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EXPLORING\_SEASONAL\_AFFECT\_IN\_CRIMES\_2\_MUHARRAM\_PERIOD, Ahmet YÜCE

## Table of Contents

- 1 IMPORT LIBRARIES
- 2 USER DEFINED FUNCTIONS
- 3 SAMPLE DATA-1: UNC-CHAPEL HILL CAMPUS POLICE CRIME LOG\_2013-2018
- 4 SAMPLE DATA-2: LOS ANGELES CRIME DATA\_2010-2019
- 5 SAMPLE DATA-3: KANSAS CITY CRIME DATA\_2009-2016
- 6 SAMPLE DATA-4: DETROIT CRIME INCIDENTS\_2009-2016
- 7 SAMPLE DATA-5: DENVER CRIME DATASET\_2019-2023
- 8 SAMPLE DATA-6: VANCOUVER CRIME DATASET\_2003-2017
- 9 SAMPLE DATA-7: CHICAGO CRIME DATASET\_2001-2023
- 10 SAMPLE DATA-8: BALTIMORE CRIME DATASET\_2011-2015
- 11 SAMPLE DATA-9: ATLANTA CRIME DATASET\_2009-2017
- 12 SAMPLE DATA-10: OAKLAND CRIME STATISTICS\_2011-2016
- 13 CONCLUSION

## IMPORT LIBRARIES

```
In [1]: # pip install hijri_converter
from hijri_converter import convert
```

```
In [2]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
from datetime import datetime
pd.set_option('display.max_rows', 300) # None
```

## USER DEFINED FUNCTIONS

```
In [3]: def highlight_greater_than(value, threshold):
    if value > threshold:
        return 'background-color: yellow'
    else:
        return ''
```

```
In [4]: # Filter rows that fall within the first ten days of the 12th months
def filter_first_ten_days_of_1th_months(date):
    # Extract the month and day from the Hijri_Date column
    month = int(date.split('-')[1])
    day = int(date.split('-')[2])

    # Check for the month: whether it's the 1th month and day: whether it's between 1 and 10
    return month == 1 and day <= 10
```

```
In [5]: def common_codes(df):
    count_days = (max(df.date) - min(df.date)).days + 1
    df['Hijri_Date'] = df['date'].apply(lambda x: convert.Gregorian(x.year, x.month, x.day).to_hijri())
    df['Hijri_Year_Month'] = df['Hijri_Date'].astype(str).str[:-3]
    muharrem_df = df[df['Hijri_Date'].astype(str).apply(filter_first_ten_days_of_1th_months)]
    muharrem_dates_list_in_gregorian = pd.to_datetime(muharrem_df['date']).dt.strftime('%Y-%m-%d').unique().tolist()
    muharrem_dates_list_in_gregorian = sorted(muharrem_dates_list_in_gregorian, key=lambda x: datetime.strptime(x, '%Y-%m-%d'))
    count_muharrem_days = df.Hijri_Year_Month[df['Hijri_Year_Month'].astype(str).str.endswith("01")].nunique() * 10
    count_other_days = count_days - count_muharrem_days
    return count_days, count_other_days, df['Hijri_Date'], df['Hijri_Year_Month'], muharrem_df, muharrem_dates_list_in_gregorian,
```

```
In [6]: def muharrem_10_days(df):
    df['date'] = pd.to_datetime(df['date'])
    count_days, count_other_days, df['Hijri_Date'], df['Hijri_Year_Month'], muharrem_df, muharrem_dates_list_in_gregorian, count_
    print("Total number of days:", count_days)
    print(len("Total number of days:") * "-")
    print("Total number of cases:", len(df))
    print(len("Total number of cases:") * "-")
```

```

average_case_count = round((len(df) / count_days), 2)
print("Average Daily Case Count:", average_case_count)
print(len("Average Daily Case Count:") * "-")

print("Yearly case counts according to the Gregorian calendar:")
print(len("Yearly case counts according to the Gregorian calendar:") * "-")
print(df.date.dt.year.value_counts())
print(len("Case counts according to the Hijri calendar:") * "-")

print("Case counts according to the Hijri calendar:")
print(len("Case counts according to the Hijri calendar:") * "-")
print(df['Hijri_Date'].astype(str).str[:6].value_counts())
print(len("Average case count in the first ten days of Muharram months:") * "-")

# Total number of cases in the first ten days of Muharram months (rows)
count_muharrem_rows = len(muharrem_df)

# Average case count in the first ten days of Muharram months:
avg_count_of_muharrem_incidents = count_muharrem_rows / count_muharrem_days
print("Average case count in the first ten days of Muharram months:", round(avg_count_of_muharrem_incidents,4))
print(len("Average case count in the first ten days of Muharram months:") * "-")

# Total number of cases in other days (rows)
count_other_rows = len(df[~df['Hijri_Date']].astype(str).apply(filter_first_ten_days_of_1th_months))
count_other_days = count_days - count_muharrem_days
avg_count_of_other_incidents = count_other_rows / count_other_days
print("Average case count in other days:", round(avg_count_of_other_incidents,4))
print(len("Average case count in other days:") * "-")

print("Ratio of Muharram cases to other cases:", f"{avg_count_of_muharrem_incidents / avg_count_of_other_incidents:.{4}f}")
print(len("Ratio of Muharram cases to other cases:") * "-")

```

In [7]:

```

def incidents_by_types(df):
    # Explore distribution of incidents by types

    count_days, count_other_days, df['Hijri_Date'], df['Hijri_Year_Month'], muharrem_df, muharrem_dates_list_in_gregorian, count_all_incidents_count = df.incident.value_counts()

    muharrem_incidents = df[df['date'].astype(str).isin(muharrem_dates_list_in_gregorian)]
    muharrem_incidents_count = muharrem_incidents["incident"].value_counts()

    other_days_incidents = df[~df['date'].astype(str).isin(muharrem_dates_list_in_gregorian)]

```

```

other_days_incidents_count = other_days_incidents["incident"].value_counts()

# Top 30 incidents by the highest frequencies
muharrem_grouped = muharrem_incidents.groupby('incident').size().nlargest(30)
other_days_grouped = other_days_incidents.groupby('incident').size().nlargest(30)

# Bar plot
plt.figure(figsize=(12, 10))
# Muharram Days bar plot
plt.bar(muharrem_grouped.index, muharrem_grouped/count_muharrem_days, label='Muharram Days')
# Other Days bar plot
plt.bar(other_days_grouped.index, other_days_grouped/count_other_days, alpha=0.6, label='Other Days')
plt.xlabel('Incident Types')
plt.ylabel('Average Daily Frequency')
plt.title('Top 30 Incidents by Type')
plt.legend()
plt.xticks(rotation=90, ha='center')
plt.tight_layout()
plt.show()

# describe() statistics
muharrem_incidents_desc = df[df['date'].astype(str).isin(muharrem_dates_list_in_gregorian)]["incident"].describe()
other_days_incidents_desc = df[~df['date'].astype(str).isin(muharrem_dates_list_in_gregorian)]["incident"].describe()

incident_ratios = pd.DataFrame({'muharrem incidents': muharrem_incidents_count, 'all incidents': all_incidents_count})
incident_ratios["muharrem incidents/total incidents"] = incident_ratios["muharrem incidents"] / incident_ratios["all incidents"]
incident_ratios["muharrem incidents/total incidents"] = round(incident_ratios["muharrem incidents/total incidents"], 4)
sorted_ratios = incident_ratios.sort_values(by="muharrem incidents/total incidents", ascending=False)[:30]
equal_ratio = count_muharrem_days / count_days
sorted_ratios['muharrem incidents'] = sorted_ratios['muharrem incidents'].astype(int)
sorted_ratios = sorted_ratios.style.applymap(lambda x: highlight_greater_than(x, equal_ratio), subset=['muharrem incidents/total incidents'])

muharrem_dominant_incidents = incident_ratios[incident_ratios["muharrem incidents/total incidents"] > equal_ratio]
muharrem_dominant_incidents = muharrem_dominant_incidents.sort_values(by="muharrem incidents", ascending=False)
muharrem_dominant_incidents['muharrem incidents'] = muharrem_dominant_incidents['muharrem incidents'].astype(int)

return sorted_ratios, muharrem_dominant_incidents, muharrem_incidents_desc, other_days_incidents_desc

```

In [8]: `def monthly_count_plot ():`

```

# Extract Year-Month part of the dates
def extract_hijri_year_month(date):
    year_month = date.split('-')[:2]

```

```

return '-' .join(year_month)

# Add 'Hijri_Year_Month' column
df['Hijri_Year_Month'] = df['Hijri_Date'].astype(str).apply(extract_hijri_year_month)

# Count monthly incidents
monthly_count = df.groupby('Hijri_Year_Month')['Hijri_Date'].count()

# Avg count of incidents on Hijri_Year_Month basis
monthly_avg = monthly_count.groupby('Hijri_Year_Month').mean()

# Overall Avg count of incidents
overall_avg = monthly_count.mean()

# Line plot
plt.figure(figsize=(10, 6))

# Line of Avg Incident counts
plt.axhline(y=overall_avg, color='g', linestyle='--', label=f'Overall Average: {overall_avg:.2f}')

# Line of monthly count of incidents
plt.plot(monthly_avg.index, monthly_avg.values, marker='o', linestyle='-', color='b', label='Monthly Count')

# Mark 9th. months
first_month = [i for i, month in enumerate(monthly_avg.index) if '01' in month]
plt.scatter(monthly_avg.index[first_month], monthly_avg.values[first_month], color='red', s=100, label='1th Month:Muharram')

# Plot
plt.title('Monthly Count of Incidents on Hijri Calendar')
plt.xlabel('Hijri_Year-Month')
plt.ylabel('Monthly Count of Incidents')
plt.xticks(rotation=90)
plt.legend()
plt.tight_layout()
plt.show()

```

## SAMPLE DATA-1: UNC-CHAPEL HILL CAMPUS POLICE CRIME LOG\_2013-2018

<https://data.world/skillenberg/unc-police-incidents-2013-2018>

```
In [9]: df = pd.read_excel("unc-police-data-killenberg.xlsx", sheet_name=1)
df
```

```
Out[9]:
```

	incident	date-time	year	date-no year	location	res hall	alcohol	
0		NaN	1/1/13 0:00	2013	01/01	E FRANKLIN ST	NaN	NaN
1	EMS ASSIST	1/1/13 2:25	2013	01/01	AYCOCK CIRCLE PARKING LOT UNC	NaN	NaN	
2	SUSPICIOUS CONDITION (NON-CRIMINAL)	1/1/13 2:49	2013	01/01	S COLUMBIA ST/E CAMERON AVE	NaN	NaN	
3	EMS ASSIST	1/1/14 12:25	2014	01/01	FINLEY CLUB HOUSE UNC	NaN	NaN	
4	WELL-BEING CHECK	1/1/14 20:17	2014	01/01	CRAIGE RES HALL UNC	RES HALL	NaN	
...	...	...	...	...	...	...	...	
12812	EMS ASSIST	9/9/17 4:24	2017	09/09	OLD EAST RES HALL UNC	RES HALL	NaN	
12813	FOUND PROPERTY	9/9/17 8:19	2017	09/09	DOGWOOD PARKING DECK UNC	NaN	NaN	
12814	LARCENY - FROM BUILDING	9/9/17 9:48	2017	09/09	BERRYHILL UNC	NaN	NaN	
12815	ASSIST OTHER AGENCY	9/9/18 2:40	2018	09/09	E FRANKLIN ST	NaN	NaN	
12816	DWI-ALCOHOL	9/9/18 3:35	2018	09/09	COUNTRY CLUB RD	NaN	DWI-ALCOHOL	

12817 rows × 7 columns

```
In [10]: df = df.drop_duplicates()
```

```
In [11]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 12714 entries, 0 to 12816
Data columns (total 7 columns):
 #   Column      Non-Null Count Dtype  
--- 
 0   incident    9518 non-null   object  
 1   date-time   12714 non-null   object  
 2   year        12714 non-null   int64  
 3   date-no year 12714 non-null   object  
 4   location    12711 non-null   object  
 5   res hall    2262 non-null   object  
 6   alcohol     746 non-null   object  
dtypes: int64(1), object(6)
memory usage: 794.6+ KB
```

```
In [12]: df["incident"].value_counts().count()
```

```
Out[12]: 730
```

```
In [13]: df["incident"].value_counts()[:15]
```

```
Out[13]: EMS ASSIST                    1875
FOUND PROPERTY                   597
LARCENY - FROM BUILDING       546
ALCOHOL - UNDERAGE CONSUMPTION 544
INFORMATIONAL                  440
VANDALISM / PROPERTY DAMAGE    388
LARCENY OF BICYCLE              306
SUSPICIOUS CONDITION (NON-CRIMINAL) 293
PROPERTY DAMAGE                 259
ASSIST OTHER AGENCY             208
CALLS FOR SERVICE               159
WELL-BEING CHECK                138
LARCENY-ALL OTHER                134
VOLUNTARY COMMITMENT             119
LOST PROPERTY                   118
Name: incident, dtype: int64
```

```
In [14]: df = df.rename(columns = {'date-time':'date'})
```

```
In [15]: df['date'] = pd.to_datetime(df['date']).dt.strftime('%Y-%m-%d')
```

```
In [16]: min(df.date), max(df.date)
```

```
Out[16]: ('2013-01-01', '2018-10-10')
```

```
In [17]: df = df.iloc[:, [0,1]]  
# df.to_csv("UNC.csv")
```

```
In [18]: df.info()
```

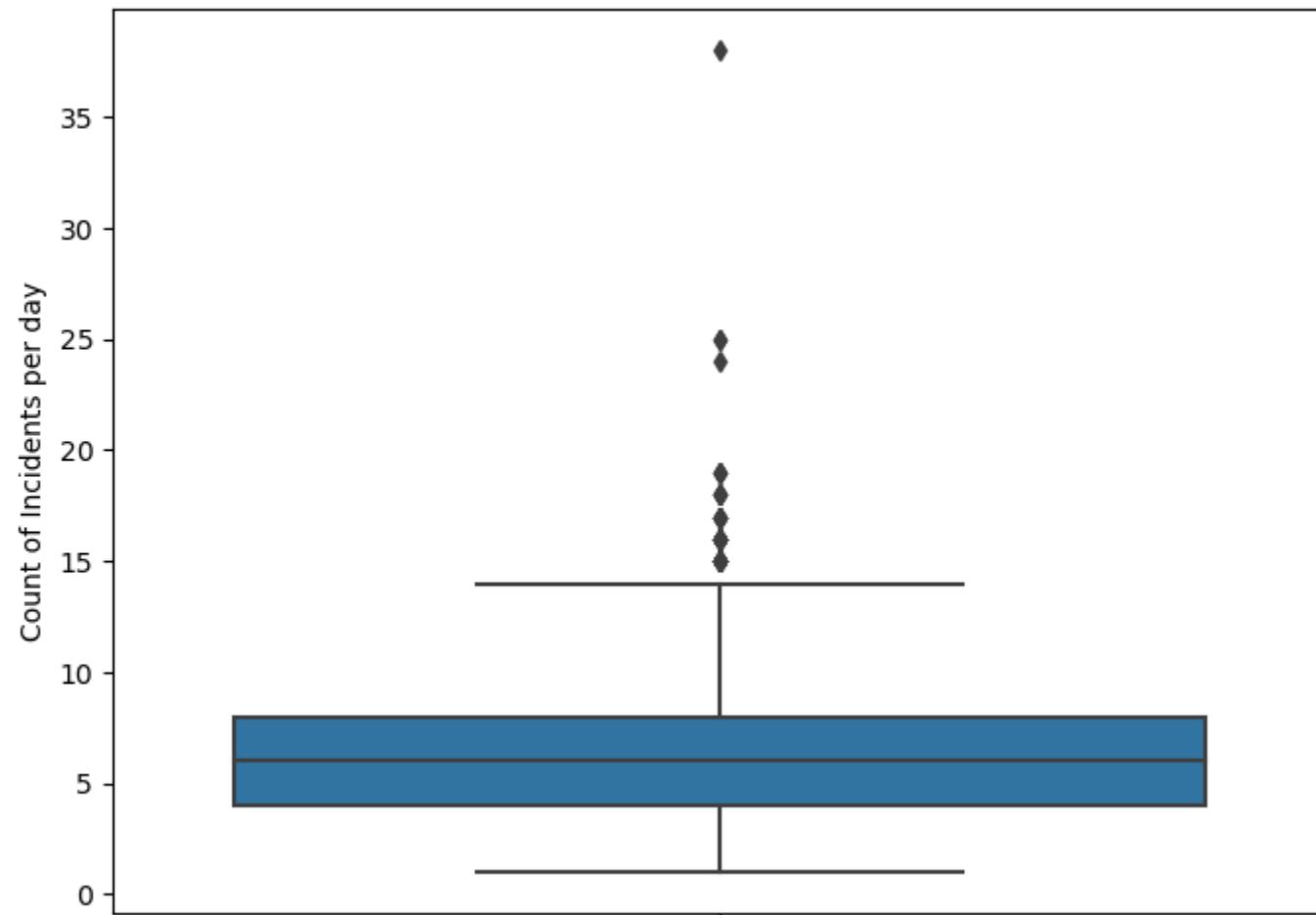
```
<class 'pandas.core.frame.DataFrame'>  
Int64Index: 12714 entries, 0 to 12816  
Data columns (total 2 columns):  
 #   Column      Non-Null Count  Dtype     
---  --          --          --  
 0   incident    9518 non-null    object    
 1   date        12714 non-null    object    
 dtypes: object(2)  
 memory usage: 298.0+ KB
```

```
In [19]: daily_incident_counts_stats = df.groupby("date")['date'].value_counts().describe([.25, .5, .75, .95, .98, .99]).astype(int)  
daily_incident_counts_stats
```

```
Out[19]: count      2057  
mean         6  
std          3  
min          1  
25%          4  
50%          6  
75%          8  
95%         12  
98%         15  
99%         16  
max         38  
Name: date, dtype: int32
```

```
In [20]: # Display the days with high incident numbers  
plt.figure(figsize=(8, 6))  
sns.boxplot(y=df.groupby("date")['date'].value_counts())  
plt.title('Daily Counts of Incidents')  
plt.ylabel('Count of Incidents per day')  
plt.show()
```

Daily Counts of Incidents



In [21]: df.date

```
Out[21]: 0      2013-01-01  
1      2013-01-01  
2      2013-01-01  
3      2014-01-01  
4      2014-01-01  
     ...  
12812    2017-09-09  
12813    2017-09-09  
12814    2017-09-09  
12815    2018-09-09  
12816    2018-09-09  
Name: date, Length: 12714, dtype: object
```

```
In [22]: df.date.nunique()
```

```
Out[22]: 2057
```

As seen below, our dataset spans a total of 2109 days. During this period, incidents occurred on 2057 days, while there were no records of incidents on the remaining 52 days.

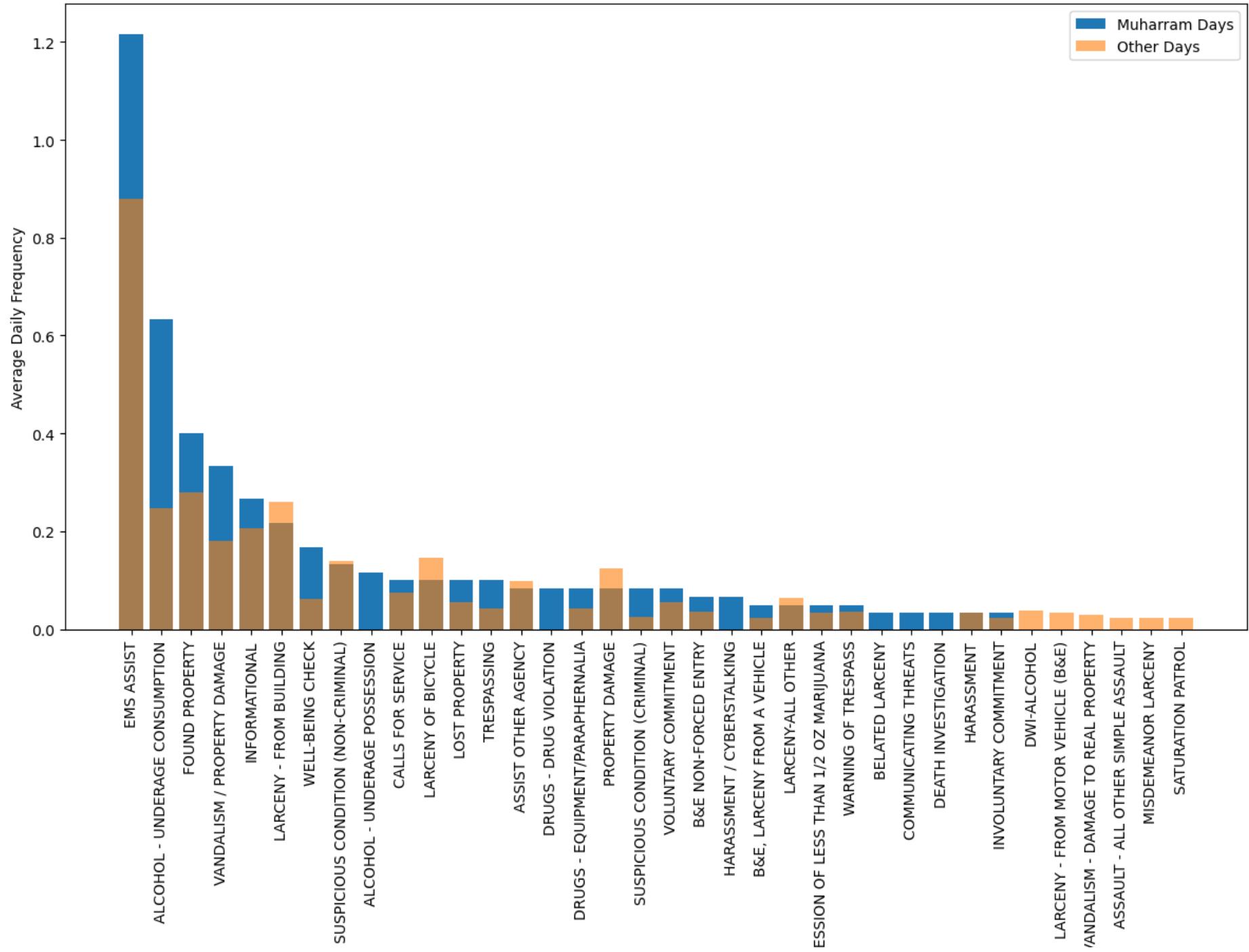
```
In [23]: muharrem_10_days (df)
```

```
Total number of days: 2109
-----
Total number of cases: 12714
-----
Average Daily Case Count: 6.03
-----
Yearly case counts according to the Gregorian calendar:
-----
2017    2491
2015    2268
2014    2239
2016    2224
2013    2109
2018    1383
Name: date, dtype: int64
-----
Case counts according to the Hijri calendar:
-----
1438    2385
1435    2157
1437    2135
1436    2123
1439    1973
1434    1779
1440    162
Name: Hijri_Date, dtype: int64
-----
Average case count in the first ten days of Muharram months: 7.4833
-----
Average case count in other days: 5.9858
-----
Ratio of Muharram cases to other cases: 1.2502
```

**We observe a 25.027% higher crime rate during the initial 10 days of the Muharram month compared to the annual average.**

```
In [24]: sorted_ratios, muharrem_dominant_incidents, muharrem_incidents_desc, other_days_incidents_desc = incidents_by_types(df)
```

Top 30 Incidents by Type



## Incident Types

```
In [25]: # Top 30 incident types sorted by "muharrem incidents / total incidents" ratio  
sorted_ratios
```

Out[25]:

	muharrem incidents	all incidents	muharrem incidents/total incidents
(NON-CRIMINAL) CIVIL MATTER	1	1	1.000000
DRUGS - LESS THEN 1/2 OZ SCH VI	1	1	1.000000
SERVICE CALL - REPAIRS	1	1	1.000000
POSSESSION OF A CONTROLLED SUBSTANCE	1	1	1.000000
MISSING PROPERTY	1	1	1.000000
LARCENY-FROM VEHICLE	1	1	1.000000
INFORMATION-ASSIST OTHER AGENCY	1	1	1.000000
FELONY POSSESSION OF COCAINE	1	1	1.000000
DRUGS -POSSESS HASHISH	1	1	1.000000
WHILE LICENSE REVOKED	1	1	1.000000
ASSISTED THE FIRE DEPARTMENT	1	1	1.000000
EMS	1	2	0.500000
FIRE DAMAGE	1	2	0.500000
ROAD RAGE	1	2	0.500000
ODOR INVESTIGATION	2	5	0.400000
DEATH INVESTIGATION	2	5	0.400000
ASSAULT-AGGRAVATED	1	3	0.333300
SEXUAL BATTERY	1	3	0.333300
HARASSMENT / STALKING	1	4	0.250000
SMOKE INVESTIGATION	1	4	0.250000
COMMUNICATING THREATS	2	8	0.250000
DRUGS - PARAPHERNALIA - POSSESSING	1	4	0.250000
PROPERTY DAMAGE (NON-CRIMINAL)	1	5	0.200000
DRIVERS LICENSE CHECKPOINT	1	5	0.200000

	<b>muharrem incidents</b>	<b>all incidents</b>	<b>muharrem incidents/total incidents</b>
<b>DRUNK AND DISRUPTIVE</b>	1	5	0.200000
<b>FRAUD-CREDIT CARD</b>	1	5	0.200000
<b>COMMUNICATE THREATS</b>	1	6	0.166700
<b>CLERY REPORT FORCIBLE FONDLING</b>	1	6	0.166700
<b>ALCOHOL - UNDERAGE POSSESSION</b>	7	48	0.145800
<b>CLERY - ALLEGATION OF FONDLING</b>	1	7	0.142900

In [26]: *# In which categories were more crimes committed during the first ten days of Muharram?*  
muharrem\_dominant\_incidents

Out[26]:

	muharrem incidents	all incidents	muharrem incidents/total incidents
<b>EMS ASSIST</b>	73	1875	0.0389
<b>ALCOHOL - UNDERAGE CONSUMPTION</b>	38	544	0.0699
<b>FOUND PROPERTY</b>	24	597	0.0402
<b>VANDALISM / PROPERTY DAMAGE</b>	20	388	0.0515
<b>INFORMATIONAL</b>	16	440	0.0364
<b>WELL-BEING CHECK</b>	10	138	0.0725
<b>ALCOHOL - UNDERAGE POSSESSION</b>	7	48	0.1458
<b>TRESPASSING</b>	6	92	0.0652
<b>LOST PROPERTY</b>	6	118	0.0508
<b>CALLS FOR SERVICE</b>	6	159	0.0377
<b>VOLUNTARY COMMITMENT</b>	5	119	0.0420
<b>SUSPICIOUS CONDITION (CRIMINAL)</b>	5	58	0.0862
<b>DRUGS - EQUIPMENT/PARAPHERNALIA</b>	5	94	0.0532
<b>DRUGS - DRUG VIOLATION</b>	5	50	0.1000
<b>B&amp;E NON-FORCED ENTRY</b>	4	77	0.0519
<b>HARASSMENT / CYBERSTALKING</b>	4	38	0.1053
<b>B&amp;E, LARCENY FROM A VEHICLE</b>	3	50	0.0600
<b>POSSESSION OF LESS THAN 1/2 OZ MARIJUANA</b>	3	73	0.0411
<b>WARNING OF TRESPASS</b>	3	76	0.0395
<b>ODOR INVESTIGATION</b>	2	5	0.4000
<b>MISDEMEANOR LARCENY</b>	2	50	0.0400
<b>SATURATION PATROL</b>	2	50	0.0400
<b>SUSPICIOUS CONDITION</b>	2	16	0.1250
<b>DEATH INVESTIGATION</b>	2	5	0.4000

	<b>muharrem incidents</b>	<b>all incidents</b>	<b>muharrem incidents/total incidents</b>
<b>COMMUNICATING THREATS</b>	2	8	0.2500
<b>LOST / FOUND PROPERTY</b>	2	44	0.0455
<b>INVOLUNTARY COMMITMENT</b>	2	50	0.0400
<b>BELATED LARCENY</b>	2	17	0.1176
<b>MISSING PERSONS</b>	1	23	0.0435
<b>POSSESSION OF A CONTROLLED SUBSTANCE</b>	1	1	1.0000
<b>MISSING PROPERTY</b>	1	1	1.0000
<b>(NON-CRIMINAL) CIVIL MATTER</b>	1	1	1.0000
<b>SEXUAL BATTERY</b>	1	3	0.3333
<b>PROPERTY DAMAGE (NON-CRIMINAL)</b>	1	5	0.2000
<b>RAPE - FORCIBLE</b>	1	11	0.0909
<b>ROAD RAGE</b>	1	2	0.5000
<b>SERVICE CALL - REPAIRS</b>	1	1	1.0000
<b>LARCENY OF CELL PHONE</b>	1	20	0.0500
<b>SIMPLE ASSAULT</b>	1	15	0.0667
<b>SIMPLE POSSESSION OF MARIJUANA</b>	1	28	0.0357
<b>SMOKE INVESTIGATION</b>	1	4	0.2500
<b>SUSPICIOUS PERSON</b>	1	24	0.0417
<b>UNDERAGE DRINKING</b>	1	14	0.0714
<b>VANDALISM</b>	1	7	0.1429
<b>LARCENY-FROM VEHICLE</b>	1	1	1.0000
<b>FRAUD-CREDIT CARD</b>	1	5	0.2000
<b>LARCENY OF A LAPTOP</b>	1	15	0.0667
<b>LARCENY - AUTO PART &amp; ACCESSORIES</b>	1	24	0.0417

	muharrem incidents	all incidents	muharrem incidents/total incidents
ANIMAL COMPLAINT	1	14	0.0714
ASSAULT - COMMUNICATE THREATS	1	35	0.0286
ASSAULT-AGGRAVATED	1	3	0.3333
ASSISTED THE FIRE DEPARTMENT	1	1	1.0000
BURGLARY- NON-FORCED ENTRY (STRUCTURES)	1	18	0.0556
CLERY - ALLEGATION OF FONDLING	1	7	0.1429
CLERY - ALLEGATION OF RAPE	1	25	0.0400
CLERY - REPORT STALKING	1	19	0.0526
CLERY REPORT FORCIBLE FONDLING	1	6	0.1667
COMMUNICATE THREATS	1	6	0.1667
DAYTIME CHECK POINT (PART)	1	17	0.0588
DAYTIME CHECKPOINT (HOST)	1	25	0.0400
DISORDERLY CONDUCT	1	9	0.1111
DISTURBANCE	1	21	0.0476
DRIVERS LICENSE CHECKPOINT	1	5	0.2000
DRUGS - LESS THEN 1/2 OZ SCH VI	1	1	1.0000
DRUGS - PARAPHERNALIA - POSSESSING	1	4	0.2500
DRUGS -POSSESS HASHISH	1	1	1.0000
DRUNK AND DISRUPTIVE	1	5	0.2000
EMS	1	2	0.5000
EMS ASSIST - ALCOHOL	1	15	0.0667
FELONY POSSESSION OF COCAINE	1	1	1.0000
FIRE DAMAGE	1	2	0.5000
FRAUD - ALL OTHER	1	18	0.0556

	<b>muharrem incidents</b>	<b>all incidents</b>	<b>muharrem incidents/total incidents</b>
<b>FRAUD - WIRE/COMPUTER/OTHER ELECTRONIC</b>	1	11	0.0909
<b>HARASSMENT / STALKING</b>	1	4	0.2500
<b>INFORMATION-ASSIST OTHER AGENCY</b>	1	1	1.0000
<b>WHILE LICENSE REVOKED</b>	1	1	1.0000

More crimes were committed in the above-mentioned crime categories during the first ten days of Muharram compared to the other days of the year.

```
In [27]: df.incident.nunique(), muharrem_dominant_incidents.count()[0]
```

```
Out[27]: (730, 76)
```

```
In [28]: muharrem_incidents_desc
```

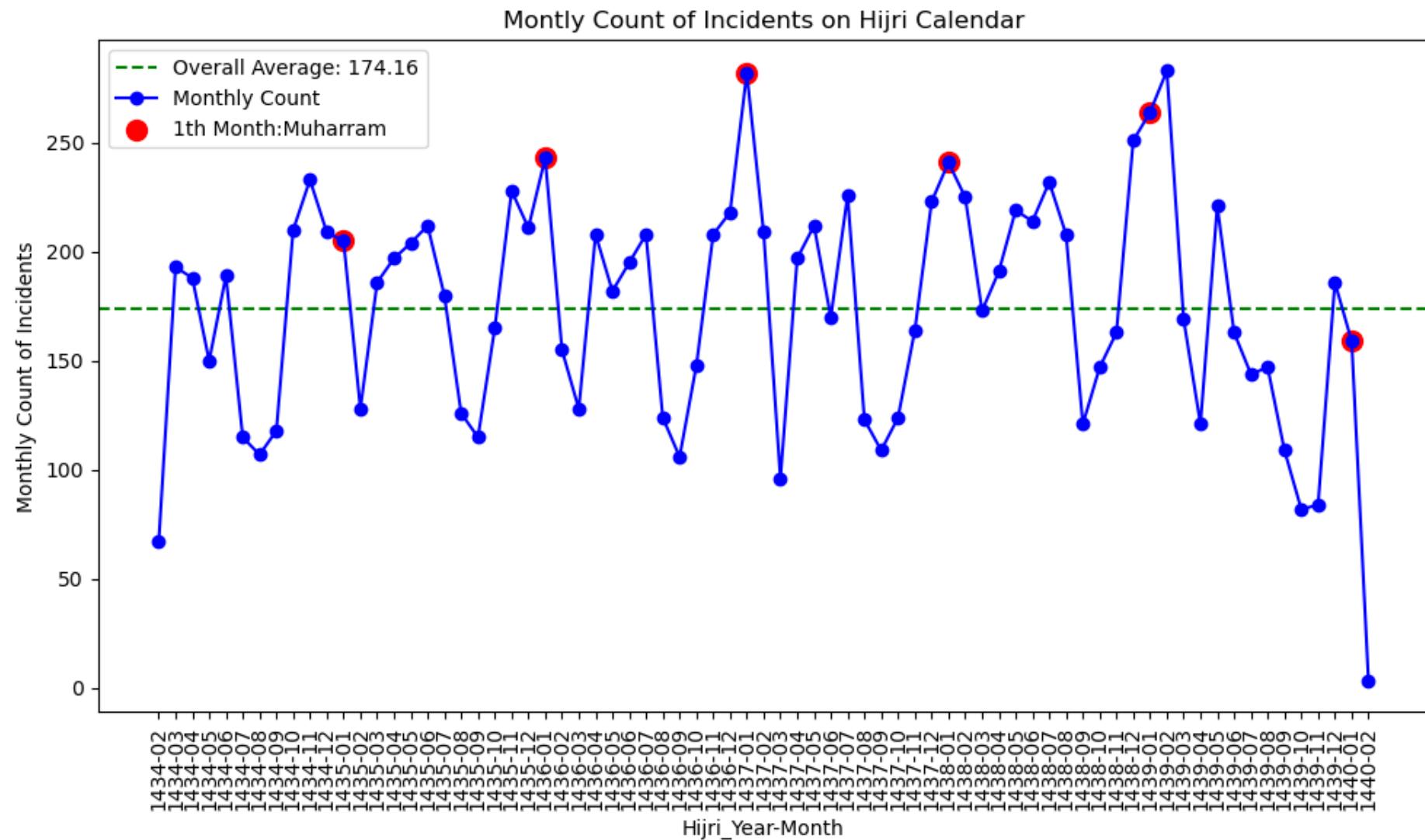
```
Out[28]: count      358
unique      90
top        EMS ASSIST
freq       73
Name: incident, dtype: object
```

```
In [29]: other_days_incidents_desc
```

```
Out[29]: count      9160
unique     719
top        EMS ASSIST
freq      1802
Name: incident, dtype: object
```

UNC dataset encompasses 730 distinct incident types. During the first ten days of Muharram, crimes were committed across 90 incident categories, with 76 of these categories experiencing incident counts exceeding the annual averages.

```
In [30]: monthly_count_plot()
```



## SAMPLE DATA-2: LOS ANGELES CRIME DATA\_2010-2019

<https://www.kaggle.com/datasets/cityofLA/los-angeles-crime-arrest-data/?select=crime-data-from-2010-to-present.csv>

```
In [73]: df = pd.read_csv("Los_Angles_crime-data-from-2010-to-present.csv")
df.head()
```

Out[73]:

	DR Number	Date Reported	Date Occurred	Time Occurred	Area ID	Area Name	Reporting District	Crime Code	Crime Code Description	MO Codes	...	Weapon Description	Status Code	Status Description	Crime Code 1	C
0	102005556	2010-01-25T00:00:00	2010-01-22T00:00:00	2300	20	Olympic	2071	510	VEHICLE - STOLEN	NaN	...	NaN	IC	Invest Cont	510.0	
1	101822289	2010-11-11T00:00:00	2010-11-10T00:00:00	1800	18	Southeast	1803	510	VEHICLE - STOLEN	NaN	...	NaN	IC	Invest Cont	510.0	
2	101105609	2010-01-28T00:00:00	2010-01-27T00:00:00	2230	11	Northeast	1125	510	VEHICLE - STOLEN	NaN	...	NaN	IC	Invest Cont	510.0	
3	101620051	2010-11-11T00:00:00	2010-11-07T00:00:00	1600	16	Foothill	1641	510	VEHICLE - STOLEN	NaN	...	NaN	IC	Invest Cont	510.0	
4	101910498	2010-04-07T00:00:00	2010-04-07T00:00:00	1600	19	Mission	1902	510	VEHICLE - STOLEN	NaN	...	NaN	IC	Invest Cont	510.0	

5 rows × 26 columns

duplicate\_values = df.duplicated(subset=None, keep='first').sum() df = df.drop\_duplicates()

In [74]: df.duplicated().value\_counts()

Out[74]: False 1993259  
dtype: int64

In [75]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1993259 entries, 0 to 1993258
Data columns (total 26 columns):
 #   Column           Dtype  
 --- 
 0   DR Number        int64  
 1   Date Reported    object  
 2   Date Occurred    object  
 3   Time Occurred    int64  
 4   Area ID          int64  
 5   Area Name         object  
 6   Reporting District int64  
 7   Crime Code        int64  
 8   Crime Code Description  object  
 9   MO Codes          object  
 10  Victim Age        int64  
 11  Victim Sex        object  
 12  Victim Descent   object  
 13  Premise Code      float64 
 14  Premise Description object  
 15  Weapon Used Code float64 
 16  Weapon Description object  
 17  Status Code        object  
 18  Status Description object  
 19  Crime Code 1       float64 
 20  Crime Code 2       float64 
 21  Crime Code 3       float64 
 22  Crime Code 4       float64 
 23  Address           object  
 24  Cross Street      object  
 25  Location          object  
dtypes: float64(6), int64(6), object(14)
memory usage: 395.4+ MB
```

```
In [76]: df = pd.read_csv("Los_Angeles_crime-data-from-2010-to-present.csv", usecols=[0,2,8])
```

```
In [77]: df["Crime Code Description"].value_counts()[:15]
```

```
Out[77]:
```

BATTERY - SIMPLE ASSAULT	180434
BURGLARY FROM VEHICLE	153451
VEHICLE - STOLEN	151622
THEFT PLAIN - PETTY (\$950 & UNDER)	141489
BURGLARY	140926
THEFT OF IDENTITY	120835
INTIMATE PARTNER - SIMPLE ASSAULT	107900
VANDALISM - FELONY (\$400 & OVER, ALL CHURCH VANDALISMS)	102589
ASSAULT WITH DEADLY WEAPON, AGGRAVATED ASSAULT	86829
VANDALISM - MISDEAMEANOR (\$399 OR UNDER)	86440
THEFT FROM MOTOR VEHICLE - PETTY (\$950 & UNDER)	82791
ROBBERY	79392
THEFT-GRAND (\$950.01 & OVER)EXCPT,GUNS,FOWL,LIVESTK,PROD	70081
CRIMINAL THREATS - NO WEAPON DISPLAYED	53959
SHOPLIFTING - PETTY THEFT (\$950 & UNDER)	45493

Name: Crime Code Description, dtype: int64

```
In [78]: df = df.rename(columns = {'Date Occurred':'date'})  
df = df.rename(columns = {'Crime Code Description':'incident'})
```

```
In [79]: df['date'] = pd.to_datetime(df['date']).dt.strftime('%Y-%m-%d')
```

```
In [80]: min(df.date), max(df.date)
```

```
Out[80]: ('2010-01-01', '2019-06-22')
```

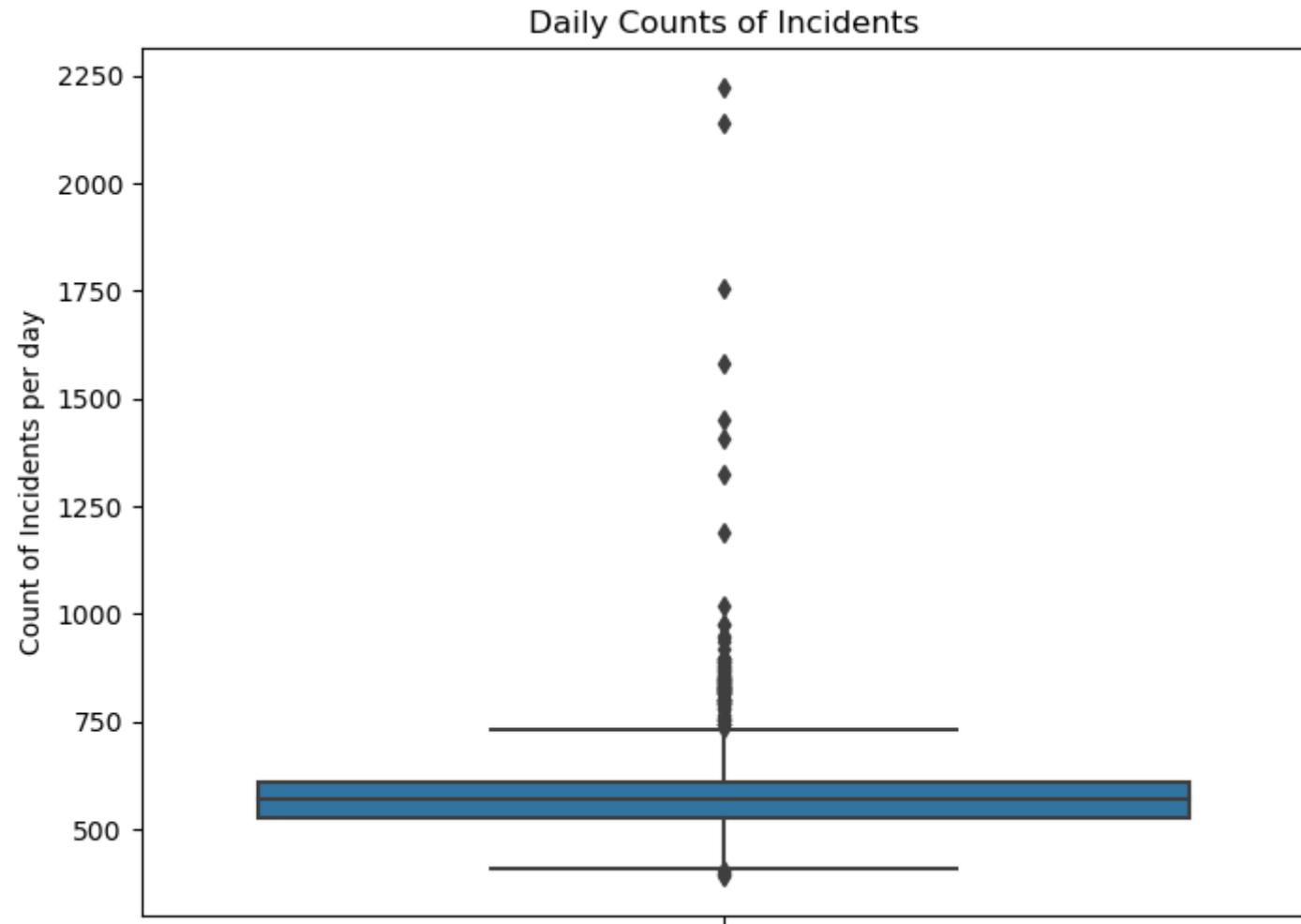
```
In [81]: daily_incident_counts_stats = df.groupby("date")['date'].value_counts().describe([.25, .5, .75, .95, .98, .99]).astype(int)  
daily_incident_counts_stats
```

```
Out[81]:
```

count	3460
mean	576
std	89
min	390
25%	528
50%	568
75%	610
95%	683
98%	820
99%	854
max	2222

Name: date, dtype: int32

```
In [82]: # Display the days with high incident numbers
plt.figure(figsize=(8, 6))
sns.boxplot(y=df.groupby("date")['date'].value_counts())
plt.title('Daily Counts of Incidents')
plt.ylabel('Count of Incidents per day')
plt.show()
```



```
In [83]: df.date.nunique()
```

```
Out[83]: 3460
```

As seen below, our dataset spans a total of 3460 days. Every day in the dataset contains a record of an incident. In other words, there are no days without any recorded incidents.

```
In [84]: muharrem_10_days (df)
```

Total number of days: 3460

-----  
Total number of cases: 1993259

-----  
Average Daily Case Count: 576.09

-----  
Yearly case counts according to the Gregorian calendar:

-----  
2017 229930  
2018 226909  
2016 224645  
2015 214822  
2010 208823  
2012 201170  
2011 200437  
2014 195022  
2013 192211  
2019 99290

Name: date, dtype: int64

-----  
Case counts according to the Hijri calendar:

-----  
1439 222769  
1438 221164  
1437 215516  
1436 205095  
1433 195939  
1431 195346  
1432 194561  
1434 188032  
1435 186913  
1440 167924

Name: Hijri\_Date, dtype: int64

-----  
Average case count in the first ten days of Muharram months: 518.65

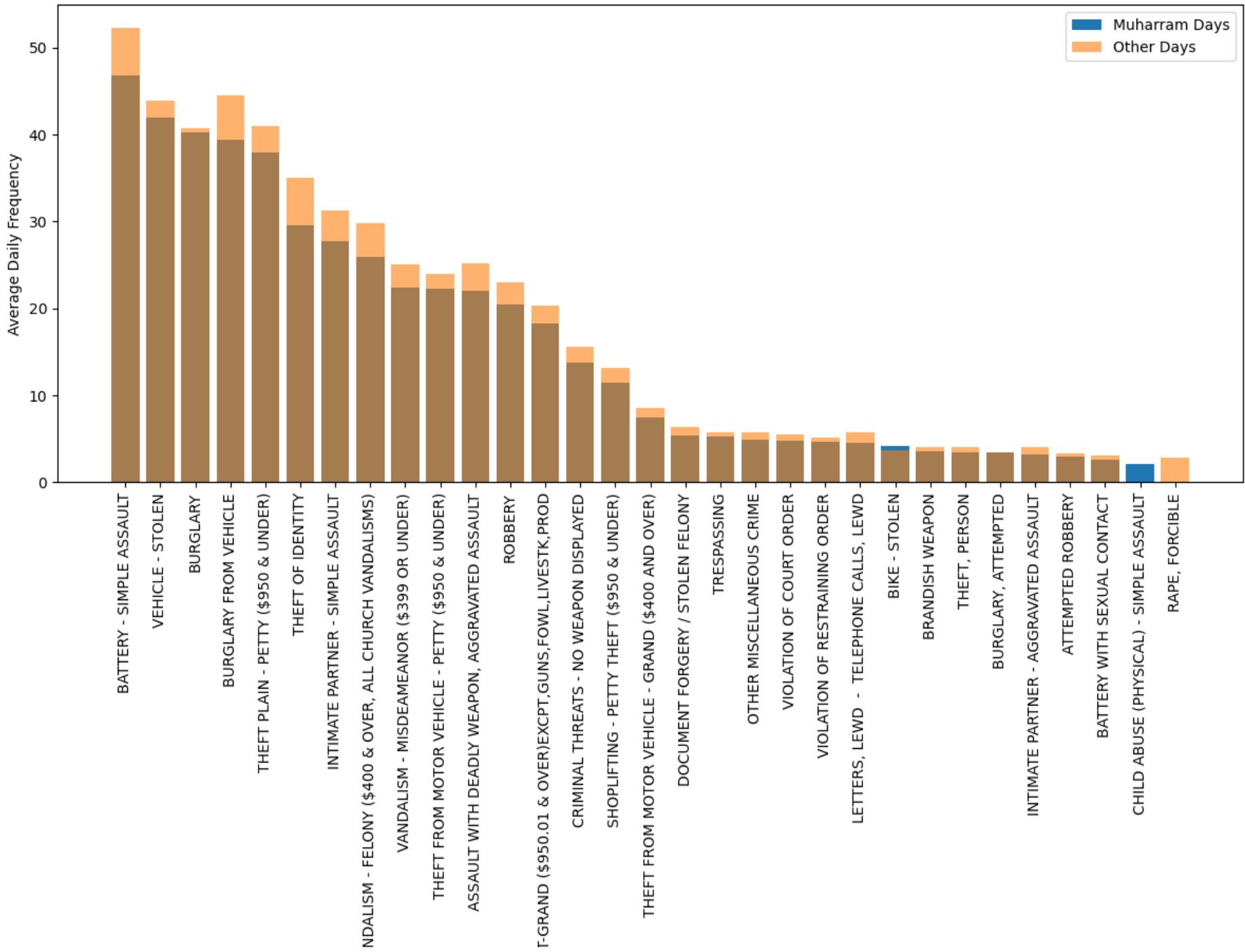
-----  
Average case count in other days: 577.7958

-----  
Ratio of Muharram cases to other cases: 0.8976

-----  
**We observe a -10.24% lower crime rate during the initial 10 days of the Muharram month compared to the annual average.**

```
In [85]: sorted_ratios, muharrem_dominant_incidents, muharrem_incidents_desc, other_days_incidents_desc = incidents_by_types(df)
```

Top 30 Incidents by Type



VA

THEF

### Incident Types

```
In [86]: # Top 30 incident types sorted by "muharrem incidents / total incidents" ratio  
sorted_ratios
```

Out[86]:

	muharrem incidents	all incidents	muharrem incidents/total incidents
INCEST (SEXUAL ACTS BETWEEN BLOOD RELATIVES)	2	9	0.222200
FAILURE TO DISPERSE	2	20	0.100000
TELEPHONE PROPERTY - DAMAGE	3	35	0.085700
DISRUPT SCHOOL	3	41	0.073200
THEFT, COIN MACHINE - GRAND (\$950.01 & OVER)	3	43	0.069800
DRUNK ROLL	2	34	0.058800
TILL TAP - PETTY (\$950 & UNDER)	5	93	0.053800
DRIVING WITHOUT OWNER CONSENT (DWOC)	21	450	0.046700
PICKPOCKET, ATTEMPT	1	22	0.045500
COUNTERFEIT	36	808	0.044600
CHILD STEALING	47	1053	0.044600
LYNCHING - ATTEMPTED	1	23	0.043500
REPLICA FIREARMS(SALE,DISPLAY,MANUFACTURE OR DISTRIBUTE)	1	24	0.041700
BEASTIALITY, CRIME AGAINST NATURE SEXUAL ASSLT WITH ANIM	1	25	0.040000
LEWD/LASCIVIOUS ACTS WITH CHILD	8	213	0.037600
CHILD PORNOGRAPHY	7	189	0.037000
CONSPIRACY	2	54	0.037000
KIDNAPPING	71	1929	0.036800
WEAPONS POSSESSION/BOMBING	6	163	0.036800
EMBEZZLEMENT, PETTY THEFT (\$950 & UNDER)	20	560	0.035700
THEFT PLAIN - ATTEMPT	56	1589	0.035200
KIDNAPPING - GRAND ATTEMPT	23	689	0.033400
BRIBERY	1	30	0.033300
DOCUMENT WORTHLESS (\$200 & UNDER)	2	60	0.033300

	muharrem incidents	all incidents	muharrem incidents/total incidents
<b>CREDIT CARDS, FRAUD USE (\$950 &amp; UNDER</b>	9	272	0.033100
<b>BOMB SCARE</b>	37	1126	0.032900
<b>BIKE - STOLEN</b>	421	12996	0.032400
<b>SHOPLIFTING - ATTEMPT</b>	7	216	0.032400
<b>DEFRAUDING INNKEEPER/THEFT OF SERVICES, \$400 &amp; UNDER</b>	64	2068	0.030900
<b>PICKPOCKET</b>	27	899	0.030000

In [87]: *# In which categories were more crimes committed during the first ten days of Muharram?*  
muharrem\_dominant\_incidents

Out[87]:

	muharrem incidents	all incidents	muharrem incidents/total incidents
BIKE - STOLEN	421	12996	0.0324
VEHICLE - ATTEMPT STOLEN	94	3190	0.0295
KIDNAPPING	71	1929	0.0368
DEFRAUDING INNKEEPER/THEFT OF SERVICES, \$400 & UNDER	64	2068	0.0309
THEFT PLAIN - ATTEMPT	56	1589	0.0352
CHILD STEALING	47	1053	0.0446
THROWING OBJECT AT MOVING VEHICLE	45	1529	0.0294
BOMB SCARE	37	1126	0.0329
COUNTERFEIT	36	808	0.0446
PURSE SNATCHING	33	1139	0.0290
PEEPING TOM	33	1113	0.0296
PICKPOCKET	27	899	0.0300
KIDNAPPING - GRAND ATTEMPT	23	689	0.0334
DRIVING WITHOUT OWNER CONSENT (DWOC)	21	450	0.0467
EMBEZZLEMENT, PETTY THEFT (\$950 & UNDER)	20	560	0.0357
CREDIT CARDS, FRAUD USE (\$950 & UNDER)	9	272	0.0331
LEWD/LASCIVIOUS ACTS WITH CHILD	8	213	0.0376
CHILD PORNOGRAPHY	7	189	0.0370
SHOPLIFTING - ATTEMPT	7	216	0.0324
WEAPONS POSSESSION/BOMBING	6	163	0.0368
TILL TAP - PETTY (\$950 & UNDER)	5	93	0.0538
TELEPHONE PROPERTY - DAMAGE	3	35	0.0857
DISRUPT SCHOOL	3	41	0.0732
THEFT, COIN MACHINE - GRAND (\$950.01 & OVER)	3	43	0.0698

	muharrem incidents	all incidents	muharrem incidents/total incidents
INCEST (SEXUAL ACTS BETWEEN BLOOD RELATIVES)	2	9	0.2222
FAILURE TO DISPERSE	2	20	0.1000
DRUNK ROLL	2	34	0.0588
DOCUMENT WORTHLESS (\$200 & UNDER)	2	60	0.0333
CONSPIRACY	2	54	0.0370
LYNCHING - ATTEMPTED	1	23	0.0435
PICKPOCKET, ATTEMPT	1	22	0.0455
REPLICA FIREARMS(SALE,DISPLAY,MANUFACTURE OR DISTRIBUTE)	1	24	0.0417
BRIBERY	1	30	0.0333
BEASTIALITY, CRIME AGAINST NATURE SEXUAL ASSLT WITH ANIM	1	25	0.0400

More crimes were committed in the above-mentioned crime categories during the first ten days of Muharram compared to the other days of the year.

```
In [88]: df.incident.nunique(), muharrem_dominant_incidents.count()[0]
```

```
Out[88]: (140, 34)
```

```
In [89]: muharrem_incidents_desc
```

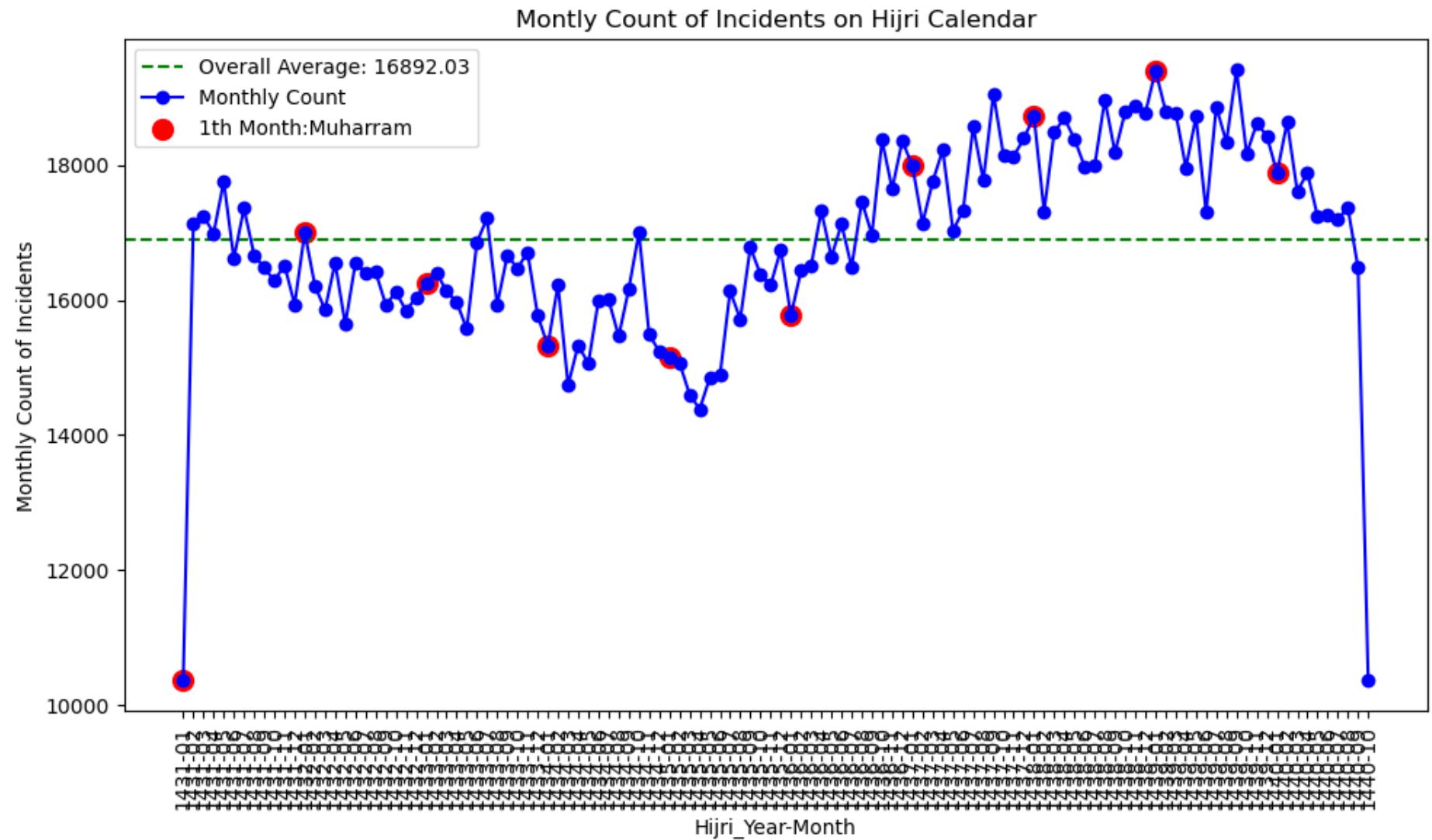
```
Out[89]: count          51865
unique         122
top      BATTERY - SIMPLE ASSAULT
freq           4677
Name: incident, dtype: object
```

```
In [90]: other_days_incidents_desc
```

```
Out[90]: count          1941394
unique         140
top      BATTERY - SIMPLE ASSAULT
freq           175757
Name: incident, dtype: object
```

Los Angeles dataset encompasses 140 distinct incident types. During the first ten days of Muharram, crimes were committed across 122 incident categories, with 34 of these categories experiencing incident counts exceeding the annual averages.

```
In [91]: monthly_count_plot()
```



## SAMPLE DATA-3: KANSAS CITY CRIME DATA\_2009-2016

<https://data.world/data-society/kansas-city-crime-data>

```
In [92]: df2 = pd.read_csv("KCPD_Crime_Data_2009.csv")
df3 = pd.read_csv("KCPD_Crime_Data_2010.csv")
df4 = pd.read_csv("KCPD_Crime_Data_2011.csv")
df5 = pd.read_csv("KCPD_Crime_Data_2012.csv")
df6 = pd.read_csv("KCPD_Crime_Data_2013.csv")
df7 = pd.read_csv("KCPD_Crime_Data_2014.csv")
df8 = pd.read_csv("KCPD_Crime_Data_2015.csv")
df9 = pd.read_csv("KCPD_Crime_Data_2016.csv")
```

```
In [93]: frames = [df2, df3, df4, df5, df6, df7, df8, df9]
df = pd.concat(frames)
```

```
In [94]: df.head()
```

Out[94]:

	Report_No	Reported_Date	Reported_Time	From_Date	From_Time	To_Date	To_Time	Offense	IBRS	Description	...	Involvement	Race	Sex	Age
0	70059279	10/06/2009 12:00:00 AM	3:24	10/05/2009 12:00:00 AM	22:56	10/05/2009 12:00:00 AM	23:10	1850	35B	Possession of Drug E	...	ARR	B	F	28.0
1	80005443	02/05/2009 12:00:00 AM	11:45	01/22/2008 12:00:00 AM	12:00	Nan	Nan	121	09C	Justifiable Homicide	...	SUS	W	M	27.0
2	80019629	06/18/2009 12:00:00 AM	22:50	06/18/2009 12:00:00 AM	21:15	Nan	Nan	1849	35A	Possession/Sale/Dist	...	ARR	W	M	22.0
3	70060962	01/28/2009 12:00:00 AM	18:44	01/28/2009 12:00:00 AM	18:44	Nan	Nan	1352	280	Stolen Property OFFE	...	VIC	U	U	Nan
4	80005443	02/05/2009 12:00:00 AM	11:45	01/22/2008 12:00:00 AM	12:00	Nan	Nan	121	09C	Justifiable Homicide	...	SUS	W	M	28.0

5 rows × 28 columns

In [95]: df.duplicated().value_counts()
Out[95]: False 1007956 True 3518 dtype: int64
In [96]: df = df.drop_duplicates()
In [97]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1007956 entries, 0 to 110891
Data columns (total 28 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   Report_No        1007956 non-null   int64  
 1   Reported_Date    1007956 non-null   object  
 2   Reported_Time    897459 non-null   object  
 3   From_Date        1006558 non-null   object  
 4   From_Time        895625 non-null   object  
 5   To_Date          422549 non-null   object  
 6   To_Time          378834 non-null   object  
 7   Offense          1007956 non-null   int64  
 8   IBRS             999468 non-null   object  
 9   Description       1007956 non-null   object  
 10  Beat              1006287 non-null   object  
 11  Address           883108 non-null   object  
 12  City              883108 non-null   object  
 13  Zip Code          976536 non-null   float64 
 14  Rep_Dist          1005055 non-null   object  
 15  Area              1005028 non-null   object  
 16  DVFlag            1007956 non-null   object  
 17  Invl_No          1007956 non-null   int64  
 18  Involvement       1007956 non-null   object  
 19  Race              875255 non-null   object  
 20  Sex                875255 non-null   object  
 21  Age                582586 non-null   float64 
 22  Location_1        1007262 non-null   object  
 23  Firearm Used Flag 775917 non-null   object  
 24  Firearm Used Flag 232039 non-null   object  
 25  Reported_Time     110497 non-null   object  
 26  From_Time         110180 non-null   object  
 27  To_Time           39925 non-null    object  
dtypes: float64(2), int64(3), object(23)
memory usage: 223.0+ MB
```

```
In [98]: df["Description"].value_counts()[:15]
```

```
Out[98]: Burglary - Residence    93609  
Property Damage                87921  
Stealing From Auto             68821  
Non Agg Assault Dome          63608  
Auto Theft                     61302  
Stealing Auto Parts/           52498  
Non Aggravated Assau          52272  
Misc Violation                 51407  
Stealing Shoplifting            46401  
Stealing from Buildi           43149  
Stealing All Other              41074  
Aggravated Assault (           40332  
Possession/Sale/Dist          34013  
Armed Robbery                  30324  
Trespassing                    23800  
Name: Description, dtype: int64
```

```
In [99]: df = df.rename(columns = {'Reported_Date':'date'})  
df = df.rename(columns = {'Description':'incident'})
```

```
In [100...]: df['date'] = pd.to_datetime(df['date']).dt.strftime('%Y-%m-%d')
```

```
In [101...]: df.date.min(), df.date.max()
```

```
Out[101]: ('2009-01-01', '2016-11-06')
```

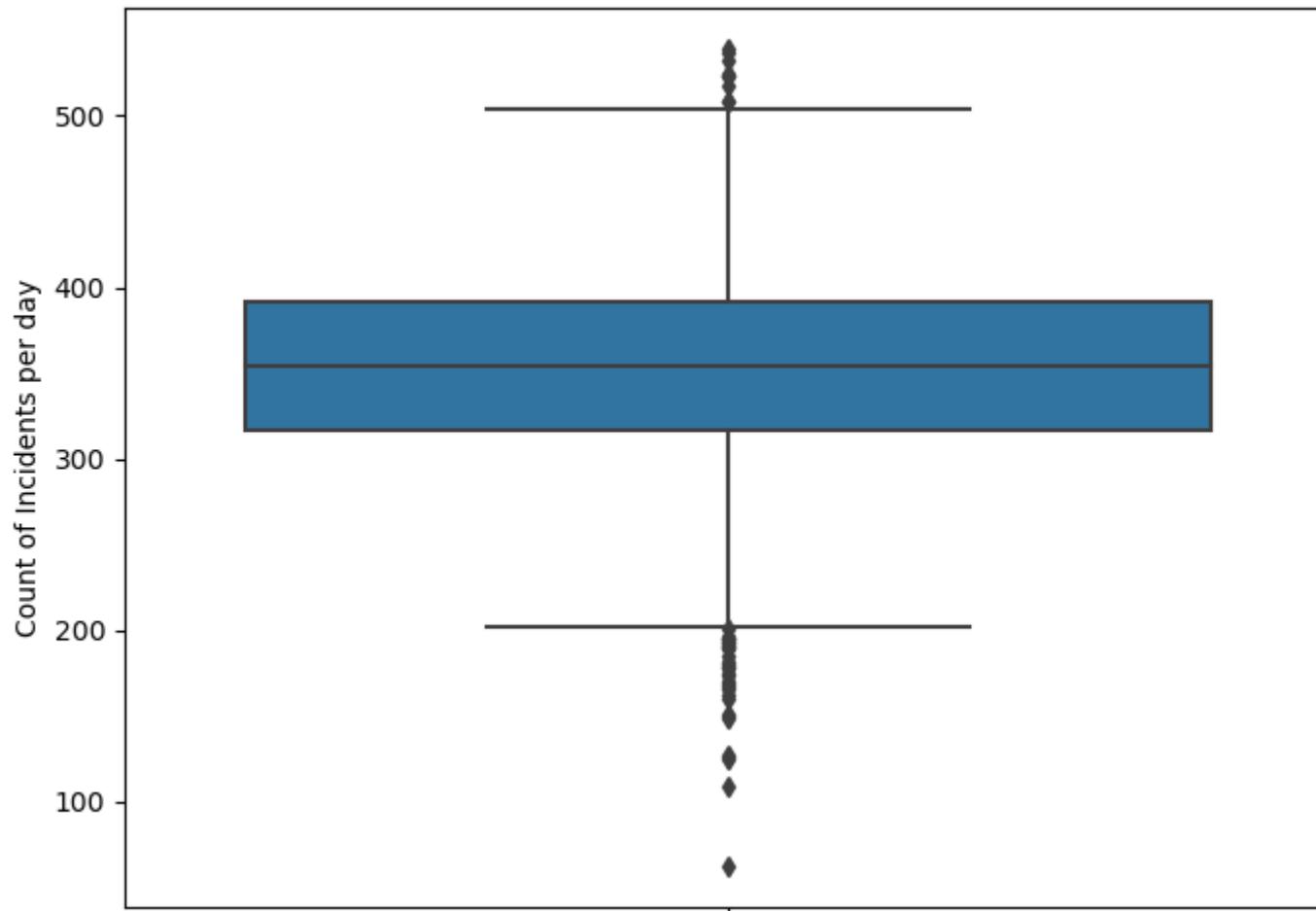
```
In [102...]: df = df.iloc[:, [1,9]]  
# df.to_csv("Kansas.csv", index=False)
```

```
In [103...]: daily_incident_counts_stats = df.groupby("date")['date'].value_counts().describe([.25, .5, .75, .95, .98, .99]).astype(int)  
daily_incident_counts_stats
```

```
Out[103]: count    2858
          mean     352
          std      58
          min      62
          25%    316
          50%    354
          75%    392
          95%    443
          98%    468
          99%    484
          max     539
Name: date, dtype: int32
```

```
In [104...]: # Display the days with high incident numbers
plt.figure(figsize=(8, 6))
sns.boxplot(y=df.groupby("date")['date'].value_counts())
plt.title('Daily Counts of Incidents')
plt.ylabel('Count of Incidents per day')
plt.show()
```

### Daily Counts of Incidents



```
In [105]: df.date.unique()
```

```
Out[105]: 2858
```

As seen below, our dataset spans a total of 2867 days. During this period, incidents occurred on 2858 days, while there were no records of incidents on the remaining 9 days.

```
In [106]: muharrem_10_days (df)
```

```
Total number of days: 2867
```

```
-----  
Total number of cases: 1007956
```

```
-----  
Average Daily Case Count: 351.57
```

```
-----  
Yearly case counts according to the Gregorian calendar:
```

```
-----  
2010    136056  
2009    132535  
2012    130290  
2011    128072  
2013    124732  
2014    124232  
2015    121542  
2016    110497
```

```
Name: date, dtype: int64
```

```
-----  
Case counts according to the Hijri calendar:
```

```
-----  
1431    131791  
1430    128579  
1433    126531  
1434    126102  
1432    124047  
1437    123207  
1435    117771  
1436    117002  
1438    12926
```

```
Name: Hijri_Date, dtype: int64
```

```
-----  
Average case count in the first ten days of Muharram months: 324.0444
```

```
-----  
Average case count in other days: 352.4638
```

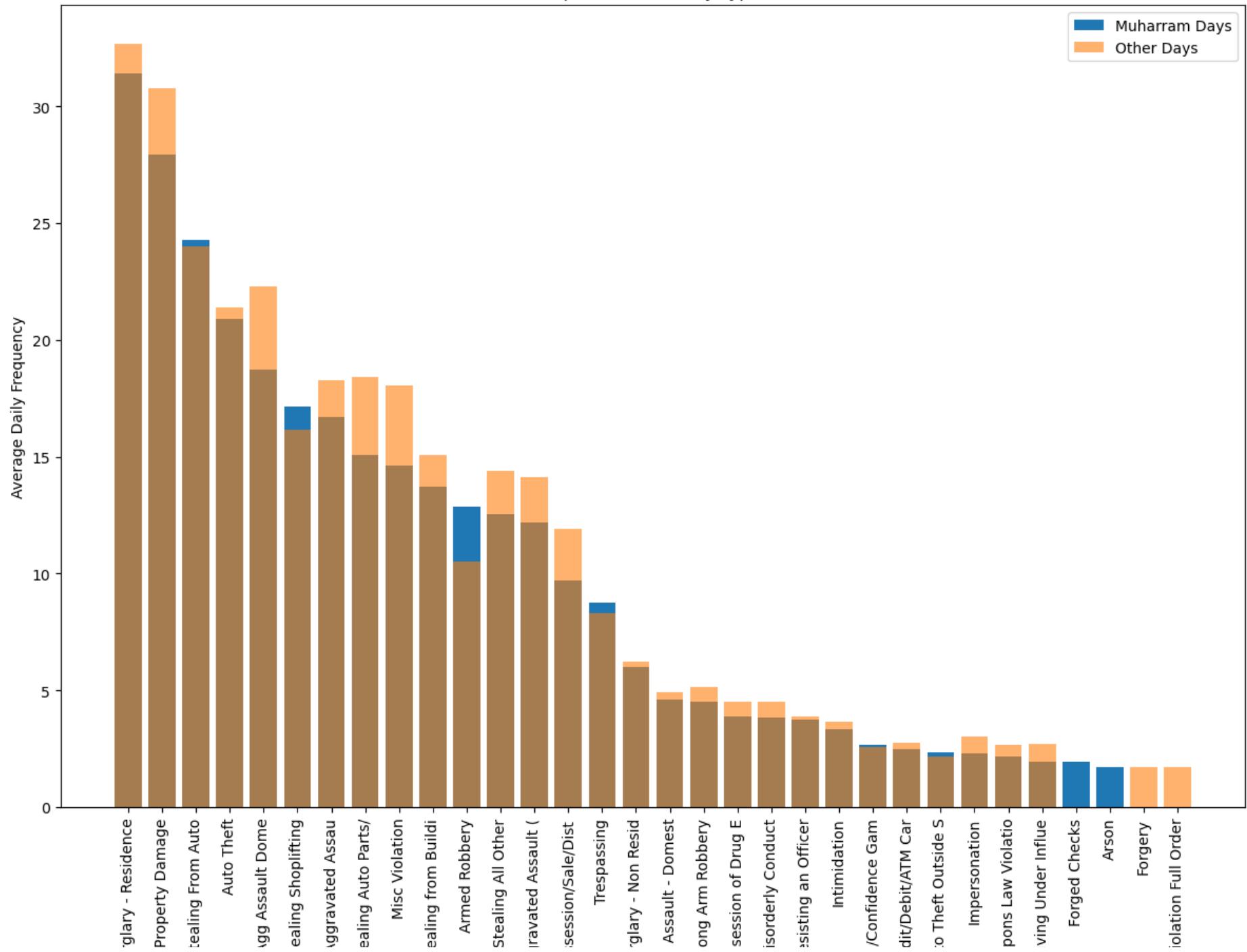
```
-----  
Ratio of Muharram cases to other cases: 0.9194
```

**We observe a -8.06% lower crime rate during the initial 10 days of the Muharram month compared to the annual average.**

```
In [107]:
```

```
sorted_ratios, muharrem_dominant_incidents, muharrem_incidents_desc, other_days_incidents_desc = incidents_by_types(df)  
# display(sorted_ratios)  
# display(muharrem_dominant_incidents)
```

Top 30 Incidents by Type



In [108]:

```
# Top 30 incident types sorted by "muharrem incidents / total incidents" ratio
sorted_ratios
```

Out[108]:

	<b>muharrem incidents</b>	<b>all incidents</b>	<b>muharrem incidents/total incidents</b>
<b>stolen/recoverd auto</b>	4	4	1.000000
<b>Harassment</b>	2	4	0.500000
<b>auto theft</b>	2	4	0.500000
<b>aggravated assault</b>	2	4	0.500000
<b>Agg Assault Dome</b>	4	10	0.400000
<b>AUTO THEFT</b>	2	6	0.333300
<b>Alien</b>	3	10	0.300000
<b>c</b>	2	8	0.250000
<b>Attempt Suicide by G</b>	1	9	0.111100
<b>False Bomb Report/Bo</b>	2	29	0.069000
<b>Suicide by Other Mea</b>	1	17	0.058800
<b>Stalking</b>	4	80	0.050000
<b>Forged Checks</b>	173	3494	0.049500
<b>Impersonation - NOT</b>	26	540	0.048100
<b>Kidnapping/Abduction</b>	40	874	0.045800
<b>Sex Off Indecent Con</b>	31	682	0.045500
<b>Stealing Purse Snatc</b>	50	1154	0.043300
<b>Passing Bad Checks</b>	14	325	0.043100
<b>Dangerous and Concea</b>	8	189	0.042300
<b>Stealing Pickpocket</b>	45	1074	0.041900
<b>Statutory Rape</b>	29	703	0.041300
<b>Pornography</b>	10	249	0.040200
<b>HOMICIDE</b>	2	52	0.038500
<b>Counterfeiting</b>	33	862	0.038300

	<b>muharrem incidents</b>	<b>all incidents</b>	<b>muharrem incidents/total incidents</b>
<b>Armed Robbery</b>	1157	30324	0.038200
<b>Interference with Cu</b>	27	732	0.036900
<b>Arson</b>	155	4311	0.036000
<b>Attempt Suicide by H</b>	4	112	0.035700
<b>Arson with Fire Bomb</b>	5	142	0.035200
<b>Attempt Suicide by O</b>	8	228	0.035100

In [109]:

```
# In which categories were more crimes committed during the first ten days of Muharram?
muharrem_dominant_incidents
```

Out[109]:

	muharrem incidents	all incidents	muharrem incidents/total incidents
<b>Stealing From Auto</b>	2184	68821	0.0317
<b>Stealing Shoplifting</b>	1545	46401	0.0333
<b>Armed Robbery</b>	1157	30324	0.0382
<b>Trespassing</b>	787	23800	0.0331
<b>Fraud/Confidence Gam</b>	241	7380	0.0327
<b>Auto Theft Outside S</b>	212	6255	0.0339
<b>Forged Checks</b>	173	3494	0.0495
<b>Arson</b>	155	4311	0.0360
<b>Liquor Law Violaton</b>	71	2130	0.0333
<b>Stealing Purse Snatc</b>	50	1154	0.0433
<b>Stealing Pickpocket</b>	45	1074	0.0419
<b>Kidnapping/Abduction</b>	40	874	0.0458
<b>Counterfeiting</b>	33	862	0.0383
<b>Sex Off Indecent Con</b>	31	682	0.0455
<b>Statutory Rape</b>	29	703	0.0413
<b>Interference with Cu</b>	27	732	0.0369
<b>Impersonation - NOT</b>	26	540	0.0481
<b>Passing Bad Checks</b>	14	325	0.0431
<b>Pornography</b>	10	249	0.0402
<b>Dangerous and Concea</b>	8	189	0.0423
<b>Attempt Suicide by O</b>	8	228	0.0351
<b>Loitering</b>	7	219	0.0320
<b>Arson with Fire Bomb</b>	5	142	0.0352
<b>Stalking</b>	4	80	0.0500

	<b>muharrem incidents</b>	<b>all incidents</b>	<b>muharrem incidents/total incidents</b>
<b>stolen/recoverd auto</b>	4	4	1.0000
<b>Agg Assault Dome</b>	4	10	0.4000
<b>Hit and Run of a Per</b>	4	121	0.0331
<b>Attempt Suicide by H</b>	4	112	0.0357
<b>Alien</b>	3	10	0.3000
<b>Harassment</b>	2	4	0.5000
<b>HOMICIDE</b>	2	52	0.0385
<b>False Bomb Report/Bo</b>	2	29	0.0690
<b>aggravated assault</b>	2	4	0.5000
<b>auto theft</b>	2	4	0.5000
<b>c</b>	2	8	0.2500
<b>AUTO THEFT</b>	2	6	0.3333
<b>Attempt Suicide by G</b>	1	9	0.1111
<b>Suicide by Other Mea</b>	1	17	0.0588

More crimes were committed in the above-mentioned crime categories during the first ten days of Muharram compared to the other days of the year.

```
In [110]: df.incident.nunique(), muharrem_dominant_incidents.count()[0]
```

```
Out[110]: (259, 38)
```

```
In [111]: muharrem_incidents_desc
```

```
Out[111]: count          29164
unique           96
top      Burglary - Residence
freq            2827
Name: incident, dtype: object
```

```
In [112]: other_days_incidents_desc
```

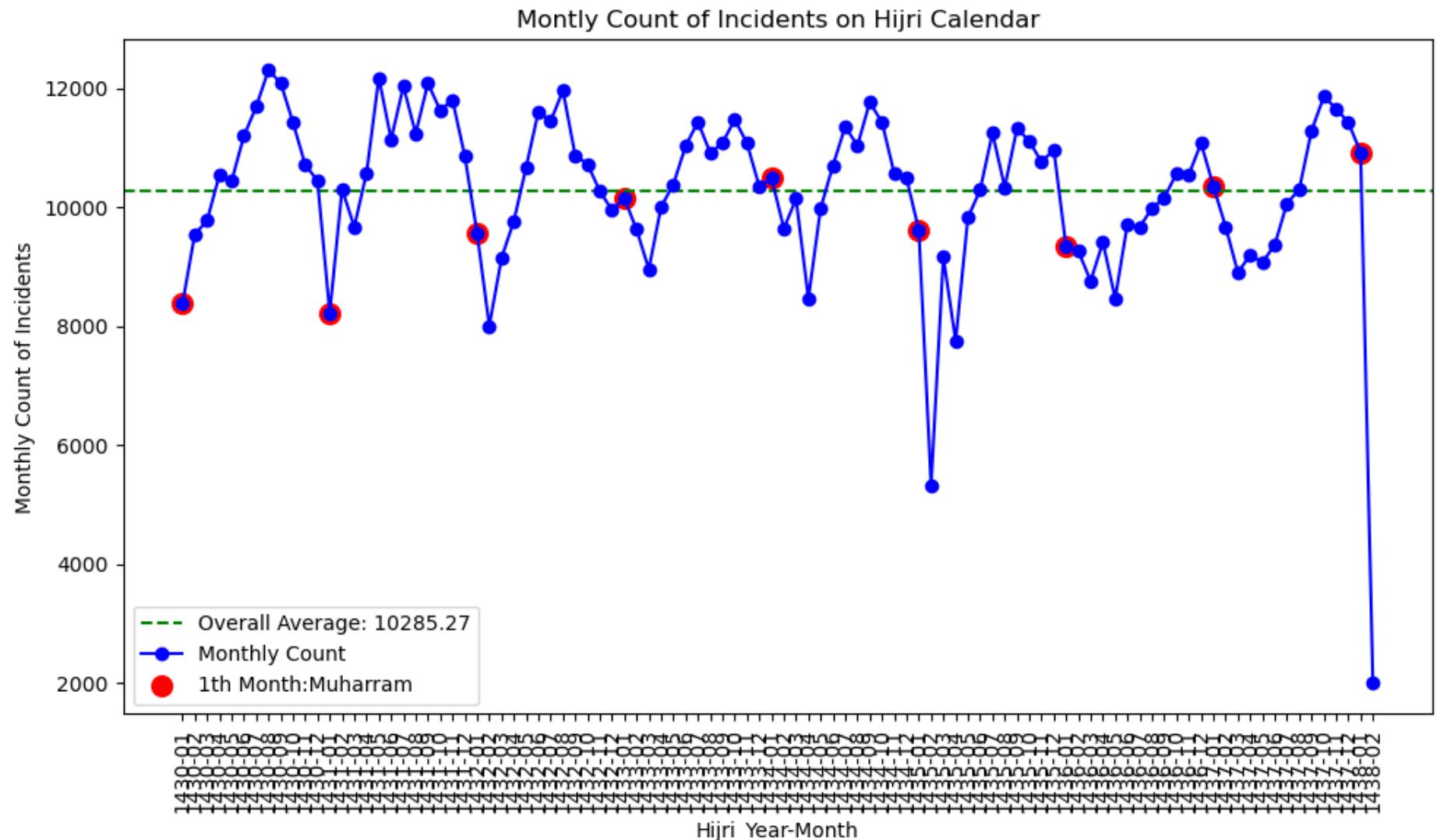
```
Out[112]: count          978792  
unique           258  
top    Burglary - Residence  
freq            90782  
Name: incident, dtype: object
```

```
In [113]: muharrem_dominant_incidents.count()[0]
```

```
Out[113]: 38
```

Kansas dataset encompasses 259 distinct incident types. During the first ten days of Muharram, crimes were committed across 96 incident categories, with 38 of these categories experiencing incident counts exceeding the annual averages.

```
In [114]: monthly_count_plot()
```



## SAMPLE DATA-4: DETROIT CRIME INCIDENTS\_2009-2016

<https://data.world/detroit/dpd-crime-incidents-2009-2016>

In [115]:

```
df = pd.read_csv("Detroit_crime-incidents-2009-2016.csv", index_col=0, low_memory=False)  
df
```

Out[115]:

	CASEID	CRIMEID	CRNO	ADDRESS	CATEGORY	OFFENSEDESCRIPTION	STATEOFFENSEFILECLASS	INCIDENTDATE	HOUR	\$
ROWNUM										
1	1099487	1321797	0910020373.1	18000 WEXFORD	MISCELLANEOUS	MISCELLANEOUS - GENERAL NON-CRIMINAL	99009.0	01/01/2009	0	110
2	1117507	1344185	0911060289.1	00 UNKNOWN	MISCELLANEOUS	MISCELLANEOUS - GENERAL NON-CRIMINAL	99009.0	01/01/2009	0	N
3	985415	1181882	0902190512.1	02000 CALVERT	MISCELLANEOUS	MISCELLANEOUS - ABANDONED VEHICLE	99009.0	01/01/2009	0	100
4	986019	1182632	0902200294.1	00 W GRAND BLVD AND W FORT	MISCELLANEOUS	MISCELLANEOUS - GENERAL NON-CRIMINAL	99009.0	01/01/2009	0	41
5	996883	1195867	0903170149.1	12500 CONNER	LARCENY	LARCENY - FROM BUILDING (INCLUDES LIBRARY, OFF...	23003.0	01/01/2009	0	90
...	...	...	...	...	...	...	...	...	...	...
1150376	2104068	2593922	1606250233.1	00 WOODWARD AND WEBB	DANGEROUS DRUGS	COCAINE -POSSESS	35001.0	06/25/2016	17	30
1150499	2104173	2594059	1606260030.1	20100 STANSBURY	MISCELLANEOUS	MISCELLANEOUS - GENERAL ASSISTANCE	99008.0	06/26/2016	1	120
1150527	2104193	2594076	1606260049.1	12100 FORRER	BURGLARY	BURGLARY - BURGLARY - FORCED ENTRY - RESIDENCE	22001.0	06/26/2016	3	60
1150614	2104329	2594236	1606260182.1	00 PURITAN GREENFIELD	MISCELLANEOUS	MISCELLANEOUS - IMPOUNDED VEHICLE	99009.0	06/26/2016	12	20
1150712	2104430	2594364	1606260281.1	15100 LAHSER	ASSAULT	ASSAULT AND BATTERY/SIMPLE ASSAULT	13001.0	06/26/2016	20	60

```
In [116]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1151019 entries, 1 to 1150712
Data columns (total 17 columns):
 #   Column            Non-Null Count  Dtype  
---  --  
 0   CASEID           1151019 non-null   int64  
 1   CRIMEID          1151019 non-null   int64  
 2   CRNO              1151019 non-null   object  
 3   ADDRESS           1151019 non-null   object  
 4   CATEGORY          1151019 non-null   object  
 5   OFFENSEDESCRIPTION 1150959 non-null   object  
 6   STATEOFFENSEFILECLASS 1150959 non-null   float64 
 7   INCIDENTDATE      1151019 non-null   object  
 8   HOUR               1151019 non-null   int64  
 9   SCA                1142973 non-null   float64 
 10  PRECINCT          1142973 non-null   float64 
 11  COUNCIL            1127234 non-null   object  
 12  NEIGHBORHOOD       1136581 non-null   object  
 13  CENSUSTRACT        1072395 non-null   float64 
 14  LON                1151018 non-null   float64 
 15  LAT                1151018 non-null   float64 
 16  LOCATION           1151019 non-null   object  
dtypes: float64(6), int64(3), object(8)
memory usage: 158.1+ MB
```

```
In [117]: df.duplicated().value_counts()
```

```
Out[117]: False    1151019
dtype: int64
```

```
In [118]: df["CATEGORY"].value_counts()
```

Out[118]:

MISCELLANEOUS	174164
ASSAULT	141608
LARCENY	133666
BURGLARY	109073
DAMAGE TO PROPERTY	93781
STOLEN VEHICLE	89445
AGGRAVATED ASSAULT	72577
MURDER/INFORMATION	71694
TRAFFIC	63890
FRAUD	40357
ROBBERY	39292
DANGEROUS DRUGS	28081
ESCAPE	13617
WEAPONS OFFENSES	13268
OBSTRUCTING JUDICIARY	11345
DISORDERLY CONDUCT	9252
OUIL	8557
ARSON	6891
SOLICITATION	3872
OBSTRUCTING THE POLICE	3268
STOLEN PROPERTY	3249
OTHER	3135
OTHER BURGLARY	3065
HOMICIDE	2541
FAMILY OFFENSE	1997
FORGERY	1609
KIDNAPING	1588
RUNAWAY	1457
VAGRANCY (OTHER)	1138
EXTORTION	1099
LIQUOR	782
ENVIRONMENT	563
EMBEZZLEMENT	346
CIVIL	176
IMMIGRATION	159
JUSTIFIABLE HOMICIDE	136
NEGLIGENT HOMICIDE	67
KIDNAPPING	64
OBSCENITY	46
GAMBLING	39
BRIBERY	19
DRUNKENNESS	19
MISCELLANEOUS ARREST	17
TRAFFIC OFFENSES	5

```
MILITARY          4  
ABORTION          1  
Name: CATEGORY, dtype: int64
```

```
In [119]: df["OFFENSEDESCRIPTION"].value_counts()
```

```
Out[119]: ASSAULT AND BATTERY/SIMPLE ASSAULT      98560  
VEHICLE THEFT           82957  
INFORMATION            71694  
DAMAGE TO PROPERTY - PRIVATE PROPERTY       68202  
BURGLARY - BURGLARY - FORCED ENTRY - RESIDENCE 67025  
...  
ARSON - BUSINESS - DEFRAUD INSURER           1  
TRAFFIC VIOLATIONS - ILLEGAL TOWING EQUIPMENT 1  
PERMITTED PERSON UNDER THE INFLUENCE OF DRUGS TO OPERATE 1  
TRAFFIC VIOLATIONS - DEFECTIVE OR IMPROPER BRAKES    1  
ACCIDENTS, ALL OTHER NON-CRIMINAL - AIRCRAFT        1  
Name: OFFENSEDESCRIPTION, Length: 584, dtype: int64
```

```
In [120]: df = df.rename(columns = {'INCIDENTDATE':'date'})  
df = df.rename(columns = {'CATEGORY':'incident'})
```

```
In [121]: df['date'] = pd.to_datetime(df['date']).dt.strftime('%Y-%m-%d')
```

```
In [122]: df.date.min(), df.date.max()
```

```
Out[122]: ('2009-01-01', '2016-06-28')
```

```
In [123]: df = df.iloc[:, [4,7]]  
# df.to_csv("Detroit.csv", index=False)
```

```
In [124]: daily_incident_counts_stats = df.groupby("date")['date'].value_counts().describe([.25, .5, .75, .95, .98, .99]).astype(int)  
daily_incident_counts_stats
```

```
Out[124]: count    2736  
mean      420  
std       68  
min       1  
25%     374  
50%     417  
75%     465  
95%     539  
98%     565  
99%     584  
max     655  
Name: date, dtype: int32
```

```
In [125...]  
# Display the days with high incident numbers  
plt.figure(figsize=(8, 6))  
sns.boxplot(y=df.groupby("date")['date'].value_counts())  
plt.title('Daily Counts of Incidents')  
plt.ylabel('Count of Incidents per day')  
plt.show()
```



```
In [126]: df.date.unique()
```

```
Out[126]: 2736
```

As seen below, our dataset spans a total of 2736 days. Every day in the dataset contains a record of an incident. In other words, there are no days without any recorded incidents.

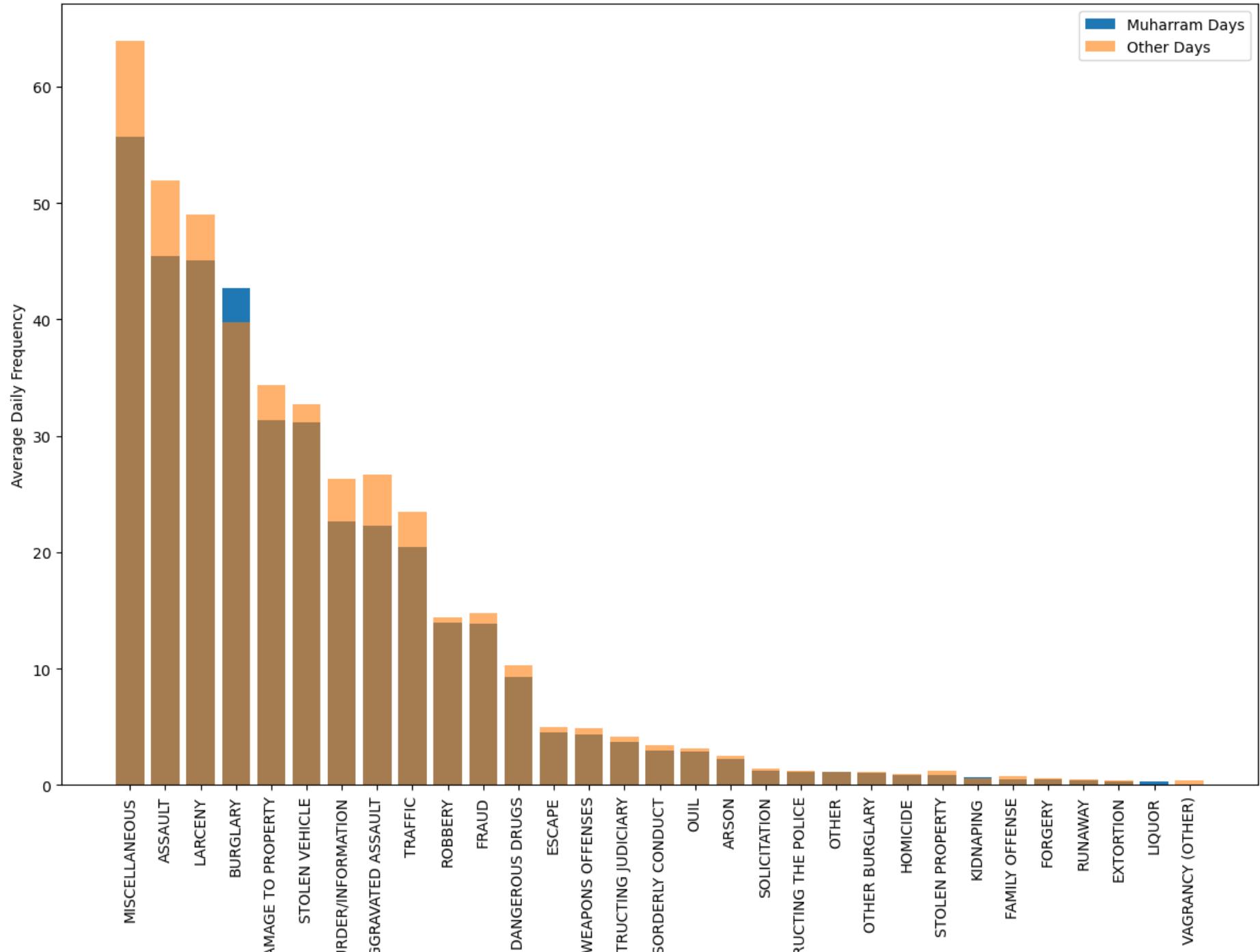
```
In [127]: muharrem_10_days(df)
```

```
Total number of days: 2736
-----
Total number of cases: 1151019
-----
Average Daily Case Count: 420.69
-----
Yearly case counts according to the Gregorian calendar:
-----
2009    181681
2010    170599
2011    157248
2012    156133
2013    146908
2015    137044
2014    136628
2016    64778
Name: date, dtype: int64
-----
Case counts according to the Hijri calendar:
-----
1430    175663
1431    166733
1433    153006
1432    152251
1434    144344
1435    132697
1436    132393
1437    93932
Name: Hijri_Date, dtype: int64
-----
Average case count in the first ten days of Muharram months: 384.4375
-----
Average case count in other days: 421.7861
-----
Ratio of Muharram cases to other cases: 0.9115
```

**We observe a -8.85% lower crime rate during the initial 10 days of the Muharram month compared to the annual average.**

```
In [128]: sorted_ratios, muharrem_dominant_incidents, muharrem_incidents_desc, other_days_incidents_desc = incidents_by_types(df)
# display(sorted_ratios)
# display(muharrem_dominant_incidents)
```

Top 30 Incidents by Type



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Incident Types

```
In [129]: # Top 30 incident types sorted by "muharrem incidents / total incidents" ratio  
sorted_ratios
```

Out[129]:

	muharrem incidents	all incidents	muharrem incidents/total incidents
<b>MISCELLANEOUS ARREST</b>	1	17	0.058800
<b>EMBEZZLEMENT</b>	18	346	0.052000
<b>KIDNAPING</b>	53	1588	0.033400
<b>LIQUOR</b>	25	782	0.032000
<b>BURGLARY</b>	3417	109073	0.031300
<b>HOMICIDE</b>	73	2541	0.028700
<b>ROBBERY</b>	1115	39292	0.028400
<b>OTHER</b>	89	3135	0.028400
<b>STOLEN VEHICLE</b>	2495	89445	0.027900
<b>OBSTRUCTING THE POLICE</b>	91	3268	0.027800
<b>OTHER BURGLARY</b>	85	3065	0.027700
<b>FRAUD</b>	1111	40357	0.027500
<b>LARCENY</b>	3607	133666	0.027000
<b>OUIL</b>	231	8557	0.027000
<b>DAMAGE TO PROPERTY</b>	2505	93781	0.026700
<b>DANGEROUS DRUGS</b>	746	28081	0.026600
<b>ESCAPE</b>	361	13617	0.026500
<b>ARSON</b>	181	6891	0.026300
<b>OBSTRUCTING JUDICIARY</b>	295	11345	0.026000
<b>WEAPONS OFFENSES</b>	344	13268	0.025900
<b>ASSAULT</b>	3635	141608	0.025700
<b>MISCELLANEOUS</b>	4456	174164	0.025600
<b>GAMBLING</b>	1	39	0.025600
<b>TRAFFIC</b>	1633	63890	0.025600

	<b>muharrem incidents</b>	<b>all incidents</b>	<b>muharrem incidents/total incidents</b>
<b>EXTORTION</b>	28	1099	0.025500
<b>DISORDERLY CONDUCT</b>	235	9252	0.025400
<b>MURDER/INFORMATION</b>	1812	71694	0.025300
<b>SOLICITATION</b>	97	3872	0.025100
<b>ENVIRONMENT</b>	14	563	0.024900
<b>AGGRAVATED ASSAULT</b>	1782	72577	0.024600

In [130]: # In which categories were more crimes committed during the first ten days of Muharram?  
muharrem\_dominant\_incidents

	<b>muharrem incidents</b>	<b>all incidents</b>	<b>muharrem incidents/total incidents</b>
<b>BURGLARY</b>	3417	109073	0.0313
<b>KIDNAPING</b>	53	1588	0.0334
<b>LIQUOR</b>	25	782	0.0320
<b>EMBEZZLEMENT</b>	18	346	0.0520
<b>MISCELLANEOUS ARREST</b>	1	17	0.0588

More crimes were committed in the above-mentioned crime categories during the first ten days of Muharram compared to the other days of the year.

In [131]: df.incident.nunique(), muharrem\_dominant\_incidents.count()[0]

Out[131]: (46, 5)

In [132]: muharrem\_incidents\_desc

Out[132]:

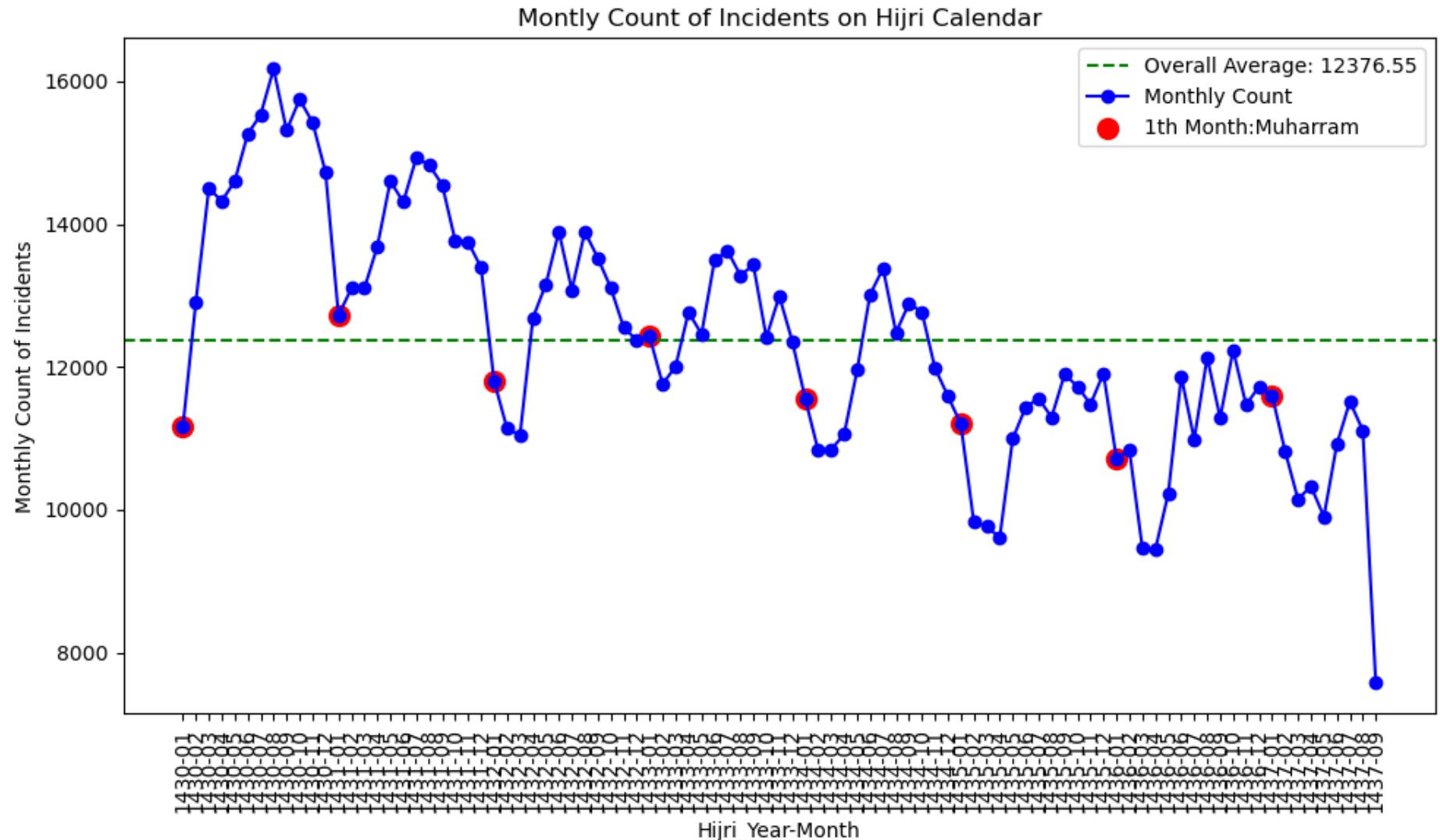
count	30755
unique	40
top	MISCELLANEOUS
freq	4456
Name: incident, dtype: object	

In [133]: other\_days\_incidents\_desc

```
Out[133]: count      1120264  
unique       46  
top    MISCELLANEOUS  
freq      169708  
Name: incident, dtype: object
```

Detroit dataset encompasses 46 distinct incident types. During the first ten days of Muharram, crimes were committed across 40 incident categories, with 5 of these categories experiencing incident counts exceeding the annual averages.

```
In [134... monthly_count_plot()
```



## SAMPLE DATA-5: DENVER CRIME DATASET\_2019-2023

<https://www.denvergov.org/opendata/dataset/city-and-county-of-denver-crime>

In [135...]

```
df = pd.read_csv("denver_crime.csv", index_col=0, encoding="Latin-1", low_memory=False)
df
```

Out[135]:

incident_id	offense_id	offense_code	offense_code_extension	offense_type_id	offense_category_id	first_occurrence_date	last_occurrence_date	re
202268791	202268791299900	2999		0	criminal-mischief-other	public-disorder	2/10/2022 2:50:00 AM	NaN
2021387586	2021387586299900	2999		0	criminal-mischief-other	public-disorder	7/7/2021 9:02:00 PM	NaN
2020641486	2020641486299900	2999		0	criminal-mischief-other	public-disorder	10/29/2020 1:30:00 AM	NaN
2018612468	2018612468299900	2999		0	criminal-mischief-other	public-disorder	9/6/2018 5:00:00 PM	9/6/2018 11:00:00 PM
2020293614	2020293614299900	2999		0	criminal-mischief-other	public-disorder	5/8/2020 5:00:00 AM	5/8/2020 6:30:00 PM
...	...	...		...	...	...	...	...
2023654815	2023654815260500	2605		0	theft-unauth-use-of-ftd	white-collar-crime	12/7/2023 4:45:00 PM	NaN
2023652916	2023652916260900	2609		0	fraud-by-use-of-computer	white-collar-crime	12/4/2023 3:00:00 PM	12/5/2023 3:00:00 PM
2023652471	2023652471260900	2609		0	fraud-by-use-of-computer	white-collar-crime	12/5/2023 4:30:00 PM	12/6/2023 8:00:00 AM
2023652591	2023652591269903	2699		3	theft-of-services	larceny	11/6/2023 10:00:00 AM	12/2/2023 5:00:00 PM
2023654247	2023654247269905	2699		5	pawn-broker-viol	all-other-crimes	12/7/2023 10:00:00 AM	12/7/2023 11:00:00 AM

398091 rows × 19 columns

In [136... df.info()

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 398091 entries, 202268791 to 2023654247
Data columns (total 19 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   offense_id       398091 non-null   int64  
 1   offense_code     398091 non-null   int64  
 2   offense_code_extension 398091 non-null   int64  
 3   offense_type_id  398091 non-null   object  
 4   offense_category_id 398091 non-null   object  
 5   first_occurrence_date 398091 non-null   object  
 6   last_occurrence_date 217265 non-null   object  
 7   reported_date    398091 non-null   object  
 8   incident_address 382236 non-null   object  
 9   geo_x            382236 non-null   float64 
 10  geo_y            382236 non-null   float64 
 11  geo_lon          381975 non-null   float64 
 12  geo_lat          381975 non-null   float64 
 13  district_id      398035 non-null   object  
 14  precinct_id      398091 non-null   int64  
 15  neighborhood_id  397405 non-null   object  
 16  is_crime         398091 non-null   int64  
 17  is_traffic       398091 non-null   int64  
 18  victim_count     398091 non-null   int64  
dtypes: float64(4), int64(7), object(8)
memory usage: 60.7+ MB
```

In [137]: df.duplicated().value\_counts()

Out[137]: False 398091  
dtype: int64

In [138]: df["offense\_type\_id"].value\_counts()

```
Out[138]:
```

theft-of-motor-vehicle	56767
theft-items-from-vehicle	40388
theft-parts-from-vehicle	26244
criminal-mischief-mtr-veh	25687
theft-other	23994
criminal-mischief-other	16485
criminal-trespassing	15035
assault-simple	14280
theft-shoplift	13096
theft-bicycle	9889
burglary-residence-no-force	9057
burglary-business-by-force	8624
theft-from-bldg	8149
weapon-unlawful-discharge-of	7881
aggravated-assault	7145
burglary-residence-by-force	6426
threats-to-injure	5297
assault-dv	5163
menacing-felony-w-weap	4962
drug-poss-paraphernalia	4533
disturbing-the-peace	4196
drug-methamphetamine-possess	3874
public-order-crimes-other	3799
violation-of-restraining-order	3555
drug-pcs-other-drug	3390
robbery-street	3344
aggravated-assault-dv	3223
violation-of-court-order	2686
liquor-possession	2600
criminal-mischief-graffiti	2587
burglary-business-no-force	2495
sex-aslt-rape	2465
robbery-business	1999
police-false-information	1817
weapon-by-prev-offender-powpo	1770
fraud-by-telephone	1493
harassment	1381
fraud-by-use-of-computer	1374
theft-of-services	1362
sex-off-fail-to-register	1357
drug-heroin-possess	1317
drug-cocaine-possess	1293
police-interference	1292
drug-cocaine-sell	1237

weapon-fire-into-occ-bldg	1227
drug-methamphetamine-sell	1130
theft-stln-vehicle-trailer	1067
robbery-car-jacking	993
forgery-checks	895
theft-unauth-use-of-ftd	841
sex-aslt-fondle-adult-victim	794
agg-aslt-shoot	790
police-resisting-arrest	742
weapon-poss-illegal-dangerous	737
assault-police-simple	730
theft-fail-return-rent-veh	726
sex-aslt-non-rape	707
indecent-exposure	697
drug-opium-or-deriv-sell	683
burg-auto-theft-resd-no-force	673
weapon-other-viol	663
theft-from-mails	662
curfew	618
fraud-criminal-impersonation	615
harassment-dv	565
false-imprisonment	558
prostitution-engaging-in	538
public-fighting	518
harassment-sexual-in-nature	460
burglary-poss-of-tools	447
weapon-carrying-concealed	415
public-peace-other	412
agg-aslt-police-weapon	395
weapon-flourishing	394
homicide-other	387
contraband-into-prison	386
drug-heroin-sell	381
robbery-residence	375
harassment-stalking-dv	371
weapon-fire-into-occ-veh	356
burg-auto-theft-busn-w-force	319
weapon-carrying-prohibited	313
arson-other	309
theft-purse-snatch-no-force	300
extortion	297
drug-marijuana-possess	293
police-disobey-lawful-order	289
liquor-sell	285

drug-opium-or-deriv-possess	274
forgery-other	260
kidnap-dv	254
arson-vehicle	242
kidnap-adult-victim	242
stolen-property-buy-sell-rec	239
robbery-purse-snatch-w-force	239
sex-off-registration-viol	235
obstructing-govt-operation	228
robbery-bank	228
bomb-threat	197
drug-marijuana-sell	196
sex-aslt-rape-pot	181
drug-make-sell-other-drug	173
drug-synth-narcotic-sell	163
burg-auto-theft-resd-w-force	157
animal-cruelty-to	157
sex-aslt-non-rape-pot	156
property-crimes-other	155
arson-residence	151
theft-pick-pocket	151
illegal-dumping	150
burglary-vending-machine	150
fraud-nsf-closed-account	143
arson-business	130
burglary-safe	123
intimidation-of-a-witness	123
drug-fraud-to-obtain	122
reckless-endangerment	116
theft-embezzle	111
burg-auto-theft-busn-no-force	111
drug-marijuana-cultivation	110
other-enviornment-animal-viol	103
fireworks-possession	98
forgery-poss-of-forged-inst	97
window-peeping	93
drug-synth-narcotic-possess	92
police-obstruct-investigation	90
accessory-conspiracy-to-crime	78
drug-hallucinogen-possess	76
theft-stln-veh-const-eqpt	71
escape	69
violation-of-custody-order	65
drug-hallucinogen-sell	65

theft-of-rental-property	61
littering	61
forgery-counterfeit-of-obj	54
sex-asslt-sodomy-man-strng-arm	49
sex-aslt-w-object	46
bribery	45
disarming-a-peace-officer	43
drug-forgery-to-obtain	42
impersonation-of-police	40
theft-confidence-game	39
contraband-possession	39
police-making-a-false-rpt	38
drug-methamphetamine-mfr	38
pawn-broker-viol	38
fraud-identity-theft	38
theft-gas-drive-off	34
forgery-posses-forge-device	33
obscene-material-possess	32
forgery-poss-of-forged-ftd	31
homicide-family	30
explosive-incendiary-dev-pos	25
weapon-altering-serial-number	22
explosive-incendiary-dev-use	20
arson-public-building	20
aslt-agg-police-gun	19
sex-aslt-w-object-pot	13
drug-barbiturate-possess	11
prostitution-pimping	9
animal-poss-of-dangerous	9
probation-violation	8
parole-violation	7
drug-barbiturate-sell	7
drug-hallucinogen-mfr	6
wiretapping	5
obscene-material-mfr	5
weapon-unlawful-sale	5
loitering	5
homicide-police-by-gun	4
prostitution-aiding	4
altering-vin-number	4
money-laundering	4
gambling-gaming-operation	4
liquor-manufacturing	3
eavesdropping	2

```
homicide-conspiracy           2
homicide-negligent            2
escape-aiding                 2
riot-incite                   2
gambling-betting-wagering    1
bigamy                         1
liquor-other-viol             1
theft-of-cable-services       1
drug-barbiturate-mfr          1
homicide-accessory-to         1
Name: offense_type_id, dtype: int64
```

```
In [139]: df["offense_category_id"].value_counts()
```

```
theft-from-motor-vehicle      66632
public-disorder                58617
auto-theft                      57905
larceny                          57788
all-other-crimes               47898
burglary                         28432
drug-alcohol                     22354
other-crimes-against-persons   21000
aggravated-assault              17703
robbery                           7178
white-collar-crime              6898
sexual-assault                  4411
arson                             852
murder                            423
Name: offense_category_id, dtype: int64
```

```
In [140]: df = df.rename(columns = {'first_occurrence_date':'date'})
df = df.rename(columns = {'offense_category_id':'incident'})
```

```
In [141]: df['date'] = pd.to_datetime(df['date']).dt.strftime('%Y-%m-%d')
```

```
In [142]: df.date.min(), df.date.max()
```

```
Out[142]: ('2018-01-02', '2023-12-07')
```

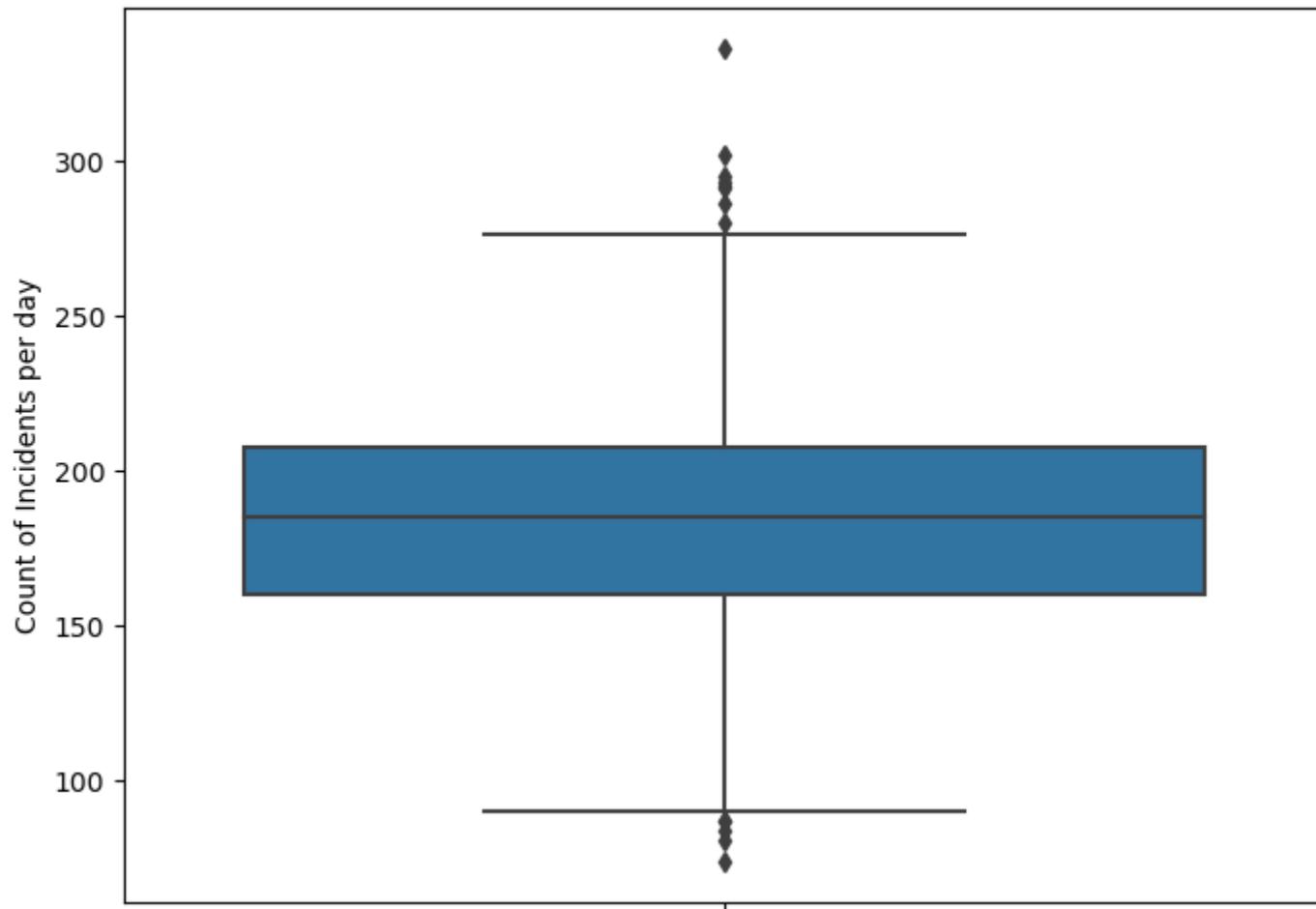
```
In [143]: df = df.iloc[:, [4,5]]
# df.to_csv("Denver.csv", index=False)
```

```
In [144]: daily_incident_counts_stats = df.groupby("date")['date'].value_counts().describe([.25, .5, .75, .95, .98, .99]).astype(int)
daily_incident_counts_stats
```

```
Out[144]: count    2166
mean      183
std       33
min       74
25%     160
50%     185
75%     207
95%     237
98%     250
99%     259
max     336
Name: date, dtype: int32
```

```
In [145...]: # Display the days with high incident numbers
plt.figure(figsize=(8, 6))
sns.boxplot(y=df.groupby("date")['date'].value_counts())
plt.title('Daily Counts of Incidents')
plt.ylabel('Count of Incidents per day')
plt.show()
```

### Daily Counts of Incidents



```
In [146]: df.date.unique()
```

```
Out[146]: 2166
```

As seen below, our dataset spans a total of 2166 days. Every day in the dataset contains a record of an incident. In other words, there are no days without any recorded incidents.

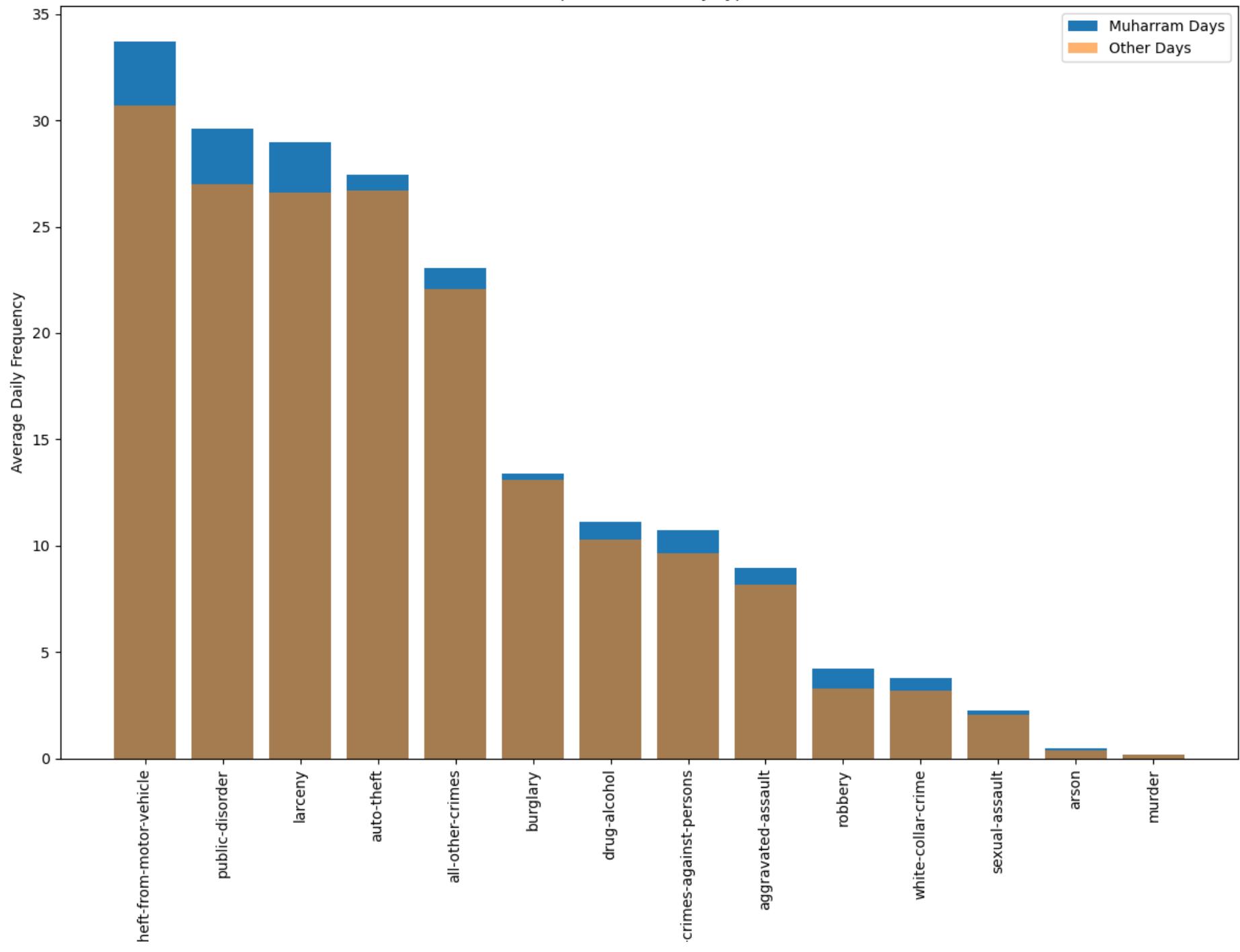
```
In [147]: muharrem_10_days(df)
```

```
Total number of days: 2166
-----
Total number of cases: 398091
-----
Average Daily Case Count: 183.79
-----
Yearly case counts according to the Gregorian calendar:
-----
2022    76854
2021    72561
2023    71028
2020    63754
2019    57625
2018    56269
Name: date, dtype: int64
-----
Case counts according to the Hijri calendar:
-----
1444    74148
1443    73197
1442    68855
1441    58223
1440    55247
1439    39212
1445    29209
Name: Hijri_Date, dtype: int64
-----
Average case count in the first ten days of Muharram months: 197.8833
-----
Average case count in other days: 183.3894
-----
Ratio of Muharram cases to other cases: 1.0790
```

**We observe a 7.90% higher crime rate during the initial 10 days of the Muharram month compared to the annual average.**

```
In [148...]: sorted_ratios, muharrem_dominant_incidents, muharrem_incidents_desc, other_days_incidents_desc = incidents_by_types(df)
# display(sorted_ratios)
# display(muharrem_dominant_incidents)
```

Top 30 Incidents by Type





```
In [149]: # Top 30 incident types sorted by "muharrem incidents / total incidents" ratio
sorted_ratios
```

Out[149]:

	muharrem incidents	all incidents	muharrem incidents/total incidents
<b>robbery</b>	253	7178	0.035200
<b>arson</b>	29	852	0.034000
<b>white-collar-crime</b>	226	6898	0.032800
<b>other-crimes-against-persons</b>	643	21000	0.030600
<b>sexual-assault</b>	135	4411	0.030600
<b>aggravated-assault</b>	536	17703	0.030300
<b>public-disorder</b>	1777	58617	0.030300
<b>theft-from-motor-vehicle</b>	2021	66632	0.030300
<b>larceny</b>	1738	57788	0.030100
<b>drug-alcohol</b>	667	22354	0.029800
<b>all-other-crimes</b>	1384	47898	0.028900
<b>auto-theft</b>	1647	57905	0.028400
<b>murder</b>	12	423	0.028400
<b>burglary</b>	805	28432	0.028300

```
In [150]: # In which categories were more crimes committed during the first ten days of Muharram?
muharrem_dominant_incidents
```

```
Out[150]:
```

	muharrem incidents	all incidents	muharrem incidents/total incidents
<b>theft-from-motor-vehicle</b>	2021	66632	0.0303
<b>public-disorder</b>	1777	58617	0.0303
<b>larceny</b>	1738	57788	0.0301
<b>auto-theft</b>	1647	57905	0.0284
<b>all-other-crimes</b>	1384	47898	0.0289
<b>burglary</b>	805	28432	0.0283
<b>drug-alcohol</b>	667	22354	0.0298
<b>other-crimes-against-persons</b>	643	21000	0.0306
<b>aggravated-assault</b>	536	17703	0.0303
<b>robbery</b>	253	7178	0.0352
<b>white-collar-crime</b>	226	6898	0.0328
<b>sexual-assault</b>	135	4411	0.0306
<b>arson</b>	29	852	0.0340
<b>murder</b>	12	423	0.0284

More crimes were committed in the above-mentioned crime categories during the first ten days of Muharram compared to the other days of the year.

```
In [151...]: df.incident.nunique(), muharrem_dominant_incidents.count()[0]
```

```
Out[151]: (14, 14)
```

```
In [152...]: muharrem_incidents_desc
```

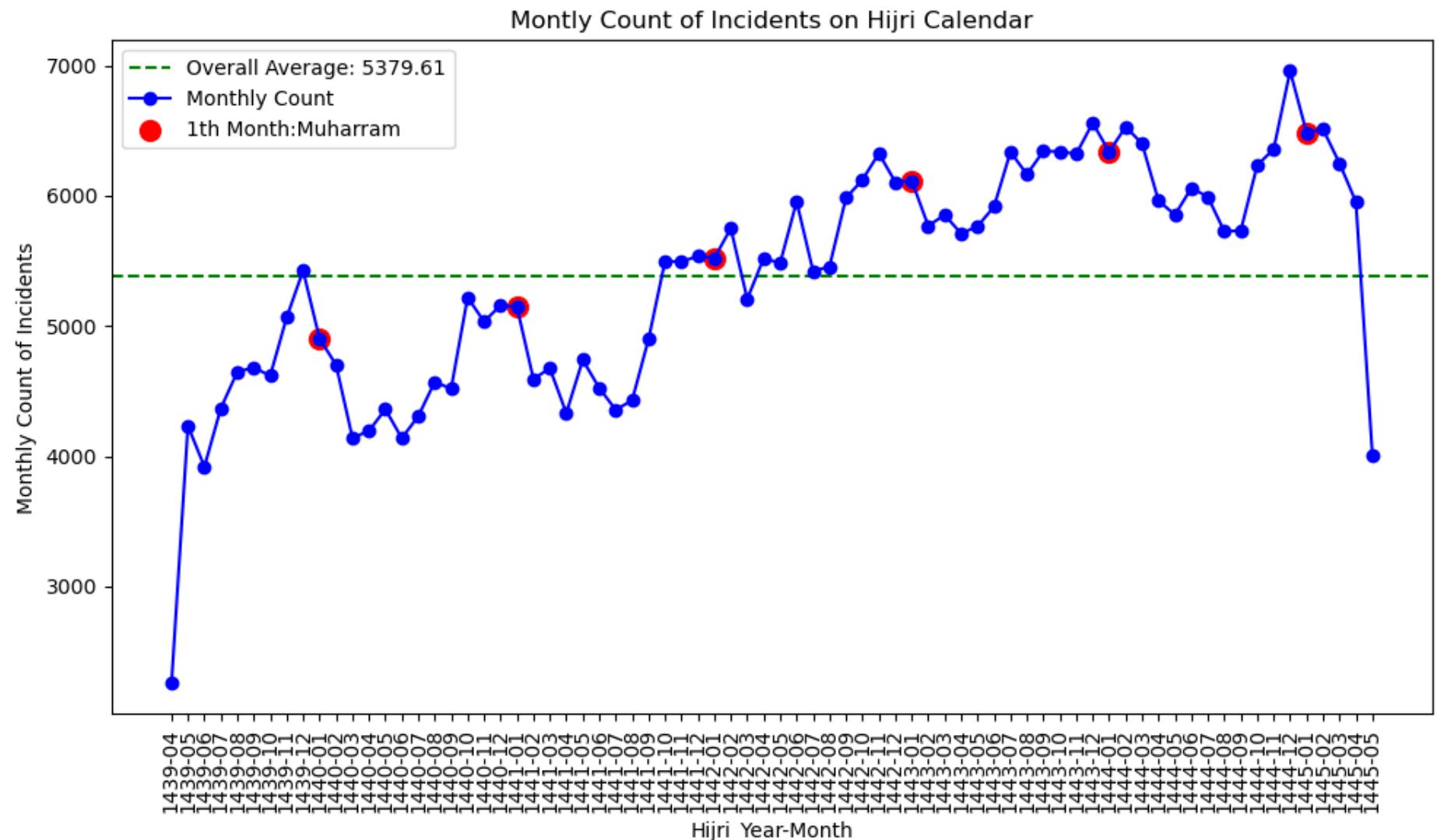
```
Out[152]: count          11873
unique         14
top    theft-from-motor-vehicle
freq          2021
Name: incident, dtype: object
```

```
In [153...]: other_days_incidents_desc
```

```
Out[153]: count          386218  
unique           14  
top    theft-from-motor-vehicle  
freq            64611  
Name: incident, dtype: object
```

Denver dataset encompasses 14 distinct incident types. During the first ten days of Muharram, crimes were committed across 14 incident categories, with 14 of these categories experiencing incident counts exceeding the annual averages.

```
In [154... monthly_count_plot()
```



## SAMPLE DATA-6: VANCOUVER CRIME DATASET\_2003-2017

<https://www.kaggle.com/datasets/wosaku/crime-in-vancouver>

```
In [155]: df = pd.read_csv("crime_vancouver.csv", low_memory=False)
df
```

Out[155]:

	TYPE	YEAR	MONTH	DAY	HOUR	MINUTE	HUNDRED_BLOCK	NEIGHBOURHOOD	X	Y	Latitude	Longitude
0	Other Theft	2003	5	12	16.0	15.0	9XX TERMINAL AVE	Strathcona	493906.50	5457452.47	49.269802	-123.083763
1	Other Theft	2003	5	7	15.0	20.0	9XX TERMINAL AVE	Strathcona	493906.50	5457452.47	49.269802	-123.083763
2	Other Theft	2003	4	23	16.0	40.0	9XX TERMINAL AVE	Strathcona	493906.50	5457452.47	49.269802	-123.083763
3	Other Theft	2003	4	20	11.0	15.0	9XX TERMINAL AVE	Strathcona	493906.50	5457452.47	49.269802	-123.083763
4	Other Theft	2003	4	12	17.0	45.0	9XX TERMINAL AVE	Strathcona	493906.50	5457452.47	49.269802	-123.083763
...	...	...	...	...	...	...	...	...	...	...	...	...
530647	Break and Enter Residential/Other	2017	3	3	9.0	16.0	31XX ADANAC ST	Hastings-Sunrise	497265.49	5458296.71	49.277420	-123.037595
530648	Mischief	2017	5	29	22.0	30.0	14XX E 7TH AVE	Grandview-Woodland	494533.97	5456824.97	49.264163	-123.075129
530649	Offence Against a Person	2017	4	13	Nan	Nan	OFFSET TO PROTECT PRIVACY	Nan	0.00	0.00	0.000000	0.000000
530650	Theft from Vehicle	2017	6	5	17.0	0.0	8XX HAMILTON ST	Central Business District	491487.85	5458385.78	49.278168	-123.117031
530651	Vehicle Collision or Pedestrian Struck (with I...)	2017	6	6	17.0	38.0	13XX BLOCK PARK DR	Marpole	490204.00	5451444.00	49.215706	-123.134512

530652 rows × 12 columns

In [156...]

df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 530652 entries, 0 to 530651
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   TYPE              530652 non-null   object  
 1   YEAR              530652 non-null   int64  
 2   MONTH             530652 non-null   int64  
 3   DAY               530652 non-null   int64  
 4   HOUR              476290 non-null   float64 
 5   MINUTE             476290 non-null   float64 
 6   HUNDRED_BLOCK    530639 non-null   object  
 7   NEIGHBOURHOOD    474028 non-null   object  
 8   X                  530652 non-null   float64 
 9   Y                  530652 non-null   float64 
 10  Latitude           530652 non-null   float64 
 11  Longitude          530652 non-null   float64 
dtypes: float64(6), int64(3), object(3)
memory usage: 48.6+ MB
```

```
In [157]: df.duplicated().value_counts()
```

```
Out[157]: False    481814
           True     48838
           dtype: int64
```

```
In [158]: df=df.drop_duplicates()
```

```
In [159]: df["TYPE"].value_counts()
```

```
Out[159]: Theft from Vehicle                172699
           Mischief                      70413
           Break and Enter Residential/Other 60862
           Other Theft                     52167
           Theft of Vehicle                 38418
           Break and Enter Commercial      33845
           Theft of Bicycle                 25730
           Vehicle Collision or Pedestrian Struck (with Injury) 21901
           Offence Against a Person        5307
           Vehicle Collision or Pedestrian Struck (with Fatality) 254
           Homicide                       218
           Name: TYPE, dtype: int64
```

```
In [ ]: df['date'] = pd.to_datetime(df[['YEAR', 'MONTH', 'DAY']])
```

```
In [ ]: df['date'] = pd.to_datetime(df['date']).dt.strftime('%Y-%m-%d')
```

```
In [162...]: df = df.rename(columns={'TYPE':'incident'})
```

```
In [163...]: df.date.min(),df.date.max()
```

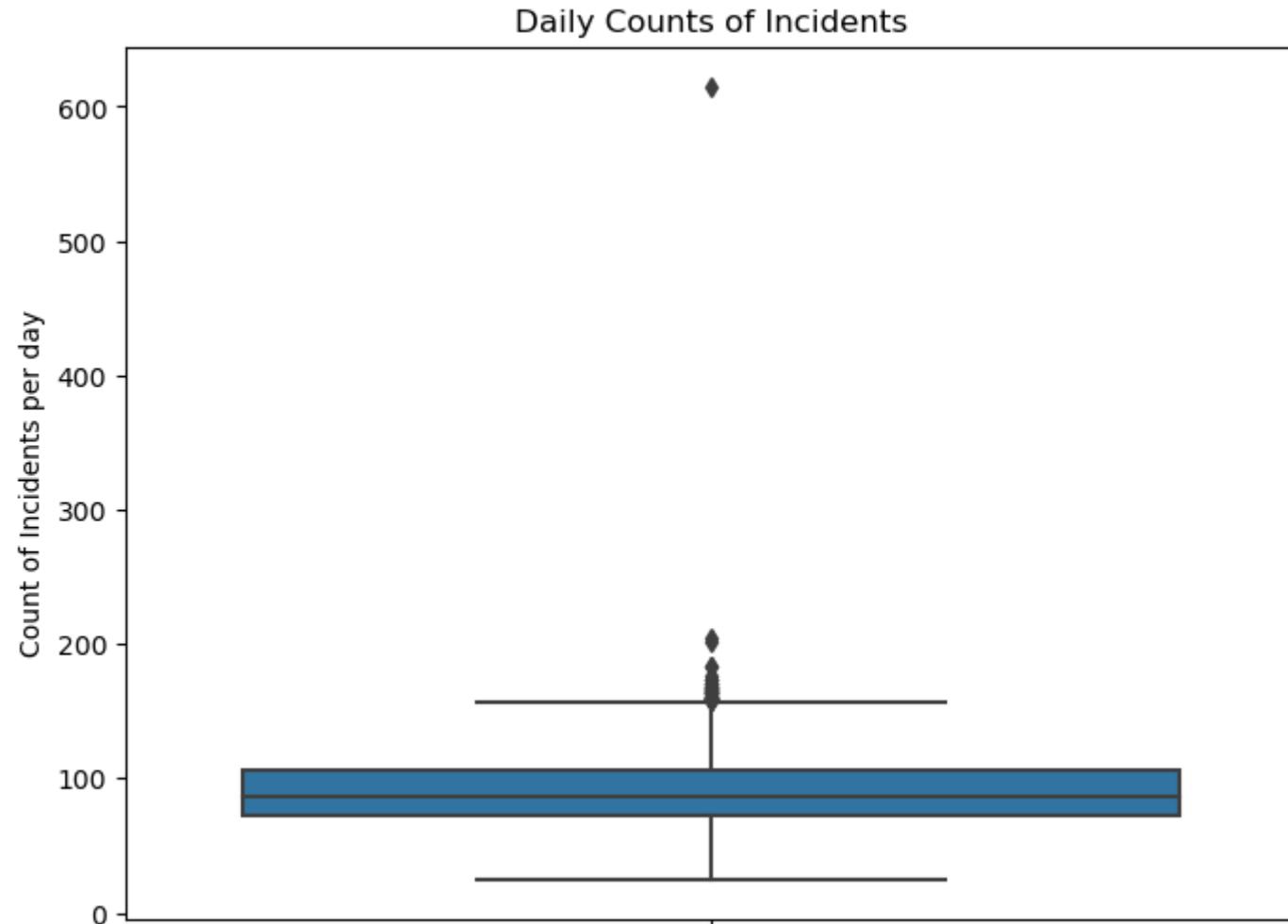
```
Out[163]: ('2003-01-01', '2017-07-13')
```

```
In [164...]: df = df.iloc[:, [0,12]]  
# df.to_csv("Vancouver.csv", index=False)
```

```
In [165...]: daily_incident_counts_stats = df.groupby("date")['date'].value_counts().describe([.25, .5, .75, .95, .98, .99]).astype(int)  
daily_incident_counts_stats
```

```
Out[165]: count      5308  
mean        90  
std         25  
min         25  
25%        72  
50%        87  
75%       106  
95%       137  
98%       149  
99%       157  
max       615  
Name: date, dtype: int32
```

```
In [166...]: # Display the days with high incident numbers  
plt.figure(figsize=(8, 6))  
sns.boxplot(y=df.groupby("date")['date'].value_counts())  
plt.title('Daily Counts of Incidents')  
plt.ylabel('Count of Incidents per day')  
plt.show()
```



```
In [167]: df.date.unique()
```

```
Out[167]: 5308
```

As seen below, our dataset spans a total of 5308 days. Every day in the dataset contains a record of an incident. In other words, there are no days without any recorded incidents.

```
In [168]: muharrem_10_days(df)
```

Total number of days: 5308

-----

Total number of cases: 481814

-----

Average Daily Case Count: 90.77

-----

Yearly case counts according to the Gregorian calendar:

-----

2003	46785
2004	45841
2005	41257
2006	38336
2016	34991
2007	33645
2008	31554
2015	31491
2014	29866
2009	28652
2010	26322
2012	25802
2013	25758
2011	25068
2017	16446

Name: date, dtype: int64

-----

Case counts according to the Hijri calendar:

-----

1424	44964
1425	44520
1426	40126
1427	36870
1437	34998
1428	32436
1429	30522
1436	29213
1435	28641
1430	27944
1431	25668
1433	24866
1434	24799
1432	24377
1438	24138
1423	7732

Name: Hijri\_Date, dtype: int64

Average case count in the first ten days of Muharram months: 90.5267

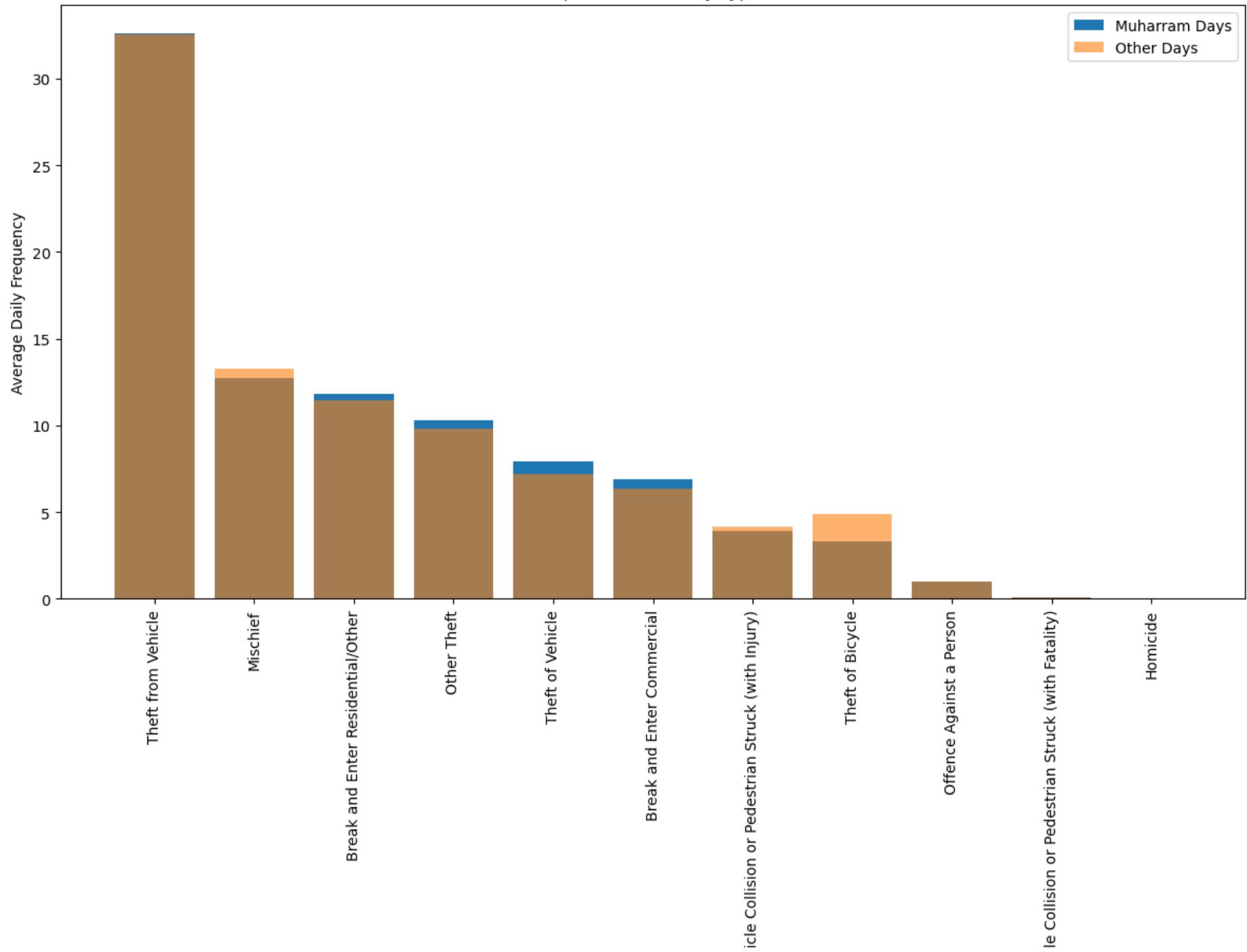
Average case count in other days: 90.7784

Ratio of Muharram cases to other cases: 0.9972

***We observe a -0.28% lower crime rate during the initial 10 days of the Muharram month compared to the annual average.***

```
In [169]: sorted_ratios, muharrem_dominant_incidents, muharrem_incidents_desc, other_days_incidents_desc = incidents_by_types(df)
# display(sorted_ratios)
# display(muharrem_dominant_incidents)
```

Top 30 Incidents by Type





```
In [170]: # Top 30 incident types sorted by "muharrrem incidents / total incidents" ratio
sorted_ratios
```

	muharrem incidents	all incidents	muharrem incidents/total incidents
<b>Vehicle Collision or Pedestrian Struck (with Fatality)</b>	8	254	0.031500
<b>Theft of Vehicle</b>	1186	38418	0.030900
<b>Break and Enter Commercial</b>	1032	33845	0.030500
<b>Other Theft</b>	1541	52167	0.029500
<b>Break and Enter Residential/Other</b>	1771	60862	0.029100
<b>Offence Against a Person</b>	150	5307	0.028300
<b>Theft from Vehicle</b>	4891	172699	0.028300
<b>Mischief</b>	1910	70413	0.027100
<b>Vehicle Collision or Pedestrian Struck (with Injury)</b>	589	21901	0.026900
<b>Theft of Bicycle</b>	499	25730	0.019400
<b>Homicide</b>	2	218	0.009200

```
In [171]: # In which categories were more crimes committed during the first ten days of Muharram?
muharrrem_dominant_incidents
```

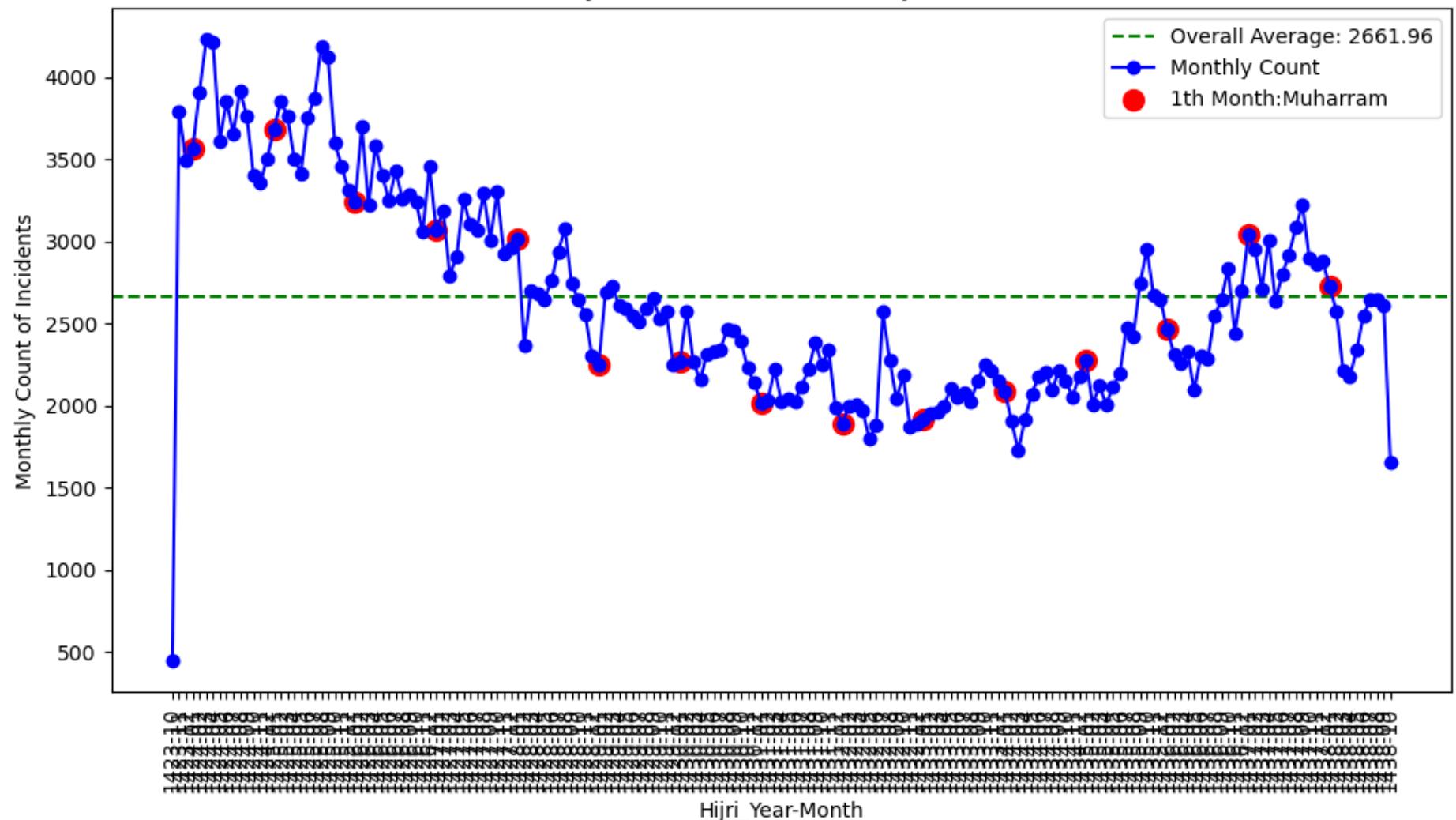
Out[171]:

	muharrem incidents	all incidents	muharrem incidents/total incidents
<b>Theft from Vehicle</b>	4891	172699	0.0283
<b>Break and Enter Residential/Other</b>	1771	60862	0.0291
<b>Other Theft</b>	1541	52167	0.0295
<b>Theft of Vehicle</b>	1186	38418	0.0309
<b>Break and Enter Commercial</b>	1032	33845	0.0305
<b>Offence Against a Person</b>	150	5307	0.0283
<b>Vehicle Collision or Pedestrian Struck (with Fatality)</b>	8	254	0.0315

In [172...]

```
monthly_count_plot()
```

### Monthly Count of Incidents on Hijri Calendar



More crimes were committed in the above-mentioned crime categories during the first ten days of Muharram compared to the other days of the year.

```
In [173]: df.incident.nunique(), muharrem_dominant_incidents.count()[0]
```

```
Out[173]: (11, 7)
```

```
In [174]: muharrem_incidents_desc
```

```
Out[174]: count          13579  
unique           11  
top    Theft from Vehicle  
freq            4891  
Name: incident, dtype: object
```

```
In [175... other_days_incidents_desc
```

```
Out[175]: count          468235  
unique           11  
top    Theft from Vehicle  
freq            167808  
Name: incident, dtype: object
```

Vancouver dataset encompasses 11 distinct incident types. During the first ten days of Muharram, crimes were committed across 11 incident categories, with 7 of these categories experiencing incident counts exceeding the annual averages.

## SAMPLE DATA-7: CHICAGO CRIME DATASET\_2001-2023

[https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-Present/ijzp-q8t2/data\\_preview](https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-Present/ijzp-q8t2/data_preview)

```
In [176... df = pd.read_csv("Chicago_Crimes_2001_to_Present.csv", index_col=0)  
# to drop the duplicated rows with the same index numbers use index_col=0  
df.head()
```

Out[176]:

	Case Number	Date	Block	IUCR	Primary Type	Description	Location Description	Arrest	Domestic	Beat	...	Ward	Community Area	FBI Code	Coordinates
ID															
<b>11037294</b>	JA371270	03/18/2015 12:00:00 PM	0000X W WACKER DR	1153	DECEPTIVE PRACTICE	FINANCIAL IDENTITY THEFT OVER \$ 300	BANK	False	False	111	...	42.0	32.0	11	I
<b>11646293</b>	JC213749	12/20/2018 03:00:00 PM	023XX N LOCKWOOD AVE	1154	DECEPTIVE PRACTICE	FINANCIAL IDENTITY THEFT \$300 AND UNDER	APARTMENT	False	False	2515	...	36.0	19.0	11	I
<b>11645836</b>	JC212333	05/01/2016 12:25:00 AM	055XX S ROCKWELL ST	1153	DECEPTIVE PRACTICE	FINANCIAL IDENTITY THEFT OVER \$ 300	NaN	False	False	824	...	15.0	63.0	11	I
<b>11645959</b>	JC211511	12/20/2018 04:00:00 PM	045XX N ALBANY AVE	2820	OTHER OFFENSE	TELEPHONE THREAT	RESIDENCE	False	False	1724	...	33.0	14.0	08A	I
<b>11645601</b>	JC212935	06/01/2014 12:01:00 AM	087XX S SANGAMON ST	1153	DECEPTIVE PRACTICE	FINANCIAL IDENTITY THEFT OVER \$ 300	RESIDENCE	False	False	2222	...	21.0	71.0	11	I

5 rows × 21 columns

In [177... df.info()

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7953830 entries, 11037294 to 12002171
Data columns (total 21 columns):
 #   Column           Dtype  
 --- 
 0   Case Number      object  
 1   Date             object  
 2   Block            object  
 3   IUCR             object  
 4   Primary Type     object  
 5   Description      object  
 6   Location Description  object  
 7   Arrest            bool    
 8   Domestic          bool    
 9   Beat              int64  
 10  District          float64 
 11  Ward              float64 
 12  Community Area   float64 
 13  FBI Code          object  
 14  X Coordinate     float64 
 15  Y Coordinate     float64 
 16  Year              int64  
 17  Updated On        object  
 18  Latitude          float64 
 19  Longitude          float64 
 20  Location          object  
dtypes: bool(2), float64(7), int64(2), object(10)
memory usage: 1.2+ GB
```

```
In [178...]: # df = pd.read_csv("Chicago_Crimes_2001_to_Present.csv", usecols=[0, 2, 5, 6])
```

```
In [179...]: df.duplicated().value_counts()
```

```
Out[179]: False    7953669
True      161
dtype: int64
```

```
In [180...]: df = df.drop_duplicates()
```

```
In [181...]: df = df.iloc[:, [1, 4, 5]]
```

```
In [182...]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7953669 entries, 11037294 to 12002171
Data columns (total 3 columns):
 #   Column      Dtype  
 --- 
 0   Date        object 
 1   Primary Type object 
 2   Description object 
dtypes: object(3)
memory usage: 242.7+ MB
```

In [183... df["Primary Type"].value\_counts()

```
Out[183]:
```

THEFT	1679300
BATTERY	1451708
CRIMINAL DAMAGE	906654
NARCOTICS	750859
ASSAULT	521978
OTHER OFFENSE	493465
BURGLARY	429109
MOTOR VEHICLE THEFT	393673
DECEPTIVE PRACTICE	356129
ROBBERY	299815
CRIMINAL TRESPASS	217211
WEAPONS VIOLATION	112009
PROSTITUTION	69958
OFFENSE INVOLVING CHILDREN	56968
PUBLIC PEACE VIOLATION	52892
SEX OFFENSE	31684
CRIM SEXUAL ASSAULT	27555
INTERFERENCE WITH PUBLIC OFFICER	18746
LIQUOR LAW VIOLATION	15014
GAMBLING	14630
ARSON	13586
HOMICIDE	12820
CRIMINAL SEXUAL ASSAULT	7881
KIDNAPPING	7320
STALKING	5136
INTIMIDATION	4817
CONCEALED CARRY LICENSE VIOLATION	1205
OBSCENITY	840
PUBLIC INDECENCY	197
NON-CRIMINAL	184
OTHER NARCOTIC VIOLATION	149
HUMAN TRAFFICKING	105
NON - CRIMINAL	38
RITUALISM	24
NON-CRIMINAL (SUBJECT SPECIFIED)	9
DOMESTIC VIOLENCE	1

Name: Primary Type, dtype: int64

```
In [184...]
```

```
df = df.rename(columns = {'Date':'date'})  
df = df.rename(columns = {'Primary Type':'incident'})
```

```
In [185...]
```

```
df['date'] = pd.to_datetime(df['date']).dt.strftime('%Y-%m-%d')
```

```
In [186]: df.date.min(), df.date.max()
```

```
Out[186]: ('2001-01-01', '2023-12-03')
```

```
In [187]: # df.to_csv("Chicago.csv", index=False)
```

```
In [188]: daily_incident_counts_stats = df.groupby("date")['date'].value_counts().describe([.25, .5, .75, .95, .98, .99]).astype(int)
daily_incident_counts_stats
```

```
Out[188]: count    8372
mean      950
std       283
min       11
25%      716
50%      894
75%     1199
95%     1406
98%     1470
99%     1523
max      2033
Name: date, dtype: int32
```

```
In [189...]: # Display the days with high incident numbers
plt.figure(figsize=(8, 6))
sns.boxplot(y=df.groupby("date")['date'].value_counts())
plt.title('Daily Counts of Incidents')
plt.ylabel('Count of Incidents per day')
plt.show()
```



```
In [190]: df.date.unique()
```

```
Out[190]: 8372
```

As seen below, our dataset spans a total of 8372 days. Every day in the dataset contains a record of an incident. In other words, there are no days without any recorded incidents.

```
In [191]: muharrem_10_days(df)
```

```
Total number of days: 8372
```

```
-----  
Total number of cases: 7953669
```

```
-----  
Average Daily Case Count: 950.03
```

```
-----  
Yearly case counts according to the Gregorian calendar:
```

```
2002    486807
```

```
2001    485896
```

```
2003    475976
```

```
2004    469423
```

```
2005    453774
```

```
2006    448176
```

```
2007    437082
```

```
2008    427177
```

```
2009    392824
```

```
2010    370507
```

```
2011    351990
```

```
2012    336322
```

```
2013    307541
```

```
2014    275801
```

```
2016    269840
```

```
2017    269108
```

```
2018    268927
```

```
2015    264807
```

```
2019    261391
```

```
2023    240008
```

```
2022    239057
```

```
2020    212263
```

```
2021    208972
```

```
Name: date, dtype: int64
```

```
-----  
Case counts according to the Hijri calendar:
```

```
1422    470958
```

```
1423    470195
```

```
1424    461123
```

```
1425    455377
```

```
1426    445279
```

```
1427    434421
```

```
1428    425843
```

```
1429    413583
```

```
1430    383982
```

```
1431    362344
1432    340567
1433    328725
1434    303696
1435    271358
1439    261354
1438    260778
1437    259935
1436    256965
1440    256539
1444    249476
1441    220744
1443    215897
1442    199257
1421    104539
1445    100734
```

Name: Hijri\_Date, dtype: int64

Average case count in the first ten days of Muharram months: 923.0042

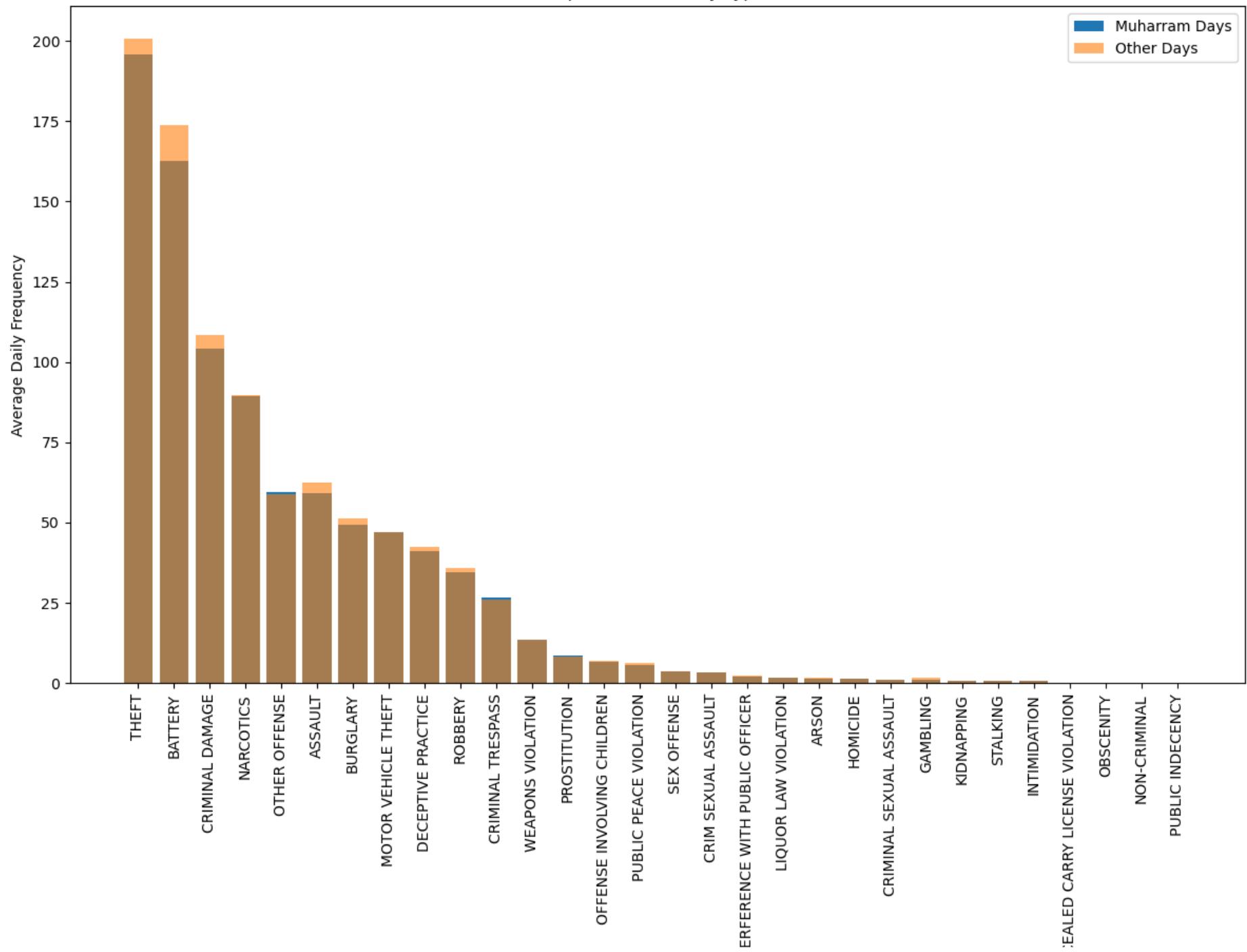
Average case count in other days: 950.8298

Ratio of Muharram cases to other cases: 0.9707

**We observe a -2.93% lower crime rate during the initial 10 days of the Muharram month compared to the annual average.**

```
In [192]: sorted_ratios, muharrem_dominant_incidents, muharrem_incidents_desc, other_days_incidents_desc = incidents_by_types(df)
# display(sorted_ratios)
# display(muharrem_dominant_incidents)
```

Top 30 Incidents by Type



INT

CONC

### Incident Types

```
In [193]: # Top 30 incident types sorted by "muharrem incidents / total incidents" ratio  
sorted_ratios
```

Out[193]:

	muharrem incidents	all incidents	muharrem incidents/total incidents
RITUALISM	1	24	0.041700
NON-CRIMINAL	7	184	0.038000
PUBLIC INDECENCY	7	197	0.035500
OTHER NARCOTIC VIOLATION	5	149	0.033600
CONCEALED CARRY LICENSE VIOLATION	40	1205	0.033200
STALKING	165	5136	0.032100
INTIMIDATION	147	4817	0.030500
OBSCENITY	25	840	0.029800
CRIMINAL SEXUAL ASSAULT	233	7881	0.029600
PROSTITUTION	2066	69958	0.029500
CRIMINAL TRESPASS	6386	217211	0.029400
WEAPONS VIOLATION	3261	112009	0.029100
CRIM SEXUAL ASSAULT	802	27555	0.029100
OTHER OFFENSE	14319	493465	0.029000
MOTOR VEHICLE THEFT	11313	393673	0.028700
NARCOTICS	21484	750859	0.028600
SEX OFFENSE	892	31684	0.028200
LIQUOR LAW VIOLATION	423	15014	0.028200
KIDNAPPING	205	7320	0.028000
THEFT	46956	1679300	0.028000
OFFENSE INVOLVING CHILDREN	1588	56968	0.027900
ROBBERY	8324	299815	0.027800
DECEPTIVE PRACTICE	9885	356129	0.027800
BURGLARY	11865	429109	0.027700

	<b>muharrem incidents</b>	<b>all incidents</b>	<b>muharrem incidents/total incidents</b>
<b>HOMICIDE</b>	355	12820	0.027700
<b>CRIMINAL DAMAGE</b>	25014	906654	0.027600
<b>ASSAULT</b>	14214	521978	0.027200
<b>ARSON</b>	368	13586	0.027100
<b>BATTERY</b>	39063	1451708	0.026900
<b>INTERFERENCE WITH PUBLIC OFFICER</b>	494	18746	0.026400

In [194]:

```
# In which categories were more crimes committed during the first ten days of Muharram?
muharrem_dominant_incidents
```

```
Out[194]:
```

	muharrem incidents	all incidents	muharrem incidents/total incidents
OTHER OFFENSE	14319	493465	0.0290
MOTOR VEHICLE THEFT	11313	393673	0.0287
CRIMINAL TRESPASS	6386	217211	0.0294
WEAPONS VIOLATION	3261	112009	0.0291
PROSTITUTION	2066	69958	0.0295
CRIM SEXUAL ASSAULT	802	27555	0.0291
CRIMINAL SEXUAL ASSAULT	233	7881	0.0296
STALKING	165	5136	0.0321
INTIMIDATION	147	4817	0.0305
CONCEALED CARRY LICENSE VIOLATION	40	1205	0.0332
OBSCENITY	25	840	0.0298
NON-CRIMINAL	7	184	0.0380
PUBLIC INDECENCY	7	197	0.0355
OTHER NARCOTIC VIOLATION	5	149	0.0336
RITUALISM	1	24	0.0417

More crimes were committed in the above-mentioned crime categories during the first ten days of Muharram compared to the other days of the year.

```
In [195...]: df.incident.nunique(), muharrem_dominant_incidents.count()[0]
```

```
Out[195]: (36, 15)
```

```
In [196...]: muharrem_incidents_desc
```

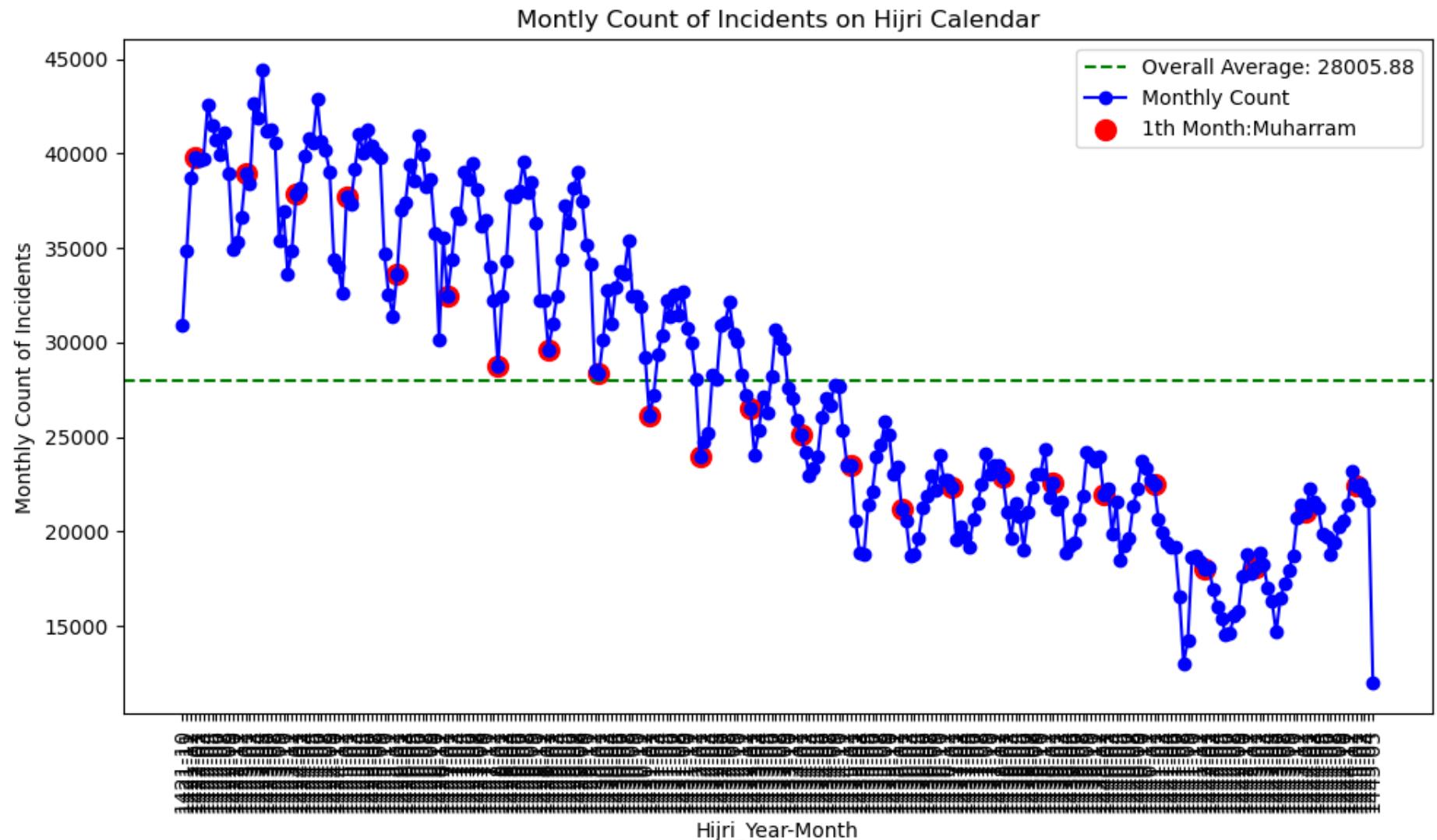
```
Out[196]: count    221521
unique     34
top      THEFT
freq     46956
Name: incident, dtype: object
```

```
In [197...]: other_days_incidents_desc
```

```
Out[197]: count    7732148  
unique      36  
top        THEFT  
freq     1632344  
Name: incident, dtype: object
```

Chicago dataset encompasses 36 distinct incident types. During the first ten days of Muharram, crimes were committed across 34 incident categories, with 15 of these categories experiencing incident counts exceeding the annual averages.

```
In [198...]: monthly_count_plot()
```



## SAMPLE DATA-8: BALTIMORE CRIME DATASET\_2011-2015

[https://data.world/baltimore/baltimore-crime-data/workspace/file?filename=BPD\\_Part\\_1\\_Victim\\_Based\\_Crime\\_Data.csv](https://data.world/baltimore/baltimore-crime-data/workspace/file?filename=BPD_Part_1_Victim_Based_Crime_Data.csv)

```
In [199]: df = pd.read_csv("BPD_Part_1_Victim_Based_Crime_Data.csv", low_memory=False)
df.head()
```

Out[199]:

	CrimeDate	CrimeTime	CrimeCode	Location	Description	Weapon	Post	District	Neighborhood	Location 1	Total Incidents
0	06/18/2016	00:33:00	4E	2700 CHESLEY AVE	I	HANDS	424.0	NORTHEASTERN	North Harford Road	(39.3679000000, -76.5555900000)	1
1	06/18/2016	00:39:00	4B	2700 FAIT AVE	O	KNIFE	232.0	SOUTHEASTERN	Canton	(39.2831500000, -76.5783400000)	1
2	06/18/2016	0015	9S	2400 CYLBURN AV	Outside	FIREARM	532.0	NORTHERN	Levindale	(39.3510400000, -76.6597600000)	1
3	06/18/2016	01:53:00	3AF	2300 ORLEANS ST	O	FIREARM	221.0	SOUTHEASTERN	McElberry Park	(39.2955600000, -76.5844600000)	1
4	06/18/2016	02:05:00	6C	800 N WOLFE ST	I	NaN	321.0	EASTERN	Middle East	(39.3002700000, -76.5909700000)	1

In [200...]: df.duplicated().value\_counts()

Out[200]:

False	253900
True	10596
	dtype: int64

In [201...]: df = df.drop\_duplicates()

In [202...]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 253900 entries, 0 to 264495
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   CrimeDate        253900 non-null   object 
 1   CrimeTime         253900 non-null   object 
 2   CrimeCode         253900 non-null   object 
 3   Location          252173 non-null   object 
 4   Description       250114 non-null   object 
 5   Weapon            82019 non-null   object 
 6   Post              253701 non-null   float64
 7   District          253842 non-null   object 
 8   Neighborhood      252105 non-null   object 
 9   Location 1        252175 non-null   object 
 10  Total Incidents   253900 non-null   int64  
dtypes: float64(1), int64(1), object(9)
memory usage: 23.2+ MB
```

In [203...]

```
df[ "CrimeCode" ].value_counts()
```

```
Out[203]:
```

4E	41377
6D	35539
5A	25352
7A	22986
6G	15212
6J	11980
6C	11939
6E	11702
4C	9312
5D	7677
4B	6393
3AF	5660
3B	5296
4A	4019
4D	3482
5B	3367
6B	3345
5C	3187
4F	3167
6F	2436
9S	2118
3CF	1697
7C	1597
3K	1393
3AK	1381
2A	1354
1F	1047
3AO	949
5F	798
3AJF	742
5E	687
8H	652
3JF	645
3D	625
3P	544
6A	439
6L	373
3CK	259
8AO	243
2B	223
3GF	222
3BJ	221
3CO	194
3JK	185

```
3NF      179
3JO      151
1K       146
8J       145
6H       138
8FO      95
3H       92
10      88
3NK      80
7B       80
8AV      68
8BO      67
3AJK     65
3EF      60
3M       58
3AJ0     52
8EO      50
3NO      43
3F       40
3GK      35
3LF      21
3GO      20
3LO      17
8GO      15
3EK      13
8BV      12
8CO      10
8EV      8
3EO      7
8I       7
8GV      5
3N       5
8CV      4
6K       3
8FV      3
3LK      1
8DO      1
Name: CrimeCode, dtype: int64
```

```
In [204...]: df = df.rename(columns = {'CrimeDate':'date'})
df = df.rename(columns= {'CrimeCode' : 'incident'})
```

```
In [205...]: df['date'] = pd.to_datetime(df['date']).dt.strftime('%Y-%m-%d')
```

```
In [206... df.date.min(), df.date.max()
```

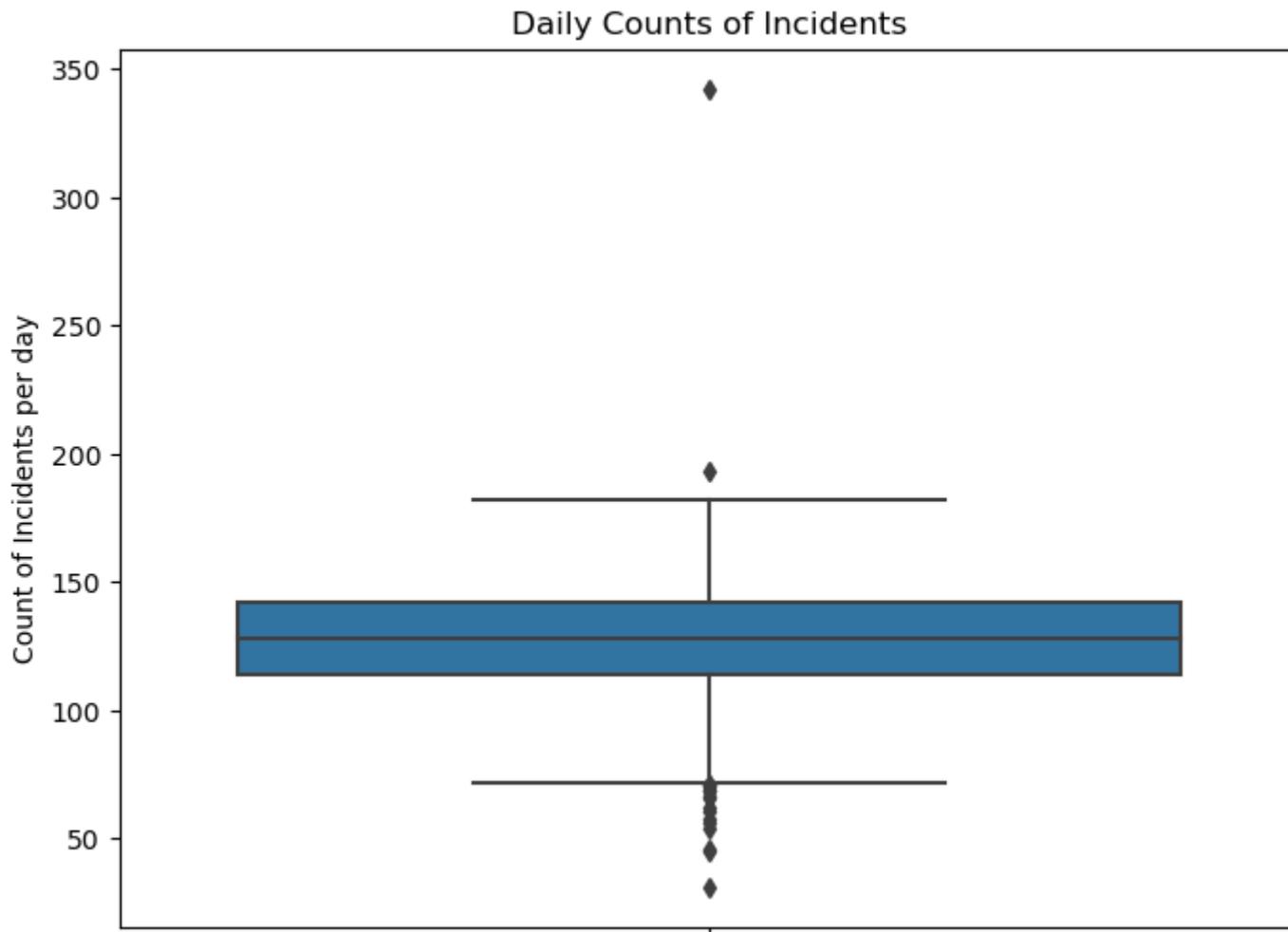
```
Out[206]: ('2011-01-01', '2016-06-18')
```

```
In [207... df = df.iloc[:, [0,2]]  
# df.to_csv("Baltimore.csv", index=False)
```

```
In [208... daily_incident_counts_stats = df.groupby("date")['date'].value_counts().describe([.25, .5, .75, .95, .98, .99]).astype(int)  
daily_incident_counts_stats
```

```
Out[208]: count    1996  
mean     127  
std      21  
min      31  
25%     114  
50%     128  
75%     142  
95%     160  
98%     167  
99%     171  
max     342  
Name: date, dtype: int32
```

```
In [209... # Display the days with high incident numbers  
plt.figure(figsize=(8, 6))  
sns.boxplot(y=df.groupby("date")['date'].value_counts())  
plt.title('Daily Counts of Incidents')  
plt.ylabel('Count of Incidents per day')  
plt.show()
```



```
In [210]: df.date.unique()
```

```
Out[210]: 1996
```

As seen below, our dataset spans a total of 1996 days. Every day in the dataset contains a record of an incident. In other words, there are no days without any recorded incidents.

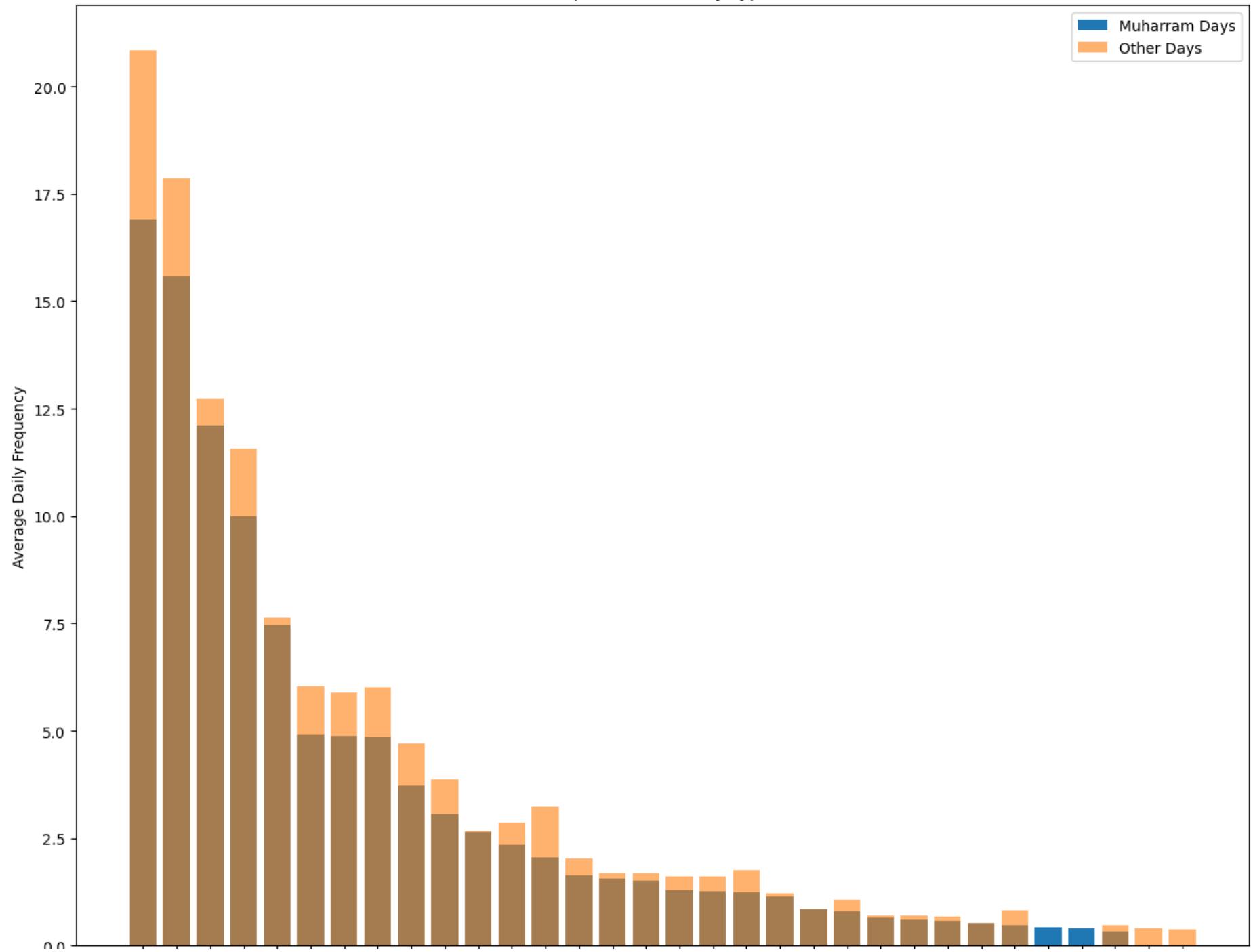
```
In [211]: muharrem_10_days(df)
```

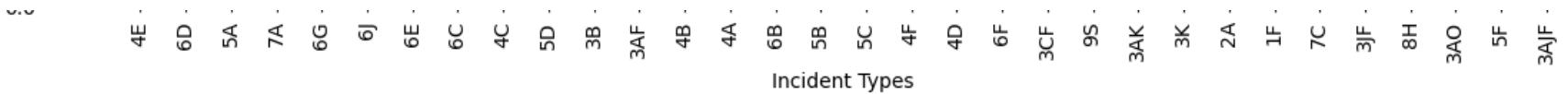
```
Total number of days: 1996
-----
Total number of cases: 253900
-----
Average Daily Case Count: 127.2
-----
Yearly case counts according to the Gregorian calendar:
-----
2011    48555
2012    47643
2013    47569
2015    46643
2014    44343
2016    19147
Name: date, dtype: int64
-----
Case counts according to the Hijri calendar:
-----
1433    46536
1434    45861
1436    44720
1432    43976
1435    43592
1437    29215
Name: Hijri_Date, dtype: int64
-----
Average case count in the first ten days of Muharram months: 108.6167
-----
Average case count in other days: 127.7805
-----
Ratio of Muharram cases to other cases: 0.8500
```

**We observe a -15% lower crime rate during the initial 10 days of the Muharram month compared to the annual average.**

```
In [212]: sorted_ratios, muharrem_dominant_incidents, muharrem_incidents_desc, other_days_incidents_desc = incidents_by_types(df)
# display(sorted_ratios)
# display(muharrem_dominant_incidents)
```

Top 30 Incidents by Type





In [213]:

```
# Top 30 incident types sorted by "muharrem incidents / total incidents" ratio
sorted_ratios
```

Out[213]:

	<b>muharrem incidents</b>	<b>all incidents</b>	<b>muharrem incidents/total incidents</b>
<b>3N</b>	1	5	0.200000
<b>3GK</b>	3	35	0.085700
<b>8FO</b>	7	95	0.073700
<b>7B</b>	4	80	0.050000
<b>3NO</b>	2	43	0.046500
<b>8BO</b>	3	67	0.044800
<b>3JF</b>	25	645	0.038800
<b>3NK</b>	3	80	0.037500
<b>8H</b>	24	652	0.036800
<b>3P</b>	19	544	0.034900
<b>6L</b>	13	373	0.034900
<b>3NF</b>	6	179	0.033500
<b>3JO</b>	5	151	0.033100
<b>3H</b>	3	92	0.032600
<b>1F</b>	32	1047	0.030600
<b>3CF</b>	51	1697	0.030100
<b>3B</b>	159	5296	0.030000
<b>6G</b>	448	15212	0.029500
<b>5A</b>	726	25352	0.028600
<b>6F</b>	69	2436	0.028300
<b>3AK</b>	39	1381	0.028200
<b>6B</b>	94	3345	0.028100
<b>5E</b>	19	687	0.027700
<b>5B</b>	90	3367	0.026700

	<b>muharrem incidents</b>	<b>all incidents</b>	<b>muharrem incidents/total incidents</b>
<b>6D</b>	935	35539	0.026300
<b>7A</b>	599	22986	0.026100
<b>3CO</b>	5	194	0.025800
<b>3K</b>	36	1393	0.025800
<b>2A</b>	34	1354	0.025100
<b>6E</b>	292	11702	0.025000

In [214]:

```
# In which categories were more crimes committed during the first ten days of Muharram?
muharrem_dominant_incidents
```

Out[214]:

muharrem incidents all incidents muharrem incidents/total incidents

	muharrem incidents	all incidents	muharrem incidents/total incidents
<b>3CF</b>	51	1697	0.0301
<b>1F</b>	32	1047	0.0306
<b>3JF</b>	25	645	0.0388
<b>8H</b>	24	652	0.0368
<b>3P</b>	19	544	0.0349
<b>6L</b>	13	373	0.0349
<b>8FO</b>	7	95	0.0737
<b>3NF</b>	6	179	0.0335
<b>3JO</b>	5	151	0.0331
<b>7B</b>	4	80	0.0500
<b>3GK</b>	3	35	0.0857
<b>3H</b>	3	92	0.0326
<b>3NK</b>	3	80	0.0375
<b>8BO</b>	3	67	0.0448
<b>3NO</b>	2	43	0.0465
<b>3N</b>	1	5	0.2000

More crimes were committed in the above-mentioned crime categories during the first ten days of Muharram compared to the other days of the year.

In [215...]

```
df.incident.nunique(), muharrem_dominant_incidents.count()[0]
```

Out[215]:

(81, 16)

In [216...]

```
muharrem_incidents_desc
```

Out[216]:

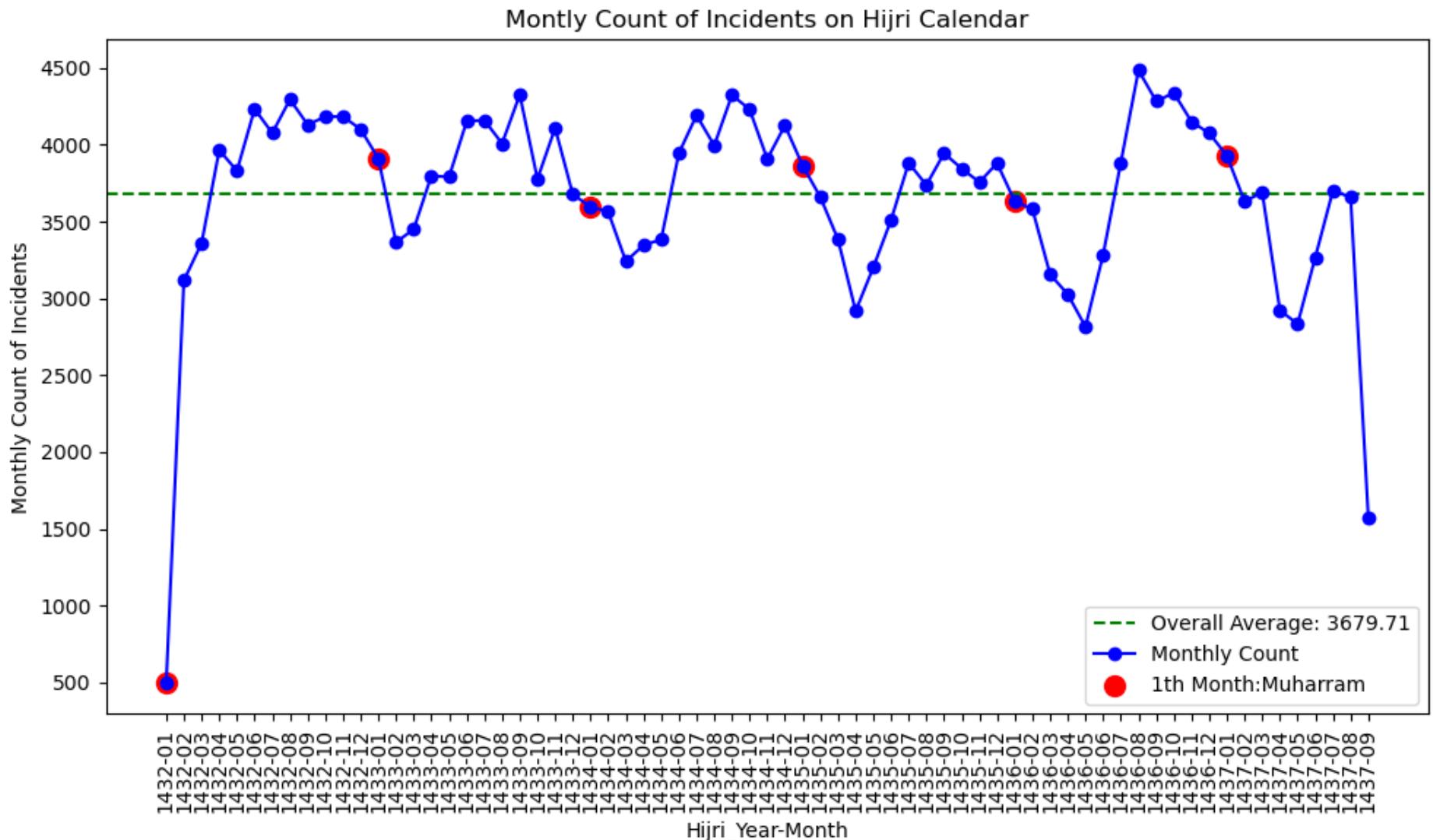
```
count      6517
unique     60
top        4E
freq       1015
Name: incident, dtype: object
```

```
In [217]: other_days_incidents_desc
```

```
Out[217]: count    247383  
unique     81  
top        4E  
freq     40362  
Name: incident, dtype: object
```

Baltimore dataset encompasses 81 distinct incident types. During the first ten days of Muharram, crimes were committed across 60 incident categories, with 16 of these categories experiencing incident counts exceeding the annual averages.

```
In [218]: monthly_count_plot()
```



## SAMPLE DATA-9: ATLANTA CRIME DATASET\_2009-2017

<https://data.world/bryantahb/crime-in-atlanta-2009-2017>

In [219...]

```
df = pd.read_csv("atlcrime.csv", low_memory=False)
df.drop(columns="Unnamed: 0", inplace=True)
```

```
df
```

		crime	number	date	location	beat	neighborhood	npu	lat	long
0		LARCENY-NON VEHICLE	103040029	10/31/2010	610 SPRING ST NW	509	Downtown	M	33.77101	-84.38895
1		AUTO THEFT	103040061	10/31/2010	850 OAK ST SW	401	West End	T	33.74057	-84.41680
2		LARCENY-FROM VEHICLE	103040169	10/31/2010	1344 METROPOLITAN PKWY SW	301	Capitol View Manor	X	33.71803	-84.40774
3		AUTO THEFT	103040174	10/31/2010	1752 PRYOR RD SW	307	Betmar LaVilla	Y	33.70731	-84.39674
4		LARCENY-NON VEHICLE	103040301	10/31/2010	JOHN WESLEY DOBBS AVE NE / CORLEY ST NE	604	Old Fourth Ward	M	33.75947	-84.36626
...		...	...	...	...	...	...	...	...	...
270683		BURGLARY-RESIDENCE	92442142	09/01/2009	1226 PORTLAND AVE SE	612	East Atlanta	W	33.73927	-84.34741
270684		LARCENY-FROM VEHICLE	92442164	09/01/2009	317 PICKFAIR WAY SW	307	Lakewood Heights	Y	33.70436	-84.40013
270685		LARCENY-NON VEHICLE	92448045	09/01/2009	6234 SPINE RD @atrium	50	NaN	NaN	33.64068	-84.44204
270686		LARCENY-NON VEHICLE	92440866	09/01/2009	30 WARREN ST	610	Kirkwood	O	33.75374	-84.32600
270687		HOMICIDE	92440372058	09/01/2009	2860 MARTIN L KING JR DR SW	405	Harland Terrace	I	33.75399	-84.48138

270688 rows × 9 columns

```
In [220...]: df.duplicated().value_counts()
```

```
Out[220]: False  
dtype: int64
```

```
In [221...]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 270688 entries, 0 to 270687
Data columns (total 9 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   crime             270688 non-null   object 
 1   number            270688 non-null   int64  
 2   date              270688 non-null   object 
 3   location          270686 non-null   object 
 4   beat               270688 non-null   object 
 5   neighborhood       258928 non-null   object 
 6   npu                268592 non-null   object 
 7   lat                270688 non-null   float64
 8   long               270688 non-null   float64
dtypes: float64(2), int64(1), object(6)
memory usage: 18.6+ MB
```

```
In [222]: df["crime"].value_counts()
```

```
Out[222]:
```

LARCENY-FROM VEHICLE	77345
LARCENY-NON VEHICLE	64697
BURGLARY-RESIDENCE	42941
AUTO THEFT	38168
AGG ASSAULT	19133
ROBBERY-PEDESTRIAN	14446
BURGLARY-NONRES	8505
ROBBERY-RESIDENCE	1880
ROBBERY-COMMERCIAL	1855
RAPE	990
HOMICIDE	728

Name: crime, dtype: int64

```
In [223]: df = df.rename(columns= {'crime' : 'incident'})
```

```
In [224]: df['date'] = pd.to_datetime(df['date']).dt.strftime('%Y-%m-%d')
```

```
In [225]: df.date.min(), df.date.max()
```

```
Out[225]: ('2009-01-01', '2017-02-28')
```

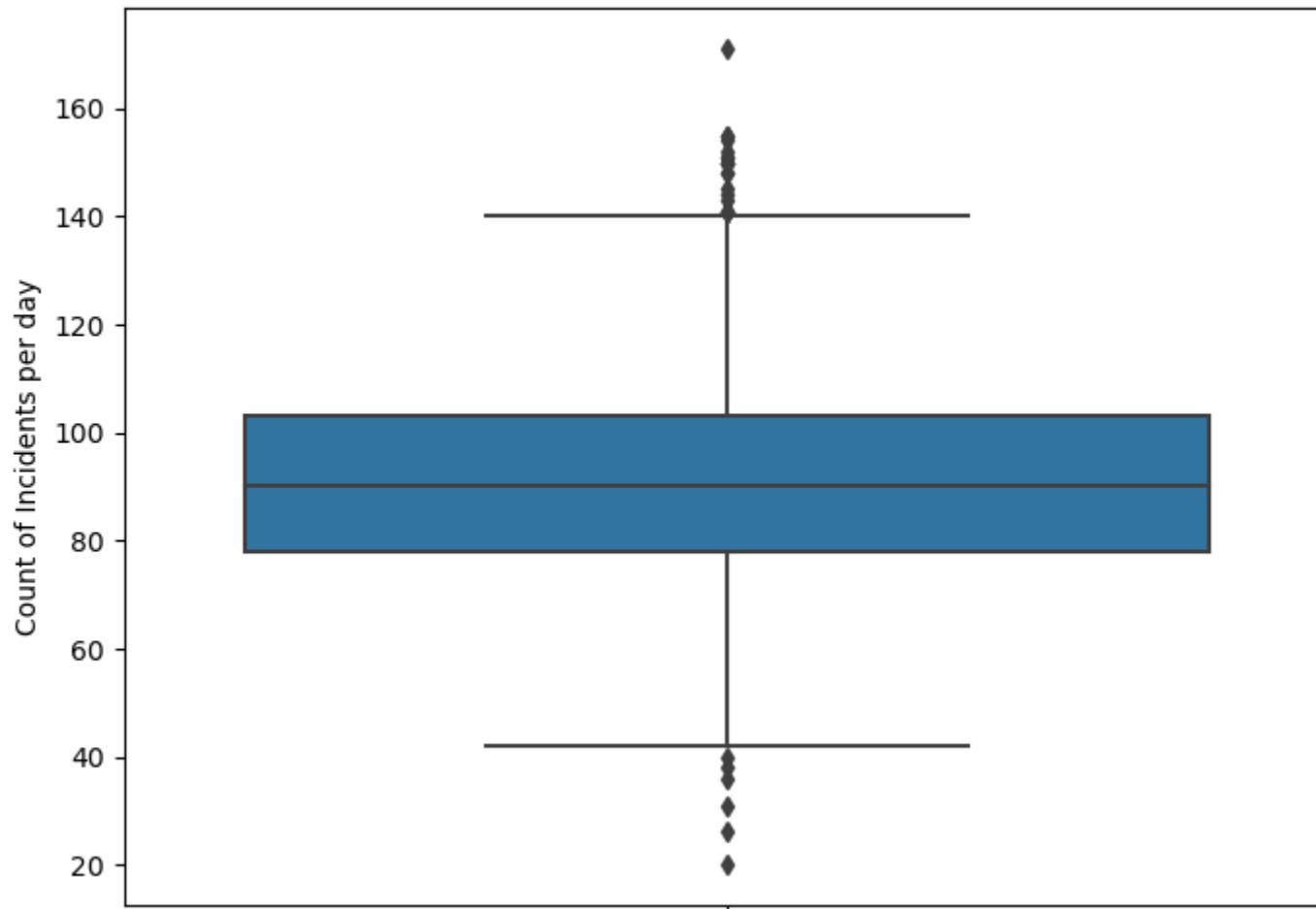
```
In [226]: df = df.iloc[:, [0,2]]
# df.to_csv("Atlanta.csv", index=False)
```

```
In [227]: daily_incident_counts_stats = df.groupby("date")['date'].value_counts().describe([.25, .5, .75, .95, .98, .99]).astype(int)
daily_incident_counts_stats
```

```
Out[227]: count    2981
mean      90
std       18
min      20
25%     78
50%     90
75%    103
95%    121
98%    130
99%    137
max     171
Name: date, dtype: int32
```

```
In [228]: # Display the days with high incident numbers
plt.figure(figsize=(8, 6))
sns.boxplot(y=df.groupby("date")['date'].value_counts())
plt.title('Daily Counts of Incidents')
plt.ylabel('Count of Incidents per day')
plt.show()
```

### Daily Counts of Incidents



```
In [229]: df.date.unique()
```

```
Out[229]: 2981
```

As seen below, our dataset spans a total of 2981 days. Every day in the dataset contains a record of an incident. In other words, there are no days without any recorded incidents.

```
In [230]: muharrem_10_days(df)
```

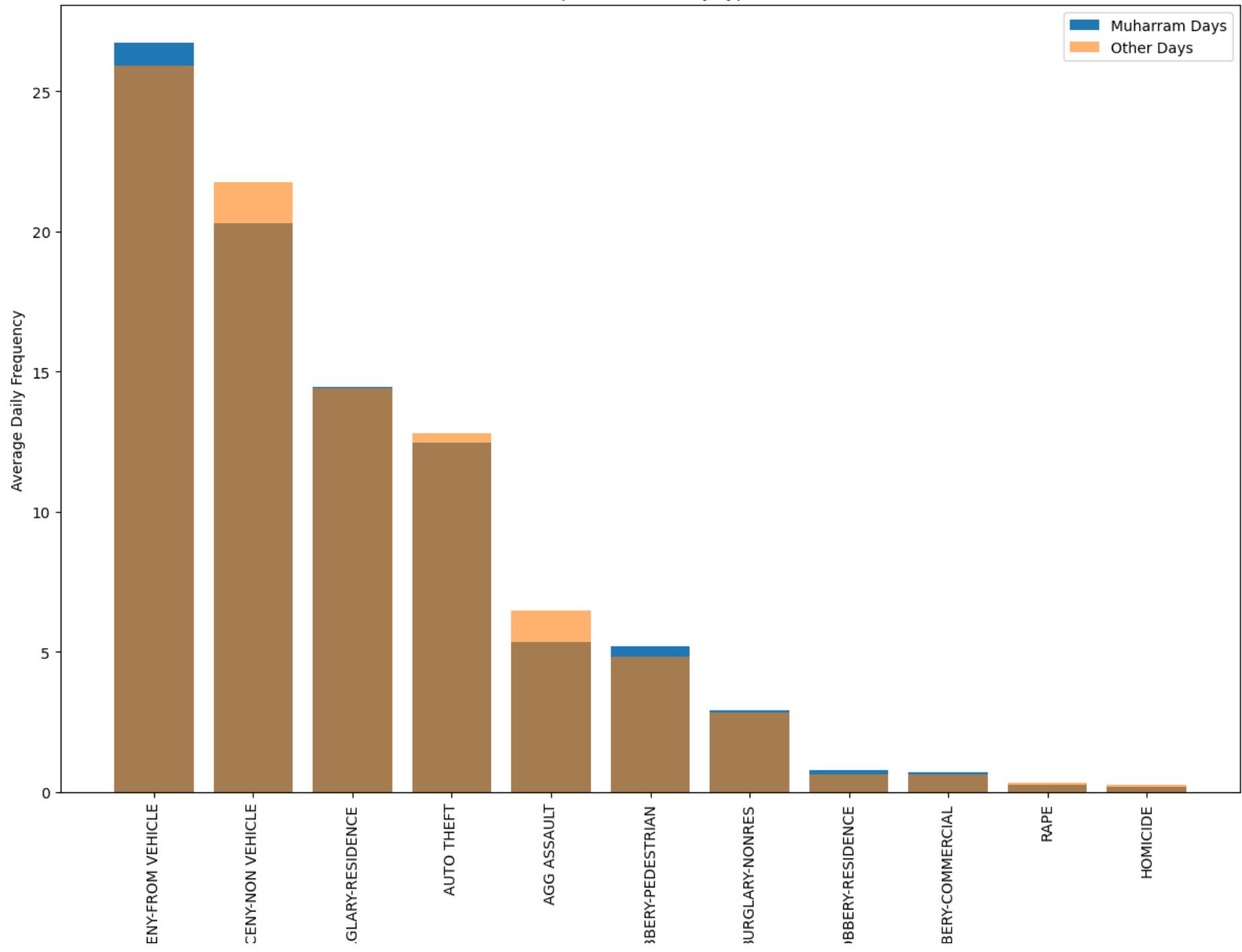
```
Total number of days: 2981
-----
Total number of cases: 270688
-----
Average Daily Case Count: 90.8
-----
Yearly case counts according to the Gregorian calendar:
-----
2009    39626
2010    35770
2011    35174
2012    33394
2013    32303
2014    31166
2015    30117
2016    29131
2017    4007
Name: date, dtype: int64
-----
Case counts according to the Hijri calendar:
-----
1430    38259
1431    34884
1432    34032
1433    32539
1434    31776
1436    30133
1435    29559
1437    28162
1438    11344
Name: Hijri_Date, dtype: int64
-----
Average case count in the first ten days of Muharram months: 89.3333
-----
Average case count in other days: 90.8502
-----
Ratio of Muharram cases to other cases: 0.9833
```

**We observe a -1.67% lower crime rate during the initial 10 days of the Muharram month compared to the annual average.**

```
In [231...]: sorted_ratios, muharrem_dominant_incidents, muharrem_incidents_desc, other_days_incidents_desc = incidents_by_types(df)
# display(sorted_ratios)
```

```
# display(muharrem_dominant_incidents)
```

Top 30 Incidents by Type



LARC

LAR

BUR

ROF

E

RC

ROB

## Incident Types

In [232]: # Top 30 incident types sorted by "muharrem incidents / total incidents" ratio  
sorted\_ratios

Out[232]:

	muharrem incidents	all incidents	muharrem incidents/total incidents
<b>ROBBERY-RESIDENCE</b>	70	1880	0.037200
<b>ROBBERY-COMMERCIAL</b>	63	1855	0.034000
<b>ROBBERY-PEDESTRIAN</b>	466	14446	0.032300
<b>LARCENY-FROM VEHICLE</b>	2406	77345	0.031100
<b>BURGLARY-NONRES</b>	263	8505	0.030900
<b>BURGLARY-RESIDENCE</b>	1300	42941	0.030300
<b>AUTO THEFT</b>	1123	38168	0.029400
<b>LARCENY-NON VEHICLE</b>	1827	64697	0.028200
<b>AGG ASSAULT</b>	482	19133	0.025200
<b>HOMICIDE</b>	17	728	0.023400
<b>RAPE</b>	23	990	0.023200

In [233]: # In which categories were more crimes committed during the first ten days of Muharram?  
muharrem\_dominant\_incidents

```
Out[233]:
```

	muharrem incidents	all incidents	muharrem incidents/total incidents
<b>LARCENY-FROM VEHICLE</b>	2406	77345	0.0311
<b>BURGLARY-RESIDENCE</b>	1300	42941	0.0303
<b>ROBBERY-PEDESTRIAN</b>	466	14446	0.0323
<b>BURGLARY-NONRES</b>	263	8505	0.0309
<b>ROBBERY-RESIDENCE</b>	70	1880	0.0372
<b>ROBBERY-COMMERCIAL</b>	63	1855	0.0340

More crimes were committed in the above-mentioned crime categories during the first ten days of Muharram compared to the other days of the year.

```
In [234...]: df.incident.nunique(), muharrem_dominant_incidents.count()[0]
```

```
Out[234]: (11, 6)
```

```
In [235...]: muharrem_incidents_desc
```

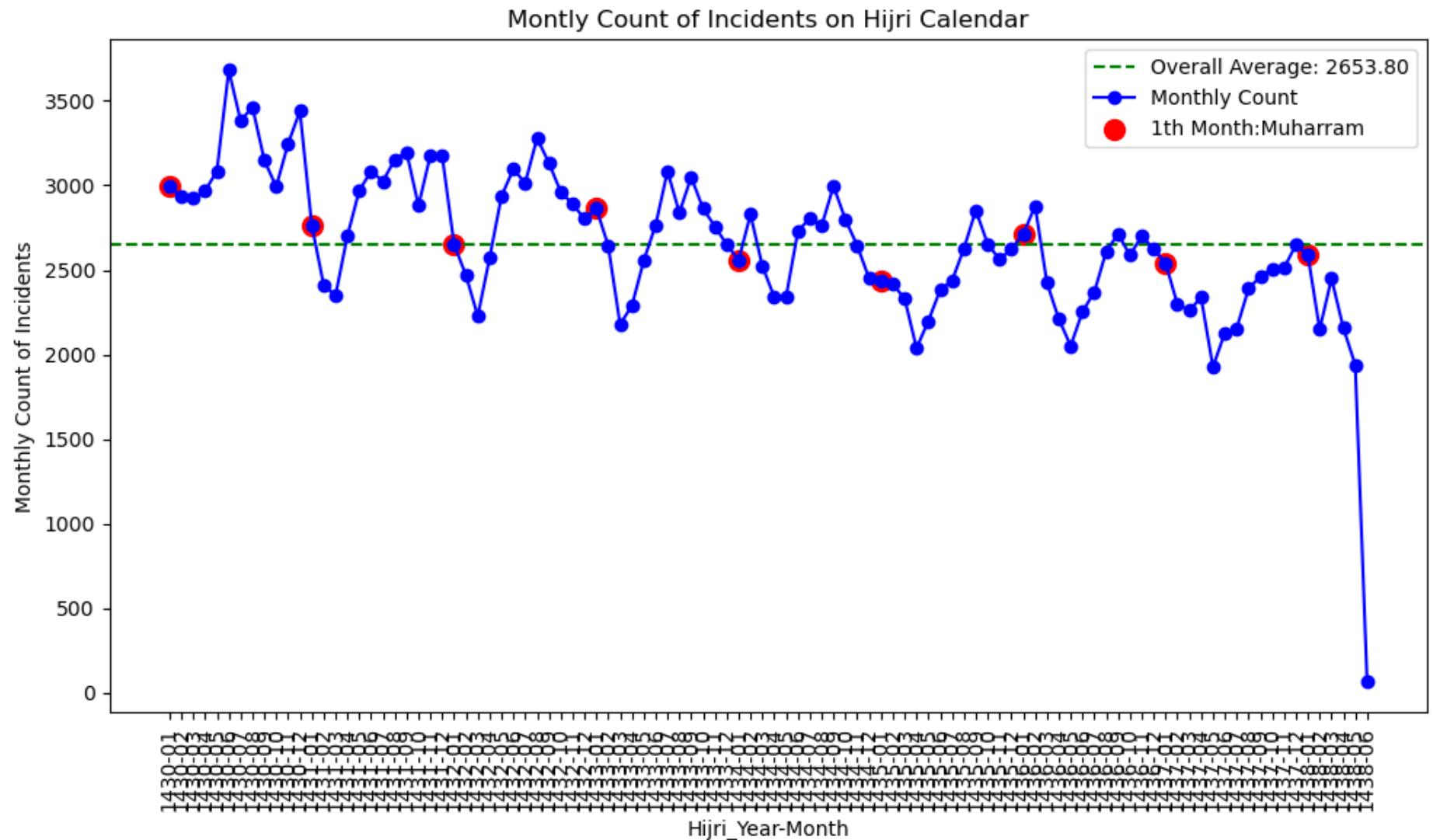
```
Out[235]: count          8040
unique           11
top    LARCENY-FROM VEHICLE
freq            2406
Name: incident, dtype: object
```

```
In [236...]: other_days_incidents_desc
```

```
Out[236]: count          262648
unique           11
top    LARCENY-FROM VEHICLE
freq            74939
Name: incident, dtype: object
```

Atlanta dataset encompasses 11 distinct incident types. During the first ten days of Muharram, crimes were committed across 11 incident categories, with 6 of these categories experiencing incident counts exceeding the annual averages.

```
In [237...]: monthly_count_plot()
```



## SAMPLE DATA-10: OAKLAND CRIME STATISTICS\_2011-2016

<https://www.kaggle.com/datasets/cityofoakland/oakland-crime-statistics-2011-to-2016/>

In [238...]

```
df2 = pd.read_csv("records-for-2011.csv")
df3 = pd.read_csv("records-for-2012.csv")
```

```
df4 = pd.read_csv("records-for-2013.csv")
df5 = pd.read_csv("records-for-2014.csv")
df6 = pd.read_csv("records-for-2015.csv")
df7 = pd.read_csv("records-for-2016.csv")
```

In [239...]

```
frames = [df2, df3, df4, df5, df6, df7]
df = pd.concat(frames)
df.head()
```

Out[239]:

	Agency	Create Time	Location	Area Id	Beat	Priority	Incident Type Id	Incident Type Description	Event Number	Closed Time	Location 1	Zip Codes	Location
0	OP	2011-01-01T00:00:00.000	ST&SAN PABLO AV	1.0	06X	1.0	PDOA	POSSIBLE DEAD PERSON	LOP110101000001	2011-01-01T00:28:17.000	NaN	NaN	NaN
1	OP	2011-01-01T00:01:11.000	ST&HANNAH ST	1.0	07X	1.0	415GS	415 GUNSHOTS	LOP110101000002	2011-01-01T01:12:56.000	NaN	NaN	NaN
2	OP	2011-01-01T00:01:25.000	ST&MARKET ST	1.0	10Y	2.0	415GS	415 GUNSHOTS	LOP110101000003	2011-01-01T00:07:20.000	NaN	NaN	NaN
3	OP	2011-01-01T00:01:35.000	PRENTISS ST	2.0	21Y	2.0	415GS	415 GUNSHOTS	LOP110101000005	2011-01-01T00:02:28.000	NaN	NaN	NaN
4	OP	2011-01-01T00:02:10.000	AV&FOOTHILL BLVD	2.0	20X	1.0	415GS	415 GUNSHOTS	LOP110101000004	2011-01-01T00:50:04.000	NaN	NaN	NaN

In [240...]

```
df.duplicated().value_counts()
```

Out[240]:

```
False    1046388
dtype: int64
```

In [241...]

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1046388 entries, 0 to 110827
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   Agency            1046384 non-null   object  
 1   Create Time       1046384 non-null   object  
 2   Location          483425 non-null   object  
 3   Area Id           864023 non-null   object  
 4   Beat              1040583 non-null   object  
 5   Priority          1046384 non-null   float64 
 6   Incident Type Id 1046384 non-null   object  
 7   Incident Type Description 1045996 non-null   object  
 8   Event Number      1046384 non-null   object  
 9   Closed Time       1046359 non-null   object  
 10  Location 1        374799 non-null   object  
 11  Zip Codes         352 non-null      float64 
 12  Location          188052 non-null   object  
dtypes: float64(2), object(11)
memory usage: 111.8+ MB
```

In [242...]: df["Incident Type Description"].value\_counts()[:30]

```
Out[242]:
```

ALARM-RINGER	98497
SECURITY CHECK	70965
911 HANG-UP	54935
STOLEN VEHICLE	47958
DISTURBING THE PEACE	38257
MENTALLY ILL	37218
415 UNKNOWN	33470
BATTERY	30636
SUSPICIOUS PERSON	26984
BATTERY ON CO-HABITA	23964
415 GUNSHOTS	21520
415 FAMILY	21372
SUSPICIOUS VEHICLE	20781
ROBBERY	19452
HAZARDOUS SITUATION/	18948
WELFARE CHECK -- CHE	17450
TRESPASS:	14819
VEHICLE COLLISION-PE	13782
ASSAULT W/DEADLY WEA	12982
415 THREATS	12819
HIT & RUN (PROPERTY	12417
FIGHT	12062
STAND BY AND PRESERV	10584
DISTURBANCE-NEIGHBOR	10553
SUBJECT ARMED WITH W	10376
BURGLARY	10001
OBSTRUCT PERSON'S MO	9782
RUNAWAY	9557
ALARM-MANUALLY ACTIV	9356
DISTURBANCE-CUSTOMER	8543

Name: Incident Type Description, dtype: int64

```
In [243...]
```

```
df = df.rename(columns = {'Create Time':'date'})  
df = df.rename(columns = {'Incident Type Description':'incident'})
```

```
In [244...]
```

```
# df[df['date'].isnull()]  
df = df.dropna(subset=['date'])
```

```
In [245...]
```

```
df['date'] = pd.to_datetime(df['date']).dt.strftime('%Y-%m-%d')
```

```
In [246...]
```

```
df.date.min(), df.date.max()
```

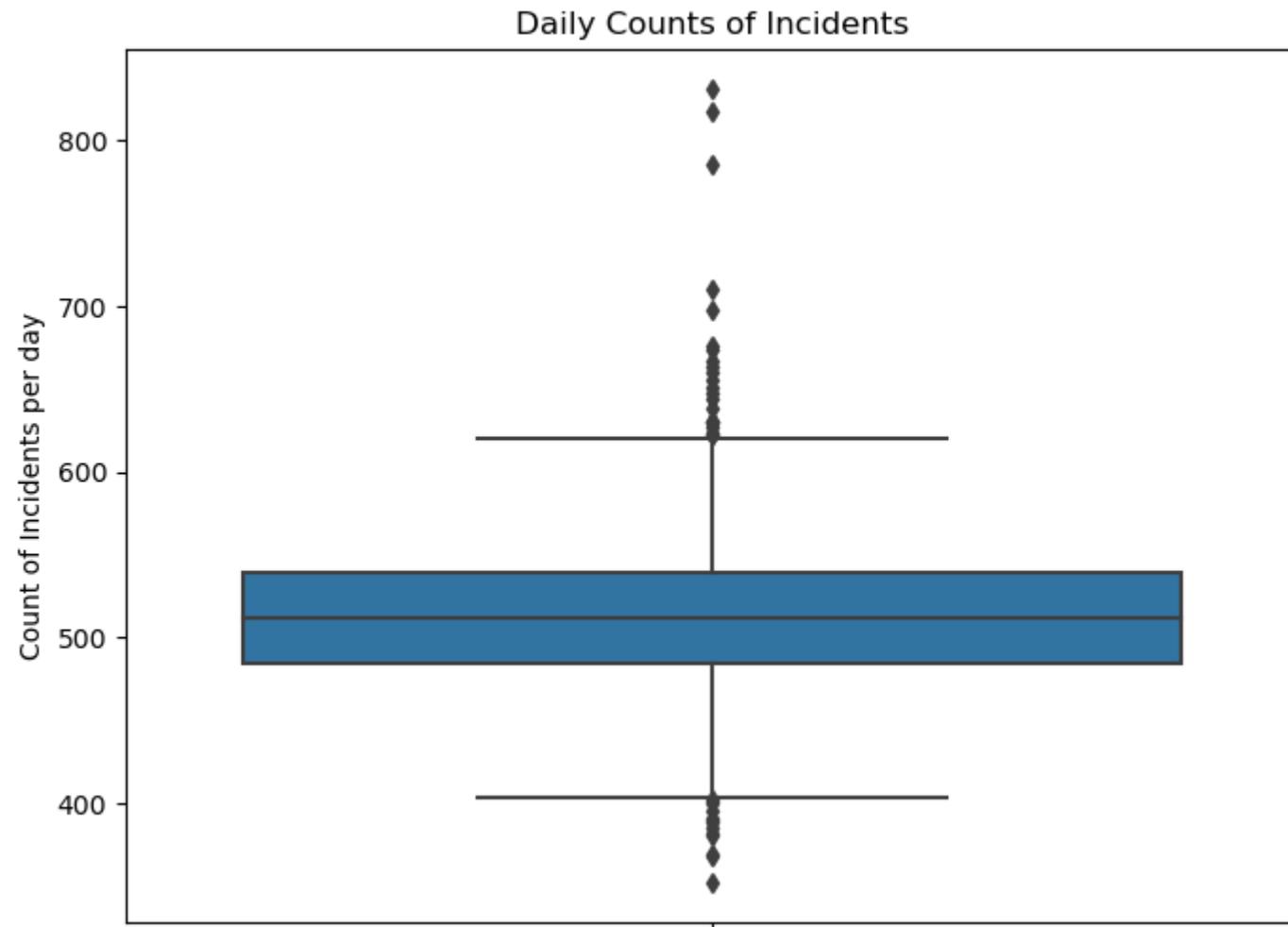
```
Out[246]: ('2011-01-01', '2016-07-31')
```

```
In [247... df = df.iloc[:, [1,7]]  
# df.to_csv("Oakland.csv", index=False)
```

```
In [248... daily_incident_counts_stats = df.groupby("date")['date'].value_counts().describe([.25, .5, .75, .95, .98, .99]).astype(int)  
daily_incident_counts_stats
```

```
Out[248]: count    2039  
mean      513  
std       44  
min      352  
25%     485  
50%     512  
75%     539  
95%     584  
98%     607  
99%     623  
max     831  
Name: date, dtype: int32
```

```
In [249... # Display the days with high incident numbers  
plt.figure(figsize=(8, 6))  
sns.boxplot(y=df.groupby("date")['date'].value_counts())  
plt.title('Daily Counts of Incidents')  
plt.ylabel('Count of Incidents per day')  
plt.show()
```



```
In [250]: df.date.nunique()
```

```
Out[250]: 2039
```

As seen below, our dataset spans a total of 2039 days. Every day in the dataset contains a record of an incident. In other words, there are no days without any recorded incidents.

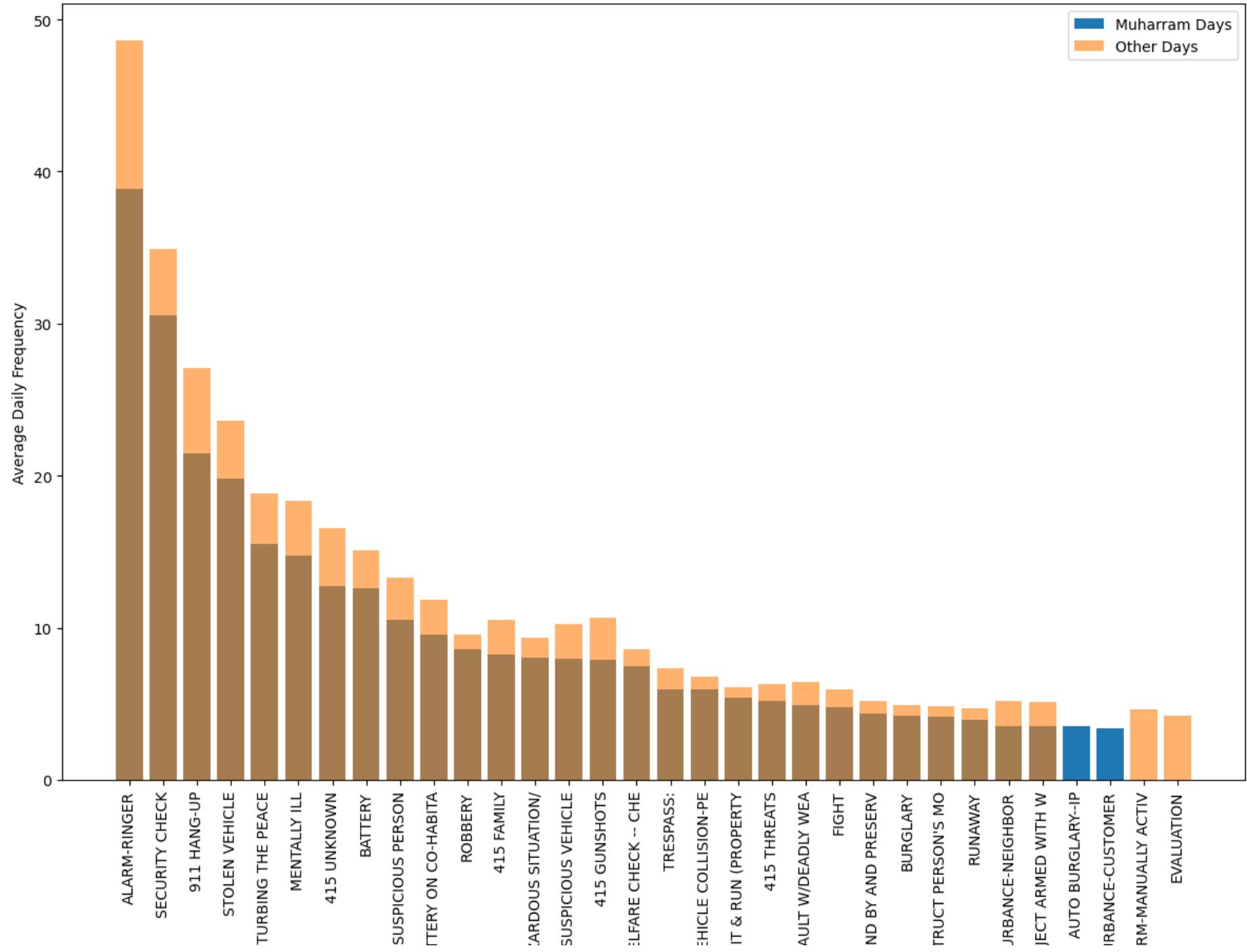
```
In [251]: muharrem_10_days(df)
```

```
Total number of days: 2039
-----
Total number of cases: 1046384
-----
Average Daily Case Count: 513.18
-----
Yearly case counts according to the Gregorian calendar:
-----
2015    192581
2013    188051
2014    187480
2012    187430
2011    180015
2016    110827
Name: date, dtype: int64
-----
Case counts according to the Hijri calendar:
-----
1436    188396
1434    184302
1435    180329
1433    180248
1432    163146
1437    149963
Name: Hijri_Date, dtype: int64
-----
Average case count in the first ten days of Muharram months: 415.0167
-----
Average case count in other days: 516.1612
-----
Ratio of Muharram cases to other cases: 0.8040
```

**We observe a -19.60% lower crime rate during the initial 10 days of the Muharram month compared to the annual average.**

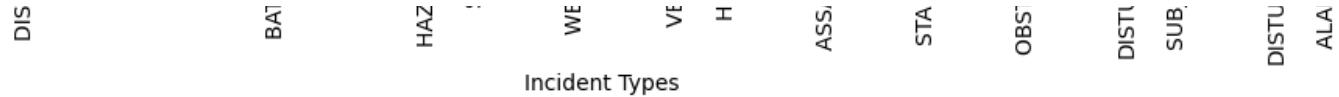
```
In [252]: sorted_ratios, muharrem_dominant_incidents, muharrem_incidents_desc, other_days_incidents_desc = incidents_by_types(df)
# display(sorted_ratios)
# display(muharrem_dominant_incidents)
```

Top 30 Incidents by Type



In [253...]

```
# Top 30 incident types sorted by "muharrem incidents / total incidents" ratio
sorted_ratios
```



Out[253]:

	<b>muharrem incidents</b>	<b>all incidents</b>	<b>muharrem incidents/total incidents</b>
<b>VICE</b>	1	1	1.000000
<b>ESCAPE DETENTION</b>	2	7	0.285700
<b>INTERFERE WITH POWER</b>	2	8	0.250000
<b>PROTECTIVE CUSTODY-N</b>	1	8	0.125000
<b>POSSESS FORGED NOTES</b>	1	9	0.111100
<b>VEHICLE PARKED ON SI</b>	1	10	0.100000
<b>FALSE REPORT OF CRIM</b>	1	12	0.083300
<b>SEWER PROBLEMS</b>	2	27	0.074100
<b>OBSTRUCTING JUSTICE-</b>	2	29	0.069000
<b>LOCATED MISSING PERS</b>	3	49	0.061200
<b>MAYHEM</b>	2	33	0.060600
<b>GAS LEAK</b>	30	507	0.059200
<b>FAILURE TO PROVIDE F</b>	3	55	0.054500
<b>CHILD TAKEN INTO PRO</b>	1	19	0.052600
<b>AGGRAVATED ASSAULT</b>	5	98	0.051000
<b>SURRENDER OF GUN OR</b>	2	43	0.046500
<b>HATE CRIME</b>	2	43	0.046500
<b>AUTO IMPROPERLY PARK</b>	2	44	0.045500
<b>ELECTRICITY</b>	2	46	0.043500
<b>INTIMIDATION OF A WI</b>	4	92	0.043500
<b>PICKETERS/PROTESTERS</b>	30	713	0.042100
<b>FOUND PROPERTY</b>	9	215	0.041900
<b>ANIMAL-STRAYING</b>	4	96	0.041700
<b>LOST PERSON</b>	6	147	0.040800

	<b>muharrem incidents</b>	<b>all incidents</b>	<b>muharrem incidents/total incidents</b>
<b>TARASOFF</b>	4	98	0.040800
<b>ATTEMPTED RAPE</b>	4	100	0.040000
<b>CONTRIBUTING TO THE</b>	4	100	0.040000
<b>PASS FICTITIOUS CHEC</b>	3	77	0.039000
<b>ABSENT WITHOUT LEAVE</b>	16	419	0.038200
<b>PURSUIT</b>	26	688	0.037800

In [254]:

```
# In which categories were more crimes committed during the first ten days of Muharram?
muharrem_dominant_incidents
```

Out[254]:

	<b>muharrem incidents</b>	<b>all incidents</b>	<b>muharrem incidents/total incidents</b>
<b>INDECENT EXPOSURE</b>	76	2559	0.0297
<b>ATTEMPTED BURGLARY</b>	44	1190	0.0370
<b>CRUELTY TO DEPENDENT</b>	35	1017	0.0344
<b>AUTO ALARM</b>	32	1010	0.0317
<b>PICKETERS/PROTESTERS</b>	30	713	0.0421
<b>GAS LEAK</b>	30	507	0.0592
<b>PURSUIT</b>	26	688	0.0378
<b>SMOKE</b>	25	711	0.0352
<b>CHECK VEHICLE</b>	25	804	0.0311
<b>ASSAULT WITH CAUSTIC</b>	19	580	0.0328
<b>FOUND GUN</b>	19	622	0.0305
<b>ABSENT WITHOUT LEAVE</b>	16	419	0.0382
<b>FOUND PROPERTY</b>	9	215	0.0419
<b>ATTEMPTED AUTO THEFT</b>	7	222	0.0315
<b>LOST PERSON</b>	6	147	0.0408
<b>AGGRAVATED ASSAULT</b>	5	98	0.0510
<b>TARASOFF</b>	4	98	0.0408
<b>CONTRIBUTING TO THE</b>	4	100	0.0400
<b>ATTEMPTED RAPE</b>	4	100	0.0400
<b>ANIMAL-STRAYING</b>	4	96	0.0417
<b>INTIMIDATION OF A WI</b>	4	92	0.0435
<b>FAILURE TO PROVIDE F</b>	3	55	0.0545
<b>PASS FICTITIOUS CHEC</b>	3	77	0.0390
<b>LOCATED MISSING PERS</b>	3	49	0.0612

	<b>muharrem incidents</b>	<b>all incidents</b>	<b>muharrem incidents/total incidents</b>
<b>SEWER PROBLEMS</b>	2	27	0.0741
<b>SCOOTERS INVOLVED IN</b>	2	62	0.0323
<b>SURRENDER OF GUN OR</b>	2	43	0.0465
<b>OBSTRUCTING JUSTICE-</b>	2	29	0.0690
<b>SODOMY</b>	2	62	0.0323
<b>INTERFERE WITH POWER</b>	2	8	0.2500
<b>ELECTRICITY</b>	2	46	0.0435
<b>HATE CRIME</b>	2	43	0.0465
<b>AUTO IMPROPERLY PARK</b>	2	44	0.0455
<b>ESCAPE DETENTION</b>	2	7	0.2857
<b>MAYHEM</b>	2	33	0.0606
<b>CONTEMPT OF COURT/DI</b>	2	67	0.0299
<b>CHOP SHOP OWNERSHIP/</b>	1	27	0.0370
<b>VEHICLE PARKED ON SI</b>	1	10	0.1000
<b>SUSPECTS</b>	1	28	0.0357
<b>CHILD TAKEN INTO PRO</b>	1	19	0.0526
<b>SPOUSAL RAPE</b>	1	31	0.0323
<b>OAKLAND TRAFFIC CODE</b>	1	32	0.0312
<b>FALSE REPORT OF CRIM</b>	1	12	0.0833
<b>PROTECTIVE CUSTODY-N</b>	1	8	0.1250
<b>POSSESSION OR PURCHA</b>	1	33	0.0303
<b>POSSESS FORGED NOTES</b>	1	9	0.1111
<b>KIDNAPPING FOR RANSO</b>	1	30	0.0333
<b>VICE</b>	1	1	1.0000

More crimes were committed in the above-mentioned crime categories during the first ten days of Muharram compared to the other days of the year.

```
In [255...]: df.incident.nunique(), muharrem_dominant_incidents.count()[0]
```

```
Out[255]: (288, 48)
```

```
In [256...]: muharrem_incidents_desc
```

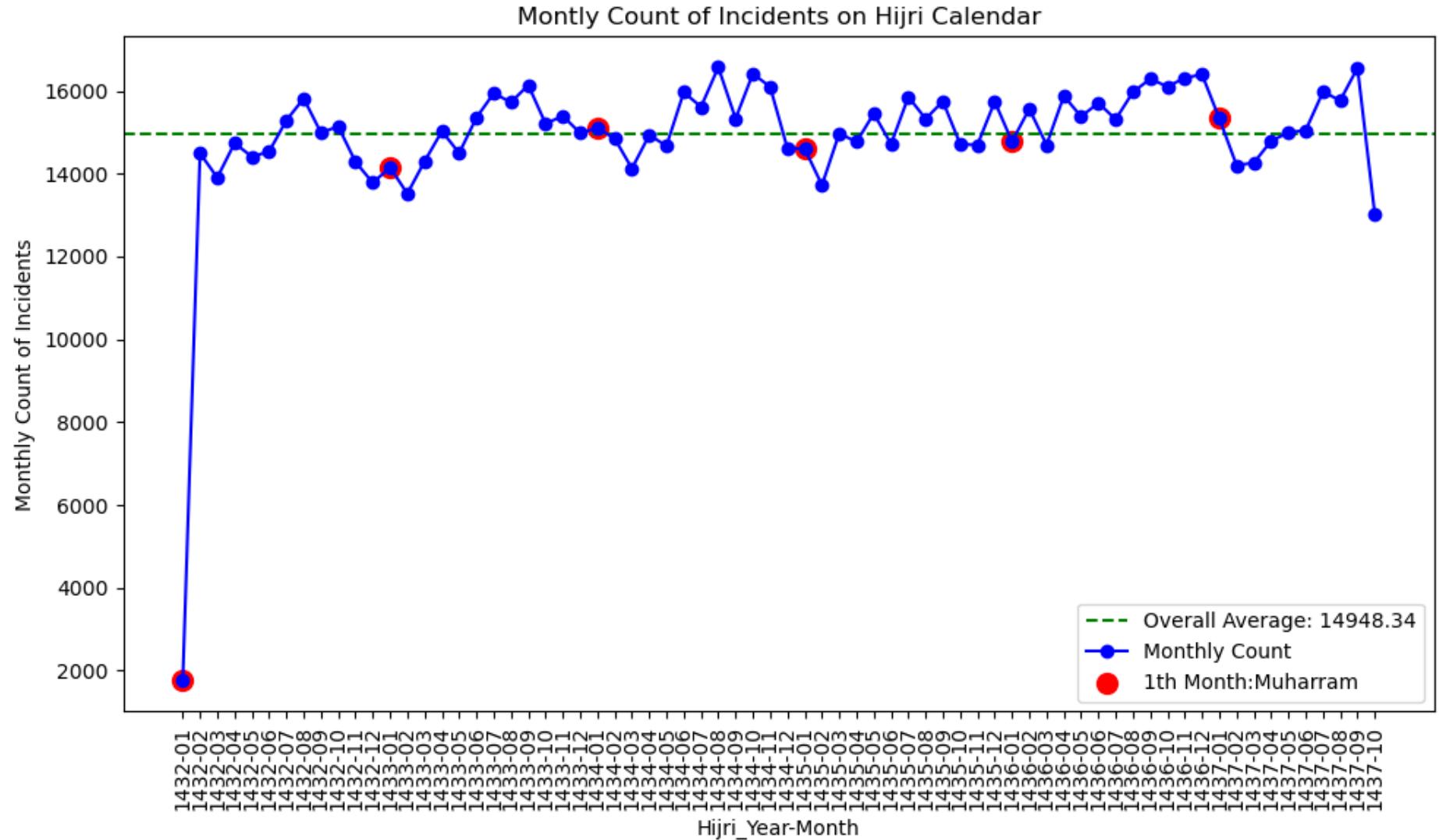
```
Out[256]: count      24889  
unique       221  
top    ALARM-RINGER  
freq        2333  
Name: incident, dtype: object
```

```
In [257...]: other_days_incidents_desc
```

```
Out[257]: count      1021107  
unique       287  
top    ALARM-RINGER  
freq        96164  
Name: incident, dtype: object
```

Oakland dataset encompasses 288 distinct incident types. During the first ten days of Muharram, crimes were committed across 221 incident categories, with 48 of these categories experiencing incident counts exceeding the annual averages.

```
In [258...]: monthly_count_plot()
```



## CONCLUSION

Up to this point, we've examined whether there is an increase or decrease in the first ten days of Muharram compared to the other days of the year in ten different datasets. By making slight adaptations in our code, we also specifically analyzed the 10th Muharram (Ashura Day), and compared them to the remaining days separately. The results obtained are displayed in the table below. The table below displays the percentage ratio of the daily average number of crimes committed

during the first ten days of Muharram to the daily average of crimes committed during the rest of the year. Positive percentages indicate a higher incidence of crimes during the Muharram days, while negative values signify a lower incidence during these days compared to the rest of the year.

```
In [259]: results = pd.DataFrame({'UNC CHAPEL HILL': [25, 7.85],  
                           'LOS ANGELES': [-10.24, -8.75],  
                           'KANSAS': [-8.06, -7.01],  
                           'DETROIT': [-8.85, -3.83],  
                           'DENVER': [7.90, -0.25],  
                           'VANCOUVER': [-0.28, -3.43],  
                           'CHICAGO': [-2.93, -4.12],  
                           'BALTIMORE': [-15, -14.09],  
                           'ATLANTA': [1.67, 2.06],  
                           'OAKLAND': [-19.60, -19.99]  
                          })
```

```
In [260]: results.index = ['Muharram First 10 Days / Other Days Ratio(%)', 'Only Ashura(10th Muharram) Day / Other Days Ratio(%)']  
daily_crime_ratios = results.T
```

```
In [261]: daily_crime_ratios
```

	Muharram First 10 Days / Other Days Ratio(%)	Only Ashura(10th Muharram) Day / Other Days Ratio(%)
UNC CHAPEL HILL	25.00	7.85
LOS ANGELES	-10.24	-8.75
KANSAS	-8.06	-7.01
DETROIT	-8.85	-3.83
DENVER	7.90	-0.25
VANCOUVER	-0.28	-3.43
CHICAGO	-2.93	-4.12
BALTIMORE	-15.00	-14.09
ATLANTA	1.67	2.06
OAKLAND	-19.60	-19.99

Interestingly, except for UNC, Denver, and Atlanta seven data sets/cities showed lower crime rates during the Muharram period. The fact that only 10 days of the year showcased a substantial difference, up to -20% in crime rates compared to other days, presents a significant finding.

In this analysis, the results have shown an opposite effect compared to our examination of Zilhijjah days. It appears that while crime rates increase during Zilhijjah days, there is a decrease during Muharram days. In seven out of ten datasets, fewer crimes were committed during the first ten days of Muharram. Even on the tenth day, the Day of Ashura, the results remain consistent, with fewer crimes observed in eight out of ten datasets. The occurrence of fewer crimes during Muharram days aligns with the Islamic context as well. It's worth recalling that the month of Muharram is regarded as a time of deliverance from calamities, seeking healing from illnesses, attaining peace and forgiveness, emphasizing not wrath but mercy and pardon from Allah, signifying days abundant in tranquility and well-being. Interestingly, the isolated Ashura Day alone displays crime rates well below the yearly averages, with decreases reaching up to 20% in certain datasets. These findings suggest a tendency toward decreased criminal activity during the initial ten days of the Muharram month.

- Contrary to Zilhijjah, seven out of ten datasets reveal lower crime rates during the initial ten days of Muharram, with reductions of up to -19.60% compared to annual averages. - Crimes against individuals decrease during this period, aligning with Islamic contexts that emphasize peace, forgiveness, and deliverance from calamities during Muharram.