Privacy and Security in Online Social Networks
Prof. Ponnurangam Kumaraguru ("PK")
Department of Computer Science and Engineering
Indian Institute of Technology, Madras

Week - 10.1
Lecture – 32
Beware of What You Share inferring Home Location in Social Networks

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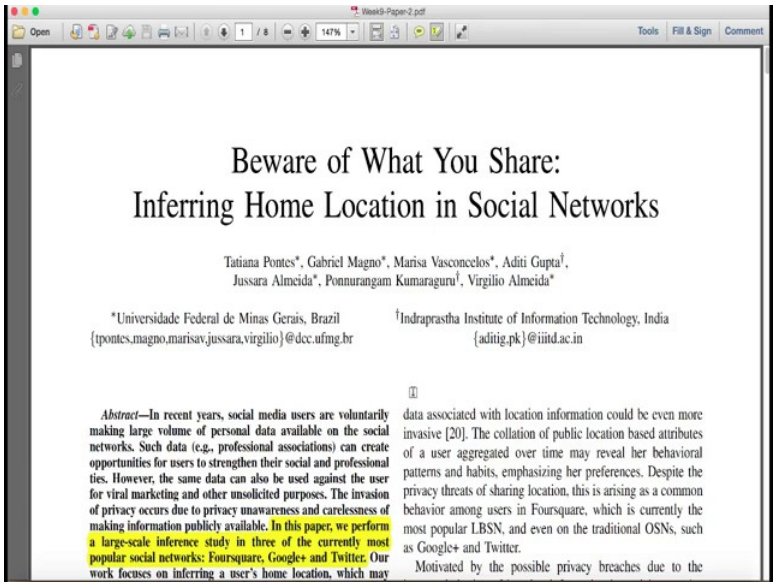

Welcome back to the course Privacy and Security in Online Social Media. Continuing the trend that I did last lecture, I am going to continue actually looking at some papers which are basically addressing the problem of privacy leakages from location based services. If you remember last lecture, we had paper which looked at Foursquare, and the paper analyzed, how they can actually identify, where a person lives. That was only using the Foursquare mayorship, tips and dones. And what we are going to see now is almost the same topic, but we are going to actually compare it with different social networks.

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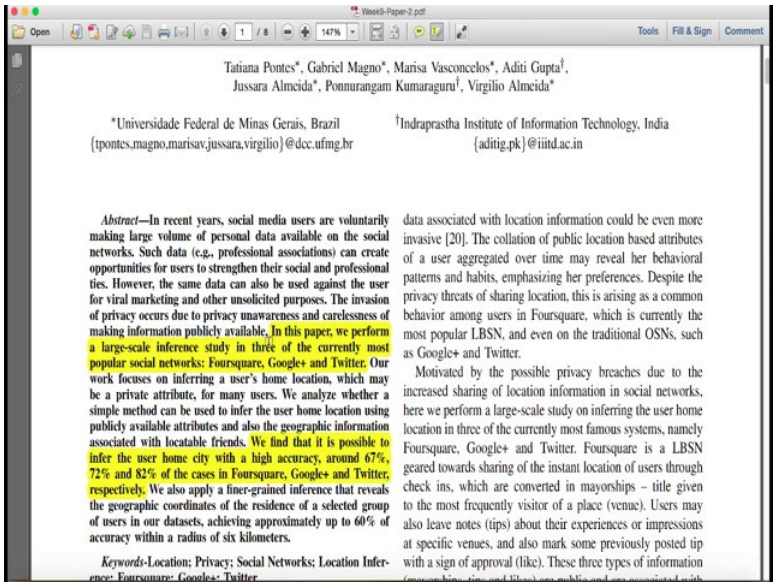

Tatiana Pontes*, Gabriel Magno*, Marisa Vasconcelos*, Aditi Gupta†,
Jussara Almeida*, Ponnurangam Kumaraguru†, Virgilio Almeida*

*Universidade Federal de Minas Gerais, Brazil
{tpontes,magno,marisav,jussara,virgilio}@dcc.ufmg.br

†Indraprastha Institute of Information Technology, India
{aditig.pk}@iiitd.ac.in

***Abstract*—In recent years, social media users are voluntarily making large volume of personal data available on the social networks. Such data (e.g., professional associations) can create opportunities for users to strengthen their social and professional ties. However, the same data can also be used against the user for viral marketing and other unsolicited purposes. The invasion of privacy occurs due to privacy unawareness and carelessness of making information publicly available. In this paper, we perform a large-scale inference study in three of the currently most popular social networks: Foursquare, Google+ and Twitter. Our work focuses on inferring a user's home location, which may be a private attribute, for many users. We analyze whether a simple method can be used to infer the user home location using publicly available attributes and also the geographic information associated with locatable friends. We find that it is possible to infer the user home city with a high accuracy, around 67%, 72% and 82% of the cases in Foursquare, Google+ and Twitter, respectively. We also apply a finer-grained inference that reveals the geographic coordinates of the residence of a selected group of users in our datasets, achieving approximately up to 60% of accuracy within a radius of six kilometers.**

***Keywords*-Location; Privacy; Social Networks; Location Inference; Foursquare; Google+; Twitter**

data associated with location information could be even more invasive [20]. The collation of public location based attributes of a user aggregated over time may reveal her behavioral patterns and habits, emphasizing her preferences. Despite the privacy threats of sharing location, this is arising as a common behavior among users in Foursquare, which is currently the most popular LBSN, and even on the traditional OSNs, such as Google+ and Twitter.

Motivated by the possible privacy breaches due to the increased sharing of location information in social networks, here we perform a large-scale study on inferring the user home location in three of the currently most famous systems, namely Foursquare, Google+ and Twitter. Foursquare is a LBSN geared towards sharing of the instant location of users through check ins, which are converted in mayorships – title given to the most frequently visitor of a place (venue). Users may also leave notes (tips) about their experiences or impressions at specific venues, and also mark some previously posted tip with a sign of approval (like). These three types of information

So, if you see here in this paper the authors perform a large scale inference study in three of the currently most popular social networks like Foursquare, Google plus and Twitter. So, the goal in this paper is very similar to the paper that we saw last time, but it is going to be looking at different social networks not just only Foursquare. So, in this authors looked at Foursquare, Google plus and Twitter. You know as part of this course, you have already seen all three social networks in terms of their content, in terms of the data collection that is done and information that you can actually collect from the social networks.

The authors actually find that it is possible to infer the user home city with the high accuracy around 67 percent, 72 percent and 82 percent in the case of Foursquare, Google plus and Twitter, which is 67 percent for Foursquare, 72 percent for Google plus and 82 percent for Twitter. I am sure as we move along; you will actually understand why Twitter is actually high in terms of finding out the home location.

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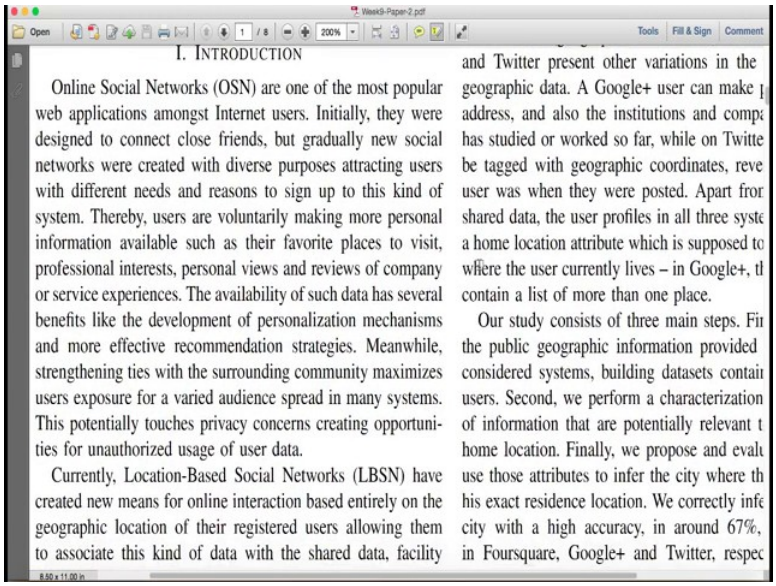

I. Introduction

Online Social Networks (OSN) are one of the most popular web applications amongst Internet users. Initially, they were designed to connect close friends, but gradually new social networks were created with diverse purposes attracting users with different needs and reasons to sign up to this kind of system. Thereby, users are voluntarily making more personal information available such as their favorite places to visit, professional interests, personal views and reviews of company or service experiences. The availability of such data has several benefits like the development of personalization mechanisms and more effective recommendation strategies. Meanwhile, strengthening ties with the surrounding community maximizes users exposure for a varied audience spread in many systems. This potentially touches privacy concerns creating opportunities for unauthorized usage of user data.

Currently, Location-Based Social Networks (LBSN) have created new means for online interaction based entirely on the geographic location of their registered users allowing them to associate this kind of data with the shared data, facility and Twitter present other variations in the geographic data. A Google+ user can make address, and also the institutions and compa has studied or worked so far, while on Twitte be tagged with geographic coordinates, reve user was when they were posted. Apart fror shared data, the user profiles in all three syste a home location attribute which is supposed to where the user currently lives – in Google+, tl contain a list of more than one place.

Our study consists of three main steps. Fir the public geographic information provided considered systems, building datasets contai users. Second, we perform a characterization of information that are potentially relevant t home location. Finally, we propose and evalu use those attributes to infer the city where th his exact residence location. We correctly infe city with a high accuracy, in around 67%, in Foursquare, Google+ and Twitter, respec

So, now let us look at the paper in terms of the same structure as we saw last time, introduction, talking about what a location based social networks are.

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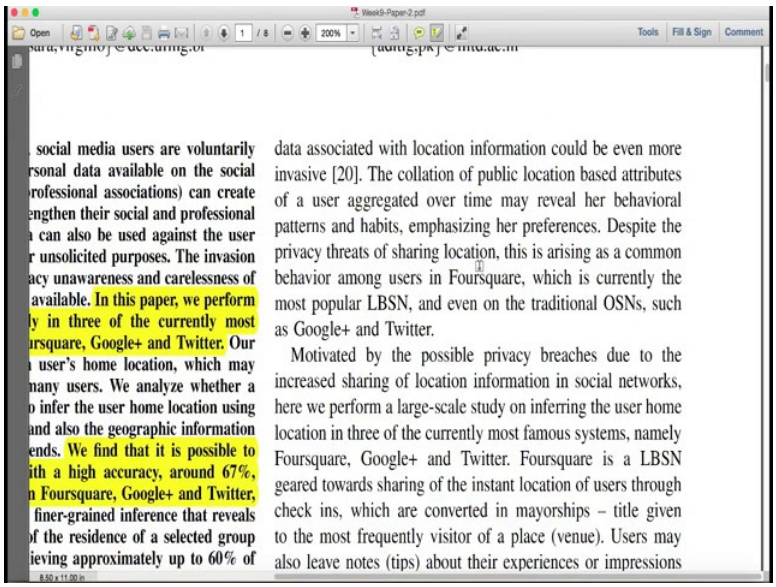

social media users are voluntarily rsonal data available on the social rofessional associations) can create engthen their social and professional can also be used against the user r unsolicited purposes. The invasion acy unawareness and carelessness of available. In this paper, we perform y in three of the currently most rsquare, Google+ and Twitter. Our user's home location, which may nany users. We analyze whether a o infer the user home location using and also the geographic information ends. We find that it is possible to ith a high accuracy, around 67%, n Foursquare, Google+ and Twitter, finer-grained inference that reveals f the residence of a selected group ieving approximately up to 60% of

data associated with location information could be even more invasive [20]. The collation of public location based attributes of a user aggregated over time may reveal her behavioral patterns and habits, emphasizing her preferences. Despite the privacy threats of sharing location, this is arising as a common behavior among users in Foursquare, which is currently the most popular LBSN, and even on the traditional OSNs, such as Google+ and Twitter.

Motivated by the possible privacy breaches due to the increased sharing of location information in social networks, here we perform a large-scale study on inferring the user home location in three of the currently most famous systems, namely Foursquare, Google+ and Twitter. Foursquare is a LBSN geared towards sharing of the instant location of users through check ins, which are converted in mayorships – title given to the most frequently visitor of a place (venue). Users may also leave notes (tips) about their experiences or impressions

Talking about collecting data from a different social media services like Google plus Foursquare and Twitter and different research that are done in the context of Foursquare Google plus and Twitter. And I am talking about what information was collected, and a little bit of conclusions of the paper itself, and then talking about how the paper is out maxed.

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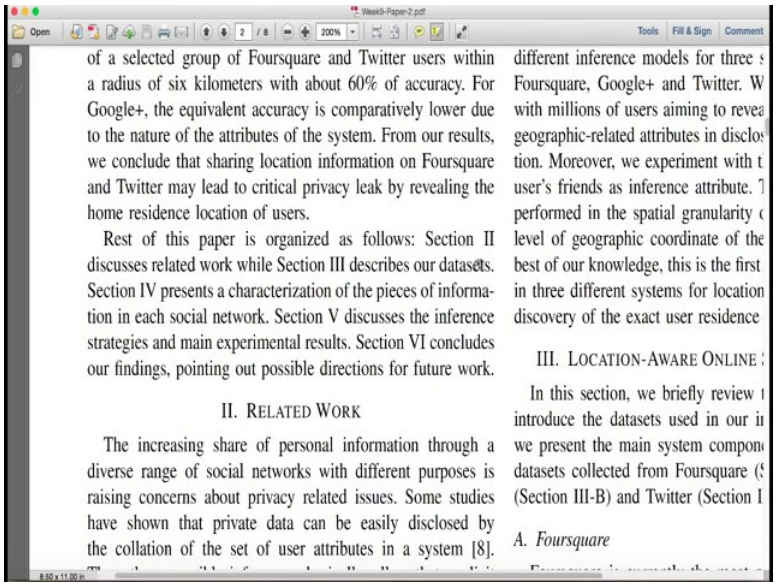
of a selected group of Foursquare and Twitter users within a radius of six kilometers with about 60% of accuracy. For Google+, the equivalent accuracy is comparatively lower due to the nature of the attributes of the system. From our results, we conclude that sharing location information on Foursquare and Twitter may lead to critical privacy leak by revealing the home residence location of users.

Rest of this paper is organized as follows: Section II discusses related work while Section III describes our datasets. Section IV presents a characterization of the pieces of information in each social network. Section V discusses the inference strategies and main experimental results. Section VI concludes our findings, pointing out possible directions for future work.

II. Related Work

The increasing share of personal information through a diverse range of social networks with different purposes is raising concerns about privacy related issues. Some studies have shown that private data can be easily disclosed by the collation of the set of user attributes in a system [8].

different inference models for three
Foursquare, Google+ and Twitter. W
with millions of users aiming to revea
geographic-related attributes in disclo
tion. Moreover, we experiment with t
user's friends as inference attribute.
performed in the spatial granularity
level of geographic coordinate of the
best of our knowledge, this is the first
in three different systems for location
discovery of the exact user residence

III. Location-Aware Online

In this section, we briefly review
introduce the datasets used in our i
we present the main system compon
datasets collected from Foursquare (
(Section III-B) and Twitter (Section I

A. Foursquare

So, this is generally the structure that we saw even the last time, meaning almost all papers appears see the structure would be the same a paragraph about the 30,000 feet high view of the problem. Then the paragraph about the current problem and what is missing, then the paragraph about what is, what was done in this paper and then some kind of a contribution from this paper. Related work again I am not going to detail in this particular related work.

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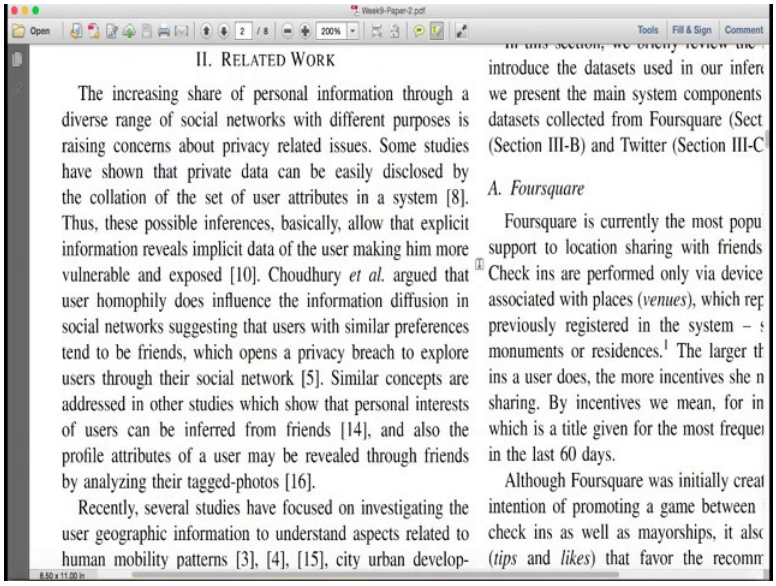
II. Related Work

The increasing share of personal information through a diverse range of social networks with different purposes is raising concerns about privacy related issues. Some studies have shown that private data can be easily disclosed by the collation of the set of user attributes in a system [8]. Thus, these possible inferences, basically, allow that explicit information reveals implicit data of the user making him more vulnerable and exposed [10]. Choudhury *et al.* argued that user homophily does influence the information diffusion in social networks suggesting that users with similar preferences tend to be friends, which opens a privacy breach to explore users through their social network [5]. Similar concepts are addressed in other studies which show that personal interests of users can be inferred from friends [14], and also the profile attributes of a user may be revealed through friends by analyzing their tagged-photos [16].

Recently, several studies have focused on investigating the user geographic information to understand aspects related to human mobility patterns [3], [4], [15], city urban develop-

introduce the datasets used in our infer
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datasets collected from Foursquare (Sect
(Section III-B) and Twitter (Section III-C

A. Foursquare

Foursquare is currently the most popu
support to location sharing with friends
Check ins are performed only via device
associated with places (*venues*), which rep
previously registered in the system –
monuments or residences.[1] The larger th
ins a user does, the more incentives she n
sharing. By incentives we mean, for in
which is a title given for the most freque
in the last 60 days.

Although Foursquare was initially creat
intention of promoting a game between
check ins as well as mayorships, it also
(*tips* and *likes*) that favor the recomm

But related work generally talks about these kind of privacy leakages from location based services and work done on collecting data from these three social networks and inferences that were done.

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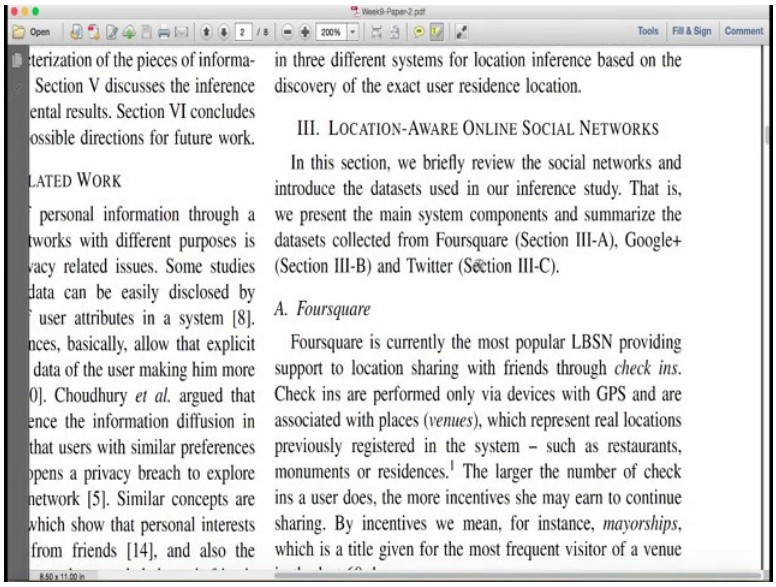
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Section V discusses the inference
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LATED WORK

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in three different systems for location inference based on the discovery of the exact user residence location.

III. Location-Aware Online Social Networks

In this section, we briefly review the social networks and introduce the datasets used in our inference study. That is, we present the main system components and summarize the datasets collected from Foursquare (Section III-A), Google+ (Section III-B) and Twitter (Section III-C).

A. Foursquare

Foursquare is currently the most popular LBSN providing support to location sharing with friends through *check ins*. Check ins are performed only via devices with GPS and are associated with places (*venues*), which represent real locations previously registered in the system – such as restaurants, monuments or residences.[1] The larger the number of check ins a user does, the more incentives she may earn to continue sharing. By incentives we mean, for instance, *mayorships*, which is a title given for the most frequent visitor of a venue

Then many a times researchers actually tend to write details about the social network that is being discussed in terms of just introducing the terminologies which we saw in the last paper also. Here it is talking about Foursquare then there would be about Google plus and then Twitter.

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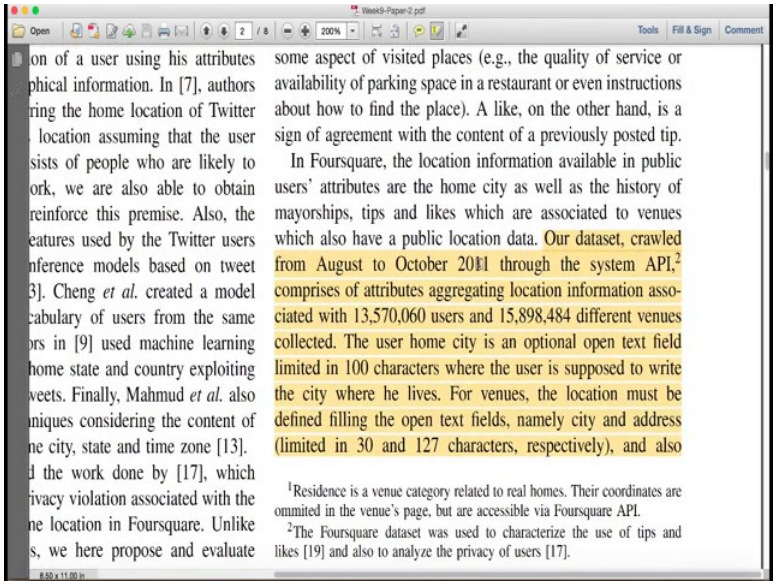
on of a user using his attributes
phical information. In [7], authors
ring the home location of Twitter
location assuming that the user
sists of people who are likely to
ork, we are also able to obtain
reinforce this premise. Also, the
eatures used by the Twitter users
nference models based on tweet
3]. Cheng *et al.* created a model
abulary of users from the same
rs in [9] used machine learning
home state and country exploiting
weets. Finally, Mahmud *et al.* also
niques considering the content of
ne city, state and time zone [13].
l the work done by [17], which
ivacy violation associated with the
ne location in Foursquare. Unlike
s, we here propose and evaluate

some aspect of visited places (e.g., the quality of service or availability of parking space in a restaurant or even instructions about how to find the place). A like, on the other hand, is a sign of agreement with the content of a previously posted tip.

In Foursquare, the location information available in public users' attributes are the home city as well as the history of mayorships, tips and likes which are associated to venues which also have a public location data. Our dataset, crawled from August to October 2011 through the system API,[2] comprises of attributes aggregating location information associated with 13,570,060 users and 15,898,484 different venues collected. The user home city is an optional open text field limited in 100 characters where the user is supposed to write the city where he lives. For venues, the location must be defined filling the open text fields, namely city and address (limited in 30 and 127 characters, respectively), and also

[1]Residence is a venue category related to real homes. Their coordinates are ommited in the venue's page, but are accessible via Foursquare API.

[2]The Foursquare dataset was used to characterize the use of tips and likes [19] and also to analyze the privacy of users [17].

So, here if you look at it, the dataset that was used in the study is the same as the last paper. Dataset crawled between October 2011, through the system and it comprises of 13 million users and about close to 16 million different venues. And the user home city is an optional open text field limited to about 100 characters. For venue, is the location must be defined filling the open text fields, namely city and address limited to 30 and 127 characters respectively. That is the kind of data and that is the kind of information that is available when you collect these data for venue, tips and dones.

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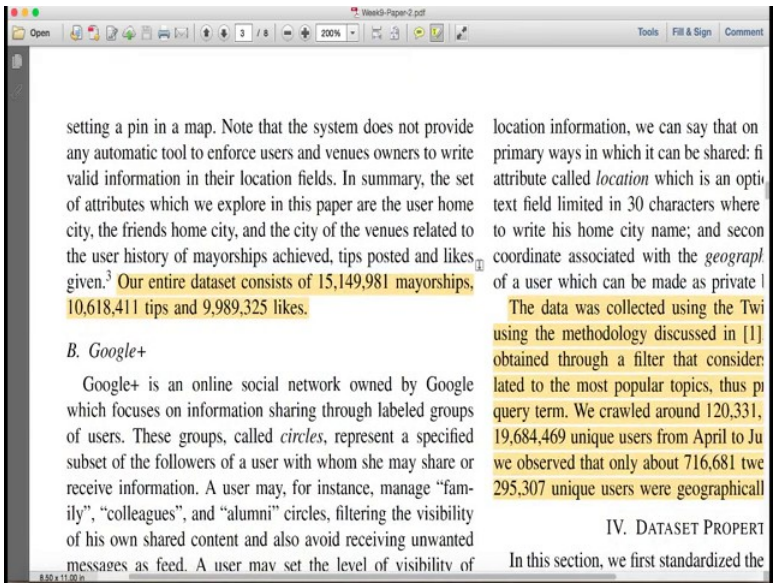

setting a pin in a map. Note that the system does not provide any automatic tool to enforce users and venues owners to write valid information in their location fields. In summary, the set of attributes which we explore in this paper are the user home city, the friends home city, and the city of the venues related to the user history of mayorships achieved, tips posted and likes given.[3] Our entire dataset consists of 15,149,981 mayorships, 10,618,411 tips and 9,989,325 likes.

B. Google+

Google+ is an online social network owned by Google which focuses on information sharing through labeled groups of users. These groups, called *circles*, represent a specified subset of the followers of a user with whom she may share or receive information. A user may, for instance, manage "family", "colleagues", and "alumni" circles, filtering the visibility of his own shared content and also avoid receiving unwanted

location information, we can say that on
primary ways in which it can be shared: fi
attribute called *location* which is an opti
text field limited in 30 characters where
to write his home city name; and secon
coordinate associated with the *geograph*
of a user which can be made as private

The data was collected using the Twi
using the methodology discussed in [1]
obtained through a filter that consider
lated to the most popular topics, thus p
query term. We crawled around 120,331,
19,684,469 unique users from April to Ju
we observed that only about 716,681 twe
295,307 unique users were geographicall

IV. DATASET PROPERT

In this section, we first standardized the

So, the entire dataset is about 15 million mayorships, close to 11 million tips, and close to ten million likes. All right? So, likes is basically dones in terms of Foursquare terminology.

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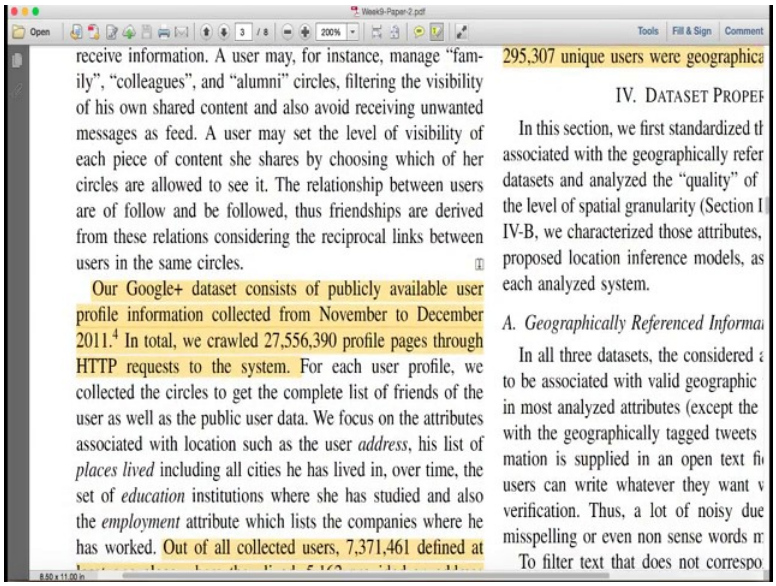
receive information. A user may, for instance, manage "family", "colleagues", and "alumni" circles, filtering the visibility of his own shared content and also avoid receiving unwanted messages as feed. A user may set the level of visibility of each piece of content she shares by choosing which of her circles are allowed to see it. The relationship between users are of follow and be followed, thus friendships are derived from these relations considering the reciprocal links between users in the same circles.

Our Google+ dataset consists of publicly available user profile information collected from November to December 2011.[4] In total, we crawled 27,556,390 profile pages through HTTP requests to the system. For each user profile, we collected the circles to get the complete list of friends of the user as well as the public user data. We focus on the attributes associated with location such as the user *address*, his list of *places lived* including all cities he has lived in, over time, the set of *education* institutions where she has studied and also the *employment* attribute which lists the companies where he has worked. Out of all collected users, 7,371,461 defined at

295,307 unique users were geographica

IV. Dataset Propef

In this section, we first standardized th associated with the geographically refer datasets and analyzed the "quality" of the level of spatial granularity (Section I IV-B, we characterized those attributes, proposed location inference models, as each analyzed system.

A. Geographically Referenced Informa

In all three datasets, the considered a to be associated with valid geographic in most analyzed attributes (except the with the geographically tagged tweets mation is supplied in an open text fi users can write whatever they want v verification. Thus, a lot of noisy due misspelling or even non sense words m

To filter text that does not correspo

So, now in terms of Google plus data, Google plus is basically a network that is very similar to, I mean, if you have a Gmail account, you essentially have a Google plus account. In total 27 million profile pages through HTTP request were crawled, and 7 million defined at least one place where they lived, and 5000 provided address information and about 7 million filled their education and about close to 6 million filled their employment.

So, these are details, meaning, if you remember, if you just recollect the social network that you use more often, which is like Facebook, you have all these details at the right places that you live, education, colleges that you study, places that you worked, places that you have lived, all of these information are taken from the users and that is what is mentioned here. Which is 7 million people have explicitly stated their education and about 6 million people have explicitly stated their employment details which is I work at IIIT Delhi.

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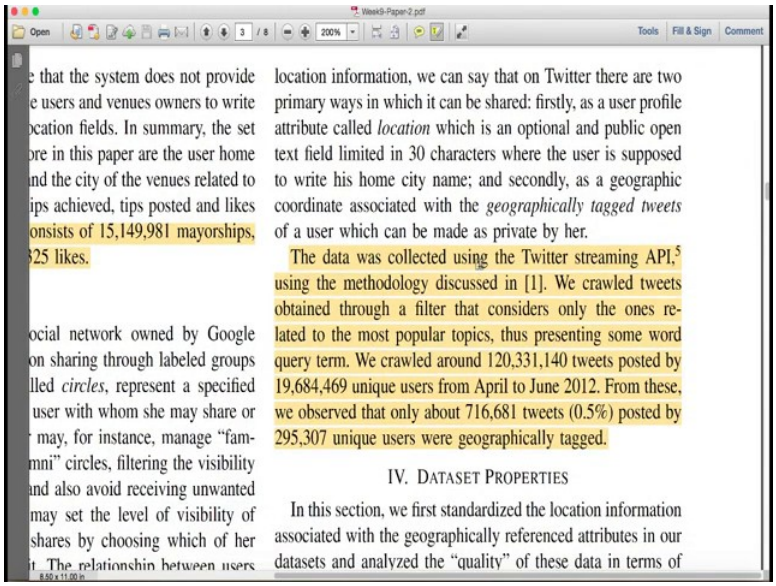

Now, let us look at the data from Twitter. So, the data the data from Twitter was collected using Streaming API, which all of you are aware of. And the crawl was done for 120 million tweets posted by about close to 20 million unique users from April to June 2012. 0.5 percent of the posts posted by unique users were geographically tagged.

So, what does this mean, this means that there are only 0.5 percent of the total posts that were collected where there is geo tagged information for the post which is geo tagged information for the users also. There were about 700,000 tweets and about 300,000 unique users. That is the exact location, which we have discussed in the past, which is latitude, longitude of the post from where the post is coming.

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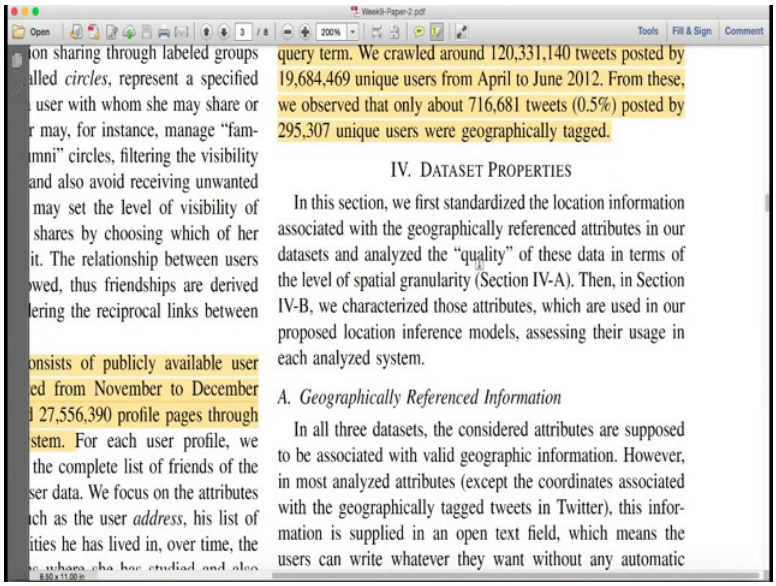

So, that is the background about the dataset. Essentially all of them are talking about in millions in Twitter it's about 0.5 million geographically tagged tweets geo tag tweets.

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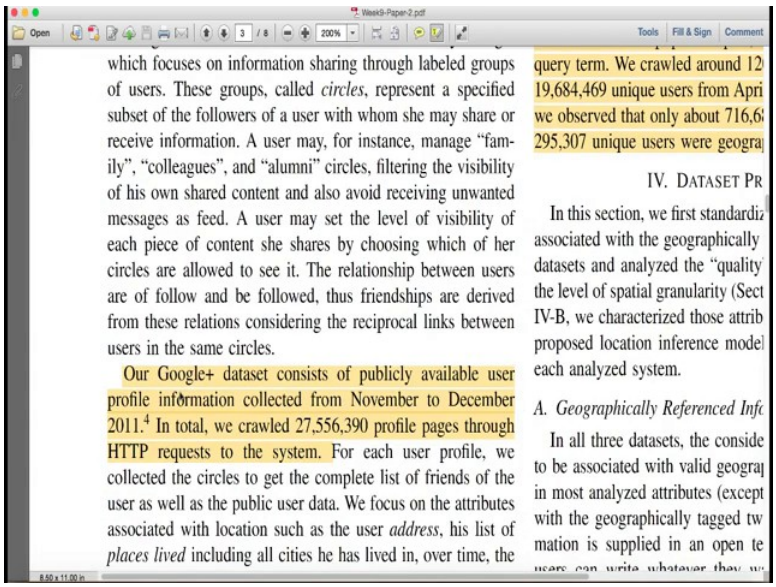

In Google plus that are about 27 million profiles that were crawled and about 7 million education and 6 million employment.

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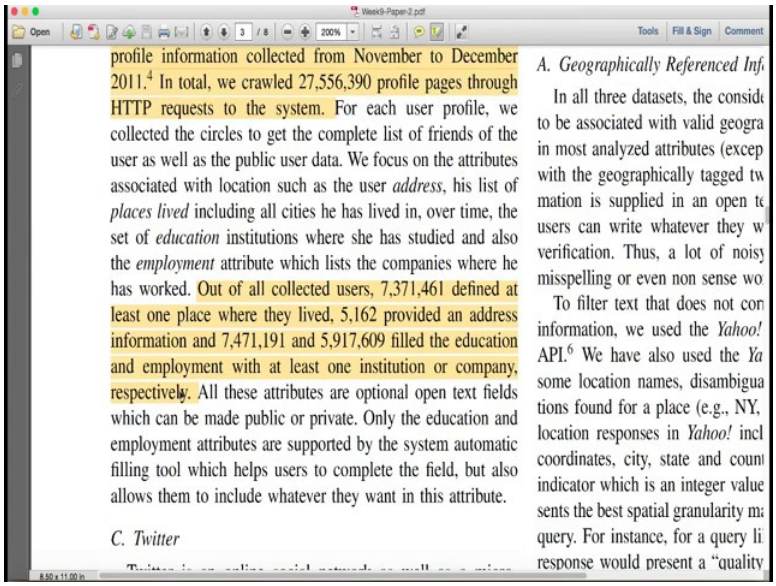
profile information collected from November to December 2011.[4] In total, we crawled 27,556,390 profile pages through HTTP requests to the system. For each user profile, we collected the circles to get the complete list of friends of the user as well as the public user data. We focus on the attributes associated with location such as the user *address*, his list of *places lived* including all cities he has lived in, over time, the set of *education* institutions where she has studied and also the *employment* attribute which lists the companies where he has worked. Out of all collected users, 7,371,461 defined at least one place where they lived, 5,162 provided an address information and 7,471,191 and 5,917,609 filled the education and employment with at least one institution or company, respectively. All these attributes are optional open text fields which can be made public or private. Only the education and employment attributes are supported by the system automatic filling tool which helps users to complete the field, but also allows them to include whatever they want in this attribute.

C. Twitter

A. Geographically Referenced Inf

In all three datasets, the conside to be associated with valid geogra in most analyzed attributes (excep with the geographically tagged tw mation is supplied in an open te users can write whatever they w verification. Thus, a lot of noisy misspelling or even non sense wo

To filter text that does not con information, we used the *Yahoo!* API.[6] We have also used the *Ya* some location names, disambigua tions found for a place (e.g., NY, location responses in *Yahoo!* incl coordinates, city, state and count indicator which is an integer value sents the best spatial granularity ma query. For instance, for a query li response would present a "quality

And Foursquare has details of about 16 million mayorship; 11 million tips and close to 10 million likes. That is the dataset we are going to play around with to do the analysis, to find inferences about the home location of the person.

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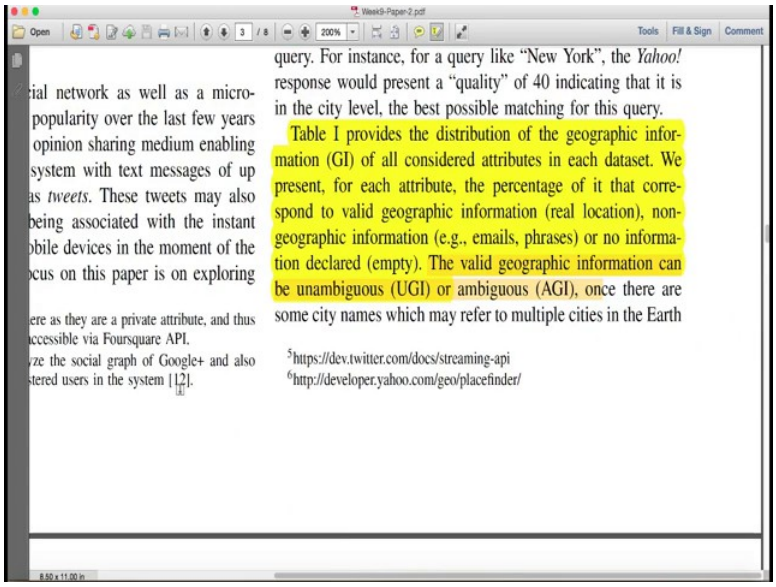
ial network as well as a micro- popularity over the last few years opinion sharing medium enabling system with text messages of up as *tweets*. These tweets may also being associated with the instant obile devices in the moment of the ocus on this paper is on exploring

ere as they are a private attribute, and thus accessible via Foursquare API.

ze the social graph of Google+ and also stered users in the system [12].

query. For instance, for a query like "New York", the *Yahoo!* response would present a "quality" of 40 indicating that it is in the city level, the best possible matching for this query.

Table I provides the distribution of the geographic information (GI) of all considered attributes in each dataset. We present, for each attribute, the percentage of it that correspond to valid geographic information (real location), non-geographic information (e.g., emails, phrases) or no information declared (empty). The valid geographic information can be unambiguous (UGI) or ambiguous (AGI), once there are some city names which may refer to multiple cities in the Earth

[5]https://dev.twitter.com/docs/streaming-api
[6]http://developer.yahoo.com/geo/placefinder/

So, in any data set, when you analyze, first you know you want to actually provide exploratory data analysis, and you want to provide what the data set looks like, because this will help reproducibility of that research. This will help others to actually collect data, if they were to, the point here is that if others want to collect the data which is very

similar to what you collected; and if others want to do the same analysis that you did the results should be the same. That is the idea for reproducibility of the research. So, explaining how you did collected the data, explaining what the data looks like is extremely important in terms of actually writing these research papers.

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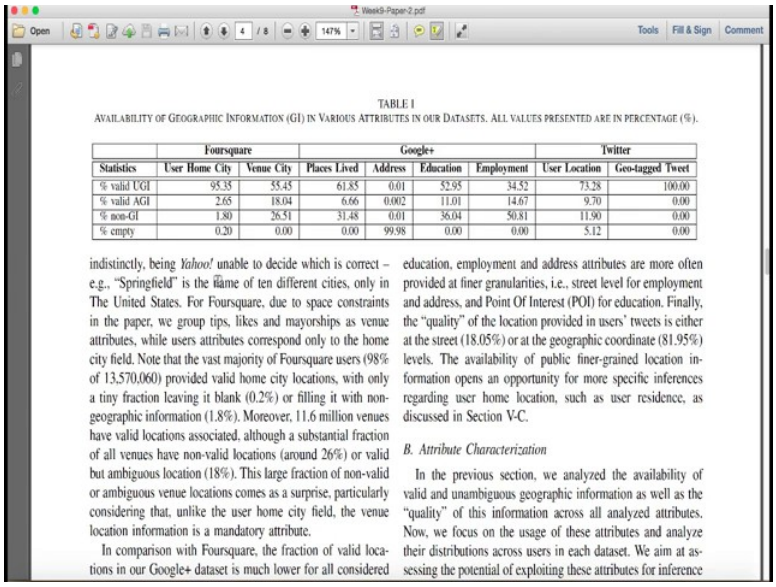

TABLE I
AVAILABILITY OF GEOGRAPHIC INFORMATION (GI) IN VARIOUS ATTRIBUTES IN OUR DATASETS. ALL VALUES PRESENTED ARE IN PERCENTAGE (%).

	Foursquare		Google+				Twitter	
Statistics	User Home City	Venue City	Places Lived	Address	Education	Employment	User Location	Geo-tagged Tweet
% valid UGI	95.35	55.45	61.85	0.01	52.95	34.52	73.28	100.00
% valid AGI	2.65	18.04	6.66	0.002	11.01	14.67	9.70	0.00
% non-GI	1.80	26.51	31.48	0.01	36.04	50.81	11.90	0.00
% empty	0.20	0.00	0.00	99.98	0.00	0.00	5.12	0.00

indistinctly, being *Yahoo!* unable to decide which is correct – e.g., "Springfield" is the name of ten different cities, only in The United States. For Foursquare, due to space constraints in the paper, we group tips, likes and mayorships as venue attributes, while users attributes correspond only to the home city field. Note that the vast majority of Foursquare users (98% of 13,570,060) provided valid home city locations, with only a tiny fraction leaving it blank (0.2%) or filling it with non-geographic information (1.8%). Moreover, 11.6 million venues have valid locations associated, although a substantial fraction of all venues have non-valid locations (around 26%) or valid but ambiguous location (18%). This large fraction of non-valid or ambiguous venue locations comes as a surprise, particularly considering that, unlike the user home city field, the venue location information is a mandatory attribute.

In comparison with Foursquare, the fraction of valid locations in our Google+ dataset is much lower for all considered education, employment and address attributes are more often provided at finer granularities, i.e., street level for employment and address, and Point Of Interest (POI) for education. Finally, the "quality" of the location provided in users' tweets is either at the street (18.05%) or at the geographic coordinate (81.95%) levels. The availability of public finer-grained location information opens an opportunity for more specific inferences regarding user home location, such as user residence, as discussed in Section V-C.

B. Attribute Characterization

In the previous section, we analyzed the availability of valid and unambiguous geographic information as well as the "quality" of this information across all analyzed attributes. Now, we focus on the usage of these attributes and analyze their distributions across users in each dataset. We aim at assessing the potential of exploiting these attributes for inference

So, table one provides the distribution of geographic information of all considered attributes in each dataset in each dataset. We present for each attribute the percentage of it that corresponds to the valid geographic. Let us look at the tables. So, this table is the one that is referred. This table talks about availability of geographic information in various attributes in the datasets. So, if you look at the second column, which is Foursquare. So, the columns are referred three different networks Foursquare, Google plus and Twitter. And if you look at the statistics which are in the rows, it is valid UGI which is user geographic information, valid AGI, valid geographic information and that is empty.

So, this basically would help you to find out, what is the amount of data that is available which is valid geographic information, valid and ambiguous geographic information, valid ambiguous geographic information and valid non geographic information and empty. What is this all mean I will I will try to explain this. Valid and ambiguous it is actually latitude or longitudinal, it is actually New Delhi; there is no ambiguity in it. Valid ambiguity it is not clear, so it says near Taj Mahal or near Govindpuri metro

station, so these things are ambiguous. And non-GI – non-geographic information which could be I think as I said before, it could be somebody's heart, h e a r t.

And information like that is actually it is not geographic information at all, and sometimes it could be actually empty. So, essentially that is what is been given in the values. They are all percentages which says user home city is about 95 percent, ambiguous is about 2.6 percent, and non-GI is 1.8 percent, and empty is about 0.2 percent.

So, in Foursquare, it is user home city and venue city. In Google plus, it is places lived address and education and employment. In Twitter, it is the user location geo tagged tweet right. So, this basically tells you different types of information are collected from different networks; I mean that is a whole body of research in terms of actually using these different sets of information from different social networks.

Then Foursquare it is user home city venue and venue. In Google plus, it is places lived address education and employment; in Twitters, it is user location and geo tagged tweet. So, if you look at the unambiguous geographic information for geo tagged tweet from Twitter it is about 100 percent. It is because all the tweets that where collected where actually at the 0.5 percent had geo tagged information in it, so that basically gives you a sense of what kind of data is collected. In terms of Google plus, 53 percent has an unambiguous education, so I studied that Carnegie Mellon University, so that is very very precise, there is unambiguity, there is no problem and actually recoding it or decoding it to a specific university.

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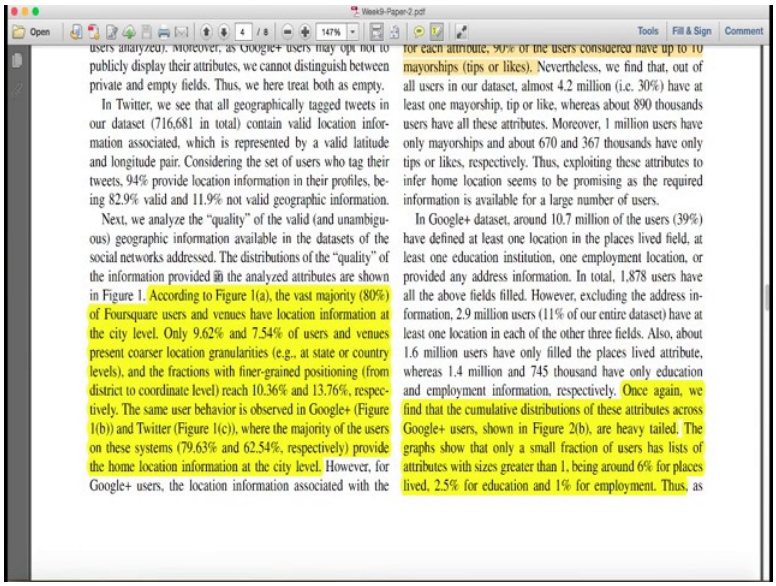

So, let us look at different figures, different analysis that is been done using this data. Figure 1 the vast majority 80 percent of Foursquare users and venues have location information at the city level. 9.6 percent and 7.4 percent of users and venues present coarser location granularities at a state or the country levels.

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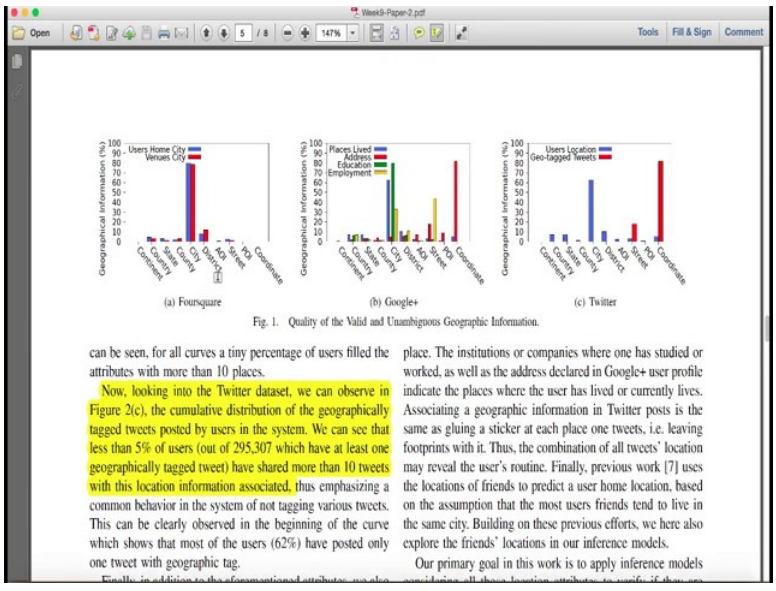

So, we look at the figures. So, this is figure 1(a), 1(b) and 1(c). So, if you look at here quality of valid and unambiguous geographic information. Foursquare, if you look at city, city gives you the users' home city and venue city; it is about close to eighty percent.

So, that is what is written here this says about vast majority 80 percent of Foursquare users and venues have location information at the city level. Some have at the country level, some have at the state level, some have at the street level, so that is the different level of details that the geographic information is available for the location from Foursquare.

So, if you look at Google plus, the information is maximum available for example, it is education that is available at a city level about 70 percent or 70 plus percentage, so that is what is its written here. The same user behavior is observed in Google plus figure 1(b) and figure 1(c) where the majority of the users of the system 79.63, 62.54 respectively provide the home location at the city level. City is highest in terms of places lived, city is highest in terms of user location also, so that basically says that we should be able to actually get the city level of information without any problem, because large amount of data for the information about the users is available at the city level.

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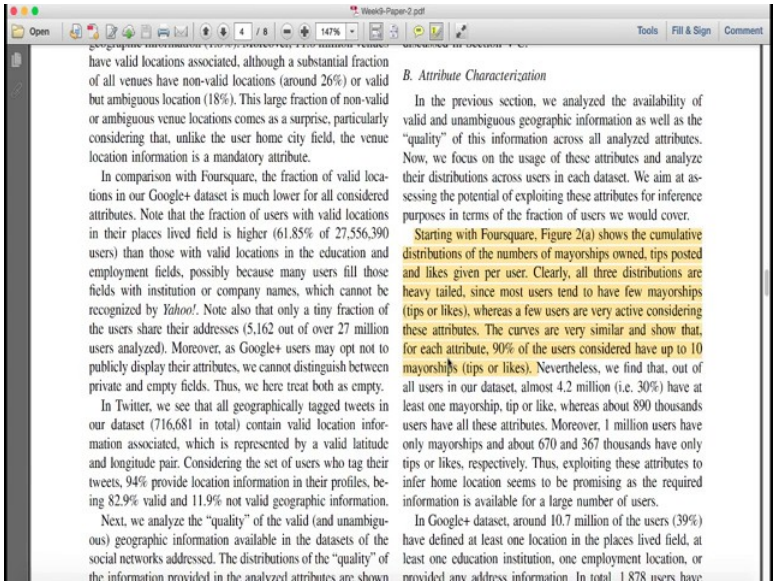

Now, let us look at more analysis with this data. So, now, figure 2(a) shows the cumulative distributions of the numbers of mayorships owned, tips, posted and likes. If you remember even in the last paper, we saw this kind of graphs, which is to show the cumulative distribution of the number of the mayors, tips and dones right. So, if you remember the graph there were small set of people who had a lot of mayorships, and a

large set of people who had less number of mayorships, so that is the kind of general social media behavior also.

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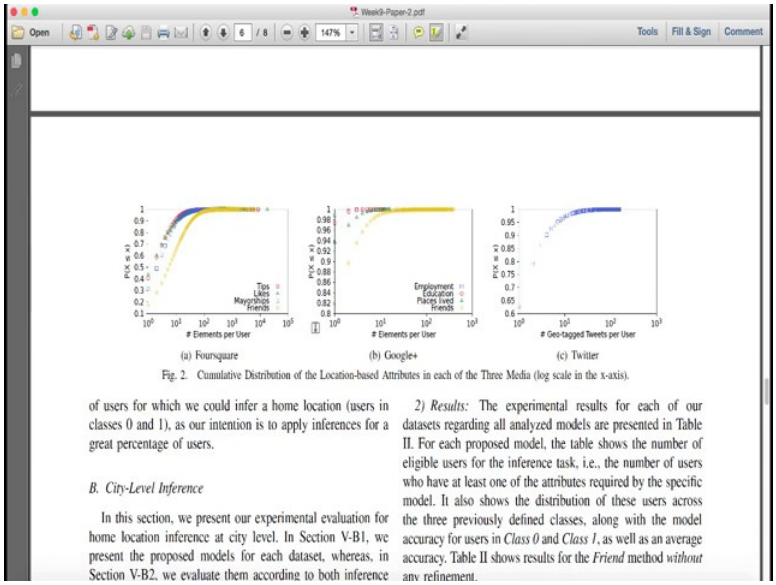

So, let us look at figure 2(a), which is giving you the distribution of the number of mayorships, tips and dones. So, if you see here, the figure 2(a) is giving you the cumulative distribution of location based attributes in each of the three media; a is for Foursquare, b is for Google plus and c is for Twitter. Given that Twitter has all of them as geo tagged you can clearly seen there is only one line, whereas in the other one there is, friends, mayorships, likes and tips that is in the Foursquare; in Google plus – employment, education, places lived and friends right. So, this is the graph and you can clearly see the graph is very similar to what we have seen in the past in terms of social media data.

So, clearly all three distributions are heavy-tailed (Refer Time: 19:31) which is what I just now said which is social media looking data, since most users tend to have few mayorships whereas a few users have very active considering these attributes. The curves are very similar and shows that each attributes 90 percent of the users considered have up to 10 mayorships right. So, it is the same principle Pareto principle that we talked about a power law that we talked about in the course all of that is playing into this data also. And this is very, very important to show because the reviewers and the readers can actually

believe that this data is actually representative of other social media research that has been done and analysis that has been done.

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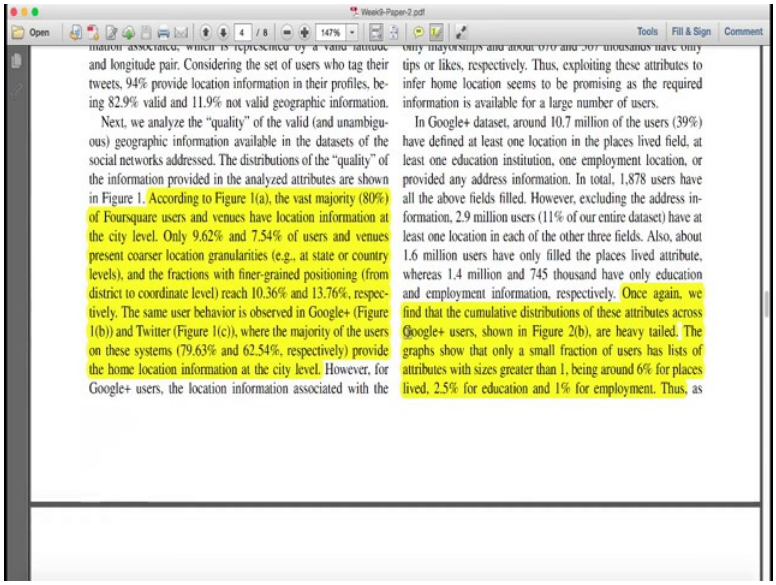

and longitude pair. Considering the set of users who tag their tweets, 94% provide location information in their profiles, being 82.9% valid and 11.9% not valid geographic information.

Next, we analyze the "quality" of the valid (and unambiguous) geographic information available in the datasets of the social networks addressed. The distributions of the "quality" of the information provided in the analyzed attributes are shown in Figure 1. According to Figure 1(a), the vast majority (80%) of Foursquare users and venues have location information at the city level. Only 9.62% and 7.54% of users and venues present coarser location granularities (e.g., at state or country levels), and the fractions with finer-grained positioning (from district to coordinate level) reach 10.36% and 13.76%, respectively. The same user behavior is observed in Google+ (Figure 1(b)) and Twitter (Figure 1(c)), where the majority of the users on these systems (79.63% and 62.54%, respectively) provide the home location information at the city level. However, for Google+ users, the location information associated with the

tips or likes, respectively. Thus, exploiting these attributes to infer home location seems to be promising as the required information is available for a large number of users.

In Google+ dataset, around 10.7 million of the users (39%) have defined at least one location in the places lived field, at least one education institution, one employment location, or provided any address information. In total, 1,878 users have all the above fields filled. However, excluding the address information, 2.9 million users (11% of our entire dataset) have at least one location in each of the other three fields. Also, about 1.6 million users have only filled the places lived attribute, whereas 1.4 million and 745 thousand have only education and employment information, respectively. Once again, we find that the cumulative distributions of these attributes across Google+ users, shown in Figure 2(b), are heavy tailed. The graphs show that only a small fraction of users has lists of attributes with sizes greater than 1, being around 6% for places lived, 2.5% for education and 1% for employment. Thus, as

Also if you see 2(b), again it's describing all the different social networks; figure 2(b) is showing you for Google plus the graph shows that only a small fraction of users has list of attributes with sizes greater than one being around 6 percent of places lived 2.5 percentage of education and 1 percent of employment.

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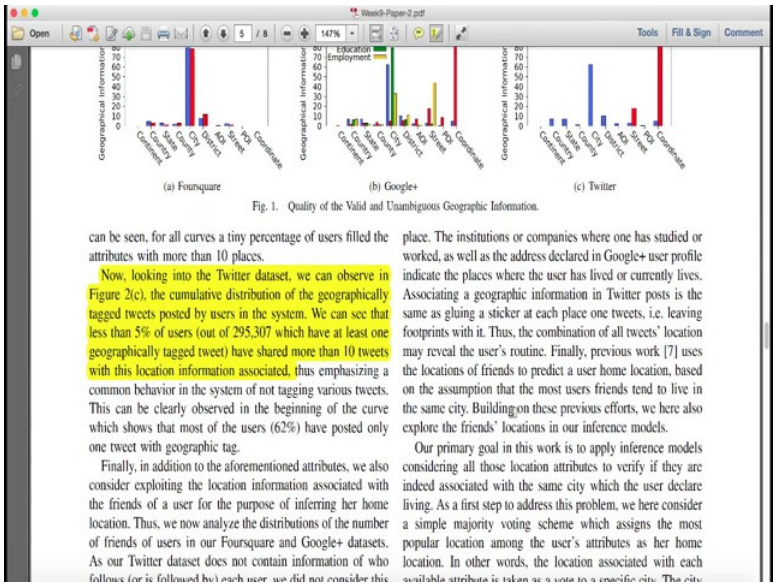

(a) Foursquare (b) Google+ (c) Twitter

Fig. 1. Quality of the Valid and Unambiguous Geographic Information.

can be seen, for all curves a tiny percentage of users filled the attributes with more than 10 places.

Now, looking into the Twitter dataset, we can observe in Figure 2(c), the cumulative distribution of the geographically tagged tweets posted by users in the system. We can see that less than 5% of users (out of 295,307 which have at least one geographically tagged tweet) have shared more than 10 tweets with this location information associated, thus emphasizing a common behavior in the system of not tagging various tweets. This can be clearly observed in the beginning of the curve which shows that most of the users (62%) have posted only one tweet with geographic tag.

Finally, in addition to the aforementioned attributes, we also consider exploiting the location information associated with the friends of a user for the purpose of inferring her home location. Thus, we now analyze the distributions of the number of friends of users in our Foursquare and Google+ datasets. As our Twitter dataset does not contain information of who

place. The institutions or companies where one has studied or worked, as well as the address declared in Google+ user profile indicate the places where the user has lived or currently lives. Associating a geographic information in Twitter posts is the same as gluing a sticker at each place one tweets, i.e. leaving footprints with it. Thus, the combination of all tweets' location may reveal the user's routine. Finally, previous work [7] uses the locations of friends to predict a user home location, based on the assumption that the most users friends tend to live in the same city. Building on these previous efforts, we here also explore the friends' locations in our inference models.

Our primary goal in this work is to apply inference models considering all those location attributes to verify if they are indeed associated with the same city which the user declare living. As a first step to address this problem, we here consider a simple majority voting scheme which assigns the most popular location among the user's attributes as her home location. In other words, the location associated with each

If you look at the Twitter data, we can observe that figure 2(c), the cumulative distribution of geographically tagged tweets posted by users in the system. We can see that less than 5 percent of the users have shared more than 10 tweets with this location information associated, which is again small percentage of people doing location information sharing, more than 10 tweets with the location associated with them.

Also now let us get into inferring location. The methodology that this paper uses is very same to the last methodology, which is written in this paragraph. We group users into three classes, class 0 consists of users who have only one vote that is only one location information that is predominant, and that is only one. Thus, allowing only a unique option to be assigned for the user's home city. Class 1 contains the user who has multiple votes with the predominant location across them.

And the class 2 as we have seen in the last paper also consists of users with multiple votes in which there is no single location that stands out. So, three categories of classes three classes that they are made 0, 1 and 2. We will see the table with 0, 1 and 2 that lets this locate the how the data was collected, how the analysis was done, how the bucketing was done. The results of our experimental evaluation are assessed using two metrics which measure the effectiveness of the proposed model. Accuracy is the fraction of correct inferences of users of class 0, or class 1, right yet again there are (Refer Time: 22:58) the current thing with class 2 will not work.

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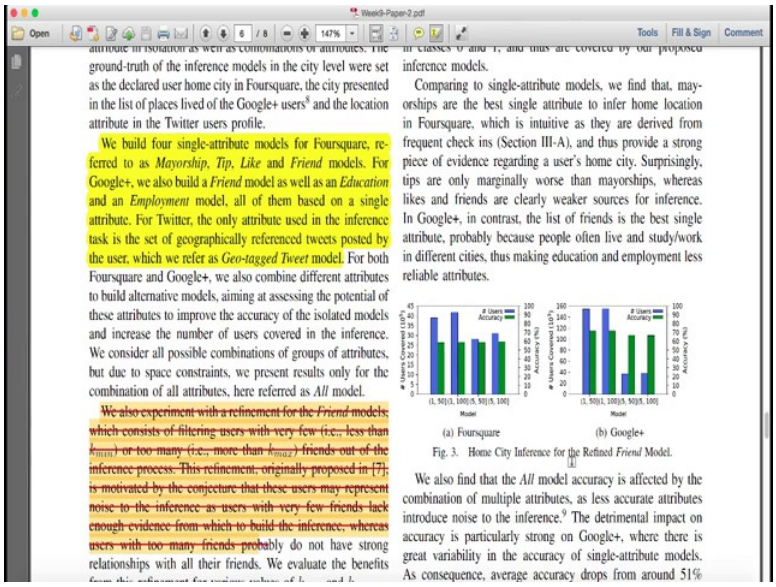

So, the model that was built was four single-attribute models for Foursquare, referred to as mayorship, tip, like and friends. For Google plus, friend model and education and employment model all of them based on single-attribute. For Twitter, the only attribute used in the inferences task is the geo tagged location right. So, basically this explains what details were used in collect and making the inference about the location.

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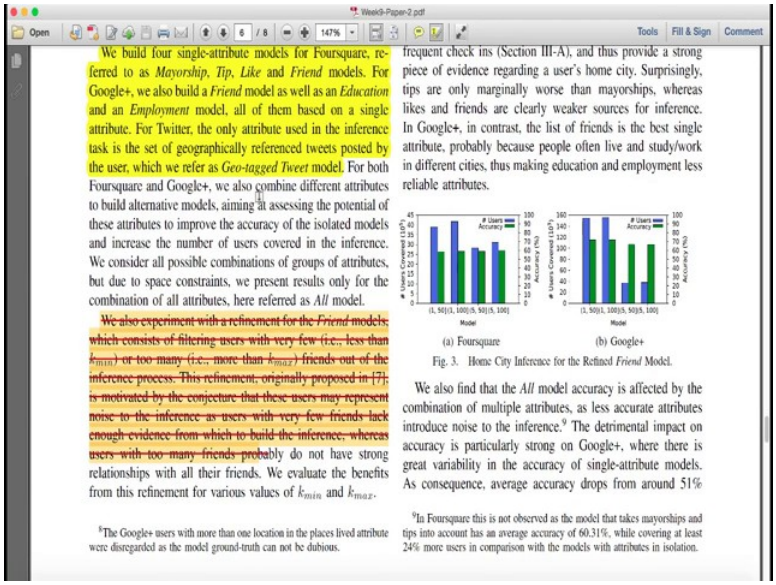

Also this is also information we also experiment with the refinement of the friends' model which consists of filtering users. So, another way just think about the another way of looking at the friends model is the use the friends from that location to make the decision, so that is filtering with a very few, less than k kilometers, or too many that is more than k max friends out of the inference process.

The refinement originally proposed is motivated by the conjecture that these users may represent noise to the inference as users with few friends lack enough evidence for which to build the inference, whereas users with too many friends probably do not have strong relationships with all their friends. It is basically saying that we build a model where we take the users with very few, less than few kilometers; because they are not going to be connected. A lot of friends who may be connected from that location also will not lead a lot of information.

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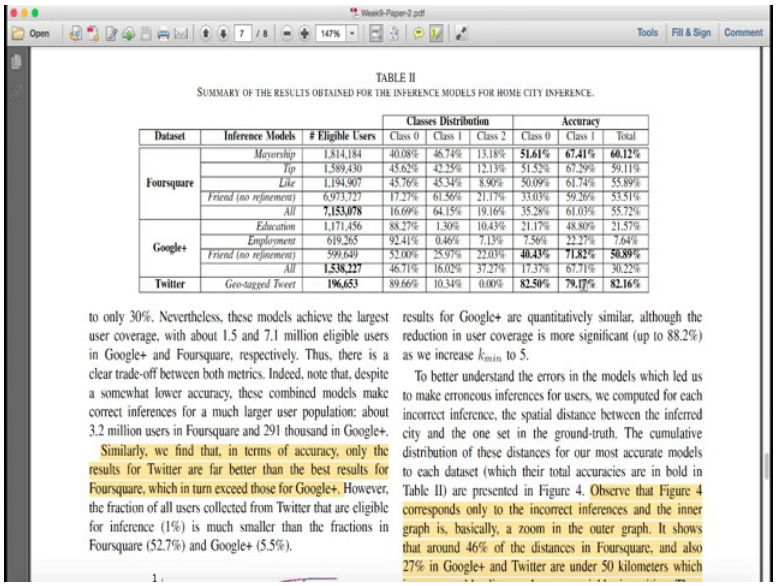

TABLE II
SUMMARY OF THE RESULTS OBTAINED FOR THE INFERENCE MODELS FOR HOME CITY INFERENCE.

Dataset	Inference Models	# Eligible Users	Classes Distribution			Accuracy		
			Class 0	Class 1	Class 2	Class 0	Class 1	Total
Foursquare	*Mayorship*	1,814,184	40.08%	46.74%	13.18%	**51.61%**	**67.41%**	**60.12%**
	Tip	1,589,430	45.62%	42.25%	12.13%	51.52%	67.29%	59.11%
	Like	1,194,907	45.76%	45.34%	8.90%	50.09%	61.74%	55.89%
	Friend (no refinement)	6,973,727	17.27%	61.56%	21.17%	33.03%	59.26%	53.51%
	All	**7,153,078**	16.69%	64.15%	19.16%	35.28%	61.03%	55.72%
Google+	*Education*	1,171,456	88.27%	1.30%	10.43%	21.17%	48.80%	21.57%
	Employment	619,265	92.41%	0.46%	7.13%	7.56%	22.27%	7.64%
	Friend (no refinement)	599,649	52.00%	25.97%	22.03%	**40.43%**	**71.82%**	**50.89%**
	All	**1,538,227**	46.71%	16.02%	37.27%	17.37%	67.71%	30.22%
Twitter	*Geo-tagged Tweet*	**196,653**	89.66%	10.34%	0.00%	**82.50%**	**79.17%**	**82.16%**

to only 30%. Nevertheless, these models achieve the largest user coverage, with about 1.5 and 7.1 million eligible users in Google+ and Foursquare, respectively. Thus, there is a clear trade-off between both metrics. Indeed, note that, despite a somewhat lower accuracy, these combined models make correct inferences for a much larger user population: about 3.2 million users in Foursquare and 291 thousand in Google+.

Similarly, we find that, in terms of accuracy, only the results for Twitter are far better than the best results for Foursquare, which in turn exceed those for Google+. However, the fraction of all users collected from Twitter that are eligible for inference (1%) is much smaller than the fractions in Foursquare (52.7%) and Google+ (5.5%).

results for Google+ are quantitatively similar, although the reduction in user coverage is more significant (up to 88.2%) as we increase k_{min} to 5.

To better understand the errors in the models which led us to make erroneous inferences for users, we computed for each incorrect inference, the spatial distance between the inferred city and the one set in the ground-truth. The cumulative distribution of these distances for our most accurate models to each dataset (which their total accuracies are in bold in Table II) are presented in Figure 4. Observe that Figure 4 corresponds only to the incorrect inferences and the inner graph is, basically, a zoom in the outer graph. It shows that around 46% of the distances in Foursquare, and also 27% in Google+ and Twitter are under 50 kilometers which

So, this table is the most important analysis or inference from this paper which is to see the summary of results obtained for inference models for a home and home city inference. Remember, we did for three networks - Foursquare, Google plus and Twitter, the inference models that was used for mayorships, tip, like, friend all, education, employment, friend all geo tagged tweets.

Classes distributed 0, 1 and 2; classes 0 and 1 are the only two things that can be done with this data(Refer Time: 25:45), so it is done 51. So, the way to read it is that just using mayorship, in the class 0, 51.61 percent you can identify the home city for that particular user in the category who has Foursquare account and mayorship data. Class 1, 67 percent; class 1 is basically there are multiple locations, one being predominant. Google plus, the highest seems to be with friend, no refinement; and in tweets, it is since the geo located the accuracy is also being more than anything else.

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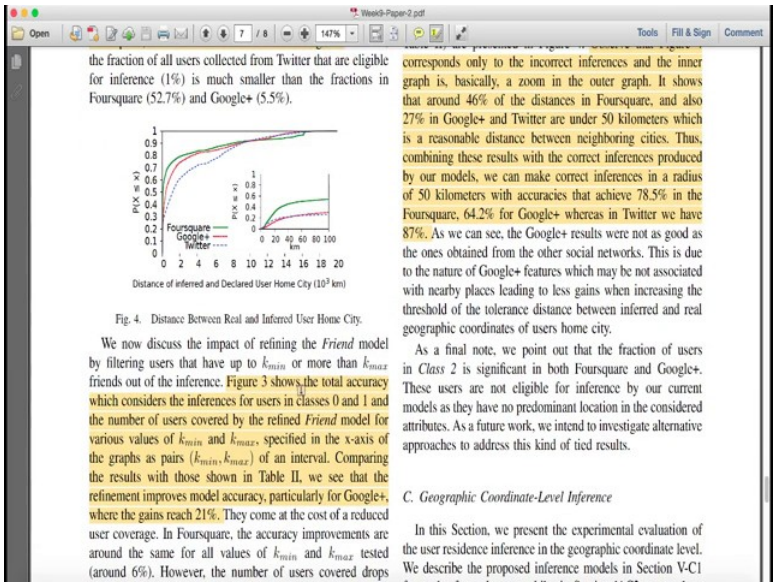

So, you can that is what I have said the accuracy for the Twitter seems to be higher than the rest of it. Let us look at figure 3, and then we will go back to the description of it. So, if you look at figure 3, figure 3 shows the total accuracy which considers the inferences for users in class 0, and 1. And the number of users covered by the refined friend model, for the various values of k min and k max specified in the x-axis of the graph. Often comparing the results with those in table 2, we see that the refinement improves model accuracy particularly for Google plus where the gain is about 21 percent.

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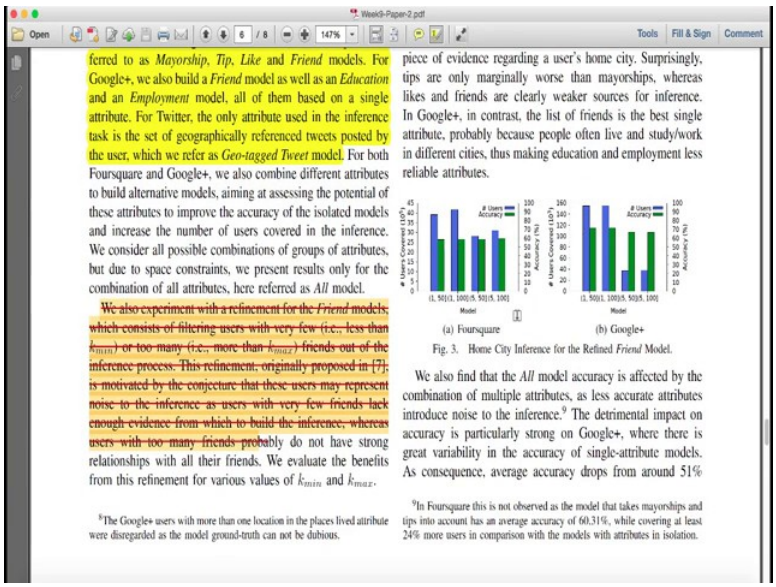

So, essentially this is x-axis is the model that was used within the kilometers and y-axis is the percentage of users that were covered. So, if you see Google plus there is if you will infer the home city for a refined friend model, which is what we said where the min and the max were removed Google plus seems to be doing much better than the added advantage of removing these friends is higher for Google plus compare to Foursquare. That is the inference there.

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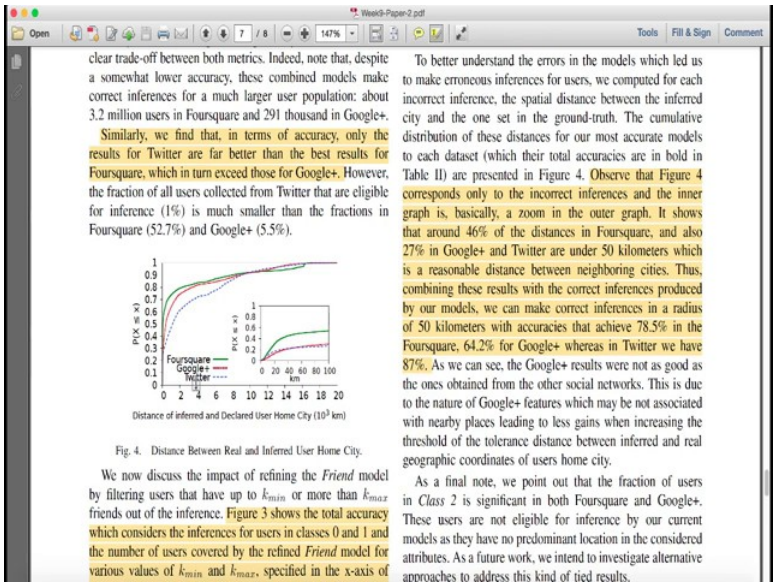

See there is another interesting inference, similar graph we saw on the last paper also. There we saw only for Foursquare; here we are seeing it for Foursquare, Google plus and Twitter. Figure 4, corresponds only to the incorrect inferences and the inner graph is basically zoomed into the outer graph. It shows that 46 percent of the distances in Foursquare, and also 27 percent in Google plus, and Twitter are under 50 kilometers. So, that is what is this here 50 kilometers is this part of the inside graph. 50 kilometers is reasonable distance between neighboring cities.

Thus combining these results with the correct inference produced we can make correct inferences in a radius of 50 kilometers with the accuracies that achieves 78.5 percent in Foursquare, 64 in Google plus and 87 in Twitter, which are the things that we saw in the table earlier. This is the representation in the graph which is x-axis is the distance of inferred and declared home city which is something that I declared. And something we were able to my account PK ponguru account has a location and I inferred through the

process the location what is the distance between these two, the lower the difference the better.

The inside graph is just showing you assumed immersion which shows that about 50 kilometers we were able to get about 46 percent, where if you see here, 50 percent and if this is about 46 percent. So, they just shows you that we are able to actually identify 46 percent of the distance in Foursquare is actually less than error of 50 kilometers, which is just neighboring cities, neighboring places, or sometimes it could be just in the same city.

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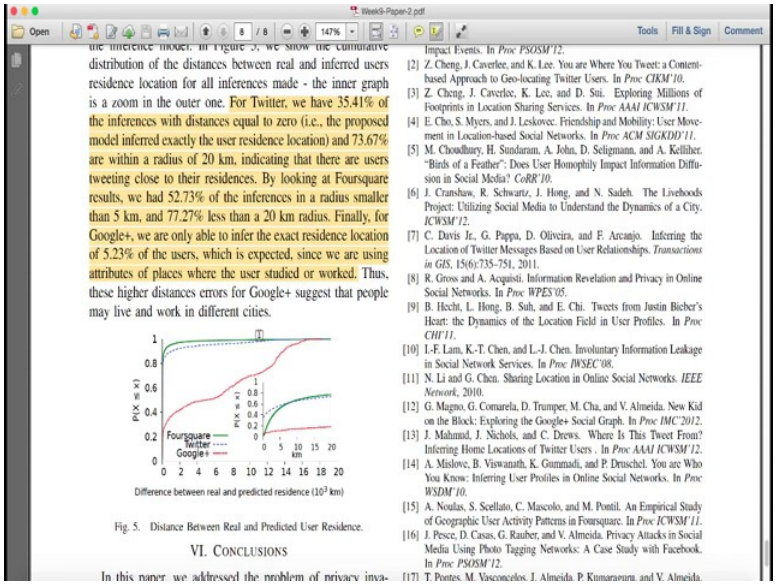

So, now the same thing you can actually do it for the residence right. Now what we did in this graph is basically showing you only the home city, whereas this graph is actually showing you the home residence. So, here is the graph for residence; red is Google plus; blue is Twitter; and green is Foursquare. You can see the inside the graph also here which is from 0 to 20 kilometers, whereas this is 0 to 20, but they are all ten to the power of 1000 kilometers is the distance here.

So, you can see that for Twitter we have 35 percent, where is Twitter, so Twitter is blue line, blue line is here, 35 percent of the inferences with distance equal to 0. So, that is the starting point here if you see, that is the proposed model inferred exactly the user residence. And the reason why this is so high and this is so accurate is because, we are, tweets were collected which were actually geo tagged right. And 73.67 percent are within the 20 kilometers radius.

So, if we see here this is 20 kilometers and if we see the blue line it is here that is about 76 percent, 73 percent, which is within the 20 kilometer difference, we were able to find out where the home is which is pretty good. Indicating that that there are users tweeting close to their residences, because I could be living in Okhla, I could be tweeting from somewhere near Jawaharlal Nehru Stadium in Delhi which is less than 20 kilometers, I went to watch a match and I actually posted tweet which is also geo tagged, so that is the kind of 20 kilometers that we can get.

By looking at Foursquare results, we find that Foursquare is green. We find that 52 percent of the inferences in the radius smaller than 5 kilometers. So, if you see here green one, if you go at that point it is about 52 percent, 52.73 percent less than 5 kilometers; 77 percent less than 20 kilometers, that is here, 77 percent. Finally, for Google plus, we are only able to infer the exact residence of 5.23 percent of the users, which is expected since we are using attributes of places where the user studied or worked, because here we are only using their employment and education details right.

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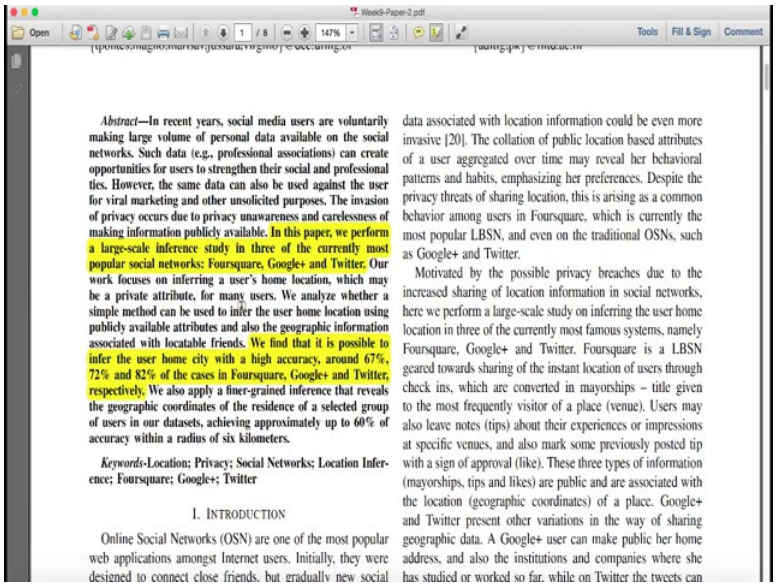

Abstract—In recent years, social media users are voluntarily making large volume of personal data available on the social networks. Such data (e.g., professional associations) can create opportunities for users to strengthen their social and professional ties. However, the same data can also be used against the user for viral marketing and other unsolicited purposes. The invasion of privacy occurs due to privacy unawareness and carelessness of making information publicly available. In this paper, we perform a large-scale inference study in three of the currently most popular social networks: Foursquare, Google+ and Twitter. Our work focuses on inferring a user's home location, which may be a private attribute, for many users. We analyze whether a simple method can be used to infer the user home location using publicly available attributes and also the geographic information associated with locatable friends. We find that it is possible to infer the user home city with a high accuracy, around 67%, 72% and 82% of the cases in Foursquare, Google+ and Twitter, respectively. We also apply a finer-grained inference that reveals the geographic coordinates of the residence of a selected group of users in our datasets, achieving approximately up to 60% of accuracy within a radius of six kilometers.

Keywords-Location; Privacy; Social Networks; Location Inference; Foursquare; Google+; Twitter

I. Introduction

Online Social Networks (OSN) are one of the most popular web applications amongst Internet users. Initially, they were designed to connect close friends, but gradually new social data associated with location information could be even more invasive [20]. The collation of public location based attributes of a user aggregated over time may reveal her behavioral patterns and habits, emphasizing her preferences. Despite the privacy threats of sharing location, this is arising as a common behavior among users in Foursquare, which is currently the most popular LBSN, and even on the traditional OSNs, such as Google+ and Twitter.

Motivated by the possible privacy breaches due to the increased sharing of location information in social networks, here we perform a large-scale study on inferring the user home location in three of the currently most famous systems, namely Foursquare, Google+ and Twitter. Foursquare is a LBSN geared towards sharing of the instant location of users through check ins, which are converted in mayorships – title given to the most frequently visitor of a place (venue). Users may also leave notes (tips) about their experiences or impressions at specific venues, and also mark some previously posted tip with a sign of approval (like). These three types of information (mayorships, tips and likes) are public and are associated with the location (geographic coordinates) of a place. Google+ and Twitter present other variations in the way of sharing geographic data. A Google+ user can make public her home address, and also the institutions and companies where she has studied or worked so far, while on Twitter the tweets can

So, that is how this paper ends, which is to show that let us go to the abstract again, which is to show that they used they used data from Foursquare, Google plus and Twitter. They used this data to infer the home location. This is an extension or the next step for the last paper that we saw which was done only on Foursquare. And they were able to actually show that about 67, 72 and 82 percent with that accuracy they were able

to find out the home city, and home location, for, with a high accuracy in terms of Twitter and then Foursquare, but with less data in a Google plus.

With that, I will stop this particular paper. I will see you soon.