EXPLORATORY DATA ANALYSIS GLOBAL TERRORISM

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INTRODUCTION

Terrorism is a global issue that affects countries and communities around the world.In this project, we will analyze global terrorism data using Python's pandas, matplotlib, and seaborn libraries.Our goal is to gain insights into the patterns and characteristics of terrorist attacks over time and across different regions. We will use pandas to clean and manipulate the data, matplotlib to create visualizations such as line plots, bar charts, and histograms, and seaborn to enhance the visualizations with additional styling and features.

Import Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
```

In [2]:
```
#reading Data.
data=pd.read_csv("C:/Users/DELL/OneDrive/Desktop/Terrorism.csv", encoding='I
data.head(5)
```

Out[2]:

	eventid	iyear	imonth	iday	approxdate	extended	resolution	country	country_txt
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 rows × 135 columns

dimention of dataset

In [3]:
```
data.shape
```

Out[3]:
```
(181691, 135)
```

dtype of each columns from dataset

In [4]:
```
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
```

mathematical overview

In [5]:
```
data.describe()
```

Out[5]:

	eventid	iyear	imonth	iday	extended	cou
count	1.816910e+05	181691.000000	181691.000000	181691.000000	181691.000000	181691.000
mean	2.002705e+11	2002.638997	6.467277	15.505644	0.045346	131.968
std	1.325957e+09	13.259430	3.388303	8.814045	0.208063	112.414
min	1.970000e+11	1970.000000	0.000000	0.000000	0.000000	4.000
25%	1.991021e+11	1991.000000	4.000000	8.000000	0.000000	78.000
50%	2.009022e+11	2009.000000	6.000000	15.000000	0.000000	98.000
75%	2.014081e+11	2014.000000	9.000000	23.000000	0.000000	160.000
max	2.017123e+11	2017.000000	12.000000	31.000000	1.000000	1004.000

8 rows × 77 columns

check columns name

In [6]:
```
data.columns.values
```

Out[6]:
```
array(['eventid', 'iyear', 'imonth', 'iday', 'approxdate', 'extended',
       'resolution', 'country', 'country_txt', 'region', 'region_txt',
       'provstate', 'city', 'latitude', 'longitude', 'specificity',
       'vicinity', 'location', 'summary', 'crit1', 'crit2', 'crit3',
       'doubtterr', 'alternative', 'alternative_txt', 'multiple',
       'success', 'suicide', 'attacktype1', 'attacktype1_txt',
       'attacktype2', 'attacktype2_txt', 'attacktype3', 'attacktype3_txt',
       'targtype1', 'targtype1_txt', 'targsubtype1', 'targsubtype1_txt',
       'corp1', 'target1', 'natlty1', 'natlty1_txt', 'targtype2',
       'targtype2_txt', 'targsubtype2', 'targsubtype2_txt', 'corp2',
       'target2', 'natlty2', 'natlty2_txt', 'targtype3', 'targtype3_txt',
       'targsubtype3', 'targsubtype3_txt', 'corp3', 'target3', 'natlty3',
       'natlty3_txt', 'gname', 'gsubname', 'gname2', 'gsubname2',
       'gname3', 'gsubname3', 'motive', 'guncertain1', 'guncertain2',
       'guncertain3', 'individual', 'nperps', 'nperpcap', 'claimed',
       'claimmode', 'claimmode_txt', 'claim2', 'claimmode2',
       'claimmode2_txt', 'claim3', 'claimmode3', 'claimmode3_txt',
       'compclaim', 'weaptype1', 'weaptype1_txt', 'weapsubtype1',
       'weapsubtype1_txt', 'weaptype2', 'weaptype2_txt', 'weapsubtype2',
       'weapsubtype2_txt', 'weaptype3', 'weaptype3_txt', 'weapsubtype3',
       'weapsubtype3_txt', 'weaptype4', 'weaptype4_txt', 'weapsubtype4',
       'weapsubtype4_txt', 'weapdetail', 'nkill', 'nkillus', 'nkillter',
       'nwound', 'nwoundus', 'nwoundte', 'property', 'propextent',
       'propextent_txt', 'propvalue', 'propcomment', 'ishostkid',
       'nhostkid', 'nhostkidus', 'nhours', 'ndays', 'divert',
       'kidhijcountry', 'ransom', 'ransomamt', 'ransomamtus',
       'ransompaid', 'ransompaidus', 'ransomnote', 'hostkidoutcome',
       'hostkidoutcome_txt', 'nreleased', 'addnotes', 'scite1', 'scite2',
       'scite3', 'dbsource', 'INT_LOG', 'INT_IDEO', 'INT_MISC', 'INT_ANY',
       'related'], dtype=object)
```

DATA CLEANING

Assuming thouse columns importent for this dataset

In [7]:
```
tdata=data[['eventid','iyear','imonth','iday','extended','gname','individual
tdata.head()
```

Out[7]:

	eventid	iyear	imonth	iday	extended	gname	individual	country	country_txt
0	197000000001	1970	7	2	0	MANO-D	0	58	Dominican Republic
1	197000000002	1970	0	0	0	23rd of September Communist League	0	130	Mexico
2	197001000001	1970	1	0	0	Unknown	0	160	Philippines
3	197001000002	1970	1	0	0	Unknown	0	78	Greece
4	197001000003	1970	1	0	0	Unknown	0	101	Japan

5 rows × 23 columns

Selected columns dtype

In [8]:
```
tdata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 181691 entries, 0 to 181690
Data columns (total 23 columns):
 #   Column           Non-Null Count   Dtype  
---  ------           --------------   -----  
 0   eventid          181691 non-null  int64  
 1   iyear            181691 non-null  int64  
 2   imonth           181691 non-null  int64  
 3   iday             181691 non-null  int64  
 4   extended         181691 non-null  int64  
 5   gname            181691 non-null  object 
 6   individual       181691 non-null  int64  
 7   country          181691 non-null  int64  
 8   country_txt      181691 non-null  object 
 9   latitude         177135 non-null  float64
 10  longitude        177134 non-null  float64
 11  city             181256 non-null  object 
 12  region           181691 non-null  int64  
 13  region_txt       181691 non-null  object 
 14  success          181691 non-null  int64  
 15  suicide          181691 non-null  int64  
 16  nkill            171378 non-null  float64
 17  weaptype1        181691 non-null  int64  
 18  attacktype1      181691 non-null  int64  
 19  attacktype1_txt  181691 non-null  object 
 20  targtype1_txt    181691 non-null  object 
 21  targtype1        181691 non-null  int64  
 22  nwound           165380 non-null  float64
dtypes: float64(4), int64(13), object(6)
memory usage: 31.9+ MB
```

Rename columns

In [9]:
```
new_data=tdata.rename(columns={"eventid":"even_id","iyear":"Year","imonth":"
new_data
```
Out[9]:

	even_id	Year	Month	Day	Extend	Terrorist_Group	individual	Number of Country	Coun
0	197000000001	1970	7	2	0	MANO-D	0	58	[
1	197000000002	1970	0	0	0	23rd of September Communist League	0	130	
2	197001000001	1970	1	0	0	Unknown	0	160	F
3	197001000002	1970	1	0	0	Unknown	0	78	
4	197001000003	1970	1	0	0	Unknown	0	101	
...	...	...	...	...	...	...	...	...	
181686	201712310022	2017	12	31	0	Al-Shabaab	0	182	
181687	201712310029	2017	12	31	0	Muslim extremists	0	200	
181688	201712310030	2017	12	31	0	Bangsamoro Islamic Freedom Movement (BIFM)	0	160	F
181689	201712310031	2017	12	31	0	Unknown	0	92	
181690	201712310032	2017	12	31	0	Unknown	0	160	F

181691 rows × 23 columns

check unique values

In [10]:
```
new_data.nunique()
```

Out[10]:
```
even_id               181691
Year                      47
Month                     13
Day                       32
Extend                     2
Terrorist_Group         3537
individual                 2
Number of Country        205
Country_Name             205
latitude               48322
longitude              48039
city                   36673
region                    12
Region_Name               12
success                    2
suicide                    2
No.of Kill               205
Typ of Weapon             12
Attacktype                 9
Attacktype_Name            9
Target Type Name          22
Target Type               22
nwound                   238
dtype: int64
```

check null values

In [11]:
```
new_data.isnull().sum()
```

Out[11]:
```
even_id                  0
Year                     0
Month                    0
Day                      0
Extend                   0
Terrorist_Group          0
individual               0
Number of Country        0
Country_Name             0
latitude              4556
longitude             4557
city                   435
region                   0
Region_Name              0
success                  0
suicide                  0
No.of Kill           10313
Typ of Weapon            0
Attacktype               0
Attacktype_Name          0
Target Type Name         0
Target Type              0
nwound               16311
dtype: int64
```

replacing nan values

In [12]:
```
new_data.city.fillna("Unknown",inplace=True)
```

replace NaN values with average of number of kill

In [13]:
```
new_data['No.of Kill'].fillna(new_data['No.of Kill'].mean(),inplace=True)
```

In [14]:
```
new_data['nwound'].fillna(new_data['nwound'].mean(),inplace=True)
```

create a new column causualties by adding 'Kill' and 'Wounded'

In [15]:
```
new_data['Causualties']=new_data['No.of Kill']+new_data['nwound']
new_data.sample(2)
```

Out[15]:

	even_id	Year	Month	Day	Extend	Terrorist_Group	individual	Number of Country	Coun
177227	201707220002	2017	7	22	1	National Liberation Army of Colombia (ELN)	0	45	
30501	198703190008	1987	3	19	0	Basque Fatherland and Freedom (ETA)	0	185	

2 rows × 24 columns

replace 0 and 1 with 'No' and "Yes"

In [16]:
```
new_data['suicide']=new_data['suicide'].map({0:"No",1:"Yes"})
new_data.sample(2)
```

Out[16]:

	even_id	Year	Month	Day	Extend	Terrorist_Group	individual	Number of Country	Coun
68833	199904280002	1999	4	28	0	Orange Volunteers (OV)	0	603	
175634	201706070014	2017	6	7	1	Unknown	0	195	

2 rows × 24 columns

In [17]:
```
new_data['success']=new_data['success'].map({0:"No",1:"Yes"})
new_data.sample(2)
```

Out[17]:

	even_id	Year	Month	Day	Extend	Terrorist_Group	individual	Number of Country	Countr
67115	199711140009	1997	11	14	0	Unknown	0	83	Gu
19745	198309130013	1983	9	13	0	Farabundo Marti National Liberation Front (FMLN)	0	61	El

2 rows × 24 columns

UNIVARIENT ANALYSIS

Frequency Of Suicide rate in attack

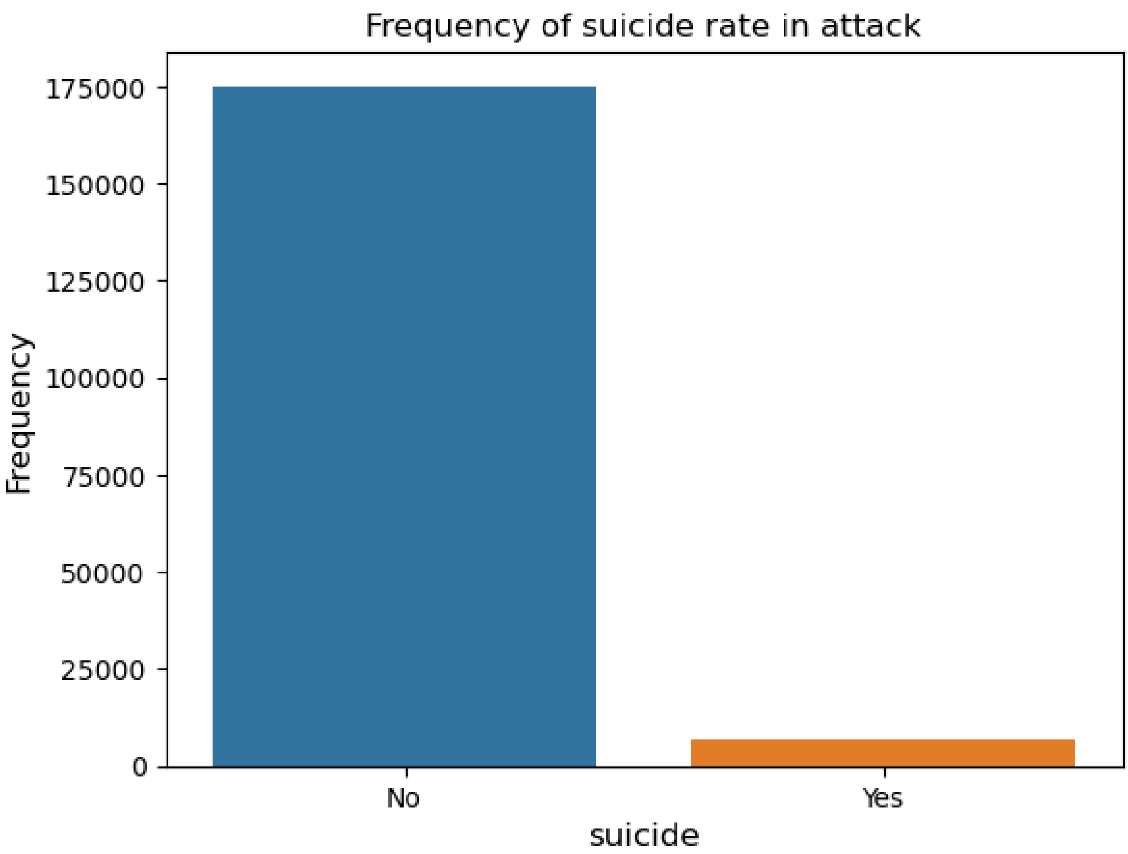
In [18]:
```
suicide=new_data['suicide'].value_counts(normalize=True)*100
suicide
```

Out[18]:
```
suicide
No      96.349296
Yes      3.650704
Name: proportion, dtype: float64
```

COUNTPLOT

In [19]:
```
sns.countplot(data=new_data,x='suicide')
plt.xlabel("suicide",fontsize=12)
plt.ylabel('Frequency',fontsize=12)
plt.title("Frequency of suicide rate in attack",fontsize=12)
```

Out[19]:
```
Text(0.5, 1.0, 'Frequency of suicide rate in attack')
```



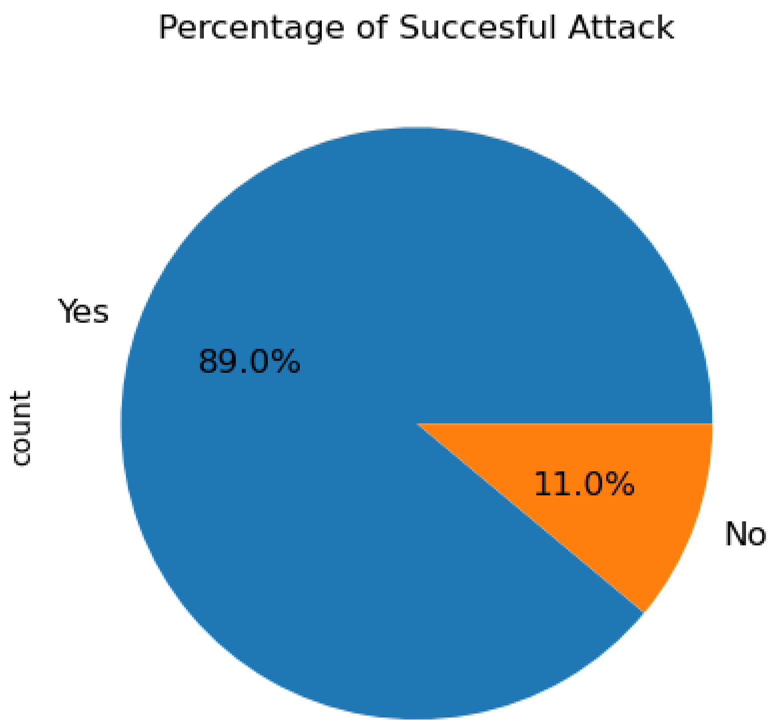
OBSERVATION

Despite the maximum frequency of attacks, the majority were not suicidal in nature.

PIE CHART

In [20]:
```
new_data['success'].value_counts().plot(kind='pie',autopct='%.1f%%',fontsize
plt.title("Percentage of Succesful Attack",fontsize=12)
```

Out[20]:
```
Text(0.5, 1.0, 'Percentage of Succesful Attack')
```



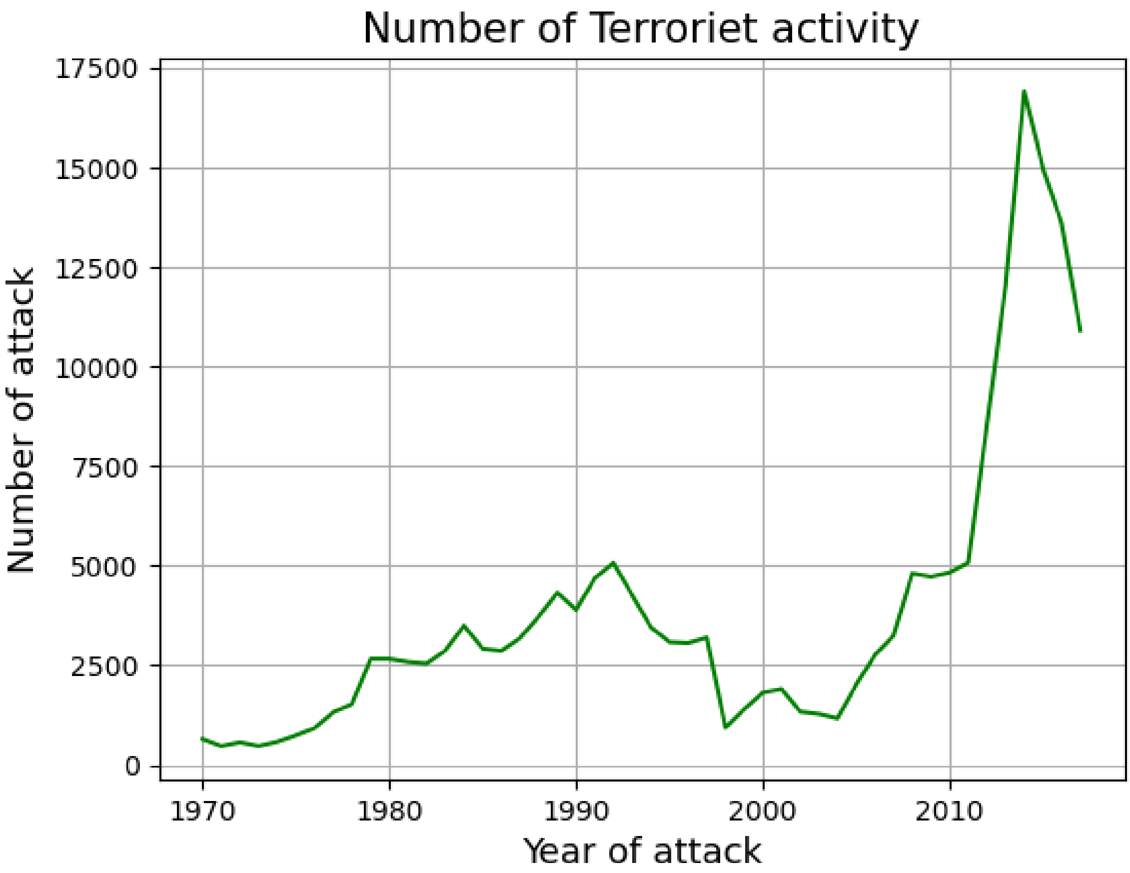
OBSERVATION

Maximum Succesfull attack Occurred

MULTIVARIENT ANALYSIS

Number of Terrorist activity each year.

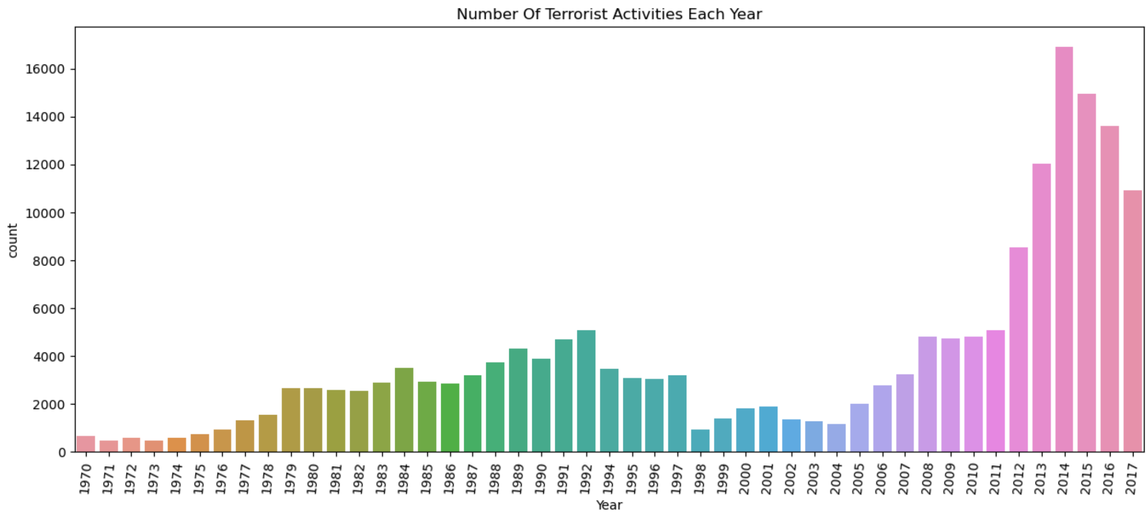
In [21]:
```
#Number of attack each year
year_of_attack=new_data['Year'].value_counts()
sns.lineplot(data=year_of_attack,x=year_of_attack.index,y=year_of_attack.val
plt.xlabel("Year of attack",fontsize=13)
plt.ylabel("Number of attack",fontsize=13)
plt.title("Number of Terroriet activity",fontsize=15)
plt.grid()
```



Number of Terroriest activity each year.

In [22]:
```
plt.subplots(figsize=(15,6))
sns.countplot(data=new_data, x='Year')
plt.xticks(rotation=85)
plt.title('Number Of Terrorist Activities Each Year')
```

Out[22]:
```
Text(0.5, 1.0, 'Number Of Terrorist Activities Each Year')
```



Observation

Global terrorist activities have shown a consistent rise over the years, peaking in 2014 with the highest recorded incidents. However, there has been a notable decrease in terrorist activity after 2014, indicating potential progress in global security efforts.

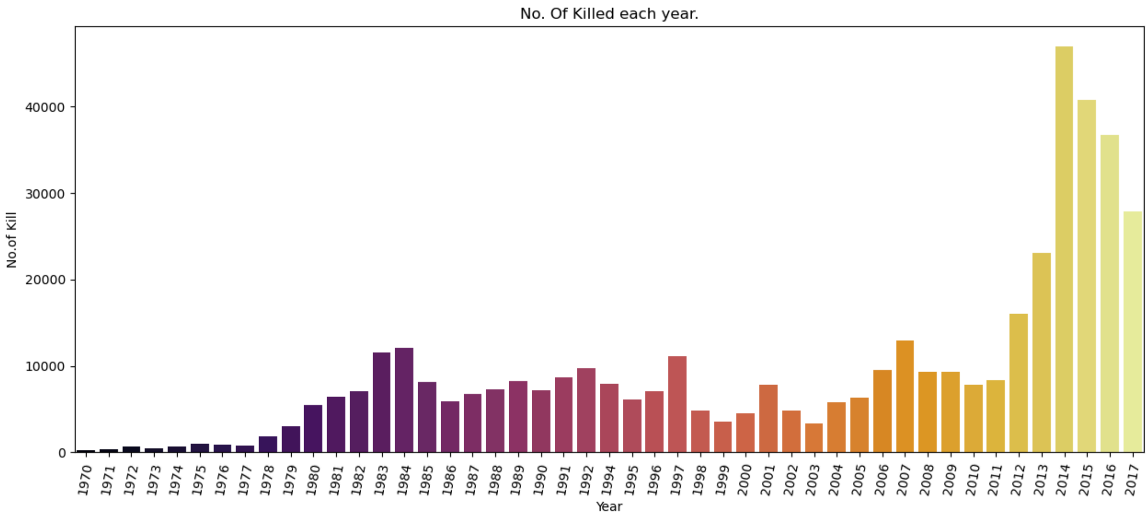
Number of Killed each year.

In [23]:
```
new_data.columns
```

Out[23]:
```
Index(['even_id', 'Year', 'Month', 'Day', 'Extend', 'Terrorist_Group',
       'individual', 'Number of Country', 'Country_Name', 'latitude',
       'longitude', 'city', 'region', 'Region_Name', 'success', 'suicide',
       'No.of Kill', 'Typ of Weapon', 'Attacktype', 'Attacktype_Name',
       'Target Type Name', 'Target Type', 'nwound', 'Causualties'],
      dtype='object')
```

In [24]:
```
killed=new_data.groupby('Year')['No.of Kill'].sum().reset_index()
plt.subplots(figsize=(15,6))
sns.barplot(data=killed,x='Year',y='No.of Kill',palette='inferno')
plt.xticks(rotation=80)
plt.title('No. Of Killed each year.')
```

Out[24]:
```
Text(0.5, 1.0, 'No. Of Killed each year.')
```



Observation

Global deaths due to terrorist activities have exhibited a consistent increase over the years, reaching a peak in 2014 with the highest recorded fatalities. Subsequently, there has been a noticeable decline in deaths post-2014, suggesting potential advancements in security measures.

Terrorist Attacks Trends in Regions

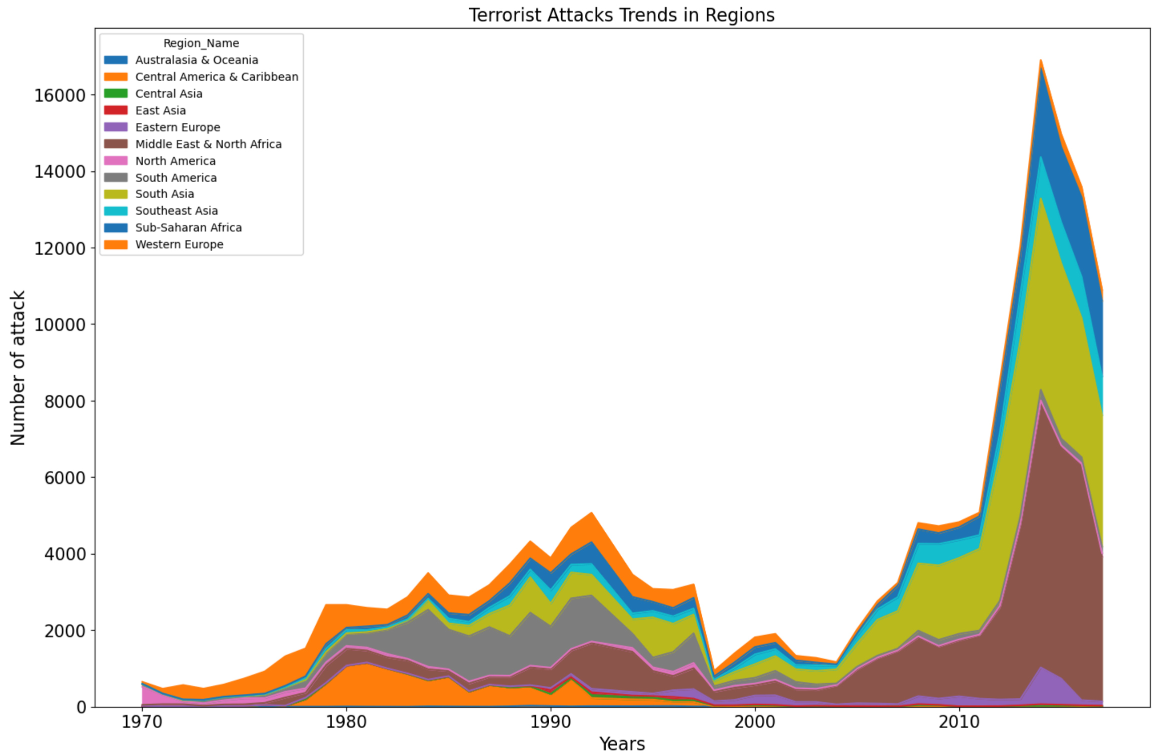
In [25]:
```
#The Trends of Regions
region=pd.crosstab(new_data.Year, new_data['Region_Name'])
region.head()
```

Out[25]:

Region_Name	Australasia & Oceania	Central America & Caribbean	Central Asia	East Asia	Eastern Europe	Middle East & North Africa	North America	South America	Sou As
Year									
1970	1	7	0	2	12	28	472	65	
1971	1	5	0	1	5	55	247	24	
1972	8	3	0	0	1	53	73	33	
1973	1	6	0	2	1	19	64	83	
1974	1	11	0	4	2	42	111	81	

```
In [26]: region.plot(kind='area',figsize=(17,11),fontsize=15)
         plt.ylabel("Number of attack",fontsize=16)
         plt.xlabel("Years",fontsize=16)
         plt.title("Terrorist Attacks Trends in Regions",fontsize=16)
```

```
Out[26]: Text(0.5, 1.0, 'Terrorist Attacks Trends in Regions')
```



Observation

Since 2010, the Middle East & North Africa region has demonstrated the highest trend of terrorist attacks, showing a consistent increase over the years. However, post-2014, there has been a notable decrease in the trends of attacks in this region.

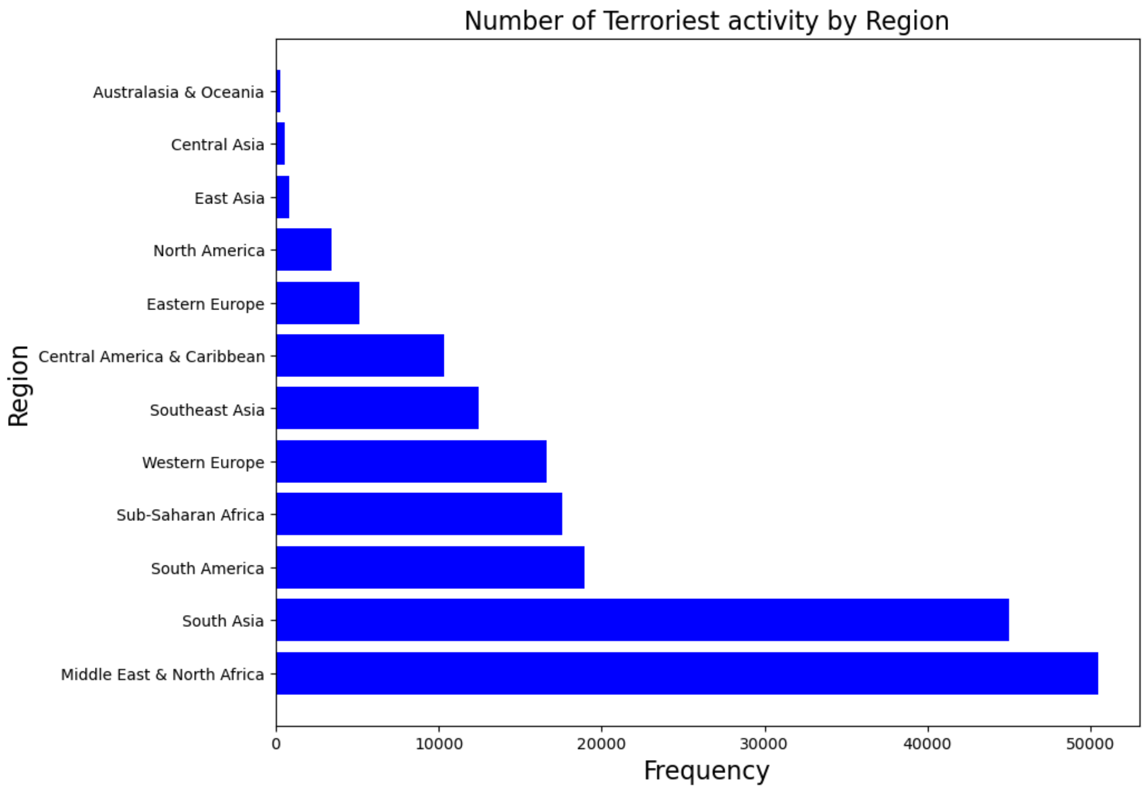
Number Of Terrorist Activities By Region

```
In [27]: new_data.columns
```

```
Out[27]: Index(['even_id', 'Year', 'Month', 'Day', 'Extend', 'Terrorist_Group',
                'individual', 'Number of Country', 'Country_Name', 'latitude',
                'longitude', 'city', 'region', 'Region_Name', 'success', 'suicide',
                'No.of Kill', 'Typ of Weapon', 'Attacktype', 'Attacktype_Name',
                'Target Type Name', 'Target Type', 'nwound', 'Causualties'],
               dtype='object')
```

In [28]:
```
region=new_data['Region_Name'].value_counts()
plt.figure(figsize=(10,8))
plt.barh(region.index,region.values,color='b')
plt.ylabel("Region",fontsize=16)
plt.xlabel('Frequency',fontsize=16)
plt.title("Number of Terroriest activity by Region",fontsize=16)
```

Out[28]:
```
Text(0.5, 1.0, 'Number of Terroriest activity by Region')
```



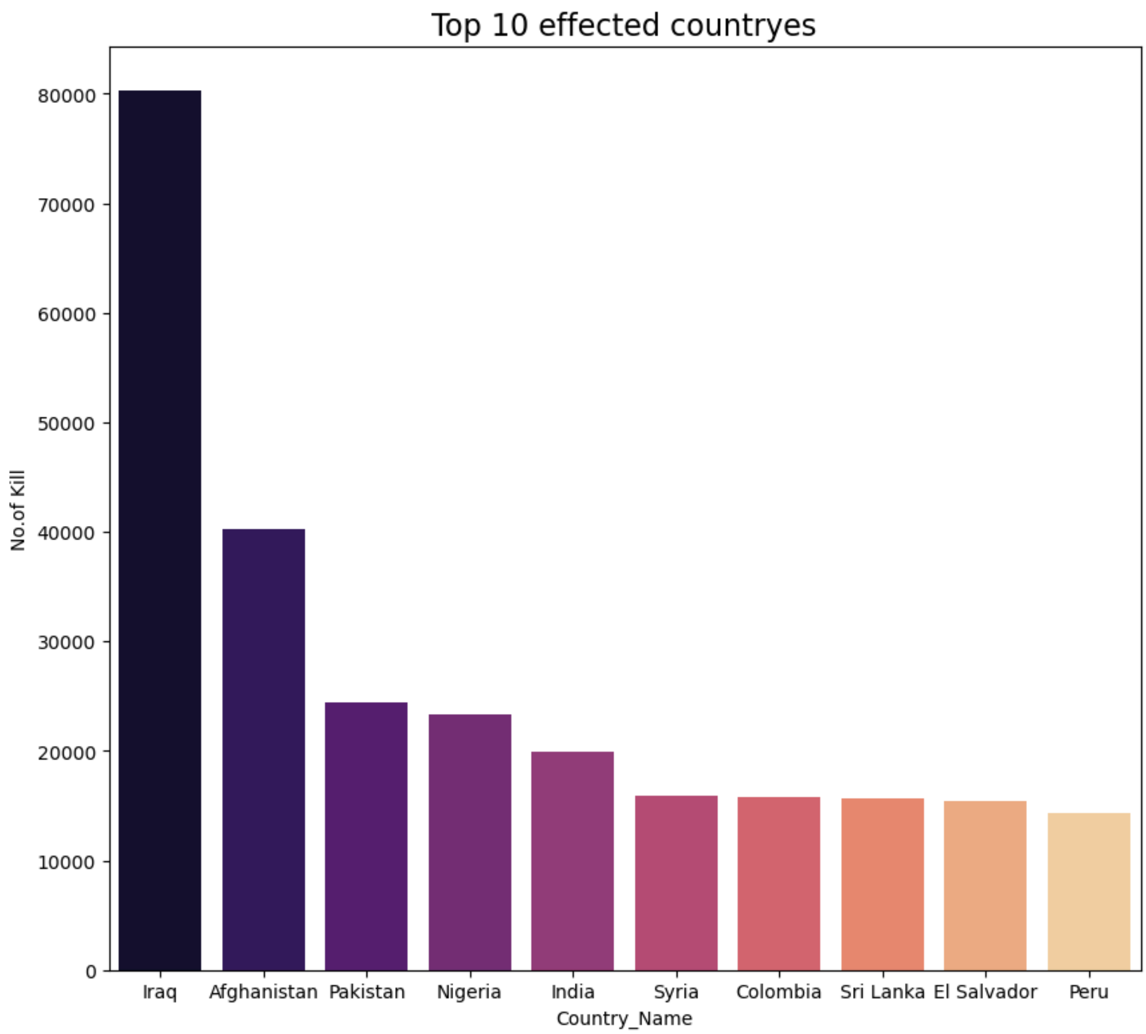
Observation

The Middle east & North Africa region has the highest frequency of attack

Top 10 Affected Countries

In [29]:
```
country=new_data.groupby('Country_Name')['No.of Kill'].sum().reset_index()
country=country.sort_values(by='No.of Kill',ascending=False).head(10)
plt.figure(figsize=(10,9))
sns.barplot(x='Country_Name',y='No.of Kill',data=country,palette='magma')
plt.title("Top 10 effected countryes",fontsize=16)
```

Out[29]:
```
Text(0.5, 1.0, 'Top 10 effected countryes')
```



Observation

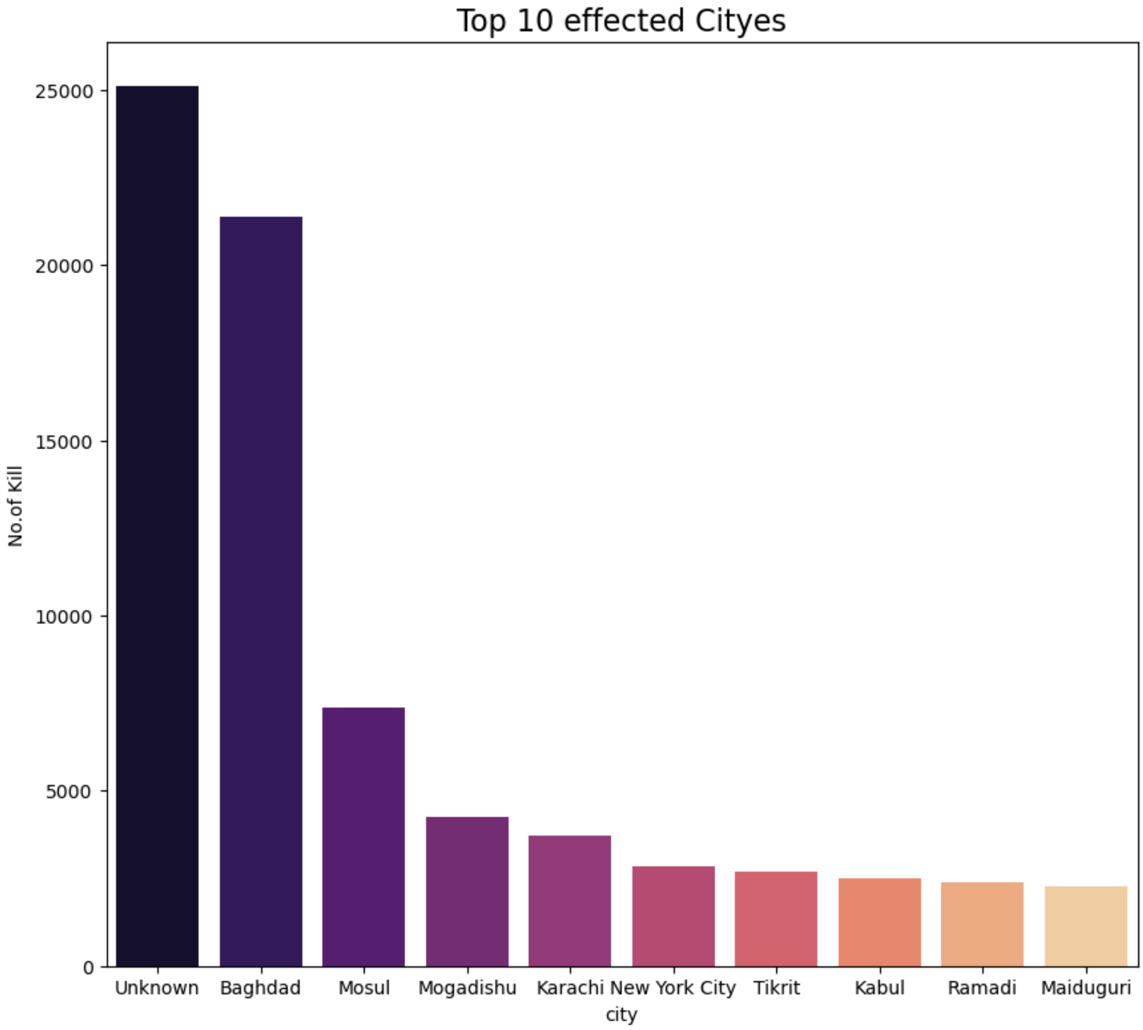
The graph highlights five countrys most effected by terrosium

1. Iraq
2. Afghanistan
3. Pakistan
4. Nigeria
5. India

Top 10 Affected Cities

In [30]:
```
city=new_data.groupby('city')['No.of Kill'].sum().reset_index()
city=city.sort_values(by='No.of Kill',ascending=False).head(10)
plt.figure(figsize=(10,9))
sns.barplot(data=city,x='city',y='No.of Kill',palette='magma')
plt.title("Top 10 effected Cityes",fontsize=16)
```

Out[30]:
```
Text(0.5, 1.0, 'Top 10 effected Cityes')
```



observation

The graph Highlights five cityes more effected by terrosium.

1. Unknown
2. Baghdad
3. Mosul
4. Mogadishu
5. Karachi

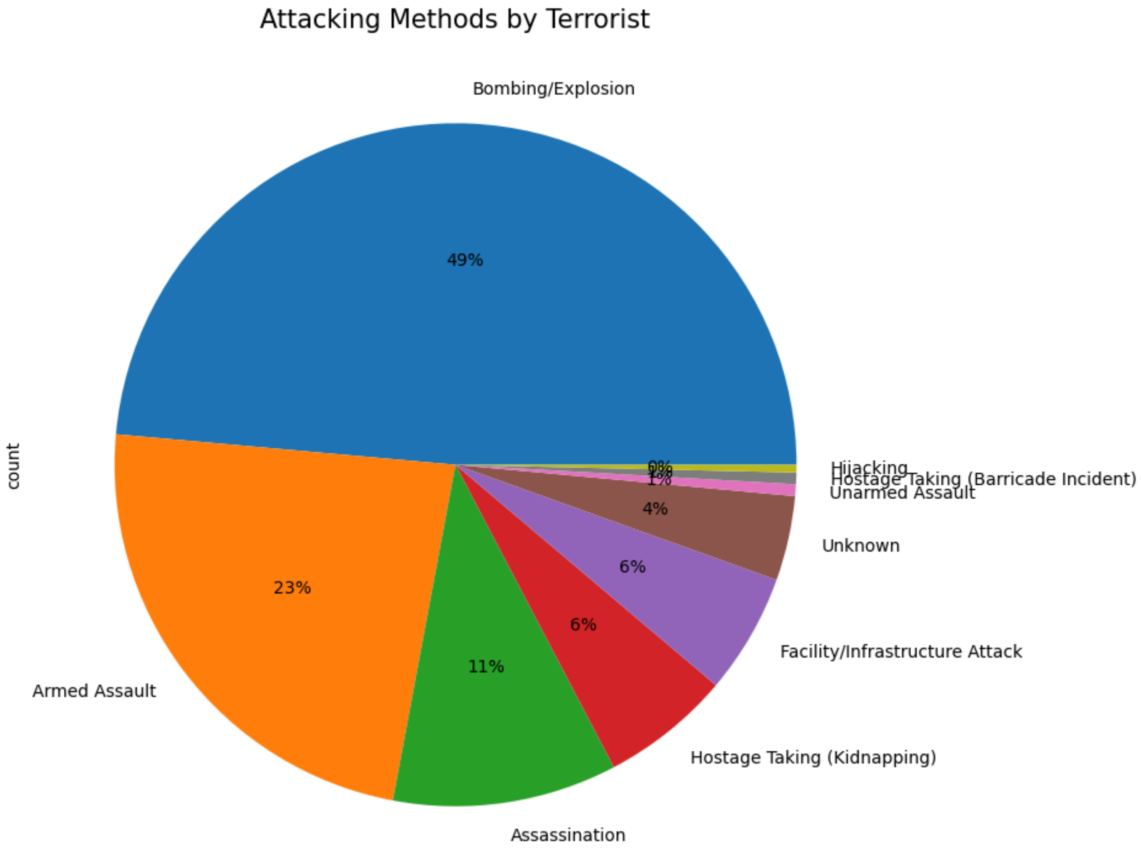
Attacking Methods by Terrorists

In [31]:
```
new_data.columns
```

Out[31]:
```
Index(['even_id', 'Year', 'Month', 'Day', 'Extend', 'Terrorist_Group',
       'individual', 'Number of Country', 'Country_Name', 'latitude',
       'longitude', 'city', 'region', 'Region_Name', 'success', 'suicide',
       'No.of Kill', 'Typ of Weapon', 'Attacktype', 'Attacktype_Name',
       'Target Type Name', 'Target Type', 'nwound', 'Causualties'],
      dtype='object')
```

In [32]:
```
attack_methods=new_data['Attacktype_Name'].value_counts()
plt.figure(figsize=(17,9))
attack_methods.plot(kind='pie',autopct='%1.0f%%')
plt.title("Attacking Methods by Terrorist",fontsize=15)
```

Out[32]:
```
Text(0.5, 1.0, 'Attacking Methods by Terrorist')
```



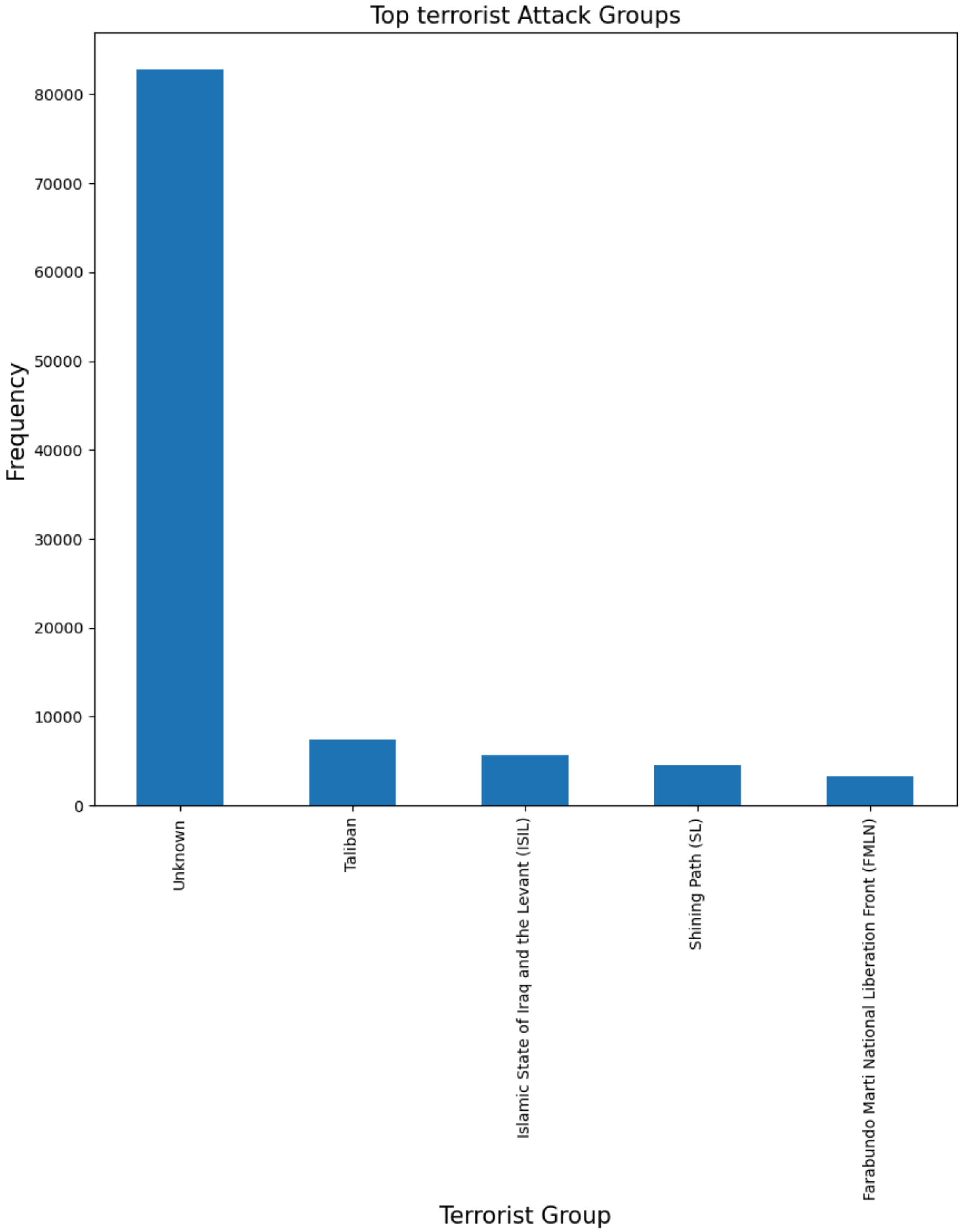
Observation

Bombing and explosion are the most commonly used methods in attacks, accounting for 49% of incidents. Additionally, armed assault is the second most frequently employed method.

Top Terrorist Attack Groups

In [33]:
```
terr_grp=new_data['Terrorist_Group'].value_counts()
terr_grp=terr_grp.sort_values(ascending=False).head(5)
plt.figure(figsize=(10,9))
terr_grp.plot(kind='bar')
plt.xlabel("Terrorist Group",fontsize=15)
plt.ylabel("Frequency",fontsize=15)
plt.title("Top terrorist Attack Groups",fontsize=15)
```

Out[33]:
```
Text(0.5, 1.0, 'Top terrorist Attack Groups')
```

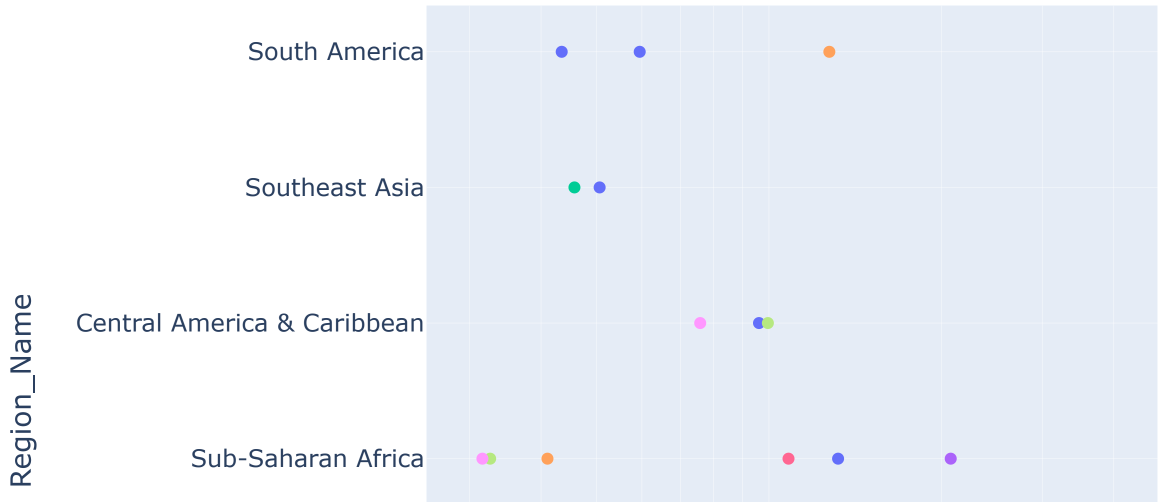


Observation

The Taliban is a prominent terrorist group, but it's important to note that the global terrorism landscape is complex. Other significant terrorist groups, like ISIS, Al-Qaeda, Boko Haram, and Al-Shabaab, also operate in various regions, making it challenging to definitively label one as the "most active" worldwide. The prominence of these groups can change over time.

Regions Attacked By Terrorist Groups

In [34]:
```
regions=new_data.groupby(['Region_Name','Terrorist_Group'])[['No.of Kill']].
regions=regions.sort_values(by='No.of Kill', ascending=False).head(25)
regions=px.scatter(regions,y='Region_Name',x='No.of Kill',color='Terrorist_G
regions.show()
```



People Killed and Wounded In Each Year

In [35]:
```
new_data.columns
```

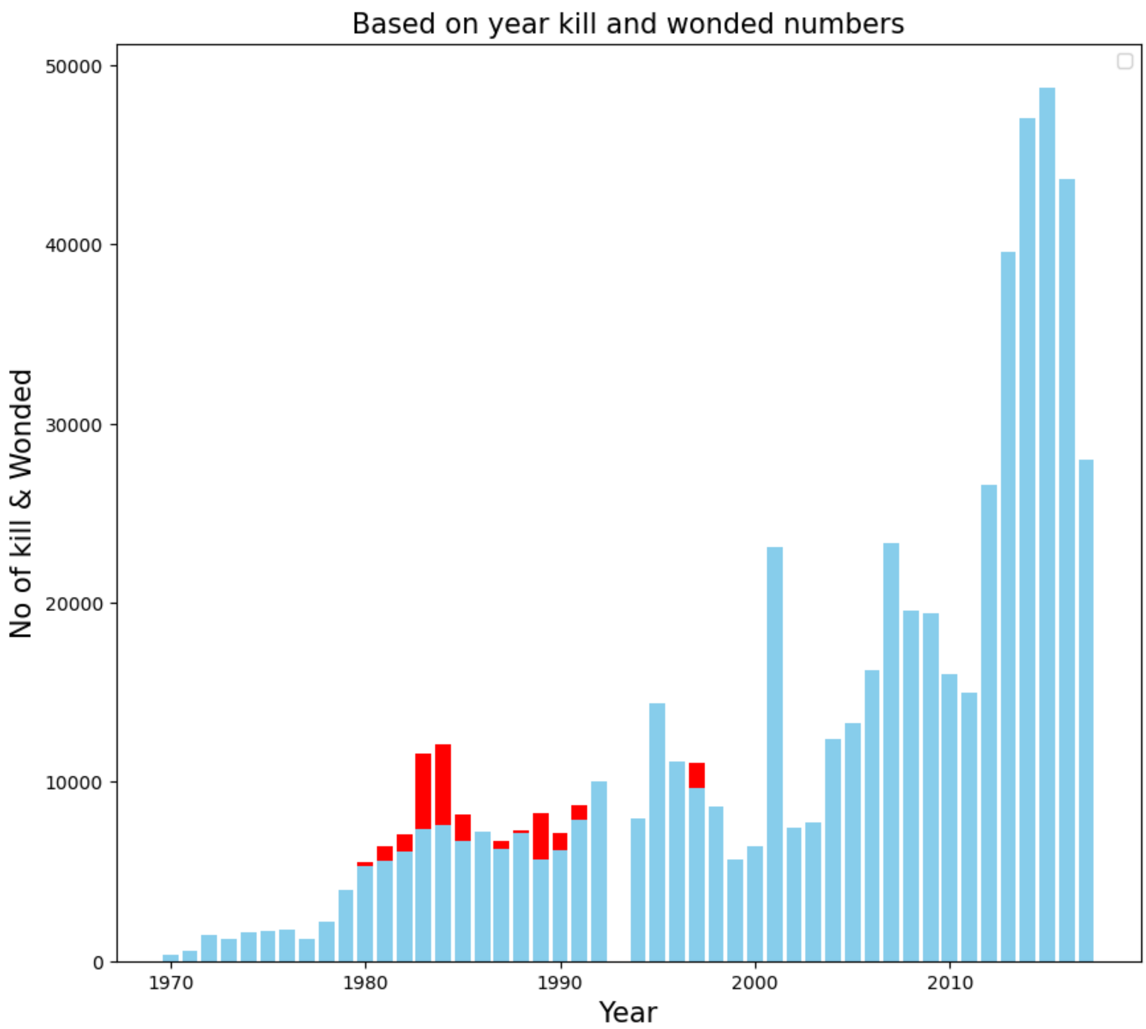
Out[35]:
```
Index(['even_id', 'Year', 'Month', 'Day', 'Extend', 'Terrorist_Group',
       'individual', 'Number of Country', 'Country_Name', 'latitude',
       'longitude', 'city', 'region', 'Region_Name', 'success', 'suicide',
       'No.of Kill', 'Typ of Weapon', 'Attacktype', 'Attacktype_Name',
       'Target Type Name', 'Target Type', 'nwound', 'Causualties'],
      dtype='object')
```

In [36]:
```
kill=new_data.groupby('Year')[['No.of Kill','nwound']].sum().reset_index()
kill=kill.sort_values(['No.of Kill','nwound'],ascending=False)
plt.figure(figsize=(10,9))
plt.bar(kill['Year'],kill['No.of Kill'],color='r',label='No.of Kill')
plt.bar(kill['Year'],kill['nwound'],color='skyblue',label='nwound')
plt.legend('No.of Kill','nwound')
plt.xlabel("Year",fontsize=15)
plt.ylabel("No of kill & Wonded",fontsize=15)
plt.title("Based on year kill and wonded numbers",fontsize=15)
```

```
C:\Users\DELL\AppData\Local\Temp\ipykernel_13092\645643231.py:6: UserWarnin
g:

Legend does not support handles for str instances.
A proxy artist may be used instead.
See: https://matplotlib.org/stable/tutorials/intermediate/legend_guide.html
#controlling-the-legend-entries (https://matplotlib.org/stable/tutorials/in
termediate/legend_guide.html#controlling-the-legend-entries)
```

Out[36]:
```
Text(0.5, 1.0, 'Based on year kill and wonded numbers')
```



People Killed and Wounded In Each Region

In [37]:
```
killed=new_data[["Region_Name","nwound"]].groupby("Region_Name").sum().sort_
killed
```

Out[37]:

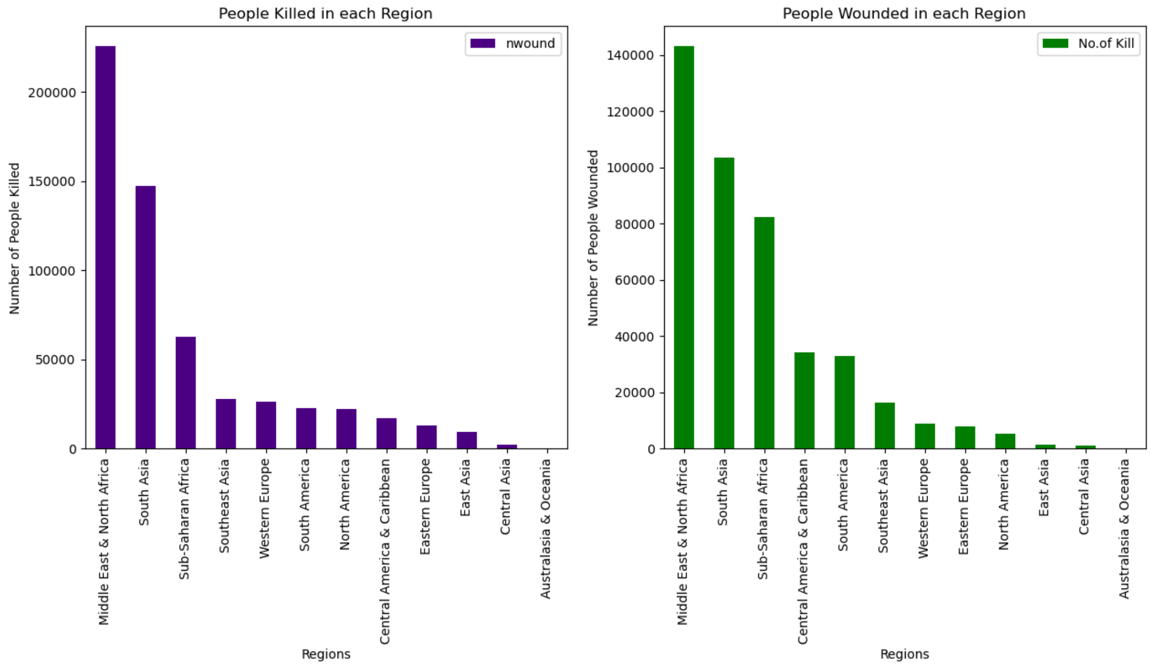
Region_Name	nwound
Middle East & North Africa	225572.228831
South Asia	147353.228613
Sub-Saharan Africa	62714.784061
Southeast Asia	27722.462801
Western Europe	26282.847684
South America	22643.378250
North America	21914.287876
Central America & Caribbean	16815.140948
Eastern Europe	12843.252437
East Asia	9355.545078
Central Asia	2034.341347
Australasia & Oceania	285.341347

In [38]:
```
wounded=new_data[["Region_Name","No.of Kill"]].groupby("Region_Name").sum().
wounded
```

Out[38]:

Region_Name	No.of Kill
Middle East & North Africa	143104.637935
South Asia	103570.866144
Sub-Saharan Africa	82262.478218
Central America & Caribbean	34288.398277
South America	32867.271283
Southeast Asia	16300.303154
Western Europe	8885.784336
Eastern Europe	7813.943202
North America	5139.504324
East Asia	1245.727620
Central Asia	1009.613089
Australasia & Oceania	164.419634

In [39]:
```
fig=plt.figure()
ax0=fig.add_subplot(1,2,1)
ax1=fig.add_subplot(1,2,2)
killed.plot(kind="bar",color="indigo",figsize=(15,6),ax=ax0)
ax0.set_title("People Killed in each Region")
ax0.set_xlabel("Regions")
ax0.set_ylabel("Number of People Killed")
wounded.plot(kind="bar",color="green",figsize=(15,6),ax=ax1)
ax1.set_title("People Wounded in each Region")
ax1.set_xlabel("Regions")
ax1.set_ylabel("Number of People Wounded")
plt.show()
```



No. Of Deaths Based on Country

In [40]:
```
loc = new_data.groupby(['Country_Name','Year'])['No.of Kill'].sum().reset_in
loc
```

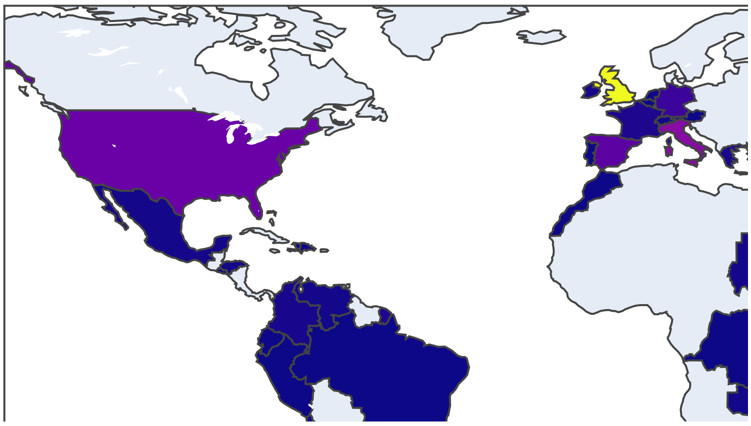
Out[40]:

	Country_Name	Year	No.of Kill
0	Afghanistan	1973	0.0
1	Afghanistan	1979	53.0
2	Afghanistan	1987	0.0
3	Afghanistan	1988	128.0
4	Afghanistan	1989	10.0
...	...	...	...
3757	Zimbabwe	2010	1.0
3758	Zimbabwe	2011	0.0
3759	Zimbabwe	2013	1.0
3760	Zimbabwe	2014	0.0
3761	Zimbabwe	2017	0.0

3762 rows × 3 columns

```
In [41]: map_ = px.choropleth(loc,
                             locationmode ='country names',
                             locations = loc['Country_Name'],
                             color = loc['No.of Kill'],animation_frame=loc['Year'],tit
         map_.show()
```

No of deaths based on country



Total Wounded by year.

```
In [42]: new_data.columns
```

```
Out[42]: Index(['even_id', 'Year', 'Month', 'Day', 'Extend', 'Terrorist_Group',
                'individual', 'Number of Country', 'Country_Name', 'latitude',
                'longitude', 'city', 'region', 'Region_Name', 'success', 'suicide',
                'No.of Kill', 'Typ of Weapon', 'Attacktype', 'Attacktype_Name',
                'Target Type Name', 'Target Type', 'nwound', 'Causualties'],
               dtype='object')
```

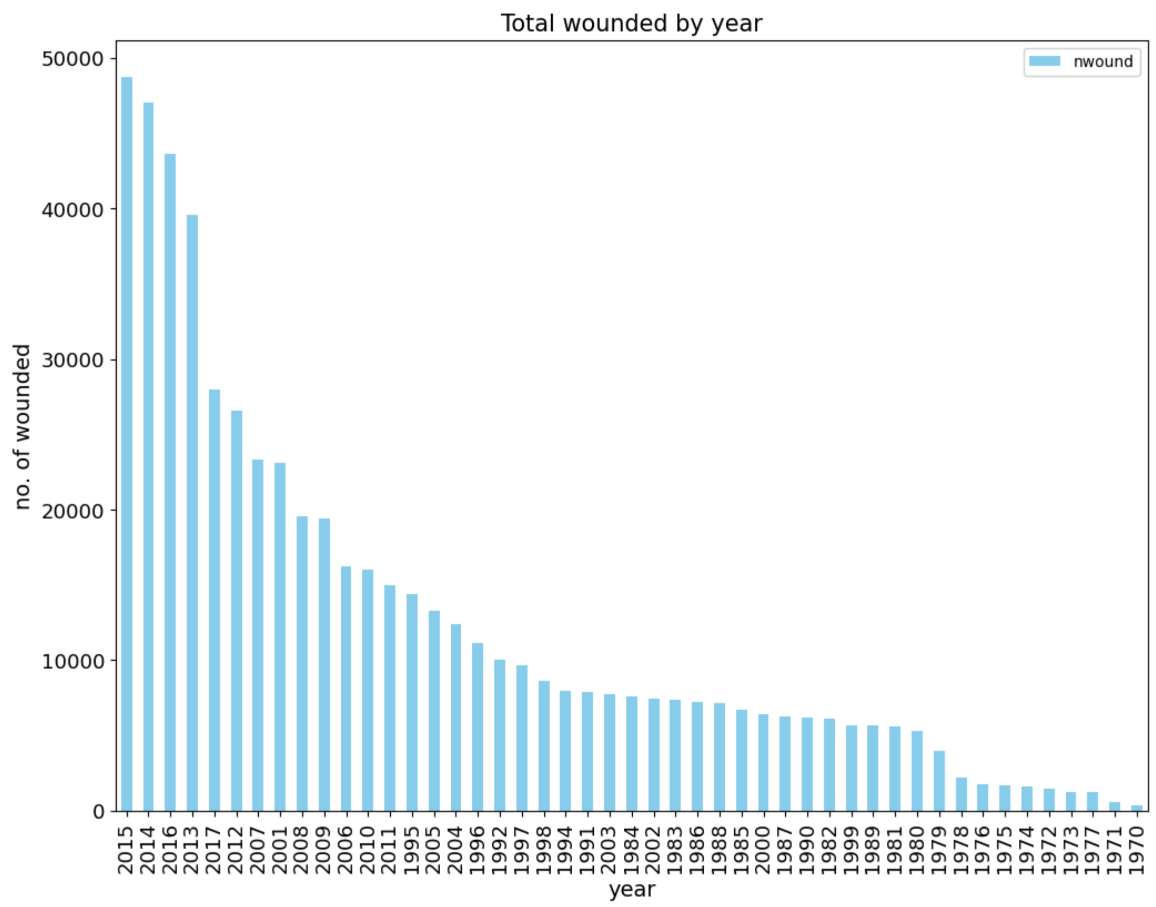
In [43]:
```
wounded=new_data.groupby('Year')[['nwound']].sum()
wounded=wounded.sort_values(by='nwound',ascending=False)
wounded.head()
```

Out[43]:

Year	nwound
2015	48743.819906
2014	47042.036903
2016	43643.818660
2013	39531.583009
2017	27964.793996

In [44]:
```
wounded.plot(kind='bar',color='skyblue',fontsize=13,figsize=(12,9))
plt.ylabel("no. of wounded",fontsize=14)
plt.xlabel("year",fontsize=14)
plt.title("Total wounded by year",fontsize=15)
```

Out[44]: Text(0.5, 1.0, 'Total wounded by year')



Types of terrorist attacks that cause deaths

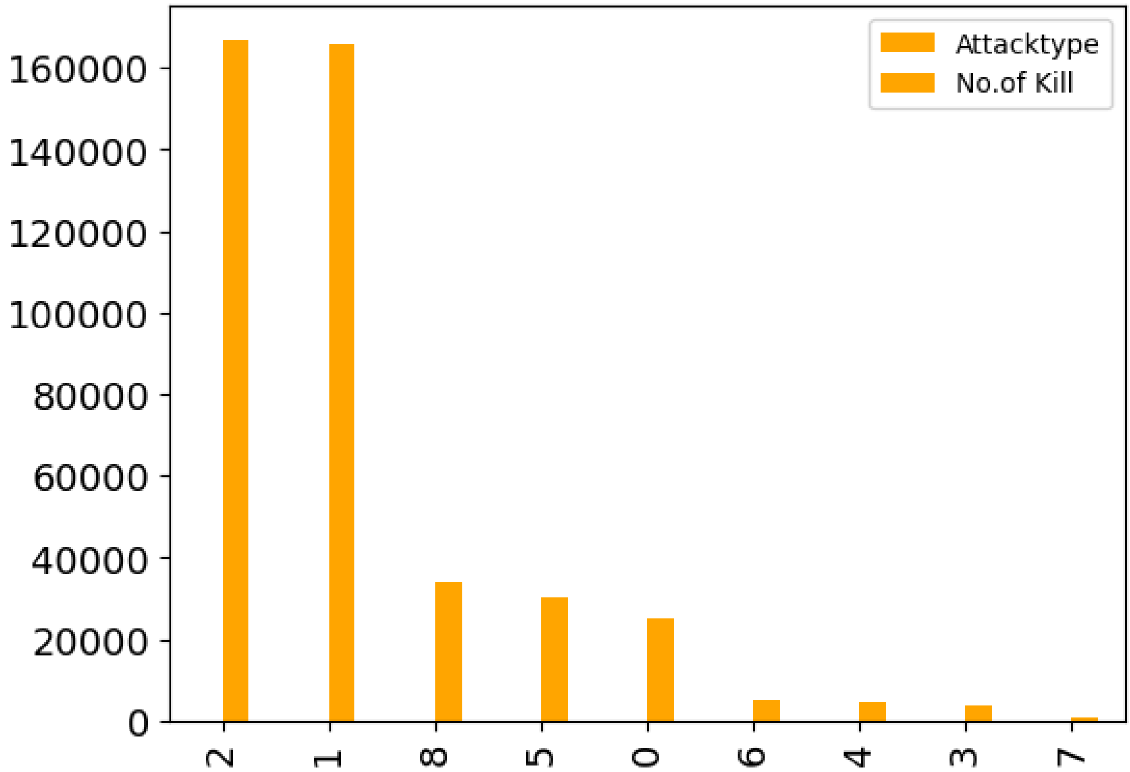
In [45]:
```
terr_attk=new_data.groupby('Attacktype')[['No.of Kill']].sum().reset_index()
terr_attk=terr_attk[terr_attk.index !='Unknown']
terr_attk=terr_attk.sort_values(by='No.of Kill',ascending=False)
terr_attk
```

Out[45]:

	Attacktype	No.of Kill
2	3	166773.069951
1	2	165862.978644
8	9	34084.920060
5	6	30354.537817
0	1	25109.858512
6	7	5007.058666
4	5	4701.504324
3	4	3845.373432
7	8	913.645812

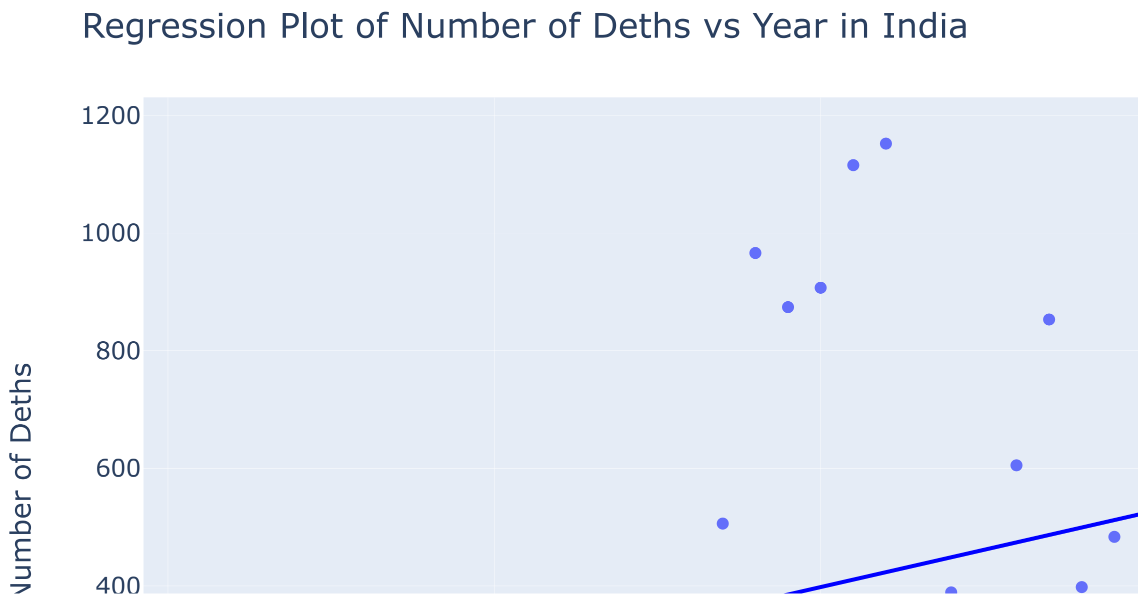
In [46]:
```
terr_attk.plot(kind='bar',color='orange',fontsize=14)
```

Out[46]: <Axes: >



Regression Plot of Number of Deths vs Year in India

In [47]:
```
india = new_data[new_data['Country_Name']== "India"]
india_group = india.groupby('Year')['No.of Kill'].sum().reset_index()
reg = px.scatter(india_group, x = 'Year', y = 'No.of Kill',trendline='ols',t
reg.update_layout(xaxis_title='Year',yaxis_title = 'Number of Deths',
                  title='Regression Plot of Number of Deths vs Year in India'
reg.show()
```



Terrorist Attack in India

In [48]:
```
new_data.columns
```

Out[48]:
```
Index(['even_id', 'Year', 'Month', 'Day', 'Extend', 'Terrorist_Group',
       'individual', 'Number of Country', 'Country_Name', 'latitude',
       'longitude', 'city', 'region', 'Region_Name', 'success', 'suicide',
       'No.of Kill', 'Typ of Weapon', 'Attacktype', 'Attacktype_Name',
       'Target Type Name', 'Target Type', 'nwound', 'Causualties'],
      dtype='object')
```

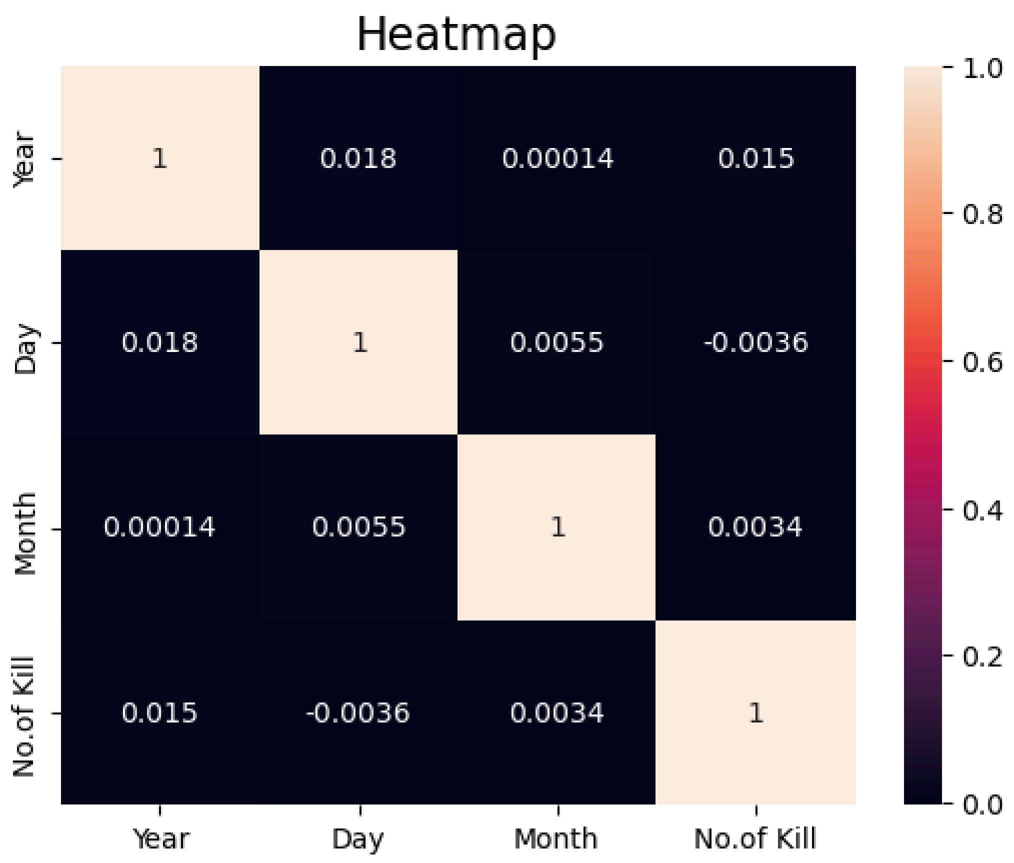
In [49]:
```
India_attk=india.groupby(['city','Terrorist_Group'])[['No.of Kill']].sum()
India_attk=India_attk.drop(index='Unknown')
India_attk=India_attk.sort_values(by='No.of Kill',ascending=False)
India_attk.head(10)
```

Out[49]:

city	Terrorist_Group	No.of Kill
Srinagar	Unknown	238.613089
Amritsar	Sikh Extremists	203.806545
Mumbai	Lashkar-e-Taiba (LeT)	188.000000
Dantewada district	Communist Party of India - Maoist (CPI-Maoist)	184.000000
Mumbai	Deccan Mujahideen	183.000000
Chandigarh	Sikh Extremists	157.403272
Ludhiana	Sikh Extremists	131.000000
Jhargam	Communist Party of India - Maoist (CPI-Maoist)	124.000000
Bombay	Muslim Militants	115.000000
Jammu	Lashkar-e-Taiba (LeT)	106.000000

In [ ]:

Heatmap Generate

In [64]:
```
sns.heatmap(new_data[['Year','Day','Month','No.of Kill']].corr(),annot=True)
plt.rcParams['figure.figsize']=(17,10);
plt.title('Heatmap',fontsize=16)
```
Out[64]:
```
Text(0.5, 1.0, 'Heatmap')
```


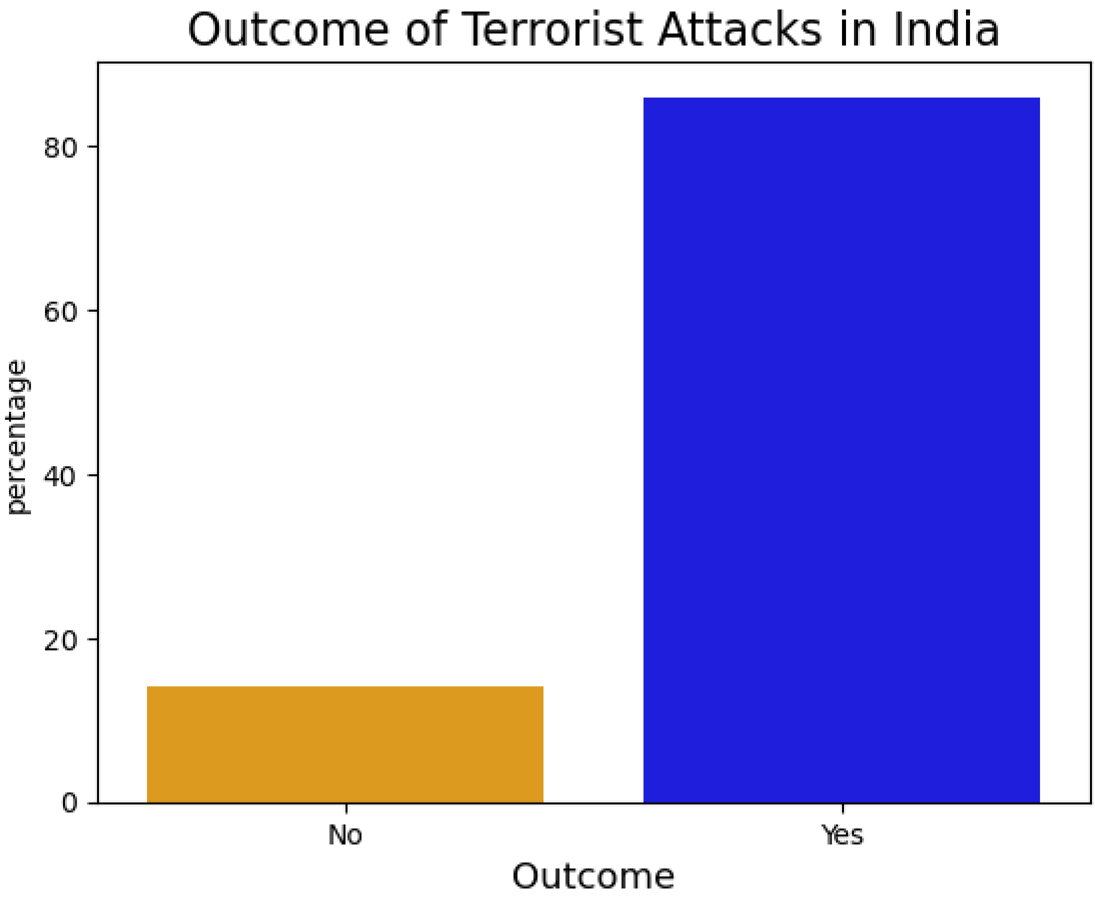
Outcome of terrorist attacked in India

In [51]:
```
outcome=india['even_id'].count()
outcome
```
Out[51]:
```
11960
```
In [52]:
```
success=india.groupby('success').size().reset_index(name='count')
success['percentage']=success['count']/outcome*100
success
```
Out[52]:

	success	count	percentage
0	No	1680	14.046823
1	Yes	10280	85.953177

In [53]:
```
sns.barplot(x='success',y='percentage',data=success,palette=['orange','blue'
plt.title("Outcome of Terrorist Attacks in India",fontsize=16)
plt.xlabel("Outcome",fontsize=13)
```

Out[53]:
```
Text(0.5, 0, 'Outcome')
```



Attack types in India and their success rates.

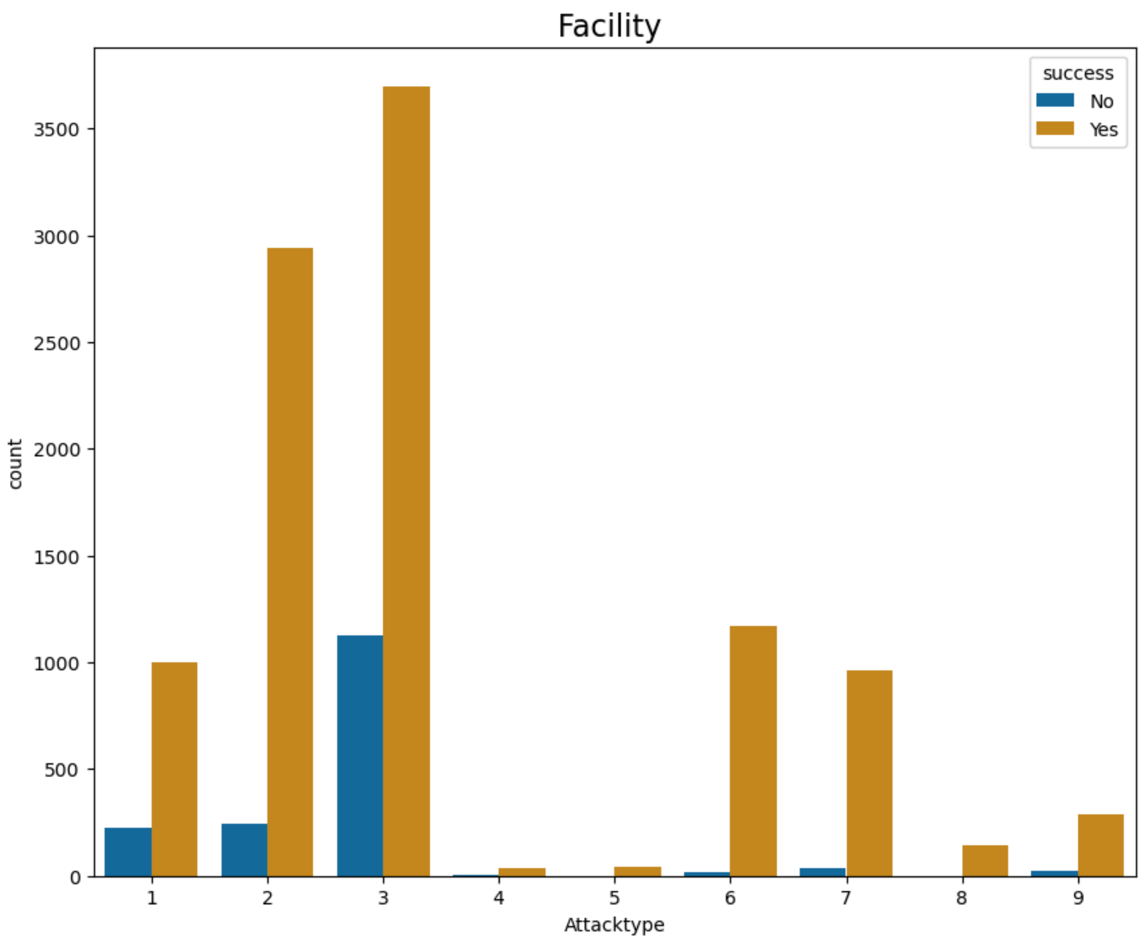
In [54]:
```
attk_type=india.groupby(['Attacktype','success']).size().reset_index(name='c
attk_type
```

Out[54]:

	Attacktype	success	count
0	1	No	228
1	1	Yes	1001
2	2	No	244
3	2	Yes	2940
4	3	No	1128
5	3	Yes	3697
6	4	No	4
7	4	Yes	39
8	5	No	1
9	5	Yes	43
10	6	No	16
11	6	Yes	1168
12	7	No	33
13	7	Yes	963
14	8	No	1
15	8	Yes	142
16	9	No	25
17	9	Yes	287

In [55]:
```
plt.figure(figsize=(10,8))
sns.barplot(data=attk_type,x='Attacktype',y='count',hue='success',palette='c
plt.title("Facility ",fontsize=16)
```

Out[55]:
```
Text(0.5, 1.0, 'Facility ')
```



Conclusion

The global community is grappling with a concerning surge in terrorism attacks, particularly evident in the Middle East and North Africa, as well as South America. These regions have witnessed a significant increase in terrorist activities, posing a serious threat to regional stability and security.

Of notable concern is the high success rate of these attacks, with a staggering 89% of incidents resulting in successful outcomes. This underscores the resilience and effectiveness of terrorist groups and individuals in achieving their objectives, exacerbating the impact on affected communities.

Moreover, the prevalent use of bombings and explosions as primary tactics in these attacks has resulted in substantial casualties and widespread destruction. The devastating consequences highlight the urgent need for comprehensive strategies to counteract the proliferation and use of explosives, as well as to address the root causes of terrorism.

In light of these challenges, concerted efforts aimed at enhancing intelligence-sharing, strengthening security measures, and fostering international cooperation are imperative to effectively combat the threat of terrorism and promote global peace and stability

Thank You

In [ ]:
```

```