San Francisco Crime Analysis

September 29, 2023

1 San Francisco Crime Analysis

1.1 Description:

Crime analysis and prediction in San Francisco is a complex and challenging task. Crime is a complex phenomenon with many contributing factors, including social, economic, and environmental factors. It is also difficult to predict crime because it is often random and unpredictable.

However, there are a number of ways to analyze and predict crime in San Francisco. One common approach is to use historical crime data to identify patterns and trends. This data can be used to identify high-crime areas and times of day, as well as the types of crimes that are most common in different neighborhoods.

Another approach to crime analysis is to use predictive analytics. Predictive analytics is a set of techniques that use historical data to predict future events. In the context of crime prediction, predictive analytics can be used to predict the likelihood of a crime occurring in a particular location at a particular time.

There are a number of different predictive analytics techniques that can be used to predict crime. Some of the most common techniques include:

- Regression analysis: Regression analysis is a statistical technique that can be used to identify the relationship between different variables. In the context of crime prediction, regression analysis can be used to identify the factors that are most associated with crime, such as poverty, unemployment, and the presence of gangs.
- **Decision trees:** Decision trees are a type of machine learning algorithm that can be used to classify data. In the context of crime prediction, decision trees can be used to classify neighborhoods as high-crime or low-crime based on their characteristics, such as poverty, unemployment, and the presence of gangs.
- Random forests: Random forests are a type of machine learning algorithm that is similar to decision trees, but instead of using a single decision tree, random forests use a large number of decision trees to make predictions. This makes random forests more accurate and less prone to overfitting than decision trees.

Predictive analytics models can be used to help the San Francisco Police Department (SFPD) allocate resources more effectively and prevent crime from happening in the first place. For example, the SFPD can use predictive analytics models to identify high-crime areas and times of day, and then deploy more officers to those areas during those times. The SFPD can also use predictive analytics models to identify individuals who are at high risk of committing crimes, and then intervene to prevent those crimes from happening.

It is important to note that crime prediction is not perfect. No predictive analytics model can accurately predict crime with 100% accuracy. However, predictive analytics models can be a valuable tool for helping the SFPD reduce crime in San Francisco.

Here are some examples of how crime analysis and prediction are being used in San Francisco:

- The SFPD is using predictive analytics models to identify high-crime areas and times of day. This information is being used to deploy more officers to those areas during those times.
- The SFPD is also using predictive analytics models to identify individuals who are at high risk of committing crimes. This information is being used to intervene to prevent those crimes from happening.
- The SFPD is working with researchers at the University of California, Berkeley to develop a new crime prediction model that uses social media data. This model is still under development, but it has the potential to be more accurate than existing crime prediction models.

Crime analysis and prediction is a complex and challenging field, but it has the potential to make a significant impact on reducing crime in San Francisco.

2 Importing Libraries

```
[]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import folium # To create interactive maps
import squarify # used to create treemaps
[]: import warnings
warnings.filterwarnings('ignore')
```

3 Reading Datasets

0

1

2

Monday

Friday 01/29/2016 12:00:00 AM

Tuesday 01/05/2016 12:00:00 AM

Friday 01/29/2016 12:00:00 AM 11:00

04/25/2016 12:00:00 AM

```
[]: data=pd.read_csv('crime.csv')
     data.head()
[]:
                                                                           Descript
        IncidntNum
                         Category
         120058272
                     WEAPON LAWS
                                                         POSS OF PROHIBITED WEAPON
     0
                                   FIREARM, LOADED, IN VEHICLE, POSSESSION OR USE
     1
         120058272
                     WEAPON LAWS
     2
         141059263
                         WARRANTS
                                                                    WARRANT ARREST
     3
                                                                     LOST PROPERTY
         160013662
                    NON-CRIMINAL
         160002740
                    NON-CRIMINAL.
                                                                     LOST PROPERTY
       DayOfWeek
                                     Date
                                            Time
                                                  PdDistrict
                                                                   Resolution \
```

11:00

14:59

23:50

ARREST, BOOKED

ARREST, BOOKED

ARREST, BOOKED

NONE

SOUTHERN

SOUTHERN

TENDERLOIN

BAYVIEW

```
4
     Friday 01/01/2016 12:00:00 AM 00:30
                                                MISSION
                                                                    NONE
                  Address
                                     X
                                                Y
  800 Block of BRYANT ST -122.403405
                                        37.775421
  800 Block of BRYANT ST -122.403405
                                        37.775421
1
2
   KEITH ST / SHAFTER AV -122.388856
                                        37.729981
3
  JONES ST / OFARRELL ST -122.412971
                                        37.785788
4
     16TH ST / MISSION ST -122.419672
                                        37.765050
                                 Location
                                                     PdId
    (37.775420706711, -122.403404791479)
0
                                           12005827212120
1
    (37.775420706711, -122.403404791479)
                                           12005827212168
2
   (37.7299809672996, -122.388856204292)
                                           14105926363010
3
  (37.7857883766888, -122.412970537591)
                                           16001366271000
  (37.7650501214668, -122.419671780296)
                                           16000274071000
```

3.0.1 The Datasets Information:

DataSets Link (Click Me)

The San Francisco crime dataset is a collection of crime reports from the San Francisco Police Department (SFPD). The dataset contains nearly 12 years of crime reports from all of San Francisco's neighborhoods.

The following are the features of the San Francisco crime dataset:

- **Dates:** The timestamp of the crime incident.
- Category: The category of the crime incident. This is the target variable for the dataset.
- **Descript:** A detailed description of the crime incident.
- DayOfWeek: The day of the week on which the crime occurred.
- PdDistrict: The name of the Police Department District in which the crime occurred.
- **Resolution:** The resolution of the crime incident.
- Address: The approximate street address of the crime incident.
- X: The longitude of the crime incident.
- **Y**: The latitude of the crime incident.

The categories of crime in the dataset are:

- Assault
- Battery
- Burglary
- Drug/Alcohol
- Fraud
- Larceny/Theft
- Miscellaneous
- Narcotics
- Robbery
- Sex Crimes
- Vehicle Theft

4 Data Exploration

• Let's check duplicate data

```
[]: data.duplicated().sum()
[]: 0
     data.shape
[]: (150500, 13)
    data.info()
[]:
    <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 150500 entries, 0 to 150499
    Data columns (total 13 columns):
     #
         Column
                      Non-Null Count
                                        Dtype
         IncidntNum
                      150500 non-null
     0
                                        int64
     1
         Category
                                        object
                      150500 non-null
     2
         Descript
                      150500 non-null
                                        object
     3
         DayOfWeek
                      150500 non-null
                                        object
     4
         Date
                                        object
                      150500 non-null
     5
         Time
                      150500 non-null
                                        object
     6
         PdDistrict
                      150499 non-null
                                        object
     7
         Resolution
                                        object
                      150500 non-null
     8
         Address
                      150500 non-null
                                        object
     9
         Х
                                        float64
                      150500 non-null
     10
                      150500 non-null
                                        float64
                                        object
     11
         Location
                      150500 non-null
     12 PdId
                      150500 non-null
                                        int64
    dtypes: float64(2), int64(2), object(9)
    memory usage: 14.9+ MB
[]: data.describe()
[]:
                                       Х
              IncidntNum
                                                       Y
                                                                   PdId
            1.505000e+05
                           150500.000000
                                                          1.505000e+05
                                           150500.000000
     count
     mean
            1.616440e+08
                             -122.423599
                                               37.768921
                                                          1.616440e+13
     std
            5.535976e+06
                                0.026210
                                                0.023637
                                                          5.535976e+11
                                               37.707922
     min
            1.135121e+07
                             -122.513642
                                                          1.135121e+12
     25%
            1.603283e+08
                             -122.434036
                                               37.756486
                                                          1.603283e+13
     50%
            1.606541e+08
                             -122.416903
                                               37.775421
                                                          1.606541e+13
     75%
            1.609764e+08
                             -122.406605
                                               37.785063
                                                          1.609764e+13
            9.910090e+08
                             -122.365565
                                               37.819975 9.910090e+13
     max
```

• Checking if any null value presents

[]: data.isnull()

[]:		${\tt IncidntNum}$	Category	Descr	ipt Da	ayOfWeek	Date	Time	PdDistrict	\
	0	False	False	Fa	lse	False	False	False	False	
	1	False	False	Fa	lse	False	False	False	False	
	2	False	False	Fa	lse	False	False	False	False	
	3	False	False	Fa	lse	False	False	False	False	
	4	False	False	Fa	lse	False	False	False	False	
	•••	•••	•••	•••	•••			•••		
	150495	False	False	Fa	lse	False	False	False	False	
	150496	False	False	Fa	lse	False	False	False	False	
	150497	False	False	Fa	lse	False	False	False	False	
	150498	False	False	Fa	lse	False	False	False	False	
	150499	False	False	Fa	lse	False	False	False	False	
		Resolution	Address	Х	Y	Locatio	n PdI	d		
	0	False	False	False	False	Fals	e Fals	е		
	1	False	False	False	False	Fals	e Fals	е		
	2	False	False	False	False	Fals	e Fals	е		
	3	False	False	False	False	Fals	e Fals	е		
	4	False	False	False	False	Fals	e Fals	е		
	•••	•••		•••	•••	•••				
	150495	False	False	False	False	Fals	e Fals	е		
	150496	False	False	False	False	Fals	e Fals	е		
	150497	False	False	False	False	Fals	e Fals	е		
	150498	False	False	False	False	Fals	e Fals	е		
	150499	False	False	False	False	Fals	e Fals	е		

[150500 rows x 13 columns]

[]: data.isnull().sum()

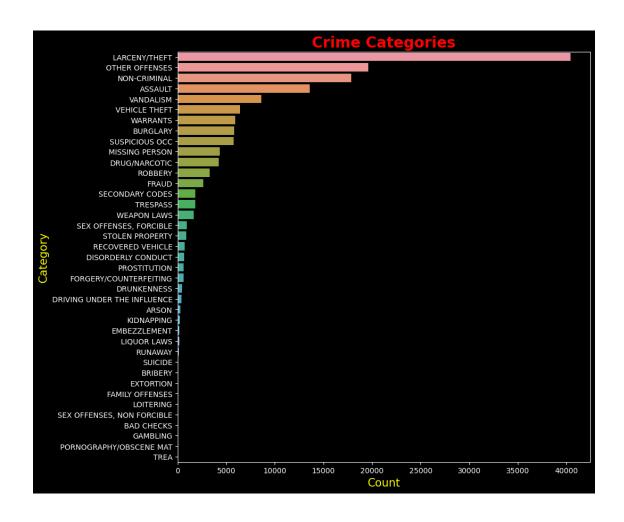
[]: IncidntNum 0 0 Category Descript 0 DayOfWeek 0 Date 0 Time PdDistrict 1 Resolution Address 0 Х 0 Y 0 Location 0 PdId 0 dtype: int64

5 Data Visualization

```
[]: plt.style.use('dark_background')
```

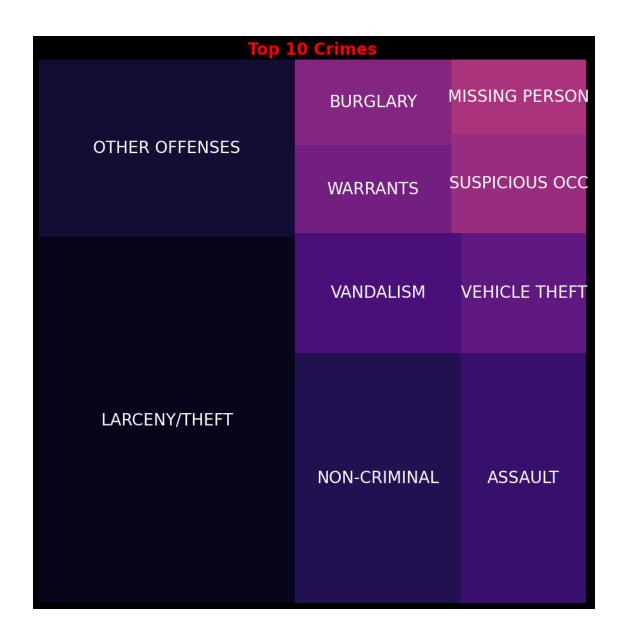
• First thing we are going to find category of crime

```
plt.figure(figsize=(10,10))
sns.countplot(y=data['Category'], order=data['Category'].value_counts().index)
plt.title('Crime Categories', fontweight='bold', fontsize=20,color='red')
plt.xlabel('Count', fontsize=15, color='yellow')
plt.ylabel('Category', fontsize=15, color='yellow')
plt.xticks(color='white')
plt.yticks(color='white')
plt.show()
```



• Let's draw tree map of a crime category

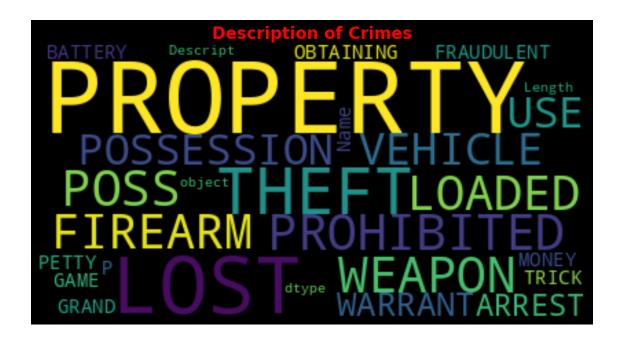
```
[]: y=data['Category'].value_counts().head(10)
plt.figure(figsize=(12,12))
squarify.plot(sizes=y.values,label=y.index,color=sns.color_palette('magma',20))
plt.rcParams.update({'font.size':20})
plt.axis('off')
plt.title('Top 10 Crimes', fontweight='bold', fontsize=20,color='red')
plt.show()
```



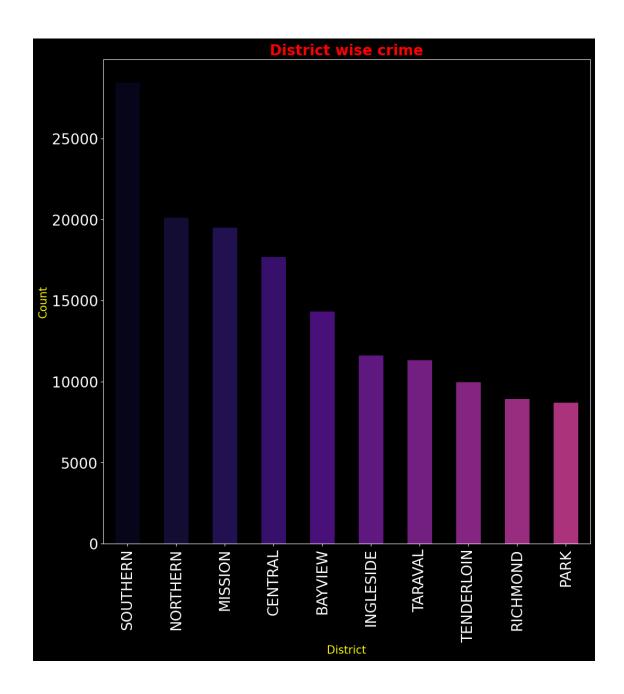
• We can observe description of crime using WordCloud

```
[]: from wordcloud import WordCloud, STOPWORDS

plt.figure(figsize=(12,12))
wc=WordCloud(background_color='black',max_words=100)
wc.generate(str(data['Descript']))
plt.imshow(wc,interpolation='bilinear')
plt.axis('off')
plt.title('Description of Crimes',fontsize=20, fontweight='bold',color='red')
plt.show()
```

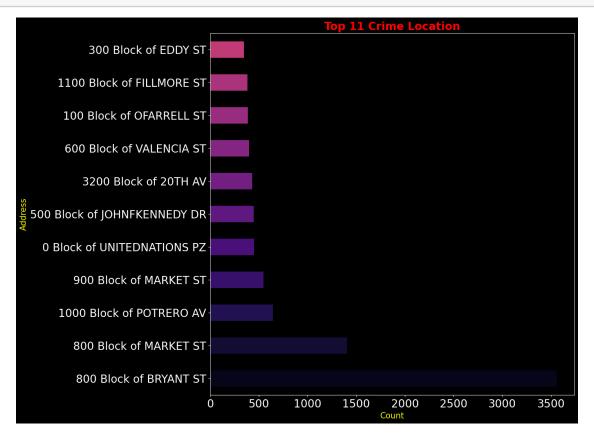


• Let's check in which District with most crime

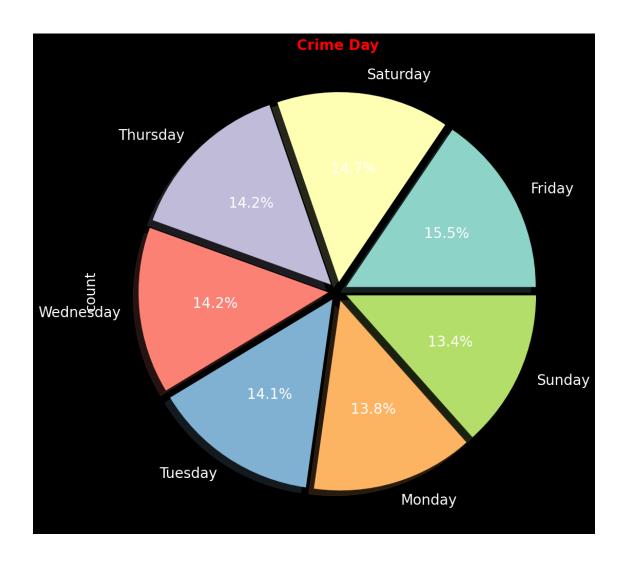


- I want to know in which area ('Addresses') crime occuring most

plt.show()

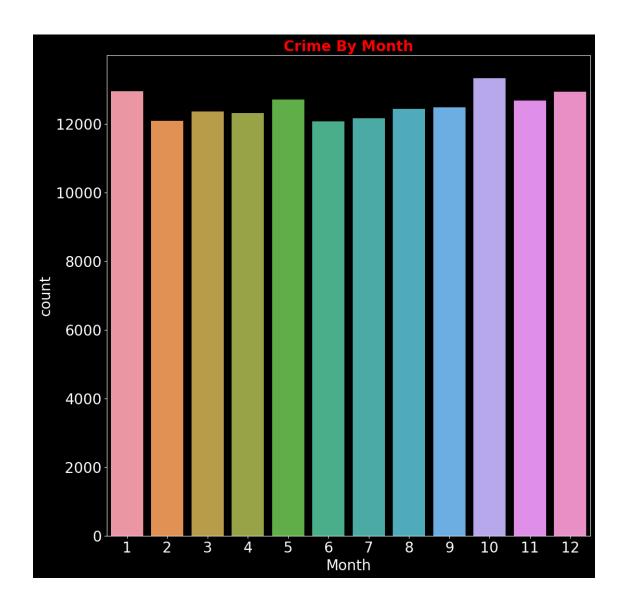


• Which day of weak crime occuring most?

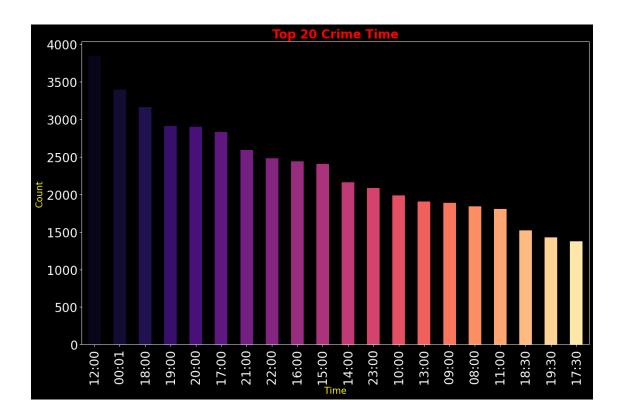


- I think friday is wrost day for San Francisco
- Yes! Now time for month after day

```
[]: plt.figure(figsize=(12,12))
  data['Date']=pd.to_datetime(data['Date'])
  data['Month']=data['Date'].dt.month
  sns.countplot(x='Month',data=data)
  plt.title('Crime By Month', fontweight='bold', fontsize=20,color='red')
  plt.show()
```



• Which time crime occurs mostly?



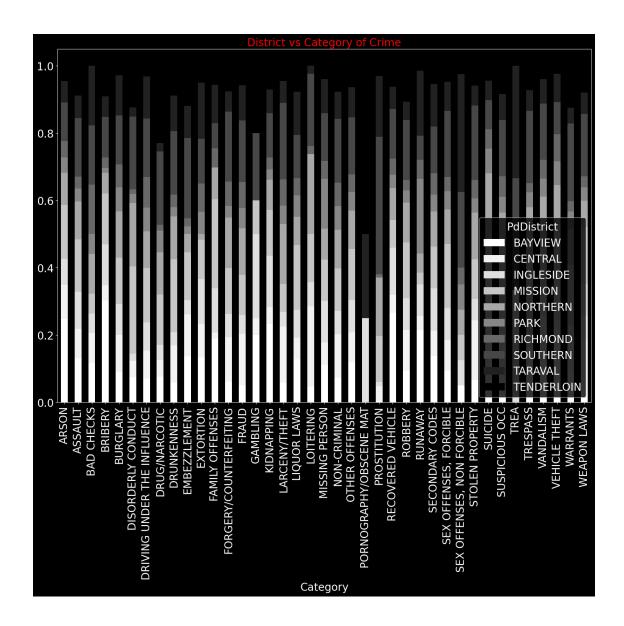
• Time for cross showdown

District vs Category of crime

```
[]: df=data.groupby(['PdDistrict','Category']).size().reset_index(name='Count')
    df=df.pivot(index='PdDistrict',columns='Category',values='Count')
    df.reset_index(inplace=True)
    df.fillna(0,inplace=True)
    df.head()
```

	di.nead()										
[]:	Category	PdDistrict	ARSON	ASSAULT	BAD CHI	ECKS	BRIBERY	BURGLARY	\		
	0	BAYVIEW	71.0	1775.0		4.0	20.0	521.0			
	1	CENTRAL	29.0	1187.0		3.0	3.0	645.0			
	2	INGLESIDE	22.0	1506.0		2.0	8.0	534.0			
	3	MISSION	46.0	2110.0		2.0	10.0	793.0			
	4	NORTHERN	27.0	1536.0		4.0	4.0	803.0			
	${\tt Category}$	DISORDERLY	CONDUCT	DRIVING	G UNDER	THE	INFLUENCE	DRUG/NARC	COTIC	\	
	0		49.0				27.0	3	327.0		
	1		32.0				31.0	2	207.0		
	2		14.0				32.0	1	191.0		
	3		171.0				61.0	ϵ	339.0		
	4		124.0				41.0	5	527.0		

```
Category DRUNKENNESS ... SEX OFFENSES, NON FORCIBLE STOLEN PROPERTY \
                                                                         27.0 ...
                                                                                                                                                                                    2.0
                                                                                                                                                                                                                                         59.0
                1
                                                                        52.0 ...
                                                                                                                                                                                    0.0
                                                                                                                                                                                                                                       156.0
                2
                                                                         18.0 ...
                                                                                                                                                                                    3.0
                                                                                                                                                                                                                                          56.0
                3
                                                                      101.0 ...
                                                                                                                                                                                    3.0
                                                                                                                                                                                                                                      104.0
                                                                        59.0 ...
                                                                                                                                                                                    3.0
                                                                                                                                                                                                                                       123.0
                Category SUICIDE SUSPICIOUS OCC TREA TRESPASS VANDALISM VEHICLE THEFT \
                                                               4.0
                                                                                                              610.0
                                                                                                                                       0.0
                                                                                                                                                                   125.0
                                                                                                                                                                                                     1059.0
                                                                                                                                                                                                                                                       1081.0
                1
                                                            10.0
                                                                                                              580.0
                                                                                                                                        0.0
                                                                                                                                                                   173.0
                                                                                                                                                                                                     1148.0
                                                                                                                                                                                                                                                          481.0
                2
                                                           16.0
                                                                                                                                                                      74.0
                                                                                                                                                                                                                                                          915.0
                                                                                                             527.0
                                                                                                                                         1.0
                                                                                                                                                                                                        761.0
                3
                                                               3.0
                                                                                                              945.0
                                                                                                                                        0.0
                                                                                                                                                                   412.0
                                                                                                                                                                                                    1091.0
                                                                                                                                                                                                                                                          932.0
                                                            14.0
                                                                                                              600.0
                                                                                                                                       0.0
                                                                                                                                                                   268.0
                                                                                                                                                                                                    1199.0
                                                                                                                                                                                                                                                          739.0
                Category WARRANTS WEAPON LAWS
                                                                                                       306.0
                                                           548.0
                1
                                                           489.0
                                                                                                       122.0
                2
                                                           307.0
                                                                                                       157.0
                3
                                                         1073.0
                                                                                                       278.0
                                                           624.0
                                                                                                       131.0
                [5 rows x 40 columns]
[]: df = pd.crosstab(data['Category'], data['PdDistrict'])
                color = plt.cm.Greys(np.linspace(0, 1, 10))
                df.div(df.sum(1).astype(float), axis = 0).plot.bar(stacked = True, color = 0).plot.bar(stacked = True,
                   \hookrightarrowcolor, figsize = (18, 12))
                plt.title('District vs Category of Crime', fontweight = 30, fontsize = 20, __
                    ⇔color = 'red')
                plt.xticks(rotation = 90)
                plt.show()
```



5.0.1 Geographical Visulization

```
[]: crimes=data['Category'].unique().tolist()
    crimes.remove('TREA')

[]: # Create a base map centered on San Francisco
    sf_map = folium.Map(location=[37.77, -122.42], zoom_start=12)

# Add markers for each incident
    for index, row in data.iterrows():
        folium.Marker([row['Y'], row['X']], tooltip=row['Category']).add_to(sf_map)
```

```
# Display the map
    sf_map.save('sf_crime_map.html')
[]: t = data.PdDistrict.value_counts()
    table = pd.DataFrame(data=t.values, index=t.index, columns=['Count'])
    table = table.reindex(["CENTRAL", "NORTHERN", "PARK", "SOUTHERN", "MISSION",
     ⇔"TENDERLOIN", "RICHMOND", "TARAVAL", "INGLESIDE", "BAYVIEW"])
    table = table.reset_index()
    table.rename({'index': 'Neighborhood'}, axis='columns', inplace=True)
    table
[]:
       PdDistrict Count
          CENTRAL 17666
         NORTHERN 20100
    1
    2
             PARK
                   8699
    3
         SOUTHERN 28446
    4
          MISSION 19503
    5 TENDERLOIN 9942
    6
         RICHMOND 8922
    7
          TARAVAL 11325
    8
        INGLESIDE 11594
    9
          BAYVIEW 14303
[]: gjson = r'https://cocl.us/sanfran_geojson'
    sf_map = folium.Map(location = [37.77, -122.42], zoom_start = 12)
    5.0.2 Dessity of crime in San Francisco
[]: sf_map.choropleth(
        geo_data=gjson,
        data=table,
         columns=['PdDistrict', 'Count'],
        key_on='feature.properties.DISTRICT',
        fill_color='YlOrRd',
        fill_opacity=0.7,
        line_opacity=0.2,
        legend_name='Crime Rate in San Francisco'
    )
    sf_map
```

[]: <folium.folium.Map at 0x7fa186789720>

6 Reference

Aman Kharwal thecleverprogrammer.com

7 Thank You!