

Analysis of Global Terrorism Incidents

The Global Terrorism Database (GTD) is a comprehensive dataset containing information on terrorist incidents worldwide. This report aims to analyze the dataset to identify trends, patterns, and insights related to global terrorism.

1-Data Acquisition and Preprocessing:

The dataset was loaded into a Pandas DataFrame and explored to understand its structure and features. Missing values were handled, and data cleaning was performed to ensure accuracy in analysis.

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+ - * < > [ ] { } ~ ↵ Markdown Python 3 (ipykernel)

[1]: import pandas as pd

[9]: df = pd.read_csv('globalterrorismdb_0718dist.csv', encoding='latin1', low_memory=False)

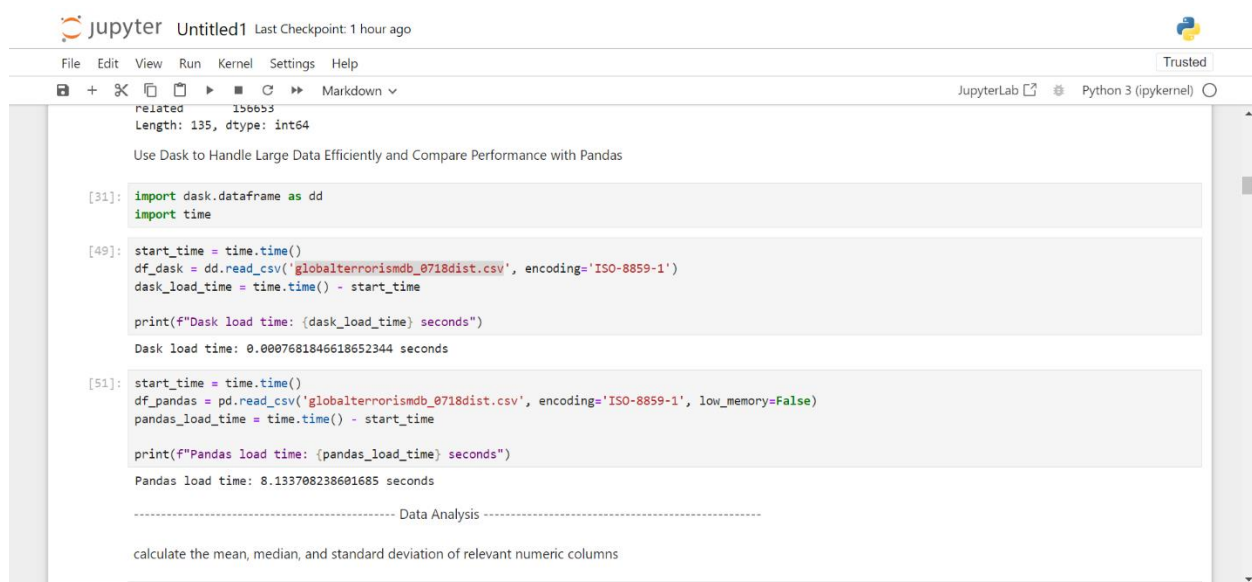
Explore the Dataset to Understand its Structure and Features:

[11]: print(df.head())

   eventid  iyear  imonth  iday approxdate  extended  resolution  country \
0  197000000001  1970      7     2      NaN          0          NaN      58
1  197000000002  1970      0     0      NaN          0          NaN     130
2  197001000001  1970      1     0      NaN          0          NaN     160
3  197001000002  1970      1     0      NaN          0          NaN      78
4  197001000003  1970      1     0      NaN          0          NaN     101

   country_txt  region  ... addnotes  scite1  scite2  scite3  dbsource \
0  Dominican Republic  2  ...      NaN  NaN  NaN  NaN  PGIS
1             Mexico  1  ...      NaN  NaN  NaN  NaN  PGIS
2      Philippines  5  ...      NaN  NaN  NaN  NaN  PGIS
3             Greece  8  ...      NaN  NaN  NaN  NaN  PGIS
4             Japan  4  ...      NaN  NaN  NaN  NaN  PGIS

   INT_LOG  INT_IDEO  INT_MISC  INT_ANY  related
0         0         0         0         0      NaN
1         0         1         1         1      NaN
2        -9        -9         1         1      NaN
3        -9        -9         1         1      NaN
4        -9        -9         1         1      NaN
```



Basic Statistical Analysis Using Numpy, we calculated the mean, median, and standard deviation for relevant numeric columns. The most frequent values in categorical columns were also identified.

Detailed Analysis Using Pandas : Number of Attacks Per Year The number of terrorist attacks per year was calculated, revealing a significant increase in incidents over the past few decades.

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----- Data Analysis -----

calculate the mean, median, and standard deviation of relevant numeric columns

```
[54]: import numpy as np
```

```
[56]: mean_values = df[numeric_cols].mean()
      median_values = df[numeric_cols].median()
      std_dev_values = df[numeric_cols].std()
```

```
[58]: print("Mean values:\n", mean_values)
      print("Median values:\n", median_values)
      print("Standard deviation values:\n", std_dev_values)
```

Mean values:

eventid	2.002705e+11
iyyear	2.002639e+03
imonth	6.467277e+00
iday	1.550564e+01
extended	4.534622e-02
...	...
nreleased	-1.661007e+00
INT_LOG	-4.543731e+00
INT_IDEO	-4.464398e+00
INT_MISC	9.000996e-02
INT_ANY	-3.945952e+00

Length: 77, dtype: float64

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Name: 0, dtype: object

Use Pandas to Group Data and Calculate Aggregate Statistics

```
[63]: # Group by year and calculate the number of attacks per year
      attacks_per_year = df.groupby('iyyear').size()
      print("Attacks per year:\n", attacks_per_year)
```

Attacks per year:

iyyear	
1970	651
1971	471
1972	568
1973	473
1974	581
1975	740
1976	923
1977	1319
1978	1526
1979	2662
1980	2662
1981	2586
1982	2544
1983	2870
1984	3495
1985	2915
1986	2860
1987	3183
1988	3721



```
[65]: # Group by region and calculate the number of attacks per region
attacks_per_region = df.groupby('region_txt').size()
print("Attacks per region:\n", attacks_per_region)
```

```
Attacks per region:
region_txt
Australasia & Oceania      282
Central America & Caribbean 10344
Central Asia              563
East Asia                 802
Eastern Europe            5144
Middle East & North Africa 50474
North America             3456
South America             18978
South Asia                44974
Southeast Asia            12485
Sub-Saharan Africa        17550
Western Europe            16639
dtype: int64
```

```
[67]: attacks_per_attack_type = df.groupby('attacktype1_txt').size()
print("Attacks per attack type:\n", attacks_per_attack_type)
```

```
Attacks per attack type:
attacktype1_txt
Armed Assault          42669
Assassination          19312
Bombing/Explosion      88255
Facility/Infrastructure Attack 10356
Hiackine               659
```



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[65]: # Group by region and calculate the number of attacks per region
attacks_per_region = df.groupby('region_txt').size()
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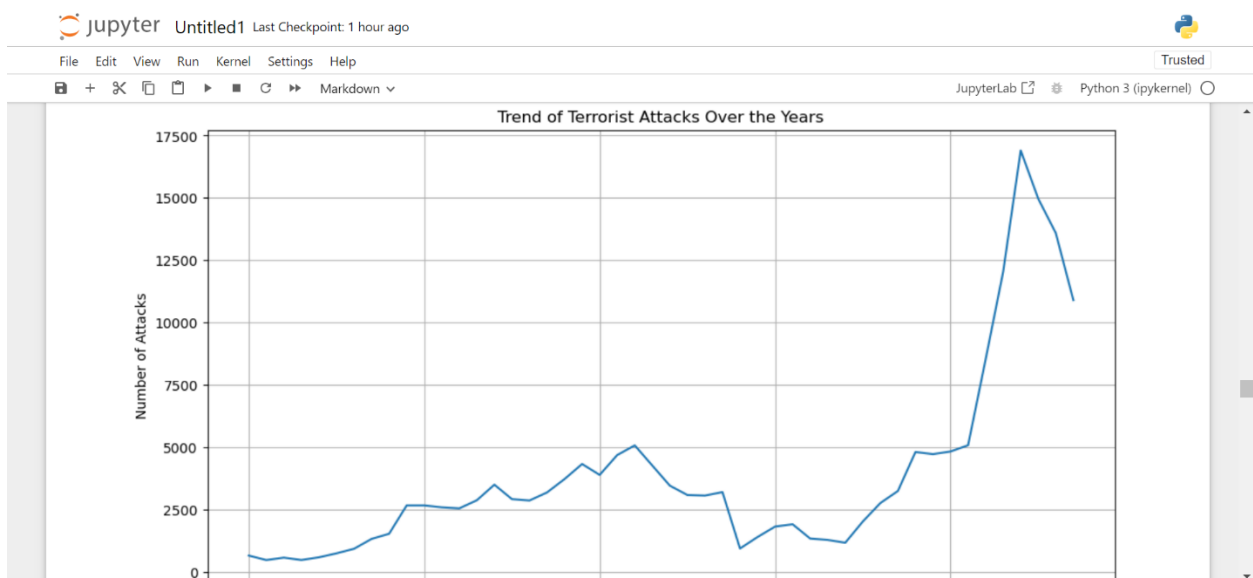
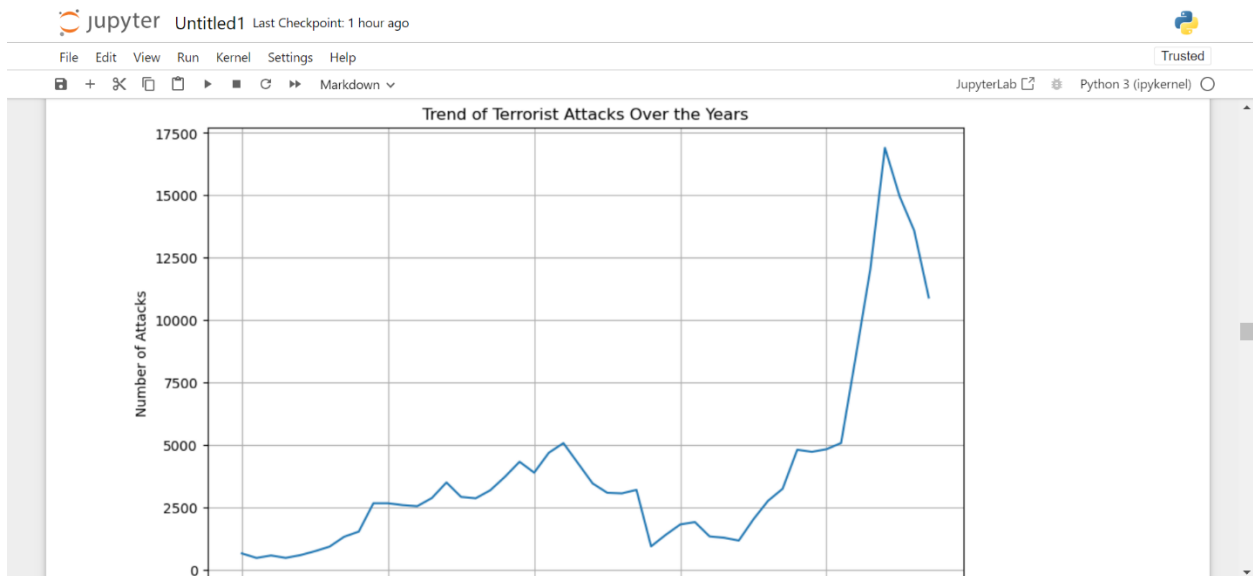
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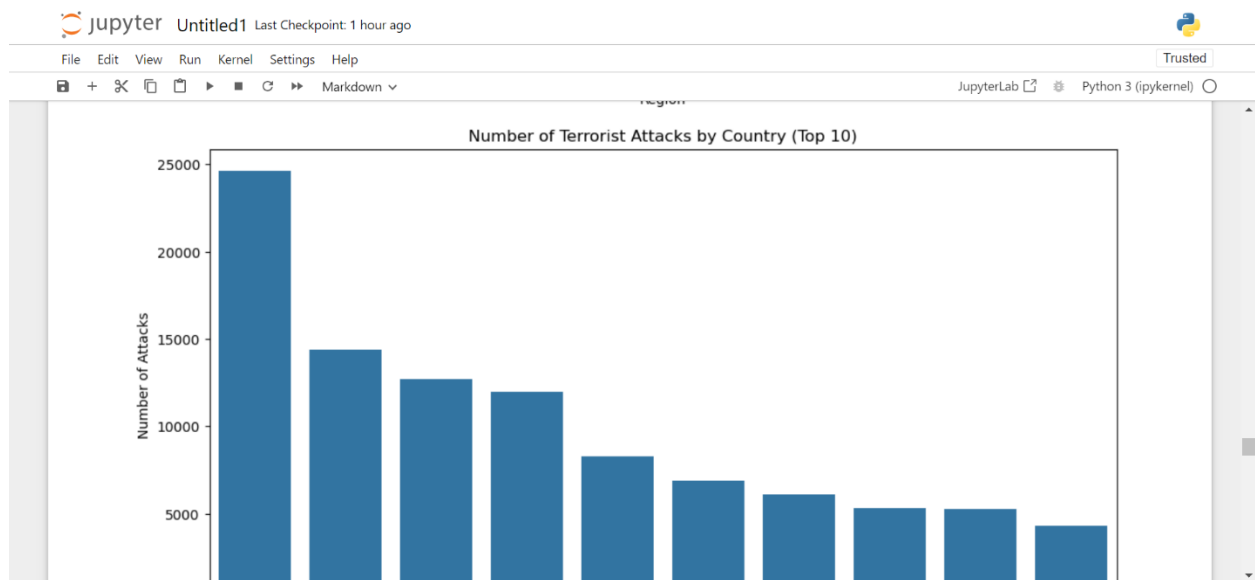
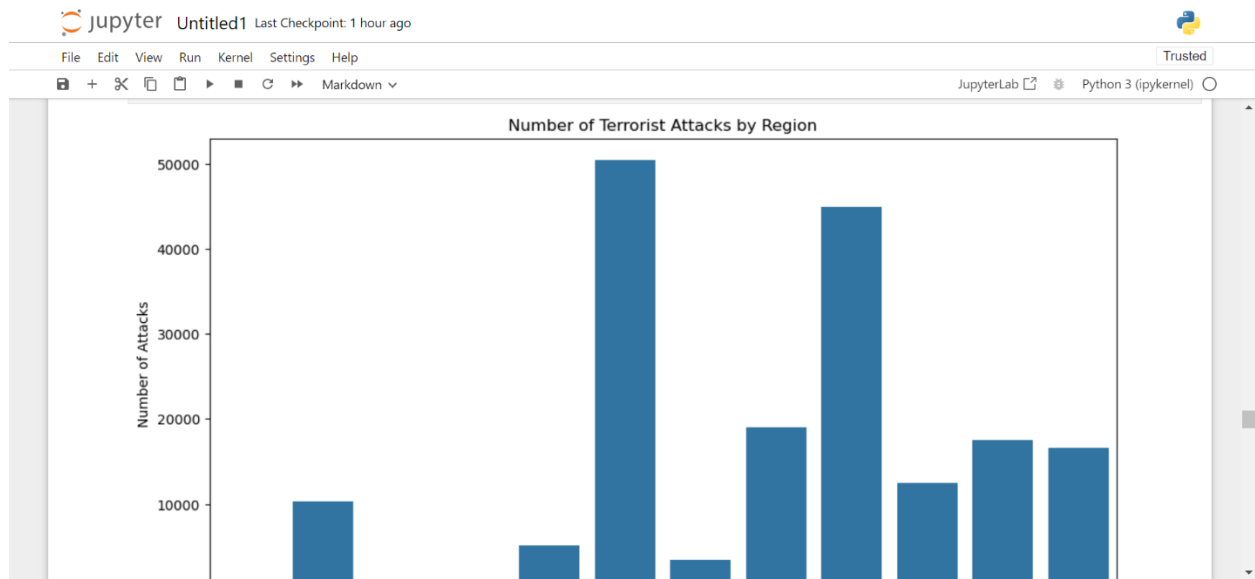
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Attacks per attack type:
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```

Data Visualizations :

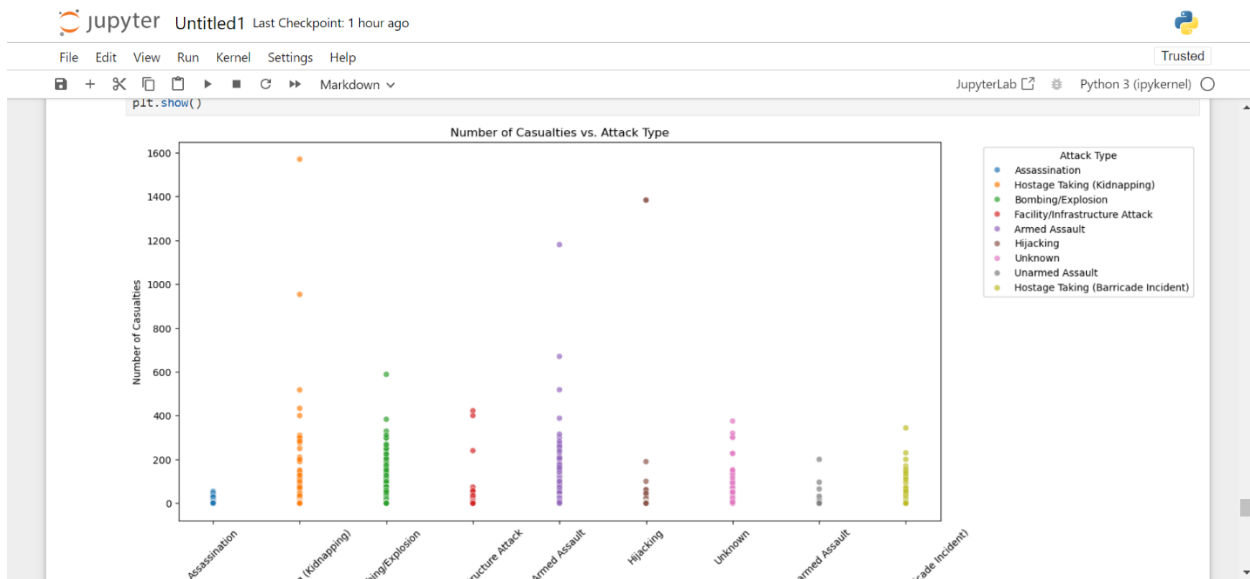
Correlation Between Features A heatmap was created to visualize the correlation between different features in the dataset.





Casualties vs. Attack Type :

A scatter plot was used to show the relationship between the number of casualties and the type of attack.



Performance Comparison with Dask :

Dask was used to perform similar operations on the dataset, demonstrating its efficiency in handling large data. Comparisons between Pandas and Dask were made in terms of time and memory usage.

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Load the Dataset Using Dask

```
[119]: import pandas as pd
import dask.dataframe as dd
import time

[121]: file_path = 'globalterrorismdb_0718dist.csv'
df = pd.read_csv(file_path, encoding='ISO-8859-1', low_memory=False)

[123]: dask_df = dd.read_csv(file_path, encoding='ISO-8859-1')

[125]: start_time = time.time()
pandas_mean = df['nkill'].mean()
pandas_time = time.time() - start_time
print(f"Pandas mean calculation time: {pandas_time} seconds")
Pandas mean calculation time: 0.002473115921020508 seconds

[127]: # Time taken for Dask operation
start_time = time.time()
dask_mean = dask_df['nkill'].mean().compute()
dask_time = time.time() - start_time
print(f"Dask mean calculation time: {dask_time} seconds")
Dask mean calculation time: 1.6403729915618896 seconds

[131]: start_time = time.time()
```

```
dask_mean = dask_df['nkill'].mean().compute()
dask_time = time.time() - start_time
print(f"Dask mean calculation time: {dask_time} seconds")

Dask mean calculation time: 1.6403729915618896 seconds
```

```
[131]: start_time = time.time()
dask_attacks_per_year = dask_df.groupby('year').size().compute()
dask_time = time.time() - start_time
print(f"Dask attacks per year calculation time: {dask_time} seconds")

Dask attacks per year calculation time: 1.5819976329803467 seconds
```

```
[133]: start_time = time.time()
dask_attacks_per_region = dask_df.groupby('region_txt').size().compute()
dask_time = time.time() - start_time
print("Dask attacks per region calculation time: {dask_time} seconds")

Dask attacks per region calculation time: 1.295663833618164 seconds
```

[]: