berlin-crime

September 25, 2024

0.1 Crimes in Berlin

0.1.1 Questions

- What part of Berlin is the most dangerous?
- What crimes are growing?
- What crimes are going low?
- Folium based heatmap.

Import Libraries

[46]:
```
import numpy as np
import pandas as pd
import plotly.express as px
import plotly.graph_objs as go
from plotly.subplots import make_subplots

import matplotlib.pyplot as plt

pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
```

Load Data

[47]:
```
df = pd.read_csv('data/berlin_crimes.csv')
```

Read Data

[48]:
```
df.head()
```

[48]:
```
   Year District   Code           Location  Robbery  Street_robbery  Injury  \
0  2012    Mitte  10111      Tiergarten Süd       70              46     586
1  2012    Mitte  10112  Regierungsviertel       65              29     474
2  2012    Mitte  10113      Alexanderplatz      242             136    1541
3  2012    Mitte  10114  Brunnenstraße Süd       52              25     254
4  2012    Mitte  10221        Moabit West      130              51     629

   Agg_assault  Threat  Theft  Car  From_car  Bike  Burglary  Fire  Arson  \
0          194     118   2263   18       328   120        68    16      4
1          123     142   3203   10       307   170        37    10      4
2          454     304   8988   81       792   822       275    49     27
```

```
3           60     66   1916   86        192   396       131    14     5
4          185    199   2470   94        410   325       161    42    22

   Damage  Graffiti  Drugs  Local
0     273        26    171   1032
1     380       124     98    870
2    1538       522    435   3108
3     428       122    213    752
4     516        64    259   1403
```

[49]:
```
df.tail()
```

[49]:
```
      Year       District    Code                                Location  \
1195  2019  Reinickendorf  123012  Nord 2 - Waidmannslust/Wittenau/Lübars
1196  2019  Reinickendorf  123021              MV 1 - Märkisches Viertel
1197  2019  Reinickendorf  123022                MV 2 - Rollbergsiedlung
1198  2019  Reinickendorf  123043     West 3 - Borsigwalde/Freie Scholle
1199  2019  Reinickendorf  129900           Bezirk (Rd), nicht zuzuordnen

      Robbery  Street_robbery  Injury  Agg_assault  Threat  Theft  Car  \
1195       34              19     372           85     123   1160   30
1196       42              22     491          123     187   1100   51
1197        6               4      84           19      34    293   13
1198        8               4      95           18      43    492   21
1199        3               2      14            7       4     59    0

      From_car  Bike  Burglary  Fire  Arson  Damage  Graffiti  Drugs  Local
1195       135   150        93    16      3     306        74    110    728
1196       224    76        40    39     19     286        11     73    986
1197        36    18        34     5      2     156        56     21    212
1198        96    69        38     6      1      79         8     31    218
1199         7    15         0     1      0       7         3      9     21
```

[50]:
```
df.iloc[0]
```

[50]:
```
Year                        2012
District                   Mitte
Code                       10111
Location          Tiergarten Süd
Robbery                       70
Street_robbery                46
Injury                       586
Agg_assault                  194
Threat                       118
Theft                       2263
Car                           18
From_car                     328
```

```
Bike                          120
Burglary                       68
Fire                           16
Arson                           4
Damage                        273
Graffiti                       26
Drugs                         171
Local                        1032
Name: 0, dtype: object
```

[75]:
```
df['Location'].unique()[:10]
```

[75]:
```
array(['Tiergarten Süd', 'Regierungsviertel', 'Alexanderplatz',
       'Brunnenstraße Süd', 'Moabit West', 'Moabit Ost', 'Osloer Straße',
       'Brunnenstraße Nord', 'Parkviertel', 'Wedding Zentrum'],
      dtype=object)
```

[52]:
```
# Checking Alexanderplatz, one of the most popular locations in Berlin
df[df['Location'] == 'Alexanderplatz']
```

[52]:
```
      Year District   Code        Location  Robbery  Street_robbery  Injury  \
2     2012    Mitte  10113  Alexanderplatz      242             136    1541
152   2013    Mitte  10113  Alexanderplatz      237             149    1442
302   2014    Mitte  10113  Alexanderplatz      203             106    1309
452   2015    Mitte  10113  Alexanderplatz      157              90    1440
602   2016    Mitte  10113  Alexanderplatz      165             102    1338
752   2017    Mitte  10113  Alexanderplatz      143              90    1763
902   2018    Mitte  10113  Alexanderplatz      130              80    1531
1052  2019    Mitte  10113  Alexanderplatz      173             102    1966

      Agg_assault  Threat  Theft  Car  From_car  Bike  Burglary  Fire  Arson  \
2             454     304   8988   81       792   822       275    49     27
152           354     333  10165   85       760   926       281    47     20
302           364     350  10510   89       710  1074       241    46     18
452           408     320  12150   83       820  1082       236    35     12
602           368     313  12479   80       779  1266       222    47     20
752           478     317  10596   87       705   929       148    45     16
902           366     309  10144   68       580   880       133    26      6
1052          500     420  11233   63       587   940       137    43     12

      Damage  Graffiti  Drugs  Local
2       1538       522    435   3108
152     1301       448    590   3029
302     1207       351    506   2984
452     1171       333    499   2973
602     1065       328    534   2825
752     1162       351    804   3227
```

```
902     1036        333    971    2798
1052    1307        381   1133    3813
```

Observation: - A lot is happening in Alexanderplatz which is not surprising because it is one of the most popular and busiest places in Berlin. - I am curious to know if there are en equal number of locations

[74]:
```
df['Location'].value_counts()[:10] # There are equal number of locations
```

[74]:
```
Location
Tiergarten Süd                        8
Plänterwald                           8
Johannisthal                          8
Oberschöneweide                       8
Niederschöneweide                     8
Adlershof                             8
Köllnische Vorstadt/Spindlersfeld     8
Altglienicke                          8
Bohnsdorf                             8
Grünau                                8
Name: count, dtype: int64
```

[73]:
```
# Are there equal number of locations for each district
df.groupby('District')['Location'].value_counts()[:10]
```

[73]:
```
District                     Location
Charlottenburg-Wilmersdorf   Barstraße                            8
                             Bezirk (Ch-Wi), nicht zuzuordnen     8
                             Charlottenburg-Nord                  8
                             Düsseldorfer Straße                  8
                             Forst Grunewald                      8
                             Grunewald                            8
                             Halensee                             8
                             Heerstrasse                          8
                             Kantstraße                           8
                             Kurfürstendamm                       8
Name: count, dtype: int64
```

For each District, each location appears 8 times

[59]:
```
# Checking the District in Alexanderplatz (Mitte)
# I would like to know if, in each year, the same locations are considered for
 ↪each district.
df[df['District'] == 'Mitte'].head()
```

[59]:
```
   Year District   Code          Location  Robbery  Street_robbery  Injury  \
0  2012    Mitte  10111    Tiergarten Süd       70              46     586
1  2012    Mitte  10112  Regierungsviertel       65              29     474
```

```
2  2012    Mitte  10113      Alexanderplatz      242              136    1541
3  2012    Mitte  10114  Brunnenstraße Süd        52               25     254
4  2012    Mitte  10221          Moabit West     130               51     629

   Agg_assault  Threat  Theft  Car  From_car  Bike  Burglary  Fire  Arson  \
0          194     118   2263   18       328   120        68    16      4
1          123     142   3203   10       307   170        37    10      4
2          454     304   8988   81       792   822       275    49     27
3           60      66   1916   86       192   396       131    14      5
4          185     199   2470   94       410   325       161    42     22

   Damage  Graffiti  Drugs  Local
0     273        26    171   1032
1     380       124     98    870
2    1538       522    435   3108
3     428       122    213    752
4     516        64    259   1403
```

[42]:
```python
# Just checking if the districts are uniform
df['District'].value_counts()
```

[42]:
```
District
Treptow-Köpenick              168
Charlottenburg-Wilmersdorf    144
Pankow                        136
Lichtenberg                   112
Reinickendorf                  96
Mitte                          88
Neukölln                       88
Spandau                        80
Marzahn-Hellersdorf            80
Friedrichshain-Kreuzberg       72
Steglitz-Zehlendorf            72
Tempelhof-Schöneberg           64
Name: count, dtype: int64
```

Observation

The number of crimes (robbery, street robbery. aggravated assault, theft, etc.) are recorded in each location yearly from 2012 to 2019.

Each location belongs to a particular district with a unique code.

Each district has many locations with a range of codes.

Question

Are the same locations considered every year?

[72]:
```
df[(df['District'] == 'Neukölln')].groupby('Year')[['District', 'Location']].
    ↪value_counts()[:10]
```

[72]:
```
Year  District  Location
2012  Neukölln  Bezirk (Nk), nicht zuzuordnen    1
                Britz                            1
                Buckow                           1
                Buckow Nord                      1
                Gropiusstadt                     1
                Köllnische Heide                 1
                Neuköllner Mitte/Zentrum         1
                Reuterstraße                     1
                Rixdorf                          1
                Rudow                            1
Name: count, dtype: int64
```

[71]:
```
df.groupby('Year')[['District', 'Location']].value_counts()[:10]
```

[71]:
```
Year  District                    Location
2012  Charlottenburg-Wilmersdorf  Barstraße                          1
                                  Bezirk (Ch-Wi), nicht zuzuordnen   1
                                  Charlottenburg-Nord                1
                                  Düsseldorfer Straße                1
                                  Forst Grunewald                    1
                                  Grunewald                          1
                                  Halensee                           1
                                  Heerstrasse                        1
                                  Kantstraße                         1
                                  Kurfürstendamm                     1
Name: count, dtype: int64
```

Observation - Every year, the same sets of locations are considered for each district. - The number of locations in each district varies. For example, Mitte has 11 locations, while Treptow-Köpenick has 21 locations.

[119]:
```
df.groupby('year')['district'].value_counts()
```

[119]:
```
year  district
2012  Treptow-Köpenick              21
      Charlottenburg-Wilmersdorf    18
      Pankow                        17
      Lichtenberg                   14
      Reinickendorf                 12
      Mitte                         11
      Neukölln                      11
      Marzahn-Hellersdorf           10
      Spandau                       10
      Friedrichshain-Kreuzberg       9
```

	Steglitz-Zehlendorf	9
	Tempelhof-Schöneberg	8
2013	Treptow-Köpenick	21
	Charlottenburg-Wilmersdorf	18
	Pankow	17
	Lichtenberg	14
	Reinickendorf	12
	Mitte	11
	Neukölln	11
	Marzahn-Hellersdorf	10
	Spandau	10
	Friedrichshain-Kreuzberg	9
	Steglitz-Zehlendorf	9
	Tempelhof-Schöneberg	8
2014	Treptow-Köpenick	21
	Charlottenburg-Wilmersdorf	18
	Pankow	17
	Lichtenberg	14
	Reinickendorf	12
	Mitte	11
	Neukölln	11
	Marzahn-Hellersdorf	10
	Spandau	10
	Friedrichshain-Kreuzberg	9
	Steglitz-Zehlendorf	9
	Tempelhof-Schöneberg	8
2015	Treptow-Köpenick	21
	Charlottenburg-Wilmersdorf	18
	Pankow	17
	Lichtenberg	14
	Reinickendorf	12
	Mitte	11
	Neukölln	11
	Marzahn-Hellersdorf	10
	Spandau	10
	Friedrichshain-Kreuzberg	9
	Steglitz-Zehlendorf	9
	Tempelhof-Schöneberg	8
2016	Treptow-Köpenick	21
	Charlottenburg-Wilmersdorf	18
	Pankow	17
	Lichtenberg	14
	Reinickendorf	12
	Mitte	11
	Neukölln	11
	Marzahn-Hellersdorf	10
	Spandau	10

```
      Friedrichshain-Kreuzberg        9
      Steglitz-Zehlendorf             9
      Tempelhof-Schöneberg            8
2017  Treptow-Köpenick               21
      Charlottenburg-Wilmersdorf     18
      Pankow                         17
      Lichtenberg                    14
      Reinickendorf                  12
      Mitte                          11
      Neukölln                       11
      Marzahn-Hellersdorf            10
      Spandau                        10
      Friedrichshain-Kreuzberg        9
      Steglitz-Zehlendorf             9
      Tempelhof-Schöneberg            8
2018  Treptow-Köpenick               21
      Charlottenburg-Wilmersdorf     18
      Pankow                         17
      Lichtenberg                    14
      Reinickendorf                  12
      Mitte                          11
      Neukölln                       11
      Marzahn-Hellersdorf            10
      Spandau                        10
      Friedrichshain-Kreuzberg        9
      Steglitz-Zehlendorf             9
      Tempelhof-Schöneberg            8
2019  Treptow-Köpenick               21
      Charlottenburg-Wilmersdorf     18
      Pankow                         17
      Lichtenberg                    14
      Reinickendorf                  12
      Mitte                          11
      Neukölln                       11
      Marzahn-Hellersdorf            10
      Spandau                        10
      Friedrichshain-Kreuzberg        9
      Steglitz-Zehlendorf             9
      Tempelhof-Schöneberg            8
Name: count, dtype: int64
```

Shape of the Dataset

[64]:
```
df.shape
```

[64]:
```
(1200, 20)
```

There are 1200 rows and 20 columns (features). How many features are objects and how many are numerical?

[69]:
```python
object_columns = df.select_dtypes(include='object').columns
object_columns
```

[69]:
```
Index(['District', 'Location'], dtype='object')
```

[70]:
```python
numerical_columns = df.select_dtypes(include=['int64', 'float64']).columns
numerical_columns
```

[70]:
```
Index(['Year', 'Code', 'Robbery', 'Street_robbery', 'Injury', 'Agg_assault',
       'Threat', 'Theft', 'Car', 'From_car', 'Bike', 'Burglary', 'Fire',
       'Arson', 'Damage', 'Graffiti', 'Drugs', 'Local'],
      dtype='object')
```

[78]:
```python
print(len(object_columns))
print(len(numerical_columns))
```

```
2
18
```

There are 2 object columns and 18 numerical columns. It will be beneficial to verify that

Data Type

[79]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1200 entries, 0 to 1199
Data columns (total 20 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Year            1200 non-null   int64
 1   District        1200 non-null   object
 2   Code            1200 non-null   int64
 3   Location        1200 non-null   object
 4   Robbery         1200 non-null   int64
 5   Street_robbery  1200 non-null   int64
 6   Injury          1200 non-null   int64
 7   Agg_assault     1200 non-null   int64
 8   Threat          1200 non-null   int64
 9   Theft           1200 non-null   int64
 10  Car             1200 non-null   int64
 11  From_car        1200 non-null   int64
 12  Bike            1200 non-null   int64
 13  Burglary        1200 non-null   int64
 14  Fire            1200 non-null   int64
 15  Arson           1200 non-null   int64
 16  Damage          1200 non-null   int64
 17  Graffiti        1200 non-null   int64
 18  Drugs           1200 non-null   int64
 19  Local           1200 non-null   int64
```

```
dtypes: int64(18), object(2)
memory usage: 187.6+ KB
```

[80]:
```
df.dtypes
```

[80]:
```
Year                 int64
District            object
Code                 int64
Location            object
Robbery              int64
Street_robbery       int64
Injury               int64
Agg_assault          int64
Threat               int64
Theft                int64
Car                  int64
From_car             int64
Bike                 int64
Burglary             int64
Fire                 int64
Arson                int64
Damage               int64
Graffiti             int64
Drugs                int64
Local                int64
dtype: object
```

0.1.2 Data Cleaning

Rename Columns (Lowercase) I prefer to have my column names in lowercase

[96]:
```
def lower_column_names(col):
    return col.lower()

# df.columns.map(lambda col: col.lower())
```

[84]:
```
df.columns = df.columns.map(lower_column_names)
df.columns
```

[84]:
```
Index(['year', 'district', 'code', 'location', 'robbery', 'street_robbery',
       'injury', 'agg_assault', 'threat', 'theft', 'car', 'from_car', 'bike',
       'burglary', 'fire', 'arson', 'damage', 'graffiti', 'drugs', 'local'],
      dtype='object')
```

[85]:
```
df.head()
```

[85]:
```
   year district   code         location  robbery  street_robbery  injury  \
0  2012    Mitte  10111   Tiergarten Süd       70              46     586
```

```
1  2012     Mitte  10112  Regierungsviertel       65              29     474
2  2012     Mitte  10113      Alexanderplatz      242             136    1541
3  2012     Mitte  10114  Brunnenstraße Süd       52              25     254
4  2012     Mitte  10221         Moabit West      130              51     629

   agg_assault  threat  theft  car  from_car  bike  burglary  fire  arson  \
0          194     118   2263   18       328   120        68    16      4
1          123     142   3203   10       307   170        37    10      4
2          454     304   8988   81       792   822       275    49     27
3           60      66   1916   86       192   396       131    14      5
4          185     199   2470   94       410   325       161    42     22

   damage  graffiti  drugs  local
0     273        26    171   1032
1     380       124     98    870
2    1538       522    435   3108
3     428       122    213    752
4     516        64    259   1403
```

Check for null values

[86]:
```
df.isnull().sum()
```

[86]:
```
year              0
district          0
code              0
location          0
robbery           0
street_robbery    0
injury            0
agg_assault       0
threat            0
theft             0
car               0
from_car          0
bike              0
burglary          0
fire              0
arson             0
damage            0
graffiti          0
drugs             0
local             0
dtype: int64
```

[87]:
```
df.isna().sum()
```

[87]:
```
year              0
district          0
code              0
location          0
robbery           0
street_robbery    0
injury            0
agg_assault       0
threat            0
theft             0
car               0
from_car          0
bike              0
burglary          0
fire              0
arson             0
damage            0
graffiti          0
drugs             0
local             0
dtype: int64
```

Check for duplicated values

[88]:
```
sum(df.duplicated())
```

[88]:
```
0
```

I think a better representation of the district column should be categorical

[89]:
```
df['district'].unique()
```

[89]:
```
array(['Mitte', 'Friedrichshain-Kreuzberg', 'Pankow',
       'Charlottenburg-Wilmersdorf', 'Spandau', 'Steglitz-Zehlendorf',
       'Tempelhof-Schöneberg', 'Neukölln', 'Treptow-Köpenick',
       'Marzahn-Hellersdorf', 'Lichtenberg', 'Reinickendorf'],
      dtype=object)
```

[90]:
```
df['district'] = df['district'].astype('category')
```

[91]:
```
df.dtypes
```

[91]:
```
year                 int64
district          category
code                 int64
location            object
robbery              int64
street_robbery       int64
injury               int64
```

```
agg_assault           int64
threat                int64
theft                 int64
car                   int64
from_car              int64
bike                  int64
burglary              int64
fire                  int64
arson                 int64
damage                int64
graffiti              int64
drugs                 int64
local                 int64
dtype: object
```

[95]:
```python
df.district.cat.categories
```

[95]:
```
Index(['Charlottenburg-Wilmersdorf', 'Friedrichshain-Kreuzberg', 'Lichtenberg',
       'Marzahn-Hellersdorf', 'Mitte', 'Neukölln', 'Pankow', 'Reinickendorf',
       'Spandau', 'Steglitz-Zehlendorf', 'Tempelhof-Schöneberg',
       'Treptow-Köpenick'],
      dtype='object')
```

0.1.3 Data Refactoring

I would like to find the total crimes for each location

[97]:
```python
crime_cols = df.copy().loc[:, ~df.columns.isin(['code', 'year', 'district',␣
 ↪'location'])]
df['total_crime_count'] = crime_cols.sum(axis=1)
```

[98]:
```python
df.head()
```

[98]:
```
   year district   code           location  robbery  street_robbery  injury  \
0  2012    Mitte  10111      Tiergarten Süd       70              46     586
1  2012    Mitte  10112  Regierungsviertel       65              29     474
2  2012    Mitte  10113      Alexanderplatz      242             136    1541
3  2012    Mitte  10114  Brunnenstraße Süd       52              25     254
4  2012    Mitte  10221        Moabit West      130              51     629

   agg_assault  threat  theft  car  from_car  bike  burglary  fire  arson  \
0          194     118   2263   18       328   120        68    16      4
1          123     142   3203   10       307   170        37    10      4
2          454     304   8988   81       792   822       275    49     27
3           60      66   1916   86       192   396       131    14      5
4          185     199   2470   94       410   325       161    42     22

   damage  graffiti  drugs  local  total_crime_count
```

```
0      273       26    171   1032                 5333
1      380      124     98    870                 6046
2     1538      522    435   3108                19314
3      428      122    213    752                 4712
4      516       64    259   1403                 6960
```

I want to get the average of a the crimes row-wise but I notice that there's disparity in the data which may indicate that the median will be the best measure of getting the average because of it's resistance to outliers.

[102]:
```
df['median_crime_count'] = crime_cols.median(axis=1)
```

[103]:
```
df.head()
```

[103]:
```
   year district   code           location  robbery  street_robbery  injury  \
0  2012    Mitte  10111     Tiergarten Süd       70              46     586
1  2012    Mitte  10112  Regierungsviertel       65              29     474
2  2012    Mitte  10113      Alexanderplatz      242             136    1541
3  2012    Mitte  10114  Brunnenstraße Süd       52              25     254
4  2012    Mitte  10221        Moabit West      130              51     629

   agg_assault  threat  theft  car  from_car  bike  burglary  fire  arson  \
0          194     118   2263   18       328   120        68    16      4
1          123     142   3203   10       307   170        37    10      4
2          454     304   8988   81       792   822       275    49     27
3           60      66   1916   86       192   396       131    14      5
4          185     199   2470   94       410   325       161    42     22

   damage  graffiti  drugs  local  total_crime_count  median_crime_count
0     273        26    171   1032               5333               119.0
1     380       124     98    870               6046               123.5
2    1538       522    435   3108              19314               444.5
3     428       122    213    752               4712               126.5
4     516        64    259   1403               6960               192.0
```

[104]:
```
df.tail()
```

[104]:
```
      year       district    code                             location  \
1195  2019  Reinickendorf  123012  Nord 2 - Waidmannslust/Wittenau/Lübars
1196  2019  Reinickendorf  123021               MV 1 - Märkisches Viertel
1197  2019  Reinickendorf  123022                 MV 2 - Rollbergsiedlung
1198  2019  Reinickendorf  123043       West 3 - Borsigwalde/Freie Scholle
1199  2019  Reinickendorf  129900            Bezirk (Rd), nicht zuzuordnen

      robbery  street_robbery  injury  agg_assault  threat  theft  car  \
1195       34              19     372           85     123   1160   30
1196       42              22     491          123     187   1100   51
1197        6               4      84           19      34    293   13
```

```
1198        8              4      95            18       43     492    21
1199        3              2      14             7        4      59     0

      from_car  bike  burglary  fire  arson  damage  graffiti  drugs  local  \
1195       135   150        93    16      3     306        74    110    728
1196       224    76        40    39     19     286        11     73    986
1197        36    18        34     5      2     156        56     21    212
1198        96    69        38     6      1      79         8     31    218
1199         7    15         0     1      0       7         3      9     21

      total_crime_count  median_crime_count
1195               3438               101.5
1196               3770                74.5
1197                993                27.5
1198               1227                34.5
1199                152                 5.5
```

[105]:
```python
df.isnull().sum()
```

[105]:
```
year                  0
district              0
code                  0
location              0
robbery               0
street_robbery        0
injury                0
agg_assault           0
threat                0
theft                 0
car                   0
from_car              0
bike                  0
burglary              0
fire                  0
arson                 0
damage                0
graffiti              0
drugs                 0
local                 0
total_crime_count     0
median_crime_count    0
dtype: int64
```

0.1.4 Exploratory Data Analysis

[108]:
```
summary = df.copy().describe().T
Q3 = summary['75%']
Q1 = summary['25%']
summary['iqr'] =  Q3 - Q1
summary
```

[108]:
```
                     count          mean           std      min       25%  \
year                1200.0   2015.500000      2.292243   2012.0   2013.75
code                1200.0  67022.786667  34813.745984  10111.0  40101.00
robbery             1200.0     34.233333     37.093447      0.0     10.00
street_robbery      1200.0     18.744167     22.171153      0.0      5.00
injury              1200.0    276.334167    243.697780      0.0    108.00
agg_assault         1200.0     68.750000     71.113959      0.0     22.00
threat              1200.0     92.583333     68.455264      0.0     42.00
theft               1200.0   1492.307500   1364.442501     17.0    639.75
car                 1200.0     42.505833     28.710164      0.0     22.00
from_car            1200.0    215.275000    150.031343      1.0    109.00
bike                1200.0    197.706667    178.704771      0.0     76.00
burglary            1200.0     69.489167     57.866415      0.0     28.00
fire                1200.0     15.990833     12.681934      0.0      7.00
arson               1200.0      6.281667      5.186014      0.0      3.00
damage              1200.0    281.582500    203.010330      0.0    133.00
graffiti            1200.0     62.884167     62.292705      0.0     20.00
drugs               1200.0     97.859167    174.802343      0.0     18.00
local               1200.0    662.415833    534.787220     10.0    269.25
total_crime_count   1200.0   3634.943333   2929.424574     62.0   1675.25
median_crime_count  1200.0     80.677083     66.869420      1.5     35.50

                        50%       75%       max      iqr
year                 2015.5   2017.25    2019.0      3.5
code                70151.5  90520.00  129900.0  50419.0
robbery                22.0     42.00     242.0     32.0
street_robbery         11.0     23.00     169.0     18.0
injury                204.5    361.00    1966.0    253.0
agg_assault            44.0     86.00     500.0     64.0
threat                 75.0    124.00     420.0     82.0
theft                1100.0   2019.75   12479.0   1380.0
car                    37.0     57.00     197.0     35.0
from_car              186.0    291.00     876.0    182.0
bike                  143.0    286.00    1288.0    210.0
burglary               59.0     96.00     446.0     68.0
fire                   13.0     22.00      74.0     15.0
arson                   5.0      9.00      31.0      6.0
damage                244.0    382.00    1538.0    249.0
graffiti               45.0     87.00     530.0     67.0
```

```
drugs                   40.0     86.00    1949.0     68.0
local                  553.5    870.25    3813.0    601.0
total_crime_count     2919.5   4767.75   22810.0   3092.5
median_crime_count      62.5    101.50     460.0     66.0
```

Observation: - For most of the crime variables, the mean is bigger than the median. The distribution of the data may be right-skewed which shows there are large values at the tail that increase the value of the mean. The median is a better measure of the average because they are less susceptible to outliers. - For some of the crime features, the IQR value is bigger than the standard deviation. - There are always theft, local, and from_car crimes. - There are an incredible amount of thefts.

Question - What are the biggest contributors to the outliers? Districts? Location? Year?

Check Categorical Columns

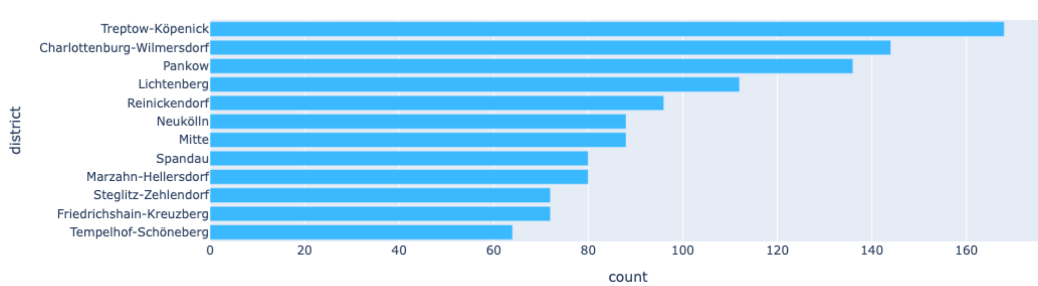
[110]:
```
cat_cols = df.select_dtypes(include=['object', 'category']).columns
df[cat_cols].describe()
```

[110]:
```
                  district         location
count                 1200             1200
unique                  12              150
top       Treptow-Köpenick  Tiergarten Süd
freq                   168                8
```

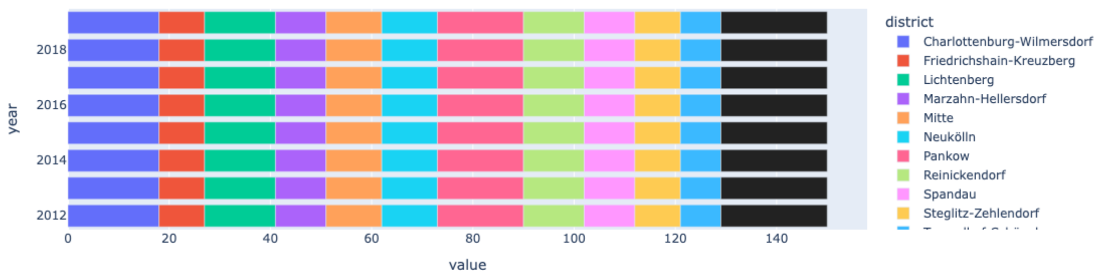
There are 12 unique districts. The data shows crime occurring more in Treptow-Köpenick which occurs 168 times (about 1.8 times the other districts). There are also 150 unique locations with Tiergarten Süd as the most frequently occurring (8 times).

[359]:
```
colors = ['#636EFA', '#EF553B', '#00CC96', '#AB63FA', '#FFA15A',
          '#19D3F3', '#FF6692', '#B6E880', '#FF97FF', '#FECB52',
          '#3BB9FF', '#222222', 'lightslategray', '#F08080', '#CCCCFF',␣
 ↪'#800080']
```

[358]:
```
# Most frequently occurring districts
district_count = df['district'].value_counts().sort_values(ascending=True)
fig = px.bar(district_count, x='count', hover_data=['count'], orientation='h',␣
 ↪color_discrete_sequence=colors)
fig.show()
```



[360]:
```
yearly_district_count = df.groupby('year', observed=False)['district'].value_counts().unstack()
fig = px.bar(yearly_district_count, orientation='h', color_discrete_sequence=colors)
fig.show()
```



[121]:
```
# Most frequently occurring locations
largest_location_count = df['location'].value_counts().nlargest()
largest_location_count
```

[121]:
```
location
Tiergarten Süd       8
Plänterwald          8
Johannisthal         8
Oberschöneweide      8
Niederschöneweide    8
Name: count, dtype: int64
```

[122]:
```
smallest_location_count = df['location'].value_counts().nsmallest()
smallest_location_count
```

[122]:
```
location
Tiergarten Süd       8
Plänterwald          8
Johannisthal         8
Oberschöneweide      8
Niederschöneweide    8
Name: count, dtype: int64
```

All the locations have equal frequencies.

Distribution of the Crimes Distribution of the crimes between 2012 and 2019

[241]:
```
crime_data = df.copy().select_dtypes('int64').iloc[:, 2:-1]
crime_data.head()
```

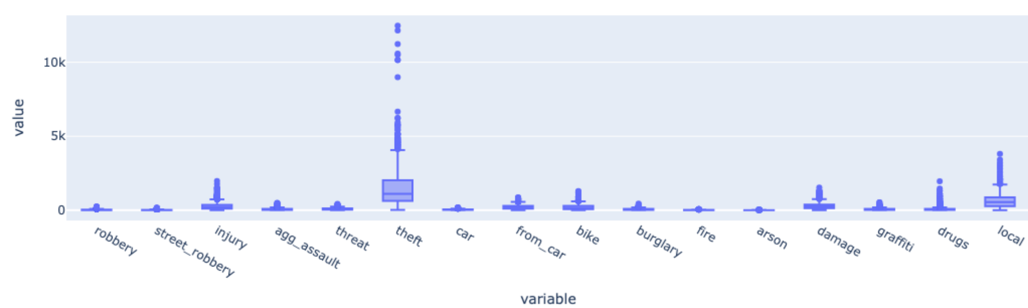
[241]:

	robbery	street_robbery	injury	agg_assault	threat	theft	car	from_car
0	70	46	586	194	118	2263	18	328
1	65	29	474	123	142	3203	10	307
2	242	136	1541	454	304	8988	81	792
3	52	25	254	60	66	1916	86	192
4	130	51	629	185	199	2470	94	410

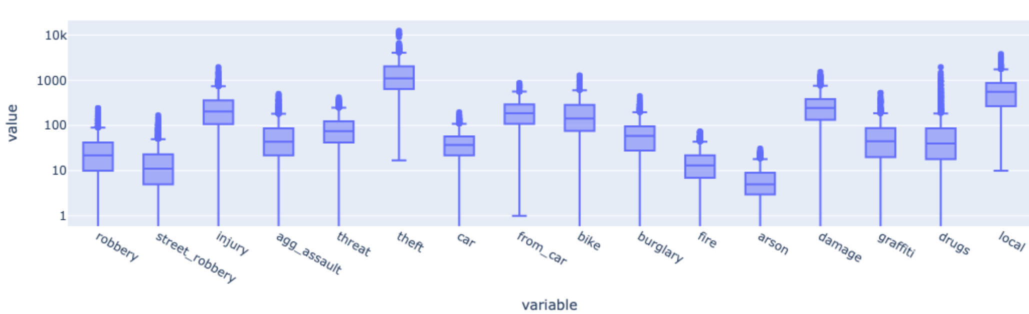
\

	bike	burglary	fire	arson	damage	graffiti	drugs	local
0	120	68	16	4	273	26	171	1032
1	170	37	10	4	380	124	98	870
2	822	275	49	27	1538	522	435	3108
3	396	131	14	5	428	122	213	752
4	325	161	42	22	516	64	259	1403

[248]:
```
fig = px.box(crime_data)
fig.show()
```



[249]:
```
fig = px.box(crime_data, log_y=True)
fig.show()
```

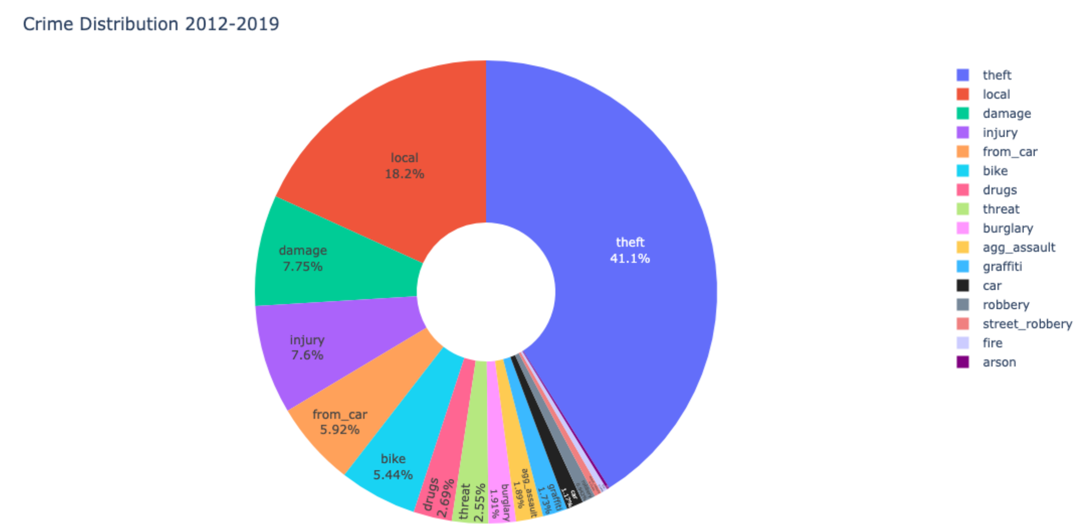


Observation

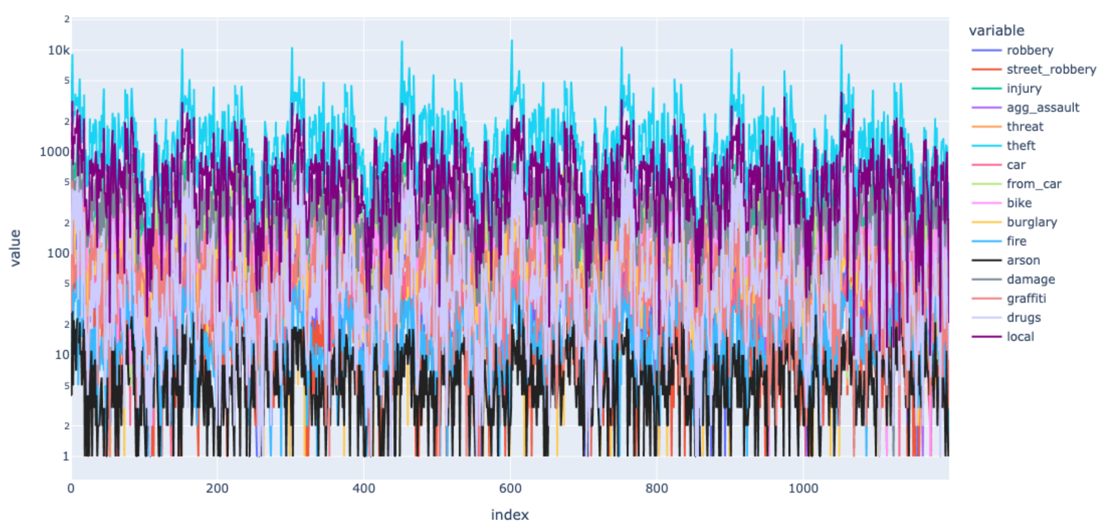
- Theft and local crimes are the most prevalent crimes with outliers in specific locations or years.

[361]:
```
perc_crime_distribution = crime_data.sum(axis=0) / crime_data.sum().sum()
print(perc_crime_distribution)
fig = px.pie(crime_data, values=perc_crime_distribution, names=crime_data.
 ↪columns, hole=.3, color_discrete_sequence=colors)
fig.update_traces(textposition='inside', textinfo='percent+label')
fig.update_layout(title_text='Crime Distribution 2012-2019', height=600)
fig.show()
```

```
robbery          0.009418
street_robbery   0.005157
injury           0.076022
agg_assault      0.018914
threat           0.025470
theft            0.410545
car              0.011694
from_car         0.059224
bike             0.054391
burglary         0.019117
fire             0.004399
arson            0.001728
damage           0.077465
graffiti         0.017300
drugs            0.026922
local            0.182236
dtype: float64
```



[362]:
```
fig = px.line(crime_data, log_y=True, color_discrete_sequence=colors)
fig.update_layout(height=600)
fig.show()
```



Yearly Total Crime Count between 2012 - 2019

[367]:
```
total_yearly_crimes = df.copy().groupby('year')[crime_data.columns].sum()
total_yearly_crimes
```

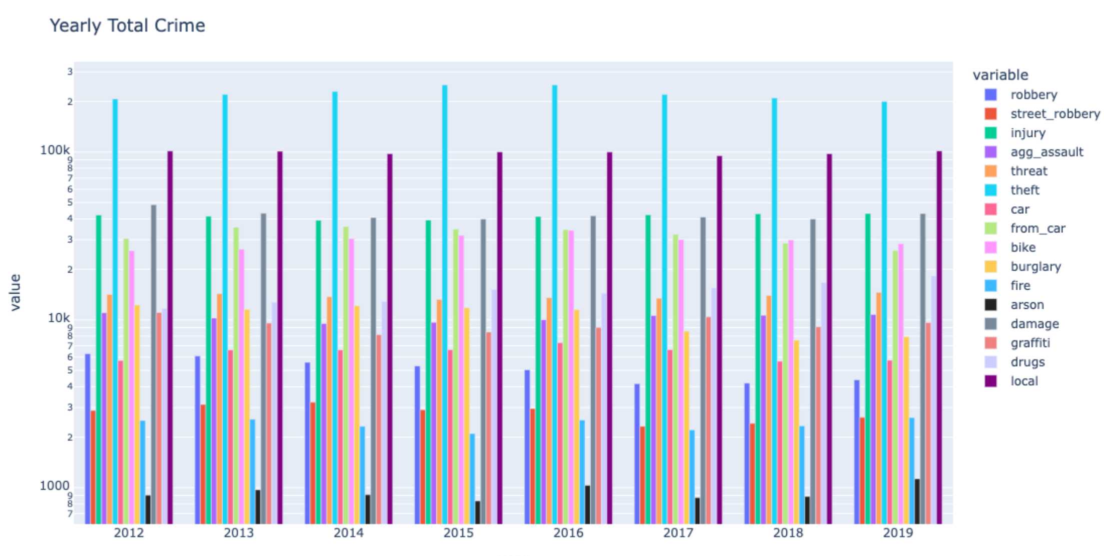
[367]:

year	robbery	street_robbery	injury	agg_assault	threat	theft	car
2012	6283	2886	42153	11032	14196	207340	5732
2013	6088	3135	41461	10247	14333	220417	6628
2014	5583	3228	39190	9515	13733	229955	6629
2015	5318	2914	39312	9664	13260	251366	6649
2016	5046	2962	41339	10024	13557	251192	7305
2017	4165	2324	42283	10608	13452	220220	6642
2018	4202	2417	42828	10656	13965	209957	5671
2019	4395	2627	43035	10754	14604	200322	5751

year	from_car	bike	burglary	fire	arson	damage	graffiti	drugs	local
2012	30503	25836	12285	2514	904	48582	11070	11687	101472
2013	35652	26389	11563	2561	972	43176	9573	12746	101063
2014	36032	30434	12149	2322	908	40678	8166	12878	97700
2015	34741	31937	11805	2103	834	39841	8471	15176	100220
2016	34515	34136	11487	2529	1032	41768	9015	14407	100073
2017	32308	30082	8572	2210	872	40985	10428	15503	95027
2018	28677	29978	7568	2334	886	39883	9103	16700	97763
2019	25902	28456	7958	2616	1130	42986	9635	18334	101581

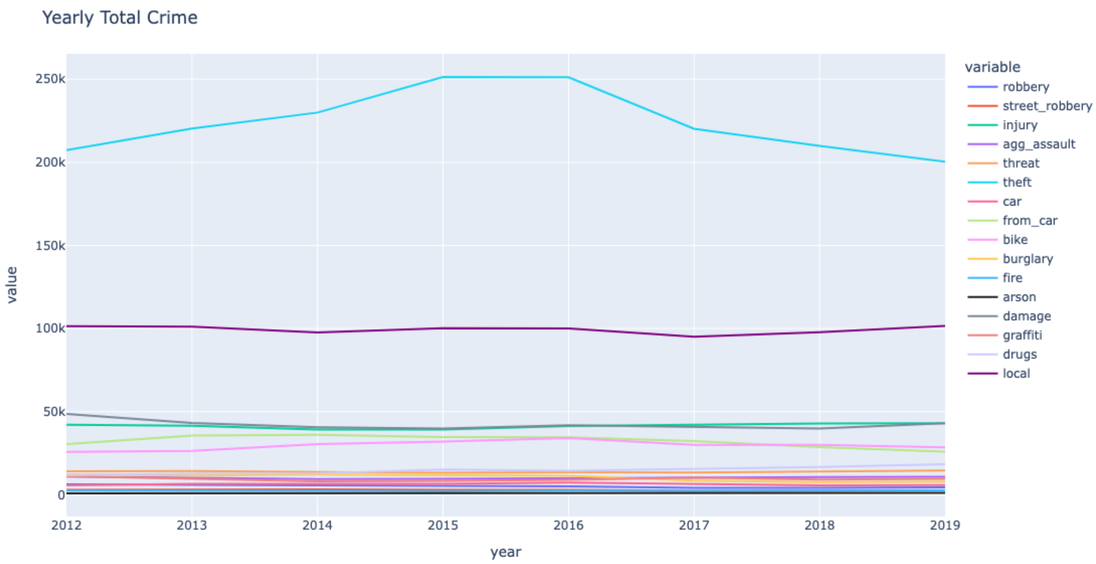
[363]:

```
fig = px.bar(total_yearly_crimes, barmode='group', log_y=True,
    color_discrete_sequence=colors)
fig.update_layout(title_text='Yearly Total Crime', height=600)
fig.show()
```



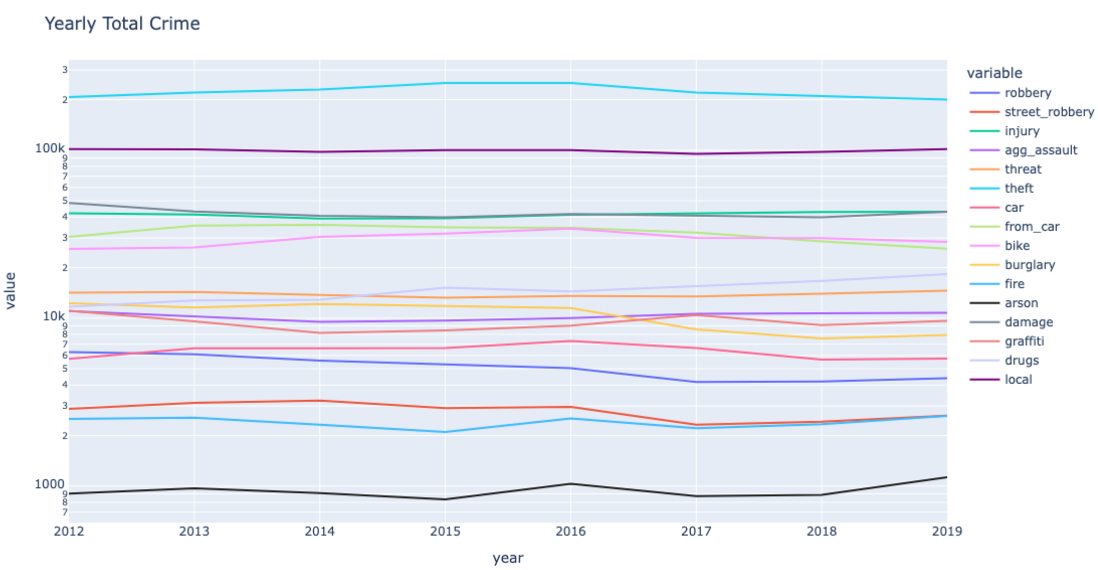
Yearly Total Crime Counts

[364]:
```
fig = px.line(total_yearly_crimes, color_discrete_sequence=colors)
fig.update_layout(title_text='Yearly Total Crime', height=600)
fig.show()
```



The theft and local makes the other variables less visible

[365]:
```
fig = px.line(total_yearly_crimes, log_y=True, color_discrete_sequence=colors)
fig.update_layout(title_text='Yearly Total Crime', height=600)
fig.show()
```



Much better but this looks like a wave. I cannot see the trend.

Feature Normalization

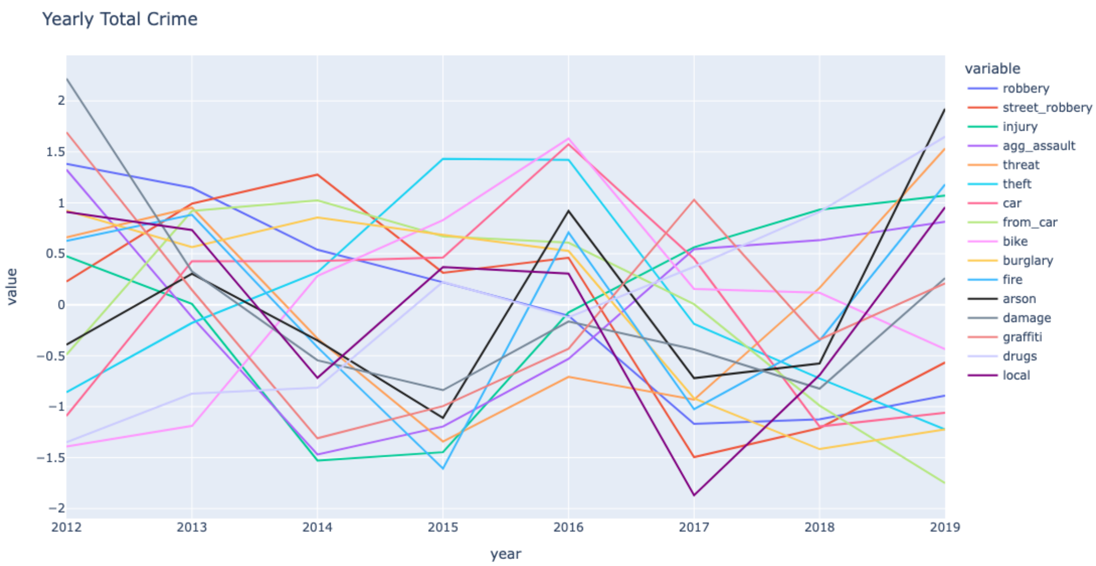
[327]:
```
data_feature_norm = (total_yearly_crimes - total_yearly_crimes.mean()) /␣
↪total_yearly_crimes.std()
data_feature_norm.head()
```

[327]:
```
       robbery  street_robbery    injury  agg_assault    threat     theft  \
year
2012  1.382428        0.228110  0.475575     1.325671  0.659970 -0.858758
2013  1.147608        0.991797  0.007358    -0.120683  0.953052 -0.178406
2014  0.539484        1.277030 -1.529233    -1.469386 -0.330520  0.317824
2015  0.220370        0.313986 -1.446686    -1.194855 -1.342402  1.431766
2016 -0.107174        0.461203 -0.075189    -0.531558 -0.707034  1.422713

           car  from_car      bike  burglary      fire     arson    damage  \
year
2012 -1.090972 -0.489774 -1.389984  0.923565  0.627096 -0.392014  2.219474
2013  0.427197  0.920457 -1.188764  0.565376  0.882555  0.304900  0.328349
2014  0.428891  1.024533  0.283091  0.856094 -0.416479 -0.351019 -0.545500
2015  0.462779  0.670948  0.829988  0.685433 -1.606807 -1.109425 -0.838299
2016  1.574296  0.609050  1.630138  0.527672  0.708626  0.919824 -0.164197

      graffiti     drugs     local
year
2012  1.693391 -1.350105  0.909978
2013  0.145177 -0.872223  0.733558
2014 -1.309957 -0.812657 -0.717059
2015 -0.994523  0.224331  0.369933
2016 -0.431912 -0.122685  0.306525
```

[366]:
```
fig = px.line(data_feature_norm, color_discrete_sequence=colors)
fig.update_layout(title_text='Yearly Total Crime', height=600)
fig.show()
```



Observation - The graph looks like a zigzag. There are variations in the data over time. - Some crimes have a sharp increase or decrease in certain years while others go in the opposite direction. For example, In 2017, all other crimes seem to have dropped except graffiti and aggravated assault. - What could have happened to cause the sharp decrease in crimes in 2017? - The increase in crimes from 2015 to 2016?

Median-Average Yearly Crime

[378]:
```
median_yearly_crimes = df.copy().groupby('year')[crime_data.columns].median()
median_yearly_crimes
```

[378]:

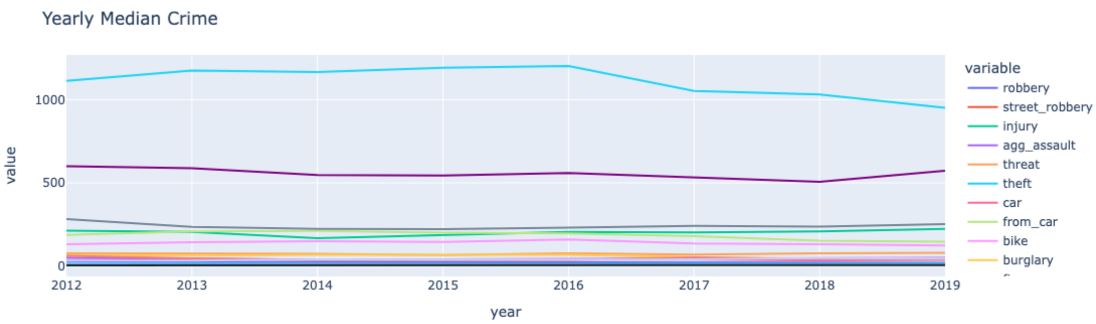
year	robbery	street_robbery	injury	agg_assault	threat	theft	car
2012	26.0	10.5	213.0	49.5	76.0	1113.5	34.0
2013	25.5	11.5	205.0	44.0	74.5	1175.0	37.5
2014	25.0	13.5	168.0	38.5	74.0	1166.5	39.5
2015	22.0	11.0	188.5	40.0	66.0	1191.5	39.5
2016	22.0	11.0	205.5	43.0	76.5	1202.5	41.0
2017	19.5	10.0	202.5	46.5	69.0	1052.5	39.0
2018	19.0	9.5	208.5	49.0	77.0	1032.0	34.0
2019	19.5	10.0	223.5	49.0	80.0	951.0	37.5

\

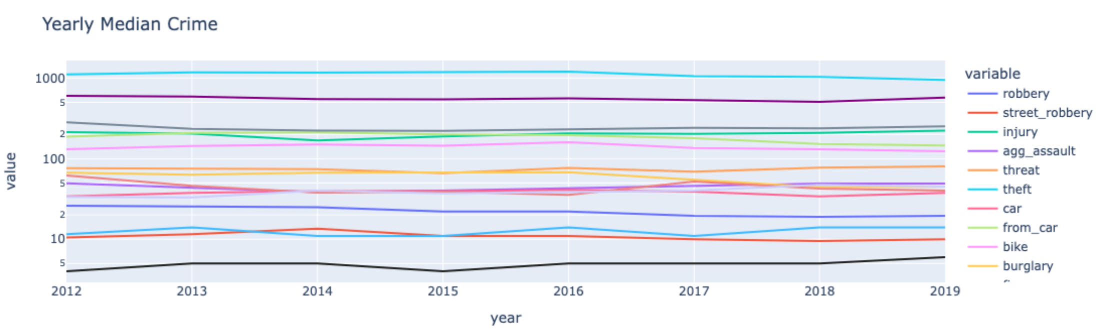
year	from_car	bike	burglary	fire	arson	damage	graffiti	drugs	local
2012	187.0	131.0	67.0	11.5	4.0	282.0	62.0	33.5	600.5
2013	209.0	143.5	63.0	14.0	5.0	235.0	46.0	33.0	588.5
2014	211.5	149.5	67.0	11.0	5.0	223.0	38.0	40.0	547.5
2015	200.0	144.5	67.0	11.0	4.0	221.5	39.0	37.0	544.0

2016	195.5	160.5	68.0	14.0	5.0	231.0	35.5	38.5	560.0
2017	179.5	136.0	54.5	11.0	5.0	241.5	52.0	40.0	534.0
2018	152.5	131.0	44.5	14.0	5.0	237.0	42.5	47.5	507.0
2019	146.0	123.5	45.0	14.0	6.0	252.0	40.0	45.0	573.0

[379]:
```
fig = px.line(median_yearly_crimes, color_discrete_sequence=colors)
fig.update_layout(title_text='Yearly Median Crime', height=600)
fig.show()
```



[380]:
```
fig = px.line(median_yearly_crimes, color_discrete_sequence=colors, log_y=True)
fig.update_layout(title_text='Yearly Median Crime', height=600)
fig.show()
```



[ ]:
```
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