On Splitting Raw Trajectories

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Abstract

With the surge of data-driven solutions for trajectory analysis operations, the need for accurate trajectory trip data has spiked. However, the available datasets are raw trajectories spanning from hours to years, not representing actual trips for downstream applications. Therefore, pre-processing steps, such as basic rules to extract trips, are needed to use the datasets. However, this paper demonstrates that the current pre-processing steps are not enough and result in low accuracy, negatively affecting the downstream applications. This paper presents an overview of an accurate and scalable algorithm for splitting raw trajectories for trip extraction. We go beyond the basic rules to introduce a realistic definition of a trip and offer two scalable heuristics over the exhaustive brute force approach of the algorithm with similar accuracy. Experimental results show that the proposed algorithm is: (a) far more accurate than the basic rules, (b) scalable when employing either of the heuristics.

CCS Concepts

• **Information systems** → *Location based services.*

Keywords

Trajectory, Trips, Segmentation, Spatial-temporal

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1 Introduction

The wide spread of internet of things, location detection technology, and location-tracking devices have enabled the means to collect real trajectory movement data where many are publicly available (e.g., [4, 7, 13, 24, 27, 29, 38, 44]). There is even an industry that sells such datasets (e.g., [28, 35, 36]). The availability of such data has empowered a myriad of trajectory analysis needs (e.g., see [40, 48] for surveys) that are deemed essential for various important applications and domains, e.g., transportation [12, 26], location-based services [1, 21, 23, 49], urban planning [32, 42], the health domain [3, 33], and evaluating trajectory analysis techniques [16–19, 45].

Despite their wide availability and usefulness for various applications, a large ratio of available trajectory data is not suitable to such applications. In particular, many trajectory datasets (e.g., [29, 34]) are released in their raw form as a sequence of locations spanning anywhere between hours and years. For example, the San Francisco Municipal Transportation trajectory dataset [29] is composed of 1,237 vehicles trajectories, each spanning a whole year. Such trajectories are not helpful to a wide spectrum of trajectory analysis applications that need to have access to *meaningful* trips. Examples of such applications would include anything that needs access to an Origin-Destination (OD) matrix, estimated time of arrival (ETA), routing, and trajectory similarity. However, the raw form of trajectories is composed of a set of back-to-back trips and unnecessary idle time. Hence, there is an immense need to extract meaningful trips from any raw trajectory. In practice, a pre-processing step needs to be applied before using the dataset. Commonly, this includes applying a set of *basic* rules to split each raw trajectory into individual trips. Such rules are typically about spatial, temporal, and speed constraints. For example, two consecutive GPS points have a significant spatial or temporal gap (more than a certain threshold), then they belong to two different trips. Such gaps represent the case of when the location-detection device was either not sending information or sending erroneous locations. Another rule is if a set of consecutive GPS points are in the same location, the trip will be ended at the first point in the set, duplicates will be removed, and the end point will be the start of a new trip. Such rule represents a significant idle time, e.g., parking.

This paper makes the case that these basic rules are not enough and would degrade the accuracy of downstream operations, as we define a *meaningful* trip to be a single destination trip without intermediate stops. For example, in the Estimated Time of Arrival (ETA) application, we can use the duration of a single destination as is and it will be accurate. However, if we use the duration of a multiple destination trip, because it was not detected by the basic rules, then it will be inaccurate and will give the illusion of traffic congestion between the start and end of the trip. This scenario can be wrongly interpreted by any algorithm as a traffic congestion. Unfortunately, multiple destination trips (e.g., back-to-back taxi trips) are undetectable using the basic rules as they do not have spatial or temporal gaps, or idle points, which negatively affects any historical trajectory-dependent operation or application (e.g., data-driven routing [14, 47], travel time estimation [41, 46], and edge weight inference [31, 43]). Such operations would only work accurately if fed with single-destination trips.

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The rest of the paper is organized as follows: Section 2 highlights related work. Section 3 introduces our objective function for trajectory splitting. A brute force approach to achieve the objective function is introduced in Section 4. Two scalable heuristics are presented in Section 5. Section 6 presents our experimental evaluation, while Section 7 concludes the paper.

2 Related Work

The process of splitting a long raw trajectory into a set of sub trajectories have been done for different purposes and with different titles, including trajectory segmentation [9] and trip extraction [37]. The body of work in this domain can be broadly categorized into the three below categories:

Rule-based Trajectory Segmentation. Working with raw trajectories, researchers have used some basic rules to segment each trajectory into a set of more realistic trajectories based on either finding outlier points [9], discovering idle states [10], or finding speeds exceeding a certain threshold [5]. This has then become conventional wisdom and a preprocessing step for any trajectory operation using raw trajectories. Follow up work has added more strict rules that are applicable to flight and animal trajectories [11, 37]. However, such additional rules are not suitable for vehicle trajectories, which is the focus of this paper. Applying such additional rules to vehicles would result in *over cutting*, i.e., splitting the raw trajectory into too many unnecessary splits. For example, while a sharp u-turn would be allowed in a vehicle trajectory, it is not for flight trajectories. Hence, applying such rule would result in an unnecessary split (i.e., over cut) of the raw vehicle trajectories, which will degrade the accuracy of downstream operations.

Modality-based Trajectory Segmentation. This category of work aims to segment personal trajectories based on their modality, e.g., walking, biking, bus, and vehicle. This is the most common purpose of segmentation, as each type of trajectories can be processed individually for a different purpose, e.g., walking trajectories can help in understanding customers' behavior while vehicle trajectories can help in traffic studies. There have been numerous approaches for such segmentation and many of them have employed various machine learning approaches to learn form historical data [6, 20, 39]. Other approaches use rule-based measures to separate each modality [30, 40]. None of these techniques are applicable to the case of trip extraction from vehicle trajectories. In fact, employing modality-based trajectory segmentation to separate vehicle trajectories may result in long *raw* vehicle trajectories that would still need to be split into individual single-destination trips.

Behavior-based Trajectory Segmentation. This is used for extracting human trips with different purposes or extracting the acceleration patterns for the same trip. A majority of the solutions utilize a rule-based approach to detect behavior changes and segment the trajectory accordingly. However, such segmentation is specific to the type of the trajectory being segmented in order to set the thresholds correctly [2]. For example, rules for human trajectories are based on human behavior [15], and rules for vehicle trajectories are based on driving behavior [22]. More recent generalized approaches use machine learning to learn and detect behavior changes with no underlying knowledge of the trajectory type [8]. Behavior change segmentation, even for trajectory vehicles, are not applicable to our case of trip extraction, as they tend to over cut, e.g., a single-destination trip with different driving behaviors in highway and residential area segments may be unnecessarily split.

3 Splitting Objective Function

This section sets our proposed objective function that any trajectory splitting algorithm should strive to achieve to produce realistic trajectory trips.

The Objective Function. *Given a raw trajectory T of N points, P_0 to P_{N-1}, split T into a set of trips S, where each trip in S starts at some trajectory point P_i and ends at P_j, and satisfies two properties: (1)* Property 1*: The actual travelled distance from P_i to P_j in trajectory T is within a deviation parameter $\alpha \geq 1$ from their shortest path road network distance, i.e., Distance(P_i,P_j) $\leq \alpha \times$ ShortestRoad(P_i,P_j), (2)* Property 2*. The end point P_j should satisfy* Property 1 *while point P_{j+1} should not. In effect, S should be as long as possible.*

The Deviation Parameter α. Drivers may not necessarily travel the shortest distance for various reasons. For example, drivers may have a personal route preference, or follow a routing service that suggested a longer, but faster, route. While this may be a common scenario, it is reasonable to assume that any route taken is still within a ratio from the shortest path. Hence, *Property 1* in our objective function introduces the deviation parameter α that controls what is considered as a reasonable, hence accurate, trip.

4 Brute Force Splitting

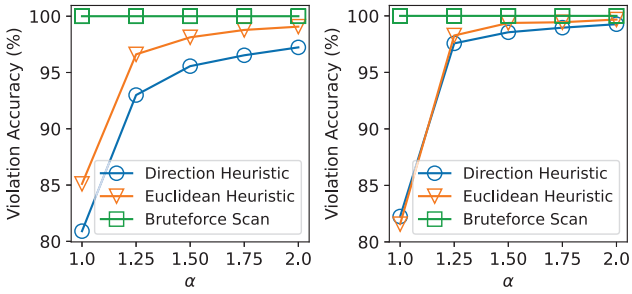
A brute force approach to achieve our proposed objective function is to simply go through each point in the raw trajectory and compute the *cumulative distance* of the current path and the *shortest path distance* from the starting point to the current point. To determine whether the current point is a splitting point, α is applied to the *shortest path distance* and if the *cumulative distance* is still larger, then the current point is a splitting point satisfying *Property 1*. Also, *Property 2* is satisfied, as all the raw trajectory points are scanned one by one, so, the brute force approach would be able to find the exact split point that will satisfy that property.

In terms of scalability, the brute force approach computes two shortest path distances for every trajectory point. This is computationally expensive and not scalable. For example, calling the shortest path function, twice per point, using OSRM API [25] takes 30 msec. Applying this for the whole San Francisco dataset [29] that has 500M trajectory points, reduced to 250M points by the *basic* rules that remove outliers and idle points, it would take 86 days to split all trajectories, which is not scalable for a preprocessing step.

5 Heuristic Splitting

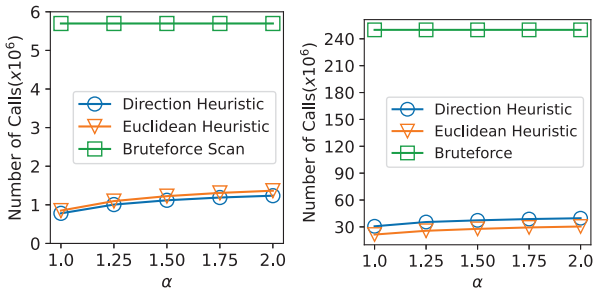
Due to the scalability challenges of the brute force approach, we are introducing two heuristics, namely, Direction and Euclidean heuristics, that aim to reduce the number of shortest path calls while maintaining the accuracy of the objective function.

Direction Heuristic. The main idea of the Direction-based Heuristic is to use the eight cardinal directions (north, northeast, east, southeast, south, southwest, west, and northwest) as a means of speculating if the given trajectory is moving back towards the starting point of the current trip. The rationale is that if the direction from the starting point is opposite to the current direction, then it



(a) T-Drive Dataset (b) San Francisco Dataset

Figure 1: Point Accuracy Ratio (%)



(a) T-Drive Dataset (b) San Francisco Dataset

Figure 2: Number of Shortest Path Calls

is a strong indication that a deviation is happening and the current point is a potential splitting point. In this case, the shortest path calls are only performed when the two directions (direction form starting point and current direction) are opposite. Calling a shortest path here does not mean that this would be a splitting point. It just means that this is a candidate to be a split point, which may end up to be a true split point or not. The optimization here comes from the fact that we call the shortest path function only for those candidate points, rather than for all points as it was the case for the brute force approach. Note that for this heuristic, the eight cardinal directions can be replaced with any other direction convention.

Euclidean Heuristic. The Euclidean-based Heuristic uses the Euclidean distance to speculate if the trajectory is moving back to its starting point or not. If the Euclidean distance from the starting point to the current point is smaller than the previous distance, then there is a high chance that a deviation is occurring and the current point is considered as a candidate split point. Same like the case of the direction heuristic, the shortest path function is called only for those candidate points rather than all points, which would be a significant performance gain over the brute force approach.

6 Experiments

This section evaluates the performance of the proposed splitting heuristics from two aspects: (1) The accuracy of the two heuristics in terms of the ratio of points satisfying *Property 1* of the objective function, and (2) The scalability of the two heuristics in terms of their ability to support much larger datasets that cannot be supported by the brute force approach. All experiments in this section run using two public datasets: (1) San Francisco dataset [29], which include 500M time stamped GPS points for 1,237 transit vehicles trajectories, each spanning the full year of 2021, sampled every minute in San Francisco CA, USA. (2) T-Drive [34], which include 15M time stamped GPS points for 10,357 taxi trajectories spanning one week of February 2008, sampled every 5 minutes in Beijing, China. All shortest path computations for all algorithms are API calls to the Open Source Routing Machine (OSRM) [25]. All experiments are performed on a Linux server with 8 CPU@3.5GHz, 64 GB Memory and 2TB HDD.

Heuristics Accuracy. This experiment studies the accuracy of both the Direction and Euclidean heuristics. As we consider that the brute force approach of the algorithm as the most accurate approach, we are measuring the accuracy of the two heuristics as a percentage from the brute force approach. If we look at the ratio of points satisfying *Property 1* of the objective function in Figure 1, we find that both heuristics achieve over 95% accuracy for α values greater than 1.5, indicating that they are effective in adhering to our trip definition. The Euclidean heuristic slightly outperforms the Direction heuristic, especially in the T-Drive dataset, although differences are minimal for the large San Francisco dataset due to high sampling rates. Overall, both heuristics hold high accuracy, with Euclidean generally offering better performance.

Heuristics Scalability. This experiment examines the scalability of the Direction and Euclidean heuristics by comparing their efficiency to the exhaustive brute force approach. If we consider the number of shortest path calls for each heuristic in Figure 2, we find that in the T-Drive dataset, the brute force method requires nearly 6 million shortest path calls, unaffected by α. Both heuristics need about one-sixth of the calls compared to brute force, making them six times more scalable. As α increases, the number of calls slightly rises due to longer trips and more split candidates. For the San Francisco dataset, the brute force method requires nearly 250 million calls while the heuristics only needed between 30 to 40 million calls, making them six to eight times more scalable. Though the Euclidean heuristic is more sensitive to α than the Direction heuristic, overall, both heuristics are highly scalable compared to the brute force approach for all values of α.

7 Conclusion

This paper makes the case of the need to go beyond just applying a set of basic rules to split raw trajectories to actual trip trajectories. The paper then introduces a new definition of what would be counted as a realistic trip, as well as introducing a clear objective function that needs to be achieved to enure realistic trajectory splitting to actual trips. A brute force algorithm that strictly adheres to the proposed objective function is introduced, yet, it would need exhaustive computations, making it not scalable to large datasets. Therefore, two heuristics are proposed, Direction-based and Euclidean-based heuristics that aim to mimic the behavior of the brute force approach, yet, in a much more scalable way, without sacrificing the accuracy in terms of adhering to the main objective function. Experimental results based on two real datasets show that both heuristics are able to achieve more than 90% accuracy with significantly much less computations.

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