```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
```

pandas: It used for data manipulation and analysis. numPy: It is a powerful Python library for numerical computing. seaborn: It provides a high-level interface for creating attractive and informative statistical graphics. matplotlib.pyplot: It provides a MATLAB-like interface for creating basic plots and visualizations.

```
df=pd.read_csv("nuclear_explosions.csv")
```

pd.read\_csv is used to read the data from the csv files df is the variable in which the data is getting stored from the csv files

df

	Location.Country	Location.Region	Data.Source	Location.Cordinates.La
0	USA	Alamogordo	DOE	
1	USA	Hiroshima	DOE	
2	USA	Nagasaki	DOE	
3	USA	Bikini	DOE	
4	USA	Bikini	DOE	
2041	CHINA	Lop Nor	HFS	
2042	INDIA	Pokhran	HFS	
2043	INDIA	Pokhran	NRD	
2044	PAKIST	Chagai	HFS	
2045	PAKIST	Kharan	HFS	

2046 rows × 16 columns

Double-click (or enter) to edit

df.head()

	Location.Country	Location.Region	Data.Source	Location.Cordinates.Latit
0	USA	Alamogordo	DOE	3
1	USA	Hiroshima	DOE	3
2	USA	Nagasaki	DOE	3
3	USA	Bikini	DOE	1
4	USA	Bikini	DOE	1

head() --> function is used to read the starting 5 lines from the dataset

df.tail()

	Location.Country	Location.Region	Data.Source	Location.Cordinates.La
2041	CHINA	Lop Nor	HFS	
2042	INDIA	Pokhran	HFS	
2043	INDIA	Pokhran	NRD	
2044	PAKIST	Chagai	HFS	
2045	PAKIST	Kharan	HFS	

tail() --> tail() function is used to read the ending 5 lines from the dataset

	Location.Country	Location.Region	Data.Source	Location.Cordinates.La
1574	USSR	Bashki Russ	MTM	
95	USSR	Semi Kazakh	DOE	
252	USSR	Nz Russ	DOE	
406	USA	Nts	DOE	
1396	USA	Nts	DOE	
1502	FRANCE	Mururoa	WTN	
1304	USSR	Jakuts Russ	MTM	
2030	CHINA	Lop Nor	HFS	

sample(8) --> function is used to get the sample of 8 rows from the given dataset

# df.dtypes

Location.Country	object
Location.Region	object
Data.Source	object
Location.Cordinates.Latitude	float64
Location.Cordinates.Longitude	float64
Data.Magnitude.Body	float64
Data.Magnitude.Surface	float64
Location.Cordinates.Depth	float64
Data.Yeild.Lower	float64
Data.Yeild.Upper	float64
Data.Purpose	object
Data.Name	object
Data.Type	object
Date.Day	int64
Date.Month	int64
Date.Year	int64
dtype: object	

dtypes --> It is used to get the datatype of the specified columns from the given datasets

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2046 entries, 0 to 2045
Data columns (total 16 columns):

#	Column	Non-N	Iull Count	Dtype
0	Location.Country	2046	non-null	object
1	Location.Region	2046	non-null	object
2	Data.Source	2046	non-null	object
3	Location.Cordinates.Latitude	2046	non-null	float64
4	Location.Cordinates.Longitude	2046	non-null	float64
5	Data.Magnitude.Body	2046	non-null	float64
6	Data.Magnitude.Surface	2046	non-null	float64
7	Location.Cordinates.Depth	2046	non-null	float64
8	Data.Yeild.Lower	2046	non-null	float64
9	Data.Yeild.Upper	2046	non-null	float64
10	Data.Purpose	2046	non-null	object
11	Data.Name	2046	non-null	object
12	Data.Type	2046	non-null	object
13	Date.Day	2046	non-null	int64
14	Date.Month	2046	non-null	int64
15	Date.Year	2046	non-null	int64
dtvpe	es: float64(7), int64(3), objec	t(6)		

dtypes: float64(7), int64(3), object(6)

memory usage: 255.9+ KB

info() --> It is used to get the Information of about each and every columns It will also tell about the no. of the cells which are non-empty by displaying their number

#### df.count()

Location.Country	2046
Location.Region	2046
Data.Source	2046
Location.Cordinates.Latitude	2046
Location.Cordinates.Longitude	2046
Data.Magnitude.Body	2046
Data.Magnitude.Surface	2046
Location.Cordinates.Depth	2046
Data.Yeild.Lower	2046
Data.Yeild.Upper	2046
Data.Purpose	2046
Data Name	2046
Data.Type	2046
Date Day	2046
Date.Month	2046
Date.Year	2046
dtyne: int6/	

dtype: int64

```
count() --> It is used to count the non-empty cells of each column It will display the number of
that sooo...
df.shape
     (2046, 16)
shape --> It is used to determine the dimensions or the size of an array or DataFrame. 1715 -->
Rows 9 --> Columns
df.columns
     Index(['Location.Country', 'Location.Region', 'Data.Source',
             'Location.Cordinates.Latitude', 'Location.Cordinates.Longitude',
            'Data.Magnitude.Body', 'Data.Magnitude.Surface',
            'Location.Cordinates.Depth', 'Data.Yeild.Lower',
     'Data.Yeild.Upper',
            'Data.Purpose', 'Data.Name', 'Data.Type', 'Date.Day', 'Date.Month',
             'Date Year'],
           dtype='object')
columns --> It will display the column names
df['Data.Magnitude.Surface'].mean()
     0.35669599217986314
mean() --> It is used to find the mean of the required column data
df['Date.Year'].median()
     1970.0
median() --> It is used to find the median of the required column data
df['Date.Year'].std()
     10.372759916312438
```

std() --> It is used to find the Standard Deviation of the required column data

```
df['Date.Year'].mode()
```

0 1962

Name: Date.Year, dtype: int64

mode() --> It is used to find the mode of the required column data

df.describe()

Location.Cordinates.Latitude Location.Cordinates.Longitude Data.Mag

count 2046.000000 2046.000000

35.462429 -36.015037

mean	35.462429	-36.015037
std	23.352702	100.829355
min	-49.500000	-169.320000
25%	37.000000	-116.051500
50%	37.100000	-116.000000
75%	49.870000	78.000000
max	75.100000	179.220000

describe() --> It is used to describe the dataset into the count,mean,std,min,25%,50% (median),75%,max It will only describe and find the values of the dataset columns which are in float or integer

df["Location.Country"].value\_counts()

USA 1031 USSR 714 FRANCE 208 UK 45 CHINA 43 INDIA 3 PAKIST 2

Name: Location.Country, dtype: int64

value\_counts() --> It will count the no. of times the specfic column name present in the dataset

df["Location.Cordinates.Depth"].unique() #list of unique entries

```
3.000e-02, -8.000e-02,
array([-1.000e-01, -6.000e-01, -2.000e-01,
        0.000e+00, -3.500e-01, -4.000e-01, -5.000e-01, -7.000e-02,
       -3.000e-02, -4.500e-01, -1.000e-03, 1.000e-02, -2.500e-01,
       -1.150e+00, -2.000e+00, -8.000e-01,
                                             2.000e-02, -1.200e+01,
       -1.500e+00, -6.800e+00,
                                3.000e-01, -2.800e+01,
                                                         2.000e-01,
        5.000e-02, -8.500e+01, -4.500e+01, -1.600e+02,
                                                          1.000e-01,
       -2.000e-03, -1.500e-01, -2.500e-02, -2.000e-02, -1.000e-02,
                                 1.500e-01, -4.000e+02,
        4.500e-01,
                    2.500e-01,
                                                          6.000e-01,
        3.500e-01,
                    5.000e-01,
                                 9.000e-01,
                                             7.130e-01,
                                                          3.050e-01,
        4.120e-01,
                    7.650e-01,
                                 7.320e-01,
                                              6.370e-01,
                                                          9.120e-01,
        1.311e+00,
                    4.170e-01,
                                 3.480e-01,
                                              1.265e+00,
                                                          8.170e-01,
        3.200e-01,
                    7.160e-01,
                                 1.451e+00,
                                              6.400e-01,
                                                          6.550e-01,
        1.219e+00,
                    1.167e+00,
                                 8.690e-01,
                                              1.237e+00,
                                                          8.790e-01,
        7.800e-01,
                    3.170e-01,
                                 4.270e-01,
                                              3.310e-01,
                                                          6.900e-01,
                    5.640e-01,
                                 5.180e-01,
                                                          3.810e-01,
        5.940e-01,
                                             7.010e-01,
        5.300e-01,
                    3.850e-01,
                                 3.720e-01,
                                              6.680e-01,
                                                          6.580e-01,
        6.330e-01,
                    6.110e-01,
                                 6.810e-01,
                                              3.880e-01,
                                                          4.420e-01,
                                                          5.790e-01,
        5.760e-01,
                    5.420e-01,
                                 6.890e-01,
                                              3.260e-01,
        5.360e-01,
                                                          4.640e-01,
                    3.350e-01,
                                 5.370e-01,
                                              3.960e-01,
        2.290e-01,
                    2.050e-01,
                                 3.690e-01,
                                              2.710e-01,
                                                          3.510e-01,
        6.450e-01,
                    6.800e-01,
                                 3.660e-01,
                                              4.240e-01,
                                                          3.900e-01,
        5.730e-01,
                    3.540e-01,
                                 3.230e-01,
                                              3.410e-01,
                                                          2.040e-01,
                    2.130e-01,
        2.940e-01,
                                 4.720e-01,
                                             4.450e-01,
                                                          4.940e-01,
                                                          4.000e-01,
        6.510e-01,
                    3.570e-01,
                                 5.700e-01,
                                              2.890e-01,
        2.160e-01,
                    4.510e-01,
                                 3.360e-01,
                                             4.130e-01,
                                                          3.040e-01,
        3.430e-01,
                    5.330e-01,
                                 2.650e-01,
                                              3.840e-01,
                                                          6.250e-01,
                    5.150e-01,
                                 6.610e-01,
                                             6.080e-01,
        4.050e-01,
                                                          2.930e-01,
        3.320e-01,
                    4.150e-01])
```

.unique() --> It is used to count the unique enteries in that column

Location.Country Location.Region Data.Source Location.Cordinates.La 0 USA DOE Alamogordo 1 **USA** Hiroshima DOE 2 USA Nagasaki DOE 3 USA Bikini DOE USA Bikini DOE 2041 **CHINA** Lop Nor **HFS** 2042 **INDIA** Pokhran **HFS** 2043 **INDIA** Pokhran NRD 2044 **PAKIST** Chagai **HFS** 2045 Kharan **PAKIST** HFS

2046 rows x 16 columns

.sort\_values() --> It will sort the values and provides u the data in the sorting manner If ascending of descending is not given then by default it will give u the data in the ascending manner/order only

#### df.isnull().sum()

Location.Country	0
Location.Region	0
Data.Source	0
Location.Cordinates.Latitude	0
Location.Cordinates.Longitude	0
Data.Magnitude.Body	0
Data.Magnitude.Surface	0
Location.Cordinates.Depth	0
Data.Yeild.Lower	0
Data.Yeild.Upper	0
Data.Purpose	0
Data.Name	0
Data.Type	0
Date.Day	0
Date.Month	0
Date.Year	0
dtype: int64	

isnull() --> It will Return u the no. of the empty cells in the row

df.drop(["Location.Cordinates.Latitude","Location.Cordinates.Longitude","Data.Ye

.drop() --> It is used to delete the specified columns As the no. of the empty cells in the column anzsic\_descriptor2 is 105 and category is 179 and this both the columns are not useful to predict the data so deleting both the columns

df.head()

	Location.Country	Location.Region	Data.Source	Data.Magnitude.Body	Data
0	USA	Alamogordo	DOE	0.0	
1	USA	Hiroshima	DOE	0.0	
2	USA	Nagasaki	DOE	0.0	
3	USA	Bikini	DOE	0.0	
4	USA	Bikini	DOE	0.0	

Checking for the deleted columns

```
df.dropna(inplace=True)
```

dropna() --> It is used to delete the rows which have very less null values and then bring the data in the equal manner.

## df.isnull().sum()

Location.Country	0
Location.Region	0
Data.Source	0
Data.Magnitude.Body	0
Data.Magnitude.Surface	0
Location.Cordinates.Depth	0
Data.Yeild.Lower	0
Data.Purpose	0
Data.Name	0
Data.Type	0
Date.Day	0
Date.Month	0
Date.Year	0
dtvpe: int64	

There is no null cell in the rows

#### df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2046 entries, 0 to 2045
Data columns (total 13 columns):

#	Column	Non-Null Count	Dtype
0	Location.Country	2046 non-null	object
1	Location.Region	2046 non-null	object
2	Data.Source	2046 non-null	object
3	Data.Magnitude.Body	2046 non-null	float64
4	Data.Magnitude.Surface	2046 non-null	float64
5	Location.Cordinates.Depth	2046 non-null	float64
6	Data.Yeild.Lower	2046 non-null	float64
7	Data.Purpose	2046 non-null	object
8	Data.Name	2046 non-null	object
9	Data.Type	2046 non-null	object
10	Date.Day	2046 non-null	int64
11	Date.Month	2046 non-null	int64
12	Date.Year	2046 non-null	int64

dtypes: float64(4), int64(3), object(6)

memory usage: 207.9+ KB

## **DETECTING OUTLIER**

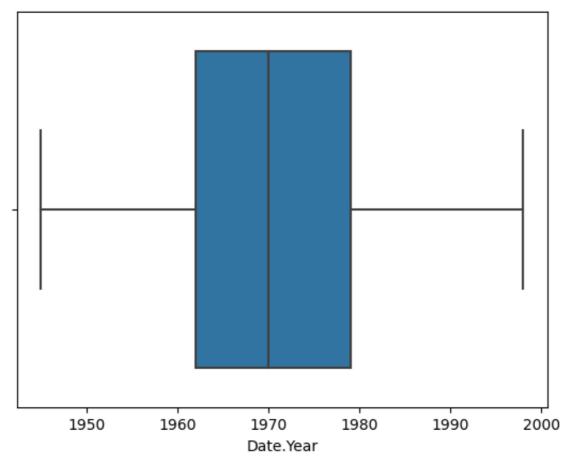
**Outlier** --> It is an extreme value that falls far outside the typical range of values in a dataset.

# It is a **Univarient Analysis**

Bcz we are analyzing using the single variable

sns.boxplot(x=df['Date.Year'])

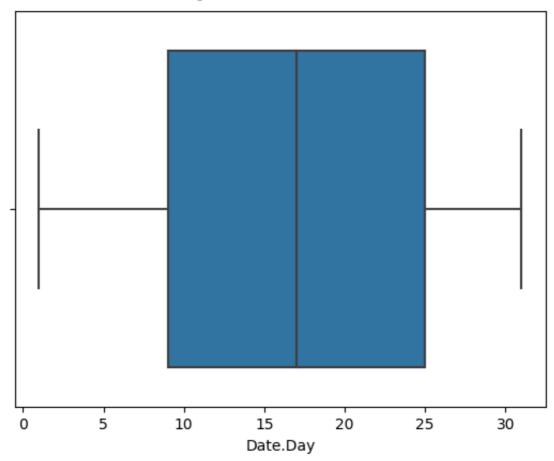
<Axes: xlabel='Date.Year'>



There is no outlier in the year column

### sns.boxplot(x=df['Date.Day'])

<Axes: xlabel='Date.Day'>



### There are outlier in the data\_val column

```
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1
print(IQR)
```

```
Data Magnitude Body
                              5.1
Data.Magnitude.Surface
                              0.0
Location.Cordinates.Depth
                              0.0
Data.Yeild.Lower
                             20.0
Date Day
                             16.0
Date.Month
                              5.0
Date Year
                             17.0
dtype: float64
<ipython-input-41-4cd70db7bbb2>:1: FutureWarning: The default value of nume
  Q1 = df.quantile(0.25)
<ipython-input-41-4cd70db7bbb2>:2: FutureWarning: The default value of nume
  Q3 = df.quantile(0.75)
```

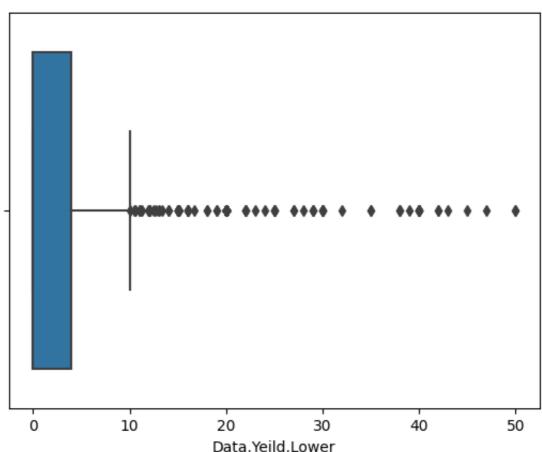
This Calculates Interquartile Range (IQR) for each column in 25 % and 75 % and then it will substract to get the 50% of Interguartile Range (IQR)

```
<ipython-input-42-f4e1682787c4>:1: FutureWarning: Automatic reindexing on D df = df[\sim((df < (Q1 - 1.5 * IQR)) |(df > (Q3 + 1.5 * IQR))).any(axis=1)] (1420, 13)
```

(df < (Q1 - 1.5 \* IQR)): This part of the expression checks if any value in the DataFrame is less than the lower bound (Q1 - 1.5 \* IQR). (df > (Q3 + 1.5 \* IQR)): This part of the expression checks if any value in the DataFrame is greater than the upper bound (Q3 + 1.5 \* IQR). The | operator is used to combine these two conditions with an OR operation.

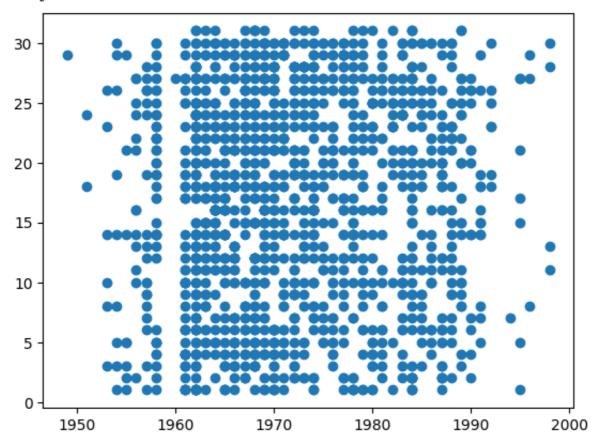
sns.boxplot(x=df['Data.Yeild.Lower'])

<Axes: xlabel='Data.Yeild.Lower'>



EDA (Exploratory Data Analysis) It is used to understand the main characteristics, patterns, and insights hidden in the data.

<matplotlib.collections.PathCollection at 0x781f5442bdf0>



Scatter PlotT It is Bivarent analysis because the 2 variables that is x and y are used. It represents data points as individual dots on a two-dimensional plane, with one variable on the x-axis and the other variable on the y-axis. Each dot represents an observation or data point. In this also year is the x axis whereas the data\_val is the y axis

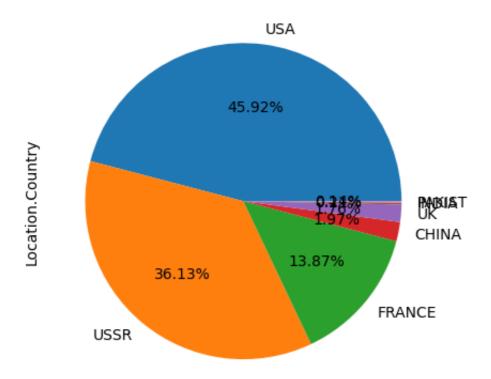
pie=df['Location.Country'].value\_counts()
pie

USA 652 USSR 513 FRANCE 197 CHINA 28 UK 25 INDIA 3 PAKIST 2

Name: Location.Country, dtype: int64

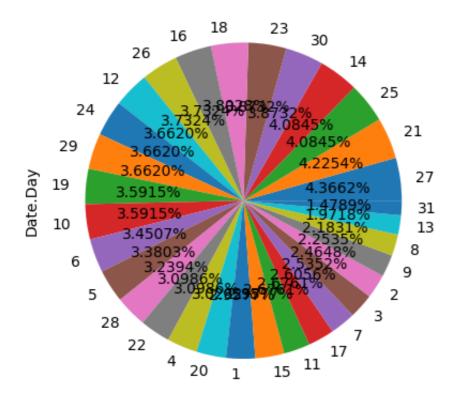
pie.plot(kind="pie",autopct="%.2f%%")

<Axes: ylabel='Location.Country'>



df["Date.Day"].value\_counts().plot(kind="pie",autopct="%.4f%")

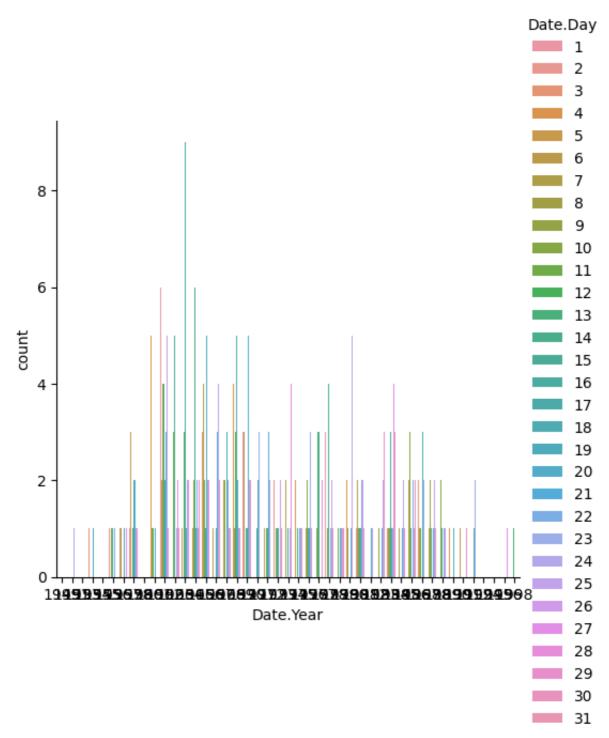
<Axes: ylabel='Date.Day'>



Pie Chart It is univarient analysis, as single variable is used. In this region and gas can show the region in the pie format. It is called a "pie chart" because the chart resembles a pie that is divided into slices, with each slice representing a particular category or data point. The size of each slice corresponds to the proportion or percentage of the whole that each category represents.

sns.catplot(x = 'Date.Year', hue = 'Date.Day', kind = 'count', data = df)

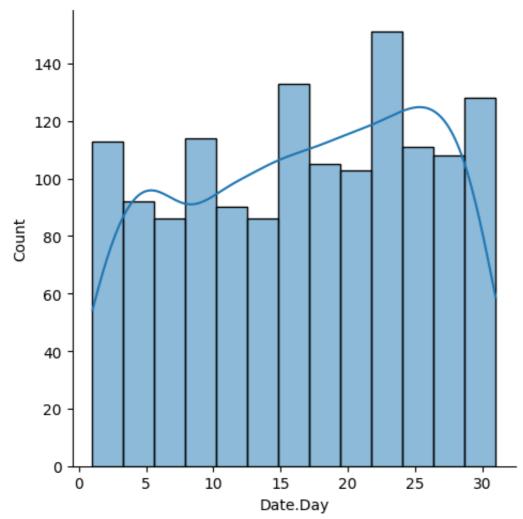
<seaborn.axisgrid.FacetGrid at 0x781f5436a5f0>



Count Plot In the Countplots height of each bar represents the number of occurrences of each category in the dataset. Countplots are particularly useful for visualizing the frequency of different categories and identifying the most common or least common categories in the data. In this the number of the gases released in each year.

sns.displot(df['Date.Day'],kde=True)

<seaborn.axisgrid.FacetGrid at 0x781f51d12020>



DisPlot displot is used to create a histogram to visualize the distribution of a numerical variable. It is used to create a KDE plot to visualize the estimated probability density function of a numerical variable. KDE plots show the smoothed continuous representation of the data distribution.

```
plt.figure(figsize=(10,5))
c= df.corr()
sns.heatmap(c,cmap="Pu0r",annot=True)
c
```

,,		Data.Ma	gnitude	.Body I	Data.Mag	nitude.	Surface	Locatio
Data.Magnitude.Bo	ody		1.0	000000			NaN	
Data.Magnitude.Surface		NaN			NaN			
Location.Cordinates.Depth		NaN			NaN			
Data.Yeild.Lower		0.246964			NaN			
Date.Day		0.073483			NaN			
Date.Month			0.0	)24775			NaN	
Date.Year			0.3	367198			NaN	
Data.Magnitude.Body -	1			0.25	0.073	0.025	0.37	1.0
Data.Magnitude.Surface -								- 0.8
Location.Cordinates.Depth -								- 0.6
Data.Yeild.Lower –	0.25			1	0.0081	0.00079	-0.11	- 0.4
Date.Day -	0.073			0.0081	1	-0.067	0.055	0.2
Date.Month -	0.025			0.00079	-0.067	1	-0.026	- 0.2
Date.Year -	0.37			-0.11	0.055	-0.026	1	- 0.0
	Data.Magnitude.Body -	Data.Magnitude.Surface -	ocation.Cordinates.Depth -	Data.Yeild.Lower -	Date.Day -	Date.Month -	Date.Year -	_

In machine learning, splitting the data into X and Y components serves the purpose of preparing the data for model training and evaluation. The X and Y components represent the features (input) and the corresponding target variable (output) for the learning process. This separation is crucial for several reasons: Training the Model: In supervised machine learning, we have a dataset with input-output pairs. The X-axis contains the input features (often denoted as X or features matrix), and the Y-axis contains the corresponding target values (often denoted as Y or target vector). During model training, the algorithm learns from the patterns in the input-output relationships to make predictions. Feature Extraction: The X-axis includes the features or attributes that are used to describe the data instances. Each row in the X-axis represents an individual data point, and each column corresponds to a specific feature. Feature extraction and selection are essential steps in machine learning, and separating features from the target variable allows you to apply different preprocessing steps to them independently. Model Evaluation: After training a machine learning model, it needs to be evaluated to assess its performance and generalization ability on unseen data. For evaluation, the model is provided with new input features (X) to make predictions, and the predictions are compared with the corresponding target values (Y) to calculate performance metrics like accuracy, mean squared error, etc. Avoiding Data Leakage: Data leakage is a situation where information from the target variable is inadvertently included in the features during model training. This can lead to overfitting, where the model performs well on the training data but poorly on new, unseen data. By keeping the target variable (Y) separate from the features (X) during training, we prevent data leakage and ensure the model's ability to generalize to new data. Cross-Validation: When performing cross-validation, where the dataset is split into multiple subsets for training and testing, keeping X and Y separate is essential. This helps ensure that during each fold of cross-validation, the model doesn't get access to the target variable of the test set, preventing any data leakage.

	Location.Country	Location.Region	Data.Source	Data.Magnitude.Body	D
8	USSR	Semi Kazakh	DOE	0.0	
18	USSR	Semi Kazakh	DOE	0.0	
19	USSR	Semi Kazakh	DOE	0.0	
50	USSR	Semi Kazakh	DOE	0.0	
51	USSR	Semi Kazakh	MTM	0.0	
2041	CHINA	Lop Nor	HFS	5.3	
2042	INDIA	Pokhran	HFS	5.3	
2043	INDIA	Pokhran	NRD	0.0	
2044	PAKIST	Chagai	HFS	0.0	
2045	PAKIST	Kharan	HFS	5.0	

1420 rows × 5 columns

In x axis we r including all the columns except the targeted row which will be the y axis

```
y=df.iloc[:,5]
    8
             0.0
    18
             0.0
    19
             0.0
    50
             0.0
    51
             0.0
    2041
             0.0
    2042
             0.0
    2043
             0.0
    2044
             0.0
    2045
    Name: Location.Cordinates.Depth, Length: 1420, dtype: float64
```

In y axis we r including the targeted row only i.e data\_val row Which will going to calculate and give us the value of the data i.e how much greenhouse gass emmision would be produced by each region in the year

