Neighborhood Level Impacts in Human Travel Patterns: Findings from the Closure of Alaskan Way Viaduct

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Introduction

Human travel pattern research has been attracting wide attention due to its great importance in urban planning, traffic forecasting, Origin-Destination estimation, and other related areas. Traditionally, travel pattern research highly rely on actively-solicited data (e.g. household travel survey), which were collected under certain transportation-related purposes. Such types of data, however, have some obvious limitations, including limited temporal and/or spatial coverage, high collection costs, relatively low update frequency, and so on (Chen et al., 2016). Contrast to actively solicited 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). They may include mobile phone data, mobile app-based data, GPS data, and etc. Such passively-generated data have shown their great potential in many transportation applications (e.g. monitoring large-scale human mobility patterns), because of their large coverage, relatively high penetration rates, longitudinal feature, and other characteristics. The data we used in this study (app-based data) belongs to passively-generated data.

The study period here is a two-week period in 2019 (Jan 5th-Jan 18th). Alaskan Way Viaduct who traversed across downtown Seattle area (Washington State) was closed on Jan 12th 2019 (see Figure 1). The study period covered one week right before and after the closure date. This research is to investigate whether or not the closure of Alaskan Way Viaduct has affected the travel patterns in Seattle on a neighborhood level. In this study, statistical hypothesis tests including Kolmogorov-Smirnov (K-S) test and t test were performed to test on each neighborhood in Seattle to examine whether there is enough evidence to demonstrate that travel pattern metrics before the closure of Alaskan Way Viaduct differs from those after the closure.

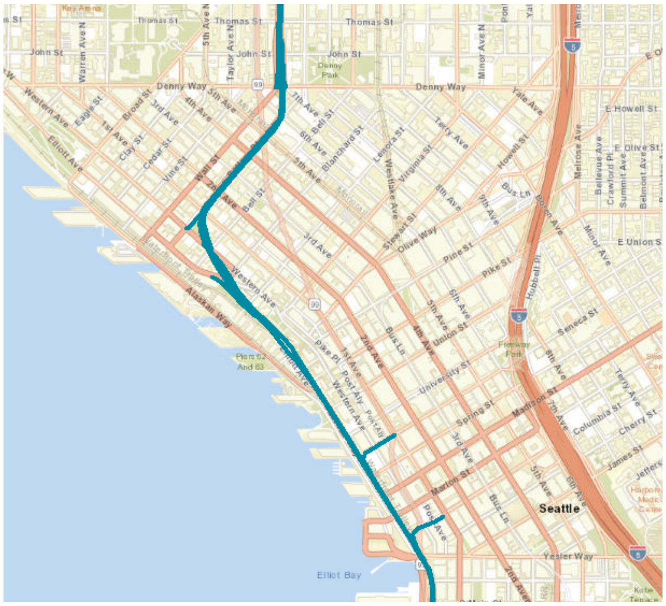


Figure 1. A layout of Alaskan Way Viaduct

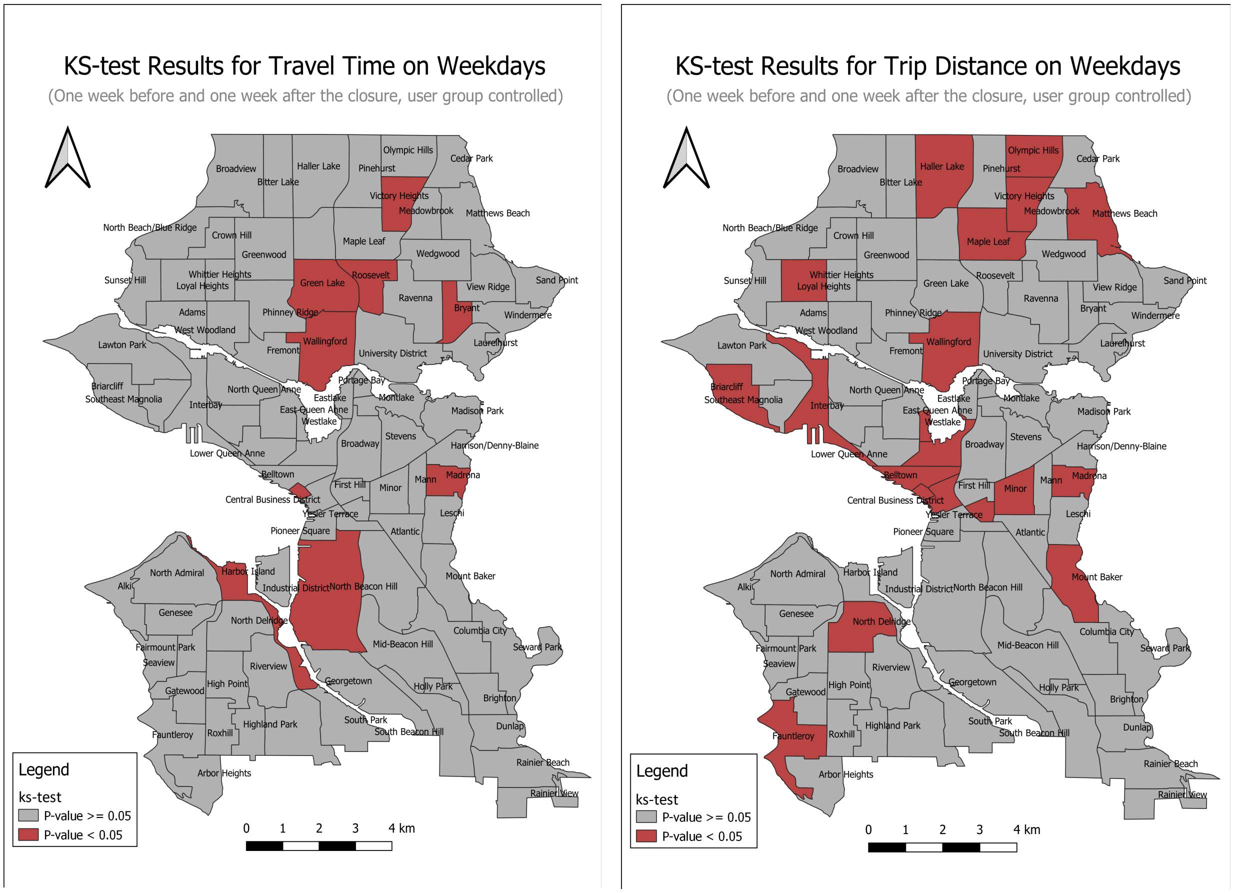
Methodology

The data provided by the data provider are raw trajectory data which only contains limited information, including ID, time stamp, longitude/latitude, location accuracy. In order to extract trip information, we employed the "Divide, Conquer and Integrate" (DCI) method by Wang et al., (2019) to process such multi-sourced raw data. After obtaining the trip information, we identified user's home locations based on the location visiting frequency, and the mobile app users can be categorized into different neighborhoods based on their home locations. For each user, we used three metrics to characterize its travel pattern: trip distance, trip duration, and trip rate. Based on these metrics, two methods are used to compare/measure the travel pattern change of users before and after the closure of Alaskan Way Viaduct: (1) Kolmogorov-Smirnov (KS) Test, and (2) statistical T-Test.

The KS-Test is a nonparametric test of the equality of continuous, one-dimensional probability distributions that can be used to compare two samples (two-sample KS test) (Goodman, 1954). The KS-test statistic quantifies a distance between the empirical distribution functions of two samples. KS test was performed here to investigate, for each neighborhood, whether there is a statistically significant difference between the travel pattern metrics before and after the closure of the viaduct in terms of distribution. On the other hand, t-test is most commonly applied when the test statistic would follow a normal distribution if the value of a scaling term in the test statistic were known. When the scaling term is unknown and is replaced by an estimate based on the data, the test statistics (under certain conditions) follow a Student's t distribution. The t-test can be used, for example, to determine if the means of two sets of data are significantly different from each other (Kim, 2015). Basically, similar to the KS-test, t test also compares two sample and examine whether there's significant difference between two samples in terms of mean.

Results

Figure 2 shows the KS test results for travel time and trip distance respectively (note: KS test is usually applied for continuous variable, so trip rate was not analyzed here). For travel time, one can observe that the red neighborhoods (with p value less than 0.05) were mostly distributed at the two ends of closed viaduct. It means that the residents living in those neighborhoods suffered statistically significant change in travel time after the viaduct closure. This is intuitive as the individuals who live closer to the viaduct entrances/exits are more likely to be affected by the closure of viaduct. Similar patterns can not be observed for the trip distance, but more neighborhoods in the north of the viaduct experienced a significant change compare with those in the south.



KS-test Results for Travel Time on Weekdays

(One week before and one week after the closure, user group controlled)

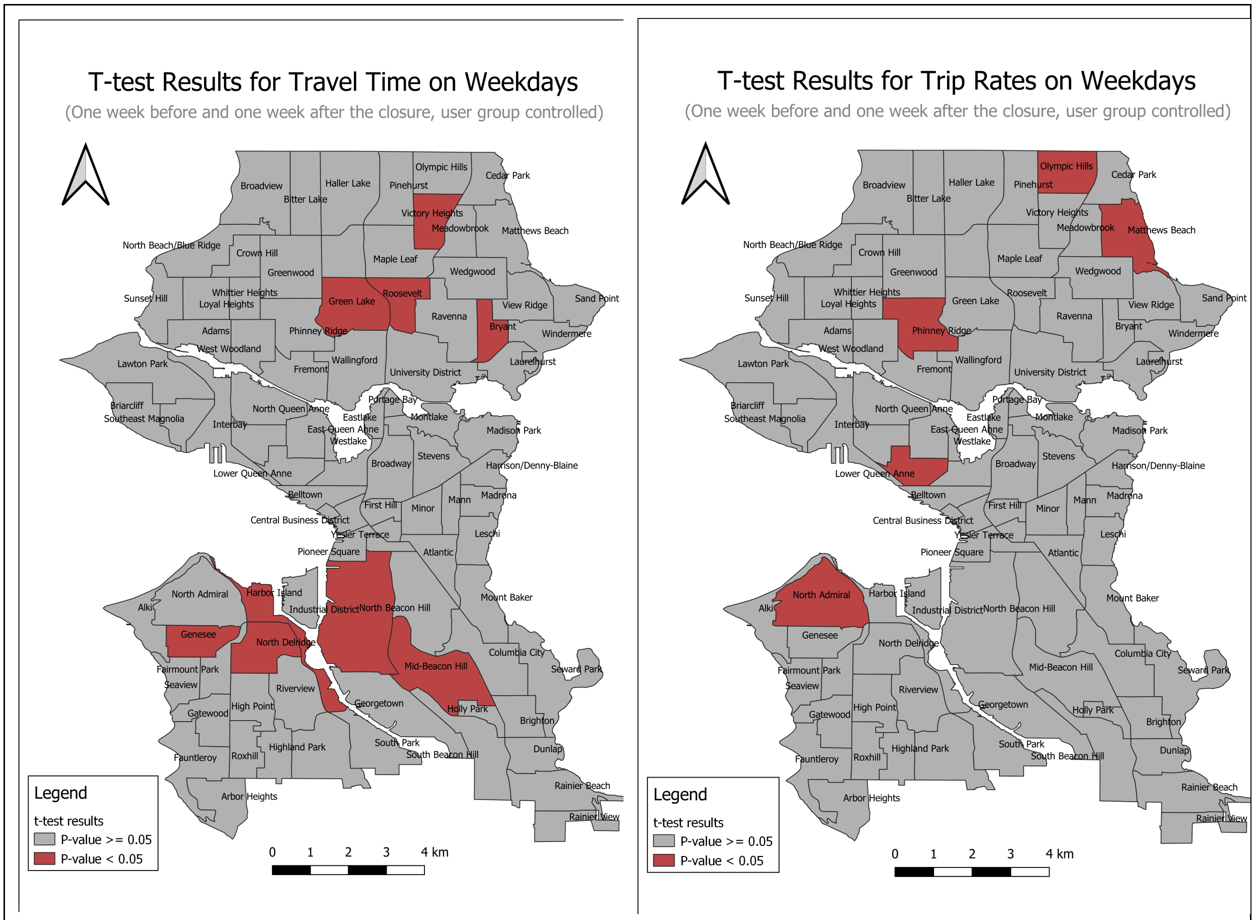
KS-test Results for Trip Distance on Weekdays

(One week before and one week after the closure, user group controlled)

(a) (b)

Figure 2. P values of KS test (a)travel time; (b)trip distance.

Figure 3 shows the results of t test analysis in terms of travel time and trip rates respectively (note: trip distance is skipped here because it violated the normality assumption in t-test). For travel time, there are 8 neighborhoods in total showing statistically significant difference. And their distribution is very similar to that in the KS-test. As for trip rates, there are 5 neighborhoods that show a statistically significant difference. We found the number of red neighborhoods for trip rates is smaller than that for travel time. A potential explanation is that trip rates is a property that is less sensitive to the variation of route choices. Specifically, detouring may lead to longer trip length or travel time, but it is less likely to affect the overall level of trip rates.



(a) (b)

Figure 3. P values of t test (a)travel time; (b)trip rates.

Conclusion

This study explored the potential impacts for human travel patterns in terms of travel time, trip distance, and trip rates from the closure of Alaskan Way Viaduct on neighborhood level. Statistical tests shown that residents in some certain areas have experienced significant change in travel patterns (e.g. individuals living in the two ends of the viaduct suffered significant travel time change). The statistical tests just told us whether such changes of travel patterns are statistically significant, but did not show whether the impact of viaduct closure is positive or negative on those metrics. Therefore we conducted the difference-in-difference analysis to investigate among all difference observed between samples before and after the closure of Alaskan Way Viaduct, how much difference can be attributed to the closure. Due to word limit, we leave this part in the presentation. In addition, we will also demonstrate a classification of the 90 neighborhoods based on statistical tests and difference-in-difference analysis. This process enables us to have a deeper understanding of the impacts of the viaduct closure, which will help us to better evaluate the effects of similar project on zone level.

References

Chen, C., Ma, J., Susilo, Y., Liu, Y., & Wang, M. (2016). The promises of big data and small data for travel behavior (aka human mobility) analysis. *Transportation research part C: emerging technologies*, *68*, 285-299.

Goodman, L. A. (1954). Kolmogorov-Smirnov tests for psychological research. *Psychological bulletin*, *51*(2), 160.

Kim, T. K. (2015). T test as a parametric statistic. *Korean journal of anesthesiology*, *68*(6), 540.

Wang, F., Wang, J., Cao, J., Chen, C., & Ban, X. J. (2019). Extracting trips from multi-sourced data for mobility pattern analysis: An app-based data example. *Transportation Research Part C: Emerging Technologies*, *105*, 183-202.