'Exploratory Data Analysis Project on Global Terrorism Activities'

Global Terrorism refers to the illicit application of force or violence against individuals or assets with the intention of intimidating or coercing a government or its populace in order to advance specific political or social aims.

Terrorism can be defined by the following characteristics:

- The utilization of violence or the threat of violence in the pursuit of goals related to politics, religion, ideology, or societal change.
- Actions perpetrated by entities outside of official government control (or by covert operatives acting on behalf of their respective governments).
- Actions that extend beyond immediate victims, affecting a broader segment of society.

The subsequent instances of violence or the threat of violence typically do not align with the definition of terrorism:

- Acts of violence, whether in wartime (even if undeclared) or peacetime, conducted by one nation-state against another, irrespective of their legal status, provided they are executed by duly recognized armed forces or lawful combatants of said nation-states.
- Justifiable acts of self-defense, which may involve the use of force to neutralize, apprehend, or penalize criminals who pose a danger to human lives or property.
- Lawful targets during times of war, such as enemy combatants and critical infrastructure integral to the enemy's war efforts, including defense-related industries and harbors.
- Unintended harm, including the accidental infliction of damage to non-combatant entities when attacking or attempting to attack legitimate wartime targets.

About DataSet - The dataset contains aprrox 180k of Terrorist activity reported under the time frame of 47 years that is from 1970 till 2017. The dataset have 135 different informative parameters under which an activity has been reported. These are - DATE,COUNTRY,STATE,REGION,Number of people KILLED,TERRORIST GROUP responsible for the attack,Attack Types etc.

Now let's first Import required libaries and download the dataset and write it into a directory.

In [92]:

```
pip install RISE
pip install nbconvert
```

```
  Cell In[92], line 1
    pip install RISE
        ^
SyntaxError: invalid syntax
```

In [2]:

```
import plotly.express as px
import plotly.figure_factory as ff
import numpy as np
import pandas as pd
import opendatasets as od
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
import plotly.offline as py
py.init_notebook_mode(connected=True)
import plotly.graph_objs as go
%matplotlib inline
```

```
C:\Users\akgat\anaconda3\lib\site-packages\numpy\_distributor_init.py:30: UserWarning: loaded more than 1 DLL from .libs:
C:\Users\akgat\anaconda3\lib\site-packages\numpy\.libs\libopenblas.FB5AE2TYXYH2IJRDKGDGQ3XBKLKTF43H.gfortran-win_amd64.dll
C:\Users\akgat\anaconda3\lib\site-packages\numpy\.libs\libopenblas64__v0.3.21-gcc_10_3_0.dll
  warnings.warn("loaded more than 1 DLL from .libs:"
```

In [6]:

```
#Loading the downloaded dataset from the directory into a dataframe using the Pandas "pd.read_csv" function.
DF=pd.read_csv('globalterrorismdb_0718dist.csv',encoding='ISO-8859-1',low_memory=False)
```

In [7]:

```
DF.head()
```

Out[7]:

	eventid	iyear	imonth	iday	approxdate	extended	resolution	country	country_txt	region	...	addnotes	scite1	scite2	scite3	dbsource	INT_
0	197000000001	1970	7	2	NaN	0	NaN	58	Dominican Republic	2	...	NaN	NaN	NaN	NaN	PGIS	
1	197000000002	1970	0	0	NaN	0	NaN	130	Mexico	1	...	NaN	NaN	NaN	NaN	PGIS	
2	197001000001	1970	1	0	NaN	0	NaN	160	Philippines	5	...	NaN	NaN	NaN	NaN	PGIS	
3	197001000002	1970	1	0	NaN	0	NaN	78	Greece	8	...	NaN	NaN	NaN	NaN	PGIS	
4	197001000003	1970	1	0	NaN	0	NaN	101	Japan	4	...	NaN	NaN	NaN	NaN	PGIS	

5 rows × 135 columns

Dataset Exploration

In [8]:

```
# DF is the datafrane that has been created with the loaded dataset.
# DF.shape function indicates the total number of rows & Columns.
DF.shape
```

Out[8]:

```
(181691, 135)
```

In [9]:

```
# DataFrame ".coulmn" function gives us the total columns names that are present within the dataset.
DF.columns
```

Out[9]:

```
Index(['eventid', 'iyear', 'imonth', 'iday', 'approxdate', 'extended',
       'resolution', 'country', 'country_txt', 'region',
       ...
       'addnotes', 'scite1', 'scite2', 'scite3', 'dbsource', 'INT_LOG',
       'INT_IDEO', 'INT_MISC', 'INT_ANY', 'related'],
      dtype='object', length=135)
```

In [11]:

```
list(DF.columns)
```

```
 'nwound',
 'nwoundus',
 'nwoundte',
 'property',
 'propextent',
 'propextent_txt',
 'propvalue',
 'propcomment',
 'ishostkid',
 'nhostkid',
 'nhostkidus',
 'nhours',
 'ndays',
 'divert',
 'kidhijcountry',
 'ransom',
 'ransomamt',
 'ransomamtus',
 'ransompaid',
```

In [16]:

```
# DataFrame ".describe" method returns description of the data in the DataFrame.

# If the DataFrame contains numerical data, the description contains these information for each column:
# count - The number of not-empty values.
# mean - The average (mean) value.
# std - The standard deviation.
# min - the minimum value.
# 25% - The 25% percentile*.
# 50% - The 50% percentile*.
# 75% - The 75% percentile*.
# max - the maximum value.
# Percentile meaning: how many of the values are less than the given percentile.

DF.describe()
```

Out[16]:

	eventid	iyear	imonth	iday	extended	country	region	latitude	longitude	speci
count	1.816910e+05	181691.000000	181691.000000	181691.000000	181691.000000	181691.000000	181691.000000	177135.000000	1.771340e+05	181685.00
mean	2.002705e+11	2002.638997	6.467277	15.505644	0.045346	131.968501	7.160938	23.498343	-4.586957e+02	1.45
std	1.325957e+09	13.259430	3.388303	8.814045	0.208063	112.414535	2.933408	18.569242	2.047790e+05	0.99
min	1.970000e+11	1970.000000	0.000000	0.000000	0.000000	4.000000	1.000000	-53.154613	-8.618590e+07	1.00
25%	1.991021e+11	1991.000000	4.000000	8.000000	0.000000	78.000000	5.000000	11.510046	4.545640e+00	1.00
50%	2.009022e+11	2009.000000	6.000000	15.000000	0.000000	98.000000	6.000000	31.467463	4.324651e+01	1.00
75%	2.014081e+11	2014.000000	9.000000	23.000000	0.000000	160.000000	10.000000	34.685087	6.871033e+01	1.00
max	2.017123e+11	2017.000000	12.000000	31.000000	1.000000	1004.000000	12.000000	74.633553	1.793667e+02	5.00

8 rows × 77 columns

In [17]:

```
# DataFrame ".info" function gives the compact information about the dataset.
# The information contains the number of columns, column labels, column data types, memory usage, range index, and the number of cells in
DF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 181691 entries, 0 to 181690
Columns: 135 entries, eventid to related
dtypes: float64(55), int64(22), object(58)
memory usage: 187.1+ MB
```

Data Structuring

In [18]:

```
DF.columns
```

Out[18]:

```
Index(['eventid', 'iyear', 'imonth', 'iday', 'approxdate', 'extended',
       'resolution', 'country', 'country_txt', 'region',
       ...
       'addnotes', 'scite1', 'scite2', 'scite3', 'dbsource', 'INT_LOG',
       'INT_IDEO', 'INT_MISC', 'INT_ANY', 'related'],
      dtype='object', length=135)
```

In [19]:

```
s={'iyear':'Year','imonth':'Month','iday':'Day', 'country_txt':'Country','provstate':'State',
         'region_txt':'Region','attacktype1_txt':'Attack_Type','target1':'Target','nkill':'Killed',
       'nwound':'Wounded','summary':'Summary','gname':'Group','targtype1_txt':'Target_type',
       'weaptype1_txt':'Weapon_type','motive':'Motive','location':'Location','latitude':'Latitude','longitude':'Longitude'},inplace=True)
```

Let's generate a new DataFrame with the above renamed columns for our analysis based only on the selected Columns/Features

In [20]:

```
df=DF[['Year','Month','Day','Country','State','Region','Attack_Type','Target','Killed','Wounded','Summary','Group','Target_type',
       'Weapon_type','Motive','Location','Longitude','Latitude']]
```

In [21]:

```
df
```

Out[21]:

	Year	Month	Day	Country	State	Region	Attack_Type	Target	Killed	Wounded	Summary	Group	Target_type	W
0	1970	7	2	Dominican Republic	NaN	Central America & Caribbean	Assassination	Julio Guzman	1.0	0.0	NaN	MANO-D	Private Citizens & Property	
1	1970	0	0	Mexico	Federal	North America	Hostage Taking (Kidnapping)	Nadine Chaval, daughter	0.0	0.0	NaN	23rd of September Communist League	Government (Diplomatic)	
2	1970	1	0	Philippines	Tarlac	Southeast Asia	Assassination	Employee	1.0	0.0	NaN	Unknown	Journalists & Media	
3	1970	1	0	Greece	Attica	Western Europe	Bombing/Explosion	U.S. Embassy	NaN	NaN	NaN	Unknown	Government (Diplomatic)	
4	1970	1	0	Japan	Fukouka	East Asia	Facility/Infrastructure Attack	U.S. Consulate	NaN	NaN	NaN	Unknown	Government (Diplomatic)	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
181686	2017	12	31	Somalia	Middle Shebelle	Sub-Saharan Africa	Armed Assault	Checkpoint	1.0	2.0	12/31/2017: Assailants opened fire on a Somali...	Al-Shabaab	Military	
181687	2017	12	31	Syria	Lattakia	Middle East & North Africa	Bombing/Explosion	Hmeymim Air Base	2.0	7.0	12/31/2017: Assailants launched mortars at the...	Muslim extremists	Military	
181688	2017	12	31	Philippines	Maguindanao	Southeast Asia	Facility/Infrastructure Attack	Houses	0.0	0.0	12/31/2017: Assailants set fire to houses in K...	Bangsamoro Islamic Freedom Movement (BIFM)	Private Citizens & Property	
181689	2017	12	31	India	Manipur	South Asia	Bombing/Explosion	Office	0.0	0.0	12/31/2017: Assailants threw a grenade at a Fo...	Unknown	Government (General)	
181690	2017	12	31	Philippines	Maguindanao	Southeast Asia	Bombing/Explosion	Unknown	0.0	0.0	12/31/2017: An explosive device was discovered...	Unknown	Unknown	

181691 rows × 18 columns

Let's first create a copy of the dataframe and then locate the numbers for the missing data in our dataset.

In [22]:

```
main_df=df.copy()
```

In [23]:

```
main_df.head(5)
```

Out[23]:

	Year	Month	Day	Country	State	Region	Attack_Type	Target	Killed	Wounded	Summary	Group	Target_type	Weapon_type	N
0	1970	7	2	Dominican Republic	NaN	Central America & Caribbean	Assassination	Julio Guzman	1.0	0.0	NaN	MANO-D	Private Citizens & Property	Unknown	
1	1970	0	0	Mexico	Federal	North America	Hostage Taking (Kidnapping)	Nadine Chaval, daughter	0.0	0.0	NaN	23rd of September Communist League	Government (Diplomatic)	Unknown	
2	1970	1	0	Philippines	Tarlac	Southeast Asia	Assassination	Employee	1.0	0.0	NaN	Unknown	Journalists & Media	Unknown	
3	1970	1	0	Greece	Attica	Western Europe	Bombing/Explosion	U.S. Embassy	NaN	NaN	NaN	Unknown	Government (Diplomatic)	Explosives	
4	1970	1	0	Japan	Fukouka	East Asia	Facility/Infrastructure Attack	U.S. Consulate	NaN	NaN	NaN	Unknown	Government (Diplomatic)	Incendiary	

In the above DataFrame we can see there is a column for Day and Month at which the incident happened and it filled with the "0" which is not possible, we will be cleaning the incorrect data for the dates and months later on this notebook.

Data Cleaning

In [24]:

```
main_df.isna().sum()
```

Out[24]:

```
Year                0
Month               0
Day                 0
Country             0
State             421
Region              0
Attack_Type         0
Target            636
Killed          10313
Wounded         16311
Summary         66129
Group               0
Target_type         0
Weapon_type         0
Motive         131130
Location       126196
Longitude        4557
Latitude         4556
dtype: int64
```

Here we can clearly see the State has 421 missing values, Target has 636, killed has 10313 and so on.

- Here we can Fill the missing data with the Mean/Median/Mode Value.
- Ignore the missing data and do the analysis without that particular data/Column in such a way that it does not effect the analysis

Let's fill the missing places for the state column as "Unknown".

In [25]:

```
main_df.State.fillna("Unknown", inplace = True)
```

In [27]:

```
main_df["State"].isna().sum()
```

Out[27]:

```
0
```

In [28]:

```
main_df.Target.fillna("Unknown", inplace = True)
```

In [29]:

```
main_df.Target.isna().sum()
```

Out[29]:

```
0
```

In [30]:

```
main_df.Killed
```

Out[30]:

```
0         1.0
1         0.0
2         1.0
3         NaN
4         NaN
         ...
181686    1.0
181687    2.0
181688    0.0
181689    0.0
181690    0.0
Name: Killed, Length: 181691, dtype: float64
```

Here there are some NAN values on the killed Column, let's find out the Mean, Median and Mode for the Column

In [31]:

```
main_df.Killed.mean()
```

Out[31]:

```
2.4032722986614385
```

In [32]:

```
main_df['Killed'].mode()
```

Out[32]:

```
0    0.0
Name: Killed, dtype: float64
```

Here we are filling up the empty/missing(NAN) values in the column with the mode value that is 0.

In [33]:

```
main_df.Killed.fillna(df.Killed.mode()[0],inplace = True)
```

In [34]:

```
main_df["Killed"]
```

Out[34]:

```
0         1.0
1         0.0
2         1.0
3         0.0
4         0.0
         ...
181686    1.0
181687    2.0
181688    0.0
181689    0.0
181690    0.0
Name: Killed, Length: 181691, dtype: float64
```

In [35]:

```
main_df.Killed.isna().sum()
```

Out[35]:

```
0
```

Filling up the Wounded column with the mode value.

In [36]:

```
main_df.Wounded.fillna(df.Wounded.mode()[0], inplace = True)
```

In [37]:

```
main_df['Wounded'].isna().sum()
```

Out[37]:

```
0
```

In [38]:

```
main_df.Wounded.value_counts()
```

Out[38]:

```
0.0      119586
1.0       16033
2.0       10219
3.0        7303
4.0        4880
          ...
727.0         1
216.0         1
751.0         1
233.0         1
316.0         1
Name: Wounded, Length: 238, dtype: int64
```

Let's now check for the duplicate data in the our main DataFrame.

In [39]:

```
main_df.duplicated().value_counts()
```

Out[39]:

```
False    172157
True       9534
dtype: int64
```

- The above **True** values refers to duplicate data in the dataset and we should always remove/drop the duplicate values.

In [40]:

```
DF1=main_df.drop_duplicates()
```

In [41]:

```
DF1
```

Out[41]:

	Year	Month	Day	Country	State	Region	Attack_Type	Target	Killed	Wounded	Summary	Group	Target_type	W
0	1970	7	2	Dominican Republic	Unknown	Central America & Caribbean	Assassination	Julio Guzman	1.0	0.0	NaN	MANO-D	Private Citizens & Property	
1	1970	0	0	Mexico	Federal	North America	Hostage Taking (Kidnapping)	Nadine Chaval, daughter	0.0	0.0	NaN	23rd of September Communist League	Government (Diplomatic)	
2	1970	1	0	Philippines	Tarlac	Southeast Asia	Assassination	Employee	1.0	0.0	NaN	Unknown	Journalists & Media	
3	1970	1	0	Greece	Attica	Western Europe	Bombing/Explosion	U.S. Embassy	0.0	0.0	NaN	Unknown	Government (Diplomatic)	
4	1970	1	0	Japan	Fukouka	East Asia	Facility/Infrastructure Attack	U.S. Consulate	0.0	0.0	NaN	Unknown	Government (Diplomatic)	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
181686	2017	12	31	Somalia	Middle Shebelle	Sub-Saharan Africa	Armed Assault	Checkpoint	1.0	2.0	12/31/2017: Assailants opened fire on a Somali...	Al-Shabaab	Military	
181687	2017	12	31	Syria	Lattakia	Middle East & North Africa	Bombing/Explosion	Hmeymim Air Base	2.0	7.0	12/31/2017: Assailants launched mortars at the...	Muslim extremists	Military	
181688	2017	12	31	Philippines	Maguindanao	Southeast Asia	Facility/Infrastructure Attack	Houses	0.0	0.0	12/31/2017: Assailants set fire to houses in K...	Bangsamoro Islamic Freedom Movement (BIFM)	Private Citizens & Property	
181689	2017	12	31	India	Manipur	South Asia	Bombing/Explosion	Office	0.0	0.0	12/31/2017: Assailants threw a grenade at a Fo...	Unknown	Government (General)	
181690	2017	12	31	Philippines	Maguindanao	Southeast Asia	Bombing/Explosion	Unknown	0.0	0.0	12/31/2017: An explosive device was discovered...	Unknown	Unknown	

172157 rows × 18 columns

In [42]:

```
DF1.shape
```

Out[42]:

```
(172157, 18)
```

In [43]:

```
DF1.isna().sum()
```

Out[43]:

```
Year                0
Month               0
Day                 0
Country             0
State               0
Region              0
Attack_Type         0
Target              0
Killed              0
Wounded             0
Summary         59002
Group               0
Target_type         0
Weapon_type         0
Motive         122233
Location       117204
Longitude        3971
Latitude         3970
dtype: int64
```

Let now remove the data which have Date and Month as "0".

In [44]:

```
DF1[DF1["Month"]==0]
```

Out[44]:

	Year	Month	Day	Country	State	Region	Attack_Type	Target	Killed	Wounded	Summary	Group	Target_type	Weapon_t
1	1970	0	0	Mexico	Federal	North America	Hostage Taking (Kidnapping)	Nadine Chaval, daughter	0.0	0.0	NaN	23rd of September Communist League	Government (Diplomatic)	Unkn
1123	1972	0	0	Philippines	Capiz	Southeast Asia	Bombing/Explosion	air manila fokker F-27p	0.0	0.0	NaN	Unknown	Airports & Aircraft	Explosi
1690	1973	0	0	Colombia	Unknown	South America	Hostage Taking (Kidnapping)	Alirio Serrano Sanchez, rancher	0.0	0.0	NaN	National Liberation Army of Colombia (ELN)	Business	Unkn
2164	1974	0	0	France	Paris	Western Europe	Bombing/Explosion	Bank Lazard	0.0	0.0	NaN	Unknown	Business	Explosi
2165	1974	0	0	Italy	Lazio	Western Europe	Bombing/Explosion	TWA Boeing 707	0.0	0.0	NaN	Unknown	Airports & Aircraft	Explosi
2744	1975	0	0	Pakistan	Punjab	South Asia	Bombing/Explosion	Pakistan Airlines Boeing 707	0.0	0.0	NaN	Unknown	Airports & Aircraft	Explosi
3484	1976	0	0	Turkey	Istanbul	Middle East & North Africa	Unknown	Turkish Army Vehicle	0.0	0.0	NaN	Armenian Secret Army for the Liberation of Arm...	Military	Unkn
3485	1976	0	0	Turkey	Ankara	Middle East & North Africa	Unknown	military base	0.0	0.0	NaN	Armenian Secret Army for the Liberation of Arm...	Military	Unkn
4407	1977	0	0	Japan	Tokyo	East Asia	Bombing/Explosion	Tokyo University	0.0	0.0	NaN	Tribal Battlefront	Educational Institution	Explosi
4408	1977	0	0	Japan	Tokyo	East Asia	Bombing/Explosion	Private Residence of President of a leading al...	0.0	0.0	NaN	Tribal Battlefront	Business	Explosi
4409	1977	0	0	Japan	Tokyo	East Asia	Bombing/Explosion	HOSEI University	0.0	0.0	NaN	Tribal Battlefront	Educational Institution	Explosi
4410	1977	0	0	France	Pyrenees-Atlantiques	Western Europe	Bombing/Explosion	Newspaper Sud Ouest	0.0	0.0	NaN	Basque Rectitudes	Journalists & Media	Explosi
4411	1977	0	0	France	Pyrenees-Atlantiques	Western Europe	Bombing/Explosion	Bayone Sindicate of Initiative	0.0	0.0	NaN	Basque Rectitudes	Business	Explosi
5726	1978	0	0	Brazil	Rio Grande do Sul	South America	Hostage Taking (Kidnapping)	married couple	0.0	0.0	NaN	Unknown	Private Citizens & Property	Unkn
5727	1978	0	0	El Salvador	San Salvador	Central America & Caribbean	Hostage Taking (Kidnapping)	Mauricio Sandoval, executive	0.0	0.0	NaN	Unknown	Business	Unkn
7252	1979	0	0	Japan	Unknown	East Asia	Unknown	students	3.0	0.0	NaN	Unknown	Private Citizens & Property	Unkn
7253	1979	0	0	Colombia	Bogota	South America	Unknown	Unknown	0.0	0.0	NaN	Popular Liberation Army (EPL)	Journalists & Media	Unkn
7254	1979	0	0	Philippines	Unknown	Southeast Asia	Unknown	town	0.0	0.0	NaN	New People's Army (NPA)	Private Citizens & Property	Unkn
15163	1982	0	0	Canada	Ontario	North America	Bombing/Explosion	consulate	0.0	0.0	NaN	Armenian Secret Army for the Liberation of Arm...	Government (Diplomatic)	Explosi
26987	1986	0	0	Sri Lanka	Unknown	South Asia	Hostage Taking (Kidnapping)	Four "prominent Tamil citizens"	0.0	0.0	NaN	Tamils	Private Citizens & Property	Unkn

In [45]:

```
DF1[DF1.Month==0].shape
```

Out[45]:

```
(20, 18)
```

Here we can see that there are total 20 rows of data that has the value "0" for the month, let's check for the Day column as well and then drop data for both the coulmns.

In [46]:

```
DF1[DF1.Day==0]
```

Out[46]:

	Year	Month	Day	Country	State	Region	Attack_Type	Target	Killed	Wounded	Summary	Group	Target_type	Weap
1	1970	0	0	Mexico	Federal	North America	Hostage Taking (Kidnapping)	Nadine Chaval, daughter	0.0	0.0	NaN	23rd of September Communist League	Government (Diplomatic)	I
2	1970	1	0	Philippines	Tarlac	Southeast Asia	Assassination	Employee	1.0	0.0	NaN	Unknown	Journalists & Media	I
3	1970	1	0	Greece	Attica	Western Europe	Bombing/Explosion	U.S. Embassy	0.0	0.0	NaN	Unknown	Government (Diplomatic)	E:
4	1970	1	0	Japan	Fukouka	East Asia	Facility/Infrastructure Attack	U.S. Consulate	0.0	0.0	NaN	Unknown	Government (Diplomatic)	Ir
96	1970	3	0	Philippines	Metropolitian Manila	Southeast Asia	Bombing/Explosion	U.S. Embassy	0.0	0.0	NaN	Unknown	Government (Diplomatic)	E:
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
104603	2011	12	0	West Bank and Gaza Strip	West Bank	Middle East & North Africa	Unarmed Assault	Christian Choir Group	0.0	0.0	12/0/2011: On or around 12/22/2011, in Nablus ...	Jewish Extremists	Private Citizens & Property	
104611	2011	12	0	Pakistan	Khyber Pakhtunkhwa	South Asia	Bombing/Explosion	Private home	0.0	0.0	12/0/2011: Sometime during the night between ...	Unknown	Private Citizens & Property	E:
104612	2011	12	0	Pakistan	Khyber Pakhtunkhwa	South Asia	Bombing/Explosion	Local School	0.0	0.0	12/0/2011: Sometime during the night between D...	Unknown	Educational Institution	E:
104613	2011	12	0	Pakistan	Khyber Pakhtunkhwa	South Asia	Bombing/Explosion	Local water tank	0.0	0.0	12/0/2011: Sometime during the night between ...	Unknown	Food or Water Supply	E:
104684	2011	12	0	Pakistan	Khyber Pakhtunkhwa	South Asia	Bombing/Explosion	1 Adult and 3 Children	1.0	3.0	12/0/2011: A child discovered an IED disguised...	Unknown	Private Citizens & Property	E:

813 rows × 18 columns

For the Day column we have 813 entries marked as Day "0". Let's drop all these columns

In [47]:

```
Data=DF1.drop(DF1[DF1.Month==0].index,axis=0)
```

In [48]:

```
Data
```

Out[48]:

	Year	Month	Day	Country	State	Region	Attack_Type	Target	Killed	Wounded	Summary	Group	Target_type
0	1970	7	2	Dominican Republic	Unknown	Central America & Caribbean	Assassination	Julio Guzman	1.0	0.0	NaN	MANO-D	Private Citizens & Property
2	1970	1	0	Philippines	Tarlac	Southeast Asia	Assassination	Employee	1.0	0.0	NaN	Unknown	Journalists & Media
3	1970	1	0	Greece	Attica	Western Europe	Bombing/Explosion	U.S. Embassy	0.0	0.0	NaN	Unknown	Government (Diplomatic)
4	1970	1	0	Japan	Fukouka	East Asia	Facility/Infrastructure Attack	U.S. Consulate	0.0	0.0	NaN	Unknown	Government (Diplomatic)
5	1970	1	1	United States	Illinois	North America	Armed Assault	Cairo Police Headquarters	0.0	0.0	1/1/1970: Unknown African American assailants ...	Black Nationalists	Police
...	...	...	...	...	...	...	...	...	...	...	...	...	...
181686	2017	12	31	Somalia	Middle Shebelle	Sub-Saharan Africa	Armed Assault	Checkpoint	1.0	2.0	12/31/2017: Assailants opened fire on a Somali...	Al-Shabaab	Military
181687	2017	12	31	Syria	Lattakia	Middle East & North Africa	Bombing/Explosion	Hmeymim Air Base	2.0	7.0	12/31/2017: Assailants launched mortars at the...	Muslim extremists	Military
181688	2017	12	31	Philippines	Maguindanao	Southeast Asia	Facility/Infrastructure Attack	Houses	0.0	0.0	12/31/2017: Assailants set fire to houses in K...	Bangsamoro Islamic Freedom Movement (BIFM)	Private Citizens & Property
181689	2017	12	31	India	Manipur	South Asia	Bombing/Explosion	Office	0.0	0.0	12/31/2017: Assailants threw a grenade at a Fo...	Unknown	Government (General)
181690	2017	12	31	Philippines	Maguindanao	Southeast Asia	Bombing/Explosion	Unknown	0.0	0.0	12/31/2017: An explosive device was discovered...	Unknown	Unknown

172137 rows × 18 columns

In [49]:

```
Data.shape
```

Out[49]:

```
(172137, 18)
```

Let's remove the incorrect data for the Day Column as well.

In [50]:

```
Data.drop(Data[Data.Day==0].index,axis=0,inplace=True)
```

In [51]:

```
Data[Data.Day==0].shape
```

Out[51]:

```
(0, 18)
```

In [52]:

```
Data.shape
```

Out[52]:

```
(171344, 18)
```

Exploratory Data Analysis and Visualization

> In this section we will be generating graphs to bring up some useful insights about the structured data

- Here we will be performing **Univariate analysis** with the help of different graphs/charts like **Barplot**, **Countplot**, **Scatterplot**, **Pie-charts** using the important libraries.
- Graphs are most useful when we need to get some insights about the data.

In [53]:

```
Data.shape
```

Out[53]:

```
(171344, 18)
```

In [54]:

```
Data.head(2)
```

Out[54]:

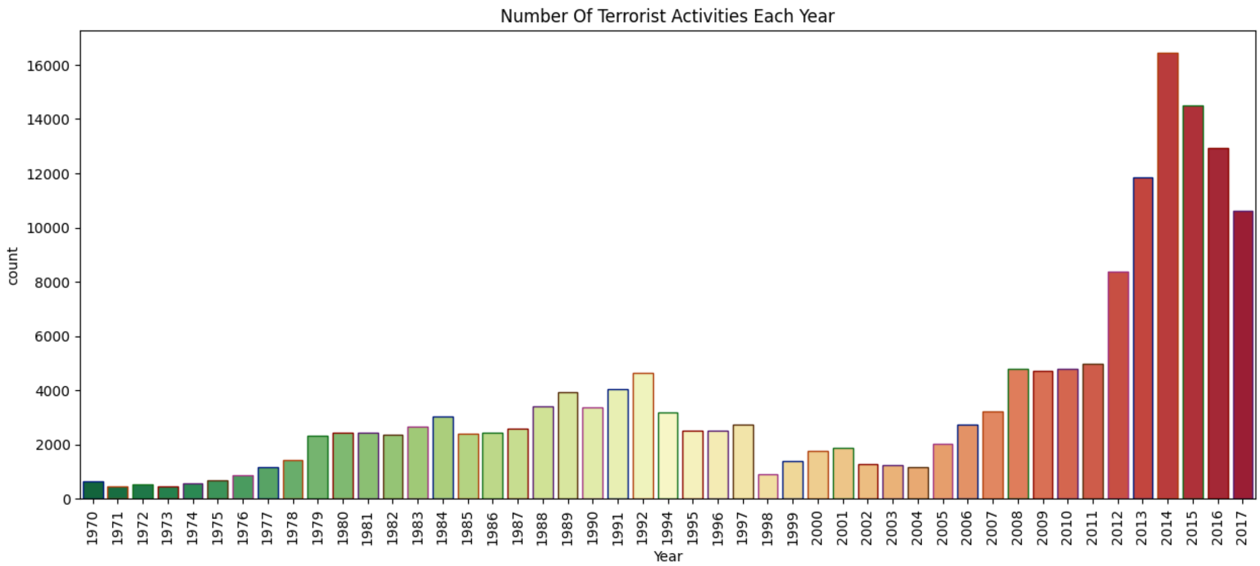
	Year	Month	Day	Country	State	Region	Attack_Type	Target	Killed	Wounded	Summary	Group	Target_type	Weapon_type	
0	1970	7	2	Dominican Republic	Unknown	Central America & Caribbean	Assassination	Julio Guzman	1.0	0.0	NaN	MANO-D	Private Citizens & Property	Unknown	
5	1970	1	1	United States	Illinois	North America	Armed Assault	Cairo Police Headquarters	0.0	0.0	1/1/1970: Unknown African American assailants ...	Black Nationalists	Police	Firearms	To th Dep

Let's first take a look at the Year Wise Distribution of Terror Activities

In [56]:

```
plt.subplots(figsize=(15,6))
sns.countplot(x='Year', data=Data, palette='RdYlGn_r', edgecolor=sns.color_palette('dark', 7))

plt.xticks(rotation=90)
plt.title('Number Of Terrorist Activities Each Year')
plt.show()
```

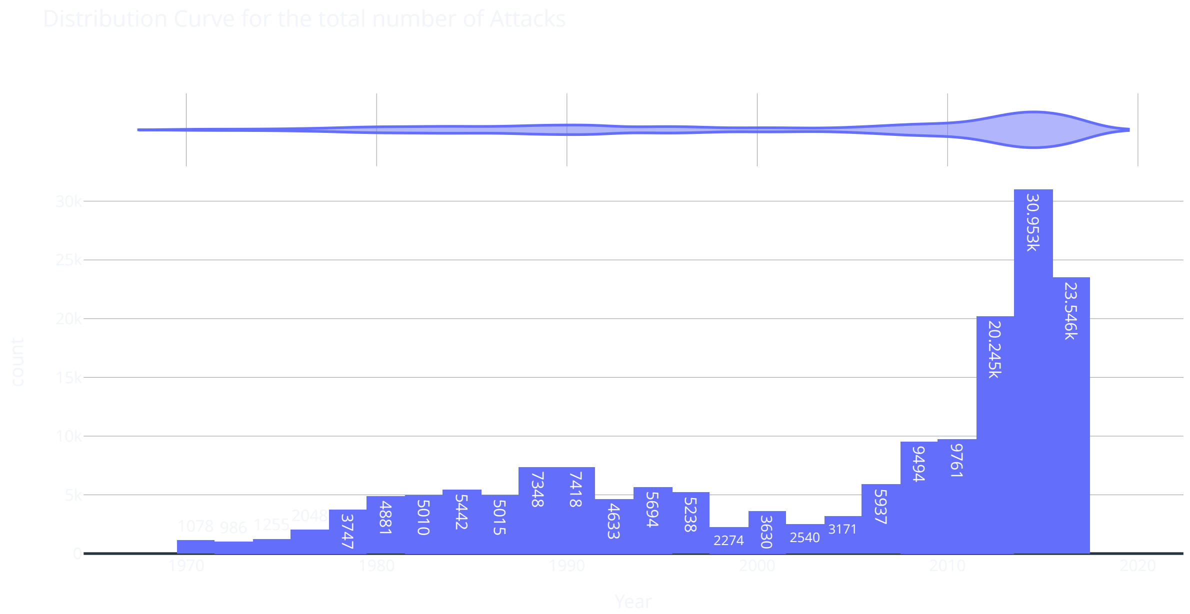


Insights

- From the above Graph we can clearly see that the Year **2014** is the most Affected Year in the entire Time-Frame.
- The subsequent years are **2015**,**2016** & **2013**.

In [57]:

```
fig=px.histogram(Data,
                 x='Year',nbins=47,
                 marginal="violin",
                 title="Distribution Curve for the total number of Attacks",
                 text_auto=True,
                 template='plotly_dark')
fig.show()
```



Insights-

- The total number of attacks in 2014-2015 crossed **30000** mark in the world wide region.
- From the above Distribution curve it is clearly visible that from the Year around 2009 till 2014-16 the number of terror activities recorded the most.
- Since 2014 onwards there is a gradual decrease in the attacks.
- The Graph clearly depicts a huge spike in the number of attacks post Year 2004.

Let's check the Top terrorist groups responsible for the most number of attacks around the world within the time frame of 47 years

In [58]:

```
Terrorrist_group=Data.Group.value_counts()[:20].drop("Unknown")
Terrorrist_group
```

Out[58]:

```
Taliban                                             7294
Islamic State of Iraq and the Levant (ISIL)         5198
Shining Path (SL)                                   3730
Al-Shabaab                                          3262
New People's Army (NPA)                             2679
Farabundo Marti National Liberation Front (FMLN)    2503
Irish Republican Army (IRA)                         2447
Boko Haram                                          2383
Revolutionary Armed Forces of Colombia (FARC)       2354
Kurdistan Workers' Party (PKK)                      2229
Basque Fatherland and Freedom (ETA)                 1889
Communist Party of India - Maoist (CPI-Maoist)      1844
Maoists                                             1603
Liberation Tigers of Tamil Eelam (LTTE)             1567
National Liberation Army of Colombia (ELN)          1387
Tehrik-i-Taliban Pakistan (TTP)                     1337
Palestinians                                        1106
Houthi extremists (Ansar Allah)                     1047
Al-Qaida in the Arabian Peninsula (AQAP)            1010
Name: Group, dtype: int64
```

In [59]:

```
type(Terrorrist_group)
```

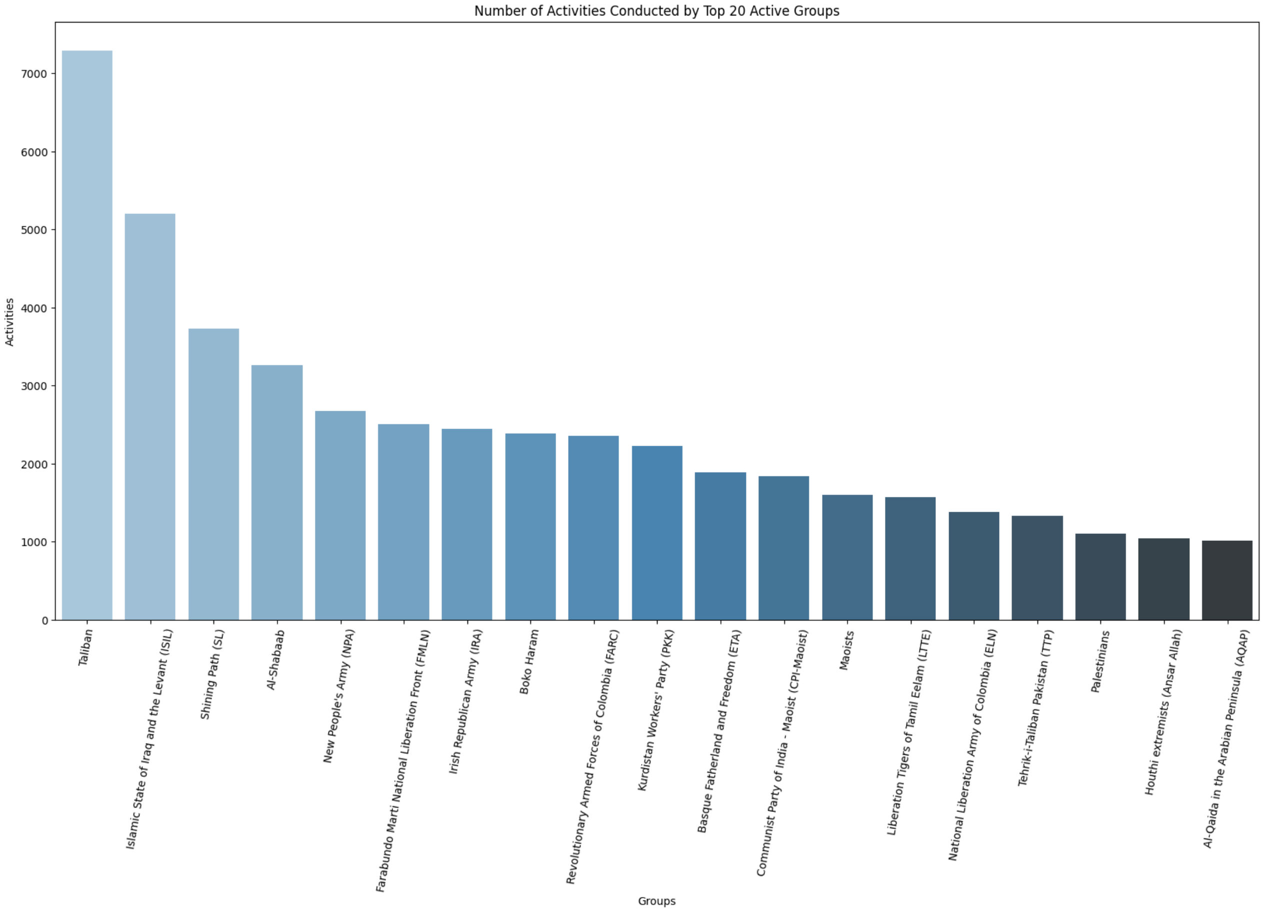
Out[59]:

```
pandas.core.series.Series
```

In [61]:

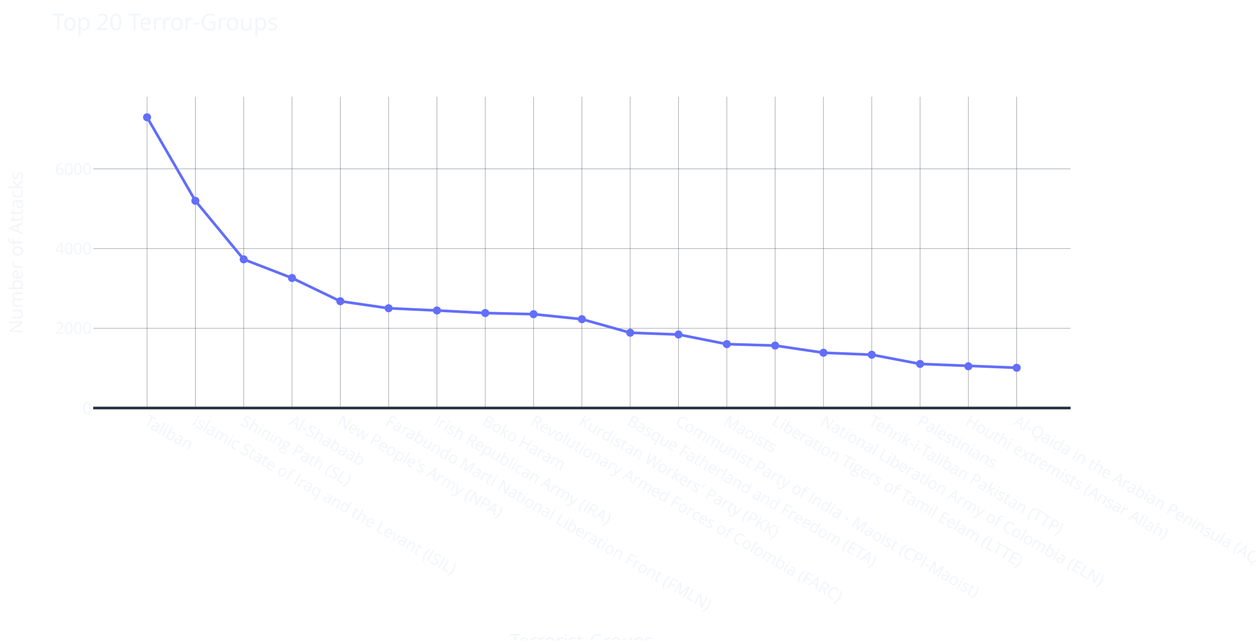
```
plt.subplots(figsize=(20, 10))
plt.xlabel('Groups')
plt.ylabel("Activities")
plt.title("Number of Activities Conducted by Top 20 Active Groups")
plt.xticks(rotation=80)
sns.barplot(x=Terrorrist_group.index, y=Terrorrist_group.values, palette='Blues_d')

plt.style.use("dark_background")
plt.show()
```



In [62]:

```
fig=px.line(x=Terrorrist_group.index,
            y=Terrorrist_group,
            title="Top 20 Terror-Groups",
            labels={'x':"Terrorist-Groups","y":"Number of Attacks"},
            markers=True,
            template='plotly_dark')
fig.update_yaxes(rangemode='tozero')
fig.show()
```



Insights-

- From the graphs it can easily derived that the most numbers of attacks are conducted by **Taliban** group.
- The graph shows that over 7000 activities has been occurred over the globe which has the direct relation to the **Taliban** Group.
- On the graph we have the Top 20 active terrorist group with the numbers of attack conducted by them through the time frame of our dataset i.e 47 years

Let's Visulalize the activites conducted in different Regions

In [65]:

```
Data.Region.unique()
```

Out[65]:

```
array(['Central America & Caribbean', 'North America', 'South America',
       'Western Europe', 'Eastern Europe', 'Sub-Saharan Africa',
       'Southeast Asia', 'Middle East & North Africa', 'East Asia',
       'Australasia & Oceania', 'South Asia', 'Central Asia'],
      dtype=object)
```

In [66]:

```
Data.Region.nunique()
```

Out[66]:

```
12
```

In [67]:

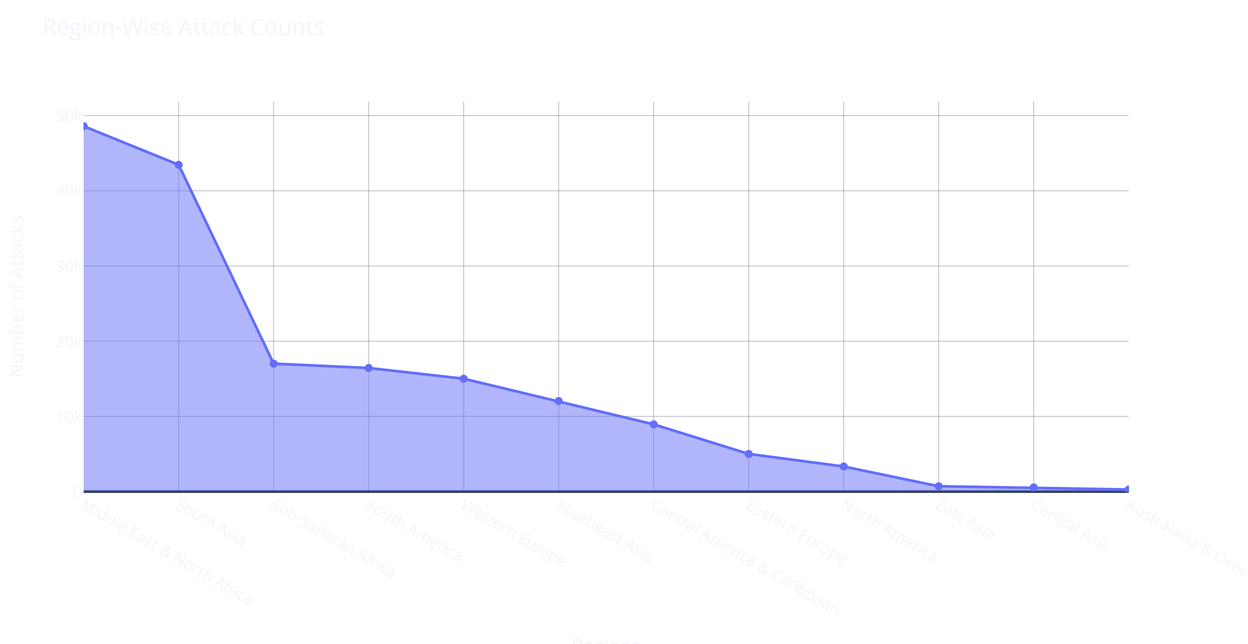
```
Regions=Data.Region.value_counts()
Regions
```

Out[67]:

```
Middle East & North Africa     48596
South Asia                     43462
Sub-Saharan Africa             17009
South America                  16434
Western Europe                 15009
Southeast Asia                 12037
Central America & Caribbean     8936
Eastern Europe                  5005
North America                   3331
East Asia                        702
Central Asia                     553
Australasia & Oceania            270
Name: Region, dtype: int64
```

In [68]:

```
fig= px.area(data_frame= Data,x=Regions.index,y=Regions.values,
             title="Region-Wise Attack Counts",template='plotly_dark',
             #height=900,
             #width=1000,
             #color="Region",
             markers = True,labels={'x':"Regions","y":"Number of Attacks"}
            )
fig.update_yaxes(rangemode="tozero")
fig.show()
```



Insights-

- As per the graphs it is clearly depicted that the Middle-East & North Africa are the most prominent region for the Terrorism.
- In Western Regions like Europe, Central America, Eastern Europe the activities are in lesser numbers.
- The activities in EAST-ASIA, CENTRAL-ASIA region are very few among with Australasia.
- As per the graph only 270 attacks are conducted in the Australasia & Oceania region in comparison of almost 49000 attacks in Middle East & North Africa Region

Let's Now Analyse the Most Affected Countries

In [69]:

```
Data.Country.value_counts()
```

Out[69]:

```
Iraq                   23464
Pakistan               13765
Afghanistan            12501
India                  11558
Colombia                7425
                       ...  
St. Lucia                  1
Antigua and Barbuda        1
Andorra                    1
North Korea                1
Wallis and Futuna          1
Name: Country, Length: 205, dtype: int64
```

In [70]:

```
Countries=Data.Country.dropna(False)
plt.subplots(figsize=(15,20))
wordcloud= WordCloud(background_color='white', width=950, height = 650).generate(' '.join(Countries))
plt.axis('off')
plt.imshow(wordcloud)
plt.show();
```

```
C:\Users\akgat\AppData\Local\Temp\ipykernel_17080\1773594900.py:1: FutureWarning:

In a future version of pandas all arguments of Series.dropna will be keyword-only.
```

Insights-

- It is clearly visible that **IRAQ** is the most affected nation across the Globe followed by **AFGHANISTAN** & **PAKISTAN**.
- Very few Activities has been reported from **ISRAEL** & **Russia**.
- **Nigeria**,**Algeria**,**Somalia**, are some of the most affected country from the **South Africa** region.

Let's check the Top 20 Countries affected by Terrorism

In [71]:

```
Attacked_country= Data.Country.value_counts()[:20]
```

In [72]:

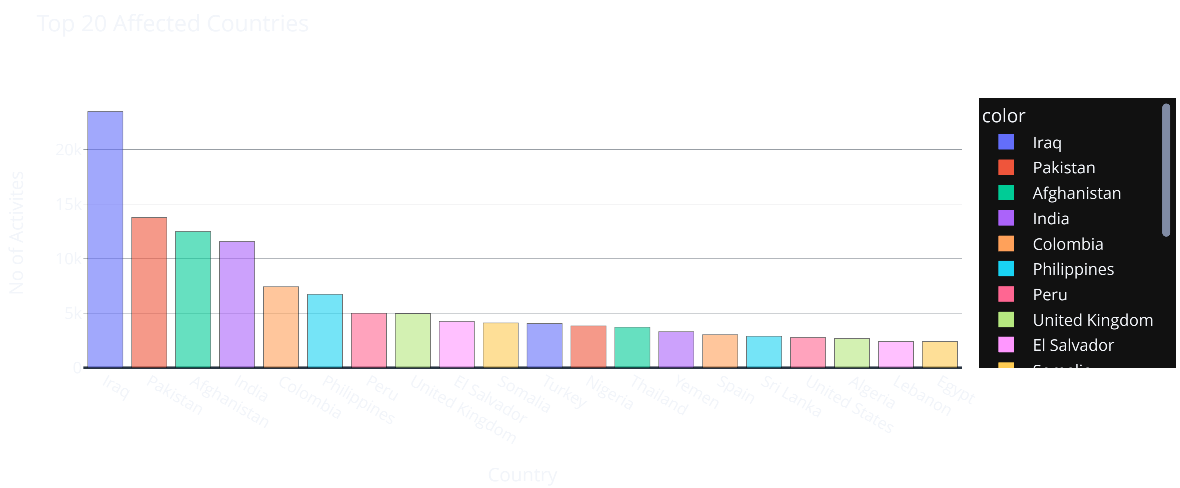
```
Attacked_country
```

Out[72]:

```
Iraq              23464
Pakistan          13765
Afghanistan       12501
India             11558
Colombia           7425
Philippines        6739
Peru               5006
United Kingdom     4970
El Salvador        4258
Somalia            4108
Turkey             4062
Nigeria            3834
Thailand           3729
Yemen              3305
Spain              3030
Sri Lanka          2898
United States      2763
Algeria            2692
Lebanon            2411
Egypt              2406
Name: Country, dtype: int64
```

In [73]:

```
fig =px.bar(Data,
               x=Attacked_country.index,
               y=Attacked_country.values,
               opacity=0.6,
               color=Attacked_country.index,
               labels={'x':'Country','y':"No of Activites"},
               title="Top 20 Affected Countries",
               template='plotly_dark',
               width=900,
               height=400
           )
fig.show()
```



Useful Points

- From the graph we can see that **Pakistan** , **Afghanistan** and **India** are at Top 4 places, that clearly show how much vulnerable these countries are to these activities.
- It is very well Depicted from the Graph that the European Countries has very less number of Occurrences of Terrorist activities as compared to South East Asian Countries.

Let's visualize the percentage of each type of attack that occurred across the World geography.

In [74]:

```
Data['Attack_Type'].unique()
```

Out[74]:

```
array(['Assassination', 'Armed Assault', 'Bombing/Explosion',
       'Facility/Infrastructure Attack', 'Hijacking', 'Unknown',
       'Hostage Taking (Kidnapping)', 'Unarmed Assault',
       'Hostage Taking (Barricade Incident)'], dtype=object)
```

In [75]:

```
type_attack=Data.Attack_Type.value_counts()
```

In [76]:

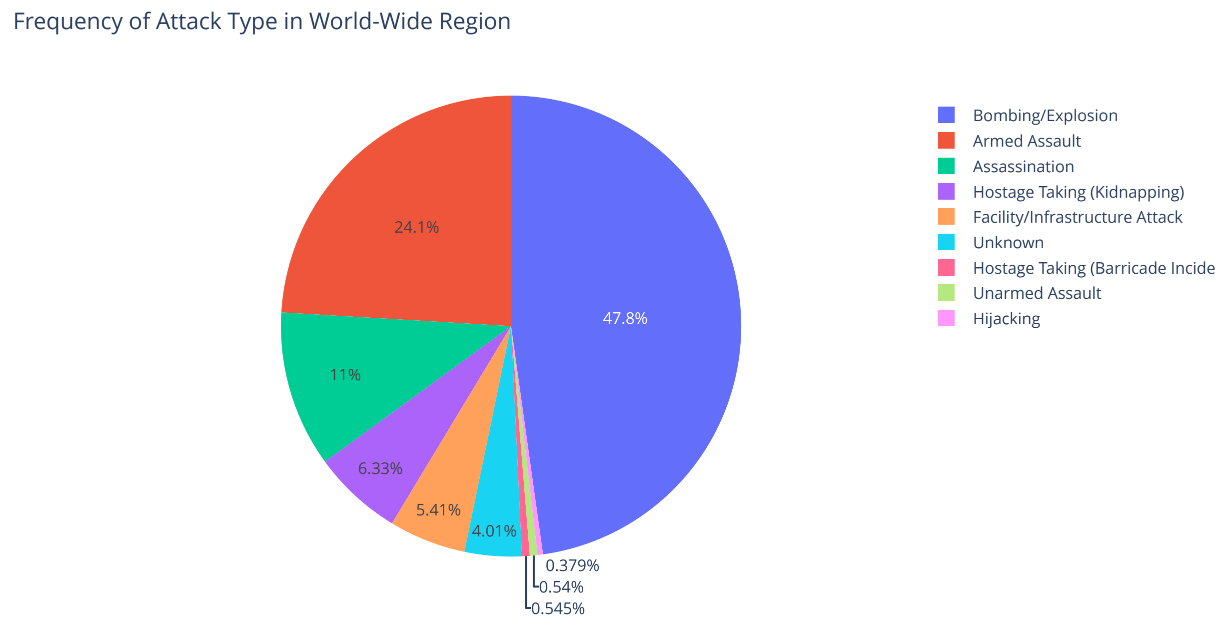
```
type(type_attack)
```

Out[76]:

```
pandas.core.series.Series
```

In [77]:

```
fig =px.pie(Data,
            values=type_attack,
            names=type_attack.index,
            title=" Frequency of Attack Type in World-Wide Region")
fig.show()
```



- From the Pie chart The Attack-Type - **Bombing** captures around **48%** of the total activities.
- It is almost of the half of the activities that has been conducted all across the world.
- From the Graph we can conclude that the Terror-groups were intently conducting Bombing/Explosions.
- Armed Assault activities takes about 24% of the total activities.However the **Assassination** activities takes occupies 11% of total activities.

In [78]:

```
Data.head(2)
```

Out[78]:

	Year	Month	Day	Country	State	Region	Attack_Type	Target	Killed	Wounded	Summary	Group	Target_type	Weapon_type	
0	1970	7	2	Dominican Republic	Unknown	Central America & Caribbean	Assassination	Julio Guzman	1.0	0.0	NaN	MANO-D	Private Citizens & Property	Unknown	
5	1970	1	1	United States	Illinois	North America	Armed Assault	Cairo Police Headquarters	0.0	0.0	1/1/1970: Unknown African American assailants ...	Black Nationalists	Police	Firearms	To th Dep

Let's take the account of total casualties and add it up as a separate column on the dataset

In [79]:

```
Data["Casualties"]= Data["Wounded"]+Data["Killed"]
```

Here we have added another column "CASUALITIES" to the dataset.

In [80]:

```
Data.shape
```

Out[80]:

```
(171344, 19)
```

In [81]:

```
Data.Casualties
```

Out[81]:

```
0         1.0
5         0.0
6         0.0
7         0.0
8         0.0
         ...
181686    3.0
181687    9.0
181688    0.0
181689    0.0
181690    0.0
Name: Casualties, Length: 171344, dtype: float64
```

Q1- Find out the Total number of casualties recorded for the MOST AFFECTED YEAR by different Weapon Types

In [82]:

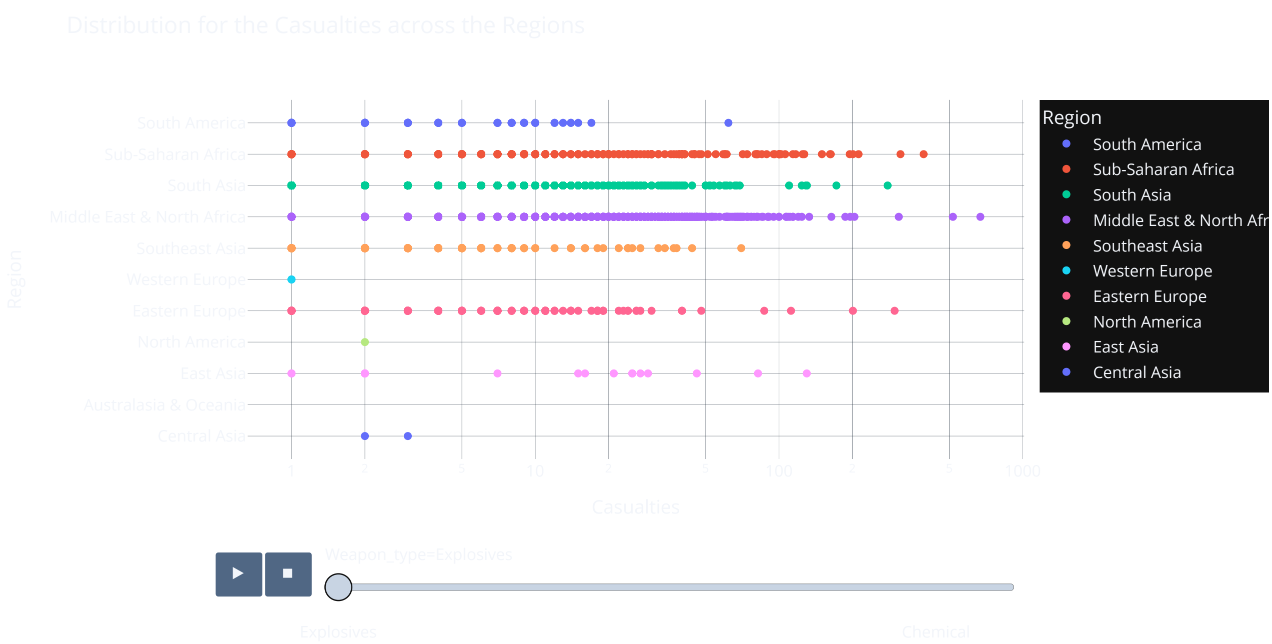
```
Most_Affected_Year=df["Year"].value_counts().idxmax()
Most_Affected_Year
```

Out[82]:

```
2014
```

In [83]:

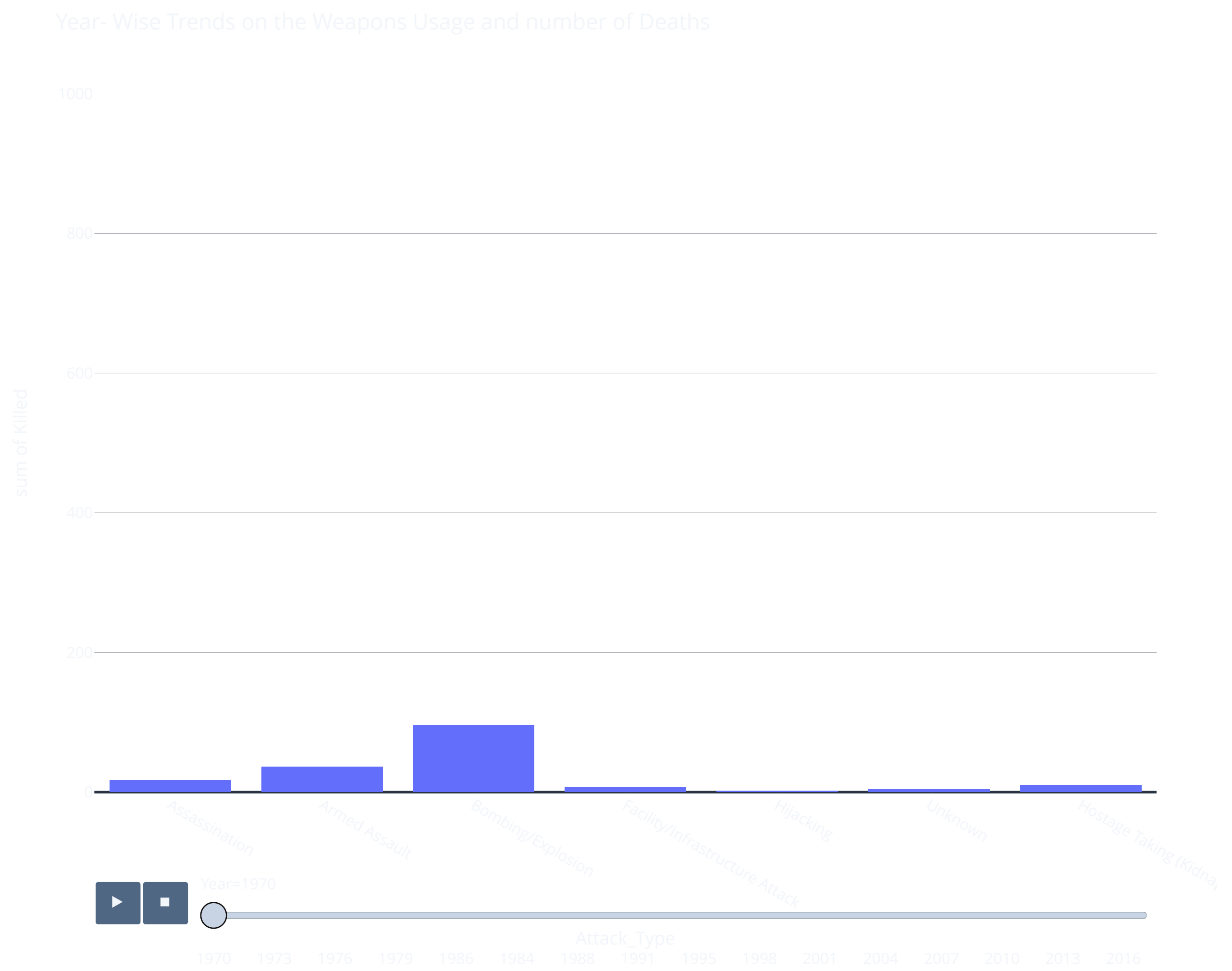
```
fig = px.scatter(Data.query("Year==2014"),
                 title="Distribution for the Casualties across the Regions",
                 x="Casualties",
                 y="Region",
                 color="Region",
                 hover_name="Country",
                 animation_frame= "Weapon_type",template="plotly_dark",
                 #width=1000,
                 #height=550,
                 log_x=True
                )
fig.show()
```



Q2- What is the Relation between the type of Attack and the number of Deaths caused by each of them Year wise.

In [84]:

```
fig=px.histogram(Data,x="Attack_Type",y="Killed",
                 title =" Year- Wise Trends on the Weapons Usage and number of Deaths ",
                 animation_frame=Data['Year'],
                 width=1000,
                 height=800,
                 template='plotly_dark'
                )
fig.update_yaxes(range = [0,1000])
fig.show()
```



- From the graph we can clearly see that the **Bombing/Explosion** activities has a major impact on the number of deaths reported.
- **Bombing/Explosion** & **Assassination** activities keeps on increasing which can be seen as we move forward in the graphical animation.
- The Increase in **Assassination** activities within a particular region or country is an alarming signs that needs to be taken care of.

Q3- Calculate the rate of increase in the Terrorist Activities within the time frame of the dataset

In [85]:

```
Year=Data.Year.value_counts().to_dict()
rate=((Year[2017]-Year[1970])/Year[2017])*100
print(Year[1970],'attacks happened in 1970 &',Year[2017],'attacks happened in 2017')
print('So the number of attacks from 1970 has increased by',np.round(rate,0),'% till 2017')
```

```
628 attacks happened in 1970 & 10621 attacks happened in 2017
So the number of attacks from 1970 has increased by 94.0 % till 2017
```

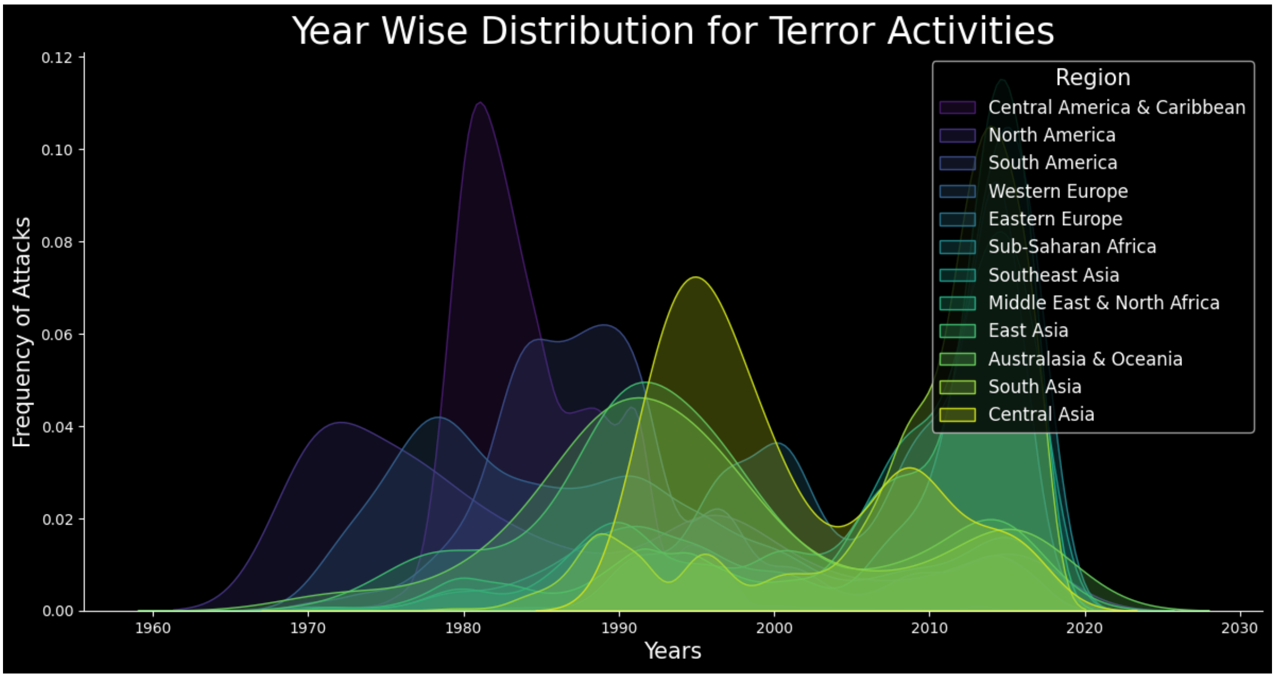
In [87]:

```
plt.figure(figsize=(15, 10))
g = sns.FacetGrid(Data, hue='Region', height=6, aspect=2, palette='viridis')
g.map(sns.kdeplot, 'Year', fill=True, common_norm=False)

plt.title('Year Wise Distribution for Terror Activities', fontsize=25)
plt.xlabel('Years', fontsize=15)
plt.ylabel('Frequency of Attacks', fontsize=15)
plt.legend(title='Region', title_fontsize=15, fontsize=12)

plt.show()
```

```
<Figure size 1500x1000 with 0 Axes>
```



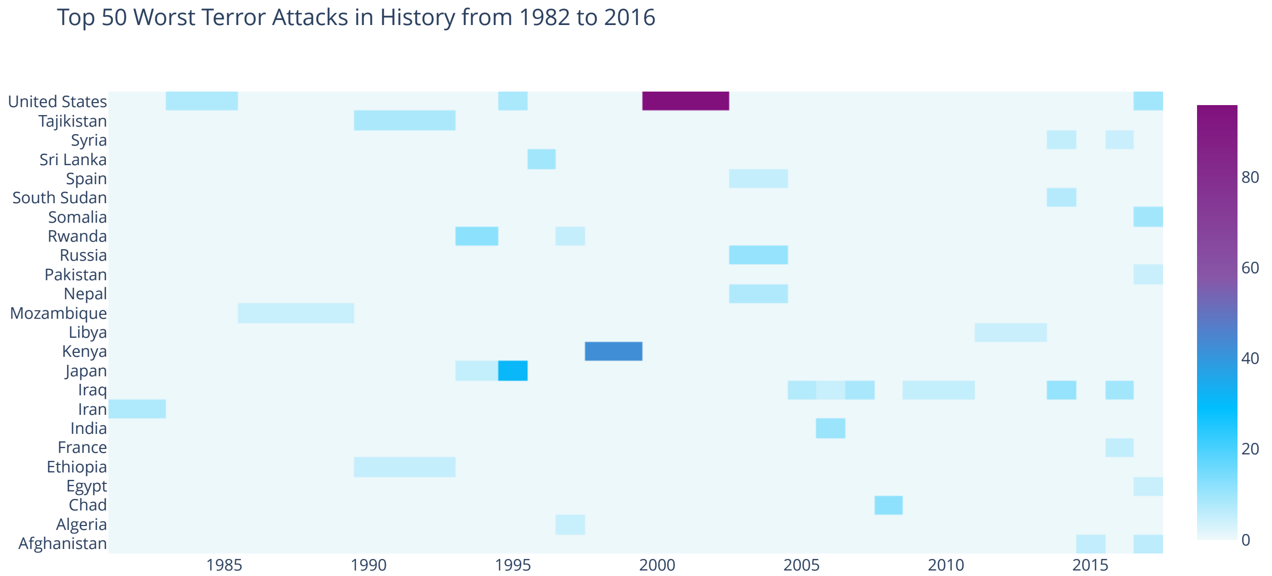
Q4- What are the Worst Terror Attacks in the history causing the most casualties?

In [88]:

```
trr1 = Data.sort_values(by='Casualties',ascending=False)[:50]

heat=trr1.pivot_table(index='Country',columns='Year',values="Casualties")

heat.fillna(0,inplace=True)
colorscale = [[0, '#edf8fb'], [.3, '#00BFFF'],  [.6, '#8856a7'],  [1, '#810f7c']]
heatmap = go.Heatmap(z=heat.values, x=heat.columns, y=heat.index,colorscale=colorscale)
data = [heatmap]
layout = go.Layout(
    title='Top 50 Worst Terror Attacks in History from 1982 to 2016')
fig = go.Figure(data=data, layout=layout)
py.iplot(fig, filename='heatmap',show_link=False)
```



Q5- What are the top most Affected States of INDIA?

In [89]:

```
India_DF= Data[(Data.Country=="India")]
```

In [90]:

```
India_DF
```

Out[90]:

	Year	Month	Day	Country	State	Region	Attack_Type	Target	Killed	Wounded	Summary	Group	Target_type	Wea
1186	1972	2	22	India	Delhi	South Asia	Hijacking	B-747	0.0	0.0	NaN	Palestinians	Airports & Aircraft	[illegible]
2764	1975	1	2	India	Bihar	South Asia	Bombing/Explosion	Lalit Narayan Mishra and a legislator	4.0	0.0	1/2/1975: The Indian Railway Minister, Lalit N...	Ananda Marga	Government (General)	[illegible]
3857	1976	5	26	India	Delhi	South Asia	Bombing/Explosion	New Delhi airport	0.0	0.0	NaN	Unknown	Airports & Aircraft	[illegible]
5327	1977	9	28	India	Maharashtra	South Asia	Hijacking	DC-8	0.0	0.0	NaN	Japanese Red Army (JRA)	Airports & Aircraft	
7337	1979	1	13	India	Assam	South Asia	Armed Assault	patrol	0.0	0.0	NaN	Naga People	Police	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
181663	2017	12	30	India	Kerala	South Asia	Bombing/Explosion	Koothuparamba Police Station	0.0	0.0	12/30/2017: Assailants threw an explosive devi...	Unknown	Police	[illegible]
181665	2017	12	30	India	Chhattisgarh	South Asia	Facility/Infrastructure Attack	Road Construction Site	0.0	0.0	12/30/2017: Assailants set fire to seven vehic...	Communist Party of India - Maoist (CPI-Maoist)	Business	
181672	2017	12	31	India	Jammu and Kashmir	South Asia	Armed Assault	Camp	8.0	3.0	12/31/2017: Assailants armed with grenades and...	Jaish-e-Mohammad (JeM)	Police	[illegible]
181684	2017	12	31	India	Assam	South Asia	Hostage Taking (Kidnapping)	Personal Security Officer of Council Member Ih...	0.0	0.0	12/31/2017: Assailants abducted Prafulla Phuka...	Zeliangrong United Front	Government (General)	
181689	2017	12	31	India	Manipur	South Asia	Bombing/Explosion	Office	0.0	0.0	12/31/2017: Assailants threw a grenade at a Fo...	Unknown	Government (General)	[illegible]

11558 rows × 19 columns

Summary and Conclusion

In the above project, we discovered some meaningful insights regarding the Global Terrorism activities. We have explored the dataset downloaded from Kaggle and laid out graphical interpolation about the trends of the top affected countries, regions, most active Terror groups, derived by the activities.

From the insights we can now conclude that the Global Terrorism activities are appreciably affecting only some of the Region where these activities are mostly occurred by the prominent Terror Groups.

FUTURE Scopes -

We can select different country or a Regions and perform deep analysis for the Terrorism activities trends and can prepare a report mentioning the difference between the respective countries or Regions.