Quantification of visits to Parks and Gardens

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***Abstract*—** Recent years have seen the rapid growth of cities all over the world. According to the United Nations Organization (UNO), 55% of the world population lives in urban areas and is expected to increase to 70% in 2050. (UNO News, 2019) In parallel with this growth, there is also an increase in pollution, the intensification of climate change, as well as an overcrowding of cities. As a result of these factors, there is increased pressure on the environment, space, mobility, and overall quality of life. The constant hustle and bustle of cities makes their inhabitants seek refuge in calmer, quieter areas where they can practice recreational and leisure activities. Urban gardens and parks are some of these areas and reflect countless social, environmental, and economic benefits.

***Keywords*—** data mining, machine learning, artificial intelligence, data analytics.

I. Introduction

Absolutely, urban green spaces such as gardens and parks are crucial for the well-being of city dwellers. They provide a place for relaxation, recreation, and connection with nature, which can significantly improve mental health. They also play a vital role in mitigating the effects of climate change by absorbing carbon dioxide, reducing heat in urban areas, and providing habitats for wildlife.

Moreover, urban green spaces can also contribute to the local economy. They can increase property values in their vicinity, attract tourists, and provide a space for community events.

However, the planning and maintenance of these urban green spaces is a complex task that requires careful consideration. It involves balancing the needs and wants of the community, the available resources, and the environmental impact. It's also important to ensure that these spaces are accessible and inclusive for all members of the community.

In the face of rapid urbanization, prioritising and investing in these urban green spaces is more important than ever. They are not just nice-to-have amenities, but essential components of sustainable and livable cities.Green spaces promote improved air quality, reduce noise and increase biodiversity. At the social level, they play an extremely important role in local communities, contributing to human health and well-being, providing opportunities for physical activity and social interaction. Several epidemiological studies also show positive effects on mental health such as reduction of depression, stress, among others (Röbbel, 2016).

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Thus, the characterization of public parks is extremely important for municipalities to understand usage patterns and, at the same time, to be able to provide visitors with what they are looking for when they frequent these spaces.

In the scope of the Curricular Unit Final Applied Project in Data Science (PFACD), we carried out a work with the goal of experiencing several specific Data Science problems. The selected dataset was the "Quantification of Visits to Parks and Gardens", provided by the Lisbon City Hall (CML). This includes information regarding the Bela Vista Park and the Monsanto Forest Park. Thus, our goal is to study information, not yet known, about the parks. Examples are the number and origin of visitors or the pattern of visits over time.

This dataset has data for the months of September to December 2021 and January 2022. In order to enrich our analysis, we complemented the information provided with meteorological data for the time period under study, in order to observe the influence of weather conditions in the behavior of park visits.

Urban green spaces are essential for enhancing human health and well-being, as well as for social interaction, economic benefits, and environmental quality improvement as cities expand and become denser [1,2,3,4]. Urban green spaces offer ecosystem services that help to lessen the effects of global climate change, such as moderating extreme weather conditions like floods and temperature changes as well as lowering air and noise pollution [5,6,7,8,9,10]. Parks and other urban green spaces offer recreation, social interaction, and a connection to nature, all of which are beneficial to health and well-being [11,12,13,14,15,16]. For sustainable and resilient urban development, it may be essential to comprehend the relationship between urban parks and human well-being amid global concerns like climate change and urbanization [17].

II. State of Art

In order to understand to what extent the issue of public gardens had been explored, a search was conducted to find articles or projects that had been developed around this theme. Using Google Scholar to perform the search, relevant literature on the use of mobile device data in understanding park visitation and visitor behavior. Here's a brief overview of what these studies might cover based on their titles:

- Using Mobile Device Data to Estimate Visitation in Parks and Protected Areas [18]: An Example from the Nature Reserve of Orange County, California: This study likely discusses how mobile device data can be used to estimate the number of visitors in parks and protected areas. The case study is based in Orange County, California, and the

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findings could provide insights into how mobile data can be used for visitor management and park planning.

- Using mobile signaling data to examine urban park service radius in Shanghai [19-20]: methods and limitations: This study appears to focus on using mobile signaling data to understand the service radius of urban parks in Shanghai. The service radius could refer to the geographical area where a park draws visitors. The study also seems to discuss the methods used for this analysis and their limitations, which could be useful for anyone looking to conduct similar research.
- Using Mobile Phone Data to Understand the Demographic Characteristics and Behavioral Patterns of Park Visitors in a Megacity, Beijing, China [21]: This study likely uses mobile phone data to gain insights into the demographic characteristics and behavioral patterns of park visitors in Beijing. This could include understanding peak visitation times, common routes taken within the park, length of stay, and other behaviors.

Published in October 2021, this project aimed to explore the demographic characteristics and behavioral patterns of park visitors. Thus, in this study using data from cell phones, the number of visits was counted, the demographic characteristics of visitors and their length of stay were identified. The Random Forest algorithm was also used to analyze the factors influencing the duration of park visits.

The results describe the impact of weather conditions on the number of visits, the parks most visited by foreigners, the age group of users, among other aspects.

These derive from the use of keywords such as "monitoring park visitors using mobile phone data", for example.

By analyzing the works found, we realize that all of them are characterized by having access to data where it is possible to trace the visitor's path, as well as to under-stand the age group to which they belong, or to define how long they stayed in the park.

These have access to more "personal" data than ours, thus allowing a more detailed and concise approach. Issues raised by the GDPR do not allow such a delin-eated information as those found. Notably, the works mostly found be-long to cities in China where the data protection policy differs from the European one.

Therefore, we also realize the importance of this work and the exploration of this topic. It is one of the first works in this area of study.

III. CRISP-DM Methodology

To prepare our study, we will use the CRISP-DM (Cross Industry Standard Process for Data Mining) methodology, which is a technique composed of several steps that structure the process of transforming data into knowledge.

Business Understanding and Data Understanding are the phases in which data is collected, described, explored and verified. In Data Preparation, corresponding to the third phase, data is selected, cleaned, explored, and verified for quality. In the fourth phase, Exploratory Data Analysis and Modeling, we identified initial questions in order to get to know the data set better and to answer questions that complement our study. In the fifth phase, Data Validation, we conducted the evaluation of the model that was selected. Finally, in the last phase, all the decisions made in the study will be presented.

The main advantage of this methodology is that it can be applied to any type of business without depending on software or services to be executed.

Thus, CRISP-DM is divided into 6 fundamental steps.

3.1 Understanding the business

The first phase of this project was to understand the goals and requirements of the job thoroughly. We assessed all available resources and determined our Data Mining Goals, thus defining the success criteria.

Finally, we outlined in detail the plans for each phase of the project, so as to always follow a guiding line. This step is fundamental to establishing all the objectives of the work.

Initially the Lisbon City Council (CML) stipulated some objectives they wanted us to achieve, however, and given the information made available to us, some of these were not possible to accomplish. An example of an objective that will not be possible to answer is "the distance people are willing to travel to use the green space (radius of influence), i.e., the visitor's place of origin or average distance traveled;" since we do not have access to information about only one visitor to the park, but at least ten visitors. This makes it impossible to understand the movements of each visitor.

Thus, it was necessary to establish more study objectives to get the most out of the data.

We have thus defined the goals that follow:

1. Study the average number of daily/monthly visits;
2. Observe the evolution and temporal pattern of the visits;
3. Understand the daily period of greatest concentration;
4. Note the percentage of foreign visitors (roaming).
5. Understand the influence of weather conditions on the behavior of park visits.
6. Observe areas of higher concentration of people and generate an alert if the park is at its maximum capacity.

Throughout the development of this project we had the opportunity to meet several times with CML. These meetings were always extremely important for the clarification of the objectives and eventual questions.

In the first contact we made with CML, via Teams, on (02/16/2022) we were presented with the problems to be solved and a brief explanation was given about the data they provided us.

In the second meeting (09/03/2022), via Teams, questions were clarified about the use of squares in the Power BI program, in order to delineate the area of the parks more correctly. In this meeting, more data was also requested, since we only had information about the month of January.

In the third meeting (03/30/2022) via Teams, we talked about our work objectives and the proposed objectives we would not study and why. We also presented the Data

Preparation: the variables we eliminated, outliers, and why we eliminated them. We showed how we had defined the park's boundaries, so as not to consider users outside the park for our study. We also talked about the classes in which we would categorize the weather factors. Finally, we presented future work.

In the fourth and last meeting (06/05/2022) before the project's final presentation, we presented all our exploratory analysis regarding Bela Vista Park. We talked again about the problem of counting visitors to the park and presented the differences between doing an analysis with the sum of all visitor records and doing this analysis with the average of visitors. We ended the meeting saying that we would proceed to the study of the Monsanto park.

Along with these meetings we also established contact via e-mail, where we ex-posed some doubts about the format in which some of the data we received came from, we questioned about the amount of antennas in the Bela Vista park.

It is also important to underline that through one of these contacts, data regarding the weather were provided, in order to be able to understand the existence of correla-tions between the weather and visitors' visitation to parks and green spaces.

3.2 Understanding the data

Data Understanding focuses on identifying, collecting, and analyzing the data sets to help us meet all the project objectives. During this phase, we will also analyze possible errors, patterns and trends in the data.

This phase is divided into the "Data Description" and the "Data Quality Check".

The data used was provided by CML. Contained in this dataset are the data collected, by antennas, through cell phones from visitors of two large parks in Lisbon. The data is presented in squares with an area of 40,000 square meters. They have information that is collected every 5 minutes and there is no way to identify the terminals. This made our study more difficult and limited certain objectives of our project, because we can find a person in a grid in those 5 minutes and if that person stays in the same grid for 1 hour it will be counted 12 times.

Therefore, it is not possible to know, in fact, the concrete number of people in the park.

Two data sets were made available, one for Bela Vista Park and the other for Monsanto Forest Park. Both data sets provided to us have the variables described in Annex 2.

This information refers to the number of distinct devices present in each square, how many of these terminals belong to roaming people (tourists), the average time that visitors stay in the park/garden (through its entrances and exits), what is the origin of tourists in these spaces, among others.

In addition to this data, we also have information about the time, day, month and year of the occurrences in each square of both parks. We will add to the sets of information about the weather conditions in order to be able to relate them to the number of visitors to the parks.

The dataset concerning atmospheric conditions is a dataset produced by the Portuguese Institute of Sea and Atmosphere (IPMA) and was provided to us by CML. This dataset includes descriptive meteorological information for the period under analysis. These data include, in addition to temperature in degrees Celsius, wind characteristics, such as its intensity per km/h, accumulated precipitation (in mm), solar radiation, among other aspects.

Bela Vista - Initially we will focus our study on the Bela Vista Park dataset, where there are antennas, collecting information about the park and its visitors.

The dataset for the Bela Vista park initially had 1,411,596 records and 24 columns. Right from the start, we noticed the complexity of the problem.

Since we developed the project through our personal computers, we encountered difficulties in data processing since this is a Big Data problem and our computers did not have enough memory/processing capacity to carry out this project in the best possible way.

This same dataset is for the period September 15, 2021 to January 24, 2022.

Data Quality

Through a brief analysis of the dataset we were able to verify the quality of the data. From the beginning we checked the type of variables, the existence of null values, duplicates and irrelevant columns for the study. In this study, it was possible to detect some errors and patterns.

Changes to the above will be explored in more detail in the next phase, Data Preparation.

At this stage, we faced the main challenge of the project. This challenge consisted of the fact that there were squares whose majority of occupation was not park. In this way, the problem arose that we were accounting, in the analysis, for people who were not inside the park. Similarly, we could count houses or roads near the park. To solve this problem, we performed three approximations.

3.3 Data Preparation

Data Preparation phase is essential because it prepares the data sets for future analysis and modeling. To accomplish this, we clean and process the data.

First, when looking at the type of each variable we noticed that the date was in the object format, so we changed it to datetime. This way we separated the date into: Hour, Minute, Month and Day.

In order to be more understandable we have changed the name of some variables, for example, "D1": "top10 countries".

CML suggested that we delete all records where there were less than 10 people in a grid cell ($C1 < 10$) in order to comply with the GDPR rules, since if there were grid cells with a number less than 10 people, it would be easier to identify a person. Thus, and since we found records with groups of less than 10 people per grid, we decided to eliminate them.

When observing the existence of null values, we noticed that they were found both in the variable "top 10 countries" and in "apps". We decided not to delete them since they correspond to people who do not have roaming, that is, PT cell phones (+351) and people who do not use apps during their visit to the park, respectively. Therefore, it would not make sense to delete them since they correspond to certain information.

Next, we observed 18% of values that are duplicates. Therefore, we proceeded to eliminate them, since they do not present coherent values for our project.

During this analysis, we found the irrelevance of some variables for solving the problems in question. Among these we have E2, E3, E4, E5, of which we eliminated. We also eliminated column E10 because all its values were equal to 0.

After this elimination, we checked from boxplots the existence of possible outliers. Through these, we noticed that in variable C1 (number of terminals in the squares) we could be facing possible outliers, since there is a peak of records of about 8000 people, in an interval of a few hours, between 4:00 and 7:30 am on December 28. The same was true for some shorter time intervals on different days.

In this same variable, we found two outliers, whose values were above 4000 and where the values for the following minutes did not match what was verified in these, since they were significantly lower. The same is true for the outputs column, as there is only one output with a value equal to 6951.

After a vast search for possible events/events on those days it was not possible to find any information associated with the agglomeration of people verified. Thus, and because this event does not reflect reality, we considered this to be a possible error and thus chose to eliminate these values.

Subsequently, we observed that some records in the combination of columns E7, E8 and E9 had values equal to 0. Since these variables represent the duration (mini-mum, average and maximum) of the presence of visitors in the grid, it would not be coherent to have times corresponding to 0 if there are people present in the grid. Therefore, we have proceeded to eliminate these records.

As mentioned earlier, we were also provided with data from IPMA regarding weather conditions in the months of the study. Initially, we eliminated some varia-bles that would not be relevant for our analysis, such as wind pressure and wind direction.

As with the House dataset, we changed the date variable to datetime. In this way, we have separated the date into: Hour, Minute, Month and Day. We also noticed that there were values in the columns equal to "-99", these are not within the range of any of the variables and because they are still a significant number, we chose to eliminate them.

So before beginning our analysis, and since there was a lot of information, we chose to group the temperature, precipitation, and wind data into the categories represented in appendices 3, 4, and 5.

Finally, we joined the atmospheric data with our data regarding the park. To do this, we had to group the data by day, month and hour from the average of the records.

After this joining, we obtained a total of 37 columns and 1,411,596 rows.

Finally, we decided to round all the variables to the units, since these values mostly referred to people and were presented as decimal values since they corresponded to extrapolations.

Methods of Grid Exclusion

As noted earlier, given the representation of the park in question is on a grid map, and in order to more accurately delineate the boundaries of the park and exclude possible records outside of it, we decided to explore three different approaches.

Approximation 1 - Subdivision by percentages of the squares

Used to eliminate the approximate percentage of the grid squares that exceeded the boundary lines. This method consisted of a division of each grid cell into four equal parts, thus obtaining each part of the grid cell 25% of the park. And if necessary, f divide again by four equal parts for that 25% of the grid cell. The following figure demonstrates an example of the above.

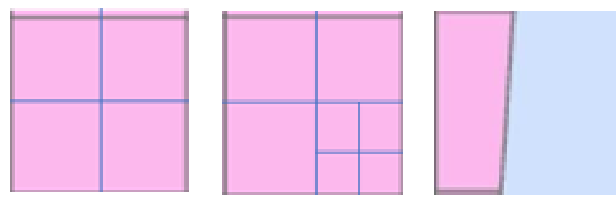

Fig. 1. - Approximation method 1

With this method, we are able to obtain a more realistic approximation regarding the percentage of park that each grid cell contains. To do this we proceed to eliminate the remaining grid cell percentage.

Approximation 2 - Exclusion of squares below 50%

From the previous approximation (Approximation 1) all squares containing a per-centage of less than 50% of the park were eliminated.

Approximation 3 - No square exclusion

This method differs from the others in that it considers the totality of the grid squares that include park boundaries. Thus, it considers devices that are outside the park boundary.

After an analysis of each of the approaches, we chose to perform all data analysis in Approach 2, since we considered it to be the most relevant. This approach re-moves all squares whose percentage is less than 50, and avoids considering people outside the park and nearby dwellings.

3.4 Visualization

Once the data was prepared it was time to start extracting some information from it. That said, some graphs were prepared in order to characterize the number of visitors, understand some patterns and try to observe what can influence these visits.

According to the data it was possible to obtain visualizations that reflect the busi-est months in the park, as well as, the days of the week, the hours among other as-pects.

With the inclusion of the temperature data we visualized which weather mood attracted the most people to the park.

The following conclusions represent statistical analyses of the Bela Vista Park, useful in its daily management. Understanding visitation flows may represent an indispensable tool in the park maintenance, the busiest periods may later indicate the need to perform a more intensive garbage collection, for example. Thus, combining this analysis with other data regarding the park and cross-referencing them may bring some interesting aspects.

In order to be able to count the number of visitors to the park we decided to use the average of variable C1 (which tells us the number of terminals present in each square). We did this because the data we are working on is updated every 5 minutes and we have no way of differentiating terminals from cell phones. Note that if a person stays 1 hour in the same grid cell this will be counted 12 times, if we add up each record of that variable. That said, if we used the sum value of variable C1 we would be facing a possible data bias, so we decided to use the average of each varia-ble.

Occupation of the Park

In the 5 months under analysis, there were 48 million distinct terminals. In view of these figures, it is always necessary to take into consideration that, since the data is collected every 5 minutes, terminals can be repeated. On the other hand, only 831 thousand foreign terminals were observed in the park. In order to better understand the adhesion of the foreign population to the park in question, we made a percentage analysis of them in relation to the total number of visitors. Thus, we noted that only about 1.8% of the total visitors to the park were of foreign origin.

The graph below (Figure 7), presents us a map with the general occupation of the park, in the months under analysis. Regarding the occupation of the park, we can notice a clear higher occupation in the southern part of the park, and a significantly lower occupation in the northern part.

The yellow spot corresponds to the square with the highest concentration, with an average of 236 people. Another area of high concentration, in the red spot, has an average of about 139 people. We consider that these squares can have high concen-tration values, since they can be considered entrances to the Bela Vista Park.

Fig. 2. - Heatmap for Bela Vista Park

Percentage of foreigners

As mentioned, the foreign population is 1.8% of the total population. By understanding how these individuals behave, we can see that there is a big peak of foreign population in the month of November with about, on average, 3 foreigners.
and in December. On the other hand, there is a sharp negative peak in the month of January, where there is only 1 person on average.

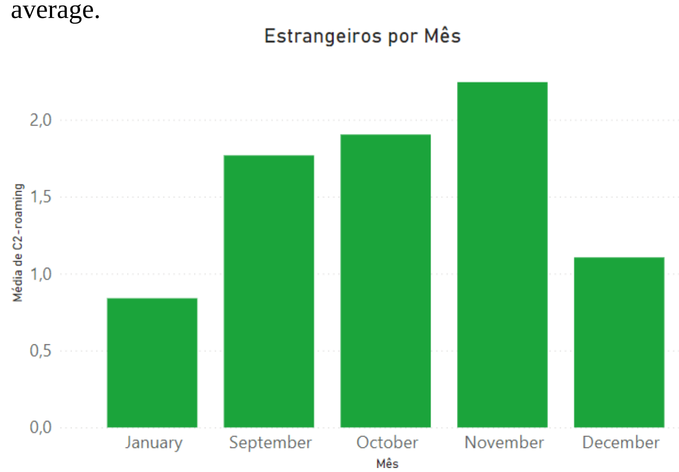

Fig. 3. - Distribution of the average number of foreigners per month

General Atmospheric Conditions Analysis

In order to analyze the influence of weather conditions on park visits we conduct-ed a more detailed analysis, in order to identify possible patterns that lead people to go to the park.

We split the dataset in order to observe, on the one hand, observations with a high number of entries of distinct terminals in the grid (variable C5) and, on the other hand, records with a low number of entries.

We consider a high number of entries when it is higher than 130 and a low num-ber when it is equal to 0. In order not to bias our analysis, we chose to use only the data between 8 am and 8 pm, since nighttime temperatures could influence our con-clusions.

In order to obtain more precise analyses, we decided to divide the observations between weekdays and weekends, since it is necessary to contemplate a possible natural deviation of the affluence to the park during these two types of days. As an example, we have the factor that free time on weekends, may bring more people to the park and is in no way influenced by weather conditions.

Thus, it is possible to identify possible factors that influence the flow of entries in the park and where a large difference is evident. Thus, when the number of entries is greater than 130 and looking at the average of each of the values, we can conclude that:

- The value of accumulated precipitation is about 5x higher in the observations where a small number of entries were recorded.
- The radiation, in the observations with more inputs, is higher by a ratio of 1.5 times.
- The average temperature recorded is around 18ºC on observations with more entries and 13ºC on days when there were not so many people in the park.

Finally, we thought it would be important to observe these same trends, but from a weekend perspective. We conclude that, the difference in the observed values for the weekends compared to those presented previously is even more pronounced for the precipitation, radiation, temperature and wind intensity variables, as can be seen:

- The average value of accumulated precipitation is about 5x higher in observa-tions where no inflows were recorded
- Radiation, in observations with more entries, is higher by a ratio of 2x
- The average recorded temperature is around 18ºC in the observations with more entries and 11ºC when no entries are recorded.
- The wind intensity in the observations with the number of null entries is about 11, while in the records with more entries it is 8.

We can then state, as expected, that the variables that have more influence in the affluence of people to the park are: precipitation, radiation and temperature. We can conclude that sunnier days, when the temperature is higher and there is no rain, are much more inviting for activities in the park.

Time

The following graph shows the distribution of people in the park throughout the hours of a day. As one would expect, the hours where there are fewer people are from 9 pm to 4 am, with a big increase from 4 am to 8 am. At 8am there is a very sharp peak, with an average of 118 people, as well as at 5pm, although less sharp. We consider that these hours may be favourable for dog walking, morning runs, walks after work, or it can also be explained because these hours are the times when most people go to their work/home and as the data studied also includes the urban network, we may be analyzing these commuting movements.

There is a lower concentration of people in the remaining hours, coinciding with work and school/college hours.

Fig. 2. - Visualizing the number of people per hour

Visits by weekday -Based on the following graph, we can observe the distribution of the average number of visits to the park on weekdays and weekends.
Proceeding to its analysis, we verify that, contrary to what was expected, it was not verified during the months under study, a higher number of visits on the weekend. This period is considered as the least visited weekly period.
It is important to note that Thursday stands out as the day with the most visits.
Overall, on average, the days chosen by visitors were Thursday, Wednesday and Monday.

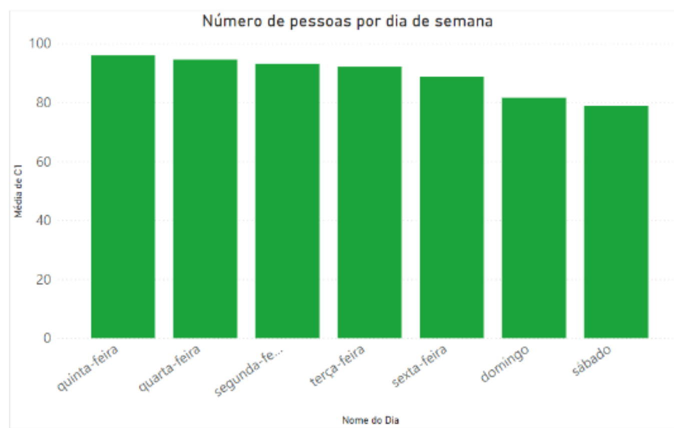

Fig. 5. - Distribution of the number of people per weekday

IV. Conclusions

Initially, the Municipality of Lisbon stipulated some goals that it wanted to be met throughout the work. When we analyzed the data that was made available, it did not allow us to respond to all the defined goals due to some limitations, mentioned below.

The fact that the data extraction is done every 5 minutes. This can make the analysis biased and doesn't allow to define the number of people in the park. One way to solve this problem without jeopardizing data confidentiality is, for example, to assign an id to each visitor. This way the data would remain anonymized and it would be possible to determine the exact number of people in the park and the distance they travel to enjoy the park.

The other major limitation we felt in doing this work was that the grid cells in which the park is inserted also count data from cell phone terminals of people who are on the road or in houses surrounding the park. In this way we are considering more people than those in the area we intend to analyze.

Regarding possible future work with this data, it would be interesting to do a more detailed analysis for specific areas of the parks, and determine a profile of visitors, for example, to know the age groups and gender of the people who visit the park the most. However, to do so, it would be necessary to have both the id and information about the cell phone terminal owners, but knowing the age range and gen-der would not jeopardize the anonymization of the data.

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