Mobility of medical staff to meet the demand for hospital beds in high impact areas for New York City during Spring 2020 COVID-19

Kaitlin Beer, Yabo Gao, James Huddleston, Ricky Lee, Samuel Moss

ABSTRACT

As the COVID-19 pandemic spread across the United States, New York City experienced one of the largest surges in the number of COVID-19 positive patients requiring admission to Intensive Care Units. The primary goal of this project was to develop a model that provided resource scheduling solutions for hospitals within the five New York City boroughs of Manhattan, The Bronx, Queens, Staten Island, and Brooklyn to aid in the rerouting of patients to hospitals with available resources. We used a discrete time, integer linear programming model to find a solution for how many COVID-19 positive patients requiring hospitalization or admission to Intensive Care Units within the boroughs of New York City could be accommodated.

Keywords: Doctor Patient Ratio, Contagious Disease, COVID19, Intensivist, Integer linear programming

---

1. Introduction

The unexpected suicide of Dr. Lorna Breen brings to light the overall well-being of those frontline medical workers (Vivinetto & Stump, 2020). Breen's sister and brother-in-law, Jennifer and Corey Feist "are speaking out about Breen in the hope of bringing awareness to the mental health issues that healthcare workers under enormous strain can face" (Vivinetto & Stump, 2020). In their interview with Today, Jennifer Feist said, "I know my sister felt like she couldn't sit down. She couldn't stop working, and she certainly couldn't tell anybody she was struggling. And that needs to be a conversation that changes. People need to be able to say they're suffering and to take a break." Hoping to alleviate this situation, we created a rotation that will distribute doctors to areas of the most need. We gathered all the pertinent data, then we did exploratory data analysis on each dataset, and ultimately implemented a distribution system based on our findings.

The COVID-19 pandemic has introduced a need to manage a group of ICU patients, in the New York City area, with a dramatically higher severity of illness than their standard baselined survey, while also meeting the needs of patients and medical workers. Medical challenges to treating patients and relieving stress on these healthcare workers means collecting data and using it to reduce the burnout and resource failures that lead to patients being mistreated in the New York City healthcare system. The challenges include not being ready for the enclave in the patient population from non-COVID-19 to COVID-19, bed occupancy demand, severity of illness in COVID-19 patients, and ventilator requirements across boroughs of New York City. A baseline may have been developed prior to the COVID-19, but was ineffective in New York City during the onset of the virus in 2020.

“Two to four of every 10,000 US adults may need hospitalization and intensive care unit (ICU) resources during the COVID-19 pandemic” (Van Beusekom, 2020) and the demand on the New York City health care resources is reaching new heights in need for beds, ICU, and doctors. Nine hundred public health care workers in New York City have been infected by COVID-19 and increased the demand for doctors to serve patients of COVID-19 (ABC Eyewitness News, 2020). An effective plan is needed to register patients, capture pertinent information to help direct the best medical care for each patient, and to implement a better way to predict helping patients get the resources for recovery. To ignore the structural inefficiencies and inequities in the data gathering will put further stress on the administrators’ abilities to treat patients efficiently.

This paper is a start to predicting the demand on the health care system during a virus pandemic for doctor to patient ratio that will be used to guide patients to the medical centers that are best suited in New York City without burdening any one facility with too much demand for health care. This paper iterates the reasons for quality reporting, initiative and understanding for ICU, overall patient beds, doctors and medical staff, and capacity and resource consumption.

2. Literature Review

The scheduling of resources within a network has been a consistent issue within many industries. From chemical plants to hospitals, linear programming models have been used to provide optimal solutions to the world’s scheduling problems. Optimal resource allocation, whether it is people or machines, utilizes linear programming to find solutions based on present limitations and the proper sequencing of tasks (Shaik & Vooradi, 2012).

Integer linear programming is utilized when the problem at hand concerns the scheduling or assigning of people or machines where any solution would have to be an integer based on the indivisibility of the units (Bekkan, 2010). When considering a problem where the optimal solution is based on a finite number of resources, it is necessary to define those constraints as integers within a model.

In cases where there is a higher degree of unpredictability and limited historical data, it is possible to obtain a feasible solution to a problem based on a discrete time period with further simulation (Miwa, 2010). The use of a discrete time-based linear programming model is beneficial when trying to achieve a quality solution within a short period of time (Lee & Maravelias, 2018). For the situation presented within this paper, it was necessary to develop a discrete time-based model as the resources, in this case ICU beds and available doctors, are incredibly pressing during the current COVID-19 pandemic within New York City.

3. Methodology

3.1 Problem Definition

Before we develop our model, we would like to define our problem and the influential variables. In response to the staffing shortage in New York, we will create a model that maximizes the number of COVID-19 patients admitted to the Emergency Ward on a borough level. We will limit the number of people being admitted on a daily basis subject to the total number of beds available in the borough as well as the total number of patients all the doctors can take. In order to not make the hospitals spread their resources too thin, we will take the minimum of the two. For this optimization project, we used the COVID-19 data provided by THE CITY.

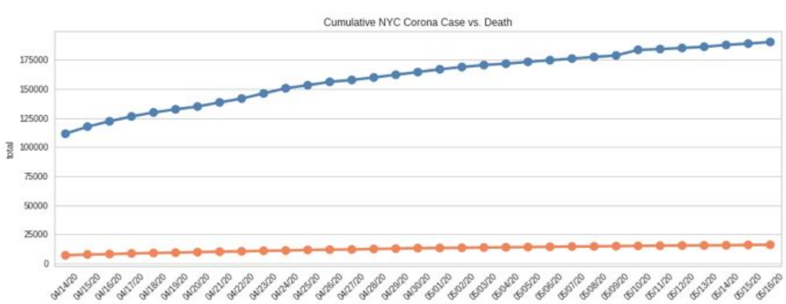
3.2 Exploratory Data Analysis

In this section, we will take a look at the following factors to better define the constants and variables. We will then use graphs/charts/other visuals to understand those factors in a greater detail. We analyzed the insights below.

- Daily number of hospitalized cases
- Daily number of cases, hospitalized, and deaths (actual & pending) over time grouped by age
- Average number of daily admits by each age group to the Emergency Ward
- Total number of cases by zip code and borough
- Daily number of COVID-19 related hospital admits with special attention dedicated to the patients in the ICU
- Daily number of hospital beds and ICU beds available
- Number of Emergency Physicians available in Manhattan

Graphs/charts for the factors above:

- Daily number of hospitalized cases
- Daily number of cases, hospitalized, and deaths (actual & pending) over time grouped by age

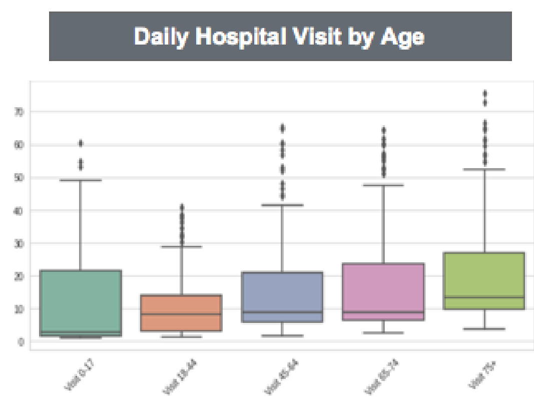


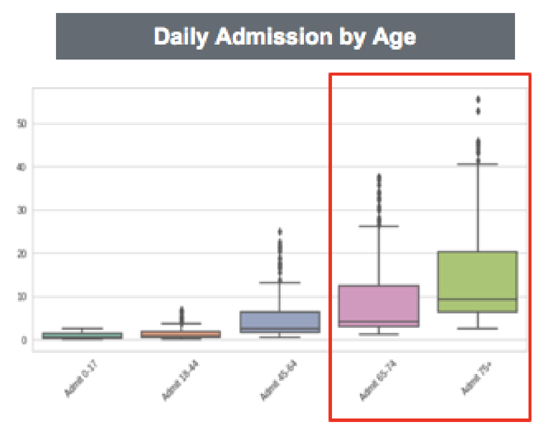
Some of the notable findings were that the number of Coronavirus patients increased consistently, while the number of deceased patients stayed relatively the same. Note that due to discrepancies in how the data were collected, the timeframe starts from April.

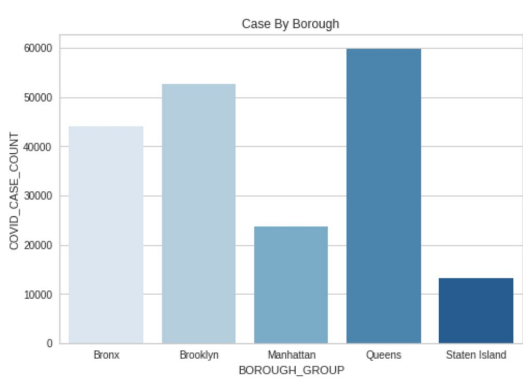
When we look at the breakdown of the coronavirus cases, we can see how the impact is far more significant on the elder generation (ages > 45) than younger cohorts.

	type	timestamp	ages_0_17	ages_18_44	ages_45_64	ages_65_74	ages_75_older	unknown	total
130	deaths-no-underlying	04/14/20	0	25	59	26	27	0	137
244	deaths-probable	05/13/20	3	125	935	930	2371	1	4365
335	ever-hospitalized	04/29/20	282	5917	14447	9480	11520	2	41648
281	deaths-underlying	04/29/20	6	401	2363	2255	4140	0	9165
267	deaths-underlying	04/15/20	3	263	1447	1369	2466	0	5548
25	cases	04/16/20	2395	45648	44460	15490	13892	263	122148
48	cases	05/09/20	4459	65645	65546	22260	20504	352	178766
321	ever-hospitalized	04/15/20	205	4636	11198	6957	7905	2	30903
218	deaths-probable	04/17/20	0	72	522	560	1244	0	2398
256	deaths-underlying	04/04/20	3	165	760	746	1145	0	2819

When assessing the daily hospital visits of the coronavirus patients, although the absolute number of patients who visit the hospital is relatively same on a daily basis, we observed the number of elder patients who were admitted and hospitalized far surpassed that of younger patients.

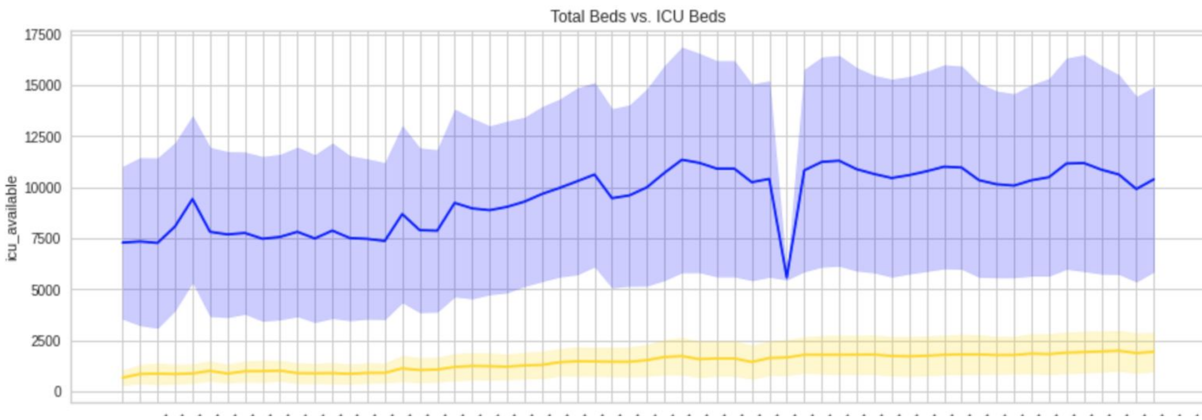






When also segmenting the number of total cases at the borough level, the number of cases in Queens, Bronx, and Brooklyn far exceeded the number of cases in Manhattan. This may indicate some socioeconomic factors that may have contributed to the prevalence in the three boroughs.

Lastly when looking at the total number of beds and ICU beds, there is a consistent increase over time, which most likely signifies the city’s response to the increase in new and potential coronavirus cases. With regards to the big dip in the graph, it seems to be attributed to an error, which can be imputed for during the analysis.



4. Optimization

With the insights gained and methodology based on literature review, we proceeded to build an integer linear programming model with a discrete timeline. To establish a baseline of an ideal doctor-to-patient model required to effectively combat COVID-19 in New York City, we needed to understand how many more coronavirus patients each borough could accommodate. Due to limited data, as well as difficulty in accurate forecasting, we needed to obtain a snapshot of a current state. This optimization model was based on the data available on May 28, 2020, which coincided with the day the Governor’s Office of New York released their last report.

4.1 Mathematical Representation

The objective of this model is to optimally maximize the number of COVID-19 patients at the borough level without drastically disrupting the current proportion of hospitalized Coronavirus and non-Coronavirus patients, while following the proposed guidelines from the Society of Critical Care Medicine (SCCM, 2020). Therefore, the objective function for this optimization model is:

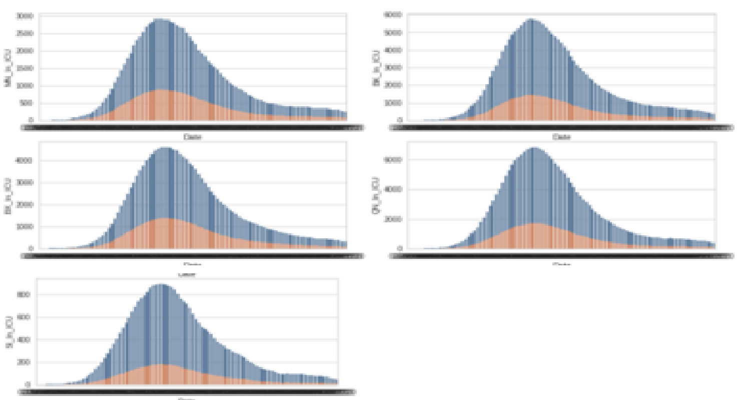
$$Maximize\ z = x1 + x2 + x3 + x4 + x5$$

where each decision variable represents the number of additional Coronavirus patients that can be hospitalized in each borough. The objective function signifies the total number of additional Coronavirus patients New York City can accommodate as of May 28, 2020.

Although a wide array of factors should be taken into consideration to accurately determine these numbers, we decided to assess three constraints: (1) Number of current Coronavirus patients as of May 28, (2) Number of available hospital beds as well as ICU beds, (3) Number of doctors and maximum patients.

4.2 Calculating Length of Hospital Stay

Based on the evidence provided by available medical research, we determined that Coronavirus patients required ICU stays for an average of 12 days. Also, based on the clinical research conducted by Harvard Global Health Institute (Jha, Tsai, Jacobson, Friedhoff, and Figeuroa, 2020), we determined that a weighted average of 30% of patients hospitalized in Manhattan and 25% of those hospitalized in other boroughs require ICU stays. This adjustment is to acknowledge availability of larger hospitals that can provide care for more acute and severe cases.



The chart on the left represents the trend of the number of COVID-19 hospitalizations, as well as ICU hospitalizations. This shows the number of hospitalized patients peaked in the month of March and gradually decreased since then. These trends are present in all five boroughs of New York.

4.3 Calculating Hospitalization Rates

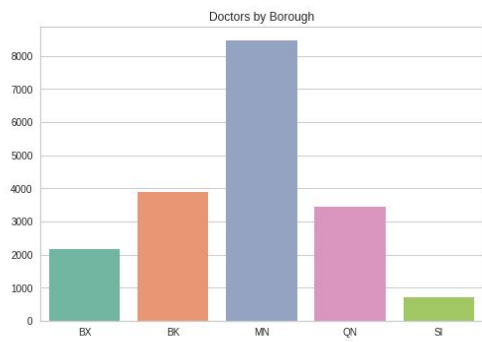
The evidence available by China Medical Treatment Expert Group for COVID-19 (Guan, et al., 2020) and Harvard Global Health Institute (Jha, Tsai, Jacobson, Friedhoff, and Figeuroa, 2020) indicated an assumption of “19% hospitalization rate in those under 65 and a 28.5% hospitalization rate in those over 65.” However, our analysis of the COVID-19 NYC data provided by The City Project showed that a higher rate of patients were admitted into hospitalization and subsequently ICU of which results seem empirically cogent given NYC hospitals prioritized severe COVID-19 cases in terms of testing as well as treatment. Therefore, we determined that a weighted average of 30% of patients hospitalized in Manhattan and 25% of those hospitalized in other boroughs require ICU.

We retrieved information about the number of available regular hospital beds and ICU beds from multiple sources, namely from New York State Department of Health Profiles as well as Harvard Global Health Institute. Also, we used the total number of available hospital beds and ICU beds from the Governor’s office. By overlaying the number of patients at the borough level and number of available hospital beds in each borough, we determined that about 63.4% of regular beds were occupied by non-COVID-19 patients, while 54.3% of ICU beds were occupied by non-COVID-19 patients. We applied the same proportion to the total number of currently available regular hospital beds as well as ICU beds to leave room for non-COVID-19 patients under a political unrest unfolding in New York.

Though the estimate may over- or under-estimate the proportion of COVID-19 and non-COVID-19 patients, this helps us highlight that this model serves as a guide in times of uncertainty given the best evidence available. Also, it is important to distinguish between COVID-19 patients and non-COVID-19 patients to adequately accommodate all patients, considering the fast spread of COVID-19 and potentially lethal nature of Coronavirus. The results of the analysis are below.

Boro	Total Regualr Hopsital Beds	Total ICU Beds	Current Covid19 Patients in ICU	Current Covid19 Patients Hospitalized	Available Reguarld Beds May28	Available_ICU_May28
MN	14834	1619	85	282	9017	760
BK	5848	638	112	447	3219	221
BX	4012	438	109	362	2153	120
QN	2873	314	115	461	1340	49
SI	927	101	11	55	526	42

4.4 Calculating Number of Doctors



According to Association of American Medical College (AAMC)'s 2019 research, there are about 375.1 doctors for every 100,000 people in the State of New York (AACM, 2019). With this data, we were able to estimate the number of doctors in NYC. When estimating the number of doctors in different boroughs, we decided to give different weights as we estimated that doctors are more likely to reside in Manhattan where there are more medical, hospital, and research facilities that tend to gravitate towards more affluent demographics. Therefore, we gave a multiplier of 1.4 to Manhattan, while giving 0.4 weight to other boroughs.

We then used the data to determine the maximum patients that the doctors in NYC can treat given the doctor-to-patient ratio recommended by The Society of Critical Care Medicine. We used an assumption that only about 5% of the doctors are intensivists and they can treat 24 patients per day, as opposed to 10 patients for the rest of the doctors, as per the tiered staffing strategy for Pandemic laid out by the Society of Critical Care Medicine (Society of Critical Care Medicine, 2020).

4.5 Building an optimization model

Using the calculated constraints, we were able to build an optimization model with the following conditions.

- Objective function: $Maximize\, z = x1 + x2 + x3 + x4 + x5$
- Decision Variables: Each decision variable represents the number of additional Coronavirus patients that can be hospitalized, expressed as Xi, where i = 1,2,3,4,5.
- Constraints:
    - Number of Available Beds For COVID-19 Patients:
      $x1,\ x2,\ x3,\ x4,\ x5$ <= [8983, 3141, 2098, 1264, 510]
    - Number of Available ICU Beds For COVID-19 Patients:
        - $0.3 * x1$ <= 760

- $0.25 * x2,\ 0.25 * x3,\ 0.25 * x4$ <= [221, 120, 49]
    - $0.2 * x5$ <= 42
  - Maximum Number of Patients Treatable (Intesivist*24 + Regular Doctor*10 - Patients already in treatment)
    - $x1,\ x2,\ x3,\ x4,\ x5$ <= [34749, 15835, 8296, 14926, 3012]

Under this condition, we determined that NYC can accommodate a maximum of 4,309 new COVID-19 patients without disrupting the current COVID-19 vs Non-COVID-19 patients proportion all while meeting the guidelines of the Tiered Staffing Strategy for Pandemic.

	Decision Variables	Manhattahn	Brooklyn	Bronx	Queens	Staten Island
	Additional Covid Patients to Accommodate	2536	887	480	196	210
Constraints	#of Available Beds for Covid19	8983	3141	2098	1264	510
	#of ICU Beds Used	760	221	120	49	42
	#of Available ICU Beds for Covid19	760	221	120	49	42
	#of Max Accommodation	34749	15835	8296	14926	3012

NYC may accommodate 4309 more serioues cases that require hospitalization

Objective Function	
MAXIMIZE	4309

Key Data					
# of Availble Beds	8983	3141	2098	1264	510
# of ICUs	760	221	120	49	42
# of Total Doctors	8465	3875	2153	3434	714
# of Intensivists	846	387	215	343	71
# Regular Doctors	4233	1938	1077	1717	357
# of Existing Patients	6720	3143	2248	1893	479
Max Patients	41469	18978	10544	16819	3491

5. Discussion & Conclusion

Based on the solution achieved within this paper, future research would be beneficial to extend and adapt the utility of the presented model. There are two primary propositions for extension of the current model that would make the application of the solution more viable for future patient scheduling/rerouting.

Defining prioritization criteria for rerouting COVID-19 positive patients in need of intensive care received concurrently would be one of the primary goals for future evolutions of the current model. Prioritization criteria for patients would require the establishment of weighted variables corresponding to patient characteristics such as the presence of pre-existing conditions and the age of the patient in question. The second focus for future research into this problem should be the average length of stay per patient based on defined criteria. This would involve collecting specific demographic and medical history data on COVID-19 positive patients admitted to the ICU, which was not possible during the current research. Applying both extensions to the present model in future research would ideally help to lower the risk of loss of life with COVID-19 positive patients who require treatment within ICUs.

5.1 Trade offs

Trade-offs are unavoidable since resources are limited. Who will get medical services and who will not? What are the criteria for determining which critically ill patient gets services and in which facilities? This depends on funding for resources in personnel, PPE-protective personnel equipment, and hardware equipment like venlators, and if outside resources are needed. There is little information and models to rely on in this early stage of the COVID-19 spread and combative response for New York City (NYC) to follow and to improve this paper. Some of the trade-offs that would need to be considered to make this model presented here to be more effective to help create a system to treat more patients in a less stressful, smarter way, are listed below (Mahoney, 2020).

- Degree of moral hazard. How institutions react to the out-of-pocket cost of health care? Insured, uninsured, and government assistance will affect the quality of care given and the ability to serve more probable chances to cover ederly, high risk, patients. A Markov simulation is an approach to trade-off between more or limited beds and patient/doctor ratio on the demand and ability to meet the demand for COVID-19 cases in each of the five boroughs of New York City.
- Elasticity of labor allocation. How will the doctors/workers react to the needed adjustments in servicing incoming patients? The demand to serve new patients, thus this paper's problem statement (doctor/patient ratio as a driver) was to redistribute doctors needed to the most immediate boroughs in NYC. A Monte Carlo simulation would assist along with more data for supportive evidence for variables in redistributing patients to the boroughs. From better data comes better modeling and criteria for meeting the redistribution of patients to doctors (the objective/problem statement here).
- Emergency Health cases choosing who to treat during Covid19. The challenge of the health care system in NYC is further challenged when COVID-19 patients are treated in emergency rooms over heart attacks, strokes, and cancer patients. Each group of medical emergencies are competing for doctors and beds (sometimes ICU). When does the administrator move patients like COVID-19 to other facilities or choose to treat in an overflowing emergency room?

5.2 Gaps

Data is available for age, and patient numbers of patients being assisted in the five NYC boroughs but excludes other demographics producing gaps in data.

Some of the gaps that would improve the reliability that is needed to improve and considered to make this model presented here to be more effective to help create a system to treat more patients in a less stressful, smarter way, are listed below.

- Race and ethnic patterns of the pandemic. There are missing data in this group. To ensure that the maximum number of patients are served and the health of people, has been missing during this crisis. Gaps in data collecting and missing from health department reporting; websites, daily updates from administrators, by political leaders and, news reports
- Unemployment data gaps in COVID-19 pandemic. As the unemployment rate increases how many unemployed are susceptible to catching the virus, and spreading the virus into NYC burroughs is unknown due to gaps in data collection. At some points in New York City no data on patients' independence is reported to scientists studying and making predictions on the demand for more beds, medical workers, or intensive care units. For this analysis, higher unemployed areas in NYC boroughs experience more cases of positive COVID-19 than others, and therefore exceed the threshold for doctor patient ratio, needing to redirect those unemployed and COVID-19 patients to another medical facility. Do these patients also require more or less medical attention like ICU beds, does

this add to more protective equipment in the areas of NYC with high unemployment? This data is lacking.

- Private vs public health centers available beds during the pandemic. Is there a prejudice to serve individuals not covered by health insurance, who come from another area of New York City to be served equally? This data is not shared and evidently not collected. This data would add to the understanding and predicting which medical facilities are most likely to have funding and capacity for the more ill patients affected by COVID-19 in New York City.
- Medical staff that are ill and infected by COVID-19 reduce the quality of patient care. No data is being captured across the New York City boroughs medical facilities to help serve patients nor the hospitals themselves. This means that the sharing between private and public hospitals are failing to meet patient care (Anonymous, 2020). For each medical staff infected with COVID-19 adds more patients to a doctor's care (Anonymous, 2020).
- In order to establish the amount of PPE that would be required, we would have to know how much PPE would be needed per staff member. Unfortunately, due to unpredictability and unknown variables regarding COVID-19, there is no hard data on the number of PPE that doctors and nurses need per day. In order to provide an estimate, we have referenced relevant research conducted on other pandemics by the CDC, such as Ebola. We believe statistics on Ebola provide a logical comparable in order to ascertain the needed PPE requirements. In doing so, research was done into the CDC's findings on how much PPE was needed for different medical staff during the Ebola pandemic (Center for Disease Control and Prevention, 2016). We believe that a nurse needs 40 PPE and a doctor needs 16 PPE on a daily basis, and we could look back whether this is a comparable estimate by assessing the current use of PPEs for COVID-19 treatment.

Due to the gaps in data this limits our ability to fully understand the criteria to concentrate on for better predictions on this pandemic for distributing patients to other medical facilities. The ICU occupancy, medical staff resourcing, and ventilator requirements are unknown at this point in the analysis due to lack of proper data collecting.

5.3 Conflicting data

Inconsistent/conflicting data between boroughs of NYC results in an unfair distribution of resources and the ability to prioritize the critically ill. This conflicting data causes miss information to administrators and decision makers/leaders that are on the front-line of the COVID-19 pandemic forcing them to use gut instinct to solve patients being served. The data inconsistencies cause the data and therefore the modeling and results to be inaccurate. A better information gathering system is needed. Medical institutions enter patients without categorizing data into intake forms. As listed above, not every institution collects this information and would be a better way to do business (Maybank, 2020).

This data would add significantly to the model here in terms of reliability and usefulness in predicting demand on medical workers/staff as the virus spreads. By improving the data collection the demand for beds, ICU, and doctors can be reduced and patients will need less time in ICU and for ventilators. Due to the gaps in data this limits our ability to fully understand the criteria to concentrate on for better predictions on this pandemic for distributing patients to other medical facilities.

To prevent a backlog of patients, many in dire straits will need medical resources, and medical workers in need of equipment are less served and not efficiently served due to the trade-off, gaps and conflicting data gathering that are required predictive analytics. The most marginalized ill patients of COVID-19 are communities of color and do not have the same access to medical care as other NYC boroughs and unemployment that prevents them from seeking care until they become extremely ill, putting more stress on the entire medical system (ICU, doctors, and hospital beds). This is data that would improve this study.

This paper has magnified the lack of quality data gathering and sharing in the science community for better identifying needs to serve the people and the greater good of society. A better leadership structure, data management system, and standardized the collecting of all types of demographic data have been lacking. Many gaps exist, many inconsistent data exist to treat more patients during a pandemic such as COVID-19 2020.

5.4 Recommendations

A centralized data center for data analysis is needed to collect and maintain data in the baselining for future virus pandemics. An example is to collect data by the hour for each ICU bed in proper New York City that will be available for COVID-19 patients that do not over-stress the medical workers (doctors). Some of the metrics to be collected, in the form of a readiness plan, for future analysis and predictions for this paper are:

- The proportion of beds occupied by severity of illness
- Proportion of ventilated patients
- Length of stay
- PPE and other medical equipment

These metrics will help hospital administration in the distribution of patients to the best suited medical facility. A standard between hospital communication for differing medical practices or resources would help in distributing patients to the best care in COVID-19 cases. Lastly, when forecasting the number of daily admission to hospitals and ICUs, we should explore the use of queuing theory to help improve the accuracy of prediction.

6. References

ABC Eyewitness News. (2020, April 15). CORONAVIRUS NEW YORK CITY. More than 900 NYC public hospital employees have tested positive for COVID-19. Eyewitness News. ABC 7. WABC-TV. New York City. Retrieved from https://abc7ny.com/doctors-with-covid-nurses-and-sick-coronavirus-nyc/6106134/

Ashish K. Jha, Thomas Tsai, Ben Jacobson, Stefanie Friedhoff and Jose Figueroa. (Ashisha, Thomas, Jacobson, Friedhoff, & Figueroa, 2020), Pandemics Explained unlocking evidence for

better decision making. Harvard Global Health Institute.
https://globalepidemics.org/our-data/hospital-capacity/ Accessed on June 3.

Bekkan, C. (Bekkan, 2010). Quantitative methods of physician scheduling at hospitals. University of Agder, Faculty of Engineering and Science Department of Engineering.

Centers for Disease Control and Prevention National Center for Emerging and Zoonotic Infectious Diseases (NCEZID). (Centers for Disease Control and Prevention, 2016). Estimated Personal Protective Equipment (PPE) Needed for Healthcare Facilities. Division of Healthcare Quality Promotion (DHQP). https://www.cdc.gov/vhf/ebola/healthcare-us/ppe/calculator.html Accessed on June 10.

Choi, Ann, Velasquez, Josefa and Welch, Will. (June, 2020). Coronavirus in New York City. THE CITY. https://projects.thecity.nyc/2020_03_covid-19-tracker/ Accessed on May 30.

Guan, W. J., Ni, Z. Y., Hu, Y., Liang, W. H., Ou, C. Q., He, J. X., ... & Du, B. (Guan, Ni, Hu, Liang, Ou, He, 2020). Clinical characteristics of coronavirus disease 2019 in China. New England journal of medicine, 382(18), 1708-1720.

Hopkins, C. (Hopkins, 2020). COVID-19 patients are flooding New York hospitals, and the peak may be 3 weeks away". Retrieved from
https://www.vox.com/2020/3/27/21197400/new-york-COVID-19-hospitals-coronavirus

Lee, H. and Maravelias, C.T. (Lee & Maravelias, 2018). Combining the advantages of discrete- and continuous-time scheduling models: Part 1. Framework and mathematical formulations. *Computers and Chemical Engineering, 116*: 176-190.

Mahoney, Neale. (Mahoney, 2020). Don't fall for the false trade-offs of COVID-19 policy. Chicago Booth Review. Retrieved from
https://review.chicagobooth.edu/economics/2020/article/don-t-fall-false-trade-offs-COVID-19-policy

Maybank, Aletha. (Maybank, 2020) The Pandemics Missing Data. New York Times.
https://www.nytimes.com/2020/04/07/opinion/coronavirus-blacks.html

Miwa, K., and Takakuwa, S. (Miwa, 2010). Optimization and analysis of staffing problems at a retail store. Proceedings of the 2010 Winter Simulation Conference, December 2010, pp.1911-1923.

Shaik, M.A., and Vooradi, R. (Shaik & Vooradi, 2012). Unification of STN and RTN based models for short-term scheduling of batch plants with shared resources. *Chemical Engineering Science, 98*: 104-124.

Society of Critical Care Medicine. (Society of Critical Care Medicine, 2020). United States Resource Availability for COVID-19. Society of Critical Care Medicine
https://www.sccm.org/Blog/March-2020/United-States-Resource-Availability-for-COVID-19
Accessed on June 3.

Van Beusekom, Mary. (Van Beusekom, 2020). Study: Wuhan-like COVID-19 scenario could crush US hospitals. Center for Infectious Disease Research and Policy. University of Minnesota. Retrieved from https://www.cidrap.umn.edu/news-perspective/2020/05/study-wuhan-COVID-19-scenario-could-crush-us-hospitals

Appendix

Appendix A. Calculations in Jupyter Notebook

A1. Python modules imported into Jupyter notebook.

```
[ ]  import numpy as np
     import pandas as pd
     import seaborn as sns
     import matplotlib.pyplot as plt
     import yellowbrick
     import datetime
```

A2. Import of data sources.

IMPORT DATA SOURCE

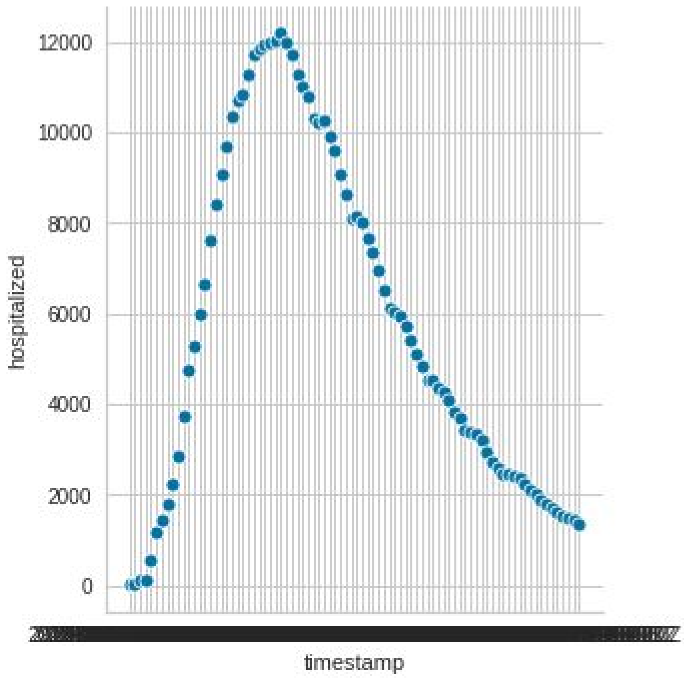
- https://github.com/thecityny/covid-19-nyc-data
- https://github.com/nychealth/coronavirus-data

```
[ ] url = ['https://raw.githubusercontent.com/thecityny/covid-19-nyc-data/master/age.csv',
           'https://raw.githubusercontent.com/thecityny/covid-19-nyc-data/master/beds.csv',
           'https://raw.githubusercontent.com/thecityny/covid-19-nyc-data/master/borough.csv',
           'https://raw.githubusercontent.com/thecityny/covid-19-nyc-data/master/gender.csv',
           'https://raw.githubusercontent.com/thecityny/covid-19-nyc-data/master/hospitalized.csv',
           'https://raw.githubusercontent.com/thecityny/covid-19-nyc-data/master/state.csv',
           'https://raw.githubusercontent.com/thecityny/covid-19-nyc-data/master/zcta.csv',
           'https://raw.githubusercontent.com/nychealth/coronavirus-data/master/data-by-modzcta.csv',
           'https://raw.githubusercontent.com/nychealth/coronavirus-data/master/tests-by-zcta.csv',
           'https://raw.githubusercontent.com/nychealth/coronavirus-data/master/syndromic_data.csv',
           'https://raw.githubusercontent.com/nychealth/coronavirus-data/master/by-boro.csv',
           'https://raw.githubusercontent.com/nychealth/coronavirus-data/master/boro/boroughs-case-hosp-death.csv']

    age = pd.read_csv(url[0], error_bad_lines=False) ## COVID BY AGE
    beds = pd.read_csv(url[1], error_bad_lines=False)
    borough = pd.read_csv(url[2], error_bad_lines=False)
    gender = pd.read_csv(url[3], error_bad_lines=False)
    hospital = pd.read_csv(url[4], error_bad_lines=False)
    state = pd.read_csv(url[5], error_bad_lines=False)
    zcta = pd.read_csv(url[6], error_bad_lines=False)
    case_by_zip = pd.read_csv(url[7], error_bad_lines=False)
    test_by_zip = pd.read_csv(url[8], error_bad_lines=False)
    admission = pd.read_csv(url[9], error_bad_lines=False)
    rate_by_boro = pd.read_csv(url[10], error_bad_lines=False)
    case_by_boro = pd.read_csv(url[11], error_bad_lines=False)
```

A3. Exploratory analysis of COVID-19 cases over time.

```
hospital.tail(5)
sns.relplot(x = 'timestamp', y = 'hospitalized', data = hospital)
```

```
<seaborn.axisgrid.FacetGrid at 0x7feeef9ff4a8>
```



A4. Jupyter notebook code for age categories.

```
[ ]  age.head()
     age['timestamp'] = pd.to_datetime(age['timestamp'])
     #age['timestamp'] = age['timestamp'].dt.strftime("%m/%d/%y")
     age.index = age['timestamp']
     age.drop('timestamp', inplace = True, axis = 1)
```

```
[ ]  age_bydate = age.groupby('type').resample('D').sum()
     age_bydate.reset_index(inplace = True)
     age_bydate['timestamp'] = age_bydate['timestamp'].dt.strftime("%m/%d/%y")
```

```
[ ]  age_bydate.sample(10)
```

A5. Sample of age categories.

```
age_bydate.sample(10)
```

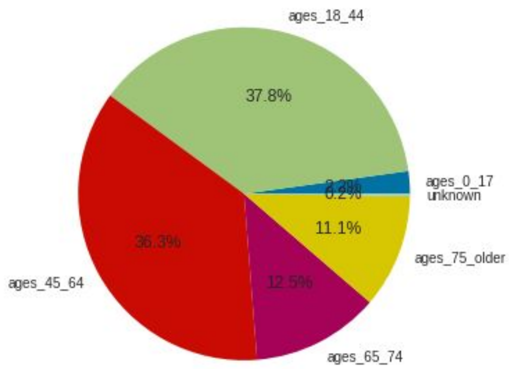
	type	timestamp	ages_0_17	ages_18_44	ages_45_64	ages_65_74	ages_75_older	unknown	total
201	deaths-pending-underlying	05/04/20	0	93	386	842	1922	1	3244
101	deaths	05/06/20	6	566	3170	3511	6907	2	14162
204	deaths-pending-underlying	05/07/20	0	100	434	908	2032	1	3475
320	ever-hospitalized	04/14/20	199	4493	10799	6659	7589	2	29741
17	cases	04/08/20	2970	60854	56665	20164	17176	342	158171
266	deaths-underlying	04/14/20	3	244	1343	1272	2289	0	5151
99	deaths	05/04/20	6	549	3078	3403	6687	1	13724
98	deaths	05/03/20	6	545	3028	3363	6593	1	13536
317	ever-hospitalized	04/11/20	190	4274	10118	6093	6782	0	27457
190	deaths-pending-underlying	04/23/20	1	79	311	728	1666	2	2787

A6. Exploratory analysis of COVID-19 cases across Age categories.

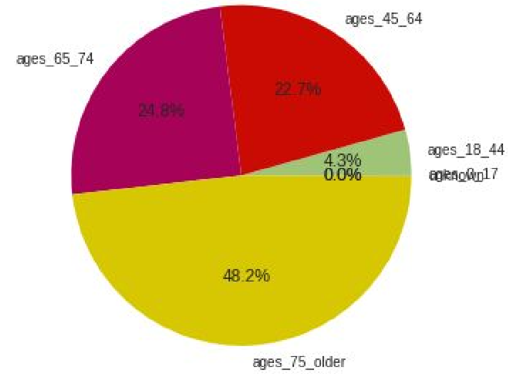
```
[ ] ages_modified=age_bydate
    ages_modified.drop('timestamp',axis=1)
    categories=ages_modified.type.unique()
```

```
for category in categories:
  new_ages = ages_modified[ages_modified['type']==category]
  first = new_ages['ages_0_17'].sum()
  second = new_ages['ages_18_44'].sum()
  third = new_ages['ages_45_64'].sum()
  fourth = new_ages['ages_65_74'].sum()
  fifth = new_ages['ages_75_older'].sum()
  other = new_ages['unknown'].sum()
  total = [first,second,third,fourth,fifth,other]
  label = ['ages_0_17','ages_18_44','ages_45_64','ages_65_74','ages_75_older','unknown']
  plt.pie(total,labels=label,autopct='%1.1f%%')
  x="Proportion of "+category+" from COVID-19 in each age group"
  plt.title(x, fontsize=16)
  plt.show()
```

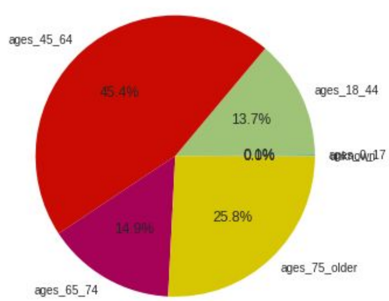
Proportion of cases from COVID-19 in each age group



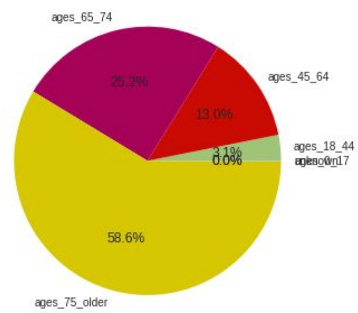
Proportion of deaths from COVID-19 in each age group



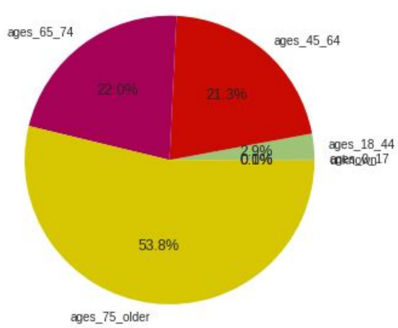
Proportion of deaths-no-underlying from COVID-19 in each age group



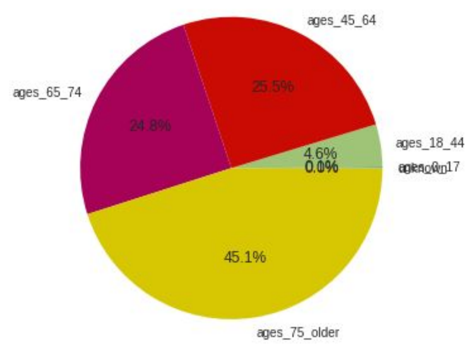
Proportion of deaths-pending-underlying from COVID-19 in each age group



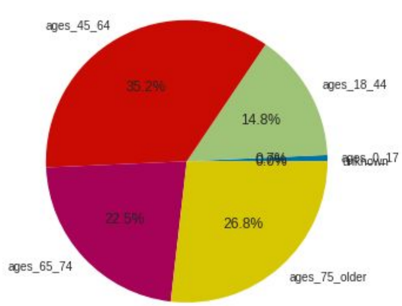
Proportion of deaths-probable from COVID-19 in each age group



Proportion of deaths-underlying from COVID-19 in each age group



Proportion of ever-hospitalized from COVID-19 in each age group



A7. Exploratory analysis of reported COVID-19 cases between March 22, 2020 to May 16, 2020.

```
plt.figure(figsize=(15, 5))
sns.pointplot(x = 'timestamp', y = 'total' , data = age_bydate[age_bydate['type']=='cases'], color='pink')
sns.pointplot(x = 'timestamp', y = 'total' , data = age_bydate[age_bydate['type']=='deaths'], color='gold')
plt.xticks(rotation = 45)
plt.title('NYC Corona Case vs. Death')
plt.show
```

A8. Creation of zipcode variable.

```
case_by_zip.head()
```

	MODIFIED_ZCTA	NEIGHBORHOOD_NAME	BOROUGH_GROUP	COVID_CASE_COUNT	COVID_CASE_RATE	POP_DENOMINATOR	COVID_DEATH_COUNT	COVID_DEATH_RATE	PERCENT_POSITIVE
0	10001	Chelsea/NoMad/West Chelsea	Manhattan	366	1553.28	23563.03	21	89.12	15.63
1	10002	Chinatown/Lower East Side	Manhattan	1054	1373.19	76755.41	149	194.12	21.14
2	10003	East Village/Gramercy/Greenwich Village	Manhattan	450	836.41	53801.62	33	61.34	12.42
3	10004	Financial District	Manhattan	31	849.17	3650.61	1	27.39	12.25
4	10005	Financial District	Manhattan	61	726.53	8396.11	2	23.82	10.87

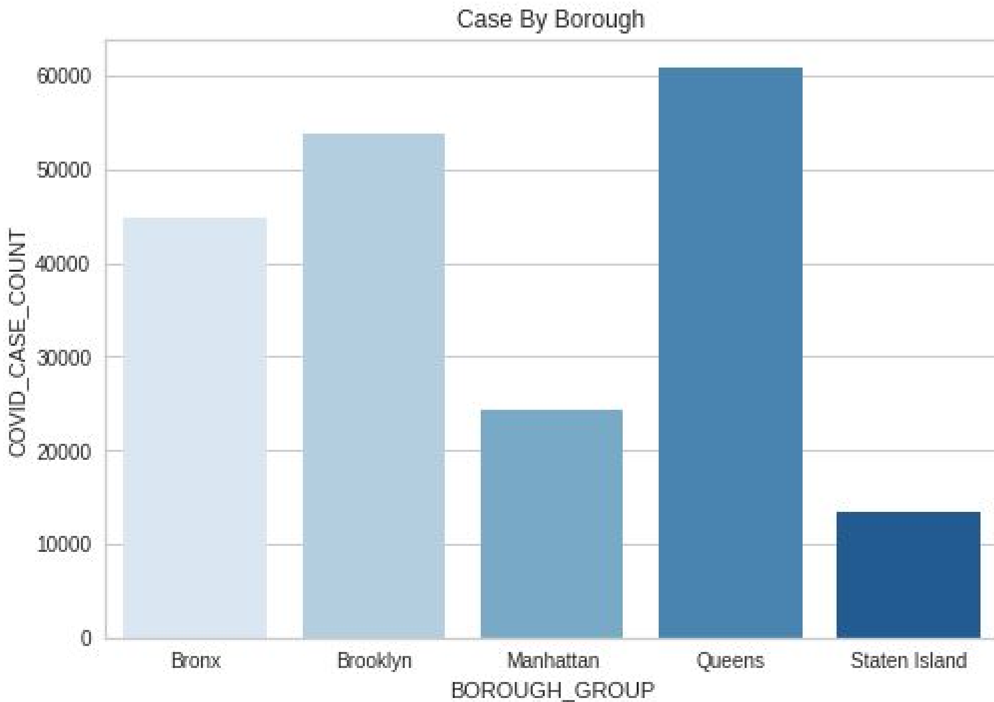
```
[ ] case_zip_group_sum = case_by_zip.groupby('BOROUGH_GROUP').sum().reset_index().drop(['MODIFIED_ZCTA','COVID_CASE_RATE','COVID_DEATH_RATE','PERCENT_POSITIVE'], axis = 1)
    case_zip_group_mean = case_by_zip.groupby('BOROUGH_GROUP').mean().reset_index().drop(['BOROUGH_GROUP','MODIFIED_ZCTA','COVID_CASE_COUNT','POP_DENOMINATOR','COVID_DEATH_COUNT'], axis = 1)
```

A9. Exploratory analysis of COVID-19 cases by New York City borough.

```
case_zip_group = pd.concat([case_zip_group_sum, case_zip_group_mean], axis=1).reindex(case_zip_group_sum.index)
case_zip_group
```

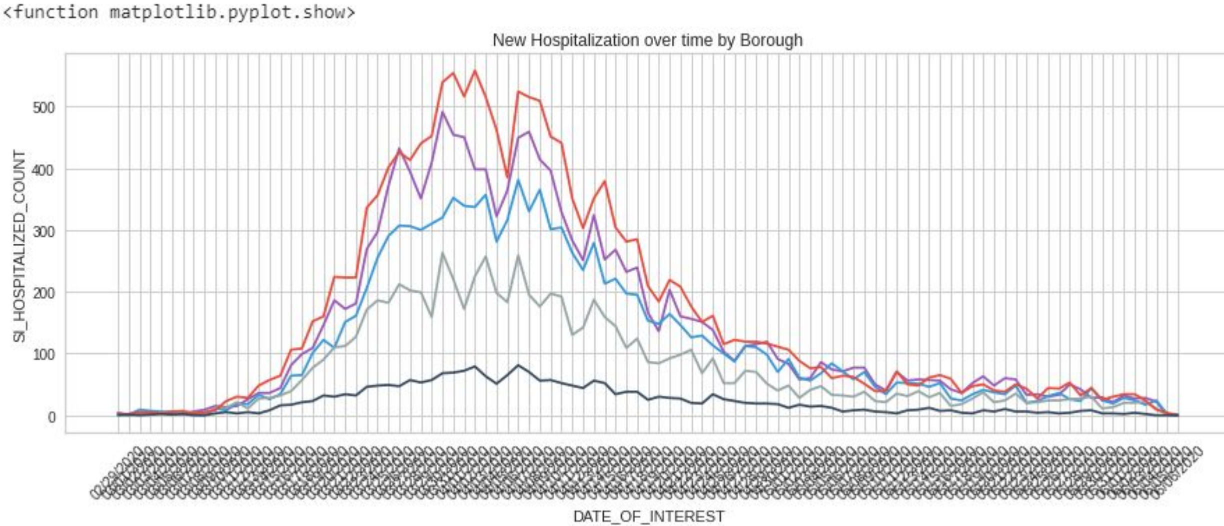
	BOROUGH_GROUP	COVID_CASE_COUNT	POP_DENOMINATOR	COVID_DEATH_COUNT	COVID_CASE_RATE	COVID_DEATH_RATE	PERCENT_POSITIVE
0	Bronx	44781	1434692.65	3592	3134.554000	243.685200	28.340000
1	Brooklyn	53735	2582829.99	5158	2050.298108	204.531081	23.485676
2	Manhattan	24252	1611943.49	2302	1408.459091	126.910909	16.382045
3	Queens	60864	2288709.82	5150	2579.622881	204.329492	26.981186
4	Staten Island	13433	476179.01	838	2836.200000	166.497500	26.594167

```
sns.barplot(x = 'BOROUGH_GROUP', y = 'COVID_CASE_COUNT', data = case_by_zip.groupby('BOROUGH_GROUP').sum().reset_index(), palette = 'Blues')
plt.title('Case By Borough')
plt.show()
```



A10. Exploratory analysis of new hospitalizations by borough.

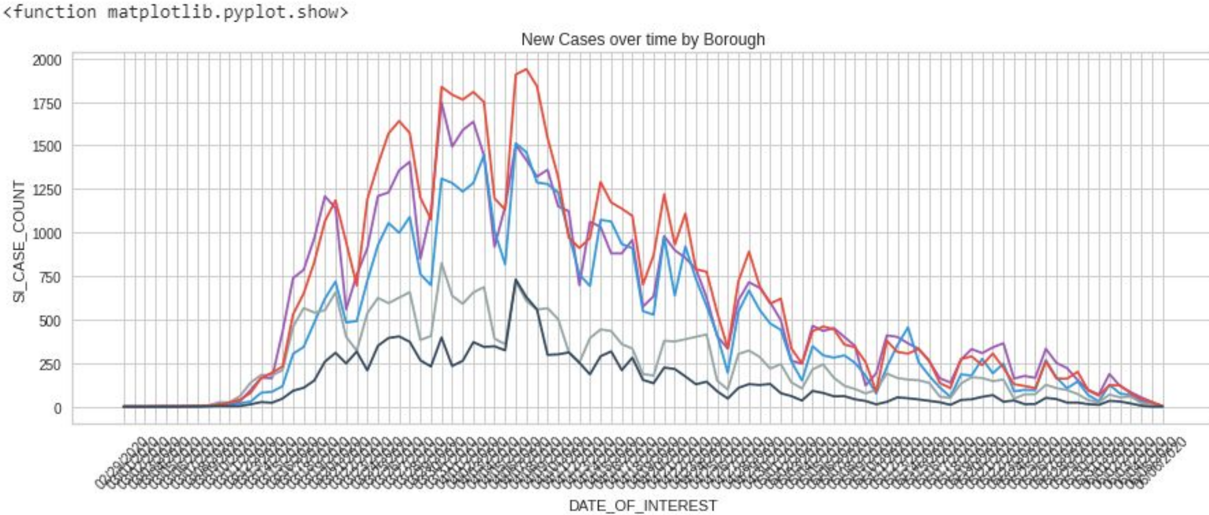
```
[ ]  plt.figure(figsize=(15, 5))
     sns.lineplot(x = 'DATE_OF_INTEREST', y = 'BK_HOSPITALIZED_COUNT' , data = case_by_boro, color=flatui[0])
     sns.lineplot(x = 'DATE_OF_INTEREST', y = 'BX_HOSPITALIZED_COUNT' , data = case_by_boro, color=flatui[1])
     sns.lineplot(x = 'DATE_OF_INTEREST', y = 'MN_HOSPITALIZED_COUNT' , data = case_by_boro, color=flatui[2])
     sns.lineplot(x = 'DATE_OF_INTEREST', y = 'QN_HOSPITALIZED_COUNT' , data = case_by_boro, color=flatui[3])
     sns.lineplot(x = 'DATE_OF_INTEREST', y = 'SI_HOSPITALIZED_COUNT' , data = case_by_boro, color=flatui[4])
     plt.xticks(rotation = 45)
     plt.title('New Hospitalization over time by Borough')
     plt.show

<function matplotlib.pyplot.show>
```



A11. Exploratory analysis of new COVID-19 cases by borough.

```
[ ]  plt.figure(figsize=(15, 5))
     sns.lineplot(x = 'DATE_OF_INTEREST', y = 'BK_CASE_COUNT' , data = case_by_boro, color=flatui[0])
     sns.lineplot(x = 'DATE_OF_INTEREST', y = 'BX_CASE_COUNT' , data = case_by_boro, color=flatui[1])
     sns.lineplot(x = 'DATE_OF_INTEREST', y = 'MN_CASE_COUNT' , data = case_by_boro, color=flatui[2])
     sns.lineplot(x = 'DATE_OF_INTEREST', y = 'QN_CASE_COUNT' , data = case_by_boro, color=flatui[3])
     sns.lineplot(x = 'DATE_OF_INTEREST', y = 'SI_CASE_COUNT' , data = case_by_boro, color=flatui[4])
     plt.xticks(rotation = 45)
     plt.title('New Cases over time by Borough')
     plt.show
```

```
<function matplotlib.pyplot.show>
```



Appendix B. Visualizing constraints in Jupyter notebook.

B1. Exploratory analysis of Constraint #1: Patients.

```
[ ]  MN_data = case_by_boro[['DATE_OF_INTEREST','MN_CASE_COUNT','MN_HOSPITALIZED_COUNT','MN_DEATH_COUNT']]
     BK_data = case_by_boro[['DATE_OF_INTEREST','BK_CASE_COUNT','BK_HOSPITALIZED_COUNT','BK_DEATH_COUNT']]
     BX_data = case_by_boro[['DATE_OF_INTEREST','BX_CASE_COUNT','BX_HOSPITALIZED_COUNT','BX_DEATH_COUNT']]
     QN_data = case_by_boro[['DATE_OF_INTEREST','QN_CASE_COUNT','QN_HOSPITALIZED_COUNT','QN_DEATH_COUNT']]
     SI_data = case_by_boro[['DATE_OF_INTEREST','SI_CASE_COUNT','SI_HOSPITALIZED_COUNT','SI_DEATH_COUNT']]
```

B1-1. Observations of COVID-19 in Manhattan hospitals by date and admission type.

```
[ ] date_list = list()
    in_hospital_list = list()

    for i in range(len(MN_data)):
      if i <= 12:
        in_hospital = sum(MN_data['MN_HOSPITALIZED_COUNT'][:i+1])+ - sum(MN_data['MN_DEATH_COUNT'][:i+1])
        date = MN_data['DATE_OF_INTEREST'][i]
        date_list.append(date)
        in_hospital_list.append(in_hospital)
      else:
        in_hospital = sum(MN_data['MN_HOSPITALIZED_COUNT'][:i+1]) - sum(MN_data['MN_HOSPITALIZED_COUNT'][:i-13])
        date = MN_data['DATE_OF_INTEREST'][i]
        date_list.append(date)
        in_hospital_list.append(in_hospital)

    icu_hospital_list = list(np.around(np.array(in_hospital_list)*0.3))

    MN_hospital_dict = {'Date': date_list, 'MN_In_Hospital':in_hospital_list, 'MN_In_ICU':icu_hospital_list}
    MN_hospital = pd.DataFrame(MN_hospital_dict)
    MN_hospital.tail(10)
```

	Date	MN_In_Hospital	MN_In_ICU
89	05/28/2020	355	106.0
90	05/29/2020	349	105.0
91	05/30/2020	345	104.0
92	05/31/2020	340	102.0
93	06/01/2020	333	100.0
94	06/02/2020	316	95.0
95	06/03/2020	317	95.0
96	06/04/2020	304	91.0
97	06/05/2020	270	81.0
98	06/06/2020	250	75.0

B1-2. Observations of COVID-19 in the Bronx hospitals by date and admission type.

```
[ ] date_list = list()
    in_hospital_list = list()

    for i in range(len(BX_data)):
      if i <= 12:
        in_hospital = sum(BX_data['BX_HOSPITALIZED_COUNT'][:i+1])
        date = BX_data['DATE_OF_INTEREST'][i]
        date_list.append(date)
        in_hospital_list.append(in_hospital)
      else:
        in_hospital = sum(BX_data['BX_HOSPITALIZED_COUNT'][:i+1]) - sum(BX_data['BX_HOSPITALIZED_COUNT'][:i-13])
        date = BX_data['DATE_OF_INTEREST'][i]
        date_list.append(date)
        in_hospital_list.append(in_hospital)

    icu_hospital_list = list(np.around(np.array(in_hospital_list)*0.3))

    BX_hospital_dict = {'Date': date_list, 'BX_In_Hospital':in_hospital_list, 'BX_In_ICU':icu_hospital_list}
    BX_hospital = pd.DataFrame(BX_hospital_dict)
    BX_hospital.tail()
```

	Date	BX_In_Hospital	BX_In_ICU
94	06/02/2020	417	125.0
95	06/03/2020	397	119.0
96	06/04/2020	387	116.0
97	06/05/2020	341	102.0
98	06/06/2020	321	96.0

B1-3. Observations of COVID-19 in Queens hospitals by date and admission type.

```
[ ] date_list = list()
    in_hospital_list = list()

    for i in range(len(QN_data)):
      if i <= 12:
        in_hospital = sum(QN_data['QN_HOSPITALIZED_COUNT'][:i+1])
        date = QN_data['DATE_OF_INTEREST'][i]
        date_list.append(date)
        in_hospital_list.append(in_hospital)
      else:
        in_hospital = sum(QN_data['QN_HOSPITALIZED_COUNT'][:i+1]) - sum(QN_data['QN_HOSPITALIZED_COUNT'][:i-13])
        date = QN_data['DATE_OF_INTEREST'][i]
        date_list.append(date)
        in_hospital_list.append(in_hospital)

    icu_hospital_list = list(np.around(np.array(in_hospital_list)*0.25))

    QN_hospital_dict = {'Date': date_list, 'QN_In_Hospital':in_hospital_list, 'QN_In_ICU':icu_hospital_list}
    QN_hospital = pd.DataFrame(QN_hospital_dict)
    QN_hospital.tail()
```

	Date	QN_In_Hospital	QN_In_ICU
94	06/02/2020	537	134.0
95	06/03/2020	521	130.0
96	06/04/2020	492	123.0
97	06/05/2020	446	112.0
98	06/06/2020	403	101.0

B1-4. Observations of COVID-19 in Staten Island hospitals by date and admission type.

```
[ ] date_list = list()
    in_hospital_list = list()

    for i in range(len(SI_data)):
      if i <= 12:
        in_hospital = sum(SI_data['SI_HOSPITALIZED_COUNT'][:i+1])
        date = SI_data['DATE_OF_INTEREST'][i]
        date_list.append(date)
        in_hospital_list.append(in_hospital)
      else:
        in_hospital = sum(SI_data['SI_HOSPITALIZED_COUNT'][:i+1]) - sum(SI_data['SI_HOSPITALIZED_COUNT'][:i-13])
        date = SI_data['DATE_OF_INTEREST'][i]
        date_list.append(date)
        in_hospital_list.append(in_hospital)

    icu_hospital_list = list(np.around(np.array(in_hospital_list)*0.20))

    SI_hospital_dict = {'Date': date_list, 'SI_In_Hospital':in_hospital_list, 'SI_In_ICU':icu_hospital_list}
    SI_hospital = pd.DataFrame(SI_hospital_dict)
    SI_hospital.tail()
```

	Date	SI_In_Hospital	SI_In_ICU
94	06/02/2020	71	14.0
95	06/03/2020	67	13.0
96	06/04/2020	57	11.0
97	06/05/2020	51	10.0
98	06/06/2020	45	9.0

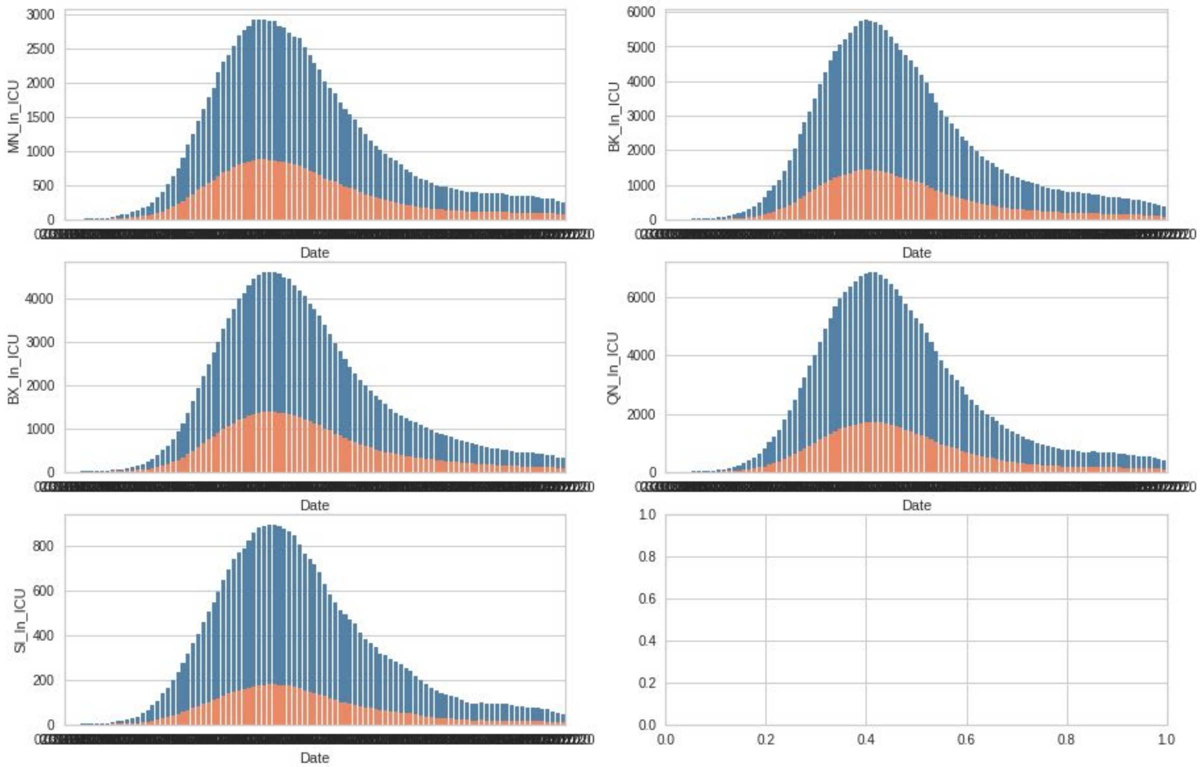
B1-5. Observations of COVID-19 in Brooklyn hospitals by date and admission type.

```
[ ] date_list = list()
    in_hospital_list = list()

    for i in range(len(BK_data)):
      if i <= 12:
        in_hospital = sum(BK_data['BK_HOSPITALIZED_COUNT'][:i+1])
        date = BK_data['DATE_OF_INTEREST'][i]
        date_list.append(date)
        in_hospital_list.append(in_hospital)
      else:
        in_hospital = sum(BK_data['BK_HOSPITALIZED_COUNT'][:i+1]) - sum(BK_data['BK_HOSPITALIZED_COUNT'][:i-13])
        date = BK_data['DATE_OF_INTEREST'][i]
        date_list.append(date)
        in_hospital_list.append(in_hospital)

    icu_hospital_list = list(np.around(np.array(in_hospital_list)*0.25))

    BK_hospital_dict = {'Date': date_list, 'BK_In_Hospital':in_hospital_list, 'BK_In_ICU':icu_hospital_list}
    BK_hospital = pd.DataFrame(BK_hospital_dict)
    BK_hospital.tail()
```

	Date	BK_In_Hospital	BK_In_ICU
94	06/02/2020	525	131.0
95	06/03/2020	505	126.0
96	06/04/2020	467	117.0
97	06/05/2020	410	102.0
98	06/06/2020	377	94.0

B2. Validation of total hospitalization and ICU admissions by borough.

```
[ ] fig, ((ax1, ax2), (ax3, ax4),(ax5,ax6)) = plt.subplots(3,2, figsize=(15,10))

    sns.barplot(x = 'Date', y = 'MN_In_Hospital', data = MN_hospital, color = 'steelblue', ax = ax1)
    sns.barplot(x = 'Date', y = 'MN_In_ICU', data = MN_hospital, color = 'coral', ax = ax1)

    sns.barplot(x = 'Date', y = 'BK_In_Hospital', data = BK_hospital, color = 'steelblue', ax = ax2)
    sns.barplot(x = 'Date', y = 'BK_In_ICU', data = BK_hospital, color = 'coral', ax = ax2)

    sns.barplot(x = 'Date', y = 'BX_In_Hospital', data = BX_hospital, color = 'steelblue', ax = ax3)
    sns.barplot(x = 'Date', y = 'BX_In_ICU', data = BX_hospital, color = 'coral', ax = ax3)

    sns.barplot(x = 'Date', y = 'QN_In_Hospital', data = QN_hospital, color = 'steelblue', ax = ax4)
    sns.barplot(x = 'Date', y = 'QN_In_ICU', data = QN_hospital, color = 'coral', ax = ax4)

    sns.barplot(x = 'Date', y = 'SI_In_Hospital', data = SI_hospital, color = 'steelblue', ax = ax5)
    sns.barplot(x = 'Date', y = 'SI_In_ICU', data = SI_hospital, color = 'coral', ax = ax5)

    plt.show()
```



B2. Exploratory analysis of Constraint #2: Hospital beds and ICU beds available by borough.

```
[ ] icu_occupied_index = [x for x in NY_Hospital.iloc[-5,:][2::2].index]
    icu_occupied = [x for x in NY_Hospital.iloc[-5,:][2::2]]
    bed_occupied_index = [x for x in NY_Hospital.iloc[-5,:][1::2].index]
    bed_occupied = [x for x in NY_Hospital.iloc[-5,:][1::2]]
    hospital_occupied = pd.DataFrame([icu_occupied,bed_occupied]).T
    hospital_occupied.columns = ['ICU', 'BED']
    hospital_occupied['Boro'] = ['MN','BK','BX','QN','SI']
    hospital_occupied['Total_by_Boro'] = [14834,5848,4012,2873,927]
    hospital_occupied
```

	ICU	BED	Boro	Total_by_Boro
0	95.0	316.0	MN	14834
1	131.0	525.0	BK	5848
2	125.0	417.0	BX	4012
3	134.0	537.0	QN	2873
4	14.0	71.0	SI	927

B2-1. Hospital bed and ICU bed total by borough.

```
[ ] from itertools import chain
```

```
[ ] TOTAL_ICU_by_Boro = [hospital_occupied['Total_by_Boro']/sum(hospital_occupied['Total_by_Boro'])*3110]
    TOTAL_ICU_by_Boro = [round(x) for x in TOTAL_ICU_by_Boro]
    TOTAL_ICU_by_Boro = list(chain.from_iterable(TOTAL_ICU_by_Boro))
    hospital_occupied['Total_ICU_by_Boro'] = TOTAL_ICU_by_Boro
    hospital_occupied
```

	ICU	BED	Boro	Total_by_Boro	Total_ICU_by_Boro
0	95.0	316.0	MN	14834	1619.0
1	131.0	525.0	BK	5848	638.0
2	125.0	417.0	BX	4012	438.0
3	134.0	537.0	QN	2873	314.0
4	14.0	71.0	SI	927	101.0

B2-2. Ratio of total beds to ICU beds.

```
[ ] basis_bed = beds[(beds['locality']=='nyc') & (beds['timestamp']=='2020-05-28T04:00:00Z')]
    basis_bed['bed_ratio_NOCOVID'] = (basis_bed['total'] - basis_bed['total_available'] - sum(hospital_occupied['BED']))/basis_bed['total']
    basis_bed['icu_ratio__NOCOVID'] = (basis_bed['icu'] - basis_bed['icu_available'] - sum(hospital_occupied['ICU']))/basis_bed['icu']
    basis_bed = basis_bed[['total', 'total_available',  'icu',  'icu_available',  'bed_ratio_NOCOVID',  'icu_ratio__NOCOVID']]
    basis_bed.reset_index()
```

	index	total	total_available	icu	icu_available	bed_ratio_NOCOVID	icu_ratio__NOCOVID
0	119	20735	5871	3110	987	0.626863	0.522186

B2-3. Available hospital and ICU beds for May 28, 2020 by borough.

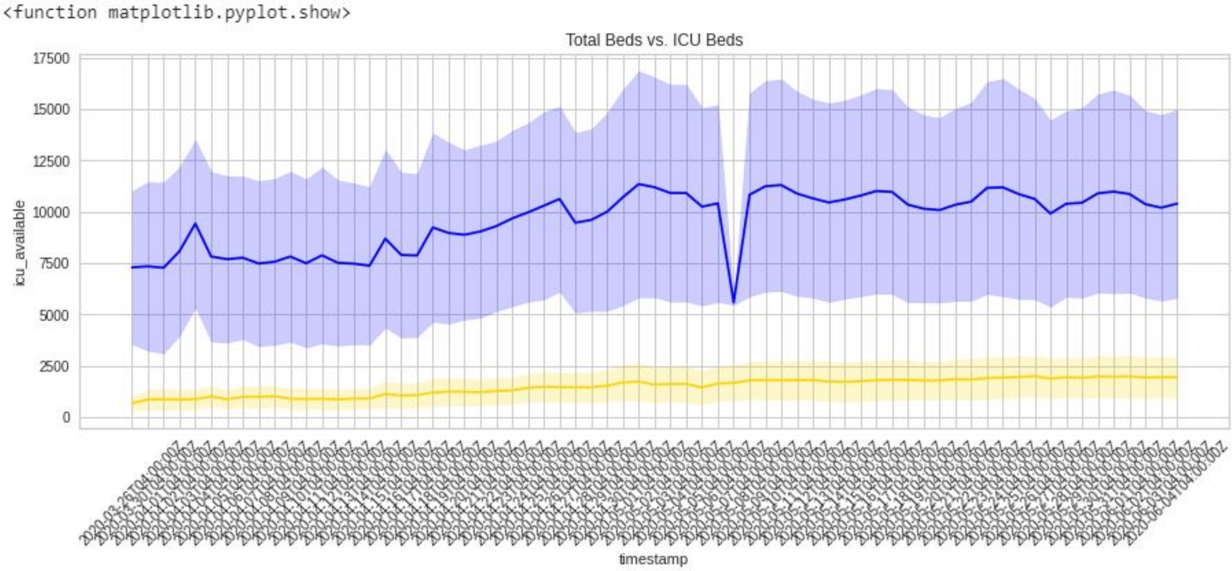
```
[ ] bed_28 = hospital_occupied['Total_by_Boro']*0.626863 -  hospital_occupied['BED']
    bed_28 = [round(x) for x in bed_28]

    icu_28 = hospital_occupied['Total_ICU_by_Boro']*0.522186 -  hospital_occupied['ICU']
    icu_28 = [round(x) for x in icu_28]

    hospital_occupied['Available_May28'] = bed_28
    hospital_occupied['Available_ICU_May28'] = icu_28
    hospital_occupied
```

	ICU	BED	Boro	Total_by_Boro	Total_ICU_by_Boro	Available_May28	Available_ICU_May28
0	95.0	316.0	MN	14834	1619.0	8983	750
1	131.0	525.0	BK	5848	638.0	3141	202
2	125.0	417.0	BX	4012	438.0	2098	104
3	134.0	537.0	QN	2873	314.0	1264	30
4	14.0	71.0	SI	927	101.0	510	39

B2-4. Visualization of total beds to ICU beds between March 26, 2020 to June 4, 2020.

```
[ ] plt.figure(figsize=(15, 5))
    sns.lineplot(x = 'timestamp', y = 'total_available' , data = beds, color='blue')
    sns.lineplot(x = 'timestamp', y = 'icu_available' , data = beds, color='gold')
    plt.xticks(rotation = 45)
    plt.title('Total Beds vs. ICU Beds')
    plt.show
```

```
<function matplotlib.pyplot.show>
```



B3. Exploratory analysis of Constraint #3: Doctors.
B3-1. Display of COVID-19 data by borough population as determined by zipcode.

```
[ ]  case_zip_group
```

	BOROUGH_GROUP	COVID_CASE_COUNT	POP_DENOMINATOR	COVID_DEATH_COUNT	COVID_CASE_RATE	COVID_DEATH_RATE	PERCENT_POSITIVE
0	Bronx	44781	1434692.65	3592	3134.554000	243.685200	28.340000
1	Brooklyn	53735	2582829.99	5158	2050.298108	204.531081	23.485676
2	Manhattan	24252	1611943.49	2302	1408.459091	126.910909	16.382045
3	Queens	60864	2288709.82	5150	2579.622881	204.329492	26.981186
4	Staten Island	13433	476179.01	838	2836.200000	166.497500	26.594167

B3-2. Distribution of doctors by borough based on rate of COVID-19 positive cases by zipcode.

```
[ ]  pop_boro = np.array(case_zip_group['POP_DENOMINATOR'])
     weight_boro = [0.4,0.4,1.4,0.4,0.4]
     doctors_est = pop_boro/100000*weight_boro*375.1
     doctors_boro = [int(round(x)) for x in doctors_est]
     doctors_boro
```

```
[2153, 3875, 8465, 3434, 714]
```

Appendix C. Exploratory Analysis of Hospital admissions rate in Jupyter notebook.
C1. Sample of New York City hospital admission rates by age group.

```
[ ]  admission_cum = admission
     admission_cum=admission_cum.drop('Date',axis=1)
     admission_cum=admission_cum.drop('Visit All ages',axis=1)
     admission_cum=admission_cum.drop('Admit All ages',axis=1)
     admission_cum
```

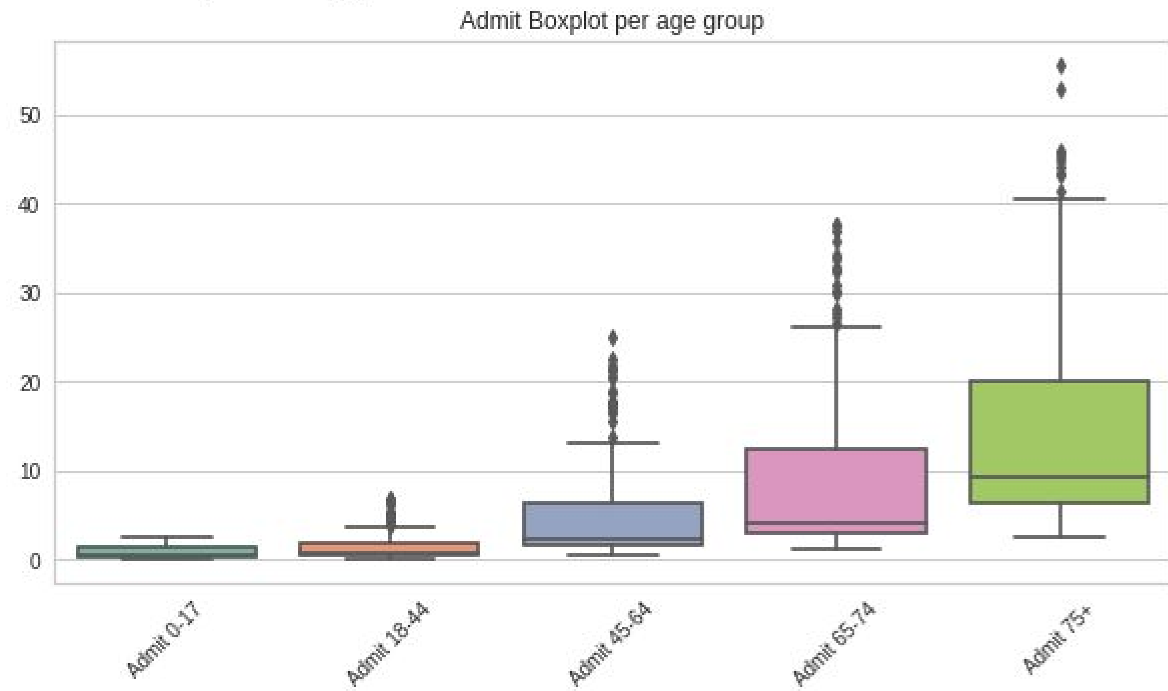
	Admit 0-17	Admit 18-44	Admit 45-64	Admit 65-74	Admit 75+	Visit 0-17	Visit 18-44	Visit 45-64	Visit 65-74	Visit 75+
0	2.026728	1.098025	2.529124	3.575934	8.044243	46.556835	13.651126	10.359680	8.296167	13.163307
1	1.563476	0.919967	1.750932	4.291121	8.409891	53.273991	13.740155	9.630125	11.156915	12.432012
2	2.489980	0.979320	3.258679	6.007570	12.980484	60.512305	15.075591	13.958818	13.159438	17.916724
3	2.316260	0.979320	1.994117	4.577196	11.152246	54.837466	16.589085	11.770153	10.584765	15.357192
4	2.142541	0.623204	2.285939	4.005046	9.141186	48.873096	14.066595	10.943324	9.869579	14.625897
...	...	...	...	...	...	...	...	...	...	...
121	0.231626	0.178058	0.632281	1.430374	2.559532	2.547887	1.454142	2.334576	3.146822	5.667535
122	0.115813	0.148382	0.826829	1.573411	3.839298	1.331850	1.483818	2.140028	3.432897	6.033183
123	0.231626	0.178058	1.313199	2.002523	5.119064	1.216037	1.246407	2.626398	2.860747	7.678596
124	0.231626	0.267087	1.167288	2.717710	5.301888	1.853008	1.780582	2.820946	4.434158	7.495772
125	0.231626	0.237411	0.729555	2.860747	4.387769	1.795102	1.424465	2.237302	5.006308	6.764477

126 rows × 10 columns

C2. Visualization of hospital admissions per age group

```
[ ]  plt.figure(figsize=(10, 5))
     sns.boxplot(palette="Set2", data=admission_cum.iloc[:,0:5])
     plt.xticks(rotation = 45)
     plt.title('Admit Boxplot per age group')
     plt.show
```

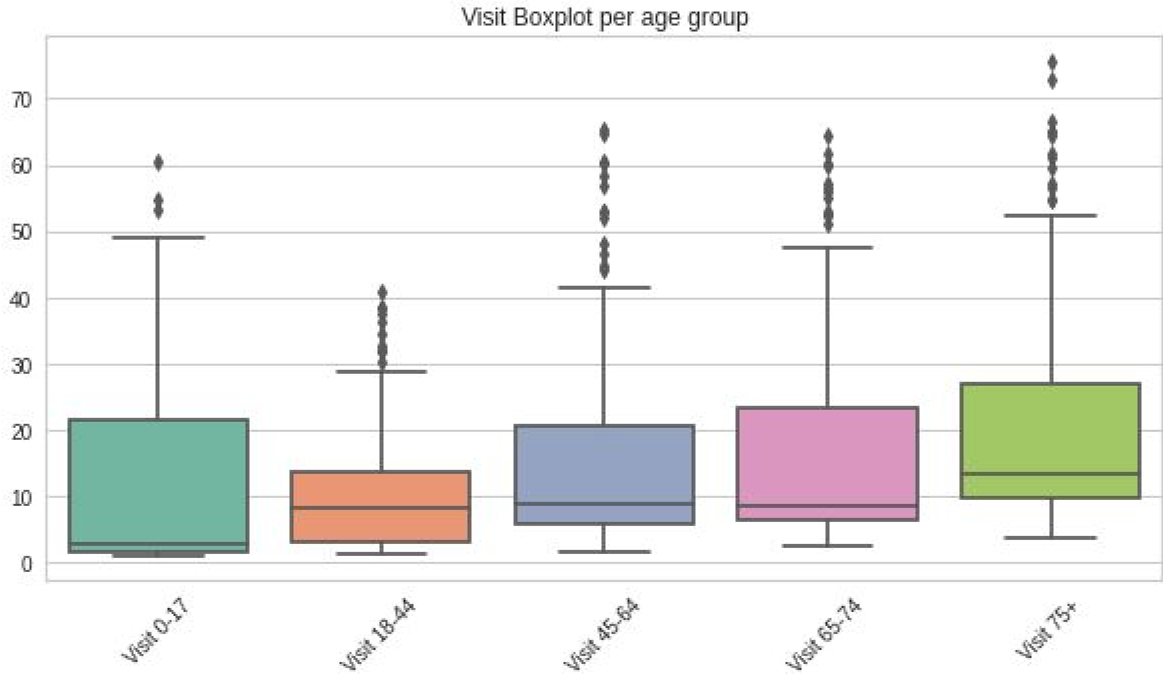
```
<function matplotlib.pyplot.show>
```



C3. Visualization of hospital visits per age group.

```
[ ]  plt.figure(figsize=(10, 5))
     sns.boxplot(palette="Set2", data=admission_cum.iloc[:,5:])
     plt.xticks(rotation = 45)
     plt.title('Visit Boxplot per age group')
     plt.show
```

```
<function matplotlib.pyplot.show>
```

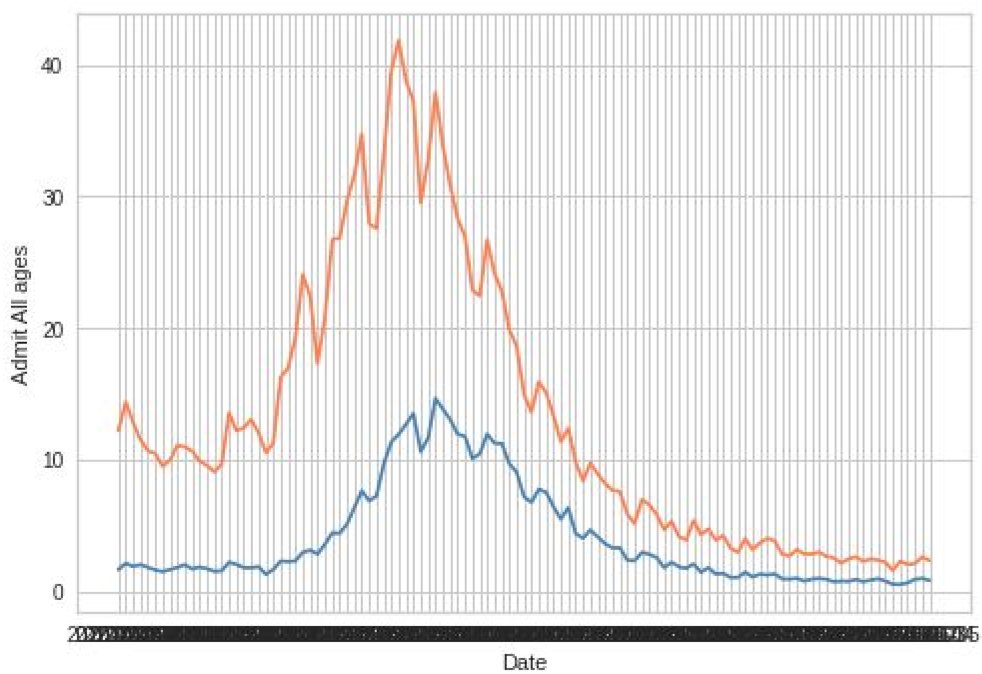


C4. Exploratory analysis of admissions rate per age group.

```
admission.mean()
```

```
Admit 0-17          0.745891
Admit 18-44         1.429411
Admit 45-64         5.447344
Admit 65-74         9.558529
Admit 75+          15.265780
Admit All ages      3.850442
Visit 0-17         12.649815
Visit 18-44        10.754383
Visit 45-64        15.955637
Visit 65-74        17.247355
Visit 75+          21.795198
Visit All ages     13.677209
dtype: float64
```

```
[ ] #admission.tail(5)
    #Visit all ages: 1.88 * Mahattan Population/100000 * manhatthan proportion
    # HOW TO GET AN IDEA OF HOW MANY PEOPLE ARE IN THE MANHATTHAN HOSPITAL.



    fig, ax = plt.subplots()
    sns.lineplot(x='Date', y='Visit All ages', data=admission[admission['Date']>'2020-02-15'], color='coral')
    sns.lineplot(x = 'Date', y = 'Admit All ages', data=admission[admission['Date']>'2020-02-15'], color = 'steelblue')
    plt.show()
```




```
#int(1611943.49/100000)
round(23624/1611943.49*100000)   #1375.302273(on Average)
```

```
1466
```

C. Data Collection

NYC Health + Hospitals/Jacobi 1400 Pelham Parkway South Bronx, New York 10461 718-918-5000	NYC Health + Hospitals/Bellevue 462 First Avenue New York, New York 10016 212-562-5555	NYC Health + Hospitals/Coney Island 2601 Ocean Parkway Brooklyn, New York 11235 718-616-3000	NYC Health + Hospitals/Elmhurst 79-01 Broadway Elmhurst, New York 11373 718-334-4000
NYC Health + Hospitals/Lincoln 234 East 149th Street Bronx, New York 10451 718-579-5000	NYC Health + Hospitals/Harlem 506 Lenox Avenue New York, New York 10037 212-939-1000	NYC Health + Hospitals/Kings County 451 Clarkson Avenue Brooklyn, New York 11203 718-245-3131	NYC Health + Hospitals/Queens 82-68 164th Street Jamaica, New York 11432 718-883-3000
NYC Health + Hospitals/North Central Bronx 3424 Kossuth Avenue Bronx, New York 10467 Appointments: 844-692-4692 General Information: 718-918-5700	NYC Health + Hospitals/Metropolitan 1901 First Avenue New York, New York 10029 212-423-6262	NYC Health + Hospitals/Woodhull 760 Broadway Brooklyn, New York 11206 718-963-8000	