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Caputring spatial distribution of people interests with web quries and location data: A large scale empirical study of metropolises in Japan

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Abstract: Capturing visitor interests in certain urban areas provides a good approach to mine interests spatial distribution that is essential for more intelligent urban designing and city planning. To learn better about a city, currently it takes urban researchers much cost on field investigation such as gathering pictures or crowd-sourcing. Meanwhile, evaluation obtained from visitors is often biased and fail to fulfill our purpose to characterize interests distribution objectively. Under the help of massive query and location data gathered from users, we conduct several empirical studies on geographic map segments. In our work, spatial interests distribution can be captured by calculating statistical features across the regions. We apply the aggregation and analysis procedure on real world dataset collected by Yahoo corporation in several cities in Japan. Our analysis results can provide a new perspective on how to characterize a city without extensive field studies.

Keywords: Urban analysis, Geo-Semantics

1. Introduction

Visitor interests analysis deals with understanding why a particular area attracts some visitors and its spatial role in the whole metropolis. Nowadays, capturing the interests of urban visitors is vital for many urban-based applications such as location recommendation [1] [2], commercial branding [3], and urban functionality discovery [4]. At the same time, to better capture the correlation between visitor activities and regional features, it is also promising to focus on spatial analysis to characterize urban regions directly [5].

Field investigation-based urban study that relies on images and comments on Point-of-Interest (POI) is a common approach to discover patterns of metropolis regions. These methods focus on utilizing user data that is semantically highly related to the target urban areas. For example, street images are significant since they accurately correspond to the places where people take the photos [6]. However, these field investigation-based studies require vast costs to gather sufficient data for interests discovery. They also suffer from biased results due to incomplete or noisy sources [7].

Recently, thanks to the widely-used location-based mobile applications, along with massive usage records, it becomes possible for urban researchers to capture urban spatial patterns without extensive field investigation. Some works have focused on how to disentangle the spatial patterns of places by user query information. Nevertheless, we conclude that their works don't consider map segmentation issues, making it hard to observe spatial interests distribution patterns by directly applying their system to query-based urban interests analysis. Sum et al. proposed a framework to capture regional interests patterns by map search queries and location data by users [8]. However, they only consider one type of user query, which is too explicit to show the correlations between users and areas they visit. Sakamoto et al. show us a new approach to use a twelve-dimensional vector with intuitive psychological interpretation on each dimension as the meter to define the interests patterns for target urban regions [9].

To this end, in our case studies, we extend the previous urban interests framework by Sakamoto et al. [9] to address the spatial application issues for metropolis areas. We adapt the framework to great-scale case studies by including administrative spatial boundary data and modify analysis pipelines. Metropolises for our case studies include Tokyo, Osaka, Yokohama, and Kawasaki, which are all populated and representative cities in Japan.

The contributions of our work are two-fold:

- We improved the framework to consider realistic map segmentation to meet our large-scale spatial interests analysis demands with more intuitive rendering.
- Our work first shows empirical studies over millions of real-world user location and web search query data on three representative metropolises regions in Japan. Our case study results can provide a new perspective on characterizing people's interests in the cities.

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Related work

Analyzing interests distributed in urban regions can be considered a learning representation of cities through urban data, which is initially motivated by studies of urban computing. In order to clarify the position of our research, we discuss Urban Computing and Representation Learning in the following parts.

Urban Computing

Urban computing is a field that aims to solve the major issues in cities, (e.g. traffic congestion, air pollution, or noise problem) through the analysis of urban data. In this field, urban data such as GPS-based mobility data and POI check-in data have been used for mobility flow modeling [10, 11], urban dynamics forecasting [12, 13], land-use pattern analysis [14], urban functionality revealing [15], and urban anomaly detection [16, 17] and prediction [18–20].

Representation Learning of Cities

To tackle the problems being addressed in the field of urban computing, there is a trend towards quantifying cities via learning how to represent the cities. One of the approaches for this topic is to represent the cities via region embeddings [6, 21, 22]. In this current, researchers address the problem of obtaining a fixed-dimensional distributed representation of each region in a city, which is used for a downstream application such as mobility flow prediction and urban functionality extraction. Fu et al. [21] presented a spatial proximity-based method for region embeddings, which considers both inter- and intra- region correlation. Another approach to representation learning is to model the atmosphere of a city [23–25]. Intuitively, the atmosphere of a town is likely to influence characteristics such as demographics and crime rates of visitors to the area. Dubey et al. [24] addressed the problem called *urban perception*, which focuses on predicting the superficial atmosphere such as safe or lively from street view images. Tsubouchi et al. [25] proposed a method to categorize the mood of POI visitors, such as childlike or businesslike, using web search queries. Different from these works, we attempt to quantify the city through the interests of its visitors by utilizing web search queries tied to user location data directly.

2. Used dataset

2.1 Mobile phone GPS dataset

We used the real-world GPS and query records of users in Japan stored in the Yahoo! Japan acquired from their mobile application with acknowledgment from users and privacy protection. The user GPS coordinates are collected intermittently during application usage under the precision of 0.001 degrees. After extracting target users who appeared in particular metropolis regions given a designated period, we further extract their web search query records collected by the Yahoo! query service. The collection periods of GPS and web search queries are showed in Table 1, from which we use the top 10,000 most used queries from the entire query set.

Table 1 Regions and data periods extracted from user records

Metropolis region	Period of GPS data	Period of query
Tokyo 23 wards	2019/10/30 ∼ 2019/11/02	2019/10/29 ∼ 2019/11/04
Osaka city	2019/10/30 ∼ 2019/11/02	2019/10/29 ∼ 2019/11/04
Kawasaki and Yokohama city	2019/10/30 ∼ 2019/11/02	2019/10/29 ∼ 2019/11/04

2.2 User web search query dataset

Previous works usually utilize word embedding techniques to represent each user query, making it hard to interpret each representation element intuitively. Therefore, we regard each query as a low-dimensional vector whose values on each dimension represent the weights of interest qualities corresponding to the query. This approach of query representation refers to the psychological works [26] and performs well in previous urban interest studies as this 12-d representation enjoys both high expressing ability and interpretability.

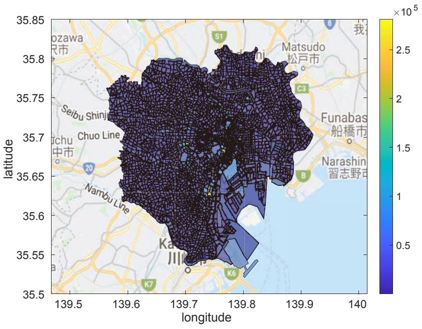
In order to simplify the language semantics for search queries, we first categorize each query into several general genres with the help of the Yahoo! query categorization service to make the query understandable to everyone. Then we further utilize the crowdsourcing platform to gather user interest scoring on their impressions towards each general genre. We conclude the following interpretations of each interest:

- **trendy(同調欲)**: Popular culture such as entertainer, idol, etc.
- **curious(好奇欲)**: News and TV programs to satisfy one's curiosity
- **unrest(生活安定欲)**: Jobs and other public affairs in community
- **greedy(金銭欲)**: Money related activities like investment and financial management
- **shopper(物欲)**: Manufacturer and shop name that meet shopping demands
- **docile(服従欲)**: Company, organization and building names that provide sense of belonging
- **entertaining(感楽欲)**: Entertainment activities including travelling, music and sports
- **knowledgeable(知識欲)**: Encyclopedia knowledge and education affairs
- **love(性欲)**: Adult contents and sexual services
- **upset(生存欲)**: Medical and health cares, along with parenting and weather
- **slack(怠惰欲)**: Transportation services that facilitate travelling
- **hungry(食欲)**: Restaurants and recipe to statisfy foody

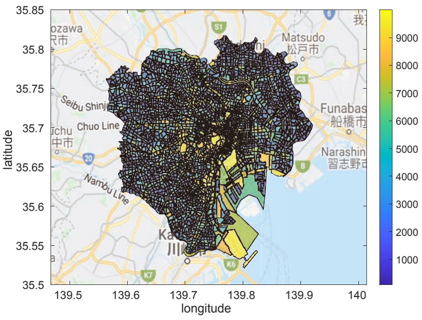
Note that the explanation we list here is corresponding to the query categories with the largest weights. Usually, a query category puts positive weights to several interests at the same time. Furthermore, when a query belongs to multiple categories, we average final interests weights of all query categories together to represent each search query in 12-d vector form.

2.3 Shapefile of Japan metropolises

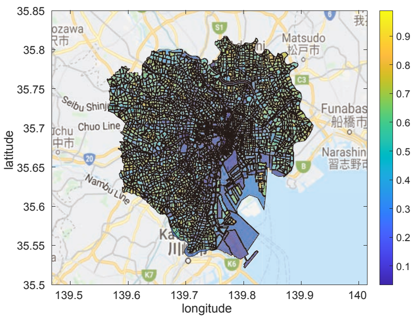
Geospatial map segmentation is an essential step for urban analysis because it defines the primary city target to analyze. Existing works that use the open dataset tend to adopt a city block segmentation approach where several roads and avenues spatially define each block. Using such an idea, we alternatively view each



(a) Extracted user number of each Cho-me in Tokyo 23 wards



(b) Used search query of each Cho-me in Tokyo 23 wards



(c) Average search query per user of each Cho-me in Tokyo 23 wards

Fig. 1 Shapefile based map segmentation in Tokyo

Cho-me level region in Japan address system as a practical segmentation unit. When analyzing metropolises in Japan, Cho-me level segmentations provide a natural approach to segmenting the whole urban region since much urban planning and demographic statistics in Japan are usually conducted at the Cho-me level first.

We use the open dataset provided by Japanese Government Statistics on Geospatial Information System [*1], which defines the boundary coordinates for each Cho-me. Fig. 1(a) shows the extracted user number of each Cho-me in Tokyo 23 wards region. The related search query number among the most common 10,000 queries by total users in the above Cho-mes is showed in Fig. 1(b). By dividing extracted user numbers with aggregated query numbers, we can get the average query number for extracted users as Fig. 1(c) shows.

3. Interests analysis framework

In this section, we introduce the interests analysis framework in order to capture spatial interests reliably. We partially refer to some interests extraction procedures proposed in Sakamoto et al. [9]. As Fig. 2 shows, our analysis framework consists of several steps. The details of each steps are as follows: extracting target users (Sec.3.1), calculate query weights (Sec.3.2), region interests representation (Sec.3.3), clustering-based analysis (Sec.3.4). In these sections, we further introduce these steps with their purposes.

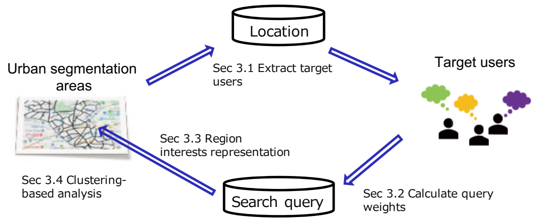


Fig. 2 The overview of spatial interests analysis framework, including extracting target users, calculating query weights, region interests representation and clustering-based interests analysis

3.1 Extract target users

Based on map segmentation of particular urban regions, we extract our target users as stated in the previous chapter. Each target segmentation area is noted as l. The overall extracted target area set is defined as L. The corresponding extracted query set is defined as $Q = \{q_1, ..., q_i\}$, where q_i represents a search query.

3.2 Calculate query weights

We define d_{q_i} to be the number of users that make query q_i in a given extracted period. To reduce processing cost, we only take 10,000 most popular queries by sorting on d_{q_i}. Then, we define $t_{q_i^{(l)}}$ as how many users make query q_i in the target area l. Given the parameter λ, we can define the weight for each query q_i towards area l as

$$w_{q_i^{(l)}} = t_{q_i^{(l)}} \log \frac{\lambda}{d_{q_i}} \tag{1}$$

This kind of weight formulation is based on a widely-used document feature called TF-IDF [27]. It considers simple word frequencies in a document and regularizes the frequency with inverse document frequency. This formulation can make queries particular to a specific region more prominent than other common queries.

3.3 Region interests representation

As mentioned in our previous chapter, we present any search query in a 12-d form $\boldsymbol{u}_{q_i^{(l)}}$. This representation vector is calculated by crowd-sourced interests weights on query categories. By applying the query weight on the query representation, we can derive the following 12-d interests representation $\boldsymbol{s}^{(l)}$ for area l:

$$\boldsymbol{s}^{(l)} = \frac{\sum_i w_{q_i^{(l)}} \boldsymbol{u}_{q_i^{(l)}}}{\sum_i w_{q_i^{(l)}}} \tag{2}$$

To ensure dimension-wise comparable between any two area interests, we further standardize $\boldsymbol{s}^{(l)}$ on each interest dimension w for all target areas L:

[*1] Statistics on Geospatial Information System
`https://www.e-stat.go.jp/gis`

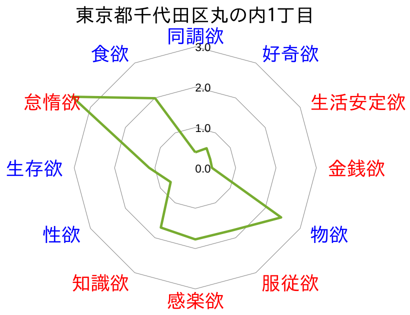


Fig. 3 One example of a 12-d region interests representation in the radar chart format

$$p_w^{(l)} = \frac{s_w^{(l)} - \overline{s_w^{(l)}}}{\sqrt{\frac{\sum_l (s_w^{(l)} - \overline{s_w^{(l)}})^2}{|L|}}} \tag{3}$$

Under this formulation, we can discover a target segmentation area by comparing which interests are prominent with other regions. Fig. 3 shows an area standardized 12-d interests representation example in a radar chart format. In the chart, red labels indicate that these interests are above average, and blue labels indicate values below average. Since the target area is located at the Tokyo station, it is reasonable to find that its slack interest is relatively higher than other regions'. This kind of rendering for segmentation interest provides us with an intuitve way to observe what kind of prominent interest the target area represents within the whole region.

3.4 Clustering-based interests analysis

We conduct two reliable clustering methods: K-means [28] and Spectral Clustering [29] on area interests set to extract spatial patterns behind aggregated segmentation area interests across metropolises regions. K-means clustering approach iteratively tries to partition area interest representation set into predefined k non-overlapping subgroups. We assign each area to one kind of interest cluster to ensure that the sum of the squared distance between the area interest representation vector and the interest cluster's centroid reaches the minimum.

Similarly, Spectral Clustering is a widely used unsupervised clustering technique, especially in graph-based analysis. We also determine the cluster number k as the input for Spectral Clustering. To generalize graph settings required in Spectral Clustering for our area interest analysis purpose, we use a Gram matrix as the adjacency matrix $\boldsymbol{A}$ in graph settings where $g(\boldsymbol{p}^{(i)}, \boldsymbol{p}^{(j)})$ denotes a Gaussian kernel between two interest vectors $\boldsymbol{p}^{(i)}$ and $\boldsymbol{p}^{(j)}$:

$$A = \begin{bmatrix} 1 & \cdots & g(\boldsymbol{p}^{(2)}, \boldsymbol{p}^{(|L|)}) \\ \vdots & \ddots & \vdots \\ g(\boldsymbol{p}^{(|L|)}, \boldsymbol{p}^{(2)}) & \cdots & 1 \end{bmatrix} \tag{4}$$

The Gaussian kernel is showed as below, where the parameter σ controls the width of the neighborhoods:

$$g(\boldsymbol{p}^{(i)}, \boldsymbol{p}^{(j)}) = \exp(-\frac{\|\boldsymbol{p}^{(i)} - \boldsymbol{p}^{(j)}\|^2}{2\sigma^2}) \tag{5}$$

After defining the adjacency matrix, we can detect interest clusters by running K-means on rows of the matrix of eigenvectors corresponding to the small eigenvalues of the graph Laplacian computed by our interest adjacency matrix $\boldsymbol{A}$.

4. Case studies of metropolises in Japan

4.1 Spatial distribution of interests

To better learn the role of each region in metropolis areas, we conduct the extraction process for spatially standardized region interests. We first make the map segmentation areas without using shapefile data, in Fig. 4 we split the 23 wards region into 4296 meshes whose size is around 400 meters. Each color block represents a segmentation area whose color indicates the standardized value on twelve interests. The results show that spatial interest distributions rendered without shapefiles lack insight into the urban structure, but can also be applied under some situations, especially when the analysis region is not so vast.

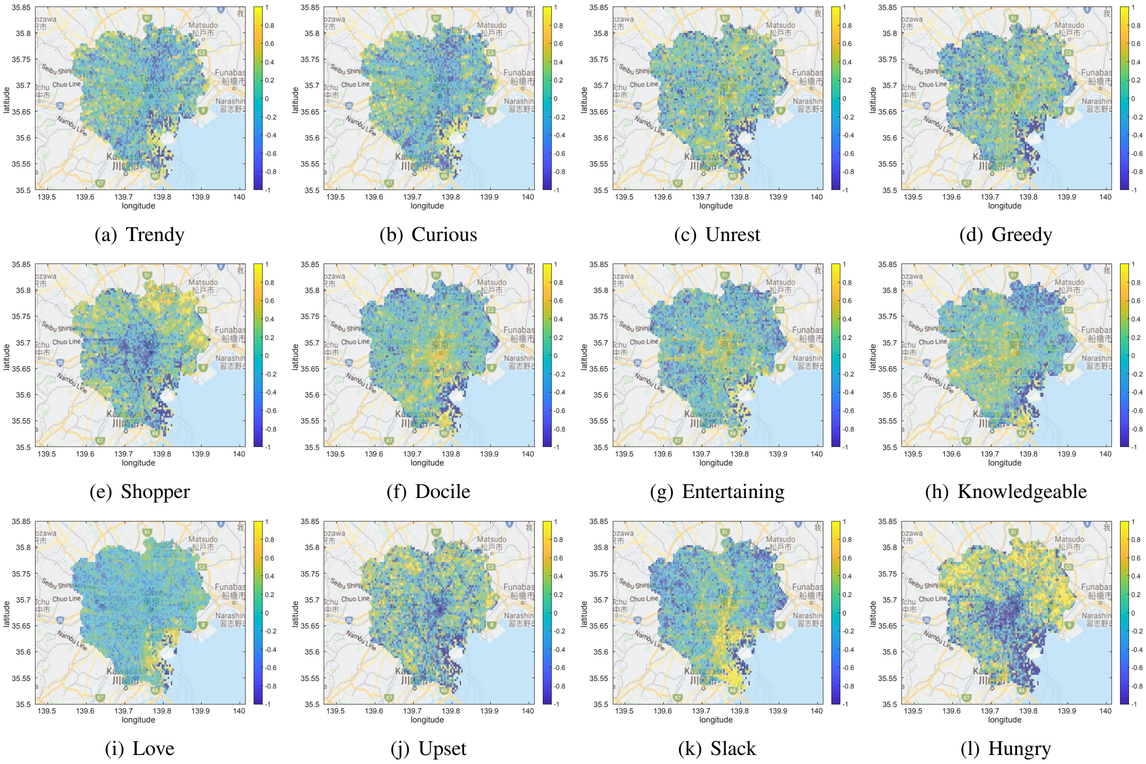
We then consider the shape information into our spatial interests analysis, as introduced in the previous chapter. Fig. 5 shows Tokyo's spatial distribution of visitor interests rendered in heat map form. Since we adopt twelve kinds of interests represented by each dimension value, we visualize the interests into twelve spatial distributions. Note that interests are extracted and calculated in each metropolis, therefore areas with positive values indicate that they are relatively prominent in these interests compared with overall areas. Fig. 6 shows the distribution of the spatial interest for Osaka-city. Fig. 7 shows the distribution of the spatial interest for Kawasaki and Yokohama city. We combine these two most populated cities in Kanagawa to make the target regions comparable to Tokyo's 23 wards regarding population and urban functionality.

With proper knowledge of city spatial development, we can verify that some interest distributions perfectly match urban land-usage patterns. For example, as shown in Fig. 5(k), the interests of slack mainly concentrate on railways and airport areas. Correspondingly, hungry interest in Fig. 5(l) is relatively high in suburban areas.

Other region-specific interest distribution trends can be found, for example, docile interest (Fig. 5(f)) concentrates on Murunouchi and Odaiba areas, and knowledgeable interest (Fig. 5(h)) is prominent in the west part of Tokyo, especially near Odakyu-line. Furthermore, the shopping interests (Fig. 5(e)) of east regions are relatively more significant compared with west residential regions.

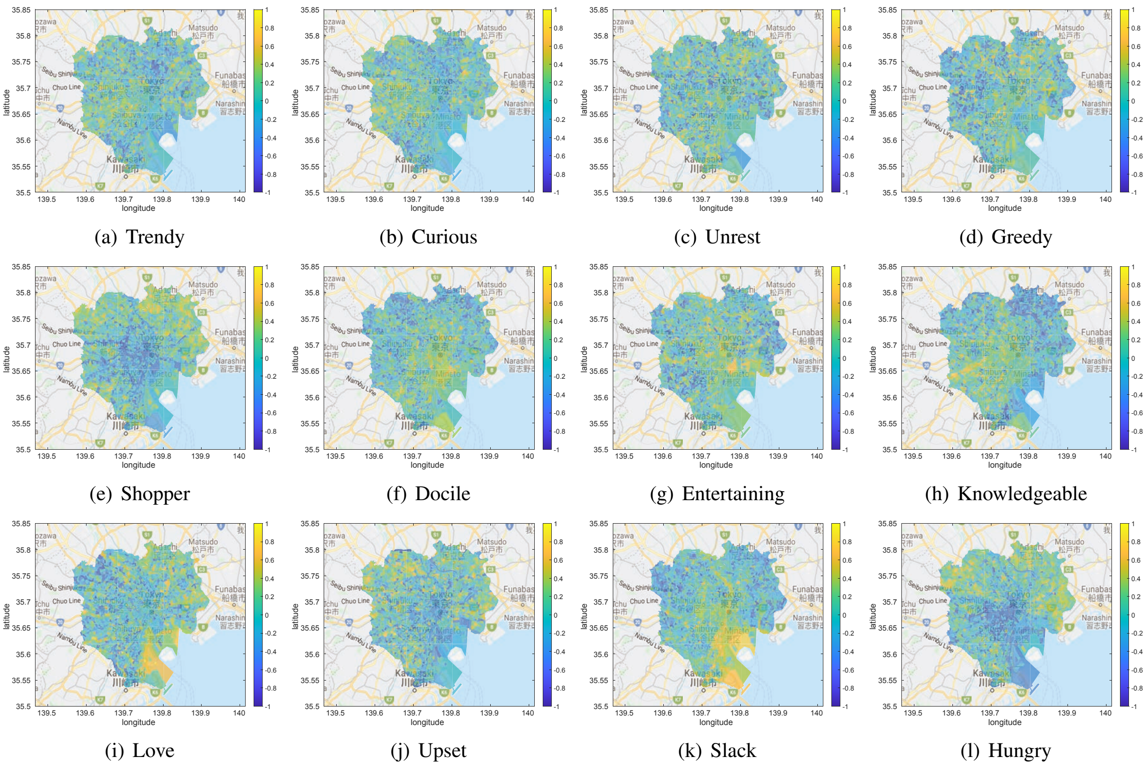
4.2 Regional pattern extraction

In this part, we conduct several clustering-based case studies on the interest distributions derived in the previous section. In order to verify that the adopted two clustering methods are reliable for the 12-d interest values, we first visualize the data distribution by T-SNE [30], which is a popular statistical method for visualizing high-dimensional data in a two-dimensional map. Fig. 8(b) and Fig. 9 show the two methods based clustering results along with their corresponding low dimensional visualization. We can conclude that K-means method leads to better-separated results on interest distributions than Spectral Clustering. Nonetheless, we also adopt Spectral Clustering due to its reliable clustering



(a) Trendy (b) Curious (c) Unrest (d) Greedy
(e) Shopper (f) Docile (g) Entertaining (h) Knowledgeable
(i) Love (j) Upset (k) Slack (l) Hungry

Fig. 4 The spatial distributions of 12 interests across 400 meter meshes in Tokyo 23 wards

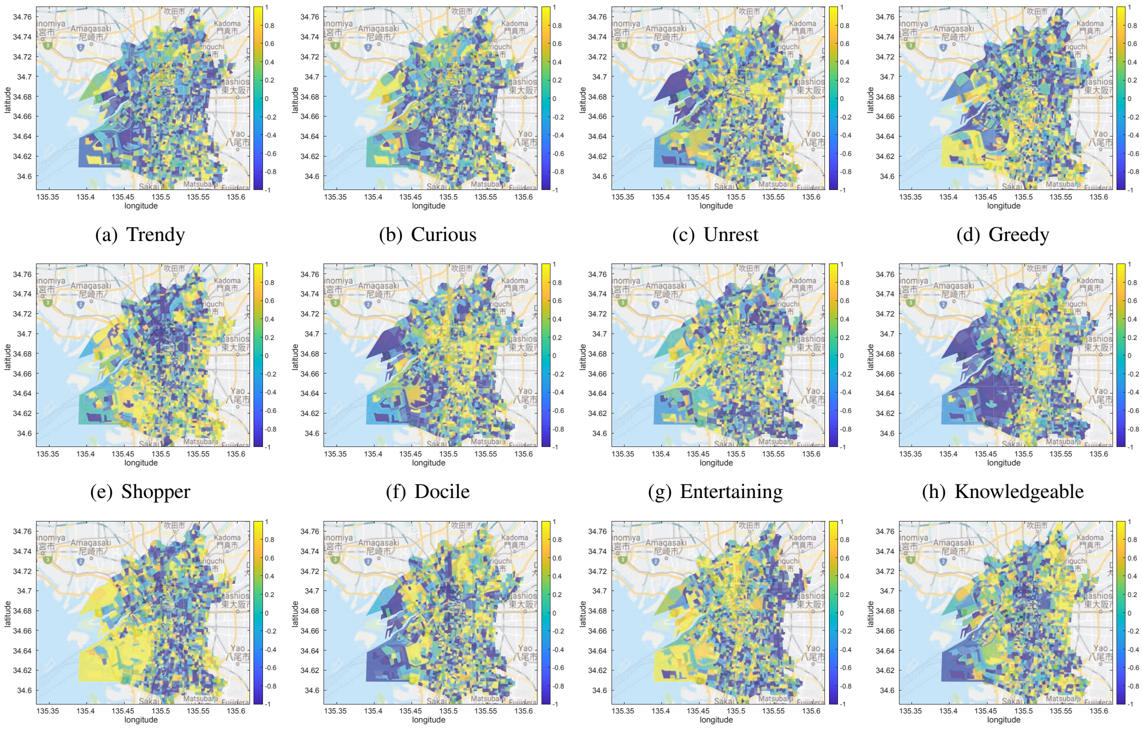


(a) Trendy (b) Curious (c) Unrest (d) Greedy
(e) Shopper (f) Docile (g) Entertaining (h) Knowledgeable
(i) Love (j) Upset (k) Slack (l) Hungry

Fig. 5 The spatial distributions of 12 interests across Tokyo 23 wards

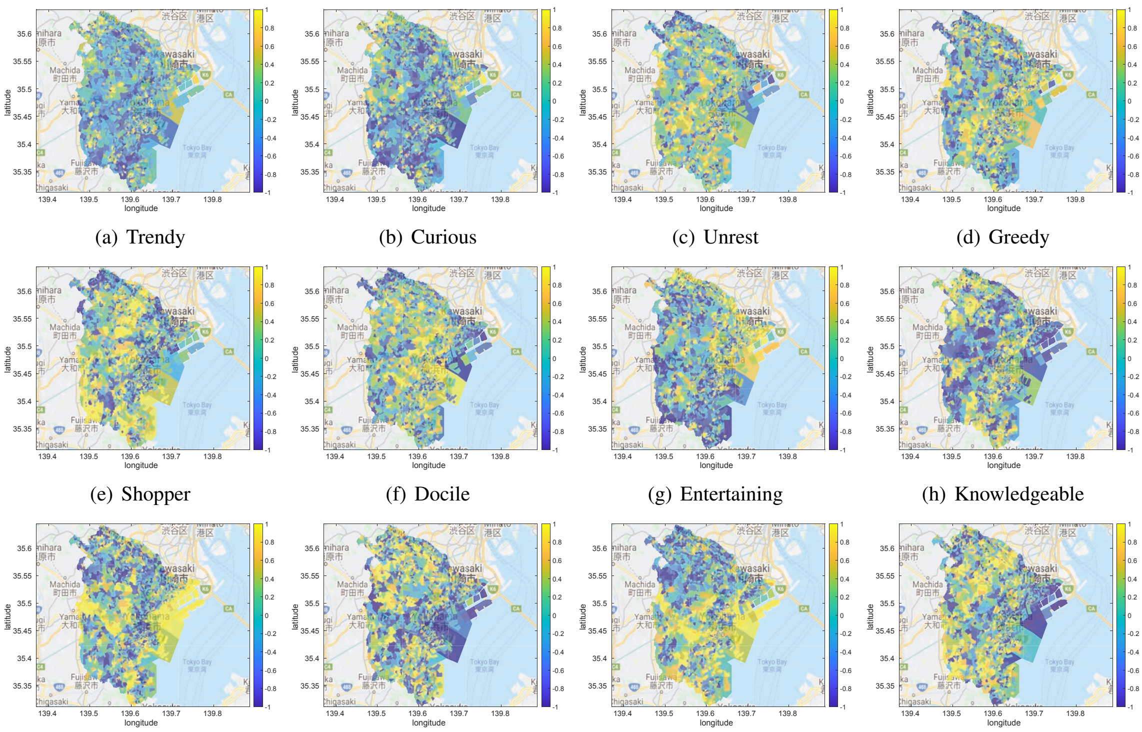
property on other pattern extraction studies.

As Fig. 10 shows, we also discuss how cluster number affects the pattern distribution. We use three common cluster numbers from 3 to 5 and make an analysis on the Tokyo region as an example. We find that small number of clusters can distinguish commercial areas from residential ones based on spatial distributions. When the clustering pattern increases, deeper spatial trends are disclosed. For example, Tokyo's northeast and northwest regions have been divided into two clusters, although they appear to be the same residential areas in Tokyo.



(a) Trendy (b) Curious (c) Unrest (d) Greedy
(e) Shopper (f) Docile (g) Entertaining (h) Knowledgeable
(i) Love (j) Upset (k) Slack (l) Hungry

Fig. 6 The spatial distributions of 12 interests across Osaka city



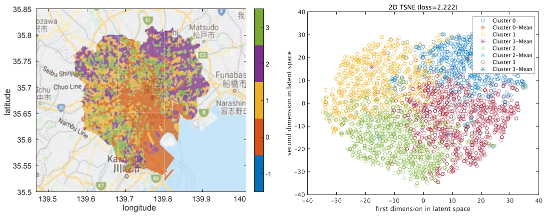
(a) Trendy (b) Curious (c) Unrest (d) Greedy
(e) Shopper (f) Docile (g) Entertaining (h) Knowledgeable
(i) Love (j) Upset (k) Slack (l) Hungry

Fig. 7 The spatial distributions of 12 interests across Kawasaki and Yokohama city

4.3 Inter-city interest patterns

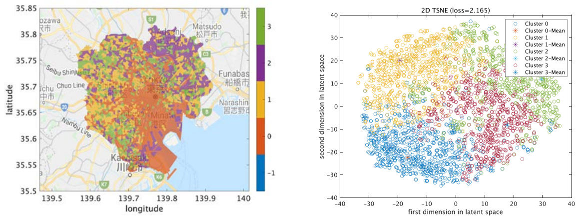
We extend our clustering analysis to all three metropolises. It is significant to observe both common interest patterns and different ones by our analysis framework. Here we regard each mean interest representation as to the representation of each cluster. The number and value of positive interests and negative interest for each mean point can be significant to show spatial homogeneity across these metropolises. Fig. 11 shows the spatial clustering as well as the mean interests for each cluster. To ensure interpretability, we choose three clusters for each metropolis.

Based on the results, it becomes obvious that clustering on our spatial interests distribution can find several significant pat-



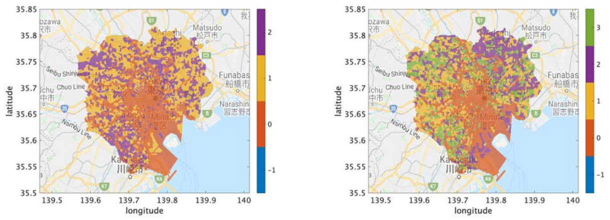
(a) K-means (b) T-sne visualization of Spectral clustering results

Fig. 8 Spatial interests K-means clustering and visualization under 4 clusters on Tokyo 23 wards

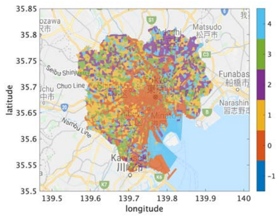


(a) Spectral Clustering (b) T-sne visualization of Spectral clustering results

Fig. 9 Spatial interests Spectral Clustering and visualization under 4 clusters on Tokyo 23 wards



(a) k=3 (b) k=4



(c) k=5

Fig. 10 Spectral clustering on Tokyo areas under different cluster numbers

terns. We conclude that the first centers shown in the first column of radar charts capture the characters of high population areas. For example, the core two positive interests are slack and unrest, whose areas are orange on the map, mainly correspond to railway areas. Furthermore, the second center shows the same high values in trendy, sexual, and curious interests, reflecting the local happiness demands for the visitors there. The third center is almost the same among all three metropolises because they represent the residential areas where people mainly intend to enjoy their basic demands on living, money, food, and trends.

5. Conclusion

Our case study employs a pipeline with several processing and analysis steps to discover spatial interest distribution based on the real-world massive web search query and location data. Spatial interests distribution in metropolises is rendered in several ways to make the results significant and insightful for us to learn better about each city.

By comparing the result with prior expert knowledge of real-world metropolises' development history, we confirm that our case studies can reflect specific actual patterns without extensive field investigation studies.

As our future work, we plan to consider temporal factors into city interests learning to clarify further how urban interests change during special periods during holidays or the COVID-19 epidemic. Currently, we select the period as weekdays to characterize more about working places. This researching approach will require finding more evidence for how cooperation distribution correlates with urban interests distribution.

To extend the application of our case studies, we need to consider more urban spatial patterns in our framework design. As for future work, we also plan to take other regional attributes like house prices and different demographics into evaluation.

References

[1] Ying, J. J.-C., Lu, E. H.-C., Kuo, W.-N. and Tseng, V. S.: Urban point-of-interest recommendation by mining user check-in behaviors, *Proceedings of the ACM SIGKDD International Workshop on Urban Computing*, pp. 63–70 (2012).

[2] Zheng, V. W., Zheng, Y., Xie, X. and Yang, Q.: Collaborative location and activity recommendations with gps history data, *Proceedings of the 19th international conference on World wide web*, pp. 1029–1038 (2010).

[3] Yang, S., Wang, M., Wang, W., Sun, Y., Gao, J., Zhang, W. and Zhang, J.: Predicting commercial activeness over urban big data, *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, Vol. 1, No. 3, pp. 1–20 (2017).

[4] Yuan, N. J., Zheng, Y., Xie, X., Wang, Y., Zheng, K. and Xiong, H.: Discovering urban functional zones using latent activity trajectories, *IEEE Transactions on Knowledge and Data Engineering*, Vol. 27, No. 3, pp. 712–725 (2014).

[5] Páez, A. and Scott, D. M.: Spatial statistics for urban analysis: a review of techniques with examples, *GeoJournal*, Vol. 61, No. 1, pp. 53–67 (2004).

[6] Wang, Z., Li, H. and Rajagopal, R.: Urban2vec: Incorporating street view imagery and pois for multi-modal urban neighborhood embedding, *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 34, No. 01, pp. 1013–1020 (2020).

[7] Zhou, J., Gou, S., Hu, R., Zhang, D., Xu, J., Jiang, A., Li, Y. and Xiong, H.: A collaborative learning framework to tag refinement for points of interest, *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pp. 1752–1761 (2019).

[8] Sun, Y., Zhu, H., Zhuang, F., Gu, J. and He, Q.: Exploring the urban region-of-interest through the analysis of online map search queries, *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pp. 2269–2278 (2018).

[9] Sakamoto, T., Yasuda, H., Tsujimoto, A., Iwamoto, M., Hayakawa, Y., Usami, T., Tsubouchi, K. and Shimosaka, M.: CityAtmosphere: VR image to glimpse wishes in the air, *Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers*, pp. 342–345 (2019).

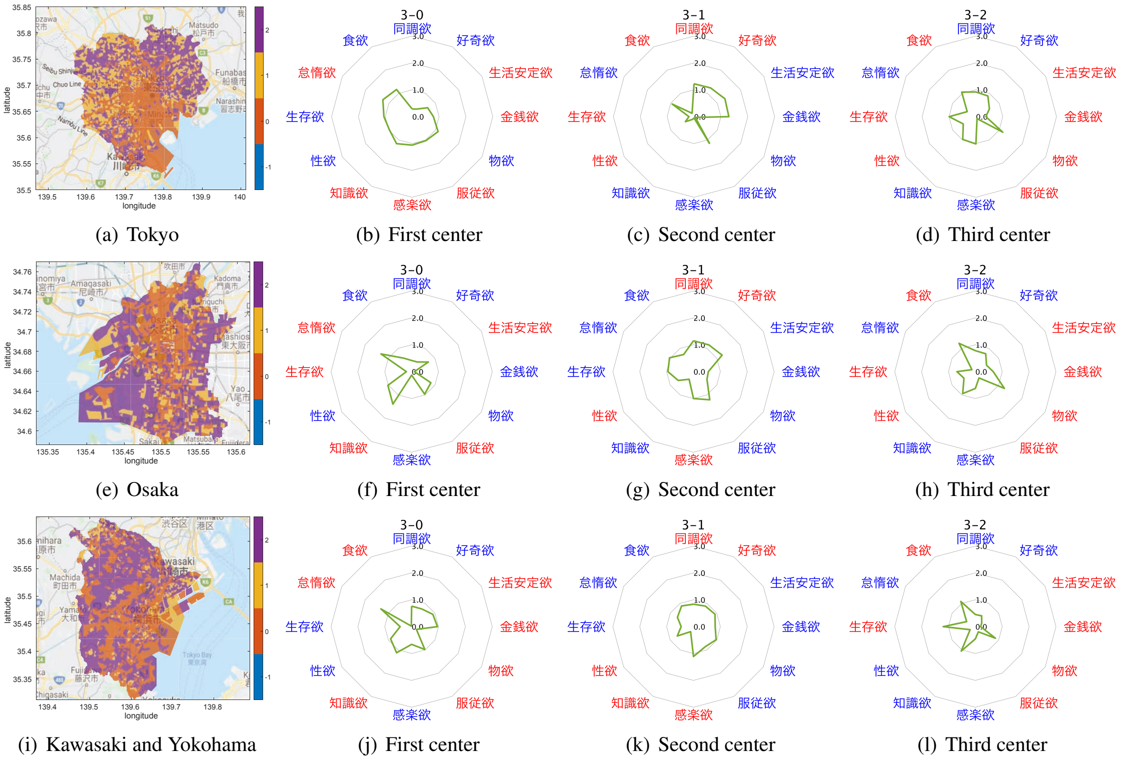
[10] Fan, Z., Song, X., Shibasaki, R. and Adachi, R.: Citymomentum: an online approach for crowd behavior prediction at a citywide level, *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pp. 559–569 (2015).

[11] Liang, Y., Ouyang, K., Sun, J., Wang, Y., Zhang, J., Zheng, Y., Rosenblum, D. and Zimmermann, R.: Fine-Grained Urban Flow Prediction, *Proceedings of the Web Conference 2021*, WWW '21 (2021).

[12] Shimosaka, M., Maeda, K., Tsukiji, T. and Tsubouchi, K.: Forecasting urban dynamics with mobility logs by bilinear Poisson regression, *Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing*, pp. 535–546 (2015).

[13] Xia, T., Li, Y., Yu, Y., Xu, F., Liao, Q. and Jin, D.: Understanding urban dynamics via state-sharing hidden markov model, *IEEE Transactions on Knowledge and Data Engineering* (2020).

[14] Xia, T. and Li, Y.: Revealing urban dynamics by learning online and



(a) Tokyo (b) First center (c) Second center (d) Third center

(e) Osaka (f) First center (g) Second center (h) Third center

(i) Kawasaki and Yokohama (j) First center (k) Second center (l) Third center

Fig. 11 Spatial clustering results and corresponding mean interests for K-means (k=3)

offline behaviours together, *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, Vol. 3, No. 1, pp. 1–25 (2019).

[15] Yuan, J., Zheng, Y. and Xie, X.: Discovering regions of different functions in a city using human mobility and POIs, *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*, pp. 186–194 (2012).

[16] Zhang, H., Zheng, Y. and Yu, Y.: Detecting urban anomalies using multiple spatio-temporal data sources, *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, Vol. 2, No. 1, pp. 1–18 (2018).

[17] Zhang, M., Li, T., Shi, H., Li, Y., Hui, P. et al.: A decomposition approach for urban anomaly detection across spatiotemporal data, *IJCAI International Joint Conference on Artificial Intelligence*, International Joint Conferences on Artificial Intelligence (2019).

[18] Wu, X., Dong, Y., Huang, C., Xu, J., Wang, D. and Chawla, N. V.: Uapd: Predicting urban anomalies from spatial-temporal data, *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, Springer, pp. 622–638 (2017).

[19] Konishi, T., Maruyama, M., Tsubouchi, K. and Shimosaka, M.: CityProphet: City-scale irregularity prediction using transit app logs, *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pp. 752–757 (2016).

[20] Anno, S., Tsubouchi, K. and Shimosaka, M.: Supervised-CityProphet: Towards Accurate Anomalous Crowd Prediction, *Proceedings of the 28th International Conference on Advances in Geographic Information Systems*, pp. 175–178 (2020).

[21] Fu, Y., Wang, P., Du, J., Wu, L. and Li, X.: Efficient region embedding with multi-view spatial networks: A perspective of locality-constrained spatial autocorrelations, *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 33, No. 01, pp. 906–913 (2019).

[22] Zhang, C., Zhang, K., Yuan, Q., Peng, H., Zheng, Y., Hanratty, T., Wang, S. and Han, J.: Regions, periods, activities: Uncovering urban dynamics via cross-modal representation learning, *Proceedings of the 26th International Conference on World Wide Web*, pp. 361–370 (2017).

[23] Guan, W., Chen, Z., Feng, F., Liu, W. and Nie, L.: Urban Perception: Sensing Cities via a Deep Interactive Multi-Task Learning Framework, *ACM Trans. Multimedia Comput. Commun. Appl.*, Vol. 17, No. 1s (2021).

[24] Dubey, A., Naik, N., Parikh, D., Raskar, R. and Hidalgo, C. A.: Deep Learning the City : Quantifying Urban Perception At A Global Scale (2016).

[25] Tsubouchi, K., Kobayashi, H. and Shimizu, T.: POI Atmosphere Categorization Using Web Search Session Behavior, *Proceedings of the 28th International Conference on Advances in Geographic Information Systems*, SIGSPATIAL '20 (2020).

[26] Murray, H. A.: Explorations in personality: A clinical and experimental study of fifty men of college age. (1938).

[27] Ramos, J. et al.: Using tf-idf to determine word relevance in document queries, *Proceedings of the first instructional conference on machine learning*, Vol. 242, No. 1, Citeseer, pp. 29–48 (2003).

[28] Likas, A., Vlassis, N. and Verbeek, J. J.: The global k-means clustering algorithm, *Pattern recognition*, Vol. 36, No. 2, pp. 451–461 (2003).

[29] Von Luxburg, U.: A tutorial on spectral clustering, *Statistics and computing*, Vol. 17, No. 4, pp. 395–416 (2007).

[30] Van der Maaten, L. and Hinton, G.: Visualizing data using t-SNE., *Journal of machine learning research*, Vol. 9, No. 11 (2008).