Nypd_Final_Project

December 4, 2024

[1]:
```
# Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import folium
from folium.plugins import HeatMap

# Step 1: Load the Raw Dataset
raw_dataset = pd.read_csv("NYPD_Arrest_Data__Year_to_Date_.csv")
```

[2]:
```
# Step 2: Data Overview
print("Raw Dataset Shape:", raw_dataset.shape)
print("Columns:", raw_dataset.columns)
print("Missing Values:\n", raw_dataset.isnull().sum())
```

```
Raw Dataset Shape: (128778, 19)
Columns: Index(['ARREST_KEY', 'ARREST_DATE', 'PD_CD', 'PD_DESC', 'KY_CD',
'OFNS_DESC',
       'LAW_CODE', 'LAW_CAT_CD', 'ARREST_BORO', 'ARREST_PRECINCT',
       'JURISDICTION_CODE', 'AGE_GROUP', 'PERP_SEX', 'PERP_RACE', 'X_COORD_CD',
       'Y_COORD_CD', 'Latitude', 'Longitude', 'New Georeferenced Column'],
      dtype='object')
Missing Values:
 ARREST_KEY                0
ARREST_DATE                0
PD_CD                      4
PD_DESC                    0
KY_CD                     15
OFNS_DESC                  0
LAW_CODE                   0
LAW_CAT_CD               770
ARREST_BORO                0
ARREST_PRECINCT            0
JURISDICTION_CODE          0
AGE_GROUP                  0
PERP_SEX                   0
PERP_RACE                  0
```

```
X_COORD_CD                    0
Y_COORD_CD                    0
Latitude                      0
Longitude                     0
New Georeferenced Column      0
dtype: int64
```

[3]:
```
# Step 3: Create a Copy for Cleaning
clean_dataset = raw_dataset.copy()
```

[4]:
```
# Step 4: Correct Missing Values
if 'pd_cd' in clean_dataset.columns:
    clean_dataset['pd_cd'].fillna(-1, inplace=True)
if 'ky_cd' in clean_dataset.columns:
    clean_dataset['ky_cd'].fillna(-1, inplace=True)
if 'law_cat_cd' in clean_dataset.columns:
    clean_dataset['law_cat_cd'].fillna('Unknown', inplace=True)
```

[6]:
```
# Check remaining missing values in key columns
print("Remaining Missing Values:\n", clean_dataset[['PD_CD', 'KY_CD',␣
 ↪'LAW_CAT_CD']].isnull().sum())
```

```
Remaining Missing Values:
 PD_CD           4
KY_CD           15
LAW_CAT_CD     770
dtype: int64
```

[7]:
```
# Step 5: Handle Duplicate Rows
duplicates = clean_dataset.duplicated()
print("Number of Duplicate Rows:", duplicates.sum())
clean_dataset = clean_dataset.drop_duplicates()
```

```
Number of Duplicate Rows: 0
```

[9]:
```
# Step 6: Convert `arrest_date` to Datetime and Format
clean_dataset['ARREST_DATE'] = pd.to_datetime(clean_dataset['ARREST_DATE'],␣
 ↪errors='coerce')
clean_dataset.dropna(subset=['ARREST_DATE'], inplace=True)
clean_dataset['ARREST_DATE'] = clean_dataset['ARREST_DATE'].dt.strftime('%m/%d/
 ↪%Y')
```

[11]:
```
# Confirm the date range after formatting
print("Date Range:", clean_dataset['ARREST_DATE'].min(),␣
 ↪clean_dataset['ARREST_DATE'].max())
```

```
Date Range: 01/01/2024 06/30/2024
```

[12]:
```
# Step 7: Map Singular Values to Descriptions
replacements = {
    'ARREST_BORO': {
        'M': 'Manhattan',
        'K': 'Brooklyn',
        'Q': 'Queens',
        'B': 'Bronx',
        'S': 'Staten Island'
    },
    'PERP_SEX': {
        'M': 'Male',
        'F': 'Female',
        'UNKNOWN': 'Unknown'
    },
    'LAW_CAT_CD': {
        'F': 'Felony',
        'M': 'Misdemeanor',
        'V': 'Violation',
        '9': 'Unknown',
        'I': 'Infraction',
        '(null)': 'Unknown'
    }
}

# Apply replacements
for column, mapping in replacements.items():
    if column in clean_dataset.columns:
        clean_dataset[column] = clean_dataset[column].replace(mapping)

# Verify replacements
for column in replacements.keys():
    if column in clean_dataset.columns:
        print(f"Unique values in {column} after replacement:")
        print(clean_dataset[column].unique())
```

```
Unique values in ARREST_BORO after replacement:
['Brooklyn' 'Queens' 'Staten Island' 'Bronx' 'Manhattan']
Unique values in PERP_SEX after replacement:
['Male' 'Female']
Unique values in LAW_CAT_CD after replacement:
['Felony' 'Misdemeanor' 'Violation' nan 'Unknown' 'Infraction']
```

[14]:
```
# Step 8: Filter Geographical Data
clean_dataset = clean_dataset[
    (clean_dataset['Latitude'].between(40.4774, 40.9176)) &
    (clean_dataset['Longitude'].between(-74.2591, -73.7004))
]
```

[15]:
```
# Final Cleaned Dataset Overview
print("Cleaned Dataset Shape:", clean_dataset.shape)
print(clean_dataset.head())
```

```
Cleaned Dataset Shape: (128776, 19)
   ARREST_KEY ARREST_DATE  PD_CD                    PD_DESC  KY_CD  \
0   279884335  01/03/2024  153.0                   RAPE 3  104.0
1   279876234  01/03/2024  105.0         STRANGULATION 1ST  106.0
2   279939192  01/04/2024  109.0  ASSAULT 2,1,UNCLASSIFIED  106.0
3   280561026  01/15/2024  203.0      TRESPASS 3, CRIMINAL  352.0
4   280084387  01/07/2024  223.0  BURGLARY,RESIDENCE,NIGHT  107.0

            OFNS_DESC    LAW_CODE   LAW_CAT_CD    ARREST_BORO  ARREST_PRECINCT  \
0                RAPE  PL 1302503       Felony       Brooklyn               77
1     FELONY ASSAULT  PL 1211200       Felony         Queens              101
2     FELONY ASSAULT  PL 1201001       Felony       Brooklyn               83
3  CRIMINAL TRESPASS  PL 140100A  Misdemeanor  Staten Island              121
4           BURGLARY  PL 1403002       Felony         Queens              107

   JURISDICTION_CODE AGE_GROUP PERP_SEX PERP_RACE  X_COORD_CD  Y_COORD_CD  \
0                  0     45-64     Male     BLACK     1003509      185018
1                  0     25-44     Male     BLACK     1053648      158969
2                  0     45-64     Male     BLACK     1007127      193705
3                  0     18-24     Male     BLACK      942827      166373
4                  0     45-64     Male     BLACK     1036732      206997

    Latitude  Longitude                    New Georeferenced Column
0  40.674496 -73.930571  POINT (-73.9305713255961 40.6744956865259)
1  40.602740 -73.750081                POINT (-73.750081 40.60274)
2  40.698323 -73.917495               POINT (-73.917495 40.698323)
3  40.623238 -74.149217               POINT (-74.149217 40.623238)
4  40.734681 -73.810626               POINT (-73.810626 40.734681)
```

[17]:
```
print(f"Clean Dataset Shape: {clean_dataset.shape}")
print(clean_dataset.head())
```

```
Clean Dataset Shape: (128776, 23)
   ARREST_KEY ARREST_DATE  PD_CD                    PD_DESC  KY_CD  \
0   279884335  01/03/2024  153.0                   RAPE 3  104.0
1   279876234  01/03/2024  105.0         STRANGULATION 1ST  106.0
2   279939192  01/04/2024  109.0  ASSAULT 2,1,UNCLASSIFIED  106.0
3   280561026  01/15/2024  203.0      TRESPASS 3, CRIMINAL  352.0
4   280084387  01/07/2024  223.0  BURGLARY,RESIDENCE,NIGHT  107.0

            OFNS_DESC    LAW_CODE   LAW_CAT_CD    ARREST_BORO  ARREST_PRECINCT  \
0                RAPE  PL 1302503       Felony       Brooklyn               77
1     FELONY ASSAULT  PL 1211200       Felony         Queens              101
2     FELONY ASSAULT  PL 1201001       Felony       Brooklyn               83
```

```
3  CRIMINAL TRESPASS  PL 140100A  Misdemeanor  Staten Island              121
4           BURGLARY  PL 1403002       Felony         Queens              107

   …  PERP_RACE X_COORD_CD Y_COORD_CD   Latitude  Longitude  \
0  …      BLACK    1003509     185018  40.674496 -73.930571
1  …      BLACK    1053648     158969  40.602740 -73.750081
2  …      BLACK    1007127     193705  40.698323 -73.917495
3  …      BLACK     942827     166373  40.623238 -74.149217
4  …      BLACK    1036732     206997  40.734681 -73.810626

                     New Georeferenced Column  arrest_year  arrest_month  \
0  POINT (-73.9305713255961 40.6744956865259)         2024             1
1                POINT (-73.750081 40.60274)         2024             1
2               POINT (-73.917495 40.698323)         2024             1
3               POINT (-74.149217 40.623238)         2024             1
4               POINT (-73.810626 40.734681)         2024             1

  day_of_week  is_weekend
0   Wednesday       False
1   Wednesday       False
2    Thursday       False
3      Monday       False
4      Sunday        True

[5 rows x 23 columns]
```

[18]:
```
# Step 1: Add Date-Based Features
clean_dataset['arrest_year'] = pd.to_datetime(clean_dataset['ARREST_DATE']).dt.
 ↪year
clean_dataset['arrest_month'] = pd.to_datetime(clean_dataset['ARREST_DATE']).dt.
 ↪month
clean_dataset['day_of_week'] = pd.to_datetime(clean_dataset['ARREST_DATE']).dt.
 ↪day_name()
clean_dataset['is_weekend'] = clean_dataset['day_of_week'].isin(['Saturday',␣
 ↪'Sunday'])
```

[20]:
```
# Displaying the outputs for Step 1
print(clean_dataset[['ARREST_DATE', 'arrest_year', 'arrest_month',␣
 ↪'day_of_week', 'is_weekend']])
```

```
       ARREST_DATE  arrest_year  arrest_month day_of_week  is_weekend
0       01/03/2024         2024             1   Wednesday       False
1       01/03/2024         2024             1   Wednesday       False
2       01/04/2024         2024             1    Thursday       False
3       01/15/2024         2024             1      Monday       False
4       01/07/2024         2024             1      Sunday        True
…              …            …             …           …           …
```

```
128773  06/14/2024          2024              6       Friday       False
128774  06/19/2024          2024              6    Wednesday       False
128775  06/20/2024          2024              6     Thursday       False
128776  06/11/2024          2024              6      Tuesday       False
128777  06/15/2024          2024              6     Saturday        True

[128776 rows x 5 columns]
```

[23]:
```
# Step 2: Create Severity Index
severity_mapping = {'Felony': 3, 'Misdemeanor': 2, 'Violation': 1}
clean_dataset['severity_index'] = clean_dataset['LAW_CAT_CD'].
 ↪map(severity_mapping)
print("\nSeverity Index Feature:")
print(clean_dataset[['LAW_CAT_CD', 'severity_index']].head())
```

```
Severity Index Feature:
    LAW_CAT_CD  severity_index
0       Felony             3.0
1       Felony             3.0
2       Felony             3.0
3  Misdemeanor             2.0
4       Felony             3.0
```

[26]:
```
# Step 3: Add Location-Based Features
clean_dataset['location_zone'] = clean_dataset.apply(
    lambda row: 'North NYC' if row['Latitude'] > 40.75 else 'South NYC', axis=1
)
clean_dataset['boro_severity'] = clean_dataset['ARREST_BORO'] + '_' +␣
 ↪clean_dataset['LAW_CAT_CD']

print("\nLocation-Based Features:")
print(clean_dataset[['Latitude', 'Longitude', 'location_zone',␣
 ↪'boro_severity']].head())
```

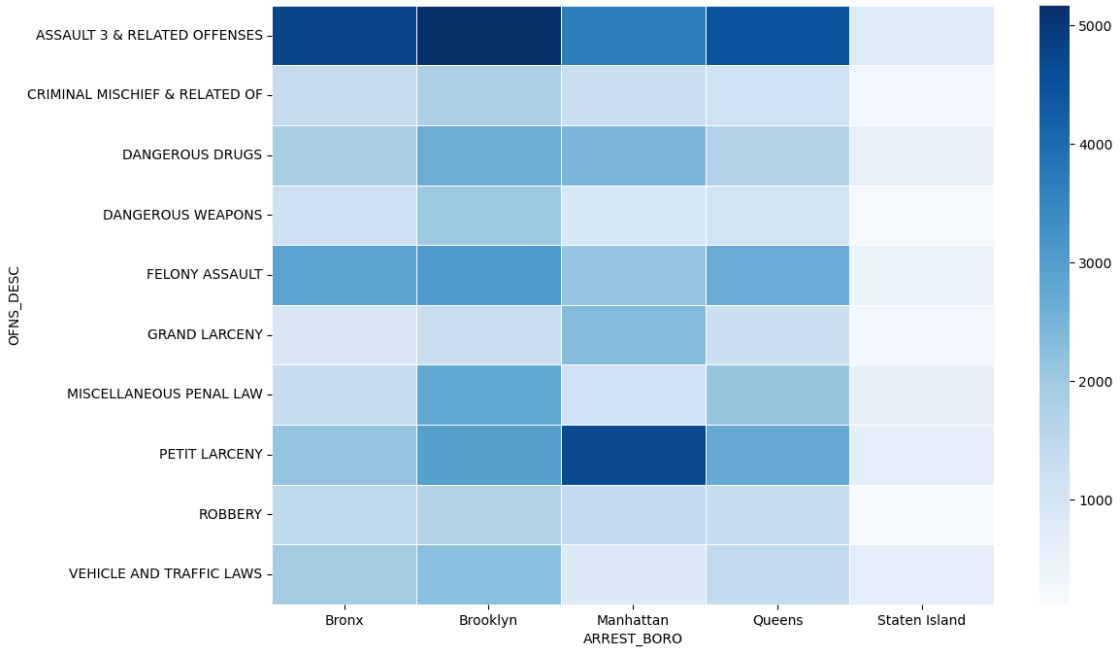
```
Location-Based Features:
    Latitude  Longitude location_zone              boro_severity
0  40.674496 -73.930571     South NYC            Brooklyn_Felony
1  40.602740 -73.750081     South NYC              Queens_Felony
2  40.698323 -73.917495     South NYC            Brooklyn_Felony
3  40.623238 -74.149217     South NYC  Staten Island_Misdemeanor
4  40.734681 -73.810626     South NYC              Queens_Felony
```

[29]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Step 1: Identify Top 10 Offenses
top_offenses = clean_dataset['OFNS_DESC'].value_counts().nlargest(10).index

# Step 2: Filter Dataset for Top Offenses
filtered_dataset = clean_dataset[clean_dataset['OFNS_DESC'].isin(top_offenses)]

# Step 3: Aggregate Data by Borough and Offense
heatmap_data = filtered_dataset.groupby(['ARREST_BORO', 'OFNS_DESC']).size().
 ↪reset_index(name='count')

# Step 4: Create a Pivot Table for Heatmap
heatmap = pd.pivot_table(heatmap_data, values='count', index='OFNS_DESC',␣
 ↪columns='ARREST_BORO', fill_value=0)

# Step 5: Plot the Heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(heatmap, cmap='Blues', annot=True, fmt='d', linewidths=.5)

# Step 6: Customize Plot Titles and Labels
plt.title('Heatmap of Top 10 Offenses by Borough', fontsize=16)
plt.xlabel('Borough', fontsize=12)
plt.ylabel('Offense Description', fontsize=12)
plt.xticks(rotation=45, ha='right', fontsize=10)
plt.yticks(fontsize=10)
plt.tight_layout()

# Step 7: Show the Heatmap
plt.show()
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Cell In[29], line 19
     17 # Step 5: Plot the Heatmap
     18 plt.figure(figsize=(12, 8))
---> 19 sns.heatmap(heatmap, cmap='Blues', annot=True, fmt='d', linewidths=.5)
     21 # Step 6: Customize Plot Titles and Labels
     22 plt.title('Heatmap of Top 10 Offenses by Borough', fontsize=16)

File ~/.local/lib/python3.11/site-packages/seaborn/matrix.py:459, in␣
 ↪heatmap(data, vmin, vmax, cmap, center, robust, annot, fmt, annot_kws,␣
 ↪linewidths, linecolor, cbar, cbar_kws, cbar_ax, square, xticklabels,␣
 ↪yticklabels, mask, ax, **kwargs)
    457 if square:
    458     ax.set_aspect("equal")
--> 459 plotter.plot(ax, cbar_ax, kwargs)
    460 return ax
```

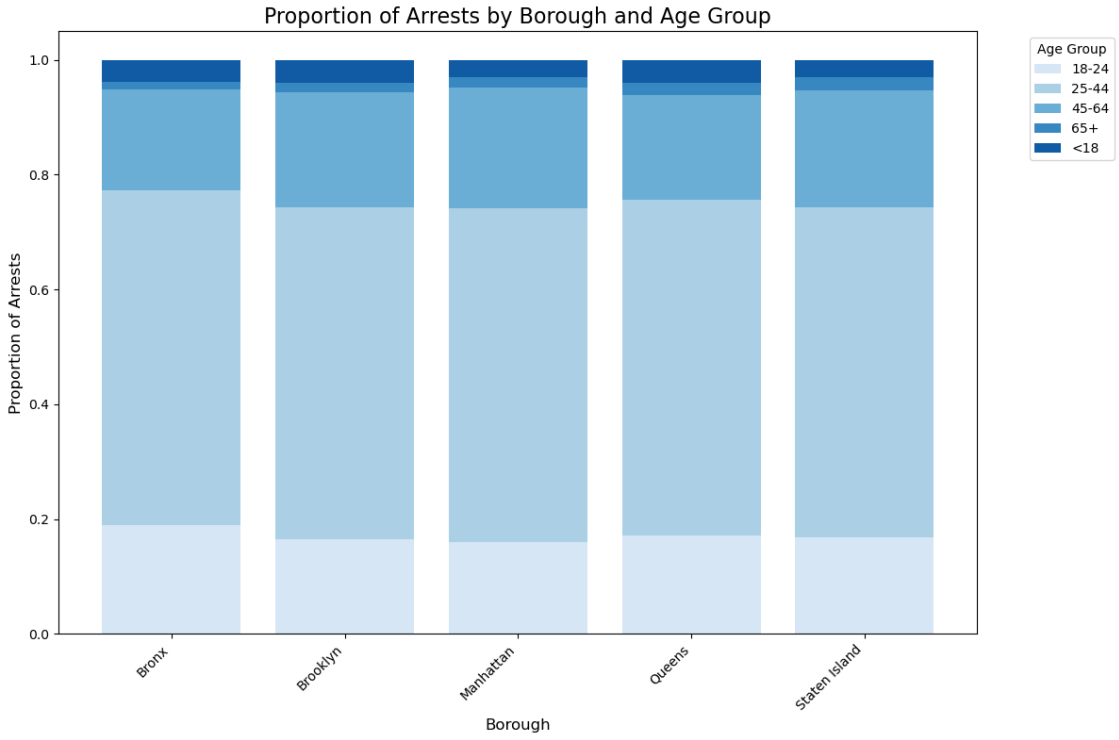
```
File ~/.local/lib/python3.11/site-packages/seaborn/matrix.py:352, in _HeatMapper.
 ↪plot(self, ax, cax, kws)
    350 # Annotate the cells with the formatted values
    351 if self.annot:
--> 352     self._annotate_heatmap(ax, mesh)

File ~/.local/lib/python3.11/site-packages/seaborn/matrix.py:260, in _HeatMapper.
 ↪_annotate_heatmap(self, ax, mesh)
    258 lum = relative_luminance(color)
    259 text_color = ".15" if lum > .408 else "w"
--> 260 annotation = ("{:" + self.fmt + "}").format(val)
    261 text_kwargs = dict(color=text_color, ha="center", va="center")
    262 text_kwargs.update(self.annot_kws)

ValueError: Unknown format code 'd' for object of type 'float'
```



[31]:
```
# Proportion of Arrests by Borough and Age Group
borough_age = clean_dataset.groupby(['ARREST_BORO', 'AGE_GROUP']).size().
 ↪reset_index(name='count')
borough_age['proportion'] = borough_age.groupby('ARREST_BORO')['count'].
 ↪transform(lambda x: x / x.sum())
borough_age_pivot = borough_age.pivot_table(index='ARREST_BORO',␣
 ↪columns='AGE_GROUP', values='proportion', aggfunc='sum')
```

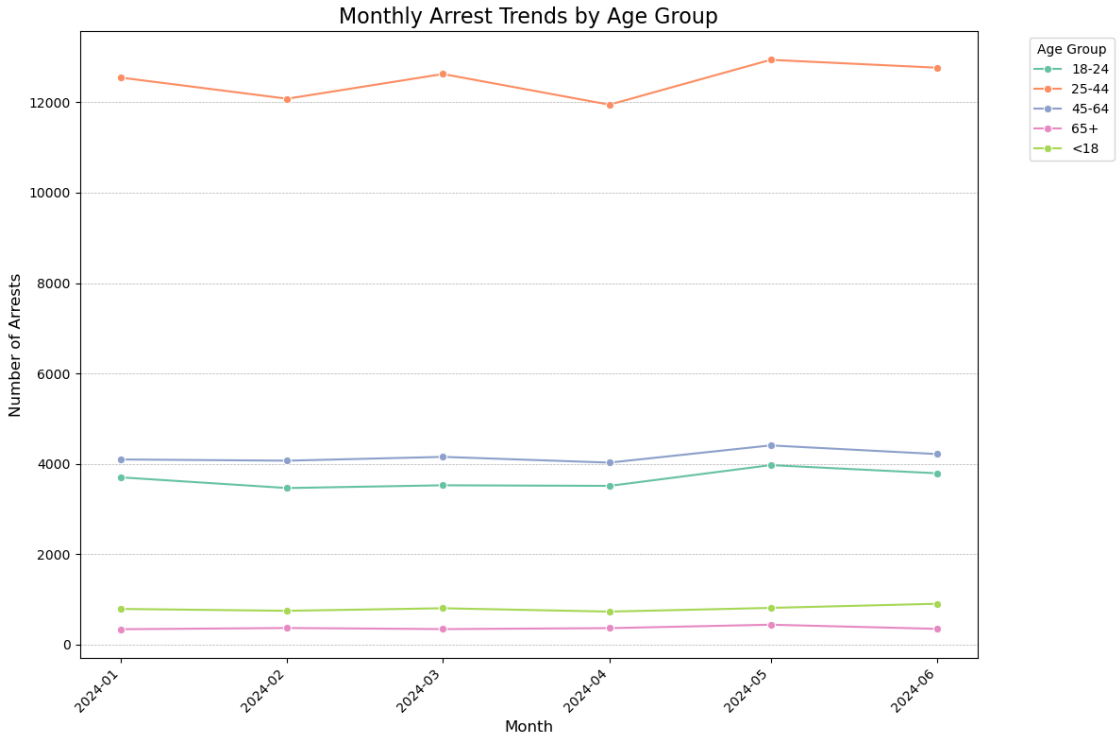
```
# Plot the Stacked Bar Chart with Uniform Color Palette
plt.figure(figsize=(12, 8))
custom_colors = sns.color_palette('Blues', n_colors=len(borough_age_pivot.
 ↪columns))
borough_age_pivot.plot(kind='bar', stacked=True, figsize=(12, 8),␣
 ↪color=custom_colors, width=0.8)

plt.title('Proportion of Arrests by Borough and Age Group', fontsize=16)
plt.xlabel('Borough', fontsize=12)
plt.ylabel('Proportion of Arrests', fontsize=12)
plt.xticks(rotation=45, ha='right', fontsize=10)
plt.yticks(fontsize=10)
plt.legend(title='Age Group', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()

plt.show()
```

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



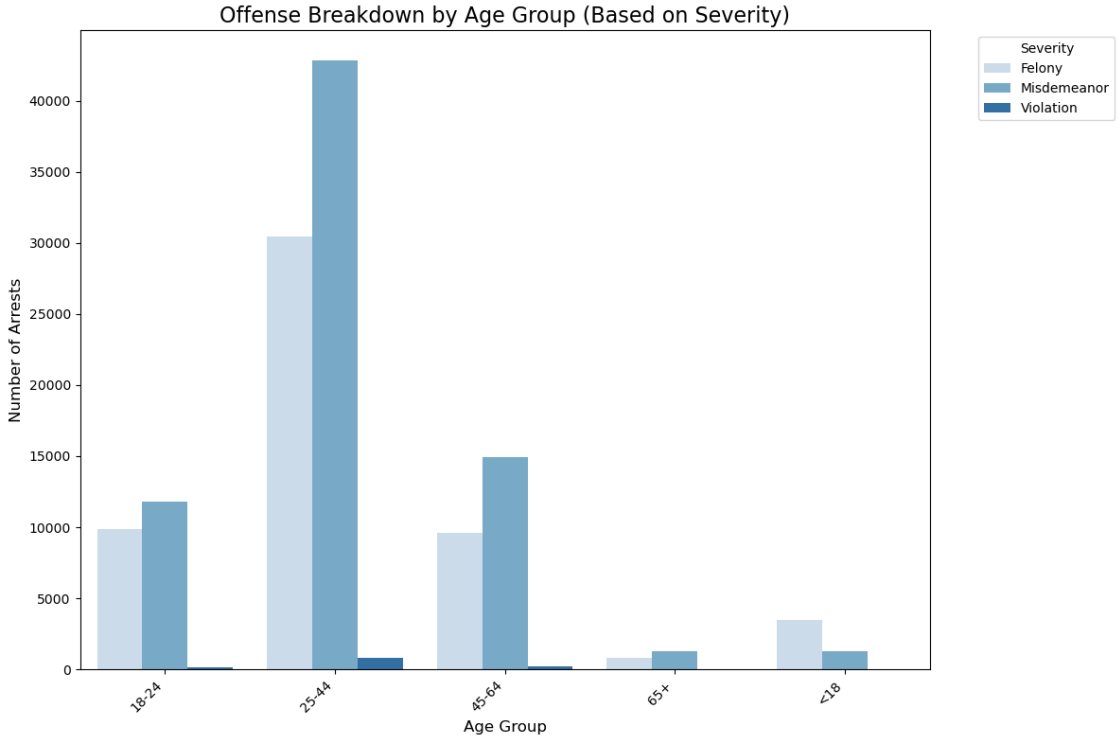
[36]:
```
# Convert 'ARREST_DATE' to datetime format if not already
clean_dataset['ARREST_DATE'] = pd.to_datetime(clean_dataset['ARREST_DATE'],␣
 ↪errors='coerce')
```

```
# Monthly Arrest Trends by Age Group
monthly_trends = (
    clean_dataset.groupby([clean_dataset['ARREST_DATE'].dt.to_period('M'),␣
 ↪'AGE_GROUP'])
    .size()
    .reset_index(name='count')
)

# Convert 'ARREST_DATE' to a proper timestamp for plotting
monthly_trends['month'] = monthly_trends['ARREST_DATE'].dt.to_timestamp()

# Ensure 'AGE_GROUP' is a categorical variable for better plotting
monthly_trends['AGE_GROUP'] = monthly_trends['AGE_GROUP'].astype('category')

# Plot the line chart
plt.figure(figsize=(12, 8))
sns.lineplot(data=monthly_trends, x='month', y='count', hue='AGE_GROUP',␣
 ↪palette='Set2', marker='o')

# Add title and labels
plt.title('Monthly Arrest Trends by Age Group', fontsize=16)
plt.xlabel('Month', fontsize=12)
plt.ylabel('Number of Arrests', fontsize=12)
plt.xticks(rotation=45, ha='right', fontsize=10)
plt.yticks(fontsize=10)
plt.legend(title='Age Group', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid(axis='y', linestyle='--', linewidth=0.5)
plt.tight_layout()

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



[37]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Map severity levels to numeric values
severity_mapping = {'Felony': 3, 'Misdemeanor': 2, 'Violation': 1}
clean_dataset['SEVERITY_INDEX'] = clean_dataset['LAW_CAT_CD'].
 ↪map(severity_mapping)

# Group by AGE_GROUP and SEVERITY_INDEX
offense_age = (
    clean_dataset.groupby(['AGE_GROUP', 'SEVERITY_INDEX'])
    .size()
    .reset_index(name='COUNT')
    .sort_values(by='SEVERITY_INDEX', ascending=False)
)

# Map numeric severity levels back to descriptive labels
severity_labels = {3: 'Felony', 2: 'Misdemeanor', 1: 'Violation'}
offense_age['SEVERITY_CATEGORY'] = offense_age['SEVERITY_INDEX'].
 ↪map(severity_labels)

# Custom color palette
custom_blues = sns.color_palette('Blues', n_colors=3)
```

```
# Plot the bar chart
plt.figure(figsize=(12, 8))
sns.barplot(data=offense_age, x='AGE_GROUP', y='COUNT',␣
 ↪hue='SEVERITY_CATEGORY', palette=custom_blues)

# Customize plot titles and labels
plt.title('Offense Breakdown by Age Group (Based on Severity)', fontsize=16)
plt.xlabel('Age Group', fontsize=12)
plt.ylabel('Number of Arrests', fontsize=12)
plt.xticks(rotation=45, ha='right', fontsize=10)
plt.legend(title='Severity', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()

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



[ ]:
```
# The Random Forest model achieved an accuracy of 62.8%, indicating that it␣
 ↪correctly predicts
# the offense severity in approximately 63% of the cases. The classification␣
 ↪report shows that
# the model performs well for the majority class (e.g., class `2`, likely the␣
 ↪most frequent severity
```

```
# level), as evidenced by higher precision and recall values for this class␣
 ↪compared to others.
# However, performance is limited for underrepresented classes (e.g., class␣
 ↪`1`), as indicated by
# low precision, recall, and F1-scores, likely due to class imbalance in the␣
 ↪dataset.

# The feature importance analysis highlights that latitude and longitude are␣
 ↪the most influential
# predictors, followed by age group and perpetrator race. Interestingly,␣
 ↪features like ARREST_BORO
# and IS_WEEKEND have relatively low importance, suggesting that geographical␣
 ↪data and demographic
# attributes play a larger role in determining offense severity.
```

[39]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪accuracy_score
from sklearn.preprocessing import LabelEncoder

# Step 1: Data Preparation
# Define features and target variable
features = ['AGE_GROUP', 'PERP_RACE', 'PERP_SEX', 'ARREST_BORO', 'is_weekend',␣
 ↪'Latitude', 'Longitude']
target = 'LAW_CAT_CD'

# Ensure all required columns exist and drop rows with missing values in␣
 ↪features or target
clean_dataset = clean_dataset.dropna(subset=features + [target])

# Encode categorical variables
label_encoders = {}
for col in features:
    if clean_dataset[col].dtype == 'object' or clean_dataset[col].dtype.name ==␣
 ↪'category':
        le = LabelEncoder()
        clean_dataset[col] = le.fit_transform(clean_dataset[col])
        label_encoders[col] = le

# Separate features and target
X = clean_dataset[features]
y = clean_dataset[target]

# Encode target variable
```

```
target_encoder = LabelEncoder()
y = target_encoder.fit_transform(y)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=42, stratify=y)

# Step 2: Model Selection
model = RandomForestClassifier(n_estimators=100, random_state=42)

# Step 3: Model Training
model.fit(X_train, y_train)

# Step 4: Model Evaluation
y_pred = model.predict(X_test)

# Evaluation Metrics
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))

# Step 5: Feature Importance
feature_importances = pd.DataFrame({
    'Feature': features,
    'Importance': model.feature_importances_
}).sort_values(by='Importance', ascending=False)

print("\nFeature Importances:\n", feature_importances)
```

```
/tmp/ipykernel_707/376868452.py: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
  clean_dataset[col] = le.fit_transform(clean_dataset[col])
/tmp/ipykernel_707/376868452.py: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
  clean_dataset[col] = le.fit_transform(clean_dataset[col])
/tmp/ipykernel_707/376868452.py: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
  clean_dataset[col] = le.fit_transform(clean_dataset[col])
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See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  clean_dataset[col] = le.fit_transform(clean_dataset[col])
Accuracy: 0.6283787302744649

Classification Report:
              precision    recall  f1-score   support

           0       0.58      0.55      0.57     16265
           1       0.00      0.00      0.00        33
           2       0.67      0.69      0.68     21623
           3       0.19      0.10      0.13       110
           4       0.45      0.26      0.33       371

    accuracy                           0.63     38402
   macro avg       0.38      0.32      0.34     38402
weighted avg       0.62      0.63      0.63     38402


Confusion Matrix:
 [[ 9017     0  7191    22    35]
 [    9     0    24     0     0]
 [ 6507     2 15005    25    84]
 [   29     0    70    11     0]
 [   47     0   225     1    98]]

Feature Importances:
        Feature  Importance
5     Latitude    0.445732
6    Longitude    0.443651
0    AGE_GROUP    0.052245
1    PERP_RACE    0.035715
3  ARREST_BORO    0.008882
2     PERP_SEX    0.006966
4   is_weekend    0.006810
```
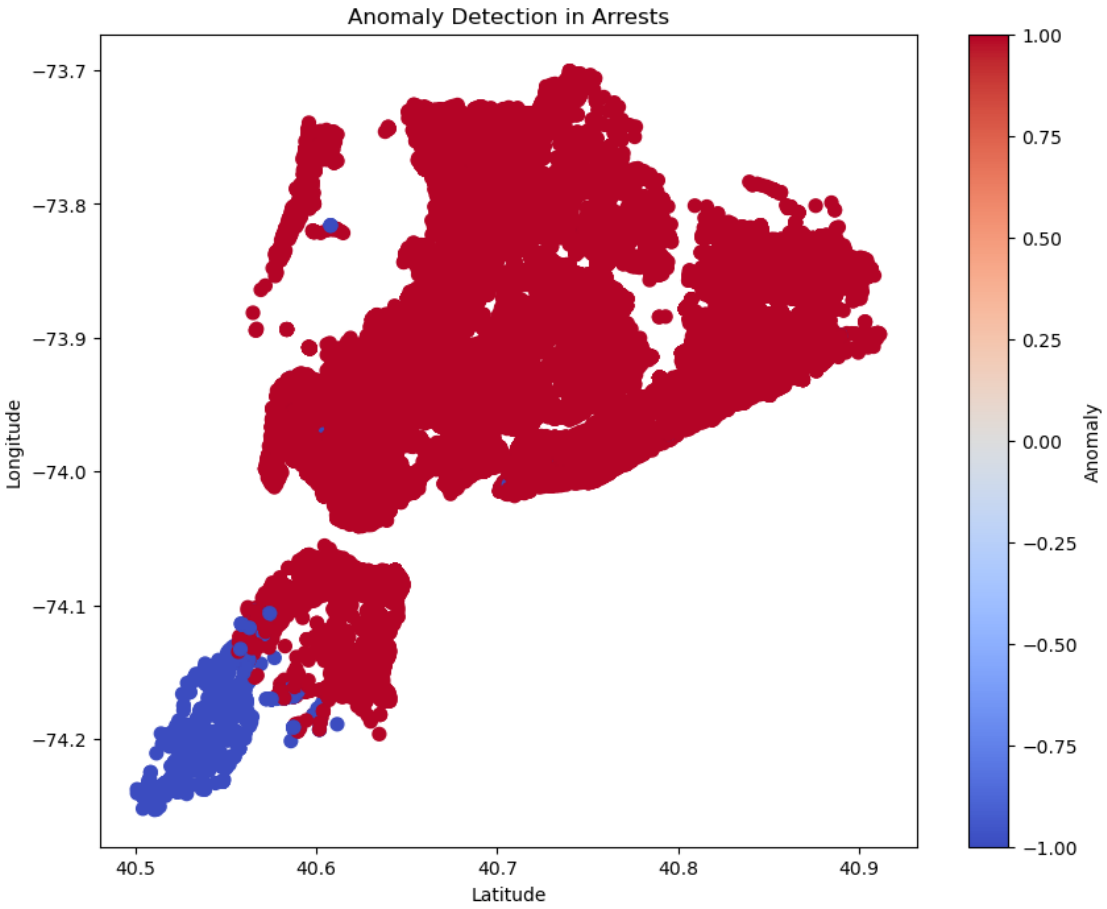

[ ]:
```
#2 Anamoly Detection:
# This visualization shows the results of anomaly detection applied to arrest␣
 ↪data
```

```
# using features like latitude, longitude, and severity index. The plot␣
 ↪highlights
# anomalous arrests (marked in blue) as distinct from normal patterns (marked␣
 ↪in red).

# The anomalies may represent unusual arrests based on location or other␣
 ↪factors,
# such as arrests occurring in areas where severe crimes are rare or infrequent␣
 ↪activity is observed.

# The use of an anomaly detection model (e.g., Isolation Forest) helps identify␣
 ↪these outliers,
# which can provide actionable insights for law enforcement, such as focusing␣
 ↪on specific
# locations or understanding rare events for improved resource allocation.
```

[40]:
```
from sklearn.ensemble import IsolationForest

# Select features for anomaly detection
anomaly_features = ['Latitude', 'Longitude', 'SEVERITY_INDEX']
X = clean_dataset[anomaly_features].dropna()

# Apply Isolation Forest
iso_forest = IsolationForest(contamination=0.01, random_state=42)
X['Anomaly'] = iso_forest.fit_predict(X)

# Visualize Anomalies
plt.figure(figsize=(10, 8))
plt.scatter(X['Latitude'], X['Longitude'], c=X['Anomaly'], cmap='coolwarm',␣
 ↪s=50)
plt.title("Anomaly Detection in Arrests")
plt.xlabel("Latitude")
plt.ylabel("Longitude")
plt.colorbar(label="Anomaly")
plt.show()
```



[42]:
```
pip install prophet
```

```
Collecting prophet
  Downloading prophet-1.1.6-py3-none-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (3.5 kB)
Collecting cmdstanpy>=1.0.4 (from prophet)
  Downloading cmdstanpy-1.2.4-py3-none-any.whl.metadata (4.1 kB)
Requirement already satisfied: numpy>=1.15.4 in /opt/conda/lib/python3.11/site-
packages (from prophet) (1.26.2)
Requirement already satisfied: matplotlib>=2.0.0 in
/opt/conda/lib/python3.11/site-packages (from prophet) (3.8.2)
Requirement already satisfied: pandas>=1.0.4 in /opt/conda/lib/python3.11/site-
packages (from prophet) (2.1.4)
Collecting holidays<1,>=0.25 (from prophet)
  Downloading holidays-0.62-py3-none-any.whl.metadata (26 kB)
Requirement already satisfied: tqdm>=4.36.1 in /opt/conda/lib/python3.11/site-
packages (from prophet) (4.66.1)
Requirement already satisfied: importlib-resources in
/opt/conda/lib/python3.11/site-packages (from prophet) (6.1.1)
```

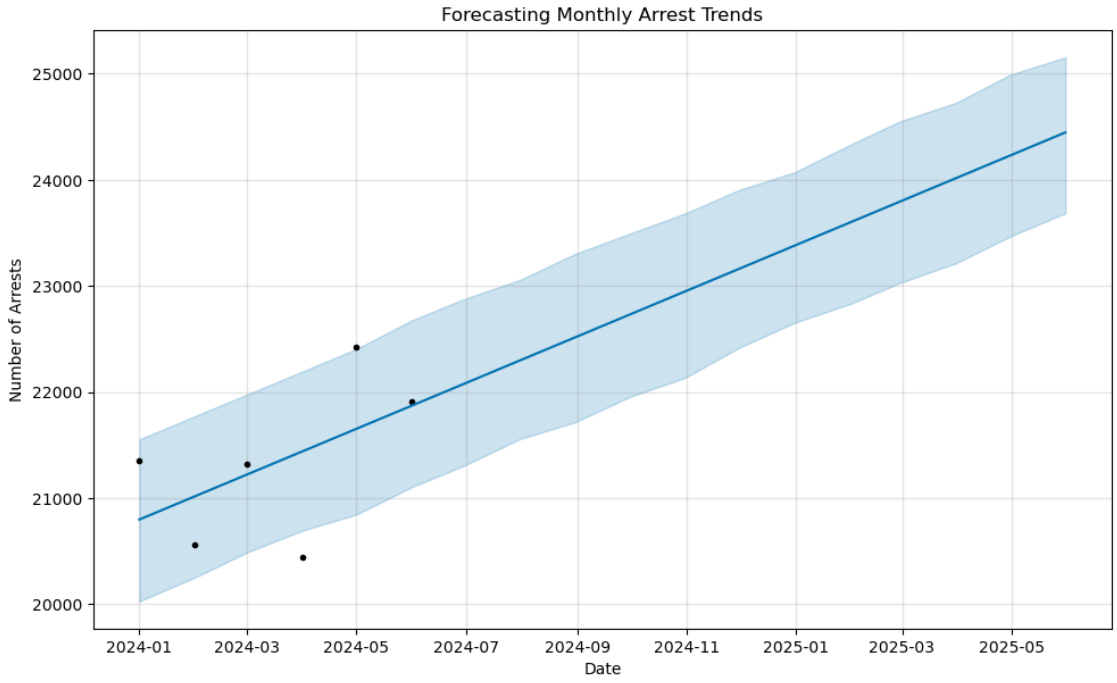
```
Collecting stanio<2.0.0,>=0.4.0 (from cmdstanpy>=1.0.4->prophet)
  Downloading stanio-0.5.1-py3-none-any.whl.metadata (1.6 kB)
Requirement already satisfied: python-dateutil in
/opt/conda/lib/python3.11/site-packages (from holidays<1,>=0.25->prophet)
(2.8.2)
Requirement already satisfied: contourpy>=1.0.1 in
/opt/conda/lib/python3.11/site-packages (from matplotlib>=2.0.0->prophet)
(1.2.0)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.11/site-
packages (from matplotlib>=2.0.0->prophet) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/opt/conda/lib/python3.11/site-packages (from matplotlib>=2.0.0->prophet)
(4.47.0)
Requirement already satisfied: kiwisolver>=1.3.1 in
/opt/conda/lib/python3.11/site-packages (from matplotlib>=2.0.0->prophet)
(1.4.5)
Requirement already satisfied: packaging>=20.0 in
/opt/conda/lib/python3.11/site-packages (from matplotlib>=2.0.0->prophet) (23.2)
Requirement already satisfied: pillow>=8 in /opt/conda/lib/python3.11/site-
packages (from matplotlib>=2.0.0->prophet) (10.1.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/opt/conda/lib/python3.11/site-packages (from matplotlib>=2.0.0->prophet)
(3.1.1)
Requirement already satisfied: pytz>=2020.1 in /opt/conda/lib/python3.11/site-
packages (from pandas>=1.0.4->prophet) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in /opt/conda/lib/python3.11/site-
packages (from pandas>=1.0.4->prophet) (2023.3)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.11/site-
packages (from python-dateutil->holidays<1,>=0.25->prophet) (1.16.0)
Downloading prophet-1.1.6-py3-none-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl (14.4 MB)
                         14.4/14.4 MB
86.8 MB/s eta 0:00:00:00:01:01
Downloading cmdstanpy-1.2.4-py3-none-any.whl (94 kB)
                         94.5/94.5 kB
17.2 MB/s eta 0:00:00
Downloading holidays-0.62-py3-none-any.whl (1.2 MB)
                         1.2/1.2 MB
72.0 MB/s eta 0:00:00
Downloading stanio-0.5.1-py3-none-any.whl (8.1 kB)
Installing collected packages: stanio, holidays, cmdstanpy, prophet
Successfully installed cmdstanpy-1.2.4 holidays-0.62 prophet-1.1.6 stanio-0.5.1
Note: you may need to restart the kernel to use updated packages.
```

[ ]:
```
#3 Forecast monthly Arrest Trends:
# This visualization presents a forecast of monthly arrest trends using the␣
 ↪Prophet model.
```

```
# The blue line represents the predicted number of arrests over time, while the␣
 ↪shaded
# area indicates the uncertainty interval around the forecast. The model has␣
 ↪captured
# the general upward trend in arrests, suggesting an increase in future months.

# This forecast is based on historical data and can be used for planning␣
 ↪purposes,
# such as allocating law enforcement resources. The uncertainty interval␣
 ↪provides a
# range within which the actual values are expected to fall, offering a measure␣
 ↪of
# confidence in the predictions.
```

[45]:
```
from prophet import Prophet

# Prepare data for forecasting
time_series = clean_dataset.groupby(clean_dataset['ARREST_DATE'].dt.
 ↪to_period('M')).size().reset_index(name='count')
time_series['ARREST_DATE'] = time_series['ARREST_DATE'].dt.to_timestamp()
time_series = time_series.rename(columns={'ARREST_DATE': 'ds', 'count': 'y'})

# Train the Prophet model
model = Prophet()
model.fit(time_series)

# Make future predictions
future = model.make_future_dataframe(periods=12, freq='M')
forecast = model.predict(future)

# Visualize the forecast
model.plot(forecast)
plt.title("Forecasting Monthly Arrest Trends")
plt.xlabel("Date")
plt.ylabel("Number of Arrests")
plt.show()
```

```
22:41:55 - cmdstanpy - INFO - Chain [1] start processing
22:41:55 - cmdstanpy - INFO - Chain [1] done processing
```


Forecasting Monthly Arrest Trends
Number of Arrests
25000
24000
23000
22000
21000
20000
2024-01
2024-03
2024-05
2024-07
2024-09
2024-11
2025-01
2025-03
2025-05
Date

[ ]: