Combining Physical and Participatory Sensing in Urban Mobility Networks

Xiao-Feng Xie [a,c], Zun-Jing Wang [b,c]

[a] The Robotics Institute, Carnegie Mellon University, Pittsburgh, PA

[b] Department of Physics, Carnegie Mellon University, Pittsburgh, PA

[c] WIOMAX LLC, Pittsburgh, PA

xie@wiomax.com, wang@wiomax.com

Abstract

It is very important to understand human mobility and activity patterns in urban environments. In smart traffic control systems, abundant traffic flow data could be collected over time by physical sensing. However, each controlled region only covers a small area, and there is no user information in the data. The rapid rise of location-based services provides another opportunity to achieve the information of human mobility, in the form of participatory sensing, where users can share their digital footprints (i.e., checkins) at different geo-locations (i.e., venues) with timestamps. These checkins provide a broad citywide coverage, but the instant number of checkins in urban areas is still limited. In this study, we focus on exploring the potentials of combining physical and participatory sensing data in urban mobility networks, based on 3.4 million checkins collected in the Pittsburgh metropolitan area, and 125 million vehicle records collected in a sub-area controlled by the SURTRAC adaptive traffic control system. First we display the spacial and temporal characteristics of the sensing data. Next, we perform user checkin statistics to reveal the distribution of user behaviors, and study entropy and regularity by cluster analysis to show a strong time-dependent predictability in human mobility patterns. Finally, we illustrate some potential usages of the sensing data in urban mobility applications, e.g., finding reasons in anomaly traffic detection, disclosing nontrivial traffic-related information in topic-specific checkins, and providing traffic origin and destination patterns based on transitions between user checkins. This work provides some essential supports for improving urban mobility.

Index terms— Participatory Sensing, Human Mobility, Urban Mobility, Traffic

1 Introduction

Understanding human mobility and activity patterns in urban environments is a significant and fundamental issue from various perspectives (Brockmann, Hufnagel, & Geisel, 2006; Simini, González, Maritan, & Barabási, 2012; Song, Koren, Wang, & Barabási, 2010; Gonzalez, Hidalgo, & Barabasi, 2008; Han, Hao, Wang, & Zhou, 2011), e.g., understanding regional socio-economics, improving traffic planning, providing local-based services, and promoting sustainable urban mobility. Traditionally, relevant information is however rarely obtained due to difficulties and costs in tracking the time-resolved locations of individuals over time.

In recent years, an increasing attention has been placed on introducing smart traffic control systems into urban road networks (Papageorgiou, Diakaki, Dinopoulou, Kotsialos, & Wang, 2003; Xie, Smith, Lu, & Barlow, 2012). The primary objectives of such systems are to reduce travel time, resolve traffic congestion, and reduce vehicle emissions. Recent work in real-time, decentralized, schedule-driven control of traffic signals has demonstrated the strong potential of real-time adaptive signal control in urban environments (Xie, Smith, Lu, & Barlow, 2012; Xie, Smith, & Barlow, 2012). The system, called SURTRAC (Scalable URban TRAffic Control), achieved improvements of over 26% reductions in travel times, over 40% reductions in idle time, and a projected reduction in emissions of over 21%, in an initial urban deployment (Xie, Smith, & Barlow, 2014). To facilitate effective real-time control, vehicle flows are monitored by different physical sensors, e.g., induction loops and video detectors, and pedestrian flows might be detected and inferred using push-buttons or other devices. Traffic flow data in fine granularity can be logged in real time, but usage of these physical sensing data is often limited to the region that is being controlled. For the broad uncontrolled regions instead, no information is available.

The rise of location-based services provides another way to achieve the information of human mobility, in the form of participatory sensing (Burke et al., 2006; Silva, Vaz de Melo, Almeida, & Loureiro, 2013; Doran, Gokhale, & Konduri, 2014). With mobile devices, *users* can share their digital footprints at various geo-locations (i.e., *venues*) with timestamps through *checkins*, e.g., geo-enabled tweets and geo-tagged photos and videos. Using of these services grows fast worldwide, although the instant sampling rate of trajectories is still very limited, and some web-based services, e.g., Waze and Facebook, do not open their location-based data to public. Different work has been conducted to understand temporal, spatial, social patterns, and some combined patterns of human mobility (Ferrari, Rosi, Mamei, & Zambonelli, 2011; Chiang, Lin, Peng, & Yu, 2013; Wang, Pedreschi, Song, Giannotti, & Barabasi, 2011; Z. Cheng, Caverlee, Lee, & Sui, 2011; Gao, Tang, Hu, & Liu, 2013; Arase, Xie, Hara, & Nishio, 2010; Cranshaw, Schwartz, Hong, & Sadeh, 2012; Noulas, Scellato,

Mascolo, & Pontil, 2011; Schneider, Belik, Couronné, Smoreda, & González, 2013).

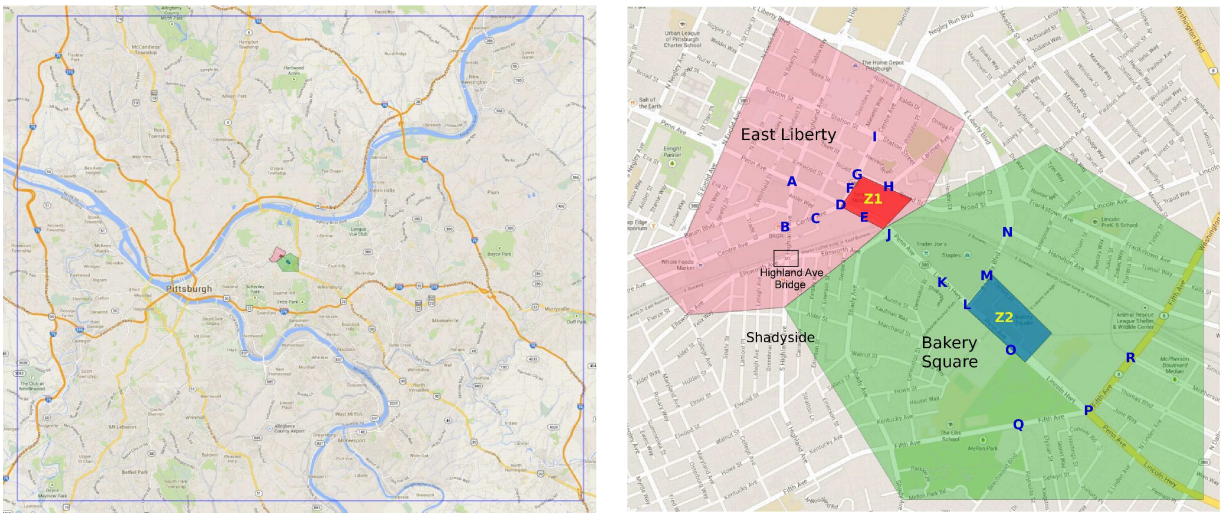
In this study, we focus on exploring the potentials of combining physical and participatory sensing data in urban mobility networks. The participatory sensing data are collected in the Pittsburgh metropolitan area with the APIs provided by the location-based services including Twitter, Foursquare, Flickr, Picasa, and Panoramio. The physical traffic flow data are collected in an area controlled by the SURTRAC adaptive traffic control system.

We first display the basic spatial and temporal characteristics of the physical and participatory sensing data. Afterward, we study human mobility patterns. User checkins are examined to disclose the distribution of user behaviors, which is a fundamental statistical properties of mobility pattern. geo-location based cluster analysis is performed to identify personal favorite *places* of users in the studied regions. User entropy is measured to reveal the degree of predictability of user activities. Time-dependent mobility patterns are analyzed to show the regularity of user behaviors, based on most visited places of users.

Finally we presented results of combining physical and participatory sensing data in urban mobility applications. We evaluate the attraction and limit in using sensing data on anomaly detection and reasoning for the time series of traffic flow. We examine if nontrivial information could be extracted from participatory sensing data to effectively recognize traffic congestion in temporal and spacial dimensions. We then choose two zones in the controlled region to check closely on the correlation between physical and participatory sensing patterns. For the two zones, we also investigate the origin and destination (O-D) patterns from the *transitions* between user checkins, which are valuable for urban mobility.

2 Data Description

We implement our study in the Pittsburgh metropolitan area. The participatory sensing data contain a list of checkins. Each checkin can be represented as a tuple <*userID*, *venueID*, *time*, [*comment*]>, where *userID* is associated with a unique user, *venueID* is associated with a venue at the geo-location of (*latitude*, *longitude*) with the precision of six decimal places. Our checkin data were collected (between March and July of 2014) from the geo-APIs of some location-sharing services, including geo-enabled tweets from Twitter and geo-tagged photos from Flickr, Picasa and Panorami. We also included existing checkin data directly crawled from Foursquare (Long, Jin, & Joshi, 2012). For studying urban mobility patterns, we only consider checkins at venues in the spacial latitude/longitude bounding box of (40.309640, -80.135014, 40.608740, -79.676678), as shown in Figure 1a. For studying up-to-date patterns, we only consider the recent data within the range of dates [1/1/2012, 7/1/2014]. The collected data contains 3,399,376 checkins of 74,658 users at 2,198,572 venues.



(a) Participatory Sensing Region (b) Region Controlled by SURTRAC

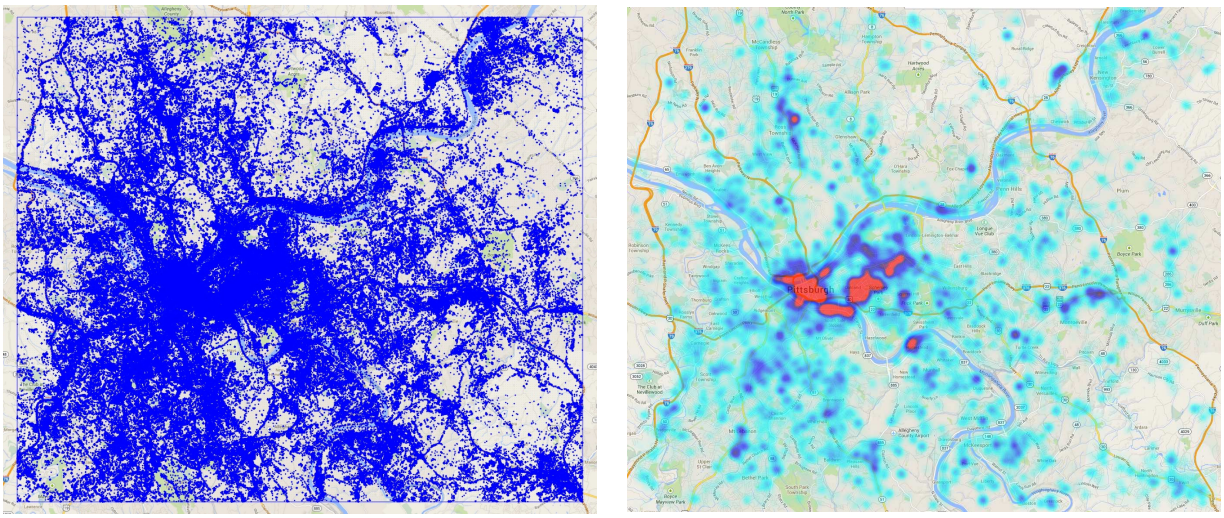
Figure 1: Participatory and Physical Sensing Regions in Pittsburgh, PA.

The physical traffic flow data are collected in a road network which is currently controlled by an adaptive traffic control system called SURTRAC (Xie, Smith, Lu, & Barlow, 2012; Xie, Smith, & Barlow, 2012, 2014) (see Figure 1a, and for more details see Figure 1b). The system was first installed on nine intersections (**A** to **I**) in the East Liberty neighborhood since June, 2012, and then expanded to nine more intersections (**J** to **R**) in the Bakery Square neighborhood since October, 2013. The total area include five major streets, Penn Ave, Centre Ave, Highland Ave, East Liberty Blvd, and Fifth Ave, with dynamic traffic flows throughout the day. For collecting real-time flow data, detectors were deployed on each entry/exit lane at the near end of each intersection and on entry lanes at the far end of boundary intersections. For each detector, a *vehicle record* is generated at the time when a vehicle is detected to pass the detector. Compared to that in a checkin, there is no userID and comment information available in a vehicle record. In total, the traffic flow data contains 125,369,318 vehicle records generated at 126 stop-bar detectors by the end of 7/1/2014.

3 Basic Spacial and Temporal Characteristics

3.1 Spatial Distribution of Checkins

We first investigate the spatial distribution of all checkins in the whole region. Figure 2a is the geo-distribution of checkins. It shows a highly non-uniform dynamics of human mobility in the urban area. A few high-density regions (red colored) are shown in the heat map (see Figure 2b), one of which overlaps with the controlled region in Figure 1b.



(a) Checkin Locations (b) Heat Map of Checkins

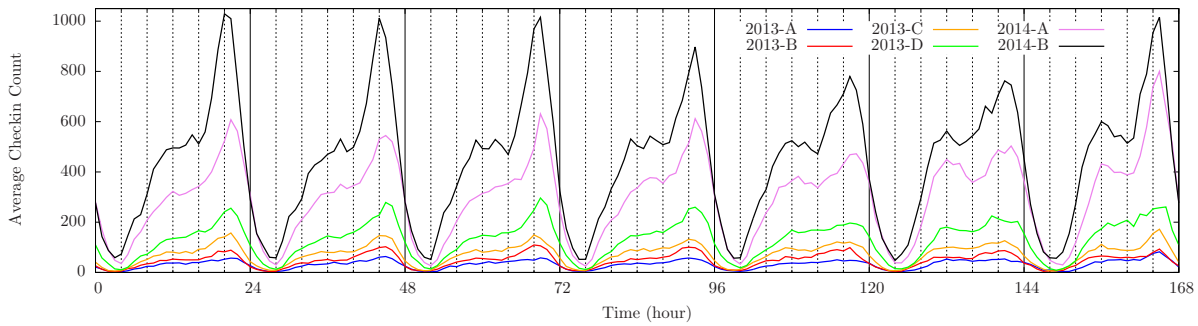
Figure 2: Distribution of Checkins in the Participatory Sensing Region.

3.2 Temporal Patterns

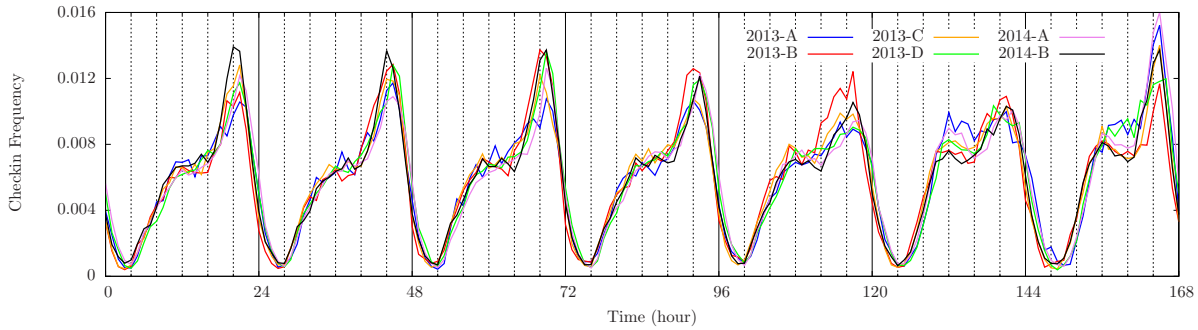
We are interested in the recurrent nature of human mobility over time. To investigate temporal mobility patterns, each week is segmented into $24 \times 7 = 168$ hourly bins (starting from Monday). For obtaining seasonal average results, each year is divided into four seasons (A to D), and the binned results are averaged over 13 weeks in each season. We considered all four seasons in 2013 and the first two seasons in 2014.

Figure 3a gives the seasonal average checkin patterns in the participatory sensing region. It shows that the number of checkins has increased significantly over the seasons. Figure 3b shows the average checkin frequency normalized by the total checkin size in each season. It shows that the checkin frequency has similar patterns for different seasons. The "social day" (Silva et al., 2013; Noulas et al., 2011) of Pittsburgh starts at around 4AM, and the checkin frequency peaks at around 8-9PM. It also shows high checkin activity during Sunday.

For vehicle flow in the controlled region (Figure 1b), we considered two pivotal intersections, i.e., intersection **D** of Centre Ave and Penn Ave in East Liberty and intersection **P** of Fifth Ave and Penn Ave in Bakery Square, which service for most vehicles in this road network. The seasonal average vehicle flow patterns are shown in Figures 4a and 4b, respectively. For intersection **P**, the vehicle flow data is only available for the two seasons in 2014. During weekdays, the traffic flow has three peaks in the morning (8AM), middle day(12PM), and afternoon (5PM). During weekends, the traffic pattern presents a smoother change that peaks at around 1PM. The flow in weekdays is heavier than that in weekends.



(a) Checkin Counts



(b) Checkin Frequency

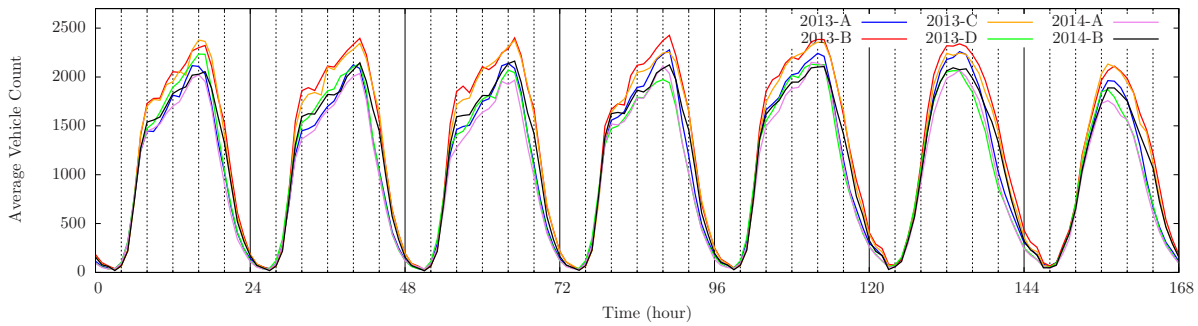
Figure 3: Seasonal Average Checkin Patterns in the Participatory Sensing Region.

4 Human Mobility Patterns

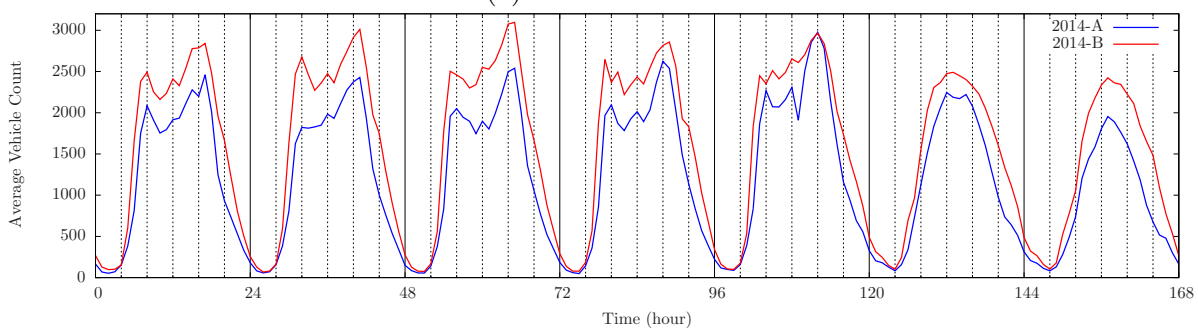
In this section, we evaluate human mobility characteristics based on user activities.

4.1 User Checkin Statistics

Figure 5 presents some basic user checkin statistics in the participatory sensing region. Let N_i be the number of checkins for user i, it turns out that the probability distribution follows a scaling law (see Figure 5a). We then consider the distribution of the radius of gyration (r_g) for each user. For user i, let V_i^j be the venue of the jth checkin, then $r_g^i = \sqrt{\frac{1}{N_i}\sum_{j=1}^{N_i}(dist(V_i^j, V_c^i))^2}$, where the $dist$ function gives the distance between a checkin V_i^j and the center of mass V_c^i for the checkins of user i. As shown in Figure 5b, most user activities are confined to a limited neighborhood within 10 km, which is similar to the findings in the ref. (Gonzalez et al., 2008). Figures 5c and 5d show the distributions in the time and distance intervals between consecutive checkins made by users, respectively. The probability of inter-checkin times decreases with the increase in time, and interestingly, it has apparent daily and weekly patterns. The distribution of inter-checkin distances is quite similar to the distribution of r_g in Figure 5b.



(a) Intersection **D**



(b) Intersection **P**

Figure 4: Seasonal Average Vehicle Flow Patterns for The Two Intersections in Figure 1b.

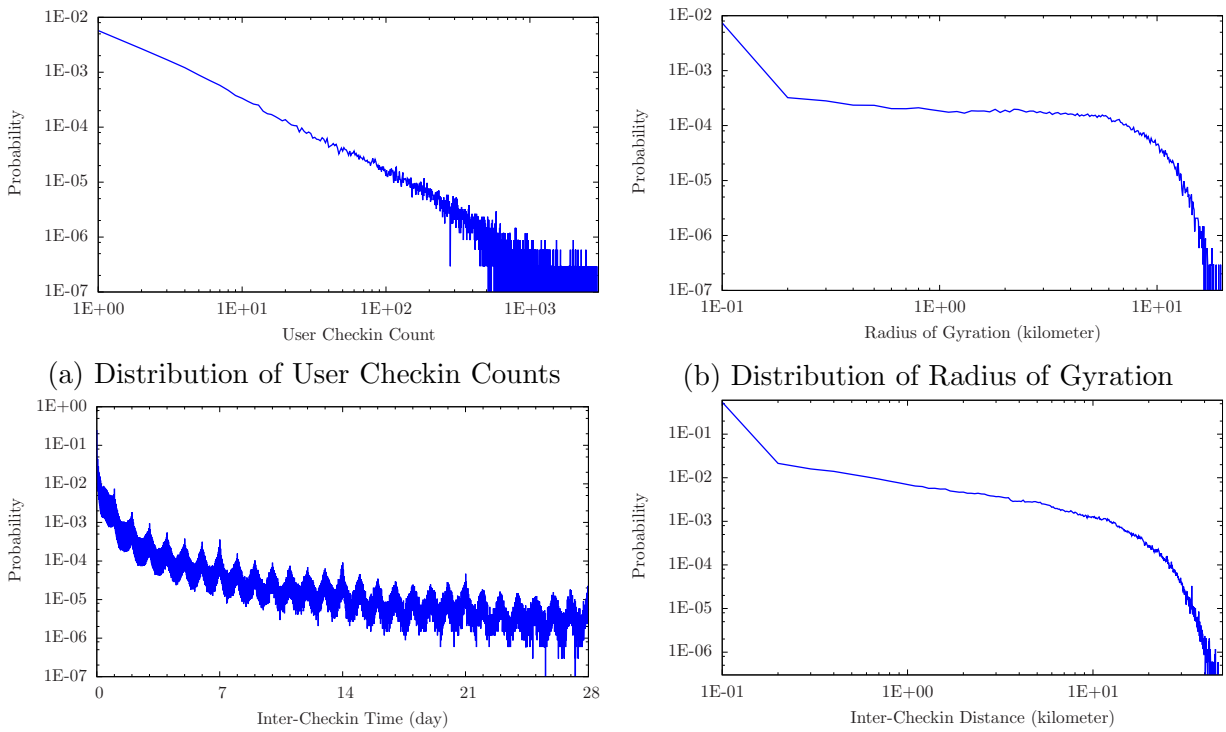
4.2 Finding Checkin Places

Each user tend to stay in a limited number of *places*, where each of places is defined to accommodate similar checkins/activities of the user in its vicinity (C. Cheng, Yang, King, & Lyu, 2012; Gao et al., 2013; Song, Qu, Blumm, & Barabási, 2010). This definition of *places* is able to tolerate some geo-location tracking errors. Notice that the existing tracking techniques (e.g., GPS, WiFi, and mobile tower) might have the location inaccuracy as high as several hundred meters (Jiang, Ferreira Jr, & Gonzalez, 2012; Song, Qu, et al., 2010).

For our collected data, we identify the checkin places by clustering, where each cluster C defines the place of a set of checkins. We use an unsupervised clustering method, DBSCAN (Ester, Kriegel, Sander, & Xu, 1996), which is a density-based clustering algorithm that requires only two parameters, i.e., *eps* to define a neighborhood threshold and *minPts* to define a density threshold. By default, *eps* =250 meters and *minPts* =2 points were used.

4.3 User Entropy

User entropy is a fundamental quantity to capture the degree of predictability for a user (Song, Qu, et al., 2010). For user i, let C_i^k be the kth cluster, and K be the number of clusters. After the clustering, the temporal-uncorrelated user entropy S_i is defined as $S_i =$



(a) Distribution of User Checkin Counts

(b) Distribution of Radius of Gyration

(c) Distribution of Inter-Checkin Times

(d) Distribution of Inter-Checkin Distances

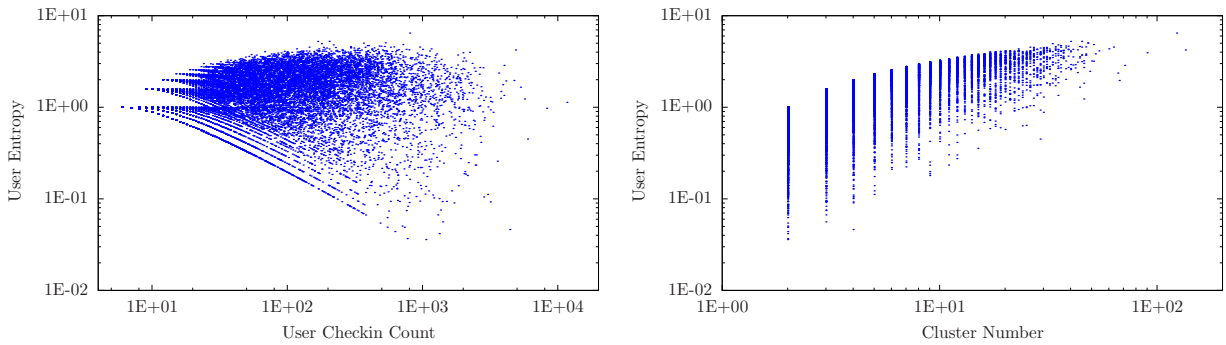
Figure 5: Basic User Checkin Statistics in the Participatory Sensing Region.

$-\sum_{k=1}^{K} p_i(k) \log_2 p_i(k)$, where $p_i(k) = |C_i^k| / \sum_{k=1}^{K} |C_i^k|$ is the probability that cluster k was visited by user i. A lower user entropy means a higher degree of predictability for visitation Patterns. Figures 6a and 6b respectively show the user entropy versus the checkin numbers (N) and the cluster numbers (K). The users in a single cluster is not shown in the log-scale figures since their user entropy are zero. As shown in Figures 6a and 6b, a larger number of checkins might lead to a lower user entropy, while a larger cluster number often leads to a higher user entropy.

4.4 Regularity

We study the mobility regularity of users by computing the probability of finding users in their primary and secondary most-visited places (ranked using $p_i(k)$) at hourly interval in a week, using DBSCAN clustering with eps ={250, 1000} meters (see Figure 7).

We first check the case for the primary most-visited places. The regularity is high during the night, and it peaks at around 4AM, the start of a "social day". In weekdays, there are minima during morning (around 8AM), middle day (1PM), and afternoon (6PM) corresponding to the transitions to other places for commuting or having lunch. In weekends, there is no local minimum during morning. This pattern indicates that the primary most-visited



(a) Checkin Counts of Users (b) Checkin Cluster Numbers of Users

Figure 6: User Entropy for Checkins in the Participatory Sensing Region.

places should contain a large portion of home places.

For the secondary most-visited places, the regularity curve peaks at around 8AM, and reaches minima during night in weekdays, but appears being quite flat in weekends. Therefore, the secondary most-visited places are likely associated with work places.

Notice that when we change *eps* from 250m to 1000m (i.e. clustering becomes more coarsed), the increase in probability for the primary most-visited places is much more than the decrease in probability for the secondary most-visited places. This means that many users perform their other activities (i.e. except for the primary and secondary activities) near their home places (primary places). During night, the probability is nearly 90% for the primary place and 10% for the secondary place.

5 Urban Mobility Applications

In this section, we explore the usage and limit of combining physical and participatory sensing data in applications of urban mobility networks by presenting a few examples.

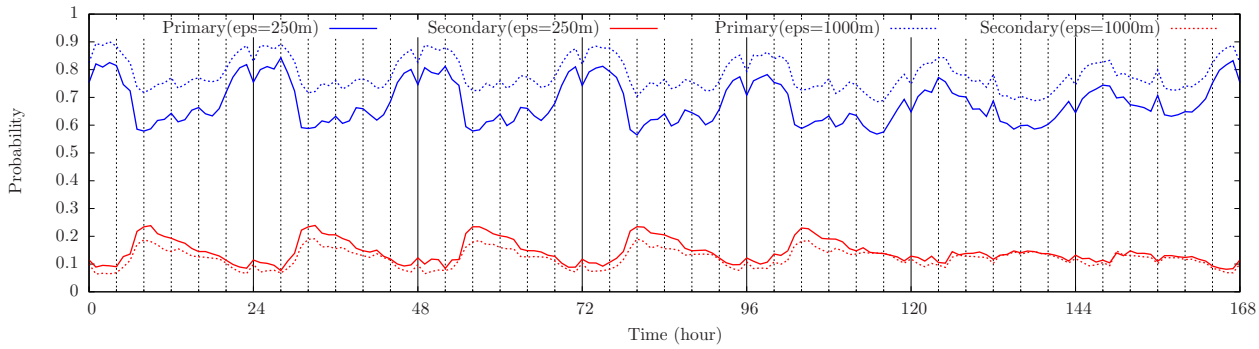


Figure 7: Mobility Regularity of Users at Primary and Secondary Most Visited Clusters.

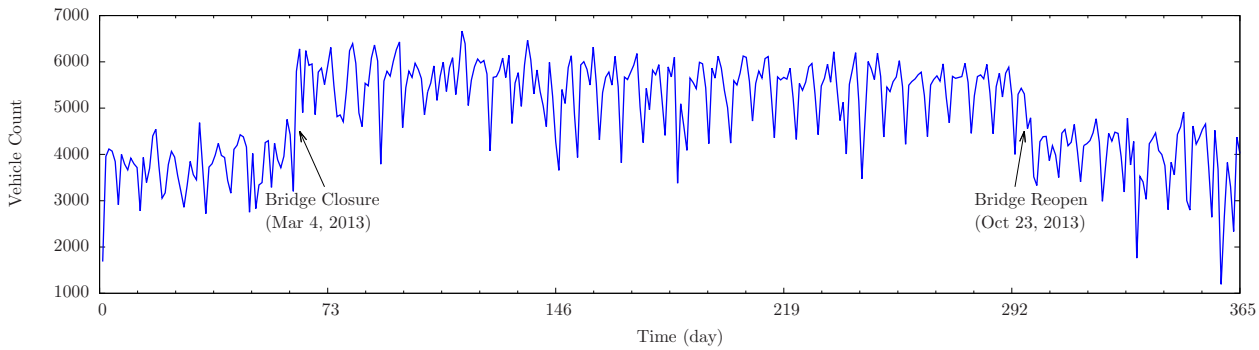


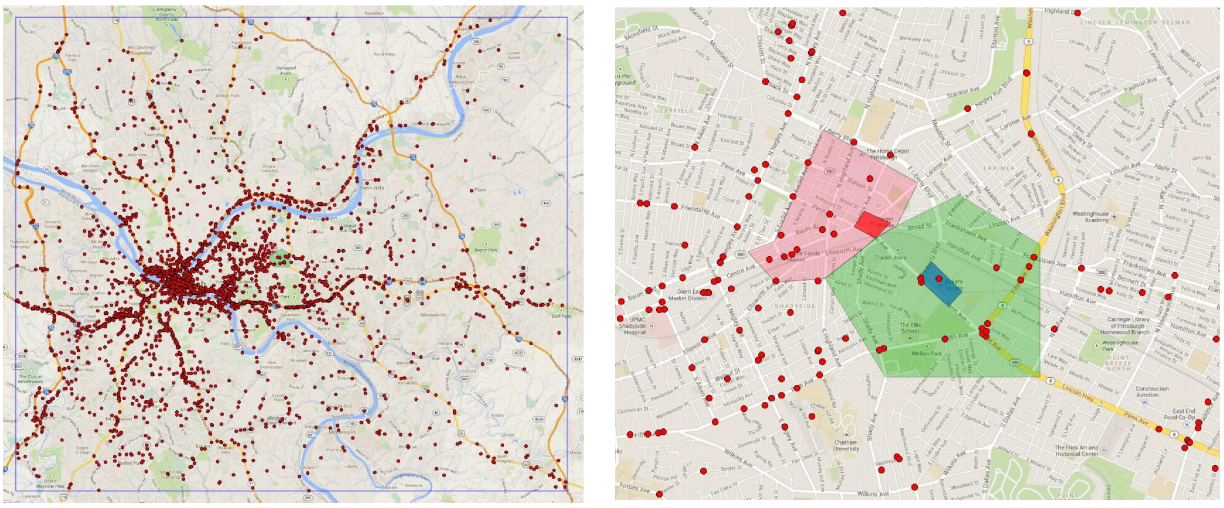
Figure 8: Vehicle Flow Pattern in Year 2013 for the Turning Movement CDE (in Fig. 1b) at Intersection **D**. (The Data in 09/01, 09/02, and 10/02 are Excluded due to Disk Full Issue.)

5.1 Anomaly Detection and Reasoning

In 2013, the bridge on South Highland Ave (location shown in 1b) was closed for replacement. This cut off the connection between Shadyside and East Liberty. Therefore a large portion of traffic (including all bus lines) on Highland Avenue was forced to pass through intersection **D**, which is a pivotal node that services for most vehicles in this road network.

Figure 8 shows the vehicle flow pattern in year 2013 for the right-turn movement at intersection **D** (see Figure 1bb, from **C** to **D** to **E**) . The flow significantly increased between early March and late October. This is a typical *change point problem* for anomaly detection in time series of traffic. Using analysis techniques of statistics (Hajji, 2005) on traffic data, we can approximately detect change points, but we are not able to find the exact time and the reason leading to the events.

Analyzing participatory sensing data is helpful at this point. A search of our geo-tagged data gives five checkins with the time of the bridge reopening ceremony. For example, at 5:47PM, October 23, a user mentioned joyfully, *Wow the bridge on South Highland is open. Life was rough for a while.* We did not find a checkin associated with the bridge closure for our collected data, which might due to the closure event happened too long time ago and the earlier data was not kept by our location-sharing services. A search of the non-geo-tagged Tweets pinpoints the time both for closure and reopening events (for which nine and fourteen tweets have been found respectively, posted by some of the users or their first-degree friends). In further studies, fusing non-geo-tagged and geo-tagged information will be very useful for anomaly detection and reasoning, especially in case the available geo-tagged checkin information is not sufficient. In fact, many users generate both non-geo-tagged and geo-tagged information in practice. In presence of a high user regularity as shown in Section 4.4 (which is a very common case), the locations of non-geo-tagged information of the users can be inferred from their geo-tagged checkins. In addition, locations can also be estimated



(a) Global View (b) Local View

Figure 9: Spatial Checkin Patterns for the "Traffic" Topic.

using content-derived information (Z. Cheng, Caverlee, & Lee, 2010).

5.2 Topic Related to Traffic

Many users generate checkins with the information of their current traffic conditions in travel. Tweet semantics has been used to build indicators for long-term traffic prediction (He, Shen, Divakaruni, Wynter, & Lawrence, 2013). By taking the search topic "traffic" as an example, we examine more potential usages of the participatory sensing checkins for obtaining important traffic information. Figures 9a and 9b show the spatial patterns of the checkins. A global view (see Figure 9a) indicates most checkins are located on major highways and congested neighborhoods. While a local view (see Figure 9a) shows most checkins are located on intersections in the urban road network. These participatory sensing information is nontrivial for marking popular route choices and for identifying congested intersections and road segments where traffic conditions should be improved significantly.

Figure 10 shows the temporal patterns of the checkins. We can clearly see that checkins mainly happened during weekdays, especially during the morning (around 8AM) and afternoon (around 5PM), reflecting the heavy traffic time during the commuting periods.

5.3 A Tale of Two Zones

Our controlled region spans some adjacent *livehoods* (Cranshaw et al., 2012) with different life activity patterns, including East Liberty and Bakery Square. Figure 11 gives two word clouds generated using the checkin comments in East Liberty and Bakery Square. Users

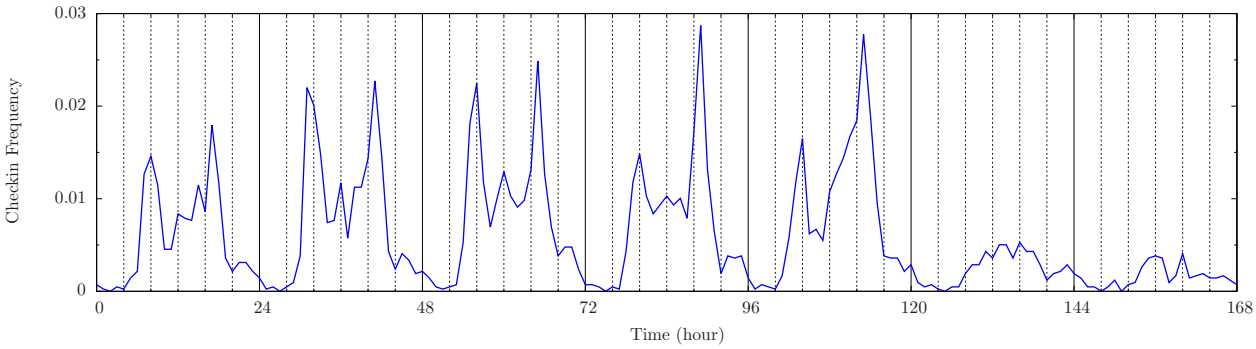


Figure 10: Temporal Checkin Patterns for the "Traffic" Topic.

(a) East Liberty

(b) Bakery Square

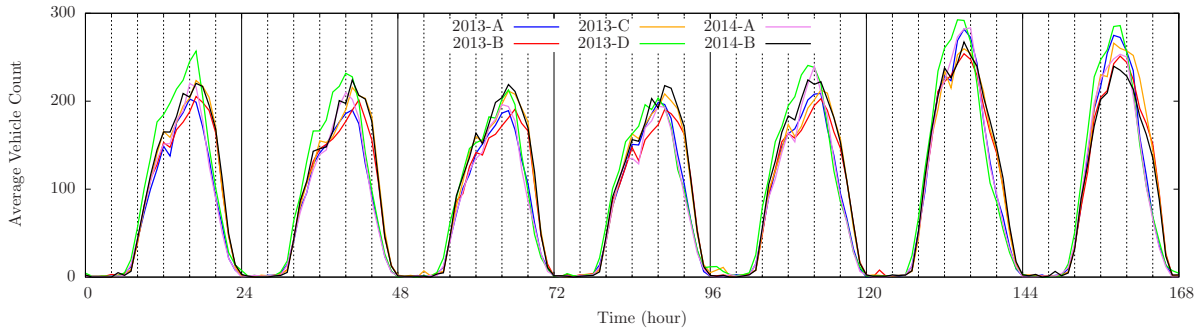
Figure 11: Word Clouds based on the Checkin Comments in East Liberty and Bakery Square.

talked about some major stores (e.g., Target and Whole Foods), and restaurants/bars (e.g., BRGR and Kelly) in East Liberty, while they mentioned some professional places (e.g., TechShop and Google) and LA fitness (LAF) in Bakery Square.

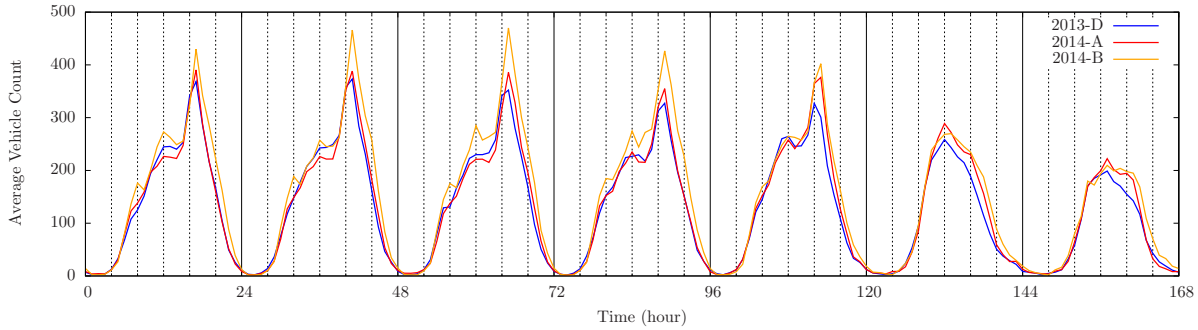
We choose two zones, **Z1** in East Liberty and **Z2** in Bakery Square as shown in Figure 1b, for a closer observation. For the two zones, accurate departure vehicle flows can be detected at the side-street exits of the intersections **F** and **H**, and of the intersections **O** and **M**, respectively.

Figure 12 shows the seasonal average vehicle flow patterns for zones **Z1** and **Z2**. In the zone **Z1**, the traffic flow in weekends is significantly higher than that in weekdays. While in the zone **Z2**, the traffic flow in weekends is significantly lower than that in weekdays. As we know, the zones **Z1** and **Z2** respectively contain a major store (Target) and a company (Google), the two figures therefore are consistent with the the common human behaviors of shopping in weekends but working in weekdays.

In the participatory sensing data, there are 2390 checkins of 1054 users in Zone **Z1**, and 5349 checkins 1260 users in Zone **Z2**. There are only 253 users appeared in both zones.

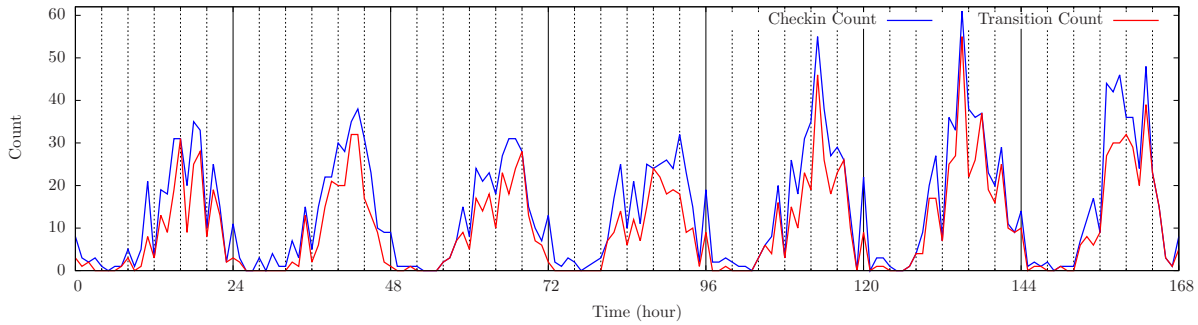


(a) Zone **Z1** in East Liberty

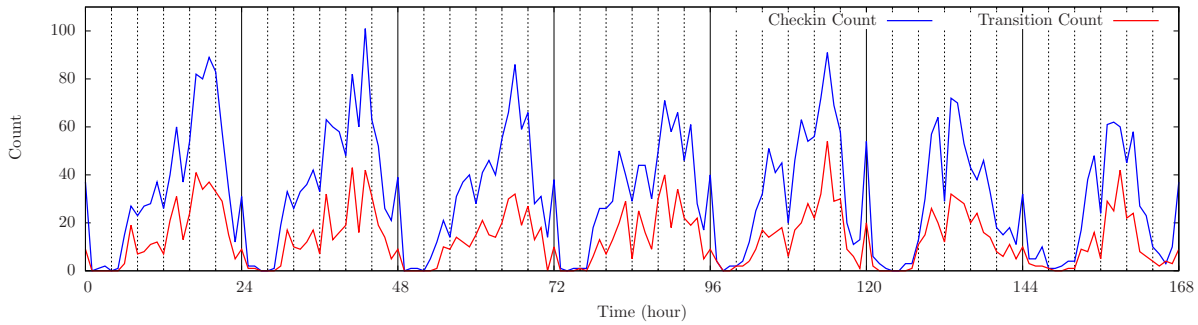


(b) Zone **Z2** in Bakery Square

Figure 12: Seasonal Average Vehicle Flow Patterns for Two Zones **Z1** and **Z2**.

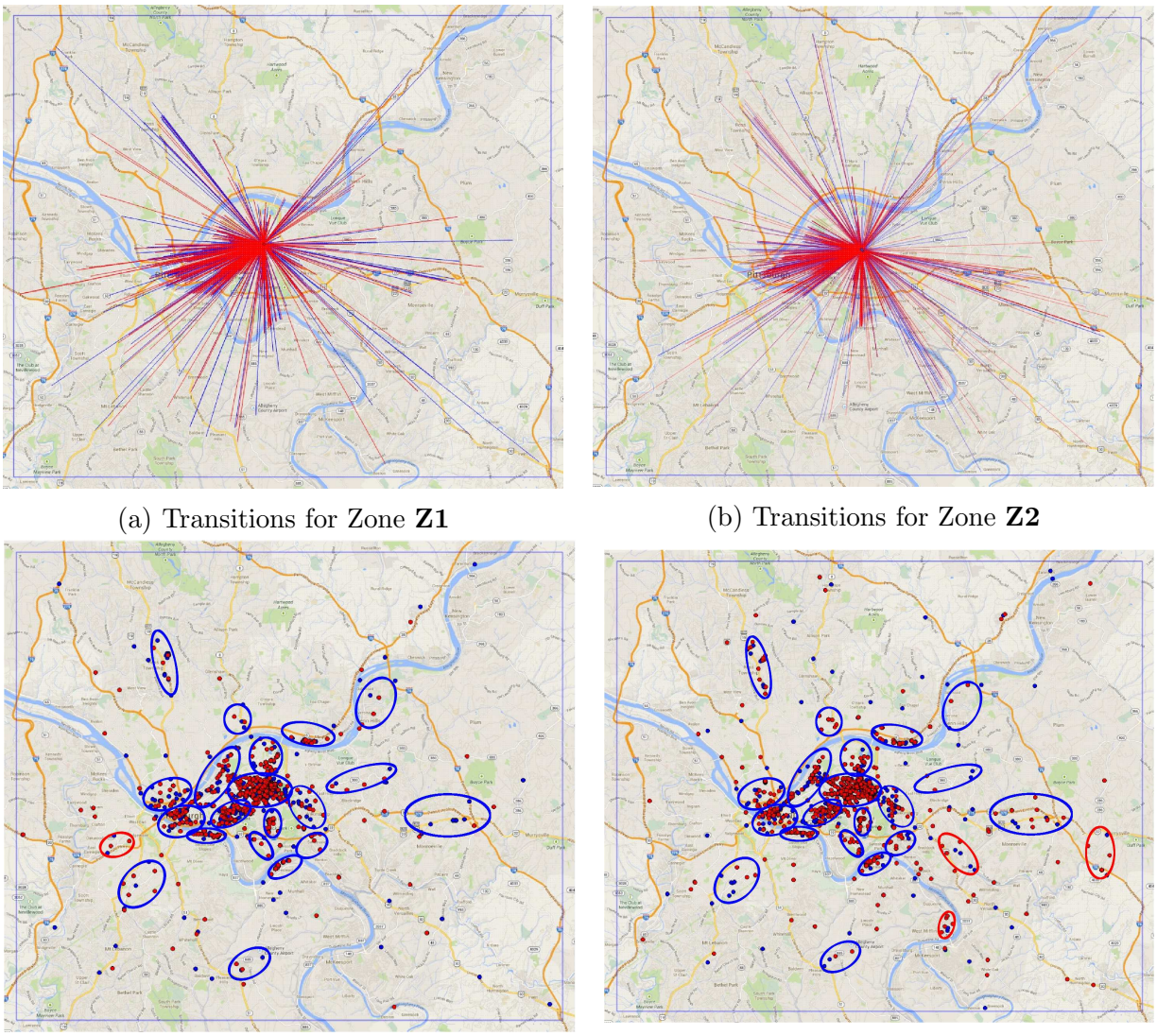


(a) Zone **Z1** in East Liberty



(b) Zone **Z2** in Bakery Square

Figure 13: Checkin and Transition Patterns for Two Zones **Z1** and **Z2**.



(a) Transitions for Zone **Z1**

(b) Transitions for Zone **Z2**

(c) Origin/Destination Checkins for Zone **Z1**

(d) Origin/Destination Checkins for Zone **Z2**

Figure 14: Users Transitions for Zones **Z1** and **Z2**.

We further find the *transitions* of users for the zones. For each zone, each user transition is defined as two consecutive checkins, one is within the zone and another is outside of the zone, made by a user in a time threshold (four hours in this paper). If the later checkin is in the zone, the transition is an *in-zone* transition, otherwise it is an *out-zone* transition. For each zone, the in-zone and out-zone transitions are more related to arrival and departure traffic. The transitions also provide origin and destination (O-D) information for each zone.

Figure 13 gives the checkin and transition patterns for the two zones. In **Z1**, most checkins have turned to be transitions, which might due to that users do not stay too long after the shopping. In **Z1**, the number of transitions is significantly lower than that of checkins, as users might stay long and send checkins in their work places. For weekdays and weekends, the

temporal checkin patterns are roughly similar to that of traffic flow patterns. The numbers of both checkins and transitions are still not large enough to support a correlation analysis in statistics with the traffic flow data shown in Figure 12. But the situation should be improved in the near future based on the rapid increasing trend as shown in Figure 3a.

Figure 14 gives the user transition information for zones **Z1** and **Z2**. The origin/destination (O-D) checkins of transitions are distributed broadly in the participatory sensing region. As shown in 14c and 14d, the O-D locations are highly clustered, and the majority of them are covered by a few clusters of sources. For the two zones, they share most of the O-D sources (clusters in blue), although they have an apparent difference in both the checkin and flow patterns. It implies that urban traffic might be mostly generated among a few clustered sources.

The O-D information might be used to further understand the traffic demands, based on some modeling frameworks, e.g., the gravity model (Yang, Jin, Wan, Li, & Ran, 2014) or the radiant model (Simini et al., 2012). Together with popular route information (Wei, Zheng, & Peng, 2012), the information beyond the traffic control region might be useful for recommending time-sensitive alternative routes (Hsieh, Li, & Lin, 2012) to help reducing traffic congestion within urban traffic control systems (Xie, Feng, Smith, & Head, 2014), especially if traffic anomaly (Pan, Demiryurek, Shahabi, & Gupta, 2013) has been quickly identified or predicted. It is also possible to provide carpooling recommendation for users based on the similarity in their O-D transition patterns.

6 Conclusions

In this study, we worked on exploring the potentials of combining physical and participatory sensing data in urban mobility networks. We first presented the basic spatial and temporal characteristics of the sensing data. Basic human mobility patterns were then extracted directly based on user checkins. For users, the entropy and time-dependent regularity were further disclosed by clustering their visitation based on geo-locations to understand the degree of predictability. Some initial results were presented for illustrating the usages of the sensing data in urban mobility applications, e.g., accurate timing and reasoning an anomaly detection, unveiling nontrivial traffic-related information in topic-specific checkins, and revealing origin and destination patterns based on transitions between user checkins. Our study might shed some lights on further studies for improving urban mobility.

Acknowledgements. This research was supported in part by the T-SET University Transportation Center at Carnegie Mellon University, and the CMU Robotics Institute.

References

Arase, Y., Xie, X., Hara, T., & Nishio, S. (2010). Mining people's trips from large scale geo-tagged photos. In *International Conference on Multimedia* (pp. 133–142).

Brockmann, D., Hufnagel, L., & Geisel, T. (2006). The scaling laws of human travel. *Nature*, *439*(7075), 462–465.

Burke, J. A., Estrin, D., Hansen, M., Parker, A., Ramanathan, N., Reddy, S., & Srivastava, M. B. (2006). Participatory sensing. In *International Workshop on World-Sensor-Web.*

Cheng, C., Yang, H., King, I., & Lyu, M. R. (2012). Fused matrix factorization with geographical and social influence in location-based social networks. In *AAAI Conference on Artificial Intelligence* (pp. 17–23).

Cheng, Z., Caverlee, J., & Lee, K. (2010). You are where you tweet: a content-based approach to geo-locating twitter users. In *ACM International Conference on Information and Knowledge Management* (pp. 759–768).

Cheng, Z., Caverlee, J., Lee, K., & Sui, D. Z. (2011). Exploring millions of footprints in lcation sharing services. In *International AAAI Conference on Weblogs and Social Media* (pp. 81–88).

Chiang, M.-F., Lin, Y.-H., Peng, W.-C., & Yu, P. S. (2013). Inferring distant-time location in low-sampling-rate trajectories. In *ACM SIGKDD international Conference on Knowledge Discovery and Data Mining* (pp. 1454–1457).

Cranshaw, J., Schwartz, R., Hong, J. I., & Sadeh, N. M. (2012). The livehoods project: Utilizing social media to understand the dynamics of a city. In *International AAAI Conference on Weblogs and Social Media* (pp. 58–65).

Doran, D., Gokhale, S. S., & Konduri, K. C. (2014). Participatory paradigms: Promises and challenges for urban transportation. In *Transportation research board annual meeting.* Washington, DC.

Ester, M., Kriegel, H.-P., Sander, J., & Xu, X. (1996). A density-based algorithm for discovering clusters in large spatial databases with noise. In *International Conference on Knowledge Discovery and Data Mining* (pp. 226–231).

Ferrari, L., Rosi, A., Mamei, M., & Zambonelli, F. (2011). Extracting urban patterns from location-based social networks. In *ACM SIGSPATIAL International Workshop on Location-Based Social Networks* (pp. 9–16).

Gao, H., Tang, J., Hu, X., & Liu, H. (2013). Modeling temporal effects of human mobile behavior on location-based social networks. In *ACM International Conference on Information and Knowledge Management* (pp. 1673–1678).

Gonzalez, M. C., Hidalgo, C. A., & Barabasi, A.-L. (2008). Understanding individual human mobility patterns. *Nature*, *453*(7196), 779–782.

Hajji, H. (2005). Statistical analysis of network traffic for adaptive faults detection. *IEEE Transactions on Neural Networks*, *16*(5), 1053–1063.

Han, X.-P., Hao, Q., Wang, B.-H., & Zhou, T. (2011). Origin of the scaling law in human mobility: Hierarchy of traffic systems. *Physical Review E*, *83*(3), 036117.

He, J., Shen, W., Divakaruni, P., Wynter, L., & Lawrence, R. (2013). Improving traffic prediction with tweet semantics. In *International Joint Conference on Artificial Intelligence* (pp. 1387–1393).

Hsieh, H.-P., Li, C.-T., & Lin, S.-D. (2012). Exploiting large-scale check-in data to recommend time-sensitive routes. In *ACM SIGKDD International Workshop on Urban Computing* (pp. 55–62).

Jiang, S., Ferreira Jr, J., & Gonzalez, M. C. (2012). Discovering urban spatial-temporal structure from human activity patterns. In *ACM SIGKDD International Workshop on Urban Computing* (pp. 95–102).

Long, X., Jin, L., & Joshi, J. (2012). Exploring trajectory-driven local geographic topics in foursquare. In *Workshop on Location-Based Social Networks* (pp. 927–934).

Noulas, A., Scellato, S., Mascolo, C., & Pontil, M. (2011). An empirical study of geographic user activity patterns in foursquare. In *International AAAI Conference on Weblogs and Social Media* (pp. 570–573).

Pan, B., Demiryurek, U., Shahabi, C., & Gupta, C. (2013). Forecasting spatiotemporal impact of traffic incidents on road networks. In *IEEE International Conference on Data Mining* (pp. 587–596).

Papageorgiou, M., Diakaki, C., Dinopoulou, V., Kotsialos, A., & Wang, Y. (2003). Review of road traffic control strategies. *Proceedings of the IEEE*, *91*, 2043–2067.

Schneider, C. M., Belik, V., Couronné, T., Smoreda, Z., & González, M. C. (2013). Unravelling daily human mobility motifs. *Journal of the Royal Society: Interface*, *10*(84), 20130246.

Silva, T. H., Vaz de Melo, P., Almeida, J. M., & Loureiro, A. A. (2013). Challenges and opportunities on the large scale study of city dynamics using participatory sensing. In *IEEE Symposium on Computers and Communications* (pp. 528–534).

Simini, F., González, M. C., Maritan, A., & Barabási, A.-L. (2012). A universal model for mobility and migration patterns. *Nature*, *484*(7392), 96–100.

Song, C., Koren, T., Wang, P., & Barabási, A.-L. (2010). Modelling the scaling properties of human mobility. *Nature Physics*, *6*(10), 818–823.

Song, C., Qu, Z., Blumm, N., & Barabási, A.-L. (2010). Limits of predictability in human mobility. *Science*, *327*(5968), 1018–1021.

Wang, D., Pedreschi, D., Song, C., Giannotti, F., & Barabasi, A.-L. (2011). Human mobility, social ties, and link prediction. In *ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1100–1108).

Wei, L.-Y., Zheng, Y., & Peng, W.-C. (2012). Constructing popular routes from uncertain trajectories. In *ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 195–203).

Xie, X.-F., Feng, Y., Smith, S., & Head, K. L. (2014). Unified route choice framework and empirical study in urban traffic control environment. In *Transportation Research Board Annual Meeting.* Washington, DC.

Xie, X.-F., Smith, S., & Barlow, G. (2012). Schedule-driven coordination for real-time traffic network control. In *International Conference on Automated Planning and Scheduling* (pp. 323–331). Sao Paulo.

Xie, X.-F., Smith, S., & Barlow, G. (2014). *Smart and Scalable Urban Signal Networks: Methods and Systems for Adaptive Traffic Signal Control* (U.S. Patent Pending, Application No. 14/308,238).

Xie, X.-F., Smith, S., Lu, L., & Barlow, G. (2012). Schedule-driven intersection control. *Transportation Research Part C*, *24*, 168-189. doi: 10.1016/j.trc.2012.03.004

Yang, F., Jin, P. J., Wan, X., Li, R., & Ran, B. (2014). Dynamic origin-destination travel demand estimation using location based social networking data. In *Transportation Research Board Annual Meeting.* Washington, DC.