Step 1: I activated the correct virtual environment and installed all the necessary libraries.

#### Step 2: Import Libraries and Read Data

Displaying the first few rows of the data helps verify that it was loaded correctly.

```
In [3]: # Step 2: Import Libraries
         import pandas as pd # Data manipulation
         import seaborn as sns # Data visualization
         import matplotlib.pyplot as plt # Plotting
         from keplergl import KeplerGl # Interactive maps
         # Step 2.1: Load the datasets
         bike data = pd.read csv('merged citibike weather.csv') # Load Citibike data
         weather_data = pd.read_csv('weather_2022.csv') # Load weather data
         # Step 2.2: Display the first few rows of both datasets for verification
         print("Bike Data Sample:\n", bike_data.head())
        print("Weather Data Sample:\n", weather_data.head())
       C:\Users\Asus\AppData\Local\Temp\ipykernel_16488\3333922557.py:8: DtypeWarning: Columns (6,8) have mixed types. Specify dtype option on import or set low_memory=False.
         bike_data = pd.read_csv('merged_citibike_weather.csv')  # Load Citibike data
                     ride_id Temperature rideable_type started_at ended_at \
       0 BFD29218AB271154 20.8 electric_bike 13:43.4 22:31.5
                               21.7 classic_bike 30:54.2 41:43.4
       1 7C953F2FD7BE1302
      2 95893ABD40CED4B8 33.1 electric_bike 52:43.1 06:35.2
3 F853B50772137378 20.2 classic_bike 35:48.2 10:50.5
       4 7590ADF834797B4B 34.0 classic_bike 14:23.0 34:57.5
                start_station_name start_station_id
                                                                   end_station_name \

      0
      West End Ave & W 107 St
      7650.05
      Mt Morris Park W & W 120 St

      1
      4 Ave & 3 St
      4028.04
      Boerum Pl\t& Pacific St

      2
      1 Ave & E 62 St
      6753.08
      5 Ave & E 29 St

      3
      2 Ave & E 96 St
      7338.02
      5 Ave & E 29 St

      4
      6 Ave & W 34 St
      6364.1
      5 Ave & E 29 St

          end_station_id start_lat start_lng end_lat end_lng member_casual
                 7685.14 40.802117 -73.968181 40.804038 -73.945925
                 4488.09 40.673746 -73.985649 40.688489 -73.991160
                                                                                 member
                 6248.06 40.761227 -73.960940 40.745168 -73.986831
                                                                                 member
                 6248.06 40.783964 -73.947167 40.745168 -73.986831
                                                                                 member
                 6248.06 40.749640 -73.988050 40.745168 -73.986831
                                          DATE PRCP TMAX TMIN
                          STATION
                year
       0 1/21/2022 USW00094728 1/21/2022 0.0 -55.0 -99.0
       1 1/10/2022 USW00094728 1/10/2022 0.0 44.0 -43.0
       2 1/26/2022 USW00094728 1/26/2022 0.0 -21.0 -66.0
       3 1/3/2022 USW00094728 1/3/2022 0.0 28.0 -55.0
       4 1/22/2022 USW00094728 1/22/2022 0.0 -16.0 -105.0
       Weather Data Sample:
               STATION DATE PRCP TMAX TMIN
       0 USW00094728 2022-01-01 201 133 100
       1 USW00094728 2022-01-02 10 150 28
       2 USW00094728 2022-01-03 0 28 -55
       3 USW00094728 2022-01-04 0 11 -71
       4 USW00094728 2022-01-05 58 83
```

## Step 3: Create a New Column and Aggregate Data

Adding a new column makes it easier to count trips between station pairs.

Grouping by start station name and end station name calculates the total trips for each route.

```
In [4]: # Step 3.1: Add a new column to represent each trip
       bike_data['new_column'] = 1 # This column will act as a counter for aggregation
       # Step 3.2: Aggregate data by start and end stations
       aggregated_df = bike_data.groupby(['start_station_name', 'end_station_name'])['new_column'].sum().reset_index()
       # Step 3.3: Rename the column to something meaningful
       aggregated_df.rename(columns={'new_column': 'trip_count'}, inplace=True)
       # Step 3.4: Display the first few rows of the aggregated data
       print("Aggregated Data Sample:\n", aggregated_df.head())
      Aggregated Data Sample:
         start_station_name end_station_name trip_count
      1 1 Ave & E 110 St 1 Ave & E 44 St
      2 1 Ave & E 110 St 1 Ave & E 68 St
      3 1 Ave & E 110 St 1 Ave & E 78 St
      4 1 Ave & E 110 St 1 Ave & E 94 St
```

# Step 4: Initialize a Kepler.gl Map

Displaying the map now lets you ensure it's rendering correctly in our notebook environment.

```
In [5]: # Step 4: Initialize a Kepler.gl map
        map = KeplerGl() # Create a new map instance
       # Display the map (in Jupyter Notebook or similar environments)
      User Guide: https://docs.kepler.gl/docs/keplergl-jupyter
      KeplerGl()
```

# Step 5: Customize the Output of Your Map

Adding data to the map makes it accessible for visualization.

Customizations (arcs, color palettes, etc.) are performed in Kepler.gl's graphical interface for simplicity.

```
In [6]: # Step 5.1: Add the aggregated data to the map
        map.add_data(data=aggregated_df, name='trip_data')
       # Note: Customize the layers, colors, and arcs directly within the Kepler.gl interface.
        # Example steps (to be done in the Kepler.gl UI):
        # 1. Go to "Layer Settings" and add a new layer.
        # 2. Set the data source to 'trip_data'.
        # 3. Add arcs between 'start_station_name' and 'end_station_name'.
        # 4. Set color based on 'trip_count'.
```

## Step 6: Add Filters and Interpret Output

#### Observations:

Add Filters:

• Filter trips where trip\_count > 10 to focus on significant routes.

#### Observations:

- 1. Busiest Routes:
  - The route from 1 Ave & E 110 St to 1 Ave & E 94 St has a trip count of 15, making it one of the busiest routes.
  - The route 1 Ave & E 110 St to itself (a round trip) is even busier with 27 trips.

#### 2. Key Stations:

- 1 Ave & E 110 St stands out as a primary hub with the highest trip counts across multiple routes.
- This station's location might suggest its importance in a densely populated or high-demand area.

#### 3. Insights on Station Usage:

- Routes with higher trip counts (e.g., 1 Ave & E 110 St to 1 Ave & E 94 St) might indicate proximity to residential areas, parks, or business districts.
- Round trips originating and ending at 1 Ave & E 110 St suggest recreational or convenience-based usage.

# Step 7: Create a Config Object and Save the Map

# Step 7.2: Save the map to an HTML file
map.save\_to\_html(file\_name='citibike\_trip\_map.html') # File will be saved locally

Map saved to citibike\_trip\_map.html!

[n [ ]: