Chicago crime trends

December 5, 2023

[12]:
```
# Will need this to run plotly for interactive figures
#pip install plotly==5.18.0
```

[13]:
```
import pandas as pd
import plotly.express as px
import seaborn as sns
# Load your dataset
data = pd.read_csv('Crimes_-_2022.csv')
# looking at null values
# our focus is only these variables:
data = data[['Primary Type', 'Description', 'Location Description', 'Arrest',␣
↪'Domestic']]
data = data.dropna()
print(" \nTotal number of missing values of each column: \n\n", data.isnull().
↪sum())
data
```

```
Total number of missing values of each column:

 Primary Type            0
Description             0
Location Description    0
Arrest                  0
Domestic                0
dtype: int64
```

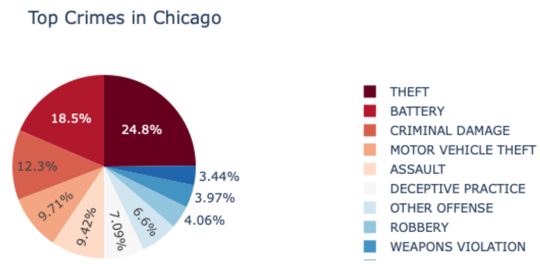
[13]:
```
                      Primary Type  \
0                      SEX OFFENSE
1                    OTHER OFFENSE
2       OFFENSE INVOLVING CHILDREN
3                      SEX OFFENSE
4                      SEX OFFENSE
…                              …
239049             CRIMINAL DAMAGE
239050                    STALKING
239051                       THEFT
239052          DECEPTIVE PRACTICE
```

```
239053                     BATTERY

                                              Description  \
0                        INDECENT SOLICITATION OF A CHILD
1                          HARASSMENT BY ELECTRONIC MEANS
2         AGGRAVATED CRIMINAL SEXUAL ABUSE BY FAMILY MEMBER
3                          SEXUAL EXPLOITATION OF A CHILD
4                        AGGRAVATED CRIMINAL SEXUAL ABUSE
…                                                       …
239049                                         TO VEHICLE
239050                                       CYBERSTALKING
239051                                       FROM BUILDING
239052              FINANCIAL IDENTITY THEFT $300 AND UNDER
239053                                              SIMPLE

                          Location Description  Arrest  Domestic
0                                    RESIDENCE   False      True
1                                    RESIDENCE   False      True
2                                    RESIDENCE   False      True
3                                    APARTMENT    True     False
4                                    RESIDENCE   False     False
…                                          …       …         …
239049                                   ALLEY   False     False
239050  PARKING LOT / GARAGE (NON RESIDENTIAL)   False      True
239051            COMMERCIAL / BUSINESS OFFICE   False     False
239052                               RESIDENCE   False     False
239053                               APARTMENT   False     False

[238172 rows x 5 columns]
```

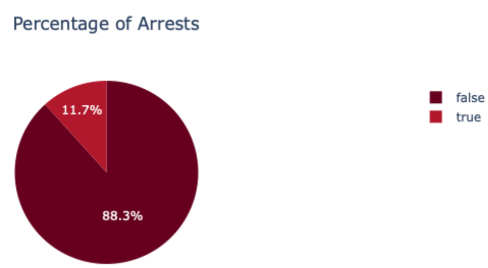
[14]:
```python
# for the pie charts
primary_type = data["Primary Type"]
arrests = data["Arrest"]
domestic = data["Domestic"]
location = data["Location Description"]
```

[15]:
```python
# for top crimes
num_crimes_type = primary_type.value_counts()
type = pd.DataFrame(data=num_crimes_type.index, columns=["Primary Type"])
type['values'] = num_crimes_type.values
```

[16]:
```python
fig = px.pie(type[:10], values='values', names='Primary Type', title='Top␣
↪Crimes in Chicago', color_discrete_sequence=px.colors.sequential.RdBu)
fig.update_layout(title_text='Top Crimes in Chicago',title_x=0.
↪5,legend=dict(yanchor="top",y=0.99,xanchor="right",x=1.2),width=800)
fig.show()
```



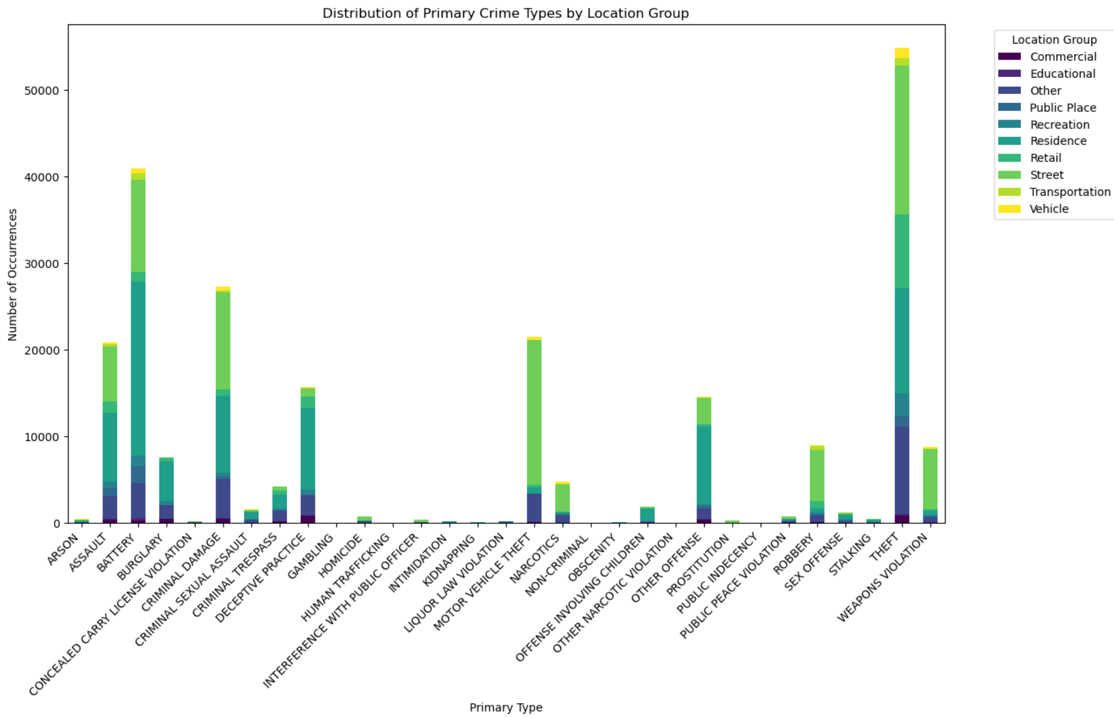
[17]:
```python
# for num of arrests
Num_arrests = arrests.value_counts()
type = pd.DataFrame(data=Num_arrests.index, columns=["Arrest"])
type['values'] = Num_arrests.values
fig = px.pie(type[:10], values='values', names='Arrest', title='Percentage of Arrests', color_discrete_sequence=px.colors.sequential.RdBu)
fig.update_layout(title_text='Percentage of Arrests', title_x=0.5)
fig.update_layout(legend=dict(yanchor="top",y=0.99,xanchor="right",x=0.90),width=800)
fig.show()
```



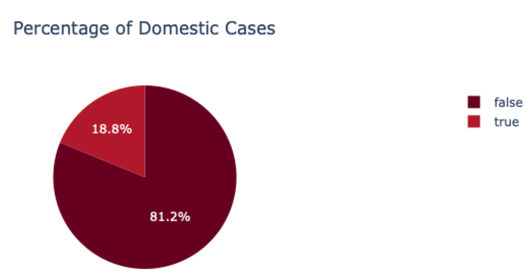
[18]:
```python
import matplotlib.pyplot as plt
location_groups = {
    'Residence': ['RESIDENCE', 'APARTMENT', 'RESIDENCE - PORCH / HALLWAY', 'HOUSE', 'CONDO'],
    'Street': ['STREET', 'SIDEWALK', 'ALLEY', 'BRIDGE', 'HIGHWAY / EXPRESSWAY'],
    'Commercial': ['COMMERCIAL / BUSINESS OFFICE', 'WAREHOUSE', 'VEHICLE - COMMERCIAL', 'WAREHOUSE', 'FACTORY / MANUFACTURING BUILDING'],
    'Public Place': ['SCHOOL - PUBLIC GROUNDS', 'SCHOOL - PUBLIC BUILDING', 'CTA PLATFORM', 'PARK PROPERTY', 'AIRPORT/AIRCRAFT'],
```

```
    'Vehicle': ['VEHICLE - COMMERCIAL', 'VEHICLE NON-COMMERCIAL', 'VEHICLE -␣
↪OTHER RIDE SHARE SERVICE (LYFT, UBER, ETC.)', 'VEHICLE - DELIVERY TRUCK'],
    'Retail': ['SMALL RETAIL STORE', 'BANK', 'GAS STATION', 'DEPARTMENT STORE',␣
↪'CONVENIENCE STORE'],
    'Transportation': ['CTA BUS STOP', 'CTA BUS', 'CTA TRAIN', 'AIRPORT␣
↪TERMINAL LOWER LEVEL - SECURE AREA', 'CTA STATION'],
    'Educational': ['SCHOOL - PRIVATE GROUNDS', 'SCHOOL - PRIVATE BUILDING',␣
↪'COLLEGE / UNIVERSITY - RESIDENCE HALL', 'COLLEGE / UNIVERSITY - GROUNDS'],
    'Recreation': ['BAR OR TAVERN', 'BARBERSHOP', 'RESTAURANT', 'ATHLETIC␣
↪CLUB', 'BOWLING ALLEY'],
    'Other': ['OTHER (SPECIFY)', 'GOVERNMENT BUILDING / PROPERTY', 'NURSING /␣
↪RETIREMENT HOME', 'ALLEY', 'OTHER RAILROAD PROPERTY / TRAIN DEPOT']
}
plt.figure(figsize=(6, 6))
data['Location Group'] = data['Location Description'].apply(lambda loc:␣
↪next((group for group, locs in location_groups.items() if loc in locs),␣
↪'Other'))
crime_location_counts = data.groupby(['Primary Type', 'Location Group']).size().
↪unstack().fillna(0)
crime_location_counts.plot(kind='bar', stacked=True, figsize=(14, 8),␣
↪colormap='viridis')
plt.title('Distribution of Primary Crime Types by Location Group')
plt.xlabel('Primary Type')
plt.ylabel('Number of Occurrences')
plt.legend(title='Location Group', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.xticks(rotation=45, ha='right')
plt.show()
```

```
<Figure size 600x600 with 0 Axes>
```



[19]:
```python
# num of domestic
num_domestic = domestic.value_counts()
type = pd.DataFrame(data=num_domestic.index, columns=["Domestic"])
type['values'] = num_domestic.values
fig = px.pie(type[:10], values='values', names='Domestic', title='Percentage of Domestic Cases', color_discrete_sequence=px.colors.sequential.RdBu)
fig.update_layout(title_text='Percentage of Domestic Cases', title_x=0.5)
fig.update_layout(legend=dict(yanchor="top",y=0.99,xanchor="right",x=0.90), width = 800)
fig.show()
```



[20]:
```
# top locations for crime
num_location = location.value_counts()
type = pd.DataFrame(data=num_location.index, columns=["Location Description"])
type['values'] = num_location.values
fig = px.pie(type[:10], values='values', names='Location Description',␣
↪title='Top Locations for Crime', color_discrete_sequence=px.colors.
↪sequential.RdBu)
fig.update_layout(title_text='Top Locations for Crime', title_x=0.5,width=800)
fig.show()
```

Logistic regression

[21]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
from sklearn.preprocessing import LabelEncoder
import warnings
import pandas as pd
warnings.filterwarnings('ignore')
# Selecting specific columns
selected_features = ['Description', 'Location Description', 'Arrest',␣
↪'Domestic']
target = 'Primary Type'
# Setting the features and the target variable
X = data[selected_features]
Y = data[target]
# # Encoding categorical values, need to do to make the machine learn from␣
↪these variables
for column in X.columns:
    if X[column].dtype == 'object' or X[column].dtype == 'bool':
        X[column] = LabelEncoder().fit_transform(X[column])
# Encoding categorical values
label_encoder = LabelEncoder()
Y_encoded = label_encoder.fit_transform(Y)
```

```python
# Splitting the data into training and testing sets
XTrain, XTest, yTrain, yTest = train_test_split(X, Y_encoded, test_size=0.2,␣
 ↪random_state=42)
# Training the Logistic Regression model
logistic_model = LogisticRegression()
logistic_model.fit(XTrain, yTrain)
# Predicting on the test set
yPred = logistic_model.predict(XTest)
# Evaluating the model
accuracy = accuracy_score(yTest, yPred)
classification_report_output = classification_report(yTest, yPred)
# Now we finally have output so we can use this for presentation
print("Accuracy: ", accuracy*100)
print("Classification Report:\n", classification_report_output)
```

```
Accuracy:  25.913718904167105
Classification Report:
               precision    recall  f1-score   support

           0       0.00      0.00      0.00        93
           1       0.00      0.00      0.00      4118
           2       0.56      0.46      0.51      8316
           3       0.00      0.00      0.00      1542
           4       0.03      0.06      0.04        34
           5       0.21      0.52      0.30      5382
           6       0.00      0.00      0.00       324
           7       0.00      0.00      0.00       837
           8       0.00      0.00      0.00      3240
          10       0.00      0.00      0.00       136
          11       0.00      0.00      0.00         5
          12       0.00      0.00      0.00        71
          13       0.00      0.00      0.00        34
          14       0.00      0.00      0.00        17
          15       0.00      0.00      0.00        42
          16       0.00      0.00      0.00      4229
          17       0.00      0.00      0.00       949
          18       0.00      0.00      0.00         1
          19       0.00      0.00      0.00        10
          20       0.00      0.00      0.00       335
          21       0.00      0.00      0.00         2
          22       0.00      0.00      0.00      2956
          23       0.00      0.00      0.00        60
          25       0.00      0.00      0.00       151
          26       0.00      0.00      0.00      1786
          27       0.00      0.00      0.00       240
          28       0.00      0.00      0.00        81
          29       0.24      0.52      0.33     10921
          30       0.00      0.00      0.00      1723
```

```
    accuracy                           0.26     47635
   macro avg       0.04      0.05      0.04     47635
weighted avg       0.18      0.26      0.20     47635
```

Logistic regression, though done on components of the data with binary states, did not provide a great fit. With an accuracy of 26%, the logistic regression provided low recall, precision, AND F1-scores, the last of which displaying low balance between recall and precision. Only a quarter of classes were correctly classified. Another model like an svm might perform a bit better.

SVM

[23]:
```
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report
import pandas as pd
# Selecting specific columns
selected_features = ['Description', 'Location Description', 'Arrest',␣
 ↪'Domestic']
target = 'Primary Type'
# Setting the features and the target vairiable
X = data[selected_features]
Y = data[target]
# Encoding categorical values, need to do to make the machine learn from these␣
 ↪variables
for column in X.columns:
    if X[column].dtype == 'object' or X[column].dtype == 'bool':
        X[column] = LabelEncoder().fit_transform(X[column])
# Splitting the data into training and testing sets
XTrain, XTest, yTrain, yTest = train_test_split(X, Y, test_size=0.2,␣
 ↪random_state=42)
# Training the SVM model
svm_model = SVC(random_state=42)
svm_model.fit(XTrain, yTrain)
# Predicting on the test set
yPred = svm_model.predict(XTest)
# Evaluating the model
accuracy = accuracy_score(yTest, yPred)
classification_report = classification_report(yTest, yPred)
# Now we finally have output so we can use this for presentation
print("This is the accuracy of the model ", accuracy)
print("Here is a classification report", classification_report)
```

```
This is the accuracy of the model  0.690542668206151
Here is a classification report                                   precision
recall  f1-score   support
```

ARSON	0.00	0.00	0.00	93
ASSAULT	0.56	0.52	0.54	4118
BATTERY	0.67	0.78	0.72	8316
BURGLARY	0.00	0.00	0.00	1542
CONCEALED CARRY LICENSE VIOLATION	0.00	0.00	0.00	34
CRIMINAL DAMAGE	0.66	0.98	0.79	5382
CRIMINAL SEXUAL ASSAULT	0.00	0.00	0.00	324
CRIMINAL TRESPASS	0.00	0.00	0.00	837
DECEPTIVE PRACTICE	0.50	0.72	0.60	3240
HOMICIDE	0.00	0.00	0.00	136
HUMAN TRAFFICKING	0.00	0.00	0.00	5
INTERFERENCE WITH PUBLIC OFFICER	0.00	0.00	0.00	71
INTIMIDATION	0.00	0.00	0.00	34
KIDNAPPING	0.00	0.00	0.00	17
LIQUOR LAW VIOLATION	0.00	0.00	0.00	42
MOTOR VEHICLE THEFT	0.85	0.94	0.89	4229
NARCOTICS	0.99	0.13	0.23	949
NON-CRIMINAL	0.00	0.00	0.00	1
OBSCENITY	0.00	0.00	0.00	10
OFFENSE INVOLVING CHILDREN	0.00	0.00	0.00	335
OTHER NARCOTIC VIOLATION	0.00	0.00	0.00	2
OTHER OFFENSE	0.62	0.54	0.58	2956
PROSTITUTION	0.00	0.00	0.00	60
PUBLIC PEACE VIOLATION	0.00	0.00	0.00	151
ROBBERY	0.81	0.59	0.68	1786
SEX OFFENSE	0.00	0.00	0.00	240
STALKING	0.00	0.00	0.00	81
THEFT	0.81	0.90	0.85	10921
WEAPONS VIOLATION	0.06	0.01	0.02	1723
accuracy			0.69	47635
macro avg	0.23	0.21	0.20	47635
weighted avg	0.63	0.69	0.64	47635

The SVM produced a learning model with an accuracy of 69%, much more accurate than the logistic regression model. While in genuine application falls short of ethically being able to "predict" crime, especially once applied to real individuals and real demographics, it can be used in general analysis to gain a broad understanding of what types of crime might be committed under certain conditions.