

Back To Normal?

ANALYZING HOW THE RISE AND FALL OF
COVID-19 CASES AFFECTS EVERYDAY
TRENDS IN NYC



Overarching Questions

As the number of new covid-19 cases rise and fall in NYC, how has it affected the way people live in the United State's largest city?

- What does the data tell us about how the lives of NYC residents changes in March when new case numbers were extremely high?
- As the number of cases fell during the summer months, did things return to normal?



Data Overview

- Defining “Normal” data
 - Going out to eat—Restaurant reservation data from open table.
 - Going into the office—Taking MTA turn-style data from the NYC subway.
 - Shopping data—Number of visits to retail stores/grocery stores from google trends.
- Covid-19 Data
 - Google trend data for new cases each day.
- API Used
 - Used Google maps to create a heat map of mobility trends within the greater NYC area over residential locations.
- Motivation/Hypothesis
 - Our group was really interested in the idea of this “new normal” that people seem to always talk about. We wanted to see if we could try and define this “normal” and see how it has fluctuated with the daily new number of covid cases.
 - We predicted that as the new number of cases went down, “normal” trends would begin to return to their previous levels.

Data Cleanup & Exploration

- Our group spent the better part of our first two working sessions cleaning and merging our data sets into a clean, workable, data-frame.
 - Merging Data—we had to merge our normal trends data with our covid case data which was a challenge. We merged based on date and had to change data types in both data sets to get it to work.
 - Cleaning Data—to clean our data we cut a good amount of columns to just get the data we were planning on using. Additionally, we renamed most columns to be more legible. Lastly, we filtered the data to just get the five metro counties we were interested in.

```
new_york_df = covid_df.loc[(covid_df["sub_region_1"] == 'New York')]  
new_york_df.head()  
  
new_york_df['date'] = pd.to_datetime(new_york_df.date)  
new_york_df['date'] = new_york_df['date'].astype(str)  
merge_data=pd.merge(new_york_df, new_covid_numbers_df, on='date')  
merge_data.sample(50)
```




M4

```
# Convert covid data to similar datetime, as well as merging tw

covid_df['date'] = pd.to_datetime(covid_df.date)
covid_df['date'] = covid_df['date'].astype(str)

mta_covid=pd.merge(mta_df, covid_df, on='date', how="left")

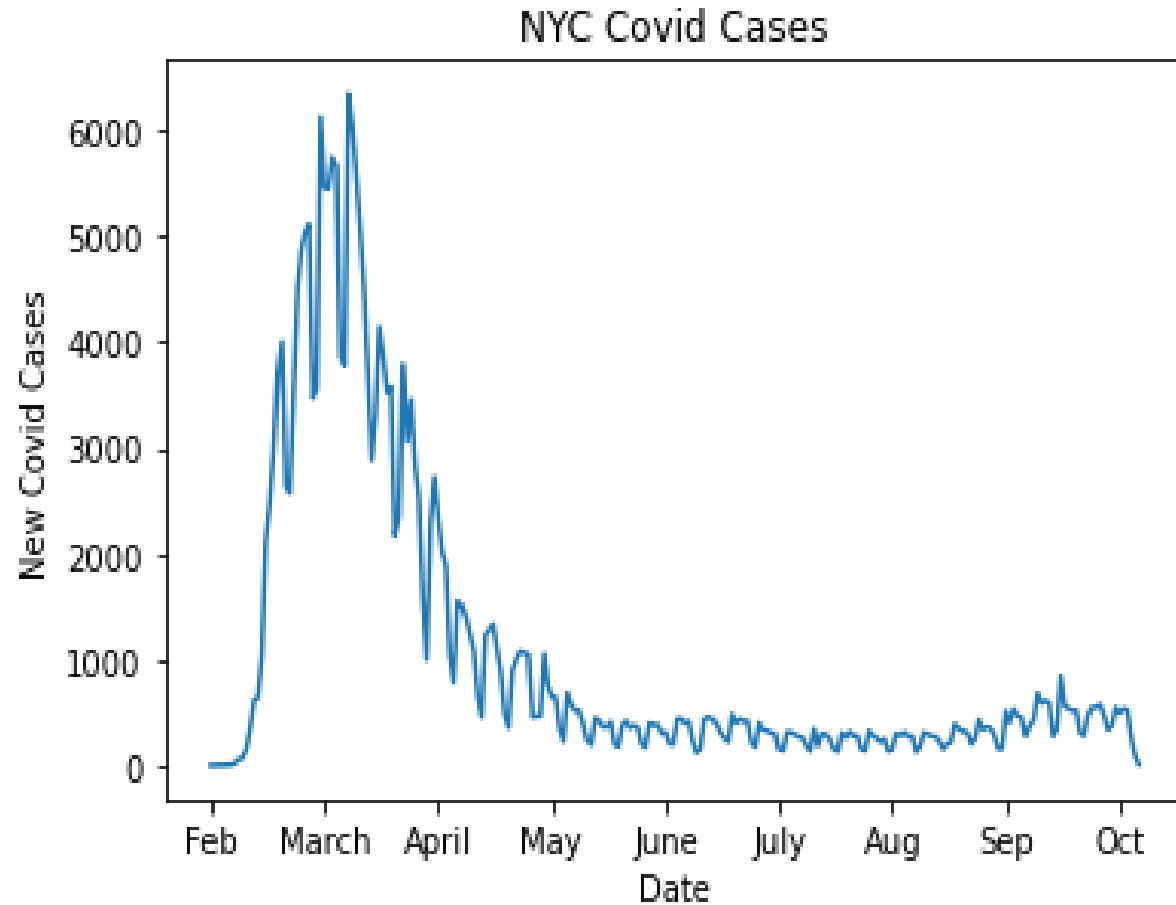
mta_covid.fillna(value=0, inplace=True)

mta_covid
```

```
New_df = merge_data[['sub_region_1', 'date', 'retail_and_recreation_percent_change_from_baseline', 'grocery_and_pharmacy',
New_df = New_df.rename(columns = {'sub_region_1': 'State', 'date': 'Date', 'retail_and_recreation_percent_change_from_b

month_ave = New_df.groupby('Month').mean().reset_index()
month_ave["Month"] = pd.to_datetime(month_ave["Month"], format='%m').dt.month_name().str.slice(stop=3)
month_ave
```

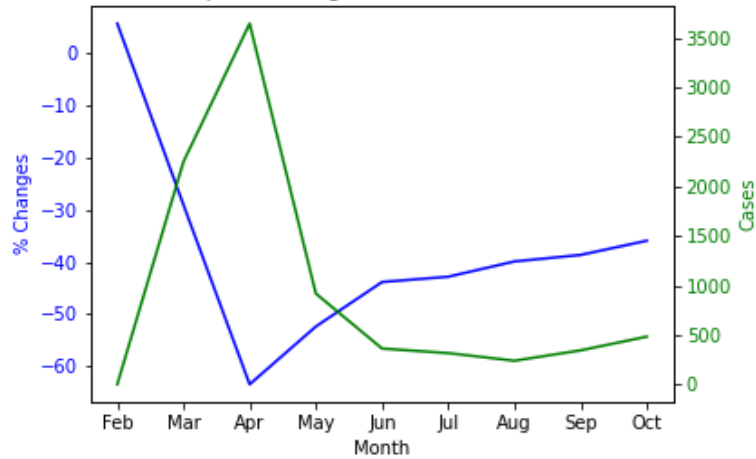
Data Analysis



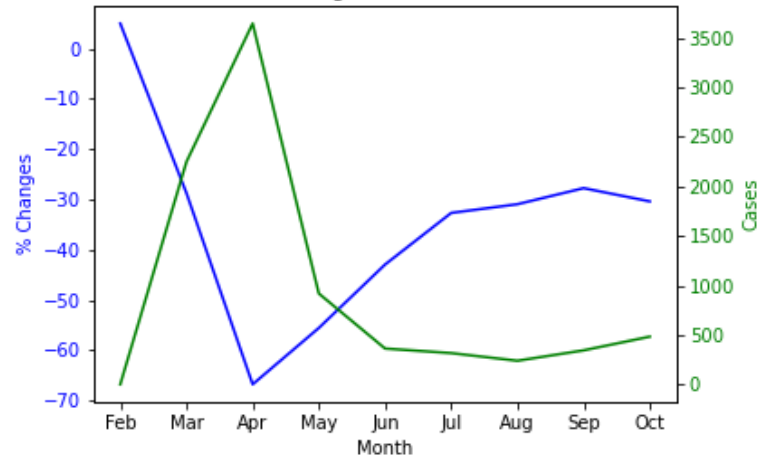
- Began our analysis plotting at a high level, figuring out new covid cases per day from Feb-Oct.
- Graphed our “normal” trends on the same plot as covid case numbers to see how those two interreacted.

Data Analysis—Google Trends Data

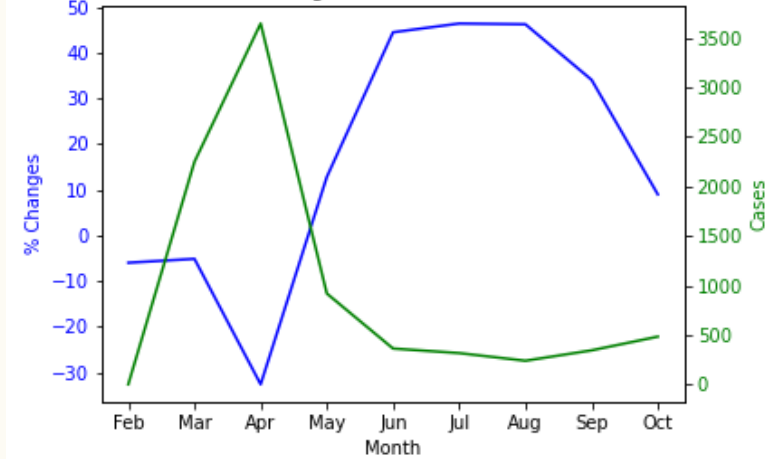
Workplace Change % vs. New Covid Cases



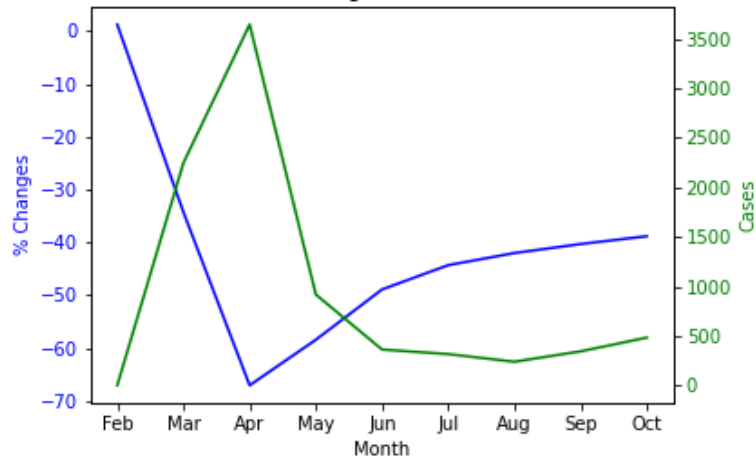
Retail % Change vs. New Covid Cases



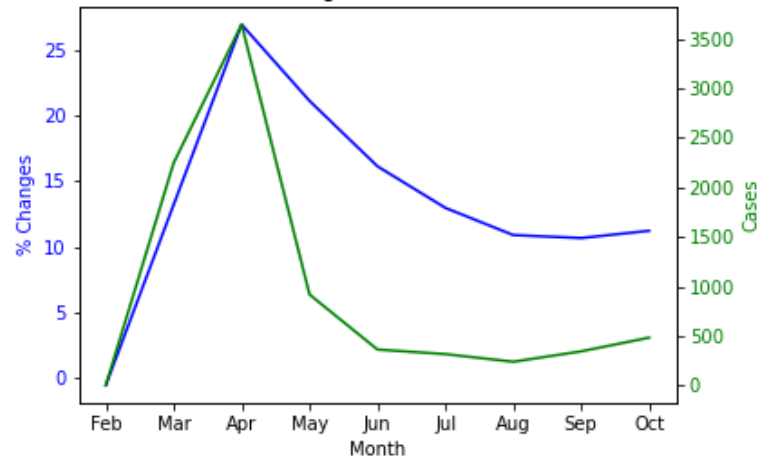
Parks Change % vs. New Covid Cases



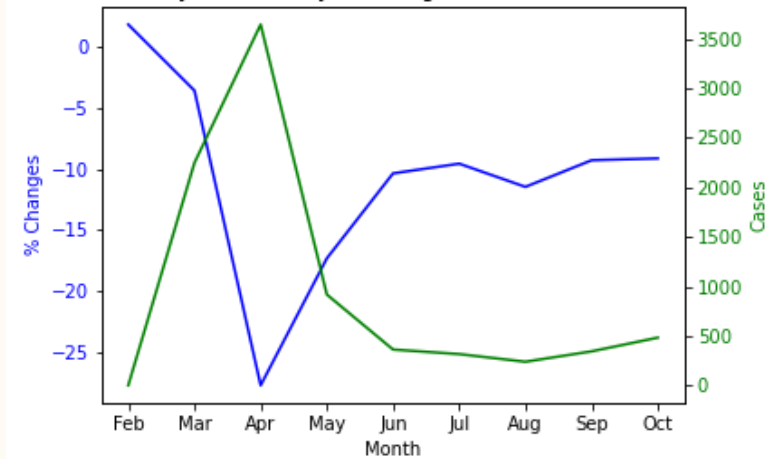
Transit Station Change % vs. New Covid Cases



Residential Change % vs. New Covid Cases

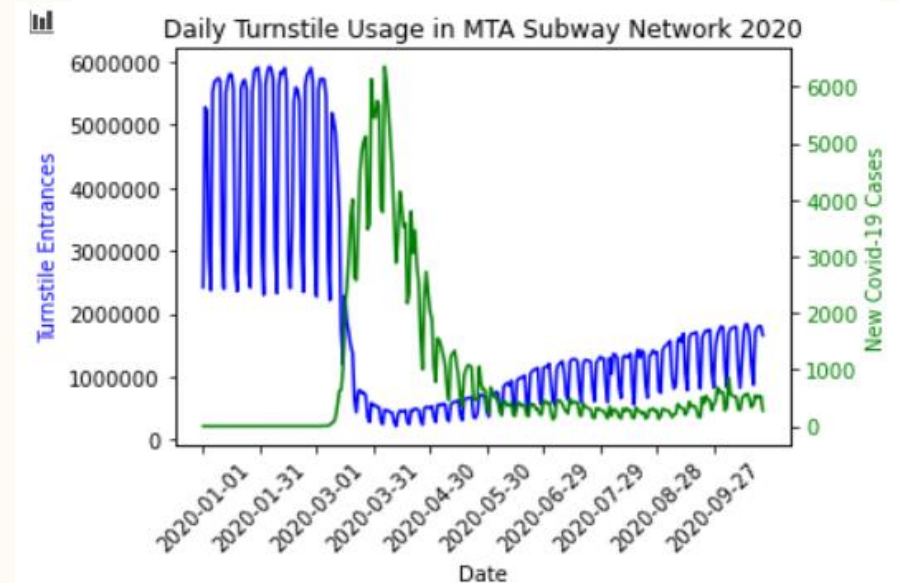
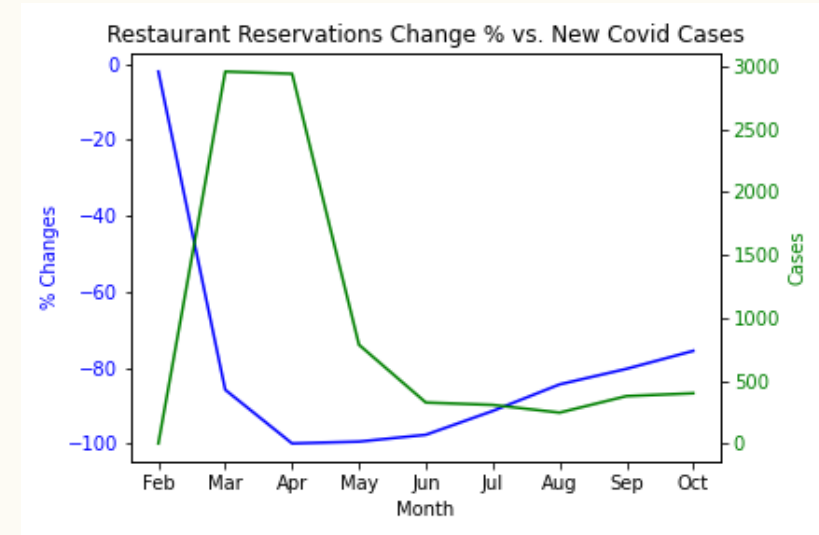


Grocery & Pharmacy % Change vs. New Covid Cases



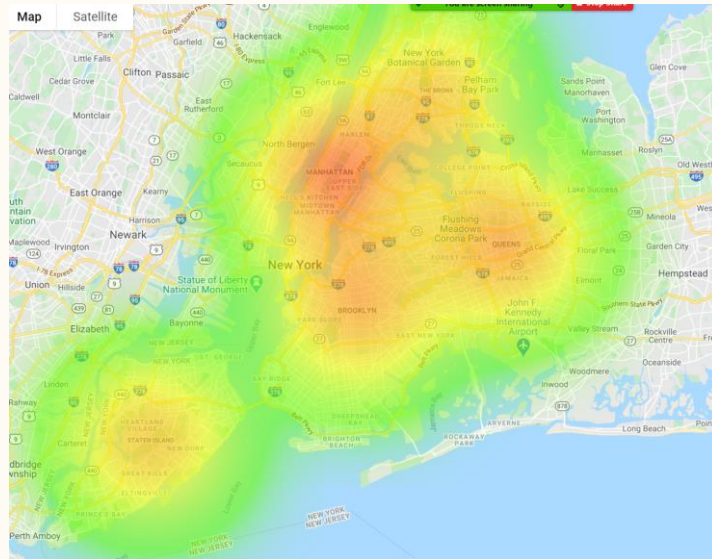
Data Analysis—Reservations and MTA

- As predicted, there was a massive decrease in restaurant reservations and subway use in the March-May timeline
- There has been some, but minimal recovery made in the number of reservations and MTA use

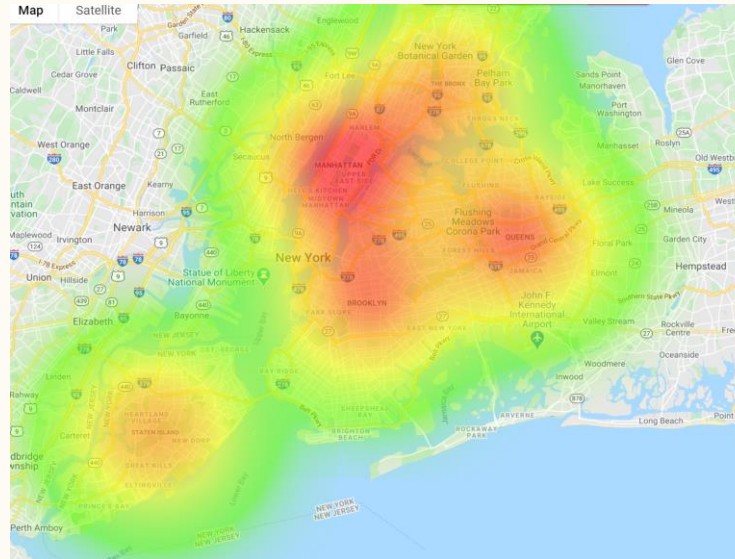


Mobility Trends Across County

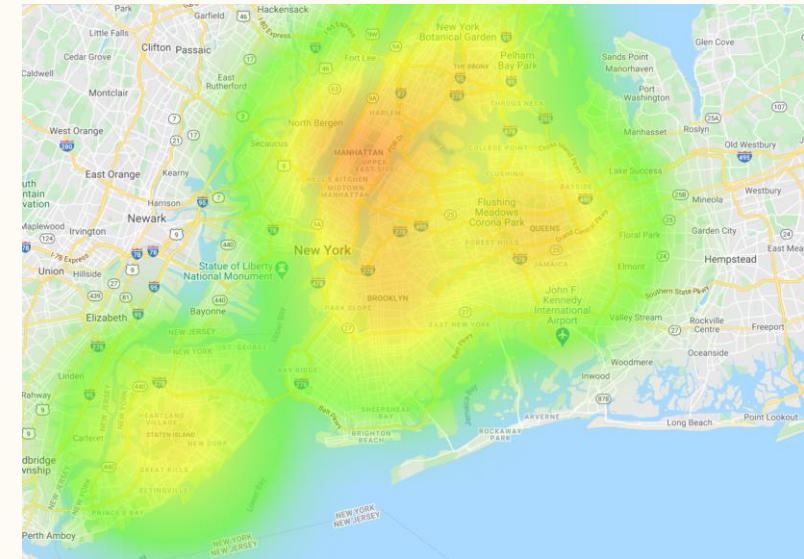
March



June



October



Discussion

- Overall, our data shows what we had anticipated—when new covid-19 cases are high, normal trends drastically drop, and when new case numbers are low, those normal trends begin to rise.
 - When new cases are high, people did not leave their houses as much—also potential lockdown implications.
 - Concerns of a new wave could impact normal trends returning
- Gap between weekday and weekend riders is still nowhere near pre-covid levels indicating fewer commuters.
- Even with new case numbers relatively low, normal trends are well below pre-pandemic levels.

Postmortem

- Difficulties
 - Cleaning the data was quite tedious. Took a lot of trial and error and googling to get the data the way we wanted.
 - Plotting—getting the data to plot the way we wanted was harder than we anticipated. X-ticks were not working as we hoped on multiple graphs, and we had to condense some data to get it to plot correctly.
 - Finding usable data—it took us a lot longer to find usable, relevant data than we had initially anticipated.
- Additional questions & What Comes Next
 - Spend more time defining normal trends locating and usable data for those trends.
 - With a lot of companies allowing virtual work, will these trends ever return to pre-pandemic levels?
- Overall Answer
 - Hard to answer if this is a new normal yet because it is still changing rapidly. We can make predictions based on the data we have right now but a true answer might be inconclusive.
 - Based on the data we have we predict New Yorkers will return to a pre pandemic norm; however, it will take quite a while to return to those normal levels.