Visualizing the Relationship Between Human Mobility and Points of Interest

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***Abstract*— In transportation studies, one fundamental problem is to analyze the departures and arrivals at locations in order to predict the travel demands for urban planning and traffic management. These movements can relate to many factors, e.g., activity distributions and household demographics. This paper presents how we use visualization to explore the relationship between people movements and activity distributions that are characterized by the points of interest (POIs). To effectively model and visualize such relationship, we introduce *POI-mobility signature*, a compact visual representation with two main components. 1) A mobility component to present major people movements information across temporal dimension. 2) A POI component to present the activity context over an area of interest in spatial domain. To derive the signature, we study assorted analytical tasks after discussing with transportation researchers, consider essential design principles, and apply the representation to study a real-world dataset, which is the massive public transportation data in Singapore with over 30 million trajectories and crowd-sourcing POIs retrieved from Foursquare. Finally, we conduct three case studies and interview three transportation experts to verify the efficacy of our method.**

***Index Terms*— Human mobility, point-of-interest, visual analytics, data-driven intelligent transportation system.**

I. Introduction

IN transportation study, there has been a long desire to understand the motivation behind people movements, i.e., what are the factors that drive people to move across a city in-between locations [33], e.g., work, shopping, studying, etc. Transportation researchers suggest that the motivation behind people movements generally relates to certain purposes/activities across different locations [32]. In other words, people movements are highly related to the distribution of activities (e.g., school, office, food stall, etc.) in different areas in urban environments. For instance, some researchers revealed that the locations of residence and business regions have strong effects on the pendulum movement pattern [22], which describes employee movements from home to work in the morning and from work to home in the evening [29].

Understanding the relationship between activities and human mobility is a fundamental research problem in transportation, which is highly useful for estimating trip distribution and travel routes [33]. Many researches have been carried out for this purpose, e.g., [16], [36]. However, they are mostly focusing on modeling macroscopic activity-based human mobility patterns over an entire city and period. These approaches often lack the feasibility to explore and compare difference for activities in different categories and in different areas. Transportation researchers prefer a visual analytics system that allows them to perform such analysis.

To uncover the relationship, the experts need to simultaneously explore the following two pieces of information: 1) human mobility, such as the volumes of departures & arrivals in a certain area of interest, and 2) activity context, i.e., available activities in the area. We introduce a novel compact visual representation, namely *POI-mobility signature*, to efficiently reveal the two pieces of information collectively.

We develop this visual representation through the following iterative design process. First, we consider the analytical tasks required by the experts. Then, we explore and compare various design alternatives to progressively refine the visual design. Next, we develop a visual analytics interface that integrates human mobility inferred from a one-week massive public transportation data in Singapore, with activity context inferred from points-of-interest (POIs) retrieved from the crowd-sourcing social media platform Foursquare [10]. Our interface allows users to interactively specify areas of interests, or POIs in different categories, and then compare and explore their relationships with human mobility by examining the visual signatures. Lastly, we present three case studies and conduct expert interviews with three transportation researchers to examine the effectiveness of our approach.

The major technical contributions of this paper include:

- First, we work closely with domain experts to study various analytical requirements and explore different design principles. From these, we iteratively design *POI-mobility signature* to present the two pieces of vital information: human mobility and activity context together.
- Second, we develop a visual analytics interface that integrates massive human mobility data (over a week with over 30 million passenger trips in Singapore) and POI data, allowing domain experts to interactively explore

Manuscript received June 29, 2016; revised October 20, 2016; accepted December 2, 2016. Date of publication January 16, 2017; date of current version July 31, 2017. This work was supported by the Singapore National Research Foundation under Grant FI 370074016. The work of C.-W. Fu was supported by The Chinese University of Hong Kong Strategic Recruitment Fund. The Associate Editor for this paper was R. Maciejewski.

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Digital Object Identifier 10.1109/TITS.2016.2639320

the relationship between human mobility and activities.
- Lastly, we conduct case studies and expert interviews, demonstrating how human mobility varies over POIs in different categories and across different areas.

II. Related Work

This section discusses the following three categories of visualization works related to this paper:

A. Time-Oriented Data Visualization

A detailed survey on time-oriented data visualization regarding visual representations, analytical methods, and user tasks can be found in [1]. Aigner *et al.* [1] suggested to employ different visual representations based on the types of time. For example, the traditional line chart and stacked graph [7] are good for linear time data, while the spiral graph [37] is good for cyclic time data. Besides visual representations, some researchers focused on studying human perceptions on visual designs. Among them, Heer *et al.* [12] studied the effects of size and layering on line charts and horizon graphs, while Javed *et al.* [15] explored user performance of different line graph methods involving multiple time series.

Based on these preliminary works, we develop the mobility component in the *POI-mobility signature*, aiming to reveal human mobility dynamics in temporal dimension. Note that we adopt a radial layout to arrange the time frame, since this layout naturally reveals a round-the-clock pattern, see Section V-C for more details. The radial layout has also been proven to be effective in revealing time-dependent movement patterns [21] and location-based social networks [28]. Besides, we further integrate radial layout with different multiple time series graphs to visualize temporal dynamics based on user requirements, e.g., braided graph for exploring differences between departure and arrival movements, and stacked graph for presenting the movements aggregation.

B. Movement Visualization

Visual analytics of movements has been a hot topic in visualization community, and extensive visual analytic tools have been developed to present the spatial and temporal perspectives of movement information. Advanced data models (e.g., taxi query model [9]), novel visual mappings (e.g., interchange circos diagram [42]) and new interaction techniques (e.g., MetroBuzz [43] and TrajectoryLenses [19]) have been developed to facilitate analytical tasks. A structured survey of these visual analytics, tools and procedures for movement data can be found in [4].

In particular, many of these visualization methods focused on revealing the origin-destination (OD) pattern that summarizes movements between locations. Traditional flow maps [34] can easily cause visual clutter problem with large number of OD pairs. To overcome this problem, movements clustering followed by visual representation of aggregates have shown to be effective [3], [11]; in addition, some novel visual representations have also been proposed, such as the OD maps [38], Flowstrates [6] and waypoints-constrained OD views [41].

Though the clutter problem can be mitigated by these methods, there are no universal solutions effective for different aspects of arbitrary OD flows [4]. In the scope of this work, we do not attempt to explore OD movements *between* locations. Rather, we focus on exploring the time-dependent departure and arrival movement patterns related to POIs. Hence, we adopt multiple time-series techniques to address this problem.

C. Semantic-Enhanced Movement Visualization

Movement data (e.g., passenger trajectories) alone lacks semantic information, thus hindering the analysis from depicting the knowledge about the movement characteristics [27]. A number of recent works [2], [40] have attempted to enrich trajectories with semantic meanings. In the community of movement visualization, a noticeable trend is semantic-enhanced movement visualization, which enriches movement data with semantic information.

Itoh *et al.* [14] explored situational explanation of passengers' behavior changes and abnormalities by extracting complaints about services from social media; Liao *et al.* [20] enhanced trajectory semantics with transaction data, and demonstrated their system's applicability in kidnapping investigation; and Andrienko *et al.* [5] devised a visual analytics approach to infer place meanings based on temporal patterns of human mobility traces. Closer to our work are Krüger *et al.* [17], [18], who enriched visual exploration of vehicle trajectories through semantic POIs extracted from Foursquare.

While the above visual analytics methods are very useful for depicting and explaining general life routines of people, e.g., work, shopping and studying, our approach focuses on efficiently revealing the relationship of time-varying human mobility pattern and activity contexts, which requires us to integrate the two pieces of information and present them collectively in an intuitive and compact manner, as presented in Section V.

III. Overview

In this section, we first introduce the domain problem and data characterization, followed by operation and data type abstraction, as suggested in [26]. Then, we provide an overview of our system workflow.

A. Domain Problem and Data Characterization

1) Domain Problem: The overall goal of this work is to facilitate transportation researchers' work in exploring the relationship between human mobility and activities (characterized by POIs). Through discussions with our collaborative transportation researchers, we found that when analyzing such relationship, they often want to explore the following questions:
- What POIs are available in an area?
- How many people depart from, and how many people arrive at the area? And how long people stay in the area?
- What are the difference between the departures & arrivals and stay durations over time, e.g., in the morning and evening? And on weekdays and weekends?

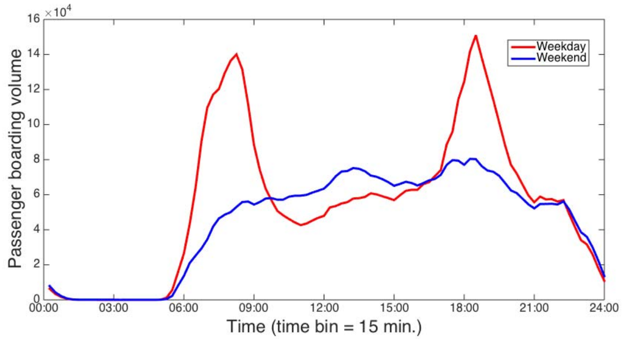


Fig. 1. Average passenger boarding volume distribution extracted from Singapore public transportation data on weekdays (red) and weekends (blue).

In general, these questions can be summarized in the following two perspectives of information:

- *Human mobility:* This includes the departure and arrival movement volumes related to an area, and stay duration in the area. In particular, the experts would like to explore how these departure and arrival patterns vary over time: at different time periods in a day, e.g., in the morning and evening peak hours; in different days of a week, e.g., weekdays and weekends.
- *Activity context:* Activity context describes the distribution of activities in different areas within an urban environment. In this work, activity context is characterized as POIs available in an area, i.e., metrics of related POIs extracted from Foursquare. Compared with the movement data, POIs are usually considered to be static in a short period of time (a week in our case), e.g., a primary school does not become a shopping mall in a week. Hence, we explore static statistics of activity context, but not the time-varying dynamics of POIs.

2) Data Characterization: To extract these information, we fuse the following datasets in this work:

a) Movement data: The movement data is a one-week public transportation data in Singapore, which consists of ~5.4 million trips/day on weekdays and ~4.3 million trips/day on weekends. In Singapore, the passengers can take public transportation, including both the metro system called mass rapid transit (MRT) and public bus system, using their personalized RFID cards. For each trip taken, the public transportation system will record the trip information, including card ID, boarding & alighting times and stops.

There are also ~4.8k public stops in total, each with a distinct ID, name, and geographic position. By referring to the stop ID, we can map a trip's boarding & alighting stops.

Fig. 1 shows passenger boarding volume distribution in every 15 minutes averaged on weekdays (red) and weekends (blue). The figure clearly shows two peak periods around 08:00 and 18:00 on weekdays, while passenger movements are more evenly distributed on weekends. Notice that there are barely any movement during 00:00−06:00 due to off service, thus we omit this period in the analysis.

b) POI data: The POIs studied in this work are extracted from venue services provided by Foursquare [10], which is a crowd-sourcing platform allowing users to check-in their current venues, and add information about the venue.

The venues are categorized into three hierarchical levels. The highest level contains ten categories, e.g., "Arts & Entertainment," "College & University," and "Event." The second level includes the subcategories of the highest level categories, e.g., "Assisted Living" and "Home (private)" under "Residence" category. The third level presents most detailed description of a POI, such as "Airport Food Court." See Fig. 10(left) for POI categories presented by our interface.

Besides the category information, each venue consists of a series of attributes, including the follows:

- *Name:* The name of a venue, such as "Singapore Changi Airport (SIN)."
- *Geographic information:* This can be inferred from *address*, *position (latitude & longitude)*, and *postal code* of a venue. In this work, we use the $latitude$ & $longitude$ information of the venues.
- *Popularity:* This includes the aggregated number of *user* counting how many users have checked-in the venue, *check-in* counting the total number of check-ins, and *tip* counting how many tips that the users have posted about the venue. In this work, no temporal references are attached to these check-ins.
  People may check-in a venue multiple times, and this will only increase the number of *check-in*, but not the number of *user*. Hence, we use *check-in* as the indicator of POI popularity, as a passenger may visit a location multiple times and our system considers all of these visits.

See Fig. 10(right) for detailed information of some POIs in "Residential Building (Apartment / Condo)" category.

B. Operation and Data Type Abstraction

1) Operation: Many researches have been carried out to study human movements in cities, e.g., [23], [25], [44]. However, none of them have been explicitly focusing on studying the relationship between human mobility and POIs. To reveal such relationship, domain experts would prefer an intuitive visual analytics system that can effectively address the following analytical tasks:

T1: *What POIs are available in an area?* And what are the percentages of these available POIs?

T2: *How do the departures and arrivals related to an area vary over time?* Specifically, the researchers would like to explore: 1) difference between the departures and arrivals, such that to know whether the area sinks or sources movements; and 2) aggregation of departures and arrivals, such as to know people crowdedness in the area.

In addition, the researchers would also like to explore:

T3: *How long are the activity durations in an area?* This is also an important indicator for different POIs, especially for distinguishing purposes of many different movements. For instance, transportation researchers expect that employees stay at their working places for a duration about 8 hours, while people go shopping for about 2−4 hours.

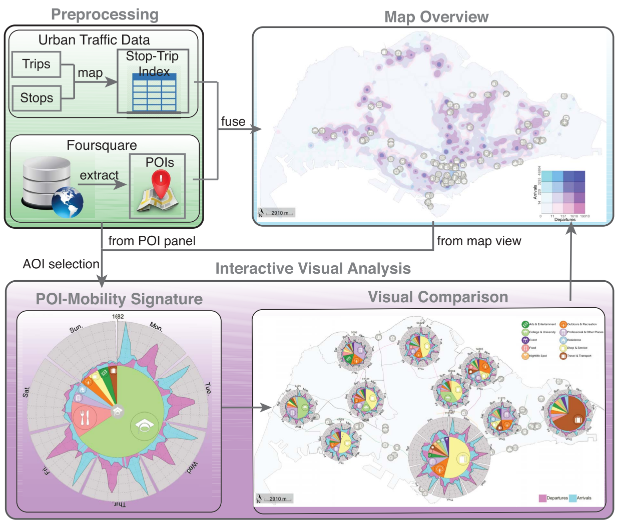


Fig. 2. Overview of the system workflow. Our system consists of three major parts: data preprocessing, map overview and interactive visual analysis.

2) Data Type Abstraction: To intuitively present these information is a non-trivial tasks. Specifically, *T1* is related to ratio-scale quantitative data visualization, where bar charts, pie charts and tree maps are usually employed. However, since the data is associated with geo-spatial positions, the visualization can be easily visual cluttered. On the other hand, *T2* & *T3* are in temporal dimension, and they require a multiple time series design to present individual piece of information.

C. System Workflow

As illustrated in Fig. 2, the workflow of our visual analytics system mainly consists of three stages: *preprocessing*, *map overview* and *interactive visual analysis*.

In the *preprocessing* stage, our system firstly creates stop-trip indexes by mapping the people movements onto the boarding and alighting stops. Each stop-trip index is basically a 2D array with two rows (one for arrival and one departure), while each column corresponds to the related movement volume partitioning in a 15-minutes time bin over a week. Besides, our system also retrieves POIs from Foursquare and organizes them in a hierarchical structure.

After preprocessing the data, our system presents a *map overview* of the people movements and POIs. The overview mainly consists of two layers: a) a bivariate density map to present the people movements, and b) a spatial distribution of major POIs in Singapore; see Section V-B for details.

In the *interactive visual analysis* stage, users can interactively specify an area and explore the related people mobility and activity context. Users can either select a POI from the POI panel and explore its surrounding area, or specify an area directly on the map. Then, our system will fuse the relevant stop-trip indexes and POIs to generate movement dynamics and activity context (Section IV). These information will be transformed to a *POI-mobility signature* consisting of mobility and POI components. Users can select multiple areas and visually compare their *POI-mobility signatures*, and a series of user interactions have also been developed to facilitate the visual exploration process (Section V).

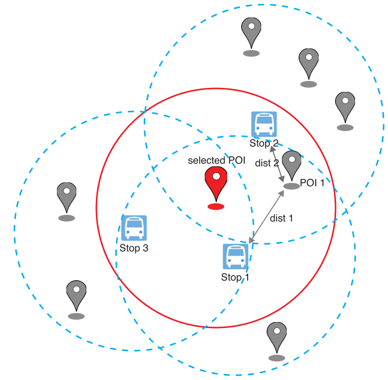


Fig. 3. Illustration of fusing related stop-trip indexes and POIs to model the POI-mobility relationship for an area of interest (red).

IV. Modeling the POI-Mobility Relationship

To model the POI-mobility relationship, our system will perform the following procedure.

A. Step 1 (Specifying an Area of Interest (AOI))

Our system allows users to specify an *AOI* in three modes:

- *Mode 1: Select a single POI*. Users can select a specific POI and explore its surrounding area. Here, we define the surrounding as ten minutes walking distance at five km/h speed around the POI, as illustrated by the red circle in Fig. 3. This distance is approximately the maximum bus stop spacing, i.e., 800m [8].
- *Mode 2: Select an administrative zone*. Users can select an area from Singapore administrative zones organized in four hierarchies, with the highest hierarchy consisting of five zones, and lowest hierarchy consisting of 96 zones.
- *Mode 3: Specify a lasso/rectangle area*. Users can also specify an AOI with the lasso and rectangle region specification tools implemented in our system.

B. Step 2 (Computing Activity Context)

After users specify an *AOI*, we will extract a list of stops (denoted as $\mathbb{S}$) and a list of POIs (denoted as POI_{AOI}) that are within the *AOI*. For each POI in POI_{AOI}, we firstly find its corresponding highest category in the top ten categories (see Fig. 4(c)), and then aggregate the POI's check-in counts to its highest POI category. The final aggregated check-in counts for all the highest ten POI categories are considered as the activity context of the *AOI*. Here we adopt check-in count as a quantitative indicator of activity context rather than the number of POIs, since check-in count reflects better the attractiveness of POIs to people.

Thus, the total check-in count $Check\text{-}in_{cat}$ of a category cat in the ten highest categories can be computed as

$$Check\text{-}in_{cat} = \sum_{i=1}^{N} Check\text{-}in_{poi_i}^{cat}, \quad N \geq 1,$$

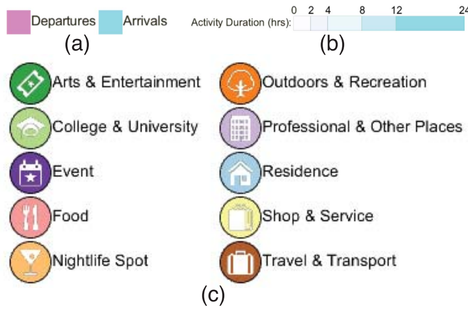


Fig. 4. Color choices of our visual design.

where N is the number of relevant POIs, i.e., $|POI_{AOI}|$, and $Check\text{-}in^{cat}_{poi_i}$ denotes the check-in counts of a POI poi_i belonging to category cat.

C. Step 3 (Computing Departure and Arrival Movement)

Here, we adopt the gravity model that is widely employed to formulate the macroscopic relationship between places in transportation [13]. In our case, the gravity model posits that people movement at a stop relating to a POI is positively associated with the check-in counts of the POI, and declines with increasing distance from the POI to the stop.

Hence, for each stop $stop_i \in \mathbb{S}$, we find its surrounding area $Area_{stop_i}$ of ten minutes walking distance at five km/h speed around the stop; see the blue circles in Fig. 3. Since the movements can be related to any POI within $Area_{stop_i}$, we then find all POIs within $Area_{stop_i}$ and denote them as POI_{stop_i}. The POIs exist in both POI_{AOI} and POI_{stop_i} are extracted and denoted as $POI_{overlap}$.

Hence, we can compute the departure movements T^D_{AOI} corresponding to a user-specified *AOI* as

$$T^D_{AOI} = \sum_{i=1}^{O} T^D_{stop_i} \times \frac{\sum_{j=1}^{P} Check\text{-}in_{poi_j} \times f(|poi_j, stop_i|)}{\sum_{h=1}^{Q} Check\text{-}in_{poi_h} \times f(|poi_h, stop_i|)},$$

where $T^D_{stop_i}$ is the departure movement at $stop_i \in \mathbb{S}$, $P = |POI_{overlap}|$ and $Q = |POI_{stop_i}|$. f is a distance decay function with $|poi, stop_i|$ referring to the Euclidean distance between a POI poi and a stop $stop_i$. Here, we adapt $1/|poi, stop_i|^2$ as the distance decay function, which can be simply replaced by any other suitable decay function. Similarly, we can compute the arrival movement T^A_{AOI} related to the *AOI*.

D. Step 4 (Computing Arrival Movements Activity Duration Distribution)

As suggested by the transportation experts, we consider the possible activity durations into five quantized periods: 0−2, 2−4, 4−8, 8−12, and 12−24 hours (Fig. 4(b)), corresponding to activities like food, shopping, studying, work and others, respectively. For each arrival movement, we compute activity duration by computing the difference between the trip arrival time and the next trip departure time.

Notice that some people may leave the area by other travel modes like taxi, or stay in the area. For these movements, we interpolate their activity durations based on the computed proportions of these five periods. Alternatively, we may have two choices: i) ignore these movements, or ii) assume that the people continue to stay in the area, so they will contribute to the 12−24 hours period. For alternative choice (i), the aggregation of all the five activity-duration volumes will, however, become smaller compared to the arrival movement volume computed in Step 3, leading to inconsistent visual cues across different forms of the mobility component (see Fig. 8(a) & (c)). For alternative choice (ii), the experts suggested that it will lead to inaccurate proportion between the activity durations, since the 12−24 hours period will be more than its real value. They prefer to visualize more accurate ratios of these activity durations, which are computed based on arrival movements with known next trip departure times.

V. Visualization Design

In this section, we first discuss the principles and primitives behind our visualization design. Then, we elaborate how we implement the map overview of the departure & arrival movements and POIs, followed by a description of the *POI-mobility signature* design.

A. Design Principles and Primitives

After we have successfully modeled the POI-mobility relationship, it remains a non-trivial and challenging task to design an intuitive and compact signature. A proper visual design is expected to meet the following design principles:

- *Complete*: The signature should present both POI context and human mobility information. Besides, it should be able to be overlaid on the map, such as to help users associate the information with their real world knowledge.
- *Compact*: Since we hypothesize that POI context and human mobility are highly related, the signature should incorporate these information in a compact manner. We do not expect a linked view design that presents these information separately.
- *Overview+Details*: The visualization system should overview people movements and POI context over the whole city. Meanwhile, interactive techniques should be provided for users to explore the details on demand.

By considering the above design principles, we formulated the following design primitives for making up the signature.

- *Radial layout*: We adapt a radial layout to compose both the POI and mobility components, arranged from inside to outside. In this way, we achieve a compact composition of both POI and human mobility information.
- *Color scheme*: We formulate consistent color scheme for our system, see Fig. 4(a) with pink and aqua colors reserved for the departure and arrival movements, respectively; we encode activity durations into five color bands in aqua corresponding to the arrival color (Fig. 4(b)); lastly, we choose ten qualitative colors (other than pink and aqua) for the highest ten POI categories (Fig. 4(c)).
- *Time frame*: We allow users to compare the departure and arrival movements over one week, as well as between weekdays and weekends. Here, the mobility component

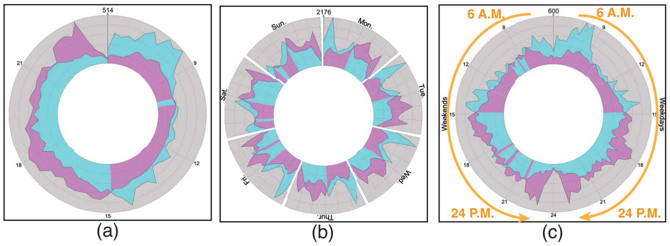


Fig. 5. Time frame in the mobility component can be divided into (a) one part representing averages over one week, (b) seven parts representing Monday to Sunday, (c) two parts representing averages over weekdays and weekends.

can be divided into one part representing averages over one week (Fig. 5(a)), seven parts representing Monday to Sunday (Fig. 5(b)), or two parts representing averages over weekdays and weekends (Fig. 5(c)).

Specifically, when dividing the time into two parts, we arrange the mobility information in left and right parts: clockwise and anti-clockwise, respectively, such that it presents a side-by-side effect, which has been shown to be effective to facilitate visual comparison in classical visual designs, e.g., [35]. We also discussed this design choice with the transportation researchers, and they all agreed that the side-by-side effect is generally more efficient to compare the movement volumes between weekdays and weekends.

- *Minimum time interval*: We choose a suitable minimum time interval for each time frame, which balances between visual clarity of the graph and details of the movement dynamics. In transportation, 15-minutes is normally chosen as the minimum time interval for movement analysis, and a recent study [45] showed that movement regularity dramatically decreases when the temporal scale is less than 15 minutes. Based on these and various options we experimented with, we find that 15-minutes is preferred for one-week (Fig. 5(a)), and weekdays and weekends time frames (Fig. 5(c)), while one-hour is suitable for seven-days time frame (Fig. 5(b)).

B. Map Overview

After preprocessing the movement and POI data, we present a map overview (Fig. 6) to provide intuitive spatial information of the departure & arrival movements and POIs. The map overview mainly consists of two layers: a bivariate density map showing the departure & arrival movements, and POI icons presenting major POIs in Singapore. Here, the density map is employed since it has been successfully applied to presenting movement patterns, e.g., [24], [30].

Here, we construct the bivariate density map in the following steps: First, we compute density fields for both the departure & arrival movements, using kernel density estimation (KDE) with a normal distribution kernel and a bandwidth the same as the distance threshold when computing activity context, i.e., ten minutes walking distance at five km/h speed. Second, we find the maximum volumes for both departure and arrival movements, and divide them into four exponentially

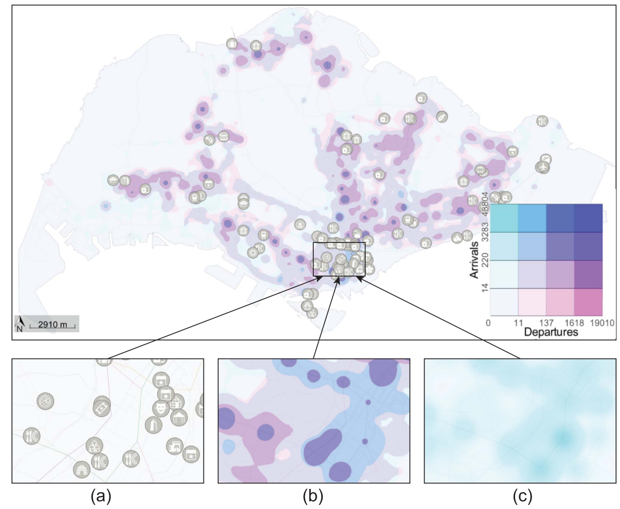


Fig. 6. The map overview consists of two layers: a bivariate density map to present the departure and arrival movements, and POI icons to present the major POIs in Singapore. Users can interactively choose to view (a) POIs, or (b) departure & arrival density, or (c) departure / arrival density only.

dived ranges from zero to the maximum values. Hence, we will have 4×4 combination of departure & arrival movement volumes, and each combination is assigned an unique color as shown in Fig. 6. Lastly, we assign colors to the whole map based on the bivariate color scheme. Users can specify time period, and the density map will update correspondingly.

On top of the density map, we present icons of major POIs extracted from Foursquare. Here, we extract top 20 POIs for each of the ten highest level categories, and then render their primary category icons on the map. Users can also select a specific POI category, and then our system will extract the corresponding top 50 POIs and display them on the map.

Besides basic map interactions, such as zoom and pan, our system allows users to filter the layers to explore, e.g., to view only the POI layer (Fig. 6(a)), or departure+arrival layer (Fig. 6(b)), or departure/arrival layer (Fig. 6(c)).

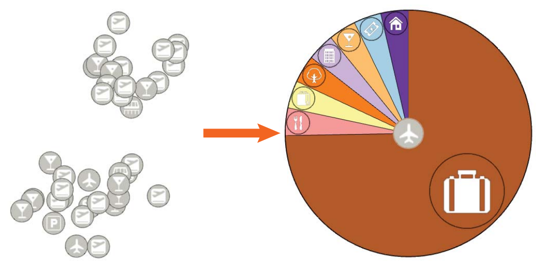
C. POI-Mobility Signature

After users specify an area of interest (*AOI*), our system will present a *POI-mobility signature* to depict the corresponding human mobility and activity context. The signature consists of mobility and POI components, which complement each other and work together to fulfill the analytical tasks.

1) POI Component: The component aims to reveal geographic information and activity context of an *AOI* (*T1*).

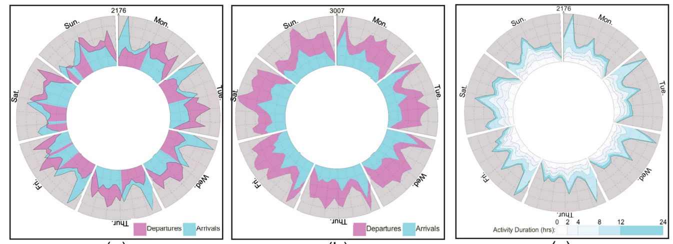
a) Geographic information: We place the POI component at the center of the *AOI*. Specifically, if *AOI* is specified by selecting a POI, we show the POI's primary category icon at the POI position, with a radius of ten-minutes walking distance at five km/h speed to illustrate the size of *AOI* on the map. In the other cases where an administrative zone or a region is selected, the zone or region will be highlighted with gray background color; see Fig. 13 for examples.

b) Activity context: To present the activity context of *AOI*, a straightforward choice is to simply display all the



(a) (b)

Fig. 7. The POI component adapts pie chart visualization to overview the activity context of a user-specified *AOI*.



(a) (b) (c)

Fig. 8. The mobility component can be visualized in three forms: (a) braided graph to present difference between departure & arrival movements, (b) stacked graph to present aggregation of the movements, and (c) stacked graph to present activity durations of arrival movements.

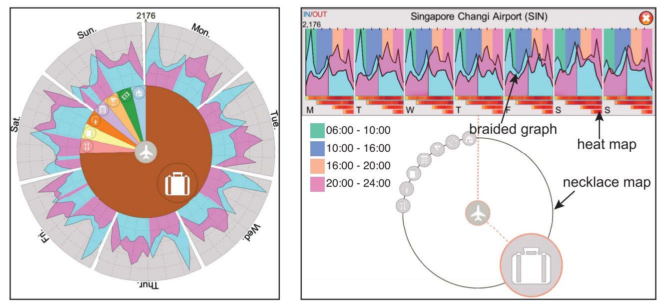


Fig. 9. Design alternatives of our *POI-mobility signature*: (left) our signature design that integrates POI and mobility components in a compact manner, (right) an alternative linked view that presents the information separately.

POI icons at their corresponding locations on the map (Fig. 7(a)). Apparently, this can easily lead to heavy visual clutter problem, especially in downtown areas where many POIs are close to each other.

To overcome the issue, Krüger *et al.* [17], [18] proposed to group nearby icons together and show the number of aggregated POIs on representative icons. Nevertheless, the number of POIs is not representative for activity context, but rather the number of check-ins for each POI. Besides, our system allows users to select and compare multiple *AOIs*. In case that two *AOIs* are close to each other, it is difficult to distinguish grouped icons belonging to which *AOI*.

To address this issue, we adapt a pie chart (Fig. 7(b)) to visualize the aggregated ratios of highest ten POI categories as the activity context of a user-specified *AOI*. The pie chart is generated in these steps: First, we aggregate check-in counts for the highest ten POI categories of all relevant POIs within *AOI* (see Section IV); second, we compute the relative quantitative ratios of these POI categories, and sort them in descending order based on their ratios; after that, we divide the circle into sectors with their sizes corresponding to the POI ratios, starting from the y-axis in clockwise order; lastly, we color the sectors for each POI category based on the color scheme illustrated in Fig. 4(c), and place the POI category icons inside the corresponding sectors with their sizes proportional to the category ratios as well.

2) Mobility Component: The component aims to present the dynamic mobility information (*T2*), and arrival movements activity durations related to an *AOI* (*T3*).

The mobility information is arranged in a radial layout where the inner circle serves as the baseline and flow volumes are proportional to the distance from the graph to the baseline. The magnitude of maximum flow volume is displayed on the top, and five dashed circles are drawn to facilitate the visual comparison of flow volumes. We also draw dashed lines to indicate the times of every three hours starting from 6:00 till midnight on every day.

Users can interactively switch between the following three visual forms based on the analytical tasks:

- *Braided graph* (Fig. 8(a)) to present the difference between departure and arrival movements (*T2*). The graph is generated in two steps: First, we identify all the *changing points* where the departure and arrival movements change volume ordering, i.e., all intersecting points between the curves that fulfill the condition $D(t_{i-1}) > A(t_{i-1})$ and $D(t_i) <= A(t_i)$ (or vice versa); Second, we sort the departure and arrival segments in between two *changing points* in descending order of movement volume, and then draw them from back to front.
- *Stacked graph* (Fig. 8(b)) to present the aggregation of departure and arrival movements (*T2*). Here, we firstly draw the arrival movement series starting from inner circle, and then draw the departure movement series with previous arrival values as the baseline.
- *Stacked graph* (Fig. 8(c)) to present activity durations of arrival movements (*T3*). Here, we compute flow volumes of activity durations in the five periods: $0-2$, $2-4$, $4-8$, $8-12$, and $12-24$ hours, and stack the flow volumes in each period from inside to outside.

D. Design Alternatives

As both the POI and mobility components are designed in a radial style, we can easily integrate them together to formulate a compact visual signature, see Fig. 9(left) for an example. Notice that the POI category ratios in POI component are measured by sector *areas*, while the movement volumes are proportional to the *distances* from the inner baseline circle to the curves, i.e., the baseline radii of the mobility component does not affect volume comparison. Considering this, we lay the mobility component outside the the POI component.

An alternative design is a linked view that presents the POI and mobility information separately as shown in Fig. 9(right). This design also consists of:

- *POI component:* As inspired by [31], we arrange a necklace map around the user-specified *AOI* to present

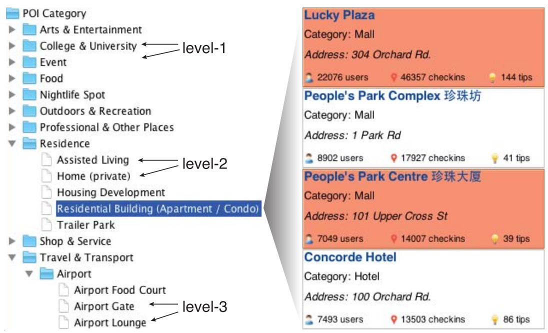


Fig. 10. Components of visual interface: (left) the POI category panel organizes all the POI categories hierarchically, and (right) the POI cell panel lists all the POIs under user specified category.

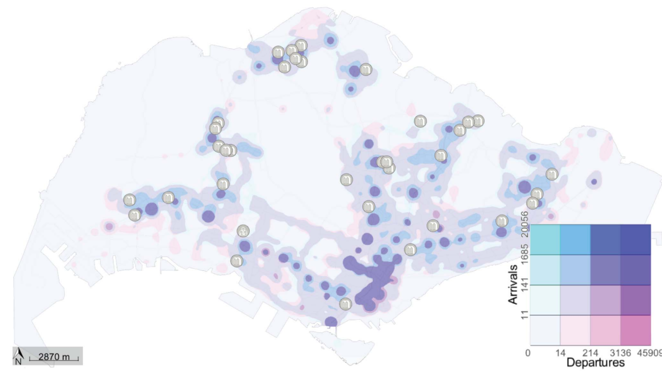


Fig. 11. Study 1: Over-viewing departure & arrival movements in between 16:00 to 20:00, and spatial distribution of POIs in residence category.

activity context of the *AOI*. The necklace map can also be generated in the same way as the pie chart, except that we lay the POI icons on boundary of the circle. Since the necklace map is connected through a thin circle, the space occupancy is less than the pie chart.
However, it is harder to compare the POI icon sizes in the necklace map than the sector sizes in the pie chart. In addition, for small POI icons, it would be even harder to identify their categories than to map the sector colors with the color map.

- *Mobility component:* The mobility component can also be rendered as braided or stacked graphs, yet it is arranged in a horizontal style. In addition, we further divide each day into four uneven time periods, i.e., 06:00−10:00, 10:00−16:00, 16:00−20:00, and 20:00−24:00, such that to help transportation researchers quickly identify movements in morning peaks, non peaks, evening peaks and night periods, respectively. And we compute activity durations for each period, and represent them as heat maps below the braided/stacked graph.
Since the design is in a horizontal style, the users can easily compare mobility variations over time. However, the horizontal layout cannot reflect well round-the-clock pattern of people movements, as compared to the radial layout. More importantly, the horizontal mobility component cannot be integrated well with the radial POI component in a compact manner, thus violating the *Compact* design principle.

In consideration of all these disadvantages, we refine the design to the *POI-mobility signature* as in Fig. 9(left).

E. User Interface

Besides the map view, our system consists of two visual interfaces as shown in Fig. 10:

POI category panel (Fig. 10(left)) organizes all the POI categories hierarchically. There are three category levels in total: ten categories exist in the highest level, such as “Arts & Entertainment” and “Residence”; the lowest level categories are in high details, such as the “Airport Food Court” and “Airport Gate.” Users are allowed to expand/fold parent categories, and select a particular category to explore.

POI cell panel (Fig. 10(right)) lists all the POIs under user-specified category. Each cell presents detailed information of a POI, including the POI name, primary category, address, and counts of users, check-ins and tips. Users are allowed to further specify one or multiple POIs, and their cell background colors will be changed to orange.

VI. Case Study

In this section, we demonstrate how our system can be applied in domain experts’ work with three case studies. Our system is implemented in Java, and run on an Intel Core i7 2 2.8GHz MacBook Pro with 16GB memory and an AMD Radeon R9 M370X graphics board.

A. Case Study 1: Over-Viewing Departure & Arrival Movements and POI Distribution

Our system firstly presents an overview of departure & arrival movements, and spatial distribution of POIs on the map, such that to provide domain experts a better understanding of areas of interest they would like to explore.

Fig. 6 presents a density map overview for movements in between the period 6:00−10:00 on Monday, and major POIs distribution for all POI categories. From the overview, we can easily find: 1) The density map is more pink (departure) than aqua (arrival movements); in particular, these pink hot spots are located around subway stations in Singapore. 2) Many POIs are concentrated in the south-central part, which is a major shopping, recreation and business area in Singapore.

In Fig. 11, we change the time period in between 16:00 to 20:00, and specify the POI category as “Residence.” In comparison with Fig. 6, we can find that: 1) The density map looks more aqua, showing people are going back home during this period. 2) The “Residence” POIs are located close to pink hot spots in Fig. 6, and aqua hot stops in Fig. 11. 3) There are many arrival movements in the south-central part, indicating some people would like to have a relax after work there.

B. Case Study 2: Comparing Departure and Arrival Movements Related to POIs in Different Categories

Our system can be applied to compare departure and arrival movements related to POIs in different categories (*T1* & *T2*),

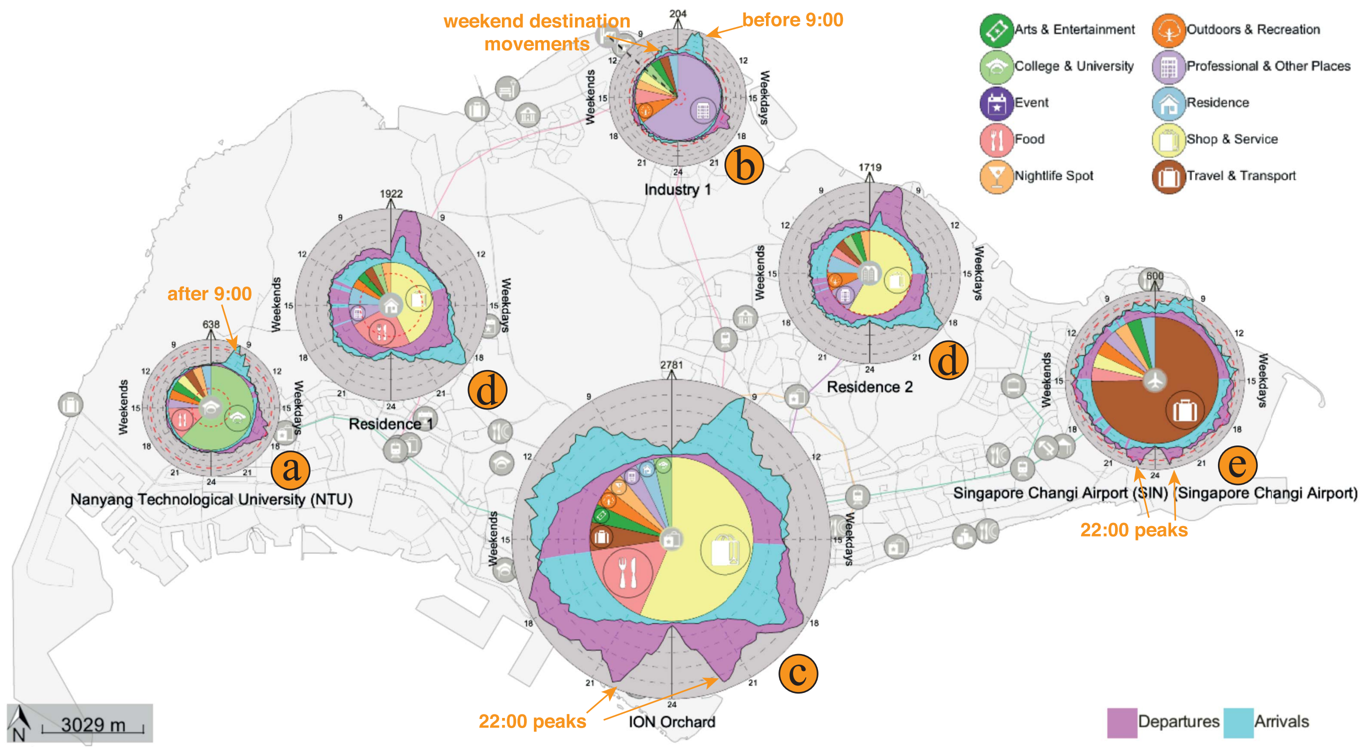


Fig. 12. Study 2: Comparing the POI-mobility relationship by exploring the *POI-mobility signatures* in different categories: a) university, b) factory, c) shopping center, d) residence, and e) airport.

by visually exploring their *POI-mobility signatures*. Notice that when users select multiple POIs for comparison, we normalize radii of their POI components based on total number of check-ins, and scale heights of their mobility components based on the departure and arrival movement volumes. We also set a minimum threshold of the radii and heights to prevent the signatures from being too small to visualize; in case this happens, we draw red dashed circles to indicate the real values when their radii are clamped by the minimum threshold (e.g., Figure 12(a), (b), (d) & (e)).

In Fig. 12, we set the time frame to be weekdays and weekends. Through exploration, we can quickly get the following observations, by comparing their *POI-mobility signatures* of POIs in the following categories:

- *University:* Fig. 12(a) shows signature of a university POI. As shown in its POI component, "College & University" category is dominating, indicating that the university is located in a remote campus without many other activities. From the mobility component, we can see that on weekdays, the university aggregates students in the morning, and distributes them in the evening, while on weekends, there are almost no movements.
- *Factory:* Fig. 12(b) shows signature of a factory, in the category of "Professional & Other Places." Similarly to the university POI, the factory POI also aggregates people movements in the morning, and distribute them in the evening on weekdays.
- *Shopping center:* Fig. 12(c) shows signature of a shopping center. The center is located at a main shopping and recreation area in Singapore, as demonstrated by the biggest "Shop & Service" POI icon in the POI component. As compared to the other signatures, we can easily see that both the radius of the POI component and the height of the mobility component are much bigger, showing a positive correlation between movements and social media usage. Besides, we can also find that the difference of departure and arrival movements between weekdays and weekends are much smaller, indicating people go there over the whole week.
- *Residence:* Fig. 12(d) shows signatures of two residential POIs. The mobility components show obvious departure movement peaks in the morning, and arrival movement peaks in the evening on weekdays. This conforms to the pendulum movement pattern describing employees leave from residential areas in the morning, and return home in the evening. In addition, the movements on weekends are nearly balanced all the day, showing residents' movement flexibility on weekends.
- *Airport:* Fig. 12(e) shows signature of Singapore Changi airport. The radius of the POI component is quite big, while the mobility component height is very small, showing that people prefer to check-in the airport on social media. The departure and arrival movements do not vary much over weekdays and weekends, showing quite a uniformly distributed flight schedules at the airport.

With deeper investigation, we can notice more details:

- *Difference between university and factory*: By comparing the signatures of the university and factory, i.e., Fig. 12(a) & (b), we can find: First, on weekdays, employee movements to the factory are more concentrated, i.e., most

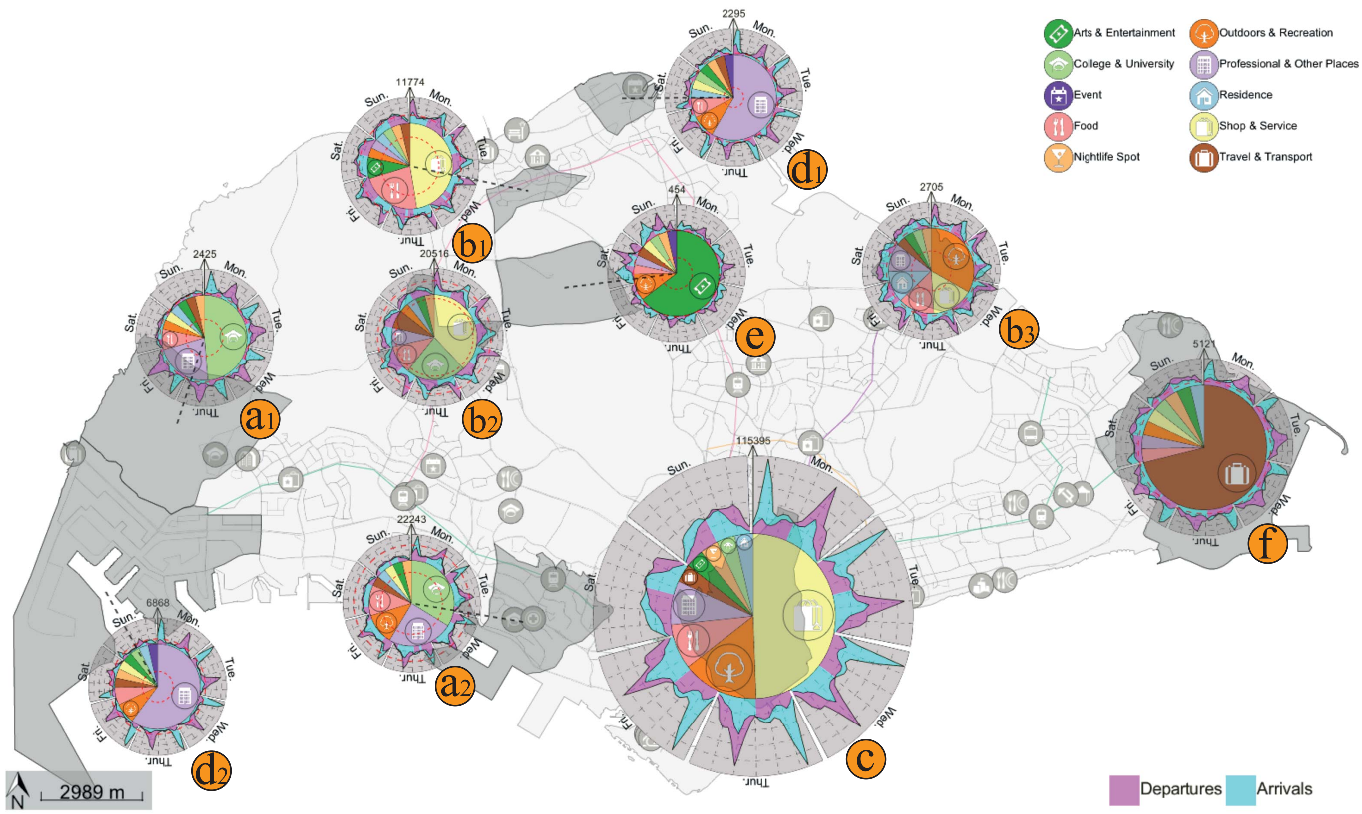


Fig. 13. Study 3: Exploring the relationship between human mobility and POIs in different areas of interest: (a) university, (b) residence, (c) shopping & recreation, (d) industry, (e) recreation and (f) airport.

movements arrive the factory before 9:00, and depart the factory at around 18:00; while for the university, many movements arrive after 9:00, and depart before 18:00. Second, on weekends, there are still a few movements go to the factory, which is not observed in the university signature. These differences can be a significant indicator to classify factories and universities.

- *22:00 peaks at shopping center and airport:* In Fig. 12(c) & (e), we can notice around 22:00 peaks of departure movements. This shows that public transportation has a great influence on human mobility. Since the services are terminated at mid-night in Singapore, people need to go back home before that. Specifically, for the airport, we suspect that these peaks exist because many people send-off their families and friends with flights after midnight, and they need to return before mid-night.
- *Activity context of residential areas:* In Fig. 12(d), we can see "Residence" category does not contribute much in all three POI components; while in the other four signatures, we can find a dominating POI category occupying over 60%. The POI components in Fig. 12(d) are quite diverse, indicating multiple activities exist at these areas. Nonetheless, with careful examination, we can find that POI categories of "Shop & Service," "Food," and "Outdoors & Recreation" occupy a big portion summing up to over 70%. The results show: 1) people are not willing to check-in their residences on social media, and 2) residential areas are strongly related to "Shop & Service," "Food," and "Outdoors & Recreation" activities.

C. Case Study 3: Exploring the Relationship Between Human Mobility and POIs in Different Areas of Interest

Study 1 shows that our system can provide an overview of areas of interest (AOIs), and study 2 shows the correlation between people movements and POIs in different categories. In this study, we show how our system can be applied to analyze the relationship between human mobility and POIs at different AOIs. Here, we select multiple administrative zones and compare their *POI-mobility signatures* as in Fig. 13.

- *University areas:* (a1) & (a2) show the signatures of two AOIs where two top universities in Singapore are located. Though the movements are very similar, we can find that the POI component in Fig. 13(a1) is more concentrated, showing the campus is located at a more remote area.
- *Residential areas:* (b1), (b2) & (b3) show the signatures of three AOIs in residence areas. The signatures are typical residential signatures, except that the activity context in (b3) are more diverse. This may be due to the reason that the area in (b3) is a new residential town in Singapore, where the government aims to build new towns with mixed functionalities, as compared to the old towns shown in (b1) & (b2).
- *Shopping & recreational area:* (c) is a main shopping & recreation area in Singapore.
- *Industrial areas:* (d1) & (d2) are two industrial areas, as both POI components showing "Professional & Other Places" category is dominating. We can see that both areas are located at outlining areas in Singapore.

- *Entertainment area:* (e) shows the signature where Singapore zoos are located. As compared to other signatures, we can clearly observe that the area attracts more movements on weekends than on weekdays.
- *Airport area:* (f) shows the signature of the area where Singapore Changi airport is located.

VII. Experts Interview

We conducted expert interviews with three independent transportation experts who are specialized in public transportation: one of them has 15+ years of experience in academic (denoted as SR), and the other two are focusing on analyzing human mobility (denoted as $R1$ and $R2$). In this work, we had continuous discussions with the researchers and kept on refining our visual designs based on their feedbacks. In fact, the idea of visually exploring the relationship between human mobility and POIs was inspired by $R1$.

In the interviews, we started with the explanation of our visual encodings and interface design, and demonstrated to them how our system works. Then, we allowed them to explore the system by themselves for about ten minutes. In the end, we also showed them the three case studies, and asked for their feedbacks on these questions:

- Q1: Is the map overview intuitive for presenting the movement densities and POI distribution?
- Q2: Are the interactions enough to support specification of AOIs on demand?
- Q3: Is the signature easy to understand? Does the signature support well the analytical tasks *T1 - T3*?
- Q4: Are the comparisons of signatures related to different POI categories and AOIs meaningful? Any insights gained from the case studies?
- Q5: What are the limitations of the system? Any suggestions to improve it?

In general, all experts thought that the way we incorporate human mobility analysis with social media data was a promising direction, and it can provide new insights that cannot be discovered by analyzing movement data only. Their detailed feedbacks are summarized below:

A. Interactive Visual Design

The experts agreed that the workflow of presenting an map overview first, and then allowing them to specify AOIs is helpful. For the bivariate density map, the experts thought it is an effective way to present movements density, though they were not familiar with it. "At a glimpse of the overview (Fig. 11), I know the south-central area is important," commented by $R2$. SR commented that it is "a bit hard for me to recognize the color" when both the departure and arrival layers are enabled, but "the situation gets better when exploring one layer at a time." The experts also agreed that AOI specification through POIs, administrative zones and lasso/rectangle tools are enough for their analysis.

All experts thought the signature is visually appealing and intuitive to understand. They agreed that the signature is well designed to effectively reveal the relationship. In particular, SR believed that "any separation of the components would result in incomplete understanding of the relationship." All experts appreciated the options to switch between the three visual forms of mobility information, as "all these information are useful." Although they were not familiar with the braided graph, the experts agreed on that it outperforms the other designs like simple graphs in presenting the differences between departure and arrival movements. Specifically, it is more visually appealing than the most frequently used simple graphs in transportation, as the changing points are more easily recognizable in braided graph. Besides, the experts also thought that summarizing and arranging the related activity context in a pie chart is a good choice, although SR pointed out that overlapping may occur when nearby AOIs are selected.

B. Case Studies

Though most of the findings revealed in the case studies are expected by the experts, they still preferred an interactive visual interface to prove their hypothesis. SR mentioned that "it is not easy for an analyst like me who are familiar with Singapore to gain new knowledge about the public transportation data, but it is good to know we should be more careful when analyzing social media data." Besides, some insights like the movement peaks at around 22:00, and mixed usage town as shown in Fig. 13(b3) are "more easily recognizable with the signatures," commented by $R1$.

C. Limitations and Improvements

The limitations of our system mainly exist in the following aspects. First, to depict the spatial information, we present signatures on the map. Since each signature occupies certain space, we can only present certain number of signatures, limited at about ten from our experiments. Second, our results can be biased by incomplete and inaccurate input data. For instance, the experts pointed out that we explore human mobility using only public transportation data, which does not cover movements though other travel modes, such as taxi and private vehicles. Besides, social media users do not cover the whole population, especially elderly people.

The experts have also given fruitful suggestions, mainly in the following two aspects. First, they suggested to validate the gravity model for measuring the relationship between movements and POIs. Although the POI check-in counts and distance are important factors, "people's activity preferences are much more comprehensive," as commented by SR. $R1$ also added, "more studies should be carried out to study how passengers are moving between buildings and bus stops." Second, they also suggested to add in more interactive features into our system. For instance, both SR & $R1$ suggested to add a time slider allowing users to interactively specify nearby distance threshold, which is currently fixed at ten-minutes walking distance with five km/h speed.

VIII. Discussion

The case studies prove that human mobility are highly related to POIs. This information can be very useful for urban planning and traffic management. For instance, Study 2 confirms that employee movements are pendulum between residential and business regions. In this sense, to reduce the travel demands caused by employee movements, urban designers would promote the design of new towns with evenly distributed residential and business functionalities, such as the one shown in Fig. 13(b3).

Meanwhile, the studies show some exceptional examples that have not been explored before, such as the differences between human movements related to factories and universities in Study 2. The experts appreciated that these insignificant details may not be observed without our visually appealing signature. The studies also imply that people do have a preference when using social media. For instance, Fig. 12(e) (airport) shows that people are more willing to post when they are traveling, while Fig. 12(d) (residence) indicate that people barely post for residence.

Our analysis can be potentially extended to further explore the relationship on POIs for movements of different groups of people, e.g., students, adults and elderly. This will increase the multi-series dimensions and bring more challenges for our visual design, but it will also bring in more applicability potential for our approach. For instance, by filtering and analyzing the elderly movements, we may figure out what POIs are more attractive to them. The result can contribute to the design of livable towns for the elderly, which is very important for aging societies like Singapore.

A. Future Works

There are several promising directions for future work. First, we would like to apply some clustering method, such as self-organizing maps to extract some general signatures for different POI categories. Second, we will implement more user interactions as suggested by the experts. Moreover, as the social media usage is highly dependent on users' preferences, we plan to generate a more precise activity context by further integrating land-use data. After this, we would like to develop a more robust POI-mobility model that can comprehensively characterize the relationship between movements and POIs. Lastly, we would like to explore the origins and destinations of movements related to an area of interest. To achieve this, we plan to integrate the contour-based treemap view [39] in our signature, such that we can further know more information about human movements, such as directions and distances.

IX. CONCLUSION

In this paper, we present a new visual representation, i.e., *POI-mobility signature*, for examining the relationship between human mobility and POIs. We show that it is a nontrivial and challenging design problem to achieve a compact visual signature that can present both the spatial and temporal information. We address this challenge by seamlessly incorporating a pie chart with a radial style time series visualization. In the end, we evaluate the design with three case studies using Singapore massive public transportation data and POIs retrieved from Foursquare. The studies demonstrate that people movements are highly related to POIs, and some other interesting findings have also been obtained. We also discuss the factors that may affect our results, such as the distance decay function used in modeling the relationship, and people's usage preferences of social media. Deeper investigation on these factors should be carried out, and advanced visual analytics systems can be developed to facilitate the analysis process.

ACKNOWLEDGMENTS

The authors thank the anonymous reviewers for their constructive comments. The research was conducted at the Future Cities Laboratory at the Singapore-ETH Centre, which was established collaboratively between ETH Zurich and Singapore's National Research Foundation (FI 370074016) under its Campus for Research Excellence and Technological Enterprise programme.

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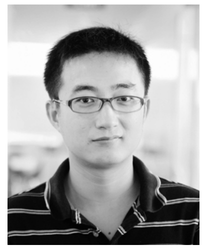

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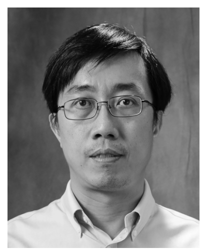

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