Explain urban regional function

Submission

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Abstract. The abstract should briefly summarize the contents of the paper in 15–250 words.

Keywords: Explanation · Urban computing · Online content · Sentiment analysis.

1 Introduction

1.1 motivation

Urban computing, defined in [1] as a process of acquisition, integration and analysis of big and heterogeneous data generated by diverse sources in urban spaces.One of the most important data source is human mobility data, e.g. pickups and drop-offs of taxicabs. Such mobility data can contribute to improve living quality of residents, e.g. optimizing urban planning [2], easing traffic congestion [3], decreasing energy consumption [18], reducing air pollution [19] and so on. Therefore, mining and modeling mobility data has attracted attentions from both academia and industry.

Identifying functional regions has been a critical step towards efficient government administration and policy making for decades. In early work, a functional region was defined as a geographical region where the majority of local population recruit and are employed within the region [14]. Due to the availability of large-scale mobility data, an increasing amount of data-driven approaches [9] have been proposed. Most of them use clustering methods on commuting data, such as origin-destination pairs of labour market data [12] while others use remote-sensor image data [4]. Later work focuses on city-level functional region identification, where a functional region is a region in a city which supports different needs of peoples urban lives [15, 16]. To obtain accurate identification, recent research tends to use complex models for various form of data, e.g. DRoF based on Dirichlet Multinomial Regression with latent factors applying in mobility data of taxicabs and points of interests (POIs) [15, 16], clustering algorithms based on the 'modularity function' [13] applying in telecommunication [6],unsupervised semantic labeling framework based on the Latent Dirichlet Allocation applying in remote-sensor data [5].

Explanation is regarded as a reason or justification given for an action or a plan. Majority of trustiness and satisfaction were highly correlated with the reliability of the explanations [30]. The complex nature of these models covers the intuition explanation of the system,which weakens the interpretability to end users and system designers.To fit with the growth of complex models,there is an emerging trend in studying explainable AI [34]. For example,graph and text with templates explanation is provided in navigation [35] and cognitive cities [36] to improve trustiness of people.To the best of our knowledge, none of the previous urban functional identification provide explanation for the results of region segmentation and functional labels automatically. To make the result more convinced,we aim to propose models to explain the identification of urban functional explanation.

In this paper,our goal is to proposed a model to explanation for our functional region clustering results. We have two data sets. One is mobility data 3 million including pick-up and drop-off coordinates and time,which provide detailed moving pattern for the dynamic urban system to discovering regions with different functions. And the other is comment data with shop address that reveal sentiment tendencies of the shop.We could exact labels as the form of 'character-opinion-sentiment' from and pick labels with strongest sentiment as our explanation. We combined the urban computing using mobility data with sentiment analysis using geo-content. Fig.1 reveal an example of our output of model.

1.2 challenge

In order to solve the problem,we face two challenges.

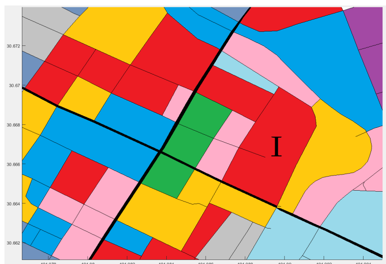
The first one of it is to extract the urban feature from comment data.Urban feature is a set of attributes that could describe characters of the Corresponding region,e.g. traffic,noise,neighbors and so on. Part of our content data comes from social media without detailed coordinates.They are full of sentiment tendencies but have difficulty to induced to a particular region. The rest are comments of shops with the shop address.The feature extracted from it is more related to shop feature than urban feature.Due to the case,existing sentiment extraction model Sentires [32] are infeasible in our models.In order to get the location information from these content data,we....

And the second challenge is that find the function of region is changing with time.The former research regarded time as a distinctive attribute of the region,put it as an input of DRoF model instead of describe its change [15].

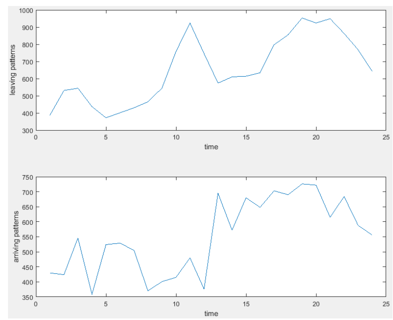
Our paper has an outstanding result in following several aspect:

- To the best of our knowledge,we are the first to give explanation to urban functional region identification , which could improve the trustiness and satisfaction of user.
- We combined the sentiment and human mobility as explanation,find the urban feature within a region.

The remainder of the paper is organized as follows. We give an overview for related work in Section 2. In Section 3, we introduce our novel models as well as proving their logic. Section 4 presents the suprior result in experiments of our models. Finally, we made a conclusion and looked forward to our future work in Section 5.

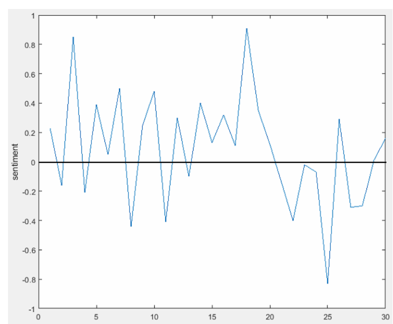


(a) An example of our identification result



(b) moving patterns

(c) POIs in region I



(d) Sentiment labels with their probability

Fig. 1. The explanation provided for functional region identification. Region I in Fig.1(a) is labeled as commercial region. Fig.1(b) revealed the mobility patterns in the region,which weekends and evenings has more patterns than work time. Fig.1(c) shows that there is more shops than other POIs within this region.And from fig.1(d) we find that people have a positive sentiment in traffic(label 18) and a negative sentiment in noise(label 25).

2 Related Work

Two lines of work are related to this paper: urban computing and online sentiment analysis .

2.1 Urban Computing

Urban computing [1] tackles the major issues that cities face by analyzing human mobility collected from different sensors. Major sources of human mobility data are check-ins in POI [26], pick-up and drop-off behavior of taxicabs [8, 3] in different locations and trajectories.

The simplest form of mobility data is check-ins data, which are collected from locating sharing services. Check-ins data usually includes a set of point revealing users' current location. Statistical association analysis is commonly conducted on check-ins. For example, radius of gyration is measured in [24], which is extended by combining with lexicon into demographics [26]. A few recent work adopts model based approaches, e.g. context-aware tensor factorization that take account of contextual factors that influence consumers refueling decision [18].

The second form of mobility data is origin-destination pairs, i.e. a pick-up point and a drop-off point of a taxi trajectory. Clustering methods including Newman modularity cluster algorithm [13] are applied in functional region identification [6]. Recently, latent factor models are proposed to treat a region as document and infer functional-specific [15].Latent activity is imported in topic model in [16] to define the specific functions of different regions.

Alternatives for origin-destination pairs are trajectory data. Applications on trajectory data include recommendation, e.g. to recommend more suitable place to drivers [8, 10] and traffic planning, e.g. to find reachable region within a given temporal period [20], or to predict travel time [21].

However, existing urban computing systems extensively rely on complex machine learning algorithms hence they act as blank-boxes for end users. The lack of explanation weakens the persuasiveness and trustworthiness of the system for users. Our work is to make up for this drawback by providing intuitive explanations of the results for users or system designers

2.2 Geographical Analysis of Online Sentiment

Recently, an emerging research interest is witnessed in exploring the geographical factors that affect online sentiment. Empirical studies have been conducted on large-scale human mobility data, such as check-in [26]and trajectory [25],to find the geographical content analysis with sentiment. Associations are found between online sentiments and geographical factors, e.g happy regions are more likely to connect with each other [23],a high check-in density region usually presents a more positive mode [26], the whole process and development of a organized movement could be tracked on the social media [22] and so on.

However, most existing work of this line employ simple statistical analysis to uncover the associations. Such a coarse-grained analysis is distorted by latent variables, such as activity of the region. Our work is the first to incorporate activity to obtain a fine-grained analysis.

3 Experiments

3.1 Data Set

The data set for our experiments including both mobility data and content data. The mobility data including the pick-up and drop-off time and coordinates in November of the year 2016 provided by DiDi, the biggest taxi platform in China.It contributed to the movement pattern of human mobility. And the online content is crawled from a website with many comments similar to Yelp called DazhongDianping and a social media named Weibo , which helps sentiment analysis of the regions.

3.2 Preparation

3.3 Baseline and other comparison

3.4 Evaluation Metrics

3.5 result

4 Conclusion

In this paper , we proposed several models to find the most possible destination region for users and add explanation for it to enhance its persuasiveness. The models have improve some extra recognition accuracy ,which have an extra contribution for functional city.

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