

¹ Outlier Detection and Comparison of ² Origin-Destination Flows using Data Depth

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¹⁶ — Abstract —

¹⁷ Advances in location-aware technology have resulted in the generation of a huge volume of trajectory data. Origin-destination (OD) trajectories provide rich information on urban flow and ¹⁸ transport demand. This study presents a new methodology to detect OD flows outliers and ¹⁹ conduct hypothesis testing between two OD flows in terms of the variations of spatial extent, ²⁰ that is, spread. The proposed method is based on data depth, which measures the centrality and ²¹ outlyingness of a point with respect to a given dataset in \mathbb{R}^d . Based on the center-outward ordering ²² property, the proposed method analyzes the underlying characteristics of OD flows, such as ²³ location, outlyingness, and spread. The ability of the proposed method to detect OD anomalies ²⁴ is compared with that of the Mahalanobis distance approach, and an F-test is used to verify the ²⁵ difference in scale. Empirical evaluation has demonstrated that the proposed method effectively ²⁶ identifies OD flows outliers in an interactive way. Furthermore, the proposed method can provide ²⁷ new perspectives by considering the overall structure of data when comparing two different OD ²⁸ flows in terms of scale.

³⁰ **2012 ACM Subject Classification** Computing methodologies → Anomaly detection

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³⁴ 1 Introduction

³⁵ With the rapid rise in ubiquity of geolocation-aware sensors, knowledge discovery is greatly ³⁶ enhanced by extracting and mining interesting patterns from spatiotemporal big data in ³⁷ various domains. Location-acquisition technologies generate large volumes of movement data,

¹ [funding]

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6:2 Outlier Detection and Comparison of Origin-Destination Flows using Data Depth

38 which are used to track people, animals, vehicles, and even natural phenomena. Such data
39 help us better model moving objects and reveal hidden patterns that are important to urban
40 planning [17], urban human mobility [29, 11], the sustainability of urban systems [1, 3], the
41 environment [4], and public security and safety [2].

42 This paper presents a new algorithm which estimates origination-destination (OD) flow
43 anomalies and conducts hypothesis testing between two sets of different OD flows. In this
44 study, the OD flow data is a subset of trajectory data, which records the origin and destination
45 of each movement while ignoring the actual trajectory route [9]. The algorithm was applied
46 to OD flows derived from extracted origin and destination data in a dataset describing New
47 York City taxi trips, in which each record contained the origin and destination of each trip,
48 without intermediate locations of the actual routes.

49 In recent years, researchers have investigated a variety of approaches to trajectory data
50 mining. Most contemporary trajectory mining methods can be classified into four categories:
51 clustering, classification, frequent/group pattern mining, and outlier detection [18, 32]. These
52 techniques can be used independently or combinatorially for trajectory mining applications.
53 This study focuses on outlier detection of OD flows. Outlier detection attempts to identify
54 trajectories that do not follow the typical flows of trajectory datasets that characterizes
55 the connectivity between regions [18]. Euclidean distance is employed by [7, 13] to find
56 outlier patterns from trajectories. Studies by [20, 14] question the Euclidean distance
57 approach because of the loss of local features and unavailability when external factors, such
58 as topography, land cover or weather condition, affect the trajectories. In their research,
59 [20, 14] addresses this by using robust distance measurements, i.e., Mahalanobis distance [20]
60 and relative distance [14]. Instead of using distance or density, anomalous trajectories are
61 detected by exploiting comparisons of the structural features of each trajectory segment [30]
62 and an isolation tree of trajectories [31]. Most of the above methods are related to trajectory
63 data analysis, and thus, it is reasonable to extend the application of these approaches to
64 the identification of OD flow anomalies. To overcome the sensitivity of Euclidean distance-
65 based approaches to non-normal distributed data and the difficulty of selecting parameters
66 for anomaly detection techniques based on distance or density, this study employs robust
67 statistics, such as data depth, to detect OD flow outliers.

68 Flow mapping, a type of visual analytics, is a common approach to analyzing OD flow
69 data. Visual representations of massive movement data facilitate comprehensive exploration
70 of data, in turn enabling perception and understanding complex flow trends. Aggregation
71 and generalization of movement data are frequently utilized to resolve visual clutter [9].
72 While visual analytics can help to extract inherent patterns from massive data, it is difficult
73 to quantitatively compare two sets of different OD flows based on a hypothesis testing. In
74 other words, it is complicated to comprehend how two OD flows differ and, more importantly,
75 the magnitude of the difference, using a test of statistical significance. Recently published
76 articles employ multidimensional spatial scan statistics [8] and local Ripley's K-function
77 [23] to identify clusters of flow data based on statistical significance tests. Thus, this paper
78 applies bivariate hypothesis testing methods based on data depth to understand the difference
79 between two OD flow datasets in terms of the amount of spatial extent.

80 It is worth noting that flow mapping approaches frequently suffer from the modifiable
81 areal unit problem (MAUP). Essentially, MAUP is the influence of different aggregations
82 determined by location on the presentation of coherent patterns. Kernel-based flow estimation
83 and smoothing are used to overcome different spatial resolutions [9]. Instead of attempting
84 to find the best areal unit by which to partition urban space and aggregates the OD flows,
85 this study adopted the established traffic analysis zones of New York City as base unit. That

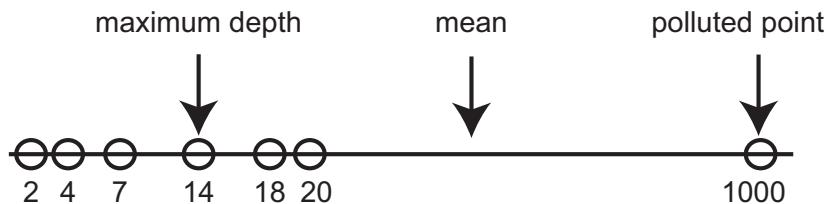


Figure 1 Robustness of halfspace depth for the univariate case

86 said, the proposed method can be adapted to other implementation of areal units. In this
 87 study, New York City taxi trip data includes the origin and destination within traffic analysis
 88 zones, while ignoring the intermediate locations of the actual routes. It is not necessary to
 89 reconstruct individual movements for flow estimation (see [5]).

90 In summary, this paper presents a new algorithm which conducts outlier detection
 91 as well as hypothesis testing on OD flow data extracted from a trajectory dataset. Our
 92 approach investigates the central regions of OD flows, based on data depth, to detect OD
 93 flow anomalies and conduct hypothesis testing between two different OD flow datasets. We
 94 believe that our method for analyzing taxi trip data has the potential to aid administrative
 95 authorities in understanding crowd patterns, in turn improving urban planning activities
 96 such as determining transportation investments.

97 The remainder of this paper is organized as follows: Section 2 overviews how to detect OD
 98 flow outliers and conduct hypothesis testing between two different OD flow datasets using
 99 the concept of data depth. Experimental design and the evaluation of the proposed method
 100 are presented in Section 3. These results are discussed in Section 4. Section 5 concludes this
 101 paper with a summary and future perspectives.

102 **2 Methods**

103 **2.1 Data Depth**

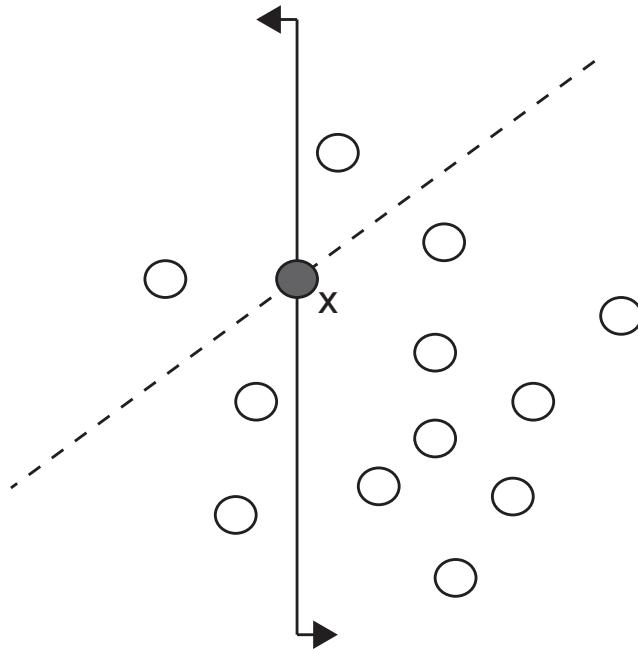
104 Data depth measures the centrality of a point with regard to a given dataset in \mathbb{R}^d . Originally
 105 developed by [24], the notion of data depth (i.e., halfspace depth) generalizes the univariate
 106 concept of ranking to multivariate data. Halfspace depth represents how deeply a point is
 107 located within a given dataset by ordering all points according to their degree of centrality.

108 Generally, the halfspace depth (HD) of point x in \mathbb{R}^d is defined as the minimum probability,
 109 P on \mathbb{R}^d , associated with any closed halfspace containing x [33].

$$110 \quad HD(x; P) = \inf\{P(H) : H \text{ is a closed halfspace}, x \in H\}, x \in \mathbb{R}^d.$$

111 For the univariate case, all values less than or equal (greater than or equal) to x form
 112 a closed halfspace. All values less (greater) than x are an open halfspace. The smallest
 113 probability associated with two closed halfspaces developed by x is the halfspace depth
 114 of point x . In Figure 1, the probability of values less than or equal to 4 is 2/7 and the
 115 probability of values greater than or equal to 4 is 6/7. Thus, the halfspace depth of 4 is 2/7,
 116 which is the minimum probability carried by any closed halfspace containing 4. Furthermore,
 117 as the sample median, 14 has the largest halfspace depth. Note that, the polluted point
 118 inflates the standard error of the sample mean, thereby distorting the view of the data.

119 Similarly, the halfspace depth of x for the bivariate case is defined by the minimal number
 120 of data points in any closed halfspace, which is determined by a hyperplane through x [21]. In



■ **Figure 2** Halfspace depth for the bivariate case

121 Figure 2, the solid line through x is rotated by 180° . The halfspace depth of x is determined
 122 by the smallest portion of data separated by such a hyperplane. For example, the halfspace
 123 depth of x is $3/13$, as determined by the dotted line. However, the halfspace depth of x
 124 determined by the solid line is $4/13$. Thus, the halfspace depth of x is $3/13$, which is the
 125 minimal number of data points in any closed halfspace through x .

126 The property of halfspace depth is a center-outward ordering of points in \mathbb{R}^d and is affine
 127 invariant [19]. These features make halfspace depth useful tool in nonparametric inference,
 128 which leads to various applications such as data classification and cluster analysis [12, 10].
 129 There are multiple approaches to calculating data depth, including halfspace depth [21],
 130 projection depth [25], and simplicial depth [15]. While the computational complexity of
 131 the projection approach is $\mathcal{O}(n^2)$ (where n is the number of points), the computational
 132 complexity of simplicial depth is $\mathcal{O}(n^3)$. This can significantly increase execution time when
 133 n is large. Thus, this paper uses the more efficient method proposed by [21], in which the
 134 computation complexity for both approaches is $\mathcal{O}(n \log n)$.

135 2.2 OD Flow Outlier Detection Based on Depth

136 The center-outward ordering in data depth is closely related to the detection of outliers. The
 137 upper level sets of data depth in \mathbb{R}^2 form the central regions. The most central region can
 138 be regarded as a median. Conversely, the lower level sets of data depth, which coincide with
 139 larger distances from the center, can be regarded as outlyingness. This concept was utilized
 140 by [22, 28] to generate bag plots, which are analogous to one-dimensional box plots based
 141 on data depth. This paper uses the bag plot to identify the outliers of OD flows. Before
 142 explaining the method of outlier detection, we first introduce a basic definition of OD flow.

143 ▶ **Definition 1.** Origin-destination (OD) flow. The OD flow $OD_i = (o_i, d_i, c_i, ts_i, te_i)$ is the
 144 number of trips from the origin ID to destination ID of traffic analysis zones between the
 145 start time (ts_i) and the end time (te_i), where $ts_i < te_i$.

Based on this basic definitions, Figure 3 depicts bag plots representing the OD flows of New York City taxi data collected on May 21, 2014 and July 1, 2014. We exploited taxi data on May 21, 2014 because the National September 11 Memorial Museum and Pavilion was opened to the public on this date. We randomly selected another data on July 1, 2014. In Figure 3a, the deepest depth of OD flows, depth median, is represented by a star symbol. This point is surrounded by a dark blue bag, which contains the half of OD flows. This region is regarded as a central region of OD flows. The OD flows in the bag are the dominant patterns. Magnifying the bag by a factor of three, relative to depth median, constructs a fence, as indicated by the light-blue area. The fence is comparable to the whiskers of a one-dimensional boxplot. The OD flows outside the fence, represented by red circles, are outliers. Every OD pair is represented by a point in Figure 3. The x-axis indicates the counts of forward OD flows (e.g., the number of OD flows from origin ID 2 to destination ID 10), and the y-axis indicates the counts of reverse OD flows (e.g., the number of OD flows from origin ID 10 to destination ID 2) in Figure 3a.

The bag plot presents the data using the following attributes: location is represented by the depth median; spread or the spatial extent of bag; correlation or the orientation of the bag; and skewness, as represented by the shape of the bag and the fence [22]. In Figure 3a, we observe that some forward OD flows have higher counts than their paired reverse OD flows. We also note the relatively linear correlation between forward OD flows and reverse OD flows and the skewness of forward (reverse) OD flows.

It is also possible to detect the outliers of OD flows of two different time stamps. In Figure 3c, we visualize the OD flows recorded on two different days. Comparing the two sets of OD flows not only indicates the central region of OD flows, it also distinguishes the significantly different OD flows.

The OD flows in high activity areas of a city are more likely to have large trip volumes. We use set operations to detect such outliers. We regard OD flows on July 1 as the control dataset (*control*); OD flows on May 21 as test dataset (*test*); and the combination of two OD flows as combination dataset (*combination*) in Figure 3. Then we can calculate the intersection of three outliers sets (*control* \cap *test* \cap *combination*), which are represented as rectangle symbols in Figure 3d.

In addition, it is interesting to detect the outliers of OD flows which are typical patterns at time t_1 and atypical behavior at time t_2 . We define the union of points in the bag, the central region, at time t_1 and t_2 . Then we calculate the intersection of two sets, the outliers of the combination set and the previous union set. These outliers are represented as triangle symbols in Figure 3e. These outliers are typical OD flows at time t_1 , located in the central regions in the bag plot. When we consider two OD flows together, they become unusual OD flows, some have more trips and some have less trips, relative to the control dataset. Thus, we can detect and treat outliers interactively based on data depth.

2.3 OD Flow Comparisons Based on Depth

Data depth can compare bivariate data from two independent groups. A t-test can be used to compare means from two independent groups. For example, the t-test reveals whether the means of two OD flows are different at two different temporal ranges. However, it is also worth examining how groups differ in terms of scale, which is also referred to as spread. Comparisons of central regions in data depth evaluate the marginal distribution, thereby considering the overall structure of the data [26].

Let X and Y be the random variables having distributions F and G for two independent groups. The quality index proposed by [16] is the probability that the depth of Y is greater

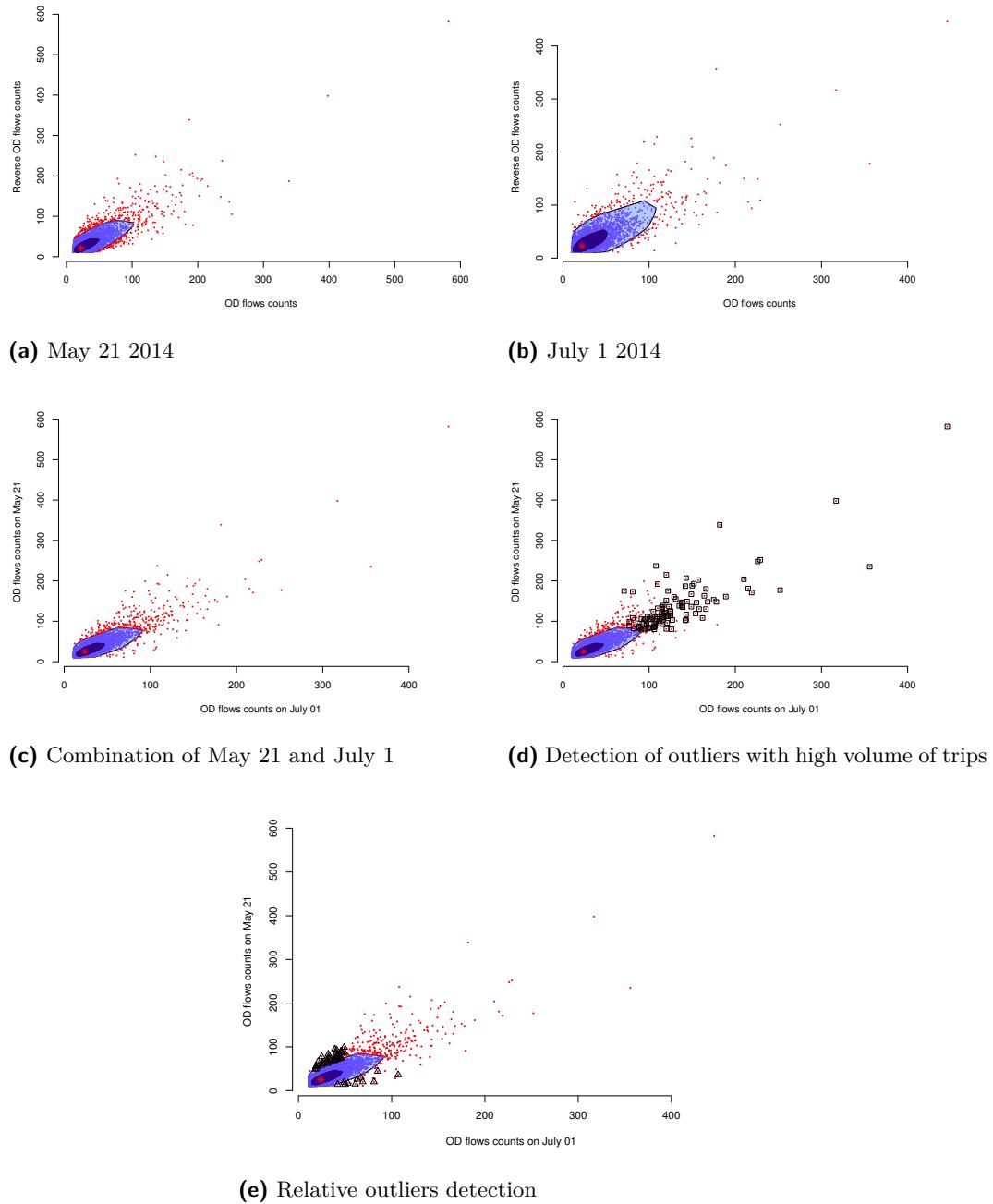


Figure 3 Outliers detection of OD flows using a bag plot

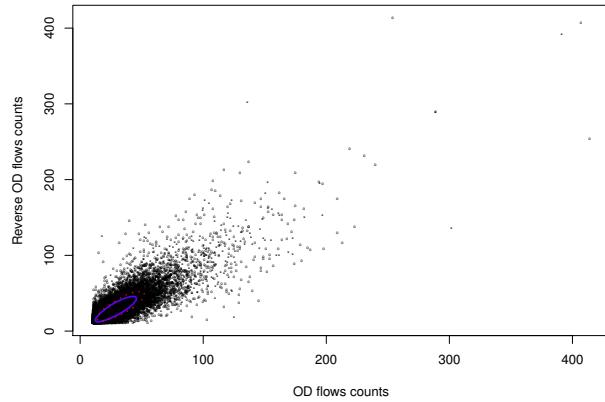


Figure 4 Central regions of two OD flows: \circ indicates the OD flows for Saturday, March 29 2014 and $*$ indicates the OD flows for a list of Saturdays; blue line presents the central region of the OD flows for the list of Saturdays and red dotted line presents the central region of the OD flows on March 29.

193 than or equal to depth of X .

194
$$Q(F, G) = P[D(X; F) \leq D(Y; F)],$$

195 where P is the probability and $D(X; F)$ is the depth of randomly sampled observations
 196 according from distribution F . The range of Q , as presented by [16], is $[0, 1]$ and $Q(F, G) = 0.5$
 197 if and only if $F = G$. If $Q < 0.5$ or if $Q > 0.5$, the scale increases or decreases from F to G .
 198 Therefore, it is possible to detect differences in scale using a bootstrap method.

199 Let X_1, \dots, X_a be a random sample from F , and Y_1, \dots, Y_b be a random sample from G .
 200 The estimate of $Q(F, G)$ is calculated as shown below.

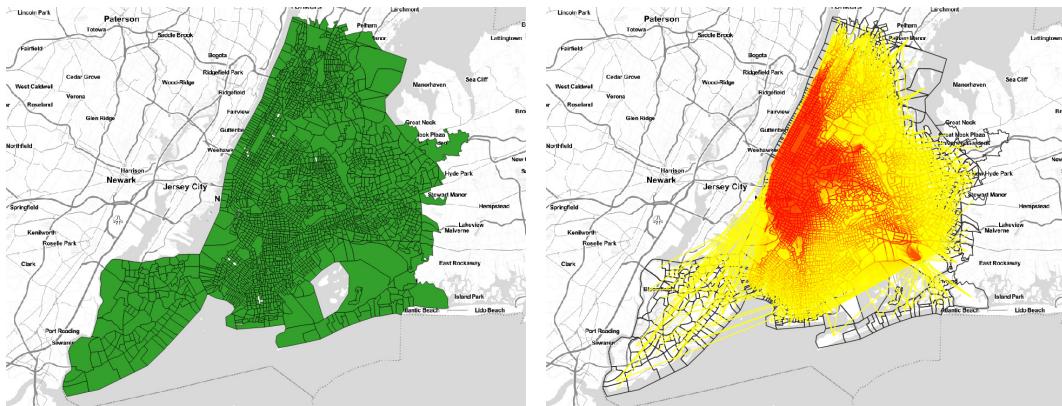
201
$$\hat{Q}(F, G) = \frac{1}{b} \sum_{i=1}^b R(Y_i; F_a),$$

202 where $R(Y_i; F_a)$ indicates the proportion of X_j which has $D(X_j; F_a) \leq D(Y_i; F_a)$. Simil-
 203 arly, the estimate of $Q(G, F)$ can be defined as follows:

204
$$\hat{Q}(G, F) = \frac{1}{a} \sum_{i=1}^a R(X_i; G_b).$$

205 Bootstrap samples are obtained by resampling from the two groups (F and G). Under the
 206 null hypothesis ($H_0 : Q(F, G) = Q(G, F)$), the difference of the resulting bootstrap estimates
 207 is $Q^*(F, G) - Q^*(G, F)$. Thus, if the confidence interval of $Q(F, G) - Q(G, F)$ does not
 208 contain zero, we can reject the null hypothesis, H_0 [16, 26].

209 For ease of understanding, Figure 4 presents the central regions of two OD flows. One
 210 dataset is OD flows for Saturday, March 29, 2014, and the other dataset includes multiple
 211 Saturdays, those of March 1, 8, 15, 22, and April 5. At 552,064 taxi trips, the day of March
 212 29 had the highest number of taxi trips for the year of 2014. The dataset for the other five



(a) 2,250 traffic analysis zones in New York City (b) OD flows on July 1 2014

Figure 5 Experimental data: New York City taxi data

Saturdays comprised 2,621,703 taxi trips. The bootstrap method reveals that the confidence interval is 0.0247 and 0.0596. This confidence interval does not include zero, thus rejecting the H_0 null hypothesis. This indicates that the amount of scale is significantly changed between two OD flow datasets. Furthermore, the OD flows from the group of Saturdays is nested within the OD flows corresponding to March 29. This additional perspective was based on data depth comparisons.

The bootstrap method is a time consuming process. For this study, we generate 2,000 bootstrap samples. To improve the execution efficiency of the bootstrap computation, we distributed the work across multiple nodes and cores by implementing an embarrassingly parallel R code.

3 Experiments

3.1 Data

This study uses New York City taxi data collected in 2014 to evaluate the effectiveness of the proposed approach. Figure 5a presents traffic analysis zones in New York City which indicate the origin and the destination IDs of the OD flows. A traffic analysis zone (TAZ) is the most commonly adopted basic geographic unit in transportation planning models. The geographic areas of TAZ are delineated by transportation officials for tabulating traffic-related data. The size of TAZ varies because it accounts the underlying population in each zone, which consists of one or more census blocks, block groups, or census tracts. The shapes of the TAZs in this study are derived from the cartographic boundary shapefiles developed by the U.S. Census Bureau in conjunction with the 2010 census (<https://www2.census.gov/geo/tiger/TIGER2010/TAZ/2010/>). Considering the TAZs are particularly useful for journey-to-work and place-of-work statistics, we employed them as the basic units for accounting the taxi trips. Figure 5b shows OD flows on July 1. Red lines indicate the dominant OD flows.

As a case study, this paper examined OD flows recorded on weekdays and weekends in June 2014. The weekday dataset includes taxi trajectories collected on June 3, 10, 17, and 24, and represents 1,721,655 taxi trips. The weekend dataset includes taxi trajectories collected on June 8, 15, 22, and 29, and describes 1,593,480.

242 3.2 Procedure

243 The performance of the proposed method was compared with alternative methods. Trajectory
 244 anomaly detection based on Mahalanobis distance [20] was used to evaluate the performance
 245 of outlier detection by the proposed method. The Mahalanobis distance is distinguished
 246 from Euclidean distance by its consideration of the correlations of the data, in this case, the
 247 two OD flow datasets. According to [20], the anomaly detection threshold can be defined as
 248 follows:

$$249 \quad d_M(OD_{t_1}, \mu_{[t_0, t_1]}) \geq 3 \cdot \sqrt{\frac{1}{N} \sum_{t \in [t_0, t_1]} (OD_t - \mu_{[t_0, t_1]})^2}.$$

250 where OD_{t_1} is the current OD flow, and $\mu_{[t_0, t_1]}$ is the median of all OD flows during $[t_0, t_1]$.
 251 In addition, we visualized the results in order to compare them and make the difference
 252 easier to understand. The difference of scale was evaluated using standard statistics, such as
 253 F-test, to compare the variance of two datasets.

254 For data cleaning process, this study used Hadoop with Pig. We developed a Hadoop
 255 program to handle the large volume of data, which was composed of 173 million taxi trip
 256 records, remove trips with invalid OD coordinates, and assign each OD locations into
 257 the corresponding traffic analysis zone. To implement the OD flow outlier detection, this
 258 study used R. The computing environment used Amazon Web Service and the Bridges
 259 supercomputer at the Pittsburgh Supercomputing Center. This study only evaluated OD
 260 flows more than 10 trips, as the low trip number OD flows could have distorted the view of
 261 the data. All the code will be released as open source (the link to the code will be added later
 262 and currently is available upon request).

263 3.3 Case study: weekdays vs weekends

264 3.3.1 Outlier Detection

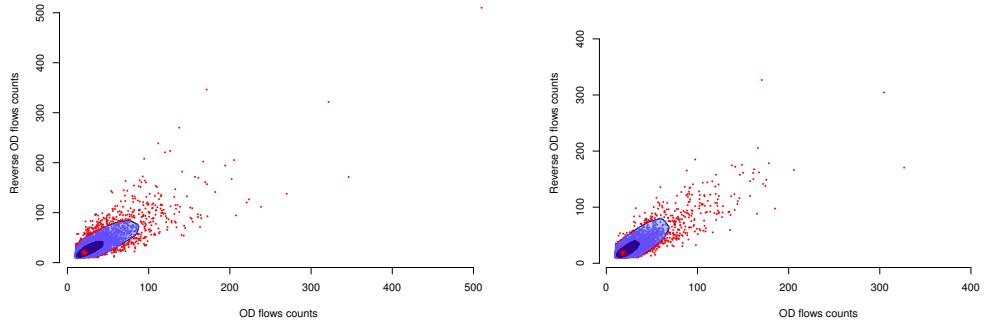
265 The bag plots presented OD flow outliers on weekdays and weekends in Figures 6a and 6b,
 266 respectively. The outliers are detected by considering forward OD flows and reverse OD
 267 flows together.

268 To find the difference between two datasets, we considered two forward OD flows together
 269 with the bag plot. Then, we identified the outliers OD flows in Figure 7a. The outliers with
 270 rectangle symbols indicate OD flows with large volumes of taxi trips during weekdays and
 271 weekends. Figure 7b depicts these outliers are superimposed on a map with red lines. The
 272 yellow lines represent the other OD flows, excluding the large volume OD flows on weekdays
 273 and weekends.

274 This case clearly demonstrates that most OD flows occurred in three broad areas: within
 275 Manhattan, between the center of Manhattan and the two major airports (J.F.K International
 276 Airport and LaGuardia Airport), and between the two airports.

277 In addition, we investigated abnormal weekend OD flows that are typical weekday OD
 278 flows. These abnormal weekend OD flows exhibited substantial variance in number of taxi
 279 trips relative to their weekday counterparts. Figure 8a presents these OD flows outliers with
 280 triangle symbols. In Figure 8b, red lines indicate the substantial increases in weekend trip
 281 volumes. Conversely, blue lines indicate the decreases in trip volume. Figure 8b reveals that
 282 OD flows between the center of Manhattan and the two airports or between the two airports
 283 were not significantly different during weekdays and weekends. However, we did observe

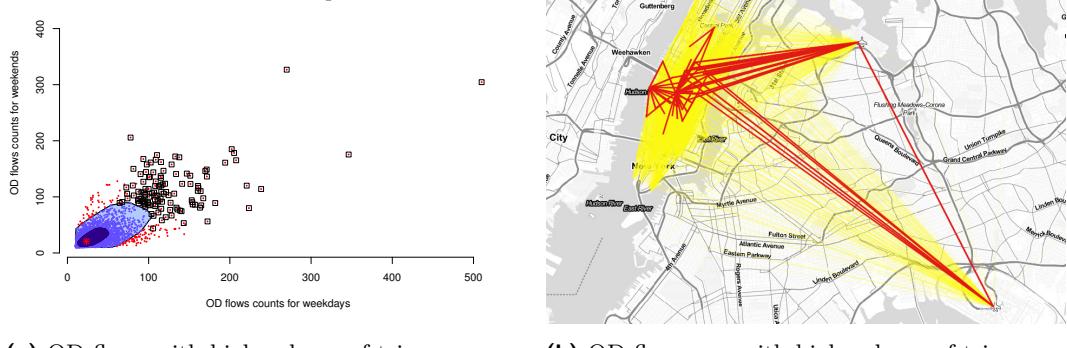
6:10 Outlier Detection and Comparison of Origin-Destination Flows using Data Depth



(a) Bag plot on weekdays

(b) Bag plot on weekends

Figure 6 Outliers detection of OD flows: X-axis indicates forward OD flows counts and Y-axis indicates reverse OD flows counts.



(a) OD flows with high volume of trips

(b) OD flow map with high volume of trips

Figure 7 Outliers with high volume of trips on weekdays and weekends: Rectangles in Figure 7a coincide with red lines in Figure 7b.

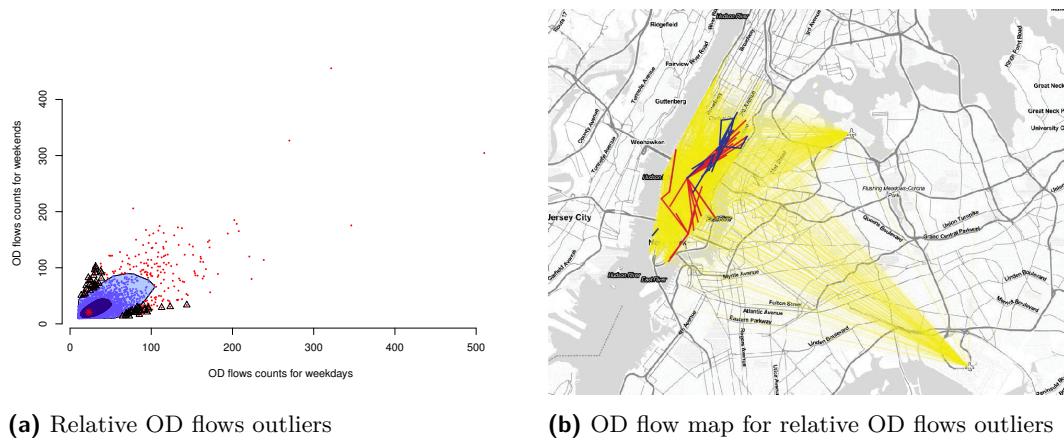


Figure 8 Relative OD flows outliers on weekdays and weekends: Triangles in Figure 8a coincide with red and blue lines in Figure 8b.

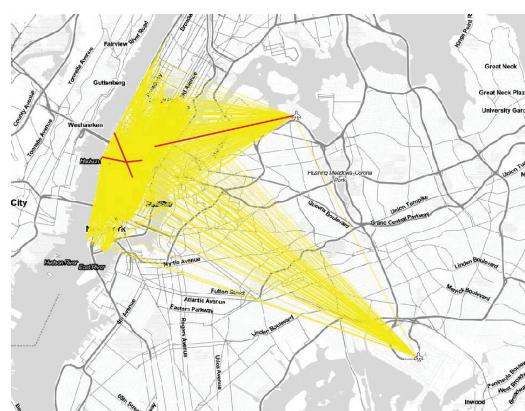


Figure 9 Outlier OD flows on weekdays and weekends based on Mahalanobis distance.

some meaningful decrease in OD flows during the weekends in business district, as depicted by the blue lines in Figure 8b.

We also detected outlier OD flows using Mahalanobis distance. The results are presented in Figure 9. Far fewer outlier OD flows were detected using Mahalanobis distance than by the proposed approach. The Mahalanobis method only considers the forward OD flows of the two datasets. It identified OD flow outliers with high volume of trips because Mahalanobis distance considers the correlations between two OD flows. Thus, Mahalanobis distance is more likely to identify outliers when two OD flows have large trip volumes. In fact, the OD flows outliers from Mahalanobis distance are a subset of the outliers identified by the proposed method, as depicted in Figure 7b. Furthermore, the Mahalanobis distance approach could not detect the outliers detected by the proposed approach in Figure 8 because the Mahalanobis distance approach cannot compare two flows to evaluate significant increases or decreases.

3.3.2 Comparisons in scale

We further investigated how two OD flows differ. Our approach is sensitive to the difference in scale. Hypothesis testing of differences between two central regions in Figure 10 inadvertently

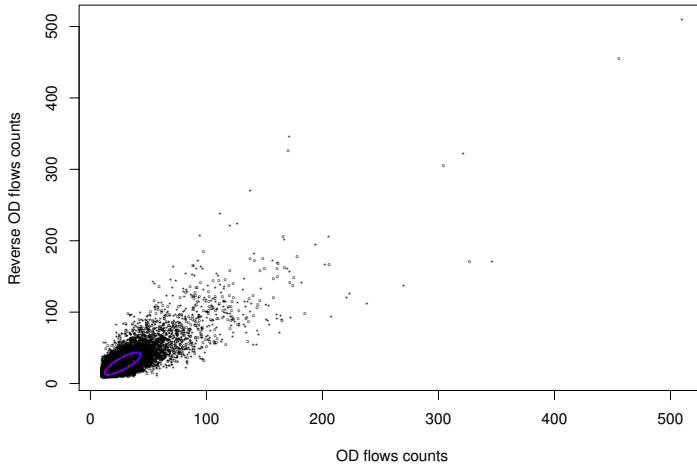


Figure 10 OD flows comparisons based on data depth: \circ indicates the OD flows on weekdays and $*$ indicates the OD flows on weekends; blue line presents the central region of the OD flows for the weekdays and red dotted line presents the central region of the OD flows on weekends.

revealed that the confidence interval was -0.0277 and 0.0157, which includes zero. Thus, failing to reject the null hypothesis. The two central regions were similar in terms of the spread.

Interestingly, the standard statistic F-test was significant, $F(9530, 7637) = 1.1786, p \leq 0.05$. The variances of two groups were significantly different. This result directly opposed that of the proposed approach.

4 Discussion

The results demonstrate that the proposed method effectively identifies outlier OD flows based on data depth. It is also possible to detect outlier OD flows by querying with conditional clauses, such as which outlier OD flows always have high trip volumes during time t_1 and time t_2 .

As an alternative method, the state-of-the-art Mahalanobis distance approach detected similar outlier OD flows. However, the number of outliers detected was different. This occurred because our OD flows data had heavy tail distributions, that is, many of the OD flows with a long distance from the depth median depicted in Figure 8a. Mahalanobis distance is known to be inadequate when the underlying data have heavy tail distributions [27]. Thus, the presence of outliers may mask the detection of other outliers in Mahalanobis distance approach. Furthermore, it can only detect OD flow outliers with high numbers of trips during time t_1 and time t_2 . It is difficult to detect OD flows outliers that have different properties, such as substantial differences in the number of trips when comparing with time t_1 and time t_2 .

In terms of the difference in spread, our approach used a bootstrap method to compare the central regions of data depth. This approach investigated the difference in scale as well as the structure of data. It can provide information how deeply points from group 1, OD flows at t_1 , tend to be located within group 2, OD flows at t_2 . General statistics such as

325 F-test only provide their difference in variation and do not further specify how groups differ.

326 Interestingly, the F-test results revealed a statistically significant difference in terms of
327 variation of OD flows on weekdays and weekends. Our approach showed no statistically
328 significant differences. The difference may be caused by the sensitivity of F-test to non-
329 normality [6], which increases the Type-I error rate. Conversely, data depth makes no
330 assumptions about the distributions of the underlying dataset.

331 **5 Conclusions and Future Work**

332 This paper provides a new methodology for identifying outlier OD flows and the difference
333 in scale between two different OD flows at t_1 and t_2 . The proposed method is based on
334 the concept of data depth. Data depth is robust statistics, which is suited to non-Gaussian
335 distribution of the underlying datasets. Compared with standard statistics, this approach
336 enhances understanding of the differences and the magnitude of the differences between tow
337 OD flows.

338 This study made no attempt to consider geographic contexts such as locational cir-
339 cumstances or surrounding environment in understanding OD flows. Ultimately, further
340 investigation should focus on integrating the analysis of OD flows with geographic context.
341 Such an effort will lead to knowledge discovery and understanding the dynamics of urban
342 flow.

343 **References**

- 344 1 Marina Alberti, John M Marzluff, Eric Shulenberger, Gordon Bradley, Clare Ryan, and
345 Craig Zumbunnen. Integrating humans into ecology: Opportunities and challenges for
346 studying urban ecosystems. *AIBS Bulletin*, 53(12):1169–1179, 2003.
- 347 2 Maike Buchin, Somayeh Dodge, and Bettina Speckmann. Similarity of trajectories taking
348 into account geographic context. *Journal of Spatial Information Science*, 2014(9):101–124,
349 2014.
- 350 3 Chao Chen, Daqing Zhang, Zhi-Hua Zhou, Nan Li, Tülin Atmaca, and Shijian Li. B-
351 planner: Night bus route planning using large-scale taxi GPS traces. In *2013 IEEE In-*
352 *ternational Conference on Pervasive Computing and Communications (PerCom)*, pages
353 225–233. IEEE, 2013.
- 354 4 Srinivas Devarakonda, Parveen Sevusu, Hongzhang Liu, Ruilin Liu, Liviu Iftode, and Badri
355 Nath. Real-time air quality monitoring through mobile sensing in metropolitan areas. In
356 *Proc. 2nd ACM SIGKDD International Workshop on Urban Computing*, page 15. ACM,
357 2013.
- 358 5 Matt Duckham, Marc van Kreveld, Ross Purves, Bettina Speckmann, Yaguang Tao, Kevin
359 Verbeek, and Jo Wood. Modeling checkpoint-based movement with the earth mover’s
360 distance. In *International Conference on Geographic Information Science*, pages 225–239.
361 Springer, 2016.
- 362 6 Andy Field, Jeremy Miles, and Zoë Field. *Discovering statistics using R*. Sage, London,
363 UK, 2012.
- 364 7 Vitor Cunha Fontes, Lucas Andre de Alencar, Chiara Renso, and Vania Bogorny. Discov-
365 ering trajectory outliers between regions of interest. In *Proc. XIV GeoInfo*, pages 49–60,
366 2013.
- 367 8 Yizhao Gao, Ting Li, Shaowen Wang, Myeong-Hun Jeong, and Kiumars Soltani. A multi-
368 dimensional spatial scan statistics approach to movement pattern comparison. *International*
369 *Journal of Geographical Information Science*, 0(0):1–22, 2018.

- 370 9 Diansheng Guo and Xi Zhu. Origin-destination flow data smoothing and mapping. *IEEE Transactions on Visualization and Computer Graphics*, 20(12):2043–2052, 2014.
- 371
- 372 10 Myeong-Hun Jeong, Yaping Cai, Clair J Sullivan, and Shaowen Wang. Data depth based clustering analysis. In *Proc. 24th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, page 29. ACM, 2016.
- 373
- 374
- 375 11 Mei-Po Kwan. Space-time and integral measures of individual accessibility: A comparative analysis using a point-based framework. *Geographical Analysis*, 30(3):191–216, 1998.
- 376
- 377 12 Tatjana Lange, Karl Mosler, and Pavlo Mozharovskyi. Fast nonparametric classification based on data depth. *Statistical Papers*, 55(1):49–69, 2014.
- 378
- 379 13 Jae-Gil Lee, Jiawei Han, and Xiaolei Li. Trajectory outlier detection: A partition-and-detect framework. In *IEEE 24th International Conference on Data Engineering*, pages 140–149. IEEE, 2008.
- 380
- 381
- 382 14 Liangxu Liu, Shaojie Qiao, Yongping Zhang, and JinSong Hu. An efficient outlying trajectories mining approach based on relative distance. *International Journal of Geographical Information Science*, 26(10):1789–1810, 2012.
- 383
- 384
- 385 15 Regina Y Liu. On a notion of data depth based on random simplices. *The Annals of Statistics*, pages 405–414, 1990.
- 386
- 387 16 Regina Y Liu and Kesar Singh. A quality index based on data depth and multivariate rank tests. *Journal of the American Statistical Association*, 88(421):252–260, 1993.
- 388
- 389 17 Jean Damascène Mazimpaka and Sabine Timpf. Exploring the potential of combining taxi GPS and flickr data for discovering functional regions. In *AGILE 2015*, pages 3–18. Springer, 2015.
- 390
- 391
- 392 18 Jean Damascène Mazimpaka and Sabine Timpf. Trajectory data mining: A review of methods and applications. *Journal of Spatial Information Science*, 2016(13):61–99, 2016.
- 393
- 394 19 Karl Mosler. *Robustness and Complex Data Structures*, chapter Depth Statistics, pages 17–34. Springer Berlin Heidelberg, Berlin, Heidelberg, 2013.
- 395
- 396 20 Bei Pan, Yu Zheng, David Wilkie, and Cyrus Shahabi. Crowd sensing of traffic anomalies based on human mobility and social media. In *Proc. 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, pages 344–353. ACM, 2013.
- 397
- 398
- 399 21 Peter J Rousseeuw and Ida Ruts. Algorithm AS 307: Bivariate location depth. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 45(4):516–526, 1996.
- 400
- 401 22 Peter J Rousseeuw, Ida Ruts, and John W Tukey. The bagplot: a bivariate boxplot. *The American Statistician*, 53(4):382–387, 1999.
- 402
- 403 23 Ran Tao and Jean-Claude Thill. Spatial cluster detection in spatial flow data. *Geographical Analysis*, 48(4):355–372, 2016.
- 404
- 405 24 John W Tukey. Mathematics and the picturing of data. In *Proc. International Congress of Mathematicians*, volume 2, pages 523–531, 1975.
- 406
- 407 25 Rand R Wilcox. Approximating tukey’s depth. *Communications in Statistics-Simulation and Computation*, 32(4):977–985, 2003.
- 408
- 409 26 Rand R Wilcox. Two-sample, bivariate hypothesis testing methods based on tukey’s depth. *Multivariate Behavioral Research*, 38(2):225–246, 2003.
- 410
- 411 27 Rand R Wilcox. *Introduction to robust estimation and hypothesis testing*. Academic Press, 2012.
- 412
- 413 28 Hans Peter Wolf and Uni Bielefeld. aplpack: Another Plot PACKage: stem.leaf, bagplot, faces, spin3r, plotsummary, plot hulls, and some slider functions, 2014. R package version 1.3.0. URL: <https://CRAN.R-project.org/package=aplace>.
- 414
- 415
- 416 29 Junjun Yin, Aiman Soliman, Dandong Yin, and Shaowen Wang. Depicting urban boundaries from a mobility network of spatial interactions: A case study of great britain with geo-located twitter data. *International Journal of Geographical Information Science*, 31(7):1293–1313, 2017.
- 417
- 418
- 419

- 420 30 Guan Yuan, Shixiong Xia, Lei Zhang, Yong Zhou, and Cheng Ji. Trajectory outlier detec-
421 tion algorithm based on structural features. *Journal of Computational Information Systems*,
422 7(11):4137–4144, 2011.
- 423 31 Daqing Zhang, Nan Li, Zhi-Hua Zhou, Chao Chen, Lin Sun, and Shijian Li. iBAT: Detecting
424 anomalous taxi trajectories from GPS traces. In *Proc. 13th International Conference on*
425 *Ubiquitous Computing*, pages 99–108. ACM, 2011.
- 426 32 Yu Zheng. Trajectory data mining: An overview. *ACM Transactions on Intelligent Systems*
427 and Technology
- 428 33 Yijun Zuo and Robert Serfling. General notions of statistical depth functions. *The Annals*
429 *of Statistics*, 28:461–482, 2000.