Explain urban regional function

Submission

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Abstract. Functional region identification is a critical step towards Urban computing. The state-of-the-art Dirichlet Multinomial Regression(DMR) has identify regions with different function based on topic cluster modeling. Due to the ingenious structure inside the complex model, its result is beyond the direct comprehension of humans. How to give them reliable explanations are the main objectives of this work. To improve the persuasiveness of its result, we proposed a post hoc framework to make explanation for it. Optimal latent factor model was applied as explanation after the identification. We use matrix factorization to get latent factors and correlate latent factors with urban feature. The selected urban feature can be labeled as the explanation. Our framework can give an strong evidence to the identification and enhance the satisfaction of users and system designers.
(15–250 words.)

Keywords: Explanation · Urban computing · Online content · Sentiment analysis · Latent Factor · Post hoc.

1 Introduction

Urban computing is a process of acquisition, integration and analysis of big and heterogeneous data generated by diverse sources in urban spaces [1]. Recently, urban computing has attracted attentions from both academy and industry. One critical step towards efficient urban computing is to identify functional regions, which is a region in a city that supports certain needs of urban lives [15, 16].

Most of previous functional region identification systems use clustering methods on mobility data [12]. such as origin-destination pairs of labour market data [12]. For example, clustering algorithm based on the 'modularity function' is applied on telecommunication data [13, 6], semantic labeling framework based on the Latent Dirichlet Allocation is applied on remote-sensor data [5], spectural clustering is applied on remote-sensor image data [4], and DMR (Dirichlet Multinomial Regression) are applied on pick-ups and drop-offs data of taxicabs and points of interests (POIs) [15, 16].

A severe drawback of existing research is the lack of explanation for functional regions. Clustering methods have long been suffering from the subjective issue, i.e. the system only provides one possible partitioning of the regions while the users have no idea what the partitioning means. Furthermore, to obtain accurate identification, recent research tends to use complex models [16] on a combination

of different data sources. The complex nature of these models is an obstacle for people to capture the "semantics" of the identification.

Explainable functional region identification is beneficial for both system designers and end users. For example, providing explanations help system designers to better intepretate the clustering results and improve the system. The explanations can incubate a series of applications for end users, including traffic flow predictions, personalized trajectory recommendation, urban planning and so on. In a bigger picture, there is a growing interest in studying explainable AI [34]. However, in geographical systems, explainable system is still in its initial stage [35, 36].

In this paper, we present a novel system for explainable functional region identification. The system provides post-hoc explanations, i.e. the explanations are not relevant to the identification algorithm. Instead, the system attempts to resolve the "semantics" of cluster labels generated by any functional region identification algorithm by (1) associating the cluster labels to a set of human activities; (2) visualizing the desired urban features and public sentiments for each activity; and (3) listing the most important urban features in the region.

As shown in Fig.1, the city of Chengdu has been functional regions delivers explanations of the functionals. To be specific, we first associate each functional with an urban activity, next we extract the most representative urban feature for each activity, finally we highlight the sentiment towards typical urban features for each functional region. For example,Fig.1 given a map of city A, reg region I corresponds to residential region while blue region II corresponds to commercial region. We found that people are most interested on traffic for a commercial region. And a residential region usually has sentiment positive on vanishing noise.

Framework. In this paper,to make the results more convincing, we build a system that provides explanations for functional region clustering results. The system is built upon two data sets. One is mobility data including more than 3 million pick-up and drop-off coordinates and timestamps,which provide fuzzy flow increment of each region units and each time bins. The increment, also called moving patterns, are the first input of topic-model-based DMR models as well as POIs. Dirichlet Multinomial Regression(DMR) identify the segmented region units as different functions. Meanwhile, comment data of shop show the sentiment relavitity between urban feature and the activity that shop related to. We pick labels with highest information entropy as urban features from all extracted features. Finally, we optimal latent factor with temporal dimension to get a location-feature matrix.

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 characters with special geographical attributes, e.g., clothes, school, bars and so on. Most of our content data are comments of shops with the shop address.The feature extracted from it is more related to shop feature than urban feature. Therefore, existing sentiment extraction model [37] can not be used directly in our models.In order to get the location information from these
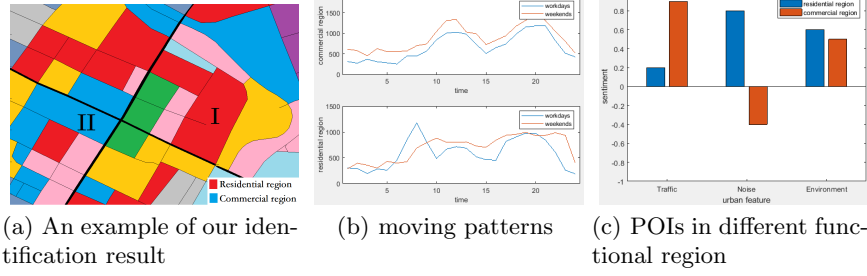
(a) An example of our identification result

(b) moving patterns

(c) POIs in different functional region

Fig. 1. The explanation provided for functional region identification. Region I in Fig.1(a) is labeled as residential region while II is commercial region. Fig.1(b) revealed differences of the mobility patterns between residential region and commercial region,workdays and weekends. Fig.**??** shows the distribution of POIs within the two regions,e.g. there is more shops in commercial region. And from fig.1(c) we find that people have a more interest in a positive sentiment in traffic for commercial and pay more attention to noise for residential region.

content data, all features are extracted as [32]. We select typical features with a high frequency and high information entropy from it.

And the second challenge is how to explain the features. If the extracted urban features used for explanations can not correspond to the labeled activity used to identify functional regions, the explanations will not have a strong explanation power for the identification, or even will not be generated. To improve the explanation power of our framework, we extract related urban feature and find the corresponding sentiment score between activity and urban feature from contents. With the probability that region units belong to which function generated by DMR, we can applied matrix factorization to find the relativity between region units and latent factor, i,e urban feature. The urban feature with highest relativity make an explanation for why corresponding region units are identified as such function.

Contribution. 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 users and urban system designers.
- After identify different functions, We use the contents with sentiment to find the typical urban feature within a region and make explanation.
- The explanation is given by latent factor model. We appplied matrix factorization to get the correlation coefficients between single region units and its features.

Structure. The remainder of the paper is organized as follows. We give an overview for related work in Section 2. In Section 3, we give an overview of our framework. Section 4 shows the process of functional region identification as well

as urban feature extraction. And Section 5 introduces the post hoc explanation model. We test the framework on our datasets and presents the superior explanation result in Section 6 Finally, we made a conclusion and looked forward to our future work in Section 7.

2   Related Work

Our work is build upon taxicabs trajectory and comment text. With the data source, 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].

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,

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   System Overview

The section make an overview introduction for our post hoc framework to explain the functional region identification. The whole structure is illustrated in Figure 3 while the corresponding steps as follow:
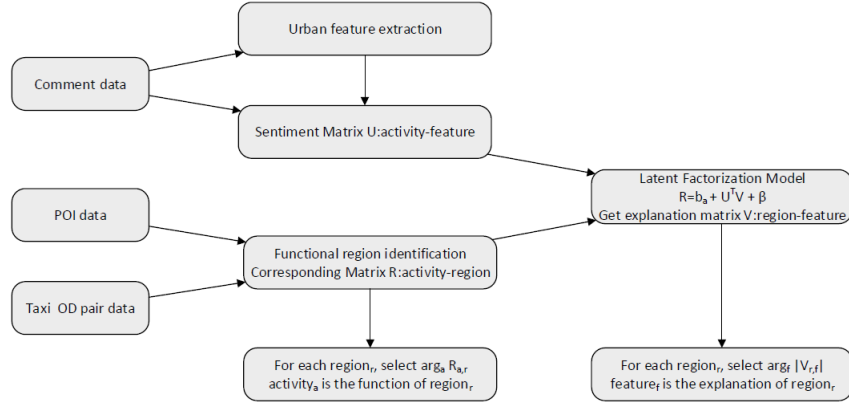

Fig. 2. The overview structure of our framework

1.Functional region identification:
The input data of first step is taxicabs OD pairs and POIs with coordinates. We can get an activity-region matrix with value of the probability that each single region units belong to each activity by DMR. And for the region, an activity with highest probability can be output as the function of this region.
2.Urban feature extraction:

This step based upon the comments of different shops and activity-region matrix output in last step. We select nouns with high frequency and low information entropy as our urban features. Meanwhile, the sentiment analyse between urban feature and different activity is also illustrated in an activity-feature matrix.

3.Train Matrix Factorization model:

With the certain activity-region matrix r and activity-feature matrix u, we performed an matrix factorization model in form of Equation 2 to get the region-feature matrix v. Training data comes from the given result of step 1 and step 2.

4.Output label explanation:

The region-feature matrix v generated in step 3 in the input of this step For each single region units,we can pick the urban features with highest sentiment score in v. These urban feature is the explanation for the functional region identification.

4   Urban Feature

4.1   Functional Region Identification

A city was segmented into single region units, which is regarded as documents with various themes in topic modeling. DMR [39] was applied in functional region identification as explained in [15]. DMR, whose structure is illustrated in Figure 3, is a topic clustering model based on Latent Dirichlet Allocation(LDA). It input some metadata, e.g. authors and publishers, in addtion to basic LDA, which make the topic modeling more accurate. As describe in [15],we regard flow increment calculated in regions as vocabulary in documents, which is marked as $m_{r,n}$ in Figure 3. And POI located in different region units are correlate to the matadata of document, which is marked as x_r in Figure 3.
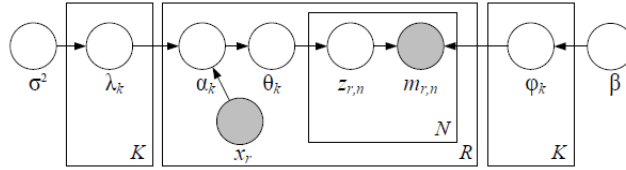

Fig. 3. The structure of DMR

4.2   Urban Feature Extraction

To get proper urban features for explaining different functions, we thought that urban features should be nouns with high frequency and low information entropy.

Considering the property of urban features, we separate comment sentences into single words and select all nouns of it. With the help of coordinates, these words can correspond to different single units. Take the sparseness of latent factor into account, we thought the words had better appear in more region units. And we filer the high-frequency nouns as features. If the frequency of a word is high enough, i.e. the shops commented with this word is much than a threshold t, we thought its frequency is high. We set the threshold t as 500.

Meanwhile, to make the urban features more distinguishing, we calculate the information entropy of words for different functional regions generated in Section 4.1. Information entropy can measure the amount of information that a word contains. Stronger distinguishing ability of a word takes lower information entropy. The information entropy is defined as:

$$H[x_i, word_j] = -\sum_i p(x_i, word_j) \log p(x_i, word_j)$$

where x_i stands for ith functional regions; $p(x_i, word_j)$ is the proportion of shops located in ith functional regions commented with jth word in all shops located in ith functional regions. We select features with lowest information entropy as our urban features, which are shown in Table 1.

Table 1. Selected Urban Features

features	Alley	Brand	Center	Square
information entropy				

4.3   Urban Feature Matrix

5   Explanation Model

In this section,we describe our post hoc framework for explanation in detail.

5.1   Latent Factor Model

A classical model has Intuitive explanation is latent factor model. It has a wide application in various fields. The form of latent factor applied in recommendation system to predict rating of user u to product p as follow:

$$\hat{r}_{u,p} = g + b_u + b_p + \boldsymbol{x_u}^T \boldsymbol{y_p} \tag{1}$$

where g is a base rating in the system while b_u and b_p is the bias of user u and product p; $\boldsymbol{x_u}$ and $\boldsymbol{y_p}$ denote vectors of latent factors for corresponding user and product.

The matrix r is rating that user u give to product p. Correlate users as activities, products as locations, we translated the matrix into the sentiment analysis score that actitivy a to region l. We can make our matrix based upon this stand latent factor model presented in Equation 1.

5.2   Our model

Considering the temporal attribute of datesets, [38] has proposed an Historical Influence Aware Latent Factor(HIALF) model take the historical influence into account, which fit our intuition well and make the power of explanation stronger.

Therefore, we define our matrix factorization model as:

$$\hat{r}_{l,i,a} = b_l + U_a^T V_l + \beta(e_{a,i}) \tag{2}$$

where $\hat{r}_{l,i,a}$ stands for the predicted probability at i-th time bin that region l belongs to activity a; b_l is the bias of region l; $\boldsymbol{U_a}$ and $\boldsymbol{V_l}$ represent the latent feature of activity a and region l; $e_{a,i}$ generated by prior expectation; and $\beta(\cdot)$ demonstrates the bias curve changing with $e_{a,i}$. Now we describe how to learn the $\beta(x)$ and generate a more realistic prior expectaion $e_{a,i}$.

Modeling the bias curve $\beta(x)$ The form of $\beta(x)$ is unknown. We can constrain it with a data-driven approach. Kernel regression is a kind of typical non-parameter learning and fit the $\beta(x)$ model well.

If we have a set of independent variables e_l and dependent variables v_l, and $v_l = \beta(e_l) + \epsilon_l$ where ϵ_l is the noise from the standard normal distribution, we can defind $\beta(x)$ as:

$$\beta(x) = \frac{\sum_{k=1}^n w(x, e_l)v_l}{\sum_{k=1}^n w(x, e_l)}$$

where $w(x, x_i) = \exp(-\kappa(x - x_i)^2)$ and κ is given by 10. Actually, e_l is given while v_l is unknown. Therefore, we set e_l as several arithmetic progression within data range and v_l is the corresponding unknown parameters so that we can learn them from datasets.

Modeling the prior expectation $e_{a,i}$

$$e_{a,i} = \frac{\sum_{k=1}^{i-1} \xi(i-k)r_{a,k}}{\sum_{k=1}^{i-1} \xi(i-k)}$$

where $\xi(d) = \exp(-\gamma \times d)$ is an exponential triggering kernel that models the decrease of histroy influence; γ controls the degree that history probability influence current probability; and $r_{a,k}$ denotes the sentiment of activity a when time bin k.

5.3   Model Inference

After build a matrix factorization model, we set up objective function as follow:

$$F = \sum_{(p,l,u)\in\mathcal{M}} (r_{l,i,a} - \hat{r}_{l,i,a})^2 + \lambda_1(b_l^2 + ||\boldsymbol{y_r}||_2^2) + \lambda_2(\sum_l v_l^2) + \lambda_3(\sum_\alpha \alpha_u^2) \tag{3}$$

where Θ stands for the unknown parameters, $\boldsymbol{y_p}$, b_u, α and v_l. $\mathcal{M}$ contains all (p, l, u) pairs, and each pair of it stands for the related parameter of region l belongs to activity a at time bin i. $r_{r,i,a}$ is the probability generated by DMR

while $\hat{r}_{r,i,a}$ is the predicted probability by Equation 2. The first item of Equation 3 is quadratic sums of the difference between real probability $r_{r,i,a}$ and predected probability $\hat{r}_{r,i,a}$. To prevent from overfitting, we three regularization terms and λ_1, λ_2 and λ_3 are given as hyperparameters.

To get our optimal $\boldsymbol{y_r}$, we aim to solve the following optimization problem and make the predicted probability $\hat{r}_{r,i,a}$ as close as possible to the real probability$r_{r,i,a}$:

$$\min_{\Theta} F$$

The approach to get it is stochastic gradient descent(SGD) algorithm due to its efficiency in learning the parameter of objective function

6   Experiments

6.1   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 timestamps 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, which helps sentiment analysis of the regions.

Table 2. Statistics of datasets

Datasets	attributes	Value
comments	shops with coordinates(POI)	109686
	shops with comments	50853
	total comments	3213264
taxicabs	effective orders	7065937
	effective days	30
road networks	geographical scope	[103.93°E,104.21°E] and [30.56°N,30.79°N]
	road segments	3712
	percentage of major roads	54.9%
	segmented regions	901

6.2   Preparation

To form the basic region of city,we segment the urban area of city into region units by the major road network and make a map simplification. The longitude of map range is [103.93,104.21] and latitude range is [30.56,30.79], which covers the main area of a city. Raster-based model is more computationally efficient and succinct for territorial analysis, which is suitable for our map scenario. We

downloaded the major road network of this region[1] and rasterized the area into a 2000×2400 grid. In the grid, the road network is converted to a binary image, as 1 stands for the road while 0 stands for the blank areas.

The main road data is present in Fig.4(a), including motorway, trunk, primary, secondary, tertiary and their links. But the Fig.4(a) is full of some unnecessary details, such as the lanes of a road and the overpasses, which disturb the distribution of regions. As explained in [16], the dilation and thinning process illustrated in Figure 4 are operated on the original road data to remove some small regions and simplify the map.
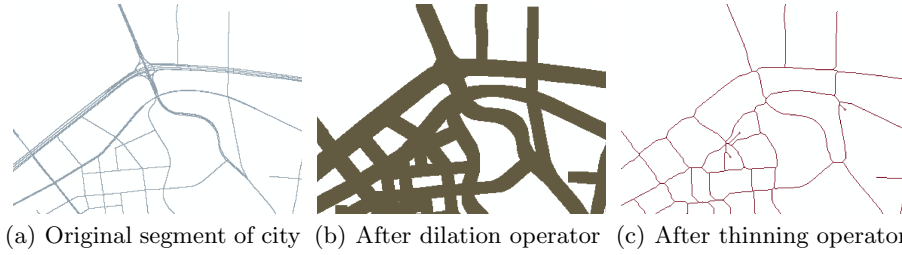
(a) Original segment of city (b) After dilation operator (c) After thinning operator

Fig. 4. The preparation process of road network

We use DMR to identify regions into 8/4 types with different regions, which is illustrated in Figure 5(b) The main function regions in the city is residence region, business region, study and science region, scenery regions and so on.
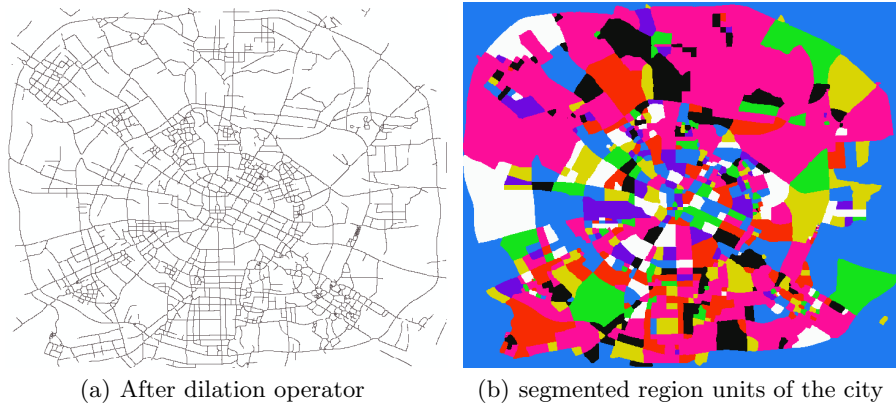
(a) After dilation operator   (b) segmented region units of the city

Fig. 5. results of DMR

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[1] http://www.bigemap.com/

6.3   Evaluation Metrics

We evaluate the functional region through two approaches. One is the percentage of regions that could find explanation label by our framework; while the other is the quality and accuracy of the explanation given by our framework.

For the evaluation of percentage of explainable region, we put forward the *explanationpercentage* to measure the proportion that regions with explainable labels as:

$$explanation\ percentage = \frac{|regions\ with\ explanation\ label|}{|all\ regions|}$$

For the second approach,we take a metric to measure the quality and accuracy of our explanation label.

6.4   Baseline and other comparison

6.5   result

Table 3. Functional Regions and corresponding urban feature

Functions	Urban Feature
Business	
Residence	
Study	
Scenery	

7   Conclusion

Function regions identification is an important part of urban computing. But its evaluation depend on human intuition and urban planning, which is hard to display in terms of statistics. To make up for the lack of persuasive explanation, we proposed a post hoc framework to give persuasive explanation for functional regions identification in this paper. Our datasets including over 3 million comments of shops and taxicabs OD pair trajectory in November 2016 generated by more than 7 million orders. We utilized the framework to general most relative labels for every single region units as explanation. According to the experiments performed in the datasets, our framework give an strong evidence to the identification and enhance its persuasiveness. The result can help users and urban system designers easily recognize the region functions, which is helpful in a variety of urban applications, such as urban planning, location choosing for a business advertisement casting, and so on.

There are some directions can improve in the future work. First is to full utilize our data sets of trajectory. Our trajectory datasets not only have origin

and destination, but also include the detail points that users have passed by. There are also some interesting patterns within these process points, and we can find new moving patterns in it. Second, we want to change our phrase-level explanation into sentence-level, which is more similar to natural language.

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