Data

Police Department Incident Reports : 2018 to Present: A documentation of a crime incident that happened from the past to the current time frame, the record includes a detailed time, date, and crime category.

Fields

Incident Reports:data contains 27 columns.

Target field

crime_category – a categorical variable representing the type of crime (e.g., larceny, assault, vandalism, etc.).

Number of attributes

Incident Reports: The original dataset contains 10 attributes, but only 7 were selected for modeling after preprocessing.

- Incident Category
- Analysis Neighborhood
- Police District
- Incident Date
- Incident Year
- Incident Day of Week
- Incident Time

Prediction Goal:

Classify the type of crime based on when and where it occurred, and other structured features. This is a multi-class classification task.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from shapely.geometry import Point
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
from google.colab import drive
from sklearn.ensemble import RandomForestRegressor
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import confusion_matrix, classification_report
```

```
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
crime_data_path = "/content/drive/Shareddrives/SF_Crime_Forecasting/Police_Department_Incident_Reports__2018_to_Present_20250429.csv"
crime_df = pd.read_csv(crime_data_path)
crime_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 952287 entries, 0 to 952286
Data columns (total 35 columns):
 #   Column                                          Non-Null Count   Dtype  
---  ------                                          --------------   -----  
 0   Incident Datetime                               952287 non-null  object 
 1   Incident Date                                   952287 non-null  object 
 2   Incident Time                                   952287 non-null  object 
 3   Incident Year                                   952287 non-null  int64  
 4   Incident Day of Week                            952287 non-null  object 
 5   Report Datetime                                 952287 non-null  object 
 6   Row ID                                          952287 non-null  int64  
 7   Incident ID                                     952287 non-null  int64  
 8   Incident Number                                 952287 non-null  int64  
 9   CAD Number                                      741646 non-null  float64
 10  Report Type Code                                952287 non-null  object 
 11  Report Type Description                         952287 non-null  object 
 12  Filed Online                                    185557 non-null  object 
 13  Incident Code                                   952287 non-null  int64  
 14  Incident Category                               951133 non-null  object 
 15  Incident Subcategory                            951133 non-null  object 
 16  Incident Description                            952287 non-null  object 
 17  Resolution                                      952287 non-null  object 
 18  Intersection                                    900362 non-null  object 
 19  CNN                                             900362 non-null  float64
 20  Police District                                 952287 non-null  object 
 21  Analysis Neighborhood                           900119 non-null  object 
 22  Supervisor District                             899893 non-null  float64
 23  Supervisor District 2012                        900228 non-null  float64
 24  Latitude                                        900362 non-null  float64
 25  Longitude                                       900362 non-null  float64
 26  Point                                           900362 non-null  object 
 27  Neighborhoods                                   888210 non-null  float64
 28  ESNCAG - Boundary File                          10984 non-null   float64
 29  Central Market/Tenderloin Boundary Polygon - Updated  127671 non-null  float64
 30  Civic Center Harm Reduction Project Boundary    124884 non-null  float64
 31  HSOC Zones as of 2018-06-05                     200793 non-null  float64
 32  Invest In Neighborhoods (IIN) Areas             0 non-null       float64
 33  Current Supervisor Districts                    900228 non-null  float64
 34  Current Police Districts                        899378 non-null  float64
dtypes: float64(14), int64(5), object(16)
memory usage: 254.3+ MB
```

```
crime_df.tail(10)
```

	Incident Datetime	Incident Date	Incident Time	Incident Year	Incident Day of Week	Report Datetime	Row ID	Incident ID	Incident Number	CAD Number	...	Longitude	Point	Neighborhoods	ESNCAG - Boundary File	Centr Market/Tenderlo Boundary Polyg - Updat
952277	2025/03/15 12:30:00 AM	2025/03/15	00:30	2025	Saturday	2025/03/15 04:41:00 PM	146967806224	1469678	256026967	NaN	...	-122.501328	POINT (-122.50132751464844 37.771785736083984)	9.0	NaN	Na
952278	2025/03/18 08:16:00 PM	2025/03/18	20:16	2025	Tuesday	2025/03/18 08:29:00 PM	146977827195	1469778	250154732	250773292.0	...	-122.419182	POINT (-122.41918182373047 37.78310012817383)	20.0	NaN	'
952279	2025/03/18 10:37:00 AM	2025/03/18	10:37	2025	Tuesday	2025/03/18 10:37:00 AM	146959719057	1469597	250153273	250771203.0	...	-122.417709	POINT (-122.41770935058594 37.784236907958984)	20.0	NaN	'
952280	2024/05/14 12:00:00 AM	2024/05/14	00:00	2024	Tuesday	2025/03/18 12:00:00 AM	146961505053	1469615	240303660	NaN	...	-122.408401	POINT (-122.40840148925781 37.788291931152344)	19.0	NaN	Na
952281	2025/03/18 05:13:00 PM	2025/03/18	17:13	2025	Tuesday	2025/03/18 05:13:00 PM	146974805083	1469748	250110358	NaN	...	-122.432144	POINT (-122.43214416503906 37.780494689941406)	97.0	NaN	Na
952282	2025/03/18 11:49:00 AM	2025/03/18	11:49	2025	Tuesday	2025/03/18 11:49:00 AM	146972662050	1469726	250153427	250771454.0	...	-122.414909	POINT (-122.41490936279297 37.77447509765625)	32.0	NaN	'
952283	2025/03/18 11:51:00 AM	2025/03/18	11:51	2025	Tuesday	2025/03/18 11:52:00 AM	146964007043	1469640	250119974	NaN	...	NaN	NaN	NaN	NaN	Na
952284	2025/03/18 06:40:00 AM	2025/03/18	06:40	2025	Tuesday	2025/03/18 04:41:00 PM	146971668030	1469716	250154130	250772559.0	...	-122.409882	POINT (-122.40988159179688 37.79844284057617)	106.0	NaN	Na
952285	2025/03/18 03:53:00 PM	2025/03/18	15:53	2025	Tuesday	2025/03/18 03:54:00 PM	146972163010	1469721	250154083	250772385.0	...	-122.405830	POINT (-122.40583038330078 37.76847457885742)	33.0	NaN	Na
952286	2025/03/18 10:55:00 AM	2025/03/18	10:55	2025	Tuesday	2025/03/18 11:02:00 AM	146960612030	1469606	250153314	250771265.0	...	-122.384087	POINT (-122.38408660888672 37.71966552734375)	79.0	NaN	Na

10 rows × 35 columns

DATA CLEANING & EXPLORAING SECTION

Let's select the column we need and see what cleaning do we need

```
# Make a copy of the original DataFrame
selected_df = crime_df.copy()
```

```
# Select only the desired columns (excluding Incident Year now)
selected_columns = [
        "Incident Category",
        "Analysis Neighborhood",
        "Police District",
        "Incident Date",
        "Incident Day of Week",
        "Incident Time"
]
selected_df = selected_df[selected_columns]

selected_df.head(10)
```

	Incident Category	Analysis Neighborhood	Police District	Incident Date	Incident Day of Week	Incident Time
0	Larceny Theft	NaN	Mission	2023/03/01	Wednesday	05:02
1	Recovered Vehicle	NaN	Out of SF	2023/03/14	Tuesday	18:44
2	Larceny Theft	NaN	Mission	2023/02/15	Wednesday	03:00
3	Larceny Theft	NaN	Central	2023/03/11	Saturday	15:00
4	Larceny Theft	NaN	Central	2023/03/13	Monday	07:30
5	Drug Violation	NaN	Out of SF	2023/03/16	Thursday	09:26
6	Assault	Potrero Hill	Bayview	2023/03/16	Thursday	17:30
7	Recovered Vehicle	NaN	Out of SF	2023/03/16	Thursday	13:49
8	Larceny Theft	NaN	Richmond	2023/03/16	Thursday	22:15
9	Larceny Theft	NaN	Central	2023/02/11	Saturday	14:00

```
selected_df.isna().sum()
```

	0
Incident Category	1154
Analysis Neighborhood	52168
Police District	0
Incident Date	0
Incident Day of Week	0
Incident Time	0

dtype: int64

Transform the columns for better implementation, here is what I did.

- REPLACE the missing value for 'Analysis Neighborhood'
- SORTED the dataframe by 'year', 'month', 'day', 'hour'
- SPLIT the time frame into 'year', 'month', 'day', 'hour' columns

- REMOVED redundance columns
- REMOVED the row that is missing 'Incident Category'(Since the missing rows are only small portion of our data)

```
crime_df_cleaned = selected_df.copy()
#
# Replace missing neighborhood values with "Out of SF"
crime_df_cleaned["Analysis Neighborhood"] = crime_df_cleaned["Analysis Neighborhood"].fillna("Out of SF")
# Drop rows where 'Incident Category' is missing
crime_df_cleaned = crime_df_cleaned.dropna(subset=["Incident Category"])
# Sort by full date and time
# Create a datetime column
numerify_crime_df_cleaned = crime_df_cleaned.copy()
numerify_crime_df_cleaned['incident_datetime'] = pd.to_datetime(
        numerify_crime_df_cleaned['Incident Date'] + ' ' + numerify_crime_df_cleaned['Incident Time'], errors='coerce'
)
numerify_crime_df_cleaned = numerify_crime_df_cleaned.drop("Incident Time", axis=1)
numerify_crime_df_cleaned['hour'] = numerify_crime_df_cleaned["incident_datetime"].dt.hour
numerify_crime_df_cleaned['day'] = numerify_crime_df_cleaned["incident_datetime"].dt.day
numerify_crime_df_cleaned['month'] = numerify_crime_df_cleaned["incident_datetime"].dt.month
numerify_crime_df_cleaned['year'] = numerify_crime_df_cleaned["incident_datetime"].dt.year

numerify_crime_df_cleaned = numerify_crime_df_cleaned.sort_values(by=["incident_datetime" ])


# STEP 6: Encode all categorical columns numerically
# # One-hot encode the categorical columns
categorical_cols = ['Incident Category', 'Analysis Neighborhood', 'Police District', 'Incident Day of Week']

# # Replace spaces with underscores in all column names
# # Make all column names lowercase and replace spaces/special characters
numerify_crime_df_cleaned.columns = (
        numerify_crime_df_cleaned.columns
        .str.strip()
        .str.lower()
        .str.replace(' ', '_')
        .str.replace(r'[^a-zA-Z0-9_]', '', regex=True)
)
numerify_crime_df_cleaned = numerify_crime_df_cleaned.drop("incident_date", axis=1)
numerify_crime_df_cleaned['year'].value_counts().sort_index()
numerify_crime_df_cleaned.tail()
```

	incident_category	analysis_neighborhood	police_district	incident_day_of_week	incident_datetime	hour	day	month	year
11633	Larceny Theft	Bernal Heights	Ingleside	Monday	2025-04-28 20:59:00	20	28	4	2025
11816	Larceny Theft	Bernal Heights	Ingleside	Monday	2025-04-28 21:05:00	21	28	4	2025
11805	Larceny Theft	Bernal Heights	Ingleside	Monday	2025-04-28 21:06:00	21	28	4	2025
11930	Larceny Theft	South of Market	Tenderloin	Monday	2025-04-28 21:56:00	21	28	4	2025
12103	Non-Criminal	Mission	Mission	Monday	2025-04-28 22:34:00	22	28	4	2025

```
# Create proper aggregation for regression task
```

```
crime_count_df = numerify_crime_df_cleaned.copy()
crime_counts = numerify_crime_df_cleaned.groupby(['year', 'month', 'day', 'hour']).size().reset_index(name='crime_count')
crime_count_df = crime_count_df.merge(crime_counts, on=['year', 'month', 'day', 'hour'], how='left')
crime_count_df.tail()
```

	incident_category	analysis_neighborhood	police_district	incident_day_of_week	incident_datetime	hour	day	month	year	crime_count
951128	Larceny Theft	Bernal Heights	Ingleside	Monday	2025-04-28 20:59:00	20	28	4	2025	5
951129	Larceny Theft	Bernal Heights	Ingleside	Monday	2025-04-28 21:05:00	21	28	4	2025	3
951130	Larceny Theft	Bernal Heights	Ingleside	Monday	2025-04-28 21:06:00	21	28	4	2025	3
951131	Larceny Theft	South of Market	Tenderloin	Monday	2025-04-28 21:56:00	21	28	4	2025	3
951132	Non-Criminal	Mission	Mission	Monday	2025-04-28 22:34:00	22	28	4	2025	1

DATA EXPLORING

Seem Cleaned!

```
crime_count_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 951133 entries, 0 to 951132
Data columns (total 10 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   incident_category      951133 non-null  object
 1   analysis_neighborhood  951133 non-null  object
 2   police_district        951133 non-null  object
 3   incident_day_of_week   951133 non-null  object
 4   incident_datetime      951133 non-null  datetime64[ns]
 5   hour                   951133 non-null  int32
 6   day                    951133 non-null  int32
 7   month                  951133 non-null  int32
 8   year                   951133 non-null  int32
 9   crime_count            951133 non-null  int64
dtypes: datetime64[ns](1), int32(4), int64(1), object(4)
memory usage: 58.1+ MB
```

Let's try to perform Anlsisy the correlation between time, incident district, and Polic District, but first we need to do some encoding

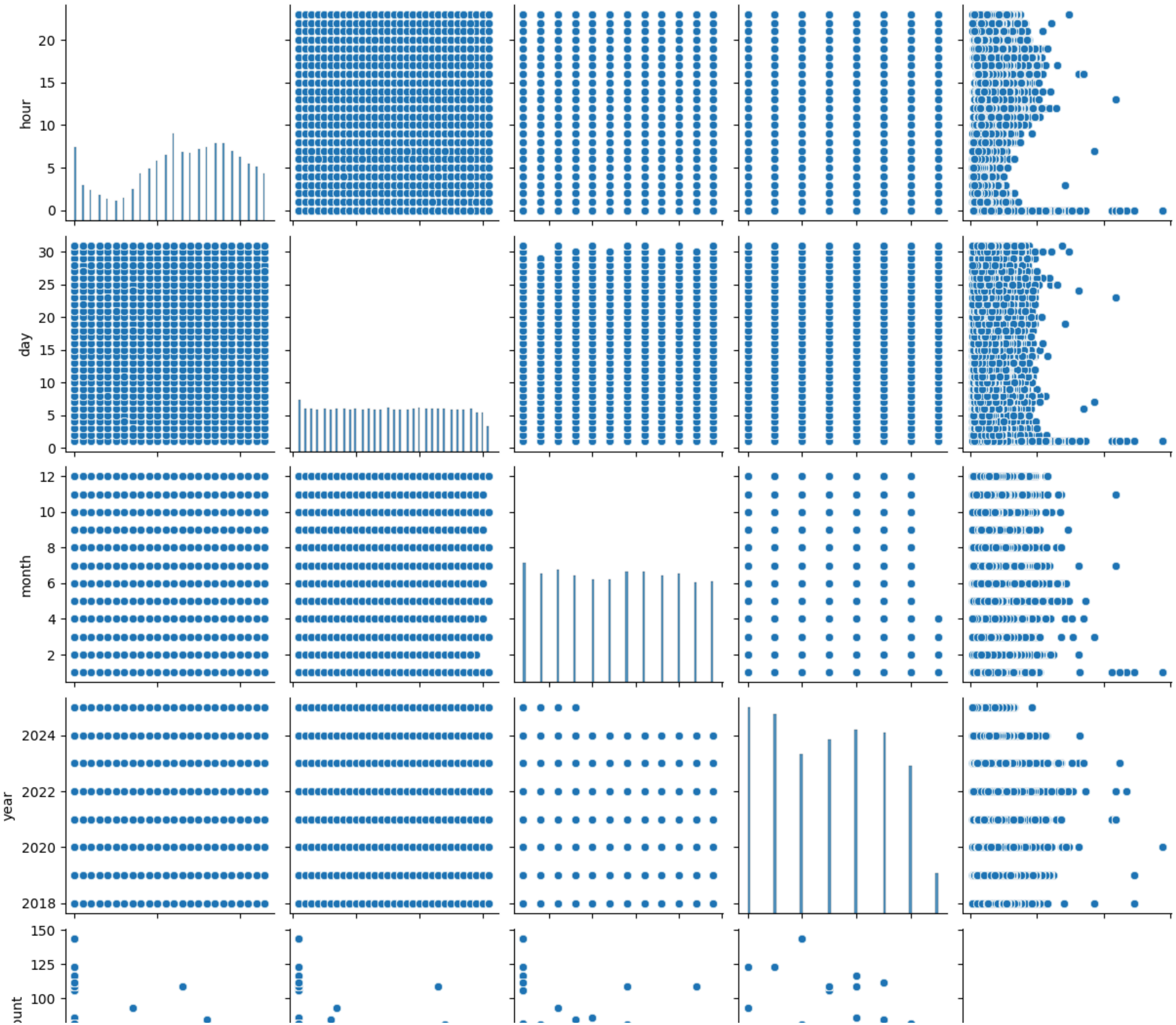
```
crime_count_df.nunique()
```

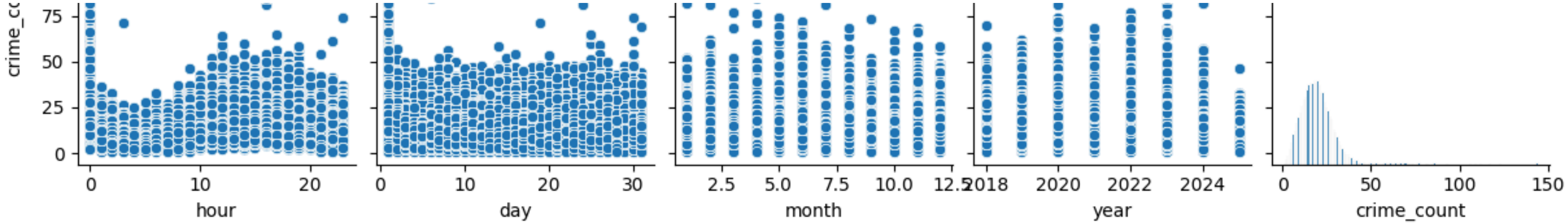
	0
incident_category	49
analysis_neighborhood	42
police_district	11
incident_day_of_week	7
incident_datetime	454889
hour	24
day	31
month	12
year	8
crime_count	86

dtype: int64

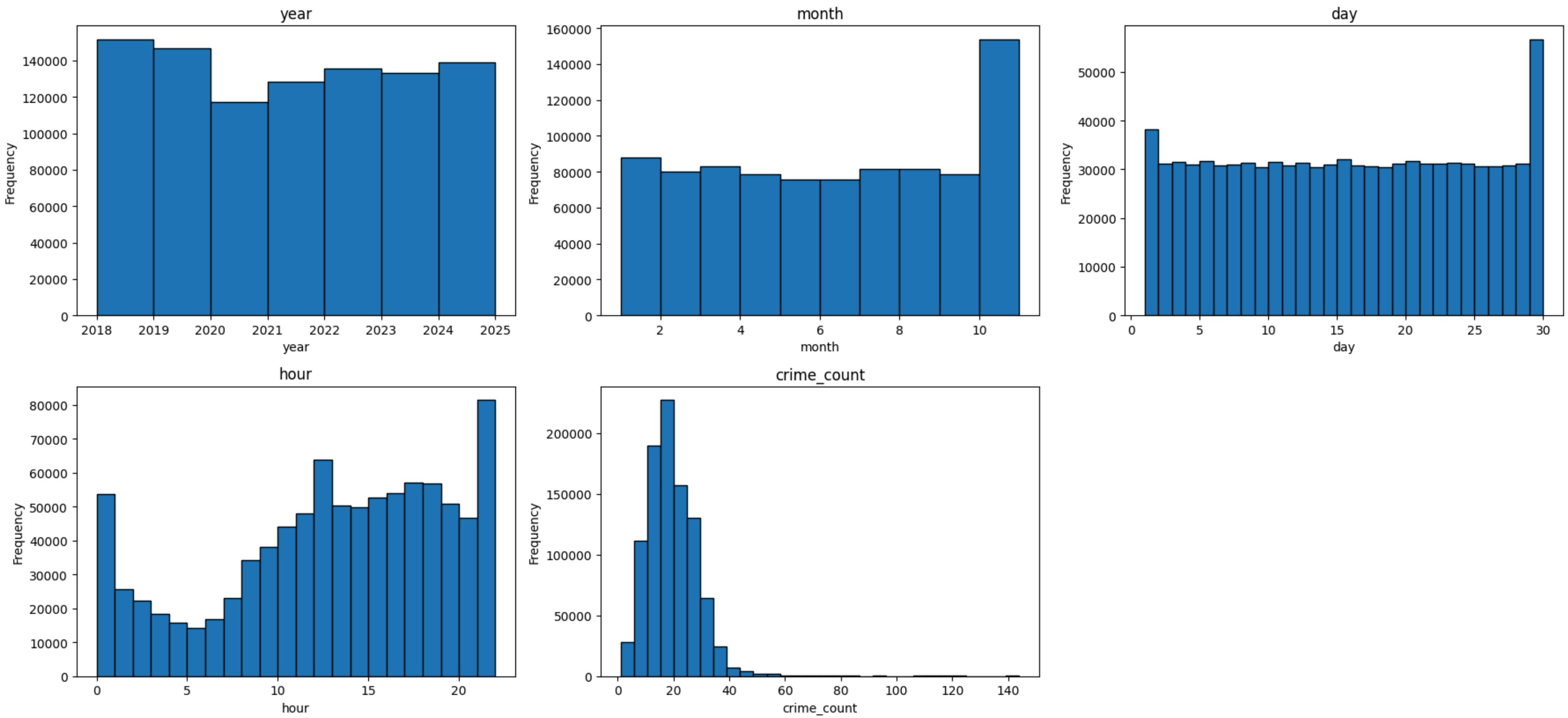
```
sns.pairplot(crime_count_df)
```

<seaborn.axisgrid.PairGrid at 0x7a2a9d13f590>



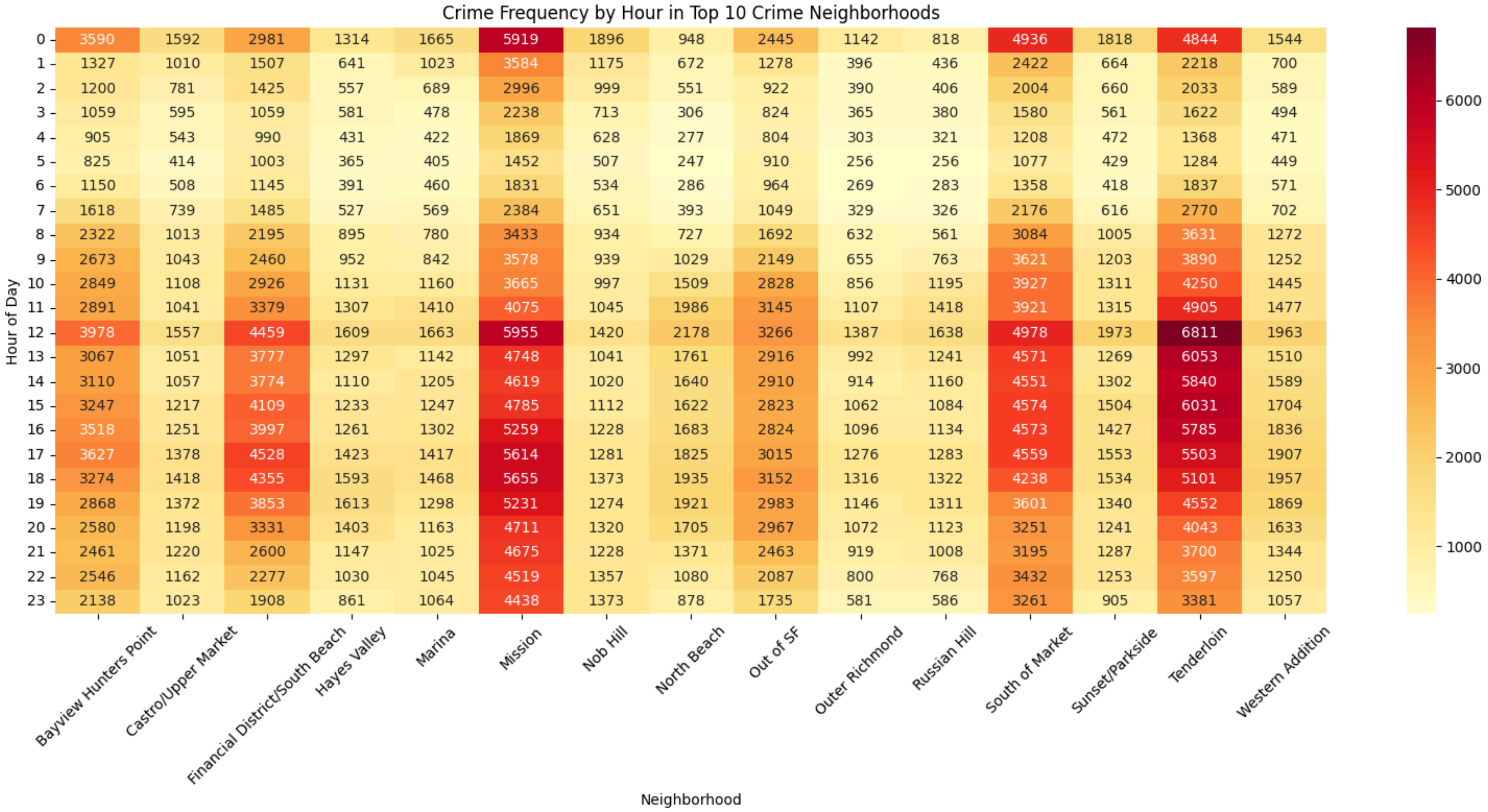



```
# Select the numeric columns you want to plot
columns_to_plot = ['year', 'month', 'day', 'hour', 'crime_count']

# Define custom bins for each column
custom_bins = {
        'year': range(crime_count_df['year'].min(), crime_count_df['year'].max() + 1),
        'month': range(1, 12),                   # 1-12
        'day': range(1, 31),                      # 1-31
        'hour': range(0, 23),                    # 0-24
        'crime_count': 30,              # use default bin count

}

# Create subplots
fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(18, 12))
axes = axes.flatten()

for i, col in enumerate(columns_to_plot):
        ax = axes[i]
        bins = custom_bins.get(col, 30)
        ax.hist(crime_count_df[col], bins=bins, edgecolor='black')
        ax.set_title(f"{col}")
        ax.set_xlabel(col)
        ax.set_ylabel("Frequency")

# Hide any unused subplots
for j in range(len(columns_to_plot), len(axes)):
        fig.delaxes(axes[j])

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




```
# Step 1: Get the top 10 most frequent neighborhoods
top_neighborhoods = (
        crime_count_df['analysis_neighborhood']
        .value_counts()
        .head(15)
        .index
)

# Step 2: Filter the original DataFrame to include only those neighborhoods
top_crime_df = crime_count_df[crime_count_df['analysis_neighborhood'].isin(top_neighborhoods)]
```

```
# Step 3: Create a pivot table: rows = hour, columns = top neighborhoods, values = crime count
pivot = top_crime_df.pivot_table(
        index='hour',
        columns='analysis_neighborhood',
        values='incident_category',    # We're just counting rows
        aggfunc='count',
        fill_value=0
)

# Step 4: Plot the heatmap
plt.figure(figsize=(16, 8))
sns.heatmap(pivot, cmap='YlOrRd', annot=True, fmt='d')
plt.title("Crime Frequency by Hour in Top 10 Crime Neighborhoods")
plt.xlabel("Neighborhood")
plt.ylabel("Hour of Day")
plt.yticks(rotation=0)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



DATA TRANFORMAING

Spliting the data into 60, 20, 20

```
# Create proper aggregation for regression task
hourly_counts = numerify_crime_df_cleaned.groupby(['year', 'month', 'day', 'hour']).size().reset_index(name='crime_count')

# Add day of week
hourly_counts['date'] = pd.to_datetime(hourly_counts[['year', 'month', 'day']])
hourly_counts['day_of_week'] = hourly_counts['date'].dt.dayofweek
```

```
# Create cyclical features
hourly_counts['hour_sin'] = np.sin(2 * np.pi * hourly_counts['hour']/24)
hourly_counts['hour_cos'] = np.cos(2 * np.pi * hourly_counts['hour']/24)
hourly_counts['day_of_week_sin'] = np.sin(2 * np.pi * hourly_counts['day_of_week']/7)
hourly_counts['day_of_week_cos'] = np.cos(2 * np.pi * hourly_counts['day_of_week']/7)
```

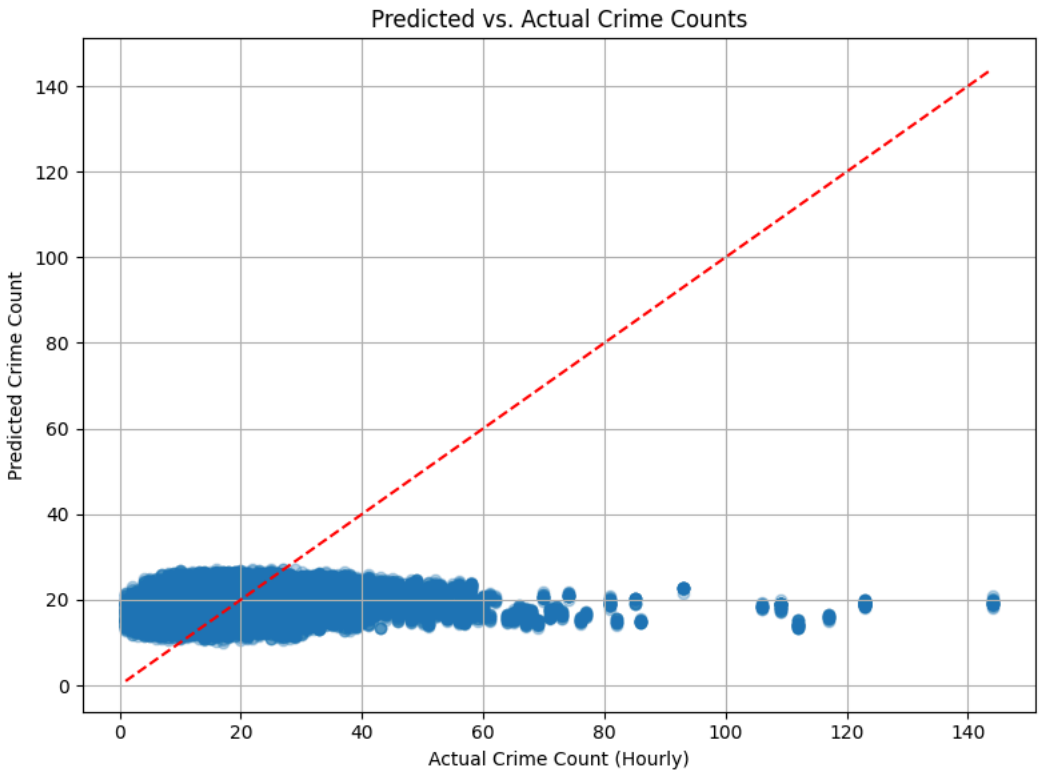
TRAINING

```
# 1. Set features (X) and target (y)
# Exclude incident_category and incident_datetime (not needed here)
# EXCLUDE count_crime_hourly from X
regression_features = crime_count_df.drop(columns=['incident_category', 'incident_datetime', 'crime_count'])
target = crime_count_df['crime_count']

# 2. Split data into training, validation, test
X_temp, X_test, y_temp, y_test = train_test_split(regression_features, target, test_size=0.2, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_temp, y_temp, test_size=0.25, random_state=42)  # 60/20/20

# 3. Column types for preprocessing
categorical_cols = X_train.select_dtypes(include='object').columns.tolist()
numerical_cols = X_train.select_dtypes(include=['int64', 'int32']).columns.tolist()

# 4. Preprocessing
preprocessor = ColumnTransformer([
        ('num', StandardScaler(), numerical_cols),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_cols)
])

# 5. Linear Regression pipeline
linreg_pipeline = Pipeline([
        ('preprocessor', preprocessor),
        ('regressor', LinearRegression())
])

# 6. Train model
linreg_pipeline.fit(X_train, y_train)

# 7. Validate model
y_pred = linreg_pipeline.predict(X_val)

# Metrics
mse = mean_squared_error(y_val, y_pred)
rmse = np.sqrt(mse)
mae = mean_absolute_error(y_val, y_pred)
r2 = r2_score(y_val, y_pred)

print(f"RF MAE: {mae:.2f}")
print(f"RF RMSE: {rmse:.2f}")
print(f"RF R²: {r2:.3f}")
```

```
RF MAE: 6.43
RF RMSE: 8.95
```

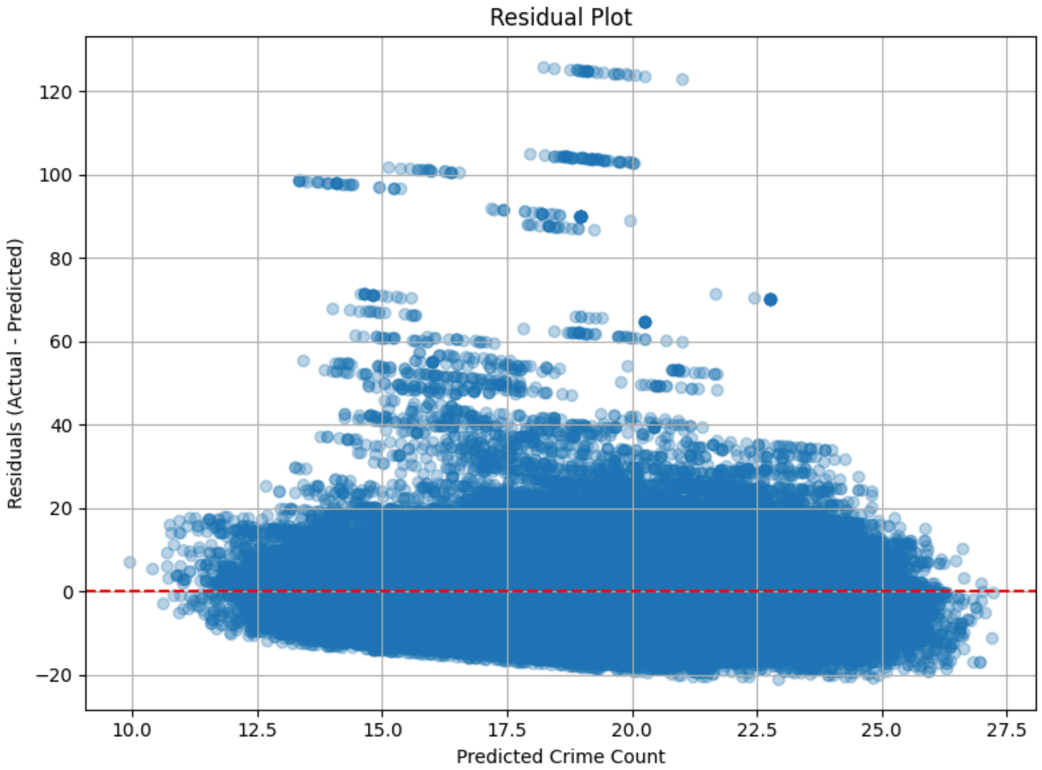
```
RF R²: 0.075
```

```
#Scatter Plot: Predicted vs. Actual Crime Counts
# This plot shows how well the model's predictions align with the actual hourly crime counts.
# Points closer to this line indicate more accurate predictions.
plt.figure(figsize=(8, 6))
plt.scatter(y_val, y_pred, alpha=0.3)
plt.plot([y_val.min(), y_val.max()], [y_val.min(), y_val.max()], 'r--')  # ideal line
plt.xlabel('Actual Crime Count (Hourly)')
plt.ylabel('Predicted Crime Count')
plt.title('Predicted vs. Actual Crime Counts')
plt.grid(True)
plt.tight_layout()
plt.show()
```




```
#Residual Plot: Error Analysis
# This plot visualizes the residuals (actual - predicted) to assess prediction errors.
# Ideally, residuals should be randomly scattered around 0, indicating unbiased predictions.

residuals = y_val - y_pred
plt.figure(figsize=(8, 6))
plt.scatter(y_pred, residuals, alpha=0.3)
```

```
plt.axhline(0, color='red', linestyle='--')
plt.xlabel('Predicted Crime Count')
plt.ylabel('Residuals (Actual - Predicted)')
plt.title('Residual Plot')
plt.grid(True)
plt.tight_layout()
plt.show()
```

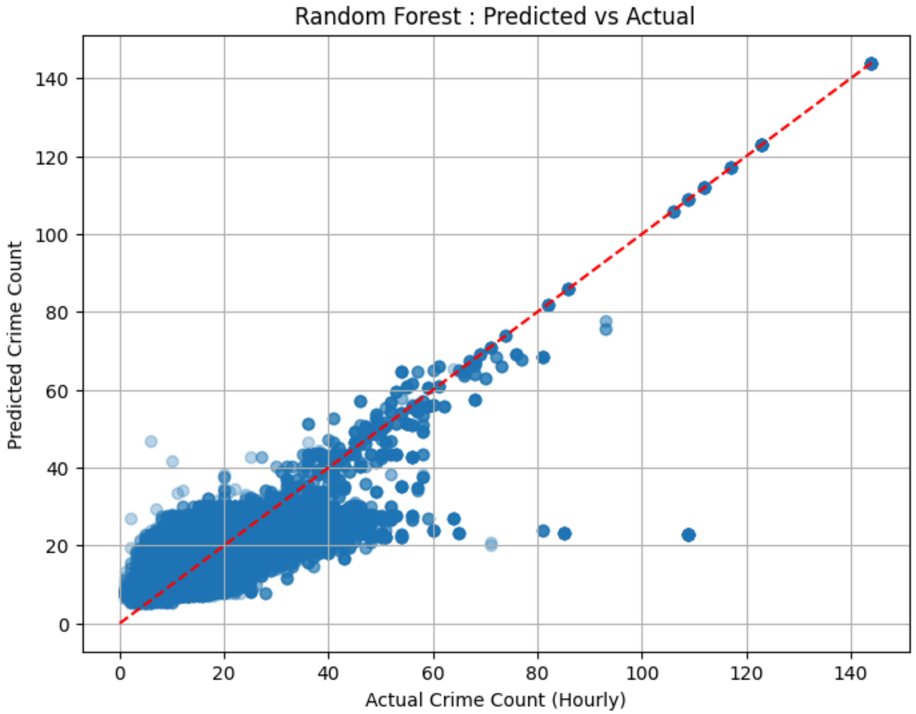



```
# Reduce to top 10 neighborhoods to limit memory
top_neighborhoods = crime_count_df['analysis_neighborhood'].value_counts().head(10).index
reduced_df = crime_count_df[crime_count_df['analysis_neighborhood'].isin(top_neighborhoods)].copy()

# Features and target
X = reduced_df.drop(columns=['incident_category', 'incident_datetime', 'crime_count'])
y = reduced_df['crime_count']

# Train/test split
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)

# Preprocessing pipeline (unchanged)
numeric_features = ['hour', 'day', 'month', 'year']
categorical_features = ['analysis_neighborhood', 'police_district', 'incident_day_of_week']
```

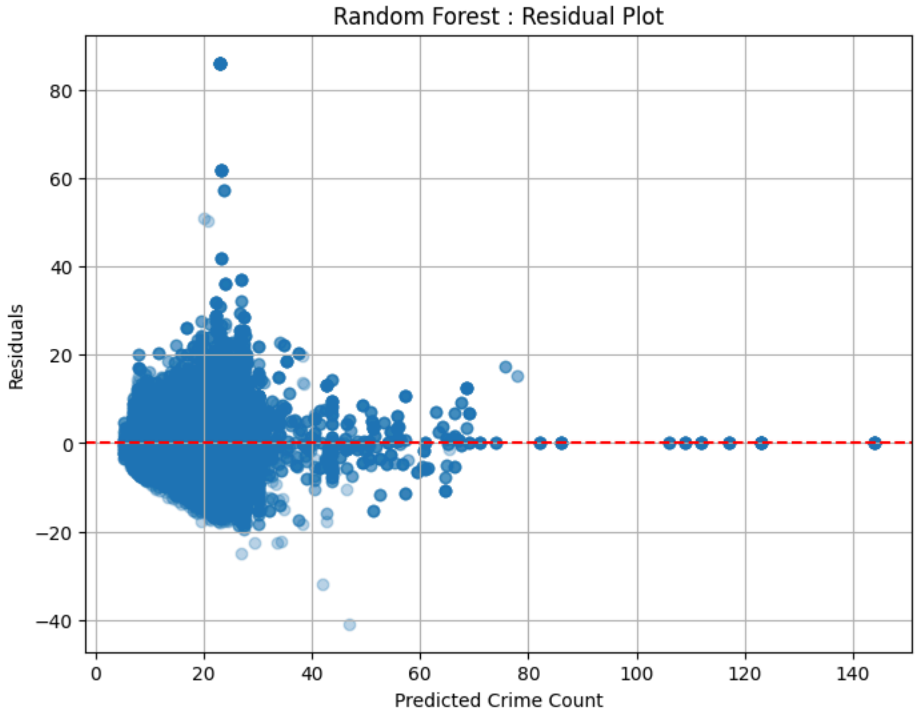
```
numeric_transformer = StandardScaler()
categorical_transformer = OneHotEncoder(handle_unknown='ignore')

preprocessor = ColumnTransformer([
    ('num', numeric_transformer, numeric_features),
    ('cat', categorical_transformer, categorical_features)
])

#  Lightweight Random Forest (smaller model)
rf_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('model', RandomForestRegressor(n_estimators=30, max_depth=10, random_state=42))
])

#  Train model
rf_model.fit(X_train, y_train)

# 📈 Predict and evaluate
y_pred = rf_model.predict(X_val)
mae = mean_absolute_error(y_val, y_pred)
rmse = np.sqrt(mean_squared_error(y_val, y_pred))
r2 = r2_score(y_val, y_pred)

print(f"RF MAE: {mae:.2f}")
print(f"RF RMSE: {rmse:.2f}")
print(f"RF R²: {r2:.3f}")
```

```
RF MAE: 4.53
RF RMSE: 6.03
RF R²: 0.583
```

```
# 📊 Predicted vs Actual
plt.figure(figsize=(8, 6))
plt.scatter(y_val, y_pred, alpha=0.3)
plt.plot([0, max(y_val)], [0, max(y_val)], 'r--')
plt.xlabel("Actual Crime Count (Hourly)")
plt.ylabel("Predicted Crime Count")
plt.title("Random Forest : Predicted vs Actual")
plt.grid(True)
plt.show()
```




```
# 📉 Residual plot
residuals = y_val - y_pred
plt.figure(figsize=(8, 6))
plt.scatter(y_pred, residuals, alpha=0.3)
plt.axhline(0, color='red', linestyle='--')
plt.xlabel("Predicted Crime Count")
plt.ylabel("Residuals")
plt.title("Random Forest : Residual Plot")
plt.grid(True)
plt.show()
```




```
# Reuse the reduced_df with top 10 neighborhoods
X = reduced_df.drop(columns=['incident_category', 'incident_datetime', 'crime_count'])
y = reduced_df['crime_count']

# Split
from sklearn.model_selection import train_test_split
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)

# Preprocessing
numeric_features = ['hour', 'day', 'month', 'year']
categorical_features = ['analysis_neighborhood', 'police_district', 'incident_day_of_week']

numeric_transformer = StandardScaler()
categorical_transformer = OneHotEncoder(handle_unknown='ignore')

preprocessor = ColumnTransformer([
        ('num', numeric_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)
])

# Decision Tree model
tree_pipeline = Pipeline([
        ('preprocessor', preprocessor),
```

```
    ('model', DecisionTreeRegressor(max_depth=10, random_state=42))
])

# Train
tree_pipeline.fit(X_train, y_train)

# Predict
y_pred = tree_pipeline.predict(X_val)

# Evaluate
mae = mean_absolute_error(y_val, y_pred)
rmse = np.sqrt(mean_squared_error(y_val, y_pred))
r2 = r2_score(y_val, y_pred)

print(f"RF MAE: {mae:.2f}")
print(f"RF RMSE: {rmse:.2f}")
print(f"RF R²: {r2:.3f}")

# Plot: Predicted vs Actual
plt.figure(figsize=(8, 6))
plt.scatter(y_val, y_pred, alpha=0.3)
plt.plot([0, max(y_val)], [0, max(y_val)], 'r--')
plt.xlabel("Actual Crime Count")
plt.ylabel("Predicted Crime Count")
plt.title("Decision Tree Regressor: Predicted vs Actual")
plt.grid(True)
plt.show()
```

```
RF MAE: 4.58
RF RMSE: 6.10
RF R²: 0.573
```

Decision Tree Regressor: Predicted vs Actual

```
#   Filter top 5 crime categories (to avoid imbalance and memory issues)
top_5_crimes = crime_count_df['incident_category'].value_counts().head(5).index
class_df = crime_count_df[crime_count_df['incident_category'].isin(top_5_crimes)].copy()

#   Define features and target
X = class_df.drop(columns=['incident_category', 'incident_datetime', 'crime_count'])
y = class_df['incident_category']
```