Predictability of Human Mobility from Highly Granular Location Data

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Summary

TODO - The goals of this thesis is to..

Preface

This thesis was prepared at the department of Informatics and Mathematical Modelling at the Technical University of Denmark in fulfilment of the requirements for acquiring an M.Sc. in Informatics.

The thesis deals with ...

The thesis consists of ...

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I would like to thank my....

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CHAPTER 1

Introduction

TODO

CHAPTER 2

Related work

There is a high interest and a huge amount of work the scientific community dedicates to understanding the patterns of human mobility. The knowledge we can gain from the results of this work has the potential to benefit a wide variety of industries from the modeling and maintenance of the transportation infrastructe, to the medical industry where we can use this knowledge in trying to prevent the spreading of epidemies. [DB08]

Various studies have been conducted in order to gain a better understanding of the human mobility patters. These studies give us results that seem to support each other in the idea that people are less spontaneous than they would like to think themselves and that, indeed, our behaviour shows that we are quite rooted into habbits when it comes to the way we travel.

2.1 Mobility patters uncovered by the disipation on bank notes

Brockmann, Hufnagel and Geisel[DB06] have analyzed the human movement based on the way bank notes were dispersed through the United States (excluding Alaska and Hawaii). Their study shows that a relatively small percentage

of bank notes (23.6%) traveled for more than 800 km, while a fraction of 19.1% did not traveled for more than 50 km even after a year of being observed. The possible explanation the authors have given for these findins are that, in general, people would be less inclined to leave the areas of the large cities or the places they usually conduct their lives.

The problem identified with this approach for tracking individuals is that the bank notes exachange hands and the behaviour which is identified by the way they circulate can't be attributed to a single individual, but rather to different ones that at any moment have had the bank note in their posession. Despite this, the result have a high scientific value as they do identify patterns in human travel behaviours in general.

2.2 Mobility patterns of mobile phone users

A. L. Barabasi, M. C. Gonzalez and C. A. Hidalgo have conducted a study [MCG08] that deals with studying the trajectories of over 100000 mobile phone users with anonymized identities. The study was conducted in order to see if there are any patterns in our mobility habbits. Among the things that have been subjected to testing was the return probability of individuals in the same place as in the past. The study shows there is, in general, a peak in the return probability after 24, 48 or 72 since they have left a particular location. This shows that we humans tend to visit locations periodically. This can be explaineQd by our going to places such as work, school, grocery shops near our home etc.

The authors have also ranked the locations the mobile phone users frequented based on the number of times they have been spotted nearby. The results for this have shown that the probability of finding someone near a location that is ranked for them with a level L can be estimated with $1/L$. Another interesting finding that is mentioned in the paper is that, in general, people seem to be spending the majority of their time in just a few locations, while diving the remaining time just between a limited number of locations that varies for the subjects from as low as 5 to around 50.

There are some note worthy plots that the authors present in the paper. They can be seen in figure and they show that most people travel over short distances, yet there is a small number of people that regularly travel over big distances.

The results of this study are a major indicator that individuals display a high level of regularity and that we have a tendency to spend most of our times in places that are familiar to us, or that require us to visit them regularly (e.g.

home, work).

2.3   Mobility patterns in massive multiplayer online games

R. Sinatra and M. Szell have studied the way in which users of a massive multiplayer online game behave inside the virtuale universe provided by the mentioned game [RS14]. It has been established that the massive multiplayer games provide people with a virtual reality where they can interact with others through their characters and can, in fact, form groups and, as such, display both individual as well as collective behaviour actions that can translate to the non-virtual world [Bal03].

This study gives an interesting insight into the habbits and actions of the characters which are controlled by the players. Among the things the authors have analyzed are the predictability of the characters, the entropy generated by the mobility of the characters in the virtual universe and general strategies or patterns that could be observed.

The game the authors have been using for the study is called Pardus [Par]. This game is quite complexe, as it allows the manifestation of normal real-life activities such as the creation of alliances or friendships, communication between the players, economic related action, or even actions which have a negative conotation such as attack of another user, removal of a friendship link etc. The universe of the game consists in hundrets of nodes which represent cities or sectors in the game. These virtual cities are tied to each other through links which mark the posibility for the users to move their characters from one place to another.

By analyzing the why in which characters have interacted through the years, the authors have observed that the mobility of the characters through the univers is highly predictable, as users in general will seem to be chosing a random location to visit next in just about 10% of the cases.

2.4   Eigenbehaviours

N. Eagle and A. S. Pentland analyze data of individulas and communities with the purpose of trying to predict and cluster the daily habbits and behaviour of

people [NE09]. The consider that the behaviour of one person throughout a day can be close to a sum of their primary eigenbahaviours throughout that day. The results of the study have shown that when having a weighted sum calculated for the first half of a day, the behaviour of the same person throughout the remaining of the day can actlully be approximated with 79% accuracy.

The results have applicability in more fields, as they allow us to consider the possibility of clustering people into various communities based on the similarity of their behaviours. It goes even further, as the findings show that this enables the possibility of calculating similarity for groups as well and thus permiting the a classification that, according to the experiment, can be 96% accurate for determining affiliations in the social network of a particular population.

As a last observation in the paper by N. Eagle and A. S. Pentland it is stated that eigenbehaviours can be used in order to identify the possible friendship ties between people. The observations in this paper have been done based on the Reality Mining dataset that tracked the behavior for 100 individuals at MIT for the duration of one year.

2.5   Human movement recorded through real traces

Studies as the ones with the travel of bank notes or the recorded location of mobile users through telephone is not very exact and does not reflect the real traces for the people. They do provide a very useful estimation, however with the technology that we have access to nowadays, we are able to record mobile phone users' real traces either through GPS or Wifi. The data that can be acquired through these means allows us to conduct studies that can take into consideration a very good approximation of the real location of individuals.

In the paper by M. Kim, D. Kotz and S. Kim [MK06], the authors present us with a method in which the locations of users can be estimated based on the WiFi signals that their devices register. The experiment is conducted cosndiering the data for a duration of 13 months. The user traces that have been used consist of the trace data from the Darmouth College. The mobility traces are defined as the lists of access points that are associated to a user's devices at a given timestamp.

The mobility traces allowed the authors to extract the tracks (locations) of the users. They have explored three methods in which the location can be extracted from the data. The first approach presumed the calculation of the center (intersection of medians) of the traingled defined by the past three access

point associations of the mobile device of the user. This approach has a downside since the devices do not necessarly change the associations in a periodic manner. This lead to the second approach which consisted in considering a time window after which the associations needed to be updated in case new associations have appeared during that time. The thrid and last approach explored the use of Kalman filters [Kal60].

The validation the path extarctors the authors have compared the results with GPS data. This validation has proven that the type of the used device has at the moment a significant importance in how acqurate the results can be as it seems that some devices can be more aggressive in updating the associations with access points while others try to stay associated with the same access points as long as possible before switching to new ones. This leads to problems as different distances between users and access points considered by different devices and as such it affects the estimated paths. The best estimations have been given in this experiment by the approach that used the Kalman filters, however both the other two appraoches have provided fairly good estimations as well.

Another paper which explores the travel patterns from real data is the one written by T. S. Azevedo, R. L. Bezerra, C. A. V. Campos and L. F. M. de Moraes [TSA09]. The authors propose another approach for analyzing the mobility of people. They take into consideration the following movement components: velocity, acceleration, direction angle change and the pause time and they are using the GPS data in order to estimate the locations of individuals. The experiment takes place in a park in Rio de Janeiro and is done based on the data received from around 120 volunteers. The results have shown that people seem to have in general smooth trajectories without abrut changes.

2.6   Entropy and predictability

One step further from understanding the way we travel from place to place is to predict our future locations based on a previous knowledge our our past patterns. There has been an extensive study done in this area of the scientific playground as well and the results which have emerged up until now are remarcable.

In the paper by C. Song, Z. Qu, N. Blumm and A. L. Barabasi [CS10], the authors take up the challenge of studying how predictable people can be. They analyze the mobility patterns of mobile phone users and calculate the entropy of these users. The locations are defined by the telephone towers the users are encountering at hourly intervals and the trajectory of the user is given by the

ordered sequence of these towers. The real entropy of each user i is calculated as $\Sigma_{T_i' \subset T_i} P(T_i') log_2(P(T_i'))$, where $P(T_i')$ represents the probability of encountering a time-ordered subsequence T_i' in the sequence of hourly encountered telephone towers T_i.

The results for this particular study show that, for the considered users, the uncertainty of where they could be at a certain moment, based on the real entropy calculated for them would be very low as they would most probably be in one of two locations.

The authors also take a look into the maximum predictability which can be expected for a user. Their results show that, with the right algorithm, a user's future location can be predicted with between $80 - 93\%$ accuracy. This shows that we are less sponatenous than we might think and that our mobility patterns are, in most cases, rooted into a very well established routine.

There have been numerous other methods or experiments conducted in order to analyze or to forcast human mobility patterns. Some of these methods include the Markov chain models [Ros09] [GL96], the neural networks [SCL03] or the Bayesian networks [AS07] as well as some that work with finite automaton [JP04]. Most of the studies support the idea that people's actions and travel behavior is indeed far from being random and thus the science world needs to dedicate further effort and time in order to use this knowledge in order to improve our quality of life and the world we live in.

Prerequisits and tools

In order to research the way in which people travel we firstly need to have access to a database of information that can be used for this purpose. As it was mentioned in Chapter 2, scientists have been trying in numerous way to identify and work with location information. During our study, we have dedicated our time in working with information about the access points that were visible to the users' mobile phones throught their day. This has allowed use to implement and analyze different ways in which locations can be extarcted from such information.

3.1 SensibleDTU

The data we are using is part of a large-scale study that aims to make observations based on the lives of volunteering students - the Copenhagen Network Study. The data is colected from a variety of sources. Some of them require the volunteers to interact with the system through questionnaires and others track them automatically through their smartphones. The aim of this project is to offer an extensible framework for different studies. The deployments from 2012 and 2013 are based at the Technical University of Denmark and are named SensibleDTU [AS14b].

The students that consented to being volunteers for this ambitious project have received smartphones that are able to track different aspects of their lives and through which they can interact with the system. The big number of volunteers [1] has allowed the gathering of a considerable amount of data regarding the mobile phone users' behaviour.

The data gathered for the SensibleDTU experiment consists in data gathered through questionnaires [2], Facebook data [3], sensor data, qualitative data and Wifi data.

Since the majority of the collected information about the students is sensitive [AS14a], keeping the data secure is and has been a top priority from the beginning of the experiment. The data is annonymzed and stored securely and the students that are part of the experiment have access to tools that allow them to see what data are they sharing, what it is done with this data and that allow them to control how much they want to share.

3.2   Using Wifi data

3.3   Implementation tools

Before starting the work on the present research, we have overviewd possible tools that can be useful in our work.

The scripts that are used for analyzing, transforming and working with the data are developed in Python. The reasons behing using Python instead of any other programming language are numerous. Python is elegant and simple to use, it allows fast development and the code can be easily adapted and reused. Due to its high scalability, it is the perfect choice for both large and small projects, being easily extensible at the same time. Another very important reason for using Python is that there is a large number of libraries that can be used with it and that allow the visualization or handling of big data. [4]

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[1] During the second iteration, there have been deployed aproximately 1000 smartphones to students who wanted to take part in the study.

[2] A survey was presented to the participants in 2012 consisting of over 90 questions. In 2013 an addition of over 300 questions were ask per participant. The questioned targeted different aspects from working habbits and various socio-econimic factors to Big Five Inventory measuring personality traits [JS99] and self-esteem.

[3] Participants have the option of allowing the gathering of Facebook data such as friendships and various interactions such as likes, statuses etc.

[4] Examples of libraries and packages used: numpy, matplotlib, pickle, datetime, sympy etc.

An additional tool that has been used for the present project is Gephi [Gep]. Gephi is a platform that allows the exploration and handeling of various networks and graphs. Further information on how this tool has proven helpfull can be found in Chapter 5.

Data processing

The present project uses data that has been selected from the database of the SensibleDTU experiment. The data is fully anonymized and the users that have been a part of the study have been chosen randomly from the database.

4.1 Statistics

We use the data collected from 131 users from the SensibleDTU database. The students that have been selected for the present study had data collected for a period of almost a year. [1]

The application that is installed on the smartphones of the students who are part of the experiment is configured to scan periodically (around every 15 seconds) for Wifi networks, however, it is also set to record the scans which are triggered by any of the other applications that are present on the mobile phone.

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[1] The starting time of collection for the 2012 deployment of SernsibleDTU is October 1st 2012 and the end is September 1st 2013.

4.2   Wifi and GPS data

For the present study we are not using all the fields that are accessible from the database of collected information. The study's aim is to analyze the predictability and patterns in the human mobility and as such we need information that can help us identify the locations of the users that are part of the study. For this we are accessing fields of the **Wifi information** associated to the selected group of users. The results reagarding the users' locations over time are afterwards compared with locations extracted from **GPS data** and as such we are accessing this information from the database as well.

For working with the Wifi information that is available in order to identify user locations, we extract from the database the fields that can be seen in Tab. 4.1.

user	timestamp	ssid	bssid	rssi	context
1	1349185621	1	1	-75	0
1	1349185685	4	4	-86	0
1	1349185700	5	5	-84	0

Table 4.1: This table shows a few examples of possible data recorded from users

A short explanation for each of the fields can be found below:

- The user (first) field gives us information about what user we are currently observing. The real identities of the users are concealed and replaced by an ID which is unique for each of them.

- The timestamp (second) field gives us information about the moment of time at which the scan occured and for which the information is gathered. The time format is Unix timestamp. [2] This timestamp can be easily manipulated and converted to any other timestamp format in Python by using the datetime module that can be found in the Python Standard Library [PSL].

- The SSID (third) field stands for Service Set Identifier and it represents the unique ID that can be used in order to identify the wireless networks. This identifier is responsible for the correct sending of data when multiple wireless networks overlap.

- The BSSID (forth) field stands for Basic Service Set identifier and it represents the MAC address of a wireless access point.

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[2]The Unix time stamp represents a way in which time can be tracked as the total number of seconds starting from January 1st, 1970 at UTC and a particular date and time.

- The RSSI (fifth) field stands for Received Signal Strength Indication and it represents the strength for a signal picked up by the mobile phone from an access point. The RSSI values in our case are registered as the real signal strength recorded in dBm and are therefore negative values. As such, the signal is stronger when the value recorded for it is closer to 0.

- The context (sixth) field is based in the ssid and it translates to the possibilities presented in Tab. 4.2

context	translation
0	unknown
1	AndroidAP
2	eduroam
3	dtu
4	device
5	eksamen
6	iPhone
7	Bedrebustur (wifi on bus)
8	CommuteNet (wifi on train)

Table 4.2: This table shows the possible contexts for the retrieved Wifi information from the students

4.3 Interferences in Wifi networks

Nowadays, Wifi networks are used for a multiple of activities from web browsing to video viewing and even to voice or text communication between people all over the world. As the useage of this technology is expanding so does the need for an even more reliable provided service. The current issue with the Wifi networks is that they are using the IEEE 802.11 protocol [WLP] that uses the 2.4 GHz Industrial, Scientific and Medical Radio Frequency band [Fli03]. This band is, however, unlicensed which means that various devices (Wifi and non-Wifi alike) can use it. This leads to the apparition of interferences.

The results of the experiment conducted by Mahanti et. al. [MCWA10] show that a variety of factors can affect the Wifi networks transmission and signal strengths. For example, microwave ovens, analog wireless video cameras, analog cordless phones and wireless jammers can have a severe impact on the Wifi operations.

However, the issue that causes the most problems in our data set is the existence of signals that come from access points which can be observed for just a very

short period of time as they or the user quickly move by, or that are sufficiently far away from the device and as such their signal level is very low and they can periodically be missing from the scanned access points in the same location [FBSW08].

4.3.1   Assumptions about noise and initial data cleaning

Before we have started eliminating the noise in our Wifi data, we have made a few assumptions on what is to be considered noise in the date for the present study. The assumptions are as follows:

- Data received from access point that are part of bus or train Wifi networks are to be ignored (meaning entries that have the context number set to 7 or 8). This assumption was made as it would be hard to determine the characteristics of a given location considering the access points present in buses or trains. For example, a person can take different buses which have a come portion of a route, yet the access points identified by the phone would be completely different and thus the locations would be impossible to be matched based only on this information.

- Data received from hot spots created from Android or iPhone devices (entries that have the context number set to 1 or 6) can also be ignored. These access points are most probably mobile and will not be present in the same locations. This means that they are not reliable when defining locations based on the Wifi networks visible to the mobile phones.

- The signal strength of the registered access points can give information about the distance between the device and the access points and as such it can be a factor in determining what access points need to be taken into consideration when computing the locations. The paper by Zhang et. al. [ZF12] presents the POLARIS system that aims to deal with localization based on Wifi and it also deals with eliminated noise or disturbances in the data. They consider that any signal that has the signal strength indication outside the range of -60 to -99 dBm can be catalogued as signal disturbances. However, during our data analysis we have observed that the devices can register signals that have a RSSI value above -60 (which means that the signal is more powerful) and as such, four our data we consider just the lower bound of -99 dBm as a limit for noise. The data registered for access points that have an RSSI value below this one are ignored in order to helps ensure that only the access points who are acceptably close to the device are taken into consideration when trying to determine the location of the user.

4.3.2   Data cleaning

Data cleaning is important as inconsistent or incorrect data might lead to inaccurate conclusions and observations. Considering this, the noise elimination in Wifi data is of high importance. Keeping in mind the previously made assumptions (Section 4.3.1), we have eliminated the entries that did not respect the previously mentioned criteria.

During our work with the data, however, we have observed that there are other cases in which additional problems can appear. These situations have been encountered when dealing with the extraction of the mobile users' locations from the information we have regarding the associations made between their phones and various access points. Some of the algorithms used for computing the locations are very time consuming and as such the presence of unnecessary data can burden even further the analysis causing an exponential increase in the execution time.

The situations in which we can struggle with data that does not give any additional information for the identification of locations and that are not necessarily solved by the noise elimination done based on the assumptions presented in the previous sections are caused by the existence of what we will name *isolated observable access points* [3].

Fig. 4.1 illustrates a possible case in which these access points can cause problems rather than help. As we can see there are 7 access points that have appeared in the mobile phone scans over a period of one day. Let us consider that access point AP1 only appears during two consecutive scans, however, it will be taken into account when computing the locations that can be identified for this scenario. A algorithm will identify location L1 and location L2 as being the same location, yet it would do the same thing in case we ignore AP1 and it would require less time to do so. A bad algorithm might not even consider location L1 and L2 as being the same in case the way in which the fingerprint for the location is calculated in a manner that will attribute a high weight to the difference between the present access points.

The above scenario considers a very small number of access points and a very short period of time. The time gains in eliminating the access point which does not provide so much information in this case would be very small. However,

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[3]We define as isolated observable access points the access points that are visible to the mobile devices for a very short period of time after which they stop being visible for a long period of time.The reason behind the access point not being visible for longer periods of time can be varied, for example: defective access point, the distance between the access point and the user is increasing very fast in the short period of time between scans etc.
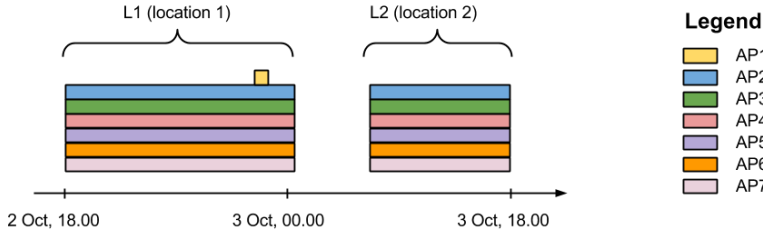
Figure 4.1: Example of an isolated observable access point

If we are, for example, looking at a month of collected data for a user, we will have entries for thousands of different access points that were observable at any moment during this time. Out of these entries there can be hundreds of access points which are never visible to the device during close scans and as such their importance when determining the fingerprints for the different locations is very limited, yet they do have a huge impact on the execution time needed to actually extract the locations.

In order to solve this issue, we eliminate from the access points those ones who are not respecting the following condition:

- There is no time window of at least 5 minutes throughout the time duration of the analyzed data in which the access point has appeared for at least 3 times.

We have chosen to use time windows of 5 minutes as we make the assumption that any user will choose to spend minimum 5 minutes at each stop location. In case the user spend less time, we can consider that they are just transitioning until the next stop location.

CHAPTER 5

Locations

Human mobility has been attracting a high degree of attention from numerous study fields among which we find urban and traffic planning, traffic prediction, the spreading of diseases and many others [AGB13] [DB08].

The studies that have been conducted on this subject have been using various ways to identify the travel behaviour of people. Some of them have focused on studying the information gathered from observing the way in which money is dispersed through time [DB06], or they have been focusing in studying the behaviour of mobile phone users by analyzing the way they move based on the communication towers their phones are connecting to when they are engaging in voice communication [MCG08]. There are studies that try to understand human mobility through the glass of social networks [YYZS10], as it can be observed that individuals prefer to meet with other people that are part of their community more often [MM07]. GPS data has also been considered for various studies [CLL14], [ZG10]. The list of elements that have been taken into consideration for trying to understand and predict the way in which we are conducting our daily travels is far from being short.

5.1   Wifi based positioning

Even from the beginning of the 21st century, research has been actively conducted for trying to use the Wifi system in order to determine real positioning and different databases for positioning systems have been created. These databases usually included the positions of the Wifi access points or RF (radiofrequency) identified fingerprints [CSC$^+$06] [CCLK05] [YA05] [BP00]. Modern databases for Wifi positioning are created with information about the signal strength for the Wifi access points and can even have information about where they were discovered.

Koo et. al. [KC11] have explored an algorithm that can help estimate the relative positions of access points corresponding to the real geographic configuration with the help of multidimensional scaling techniques. Considering the fact that access points are not able to tell real distances between themselves and other access points, the study aims to estimate the dissimilarities between different access points using scans. They have also conducted an experiment in an office building in order to test the proposed algorithm and the results showed an estimation error of approximately 7 m.

Another study conducted in this similar direction is the one by Mok et. al. [MR07]. The authors explore the possibility of determining the location of a device which can scan Wifi access points based on the signal strength that the access points are displaying at the moment of the scan. They estimate the positioning by performing a trilateration based on the information the device gets from multiple access points. The accuracy for their algorithm for the conditions that were present in their experiment was of about $1 - 3$ m.

Athanasiou et. al. [AGGP09] give a very clear and concrete description for two classes of wireless positioning systems. Their work focuses on experimenting with parameters for these algorithms in order to find the optimal solution in terms of accuracy under realistic settings. They also adapt a global map matching algorithm in order to extract travel time maps from wireless data and they propose a demonstration for showing that for high sampling frequencies, the locations identified are comparable to the ones derived from GPS data.

The two classes of algorithms that are explored by the authors are: centroid and fingerprinting. *Centroid* is presented as the fastest method for positioning, however it depends on having the real location of the access points. This information is in general unavailable and as such a proposed solution is to estimate the locations of the access points by calculating an arithmetic mean of all the coordinates at which it was visible. The *fingerprinting* method is based on the assumption that the access points are stable over time (they do not change po-

sitions). This leads to the fact that at any time, a measurement at a particular location will return the same list of access points with the same signal strengths. As such, this list can be considered as the unique fingerprint of the location.

Zhang et.al. [ZF12] propose an algorithm based on fingerprinting for estimating locations that takes into consideration the fact that the signal strength from various access points does not necessarily stay constant throught the time. They propose a way in which a similarity between fingerprints can be calculated in order to determine if two fingerprints are in fact representing the same location.

These are just a selection of works that have been conducted on finding a solution for Wifi based positioning systems. With the growth and improvement of Wifi systems, in time all barriers can be overcome and we could have a positioning system that is as accurate yet considerably cheaper than GPS positioning systems.

5.2 Determining the fingerprint of a location

In order to have a better understanding about the way in which the mobile phone users have been moving throughout the experiment, we needed to have an image of the way a given period of time would look based on their Wifi records from SensibleDTU. As it has been presented in Section 4.2, the Wifi data we are using for the present project consists in the following fields: user id, timestamp, SSID, BSSID, RSSI and the context. However, considering the amount of data involved, just by looking through the log files it is almost impossible for us to understand at what moment the user might have reached a location and when did they leave from it. In order to be able to do this, we have created various visualizations considering different options, different time frames and for multiple users in order to begin to understand what the data can tell us, what can we use, what would we need and what can we discard when moving further to defining what makes a location.

5.2.1 Signal strength over time

The first thing that we have tried to visualize was the access points (APs) that were scanned by users' mobile phones throughout different periods of time. We have plotted the APs and their registered signal strength for varied users in order to see if we notice any patterns in their movements.

In Fig. 5.1 we can see how a day from the life of a random user (referred to as userX) looks like. The day for which we have plotted the data started on a Tuesday at $12:15$ pm and ends the next day right before the same hour. The hourly intervals can be seen on the x axis, while the signal strength values can be seen on the y axis. The legend contains the top 10 most popular [1]
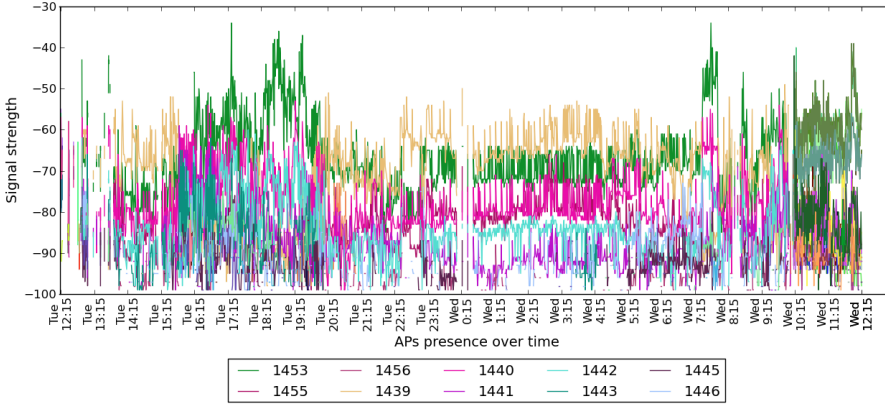
Figure 5.1: Example of the APs registered for an user throughout one day (using connecting lines markers)

The steps for creating this type of visualization are as follows:

- Retrieve data for the time duration for which the visualization is made

- Keep track of all the timestamps at which each AP has been seen and the AP's signal strength at that moment

- In case an AP is scanned no more than 2 minutes after a it was previously scanned, then a line can unite the two moments in order to mark their proximity. If the apparitions are more than 2 minutes apart there is a high possibility that there has been a location change or that the AP is experiencing technical problems and as such has stopped being active.

Although we have tried to visualize this type of information in various ways (using different types of markers), we found that this way is the easiest to interpret by people. If we leave out the lines, for example, as it can be seen in Fig. 5.2, it is quite hard to interpret where location might start or stop.

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[1] An AP is more popular than another in case it appears more times during the period of time for which the Wifi scans are analyzed
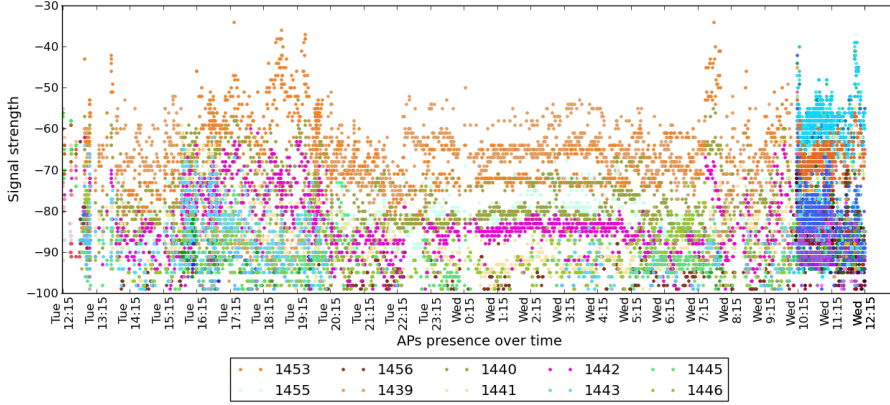
Figure 5.2: Example of the APs registered for an user throughout one day
(using point markers)

Other ways in which we have been experimenting with visualization for this can
be found in the Appendix

By looking at Fig. 5.1 we are at some level able to distinguish moments of time
at which the user seems to be arriving at a location [2], however is is hard to nice
any patterns because we are only observing a single day in the life of userX.

Let us look at the data gathered through 7 days from another user's (referred
to as userY) life. The visualization for this data can be seen in Fig. 5.3. The
image gives out some very interesting information. We can, for example, notice
the repeating patterns which are dominated by the orange, light green and blue
colors. These patterns appear during the evening and the night and we can
assume that the user is spending this time at the location which we can label
"home".

We can notice some periods of time that are free. These free gaps like, for
example, from Monday morning until Monday evening are gaps in which no
signal was scanned and can mean that either the mobile phone was closed or
that the user decided to switch off the Wifi.

We can also notice fragments in which the density of signals is quite high, for
example on Wednesday morning. This means that the user was located in a
place which has a large number of APs near and since we can notice a regularity

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[2]For example, we can say that what we notice from Wednesday at 10:15 until the same
day at 12:15 is different than anything we can see before that time so we can assume that it
is a new location.
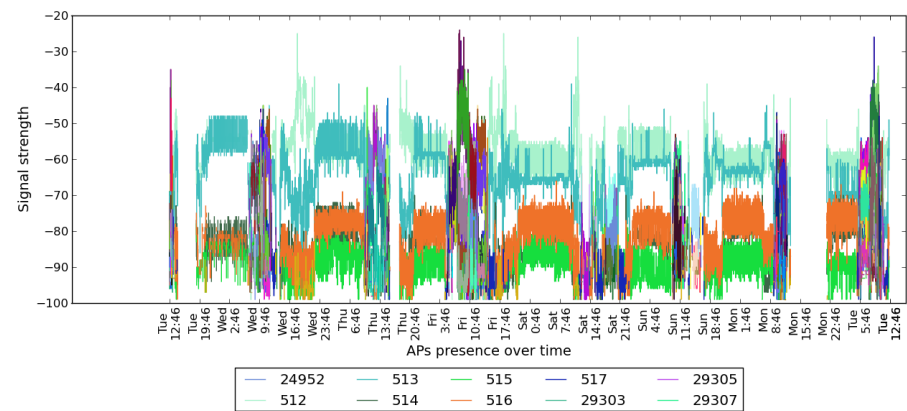
Figure 5.3: Example of the APs registered for an user throughout 7 days

in this pattern we can assume that this place can be the University. This might seem unlikely based on the fact that the patterns sometimes is identified during the night, however this particular week is set in October when there are deadlines for school projects that need to be handed in.

As we can see, these visualization can offer us a good first glance at what the locations might be like, however, they also raise some interesting questions. For example:

- Can the spikes in the signals cause any problems in determining locations?

- Does the sample density give us additional useful information for extracting the locations?

5.2.2 Sample density

5.2.3 Average signal strength

5.2.4 Running average signal strength

5.2.5 Signal presence

5.3 Extracting locations

5.4 Location matching

1. analazying what can determine a location fingerprint

   - Plot access points' presence over time considering their signal strength
   - Plot number of samples of each access point over time
   - Plot the average signal strength for various time windows for each access point identified for a user
   - Plot the running average signal strength for 2,5 and 10 min time windows for each access point identified for a user
   - Plot of access point presence in time bin (5 mins used for time bin) without considering its signal strength

2. identifying locations

   - Networks
   - Hidden Markov Models
   - Further improvements (data cleaning)

3. matching locations locations

   - Percentage similarity
   - Keeping track of previous locations
   - Creating fingerprints

4.

CHAPTER 6

Entropy and predictability

1. Calculating entropy for users

2. Calculating predictability for users

3. Observations

CHAPTER 7

Comparing results with GPS data

CHAPTER 8

Results and observations

CHAPTER 9

Future work

CHAPTER 10

Conclusions

Appendix

Appendix ...

Bibliography

[AGB13]   Fereshteh Asgari, Vincent Gauthier, and Monique Becker. A survey on human mobility and its applications. *CoRR*, abs/1307.0814, 2013.

[AGGP09]   Spiros Athanasiou, Panos Georgantas, George Gerakakis, and Dieter Pfoser. Utilizing wireless positioning as a tracking data source. In *Advances in Spatial and Temporal Databases*, pages 171–188. Springer, 2009.

[AS07]   Sherif Akoush and Ahmed Sameh. Mobile user movement prediction using bayesian learning for neural networks. In *Proceedings of the 2007 international conference on Wireless communications and mobile computing*, pages 191–196. ACM, 2007.

[AS14a]   Alex Pentland David Lazer Sune Lehmann Arkadiusz Stopczynski, Riccardo Pietri. Privacy in sensor-driven human data collection: A guide for practitioners. *CoRR*, abs/1403.5299, 2014.

[AS14b]   Piotr Sapiezynski Andrea Cuttone Mette My Madsen Jakob Eg Larsen Sune Lehmann Arkadiusz Stopczynski, Vedran Sekara. Measuring large-scale social networks with high resolution. *CoRR*, abs/1401.7233, 2014.

[Bal03]   P. Ball. The physical modelling of human social systems, 2003.

[BP00]   Paramvir Bahl and Venkata N Padmanabhan. Radar: An in-building rf-based user location and tracking system. In *INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer*

and Communications Societies. Proceedings. IEEE, volume 2, pages 775–784. IEEE, 2000.

[CCLK05]   Yu-Chung Cheng, Yatin Chawathe, Anthony LaMarca, and John Krumm. Accuracy characterization for metropolitan-scale wi-fi localization. In *Proceedings of the 3rd International Conference on Mobile Systems, Applications, and Services*, MobiSys '05, pages 233–245. ACM, 2005.

[CLL14]   Andrea Cuttone, Sune Lehmann, and Jakob Eg Larsen. Inferring human mobility from sparse low accuracy mobile sensing data. In *3rd ACM Workshop on Mobile Systems for Computational Social Science(MCSS 2014)*. ACM, 2014.

[CS10]   1 2 3 Nicholas Blumm 1 2 Albert-László Barabási 1 2 * Chaoming Song, Zehui Qu. Limits of predictability in human mobility. *Science*, 327, 2010.

[CSC$^+$06]   Mike Y. Chen, Timothy Sohn, Dmitri Chmelev, Dirk Haehnel, Jeffrey Hightower, Jeff Hughes, Anthony LaMarca, Fred Potter, Ian Smith, and Alex Varshavsky. Practical metropolitan-scale positioning for gsm phones. In *Proceedings of the 8th International Conference on Ubiquitous Computing*, UbiComp'06, pages 225–242. Springer-Verlag, 2006.

[DB06]   T. Geisel D. Brockmann, L. Hufnagel. The scaling laws of human travel. *Nature*, 439, 2006.

[DB08]   F. Theis D. Brockmann. Money circulation, trackable items, and the emergence of universal human mobility patterns. *Pervasive Computing, IEEE*, 7, 2008.

[FBSW08]   Bo Fu, Gábor Bernath, Ben Steichen, and Stefan Weber. Wireless background noise in the wi-fi spectrum. In *Wireless Communications, Networking and Mobile Computing, 2008. WiCOM'08. 4th International Conference on*, pages 1–7. IEEE, 2008.

[Fli03]   Rob Flickenger. *Building Wireless Community Community Networks*. O'Reilly & Associates, Inc., Sebastopol, CA, USA, 2 edition, 2003.

[Gep]   Gephi - the open graph viz platform.

[GL96]   G. Maguire Jr G. Liu. A class of mobile motion prediction algorithms for wireless mobile computing and communication. *Mobile Networks and Applications*, 1, 1996.

[JP04]   W. Trumler T. Ungerer L. Vintan J. Petzold, F. Bagci. Global state
             context prediction techniques applied to a smart office building,
             2004.

[JS99]   Oliver P John and Sanjay Srivastava. The big five trait taxonomy:
             History, measurement, and theoretical perspectives. *Handbook of
             personality: Theory and research*, 2(1999):102–138, 1999.

[Kal60]   R. E. Kalman. A new approach to linear filtering and prediction
             problems, 1960.

[KC11]   Jahyoung Koo and Hojung Cha. Autonomous construction of a
             wifi access point map using multidimensional scaling. In *Pervasive
             Computing*, pages 115–132. Springer, 2011.

[MCG08]   A. L. Barabasi M. C. Gonzalez, C. A. Hidalgo. Understanding
             individual human mobility patterns. *Nature*, 453, 2008.

[MCWA10]   Aniket Mahanti, Niklas Carlsson, Carey L. Williamson, and Mar-
             tin F. Arlitt. Ambient interference effects in wi-fi networks. In
             Networking, volume 6091 of *Lecture Notes in Computer Science*,
             pages 160–173. Springer, 2010.

[MK06]   S. Kim M. Kim, D. Kotz. Extracting a mobility model from real
             user traces. *The IEEE INFOCOM Proceedings*, 2006.

[MM07]   Mirco Musolesi and Cecilia Mascolo. Designing mobility models
             based on social network theory. *SIGMOBILE Mob. Comput. Com-
             mun. Rev.*, 11(3):59–70, 2007.

[MR07]   E Mok and Günther Retscher. Location determination using wifi
             fingerprinting versus wifi trilateration. *Journal of Location Based
             Services*, 1(2):145–159, 2007.

[NE09]   A. S. Pentland N. Eagle. Eigenbehaviors: identifying structure in
             routine. *Behavioral Ecology and Sociobiology*, 63, 2009.

[Par]   Pardus game.

[PSL]   The python standard library.

[Ros09]   S. M. Ross. *Introduction to probability models*. Academic Press,
             2009.

[RS14]   M. Szell R. Sinatra. Entropy and the predictability of online life,
             2014.

[SCL03]   H. C. Lu S. C. Liou. Applied neural network for location prediction and resources reservation scheme in wireless networks. *International Conference on Communication Technology Proceedings*, 2, 2003.

[TSA09]   C. A. V. Campos L. F. M. de Moraes T. S. Azevedo, R. L. Bezerra. An analysis of human mobility using real traces, 2009.

[WLP]   Ieee 802.11 - wireless lans.

[XL13]   N. Bharti A. J. Tatem L. Bengtsson X. Lu, E. Wetter. Approaching the limit of predictability in human mobility, 2013.

[YA05]   Moustafa Youssef and Ashok Agrawala. The horus wlan location determination system. In *Proceedings of the 3rd International Conference on Mobile Systems, Applications, and Services*, MobiSys '05, pages 205–218. ACM, 2005.

[YYZS10]   Shunsen Yang, Xinyu Yang, Chao Zhang, and Evangelos Spyrou. Using social network theory for modeling human mobility. *Network, IEEE*, 24(5):6–13, 2010.

[ZF12]   Nan Zhang and Jianhua Feng. Polaris: A fingerprint-based localization system over wireless networks. In *Web-Age Information Management*, pages 58–70. Springer, 2012.

[ZG10]   M. Zignani and S. Gaito. Extracting human mobility patterns from gps-based traces. In *Wireless Days (WD), 2010 IFIP*, pages 1–5, Oct 2010.