



NEW YORK

Full Data Description:-

- Provided by - NYC Open Data
- Agency - Police Department (NYPD)
- Views - 76.8K
- Downloads - 16K
- Rows - 257K
- Columns - 36
- Each row is a Complaint
- Source:-
<https://data.cityofnewyork.us/Public-Safety/NYPD-Complaint-Data-Current-Year-To-Date-/5uac-w243>

About This Dataset:-

This Dataset Includes All Valid Felony, Misdemeanour, And Violation Crimes Reported To The New York City Police Department (NYPD) For All Complete Quarters Of The Year (2019)

Background:- In Many Other Cities, Open Data Is A Technical Policy Or An Executive Order. In New York City, It's The Law. On March 7, 2012, Former Mayor Bloomberg Signed Local Law 11 Of 2012, More Commonly Known As The "Open Data Law"

Known As The "Open Data Law," Which Amended The New York City Administrative Code To Mandate That All Public Data Be Made Available On A Single Web Portal By The End Of 2018. In November 2015, January 2016, And December 2017, Mayor De Blasio Approved Several Amendments To The Open Data Law. These Laws, Which Include Stronger Requirements On Data Dictionaries And Data Retention, Response Timelines For Public Requests, And An Extension Of The Open Data Mandate Into Perpetuity, Help Make It Easier For New Yorkers To Access City Data Online And Anchor The City's Transparency Initiatives Around Open Data

Update Frequency - Quarterly

Automation - No Date Made Public - 11/1/2018

For Additional Details, Please See The Attached Source:-<https://data.cityofnewyork.us/Public-Safety/NYPD-Complaint-Data-Current-Year-To-Date-/5uac-w243>

Importing Libraries And Loading Data

In This Section We Will Load The Necessary Libraries And Load Data:-

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import squarify
import plotly.express as plx
%matplotlib inline
from datetime import datetime
import warnings
warnings.filterwarnings("ignore")
# Setting Max Rows Display to 1000
pd.set_option('display.max_columns', 1000)
# Setting Max Columns Display to 1000
pd.set_option('display.max_rows', 1000)

In [2]: # I Have Found That Null Values Are Disguised In Many Other Names Such As
# So We Need To Include Them As Well And Drop When Necessary
nan_values = ['NO CLUE', 'N/A', np.nan, "NaT", ("null"), "not available",
              "UNKNOWN", "U", "E", "D"]
df = pd.read_csv("NYPD_Complaint_Data_Current__Year_To_Date_.csv", na_va

In [3]: # Checking If These Two Columns Are Equal Or Not
df['CMPLNT_FR_TM'].equals(df['CMPLNT_TO_TM'])
```

Out[3]: False



Cleaning Data

- Looking Out For Missing/Null Values
- Structuring The Data In Proper Format
- Dropping Duplicate Values...
- Spelling Correction, Renaming Columns/Rows

```
In [4]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 256797 entries, 0 to 256796
Data columns (total 36 columns):
#   Column                Non-Null Count  Dtype
---  -
0   CMPLNT_NUM             256797 non-null object
1   ADDR_PCT_CD            256797 non-null int64
2   BORO_NM                256356 non-null object
3   CMPLNT_FR_DT           256797 non-null object
4   CMPLNT_FR_TM           256797 non-null object
5   CMPLNT_TO_DT           237423 non-null object
6   CMPLNT_TO_TM           237478 non-null object
7   CRM_ATPT_CPTD_CD       256797 non-null object
8   HADEVELOPT             815 non-null   object
```



```
8  HADEVELOPT 815 non-null object
9  HOUSING_PSA 16985 non-null float64
10 JURISDICTION_CODE 256797 non-null int64
11 JURIS_DESC 256797 non-null object
12 KY_CD 256797 non-null int64
13 LAW_CAT_CD 256797 non-null object
14 LOC_OF_OCCUR_DESC 215731 non-null object
15 OFNS_DESC 256791 non-null object
16 PARKS_NM 1421 non-null object
17 PATROL_BORO 256793 non-null object
18 PD_CD 256528 non-null float64
19 PD_DESC 256528 non-null object
20 PREM_TYP_DESC 256690 non-null object
21 RPT_DT 256797 non-null object
22 STATION_NAME 5708 non-null object
23 SUSP_AGE_GROUP 109037 non-null object
24 SUSP_RACE 143020 non-null object
25 SUSP_SEX 153472 non-null object
26 TRANSIT_DISTRICT 5708 non-null float64
27 VIC_AGE_GROUP 184109 non-null object
28 VIC_RACE 179145 non-null object
29 VIC_SEX 188130 non-null object
30 X_COORD_CD 256797 non-null int64
31 Y_COORD_CD 256797 non-null int64
32 Latitude 256797 non-null float64
33 Longitude 256797 non-null float64
34 Lat_Lon 256797 non-null object
35 New Georeferenced Column 256797 non-null object
dtypes: float64(5), int64(5), object(26)
memory usage: 70.5+ MB
```

```
In [5]: df
```

```
Out[5]:
```

	CMPLNT_NUM	ADDR_PCT_CD	BORO_NM	CMPLNT_FR_DT	CMPLNT_FR_TM	CMPL
0	242955164	79	BROOKLYN	04/22/2021	08:00:00	
1	238863220	25	MANHATTAN	12/31/2021	21:45:00	
2	242870934	46	BRONX	03/16/2018	12:00:00	
3	247126072	44	BRONX	11/10/2019	17:00:00	
4	242181297	84	BROOKLYN	03/16/2000	00:00:00	
...
256792	247399166	33	MANHATTAN	06/30/2022	22:10:00	
256793	247392181	113	QUEENS	06/30/2022	19:26:00	
256794	247383348	90	BROOKLYN	06/30/2022	12:36:00	
256795	247434393	109	QUEENS	06/30/2022	14:30:00	
256796	247376531	18	MANHATTAN	06/30/2022	12:57:00	

256797 rows x 36 columns

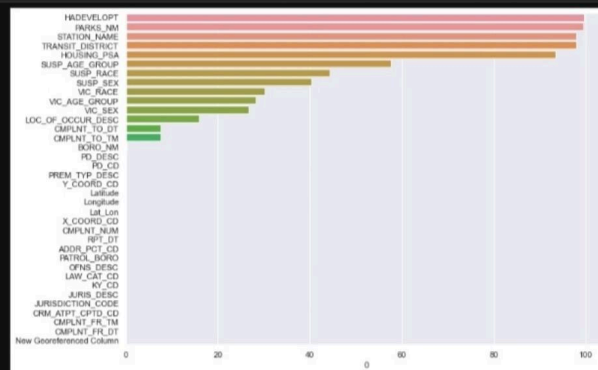
```
In [6]: # The Code Below Calculates The Percentage Of Null Values From Every Col
missing_values = df.isnull().mean().round(4).mul(100).sort_values(ascen
missing_values = pd.DataFrame(missing_values)
missing_values
```

```
Out[6]:
```

	0
HADEVELOPT	99.68
PARKS_NM	99.45
STATION_NAME	97.78
TRANSIT_DISTRICT	97.78

TRANSIT_DISTRICT	9 / 8
HOUSING_PSA	93.39
SUSP_AGE_GROUP	57.54
SUSP_RACE	44.31
SUSP_SEX	40.24
VIC_RACE	30.24
VIC_AGE_GROUP	28.31
VIC_SEX	26.74
LOC_OF_OCCUR_DESC	15.99
CMLNT_TO_DT	7.54
CMLNT_TO_TM	7.52
BORO_NM	0.17
PD_DESC	0.10
PD_CD	0.10
PREM_TYP_DESC	0.04
Y_COORD_CD	0.00
Latitude	0.00
Longitude	0.00
Lat_Lon	0.00
X_COORD_CD	0.00
CMLNT_NUM	0.00
RPT_DT	0.00
ADDR_PCT_CD	0.00
PATROL_BORO	0.00
OFNS_DESC	0.00
LAW_CAT_CD	0.00
KY_CD	0.00
JURIS_DESC	0.00
JURISDICTION_CODE	0.00
CRM_ATPT_CPTD_CD	0.00
CMLNT_FR_TM	0.00
CMLNT_FR_DT	0.00
New Georeferenced Column	0.00

```
In [7]: # I Think It Would Be Nice To Plot A Graph Of Null Values Of Every Column
sns.set(rc={'figure.figsize':(11.7,8.27)})
sns.barplot(data=missing_values, y=missing_values.index, x=0);
```



```
In [8]: # More Than 97% Of Rows Are Null Of This Column, There's No Point To Keep It
df["STATION_NAME"].value_counts()
```

```
Out[8]: 125 STREET      195
        34 ST.-PENN STATION  149
        42 ST.-PORT AUTHORITY BUS TERM  146
        14 STREET      119
```

59 ST.-COLUMBUS CIRCLE	113
42 ST.-TIMES SQUARE	108
145 STREET	77
168 ST.-WASHINGTON HTS.	73
BROADWAY-EASTERN PKWY	72
FORDHAM ROAD	70
42 ST.-GRAND CENTRAL	69
96 STREET	68
BROADWAY-EAST NEW YORK	65
W. 4 STREET	65
JAY STREET-BOROUGH HALL	63
UTICA AVE.-CROWN HEIGHTS	62
CANAL STREET	57
23 STREET	55
110 ST.-CENTRAL PARK NORTH	52
NOSTRAND AVENUE	51
116 STREET	50
MYRTLE AVENUE	50
KINGSBRIDGE ROAD	50
86 STREET	50
EUCLID AVENUE	49
59 STREET	48
34 ST.-HERALD SQ.	48
149 ST.-GRAND CONCOURSE	48
161 ST.-YANKEE STADIUM	48
3 AVENUE-149 STREET	47
47-50 STS./ROCKEFELLER CTR.	42
CHURCH AVENUE	41
FRANKLIN AVENUE	40
3 AVENUE-138 STREET	39
ATLANTIC AVENUE	39
STILLWELL AVENUE-CONEY ISLAND	38
MAIN ST.-FLUSHING	37
HUNTS POINT AVENUE	36
181 STREET	36
WOODLAWN	35
PARSONS/ARCHER-JAMAICA CENTER	34
72 STREET	33
ROOSEVELT AVE.-JACKSON HEIGHTS	32
HOYT-SCHERMERHORN	32
50 STREET	31
UNION SQUARE	31
103 ST.-CORONA PLAZA	31
PROSPECT AVENUE	30
FULTON STREET	30
170 STREET	30
SUTPHIN BLVD.-ARCHER AVE.	30
EAST 180 STREET	29
34 STREET	29
PACIFIC STREET	29
135 STREET	29
FLATBUSH AVE.-BROOKLYN COLLEGE	29
167 STREET	28
71 AVE.-FOREST HILLS	28
36 STREET	27
ESSEX STREET	27
BURNSIDE AVENUE	27
BROOKLYN BRIDGE-CITY HALL	27
QUEENSBORO PLAZA	26
ROCKAWAY AVENUE	26
LEXINGTON AVE.	26
137 ST.-CITY COLLEGE	26
CHAMBERS ST.-WORLD TRADE CENTE	26
CHAMBERS STREET	25
241 ST.-WAKEFIELD	25
MYRTLE/WYCKOFF AVENUES	23
DEKALB AVENUE	23
BROADWAY/LAFAYETTE	23
EAST BROADWAY	23
JUNCTION BLVD.	23
WEST 34 STREET/HUDSON YARDS	22
179 ST.-JAMAICA	22
MARCY AVENUE	22
42 STREET	22
SIMPSON STREET	22
28 STREET	21
7 AVENUE	20
14 ST.-UNION SQUARE	20
NEW LOTS AVENUE	19
FLUSHING AVENUE	19
QUEENS PLAZA	19
PROSPECT PARK	19
KINGS HIGHWAY	18
191 STREET	18

```
In [9]: # Checking If These Two Columns Are Duplicates
# I'm Not So Good With DateTime Datatypes,
# But If I Code Cleanly With Awareness, We Will Definitely Find Some Uni
df["CMLNT_TO_DT"].equals(df["CMLNT_FR_DT"])

Out[9]: False

In [10]: # These Are Mostly Null Columns Or Their Rows Are So Less It's Not Worth
# So I Think It's Best To Drop Them.
df.drop(["HADEVELOPT",
        "JURISDICTION_CODE",
        "TRANSIT_DISTRICT",
        "PARKS_NM",
        "STATION_NAME",
        "TRANSIT_DISTRICT",
        "HOUSING_PSA", "X_COORD_CD", "Y_COORD_CD"], axis=1, inplace=True)

In [11]: # Checking For Duplicates
df[df.duplicated()]
# There Are No Duplicate Rows

Out[11]:
      CMLNT_NUM  ADDR_PCT_CD  BORO_NM  CMLNT_FR_DT  CMLNT_FR_TM  CMLNT_TO_DT

In [12]: # After A Lot Of Cleaning There Still Remains Tons Of Null Values
# If We Drop Them All We Will Have An Insignificant Dataset. It Will Be
# So We Will Analyse Each Column Carefully From Now On.
df.isnull().sum().sort_values(ascending=False)

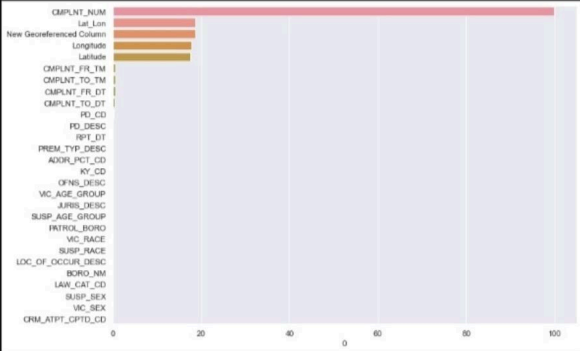
Out[12]:
SUSP_AGE_GROUP      147760
SUSP_RACE            113777
SUSP_SEX             103325
VIC_RACE              77652
VIC_AGE_GROUP        72688
VIC_SEX               68667
LOC_OF_OCCUR_DESC    41066
CMLNT_TO_DT          19374
CMLNT_TO_TM          19319
BORO_NM               441
PD_DESC              269
PD_CD                 269
PREM_TYP_DESC         107
OFNS_DESC              6
PATROL_BORO           4
Longitude             0
Latitude              0
Lat_Lon               0
CMLNT_NUM             0
RPT_DT                0
ADDR_PCT_CD           0
LAW_CAT_CD            0
KY_CD                 0
JURIS_DESC            0
CRM_ATPT_CPTD_CD      0
CMLNT_FR_TM           0
CMLNT_FR_DT           0
New Georeferenced Column
dtype: int64

In [13]: # The Code Below Calculates The Percentage Of Unique Values From Every C
unique = df.nunique().sort_values(ascending=False) / 256797 * 100
unique = pd.DataFrame(unique)
unique

Out[13]:
      0
      CMLNT_NUM  99.974688
      Lat_Lon   18.647025
      New Georeferenced Column  18.647025
      Longitude  17.724117
      Latitude   17.634162
      CMLNT_FR_TM  0.560754
      CMLNT_TO_TM  0.560754
      CMLNT_FR_DT  0.559197
      CMLNT_TO_DT  0.383961
      PD_CD       0.130843
```


PD_DESC	0.126949
RPT_DT	0.070484
PREM_TYP_DESC	0.032711
ADDR_PCT_CD	0.029985
KY_CD	0.023754
OFNS_DESC	0.022975
VIC_AGE_GROUP	0.007009
JURIS_DESC	0.006620
SUSP_AGE_GROUP	0.005062
PATROL_BORO	0.003115
VIC_RACE	0.002336
SUSP_RACE	0.002336
LOC_OF_OCCUR_DESC	0.001947
BORO_NM	0.001947
LAW_CAT_CD	0.001168
SUSP_SEX	0.000779
VIC_SEX	0.000779
CRM_ATPT_CPTD_CD	0.000779

```
In [14]: # Plotting Unique Using Barplot
sns.set(rc={'figure.figsize':(11.7,8.27)})
sns.barplot(data=unique, y=unique.index, x=0);
```



Region-wise Crime Analysis

In This Section, I Will Analyse Crime By Region, Certain Regions Are Prone To High Crime Activity While There Could Be Many Reasons For That Happening To Present An Accurate/precise Picture, We Need To Be Unbiased Of Anything Like (race, Religion, Sex, Orign Of The Person, Typical Stereotypes) And Then Only We'll Get A Precise/real Picture

Insights:-

- Brooklyn Contains The Highest Share Of Crime In New York City At 28.90%
- The Lowest Would Be Staten Island At 4.09%
- The 75th Precint Of Brooklyn Has The Highest Count Of Crime At 8834





```
In [15]: # Plotting A Treemap Using Squarify
# As I Have Mentioned Above We Have To Drop Nulls For Every Column "i"
# The Colour Of This Tree Map Will Change Randomly Every Time You Run

br = df["BORO_NM"].value_counts().head(5)
br = pd.DataFrame(br)
br.dropna(inplace=True)
lbl = [str('{:.2f}'.format(i/br['BORO_NM'].sum()*100)) + "%" for i, i in br.iterrows()]
plt.figure(figsize=(15,10))
squarify.plot(sizes=br["BORO_NM"],
              label=lbl,
              alpha=0.8,
              text_kwargs={'fontsize':15});
```



```
In [16]: # Plotting Barplot Of Precincts In NYC City
precint = df.iloc[:, [1,2]]
precint = precint.value_counts(ascending=False)
precint = pd.DataFrame(precint)
precint.reset_index(inplace=True)
precint.drop(precint[precint['BORO_NM'] == "(null)"].index, inplace = True)
sns.set(rc={'figure.figsize':(5,20)})
sns.barplot(x=precint['BORO_NM'], y=precint['count'], hue=precint['BORO_NM'])
```

A horizontal bar chart titled 'Percentage of the population aged 18 and over who are high school graduates, by census tract'. The y-axis is labeled 'ADDR_PCT_CD' and lists census tracts from 1 to 123. The x-axis is labeled '0' at the origin and has major tick marks at 0, 2000, 4000, 6000, and 8000. The legend identifies five boroughs: BROOKLYN (blue), BRONX (orange), MANHATTAN (green), QUEENS (red), and STATEN ISLAND (purple). The bars are grouped by borough. Manhattan (green) has the highest values, with tract 75 reaching approximately 8500. Queens (red) follows, with tract 114 at approximately 5500. Brooklyn (blue) has values ranging from about 1000 to 8000. Bronx (orange) has values between 2000 and 6500. Staten Island (purple) has the lowest values, around 2000 to 3500.

ADDR_PCT_CD	Borough	Percentage (approx.)
1	Manhattan	4000
5	Manhattan	2500
6	Manhattan	3000
7	Manhattan	3500
9	Manhattan	3500
10	Manhattan	2500
13	Manhattan	4500
14	Manhattan	6500
17	Manhattan	2000
18	Manhattan	4000
19	Manhattan	4500
20	Manhattan	2500
22	Manhattan	1000
23	Manhattan	3500
24	Manhattan	2500
25	Manhattan	3500
26	Manhattan	2000
28	Manhattan	2500
30	Manhattan	2500
32	Manhattan	3500
33	Manhattan	2500
34	Manhattan	3000
40	Bronx	5500
41	Bronx	3500
42	Bronx	4500
43	Bronx	6000
44	Bronx	6500
45	Bronx	3000
46	Bronx	4500
47	Bronx	5500
48	Bronx	4000
49	Bronx	3500
50	Bronx	2500
52	Bronx	5000
60	Brooklyn	3000
61	Brooklyn	3000
62	Brooklyn	3000
63	Brooklyn	2000
64	Brooklyn	2000
65	Brooklyn	2000
66	Brooklyn	4500
67	Brooklyn	2000
68	Brooklyn	2500
69	Brooklyn	2000
70	Brooklyn	3500
71	Brooklyn	3500
72	Brooklyn	3000
73	Brooklyn	4500
75	Brooklyn	8500
76	Brooklyn	1000
77	Brooklyn	3000
78	Brooklyn	2000
79	Brooklyn	3500
81	Brooklyn	2500
83	Brooklyn	3500
84	Brooklyn	2500
86	Brooklyn	2000
88	Brooklyn	2000
90	Brooklyn	3000
94	Brooklyn	2000
100	Queens	1500
101	Queens	2000
102	Queens	3000
103	Queens	4000
104	Queens	3500
105	Queens	4000
106	Queens	3500
107	Queens	3500
108	Queens	3000
109	Queens	5000
110	Queens	4500
111	Queens	1500
112	Queens	2000
113	Queens	3500
114	Queens	5500
115	Queens	4000
120	Staten Island	3500
121	Staten Island	2500
122	Staten Island	2000
123	Staten Island	1500

[illegible]

```
df['VIC_AGE_GROUP'] = df['VIC_AGE_GROUP'].replace(['-11', '-4',
                                                    '-40', '-5',
                                                    '-65', '-934',
                                                    '-955', '-964',
                                                    '-960', '-959',
                                                    '-963', '-970',
                                                    '-964', '-971'], ('UNKNOWN'))

df["VIC_AGE_GROUP"].fillna("UNKNOWN", inplace=True)
```

Time Series Analysis

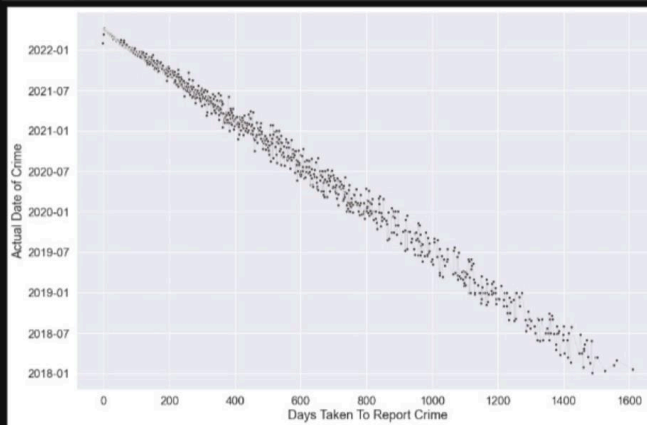
A Time Series Is A Series Of Data Points Indexed (or Listed Or Graphed) In Time Order. Most Commonly, A Time Series Is A Sequence Taken At Successive Equally Spaced Points In Time. A Time Series Is Very Frequently Plotted Via A Run Chart (which Is A Temporal Line Chart). Time Series Are Used In Statistics, Signal Processing, Pattern Recognition, Econometrics, Mathematical Finance, Weather Forecasting, Earthquake Prediction, Electroencephalography, Control Engineering, Astronomy, Communications Engineering, And Largely In Any Domain Of Applied Science And Engineering Which Involves Temporal Measurements.

Insights:-

- We Can See A Trend From 2021-07 To Till Now That The Time Between Crime Occurred And Crime Reported To Police Has Shrunk Significantly
- From 2021 We See That NYPD Was Responding To Complaints Much Faster Than Years Before That
- At `Df.loc[2]`, The Person Of This Complaint Took More Than 1440 Days To Report A Crime, Run This Command On Your Own, I Think There's A Sad Story With This
- Most Common Time For Crimes Are 12pm, 3pm, 5pm



```
In [18]: # Plotting A Lineplot Type Graph That Tells The Time Difference Betwe
# This Variable X_86 Has An Interesting Story, So Numpy Was Returning
# But I Wanted Time Difference In Days, So If You Divide "nanosecond.
#By X_86 You Get The Result In Days Rather Than Nanoseconds
x_86 = 86_400_000_000_000
rpt = df[(df["CMPLNT_FR_DT"] > "2018-01-01") & (df["CMPLNT_FR_DT"] <
rpt = rpt[["CMPLNT_FR_DT", "RPT_DT"]]
rpt["nw"] = rpt["RPT_DT"] - rpt["CMPLNT_FR_DT"]
sns.set(rc={'figure.figsize':(15,10)})
sns.set_style('darkgrid')
sns.set(font_scale=1.5)
pxx = sns.lineplot(data=rpt,
                    y="CMPLNT_FR_DT",
                    x=rpt["nw"]/x_86,
                    color="#34282C",
                    ci=None,
                    linewidth=.07,
                    marker="o",
                    markersize=4,
                    alpha=1)
pxx.set(ylabel='Actual Date of Crime', xlabel='Days Taken To Report C
plt.show()
```



```
In [19]: # This Victim Took More Than 1400 Days To Report Her Crime, I'm Sad F.
df.loc[2]
```

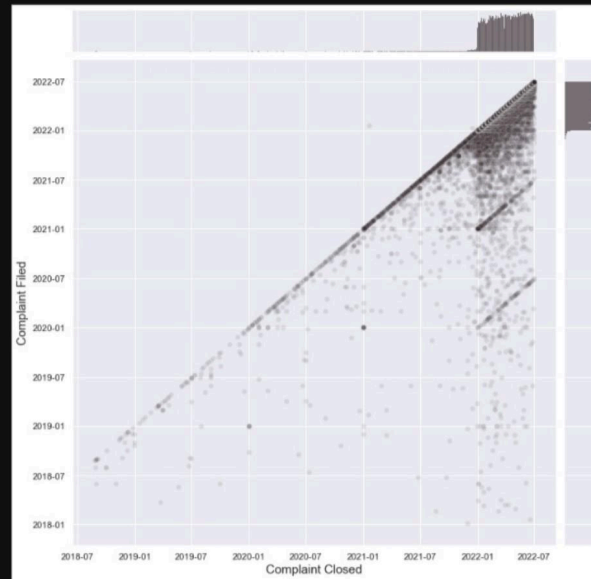
```
Out[19]: Cmplnt_Num          242870934
Addr_Pct_CD          46
Boro_Nm             BRONX
Cmplnt_Fr_Dt        2018-03-16 00:00:00
Cmplnt_Fr_Tm        2022-08-18 12:00:00
Cmplnt_To_Dt        2022-03-30 00:00:00
Cmplnt_To_Tm        2022-08-18 22:57:00
Crm_Atpt_Cptd_Cd      COMPLETED
Juris_Desc          N.Y. POLICE DEPT
Ky_Cd              112
Law_Cat_Cd          FELONY
Loc_Of_Occur_Desc    INSIDE
Ofns_Desc           THEFT-FRAUD
Patrol_Boro         PATROL BORO BRONX
Pd_Cd              739.0
Pd_Desc            FRAUD,UNCLASSIFIED-FELONY
Prem_Typ_Desc        RESIDENCE - APT. HOUSE
Rpt_Dt              2022-03-30 00:00:00
Susp_Age_Group      NaN
Susp_Race            NaN
Susp_Sex            NaN
Vic_Age_Group       25-44
Vic_Race            WHITE HISPANIC
Vic_Sex             F
Latitude             40.846629
Longitude            -73.91605
Lat_Lon              (40.846629, -73.91605)
New Georeferenced Column POINT (-73.91605 40.846629)
Name: 2, dtype: object
```

```
In [20]: # Plotting A Joint Grid That Tells When A Complaint Is Filed On Y-axis
# And When A Complaint Closed On The X-axis
```

```
pw = df[(df["Cmplnt_Fr_Dt"] > "2018-01-01") & (df["Cmplnt_Fr_Dt"] < "2022-03-30")]
pw = pw[["Cmplnt_Fr_Dt", "Cmplnt_To_Dt"]]
pw.reset_index(inplace=True, drop=True)
sns.set_style("darkgrid")
sns.set(font_scale=1)
pwc = sns.jointplot(data=pw, y="Cmplnt_Fr_Dt",
                    x="Cmplnt_To_Dt",
                    height=10,
                    ratio=10,
                    alpha=0.1,
                    color="#34282C")
pwc.set_axis_labels('Complaint Closed', 'Complaint Filed', fontsize=10)
```

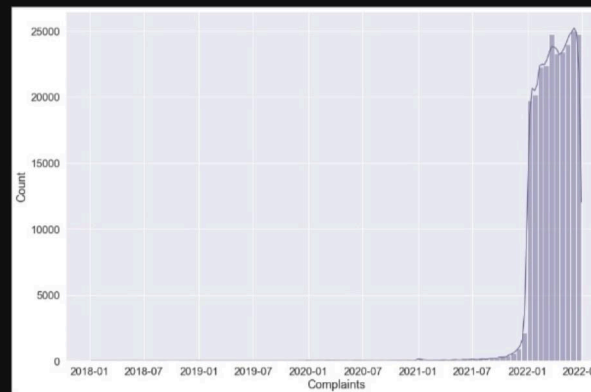
```
Out[20]: <seaborn.axisgrid.JointGrid at 0x17e81164ee0>
```

```
Out[20]: <seaborn.axisgrid.JointGrid at 0x17e81164ee0>
```



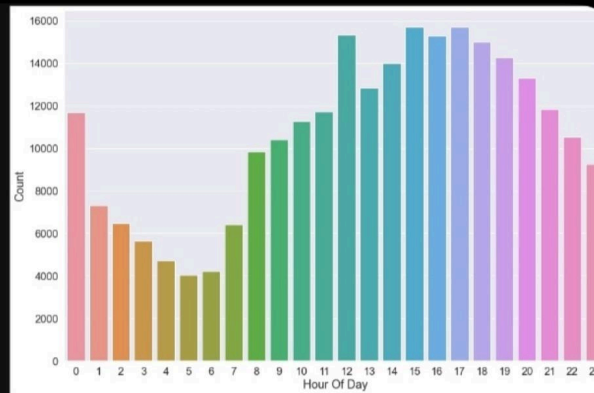
```
In [21]: # well, self-explanatory.
sns.set(rc={'figure.figsize':(15,10)})
sns.set(font_scale=1.5)
ct=sns.histplot(data=pw,x="CMLPLNT_FR_DT",bins=90 ,color="#6e6799",mul=
ct.set(xlabel='Complaints')
```

```
Out[21]: [Text(0.5, 0, 'Complaints')]
```



```
In [22]: ## Plotting Graph For The Most Common Hour For Crimes To Occur.
fr = df["CMLPLNT_FR_TM"].dt.hour
fr = pd.DataFrame(fr)
fr.reset_index(inplace=True,drop=True)
frr=sns.countplot(data=fr,x="CMLPLNT_FR_TM");
sns.set(rc={'figure.figsize':(12,8)})
sns.set(font_scale=1)
frr.set(xlabel='Hour Of Day', ylabel='Count');
```





Actual Crime Analysis

Crime Analysis Is A Law Enforcement Function That Involves Systematic Analysis For Identifying And Analyzing Patterns And Trends In Crime And Disorder. Information On Patterns Can Help Law Enforcement Agencies Deploy Resources In A More Effective Manner, And Assist Detectives In Identifying And Apprehending Suspects. Crime Analysis Also Plays A Role In Devising Solutions To Crime Problems And Formulating Crime Prevention Strategies. Quantitative Social Science Data Analysis Methods Are Part Of The Crime Analysis Process, Though Qualitative Methods Such As Examining Police Report Narratives Also Play A Role

Insights:-

- Most Common Law Classification Is A Misdemeanour
- surprising People Commit More Felonies Than Violation
- NYPD Report Crimes Far-far Above Than Any Other Policing Authority In NYC, Next Is The NY Housing Police
- Most Crimes Occur Inside Of A Structure, Contrary To Popular Belief Of Crime Occuring Outside
- Petit Larceny, Harassment And Assault Are The Most Common Crimes According To Public
- HARASSMENT-SUBDIVISION(3,4,5), LARCENY, PETIT FROM STORE-SHOPL, ASSAULT - 3, Here I Wanted To Show How Police Departments Are More Articulate/proficient When Writing Descriptions Of Crime Than Public
- People Are Likely To Commit Crimes Against People Of Their Races

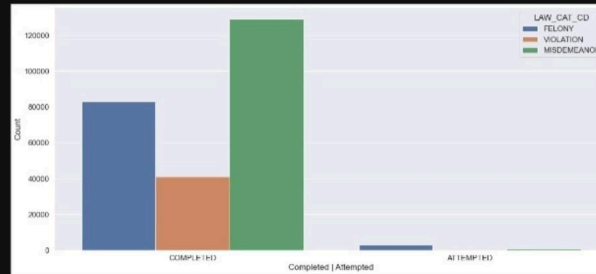


```
In [23]: sns.set(rc={'figure.figsize':(20,9)})
sns.set(font_scale=1.4)
crm = sns.countplot(x="CRM_ATPT_CPTD_CD", data= df, hue="LAW_CAT_CD")
crm.set(xlabel='Completed | Attempted', ylabel='Count')
```

Out[23]: [Text(0.5, 0, 'Completed | Attempted'), Text(0, 0.5, 'Count')]

```
In [23]: sns.set(rc={'figure.figsize':(20,9)})
sns.set(font_scale=1.4)
crm = sns.countplot(x="CRM_ATPT_CPTD_CD", data= df, hue="LAW_CAT_CD")
crm.set(xlabel='Completed | Attempted', ylabel='Count')
```

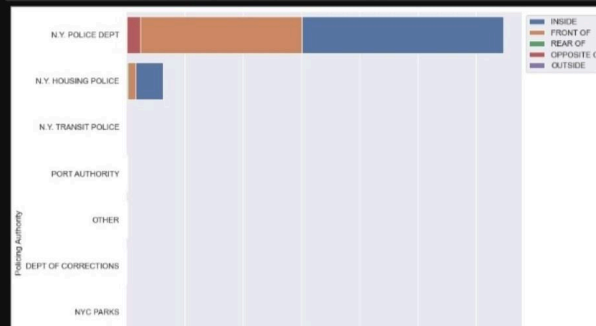
```
Out[23]: [Text(0.5, 0, 'Completed | Attempted'), Text(0, 0.5, 'Count')]
```



```
In [24]: # People Don't Commit Violations, I Guess
df[(df["LAW_CAT_CD"]=="VIOLATION") & (df["CRM_ATPT_CPTD_CD"]=="ATTEMPT")]
```

```
Out[24]: CMLNT_NUM      87
ADDR_PCT_CD      87
BORO_NM          87
CMLNT_FR_DT      87
CMLNT_FR_TM      87
CMLNT_TO_DT      81
CMLNT_TO_TM      81
CRM_ATPT_CPTD_CD  87
JURIS_DESC       87
KY_CD           87
LAW_CAT_CD       87
LOC_OF_OCCUR_DESC 73
OFNS_DESC        87
PATROL_BORO      87
PD_CD            87
PD_DESC          87
PREM_TYP_DESC    87
RPT_DT           87
SUSP_AGE_GROUP   36
SUSP_RACE        59
SUSP_SEX         67
VIC_AGE_GROUP    87
VIC_RACE         72
VIC_SEX          84
Latitude         87
Longitude        87
Lat_Lon          87
New Georeferenced Column 87
dtype: int64
```

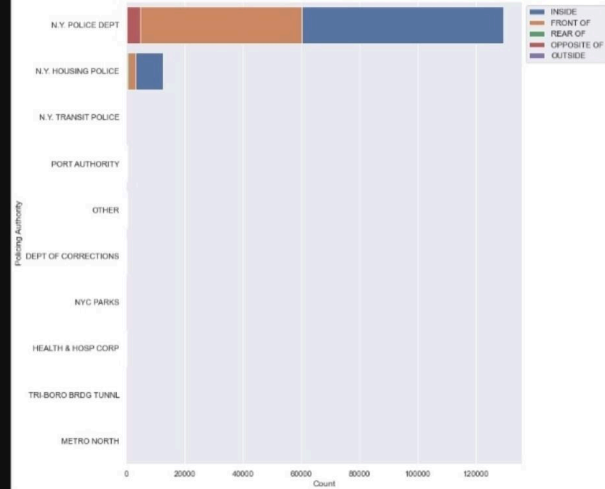
```
In [25]: # Plotting A Countplot, Policing Authority On The Y-axis, Count On The X-axis
sns.set(rc={'figure.figsize':(10,12)})
jur = sns.countplot(y=df["JURIS_DESC"], data= df, hue="LOC_OF_OCCUR_DESC", dodge=False,
                    order = df["JURIS_DESC"].value_counts().iloc[:10].index)
plt.legend(loc = 2, bbox_to_anchor = (1,1))
jur.set(xlabel='Count', ylabel='Policing Authority'),
jur = df[["JURIS_DESC", "LOC_OF_OCCUR_DESC"]]
```



```

In [25]: # Plotting A Countplot, Policing Authority On The Y-axis, Count On The X-axis
sns.set(rc={'figure.figsize':(10,12)})
jur = sns.countplot(y=df["JURIS_DESC"],
                    data= df,hue="LOC_OF_OCCUR_DESC", dodge=False,
                    order = df["JURIS_DESC"].value_counts().iloc[:10].index)
plt.legend(loc = 2, bbox_to_anchor = (1,1))
jur.set(xlabel='Count', ylabel='Policing Authority').
jur = df[["JURIS_DESC","LOC_OF_OCCUR_DESC"]]

```



```

In [26]: # Plotting Heatmap Of Crime Committed According To Public Description
# See How Police Are So Articulate When Writing Descriptions Of A Crime
ofs = df.OFNS_DESC.value_counts()
ofs = pd.DataFrame(ofs)
label = ofs.index
sns.set(rc={'figure.figsize':(8,24)})
sof = sns.heatmap(ofs,
                  vmin=0,
                  vmax=55500,
                  annot=True,
                  linewidths=2,
                  linecolor='white',
                  fmt='g')
sof.set(xlabel="COUNT",ylabel="OFFENSE")

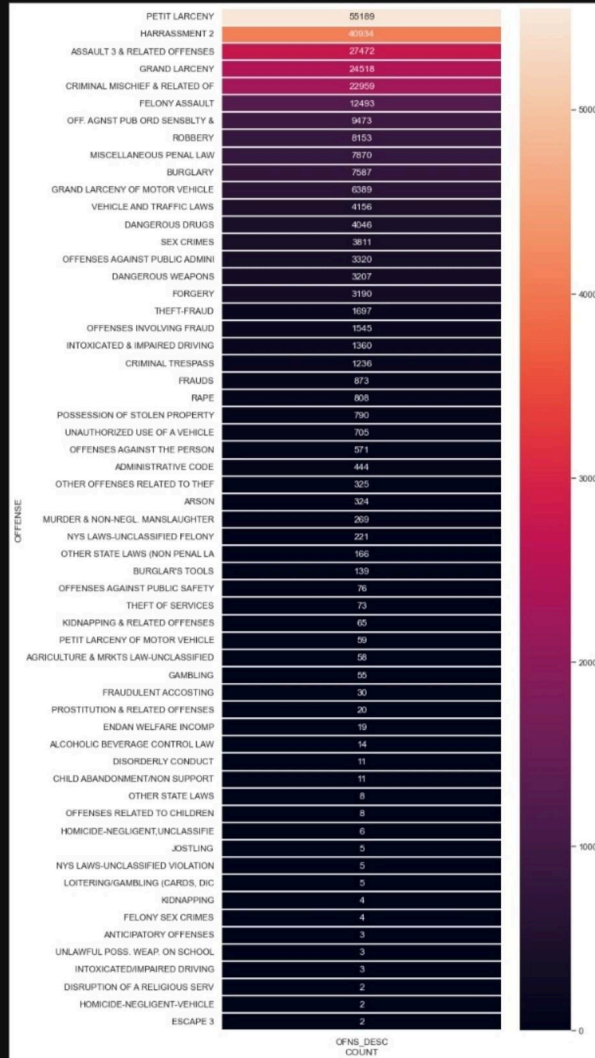
```

Out[26]: [Text(0.5, 192.5, 'COUNT'), Text(48.499999999999986, 0.5, 'OFFENSE')]



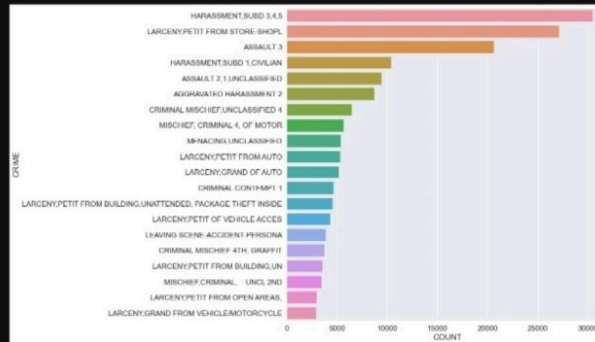
```
[26]: # Plotting Heatmap Of Crime Committed According To Public Description
# See How Police Are So Articulate When Writing Descriptions Of A Crim
ofs = df.OFNS_DESC.value_counts()
ofs = pd.DataFrame(ofs)
label = ofs.index
sns.set(rc={'figure.figsize':(8,24)})
sof = sns.heatmap(ofs,
                  vmin=0,
                  vmax=55500,
                  annot=True,
                  linewidths=2,
                  linecolor='white',
                  fmt='g')
sof.set(xlabel="COUNT",ylabel="OFFENSE")
```

```
t[26]: [Text(0.5, 192.5, 'COUNT'), Text(48.499999999999986, 0.5, 'OFFENSE')]
```



```
[27]: # Plotting Top 20 Crimes According To Police,
# See How These Are Articulated Comparing Them To The Public Descript.
pdd = df.PD_DESC.value_counts()
pdd = pd.DataFrame(pdd).head(20)
sns.set(rc={'figure.figsize':(12,12)})
```

```
(27): # Plotting Top 20 Crimes According To Police,
# See How These Are Articulated Comparing Them To The Public Descript.
pdd = df.PD_DESC.value_counts()
pdd = pd.DataFrame(pdd).head(20)
sns.set(rc={'figure.figsize':(12,12)})
sns.set(font_scale=1.4)
pddd = sns.barplot(data=pdd,x='PD_DESC',y=pdd.index);
pddd.set(xlabel="COUNT",ylabel="CRIME",pdd);
```



Race-wise Crime Analysis

Research Suggests That Police Practices, Such As Racial Profiling, Over-policing In Areas Populated By Minorities And In-group Bias May Result In Disproportionately High Numbers Of Racial Minorities Among Crime Suspects. Research Also Suggests That There May Be Possible Discrimination By The Judicial System, Which Contributes To A Higher Number Of Convictions For Racial Minorities. I Will Try To Figure Out If It's True

Insights:-

- African Americans Are Suspects Has The Highest Share In The Top 15 Crimes, And Are More Likely In Others
- Apartment, Street, Residence House, Chain Store, Drug Store Are The Top Places Where Crimes Are Most Likely To Occur
- Females Are Very Much Likely To Be Victims Of African American Suspects. Way More Than Any Other Race
- people are likely to commit crimes to the people of thier races



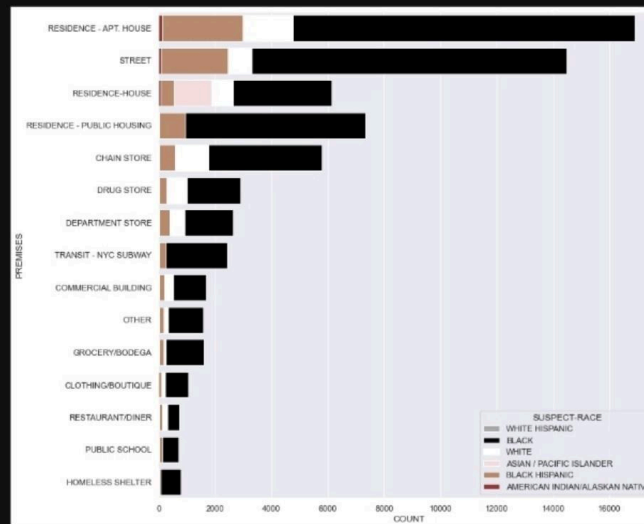
```
in [28]: # Plotting Premises Where Crimes Occurred By Race Hue
pre = df[["PREM_TYP_DESC", 'SUSP_RACE']]
pre.dropna(inplace=True)
pre.reset_index(drop=True, inplace=True)
sns.set(rc={'figure.figsize':(12,12)})
pre = sns.countplot(data=pre, y=pre['PREM_TYP_DESC'], dodge=False,
hue='SUSP_RACE')
```

```

In [28]: # Plotting Premises Where Crimes Occurred By Race Hue
pre = df[["PREM_TYP_DESC", 'SUSP_RACE']]
pre.dropna(inplace=True)
pre.reset_index(drop=True, inplace=True)
sns.set(rc={'figure.figsize':(12,12)})
pre = sns.countplot(data=pre, y=pre['PREM_TYP_DESC'], dodge=False,
                    hue="SUSP_RACE",
                    order = pre['PREM_TYP_DESC'].value_counts().iloc[0:15].
                    palette=(sns.color_palette(["#A9A9A9",
                                                "#000000",
                                                "#FFFFFF",
                                                "#fadaff",
                                                "#C68863",
                                                "#A52A2A"],
                                                n_colors=6)))
pre.set(xlabel="COUNT",ylabel="PREMISES")
plt.legend(title="SUSPECT-RACE")

```

Out[28]: <matplotlib.legend.Legend at 0x17e812a5820>



```

In [29]: vic=df[['VIC_SEX','SUSP_RACE',"LAW_CAT_CD", "VIC_RACE","SUSP_SEX"]]
vic.dropna(inplace=True)
sns.countplot(data=vic, x="VIC_SEX", hue="SUSP_RACE",
              palette=(sns.color_palette(["#A9A9A9", "#000000", "#F5E4D1",
                                          "#FFFFFF", "#C68863", "#A52A2A"],
                                          n_colors=6)))
plt.legend(title="SUSPECT-RACE")

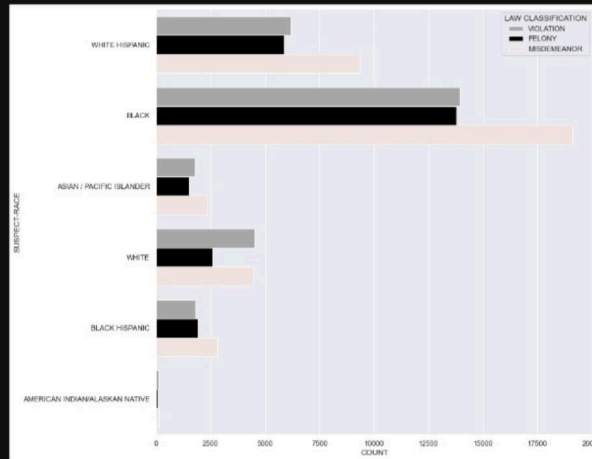
```

Out[29]: <matplotlib.legend.Legend at 0x17e82c93940>

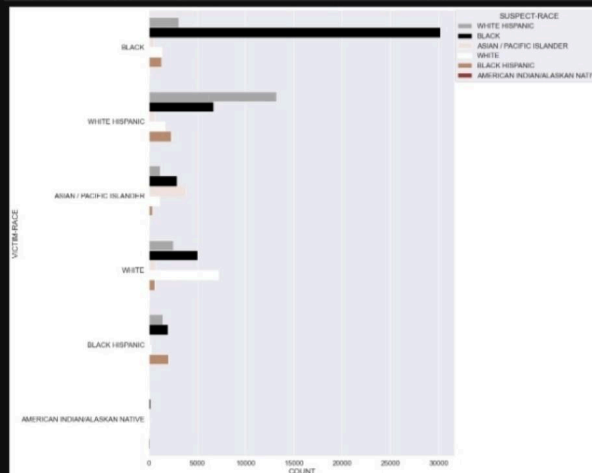



```
In [30]: lc = sns.countplot(data=vic,
                        y="SUSP_RACE",
                        hue="LAW_CAT_CD",
                        palette=(sns.color_palette(["#A9A9A9", "#000000", "#F5E4D1", "#FFFFFF", "#C68863", "#A52A2A"])),
                        plt.legend(title="LAW CLASSIFICATION")
lc.set(xlabel="COUNT",ylabel="SUSPECT-RACE")
```

```
Out[30]: [Text(0.5, 0, 'COUNT'), Text(0, 0.5, 'SUSPECT-RACE')]
```



```
In [31]: # People Are Likely To Commit Crimes Against People Of Their Races
sns.set(rc={'figure.figsize':(12,18)})
sns.set(font_scale=1.4)
vic_sus = sns.countplot(data=vic,
                        y="VIC_RACE",
                        hue="SUSP_RACE",
                        palette=(sns.color_palette(["#A9A9A9", "#000000", "#F5E4D1", "#FFFFFF", "#C68863", "#A52A2A"])),
                        plt.legend(title="SUSPECT-RACE",bbox_to_anchor=(1, 1),loc=2, border=1))
```





```
In [32]: # This Is A Very Interesting Map Of NYC City Just Hover Over It
nod = df[["VIC_AGE_GROUP", "Longitude", "Latitude", "PD_DESC"]]

mpx = plx.scatter_mapbox(nod, lon=nod["Longitude"],
                        lat=nod["Latitude"],
                        zoom=10,
                        width=890,
                        height=800,
                        hover_name = "PD_DESC",
                        opacity = 0.3, color="VIC_AGE_GROUP",
                        color_discrete_sequence=["red", "white",
                                                '#90ee90', "#00008B",
                                                "#FFFFFFE0"]);

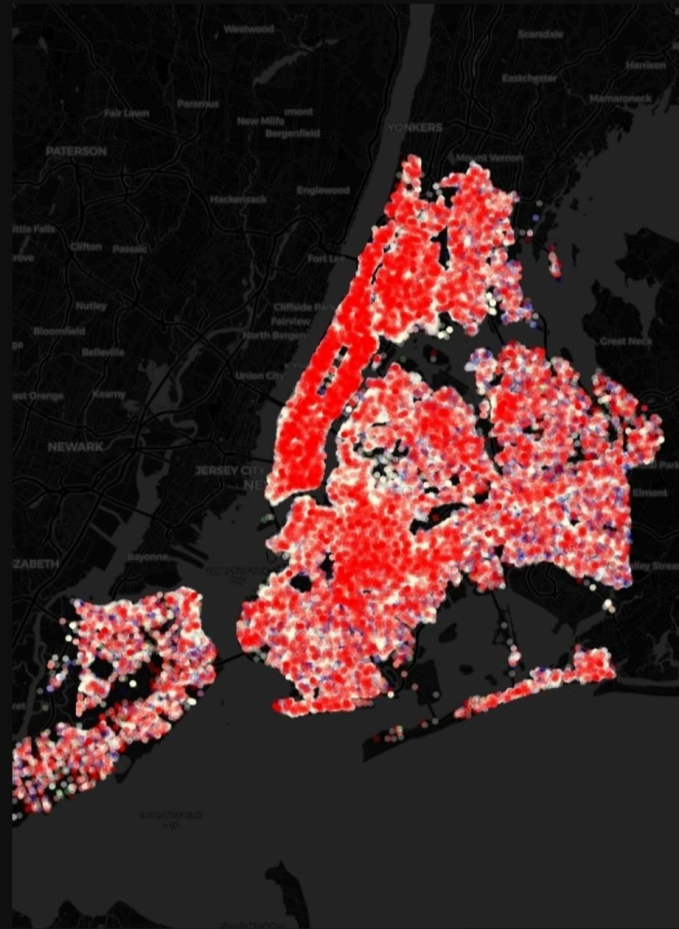
mpx.update_layout(mapbox_style="carto-darkmatter")
mpx.update_layout(margin={"r":0,"t":0,"l":0,"b":0})
mpx.show()
```



```
In [32]: # This Is A Very Interesting Map Of NYC City Just Hover Over It
nod = df[["VIC_AGE_GROUP", "Longitude", "Latitude", "PD_DESC"]]

mpx = plx.scatter_mapbox(nod, lon=nod["Longitude"],
                        lat=nod["Latitude"],
                        zoom=10,
                        width=890,
                        height=800,
                        hover_name="PD_DESC",
                        opacity=0.3, color="VIC_AGE_GROUP",
                        color_discrete_sequence=["red", "white",
                                                "#90ee90", "#00008B",
                                                "#FFFE0"]);

mpx.update_layout(mapbox_style="carto-darkmatter")
mpx.update_layout(margin={"f":0, "t":0, "l":0, "b":0})
mpx.show()
```



```
In [ ]:
```