location2vec: a situation-aware representation for visual exploration of urban locations

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***Abstract*—Understanding the relationship between urban locations is an essential task in urban planning and transportation management. Whereas prior works have focused on studying urban locations by aggregating location-based properties, our scheme preserves the mutual influence between urban locations and mobility behavior, and thereby enables situation-aware exploration of urban regions. By leveraging word embedding techniques, we encode urban locations with a vectorized representation while retaining situational awareness. Specifically, we design a spatial embedding algorithm that is precomputed by incorporating the interactions between urban locations and moving objects. To explore our proposed technique, we have designed and implemented a web-based visual exploration system that supports the comprehensive analysis of human mobility, location functionality, and traffic assessment by leveraging the proposed visual representation. Case studies demonstrate the effectiveness of our approach.**

***Index Terms*—Human mobility, word embedding, urban computing, spatio-temporal data, visual exploration.**

I. Introduction

DATA-DRIVEN urban computing approaches [1], [2], [3] widely leverage the mobility data collected by location-aware devices for discovering new insights across a variety of application domains including human mobility, urban planning, transportation management, and epidemiology. These applications commonly require a representation (e.g. flow volume or population) to explore, analyze, or compare the properties and dynamic behavior happening in distributed locations. The situation-aware representation is defined as a perception of information in the spatio-temporal of evolving situations [4] (e.g., traffic control, extreme weather). In each scenario, situation-aware representation of urban locations is essential, for two reasons: first, the data of human mobility, transportation management, and urban planning contains information of urban locations; second, crowd, vehicles as well as social networks move or change over time in different places, and thereby a situation-aware representation of the locations is needed to understand dynamic human mobility.

A large body of research has been engaged in the representation and analysis of urban locations by fully exploring the trajectories of moving objects [5], [6]. However, these approaches simply utilize aggregated values from trajectories of vehicles or population, like locational density or in/out flow between pairs of locations, for representing, visualizing and analyzing locations. The mutual influence between urban locations and mobility behavior is still unexplored. For instance, heatmap only encodes the number of persons in each location and ignores the continuity of trajectory data.

We take an alternative perspective: motivated by the manner in which a person visits places with distinctive purposes, we analyze an urban location in its context which is defined as the set of previous and successive locations in a trajectory. Since trajectory data is a kind of sequential data, exploring the functionality of a location through the context is analogous to understanding the meaning of a word within the sentence. Therefore, we regard urban locations as basic words and consider a trajectory as a document. We leverage the surrounding contexts of locations to construct the situation-aware representation of urban locations by employing the word embedding technique (e.g., word2vec [7], [8]) which is widely used in Natural Language Processing (NLP) tasks.

In this paper, we contribute a situation-aware representation for urban location, called *location2vec*. First, we employ the word2vec model to embed the urban locations into a continuous vector space by incorporating the interaction between urban locations and moving objects. Second, to support analyzing dynamic human mobility, we extend the word embedding model to learn dynamic location representation in the same vector space. We created two different artificial trajectory datasets to test and justify the advantage of our method over aggregated population flow. Figure 1(c) shows the same aggregated population flow shared by two different trajectory dataset A and B. Our representation shows that the relationships among location 3, 4 and 5 are different for two trajectory datasets. Since location 3, 4 and 5 serve as a connection in trajectory dataset A, their location vectors are close to each other in Figure 1(d). However, all trajectories in dataset B turn back at location 4 (maybe a closed road for real cases). Therefore, location 4 is far away from location 3 and 5 in vector space (see Figure 1(e)).

The location2vec representation encodes trajectory records as spatio-temporal words to enable situation-aware analysis of dynamic human mobility. Although the representation in our approach is constructed from mobile phone location data, other forms of mobility data like taxi trajectories can be used too. We design and implement a visual exploration system that supports a suite of exploration and analysis tasks. For instance, by projecting the location vectors into a 2D plane, the analyst can explore the relationship of location distribution in the vector space. The analyst can query locations with the same

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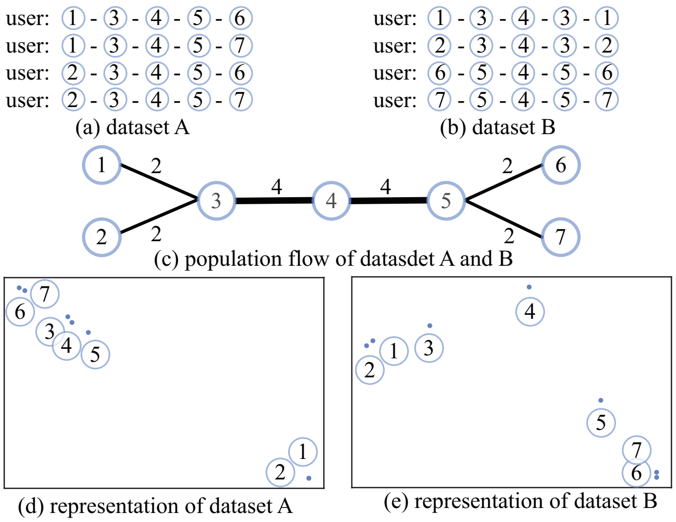


Fig. 1. Our embedding algorithm learns a situation-aware representation from trajectory data in two-dimensional space. Each location is encoded as a circle with a number. The number nears each link indicates the aggregated population flow. The relationships among locations are different for two trajectory datasets, though the population flows are the same.

function based on the similarity in the vector space. Moreover, the analyst can also explore the difference of context to analyze the dissimilarity of two locations. Case studies on real-world dataset demonstrate the effectiveness of our approach.

To summarize, this work presents two main contributions:

- A situation-aware location representation that characterizes the mutual influence between locations and contextual information;
- A visual analysis system that supports exploration and analysis of socialized and mobilized urban locations.

II. Related Work

A. Visual Analysis of Trajectory Data

A large number of visual analytics approaches have been developed to study human mobility by using the trajectory data [9]. Existing solutions can be roughly divided into two categories. The first one emphasizes the connections among locations in terms of mobility. For instance, a region is characterized by the in/out population flow of individual locations by mapping the aggregated taxi trajectories into discrete locations [5]. The MobilityGraph [6] elegantly presented a new way to reduce massive flow clutter by means of spatial and temporal simplifications. To eliminate the visual clutter caused by the large size of movement traces, adaptive hierarchical structure, alpha blending and edge splatting can be employed [10]. Vrotsou et al. [11] simplified the complexity of the trajectory structure by leveraging the attributes of trajectory segments.

The second category leverages the detailed information of trajectories to enhance the depiction of relations between locations and human activity, e.g., a novel visual representation that encodes human mobility and activity context simultaneously. TrajRank [12] focused on the dynamic change of travel time along one route. Zeng et al. [3] explored the relationship between human mobility and points of interest by extracting check-in data provided by Foursquare. More recent work has proposed the semantic analysis of trajectories for locating billboards [13] and transforming trajectories into documents to support text searches [14]. However, SemanticTraj [14] focuses on searching trajectories by text, they cannot provide deep insight into human behavior based on movement data.

Our work is different from the researches mentioned above. Rather than directly using aggregate population flow, we characterize the location with context information. Understanding mobility behavior should be built upon context information such as the purposes which a person visits places for.

B. Representation Through Word Embedding

Word embedding methods are widely employed to learn dense vector representation of words in documents and locations in mobility data.

Document. Recently, distributed representation learning has been successfully applied to Natural Language Processing. Mikolov et al. [8] proposed the efficient word embedding algorithm, word2vec. The word2vec algorithm represents each word as a vector in a latent space on large-scale document datasets. If two words frequently co-occur, they have a tendency to share similar vectors. The word2vec algorithm has been applied in various Natural Language Processing (NLP) applications, such as machine translation and sentiment analysis. Cite2vec [15] visualized the documents usage in citation contexts via word2vec.

Mobility data. Researchers apply document modeling method to learn representation from mobility data. Human mobility and points of interests are used to discover region functions in urban area [16]. Yu et al. [17] utilized the relationship between locations computed by word2vec algorithm for further traffic flow forecasting. For personalized location recommendation, the latent representations of users and locations are learned in the same latent space [18]. Further, POI2Vec [19] incorporated geographical influence and word2vec to learn the POI representations for POI prediction. However, POI2Vec learns a fixed representation and neglects the dynamic change of crowd, vehicles as well as social networks. Since we are interested in human mobility rather than POI prediction, we introduce a dynamic location representation based on word2vec to capture the dynamic relationships among locations.

III. Data

The Raw Data We employ a mobile trajectory data provided by a mobile phone service company for building the representation of urban locations. Our dataset includes 7 million mobile users in a city with 9 million residents. Thus, the citywide mobility can only be modeled. The dataset contains trajectory records of mobile phones and the information of cell stations. Each record of a trajectory is defined as $tr = (pid, sid, t)$, where pid is the mobile phone ID, sid denotes the ID of the cell station, and t is the time stamp.

Trajectory We employ the data cleaning process provided by Wu et al. [20] to remove data noise. After data cleaning, a trajectory is encoded as a sequence of records:

$$Tr = \{tr_1, tr_2, ..., tr_l\} \tag{1}$$

where $tr_i = (pid, sid, t_i)$ and l is the record number.

Location Specifically, the union of the covered zones of all cell stations constitutes the entire urban area. The placement of cell stations by mobile service providers considers the geography, demography as well as the transportation. Meanwhile, the trajectories of mobile phones are recorded as a series of cell stations. Therefore, we regard the area covered by a mobile cell station as a targeted location. The location is identified by the ID of the corresponding cell station. In particular, the information of a location (cell station) s contains its ID sid, its geographic position $(latitude, longitude)$, a textual description on its functionality (e.g., residence, business district).

Contextual Trajectory The context of a location implicates its usage under mobile phone users' visiting behaviors. Given a trajectory of a user, we define contextual trajectory of location s as the surrounding sequence of trajectory records:

$$CTr = \{tr_{i-m}, ..., tr_{i-1}, tr_i, tr_{i+1}, ..., tr_{i+m}\} \tag{2}$$

where $tr_i.sid = s.sid$ and m is the size of left/right window. Left window contains the previously visited locations and right window captures the successive locations that are visited after location s. For instance, the contextual trajectory of location s is $\{tr_{i-2}, tr_{i-1}, tr_i, tr_{i+1}, tr_{i+2}\}$ in Figure 2, where $tr_i.sid = s.sid$ and window size $m = 2$.

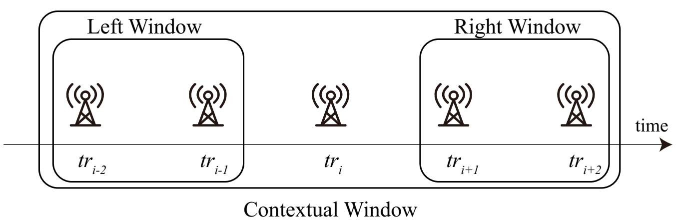


Fig. 2. An example of contextual trajectory. The subtrajectory in the contextual window of a location is defined as a contextual trajectory.

IV. Representation

A. Location2vec

Based on the above observations, we employ the well-studied distributed representation learning [7] to generate location vectors for urban locations. The location2vec representation is constructed as follows.

1. Generating words We first transform the raw trajectory data into trajectory documents. For each time interval (e.g., one hour in our implementation), a word is generated as $w = (sid, t)$ for a trajectory record $tr = (pid, sid, t)$. For instance, a raw trajectory record contains a location ID and a time stamp, such as (sid :8676, 09:38:38.42). We transform it into the spatial-temporal location formulation (8676,9), which refers to the cell station 8676 at 9:00 AM.

2. Generating documents We encode each trajectory as a document $D = \{w_k, k = 1, 2, 3, ...\}$, which is composed of a sequence of words. Each word refers to the location (cell station) covered by the trajectory at the given time interval. Given a document, we define the contextual words of word w_i as $context(w_i) = \{w_{i-m}, ..., w_{i-1}, w_{i+l}, ..., w_{i+m}\}$, where m is the size of the window.

3. The Skip-gram Model The object of the Skip-gram model is maximizing the average log probability:

$$L = \sum_{w \in C} \log p(context(w)|w) \tag{3}$$

where C is the collection of words in all documents and $context(w)$ is the contextual words of w whose size is $2m$. We slide a contextual window of length $2m+1$ over the documents to maximize the co-occurrence probability among the words that appear within a window (see Figure 2). Suppose the sequence of words is independent and identically distributed, we are able to compute the probability for corresponding contextual words given word w:

$$p(context(w)|w) = \prod_{w_c \in context(w)} p(w_c|w)$$

where w_c is one contextual word of w. We can compute the probability $p(w_c|w)$ using softmax function:

$$p(w_c|w) = \frac{v_c^T v_w}{\sum\limits_{u \in W} v_u^T v_w}$$

where v_c, v_u and v_w denote the vector of word w_c, w_u, w and W is the set of all words.

4. Optimization Directly optimizing is time consuming, because the computation complexity of $p(w_c|w)$ is $O(|C|)$. Negative sampling is proposed to improve the efficiency of optimization [8]. For each word w, we sample K negative words that do not belong to the contextual words $context(w)$. A logistic regression model is employed to classify w and negative words. Thus, the object function is defined as:

$$\begin{aligned} L = \sum_{w \in C} \sum_{x \in context(w)} & [\log \sigma(v_x^T v_w) + \\ & \sum_{w_k \in NEG(w)} \log(1 - \sigma(v_k^T v_w))] \end{aligned} \tag{4}$$

where $\sigma(x) = 1/(1+exp(-x))$ and v_x, v_k and v_w denote the vector of word x, w_k, w

5. Generating location vectors By optimizing the object function on the collections of trajectory documents, a high-dimensional vector of each word is generated. The similarity between two vectors can be measured by the cosine distance in the vector space:

$$Similarity(v_i, v_j) = \frac{\vec{v_i} \cdot \vec{v_j}}{\|v_i\|_2 \cdot \|v_j\|_2} \tag{5}$$

B. Features

We further characterize a set of features based on the representation for efficient exploration and analysis. We define the k-nearest neighbors (kNN) by the similarity in the vector space, describe the flow direction, and measure the flow volume from trajectory data.

***k*-Nearest Neighbors** Usually, the neighbors of a location implicate similar functionality. Word embedding method is applied to recommend locations by the similarity in prior works [18], [21]. We compute the similarity as the cosine distance in the vector space. We define kNN $N_k(s,t)$ as the set of k locations where people of location s at time t will visit.

Intra-distance of *k*NN To describe the range in which an individual of the location s at time t tends to move around, we denote intra-distance of kNN as the distance to next location. In practice, we compute the intra-distance of kNN, $Dis_k(s,t)$, as the average distance from location s to $N_k(s,t)$ in geographic space as:

$$Dis_k(s,t) = \frac{1}{k}\sum_{i=1}^{k} distance(s,s_i), s_i \in N_k(s,t) \tag{6}$$

where $distance(s,s_i)$ indicates the distance between s and s_i.

Fractional Anisotropy We compute fractional anisotropy (FA) to represent the degree to which trajectory records are concentrated in one direction. FA is a scalar value derived from diffusion tensor images and has been applied to describe the diffusion anisotropy in organs [22]. High FA indicates neuron fiber, because water molecules diffuse faster along the neuron fiber direction than across it [23]. We compare mobile phone users in urban networks to water molecules in organs. We employ FA to characterize the geographical distribution of k-Nearest Neighbors. Correspondingly, traffic routes, where people usually travel in one direction, may have larger FA value. We calculate a covariance matrix from the geographic positions of $N_k(s,t)$. We set the covariance matrix as a 2D tensor for each location. We can generate two eigenvalues (λ_1 and λ_2) and corresponding eigenvectors from this 2D tensor. FA on 2D tensor is computed as:

$$FA(s,t) = \sqrt{2}\frac{\sqrt{(\lambda_1-\bar{\lambda})^2+(\lambda_2-\bar{\lambda})^2}}{\sqrt{\lambda_1^2+\lambda_2^2}} \tag{7}$$

with $\bar{\lambda} = (\lambda_1+\lambda_2)/2$, $\lambda_1 > \lambda_2$.

Flow Direction To reveal the direction where trajectory records are concentrated, we set the eigenvector corresponding to λ_1 as the main flow direction of a location.

Flow Volume We calculate the total number of persons visiting and leaving the location from trajectory data.

C. Visual Encoding

We propose several visual encodings to visualize the characterized features of location2vec representation.

1) Visualizing the Vector Space: We apply a dimensionality reduction technique (i.e., LargeVis [24]) to reduce high-dimensional vector space to two-dimensional space to reveal the global pattern of location vectors. As shown in Figure 7(a), all locations are represented as dots in a specific time interval. Closer locations express more similarity based on the cosine distance in the vector space.

2) Visualizing the Features of Locations: To support the exploration of location2vec representation, we propose a compass glyph to present the summary of location features. As shown in Figure 3, the orientation of the compass encodes the flow direction and the length of the compass represents the fractional anisotropy. The width of the excircle encodes the intra-distance of kNN.

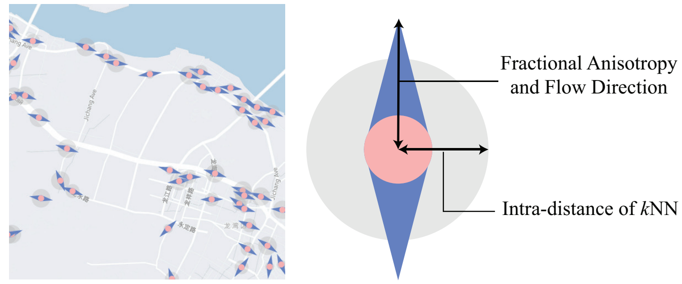


Fig. 3. The compass glyph encodes the fractional anisotropy, flow direction and intra-distance of kNN of a location.

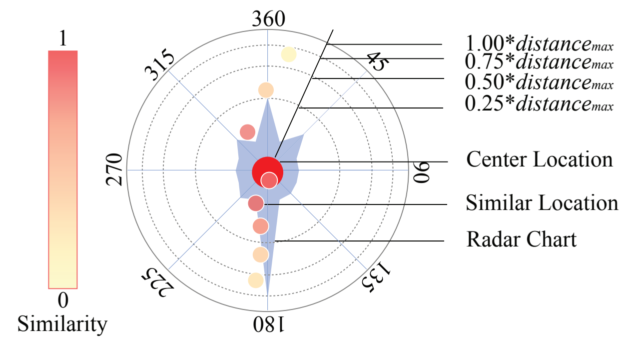


Fig. 4. The kNN glyph is designed to show the geographical distribution of $N_k(s,t)$ and the flow volume in eight directions of center location s. The color of locations in $N_k(s,t)$ is encoded with similarity and the distance to the center location s is scaled. We draw the equidistant line to illustrate the geographical scaling. A radar graph is employed to show the flow volume along 8 directions.

3) Visualizing the Location Neighbors: We design a glyph to visualize the mobility information of a location. As shown in Figure 4, the geographical distribution of $N_k(s,t)$ and the flow volume through location s are presented in the glyph. The location s is presented as a dot and placed in the center of the glyph. The other locations of $N_k(s,t)$ are shown as dots colored according to the degree of similarity to the location s and placed according to their relative geographic position to the centering location s . The coordinate (x,y) of location $s_i \in N_k(s,t)$ is computed as:

$$\begin{aligned}
\theta &= tan^{-1}\frac{\mathbf{sp}_i.latitude - \mathbf{sp}.latitude}{\mathbf{sp}_i.longitude - \mathbf{sp}.longitude} \\
r &= r_{max} * log_{10}(9*distance(s_i,s)/distance_{max}+1) \\
x &= r*cos(\theta) \\
y &= r*sin(\theta)
\end{aligned}$$

where $\mathbf{sp}.latitude$ and $\mathbf{sp}.longitude$ are the geographic coordinates of location s, $distance(s_i,s)$ indicates the geographical distance, r_{max} is the radius of the glyph and $distance_{max}$ is the longest distance from location s to location $s_i \in N_k(s)$ during all time intervals. The farthest location is placed at the boundary of the glyph ($r = r_{max}$) when $distance(s,s_i) = distance_{max}$. To illustrate the geographical scaling, we draw the line of equidistance at $0.25 * distance_{max}$, $0.50 * distance_{max}$ and $0.75 * distance_{max}$. The flow volume of each location is aggregated along eight directions (e.g., north, northeast, east, etc.). They are illustrated with a radar graph. We connect the data value in each direction.

4) Visualizing Interconnections of Locations: We employ a matrix to show the interconnection (e.g. flow volume and similarity) among locations. As shown in Figure 5, each cell in the matrix represents the interconnection between the corresponding two locations. The color of the grid encodes the similarity of two locations and the size of the circle encodes the volume of traffic.

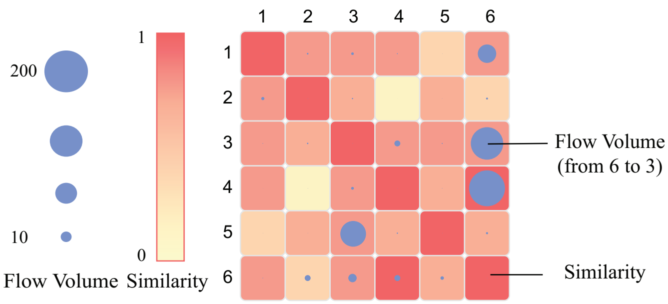


Fig. 5. The matrix shows the interconnection between locations. The color of the grid encodes the similarity of two locations and the size of the circle encodes the volume of traffic.

D. Parameters

Dimensionality We aim to learn a compact representation which facilitates the computation and storage. However, lower dimensionality results in more information loss. We set the embedding dimension to 100 which keeps the balance between information preserving and compactness.

Window size Window size captures the co-occurrence of locations. Levy et al. [25] concluded that larger window tends to capture more topic information and smaller window captures local syntactic contexts. We conduct an experiment on our trajectory data with different sizes m of windows. In Figure 6, we find that locations of $N_{11}(26722, 10)$ distribute around the center location (ID:26722) when $m = 3$. With larger windows size, locations of $N_{11}(26722, 10)$ are located along the road nearby. In general, larger window captures more mobility behaviors while smaller window reveals the geographical similarity only. In our dataset, the average length of trajectories in a day is 19. We set the window size m as 10 which captures location functionality from the daily mobility in our experiments.

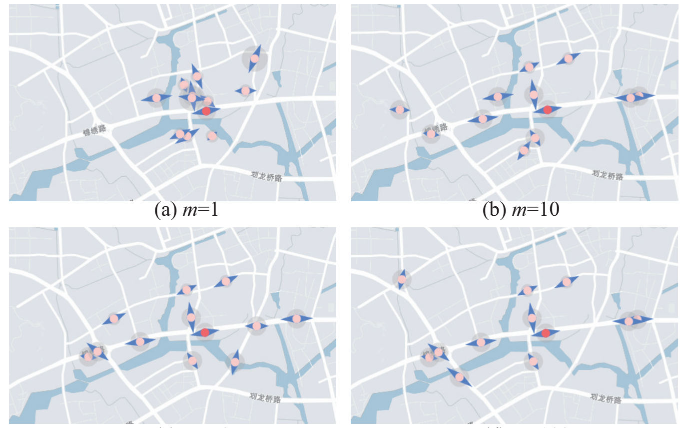
The number of neighbors When we compute intra-distance of kNN and fractional anisotropy, larger k may result in global pattern while smaller k captures local pattern. We set the number of nearest neighbors k of kNN as $2m$ according to the window size of location2vec model. Analysts can also modulate the parameter k in our visual analysis system (V-B).

V. Visual Analysis

A. Task Analysis

The location2vec representation inspires us with a new perspective to explore the urban mobility. We summarize the analysis tasks as follows.

T1. What are the global patterns of the location? In general, the analyst is concerned with the geographical



(a) m=1 (b) m=10 (c) m=50 (d) m=100

Fig. 6. The distribution of $N_{11}(26722, 10)$ on the map with different window size. The center location (ID:26722) is highlighted with red color. Larger window captures more mobility behaviors while smaller window reveals the geographical similarity only.

distribution of locations cooperating with the features, such as the flow volume and flow direction. In addition, the spatial-temporal distribution of location representation should be able to present the global pattern of urban mobility, such as periodicity, tendency or abnormality. Furthermore, exploring the relationship between the global patterns in two spaces can induce insight into the syntactic structure of the mobility-aware representation.

T2. What is the mutual influence between urban location and its contextual trajectory? Studying the interaction between human mobility and location is one of our core objectives. After exploring locations using nearest neighboring locations in the vector space, the analyst want to know the role of location under the context of human mobility, such as which location will be visited by citizens and the purposes of citizens' visiting behaviors.

T3. What is the relationship among locations? The analyst usually analyze the relationship between locations. Does the similarities between locations keeps consistent or not between the geographical space and vector space? What are the similar properties among neighboring locations in the vector space? How the relationship will change over time due to citizens' periodic behavior? The analyst would like to visualize and reason this inconsistency and temporal variation of relationship.

B. Visual Interface

To support the exploration of urban locations through location2vec representation, we propose a visual interface which consists of the characterized features (Section IV-B) and the corresponding visual encodings (Section IV-C). The interface contains a set of linked juxtaposed views (see Figure 7): an embedding view, a flow volume view, a map view, a kNN view, a matrix view and a configuration panel.

The Embedding View The embedding view shows the global pattern of locations in the embedding space (T1). As shown in Figure 7(a), we perform LargeVis [24], which is faster than tSNE [26], to project the location vectors into a 2D

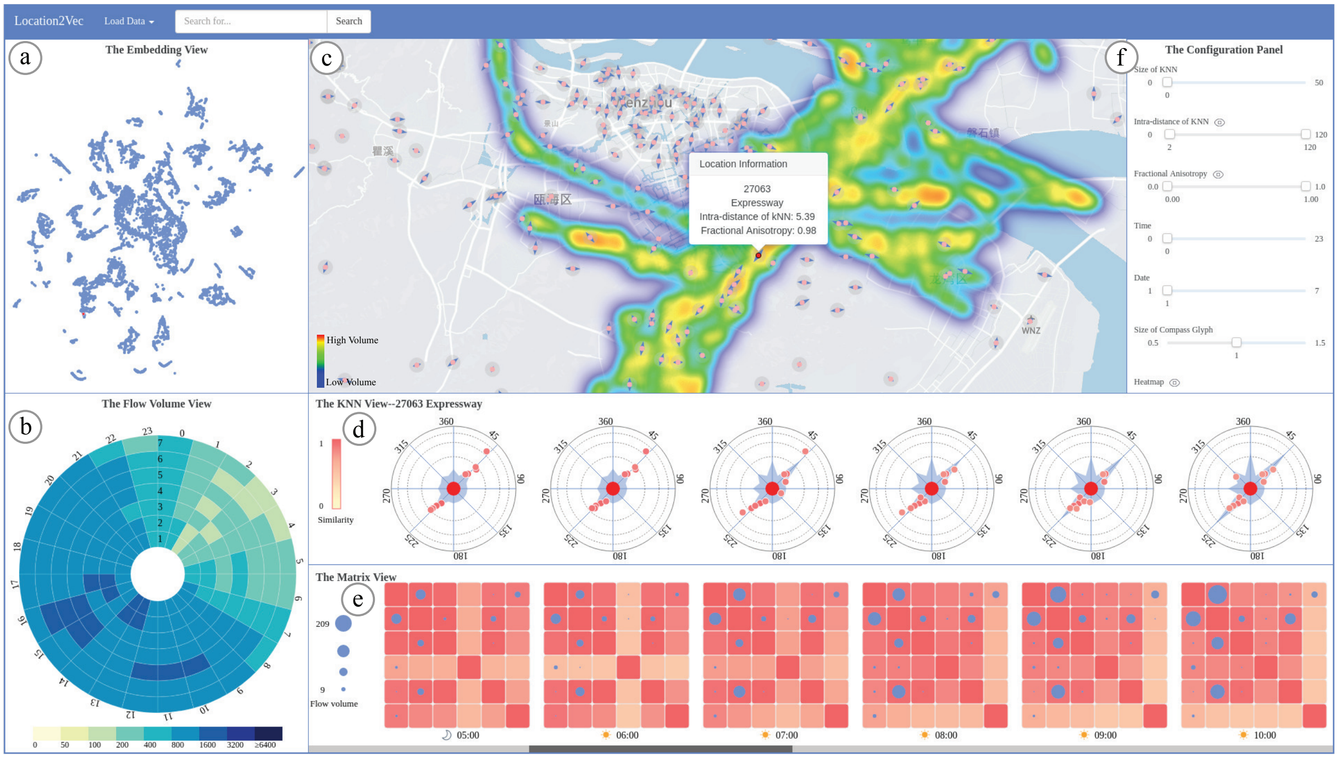


Fig. 7. The interface for exploring and analyzing urban locations with the proposed representation. (a) The embedding view illustrates locations as points in the embedding space. (b) The flow volume view shows the total flow volume through seven days of a specific location. (c) A geographical map overviews the distribution and the principle flux of urban locations. (d) The *k*NN view encodes time-varying *k*-nearest neighbors of a location. (e) The matrix view presents interconnections among locations. (f) The configuration panel offers parameter adjustment.

space and present them as dots. Lasso selection is supported in the embedding view.

The Flow Volume View We employ the flow volume view to show the total flow volume through seven days of a location (Figure 7(b)). Every day is divided into 24 hours and each unit reflects the flow volume in an hour.

The Map View As shown in Figure 7(c), the map view provides an overview of the location distribution (T1). It includes the geographic map and the compass glyph (Section IV-C2). When a compass glyph is hovered, its ID, textual description, intra-distance of *k*NN and fractional anisotropy are shown. When a compass glyph (location) is selected, the color of inner circle of its *k*-nearest neighbors represents the similarity to the selected location. Additionally, it supports the visualization of the contextual trajectory (T2). We apply a heatmap to visualize contextual trajectories.

The *k*NN View In this view, we present the *k*NN glyphs (Section IV-C3) for a urban location (T2). The glyphs are listed by hours in a row (see Figure 7(d)). We create a glyph for each time interval to show the detailed evolutionary history of a location. The *k*NN view and the matrix view share the same timeline (Figure 7(e)).

The Matrix View As shown in Figure 7(e), the matrix view (Section IV-C4) presents interconnections among multiple locations to reveal the temporal variation of relationship (T3). After a location is selected in the map view, the matrix view shows the relationship among the selected location and its 5-nearest neighbors. The analyst can also brush the locations they are interested in and study the relationship in the matrix view. When the analyst hovers over one grid (circle) in a matrix, values of similarity (flow volume) between two locations is shown in a tooltip.

The following interactions are supported:

- **Linking** Dynamic querying is supported among the map view, the embedding view, *k*NN view, and the node-link view. For instance, the analyst can gain an overview in the map view and select a location s. The map view shows the geographical position of its *k*NN. The contextual trajectories through location s are visualized by heat map. The corresponding dots of location s and its *k*NN in the embedding view will be highlighted with red color. The *k*NN view shows the human traffic data and similarity changes over time accordingly. Besides, when the analyst selects a set of locations, the matrix view represents the time-varying relationship between them.
- **Filtering** We support filtering according to the intra-distance of *k*NN and the fractional anisotropy respectively. The analyst can hide less important locations and explore the distribution of interesting locations.
- **Configuration** In the configuration panel, the analyst can modulate the parameters such as the time to explore the dynamic change. The map view and the embedding view show the features of representation at different time interval. The previous selected locations will be highlighted with red.

VI. Case Study

All experiments are performed on a PC equipped with a 3.4 GHz Intel Core i7-4770 CPU and 32 GB main memory. We store the trajectory data and traffic flow data in a MySQL database. We use gensim toolbox [27] to generate the location2vec representation, which takes 406.3 seconds on the dataset (6513 locations, 655,677 trajectories). To support the comprehensive study of region function, the input of our visualization system includes several parts: the trajectory data, the location2vec representation of each location and the features (e.g., intra-distance of *k*NN and fractional anisotropy).

A. Overview

First, we explore the overview pattern of vectorized representations in the embedding space (the top row in Figure 8) (T1). We select a region (Figure 8(a-b)) in the map view, and find that those the locations in this region are grouped into a cluster in the embedding view. It indicates that the embedding space retains the geographical similarity. We also notice that locations on the island (Figure 8(c)) fall into small clusters, which are far away from the other locations in the embedding view. It is reasonable that these areas have little connection with the other locations. Therefore, the representation also learns the location usage from mobility data (T2). Next, we study the mutual influence between urban locations and mobility behavior (see Figure 7) (T2). We filter locations whose intra-distance of *k*NN is smaller than 2 and select a location (ID: 27063) on a provincial expressway in the remaining locations. The length of the compass indicates a large fractional anisotropy of this location. The contextual trajectory also verifies that there is large motion flow along the road. Subsequently, we would like to research the interconnections between the location (ID: 27063) and its *k*NN. In the matrix view, the flow volume increases in day time. The similarity among locations increases from 5:00 AM to 10:00 AM (see Figure 7(e)). We can find the reason from the trajectory of the locations on the road: there is a huge transportation flow in the day time.

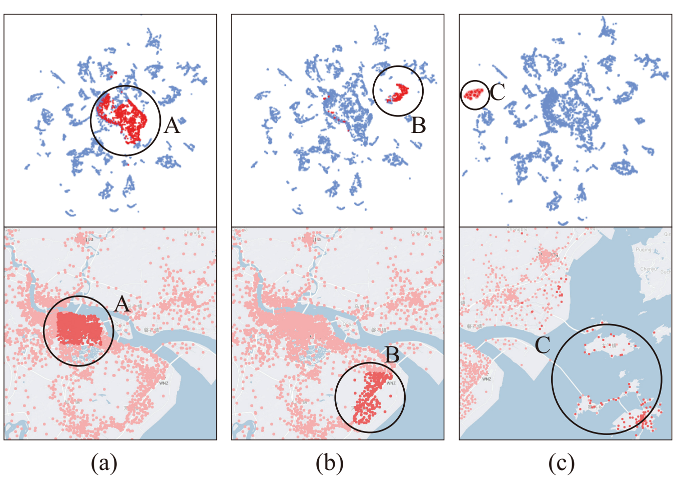


Fig. 8. Closer locations in geographic space have larger similarity with each other. Region A and B are grouped into two clusters in the embedding view. Locations (region C) on the island fall into small clusters.

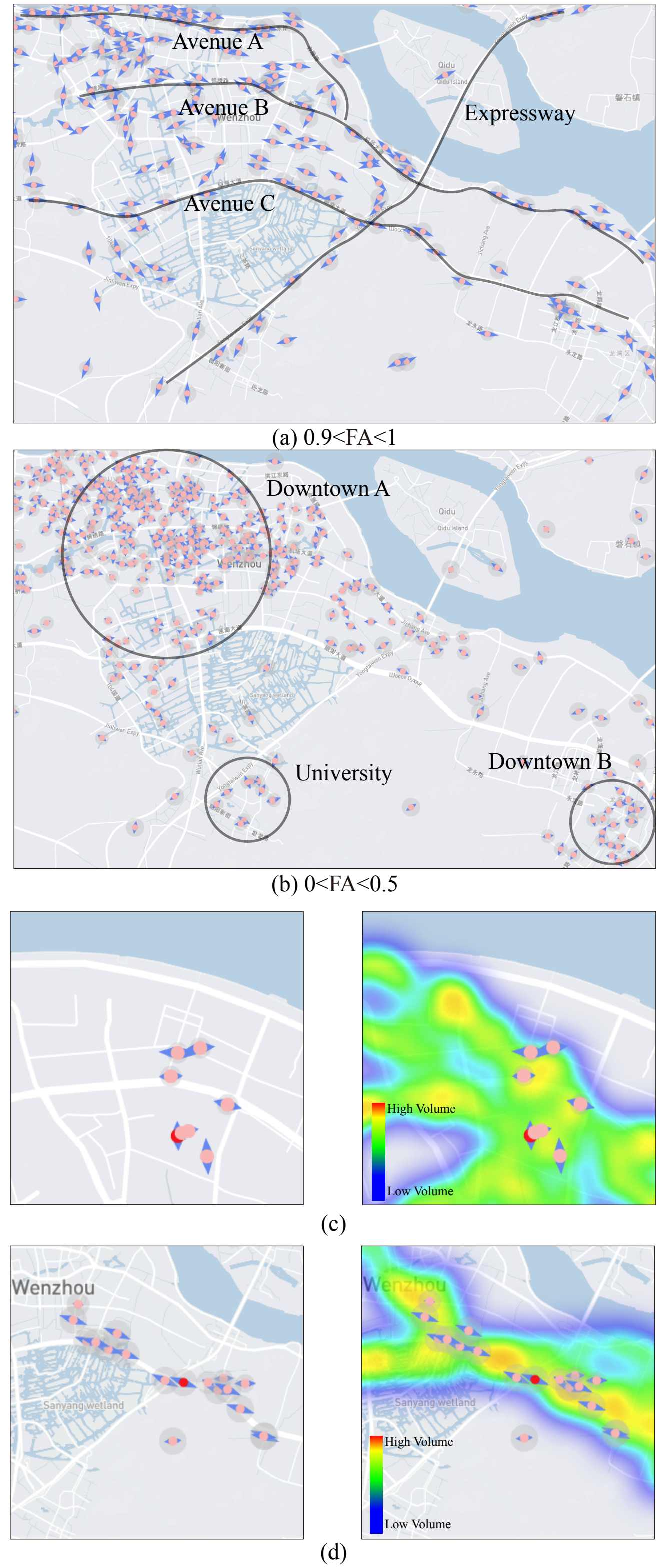
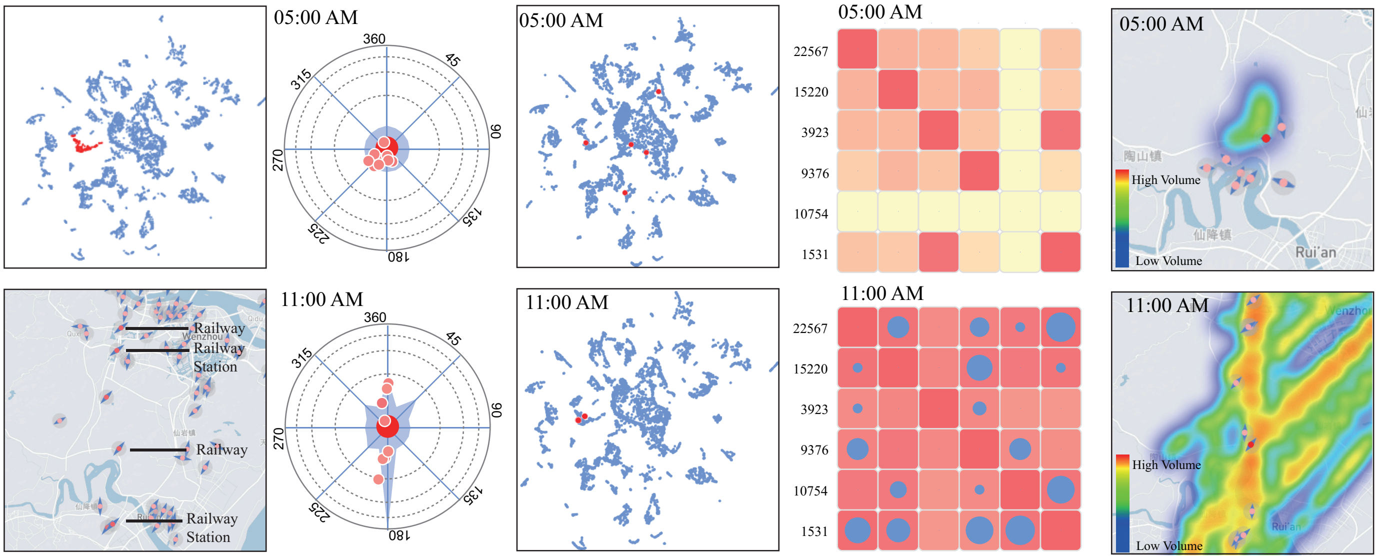


Fig. 9. (a) The locations that are distributed along the backbone tend to have large fractional anisotropic. (b) The locations lying around the downtown and university have small fractional anisotropy. (c) The similar locations are distributed around the selected location (business center) in downtown. The trajectory indicates that the human motion in business center contains all directions. (d) On the avenue connecting two districts, the similar locations with large fractional anisotropy are distributed along the road. The trajectory is highly directed, coinciding with the direction of the road.



(a) (b) (c) (d) (e)

Fig. 10. (a) The locations at the southwest of the downtown are grouped into a cluster in the embedding view. Locations with large intra-distance of kNN contain railway and railway textual description. (b) The distribution of locations in kNN of location 22567 varies over time. (c) Locations of railway generate one cluster at 11:00 AM. However, they spread out all over the entire view at 5:00 AM in the embedding view. (d) The similarity and flow volume between locations decrease at 5:00 AM and increase at 11:00 AM. (e) The trajectory passing through the locations at different time interval illustrates different patterns.

B. The Representation in Downtown and Traffic Route

One main focus of urban computing is the location functionality [28]. Location functionality is not only designed by urban planners, but also influenced by urban geolife, such as traveling, shopping, and commuting. Understanding the location functionality is a fundamental topic in urban computing [5].

We study the locations in downtown and backbone. As shown in Figure 9 (a), we first perform filtering to the locations. The map view shows locations whose fractional anisotropy is larger than 0.9 (T1). We denote three avenues and one expressway in Figure 9(a). Along the avenues, the locations have large anisotropy and obvious identical orientation. It indicates the human mobility along the roads. The locations along the same avenue are similar to each other, because they provide similar functionality in transportation. We then study the locations whose fractional anisotropy is within [0,0.5] (Figure 9 (b)). These locations lie around the downtown and the university. Therefore, locations on traffic route tend to have larger fractional anisotropy than downtown.

To enable situation-aware understanding of urban locations, we study the functionality by leveraging the distribution of kNN and the trajectory (T2). As shown in Figure 9, we select a location whose functionality description is business center. Its fractional anisotropy value is small and the orientations of nearby locations are diverse. It indicates that the human motion in this region contains all directions. In contrast, when considering a location on a traffic route, we notice that the k-nearest neighbors of the location with large fractional anisotropy distribute along the road. The contextual trajectory of the locations illustrates different patterns. In the business area, the trajectory contains motion of diverse directions. Beside the road, the trajectories are highly directed and coincide with the direction of the road. In this case, we can conclude that the location2vec representation is capable to reveal the functionality of locations.

C. The Representation Evolution of Train Route

In this case, we explore how the location2vec representation (e.g. locations vector and k-nearest neighbors) of the railway station varies over time. We first select a cluster in the embedding view (Figure 10(a) upper) (T1). The map view shows that these locations are distributed at the southwest of the downtown where a railway station is located at. This railway station serves high-speed bullet trains, while the other one at downtown serves normal trains. Then we filter out locations, whose intra-distance of kNN is less than 10 kilometers, in configuration panel. We find that the remaining locations' textual descriptions consist of railway and railway station (Figure 10(a) lower). We select a specific location (ID:22567) whose textual description includes railway stations and study the distribution of its neighbors $N_{20}(25567, t)$ using the kNN view (T2). When we adjust the time slider, we find that the distribution of similar location varies along time. At 5:00 AM, locations in $N_{20}(25567, 5)$ hold together around the center location (Figure 10(b)). At 11:00 AM, its neighbors, $N_{20}(25567, 11)$, form into a straight line (Figure 10(b)).

To analyze dynamic representations of locations on railway line, we brush the neighbors of location 22567 (T3) at 11:00 AM in the map view. We focus on the positions of these locations at different time interval in the embedding view. We find that these locations generate one or two clusters during 10:00 AM to 9:00 PM. However, they spread out all over the entire view at night (see Figure 10(c)). In the matrix view, the similarity and flow volume between locations decrease at night and increase at daytime (Figure 10(d)). Besides, the flow volume view shows that location 22567 has large flow volume from 10:00 AM to 6:00 PM. After verifying road network information, the trajectory on the map and the textual description of locations, we notice that similar locations distribute along railway line (Figure 10(d)). The contextual trajectories indicate that a large amount of persons travel through this region by train during the day. The reason is that there are few persons traveling by rail at night. The location provides services for its neighborhood at night. Massive crowd travels through this location by train at daytime. The locations along the railway line serve as a traffic route. Our location2vec representation captures the location functionality based on the evolution in human mobility.

D. Discussion

Through the case studies, we demonstrate the efficiency of our location2vec representation which enables situation-aware exploration and analysis of urban locations.

Capability of generalization Although we showcase the representation with mobile phone trajectory data, the location2vec representation can be easily applied to other movement data such as taxi trajectories. Both taxi and mobile phone trajectories can be defined as a set of records. Each record contains a position and a time stamp. Treating the records as words, and trajectories as documents, the location2vec representation provides a general model to encode location and mobility information into a compact vector.

Comparison to aggregation-based approaches Our location2vec representation preserves the spatial and temporal information and the mutual influence between urban locations and mobility behavior. First, compared to utilizing aggregated trajectories only, our representation supports the situation-aware analysis. We analyze urban locations in its context which provides a new perspective of urban mobility analysis (See Figure 1). Second, the vectorized representation is potential in machine learning and data mining models. For instance, an overview of the spatial-temporal pattern of locations can be provided in the vector space of locations. More efficient exploring operations, including querying, comparing, and clustering, are supported by this representation. The analyst can reason the inconsistency between the geographical space and vector space of close locations.

Limitations We see some limitations of our location2vec representation. First, it is time-consuming to project high-dimensional representation into 2D panel and support interactivity visualization when the number of locations increases. Currently, we pre-compute the embedding with LargeVis [24]. Second, the functionality description of a location is not taken into the location vector construction. We would like to integrate the functionality description into the location vector to support more semantic-rich analysis. At last, we generate the representation from the trajectory data during seven days. We are also interested in investigating large scale evolution with data spanning longer time.

VII. Conclusion

This paper proposes the situation-aware location2vec representation to support the analysis of urban mobility and locations. In case studies, we showcase the consequent discoveries, e.g. railway line, highway, downtown center, and their time-varying patterns. These discoveries provide a way to understand the functionality of locations. In the future, we would like to take semantic information (e.g., check-in data, point of interest data) into consideration. The semantic information provides detailed description of the purpose of mobility behavior. We are going to apply our method on other urban data (e.g., GPS trajectory) to study the representation of location in urban transportation.

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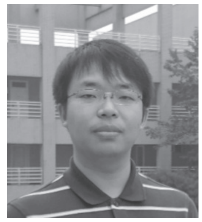

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