by Equation 5.

$$R_{(u,o)} = \frac{\sum_{v \in U} Sim_{(u,v)} IP_v Freq_{(v,o)}}{\sum_{v \in U} Sim_{(u,v)} IP_v} \qquad (5)$$

$R_{(u,o)}$ is the predicted rating of user *u* to visit location *o*.

$Sim_{(u,v)}$ is the similarity between user *u* and user *v*.

IP_v is the social impact of user *v* to others in the social network.

$Freq_{(v,o)}$ is the numbers of check-in of location o of user *u*.

The range of the predicted rating of each user is 0-1. If the predicted rating closes to 1, that user has higher probability to visit that location. On the other hand, if the predicted rating closes to 0, that user has lowly probability to visit that location. The predicted rating of users will be sorted from the highest to the lowest. The highest predicted rating which closes to 1 will be sorted as the top to recommend to users.

After the calculation of similarity and social impact in step 2 and 3, the predicted rating can be calculated to find the probability of each user to visit each location as shown below.

Table 27. Calculating predicted rating of locations of user *u*.

User *u*										
No.	Location ID	*Sim(u,v$_1$)*	*IP(v$_1$)*	*Freq(v$_1$)*	…	*Sim(u,v$_n$)*	*IP(v$_n$)*	*Freq(v$_n$)*	Calculation	Rating
1.	103988	0. 0735931	0.55826	0		0. 0312882	0.03073	0	Equation 5.	0.01205
2.	1054735	0. 0735931	0.55826	0		0. 0312882	0.03073	0		0
3.	11368	0. 0735931	0.55826	0		0. 0312882	0.03073	0		2.56804
4.	11405	0. 0735931	0.55826	0		0. 0312882	0.03073	0		0.25982
5.	14470	0. 0735931	0.55826	2		0. 0312882	0.03073	0		0.01205
6.	17831	0. 0735931	0.55826	0		0. 0312882	0.03073	0		2.01767
7.	15590	0. 0735931	0.55826	6		0. 0312882	0.03073	0		2.01257
8.	24587	0. 0735931	0.55826	0		0. 0312882	0.03073	1		0.50314
9.	27256	0. 0735931	0.55826	0		0. 0312882	0.03073	3		0
10.	9410	0. 0735931	0.55826	1		0. 0312882	0.03073	0		2.89971
…	…	…	…	…	…	…	…	…	…	…
56.	99699	0. 0735931	0.55826	0		0. 0312882	0.03073	0		0.05108

After the calculation of the probability of user *u* to visit locations, the system sorts the top 5 locations that have the highest recommendation to user *u* as follows:

Table 28. Top *5 locations to recommend to user* u*.*

User *u*		
Rank	Location ID	Rating
1.	9410	2.89971
2.	11368	2.56804
3.	17831	2.17675
4.	15590	2.01257
5.	9225	1.91226

Chapter 4. Experiments

Evaluation of the proposed method recommendation efficiency, the outcomes are compared with the two current RS methods which developed on the Location-Domain as follows:

1. PTP method which uses the combination of CBF and CF together.
2. RSGI method which uses the combination of CF and social filtering together

All 3 methods use the same dataset. These research data are supported by Yong Liu, *et al*. which are collected from Gowalla website.

4.1. Dataset

The date are last updated on 12 December 2012. There are 4 types of data as follows:

1. User profile 407,533 users.
2. Checked-in recorded 36,001,959 records.
3. Friendship data 4,418,339 friendships.
4. Location records 15,209 locations.

For this study, the dataset is filtered to get the number of data for 50 users who have complete information. This dataset will be used as the samples to evaluate the efficiency of these 3 methods. These filtered users have the history of location check-in from 1 to 621 times.

4.2. Evaluation metrics

For this study, the method efficiency evaluation can be classified into 2 types as follows:

5.2.1. Coverage

5.2.2. NDCG Average Score

4.2.1. Coverage

Coverage result is the method efficiency of the number of generated recommendations for users. It can be calculated by dividing the generated numbers from the model by the complete numbers of recommendations (for this study, the complete numbers of recommendations are 250). After that, multiplying the outcome by 100 which Coverage results will be in form of the percentile as Equation 6.

$$Coverage = \frac{Number\ of\ predictable\ suggestions}{Number\ of\ all\ suggestion} * 100 \tag{6}$$

4.2.2. NDCG Average Score

Normalized Discount Cumulative Gain (NDCG) is the method efficiency of the ranking of user recommendations. NDCG can be calculated by Equation 7.

$$NDCG_p = \frac{DCG_p}{IDCG_p} \tag{7}$$

$NDCG_p$ is the related score of the first 5 recommendations which the method provides for users (for this study).

DCG_p is the total score of the first 5 related recommendations ranking which the method provides for users (for this study).

$IDCG_p$ is the total score of the first 5 recommendations ranking (for this study) by sorting the related recommendations from the highest to the lowest.

p is the order of recommendations from 1-5 (for this study).

The range of NDCG is 0-1 when NDCG is user preference recommended by the method. If NDCG closes to 1, the method can sort recommendations which are highly related to users correctly. On the other hand, if NDCG closes to 0, the method can sort recommendations which are rarely related to users correctly.

4.3. Experimental

4.3.1. Coverage

For the calculation of Coverage result of each method, the number of locations of the first 5 generated recommendations of all users is summed (some users might not be recommended for 5 locations) and calculated by Equation 6.

Table 29 shows the generated recommendations from 3 methods

Coverage result		
Method	The number of all predicted	The number of method predicted
Proposed method	250	153
PTP method		153
RSGI method		107

The outcome of efficiency comparison of 3 methods shows that the proposed method and PTP method can generate the same amount of recommendations to users. The efficiency of Coverage result is 61.2%. RSGI can generate recommendations at the minimum number having the Coverage efficiency of 42.8% which is lower than the proposed method and PTP by 18.4% (Figure 19).

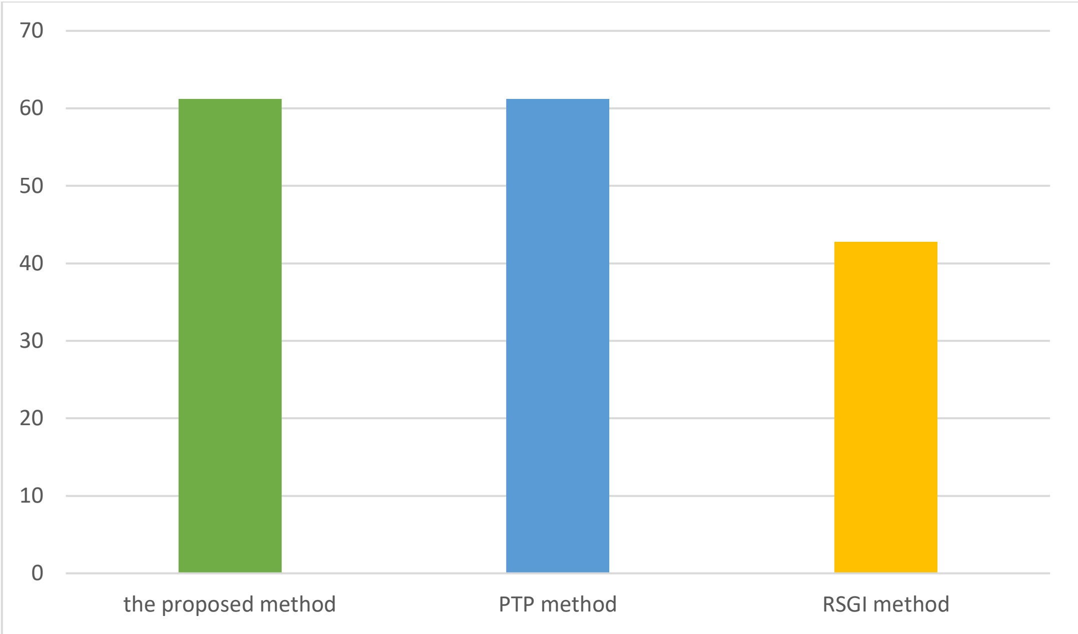

Figure 19 The outcome of efficiency comparison of coverage score among 3 methods.

4.3.2. NDCG Average Score

The calculation of NDCG Average Score efficiency of 3 methods will use only users' dataset who are recommended for 5 ranks computed by 2 methods together. The calculation of NDCG Average Score of each method can be done by calculating the average of NDCG from each user by the number of users who are recommended for 5 ranks.

The outcome of the comparison of 3 methods, the proposed method can generate the list of recommendations which are most related to users having the efficiency of NDCG Average result of 90%. Next is PTP with the efficiency of NDCG Average result equals 88%, and the last is RSGI with the efficiency of NDCG Average result equals 83%. Both of PTP and RSGI have lower efficiency than the proposed method by 2% and 7%, respectively (Figure 20).

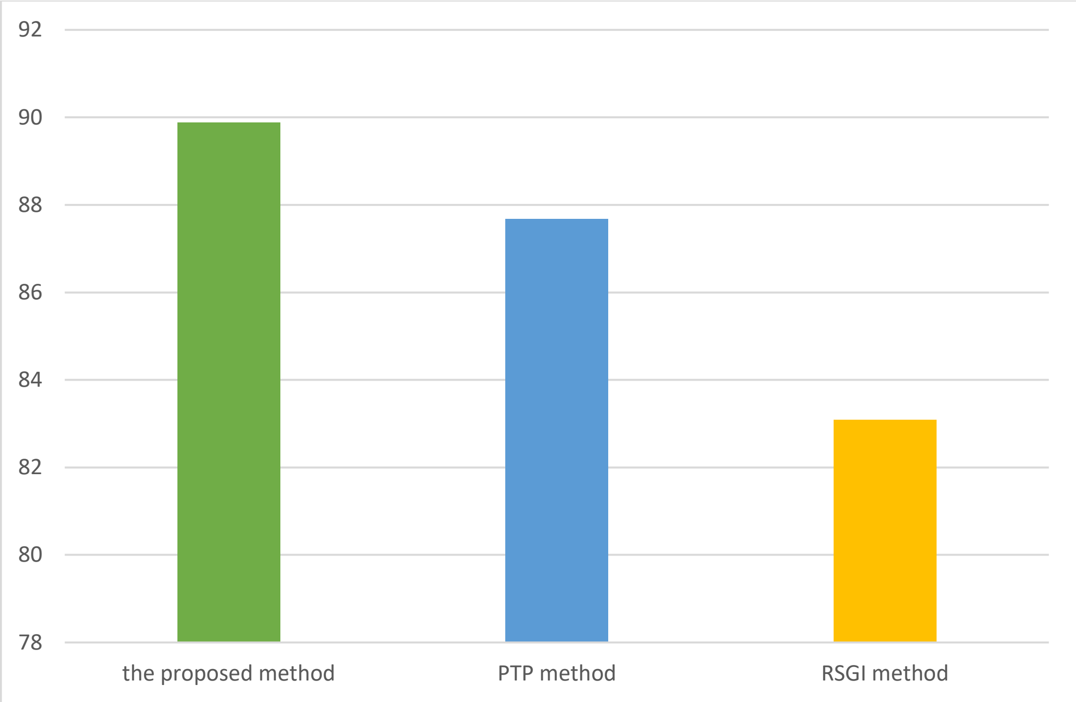

Figure 20 The outcome of efficiency comparison of NDCG average score among 3 methods.

Chapter 5. Discussion

5.1. Coverage

From the comparison of method efficiency based on the generated numbers of recommendations of 3 methods, it can be inferred as follows:

The proposed method can provide Coverage result as PTP. Both of them provide the efficiency of 61.2% because these 2 methods use the same dataset. The check-in history is the same. Moreover, the similarity calculation is the same as well. These 2 methods start from finding the similarities among users by CBF as the first step to calculate user preference of each user for visiting locations. After that, use of preference of each user to generate the preference vectors to all locations. Then, the second step is using CF to calculate the similarity among users by preference vectors from the first step. The outcome of using these 2 methods is obvious that both of methods can calculate the similarity for all users which will be used to calculate recommendations of each method later. Therefore, the two methods have the same efficiency of recommendation generation for users.

The proposed method provides the efficiency of coverage result which is better than RSGI. The proposed method can provide better efficiency by 18.4%. Although the two methods use Social filtering but we see that the methods which are used to calculate the social impact of these two methods are different. The proposed method calculates the social impact by dividing the number of friends or followers by the maximum members of friends or followers which are available in the system. Therefore, every user's social impact can be calculated. However, RSGI calculates the social impact by dividing the number of duplicated friends between 2 users by the total number of friends of these 2 users. From this, we see that in case 2 users do not have duplicated friends or they have totally different group of friends, the social impact of that user cannot be calculated. Therefore, the social impact of RSGI will be available for some users only. After the calculation of social impacts, they will be used to calculate recommendations of each method later. However, from the proposed method which can calculate social impact for all users. The generation of recommendations is higher than RSGI which some social impacts are available. Therefore, the proposed method has higher efficiency than RSGI.

5.2. NDCG Average Score

After the comparison of methods' efficiency of recommendations ranking for all 3 methods, it can be concluded as follows:

The proposed method provides better NDCG Average Score efficiency than PTP although these 2 methods use the same dataset. The check-in history and the process of similarity calculation are the same. However, PTP uses only CBF and CF to calculate the similarities which will be used to calculate recommendations. For the proposed method, Social filtering is additionally used for calculating social impacts of each user. From this, the efficiency of ranking for users by the proposed method is better than PTP.

The proposed method provides better NDCG Average Score efficiency than RSGI. The proposed method provides better outcomes by 7%. We find 2 issues which the proposed method provides make better outcome. The first is the used difference between each method. RSGI uses only CF and Social filtering to generate recommendations but the proposed method includes CBF by generating user preference of visiting locations. The proposed method prioritizes each user preference more significant than RSGI which uses only 2 techniques. The second is the used of Social filtering to calculate social impacts of each user. Although these 2 methods use this technique to incorporate social impacts in recommendation calculation, the processes are different. RSGI cannot provide social impact of all users so they cannot be used to determine recommendations for all users. The proposed method can calculate the social impact for all users so all recommendations are calculated using social impact. From these 2 issues, the efficiency of recommendation ranking of the proposed method is better than RSGI.

Chapter 6. Conclusion

For this study, we present a new method for location recommendation for users. The recommendation is obtained by CBF, CF, and social filtering techniques to calculate the outcome. The first step uses CBF to find user preference of locations and use to generate preference vectors of all locations for each user. Next step uses CF to find the similarity between users by cosine similarity equation and uses preference vectors. After that, use social filtering to find the social impact to each user. When the similarity and social impact are calculated, the recommendation is computed by using the efficiency of Coverage and NDCG Average Score and compare the efficiency of 2 methods i.e., PTP method (use of CBF and CF) and RSGI method (use of CF and social filtering). These 2 methods only use 2 techniques to calculate. From the comparison of the proposed method, the efficiency of Coverage results and the efficiency of NDCG Average Score are better than the other 2 methods.

For further development of this developed method, we recommend that the problem of users who rarely check-in or users who have never checked-in should be solved by using additional information to substitute the check-in history of users these.

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APPENDIX

Table 30 The ranking of user u_1

User u_1			User Id: 100159	
Rank	**Location id**	**Rating**	**Frequency**	**Gain**
1.	148589	0	5	0
2.	194114	0	2	0
3.	455560	0	2	0
4.	136597	0	1	0
5.	4619534	0	1	0

Table 31 The DCG and IDCG score of user u_1

User u_1			User Id: 100159	
Rank	**Location id**	**Gain**	**DCG**	**IDCG**
1.	148589	0	0	0
2.	194114	0	0	0
3.	455560	0	0	0
4.	136597	0	0	0
5.	4619534	0	0	0
Total			0	0

Table 32 The NDCG score of user u_1

User u_1	User Id: 100159		
Method	**NDCG Score**		
	DCG	**IDCG**	**NDCG**
Proposed Method	0	0	0

Table 33 The ranking of user u_2

User u_2			**User Id: 100192**	
Rank	**Location id**	**Rating**	**Frequency**	**Gain**
1.	582583	1	1	1
2.	447099	0	2	0
3.	1268842	0	1	0
4.	13319	0	1	0
5.	267201	0	1	0

Table 34 The DCG and IDCG score of user u_2

User u_2			**User Id: 100192**	
Rank	**Location id**	**Gain**	**DCG**	**IDCG**
1.	582583	1	1	1
2.	447099	0	0	0
3.	1268842	0	0	0
4.	13319	0	0	0
5.	267201	0	0	0
		Total	1	1

Table 35 The NDCG score of user u_2

User u_2		**User Id: 100192**	
Method	**NDCG Score**		
	DCG	**IDCG**	**NDCG**
Proposed Method	1	1	1

Table 36 The table ranking of user u_3

User u_3			User Id: 100315	
Rank	Location id	Rating	Frequency	Gain
1.	30471	2	3	3
2.	390881	0	3	0
3.	512551	0	2	0
4.	1003206	0	1	0
5.	104246	0	1	0

Table 37 The table of DCG and IDCG score of user u_3

User u_3			User Id: 100315	
Rank	Location id	Gain	DCG	IDCG
1.	30471	3	3	3
2.	390881	0	0	0
3.	512551	0	0	0
4.	1003206	0	0	0
5.	104246	0	0	0
		Total	3	3

Table 38 The table of NDCG score of user u_3

User u_3		User Id: 100315	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	3	3	1

Table 39 The ranking of user u_4

User u_4			User Id: 1004273	
Rank	Location id	Rating	Frequency	Gain
1.	26125	1.13335	2	2
2.	758476	0.88109	9	9
3.	23852	0.75557	1	1
4.	7135543	0.75556	1	1
5.	18535	0.62742	1	1

Table 40 The DCG and IDCG score of user u_4

User u_4			User Id: 1004273	
Rank	Location id	Gain	DCG	IDCG
1.	26125	2	2	9
2.	758476	9	9	2
3.	23852	1	0.63093	0.63093
4.	7135543	1	0.5	0.5
5.	18535	1	0.43068	0.43068
		Total	12.56161	12.56161

Table 41 The NDCG score of user u_4

User u_4		User Id: 1004273	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	12.56161	12.56161	1

Table 42 The ranking of user u_5

User u_5			User Id: 100533	
Rank	Location id	Rating	Frequency	Gain
1.	337468	0	1	0
2.	-	0	0	0
3.	-	0	0	0
4.	-	0	0	0
5.	-	0	0	0

Table 43 The DCG and IDCG score of user u_5

User u_5			User Id: 100533	
Rank	Location id	Gain	DCG	IDCG
1.	337468	0	0	0
2.	-	0	0	0
3.	-	0	0	0
4.	-	0	0	0
5.	-	0	0	0
		Total	0	0

Table 44 The NDCG score of user u_5

User u_5		User Id: 100533	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	0	0	0

Table 45 The ranking of user u_6

User u_6			User Id: 100543	
Rank	**Location id**	**Rating**	**Frequency**	**Gain**
1.	47426	0.97362	1	1
2.	17329	0.72713	1	1
3.	20536	0.493	1	1
4.	29236	0.02638	2	2
5.	411810	0	12	0

Table 46 The DCG and IDCG score of user u_6

User u_6			User Id: 10054	
Rank	**Location id**	**Gain**	**DCG**	**IDCG**
1.	47426	1	1	2
2.	17329	1	1	1
3.	20536	1	0.63093	0.63093
4.	29236	2	1	0.5
5.	411810	0	0	0
		Total	3.63093	4.13093

Table 47 The NDCG score of user u_6

User u_6		User Id: 10054	
Method	**NDCG Score**		
	DCG	**IDCG**	**NDCG**
Proposed Method	3.63093	4.13093	0.87896

Table 48 The ranking of user u_7

User u_7			User Id: 1006167	
Rank	Location id	Rating	Frequency	Gain
1.	1379036	0	1	0
2.	1404129	0	1	0
3.	349034	0	1	0
4.	6421803	0	1	0
5.	-	0	0	0

Table 49 The DCG and IDCG score of user u_7

User u_7			User Id: 1006167	
Rank	Location id	Gain	DCG	IDCG
1.	1379036	0	0	0
2.	1404129	0	0	0
3.	349034	0	0	0
4.	6421803	0	0	0
5.	-	0	0	0
		Total	0	0

Table 50 The NDCG score of user u_7

User u_7		User Id: 1006167	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	0	0	0

Table 51 The ranking of user u_8

User u_8			User Id: 1006227	
Rank	**Location id**	**Rating**	**Frequency**	**Gain**
1.	134259	2	1	1
2.	211912	1	1	1
3.	1316126	0	7	0
4.	4038903	0	5	0
5.	3398266	0	3	0

Table 52 The DCG and IDCG score of user u_8

User u_8			User Id: 1006227	
Rank	**Location id**	**Gain**	**DCG**	**IDCG**
1.	134259	1	1	1
2.	211912	1	1	1
3.	1316126	0	0	0
4.	4038903	0	0	0
5.	3398266	0	0	0
		Total	2	2

Table 53 The NDCG score of user u_8

User u_8		User Id: 1006227	
Method	**NDCG Score**		
	DCG	**IDCG**	**NDCG**
Proposed Method	2	2	1

Table 54 The ranking of user u_9

User u_9			User Id: 101846	
Rank	Location id	Rating	Frequency	Gain
1.	23261	4.384862321	1	1
2.	136217	0.102911803	1	1
3.	49555	0.026685554	1	1
4.	84064	0	3	0
5.	274956	0	2	0

Table 55 The DCG and IDCG score of user u_9

User u_9			User Id: 101846	
Rank	Location id	Gain	DCG	IDCG
1.	23261	1	1	1
2.	136217	1	1	1
3.	49555	1	0.63093	0.63093
4.	84064	0	0	0
5.	274956	0	0	0
		Total	2.63093	2.63093

Table 56 The NDCG score of user u_9

User u_9		User Id: 101846	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	2.63093	2.63093	1

Table 57 The ranking of user u_{10}

User u_{10}			**User Id: 103951**	
Rank	**Location id**	**Rating**	**Frequency**	**Gain**
1.	137887	26.39716	4	4
2.	21555	10.86942	13	13
3.	13215	2.48444	10	10
4.	219561	2.48444	7	7
5.	33610	2.48444	1	1

Table 58 The DCG and IDCG score of user u_{10}

User u_{10}			**User Id: 103951**	
Rank	**Location id**	**Gain**	**DCG**	**IDCG**
1.	137887	4	4	13
2.	21555	13	13	10
3.	13215	10	6.3093	4.416508275
4.	219561	7	3.5	2
5.	33610	1	0.43068	0.430676558
		Total	27.24	29.84718

Table 59 The NDCG score of user u_{10}

User u_{10}		**User Id: 103951**	
Method	**NDCG Score**		
	DCG	**IDCG**	**NDCG**
Proposed Method	27.24	29.84718	0.91265

Table 60 The ranking of user u_{11}

User u_{11}			User Id: 106384	
Rank	Location id	Rating	Frequency	Gain
1.	1371687	0	20	0
2.	788954	0	17	0
3.	995183	0	16	0
4.	995132	0	15	0
5.	1453915	0	10	0

Table 61 The DCG and IDCG score of user u_{11}

User u_{11}			User Id: 106384	
Rank	Location id	Gain	DCG	IDCG
1.	1371687	0	0	0
2.	788954	0	0	0
3.	995183	0	0	0
4.	995132	0	0	0
5.	1453915	0	0	0
		Total	0	0

Table 62 The NDCG score of user u_{11}

User u_{11}	User Id: 106384		
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	0	0	0

Table 63 The ranking of user u_{12}

User u_{12}			User Id: 108643	
Rank	Location id	Rating	Frequency	Gain
1.	11368	5.34941	1	1
2.	17831	4.56194	5	5
3.	9410	3.16741	1	1
4.	9246	3.13145	2	2
5.	99753	3.05712	4	4

Table 64 The DCG and IDCG score of user u_{12}

User u_{12}			User Id: 108643	
Rank	Location id	Gain	DCG	IDCG
1.	11368	1	1	5
2.	17831	5	5	4
3.	9410	1	0.63093	1.26186
4.	9246	2	1	0.5
5.	99753	4	1.72271	0.43068
		Total	9.35364	11.19254

Table 65 The NDCG score of user u_{12}

User u_{12}		User Id: 108643	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	9.35364	11.19254	0.8357

Table 66 The ranking of user u_{13}

User u_{13}			User Id: 111477	
Rank	Location id	Rating	Frequency	Gain
1.	116347	7.85332	1	1
2.	758476	2.12944	3	3
3.	66626	0.45465	2	2
4.	18535	0.28695	1	1
5.	32773	0.28695	1	1

Table 67 The DCG and IDCG score of user u_{13}

User u_{13}			User Id: 111477	
Rank	Location id	Gain	DCG	IDCG
1.	116347	1	1	3
2.	758476	3	3	2
3.	66626	2	1.26186	0.63093
4.	18535	1	0.5	0.5
5.	32773	1	0.43068	0.43068
		Total	6.19254	6.56162

Table 68 The NDCG score of user u_{13}

User u_{13}		User Id: 111477	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	6.19254	6.56162	0.94376

Table 69 The ranking of user u_{14}

User u_{14}			User Id: 112942	
Rank	Location id	Rating	Frequency	Gain
1.	19542	2.40521	2	2
2.	9410	1.85755	2	2
3.	10190	1.33791	1	1
4.	12505	0.34255	1	1
5.	709919	0.29061	1	1

Table 70 The DCG and IDCG score of user u_{14}

User u_{14}			User Id: 112942	
Rank	Location id	Gain	DCG	IDCG
1.	19542	2	2	2
2.	9410	2	2	2
3.	10190	1	0.63093	0.63093
4.	12505	1	0.5	0.5
5.	709919	1	0.43068	0.43068
		Total	5.56161	5.56161

Table 71 The NDCG score of user u_{14}

User u_{14}	User Id: 112942		
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	5.56161	5.56161	1

Table 72 The ranking of user u_{15}

User u_{15}			User Id: 11365	
Rank	Location id	Rating	Frequency	Gain
1.	19542	2.8794	1	1
2.	83235	1.1931	1	1
3.	15700	0.20109	3	3
4.	40497	0.08643	1	1
5.	40971	0.07153	1	1

Table 73 The DCG and IDCG score of user u_{15}

User u_{15}			User Id: 11365	
Rank	Location id	Gain	DCG	IDCG
1.	19542	1	1	3
2.	83235	1	1	1
3.	15700	3	1.89279	0.63093
4.	40497	1	0.5	0.5
5.	40971	1	0.43068	0.43068
		Total	4.82347	5.56161

Table 74 The NDCG score of user u_{15}

User u_{15}		User Id: 11365	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	4.82347	5.56161	0.86728

Table 75 The ranking of user u_{16}

User u_{16}			User Id: 1141687	
Rank	Location id	Rating	Frequency	Gain
1.	163035	6	1	1
2.	324373	4	1	1
3.	5702214	2	2	2
4.	4497953	2	1	1
5.	462314	2	1	1

Table 76 The DCG and IDCG score of user u_{16}

User u_{16}			User Id: 1141687	
Rank	Location id	Gain	DCG	IDCG
1.	163035	1	1	2
2.	324373	1	1	1
3.	5702214	2	1.26186	0.63093
4.	4497953	1	0.5	0.5
5.	462314	1	0.43068	0.43068
		Total	4.19254	4.56161

Table 77 The NDCG score of user u_{16}

User u_{16}	User Id: 1141687		
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	4.19254	4.56161	0.91909

Table 78 The ranking of user u_{17}

User u_{17}			User Id: 1148785	
Rank	Location id	Rating	Frequency	Gain
1.	63743	2.31401	1	1
2.	37286	0.66094	1	1
3.	14151	0.4513	1	1
4.	134420	0.16732	1	1
5.	3718479	0	6	0

Table 79 The DCG and IDCG score of user u_{17}

User u_{17}			User Id: 1148785	
Rank	Location id	Gain	DCG	IDCG
1.	63743	1	1	1
2.	37286	1	1	1
3.	14151	1	0.63093	0.63093
4.	134420	1	0.5	0.5
5.	3718479	0	0	0
		Total	3.13093	3.13093

Table 80 The NDCG score of user u_{17}

User u_{17}	User Id: 1148785		
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	3.13093	3.13093	1

Table 81 The ranking of user u_{18}

User u_{18}			User Id: 1180690	
Rank	Location id	Rating	Frequency	Gain
1.	4115406	0	1	0
2.	-	0	0	0
3.	-	0	0	0
4.	-	0	0	0
5.	-	0	0	0

Table 82 The DCG and IDCG score of user u_{18}

User u_{18}			User Id: 1180690	
Rank	Location id	Gain	DCG	IDCG
1.	4115406	0	0	0
2.	-	0	0	0
3.	-	0	0	0
4.	-	0	0	0
5.	-	0	0	0
		Total	0	0

Table 83 The NDCG score of user u_{18}

User u_{18}		User Id: 1180690	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	0	0	0

Table 84 The ranking of user u_{19}

User u_{19}			User Id: 1180690	
Rank	Location id	Rating	Frequency	Gain
1.	10259	4.61112	1	1
2.	19542	4.40752	2	2
3.	33472	1.98376	7	7
4.	32818	1.62485	1	1
5.	62666	1.57607	4	4

Table 85 The DCG and IDCG score of user u_{19}

User u_{19}			User Id: 1180690	
Rank	Location id	Gain	DCG	IDCG
1.	10259	1	1	7
2.	19542	2	2	4
3.	33472	7	4.41651	1.26186
4.	32818	1	0.5	0.5
5.	62666	4	1.72271	0.43068
		Total	9.63921	13.19254

Table 86 The NDCG score of user u_{19}

User u_{19}		User Id: 1180690	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	9.63921	13.19254	0.73066

Table 87 The ranking of user u_{20}

User u_{20}			User Id: 124343	
Rank	Location id	Rating	Frequency	Gain
1.	10075	0.85277	1	1
2.	42769	0.58293	3	3
3.	873361	0.56851	1	1
4.	9883	0.28426	1	1
5.	991117	0.28426	1	1

Table 88 The DCG and IDCG score of user u_{20}

User u_{20}			User Id: 124343	
Rank	Location id	Gain	DCG	IDCG
1.	10259	1	1	3
2.	19542	3	3	1
3.	33472	1	0.63093	0.63093
4.	32818	1	0.5	0.5
5.	62666	1	0.43068	0.43068
		Total	5.56161	5.56161

Table 89 The NDCG score of user u_{20}

User u_{20}		User Id: 124343	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	5.56161	5.56161	1

Table 90 The ranking of user u_{21}

User u_{21}			User Id: 133064	
Rank	Location id	Rating	Frequency	Gain
1.	59342	0.03901	2	2
2.	158879	0	15	0
3.	113138	0	8	0
4.	7087779	0	8	0
5.	6156954	0	7	0

Table 91 The DCG and IDCG score of user u_{21}

User u_{21}			User Id: 133064	
Rank	Location id	Gain	DCG	IDCG
1.	59342	2	2	2
2.	158879	0	0	0
3.	113138	0	0	0
4.	7087779	0	0	0
5.	6156954	0	0	0
		Total	2	2

Table 92 The NDCG score of user u_{21}

User u_{21}	User Id: 133064		
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	2	2	1

Table 93 The ranking of user u_{22}

User u_{22}			User Id: 134413	
Rank	Location id	Rating	Frequency	Gain
1.	9410	2.50146	4	4
2.	420315	2.24587	1	1
3.	17831	2.13411	4	4
4.	11368	1.73792	12	12
5.	9246	1.61648	7	7

Table 94 The DCG and IDCG score of user u_{22}

User u_{22}			User Id: 134413	
Rank	Location id	Gain	DCG	IDCG
1.	9410	4	4	12
2.	420315	1	1	7
3.	17831	4	2.52372	2.52372
4.	11368	12	6	2
5.	9246	7	3.01474	0.43068
		Total	16.5385	23.9544

Table 95 The NDCG score of user u_{22}

User u_{22}		User Id: 134413	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	16.5385	23.9544	0.69041

Table 96 The ranking of user u_{23}

User u_{23}			User Id: 139658	
Rank	Location id	Rating	Frequency	Gain
1.	42769	1.81197	1	1
2.	24767	0.32804	4	4
3.	23275	0.32804	2	2
4.	53393	0.06797	2	2
5.	46638	0.06797	1	1

Table 97 The DCG and IDCG score of user u_{23}

User u_{23}			User Id: 139658	
Rank	Location id	Gain	DCG	IDCG
1.	42769	1	1	4
2.	24767	4	4	2
3.	23275	2	1.26186	1.26186
4.	53393	2	1	0.5
5.	46638	1	0.43068	0.43068
		Total	7.69254	8.19254

Table 98 The NDCG score of user u_{23}

User u_{23}		User Id: 139658	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	7.69254	8.19254	0.93897

Table 99 The ranking of user u_{24}

User u_{24}			User Id: 1405020	
Rank	Location id	Rating	Frequency	Gain
1.	134420	1	1	1
2.	5358143	0	8	0
3.	6449807	0	6	0
4.	317370	0	3	0
5.	4944012	0	3	0

Table 100 The DCG and IDCG score of user u_{24}

User u_{24}			User Id: 1405020	
Rank	Location id	Gain	DCG	IDCG
1.	134420	1	1	1
2.	5358143	0	0	0
3.	6449807	0	0	0
4.	317370	0	0	0
5.	4944012	0	0	0
		Total	1	1

Table 101 The NDCG score of user u_{24}

User u_{24}	User Id: 1405020		
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	1	1	1

Table 102 The ranking of user u_{25}

User u_{25}			User Id: 141154	
Rank	Location id	Rating	Frequency	Gain
1.	9410	2.37907	3	3
2.	9225	2.08517	1	1
3.	9246	2.03987	1	1
4.	19542	1.8289	2	2
5.	9335	1.81742	1	1

Table 103 The DCG and IDCG score of user u_{25}

User u_{25}			User Id: 141154	
Rank	Location id	Gain	DCG	IDCG
1.	9410	3	3	3
2.	9225	1	1	2
3.	9246	1	0.63093	0.63093
4.	19542	2	1	0.5
5.	9335	1	0.43068	0.43068
		Total	6.06161	6.56161

Table 104 The NDCG score of user u_{25}

User u_{25}	User Id: 141154		
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	6.06161	6.56161	0.9238

Table 105 The ranking of user u_{26}

User u_{26}			User Id: 148584	
Rank	Location id	Rating	Frequency	Gain
1.	9410	1.98793	4	4
2.	9246	1.70022	4	4
3.	11368	1.57989	10	10
4.	420315	1.45869	1	1
5.	9220	1.45727	4	4

Table 106 The DCG and IDCG score of user u_{26}

User u_{26}			User Id: 148584	
Rank	Location id	Gain	DCG	IDCG
1.	9410	4	4	10
2.	9246	4	4	4
3.	11368	10	6.3093	2.52372
4.	420315	1	0.5	2
5.	9220	4	1.72271	0.43068
		Total	16.532	18.9544

Table 107 The NDCG score of user u_{26}

User u_{26}	User Id: 148584		
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	16.532	18.9544	0.8722

Table 108 The ranking of user u_{27}

User u_{27}			User Id: 17183	
Rank	Location id	Rating	Frequency	Gain
1.	1336784	26.4812	1	1
2.	1006598	21.4848	1	1
3.	19542	12.8097	3	3
4.	28959	8.99362	1	1
5.	39361	7.49468	1	1

Table 109 The DCG and IDCG score of user u_{27}

User u_{27}			User Id: 17183	
Rank	Location id	Gain	DCG	IDCG
1.	1336784	1	1	3
2.	1006598	1	1	1
3.	19542	3	1.89279	0.63093
4.	28959	1	0.5	0.5
5.	39361	1	0.43068	0.43068
		Total	4.82347	5.56161

Table 110 The NDCG score of user u_{27}

User u_{27}		User Id: 17183	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	4.82347	5.56161	0.86728

Table 111 The ranking of user u_{28}

User u_{28}			User Id: 175688	
Rank	Location id	Rating	Frequency	Gain
1.	23372	1.05466	1	1
2.	266339	0.10852	1	1
3.	933440	0	3	0
4.	31191	0	2	0
5.	682968	0	2	0

Table 112 The DCG and IDCG score of user u_{28}

User u_{28}			User Id: 175688	
Rank	Location id	Gain	DCG	IDCG
1.	23372	1	1	1
2.	266339	1	1	1
3.	933440	0	0	0
4.	31191	0	0	0
5.	682968	0	0	0
		Total	2	2

Table 113 The NDCG score of user u_{28}

User u_{28}		User Id: 175688	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	2	2	1

Table 114 The ranking of user u_{29}

User u_{29}			User Id: 18166	
Rank	Location id	Rating	Frequency	Gain
1.	420315	2.08053	2	2
2.	19542	1.90886	4	4
3.	9410	1.78798	3	3
4.	23256	1.24285	1	1
5.	9246	1.08647	2	2

Table 115 The DCG and IDCG score of user u_{29}

User u_{29}			User Id: 18166	
Rank	Location id	Gain	DCG	IDCG
1.	420315	2	2	4
2.	19542	4	4	3
3.	9410	3	1.89279	1.26186
4.	23256	1	0.5	1
5.	9246	2	0.86135	0.43068
		Total	9.25414	9.69254

Table 116 The NDCG score of user u_{29}

User u_{29}		User Id: 18166	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	9.25414	9.69254	0.95477

Table 117 The ranking of user u_{30}

User u_{30}			User Id: 185867	
Rank	Location id	Rating	Frequency	Gain
1.	9410	2.89971	3	3
2.	11368	2.56804	2	2
3.	17831	2.17675	1	1
4.	15590	2.01257	2	2
5.	9225	1.91226	1	1

Table 118 The DCG and IDCG score of user u_{30}

User u_{30}			User Id: 185867	
Rank	Location id	Gain	DCG	IDCG
1.	9410	3	3	3
2.	11368	2	2	2
3.	17831	1	0.63093	1.26186
4.	15590	2	1	0.5
5.	9225	1	0.43068	0.43068
		Total	7.06161	7.19254

Table 119 The NDCG score of user u_{30}

User u_{30}		User Id: 185867	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	7.06161	7.19254	0.9818

Table 120 The ranking of user u_{31}

User u_{31}			User Id: 19006	
Rank	**Location id**	**Rating**	**Frequency**	**Gain**
1.	420315	2.105	2	2
2.	9410	1.99763	1	1
3.	21714	1.3771	3	3
4.	9246	1.3482	1	1
5.	23261	1.17178	2	2

Table 121 The DCG and IDCG score of user u_{31}

User u_{31}			User Id: 19006	
Rank	**Location id**	**Gain**	**DCG**	**IDCG**
1.	420315	2	2	3
2.	9410	1	1	2
3.	21714	3	1.89279	1.26186
4.	9246	1	0.5	0.5
5.	23261	2	0.86135	0.43068
		Total	6.25414	7.19254

Table 122 The NDCG score of user u_{31}

User u_{31}	User Id: 19006		
Method	**NDCG Score**		
	DCG	**IDCG**	**NDCG**
Proposed Method	6.25414	7.19254	0.86953

Table 123 The ranking of user u_{32}

User u_{32}			User Id: 2091561	
Rank	Location id	Rating	Frequency	Gain
1.	4776798	0	2	0
2.	3486572	0	1	0
3.	-	0	0	0
4.	-	0	0	0
5.	-	0	0	0

Table 124 The DCG and IDCG score of user u_{32}

User u_{32}			User Id: 2091561	
Rank	Location id	Gain	DCG	IDCG
1.	4776798	0	0	0
2.	3486572	0	0	0
3.	-	0	0	0
4.	-	0	0	0
5.	-	0	0	0
		Total	0	0

Table 125 The NDCG score of user u_{32}

User u_{32}		User Id: 2091561	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	0	0	0

Table 126 The ranking of user u_{33}

User u_{33}			User Id: 2102618	
Rank	Location id	Rating	Frequency	Gain
1.	153204	1	7	7
2.	95034	1	5	5
3.	670703	0	54	0
4.	1263397	0	34	0
5.	970411	0	20	0

Table 127 The DCG and IDCG score of user u_{33}

User u_{33}			User Id: 2102618	
Rank	Location id	Gain	DCG	IDCG
1.	153204	7	7	7
2.	95034	5	5	5
3.	670703	0	0	0
4.	1263397	0	0	0
5.	970411	0	0	0
		Total	12	12

Table 128 The NDCG score of user u_{33}

User u_{33}	User Id: 2102618		
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	12	12	1

Table 129 The ranking of user u_{34}

User u_{34}			User Id: 2105048	
Rank	Location id	Rating	Frequency	Gain
1.	6464760	0	3	0
2.	7183680	0	3	0
3.	358048	0	2	0
4.	6864438	0	2	0
5.	6929356	0	2	0

Table 130 The DCG and IDCG score of user u_{34}

User u_{34}			User Id: 2105048	
Rank	Location id	Gain	DCG	IDCG
1.	6464760	0	0	0
2.	7183680	0	0	0
3.	358048	0	0	0
4.	6864438	0	0	0
5.	6929356	0	0	0
		Total	0	0

Table 131 The NDCG score of user u_{34}

User u_{34}		User Id: 2105048	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	0	0	0

Table 132 The ranking of user u_{35}

User u_{35}			User Id: 2124576	
Rank	Location id	Rating	Frequency	Gain
1.	6485067	0	38	0
2.	6476244	0	22	0
3.	6568453	0	21	0
4.	7140512	0	6	0
5.	6552265	0	5	0

Table 133 The DCG and IDCG score of user u_{35}

User u_{35}			User Id: 2124576	
Rank	Location id	Gain	DCG	IDCG
1.	6485067	0	0	0
2.	6476244	0	0	0
3.	6568453	0	0	0
4.	7140512	0	0	0
5.	6552265	0	0	0
		Total	0	0

Table 134 The NDCG score of user u_{35}

User u_{35}		User Id: 2124576	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	0	0	0

Table 135 The ranking of user u_{36}

User u_{36}			User Id: 2171565	
Rank	Location id	Rating	Frequency	Gain
1.	698718	0	4	0
2.	13883	0	3	0
3.	534772	0	2	0
4.	560114	0	2	0
5.	565351	0	2	0

Table 136 The DCG and IDCG score of user u_{36}

User u_{36}			User Id: 2171565	
Rank	Location id	Gain	DCG	IDCG
1.	698718	0	0	0
2.	13883	0	0	0
3.	534772	0	0	0
4.	560114	0	0	0
5.	565351	0	0	0
		Total	0	0

Table 137 The NDCG score of user u_{36}

User u_{36}		User Id: 2171565	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	0	0	0

Table 138 The ranking of user u_{37}

User u_{37}			User Id: 2177481	
Rank	Location id	Rating	Frequency	Gain
1.	6345374	0	3	0
2.	6781050	0	3	0
3.	4557339	0	2	0
4.	6542944	0	2	0
5.	6570012	0	2	0

Table 139 The DCG and IDCG score of user u_{37}

User u_{37}			User Id: 2177481	
Rank	Location id	Gain	DCG	IDCG
1.	6345374	0	0	0
2.	6781050	0	0	0
3.	4557339	0	0	0
4.	6542944	0	0	0
5.	6570012	0	0	0
		Total	0	0

Table 140 The NDCG score of user u_{37}

User u_{37}	User Id: 2177481		
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	0	0	0

Table 141 The ranking of user u_{38}

User u_{38}			User Id: 220508	
Rank	Location id	Rating	Frequency	Gain
1.	908807	0	14	0
2.	926052	0	10	0
3.	167815	0	5	0
4.	460022	0	5	0
5.	1097565	0	4	0

Table 142 The DCG and IDCG score of user u_{38}

User u_{38}			User Id: 220508	
Rank	Location id	Gain	DCG	IDCG
1.	908807	0	0	0
2.	926052	0	0	0
3.	167815	0	0	0
4.	460022	0	0	0
5.	1097565	0	0	0
		Total	0	0

Table 143 The NDCG score of user u_{38}

User u_{38}		User Id: 220508	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	0	0	0

Table 144 The ranking of user u_{39}

User u_{39}			User Id: 2265351	
Rank	Location id	Rating	Frequency	Gain
1.	11844	1.67566	2	2
2.	22639	1.45063	1	1
3.	650823	0.25785	2	2
4.	278870	0	25	0
5.	6548538	0	13	0

Table 145 The DCG and IDCG score of user u_{39}

User u_{39}			User Id: 2265351	
Rank	Location id	Gain	DCG	IDCG
1.	11844	2	2	2
2.	22639	1	1	2
3.	650823	2	1.26186	0.63093
4.	278870	0	0	0
5.	6548538	0	0	0
		Total	4.26186	4.63093

Table 146 The NDCG score of user u_{39}

User u_{39}	User Id: 2265351		
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	4.26186	4.63093	0.9203

Table 147 The ranking of user u_{40}

User u_{40}			User Id: 2296420	
Rank	Location id	Rating	Frequency	Gain
1.	571942	0	5	0
2.	6641066	0	5	0
3.	1096237	0	3	0
4.	301547	0	3	0
5.	4048231	0	2	0

Table 148 The DCG and IDCG score of user u_{40}

User u_{40}			User Id: 2296420	
Rank	Location id	Gain	DCG	IDCG
1.	571942	0	0	0
2.	6641066	0	0	0
3.	1096237	0	0	0
4.	301547	0	0	0
5.	4048231	0	0	0
		Total	0	0

Table 149 The NDCG score of user u_{40}

User u_{40}		User Id: 2296420	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	0	0	0

Table 150 The ranking of user u_{41}

User u_{41}			User Id: 2336983	
Rank	**Location id**	**Rating**	**Frequency**	**Gain**
1.	9410	2.64504	2	2
2.	420315	2.49688	4	4
3.	11368	1.88597	1	1
4.	21714	1.7136	1	1
5.	9225	1.70865	1	1

Table 151 The DCG and IDCG score of user u_{41}

User u_{41}			User Id: 2336983	
Rank	**Location id**	**Gain**	**DCG**	**IDCG**
1.	9410	2	2	4
2.	420315	4	4	2
3.	11368	1	0.63093	0.63093
4.	21714	1	0.5	0.5
5.	9225	1	0.43068	0.430677
		Total	7.561606	7.56161

Table 152 The NDCG score of user u_{41}

User u_{41}	User Id: 2336983		
Method	**NDCG Score**		
	DCG	**IDCG**	**NDCG**
Proposed Method	7.561606	7.56161	1

Table 153 The ranking of user u_{42}

User u_{42}			User Id: 283510	
Rank	Location id	Rating	Frequency	Gain
1.	63743	0.6228	6	6
2.	59342	0.5945	2	2
3.	23253	0.1599	1	1
4.	508737	0	54	0
5.	2039210	0	20	0

Table 154 The DCG and IDCG score of user u_{42}

User u_{42}			User Id: 283510	
Rank	Location id	Gain	DCG	IDCG
1.	63743	6	6	6
2.	59342	2	2	2
3.	23253	1	0.63093	0.63093
4.	508737	0	0	0
5.	2039210	0	0	0
		Total	8.6309	8.63093

Table 155 The NDCG score of user u_{42}

User u_{42}	User Id: 283510		
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	8.6309	8.63093	1

Table 156 The ranking of user u_{43}

User u_{43}			User Id: 319104	
Rank	Location id	Rating	Frequency	Gain
1.	19542	4.84902	1	1
2.	23743	0.93622	1	1
3.	11319	0.8351	1	1
4.	267716	0.69173	1	1
5.	785194	0.55394	1	1

Table 157 The DCG and IDCG score of user u_{43}

User u_{43}			User Id: 319104	
Rank	Location id	Gain	DCG	IDCG
1.	19542	1	1	1
2.	23743	1	1	1
3.	11319	1	0.63093	0.63093
4.	267716	1	0.5	0.5
5.	785194	1	0.43068	0.43068
		Total	3.56161	3.56161

Table 158 The NDCG score of user u_{43}

User u_{43}		User Id: 319104	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	3.56161	3.56161	1

Table 159 The ranking of user u_{44}

User u_{44}			User Id: 330282	
Rank	Location id	Rating	Frequency	Gain
1.	153204	2.68406	1	1
2.	95034	1.91719	1	1
3.	5702214	0.6908	2	2
4.	10190	0.59268	1	1
5.	163035	0.3454	6	6

Table 160 The DCG and IDCG score of user u_{44}

User u_{44}			User Id: 330282	
Rank	Location id	Gain	DCG	IDCG
1.	153204	1	1	6
2.	95034	1	1	2
3.	5702214	2	1.26186	0.63093
4.	10190	1	0.5	0.5
5.	163035	6	2.58406	0.43068
		Total	6.34592	9.56161

Table 161 The NDCG score of user u_{44}

User u_{44}		User Id: 330282	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	6.34592	9.56161	0.66369

Table 162 The ranking of user u_{45}

User u_{45}			User Id: 4931	
Rank	**Location id**	**Rating**	**Frequency**	**Gain**
1.	9410	1.61235	1	1
2.	23261	1.53411	2	2
3.	19542	1.47197	1	1
4.	9225	1.3791	1	1
5.	9335	0.69465	1	1

Table 163 The DCG and IDCG score of user u_{45}

User u_{45}			User Id: 4931	
Rank	**Location id**	**Gain**	**DCG**	**IDCG**
1.	9410	1	1	1
2.	23261	2	2	2
3.	19542	1	0.63093	0.63093
4.	9225	1	0.5	0.5
5.	9335	1	0.43068	0.43068
		Total	4.56161	4.56161

Table 164 The NDCG score of user u_{45}

User u_{45}		User Id: 4931	
Method	**NDCG Score**		
	DCG	**IDCG**	**NDCG**
Proposed Method	4.56161	4.56161	1

Table 165 The ranking of user u_{46}

User u_{46}			**User Id: 5659**	
Rank	**Location id**	**Rating**	**Frequency**	**Gain**
1.	17831	1.4932	1	1
2.	9410	1.48852	1	1
3.	9246	1.19156	1	1
4.	23261	1.05552	6	6
5.	9225	0.85865	2	2

Table 166 The DCG and IDCG score of user u_{46}

User u_{46}			**User Id: 5659**	
Rank	**Location id**	**Gain**	**DCG**	**IDCG**
1.	17831	1	1	6
2.	9410	1	1	2
3.	9246	1	0.63093	0.63093
4.	23261	6	3	0.5
5.	9225	2	0.86135	0.43068
		Total	6.49228	9.56161

Table 167 The NDCG score of user u_{46}

User u_{46}		**User Id: 5659**	
Method	**NDCG Score**		
	DCG	**IDCG**	**NDCG**
Proposed Method	6.49228	9.56161	0.67899

Table 168 The ranking of user u_{47}

User u_{47}			User Id: 64063	
Rank	Location id	Rating	Frequency	Gain
1.	12184	2.06277	1	1
2.	225918	1.90686	1	1
3.	37286	1.28467	1	1
4.	11824	1.28378	3	3
5.	12164	1.28378	1	1

Table 169 The DCG and IDCG score of user u_{47}

User u_{47}			User Id: 64063	
Rank	Location id	Gain	DCG	IDCG
1.	12184	1	1	3
2.	225918	1	1	1
3.	37286	1	0.63093	0.63093
4.	11824	3	1.5	0.5
5.	12164	1	0.43068	0.43068
		Total	4.56161	5.56161

Table 170 The NDCG score of user u_{47}

User u_{47}		User Id: 64063	
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	4.56161	5.56161	0.8202

Table 171 The ranking of user u_{48}

User u_{48}			User Id: 6647	
Rank	Location id	Rating	Frequency	Gain
1.	31161	2.60988	1	1
2.	47426	1	1	1
3.	17820	0.86996	1	1
4.	22650	0.86996	1	1
5.	33859	0.86996	1	1

Table 172 The DCG and IDCG score of user u_{48}

User u_{48}			User Id: 6647	
Rank	Location id	Gain	DCG	IDCG
1.	31161	1	1	1
2.	47426	1	1	1
3.	17820	1	0.63093	0.63093
4.	22650	1	0.5	0.5
5.	33859	1	0.43068	0.43068
		Total	3.56161	3.56161

Table 173 The NDCG score of user u_{48}

User u_{48}	User Id: 6647		
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	3.56161	3.56161	1

Table 174 The ranking of user u_{49}

User u_{49}			User Id: 70030	
Rank	Location id	Rating	Frequency	Gain
1.	23261	1.50519	2	2
2.	11824	1.19165	2	2
3.	12133	1.17161	1	1
4.	202215	1.17161	1	1
5.	34484	0.80112	1	1

Table 175 The DCG and IDCG score of user u_{49}

User u_{49}			User Id: 70030	
Rank	Location id	Gain	DCG	IDCG
1.	23261	2	2	2
2.	11824	2	2	2
3.	12133	1	0.63093	0.63093
4.	202215	1	0.5	0.5
5.	34484	1	0.43068	0.43068
		Total	5.56161	5.56161

Table 176 The NDCG score of user u_{49}

User u_{49}	User Id: 70030		
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	5.56161	5.56161	1

Table 177 The ranking of user u_{50}

User u_{50}			User Id: 80188	
Rank	Location id	Rating	Frequency	Gain
1.	86179	1	2	2
2.	326914	0	18	0
3.	344069	0	12	0
4.	1470197	0	7	0
5.	128424	0	5	0

Table 178 The DCG and IDCG score of user u_{50}

User u_{50}			User Id: 80188	
Rank	Location id	Gain	DCG	IDCG
1.	86179	2	2	2
2.	326914	0	0	0
3.	344069	0	0	0
4.	1470197	0	0	0
5.	128424	0	0	0
		Total	2	2

Table 179 The NDCG score of user u_{50}

User u_{50}	User Id: 80188		
Method	NDCG Score		
	DCG	IDCG	NDCG
Proposed Method	2	2	1

VITA

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