Principles of Data Science Coursework: A Tiny Data Science Project

In [2]:

```
#DATA PRE-PROCESSING
```

In [3]:

```
#Loading the datasets and merging the Crime Data from the Metropolitan Police
```

In [4]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
print(os.getcwd())

crimeMet = pd.read_csv('2019-06-metropolitan-street.csv')
```

```
C:\Users\dimin
```

In [5]:

```
#Transforming the new merged dataset, by pivoting wider to allow for easier manipulation
of the dataset
```

In [6]:

```
crime_counts = crimeMet.groupby('LSOA code')['Crime type'].nunique().reset_index(name='C
ount')
CrimeData_with_counts = pd.merge(crimeMet, crime_counts, on='LSOA code', how='left')
CrimeData_with_counts.to_csv('CrimeData_with_counts.csv', index=False)
```

In [7]:

```
aggregated_CrimeData = CrimeData_with_counts.groupby(['Count', 'Crime type', 'LSOA code'
]).size().reset_index(name='Total')
aggregated_CrimeData.to_csv('aggregated_CrimeData.csv', index=False)
```

In [8]:

```
pivot_CrimeData = aggregated_CrimeData.pivot_table(index='LSOA code',
                                         columns='Crime type',
                                         values='Total',
                                         fill_value=0)
pivot_CrimeData.to_csv('pivot_CrimeData.csv', index=True)
```

In [9]:

```
pivot_CrimeData['Total Crimes'] = pivot_CrimeData.sum(axis=1)
pivot_CrimeData.to_csv('pivot_CrimeData.csv', index=True)
print(pivot_CrimeData.head())
```

```
Crime type  Anti-social behaviour  Bicycle theft  Burglary  \
LSOA code
E01000001                       0              1         0
E01000002                       0              0         0
E01000005                       3              0         0
E01000006                       2              0         1
E01000007                      14              0         3

Crime type  Criminal damage and arson  Drugs  Other crime  Other theft  \
LSOA code
E01000001                          0      0            0            1
```

```
E01000002                          0      0            0            2
E01000005                          0      0            0            5
E01000006                          1      0            1            0
E01000007                          0      7            0            4

Crime type  Possession of weapons  Public order  Robbery  Shoplifting  \
LSOA code
E01000001                       0             0        0            2
E01000002                       0             0        0            0
E01000005                       0             0        0            0
E01000006                       0             0        1            0
E01000007                       0             1        5            1

Crime type  Theft from the person  Vehicle crime  \
LSOA code
E01000001                       1              0
E01000002                       0              0
E01000005                       3              1
E01000006                       0              0
E01000007                       3              2

Crime type  Violence and sexual offences  Total Crimes
LSOA code
E01000001                              0             5
E01000002                              0             2
E01000005                              1            13
E01000006                              3             9
E01000007                              6            46
```

In [10]:

```
#Loading the Index of Multiple Deprivation Data for London 2019 obtained from opendata.arcgis.com: Indices of Multiple Deprivation
#(IMD) 2019
```

In [11]:

```
DeprivationData = pd.read_csv('imd_2019_england_scores.csv')
```

In [12]:

```
#Merging the two datasets to allow for more efficient manipulation of both datasets. The two datasets are inner joined on the LSOA code column.
```

In [13]:

```
import pandas as pd

CrimeData_final = pd.read_csv('CrimeData_final.csv')
DeprivationData = pd.read_csv('imd_2019_england_scores.csv')

FinalData = pd.merge(CrimeData_final, DeprivationData, on='LSOA code', how='inner')
FinalData.to_csv('FinalData.csv', index=True)
```

In [14]:

```
columns_to_remove = ['HDDScore', 'CriScore', 'BHSScore', 'EnvScore', 'IDCScore', 'IDOScore', 'CYPScore', 'GBScore', 'WBScore', 'IndScore', 'OutScore', 'lsoa11nm']
FinalData = FinalData.drop(columns=columns_to_remove)
FinalData.to_csv('FinalData.csv', index=True)
```

In [15]:

```
print(FinalData.head())
```

```
   LSOA code  Anti-social behaviour  Bicycle theft  Burglary  \
0  E01000001                      0              1         0
1  E01000002                      0              0         0
2  E01000005                      3              0         0
3  E01000006                      2              0         1
4  E01000007                     14              0         3
```

```
   Criminal damage and arson  Drugs  Other crime  Other theft  \
0                          0      0            0            1   
1                          0      0            0            2   
2                          0      0            0            5   
3                          1      0            1            0   
4                          0      7            0            4   

   Possession of weapons  Public order  ...  Vehicle crime  \
0                      0             0  ...              0   
1                      0             0  ...              0   
2                      0             0  ...              1   
3                      0             0  ...              0   
4                      0             1  ...              2   

   Violence and sexual offences  Total Crimes                LADnm  IMDScore  \
0                             0             5       City of London     6.208   
1                             0             2       City of London     5.143   
2                             1            13       City of London    28.652   
3                             3             9  Barking and Dagenham    19.837   
4                             6            46  Barking and Dagenham    31.576   

   IncScore EmpScore  EduScore  ASScore  TotPop  
0     0.007    0.010     0.024    0.032    1296  
1     0.034    0.027     0.063    0.034    1156  
2     0.211    0.136    22.260    0.321    1121  
3     0.117    0.059    14.798    0.325    2040  
4     0.207    0.107    11.385    0.251    2101  

[5 rows x 23 columns]
```

In [16]:

```
#1st Question:
#Are there significant differences in crime rates or types between areas ranked higher and lower in specific aspects of deprivation, such as income, employment, or education?
#For example, do areas with higher rankings (indicating more deprivation) in income or employment deprivation show higher rates or different types of crimes compared to areas with lower rankings?
```

In [17]:

```
#Exploratory Data Analysis (EDA)
```

In [18]:

```
print(FinalData.describe(include='all'))
```

```
         LSOA code  Anti-social behaviour  Bicycle theft     Burglary  \
count         5017            5017.000000    5017.000000  5017.000000   
unique        5017                    NaN            NaN          NaN   
top      E01000001                    NaN            NaN          NaN   
freq             1                    NaN            NaN          NaN   
mean           NaN               4.399243       0.378314     1.253538   
std            NaN               5.796546       1.108180     1.704992   
min            NaN               0.000000       0.000000     0.000000   
25%            NaN               1.000000       0.000000     0.000000   
50%            NaN               3.000000       0.000000     1.000000   
75%            NaN               6.000000       0.000000     2.000000   
max            NaN             142.000000      34.000000    34.000000   

         Criminal damage and arson        Drugs  Other crime  Other theft  \
count                  5017.000000  5017.000000  5017.000000  5017.000000   
unique                         NaN          NaN          NaN          NaN   
top                            NaN          NaN          NaN          NaN   
freq                           NaN          NaN          NaN          NaN   
mean                      0.905322     0.735898     0.171816     2.093482   
std                       1.291614     1.689815     1.554043     7.896095   
min                       0.000000     0.000000     0.000000     0.000000   
25%                       0.000000     0.000000     0.000000     0.000000   
50%                       1.000000     0.000000     0.000000     1.000000   
```

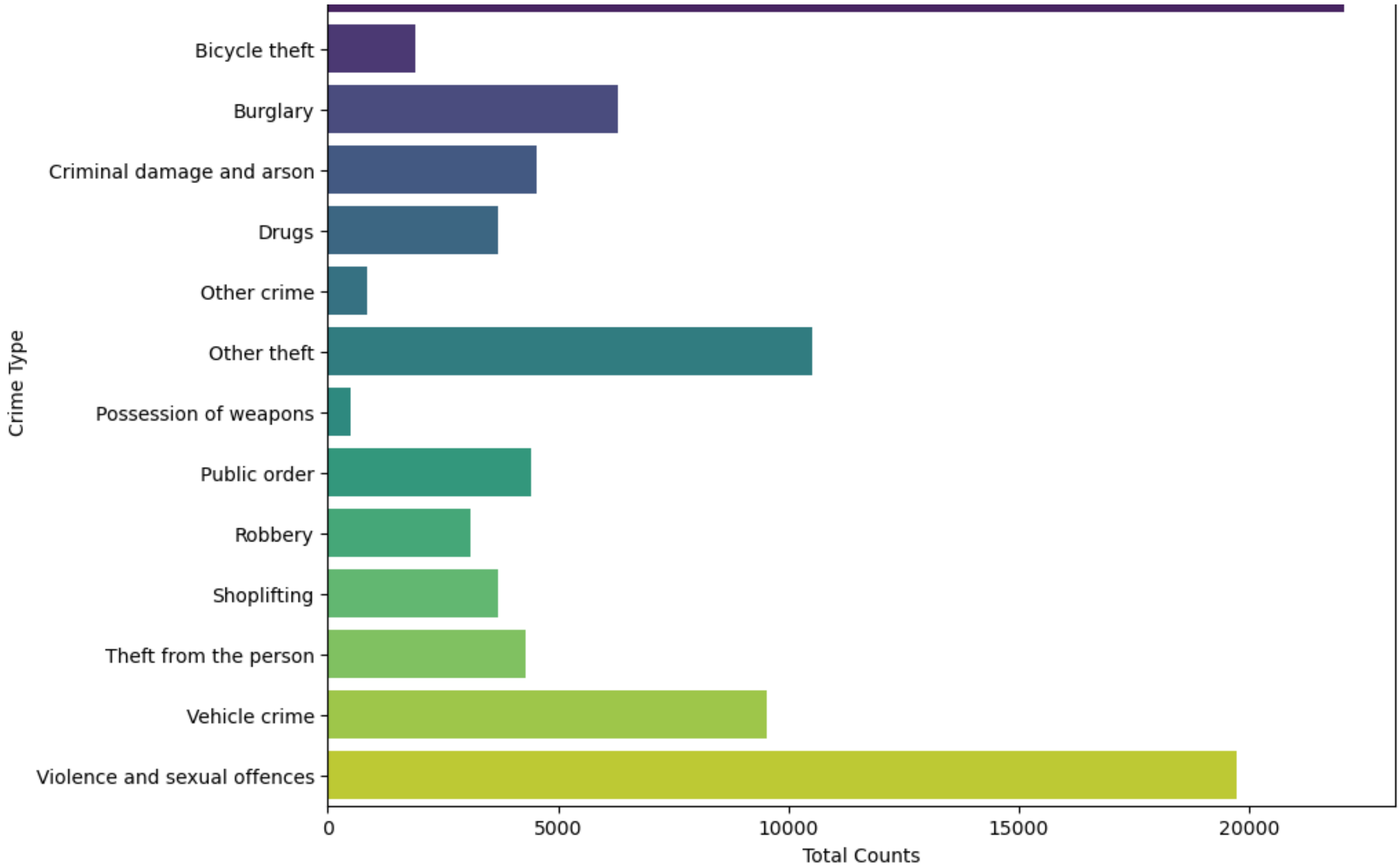
```
75%                       1.000000     1.000000     0.000000     2.000000
max                      15.000000    36.000000   105.000000   262.000000

        Possession of weapons  Public order  ...  Vehicle crime  \
count             5017.000000   5017.000000  ...    5017.000000
unique                    NaN           NaN  ...            NaN
top                       NaN           NaN  ...            NaN
freq                      NaN           NaN  ...            NaN
mean                 0.100060      0.877616  ...       1.900140
std                  0.348089      1.583964  ...       2.117509
min                  0.000000      0.000000  ...       0.000000
25%                  0.000000      0.000000  ...       0.000000
50%                  0.000000      0.000000  ...       1.000000
75%                  0.000000      1.000000  ...       3.000000
max                  6.000000     29.000000  ...      22.000000

        Violence and sexual offences  Total Crimes    LADnm     IMDScore  \
count                    5017.000000   5017.000000     5017  5017.000000
unique                           NaN           NaN      121          NaN
top                              NaN           NaN  Croydon          NaN
freq                             NaN           NaN      219          NaN
mean                        3.931234     18.957544      NaN    21.425604
std                         4.452104     29.962669      NaN    11.089005
min                         0.000000      1.000000      NaN     2.326000
25%                         1.000000      8.000000      NaN    12.242000
50%                         3.000000     13.000000      NaN    20.161000
75%                         5.000000     22.000000      NaN    29.476000
max                        94.000000    836.000000      NaN    76.553000

           IncScore     EmpScore     EduScore      ASScore       TotPop
count   5017.000000  5017.000000  5017.000000  5017.000000  5017.000000
unique          NaN          NaN          NaN          NaN          NaN
top             NaN          NaN          NaN          NaN          NaN
freq            NaN          NaN          NaN          NaN          NaN
mean       0.135304     0.087293    13.369152     0.262397  1791.507674
std        0.076504     0.047651    10.443186     0.106852   367.649394
min        0.006000     0.003000     0.013000     0.032000   614.000000
25%        0.073000     0.051000     4.929000     0.180000  1574.000000
50%        0.124000     0.078000    11.339000     0.269000  1728.000000
75%        0.188000     0.117000    19.260000     0.343000  1939.000000
max        0.490000     0.401000    85.488000     0.583000  9551.000000

[11 rows x 23 columns]
```

In [19]:

```
import seaborn as sns
import matplotlib.pyplot as plt

crime_counts = FinalData[['Anti-social behaviour', 'Bicycle theft', 'Burglary', 'Criminal damage and arson',
                     'Drugs', 'Other crime', 'Other theft', 'Possession of weapons', 'Public order',
                     'Robbery', 'Shoplifting', 'Theft from the person', 'Vehicle crime',
                     'Violence and sexual offences']].sum()

crime_counts_df = pd.DataFrame(crime_counts, columns=['Total']).reset_index()
crime_counts_df.rename(columns={'index': 'Crime Type'}, inplace=True)

plt.figure(figsize=(10, 8))
barplot = sns.barplot(x='Total', y='Crime Type', data=crime_counts_df, palette="viridis")
plt.title('Total Counts of Different Crime Types')
plt.xlabel('Total Counts')
plt.ylabel('Crime Type')
```

Out[19]:

```
Text(0, 0.5, 'Crime Type')
```

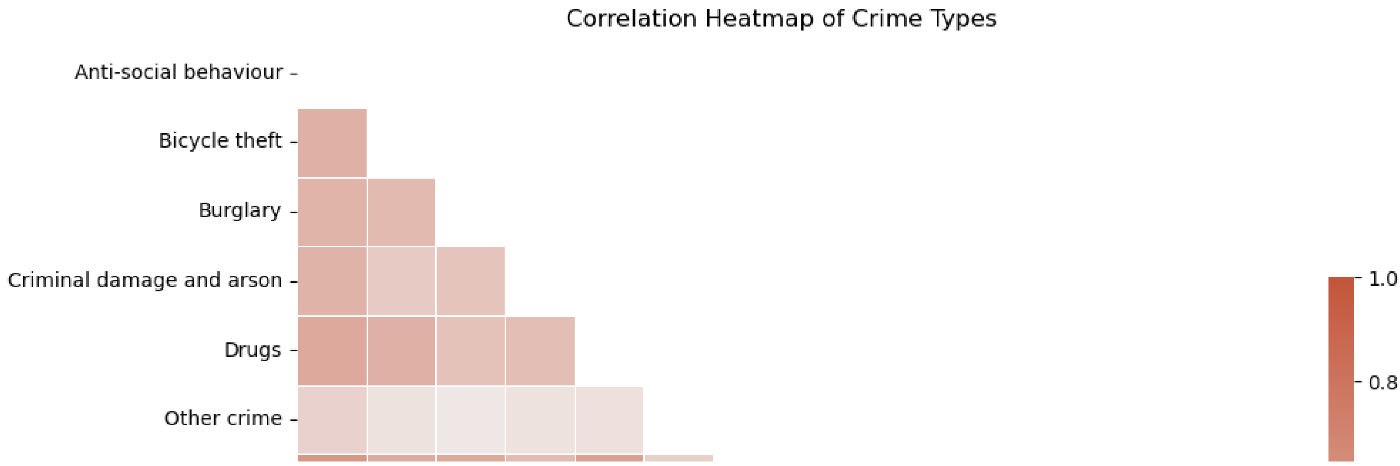


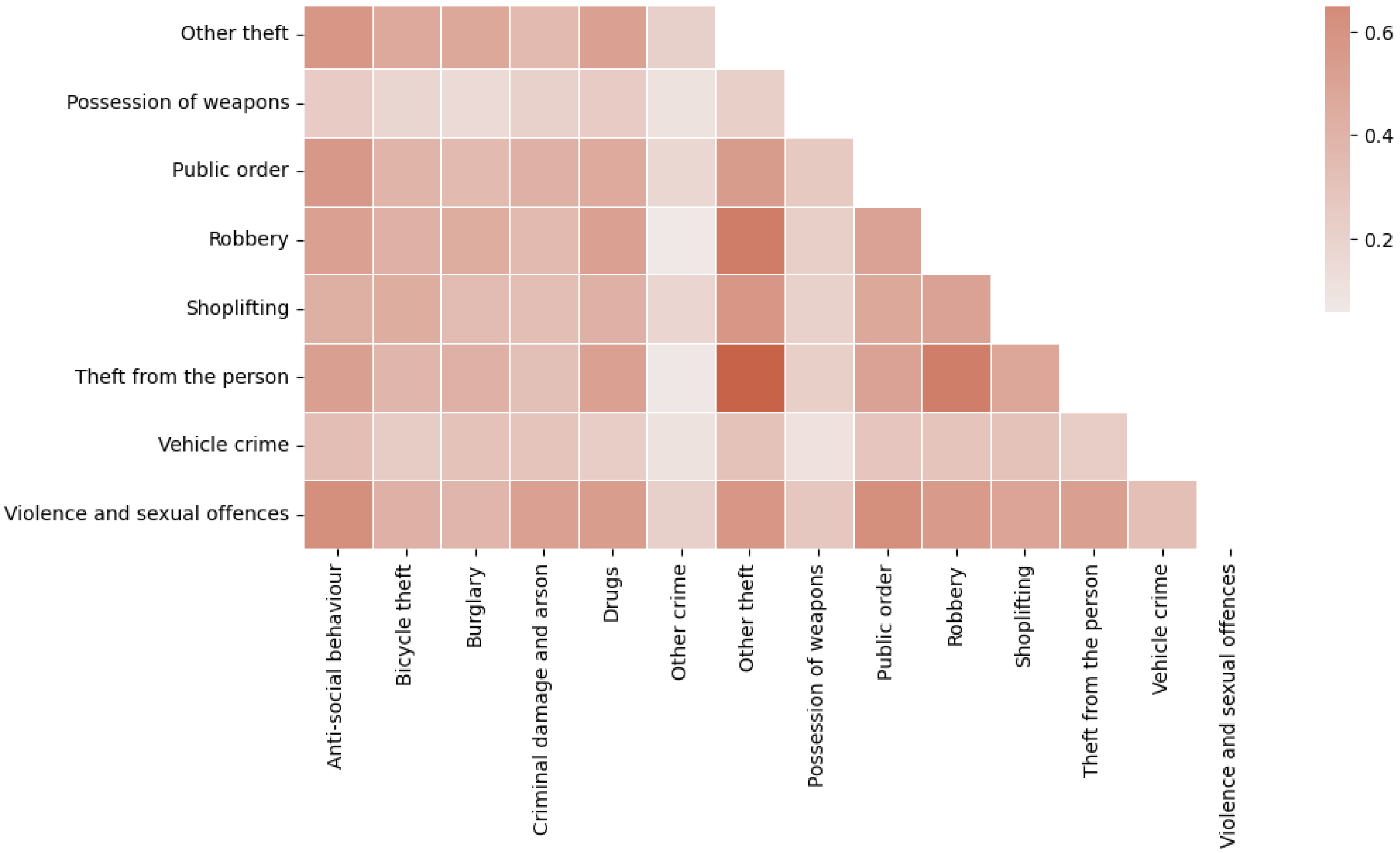
In [20]:

```
#As seen from the bar chart plotted above, the most frequent crime type is Anti-Social Be
haviour, whilst the least frequent is
#weapon possesion.
```

In [21]:

```
import numpy as np

crime_types = [
    'Anti-social behaviour', 'Bicycle theft', 'Burglary',
    'Criminal damage and arson', 'Drugs', 'Other crime',
    'Other theft', 'Possession of weapons', 'Public order',
    'Robbery', 'Shoplifting', 'Theft from the person',
    'Vehicle crime', 'Violence and sexual offences'
]
crime_data_selected = CrimeData_final[crime_types]
corr_matrix = crime_data_selected.corr()
mask = np.triu(np.ones_like(corr_matrix, dtype=bool))
f, ax = plt.subplots(figsize=(11, 9))
cmap = sns.diverging_palette(230, 20, as_cmap=True)
sns.heatmap(corr_matrix, mask=mask, cmap=cmap, vmax=1.0, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
plt.title('Correlation Heatmap of Crime Types')
plt.show()
```



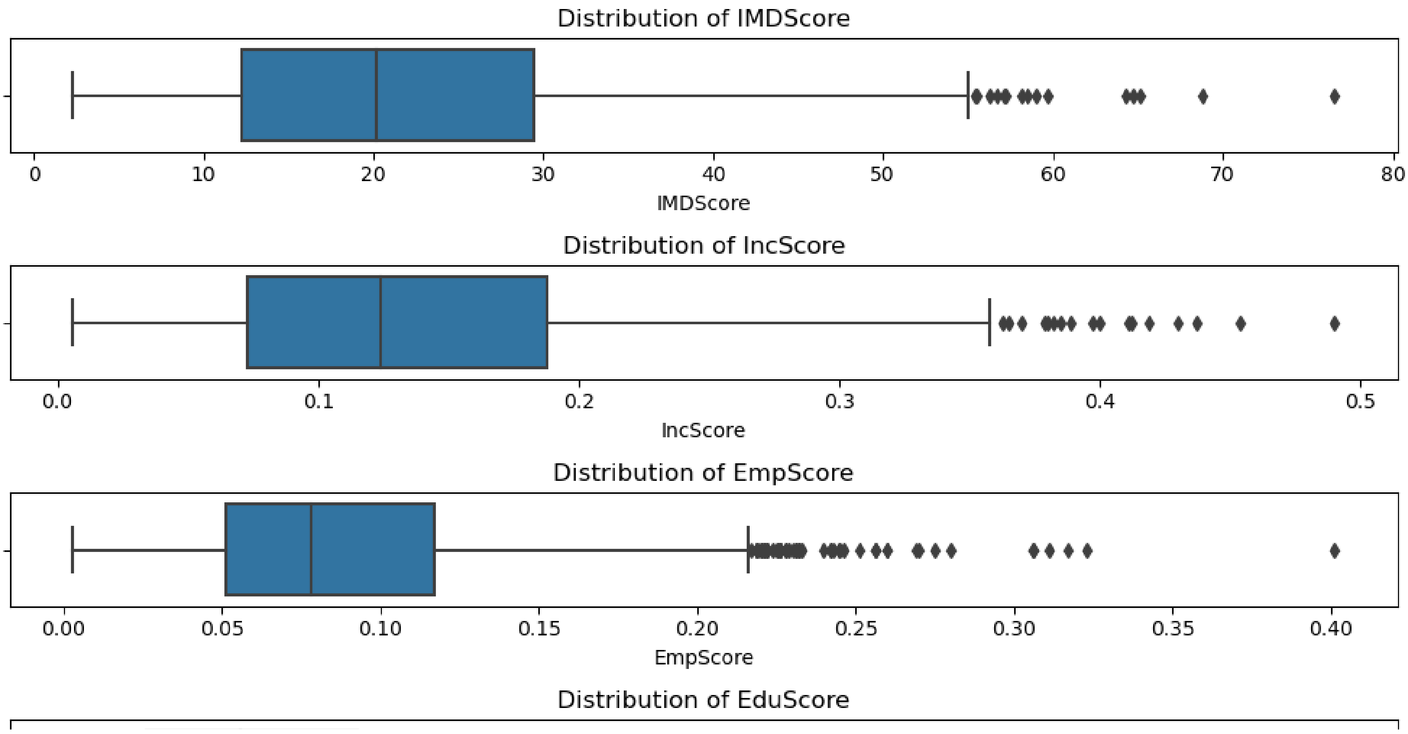


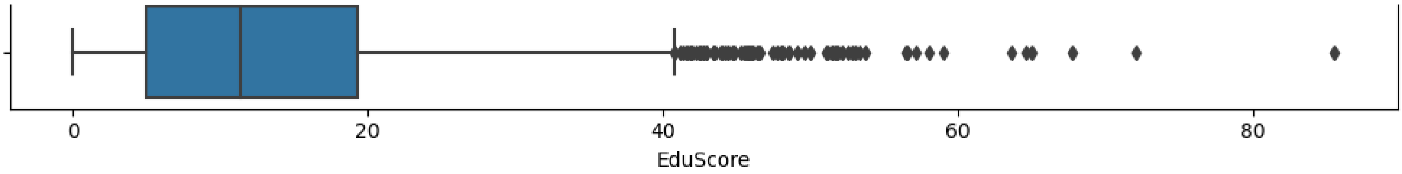
In [22]:

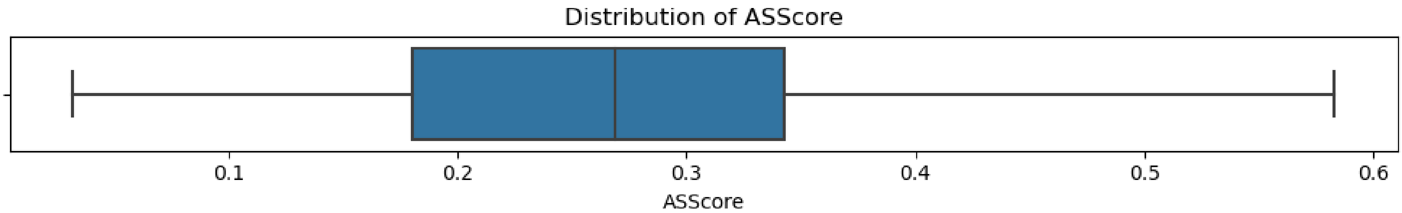
```
#This is a correlation heatmap between the types of crimes.
```

In [23]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

score_columns = ['IMDScore', 'IncScore', 'EmpScore', 'EduScore', 'ASScore']
plt.figure(figsize=(10, 8))
for i, col in enumerate(score_columns):
    plt.subplot(len(score_columns), 1, i+1)
    sns.boxplot(x=col, data=FinalData)
    plt.title(f'Distribution of {col}')
plt.tight_layout()
plt.show()
```

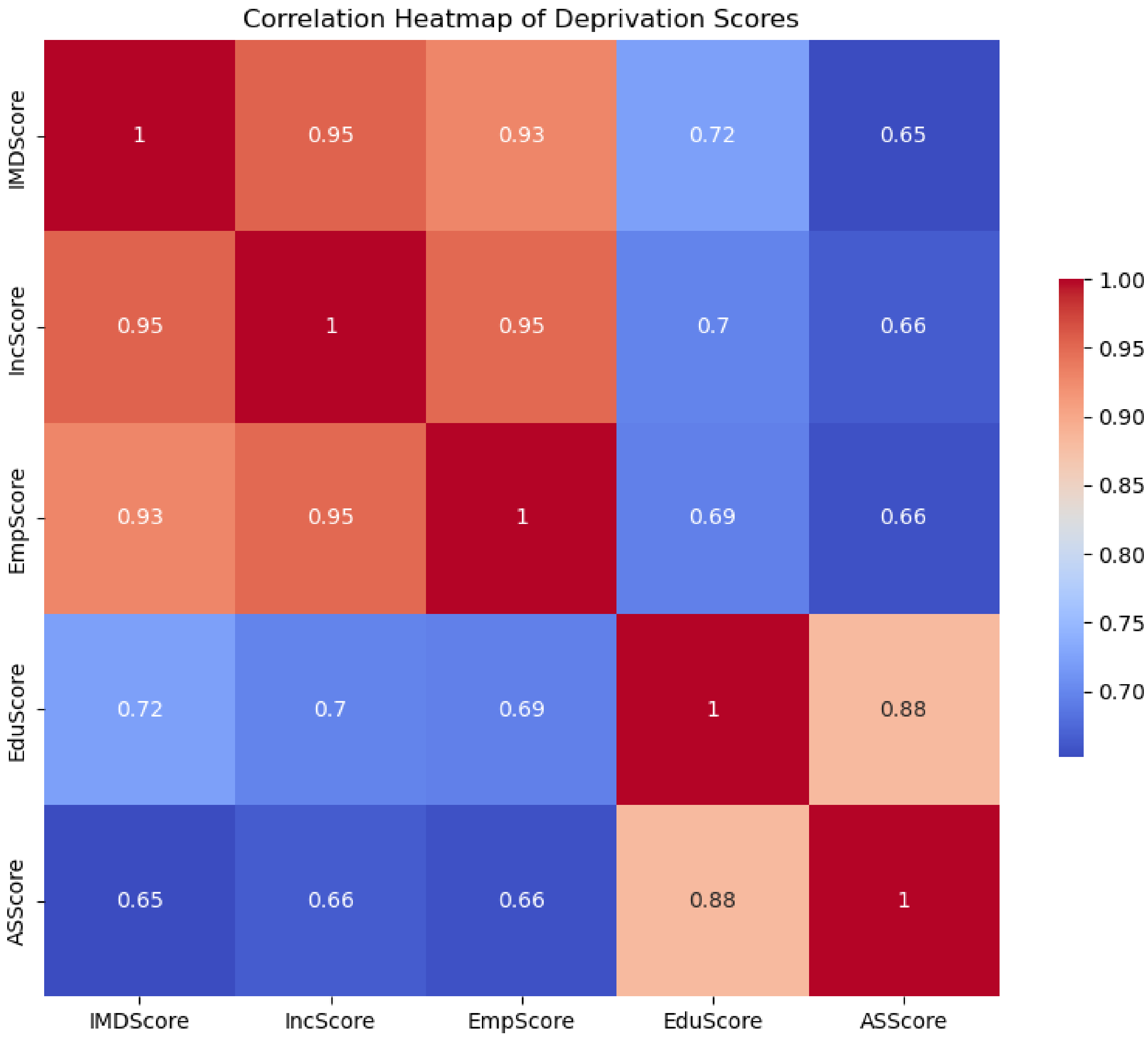






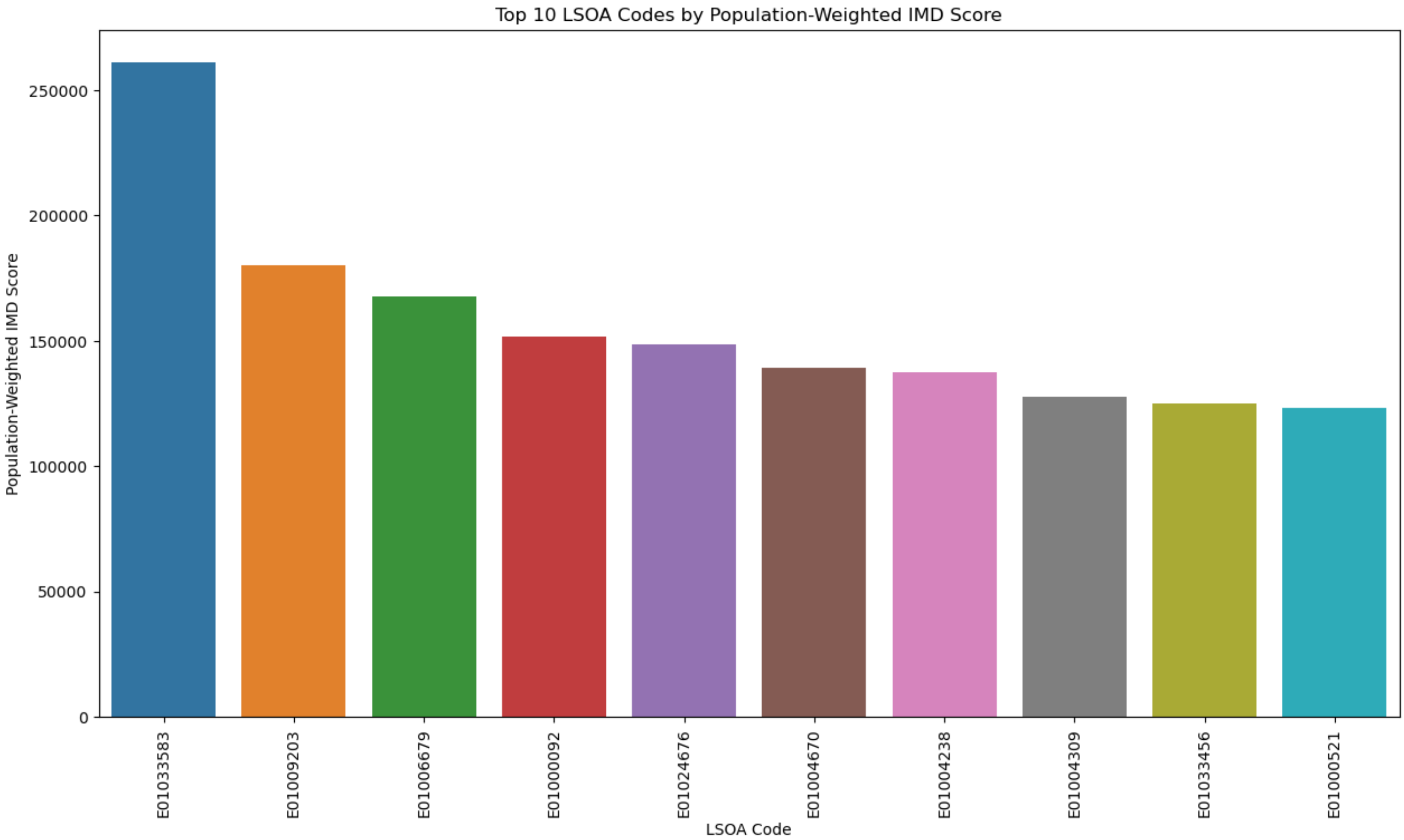
In [24]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

score_columns = ['IMDScore', 'IncScore', 'EmpScore', 'EduScore', 'ASScore']
corr_matrix = FinalData[score_columns].corr()
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, square=True, cmap='coolwarm', cbar_kws={"shrink": .
5})
plt.title('Correlation Heatmap of Deprivation Scores')
plt.show()
```



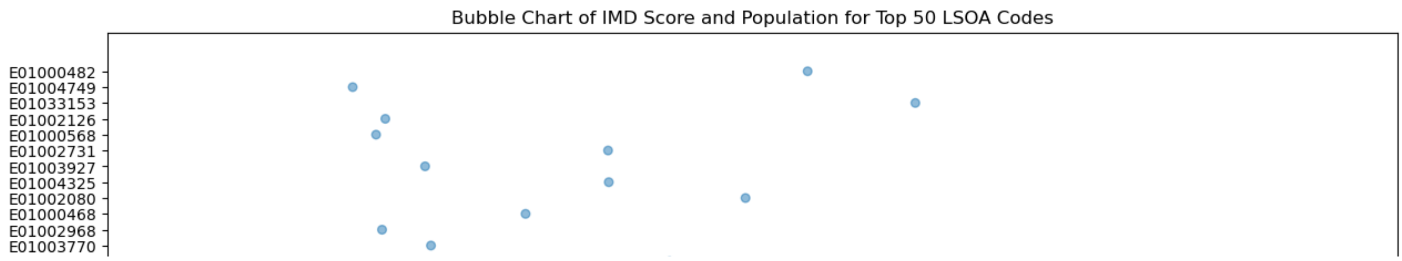
In [25]:

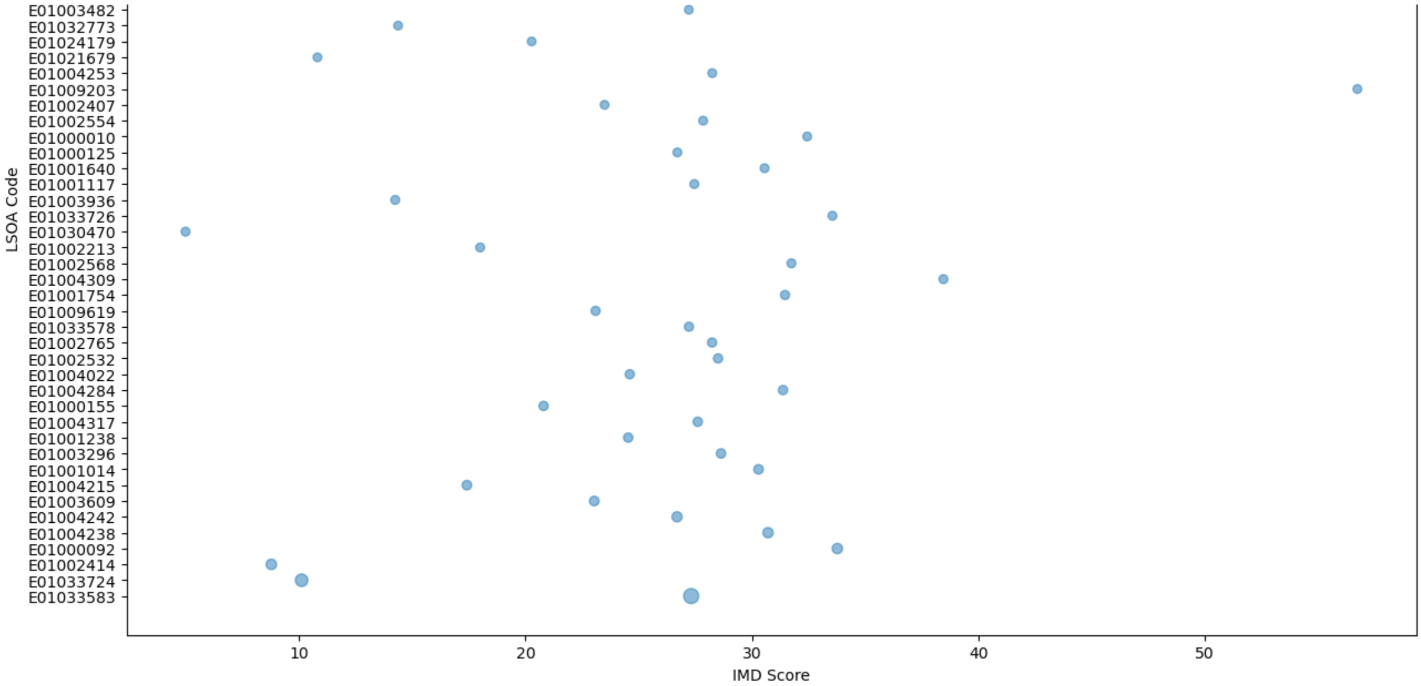
```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

FinalData['PopWeightedScore'] = FinalData['IMDScore'] * FinalData['TotPop']

N = 10
top_data = FinalData.sort_values(by='PopWeightedScore', ascending=False).head(N)

plt.figure(figsize=(15, 8))
sns.barplot(x='LSOA code', y='PopWeightedScore', data=top_data)
plt.title(f'Top {N} LSOA Codes by Population-Weighted IMD Score')
plt.ylabel('Population-Weighted IMD Score')
plt.xlabel('LSOA Code')
plt.xticks(rotation=90)
plt.show()
```



In [26]:

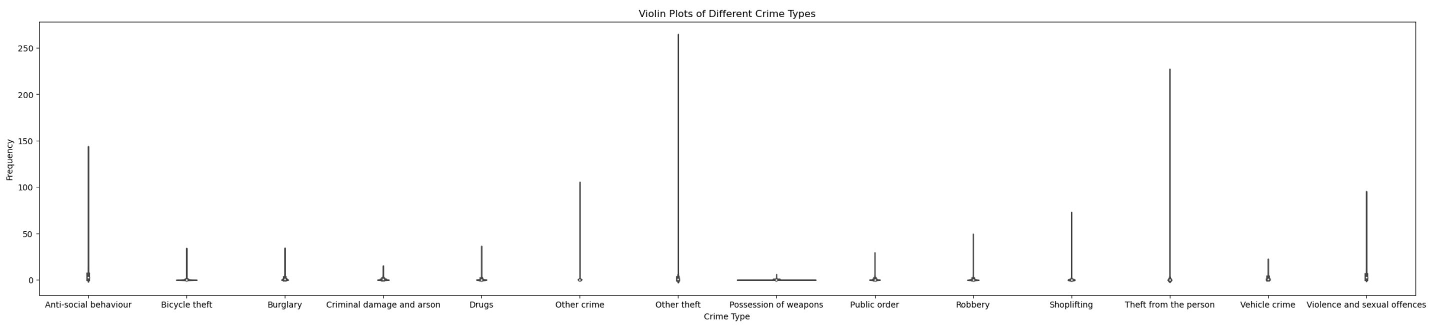
```python
import pandas as pd
import matplotlib.pyplot as plt

top_50_data = FinalData.nlargest(50, 'TotPop')

plt.figure(figsize=(15, 10))

plt.scatter(top_50_data['IMDScore'], top_50_data['LSOA code'], s=top_50_data['TotPop'] /
100, alpha=0.5)

plt.xlabel('IMD Score')
plt.ylabel('LSOA Code')
plt.title('Bubble Chart of IMD Score and Population for Top 50 LSOA Codes')

plt.show()
```





In [27]:

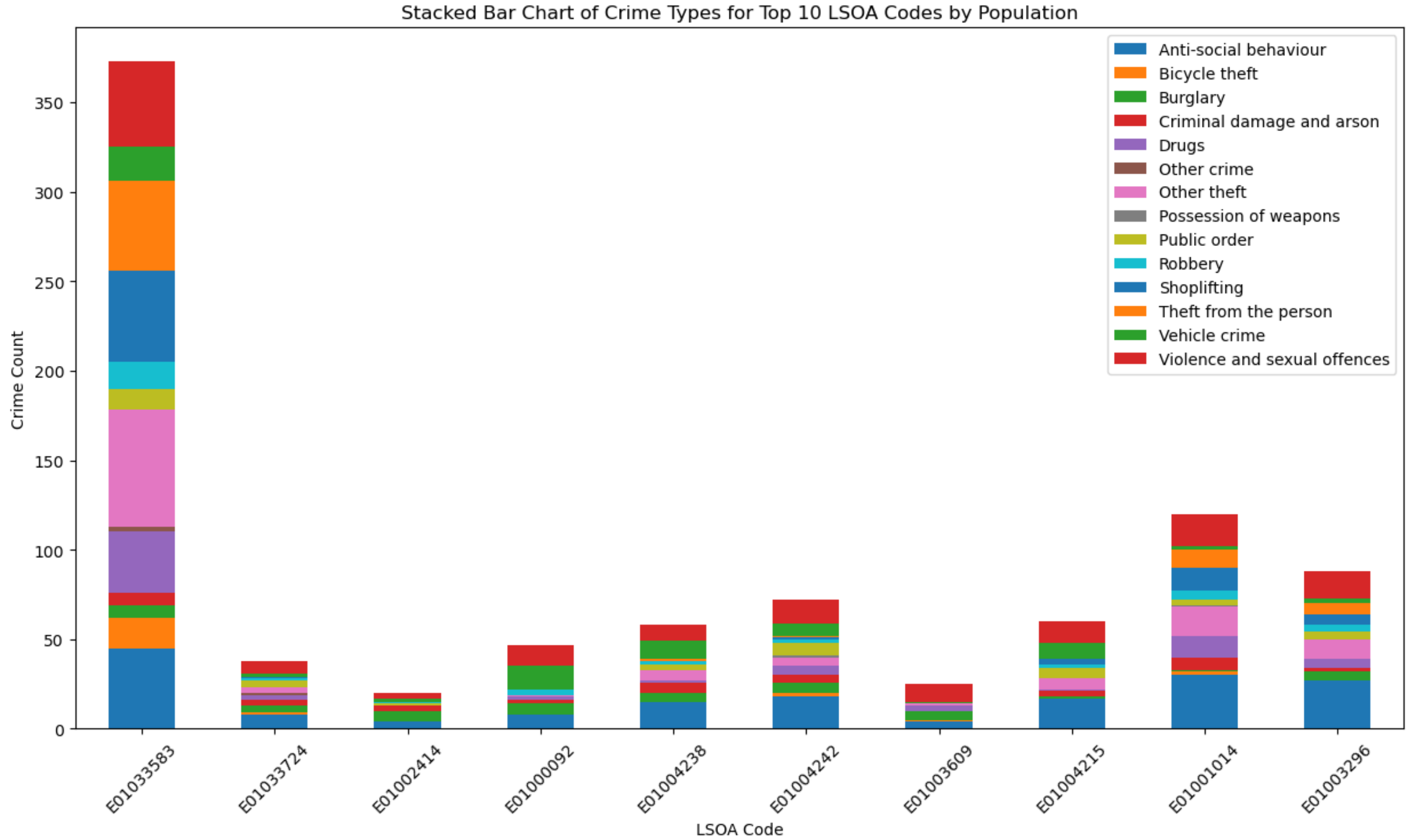
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

crime_types = ['Anti-social behaviour', 'Bicycle theft', 'Burglary', 'Criminal damage an
d arson', 'Drugs', 'Other crime', 'Other theft', 'Possession of weapons', 'Public order'
, 'Robbery', 'Shoplifting', 'Theft from the person', 'Vehicle crime', 'Violence and sexua
l offences']

melted_data = FinalData.melt(value_vars=crime_types, var_name='Crime Type', value_name='
Count')

plt.figure(figsize=(30, 6))
sns.violinplot(x='Crime Type', y='Count', data=melted_data)
plt.title('Violin Plots of Different Crime Types')
plt.ylabel('Frequency')
plt.xlabel('Crime Type')

plt.show()
```



In [28]:

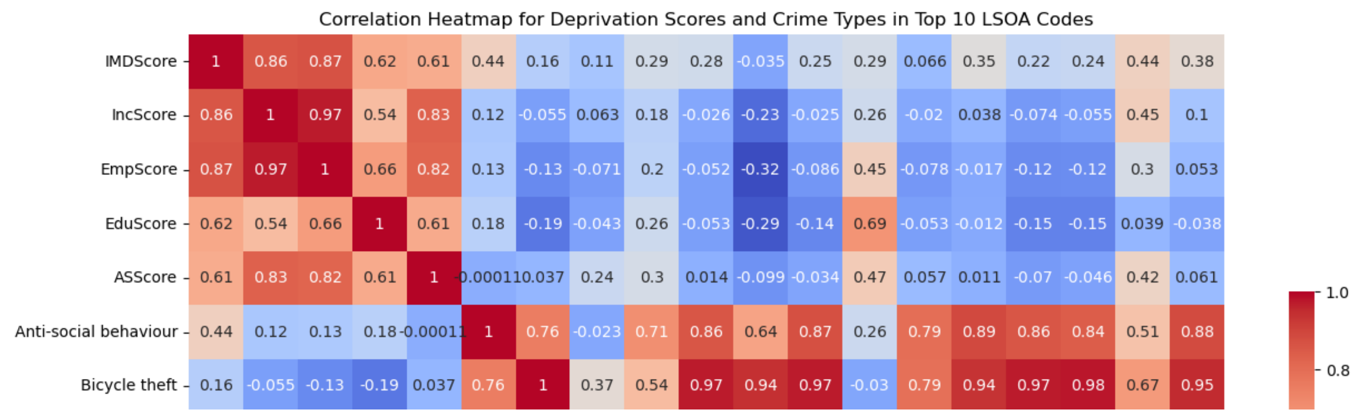
```
import pandas as pd
import matplotlib.pyplot as plt

crime_types = ['Anti-social behaviour', 'Bicycle theft', 'Burglary', 'Criminal damage an
d arson', 'Drugs', 'Other crime', 'Other theft', 'Possession of weapons', 'Public order'
, 'Robbery', 'Shoplifting', 'Theft from the person', 'Vehicle crime', 'Violence and sexua
l offences']

top_10_lsoa = FinalData.nlargest(10, 'TotPop')

top_10_lsoa.set_index('LSOA code')[crime_types].plot(kind='bar', stacked=True, figsize=(
15, 8))
```

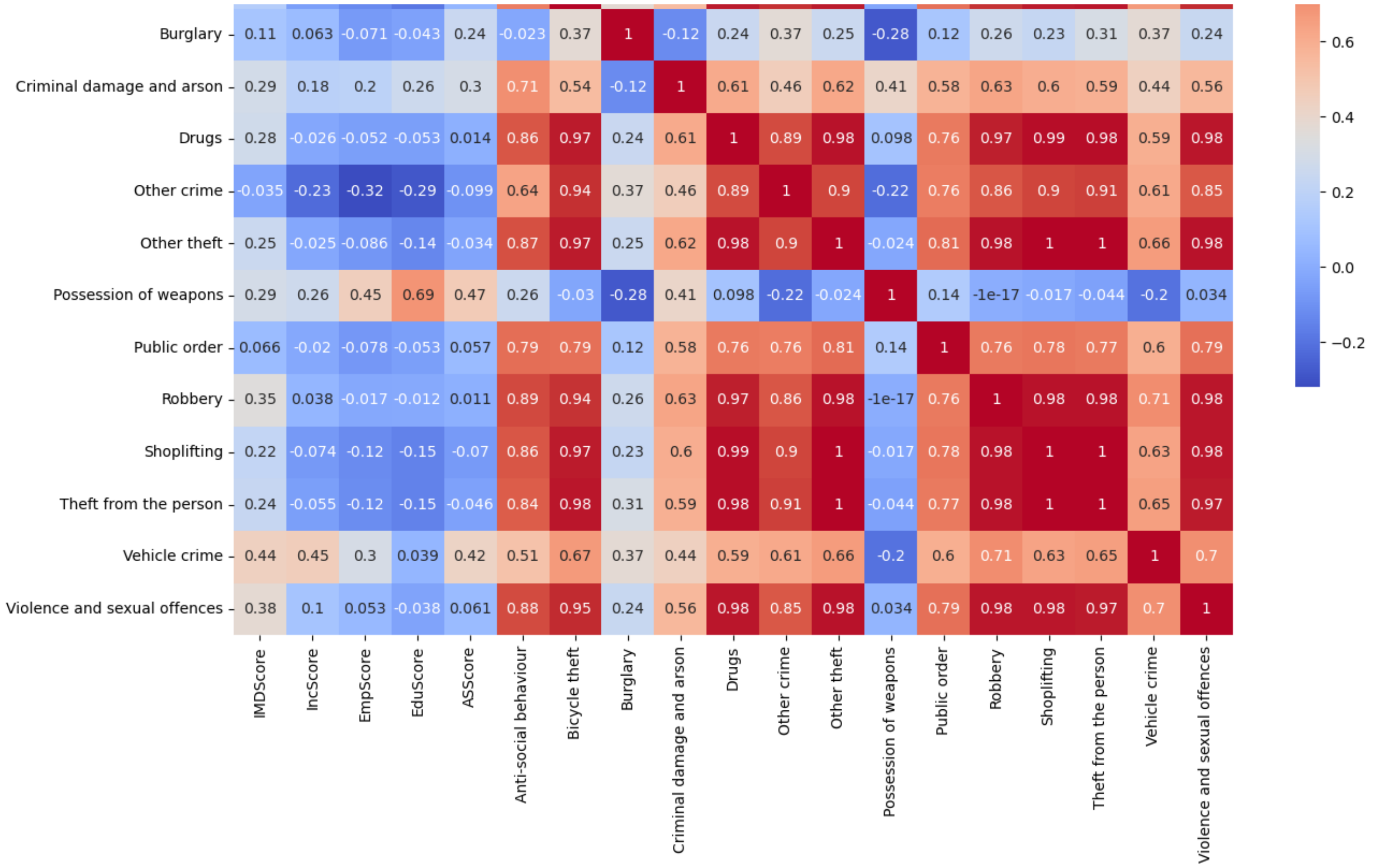
```
plt.title('Stacked Bar Chart of Crime Types for Top 10 LSOA Codes by Population')
plt.xlabel('LSOA Code')
plt.ylabel('Crime Count')
plt.xticks(rotation=45)

plt.show()
```



In [29]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

top_10_data = FinalData.nlargest(10, 'TotPop')

deprivation_scores = ['IMDScore', 'IncScore', 'EmpScore', 'EduScore', 'ASScore']
crime_types = ['Anti-social behaviour', 'Bicycle theft', 'Burglary', 'Criminal damage an
d arson', 'Drugs', 'Other crime', 'Other theft', 'Possession of weapons', 'Public order'
, 'Robbery', 'Shoplifting', 'Theft from the person', 'Vehicle crime', 'Violence and sexua
l offences']

correlation_data = top_10_data[deprivation_scores + crime_types]
corr_matrix = correlation_data.corr()

plt.figure(figsize=(15, 12))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', cbar_kws={"shrink": .5})
plt.title('Correlation Heatmap for Deprivation Scores and Crime Types in Top 10 LSOA Code
s')
plt.show()
```

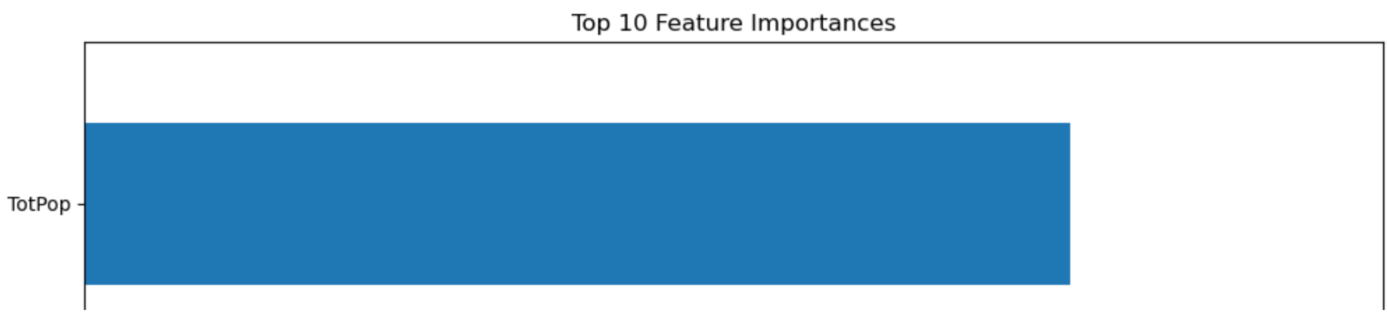


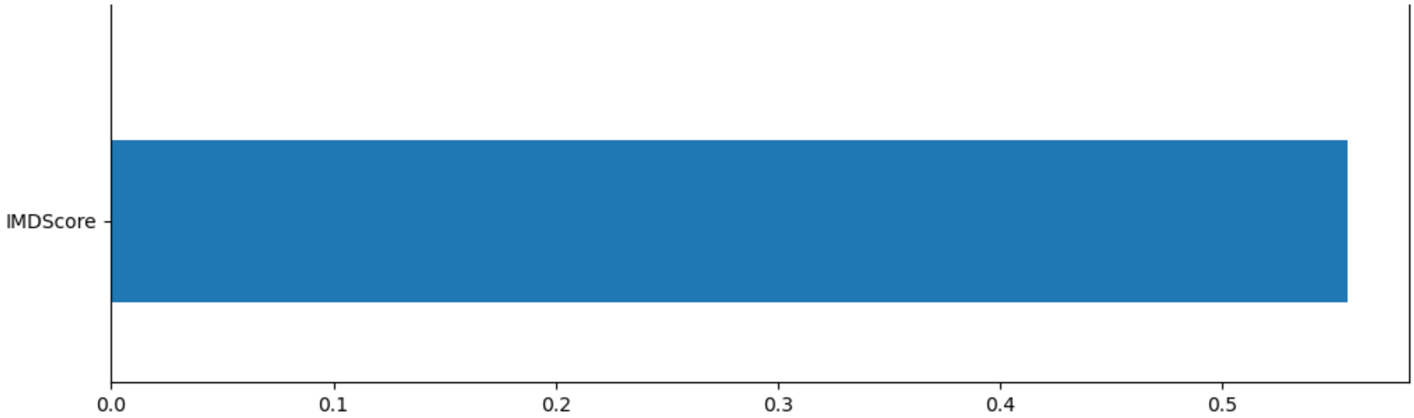


In [35]:

```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.ensemble import RandomForestRegressor
import matplotlib.pyplot as plt


X = FinalData[['IMDScore', 'TotPop']]
y = FinalData['Total Crimes']

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

RandomForest_model = RandomForestRegressor(n_estimators=100, random_state=42)

RandomForest_model.fit(X_train, y_train)
predictions_rf = RandomForest_model.predict(X_test)
mse_rf = mean_squared_error(y_test, predictions_rf)
print(f'Random Forest Mean Squared Error: {mse_rf}')

feature_importances = pd.Series(RandomForest_model.feature_importances_, index=X_train.c
olumns)
plt.figure(figsize=(12, 6))
feature_importances.nlargest(10).plot(kind='barh')
plt.title('Top 10 Feature Importances')
plt.show()
```

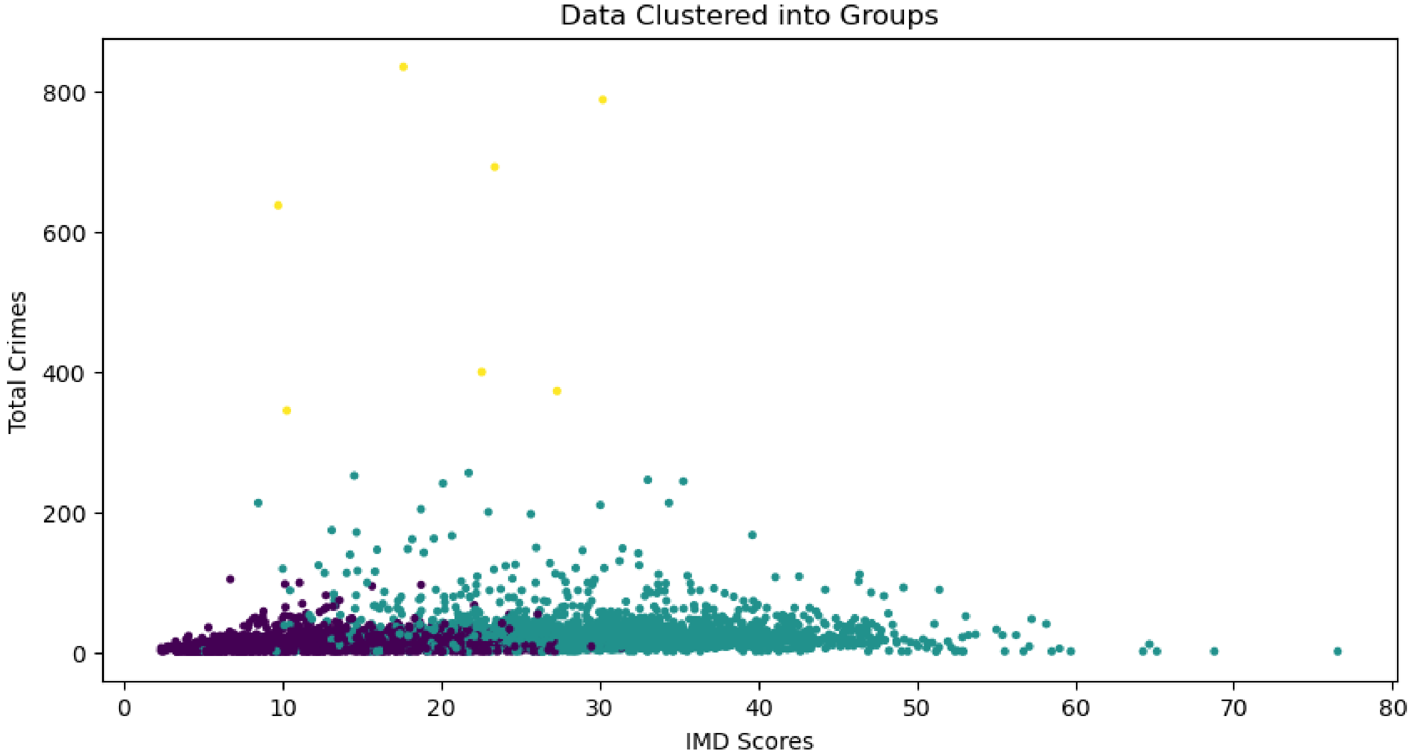
```
Random Forest Mean Squared Error: 499.69940118924313
```





In [49]:

```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

features = FinalData[['IMDScore', 'TotPop', 'Total Crimes']]

scaler = StandardScaler()
scaled_features = scaler.fit_transform(features)

kmeans = KMeans(n_clusters=3, n_init=100, random_state=42)
clusters = kmeans.fit_predict(scaled_features)

FinalData['Cluster'] = clusters

plt.figure(figsize=(10, 5))
plt.scatter(FinalData['IMDScore'], FinalData['Total Crimes'], c=FinalData['Cluster'], s=
7)
plt.xlabel('IMD Scores')
plt.ylabel('Total Crimes')
plt.title('Data Clustered into Groups')
plt.show()
```



In [50]:

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

```python
from sklearn.preprocessing import StandardScaler

top_50 = FinalData.nlargest(50, 'TotPop')

features = top_50[['IMDScore', 'Total Crimes', 'TotPop']]

scaler = StandardScaler()
scaled_features = scaler.fit_transform(features)

Z = linkage(scaled_features, method='ward')

plt.figure(figsize=(12, 8))
dendrogram(Z, labels=top_50['LSOA code'].values, orientation='top', leaf_rotation=90)
plt.title('Hierarchical Clustering Dendrogram')
plt.xlabel('LSOA Code')
plt.ylabel('Distance')
plt.show()
```