Explainable Functional Region Identification

Submission

No Institute Given

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: Explainable AI · Urban computing · Online Sentiment analysis · Big data analysis · Functional region identification

1 Introduction

Urban computing is a process to acquire, integrate and analyze 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 are regions in a city that support certain needs of urban lives [15, 16].

Most of previous *Functional Region Identification* (FRI) systems use clustering methods on mobility data [12]. For example, clustering algorithm based on the 'modularity function' is applied on telecommunication data [13, 6], spectral clustering is applied on remote-sensor image data [4], variants of Latent Dirichlet Allocation (LDA) is applied on remote-sensor data [5] and taxicab pick-ups and drop-offs data [15, 16].

A severe drawback of existing research is the lack of explanation for functional regions. Clustering methods generate cluster labels that 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 such as the Dirichlet Multinomial Regression model in [16] . The complex nature of these models is an obstacle for people to capture the "semantics" of the clustering results.

There is a strong incentive to develop *Explainable Functional Region Identification* (EFRI) system, which *explains* the identification of functional regions. EFRI is beneficial for both system designers and end users. For system designers, explanations help them better diagnose the system and improve system performance. For end users, explanations not only facilitate interpretation of the clustering results, but also incubate a wide range of applications, including traffic flow predictions, personalized trajectory recommendation, urban planning and so on.

Though there is a growing interest in studying explainable AI [34], in geographical systems, explainable system is still in its initial stage [35, 36]. In this paper, we present a novel EFRI system by integrating heterogeneous data sources. Our system provides post-hoc explanations, i.e. the explanations are not relevant to the FRI algorithm. Instead, for an arbitrary FRI algorithm, the system attempts to resolve the "semantics" of the generated cluster labels by (1) associating the cluster labels to a set of human activities; (2) visualizing the desired urban features for each activity; and (3) listing the most important urban features in the region.

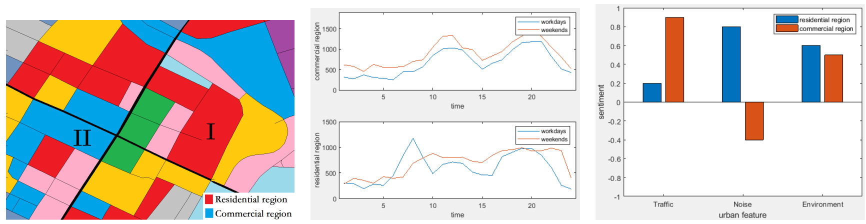
As shown in Fig.1, the city has been partitioned into several functional regions. For a specific region r_1 with label l, the system delivers textual and visual descriptions. Firstly label l is most likely to relate to a mixture of activities "" and "", because from the analysis of mobility data, these two activities bring in % of the traffic flow to region r_1. Secondly, under activity "", two urban features "" and "" are most popular, with highly positive sentiments collected from online reviews. Finally region r_1's most representative urban features are exactly "" and "", thus the system explains why r_1 is labeled as l.

We highlight a key property of the proposed EFRI system: **the power to integrate heterogenous data sources to offer semantic explanations for mobility patterns**. On one hand, explanations essentially involve semantics, which are not available in pure mobility data (i.e. taxicab pick-ups and drop-offs). In our system, the semantics of labels are expressed through urban activities and urban features, both of which are extracted from textual data (i.e. online review data). On the other hand, the identification of functional region is based on mobility patterns. To generate reasonable explanations, our system blends in the semantics extracted from textual data and moving patterns discovered in mobility data.

In building such a system, we face two challenges.

The first challenge is how to efficiently extract urban features from online review data. A naive approach is to maintain a manually constructed lexicon of urban features. However, the lexicon is expensive to construct and maintain. An alternative approach is to classify textual phrases with the supervision of a labelled set. Again, the supervision is costly to obtain.

To address the first challenge, we adopt an unsupervised approach to extract urban features from online review data. Urban features are characterized with geographical attributes, existing product feature extraction methods such as [37] are not directly applicable. Therefore, we first adopt NLP techniques to



(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.

select a candidate set of features. Then we filter urban features which are most representative in geographical texts.

The second challenge arises from the integration of textual and mobility data. To fully explain the functional of a region, our goal is to simultaneously discover semantic associations (i.e. how the given region is associated to each urban activity and urban feature) and mobility patterns (i.e. how the current traffic flow of a given region is affected by previous traffic flow). This is not a trivial task. The mobility patterns can be highly diverse for each region and time sensitive. For example, people tend to gather in school region in the day, while in residence regions produces they gather at night. Restraining a global form shared by all mobility patterns is problematic.

To address the second challenge, we adopt a layered regression model to embed the semantic associations to predict traffic flows, i.e. the traffic flow of a region is aggregated over all activities, where each activity specific traffic flow is predicted by people's preferences on multiple urban features and the region's association with the same set of urban features. Furthermore, we incorporate a bias curve in the prediction formula to represent mobility patterns. The bias curve is free shaped so that the forms of mobility patterns are not restrained.

Contribution of this work is three-fold. (1) **An Unexplored Problem.** To the best of our knowledge, we are the first to study the problem of explainable functional region identification. (2) **A New Form of Explanations.** We propose a novel framework to deliver explanations. The proposed EFRI explains the functional of a region by demonstrating both the semantics of functional (through urban activities and urban features) and mobility patterns of the functional (time sensitive mobility patterns). Such informative explanations can greatly improve user experience and might shed some insights in other domains such as explainable recommendations. (3) **A Novel Model.** We present a unsupervised framework to extract urban activities and urban features from online review data. We then adopt a layered regression model to semanticaly associate regions to urban features. We also embed a free-form bias curve to represent mobility pattrerns in mobility data.

The remainder of the paper is organized as follows. We briefly overview related work in Section 2. The EFRI system is presented in Section 4 and Section 5. In Section 4, we describe technical details to extract urban activities and urban features in online review data. In Section 5, we give the intuition and inference of the layered regression model to generate explanations that cover both semantic associations and mobility patterns. We evaluate the EFRI system and analyze the experimental results in Section 6. Finally, we conclude this work in Section 7.

2 Related Work

As our work makes use of taxicab pick-ups and drop-offs data and online review data, two lines of work are related: urban computing on mobility data and online review analysis .

2.1 Urban Computing on Mobility Data

Urban computing [1] tackles issues that cities face by analyzing human mobility data. Major sources of mobility data are check-ins data [24, 26], origin-destination pairs data [8, 3] and trajectory data [8, 10, 20, 21].The simplest form among them are check-ins data, which is a set of points revealing users' current locations collected from location sharing services. Check-ins data are previously adopted for revealing demographic associations [26] and POI recommendation [24]. Origin-destination data consists of a set of pairwise location points, e.g. a pick-up point and a drop-off point of a taxi trajectory. Most functional region identification systems are based on origin-destination pairs [**?**,12], e.g. from commute data [**?**,**?**,36], or from remote-sensor image data [4]. Trajectory data consists of a set of routes, where each route is a sequence of location points. Taxi driver trajectory [8, 10] data is more suitable for traffic planning.

A major and ongoing thrust of research on urban computing concerns the identification of functional regions. 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]. Recent studies focus on city-level FRI, i.e. identification of regions in a city that support certain needs of urban lives [15, 16]. Traditional FRI systems are rule-based [14], i.e. a city's labor market statistics satisfying certain requirements is considered to be a functional region. 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 [12]. To name a few, clustering algorithm based on the 'modularity function' [13, 6], spectral clustering [4], Latent Dirichlet Allocation (LDA) [5] and Dirichlet Multinomial Regression (DMR) [15, 16].

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 end-users. Our work is to make up for this drawback by providing intuitive explanations of the results for end-users and system designers

2.2 Online Review Analysis

Online review data has been extensively studied in opinion mining []. Given a set of product features, the user sentiments in each review are extracted either as binary sentiment polarity [] or as numerical sentimental strength []. Opinion mining has been combined with recommender systems to generate explainable recommendations []. Typically, a latent factor model [] is utilized to decompose user-item ratings to a latent feature space of user preferences and item attributes. Though there are fruitful research results in this domain, due to the lack of geographical analysis, these methods are not directly applicable to generate explanations for FRI.

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:

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.

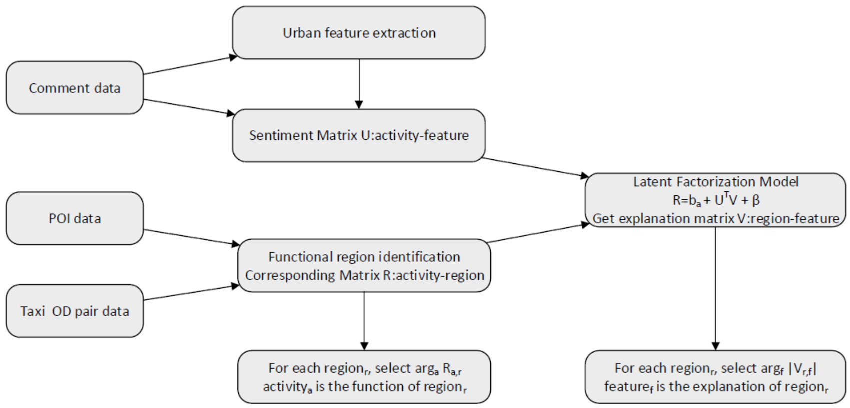


Fig. 2. The overview structure of our framework

3.Train Matrix Factorization model:

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

4.Output label explanation:

The region-feature matrix $\boldsymbol{v}$ 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 $\boldsymbol{v}$. These urban feature is the explanation for the functional region identification.

4 Urban Feature

4.1 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				

4.2 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:

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

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:

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

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.3(a), including motorway, trunk, primary, secondary, tertiary and their links. But the Fig.3(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 3 are operated on the original road data to remove some small regions and simplify the map.

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

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

(a) Original segment of city (b) After dilation operator (c) After thinning operator

Fig. 3. The preparation process of road network

(a) After dilation operator (b) segmented region units of the city

Fig. 4. results of DMR

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.

Table 3. Functional Regions and corresponding urban feature

Functions	Urban Feature
Business	
Residence	
Study	
Scenery	

6.4 Baseline and other comparison

6.5 result

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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