# AN EXPLORATORY ANALYSIS OF INTERCITY TRAVEL PATTERNS USING BACKEND DATA FROM A TRANSIT SMARTPHONE APPLICATION

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**ABSTRACT**

Smartphone applications ("apps") providing transit information are commonly used in urban areas. Many of these apps are available in multiple cities and automatically detect a user's location via the location services in the smartphone. The multi-city nature of these apps provides a unique opportunity to understand how transit riders seek information as they travel between cities. The objective of this paper is to identify intercity travelers to/from the New York metropolitan region using one month of backend data from an application called "Transit". Intercity travelers are identified based on the number of days each user has opened the app inside and outside of the New York region. To further categorize intercity travelers, a manual classification method is implemented and distinct subgroups of intercity travelers are identified, including visitors and New York residents. Then, the manual classification method was validated by comparing the results to self-reported home locations stored in the app by a small number of users. However, the validation only confirmed a small number of visitors as having the correct home city. This may be because only one month of the Transit app data was used or because only a small number of users stored their home location in the app. In conclusion, this exploratory analysis utilized a rich new data source and has identified many areas to refine the methodology in future analyses, such as considering consecutive days in the same city, studying travelers' pattern by day of the week, and validating the results using travel surveys.

## INTRODUCTION

Data about intercity travel behavior can be difficult to collect using traditional sources, such as household travel surveys. However, new datasets from mobile phones have the potential to identify intercity travelers and examine their travel behavior. This exploratory study proposes a new method to identify intercity travelers using backend data from a smartphone application. Specifically, data from a multiple-city transit information smartphone application called "Transit" are used. This dataset is unique in that it provides an opportunity to study intercity movements of transit riders using automatically collected data.

This paper proceeds as follows. First, literature pertaining to intercity travel behavior and mobile phone data is briefly reviewed. Then, the specific research objectives are set forth, and the smartphone-based dataset is discussed. Next, the methodology for identifying intercity travelers is presented, and a manual classification method is used to identify subgroups of intercity travelers. This method is then validated using self-report home location data. Next, examples of the intercity travel behavior of two app users are visualized. Finally, conclusions and areas for future research are presented.

## LITERATURE REVIEW

In this section, a brief overview of prior research related to intercity travel and mobile phone-based data is provided. There is a relatively large literature pertaining to intercity travel, which includes developing statistical methods and intercity travel demand models to predict mode choice, traffic volumes, travel time and frequency of long distance trips. Data sources used to conduct such analyses primarily include surveys (such as household travel surveys, stated preference surveys, revealed preference surveys, and online surveys) and data obtained from public or private transportation operators *(e.g., 1, 2, 3, 4, 5, 6)*. One recent study provides a general overview of intercity travel demand models, including discussing different data collection methods; however, use of cell phone data was not considered *(7)*.

There is also a growing body of literature pertaining to the use of cellular phone data for transportation analysis. This includes using cell phone data to estimate demand, trip times and speeds *(8, 9)* and for extracting origin-destination matrices *(10, 11, 12)*. NCHRP Report 775 provides general guidelines for using GPS data in travel demand analysis; this report suggests that cell phone data are valuable in transportation planning because they can passively trace activity patterns of large populations *(13)*. Notably, only a small number of prior studies have specifically aimed to assess intercity travel patterns using mobile phone data *(14, 15)*.

This brief review of prior research shows that some studies have used cellular phone data to estimate intercity travel patterns, but few, if any studies have used backend data from a transportation information smartphone application to assess intercity travel. Also, few prior studies have focused specifically on the transit travel patterns of intercity travelers.

## OBJECTIVE

The objective of this study is to develop a method to identify intercity travelers using backend data from a multi-city transit information smartphone application. This is done for app users based on the number of days they have opened the app inside and outside New York region in one month. Then, a manual classification method is used to further classify intercity travelers into subgroups.

## DATASET

This section contains a general description of the data used in this analysis. The first part gives a brief introduction of the smartphone app, and the second part defines the geographic area of the study. Next, there is a detailed description of the data files used in the analysis and finally, an overview of the cleaning process of the dataset.

### Overview of the Smartphone Application

"Transit" is a company based in Montreal, Canada that developed a free smartphone application providing urban transportation information. Transit's app is available on iPhone and Android platforms and has widespread coverage in over 125 cities in nine countries. The app offers many features, including real-time transit vehicle information, trip planning, service alerts, and multimodal support (including bike-sharing, car-sharing, and Uber). The most heavily used features of the app are those providing real-time transit information. Additionally, users can store their favorite locations in the app, such as home or work, to facilitate quickly finding information that they commonly use *(16)*.

Figure 1 shows Transit's Android interface displaying real-time transit information for nearby routes (left), trip planning (center) and a stored home location (right), respectively.

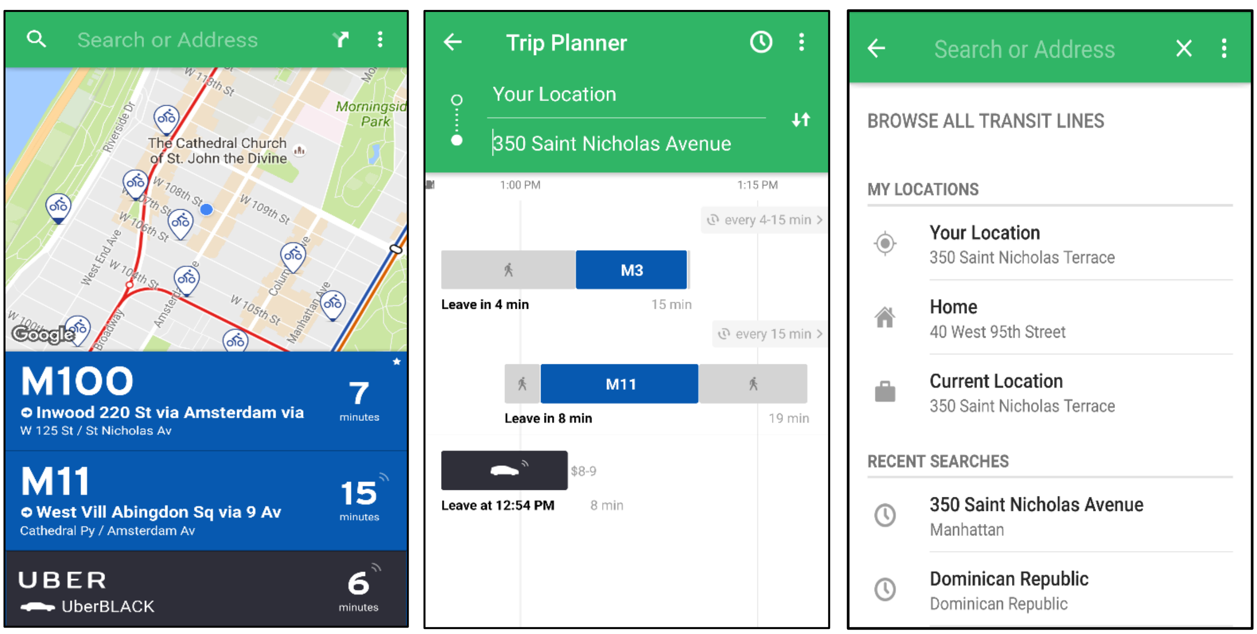


**FIGURE 1 Transit App Screenshots.**

### Area of Analysis

The geographic area selected for this study is the New York metropolitan region. New York City is one of the most popular cities for tourists in the world with almost 60 million tourists annually *(17)*, suggesting that there should be many intercity travelers visiting for leisure purposes. The New York City region also has the highest concentration of transit trips in the United States *(18)*, and is among the highest usage of the smartphone application, Transit, in the United States.

The New York metropolitan area was selected using the geographic area defined by New York Metropolitan Transportation Council (NYMTC) *(19)*. A bounding box was drawn for the maximum and minimum latitude and longitude of NYMTC's area. Figure 2 shows the area defined by NYMTC and the bounding box around it. As can be seen in this map, the bounding box contains Philadelphia and all of Connecticut. This boundary presents roughly the dimensions of the regional commuter rail network. App usage within the borders is considered to be local, and usage outside of the box is considered to be in another region.

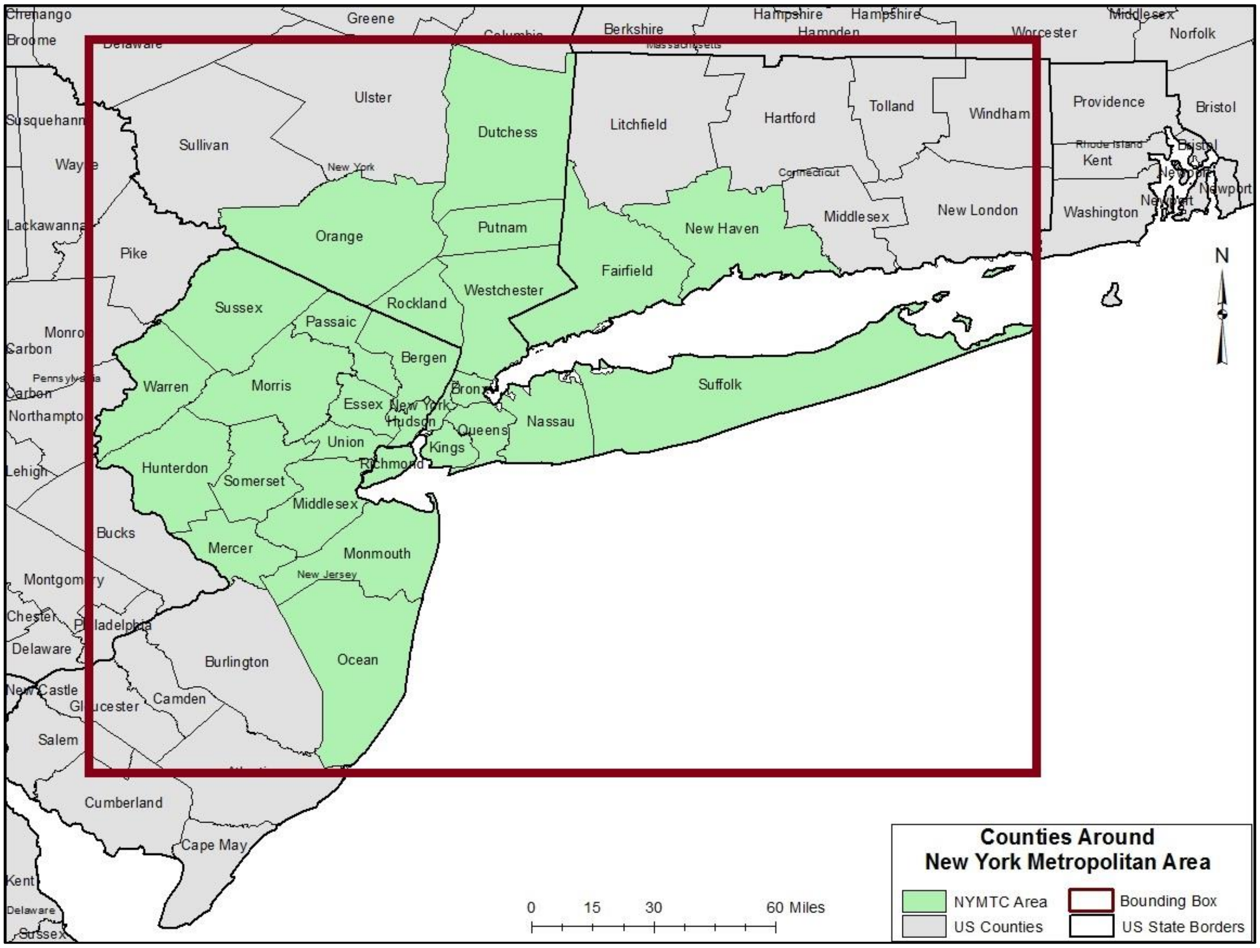


**FIGURE 2 Bounding Box Defining Inside and Outside of the New York Metropolitan Area.**

## Data Files and Description

The smartphone app dataset for this study was obtained directly from developers at Transit. It contains data for any user that opened the app at least once during a single month in 2014 in the New York City region. This dataset includes the user location (latitude/longitude), which is recorded whenever the application is opened. For privacy purposes, all geographic coordinates contained in these files were offset by the app developers by a random number. Anonymizing the data ensured that this analysis did not contain personally identifiable information. Locations refer to the anonymized version of the data point (e.g., a reference to “home locations” refers to the anonymized home locations).

The raw dataset used for this analysis included two files in a Comma Separated Values (CSV) format. The first was the locations file. Every time users open the app, regardless of what feature they are using; their location is sent to Transit’s server based on the coordinates from the location services in their smartphone. In the analysis, users' coordinates are considered to be the users' start coordinates (i.e., where they were when opening the Transit app). A unique session ID is created each time a user opens the app, and the date and time are recorded. Also, a unique ID is assigned to every smartphone, and this is referred to as the device ID. A total of 13,283,354 records were sent to the Transit app server by 169,631 unique device IDs (i.e., individual users) and saved in the locations file during the one month long period of analysis.

The second file used for this analysis is the placemarks file. This file included coordinates of home and work locations that users stored in the app. This represents data from an optional function in the app where users can store places that they often go to easily access relevant transit information for that specific location. This file contains the coordinates of these locations, of which there were a total of 13,537 coordinates divided into 9,185 home locations and 4,352 work locations.

### Data Preparation and Cleaning

A data cleaning process was undertaken to address some issues with the files pertaining to inaccurate timestamps and geographic coordinates. First, a small number of records in the locations file had dates other than the month of study and were therefore removed. Second, some records were "simulated" sessions, meaning that the user moved the GPS point on the map interface of the app to a location other than where they actually were to search for transit information there. These "simulated" records were deleted as well. After removing the irrelevant dates and simulated records, the number of records in the locations file was reduced to 10,8444,349 records made by 146,597 unique device IDs (i.e., individual users).

## METHODOLOGY

After the initial data preparation process was completed, an analysis was conducted to identify Transit app users who are intercity travelers based on the number of days they checked the app inside and outside of the bounding box around the New York metropolitan area in one month. The first part of this analysis explains how the records of Transit app users were divided by the geographic bounding box, and users who have records both inside and outside the box are identified as intercity travelers. The second part presents a method to further classify intercity travelers in order to identify their home city based on the number of days inside and outside the bounding box. In order to validate the classification method, the results were compared to the Transit app users' self-reported home locations. Finally, travel behavior patterns of two users identified as intercity travelers are illustrated.

### Identifying Intercity Travel

The following analysis was conducted using the Python programing language and software *(20)*. First, each record in the cleaned dataset was classified as being inside or outside the New York metropolitan area bounding box based on the location (lat/long) of the Transit app session. Then, the device IDs that had records both inside and outside of the bounding box were identified. A total of 3,778 unique device IDs had sessions both inside and outside of the bounding box, and therefore, these smartphone devices were assumed to belong to intercity travelers. These 3,778 intercity travelers had a total of 552,280 records inside of the New York metropolitan area and 64,715 records outside of the New York metropolitan area during the month of study in 2014. Table 1 shows the size of dataset beginning with the original data, then after the cleaning procedure, and finally, the dataset with only intercity travelers.

**Table 1 Size of Dataset in Each Step of Analysis**

| | Number of Device IDs | Number of Records |
|---|---|---|
| Original Dataset | 169,631 | 13,283,354 |
| Cleaned Dataset | 146,597 | 108,444,349 |
| Intercity Travelers | 3,778 | 616,995 |

Figure 3 is a map with dots that displays the locations of app records from intercity travelers outside of New York metropolitan area. This map shows some of the 64,715 records - specifically those in the United States but outside of the New York metropolitan area - made by the 3,778 intercity travelers. As can be seen in Figure 3, intercity travelers have used the Transit app across many cities in the United States and have likely made many long distance trips as well as numerous shorter trips during the month of study in 2014.

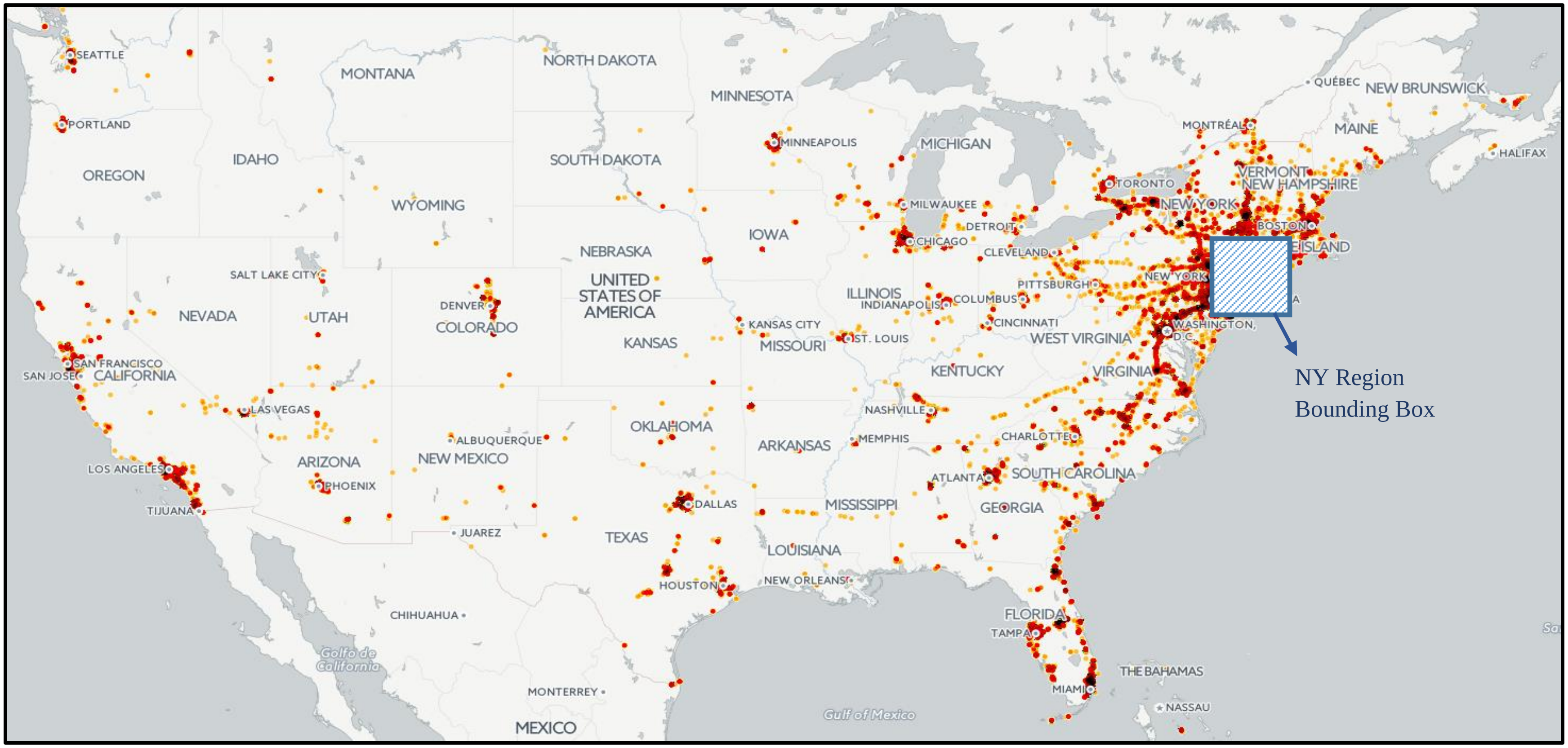


**Figure 3 Transit App Records of Intercity Travelers Outside of the New York Region Bounding Box.**

*Note: Records outside of the United States are not shown.*

**Manual Classification**

The 3,778 device IDs of the intercity travelers were then analyzed to further classify travel behavior in an attempt to identify their home city. A manual classification of the 3,778 intercity travelers was undertaken by counting the number of days each intercity traveler has used the Transit app inside and outside of the New York region bounding box. Examining the timestamps of sessions associated with each intercity traveler (i.e., unique device IDs) revealed that for some device IDs, the same session ID was observed in two distinct locations with significant distance between them in a very small time gap (e.g., five seconds). This could be due to errors sending records from a smartphone to the Transit app server; if there was poor cell service or if the phone was turned off before the records were sent, the time that data were received (timestamp) would differ from the time that the session actually happened. To address this error, the unique session IDs for each device ID were identified, and the location associated with the minimum timestamp recorded for each unique session ID was identified and selected as the (likely) accurate location of that session.

A graph showing the count of intercity travelers by the number of days inside and outside of the New York region bounding box is shown in Figure 4. The x-axis in this bar chart shows the number of days inside of the New York region, and the y-axis shows the number of days outside of it. The value of each cell is presented on z-axis and shows the number of device IDs (or individual Transit app users); the total count sums to 3,778 intercity travelers.

The bar chart was then used to manually categorize intercity travelers into four subgroups: probable visitors to New York, probable frequent travelers, probable infrequent Transit app users, and probable New York residents. Criteria for this grouping of users are discussed below.

*Group 1: Probable Visitors to New York*

The first subgroup of intercity travelers are probably visitors to New York because these Transit app users utilized the app on more days when they were outside New York than inside the New York region. Specifically, this group was defined as the Transit app users who checked the app more than 3 days outside of the bounding box and fewer days inside the box. There were 167 unique device IDs (or intercity travelers) in this group, which is shown in beige in Figure 4.

*Group 2: Probable Frequent Travelers*

The second subgroup of intercity travelers is considered to be frequent travelers because they frequently used the Transit app both inside and outside of the New York region. Specifically, this group includes users who have checked the app more than 3 days and had almost equal usage outside and inside of the bounding box. In total, 159 app users were categorized as frequent travelers, which is highlighted in yellow in Figure 4.

*Group 3: Probable Infrequent Transit App Users*

The third subgroup of intercity travelers is infrequent Transit app users, which makes them difficult to further classify. These users checked the app less than 3 days per month either inside or outside of the New York area; therefore, little information is available about them. Individuals in this group are either infrequent Transit app users or infrequent transit system users. There are 995 individual users in this category, which is shown in dark orange in Figure 4.

*Group 4: Probable New York Residents*

The last subgroup of intercity travelers are probably New York residents because they used the Transit app more frequently within the New York region and traveled only infrequently outside of New York. Specifically, any user with more than 3 days inside and less than 3 days outside of the bounding box was considered to be a resident of New York region. A total of 2,457 device IDs are likely to be residents of New York, as shown in green in Figure 4.

Additionally, the New York residents group can potentially be divided into more detailed subgroups. One of these smaller groups is likely to be regular commuters because these users checked the Transit app between 19 to 23 days inside the New York region (there were 23 weekdays in the month of study). Another one of these smaller groups likely represents every day Transit app users because they utilized the app nearly every day during the month of study (more than 23 days inside the New York region). These detailed subgroups (commuters and everyday users) are labeled in Figure 4.

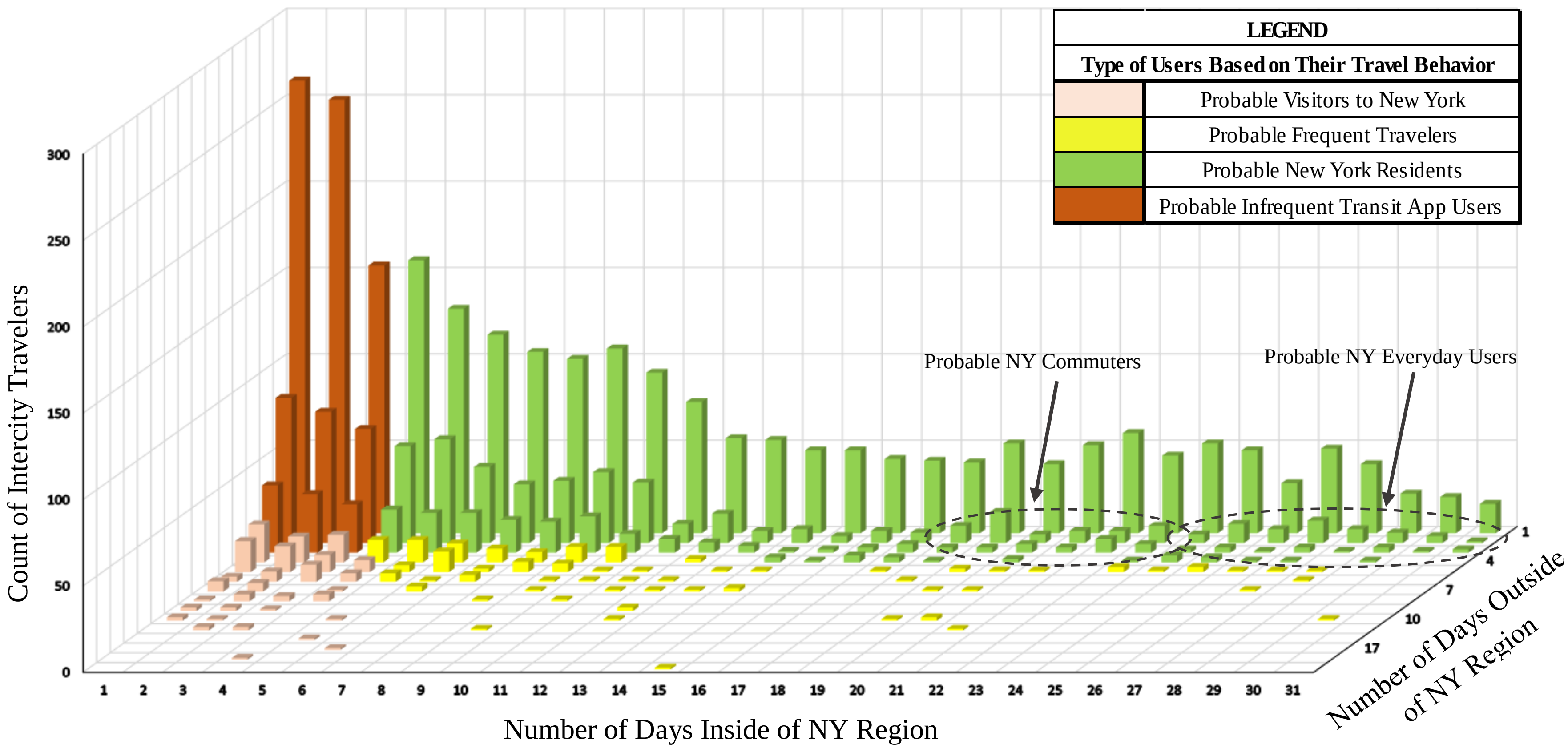


**Figure 4 Count of Intercity Travelers by Number of Days Inside and Outside of New York Metropolitan Area by Manual Classification.**

**Validation**

In this section, the results of the manual classification are validated using the placemarks file. The Transit app allows users to store favorite locations, such as their home, in the app for ease of use. This self-reported home location provides a sample of data that the intercity travelers groups can be compared against. Home locations of intercity travelers were obtained from the placemarks file; out of 3,778 intercity travelers, only 272 users stored their home location.

Table 2 shows the number of intercity travelers in each group of manual classification with their self-reported home location relative to the bounding box around the New York metropolitan area.

**Table 2 Number and Percentage of Intercity Travelers by Home Location and Group**

| Validation of Manual Classification | | | | | | | |
|---|---|---|---|---|---|---|---|
| Group | All Intercity Travelers | | Intercity Travelers with Self-Reported Home Locations | | | | |
| | Total Number | Percentage of Column | Home Inside NY Region | Percentage of Row | Home Outside NY Region | Percentage of Row | Total Number of Stored Homes |
| Probable Visitors to NY | 167 | 4% | 7 | 70% | 3 | 30% | 10 |
| Probable Frequent Travelers | 159 | 4% | 10 | 100% | 0 | 0% | 10 |
| Probable NY Residents | 2,457 | 65% | 181 | 92% | 16 | 8% | 197 |
| Probable Infrequent Transit App Users | 995 | 26% | 36 | 65% | 19 | 35% | 55 |
| Total | 3,778 | | 234 | | 38 | | 272 |

Among the group of probable visitors to New York, only 10 users stored their home location in the app. Of these 10 users, 7 (70%) reported homes inside the bounding box and 3 (30%) were outside. Therefore, this group did not perform well in the validation, as one would expect all of their home locations to be outside of New York.

For the frequent travelers group, all stored home locations were inside the bounding box. Since this group of intercity travelers spent nearly equal number of days inside and outside of the bounding box, classification alone could not define if they are New York residents or not; however, this table suggests that intercity travelers in this group are New York residents who travel to other regions frequently.

For the New York residents group, the vast majority of self-reported home locations (181 out of 197, or 92%) were inside the bounding box, suggesting that almost all members are New York residents and were classified correctly.

Approximately two thirds (65%) of the infrequent users group had self-reported home locations inside of the bounding box, suggesting that they are primarily New York residents.

**Visualization of Two Intercity Travelers**

Two individual intercity travelers who did not have self-reported home locations in the app and were classified as visitors in the previous analysis were selected to visualize their spatial and temporal travel patterns.

The activity pattern of the first visitor is shown in Figure 5. In this map, each dot represents the user's aggregated Transit app records in that area; larger sized dots represent higher usage in that specific area. The user shown in Figure 5 searched for transit information in Miami, Florida on four days during the month of study in 2014. On the fourth day, this user utilized the Transit app in Miami as well as New York, and the map in Figure 5 shows records in both in the Fort Lauderdale airport and New York's LaGuardia airport. Because this user is observed in Miami for four days and in New York for one day during the month of study, s/he is likely a resident of Miami and a visitor to New York. However, it is also possible that s/he is from New York and traveled to Miami for four days and checks the Transit app more frequently in Miami because s/he is unfamiliar with the transit system there.

Figure 6 shows the travel behavior of a second intercity traveler, and this traveler made an international trip. This user has records on three days in one month of 2014 in New York and on eight days of the same month in different cities in the Dominican Republic. In Figure 6, each dot represents the user's aggregated Transit App records during eight days; it should be noted that there were additional records in other cities of the Dominican Republic during the month of study that are not shown. This user was classified as a visitor to New York in the previous analysis, but it is also possible that s/he is resident of New York and visited the Dominican Republic for approximately one week. An interesting fact is that Dominican Republic is not among the coverage areas of the Transit app, and it is unclear why this user has opened the app in a region not supported with transit information.

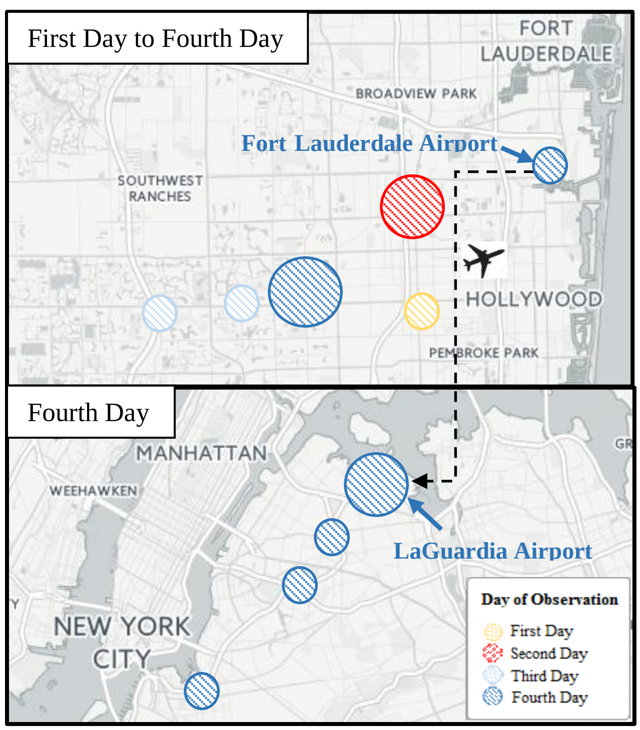


**FIGURE 5 Spatial Pattern of an Intercity Traveler in the United States.**

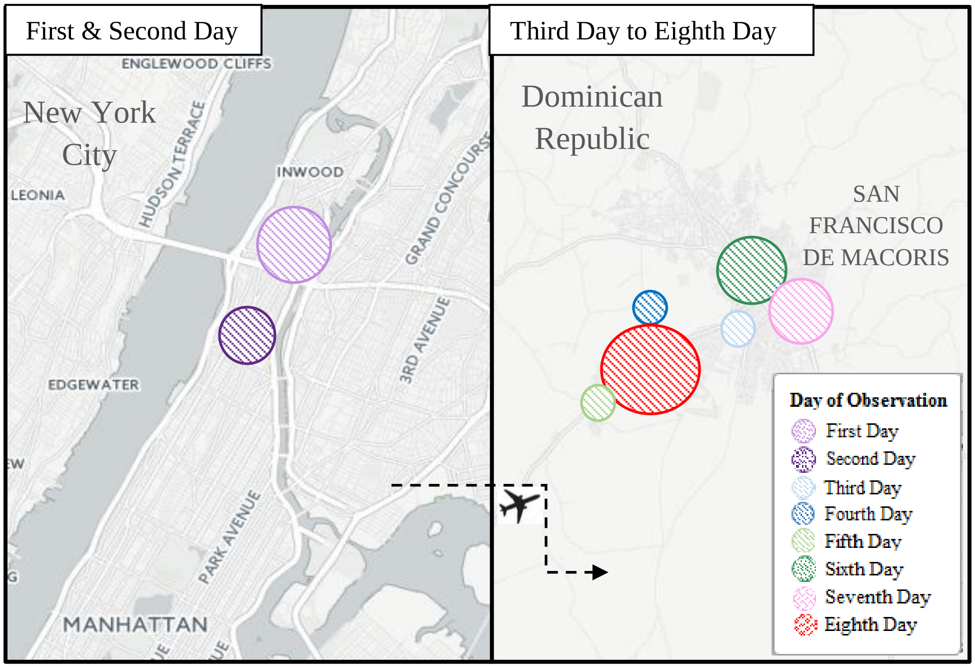


**FIGURE 6 Spatial Pattern of an International Intercity Traveler.**

## CONCLUSIONS

This exploratory analysis utilized a rich new data source for studying intercity travel behavior in the New York metropolitan area. The dataset used here was obtained from backend servers of the Transit app, a multi-city transit information application. The app users were identified as intercity travelers based on if they were observed inside and outside of a bounding box drawn around the New York metropolitan area over the course of one month, and a total of 3,778 intercity travelers were identified. Then, this group of intercity travelers was further classified into subgroups using a manual classification method. The method identified four distinct groups of intercity travelers: probable visitors to New York, intercity travelers who frequently travel between cities, probable residents of New York who infrequently leave the region, and infrequent Transit app users. The methodology used for the analysis was then validated using a small sample of the Transit app users who stored their home location in the app for ease of use. The validation confirmed the home location of many Transit app users who were classified as New York residents; however, the subgroup classified as probable visitors to New York did not perform as well in the validation of home city, which may be because there were a very small number of app users who self-reported their home locations (272 in total of 3,778 intercity travelers). Despite this, this methodology demonstrates an important first step toward identifying intercity travelers using backend data from a smartphone transit application.

## AREAS FOR IMPROVEMENT AND FUTURE RESEARCH

The dataset used in this study contains rich geographic and temporal information about transit riders. However, there are limitations associated with data sources obtained from transit smartphone applications. For example, they are limited to travelers who are transit riders and get their needed transit information from the Transit app, which could result in biases. Furthermore, the methodology used in this exploratory study to identify and classify intercity travelers could benefit from refinement in future analyses. One potential area of improvement is to use a longer timeframe (i.e., at least one year) to better capture the Transit app users' activities, particularly infrequent intercity travel. The manual classification methodology could also be improved if the consecutive number of days in a location is used instead of the count of days inside and outside of a city. For example, if a user is observed in one city on the 3rd, 4th and 5th days of a month and then observed in another city on 10th and 15th days of the same month, it is likely that the user spent three days in the first city and five days in the second city; however, the manual classification method used in this preliminary analysis would not have identified this. Similarly, analysis of travel patterns by days of the week (i.e., weekdays vs. weekends) could provide a better understanding of work-related trips that are likely occurring on weekdays versus leisure trips that are likely occurring on weekends. Another area for future research is to use travel distance to classify intercity travelers. As a further validation method, the results could be compared against a long distance travel survey. Finally, given the multi-regional nature of the Transit app, these methods could be expanded to many other cities in the future.

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