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Assessing Individual and Group Behavior from Mobility Data: Technological Advances and Emerging Applications

Giuseppe Lugano
ERAdiate Team, University of Žilina, Žilina, Slovakia

Synonyms

Activity modelling; Behavioral patterns; Big data; Complex social networks; Machine learning; Mobile sensing technologies; Mobile social network; Mobility/Activity diary; Quantified self; Reality mining; Routine discovery; Smartphone proximity networks; Statistical analysis

Glossary

Big Data	Very large datasets that cannot handled with traditional data processing applications. Big data often include behavioral and mobility variables collected via smartphone applications.
Computational Social Science	Also known as computational sociology, it studies and infers social phenomena by analyzing them with a variety of computational approaches that make use of large-scale datasets of sensed human behavior
COST (European Cooperation in Science and Technology)	Europe's longest-running intergovernmental framework for science and technology cooperation. COST is a unique program in the European Research Area (ERA) successfully funding scientific collaboration networks (i.e., COST Actions) for over 40 years, bringing together communities of researchers, allowing innovative ideas to flourish, and adapting to evolving societal and scientific challenges
Data Mining	Set of techniques that allow discovering patterns from a large dataset.
Intelligent Transport Systems (ITS)	Interdisciplinary area related to the application of advanced technologies and innovative services to improve transportation and mobility systems.
Machine Learning	Approach to the development of algorithms of artificial intelligence that produce predictions by exploiting

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	known properties learned from a dataset.
Mobile Sensing	The use of sensors embedded in mobile technologies to collect contextual and human behavioral data.
Mobility/ Activity Diary	Personal diary or log describing mobility and activity behaviors. Often employed in transportation projects, thanks to recent technological advances mobility and activity diaries are increasingly implemented as smartphone apps and automatically collecting mobility and behavioral data.
Quantified Self	Expression referring to the habit of self-tracking and auto-analytics to better understand the self and to optimize own behaviors and performances.
Reality Mining	Pioneering project from MIT in the area of computational social science.
Smartphone Proximity Network	A social network generated by smartphone sensors (typically Bluetooth) detecting users, who share the same physical environment and are likely to interact with each other.
Value of Travel Time (VTT)	Defined as the cost of time spent on transport, its meaning is typically linked to time savings. This is currently being reconsidered from a broader perspective of additional mobility and behavioral indicators estimating also the "quality of time" spend while on the move.

Definition

The assessment of individual and group behavior is increasingly based on mobility and behavioral datasets, which are collected via sensors and/or smartphone applications and analyzed through advanced methods and techniques from computational social science.

Introduction

The study of individual and group behavior is an important area of the social sciences, traditionally associated with theories and models on groups and organizations. This research area aims at understanding the internal and external factors explaining why single individuals or social groups interact in a certain manner in specific contexts or under particular circumstances. When considering the individual perspective, two classic themes of interest are decision-making or socialization processes. A well-known example is Granovetter's study on the strength of "weak ties" in job searches (Granovetter 1973). As far as collective behaviors are concerned, models and theories of both individual and group behavior have found a large number of applications, especially in organizational contexts. These concern the formation, evolution, and dynamics of small and large social groups. Among the areas of interest, there has been a large amount of work on group norms, values, roles, collaboration, communication patterns, and conflict resolution strategies. It goes without saying that these issues, both at individual and collective levels, have been widely investigated across disciplinary areas. These include the use of emotional vs rational behavior, the study of local and virtual communities, the fields of consumer behavior, organizational behavior, and travel behavior.

Traditionally, the study of individual and group behavior was based on the collection and analysis of demographic, psychographic, and behavioral data from a small number of participants via surveys, interviews, or observations. Within this context, the collection of mobility data – information about human mobility and associated activity/purpose in a physical context (e.g., when, where, what, how, why) remained a niche area relevant to urban sociology and transport research. The basis for the mobility data collection was an activity/mobility diary to be filled in by the study participants over a well-defined period of time. From a methodological viewpoint, traditional approaches to data collection of mobility and behavioral suffered from several limitations: for instance, they could not be used to collect data over lengthy periods of time, such as months or years. Additionally, self-reported data could not cover the entire day (i.e., it is not "continuous") and may be inaccurate. Furthermore, studies typically involved only a small number of participants and could not address more complex large-scale group interactions.

In the last 15 years, mobile devices – smartphones in particular – have emerged as a new powerful instrument that overcomes the limitations of traditional research methods by collecting rich and continuous mobility and behavioral data over extended periods of time in a relatively inexpensive manner. This opportunity has been increasingly exploited in social science, transport research, and urban planning, among others (Eagle and Pentland 2006; Raento et al. 2009; Kiukkonen et al. 2010; Olguin et al. 2011; Cottrill et al. 2013; Khan et al. 2013; Attard et al. 2016). Mobile devices are ubiquitous and are carried almost always and everywhere by their owners; as such they can continuously and unobtrusively record mobility, behavioral, and communication variables. This emerging branch of the social sciences, described as computational social science (Lazer et al. 2009), is based on the capacity to collect and analyze big data by making use of statistical approaches such as machine learning and data mining. This research field has grown and gained popularity in the last few years, providing new insight on the way we perceive, describe, and experience societies from micro to macro levels.

What has been so far learned from the body of knowledge on computational social science? Applications of computational social science are endless and range from epidemiology to transport research and urban planning, security, and even to the modeling of political opinions. As far as the study of individual behavior is concerned, the analysis of mobile-sensed data has confirmed that human behavior is predictable and techniques exist to discover and predict individual habits and routines (Farrahi and Gatica-Perez 2008; Choujaa and Dulay 2010). At the level of small groups and communities, much attention has been devoted to the study of mobile social networks (Lugano 2016): Lugano (2008) found out that although mobile address books list hundreds of contacts, on average only about a fourth of them are regularly used (Lugano 2008). This follows the principle of "vital few and trivial many" stated by the Italian economist Pareto in the 1930s. By analyzing data on proximity networks, Eagle et al. (2009) claim that 95% of friendships can be accurately inferred on the basis on the observational data alone. In particular, studies on location-based social networks (Scellato et al. 2011; Gao et al. 2012) are offering an insight on the sociospatial properties of contextual interactions. This does not allow only better understanding social dynamics as such but also characterizing locations (e.g., "trending place") and events in real time. At macro level, it has been argued that mobile sensing technologies have the potential to describe phenomena of an entire society such as health and opinion change (Madan et al. 2011).

Computational social science has already contributed to advance knowledge and applications in various disciplines such as social network analysis and complex networks, sociology, and computer science. For its insight on dynamics at societal level, computational methods collecting and analyzing big data are increasingly adopted as a support to policy making in areas like public health, security, and urban planning. As it will be described in this chapter, an emerging application area concerns the estimation of travel time value and these approaches are increasingly employed in real-world applications to improve transportation and mobility systems (Vlassenroot et al. 2015; Baghoussi 2016; Ambrosch et al. 2017).

A related concept is the "quantified self," which refers to the process of self-tracking and self-analyzing data about oneself with the aim of increasing knowledge of the self and optimizing own behaviors and performances. A popular application of the quantified self is in the areas of personal well-being and sustainable mobility: via smartphone apps and wearables, people track their daily movements (e.g., walking, running, cycling), and monitor their performances in relation to well-being and/or sustainability targets (e.g., walking at least 30 min per day, decreasing car usage). Sometimes personal statistics and performances are also shared via social networks to promote healthy lifestyles and behaviors, as well as to compare own performances with the ones of other peers. Smartphone apps optimized for this kind of behaviors employ "gamification" approaches (e.g., game-like incentives, points, rankings) to promote sustainable behavioral change within communities of interest.

The "quantified self" and the sophisticated smartphone apps collecting mobility and behavioral data allow complementing the general level of transportation systems optimization with the individual level of mobility behaviors and activity optimization. Relevant commercial smartphone apps are in rapid expansion and allow better understanding and enhancing personal mobility routines, lifestyle, and health. Soon these computational methods will also allow designing personalized and group/community-tailored services, to be used in physical spaces, public and private, as an integral part of smart environments.

Key Points

- The study of individual and group behavior is an important area of the social sciences, traditionally associated with theories and models on groups and organizations.
- Traditional methods and tools for the assessment of individual and group behavior are quite limited.
- In the last 15 years, the area of computational social science has emerged: at its core, there are methods based on smartphone-based collection of mobility and behavioral data that overcome the traditional limitations of the data collection process.
- Smartphone apps collecting mobility and activity behavior are not used only by the research community, but also by end users for self-tracking and self-analyzing personal data with the aim of increasing knowledge of the self and optimizing own behaviors and performances.
- A special case of interest concerns the use of smartphone apps for collecting mobility and activity data to better understand and make best use of own time, in particular travel time.
- There is an ongoing process toward making use of collected mobility and behavioral data on the one hand to shaping and evaluating policies, and on the other hand to explain and promote sustainable behaviors.

Historical Background

The history of smartphone-based collection of mobility and behavioral data is relatively short, as the early attempts can be traced back to the early 2000s. Groundwork in this area has been conducted by the research group led by Alex Pentland at the MIT Media Laboratory, which developed computational models of individual and group interactions based on the use of wearable devices like the sociometer (Choudhury and Pentland 2002). Building on this knowledge, the advances in mobile sensing technologies were made possible using smartphones as wearable sensors to launch the ambitious Reality mining project in 2004 (Eagle and Pentland 2006). A total of 100 MIT students were recruited and given a smartphone (i.e., a Nokia 6600) for 9 months. The collected dataset consisted in about 450,000 h of information about users' location, mobile communication, and usage patterns. By employing statistical methods, the dataset allowed inferring users' routines, locations of interest, and social relationships, as well as modeling the evolution of a community and organizational dynamics.

The public version of the Reality mining dataset stimulated a large interest from the research community, which contributed with several studies on the topic (Farrahi and Gatica-Perez 2008; Choujaa and Dulay 2010). In Europe, research at Idiap laboratory and EPFL in Switzerland has found a strong partner in Nokia; the outcome of this partnership was the Lausanne Data Collection Campaign (LDCC), which collected longitudinal smartphone data from about 200 volunteers (Kiukkonen et al. 2010). While similar to Reality mining, the LDCC project adopted a "privacy-by-design" principle to address and overcome privacy concerns, which represent the major obstacle related to the application of mobile sensing technologies.

In addition to the efforts of individual research groups at various institutions, academic networks on this topic emerged to share knowledge and to further develop the field. One of the notable examples is represented by the COST Action "Knowledge Discovery from Moving Objects" (MOVE), which run between 2009 and 2013 bringing together scientists from 24 different countries with the goal of developing improved methods for knowledge extraction from large amount of mobility data. More recently, the EU project SoBigData (2015–2019) was launched to develop an open research infrastructure for social mining and big data ecosystem. The project employs a repertoire of methods such as trajectory pattern mining, clustering, and classification, as well as location prediction to discover useful knowledge about human movement behavior from mobility data.

Smartphone Apps Collecting Mobility and Activity Behavior

With the emergence of computational social science approaches, a variety of smartphone apps to collect mobility and behavioral data have been developed. Particularly relevant is the category of "activity/mobility survey" apps, which is the equivalent version of the traditional paper/phone surveys used to assess mobility behaviors.

In this respect, a milestone is represented by the app developed within the Future Mobility Sensing (FMS) project at MIT (Cottrill et al. 2013). The aim of the data collection of the FMS project was to provide evidence for transportation modelling and urban planning. The FMS smartphone app collected both demographic and travel data from participants such as "Stop locations," "Stop durations (start and end time)," "Activities performed in those locations," "Travel modes taken between stops," and "Costs/options associated with travel modes." The FMS project identified as a major design challenge the collection of accurate and easy-to-intepret "qualitative" input (e.g., on activities and options associated with travel modes). Despite this challenge, the FMS app was successfully used in a field study in Singapore between 2012 and 2013. The study involved more than 1500 participants and revealed that the smartphone-based methodology delivers a substantially richer and accurate travel and activity dataset.

The MEILI smartphone app developed within the SPOT project by KTH in Sweden is another relevant research initiative implemented to collect activity/mobility behavior. The SPOT project included a comparison of traditional paper-based and emerging smartphone-based methodologies (Allström et al. 2016). To carry out such comparison, both methodologies were tested in the same locations, at the same time, and with the same data collection participants. The study found that traditional paper-based data collection has a lower "involvement" threshold compared to the smartphone approach. As such, one of the recommendations given is to invest in the usability of the app and to simplify the user registration as much as possible, otherwise the risk is that many participants may drop-out from the data collection.

Another app worth mentioning is Modalyzer developed by InnoZ in Germany. The aim of this app was to establish a new survey tool for mobility research. Unlike other tools, designed specifically for the needs and goals of a single research project, Modalyzer has been employed in various research projects and in different EU countries. The largest study was carried out in Germany and involved more than 700 participants.

In addition to smartphone apps developed and used as research tools, there is an increasing number of commercial applications that collect and make use of mobility and behavioral data to satisfy users' mobility/activities needs. These applications fall into two broad categories, namely "journey/trip planners" and "mobility/activity" diaries. Journey planners typically do not include "tracking" features, but rather rely on self-reported input about travel plans and preferences.

As such, these are often developed as web-based applications rather than specialized apps. Local transport companies often deliver journey planner apps to facilitate urban navigation. The "tracking" features are instead central to activity/mobility diaries, which are typically presented as "health-related" applications promoting individual well-being and more sustainable lifestyles.

In conclusion, smartphone-based data collection is increasingly adopted to support projects investigating mobility and behavioral data. In parallel, a number of commercial applications support mobility and activity needs, respectively through "journey planners" and "activity/mobility diaries."

Key Applications

A notable and emerging area of application for mobility and behavioral data collected via smartphone apps concerns the estimation of time value, in particular the value of travel time (VTT). This is defined as the cost of time spent on transport. It has been found that people on average spend 1 h per day in commuting (Marchetti's constant) (Marchetti 1994). Accordingly, VTT is also defined as the maximum amount of money that one is willing to pay to save a minute of travel time.

Interestingly, both definitions of VTT are firmly grounded on two (interconnected) key variables, namely time and cost. Furthermore, these two definitions hint that VTT models generally assume that a person aims at maximizing utility by acting in a rational way. Such utility depends on consumed goods and time spent in different activities, including work and travel. Work or leisure time are often discussed differently in VTT literature: in the former case, VTT is a cost to employers for the time spent on travel by employees, while in the latter it is a cost for personal (unpaid) time spent on travel. The association of value of time to cost is in line with the idea that "time is money."

A Transport Note by the World Bank (2005) clearly explains this logic:

> The conceptual model underlying the valuation of travel time savings is one of consumer welfare maximization. It postulates that each individual maximizes the satisfaction or utility he gets by consuming and by engaging in leisure activities. Consumption of goods and leisure activities is constrained in two important ways.
>
> - First, expenditure is limited by income which must be earned by devoting time to working.
> - Second, work, leisure activities, and travel compete for an amount of time available strictly limited by the number of hours in the day.
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> In allocating time between activities, the individual must trade off the extra consumption that work earns against the foregone leisure which he requires. But he also has possibilities of extending the amount of working or leisure time available by spending extra money to save travel time. This may arise in the narrow context of choice between fast and expensive modes or routes and cheaper, slower, alternatives or in the broader context of choices of activity or residential location. By analyzing the relative sensitivity of such choices to variations in money and time cost, the implicit value of time of travelers can be identified.

Following this approach, projects having the goal of increasing value of travel time normally aim at achieving time savings. As such, the Value of Travel Time Savings is associated with the benefits of faster travel that saves time. From this viewpoint, the enhancement of transport infrastructure to reduce road congestion could be an example of effort to increase VTT.

Although not always explicitly mentioned, travel time has a negative value because it is associated with nonproductive time, while productive activities are carried out at origin or destination. In other words, people are willing to pay more to spend less time in travelling to receive in return more productive time. The general view of travel time as nonproductive time may be misleading, as people can increasingly carry out a variety of productive tasks while on the move, particularly thanks to the support of mobile devices such as smartphones, tablets, and laptops connected to the Internet.

Furthermore, the concept of productive time as time having an economic value in the marketplace is changing as well: for instance, the time devoted to bike to work can be regarded as productive time producing benefits both to personal health and to the environment. Due to these benefits, which can be also described in economic terms, a person may consider it more valuable to spend 10 or 15 min more to go to work by bike rather than going by car or by public transport.

Recent research hints on the need to explore broader meanings to assign to the concept of value of travel time. Thus, new approaches combining happiness and transport economics are emerging: according to Duarte et al. (2010), "*research developments of the latest decades have strengthened the importance on the individuals' behavior to understand, not only their choices, but also how can this be incorporated in the modelling tools that are used to picture present demands and future calls on society levels such as economy, transport and social policies, among other.*"

Traditional views of VTT are limited in incorporating knowledge on users' attitudes and choices with respect to travel time, reasons behind reorganization of transport routes and schedules, as well as factors explaining preference for a slower transport option or a longer route increasing travel time. The acknowledgement of these aspects as central in VTT estimation determines a shift from the economic focus to a broader behavioral focus centered on *what value of travel time means for the traveler*, and *how such value could be increased in the context of individual decisions*. In turn, this knowledge would also allow macro considerations at the level of cities, regions, and countries, with clear policy implications.

The shift from economic to behavioral approaches to VTT has the potential to contribute to the development of information societies with a human face. Jana Carp (2014) explains well this concept by introducing the Slow City movement, a vision for sustainable cities combining pleasure and productivity:

> Correlated with digital and transportation technologies, high speed can be an advantage in discrete situations, but it has significant secondary effects that reduce overall quality of life, inhibit personal and public relationship, and exacerbate injury to people and ecosystems. At a time when we face the unprecedented question of human sustainability, and cities increasingly invest in digital innovations to improve the efficiency of urban systems (the Smart City), certain aspects of speed hinder capacity-building for social and ecological resilience. [. . .] Good quality of life, and better business results, depend in large part on strategic employment of fast and slow. It is not about pace in itself but what pace affords. When fast people slow down, they experience other people, the incidental pleasures of life, the character of the land, the weather, sounds, smells, and tastes. This embodied awareness of place and people is part of what signifies the quality of life promoted by the Slow movement. It is not envisioned as a period of leisure outside work life, but as characteristic of the social and ecological environments in which people live their whole lives.

It is worth underlining the role of ICT in shaping VTT. It is generally acknowledged that digital personal devices such as smartphones, tablets, and laptops have a positive effect on VTT (i.e., increase the marginal utility of travel time) since they allow carrying out productive activities while on the move. They do not only support navigation tasks thanks to location-based technologies (e.g., journey planner), but also information and communication tasks during the travel time (e.g., chats, social media access, gaming, emails). In short, when wisely used they can enrich the travel time. In this context, the availability of free and wireless internet access may contribute to this enrichment. On the other hand, digital personal devices also require travelers to engage in "travel multitasking" (Berliner et al., 2015), a complex and cognitively demanding task. In addition to the cognitive load and difficulty to focus, some studies have also highlighted other negative effects of the "constant connectivity," namely increased tiredness and stress, emergence of "checking habit" (the brief, repetitive inspection of dynamic content) and even addiction.

In a way or in another, digital personal devices strongly influence mobility and activity patterns of individuals, and by collecting data on these activities such patterns emerge and can be presented back to the user to further promote more sustainable behaviors, well-being, and life balance. A number of smartphone apps (e.g., Google Fit, iPhone activity tracker, Apple Health, Facebook Moves, MotionTag, Life Cycle) indicate for instance the daily distance walked or cycled, and the calories burnt. Although these apps draw the user's attention on certain mobility behaviors, the relation of these behaviors to VTT is still an under-researched area that deserves further attention.

Future Directions

While the field of computational social science has still much potential to be uncovered, it has quickly gained popularity beyond the academic context. As a matter of fact, many "big data" applications are based on concepts and methods from this field. In relation to mobility data, its systematic collection, analysis, and curation is increasingly employed in the (related) fields of personal well-being and sustainable mobility – in particular to measure progress toward the achievement of general sustainability goals. While many of these initiatives stay at local and national levels, there are also global attempts toward shaping indexes and indicators of well-being and sustainability such as OECD "Better Life Index," Eurostat "Quality of Life Scoreboard," and ISO standards 37101 and 37120. Although it is too early to draw conclusions, there is an ongoing process toward making use of collected data on the one hand to shape and evaluate policies, and on the other hand to explain and promote sustainable behaviors.

Cross-References

▶ Computational Trust Models
▶ Data Mining
▶ Distance and Similarity Measures
▶ Ethical Issues Surrounding Data Collection in Online Social Networks
▶ Ethics of Social Networks and Mining
▶ Group Representation and Profiling
▶ Human Behavior and Social Networks
▶ Inferring Social Ties
▶ Mobile Communication Networks
▶ Modeling and Analysis of Spatiotemporal Social Networks
▶ Models for Community Dynamics
▶ Probabilistic Analysis
▶ Probabilistic Logic and Relational Models
▶ Social Computing
▶ Social Network Datasets
▶ Statistical Research in Networks – Looking Forward
▶ User Behavior in Online Social Networks, Influencing Factors

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