Discovering Urban Functions of High-Definition Zoning with Continuous Human Traces

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ABSTRACT

Identifying the dynamic functions of different urban zones enables a variety of smart city applications, such as intelligent urban planning, real-time traffic scheduling, and community precision management. Traditional urban function research using government administrative zoning systems is often conducted in a coarse resolution with fixed split, and ignore the reshaping of zones by city growth. To solve this problem, we propose a two-stage framework in order to represent the high-definition distribution of urban function across the city, by analyzing continuous human traces extracted from the dense, widespread, and full-time cellular data. At the representation stage, we embed the locations of base stations by modeling the user movements with staying and transfer events, along with the consideration of dynamic trip purposes in continuous human traces. At the annotation stage, we first divide the city into the finest unit zones and each covers at least one base station. By clustering the base stations, we further group the unit zones into functional zones. Last, we annotate functional zones based on the local point-of-interest (POI) information. In experiments, we evaluate the proposed high-definition function study in two tasks: (i) in-zone crowd flow prediction, and (ii) zone-enhanced POI recommendation. The results demonstrate the advantage of the proposed method with both the effectiveness of city split and the high-quality function annotation.

CCS CONCEPTS

• **Information systems → Data mining**.

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KEYWORDS

Urban computing, fine-grained functional zone, mobile trajectory, zone embedding, signaling data;

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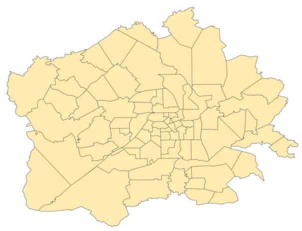
1 INTRODUCTION

Urban function describes the land use for certain categories of human activity, which varies from one zone to another, shaped by diverse factors such as geography, population, and history [13]. A rational city zoning and the discovery of zone function are desirable for urban studies in terms of understanding the city of today and developing the city of tomorrow [19]. Enabled by the rapid development of mobile computing, massive human mobility traces have been collected and provide an unprecedented opportunity to address this task from a new angle [5]. Base on these data, we can develop precise and timely zoning approaches with high-definition on urban function distribution.

Existing literature has shown efficient results of studying human mobility patterns. [24] analyzes urban functions through exploiting the origin and destination information of taxi trip data. [3] utilizes location-based social networks to learn the urban dynamics using geo-tagged and time-stamped online posts. [26] [25] discover region functions based on the human mobility extracted from transportation trips and point-of-interest (POI) check-ins. However, three critical limitations still exist. First, the point-wise check-ins or the pair-wise origin-destination trips in previous studies are insufficient to uncover the panoramic view of a person’s activities in a full-time (e.g., a whole day) trajectory. Second, the use of administrative zoning makes a city’s function distribution illustrated in a coarse granularity. Third, making a zone exclusively labelled with a single function ignores the complexity of land uses, wherein multiple functions present frequently for real-world zones.

To address the challenges above, we propose to exploit cellular data with broader geographical coverage and full-time monitoring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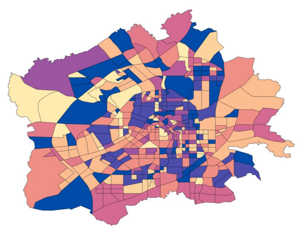
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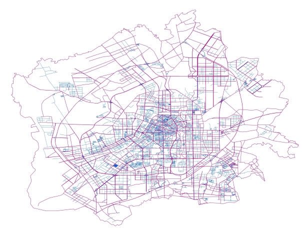
Figure 1: The Changchun City split by (a) predefined administrative zoning, and (b) proposed high-definition resolution functional zoning.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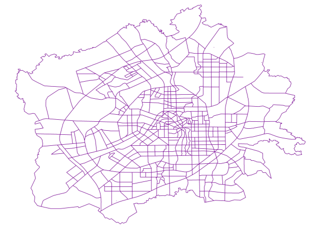
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Figure 2: (a) Primary and secondary road networks of Changchun city. (b) The fine-grained functional zones divided by road network.

capacity. The advantage of using this data is that its geographic scope is not constrained by the availability of traffic as many transportation data do, or by the number of business sites as many POI data do. Since mobile devices always automatically connect to the nearest base station, the cells of base station provide us a fine radius of action to observe mobile users' location. Second, we comprehensively model the human traces with two mobility events: staying and transfer events, including location, time, and status, so that the user situation at each time step can be precisely characterized. In order to learn the representation of base station cells, we propose to consider the continuation of human traces in a full-time trajectory (e.g., a whole day), so that the purpose of each mobility trip can be dynamically modeled with rich contexts of adjacent activities. Last, instead of using the predefined government administrative zones, we proposed to use finer unit zones divided by local roads to make up the final function zones, which are more coherent with the distribution of urban function and the growth of the city as shown in Figure 1.

Along this line, we present a high-definition resolution functional zoning method (HrF-ZR) that leverages continuous human traces to represent and annotate function zones. Specifically, we encode the staying and transfer events with a word2vec based embedding method to obtain the pointwise embedding of user status at each time step for the representation stage. We further learn a continuous function embedding LSTM network with a two-layer bidirectional setting to capture the dynamic trip purposes based on the rich contexts of user situation and higher-order zone dependency. For the annotation stage, we divide the city into the fine-grained unit zones based on the local road network, and cluster them to make up the high-definition function zones. For each function zones, we annotate its particular functions with the comprehensive POI characteristics.

Finally, we apply the results of high-definition function zoning on two experimental tasks for validation, including the crowd flow prediction and zone-enhanced POI recommendation. The performances obtained from both tasks combined with the qualitative studies demonstrate the advantage of the proposed method.

The main contribution of this paper is three-fold:

- We propose a high-definition resolution function representation framework that learns continuous human traces. In detail, we model the time-aware mobility events at the level of cellular base station neighborhood and learn their function representation through capturing the dynamic trip purposes within the continuous traces in a full-time trajectory.
- We propose a sophisticated annotation approach that uses the finer-scale unit zones obtained with the local road network to make up the final function zones, and further annotate each function zone with the comprehensive human activities extracted from the POI information.
- With the real-world, large-scale mobility datasets of Changchun City, we apply two validation tasks for quantitative evaluation, including the crowd flow prediction and the zone-enhanced POI recommendation. In addition, we conduct multiple qualitative experiments to demonstrate the advantage of our high-definition function zoning method. The results from all experiments validate the effectiveness of our approach.

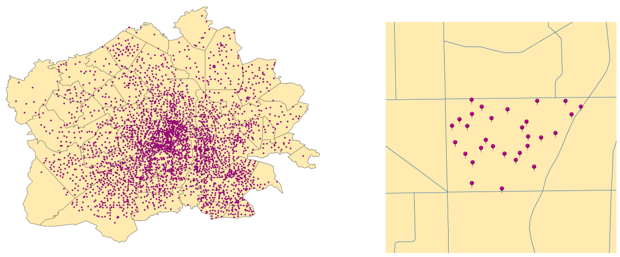
2 PRELIMINARY

In this section, we first describe the background of functional unit zones and base station cells. Then, we define the preliminary concepts in our work.

2.1 Background

Unit Zone: A set of fine-grained zones obtained by dividing the city with primary and trunk roads. Figure 2(a) shows the distribution of roads in Changchun City, where the brown lines indicate the trunk and primary roads, the blue lines indicate the secondary and tertiary roads. Among all the road graded with 15 levels in Changchun, We sampled 60% of the top four grade roads which basically cover the most important road network all over the city. Then we use the map editing tool *ARCMAP* to further process the selected roads as boundary to divide the entire city area into basic and fine-grained functional zones. Figure 2(b) shows the results of functional zones by road network division. We can observe that the areas in downtown (central part) are more dense and small comparing to suburban areas, which reflects the distribution of roads and cooresponding population.

Base Station Cell: Each base station has its signal-covered cell called base station cell. When a mobile user travels from one base station cell to another base station cell, their devices switch to the new base station from the previous one. Figure 3(a) shows the



(a) (b)

Figure 3: (a) The distribution of base stations. (b) Base stations in a unit zone.

distribution of base stations for transmitting the cellular signal in Changchun City, and Figure 3(b) illustrates the locations of base stations in a particular functional zone.

2.2 Definition

Definition 1. (Staying event): A staying event $sp = (p_c, p_{t.a}, p_{t.l})$ is a triple extracted from the cellular signaling data, which contains the following three information: the position of base station p_c, arrival time $p_{t.a}$ and leaving time $p_{t.l}$.

Definition 2. (Transfer event): A transfer event $trans = (trans.c, trans.t)$ is a duple extracted from staying events when the mobile users move from the current staying event sp_i to the next zone sp_{i+1}. We obtain two transfer events: the arrival transfer event $trans_A = (trans.c_A, trans.t_A)$, where $trans.c$ is the position of the transfer event and $trans.t$ is the time of transfer event.

Definition 3. (Mobility trace): A mobility trace = $(sp_1, trans_1, sp_2, trans_2, ..., sp_{i-1}, trans_{i-1}, sp_i)$ is a directional trajectory composed by all the staying events and transfer events that one mobile user travels in one day. It can reflect the user's mobile status and purpose reflecting the relevance and difference among cells, which can be utilized to explore the functional distribution of urban areas.

3 FRAMEWORK OF HRF-ZR

Figure 4 shows the overview of the proposed a high-definition resolution functional zoning method: HrF-ZR. It is mainly composed of two parts: function representation module and function annotation module.

3.1 Function Representation

Firstly, the urban area is divided into fine-grained unit zones according to the road networks. Each unit zone consists of one or multiple base station cells. Secondly, the continuous human traces obtained from cellular data are analyzed through the extraction of users' stay and transfer event as well as sequential mobility trips. The modeling of event representation is realized based on a static embedding and a recurrent processing of base station cells. Finally, the vector of each base station cell is obtained for the function annotation in next step.

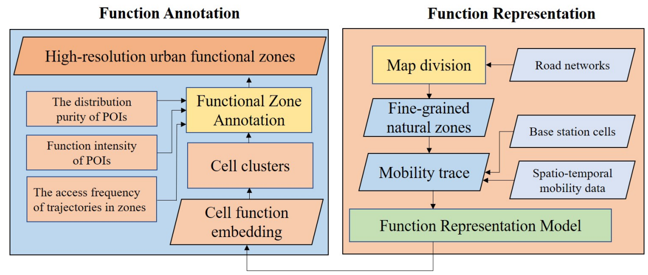


Figure 4: Framework for representing the high-definition resolution urban functional zones.

3.2 Function Annotation

To annotate the unit zones with proper functions, we firstly adopt a clustering algorithm to aggregate similar base station cells, Then each base station cells is annotated by mobility data and POI data to identify specific functional characteristics. Last, by summarizing all the base station cells in the unit zones, we obtaining high-definition function zoning.

In detail, We perform k-means [10] clustering on the learned cell representation for obtaining different functional similarities. Then, the cells within each high-definition unit zone are quantitatively annotated based on a three-fold criterion: (1) the access frequency of trajectories from mobility data, (2) the purity of categories regarding the in-area POIs, and (3) the intensity of function regarding the in-area POIs. Finally, we output the final functions of high-definition unit zones for the entire city.

4 HIGH-DEFINITION UNIT ZONING

In this section, we first elaborate on the function representation in order to learn spatio-temporal mobility trajectories. Then we introduce the method of zone clustering and function annotation.

4.1 Function Representation model.

The model of urban function representation is composed of static pointwise event function embedding and recurrent trace function embedding, based on word2vec [17] and LSTM [6] , respectively. Figure 5 is the data flow diagram for function representation model. Firstly, we obtain the pointwise event embedding for cell embedding of base station cells through the method of word embedding. Then, mobility trace representation is processed through the two-layer biLSTM training model, which aims at dynamically analyzing the function of cells by high-order location and time contexts in mobility traces.

(1) Pointwise event function embedding. We extract transfer events from mobility trajectories and learn the embedding of staying events where the transfer event occurs as the context events. In word embedding, each word acts as a target word or a context word, the correlation between them is reflected in word sequence in sentences [18]. In our model, the staying event is regarded as target "words", and transfer event is regarded as context "words".

We analyze the correlations of function between the current stay base station cell and relevant transfer cell in mobility traces, which maps the corresponding static cell embedding and calculates

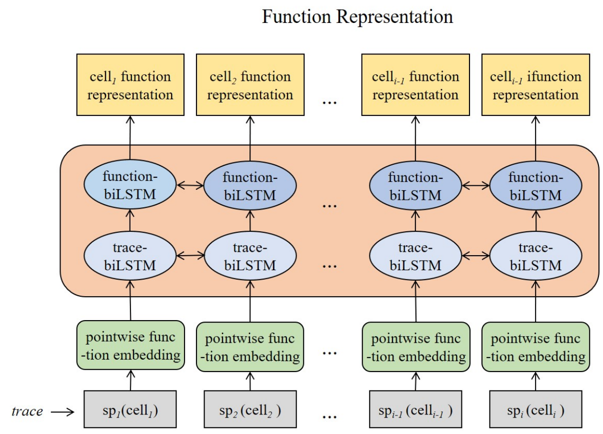


Figure 5: Data flow diagram for function representation model.

the relevance. Therefore, in the target static cells, the pointwise function embedding of cells are represented as:

$$C_{ij} = \mathrm{sp_i}^{\mathrm{T}}\mathrm{trans_j}, \tag{1}$$

where $\mathrm{sp_i}$ is the pointwise function embedding of staying events sp_i, $\mathrm{trans_j}$ is the embedding of transfer event. C_{ij} measures the correlation among cells:

$$C_{ij} = \log\left(\frac{\#(sp_i, trans_j) \cdot |L|}{\#(sp_i) \cdot \#(trans_j)}\right), \tag{2}$$

where $\#(sp_i, trans_j)$ counts the number of times that staying events sp_i and transfer event $trans_j$ occurrence, $\#(sp_i)$, $\#(trans_j)$ respectively count the number of single occurrence of sp_i and $trans_j$, and $|L|$ is the number of $(sp, trans)$ from all mobility traces. In this paper, considering the noise problem, we measure positive PC_{ij} to represent the association of cells:

$$PC_{ij} = \max\left(\log\left(\frac{\#(sp_i, trans_j) \cdot |L|}{\#(sp_i) \cdot \#(trans_j)} \cdot \frac{1}{k}\right), 0\right), \tag{3}$$

where k is the number of negative sample.

In matrix PC, we obtain the pointwise function embedding Ez of each cell, which is fed into the two-layer biLSTM for recurrently embedding cells in mobility traces to capture the dynamic functions in the sequential trajectory contexts trajectory.

(2) Recurrent trace function representation. The mobile trajectory is a directional path that changes with place and time recurrently. Therefore, according to the trajectory's time and direction, the mobility trajectory has different effects on different cells' representation. To optimize the function representation, we build a two-layer biLSTM model to obtain the functions of cells passing by the trace dynamically. The biLSTM model contains a forward LSTM model and a backward LSTM model.

Given a trace with N zones $C = (c_1, c_2, ..., c_n)$, the forward trace function representation model needs to predict the next cell c_i by the preceding cells $(c_1, c_2, ..., c_{i-1})$:

$$C(c_1, c_2, ..., c_n) = \prod_{i=0}^{n} C(c_i | c_1, c_2, ..., c_{i-1}), \tag{4}$$

and the backward model needs to predict the previous cell by the following cells $(c_{i+1}, c_{i+2}, ..., c_n)$:

$$C(c_1, c_2, ..., c_n) = \prod_{i=0}^{n} C(c_i | c_{i+1}, c_{i+2}, ..., c_n). \tag{5}$$

For the first layer of biLSTM, we obtained the trace cell embedding structure containing continuous motion trajectory information through biLSTM training. The input for each cell $(c_1, c_2, ..., c_n)$ is the correspondent pointwise function embedding vector $(E_{c1}, E_{c2}, ..., E_{cn})$. After training the forward LSTM and backward LSTM, we can get the forward outputs $(Lf_{z1}, Lf_{z2}, ..., Lf_{zn})$ and backward outputs $(Lb_{c1}, Lb_{c2}, ..., Lb_{cn})$, respectively.

For the second layer biLSTM, we get the function embedding containing cell functional information which are covered by trajectories. Similar to the first layer, the forward outputs $(L1f_{c1}, L1f_{c2}, ..., L1f_{cn})$ and backward outputs $(L1b_{c1}, L1b_{c2}, ..., L1b_{cn})$ of the first biLSTM are used as inputs the second layer biLSTM. Similarly, the forward outputs $(L2f_{z1}, L2f_{z2}, ..., L2f_{zn})$ and backward $(L2b_{c1}, L2b_{c2}, ..., L2b_{cn})$ outputs are obtained respectively through the forward LSTM model and the backward model.

Finally ,we can get the cell function representation contains $(E_{ci}, L1f_{ci}, L1b_{ci}, L2f_{ci}, L2b_{ci})$, each zone with five vectors. Nevertheless, in different layers of cell representation model, the training emphasis of each layer is different. In pointwise function embedding, we obtain the results E_{zi} independent of trajectory behavior and moving purpose. In trace function embedding, the output $(L1f_{ci}, L1b_{ci})$ of the first biLSTM layer pay more attention to functions related to the trace structure, while the output $(L2f_{ci}, L2b_{ci})$ of the second layer biLSTM lays more emphasis on the functions related to the trace purpose semantics.

Therefore, based on the purpose and emphasis of trace analysis, the output of biLSTM in the second layer is taken due to function representation: $FZ = (L2f, L2b)$.

4.2 Functional Zone Aggregation.

As the functions of the urban zone is gradually developed with the city, the functional composition of a zone is not uniform [9] [27]. Comprehensive factors should be considered when labeling regional functions. For example, commercial functions such as dining and shopping zones are often accompanied by transportation zones and school zones in modern cities [7].

In our method,So we get the functional classification of cells in zones by clustering, and annotate a unit zone by considering the following 3 aspects:

(1) The distribution purity of POIs in zones (DP).

$$DP_{POI_{k,Z}} = \frac{N_{POI_{k,Z}}}{N_{POI,Z}}, \tag{6}$$

where $N_{POI_{k,Z}}$ is the number of class k POI, $N_{POI,Z}$ is the total number of POIs in the zone. POI has its functional properties, and a large number of trajectories are generated based on POI (moving from one POI to another). If all POIs distributed in the zone are banks, the zone must be a financial unit zone.

(2) The function intensity of POI in zones (FI): The function of POI has different levels of intensity, which affects the zone's function. Table 1 shows the POI function strength rankings defined, with #1 being the highest and #12 being the lowest. For example,

there are many restaurants and shops in a station zone, but these lifestyle and entertainment POIs are attached to the station POI, so the rank of the station POI is significantly higher than the lifestyle and entertainment POI around it.

Table 1: Function intensity of POI

Ranking	POI	Ranking	POI
#1	tourism	#7	car serve
#2	education	#8	enterprise
#3	hospital	#9	leisure
#4	traffic	#10	living serve
#5	government	#11	residence
#6	culture	#12	office

(3) The access frequency of trajectories within zones (AF).

$$AF_{cell_i} = \frac{FN_{cell_i}}{\sum_{j=1}^{Z} FN_{cell_j}}, \tag{7}$$

where FN_{cell_i} is the frequency of accessing $cell_i$ in the unit zone. It intuitively reflects the functions of zones. If the trajectory access frequency of a specific functional type is much higher than other types, the function of this zone is dominated by the highest access frequency function.

The distance of function representation are smaller when cells have similar functions. In detail, k-means clustering is performed on all base station cells' function representation results to obtain base station cell categories with different functions. Therefore, based on the mixed distribution of POI in each zone, we combined with the three indicators of zones, and a weighted voting method is used to divide the city into 10 functions. The weighted voting rules of this paper are selected as follows: the top three functions in each evaluation index. The first is 3 points, the second is 2 points, and the third is 1 point; their priority is DP<FI<AF. Finally, the function categories of zones are the results of comprehensive annotation, and there is no coordination and unification relationship with the POI function category.

5 EXPERIMENTS

In this section, we first introduce the city's datasets. Then, we explain the basic functional zones division method and several SOTA methods using different division algorithms. Finally, we illustrate and analyze the experimental results.

5.1 Data Description.

We use the following datasets for the evaluation.

Mobility data: we use Changchun cellular signaling data to obtain mobility traces. Since cellular data covers the whole city without missing data due to regional marginalization, and it contains almost all trip modes to ensure the comprehensiveness of the data. We use Changchun signaling data in the first week of each month from July to December in 2017, which contains 26,514,891 users, 481,308,051 check-ins to learn trajectory representation, and the data capacity is 160G.

Point of interest: The Changchun POI dataset covers 119412 POIs from the year 2017, divided from 159 precise categories into 12 functional categories according to POI function classification.

Road network: The road network of Changchun is used to segment the urban area into zones, which selects the top 40% of main roads from 21100 roads according to road distribution.

Urban functional area: The selected area is down-town area of Changchun, which contains 3,402 cells because the area around Changchun suburb is mostly farmland and mountainous with no urban function.

The details of our datasets after preprocessing are shown in Table 2.

Table 2: Description of ChangChun Datasets

Datasets	number & size
Cellular data	4,079,214 users 68,758,293 check-ins
Point of interest	119,412 POIs 12 functional categories
Road network	21,100 roads
Functional area	3,402 cell zones Changchun down-town area

5.2 Baselines

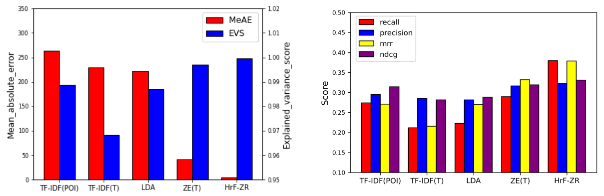
The experimental study compares our proposed High-definition resolution Urban Functional Zone Representation (HrF-ZR) with zone division with different area sizes and the following approaches of zone functional representation for urban exploration. Due to the limitation of data acquisition, there are relatively few related researches at present, and the baselines we choose in this research are classic methods and similar types of work.

CUF-ZR: Coarse-grained Urban Functional Zone Representation. This baseline uses the zone representation with spatio-temporal factor proposed in this paper to redefine functions of the official partitioning administrative zones, which does not redistribute the original urban zones.

TF-IDF (POI): Term frequency-inverse document frequency (TF-IDF) is one of the most common methods for semantic mining [20]. We use TF-IDF to learn the importance of different POI functions to a unit zone. Specially, each TF-IDF is POI category values in a unit zone, which is calculated according to the number of POI in the corresponding zone. Then we perform k-means clustering on TF-IDF values of base station cells.

TF-IDF (T): This baseline still adopts TF-IDF method, which uses mobility trajectory frequency from signaling data. We calculate TF-IDF value of each zone according to the trajectory data passing through the unit zone.

LDA Topic Model: Latent Dirichlet Allocation can be used to analyze regional themes and understand the functional distributions of city [14]. According to the LDA model, we integrate signaling data into mobility trajectory and zones, which are treated as words and documents, to analyze the topics of zones. Then we perform k-means clustering on LDA topic model results.



(a) Prediction (b) Recommendition

Figure 6: The results of evaluation metrics in two applications with different zone representation.

Zone Embedding (ZE(T)): The Zone Embedding model is based on the Word Embedding method to study unit zone functions from the mobile trajectory.

5.3 Evaluation

In this paper, we evaluate the effectiveness of HrF-ZR method by following two validation aspects: quantitative verification and qualitative verification.

5.3.1 Quantitative verification. In quantitative verification: we apply the functional zone representation to two applications: (i) crowd flow prediction and (ii) zone enhanced POI recommendation. We measured the results of zone representation through evaluation metrics of prediction and recommendation applications.

(1) Crowd flow prediction.

The research shows that the future crowd flow in the zone can be predicted according to the crowd flow in each zone of a city, which can respond to the sudden situation or emergency in the urban.

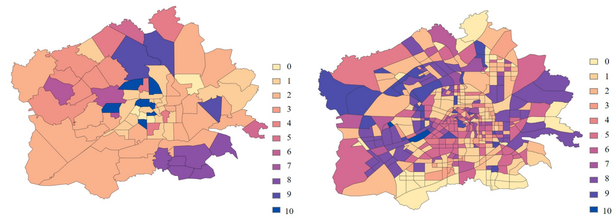
Therefore, in this application, we use the urban trajectory data to conduct the crowd flow data statistics and predict the crowd flow in each city zone. To evaluate the effectiveness of our proposed functional zone representation, we extract trajectories and functional zone representation of each algorithm as features. The fusion model of xgboost and lgbboost is used to predict the crowd flow through the features.

Evaluation Metrics: we utilize the median-absolute-error (MeAE) and explained-variance-score (EVS) to evaluate the performance.

(2) Zone enhanced POI recommendation.

Point-of-interest (POIs) recommendation introduces unexplored points to consumers. Existing POI recommendation systems usually learn latent vectors to represent both consumers and POIs from historical check-ins. It typically learns potential vectors from historical check-ins to represent consumers and POIs and makes recommendations within time and space constraints. At the same time, the check-ins of POIs are affected by the zone to which it belongs.

The spatial effect is an important part of candidate metric and recommendation methods, and the traditional POI recommendation usually uses radius as the POIs candidate metric or uses a grid segmentation map to select the POIs candidate metric. Both of these recommendation models can be confused or misleading, and the spatial effects of proximity to the grid are not convincing.



(a) CUF-ZR (b) HrF-ZR

Figure 7: The results of different dimensional zoning results by CUF-ZR and HrF-ZR (The label legend of each figure is different, and the same name of each legend may represent different categories).

Therefore, in order to solve this problem, we propose to use unit zones as a candidate metric for POI recommendation, and introduce spatial zone effect into POI embedding. Each unit zone has a functional representation, and the function of each POI is enhanced or weakened by the function of the zone in which it is located. This results in an accurate POI recommendation with a zone effect, which enhances the interpretability of the recommendation.

Evaluation Metrics: We utilize the recall, precision, mean reciprocal rank (mrr) and normalized discounted cumulative gain (NDCG) to evaluate the performance.

5.3.2 Qualitative verification. In qualitative verification, we compared the results of high-definition unit zones with two authoritative maps and manual verification. (1) We compared the results with Changchun Land Use Planning 2006-2020 to test the rationality. (2) We matched against real-time satellite maps to detect the accuracy of results.

6 EXPERIMENTAL RESULTS

6.1 Quantitative Results

Figure 6(a) shows the prediction results of MeAE and EVS in different zone representation algorithms. It can be seen that the zone representation of HrF-ZR, as a prediction feature, can well improve the prediction performance of population flow when compared with other baselines. Figure 6(b) shows four evaluation metrics of the zone-enhanced recommendation. The results of recall, precision, MRR, and NDCG show the same performance of prediction application, HrF-ZR can achieve the best enhancement effect in POI recommendation compared with other algorithms.

Specifically, TF-IDF (POI) does not perform well against other models. An important reason is that TFIDF(POI) makes the zone representation similar for many zones with different functions. Therefore, when classifying TF-IDF (POI) zone representation, many zones with different functions are divided into the same category by mistake. In the prediction application, the wrong clustering results as features harm the prediction. In recommendation application, it does not provide correct zone enhancement information, and inaccurate zone function representation can not support beneficial help but provide error-inducing information to the recommendation.

Compared with HrF-ZR method, TF-IDF(T) has the worst performance and has a great wrong effect on the prediction results because the trajectory data is distributed unevenly among different zones, making it more difficult to distinguish between popular and unpopular zones. Therefore, its inaccurate functional zone division causes a great interference to the zone crowd flow prediction and mislead the zone POI recommendation. LDA learns about potential themes of urban zone functions, whose performance in prediction and recommendation applications are similar to that of TFIDF (POI). It shows that LDA can not accurately and reasonably divide the functions of fine-grained urban zones. Moreover, the results of zone representation provide limited help for the subsequent applications. ZE(T) presents superior evaluation metrics and can obtain more reasonable results of zone representation and zone categories than the previous three algorithms. However, the performance results are still weaker than HrS for the performance of the two applications. This indicates that the Word2vec model can only analyze static trajectories, and its performance on urban functions based on sequential trajectories is not ideal.

6.2 Qualitative Results

As shown in Figure 7 and 8, according to the verification standards, the method proposed in this paper can be used to obtain the functions of urban unit zones more accurately. Figure 7 shows the different dimensional zoning results of CUF-ZR and HrF-ZR. Figure 8 (a) - (e) shows the functional zoning results of five fine-grained algorithm methods: TF-IDF (POI), TF-IDF (T), LDA Topic Model, Zone Embedding (ZE(T)) and HrF-ZR, where different colors represent different functions. Figure 8(f) shows the six test zones of A-F randomly selected. Figure 9 is the real enlarged picture of A-F partitions in Figure 8.

6.2.1 Functional Zoning Results. Compared CUF-ZR with HrF-ZR in Figure 7, the result is redefined regional functions on the coarse-grained administrative zones officially divided, using the zone representation method with spatial-temporal factors. Through the previous baselines, it can be found that compared with other zoning algorithms, the zone representation method in this paper can get a good result of functional partition. Due to the large proportion of regional division, each administrative zone contains multiple high-definition unit zones, making it unable to recognize the accurate functions of each fine-grained zone and distinguish the functional differences among zones.

Compared HrF-ZR with algorithm baselines in Figure 8, for TF-IDF (POI) and TF-IDF (T), identifying functions' result is limited, the confusion of zone function is serious, and many zones with different functions are divided into the same category. For LDA Topic Model, there is still a defect of the missing zone function tag, which greatly affects the accuracy of function recognition. For Zone Embedding with trajectory (signaling data), the result is better than others but does not consider the sequential relationship trajectory. For CUF-ZR, the result performs terribly because of the large dimension of zones partitioned by official, though the method is zone embedding.

As shown in the six corresponding zones of A-F in Figure 8 and Figure 9, Zone A is the famous South Lake Park in Changchun, while the school zones are at the bottom right of the park. However, the two methods of TF-IDF fail to distinguish the zones correctly. Zone B is a dense zone of universities with the central campus of JILIN University and Jilin Institute of Architecture. TF-IDF and LDA topic models can not be completely identified. Zone C is a science and technology area surrounded by residence and business. TF-IDF (T) fails to distinguish it from other zones and divides them into the same unit zone, which still has incorrect functions. Zone D is Changchun South Railway Station, which is the core of traffic in Changchun. Neither TF-IDF nor LDA can clearly distinguish it from surrounding commerce zones and car service zones. Meanwhile, zone E is Changchun Puppet Palace Museum, surrounded by dense residential zones. Compared with the previous three methods, LDA can accurately identify and judge the function. Zone F is FAW-Volkswagen Group, the famous No.1 automobile factory in Changchun. HrF-ZR can accurately identify the car zones throughout the city, while other methods are vaguely classified as commercial zones or business zones.

6.2.2 Functional Zoning Annotation. Table 3 shows the rank of the distribution purity of POI in zones and the access frequency of trajectories within zones (blank spaces in the table indicate that there are no such POI in zones). The color depth in the table is the top three functions in terms of purity and access frequency (the first is the darkest and the third is the lightest). On the left of the table is the function intensity defined in this paper (#1-#12 is the intensity sorted from high to low). We annotate the function results of high-definition urban unit zone representation as follows:

Func0 (Residential Zone). The number of residential POIs is the largest and its visit frequency are the highest, and its life service, leisure, and entertainment facilities are all perfect to support people's lives.

Func1 (Commercial Zone). The distribution purity and access frequency of companies and entertainment are highly ranked, dotted with numbers of entertainment venues such as shopping malls and restaurants.

Func2 (Business Zone). There are significant business and office buildings, which contain many POIs like finance, corporations, industrial parks, and many life service facilities such as restaurants and convenience stores.

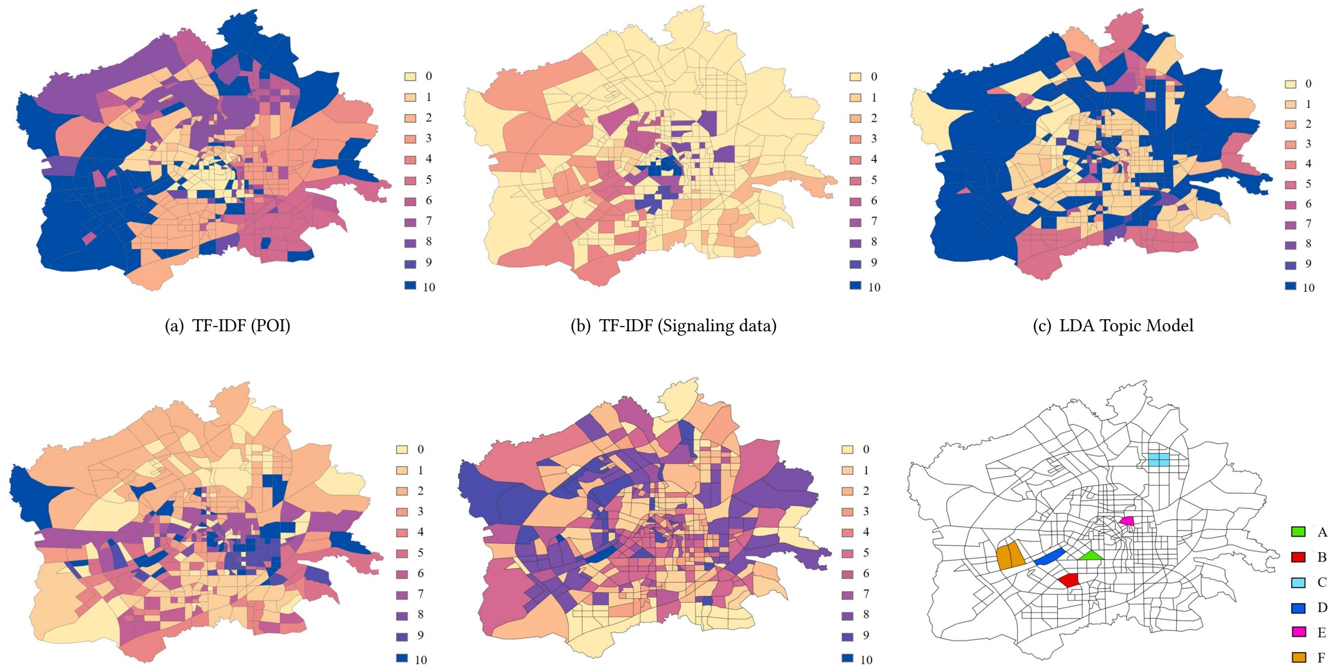
Func3 (Station Zone). Station POIs have a high access frequency and function intensity, distributing numerous POIs of life services such as restaurants, convenience stores, and hotels.

Func4 (Medical Zone). There are mainly centered around large hospitals and surrounded by vast pharmacies, medical appliance stores, and life service POIs. Moreover, hospital POI visits are frequent and intensive.

Func5 (Educational and Technology Zone). There are significant educational and scientific POIs, and many life services and leisure facilities are distributed around them. For example, Jilin University and Northeast Normal University are located in the zones.

Func6 (Government Agency Zone). Governmental agencies and public organizations are functionally distributed with higher purity and access frequency than other functions.

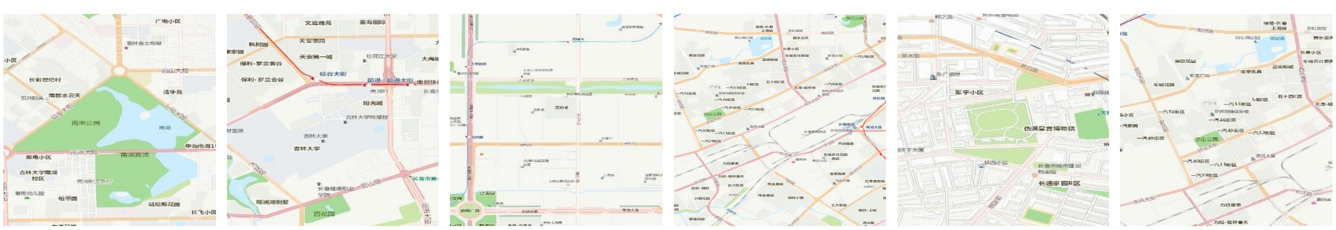
Func7 (Tourism Zone). The function intensity of tourism and the frequency of visits within the zones are the highest than other functions, though large office buildings and residential zones are densely distributed around them.



(a) TF-IDF (POI) (b) TF-IDF (Signaling data) (c) LDA Topic Model

(d) Zone Embedding (e) HrF-ZR (f) A-F validating zones

Figure 8: The function results of fine-definition unit zones by different algorithm methods (The label legend of each figure is different, and the same name of each legend may represent different categories. The legend in Fig.7(a) corresponds to the functional types to the left of Table 3).



(a) Zone A (b) Zone B (c) Zone C (d) Zone D (e) Zone E (f) Zone F

Figure 9: (a) South Lake Park. (b) JILIN University. (c) A science and technology area. (d) Changchun South Railway Station. (e) Changchun Puppet Palace Museum. (f) FAW-Volkswagen Group.

Func8 (Automobile Service Zone). The POI categories are evenly distributed, but most of the functions are related to automobile service.The automobile industry is widely distributed in Changchun that can be regarded as a separate function.

Func9 (Leisure Entertainment Zone). Large leisure, entertainment, and life service POIs are distributed daily, where are usually located squares or parks nearby.

Func10 (New Development Zone). They are generally distributed in the fringe zones of a city, with a small number of POIs and imperfect category allocation. Its access frequency is also obviously lower than other developed functional zones.

7 RELATED WORK

This section introduces the related work from three research perspectives of urban functional zoning: mobility trajectory research, embedding learning, and urban function analysis.

7.1 Mobility trajectory research

Mobility trajectory data has been widely used in urban intelligent computing and mobile intelligence analysis. Janecek A et al.proposed a method to solve the problem of sparse call detail record (CDR) data on the expressway by using the signaling event set generated by idle and active equipment [16] Zheng L et al. used the taxi trajectory data to study the spatio-temporal characteristics of the attractive areas for residents to travel and the thermal

Table 3: POI purity and access frequency ranking within unit zones

	Func0		Func1		Func2		Func3		Func4		Func5		Func6		Func7		Func8		Func9		Func10	
POI	**DP**	**FR**	**DP**	**FR**	**DP**	**FR**	**DP**	**FR**	**DP**	**FR**	**DP**	**FR**	**DP**	**FR**	**DP**	**FR**	**DP**	**FR**	**DP**	**FR**	**DP**	**FR**
#1 tourism	0.006	8	0.002	10	0.006	12	0.002	11	0.006	12	0.005	12	0.010	10	0.178	1	0.004	11	0.031	5		
#2 education	0.046	7	0.037	6	0.040	4	0.026	10	0.053	7	0.162	1	0.059	7	0.038	11	0.032	9	0.050	6	0.056	6
#3 hospital	0.058	10	0.047	9	0.061	9	0.033	8	0.232	1	0.052	10	0.065	12	0.073	8	0.028	7	0.059	7	0.119	8
#4 traffic	0.002	6	0.005	7	0.003	6	0.009	1	0.003	9	0.003	7	0.003	9	0.004	3	0.007	10	0.004	11	0.007	7
#5 government	0.027	11	0.039	11	0.027	8	0.042	7	0.063	5	0.048	9	0.191	1	0.046	5	0.029	8	0.037	9	0.091	10
#6 culture	0.001	12	0.003	12	0.004	10	0.002	12	0.008	11	0.007	8	0.012	11	0.002	12	0.001	12	0.011	12		
#7 car serve	0.037	9	0.030	8	0.041	11	0.042	6	0.030	10	0.021	11	0.038	8	0.043	9	0.185	1	0.051	10	0.014	9
#8 enterprise	0.144	5	0.474	2	0.197	2	0.235	4	0.090	2	0.214	4	0.219	3	0.33	6	0.360	4	0.228	4	0.147	4
#9 leisure	0.135	3	0.110	3	0.136	1	0.096	5	0.117	8	0.126	3	0.119	5	0.183	2	0.067	5	0.210	1	0.210	3
#10 living serve	0.070	2	0.058	4	0.027	3	0.275	2	0.056	3	0.089	2	0.045	4	0.129	7	0.128	2	0.136	2	0.304	1
#11 residence	0.437	1	0.010	5	0.011	7	0.030	9	0.021	6	0.034	6	0.013	6	0.014	10	0.021	6	0.029	8	0.021	5
#12 office	0.035	4	0.184	1	0.447	5	0.208	3	0.262	4	0.239	5	0.224	2	0.259	4	0.138	3	0.154	3	0.032	2

* *DP: the distribution purity of POIs. FR: the ranking of POIs access frequency.*

paths [28]. Kim K et al. adopted data mining technology to avoid the deviation of trajectory data distribution, which combined with the data of subway and taxi, and revealed the factors affecting the mobility of people [11]. Xu Y et al. comprehensively analyzed data sets related to mobile phones and urban social economy to understand human travel patterns and their relationship with travelers' socioeconomic status [1].

7.2 Embedding learning

The embedding method has been widely studied as the semantic learning model and plays an important role in representation learning. For example, word embedding was originally used as a research model for learning word semantics. With natural language processing (NLP), word embedding has been widely used in various fields such as recommendation systems and deep learning. Mikolov T et al. proposed two word2vec model structures: CBOW and skip-gram, and used cyclic neural network language model (RNNLM) to train word vectors with semantic representation ability on large scale corpus [15]. Rong X et al.described the details of skip-gram model and training methods for Hierarchical Softmax and Negative Sampling[17]. Brakan O et al. extended the application of word2vec from natural language processing (NLP) to the recommendation, advertising, search, and other fields where the sequence can be generated [2]. Bilong Shen et al. proposed a spatial-temporal mobility event prediction framework based on a deep neural network simultaneously with all correlated spatial and temporal mobility patterns [18]. Ying Li et al.proposed a text classification model base on region embedding and LSTM and use LSTM's long-term memory of text information to extract the global characteristics [12]. Xu C et al.use the continuous bag-of-words model to represent word identity and propose two low-dimensional word embeddings derived from a neural network to obtain class and context information [22].

7.3 Urban function analysis

In recent years, data-driven methods have been used to analyze the regional distribution of urban functions. Liu X et al. constructed the spatially embedded network based on the trip data of Shanghai taxis and provided new insights for the use of emerging data sources to reveal the travel mode and urban structure [21]. Du S et al. proposed a multi-scale segmentation method to extract ultrahigh-resolution image information and reveal large city functions based on context relations [4]. Gan J et al. explored the urban function area distribution and crowd mobility information from the public bicycle travel information [8]. Zhong C et al. combined unsupervised learning algorithms with spatial metrics to reveal spatial patterns of various Twitter users at the spatial aggregation level [29]. Yang J et al. proposed a POI-driven method to successfully identify functional zones in suburban and urban zones [23].

8 CONCLUSION

This work breaks the limitations of analyzing changes in functional areas based on the division of fixed administrative regions. By proposing the high-definition urban functional zone representation framework, we study urban functions effectively. Specially, we utilize the road network to divide fine-grained unit zones, then represent the distribution of regional functions through the mobility trajectories with spatio-temporal information extracted from signaling data. Last, we mark the actual functions of the divided zones comprehensively according to the three indicators. It provides powerful help for urban intelligent computing and a new idea for location-based trajectories analysis and location recommendations. In the future, we will explore the dynamic functions of urban zones based on existing research. It may be a trend to utilize multiple spatio-temporal data for analyzing the regional function distribution of the city's multi-level spatial structure.

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