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Understanding human activity patterns based on space-time-semantics

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ABSTRACT

Understanding human activity patterns plays a key role in various applications in an urban environment, such as transportation planning and traffic forecasting, urban planning, public health and safety, and emergency response. Most existing studies in modeling human activity patterns mainly focus on spatiotemporal dimensions, which lacks consideration of underlying semantic context. In fact, what people do and discuss at some places, inferring what is happening at the places, cannot be simple neglected because it is the root of human mobility patterns. We believe that the geo-tagged semantic context, representing what individuals do and discuss at a place and a specific time, drives a formation of specific human activity pattern. In this paper, we aim to model human activity patterns not only based on space and time but also with consideration of associated semantics, and attempt to prove a hypothesis that similar mobility patterns may have different motivations. We develop a spatiotemporal-semantic model to quantitatively express human activity patterns based on topic models, leading to an analysis of space, time and semantics. A case study is conducted using Twitter data in Toronto based on our model. Through computing the similarities between users in terms of spatiotemporal pattern, semantic pattern and spatiotemporal-semantic pattern, we find that only a small number of users (2.72%) have very similar activity patterns, while the majority (87.14%) show different activity patterns (i.e., similar spatiotemporal patterns and different semantic patterns, similar semantic patterns and different spatiotemporal patterns, or different in both). The population of users that has very similar activity patterns is decreased by 56.41% after incorporating semantic information in the corresponding spatiotemporal patterns, which can quantitatively prove the hypothesis.

1. Introduction

Human activities influence the way urban system works. Urban system, on the other hand, mediates feedback to human activities through a diversity set of processes and mechanisms, including movement, behavior, thoughts, language, psychology, etc. Researches on how human activity patterns form thus play an essential role in various applications in an urban environment, such as transportation planning and traffic forecasting, urban planning, public health and safety, and emergency response. In the Big Data era, emerging smart and wearable devices have provided good channels to continuously record individuals' movements. Moreover, social media (e.g., Twitter, Facebook, Flicker, Instagram, etc.) enables people to share textual, pictorial and emotional information (e.g., texts about normal life and opinion on current issues or events), which provides an opportunity to conveniently and deeply explore and understand human activity patterns.

Existing work on analyzing human activity patterns mainly places an emphasis on spatiotemporal aspects using space and time datasets, including human movement trajectories collected by GPS receivers (Huang et al., 2015; Zheng et al., 2009) and mobile phone callings (Gonzalez et al., 2008). They focus on exploring, understanding and/or modeling human activity patterns of either single or multiple individuals in terms of spatial and temporal dimensions. For example, Asahara et al. (2011), Ashbrook and Starner (2003), Etter et al. (2013), Gambs et al. (2012), Mathew et al. (2012), Ying et al. (2013) developed a series of predictive models to infer where individuals are going based on analysis of human trajectories. Previously, we also developed a predictive model to predict human movement from GPS trajectories (Huang et al., 2015). We proposed an algorithm to detect the location changes of activities in advance, which can improve the accuracy of human movement prediction. Considering activity changes, the predictive accuracy can be significantly increased as proven

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in our experiment (R^2 is improved from 0.295 to 0.762). However, it is still difficult to clearly infer the motivation behind these changes only from a spatiotemporal dataset. Therefore, to determine what exactly cause such changes, which may provide another perspective to model such changes, becomes necessary. Moreover, some spatiotemporal rules and discoveries about human mobility have been recently revealed. Gonzalez et al. (2008) found that people are intended to return to a few highly frequent locations, which could be characterized by a single spatial probability distribution that indicates the dynamics behind the reproducible scaling patterns. Candia et al. (2008) discovered that the time interval of consecutive phone calls follow a heavy-tailed distribution. Song et al. (2010) claimed that 93% is the limit of the potential predictability in human mobility. Based on human mobility patterns, efforts have been made on comparing the similarity of human mobility (Eagle et al., 2009; Joh et al., 2002; Xia et al., 2011; Yuan and Raubal, 2014) since it may contribute to understanding of the social interaction among different demographic groups, and generating of specific recommendations in social network applications (Zheng et al., 2011).

Despite of these attempts, the aforementioned studies can only discover some activity patterns of individuals from spatiotemporal aspects only. More accurately, what they have done is to explore human mobility patterns. In fact, what people do and discuss at a place and a time cannot be ignored since activity patterns and human movements are cross-correlated. If a mobility pattern is illustrated as a type of expression of human behavior in terms of spatiotemporal dimensions, the mechanism or motivation that leads to the formation of such expression should be reflected by the specific semantic information (i.e., texts recording normal life and opinion on current issues and events). If we can uncover and interpret the motivation, how people move can be more reasonably and accurately predicted that may contribute to better design of our urban systems.

To determine the motivation behind human movements, it is necessary to know what is happening at a specific place where individuals stay for some time. For example, normally people sleep at home, work in office, and do exercise in gym. Furthermore, some individuals go to certain places for attending specific events, such as a concert, a meeting or a ceremony. If we consider the location and time of individuals' stay as their spatiotemporal attributes, the information illustrating what they do and discuss can be seen as their semantic attributes, which should be considered when analyzing human mobility patterns.

To extract such attributes, one can analyze some specific geotagged texts that describe life, share opinions of topics or discuss social incidents (Pak and Paroubek, 2010), for example, short texts posted on Twitter and Facebook with geo-coordinates. Through inferring topics of these texts or events hidden in the texts, what is happening at a certain place and specific time could be inferred. An intensive of research have already been done to analyze people's sentiment or detect social events from social networks, such as detecting mood (e.g., happiness or sadness) (Bertrand et al., 2013; Thelwall et al., 2011), attitude (e.g., positive or negative) about an certain incident (Pak and Paroubek, 2010; Tumasjan et al., 2010), activity (e.g., attending a party, hanging out in a bar, or eating in a restaurant) (Becker et al., 2011; Weng and Lee, 2011) or disasters (e.g., earthquake, traffic accident, or disease outbreak) (Li et al., 2012; Sakaki et al., 2010). Some efforts have also been made on extracting semantics of a place by analyzing trajectories (e.g., Andrienko and Andrienko (2007)). However, these studies do not further analyze how the spatiotemporal patterns would be affected by the semantic attributes.

In this paper, we propose a spatiotemporal-semantic model to quantitatively describe human activity patterns, which models human activity patterns not only based on space and time but also with associated semantics. The model is built upon the use of topic models, which aims to understand human activity patterns in terms of not only spatiotemporal dimensions but also related topics people may be interested. Subsequently, we compute the similarity of the patterns with a case study using geo-tagged tweets posted in Toronto, Canada, since Twitter has been proven as a useful proxy for human mobility (Jurdak et al., 2015) and it allows users to post texts embedded with geolocations. The motivation related to an activity pattern is inferred by exploring the associated topics. The ultimate goal is to prove that the motivations of similar mobility patterns may be different.

2. Methodology

This section starts by first defining two important terms that help understand the method described in the subsequent sections. Topic models are then introduced, which provide basis for the discussion of spatiotemporal-semantic modeling for human activity patterns.

2.1. Preliminary definitions

Definition 1. A **stayed place**, p, is a place where there exist certain activities. A p can be represented as a set of triples $\{d_w, p_c, t_d\}$, where d_w, p_c and t_d refer to day of week, category of places and time of day, respectively. For example, a stayed place can be a restaurant where a person has a meal at 1:00 pm on Monday. In this case, p can be indicated by {Monday, Restaurant, 1:00 pm}.

Definition 2. A **semantics**, s, illustrates a type of non-spatial attribute about a person. The attributes may reflect a life style (e.g., jogging, vegetarian, or commuting to work by car), an event (e.g., attending a concert, watching a sport game, or participating a parade), a type of hobby (e.g., listening music, doing sports, or reading books), a topic (e.g., U.S. president election, NBA final, or performance of a new smart phone), and so on, by means of topics in which people is interested in. We define s as a distribution over words. For example, s = {Lakers (0.3), nice (0.1), shot (0.2), Kobe (0.4)} indicates a topic about a nice L.A. Lakers' game where Kobe Bryant outperforms the game. Here we can infer that this person could have an attribute indicating that he is a fan of L.A. Lakers.

2.2. Probabilistic topic models

Topic modeling was originally proposed for understanding the topics in large text corpora within the domain of machine learning (Blei et al., 2003; Griffiths and Steyvers, 2002, 2004; Griffiths et al., 2003; Hofmann, 1999, 2001). The basic idea of topic modeling is that documents are mixtures of topics (a probability distribution over topics), where a topic is a probability distribution over words. A topic model is a generative model specifying a simple probabilistic procedure. Documents can be generated by this probabilistic procedure. More specifically, a distribution over topics is initially chosen to make a new document. Then, for each word in that document, a topic is randomly chosen and a word can be drawn from that topic according to a distribution over words. This process can be inverted by using standard statistical techniques, which can infer the set of topics involved in generating a collection of documents and a set of words involved in generating a collection of the topics. Only words in documents can be observed (i.e., observed data). Based on certain probabilistic sampling rules, how words distributed in documents might be generated on the