UBER PICKUPS IN NYC

In this project, we are going to analyse the Uber Pickups in New York City.

ABOUT THE DATASET

The dataset provided contains data on over 4.5 million Uber pickups in New York City from April to September 2014, and 14.3 million more Uber pickups from January to June 2015.

Uber trip data from 2014

There are six files of raw data on Uber pickups in New York City from April to September 2014. The files are separated by month and each has the following columns:

- **Date/Time** : The date and time of the Uber pickup
- **Lat** : The latitude of the Uber pickup
- **Lon** : The longitude of the Uber pickup
- **Base** : The TLC (Taxi & Limousine Commission) base company code affiliated with the Uber pickup

These files are named:

- `uber-raw-data-apr14.csv`
- `uber-raw-data-aug14.csv`
- `uber-raw-data-jul14.csv`
- `uber-raw-data-jun14.csv`
- `uber-raw-data-may14.csv`
- `uber-raw-data-sep14.csv`

Uber trip data from 2015

Also included is the `file uber-raw-data-janjune-15.csv`. This file has the following columns:

- **Dispatching_base_num** : The TLC base company code of the base that dispatched the Uber
- **Pickup_date** : The date and time of the Uber pickup
- **Affiliated_base_num** : The TLC base company code affiliated with the Uber pickup
- **locationID** : The pickup location ID affiliated with the Uber pickup

The `base` codes are for the following Uber bases (In the parentheses, we have code names in German which are used internally by Uber to categorize and manage their various service offerings.) :

- **B02512 (Unter):** This corresponds to the Uber service category "UberX", which is the basic and most common service offering.
- **B02598 (Hinter):** This corresponds to the Uber service category "UberPOOL", which allows riders heading in the same direction to share a ride and split the cost.
- **B02617 (Weiter):** This corresponds to the Uber service category "UberXL", which offers larger vehicles such as SUVs and minivans for accommodating more passengers.
- **B02682 (Schmecken):** This corresponds to the Uber service category "UberSELECT", which provides premium rides with high-end vehicles.
- **B02764 (Danach-NY):** This corresponds to the Uber service category "UberWAV", which offers wheelchair-accessible vehicles for riders with accessibility needs.
- **B02765 (Grun):** This corresponds to the Uber service category "UberBLACK", which provides luxury black car services with professional drivers.
- **B02835 (Dreist):** This corresponds to the Uber service category "UberSUV", which offers larger luxury vehicles for accommodating more passengers.
- **B02836 (Drinnen):** This corresponds to the Uber service category "UberLUX", which provides high-end luxury vehicles for a premium ride experience.

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0. Meeting the library requirements

In Jupyter Notebooks, you may encounter situations where you want to suppress warning messages that would normally be displayed. The `warnings` module in Python provides a way to control warning behavior in your code. By calling `filterwarnings('ignore')`, you instruct Python to ignore all warnings and not display them in the output.

This can be useful in certain situations where you want to suppress warnings that might be irrelevant or distracting for your specific task. However, it's important to note that ignoring warnings globally can sometimes hide important information about potential issues or bugs in your code. It's generally recommended to use caution when suppressing warnings and consider whether it's necessary for your particular use case.

In [1]:

```
import warnings
warnings.filterwarnings('ignore')
```

Run the following cell to install the required libraries. Let's break down the command and its components:

- `!`: The exclamation mark (!) at the beginning of the line indicates that the command should be executed as a shell command, rather than as a Python statement.
- `pip3`: pip3 is a package installer for Python 3, used to install Python packages from the Python Package Index (PyPI).

- `-q` : The -q flag stands for "quiet" and is used to suppress output or progress messages during the installation process. It makes the installation process less verbose.
- `install:` This keyword tells pip3 that you want to install packages.
- `numpy pandas matplotlib seaborn geopy folium datetime scipy sklearn tensorflow` : These are the names of the packages you want to install.

In [2]:
```
!pip3 -q install numpy pandas matplotlib seaborn geopy folium datetime sc
```

```
[notice] A new release of pip is available: 23.0.1 -> 23.1.2
[notice] To update, run: /Library/Developer/CommandLineTools/usr/bin/pyt
hon3 -m pip install --upgrade pip
```

In [3]:
```
# Importing the libraries installed

%matplotlib inline

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import geopy.distance

from math import radians,cos,sin,asin,sqrt

import folium
from folium.plugins import HeatMap

import datetime
from scipy.stats import ttest_ind

import matplotlib
matplotlib.rcParams.update({'font.size': 12})
```

1. Loading the data

Let's pick up the 2014 data for our analysis. We can see that there are 6 files for that. Out of which, we will pick `uber-raw-data-jul14.csv` to begin with.

In [4]:
```
uber_data = pd.read_csv('./data/uber-raw-data-jul14.csv')
```

In [5]:
```
# Print the first 10 elements
display(uber_data.head(10))
```

	Date/Time	Lat	Lon	Base
0	7/1/2014 0:03:00	40.7586	-73.9706	B02512
1	7/1/2014 0:05:00	40.7605	-73.9994	B02512
2	7/1/2014 0:06:00	40.7320	-73.9999	B02512
3	7/1/2014 0:09:00	40.7635	-73.9793	B02512
4	7/1/2014 0:20:00	40.7204	-74.0047	B02512
5	7/1/2014 0:35:00	40.7487	-73.9869	B02512
6	7/1/2014 0:57:00	40.7444	-73.9961	B02512
7	7/1/2014 0:58:00	40.7132	-73.9492	B02512
8	7/1/2014 1:04:00	40.7590	-73.9730	B02512
9	7/1/2014 1:08:00	40.7601	-73.9823	B02512

2. Pre-processing the data

Let's first see the information about the dataframe.

In [6]:
```
print(uber_data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 796121 entries, 0 to 796120
Data columns (total 4 columns):
 #   Column     Non-Null Count   Dtype  
---  ------     --------------   -----  
 0   Date/Time  796121 non-null  object 
 1   Lat        796121 non-null  float64
 2   Lon        796121 non-null  float64
 3   Base       796121 non-null  object 
dtypes: float64(2), object(2)
memory usage: 24.3+ MB
None
```

1. Change the type of the data in a column

Column `Date/Time` shows the data type as object. To find which object is that, we print the type of data in the first cell of the `Date/Time` column. On doing that, we come to know - it's of string type.

In [7]:
```
# Print the type of data in Date/Time
print(type(uber_data.loc[0,'Date/Time']))
```

```
<class 'str'>
```

Let's convert it to datetime format for easy indexing.

- `pd.to_datetime():` This is a pandas function that converts a given input into a datetime object. It is used here to convert the values of the 'Date/Time' column to datetime format.

In [8]:
```
uber_data['Date/Time'] = pd.to_datetime(uber_data['Date/Time'])
```

2. Dividing the data in bins

Let us divide each hour in existing Date/Time column into four smaller bins of 15 mins each: [0 mins - 15 mins], [15 mins - 30 mins], [30 mins - 45 mins] and [45 mins - 60 mins]. The purpose of binning the time values in this way could be to aggregate or group the data based on time intervals, allowing for analysis at a coarser level of granularity. This can be useful when analyzing patterns or trends that occur within specific time intervals. This will allow us to visualize the data more precisely.

- `uber_data['Date/Time']` : This accesses the 'Date/Time' column in the uber_data DataFrame.
- `.dt.floor('15min'):` This is a pandas datetime accessor (dt) method that performs floor division to round down the time values to the nearest 15-minute interval. The '15min' argument specifies the desired time interval.

In [9]:
```
# Create a new column to store this new binned column
uber_data['BinnedHour'] = uber_data['Date/Time'].dt.floor('15min')
```

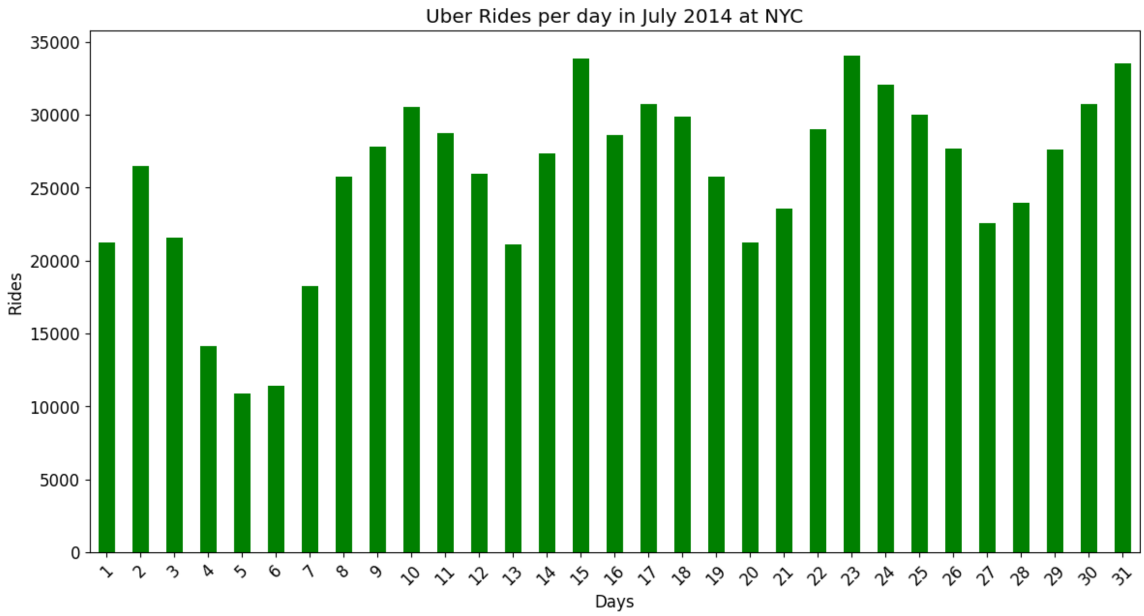
In [10]:
```
# Printing the new column - BinnedHour
display(uber_data['BinnedHour'])
```

```
0        2014-07-01 00:00:00
1        2014-07-01 00:00:00
2        2014-07-01 00:00:00
3        2014-07-01 00:00:00
4        2014-07-01 00:15:00
                 ...
796116   2014-07-31 23:15:00
796117   2014-07-31 23:15:00
796118   2014-07-31 23:15:00
796119   2014-07-31 23:30:00
796120   2014-07-31 23:45:00
Name: BinnedHour, Length: 796121, dtype: datetime64[ns]
```

3. Visualising the data

1. Let us visualize the total uber rides per day in the month of July 2014

In [11]:
```
plt.figure(figsize=(14,7))
uber_data['BinnedHour'].dt.day.value_counts().sort_index().plot(kind='bar
for item in plt.gca().get_xticklabels():
    item.set_rotation(45)
plt.title('Uber Rides per day in July 2014 at NYC')
plt.xlabel('Days')
plt.ylabel('Rides')
plt.show()
```



Let's understand what's happening here.

The first line, `plt.figure(figsize=(14,7))`, creates a new figure object with a specific size of 14 inches in width and 7 inches in height. This sets the dimensions of the plot that will be created.

The next line, `uber_data['BinnedHour'].dt.day.value_counts().sort_index().plot(kin` generates the bar chart using the 'BinnedHour' column. It performs several operations in sequence:

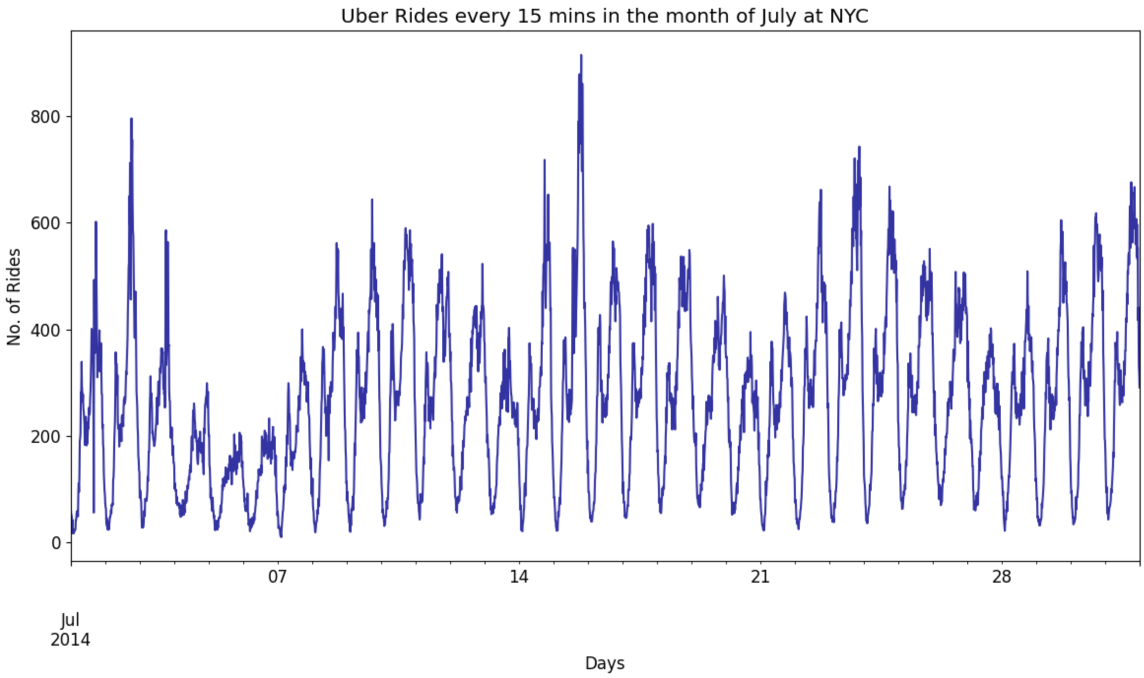
- `.dt.day:` The .dt accessor allows access to datetime properties, and .day extracts the day component from the 'BinnedHour' column, considering the binned time values.
- `.value_counts():` This method counts the occurrences of each unique day in the 'BinnedHour' column, providing a count for the number of rides on each day.
- `.sort_index():` This sorts the index (day values) in ascending order.
- `.plot(kind='bar', color='green'):` This plots the sorted counts as a bar chart, with each bar representing a day. The kind='bar' parameter specifies the type of plot, and color='green' sets the color of the bars to green.

Then the lines `for item in plt.gca().get_xticklabels():` `item.set_rotation(45)` rotate the x-axis tick labels by 45 degrees to improve readability.

Observation 1: There is a recurring pattern in the data! The frequency of trips increases and then decreases in a repeating pattern.

2. Let us have a more closer look at it, say every 15 minutes from July 1 to July 31.

In [12]:
```
plt.figure(figsize=(14,7))
uber_data['BinnedHour'].value_counts().sort_index().plot(c='darkblue', al
plt.title('Uber Rides every 15 mins in the month of July at NYC')
plt.xlabel('Days')
plt.ylabel('No. of Rides')
plt.show()
```



Observation 2: The underlying trend is clearly visible now. It conveys that in a day there are times when the pickups are very low and very high, and they seem to follow a pattern.

Q. Which times correspond to the highest and lowest peaks in the plot above?

In [13]:
```
display(uber_data['BinnedHour'].value_counts())
```

```
2014-07-15 19:15:00    915
2014-07-15 18:15:00    879
2014-07-15 17:45:00    877
2014-07-15 18:00:00    872
2014-07-15 20:00:00    861
                      ...
2014-07-01 02:00:00     17
2014-07-07 01:45:00     15
2014-07-07 02:15:00     14
2014-07-07 02:00:00     12
2014-07-07 02:30:00     10
Name: BinnedHour, Length: 2976, dtype: int64
```

Ans.

The highest peak corresponds to the time 19:15 (7:15 PM), 15th July 2014 and has a ride count of 915 and the lowest peak corresponds to the time 02:30, 7th July 2014 and has a ride count of 10.

3. Lets visualize the week wise trends in the data.

For this, we will have to map each date into its day name using a dictionary.

In [14]:
```
# Defining a dictionary to map the weekday to day name
DayMap = {0:'Monday', 1:'Tuesday', 2:'Wednesday', 3:'Thursday', 4:'Friday
uber_data['Day'] = uber_data['BinnedHour'].dt.weekday.map(DayMap)
display(uber_data['Day'])
```

```
0          Tuesday
1          Tuesday
2          Tuesday
3          Tuesday
4          Tuesday
            ...
796116    Thursday
796117    Thursday
796118    Thursday
796119    Thursday
796120    Thursday
Name: Day, Length: 796121, dtype: object
```

In [15]:
```
# Separating the date and time to other columns
uber_data['Date'] = uber_data['BinnedHour'].dt.date
uber_data['Time'] = uber_data['BinnedHour'].dt.time
display(uber_data[['Date', 'Time']])
```

	Date	Time
0	2014-07-01	00:00:00
1	2014-07-01	00:00:00
2	2014-07-01	00:00:00
3	2014-07-01	00:00:00
4	2014-07-01	00:15:00
...	...	...
796116	2014-07-31	23:15:00
796117	2014-07-31	23:15:00
796118	2014-07-31	23:15:00
796119	2014-07-31	23:30:00
796120	2014-07-31	23:45:00

796121 rows × 2 columns

In [16]:
```
# Defining ordered category of week days for easy sorting and visualizati
uber_data['Day'] = pd.Categorical(uber_data['Day'],
                                  categories=['Monday','Tuesday','Wednesd
                                  ordered=True)
display(uber_data['Day'])
```

```
0          Tuesday
1          Tuesday
2          Tuesday
3          Tuesday
4          Tuesday
             ...
796116    Thursday
796117    Thursday
796118    Thursday
796119    Thursday
796120    Thursday
Name: Day, Length: 796121, dtype: category
Categories (7, object): ['Monday' < 'Tuesday' < 'Wednesday' < 'Thursday'
< 'Friday' < 'Saturday' < 'Sunday']
```

We now rearrange the dataset a bit for weekly analysis.

In [17]:
```
weekly_data = uber_data.groupby(['Date','Day','Time']).count().dropna()\
                .rename(columns={'BinnedHour':'Rides'})['Rides'].reset_in
weekly_data.head(10)
```

Out[17]:

	Date	Day	Time	Rides
0	2014-07-01	Monday	00:00:00	0
1	2014-07-01	Monday	00:15:00	0
2	2014-07-01	Monday	00:30:00	0
3	2014-07-01	Monday	00:45:00	0
4	2014-07-01	Monday	01:00:00	0
5	2014-07-01	Monday	01:15:00	0
6	2014-07-01	Monday	01:30:00	0
7	2014-07-01	Monday	01:45:00	0
8	2014-07-01	Monday	02:00:00	0
9	2014-07-01	Monday	02:15:00	0

We now group weekly data by days to plot total rides per week in July 2014.

In [18]:
```
# Grouping the weekly_data daywise
daywise = weekly_data.groupby('Day').sum()
display(daywise)
```

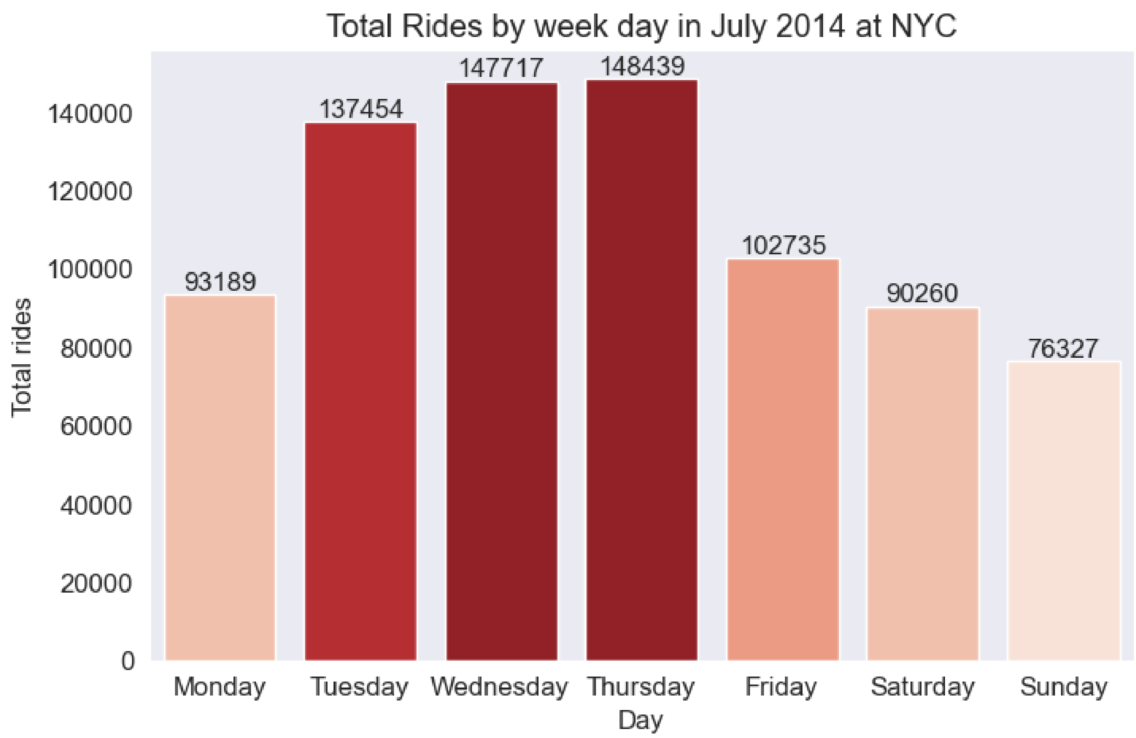
Day	Rides
Monday	93189
Tuesday	137454
Wednesday	147717
Thursday	148439
Friday	102735
Saturday	90260
Sunday	76327

In [19]:

```
# Plotting the graphs for a better visualization
sns.set_style("dark")
plt.figure(figsize=(8,5))

# Creating a customized color palette for custom hue according to height
vals = daywise.to_numpy().ravel()
normalized = (vals - np.min(vals)) / (np.max(vals) - np.min(vals))
indices = np.round(normalized * (len(vals) - 1)).astype(np.int32)
palette = sns.color_palette('Reds', len(vals))
colorPal = np.array(palette).take(indices, axis=0)

# Creating a bar plot
ax = sns.barplot(x = daywise.index,y= vals,palette=colorPal)
plt.ylabel('Total rides')
plt.title('Total Rides by week day in July 2014 at NYC')
for rect in ax.patches:
    ax.text(rect.get_x() + rect.get_width()/2.0,rect.get_height(),int(rec
```



Observation 3: According to the bar plot above, rides are maximum on Thursdays and minimum on Sundays. Sundays having the lowest

number of rides makes sense logically, as it's a holiday and people often take rest on that day.

In [20]:
```
weekly_data = weekly_data.groupby(['Day','Time']).mean()['Rides']
display(weekly_data.head(10))
```

```
Day     Time
Monday  00:00:00    13.225806
        00:15:00    10.967742
        00:30:00     8.741935
        00:45:00     7.709677
        01:00:00     6.935484
        01:15:00     5.354839
        01:30:00     3.838710
        01:45:00     3.645161
        02:00:00     2.612903
        02:15:00     3.161290
Name: Rides, dtype: float64
```

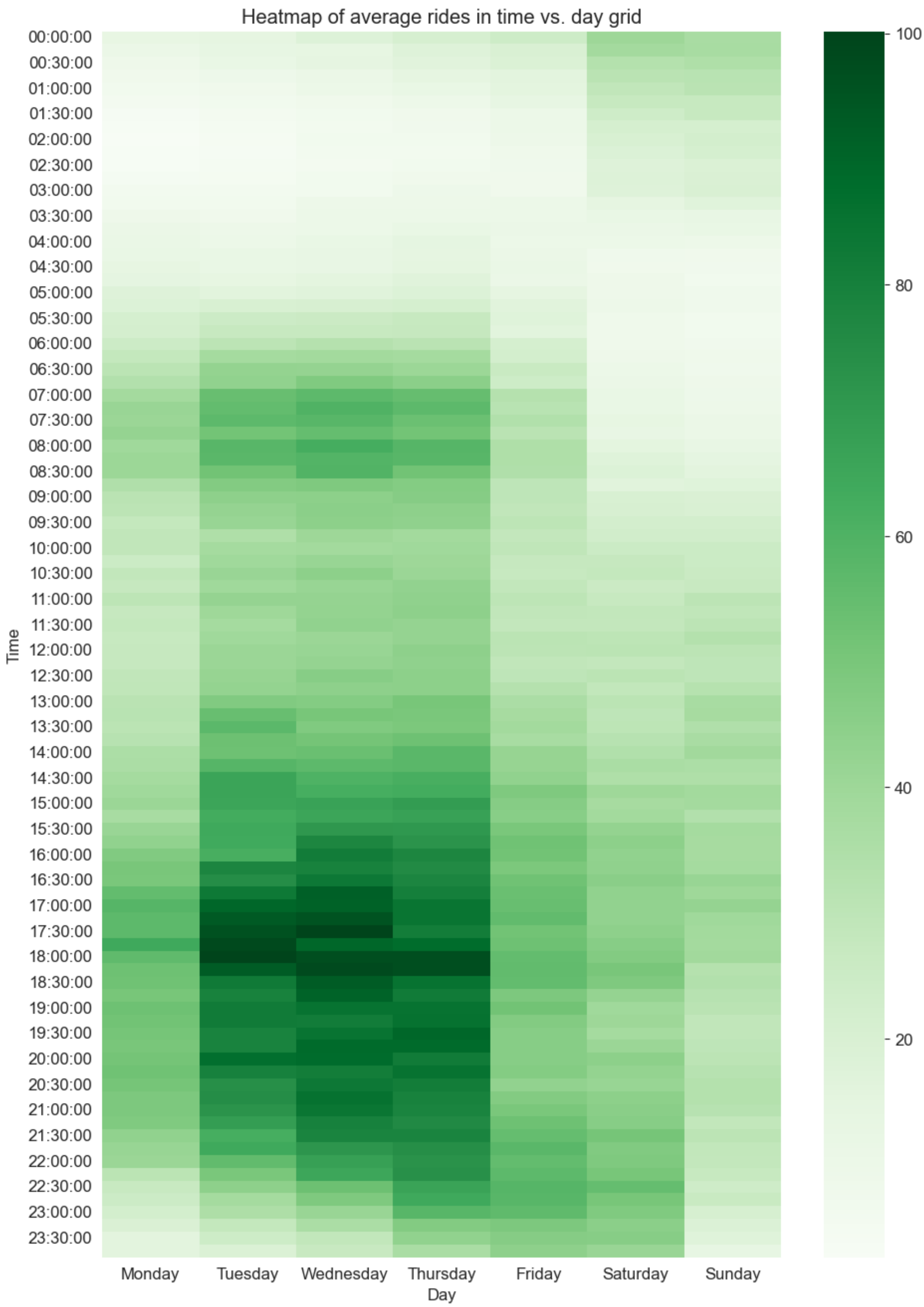
In [21]:
```
# Unstacking the data to create heatmap
weekly_data= weekly_data.unstack(level=0)
display(weekly_data)
```

Day	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sun
Time							
00:00:00	13.225806	14.129032	18.096774	21.032258	24.677419	40.258065	36.709
00:15:00	10.967742	13.290323	13.741935	17.645161	19.870968	38.419355	37.129
00:30:00	8.741935	11.967742	14.387097	16.612903	19.096774	33.096774	34.903
00:45:00	7.709677	9.290323	10.967742	14.064516	15.709677	31.483871	31.903
01:00:00	6.935484	7.870968	10.129032	12.354839	15.483871	29.129032	31.322
...	...	...	...	...	...	...	
22:45:00	24.903226	37.741935	48.354839	64.064516	58.096774	50.258065	26.322
23:00:00	22.225806	35.290323	41.258065	58.193548	56.129032	48.000000	21.258
23:15:00	19.645161	28.096774	36.096774	47.516129	48.935484	45.032258	18.870
23:30:00	15.645161	24.516129	28.870968	43.548387	46.612903	46.193548	17.354
23:45:00	15.580645	19.290323	26.870968	36.419355	44.354839	41.419355	13.419

96 rows × 7 columns

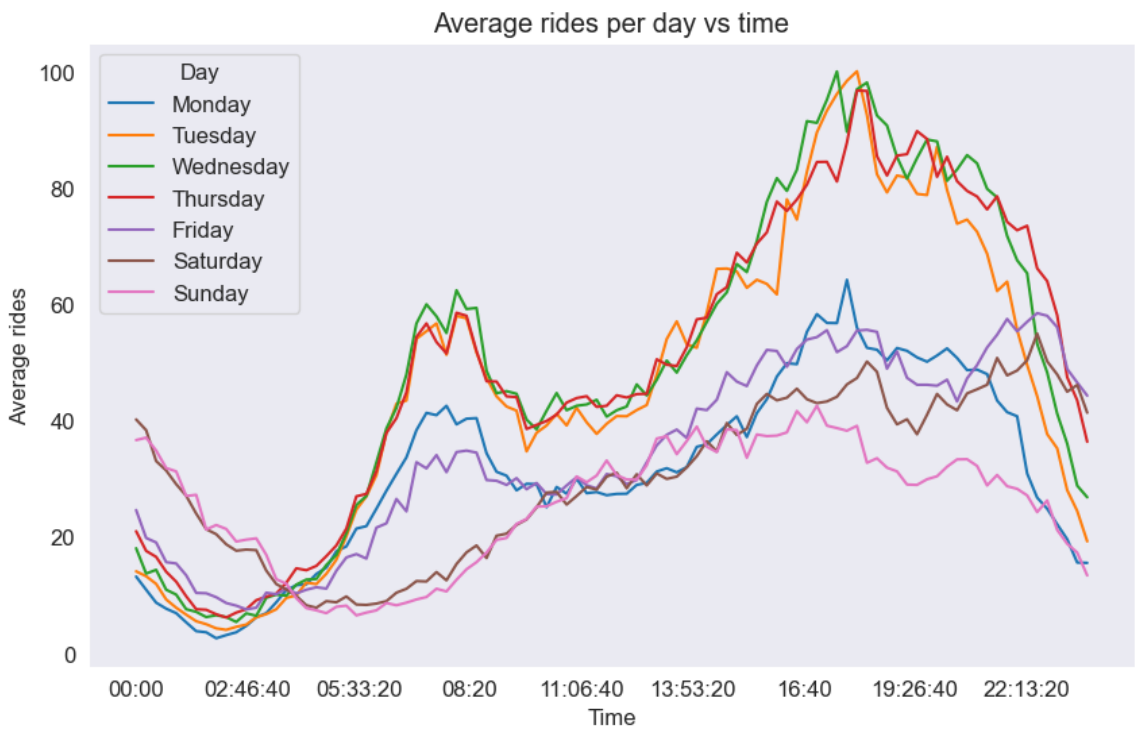
In [22]:
```
plt.figure(figsize=(11,16))
sns.heatmap(weekly_data, cmap='Greens')
plt.title('Heatmap of average rides in time vs. day grid')
```

Out[22]:
```
Text(0.5, 1.0, 'Heatmap of average rides in time vs. day grid')
```



Here's another way to look at it using line graphs.

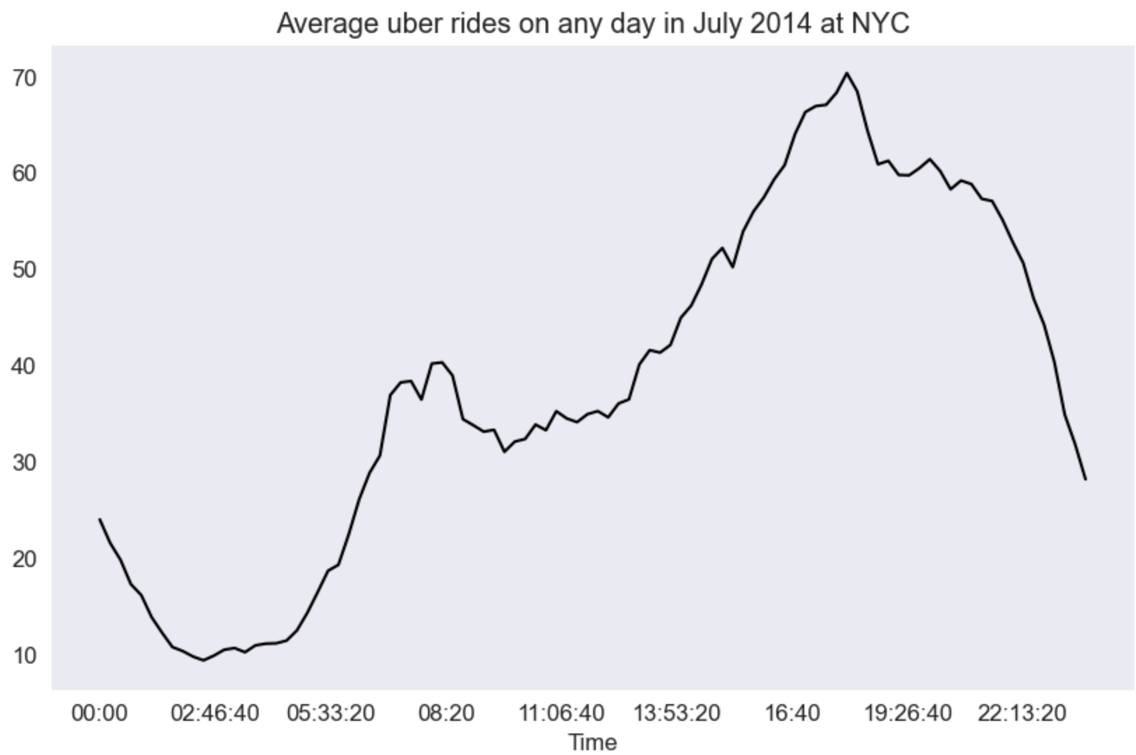
In [23]:
```
plt.figure(figsize=(10,6))
weekly_data.plot(ax=plt.gca())
plt.title('Average rides per day vs time')
plt.ylabel('Average rides')
plt.locator_params(axis='x', nbins=10)
plt.show()
```



We can also plot the average rides on any day as follows.

In [24]:

```
plt.figure(figsize=(10,6))
weekly_data.T.mean().plot(c = 'black')
plt.title('Average uber rides on any day in July 2014 at NYC')
plt.locator_params(axis='x', nbins=10)
plt.show()
```

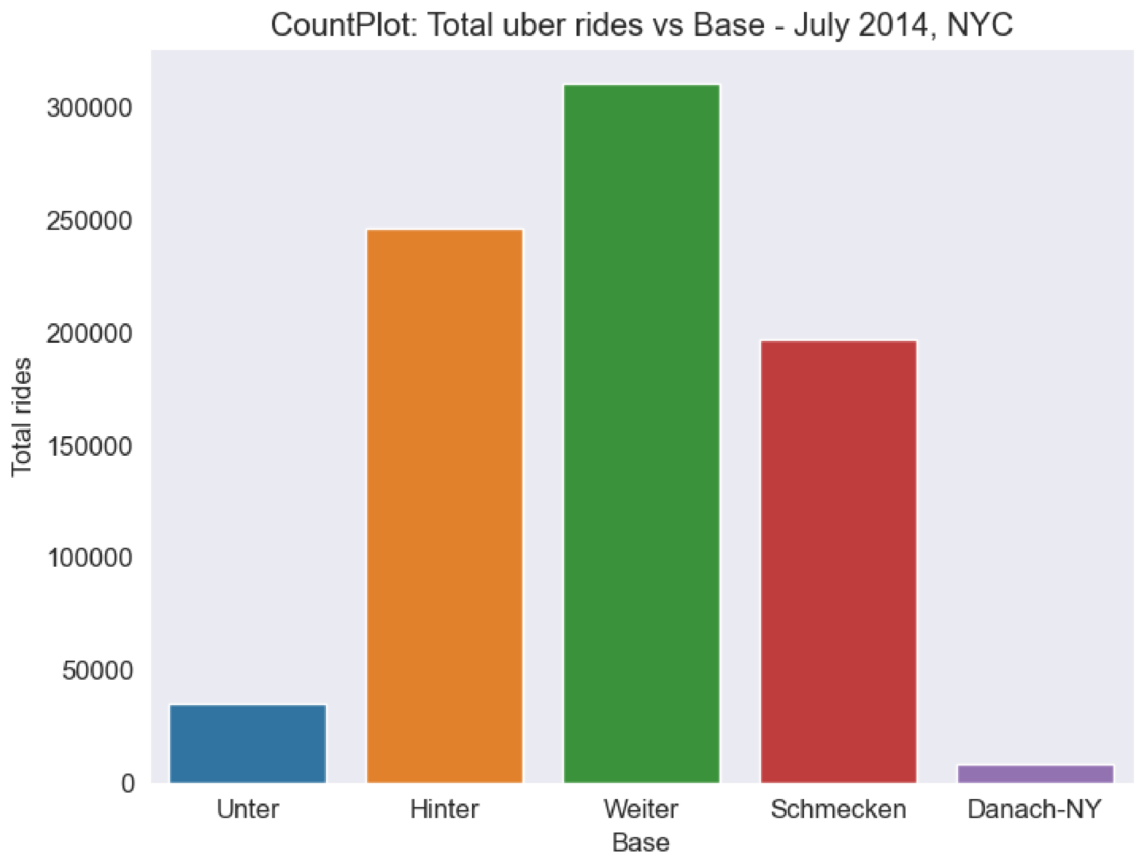


Observation 4: This plot further confirms that the average rides on any given day is lowest around 2 AM and highest in the around 5:30 PM.

4. Let's visualise the relationship between Base and total number of rides in July 2014.

In [25]:
```
# A mapper to map base number with its name
BaseMapper = {'B02512' : 'Unter', 'B02598' : 'Hinter', 'B02617' : 'Weiter
              'B02764' : 'Danach-NY'}
```

In [26]:
```
# Count plot of Base
plt.figure(figsize=(8,6))
sns.set_style("dark")
sns.countplot(x=uber_data['Base'].map(BaseMapper))
plt.ylabel('Total rides')
plt.title('CountPlot: Total uber rides vs Base - July 2014, NYC')
plt.show()
```



Observation 5: The above plot tells us that most uber rides originated from Weiter Base and least from Danach-NY.

5. Now let's make use of latitude and longitude data to see how the uber trips' frequency is distributed across NYC.

We will need some center of city to act as origin and we will plot the rest of the coordinates around it.

For the example given below, we consider the center as Metropolitan Museum in NYC, whose coordinates are `metro_art_coordinates = (40.7794,-73.9632)`.

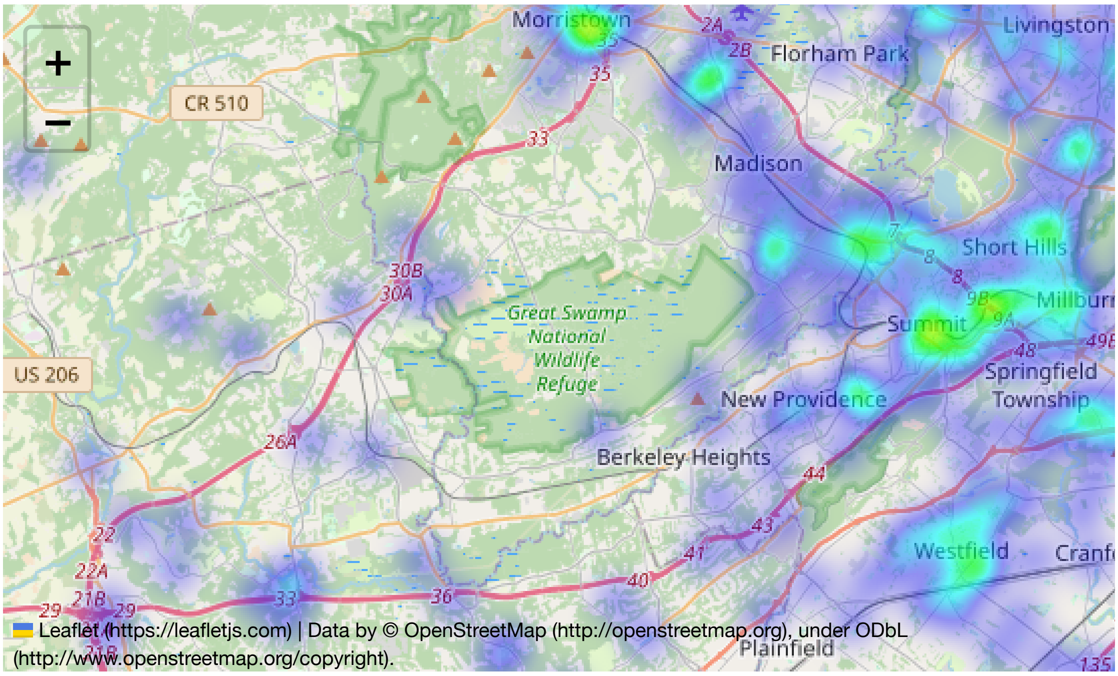
In [27]:
```
metro_art_coordinates = (40.7794,-73.9632)
```

In [28]:
```python
# Initilize the map around NYC and set the zoom level to 10
uber_map = folium.Map(location=metro_art_coordinates, zoom_start=10)

# Lets mark MM on the map
folium.Marker(metro_art_coordinates, popup = "Metropolitan Museum").add_t

# Convert to numpy array and plot it
Lat_Lon = uber_data[['Lat','Lon']].to_numpy()
folium.plugins.HeatMap(Lat_Lon,radius=10).add_to(uber_map)

# Displaying the map
display(uber_map)
```



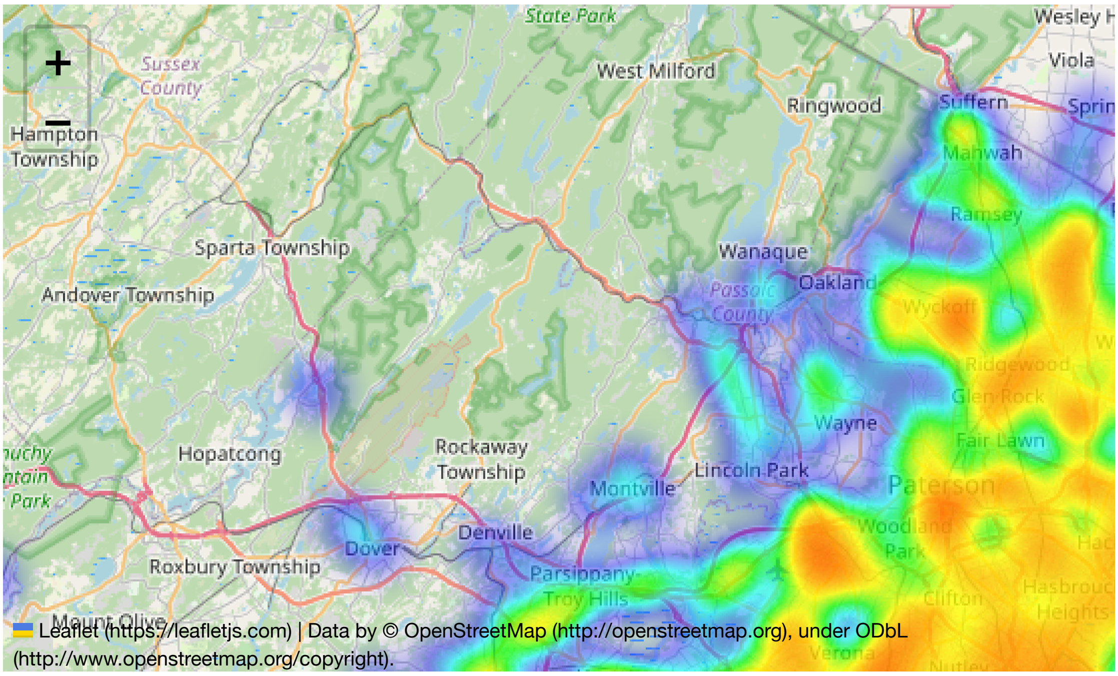
We can observe that the boundaries and the intensity distribution of the heatmap on the map is not clear. To fix this, we reduce the intensity of each point on the heatmap by using a weight of 0.5 (by default it is 1).

In [29]:
```python
uber_data['Weight'] = 0.5

Lat_Lon = uber_data[['Lat','Lon','Weight']].to_numpy()

# Plotting
uber_map = folium.Map(metro_art_coordinates, zoom_start=10)
folium.Marker(metro_art_coordinates, popup = "Metropolitan Museum").add_t
folium.plugins.HeatMap(Lat_Lon, radius=15).add_to(uber_map)

display(uber_map)
```



6. Let's visualize the timed data of trips, as a time lapse on a map!

In [30]:
```
# Create a copy of the data
map_data = uber_data.copy()

# Use a smaller weight
map_data['Weight'] = 0.4

# Generate samples for each timestamp in "BinnedHour" (these are the poin
map_data = map_data.groupby("BinnedHour").apply(lambda x: x[['Lat','Lon',
                                                 .sample(int(len(x)/3)).to
```

In [31]:
```
display(map_data)
```

```
BinnedHour
2014-07-01 00:00:00    [[40.7471, -73.9929, 0.4], [40.7133, -74.04, 0...
2014-07-01 00:15:00    [[40.7215, -73.9886, 0.4], [40.708, -73.9543, ...
2014-07-01 00:30:00    [[40.6483, -73.7825, 0.4], [40.6517, -73.949, ...
2014-07-01 00:45:00    [[40.8116, -73.9446, 0.4], [40.7483, -73.9568,...
2014-07-01 01:00:00    [[40.6952, -74.1787, 0.4], [40.7683, -73.9847,...
                                              ...
2014-07-31 22:45:00    [[40.8562, -73.8889, 0.4], [40.7591, -73.983, ...
2014-07-31 23:00:00    [[40.7844, -73.9492, 0.4], [40.6775, -74.0162,...
2014-07-31 23:15:00    [[40.7615, -73.9868, 0.4], [40.6707, -73.9878,...
2014-07-31 23:30:00    [[40.6878, -74.1821, 0.4], [40.729, -74.001, 0...
2014-07-31 23:45:00    [[40.7319, -74.0037, 0.4], [40.6447, -73.7822,...
Length: 2976, dtype: object
```

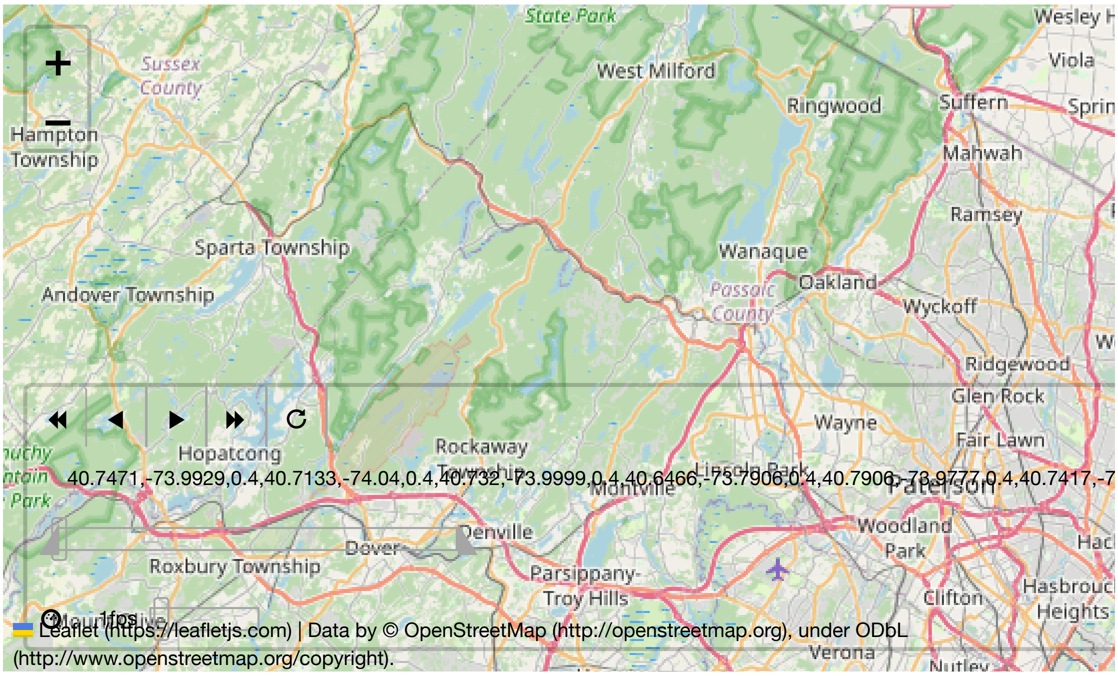
In [36]:
```
# The index to be passed on to heatmapwithtime needs to be a time series
data_hour_index = [x.strftime("%m%d%Y, %H:%M:%S") for x in map_data.index

# Convert to list to feed it to heatmapwithtime
date_hour_data = map_data.tolist()

# Initialize map
uber_map = folium.Map(location=metro_art_coordinates, zoom_start=10)
```

In [37]:
```
# Plotting
hm = folium.plugins.HeatMapWithTime(date_hour_data, index=date_hour_data)

# Add heatmap to folium map (uber_map)
hm.add_to(uber_map)
display(uber_map)
```



7. Finally, let's make one hypothesis and test if it is true by visualizing the data for that case.

Hypothesis: In early morning, weekends have more rides. The reasoning is - People often go out at night during the weekends.

In [38]:
```
weekends = weekly_data[['Saturday','Sunday']]
weekdays = weekly_data.drop(['Saturday','Sunday'], axis=1)
```

In [39]:
```
weekends = weekends.mean(axis=1)
weekdays = weekdays.mean(axis=1)

display(weekends)
display(weekdays)
```

```
Time
00:00:00    38.483871
00:15:00    37.774194
00:30:00    34.000000
00:45:00    31.693548
01:00:00    30.225806
              ...
22:45:00    38.290323
23:00:00    34.629032
23:15:00    31.951613
23:30:00    31.774194
23:45:00    27.419355
Length: 96, dtype: float64
```

```
Time
00:00:00    18.232258
00:15:00    15.103226
00:30:00    14.161290
00:45:00    11.548387
01:00:00    10.554839
              ...
22:45:00    46.632258
23:00:00    42.619355
23:15:00    36.058065
23:30:00    31.838710
23:45:00    28.503226
Length: 96, dtype: float64
```

In [40]:

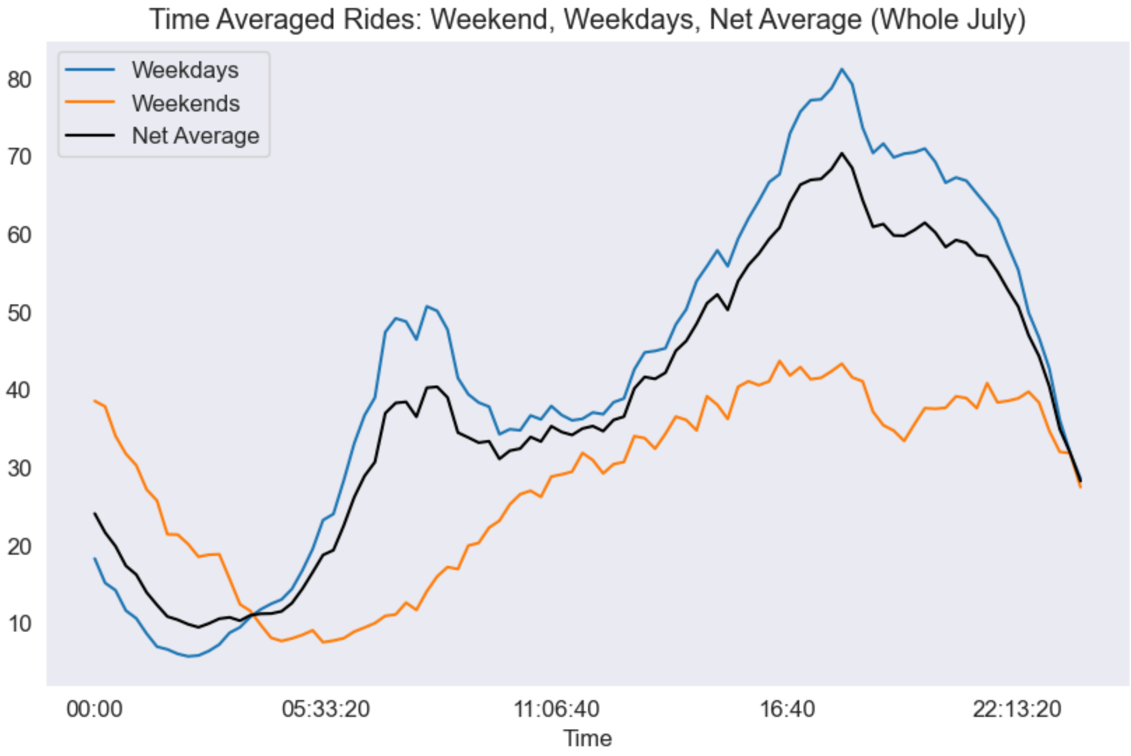
```
weekdays_weekends = pd.concat([weekdays,weekends],axis=1)
weekdays_weekends.columns = ['Weekdays','Weekends']
display(weekdays_weekends)
```

	Weekdays	Weekends
Time		
00:00:00	18.232258	38.483871
00:15:00	15.103226	37.774194
00:30:00	14.161290	34.000000
00:45:00	11.548387	31.693548
01:00:00	10.554839	30.225806
...	...	...
22:45:00	46.632258	38.290323
23:00:00	42.619355	34.629032
23:15:00	36.058065	31.951613
23:30:00	31.838710	31.774194
23:45:00	28.503226	27.419355

96 rows × 2 columns

In [42]:

```
plt.figure(figsize=(10,6))
weekdays_weekends.plot(ax=plt.gca())
weekly_data.T.mean().plot(ax=plt.gca(),c = 'black',label='Net Average')
plt.title('Time Averaged Rides: Weekend, Weekdays, Net Average (Whole Jul
plt.legend()
plt.show()
```



Observation 6: The plot clearly shows - In early morning, weekends have more rides. This makes sense as people often go out at night during the weekends.

The number of rides around 8 AM is less on weekends, but more on weekdays as it is usually the time when people goto work. Also, in the weekends, there is a surge in the number of evening rides as people return from work.

With this, we finish our analysis of our Uber Pickups NYC Data.
