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Bus Reliability Metrics using Public MTA Bus Time Data

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Abstract—With the growing demand for public transportation, bus becomes an important issue. New York Universitys Center for Urban Science and Progress (CUSP) collaborates with the New York City Department of Transportation (DOT) to provide user focused reliability metrics relevant to the agencys capabilities to improve user experience. This paper summarizes and analyses common bus reliability metrics. Based on the public Bus Time Advanced Vehicle Location (AVL) data from the public Metropolitan Transportation Authority (MTA) and the schedule data (GTFS), this paper discusses data extraction and parsing, data quality, big data techniques, and inference of time at stops to aim at measuring bus reliability. Several extraction, parsing and interpolation exercises are critically discussed. By comparing with Bus Service Measurement Standards (NYCT), this paper presents a method using the AVL system to improve bus operations. Finally, it aims at aiding the DOT with some bus operation, traffic, and some other potential elements that affect bus reliability to help the agency control and improve bus performance on the planning level.

Index Terms—reliability; MTA Bus Time data; Big Data; AVL systems; bus performance.

1 Introduction

Despite a growing demand for public transportation in New York City, bus ridership levels are declining. This can be explained by drops in vehicle speeds and customers perceptions of dependability. The New York City Department of Transportation wishes to engage CUSP to explore the use of public data from the MTA open vehicle location system Bus Time to generate operational information relevant to NYC DOT planning decisions. This information will be provided in the form of reliability metrics for the bus service. Based on the MTA Bus Time data, this project uses big data techniques and data analysis methods and algorithms. At the end, it will provide methods for estimating bus travel times, measuring reliability, and potentially identifying the distribution of those measurements as a functions of factors regarded as relevant. The MTA is the designated authority for transit operations, and it has internally defined metrics that are used for schedule planning and analysis of the bus network. Despite of this, the MTA pays more attention to the bus level but not to the whole system level, which is more of the interest of the DOT. The Department of Transportation has already collected the Bus Time data, but they lack a formal process for compiling and using it for decisions that are more relevant to them, such as those related with road design and traffic management. Unlike the MTA, the DOT takes more responsibility on traffic planning instead of bus operation management and concerns more about customers expectation. To help the DOT improve their planning efficiency, this project aims to figure out the dependent variable metrics related to bus performance and reliability, so in a further analysis the agency can analyse the effect of independent variables that affect service quality. CUSP will collaborate with the DOT to develop methods for estimating bus travel times and measuring reliability, while performing data quality analysis of the Bus Time data and the MTA schedule data (referred to as GTFS in this document for its format, General Transit Feed Specification). In the first phase of the project, CUSP will develop algorithms to measure or estimate certain types of events associated with

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bus vehicles trips using publically available data, such as departures from terminals, vehicle arrivals at stops and interruptions between stops. In the second phase, CUSP will analyze the resulting data and calculate metrics related to the performance of the buses with respect to their planned schedule. Finally, in consultation with the DOT, CUSP will develop hypotheses about the significance of contextual factors on those performance metrics. The entire process has been and will continue to be documented and flexible in the code, so both data quality assessment and reliability measurements are more clearly evaluated.

2 Literature review and related previous work

Bus service reliability has been widely noticed since it has a great influence on the daily life of public. Large number of studies have been conducted to measure bus reliability as well as analyze factors with influence. The work of Sterman and Schofer (1976) was among the early studies on bus service reliability in the United States. Using data from bus services in the Chicago area, the study aimed to test the inverse of the standard deviation of point-to-point travel times, which is a particular measurement of reliability. Although found to be useful and easy-collected, the form of reliability measurement is significantly degraded by increasing the route length, intensity of intersection control, traffic volumes, and, with less certainty, bus passenger loadings. Abkowitz and Engelstein (1983, 1984) studied factors affecting the running time on transit routes and methods for maintaining transit service regularity. The proposed method for maintaining service regularity through improved scheduling and real-time control was found to be a reasonable solution to increase reliability. Based on bus data in Portland, Oregon, Strathman and Hopper (1993) presented an empirical assessment of factors affecting the on-time performance of the fixed route bus system. The logit model results showed that the probability of on-time failures increased during PM peak periods, with longer headways and higher levels of passenger activity and as buses progress further along their routes. Nakanishi (1997) described NYCTs new bus performance indicators.The Performance Indicator (PI) program was established in 1994 in response to the MTA Inspector. Generals research recommending the need for measures of service reliability other than the traditional Terminal On-Time Performance (TOTP).

An exhaustive list of transit reliability measure examples was shown in the Transit Capacity and Quality of Service Manual (TCQSM) (Kittelson et al., 2003). On-time performance and headway adherence, the most widely used reliability measures in the transit industry, were especially discussed. Taking into account the interaction between the network performance and passengers route choice behavior, Yin et al. (2004) developed a generic simulation-based approach to assess transit service reliability.Three types of the reliability, system wide travel time reliability, schedule reliability, and direct boarding waiting-time reliability, were defined from perspectives of the community or transit administration, the operator, and passengers. Lu and Ismutulla (2006) set up a model that contained the transferring via three public transport routes with different running time reliabilities. The study suggested that the on-time/punctuality performance and headway evenness are primary focuses in the practice of bus reliability analysis. Xumei Chen, Lei Yu, Yushi Zhang and Jifu Guo (2009) established a system to measure bus reliability on stop, route and network levels based on bus service data in Beijing. The results indicate low service reliability for buses in Beijing and a high correlation between service reliability and route length, headway, distance from the stop to the origin terminal, and the provision of exclusive bus lanes.

3 Data description

3.1 Data generating process

3.1.1 *Schedule*

MTA develops bus schedules for 3-4 months at a time. Schedule planning works with operating departments to ensure schedules align with resource constraints, meet the organizations operating metrics, and maximize service to customers. Schedules are valid for date ranges included in the publications, or until a superceding schedule is released for the same time period.

Schedule data is published according to the General Transit Feed Specification, a standard established in 2006 and now widely used by transit agencies and developers. One transit feed is essentially a small relational database, containing a minimum of six tables and any of seven optional tables. Basic required data in a transit feed file are routes, trips, stops, stop times, and effective date ranges. MTA does not include optional metadata that can be used to distinguish multiple publications covering the same schedule period.

The median duration of a trip in the schedule is 44 minutes, but approximately 5 percent are shorter than 10 minutes.

3.1.2 Operations

Buses are equipped with Automated Vehicle Location systems, which combine GPS and other positioning technology with a wireless transponder in order to report vehicle information at some frequency back to a central database.

In 2012, Dead Reckoning Units on earlier buses was upgraded. Dead-reckoning sensors use direction/bearing and distance/speed to determine relative location from a fixed point. Compasses, odometers, and inertial platforms (gyroscopes and accelerometers) are all dead-reckoning sensors. The newer installed units by Cubic were more accurate than the earlier model by Veriphone.

The vehicle movement Operator login includes route and headsign. However trip reference and phase are inferred automatically on the server side.

MTA BusTime tries to assign buses to blocks-a sequence of trips that start and end at a depot. This allows the system to make a statement about what a bus will do after it reaches the end of its current trip. However, there is not always enough affirmative and corresponding evidence to make such a strong statement. In this case, MTA BusTime falls back to a trip-level assignment, where it just picks a trip from the schedule that is representative of the route and stopping pattern that the bus is likely to pursue.

The SIRI API now reflects this distinction as described here and in other items below. If the assignment is block-level, the new BlockRef field of the MonitoredVehicleJourney is present, and populated with the assigned block id.

(table goes here)

Occasionally, no data is available for any vehicles during a long period of time, indicating a problem with the real-time database or the interface used by CUSP for extraction of the data.

Short trips are obscured disproportionately by the long breaks in the data feed. 72% of days contained at least one break of longer than 30 minutes, which almost always occurred during weekday peak traffic times of 8am-10am and 6pm-8pm; 30% of days contained three or more such breaks. These long breaks results in no data for more than 25% of scheduled trips, on certain days.

3.1.3 Holes in the data

Many elements of the reported data are inferred automatically upon processing and storage to MTAs database. As these inferences are made real-time, there are irregularities in that may be improved with additional information, or by processing longer periods analytically rather than transactionally.

Major disruptions to service are clearly identifiable based on the number of vehicles reporting throughout the day. A large area of the Northeast was hit by a noreaster on January 26, 2015, with blizzard conditions lasting overnight and leaving more than 2 feet of snow in some cases. On January 27, 2016, the number of vehicles reporting throughout the day was less than 50% of the average over comparable time periods. News outlets and press releases are available to corroborate the cause of the large deviation observed. This allows a straightforward decision to eliminate the time period entirely from any analysis.

However, small disruptions are more difficult to detect and research.

4 METHODOLOGY

The project has been structured to have the following milestones: Bibliography review; Data extraction; Estimation of the departure and arrival times at bus stops and other locations (in other words, interpolation); Measurement of bus performance and reliability metrics, with a flexible implementation; and Potentially hypothesizing about the possible factors that influence bus reliability. Along the development of the stated milestones, an important amount data quality analysis have been performed, even taking more time and effort than the rest of the steps.

4.0.4 Details on interpolation

The Bus Time data framework includes a variable that indicates the distance along each route where each station is located, and the distance from each ping to the next station. It is fairly simple to calculate the location of each ping along the route by subtracting these two features. After this calculation, a linear interpolation and extrapolation exercise was done by first interpolating the bus pings (time and position) for all trips along one route in a sample day, and then inferring, with extrapolation, the time at which each bus was at each stop.

The AVL system that generates the data automatically detects the nearest station to a each point. At the beginning and end of each trip there is a tail and a head accounting for the time that the bus takes to leave the warehouse and actually start the route, and to return. This was treated by choosing only the first point of the tail and the last point of the head.

4.0.5 Details on Big Data techniques

The total size of our Dataset is around 3 terabytes for SIRI API data and 5 Gigabytes for the schedule data . In order to fully utilize the data, we must deem it as Big Data Challenge since the more data we use, the more accurate result and less bias we can achieve.

Terminology

HDFS HDFS (Hadoop File System) is a Java-based file system that provides scalable and reliable data storage, and it was designed to span large clusters of commodity servers. The data must be first uploaded into HDFS to perform big data operations. Apache Spark Apache Spark is an open source cluster computing framework that performs parallelized stream computing using multiple CPU cores. Apache Spark is proved to be the fastest open source framework (100 times faster than Hadoop). Spark SQL Spark SQL is a Spark module for structured data processing. Spark SQL relies on Spark Dataframe to operate, while Spark Dataframe is a column structured data collection that can be easily saved to csv for further analysis. Spark SQL is efficient and reliable and SQL files are easy to share and cooperate. Data Schema The original data is stored in nested json format with lots of redundant information. The schema function based on Spark Dataframe allows us to understand the data structure in a more distinguishable fashion. We can manually set data schema along with data type to fasten the operation CSV to Dataframe Tool by Databricks Databricks published the tool that can directly read CSV file into Spark DataFrame. Time Series for Spark(interpolation) A Scala / Java / Python library for interacting with time series data on Apache Spark. **Operation**

Data parsing and Extraction After we uploading the data onto HDFS, we can then submit Spark Script to perform data parsing and extraction. The first step of data parsing is learning the data schema in order to select the right elements to parse by after reading the JSON files into Spark DataFrame. The details of element selected are stored in separate SQL query script, which will be submitted along with the Spark Script simultaneously After we extract the elements we need, we temporarily keep the data in DataFrame. Data Cleaning and Storing Because the data was originally stored in JSON array format, the data extracted for each element is a list of arrays. In order to use those data, we must first flatten the arrays by Applying Flatmap function on the DataFrame. The data extracted from SIRI has prefixes such as *MTA_* and *MTA NYCT_*. In order to further merge with the schedule data, we must remove those prefixes by applying map on replacing the prefixes as empty strings. After all those processing, we save it into CSV format by map-ping and joining each item. Measuring Data Coverage As previously mentioned in section 3, We noticed that partial of trips has not been recorded in the SIRI dataset. With the extracted dataset,we can easily check the data coverage for each line for each day We can achieve the measurement by groupby on data and bus line and count on trips to get how many trips actually get recorded for each bus line and day.

Data Merging and manipulation

By applying interpolation using spark time-series tool on the extracted SIRI data, we can calculate the actual stop times of each stop for each bus line. With the calculated stop times for each bus line, we can then calculate the actual headways on each stop for each line.

Finally, we can merge the actual stop times with scheduled stops. We can then calculate the delays and differences of headways at each stop between actual time and scheduled time.

4.0.6 Performance indicators - reliability

¡¡¡¡¡¡¡ HEAD Based on the formal research, we choose the most common indexes below to measure the reliability of bus performance. 1. Percentage of completed trip The percent of total scheduled bus trips completed (by lines/dates) The Performance Indicator (PI) program was established in 1994 in response to the MTA Inspector Generals research (4) recommending the need for measures of service reliability other than the traditional Terminal On-Time Performance (TOTP).

1. Percentage of completed trips (PI) The percent of total scheduled bus trips completed (by lines/dates)

$$PCT_i = \frac{CT_i}{T_i} * 100\%$$

2. Bus "on-time performance" (PI) The percentage reflects the number of buses that arrive within a certain time before or after the published schedule. (During low-frequency period, the on-time percentage is more important while during the high frequency period, the headways matter more.)

$$OP = \frac{OT_i}{T_i} * 100\%$$

Cons: The single on-time performance percentage also does not identify problems with bus bunching, especially on frequent routes. 3. Excess waiting time (improved on-time performance measurement by London) All that time you have to wait for a bus that's running late or is bunched with others is added up and averaged over the route, and the excess waiting is compared to how much you'd normally have to wait assuming you come to the bus stop randomly.

$$EWT_i = \frac{1}{n}\sum_{j=1}^{n} \max\{0, ah_{ij} - sh_{ij}\}$$

(Under the London system, buses don't get credit for making you wait less than average.) Pros: This makes it easy to see when high-frequency buses are not meeting the required headways 4. Headway a measurement of the minimum possible distance or time between vehicles in a transit system, without a reduction in the speed of vehicles. Headway variance is the difference among the real headway and schedule headway. 5. Wait Assessment (PI) The percent of actual intervals between buses that are no more than the scheduled interval plus 3 minutes during peak hours (6 AM - 9 PM) and plus 5 minutes during off-peak hours (9 AM - 4 PM and 7 PM - midnight). Wait assessment is measured weekdays between 6:00 AM and midnight when service is relatively frequent. measures customers maximum wait times while waiting to board at stations

$$RTA_i = \frac{\left(\sum_{j=1}^{n} \frac{|art_{ij} - srt_{ij}|}{srt}\right)}{n} * 100\%$$

Defined as percent of headways between trains not exceeding 125% of scheduled headways

6. Interruption data rate (count or sum duration, normalized for trip distance or time)

$$WT_i = \frac{WT_i}{T_i} * 100\%$$

$$WT_i = card\left(\{bus : bus \in route_i, t_{bus0} - t_{bus} < T\}\right)$$

======= Based on the formal research, we choose the most common indexes below to measure the reliability of bus performance: Wait Assessment, On Time Performance, Running Time Adherence and Headway Regularity.

Wait Assessment is a metric used by New York City Transit, defined in the Transit Capacity and Quality of Service Manual as the percentage of actual headways between successive vehicle arrivals that are less than or equal to a given standard. On Time Performance, which compared the actual arrival time with the scheduled arrival time directly, is a universal wide indecator for bus reliability performance. Both running time aherence as well as headway regularity are defined as the average difference between scheduled and actual, normalized by the schedule data. The higher the running time metrics the worse the running time adherence. A high headway metric value indicates poor headway regularity adherence. Bus bunching is an extreme example of short headway.

1. Wait Assessment (PI)
It is defined as the percentage of observed service intervals that are no more than the scheduled interval plus 3 minutes during peak (7 a.m. - 9 a.m., 4 p.m. - 7 p.m.) and plus 5 minutes during off-peak (12 a.m - 7 a.m., 9 a.m. - 4 p.m, 7 p.m. - 12 a.m.). Wait Assessment is a simple calculation that can be performed after all headway calculations have been performed for a given location.

$$WT_i = \frac{WT_i}{T_i} \times 100\%$$

where WT_i is number of actual intervals between buses that are no more than the scheduled interval plus 3 minutes during peak hours (7 a.m. - 9 a.m., 4 p.m. - 7 p.m.) and plus 5 minutes during off-peak hours of bus route i. That is:

$$WT_i = card\left(\{bus : bus \in route_i, t_{bus_0} - t_{bus} < T\}\right)$$

where,
$card$ is a mathematics function which counts the elements of a given set.
$route_i$ is the set of all buses of bus route i.
$t_b us$ is the time when arrived a particular station.
bus_0 is the nearest bus ahead of bus.
T equals 3 minutes during peak hours (7 a.m. - 9 a.m., 4 p.m. - 7 p.m.) and 5 minutes during off-peak hours.

2. On Time Performance (OTP)
It is defined as the positive difference between actual arrival time and schedule arrival time. However, During low-frequency period, on-time performance is more important while during the high frequency period, the headways matter more.

$$OTP_{ij} = |aat_{ij} - sat_{ij}|$$

where,
aat_{ij} is the jth actual arrival time of bus route i.
sat_{ij} is the jth scheduled arrival time of bus route i.

3.Running Time Adherence (RTA)
(measured in %) is defined as the average difference between the actual and the scheduled running times relative to the scheduled running time.

$$RTA_i = \frac{1}{n} \times \left(\sum_{j=1}^{n} \frac{|art_{ij} - srt_{ij}|}{srt}\right) * 100\%$$

where,
art_{ij} is the jth actual running time of bus route i.
srt_{ij} is the jth scheduled running time of bus route j.
n is the number of stop route i has.

4.Headway Regularoty (HR)
(measured in %) is defined as the average difference between the actual and the scheduled headways relative to the scheduled headway.

$$HR_i = \frac{1}{n} \times \left(\sum_{j=1}^{n} \frac{|ah_{ij} - sh_{ij}|}{sh}\right) * 100\%$$

where,
ah_{ij} is the jth actual headway of bus route i.
sh_{ij} is the jth scheduled headway of bus route j.
n is the number of stop route i has.

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5 Results and implications

Projection of location onto shape lines.

Result and Limitations(RM only) Result: According to the analysis above, the bus reliability varies with time and locations. It also differs by the measurement we choose. General introduction of bus reliability based on different measurement. which measurements have similar results whats the meaning of each one, are they reasonable? General introduction of bus reliability based on different time and location. Distribution description The most reliable and unreliable time/location, explain the reasons for unreliability Limitation: Each measurement reflects a part. Lack of a general assessment for bus reliability The impact of each measurement is different.

Time at location

Some time at location exercises (without accounting for time at stops) were performed in one day for all the trips in one route. The following images represent some of the partial results, as there is no validation data to measure accuracy.

Critical review of reliability metrics

6 Limitations of the analysis and ways to address these in the future

Accuracy of the location and time data, when reported, is not in question. However some of the elements are inferred and may cause errors if not handled properly. Limitations are generally the result of information gaps - specifically when no data is reported where expected. When no data is reported: It is unknown if there was actually an operating bus, but a problem arose with hardware or software If there was a bus (for example, present in earlier and later data), it is possible that the bus did not follow the scheduled route If there was no bus, the cause is unknown

Trips with data from more than one vehicles - use combination of reported trip_id and vehicle Trips with no data - show sensitivity of metrics by assuming trip operated as scheduled Dwell time Lacks instantaneous speed information Schedule metadata Disappearing and reappearing bus

60-90 second frequency is insufficient for analysis of vehicle behavior on individual street segments and intersections. 30 second frequency is insufficient for measurement of dwell time. Frequent, long gaps in the data make unbiased performance analysis impossible over full days or date ranges. Because the gaps tend to arise at the same times each day, any statistical measurement involve time-of-day as an input variable will be biased. Some analysis may leave time-of-day as an unobserved component of the error term and still show significance in other variables, such as distance-along-trip or street features. Incomplete reporting of trips may cause bias in calculation of trip-based measurements, such as running time and On Time Performance, if not normalized. Inferences of points beyond the range of data need to be need to be flagged specially given the possibility that the vehicle did not operate the trip as planned. If better density is useful, DOT should request the additional elements in the static files provided by MTA

7 Conclusions and future research

7.1 Conclusions

7.1.1 Conclusion for the model this project used. (Introduction, Pros and Cons, Bias) Model for time estimation Bus time data which is collected by GPS was offered by MTA. The MTA bus GPS database collects the location of each bus every 30 seconds. This project used these data to estimating the departure and arrival time for each stop. Taking one-year data as this projects object of study, the data is extremely huge so that big data technology like Spark is widely used in time estimation. After using spark to deal with the bus time data, this project got a new dataset contained all the information such as the coordinates and timestamp which is more clear and easy for future analyzing. Measurement for bus performance After estimating the departure and arrival time for each stop, this project used headways and wait assessment as the measurement to figure out the bus performance and reliability. This will help DOT in future improvement in bus performance and traffic planning. In order to make the work easy to share and reproduce, this project choose to use SQL API to manipulate the data, which enable DOT to easily make change by editing the SQL script. Method for feature selection

7.1.2 Conclusion for the results this project got. (How the result influence the future operation) 7.1.3 Conclusion for the whole analysis process. (Pros and Cons, Bias, Influence) Pro: 1. Focus on the viewpoint of DOT, the correlation elements this project chose not only focus on the bus operation, but also other traffic elements. 2. With such large dataset and big data technique, the result of this projects analysis is more persuasive compared to traditional sample study. 3. Comparison among models(different models to estimate time as well as to measure performance) Cons: 1. The choice of elements based on formal studies, the objective of which are not all NYC. 2. Too much assumptions. 3. The departure and arrival time for each bus at each stop comes from indirect approximate methods, it is better for MTA to collect the accurate data to help the model works better. Influence The main goal for this project is to figure out the other potential influence factor besides operation to help DOT control and improve bus performance on planning level. Similar methodology and concept could be used in other cities and traffic mode. The big data technology applied in not only traffic analysis but also city wide urban issue offers more reliable result compared with traditional sample studies. 7.2 Future work Feature Selection optimization: Pre study and investigation for NYC Visualization: Use Javascript to create interactive heat map that predicts the chance of delay of specific bus line or stops Algorithm optimization: Many analyses right now are not computed using big data technique, which means those analyses are hard to applied in large scale such as one year data. In order to analyse quickly in large scale, we must optimize our algorithms to ensure compatibility with big data techniques such as Spark. Interpolation: 1. Extend sample analysis to all the trips for all the routes in one day. 2. Include the waiting time at stops. Explore previous MTA analysis on Bus Time data to see if they can provide with a reasonable guess for the dwell time. 3. Compare with the GTFS schedule data to actually implement one of the reliability metrics. It is still unclear if the distance along the route feature is equivalent among both Bus Time and GTF representations. 4. Manage exceptions where there was missing or defectuous data. 5. Apply this analysis for the entire year of Bus Time feed (2015). 6. Consider alternatives for treating deceiving data points at the beginning and end of each trip (tail and head). 7.3 Further Application Other cities (need to pay attention to data structure, bus GPS data in some cities collect departure and arrival time instead of location) Other traffic mode (eg. Subway, city bike. Need to pay attention to the different features of each kinds of traffic mode)

Appendix A
Sample results table

Appendix one text goes here.

Appendix B
Visualization of a single line

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