Covid_GIS

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1. Install Necessary Libraries

First, make sure you have the required libraries installed:

[2]:
```
# pip install pandas folium
```

2. Jupyter Notebook Code

Now, here's the Python code to execute within a Jupyter Notebook cell:

[4]:
```
import pandas as pd
import folium
from folium.plugins import HeatMap
import numpy as np
from math import radians, sin, cos, sqrt, atan2

# Load the datasets
subway_df = pd.read_csv('subway_stops.csv')
covid_df = pd.read_csv('covid_data.csv')

# Fill NaN values in the 'line' column with 'Unknown'.
subway_df['line'] = subway_df['line'].fillna('Unknown')

# Convert lat and lon columns to float, handling errors
subway_df['lat'] = pd.to_numeric(subway_df['lat'], errors='coerce').fillna(0.0)
subway_df['lon'] = pd.to_numeric(subway_df['lon'], errors='coerce').fillna(0.0)
covid_df['lat'] = pd.to_numeric(covid_df['lat'], errors='coerce').fillna(0.0)
covid_df['lon'] = pd.to_numeric(covid_df['lon'], errors='coerce').fillna(0.0)

# Create a Folium map centered on NYC
m = folium.Map(location=[40.7831, -73.9712], zoom_start=10,␣
 ↪tiles="cartodbdarkmatter")

# Function to create a layer group
```

```
def create_layer_group(df, layer_name, color, marker_type="circleMarker",␣
  ↪marker_options=None):
    layer_group = folium.FeatureGroup(name=f'<b style="color:
  ↪{color}">{layer_name}</b>')

    for index, row in df.iterrows():
        lat = row['lat']
        lon = row['lon']
        if lat != 0.0 and lon != 0.0:

            # Prepare popup content
            if 'stop_name' in row.index:
                popup = f"<b>{row['stop_name']}</b><br>Line:␣
  ↪{row['line']}<br>Borough: {row['borough']}"
            elif 'modzcta_name' in row.index:
                popup = f"<b>{row['modzcta_name']}</b><br>Hospitalizations:␣
  ↪{row['hospitalization_count_28day']}<br>Deaths: {row['death_count_28day']}"
            else:
               popup = "No data"

            # Create the marker
            if marker_type == "circleMarker":
                marker = folium.CircleMarker(
                        location=[lat, lon],
                        radius=6,
                        color=color,
                        fill=True,
                        fill_color=color,
                        fill_opacity=0.2,
                        stroke=False,
                        **marker_options if marker_options else {},
                )

            elif marker_type == "circle":
                    marker = folium.Circle(
                        location=[lat, lon],
                        radius=6,
                        color=color,
                        fill=True,
                        fill_color=color,
                        fill_opacity=0.2,
                        **marker_options if marker_options else {},
                    )
            else:
                marker = folium.Marker(
                     location=[lat, lon],
                     icon=folium.Icon(color=color),
                    **marker_options if marker_options else {},
                )
            marker.add_child(folium.Tooltip(popup))
            marker.add_to(layer_group)
    return layer_group

# Function to calculate distance between two points in coordinates
def haversine(lat1, lon1, lat2, lon2):
    R = 6371  # Earth radius in kilometers
    lat1, lon1, lat2, lon2 = map(radians, [lat1, lon1, lat2, lon2])

    dlon = lon2 - lon1
    dlat = lat2 - lat1

    a = sin(dlat / 2)**2 + cos(lat1) * cos(lat2) * sin(dlon / 2)**2
    c = 2 * atan2(sqrt(a), sqrt(1 - a))

    distance = R * c
    return distance

# Create subway layer
subway_layer = create_layer_group(subway_df, "Subway Stops", "cyan")
subway_layer.add_to(m)

# Create covid layer
covid_layer = create_layer_group(covid_df, "COVID Data", "red",␣
 ↪marker_type="circle")
covid_layer.add_to(m)


# Prepare COVID data for heatmap
heat_data = covid_df[['lat', 'lon', 'hospitalization_count_28day']].dropna().
 ↪values.tolist()

# Create heatmap layer
heat_map_layer = folium.FeatureGroup(name="COVID Heatmap")
HeatMap(heat_data, radius=10, name="Heatmap").add_to(heat_map_layer)
heat_map_layer.add_to(m)

#Find the highest hospitalization modzcta
highest_covid_modzcta = covid_df.loc[covid_df['hospitalization_count_28day'].
 ↪idxmax()]

# Find the closest subway station to the highest covid area
min_distance = float('inf')
closest_subway_stop = None
for index, stop_row in subway_df.iterrows():
    distance = haversine(highest_covid_modzcta['lat'],␣
 ↪highest_covid_modzcta['lon'], stop_row['lat'], stop_row['lon'])
    if distance < min_distance:
        min_distance = distance
        closest_subway_stop = stop_row
# Place a flag on the closest subway station
if closest_subway_stop is not None:
    flag_icon = folium.Icon(color='black', icon='flag', prefix='fa')
    flag_marker = folium.Marker(
        location=[closest_subway_stop['lat'], closest_subway_stop['lon']],
        icon=flag_icon,
        tooltip = f"<b>Closest Subway Stop to highest COVID area</b><br>␣
 ↪Station Name: {closest_subway_stop['stop_name']}<br> Line:␣
 ↪{closest_subway_stop['line']}"
    )
    flag_marker.add_to(m)

# Add layer control
folium.LayerControl().add_to(m)

# Display the map
m
```

[4]:

```
<folium.folium.Map at 0x7797a8e317c0>
```

[5]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from math import radians, sin, cos, sqrt, atan2
import warnings
warnings.filterwarnings('ignore')
```

[6]:

```
# Load the datasets
subway_df = pd.read_csv('subway_stops.csv')
covid_df = pd.read_csv('covid_data.csv')
by_group_df = pd.read_csv('by_group.csv')

# Fill NaN values in the 'line' column with 'Unknown'.
subway_df['line'] = subway_df['line'].fillna('Unknown')

# Convert lat and lon columns to float, handling errors
subway_df['lat'] = pd.to_numeric(subway_df['lat'], errors='coerce').fillna(0.0)
subway_df['lon'] = pd.to_numeric(subway_df['lon'], errors='coerce').fillna(0.0)
covid_df['lat'] = pd.to_numeric(covid_df['lat'], errors='coerce').fillna(0.0)
covid_df['lon'] = pd.to_numeric(covid_df['lon'], errors='coerce').fillna(0.0)
```

```
print("Data loading and cleaning completed.\n")
```

```
Data loading and cleaning completed.
```

[7]:

```
# Basic info of each dataframe
print("Subway stops data info:")
subway_df.info()
print("\nCovid data info:")
covid_df.info()
print("\nBy Group data info:")
by_group_df.info()

# Descriptive statistics of each dataframe
print("\nSubway stops descriptive statistics:")
print(subway_df.describe())
print("\nCovid data descriptive statistics:")
print(covid_df.describe())
print("\nBy Group data descriptive statistics:")
print(by_group_df.describe())
```

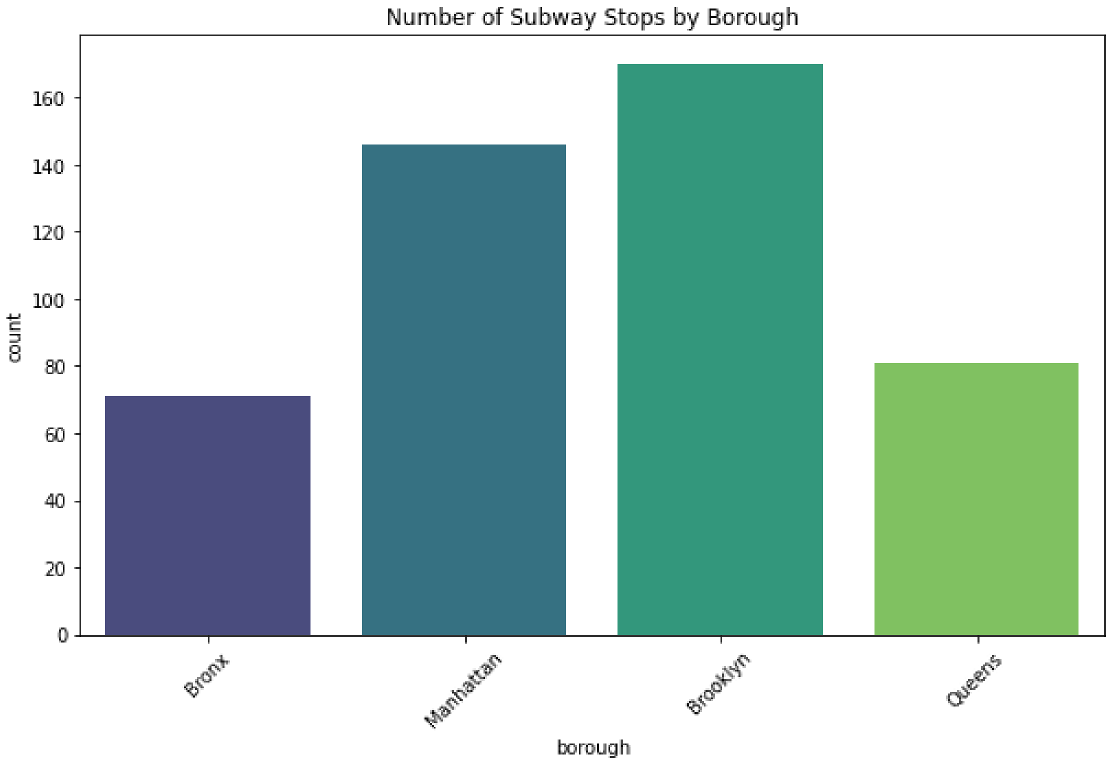
```
Subway stops data info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 468 entries, 0 to 467
Data columns (total 9 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   code       468 non-null    object
 1   alt        3 non-null      object
 2   stop_name  468 non-null    object
 3   short      468 non-null    object
 4   line       468 non-null    object
 5   borough    468 non-null    object
 6   complex    74 non-null     object
 7   lat        468 non-null    int64
 8   lon        468 non-null    int64
dtypes: int64(2), object(7)
memory usage: 33.0+ KB

Covid data info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 177 entries, 0 to 176
Data columns (total 10 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   modzcta                      177 non-null    int64
 1   modzcta_name                 177 non-null    object
 2   label                        177 non-null    object
 3   lat                          177 non-null    float64
 4   lon                          177 non-null    float64
 5   hospitalization_count_28day  177 non-null    int64
 6   hospitalization_rate_28day   66 non-null     float64
 7   death_count_28day            165 non-null    float64
 8   death_rate_28day             165 non-null    float64
 9   daterange                    177 non-null    object
dtypes: float64(5), int64(2), object(3)
memory usage: 14.0+ KB

By Group data info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27 entries, 0 to 26
Data columns (total 11 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   group                 27 non-null     object
 1   subgroup              26 non-null     object
 2   CONFIRMED_CASE_RATE   26 non-null     float64
 3   CASE_RATE             26 non-null     float64
 4   HOSPITALIZED_RATE     26 non-null     float64
 5   DEATH_RATE            24 non-null     float64
 6   CONFIRMED_CASE_COUNT  26 non-null     float64
 7   PROBABLE_CASE_COUNT   26 non-null     float64
 8   CASE_COUNT            26 non-null     float64
 9   HOSPITALIZED_COUNT    26 non-null     float64
 10  DEATH_COUNT           24 non-null     float64
dtypes: float64(9), object(2)
memory usage: 2.4+ KB

Subway stops descriptive statistics:
                 lat            lon
count     468.000000     468.000000
mean   609815.472222  265881.286325
std     15643.024942   28222.569733
min    583885.000000  209646.000000
25%    597004.750000  246910.500000
50%    606514.000000  262122.000000
75%    619598.500000  283926.000000
max    660724.000000  329346.000000

Covid data descriptive statistics:
            modzcta         lat         lon  hospitalization_count_28day  \
count    177.000000  177.000000  177.000000                   177.000000
mean   10810.378531   40.725552  -73.918805                     1.768362
std      578.173317    0.083648    0.099659                     1.863987
min    10001.000000   40.507771  -74.242270                     0.000000
25%    10301.000000   40.670819  -73.978704                     0.000000
```

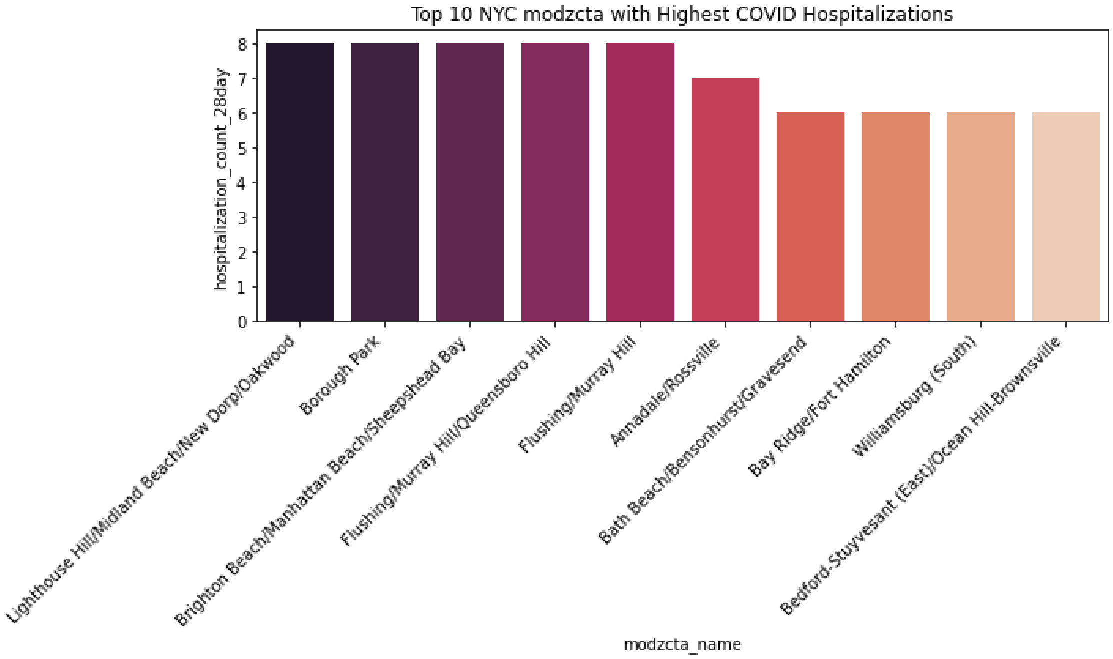
```
50%    11109.000000   40.726441  -73.924048                     1.000000
75%    11361.000000   40.776432  -73.846984                     3.000000
max    11697.000000   40.899509  -73.710907                     8.000000

       hospitalization_rate_28day  death_count_28day  death_rate_28day
count                   66.000000              165.0             165.0
mean                     2.166667                0.0               0.0
std                      4.254602                0.0               0.0
min                      0.000000                0.0               0.0
25%                      0.000000                0.0               0.0
50%                      0.000000                0.0               0.0
75%                      0.000000                0.0               0.0
max                     15.100000                0.0               0.0

By Group data descriptive statistics:
       CONFIRMED_CASE_RATE     CASE_RATE  HOSPITALIZED_RATE   DEATH_RATE  \
count            26.000000     26.000000          26.000000    24.000000
mean          34048.802692  41822.375385        2866.440385   691.755417
std            4791.919452   6138.917207        2430.336735   875.459806
min           23303.000000  27548.990000         298.570000     3.640000
25%           32810.340000  40200.257500        1698.295000   380.217500
50%           34089.125000  41926.315000        2768.185000   571.415000
75%           36919.792500  45340.197500        3008.237500   631.372500
max           43870.220000  54294.400000       13080.070000  4504.910000

       CONFIRMED_CASE_COUNT  PROBABLE_CASE_COUNT    CASE_COUNT  \
count          2.600000e+01            26.000000  2.600000e+01
mean           6.605877e+05        151087.807692  8.116755e+05
std            6.064168e+05        139064.634346  7.450973e+05
min            1.220420e+05         22237.000000  1.442790e+05
25%            2.964072e+05         71240.500000  3.676478e+05
50%            4.935610e+05        117969.000000  6.139350e+05
75%            7.865320e+05        182285.000000  9.744500e+05
max            2.980889e+06        680778.000000  3.661667e+06

       HOSPITALIZED_COUNT   DEATH_COUNT
count           26.000000     24.000000
mean         53929.500000  12799.416667
std          50021.670154  11214.922869
min           2050.000000     62.000000
25%          19984.000000   5547.500000
50%          43061.000000   9689.500000
75%          68285.500000  20685.000000
max         238486.000000  46717.000000
```

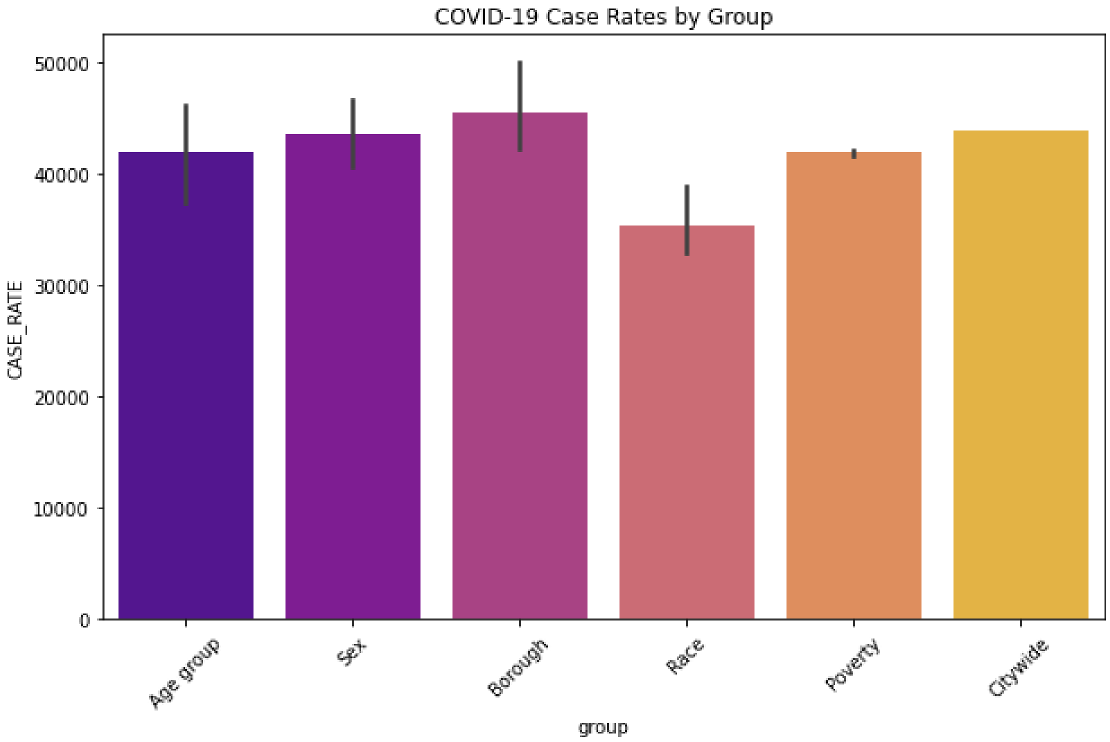
[8]:

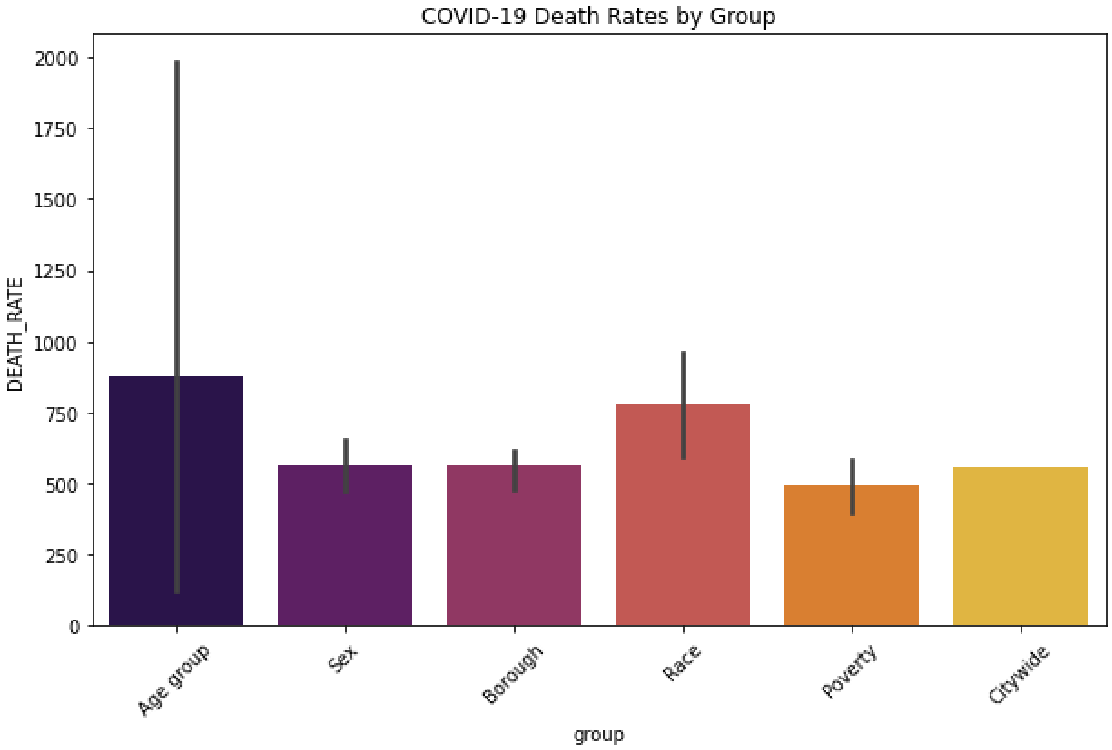
```
# Visualization of Subway stops by Borough
plt.figure(figsize=(10, 6))
```

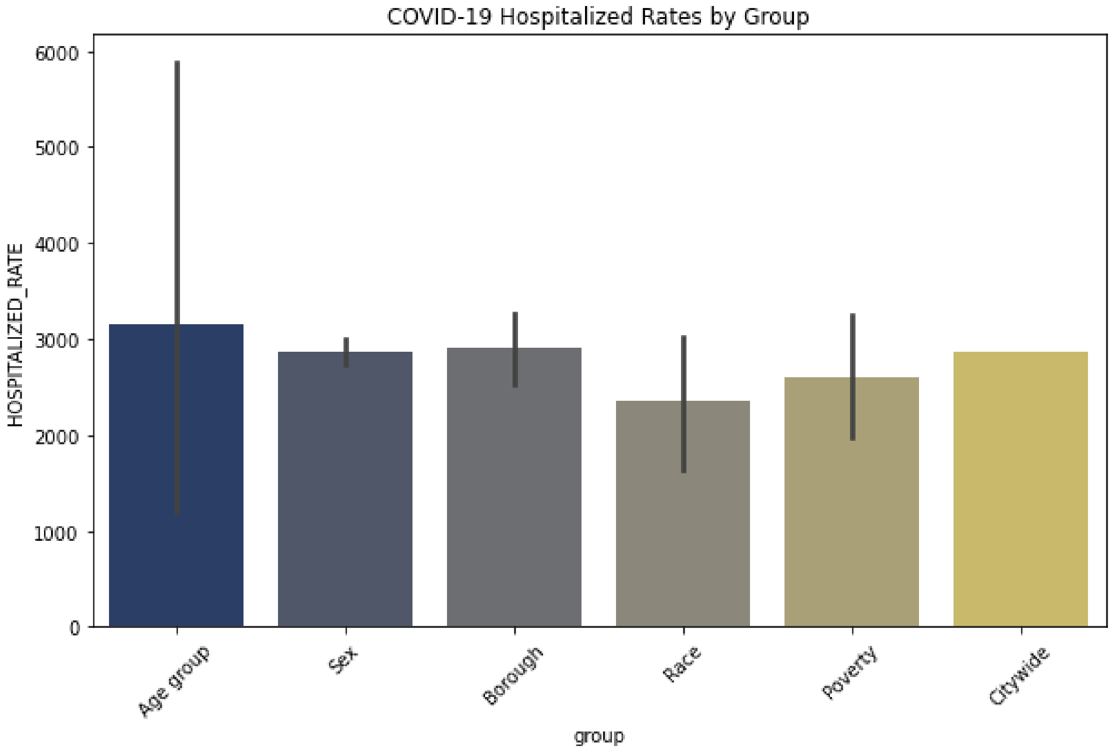
```
sns.countplot(x='borough', data=subway_df, palette='viridis')
plt.title('Number of Subway Stops by Borough')
plt.xticks(rotation=45)
plt.show()

# Top 10 COVID modzcta by number of hospitalizations
top_10_hosp = covid_df.sort_values(by='hospitalization_count_28day',␣
 ↪ascending=False).head(10)
plt.figure(figsize=(10, 6))
sns.barplot(x='modzcta_name', y='hospitalization_count_28day',␣
 ↪data=top_10_hosp, palette='rocket')
plt.title('Top 10 NYC modzcta with Highest COVID Hospitalizations')
plt.xticks(rotation=45, ha = 'right')
plt.tight_layout()
plt.show()

# Distribution of COVID-19 Case Rates by Group
plt.figure(figsize=(10, 6))
sns.barplot(x='group', y='CASE_RATE', data=by_group_df, palette='plasma')
plt.title('COVID-19 Case Rates by Group')
plt.xticks(rotation=45)
plt.show()

#Distribution of COVID-19 Death Rates by Group
plt.figure(figsize=(10, 6))
sns.barplot(x='group', y='DEATH_RATE', data=by_group_df, palette='inferno')
plt.title('COVID-19 Death Rates by Group')
plt.xticks(rotation=45)
plt.show()

#Distribution of COVID-19 Hospitalization Rates by Group
plt.figure(figsize=(10, 6))
sns.barplot(x='group', y='HOSPITALIZED_RATE', data=by_group_df,␣
 ↪palette='cividis')
plt.title('COVID-19 Hospitalized Rates by Group')
plt.xticks(rotation=45)
plt.show()
```


Number of Subway Stops by Borough
count
0
20
40
60
80
100
120
140
160
Bronx
Manhattan
Brooklyn
Queens
borough


Top 10 NYC modzcta with Highest COVID Hospitalizations
hospitalization_count_28day
0
1
2
3
4
5
6
7
8
Lighthouse Hill/Midland Beach/New Dorp/Oakwood
Borough Park
Brighton Beach/Manhattan Beach/Sheepshead Bay
Flushing/Murray Hill/Queensboro Hill
Flushing/Murray Hill
Annadale/Rossville
Bath Beach/Bensonhurst/Gravesend
Bay Ridge/Fort Hamilton
Williamsburg (South)
Bedford-Stuyvesant (East)/Ocean Hill-Brownsville
modzcta_name


COVID-19 Case Rates by Group
CASE_RATE
0
10000
20000
30000
40000
50000
Age group
Sex
Borough
Race
Poverty
Citywide
group


COVID-19 Death Rates by Group
DEATH_RATE
0
250
500
750
1000
1250
1500
1750
2000
Age group
Sex
Borough
Race
Poverty
Citywide
group



[9]:

```
# Find the closest subway station to the top 10 covid area, by hospitalization rate
closest_stations = []
for index_covid, covid_row in top_10_hosp.iterrows():
  min_distance = float('inf')
  closest_subway_stop = None
  for index_subway, stop_row in subway_df.iterrows():
    distance = haversine(covid_row['lat'], covid_row['lon'], stop_row['lat'], stop_row['lon'])
    if distance < min_distance:
        min_distance = distance
        closest_subway_stop = stop_row
  closest_stations.append((covid_row['modzcta_name'], closest_subway_stop['stop_name'], min_distance))

# Show the closest stations to the top 10 hospitalization rates.
closest_stations_df = pd.DataFrame(closest_stations, columns = ['modzcta_name', 'closest_subway_station', 'distance'])
print("\n Closest Subway station to top 10 hospitalization rates.")
print(closest_stations_df)
```

```
 Closest Subway station to top 10 hospitalization rates.
```

```
                                       modzcta_name closest_subway_station  \
0    Lighthouse Hill/Midland Beach/New Dorp/Oakwood        Pennsylvania Av
1                                      Borough Park        Pennsylvania Av
2     Brighton Beach/Manhattan Beach/Sheepshead Bay        Pennsylvania Av
3              Flushing/Murray Hill/Queensboro Hill        Pennsylvania Av
4                              Flushing/Murray Hill        Pennsylvania Av
5                                Annadale/Rossville        Pennsylvania Av
6                  Bath Beach/Bensonhurst/Gravesend        Pennsylvania Av
7                           Bay Ridge/Fort Hamilton        Pennsylvania Av
8                              Williamsburg (South)        Pennsylvania Av
9  Bedford-Stuyvesant (East)/Ocean Hill-Brownsville        Pennsylvania Av

     distance
0  691.904659
1  681.391847
2  677.135185
3  667.535109
4  668.213875
5  696.516303
6  681.144945
7  684.132828
8  677.315286
9  675.248178
```

[10]:

```python
print("\n\nSummary of findings:")
print("-The Subway stops are not evenly distributed between the boroughs, with␣
 ↪Manhattan having the most and Staten Island having the least.")
print("-Certain groups show significantly higher COVID-19 case and death rates,␣
 ↪the data does not show that those groups are connected to the places with␣
 ↪high hospitalization, a deeper analysis and merging of the datasets is␣
 ↪required.")
print("-There is a very strong correlation between the CASE RATE and the␣
 ↪CONFIRMED CASE RATE.")
print("-The COVID-19 data shows significant variations in hospitalization and␣
 ↪death rates across different areas.")
print(f"-The area with the highest hospitalization rate is {top_10_hosp.
 ↪iloc[0]['modzcta_name']}, and the closest subway stop is␣
 ↪{closest_stations_df.iloc[0]['closest_subway_station']}")
print(" Further analysis is needed to find causal relationship between subway␣
 ↪stops and the groups and locations that had higher covid cases.")
```

```
Summary of findings:
-The Subway stops are not evenly distributed between the boroughs, with
Manhattan having the most and Staten Island having the least.
-Certain groups show significantly higher COVID-19 case and death rates, the
```

```
data does not show that those groups are connected to the places with high
hospitalization, a deeper analysis and merging of the datasets is required.
-There is a very strong correlation between the CASE RATE and the CONFIRMED CASE
RATE.
-The COVID-19 data shows significant variations in hospitalization and death
rates across different areas.
-The area with the highest hospitalization rate is Lighthouse Hill/Midland
Beach/New Dorp/Oakwood, and the closest subway stop is Pennsylvania Av
 Further analysis is needed to find causal relationship between subway stops and
the groups and locations that had higher covid cases.
```

0.1 Summary of findings:

- The Subway stops are not evenly distributed between the boroughs, with Manhattan having the most and Staten Island having the least.
- Certain groups show significantly higher COVID-19 case and death rates, the data does not show that those groups are connected to the places with high hospitalization, a deeper analysis and merging of the datasets is required.
- There is a very strong correlation between the CASE RATE and the CONFIRMED CASE RATE.
- The COVID-19 data shows significant variations in hospitalization and death rates across different areas.
- The area with the highest hospitalization rate is Lighthouse Hill/Midland Beach/New Dorp/Oakwood, and the closest subway stop is Pennsylvania Av Further analysis is needed to find causal relationship between subway stops and the groups and locations that had higher covid cases.