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Spatial Data Mining for Location Based Services

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Abstract

Objectives: The small and medium enterprise business utilizes the social networking sites to send advertisement without knowing the user location and information. In this research work, high scalable Location Based-Social Network Advertisement System (LB-SNAS) is developed to find user mobility patterns and provide value service with respect to their geo-presence. **Methods/Statistical Analysis:** In order to find the user mobility, the continuous geo-data of every user along with the time stamp should be known. In LB-SNAS, a novel Maximum Residing Point (MRP) algorithm is implemented to predict where the user resides most. The spatial and temporal presence of the twitter users is understood by visualizing their geo-tagged data. **Findings:** Hence, it is observed that 60% of similar user resides at different hotspot at various time periods a day. The existing time based clustering algorithm clusters the user with respect to the time and geo-presence and shows high time complexity. Because whole dataset is subjected to the algorithm. But in the MRP algorithm the difference of each data points are calculated and the data points that are below the threshold are clustered. A single random data point from each cluster is chosen for calculating maximum residing point of user. The execution time is highly reduced in this approach and some useful patterns like similarity mining and crowd strength is determined with respect to spatial temporal parameters. To demonstrate the LB-SNAS, twitter data is used for mining users and their location and foursquare venue data is used as test data to provide location based advertisement. Experimental results show that the users who are constantly moving will have diverse temporary social geo presence and will be definitely having a permanent halt point. **Applications and Improvement:** A different user who shares similar movements is grouped and hence it derives a key idea for location based group services. This approach helps the online advertisers, social media marketers, small medium enterprise organization to make location based advertisement.

Keywords: Maximum Residing Point Algorithm, Social Data Analytics, Spatial Data Mining, Location based Services, Twitter Data Mining, User Mobility Behavior

1. Introduction

Location based service (LBS)[1] is broadly defined as offering value added and interesting service or information to the user, corresponding to the user geo location coordinate where the user is present. The rapid increase in smart phones fitted with the GPS device gives the way for this new technology[2].Smart phones are considered to be one of the prominent gadgets among user of all ages and they use them in all scenarios. One of the major benefits for users using smartphone is, they are constantly connected to the social network applications such as, facebook[3]twitter[4]etc. The combination of smartphones and social networking applications have attracted billions of users as they can be continuously connected to their friends and loved ones and share posts, photos, videos, location information etc. The LBS technique created an opportunity to know where the user is present and helps to mine user behavior[5] from the digital footprints which was left by the users[6], which helps in providing network analysis, targeted marketing, and community detection[7].

On the other side there are many Small Medium Enterprise (SME) business centers filled in every corner of the city (e.g., café shop, restaurant, saloon) with a vision to acquire customer and accelerate growth in their business. All they need is to get idea about how to acquire new customer and to engage with the existing customer for longer consumer relationship. Now the SMEs and branded promoters also utilize the social networking sites (e.g., Facebook page, Twitter) to exhibit

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their business information and to provide promotions and offer information and coupons[8,9]. These promotional offers and advertisement coupons can be viewed only by the people who liked their business page on Facebook and who are all following them on twitter. Even though the social media have the platform for digital marketing, the major beneficiary of it is only the branded promoters and rarely for SME. The SME would not send advertisement only to the specified users who are few meters around the business area and lacks in efficient targeted advertisement. So, they publish advertisement to wider people as they are unaware of user location information and user mobility history information.

After analyzing the difficulties in digital marketing[10,11],in this research work a location based social network advertisement system is proposed which aims to provide location based online instance advertisement on the users social networking page instantly by obtaining the user location coordinates who shares along with the twitter tweets. Twitter. com, a social medium platform has been chosen for the LB-SNAS and foursquare.com[12] for acquiring vendors or venues data (e.g., Coffee shop, restaurant, saloon, etc.) for the advertisement dataset. As twitter allows public data streaming API, real time twitter data is obtained. This includes twitter user id, profile name, unique username along with geo location coordinates tag and its data if the user wish to share it[13].

If the user use twitter in smart phone and wish to share his geo location coordinates, the mobile phone uses its Global Positioning System (GPS) gives the users raw geo location coordinates (i.e., latitude and longitude) and represent the exact location of the user presence.After obtaining the location information and user-id by the system, now the system checks with the advertisement dataset and post the advertisements which are nearer to him as a tweet data. It also embeds a hyperlink with the tweet data which takes him to the detailed advertisement page or vendor home page of every individual advertisement.

Hence, if a person tweets with someone along with his location tag, he gets advertisement only from the shops or vendors which are near to him by taking his geo presence as a midpoint. By this mechanism the location based brand awareness could be improved and advertisement cost can be significantly brought down by making social media mass advertisement[14] as social media location based advertisement.

After we found that the recent increase of users towards the location based social network, a spatial temporal activity preference (STAP) model[15] which finds the users most preference location, based on his frequent checkins. A correlation technique was implemented to mine similarity user which exhibits similar life style among them to have similar location or activity preference at similar time. With this approach, users' preference towards location and clustering the users of similar interest is done. These clustered result are mapped with location preference which helps for pushing advertisement only from the point where the user made frequent checkins. Secondly, the people who never made checkins but frequent passerby close to the business area or venue would not be getting any advertisement. The digital data left by the user contains not only the spatial and temporal stamps but also its semantic information, which helps in personalized context aware advertisement and group advertising. As location based social network is concern about high dimensional data ie., user-location-time-activity quadruples it suffers from data parsity problem.

The offline marketing is more popular among different brands which helps to make face-to-face, direct and close contact with their customers. A novel framework[16] that assists the marketing professionals to improve their marketing strategy by conducting an offline sponsored event only to the selective users. This framework discloses the marketing or event venue, products to be presented in the event and its scale to the user. Then the marketer checks for users who are all influenced to the venues for the marketed product. The location based social network user are leveraged to the sponsored marketing event of that location for offline marketing. It may not be fully qualified feasible marketing strategy as because of its difficulty in expecting that every user would be attending the event. Thisis a heavy time consuming process in waiting for users to show their interest towards the product and at one-point accumulating and inviting them to the event venue.

The geo-tagged embeddedphoto on social media sites would be able to provide more information about that location. A recommendation system[17] for tourism application which recommends interesting tourist location to the new tourist or traveller based on the previous collected geo-tag embedded photos. The context (i.e., time, date, weather) of location are also considered

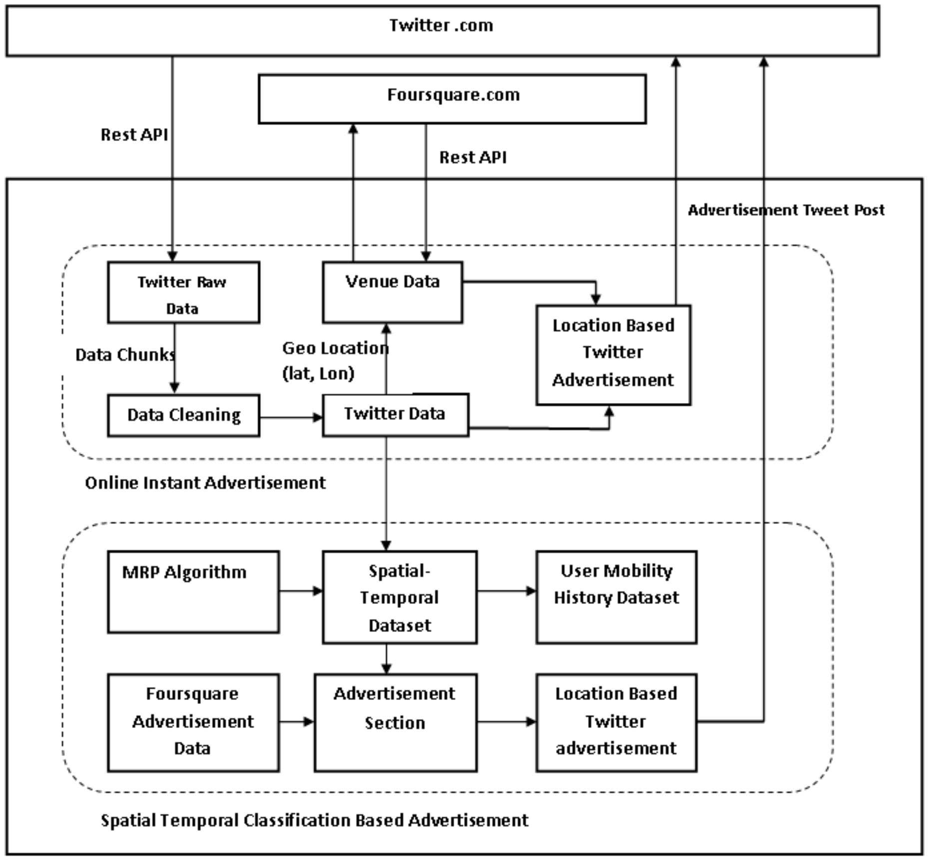

Figure 1. Location based social network advertisement system.

for efficient recommendation. Its user generated content about the place in photo makes high impact about that location. Mining User's geo tagged location and referring those locations to other tourist were performed but he has not dealt with any location based advertisement to the user. The recent surge of Location Based Social Networks(LBSNs) and its diverse user presence and their digital footprints[18], location information and profile data are easily accessible to the service provider for providing value added service by obtaining the meaningful patterns about users and their location. It is found that the LBSNs doesn't have any community structure. A novel multi mode multi-attribute edge centric coclustering frame work was proposed for the quality community detection among the LBSNs users. Thus it helps to send group advertising or mass marketing only to the selected community people. But, it will not be a good marketing strategy for the venues that send advertisement only to the people who made frequent checkins to the store.

As LBSN is concerned, most of the users' application is capable of running on smart phone. As people are constantly moving and staying connected with the social media, it is feasible to send location based advertisement to the user on their social media page once their location coordinate is obtained. Pushing the advertisement to their social media page would be having a higher chance of response rate towards the advertisement than making it a separate platform for advertising[19,20].People who visit the venue could not be made sure that he will visit the venue again unless we pull them with offer codes or coupons. So, there is a need to find out where the user resides for a longer time and push advertisement which are closer to them.

As per comScore local search usage study, 2013 says that 78% of people who search locally on their phone make a purchase.

2. System Design

2.1 System Design

In LB-SNAS, the system entities include twitter. com for user information and location coordinates data and foursquare. com for advertisement for vendor location coordinates. This system includes the two sub system, namely an . online instant advertisement and . Spatial temporal classification based advertisement. The architecture framework ofLB-SNAS is represented in Figure 1.

2.2 Online instant Advertisement on LB-SNAS

The role of online instant advertisement system is to send the location based advertisement to the twitter user instantly when he tweets along with his geo location tag. The twitter public streaming data is obtained with the help of twitter REST API. These data are raw data which contains many field/value pairs in a javascript object notation (json) format[21]. The data cleaning process is performed on the streaming twitter data to get only required name/value pairs such as, twitter user id (U_{id}), tweet created date and time (UT(dt)), tweet geo location coordinates (UT(loc)) tagand it is represented as twitter data (TD_i), where 'i' represent the data count in the data set.

$$TD_i = \{U_{id}, (UT(loc, dt))_n\}$$

The UT(lat, lon) is shortly represented as UT(loc) which represent the latitude and longitude coordinates of arrived tweet. After knowing the user location coordinates the next task is to push advertisement related to his current geo presence. The advertisements are literally related to advertisement data or promotional offer messages broadcasted by the shop or vendors (eg., café, restaurant, salon, hotel)through digital medium. In the LB-SNAS, foursquare vendor data is used through foursquare venue search API[22]. The obtained user location UT(loc) from the twitter's tweet tag is sent to the foursquare. The foursquare search API search for the vendors or venues related to the user geo location and sends back the list of vendors to the system as a response message. This response message contains all the vendors in that geo-location area such as hospitals, schools, railway station, etc. These response messages are filtered to get only the required vendor information (eg., restaurants, salons and cafes) with the help of category tag mentioned in the response message. The vendor data is represented as VD_i, where 'i' represent the data count in the data set.

$$VD_i=\{V_{id,}(loc, data)\}$$

The system post advertisement data to the user (U_{id}) which will be available as tweet message along with their other tweets. The LB-SNAS keeps count of all the tweets twitted by the user and the advertisement message sent to them. In online instant advertisement system, the system is set to one advertisement of every six hours per tweet.

Algorithm for Online Instant Advertising

1. Get twitter data TD_i
2. cleanData(TD_i_chunks)
   #$TD_i \leftarrow \{U_{id}, (UT(loc, dt))n\}$
3. Get Venue Data (VD) with user location as center point with specified radius r
   #getVenueData(U_{id}(UT(loc))(r))
   #$VD \leftarrow \{V_{id}, (loc, data)\}$
4. **If**VD == NULL **then**
5. **return** Null
6. Else
7. Push Advetisement Ad to twitter user U_{id}
   #$Ad \leftarrow (U_{id}(UT(loc))) \cup (V_{id}(data))$
   #pushAd(U_{id}(Ad))
8. End If

3. Spatial Temporal Classification based Advertisement

The online instant advertisement system has some limitations. It is found that most of the users are in mobility. That is, the users with smart phones use twitter on their go. As the user travels, the user's location is changed continuously. For example, when user starts his day to office from his home location (l_1) he might tweet from his home and his next tweet might be on his way (l_2) and his next tweet might be from office area (l_3) and so on. Thus sending advertisement tweet message for each and every tweet made by the user makes the user disturbed with this advertisement system and might block the advertisement service. Hence, a MRP algorithm is proposed to find out where the user resides for a long time and spatial temporal classification based advertisement is pushed based on his maximum geo presence. So when the user login to twitter he would be able to view those advertisements.

The spatial temporal classification based advertisement system is the subsystem of the LB-SNAS which helps in publishing the advertisement tweets based on the user's maximum presence on a particular geo-location. These are found by the MRP algorithm by mining maximum number of geo tag embedded consecutive tweets of every individual user. The geo distance between the users arriving tweets $U_{id}(t_i)$ must be less than or equal to a specified distance($ß_{dist}$), where 't' refers to tweet, $t_i=\{t_1, t_2 \ldots t_i\}$. The distance between the two geo location points is calculated by haversine formula[23]. When the user's 'n'consecutive twits are not found within the specified distance ($ß_{dist}$) then the previous n-1 tweets are considered to be a one group and any of its geo coordinates is taken randomly and considered to be a midpoint of that user geospatial presence as represented in Figure 2.

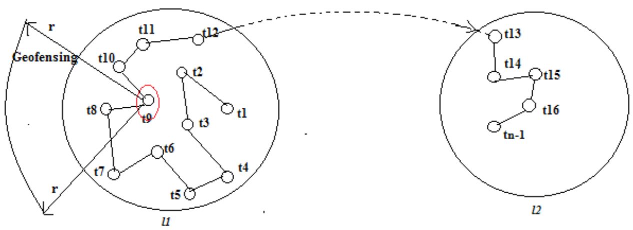

Figure 2. Geofensing based on user maximum residing point.

The radius(r) is assigned to the midpoint and formed a geofensing around the user presence.

$a = \sin^2(\Delta\varphi/2) + \cos \varphi_1 \cdot \cos \varphi_2 \cdot \sin^2(\Delta\lambda/2)$

$c = 2 \cdot \mathrm{atan2}(\sqrt{a}, \sqrt{(1-a)})$

$d = R \cdot c$

Where,

$\varphi 1 = lat1$

$\varphi 2 = lat2$

$\Delta\varphi = (lat2-lat1)$

$\Delta\lambda = (lon2-lon1)$

R is the radius of the earth

Algorithm II: Spatial Temporal Classification Algorithm.

Input:

TD - Twitter data

t_i-Current tweet

t_{i-1}- Previous tweet

ß(dist) – pre defined distance in meters

d- Distance between current tweet and previous tweet.

Output:

$U_{id}G[\ ]_k$ – Group for individual user

1. Get twitter data TD_i
   $\#TD_i \leftarrow \{U_{id}, (UT(loc, dt))n\}$
2. **For** each TD_i **do**
3. **If**user U_{id} has group G**then**
4. Find group count k;
5. Move to $U_{id}G[\ ]_k$
6. $d = U_{id}(t_{i-1} - t_i)$
7. **If** d == NULL || d <= ß(dist) **then**
8. push twitter data TD_i to group $G[\ ]_k$
   $\#U_{id}G[\ ]k \leftarrow push(TD_i)$
9. **Else**
10. k=k++;
11. Creategroup $G[]_K$ for user U_{id}
12. Push twitter data to group $G[\ ]_k$
    $\#U_{id}G[\ ]_{k+1} \leftarrow push(TD_i)$
13. **End If**
14. **Else**
15. Assign k=0;
16. Create group G for user $U_{id.}$
    $\# U_{id}G[\ ]_k$
17. Push twitter data TD_i to group $G[]_k$
    $\#U_{id}G[\ ]_k \leftarrow push(TD_i)$
18. End if
19. End for

Algorithm III: MRP Algorithm.

Input:

$U_{id}G[]_k$ – Users twitter data within the group.

r – Radius

VD - Venue Data

Output:

Ad – Advertisement

1. **For** each $U_{id}G[]_k$**do**
   $\#U_{id} = G[\ ]_{k=1,2,3,4,..n.}$
2. Create midpoint in user group by randomly selecting any of it twitter data location coordinates.
   $\#U_{id}midpointG[]_k \leftarrow RAND(U_{id}G[TD]_k)$
3. Assign radius 'r' to each group from midpoint
   $\#U_{id}midpointG[]_k(r)$
4. Aggregate users presence with respect to user midpoint $U_{id}midpointG[]_k$, time $U_{id}UT(dt)$.
5. Find users maximum presence on location
   $\# MAX(U_{id}UT(loc)$
6. Get venue data VD based on maximum user presence location with in radius 'r'.
   $\#VD \leftarrow MAX(U_{id}(UT(loc))(r))$
7. **If**VD == NULL **then**
8. **return** Null
9. **Else**
10. Push Advertisement to twitter user
    $\#Ad \leftarrow MAX(U_{id}(UT(loc))) \cup (V_{id}(data))$

#pushAd(U_{id}(Ad))
11. End if
12. End for

The larger time difference between the first tweet and the last tweet of the group on same day or on consecutive or maximum alternate days within the same geofensing is considered as the maximum residing point of the user.

4. Experimental Result

The real time twitter data is collected by using twitter streaming API which is being provided by twitter.com. The twitter public streaming API streams all the public tweets made by the globally presented twitter users. As the concern is about location based service the global streaming data is

narrowed down to area based streaming data. The data is collected from the user which are arrived within the specified boundary on the earth surface.The data has been collected across Chennai city, India and it is visualized on man as show in Figure 3.

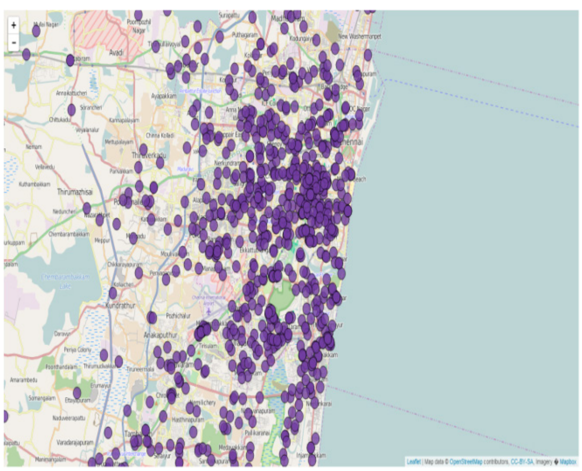

Figure 3. Visualizing the location of arrived tweets.

Nearly five lakh tweets with embedded geo-tag was collected. For each geo-tag which comes with the twitter data, a list of venues and its details (shop name, address, location coordinates, and service details) has been obtained in and around Chennai area. This is done by passing the location coordinates to foursquare.com through its API access. It pushes all the venues e.g., policestation, bus stop, hospital café shop, restaurant as a response result. The search results are narrowed down only to venues where the people used to visit most often like the venues under "food, restaurant, pizza places, ice cream shop categories".

4.1 Performance Evaluation

In this research work each geo-coordinate point is divided into different clusters (algorithm II) based on time $U_{id}UT(dt)$ and geo-distance threshold ß(dist). Now, from each clusters of individual user $U_{id}G[]_K$ a random geo-coordinate point is chosen and it is aggregated together with respect to time and location (algorithm III). The reason to choose a geo-coordinate randomly from each user cluster is that, each geo-coordinate point in a cluster would share the same location meaning as every other geo-coordinate point in that cluster. ie; each geo-coordinate points in the cluster is less than or equal to the threshold geo-distance (ß(dist)) with the previous geo-coordinate points in that cluster. Hence this approach minimizes the dataset size without changing its precision. We evaluate the performance of our MRP algorithm with the existing time basedclustering algorithm[24] for visit point extraction. The existing algorithm has the linear time complexity problem because it does not involve in any data minimization O(|T|) as show in Figure 4. The proposed MRP algorithm performs well in terms of time complexity because the dataset is refined to have only single geo-coordinate point from each cluster.

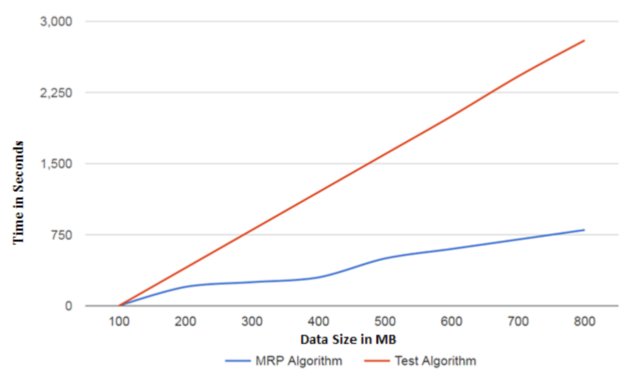

Figure 4. Performance evaluation with respect to time.

5. User Similarity Mining

From the obtained cluster result we could able to mine deep to find the similar users who are all making routine mobility towards same place at same time. In order to find out user similarity on different geo-location with respect to time we made the fixed geo-location point as hotspots (hp) across different geo-presence which acts as the reference to that place name. Nearly [25] hotspots points across the city where chosen. Once the system gets geo-tagged tweet with respect to any of its hotspot (within 500 meters radius), will be updated continuously in database with respect to time.

The user maximum presence at the particular location or hotspot as shown in Table 1.

The cumulative of user presence with respect to time on different geo-location is show in Table 2.

Table 1. Maximum residing point of user at each hotspot

	hp1	hp2	hp3	hp4	…	hp25
User 1	3hrs	1hrs	6hrs		…	1hrs
User 2	1hrs	3hrs	1hrs	0.5hrs	…	9hrs
User 3		2hrs		4hrs	…	3hrs
User n	7hrs		6hrs	1hrs	…	1hrs

Table 2. No. of users at each hotspot with respect to time

	9-10	10-11	11-12	…	22-23
hp1	400	300	800	…	248
hp2	200	730	495	…	923
hp3	240	173	390	…	150
hp4	174	198	345	…	110

Now we will find the percentage of user presence at each hotspot (hp_i) with respect to day and time (D_iT_k) as show in equation and it is visualized in graph Figures 5 and 6.

where,

D_i represent {day1, day2, day3, …day30}.

T_k represent {time1=(9-10), time2=(10-11).. time24=(8-9)}

$$\% \text{ of user at hp } (D_iT_k) = \frac{\text{No of users in a hotspot}}{\text{Total no of users}} 100$$

From the obtained number of users at each hotspot with respect to time of a single day, we could able to mine similar users who visit the place frequently by comparing with the users geo-presence data associated with the hotspot of the previous day or the next consecutive days with the help of cosine coefficient similarity function.

LetX = Uid(D1T1)hp_i = {User 1, User 2 … User n}

Y = Uid(D2T1)hp_i = {User 1, User 2 … User n}

Were Uid(D1T1) represents unique user id of each person associated with the respective hotspot at day=1 and time=1

$$\text{Cosine similarity} = \frac{\sum_{j=1}^{n} X_j Y_j}{\sqrt{\sum_{j=1}^{n} X_j^2}\sqrt{\sum_{j=1}^{n} Y_j^2}}$$

The users' similarity coefficient between two days on same time on different hotspots is identified and the user similarity index between two hotspots is visualized in graph as shown in Figure 7. From the graph it is found that the hotspots hp1 hp11 and hp12 has higher similarity index i.e.; the user visited on the day1 are also made a visit on day2. Through this approach strength of similar user at a particular place with respect to time is obtained which helps in event planning and location based group advertising.

6. Visualizing User and Venue Location Presences

The users' geo presences are visualized based on their user geo-tag information which arrives with the users'

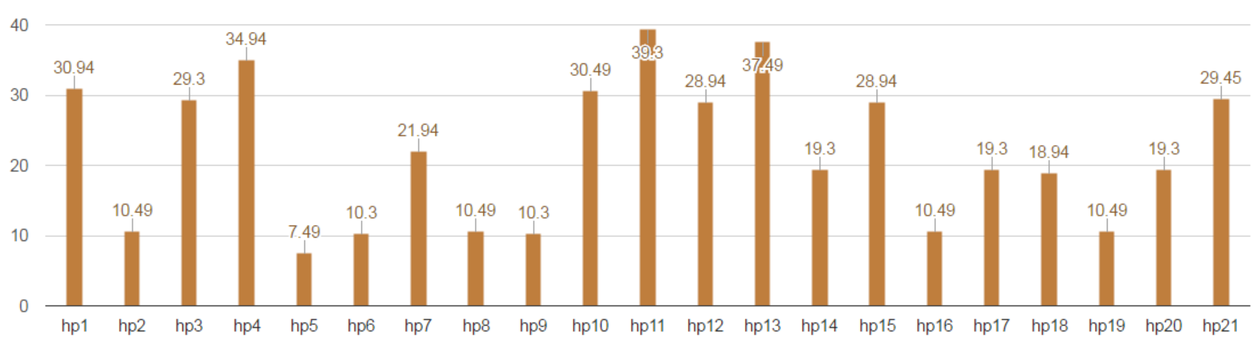

Figure 5. Percentage of user at each hotspot on Day=1 Time=1(D1T1).

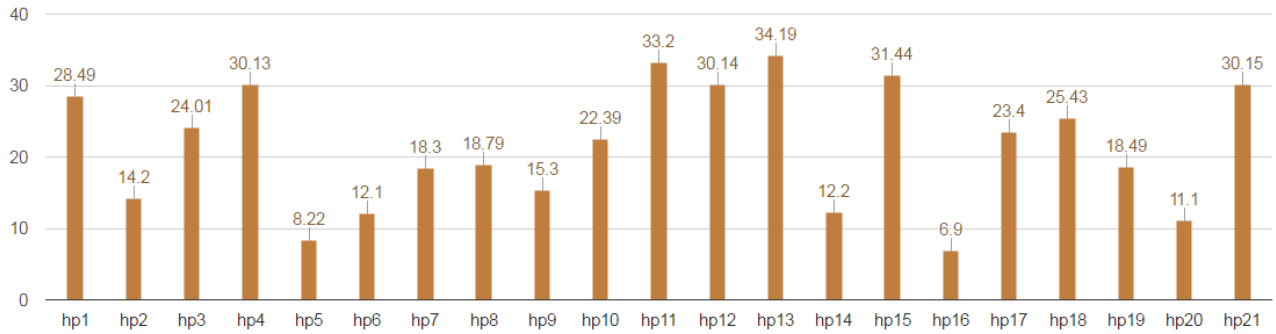

Figure 6. Percentage of user at each hotspot on Day=2 Time=1(D2T1).

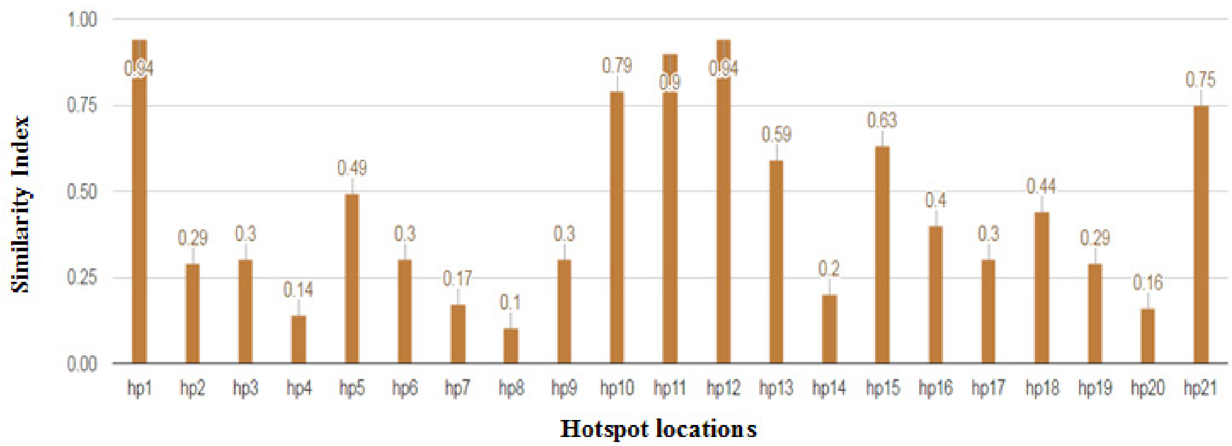

Figure 7. Percentage of user at each hotspot on Day=2 Time=1(D2T1).

twitter data, as shown in Figure 3. This visualization of the user presences helps to get information about the number of usersavailable in that location with respect to day/time series calculation. This helps the LB-SNAS to monitorpeople mobility or the crowd strength near to the business area of vendor which helps to push advertisement on twitter only to the people who are close to his shop. The proposed methodology minimizes them the advertisement cost and improvesthe marketing strategy. Likewise, the vendor location is also visualized on the map by using its geo coordinates obtained from foursquare.com and it is shown in Figure 4. Hence, thenumber of users near to the venues on a particular day or time is visualized.

7. Mapping user Presence to Venues Location

As shown in Figure 3 the twitter users are filled all over the place. As the twitter user tweet from his mobile phone along with his location information as geo tag, it is the responsibility of the online instant advertisement to tweet back the advertisement tweet card to the twitted user with respective to his arrived tweet location. When the geo tag embedded tweet data arrived to the system, the system has to map the available venues with the location of the arrived tweets and should push advertisement as a twitter message or advertisement twitter card to the respective twitter user.This is achieved by making the arrived location coordinates as a center point and fix a radius ‘r’ from the center point. Its then forms a geofencing around the user as shown in Figure 8and the system searchesfor venues with in the geofencing area. The information of venues is obtained from the foursquare.com through API call. The list of venues V with the user location coordinates U_{id}(loc) asthe center point with the radius ‘r’ is represented as,

$$V(U_{id}\,(loc)r) = \{ V_{id}(loc, Ad)_1, V_{id}(loc, Ad)_2, V_{id}(loc, Ad)_n \}$$

V_{id} is venue unique id,

V_{id}(loc) is the venue location,

V_{id}(Ad) is the advertisement data.

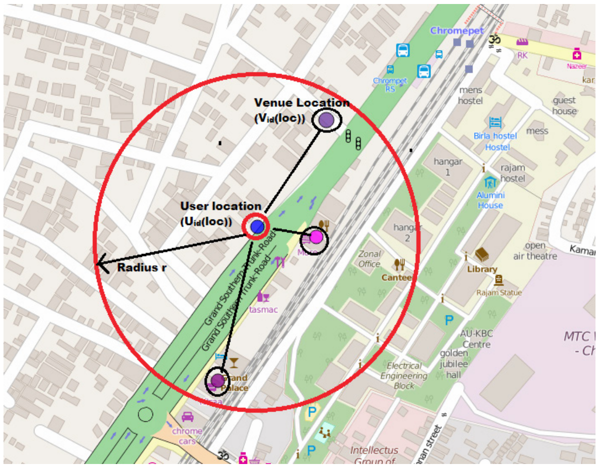

Figure 8. Circular Geo-Fencing the user with radius 'r'.

If the venue owner posted any promotional or advertisement message on foursquare.com advertisement page, it gets pushed to the users' twitter account as a tweet message. As the advertisement message appears on the users' twitter page along with his other tweets it makes an easy way for the user to respond to the advertisement instantly and this system makes the vendors to push advertisement only to the user who are close to their business area. By analyzing the impact of the service or advertisement with respect to location and time we could able to recommend similar service or advertisement to them which makes them to encage more with our advertisement system[25].

Unlike the online instant advertisement, the spatial and temporal classification based advertisement also deals with sending the advertisement to the twitter user by classifying the user mobility distance patterns which varies with respect to time and location and estimate the user's maximum residing point through the MRP algorithm. For every individual user, a group is formed based on spatial temporal classification algorithm, as shown in Figure 9.The location coordinates of every twitter data within the groups get aggregated under the group midpoint (i.e., randomly chosen location coordinates in the group is assumed as group midpoint) and date as a common field. Now, if the distance between the first tweet and last tweet within a group is higher than the specified time on the same day or on the consecutive days of same location coordinates is said to be a maximum residing point of the user. Now the system pushes advertisement only specific to the location coordinates of the group by taking the groups midpoint (latitude, longitude) and search for venues in foursquare.com through API and returns advertisement to the twitter user.

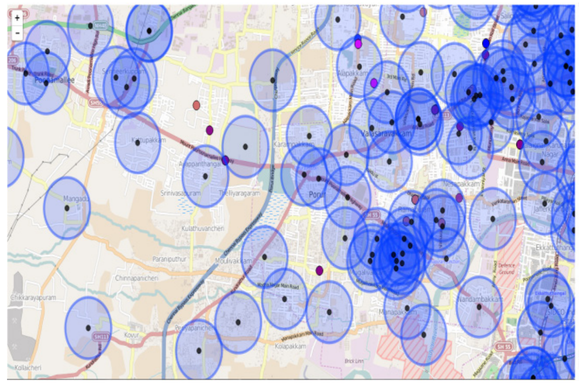

Figure 9. Group formation for every user.

8. Conclusion

The location based advertisement system on the social media platform was discussed. The advertisement on social media platform is mostly occupied by the branded promoters and rarely by the small medium enterprise. This research work proposed a platform for every SME to promote their business and publish promotional advertisement to the users who are close to their business area. The twitter. com is chosen for this research work to obtain the users current location coordinates from his tweet and publish back the advertisement with respect to his current location to the user which is nearer to him as a twitter message. The advertisement messages are obtained from foursquare.com through API call. This framework has two sub-systems. The first one is the online instant advertisement system which sends advertisement tweet as soon as the system gets the users current location coordinates. If the user gets continuous advertisement for each and every tweet made by him, it would have a bad impact on the advertisement system. Hence a MRP algorithm is used to identify where the user resides most. The system sends advertisement tweet only about the venues which are located under his maximum residing location. By this approach the advertisement cost is minimized (instead of choosing mass marketing) as marketing is doneonly to the people who are close to their business area which increase their intention to make purchase.

In future, it is planned to broaden this paper in several directions. The text twitted by the user is concentrated for our enhanced work using linguistic technique. We planned to apply text mining, categorization and analytics to know what the user is talking about with respect to spatial temporal aspects of the user.

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