Visual Comparison of Customer Stickiness in Retail Stores

Tao Jiang
Institute of Software, Chinese Academy of Sciences
Beijing, China
hijiangtao@gmail.com

Lei Shi
Institute of Software, Chinese Academy of Sciences
Beijing, China
shil@ios.ac.cn

Ye Zhao
Department of Computer Science, Kent State University
Kent, United States
zhao@cs.kent.edu

Xiatian Zhang
Beijing Tendcloud Tianxia Technology Co., Ltd
Beijing, China
xiatian.zhang@tendcloud.com

Yao Lu
Beijing Tendcloud Tianxia Technology Co., Ltd
Beijing, China
yao.lu@tendcloud.com

ABSTRACT

The daunting task of understanding market trends and forming competitive promotion strategies has been a major pain point of retail store managers ever since they stepped into business. One of the everyday challenges includes the lack of effective tools for in-depth customer analysis that can help managers in decision-makings related to the retail store operation. In this work, we propose to apply visual analytics techniques to address these challenges, based on the huge mobile location data available only very recently. We present a system that focuses on the analysis of customer stickiness which represents the customer's affinity to retail stores in both space and time. We introduce a full life cycle of analyzing the huge mobile location data to understand the customer stickiness, including the data pre-processing, context analysis, multi-view visualization design, and a set of interactions. These visual analytics techniques are designed for two main types of user tasks, one to understand the spatio-temporal distribution of customers in relation to the retail store business, and the other to evaluate the performance and trend of multiple retail stores through visual comparison. We have demonstrated the effectiveness of the system through three case studies on important daily tasks such as advertisement placement, shuttle bus planning and branch reconfiguration.

CCS Concepts

•**Human-centered computing** → **Visual analytics;** *Visualization systems and tools;*

Keywords

Spatio-Temporal; Visual Comparison; Retail Store Analysis; Location Based Marketing

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1. INTRODUCTION

With the growing penetration of smart devices [6], a majority of mobile Internet users are being monitored in real-time and at unprecedented granularity for their status, behavior and mobility. The result of this trend, i.e., the availability of big mobile location data, becomes the core competence of many online services and products.

Applying big mobile location data to the traditional marketplace analysis, in particular for offline retail stores and supermarkets, poses an interesting scenario beyond their immediate usage in e-commerce. For example, with the fierce competition from online purchasing, the offline retail stores are eager to expand their influence through sales campaigns, saturation advertising, and aggressive branch reconfiguration. The big mobile location data capturing fine-grained customer information in space and time serves as an extremely valuable data source to initiate the campaigns, advertisements and reconfigurations in the most appropriate place and time. In this work, we focus on one important user-centered factor in the marketplace analysis - Customer Stickiness, a concept intensively used to describe the customer's tendency to come, stay and purchase in certain stores. We consider a series of practical questions. What relevant information to extract from the big mobile location data to help analyze the customer stickiness? How to visualize the extracted spatiotemporal data to let retail store managers, our target user, effectively understand the customer portrait and the ongoing trend? How to further visually compare the customer stickiness of different retail stores to take effective measures in the competition?

Despite of the promise to apply big mobile location data in our scenario, the underlying techniques to accomplish our goal are far from straightforward. The main challenges are three-fold. First, the unprocessed mobile location data are huge, i.e., comes with a big number of records, but with very few attributes attached to each record. That is, the raw data is tall and skinny in nature, which makes it hard to extract user's behavior patterns directly and apply them in practice. Second, there is a need to integrate mobile location data by visual comparison in retail store customer analysis. Nowadays, big mobile location data has shown great advantages for analyzing customer behavior. However, few approach adopts mobile location data to support retail store customer analysis through visual comparison. Third, it is indispensable to combine domain knowledge with the data analysis competence in analyzing the customer stickiness. The real users, e.g., retail store managers, are more familiar with the business logic of retails and everyday task. The visual analytics approach fills the gap to integrate the manager's domain knowledge into the analysis of customer stickiness from big mobile location data.

In this paper, we present a visual comparison system, which helps retail store managers visualize and compare the customer stickiness through their spatio-temporal behavior reconstructed from the big mobile location data. Managers can explore, analyze and compare the customer stickiness represented by their mobile location data. The major contributions of this paper can be summarized as follows:

* *Visual analytics framework for the mobile location data:* We design a visual analytics framework and several use cases to support multiple tasks as characterized in our study. The users, i.e., retail store managers, can follow these use cases to analyze customer's spatio-temporal distribution, mobility and fine-grained behavior.

* *Task characterization:* We design several data analysis techniques and visualization components according to the user task characterized. When a specific task such as branch reconfiguration is conducted by managers, it is decomposed into some sub-tasks, and executed by interacting with a combination of visualization components in our system. Users are allowed to incorporate his domain knowledge in solving these tasks.

* *Novel visualization design:* A set of visualization techniques are presented to empower users to make visual comparison on retail store customer analysis, these visual design can also be combined to cover managers' other daily tasks.

The rest of this paper is organized as follows. In Section 2.1, we discuss related work and identify their key differences from our work; in section 2.2, we characterize managers' tasks; we describe the data set and the analysis pipeline in section 2.3; in section 2.4, we propose the visualization and comparison design; several case studies are conducted in section 2.5 to showcase how our system can help managers. We finally conclude the work in Section 3.

2. THE METHODOLOGY

2.1 Related Work

To extract behavior pattern from the spatio-temporal data, the key is to construct a data model that can represent the temporal evolution of spatial objects [8]. Many researchers has attempted to obtain information from mobile location data, Zheng uses a HITS-based inference model [17] to figure out interesting locations and classical travel sequences in a given geospatial region, while Zheng applys a collective matrix factorization method [15] to discover places for recommendations. Researchers propose a supervised learning approach to infer people's motion modes from their GPS logs [16], Wu et al. develop two automated models to classify major time activity patterns from GPS tracking data [13]. In this paper, we enrich semantic attributes of mobile location data, in order to utilize the spatio-temporal data in visual comparison of customer stickiness.

In spatio-temporal data analysis, there is a critical need to combine analysis process with visualization expression. Space-time cube [1] is used to display objects' dynamic trajectory, node-link plot and points plot [17] are used to demonstrates the correlations between users and location records, heatmap is often used to visualize density of users' location distribution. Some researchers also focus on visualization system's researching. Wu presents an interactive visual analytics system called TelCoVis [14], which helps domain experts gain insight into the co-occurrence in urban human mobility, Ko et al. present an interactive visual analytics system in helping vendors to increase their competitive intelligence [5].

Spatio-temporal data analysis has received considerable attention these years. Landesberger et al. present a new approach which interactively combines geographic and categoric changes visualization to detect expected events [10], Guo et al. propose a graph-based approach that converts trajectory data to a graph-based representation and use it to facilitate the understanding of spatio-temporal patterns in trajectories [3]. As one of the most fundamental visualization tasks [4], visual comparison can be divided into three categories: juxtaposition, superposition and explicit encodings [2]. To our knowledge, different visual comparison tasks had been proposed for various problems, while it has not been systematically studied in the areas of applying mobile location data to customer stickiness analysis.

2.2 Task Characteristics

Retail store is a place for retailing all kinds of goods, attempts are made to increase demand through advertising and necessary methods [12]. Commercial area, one of the factors that should be considered in retailers' development process, is important to marketing strategies' planning. Commercial areas are usually composed of commercial buildings [11], such as banks and downtown. Attracted by the huge people flow, retailers prefer to select this kind of places as mall location, or apply attractive marketing strategies in these area. Managers are facing lots of challenges when maintain the stability and reputation of stores. With rapid growth of e-commerce, managers not only need to face the competitors' expansion, but also have to bear part of their customers tend to shopping online instead.

After discussing with related people, we focus on managers' three concerning tasks: 1)Advertising strategy decision; 2)Shuttle routes plan; 3)Suggesting retail store location. By finding the potential relation between people's location records and shopping behavior, we think our method can help managers in following aspects:

* *Choosing appropriate ads delivery time and place:* an appropriate ads delivery should maximize its effectiveness in suitable place and good time. Comparing with tranditional advertising, Audience On Demand Advertising allows ads be delivered to more target individual with lower cost. A good study into big mobile location data can help managers find out when is the best advertising time and where is the best ads deliver place.

* *Planning suitable shuttle routes for retail store customers:* to plan a suitable shuttle route, the key is to minimize customers' time spending in road to retail store. Mobile location data can help us locate users' gathered area before they arrive at retail store.

* *Suggesting suitable retail store location:* to choose a suitable place for retail store's new branch, managers should be aware of the market and customers behavior of its' competitors. In the background of lacking of quantitative market data, we can be familiar with competitor's customers and the market by analyzing huge mobile location data.

2.3 Data and Analysis

In this paper, the data is collected from TalkingData SDK integrated within mobile apps TalkingData serves under the service term between TalkingData and mobile app developers. It is consists of massive records and each record contains device ID, location time, latitude and longitude. It contains all covered Shenzhen devices' location records in January, 2015. There is total 4242579 different devices, 212185208 records in our data set, one data entry shows in Table 1. Obviously, there are some invalid records in the raw data. By discussing with data providers, we filtered out the three kinds of records: 1) Records of users who have never been to one retail store during whole January; 2) Records with invaild timestamp or location; 3) Record's location time is beyond the scope of January, 2015. Finally, 16118 users with 38149723 records remains in the data set.

Table 1: One data entry

Attribute	Value
ID	018F6160-75CE-4B88-B9FD-64E7B7E0D
timestamp	2015-01-06 12:19:52
latitude	22.544419210748497
longitude	114.08079964920454

We also use Shenzhen POI information to describe retail store's boundary. According to our survey of Shenzhen retail industry, 8 retail stores are chosen as analyzed targets, the stores list shows in Table 2.

Table 2: Retail Store Information

GeoID	Store Name	District
3392	海岸城购物中心	南山区
4078	沃尔玛	工业大道和东滨路交汇处
3726	世贸百货	龙岗区
171	华强电子世界	福田区
11249	大兴购物广场	龙岗区吉华路999号
11236	家润百货	坂田坂雪岗大道163号
5173	金光华广场	罗湖区
5182	天虹商场	罗湖区

We conducted two key analyses on the mobile location data: 1) Enriching data's attributes with their context; 2) Applying interactive query in visual comparison process.

After grouping mobile location data by device ID, each device's location records shows in the left part of Figure 1. By sorting each group's location records in chronological order, the trajectory shows in the right part of Figure 1. In this part, we enrich the raw data with attributes like the customer's visiting state, their sojourn time in store, their origin districts and moving distance. For example in Figure 1, location records before p_2 or after p_6 should be considered as leaving state, the red points represent location records in two retail stores. The bottom part of Figure 1 shows data expansion result of one data entry.

Visiting state: For each data entry in Figure 1, we apply the stay point detection algorithm [7] to compute whether

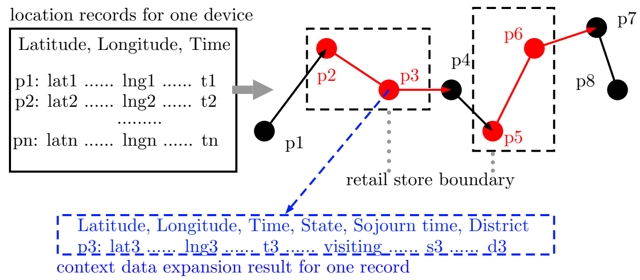

Figure 1: Data structure of one device, computation of customer sojourn time and context data expansion results

the current location is inside one of the retail stores and record it as visiting state. For example, points p_2, p_3, p_5, p_6 in Figure 1 are considered as "inside". In more detail, given the boundary of each retail store, i.e., a polygon, the ray-casting based algorithm [9] is used to calculate whether the record is inside this polygon.

Sojourn time in stores: After calculating records' visiting state, each sequential series of "inside" points could be considered as an "inside" record segment, aware of the limitations of our data's precision, we assume one customer would locate himself when he change his state. For each visiting state record segment. In this case, we define the first point in each "inside" record segment as check-in state point p_s and the next point of each visiting state record segment as check-out state point p_e, then the sojourn time for this record segment is defined as $T = t_e - t_s$. For example, the two sojourn time in Figure 1 are $t_4 - t_2$ and $t_7 - t_5$. In this paper, we set time threshold value as 2 minutes, and consider those points that sojourn time less than 2 minutes as deviations.

To calculate the attributes and merge them into existing data, we use ray-casting based algorithm [9] iteratively and filter records with pre-defined time threshold, shown as Algorithm 1.

Algorithm 1 Visiting state detection and sojourn time calculation

INPUT: GPS log P, retail store boundary B, time threshold *thre*
OUTPUT: Enriched GPS log P

```
i = 0, num = |P|, ind = 0
while i < num do
    Skip the points P_i not in B
    j = i + 1; flag = 0;
    while j < num do
        if P_j not in B & p_j.T − p_ind.T > thre then
            P_[ind,j−1].update(P.state, P_j.T − P_ind.T)
            ind = j; i = j; flag = 1;
            break
        end if
        if flag then
            break
        end if
        j = j + 1;
    end while
end while
```

2.4 Visualization

2.4.1 *Visual Design*

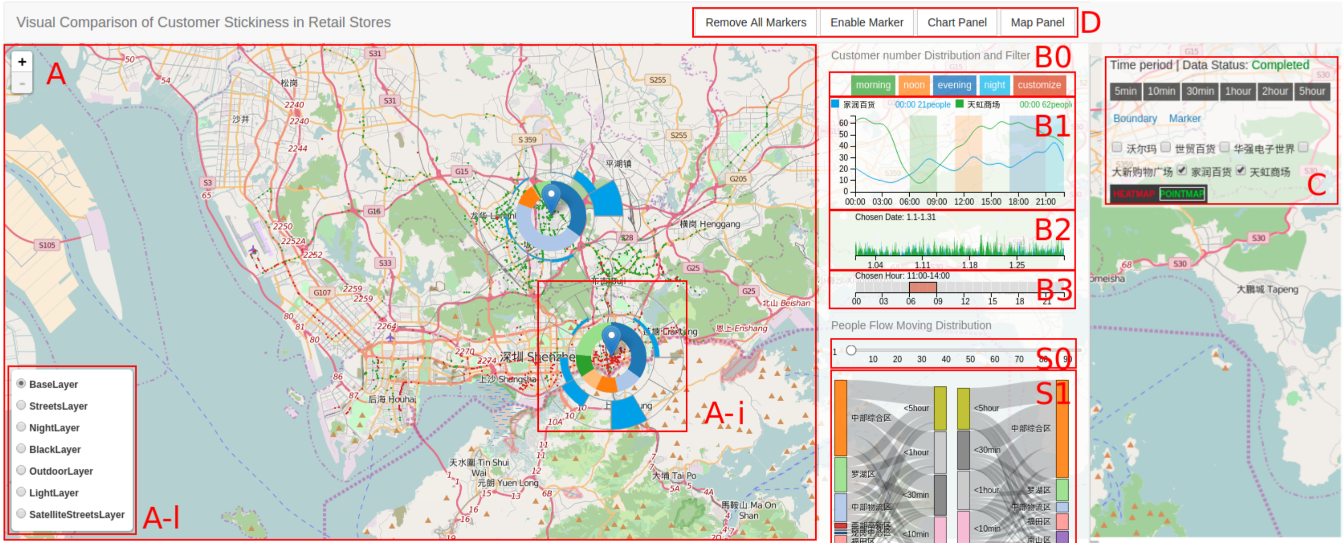

Figure 2: Visual Comparison of Customer Stickiness in Retail Stores System Interface

The visual comparison interface is composed of 3 panels: 1) The map view to visualize customers' geo-spatial distribution (Figure 2(A)). 2) The chart and configuration panel. Figure 2(B0-B3) shows customer number distribution and figure 2(S0-S1) shows customer moving distribution. Figure 2(C) is parameter setting box. 3) The menu (Figure 2(D)) allows users to add/remove markers and switch panels.

For example, Figure 2 shows customers' mobile location data of store(GeoID: 11236) and store(GeoID: 5182), Figure 2(A) is the points plot of customers' 5-hour location records before they arrived target stores, a series points with the same color represents data of one store. Figure 2(A-i outer chart) shows customers' origin districts distribution, each slice in the chart represents one district, the length of each slice extending outward to the edge represents the people number in the district, and length of maximum district people number is normalized to the radius of chart. Figure 2(A-i inner chart) shows customers' sojourn time distribution, 6 sojourn time groups are pre-defined, and arc length of each slice represents customer number belonged to this group. Users are allowed to switch different map layer to observe the records by layer button (Figure 2(A-l)). Line chart 2(B1) shows retail stores' customer number distribution by hour. Buttons and brushes (Figure 2(B0, B2, B3)) allows users to filter analyzed customer by their check-in time range or date, the time range is emphasized by bar regions in chart, the color of region correpsonds to the button's backgruound color. In Figure 2(S1), the left sankey diagram shows the relation between customer origin districts and their belonged sojourn time group, while the right one shows the relation between customer belonged sojourn time group and their destination districts.

Figure 2(B) shows customer number distribution chart and filtering brushes. Figure 2(B0) gives 5 different buttons, each represents one check-in time range. According to different customers check-in time, we define 4 check-in groups: morning (6:00-9:00), noon (11:00-14:00), evening (17:00-21:00) and night (21:00-24:00). Besides, users can use hour brush (Figure 2(B3)) to select a time range to filter analyzed customers. These 5 groups people correspond to the 5 buttons in B0. In B1, one day is discretized into 24 hours in x-axis, all customers checked in the hour of a day are cast up and the result shows in y-axis, the system select whole month mobile location data in Jan, 2015 as default. To customize dataset, Users can use date brush (Figure 2(B2)) to filter customers for line chart.

Figure 2(S) shows a set of sankey diagrams, the information that sankey diagrams want to express includes two parts: before customers arrived retail stores and after they left retail stores. The former part is the left sankey diagram in Figure 2(S1), in the diagram, each left node represents one district, each right node represents one sojourn time group, and the edges between node l_i and node r_j means certain number of people came from district l_i and spent around r_j time in target retail store. The height of node corresponds to the people number. In the right diagram, each left node represents one sojourn time group and each right node represents one district, the edges between node l_i and node r_j means certain number of people spent arround l_i time in target retail store and left for district r_j. Figure 2(S0) is a threshold slider to control displayed diagram structure. The nodes that have people number less than threshold will be hide and its associated edges will be removed from the diagrams.

In map view, to visualize the density of location records, heatmap is presented, one color scheme is used for one retail store data. Besides, points plot (Figure 2(A)) is also introduced to presents location records distribution, each location record is mapped to one point in the map.

2.4.2 *Interactive Comparison*

Selection of analyzed objects: The analyzed objects that users want to explore contains two parts: the retail store and customers. A group of checkbox (Figure 2(C)) allows users to change dataset between different retail stores. As depicted in previous chapter, according to difference of arriving time, customers can be roughly divided into several groups, users can use button group (Figure 2(B0)) to specify analyzed customers, or he can filter customer by time range brush (Figure 2(B3)). To generate different location records according to the duration before they check in, users can use setting box (Figure 2(C)) to control records' duration value.

Two retail stores' comparison: The interface allows users to observe customer location records from two different retail stores at one time. In Figure 2(A), points plot or

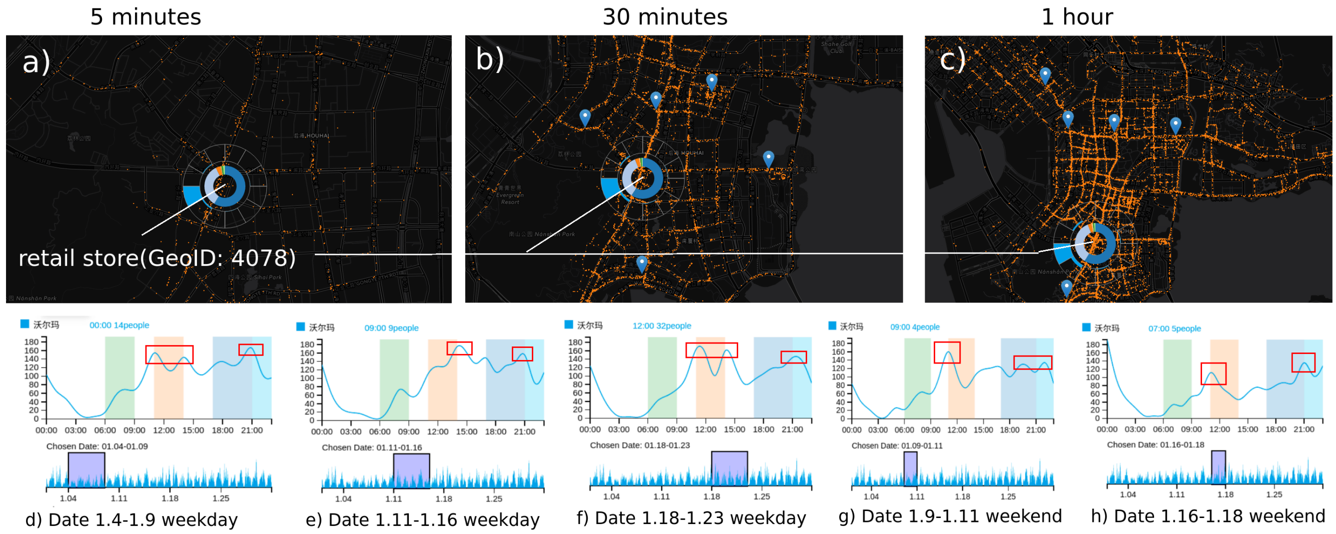

Figure 3: Points plot of noon-arrived customers' location records before they arrived retail store (GeoID: 4078). According to the duration before customer check in, a)-c) are 5-minute, 30-minute and 1-hour duration results. d)-h) are 5 customer number chart filtered by different date ranges.

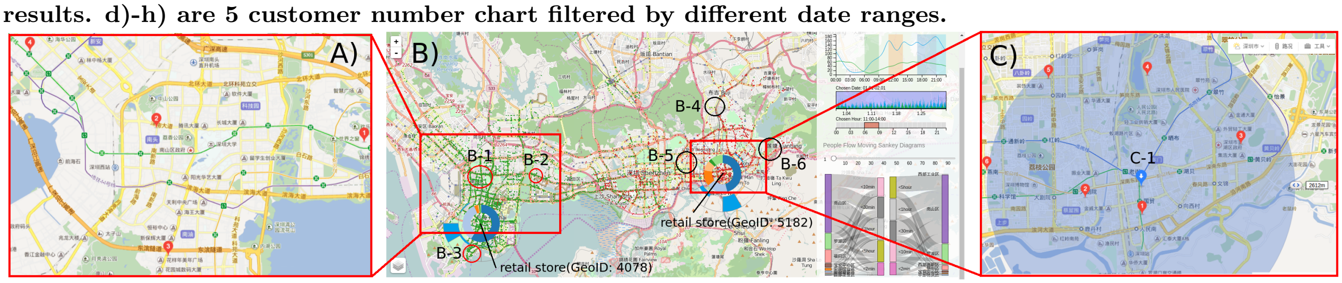

Figure 4: Points plot of retail stores (GeoID: 4078 and 5182). A) is all Wal-Mart Store locations searching from BaiduMap API, B) shows customers' 30 minutes location distribution before they check in, C) is Wal-Mart Stores results of less than 2612 meters away from retail store (GeoID: 5182).

heatmap view shows the customer location records of two compared retail store, a overlapping visualized charts above the map shows customers' sojourn time distribution and administrative division distribution. Users are allowed to click slices of chart (Figure 2(A-i)), and the heatmap (or points plot) view will update to display specific customers' location records (filtered by district or sojourn time).

Overview of customer number distribution: Figure 2(B1) is designed to give managers insights in deciding analyzed target. Users can use date brush (Figure 2(B2)) to filter customer by locating date range. The system will compute and update Figure 2(B1) when user finish interactions.

Interactions of Sankey Diagram: Users can hover on the edge of diagrams, to observe exact information. All nodes in the diagram (Figure 2(S1)) is designed to be able be dragged up and down. As depicted previously, Figure 2(S0) is a threshold slider used to judge which nodes and edges should be displayed in sankey diagrams.

2.5 Case Study

2.5.1 *Visual comparison of billboards placement*

In this scenario, explorations are aimed to visualize and compare target customers location distribution, in order to give advice to decide billboards placement.

We query customers' several periods' location records according to the duration before they arrived retail stores (Figure 3). As observed in Figure 3(a), 5-minute duration location records are distributed mainly over Nanhai Road (white box emphasized) and neighbouring regions, because retail store (GeoID: 4078) is located in Nanhai Road; location records of 30-minute duration and 1-hour duration shows a broader and more detailed trajectory in map (Figure 3(b, c)). Areas with high density points in maps are caused by one of two issues below: 1) Area with lots of people flow; 2) Area with low traffic speed. They both reflects a heavy traffic situation, as well as a broader population coverage. One suggestion is to place ads at these places (Figure 3(markers in b, c)). By discussing with managers, they agree that these areas may attract more potential customers.

Managers are required to make an efficient ads delivering plan, so a precise plan to determine the ads delivering time is needed. By using date brush (Figure 2(B2)), different filtering results shows in Figure 2(B1), time periods before customer flow peak happens is recommended (Figure3(red box emphasized in d-h)). As observed by managers, there is also differences between weekday and weekend, for example, more weekday customers are willing to visit retail store (GeoID: 4078) arround noon, while weekend customer flow peak appears more at evening. In general, these phenomenon can be explained as people will shop arround noon at weekdays, while they prefer to go to retail store in the evening with their family at weekends. More interesting patterns can be found by combining managers' experience.

2.5.2 *Suggesting retail store location*

This scenario aims to demonstrate the visual comparison of customer location records in giving suggestions on location of retail store's new branch.

We first select morning check-in customers and visualize their 30 minutes location records before they check in, as shown in Figure 4(B). Retail store(GeoID: 4078) is a famous Wal-Mart Store in shenzhen, it's quite clear to get customers' location distribution before they check-in, such as B-1, B-2, B-3 in Figure 4(B). Generally, high traffic area is expected to gain more customers, due to these area always has a bad traffic state, the high density points plot area in map view (Figure 4(B)) can be regarded as candidate places. By querying with BaiduMap API, we get Wal-Mart store locations near retail store (GeoID: 4078), as shown in Figure 4(A), they are quite similar with B-1,2,3 in Figure 4(B), marker 2 and 4 are two branches in high traffic area, marker 1 is a branch near Happy Valley.

As observed by managers, a suitable position near its' competitor may also be a good choice. Regardless of goods the retail store sold, a place with rapidly change of competitor's customers can be regarded as candidate position. It means that people will spend quite the same cost in reaching current competitor's store or candidate position, and managers can plan a good promoting strategy to gain them from competitors. B-4,5,6 are three selected candidate positions for retail store (GeoID: 4078) by managers, customers of retail store (GeoID: 5182) have rapidly change in these areas. To evaluate if managers' suggestions works, the query Wal-Mart Stores results of retail store (GeoID: 5182)'s distance circle is given. We suppose people walking speed as $1.5m/s$, and the distance threshold is set to 2612 meters (equals to 30 minutes walking distance). As shown in Figure 4(C), C-1 is the position of retail store (GeoID: 5182), and all other red markers are its surrounding Wal-Mart Stores, C-1 is similar to B-6 in geographical position.

3. CONCLUSIONS

In this paper, we study the problem of visually comparing customer stickiness in retail store, using massive mobile location data available only recently. By discussing with retail store managers, we characterize several key daily tasks for these managers and introduce a visual comparison system to assist them in completing their tasks. By analyzing the customer stickiness reconstructed from the customer's spatiotemporal behavior out of big mobile location data, the system helps to evaluate the performance and trend of in different aspects of their business output. We present both task-oriented data analysis and a comprehensive interface for the visual comparison of customer stickiness. Several case studies are conducted to demonstrate the effective of our system. In future, we plan to extend our work in several aspects. First, we will integrate more data sources to enhance the credibility of the system. Second, a few more visual designs can be incorporated to display the undermined dimension of the current data. Third, flexibility can be provided to users through customized interactions to tackle more relevant tasks, such as store transaction analysis.

4. REFERENCES

[1] N. Andrienko, G. Andrienko, and P. Gatalsky. Exploratory spatio-temporal visualization: an analytical review. *Journal of Visual Languages & Computing*, 14(6):503–541, 2003.

[2] M. Gleicher, D. Albers, R. Walker, I. Jusufi, C. D. Hansen, and J. C. Roberts. Visual comparison for information visualization. *Information Visualization*, 10(4):289–309, 2011.

[3] D. Guo, S. Liu, and H. Jin. A graph-based approach to vehicle trajectory analysis. *Journal of Location Based Services*, 4(3-4):183–199, 2010.

[4] J. Kehrer and H. Hauser. Visualization and visual analysis of multifaceted scientific data: A survey. *IEEE transactions on visualization and computer graphics*, 19(3):495–513, 2013.

[5] S. Ko, R. Maciejewski, Y. Jang, and D. S. Ebert. Marketanalyzer: an interactive visual analytics system for analyzing competitive advantage using point of sale data. In *Computer Graphics Forum*, volume 31, pages 1245–1254. Wiley Online Library, 2012.

[6] J. K. Laurila, D. Gatica-Perez, I. Aad, O. Bornet, T.-M.-T. Do, O. Dousse, J. Eberle, M. Miettinen, et al. The mobile data challenge: Big data for mobile computing research. In *Pervasive Computing*, number EPFL-CONF-192489, 2012.

[7] Q. Li, Y. Zheng, X. Xie, Y. Chen, W. Liu, and W.-Y. Ma. Mining user similarity based on location history. In *Proceedings of the 16th ACM SIGSPATIAL international conference on Advances in geographic information systems*, page 34. ACM, 2008.

[8] N. Mamoulis. Spatio-temporal data mining. In *Encyclopedia of Database Systems*, pages 2725–2730. Springer, 2009.

[9] M. Shimrat. Algorithm 112: position of point relative to polygon. *Communications of the ACM*, 5(8):434, 1962.

[10] T. von Landesberger, S. Bremm, N. Andrienko, G. Andrienko, and M. Tekušová. Visual analytics methods for categoric spatio-temporal data. In *Visual Analytics Science and Technology (VAST), 2012 IEEE Conference on*, pages 183–192. IEEE, 2012.

[11] Wikipedia. Commercial area — wikipedia, the free encyclopedia, 2016. [Online; accessed 27-July-2016].

[12] Wikipedia. Retail — wikipedia, the free encyclopedia, 2016. [Online; accessed 28-June-2016].

[13] J. Wu, C. Jiang, D. Houston, D. Baker, and R. Delfino. Automated time activity classification based on global positioning system (gps) tracking data. *Environmental Health*, 10(1):1, 2011.

[14] W. Wu, J. Xu, H. Zeng, Y. Zheng, H. Qu, B. Ni, M. Yuan, and L. M. Ni. Telcovis: Visual exploration of co-occurrence in urban human mobility based on telco data. *IEEE transactions on visualization and computer graphics*, 22(1):935–944, 2016.

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

[16] Y. Zheng, Q. Li, Y. Chen, X. Xie, and W.-Y. Ma. Understanding mobility based on gps data. In *Proceedings of the 10th international conference on Ubiquitous computing*, pages 312–321. ACM, 2008.

[17] Y. Zheng, L. Zhang, X. Xie, and W.-Y. Ma. Mining interesting locations and travel sequences from gps trajectories. In *Proceedings of the 18th international conference on World wide web*, pages 791–800. ACM, 2009.