# New York City Crime analysis

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# 1. Project Overview

With the number of crime incidents increasing daily, we thought of analyzing NYC crime data and find out whether the below factors have any influence on perpetrator

- Weather (Gathered last 10 years data from Open data)

  Data Source: http://w2.weather.gov/climate/index.php?wfo=okx

- Stock Market

  Data Source: http://www.macrotrends.net/1358/dow-jones-industrial-average-last-10-years

- Mean Household Income (Collected last 10 years of population in NYC on various zip code and there median and mean Income)

  Data Source: https://www.psc.isr.umich.edu/dis/census/Features/tract2zip/

We also took this opportunity to find number of crime incidents near frequently visited places

- Compiled the list of safe and unsafe hotels in New York city

  Data Source: Trip Advisor http://times.cs.uiuc.edu/~wang296/Data/LARA/TripAdvisor/TripAdvisorJson.tar.bz2

- Compiled the list of safe and unsafe Bars in New York city

  Data Source: https://data.ny.gov/Economic-Development/Liquor-Authority-Quarterly-List-of-Active-Licenses/hrvs-fxs2/data

# 2. Crime Dataset

The Crime dataset has 24 columns as shown below.

---

*CMPLNT_NUM CMPLNT_FR_DT CMPLNT_FR_TM CMPLNT_TO_DT*
*CMPLNT_TO_TM RPT_DT KY_CD OFNS_DESC PD_CD PD_DESC*
*CRM_ATPT_CPTD_CD LAW_CAT_CD JURIS_DESC BORO_NM ADDR_PCT_CD*
*LOC_OF_OCCUR_DESC PREM_TYP_DESC PARKS_NM HADEVELOPT X_COORD_CD*
*Y_COORD_CD Latitude Longitude Lat_Lon*

---

We started by analyzing importance of each field. As, we did not find good metadata for the data.

- After analyzing the data, we found out there are three major types of crime

  Code: crime_df.select("LAW_CAT_CD").distinct().show()

  Results: *Felony, Misdemeanor, Violation*

- We also saw how many unique OFNS_Description are there in dataset

  Code: crime_df.select("OFNS_DESC").distinct().count()

  Result: We found out 71 unique description.

- We wanted to plot data in map based on zip code, but zip code was not present in dataset. So, we extracted zip code from latitude and longitude using google reverse geocoding API. This was the most challenging part of the project. As we ran out of limitation on calling the API and we had to gather the data for almost a week to get complete data (P.S we upgraded our google account to premium account to get the data)

```
import requests
from pyspark.sql.types import StringType

def get_pincode(lat, lng):
 try:
        sensor = 'true'
        base = "https://maps.googleapis.com/maps/api/geocode/json?key= &"
        params = "latlng={lat},{lon}&sensor={sen}".format(lat=lat,lon=lng,sen=sensor)
        url = "{base}{params}".format(base=base, params=params)
        response = requests.get(url).json()
        results = response["results"]
        address_components = list(map(lambda x: x["address_components"], results))
        flatten = [item for sublist in address_components for item in sublist]
        postal_objects = list(filter(lambda x: x["types"] == ["postal_code"], flatten))
        postal_codes = list(map(lambda x: x["long_name"], postal_objects))
        return str(postal_codes[0]);
 except Exception as e:
   return None


udf_getZip = udf(get_pincode, StringType())
```

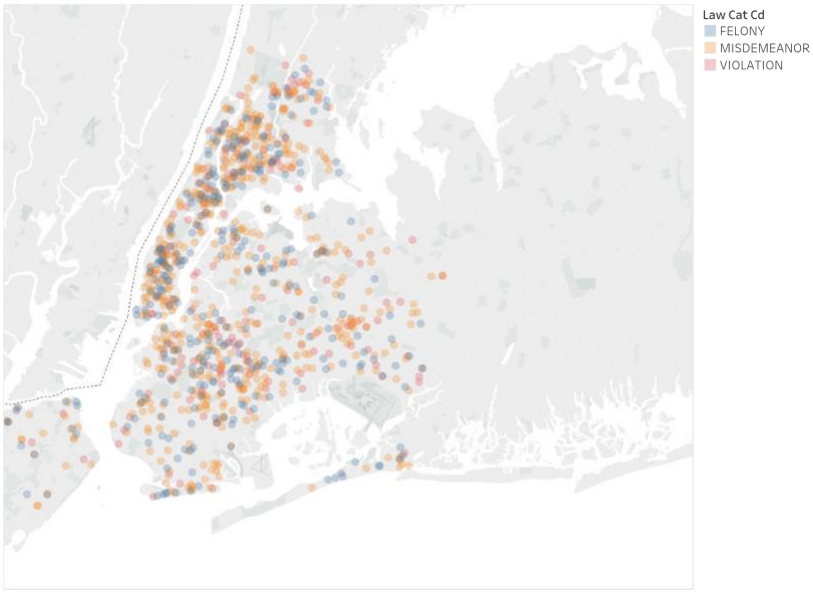
*Figure 1 Code Snippet to get zipcode form Lat,Lon*

We then visualized the crime data we had and gathered some meaningful insights from it. We also normalized the date and time to visualize data as shown below.

```
# Date conversion
from pyspark.sql.functions import udf

crime_df_date = crime_df.select("CMPLNT_FR_DT", "CMPLNT_FR_TM", "OFNS_DESC", "LAW_CAT_CD",
"Latitude", "Longitude", "PD_DESC")

def crime_date_convert(date, time):
 try:
        k = date.split("/")
        full_date = "-".join(k[2:] + k[1:2] + k[0:1])
        full_date = full_date + " " + time.split(":")[0]
        return full_date
 except:
   return "2021-01-01 00"

udf_crime_date_convert = udf(crime_date_convert, StringType())

with_crime_date_conversion = crime_df_date.withColumn("normalized_date",
udf_crime_date_convert("CMPLNT_FR_DT", "CMPLNT_FR_TM")).select("normalized_date",
"OFNS_DESC", "LAW_CAT_CD", "Latitude", "Longitude", "PD_DESC")
```

# 3. Visualizing crime data

## 3.1 Crimes week visualization for the Week of June 12, 2016




**Map based on Longitude and Latitude.  Color shows details about Law Cat Cd.**

We visualized the three-different type of crime on map for the week of June 12, 2016 and tried understanding what are the locations which has most number of Incidents

## 3.2 Crimes in NYC

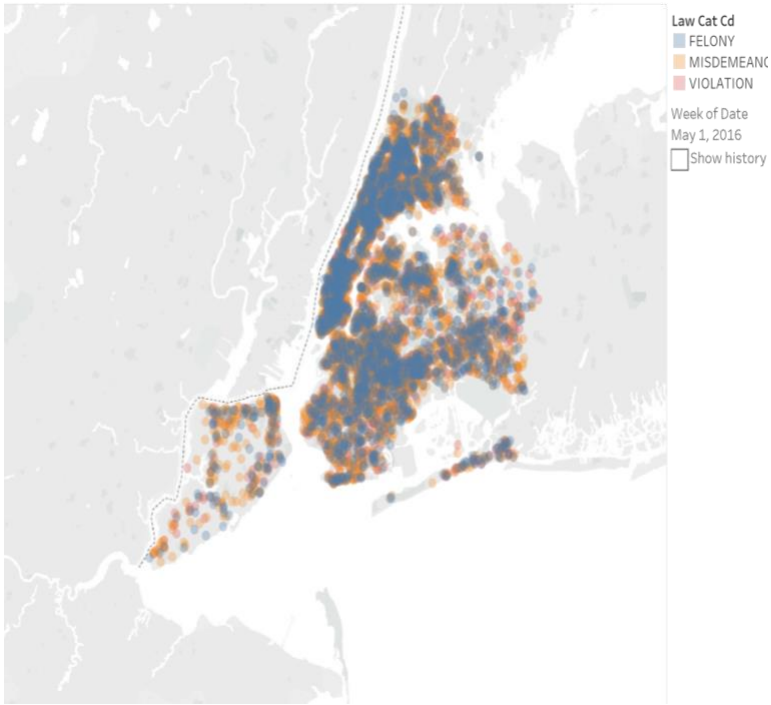



*Figure 2 Crime in NYC for Last 10 years*

We also tried to see that over a period of time which type of crime occurs at a particular location

## 3.3 Per Hour Average Crime count

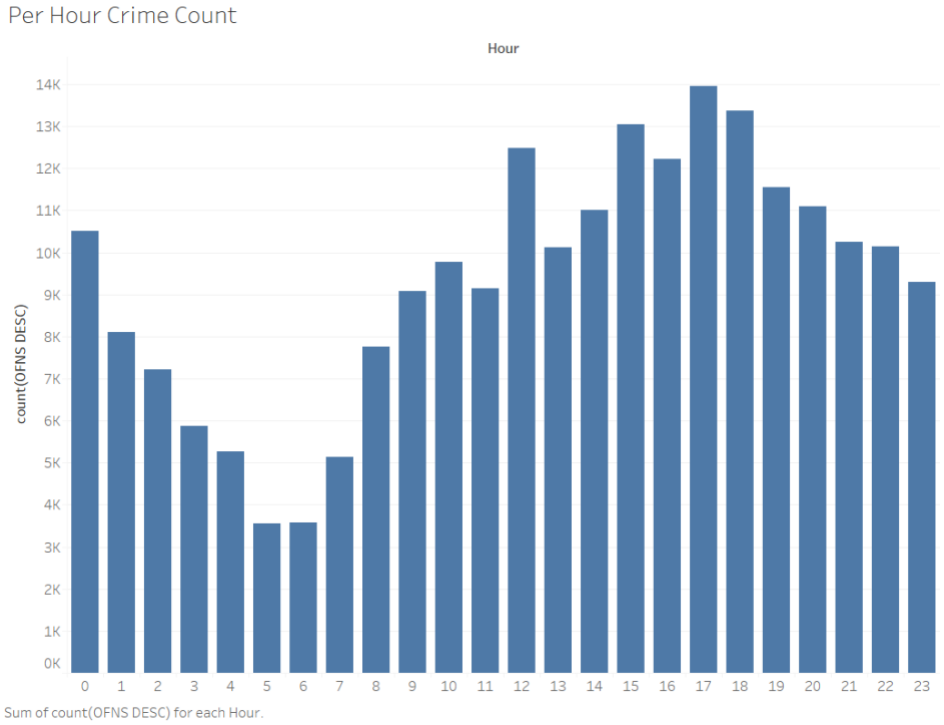



*Figure 3 Average Crime Count every hour*

We then tried to see that hour in the day has any co-relation with crime. The finding was interesting, we saw that crime was maximum around 06:00'clock in the evening when people return to their home.

## 3.4 Month Vs Crime

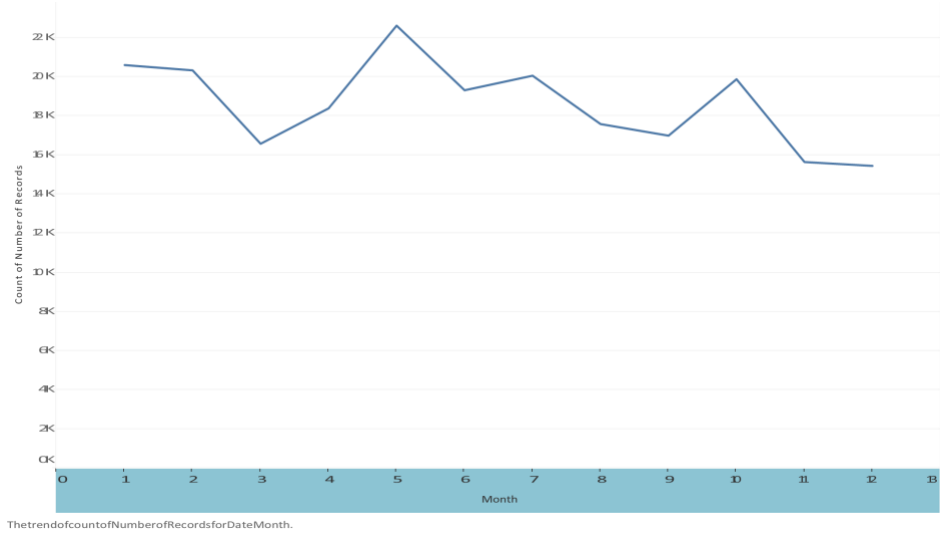
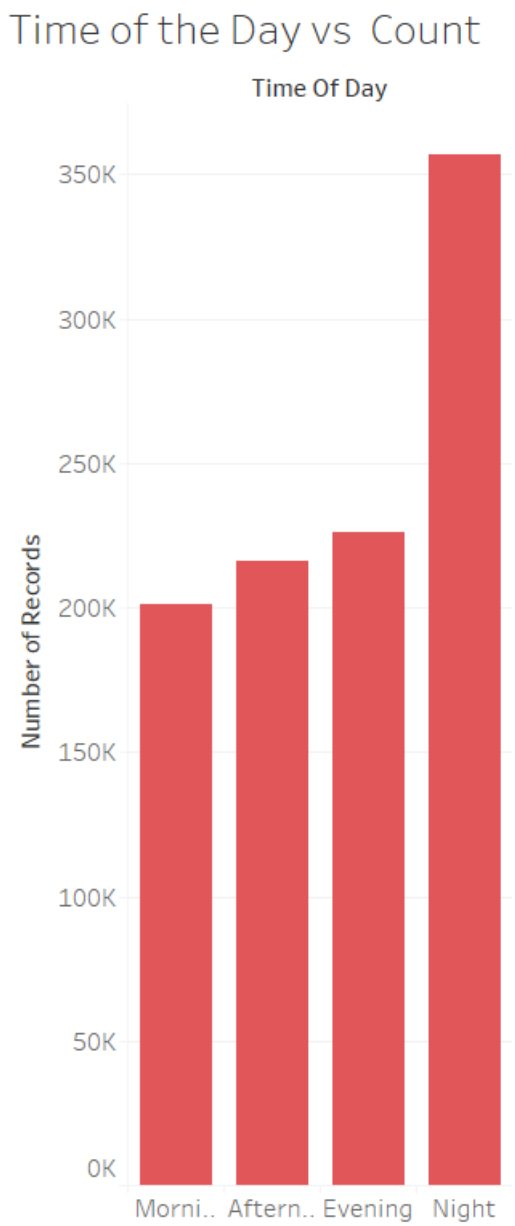


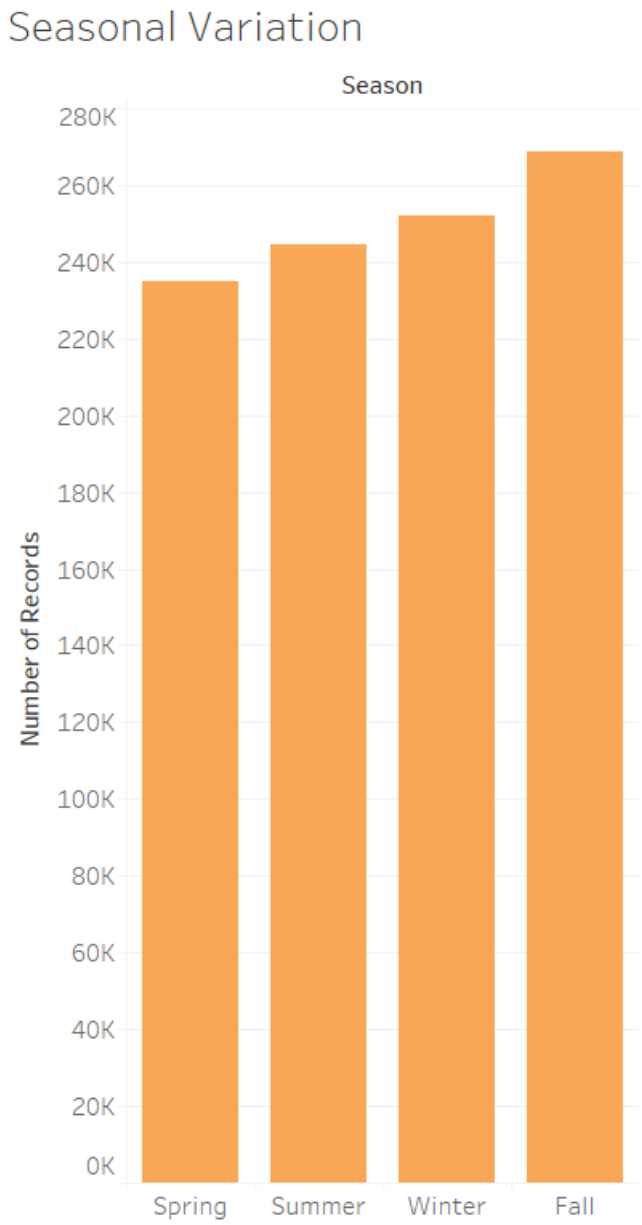

*Figure 4 Month and Crime*

We then tried to see if crime depends on the month of the year. It was interesting to see that the crime drastically dropped in month of December. This correlation was difficult to digest as the tourist come in this part of the year. May be the chilly weather stops the perpetuator.

## 3.4 Crime at hour of day, season of the year




Sum of Number of Records for each Time Of Day.




Sum of Number of Records for each Season.

We then plotted the graph to see if time of day or season has impact on crime. The results where as expected, the crime was more at Night time and was lowest in morning.

The crime was also highest in fall, which was interesting correlation.

# 4. Correlation of Crime with weather

We then gathered weathered data for NYC and imported it in spark. We got hourly weather data for last 10 years and it had 90 columns as shown below.

---

*'STATION', 'STATION_NAME', 'ELEVATION', 'LATITUDE', 'LONGITUDE', 'DATE', 'REPORTTPYE', 'HOURLYSKYCONDITIONS', 'HOURLYVISIBILITY', 'HOURLYPRSENTWEATHERTYPE', 'HOURLYDRYBULBTEMPF', 'HOURLYDRYBULBTEMPC', 'HOURLYWETBULBTEMPF', 'HOURLYWETBULBTEMPC', 'HOURLYDewPointTempF', 'HOURLYDewPointTempC', 'HOURLYRelativeHumidity', 'HOURLYWindSpeed', 'HOURLYWindDirection', 'HOURLYWindGustSpeed', 'HOURLYStationPressure', 'HOURLYPressureTendency', 'HOURLYPressureChange', 'HOURLYSeaLevelPressure', 'HOURLYPrecip', 'HOURLYAltimeterSetting', 'DAILYMaximumDryBulbTemp', 'DAILYMinimumDryBulbTemp', 'DAILYAverageDryBulbTemp', 'DAILYDeptFromNormalAverageTemp', 'DAILYAverageRelativeHumidity', 'DAILYAverageDewPointTemp', 'DAILYAverageWetBulbTemp', 'DAILYHeatingDegreeDays', 'DAILYCoolingDegreeDays', 'DAILYSunrise', 'DAILYSunset', 'DAILYWeather', 'DAILYPrecip', 'DAILYSnowfall', 'DAILYSnowDepth', 'DAILYAverageStationPressure', 'DAILYAverageSeaLevelPressure', 'DAILYAverageWindSpeed', 'DAILYPeakWindSpeed', 'PeakWindDirection', 'DAILYSustainedWindSpeed', 'DAILYSustainedWindDirection', 'MonthlyMaximumTemp', 'MonthlyMinimumTemp', 'MonthlyMeanTemp', 'MonthlyAverageRH', 'MonthlyDewpointTemp', 'MonthlyWetBulbTemp', 'MonthlyAvgHeatingDegreeDays', 'MonthlyAvgCoolingDegreeDays', 'MonthlyStationPressure', 'MonthlySeaLevelPressure', 'MonthlyAverageWindSpeed', 'MonthlyTotalSnowfall', 'MonthlyDeptFromNormalMaximumTemp', 'MonthlyDeptFromNormalMinimumTemp', 'MonthlyDeptFromNormalAverageTemp', 'MonthlyDeptFromNormalPrecip', 'MonthlyTotalLiquidPrecip', 'MonthlyGreatestPrecip', 'MonthlyGreatestPrecipDate', 'MonthlyGreatestSnowfall', 'MonthlyGreatestSnowfallDate', 'MonthlyGreatestSnowDepth', 'MonthlyGreatestSnowDepthDate', 'MonthlyDaysWithGT90Temp', 'MonthlyDaysWithLT32Temp', 'MonthlyDaysWithGT32Temp', 'MonthlyDaysWithLT0Temp', 'MonthlyDaysWithGT001Precip', 'MonthlyDaysWithGT010Precip', 'MonthlyDaysWithGT1Snow', 'MonthlyMaxSeaLevelPressureValue', 'MonthlyMaxSeaLevelPressureDate', 'MonthlyMaxSeaLevelPressureTime', 'MonthlyMinSeaLevelPressureValue', 'MonthlyMinSeaLevelPressureDate', 'MonthlyMinSeaLevelPressureTime', 'MonthlyTotalHeatingDegreeDays', 'MonthlyTotalCoolingDegreeDays', 'MonthlyDeptFromNormalHeatingDD', 'MonthlyDeptFromNormalCoolingDD', 'MonthlyTotalSeasonToDateHeatingDD', 'MonthlyTotalSeasonToDateCoolingDD*

---

We were perplexed by the temperature value in this column and then finally decided to go with HourlyBulbTemperature to co-relate with crime. We normalized the dates and then cleaned the dataset,

Finally, we merged the crime and weather data set based on hour and day and gathered some insights as discussed below.

## 4.1 Crime Count vs Temperature in Degree Celsius

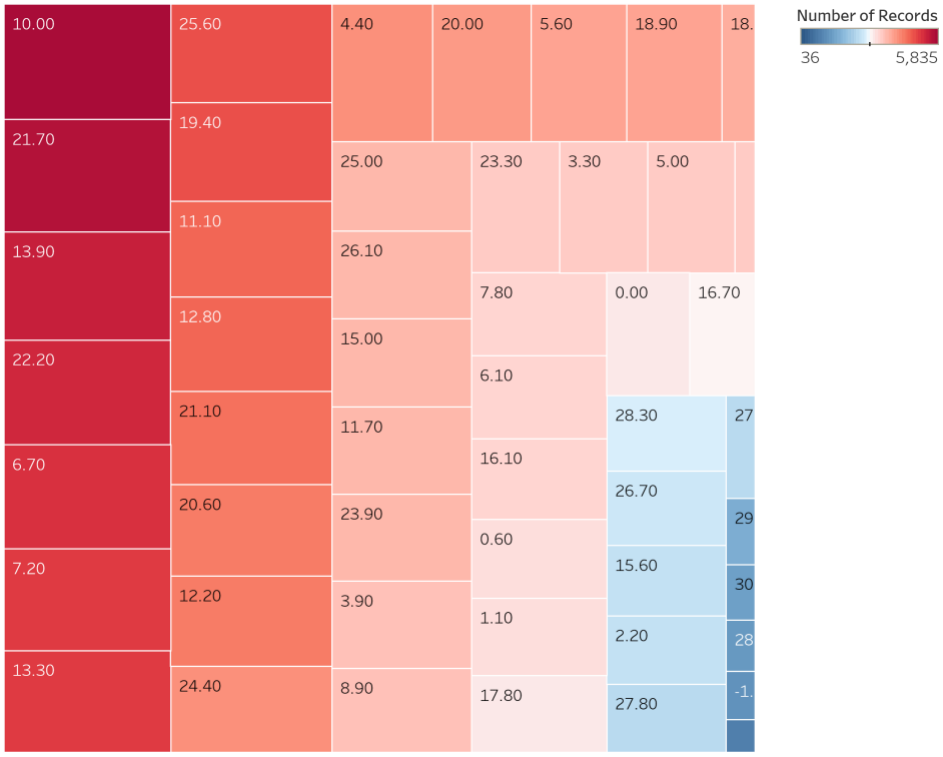



*Figure 5 Temperature and Crime count*

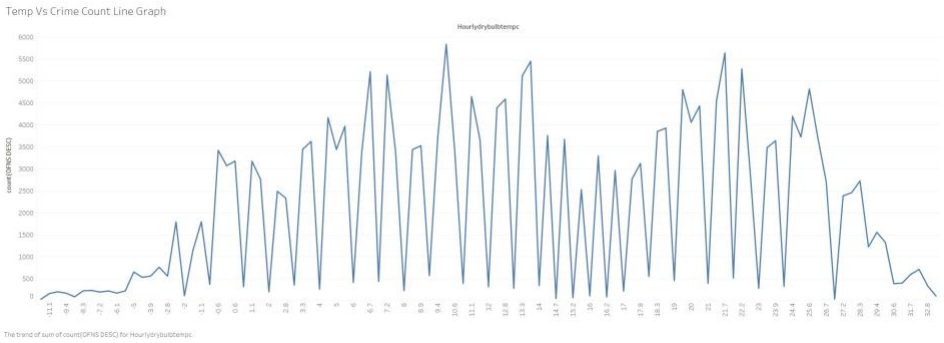



*Figure 6 Temperature and Crime count for 2016*

We started plotting crime count based on temperature and saw the crime was highest at 10 degrees and lowest at -1. This correlation was kind of expected, as we expect perpetrator to commit less crime on a very chilly day.

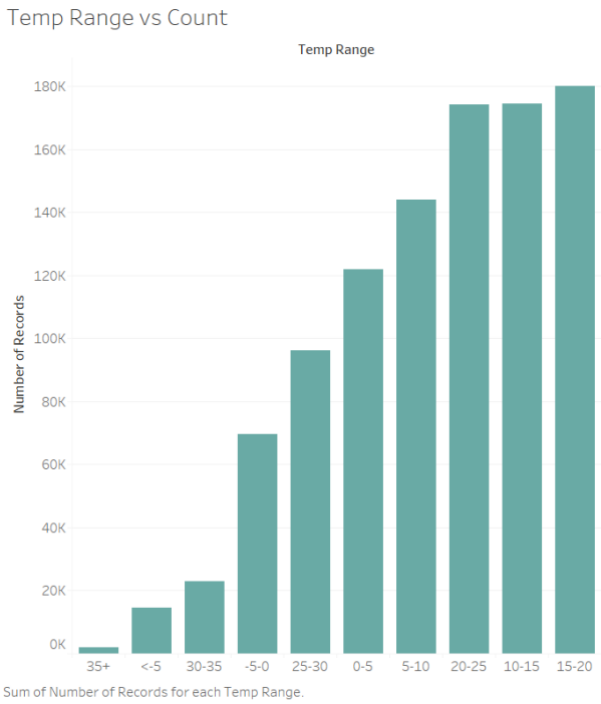



*Figure 7 Range of Temperature and Crime*

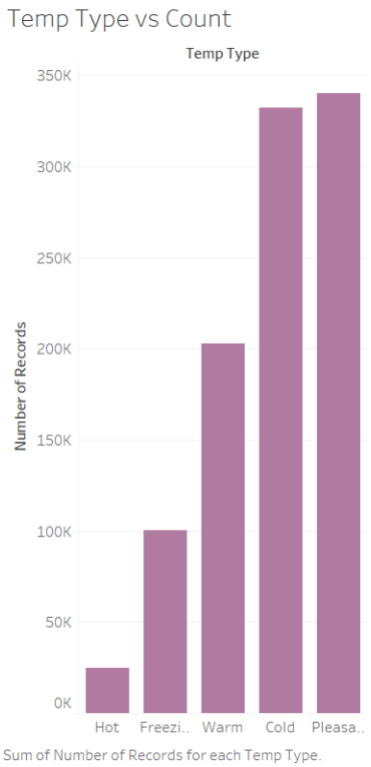
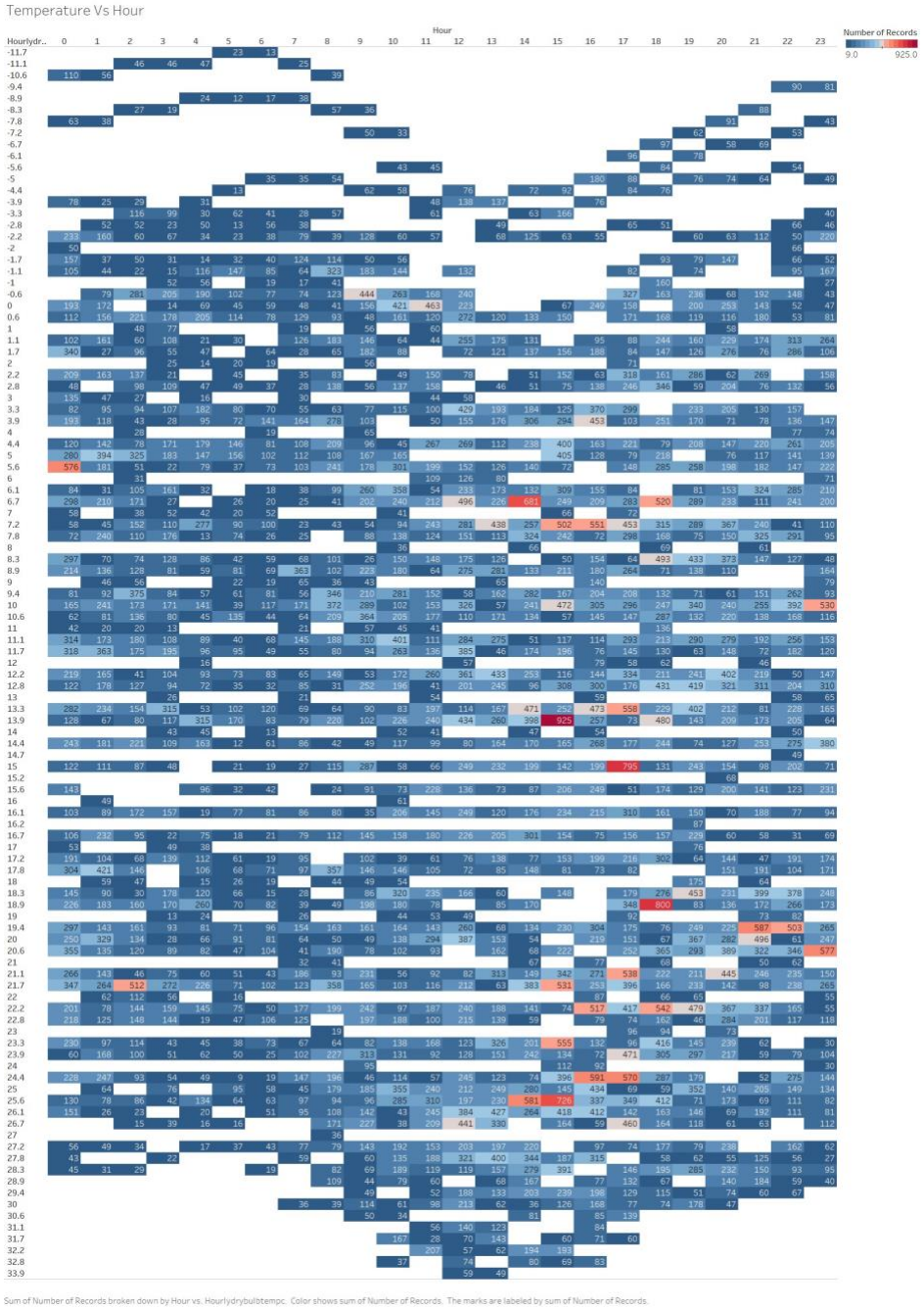



*Figure 8 Temperature type and Crime*

We visualized the crime was maximum in pleasant temperature and was minimum In hot temperature.

## 4.2 Number of Crimes Vs Temperature vs Hour of the Day




We then plotted a graph from temperature and time of the day to see what is the most favorable condition and find out that if it is 03:00pm and it is 20 degrees Celsius the chances of you being a victim are very high. Which was an interesting finding.

# 5. Correlation of Crime with population and Median Income

We also download the population and median income dataset and cleaned it. We then merged the census data based on zip code and started analyzing crime based on population and wealth.

## 5.1 Crime in different areas of NYC

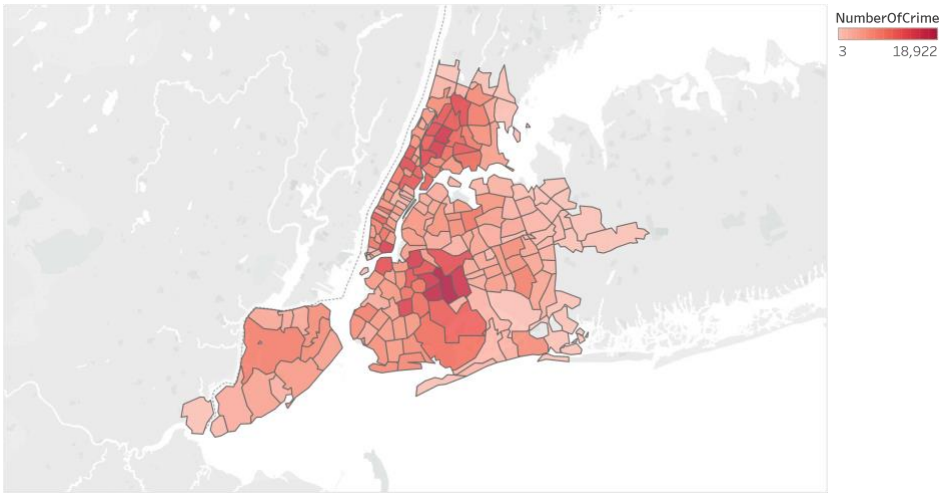
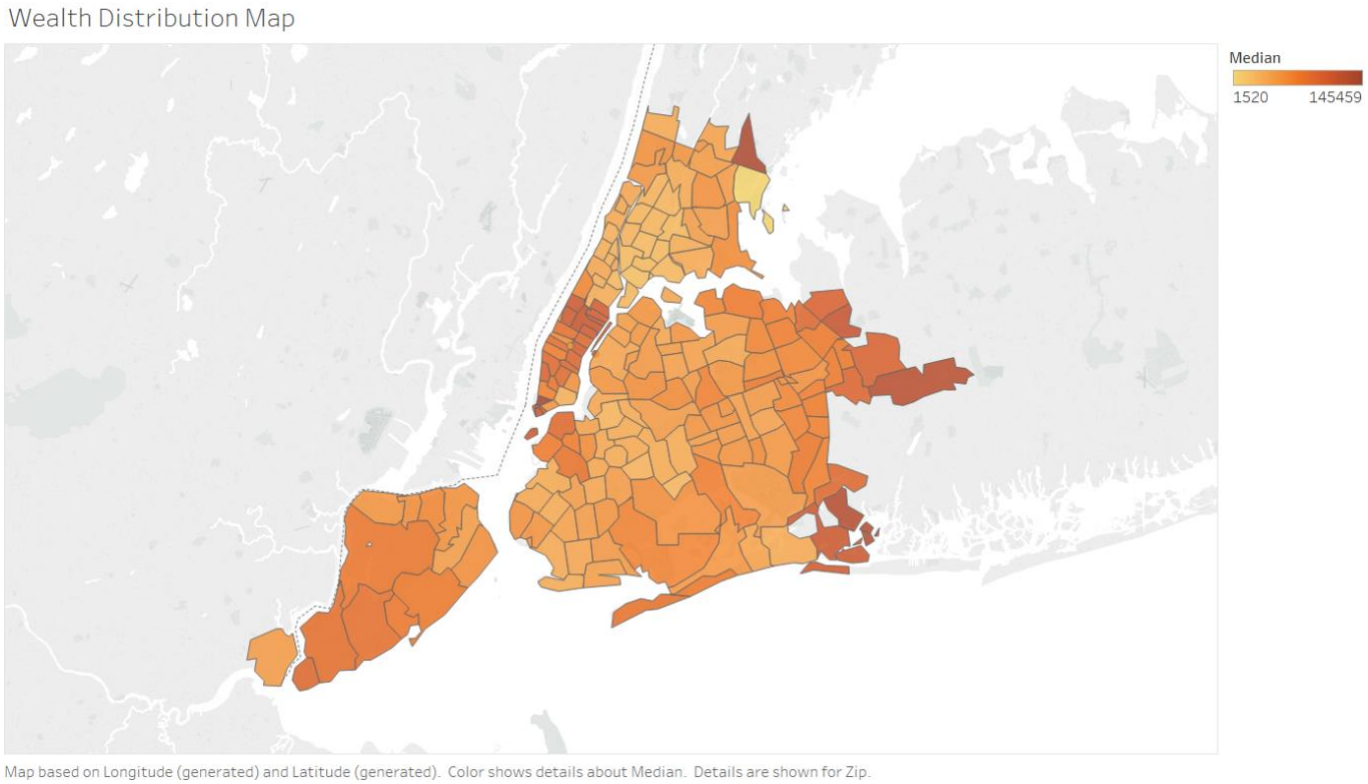



*Figure 9 Map based on Longitude (generated) and Latitude (generated). Color shows sum of NumberOfCrime. Details are shown for Zipcode.*

We visualized that crime was more in some parts of Queens and Upper Manhattan. We were interested to see what is the population in that part and what is the median income there.

## 5.2 Median Income in different areas of NYC




The results showed that where the crime was more the income was less. This was kind of expexted.

## 5.3 Population in different areas of NYC

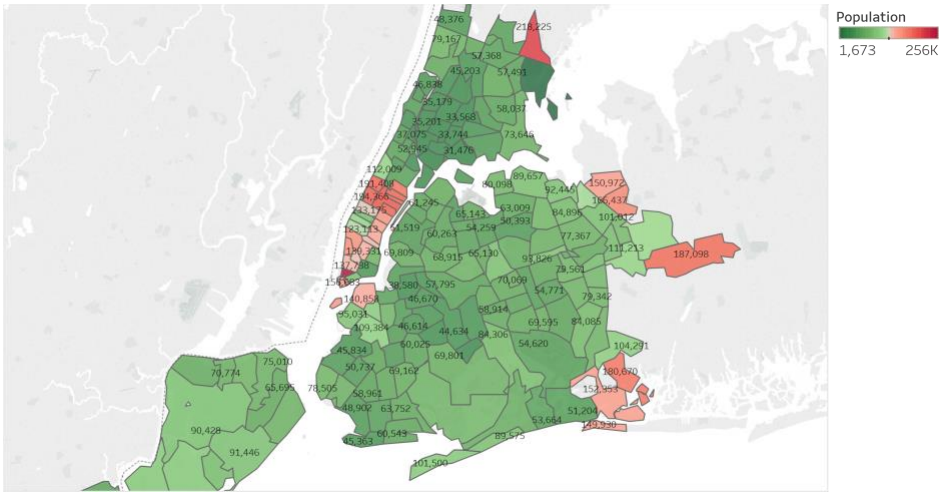
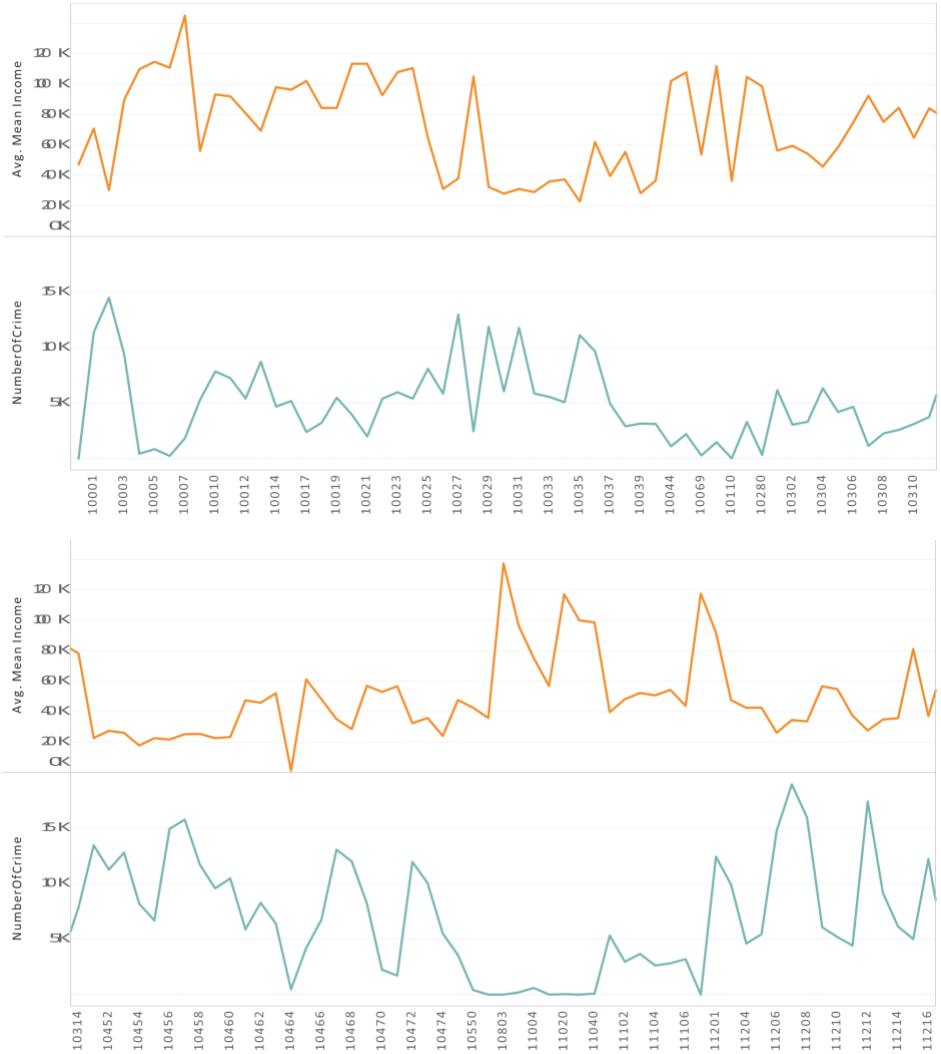



*Figure 10 Map based on Longitude (generated) and Latitude (generated). Color shows sum of Population. The marks are labeled by sum of Population. Details are shown for Zipcode.*

The population had a minor impact on crime. The conclusion we derived was that with low population the crime gradually increases which can be seen from the above map.

## 5.4 Mean Income Vs Crime




We then plotted graph to visualize the crime count and median income. Crime is clearly inversely proportional to income

# 6. Correlation of Crime with Markets

We then downloaded the stock market data for last 10 years. We then cleaned the dataset and normalized the date of the data and merged ii with crime data.

## 6.1 Decrease in Crime with Increase in Dow Jones Index

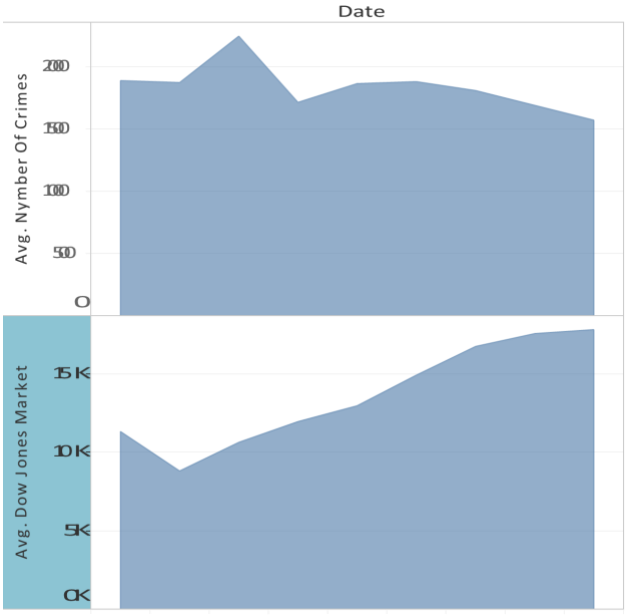



*Figure 11 Average of Count and average of Value for each Date Year.*

We saw that as the Dow zone index increased the crime has decreased. But this can be a coincidence as well, It is a possibility that crime has decreased over year due to strict law enforcement.

## 6.2 Impact of 2008 recession on crime

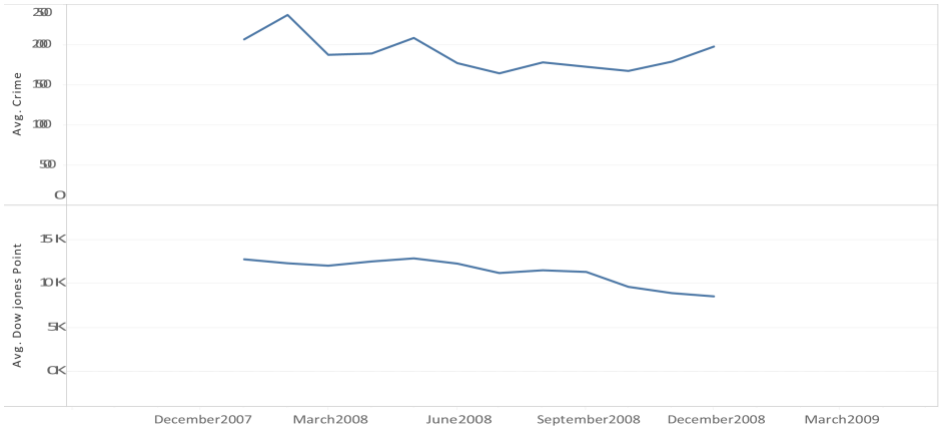



*Figure 12 The trends of average of Count and average of Value for Date Month. The data is filtered on Date Year, which keeps 2008.*

We then wondered that when the market crashed in 2008 did it impact crime? The answer to this is visible in the graph above. We can clearly see that there was an increase in crime when the market crashed. So, there is for sure some correlation between stock market and crime.

# 7. Recommendation based on Crime

When a person travels to a new city his biggest concern is wherever he is booking the hotel, the area should be safe. We downloaded the trip advisor dataset and filtered hotels of New York and then extracted zip code of each hotel and merged the hotel dataset with crime dataset based on zip code. We then visualized few hotels and crime near them.

## 7.1 Hotels in NYC

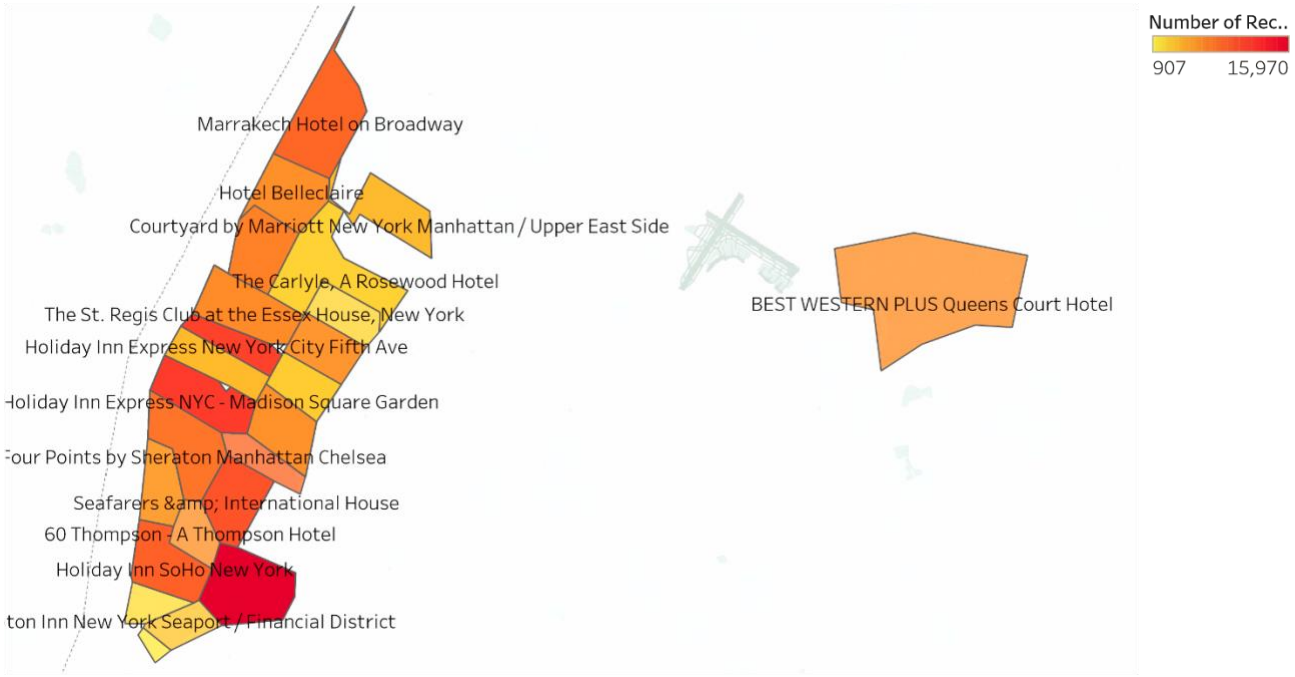



*Figure 13 Map based on Longitude (generated) and Latitude (generated).*

The above map gives some valuable insights about the hotels one should book based on location.

We also came up with top 10 and bottom 10 hotels based on location

| Hotel Name | Number of reported Incidents near them |
|---|---|
| **Club Quarters Downtown** | 1981 |
| **Millenium Hilton** | 4004 |
| **254 East Vacation** | 4636 |
| **Loews Regency Hotel** | 4636 |
| **The Carlyle, A Rosewood Hotel** | 4636 |
| **The Helmsley Carlton House** | 4636 |
| **The Bentley Hotel** | 5018 |
| **Dylan Hotel** | 5372 |
| **Helmsley Middletowne Hotel** | 5372 |
| **Hilton Manhattan East** | 5372 |
| **New York Marriott East Side** | 5372 |
| **Roger Smith Hotel** | 5372 |
| **The Alex Hotel** | 5372 |
| **The New York Helmsley** | 5372 |
| **The Roosevelt Hotel** | 5372 |

Safe hotels in NYC

| Hotels | Number of Incidents Near them |
|---|---|
| **Chelsea Star Hotel** | 24539 |
| **Comfort Inn Manhattan** | 24539 |
| **Herald Square Hotel** | 24539 |
| **Holiday Inn Express NYC - Madison Square Garden** | 24539 |
| **Hotel Pennsylvania New York** | 24539 |
| **Hotel Stanford** | 24539 |
| **La Quinta Inn Manhattan** | 24539 |
| **Radisson Martinique on Broadway** | 24539 |
| **Wingate by Wyndham Manhattan Midtown** | 24539 |
| **nyma, the New York Manhattan Hotel** | 24539 |
| **Hotel on Rivington** | 33605 |
| **Off Soho Suites** | 33605 |
| **Windsor Hotel** | 33605 |

Not so Safe hotels in NYC

## 7.2 Bars in NYC

We then downloaded the bar license dataset, cleaned it and merged it with crime data set to come out with list of safe and not so safe bars.

| Bars | Crime Count |
|---|---|
| **111 AGAM CORPORATION, 10704** | 1 |
| **1132 CONVENIENCE CORP, 10704** | 1 |
| **1160 YONKERS AVE FOOD CORP, 10704** | 1 |
| **115 WOLFS LANE RESTAURANT CORP, 10803** | 6 |
| **2016 NEW HOPE GROCERY CORP, 10705** | 19 |
| **2020 YONKERS DELI GROCERY CORP, 10705** | 19 |
| **208 SARATOGA FOOD CORP, 10705** | 19 |
| **108 COVERT AVENUE PUB INC, 11530** | 93 |
| **2048 HILLSIDE RESTAURANT CORP, 11040** | 188 |
| **205 SERVICE STATION INC, 11040** | 188 |
| **2201 GAS CORP, 11040** | 188 |

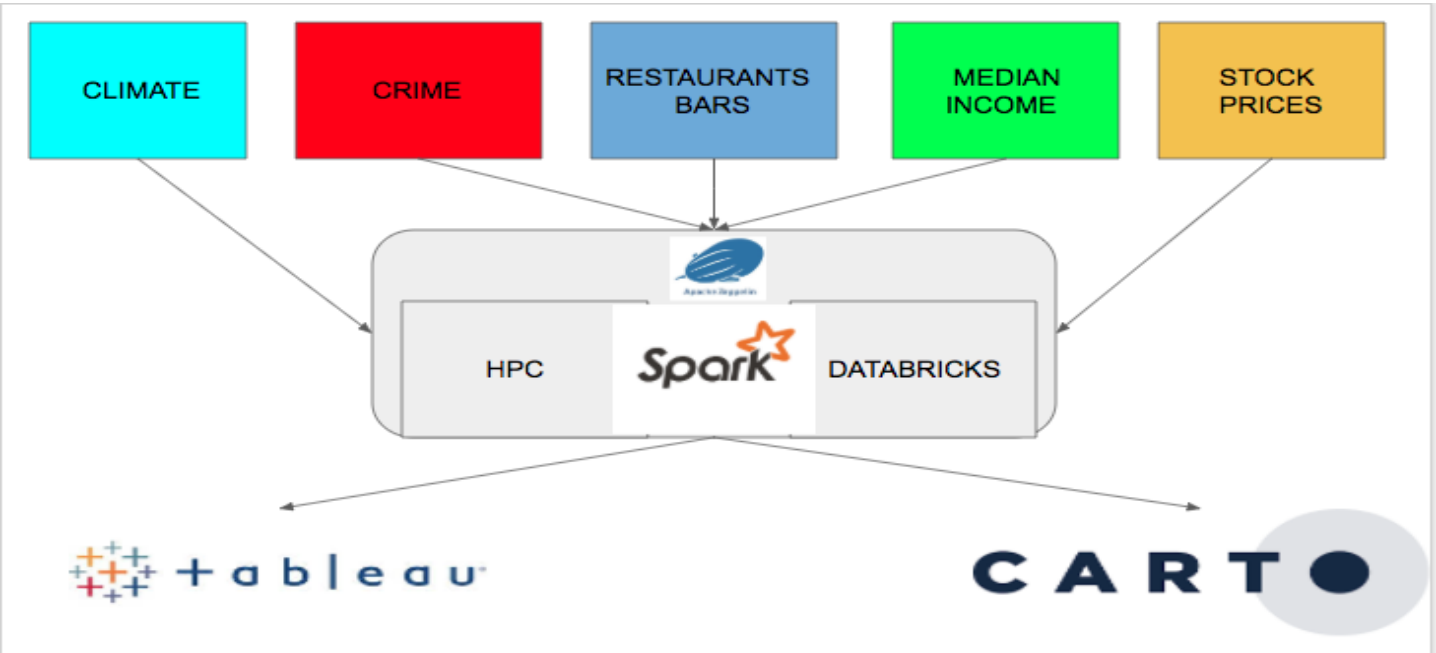
Safe bars in NYC

| Bars | Crime Count |
|---|---|
| 230 JC DELI GROCERY INC, 10457 | 36327 |
| 1155 NEW WAY DELI CORP, 11208 | 36558 |
| 1176 LIBERTY FOOD CORP, 11208 | 36558 |
| 1290 SUTTER GROCERY INC, 11208 | 36558 |
| 160 CRESCENT DELI & GROCERY CORP, 11208 | 36558 |
| 208 CRESCENT MEAT & PRODUCE INC, 11208 | 36558 |
| 2552 DELI CORP, 11208 | 36558 |
| 255 E 95 ST FOOD CORP, 11212 | 38172 |
| 1115 PENNSYLVANIA MEAT CORP, 11207 | 42442 |
| 200 JAMAICA FOOD CORP, 11207 | 42442 |
| 2053 PITKIN MINIMARKET INC, 11207 | 42442 |
| 106 AMSTERDAM REST CORP, 10029 | 55808 |

Not so safe bars in NYC

## 8. Architecture and Workflow

- Each data set is collected from the respective sources listed in the first section
- All the datasets are loaded independently in HPC(Pyspark shell, Zeppelin) using Databricks CSV package and Databricks cloud platform for some in-built visualization tools and to avoid sporadic reset of Zeppelin in HPC
- Data clean up is performed on all the datasets to remove various spurious fields that later aided in faster development and data analysis
- Once all the processing is performed using various paradigms of Spark like partitioning, combining, parallelizing etc. completely churned and aggregated data is exported to the respective CSVs to be fed to the visualization tools Tableu and Carto



# 9. Technology Used

- Apache Zeppelin
- Apache Spark
- Scala
- Python
- Tableau
- Databricks cloud platform
- Google Reverse geocoding API

# 10. Conclusion

As we write this report there is a crime happening somewhere in NYC. The crimes in New York is mundane. This project gave us a good insight on how crime occurs in different areas of NYC. These insights can be used to control the crime. We have good insights how crime varies in month and the location which are impacted the most. If these insights are considered by NYPD we can work together for a better New York. Crime rate in a locality can become one factor for people to decide which hotel to stay or which bars to visit.