Explain urban regional function

submission

No Institute Given

1 Introduction

Urban computing importance [1] discovering regions of different functions [3]

Previous model model complex, deep model data heterogenous explainability -¿ disadvantage Explaining the result is of crucial importance

Our goal is to label and cluster the region. Furthermore, provide xxx explainations, activity , focus on aspects activity opinion Example (figure)

segment regions = group regions with similar functions

function = distribution of activitys and opinions

previous research

Our paper has an outstanding result in following several aspect:

- According to what I have learnt,we are the first one to ap
- 2
- 3

The structure of our paper is listed as follow.Some previous work of former scholars are listed in Section 2.

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 [1] 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 [6],a high check-in density region usually presents a more positive moode [],

However, most existing work of this line employ simple statististical 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 Application

Our models have a wide range of application and their value

3.1 Billboard

Billboard

3.2 Trajectory

4 Conclusion

In this paper , we propose several novel models to d The models have improve some extra recognition accuracy ,which have an extra contribution for functional city.

5 Reference

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