Global Terrorism

June 2, 2024

1 Exploratory Analysis - Terrorism

Data Set: https://www.kaggle.com/datasets/itssuru/global-terrorism

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1.0.1 *1. Importing Dependencies*

[2]:
```
import numpy as np #provides a high-performance multidimensional array object
import pandas as pd #allows us to perform analysis of big data
import matplotlib as mpl #data visualization library
import matplotlib.pyplot as plt #used for data visualization and plotting on␣
↪graphs
import seaborn as sns #library for making statistical graphics
import sklearn
import warnings
import os
import mpl_toolkits
import json
import pygal
%matplotlib inline
```

[3]:
```
from sklearn.cluster import KMeans
from pandas.plotting import scatter_matrix
```

1.0.2 *2. Data Collecting*

[4]:
```
df_terrorism = pd.read_csv("C:\\Users\\zeelt\\Desktop\\Python Projects\\Global␣
↪Terrorism\\globalterrorismdb_0718dist.csv",␣
↪on_bad_lines='skip',encoding="latin1", low_memory=False)
pd.set_option("display.max_columns",500)
df_terrorism
```

[4]:
```
         eventid  iyear  imonth  iday approxdate  extended resolution  \
0   197000000001   1970       7     2        NaN         0        NaN
1   197000000002   1970       0     0        NaN         0        NaN
2   197001000001   1970       1     0        NaN         0        NaN
```

```
3       197001000002   1970       1     0        NaN         0        NaN
4       197001000003   1970       1     0        NaN         0        NaN
…              …    …      …    …         …        …         …
181686  201712310022   2017      12    31        NaN         0        NaN
181687  201712310029   2017      12    31        NaN         0        NaN
181688  201712310030   2017      12    31        NaN         0        NaN
181689  201712310031   2017      12    31        NaN         0        NaN
181690  201712310032   2017      12    31        NaN         0        NaN

        country         country_txt  region                   region_txt  \
0            58  Dominican Republic       2  Central America & Caribbean
1           130              Mexico       1                North America
2           160         Philippines       5               Southeast Asia
3            78              Greece       8               Western Europe
4           101               Japan       4                    East Asia
…         …                   …   …                         …
181686      182             Somalia      11           Sub-Saharan Africa
181687      200               Syria      10   Middle East & North Africa
181688      160         Philippines       5               Southeast Asia
181689       92               India       6                   South Asia
181690      160         Philippines       5               Southeast Asia

              provstate           city   latitude   longitude  specificity  \
0                   NaN  Santo Domingo  18.456792  -69.951164          1.0
1               Federal    Mexico city  19.371887  -99.086624          1.0
2                Tarlac        Unknown  15.478598  120.599741          4.0
3                Attica         Athens  37.997490   23.762728          1.0
4               Fukouka        Fukouka  33.580412  130.396361          1.0
…                     …              …          …          …            …
181686  Middle Shebelle  Ceelka Geelow   2.359673   45.385034          2.0
181687         Lattakia         Jableh  35.407278   35.942679          1.0
181688      Maguindanao       Kubentog   6.900742  124.437908          2.0
181689          Manipur         Imphal  24.798346   93.940430          1.0
181690      Maguindanao  Cotabato City   7.209594  124.241966          1.0

        vicinity                                         location  \
0              0                                              NaN
1              0                                              NaN
2              0                                              NaN
3              0                                              NaN
4              0                                              NaN
…          …                                                  …
181686         0     The incident occurred near the town of Balcad.
181687         1     The incident occurred at the Humaymim Airport.
181688         0  The incident occurred in the Datu Hoffer distr…
181689         0  The incident occurred in the Mantripukhri neig…
181690         0                                              NaN
```

```
                                                  summary  crit1  crit2  \
0                                                     NaN      1      1
1                                                     NaN      1      1
2                                                     NaN      1      1
3                                                     NaN      1      1
4                                                     NaN      1      1
…                                                     …    …    …
181686  12/31/2017: Assailants opened fire on a Somali…      1      1
181687  12/31/2017: Assailants launched mortars at the…      1      1
181688  12/31/2017: Assailants set fire to houses in K…      1      1
181689  12/31/2017: Assailants threw a grenade at a Fo…      1      1
181690  12/31/2017: An explosive device was discovered…      1      1

        crit3  doubtterr  alternative            alternative_txt  multiple  \
0           1        0.0          NaN                        NaN       0.0
1           1        0.0          NaN                        NaN       0.0
2           1        0.0          NaN                        NaN       0.0
3           1        0.0          NaN                        NaN       0.0
4           1       -9.0          NaN                        NaN       0.0
…         …        …          …                        …       …
181686      0        1.0          1.0  Insurgency/Guerilla Action       0.0
181687      0        1.0          1.0  Insurgency/Guerilla Action       0.0
181688      1        0.0          NaN                        NaN       0.0
181689      1        0.0          NaN                        NaN       0.0
181690      1        0.0          NaN                        NaN       0.0

        success  suicide  attacktype1                  attacktype1_txt  \
0             1        0            1                    Assassination
1             1        0            6      Hostage Taking (Kidnapping)
2             1        0            1                    Assassination
3             1        0            3                Bombing/Explosion
4             1        0            7  Facility/Infrastructure Attack
…           …      …          …                              …
181686        1        0            2                    Armed Assault
181687        1        0            3                Bombing/Explosion
181688        1        0            7  Facility/Infrastructure Attack
181689        0        0            3                Bombing/Explosion
181690        0        0            3                Bombing/Explosion

        attacktype2 attacktype2_txt  attacktype3 attacktype3_txt  targtype1  \
0               NaN             NaN          NaN             NaN         14
1               NaN             NaN          NaN             NaN          7
2               NaN             NaN          NaN             NaN         10
3               NaN             NaN          NaN             NaN          7
4               NaN             NaN          NaN             NaN          7
…             …             …          …             …        …
```

```
181686         NaN            NaN          NaN             NaN           4
181687         NaN            NaN          NaN             NaN           4
181688         NaN            NaN          NaN             NaN          14
181689         NaN            NaN          NaN             NaN           2
181690         NaN            NaN          NaN             NaN          20

                   targtype1_txt  targsubtype1  \
0       Private Citizens & Property          68.0
1           Government (Diplomatic)          45.0
2               Journalists & Media          54.0
3           Government (Diplomatic)          46.0
4           Government (Diplomatic)          46.0
…                               …            …
181686                     Military          36.0
181687                     Military          27.0
181688  Private Citizens & Property          76.0
181689        Government (General)          21.0
181690                      Unknown           NaN

                                        targsubtype1_txt  \
0                                         Named Civilian
1       Diplomatic Personnel (outside of embassy, cons…
2                         Radio Journalist/Staff/Facility
3                                       Embassy/Consulate
4                                       Embassy/Consulate
…                                                     …
181686                                Military Checkpoint
181687     Military Barracks/Base/Headquarters/Checkpost
181688                           House/Apartment/Residence
181689                  Government Building/Facility/Office
181690                                                NaN

                             corp1                  target1  natlty1  \
0                              NaN             Julio Guzman     58.0
1       Belgian Ambassador Daughter  Nadine Chaval, daughter     21.0
2                  Voice of America                 Employee    217.0
3                              NaN              U.S. Embassy    217.0
4                              NaN             U.S. Consulate    217.0
…                               …                        …       …
181686   Somali National Army (SNA)              Checkpoint    182.0
181687            Russian Air Force         Hmeymim Air Base    167.0
181688               Not Applicable                   Houses    160.0
181689     Forest Department Manipur                  Office     92.0
181690                      Unknown                  Unknown    160.0

              natlty1_txt  targtype2 targtype2_txt  targsubtype2  \
0       Dominican Republic        NaN           NaN           NaN
```

```
1                Belgium        NaN           NaN           NaN
2          United States        NaN           NaN           NaN
3          United States        NaN           NaN           NaN
4          United States        NaN           NaN           NaN
…                      …        …            …            …
181686           Somalia        NaN           NaN           NaN
181687            Russia        NaN           NaN           NaN
181688       Philippines        NaN           NaN           NaN
181689             India        NaN           NaN           NaN
181690       Philippines        NaN           NaN           NaN

       targsubtype2_txt corp2 target2  natlty2 natlty2_txt  targtype3  \
0                   NaN   NaN     NaN      NaN         NaN        NaN
1                   NaN   NaN     NaN      NaN         NaN        NaN
2                   NaN   NaN     NaN      NaN         NaN        NaN
3                   NaN   NaN     NaN      NaN         NaN        NaN
4                   NaN   NaN     NaN      NaN         NaN        NaN
…                     …    …       …       …          …         …
181686              NaN   NaN     NaN      NaN         NaN        NaN
181687              NaN   NaN     NaN      NaN         NaN        NaN
181688              NaN   NaN     NaN      NaN         NaN        NaN
181689              NaN   NaN     NaN      NaN         NaN        NaN
181690              NaN   NaN     NaN      NaN         NaN        NaN

       targtype3_txt  targsubtype3 targsubtype3_txt corp3 target3  natlty3  \
0                NaN           NaN              NaN   NaN     NaN      NaN
1                NaN           NaN              NaN   NaN     NaN      NaN
2                NaN           NaN              NaN   NaN     NaN      NaN
3                NaN           NaN              NaN   NaN     NaN      NaN
4                NaN           NaN              NaN   NaN     NaN      NaN
…                 …             …               …    …      …       …
181686           NaN           NaN              NaN   NaN     NaN      NaN
181687           NaN           NaN              NaN   NaN     NaN      NaN
181688           NaN           NaN              NaN   NaN     NaN      NaN
181689           NaN           NaN              NaN   NaN     NaN      NaN
181690           NaN           NaN              NaN   NaN     NaN      NaN

       natlty3_txt                                      gname gsubname  \
0              NaN                                     MANO-D      NaN
1              NaN          23rd of September Communist League      NaN
2              NaN                                    Unknown      NaN
3              NaN                                    Unknown      NaN
4              NaN                                    Unknown      NaN
…             …                                          …      …
181686         NaN                                 Al-Shabaab      NaN
181687         NaN                          Muslim extremists      NaN
181688         NaN  Bangsamoro Islamic Freedom Movement (BIFM)      NaN
```

```
181689         NaN                                     Unknown      NaN
181690         NaN                                     Unknown      NaN

       gname2 gsubname2 gname3 gsubname3 motive  guncertain1  guncertain2  \
0         NaN       NaN    NaN       NaN    NaN          0.0          NaN
1         NaN       NaN    NaN       NaN    NaN          0.0          NaN
2         NaN       NaN    NaN       NaN    NaN          0.0          NaN
3         NaN       NaN    NaN       NaN    NaN          0.0          NaN
4         NaN       NaN    NaN       NaN    NaN          0.0          NaN
…       …       …    …       …    …          …          …
181686    NaN       NaN    NaN       NaN    NaN          0.0          NaN
181687    NaN       NaN    NaN       NaN    NaN          0.0          NaN
181688    NaN       NaN    NaN       NaN    NaN          0.0          NaN
181689    NaN       NaN    NaN       NaN    NaN          0.0          NaN
181690    NaN       NaN    NaN       NaN    NaN          0.0          NaN

        guncertain3  individual  nperps  nperpcap  claimed  claimmode  \
0               NaN           0     NaN       NaN      NaN        NaN
1               NaN           0     7.0       NaN      NaN        NaN
2               NaN           0     NaN       NaN      NaN        NaN
3               NaN           0     NaN       NaN      NaN        NaN
4               NaN           0     NaN       NaN      NaN        NaN
…               …           …     …       …      …        …
181686          NaN           0   -99.0       0.0      1.0       10.0
181687          NaN           0   -99.0       0.0      0.0        NaN
181688          NaN           0   -99.0       0.0      0.0        NaN
181689          NaN           0   -99.0       0.0      0.0        NaN
181690          NaN           0   -99.0       0.0      0.0        NaN

       claimmode_txt  claim2  claimmode2 claimmode2_txt  claim3  claimmode3  \
0                NaN     NaN         NaN            NaN     NaN         NaN
1                NaN     NaN         NaN            NaN     NaN         NaN
2                NaN     NaN         NaN            NaN     NaN         NaN
3                NaN     NaN         NaN            NaN     NaN         NaN
4                NaN     NaN         NaN            NaN     NaN         NaN
…                …     …         …            …     …         …
181686       Unknown     NaN         NaN            NaN     NaN         NaN
181687           NaN     NaN         NaN            NaN     NaN         NaN
181688           NaN     NaN         NaN            NaN     NaN         NaN
181689           NaN     NaN         NaN            NaN     NaN         NaN
181690           NaN     NaN         NaN            NaN     NaN         NaN

       claimmode3_txt  compclaim  weaptype1 weaptype1_txt  weapsubtype1  \
0                 NaN        NaN         13       Unknown           NaN
1                 NaN        NaN         13       Unknown           NaN
2                 NaN        NaN         13       Unknown           NaN
3                 NaN        NaN          6    Explosives          16.0
```

```
4                NaN        NaN          8    Incendiary           NaN
…              …        …        …          …          …
181686           NaN        NaN          5      Firearms           5.0
181687           NaN        NaN          6    Explosives          11.0
181688           NaN        NaN          8    Incendiary          18.0
181689           NaN        NaN          6    Explosives           7.0
181690           NaN        NaN          6    Explosives          16.0

                                 weapsubtype1_txt  weaptype2 weaptype2_txt  \
0                                             NaN        NaN           NaN
1                                             NaN        NaN           NaN
2                                             NaN        NaN           NaN
3                           Unknown Explosive Type        NaN           NaN
4                                             NaN        NaN           NaN
…                                             …        …           …
181686                           Unknown Gun Type        NaN           NaN
181687  Projectile (rockets, mortars, RPGs, etc.)        NaN           NaN
181688                                 Arson/Fire        NaN           NaN
181689                                    Grenade        NaN           NaN
181690                     Unknown Explosive Type        NaN           NaN

        weapsubtype2 weapsubtype2_txt  weaptype3 weaptype3_txt  weapsubtype3  \
0                NaN              NaN        NaN           NaN           NaN
1                NaN              NaN        NaN           NaN           NaN
2                NaN              NaN        NaN           NaN           NaN
3                NaN              NaN        NaN           NaN           NaN
4                NaN              NaN        NaN           NaN           NaN
…             …              …        …           …           …
181686           NaN              NaN        NaN           NaN           NaN
181687           NaN              NaN        NaN           NaN           NaN
181688           NaN              NaN        NaN           NaN           NaN
181689           NaN              NaN        NaN           NaN           NaN
181690           NaN              NaN        NaN           NaN           NaN

       weapsubtype3_txt  weaptype4 weaptype4_txt  weapsubtype4  \
0                   NaN        NaN           NaN           NaN
1                   NaN        NaN           NaN           NaN
2                   NaN        NaN           NaN           NaN
3                   NaN        NaN           NaN           NaN
4                   NaN        NaN           NaN           NaN
…                 …        …           …           …
181686              NaN        NaN           NaN           NaN
181687              NaN        NaN           NaN           NaN
181688              NaN        NaN           NaN           NaN
181689              NaN        NaN           NaN           NaN
181690              NaN        NaN           NaN           NaN
```

```
       weapsubtype4_txt                                         weapdetail  \
0                   NaN                                                NaN
1                   NaN                                                NaN
2                   NaN                                                NaN
3                   NaN                                          Explosive
4                   NaN                                         Incendiary
…                 …                                                  …
181686              NaN                                                NaN
181687              NaN                     Mortars were used in the attack.
181688              NaN                                                NaN
181689              NaN         A thrown grenade was used in the attack.
181690              NaN  An explosive device containing a detonating co…

        nkill  nkillus  nkillter  nwound  nwoundus  nwoundte  property  \
0         1.0      NaN       NaN     0.0       NaN       NaN         0
1         0.0      NaN       NaN     0.0       NaN       NaN         0
2         1.0      NaN       NaN     0.0       NaN       NaN         0
3         NaN      NaN       NaN     NaN       NaN       NaN         1
4         NaN      NaN       NaN     NaN       NaN       NaN         1
…       …      …        …       …       …       …        …
181686    1.0      0.0       0.0     2.0       0.0       0.0        -9
181687    2.0      0.0       0.0     7.0       0.0       0.0         1
181688    0.0      0.0       0.0     0.0       0.0       0.0         1
181689    0.0      0.0       0.0     0.0       0.0       0.0        -9
181690    0.0      0.0       0.0     0.0       0.0       0.0         0

        propextent propextent_txt  propvalue  \
0              NaN            NaN        NaN
1              NaN            NaN        NaN
2              NaN            NaN        NaN
3              NaN            NaN        NaN
4              NaN            NaN        NaN
…           …              …         …
181686         NaN            NaN        NaN
181687         4.0        Unknown      -99.0
181688         4.0        Unknown      -99.0
181689         NaN            NaN        NaN
181690         NaN            NaN        NaN

                                              propcomment  ishostkid  \
0                                                     NaN        0.0
1                                                     NaN        1.0
2                                                     NaN        0.0
3                                                     NaN        0.0
4                                                     NaN        0.0
…                                                   …        …
181686                                                NaN        0.0
```

```
181687  Seven military planes were damaged in this att…       0.0
181688                Houses were damaged in this attack.       0.0
181689                                                NaN       0.0
181690                                                NaN       0.0

        nhostkid  nhostkidus  nhours  ndays divert kidhijcountry  ransom  \
0            NaN         NaN     NaN    NaN    NaN           NaN     0.0
1            1.0         0.0     NaN    NaN    NaN        Mexico     1.0
2            NaN         NaN     NaN    NaN    NaN           NaN     0.0
3            NaN         NaN     NaN    NaN    NaN           NaN     0.0
4            NaN         NaN     NaN    NaN    NaN           NaN     0.0
…          …         …      …     …    …          …      …
181686       NaN         NaN     NaN    NaN    NaN           NaN     NaN
181687       NaN         NaN     NaN    NaN    NaN           NaN     NaN
181688       NaN         NaN     NaN    NaN    NaN           NaN     NaN
181689       NaN         NaN     NaN    NaN    NaN           NaN     NaN
181690       NaN         NaN     NaN    NaN    NaN           NaN     NaN

        ransomamt  ransomamtus  ransompaid  ransompaidus ransomnote  \
0             NaN          NaN         NaN           NaN        NaN
1        800000.0          NaN         NaN           NaN        NaN
2             NaN          NaN         NaN           NaN        NaN
3             NaN          NaN         NaN           NaN        NaN
4             NaN          NaN         NaN           NaN        NaN
…             …          …         …           …        …
181686        NaN          NaN         NaN           NaN        NaN
181687        NaN          NaN         NaN           NaN        NaN
181688        NaN          NaN         NaN           NaN        NaN
181689        NaN          NaN         NaN           NaN        NaN
181690        NaN          NaN         NaN           NaN        NaN

        hostkidoutcome hostkidoutcome_txt  nreleased addnotes  \
0                  NaN                NaN        NaN      NaN
1                  NaN                NaN        NaN      NaN
2                  NaN                NaN        NaN      NaN
3                  NaN                NaN        NaN      NaN
4                  NaN                NaN        NaN      NaN
…                  …                …        …      …
181686             NaN                NaN        NaN      NaN
181687             NaN                NaN        NaN      NaN
181688             NaN                NaN        NaN      NaN
181689             NaN                NaN        NaN      NaN
181690             NaN                NaN        NaN      NaN

                                           scite1  \
0                                             NaN
1                                             NaN
```

```
2                                                     NaN
3                                                     NaN
4                                                     NaN
…                                                 …
181686  "Somalia: Al-Shabaab Militants Attack Army Che…
181687  "Putin's 'victory' in Syria has turned into a …
181688  "Maguindanao clashes trap tribe members," Phil…
181689  "Trader escapes grenade attack in Imphal," Bus…
181690  "Security tightened in Cotabato following IED …

                                                  scite2  \
0                                                     NaN
1                                                     NaN
2                                                     NaN
3                                                     NaN
4                                                     NaN
…                                                 …
181686  "Highlights: Somalia Daily Media Highlights 2 …
181687  "Two Russian soldiers killed at Hmeymim base i…
181688                                                NaN
181689                                                NaN
181690  "Security tightened in Cotabato City," Manila …

                                                  scite3  \
0                                                     NaN
1                                                     NaN
2                                                     NaN
3                                                     NaN
4                                                     NaN
…                                                 …
181686  "Highlights: Somalia Daily Media Highlights 1 …
181687  "Two Russian servicemen killed in Syria mortar…
181688                                                NaN
181689                                                NaN
181690                                                NaN

                        dbsource  INT_LOG  INT_IDEO  INT_MISC  INT_ANY related
0                           PGIS        0         0         0        0     NaN
1                           PGIS        0         1         1        1     NaN
2                           PGIS       -9        -9         1        1     NaN
3                           PGIS       -9        -9         1        1     NaN
4                           PGIS       -9        -9         1        1     NaN
…                            …      …       …       …       …      …
181686  START Primary Collection        0         0         0        0     NaN
181687  START Primary Collection       -9        -9         1        1     NaN
181688  START Primary Collection        0         0         0        0     NaN
181689  START Primary Collection       -9        -9         0       -9     NaN
```

```
181690  START Primary Collection       -9         -9           0         -9      NaN

[181691 rows x 135 columns]
```

[5]:
```
df_terrorism.shape
```

[5]:
```
(181691, 135)
```

3. Cleaning Data

—>**Selection of Required Columns**

[6]:
```
#extracting columns and storing in cols variable
use_cols = [1, 5, 8,␣
↪10,11,12,13,14,25,26,27,29,35,58,69,71,82,98,100,101,103,104,106]
rename_cols= {'latitude' : 'lat',
              'longitude' : 'lon',
              'iyear': u'year',
              'country_txt': u'country',
              'region_txt':'region',
              'attacktype1_txt': u'attacktype',
              'targtype1_txt': u'targtype',
              'weaptype1_txt':'weaptype',
              'nperps': u'nter',
              'nkill': u'killed',
              'nkillter': u'killedter',
              'nwound': u'wounded',
              'nwoundte': u'woundedter',
              'propextent_txt': u'propertyextent',
              }
```

—> ***Rereading data with new filtered column values***

[7]:
```
import pandas as pd

# Read the CSV file into a DataFrame
df_terrorism = pd.read_csv(
    "C:\\Users\\zeelt\\Desktop\\Python Projects\\Global␣
↪Terrorism\\globalterrorismdb_0718dist.csv",
    on_bad_lines='skip',
    encoding="ISO-8859-1",
    usecols=use_cols,
    low_memory=False
)

# Rename the columns
df_terrorism.rename(columns=rename_cols, inplace=True)

# Apply the lambda function to strip strings
```

```
df_terrorism = df_terrorism.apply(lambda x: x.str.strip() if x.dtype ==␣
↪"object" else x)

# Print success message
print("Data Read Successfully")
```

```
Data Read Successfully
```

[8]:
```
df_terrorism.columns
```

[8]:
```
Index(['year', 'extended', 'country', 'region', 'provstate', 'city', 'lat',
       'lon', 'multiple', 'success', 'suicide', 'attacktype', 'targtype',
       'gname', 'nter', 'claimed', 'weaptype', 'killed', 'killedter',
       'wounded', 'woundedter', 'property', 'propertyextent'],
      dtype='object')
```

[9]:
```
df_terrorism.shape
```

[9]:
```
(181691, 23)
```

—> ***Removing unknown values from coordinates***

[10]:
```
df_terrorism = df_terrorism[pd.notnull(df_terrorism.lat)]
df_terrorism = df_terrorism[pd.notnull(df_terrorism.lon)]
```

—> ***Unknown values in numeric columns***

[11]:
```
# We dont want any NaN's as they automatically convert the column to dtype=float
exclude_cols = ['year', 'lat', 'lon']
float_cols = [c for c in df_terrorism.select_dtypes(include=[float]).columns.
↪tolist() if c not in exclude_cols]
```

—> ***Calculating and Cleaning Duplicate Values***

[12]:
```
df_terrorism.duplicated().sum()
```

[12]:
```
21123
```

[13]:
```
df_terrorism.drop_duplicates(keep=False,inplace=True)
```

—> ***Calculating and Cleaning Null Values***

[14]:
```
df_terrorism.isnull().sum()
```

[14]:
```
year                 0
extended             0
country              0
region               0
provstate          409
city               367
lat                  0
```

```
lon                 0
multiple            1
success             0
suicide             0
attacktype          0
targtype            0
gname               0
nter            51729
claimed         47212
weaptype            0
killed           7555
killedter       48051
wounded         12494
woundedter      50093
property            0
propertyextent  94965
dtype: int64
```

[15]:
```python
df_terrorism.fillna(0, inplace=True)
```

[16]:
```python
df_terrorism.isnull().sum()
```

[16]:
```
year              0
extended          0
country           0
region            0
provstate         0
city              0
lat               0
lon               0
multiple          0
success           0
suicide           0
attacktype        0
targtype          0
gname             0
nter              0
claimed           0
weaptype          0
killed            0
killedter         0
wounded           0
woundedter        0
property          0
propertyextent    0
dtype: int64
```

4. Exploratory Data Analysis

[17]:
```
df_terrorism.columns
```

[17]:
```
Index(['year', 'extended', 'country', 'region', 'provstate', 'city', 'lat',
       'lon', 'multiple', 'success', 'suicide', 'attacktype', 'targtype',
       'gname', 'nter', 'claimed', 'weaptype', 'killed', 'killedter',
       'wounded', 'woundedter', 'property', 'propertyextent'],
      dtype='object')
```

—> ***Displaying data type of all columns and converting type for those needed***

[18]:
```
df_terrorism.dtypes
```

[18]:
```
year                int64
extended            int64
country            object
region             object
provstate          object
city               object
lat               float64
lon               float64
multiple          float64
success             int64
suicide             int64
attacktype         object
targtype           object
gname              object
nter              float64
claimed           float64
weaptype           object
killed            float64
killedter         float64
wounded           float64
woundedter        float64
property            int64
propertyextent     object
dtype: object
```

[19]:
```
df_terrorism['multiple'] = df_terrorism['multiple'].astype(int)
df_terrorism['nter'] = df_terrorism['nter'].astype(int)
df_terrorism['claimed'] = df_terrorism['claimed'].astype(int)
df_terrorism['killed'] = df_terrorism['killed'].astype(int)
df_terrorism['killedter'] = df_terrorism['killedter'].astype(int)
df_terrorism['wounded'] = df_terrorism['wounded'].astype(int)
df_terrorism['woundedter'] = df_terrorism['woundedter'].astype(int)
```

[20]:
```
df_terrorism.dtypes
```

[20]:

```
year                int64
extended            int64
country            object
region             object
provstate          object
city               object
lat               float64
lon               float64
multiple            int32
success             int64
suicide             int64
attacktype         object
targtype           object
gname              object
nter                int32
claimed             int32
weaptype           object
killed              int32
killedter           int32
wounded             int32
woundedter          int32
property            int64
propertyextent     object
dtype: object
```

[21]:

```
df_terrorism.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 146986 entries, 0 to 181690
Data columns (total 23 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   year            146986 non-null  int64
 1   extended        146986 non-null  int64
 2   country         146986 non-null  object
 3   region          146986 non-null  object
 4   provstate       146986 non-null  object
 5   city            146986 non-null  object
 6   lat             146986 non-null  float64
 7   lon             146986 non-null  float64
 8   multiple        146986 non-null  int32
 9   success         146986 non-null  int64
 10  suicide         146986 non-null  int64
 11  attacktype      146986 non-null  object
 12  targtype        146986 non-null  object
 13  gname           146986 non-null  object
 14  nter            146986 non-null  int32
 15  claimed         146986 non-null  int32
```

```
 16  weaptype       146986 non-null  object
 17  killed         146986 non-null  int32
 18  killedter      146986 non-null  int32
 19  wounded        146986 non-null  int32
 20  woundedter     146986 non-null  int32
 21  property       146986 non-null  int64
 22  propertyextent  146986 non-null  object
dtypes: float64(2), int32(7), int64(5), object(9)
memory usage: 23.0+ MB
```

—> ***Count values in each column***

[22]:
```
df_terrorism.count()
```

[22]:
```
year              146986
extended          146986
country           146986
region            146986
provstate         146986
city              146986
lat               146986
lon               146986
multiple          146986
success           146986
suicide           146986
attacktype        146986
targtype          146986
gname             146986
nter              146986
claimed           146986
weaptype          146986
killed            146986
killedter         146986
wounded           146986
woundedter        146986
property          146986
propertyextent    146986
dtype: int64
```

[23]:
```
df_terrorism.nunique()
```

[23]:
```
year                 47
extended              2
country             204
region               12
provstate          2823
city              34806
lat               47873
```

```
lon                47588
multiple               2
success                2
suicide                2
attacktype             9
targtype              22
gname               3401
nter                 109
claimed                3
weaptype              12
killed               201
killedter             96
wounded              237
woundedter            44
property               3
propertyextent         5
dtype: int64
```

—> ***Year values in the dataset***

[24]:
```python
df_terrorism['year'].unique()
```

[24]:
```
array([1970, 1971, 1972, 1973, 1974, 1975, 1976, 1977, 1978, 1979, 1980,
       1981, 1986, 1982, 1983, 1984, 1985, 1987, 1988, 1989, 1990, 1991,
       1992, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003,
       2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014,
       2015, 2016, 2017], dtype=int64)
```

[25]:
```python
df_terrorism['year'].value_counts()
```

[25]:
```
year
2014    14303
2015    12449
2016    11060
2013    10435
2017     9665
2012     7604
2008     4333
2009     4169
2011     4167
2010     4103
1992     3753
1991     3236
1989     3163
2007     2925
1988     2792
1994     2637
1990     2572
```

```
2006    2542
1984    2279
1997    2267
1983    2166
1996    2146
1987    2085
1981    2021
1980    1998
1995    1998
1982    1961
1979    1949
1986    1946
1985    1923
2005    1901
2001    1782
2000    1643
2002    1244
1999    1239
1978    1205
2003    1186
2004    1104
1977     986
1998     826
1976     688
1975     575
1970     518
1974     424
1971     366
1973     349
1972     303
Name: count, dtype: int64
```

—> ***Count of Regions in the dataset***

[26]:
```
df_terrorism['region'].value_counts()
```

[26]:
```
region
South Asia                     39971
Middle East & North Africa     39491
Sub-Saharan Africa             15423
South America                  12978
Western Europe                 12285
Southeast Asia                 10980
Central America & Caribbean     6995
Eastern Europe                  4599
North America                   2879
East Asia                        628
Central Asia                     498
```

```
Australasia & Oceania           259
Name: count, dtype: int64
```

—> ***Count of Cities in the dataset***

[27]:
```python
df_terrorism['city'].value_counts()
```

[27]:
```
city
Unknown       5760
Baghdad       4106
Karachi       1493
Mosul         1455
Mogadishu     1250
              …
Koh Mak          1
Shambuko         1
Baladweyne       1
Riverine         1
Kubentog         1
Name: count, Length: 34806, dtype: int64
```

—> ***Count of Terrorist group names in the dataset***

[28]:
```python
df_terrorism['gname'].value_counts()
```

[28]:
```
gname
Unknown                                              66397
Taliban                                               7135
Islamic State of Iraq and the Levant (ISIL)           4641
Al-Shabaab                                            2892
Shining Path (SL)                                     2758
                                                     …
Shahin (Falcon)                                          1
Militant Movement for Madagascan Socialism (MMSM)        1
BZers                                                    1
Basic People's Congresses                                1
Panama Defense Force                                     1
Name: count, Length: 3401, dtype: int64
```

—> ***Count of Attack Types in the dataset***

[29]:
```python
df_terrorism['attacktype'].value_counts()
```

[29]:
```
attacktype
Bombing/Explosion                      67298
Armed Assault                          36845
Assassination                          16348
Hostage Taking (Kidnapping)            10018
Facility/Infrastructure Attack          7878
Unknown                                 6303
```

```
Hostage Taking (Barricade Incident)      846
Unarmed Assault                          844
Hijacking                                606
Name: count, dtype: int64
```

—> ***Count of Target Types in the dataset***

[30]:
```
df_terrorism['targtype'].value_counts()
```

[30]:
```
targtype
Private Citizens & Property       34737
Military                          24514
Police                            21594
Government (General)              17536
Business                          14623
Transportation                     5309
Unknown                            4096
Religious Figures/Institutions     3875
Educational Institution            3497
Government (Diplomatic)            3128
Utilities                          2896
Terrorists/Non-State Militia       2778
Journalists & Media                2541
Violent Political Party            1644
Airports & Aircraft                1226
NGO                                 908
Telecommunication                   809
Tourists                            397
Maritime                            285
Food or Water Supply                266
Abortion Related                    203
Other                               124
Name: count, dtype: int64
```

Statistical Summary of Data

[31]:
```
df_terrorism.describe()
```

[31]:
```
                year       extended            lat           lon  \
count  146986.000000  146986.000000  146986.000000  1.469860e+05
mean     2003.593499       0.050590      23.688252 -5.548676e+02
std        12.936236       0.219159      17.899265  2.248011e+05
min      1970.000000       0.000000     -53.154613 -8.618590e+07
25%      1992.000000       0.000000      11.400638  8.808213e+00
50%      2010.000000       0.000000      31.322678  4.376645e+01
75%      2014.000000       0.000000      34.621521  6.980546e+01
max      2017.000000       1.000000      74.633553  1.793667e+02

            multiple        success        suicide           nter  \
```

```
count  146986.000000  146986.000000  146986.000000  146986.000000
mean        0.086716       0.886499       0.043460     -42.688957
std         0.281419       0.317205       0.203891     108.563825
min         0.000000       0.000000       0.000000     -99.000000
25%         0.000000       1.000000       0.000000     -99.000000
50%         0.000000       1.000000       0.000000       0.000000
75%         0.000000       1.000000       0.000000       0.000000
max         1.000000       1.000000       1.000000   25000.000000

             claimed         killed      killedter        wounded  \
count  146986.000000  146986.000000  146986.000000  146986.000000
mean        0.033398       2.578225       0.383615       3.312152
std         0.934334      12.194752       3.697621      38.061656
min        -9.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000       0.000000
50%         0.000000       0.000000       0.000000       0.000000
75%         0.000000       2.000000       0.000000       2.000000
max         1.000000    1570.000000     500.000000    8191.000000

          woundedter       property
count  146986.000000  146986.000000
mean        0.079967      -0.596417
std         1.298710       3.148533
min         0.000000      -9.000000
25%         0.000000       0.000000
50%         0.000000       0.000000
75%         0.000000       1.000000
max       200.000000       1.000000
```

Correlation among the columns

[32]:
```python
# Select only numeric columns
numeric_df = df_terrorism.select_dtypes(include=[float, int])

# Calculate correlation matrix
corr_values = numeric_df.corr()
corr_values
```

[32]:
```
              year  extended       lat       lon  multiple   success  \
year      1.000000  0.087284  0.139096  0.004487  0.193094 -0.057795
extended  0.087284  1.000000 -0.030879  0.000609  0.003550  0.078878
lat       0.139096 -0.030879  1.000000  0.001662  0.016759 -0.060591
lon       0.004487  0.000609  0.001662  1.000000  0.000824 -0.000942
multiple  0.193094  0.003550  0.016759  0.000824  1.000000  0.011408
success  -0.057795  0.078878 -0.060591 -0.000942  0.011408  1.000000
suicide   0.137812 -0.041591  0.074789  0.000571  0.063561 -0.029239
nter     -0.311391 -0.028576 -0.075284 -0.001061 -0.065299  0.025294
claimed   0.078669  0.008195  0.018524  0.000097  0.050722 -0.004817
```

```
killed       0.015626  0.011553 -0.018130 -0.000520  0.029170  0.052270
killedter    0.073930  0.009054  0.013955  0.000278  0.033471 -0.022147
wounded      0.011550 -0.011720  0.015584  0.000231  0.025853  0.024457
woundedter   0.048757  0.003929  0.024175  0.000168  0.017624 -0.014449
property    -0.248604  0.001607 -0.067313 -0.001360 -0.079118 -0.037473

             suicide      nter   claimed    killed  killedter   wounded  \
year        0.137812 -0.311391  0.078669  0.015626   0.073930  0.011550
extended   -0.041591 -0.028576  0.008195  0.011553   0.009054 -0.011720
lat         0.074789 -0.075284  0.018524 -0.018130   0.013955  0.015584
lon         0.000571 -0.001061  0.000097 -0.000520   0.000278  0.000231
multiple    0.063561 -0.065299  0.050722  0.029170   0.033471  0.025853
success    -0.029239  0.025294 -0.004817  0.052270  -0.022147  0.024457
suicide     1.000000  0.057148  0.038451  0.133932   0.100651  0.094581
nter        0.057148  1.000000 -0.053815  0.032582   0.008837  0.017312
claimed     0.038451 -0.053815  1.000000  0.013441   0.028469  0.005461
killed      0.133932  0.032582  0.013441  1.000000   0.351714  0.449810
killedter   0.100651  0.008837  0.028469  0.351714   1.000000  0.026830
wounded     0.094581  0.017312  0.005461  0.449810   0.026830  1.000000
woundedter  0.005092 -0.001160  0.021594  0.110741   0.359480  0.034977
property   -0.073900  0.083877  0.040990 -0.014897  -0.046847 -0.008023

            woundedter  property
year          0.048757 -0.248604
extended      0.003929  0.001607
lat           0.024175 -0.067313
lon           0.000168 -0.001360
multiple      0.017624 -0.079118
success      -0.014449 -0.037473
suicide       0.005092 -0.073900
nter         -0.001160  0.083877
claimed       0.021594  0.040990
killed        0.110741 -0.014897
killedter     0.359480 -0.046847
wounded       0.034977 -0.008023
woundedter    1.000000 -0.023722
property     -0.023722  1.000000
```

Covariance between set of Variables

[33]:
```python
numerical_df = df_terrorism.select_dtypes(include=[float, int])
covariance_values = numerical_df.cov()
covariance_values
```

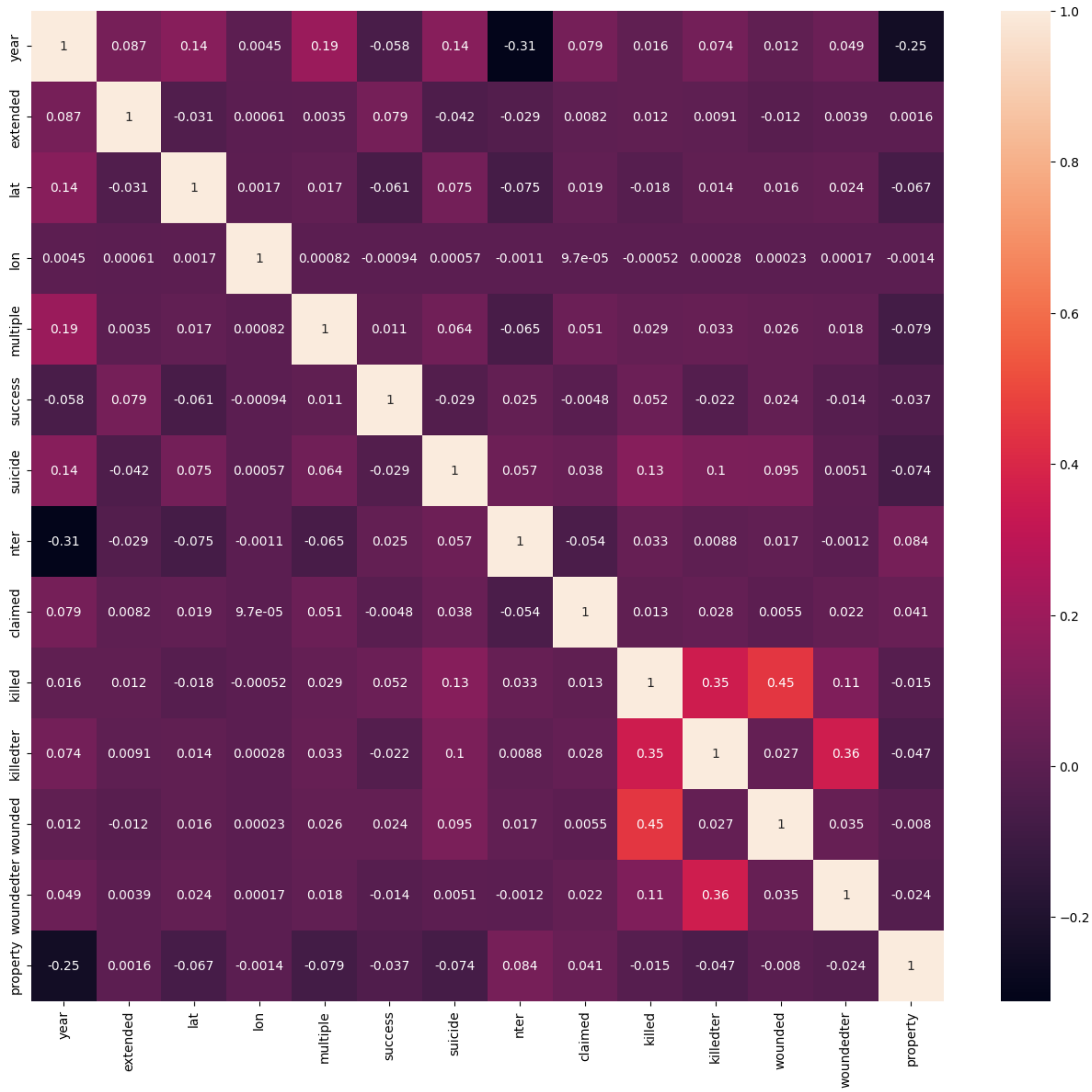
[33]:
```
                  year  extended         lat           lon  multiple  \
year        167.346202  0.247459   32.207670  1.304927e+04  0.702958
extended      0.247459  0.048031   -0.121132  2.998204e+01  0.000219
lat          32.207670 -0.121132  320.383693  6.688909e+03  0.084419
```

```
lon         13049.272898  29.982042  6688.908736  5.053552e+10  52.132551
multiple        0.702958   0.000219     0.084419  5.213255e+01   0.079197
success        -0.237158   0.005483    -0.344017 -6.716230e+01   0.001018
suicide         0.363491  -0.001858     0.272940  2.617076e+01   0.003647
nter         -437.320231  -0.679892  -146.292134 -2.589151e+04  -1.995010
claimed         0.950856   0.001678     0.309800  2.039484e+01   0.013337
killed          2.465095   0.030876    -3.957379 -1.424193e+03   0.100105
killedter       3.536334   0.007337     0.923611  2.309598e+02   0.034830
wounded         5.687139  -0.097759    10.617033  1.973007e+03   0.276915
woundedter      0.819138   0.001118     0.561982  4.917811e+01   0.006441
property      -10.125665   0.001109    -3.793537 -9.623828e+02  -0.070103

              success    suicide          nter    claimed       killed  \
year        -0.237158   0.363491   -437.320231   0.950856     2.465095
extended     0.005483  -0.001858     -0.679892   0.001678     0.030876
lat         -0.344017   0.272940   -146.292134   0.309800    -3.957379
lon        -67.162296  26.170763 -25891.506262  20.394835 -1424.193236
multiple     0.001018   0.003647     -1.995010   0.013337     0.100105
success      0.100619  -0.001891      0.871042  -0.001428     0.202194
suicide     -0.001891   0.041571      1.264987   0.007325     0.333009
nter         0.871042   1.264987  11786.104136  -5.458706    43.135940
claimed     -0.001428   0.007325     -5.458706   0.872981     0.153148
killed       0.202194   0.333009     43.135940   0.153148   148.711985
killedter   -0.025976   0.075882      3.547284   0.098356    15.859341
wounded      0.295273   0.733986     71.534121   0.194194   208.780194
woundedter  -0.005952   0.001348     -0.163486   0.026203     1.753863
property    -0.037426  -0.047441     28.670542   0.120582    -0.571969

             killedter      wounded  woundedter    property
year          3.536334     5.687139    0.819138  -10.125665
extended      0.007337    -0.097759    0.001118    0.001109
lat           0.923611    10.617033    0.561982   -3.793537
lon         230.959788  1973.006510   49.178114 -962.382776
multiple      0.034830     0.276915    0.006441   -0.070103
success      -0.025976     0.295273   -0.005952   -0.037426
suicide       0.075882     0.733986    0.001348   -0.047441
nter          3.547284    71.534121   -0.163486   28.670542
claimed       0.098356     0.194194    0.026203    0.120582
killed       15.859341   208.780194    1.753863   -0.571969
killedter    13.672399     3.775923    1.726271   -0.545399
wounded       3.775923  1448.689634    1.728965   -0.961494
woundedter    1.726271     1.728965    1.686649   -0.097001
property     -0.545399    -0.961494   -0.097001    9.913257
```

4. Visualization of Data

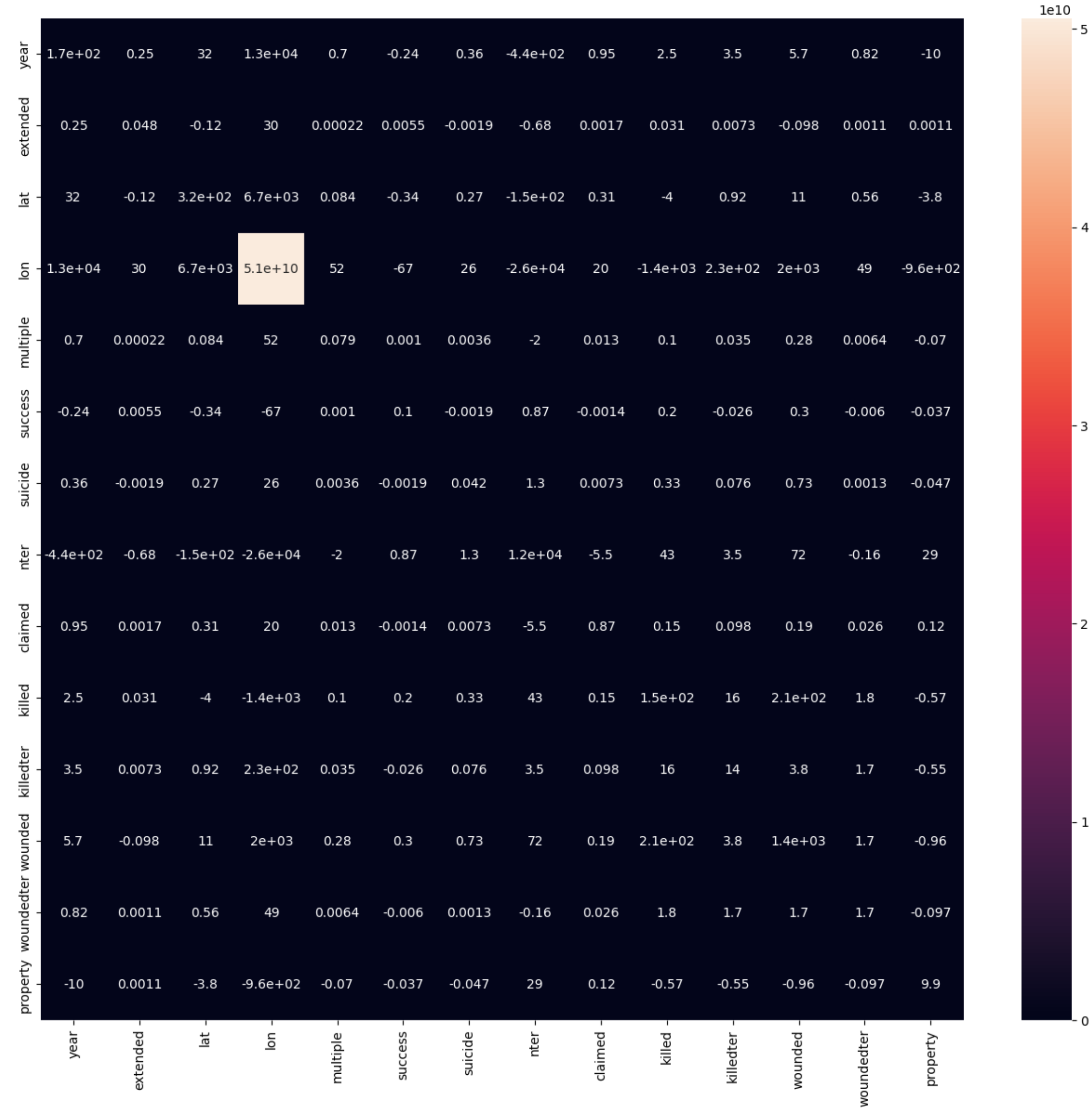
A. Heatmap of correlation values

```
[34]: fig,axes = plt.subplots(1,1,figsize=(16,14))
      sns.heatmap(corr_values, annot=True)
      plt.show()
```



B. Heatmap of correlation values

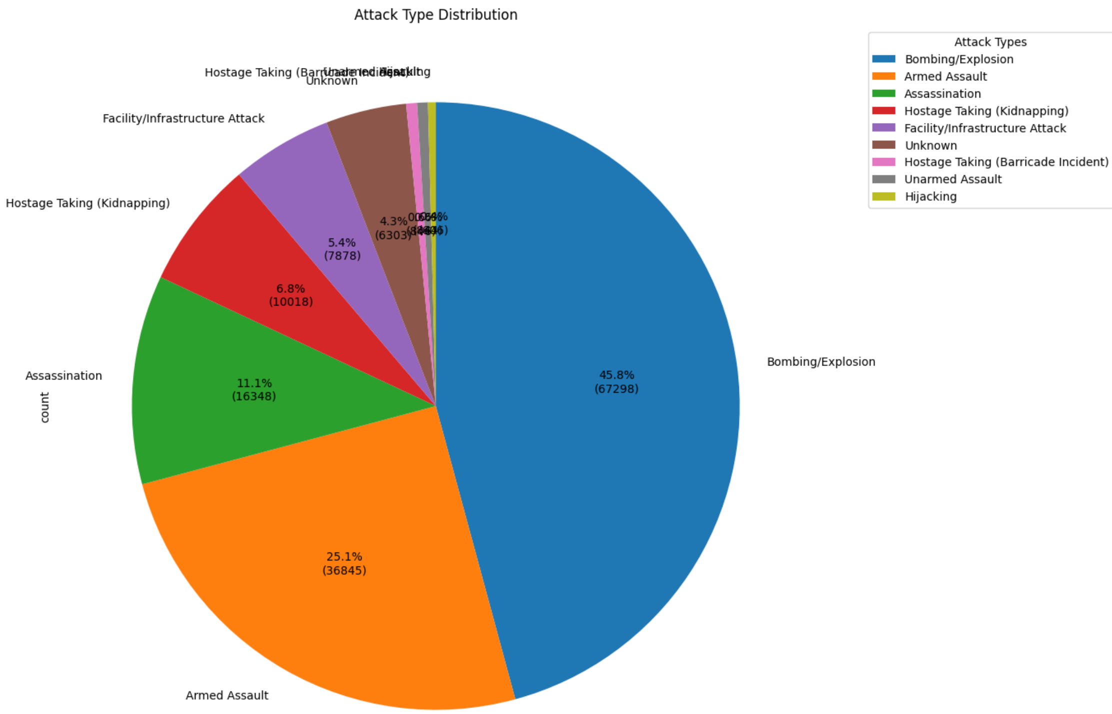
```
[35]: fig,axes = plt.subplots(1,1,figsize=(16,14))
      sns.heatmap(covariance_values, annot=True)
      plt.show()
```



C. Pie Chart of Attack Types

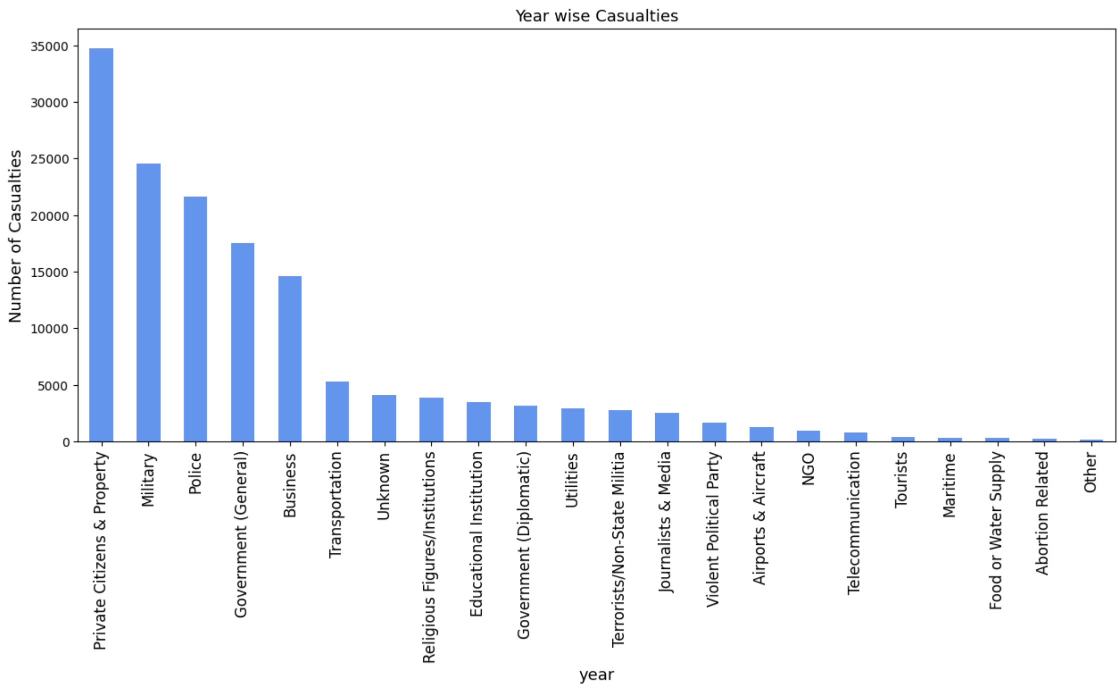
[36]:
```python
import matplotlib.pyplot as plt

# Create a function to format the labels
def autopct_format(values):
    def my_format(pct):
        total = sum(values)
        val = int(round(pct*total/100.0))
        return f'{pct:.1f}%\n({val:d})'
    return my_format
```

```
# Get the value counts for the 'attacktype' column
attacktype_counts = df_terrorism['attacktype'].value_counts()

# Increase the size of the figure
plt.figure(figsize=(12, 12))

# Plot the pie chart with values
attacktype_counts.plot.pie(autopct=autopct_format(attacktype_counts), startangle=90, counterclock=False)

# Set the title (optional)
plt.title('Attack Type Distribution')

plt.legend(attacktype_counts.index, title="Attack Types", loc="upper right", bbox_to_anchor=(1.4, 1))

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



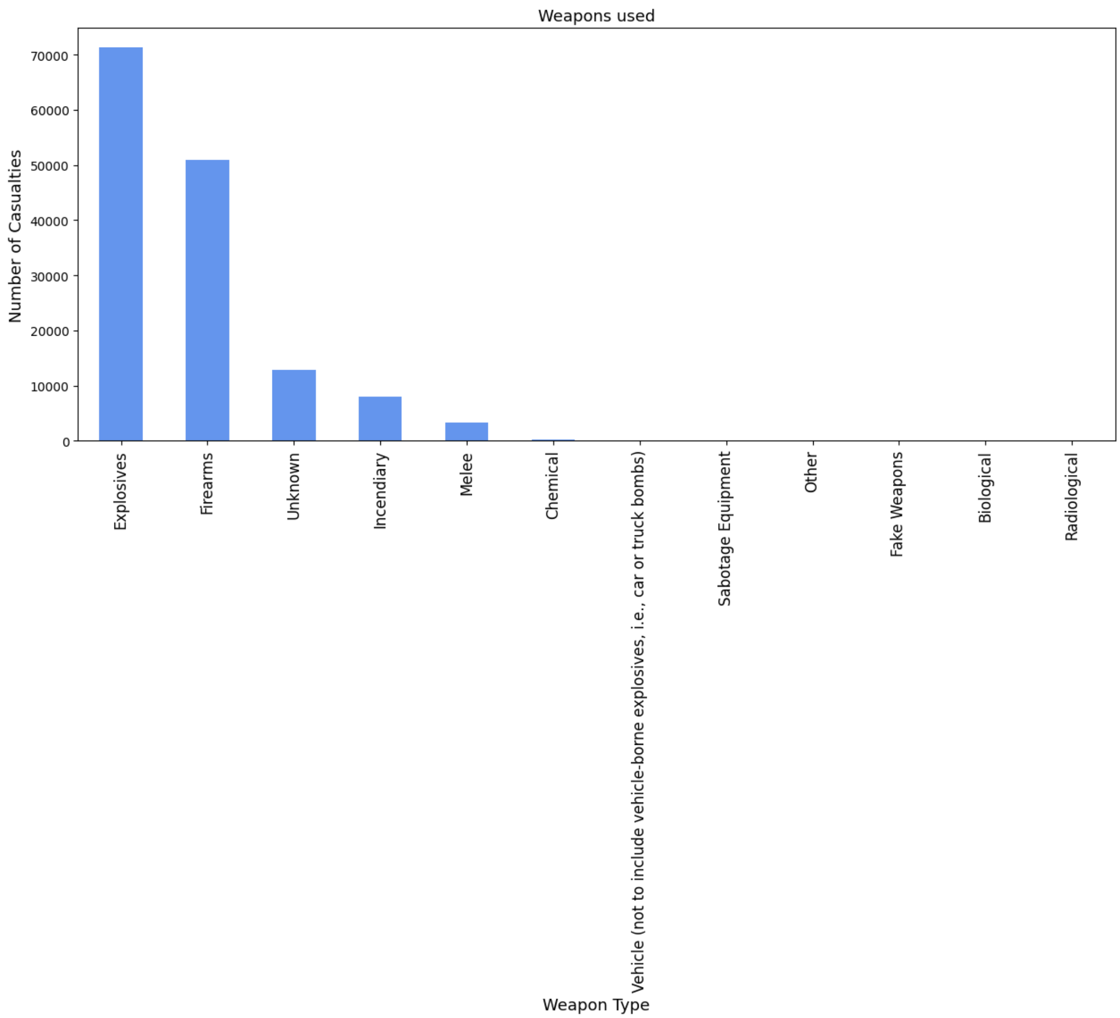
D. Histogram of Target Types

```
[37]: targettype_counts = df_terrorism['targtype'].value_counts()

targettype_counts.plot(kind="bar",color="cornflowerblue",figsize=(15,6))
plt.title("Year wise Casualties",fontsize=13)
plt.xlabel("year",fontsize=13)
plt.xticks(fontsize=12)
plt.ylabel("Number of Casualties",fontsize=13)
plt.show()
```



E. Histogram of Weapon Types

```
[38]: weapon_counts = df_terrorism['weaptype'].value_counts()

weapon_counts.plot(kind="bar",color="cornflowerblue",figsize=(15,6))
plt.title("Weapons used",fontsize=13)
plt.xlabel("Weapon Type",fontsize=13)
plt.xticks(fontsize=12)
plt.ylabel("Number of Casualties",fontsize=13)
plt.show()
```



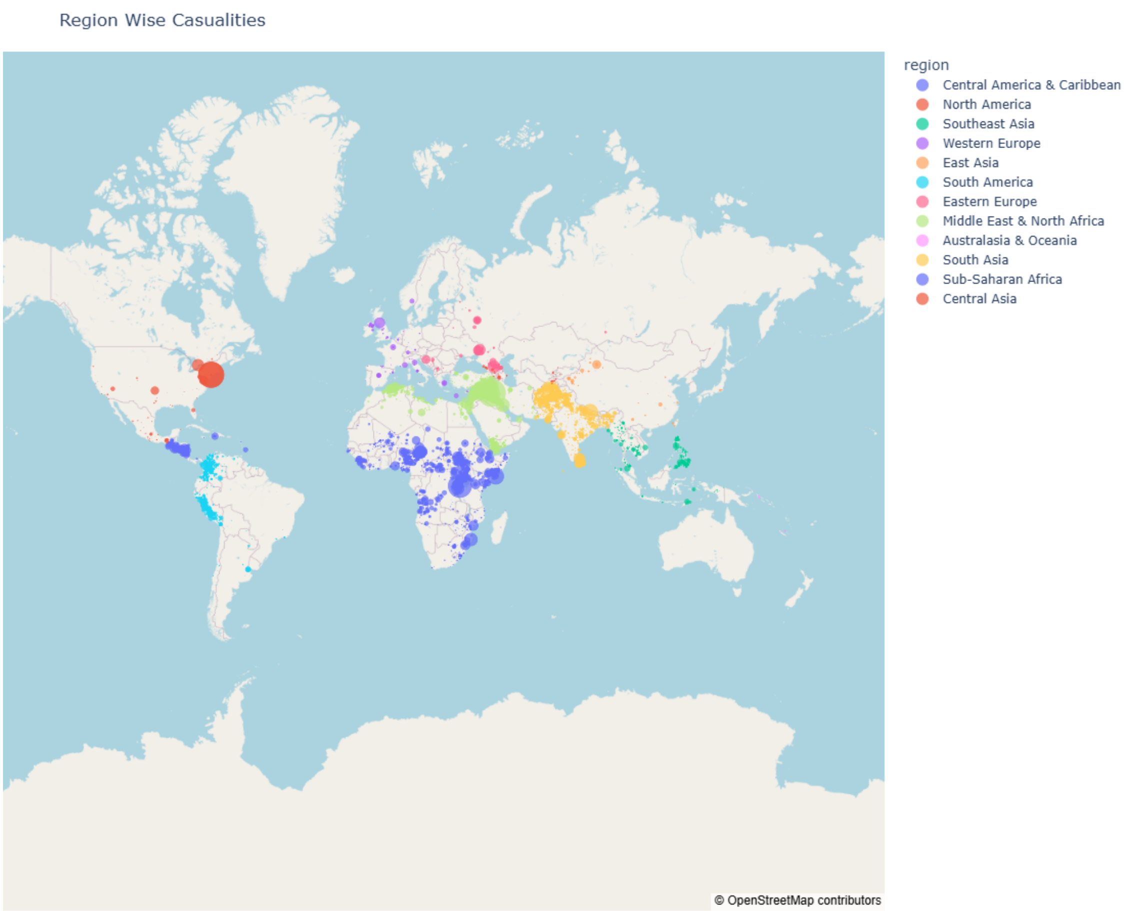
F. Heat Map of Region Affected

[39]:
```python
region_counts = df_terrorism['region'].value_counts()
region_counts
```

[39]:
```
region
South Asia                     39971
Middle East & North Africa     39491
Sub-Saharan Africa             15423
South America                  12978
Western Europe                 12285
Southeast Asia                 10980
Central America & Caribbean     6995
Eastern Europe                  4599
North America                   2879
East Asia                        628
```

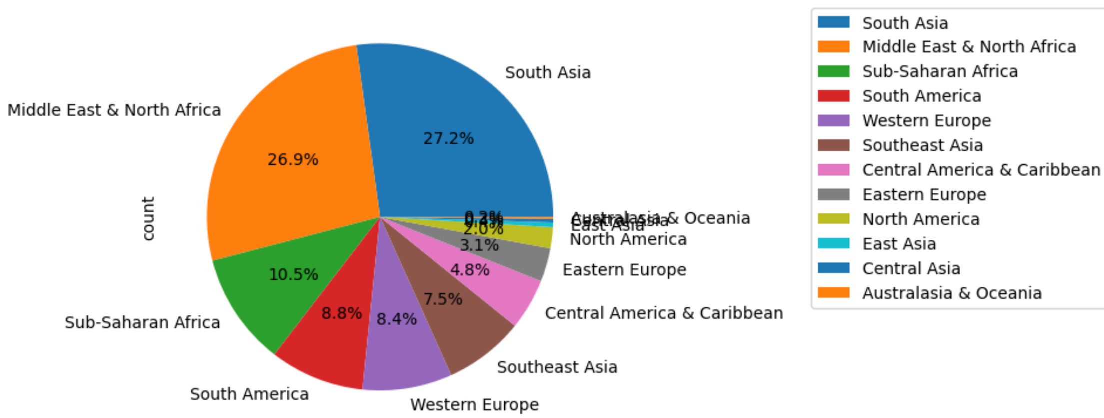
```
Central Asia                       498
Australasia & Oceania              259
Name: count, dtype: int64
```

[40]:
```python
import plotly.express as px

fig = px.scatter_mapbox(df_terrorism,
                        lon = df_terrorism['lon'],
                        lat = df_terrorism['lat'],zoom = 2,
                        color = df_terrorism['region'],
                        size = df_terrorism['killed'],width = 1100, height =␣
 ↪900, title = 'Region Wise Casualities')

fig.update_layout(mapbox_style='open-street-map')
fig.update_layout(margin={"r":0, "t":50, "l": 0, "b": 10})
```



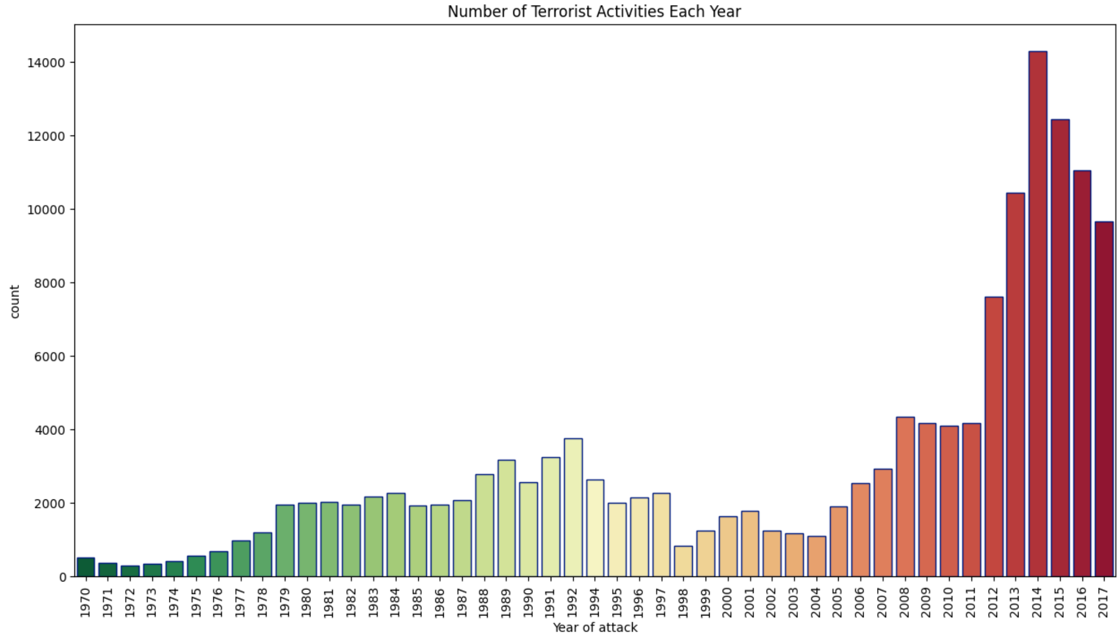
[41]:
```python
df_terrorism['region'].value_counts().plot.pie(autopct = "%1.1f%%")
plt.legend(loc='upper right', bbox_to_anchor=(2.2, 1))
```

```
plt.show()
```



G. Number of Terrorist Activities Each Year

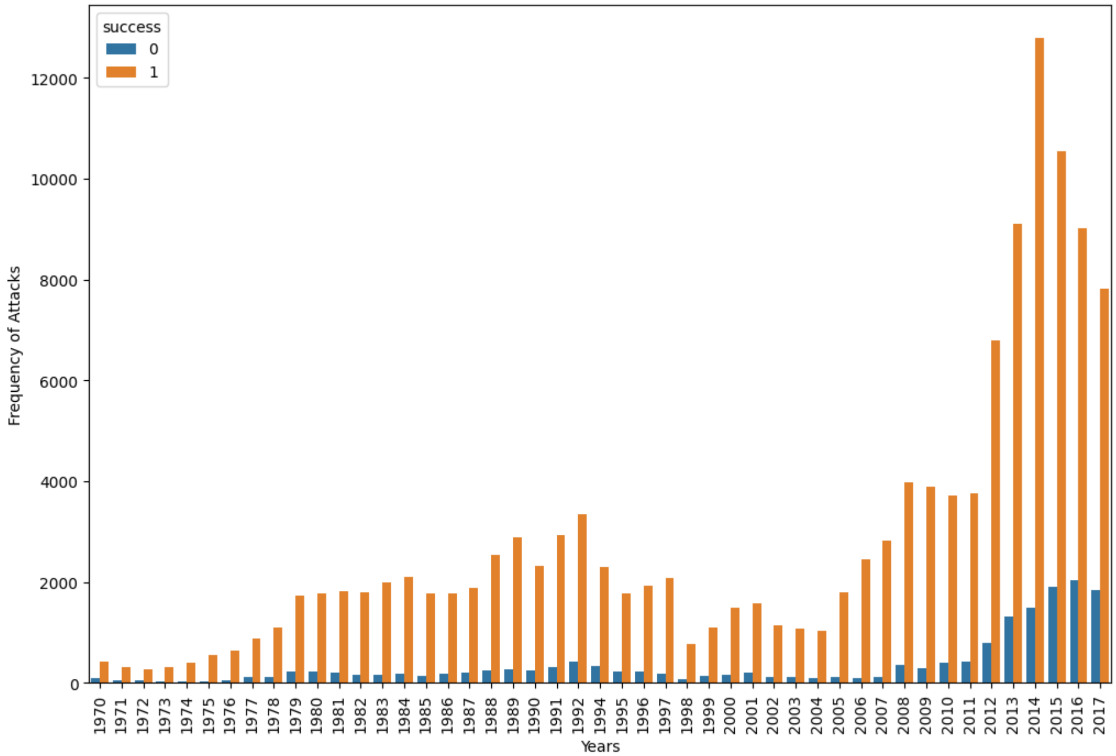
[42]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Create a figure and axes
fig, ax = plt.subplots(figsize=(15, 8))

# Plot the countplot
sns.countplot(x='year', hue='year', data=df_terrorism, palette='RdYlGn_r',
 ↪edgecolor=sns.color_palette('dark', 7), ax=ax, legend=False)
plt.xticks(rotation=90)
plt.xlabel('Year of attack')
plt.title('Number of Terrorist Activities Each Year')
plt.show()
```



H. Frequency of Attacks

[45]:
```
plt.figure(figsize=(12,8))
sns.countplot(x=df_terrorism['year'],hue='success',data = df_terrorism)
plt.xlabel('Years')
plt.xticks(rotation=90)
plt.ylabel('Frequency of Attacks')
```

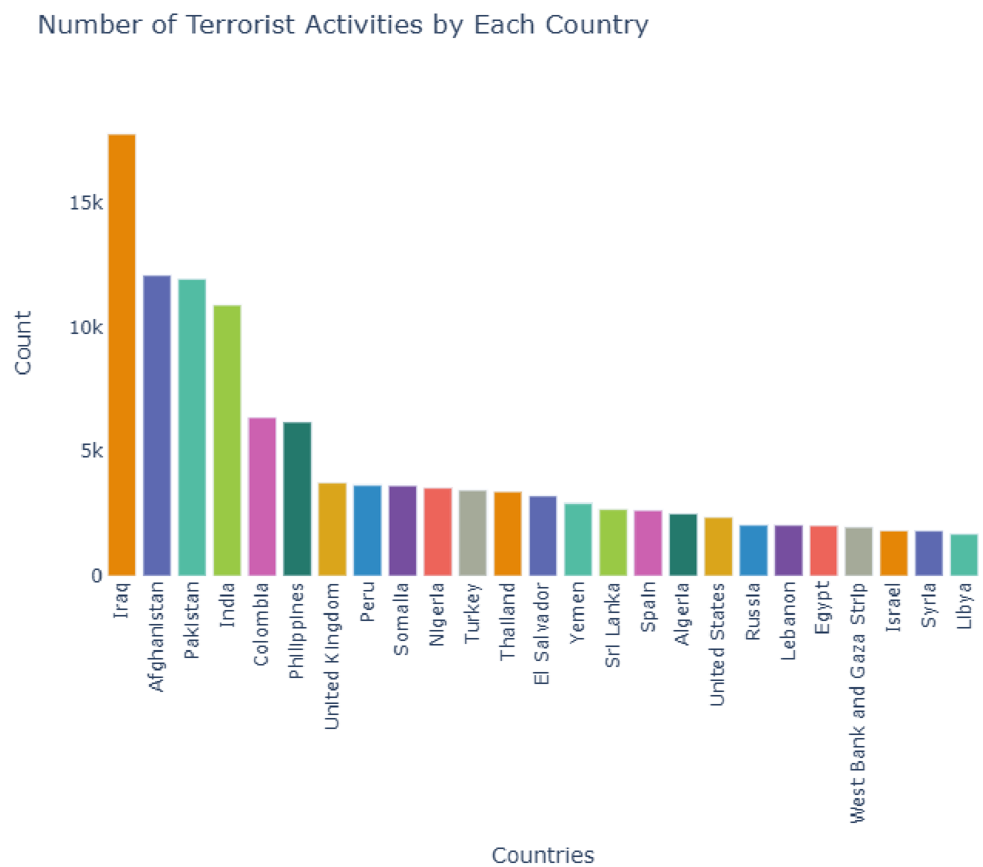
[45]:
```
Text(0, 0.5, 'Frequency of Attacks')
```



I. Number of Terrorist Activities Country Wise

[71]:
```python
import pandas as pd
import plotly.express as px

country_counts = df_terrorism['country'].value_counts()[:25].reset_index()
country_counts.columns = ['Country', 'Count']

# Creating the bar plot with Plotly
fig = px.bar(country_counts, x='Country', y='Count', title="Number of Terrorist␣
 ↪Activities by Each Country",
             labels={'Country': 'Countries', 'Count': 'Count'},
             hover_data={'Country': True, 'Count': True},
             color='Country',  # This assigns different colors to each country
             color_discrete_sequence=px.colors.qualitative.Vivid)  # You can␣
 ↪choose any color palette here

# Updating layout for better visualization
fig.update_layout(
    xaxis_title="Countries",
    yaxis_title="Count",
    xaxis_tickangle=-90,
    plot_bgcolor='rgba(0,0,0,0)',  # Set background color to transparent
```

```
    width=1060,
    height=600,
    showlegend=False# Hide the legend
)

# Display the plot
fig.show()
```

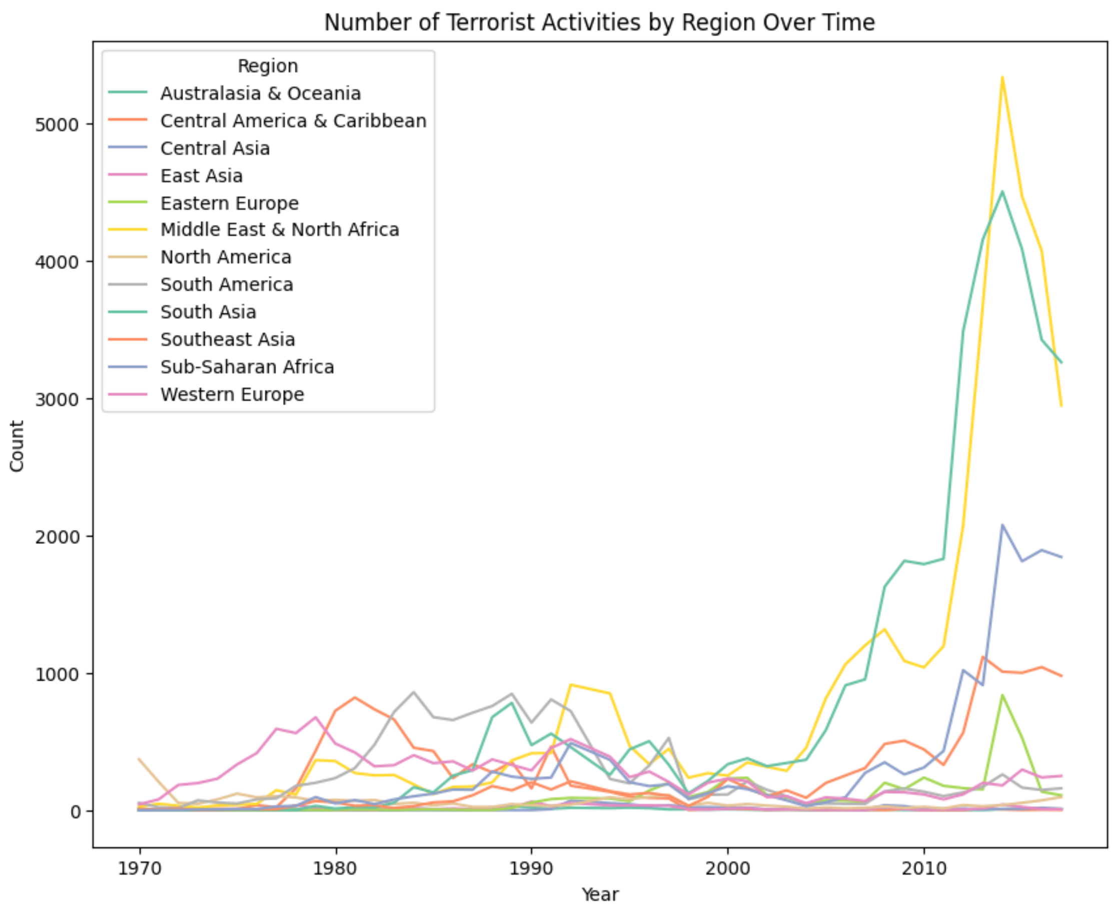


J. Number of Terrorist Activities Region Wise

[69]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Creating a crosstab DataFrame
df_region = pd.crosstab(df_terrorism.year, df_terrorism.region)

# Plotting the crosstab DataFrame with Seaborn and Matplotlib
plt.figure(figsize=(15, 8))  # Set the figure size
```

```
df_region.plot(color=sns.color_palette('Set2', 12))

# Setting labels and title
plt.xlabel('Year')
plt.ylabel('Count')
plt.title('Number of Terrorist Activities by Region Over Time')
plt.legend(title='Region', loc='upper left')

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

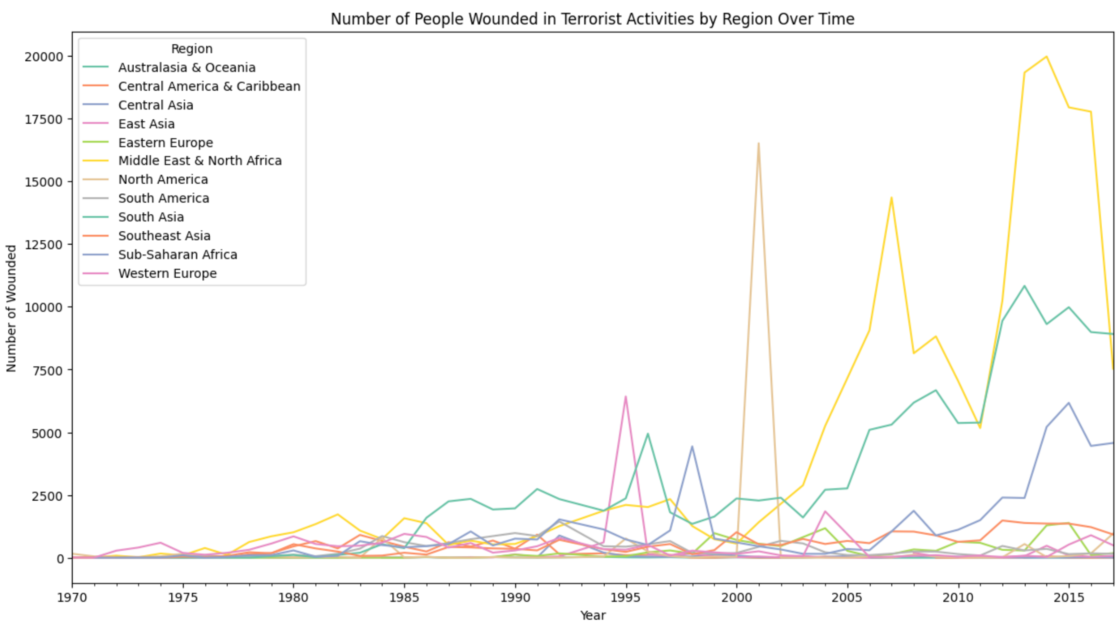
<Figure size 1500x800 with 0 Axes>



K. Number of People Wounded Year Wise

[75]:
```
# Grouping by year and region, and summing the 'wounded' values
d = df_terrorism.groupby(['year', 'region'])['wounded'].sum()

# Unstacking the 'region' level to create a DataFrame suitable for plotting
```

```
plot_df_terrorism = d.unstack('region')

# Converting the index to a PeriodIndex with yearly frequency
plot_df_terrorism.index = pd.PeriodIndex(plot_df_terrorism.index.tolist(),␣
↪freq='A')

# Plotting the DataFrame
plot_df_terrorism.plot(figsize=(15, 8), color=sns.color_palette('Set2', 12))

# Setting labels and title
plt.xlabel('Year')
plt.ylabel('Number of Wounded')
plt.title('Number of People Wounded in Terrorist Activities by Region Over␣
↪Time')
plt.legend(title='Region', loc='upper left')

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

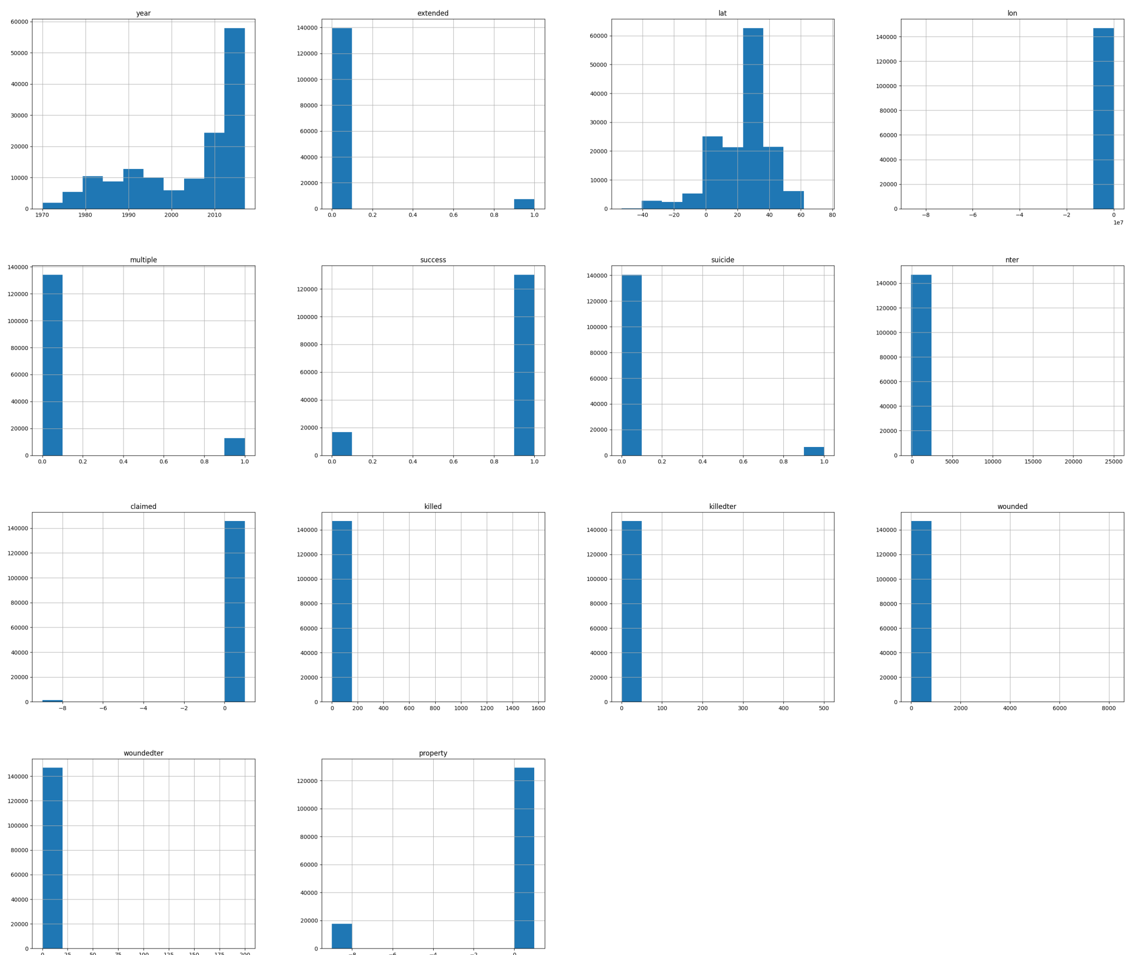


L. Histograms of Various Columns of Data Set

[79]:
```
df_terrorism.hist(figsize=(35,30))
```

[79]:
```
array([[<Axes: title={'center': 'year'}>,
        <Axes: title={'center': 'extended'}>,
        <Axes: title={'center': 'lat'}>, <Axes: title={'center': 'lon'}>],
       [<Axes: title={'center': 'multiple'}>,
```

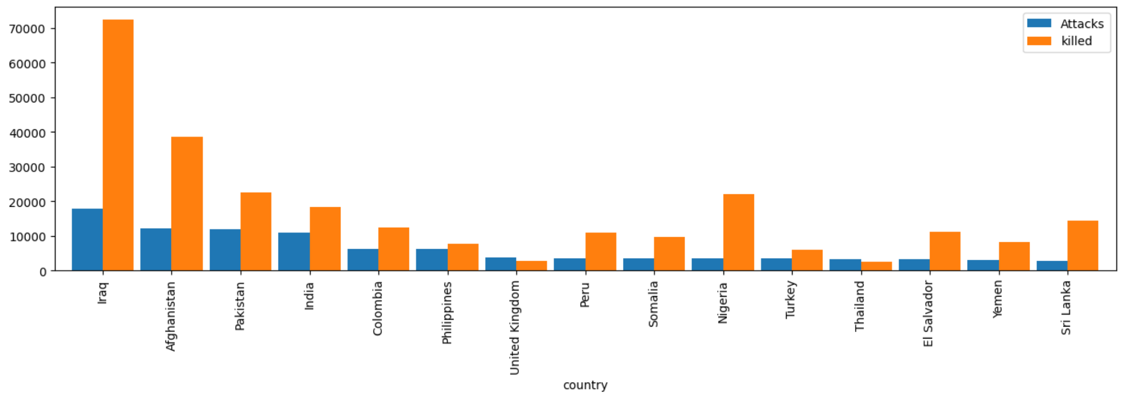
```
 <Axes: title={'center': 'success'}>,
 <Axes: title={'center': 'suicide'}>,
 <Axes: title={'center': 'nter'}>],
[<Axes: title={'center': 'claimed'}>,
 <Axes: title={'center': 'killed'}>,
 <Axes: title={'center': 'killedter'}>,
 <Axes: title={'center': 'wounded'}>],
[<Axes: title={'center': 'woundedter'}>,
 <Axes: title={'center': 'property'}>, <Axes: >, <Axes: >]],
dtype=object)
```



M. Attack vs Killed Figure

[83]:
```python
count_terror = df_terrorism['country'].value_counts()[:15].to_frame()
count_terror.columns=['Attacks']
count_kill=df_terrorism.groupby('country')['killed'].sum().to_frame()
count_terror.merge(count_kill,left_index = True, right_index = True,␣
 ↪how='left').plot.bar(width=0.9)
```

```
fig=plt.gcf()
fig.set_size_inches(16,4)
plt.show()
```



1.1 CONCLUSION

1. Country with Highest Number of Attacks : Iraq
2. Region with Highest Number of Terrorist Attacks : Middle East and North Africa
3. Maximum Number of People Killed : 1570 (In Iraq)
4. Year with Most Attacks : 2014
5. Month with Mose Attacks : May
6. Group that carried out most attacks : Taliban
7. Type of Attack most carried out : Bombing / Explosion

[ ]:
```

```