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 · Sentiment analysis.

1 Introduction

1.1 motivation

Urban computing is defined by Zheng et al. [?] as an concept where many factors ,such as sensors,prople,vehicles and so on, consist of a dynamic urban system.The aims of urban computing include improve the life level of residents,optimizing urban planning, decreasing traffic jams, reducing various pollution and so on. With the improvement of living life of urban residents,GPS-embedded taxi begin to play an important part of urban computing.And the data of taxi mobility provide us an valuable way to compute urban system.For example,Zheng et al. [?] detect the flaws in the existing urban planning of a city using the GPS trajectories of taxis traveling in the urban areas. Meng et al.[?] propose a framework to infer the city-wide traffic volume information with loop detectors and taxi trajectories.Garg et al.[?]minimizing distance through Monte Carlo tree search to decrease the rate of empty carrying and improve taxi drivers' profits. As you can see, Urban computing is closely linked with urban life.

Discovering regions of different function is a step towards urban computing.In this direction,Yuan et al. [?,?,?] do well in discovering regions of different functions

1.2 explain power

The approaches to explanation recommendation system was developing recently.At the early time,the fundamental methods of personal recommendation is recommendation systems with user-based and item-based. Resnick et al.[?] found user-based collaboration filtering recommendation system.The explanation is the similar neighbors whose interests and rates tend to be consistent with target user.Analogously,Sarwar et al. [?] proposed the recommendation with item-based could find the suitable items which has similar features with purchased items.

Variants of these basic model constitute the majority of explanation recommendation systems.e.g.,Pazzani et al.[?] As time going

We can see that early recommendation systems tend to base on intuition and full with common sense,which improve users' satisfaction easily. Now the explanation recommendation systems is developing with more accuracy , which generate more satisfying results.Nevertheless ,the complexity of models is increasing at the meantime,which covers the intuition of whole structure and weakens the persuasiveness of models.So the explanation is playing an important part in recommendation systems.Majority of users trust and choice satisfaction were highly correlated with the reliability of the explanations for recommendations.Herlocker et al. [?] do an investigation which shows that explanation facilities can improve the acceptance of recommendation systems.The following experiments,e.g.,by Ferwerda et al. [?] has proven the conclusion.We aim to propose models to explain the destination why we recommend it more persuasively

Our goal is to proposed a model to predict taxi destination and provide persuasive explanation for it.

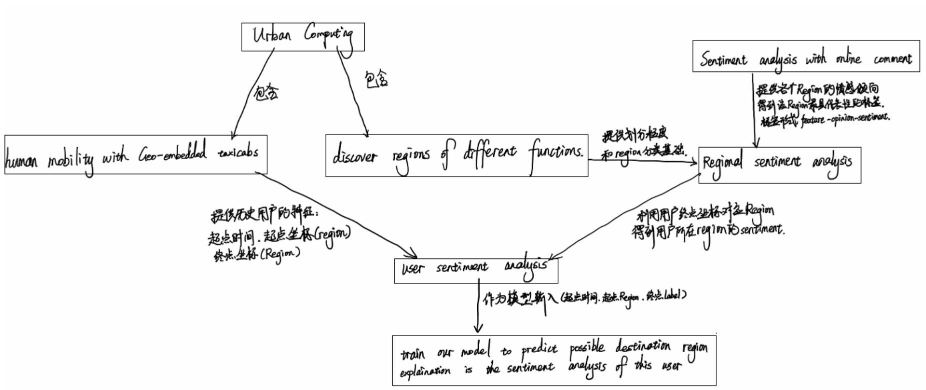

Fig. 1. The general structure of our paper

1.3 problem

For solve the problem,we face two challenges.One of it is...and the other is ...
segment regions = group regions with similar functions

function = distribution of activitys and opinions

previous research

1.4 contribution

Our paper has an outstanding result in following several aspect:

- According to what I have learned,we are the first one to state-of-the-art
- 2
- 3

1.5 paper structure

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.

2 Related Work

Two lines of work are related to this paper: sentiment analysis into human mobility,content from social media also provide great help for us. Many scholars have made fundamental contributions,and we combined them to find interesting patterns and extended the application .

To the best of our knowledges,we are the first to combined the sentiment into human mobility.

2.1 Urban Computing

Urban computing [**?**] tackles the major issues that cities face by analyzing human mobility collected from different sensors. Major sources of human mobility data are checkins in POI [], pick-up and drop-off behavior of taxicabs [] in different locations and trajectories []. For checkins data, the most commonly adopted model is. For taxicabs data, to fully utilize pick-up and drop-off, xxx is adopted to enhance xxx For trajectory data, as it involves multiple points

The aim of mobility mining is to uncover informative patterns of improve incomes of taxi drivers [], attracts an increasing research interest []. However, existing urban computing systems extensively rely on complex machine learning algorithms hence they act as blank-boxes for end users. The lack of explainability weakens the persuasiveness and trustworthiness of the system for users Our work is to provide intuitive explanations of the results for users or system designers

2.2 Geographical Analysis of Online Sentiment

Recently, an emrging 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 checkins [], trajectory, xxx [] Associations are found between online sentiments and geographical factors, e.g happy regions are more likely to connect with each other [**?**],a high check-in density region usually presents a more positive moode [],

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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