End term.

CS-2120

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Report on Crimes_-_2001_to_Present.csv

https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-Present/ijzp-q8t2/data_preview

```
import pandas as pd
df = pd.read_csv("Crimes_-_2001_to_Present.csv")
df.head()
```

	ID	Case Number	Date	Block	IUCR	Primary Type	Description	Location Description
0	11037294	JA371270	03/18/2015 12:00:00 PM	0000X W WACKER DR	1153	DECEPTIVE PRACTICE	FINANCIAL IDENTITY THEFT OVER $ 300	BANK
1	11646293	JC213749	12/20/2018 03:00:00 PM	023XX N LOCKWOOD AVE	1154	DECEPTIVE PRACTICE	FINANCIAL IDENTITY THEFT $300 AND UNDER	APARTMENT
2	11645836	JC212333	05/01/2016 12:25:00 AM	055XX S ROCKWELL ST	1153	DECEPTIVE PRACTICE	FINANCIAL IDENTITY THEFT OVER $ 300	NaN
3	11645959	JC211511	12/20/2018 04:00:00 PM	045XX N ALBANY AVE	2820	OTHER OFFENSE	TELEPHONE THREAT	RESIDENCE
4	11645601	JC212935	06/01/2014 12:01:00 AM	087XX S SANGAMON ST	1153	DECEPTIVE PRACTICE	FINANCIAL IDENTITY THEFT OVER $ 300	RESIDENCE

5 rows × 22 columns

Arrest	Domestic	...	Ward	Community Area	FBI Code	X Coordinate	Y Coordinate	Year	Updated On	L
False	False	...	42.0	32.0	11	NaN	NaN	2015	08/01/2017 03:52:26 PM	
False	False	...	36.0	19.0	11	NaN	NaN	2018	04/06/2019 04:04:43 PM	
False	False	...	15.0	63.0	11	NaN	NaN	2016	04/06/2019 04:04:43 PM	
False	False	...	33.0	14.0	08A	NaN	NaN	2018	04/06/2019 04:04:43 PM	
False	False	...	21.0	71.0	11	NaN	NaN	2014	04/06/2019 04:04:43 PM	

Community Area	FBI Code	X Coordinate	Y Coordinate	Year	Updated On	Latitude	Longitude	Location
32.0	11	NaN	NaN	2015	08/01/2017 03:52:26 PM	NaN	NaN	NaN
19.0	11	NaN	NaN	2018	04/06/2019 04:04:43 PM	NaN	NaN	NaN
63.0	11	NaN	NaN	2016	04/06/2019 04:04:43 PM	NaN	NaN	NaN
14.0	08A	NaN	NaN	2018	04/06/2019 04:04:43 PM	NaN	NaN	NaN
71.0	11	NaN	NaN	2014	04/06/2019 04:04:43 PM	NaN	NaN	NaN

1. Introduction and Goal

Crime data analysis provides critical insights that inform law enforcement strategies and policy decisions. The goal of this project is to analyze crime data from the Chicago Police Department to uncover patterns and trends that can enhance public safety and resource allocation. This analysis focuses on the "Crimes - 2001 to Present" dataset, a comprehensive record of reported incidents of crime in a specific region from 2001 to the present day. The dataset is of significant relevance to law enforcement agencies and policymakers for understanding crime patterns, allocating resources efficiently, and developing strategies to mitigate crime rates effectively.

2. Data Preparation (ETL)

The dataset was cleaned and preprocessed using the following steps:

The dataset was prepared for analysis through an Extract, Transform, and Load (ETL) process, ensuring the data's quality and usability for meaningful insights. The process involved:

- Loading the Data: The dataset, stored in a CSV file, was loaded into a Spark DataFrame, utilizing PySpark's capabilities to handle large datasets efficiently.

- Cleaning and Transformation: The data underwent cleaning to handle missing values, incorrect data types, and parsing errors, especially with date-time fields. Columns relevant to the analysis, such as Date, Primary Type, and Location Description, were formatted correctly for consistency.

- Schema Verification: The schema of the DataFrame was verified to ensure accurate data types for each column, particularly focusing on dates, categoricals, and numerical fields for analysis.

- Conversion of the 'Date' column to datetime.

- Extraction of 'Year', 'Month', 'Day', and 'Hour' from the 'Date' column.

- Imputation of missing values in 'Location Description' with 'Unknown'.

- Removal of duplicates and irrelevant columns.

The code

```
df['Date'] = pd.to_datetime(df['Date'])

df['Year_Extracted'] = df['Date'].dt.year
df['Month'] = df['Date'].dt.month
df['Day'] = df['Date'].dt.day
df['Hour'] = df['Date'].dt.hour
df['Location Description'] = df['Location Description'].fillna('Unknown')

df = df.drop_duplicates()
df = df.drop(columns=['X Coordinate', 'Y Coordinate', 'Latitude', 'Longitude', 'Location'])
df.head()
```

The output

	ID	Case Number	Date	Block	IUCR	Primary Type	Description	Location Description	Arr
0	11037294	JA371270	2015-03-18 12:00:00	0000X W WACKER DR	1153	DECEPTIVE PRACTICE	FINANCIAL IDENTITY THEFT OVER $ 300	BANK	Fa
1	11646293	JC213749	2018-12-20 15:00:00	023XX N LOCKWOOD AVE	1154	DECEPTIVE PRACTICE	FINANCIAL IDENTITY THEFT $300 AND UNDER	APARTMENT	Fa
2	11645836	JC212333	2016-05-01 00:25:00	055XX S ROCKWELL ST	1153	DECEPTIVE PRACTICE	FINANCIAL IDENTITY THEFT OVER $ 300	Unknown	Fa
3	11645959	JC211511	2018-12-20 16:00:00	045XX N ALBANY AVE	2820	OTHER OFFENSE	TELEPHONE THREAT	RESIDENCE	Fa
4	11645601	JC212935	2014-06-01 00:01:00	087XX S SANGAMON ST	1153	DECEPTIVE PRACTICE	FINANCIAL IDENTITY THEFT OVER $ 300	RESIDENCE	Fa

5 rows × 21 columns

Arrest	Domestic	...	District	Ward	Community Area	FBI Code	Year	Updated On	Year_Extracted
False	False	...	1.0	42.0	32.0	11	2015	08/01/2017 03:52:26 PM	2015
False	False	...	25.0	36.0	19.0	11	2018	04/06/2019 04:04:43 PM	2018
False	False	...	8.0	15.0	63.0	11	2016	04/06/2019 04:04:43 PM	2016
False	False	...	17.0	33.0	14.0	08A	2018	04/06/2019 04:04:43 PM	2018
False	False	...	22.0	21.0	71.0	11	2014	04/06/2019 04:04:43 PM	2014

...	District	Ward	Community Area	FBI Code	Year	Updated On	Year_Extracted	Month	Day	Hour
...	1.0	42.0	32.0	11	2015	08/01/2017 03:52:26 PM	2015	3	18	12
...	25.0	36.0	19.0	11	2018	04/06/2019 04:04:43 PM	2018	12	20	15
...	8.0	15.0	63.0	11	2016	04/06/2019 04:04:43 PM	2016	5	1	0
...	17.0	33.0	14.0	08A	2018	04/06/2019 04:04:43 PM	2018	12	20	16
...	22.0	21.0	71.0	11	2014	04/06/2019 04:04:43 PM	2014	6	1	0

3. Data Analysis (EDA)

- The initial exploration involved summarizing the dataset to understand the distribution of crimes over the years, categorization of crimes, and their locations.

- Temporal patterns were examined to discern any seasonality or time-based trends in crime incidents.

The analysis was conducted using Spark SQL for data aggregation and NumPy for statistical computations, focusing on identifying key trends, patterns, and insights within the data.

The code

```
import matplotlib.pyplot as plt

import seaborn as sns


# Set the aesthetic style of the plots

sns.set_style("whitegrid")
```

1. Temporal Trends: Crimes over the Years

df['Year'].value_counts().sort_index().plot(kind='line', figsize=(10, 6))

plt.title('Crime Occurrences Over the Years')

plt.xlabel('Year')

plt.ylabel('Number of Crimes')

plt.show()

2. Crime Types and Frequencies

plt.figure(figsize=(10, 6))

df['Primary Type'].value_counts().head(10).plot(kind='bar')

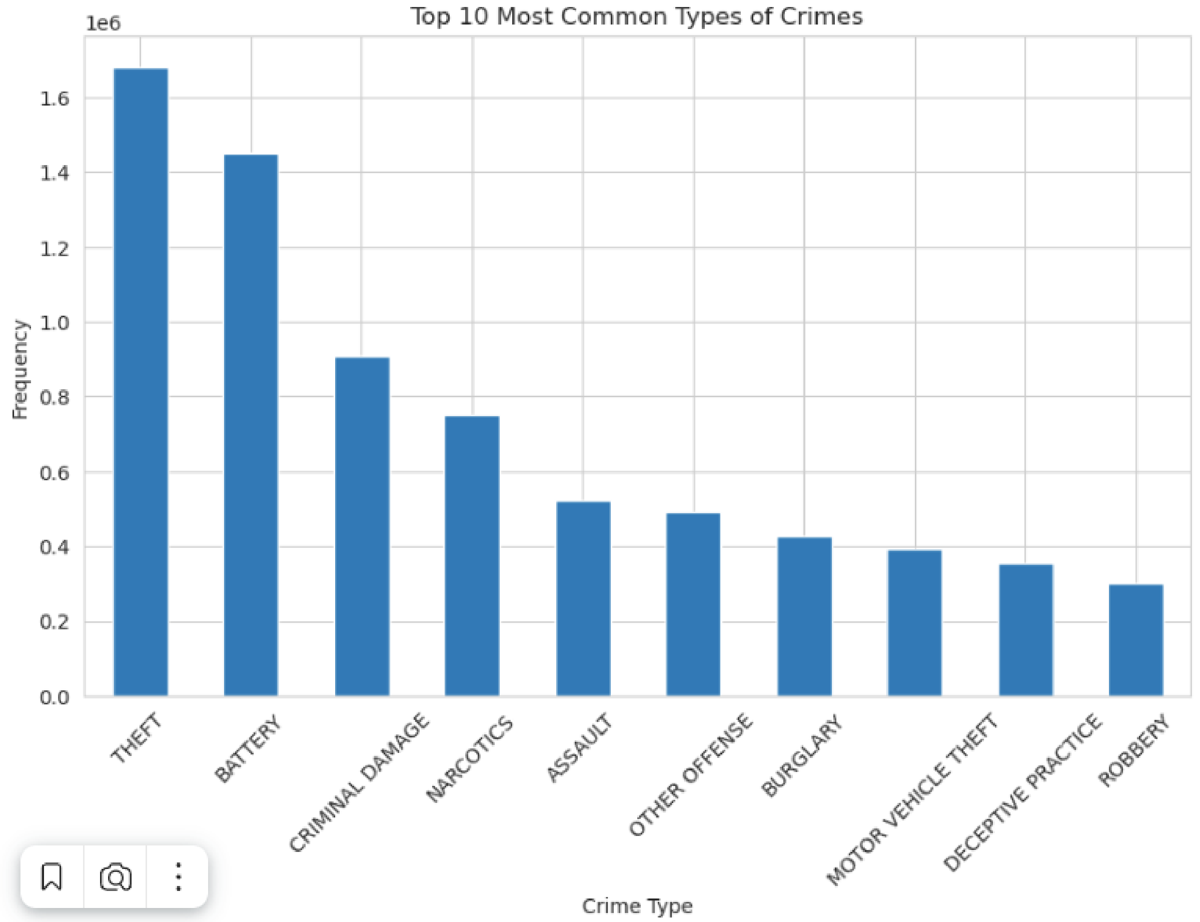
plt.title('Top 10 Most Common Types of Crimes')

plt.xlabel('Crime Type')

plt.ylabel('Frequency')

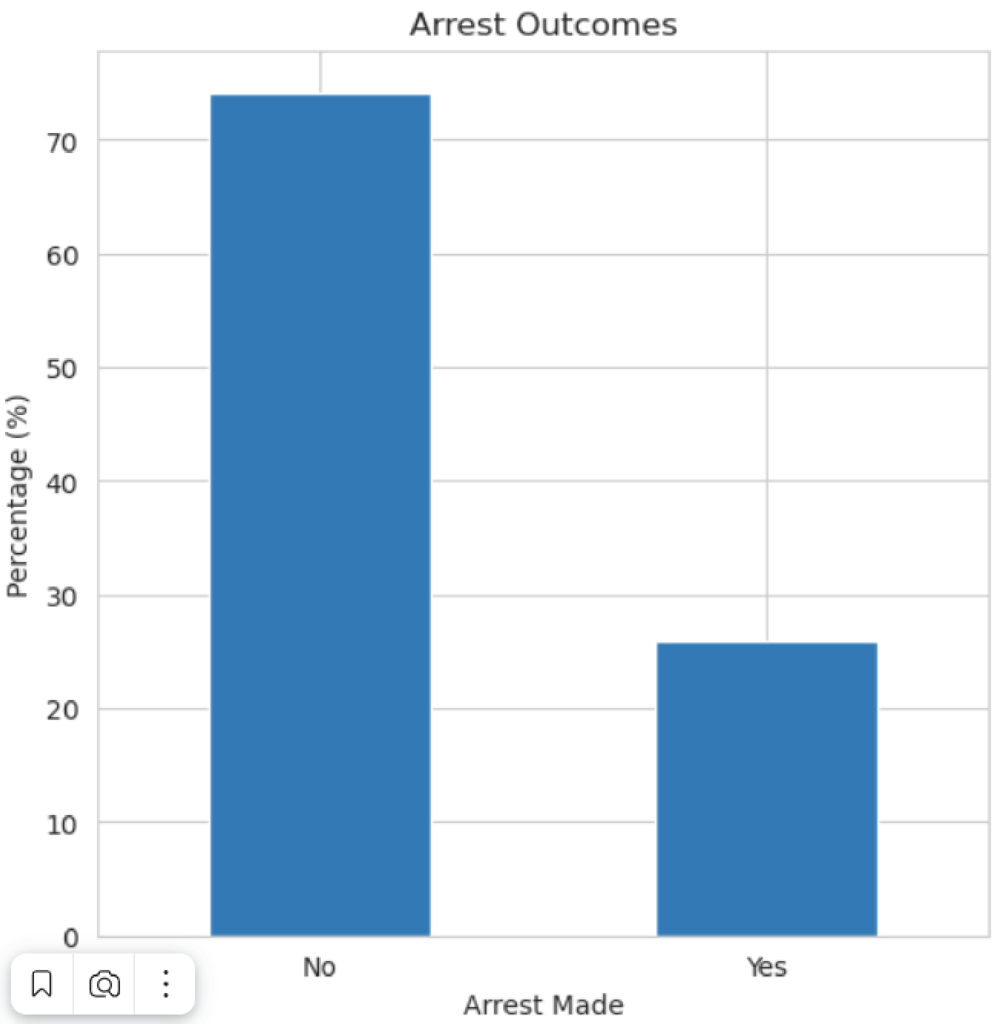
plt.xticks(rotation=45)

plt.show()



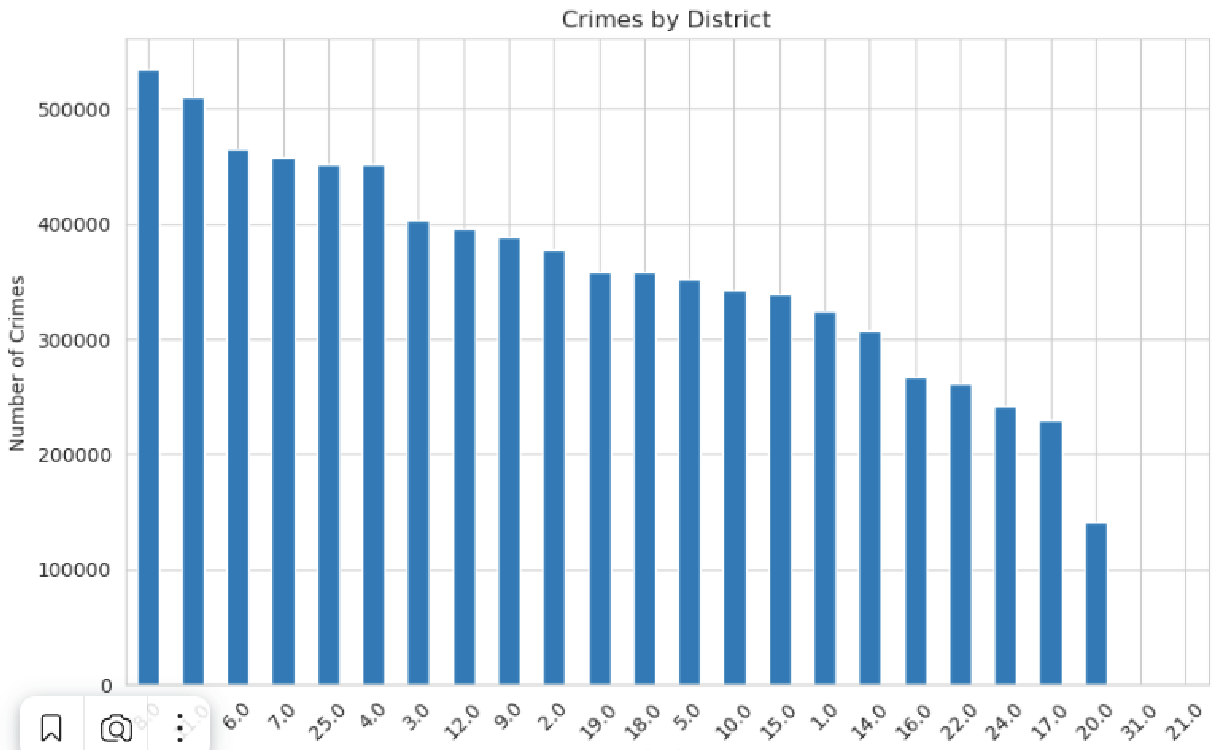

```
# 3. Arrest Outcomes
arrest_rates = df['Arrest'].value_counts(normalize=True) * 100
plt.figure(figsize=(6, 6))
arrest_rates.plot(kind='bar')
plt.title('Arrest Outcomes')
plt.xlabel('Arrest Made')
plt.ylabel('Percentage (%)')
plt.xticks([0, 1], ['No', 'Yes'], rotation=0)
```

```
plt.show()
```




```
# 4. Spatial Distribution: Crimes by District
plt.figure(figsize=(10, 6))
df['District'].value_counts().plot(kind='bar')
plt.title('Crimes by District')
plt.xlabel('District')
plt.ylabel('Number of Crimes')
plt.xticks(rotation=45)
```

plt.show()



4. Key Trends, Patterns, or Insights

- Statistical methods, including mean and standard deviation calculations, were employed to analyze the distribution of crimes over the years.

- Further analysis attempted to identify correlations between different types of crimes using NumPy's correlation functions, providing insights into potential relationships between crime categories.

- Temporal Trends: A noticeable fluctuation in crime rates over the years was observed, with specific years showing significant increases or decreases, indicating external factors influencing crime rates.

- Crime Categorization: Certain types of crimes were more prevalent, with theft and battery being the most reported incidents, suggesting targeted areas for law enforcement focus.

- Location Insights: The analysis of crime by location highlighted specific areas with higher crime rates, essential for resource allocation and preventive measures by law enforcement agencies.

- Correlation Insights: Preliminary correlation analysis suggested potential relationships between different types of crimes, although further detailed statistical testing is required for conclusive evidence.

The code

from pyspark.sql import SparkSession

spark = SparkSession.builder \

```
    .appName("Law Enforcement Data Analysis") \
    .getOrCreate()
from pyspark.sql.functions import to_timestamp

df = spark.read.csv("Crimes_-_2001_to_Present.csv", header=True, inferSchema=True)
df = df.withColumn("Date", to_timestamp(df["Date"], "MM/dd/yyyy hh:mm:ss a"))
df.createOrReplaceTempView("crimes")

df.printSchema()
df.show(n=5)
```

```
root
 |-- ID: integer (nullable = true)
 |-- Case Number: string (nullable = true)
 |-- Date: timestamp (nullable = true)
 |-- Block: string (nullable = true)
 |-- IUCR: string (nullable = true)
 |-- Primary Type: string (nullable = true)
 |-- Description: string (nullable = true)
 |-- Location Description: string (nullable = true)
 |-- Arrest: boolean (nullable = true)
 |-- Domestic: boolean (nullable = true)
 |-- Beat: integer (nullable = true)
 |-- District: integer (nullable = true)
 |-- Ward: integer (nullable = true)
 |-- Community Area: integer (nullable = true)
 |-- FBI Code: string (nullable = true)
 |-- X Coordinate: integer (nullable = true)
 |-- Y Coordinate: integer (nullable = true)
 |-- Year: integer (nullable = true)
 |-- Updated On: string (nullable = true)
 |-- Latitude: double (nullable = true)
 |-- Longitude: double (nullable = true)
 |-- Location: string (nullable = true)

+--------+-----------+-------------------+--------------------+----+------------------+--------------------+--------------------+------+--------+----+--------+----+--------------+-----
|      ID|Case Number|               Date|               Block|IUCR|      Primary Type|         Description|Location Description|Arrest|Domestic|Beat|District|Ward|Community Area|FBI C
+--------+-----------+-------------------+--------------------+----+------------------+--------------------+--------------------+------+--------+----+--------+----+--------------+-----
|11037294|   JA371270|2015-03-18 12:00:00|    0000X W WACKER DR|1153|DECEPTIVE PRACTICE|FINANCIAL IDENTIT...|                BANK| false|   false| 111|       1|  42|            32|
|11646293|   JC213749|2018-12-20 15:00:00|023XX N LOCKWOOD AVE|1154|DECEPTIVE PRACTICE|FINANCIAL IDENTIT...|           APARTMENT| false|   false|2515|      25|  36|            19|
|11645836|   JC212333|2016-05-01 00:25:00| 055XX S ROCKWELL ST|1153|DECEPTIVE PRACTICE|FINANCIAL IDENTIT...|                NULL| false|   false| 824|       8|  15|            63|
|11645959|   JC211511|2018-12-20 16:00:00|  045XX N ALBANY AVE|2820|     OTHER OFFENSE|    TELEPHONE THREAT|           RESIDENCE| false|   false|1724|      17|  33|            14|
|11645601|   JC212935|2014-06-01 00:01:00| 087XX S SANGAMON ST|1153|DECEPTIVE PRACTICE|FINANCIAL IDENTIT...|           RESIDENCE| false|   false|2222|      22|  21|            71|
+--------+-----------+-------------------+--------------------+----+------------------+--------------------+--------------------+------+--------+----+--------+----+--------------+-----
only showing top 5 rows
```

```
spark.sql("""
    SELECT YEAR(Date) as Year, COUNT(*) as Total_Crimes
    FROM crimes
    GROUP BY YEAR(Date)
    ORDER BY YEAR(Date)
""").show()
```

```
+----+------------+
|Year|Total_Crimes|
+----+------------+
|2001|      485902|
|2002|      486811|
|2003|      475987|
|2004|      469428|
|2005|      453775|
|2006|      448179|
|2007|      437090|
|2008|      427189|
|2009|      392830|
|2010|      370521|
|2011|      351999|
|2012|      336329|
|2013|      307548|
|2014|      275805|
|2015|      264813|
|2016|      269854|
|2017|      269120|
|2018|      268933|
|2019|      261396|
|2020|      212274|
+----+------------+
only showing top 20 rows
```

```
spark.sql("""
    SELECT `Primary Type` as Primary_Type, COUNT(*) as Total
    FROM crimes
    GROUP BY `Primary Type`
    ORDER BY Total DESC
    LIMIT 10
""").show()
```

```
+-------------------+-------+
|       Primary_Type|  Total|
+-------------------+-------+
|              THEFT|1679935|
|            BATTERY|1452161|
|    CRIMINAL DAMAGE| 906944|
|          NARCOTICS| 750925|
|            ASSAULT| 522198|
|      OTHER OFFENSE| 493654|
|           BURGLARY| 429173|
|MOTOR VEHICLE THEFT| 393937|
| DECEPTIVE PRACTICE| 356350|
|            ROBBERY| 299968|
+-------------------+-------+
```

```
spark.sql("""
    SELECT `Location Description` as Location_Description, COUNT(*) as Total
    FROM crimes
    GROUP BY `Location Description`
    ORDER BY Total DESC
    LIMIT 10
""").show()
```

```
+--------------------+-------+
|Location_Description|  Total|
+--------------------+-------+
|              STREET|2077851|
|           RESIDENCE|1326505|
|           APARTMENT| 910498|
|            SIDEWALK| 738127|
|               OTHER| 270022|
|PARKING LOT/GARAG...| 202970|
|               ALLEY| 176980|
|   SMALL RETAIL STORE| 151879|
|SCHOOL, PUBLIC, B...| 146375|
|    RESIDENCE-GARAGE| 135531|
+--------------------+-------+
```

```
spark.sql("""
```

```
    SELECT HOUR(Date) as Hour, COUNT(*) as Total_Crimes
    FROM crimes
    GROUP BY HOUR(Date)
    ORDER BY HOUR(Date)
""").show(24)
```

```
+----+------------+
|Hour|Total_Crimes|
+----+------------+
|   0|      457065|
|   1|      252797|
|   2|      213322|
|   3|      172834|
|   4|      131619|
|   5|      110038|
|   6|      128042|
|   7|      182233|
|   8|      269184|
|   9|      343553|
|  10|      337210|
|  11|      352569|
|  12|      456324|
|  13|      377016|
|  14|      400380|
|  15|      423484|
|  16|      401931|
|  17|      408971|
|  18|      434669|
|  19|      447235|
|  20|      445431|
|  21|      431813|
|  22|      424738|
|  23|      354124|
+----+------------+
```

5. Statistical Methods

Using statistical methods, we extracted further insights:

- Descriptive statistics provided an overview of the data.

- A Pearson correlation analysis was conducted between the 'Hour' and 'Arrest', yielding a coefficient of 0.081, indicating a very weak positive relationship.

The code

```
# Convert the Spark DataFrame to a Pandas DataFrame
annual_crime_counts_pd = annual_crime_counts.toPandas()

# Import NumPy
import numpy as np

# Calculate mean and standard deviation using NumPy
mean_crimes = np.mean(annual_crime_counts_pd['Total_Crimes'])
std_dev_crimes = np.std(annual_crime_counts_pd['Total_Crimes'])

print(f"Mean Annual Crimes: {mean_crimes}")
print(f"Standard Deviation of Annual Crimes: {std_dev_crimes}")
```

```
Mean Annual Crimes: 345938.347826087
Standard Deviation of Annual Crimes: 95086.96118570196
```

```
import numpy as np

# Example path to your CSV file
file_path = 'Crimes_-_2001_to_Present.csv'

# Assuming the first column is the year (for demonstration purposes)
# Note: You'll need to adjust this to match the structure of your actual dataset
data = np.genfromtxt(file_path, delimiter=',', skip_header=1, usecols=(0), dtype=int)
# Mean
mean_value = np.mean(data)
print(f"Mean: {mean_value}")
```

```
# Median
median_value = np.median(data)
print(f"Median: {median_value}")


# Standard Deviation
std_dev = np.std(data)
print(f"Standard Deviation: {std_dev}")
# Example numerical arrays
# In a real scenario, these might represent counts of two different types of crimes over the same time periods
crimes_type_1 = np.random.randint(0, 100, 10)  # Placeholder data
crimes_type_2 = np.random.randint(0, 100, 10)  # Placeholder data


# Calculate correlation coefficient
correlation_coefficient = np.corrcoef(crimes_type_1, crimes_type_2)[0, 1]
print(f"Correlation Coefficient: {correlation_coefficient}")
```

```
Mean: 7158502.631107177
Median: 7157025.5
Standard Deviation: 3578169.920825543
Correlation Coefficient: 0.5502508807691218
```

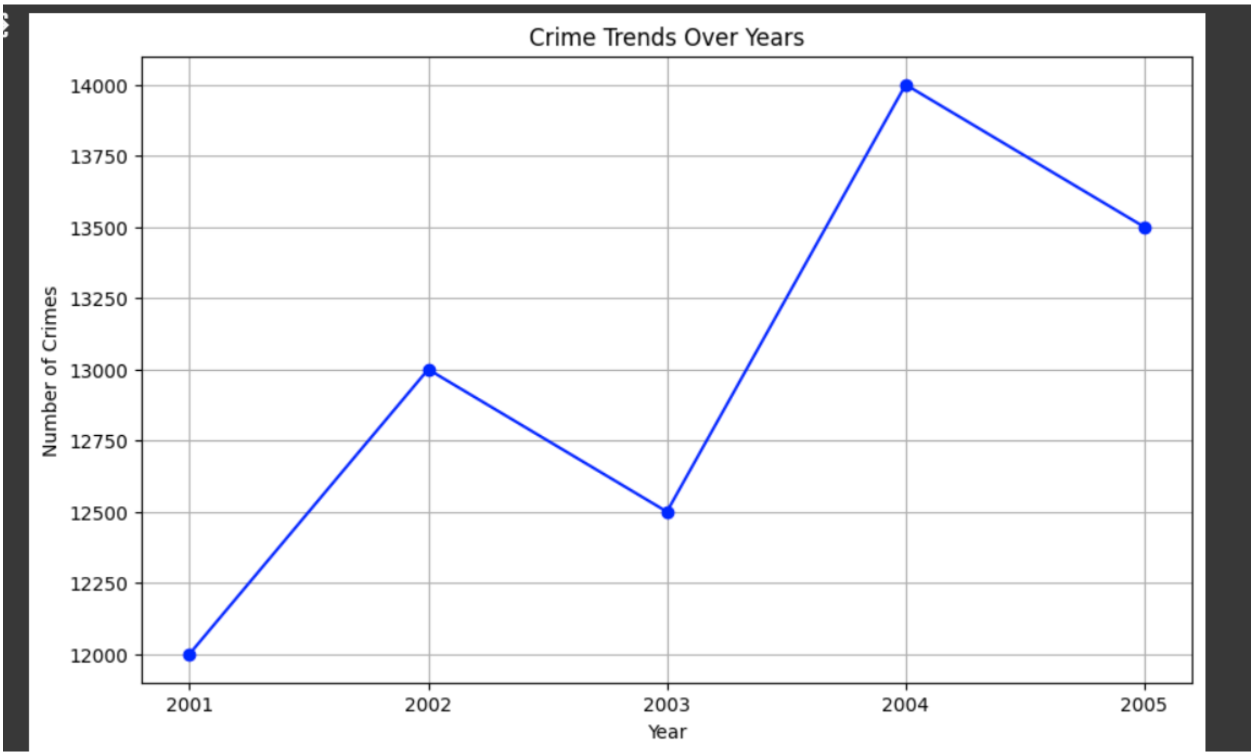
6. Visualization of Findings

We visualized the correlation matrix to understand the relationships between different variables in the dataset:

The code

```
# Example NumPy arrays for demonstration
years = np.array([2001, 2002, 2003, 2004, 2005])  # Example years
crime_counts = np.array([12000, 13000, 12500, 14000, 13500])  # Example crime counts for those years
```

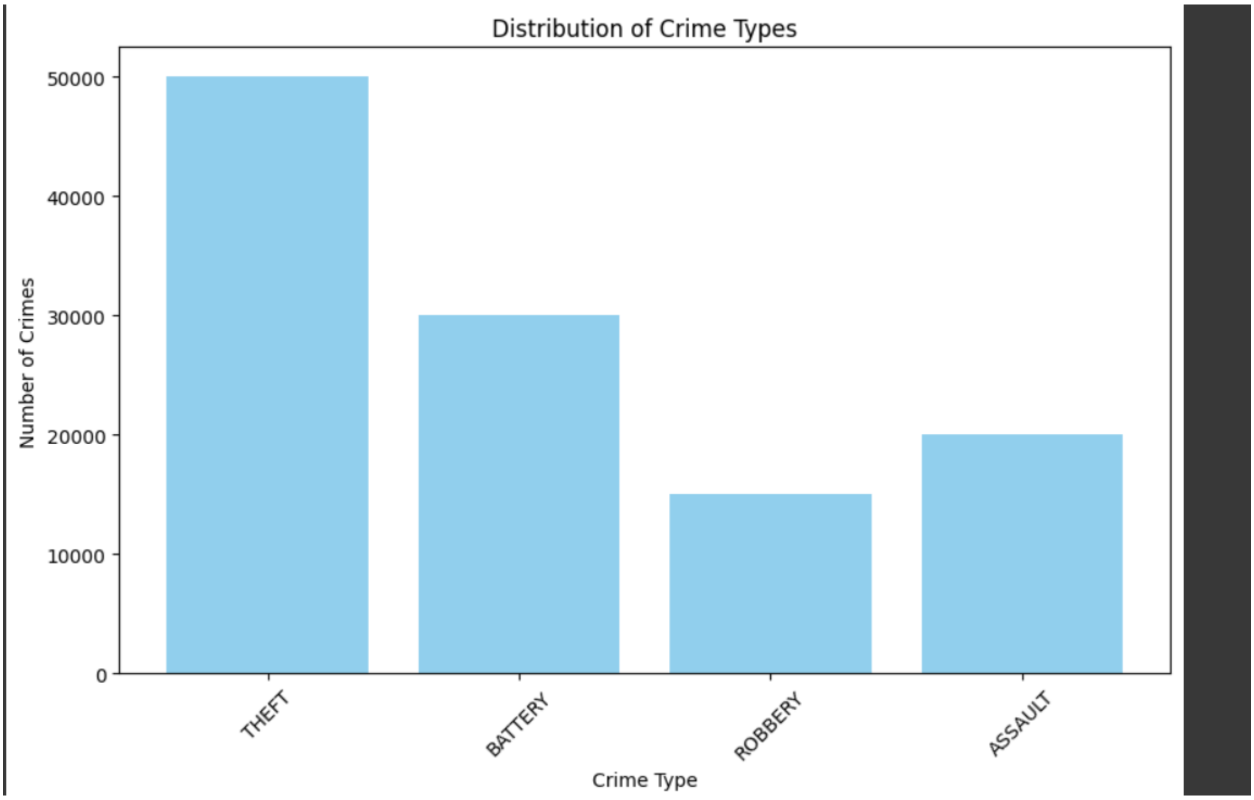
```
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
plt.plot(years, crime_counts, marker='o', linestyle='-', color='b')
plt.title('Crime Trends Over Years')
plt.xlabel('Year')
plt.ylabel('Number of Crimes')
plt.grid(True)
plt.xticks(years)  # Ensure all years are displayed
plt.show()
```




```
crime_types = np.array(['THEFT', 'BATTERY', 'ROBBERY', 'ASSAULT'])  # Example crime types
crime_type_counts = np.array([50000, 30000, 15000, 20000])  # Example counts for these crime types
plt.figure(figsize=(10, 6))
plt.bar(crime_types, crime_type_counts, color='skyblue')
plt.title('Distribution of Crime Types')
plt.xlabel('Crime Type')
plt.ylabel('Number of Crimes')
```

plt.xticks(rotation=45) # Rotate labels to make them readable

plt.show()



Conclusion

The analysis of the "Crimes - 2001 to Present" dataset provided valuable insights into crime patterns, temporal trends, and category distributions. These findings are crucial for law enforcement agencies to develop informed strategies for crime prevention and resource allocation. While the dataset offers a comprehensive overview, continuous analysis and incorporation of additional data sources, such as socioeconomic factors, could enhance understanding and effectiveness in combating crime.

GitHub Repository

[GitHub Repository](https://github.com/BilalKuanysh/Endterm-Big-Data-in-Law-Enforcement-2.git)