

ANALYSIS OF SOCIAL NETWORKING BASED ON LOCATION CENTRIC USING BIG DATA

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ABSTRACT

Past recent years the growth of social network advances in position confinement systems have in a general sense upgraded long range informal communication administrations, permitting clients to share their areas and area related substance, for example, geo-labelled photographs and notes. We allude to these informal organizations as area based on location-based social networks (LBSNs). Area information both conquers any hindrance between the physical and computerized universes and empowers a more profound comprehension of client inclinations and conduct. This expansion of unlimited geospatial datasets has animated examination into novel recommender frameworks that look to encourage clients' ventures and social cooperation's. In this paper, we talk about the new properties and difficulties that area conveys to suggestion frameworks for location-based social networks (LBSNs). We present a novel work and create a system that gives a fruitful result based on Location based analysis that gives and help marketing and advertisement business to explore their business those areas that are hidden and make possible to grow their business on different geographical areas that are untouched before analysis.

Keywords: Database Applications, Data mining, Spatial databases and GIS, Big data, Hadoop.

I INTRODUCTION

With a large number of clients, long range interpersonal communication administrations like Facebook and Twitter have turned into a few of the most prevalent Internet applications. The rich information that has aggregated in these social locales empowers an assortment of suggestion frameworks for new companions and media. As of late, advances in area securing and remote correspondence innovations have empowered the production of area based long range interpersonal communication administrations, for example, Foursquare, Twinkle, and GeoLife [1,7]. In such an administration, clients can without much of a stretch share their geospatial areas and area related substance in the physical world by means of online stages. For instance, a client with a cellular telephone can impart remarks to his informal community around an eatery at which he has feasted on an online social website. Different clients can grow their social systems utilizing companion recommendations got from covered area histories. For example, individuals who always trek on the same mountain can be placed in contact.

The area measurement crosses over any barrier between the physical world and the advanced online social organizing administrations, offering ascend to new open doors and difficulties in customary recommender frameworks in the accompanying viewpoints:

- a) Rich Knowledge: An area is a standout amongst the most vital segments characterizing a client's setting. Broad information around a client's conduct and inclinations can be scholarly by means of their area history [Ye et al. 2009]. The colossal volume of area related information produced by clients moves forward the probability that social suppositions, e.g., the most loved dish in an eatery or the most prevalent action at a state of interest, can be precisely surveyed by proposal frameworks.
- b) Complex objects and relations: An area is another item in area based informal communities (LBSNs), producing new relations between clients, amongst areas, and amongst clients and areas. New proposal situations, similar to area and schedule suggestions, can be empowered utilizing this new learning, and customary proposal situations, for example, companion what's more, media proposal, can be upgraded. Notwithstanding, doing as such requires new systems for producing superb proposals.

These open doors and difficulties have been handled by numerous new ways to deal with proposal frameworks, utilizing distinctive information sources and philosophies to create various types of suggestions. In this article, we give a study of these frameworks, and the distributions proposing them, with a precise audit on more than fifty articles distributed in the course of the most recent four years in the significant diaries, meetings, and workshops, including KDD, WWW, Ubicomp, ACM SIGSPATIAL, LBSN, RecSys, ACM TIST[2,3] and VLDB. For every distribution, we dissect 1) what a created suggestion is (i.e., the target of a proposal), 2) the system utilized to produce a suggestion, and 3) the information source it utilized. As indicated by these three viewpoints, we propose three scientific categorizations to separately parcel the recommender frameworks. This study exhibits a scene of the suggestions in area based informal communities with an adjusted profundity, encouraging exploration into this rising point. The commitments of this article are nitty gritty as takes after:

- We recognize LBSNs from customary informal communities and characterize their one of a kind properties, difficulties, and open doors.
- We order the major recommender frameworks for LBSNs in three scientific classifications, sorted out by information sources, systems, and proposal destinations. In every class, we outline the objectives and commitments of every framework. Likewise, we highlight one agent framework in every classification, giving a more top to bottom perspective of the system.
- We abridge the significant strategies for assessing the proposals in LBSNs .
- We call attention to promising examination headings in LBSN proposal frameworks, paying extraordinary consideration regarding headings that outcome from the investigation and blend of the diverse suggestion framework classes[4,5].

II BIG DATA TECHNOLOGY

Huge Data is an expression used to mean an enormous volume of both structured and unstructured information that is so vast it is hard to process utilizing conventional database and programming procedures. In most endeavour situations the volume of information is too huge or it moves too quick or it surpasses current preparing limit.

Enormous Data can possibly help organizations enhance operations and make speedier, more keen choices. This information, when caught, designed, controlled, put away, and dissected can help an organization to increase valuable knowledge to expand incomes, get or hold clients, and enhance operations.

While the term may appear to reference the volume of information, that isn't generally the case. The term Big Data, particularly when utilized by sellers, may allude to the innovation (which incorporates instruments and procedures) that an association requires to handle the a lot of information and storerooms. The term is accepted to have started with Web look organizations who expected to question substantial appropriated collections of approximately organized information.

A case of Big Data may be petabytes (1,024 terabytes) or exabytes (1,024 petabytes) of information comprising of billions to trillions of records of a huge number of individuals—all from various sources (e.g. Web, deals, client contact focus, online networking, portable information etc). The information is normally inexactly organized information that is regularly inadequate and unavailable[7].

III LITERATURE REVIEW

3.1 Evolution of a Location-based Online Social Network: Analysis and Models

Associations built up by clients of online informal communities are impacted by systems, for example, particular connection what's more, triadic conclusion. However, late research has found that geographic elements additionally compel clients: spatial vicinity cultivates the formation of online social ties. While the impact of space may should be consolidated to these social instruments, it is not clear to which degree this is valid and in which way this is best accomplished. To address these inquiries, we display an estimation investigation of the transient advancement of an online area based informal community. We have gathered longitudinal follows more than 4 months, including data about when social connections are made and which spots are gone to by clients, as uncovered by their versatile registration. Because of this fine-grained fleeting data, we test and think about whether diverse probabilistic models can clarify the watched information receiving a methodology taking into account probability estimation, quantitatively contrasting their factual force with repeat genuine occasions[8,9].

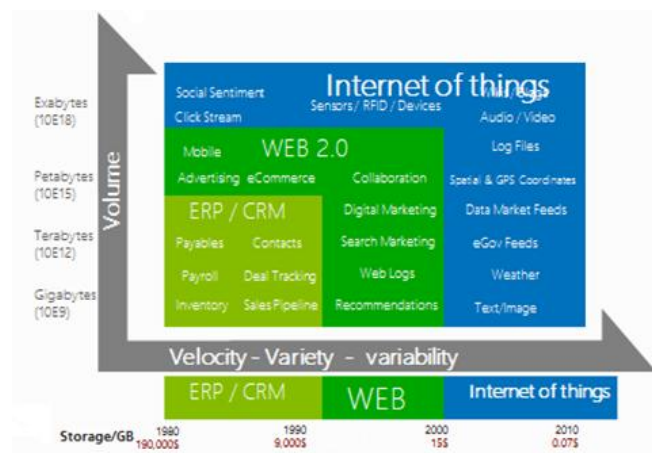


Figure 1 BIG DATA Technology



They exhibit that geographic separation plays an imperative part in the production of new social associations: hub degree what's more, spatial separation can be joined in a gravitational connection handle that repeats genuine follows. Rather, we find that connections emerging in light of triadic conclusion, where clients shape new ties with companions of existing companions, and due to basic center, where associations emerge among clients going to the same spot, seem, by all accounts, to be primarily determined by social variables. We misuse our discoveries to portray another model of system development that consolidates spatial and social variables. We broadly assess our model and its varieties, illustrating that it can duplicate the social and spatial properties saw in our follows. Our outcomes offer helpful bits of knowledge for frameworks that exploit the spatial properties of online social administrations .

3.2 Human Urban Mobility in Location-based Social Networks: Analysis, Models and Applications.

Area based informal organizations have pulled in light of a legitimate concern for a huge number of clients who can now not just interface and communicate with their companions, as on account of customary online social systems, yet can share their whereabouts progressively abusing GPS sensors installed in cell phones with Internet availability. Certifiable spots are a centre element of location based informal organizations and as clients travel between them, urban portability is spoken to with extraordinary extravagance as far as geographic scale and spatial granularity.

As an outcome, area based administrations offer new open doors in the space of portable applications, additionally the possibility to permit vast scale observational acceptance of hypotheses of human development. Nonetheless, this new information worldview accompanies the sparsely that is a direct result of the substantial followed disseminations portraying client movement in online social administrations. In this thesis, we play out an examination of a large number of client developments in 34 huge metropolitan territories around the globe[10,11].

Their underlying perception is that there is huge heterogeneity crosswise over urban communities while considering the factual properties introduced by the development of clients in the urban setting. We distinguish the wellspring of this heterogeneity to be varieties in the geographic thickness of spots crosswise over various urban situations.

In specific, we find that in human urban development it is the relative thickness between the birthplace and the goal put that matters - not their supreme geographic separation. Next, we address a portability forecast situation whose application point is the proposal of the following spot to be gone to by a versatile client progressively. Since the restricted accessibility of noteworthy data for every client blocks the utilization of forecast structures that model particularly the developments of an individual, we propose a novel administered learning preparing procedure that depends on data worked by spot inclinations of client groups.

At long last, we highlight that right around two out of three spots went to by clients in area based informal organizations are new places, not watched being gone to by that client verifiably. In the light of this perception the issue is set to be the proposal of new venues for portable clients to visit in future eras. We appear how cutting edge web separating calculations are outflanked by an arbitrary stroll with restart strategy that can flawlessly join numerous information flags and adapt to the scanty representations of clients in the administration.

3.3 How Location-Based Social Network Applications Are Being Used

Area based informal community applications have internationally turned out to be extremely mainstream with the development of cell phone utilization. Area based informal communities (LBSN) can be characterized as a website that utilizes Web 2.0 innovation, GPS, WiFi situating or cell phones to permit individuals to share their areas, which is alluded to normally as a registration, and to associate with their companions, find spots of interest, and leave surveys or tips on particular venues. The point of this study was to look at how area based social applications are being utilized[12].

The strategies for this study contained a writing survey and a talk on earlier research in view of a determination of client studies on area based social systems. This concentrate additionally went for noting various sub-questions on client conduct, for example, action designs, inspirations for sharing area, protection concerns, and present and future patterns in the field. Twelve LBSN client conduct studies were surveyed in this study. Eight of the client thinks about surveyed included the application Foursquare.

Research techniques on eight of the looked into studies were studies using databases of the registration from the application itself or using Twitter in their investigation. Four of the explored studies were client thinks about including interviews and reviews. Three principle subjects risen up out of the articles, which were movement designs, inspirations for sharing, what's more, security concerns. It was found that action designs included regular registration venues, for example, eateries, bars, shops, and stimulation venues alongside the same times of day (early morning, lunchtime, and early night) also, having bigger registration happen in urban ranges. Inspirations for sharing area demonstrated that clients share their area to showcase it to their companions furthermore to present one's self. Concerning security, it was generally found that clients don't prefer to impart their area to outsiders. Future examination could incorporate taking a gander at how sexual orientation, diverse age gatherings, and online networking use associate with LBSN application utilization notwithstanding how contrasts between iPhone and Android clients associate with it[13,14].

IV DATASET

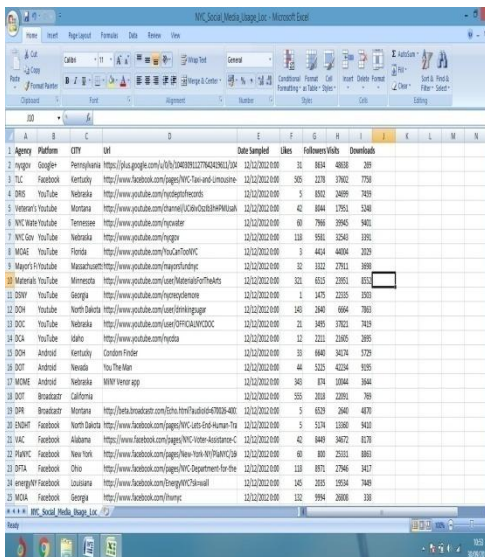
I took a dataset from NYC Social media usage. In this dataset various fields like Agency, Platform, City, Url, Date Sampled, Likes, Followers, Visits and Downloads. Our work is related to platform and city. In this we are trying to summarize a result based on which social media site is maximum approached from which city in USA[15]. If we conclude this we can say that from USA these are the city have maximum users uses the social site, through this marketing and advertisement agency are grow their business in those cities. The snapshot of dataset is shown below in figure 2.

V HADOOP PROGRAM FOR ANALYSIS

Here a Skelton of our program is given

```
import java.io.DataInput;  
import java.io.DataOutput;  
import java.io.IOException;  
import java.util.Iterator;
```

```
import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.IntWritable;
import org.apache.hadoop.io.LongWritable;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.io.WritableComparable;
import org.apache.hadoop.io.WritableUtils;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.Mapper;
import org.apache.hadoop.mapreduce.Reducer;
import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;
public class LOC_City_Analysis { public static class Composite_KeyMapper extends
Mapper<Long Writable, Text, Composite GroupKey, IntWritable> {
Composite GroupKey cntry = new Composite GroupKey();Text cntText = new Text();
Text state Text = new Text();
```



Agency	Platform	City	URL	Date Sampled	Likes	Followers/Follows	Downloads
1. NYS Gov	Google+	Pennsylvania	https://plus.google.com/u/0/b/104339122704243612704	12/12/2012 0:00	35	8834	4838
2. TWC	Facebook	Kentucky	http://www.facebook.com/pages/NYC-Ten-and-Lionsville	12/12/2012 0:00	350	1278	1790
3. TWC	YouTube	Nevada	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	5	8762	2495
4. Vets	YouTube	Montana	http://www.youtube.com/watch?v=0x0383H9M5U	12/12/2012 0:00	42	1844	1793
5. NYS Gov	YouTube	Tennessee	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	60	7966	2960
6. NYS Gov	YouTube	Nevada	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	138	1591	1341
7. NYS Gov	YouTube	Florida	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	3	4424	4400
8. NYS Gov	YouTube	Massachusetts	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	32	1332	2763
9. NYS Gov	YouTube	Minnesota	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	32	1332	2763
10. NYS Gov	YouTube	Georgia	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	1	1475	2335
11. NYS Gov	YouTube	North Dakota	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	140	2440	684
12. NYS Gov	YouTube	Nevada	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	21	1485	1762
13. NYS Gov	YouTube	Idaho	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	12	1211	2485
14. NYS Gov	YouTube	Kentucky	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	33	1440	3478
15. NYS Gov	YouTube	Nevada	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	48	1525	4239
16. NYS Gov	YouTube	Nevada	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	343	1044	1644
17. NYS Gov	YouTube	California	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	553	2013	2355
18. NYS Gov	YouTube	Montana	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	5	6329	2440
19. NYS Gov	YouTube	North Dakota	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	5	1574	1338
20. NYS Gov	YouTube	Alabama	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	42	1440	3478
21. NYS Gov	YouTube	New York	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	60	880	2533
22. NYS Gov	YouTube	Ohio	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	138	1591	1341
23. NYS Gov	YouTube	Louisiana	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	140	2440	684
24. NYS Gov	YouTube	Georgia	http://www.youtube.com/user/nyccityrecorder	12/12/2012 0:00	132	1594	2688

Figure 2 Data Set Of NYS Social Usage

```
IntWritable populat = new Int Writable();
public void map(Long Writable key, Text value, Context context)
throws IO Exception, InterruptedException {
String line = value.toString(); String[] keyvalue = line.split(",");
populat.set(Integer.parseInt (keyvalue[3])); Composite Group Key cntry = new Composite Group Key("",keyvalue[1]);
context.write(cntry, populat);}
```



```
public static class Composite Key Reducer extends Reducer<Composite Group Key, Int Writable, Composite Group Key,
IntWritable> { private IntWritable result = new IntWritable();

public void reduce(CompositeGroupKey key, Iterable<IntWritable> values,
Context context) throws IOException, InterruptedException {}

private static class CompositeGroupKey implements WritableComparable<CompositeGroupKey> {String country;String
state; public CompositeGroupKey() { }

public CompositeGroupKey(String country, String state) {this.country = "city"; this.state = state;}

public void write(DataOutput out) throws IOException {} public String toString() {}

return country.toString() + ":" + state.toString();}}

public static void main(String[] args) throws IOException,
ClassNotFoundException, InterruptedException { Configuration conf = new Configuration();
Job job = Job.getInstance(conf, "CompositeKey"); job.setJarByClass(LOCCityAnalysis.class);
job.setMapperClass(CompositeKeyMapper.class);
System.exit(job.waitForCompletion(true) ? 0 : 1)}
```

VI RESULTS AND CONCLUSION

After running the above program we find the following result given below the Table 1,2,3 and Table 4 and the graphical form of output is given in Figure 3,4,5 and figure 6. These all tables are coming from the output of the above program shown in this paper. The Hadoop clustered output is running as our expectation and what we want as it satisfying.

Table 1 Facebook and Android

Application	city	Hit	Application	city	Hit
Facebook	Alabama	73130	Android	Alabama	45471
	California	71597		California	10310
	Florida	57095		Florida	25883
	Georgia	71842		Georgia	29517
	Hawaii	50907		Hawaii	10001
	Idaho	79447		Idaho	27828
	Iowa	11738		Iowa	46986
	Kansas	60676		Kansas	20987
	Kentucky	59368		Kentucky	59886
	Louisiana	36686		Louisiana	28148
	Maryland	53627		Maryland	40578
	Massachusetts	90593		Massachusetts	25246
	Minnesota	32041		Minnesota	57159
	Mississippi	84392		Mississippi	16120
	Missouri	29974		Missouri	41225
	Montana	48747		Montana	25774
	Nebraska	65247		Nebraska	47717
	New Mexico	53243		New Mexico	43166
	New York	68921		New York	25430
	North Dakota	18931		North Dakota	57943
	Ohio	14703		Ohio	10901
	Oregon	27846		Oregon	27954
	Pennsylvania	16048		Pennsylvania	11864
	Tennessee	55881		Tennessee	50208

Table 2 Broadcastr and Flickr

Application	city	Hit	Application	city	Hit
Broadcastr	Alabama	22892	Flickr	Alabama	33886
	California	38335		California	82804
	Florida	27763		Florida	51328
	Georgia	13121		Georgia	16097
	Hawaii	39689		Hawaii	98596
	Idaho	32432		Idaho	68740
	Iowa	42364		Iowa	78822
	Kansas	20839		Kansas	86327
	Kentucky	27812		Kentucky	66563
	Louisiana	13513		Louisiana	20203
	Maryland	43684		Maryland	43573
	Massachusetts	45202		Massachuse	89706
	Minnesota	30701		Minnesota	41858
	Mississippi	15488		Mississippi	24604
	Missouri	12131		Missouri	31387
	Montana	16873		Montana	78508
	Nebraska	34300		Nebraska	13266
	New Mexico	14759		New Mexico	10703
	New York	40703		New York	95095
	North Dakota	17552		North Dakot	48050
	Ohio	21846		Ohio	90050
	Oregon	29470		Oregon	46976
	Pennsylvania	32674		Pennsylvania	68708
	Tennessee	40678		Tennessee	67590

Table 3 Foursquare and Google+

Table 4 Instagram and Pinterest

Application	city	Hit	Application	city	Hit	Application	city	Hit	Application	city	Hit
Foursquare	Alabama	51003	Google+	Alabama	79818	Instagram	Alabama	93951	Pinterest	Alabama	88963
	California	124742		California	61828		California	63702		California	88907
	Florida	69831		Florida	127810		Florida	134048		Florida	72981
	Georgia	96011		Georgia	57358		Georgia	107751		Georgia	80404
	Hawaii	133876		Hawaii	122820		Hawaii	66858		Hawaii	90743
	Idaho	79101		Idaho	118788		Idaho	127606		Idaho	87517
	Iowa	96438		Iowa	135464		Iowa	92174		Iowa	31636
	Kansas	65874		Kansas	97940		Kansas	106964		Kansas	61508
	Kentucky	111567		Kentucky	145912		Kentucky	106443		Kentucky	51712
	Louisiana	55957		Louisiana	67475		Louisiana	117730		Louisiana	91583
	Maryland	55051		Maryland	83500		Maryland	83365		Maryland	76691
	Massachusetts	102968		Massachusetts	149851		Massachusetts	119761		Massachusetts	83533
	Minnesota	105317		Minnesota	91803		Minnesota	111089		Minnesota	45941
	Mississippi	64301		Mississippi	126526		Mississippi	67661		Mississippi	73200
	Missouri	149071		Missouri	65048		Missouri	129725		Missouri	45654
	Montana	149325		Montana	111194		Montana	144569		Montana	66147
	Nebraska	56805		Nebraska	56772		Nebraska	107859		Nebraska	88269
	New Mexico	60419		New Mexico	86139		New Mexico	121357		New Mexico	20664
	New York	126243		New York	93008		New York	50402		New York	52903
	North Dakota	60070		North Dakota	147637		North Dakota	106845		North Dakota	64496
	Ohio	64765		Ohio	99117		Ohio	126085		Ohio	29852
	Oregon	69158		Oregon	129333		Oregon	126721		Oregon	38017
	Pennsylvania	144000		Pennsylvania	82501		Pennsylvania	97025		Pennsylvania	907823
	Tennessee	88886		Tennessee	78915		Tennessee	95159		Tennessee	27517

The table shown above is based on the users approaches from the different cities of USA and different social networks. Below here the graphical pictorial representation is given.



Figure 3 Graphical Representation of Broadcastr and Flickr Analysis



Figure 4 Graphical Representation of Facebook, Android Analysis

After completing the execution we were founded the output(Shown in figure 3 and 4 and Table 1,2,3 and 4) we can conclude that our research work has been done successfully. We were founded the maximum hit for each social media website according to different cities. With the help of this result the marketing and advertising company can promote their product in different citi according to the approaches fined by users. They have one more advantages from this result they can work out those areas where minimum approached has been fined.



Figure 5 Graphical Representation of Foursquare, Google+ Analysis



Figure 6 Graphical Representation of Instagram and Pinterest Analysis.

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