Markov Chain Model of Orange Line Shutdown

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Abstract

This project aims to conduct an analysis of the MBTA Orange Line and its shutdown for one month during quarter three in 2022. Our analysis focuses on modeling the schedule deviation on the Tee lines while the Orange Line was open and shutdown as well as calculating the probability of delay a rider may experience in Downtown Boston during the shutdown. We utilize MCRoute, a Python library developed to analyze transit systems through Markov Chain processes. Alternate routes opened during the Orange Line shutdown are implemented in MCRoute, along with the Orange Line preshutdown in order to make meaningful comparisons between commute time as well as probability of delay.

The Problem

The Massachusetts Bay Transportation Authority (MBTA) is one of the largest public transit systems in America. The MBTA connects over 200 cities and towns with nearly 1 million riders every day. Because of this, it is essential that residents of Massachusetts can rely on the transportation system. Riders can typically predict in an accurate range the time their commute will take on the T as they are underground, not subject to traffic or weather conditions. There are, however, occasional closures for repairs or other issues.

When there are outages on the T, replacement buses typically fill the closed lines. The replacement buses are not an ideal replacement as they introduce new variables such as traffic, capacity limits, bus drivers, and street routes. These added variables introduce uncertainty into predicting commuting times. In the summer of 2022, the Orange Line completely shutdown. We have two objectives. First is to model the difference in delays a rider will experience both before and during the shutdown. Second, we will predict the reliability of alternative routes, such as replacement buses, other Tee lines, usual buses, and walking, during the shutdown. The problem is constrained by the number of buses running, the routes the buses run, the capacity of the buses, and the traffic conditions at different times of the day.

Literature Review

We began our literature review by investigating the methods used by previous research on public transit travel time modeling. In 2016, Yin et al. simulated travel costs for intermittent station closures in rail transit networks. Their analysis utilized integer programming to minimize the impact of a station closure on travel time. Yin et al. (2016) chose integer programming because they were modeling random unpredictable transit closures with known alternate route times. As our problem considers an entire line of the T being shutdown with the uncertainty lying in the available alternate routes, we will not be able to follow the integer programming methodology. This led us to look for literature on Markov Chains for transit models.

This search led us to Sodachi & Valili in a case study on the Hamburg Public Transit System. This paper develops a method to determine bus arrival times at nearby stations using parameters determined from data collected by the public transit system in Hamburg. They then stochastically vary these parameters and utilize Markov Chains to determine the approximate arrival times of buses. This paper also contains a literature review which covers the works of many other researchers, all of whom utilized Markov chains to study existing algorithms for determining bus arrival times.

We then discovered a paper by University of Toronto's Willem Klumpenhaur (2021). Klumpenhaur's work outlined several methods of conducting transit analysis utilizing Markov Chains and contained information regarding a Python library known as MCRoute that Klumpenhaur developed. MCRoute allows for quick setup of MC networks and associated nodes and transition matrices. This tool has become critical in our analysis, and a more in depth look at its functionality will be explained in the following sections. As an aside, we actually made an effort to reach out to Klumpenhaur to try and ask a few questions about the nature of his code. After a brief conversation, however, we were unfortunately no longer able to reach him, so we were unable to discuss his code or our project.

Methods

Data Cleaning

This project seeks to model the likelihood of a rider arriving to his destination on-time when taking the Orange Line replacement buses, alternative trains and buses, and walking. We first began taking bus and train travel data from the MBTA Blue Books. The Blue Books provided information for every train and bus that was driven throughout the entire year of 2022 up through September 30th. The information included the expected and actual arrival and departure times from each stop for every bus or train that was run prior to September 30th. Therefore, we had to minimize what data points we wanted to look out in order to be able to realistically create our model. Therefore, we determined when the Orange Line was shutdown: August 19th to September 18th. The MBTA breaks up the year into 3 month quarters, which would mean this shutdown occurred during quarter 3 of the year. We decided to only look at ridership data during quarter 3 in order to maintain a uniform ridership density as the summer months see fewer riders as compared to the remaining part of the year. After truncating our data to quarter 3, we also separated the data into two groups for when the Orange Line was open, July 1st to August 18th and September 17th to September 30th, and for when it was closed, August 19th to September 18th. From there we wanted to divide the day into different time periods in order to compare the probability of arriving on time for similar ridership density through the day. Therefore, we separated the day into five segments based off the 9 segments used by the MBTA:

1. 3:00 AM - 7:00 AM (Early AM)
2. 7:00 AM - 9:00 AM (AM Peak)
3. 9:00 AM - 4:00 PM (Midday)
4. 4:00 PM - 6:30 PM (PM Peak)
5. 6:30 PM - 3:00 AM (Evening)

From there, we needed to create data frames for each of the bus routes and train routes. In other words, we had a data frame for the orange line, the red line, and the 92 bus route as examples. By doing this, we are able to have start time after midnight, end time after midnight, and travel time, all in seconds, for each stop. Therefore, we can make paths throughout the same colored line and find the total travel time or utilize different train and bus routes together to find the total travel time after exchanging.

Model

Our model is structured around the MCRoute Python library discussed briefly in the Literature review section. It is a library specifically designed to quickly setup Markov-Chain based transportation networks and contains tools that are useful for conducting analyses on these systems.

The basic structure of MCRoute allows you to generate a transportation network which is defined as a directed graph with edges, nodes, and states. The states are defined by your state space, which represent any number of things. For instance, you could create a state space which is representative of the discomfort of your passengers, or how many minutes late a bus is running. Using this state space, we can develop a transition probability matrix for each node or edge, and from there the stochastic model is functionally set up. The only difference is that MCRoute allows us to do this in a handful of lines of code, as opposed to the several hundred it may normally take to set this up from scratch.

With MCRoute to help us, we decided to build two models. First, we modeled the deviation which a rider could expect on their commute on the red, orange, and green lines before and during the shutdown of the orange line. We began by calculating the mean travel time and the standard deviation of that travel time for all stops on the T lines. Next, we added the first 12 nodes (stations) and edges (mean time, standard deviation of time) for each line to the graph. The edges created the transition probability matrices for each T line. To study only the impact of traveling between stations, the chance of delay between arriving at a station and leaving that station was not considered. This is to say that the probability of that transition occurring on time was 100%. Then, we defined our state space to represent the seconds late a rider will arrive. The range of our state space was 0 seconds to 240 seconds late.

With the graph, we calculated the mean deviation from the expected arrival time at between stops. We then plotted this deviation to visualize the impact. We then constructed a second network which was identical to the first but with the mean and standard deviation data of the lines during the Orange Line shutdown. The schedule deviations along the routes were compared to identify the impact of the Orange Line replacement shuttle buses.

Second, we modeled the confidence with which a rider should assume they will arrive within their expected travel time on a path while the Orange Line was shut down. This model required alternate paths to the T. We added in bus routes and walking paths. We only had data on the deviation of travel time on buses, so we added mean travel time from Google Maps. We also utilized Google Maps for mean walking times and assumed the standard deviation of walking was minimal. We then built small scale models to look at specific areas of downtown Boston which have multiple path options. Lastly, we picked certain beginning and ending stations within this small scale model to identify which paths offer riders the most confidence.

Assumptions

As is the case in many analyses, some assumptions were made in order to make the process a bit smoother. In our case, many of our assumptions are ones meant to simplify the nature of the problem without necessarily diluting the weight of our results.

First, we have to assume the validity of our starting points. Thus, we take the MBTA data to be a valid and reliable data source which we can take values from without any considerations to its consistency. This is simply due to not having alternative data sources to consider. Conducting this analysis quantitatively without the MBTA Blue Book data, would be functionally impossible, so we assume this is true. We also take the MCRoute python library to be accurate, which, to the furthest extent possible, we have tested and verified via our own experience with the library, as well as verification from example cases given in the documentation.

We also make a handful of assumptions about our analysis in order to provide meaningful limits and boundaries in our analysis. For instance, we assume in this case that you can't catch up after you have been delayed. We do this for a couple of reasons, one of which being that generalizing our analysis becomes difficult when we have to account for the exact arrival and departure times of each shuttle, bus, or alternative mode of transportation compared to each other. This becomes especially true when considering if we are actually considering a passenger on their journey or not. Since our model doesn't actually consider how an individual traveler experiences the MBTA, but rather general trends over many routes, we consider there is no such thing as "getting caught up" or arriving early at your final destination.

This is something we will discuss more in the "Further Research" section, as there are likely some alternative ways to represent this data and to account for catching up, just not for this particular modeling scenario.

We are also assuming that most of the traffic issues related to bus routes are accounted for in the standard deviations we calculate given the MBTA data. This allows us to hide several possible contributing factors behind a single value, thus greatly simplifying the nature of the problem.

Lastly, we made assumptions about the lack of data associated with some travel time of Green Line stops during the shutdown of the Orange Line. If there was no data provided, we assumed there was no change in travel time compared to when the Orange Line was fully operational. This happened, as an example, for the Green Line B extension from Boston College to South Street. It typically only occurred at the terminal points of the Green Line. This issue also arose with travel time between Park Street and Downtown Crossing on the Red Line. We made an assumption using Google Maps to say that the mean travel time is 2 minutes or 120 seconds.

Analysis

In our project, we first assessed the impact of the Orange Line shutdown by segmenting the data for the Orange, Red, and Green T Lines into before and during the shutdown to see how schedule deviation changed.

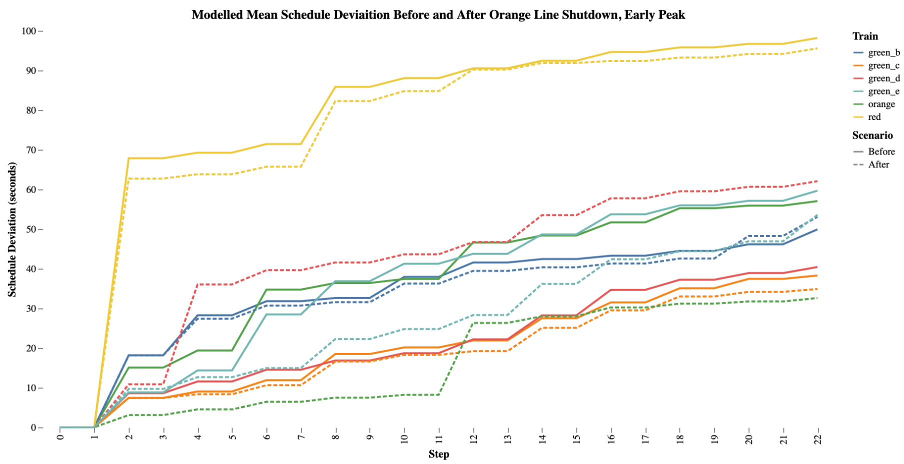

Figure 1

We analyzed three times in the day which citizens rely on the T the most: the early peak, the midday, and the afternoon peak. In **Figure 1**, the model displays the mean schedule deviation a rider could expect during the morning peak travel time, 7 - 9 AM. **Figures 2 and 3** in the appendix display the mean schedule deviation a rider could expect during the afternoon peak travel time, 4 - 6:30 PM, and midday, 9:01 AM - 3:59 PM respectively. All three models look identical. The result of the models is a piecewise function graph which explains that overall, not only did the Orange Line shutdown not delay riders, but the replacement shuttle buses actually led to less schedule deviation for riders. The only instance where the shutdown increased schedule deviation was the Green D Line. One explanation for this was that the Green D also had replacement shuttles during the Orange Line shutdown. The Orange Line replacement buses minimally decreased the schedule deviation for the Red, Green B, and Green C Lines. This effect leads us to believe that there is minimal interaction between the Red, Green B, Green C Lines and the Orange Line. The largest decrease in schedule deviation can be seen in the Orange and Green E Lines. One explanation for the decrease in deviation in the Orange Line may be related to Boston shutting down certain streets, so that the replacement buses could travel without traffic.

Our second model output confidence interval information for alternate paths. We decided to look at paths that only existed in Downtown Boston. This included the northernmost stop of Haymarket and the southernmost stop of Tufts Medical. The routes included the Green Line, Red Line, Orange Line, 501 Bus, and walking. The mean time in order to walk between stations was determined by using Google Maps time of travel. **Figure 4** can be found below with a drawing of the different stations as nodes and travel routes and edges. We decided to choose the two boundary stations, Haymarket and Tufts Medical Center, in order to show how the longest path should be traversed. This is because we found any shorter path using stops within these two boundary points would follow the path of this extreme case.

We found the path for 3 cases:

1. Using the mean travel times between each station
2. Using the mean travel times within 1 standard deviation
3. Using the mean travel times within 2 standard deviations

For each of the 3 cases, the path started with Haymarket to Government Center using the Green Line. Then, Government Center to Park Street using the Green Line. Then, Park Street to Downtown Crossing using the Red Line. Lastly, Downtown Crossing to Chinatown to Tufts Med by walking. We found the 3 cases using the same optimal path to be interesting, especially because we determined that using T trains as often as possible would lead to the most success of arriving on time. One plausible explanation could be that each of the train station stops are well-placed throughout the city and far enough away that car traffic would prevent a bus from being faster. Furthermore, even though there is deviation of on-time arrival for each train route and the inability to make up lost time, this result shows the timeliness of the T within a certain margin of error.

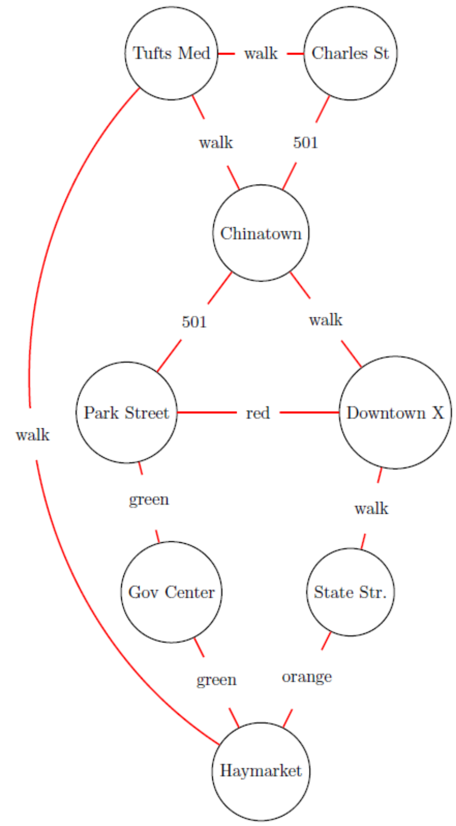

Figure 4

Limitations

Our project considered paths along the Orange Line and additional routes during the closure of the Orange Line. Currently, the Green Line D train extends from Lechemere to Union Square, where it ends. Also, the Green Line E train extends from Lechemere to East Somerville through Tufts/Medford. However, the Green Line E train was not running through Lechmere during quarter 3 and did not open until December 12th. On the other hand, the Green Line D train did extend to Union Square beginning in March of 2022. However, the data provided through the MBTA Blue Books did not provide information about this extension. Therefore, we were unable to consider alternative routes during the shutdown of the Orange Line that utilized the Union Square stop. This did not impact the majority of the alternative routes we considered because the use of the Union Square stop would only be considered if we wanted to take a longer distance and time route, on average. However, this would not be a logical alternative.

Another limitation of our project is we only considered the impact of the Orange Line closure on riders taking the Orange Line and how their rides were impacted. We noticed that the closure of the Orange Line led to lower mean travel times and lower standard deviation times while using the shuttle buses. Furthermore, this improvement in mean travel time may only occur because road closures existed during a one month period. Therefore, our assumption of improved travel time may have only existed because our data comes during the quieter summer months and this road closure would not be a sustainable alternative route.

Further Research

One area of research that has been left out of the analysis conducted here is on how one could incorporate the bus capacities into the model we utilized here. The difficulties we face trying to do this were primarily based on how a bus possibly being full at any given point on the route could affect the transition probability matrices of each edge. There was also the difficulty of not having a lot of reliable information regarding how full the buses were at any given point, which stopped us from being able to determine the actual probabilities associated with a full bus interfering with the route.

We also considered how one could account for "catching up" on your route. For instance, if your bus is five minutes late, but you are still able to catch the red line train on time, then you will have caught up on your route and will technically be on time again. Modeling this into our system was difficult for many of the same reasons as modeling the bus capacities. One way you could accomplish this is by modeling travelers in a Monte Carlo simulation where the buses and trains have individual departure times with standard deviations attached. Then you could mass model the passengers to determine how on time they are, but our model is not set up to handle this kind of scenario.

Conclusion

Overall, we see that Markov Chains are an efficient way to model transportation, and specifically delays in transit. With the assumption that the probability of delay depends only on the state before, Markov Chain modeling was able to provide an unexpected understanding of the impact of the Orange Line Shutdown this past summer. We found that the shutdown actually had an almost entirely positive impact on the MBTA system. The amount of time a rider could expect to arrive late decreased for all T lines, with the exception of the Green D Line. Although this finding may seem to make the argument for shutting down the orange line and using shuttle buses instead, there are multitude of factors which were not included in this analysis and may counter that argument. For example, streets which are typically open to cars in Downtown Boston were closed so that the replacement buses could run without traffic. Another excluded factor was the time of year. The closure occurred when it was warm out which could have meant that people were more willing to walk than during the cold months. Moreover, in most cases, the change in schedule deviation was not drastically different than when the Orange Line was open.

When isolating Downtown Boston in our second model, we learned that the T system is quite effective, and using the lines that were open while the Orange Line stops were closed without replacement buses remained the shortest route even when factoring two standard deviations of delay. This provides evidence that the MBTA system has well placed and efficient T stops. Riders can rely on the T to be both the fastest and most reliable mode of transportation in the city.

Having a better understanding of the ways in which multiple modes of transportation interact with one another can also be insightful for governments when deciding where to build new stops along a route, how to temporarily or permanently close a grouping of stations without causing major disruptions to the system, and daily predictions of arrival time.

Appendix

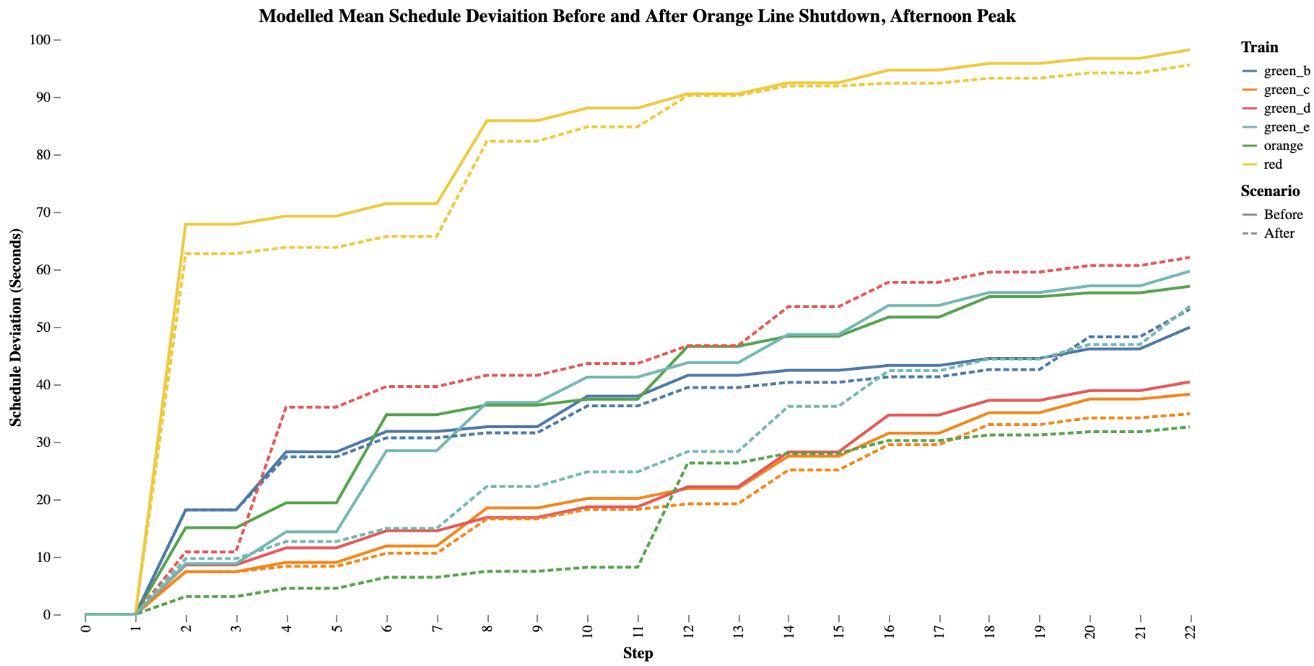

Figure 2

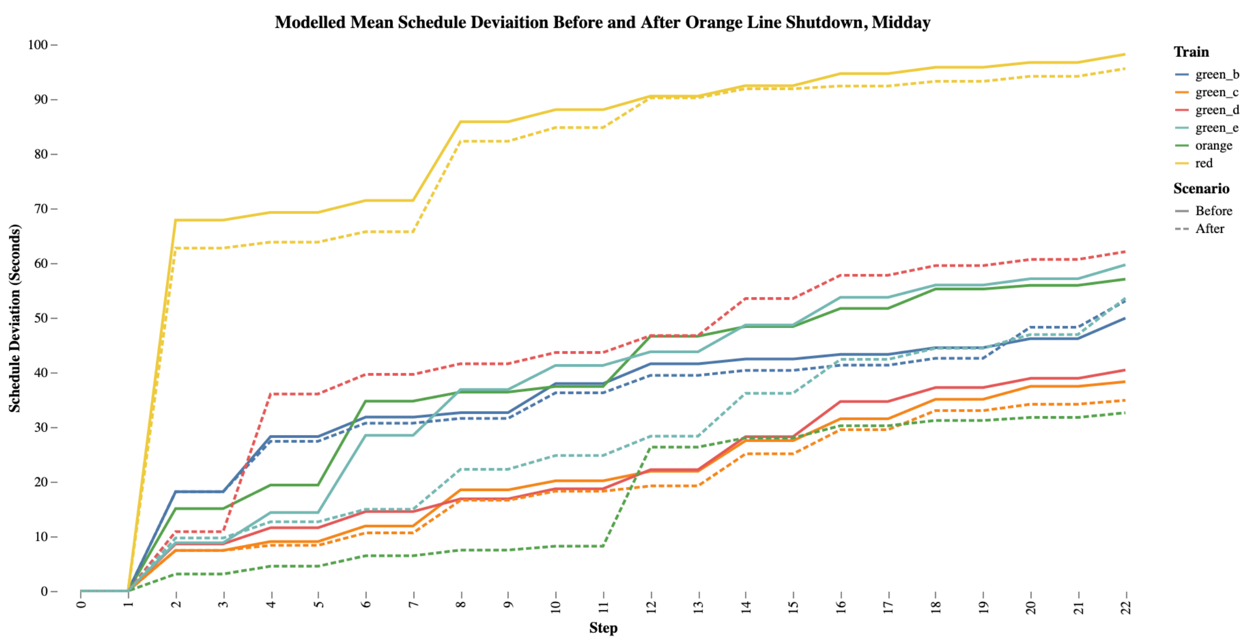

Figure 3

Group Participation

The participation of each group member for the project was evenly divided. Although each group member had more of a hand in the creation of certain aspects, every group member had input through discussions and questions. Marley did most of the data cleaning with assistance from Chris in what information would be important when modeling. Nathan focused on the background research, specifically with MCRoute and how it would relate to our project. Chris produced the description of the methods section with assistance from both Nathan and Marley. The figures and analysis were created from the use of Marley's code. However, the analysis was discussed and thought through all together in order to understand the result of the code and how it related back to our original research topic. Overall, we all enjoyed working together and seeing what we had learned in this class be put into a final project.

Sources

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