LOCATION BASED RECOMMENDOR SYSTEM USING ENHANCED RANDOM WALK MODEL

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CERTIFICATE

This is to certify that **Manika (2K14/ISY/06)** has carried out the major project titled "**Location Based Recommender System Using Enhanced Random Walk Model**" in partial fulfilment of the requirements for the award of Master of Technology degree in Information Systems by **Delhi Technological University**.

The major project is bonafide piece of work carried out and completed under my supervision and guidance during the academic session 2014-2016. To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University/Institute for the award of any degree or diploma.

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ABSTRACT

The increasing adoption of location-enabled smartphones has given rise to a number of social services (such as Foursquare and Google Places) that people can use to trace, annotate, and share their experiences about the locations they visit as they navigate through their daily lives. Users notify their friends of the place where they are with a check-in, leaving a digital trace of their movements. These services therefore now hold and collect huge datasets that can location users' mobility to both their social connections and the spatial layout of their cities; providers are also beginning to apply a host of machine learning approaches to their data in order to turn check-in services into fully fledged location recommendation systems.

First, location recommendation can help users to find potential friends, a function that improves user experience in social networking and attracts more users consequently. Compared with the usual passive ways of locating possible friends, the users on these social networks are provided with a list of potential friends, with a simple confirmation click. Second, location recommendation helps the social networking sites grow fast. A more complete social graph not only improves user involvement, but also provides the monetary benefits associated with a wide user base such as a large publisher network for advertisements.

This work proposed a framework using both attribute and structural properties to recommend potential location in social networks. To compute accurate location recommendations in social networks, we propose a list of desired criteria. A random walk framework on the augmented social graphs using both attribute and structural properties is further proposed, which satisfies all the criteria. We also discuss different methods for setting edge weights in the augmented social graph which considers both global and local characteristics of the attributes

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Chapter 1

INTRODUCTION

The expanding appropriation of location-enabled smart phones has offered ascend to various social administrations, (for example, Foursquare and Google Places) that individuals can use to annotate and share their experiences about the locations they visit as they explore through their day by day lives. Users inform their companions of the spot where they are with a registration, leaving an advanced hint of their developments. These administrations in this manner now hold and gather gigantic datasets that can location users' portability to both their social associations and the spatial design of their urban locations; suppliers are additionally starting to apply a large group of machine learning ways to deal with their information to transform registration administrations into completely fledged location proposal frameworks.

The location recommendation can help users to discover potential companions, a capacity that enhances user involvement in long range informal communication and draws in more users thus. Contrasted and the standard latent methods for finding conceivable companions, the users on these informal communities are given a list of potential companions, with a basic affirmation click. Second, location recommendation helps the person to person communication locales develop quickly. A more finish social diagram enhances user inclusion, as well as gives the fiscal advantages connected with a wide user base, for example, an extensive distributer system for notices.

This work proposed a system utilizing both credit and auxiliary properties to suggest potential location in informal organizations. To process precise location proposals in interpersonal organizations, we propose a list of craved criteria. An irregular walk system on the expanded social charts utilizing both quality and auxiliary properties is further proposed, which fulfils every one of the criteria. We likewise talk about various strategies for context edge weights in the enlarged social diagram which considers both worldwide and nearby qualities of the characteristics.

A Context Aware Group Recommendation System is a Recommendation System that prescribes items for groups of individuals rather than a solitary individual. The group and connection part adds extra difficulties contrasted with a typical Recommendation System. A group of individuals is more dynamic than a solitary individual. You need to consider how the group is shaped, how you can join the group so that brought together recommendations for the entire group can be given, and the flow inside the group. Context comes in numerous structures, however can be seen as outer limitations that influences the recommendation procedure. This normally makes the algorithms more confused when it must be considered. The motivation behind this proposition is to develop a Context Aware Group Recommendation System for Concerts that takes the location and time of a user into record when making proposals. This is done to demonstrate that customary strategies for Music Recommendation Systems can likewise be connected when shows are prescribed and additional context must be considered.

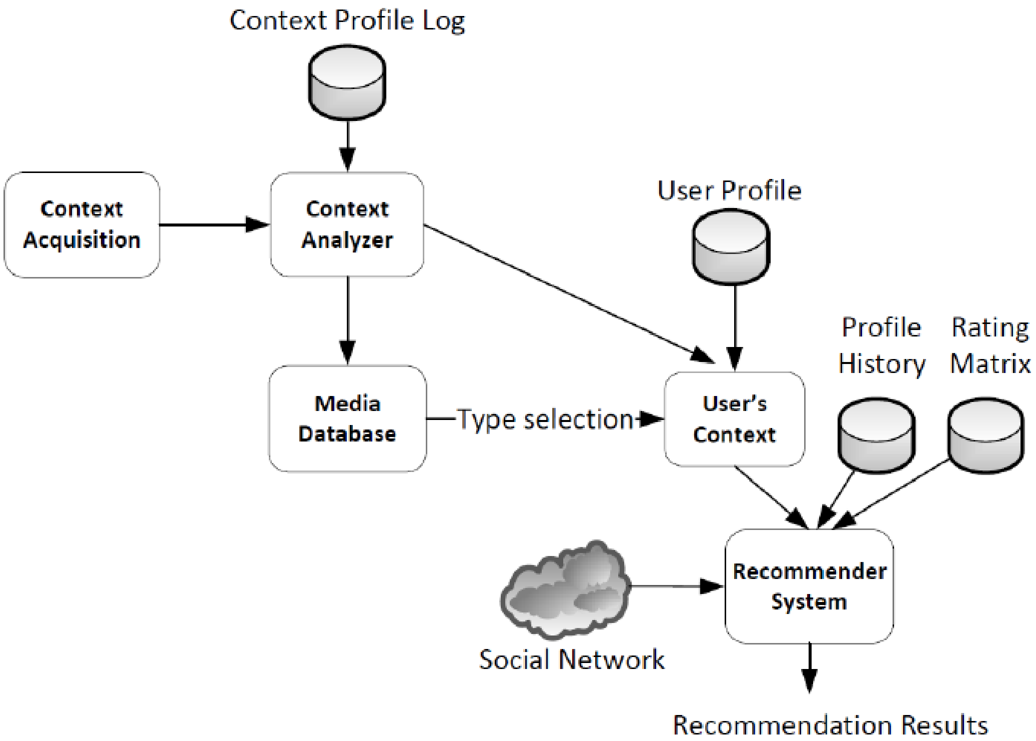

Figure 1: High-level context-based recommendation process

Context can be utilized to distinguish the appropriate sort of media to be introduced. Every user would have a list of media classifications to make a recommendation list. Figure 1.1 demonstrates the essential pattern proposed for context based proposals for both express and understood recommendation demands. The procedure starts by getting the majority of the accessible relevant data inside the user's surroundings.

1.1 OBJECTIVE

To propose a unified location recommendation system have user preferences and which satisfies the desired criteria of context-aware search.

1.2 MOTIVATION

These days, we expend distinctive sorts of mixed media content utilizing a considerable assortment of gadgets and stages. These gadgets run autonomously, and have content sharing confinements. Significant endeavours are made to upgrade the user experience. From one viewpoint, unique individuals have diverse explanations behind perusing or devouring interactive media content, including amusement, keeping up their prosperity, or learning. Then again, savvy motors, for example, those worked to give recommendations, search and control the media accumulations for an assortment of business purposes, for example, publicizing, concentrating on purchaser conduct, and different business related destinations. It stays trying for both sides to choose the most reasonable, favoured, and suitably related content utilizing context data from the conventional user item datasets [4]. Subsequently, it is advantageous to look at connection in a way that can be gainful to customized proposal. Be that as it may, absence of accessible context data is a vital test when outlining any connection based proposal. The technique for cooperation between the user and recommender frameworks that require context data to give criticism is still an exploration issue that should be handled. The estimation of appropriateness of interactive media content to a given sort of connection is another issue to address. Such estimation relies on upon the reasonable determination of context measurements to be considered in the recommendation procedure. Also, this proposal displays the capability of including a user's organic flag and utilizing it inside an adjusted cooperative separating algorithm in the recommendation procedure

1.3 GOAL

The proposed recommendation model makes the accompanying commitments toward proposal models: First, the model distinguishes the shrouded inclinations of users in particular connections, the concealed inclinations of items toward contexts, and also the shrouded inclinations of users toward new and devoured items. The proposed model contemplates the need an effectively relevant model to fit the extent of particular connection recommendation applications. Moreover, the model considers the context data by pondering the social labels accessible online to investigate the concealed inclinations between users, items, and contexts. In particular, the model can join not just the inclinations of a solitary user in a given connection, additionally the decisions different purchasers made in a comparable context. Second, we propose a rating algorithm for connection based items, which overcomes any issues between the media assets, users' individual and joint inclinations, and the recognized relevant data.

1.4 ORGANISATION OF THE THESIS

Chapter 2 includes background knowledge of recommender systems. The articulation is defined by telling about approach made by combining random walk approach, dimensionality reductions etc

Chapter 3 discusses methods and materials used in recommender systems. Here we started with probabilistic model for matrix development and then develop the model as we go along. Also some mathematical theory is proposed

Chapter 4 illustrates the proposed work that we have designed for our system. It explains all the vital elements that we need to propose this new type of recommender system

Chapter 5 analyses security of proposed algorithm and experimental results are presented along with discussion and analysis

Chapter 6 presents conclusion and future directions.

Chapter 2

BACKGROUND WORK

In recent years, the development of RSs has attracted in significant exploration enthusiasm for an endeavor to find the connection amongst users and the items they devour. Past studies examined the shrouded connections amongst users and items, and proposed a few strategies that are presently standard methods for context up recommendation s. Conventional recommendation algorithms prescribe items (i) to user (u) by considering diverse properties and measurements. These qualities can comprise of a user's unequivocal or verifiable appraisals, or of past enthusiasm for comparative items. Such frameworks assemble and break down other data keeping in mind the end goal to make proposals, for example, the comparability amongst users and the closeness of items expended in like manner. The proposal strategies either rely on upon data about the items (content-based), data about the connections amongusers (community oriented), or a blend of both sorts of data (cross breed). Consolidating relevant data has advanced and improved conventional proposal approaches.

a. **Content-Based Filtering (CBF):** The CBF approach prescribes items in view of the investigation of the item content and makes a profile with relegated elements, for example, sort, class, and extraordinary qualities. The subsequent profile is coordinated with the express appraisals that represent to the user's involvement with that specific item. This methodology is generally used to prescribe music, where a user's past rating scores and their verifiable choice of music anticipate their level of enthusiasm for the new items.

b. **Collaborative Filtering (CF):** CF prescribes items in light of the investigation of users instead of just items. For example, first discovering similarities between users who have the same interests, and afterward discovering all items that have not been devoured by that specific user or group. The social perspectives and the idea of sharing interests are exceedingly considered in this methodology.

c. **Hybrid Recommendation:** To conquer certain issues that exist in CBF and CF and expansion the execution of the recommendation, the half breed system consolidates the methodologies of the two proposal approaches. In particular, CF relies on upon the separation between users, in light of the quantity of items that they share.

2.1CONTEXT-AWARENESS AND RECOMMENDER SYSTEMS

2.1.1 Context-Aware Computing

Nowadays, the combination of technology, which focuses on the associations amongst users and smart frameworks, and an assortment of recommendation administrations, is getting more consideration from industry. In particular, the emphasis is on the making of a superior situation for the user to get and devour online assets. For the most part, evaluating the user's enthusiasm for an online asset is a test. This is valid since the user's advantage relies on upon different choice criteria, which can be considered as their relevant measurements. As needs be, to customize a proposal, we require a strategy that can recognize the user's state and gather all the related must-have context data about their surroundings. Along these lines, as of late, context careful figuring has been a zone of high enthusiasm for the field of mixed media adjustment and recommendation.

Connection careful registering and the idea of adjustments bolster AmI-based frameworks. For example, Ceccaroni and Verdaguer [1] outlined an intelligent mirror as the primary interface to give an intuitive TV, updates, individual inspiration content, and a customized set of interactive media shows, for example, the climate estimate. Beside the reasonable outline of their model, some administrations were mimicked as opposed to genuine usage. OnurAsan et al. [2] proposed another intuitive mirror that is to be set in the lavatory, to permit the user to perform distinctive exercises, for example, checking messages, the climate figure, or their everyday plan.

2.1.2 Context-Aware Recommendations

Contextual information supports the adequacy of conventional recommender frameworks, which consider just the user, items, or their related data to observe the following anticipated that item would be chosen. Along these lines, utilizing context data to improve the nature of proposals has demonstrated positive results in various studies. Diverse connection measurements can be considered by application's situations, for example, time, season, area and climate, and also social and physical conditions (e.g. stress level and frequency). Such relevant data can expand the nature of the recommendation and upgrade the user's experience [6].

Zhang et al. [14] proposed a virtual rating strategy to upgrade the recommendation precision utilizing CF show. Relevant data is found inside a brilliant situation for media recommendation s. For example, in a keen auto environment, Balturnas et al. propose playing distinctive music as indicated by the movement conditions and the driver's state of mind.

Amato et al. [16] manufactured a savvy contextcareful environment for social legacy applications. Taking into account the user's area in a keen city, they can scan and investigate that city from a traveler's point of view. Yang et al. [17] proposed a RS that considers the user's shopping area to prescribe offers and advancements to the user. In light of their area in the shopping territory, customers would get advancements and extraordinary offers as pages, through their cell phone.

Recently, RSs depend on interpersonal organizations with a specific end goal to gather boundless measures of data about the user, their sight and sound decisions, and their conduct. For example, Zangerle et al. [23] presents a help way to deal with gather a user's music dataset from Twitter, expecting the user's music player shares such data on Twitter. All the more as of late, network factorization is a method utilized as a part of various algorithms proposed to target expansive scale recommendation issues.

2.1.3 **Physio context-Related Recommendations**

Today's innovation empowers people to end up careful of their different physio-context capacities and screen those utilizing biomedical sensors and PC frameworks. One of the reasons for expending a specific sort of interactive media content is keeping up an individual's prosperity. For example, music has been utilized as a part of various approaches to advance unwinding and control the level of anxiety. Krout [29] examines the significance of a user's inclinations while picking the right sort of music to unwind. In another study [30], 750 individuals overviewed show that the kind of movement being done influences the audience's disposition, therefore influencing their decision of music.

2.2COMPARISON OF EXISTING STUDIES

Some prior studies show the significance of recognizing the user's connection keeping in mind the end goal to customize the results of a RS. Such past work more often than not fuses the con printed data into the proposal procedure in two routes: amid the pursuit procedure (pre-sifting), and by adjusting the recommendation results to the users decisions (post-separating, for example, in the work distributed by Pombinho et al. Fusing context data can be alluded to adjusting a recommendation algorithm to consider a relevant kind of data.

Table 1: A summary of related literature about evaluating context-based recommender systems

Reference work	**Experiment setup**	**Number and types of content**	**Number of subjects**
Adomavicius et. al	Collected ratings using a developed movie web-based tool	202 movies	117 students, dropped to 62 students
Park et. al.	Subjective evaluation	322 songs	10 students
Kim et. al.	Evaluated recommendation performance using a 3-	300 pop songs	50 users

	question survey		
Choi et. al.	Recommended restaurants, news and movies using push messages	Recommendation messages	200 mobile users
Lee & Lee et. al.	Evaluated performance using training and test datasets	Music	659 customers of a Korean music streaming company
Lui et. al.	Collected ratings using a system platform	115 songs	56 users
Baltrunas et. al.	Collected ratings using a developed ratings web-based tool	139 music tracks	59 users evaluated the relevance of contextual information
Nirjon et. al.	Collected music recommendation ratings using a smartphone	Music	37 users, 48 patients and 17 invited users for evaluation participated in the experiment

Different studies target diverse issues identified with connection recognition, context adjustment, or connection based recommendation s. Case in point, Hossain et al. [40] addresses the issue of selecting media administrations for a home situation in a versatile way. It was said that user context and fulfillment were not being appropriately considered in the past work, in light of the dynamic and intelligent nature of collaborations.

Chapter 3

MATERIAL AND METHODS

This Chapter discusses additional capabilities of recommendation system and we will also review possible applications of used approach

3.1 DESIGN OF RECOMMENDATION ALGORITHM

In a Recommendation System for Locations(CRS), an arrangement of locations, v; expert nodes, an; and users, U; are utilized to show proposals to a user u. Each of the locations has a probability of being selected. Each of the users in U has given a rating . A subgraph, G, comprises of one or more users. This subgraph has selected number of users that are of use further in future and which tells more regarding the checkin behaviour

In this anticipate, fundamental algorithms were actualized and utilized for the proposal procedure. A graph construction algorithm was executed, finding the k most comparable users to the user discovering proposals, then utilizing the specialists these users have listened to and utilizing them for recommendation. Random walk algorithm selects random two locations and then find whether they are near-by and give a better result than other two nodes, the nodes are continuously added into a vector that gives the final output. Expert nodes are the ones who are the most visited as compared to other nodes.

The recommendation part of this project consists of five main phases:

i.) Listen count normalization
ii.) Filter dataset
iii.) Make Hybrid recommendations
iv.) Context definition
v.) Calculate individual recommendations

In stage one, context definition, the connection to be connected to the proposal procedure is characterized. The context in this anticipates is characterized as the area and time of a show, notwithstanding the users asking for the proposals. In stage two, the quantity of times a user has visited a particular location is taken. In stage three, the dataset is separated, so that lone items that affect the outcome will be considered. In the ascertain singular recommendations stage, the top N shows for each of the individuals from the group characterized in stage one is discovered, utilizing the k-Nearest Neighbor and Random walk algorithm. Stage five comprises of making recommendations by conglomerating the outcomes given from the past stage into a solitary list of prescribed shows for the greater part of the individuals from the group.

3.2 LSBN NETWORK STRUCTURES

The social and spatial plane of a LBSN can characterize numerous sorts of relations. The quickest one - existing in each advanced informal organization - is that of social-companionship; Jack and Eve are associated with each other in the event that they have proclaimed so. Be that as it may, we can consider Jack and Eve having a connection regardless of the possibility that they have not pronounced each different as a companion. For instance, on the off chance that they have both gone by X regular spots (not as a matter of course in the meantime) we can expect they are associated. This makes the idea of area companions; an edge at the area fellowship diagram amongst Jack and Bob exists if that has been to at any rate X regular spots. By including the thought of time and subsequently, that of co-area, we can get another system structure, that of co-area companions. Obviously these structures are distinctive and can uncover differing data about the ties of the hidden system. For example, the structure of co-area kinship system is essential and can be useful for concentrating on plague episodes.

A LBSN can be demonstrated as an association system, and in this way, areas/venues can likewise be viewed as dynamic members of the system. Considering them as the objects of the system structure we can get another entire arrangement of system structures that catch different connections between the venues. Case in point, in a successive stream diagram each hub speaks to a venue. An edge between two venues u and v exists if u and v are available in at any rate K groupings of registration, such that each pair of successive registration happen in under Z minutes. The registration arrangements are figured for each user separately and over all users. This diagram basically associates venues that are gone to by users in groups, and consequently, they are connected.

We utilize various datasets from various frameworks to acquire these structures and concentrate any contrast between them, both between structures and in addition crosswise over frameworks. Our first dataset is gotten from Stanford's Large Network Dataset Collection. It incorporates information from two LBSNs, specifically, Gowalla and Brighkite. The primary comprises of 6,442,892 open registration information performed by 196,591 Gowalla users in 647,923 particular spots, amid the period between February 2009 and October 2010. Gowalla users additionally take part in a fellowship system with complementary relations, which comprise of 950,327 connections. Brighkite's dataset comprises of 4,491,143 open registration information performed by 58,228 Brightkite users in 772,966 unmistakable spots, amid the period between April 2008 and October 2010. Brighkite users additionally take an interest in a kinship system, which comprises of 214,078 connections.

Our second dataset is gotten from Foursquare between September 2010 and January 2011. The first dataset was gotten by means of Twitter, since Foursquare users push their registration to twitter. This incorporated some tweets that were insignificant with registration (i.e., reaction or notice to a registration tweet and so forth.). In the wake of expelling comparative tuples , and keeping just venues that have no less than 10 registration altogether, our last dataset incorporates 6,699,516 registration, 188,450 users and 461,781 particular venues. For this dataset, we don't have the social graph.

Location-friends

We begin by considering the area fellowships. We distinguish the current area fellowships utilizing distinctive qualities for the limit X of the basic venues required for the presence of an edge. Specifically, we pick X={5,10,50,100}. As we can watch for the figures underneath, the area fellowship chart is getting to be sparser as we build the limit X. In the event that we consider the quantity of regular spots went to by two users as a marker of the quality of their tie (or comparability), we can see that most of the ties are powerless, since just a couple of them stay as X increments.

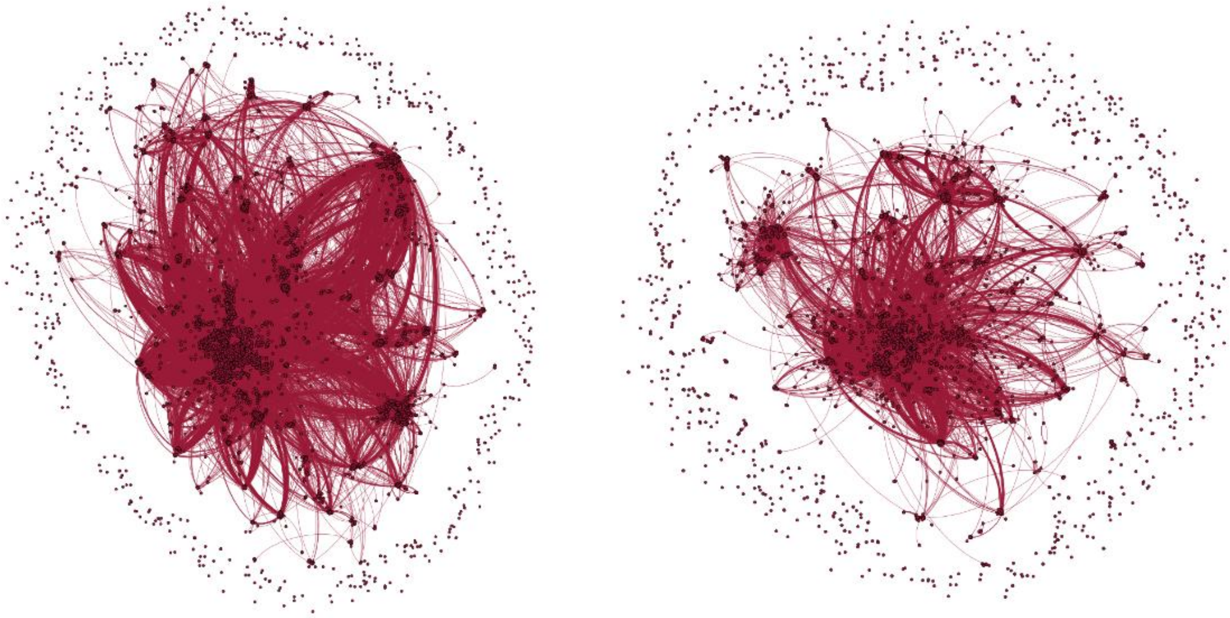

FIGURE 2 Lo*cation-friendship graph for Gowalla dataset; X = 5 (left figure) and X = 10 (right figure)*

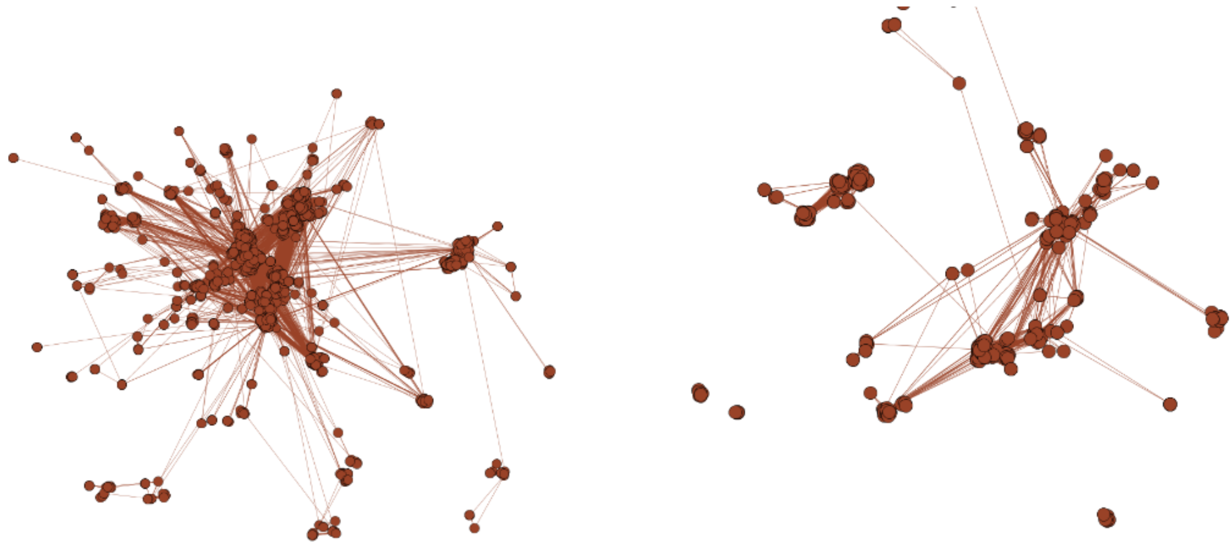

FIGURE 3 *Location-friendship graph for Brightkite dataset; X = 5 (left figure) and X = 10 (right figure).*

Frequent flow-graph

We now consider the venues and attempt to recognize relations between them as caught from the visits of the users. We first distinguish groupings of registration of all users, for which two continuous registration are inside Z mins. Sets of venues that show up in the same groupings for in any event K times are associated through an edge.

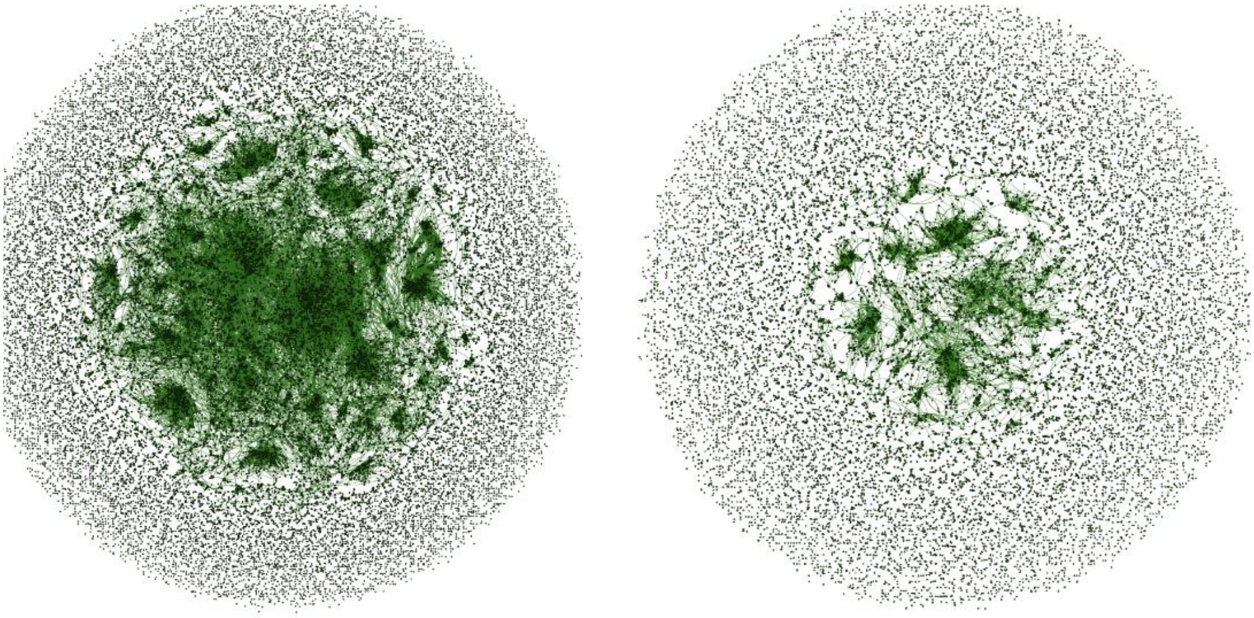

FIGURE 4 *Frequent flow-graph for Foursquare dataset; K = 2 (left figure) and K = 4 (right figure) - Z = 90mins.*

3.3 Enhanced Random Walk Algorithm

Recommendation system can be adopted for following processes:

3.3.1 Defining context

Contextual information is the essential center of this theory, and is utilized for multi-media recommendations, including strategy for conveyance. This segment clarifies how the straightforward User-Item procedure, which we presented in Chapter 2, can be upgraded by utilizing a shared strategy to enhance the proposal precision with extra context measurements and social labeling. We utilize the expression "Items" (curtailed to I) to speak to any media assets that a framework should prescribe, for example, venues.

Hence, the new dimension is incorporated into the User-Item evaluations to produce the proposal list. These ascribes can be assessed to channel and discover items that are most likely important to the user. The utilization of an understood expectation instead of unequivocal inputs from the user is an intelligent method for assessing appraisals in light of particular traits. For instance, if the framework recommends a tune (sk) to the user, and the media player enlists the way that the user changes to another tune or rapidly quits playing the tune through and through, it shows that the user is not really inspired by that melody (sk). Here, the user does not need to try telling the framework what he/she feels about the melody, since it may be an exhausting and tedious assignment to do as such. Notwithstanding the rating, every context is doled out to a relationship amongst ux and itemiy.

We expect that a user u gets a list of prescribed items that are important to a given context $c \in C$. Any RS can profit by our proposed model of suggesting items in light of numerous contexts, either by joining connections into another assembled context task, or by utilizing a conglomeration capacity to choose the most compelling context among them.

Every user would have a list of media classes to make a recommendation list. It demonstrates the essential outline proposed for context based proposals for both express and certain recommendation demands. The procedure begins by gaining the greater part of the accessible relevant data inside the user's surroundings. The recommender framework then breaks down the gathered context information and matches it with the historical backdrop of the user's contexts. Next, if the user has not indicated, as input, the kind of media substance he/she needs, the framework predicts the fitting classification in light of the historical backdrop of the distinguished context. Subsequent to distinguishing the user's context and the sort of media required, the user's profile, and the profiles of their companions on informal organizations are passed to the recommendation motor to produce the proposal list.

Chapter 4

PROPOSED WORK

4.1 NOTATIONS USED IN PROPOSED ALGORITHM

Notations used in our proposed algorithm are represented in Table 4.1 below

TABLE 2 *Notations used in proposed algorithm*

Notations	Meaning
P	Precision
R	Recall
F1	F1
MAE	Mean Absolute Error

4.2 PROPOSED SYSTEM

In order to calculate the location relevance based on the criteria of probability of user preferences, this work proposes a random walk based algorithm on the newly constructed graph to simulate the friendship hunting behaviour. The stationary probabilities of random walk starting from a given person node are considered as the link relevance between the person node and the respective nodes in the probability distribution. Random walk process on the newly constructed graph satisfies the criteria of context aware for link relevance in the following ways.

1. Home influence: If two persons share more attributes, the corresponding person nodes in the graph will have more connected attribute nodes in common. Therefore, the random walk probability from one person node to the other is high.
2. Rarity or new coming: If one attribute is rare, there are fewer out-links for the corresponding attribute node. The weight of each out-link is larger, because there are

fewer out-links. Therefore, the probability of a random walk originating from a person and reaching the other person node via this attribute node is larger, which implies that the rare attribute plays a more important role than the popular attribute.

3. Social influence: If one attribute is shared by many of the existing linked persons of the given person, the random walk will pass through the existing linked person nodes to this attribute node. Therefore, the random walk probability from the given person node to this attribute node is large, so this attribute is likely to be important to the given person for link recommendation.
4. Common friendship: If two persons share many friends, these two person nodes have a large number of common neighbours in the graph. Therefore, the random walk probability from one person to the other is high.
5. Social closeness: If two persons are close to each other in the graph, the random walk probability from one to the other is likely to be larger than if they are far away from each other.

4.3 Psuedo Code

```
Initialize number of users

Initialize number of venues

Initialize visit time for all users

Initialize a vector Expert User

  Initialize Vector expert Venue

for all users, check whether its id matches that of expert user,

if Yes, return true

else return false



for all users, check whether its id matches that of popular venue,

if Yes, return true
```

else return false

for all locations v1,v2,.....vn, compute whether locations are near by

compute r=(v1+vi)%100

and if r>50 return true

else return false

for all users f1,f2....fn, determine whether they are friends

compute r=(f1+f2)%100

if(r>40) return true

else return false

Load dataset

For all users u and venues v,

if they lie in domain, then increment its visit time

and if after incrementing, the total visit becomes greater than 10, then add that user in vector expertuser

For subgraph construction, check whether the two locations are nearby, if yes, then include that in subgraph. and also increment visit time

for all nodes in subgraph,

check if its value is greater than 0, then initialize new location for it.

Random walk approach:

Initialize step as 1, then initialize total as size

Initialize vector recomm for saving recommended values for user,

and then loop for step from 1 to size, compute r = random value for total-1

then increment subgraph value for i and j,

Add that position to vector recomm

if venue is a popular venue, then increment its value

compute acc=pc*1.0/size of recommendation vector

return acc

4. 4 Flow diagram of proposed algorithm:

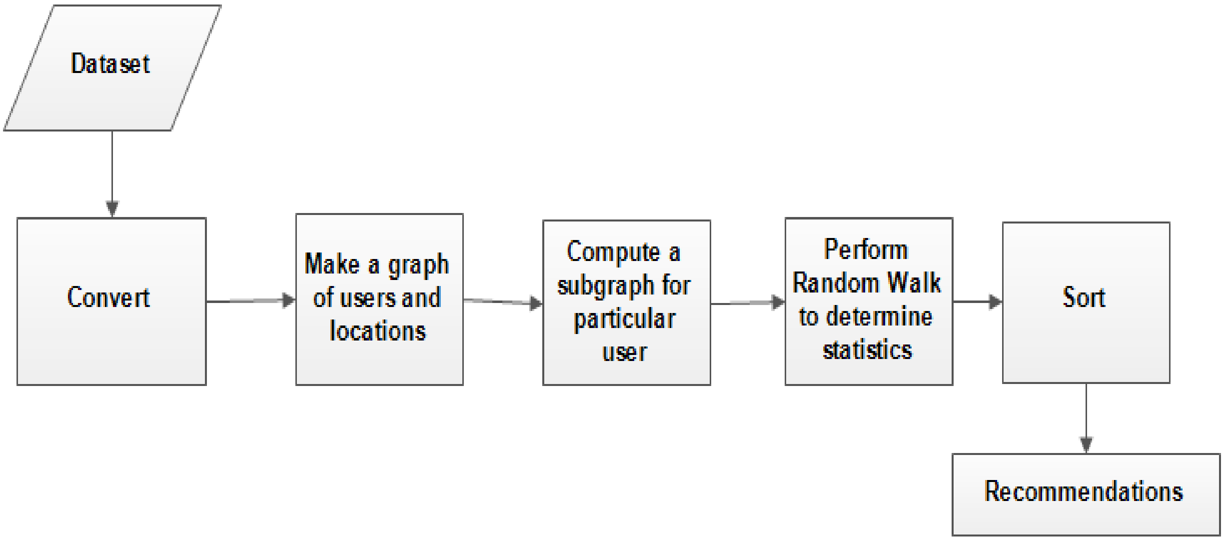

FIGURE 5 *Flow diagram of proposed algorithm*

Chapter 5

RESULTS

5.1 DATA SETS

- **FOURSQUARE**

This dataset incorporates registration, tips and labels information of eatery venues in NYC collected from Foursquare from 24 October 2011 to 20 February 2012. It contains three records in tsv group, including 3112 users and 3298 venues with 27149 check-ins and 10377 tips.

- **GOWALLA**

Gowalla is LBSN website wherein users can share their locations after checking-in. It has undirected friendship network and can be collected using their public API, and consists 196,591 nodes and 950,327 edges. Total 6,442,890 check-ins of these users are there.

- **BRIGHTKITE**

Brightkite was once a LBSN service provider of users sharing their locations by checking in. The friendship network is collected using their public API, and consists of 58,228 nodes and 214,078 edges. This network is originally directed but recently, Stanford has constructed a network with undirected edges in case of friendship that is both ways. Total of 4,491,143 checkins are totally there.

5.2 RESULTS

The emphasis should be put on the lesser known authors, the long tail of the listen tally bends. In any case, amid the improvement and testing of this model, it was watched that a full concentrate on this may not be the best approach for a CRS. Individuals have a tendency to want to go to shows with craftsmen they are as of now acquainted with. It is simpler, more advantageous, and less expensive to find and getting comfortable with new specialists in the first place, before choosing to go to a show with them. This may be one of the causes in why the kNN and Hybrid methodologies got better appraisals from the test users when it came to nature of recommendations, as CF methodologies have a tendency to have a prevalence predisposition bringing about the more well-known craftsmen to be prescribed. It shows an improvement of 20% over the past methods

Prediction evaluation metrics measurements

To assess top-N recommendation we utilize two measurements generally utilized as a part of the data recovery (IR) people group specifically review and exactness. In any case, we marginally change the meaning of review and accuracy as our trial is not the same as standard IR. We partition the items into two sets: the test set and top-N set. Items that show up in both sets are individuals from the hit set. We now characterize review and exactness as the accompanying:

- Recall with regards to the recommender framework is characterized as:

$$\text{Recall} = \text{size of hit set}/\text{size of test set} = (|\text{ test} \cap \text{top N}|)/|\text{test}| \quad (1)$$

- Precision is characterized as:

$$\text{Precision} = \text{size of hit set}/\text{size of topN set} = (|\text{ test} \cap \text{top N}|)/N \quad (2)$$

These two measures are, in any case, regularly clashing in nature. Case in point, expanding the number N tends to build review yet diminishes accuracy. The way that both are basic for the quality judgment drives us to utilize a blend of the two. Specifically, we utilize the standard F1 metric that gives square with weight to them both and are registered as takes after:

$$F1 = (2* Recall * Precision)/(Recall + Precision) \quad (3)$$

We process F1 for every individual user and figure the normal quality to use as our metric.

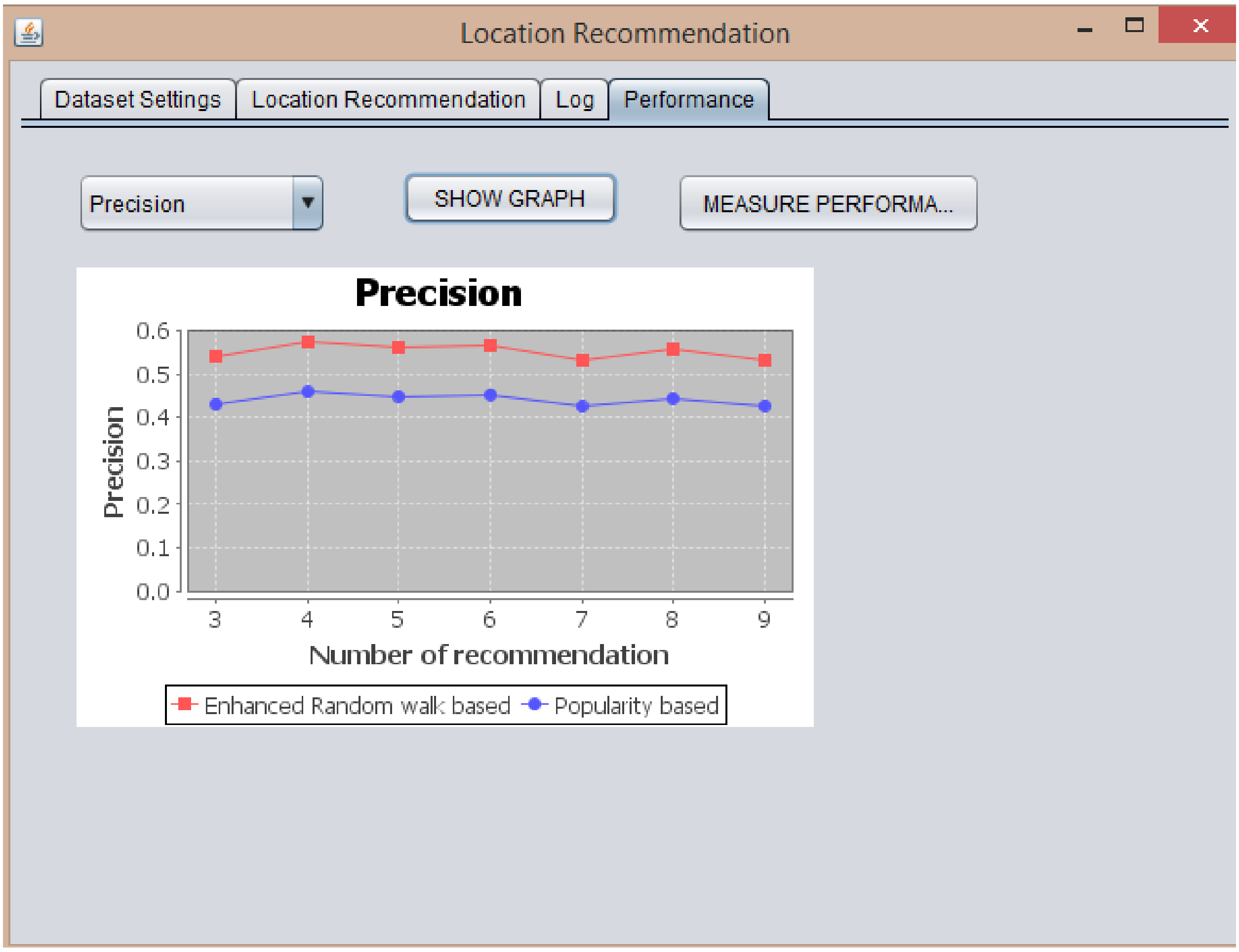

FIGURE 6 Comparison *results of Precision for different number of recommendations between Enhanced Random walk based and Popularity based*

TABLE 3 Comparison *results of Precision for different number of recommendations between Random walk based and Popularity based*

Number of recommendation	Random walk based	Popularity based
3	0.41	0.52
4	0.38	0.5
5	0.47	0.62
6	0.42	0.51
7	0.4	0.51
8	0.41	0.48
9	0.48	0.59

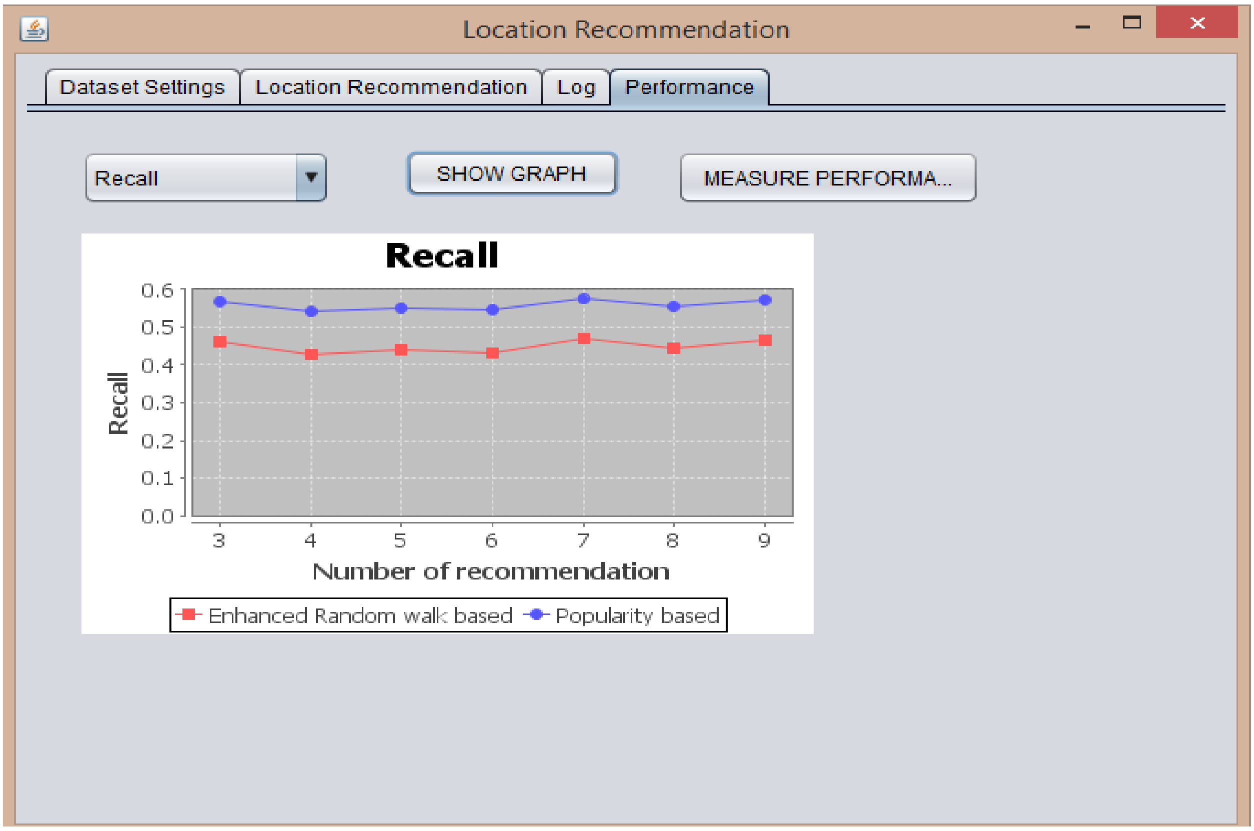

FIGURE 7 Comparison *results of Recall for different number of recommendations between Enhanced Random walk based and Popularity based*

TABLE 4 Comparison *results of Recall for different number of recommendations between Random walk based and Popularity based*

Number of recommendation	Random walk based	Popularity based
3	0.43	0.52
4	0.4	0.5
5	0.5	0.6
6	0.45	0.52
7	0.44	0.5
8	0.45	0.49
9	0.49	0.59

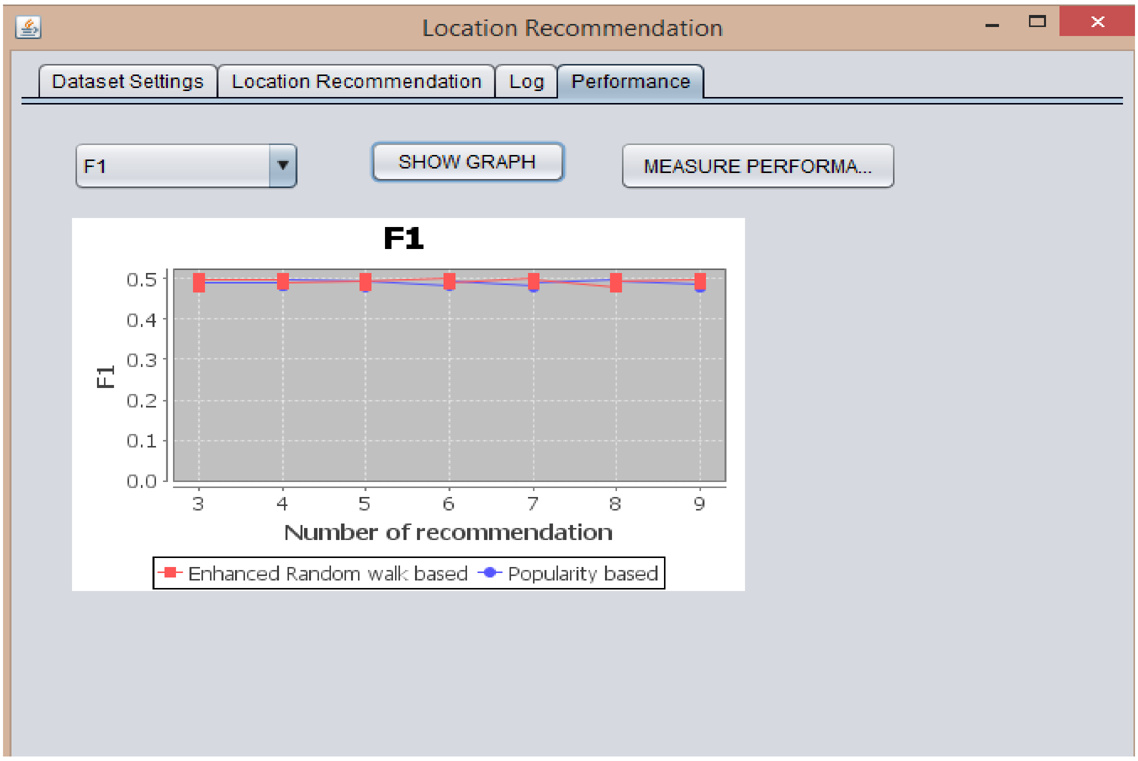

Figure 8 shows comparison between f1 values for different number of recommendations between Random walk model and popularity based model

Table 5 Comparison *results of f1 for different number of recommendations between Random walk based and Popularity based*

Number of Recommendations	Enhanced Random Walk Based	Popularity based
3	0.5	0.48
4	0.51	0.49
5	0.49	0.48
6	0.47	0.47

7	0.52	0.51
8	0.51	0.50
9	0.50	0.49

Chapter 6

CONCLUSION AND FUTURE WORK

In this proposition, a model of a Context Aware group Recommendation System for Checkins was displayed. The model executed three unique algorithms, Subgraph Construction Algorithm and Random Walk Algorithm. The objective for the proposition was to enhance the ease of use and nature of proposals given by the model executed. Altogether, the model got an improvement of 20% which is a decent sign on that the users found the ease of use of the model agreeable.

The results was likewise attempted to perceive how distinctive number of recommendations influenced the result of work. In every case, the output was checked with respect to recall, precision and f1 values for three datasets- Foursquare, Gowalla, Brightkite. In any dataset, results aligned in a manner that clearly shows an improvement from previous used methods.. All items considered, these outcomes demonstrate that understood strategies for proposal frameworks can be connected effectively to a Context Aware Recommendation System for locations.

Some promising future work directions are as follows:

1. By extending the framework provided, different algorithms for recommendation frameworks can be executed and contrasted with the current ones to perceive how they perform.
2. In future the context important part of the application can be reached out for any advantage in making unwinding of connection a verifiable part of the algorithm as opposed to some item performed by the user unequivocally

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