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Insight into traffic security: A correlation discovery of urban spatial features and traffic flow patterns

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***Abstract*—With the rapid development of urbanization, urban traffic security problems become increasingly prominent, and traffic accidents occur frequently. It is becoming increasingly critical to use data mining methods to solve actual problems in traffic security. But we don't just rely on the analysis of urban traffic surface operation rules, it is to study the mechanism of traffic operation. Therefore, in this paper, we aim to discover the correlation between spatial features and traffic flow patterns in urban regions to improve traffic security. In order to obtain deeper spatial semantic meanings for every urban region, we propose a spatial feature method based on regional hierarchy, which fuses the hierarchical structure of region and POI (point of interest) information. For traffic flow patterns, we propose a self-representation learning optimization method to find the similarity of region traffic flow. Then, we match the spatial features and flow patterns to discover the correlation of them. Experiments show that our approaches are effective.**

***Index Terms*—urban region, spatial features, flow patterns**

I. Introduction

With the acceleration of urbanization, more and more urban traffic security problems have emerged, such as chaos in traffic order and traffic congestion. The chaotic traffic order will lead to traffic congestion. The urban traffic congestion seriously affects the daily travel efficiency and quality of life of urban residents, and also affects economic development, aggravating energy loss and air pollution. Under this background, we should pay more attention to the solution to such problems. However, simple statistical methods can't meet our needs well. It can be seen that the current urban development urgently needs an intelligent transportation solution that solves urban transportation problems, and at the same time, a large and diverse amount of city data is needed as a support for intelligent transportation construction.

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At present, the construction of urban informatization is constantly accelerating, which has enabled the accumulation of rich urban data such as taxi trajectories and road networks. Based on these multiple data, more and more data mining methods are used to discover the rules of urban traffic. For example, we can find urban traffic congestion by anomaly detection methods [1]–[5]. Through deep spatio-temporal models, we can perform traffic flow prediction tasks to obtain the flow change rules of various periods [6], [7]. Recommend algorithms can help us choose the most convenient and fast driving route for drivers [8]–[10], and so on. Applications such as these can make recommendations for traffic planning and traffic management through analysis of traffic patterns, thereby alleviating existing urban traffic security problems.

However, the current research on urban traffic only focuses on discovering the traffic rules. Although the traffic problems can be alleviated by analyzing the traffic rules, this way only analyzes the surface phenomena. The formation of urban traffic rules is closely related to the urban spatial structure. Therefore, the research thinking should not be limited to surface phenomena, but explore the correlation between the traffic rules and the internal structure of the urban space, so that we can have a deeper understanding of the urban traffic rules. For example, traffic congestion in a certain location is actually related to the surrounding office buildings, restaurants ,and other spatial structures. By discovering this kind of correlation, we can make targeted traffic management decisions and guide traffic planning based on the results, so that get more meaningful conclusions. In addition, by discovering the relationship between the regional spatial structure and the flow pattern, traffic order can be regulated to a certain extent, traffic congestion can be relieved, and certain strategies can be provided for urban traffic safety.

Here we briefly list our contributions as follows:

- We propose a SFRH (Spatial Feature method based on

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Regional Hierarchy) to model the urban region spatial features, which use poincare ball-based representation learning to obtain the attributes of urban regions, further use hierarchical information and POI information to obtain more informative urban region spatial features.

- We propose a Self-representation Learning Optimization Method (SLOM) and combines the alternating direction multiplier method to find the correlation of urban traffic flow, so that obtain the traffic flow pattern of an urban region.
- We find the correlation between the spatial features of urban regions and flow patterns by measuring the classification matching of them. We validate the effectiveness of our methods based on data from Beijing taxi trajectories, the urban road networks within the fifth ring road, and Beijing POI data.

II. Related Works

The use of big data for urban transportation research has been a hotspot in recent years, and many good research methods and results have emerged. [11] studies the number of people flowing in and out of a certain area and capture abnormal events based on the difference of them. [12] used greedy network expansion framework and spatial clustering to analyze the driving trajectory of shared bicycles. In addition, the task of traffic flow prediction is also an important research issue in the field of transportation. [6] proposed a new spatial-temporal dynamic network (STDN) to predict traffic flow. [7] proposed a spatio-temporal multi-graph convolutional network for passenger demand forecasting, which first encodes the non-Euclidean correlation between regions into multiple graphs.

At present, some scholars have also researched on urban spatial layout and functional distribution. One of the typical tasks is to study the similar characteristics of urban areas, such as the discovery and search of similar areas. [13] and [14] search for similar regions from POI recommendation and regional recommendation tasks, respectively. Further, [15] not only stays on the task of POI recommendation and regional recommendation, but finds similar areas from the perspective of functional zone analysis, and uses three different basic classification criteria, their combination will provide 14 theoretical possibilities. The research on the search of similar areas is also a research direction. [16] proposed a geographic area search model, and called such queries similar area queries. Kafsi et al [17] used the label of the image data set to build a hierarchical tree of urban areas through the structure of country-city-neighbor cities, associate each node in the hierarchy with the label that specifically describes it. Moreover, it quantifies the uniqueness of the neighborhood, and find mappings between similar but geographically remote neighborhoods.

Based on the above, it can be found that the main problem in the current research is only studying the discovery of urban traffic laws, or only studying the spatial structure of a city and a specific application, without considering these two factors together. Therefore, this paper intends to discover the possible

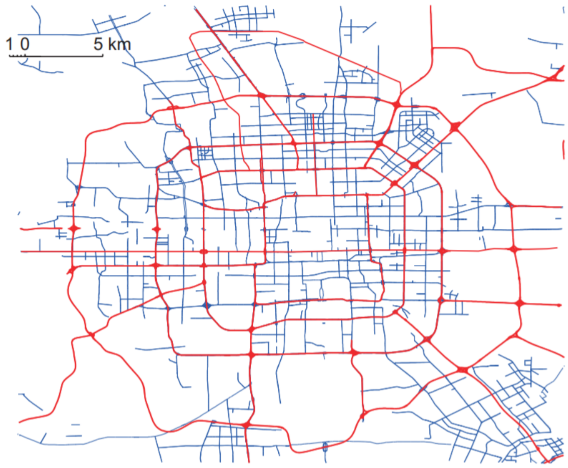

Fig. 1. Beijing road network. red: level-0/1; blue: level-2

internal relationship between urban spatial characteristics and flow patterns.

III. Methodology

In this section, we first study the urban regional spatial features and traffic flow patterns separately, and then the two are effectively merged to study the correlation between them.

A. Preliminary

Map Segmentation. In order to describe our model better, we divide the Beijing city within the fifth ring roads into several regions. As we known, A road network usually contains some major roads like highways and ring roads, which naturally partition a city into regions. For example, as shown in Fig. 1, the red segments denote highways and city expressways in Beijing, and blue segments represent urban arterial roads. The three kinds of roads are associated with a road level 0, 1, and 2 respectively (in a road network database), forming a natural segmentation of the urban area of Beijing [18]. Here, we use the roads associated with road level 2 to form a natural segmentation of Beijing city within the fifth ring roads. Intuitively, we regard each segmented region as a basic research unit.

OD Pairs Extraction. In order to construct a region network, we first extract OD (Origin-Destination) pairs from trajectory data. The taxi trajectory data is composed of a series of GPS points, and the information of each point can be represented by a tuple $< (lat, lon), f >$. Among them, lat refers to latitude, lon refers to longitude, and $f \in \{0, 1\}$ carries passenger information. The empty taxi is 0, otherwise, $f = 1$. When f changes from 0 to 1, the point is recorded as the origin. Otherwise, the point is recorded as a destination.

GPS Points Matching. After obtaining the OD pairs, we match all the GPS points of origins, destinations, and POIs to each segmented region. Since the regions, which take the city's roads associated with level 2 as the edges, can be regarded as a polygon. The Ray Judgment method (RJ) is used here to determine whether a point is in the polygon. In this way, the GPS coordinates of all origins, destinations, and POIs can be matched into urban regions.

B. Spatial Feature method based on Regional Hierarchy

We combine the hierarchical structure information of the regions with the POI information to obtain the urban regions' spatial features. We propose a SFRH(Spatial Feature method based on Regional Hierarchy) model, which uses poincaré representation learning to obtain the hierarchical structure of urban regions, and uses the correlation between each POI and the hierarchical structure as weights for POIs. We consider that POIs that contain the inherent spatial attributes of the region have a greater impact on the hierarchical structure of the regions, so that the weighted POI information has deeper meaning.

According to the OD pairs, we construct an urban region network $G = (V, E, W)$, where V represents the regions, E represents the OD information of the taxi, W represents the weights on the edges. For each $e_{ij} \in E$, the weight w_{ij} refer to the number of trajectories starting from node i and end with node j.

In order to obtain the regions' hierarchical structure information, we adopt Poincaré representation learning method. Namely, we embed all the regions into hyperbolic space, or more precisely into an d-dimensional Poincaré ball [19]. In particular, let $\mathcal{B}^d = \{\mathbf{x} \in \mathbb{R}^d | \|\mathbf{x}\| < 1\}$ be the open d-dimensional unit ball, where $\|\cdot\|$ denotes the Euclidean norm. For a given two urban area nodes u and v, their distance on the open unit ball is:

$$d(\mathbf{u}, \mathbf{v}) = cosh^{-1}(1 + 2\frac{\|\mathbf{u}\text{-}\mathbf{v}\|^2}{(1 - \|\mathbf{u}\|^2)(1 - \|\mathbf{v}\|^2)}) \quad (1)$$

We learn embedding for each region as follows: Let $\mathcal{D} = \{(u, v)\}$ be the set of observed hypernymy relations under the Poincaré ball. Since the pair of nodes with hypernymy relations in Poincaré ball are also as close as possible in the hidden space. Therefore, we minimize the loss function

$$\mathcal{L}(\theta) = \sum_{(u,v)\in\mathcal{D}} \log \frac{e^{-d(\mathbf{u},\mathbf{v})}}{\sum_{v'\in\mathcal{N}(u)} e^{-d(\mathbf{u},\mathbf{v'})}}, \quad (2)$$

where $\mathcal{N}(u)$ is the set of negative samples for u. The negative samples come from the following distributions

$$P((u, v) = 1|\theta) = \frac{1}{e^{\frac{d(\mathbf{u},\mathbf{v})-r}{t}} + 1}, \quad (3)$$

where $r, t > 0$ are hyperparameters, r refers to the radius around each node u, that is, the node v within the radius is likely to have an edge with u. The hyperparameter t determines the steepness of the function. It can be determined whether there are edges between two nodes, if not, they will be a pair negative samples.

By minimizing equation (2), we can get the vector of each region that can reflect the hierarchical structure. Due to the hierarchical characteristics of the Poincaré ball, we can obtain the absolute position of each node in the overall hierarchy by taking the norm of the learned urban region representation vector. This result is called the hierarchical score. And normalize the hierarchical score between 0 and 1. The lower the score, the higher the region's hierarchical structure. For each region $v \in V$, we define the hierarchical score $score_v$, then scores are divided into one level every 0.1 intervals. For example, if $0.1 < score_v \leq 0.2$, the level of region v is $level_1$. If $0.9 < score_v \leq 1.0$, the level of region v is $level_9$ and so on.

After get the level of urban regions, the POI information is weighted according to the hierarchical information of each urban region. Here we consider the region level y_i as the label, the number of each POI $\mathbf{x}_i$ in the region as feature, and then use softmax regression for training. Suppose the input data $\{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \cdots, (\mathbf{x}_m, y_m)\}$, where k=9, m=278, then softmax regression is mainly to estimate the probability that $\mathbf{x}_i$ belongs to j, that is,

$$p(y_i = j|\mathbf{x}_i; \theta) = \frac{e^{\theta_j^T \mathbf{x}_i}}{\sum_{l=1}^{k} e^{\theta_l^T \mathbf{x}_i}}, \quad (4)$$

where $\theta_1, \theta_2, \cdots, \theta_k \in \theta$ are the parameters of this model. In order to obtain the optimizest parameters, we define the loss function as follows:

$$L(\theta) = -\frac{1}{m}[\sum_{i=1}^{m}\sum_{j=1}^{k} \mathbb{I}\{y_i = j\} \log \frac{e^{\theta_j^T \mathbf{x}_i}}{\sum_{l=1}^{k} e^{\theta_l^T \mathbf{x}_i}}], \quad (5)$$

where $\mathbb{I}\{\cdot\}$ is the indicative function.

Through this model, we can get the weight of each POI in each region. The result of multiplying the number of POIs and the weight is used as a vector that finally reflects the spatial features of the region. More formally,

$$\mathbf{f}_i = (\theta_i^1 \times x_i^1, \theta_i^2 \times x_i^2, \cdots, \theta_i^d \times x_i^d), \quad (6)$$

where $\mathbf{f}_i$ represent the region i's spatial feature, d represent the total categories of POI.

C. Extraction of traffic flow patterns in urban regions

We use a Self-representation Learning Optimization Method (SLOM) [20] to obtain the similarity matrix of urban region traffic flow. The input data that needs to be used is the traffic matrix of the urban region. The row of the matrix is the urban region, the columns are listed as time. Since the research goal is to analyze the entire period of the entire city range, we choose to count the region traffic flow at an hour. The value is the average of traffic flow for all dates during that period.

The original input traffic flow matrix is defined as F, which is a dense matrix. It is hoped that a sparse matrix E that can reflect the traffic similarity among urban regions can be obtained from this process. According to [20], we hypothesise that $FE = F$. Our aim is to choose an E which minimizes the difference between F and FE. Thus, the final optimization problem can be stated as

$$
\begin{aligned}
min \, \|E\|_1 \\
sub \quad to \quad F = FE \\
diag(E) = 0 \\
E \geq 0
\end{aligned}
\tag{7}
$$

where $\|\cdot\|_1$ refer to $\cdot$'s $L1$-norm. We solve the above optimization problem using Alternating Direction Method of Multipliers (ADMM) framwork [21].

Finally, a matrix E representing the similarity between the two regions can be obtained, and the next task is to use the similarity matrix to obtain the traffic flow patterns. We use Affinity Propagation (AP) clustering [22] to classify the urban region traffic patterns. Through this process, It can be found that regions with similar traffic flow pattern and group them into a cluster. This method can not only find adjacent regions with the same traffic flow patterns but also find regions that are not adjacent but have similar traffic flow changes.

D. The relationship between urban spatial features and traffic flow patterns

Through the above methods, we can obtain effective vectors that can represent the spatial features of urban regions and traffic flow patterns. The following is to verify the relationship between them. In order to match the classification of traffic flow patterns, we use the k-means clustering algorithm to cluster the vectors of the spatial features so that the number of clusters obtained by the two methods is the same. Finally, different metrics are used to measure the matching degree of the two clustering results.

IV. Experiments

In order to verify the validity of the spatial feature results of urban regions, we conduct experiments and analysis to answer the following research questions:

Q1: Is the hierarchical division of urban regions reasonable?

Q2: Does the traffic flow pattern learned by SLOM well reflect the relationship of traffic flow between regions?

Q3: Can the region spatial features and traffic flow patterns learned by SFRH and SLOM capture the relationship between them well?

A. Dataset

We use three different sets of data to experiment: Beijing taxi trajectory data, road networks within the fifth ring road of Beijing,and Beijing POI data.

- **TaxiBJ**: Trajectory data is the taxicab GPS data in Beijing from 1st May.2015 - 31th May.2015. The average sampling rates are 31s, the number of taxicabs is 30334.
- **Road networks**: The road network data is within the fifth road of Beijing, the urban area is divided with the secondary road as the boundary, the average size of the actual block is about 2.03 square kilometers. The original map information comes from the Open Street Map (OSM).

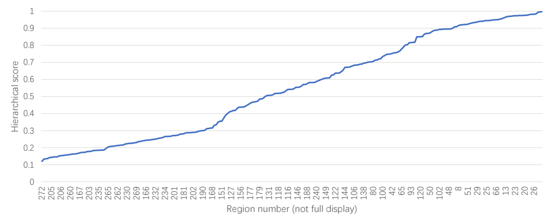

Fig. 2. The score distribution for all regions.

- **Beijing POI**: The main categories of POI information include leisure, entertainment, residential, hospitals, etc, a total of 9 categories. Each piece of POI data consists of its name, type, and GPS point where it is located, a total of 64,020 data points.

B. The analysis of urban area spatial feature

To answer Q1, we use the learned region vectors to analyze the hierarchy of urban regions. The score distribution for all regions is shown in Fig. 2. It is worth noting that the calculation method of the score is in III-B. According to the results, the hierarchical structure is divided into 9 levels, and the score is divided into a class every 0.1 intervals. Let the score of the i-th area be $score_i$, where the region with $0.1 < score_i \leq 0.2$ is the first level, the region with $0.2 < score_i \leq 0.3$ is the second level, and so on. Based on this, we obtain the region hierarchical classification results.

Fig. 3 shows the hierarchical classification visualization results. The figure shows the regions within the five-ring road. The horizontal and vertical coordinates are longitude and latitude. Different colors represent different levels of hierarchy. The levels from high to low are pink, orange, yellow, light green, dark green, light blue, dark blue, purple, gray, and brown. The brown area marks the area where taxis rarely appear and is not involved in the analysis here. In order to facilitate the analysis of the results, letters are marked with icons in the text. Among the regions marked with letters, the highest level is A and the lowest is F.

C. The analysis of flow pattern

To answer the Q2, we verify and analyze whether the flow patterns learned by SLOM can well reflect the relationship of traffic flow between urban regions. In order to verify the effectiveness of SLOM, we select the method of Non-negative Matrix Factorization (NMF) [23] as the baseline.

The evaluation metric used in this experiment is to calculate the similarity of flow changes in each category and take the average of all categories. The time series is segmented during the calculation, and then the distance between each segment is calculated to obtain the similarity.

The NMF model was used to obtain 30 groups of flow patterns for similar urban regions, of which 5 regions were classified as a single class. And the average similarity of the flow patterns within the class was 0.2585. The flow pattern extraction method used in this paper SLOM obtained a total

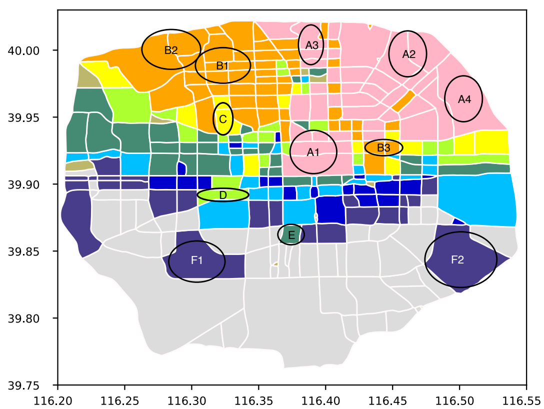

Fig. 3. The results of the hierarchical classification.

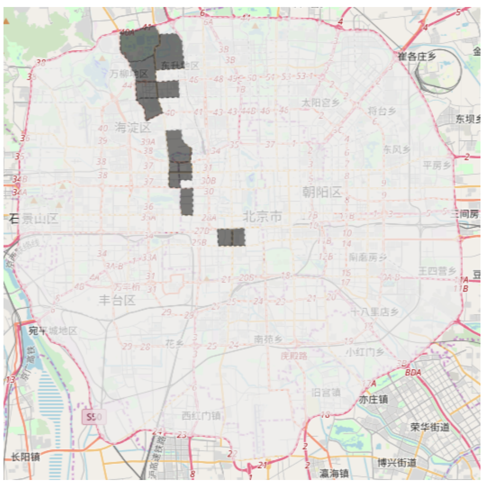

Fig. 4. The distribution of a group of flow patterns.

of 48 groups of similar patterns. No region is a single group. The average intra-class flow pattern similarity is 0.2623. It can be seen that both the grouping effect and the quality of the data in the group are better than NMF.

Fig. 4 shows the distribution of a group of flow patterns on the map. Fig. 5 is the flow change of this group, where a line represents the flow change of a region. First, from the figure of flow change trend, it can be found that the flow changes obtained by the model are similar. A group can be seen in Fig. 4, regions with similar flow patterns are mostly not geographically adjacent. Looking further at the actual map situation, this group of regions includes buildings, offices ,and schools. This group of flow patterns will change at a total of four-time frames. As shown by the red dashed line in Fig. 5, the traffic flow shows an upward trend from 5 o'clock, and the traffic starts to decrease around 10 o'clock. This part can be understood as the traffic flow of office workers. The working hours of different companies are different, and the traffic is basically until 10 o'clock. Therefore, it shows a downward

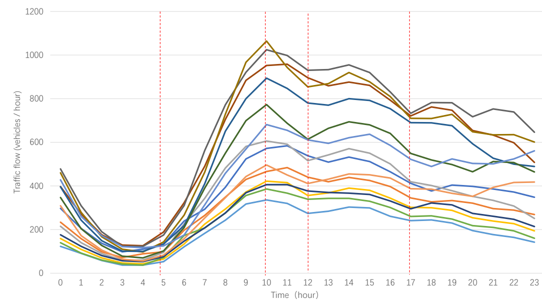

Fig. 5. The traffic flow change of this group.

trend. At the same time, there is a sudden change in traffic at 12 o'clock, which may be due to the existence of traffic congestion, resulting in a short-term decline in traffic flow and then an upward trend. Until 17 o'clock rush hour ushered in, causing traffic congestion. Because companies have different off-hours, the congestion duration is longer. Therefore, the traffic flow changes slowly after 17:00. Looking at the map from an intuitive perspective, we can see that the flow changes in these regions are similar and reasonable.

D. The analysis of relationship

To answer the Q3, we need to verify the relationship of urban region spatial features and flow patterns. In order to cope with the classification of flow patterns, we cluster the spatial feature vectors using the K-means method, and the number of clusters is the same as flow patterns. Then, use four evaluation metrics to measure the matching degree of the two clustering results, namely, Normalized Mutual Information (NMI), Homogeneity, Completeness ,and V-measure.

Here, the baseline comes from different urban area spatial feature mining methods and different flow pattern extraction methods. The comparison methods of urban region spatial feature mining include the model used to find urban functional regions based on LDA [18], the model used to discover functional regions based on DMR, and the SAZE method to find urban functional regions [24]. The comparison method of the flow pattern extraction task is based on NMF method mentioned in [23].

The results are shown in TABLE I. It can be seen that when the flow pattern extraction method selects NMF, the spatial feature mining method with the best matching effect is the SFRH proposed in this paper. When the flow pattern extraction method is the SLOM with this paper, the spatial feature mining method with the best matching effect is still SFRH. The matching effect of LDA, DMR and SAZE methods with SLOM is higher than the result of matching with NMF method. It is worth noting that the combination of SFRH and SLOM methods surpasses other comparison methods in the three indicators of NMI, V-measure and Completeness, while the effect on the Homogeneity indicator is slightly worse than the combination of SAZE and NMF methods. This shows that

TABLE I
THE RESULTS OF THE RELATIONSHIP BETWEEN URBAN SPATIAL FEATURES AND FLOW PATTERNS.

model: spatial features	model: flow patterns	NMI	V-measure	Homogeneity	Completeness
LDA	NMF	0.37	0.37	0.42	0.33
DMR	NMF	0.28	0.28	0.29	0.26
SAZE	NMF	0.30	0.25	0.58	0.16
SFRH	NMF	0.42	0.42	0.44	0.41
SFRH	**SLOM**	**0.52**	**0.52**	**0.54**	**0.50**
LDA	**SLOM**	0.40	0.39	0.34	0.46
DMR	**SLOM**	0.44	0.44	0.44	0.45
SAZE	**SLOM**	0.41	0.40	0.36	0.46

our proposed method is better than the comparative method on the whole. This also illustrates the SFRH method and SLOM used in this paper can well discover the correlation between urban spatial features and flow patterns to a certain degree.

V. CONCLUSIONS

In this paper, we proposed a method based on the dimension of the urban regions to discover the correlation between spatial features and flow patterns. In order to obtain the spatial feature of urban regions, we propose a SFRH model, which uses poincaré representation learning to learn the hierarchical structure of urban regions, and weights the correlation between each POI in the region and the hierarchical structure as weights for POIs. We recognize that the weighted POI implies deeper meaning for the urban region. For the flow patterns, we use the SLOM method to obtain the similarity matrix of urban traffic flow. Then, the AP clustering algorithm is used to classify the flow patterns. Finally, we use the k-means algorithm to cluster the spatial feature vectors to measure the classification of flow patterns. Experiments show that our approach is effective. In the future, we will take a closer look at the causal relationships that urban regions influence each other.

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