```python
#!pip install numpy==1.26.4

#!pip install scikit-learn-extra

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn_extra.cluster import KMedoids
from sklearn.cluster import KMeans

print(np.__version__)
```

```
1.26.4
```

```python
df = pd.read_csv('train.csv')

df.info()
```

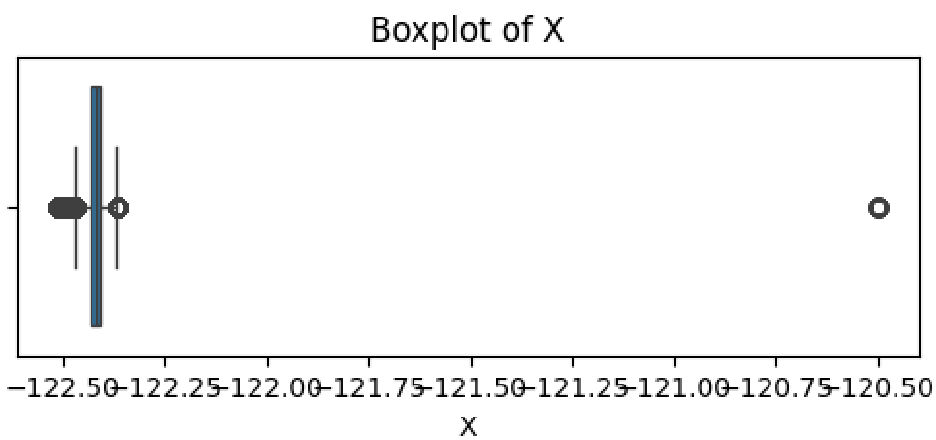
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 878049 entries, 0 to 878048
Data columns (total 9 columns):
 #   Column      Non-Null Count   Dtype  
---  ------      --------------   -----  
 0   Dates       878049 non-null  object 
 1   Category    878049 non-null  object 
 2   Descript    878049 non-null  object 
 3   DayOfWeek   878049 non-null  object 
 4   PdDistrict  878049 non-null  object 
 5   Resolution  878049 non-null  object 
 6   Address     878049 non-null  object 
 7   X           878049 non-null  float64
 8   Y           878049 non-null  float64
dtypes: float64(2), object(7)
memory usage: 60.3+ MB
```

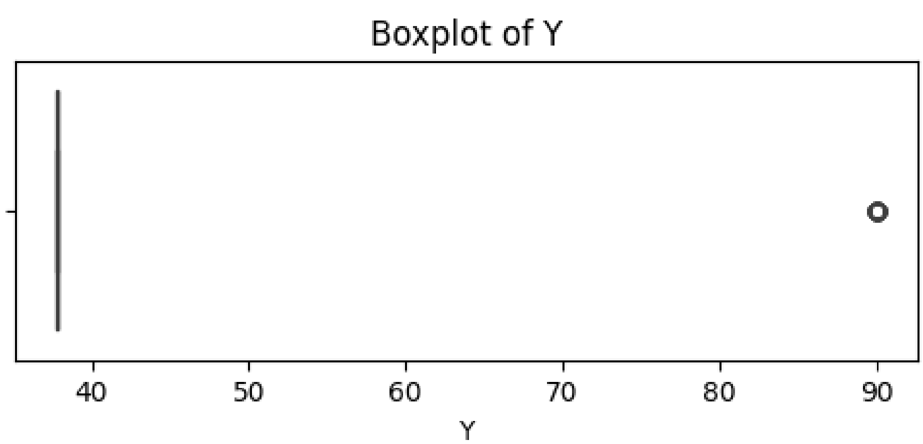
```python
df.isna().sum()
```

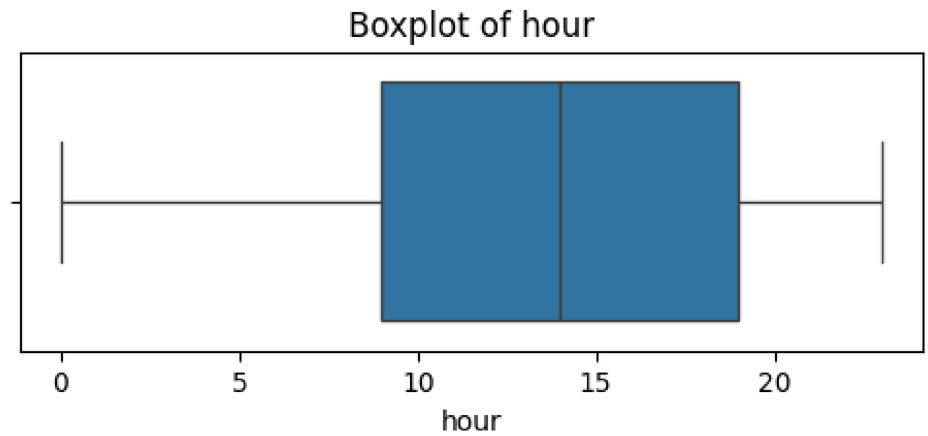
```
Dates         0
Category      0
Descript      0
DayOfWeek     0
PdDistrict    0
Resolution    0
Address       0
X             0
Y             0
dtype: int64
```

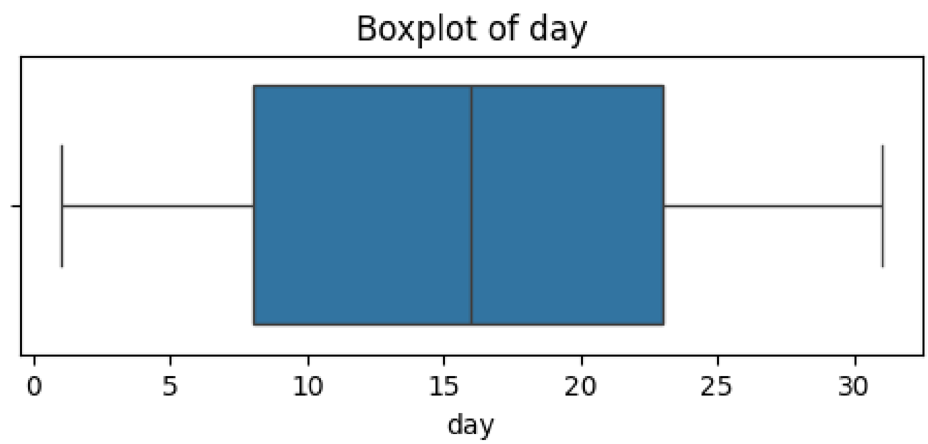
```python
df.dropna(inplace=True)

df.duplicated().sum()
```

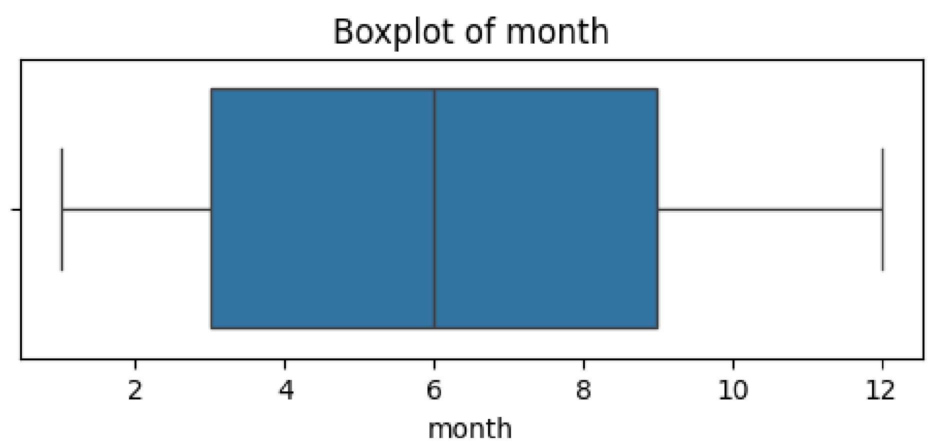
```
2323

df.drop_duplicates(inplace = True)

df['Dates'] = pd.to_datetime(df['Dates'])

df['year'] = df['Dates'].dt.year
df['month'] = df['Dates'].dt.month
df['day'] = df['Dates'].dt.day
df['hour'] = df['Dates'].dt.hour



numerical_cols = ['X', 'Y', 'hour', 'day', 'month']
for col in numerical_cols:
    plt.figure(figsize=(6, 2))
    sns.boxplot(x=df[col])
    plt.title(f"Boxplot of {col}")
    plt.show()
```







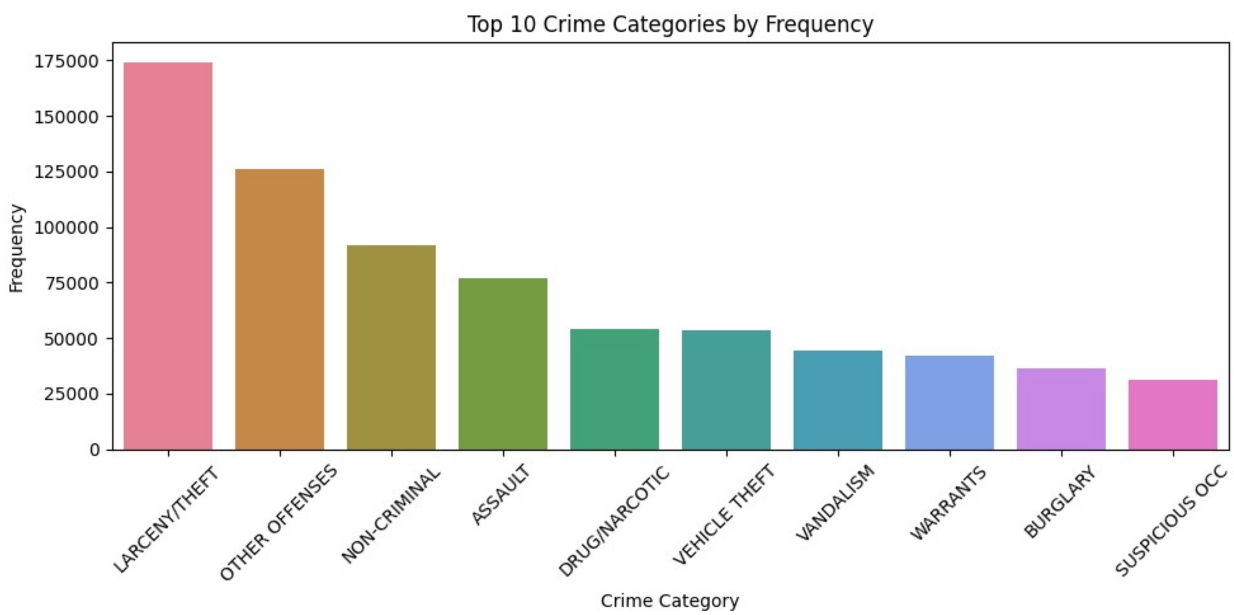





```
df = df[(df['Y'] < 38) & (df['Y'] > 37) & (df['X'] < -122) & (df['X']
> -123)]



plt.figure(figsize=(10, 5),constrained_layout=True)
```

```
# Get top 10 categories
tmp = df['Category'].value_counts().head(10)

# Create a colored barplot
sns.barplot(x=tmp.index, y=tmp.values, palette='husl')  # You can
change 'viridis' to any other palette

plt.title('Top 10 Crime Categories by Frequency')
plt.xticks(rotation=45)
plt.xlabel('Crime Category')
plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```

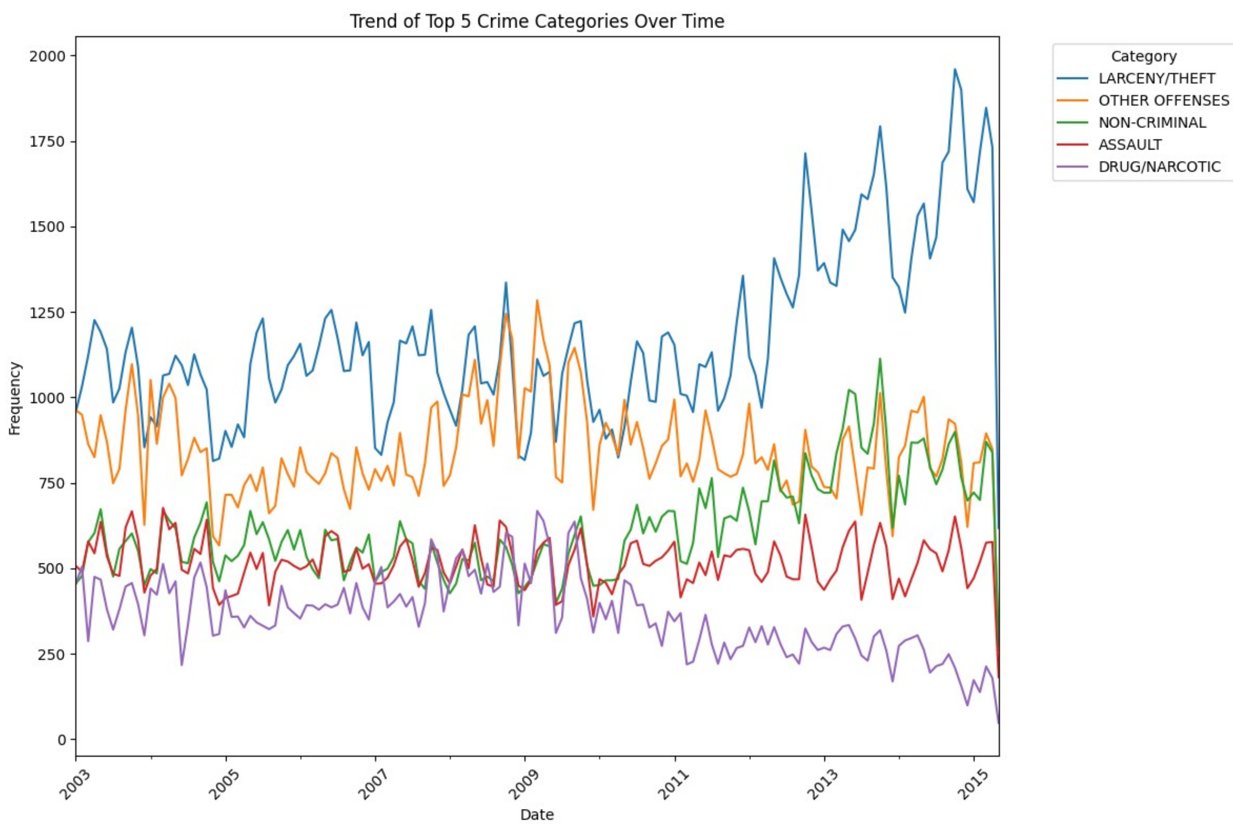
```
<ipython-input-67-2225c78d2a53>:7: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x=tmp.index, y=tmp.values, palette='husl')  # You can
change 'viridis' to any other palette
<ipython-input-67-2225c78d2a53>:13: UserWarning: The figure layout has
changed to tight
  plt.tight_layout()
```




```
dates_indexed = df.set_index('Dates')

category_trend = dates_indexed.groupby(
    [pd.Grouper(freq='M'), 'Category']).size().unstack(fill_value=0)
```

```
# Get the top N categories by total count
top_categories =
dates_indexed['Category'].value_counts().nlargest(5).index

# Filter the category trend data to only include top categories
top_category_trend = category_trend[top_categories]

# Plot only the top categories
top_category_trend.plot(kind='line', figsize=(12, 8))
plt.title('Trend of Top 5 Crime Categories Over Time')
plt.ylabel('Frequency')
plt.xlabel('Date')
plt.xticks(rotation=45)
plt.legend(title='Category', bbox_to_anchor=(1.05, 1), loc='upper
left')
plt.tight_layout()
plt.show()
```

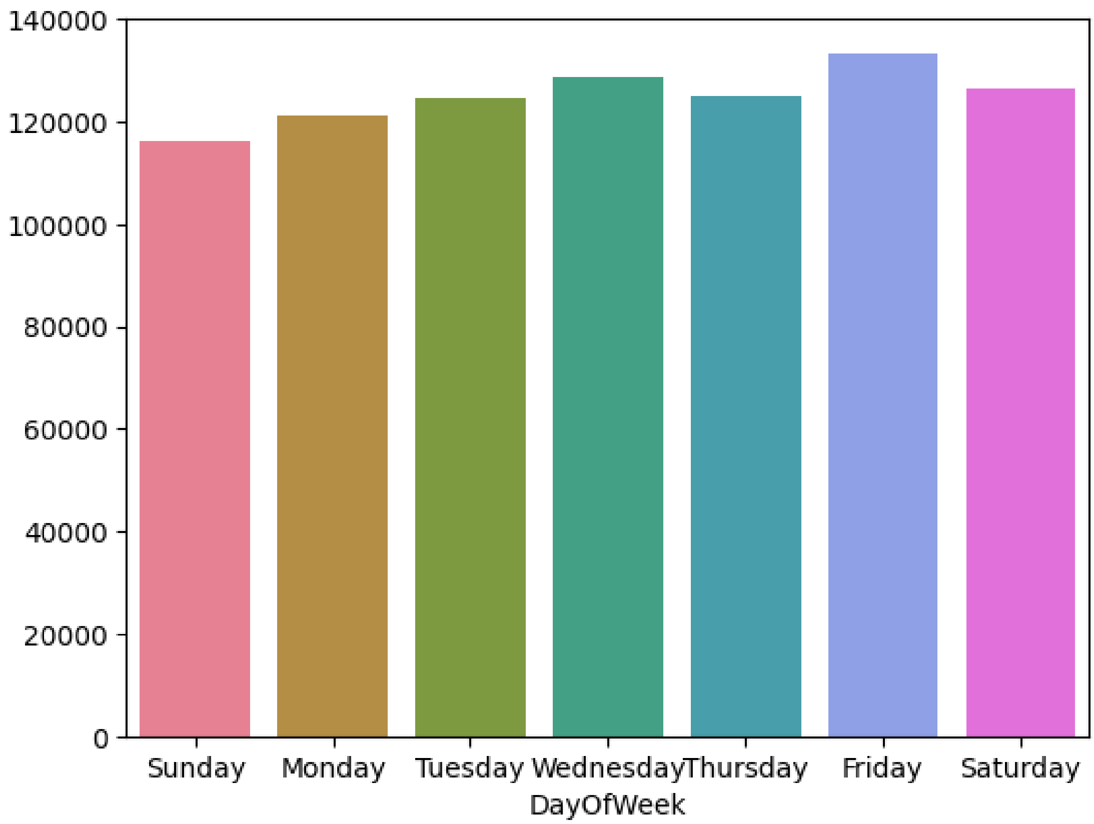
```
<ipython-input-68-784c25f3e55a>:4: FutureWarning: 'M' is deprecated
and will be removed in a future version, please use 'ME' instead.
  [pd.Grouper(freq='M'), 'Category']).size().unstack(fill_value=0)
```




```
sns.barplot(
    x=df.DayOfWeek.value_counts().index,
```

```
    y=df.DayOfWeek.value_counts().values,
    order=['Sunday', 'Monday', 'Tuesday', 'Wednesday', 'Thursday',
'Friday', 'Saturday'],
    palette='husl'
)
```

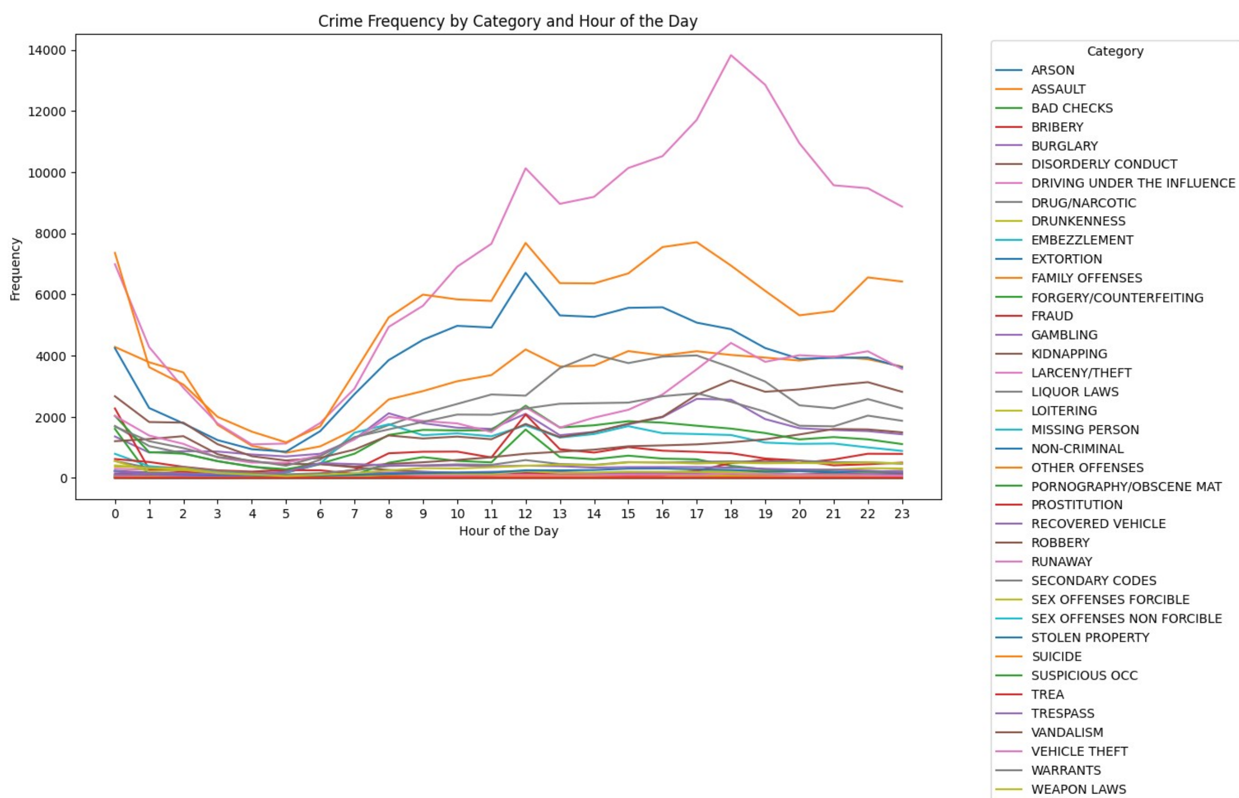
```
<ipython-input-69-4d25189fd6cd>:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(

<Axes: xlabel='DayOfWeek'>
```




```
# Group by hour and category, count occurrences
hourly_category_trend = df.groupby(['hour',
'Category']).size().unstack(fill_value=0)

# Plot the category trends by hour
plt.figure(figsize=(12, 8))
hourly_category_trend.plot(kind='line', figsize=(14, 8))
plt.title('Crime Frequency by Category and Hour of the Day')
```

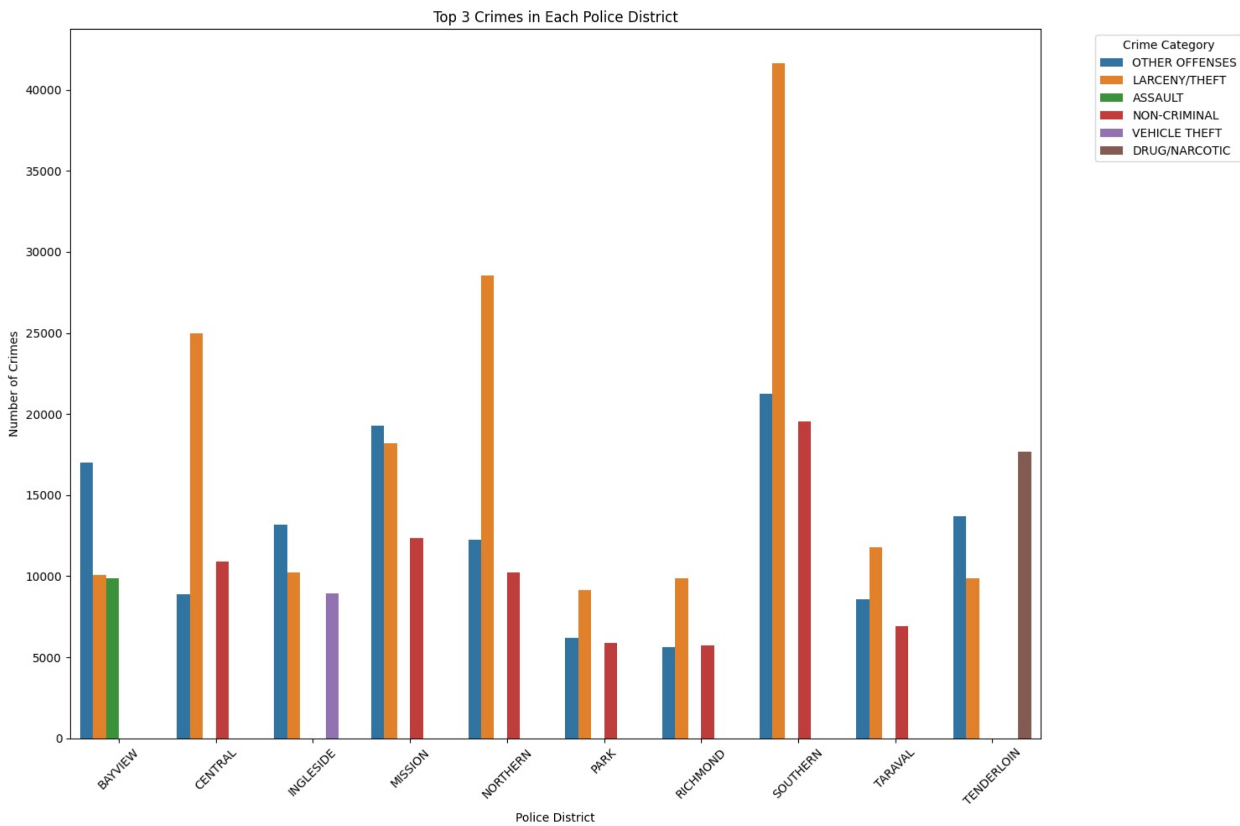
```python
plt.ylabel('Frequency')
plt.xlabel('Hour of the Day')
plt.xticks(ticks=range(0, 24), labels=range(0, 24))  # Ensure x-axis
has all hours
plt.legend(title='Category', bbox_to_anchor=(1.05, 1), loc='upper
left')
plt.tight_layout()
plt.show()
```

```
<Figure size 1200x800 with 0 Axes>
```



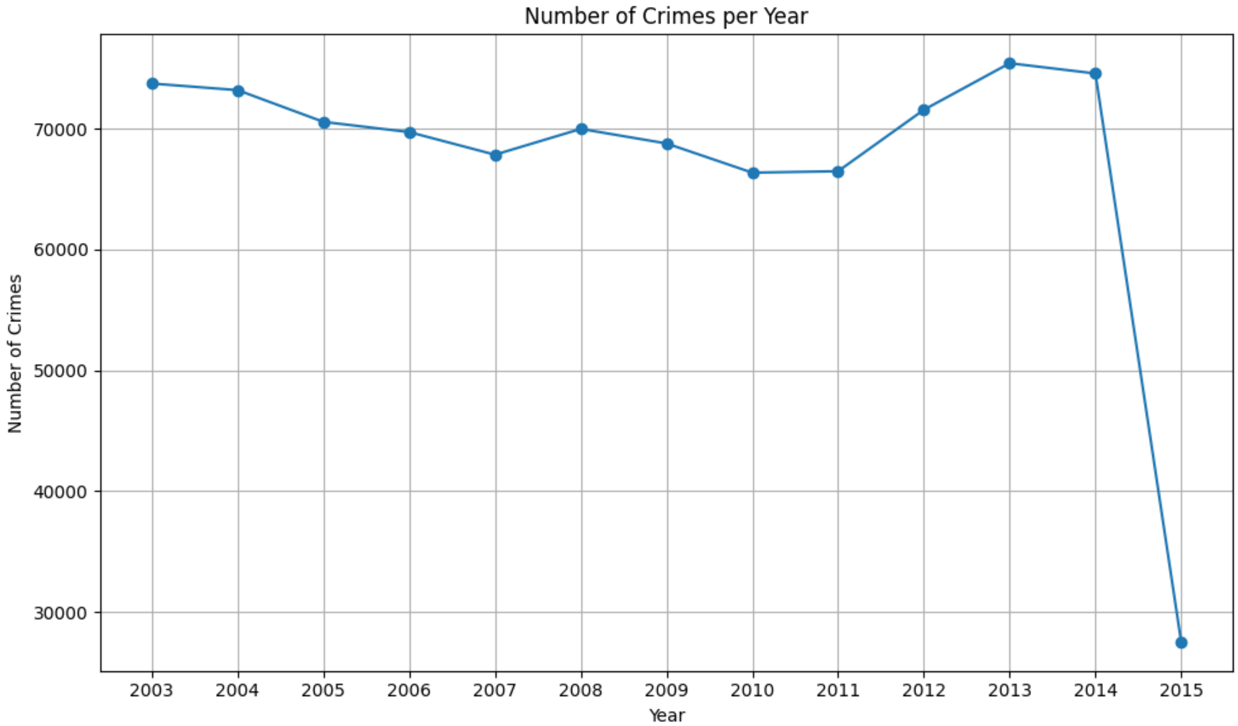

```python
district_crime_counts = df.groupby(['PdDistrict',
'Category']).size().reset_index(name='Count')

# Sort and pick top 3 crimes per district
top3_crimes_per_district = (
    district_crime_counts
    .sort_values(['PdDistrict', 'Count'], ascending=[True, False])
    .groupby('PdDistrict')
    .head(3)
)

# Now plot
plt.figure(figsize=(15, 10))
sns.barplot(data=top3_crimes_per_district, x='PdDistrict', y='Count',
```

```
hue='Category')

plt.title('Top 3 Crimes in Each Police District')
plt.xlabel('Police District')
plt.ylabel('Number of Crimes')
plt.xticks(rotation=45)
plt.legend(title='Crime Category', bbox_to_anchor=(1.05, 1),
loc='upper left')
plt.tight_layout()
plt.show()
```

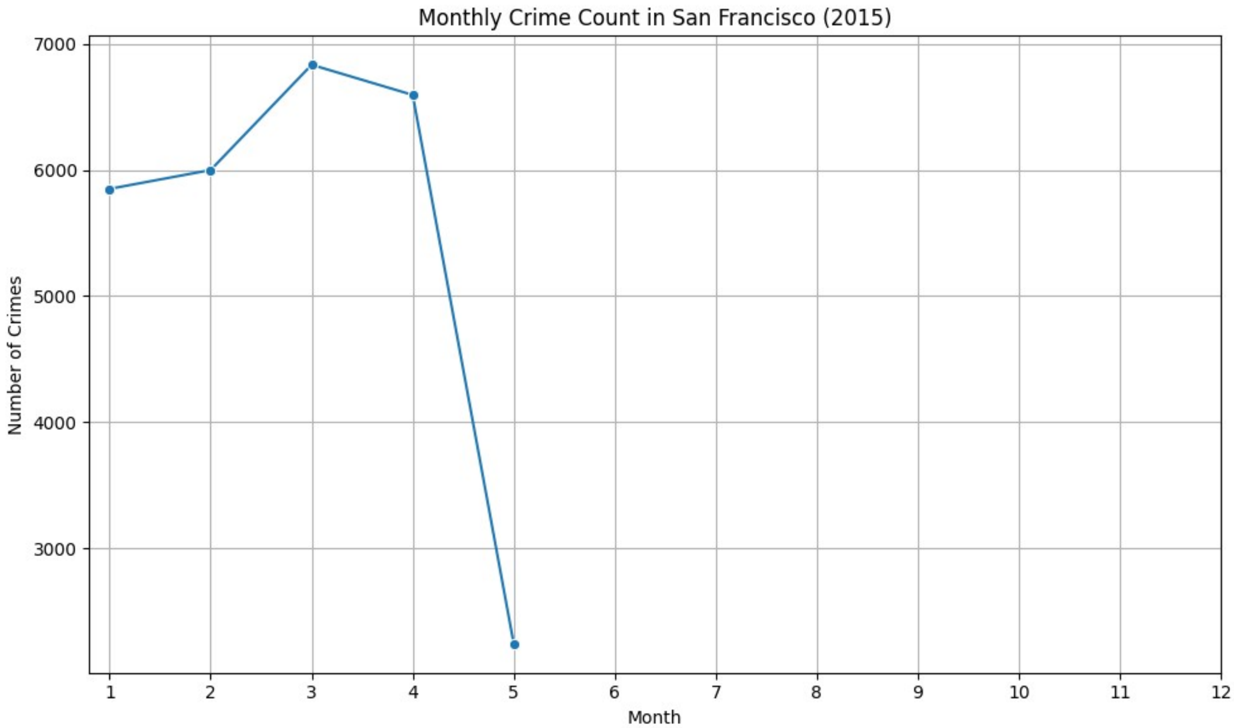



```
crime_counts_by_year = df.groupby('year').size()

# Plot
plt.figure(figsize=(10, 6))
plt.plot(crime_counts_by_year.index, crime_counts_by_year.values,
marker='o')
plt.title('Number of Crimes per Year')
plt.xlabel('Year')
plt.ylabel('Number of Crimes')
plt.grid(True)
plt.xticks(crime_counts_by_year.index)  # show all years on x-axis
```

```
plt.tight_layout()
plt.show()
```




```
# Filter for 2015
df_2015 = df[df['Dates'].dt.year == 2015]

# Group by month
monthly_crimes_2015 =
df_2015.groupby(df_2015['Dates'].dt.month).size().reset_index(name='cr
ime_count')

# Plot
plt.figure(figsize=(10, 6))
sns.lineplot(data=monthly_crimes_2015, x='Dates', y='crime_count',
marker='o')

plt.title('Monthly Crime Count in San Francisco (2015)')
plt.xlabel('Month')
plt.ylabel('Number of Crimes')
plt.xticks(range(1, 13))
plt.grid(True)
plt.tight_layout()
plt.show()
```




```
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import LabelEncoder



df1=df[(df["year"]==2015)]

sc=MinMaxScaler()
sc.fit(df1[["X"]])
df1["X_scale"]=sc.transform(df1[["X"]])


sc.fit(df1[["Y"]])
df1["Y_scale"]=sc.transform(df1[["Y"]])

le=LabelEncoder()
df1["Category"]=le.fit_transform(df1["Category"])

sc.fit(df1[["Category"]])
df1["cat_sc"]=sc.transform(df1[["Category"]])
df1.head()
```

```
<ipython-input-74-db92acb92d79>:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
```

```
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df1["X_scale"]=sc.transform(df1[["X"]])
<ipython-input-74-db92acb92d79>:14: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df1["Y_scale"]=sc.transform(df1[["Y"]])
<ipython-input-74-db92acb92d79>:17: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df1["Category"]=le.fit_transform(df1["Category"])
<ipython-input-74-db92acb92d79>:20: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  df1["cat_sc"]=sc.transform(df1[["Category"]])
```

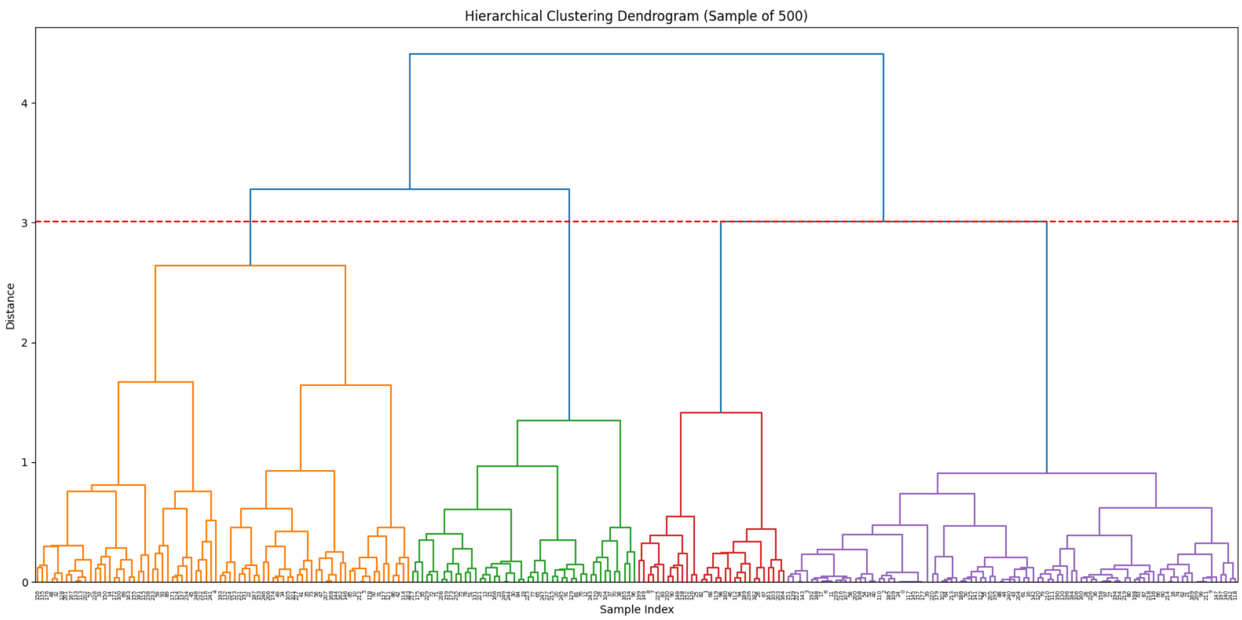

```
{"summary":"{\n  \"name\": \"df1\",\n  \"rows\": 27522,\n  \"fields\":
[\n    {\n      \"column\": \"Dates\",\n      \"properties\": {\n
\"dtype\": \"date\",\n        \"min\": \"2015-01-05 00:01:00\",\n
\"max\": \"2015-05-13 23:53:00\",\n        \"num_unique_values\":
12096,\n        \"samples\": [\n          \"2015-05-11 11:10:00\",\n
\"2015-01-07 14:02:00\",\n          \"2015-05-03 23:03:00\"\
n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Category\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 9,\n        \"min\": 0,\n
\"max\": 36,\n        \"num_unique_values\": 37,\n        \"samples\":
[\n          19,\n          7,\n          33\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Descript\",\n      \"properties\":
{\n        \"dtype\": \"category\",\n        \"num_unique_values\":
559,\n        \"samples\": [\n          \"VANDALISM OR GRAFFITI TOOLS,
POSSESSION\",\n          \"INTOXICATED JUVENILE\",\n
\"BURGLARY,BLDG. UNDER CONSTRUCTION, UNLAWFUL ENTRY\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"DayOfWeek\",\n
\"properties\": {\n        \"dtype\": \"category\",\n
\"num_unique_values\": 7,\n        \"samples\": [\n
```

```
\"Wednesday\",\n          \"Tuesday\",\n          \"Friday\"\
n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"PdDistrict\",\n      \"properties\": {\n        \"dtype\":
\"category\",\n        \"num_unique_values\": 10,\n
\"samples\": [\n          \"MISSION\",\n          \"PARK\",\n
\"CENTRAL\"\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Resolution\",\n      \"properties\": {\n        \"dtype\":
\"category\",\n        \"num_unique_values\": 10,\n
\"samples\": [\n          \"CLEARED-CONTACT JUVENILE FOR MORE INFO\",\
n          \"NONE\",\n          \"UNFOUNDED\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Address\",\n      \"properties\":
{\n        \"dtype\": \"category\",\n        \"num_unique_values\":
8115,\n        \"samples\": [\n          \"900 Block of SCOTT ST\",\n
\"BEACH ST / STOCKTON ST\",\n          \"14TH ST / MINNA ST\"\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"X\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0.026236931909153344,\n
\"min\": -122.513642064265,\n        \"max\": -122.365565425353,\n
\"num_unique_values\": 8885,\n        \"samples\": [\n          -
122.470873483267,\n          -122.478575817534,\n          -
122.389487749378\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Y\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 0.024450013487924846,\n        \"min\": 37.7080829769335,\n
\"max\": 37.819923463743,\n        \"num_unique_values\": 8885,\n
\"samples\": [\n          37.7492742889732,\n
37.7850879697075,\n          37.724599376829296\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"year\",\n      \"properties\": {\n
\"dtype\": \"int32\",\n        \"num_unique_values\": 1,\n
\"samples\": [\n          2015\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"month\",\n      \"properties\": {\n        \"dtype\":
\"int32\",\n        \"num_unique_values\": 5,\n        \"samples\": [\
n          4\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"day\",\n      \"properties\": {\n        \"dtype\": \"int32\",\n
\"num_unique_values\": 30,\n        \"samples\": [\n          23\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"hour\",\n      \"properties\":
{\n        \"dtype\": \"int32\",\n        \"num_unique_values\": 24,\n
\"samples\": [\n          15\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"X_scale\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 0.1771848152546543,\n        \"min\":
0.0,\n        \"max\": 1.0,\n        \"num_unique_values\": 8885,\n
```

```
\"samples\": [\n          0.2888273350356485\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Y_scale\",\n      \"properties\":
{\n        \"dtype\": \"number\",\n        \"std\":
0.21861504885587024,\n        \"min\": 0.0,\n        \"max\": 1.0,\n
\"num_unique_values\": 8885,\n        \"samples\": [\n
0.368304119686627\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"cat_sc\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 0.2622990554348488,\n        \"min\": 0.0,\n        \"max\":
1.0,\n        \"num_unique_values\": 37,\n        \"samples\": [\n
0.5277777777777778\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe","variable_name":"df1"}
```


```python
from scipy.cluster.hierarchy import linkage, dendrogram, fcluster
import matplotlib.pyplot as plt
import pandas as pd

# 1. Take a random sample (e.g., 500 rows)
sample_df = df1.sample(n=250, random_state=42)  # Set random_state for
reproducibility

# 2. Prepare the data for clustering
X = sample_df[['X_scale', 'Y_scale', 'cat_sc']]

# 3. Compute the linkage matrix
linked = linkage(X, method='ward')

# 4. Plot the dendrogram
num_clusters = 3
plt.figure(figsize=(16, 8))
dendrogram(linked,
           orientation='top',
           distance_sort='descending',
           show_leaf_counts=True,
           color_threshold=linked[-num_clusters, 2],
           no_labels=False)
plt.axhline(y=linked[-num_clusters, 2], color='red', linestyle='--')
plt.title("Hierarchical Clustering Dendrogram (Sample of 500)")
plt.xlabel("Sample Index")
plt.ylabel("Distance")
plt.tight_layout()
plt.show()

# 5. Assign cluster labels
sample_df['hier_cluster'] = fcluster(linked, num_clusters,
criterion='maxclust')

# Optional: Add a distance-based superclass
```

```
sample_df['superclass'] = fcluster(linked, t=12, criterion='distance')

# 6. Display result
print(sample_df[['X_scale', 'Y_scale', 'cat_sc', 'hier_cluster',
'superclass']].head())
```




```
         X_scale   Y_scale    cat_sc  hier_cluster  superclass
24360  0.744461  0.602087  0.444444             1           1
18715  0.684729  0.665889  0.027778             1           1
13348  0.715824  0.616021  0.444444             1           1
22221  0.834068  0.727802  0.444444             1           1
10046  0.402816  0.075044  0.027778             3           1
```

```
from sklearn.metrics import silhouette_score

# Use the same feature matrix X
score = silhouette_score(X, sample_df['hier_cluster'])
print(f"Silhouette Score for Hierarchical Clustering
(k={num_clusters}): {score:.4f}")
```

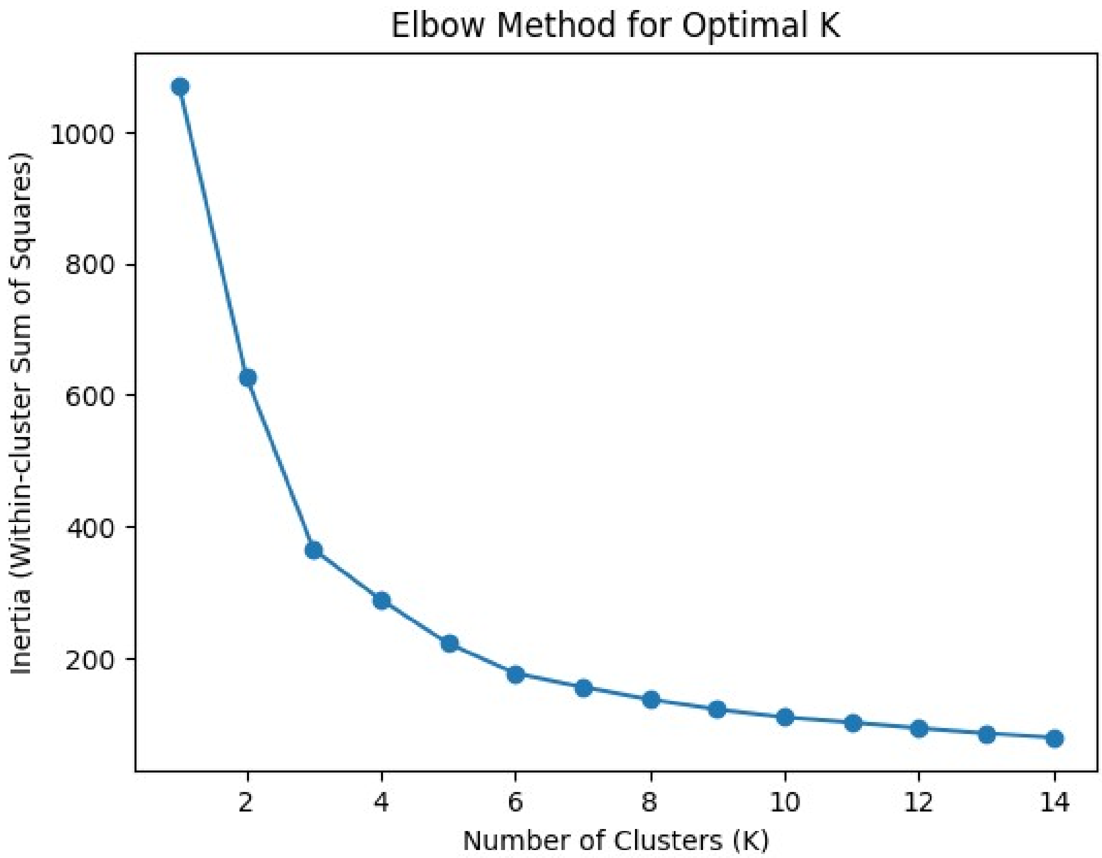
```
Silhouette Score for Hierarchical Clustering (k=3): 0.3069
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 875659 entries, 0 to 878048
Data columns (total 13 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   Dates       875659 non-null  datetime64[ns]
 1   Category    875659 non-null  object
```

```
 2   Descript    875659 non-null  object
 3   DayOfWeek   875659 non-null  object
 4   PdDistrict  875659 non-null  object
 5   Resolution  875659 non-null  object
 6   Address     875659 non-null  object
 7   X           875659 non-null  float64
 8   Y           875659 non-null  float64
 9   year        875659 non-null  int32
 10  month       875659 non-null  int32
 11  day         875659 non-null  int32
 12  hour        875659 non-null  int32
dtypes: datetime64[ns](1), float64(2), int32(4), object(6)
memory usage: 80.2+ MB
```

```python
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

best = []
for i in range(1, 15):
    km1 = KMeans(n_clusters=i, random_state=42)
    km1.fit(df[["X", "Y"]])  # Combine X and Y features
    best.append(km1.inertia_)

plt.plot(range(1, 15), best, marker='o')
plt.xlabel("Number of Clusters (K)")
plt.ylabel("Inertia (Within-cluster Sum of Squares)")
plt.title("Elbow Method for Optimal K")
plt.show()
```




```
!pip install scikit-learn-extra
```

```
Requirement already satisfied: scikit-learn-extra in
/usr/local/lib/python3.11/dist-packages (0.3.0)
Requirement already satisfied: numpy>=1.13.3 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn-extra)
(1.26.4)
Requirement already satisfied: scipy>=0.19.1 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn-extra)
(1.15.2)
Requirement already satisfied: scikit-learn>=0.23.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn-extra)
(1.6.1)
Requirement already satisfied: joblib>=1.2.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn>=0.23.0-
>scikit-learn-extra) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn>=0.23.0-
>scikit-learn-extra) (3.6.0)
```

#Kmedoids when K = 5

```
k=5

# Combine features into a single matrix
X = df1[['X', 'Y']]

# Fit KMedoids with the combined feature matrix
kmedoids = KMedoids(n_clusters=k).fit(X)

clusters = kmedoids.cluster_centers_
labels = kmedoids.labels_
```

```
/usr/local/lib/python3.11/dist-packages/sklearn_extra/cluster/
_k_medoids.py:329: UserWarning: Cluster 2 is empty!
self.labels_[self.medoid_indices_[2]] may not be labeled with its
corresponding cluster (2).
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/sklearn_extra/cluster/_k_medoi
ds.py:329: UserWarning: Cluster 3 is empty!
self.labels_[self.medoid_indices_[3]] may not be labeled with its
corresponding cluster (3).
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/sklearn_extra/cluster/_k_medoi
ds.py:329: UserWarning: Cluster 4 is empty!
self.labels_[self.medoid_indices_[4]] may not be labeled with its
corresponding cluster (4).
  warnings.warn(
```

```
# Drop unwanted columns
df_2 = df1.drop(["Descript", "Resolution", "Address", "PdDistrict",
"DayOfWeek"], axis=1)

# Assign the cluster labels from K-Medoids
df_2['cluster'] = kmedoids.labels_

import plotly.express as px
figure1 = px.scatter_mapbox(df_2,
                            lat="Y", lon="X",  # Latitude and
Longitude columns
                            color="cluster",  # Color by cluster
                            hover_data=["Category", "X", "Y",
"cluster"],  # Hover information
                            title="K-Medoids Clustering of Crime
Locations",
                            center=dict(lat=37.8, lon=-122.4),  # Set
center for map (adjust if needed)
                            zoom=9,  # Zoom level for the map
                            width=1100,
                            height=700,
                            mapbox_style="open-street-map")  # Map
```

```python
style

# Show the plot
figure1.show()

from sklearn.metrics import silhouette_score

sil_score = silhouette_score(X, labels)
print(f"Silhouette Score: {sil_score:.4f}")
```

```
Silhouette Score: 0.3984
```

```python
from sklearn.metrics import davies_bouldin_score

db_score = davies_bouldin_score(X, labels)
print(f"Davies-Bouldin Index: {db_score:.4f}")
```

```
Davies-Bouldin Index: 0.8651
```

```python
df_2.head()
```


```
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\"fields\": [\n    {\n      \"column\": \"Dates\",\n
\"properties\": {\n        \"dtype\": \"date\",\n        \"min\":
\"2015-01-05 00:01:00\",\n        \"max\": \"2015-05-13 23:53:00\",\n
\"num_unique_values\": 12096,\n        \"samples\": [\n
\"2015-05-11 11:10:00\",\n          \"2015-01-07 14:02:00\",\n
\"2015-05-03 23:03:00\"\n        ],\n        \"semantic_type\": \"\",\
n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"Category\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 9,\n        \"min\": 0,\n
\"max\": 36,\n        \"num_unique_values\": 37,\n        \"samples\":
[\n          19,\n          7,\n          33\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"X\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 0.026236931909153344,\n
\"min\": -122.513642064265,\n        \"max\": -122.365565425353,\n
\"num_unique_values\": 8885,\n        \"samples\": [\n          -
122.470873483267,\n          -122.478575817534,\n          -
122.389487749378\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"Y\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 0.024450013487924846,\n        \"min\": 37.7080829769335,\n
\"max\": 37.819923463743,\n        \"num_unique_values\": 8885,\n
\"samples\": [\n          37.7492742889732,\n
37.7850879697075,\n          37.724599376829296\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"year\",\n      \"properties\": {\n
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\"samples\": [\n          2015\n        ],\n        \"semantic_type\":
\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
```

```
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\"int32\",\n        \"num_unique_values\": 5,\n        \"samples\": [\
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\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"day\",\n      \"properties\": {\n        \"dtype\": \"int32\",\n
\"num_unique_values\": 30,\n        \"samples\": [\n          23\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    },\n    {\n      \"column\": \"hour\",\n      \"properties\":
{\n        \"dtype\": \"int32\",\n        \"num_unique_values\": 24,\n
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\"\",\n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"X_scale\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 0.1771848152546543,\n        \"min\":
0.0,\n        \"max\": 1.0,\n        \"num_unique_values\": 8885,\n
\"samples\": [\n          0.2888273350356485\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"Y_scale\",\n      \"properties\":
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\"num_unique_values\": 8885,\n        \"samples\": [\n
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\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"cat_sc\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 0.2622990554348488,\n        \"min\": 0.0,\n        \"max\":
1.0,\n        \"num_unique_values\": 37,\n        \"samples\": [\n
0.5277777777777778\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"cluster\",\n      \"properties\": {\n        \"dtype\": \"number\",\
n        \"std\": 1,\n        \"min\": 0,\n        \"max\": 4,\n
\"num_unique_values\": 5,\n        \"samples\": [\n          0\n
],\n        \"semantic_type\": \"\",\n        \"description\": \"\"\n
}\n    }\n  ]\n}","type":"dataframe","variable_name":"df_2"}
```


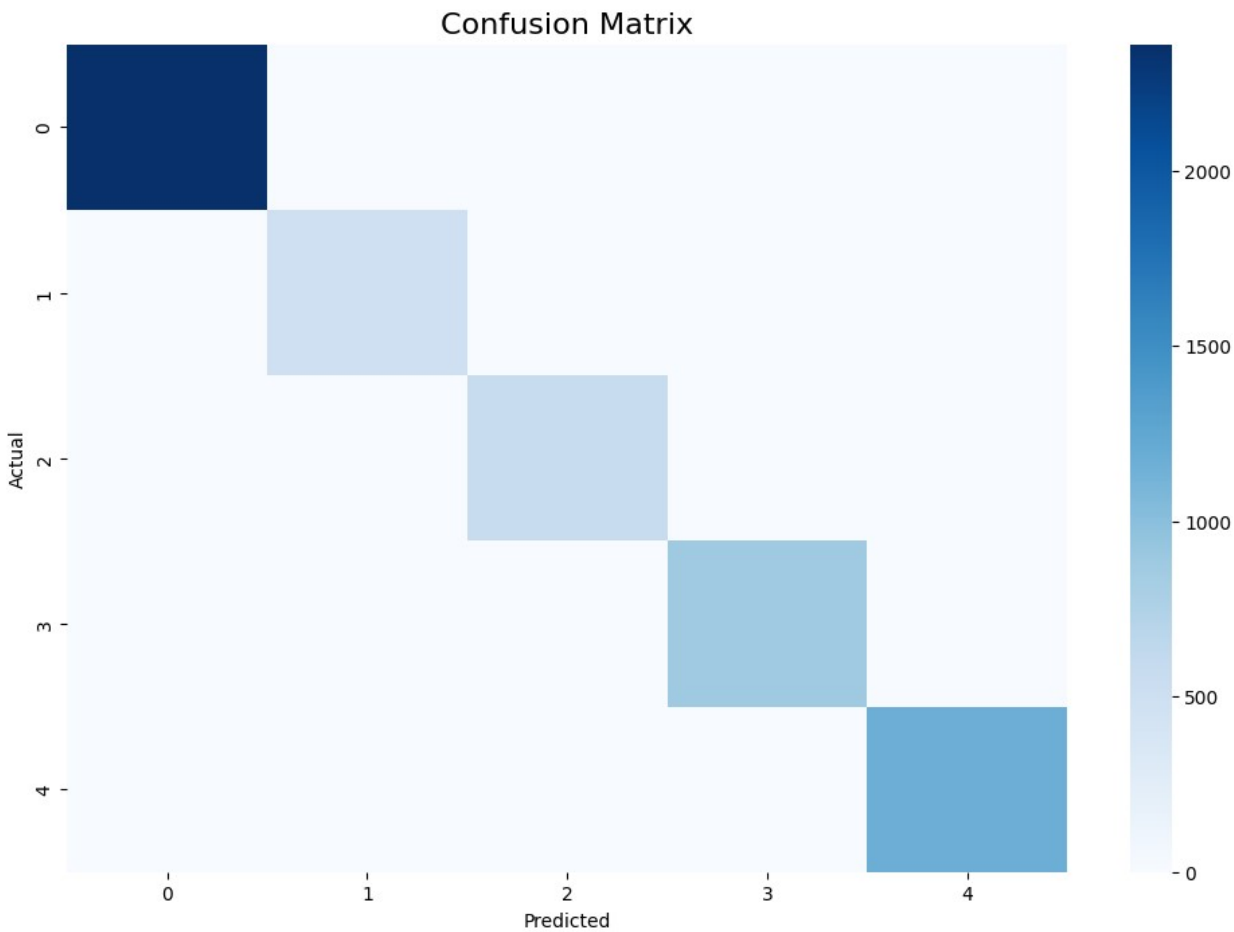
$$\text{Log Loss} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K} y_{i,k} \cdot \log(p_{i,k})$$

$$\hat{y}_i^{(1)} = \hat{y}_i^{(0)} + \eta \cdot f_1(x_i)$$

```
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
from xgboost import XGBClassifier
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

def train_and_evaluate_xgboost(df):
    X = df.drop(columns=['cluster','Dates'])
    y = df['cluster']

    X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

    model = XGBClassifier(eval_metric='mlogloss', random_state=42)
    model.fit(X_train, y_train)

    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    print(f" Accuracy: {acc * 100:.2f}%\n")

    print(" Classification Report:")
    print(classification_report(y_test, y_pred))

    plt.figure(figsize=(12, 8))
    sns.heatmap(confusion_matrix(y_test, y_pred), annot=False,
fmt='d', cmap='Blues')
    plt.title("Confusion Matrix", fontsize=16)
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

    return model

model = train_and_evaluate_xgboost(df_2)
```

```
 Accuracy: 99.76%

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

```
              0       1.00      1.00      1.00      2363
              1       0.99      0.99      0.99       498
              2       0.99      0.99      0.99       582
              3       1.00      1.00      1.00       883
              4       1.00      1.00      1.00      1179

       accuracy                           1.00      5505
      macro avg       1.00      1.00      1.00      5505
   weighted avg       1.00      1.00      1.00      5505
```



#Kmedoids when K = 3

```
from sklearn_extra.cluster import KMedoids
k=3

# Combine features into a single matrix
X = df1[['X_scale', 'Y_scale','cat_sc']]

# Fit KMedoids with the combined feature matrix
```

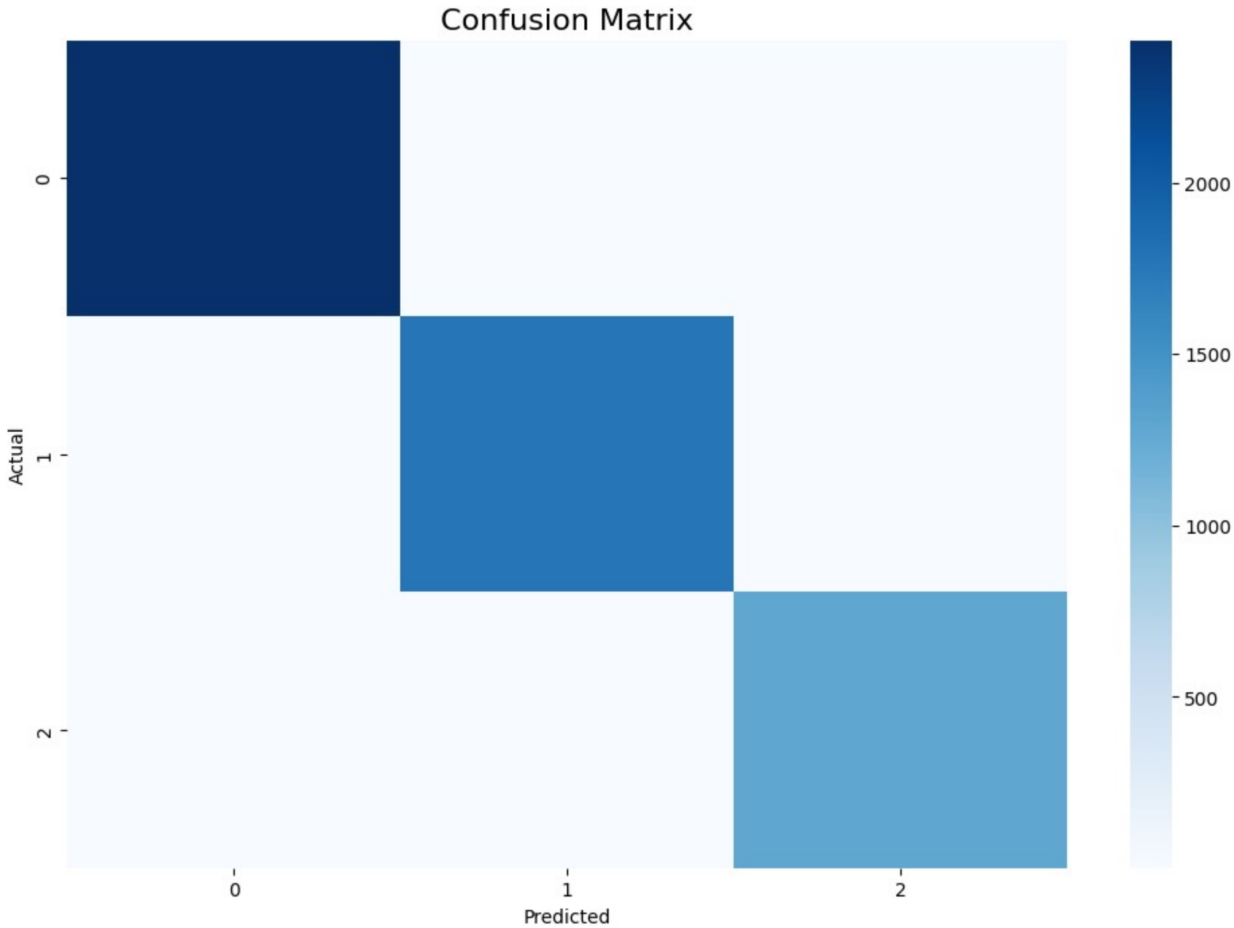
```
kmedoids = KMedoids(n_clusters=k).fit(X)

clusters = kmedoids.cluster_centers_
labels = kmedoids.labels_

sil_score = silhouette_score(X, labels)
db_score = davies_bouldin_score(X, labels)

print(f"Silhouette Score: {sil_score:.4f}")
print(f"Davies-Bouldin Index: {db_score:.4f}")
```

```
/usr/local/lib/python3.11/dist-packages/sklearn_extra/cluster/
_k_medoids.py:329: UserWarning:

Cluster 1 is empty! self.labels_[self.medoid_indices_[1]] may not be
labeled with its corresponding cluster (1).


Silhouette Score: 0.2508
Davies-Bouldin Index: 1.2784
```

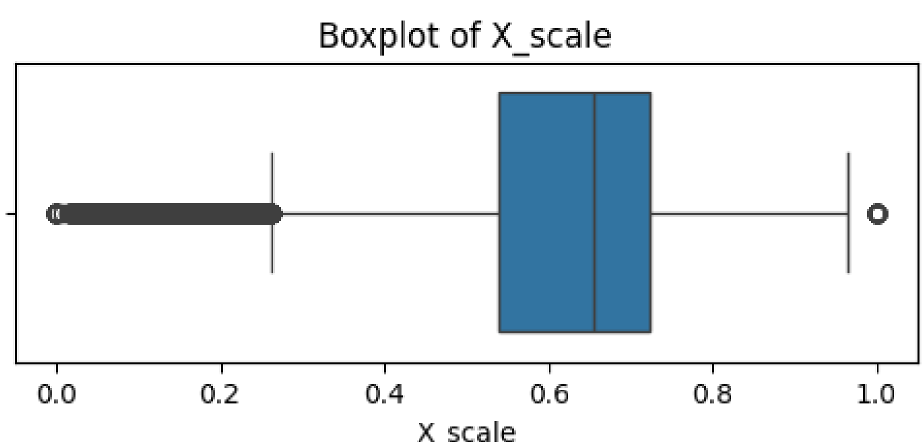
```
# Drop unwanted columns
df_2 = df1.drop(["Descript", "Resolution", "Address", "PdDistrict",
"DayOfWeek"], axis=1)

# Assign the cluster labels from K-Medoids
df_2['cluster'] = kmedoids.labels_


import plotly.express as px
figure1 = px.scatter_mapbox(df_2,
                            lat="Y", lon="X",  # Latitude and
Longitude columns
                            color="cluster",  # Color by cluster
                            hover_data=["Category", "X", "Y",
"cluster"],  # Hover information
                            title="K-Medoids Clustering of Crime
Locations",
                            center=dict(lat=37.8, lon=-122.4),  # Set
center for map (adjust if needed)
                            zoom=9,  # Zoom level for the map
                            width=1100,
                            height=700,
                            mapbox_style="open-street-map")  # Map
style

# Show the plot
figure1.show()

from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
```

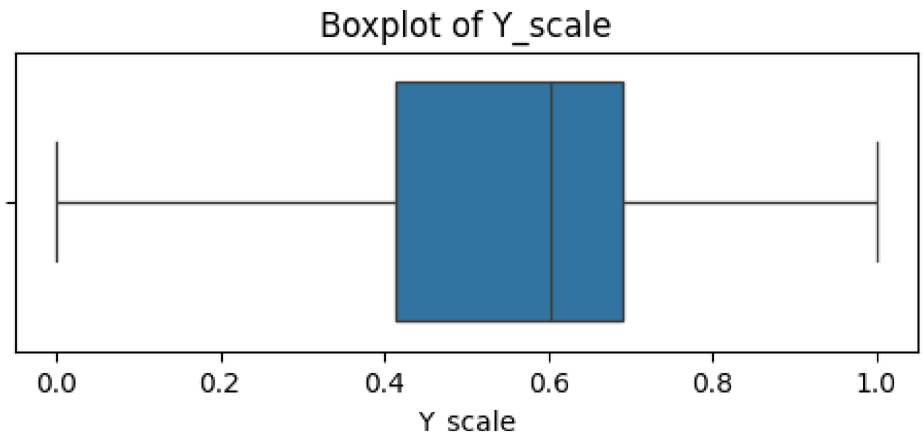
```
from xgboost import XGBClassifier
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

def train_and_evaluate_xgboost(df):
    X = df.drop(columns=['cluster','Dates'])
    y = df['cluster']

    X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

    model = XGBClassifier(eval_metric='mlogloss', random_state=42)
    model.fit(X_train, y_train)

    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    print(f" Accuracy: {acc * 100:.2f}%\n")

    print(" Classification Report:")
    print(classification_report(y_test, y_pred))

    plt.figure(figsize=(12, 8))
    sns.heatmap(confusion_matrix(y_test, y_pred), annot=False,
fmt='d', cmap='Blues')
    plt.title("Confusion Matrix", fontsize=16)
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

    return model

model = train_and_evaluate_xgboost(df_2)
```

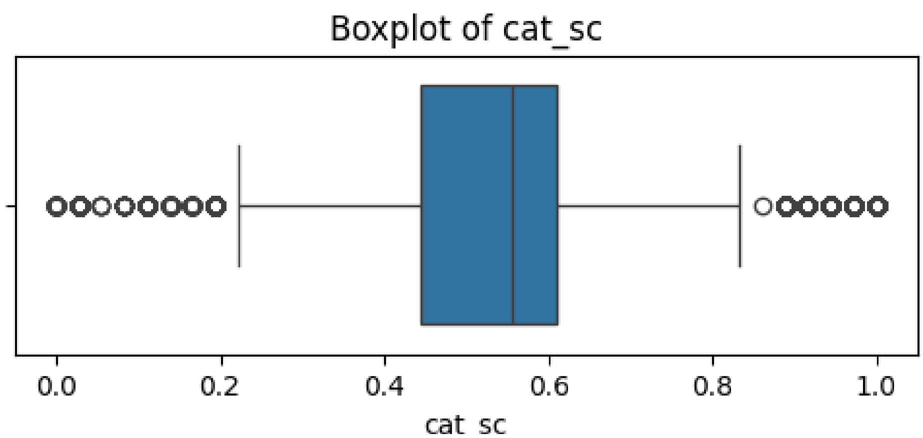
```
 Accuracy: 99.49%

 Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      0.99      2430
           1       0.99      0.99      0.99      1777
           2       1.00      1.00      1.00      1298

    accuracy                           0.99      5505
   macro avg       0.99      1.00      1.00      5505
weighted avg       0.99      0.99      0.99      5505
```



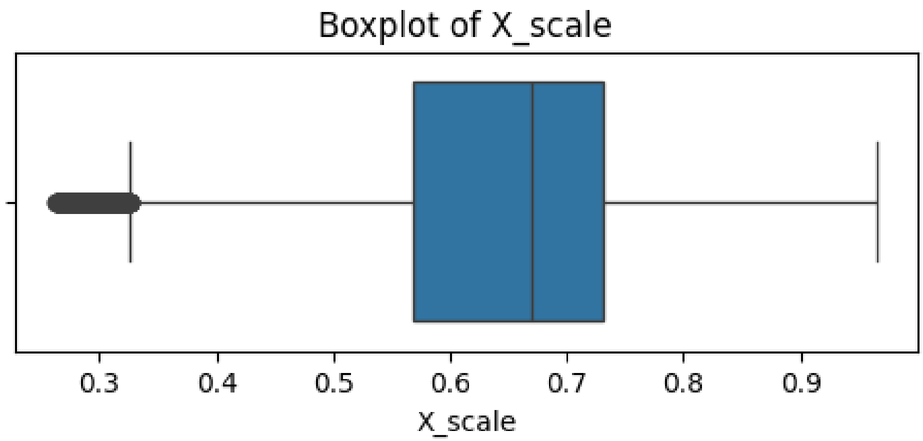

```
numerical_cols = ['X_scale', 'Y_scale', 'cat_sc']
for col in numerical_cols:
    plt.figure(figsize=(6, 2))
    sns.boxplot(x=df1[col])
    plt.title(f"Boxplot of {col}")
    plt.show()
```

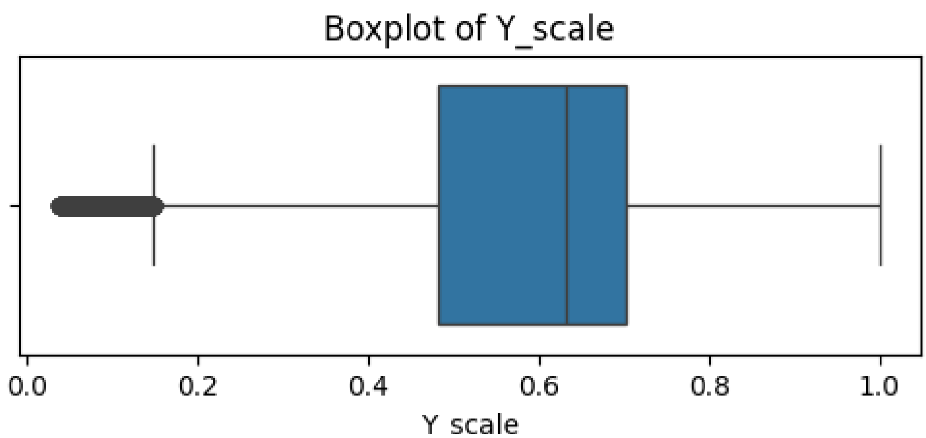


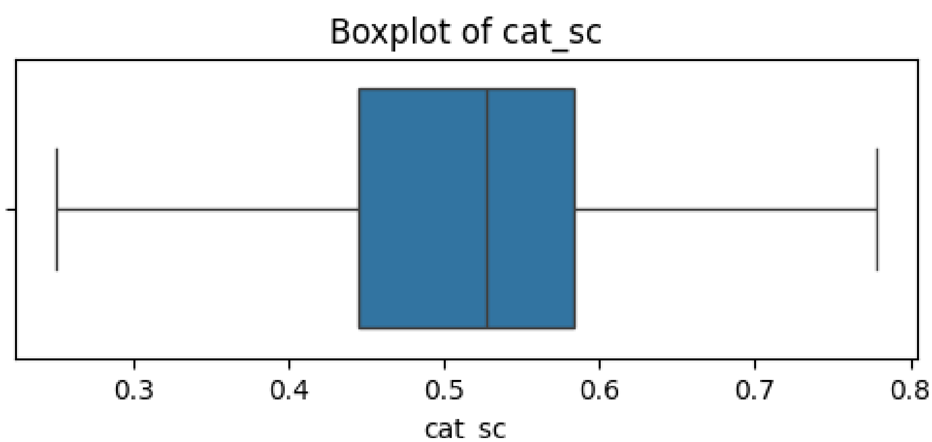





```
numerical_cols = ['X_scale', 'Y_scale', 'cat_sc']

for col in numerical_cols:
    IQR = df1[col].quantile(0.75) - df1[col].quantile(0.25)
    Lower_fence = df1[col].quantile(0.25) - (IQR * 1.5)
    Upper_fence = df1[col].quantile(0.75) + (IQR * 1.5)

    # Keep only the rows within the fences
    df1 = df1[(df1[col] >= Lower_fence) & (df1[col] <= Upper_fence)]

numerical_cols = ['X_scale', 'Y_scale', 'cat_sc']
for col in numerical_cols:
    plt.figure(figsize=(6, 2))
    sns.boxplot(x=df1[col])
    plt.title(f"Boxplot of {col}")
    plt.show()
```







#Kmedoids when K = 3 + category column

```
from sklearn_extra.cluster import KMedoids
k=3

# Combine features into a single matrix
X = df1[['X_scale', 'Y_scale','cat_sc']]
```

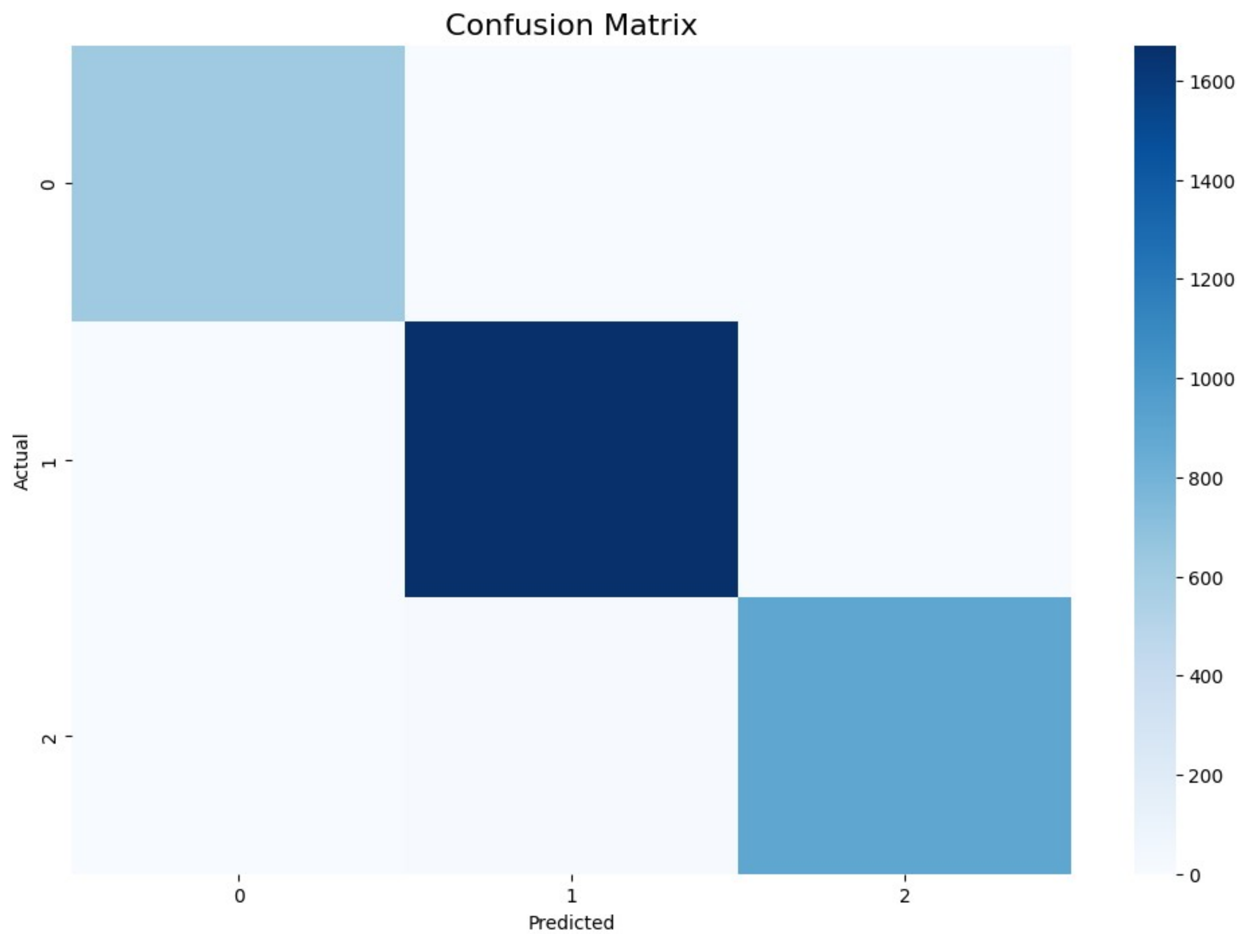
```
# Fit KMedoids with the combined feature matrix
kmedoids = KMedoids(n_clusters=k).fit(X)

clusters = kmedoids.cluster_centers_
labels = kmedoids.labels_

sil_score = silhouette_score(X, labels)
db_score = davies_bouldin_score(X, labels)

print(f"Silhouette Score: {sil_score:.4f}")
print(f"Davies-Bouldin Index: {db_score:.4f}")
```

```
/usr/local/lib/python3.11/dist-packages/sklearn_extra/cluster/
_k_medoids.py:329: UserWarning:

Cluster 1 is empty! self.labels_[self.medoid_indices_[1]] may not be
labeled with its corresponding cluster (1).


Silhouette Score: 0.3216
Davies-Bouldin Index: 1.2169
```

```
# Drop unwanted columns
df_2 = df1.drop(["Descript", "Resolution", "Address", "PdDistrict",
"DayOfWeek"], axis=1)

# Assign the cluster labels from K-Medoids
df_2['cluster'] = kmedoids.labels_


import plotly.express as px
figure1 = px.scatter_mapbox(df_2,
                            lat="Y", lon="X",  # Latitude and
Longitude columns
                            color="cluster",  # Color by cluster
                            hover_data=["Category", "X", "Y",
"cluster"],  # Hover information
                            title="K-Medoids Clustering of Crime
Locations",
                            center=dict(lat=37.8, lon=-122.4),  # Set
center for map (adjust if needed)
                            zoom=9,  # Zoom level for the map
                            width=1100,
                            height=700,
                            mapbox_style="open-street-map")  # Map
style

# Show the plot
figure1.show()
```

```python
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
from xgboost import XGBClassifier
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

def train_and_evaluate_xgboost(df):
    X = df.drop(columns=['Dates','cluster'])
    y = df['cluster']

    X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

    model = XGBClassifier(eval_metric='mlogloss', random_state=42)
    model.fit(X_train, y_train)

    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    print(f" Accuracy: {acc * 100:.2f}%\n")

    print(" Classification Report:")
    print(classification_report(y_test, y_pred))

    plt.figure(figsize=(12, 8))
    sns.heatmap(confusion_matrix(y_test, y_pred), annot=False,
fmt='d', cmap='Blues')
    plt.title("Confusion Matrix", fontsize=16)
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

    return model

model = train_and_evaluate_xgboost(df_2)
```

```
 Accuracy: 99.47%

 Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       624
           1       0.99      1.00      1.00      1674
           2       0.99      0.99      0.99       906

    accuracy                           0.99      3204
   macro avg       1.00      0.99      0.99      3204
weighted avg       0.99      0.99      0.99      3204
```


Confusion Matrix
Actual
0
1
2
Predicted
0
1
2
1600
1400
1200
1000
800
600
400
200
0