Extracting Trips from Multi-Sourced Data for Mobility Pattern Analysis: An App-Based Data Example

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Abstract

Passively-generated data, such as GPS data and cellular data, bring tremendous opportunities for human mobility analysis and transportation applications. Since their primary purposes are often non-transportation related, the passively-generated data need to be processed to extract trips. Most existing trip extraction methods rely on data that are generated via a single positioning technology such as GPS or triangulation through cellular towers (thereby called single-sourced data), and methods to extract trips from data generated via multiple positioning technologies (or, multi-sourced data) are absent. And yet, multi-sourced data are now increasingly common. Generated using multiple technologies (e.g., GPS, cellular network- and WiFi-based), multi-sourced data contain high variances in their temporal and spatial properties. In this study, we propose a “Divide, Conquer and Integrate” (DCI) framework to extract trips from multi-sourced data. We evaluate the proposed framework by applying it to an app-based data, which is multi-sourced and has high variances in both location accuracy and observation interval (i.e. time interval between two consecutive observations). On a manually labeled sample of the app-based data, the framework outperforms the state-of-the-art SVM model that is designed for GPS data. The effectiveness of the framework is also illustrated by consistent mobility patterns obtained from the app-based data and an externally collected household travel survey data for the same region and the same period.

Key words:
Trip extraction methods, DCI framework, multi-sourced data, app-based data, mobility patterns.

1. Introduction

The prevalence of mobile sensors has brought passively-generated data as viable data sources for human mobility analysis (Cui et al., 2018; Huang et al., 2018; Wang et al., 2018) and transportation applications (Bachir et al., 2019). Contrast to actively solicited data such as household travel survey data, the passively-generated data are usually location- and time-stamped and are the by-product of some non-transportation related purposes (Chen et al., 2016). Among them two kinds of data are widely used: cellular data generated from cellular networks for mobile phone billing purposes (Alexander et al., 2015; Wang and Chen, 2018) and vehicular GPS data generated from the processes of, for example, freight/taxi/buses management and operation (Yang et al., 2014). Besides data that are generated from single positioning technology (e.g., cellular tower based or GPS), data are also emerging from the combined use of multiple positioning technologies, including GPS-, WiFi-, Bluetooth-, and cellular-towers-based technologies. In this paper, we define the data generated from single and multiple positioning technologies as single-sourced and multi-sourced data, respectively. Following this definition, cellular data and vehicular GPS data (shorted as GPS data hereafter) are single-sourced data. App-based
data\(^1\), on the other hand, are multi-sourced data, as they are generated from the use of various mobile phone applications (e.g., weather, shopping, dating, and navigation), each of which may use one or more positioning technologies available to position the device according to users’ settings, for example, the battery-saving mode. Passively-generated from primarily non-transportation related purposes, both single-sourced and multi-sourced data need to be processed to extract trips before they can be used for transportation applications (Chen et al., 2016).

Use of specific data processing methods depends on the specific properties associated with each type of data. Despite some similarities such as large sample size (e.g., millions of users) and broad coverage in space and time, passively-generated data can be quite different from each other due to their distinctive generation processes, which are closely related to the positioning technologies in use (as discussed above) and the events that trigger the data generation. As an example, cellular data are generated as a result of phone calling or texting activities, while GPS data are often triggered through navigation or fleet control. On the other hand, different types of events trigger app-based data, depending on what apps are used. As a result of these distinctive generation processes, the collected data can be different in terms of their temporal continuity represented by the time interval between two consecutive observations (hereafter referred to as “observation interval”) and spatial precision represented by location accuracy of observations. GPS data, when recording a trip, could be temporally continuous (with very small observation interval such as in seconds) and of high location accuracy (or low error margins such as in several meters\(^2\)), while cellular data are much more sparse in observation interval (from minutes to hours) and coarse in location accuracy (from hundreds of meters to kilometers). Multi-sourced data are characterized by large variances in both observation interval and location accuracy.

Methods have been proposed in the past to extract trips from passively generated data. However, most existing trip extraction methods rely on single-sourced data with each method designed in accordance with the unique characteristic of each data set. Trip extraction methods for multi-sourced data are absent. As multi-sourced data are becoming more popular, there is a critical need to develop trip extraction methods using such data. In this study, we propose a “Divide, Conquer and Integrate” (DCI) framework to extract trips from multi-sourced data. It consists of three steps: (1) data partition; (2) trip extraction from each partition; and (3) integrating trips that are extracted from each partition with a novel algorithm. The first step aims to partition a multi-sourced dataset into multiple data sets such that each one contains small variances in terms of temporal and spatial properties. The second step is to extract trips from each data set independently using methods that are designed according to unique characteristics of the data set. Inspired by how a geographic information system (GIS) manages and organizes data from multiple sources, the third step treats extracted trips in each data set as a layer with each trip as a feature in the layer and integrates these trips by joining layers according to the spatiotemporal relationship of their features.

To test the framework, an app-based dataset is applied. The data was collected in the Puget Sound region (in State of Washington) from April 4th, 2017 to June 5th, 2017, and contains about half a million anonymous mobile devices. We show in Section 3 that the app-based data has high variances in its spatiotemporal properties. We implement the proposed DCI framework and partition the data into two sets according to the bimodal distribution of location accuracy for observations. One is referred to as the “GPS data set” containing those observations of high location accuracy; the other is referred to as the “cellular data set” taking the remaining observations with lower location accuracy. A trace-segmentation

\(^1\) App-based data typically would be accessible from companies who provide Application Programming Interface (APIs) or Software Development Kit (SDKs) to these applications.

\(^2\) Depending on the application, a location accuracy of several meters may be considered low, e.g., for lane navigation. For the purpose of this paper which is to derive mobility patterns on where people go and stay, it is considered as high accuracy.
method is applied to extract trips from the GPS data set, while the cellular data set is processed using an incremental clustering method. At last, the designed algorithm is applied to integrating trips extracted from the two data sets. Using a manually labeled testing dataset, the framework is first compared against the state-of-the-art SVM model that is designed for GPS data. For further validation, we compare some mobility patterns (e.g., trip length) obtained from the processed app-based data with those from the Puget Sound Region household travel survey collected during the same time period (spring of 2017). We show that the trip length distribution is consistent with that obtained from survey data. In addition, even with a simple rule for inferring home locations at the census tract-level from the extracted trip information, the spatial distribution pattern of inferred tract-level homes is closely related to that of census population (2010 U.S. Census), with a correlation coefficient of 0.91. These findings suggest the effectiveness of our proposed framework.

The remaining of the paper is organized as follows. After reviewing related works in Section 2, Section 3 introduces the app-based data and the Puget Sound Regional Council (PSRC) household travel survey data used in our study. In Section 4, we describe the DCI framework, using the app-based data for the convenience of description. Through analyzing the processed data and comparing with results from the household travel survey data, we show the effectiveness of our framework. Section 5 covers this part of the work. Lastly, in Section 6, we conclude and discuss our study and point out future research directions.

2. Related works

For mobility pattern analysis, passively collected data have to be processed to extract trips. Various data processing methods have been developed for single-sourced data. The essential of extracting trips is to identify stays from the data, i.e., where an anonymous user stays for some time to conduct meaningful activities. Then a trip is extracted as a pair of consecutive stays. For GPS data, there are generally two types of methods: threshold-based and machine learning methods. Threshold-based methods, as the name suggests, scan through trajectories (one trajectory of a user refers to the user’s available observations of one day) and identify stays by setting some thresholds that are related to temporal and spatial characteristics of the data, such as spatial density, duration, speed, change of heading, etc (Hariharan and Toyama, 2004; Jiang et al., 2013). One widely used trace-segmentation method (Zheng, 2015) segments one trajectory into several sequences of consecutive observations. A stay is identified if a sequence of observations is bounded by both spatial and temporal constraints that correspond to the positioning error and the minimum time needed for meaningful activities, respectively. Threshold-based methods require thresholds to be predetermined, which are related to characteristics of the data to be processed and are subjected to analysts’ knowledge on that data.

To be robust against thresholds selection, some machine learning methods were proposed to identify stays from GPS data (Gong et al., 2015; Yang et al., 2014). Yang et al. (2014) used a Support Vector Machine (SVM) classifier to identify delivery stops (stays) of trucks from freight GPS data. They extracted three features for the SVM model: stop duration, distance between a potential stop location to the city center as well as to the closest major bottleneck (such as bridges and tunnels). They reported an identification accuracy as high as 99% for their case study. Zhou et al. (2017) used a Random Forest Method to identify traveling and non-traveling status. Then a non-traveling status indicates a stay identified. Their model was built on a set of features of GPS observations, such as the time interval to the next adjacent observation, instantaneous speed, average speed, and acceleration, etc. One challenge of applying machine learning methods to passively generated data is to obtain ground-truth data for training. The study in (Yang et al., 2014), for example, trained the SVM model using delivery logs from truck
drivers and some manually labeled training datasets from the authors; Zhou et al. (2017) trained their model using data acquired by soliciting users’ travel patterns via online surveys.

Methods for processing cellular data are usually adapted from those designed for GPS data and are mostly threshold-based. The trace-segmentation method, for example, is often modified to process cellular data, with temporal and spatial constraints adapted according to properties of cellular data (Calabrese et al., 2011a, 2013; Jiang et al., 2013). However, its first rule—requiring any two observations in a sequence of observations to satisfy a unified spatial constraint—can be too strict in processing cellular data (Wang and Chen, 2018). More specifically, the existence of outliers in a sequence of observations for one stay, which is common in cellular data due to the coarse location accuracy, could fail the identification of the stay. Wang et al. (2018) proposed a revised incremental clustering method to address the coarse location accuracy of cellular data by utilizing the longitudinal nature of the data. It first clusters those observations close in space without considering the temporal information and then comes back to individual trajectories to identify visits at each cluster. Then a visit with a duration exceeding a given time threshold (e.g., five minutes) is identified as a stay. The method is shown to be robust to outliers presented in observations and is able to identify common stays visited on multiple days, which is useful for individual mobility analysis. The authors also proposed to determine thresholds used in the method via sensitivity analysis, which could be computationally expensive when handling massive data.

3. The data sets

3.1. The app-based data

As mentioned earlier, we use an app-based dataset including about half a million anonymous users who opted in to share location data in the Puget Sound region (consisting of four counties in Washington State, US) from April 4th, 2017 to June 5th, 2017 (Figure 1). Observations in the app-based data were recorded passively when anonymous users were using mobile phone apps (e.g., shopping and navigation, among others). The data is provided by Cuebiq, a location intelligence and measurement company that supplies a patented software development kit (SDK) to mobile app developers, providing a privacy compliant path for anonymous users to opt-in to share location data. Each observation provides information including an encrypted and hashed identification number (ID), a time stamp, a location record (in the form of a pair of latitude and longitude), and the location accuracy associated with the data record (in meters). Table 1 gives a synthetic sample of the observations, which have been modified to further preserve privacy.
Table 1 A synthetic sample of the app-based data

| Device ID          | \(^a\)Time stamp \(t\) | \(^b\)Latitude \(lat\) | Longitude \(lng\) | \(^c\)Location accuracy \(r\) (meters) |
|--------------------|-------------------------|-------------------------|------------------|-------------------------------------|
| 4ab844ff98c206b8d7 | 1491398264              | 47.9205809              | -122.2535626     | 5                                   |
| 4ab844ff98c206b8d7 | 1491403834              | 47.9229781              | -122.2903396     | 25                                  |
| 4ab844ff98c206b8d7 | 1491403961              | 47.9222743              | -122.2998663     | 60                                  |
| 4ab844ff98c206b8d7 | 1491412669              | 47.8994576              | -122.2915348     | 60                                  |
| 4ab844ff98c206b8d7 | 1491412963              | 47.8856073              | -122.2908753     | 300                                 |
| 4ab844ff98c206b8d7 | 1491413263              | 47.8850917              | -122.2806468     | 1399                                |

\(^a\)In UNIX Epoch time; \(^b\)Values are modified for privacy concern. \(^c\)The location accuracy is returned by the device operating system, when an app sends a request to the operation system for the device location (more details can be found in developer documents of operation systems).

Location accuracy in the app-based data varies, depending on the technology that was applied to positioning the device. It could be as accurate as several meters when the GPS chip was on and around 20 meters when apps recorded locations using WiFi, assisted GPS, Bluetooth proximity, etc (Schewel, 2017). In the worst cases, the accuracy could be of hundreds or thousands of meters when cellular towers are used. Figure 2 gives the distribution of location accuracy of the app-based data, showing two modes: one presenting observations of high accuracy (mainly smaller than 100 meters) and the other presenting observations of accuracy about 1000 meters. Generally, about 15% of the observations have location accuracy larger than 100 meters. The large variances can also be observed in the distribution of observation interval (Figure 3): half of the intervals are within 120 seconds, and 20% of them could be longer than 300 seconds, ranging from several
minutes to hours. More properties of the temporal and spatial properties on the app-based data can be found in a recent technical report by the authors (Ban et al., 2018).

![Figure 2 Distribution of location accuracy](image1)

![Figure 3 Distribution of observation interval](image2)

3.2. PSRC household travel survey data

Household survey data collected in the same geographical area and time period are used as a benchmark for evaluating the proposed framework. The survey data contains 6,254 persons (in 3,285 households) in the Puget Sound region, with a sample rate of 0.21%. The sample rate is smaller than the ones for similar studies (0.5-1%) (Michalowski, 2017), because this sample is the first wave of a planned continuous three-wave data collection, with the goal to provide timely data from regular and short-interval surveys for monitoring regional travel trends (PSRC Household Travel Survey Program, 2017).
4. Methodology

We describe the three steps in the DCI framework for extracting trips from multi-sourced data: (1) Partition the multi-sourced data into multiple data sets such that each contains small variance in spatio-temporal properties; (2) Extract trips from each data set independently by applying methods in accordance with the characteristics of the data set; (3) Integrate trips extracted from all data sets by applying an algorithm that is designed based on their spatiotemporal relationship.

4.1. Partition data into low-variance sets

To extract trips from the data, we need to identify stays first. Then a trip will be a pair of two consecutive stays, representing origin and destination of the trip. A stay is usually identified if the device does not move (e.g., more than 5 meters for GPS data and 1000 meters for cellular data) during a certain amount of time (e.g., 5 minutes). However, the variations embedded in a multi-sourced dataset suggest that the threshold values for identifying stays shall be variable: given the bimodal distribution of location accuracy in the app-based data (Figure 2), there exists no universal spatial constraint to identify a stay. This can be illustrated in Figure 4, where one individual visited three places \((l_0, l_1\) and \(l_2\)). Observations recorded at \(l_2\) have lower location accuracy than those at \(l_0\) and \(l_1\) and therefore appear dispersed in space. To identify the stay at \(l_2\), one may want to use a spatial threshold larger than \(R_1\). However, if the same threshold value is applied to \(l_0\) and \(l_1\), the two stays could be mistakenly identified as one when \(R_1 > 2R_0\). In Appendix A.2, we show that without considering the large variations of location accuracy embedded in multi-sourced data, the direct use of a rule-based method may lead to biased estimation on trip length distributions.

![Figure 4](https://via.placeholder.com/150)

**Figure 4** A trajectory with three stays: the illustration of variable thresholds for stay identification

The DCI framework works to partition the data, such that each partitioned data set has small variance in location accuracy, based on which methods can be developed and applied to each data set. We observe that the app-based data is dominated by observations of high location accuracy and short observation interval, which appears similar to the GPS data (Figure 5) and could be handled by a GPS-data-based method. Therefore, we partition the app-based data into two sets: one set contains observations with location accuracy no larger than a threshold \(p\) and the other set takes the remaining observations. In our study, we use \(p=100\) meters following the bi-modal distribution of location accuracy (Figure 2). As shown in the sensitivity analysis in Appendix A.3.1, the framework is robust to the selection of \(p\) (e.g., 60, 140 and 180 meters). We attribute this robustness to the integration step of the proposed DCI method (introduced in the following): potential stays may be partitioned into different datasets under different thresholds, while the integration step integrates them together.

Since observations with location accuracy larger than 100 meters account for about 15% of the whole data set, simply removing them may miss certain important trips. Figure 5 provides a case where a trip...
would be missed if we remove low-accuracy observations (location accuracy larger than 100 meters). Indeed, as we show in the Results section, without considering those low-accuracy observations, the trip rate (number of trips per day) would have reduced by 6%. In addition, some users can be removed from the data completely if we simply dump the observations with low location accuracy, and the resulting effect on the representativeness of the data is unknown. Figure 6 shows that a considerable percentage of users have low-accuracy observations dominating their records and about 10% of users have only low-accuracy observations available for analysis. This means that removing low-accuracy observations would remove these users completely, which potentially biases the analysis of travel patterns of the population, especially when the correlation between users’ travel patterns and data properties is not clear.

Figure 5 A case where a trip is missed (in circle) if observations of low location accuracy are filtered out.

Figure 6 Fraction of low-accuracy observations (larger than \(p=100\) meters) in users’ records.
4.2. Extract trips from each data set independently

The partition step results in two data sets. The first one is similar to GPS data such that it can be processed using methods designed for GPS data. The second one contains observations with location accuracy distributing around 1000 meters, which resembles cellular data. This observation is consistent with the data generation process, where cellular towers are used to locate a device when other technologies are not available. We thus propose to address the second data set using methods that are developed for cellular data. For clarity, hereafter, we refer to the first data set as the “GPS data set” and the second one as the “cellular data set”. In the following sections, the two data sets are processed independently to extract trips.

4.2.1. Extract trips from the GPS data set

Methods have been well developed to extract stays from GPS data. A commonly-used trace-segmentation method (Hariharan and Toyama, 2004; Ye et al., 2009) is applied to extract stays from the GPS set. For each trajectory of one user \( traj \{ d(t_1; lng_1, lat_1), d(t_2; lng_2, lat_2), \ldots, d(t_i; lng_i, lat_i) \} \) \( t_1 \leq t_2 \leq \ldots \leq t_i \), we extract stays by scanning through the trajectory and segmenting it into multiple sequences of observations with two parameters: signal roaming distance \( \Delta l_{roam} \) and stay duration \( \Delta t_{dur} \). A stay is extracted as a sequence of observations \( \{ d_m(t_m; lng_m, lat_m), d_{m+1}(t_{m+1}; lng_{m+1}, lat_{m+1}), \ldots, d_n(t_n; lng_n, lat_n) \} \) \( t_1 \leq t_m \leq t_{m+1} \leq \ldots \leq t_n \leq t_1 \) satisfying both thresholds: the distance between any two observations in the sequence should be shorter than \( \Delta l_{roam} \) and the duration (i.e. the time difference between the last and the first observation of this sequence \( t_n - t_m \)) must be no less than \( \Delta t_{dur} \). This can be achieved by following the algorithm proposed in (Hariharan and Toyama, 2004). Intuitively, \( \Delta l_{roam} \) defines the maximum distance that the user could stray from a location; \( \Delta t_{dur} \) defines the minimum duration that the user has to be within the roaming distance to qualify as staying at that location. In our study, we use 200 meters and five minutes as \( \Delta l_{roam} \) and \( \Delta t_{dur} \), respectively. This five-minute threshold follows the rule used in many household travel surveys to define what counts for an activity (Transportation Research Board, 2005) and is also used as an appropriate threshold for an activity location in activity based modeling (Yin et al., 2017). Additionally, an exploration using the PSRC survey data shows that the distribution of activity duration peaks at five-minutes (see Figure 19). \( \Delta l_{roam} \) is set as 200 meters such that a displacement of 200 meters in five minutes corresponds to half of average walking speed (0.7 m/s), which is commonly used to distinguish between a stay and a movement (Bernardin, 2017). Therefore, in the study, the trace-segmentation method identifies a stay as a sequence of observations that remain within 200 meters for at least five minutes. We replace locations in the sequence with their centroid \( (lng_c, lat_c) \). Then, a sequence of observations representing a stay is simplified as \( s(t_m, t_{m+1}, \ldots, t_n; lng_c, lat_c) \). A discussion on using other combinations of \( \Delta l_{roam} \) and \( \Delta t_{dur} \) is provided in Appendix A.3.2.

To analyze mobility patterns such as regular returns to certain places (e.g., home, workplaces), we need to identify common stays. One common stay represents a single place that is associated with multiple visits by one user at different times. However, using the trace-segmentation method, extracted stays at different time are unique in their longitude and latitude coordinates, as each stay is represented by the centroid of a unique cluster (Figure 7b). To identify those common stays, we ignore the temporal scale of stays and aggregate stays close in space via an agglomerative clustering algorithm (Jiang et al., 2013). Specifically, we put together all stays identified in one user’s trajectories, aggregate those close in space into one cluster and replace locations of those stays (i.e. their centroids) with the centroid of the cluster (Figure 7c). Then, a stay \( s(t_m, t_{m+1}, \ldots, t_n; lng_c, lat_c) \) is modified as \( s_c(t_m, t_{m+1}, \ldots, t_n; lng_{cc}, lat_{cc}; r_{cc}) \), where the location \( (lng_{cc}, lat_{cc}) \) is the centroid of the cluster where \( s \) belongs. And the stay radius \( r_{cc} \) reflects the

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3 Here, \( t_i \) stands for the timestamp and \( (lng_i, lat_i) \) stands for the location coordinates of the observation.

4 The algorithm is attached in Appendix A.1 for readers’ convenience.
uncertainty of location $s_{cc}$ that is given by the radii of the cluster (i.e. the longest distance from the centroid to any stays in the cluster). The data structure $s_{cc}(t_m, t_{m+1}, \ldots, t_n; lng_{cc}, lat_{cc}; r_{cc})$ will be useful in the last step of our DCI framework. In this paper, we apply the agglomerative clustering starting from each stay as individual cluster and set 200 meters (the same as the previous definition of roaming distance $\Delta t_{roam}$) as the criterion to stop the algorithm. This means trips shorter than 200 meters would not be identified. However, the effect would be limited, as we found that only about 3% of trips recorded in the PSRC survey data are shorter than 200 meters (see Figure 13 in the Results section). Figure 7 illustrates the process of identifying stays from the GPS data set, where one common stay visited on two days is identified.

![Figure 7 Illustration of identifying stays from the GPS data set.](image)

4.2.2. Extract trips from the cellular data set

Given the low location accuracy and observation interval of the cellular data set, the trace-segmentation method that is designed for GPS data is no longer suitable. A framework developed by Wang and Chen (2018) for cellular data is applied in this study. The framework addresses the locational uncertainty and temporal sparsity of cellular data with a revised incremental clustering method, which takes advantage of the longitudinal nature of cellular data. Following the framework, we put together all
cellular observations belonging to one user as a list \( d \) and the list is clustered without regarding their time ordering:

1. starting from an observation \( d_i \), one new cluster \( C_i \) is created and \( d_i \) is the center;
2. each observation that has not been clustered will be checked and the one within a distance \( R_c \) to the center of \( C_i \) is clustered into \( C_i \) and the center of \( C_i \) is correspondingly updated;
3. if no observation could be aggregated in the current cluster, one new cluster is created containing a non-clustered observation.

This procedure repeats itself until all observations in \( d \) are clustered. This clustering returns a set of clusters, each of which contains observations that are close in space. Then, we come back to the time-ordered trajectories where temporal information is used such that a stay is identified as a sequence of observations within the same cluster and with duration exceeds a given threshold \( T_s \) (set as five minutes following the one for GPS data). Similarly, a stay is represented by \( s_i(t, t+1, \ldots, k; lng, lat; r_c) \), where \( (lng, lat) \) and \( r_c \) are the centroid and the radii of the cluster containing the sequence of observations, respectively. Similar to the method for the GPS data set, through aggregating observations that are close in space but may be far away in time (e.g., several days), this method is able to identify common stays visited on multiple days. The spatial constraint \( R_c \) in the algorithm is set as 1000 meters, which follows the data characteristics observed in Figure 2 as well as previous studies on cellular data (Widhalm et al., 2015; Wang and Chen, 2018). A sensitivity analysis on \( R_c \) is presented in Appendix A.3, showing that the framework is robust to the selection of \( R_c \).

4.3. Integrate trips extracted from both data sets

Following the previous step, each extracted stay in the GPS data set and the cellular data set is represented by a sequence of observations, with the cluster centroid representing the stay location, stay radius reflecting location uncertainty as well as relevant time information. Observations that do not belong to any stay are “passing-by” observations. As the last step of the DCI framework, stays extracted from the two data sets are integrated.

The integration step is not simply to insert stays of one user identified in one data set into stays of the same user in another data set following the time order; instead it requires comprehensive examinations on their spatiotemporal relationships. For example, one case that cannot be inserted directly is that if a cellular stay and a GPS stay are identified on the same morning, the two could be a single stay at one place, but with the cellular stay being a coarser locational representation (i.e., higher location uncertainty). To handle complex cases like this, we design an algorithm by referring to the concepts of space-time relationship analyses in Geographic Information System (GIS) (Longley et al., 2005). In GIS, geometries in multiple layers/data sources can be spatially and temporally related in different ways, including spatially/temporally contained and adjacent (Peuquet, 1994; Peuquet and Duan, 1995). These geometries are joint by determining what type of relations they represent. For example, counts of two adjacent polygons in a same time period can be integrated. Similarly, we treat each data set as a layer and identify stays as features in the layer. The time and location information (i.e., centroid and radius) of each stay act as the temporal and spatial attributes, respectively. Then, features (i.e., stays) from multiple layers (i.e., data sets) are combined by measuring their spatiotemporal relationship based on their temporal and spatial attributes.

For the app-based data, we use the predominant GPS data set (representing about 85% of the app-based data) as the basis. Then, for each of the cellular stay in a cellular trajectory \( trj_c \), we check its relationship with the processed GPS trajectory \( trj_g \) (observations of the same user on the same day), and decide how to combine it into the GPS trajectory. In the following, we define the temporal and spatial relationship between the stays identified from the two datasets.
The temporal relationship is defined in three categories:
1) Temporally separate: given a cellular stay \(a(t_{a1}, t_{a2}, \ldots, t_{ai}; \text{lng}_a, \text{lat}_a; r_a)\) and time-ordered GPS stays \{\ldots, b(t_{b1}, t_{b2}, \ldots, t_{bj}; \text{lng}_b, \text{lat}_b; r_b), c(t_{c1}, t_{c2}, \ldots, t_{ck}; \text{lng}_c, \text{lat}_c; r_c), \ldots\}\) that are neighbors of \(a\) in time, we say \(a\) is temporally separate with GPS stays if \(t_{a1} > t_{bj}\) and \(t_{ai} < t_{c1}\) (Figure 8a).
2) Temporally contained: given a cellular stay \(a(t_{a1}, t_{a2}, \ldots, t_{ai}; \text{lng}_a, \text{lat}_a; r_a)\), if there exists a GPS stay \(b(t_{b1}, \ldots, t_{bu}, t_{bv}, \ldots, t_{bj}; \text{lng}_b, \text{lat}_b; r_b)\) such that \(t_{bu} < t_{a1} < t_{ai} < t_{bv}\), we say \(a\) is temporally contained in \(b\) (Figure 8b).
3) Temporally intersected: given a cellular stay \(a(t_{a1}, \ldots, t_{au}, t_{av}, \ldots, t_{ai}; \text{lng}_a, \text{lat}_a; r_a)\), if it satisfies neither 1) nor 2), we say \(a\) is temporally intersected with GPS stays (Figure 8c).

For the spatial relationship, we check whether the cellular stay is spatially contiguous with GPS stays or not. Here, two stays are defined spatially contiguous if the difference of their stay radii is greater than their spatial distance. Figure 9 gives an example where the stay \(a\) is spatially contiguous with \(b\), as the difference between their stay radii (i.e. \(r_a - r_b\)) is greater than the distance between centroids of the two stays \(D_{ab}\). It is possible that a cellular stay is spatially contiguous with more than one GPS stays. In such cases, we suggest to integrate the cellular stay with the GPS stay whose centroid is closest to the centroid of the cellular stay.

Due to the location uncertainty in the data, a statistical definition may be better for the spatial relationship than a deterministic one as we propose here. With a manually-labeled sample dataset, we test a logistic classifier, where a logistic function is learned to give the probability of two stays being spatially contiguous. The test suggests that the proposed deterministic definition works well, while a statistical definition such as the logistic classifier would need labelled data, which are typical limited or not available in passively collected data. The test also shows that the two spatial classes (being spatially contiguous or not) are separable based on a deterministic definition that reflects the relationship between the centroid distance and uncertainty radii of two stays, and the separation is robust to how the relationship is expressed. More details of the test can be found in Appendix A.4.
Following these definitions, the spatiotemporal relationship of each cellular stay with GPS stays is determined, based on which decision of the integration is made. For a cellular stay \( a(t_{a1}, t_{a2}, \ldots, t_{ai}; \text{lng}_{a}, \text{lat}_{a}; r_{a}) \):

I. If it is temporally separate with its neighboring GPS stays \( b \) and \( c \), \( a \) would either be a visit to a new place, or be the same visit at \( b \) or \( c \) but with a coarser location representation. This depends on whether \( a \) is spatially contiguous with \( b \) or \( c \). If not, \( a \) is added as a new stay; otherwise, \( a \) is combined with \( b \) or \( c \) by replacing the location of \( a \) with that of \( b \) or \( c \), depending on which one \( a \) is spatially contiguous with. Figure 8a gives an example where \( a \) is temporally separate and spatially contiguous with \( c \). As a result, \( a \) is combined with \( c \) in a way that \( a \) is discarded and \( c \) is modified as \( c(t_{a1}, \ldots, t_{ai}, t_{c1}, t_{c2}, \ldots, t_{ci}; \text{lng}_{c}, \text{lat}_{c}; r_{c}) \).

II. If it is temporally contained in a GPS stay \( b \), similarly, we check whether it is spatially contiguous with \( b \) or not. If yes, \( a \) is discarded; otherwise, \( a \) is inserted as a new stay and \( b \) could be split into two stays. For the example in Figure 8b, if stay \( a \) is not spatially contiguous with \( b \), stay \( b \) is split into \( b'(t_{b1}, \ldots, t_{bu}; \text{lng}_{b}, \text{lat}_{b}; r_{b}) \) and \( b''(t_{b1}, \ldots, t_{b v}; \text{lng}_{b}, \text{lat}_{b}; r_{b}) \). Note that \( b' \) (\( b'' \)) will not be counted as a stay, if its duration \( t_{bu} - t_{bi} \) (\( t_{b v} - t_{b i} \)) is shorter than the temporal threshold of being a stay (i.e. five minutes), in which case stay \( b \) remains unchanged (and \( a \) is discarded).

III. If it is temporally intersected with one (or more) GPS stay \( b \), stay \( a \) is segmented such that each segment is not temporally intersected with any GPS stay. Then for each segment, procedure I or II is followed depending on the temporal relationship (i.e., temporally separate or contained). For the example in Figure 8c, stay \( a(t_{a1}, \ldots, t_{au}; \text{lng}_{a}, \text{lat}_{a}; r_{a}) \) is segmented into \( a'(t_{a1}, \ldots, t_{ai}; \text{lng}_{a}, \text{lat}_{a}; r_{a}) \) and \( a''(t_{ai}, \ldots, t_{au}; \text{lng}_{a}, \text{lat}_{a}; r_{a}) \), with \( a' \) being temporally separated with and \( a'' \) being temporally contained in stay \( b \). Therefore, we follow procedure I for \( a' \) and procedure II for \( a'' \) to decide how to combine \( a' \) and \( a'' \) into GPS trajectory. Note that if the duration of one segment is shorter than the temporal threshold of being a stay (i.e. five minutes), this segment will be discarded.

A summary of the integration step is shown in Figure 10. The integration process repeats itself until all cellular stays in cellular trajectories are processed. Since the duration of some stays would change during the integration process, we scan through each combined trajectory to update the duration of stays.
Figure 10. Flow chart for integrating cellular stays in a processed cellular trajectory

5. Results

In this section, we present results on stays and trips that are extracted following the DCI framework. The results are compared with the state-of-the-art SVM model that is designed for GPS data (Yang et al., 2014) as well as external data sources to examine the effectiveness of the framework.
Prior to the comparison, we remove false trips that are generated from signaling noises/jumps in the app-based data. These trips do not reflect users’ actual movements. For example, some devices may be observed switching between two (or more) faraway locations with high frequencies and the switching speed (if calculated) could be incredibly high (e.g., several hundreds of miles per hour). To avoid these false trips, we use a time-window-based method (Wang and Chen, 2018) to detect and remove observations that are generated from the occurrence of the signaling noises. It scans trajectories with a short time window (five minutes), which always starts at the last observation of a stay and returns a sequence of observations. Among the sequences returned, the one containing at least one circular event is considered as a noise sequence and trips in the noise sequence are removed. Here, a circular event refers to a tour when one device is initially observed at one location, later jumps to other distinct locations, and then comes back to the initial location. Since it is less likely for any user to make a tour within a short time window, the noise sequences detected may contain observations generated from signaling noises and therefore are removed. Readers are referred to Wang and Chen (2018) for more details on the time-window-based method. It is found that false trips in the app-based data lead to overestimation on users’ daily trip rates. For example, before the removal, it is observed that in the app-based data there are 1.5% of user-days having more than 20 trips, which is surprisingly high compared with 0.5% in the survey data. It drops sharply to 0.4% after removing false trips.

5.1. Compare against SVM model

We evaluate the effectiveness of our framework by checking the extracted stays. The framework is first compared with an SVM model. This comparison is based on a small sample dataset, consisting of observations of randomly selected users. As the only way to obtain the ground truth data for model training and testing, we manually identify stays from this sample dataset. In total, the sample dataset contains 346 stays, among which 11 stays (3%) are contributed by the observations of low location accuracy.

The DCI framework yields a success ratio of 0.92, meaning 92% of stays are successfully extracted. Specifically, the DCI framework identifies 340 stays, 6% of which are false positive errors (21 false stays), not belonging to the manually labeled stays. The correctly identified 319 stays accounts for 92% of the manually labeled (346) stays, and the remaining 8% (27 stays) are false negative errors. With close examinations, we find that the false positive errors occur mainly when a device moves slowly on the roads (e.g., due to congestions). Two main reasons account for the 27 false negative errors. First, the duration of a stay is less than the temporal threshold due to the temporal sparsity issue that leads to limited observations during the stay. Second, the distance between two observations in a stay is larger than the spatial threshold when, for example, the only two observations in the stay are not located closely at a commercial center or a park. Although these false negative errors could be reduced by reducing the temporal threshold or increasing the spatial threshold, we find that either modification on the thresholds could induce false positive errors. Therefore, the selection of thresholds should balance the two types of errors. The balanced false negatives and false negatives here (27 vs 21) supports the current selection of the temporal and spatial threshold. In Discussion Section, we provide suggestions on how to reduce the two types of errors by incorporating external data (e.g., land use data and road network data) into the DCI framework.

Following the work of Yang et al. (2014), we develop an SVM model that contains three stages: 1) data processing to obtain potential stops; 2) feature extraction; and 3) implementation of a linear SVM. The first stage of the SVM method would be important as the information in the app-based data is limited: different with a vehicle GPS trajectory dataset which contains relatively rich information such as speed, velocity or acceleration (Yang et al., 2014), the app-based data only includes timestamp, geo-location and location accuracy (Table 1). This makes it hard to label a potential stop with the limited
information. Therefore, the trace-segmentation method is applied to create stops. We design the temporal and spatial thresholds so that the trace-segment method creates a large number of stops (i.e., potential stays) that consist a superset of almost all actual stays. The idea of creating potential stays followed by a machining learning technique has been shown a good practice in processing data with limited features (Gong et al., 2015). Here, when implementing the trace-segmentation method, we try various settings to obtain the best SVM performance. More specifically, we try whether or not filter out observations of low location accuracy (using the threshold of 100 meters) as well as multiple combinations of temporal and spatial constraints (including 1, 3, 5 and 7 minutes for the temporal constraint and 100, 200 and 300 meters for the spatial constraint). In the second stage, we manually explore the sample dataset and extract features from the created stops for the SVM model including duration, the largest distance between any two observations in a stop, the average switching speed between two consecutive observations in a stop, heading direction, and the speed between two stops. With trials and errors, we find that the first three features perform the best. For the third stage, a K-fold cross-validation procedure is used to obtain an average performance of the SVM model (more specifically, eight-fold in our implementation).

Among the trials of using different settings in the trace-segmentation method to produce inputs for the SVM model, the best performance of the SVM model gives a success ratio of 0.88, when observations of low location accuracy are filtered out and the temporal and spatial thresholds are set as 5 minutes and 100 meters, respectively. The DCI framework outperforms the SVM model due to a few reasons. The first reason is related to the unique properties of passively collected data. The app-based data, for example, do not contain some of the detailed features such as speed information, which have been shown important for stay identification using a SVM model (e.g., close to zero speeds indicate stays). Also there is no ground-truth data for our trip extraction using the app-based data, which is a critical issue for supervised learning methods such as SVM (Yang et al. (2014), e.g., has log data as the ground truth). In addition, the SVM model was initially proposed for dealing with GPS data that are of high location accuracy, while the app-based data consists of location information from multiple techniques (GPS, WiFi, Bluetooth, etc.) and contains large variations in terms of location accuracy. The second reason is related to the complexity of the task: we try to identify all types of stays which is more challenging than identifying stays of certain purposes (e.g., freight delivery stops). To address the challenge, we apply the domain knowledge of travel patterns (e.g., five-minutes for a meaningful stay) in the DCI framework, while SVM is purely data driven.

We should point out that our comparison here just shows that SVM does not perform well for the dataset we have (due to limited data features) and should not be extended to the general performances of SVM for other cases. In fact, the relatively good (but not super) performance of SVM (88% success ratio) using limited features does show that (i) SVM, as one of the learning methods, heavily depends on data, which may not perform well if data is limited (in terms of either quantity or quality such as features); and (ii) the SVM method may perform comparably well with the proposed DCI method if more data features are available. We plan to investigate this in future research provided that more features can be provided by the vendor.

5.2. Evaluate with external data sources

5.2.1. Stays

As a further evaluation, we use stay information extracted from the app-based data to infer the census tract-level home location for each anonymous user. Home census tract is inferred based on a simple rule: the home tract is identified as the tract containing the stay with the most frequent visits during the night time (22:00 pm to 6:00 am the next day), with the condition that it has to be visited at least eight times, representing once a week during the two-month study period. Figure 11 shows that the spatial distribution
of inferred home tracts is similar with that of the census population (2010 U.S. Census). The number of anonymous users with a home tract inferred (hereafter called the inferred residents) represents about 3% of the population in the study area, which is comparable to the results using cellular data (e.g., 4.3% in (Calabrese et al., 2011b)). Figure 12 shows that the estimated density of home locations scales consistently with census population, with a Pearson correlation coefficient of 0.91 at the census tract level. This is much higher than the ones obtained from cellular data (e.g., 0.4 in (Chen et al., 2017)), suggesting smaller sample bias in app-based data users for representing residents in the Puget Sound region.

Figure 11 Comparison between inferred tract-level home locations from the app-based data and the population from the census data. (a) Inferred home location density; and (b) Census population density.

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5Due to the limited sample size, PSRC survey data is not suitable for a comparison here.
5.2.2. Trips

We then evaluate the framework by comparing the extracted trips from the app-based data with the ones obtained from the PSRC survey data. Comparisons include properties of trips (e.g., trip length) and trajectories (e.g., number of trips per day). To be comparable with records in the survey data, we only consider residents inferred from the app-based data and use their workday trips.

Figure 13 gives distributions of trip lengths inferred from the app-based data (calculated in the Euclidean distance) and those recorded in the travel survey (in network distance). We see that both distributions are in exponential truncated power-law form (Figure 13a), suggesting the heterogeneity embedded in individual mobility: though 90% of trips are within 21 kilometers, there are some travelers travel as far as 100 kilometers (Figure 13b). This pattern is consistent with previous studies such as those using cellular data (González et al., 2008) and taxi trajectory data (Zhang et al., 2018). The comparison suggests that trip lengths inferred from the app-based data are generally consistent with those from travel survey, despite the overestimation on the short trips that may be due to the use of Euclidean distance. Note that fluctuations observed in the survey data likely results from the limited sample size as we mentioned in Section 3.
The processed trajectories consisting of extracted trips give a mean trip rate (number of trips observed per anonymous user per day) of 3.3 on weekdays. Note that it would be 3.1 (i.e., 6% reduction) without considering low-accuracy observations, suggesting the necessity of the integration step in the DCI framework. The mean trip rate, however, is found lower than 4.4 that is obtained from the survey data. The underestimation is likely related to the temporal sparsity of the app-based data, which is a common issue in passively-generated data (Yuan et al., 2012; Chen et al., 2016). As a result, some trips were not recorded (i.e., missing trips) due to the lack of observations. This is supported by the greatly mitigated morning and evening peaks in the departure time distribution derived from the app-based data (Figure 14). Indeed, missing trips due to the temporal sparsity also lead to the discrepancy in the distribution of trip rates (Figure 15): in general, the travel patterns with more than four trips a day tend to be underestimated, while other patterns are likely overestimated, especially that conducting one trip a day.

Figure 13 Distribution of trip lengths: (a) density and (b) cumulative density distribution.

Figure 14 Departure time distribution. Compared with the two morning and evening peaks obtained from the survey data, the two peaks estimated from the app-based data are greatly mitigated.
6. Discussions

As multi-sourced data are becoming popular in the “big data” era, there is a critical need to develop trip extraction methods using such data sources. Though various methods have been developed in the literature to extract trips from single-sourced data sources, such as cellular data and GPS data, solutions for processing multi-sourced data are limited. Our study proposes a “Divide, Conquer and Integrate” (DCI) framework to extract trips from a multi-sourced data set by three major steps by: (i) partitioning the data into multiple data sets; (ii) processing each set independently according to its unique characteristic; and (iii) designing a novel algorithm to combine the trips extracted from each data set. We evaluate the proposed framework by applying it to an app-based data set, which is multi-sourced and has high variances in both location accuracy and observation interval. We show that, on a manually labeled sample of the app-based data, the framework outperforms the SVM model. The effectiveness of the framework is illustrated by the consistency between mobility patterns (e.g., home location and trip length distributions) that are inferred based on the extracted trips from the app-based data and those obtained from external data sources.

The proposed framework provides transportation researchers and professionals methods and tools of analyzing multi-sourced data for travel pattern analysis. These methods leverage differential and unique characteristics typically present in the multi-sourced data. Certainly, for better deriving mobility patterns from such data, enhanced understanding of how various spatial and temporal characteristics of passively generated data affect patterns observed would be very much needed. As shown in our study, mobility patterns such as departure time and trip rate distributions derived from the app-based data can be biased due to temporal sparsity issue of the data, calling for deeper understanding of the app-based data.

Two directions would be the focus of future studies. First, the proposed DCI framework could be improved (reducing false negatives and false positives) by incorporating external data sources, such as land use data and road network data. Using the land use data, for example, if the observations of a potential stay are all located at a commercial center or a park, we could label it as a stay although it does not satisfy the temporal or spatial constraint. With the road network data, we could reduce the false positives by differentiating trip ends from temporary stops such as those at traffic bottlenecks and ferry
terminals. The second direction is to further validate the framework by acquiring ground-truth data. One potential dataset that could serve as the ground-truth is a household travel survey dataset collected via rMove—a smartphone app that assists travel survey by collecting participants’ GPS trajectories. The rMove data was collected at the same time period and the same region, containing 1240 participants. If we could successfully match trajectories in the rMove data with those in the app-based data, the matched trajectories then could be used as the ground-truth. However, how to match trajectories could be challenging and merits further studies.

Appendix

A.1. The algorithm used in the trace-segmentation method for trip ends identification

For each trajectory of one user \( \{d_1(t_1; lng_1, lat_1), d_2(t_2; lng_2, lat_2), \ldots, d_m(t_m; lng_m, lat_m)\} (t_1 \leq t_2 \leq \ldots \leq t_m) \), we identify trip ends in the trajectory following the following algorithm (Figure 16) that is adapted from (Hariharan and Toyama, 2004).

```plaintext
Input: a trajectory \( \{d_1(t_1; lng_1, lat_1), d_2(t_2; lng_2, lat_2), \ldots, d_m(t_m; lng_m, lat_m)\} (t_1 \leq t_2 \leq \ldots \leq t_m) \);
Output: a set of trip ends \( S = \{s_k\} \);
Arguments: temporal constraint \( \Delta t_{dur} \), spatial constraint \( \Delta l_{roam} \);
Functions: Diameter\((d, i, j)\) returns the maximum distance between any two observations in \( \{d_1(t_1; lng_1, lat_1), \ldots, d_j(t_j; lng_j, lat_j)\} \); Centroid\((d, i, j)\) returns the centroid \( (lng_c, lat_c) \) of \( \{d_i(t_i; lng_i, lat_i), \ldots, d_j(t_j; lng_j, lat_j)\} \);

Initialize: \( i \leftarrow 1 \), \( S \leftarrow \emptyset \);
while \( i < m \) do
    \( j' \leftarrow \) the minimum \( j \) such that \( t_j - t_i \geq \Delta t_{dur} \);
    if \( \text{Diameter}(d, i, j') > \Delta l_{roam} \)
        \( i \leftarrow i + 1 \);
    else
        \( j' \leftarrow \) the maximum \( j \) such that \( \text{Diameter}(d, i, j) > \Delta l_{roam} \);
        add a new trip end \( s(t_i; t_{i+1}, \ldots, t_j; \text{Centroid}(d, i, j')) \) to \( S \);
        \( i \leftarrow j' + 1 \);
end if
end while

Figure 16 The algorithm for extracting trip ends from the GPS data set (Hariharan and Toyama, 2004)

A.2. Test of the direct use of rule-based methods without data partition

We test the direct use of the traditional rule-based trace-segmentation method to the app-based data. The results are compared with the proposed DCI framework.

Without partitioning the data, we directly follow a trace-segmentation method and extract stays by scanning through the trajectory and segmenting it into multiple sequences of observations. A stay is extracted as a sequence of observations satisfying both the spatial constraint \( \Delta l_{roam} \) and the temporal constraint \( \Delta t_{dur} \): the distance between any two observations in the sequence should be shorter than \( \Delta l_{roam} \) and the duration (i.e. the time difference between the last and the first observation of this sequence) must be no less than \( \Delta t_{dur} \). As argued in the main text, there exists no universal spatial constraint to identify stays from the app-based data. We testify this argument by testing a small (\( \Delta l_{roam}=200 \text{ meter} \)) and a large

\(^6\) https://rmove.rsginc.com/
spatial constraint $\Delta l_{roam}=1000$ meter). Both tests are based on a sample containing 10% randomly selected users (the same for following sensitivity analysis).

In Figure 17, we compare trip lengths obtained from these two tests with the one using the proposed DCI framework. We observe that compared with the DCI framework, the direct use of the trace-segmentation method is more likely to lead to biased estimation of trip length distributions. With a small spatial constraint ($\Delta l_{roam}=200$ meter), the trace-segmentation method is likely to overestimate the percentage of short-distance trips. This may be because a stay represented by observations of low location accuracy (e.g. stay $l_2$ in Figure 4) is split and two stays are identified, resulting into a short-distance trip. On the contrary, with a large spatial constraint ($\Delta l_{roam}=1000$ meter), the trace-segmentation method tends to underestimate short-distance trips. The reason may be that two consecutive and nearby stays represented by observations of high location accuracy (e.g. stay $l_0$ and $l_1$ in Figure 4) is combined, and therefore the short-distance trip from $l_0$ to $l_1$ is not extracted. Therefore, the direct use of a rule-based method cannot address the location accuracy variation embedded in the multi-sourced data.

![Figure 17. Comparison of the trace-segmentation method with the proposed DCI framework (TS in the legend stands for the trace-segmentation method).](image)

A.3. Sensitivity analysis

A.3.1. On the partition threshold $p$

A sensitivity analysis on the threshold $p$ for partitioning the app-based data is presented below. Besides $p=100$ meters that is used in the main text, we apply $p = 60, 140$ and $180$ meters to the framework. Values are chosen following the distribution of location accuracy (Figure 2). Figure 18 gives distributions and means of trip rate obtained from different $p$, suggesting the framework is robust on the selection of $p$. 

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A.3.2. On the parameters for extracting trips from the GPS data set

We discuss here the use of other combinations of \( \Delta l_{roam} \) and \( \Delta t_{dur} \). Figure 19 gives the distribution of activity duration obtained from the PSRC survey data (for clarity only activity durations shorter than 30 minutes are presented). We can observe that the distribution reaches the highest peak at five minutes. Given our definition of a stay, this observation suggests that, using a \( \Delta t_{dur} \) longer than five minutes, we would miss considerable percent of stays having a duration shorter than \( \Delta t_{dur} \). For \( \Delta t_{dur} \) shorter than five minutes, here we try a combination of \( \Delta t_{dur} \) being three minutes and \( \Delta l_{roam} \) being 120 meters (noted as \( cmb_{(3,120)} \)). The combination yields the half of the walking speed of 0.7 m/s (see the main text). Figure 20 gives the resulting trip rate distribution, which is also compared with the one obtained using the combination justified in the main text (i.e., \( \Delta t_{dur} \)=five minutes and \( \Delta l_{roam} \)=200 meters (noted as \( cmb_{(5,200)} \))). The comparison shows that if using \( cmb_{(3,120)} \), we tend to count more trips: \( cmb_{(3,120)} \) gives a mean of 3.88 per day, which is 21% larger than the 3.20 obtained using \( cmb_{(5,200)} \) (Figure 20). Particularly, \( cmb_{(3,120)} \) suggests 1.4% of user-days exceeding 18 trips, which is much higher than the 0.36% obtained using \( cmb_{(5,200)} \) (Figure 20). In addition, the distribution of trip lengths (Figure 21) suggests that \( cmb_{(3,120)} \) tends to overcount short trips. All these observations suggest that a short \( \Delta t_{dur} \) such as three minutes is likely to mistake temporary stops (e.g., those at signal lights and stops-and-goes in congested traffic) as meaningful stays.
Figure 19 Distribution of activity duration obtained from the PSRC survey data.

Figure 20 Trip rate distribution comparing different combinations of $\Delta t_{dur}$ and $\Delta t_{roam}$.
A.3.3. On the parameter for extracting trips from the cellular data set

We further conduct a sensitivity analysis on the spatial constraint $R_c$ for extracting trips from the cellular data set. Besides $R_c = 1000$ meters that is used in the main text, we apply $R_c = 500$ and 1500 meters to the framework. Figure 22 compares the resulting distributions and means of trip rate, indicating the framework is robust on the selection of $R_c$.

Figure 21 Trip rate distribution comparing different combinations of $\Delta t_{dur}$ and $\Delta t_{roam}$

Figure 22 Trip rate distribution comparing different $R_c$

A.4. Alternative definitions of the spatial relationship between two stays
Due to the uncertainty, a statistical definition may be better for the spatial relationship than a deterministic one. Here we test a logistic classifier, where a logistic function gives the probability of two stays being spatially contiguous. The logistic function is in the form of

$$\Pr(y = 1) = \frac{1}{1 + \exp(-(1, x) \cdot \beta)}$$

where $x$ is the input vector describing features of the two stays, and $\beta$ is the parameter vector associated to the input feature vector. $y = 1$ represents the two stays being spatially contiguous and $y = 0$ otherwise. With this classifier, the two stays are taken as spatially contiguous and integrated if $\Pr(y = 1) > \Pr(y = 0)$ (i.e. $\Pr(y = 1) > 0.5$).

To apply this classifier, we have to learn the parameter vector $\beta$ from labeled data. As a test, we manually label some randomly selected pairs of GPS and cellular stays. A label $y = 1$ is given to a pair if its two stays are spatially contiguous and $y = 0$ otherwise. Then, for a balance classification, we randomly take 10 sample pairs with $y = 1$ and 10 sample pairs with $y = 0$. Note that we start from this small sample dataset due to the massive work needed for the manual labeling. As shown later by another test on 10000 sample pairs (not labelled), this small sample is helpful for testing the classifier.

We then construct features for these 20 pairs of stays. Four features are constructed including $r_a$ as the certainty radius of the cellular stay, $r_b$ as the certainty radius of the GPS stay, $D_{ab}$ as the distance between centroids of the two stays, and $\frac{r_a - r_b}{D_{ab}}$ following our deterministic definition of spatially contiguous, which defines the two stays being spatially contiguous if $\frac{r_a - r_b}{D_{ab}} > 1.0$.

We learn the logistic function with the labels and the features constructed. It turns out that a single feature $\frac{r_a - r_b}{D_{ab}}$ gives a perfect classification, suggesting the two classes (being spatially contiguous or not) are well separable based on this feature solely. This can be shown in Figure 23, where we plot labels of the 20 samples against $\frac{r_a - r_b}{D_{ab}}$ and the labels are learned with a logistic function (the red line). The learned classifier suggests that for the manually labelled pairs of stays, two stays would be classified as spatially contiguous if $\frac{r_a - r_b}{D_{ab}} > 0.85$. This is close to our deterministic definition (i.e. $\frac{r_a - r_b}{D_{ab}} > 1.0$) given the small sample size for the learning. In fact, if the deterministic definition (see the blue dash in Figure 23) is applied to these 20 samples, only one sample (with $\frac{r_a - r_b}{D_{ab}}$ being 0.99) is mislabeled. The mislabeled sample is highlighted in yellow in Figure 23.
We notice that the mislabeled sample can be corrected by modifying the definition. We introduce here alternative definitions. We first introduce two uncertainty circles: one uncertainty circle with a radii $r_a$ and centered at the centroid of stay $a$; the other circle with a radii $r_b$ and centered at the centroid of stay $b$.

Two alternative definitions of being spatially contiguous can be explained as: the uncertainty circle of $b$ intersects with the uncertainty circle of $a$ (Figure 24a); the centroid of stay $b$ falls into the uncertainty circle of $a$ (Figure 24b). The two alternatives can be expressed as stay $a$ and $b$ are spatially contiguous if \( \frac{r_a + r_b}{D_{ab}} > 1.0 \); \( \frac{r_a}{D_{ab}} > 1.0 \) and \( \frac{r_a - r_b}{D_{ab}} > 1.0 \) (the proposed definition in the manuscript). Here, the proposed definition in the manuscript is shown in Figure 24c, where uncertainty circle $b$ completely falls into uncertainty circle $a$. It is clear that the definition of being spatially contiguous goes more conservative from Figure 24a, Figure 24b to Figure 24c. It turns out that the mislabeled sample can be corrected if we use either one of the two alternative definitions. However, the investigation below suggests the three definitions have no much differences in our study.

By applying the three different definitions to 10000 randomly selected pairs of GPS and cellular stays, we found that at worst only 2% of output labels are different. More specifically, applying the proposed conservative definition (Figure 24c), we label each pair of the 10000 samples to be spatially contiguous or
not, and repeat the process using the other two alternatives. Then we compare the labels obtained from these three definitions. The mostly mismatching comparison is the one between the proposed definition and the first alternative (Figure 24a). Even in this comparison, we found only 177 labels are different. This finding confirms that the two classes (being spatially contiguous or not) are separable based on a deterministic definition that reflects the relationship between the centroid distance and uncertainty radii of two stays, and the separation is robust to the three alternative definitions. Note that the two classes are nearly balanced in the 10000 sample pairs: 5522 pairs are identified as spatially contiguous with the proposed definition.

To sum up, the proposed deterministic definition works sufficiently well in our study. On the other hand, if logistic classifier or other statistical models are used, labelled data will be required to train such learning models. The challenge is that labelled data are typical limited or not available in passively collected data, making the learned models not reliable due to limited training data.

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