Revealing daily travel patterns and city structure with taxi trip data

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Abstract: Detecting regional spatial structures based on spatial interactions is crucial in applications ranging from urban planning to traffic control. In the big data era, various movement trajectories are available for studying spatial structures. This research uses large scale Shanghai taxi trip data extracted from GPS-enabled taxi trajectories to reveal traffic flow patterns and urban structure of the city. Using the network science methods, 15 temporally stable regions reflecting the scope of people’s daily travels are found using community detection method on the network built from short trips, which represent residents’ daily intra-urban travels and exhibit a clear pattern. In each region, taxi traffic flows are dominated by a few ‘hubs’ and ‘hubs’ in suburbs impact more trips than ‘hubs’ in urban areas. Land use conditions in urban regions are different from those in suburban areas. Additionally, ‘hubs’ in urban area associate with office buildings and commercial areas more, whereas residential land use is more common in suburban ‘hubs’. The taxi flow structures and land uses reveal the polycentric and layered concentric structure of Shanghai. Finally, according to the temporal variations of taxi flows and the diversity levels of taxi trip lengths, we explore the total taxi traffic properties of each region and proved the city structure we find. External trips across regions also take large proportion of the total traffic in each region, especially in suburbs. The results could help transportation policy making and shed light on the way to reveal urban structures with big data.

Keywords: GPS-enabled taxi data, intra-urban human mobility, urban structure, land use condition, Shanghai

1. Introduction

Human mobility is a crucial topic for individual behavior modeling, urban research, transportation control, contagious disease control and so on. Since information and communication technologies (ICT) are developing rapidly, big data like mobile phone records (Kang et al. 2012), social media check-ins (Cheng et al. 2011), taxi trajectories and public transportation smart card data (Chen, Chen and Barry 2009) are available for approximating movements of people, which enormously boosted the research of human mobility. Compared with the data collected using conventional methods, such as questionnaires or simulations (Chowell et al. 2003), big data are more accurate, objective, plentiful and highly accessible, providing opportunities to better describe and understand human mobility (Lu and Liu 2012, Brockmann, Hufnagel and Geisel 2006, Rhee et al. 2011, Gonzalez, Hidalgo and Barabasi 2008, Song et al. 2010).
Since GPS (Global Positioning System) trajectories of taxis are highly accessible and do not involve privacy issues, they are now applied in many related research fields, such as traffic prediction (Gao et al. 2013), urban planning (Zheng et al. 2011, Veloso, Phithakkitnukoon and Bento 2011), land use analysis (Yuan, Zheng and Xie 2012, Liu et al. 2012b, Qi et al. 2011) and spatial model calibration (Yue et al. 2012). GPS-enabled taxi trajectory is also an important data source for human mobility studies. Although taxi GPS data is not able to reflect continuous displacements of a specific person, it well approximates collective human mobility patterns of intra-city travels with accurate positions and time stamps, and these advantages triggered great interest from researchers. Liang et al. (2012) studied the displacement distribution of human mobility by taxis and Liu et al. (2012a) constructed a model of intra-urban mobility by taxis considering geographical heterogeneity and distance decay.

Spatial interaction, a core issue in geographical research, also benefit from big data generated by ICT devices. Spatial interactions could on large scales reflect the strength of economic and cultural ties between regions, and on small scales depict city structure and urban dynamics. Large amount of big data are able to record displacements of people. Since a trip implies strong relationship between the origin and the destination, much research (Thiemann et al. 2010, Brockmann et al. 2006, Gonzalez et al. 2008, Noulas et al. 2012, Cheng et al. 2011, Kang et al. 2012) investigated topics related to spatial interactions based on people’s movements. Some studies also use city relationship data (Kang et al. 2013, Ratti et al. 2010) or friendship data (Liben-Nowell et al. 2005, Onnela et al. 2011) to explore spatial interaction issues.

Interactions between different regions can be modeled by a spatially embedded network, in which nodes and edges are constrained in space. Constructing networks based on movements (or more generally, interactions) of people helps us to detect to find reasonable subdivisions and better understand the spatial structure of a region (Chowell et al. 2003). Community detection methods are frequently applied in those studies. The methods could divide a network into sub networks that have stronger connectivity within themselves than with others. Given a spatial embedded network, the sub networks represent regions that have strong spatial interactions inside them. On large scales like a country, researchers try to find whether the existing administrative boundaries are still reasonable (Thiemann et al. 2010), explore the relations between commuting properties and socio-demographic variables (De Montis et al. 2007), and give suggestions for regional partitions (Montis, Caschili and Chessa 2013). Relatively fewer studies focus on small scales like a city, whereas city structure reflected by regional partitioning based on spatial interactions is vital for urban design and transportation planning. Tanahashi et al. (2012) applied graph partitioning methods on the human mobility network extracted from phone records in New York City, but they emphasis on inferring human travel patterns between the partitioned sub-regions instead of revealing regional structure.

Most existing human mobility studies focus on the fat tail properties of displacement distributions and the characteristics of consecutive individual traces. In fact, short and medium length trips take up large part of the total traffic. The detailed characteristics and structure of those travels that have stronger influence on traffic flows and human mobility have seldom been explored. Compared with individual traces, collective movements uncover urban dynamics better,
and the spatial interactions based on the displacements depict a detailed and objective structure of the city. Exploring city structure with big data also makes up for the shortcomings of lacking validation data in traditional research. Polycentric city structure and the role of urban hubs in urban dynamics has long been a research hotspot, but few studies investigated into this topic with big data. Roth et al. (2011) utilized individual travel information of London subway to explore this issue, but the routes traveling by subway is constrained so that the results are not able to fully reflect the dynamics of the city.

In this study, we use GPS-enabled taxi data of Shanghai, China to explore the structure of urban flows and the city, helping make policies on reducing traffic flow amount, relieving traffic congestions and giving suggestions on urban planning. We select taxi trips that reflect daily travels of residents and apply community detection method to find sub regions that have strong internal interactions reflected by daily resident travels. Based on those sub regions and accompanied with land use conditions, we study patterns of daily traffic flows, the effects of hubs on urban dynamics and the polycentric and layered concentric structure of the city. The rest of the paper is organized as follows. Section 2 describes the study area and the preparation of data. Section 3 divides taxi trips into 3 groups and constructs networks from those trips. The following sections focus on the network constructed from short length trips because they represent daily travels of residents and have stronger spatial patterns. Section 4 reveals the taxi traffic flow patterns and the urban structure with network methods and land use conditions. Traffic flow properties of all length range trips are also studied in this section. Discussion and conclusions are stated in Section 5, giving suggestions on policy making.

2. Study area and data preparation

2.1 Shanghai districts

As the economic center of China, Shanghai (Fig. 1) is a populous city and a typical world-level metropolis. It consists of 16 districts and 1 county in 2012, and the eight districts in Puxi accompanied with the Lujiazui area in Pudong are the core urban area of Shanghai (shown in the rectangle frame in Fig. 1). Shanghai has two airports, namely Shanghai Pudong International Airport and Shanghai Hongqiao International Airport. Shanghai Railway Station, Shanghai South Railway Station and Shanghai Hongqiao Railway Station are the three major railway stations. The study area includes all the Shanghai districts except for the Chongming Island.

Even though the public transport system is well developed in Shanghai, taxis form an important supplement for buses and metros, taking up 19.3% of the intra-urban trips by public transportation services in 20101. Traveling by taxi has flexible origins and destinations and is more time saving. In China, taxi trajectories are plausible for urban studies given the capacity to

1 http://www.shanghai.gov.cn/shanghai/node2314/node25307/node25455/node25459/u21ai605264.html
capture a large proportion of passenger flows inside a city.

Fig. 1. Shanghai, the study area. The red districts accompanied with the Lujiazui Area of Pudong are the core urban area of Shanghai. The districts colored blue, the rest part of Pudong and Chongming are the suburban and rural districts.

2.2 Taxi trip data and data preparation

The source data set contains GPS trajectories of more than 6,600 taxis in Shanghai. People travel more regularly on weekdays since they travel for activities that are more diverse on weekends. Taxi trips on weekdays are more proper to reveal urban structure, excluding data of Friday because people have more trips for entertainment on Friday night. Therefore, we use a data set that covers four consecutive days from Monday (June 1, 2009) to Thursday (June 4, 2009). Since the interactions between places, we simplify the taxi trajectories into vectors consisting of origins and destinations, ignoring the route details. We extract 924,977 taxi trips from data set the and further remove the trips that are not complete, less than 500 meters, with velocity faster than 70 m/s or beyond the administrative boundary of Shanghai. Finally, 879,417 trips are used in this study, of which each record contains information of taxi ID, pick-up time, pick-up point coordinates, drop-off time, drop off point coordinates, trip duration and trip length. We use actual trajectory distance instead of Euclidean distance between origin and destination as the length of the trip, because traveling by taxi cost more than other means of transportation so that people are sensitive to the price of the trip, which correlate with the actual trajectory distance.
3. Constructing networks

3.1 Patterns of trips with different lengths

The trip distance distribution is an important statistical property when research into human mobility. Previous study used an exponentially truncated power law distribution to fit the distance distribution of taxi trips in Shanghai (Liu et al. 2012a). However, with the intuitive notion that people travel with different lengths for different purposes, we divide the distribution into three parts according to the two observed elbows, 5 km and 15 km (Fig. 2). The three parts are named as Short Length Trip Group (470,466 trips), Medium Length Trip Group (343,743 trips) and Long Length Trip Group (65,208 trips). Trip distances in each group follow a power-law distribution \( P(d) \sim d^{-\alpha} \) and \( \alpha \) increases with the distance, indicating that the number of trips decreases rather faster when trip distance grows. It makes sense as taxi trips cost more than other modes of transportation so that less people would have long trips by taxi. However, the distribution of long length trip group is still fat-tailed, suggesting that people making long taxi trips are less sensitive to the cost.

![Log-log plot of the distribution of taxi trip distances. Trips are divided into 3 groups according to the elbows, namely trip with length less than 5 km, between 5 and 15 km and more than 5km. Distribution of trips in each group fits a power-law distribution \( P(d) \sim d^{-\alpha} \) and \( \alpha \) grows with trip length.](image)

Grouping taxi trips by length could also be proved reasonable by the differences in their temporal variations and direction distributions. The temporal variations of trips from the three groups are different (Fig. 3). The number of short trips peaks around 2 pm, while the trip numbers of the

Fig. 2. Log-log plot of the distribution of taxi trip distances. Trips are divided into 3 groups according to the elbows, namely trip with length less than 5 km, between 5 and 15 km and more than 5km. Distribution of trips in each group fits a power-law distribution \( P(d) \sim d^{-\alpha} \) and \( \alpha \) grows with trip length.
other two groups fluctuate slightly during day time and have two small peaks in the morning and evening. The direction of a trip is defined as the azimuth of the vector from origin to destination. The directions of short and medium trips distribute more uniformly than the ones of long trips (Fig. 4). The two major directions of long trips are southeast east (SEE) and southwest west (SWW), which are the same as the directions from the city center to the two airports, indicating that long trips may be influenced more by scarce facilities in the city.

**Fig. 3.** Temporal variations of trips with different lengths according to their (a) pick-up time and (b) drop-off time. The number of short trips peaks around 2 pm, and the other two groups have two small peaks separately in the morning and evening.

**Fig. 4.** Direction distributions of trips in different length groups. The direction distributions of short and medium trips are more uniform than the long ones.

We also discretize the study area into $1km \times 1km$ cells, and count the number of pick-up and
drop-off points of the three groups in each cell, generating six heat maps (Fig. 5). The hotspots of pick-up and drop-off points for short length trips concentrate in the central urban area, and they are more likely to be generated by daily activities of people, such as traveling to nearby workplaces, shops and restaurants or going home. Conversely, long length trips spread broadly over the city, and hotspots center on the airports and the railway stations. It is reasonable to claim that long length trips are produced by special activities of citizens, such as going to the railway station or the airport, or traveling to a relatively faraway place for a meeting or a party. They may also result from tourists because traveling by taxi is the most convenient way for them to find unfamiliar places efficiently. Medium length trips concentrate in urban area and some suburban railway stations, acting as the transition between the long and short length trips. Generally speaking, taxi trips in different length groups are activated by different purposes and have different patterns.

![Heat maps of taxi trips](image)

(a) PUP of short length trips  (b) PUP of medium length trips  (c) PUP of long length trips

(d) DOP of short length trips  (e) DOP of medium length trips  (f) DOP of long length trips

Fig. 5. Spatial distributions of pick-up points (POP) and drop-off points (DOP) of different length trips. Short trip hotspots concentrate in urban area while long trips spread broadly and their hotspots center on airports and railway stations.

### 3.2 Constructing networks from taxi trips

Given that people have several revisited points in their daily activities (Song et al. 2010), such as their homes, offices or shops and restaurants around them, we assume that short length trips reflecting daily travels of city residents have a more regular spatial pattern and can better reveal
the urban dynamics than trips in other groups, which would be proved with network models. In this study, we discretize the study area into $1\text{km} \times 1\text{km}$ cells as the nodes of networks, building networks from the aggregation level. There exists an edge connecting two cells if taxi trips generated from one cell and ended in the other, and the edge is pointing from the origin cell to the destination cell. The number of taxi trips between the two cells is the weight of the edge, thus forming directed and weighted networks. Trips generated and ended in the same cell are deleted when building networks. We choose $1\text{km} \times 1\text{km}$ cells based on relevant studies (Liu et al. 2012b) and the cell size is small enough to depict the urban structure.

We build three networks based on trips of the three groups separately. $N_s$ is the network formed by short length trips, $N_m$ by medium length trips and $N_l$ by long length trips. The basic statistics of the networks are illustrated in Table 1. Surprisingly, although $N_l$ is structured with the least trips, it has the most nodes among the three networks. The average edge weight also decreases sharply as the trip length grows, indicating that spatial interactions generated by short length trips are much more intensive. These characteristics illustrate that short trips, which represent daily travels of residents, have a more regular spatial pattern. Since the number of locations people visit in their daily activities and the routes visiting them are limited and fixed, $N_s$ has the least number of nodes and edges but take up more than half the of total trips. On the contrary, long trips connect places that are more diverse and most edges contain few trips, suggesting that long trips have weak spatial patterns and happen more spatially randomly. As the transition type, medium length trips combine the characteristics of both the short length trips and the long ones. The edge weight distributions of the three networks are all fitted into power-law distribution $P(w) \sim w^{-\alpha}$ (Fig. 6), indicating that more trips link the same two nodes than in a random network. Many other studies related to spatial interactions (Brockmann et al. 2006, Cheng et al. 2011, Kang et al. 2013, Onnela et al. 2011) also illustrate that the distribution of spatial interaction intensity can be described by power-law functions. The value of parameter $\alpha$ increases with trip length, meaning that the percentage of large weight edges decrease as the trip length grows, which confirms that short length trips have a more regular spatial pattern than trips in other groups.

Table 1. Basic statistics of networks constructed from trips with different lengths

| Trip number | Nodes | Edges | Average edge weight | $\alpha$ |
|-------------|-------|-------|---------------------|---------|
| $N_s$       | 453,850 | 2089  | 31,776              | 217.257 | 1.895 |
| $N_m$       | 342,246 | 2171  | 95,022              | 3.602   | 2.671 |
| $N_l$       | 64,703  | 2507  | 46,723              | 1.385   | 2.758 |
The distributions fit power-law function $P(w) \sim w^{-\alpha}$ and $\alpha$ increases as trip length increases (Table 1), indicating that trips have more certain routes than the random situation and short trips have stronger spatial patterns.

According to the above analysis, short length trips have a more regular spatial pattern than medium and long length trips. Moreover, the city structure revealed by short length trips is more applicable for transportation planning and regional land use optimization since those trips have strong relation with daily resident travels. On the contrary, long distance travels caused by infrequent activities or tourists may obscure the structure of the urban area. Therefore, the following sections focus on trips in Short Length Trip Group and the sub-network $N_s$ to explore the urban dynamics and spatial structure of Shanghai. Although medium trips also contain some daily travels, we neglect them since short trips account for more than half of the total number of trips and it is difficult to extract those daily travels from the Medium Length Trip Group.

4. Urban mobility and urban structure

4.1 Community detection of networks

Community detection is an important topic in network theory. The nodes in the same community have more connections than with the ones in other communities. Since nodes are $1\,km \times 1\,km$ cells in this study, regions that have more interactions can be found through community detection. Many studies applied community detection methods based on modularity, such as the fast-Greedy method (Clauset, Newman and Moore 2004) and the Multi-level method (Blondel et al. 2008). However, it is not applicable to use these methods on weighted and directed networks. We thus adopt the Infomap method (Rosvall and Bergstrom 2008), which is able to handle the weighted and directed networks and performs stably and fast (Fortunato 2010), to detect communities from $N_s$. 

Fig. 6. Log-log plot of edge weight distributions of networks formed by trips with different lengths. The distributions fit power-law function $P(w) \sim w^{-\alpha}$ and $\alpha$ increases as trip length increases (Table 1), indicating that trips have more certain routes than the random situation and short trips have stronger spatial patterns.
About 200 regions are found from $N_s$ using the Infomap method (Fig. 7a). Communities in the urban area have spatially continuous large areas with diameters ranging from 5 km to 10 km. The spatially continuous property illustrates the distance decay effect in space and is in accord with existing studies (Ratti et al. 2010, Thiemann et al. 2010). However, most of the communities in suburban and rural areas consist of very few grids, except for some communities lying around the centers of the outskirt districts. These small communities result from low taxi flows. Some of the relatively large communities in suburbs also have relatively weak taxi flows. All the communities circle in layers around the city center. Most of the communities have different shapes from the govern districts because administrative boundaries have less effect on intra-city travels than inter-city travels.

To explore the temporal properties of the communities, we build 20 sub networks of $N_s$, each of which consists of short trips in one hour according to their drop-off time from 5 am to 1 am the next day. Trips from 1 am to 5 am are ignored due to the insufficient amount. We detect communities of those 20 sub networks and overlay the community boundaries of the results. The more frequent a boundary exists, the thicker it appears in Fig. 7b. It is obvious that there are 15 “core” communities, which lies in or near the urban area and have large spatial continuous regions with stable boundaries throughout the day. The temporally stable community boundaries demonstrate that there are more daily trips inside each community the whole day than across them. It may be on one hand because each community contains various locations that are sufficient for daily activities of residents, on the other hand also due to the specific functionality of the community in the city, which lead to large amount of certain kinds of daily activities. In addition, the boundaries of those 15 communities are consistent with those detected from $N_s$, demonstrating that the result of community detection of $N_s$ is plausible and meaningful. So we select those 15 communities from the community detection result of $N_s$ and name them as Daily Travel Zones (DTZ). The following part will focus on the 15 DTZs and look deep into the structure of the city.

Fig. 7. (a) Community detection result of the network based on short length trips (b) Overlaid result of community detection results of networks built from short length trips of different hours
of the day. The 15 “core” communities in (b) that have temporally stable boundaries well correspond to the result depicted in (a).

4.2 Network statistics of DTZs

The 15 DTZs are depicted in Fig. 8 and they can be divided into three levels. DTZ 1, which belongs to level 1, lies in the center of Shanghai and contains the largest number of taxi trips. Level 2 contains DTZs from 2 to 7, which cover the urban districts of Shanghai on Puxi and the central region of Pudong New District. Level 1 and level 2 DTZs can be referred to as the urban area of Shanghai. DTZs from 8 to 15 lie in suburbs and are included in level 3. The DTZs in the same level lie in the same concentric tier except DTZ 8, but DTZ 8 may develop fast due to the 2010 Shanghai EXPO and gradually catch up with the level 2 DTZs.

Fig. 8. The 15 Daily Travel Zones (DTZs) in Shanghai. DTZs 1 to 7 cover the major urban area of Shanghai and DTZs 9 to 15 lies in suburbs. The 15 DTZs lie in three concentric tiers.

Since large proportion of everyday taxi trips of residents are constrained in a certain area, namely the DTZ in this study, the DTZs have the closure property, which means that most of the trips start in the DTZ also end in it. On average 77.37% of the short length trips started in a DTZ also end in the same DTZ and those trips on average even take up 38.98% of the total taxi flow of all length range generated in a DTZ. These facts also indicate that taxi travels driven by daily activities play an important role in transportation and should be treated with great attention.

To further explore the structure of traffic flows within each DTZ, we analyze properties of the 15 sub networks of \( N_s \) corresponding to the 15 DTZs. Each sub network contains all short length trips start and end in the corresponding DTZ. However, we neglect the directions of the network edges when calculating statistical metrics since the undirected metrics are easier to understand and can depict the spatial interactions clear enough.

The overall characteristics of the 15 sub networks are illustrated in Table 2. Degree is a basic measure of the topological centrality of a node and the degree \( k \) of a node is defined as the
number of nodes connecting to it. The average degree of a network indicates the intensity of interactions between different nodes. Graph density means the ratio of the number of edges in the network to the number of maximal possible edges in it, which measures how close the network is to a complete connected one. Diameter of a network is the longest shortest path between any two nodes and measures the connectivity of the network. Clustering coefficient is defined as the possibility that two nodes connected to the same node are connected and it quantifies local clustering. The 15 DTZ networks are high in average degree and graph density, demonstrating that residents travel diversely in a DTZ and the locations within a DTZ interact with each other broadly. Moreover, the value of average degree, average edge weight and graph density are relatively higher of DTZs in level 1 and 2 than in level 3, caused by the difference of the amount of traffic flows. As these 15 networks are well connected, the diameters are fairly small comparing to the number of nodes, and the values of average clustering coefficient are high. Generally, the 15 sub networks have similar topological structure but sub networks in urban areas consist of larger traffic flows and have broader connections between nodes than sub networks in suburbs.

Table 2. Overall properties of networks built from short length trips of different DTZs

| Community | Trips  | Nodes | Edges | Average Degree | Average Edge Weight | Graph Density | Diameter | Average Clustering Coefficient |
|-----------|--------|-------|-------|----------------|--------------------|---------------|---------|-------------------------------|
| 1         | 131444 | 59    | 1104  | 37.424         | 119.062            | 0.645         | 3       | 0.803                         |
| 2         | 52196  | 84    | 1504  | 35.810         | 34.705             | 0.431         | 3       | 0.744                         |
| 3         | 32013  | 75    | 1241  | 33.093         | 25.796             | 0.477         | 4       | 0.724                         |
| 4         | 30537  | 56    | 833   | 29.750         | 36.659             | 0.541         | 3       | 0.785                         |
| 5         | 13126  | 32    | 388   | 24.250         | 33.830             | 0.782         | 2       | 0.868                         |
| 6         | 33204  | 45    | 696   | 30.933         | 47.707             | 0.703         | 2       | 0.822                         |
| 7         | 15783  | 56    | 666   | 23.786         | 23.698             | 0.432         | 3       | 0.731                         |
| 8         | 7775   | 57    | 606   | 21.263         | 12.830             | 0.380         | 3       | 0.746                         |
| 9         | 6337   | 39    | 383   | 19.641         | 16.546             | 0.517         | 3       | 0.763                         |
| 10        | 2690   | 44    | 372   | 16.909         | 7.231              | 0.393         | 4       | 0.757                         |
| 11        | 5321   | 37    | 361   | 19.514         | 14.740             | 0.542         | 3       | 0.779                         |
| 12        | 4988   | 43    | 351   | 16.326         | 14.211             | 0.389         | 4       | 0.821                         |
| 13        | 3091   | 46    | 282   | 12.261         | 10.961             | 0.272         | 3       | 0.749                         |
| 14        | 10405  | 53    | 766   | 28.906         | 13.584             | 0.556         | 3       | 0.772                         |
| 15        | 1098   | 32    | 194   | 12.125         | 5.660              | 0.391         | 2       | 0.730                         |
| **Average** | 23334  | 51    | 650   | 24.133         | 35.909             | 0.497         | 3       | 0.773                         |

Strength of nodes and the weight of edges are also important metrics to reveal the structure of each network. Strength of a node is defined as the total weight of edges connecting to it, which characterizing the total traffic volume of each node. We plot the complementary cumulative distribution functions (CCDF) of degree, strength of nodes and weight of edges of the 15 networks (Fig. 9). In order to compare the curves of different DTZs, we normalize the three metrics separately by dividing them by the maximum value of the metric in each DTZ. The CCDF decrease linearly with normalized degree in most of the DTZS, suggesting that the node degrees
in each DTZ are more likely to follow a uniform distribution. The CCDF of normalized strength decrease faster with small values and slower with large values in each DTZ network, which shows more nodes have low taxi traffic flow and the hubs in each DTZ have much larger traffic volume than other nodes. The edge weights are even more heterogeneous as they follow exponential distribution. These results illustrate that some nodes play roles as hubs in the networks, attracting or generating a large percentage of the total traffic and interact with the most nodes. The different intensity of connections between nodes within a DTZ may result from land use conditions, population distributions and other geographical heterogeneity factors. However, besides these common properties, the networks of DHRMs in level 1 and 2 perform slightly different from those in level 3. More nodes in networks of level 1 and 2 have larger degrees and the heterogeneity of node strengths appears less strong than those in level 3. The edges with larger weight of DHRMs in level 1 and 2 also take slightly smaller percentage than the ones in level 3. It can be inferred that DTZs in level 3 are affected more by geographic heterogeneity and hubs are more influential in level 3 networks.

Fig. 9. Complementary cumulative distribution functions (CCDF) of (a) normalized degree (b) normalized strength and (c) normalized weight of networks of the 15 DTZs.
We apply two other network metrics to confirm our findings. One is betweenness centrality of nodes \(g(i)\), defined as (Freeman 1977) 
\[
g(i) = \sum_{s \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}}
\]
where \(\sigma_{st}(i)\) is the number of shortest paths going from node \(s\) to node \(t\) through node \(i\) and \(\sigma_{st}\) is the number of all the shortest paths going from node \(s\) to node \(t\). Betweenness centrality measures the importance of a node in organizing flows in the network. The other metric is disparity \(Y_2(i)\), defined as 
\[
Y_2(i) = \sum_{ij} \left( \frac{w_{ij}}{s_i} \right)^2
\]
where \(s_i\) is the strength of node \(i\) and \(w_{ij}\) is the weight of edge connecting node \(i\) and node \(j\) (Barthélemy et al. 2005). Disparity measures the diversity of edge weights connecting to a node. \(Y_2(i)\) is small when the edge weights are similar to each other while \(Y_2(i)\) is large when edge weights are heterogeneous and few weights dominate the others. We explore how betweenness and disparity changes with degree and strength, respectively.

Degree and strength of nodes are normalized in each DTZ to the range of 1 to 100 in order to compare between the 15 DTZs. The average betweenness of nodes with the same degree 
\[
g(k) = \frac{\sum_{i \in k} g(i)}{N(k)},
\]
in which \(N(k)\) is the number of nodes with the same degree, increase exponentially with \(k\) in the form of \(g(k) \sim e^{\lambda k}\). The increase implies that many low-degree nodes do not have directly interactions between them while high degree nodes connect directly to large proportion of nodes in different parts of the DTZ. Disparity decreases logarithmically with the strength of the node as \(Y_2(s) \sim s^{-\beta}\), demonstrating that nodes with low taxi traffic flows often have few relatively heavy weight edges and most of those edges are connected to hubs of the DTZ, whereas hubs have taxi traffic flows to a broad range of places and no edges of the hub can absolutely dominate others. Besides those common structures, there also exist some differences between DTZs in urban areas and in suburbs. The exponent \(\lambda\) and the parameter \(\beta\) are larger on average in DTZs of level 3 than the ones in urban area (Fig. 10), which means that betweenness grows faster and disparity decrease faster in suburban areas. It is consistent with earlier findings, showing that hubs influence more traffic in suburban DTZs and low degree or strength nodes have more interactions between each other in urban areas.

![Fig. 10. \(\lambda\) (a) and \(\beta\) (b) values of different DTZs. Values of \(\lambda\) and \(\beta\) are both larger on average in suburbs.](image-url)
In general, the 15 DMHRs share many characteristics. They have the closure property, and hubs in each DTZ take large proportion of taxi flows and dominate in organizing taxi flows of the whole DTZ. However, suburban DTZs are more influenced by geographical heterogeneity and hubs are more vital in suburban local traffic. If we define the node with the highest strength value as the hub of the DTZ to make the results among DTZs comparable, the number of taxi trips originated or ended in the hub on average take 20.87% of the total amount of taxi traffic flows within the DTZ. Hubs in suburban DTZs generally account for a greater proportion of trips (Fig. 11). The flow amount statistics also prove the conclusions. Differences in traffic flow amount and structure between urban area and suburbs depict the layered concentric urban structure of Shanghai from the view of spatial interactions. At the same time, the important influence of hubs on local traffic also shows the polycentric structure of the city.

Fig. 11. The percentage of internal taxi flows related with hubs in different DTZs. Suburban hubs on average take larger percent of the total internal taxi flows.

4.3 Hubs and land use conditions in DTZs

Urban travels are linked to specific land use. Land use conditions in urban and suburban DTZs may have some common properties because the topological structures of their corresponding networks are similar. Differences may also exist since urban and suburban DTZs have some different characteristics. We use point of Interest (POI) data collected by a web map provider in 2007 to further investigate into land use conditions of different DTZs and select POIs of residential subdivisions, supermarkets and shopping stores, restaurants, office buildings and factories to reflect different land use types. POI numbers of each DTZ are normalized by dividing the max POI number of each kind among the 15 DTZs and are depicted in Fig. 12. It is natural that DTZs in urban areas contain more POIs than those in suburbs. We find that POIs of residential subdivisions, supermarkets and shopping stores and restaurants have very close ratios between each other in different DTZs. The similar ratios may guarantee daily lives of residents, thus gathering taxi trips reflecting daily activities in those regions. However, office building POIs have
higher percentage in urban areas, especially in DTZ 1, whereas factory POIs dominate the suburban DTZs. The differences show the different functions of urban and suburban regions and the layered structure of Shanghai from the perspective of land use conditions.

![Diagram of land use characteristics of 15 DTZs]

**Fig. 12.** Land use characteristics of 15 DTZs. The five land use types are: Residential Subdivision (RS), Factory (F), Office Building (O), Supermarket and Shopping Store (S) and Restaurant (R). Urban DTZs have more POIs and higher percentage of office land use. Suburban DTZs have higher percentage of factory land use. Residential, shopping and eating POIs have relatively similar proportion in each DTZ.

In this study, we find that a small amount of cells in each DTZ are related to large amount of taxi flows. Discovering the reason why those hubs have such strong influences in taxi flows have great practical meanings for transportation optimization and urban planning. We try to answer this question from the land use perspective and still define the node with the highest strength value as the hub of the DTZ for comparison reason. Nowadays land use is more intensive and diverse, especially in the urban area of a metropolis like Shanghai. Simply concerning POIs without intensity of them is hard to judge which kind of POIs attribute more in forming the hub. However, the temporal variations of pick-up and drop-off points of taxis strongly correlate with land use features (Liu et al. 2012b). In order to accurately and objectively reflect the land use type of hubs, we compute the total number of pick-up and drop-off points of each hub in each hour of the day, and plot the results in Fig. 13. We analyze these figures with Google Map information and detailed pick-up and drop-off point locations in each hub. For hubs in the urban area, hub of DTZ 1 lies in one of the central districts of Shanghai and characterize for large amount of office buildings and commercial areas with high level of taxi flows during the daytime. The number of drop-off points overwhelms the pick-up points in the morning and it is the opposite situation in the evening. The trend of the curve shows that it is indeed the office buildings and commercial areas that influence the taxi flows in this hub. The temporal variation of hubs in DTZ 4 and 6 are similar to hub of DTZ 1, and detailed studies demonstrate that those two hubs also consist of important office buildings and commercial areas that attract large amount of taxi flows. Commercial centers are the most influential factors in hubs of DTZ 2 and 3, so that the two hubs both peak in the afternoon and evening as people would go shopping more in the evening on weekdays, and the small peak of DTZ 3 in the morning may be caused by a metro station.
Residential areas take a large part of land use type of hubs in DTZ 5 and 7 and their two curves intertwine with each other tightly. Their peaks in the morning may result from hospitals in the hubs and the pick-up number is larger than the drop-off number in hub of DTZ 7 due to the combination land use of commercial with residential. However, unlike the hubs in urban areas are strongly influenced by office buildings and commercial areas, most hubs in suburban areas are strongly influenced by residential land use, including hubs 8, 10, 11, 14 and 15. Curves of DTZ 8 are slightly different from other hubs because in 2009 this area was busy preparing for the EXPO 2010 in Shanghai. Since DTZs in suburbs may have special functions according to the development policy, other hubs may be influenced by specific factors such as important metro station as hub 9 and hub 13, and high-tech industrial park as hub 12. In conclusion, hubs in DTZs heavily influence local taxi traffic flows due to their concentration of resources and high utilization of land. Even though hubs may have different land use types according to the functions of the DTZs, hubs in urban area tend to characterize office and commercial factors more while hubs in suburbs are more influenced by residential land use factors.
Fig. 13. Temporal variations of pick-up and drop-off points of hubs in each DTZ.

4.4 Traffic flow properties of taxi trips in DTZs

The 15 DTZs are detected based on short length trips and concentrate residents’ daily activities. The city structure revealed from short length trips may strongly relate to traffic situations of all length range trips and DTZs in the same level may also have common properties considering all the trips.

Temporal variations of taxi flows and trip length diversity levels could depict the traffic situations of a region. Besides, the temporal variations of taxi flows have strong relations with the land use conditions and the numbers of taxi trips with different lengths are important to reflect
functionality of a region. We explore traffic situations according to those two metrics for cells base on the same $1km \times 1km$ grid with previous sections because conditions may vary greatly within a large area. The cells are clustered into classes based on the amount of taxi flows and the diversity level. We define 5 time intervals during a day, in which have sufficient trips in each interval for analysis. The five time intervals are: “Early Morning” (5 am to 9 am), “Morning and Noon” (9 am to 13 pm), “Afternoon” (13 pm to 17 pm), “Evening” (17 pm to 21 pm) and “Night” (21 pm to 1 am). Based on Shannon entropy, which has been successfully applied in related study (Eagle, Macy and Claxton 2010), we define the diversity level of each grid $D(i)$ as

$$D(i) = -\sum_{j=1}^{k} p_d \log(p_d)$$

and $p_d = \frac{V_d}{\sum_{d=1}^{k} V_d}$, where $V_d$ is the taxi trip number from or to the grid cell in a certain distance range and $k$ is the total number of taxi trip groups divided according to their trip lengths. We choose 5 km as the grouping intervals here, which means $V_1$ represents taxi flows related to the grid cell with length less than 5 km, $V_2$ represents taxi flows between 5 km and 10 km and so on. Since pick-up and drop-off points have different patterns, we calculate pick-up numbers, drop-off numbers, pick-up trip diversity levels and drop-off trip diversity levels in five time periods for each grid cell, that is to say, each cell has 20 characteristics. We ignore those cells that have no taxi flows in any of these five time periods and apply k-means clustering method to classify all the other cells.

The grid cells are classified into 7 classes (Fig. 14). Cells in classes 1, 2, and 3 have large traffic flow amount and similar temporally changing diversity level. Among those cells, the ones in central areas have higher drop-off diversity levels in the evening and the ones in relatively remote areas have higher pick up diversity levels in the morning, which is consistent with activity patterns of people. Cells of classes 4 to 6 have small traffic flow amount throughout the day. Cells in class 5 have high diversity levels all day and diversity level of class 6 cells vary temporally. Class 7 cells have very few trips throughout the day.

The spatial distribution of the 7 class grids clearly depict the concentric layers of Shanghai, which cannot be observed simply through the diversity levels or the taxi flow amount. Class 1 cells cover the center of the city and the three railway stations. Cells in classes 2 to 4 sequentially lie in concentric ties around the city center, and most cell of the classes 5 to 7 are located in suburbs. Cells in class 5 cover the airports and the central area of suburban or rural districts, where the taxi trips have lengths of all ranges. DTZs in the same level consist of the same kinds of grid cells, indicating the layered concentric structure. Urban DTZs contain those cells that have more traffic flows and regular temporally changes in diversity level. High diversity level cells and low traffic amount cells cover more area in suburban DTZs. In addition, a few cells in each DTZ that have higher traffic flows correspond to the local hubs, illustrating the polycentric structure of the city. The city structure revealed by traffic conditions of cells well correspond to the one depicted by DTZs, confirming the reasonableness of the conclusions in the previous sections.
Fig. 14. Diversity level (a) and taxi trip amount (b) of the 7 class grid cells, and the spatial distribution of grid cells in different classes (c). Grid cells are classified by their diversity levels of pick-up points (DU) and drop-off points (DO), and flow amount of pick-up points (FU) and drop-off points (FD) in 5 time periods. Cells in the same class have similar traffic flow properties. DTZs in the same level consist of grid cells in the same class.

The total trip length generated from a region is also a practical traffic flow property for transportation and urban planning. On average, 78% trip length generated from the 15 DTZs is the length of external trips (trips end outside the DTZs). External trip length take up more percent in suburban DTZs due to more demand traveling to urban area (Fig. 15), which confirms the layered city structure. In addition, medium trips took up the most part of the total length in 13
DTZs, and merely 24.8% medium taxi trips are internal trips on average. If the local hubs could attract more local trips and turn a portion of external trips into internal trips, the total travel length could be reduced effectively.

![Graph showing the percentage of external taxi trips in each DTZ. The percentages in suburban DTZs are larger than the urban ones.](image)

**Fig. 15.** The percentage external taxi trips take up in trips generated in each DTZ. The percentages in suburban DTZs are larger than the urban ones.

## 5. Discussion and conclusions

This research introduces network science methods to analyze taxi trajectory data so that urban structure and the corresponding traffic characteristics can be uncovered. Taxi is an important supplement for other means of public transportation. Bus trips and metro trips are the largest and second largest kind of public traffic in Shanghai. Since buses and metros have fixed stops, taxi flows highlight the areas where traffic demand exceeds the current service level. Effort should be made to improve the public transportation conditions in those areas to meet the traffic demand, especially in the hub areas. Considering the layered concentric structure of Shanghai, policies should take different land use conditions of different layers into account. According to this study, more bus lines should be designed passing through the office building areas and commercial areas in urban hubs. Public transport facilities of residential areas in suburban hubs should also be improved. Since those areas generate large amount of taxi trips and dominate local taxi traffic, reasonably improving public transportation facilities in those crucial areas can reduce unnecessary traffic flows to some extent and it will be more convenient for residents to make intra-city travels. Compared with directly using hot spots generated from the original data, traffic flows related to hubs in this study have more clear patterns and are local traffics.

The research illustrates that medium length trip group also contains residents’ daily travels and the total trip length of medium length trips generated in those 15 DTZs take up 41% of the total trip length generated from those regions. However, merely a small proportion of medium taxi trip origin and end in the same DTZ. Trip length of external medium trips even take up more than 90%
of total medium trip length generated in some DTZs. Improving land use conditions in DTZs could help attract more trips, turning some external medium trips into internal short trips. If up to 50% medium length trips could be turn into short length internal trips, using the median of short trip length and medium trip length for calculation, the total traffic length generated from those DTZs could be reduced by 15.7%.

In summary, this study firstly classifies taxi trips into groups according to their lengths. Given that short length trips are more likely to be driven by residents’ daily activities and they are more structured and organized, we further our study on the network built from short length trips. We partition it using community detection method into sub regions, the DTZs, in which internal taxi travels are much more than external taxi travels. Taxi flows in each DTZ have similar structure but the ones in urban area have some differences from those in suburbs. The hubs in each DTZ are related to large percent of internal taxi flows and have large betweenness centrality values and small disparity values, whereas hubs in suburbs are more important in local traffic. As land use conditions are quite different between urban and suburban DTZs, hubs in urban area are more likely to have important office buildings and commercial centers, whereas hubs in suburbs lies more often in residential area and may have spatial land use type due to the function of DTZ. Finally, we explore traffic flow properties of all taxi trips in DTZs. DTZs in different levels consist of different kinds of grid cells based on their temporal variations of taxi flows and trip length diversity level. The spatial distribution of the cells also depicts the polycentric and layered concentric structure of Shanghai. External trips also take up most of the total length of all length range trips in each DTZ and turning them into internal trips may reduce the total trips length of taxis to some extent.

The urbanization process is rapid in China. More centers appear in urban area, and urban structures of world cities such as Shanghai are becoming more polycentric and complex. Big data provide us opportunities to conduct empirical research on human mobility and the corresponding urban structure, showing evidence for theoretical studies and contribute to urban planning and transportation control. This study also has some deficiencies due to the limitation of data. Taxi travels depict the urban mobility from one facet. Some daily activities of residents, such as long distance commuting, are hardly reflected by taxi trajectories. Further studies may expand the data source and include private car trips, bus trips and metro trips. The combination of diverse data could describe human mobility and urban structure from more dimensions, giving a whole picture of the urban dynamics.

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