T-Ridership: a web tool for reprogramming public transportation fleet to minimize COVID-19 transmission

Saba Imani¹, Majid Vahed², Mohammad Vahed³

¹ Urban Planning and Policy, University of Illinois at Chicago, 412 S. Peoria, 237 CUPPA Hall, MC 348, Chicago, IL 60607, USA

² Pharmaceutical Sciences Research Center, Shahid Beheshti University of Medical Sciences, Niayesh Highway, Valiasr Ave, Tehran, Iran

³ David Geffen School of Medicine, UCLA, 615 Charles E. Young Drive South, lab: BSRB 346, Los Angeles, CA 90095, USA

¶Correspondence:

Mohammad Vahed

E-mail: mvahed@ucla.edu

Tel: +1-734-934-2556

Key words: Novel coronavirus disease (COVID-19), Social distancing, Public transit, Neural networks, High-density, Human contact

Abstract

As the outbreak of novel coronavirus disease (COVID-19) continues to spread rapidly throughout the world, steps are being taken to limit the impact on public health. In the realm of infectious diseases like COVID-19, social distancing is effective to avoid exposure to the virus and reduce its spread. However, current studies about public transit did not consider social distancing which plays a fundamental role in the current outbreak. Therefore, it is vital to study how to optimally manage public transit systems in order to minimize risks related to COVID-19. In this study we present a novel web-based application, T-Ridership based on a hybrid optimized dynamic programming inspired by neural networks algorithm to optimize public transit for safety with respect to COVID-19.

Two main steps are taken in the analysis through Metropolitan Transportation Authority (MTA): the first is detecting high-density stations by input data normalization, and then, using these results, the T-Ridership tool automatically determines optimal station order planning.

These results can be used in expanding on and improving policy in public transit, to better plan the schedule time of trains in a way that prevents high-volume human contact, increasing social distance and reducing the possibility of disease transmission (available at: <http://t-ridership.com>).

1. Introduction

COVID-19 is changing the world significantly by affecting all economics, education, and transportation. The highly transmitted property of COVID-19 between individuals deserves significantly alert. The response to the COVID-19 becomes an officially pandemic after barreling through all countries and the spread is infiltrating every aspect of our lives with consideration of facing recurring outbreaks over the next decades [1]. COVID-19 virus can be seen as a wake-up call to improve outbreak responses, and lessons from this pandemic can be used to keep diseases like coronavirus under control before spreading widely.

Recent findings have been detected the transmission of COVID-19 is spread by contact, droplet, airborne routes, and even studies generate that a considerable rate of people infected by different respiratory viruses like COVID-19 is through tidal breathing that shows the efficacy of social distancing and also face masks in preventing virus dissemination in exhaled breath. These causative agents, explaining large community outbreak of COVID-19, emerging us the necessity of social distancing as an implication for infection prevention, and all future efforts at prevention and control must take into consideration the potential for exhaled breath spread of this virus [2-6].

Preventive measures, such as social distancing restrictions in mass urban transportation and public areas, need to be implemented effectively by government

agencies and other responsible institutes. These restrictions can play a highly significant role in unpredictable future outbreaks (epidemic and pandemic disease) to slow down the virus spread [7].

Based on this study research, there is evidence that human-to-human transmission has occurred among close contacts. To control outbreaks happening anytime and anywhere else, considerable primary efforts to avoid transmission are required.

Proceedings to prevent or reduce transmission should be implemented in populations at risk, and public places, especially public transport that is the lifeblood of our cities and should continue running as long as possible to transport essential workers. If we have to travel using public transportation, the preference is to use the least-crowded bus or subway car as possible. To an extent, a public health crisis like the coronavirus outbreak, is an urban planning problem, as public spaces impact how we interact with one another, and how a disease like COVID-19 can spread [8]. The qualities that make urban places vulnerable during COVID-19 are also the keys to containing the disease's spread. Public transportation, which is one of the principal arteries of the cities, also makes them dangerous in a pandemic. Many research institutes are trying to provide physical and public places for recovery, besides working to defeat the virus by developing a vaccine and identifying places and populations with the highest need. Urban places responses to the pandemic are revealing that mandated distancing, physical, and social

structures of communities significantly influence places' ability to cope with the immediate crisis.

As the virus continues to spread, the physical density and design of public places will continue to influence how well they overcome the pandemic. For many communities and populations, the impacts of COVID-19 are likely to be dire. But efforts that nurture and support workers and will be vital to mitigating the fallout. Crowded and high-density public transportation systems furthered the spread of the virus. Despite serious downsides, the quality of densely connected places like public transportation can also make life amid social distancing more livable, and this is causing any public transit agencies across the world to seek to ramp up plans for contagious virus response.

Virus infections play an important role in the public transit fleet. Analyzing subway entries as measured by turnstile entry records [9] and the number of new cases reported by the New York City Department of Health [10] shows that newly reported cases finally decreased around March 16th, as subway use was cratering. It is expanding the idea of the relation between the two trends turnstile entries and coronavirus incidence [11]. Also, in the simulations shown in other recent research, controlling virus transmission in the public transportation system reduces the speed of virus spread and the height of the peak by approximately 20%. Evidently, this does not indicate a reaction of reducing public transport capacities, but more

willingly use it to plan lower densities of public transportation and thus reduced infection rates. In addition, at home or in private vehicles, one interacts with the same persons repeatedly, effectively decreasing the infection probability. However, public transport is much different: One sits or stands next to other persons every day. In consequence, public transportation is increasing possible infection paths between different persons every day, especially while squeezed together. Since they run back into their respective homes, public transport results in strong mixing. [12].

However, public transportation is highly vulnerable facing with outbreaks as COVID-19, it is essential to continue running to move needed workers, as well as considering controlling the spread of the virus in public transport is a big step in containing the disease [13]. Mass public crowds are an important worry in the spread of the Coronavirus. Over the disease, which caused restrictions in public transportation [14]. With an overview of the speed of spreading Coronavirus in the US, it is inferred that the cities where public transportation is more common to be used, as in New York, and other big crowded cities, the outbreak is higher than the ones using public transportation less [11].

As a result of the experience gained after outbreaks like COVID-19, now we should focus more and think of the different ways to define a transit system reliable. Considering all other factors that are effective in transmitting infection

disease, public transit will be a big step forward in future plans and decisions to prevent the disease from becoming a pandemic. In the current pandemic situation, an increasing number of agencies have begun to define new policies for transportation systems, trying to keep running, and are taking steps to incorporate social distancing into the transportation planning process.

It is urgent to find concrete strategies to reduce the spread of the virus on public transportation to limit the spread of the disease.

This study reviews methodologies for public transportation decision making, their performance, and demonstrates a framework for incorporating social distancing considerations in transportation planning and decision making through predetermined dates overviewing method to reprogram transit timetabling. In the first part of our study, we are aiming to understand how to measure the performance of a transit line density. Through a case study using data from the Metropolitan Transportation Authority (MTA), and wrangling them into a form suitable for analysis and then creating a map of the chosen MTA line stations, the study evaluates competing for our new method for reprogramming public transit and decision making based on predetermined dates overviewing using novel normalizing T-Ridership web tool analyses.

In the next part, a decision support web tool, namely T-Ridership, is proposed to analyze and visualize the data and the evaluation to effectively reflect density

changes. The proposed framework should help decision-makers with incorporating social distancing considerations into transportation planning.

COVID-19 spreads massively among people who are in close contact for a prolonged period. There are many guidelines to follow for practicing and considering social distancing options to travel safely when there are demands for running errands or commuting to and from work using public transit- for example, when you are selecting seats on a bus or train to keep at least 6 feet distance. But many people have personal circumstances or situations that present challenges with practicing social distancing to prevent the spread of COVID-19, so there should be more strict rules that automatically apply social distancing in public places such as public transportation, apart from people's personal preferences.

In the current pandemic situation, an increasing number of agencies have begun to define new policies for transportation systems, trying to keep running, and are taking steps to incorporate social distancing into the transportation planning process. This study reviews methodologies for public transportation decision making, their performance, and demonstrates a framework for incorporating social distancing considerations in transportation planning and decision making through predetermined dates overviewing method to reprogram transit timetabling.

2. Materials and Methods

2.1 Hybrid optimized dynamic programming

In this paper, we designed a hybrid structure based on the inspiration from neural network algorithms. Our idea is motivated by the design of the neural network structures to make our network structure easy to analyze public transportation trips. We propose a hybrid model that may lead an optimized algorithm of neural network structure.

To make our network structure easy to generalize to other datasets, our methodology separates the structure design and weights search. Taking inspiration from the neural networks, that have become a powerful and most successful tool in machine learning, our presented optimized training algorithm evolves the performance of the fully connected model of neural network which just works with some prepared functions.

The presented study embraced the neural network method along with dynamic programming to analyze public transportation trip flows and minimize Coronavirus exposure by using public transportation.

Neural network (NN) is one of the emerging technologies, which interprets novelty detection in transportation and urban planning area. Among all different methodologies for modeling transportation parameters and available data analysis research tools, a neural network has been suggested as the most successful

alternative. Neural network (NN), an extremely popular class of CI models, has been widely applied to evaluate various transportation issues [15-23].

In standard feed-forward neural network modeling that is applied to this paper, there is one set of connections fully connecting the input layer to the next layers, resulting in the activations of the nodes until getting the output. In this procedure, neurons are the basic common features in neural network composition, which take data in and joining to the next transmission process by weighted connections to compute an output [24 and 25].

The defined method in this paper is inspired by neuron network to implement programming and suggest a hybrid system using dynamic programming which lets the errors in analysis to correct themselves through a recursive function and enables the function to repeat itself several times, to eventually output the result [26].

The study is carried out under the motivation of knowing that modeling daily trips for traffic flow prediction will optimize the issues affecting mass density in public transit modes.

Moreover, the suggested hybrid neural network approach and dynamic recursion function improved the proposed models for public transit planning, and different data analysis indicates more robust models comparing to other transportation programming systems.

The model is calibrated based on passenger's origin, destination, and population density in each station. This reduces passenger's indoor wait time, congestion, population density, and person-to-person contact. This approach is willing to find a solution to reduce the number of passengers in the same direction with different destinations in peak time. The Neural network takes the processing elements from data resources using a transfer function joining by weights connections; data flow along with these connections and wherever finds the statistics exceed the intended density, a recursion function through dynamic programming lets the errors to correct themselves from the beginning, figures out the most populated stations and skips the stations with high density and transfer it to an excessive line to divide passengers in a common route into different trains, and repeats the procedure to finally get to the output with the least skipped stations. Using an algorithm to achieve the best travel estimation for less population traffic is the basis of this study.

As shown in figure 1, in the neural network model, the neuron is the basic component that is in place of stations, and a multilayer perceptron structure is a fully interconnected set of layers of neurons. Each neuron ($N_1 \cdots n$) of a layer is connected to each neuron of the next layer, from the input layer to the output layer. Figure 1 is a schematic representation of the process involved.

Fig. 1. Multilayer Perceptron Hybrid Dynamic Model.

A schematic representation of the process involved that each station is considered as a neuron and connected to the next layer with its own weight, which is the number of passengers between two stations. After calculation, If the number exceeds the Max, then the recursion function is used to go back and repeat itself, to finally program 2 lines with allowed capacity consideration.

2.2 Implemented T-Ridership web tool

The idea and the created algorithm are followed by an implemented web tool which is freely available to be used online. There are no similar web tools comparing to our designated one, which can automatically normalize the density in public transportation vehicles with social distancing consideration, which has

become one of the top priorities in the recent outbreak of COVID-19. Our web tool is flexible to apply to any kind of public transit such as taxi, bus, or train.

2.3 T-Ridership

The algorithm of T-Ridership web tool works through an iterative process of calculating transit data. The T-Ridership is implemented in C# (C-Sharp), and also, we use several other languages.

T-Ridership is a free web tool for reprogramming the public transportation fleet to reduce Covid-19 infection transmission by social distancing consideration. While coding our database, we use neuron network algorithm. Each station is considered as a neuron and connected to the next layer with its own weight, which is the number of passengers between two stations. By considering the capacity of each bus or each train car that social distancing is applied, a maximum number is fixed, and the system automatically skips the stations that exceed the fixed number.

The designated T-Ridership web tool works with two methods; the first method calculates the number of passengers in a route; when we just have passenger's statistics in each station without knowing their origin and destination station. In other words, when the only available data is the number of passengers entering and exiting each station, without knowing each passenger's specific origin and destination and how many stations are traveling by each.

In our second method which is designed to be used by knowing the number of passengers with their specific origin and destination with creating an $n \times n$ matrix that n is the number of stations in one route, and contains our input data consisting of the columns, showing the number of passengers exit in different stations from a specific origin, and the rows showing the number of exit passengers from diverse origins but in a particular destination. The last column of the matrix indicates the number of passengers transit between two continuous stations.

The significance of this method is, besides having its complexity for collecting input data and calculations, it is highly accurate (Figure 2). First method (A) calculates number of passengers in a route according to each station's entrance and exit, without considering the number of stations traveled by individual passenger. Second method (B) calculates number of passengers in a route according to each station's entrance and exit, considering the number of stations traveled by individual passenger.

PT-Ridership Home App Contact

Public Transportation Ridership:

Use this for local public transportation information

Select the number of stations: 20 Capacity of public transportation between two stations: 20

Find Lines Order

Passenger Ridership Statistics

STATIONS	Station 1	Station 2	Station 3	Station 4	Station 5	Station 6	Station 7	Station 8	Station 9	Station 10	Station 11	Station 12	Station 13	Station 14	Station 15	Station 16	Station 17	Station 18	Station 19	Station 20
Input	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Output	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Transfer																				

Line1 Line2

Predicted lines after calculation with minimum skipped stations

Find Lines Order

Matrix of Input & Output Passengers with Specified Origin & Destination

Matrix of Input & Output Passengers with Specified Origin & Destination	Station 1	Station 2	Station 3	Station 4	Station 5	Station 6	Station 7	Station 8	Station 9	Station 10	Station 11	Station 12	Station 13	Station 14	Station 15	Station 16	Station 17	Station 18	Station 19	Station 20	Total
Station 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Station 20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Fig. 2. T-Ridership Web Tool:

This shown template is the computational structure and it is designated to be user-friendly. (A) The first method: calculates the number of passengers in a route according to each station's entrance and exit, without considering the number of stations traveled by individual passengers. (B) Second method: calculates the number of passengers in a route according to each station's entrance and exit, considering the number of stations traveled by individual passenger.

As the output of the designated web tools, the result is shown as text and also graphical illustration, featuring all stations divided into different lines with their stops and skipped stations (Figure 3).

(A)

(B)

Fig. 3. Web tool output.

As the output of the designated web tools, the result is shown as text and also graphical illustration, featuring all stations divided into different runs with their stops and skipped stations.

In the first step, the main aim is finding the real number of passengers traveling inside a public transportation vehicle in a route, which is essential in our research as it is affecting the virus transmission. The first step capacity calculation is based on real data extracted from available turnstile open data. User can input any time limit data in the web tool and get result.

A public transit route has n stations. The number of passengers who are expected to get on and off at the i th station during a given time period are known, donated as x_i and y_i respectively.

At each station i , the total of passengers leaving for the next station is denoted P_i

$$P_i = x_1, i=1 \quad P_{i-1} + x_i - y_i, 1 < i \leq n$$

Then suppose social distancing policy allows no more than S passengers in the vehicle at any given time, and a feed-forward process is done:

- (1) Ridership feed-forward parameters (n, x_i, y_i, P_i, S)
- (2) for $i=1$ to n
- (3) do
- (4) if $(P_i > S)$
- (5) skip station i //in first train
- (6) $P_{i+1} = P_i - y_i - x_i$ //subtract number of passengers entering and exiting passengers in station i from next station
- (7) Until reach the last station
- (8) return skipped stations

With this algorithm train 1 is set with its stops and skipped stations.

Then for the next train we use the following algorithm:

- (1) Recursion algorithm to find next train stops
- (2) given: skipped stations from first train $m_{[1..j]}$

- (3) for $i=m$ to 1 //until first station or the previous skipped station
- (4) do
- (5) find biggest P_i and skip it //for current train
- (6) call feed-forward //to check maximum capacity
- (7) return skipped stations

Fig. 4. Algorithm flowchart.

We considered two ways to find route updates in our algorithm. First, when users have access to detailed data including each passenger's origin and destination, and second when users just have access to entering and exiting passengers of each station. Based on what kind of data is available we go through this algorithm to gain the first run, and relatively re-reading the data for having the second run.

3. Case study

3.1 Input data set

As the basis of input data, automatic passenger counting can be done by contact-type counters, optical sensors, vision-based systems, and IC cards. All these counters can be applied in many public places with entrances, such as subways and bus stations. Subway passenger flow has obvious time-varying characteristics with easily identifiable peaks [27].

We are using open transit data Toolkit [9] that is helping to utilize transit data.

Through the analysis of IC card data, we can understand the time distribution characteristics of bus passenger flow, make in planning the frequency of shifts, and improve the operating efficiency of the entire bus system.

3.2 Case Study Dataset

In this section, we present the dataset used for our study, as well as the pre-processing step conducting in order to make statistical analysis of the data obtained from the Metropolitan Transportation Authority (MTA) that is a public benefit corporation responsible for public transportation in the U.S. state of New York [26]. As the first step, we used Open Transit Data Toolkit for measuring and analyzing the transit systems to be used in the next step, which in programming the

prepared data and visualizing transit data. These data are not clear enough to use directly in T-Ridership web tools. At first, we did the clarifying to be used for the next step.

After examining the peak hour and density of each station, we will map each station's density.

However, there were different days and months' data had been examined and had the same result; we looked into using data for the first week in May 2020 to illustrate the results in charts.

We captured data for the Q Line in New York City Subway in Brooklyn, entering the turnstile at the Prospect Park stop, located within the 40.66161 latitudes and -73.96225 longitude, to the station at the Ocean Pkwy stop at the end of the line, from May 2nd to May 8th, 2020, knowing that missing or incomplete data is a frequent challenge in data wrangling.

Figure 5 superimposes the stops that tens of thousands of passengers take every day back and forth between stations in downtown Brooklyn.

Fig. 5. New York Subway plan with chosen stations in Brooklyn [27].

Superimposes the stops that tens of thousands of passengers take every day back and forth between stations in downtown Brooklyn.

3.3. Result of selected line stations' density

As shown in figure 6, each station in line Q consisting of 15 stations from May 2, 2020, to May 8, 2020, is analyzed individually. As a result, obviously, neighborhoods with more population and density had more crowded stations. As shown in figure 5, the King's Highway and Church Av had the most passengers and density.

Fig. 6. MTA Subway Turnstile Entries from May 2nd to May 8th. Each station in line Q consisting of 15 stations from May 2, 2020, to May 8, 2020, is analyzed individually. As a result, obviously neighborhoods with more population and density had more crowded stations.

Policy determiners can use the result of the current study to make decisions and change the public transit ordination to avoid over-crowded stations and trains. By detection of T-Ridership web tool, identified stations with high density should change their time-table scheduled time and frequency.

3.4 Results of T-Ridership

We use statistics and information of ridership to illustrate the lines' density, and by comparing the target lines, we figure out the most ridership lines. Therefore, there is a high-resolution human contact in those routes that plays a fundamental role in infectious disease transmission.

The data resulted in the previous section can be performed in the measurement that trains transfer within a defined period of time. The stations that each train should stop in a scheduled time and decide the stations that should be skipped.

By the location coordinates of the stations, the following chart shows our sample of the line in Brooklyn neighborhood in the New York subway. As explained before in this section, we chose a sample with real data for May 2020 containing

15 sequence stations, with evaluating their entry and exit for one week and as a result, two stations recognized as the most crowded in comparison with others as shown in figure 6, Then we took out an average from our first results to put in the T-Ridership web tool, and it shows the best performance to decrease the number of passengers in overcrowded stations. Figure 7 shows the efficiency of the T-Ridership web tool to decrease the number of passengers in a route and divide them into two different timetable transit.

Fig. 7. Passenger Density comparison after and before Application of T-Ridership Web Tool. It shows the efficiency of the T-Ridership web tool to decrease the number of passengers in a route and divide them into two different timetable transit.

4. Discussions and Conclusions

In this paper, we use the inspiration from neural networks to design an optimized hybrid dynamic programming that can capture sequence analysis tasks. The effectiveness of the proposed methodology was evaluated using a real dataset issued from the public transport network of New York in the US. We also investigated the effect of this information on the transportation system on the social distancing accuracy. The results obtained from T-Ridership web tool that can use both subway and bus data do indeed improve on all the data set prediction performances.

All investigations have been carried out to enhance and consolidate these results. Particular attention has been given to reduce human-to-human contact. Our simulation system and T-Ridership web tool are minimizing the contact of passengers in an indoor place like bus and train by preventing getting overcrowded that results in reducing coronavirus outbreak.

Thus, allowing for better optimization of public transportation setup, this methodology can be extended to the whole public transport network, and policy determiners can use the result of the current study to make decisions and change the public transit ordination to avoid over-crowded stations and trains. By

detection of T-Ridership web tool, identified stations with high density should change their time-table schedule time and frequency.

The main limitation of this research was the capacity of adding vehicles in the public transportation system, due to limited transportation earmarked funding.

Although adding more vehicles in high-density routes could help the better performance of our work, it is not practically possible. Based on this, our research's main idea is not to add any vehicle, and change the frequency and timetabling of trains in a route. In this method, the only problem is that the waiting time for some limited passengers in skipped stations increases; however the other passengers will wait less for the train and also spend less time inside the vehicle. Despite the increase in waiting time in some stations, this is still beneficial in the outbreak to avoid shutting down public transportation entirely.

If we can solve the funding problem, we intend to add a maximum of one vehicle to optimize the increase in waiting time. The more our idea makes financial sense, the more it encourages decision-makers to follow and use it.

Declarations

Availability of data and material

Project name: T-Ridership

Project home page: <http://t-ridership.com/>

Operating systems: Platform independent

Programming language: C#

License: GNU v3

Any restrictions to use by non-academics: No

Authors' contributions

Saba Imani, analyzed the data, and wrote the manuscript. Majid Vahed participated in designing and coordinating the study. Mohammad Vahed initiated, implemented the software, supervised the project, and wrote the manuscript. All authors read and approved the final manuscript.

Acknowledgements

We would like to thank Prof. Satoshi Okada (Chiba University, Japan) and Prof. Kazuya Kawamura (University of Illinois at Chicago, USA) for their fruitful discussions.

References

- 1- Resnick, B. (2020, March 17). Scientists warn we may need to live with social distancing for a year or more. Retrieved from Vox website: <https://www.vox.com/science-and-health/2020/3/17/21181694/coronavirus-covid-19-lockdowns-end-how-long-months-years>
- 2- Wölfel, R., Corman, V. M., Guggemos, W., Seilmaier, M., Zange, S., Müller, M. A., ... Wendtner, C. (2020). Virological assessment of hospitalized patients with COVID-2019. *Nature*.
<https://doi.org/10.1038/s41586-020-2196-x>
- 3- Guan, W., Ni, Z., Hu, Y., Liang, W., Ou, C., He, J., ... Zhong, N. (2020). Clinical Characteristics of Coronavirus Disease 2019 in China. *New England Journal of Medicine*.
<https://doi.org/10.1056/nejmoa2002032>
- 4- Leung, N. H. L., Chu, D. K. W., Shiu, E. Y. C., Chan, K.-H., McDevitt, J. J., Hau, B. J. P., ... Cowling, B. J. (2020). Respiratory virus shedding in exhaled breath and efficacy of face masks. *Nature Medicine*, 1–5. <https://doi.org/10.1038/s41591-020-0843-2>
- 5- Shiu, E. Y. C., Leung, N. H. L., & Cowling, B. J. (2019). Controversy around airborne versus droplet transmission of respiratory viruses. *Current Opinion in Infectious Diseases*, 32(4), 372–379.
<https://doi.org/10.1097/qco.0000000000000563>
- 6- Bourouiba, L. (2020). Turbulent Gas Clouds and Respiratory Pathogen Emissions. *JAMA*.
<https://doi.org/10.1001/jama.2020.4756>
- 7- Pham, Q.-V., Nguyen, D. C., Huynh-The, T., Hwang, W.-J., & Pathirana, P. N. (2020). *Artificial Intelligence (AI) and Big Data for Coronavirus (COVID-19) Pandemic: A Survey on the State-of-the-Arts*. <https://doi.org/10.20944/preprints202004.0383.v1>

- 8- Is the Coronavirus Changing How We Look At Public Spaces? | The Takeaway. (n.d.). Retrieved August 14, 2020, from WNYC Studios website:
<https://www.wnycstudios.org/podcasts/takeaway/segments/coronavirus-public-spaces>
- 9- mta.info | Turnstile Data. (n.d.). Retrieved August 14, 2020, from web.mta.info website:
<http://web.mta.info/developers/turnstile.html>
- 10- New York State Department of Health. (n.d.). Retrieved August 14, 2020, from health.ny.gov website: <https://health.ny.gov/>
- 11- Harris, J. E. (2020). The Subways Seeded the Massive Coronavirus Epidemic in New York City. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3574455>
- 11- Muller, S. A., Balmer, M., Neumann, A. (2020). Mobility traces and spreading of COVID-19. *MedRxiv*. <https://doi.org/10.1101/2020.03.27.20045302>
- 13- Wong, Y. Z. (n.d.). To limit coronavirus risks on public transport, here's what we can learn from efforts overseas. Retrieved August 14, 2020, from The Conversation website:
<https://theconversation.com/to-limit-coronavirus-risks-on-public-transport-heres-what-we-can-learn-from-efforts-overseas-133764>
- 14- How COVID-19 Spreads in Public Places and How to Protect Yourself. (n.d.). Retrieved from Healthline website: <https://www.healthline.com/health-news/public-places-and-the-coronavirus-what-to-know>
- 15- Vlahogianni, E. I., Karlaftis, M. G., & Golias, J. C. (2005). Optimized and meta-optimized neural networks for short-term traffic flow prediction: A genetic approach. *Transportation Research Part C: Emerging Technologies*, 13(3), 211–234. <https://doi.org/10.1016/j.trc.2005.04.007>

- 16- Çetiner, B., Sari, M., & Borat, O. (2010). A Neural Network Based Traffic-Flow Prediction Model. *Mathematical and Computational Applications*, 15(2), 269–278.
<https://doi.org/10.3390/mca15020269>
- 17- Ma, X., Tao, Z., Wang, Y., Yu, H., & Wang, Y. (2015). Long short-term memory neural network for traffic speed prediction using remote microwave sensor data. *Transportation Research Part C: Emerging Technologies*, 54, 187–197. <https://doi.org/10.1016/j.trc.2015.03.014>
- 18- Faghri, A., & Hua, J. (n.d.). *Evaluation of Artificial Neural Network Applications in Transportation Engineering*. Retrieved from <http://onlinepubs.trb.org/Onlinepubs/trr/1992/1358/1358-012.pdf>
- 19- Karlaftis, M. G., & Vlahogianni, E. I. (2011). Statistical methods versus neural networks in transportation research: Differences, similarities and some insights. *Transportation Research Part C: Emerging Technologies*, 19(3), 387–399. <https://doi.org/10.1016/j.trc.2010.10.004>
- 20- Haykin, S. S. (1999). *Neural networks : a comprehensive foundation*. Upper Saddle River, N.J.: Prentice Hall.
- 21- Celikoglu, H. B., & Cigizoglu, H. K. (2007a). Modelling public transport trips by radial basis function neural networks. *Mathematical and Computer Modelling*, 45(3–4), 480–489.
<https://doi.org/10.1016/j.mcm.2006.07.002>
- 22- Celikoglu, H. B., & Cigizoglu, H. K. (2007b). Public transportation trip flow modeling with generalized regression neural networks. *Advances in Engineering Software*, 38(2), 71–79.
<https://doi.org/10.1016/j.advengsoft.2006.08.003>
- 23- Hawkins, J., & Boden, M. (2005). The Applicability of Recurrent Neural Networks for Biological Sequence Analysis. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 2(3), 243–253. <https://doi.org/10.1109/tcbb.2005.44>

- 24- Dougherty, M. (1995). A review of neural networks applied to transport. *Transportation Research Part C: Emerging Technologies*, 3(4), 247–260. [https://doi.org/10.1016/0968-090x\(95\)00009-8](https://doi.org/10.1016/0968-090x(95)00009-8)
- 25- Mitten, L. G. (1974). Preference Order Dynamic Programming. *Management Science*, 21(1), 43–46. <https://doi.org/10.1287/mnsc.21.1.43>
- 26- Toque, F., Come, E., El Mahrsi, M. K., & Oukhellou, L. (2016). Forecasting dynamic public transport Origin-Destination matrices with long-Short term Memory recurrent neural networks. *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*. <https://doi.org/10.1109/itsc.2016.7795689>
- 27- MTA - Transportation Network. (n.d.). Retrieved August 14, 2020, from web.mta.info website: <http://web.mta.info/mta/network.htm>
- 28- Qu, E., Ns, B., Oo, K., & Yn. (n.d.). *WESTCHESTER THE BRONX*. Retrieved from <https://new.mta.info/map/7551>