ÓBUDAI EGYETEM
ÓBUDA UNIVERSITY

Thesis Booklet

Analyzing the Mobility Customs of the Urban Population Using Mobile Network Data

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Contents

Abbreviations

CDR Call Detail Record. 4–6, 9

ICT information and communication technology. 6

KSH Központi Statisztikai Hivatal, Hungarian Central Statistical Office. 12

PCA Principal Component Analysis. 11, 15, 16

SES Social Economic Status. 5, 11

SIM Subscriber Identity Module. 7, 9, 10, 14

SWC sleep wake cycle. 4, 6

1 Background

Mobile phones are now fundamental parts of our life; they are practically always with us, wherever we go, almost as if they were a part of our body. The continuous communication between a device and the mobile networks leaves traces of our whereabouts in the operator's system. Via these devices, the mobile network can "sense" our movements, which is the basis of the "Smart City" concept [1].

In the last few decades, anonymized Call Detail Records (CDR) have become a common information source for analyzing the characteristics of human mobility. Numerous research has been published utilizing this source of data from all around the world, even from Hungary, e.g., [2, 3, 4]. The research focuses on Budapest and its agglomeration. CDRs contain the billed activities of the subscribers, providing information about the whereabouts of the population. Based on this massive information source, human mobility analysis is utilized in fields — among others — like social sensing, epidemiology, transportation engineering, urban planning, and sociology. Furthermore, the human sleep-wake cycle (SWC) is also studied by analyzing mobile phone network data.

The analysis of the human movement patterns based on the CDR data, which makes it possible to examine a large population cost-effectively, resulted in several discoveries about human dynamics. These works usually consider the population as a homogeneous group, and the classification is based on some mobility indicators [5]. The next step was adding external data sources to the mobile network data, extending the investigation to other population characteristics. Often, this external source is used to classify the data (e.g., by gender) and to analyze the classes using the previously introduced mobility indicators. Among others: social network data [6], transportation data [7], taxi trips [8], socioeconomic indicators (income, education rate, unemployment rate and deprivation index) [9], sale price of residential properties [10].

A part of this work also fits into the trends, using housing prices as a socioeconomic indicator. Housing price, however, is an indirect indicator for the SES, so a more direct indicator, the cellphone price, was also investigated. While Blumenstock et al. used the call history as a factor of socioeconomic status [11], Sultan et al. [12] applied mobile phone prices as a socioeconomic indicator and identified areas where more expensive phones appear more often. However, only manually collected phone prices were used, and the analysis was not performed on the subscriber level.

2 Research Goals

The goal of my research was to develop a methodology and implement a data processing framework that can evaluate mobile network data. This framework should also be able to calculate mobility indicators and associate socioeconomic indicators with the subscribers. As the mobility patterns of the subscribers can be extracted from the CDR, the people can be distinguished based on their mobility customs. One of the main goals was to find a correlation between mobility and socioeconomic status.

As the mobile network data does not contain information about the subscribers' income, the CDRs were required to be enriched with other data sources. My research focused on an indirect and a more direct feature in this regard. The indirect is the housing prices because the level of a neighborhood is used to infer the SES. When the home location of a subscriber is known, the typical housing price of that area can be associated with the subscriber. Considering if someone lives in a more expensive area, their socioeconomic status should be higher, as well.

A more direct feature would be the price of the subscriber's cellphone. As the actual purchase price of a mobile phone can depend on several factors, the age of the device may be used in line with the recommended retail price.

Another goal was to analyze the commuting tendencies of the capital and its agglomeration. Kiss et al. state that although commuting is an essential and common phenomenon, its measurement is occasional and inadequate [13]. Commuting is predominantly analyzed by the census, but that is performed only once in a decade; thus cannot follow sudden but permanent changes. They also stress that commuting should be examined frequently, and its methodology should be established [13].

As questioning the population is a slow, tedious and expensive task, it would be obvious to automate the process with the available info-communication technologies (ICT). In this research, the application of CDR processing was presented to examine commuting, mainly to Budapest, and the findings were validated by the results of studies that analyzed commuting using census.

Economic models distinguish city parts such as residential areas, industrial areas, business districts, and so on, but that is a relatively static, slowly evolving city layer. Mobile phone network data has the potential to describe the city structure via the inhabitants' mobility patterns. The next part of this research focuses on the effect of the SWC on the city structure. In this regard, it continued the commuting analysis, but the city structure was analyzed by the circadian rhythm of the people who live and work in a given area of Budapest.

Is it possible to cluster city areas by the time when the activity of the inhabitants, the workers, or the passers-by starts their activity in the morning or halts in the evening? Do city parts have "chronotypes"? Is there a structural or socioeconomic connection between the areas with the same "chronotype"? Can neighborhoods or districts be described by the terms "morningness" or "eveningness"? Another goal of this research was to answer these questions.

3 Methods of Investigation

3.1 Home and Work Locations

Most of the inhabitants in cities spend a significant time of a day at two locations: their homes and workplaces. To find the relationship between these most important locations, first, their positions of these locations had to be determined. There are a few approaches used to find home locations via mobile phone data analysis [14, 15, 16, 17, 18]. The solution applied is similar to the most common approach. The most frequent cell where a SIM card was present during working hours was considered as the work location, on workdays between 09:00 and 16:00. The home location was calculated as the most frequent cell where a SIM card was present during the evening and the night on workdays (from 22:00 to 06:00) and all day on holidays. Although people do not always stay at home on the weekends, it is assumed that a significant amount of activity was generated from their home locations. I have used census data indirectly, via commuting trends, to validate the estimated home and work locations.

3.2 Mobility Metrics

Along with the home and work locations, the Radius of Gyration and the Entropy are commonly used [5, 19, 10, 20, 17, 21, 22] indicators of human mobility, which were determined for every subscriber.

The Radius of Gyration [23] defines a circle where an individual can usually be found. It was originally defined in (1), where L is the set of locations visited by the individual, r_{cm} is the center of mass of these locations, and N is the total number of visits of time spent at these locations. The r_i is the coordinate of location i, and n_i is the number of visits or the time spent at location i [5].

$$r_g = \sqrt{\frac{1}{N}\sum_{i \in L} n_i (r_i - r_{cm})^2} \tag{1}$$

The mobility entropy (or mobility diversity) characterizes the diversity of locations visited using an individual's movements, defined as (2), where L is the set of locations visited by an individual, l represents a single location, $p(l)$ is the probability of an individual

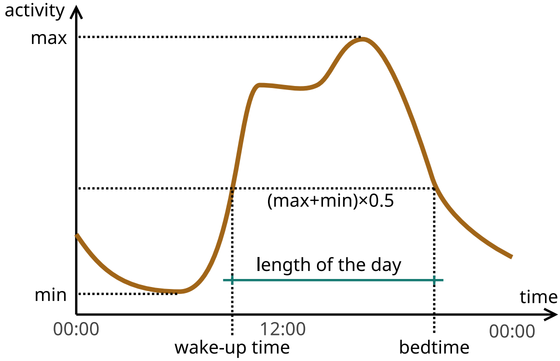


Figure 1: Calculation of the wake-up and the bedtimes.

being active at a location l, and N is the total number of activities taking part in by an individual [19, 20].

$$MD = -\frac{\sum_{l \in L} p(l) \log p(l)}{\log N} \tag{2}$$

3.3 Wake-up Time

The Call Detail Records were aggregated for every cell and 10-minute time intervals. Then, the moving average was applied with the window of 12. The minimum of the aggregated records is usually in the middle of the night, and the maximum is in the afternoon. The wake-up time is considered when the activity value reaches the arithmetic mean of the minimum and the maximum value on the positive edge of the activity curve. Figure 1, illustrates the concept.

This process was repeated in the case of every day, then the median of the daily wake-up times was determined. Analogously to the wake-up time, the bedtime can be calculated to describe when the mobile phone activity decreases significantly by selecting the mean value on the negative edge. Note that these values are naturally not the actual times when people wake up or fall asleep. Those moments cannot be determined using only the mobile phone network. Using the screen-on events of the phone [24] can be much closer to the actual values. Especially in the case of the wake-up time, if the phone is used as an alarm clock. In spite of this, it is supposed that this approximating method can reveal the rough tendencies of the daily routine. Still, the terms "wake-up time" and "bedtime" are used to refer to the time of the positive/rising and negative/falling edges of the daily activity curve, respectively.

3.4 Calculating Indicators

The data was stored in a PostgreSQL database that was not only used for storage but also part of the computation. Considering that most of CDR processing happened at the subscriber level, and the subscribers were independent of each other, it seemed the best solution to partition the processing at subscribers and process the activity records of a single subscriber in a single thread, that can be executed by a relatively slow interpreted language.

The *Pool* object, from the *multiprocessing* package, provides a convenient tool to parallelize the execution. A SIM ID was associated with a worker that executes a query to filter its activity records. Naturally, the query can contain spatial or temporal constraints as well. The database engine can efficiently select the activity records of a SIM card, utilizing the available many-core environment [1]. Then, the indicators were calculated per SIM card, and the partial results were collected and saved. The analysis and the visualization did not require considerable computing power and thus were often performed on a laptop.

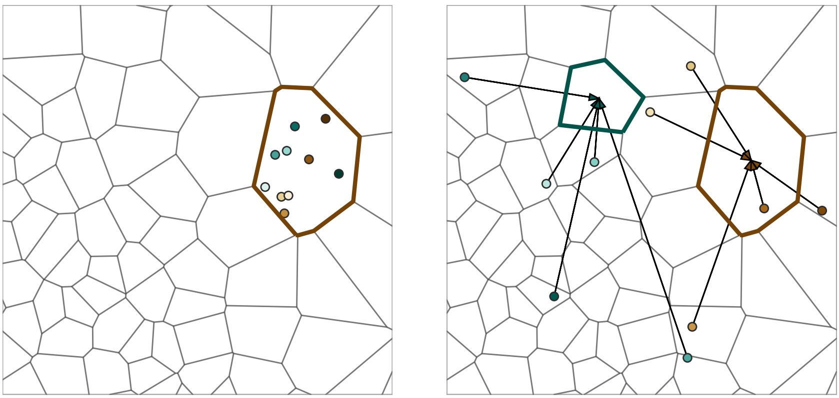
3.5 Aggregation of the Subscribers

The activity of a single device is also sporadic and does not provide enough data to identify an activity increase for all the days. Because

[1]Lenovo x3650 M5 server, with 1024 GB of RAM, and two 18-core CPUs with HT, resulting in 72 logical cores.

of the sporadic nature, the devices were grouped, which could be performed in two ways. Calculating the wake-up time of an area (a cell or a cell group) or the inhabitants of an area.

In the first approach, the activity records were aggregated that took place in a given cell, regardless of which SIM cards produce them. In the case of the second version, those activity records were used, which were produced by the inhabitants of the given cell, regardless of where the activity took place. The first approach could be called cell-based grouping, and the latter inhabitant-based grouping. The two approaches are illustrated in Figure 2. Cells can be grouped further to examine a larger area (e.g., residential, suburb, district).



(a) (b)

Figure 2: Visualizing the difference between the cell-based (**a**) and the inhabitant-based (**b**) approaches. The former considers subscribers present in a given cell wherever they live. The latter aggregates activity of the inhabitants to the home cell, regardless where the activity occurred.

3.6 Applying Principal Component Analysis

The SIM cards were aggregated by socioeconomic category — housing price category (0.2–1.2 million HUF/ m^2) or cell phone price category (100 EUR steps to 700 EUR) — and the twelve Radius of Gyration and Entropy categories (using 0.5 km distance ranges between 0.5 and 20 km for the Radius of Gyration and Entropy values with 0.05 steps between 0.05 and 1.00). The data structure used for the Principal Component Analysis is defined as follows. Every row consists of 40 columns representing 40 Gyration Radius bins between 0.5 and 20 km and 20 columns representing 20 Entropy bins between 0.05 and 1.00. The bins contain the number of SIM cards that have been normalized by metrics to compare them. Although the workdays and the holidays were treated separately during the whole study, the data were not explicitly labeled by them. The same table was constructed using weekend/holiday metrics, and its rows were appended after the weekday ones. The socioeconomic categories were not provided to the Principal Component Analysis (PCA) algorithm.

The relationship between the mobility metrics (during weekdays and weekends) and the Social Economic Status (SES) was investigated using the result of Principal Component Analysis (PCA). After the PCA was applied, the 60-dimension vector was reduced to two dimensions, which variables were plotted to be analyzed.

4 New Scientific Results

Thesis 1: New Method for Evaluation of the Commuting based on Mobile Network Data

I have designed a method to describe the commuting patterns of the population quantitatively. The method is based on the statistical detection of the home and work locations using anonymized mobile network data. I have validated the results by comparing them to census-based commuting analyses and found good agreement between the determined mobility patterns and census-based data.

I have compared the detected population of the districts of Budapest and the settlements of the agglomeration with the population data of

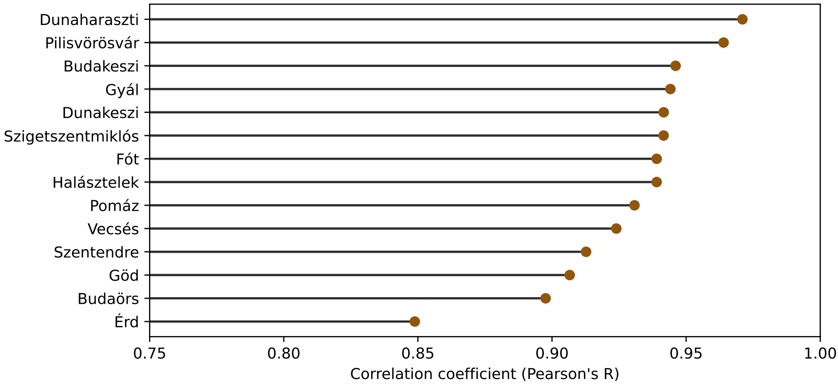
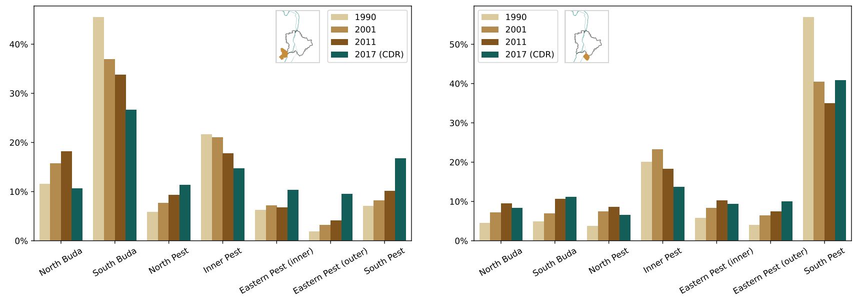


Figure 3: Correlation coefficients (Pearson's R) of commuting distribution with [26].

KSH [25] and the correlation coefficient (Pearson's R) was 0.9213. The commuting from the sectors of the agglomeration to the districts of Budapest was also evaluated, based on [26]. Lakatos and Kapitány analyzed commuting directions in the case of 14 settlements. Using the census data, they determined to which district group the inhabitants of these settlements commute. I have replicated this analysis using mobile network data, and the correlation was between 0.8488 (Érd) and 0.971 (Dunaharaszti). Figure 3, summarizes the correlation coefficients of this analysis. Figure 4, shows the detailed results of Érd and Dunaharaszti along with the results of [26]. As can be seen, the results fit into the trends of the last three censuses.

Koltai and Varró analyzed the commuters' composition based on the age from the sectors of the agglomeration to the district groups of Budapest [27]. The results were compared to theirs, and a strong correlation was found in this regard as well: Pearson's R was 0.8977.

My publication pertaining to this thesis: [28*].



(a) (b)

Figure 4: Commuting to the seven districts groups of Budapest from Érd (**a**) and Dunaharaszti (**b**), comparing census (1990, 2001 and 2011) and mobile network data.

Thesis 2: Correlation between Home and Workplace Price-levels

Using anonymous mobile network data, I have demonstrated that people living in a less expensive neighborhood usually work in a less expensive area, based on housing prices of the home and the work locations. It has also been presented that people, who live in a more expensive neighborhood, tend to work in a more expensive area.

Figure 5a shows a moderate correlation between the home-work distance and the price level of the home location. Figure 5b illustrates the correlation between the price level of the home and the work location, supporting the thesis.

My publications pertaining to this thesis: [28*].

Thesis 3: New Indicators for Characterizing Mobility Customs

I have introduced new indicators for quantitative evaluation of wake-up time and bedtime in an urban environment. The wake-up and bedtime conditions were determined by the rate of mobile network

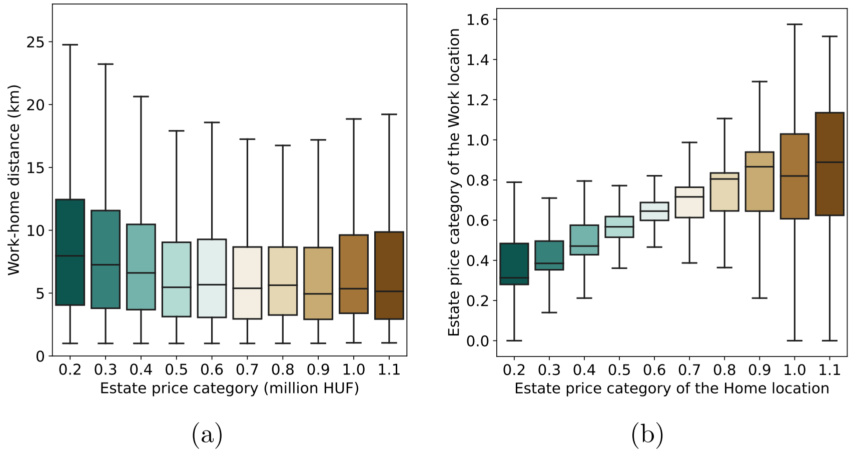


Figure 5: Home-work distances (**a**) and the workplace housing prices in contrast to the housing prices of the workers' home locations (**b**).

activity in the morning and evening hours. Two subscriber aggregation methods (area and inhabitant-based) have been developed to determine the wake-up characteristics of a geographical area or a group of subscribers.

In the area-based approach, the activity records are aggregated that take place in a given cell, regardless of which SIM cards produce them. In the inhabitant-based approach, activity records produced by the inhabitants of the given cell were considered, regardless of where the activity occurred.

Bedtime, the counterpart of this indicator, describes when a group of people cease to use the mobile network in the evenings. The day length can be estimated using the wake-up and bedtime, as this indicator correlates with the astronomical day lengths. The Sun went under at 19:33 on the 15th of April 2017, and at 20:42 on the 15th of June 2016, which is a 69-minute difference. The average workday bedtime values are 19:43 and 20:47, respectively. Moreover, the length of the working hour can also be estimated using the inhabitant-based approach.

My publications pertaining to this thesis: [29*, 30*].

Thesis 4: New method to Analyze the Correlation of Mobility and Socioeconomic Status

I have designed a method using Principal Component Analysis to evaluate socioeconomic status depending on the indicators of human mobility. Housing prices have been used to characterize the socioeconomic status of the population. I have found differences in the mobility customs within the different socioeconomic classes, so that the socioeconomic status can be inferred from the mobility.

Figure 6, shows the first two components of an unsupervised PCA analysis. The brown colors represent the workdays, the green ones the holidays, and they form two separate clusters. Marker size represents the housing price at the home location. While there is a marked tendency along the PC2 axis as the markers increase, the PC1 axis separates the estate price of the workplaces.

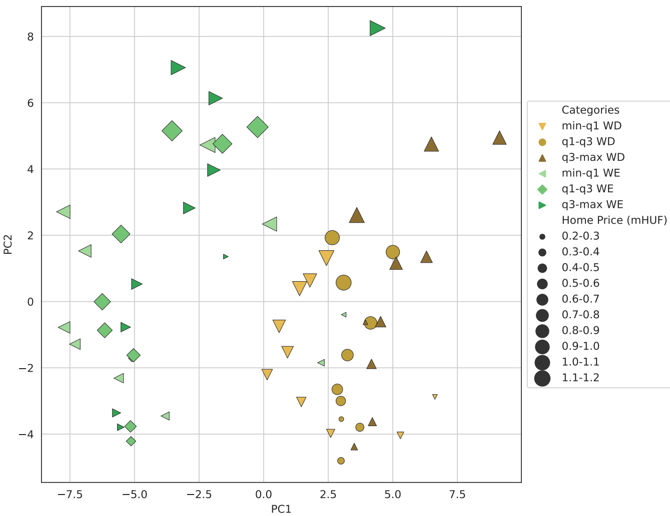


Figure 6: Scatter plot of the 2-component PCA. Marker size indicates the home price category, the type denotes work price category and the color refers to Weekdays or Weekends.

My publication pertaining to this thesis: [28*]

Thesis 5: Introduction of Cellphone Price as Socioeconomic Status Indicator

I have fused cellphone prices and release dates with the mobile network data to analyze the mobility customs in contrast to the price and the age of the subscribers' cellphone. I found that the cellphone price and age are eligible to characterize a subscriber's socioeconomic status.

Figure 7 does not only show that the phone price forms clusters but also reveals the differences between workdays and holidays in the mobility, which is the most notable in the case of the subscribers with the least expensive cellphones.

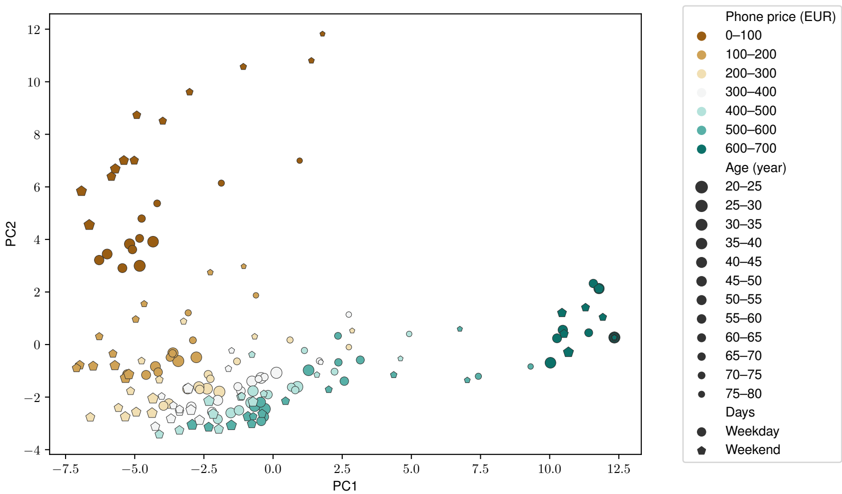


Figure 7: Scatter plot of the 2-component PCA. Marker size indicates subscriber age category, the color represents the phone price category and the workdays and holidays are distinguished by the marker type.

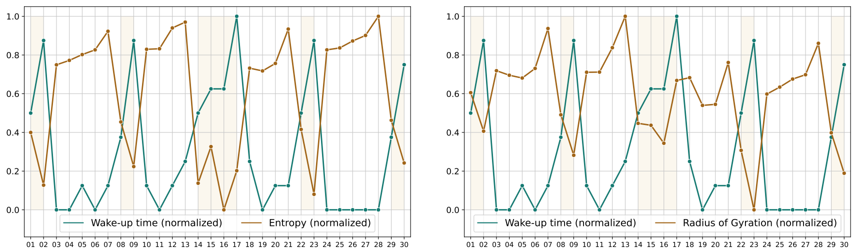
My publication pertaining to this thesis: [31*].

Thesis 6: The Relation of Wake-up Time and Socioeconomic Status

I demonstrated a relationship between the wake-up time and the mobility customs, as well as the socioeconomic status. The subscribers living in less expensive apartments get up earlier than those who live in pricier neighborhoods. The same tendency holds regarding mobile phone prices: subscribers who own more expensive cellphones tend to get up later.

Figure 8 shows the daily wake-up times in contrast to daily mobility indicators. A strong negative correlation was found, especially in the case of Entropy.

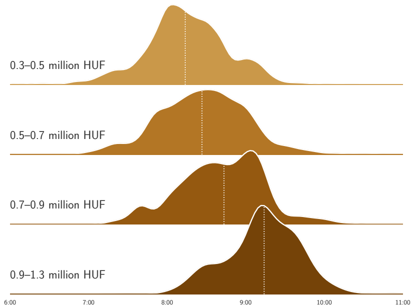
Figure 9a and 9b, illustrate the wake-up time distribution by housing price and phone price categories, respectively. Although there is an increasing tendency in both cases, the connection between the housing price and the wake-up time is stronger.



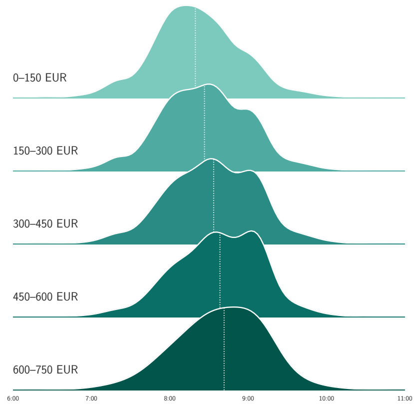
(a) (b)

Figure 8: Normalized, inhabitant-based wake-up times in contrast of the normalized daily Entropy (**a**) and Radius of Gyration (**b**). Pearson's Rs are -0.9019 and -0.6869, respectively.

My publication pertaining to this thesis: [30*].



(a)



(b)

Figure 9: Wake-up time distribution by housing price (**a**) and phone price (**b**) categories, with medians denoted by dotted vertical lines.

5 Practical Applicability

Sociological studies are usually performed based on censuses or direct questionnaires. An application of this research would be to support these studies using the anonymized mobile network data as a frequent, countrywide, and cost-effective alternative. Naturally, this application would require legal regulation, as a cooperation with the mobile operators and the Central Statistical Office.

These results may help to analyze further the city structures by identifying “early bird” or “night owl” areas and possible connections between them. City parts with early morning or late night activities may require different public transport services, for example, and can aid the transportation infrastructure planning. Business development could also benefit from the detailed insight of the neighborhood chronotypes, especially with the associated information on the home locations and the socioeconomic status of the subscribers. The socioeconomic findings of this research can also contribute to a better understanding of the social structure of urban and rural environments if the analyses are performed at the country level.

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7 Own Publications Related to Theses

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