LGMVIP_DS_October_23_Task_Number_2-1

EDA on GLOBAL TERRORISM

By Mouli Nahal

Importing Libraries

In [1]:

```
pip install squarify
```

```
Requirement already satisfied: squarify in c:\users\mouli nahal\anaconda3\lib\site
-packages (0.4.3)
Note: you may need to restart the kernel to use updated packages.
```

In [2]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
import squarify
import imageio
import time
from IPython.display import display,Image as IPImage
from PIL import Image as PILImage
```

Importing Data:

In [4]:

```
data=pd.read_csv('globalterrorismdb_0718dist.csv',encoding='ISO-8859-1')
data.head(30)
```

Out[4]:

	eventid	iyear	imonth	iday	approxdate	extended	resolution	country	country_txt	r
0	197000000001	1970	7	2	NaN	0	NaN	58	Dominican Republic	
1	197000000002	1970	0	0	NaN	0	NaN	130	Mexico	
2	197001000001	1970	1	0	NaN	0	NaN	160	Philippines	
3	197001000002	1970	1	0	NaN	0	NaN	78	Greece	
4	197001000003	1970	1	0	NaN	0	NaN	101	Japan	
5	197001010002	1970	1	1	NaN	0	NaN	217	United States	
6	197001020001	1970	1	2	NaN	0	NaN	218	Uruguay	
7	197001020002	1970	1	2	NaN	0	NaN	217	United States	
8	197001020003	1970	1	2	NaN	0	NaN	217	United States	
9	197001030001	1970	1	3	NaN	0	NaN	217	United States	
10	197001050001	1970	1	1	NaN	0	NaN	217	United States	
11	197001060001	1970	1	6	NaN	0	NaN	217	United States	
12	197001080001	1970	1	8	NaN	0	NaN	98	Italy	
13	197001090001	1970	1	9	NaN	0	NaN	217	United States	
14	197001090002	1970	1	9	NaN	0	NaN	217	United States	
15	197001100001	1970	1	10	NaN	0	NaN	499	East Germany (GDR)	

	eventid	iyear	imonth	iday	approxdate	extended	resolution	country	country_txt	r
16	197001110001	1970	1	11	NaN	0	NaN	65	Ethiopia	
17	197001120001	1970	1	12	NaN	0	NaN	217	United States	
18	197001120002	1970	1	12	NaN	0	NaN	217	United States	
19	197001130001	1970	1	13	NaN	0	NaN	217	United States	
20	197001140001	1970	1	14	NaN	0	NaN	217	United States	
21	197001150001	1970	1	15	NaN	0	NaN	218	Uruguay	
22	197001190002	1970	1	19	NaN	0	NaN	217	United States	
23	197001190003	1970	1	19	NaN	0	NaN	217	United States	
24	197001190004	1970	1	19	January 19-20, 1970	0	NaN	217	United States	
25	197001200001	1970	1	20	NaN	0	NaN	83	Guatemala	
26	197001210001	1970	1	21	NaN	0	NaN	160	Philippines	
27	197001220001	1970	1	22	NaN	0	NaN	222	Venezuela	
28	197001220002	1970	1	22	NaN	0	NaN	217	United States	
29	197001250001	1970	1	25	NaN	0	NaN	217	United States	

In [5]:
```
data.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
```

In [6]:
```
data.describe()
```

Out[6]:

	eventid	iyear	imonth	iday	extended	country
count	1.816910e+05	181691.000000	181691.000000	181691.000000	181691.000000	181691.000000
mean	2.002705e+11	2002.638997	6.467277	15.505644	0.045346	131.968501
std	1.325957e+09	13.259430	3.388303	8.814045	0.208063	112.414535
min	1.970000e+11	1970.000000	0.000000	0.000000	0.000000	4.000000
25%	1.991021e+11	1991.000000	4.000000	8.000000	0.000000	78.000000
50%	2.009022e+11	2009.000000	6.000000	15.000000	0.000000	98.000000
75%	2.014081e+11	2014.000000	9.000000	23.000000	0.000000	160.000000
max	2.017123e+11	2017.000000	12.000000	31.000000	1.000000	1004.000000

8 rows × 77 columns

In [7]:
```
data.shape
```

Out[7]:
```
(181691, 135)
```

In [8]:
```
data.columns
```

Out[8]:
```
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 [9]:
```
data_new=data[['iyear','imonth','country_txt','region_txt','provstate','city','lati
```

In [10]:
```
data_new.head()
```

Out[10]:

	iyear	imonth	country_txt	region_txt	provstate	city	latitude	longitude	location	su
0	1970	7	Dominican Republic	Central America & Caribbean	NaN	Santo Domingo	18.456792	-69.951164	NaN	
1	1970	0	Mexico	North America	Federal	Mexico city	19.371887	-99.086624	NaN	
2	1970	1	Philippines	Southeast Asia	Tarlac	Unknown	15.478598	120.599741	NaN	
3	1970	1	Greece	Western Europe	Attica	Athens	37.997490	23.762728	NaN	
4	1970	1	Japan	East Asia	Fukouka	Fukouka	33.580412	130.396361	NaN	

5 rows × 26 columns

Exploratory Data Analysis:

In [11]:

```
data_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 181691 entries, 0 to 181690
Data columns (total 26 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   iyear             181691 non-null  int64  
 1   imonth            181691 non-null  int64  
 2   country_txt       181691 non-null  object 
 3   region_txt        181691 non-null  object 
 4   provstate         181270 non-null  object 
 5   city              181257 non-null  object 
 6   latitude          177135 non-null  float64
 7   longitude         177134 non-null  float64
 8   location          55495 non-null   object 
 9   summary           115562 non-null  object 
 10  success           181691 non-null  int64  
 11  suicide           181691 non-null  int64  
 12  attacktype1_txt   181691 non-null  object 
 13  attacktype2_txt   6314 non-null    object 
 14  attacktype3_txt   428 non-null     object 
 15  targtype1_txt     181691 non-null  object 
 16  targsubtype1_txt  171318 non-null  object 
 17  target1           181055 non-null  object 
 18  gname             181691 non-null  object 
 19  motive            50561 non-null   object 
 20  weaptype1_txt     181691 non-null  object 
 21  nkill             171378 non-null  float64
 22  propextent_txt    64065 non-null   object 
 23  ransomamt         1350 non-null    float64
 24  addnotes          28289 non-null   object 
 25  scite1            115500 non-null  object 
dtypes: float64(4), int64(4), object(18)
memory usage: 36.0+ MB
```

In [12]:

```
data_null_perc=data.isnull().sum()/len(data)*100
data_null_perc
```

Out[12]:

```
eventid        0.000000
iyear          0.000000
imonth         0.000000
iday           0.000000
approxdate    94.914993
                 ...
INT_LOG        0.000000
INT_IDEO       0.000000
INT_MISC       0.000000
INT_ANY        0.000000
related       86.219461
Length: 135, dtype: float64
```

In [13]:

```
data1=data[data_null_perc[data_null_perc<=50].index]
data1.head()
```

Out[13]:

	eventid	iyear	imonth	iday	extended	country	country_txt	region	region_txt	provsta
0	197000000001	1970	7	2	0	58	Dominican Republic	2	Central America & Caribbean	N
1	197000000002	1970	0	0	0	130	Mexico	1	North America	Fede
2	197001000001	1970	1	0	0	160	Philippines	5	Southeast Asia	Tar
3	197001000002	1970	1	0	0	78	Greece	8	Western Europe	Att
4	197001000003	1970	1	0	0	101	Japan	4	East Asia	Fukou

5 rows × 58 columns

In [14]:

```
data1.columns
```

Out[14]:

```
Index(['eventid', 'iyear', 'imonth', 'iday', 'extended', 'country',
       'country_txt', 'region', 'region_txt', 'provstate', 'city', 'latitude',
       'longitude', 'specificity', 'vicinity', 'summary', 'crit1', 'crit2',
       'crit3', 'doubtterr', 'multiple', 'success', 'suicide', 'attacktype1',
       'attacktype1_txt', 'targtype1', 'targtype1_txt', 'targsubtype1',
       'targsubtype1_txt', 'corp1', 'target1', 'natlty1', 'natlty1_txt',
       'gname', 'guncertain1', 'individual', 'nperps', 'nperpcap', 'claimed',
       'weaptype1', 'weaptype1_txt', 'weapsubtype1', 'weapsubtype1_txt',
       'weapdetail', 'nkill', 'nkillus', 'nkillter', 'nwound', 'nwoundus',
       'nwoundte', 'property', 'ishostkid', 'scite1', 'dbsource', 'INT_LOG',
       'INT_IDEO', 'INT_MISC', 'INT_ANY'],
      dtype='object')
```

In [15]:

```
data1.drop(['eventid','iday','extended','country','region','specificity','vicinity'
           'multiple','attacktype1','targtype1','targsubtype1','corp1','natlty1','r
           ,'nperpcap','claimed','weaptype1','weapsubtype1','weapsubtype1_txt','wea
           'nwoundte','property','ishostkid','dbsource','INT_LOG','INT_IDEO','INT_M
```

In [16]:

```
data1.columns
```

Out[16]:

```
Index(['iyear', 'imonth', 'country_txt', 'region_txt', 'provstate', 'city',
       'latitude', 'longitude', 'summary', 'success', 'suicide',
       'attacktype1_txt', 'targtype1_txt', 'targsubtype1_txt', 'target1',
       'gname', 'weaptype1_txt', 'nkill', 'scite1'],
      dtype='object')
```

```
In [17]: data1.head()
```

Out[17]:

	iyear	imonth	country_txt	region_txt	provstate	city	latitude	longitude	summary
0	1970	7	Dominican Republic	Central America & Caribbean	NaN	Santo Domingo	18.456792	-69.951164	NaN
1	1970	0	Mexico	North America	Federal	Mexico city	19.371887	-99.086624	NaN
2	1970	1	Philippines	Southeast Asia	Tarlac	Unknown	15.478598	120.599741	NaN
3	1970	1	Greece	Western Europe	Attica	Athens	37.997490	23.762728	NaN
4	1970	1	Japan	East Asia	Fukouka	Fukouka	33.580412	130.396361	NaN

```
In [18]: data1.isnull().sum()/len(data1)*100
```

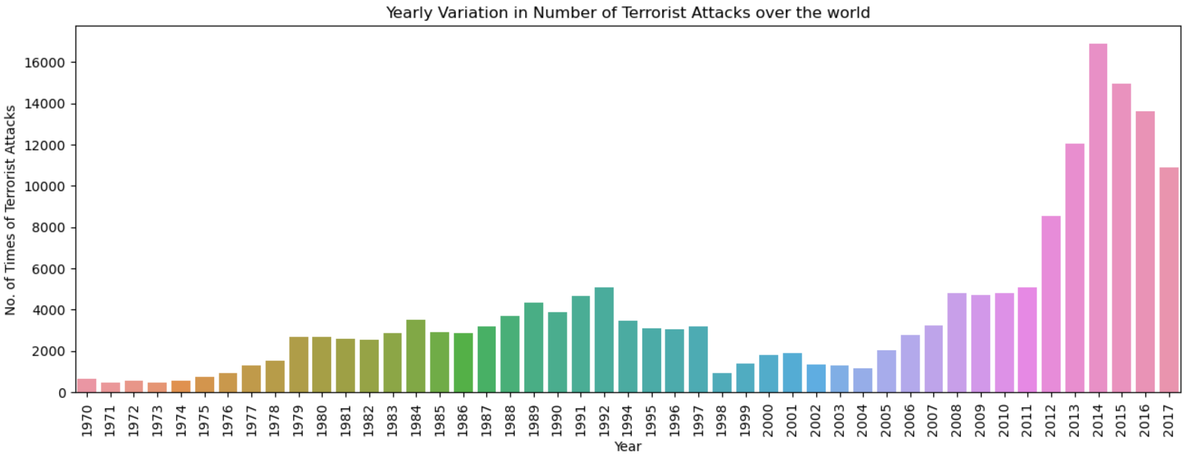
```
Out[18]: iyear                0.000000
         imonth               0.000000
         country_txt          0.000000
         region_txt           0.000000
         provstate            0.231712
         city                 0.238867
         latitude             2.507554
         longitude            2.508104
         summary             36.396409
         success              0.000000
         suicide              0.000000
         attacktype1_txt      0.000000
         targtype1_txt        0.000000
         targsubtype1_txt     5.709144
         target1              0.350045
         gname                0.000000
         weaptype1_txt        0.000000
         nkill                5.676120
         scite1              36.430533
         dtype: float64
```

```
In [19]: data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 181691 entries, 0 to 181690
Data columns (total 19 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   iyear             181691 non-null  int64  
 1   imonth            181691 non-null  int64  
 2   country_txt       181691 non-null  object 
 3   region_txt        181691 non-null  object 
 4   provstate         181270 non-null  object 
 5   city              181257 non-null  object 
 6   latitude          177135 non-null  float64
 7   longitude         177134 non-null  float64
 8   summary           115562 non-null  object 
 9   success           181691 non-null  int64  
 10  suicide           181691 non-null  int64  
 11  attacktype1_txt   181691 non-null  object 
 12  targtype1_txt     181691 non-null  object 
 13  targsubtype1_txt  171318 non-null  object 
 14  target1           181055 non-null  object 
 15  gname             181691 non-null  object 
 16  weaptype1_txt     181691 non-null  object 
 17  nkill             171378 non-null  float64
 18  scite1            115500 non-null  object 
dtypes: float64(3), int64(4), object(12)
memory usage: 26.3+ MB
```

In [20]:

```
# Plotting Yearly variation of Terror Attacks over the world
plt.figure(figsize=(15,5))
sns.countplot(data=data1,x='iyear')
plt.xticks(rotation=90)
plt.xlabel('Year')
plt.ylabel('No. of Times of Terrorist Attacks')
plt.title('Yearly Variation in Number of Terrorist Attacks over the world')
plt.show()
```



In [21]:

```
data1.country_txt.value_counts()
```

Out[21]:

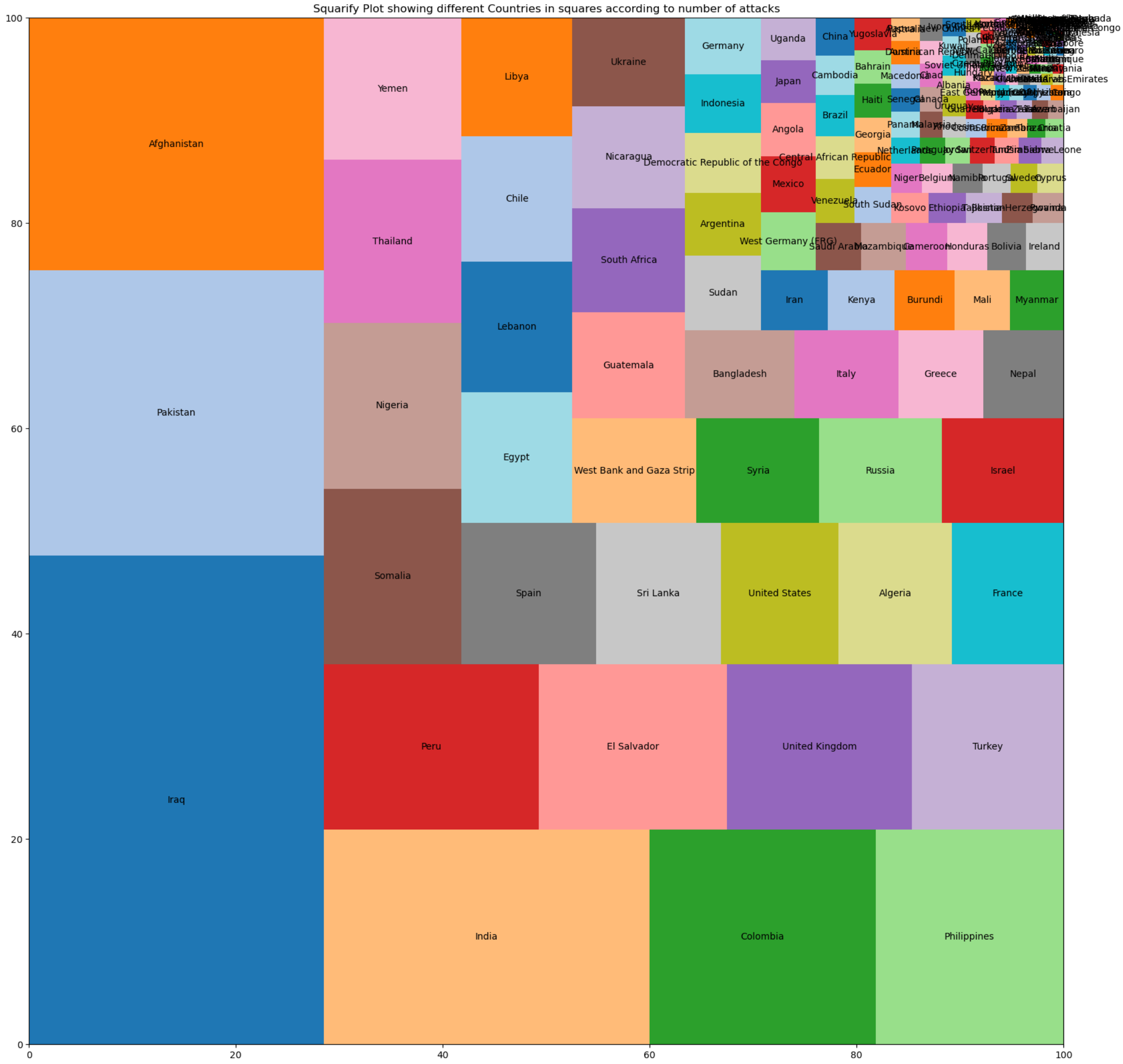
```
Iraq                       24636
Pakistan                   14368
Afghanistan                12731
India                      11960
Colombia                    8306
                           ...  
International                  1
Wallis and Futuna              1
South Vietnam                  1
Andorra                        1
Antigua and Barbuda            1
Name: country_txt, Length: 205, dtype: int64
```

In [22]:

```
# Plotting Squarify Plot
plt.figure(figsize=(20,20))
squarify.plot(sizes=data1.country_txt.value_counts().values,label=data1.country_txt
plt.title('Squarify Plot showing different Countries in squares according to number
```

Out[22]:

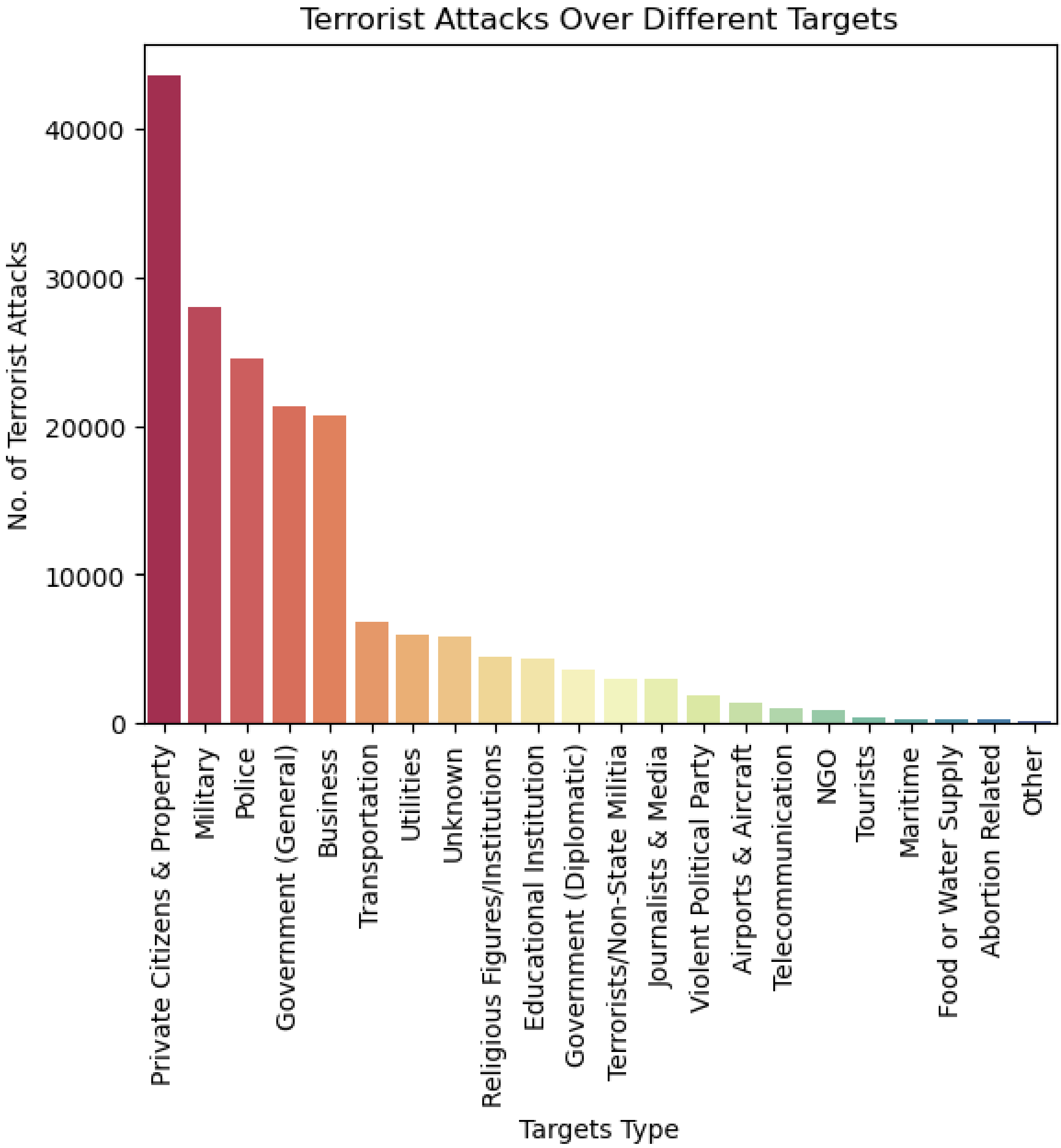
```
Text(0.5, 1.0, 'Squarify Plot showing different Countries in squares according to
number of attacks')
```



'Iraq' country is the most hotspot for Terrorist Attacks over many years.

In [23]:

```
# Countplot of Targets involved in Terrorist Attacks
sns.countplot(x='targtype1_txt',data=data1,order=data1.targtype1_txt.value_counts()
plt.xticks(rotation=90)
plt.xlabel('Targets Type')
plt.ylabel('No. of Terrorist Attacks')
plt.title('Terrorist Attacks Over Different Targets')
plt.show()
```



'Private Citizens & Property', 'Military', 'Police' are the top Targets over which attacks been made by Terrorists

In [24]:
```
pip install folium
```

```
Collecting folium
  Downloading folium-0.14.0-py2.py3-none-any.whl (102 kB)
     ------------------------------------ 102.3/102.3 kB 979.2 kB/s eta 0:00:00
Requirement already satisfied: requests in c:\users\mouli nahal\anaconda3\lib\site
-packages (from folium) (2.28.1)
Requirement already satisfied: numpy in c:\users\mouli nahal\anaconda3\lib\site-pa
ckages (from folium) (1.23.5)
Requirement already satisfied: jinja2>=2.9 in c:\users\mouli nahal\anaconda3\lib\s
ite-packages (from folium) (3.1.2)
Collecting branca>=0.6.0
  Downloading branca-0.6.0-py3-none-any.whl (24 kB)
Requirement already satisfied: MarkupSafe>=2.0 in c:\users\mouli nahal\anaconda3\l
ib\site-packages (from jinja2>=2.9->folium) (2.1.1)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\mouli nahal\anaconda
3\lib\site-packages (from requests->folium) (2023.7.22)
Requirement already satisfied: charset-normalizer<3,>=2 in c:\users\mouli nahal\an
aconda3\lib\site-packages (from requests->folium) (2.0.4)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in c:\users\mouli nahal\anaco
nda3\lib\site-packages (from requests->folium) (1.26.14)
Requirement already satisfied: idna<4,>=2.5 in c:\users\mouli nahal\anaconda3\lib
\site-packages (from requests->folium) (3.4)
Installing collected packages: branca, folium
Successfully installed branca-0.6.0 folium-0.14.0
Note: you may need to restart the kernel to use updated packages.
```

In [25]:

```
pip install basemap
```

```
Collecting basemap
  Downloading basemap-1.3.8-cp310-cp310-win_amd64.whl (487 kB)
     ------------------------------------ 487.2/487.2 kB 462.1 kB/s eta 0:00:00
Requirement already satisfied: numpy<1.26,>=1.21 in c:\users\mouli nahal\anaconda3
\lib\site-packages (from basemap) (1.23.5)
Collecting basemap-data<1.4,>=1.3.2
  Downloading basemap_data-1.3.2-py2.py3-none-any.whl (30.5 MB)
     -------------------------------------- 30.5/30.5 MB 582.0 kB/s eta 0:00:00
Collecting pyproj<3.7.0,>=1.9.3
  Downloading pyproj-3.6.1-cp310-cp310-win_amd64.whl (6.1 MB)
     ---------------------------------------- 6.1/6.1 MB 567.1 kB/s eta 0:00:00
Requirement already satisfied: matplotlib<3.8,>=1.5 in c:\users\mouli nahal\anacon
da3\lib\site-packages (from basemap) (3.7.0)
Collecting pyshp<2.4,>=1.2
  Downloading pyshp-2.3.1-py2.py3-none-any.whl (46 kB)
     ---------------------------------------- 46.5/46.5 kB 1.2 MB/s eta 0:00:00
Requirement already satisfied: packaging>=20.0 in c:\users\mouli nahal\anaconda3\l
ib\site-packages (from matplotlib<3.8,>=1.5->basemap) (22.0)
Requirement already satisfied: pillow>=6.2.0 in c:\users\mouli nahal\anaconda3\lib
\site-packages (from matplotlib<3.8,>=1.5->basemap) (9.4.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\mouli nahal\anaconda3
\lib\site-packages (from matplotlib<3.8,>=1.5->basemap) (1.4.4)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\mouli nahal\anaconda3
\lib\site-packages (from matplotlib<3.8,>=1.5->basemap) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\mouli nahal\anacon
da3\lib\site-packages (from matplotlib<3.8,>=1.5->basemap) (2.8.2)
Requirement already satisfied: cycler>=0.10 in c:\users\mouli nahal\anaconda3\lib
\site-packages (from matplotlib<3.8,>=1.5->basemap) (0.11.0)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\mouli nahal\anaconda3
\lib\site-packages (from matplotlib<3.8,>=1.5->basemap) (1.0.5)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\mouli nahal\anaconda3
\lib\site-packages (from matplotlib<3.8,>=1.5->basemap) (4.25.0)
Requirement already satisfied: certifi in c:\users\mouli nahal\anaconda3\lib\site-
packages (from pyproj<3.7.0,>=1.9.3->basemap) (2023.7.22)
Requirement already satisfied: six>=1.5 in c:\users\mouli nahal\anaconda3\lib\site
-packages (from python-dateutil>=2.7->matplotlib<3.8,>=1.5->basemap) (1.16.0)
Installing collected packages: pyshp, pyproj, basemap-data, basemap
Successfully installed basemap-1.3.8 basemap-data-1.3.2 pyproj-3.6.1 pyshp-2.3.1
Note: you may need to restart the kernel to use updated packages.
```

In [26]:

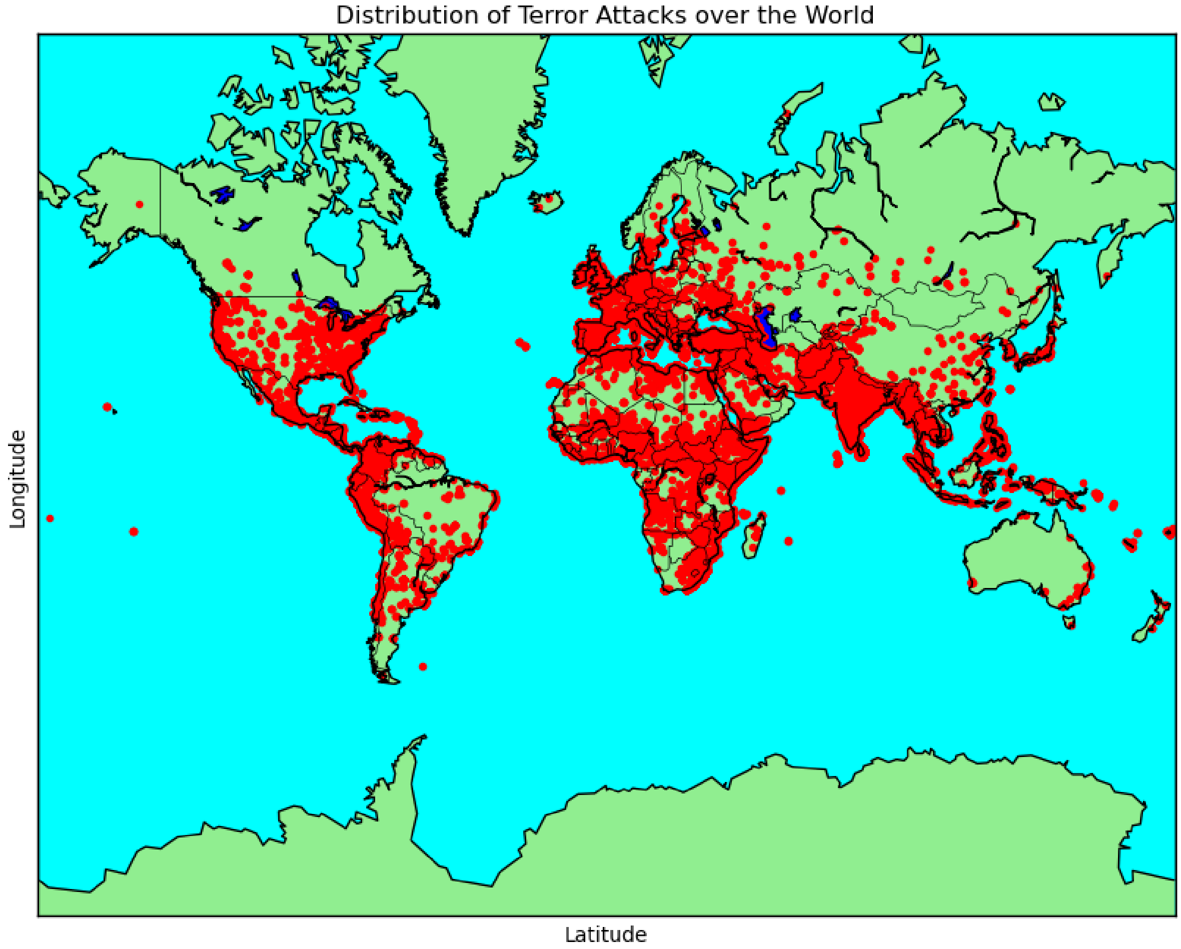
```
latitudes=list(data1.latitude)
longitudes=list(data1.longitude)
```

In [27]:

```
from mpl_toolkits.basemap import Basemap
```

In [28]:

```
# plottin world to see various locations over which terror attacks happended during
plt.figure(figsize=(10,10))
worldmap=Basemap(projection='merc',resolution='c',llcrnrlat=-80,urcrnrlat=80,llcrnr
worldmap.drawcoastlines()
worldmap.drawcountries()
x,y=worldmap(longitudes,latitudes)
worldmap.fillcontinents(color='lightgreen',lake_color='blue')
worldmap.drawmapboundary(fill_color='aqua')
worldmap.scatter(x,y,color='red',marker='.')
plt.ylabel('Longitude')
plt.xlabel('Latitude')
plt.title('Distribution of Terror Attacks over the World')
plt.show()
```

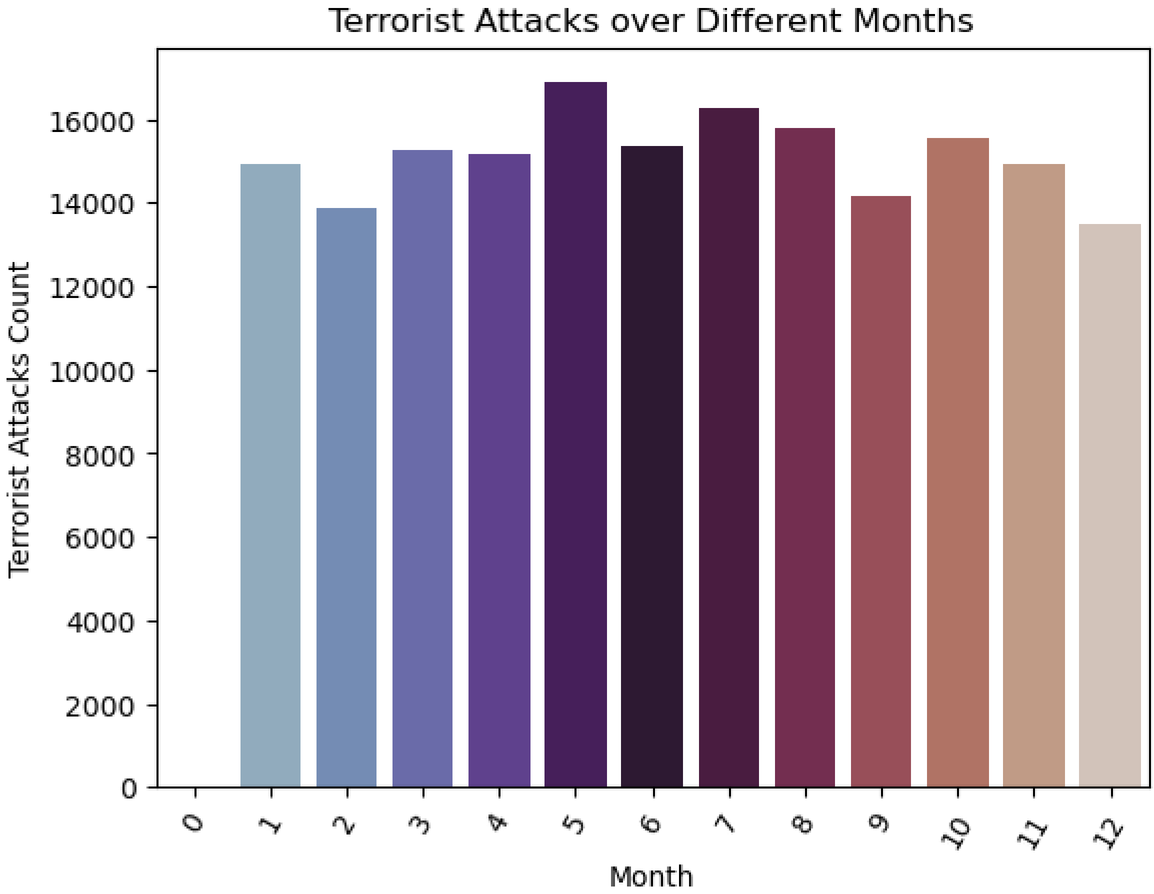


In [38]:
```
data1.columns
```

Out[38]:
```
Index(['iyear', 'imonth', 'country_txt', 'region_txt', 'provstate', 'city',
       'latitude', 'longitude', 'summary', 'success', 'suicide',
       'attacktype1_txt', 'targtype1_txt', 'targsubtype1_txt', 'target1',
       'gname', 'weaptype1_txt', 'nkill', 'scite1'],
      dtype='object')
```

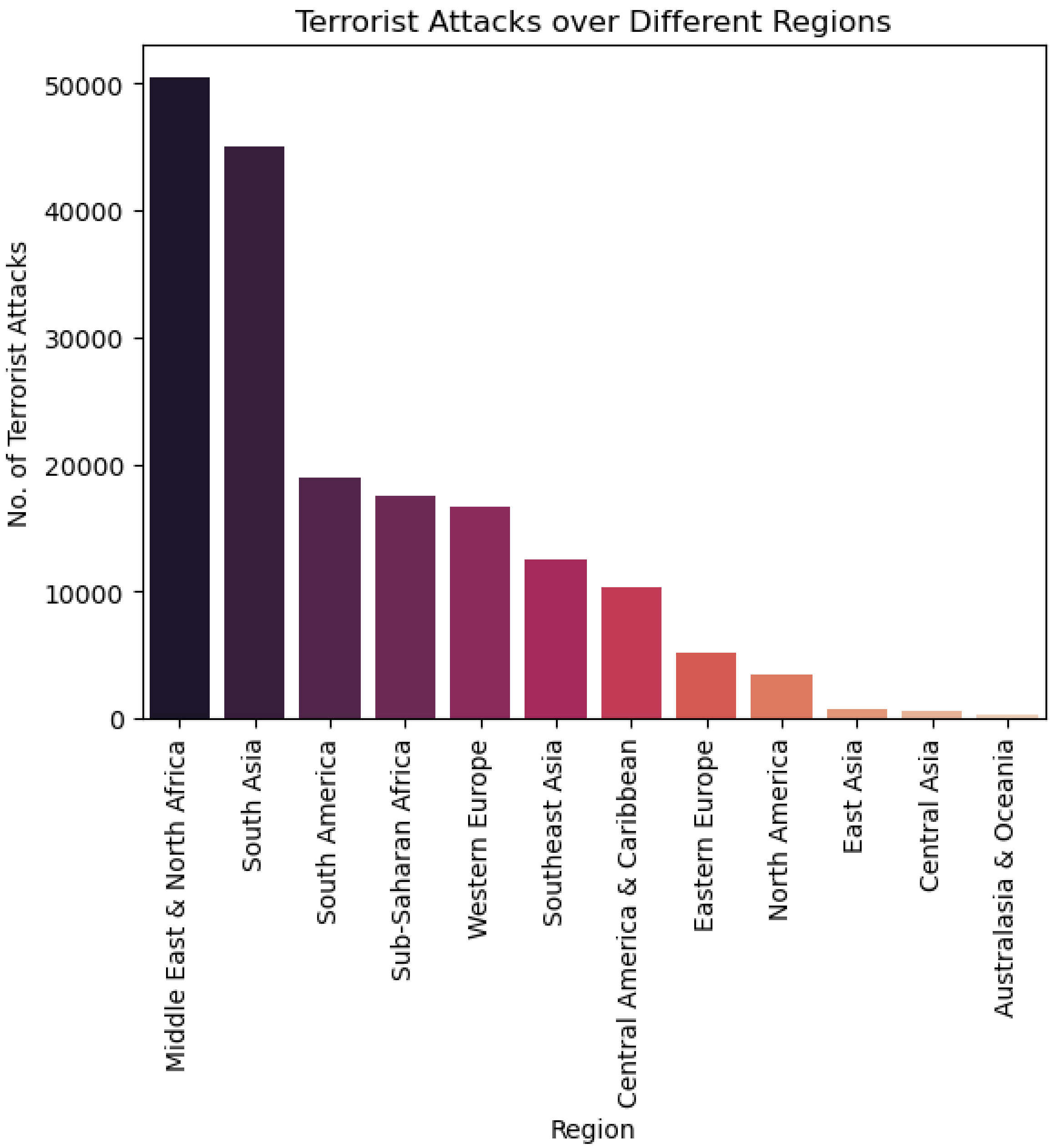
In [39]:
```
# Countplot of Months during which terror attacks happened
sns.countplot(data=data1,x=data1.imonth,palette='twilight')
plt.xticks(rotation=60)
plt.xlabel('Month')
plt.ylabel('Terrorist Attacks Count')
plt.title('Terrorist Attacks over Different Months')
```

Out[39]:
```
Text(0.5, 1.0, 'Terrorist Attacks over Different Months')
```



In [40]:
```
# Countplot to see different regions over which terror attacks happened
sns.countplot(data=data1,x=data1.region_txt,order=data1.region_txt.value_counts().i
plt.xticks(rotation=90)
plt.xlabel('Region')
plt.ylabel('No. of Terrorist Attacks')
plt.title('Terrorist Attacks over Different Regions')
```

Out[40]:
```
Text(0.5, 1.0, 'Terrorist Attacks over Different Regions')
```



'Middle East & North Africa' and 'South Asia' are the most hotspot regions of the Terrorist Attacks.

In [41]:
```
print('Out of Total Terror Attacks, the percentage of successful Terror Attacks is:
```

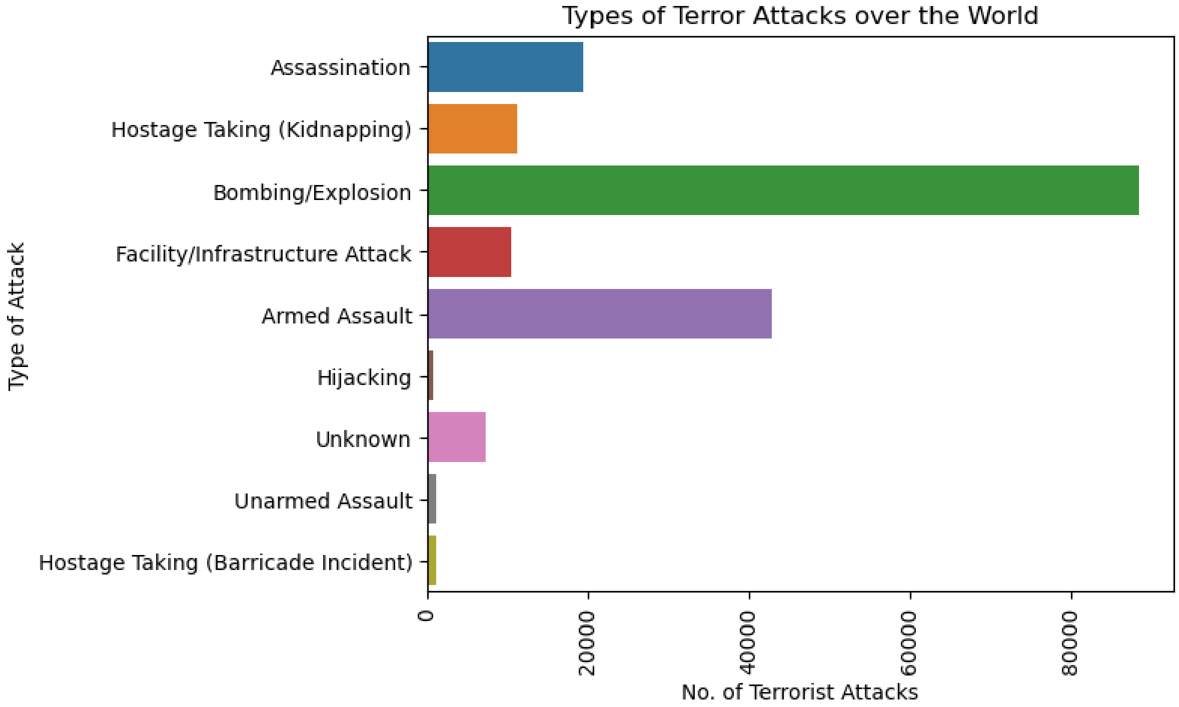
```
Out of Total Terror Attacks, the percentage of successful Terror Attacks is: 88.95
982739926579
```

In [42]:
```
print('Out of Total Successful Terror Attacks, the percentage of Suicide Attacks is
```

```
Out of Total Successful Terror Attacks, the percentage of Suicide Attacks is: 4.10
37665808750745
```

In [43]:
```
# Countplot of types of terror attacks happened over the world
sns.countplot(data=data1,y='attacktype1_txt')
plt.xticks(rotation=90)
plt.ylabel('Type of Attack')
plt.xlabel('No. of Terrorist Attacks')
plt.title('Types of Terror Attacks over the World')
```

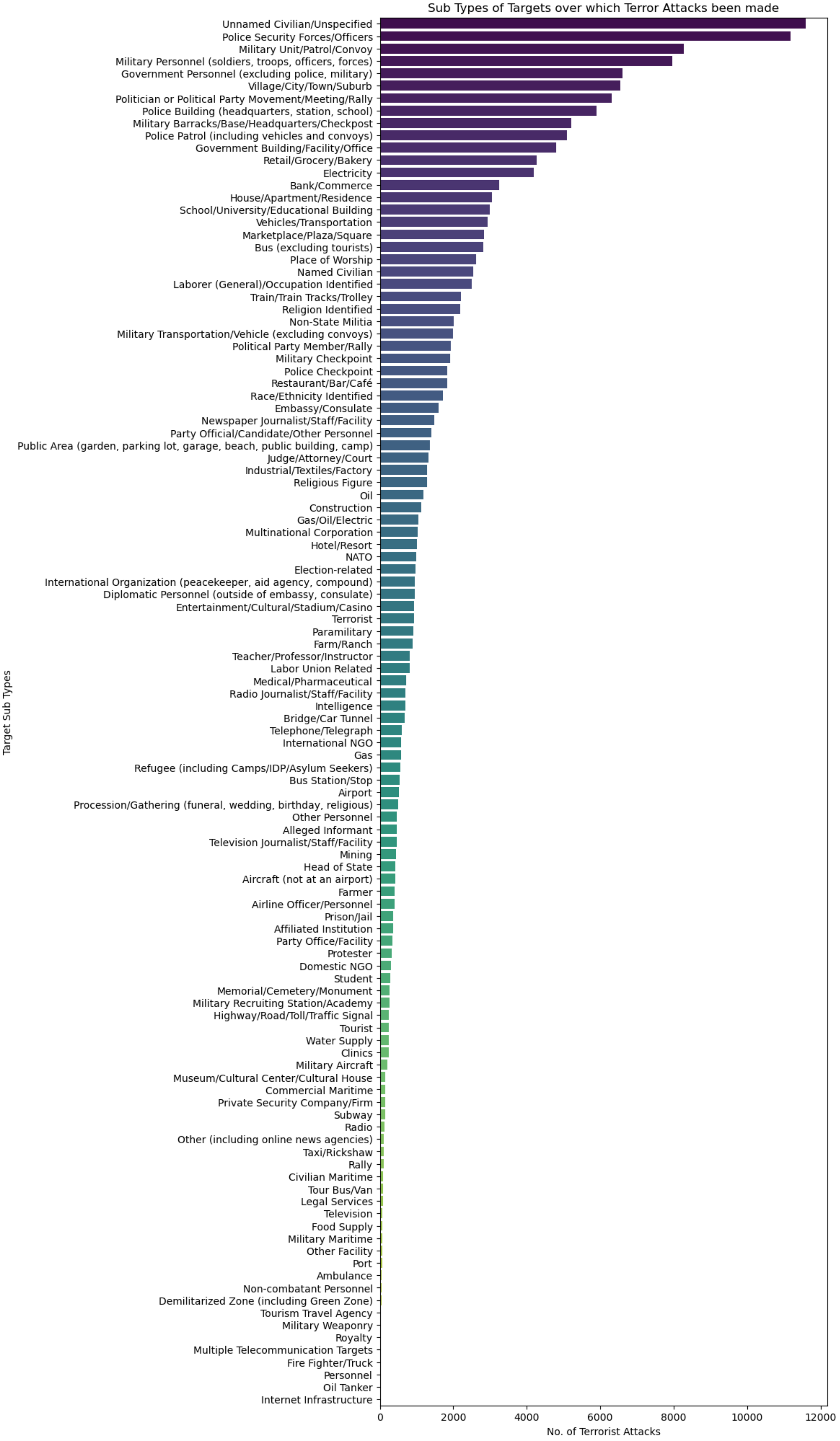
Out[43]:
```
Text(0.5, 1.0, 'Types of Terror Attacks over the World')
```



'Bombing/Explosion', 'Armed Assault' are the major types of Terror Attacks.

In [44]:
```
# Countplot of Sub Target Types over which terror attacks happened
plt.figure(figsize=(8,25))
sns.countplot(data=data1,y='targsubtype1_txt',palette='viridis',order=data1.targsub
plt.ylabel('Target Sub Types')
plt.xlabel('No. of Terrorist Attacks')
plt.title('Sub Types of Targets over which Terror Attacks been made')
```

Out[44]:
```
Text(0.5, 1.0, 'Sub Types of Targets over which Terror Attacks been made')
```


Sub Types of Targets over which Terror Attacks been made
Target Sub Types
Unnamed Civilian/Unspecified
Police Security Forces/Officers
Military Unit/Patrol/Convoy
Military Personnel (soldiers, troops, officers, forces)
Government Personnel (excluding police, military)
Village/City/Town/Suburb
Politician or Political Party Movement/Meeting/Rally
Police Building (headquarters, station, school)
Military Barracks/Base/Headquarters/Checkpost
Police Patrol (including vehicles and convoys)
Government Building/Facility/Office
Retail/Grocery/Bakery
Electricity
Bank/Commerce
House/Apartment/Residence
School/University/Educational Building
Vehicles/Transportation
Marketplace/Plaza/Square
Bus (excluding tourists)
Place of Worship
Named Civilian
Laborer (General)/Occupation Identified
Train/Train Tracks/Trolley
Religion Identified
Non-State Militia
Military Transportation/Vehicle (excluding convoys)
Political Party Member/Rally
Military Checkpoint
Police Checkpoint
Restaurant/Bar/Café
Race/Ethnicity Identified
Embassy/Consulate
Newspaper Journalist/Staff/Facility
Party Official/Candidate/Other Personnel
Public Area (garden, parking lot, garage, beach, public building, camp)
Judge/Attorney/Court
Industrial/Textiles/Factory
Religious Figure
Oil
Construction
Gas/Oil/Electric
Multinational Corporation
Hotel/Resort
NATO
Election-related
International Organization (peacekeeper, aid agency, compound)
Diplomatic Personnel (outside of embassy, consulate)
Entertainment/Cultural/Stadium/Casino
Terrorist
Paramilitary
Farm/Ranch
Teacher/Professor/Instructor
Labor Union Related
Medical/Pharmaceutical
Radio Journalist/Staff/Facility
Intelligence
Bridge/Car Tunnel
Telephone/Telegraph
International NGO
Gas
Refugee (including Camps/IDP/Asylum Seekers)
Bus Station/Stop
Airport
Procession/Gathering (funeral, wedding, birthday, religious)
Other Personnel
Alleged Informant
Television Journalist/Staff/Facility
Mining
Head of State
Aircraft (not at an airport)
Farmer
Airline Officer/Personnel
Prison/Jail
Affiliated Institution
Party Office/Facility
Protester
Domestic NGO
Student
Memorial/Cemetery/Monument
Military Recruiting Station/Academy
Highway/Road/Toll/Traffic Signal
Tourist
Water Supply
Clinics
Military Aircraft
Museum/Cultural Center/Cultural House
Commercial Maritime
Private Security Company/Firm
Subway
Radio
Other (including online news agencies)
Taxi/Rickshaw
Rally
Civilian Maritime
Tour Bus/Van
Legal Services
Television
Food Supply
Military Maritime
Other Facility
Port
Ambulance
Non-combatant Personnel
Demilitarized Zone (including Green Zone)
Tourism Travel Agency
Military Weaponry
Royalty
Multiple Telecommunication Targets
Fire Fighter/Truck
Personnel
Oil Tanker
Internet Infrastructure
0
2000
4000
6000
8000
10000
12000
No. of Terrorist Attacks

1.'Unnamed Civilians/Unspecified' and 'Police Security Forces/Officers' are top two sub target types for Terror Attacks.

2.Next to them are 'Military Unit' and 'Military Personnel' are top sub target types for Terror Attacks.

In [45]:
```
fig1=plt.figure(figsize=(8,8))
# function for plotting world map and indicating locations over which terror attack
def year_wise(year):
    plt.clf()
    worldmap=Basemap(projection='merc',resolution='c',llcrnrlat=-80,urcrnrlat=80,ll
    worldmap.drawcoastlines()
    worldmap.drawcountries()
    worldmap.fillcontinents(color='lightgreen',lake_color='blue')
    worldmap.drawmapboundary(fill_color='aqua')
    data_year=data1[data1.iyear==year]
    lat=list(data_year.latitude)
    lon=list(data_year.longitude)
    x,y=worldmap(lon,lat)
    worldmap.scatter(x,y,color='red',marker='.',s=data_year.nkill.values*0.7)
    plt.title('Distribution of Terror Attacks in '+f'Year {year}')
    plt.axis('off')
    plt.savefig('basemap'+str(year)+'.png', dpi=300)
    plt.close()
    image = PILImage.open('basemap'+str(year)+'.png')
    return image
```

```
<Figure size 800x800 with 0 Axes>
```

In [46]:
```
years=np.arange(1970,2018)
frames=[]
for year in years:
    image=year_wise(year)
    frames.append(image)
    time.sleep(0.5)
imageio.mimsave('output.gif',frames,fps=0.67)
```

In [47]:
```
display(IPImage('output.gif'))
```

```
<IPython.core.display.Image object>
```

In [48]:
```
data_india=data1[data1.country_txt=='India']
```

In [49]:
```
fig2=plt.figure(figsize=(6,8))
def india_year_wise(year):
    plt.clf()
    indiamap=Basemap(projection='merc',llcrnrlat=6,urcrnrlat=38,llcrnrlon=68,urcrnr
    indiamap.drawcoastlines()
    indiamap.drawcountries()
    indiamap.drawstates()
    indiamap.fillcontinents(color='lightgreen',lake_color='blue')
    indiamap.drawmapboundary(fill_color='aqua')
    data_indiayear=data_india[data_india.iyear==year]
    lat=list(data_indiayear.latitude)
    lon=list(data_indiayear.longitude)
    x,y=indiamap(lon,lat)
    indiamap.scatter(x,y,color='red',marker='.',s=data_indiayear.nkill.values*0.7)
    plt.title('Distribution of Terror Attacks in India in the '+f'Year {year}')
    plt.axis('off')
    plt.savefig('Indiamap'+str(year)+'.png', dpi=300)
    plt.close()
    image = PILImage.open('Indiamap'+str(year)+'.png')
    return image
```

```
<Figure size 600x800 with 0 Axes>
```

In [50]:

```
years=np.arange(1970,2018)
indiaframes=[]
for year in years:
    image=india_year_wise(year)
    indiaframes.append(image)
    time.sleep(0.5)
imageio.mimsave('India.gif',indiaframes,fps=0.67)
```

In [51]:

```
display(IPImage('India.gif'))
```

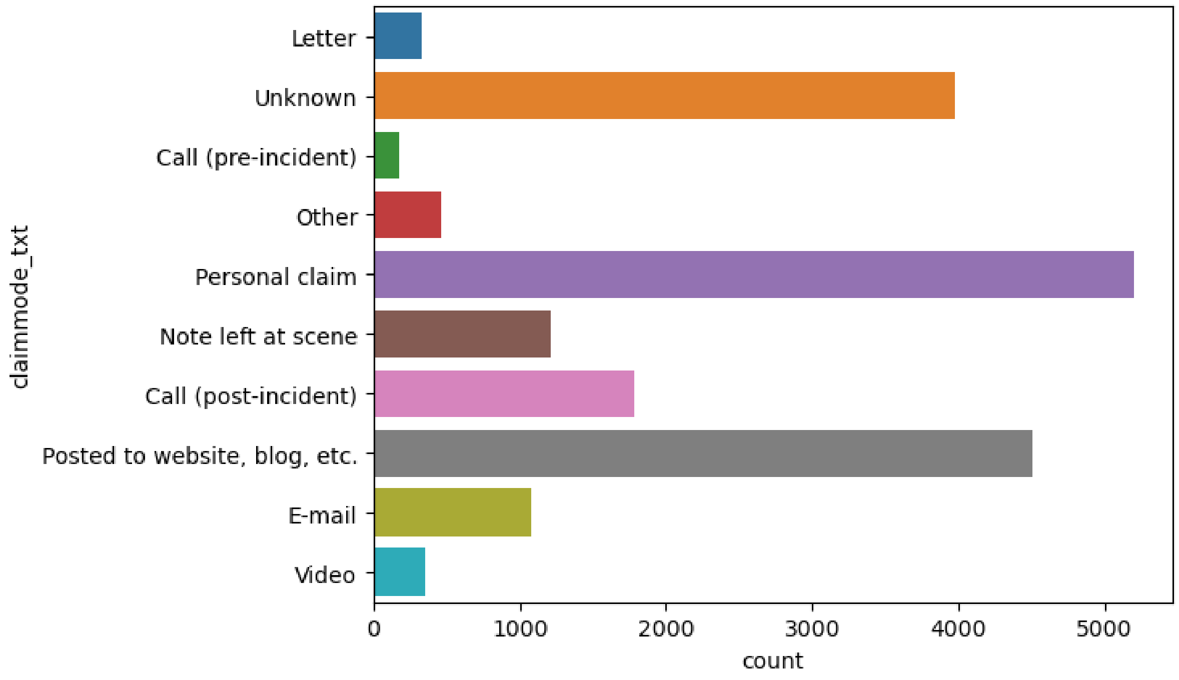
```
<IPython.core.display.Image object>
```

In [52]:

```
# Countplot of mode over which terror claims were made
sns.countplot(data=data,y='claimmode_txt')
```

Out[52]:

```
<Axes: xlabel='count', ylabel='claimmode_txt'>
```

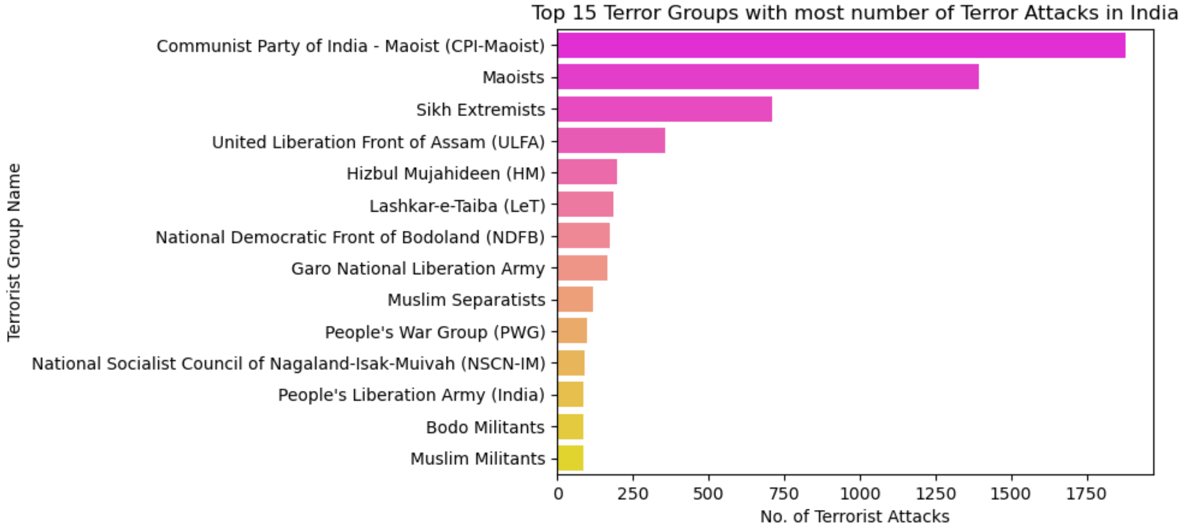


In [53]:

```
# Countplot of different Groups or Organisations responsible for Terror Attacks ove
sns.countplot(data=data_india,y='gname',order=data_india.gname.value_counts().index
plt.xlabel('No. of Terrorist Attacks')
plt.ylabel('Terrorist Group Name')
plt.title('Top 15 Terror Groups with most number of Terror Attacks in India')
```

Out[53]:

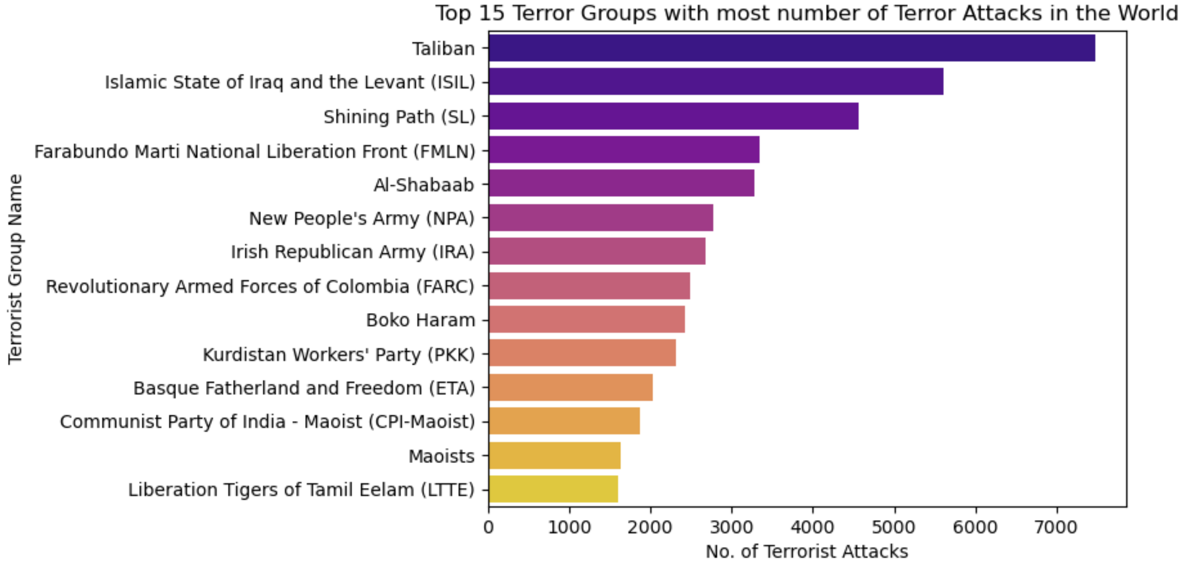
```
Text(0.5, 1.0, 'Top 15 Terror Groups with most number of Terror Attacks in India')
```



From the above graph, we can see that 'CPI-Maoist','Maoists','Sikh Extremists','ULFA' are the major terrror groups in India.

```
In [54]: # Countplot of Top 15 Terror Groups with most number of Terror Attacks in the worlc
         sns.countplot(data=data,y='gname',order=data.gname.value_counts().index[1:15],palet
         plt.xlabel('No. of Terrorist Attacks')
         plt.ylabel('Terrorist Group Name')
         plt.title('Top 15 Terror Groups with most number of Terror Attacks in the World')
```

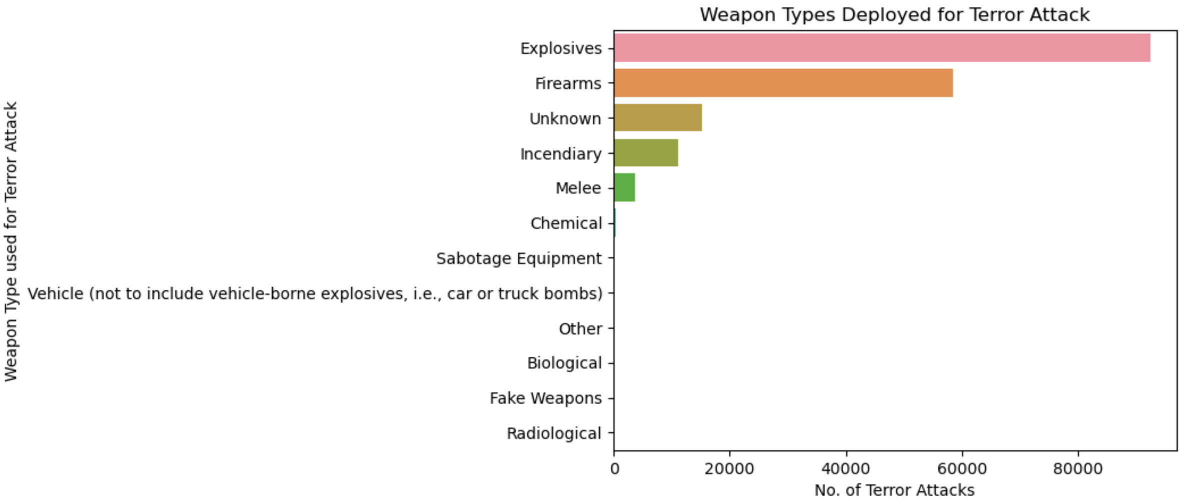
```
Out[54]: Text(0.5, 1.0, 'Top 15 Terror Groups with most number of Terror Attacks in the Wor
         ld')
```



From the above graph, we can see that 'Taliban', 'ISIL', 'SL', 'FMLN' are the major terror groups with most number of terror attacks in the world.

```
In [55]: # Countplot of Weapon Types used for terror attack
         sns.countplot(data=data1,y='weaptype1_txt',order=data1.weaptype1_txt.value_counts()
         plt.xlabel('No. of Terror Attacks')
         plt.ylabel('Weapon Type used for Terror Attack')
         plt.title('Weapon Types Deployed for Terror Attack')
```

```
Out[55]: Text(0.5, 1.0, 'Weapon Types Deployed for Terror Attack')
```



'Explosives', 'Firearms' are the major weapon types chosen for Terror Attack

NLP Analysis of Articles covering Terror News:

In [56]:
```
pip install wordcloud
```

```
Collecting wordcloud
  Downloading wordcloud-1.9.2-cp310-cp310-win_amd64.whl (152 kB)
     ------------------------------------ 152.1/152.1 kB 349.4 kB/s eta 0:00:00
Requirement already satisfied: matplotlib in c:\users\mouli nahal\anaconda3\lib\site-packages (from wordcloud) (3.7.0)
Requirement already satisfied: numpy>=1.6.1 in c:\users\mouli nahal\anaconda3\lib\site-packages (from wordcloud) (1.23.5)
Requirement already satisfied: pillow in c:\users\mouli nahal\anaconda3\lib\site-packages (from wordcloud) (9.4.0)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\mouli nahal\anaconda3\lib\site-packages (from matplotlib->wordcloud) (1.0.5)
Requirement already satisfied: packaging>=20.0 in c:\users\mouli nahal\anaconda3\lib\site-packages (from matplotlib->wordcloud) (22.0)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\mouli nahal\anaconda3\lib\site-packages (from matplotlib->wordcloud) (4.25.0)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\mouli nahal\anaconda3\lib\site-packages (from matplotlib->wordcloud) (2.8.2)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\mouli nahal\anaconda3\lib\site-packages (from matplotlib->wordcloud) (1.4.4)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\mouli nahal\anaconda3\lib\site-packages (from matplotlib->wordcloud) (3.0.9)
Requirement already satisfied: cycler>=0.10 in c:\users\mouli nahal\anaconda3\lib\site-packages (from matplotlib->wordcloud) (0.11.0)
Requirement already satisfied: six>=1.5 in c:\users\mouli nahal\anaconda3\lib\site-packages (from python-dateutil>=2.7->matplotlib->wordcloud) (1.16.0)
Installing collected packages: wordcloud
Successfully installed wordcloud-1.9.2
Note: you may need to restart the kernel to use updated packages.
```

In [57]:
```python
import nltk
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from wordcloud import WordCloud
import re
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
```

```
[nltk_data] Downloading package punkt to C:\Users\Mouli
[nltk_data]     Nahal\AppData\Roaming\nltk_data...
[nltk_data]   Unzipping tokenizers\punkt.zip.
[nltk_data] Downloading package stopwords to C:\Users\Mouli
[nltk_data]     Nahal\AppData\Roaming\nltk_data...
[nltk_data]   Unzipping corpora\stopwords.zip.
[nltk_data] Downloading package wordnet to C:\Users\Mouli
[nltk_data]     Nahal\AppData\Roaming\nltk_data...
```

Out[57]:

```
True
```

In [58]:

```python
wordnetlemmatizer=WordNetLemmatizer()
```

In [59]:

```python
data1_scite1=data1.scite1.dropna()
```

In [60]:

```python
nltk.download('omw-1.4')
```

```
[nltk_data] Downloading package omw-1.4 to C:\Users\Mouli
[nltk_data]     Nahal\AppData\Roaming\nltk_data...
```

Out[60]:

```
True
```

In [61]:

```python
def clean_text(text):
    cleaned=text.lower()
    cleaned=re.sub(r'https?://\S+',"",cleaned) #finds pattern https:// or http:// a
                                               #replaces it along with non white sp
                                               #characters present beside it with b
    cleaned=re.sub(r'\\n'," ",cleaned) #replaces new line characters with blank spa
    cleaned=re.sub(r'[@#!&](\w+)',r' \1',cleaned) # replaces special characters
    cleaned=re.sub(r'[.,\':/;-]',' ',cleaned) # replaces .,: and other characters
    return cleaned
```

In [62]:

```python
# Function for tokenizing documents and lemmatizing words
def tokenize(text):
    cleaned=word_tokenize(text)
    cleaned=[wordnetlemmatizer.lemmatize(word) for word in cleaned if word not in s
    cleaned_text=" ".join(cleaned)
    return cleaned_text
```

In [63]:

```python
data_clean=data1.dropna()
```

In [64]:

```python
# creating new column consisting cleaned text
data_clean['cleaned_text']=data_clean['scite1'].apply(lambda x:clean_text(x))
data_clean['cleaned_text']=data_clean['cleaned_text'].apply(lambda x:tokenize(x))
```

In [65]:

```python
data_clean['cleaned_text']
```

Out[65]:

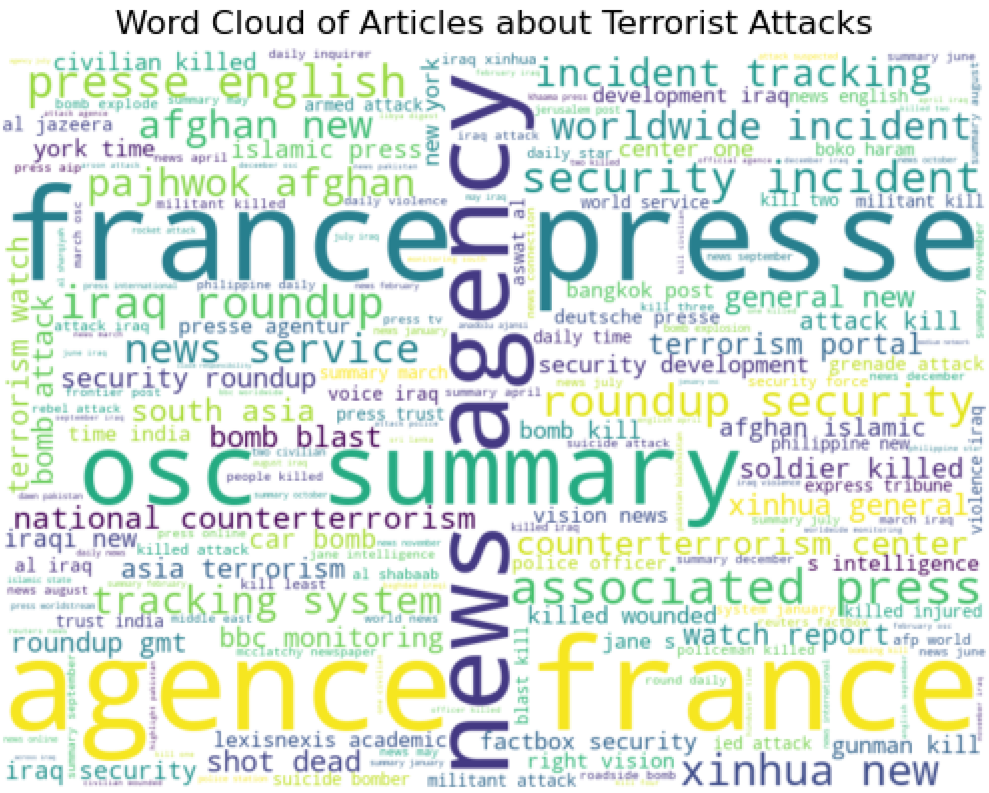
```
5         `` police chief quits `` washington post janua...
7         committee government operation united state se...
8         tom bates `` rad 1970 bombing army math resear...
9         committee government operation united state se...
11        committee government operation united state se...
                                ...
181685    `` 4 people injured farayb explosion `` pajhwo...
181686    `` somalia al shabaab militant attack army che...
181687    `` putin victory syria turned farce turchynov ...
181688    `` maguindanao clash trap tribe member `` phil...
181689    `` trader escape grenade attack imphal `` busi...
Name: cleaned_text, Length: 102998, dtype: object
```

In [66]:

```python
# Plotting Wordcloud
wordcloud=WordCloud(width=800, height=600, background_color='white').generate(" ".j
plt.imshow(wordcloud, interpolation='bilinear')
plt.title('Word Cloud of Articles about Terrorist Attacks')
plt.axis('off')
```

Out[66]:

```
(-0.5, 799.5, 599.5, -0.5)
```



In [ ]:

In [ ]:

In [ ]: