

Muley_Tushar_Project_1

January 9, 2022

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Assignment: Project 1 - Human and Economic Cost of Hurricanes

Date: Jan 9, 2022

```
[1]: # Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
import math
import statsmodels.api as sm
from statsmodels.formula.api import ols
```

```
[2]: # Setting changes
pd.set_option('display.max_columns', None)
```

```
[3]: # Load data into a dataframe
file = "natural-disasters.csv"

disaster_df = pd.read_csv(file)
```

```
[5]: # Check the dimension of the table/look at the data
print("The dimension of the table is: ", disaster_df.shape)
```

The dimension of the table is: (5569, 169)

```
[6]: # View the information on the data
disaster_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5569 entries, 0 to 5568
Columns: 169 entries, Number of deaths from drought to
total_damages_pct_gdp_glacial_lake
```

```
dtypes: float64(159), int64(9), object(1)
memory usage: 7.2+ MB
```

```
[7]: # Print the columns names
print("Column names: ", disaster_df.columns)
```

```
Column names: Index(['Number of deaths from drought',
                    'Number of people injured from drought',
                    'Number of people affected from drought',
                    'Number of people left homeless from drought',
                    'Number of total people affected by drought',
                    'Reconstruction costs from drought', 'Insured damages against drought',
                    'Total economic damages from drought', 'Death rates from drought',
                    'Injury rates from drought',
                    ...,
                    'Total economic damages from extreme temperatures as a share of GDP',
                    'Total economic damages from floods as a share of GDP',
                    'Total economic damages from landslides as a share of GDP',
                    'Total economic damages from mass movements as a share of GDP',
                    'Total economic damages from storms as a share of GDP',
                    'Total economic damages from volcanic activity as a share of GDP',
                    'Total economic damages from volcanic activity as a share of GDP.1',
                    'Entity', 'Year', 'total_damages_pct_gdp_glacial_lake'],
                    dtype='object', length=169)
```

```
[8]: # What type of variables are in the table before dropping variables.
print("Describe Data")
print(disaster_df.describe())
```

Describe Data

	Number of deaths from drought	Number of people injured from drought \
count	8.120000e+02	812.000000
mean	2.889513e+04	0.078818
std	2.234236e+05	1.587154
min	0.000000e+00	0.000000
25%	0.000000e+00	0.000000
50%	0.000000e+00	0.000000
75%	0.000000e+00	0.000000
max	3.000000e+06	32.000000

	Number of people affected from drought \
count	8.120000e+02
mean	6.791441e+06
std	3.268972e+07
min	0.000000e+00
25%	0.000000e+00
50%	1.975000e+05
75%	1.890100e+06
max	3.829851e+08

	Number of people left homeless from drought \
count	812.0
mean	0.0
std	0.0
min	0.0
25%	0.0
50%	0.0
75%	0.0
max	0.0

	Number of total people affected by drought \
count	8.120000e+02
mean	6.791441e+06
std	3.268972e+07
min	0.000000e+00
25%	0.000000e+00
50%	1.975000e+05
75%	1.890100e+06
max	3.829851e+08

	Reconstruction costs from drought	Insured damages against drought \
count	812.0	8.120000e+02
mean	0.0	5.161084e+04
std	0.0	8.027164e+05
min	0.0	0.000000e+00
25%	0.0	0.000000e+00
50%	0.0	0.000000e+00
75%	0.0	0.000000e+00
max	0.0	1.600000e+07

	Total economic damages from drought	Death rates from drought \
count	8.120000e+02	805.000000
mean	4.554066e+05	121.478088
std	1.909631e+06	1239.616752
min	0.000000e+00	0.000000
25%	0.000000e+00	0.000000
50%	0.000000e+00	0.000000
75%	1.570000e+04	0.000000
max	2.548120e+07	17699.115044

	Injury rates from drought \
count	805.000000
mean	0.000094
std	0.002523
min	0.000000
25%	0.000000
50%	0.000000

75%	0.000000
max	0.071459

	Number of people affected by drought per 100,000 \
count	805.000000
mean	8788.592155
std	17878.585188
min	0.000000
25%	0.000000
50%	1446.591830
75%	8838.902115
max	120967.741935

	Homelessness rate from drought \
count	805.0
mean	0.0
std	0.0
min	0.0
25%	0.0
50%	0.0
75%	0.0
max	0.0

	Total number of people affected by drought per 100,000 \
count	805.000000
mean	8788.592250
std	17878.585143
min	0.000000
25%	0.000000
50%	1446.591830
75%	8838.902115
max	120967.741935

	Number of deaths from earthquakes \
count	1148.000000
mean	4070.986063
std	21293.115522
min	0.000000
25%	2.000000
50%	27.000000
75%	360.250000
max	277005.000000

	Number of people injured from earthquakes \
count	1148.000000
mean	4886.367596
std	26869.490001
min	0.000000

25%	0.000000
50%	55.500000
75%	513.500000
max	370939.000000

	Number of people affected by earthquakes \
count	1.148000e+03
mean	3.027026e+05
std	2.240501e+06
min	0.000000e+00
25%	0.000000e+00
50%	5.000000e+02
75%	2.252475e+04
max	4.672439e+07

	Number of people left homeless from earthquakes \
count	1.148000e+03
mean	4.410635e+04
std	2.659460e+05
min	0.000000e+00
25%	0.000000e+00
50%	0.000000e+00
75%	3.038000e+03
max	5.151700e+06

	Number of total people affected by earthquakes \
count	1.148000e+03
mean	3.516953e+05
std	2.325692e+06
min	0.000000e+00
25%	1.200000e+02
50%	3.316500e+03
75%	4.457050e+04
max	4.751247e+07

	Reconstruction costs from earthquakes \
count	1.148000e+03
mean	1.151556e+05
std	1.606288e+06
min	0.000000e+00
25%	0.000000e+00
50%	0.000000e+00
75%	0.000000e+00
max	3.500000e+07

	Insured damages against earthquakes \
count	1.148000e+03
mean	1.785274e+05

std	2.065232e+06
min	0.000000e+00
25%	0.000000e+00
50%	0.000000e+00
75%	0.000000e+00
max	5.169400e+07

	Total economic damages from earthquakes	Death rates from earthquakes \
count	1.148000e+03	1121.000000
mean	1.457443e+06	10.163333
std	1.125521e+07	80.413816
min	0.000000e+00	0.000000
25%	0.000000e+00	0.005047
50%	0.000000e+00	0.071841
75%	5.000000e+04	1.041749
max	2.302998e+08	2237.109257

	Injury rates from earthquakes \
count	1121.000000
mean	11.667370
std	113.956132
min	0.000000
25%	0.000000
50%	0.122903
75%	1.047073
max	3015.378430

	Number of people affected by earthquakes per 100,000 \
count	1121.000000
mean	437.986043
std	2759.493505
min	0.000000
25%	0.000000
50%	1.257862
75%	46.355138
max	56826.791938

	Homelessness rate from earthquakes \
count	1121.000000
mean	82.779595
std	723.743783
min	0.000000
25%	0.000000
50%	0.000000
75%	4.382275
max	17669.343840

Total number of people affected by earthquakes per 100,000 \

count	1121.000000
mean	532.433009
std	3317.209327
min	0.000000
25%	0.274970
50%	8.816992
75%	93.174936
max	75662.979239

Number of deaths from disasters \

count	5.569000e+03
mean	8.194785e+03
std	1.193417e+05
min	0.000000e+00
25%	1.000000e+00
50%	1.600000e+01
75%	1.150000e+02
max	3.718976e+06

Number of people injured from disasters \

count	5.569000e+03
mean	2.754367e+03
std	4.035970e+04
min	0.000000e+00
25%	0.000000e+00
50%	0.000000e+00
75%	3.500000e+01
max	1.884112e+06

Number of people affected by disasters \

count	5.569000e+03
mean	2.882401e+06
std	2.270438e+07
min	0.000000e+00
25%	0.000000e+00
50%	5.000000e+03
75%	1.100000e+05
max	6.570457e+08

Number of people left homeless from disasters \

count	5.569000e+03
mean	6.375854e+04
std	6.909609e+05
min	0.000000e+00
25%	0.000000e+00
50%	0.000000e+00
75%	5.000000e+02
max	2.942487e+07

	Number of total people affected by disasters \
count	5.569000e+03
mean	2.948914e+06
std	2.305264e+07
min	0.000000e+00
25%	8.500000e+01
50%	8.250000e+03
75%	1.333620e+05
max	6.574532e+08

	Reconstruction costs from disasters	Insured damages against disasters \
count	5.569000e+03	5.569000e+03
mean	2.663307e+04	3.119986e+05
std	7.623283e+05	3.612870e+06
min	0.000000e+00	0.000000e+00
25%	0.000000e+00	0.000000e+00
50%	0.000000e+00	0.000000e+00
75%	0.000000e+00	0.000000e+00
max	3.751550e+07	1.270846e+08

	Total economic damages from disasters	Death rates from disasters \
count	5.569000e+03	5491.000000
mean	1.327784e+06	20.630260
std	1.173243e+07	421.357312
min	0.000000e+00	0.000000
25%	0.000000e+00	0.005711
50%	0.000000e+00	0.098312
75%	6.000000e+04	0.510515
max	3.640952e+08	17699.115044

	Injury rates from disasters \
count	5491.000000
mean	6.268850
std	124.020006
min	0.000000
25%	0.000000
50%	0.000000
75%	0.129953
max	6516.094700

	Number of people affected by disasters per 100,000 \
count	5491.000000
mean	2777.972841
std	9884.964674
min	0.000000
25%	0.000000
50%	45.266823

75%	823.929487
max	120967.741935

	Homelessness rate from disasters \
count	5491.000000
mean	144.208504
std	1930.735467
min	0.000000
25%	0.000000
50%	0.000000
75%	1.877319
max	109090.909091

	Total number of people affected by disasters per 100,000 \
count	5491.000000
mean	2928.450194
std	10264.056117
min	0.000000
25%	0.500841
50%	72.728819
75%	953.976696
max	155865.957447

	Number of deaths from volcanic activity \
count	293.000000
mean	592.505119
std	3420.146402
min	0.000000
25%	0.000000
50%	0.000000
75%	43.000000
max	38690.000000

	Number of people injured from volcanic activity \
count	293.000000
mean	176.771331
std	1243.347136
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	14114.000000

	Number of people affected by volcanic activity \
count	2.930000e+02
mean	6.141873e+04
std	2.054935e+05
min	0.000000e+00

25%	0.000000e+00
50%	5.000000e+03
75%	3.084500e+04
max	1.901284e+06

	Number of people left homeless from volcanic activity \
count	293.000000
mean	2565.119454
std	12073.160049
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	110000.000000

	Number of total people affected by volcanic activity \
count	2.930000e+02
mean	6.416062e+04
std	2.067275e+05
min	0.000000e+00
25%	2.000000e+02
50%	5.600000e+03
75%	3.995800e+04
max	1.915398e+06

	Reconstruction costs from volcanic activity \
count	293.0
mean	0.0
std	0.0
min	0.0
25%	0.0
50%	0.0
75%	0.0
max	0.0

	Insured damages against volcanic activity \
count	293.0
mean	0.0
std	0.0
min	0.0
25%	0.0
50%	0.0
75%	0.0
max	0.0

	Total economic damages from volcanic activity \
count	293.000000
mean	33207.590444

std	136252.752850
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1000000.000000

Death rates from volcanic activity \

count	290.000000
mean	16.662702
std	201.111584
min	0.000000
25%	0.000000
50%	0.000000
75%	0.085050
max	3365.519021

Injury rates from volcanic activity \

count	290.000000
mean	0.237749
std	1.368176
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	16.693933

Number of people affected by volcanic activity per 100,000 \

count	290.000000
mean	1154.709266
std	5912.139165
min	0.000000
25%	0.000000
50%	16.598252
75%	102.389926
max	50000.000000

Homelessness rate from volcanic activity \

count	290.000000
mean	18.290761
std	142.349076
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1811.594203

Total number of people affected by volcanic activity per 100,000 \

count	290.000000
mean	1173.237776
std	5919.423063
min	0.000000
25%	0.770507
50%	19.473166
75%	112.055458
max	50000.000000

	Number of deaths from floods	Number of people injured from floods \
count	3.056000e+03	3056.000000
mean	4.575145e+03	897.586387
std	1.084255e+05	10942.935683
min	0.000000e+00	0.000000
25%	1.000000e+00	0.000000
50%	1.300000e+01	0.000000
75%	6.200000e+01	0.000000
max	3.700000e+06	252827.000000

	Number of people affected by floods \
count	3.056000e+03
mean	2.474700e+06
std	1.588563e+07
min	0.000000e+00
25%	3.650000e+02
50%	1.004450e+04
75%	1.050000e+05
max	2.755356e+08

	Number of people left homeless from floods \
count	3.056000e+03
mean	6.093493e+04
std	5.934142e+05
min	0.000000e+00
25%	0.000000e+00
50%	0.000000e+00
75%	2.525000e+02
max	1.800310e+07

	Number of total people affected by floods \
count	3.056000e+03
mean	2.536533e+06
std	1.627298e+07
min	0.000000e+00
25%	1.000000e+03
50%	1.403500e+04
75%	1.238645e+05
max	2.936627e+08

	Reconstruction costs from floods	Insured damages against floods \
count	3.056000e+03	3.056000e+03
mean	2.169498e+03	5.432668e+04
std	4.520501e+04	4.607332e+05
min	0.000000e+00	0.000000e+00
25%	0.000000e+00	0.000000e+00
50%	0.000000e+00	0.000000e+00
75%	0.000000e+00	0.000000e+00
max	1.440751e+06	1.128800e+07

	Total economic damages from floods	Death rates from floods \
count	3.056000e+03	3032.000000
mean	5.766453e+05	1.664863
std	3.550686e+06	31.996619
min	0.000000e+00	0.000000
25%	0.000000e+00	0.003909
50%	0.000000e+00	0.052546
75%	3.000000e+04	0.192962
max	7.075905e+07	1348.379905

	Injury rates from floods \
count	3032.000000
mean	0.489515
std	8.296810
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	379.987334

	Number of people affected by floods per 100,000 \
count	3032.000000
mean	1025.080836
std	3437.191660
min	0.000000
25%	1.576583
50%	65.446396
75%	487.460884
max	52369.730296

	Homelessness rate from floods \
count	3032.000000
mean	67.255193
std	938.132184
min	0.000000
25%	0.000000
50%	0.000000

75%	0.785303
max	49295.774648

	Total number of people affected by floods per 100,000 \
count	3032.000000
mean	1092.825544
std	3631.016410
min	0.000000
25%	5.557691
50%	83.860588
75%	538.652468
max	55279.159757

	Number of deaths from mass movements \
count	77.000000
mean	120.623377
std	320.823900
min	0.000000
25%	16.000000
50%	45.000000
75%	76.000000
max	2000.000000

	Number of people injured from mass movements \
count	77.000000
mean	10.779221
std	25.087019
min	0.000000
25%	0.000000
50%	0.000000
75%	5.000000
max	115.000000

	Number of people affected by mass movements \
count	77.000000
mean	549.038961
std	1542.815134
min	0.000000
25%	0.000000
50%	0.000000
75%	200.000000
max	8000.000000

	Number of people left homeless from mass movements \
count	77.000000
mean	155.350649
std	428.730647
min	0.000000

25%	0.000000
50%	0.000000
75%	0.000000
max	2000.000000

	Number of total people affected by mass movements \
count	77.000000
mean	715.168831
std	1598.227731
min	0.000000
25%	0.000000
50%	0.000000
75%	697.000000
max	8000.000000

	Reconstruction costs from mass movements \
count	77.0
mean	0.0
std	0.0
min	0.0
25%	0.0
50%	0.0
75%	0.0
max	0.0

	Insured damages against mass movements \
count	77.0
mean	0.0
std	0.0
min	0.0
25%	0.0
50%	0.0
75%	0.0
max	0.0

	Total economic damages from mass movements \
count	77.000000
mean	5428.571429
std	32007.576641
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	200000.000000

	Death rates from mass movements	Injury rates from mass movements \
count	74.000000	74.000000
mean	0.880867	0.026166

std	3.060634	0.080224
min	0.000000	0.000000
25%	0.015363	0.000000
50%	0.113817	0.000000
75%	0.443672	0.000374
max	18.606382	0.392519

Number of people affected by mass movements per 100,000 \

count	74.000000
mean	1.224912
std	3.839277
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	22.732439

Homelessness rate from mass movements \

count	74.000000
mean	0.768331
std	2.557920
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	12.759985

Total number of people affected by mass movements per 100,000 \

count	74.000000
mean	2.019409
std	4.979931
min	0.000000
25%	0.000000
50%	0.000000
75%	0.660369
max	22.732439

	Number of deaths from storms	Number of people injured from storms \
count	2332.000000	2332.000000
mean	1200.503431	1193.894511
std	11718.621158	18488.618227
min	0.000000	0.000000
25%	1.000000	0.000000
50%	11.000000	0.000000
75%	100.000000	33.000000
max	304495.000000	601939.000000

Number of people affected by storms \

count	2.332000e+03
mean	1.008452e+06
std	5.911747e+06
min	0.000000e+00
25%	0.000000e+00
50%	2.000000e+02
75%	3.128750e+04
max	1.111119e+08

Number of people left homeless from storms \

count	2.332000e+03
mean	4.629072e+04
std	4.196207e+05
min	0.000000e+00
25%	0.000000e+00
50%	0.000000e+00
75%	0.000000e+00
max	1.117116e+07

Number of total people affected by storms \

count	2.332000e+03
mean	1.055937e+06
std	6.004925e+06
min	0.000000e+00
25%	0.000000e+00
50%	1.000000e+03
75%	4.099550e+04
max	1.111626e+08

Reconstruction costs from storms Insured damages against storms \

count	2.332000e+03	2.332000e+03
mean	3.515866e+03	5.174520e+05
std	7.857675e+04	4.398694e+06
min	0.000000e+00	0.000000e+00
25%	0.000000e+00	0.000000e+00
50%	0.000000e+00	0.000000e+00
75%	0.000000e+00	0.000000e+00
max	2.512500e+06	1.087646e+08

Total economic damages from storms Death rates from storms \

count	2.332000e+03	2302.000000
mean	1.369009e+06	8.026993
std	1.024531e+07	134.027837
min	0.000000e+00	0.000000
25%	0.000000e+00	0.003264
50%	5.000000e+02	0.045400
75%	1.000000e+05	0.308354
max	2.729390e+08	4915.816640

Injury rates from storms \	
count	2302.000000
mean	5.697505
std	108.746322
min	0.000000
25%	0.000000
50%	0.000000
75%	0.084705
max	4166.666667

Number of people affected by storms per 100,000 \	
count	2302.000000
mean	1812.438867
std	8663.247482
min	0.000000
25%	0.000000
50%	0.876989
75%	281.042629
max	106382.978723

Homelessness rate from storms \	
count	2302.000000
mean	211.151924
std	2731.769660
min	0.000000
25%	0.000000
50%	0.000000
75%	0.009410
max	109090.909091

Total number of people affected by storms per 100,000 \	
count	2302.000000
mean	2029.288296
std	9496.501755
min	0.000000
25%	0.000000
50%	6.658198
75%	379.148989
max	155865.957447

Number of deaths from landslides \	
count	655.000000
mean	204.320611
std	786.877243
min	0.000000
25%	17.000000
50%	41.000000

75%	125.500000
max	12000.000000

	Number of people injured from landslides \
count	655.000000
mean	36.983206
std	181.817358
min	0.000000
25%	0.000000
50%	0.000000
75%	14.500000
max	3000.000000

	Number of people affected by landslides \
count	6.550000e+02
mean	3.169583e+04
std	2.592852e+05
min	0.000000e+00
25%	0.000000e+00
50%	0.000000e+00
75%	5.075000e+02
max	4.000000e+06

	Number of people left homeless from landslides \
count	6.550000e+02
mean	1.300046e+04
std	1.512823e+05
min	0.000000e+00
25%	0.000000e+00
50%	0.000000e+00
75%	0.000000e+00
max	2.500366e+06

	Number of total people affected by landslides \
count	6.550000e+02
mean	4.473327e+04
std	3.001016e+05
min	0.000000e+00
25%	0.000000e+00
50%	3.700000e+01
75%	1.976500e+03
max	4.000000e+06

	Reconstruction costs from landslides \
count	655.000000
mean	9.160305
std	165.646902
min	0.000000

25%	0.000000
50%	0.000000
75%	0.000000
max	3000.000000

Insured damages against landslides \	
count	655.000000
mean	1355.419847
std	14495.822358
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	200000.000000

Total economic damages from landslides		Death rates from landslides \	
count	6.550000e+02		646.000000
mean	3.361507e+04		0.832527
std	1.442824e+05		5.732425
min	0.000000e+00		0.000000
25%	0.000000e+00		0.018526
50%	0.000000e+00		0.071530
75%	0.000000e+00		0.286839
max	1.277078e+06		94.307848

Injury rates from landslides \	
count	646.000000
mean	0.084109
std	0.529415
min	0.000000
25%	0.000000
50%	0.000000
75%	0.011163
max	7.808944

Number of people affected by landslides per 100,000 \	
count	646.000000
mean	36.587989
std	283.779783
min	0.000000
25%	0.000000
50%	0.000000
75%	0.831151
max	4667.607968

Homelessness rate from landslides \	
count	646.000000
mean	9.387541

std	99.013506
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	2158.273381

Total number of people affected by landslides per 100,000 \

count	646.000000
mean	46.059639
std	302.820861
min	0.000000
25%	0.000000
50%	0.075773
75%	2.999416
max	4667.607968

	Number of deaths from fog	Number of people injured from fog \
count	2.0	2.0
mean	4000.0	0.0
std	0.0	0.0
min	4000.0	0.0
25%	4000.0	0.0
50%	4000.0	0.0
75%	4000.0	0.0
max	4000.0	0.0

Number of people affected by fog \

count	2.0
mean	0.0
std	0.0
min	0.0
25%	0.0
50%	0.0
75%	0.0
max	0.0

Number of people left homeless from fog \

count	2.0
mean	0.0
std	0.0
min	0.0
25%	0.0
50%	0.0
75%	0.0
max	0.0

Number of total people affected by fog Reconstruction costs from fog \

count	2.0	2.0
mean	0.0	0.0
std	0.0	0.0
min	0.0	0.0
25%	0.0	0.0
50%	0.0	0.0
75%	0.0	0.0
max	0.0	0.0

	Insured damages against fog	Total economic damages from fog \
count	2.0	2.0
mean	0.0	0.0
std	0.0	0.0
min	0.0	0.0
25%	0.0	0.0
50%	0.0	0.0
75%	0.0	0.0
max	0.0	0.0

	Death rates from fog	Injury rates from fog \
count	2.000000	2.0
mean	7.897179	0.0
std	0.000000	0.0
min	7.897179	0.0
25%	7.897179	0.0
50%	7.897179	0.0
75%	7.897179	0.0
max	7.897179	0.0

	Number of people affected by fog per 100,000 \
count	2.0
mean	0.0
std	0.0
min	0.0
25%	0.0
50%	0.0
75%	0.0
max	0.0

	Homelessness rate from fog \
count	2.0
mean	0.0
std	0.0
min	0.0
25%	0.0
50%	0.0
75%	0.0
max	0.0

	Total number of people affected by fog per 100,000 \
count	2.0
mean	0.0
std	0.0
min	0.0
25%	0.0
50%	0.0
75%	0.0
max	0.0

	Number of deaths from wildfires \
count	407.000000
mean	21.852580
std	78.697669
min	0.000000
25%	0.000000
50%	1.000000
75%	14.000000
max	1000.000000

	Number of people injured from wildfires \
count	407.000000
mean	55.208845
std	209.573572
min	0.000000
25%	0.000000
50%	0.000000
75%	9.500000
max	2292.000000

	Number of people affected by wildfires \
count	4.070000e+02
mean	8.375322e+04
std	7.395070e+05
min	0.000000e+00
25%	0.000000e+00
50%	0.000000e+00
75%	1.804500e+03
max	1.004653e+07

	Number of people left homeless from wildfires \
count	407.000000
mean	1179.592138
std	4434.044965
min	0.000000
25%	0.000000
50%	0.000000

75%	280.500000
max	50540.000000

	Number of total people affected by wildfires \
count	4.070000e+02
mean	8.498802e+04
std	7.399048e+05
min	0.000000e+00
25%	0.000000e+00
50%	2.000000e+02
75%	4.000000e+03
max	1.005676e+07

	Reconstruction costs from wildfires	Insured damages against wildfires \
count	407.000000	4.070000e+02
mean	3159.705160	2.581622e+05
std	42539.307212	1.540124e+06
min	0.000000	0.000000e+00
25%	0.000000	0.000000e+00
50%	0.000000	0.000000e+00
75%	0.000000	0.000000e+00
max	643000.000000	1.650000e+07

	Total economic damages from wildfires	Death rates from wildfires \
count	4.070000e+02	403.000000
mean	5.852544e+05	0.055872
std	2.286453e+06	0.173391
min	0.000000e+00	0.000000
25%	0.000000e+00	0.000000
50%	0.000000e+00	0.001097
75%	1.000000e+05	0.020800
max	2.280200e+07	1.078981

	Injury rates from wildfires \
count	403.000000
mean	0.120676
std	0.532678
min	0.000000
25%	0.000000
50%	0.000000
75%	0.006502
max	5.702338

	Number of people affected by wildfires per 100,000 \
count	403.000000
mean	165.828932
std	2427.198194
min	0.000000

25%	0.000000
50%	0.000000
75%	3.946414
max	48426.150121

Homelessness rate from wildfires \	
count	403.000000
mean	6.532515
std	52.878282
min	0.000000
25%	0.000000
50%	0.000000
75%	0.190189
max	986.193294

Total number of people affected by wildfires per 100,000 \	
count	403.000000
mean	172.482123
std	2427.353627
min	0.000000
25%	0.000000
50%	0.503728
75%	9.263234
max	48426.150121

Number of deaths from extreme temperatures \	
count	572.000000
mean	674.101399
std	4779.906351
min	0.000000
25%	4.000000
50%	32.000000
75%	182.250000
max	74698.000000

Number of people injured from extreme temperatures \	
count	5.720000e+02
mean	7.172993e+03
std	1.064309e+05
min	0.000000e+00
25%	0.000000e+00
50%	0.000000e+00
75%	0.000000e+00
max	1.800413e+06

Number of people affected by extreme temperatures \	
count	5.720000e+02
mean	3.542953e+05

std	4.624017e+06
min	0.000000e+00
25%	0.000000e+00
50%	0.000000e+00
75%	0.000000e+00
max	7.917050e+07

Number of people left homeless from extreme temperatures \

count	572.000000
mean	893.660839
std	13796.864858
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	233000.000000

Number of total people affected by extreme temperatures \

count	5.720000e+02
mean	3.623619e+05
std	4.625901e+06
min	0.000000e+00
25%	0.000000e+00
50%	0.000000e+00
75%	3.595000e+02
max	7.917120e+07

Reconstruction costs from extreme temperatures \

count	572.0
mean	0.0
std	0.0
min	0.0
25%	0.0
50%	0.0
75%	0.0
max	0.0

Insured damages against extreme temperatures \

count	5.720000e+02
mean	2.094825e+04
std	1.451951e+05
min	0.000000e+00
25%	0.000000e+00
50%	0.000000e+00
75%	0.000000e+00
max	1.600000e+06

Total economic damages from extreme temperatures \

count	5.720000e+02
mean	2.209313e+05
std	1.457786e+06
min	0.000000e+00
25%	0.000000e+00
50%	0.000000e+00
75%	0.000000e+00
max	2.194000e+07

Death rates from extreme temperatures \

count	566.000000
mean	0.830026
std	3.885326
min	0.000000
25%	0.010742
50%	0.048426
75%	0.168456
max	38.862828

Injury rates from extreme temperatures \

count	566.000000
mean	12.407698
std	273.920010
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	6516.072980

Number of people affected by extreme temperatures per 100,000 \

count	566.000000
mean	410.186358
std	3120.655302
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	48169.556840

Homelessness rate from extreme temperatures \

count	566.000000
mean	0.187956
std	2.302845
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	45.117845

	Total number of people affected by extreme temperatures per 100,000 \
count	566.000000
mean	422.782012
std	3135.553750
min	0.000000
25%	0.000000
50%	0.000000
75%	1.135364
max	48169.556840

	Number of deaths from glacial lake outbursts \
count	0.0
mean	NaN
std	NaN
min	NaN
25%	NaN
50%	NaN
75%	NaN
max	NaN

	Number of people injured from glacial lake outbursts \
count	0.0
mean	NaN
std	NaN
min	NaN
25%	NaN
50%	NaN
75%	NaN
max	NaN

	Number of people affected by glacial lake outbursts \
count	0.0
mean	NaN
std	NaN
min	NaN
25%	NaN
50%	NaN
75%	NaN
max	NaN

	Number of people left homeless from glacial lake outbursts \
count	0.0
mean	NaN
std	NaN
min	NaN
25%	NaN
50%	NaN

75%	NaN
max	NaN

	Number of total people affected by glacial lake outbursts \
count	0.0
mean	NaN
std	NaN
min	NaN
25%	NaN
50%	NaN
75%	NaN
max	NaN

	Reconstruction costs from glacial lake outbursts \
count	0.0
mean	NaN
std	NaN
min	NaN
25%	NaN
50%	NaN
75%	NaN
max	NaN

	Insured damages against glacial lake outbursts \
count	0.0
mean	NaN
std	NaN
min	NaN
25%	NaN
50%	NaN
75%	NaN
max	NaN

	Total economic damages from glacial lake outbursts \
count	0.0
mean	NaN
std	NaN
min	NaN
25%	NaN
50%	NaN
75%	NaN
max	NaN

	Death rates from glacial lake outbursts \
count	0.0
mean	NaN
std	NaN
min	NaN

25%	NaN
50%	NaN
75%	NaN
max	NaN

Injury rates from glacial lake outbursts \	
count	0.0
mean	NaN
std	NaN
min	NaN
25%	NaN
50%	NaN
75%	NaN
max	NaN

Number of people affected by glacial lake outbursts per 100,000 \	
count	0.0
mean	NaN
std	NaN
min	NaN
25%	NaN
50%	NaN
75%	NaN
max	NaN

Homelessness rate from glacial lake outbursts \	
count	0.0
mean	NaN
std	NaN
min	NaN
25%	NaN
50%	NaN
75%	NaN
max	NaN

Total number of people affected by glacial lake outbursts per 100,000 \	
count	0.0
mean	NaN
std	NaN
min	NaN
25%	NaN
50%	NaN
75%	NaN
max	NaN

Total economic damages from disasters as a share of GDP \	
count	4485.000000
mean	1.142727

std	9.431985
min	0.000000
25%	0.000000
50%	0.000000
75%	0.140063
max	280.087777

Total economic damages from drought as a share of GDP \

count	722.000000
mean	0.288242
std	1.303854
min	0.000000
25%	0.000000
50%	0.000000
75%	0.037417
max	17.598331

Total economic damages from earthquakes as a share of GDP \

count	769.000000
mean	0.798568
std	5.104692
min	0.000000
25%	0.000000
50%	0.001745
75%	0.070481
max	95.930842

Total economic damages from extreme temperatures as a share of GDP \

count	545.000000
mean	0.061597
std	0.772519
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	16.274852

Total economic damages from floods as a share of GDP \

count	2755.000000
mean	0.207195
std	1.402456
min	0.000000
25%	0.000000
50%	0.000000
75%	0.039742
max	56.383921

Total economic damages from landslides as a share of GDP \

count	579.000000
mean	0.061634
std	0.566196
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	9.061466

Total economic damages from mass movements as a share of GDP \

count	61.000000
mean	0.199554
std	1.092590
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	6.084995

Total economic damages from storms as a share of GDP \

count	1854.000000
mean	1.885051
std	13.769081
min	0.000000
25%	0.000000
50%	0.002782
75%	0.112616
max	280.087777

Total economic damages from volcanic activity as a share of GDP \

count	228.000000
mean	0.061460
std	0.313755
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000862
max	2.865788

Total economic damages from volcanic activity as a share of GDP.1 \

count	377.000000
mean	0.486609
std	6.719902
min	0.000000
25%	0.000000
50%	0.000000
75%	0.014476
max	127.277641

	Year	total_damages_pct_gdp_glacial_lake
count	5569.000000	0.0
mean	1989.666906	NaN
std	25.467663	NaN
min	1900.000000	NaN
25%	1978.000000	NaN
50%	1997.000000	NaN
75%	2008.000000	NaN
max	2020.000000	NaN

```
[9]: # Check of missing data values.
for a in disaster_df.columns:
    miss=disaster_df[a].isnull().sum()
    if miss > 0:
        print('{} has {} missing values'.format(a,miss))
    else:
        print('{} has NO missing values'.format(a))
```

Number of deaths from drought has 4757 missing values
 Number of people injured from drought has 4757 missing values
 Number of people affected from drought has 4757 missing values
 Number of people left homeless from drought has 4757 missing values
 Number of total people affected by drought has 4757 missing values
 Reconstruction costs from drought has 4757 missing values
 Insured damages against drought has 4757 missing values
 Total economic damages from drought has 4757 missing values
 Death rates from drought has 4764 missing values
 Injury rates from drought has 4764 missing values
 Number of people affected by drought per 100,000 has 4764 missing values
 Homelessness rate from drought has 4764 missing values
 Total number of people affected by drought per 100,000 has 4764 missing values
 Number of deaths from earthquakes has 4421 missing values
 Number of people injured from earthquakes has 4421 missing values
 Number of people affected by earthquakes has 4421 missing values
 Number of people left homeless from earthquakes has 4421 missing values
 Number of total people affected by earthquakes has 4421 missing values
 Reconstruction costs from earthquakes has 4421 missing values
 Insured damages against earthquakes has 4421 missing values
 Total economic damages from earthquakes has 4421 missing values
 Death rates from earthquakes has 4448 missing values
 Injury rates from earthquakes has 4448 missing values
 Number of people affected by earthquakes per 100,000 has 4448 missing values
 Homelessness rate from earthquakes has 4448 missing values
 Total number of people affected by earthquakes per 100,000 has 4448 missing values
 Number of deaths from disasters has NO missing values
 Number of people injured from disasters has NO missing values

Number of people affected by disasters has NO missing values
 Number of people left homeless from disasters has NO missing values
 Number of total people affected by disasters has NO missing values
 Reconstruction costs from disasters has NO missing values
 Insured damages against disasters has NO missing values
 Total economic damages from disasters has NO missing values
 Death rates from disasters has 78 missing values
 Injury rates from disasters has 78 missing values
 Number of people affected by disasters per 100,000 has 78 missing values
 Homelessness rate from disasters has 78 missing values
 Total number of people affected by disasters per 100,000 has 78 missing values
 Number of deaths from volcanic activity has 5276 missing values
 Number of people injured from volcanic activity has 5276 missing values
 Number of people affected by volcanic activity has 5276 missing values
 Number of people left homeless from volcanic activity has 5276 missing values
 Number of total people affected by volcanic activity has 5276 missing values
 Reconstruction costs from volcanic activity has 5276 missing values
 Insured damages against volcanic activity has 5276 missing values
 Total economic damages from volcanic activity has 5276 missing values
 Death rates from volcanic activity has 5279 missing values
 Injury rates from volcanic activity has 5279 missing values
 Number of people affected by volcanic activity per 100,000 has 5279 missing values
 Homelessness rate from volcanic activity has 5279 missing values
 Total number of people affected by volcanic activity per 100,000 has 5279 missing values
 Number of deaths from floods has 2513 missing values
 Number of people injured from floods has 2513 missing values
 Number of people affected by floods has 2513 missing values
 Number of people left homeless from floods has 2513 missing values
 Number of total people affected by floods has 2513 missing values
 Reconstruction costs from floods has 2513 missing values
 Insured damages against floods has 2513 missing values
 Total economic damages from floods has 2513 missing values
 Death rates from floods has 2537 missing values
 Injury rates from floods has 2537 missing values
 Number of people affected by floods per 100,000 has 2537 missing values
 Homelessness rate from floods has 2537 missing values
 Total number of people affected by floods per 100,000 has 2537 missing values
 Number of deaths from mass movements has 5492 missing values
 Number of people injured from mass movements has 5492 missing values
 Number of people affected by mass movements has 5492 missing values
 Number of people left homeless from mass movements has 5492 missing values
 Number of total people affected by mass movements has 5492 missing values
 Reconstruction costs from mass movements has 5492 missing values
 Insured damages against mass movements has 5492 missing values
 Total economic damages from mass movements has 5492 missing values
 Death rates from mass movements has 5495 missing values

Injury rates from mass movements has 5495 missing values
Number of people affected by mass movements per 100,000 has 5495 missing values
Homelessness rate from mass movements has 5495 missing values
Total number of people affected by mass movements per 100,000 has 5495 missing values
Number of deaths from storms has 3237 missing values
Number of people injured from storms has 3237 missing values
Number of people affected by storms has 3237 missing values
Number of people left homeless from storms has 3237 missing values
Number of total people affected by storms has 3237 missing values
Reconstruction costs from storms has 3237 missing values
Insured damages against storms has 3237 missing values
Total economic damages from storms has 3237 missing values
Death rates from storms has 3267 missing values
Injury rates from storms has 3267 missing values
Number of people affected by storms per 100,000 has 3267 missing values
Homelessness rate from storms has 3267 missing values
Total number of people affected by storms per 100,000 has 3267 missing values
Number of deaths from landslides has 4914 missing values
Number of people injured from landslides has 4914 missing values
Number of people affected by landslides has 4914 missing values
Number of people left homeless from landslides has 4914 missing values
Number of total people affected by landslides has 4914 missing values
Reconstruction costs from landslides has 4914 missing values
Insured damages against landslides has 4914 missing values
Total economic damages from landslides has 4914 missing values
Death rates from landslides has 4923 missing values
Injury rates from landslides has 4923 missing values
Number of people affected by landslides per 100,000 has 4923 missing values
Homelessness rate from landslides has 4923 missing values
Total number of people affected by landslides per 100,000 has 4923 missing values
Number of deaths from fog has 5567 missing values
Number of people injured from fog has 5567 missing values
Number of people affected by fog has 5567 missing values
Number of people left homeless from fog has 5567 missing values
Number of total people affected by fog has 5567 missing values
Reconstruction costs from fog has 5567 missing values
Insured damages against fog has 5567 missing values
Total economic damages from fog has 5567 missing values
Death rates from fog has 5567 missing values
Injury rates from fog has 5567 missing values
Number of people affected by fog per 100,000 has 5567 missing values
Homelessness rate from fog has 5567 missing values
Total number of people affected by fog per 100,000 has 5567 missing values
Number of deaths from wildfires has 5162 missing values
Number of people injured from wildfires has 5162 missing values
Number of people affected by wildfires has 5162 missing values

Number of people left homeless from wildfires has 5162 missing values
 Number of total people affected by wildfires has 5162 missing values
 Reconstruction costs from wildfires has 5162 missing values
 Insured damages against wildfires has 5162 missing values
 Total economic damages from wildfires has 5162 missing values
 Death rates from wildfires has 5166 missing values
 Injury rates from wildfires has 5166 missing values
 Number of people affected by wildfires per 100,000 has 5166 missing values
 Homelessness rate from wildfires has 5166 missing values
 Total number of people affected by wildfires per 100,000 has 5166 missing values
 Number of deaths from extreme temperatures has 4997 missing values
 Number of people injured from extreme temperatures has 4997 missing values
 Number of people affected by extreme temperatures has 4997 missing values
 Number of people left homeless from extreme temperatures has 4997 missing values
 Number of total people affected by extreme temperatures has 4997 missing values
 Reconstruction costs from extreme temperatures has 4997 missing values
 Insured damages against extreme temperatures has 4997 missing values
 Total economic damages from extreme temperatures has 4997 missing values
 Death rates from extreme temperatures has 5003 missing values
 Injury rates from extreme temperatures has 5003 missing values
 Number of people affected by extreme temperatures per 100,000 has 5003 missing values
 Homelessness rate from extreme temperatures has 5003 missing values
 Total number of people affected by extreme temperatures per 100,000 has 5003 missing values
 Number of deaths from glacial lake outbursts has 5569 missing values
 Number of people injured from glacial lake outbursts has 5569 missing values
 Number of people affected by glacial lake outbursts has 5569 missing values
 Number of people left homeless from glacial lake outbursts has 5569 missing values
 Number of total people affected by glacial lake outbursts has 5569 missing values
 Reconstruction costs from glacial lake outbursts has 5569 missing values
 Insured damages against glacial lake outbursts has 5569 missing values
 Total economic damages from glacial lake outbursts has 5569 missing values
 Death rates from glacial lake outbursts has 5569 missing values
 Injury rates from glacial lake outbursts has 5569 missing values
 Number of people affected by glacial lake outbursts per 100,000 has 5569 missing values
 Homelessness rate from glacial lake outbursts has 5569 missing values
 Total number of people affected by glacial lake outbursts per 100,000 has 5569 missing values
 Total economic damages from disasters as a share of GDP has 1084 missing values
 Total economic damages from drought as a share of GDP has 4847 missing values
 Total economic damages from earthquakes as a share of GDP has 4800 missing values
 Total economic damages from extreme temperatures as a share of GDP has 5024 missing values

Total economic damages from floods as a share of GDP has 2814 missing values
 Total economic damages from landslides as a share of GDP has 4990 missing values
 Total economic damages from mass movements as a share of GDP has 5508 missing values
 Total economic damages from storms as a share of GDP has 3715 missing values
 Total economic damages from volcanic activity as a share of GDP has 5341 missing values
 Total economic damages from volcanic activity as a share of GDP.1 has 5192 missing values
 Entity has NO missing values
 Year has NO missing values
 total_damages_pct_gdp_glacial_lake has 5569 missing values

Note: Missing values are in the range of 4,421 and 5,279

```
[ ]: # Check out a few rows
disaster_df.head()
```

```
[4]: # Filter data down to US only
disaster_us_df = disaster_df[disaster_df['Entity'] == 'United States']
```

```
[5]: # Check the dimension of the table/look at the data
print("The dimension of the table is: ", disaster_us_df.shape)
```

The dimension of the table is: (99, 169)

```
[12]: # Drop all NaN Values from dataset
disaster_us_df.dropna()
```

[12]: Empty DataFrame

Columns: [Number of deaths from drought, Number of people injured from drought, Number of people affected from drought, Number of people left homeless from drought, Number of total people affected by drought, Reconstruction costs from drought, Insured damages against drought, Total economic damages from drought, Death rates from drought, Injury rates from drought, Number of people affected by drought per 100,000, Homelessness rate from drought, Total number of people affected by drought per 100,000, Number of deaths from earthquakes, Number of people injured from earthquakes, Number of people affected by earthquakes, Number of people left homeless from earthquakes, Number of total people affected by earthquakes, Reconstruction costs from earthquakes, Insured damages against earthquakes, Total economic damages from earthquakes, Death rates from earthquakes, Injury rates from earthquakes, Number of people affected by earthquakes per 100,000, Homelessness rate from earthquakes, Total number of people affected by earthquakes per 100,000, Number of deaths from disasters, Number of people injured from disasters, Number of people affected by disasters, Number of people left homeless from disasters, Number of total people affected by disasters, Reconstruction costs from disasters, Insured damages against disasters, Total economic damages from disasters, Death rates from disasters, Injury rates from disasters, Number of people affected by disasters per 100,000,

Homelessness rate from disasters, Total number of people affected by disasters per 100,000, Number of deaths from volcanic activity, Number of people injured from volcanic activity, Number of people affected by volcanic activity, Number of people left homeless from volcanic activity, Number of total people affected by volcanic activity, Reconstruction costs from volcanic activity, Insured damages against volcanic activity, Total economic damages from volcanic activity, Death rates from volcanic activity, Injury rates from volcanic activity, Number of people affected by volcanic activity per 100,000, Homelessness rate from volcanic activity, Total number of people affected by volcanic activity per 100,000, Number of deaths from floods, Number of people injured from floods, Number of people affected by floods, Number of people left homeless from floods, Number of total people affected by floods, Reconstruction costs from floods, Insured damages against floods, Total economic damages from floods, Death rates from floods, Injury rates from floods, Number of people affected by floods per 100,000, Homelessness rate from floods, Total number of people affected by floods per 100,000, Number of deaths from mass movements, Number of people injured from mass movements, Number of people affected by mass movements, Number of people left homeless from mass movements, Number of total people affected by mass movements, Reconstruction costs from mass movements, Insured damages against mass movements, Total economic damages from mass movements, Death rates from mass movements, Injury rates from mass movements, Number of people affected by mass movements per 100,000, Homelessness rate from mass movements, Total number of people affected by mass movements per 100,000, Number of deaths from storms, Number of people injured from storms, Number of people affected by storms, Number of people left homeless from storms, Number of total people affected by storms, Reconstruction costs from storms, Insured damages against storms, Total economic damages from storms, Death rates from storms, Injury rates from storms, Number of people affected by storms per 100,000, Homelessness rate from storms, Total number of people affected by storms per 100,000, Number of deaths from landslides, Number of people injured from landslides, Number of people affected by landslides, Number of people left homeless from landslides, Number of total people affected by landslides, Reconstruction costs from landslides, Insured damages against landslides, Total economic damages from landslides, Death rates from landslides, ...]
Index: []

```
[14]: # Check the dimension of the table/look at the data
print("The dimension of the table is: ", disaster_us_df.shape)
```

The dimension of the table is: (99, 169)

```
[14]: # Write file down to csv
disaster_us_df.to_csv('disaster_us.csv', index=False)
```

```
[4]: # Reload data
file2 = "disaster_us_storm.csv"
disaster_us_storm_df = pd.read_csv(file2)
```

```
# Additional file
file3= "north_atlantic_hurricanes_stats.csv"
hurricanes_us_df = pd.read_csv(file3)
```

Disasters US Storms

```
[20]: # Check the dimension of the table/look at the data
print("The dimension of disaster_us_storm_df is: ", disaster_us_storm_df.shape)
```

The dimension of disaster_us_storm_df is: (99, 16)

```
[21]: # What type of variables are in the table before dropping variables.
print("Describe Data disaster_us_storm_df")
print(disaster_us_storm_df.describe())
```

Describe Data disaster_us_storm_df

	no_deaths_storms	no_people_injured_storms	no_people_affected_storms \
count	95.000000	95.000000	9.500000e+01
mean	326.189474	158.926316	1.063053e+06
std	656.820570	420.195325	8.731234e+06
min	1.000000	0.000000	0.000000e+00
25%	103.500000	0.000000	0.000000e+00
50%	190.000000	0.000000	0.000000e+00
75%	303.000000	165.000000	9.184000e+03
max	6000.000000	3593.000000	8.501880e+07

	no_people_left_homeless_storms	no_total_people_affected_storms \
count	95.000000	9.500000e+01
mean	5622.442105	1.068834e+06
std	28403.032587	8.730827e+06
min	0.000000	0.000000e+00
25%	0.000000	0.000000e+00
50%	0.000000	0.000000e+00
75%	81.000000	1.080450e+04
max	250000.000000	8.501947e+07

	reconstruction_costs_storms	insured_damages_storms \
count	95.000000	9.500000e+01
mean	657.894737	4.525446e+06
std	6412.364701	1.249115e+07
min	0.000000	0.000000e+00
25%	0.000000	0.000000e+00
50%	0.000000	0.000000e+00
75%	0.000000	3.690250e+06
max	62500.000000	8.296500e+07

	total_economic_damages_storms	death_rates_storms	injury_rates_storms \
count	9.500000e+01	95.000000	95.000000
mean	9.607543e+06	0.232532	0.056396

std	2.677974e+07	0.801661	0.142446
min	0.000000e+00	0.000412	0.000000
25%	1.950000e+04	0.042962	0.000000
50%	4.080000e+05	0.077257	0.000000
75%	5.472500e+06	0.207161	0.065360
max	1.711100e+08	7.713919	1.153140

	no_people_affected_storms_per_100000	homelessness_rate_storms \
count	95.000000	95.000000
mean	334.708298	2.069297
std	2704.323998	10.746575
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	3.012068	0.027080
max	26320.306110	97.279668

	total_no_people_affected_storms_per_100000 \
count	95.000000
mean	336.833992
std	2704.172894
min	0.000000
25%	0.000000
50%	0.000000
75%	3.885984
max	26320.512920

	total_economic_damages_storms_share_GDP	Year
count	60.000000	99.000000
mean	0.129685	1968.959596
std	0.208821	32.009858
min	0.000000	1900.000000
25%	0.026670	1946.500000
50%	0.062040	1971.000000
75%	0.133962	1995.500000
max	1.213737	2020.000000

Hurricanes stats

```
[22]: # Check the dimension of the table/look at the data
print("The dimension of north_atlantic_hurricanes_stats is: ", hurricanes_us_df.
      ↪shape)
```

The dimension of north_atlantic_hurricanes_stats is: (169, 13)

```
[23]: # What type of variables are in the table before dropping variables.
print("Describe Data north_atlantic_hurricanes_stats")
print(hurricanes_us_df.describe())
```

Describe Data north_atlantic_hurricanes_stats

	Year	no_us_hurricanes_HUDRAT_NOAA \
count	169.000000	169.000000
mean	1935.000000	1.804734
std	48.930222	1.524710
min	1851.000000	0.000000
25%	1893.000000	1.000000
50%	1935.000000	2.000000
75%	1977.000000	3.000000
max	2019.000000	8.000000

	no_major_us_hurricanes_HUDRAT_NOAA \
count	169.000000
mean	0.568047
std	0.777157
min	0.000000
25%	0.000000
50%	0.000000
75%	1.000000
max	4.000000

	no_major_north_atlantic_hurricanes_HUDRAT_NOAA \
count	169.000000
mean	1.875740
std	1.604292
min	0.000000
25%	1.000000
50%	2.000000
75%	3.000000
max	7.000000

	no_noth_atlantic_hurricanes_HUDRAT_NOAA \
count	169.000000
mean	5.473373
std	2.540306
min	0.000000
25%	4.000000
50%	5.000000
75%	7.000000
max	15.000000

	accumulated_cyclone_energy_ACE_HUDRAT_NOAA \
count	169.000000
mean	88.331361
std	52.976042
min	3.000000
25%	50.000000
50%	74.000000
75%	113.000000

max 259.000000

	cyclone_power_dissipation_index_PDI_HUDRAT_NOAA \
count	163.000000
mean	0.983188
std	1.386486
min	0.000000
25%	0.000000
50%	0.000000
75%	2.025500
max	6.003000

	hurricane_fatality_rate	ACE	deaths_hurricanes_us \
count	165.000000	169.000000	120.000000
mean	0.095924	88.764290	256.775000
std	0.365453	53.285074	599.146262
min	0.000000	2.530000	0.000000
25%	0.000000	49.710000	30.000000
50%	0.000000	76.062500	150.500000
75%	0.041278	115.837500	272.750000
max	3.438047	258.570000	6000.000000

	total_economic_damages_storms	death_bin
count	1.200000e+02	120.000000
mean	7.115763e+06	2.541667
std	2.366521e+07	2.007950
min	0.000000e+00	1.000000
25%	0.000000e+00	1.000000
50%	8.650000e+04	2.000000
75%	2.549200e+06	3.000000
max	1.711100e+08	10.000000

```
[11]: # Importing Autoviz class
from autoviz.AutoViz_Class import AutoViz_Class#Instantiate the AutoViz class
AV = AutoViz_Class()
```

Imported AutoViz_Class version: 0.0.81. Call using:

```
from autoviz.AutoViz_Class import AutoViz_Class
AV = AutoViz_Class()
AV.AutoViz(filename, sep=',', depVar='', dfte=None, header=0, verbose=0,
lowess=False,chart_format='svg',max_rows_analyzed=150000,max_cols_analyzed=30)
Note: verbose=0 or 1 generates charts and displays them in your local Jupyter
notebook.
```

verbose=2 saves plots in your local machine under AutoViz_Plots directory
and does not display charts.

```
[22]: #north_atlantic_hurricanes_stats is: hurricanes_us_df
#Trying this to see what happens
```

```
df = AV.AutoViz('north_atlantic_hurricanes_stats.csv')
```

Shape of your Data Set: (168, 10)

C L A S S I F Y I N G V A R I A B L E S

Classifying variables in data set...

Number of Numeric Columns = 4

Number of Integer-Categorical Columns = 3

Number of String-Categorical Columns = 0

Number of Factor-Categorical Columns = 0

Number of String-Boolean Columns = 0

Number of Numeric-Boolean Columns = 0

Number of Discrete String Columns = 0

Number of NLP String Columns = 0

Number of Date Time Columns = 0

Number of ID Columns = 1

Number of Columns to Delete = 2

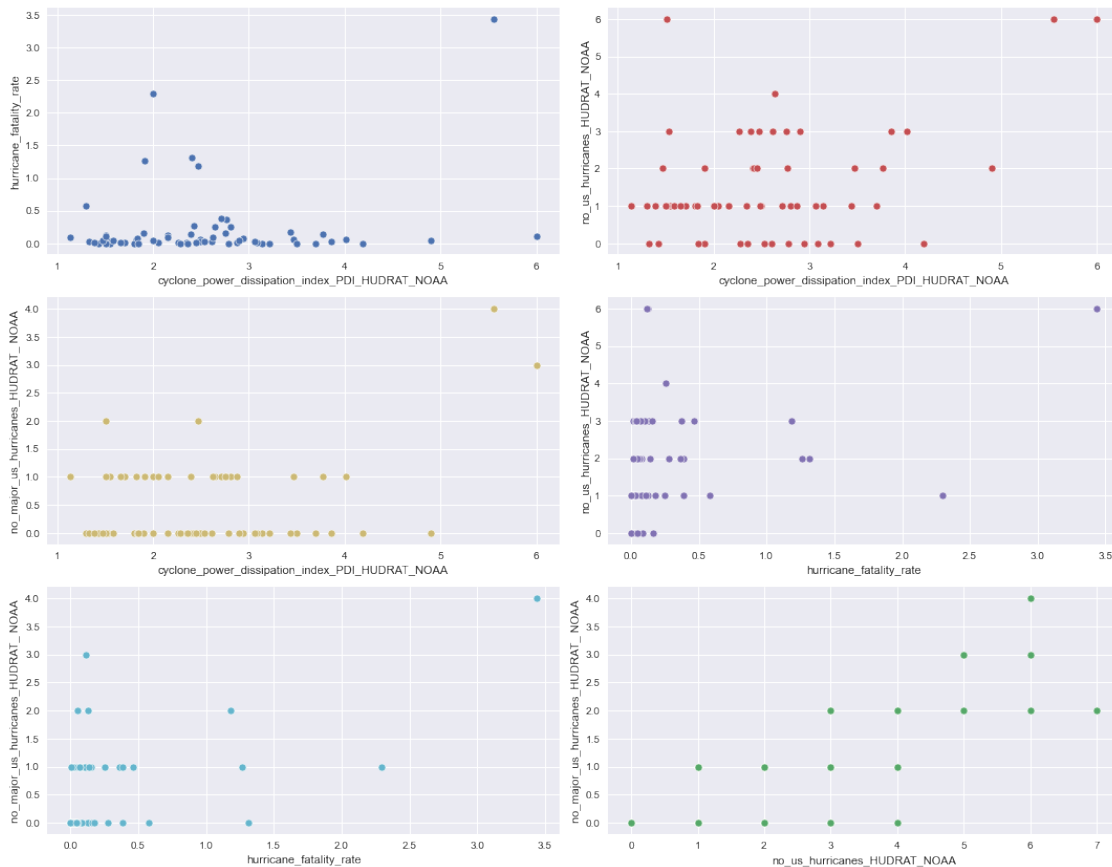
10 Predictors classified...

This does not include the Target column(s)

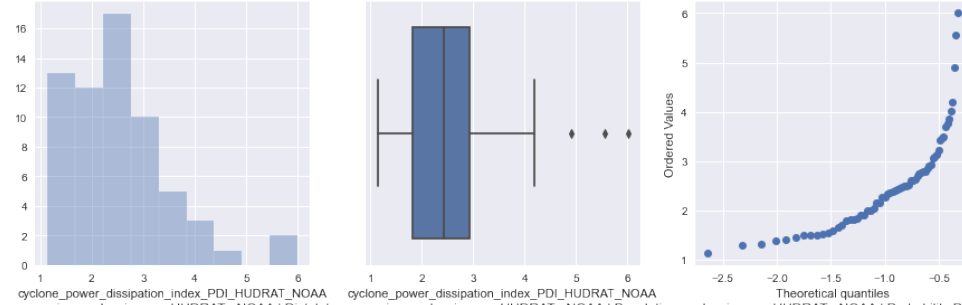
3 variables removed since they were ID or low-information variables

Number of All Scatter Plots = 10

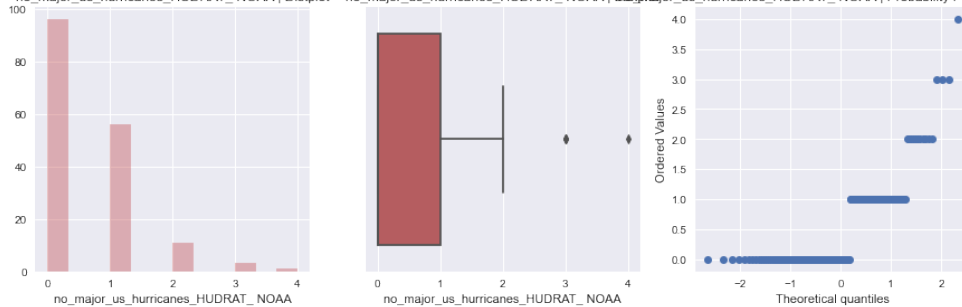
Pair-wise Scatter Plot of all Continuous Variables



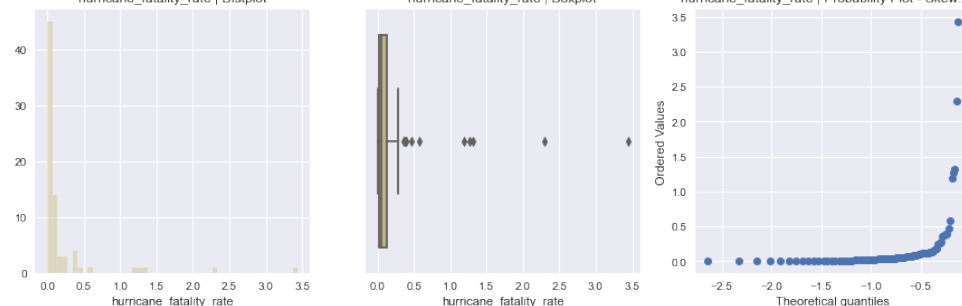
cyclone_power_dissipation_index_PDI_HUDRAT_NOAA | Distplot
cyclone_power_dissipation_index_PDI_HUDRAT_NOAA | Boxplot
cyclone_power_dissipation_index_PDI_HUDRAT_NOAA | Probability Plot - Skew: 1.3



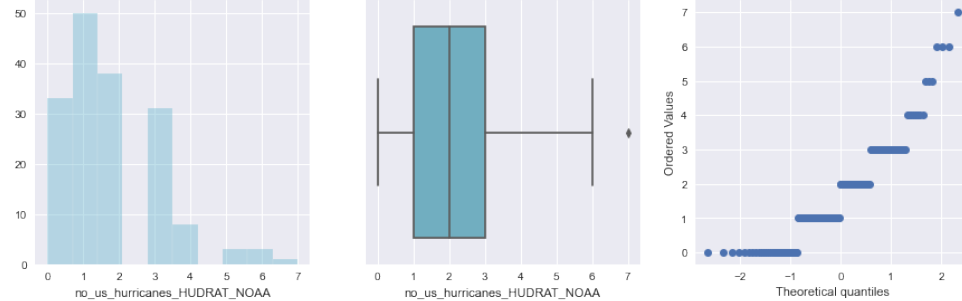
cyclone_power_dissipation_index_PDI_HUDRAT_NOAA | Distplot
no_major_us_hurricanes_HUDRAT_NOAA | Boxplot
no_major_us_hurricanes_HUDRAT_NOAA | Probability Plot - Skew: 1.6



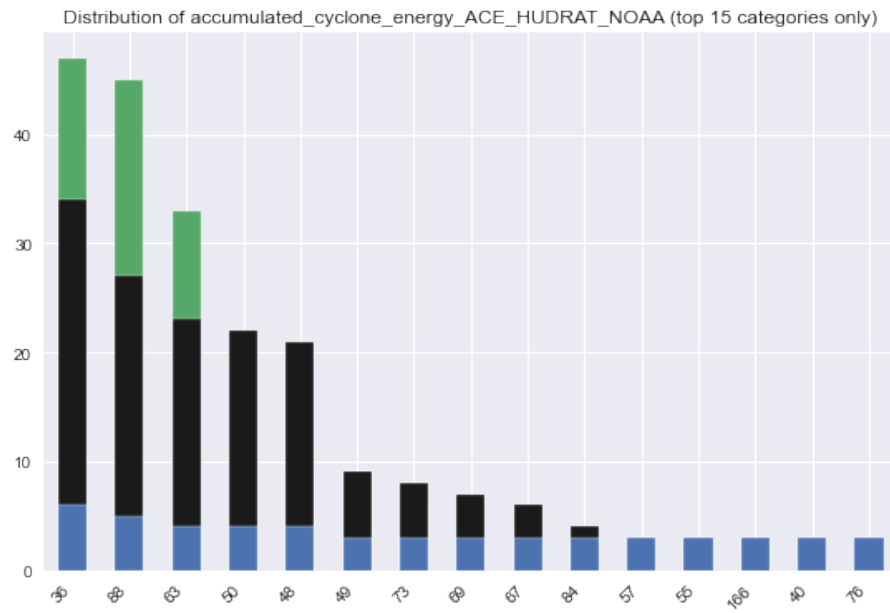
hurricane_fatalities_HUDRAT_NOAA | Distplot
hurricane_fatalities_HUDRAT_NOAA | Boxplot
hurricane_fatalities_HUDRAT_NOAA | Probability Plot - Skew: 4.5



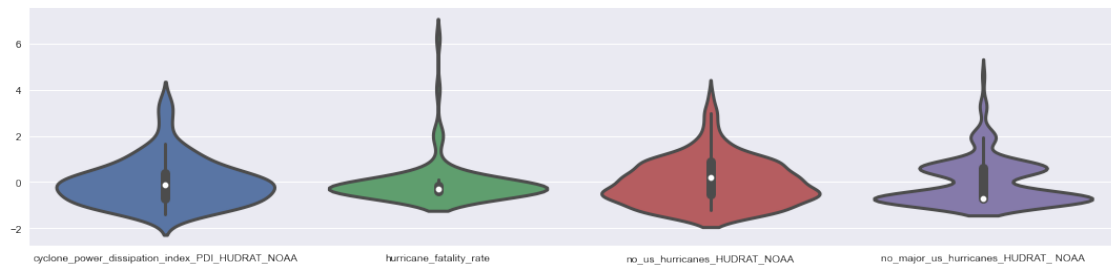
no_us_hurricanes_HUDRAT_NOAA | Distplot
no_us_hurricanes_HUDRAT_NOAA | Boxplot
no_us_hurricanes_HUDRAT_NOAA | Probability Plot - Skew: 0.9



Histograms (KDE plots) of all Continuous Variables



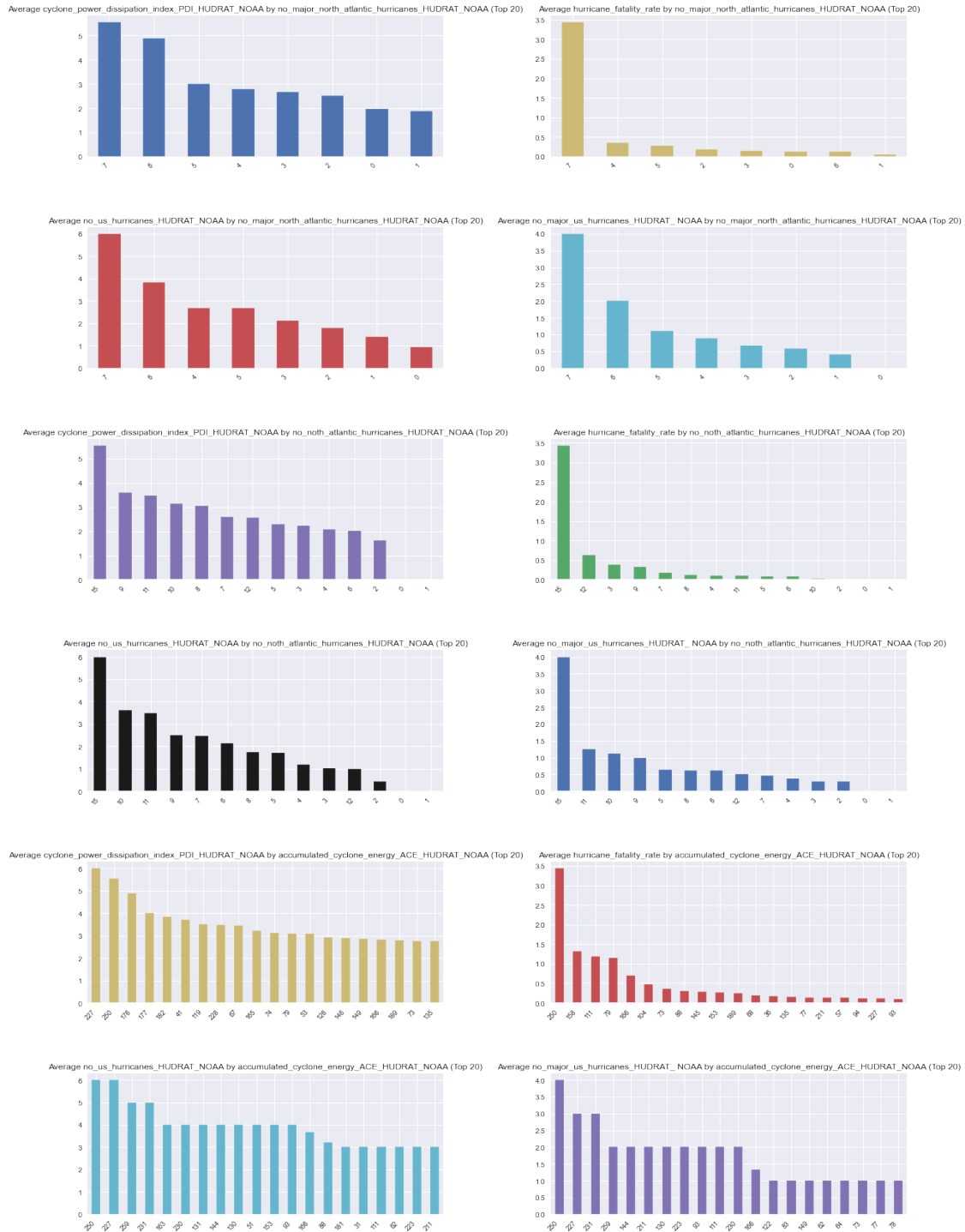
Violin Plot of all Continuous Variables



Heatmap of all Continuous Variables including target =



Bar plots for each Continuous by each Categorical variable



Time to run AutoViz (in seconds) = 13.330

VISUALIZATION Completed

```
[12]: #disaster_us_storm_df is:, disaster_us_storm_df
      #Trying this to see what happens
      df2 = AV.AutoViz("disaster_us_storm.csv")
```

Shape of your Data Set: (99, 16)

C L A S S I F Y I N G V A R I A B L E S

Classifying variables in data set...

Number of Numeric Columns = 13

Number of Integer-Categorical Columns = 0

Number of String-Categorical Columns = 0

Number of Factor-Categorical Columns = 0

Number of String-Boolean Columns = 0

Number of Numeric-Boolean Columns = 1

Number of Discrete String Columns = 0

Number of NLP String Columns = 0

Number of Date Time Columns = 1

Number of ID Columns = 0

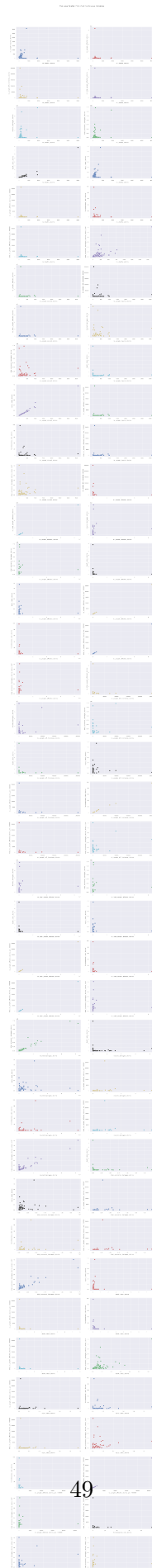
Number of Columns to Delete = 1

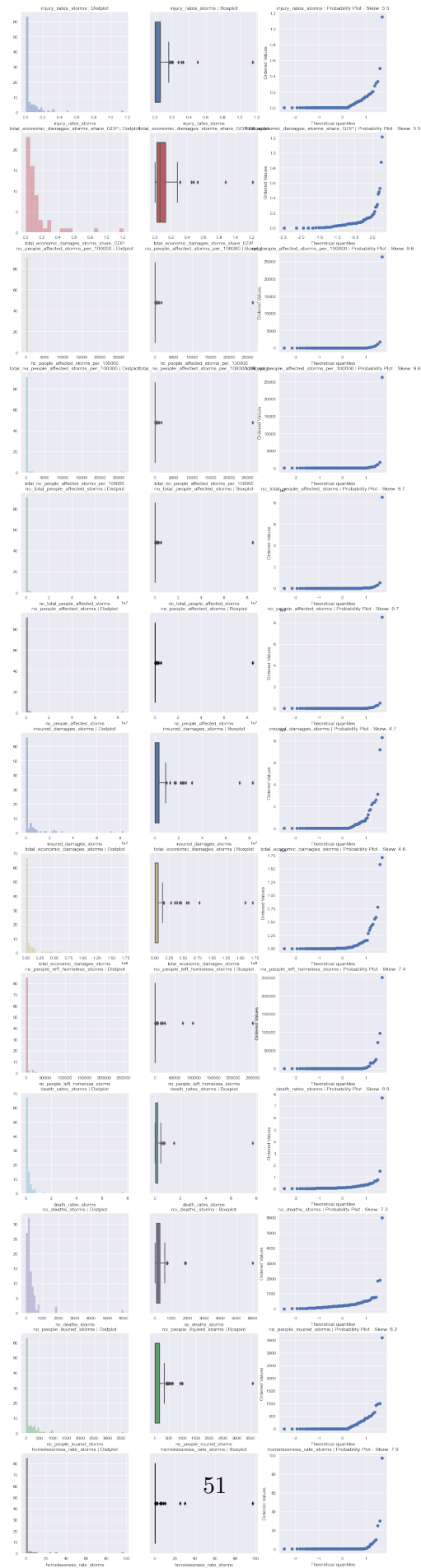
16 Predictors classified...

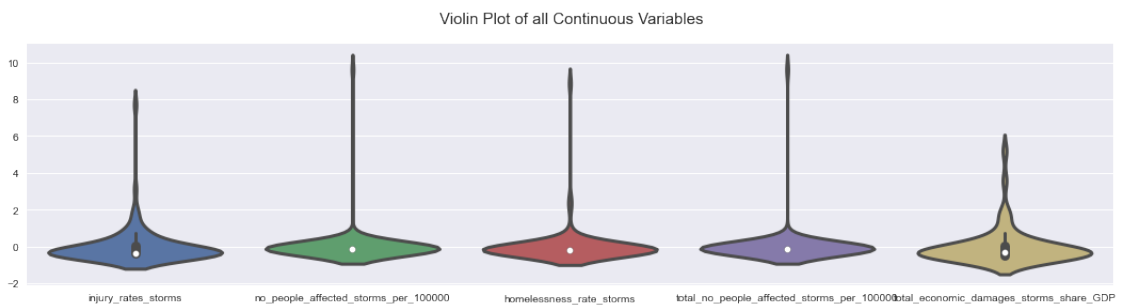
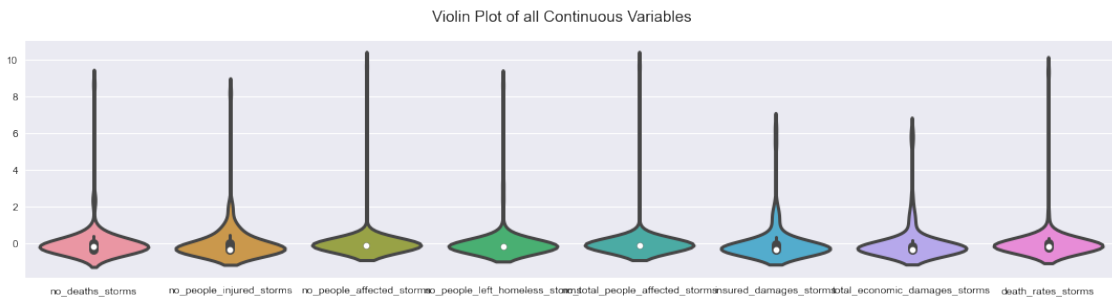
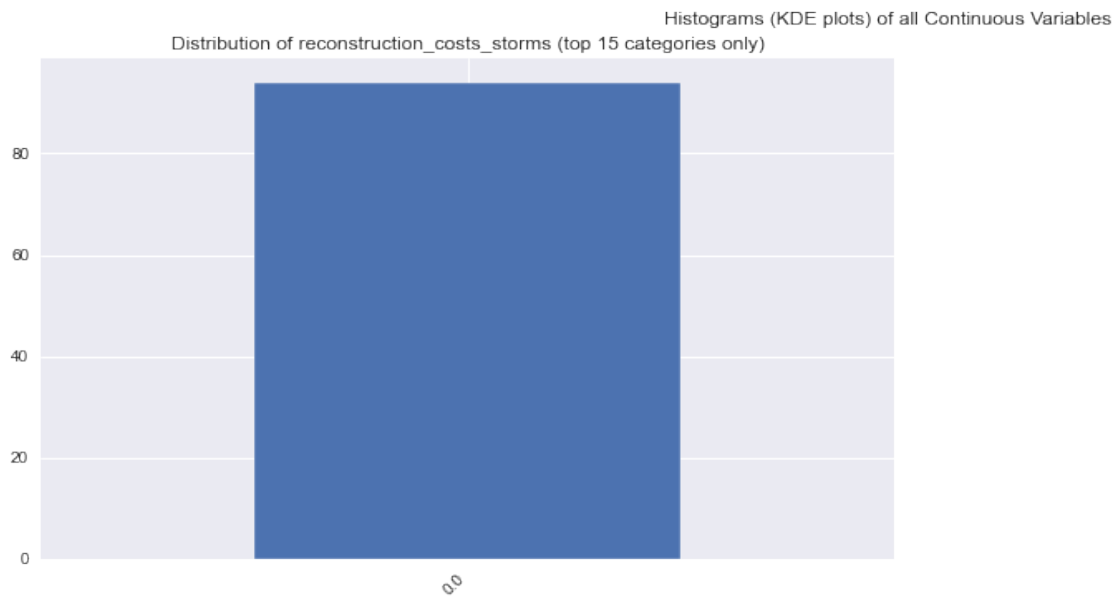
 This does not include the Target column(s)

 1 variables removed since they were ID or low-information variables

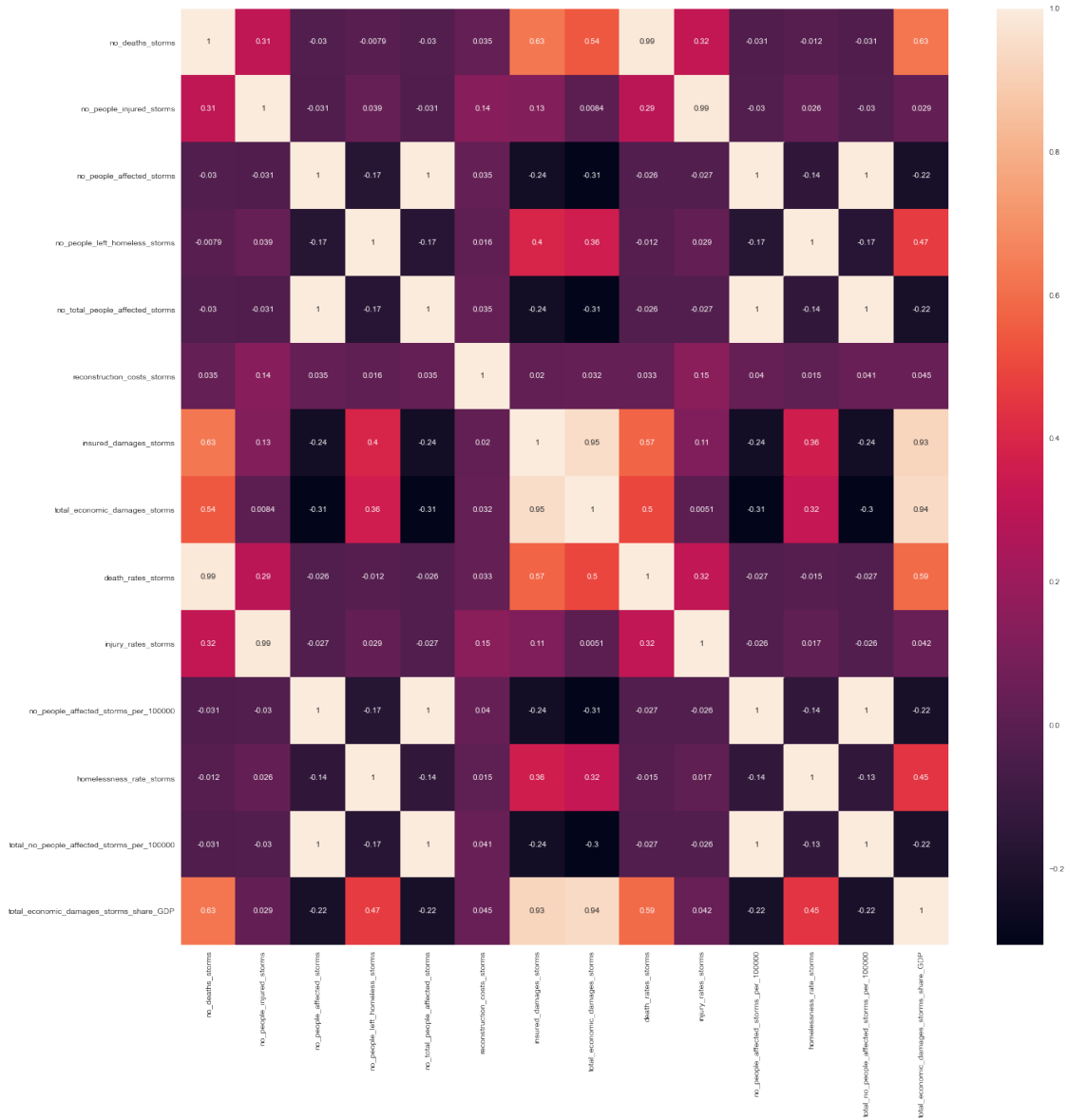
Number of All Scatter Plots = 91







Time Series Data: Heatmap of Differenced Continuous vars including target =



No categorical or numeric vars in data set. Hence no bar charts.

Time to run AutoViz (in seconds) = 49.251

VISUALIZATION Completed



```
[9]: # Column names
hurricanes_us_df.columns
```

```
[9]: Index(['Entity', 'Year', 'no_us_hurricanes_HUDRAT_NOAA',
        'no_major_us_hurricanes_HUDRAT_NOAA',
        'no_major_north_atlantic_hurricanes_HUDRAT_NOAA',
        'no_noth_atlantic_hurricanes_HUDRAT_NOAA',
        'accumulated_cyclone_energy_ACE_HUDRAT_NOAA',
        'cyclone_power_dissipation_index_PDI_HUDRAT_NOAA',
        'hurricane_fatality_rate', 'ACE', 'deaths_hurricanes_us',
        'total_economic_damages_storms', 'death_bin'],
        dtype='object')
```

```
[10]: # Second file column names
disaster_us_storm_df.columns
```

```
[10]: Index(['no_deaths_storms', 'no_people_injured_storms',
        'no_people_affected_storms', 'no_people_left_homeless_storms',
        'no_total_people_affected_storms', 'reconstruction_costs_storms',
        'insured_damages_storms', 'total_economic_damages_storms',
        'death_rates_storms', 'injury_rates_storms',
        'no_people_affected_storms_per_100000', 'homelessness_rate_storms',
        'total_no_people_affected_storms_per_100000',
        'total_economic_damages_storms_share_GDP', 'Entity', 'Year'],
        dtype='object')
```

```
[19]: # Pearson Ranking
# set up the figure size

# New features
num_features = ['no_us_hurricanes_HUDRAT_NOAA', 'no_major_us_hurricanes_HUDRAT_
↳ NOAA',
               ↳
↳ 'no_major_north_atlantic_hurricanes_HUDRAT_NOAA', 'no_noth_atlantic_hurricanes_HUDRAT_NOAA',
               'accumulated_cyclone_energy_ACE_HUDRAT_NOAA',
               ↳
↳ 'cyclone_power_dissipation_index_PDI_HUDRAT_NOAA', 'hurricane_fatality_rate']
plt.rcParams['figure.figsize'] = (12, 12)

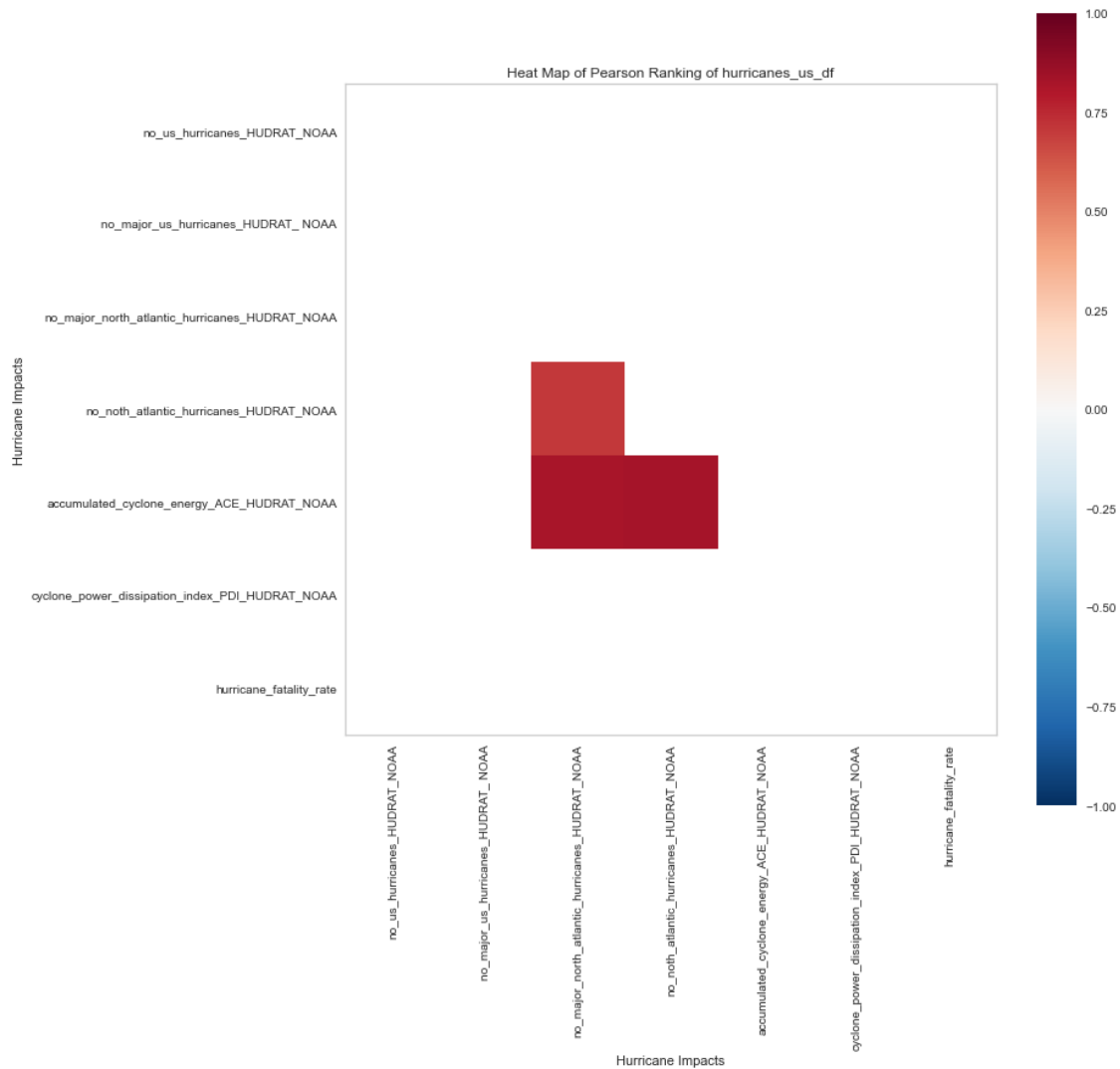
# Import the package for visulization of the correlation
from yellowbrick.features import Rank2D

# Extract the numpy arrays from the data frame
X = hurricanes_us_df[num_features].to_numpy()
```

```

# instantiate the visualizer with the Covariance ranking algorithm
visualizer = Rank2D(features=num_features, algorithm='pearson')
visualizer.fit(X) # Fit the data to the visualizer
visualizer.transform(X) # Transform the data
plt.title("Heat Map of Pearson Ranking of hurricanes_us_df")
plt.xlabel("Hurricane Impacts")
plt.ylabel("Hurricane Impacts")
plt.show()

```



```

[20]: # Pearson Ranking
# set up the figure size

# New features

```



```

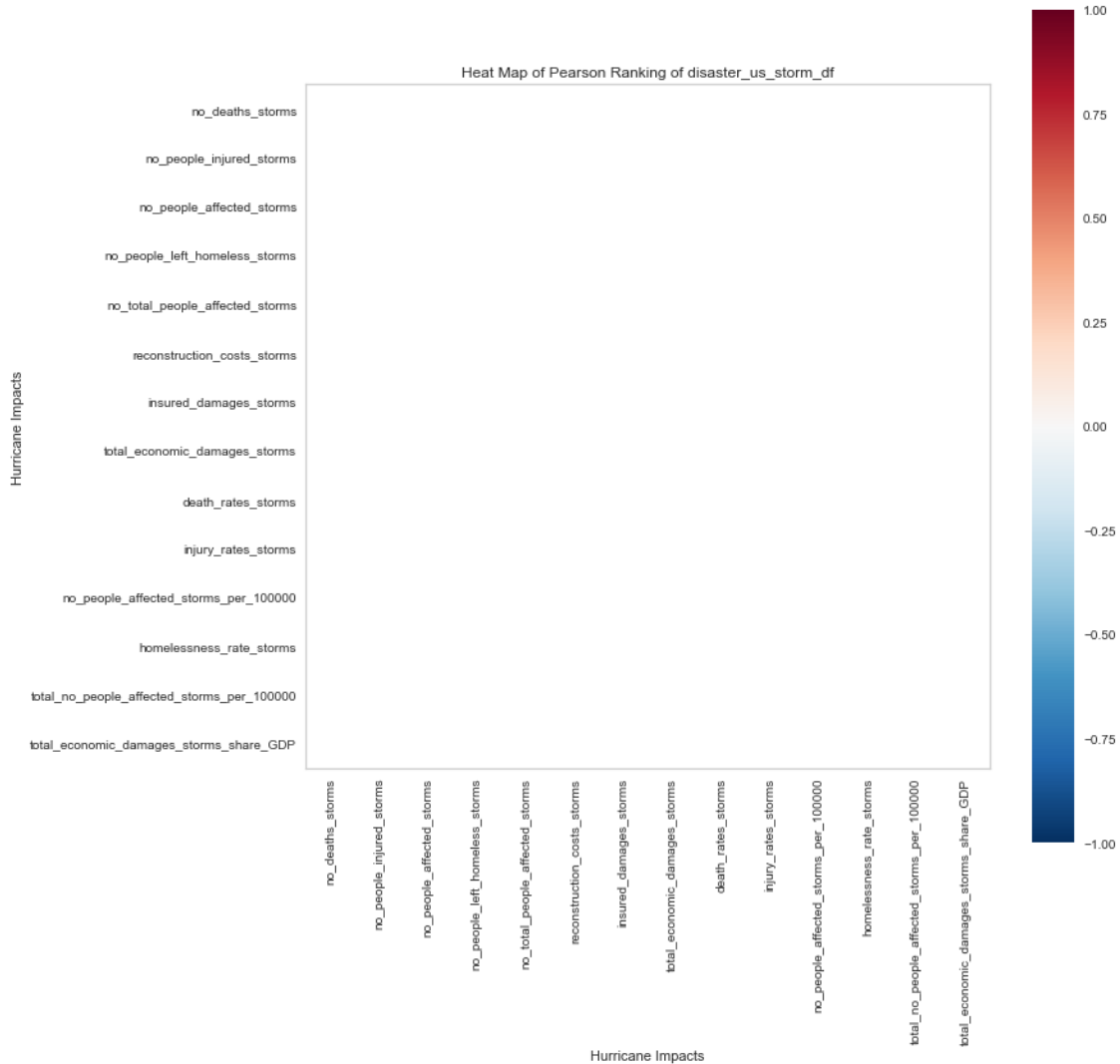
num_features = ['no_deaths_storms',␣
↳ 'no_people_injured_storms', 'no_people_affected_storms',␣
↳ 'no_people_left_homeless_storms',
               'no_total_people_affected_storms',␣
↳ 'reconstruction_costs_storms',
               'insured_damages_storms',␣
↳ 'total_economic_damages_storms', 'death_rates_storms', 'injury_rates_storms',
               'no_people_affected_storms_per_100000',␣
↳ 'homelessness_rate_storms',
               ␣
↳ 'total_no_people_affected_storms_per_100000', 'total_economic_damages_storms_share_GDP']
plt.rcParams['figure.figsize'] = (12, 12)

# Import the package for visualization of the correlation
from yellowbrick.features import Rank2D

# Extract the numpy arrays from the data frame
X = disaster_us_storm_df[num_features].to_numpy()

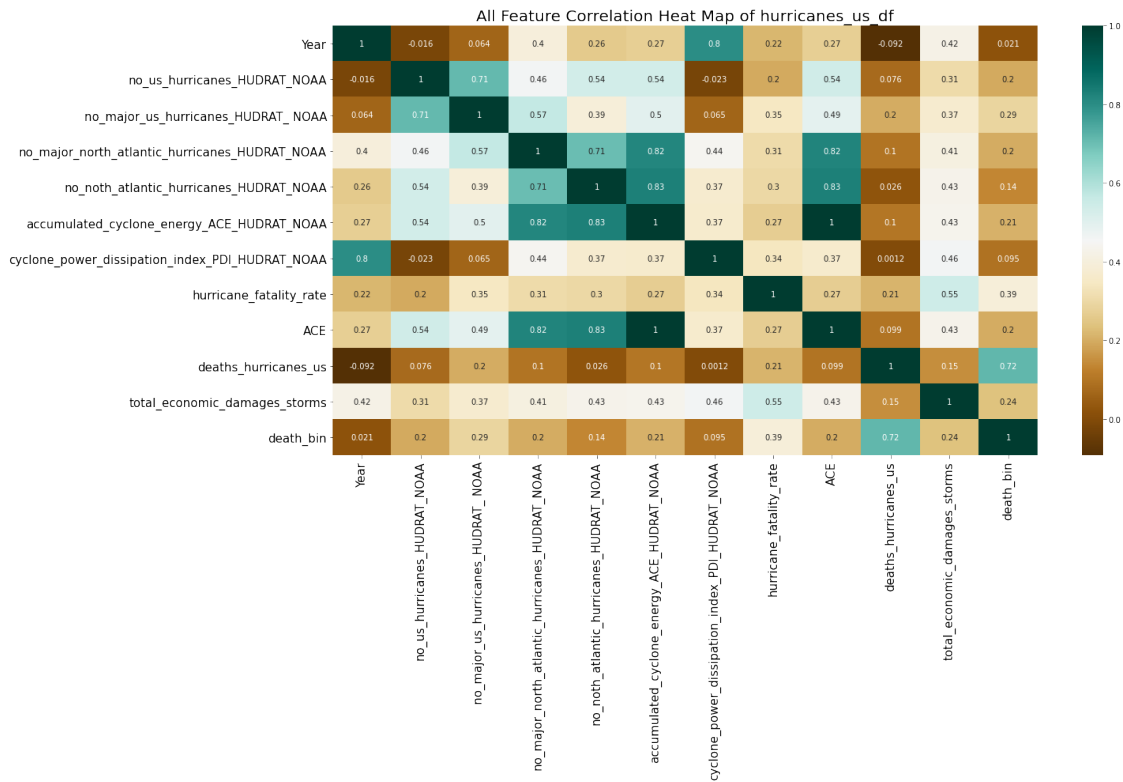
# instantiate the visualizer with the Covariance ranking algorithm
visualizer = Rank2D(features=num_features, algorithm='pearson')
visualizer.fit(X)                # Fit the data to the visualizer
visualizer.transform(X)         # Transform the data
plt.title("Heat Map of Pearson Ranking of disaster_us_storm_df")
plt.xlabel("Hurricane Impacts")
plt.ylabel("Hurricane Impacts")
plt.show()

```



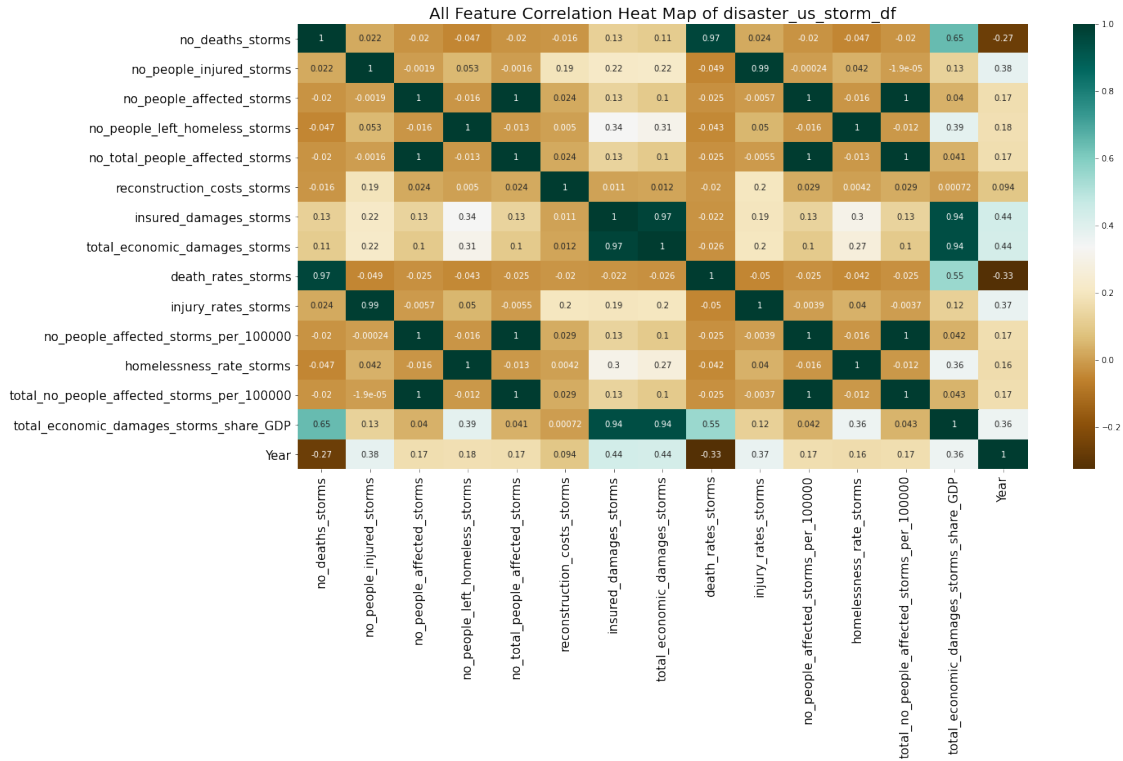
```
[24]: # Run full correlation on the data set using heat map
plt.figure(figsize=(20,10))
c= hurricanes_us_df.corr()
plt.title("All Feature Correlation Heat Map of hurricanes_us_df",fontsize=20)
plt.xlabel("Hurricanes Impact")
plt.ylabel("Hurricanes Impact")
plt.xticks(fontsize= 15)
plt.yticks(fontsize= 15)
sns.heatmap(c,cmap="BrBG",annot=True)
```

```
[24]: <AxesSubplot:title={'center': 'All Feature Correlation Heat Map of
hurricanes_us_df'}>
```



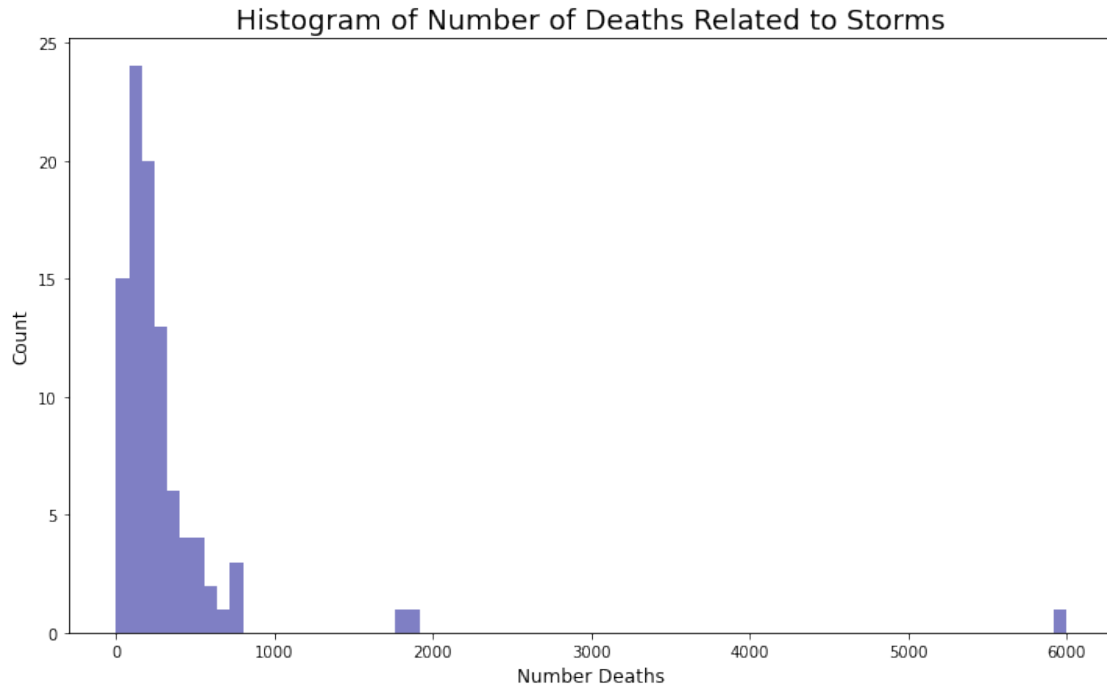
```
[22]: # Run full correlation on the data set using heat map
plt.figure(figsize=(20,10))
c= disaster_us_storm_df.corr()
plt.title("All Feature Correlation Heat Map of disaster_us_storm_df",
fontsize=20)
plt.xlabel("Hurricanes Impact")
plt.ylabel("Hurricanes Impact")
plt.xticks(fontsize= 15)
plt.yticks(fontsize= 15)
sns.heatmap(c,cmap="BrBG",annot=True)
```

```
[22]: <AxesSubplot:title={'center': 'All Feature Correlation Heat Map of
disaster_us_storm_df'}>
```



```
[25]: # Histogram of death by year

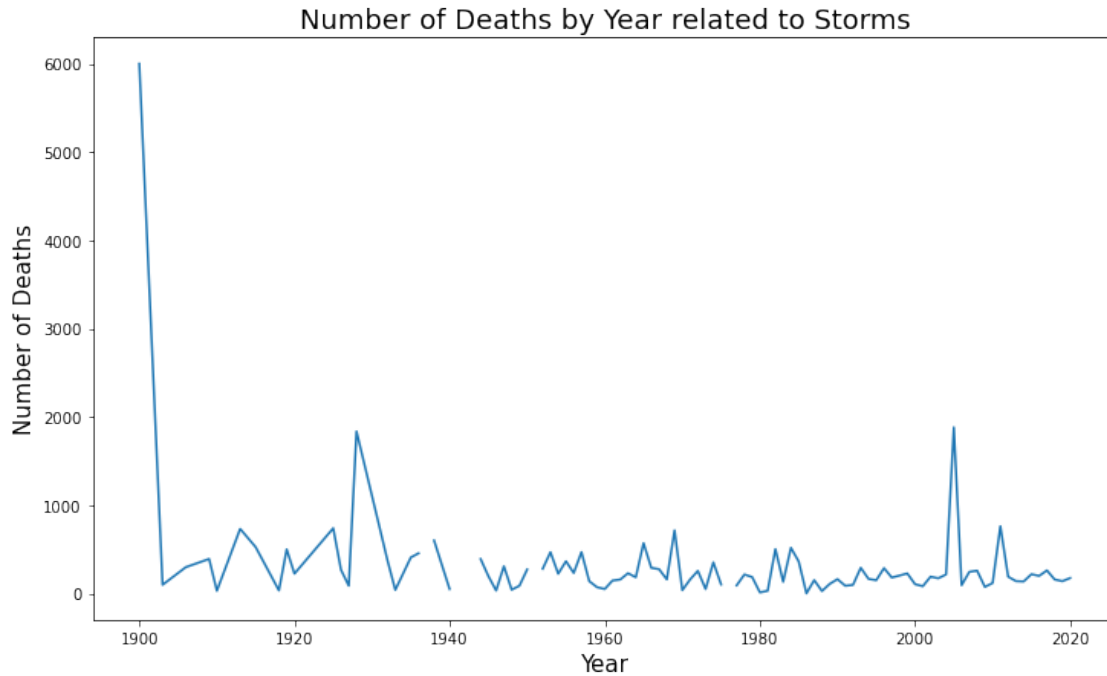
plt.rcParams['figure.figsize'] = (12, 7)
plt.hist(disaster_us_storm_df['no_deaths_storms'].dropna(), bins=75,
        ↳facecolor='darkblue', alpha=0.5)
#Labels
plt.title('Histogram of Number of Deaths Related to Storms', fontsize = 18)
plt.xlabel('Number Deaths', fontsize = 12)
plt.ylabel('Count', fontsize = 12)
plt.ticklabel_format(axis='x', style='plain')
plt.show()
```



```
[12]: # line chart number of deaths realated to storms
```

```
x1 = disaster_us_storm_df['Year']
y1 = disaster_us_storm_df['no_deaths_storms']

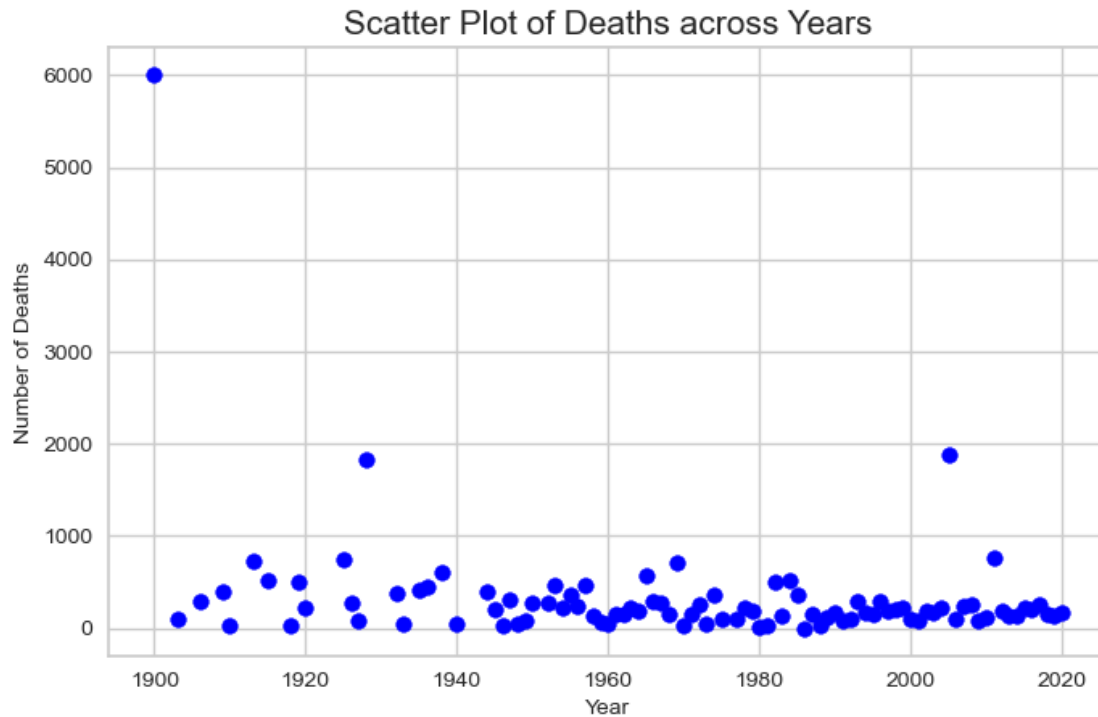
plt.rcParams['figure.figsize'] = (12, 7)
plt.plot(x1, y1)
plt.title('Number of Deaths by Year related to Storms', fontsize = 18)
plt.xlabel('Year', fontsize = 15)
plt.ylabel('Number of Deaths', fontsize = 15)
plt.show()
```



```
[51]: # Scatterplot - To check data
x = disaster_us_storm_df['Year']
y = disaster_us_storm_df['no_deaths_storms']

# Plot
plt.scatter(x,y,color='blue')
plt.rcParams.update({'figure.figsize':(8,5), 'figure.dpi':100})

# Labels
plt.title('Scatter Plot of Deaths across Years',fontsize=15)
plt.xlabel('Year',fontsize=10)
plt.ylabel('Number of Deaths',fontsize=10)
plt.ticklabel_format(axis='x', style='plain')
plt.ticklabel_format(axis='y', style='plain')
plt.show()
```



```
[26]: hurricanes_us_df.columns
```

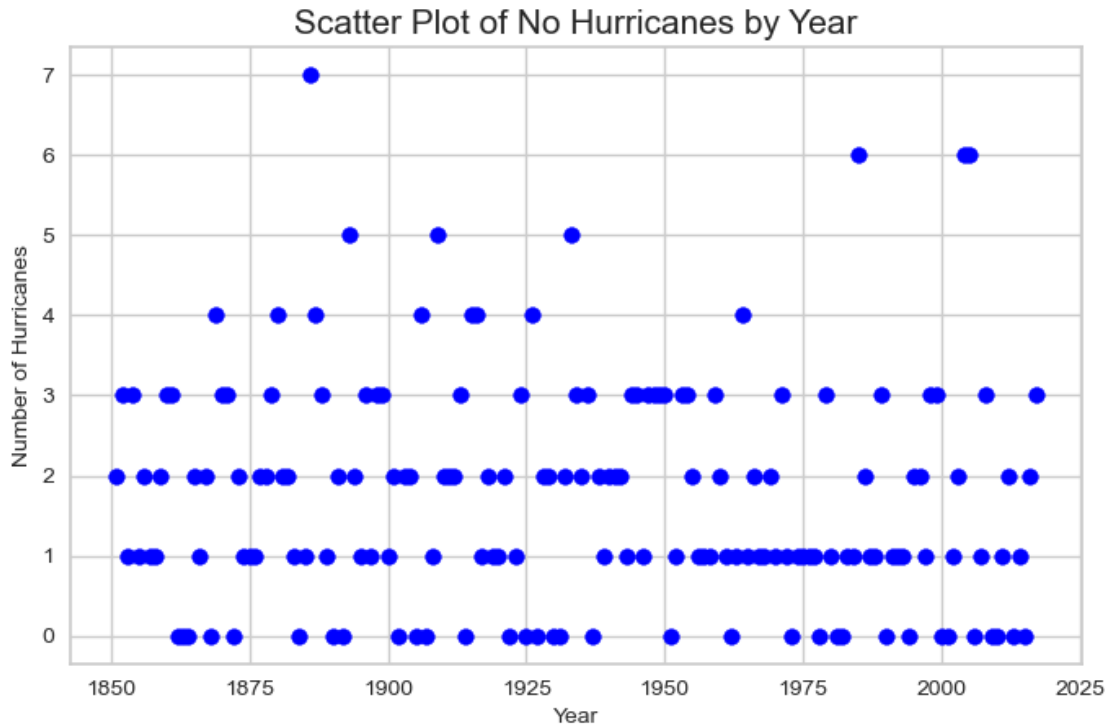
```
[26]: Index(['Entity', 'Year', 'no_us_hurricanes_HUDRAT_NOAA',
        'no_major_us_hurricanes_HUDRAT_NOAA',
        'no_major_north_atlantic_hurricanes_HUDRAT_NOAA',
        'no_noth_atlantic_hurricanes_HUDRAT_NOAA',
        'accumulated_cyclone_energy_ACE_HUDRAT_NOAA',
        'cyclone_power_dissipation_index_PDI_HUDRAT_NOAA',
        'hurricane_fatality_rate', 'ACE', 'deaths_hurricanes_us',
        'total_economic_damages_storms', 'death_bin'],
        dtype='object')
```

```
[53]: # Scatterplot - To check data
x = hurricanes_us_df['Year']
y = hurricanes_us_df['no_us_hurricanes_HUDRAT_NOAA']

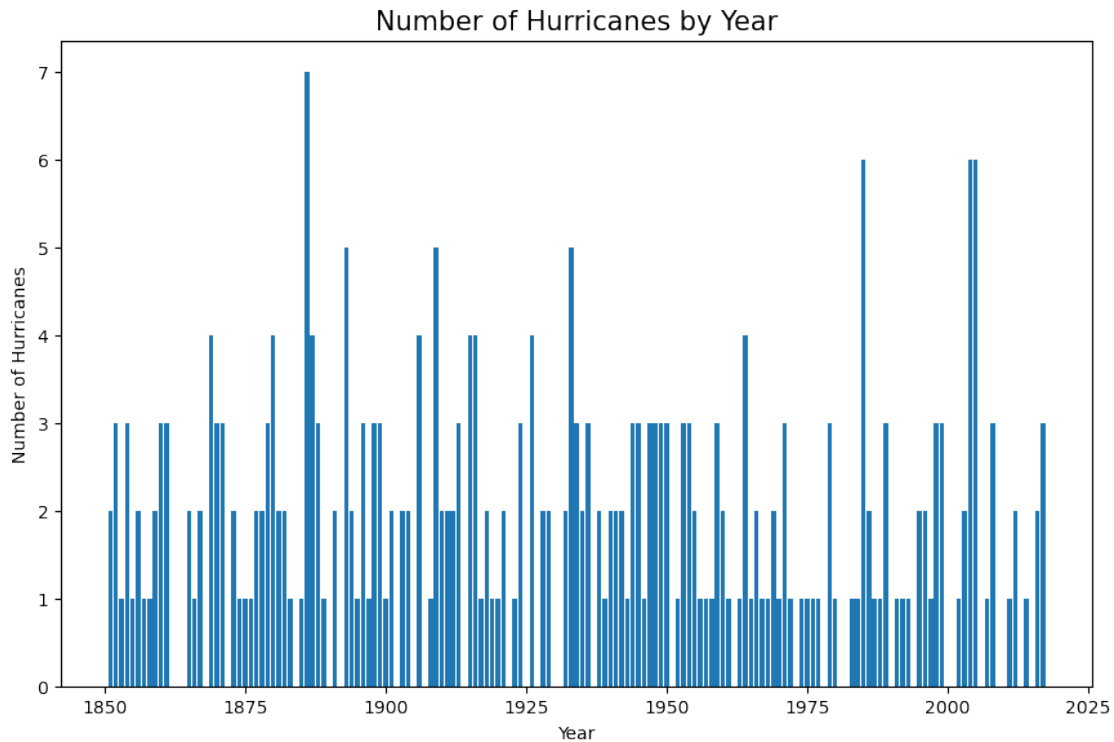
# Plot
plt.scatter(x,y,color='blue')
plt.rcParams.update({'figure.figsize':(8,5), 'figure.dpi':100})

#Labels
plt.title('Scatter Plot of No Hurricanes by Year',fontsize=15)
plt.xlabel('Year',fontsize=10)
```

```
plt.ylabel('Number of Hurricanes',fontsize=10)
plt.ticklabel_format(axis='x', style='plain')
plt.ticklabel_format(axis='y', style='plain')
plt.show()
```



```
[11]: fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
year = hurricanes_us_df['Year']
no_h = hurricanes_us_df['no_us_hurricanes_HUDRAT_NOAA']
ax.bar(year,no_h)
plt.title('Number of Hurricanes by Year',fontsize=15)
plt.xlabel('Year',fontsize=10)
plt.ylabel('Number of Hurricanes',fontsize=10)
plt.show()
```

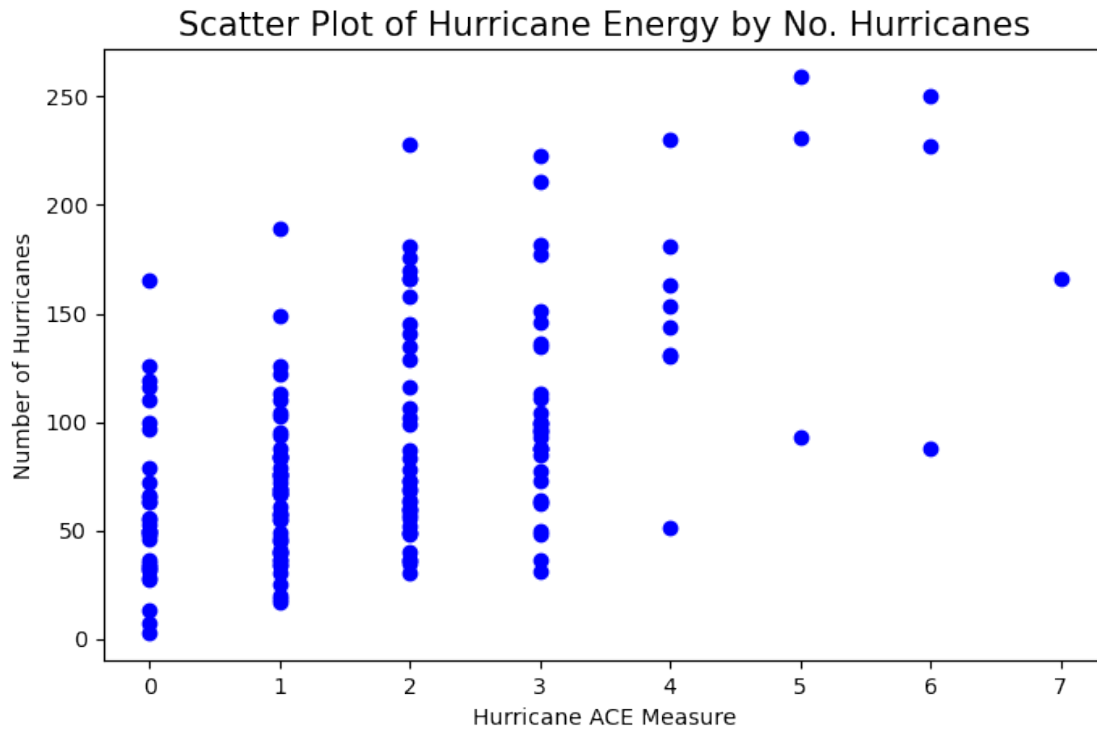



```
[9]: # Scatterplot - To check data
plt.clf()

x = hurricanes_us_df['no_us_hurricanes_HUDRAT_NOAA']
y = hurricanes_us_df['accumulated_cyclone_energy_ACE_HUDRAT_NOAA']

# Plot
plt.scatter(x,y,color='blue')
plt.rcParams.update({'figure.figsize':(8,5), 'figure.dpi':100})

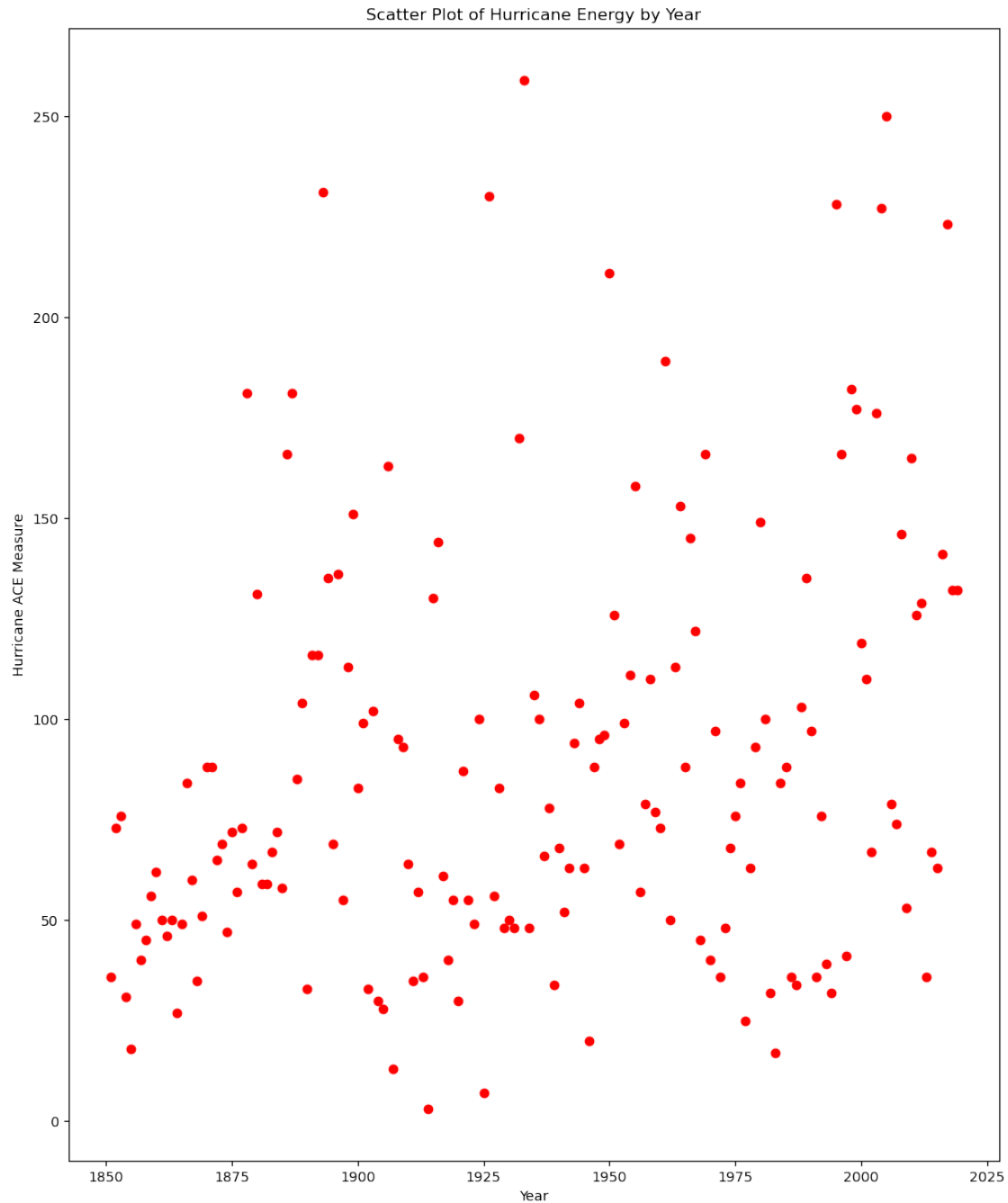
#Labels
plt.title('Scatter Plot of Hurricane Energy by No. Hurricanes',fontsize=15)
plt.xlabel('Hurricane ACE Measure',fontsize=10)
plt.ylabel('Number of Hurricanes',fontsize=10)
plt.ticklabel_format(axis='x', style='plain')
plt.ticklabel_format(axis='y', style='plain')
plt.show()
```



```
[16]: # Scatterplot - To check data
y = hurricanes_us_df['accumulated_cyclone_energy_ACE_HUDRAT_NOAA']
x = hurricanes_us_df['Year']

# Plot
plt.scatter(x,y,color='red')
plt.rcParams.update({'figure.figsize':(8,8), 'figure.dpi':100})

#Labels
plt.title('Scatter Plot of Hurricane Energy by Year',fontsize=12)
plt.ylabel('Hurricane ACE Measure',fontsize=10)
plt.xlabel('Year',fontsize=10)
plt.ticklabel_format(axis='x', style='plain')
plt.ticklabel_format(axis='y', style='plain')
plt.show()
```



Note: reducing the data to 1950 and greater since economic damages have not been record before 1950.

```
[17]: # Filter data down to US only
hurricanes_us_1900_df = hurricanes_us_df[hurricanes_us_df['Year'] >= 1900]
```

```
[18]: # Drop hurricane_fatality_rate
hurricanes_us_1900_df.drop(['hurricane_fatality_rate'], axis=1)
```

```
[18]:
```

	Entity	Year	no_us_hurricanes_HUDRAT_NOAA \
49	North Atlantic	1900	1
50	North Atlantic	1901	2
51	North Atlantic	1902	0
52	North Atlantic	1903	2
53	North Atlantic	1904	2
..
164	North Atlantic	2015	0
165	North Atlantic	2016	2
166	North Atlantic	2017	3
167	North Atlantic	2018	8
168	North Atlantic	2019	6

	no_major_us_hurricanes_HUDRAT_ NOAA \
49	1
50	0
51	0
52	0
53	0
..	...
164	0
165	0
166	2
167	2
168	3

	no_major_north_atlantic_hurricanes_HUDRAT_NOAA \
49	2
50	0
51	0
52	1
53	0
..	...
164	2
165	4
166	6
167	2
168	2

	no_noth_atlantic_hurricanes_HUDRAT_NOAA \
49	3
50	6
51	3
52	7

53	4
..	...
164	4
165	7
166	10
167	8
168	8

accumulated_cyclone_energy_ACE_HUDRAT_NOAA \	
49	83
50	99
51	33
52	102
53	30
..	...
164	63
165	141
166	223
167	132
168	132

cyclone_power_dissipation_index_PDI_HUDRAT_NOAA			ACE \
49	0.0	83.3450	
50	0.0	98.9750	
51	0.0	32.6500	
52	0.0	102.0700	
53	0.0	30.3450	
..	
164	NaN	62.6850	
165	NaN	141.2525	
166	NaN	224.8775	
167	NaN	132.5825	
168	NaN	132.2025	

deaths_hurricanes_us	total_economic_damages_storms	death_bin	
49	6000.0	30000.0	10.0
50	0.0	0.0	1.0
51	0.0	0.0	1.0
52	98.0	0.0	1.0
53	0.0	0.0	1.0
..
164	218.0	15720000.0	3.0
165	199.0	28050000.0	2.0
166	261.0	171110000.0	3.0
167	158.0	38875000.0	2.0
168	139.0	11325000.0	2.0

[120 rows x 12 columns]

```
[28]: hurricanes_us_1900_df.columns
```

```
[28]: Index(['Entity', 'Year', 'no_us_hurricanes_HUDRAT_NOAA',
        'no_major_us_hurricanes_HUDRAT_NOAA',
        'no_major_north_atlantic_hurricanes_HUDRAT_NOAA',
        'no_north_atlantic_hurricanes_HUDRAT_NOAA',
        'accumulated_cyclone_energy_ACE_HUDRAT_NOAA',
        'cyclone_power_dissipation_index_PDI_HUDRAT_NOAA',
        'hurricane_fatality_rate', 'ACE', 'deaths_hurricanes_us',
        'total_economic_damages_storms', 'death_bin'],
        dtype='object')
```

0.1 Modeling

```
[19]: # Import libraries
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
import statsmodels.api as sm
from statsmodels.formula.api import ols
```

Notes: Reduce years from 1850 to 1900 due to a lot of missing data.

```
[20]: # filter for future use
hurricanes_1900_df = hurricanes_us_df[hurricanes_us_df['Year'] >= 1900]
```

```
[21]: hurricanes_1900_df.head
```

```
[21]: <bound method NDFrame.head of
no_us_hurricanes_HUDRAT_NOAA \
49  North Atlantic  1900      1
50  North Atlantic  1901      2
51  North Atlantic  1902      0
52  North Atlantic  1903      2
53  North Atlantic  1904      2
..      ...      ...
164 North Atlantic  2015      0
165 North Atlantic  2016      2
166 North Atlantic  2017      3
167 North Atlantic  2018      8
168 North Atlantic  2019      6

no_major_us_hurricanes_HUDRAT_NOAA \
49      1
```

50	0
51	0
52	0
53	0
..	...
164	0
165	0
166	2
167	2
168	3

	no_major_north_atlantic_hurricanes_HUDRAT_NOAA \
49	2
50	0
51	0
52	1
53	0
..	...
164	2
165	4
166	6
167	2
168	2

	no_noth_atlantic_hurricanes_HUDRAT_NOAA \
49	3
50	6
51	3
52	7
53	4
..	...
164	4
165	7
166	10
167	8
168	8

	accumulated_cyclone_energy_ACE_HUDRAT_NOAA \
49	83
50	99
51	33
52	102
53	30
..	...
164	63
165	141
166	223

```

167                                     132
168                                     132

cyclone_power_dissipation_index_PDI_HUDRAT_NOAA hurricane_fatality_rate \
49                                     0.0                0.000000
50                                     0.0                0.000000
51                                     0.0                0.000000
52                                     0.0                0.000000
53                                     0.0                0.000000
..                                     ...                ...
164                                    NaN                0.043557
165                                    NaN                NaN
166                                    NaN                NaN
167                                    NaN                NaN
168                                    NaN                NaN

```

```

ACE deaths_hurricanes_us total_economic_damages_storms death_bin
49  83.3450             6000.0             30000.0          10.0
50  98.9750              0.0              0.0           1.0
51  32.6500              0.0              0.0           1.0
52 102.0700             98.0              0.0           1.0
53  30.3450              0.0              0.0           1.0
..      ...              ...              ...           ...
164  62.6850             218.0            15720000.0         3.0
165 141.2525             199.0            28050000.0         2.0
166 224.8775             261.0            171110000.0        3.0
167 132.5825             158.0            38875000.0         2.0
168 132.2025             139.0            11325000.0         2.0

```

```
[120 rows x 13 columns]>
```

```
[22]: # Change data types for modeling
```

```

hurricanes_1900_df['no_us_hurricanes_HUDRAT_NOAA'] =
    ↪hurricanes_1900_df['no_us_hurricanes_HUDRAT_NOAA'].astype(int)
hurricanes_1900_df['no_major_us_hurricanes_HUDRAT_NOAA'] =
    ↪hurricanes_1900_df['no_major_us_hurricanes_HUDRAT_NOAA'].astype(int)
hurricanes_1900_df['no_major_north_atlantic_hurricanes_HUDRAT_NOAA'] =
    ↪hurricanes_1900_df['no_major_north_atlantic_hurricanes_HUDRAT_NOAA'].
    ↪astype(int)
hurricanes_1900_df['no_noth_atlantic_hurricanes_HUDRAT_NOAA'] =
    ↪hurricanes_1900_df['no_noth_atlantic_hurricanes_HUDRAT_NOAA'].astype(int)
hurricanes_1900_df['accumulated_cyclone_energy_ACE_HUDRAT_NOAA'] =
    ↪hurricanes_1900_df['accumulated_cyclone_energy_ACE_HUDRAT_NOAA'].astype(int)
hurricanes_1900_df['death_bin'] = hurricanes_1900_df['death_bin'].astype(int)

```

```
<ipython-input-22-ac42eb629da4>:3: SettingWithCopyWarning:
```


A value is trying to be set on a copy of a slice from a DataFrame.
Try using `.loc[row_indexer,col_indexer] = value` instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
hurricanes_1900_df['no_us_hurricanes_HUDRAT_NOAA'] =  
hurricanes_1900_df['no_us_hurricanes_HUDRAT_NOAA'].astype(int)
```

<ipython-input-22-ac42eb629da4>:4: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using `.loc[row_indexer,col_indexer] = value` instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
hurricanes_1900_df['no_major_us_hurricanes_HUDRAT_NOAA'] =  
hurricanes_1900_df['no_major_us_hurricanes_HUDRAT_NOAA'].astype(int)
```

<ipython-input-22-ac42eb629da4>:5: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using `.loc[row_indexer,col_indexer] = value` instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
hurricanes_1900_df['no_major_north_atlantic_hurricanes_HUDRAT_NOAA'] =  
hurricanes_1900_df['no_major_north_atlantic_hurricanes_HUDRAT_NOAA'].astype(int)
```

<ipython-input-22-ac42eb629da4>:6: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using `.loc[row_indexer,col_indexer] = value` instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
hurricanes_1900_df['no_noth_atlantic_hurricanes_HUDRAT_NOAA'] =  
hurricanes_1900_df['no_noth_atlantic_hurricanes_HUDRAT_NOAA'].astype(int)
```

<ipython-input-22-ac42eb629da4>:7: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using `.loc[row_indexer,col_indexer] = value` instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
hurricanes_1900_df['accumulated_cyclone_energy_ACE_HUDRAT_NOAA'] =  
hurricanes_1900_df['accumulated_cyclone_energy_ACE_HUDRAT_NOAA'].astype(int)
```

<ipython-input-22-ac42eb629da4>:8: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using `.loc[row_indexer,col_indexer] = value` instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
hurricanes_1900_df['death_bin'] = hurricanes_1900_df['death_bin'].astype(int)
```

```
[23]: # Change year to to int
hurricanes_1900_df['Year'] = hurricanes_1900_df['Year'].astype(int)
```

```
<ipython-input-23-b1ff7401944b>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
hurricanes_1900_df['Year'] = hurricanes_1900_df['Year'].astype(int)
```

```
[34]: hurricanes_1900_df.head()
```

```
[34]:
```

	Entity	Year	no_us_hurricanes_HUDRAT_NOAA	\
49	North Atlantic	1900	1	
50	North Atlantic	1901	2	
51	North Atlantic	1902	0	
52	North Atlantic	1903	2	
53	North Atlantic	1904	2	

	no_major_us_hurricanes_HUDRAT_NOAA	\
49	1	
50	0	
51	0	
52	0	
53	0	

	no_major_north_atlantic_hurricanes_HUDRAT_NOAA	\
49	2	
50	0	
51	0	
52	1	
53	0	

	no_noth_atlantic_hurricanes_HUDRAT_NOAA	\
49	3	
50	6	
51	3	
52	7	
53	4	

	accumulated_cyclone_energy_ACE_HUDRAT_NOAA	\
49	83	
50	99	
51	33	
52	102	
53	30	

	cyclone_power_dissipation_index_PDI_HUDRAT_NOAA	hurricane_fatality_rate	\
49	0.0	0.0	
50	0.0	0.0	
51	0.0	0.0	
52	0.0	0.0	
53	0.0	0.0	

	ACE	deaths_hurricanes_us	total_economic_damages_storms	death_bin
49	83.345	6000.0	30000.0	10
50	98.975	0.0	0.0	1
51	32.650	0.0	0.0	1
52	102.070	98.0	0.0	1
53	30.345	0.0	0.0	1

0.1.1 Linear regression model

```
[36]: # split the data in training and Test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳random_state=0)
```

```
[37]: # train the model using linear regression
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

```
[37]: LinearRegression()
```

```
[69]: # used deaths_hurricanes_us
coeff = pd.DataFrame(regressor.coef_, X.columns, columns=['Coefficient'])
coeff
```

```
[69]:
```

	Coefficient
no_us_hurricanes_HUDRAT_NOAA	-53.974540
no_major_us_hurricanes_HUDRAT_NOAA	262.029082
no_major_north_atlantic_hurricanes_HUDRAT_NOAA	-42.694718
no_noth_atlantic_hurricanes_HUDRAT_NOAA	-44.326837
accumulated_cyclone_energy_ACE_HUDRAT_NOAA	3.175403

```
[70]: # used deaths_hurricanes_us

y_pred = regressor.predict(X_test)
```

```
[71]: # used deaths_hurricanes_us
print(regressor.score(X_test, y_test))
```

```
-2.4876948515430244
```

```
[72]: # calculate rmse and r2
# used deaths_hurricanes_us
```

```
from sklearn.metrics import mean_squared_error, r2_score
rmse = np.sqrt(mean_squared_error(y_test,y_pred))
r2 = r2_score(y_test,y_pred)
```

```
[73]: # print rmse
rmse
```

```
[73]: 312.24188966237466
```

```
[74]: # print r
r2
```

```
[74]: -2.4876948515430244
```

```
[75]: # Calculation of Mean Squared Error (MSE)
mean_squared_error(y_test,y_pred)
```

```
[75]: 97494.99765993055
```

```
[76]: mean_absolute_error(y_test,y_pred)
```

```
[76]: 270.6704113740778
```

```
[77]: df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
df.head(25)
```

```
[77]:
```

	Actual	Predicted
97	42.0	251.255390
143	165.0	254.858900
144	150.0	463.229674
57	0.0	225.259542
146	180.0	186.768272
71	0.0	285.198459
56	0.0	327.506747
59	30.0	205.828009
94	196.0	541.387837
138	108.0	419.334123
82	40.0	619.077922
99	272.0	574.607641
51	0.0	258.034303
109	50.0	409.414166
168	139.0	727.615619
123	352.0	447.511690
79	0.0	270.953562
92	0.0	223.716258
160	762.0	151.286056
125	0.0	147.635387

112	229.0	152.700530
108	71.0	235.160728
65	0.0	394.902630
73	0.0	134.819598

```
[47]: print(('R-Squared :'), regressor.score(X_test, y_test))
```

```
R-Squared : -2.4876948515430244
```

```
[48]: sns.distplot(y_pred, hist = False, color = 'r', label = 'Predicted Values')
sns.distplot(y_test, hist = False, color = 'b', label = 'Actual Values')
plt.title('Linear Regression Actual vs Predicted Values', fontsize = 18)
plt.xlabel('Values', fontsize = 16)
plt.ylabel('Frequency', fontsize = 16)
plt.legend(loc = 'upper left', fontsize = 16)
plt.ticklabel_format(style='plain', axis='x')

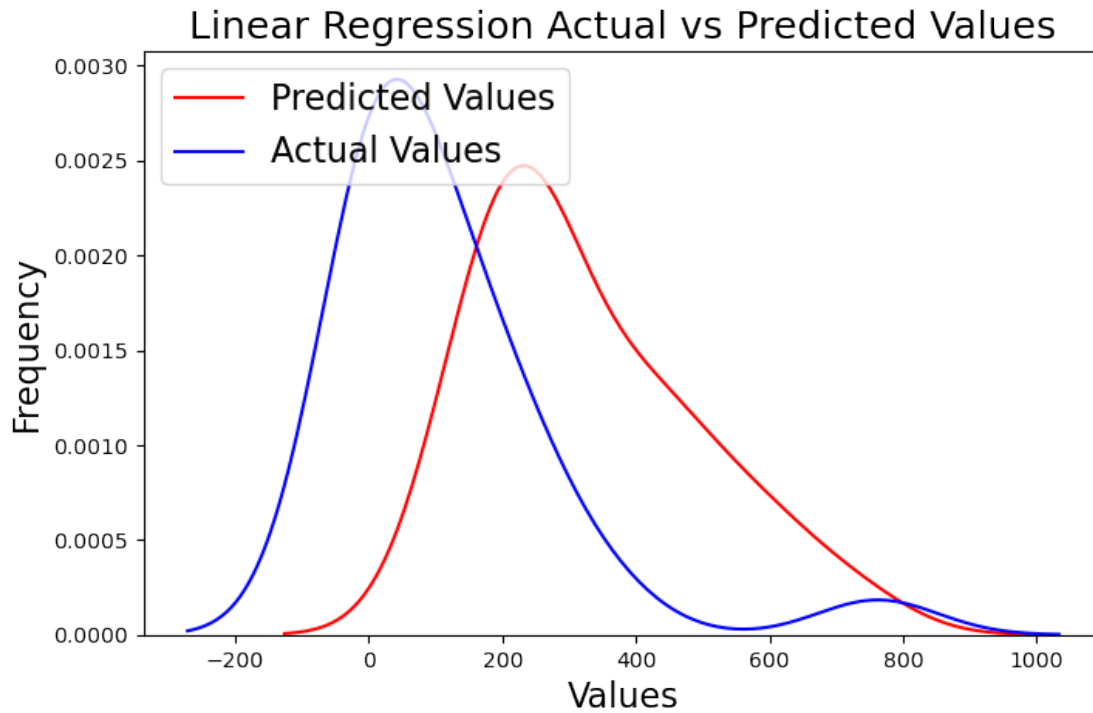
plt.savefig('ap.png')
```

```
C:\Users\Tushar\anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).
```

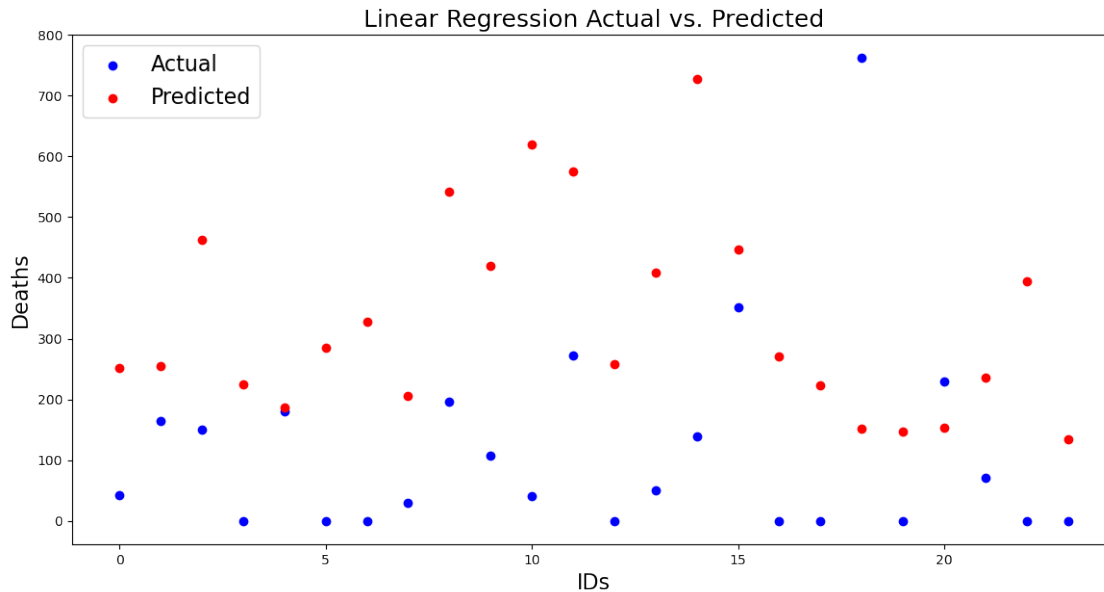
```
warnings.warn(msg, FutureWarning)
```

```
C:\Users\Tushar\anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).
```

```
warnings.warn(msg, FutureWarning)
```



```
[49]: plt.figure(figsize=(14,7))
plt.scatter(range(len(y_test)), y_test, color='blue', label='Actual')
plt.scatter(range(len(y_pred)), y_pred, color='red', label='Predicted')
plt.title('Linear Regression Actual vs. Predicted', fontsize = 18)
plt.xlabel('IDs', fontsize = 16)
plt.ylabel('Deaths', fontsize = 16)
plt.legend(loc = 'upper left', fontsize = 16)
plt.ticklabel_format(style='plain', axis='x')
plt.show()
```



Using `death_bin` as alternative to using actual number of deaths. Note: below is done with binning of deaths to see if that increases model accuracy

```
[24]: # split out X and y
      # Updated from deaths_hurricanes_us to death_bin

X = hurricanes_1900_df[['no_us_hurricanes_HUDRAT_NOAA',
                        'no_major_us_hurricanes_HUDRAT_NOAA',
                        'no_major_north_atlantic_hurricanes_HUDRAT_NOAA',
                        'no_north_atlantic_hurricanes_HUDRAT_NOAA',
                        'accumulated_cyclone_energy_ACE_HUDRAT_NOAA']]

y = hurricanes_1900_df['death_bin']

[25]: # split the data in training and Test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
                                                    random_state=0)

[26]: # train the model using linear regression
regressor = LinearRegression()
regressor.fit(X_train, y_train)

[26]: LinearRegression()

[39]: # used death_bin
coeff2 = pd.DataFrame(regressor.coef_, X.columns, columns=['Coefficient'])
coeff2
```

```
[39]:
```

	Coefficient
no_us_hurricanes_HUDRAT_NOAA	-0.011755
no_major_us_hurricanes_HUDRAT_ NOAA	0.922708
no_major_north_atlantic_hurricanes_HUDRAT_NOAA	-0.154419
no_noth_atlantic_hurricanes_HUDRAT_NOAA	-0.099639
accumulated_cyclone_energy_ACE_HUDRAT_NOAA	0.010755

```
[40]: y_pred = regressor.predict(X_test)
```

```
[41]: print(regressor.score(X_test, y_test))
```

```
-1.0763589168854542
```

Note: The number improved with using binning. Original r2 was -2.47

```
[42]: from sklearn.metrics import mean_squared_error, r2_score
rmse = np.sqrt(mean_squared_error(y_test,y_pred))
r2 = r2_score(y_test,y_pred)
```

```
[43]: # print rmse
rmse
```

```
[43]: 1.9501418472777152
```

```
[44]: r2
```

```
[44]: -1.0763589168854542
```

```
[45]: mean_squared_error(y_test,y_pred)
```

```
[45]: 3.80305322450374
```

```
[46]: mean_absolute_error(y_test,y_pred)
```

```
[46]: 1.6580823413052255
```

```
[53]: df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
df.head(25)
```

```
[53]:
```

	Actual	Predicted
97	1	2.830455
143	2	2.182054
144	2	3.619981
57	1	2.394514
146	2	2.112673
71	1	2.274995
56	1	2.276630
59	1	2.348278

94	2	3.817487
138	2	3.469845
82	1	4.686403
99	3	4.193684
51	1	2.192809
109	1	3.113721
168	2	5.148093
123	4	3.071702
79	1	2.166441
92	1	2.328979
160	7	2.165016
125	1	2.121792
112	3	2.179623
108	1	2.846068
65	1	3.715417
73	1	2.369998

```
[48]: df.columns
```

```
[48]: Index(['Actual', 'Predicted'], dtype='object')
```

```
[50]: print(('R-Squared :'), regressor.score(X_test, y_test))
```

```
R-Squared : -1.0763589168854542
```

```
[51]: sns.distplot(y_pred, hist = False, color = 'r', label = 'Predicted Values')
sns.distplot(y_test, hist = False, color = 'b', label = 'Actual Values')
plt.title('Linear Regression Actual vs Predicted Values Death Bin', fontsize = 18)
plt.xlabel('Values', fontsize = 16)
plt.ylabel('Frequency', fontsize = 16)
plt.legend(loc = 'upper left', fontsize = 16)
plt.ticklabel_format(style='plain', axis='x')

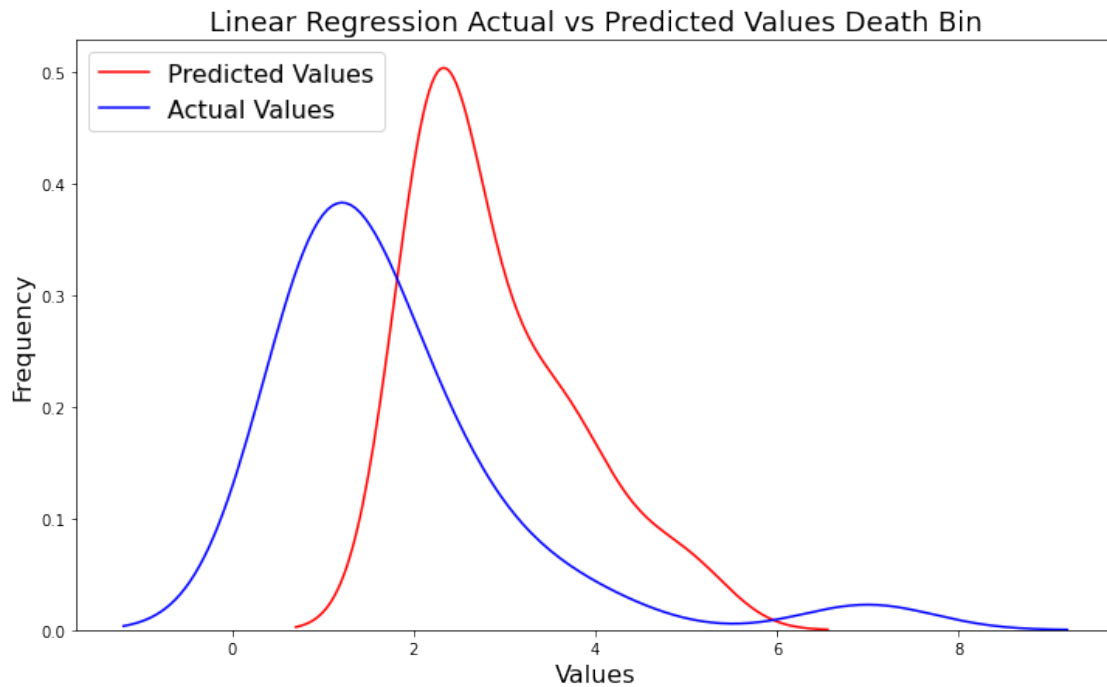
plt.savefig('ap.png')
```

```
C:\Users\Tushar\anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).
```

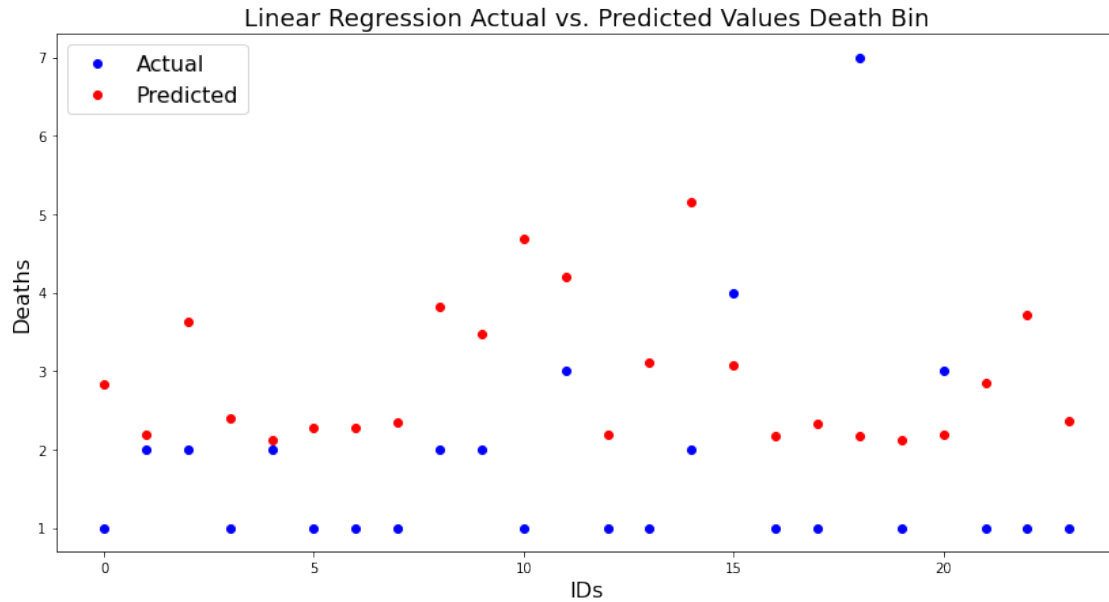
```
warnings.warn(msg, FutureWarning)
```

```
C:\Users\Tushar\anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).
```

```
warnings.warn(msg, FutureWarning)
```



```
[52]: plt.figure(figsize=(14,7))
plt.scatter(range(len(y_test)), y_test, color='blue', label='Actual')
plt.scatter(range(len(y_pred)), y_pred, color='red', label='Predicted')
plt.title('Linear Regression Actual vs. Predicted Values Death Bin', fontsize = 18)
plt.xlabel('IDs', fontsize = 16)
plt.ylabel('Deaths', fontsize = 16)
plt.legend(loc = 'upper left', fontsize = 16)
plt.ticklabel_format(style='plain', axis='x')
plt.show()
```



0.1.2 Decision Tree Model

```
[55]: # using decision tree model
from sklearn.tree import DecisionTreeRegressor
dtr = DecisionTreeRegressor()
dtr.fit(X_train, y_train)
```

```
[55]: DecisionTreeRegressor()
```

```
[79]: y_pred = dtr.predict(X_test)
```

```
[80]: df2 = pd.DataFrame({'Real Values':y_test, 'Predicted Values':y_pred})
```

```
[81]: df2.head(25)
```

```
[81]:
```

	Real Values	Predicted Values
97	42.0	391.0
143	165.0	503.0
144	150.0	227.0
57	0.0	162.0
146	180.0	87.0
71	0.0	87.0
56	0.0	739.0
59	30.0	0.0
94	196.0	0.0
138	108.0	87.0
82	40.0	1882.0

99	272.0	261.0
51	0.0	503.0
109	50.0	97.0
168	139.0	158.0
123	352.0	0.0
79	0.0	0.0
92	0.0	162.0
160	762.0	0.0
125	0.0	517.0
112	229.0	105.0
108	71.0	102.0
65	0.0	183.0
73	0.0	455.0

```
[82]: X_test.shape
```

```
[82]: (24, 5)
```

```
[83]: y_test.shape
```

```
[83]: (24,)
```

```
[84]: y_pred.shape
```

```
[84]: (24,)
```

```
[85]: # Visualising the Decision Tree Regression Results
plt.figure(figsize=(10,10))

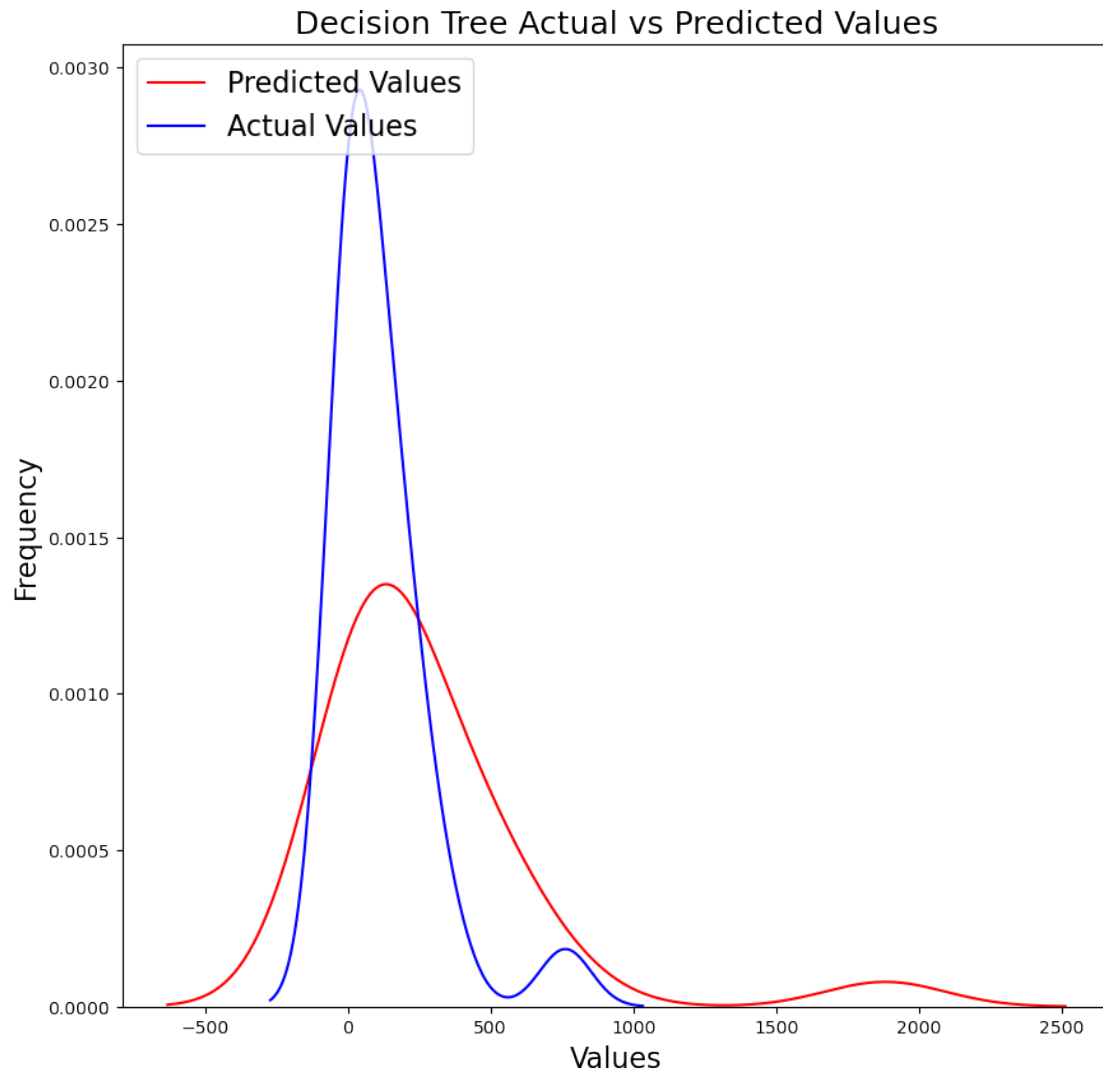
sns.distplot(y_pred, hist = False, color = 'r', label = 'Predicted Values')
sns.distplot(y_test, hist = False, color = 'b', label = 'Actual Values')
plt.title('Decision Tree Actual vs Predicted Values', fontsize = 18)
plt.xlabel('Values', fontsize = 16)
plt.ylabel('Frequency', fontsize = 16)
plt.legend(loc = 'upper left', fontsize = 16)
plt.ticklabel_format(style='plain', axis='x')
```

C:\Users\Tushar\anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `kdeplot` (an axes-level function for kernel density plots).

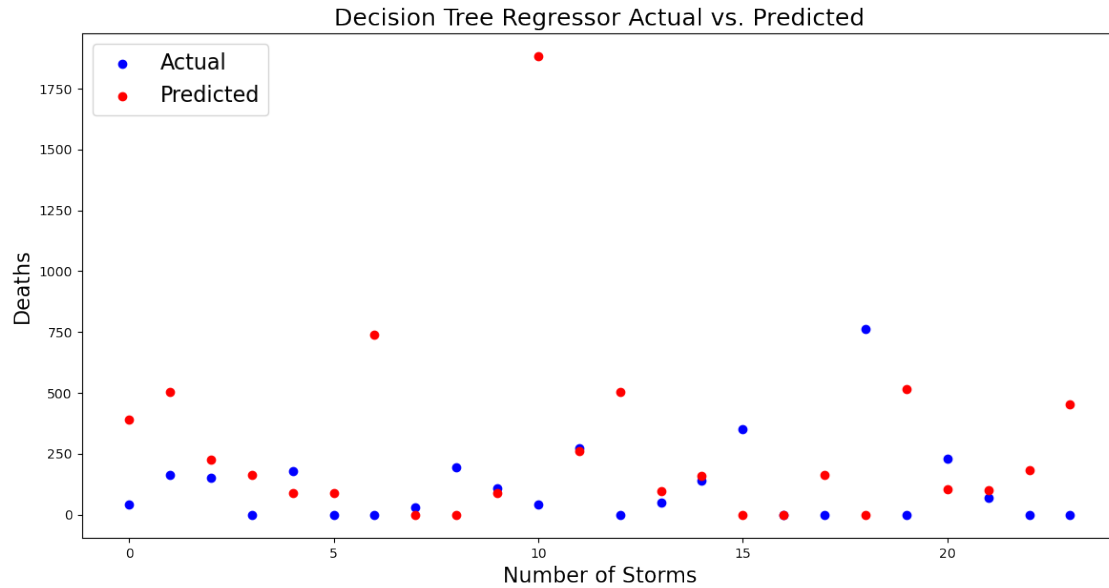
warnings.warn(msg, FutureWarning)

C:\Users\Tushar\anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `kdeplot` (an axes-level function for kernel density plots).

```
warnings.warn(msg, FutureWarning)
```



```
[93]: plt.figure(figsize=(14,7))
plt.scatter(range(len(y_test)), y_test, color='blue', label='Actual')
plt.scatter(range(len(y_pred)), y_pred, color='red', label='Predicted')
plt.title('Decision Tree Regressor Actual vs. Predicted', fontsize = 18)
plt.xlabel('Number of Storms', fontsize = 16)
plt.ylabel('Deaths', fontsize = 16)
plt.legend(loc = 'upper left', fontsize = 16)
plt.ticklabel_format(style='plain', axis='x')
plt.show()
```



```
[87]: # calculate rmse and r2
      #rmse = np.sqrt(mean_squared_error(y_test,y_pred))
      #r2 = r2_score(y_test,y_pred)

      corr_matrix = np.corrcoef(y_test, y_pred)
      corr = corr_matrix[0,1]
      R_sq = corr**2
```

```
[88]: R_sq
```

```
[88]: 0.07097932327541905
```

```
[89]: # Calculation of Mean Squared Error (MSE)
      mean_squared_error(y_test,y_pred)
```

```
[89]: 240579.58333333334
```

```
[90]: # rmse metric
      math.sqrt(mean_squared_error(y_test,y_pred))
```

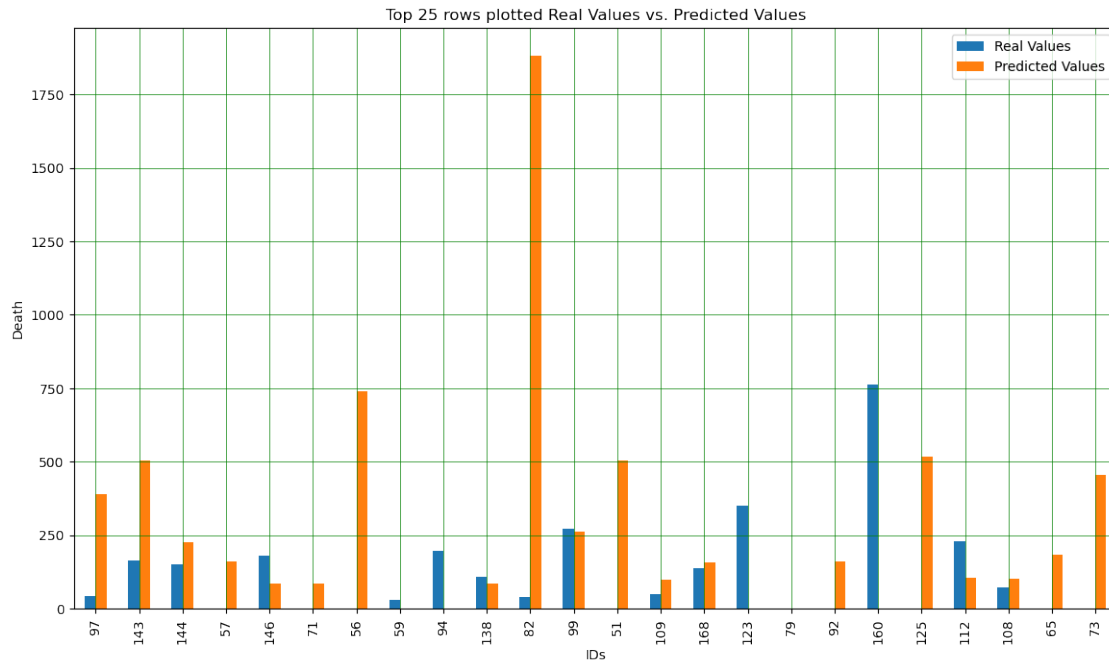
```
[90]: 490.4891266209001
```

```
[91]: # mae
      mean_absolute_error(y_test,y_pred)
```

```
[91]: 295.8333333333333
```

```
[92]: df = df2.head(25)
df.plot(kind='bar',figsize=(14,8))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
plt.title('Top 25 rows plotted Real Values vs. Predicted Values')
plt.xlabel('IDs')
plt.ylabel('Death')

plt.show()
```



0.1.3 Decision Tree using death_bin

```
[56]: y_pred_death_bin = dtr.predict(X_test)
```

```
[57]: df_death_bin = pd.DataFrame({'Real Values':y_test, 'Predicted Values':
    ↪ y_pred_death_bin})
```

```
[58]: df_death_bin.head(25)
```

```
[58]:      Real Values  Predicted Values
97          1          4.0
143         2          3.0
144         2          3.0
57          1          1.0
146         2          1.0
```

71	1	1.0
56	1	7.0
59	1	1.0
94	2	1.0
138	2	2.0
82	1	3.0
99	3	3.0
51	1	3.0
109	1	1.0
168	2	2.0
123	4	2.0
79	1	1.0
92	1	1.0
160	7	1.0
125	1	6.0
112	3	1.0
108	1	1.0
65	1	2.0
73	1	5.0

```
[59]: # Visualising the Decision Tree Regression Results
plt.figure(figsize=(10,10))

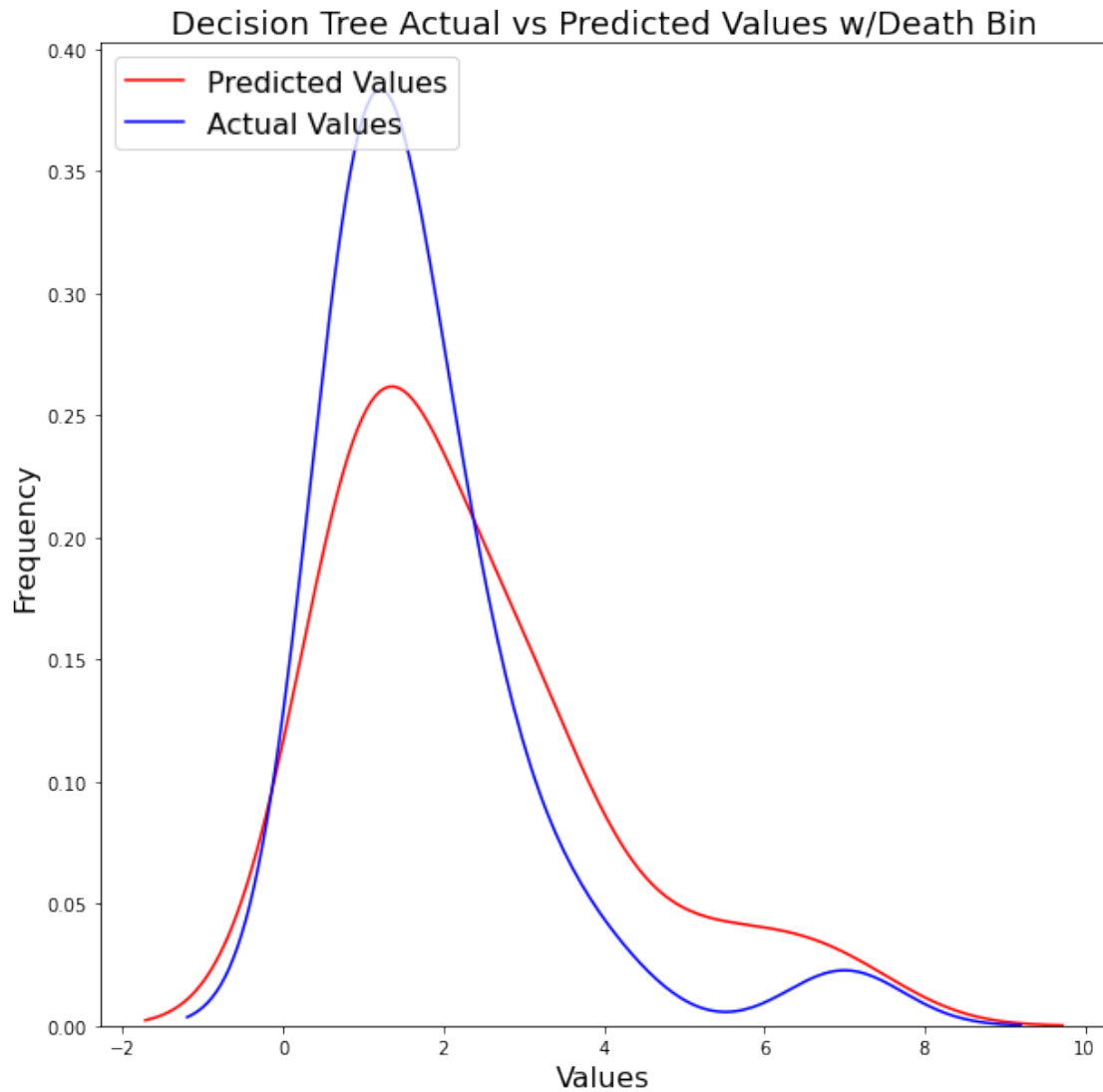
sns.distplot(y_pred_death_bin, hist = False, color = 'r', label = 'Predicted_
↪Values')
sns.distplot(y_test, hist = False, color = 'b', label = 'Actual Values')
plt.title('Decision Tree Actual vs Predicted Values w/Death Bin', fontsize = 18)
plt.xlabel('Values', fontsize = 16)
plt.ylabel('Frequency', fontsize = 16)
plt.legend(loc = 'upper left', fontsize = 16)
plt.ticklabel_format(style='plain', axis='x')
```

C:\Users\Tushar\anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).

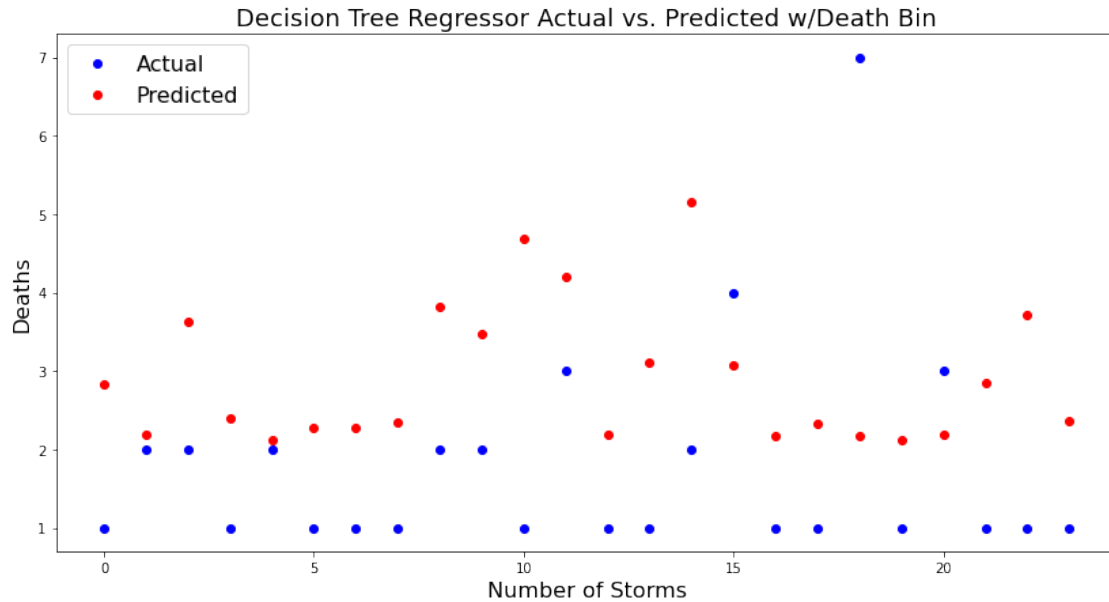
warnings.warn(msg, FutureWarning)

C:\Users\Tushar\anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).

warnings.warn(msg, FutureWarning)



```
[60]: plt.figure(figsize=(14,7))
plt.scatter(range(len(y_test)), y_test, color='blue', label='Actual')
plt.scatter(range(len(y_pred)), y_pred, color='red', label='Predicted')
plt.title('Decision Tree Regressor Actual vs. Predicted w/Death Bin', fontsize=18)
plt.xlabel('Number of Storms', fontsize = 16)
plt.ylabel('Deaths', fontsize = 16)
plt.legend(loc = 'upper left', fontsize = 16)
plt.ticklabel_format(style='plain', axis='x')
plt.show()
```



```
[61]: # calculate rmse and r2
      #rmse = np.sqrt(mean_squared_error(y_test,y_pred))
      #r2 = r2_score(y_test,y_pred)

      corr_matrix = np.corrcoef(y_test, y_pred)
      corr = corr_matrix[0,1]
      R_sq = corr**2
```

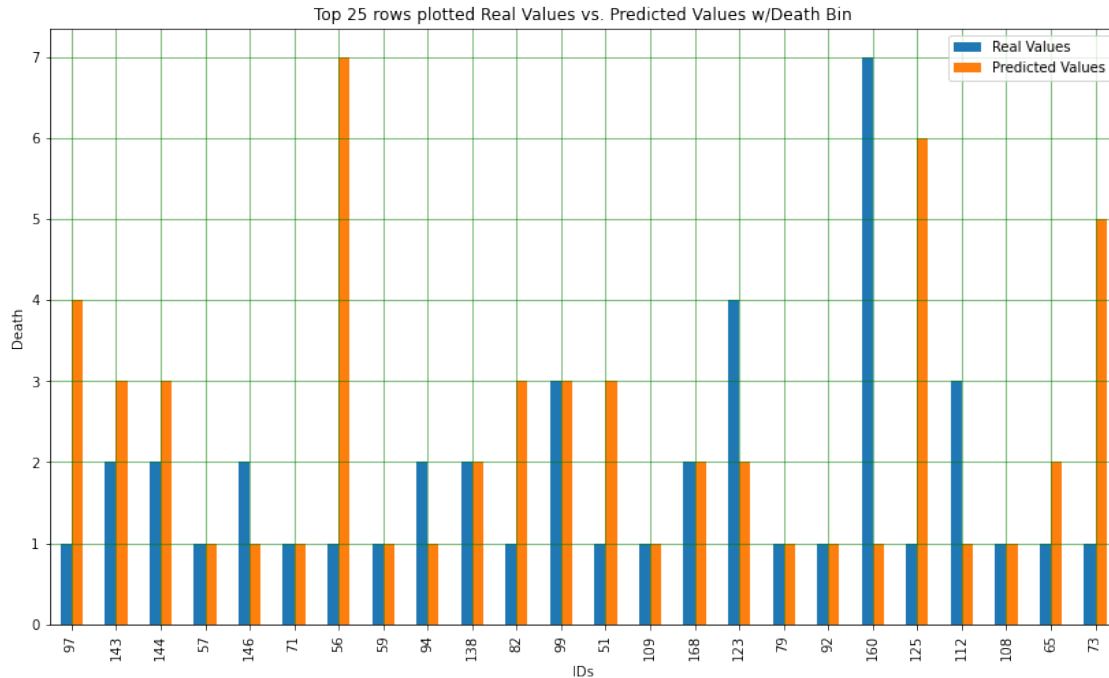
```
[62]: R_sq
```

```
[62]: 4.10226712746072e-05
```

R_sq is 0.0000410226712746072

```
[63]: df = df_death_bin.head(25)
      df.plot(kind='bar',figsize=(14,8))
      plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
      plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
      plt.title('Top 25 rows plotted Real Values vs. Predicted Values w/Death Bin')
      plt.xlabel('IDs')
      plt.ylabel('Death')

      plt.show()
```



OSL with Death Bin

```
[64]: #add the column of ones to the inputs to calculate the intercept
X = sm.add_constant(X)
```

```
[65]: #create regression model based on ordinary least squares
model = sm.OLS(y, X)
```

```
[66]: #variable results
results = model.fit()

print(results.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          death_bin    R-squared:                0.095
Model:                  OLS          Adj. R-squared:           0.056
Method:                 Least Squares F-statistic:              2.401
Date:                   Thu, 30 Dec 2021 Prob (F-statistic):       0.0413
Time:                   21:54:23      Log-Likelihood:          -247.42
No. Observations:      120          AIC:                    506.8
Df Residuals:          114          BIC:                    523.6
Df Model:               5
Covariance Type:       nonrobust
=====
=====
```

			coef	std err	t
P> t	[0.025	0.975]			

const			2.1189	0.429	4.942
0.000	1.269	2.968			
no_us_hurricanes_HUDRAT_NOAA			-0.0638	0.181	-0.353
0.725	-0.422	0.295			
no_major_us_hurricanes_HUDRAT_NOAA			0.6875	0.350	1.962
0.052	-0.007	1.382			
no_major_north_atlantic_hurricanes_HUDRAT_NOAA			-0.0305	0.226	-0.135
0.893	-0.478	0.417			
no_noth_atlantic_hurricanes_HUDRAT_NOAA			-0.0992	0.137	-0.726
0.469	-0.370	0.172			
accumulated_cyclone_energy_ACE_HUDRAT_NOAA			0.0081	0.008	0.990
0.324	-0.008	0.024			
=====					
Omnibus:	45.914		Durbin-Watson:	2.113	
Prob(Omnibus):	0.000		Jarque-Bera (JB):	91.062	
Skew:	1.664		Prob(JB):	1.68e-20	
Kurtosis:	5.672		Cond. No.	265.	
=====					

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
[69]: sns.distplot(y_pred_death_bin, hist = False, color = 'r', label = 'Predicted_
      ↪Values', kde_kws=dict(linewidth=1))
      sns.distplot(y, hist = False, color = 'b', label = 'Actual Values', 
      ↪kde_kws=dict(linewidth=1))
      sns.set(rc = {'figure.figsize':(15,15)})
      plt.title('OLS Actual vs Predicted Values w/Death Bin', fontsize = 16)
      plt.xlabel('Values', fontsize = 12)
      plt.ylabel('Frequency', fontsize = 12)
      plt.legend(loc = 'upper right', fontsize = 8)
      plt.ticklabel_format(style='plain', axis='x')
      plt.xlim(0)
```

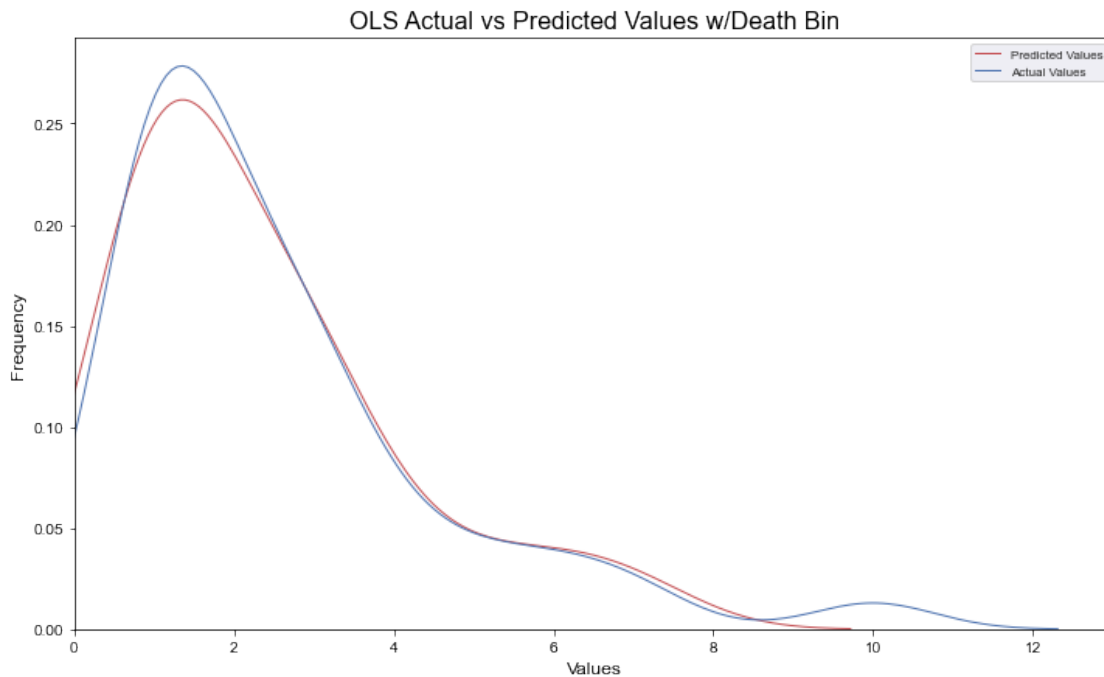
C:\Users\Tushar\anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `kdeplot` (an axes-level function for kernel density plots).

warnings.warn(msg, FutureWarning)
C:\Users\Tushar\anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level

function with similar flexibility) or ``kdeplot`` (an axes-level function for kernel density plots).

```
warnings.warn(msg, FutureWarning)
```

```
[69]: (0.0, 13.013805010457247)
```



0.2 *****

Model with 1950 data including economic damage

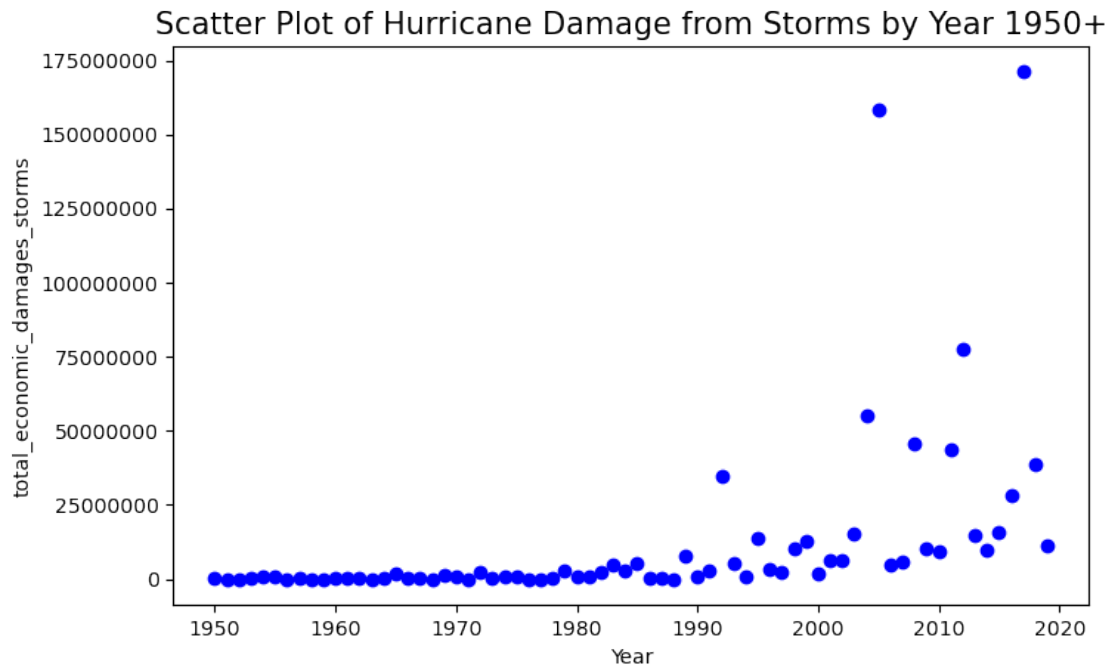
```
[27]: # Filter data down to US only
hurricanes_us_df_1950 = hurricanes_us_df[hurricanes_us_df['Year'] >= 1950]
```

```
[32]: # For graph
y = hurricanes_us_df_1950['total_economic_damages_storms']
x = hurricanes_us_df_1950['Year']

# Plot
plt.scatter(x,y,color='blue')
plt.rcParams.update({'figure.figsize':(8,5), 'figure.dpi':100})

#Labels
plt.title('Scatter Plot of Hurricane Damage from Storms by Year_
↳1950+',fontsize=15)
plt.ylabel('total_economic_damages_storms',fontsize=10)
plt.xlabel('Year',fontsize=10)
```

```
plt.ticklabel_format(axis='x', style='plain')
plt.ticklabel_format(axis='y', style='plain')
plt.show()
```



```
[19]: hurricanes_us_df_1950.columns
```

```
[19]: Index(['Entity', 'Year', 'no_us_hurricanes_HUDRAT_NOAA',
        'no_major_us_hurricanes_HUDRAT_NOAA',
        'no_major_north_atlantic_hurricanes_HUDRAT_NOAA',
        'no_noth_atlantic_hurricanes_HUDRAT_NOAA',
        'accumulated_cyclone_energy_ACE_HUDRAT_NOAA',
        'cyclone_power_dissipation_index_PDI_HUDRAT_NOAA',
        'hurricane_fatality_rate', 'ACE', 'deaths_hurricanes_us',
        'total_economic_damages_storms'],
        dtype='object')
```

```
[30]: hurricanes_us_df_1950['no_us_hurricanes_HUDRAT_NOAA'] =
    ↳hurricanes_us_df_1950['no_us_hurricanes_HUDRAT_NOAA'].astype(int)
hurricanes_us_df_1950['no_major_us_hurricanes_HUDRAT_NOAA'] =
    ↳hurricanes_us_df_1950['no_major_us_hurricanes_HUDRAT_NOAA'].astype(int)
hurricanes_us_df_1950['no_major_north_atlantic_hurricanes_HUDRAT_NOAA'] =
    ↳hurricanes_us_df_1950['no_major_north_atlantic_hurricanes_HUDRAT_NOAA'].
    ↳astype(int)
hurricanes_us_df_1950['no_noth_atlantic_hurricanes_HUDRAT_NOAA'] =
    ↳hurricanes_us_df_1950['no_noth_atlantic_hurricanes_HUDRAT_NOAA'].astype(int)
```

```
hurricanes_us_df_1950['accumulated_cyclone_energy_ACE_HUDRAT_NOAA'] =
↳hurricanes_us_df_1950['accumulated_cyclone_energy_ACE_HUDRAT_NOAA'].
↳astype(int)
hurricanes_us_df_1950['Year'] = hurricanes_us_df_1950['Year'].astype(int)
hurricanes_us_df_1950['cyclone_power_dissipation_index_PDI_HUDRAT_NOAA'] =
↳hurricanes_us_df_1950['cyclone_power_dissipation_index_PDI_HUDRAT_NOAA']
```

<ipython-input-30-e6864baa302a>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
hurricanes_us_df_1950['no_us_hurricanes_HUDRAT_NOAA'] =
hurricanes_us_df_1950['no_us_hurricanes_HUDRAT_NOAA'].astype(int)
```

<ipython-input-30-e6864baa302a>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
hurricanes_us_df_1950['no_major_us_hurricanes_HUDRAT_NOAA'] =
hurricanes_us_df_1950['no_major_us_hurricanes_HUDRAT_NOAA'].astype(int)
```

<ipython-input-30-e6864baa302a>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
hurricanes_us_df_1950['no_major_north_atlantic_hurricanes_HUDRAT_NOAA'] = hurr
icanes_us_df_1950['no_major_north_atlantic_hurricanes_HUDRAT_NOAA'].astype(int)
```

<ipython-input-30-e6864baa302a>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
hurricanes_us_df_1950['no_noth_atlantic_hurricanes_HUDRAT_NOAA'] =
hurricanes_us_df_1950['no_noth_atlantic_hurricanes_HUDRAT_NOAA'].astype(int)
```

<ipython-input-30-e6864baa302a>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
hurricanes_us_df_1950['accumulated_cyclone_energy_ACE_HUDRAT_NOAA'] =
hurricanes_us_df_1950['accumulated_cyclone_energy_ACE_HUDRAT_NOAA'].astype(int)
```

<ipython-input-30-e6864baa302a>:6: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using `.loc[row_indexer,col_indexer] = value` instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
`hurricanes_us_df_1950['Year'] = hurricanes_us_df_1950['Year'].astype(int)`
<ipython-input-30-e6864baa302a>:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using `.loc[row_indexer,col_indexer] = value` instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
`hurricanes_us_df_1950['cyclone_power_dissipation_index_PDI_HUDRAT_NOAA'] = hurricanes_us_df_1950['cyclone_power_dissipation_index_PDI_HUDRAT_NOAA']`

```
[31]: # split out X and y
X = hurricanes_us_df_1950[['no_us_hurricanes_HUDRAT_NOAA',
    'no_major_us_hurricanes_HUDRAT_NOAA',
    'no_major_north_atlantic_hurricanes_HUDRAT_NOAA',
    'no_north_atlantic_hurricanes_HUDRAT_NOAA',
    'accumulated_cyclone_energy_ACE_HUDRAT_NOAA',
    'deaths_hurricanes_us']]

y = hurricanes_us_df_1950['total_economic_damages_storms']
```

```
[32]: # split the data in training and Test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    random_state=0)
```

```
[39]: # using decision tree model
from sklearn.tree import DecisionTreeRegressor
dtr = DecisionTreeRegressor()
dtr.fit(X_train, y_train)
```

```
[39]: DecisionTreeRegressor()
```

```
[40]: y_pred = dtr.predict(X_test)
```

```
[41]: df2 = pd.DataFrame({'Real Values':y_test, 'Predicted Values':y_pred})
```

```
[42]: df2.head(25)
```

```
[42]:
```

	Real Values	Predicted Values
125	0.0	50000.0
126	0.0	4655000.0
147	10053450.0	15148400.0
121	2100000.0	5125000.0
129	910000.0	7880000.0

150	6328800.0	1865600.0
106	150000.0	1000000.0
158	10390000.0	50000.0
133	2545600.0	1610000.0
168	11325000.0	38875000.0
155	4727860.0	2560000.0
127	100000.0	15720000.0
130	861000.0	1865600.0
141	34500000.0	4655000.0

```
[43]: # Visualising the Decision Tree Regression Results
plt.figure(figsize=(10,10))

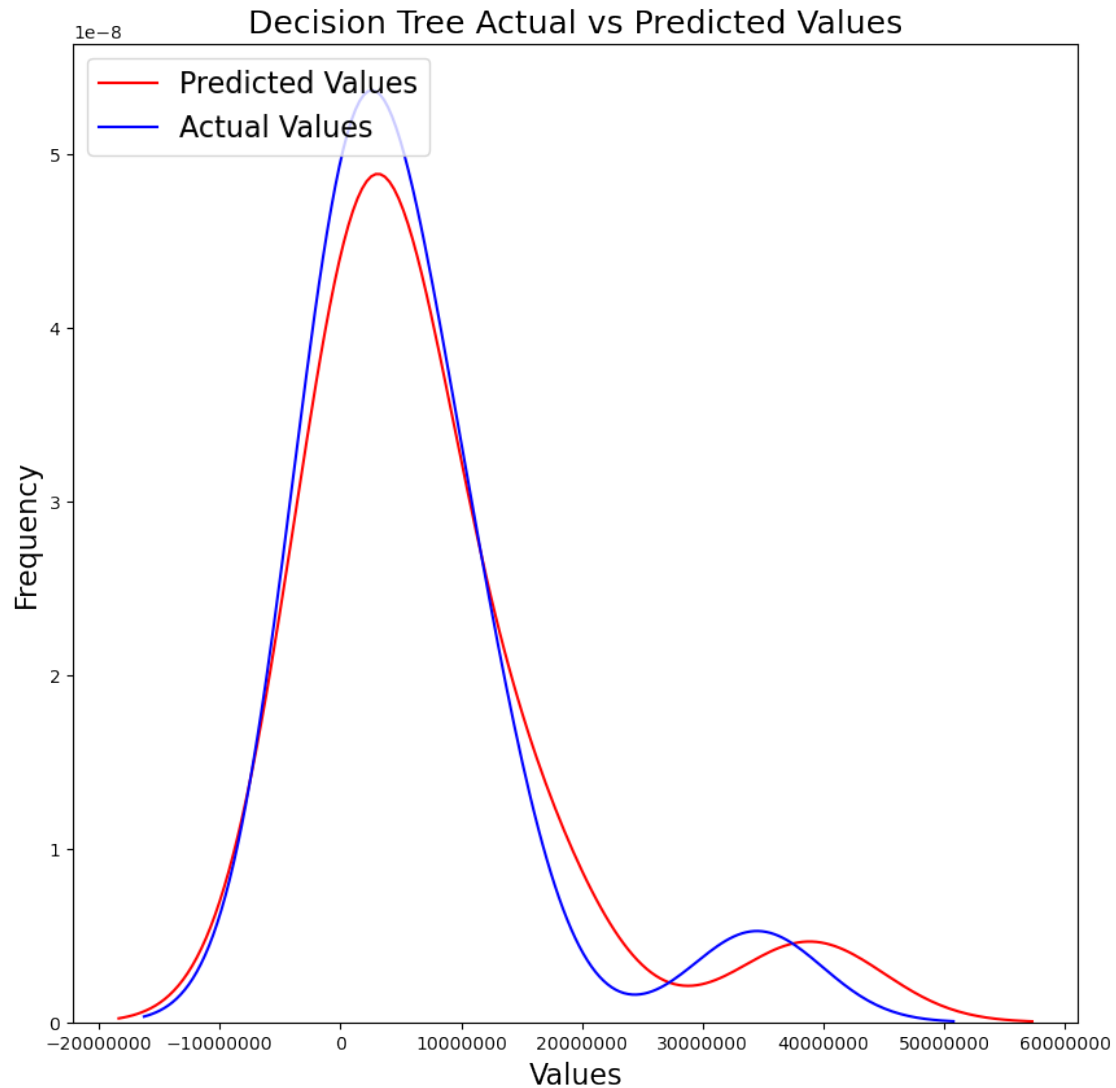
sns.distplot(y_pred, hist = False, color = 'r', label = 'Predicted Values')
sns.distplot(y_test, hist = False, color = 'b', label = 'Actual Values')
plt.title('Decision Tree Actual vs Predicted Values', fontsize = 18)
plt.xlabel('Values', fontsize = 16)
plt.ylabel('Frequency', fontsize = 16)
plt.legend(loc = 'upper left', fontsize = 16)
plt.ticklabel_format(style='plain', axis='x')
```

C:\Users\Tushar\anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).

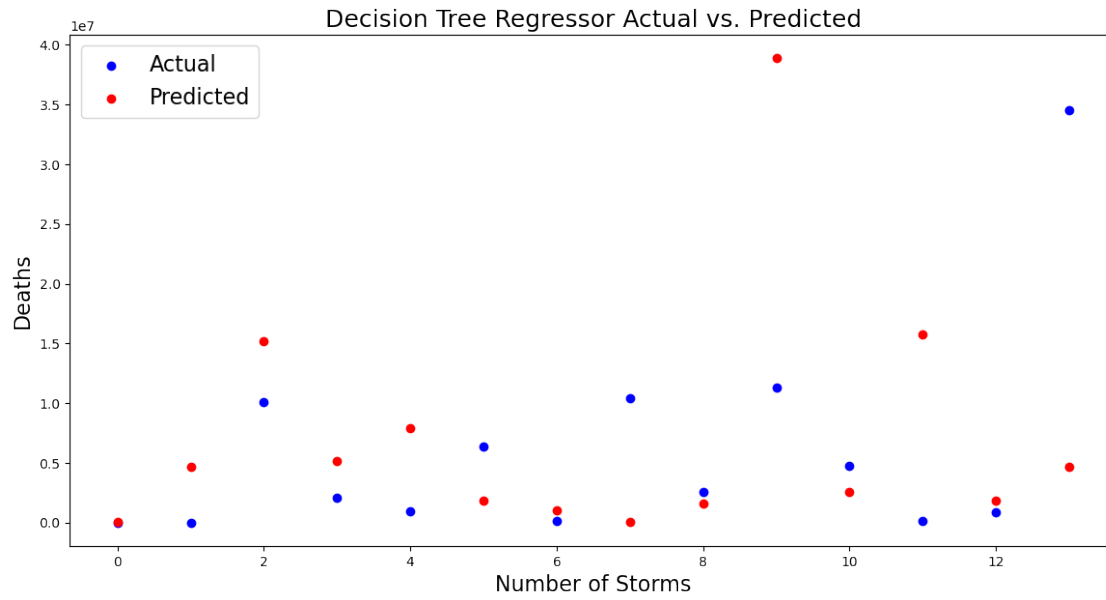
warnings.warn(msg, FutureWarning)

C:\Users\Tushar\anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).

warnings.warn(msg, FutureWarning)



```
[44]: plt.figure(figsize=(14,7))
plt.scatter(range(len(y_test)), y_test, color='blue', label='Actual')
plt.scatter(range(len(y_pred)), y_pred, color='red', label='Predicted')
plt.title('Decision Tree Regressor Actual vs. Predicted', fontsize = 18)
plt.xlabel('Number of Storms', fontsize = 16)
plt.ylabel('Deaths', fontsize = 16)
plt.legend(loc = 'upper left', fontsize = 16)
plt.ticklabel_format(style='plain', axis='x')
plt.show()
```



```
[45]: # calculate rmse and r2
      #rmse = np.sqrt(mean_squared_error(y_test,y_pred))
      #r2 = r2_score(y_test,y_pred)

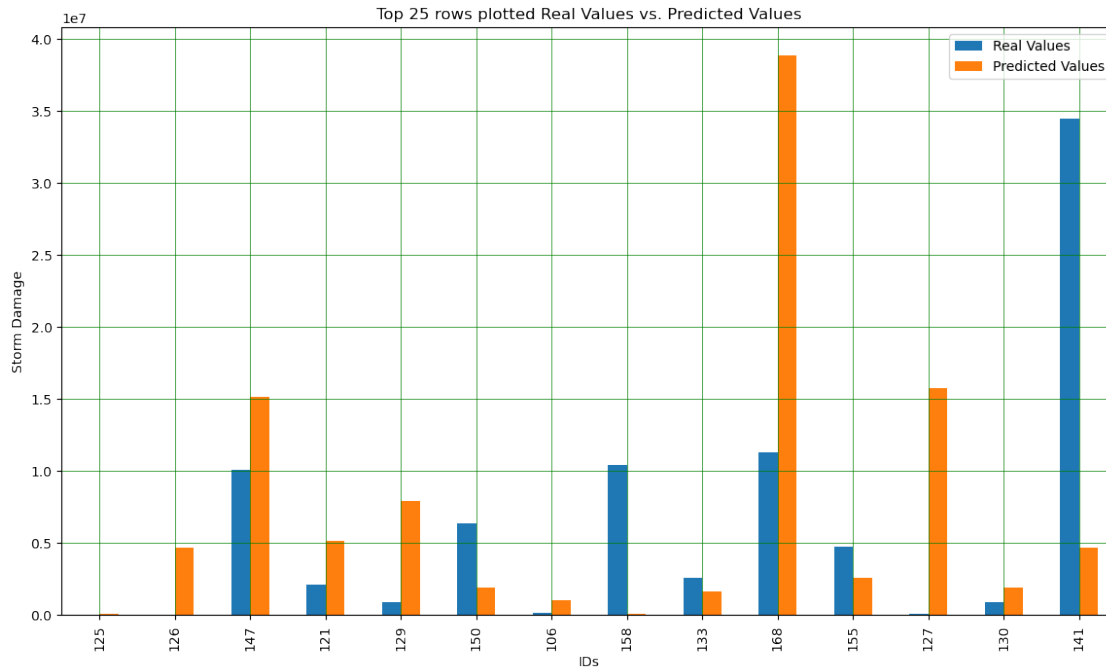
      corr_matrix = np.corrcoef(y_test, y_pred)
      corr = corr_matrix[0,1]
      R_sq = corr**2
```

```
[46]: R_sq
```

```
[46]: 0.02501494202440917
```

```
[48]: df = df2.head(25)
      df.plot(kind='bar',figsize=(14,8))
      plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
      plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
      plt.title('Top 25 rows plotted Real Values vs. Predicted Values')
      plt.xlabel('IDs')
      plt.ylabel('Storm Damage')

      plt.show()
```



OLS Model Ordinary Least Squares

```
[12]: hurricanes_us_df_1950.columns
```

```
[12]: Index(['Entity', 'Year', 'no_us_hurricanes_HUDRAT_NOAA',
          'no_major_us_hurricanes_HUDRAT_NOAA',
          'no_major_north_atlantic_hurricanes_HUDRAT_NOAA',
          'no_noth_atlantic_hurricanes_HUDRAT_NOAA',
          'accumulated_cyclone_energy_ACE_HUDRAT_NOAA',
          'cyclone_power_dissipation_index_PDI_HUDRAT_NOAA',
          'hurricane_fatality_rate', 'ACE', 'deaths_hurricanes_us',
          'total_economic_damages_storms'],
          dtype='object')
```

```
[33]: X = hurricanes_us_df_1950[['no_us_hurricanes_HUDRAT_NOAA',
          'no_major_us_hurricanes_HUDRAT_NOAA',
          'no_major_north_atlantic_hurricanes_HUDRAT_NOAA',
          'no_noth_atlantic_hurricanes_HUDRAT_NOAA',
          'accumulated_cyclone_energy_ACE_HUDRAT_NOAA',
          'deaths_hurricanes_us']]

y = hurricanes_us_df_1950['total_economic_damages_storms']
```

```
[34]: hurricanes_us_df_1950
```

```

[34]:
      Entity Year no_us_hurricanes_HUDRAT_NOAA \
99 North Atlantic 1950 3
100 North Atlantic 1951 0
101 North Atlantic 1952 1
102 North Atlantic 1953 3
103 North Atlantic 1954 3
..      ...      ...
164 North Atlantic 2015 0
165 North Atlantic 2016 2
166 North Atlantic 2017 3
167 North Atlantic 2018 8
168 North Atlantic 2019 6

      no_major_us_hurricanes_HUDRAT_ NOAA \
99 2
100 0
101 0
102 0
103 2
..  ...
164 0
165 0
166 2
167 2
168 3

      no_major_north_atlantic_hurricanes_HUDRAT_NOAA \
99 6
100 3
101 2
102 3
103 3
..  ...
164 2
165 4
166 6
167 2
168 2

      no_noth_atlantic_hurricanes_HUDRAT_NOAA \
99 11
100 8
101 5
102 7
103 7
..  ...
164 4

```

165	7
166	10
167	8
168	8

	accumulated_cyclone_energy_ACE_HUDRAT_NOAA \
99	211
100	126
101	69
102	99
103	111
..	...
164	63
165	141
166	223
167	132
168	132

	cyclone_power_dissipation_index_PDI_HUDRAT_NOAA	hurricane_fatality_rate \
99	0.0000	0.124777
100	2.7846	0.000000
101	2.3445	0.019041
102	2.2639	0.012486
103	2.4730	1.183861
..
164	NaN	0.043557
165	NaN	NaN
166	NaN	NaN
167	NaN	NaN
168	NaN	NaN

	ACE	deaths_hurricanes_us	total_economic_damages_storms	death_bin
99	211.2825	272.0	100000.0	3.0
100	126.3250	0.0	0.0	1.0
101	69.0800	279.0	0.0	3.0
102	98.5075	468.0	52000.0	5.0
103	110.8800	223.0	731000.0	3.0
..
164	62.6850	218.0	15720000.0	3.0
165	141.2525	199.0	28050000.0	2.0
166	224.8775	261.0	171110000.0	3.0
167	132.5825	158.0	38875000.0	2.0
168	132.2025	139.0	11325000.0	2.0

[70 rows x 13 columns]

```
[35]: #add the column of ones to the inputs to calculate the intercept
X = sm.add_constant(X)
```

```
[36]: #create regression model based on ordinary least squares
model = sm.OLS(y, X)
```

```
[37]: #variable results
results = model.fit()

print(results.summary())
```

OLS Regression Results

```
=====
Dep. Variable:    total_economic_damages_storms    R-squared:
0.410
Model:                OLS    Adj. R-squared:
0.354
Method:            Least Squares    F-statistic:
7.302
Date:                Mon, 03 Jan 2022    Prob (F-statistic):
6.00e-06
Time:                22:14:19    Log-Likelihood:
-1285.6
No. Observations:    70    AIC:
2585.
Df Residuals:        63    BIC:
2601.
Df Model:            6
Covariance Type:    nonrobust
=====
=====
```

			coef	std err	t
P> t	[0.025	0.975]			
const			-1.727e+07	7.91e+06	-2.182
0.033	-3.31e+07	-1.46e+06			
no_us_hurricanes_HUDRAT_NOAA			6.438e+05	2.66e+06	0.242
0.810	-4.67e+06	5.96e+06			
no_major_us_hurricanes_HUDRAT_NOAA			5.942e+06	5.36e+06	1.108
0.272	-4.77e+06	1.67e+07			
no_major_north_atlantic_hurricanes_HUDRAT_NOAA			2.477e+05	3.48e+06	0.071
0.943	-6.7e+06	7.19e+06			
no_noth_atlantic_hurricanes_HUDRAT_NOAA			1.432e+05	2.39e+06	0.060
0.952	-4.63e+06	4.91e+06			
accumulated_cyclone_energy_ACE_HUDRAT_NOAA			1.368e+05	1.36e+05	1.009
0.317	-1.34e+05	4.08e+05			

deaths_hurricanes_us		4.017e+04	1.31e+04	3.075
0.003	1.41e+04	6.63e+04		

```
=====
```

Omnibus:	69.945	Durbin-Watson:	1.411
Prob(Omnibus):	0.000	Jarque-Bera (JB):	640.020
Skew:	2.817	Prob(JB):	1.05e-139
Kurtosis:	16.700	Cond. No.	988.

```
=====
```

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
[39]: ypred = results.predict(X)
      print('predicted response:', ypred, sep='\n')
```

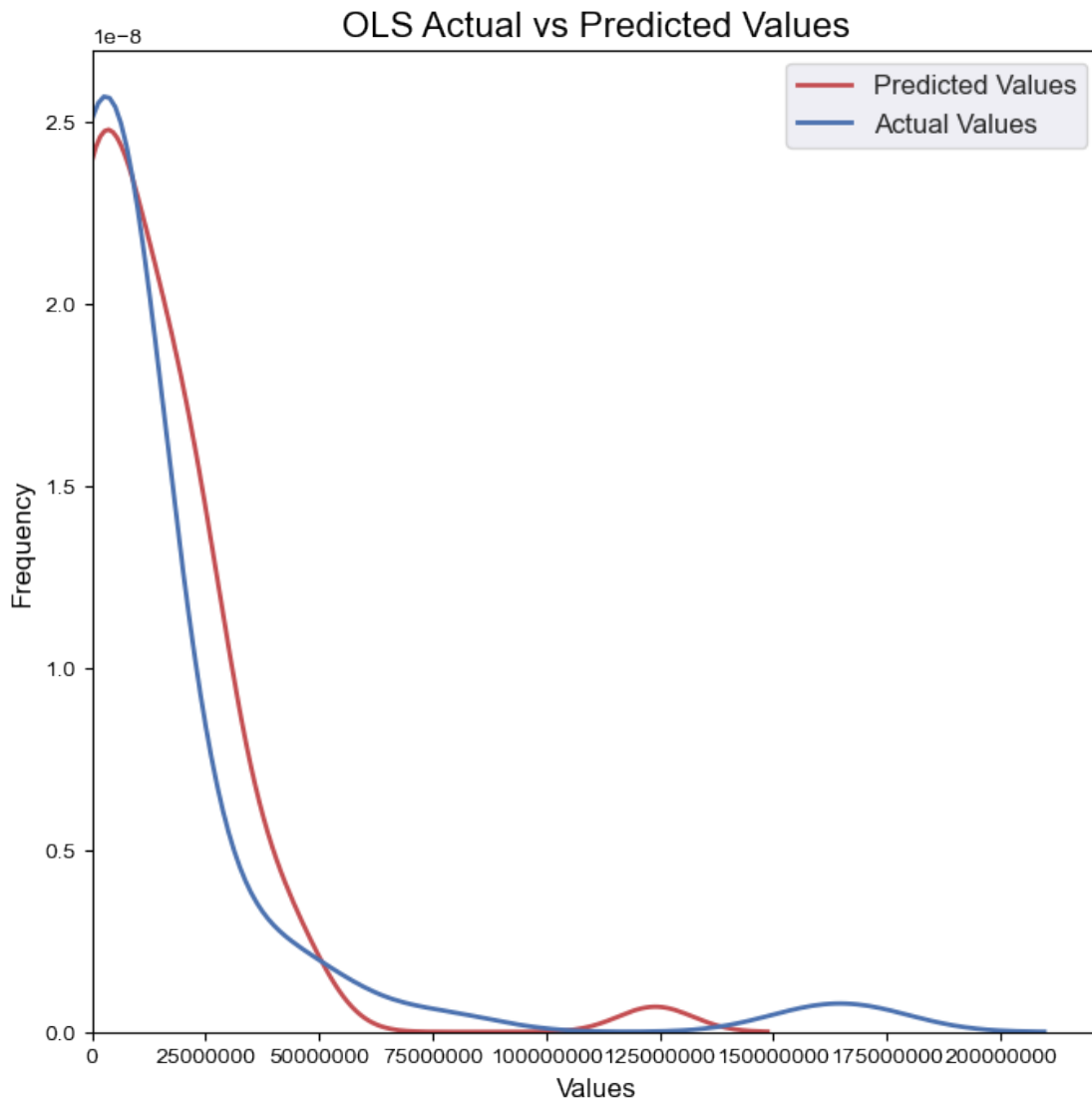
```
predicted response:
99      3.939034e+07
100     1.852374e+06
101     5.229120e+06
102     1.874506e+07
103     2.242950e+07
...
164     1.171444e+06
165     1.328883e+07
166     4.044656e+07
167     2.580538e+07
168     2.969652e+07
Length: 70, dtype: float64
```

```
[40]: sns.distplot(ypred, hist = False, color = 'r', label = 'Predicted Values',
      ↪kde_kws=dict(linewidth=2))
      sns.distplot(y, hist = False, color = 'b', label = 'Actual Values',
      ↪kde_kws=dict(linewidth=2))
      sns.set(rc = {'figure.figsize':(15,15)})
      plt.title('OLS Actual vs Predicted Values', fontsize = 16)
      plt.xlabel('Values', fontsize = 12)
      plt.ylabel('Frequency', fontsize = 12)
      plt.legend(loc = 'upper right', fontsize = 12)
      plt.ticklabel_format(style='plain', axis='x')
      plt.xlim(0)
```

C:\Users\Tushar\anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `kdeplot` (an axes-level function for kernel density plots).
warnings.warn(msg, FutureWarning)


```
C:\Users\Tushar\anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).
warnings.warn(msg, FutureWarning)
```

```
[40]: (0.0, 222070229.6450136)
```



```
[44]: ols_df = pd.DataFrame({'Real Values':y, 'Predicted Values':ypred})
```

```
[45]: ols_df
```

```
[45]:
```

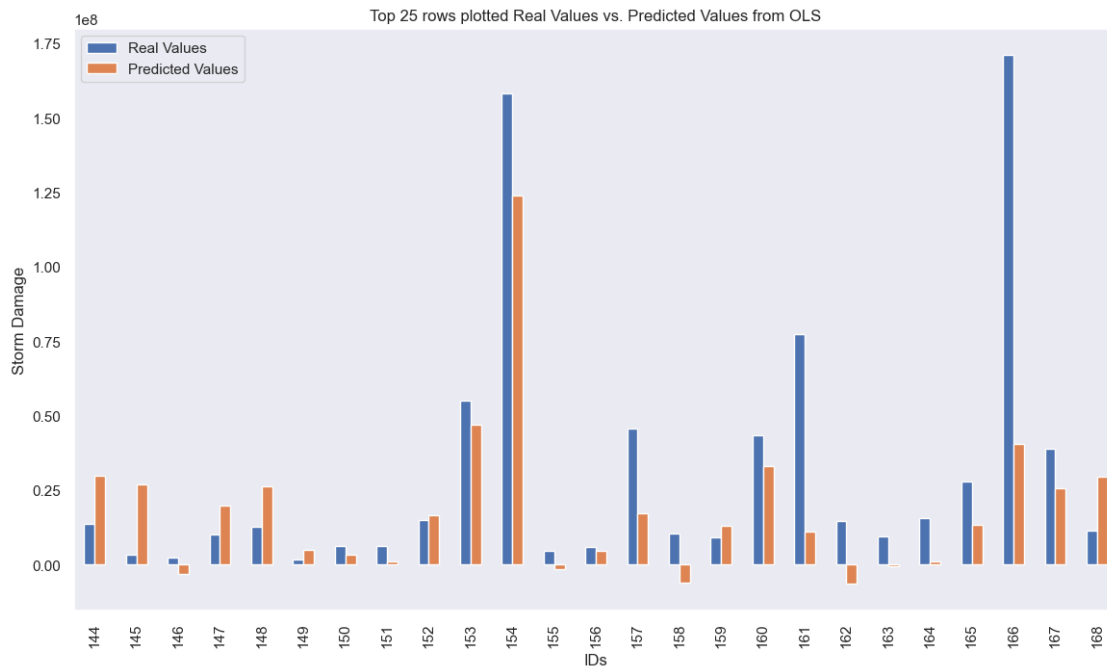
	Real Values	Predicted Values
99	100000.0	3.939034e+07
100	0.0	1.852374e+06
101	0.0	5.229120e+06
102	52000.0	1.874506e+07
103	731000.0	2.242950e+07
..
164	15720000.0	1.171444e+06
165	28050000.0	1.328883e+07
166	171110000.0	4.044656e+07
167	38875000.0	2.580538e+07
168	11325000.0	2.969652e+07

[70 rows x 2 columns]

```
[48]:
```

```
ols = ols_df.tail(25)
ols.plot(kind='bar',figsize=(14,8))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
plt.title('25 rows plotted Real Values vs. Predicted Values from OLS')
plt.xlabel('IDs')
plt.ylabel('Storm Damage')

plt.show()
```



Deaths by OLS

```
[49]: # split out X and y
X = hurricanes_us_df_1950[['no_us_hurricanes_HUDRAT_NOAA',
    'no_major_us_hurricanes_HUDRAT_NOAA',
    'no_major_north_atlantic_hurricanes_HUDRAT_NOAA',
    'no_noth_atlantic_hurricanes_HUDRAT_NOAA',
    'accumulated_cyclone_energy_ACE_HUDRAT_NOAA']]

y = hurricanes_us_df_1950['deaths_hurricanes_us']

[50]: #add the column of ones to the inputs to calculate the intercept
X = sm.add_constant(X)

[51]: #create regression model based on ordinary least squares
model = sm.OLS(y, X)

[52]: #variable results
results = model.fit()

print(results.summary())
```

OLS Regression Results

```
=====
Dep. Variable:    deaths_hurricanes_us    R-squared:                0.224
Model:                OLS    Adj. R-squared:            0.163
Method:            Least Squares    F-statistic:                3.695
Date:                Mon, 03 Jan 2022    Prob (F-statistic):        0.00532
Time:                22:30:56    Log-Likelihood:            -477.21
No. Observations:    70    AIC:                    966.4
Df Residuals:        64    BIC:                    979.9
Df Model:            5
Covariance Type:    nonrobust
=====
=====
```

			coef	std err	t
P> t	[0.025	0.975]			

const			54.4223	75.425	0.722
0.473	-96.256	205.101			
no_us_hurricanes_HUDRAT_NOAA			-6.8552	25.447	-0.269
0.788	-57.691	43.980			
no_major_us_hurricanes_HUDRAT_NOAA			107.4614	49.510	2.171
0.034	8.554	206.369			
no_major_north_atlantic_hurricanes_HUDRAT_NOAA			25.7825	33.102	0.779
0.439	-40.346	91.911			
no_noth_atlantic_hurricanes_HUDRAT_NOAA			23.6061	22.647	1.042
0.301	-21.636	68.848			

accumulated_cyclone_energy_ACE_HUDRAT_NOAA	-0.8826	1.293	-0.683
0.497	-3.465	1.700	

```
=====
Omnibus:                    52.265    Durbin-Watson:                2.239
Prob(Omnibus):              0.000    Jarque-Bera (JB):          242.618
Skew:                      2.190    Prob(JB):                  2.07e-53
Kurtosis:                   11.000    Cond. No.                  330.
=====
```

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
[53]: ypred = results.predict(X)
      print('predicted response:', ypred, sep='\n')
```

predicted response:

```
99      476.919593
100     209.415030
101     156.265427
102     189.072613
103     393.404592
```

...

```
164     144.809959
165     184.642379
166     442.722593
167     338.417981
168     459.589881
```

Length: 70, dtype: float64

```
[54]: sns.distplot(ypred, hist = False, color = 'r', label = 'Predicted Values',
      ↪kde_kws=dict(linewidth=2))
sns.distplot(y, hist = False, color = 'b', label = 'Actual Values',
      ↪kde_kws=dict(linewidth=2))
sns.set(rc = {'figure.figsize':(15,15)})
plt.title('OLS Model Actual vs Predicted Values for Deaths ', fontsize = 16)
plt.xlabel('Values', fontsize = 12)
plt.ylabel('Frequency', fontsize = 12)
plt.legend(loc = 'upper right', fontsize = 12)
plt.ticklabel_format(style='plain', axis='x')
plt.xlim(0)
```

C:\Users\Tushar\anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `kdeplot` (an axes-level function for kernel density plots).

warnings.warn(msg, FutureWarning)

```
C:\Users\Tushar\anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `kdeplot` (an axes-level function for
kernel density plots).
warnings.warn(msg, FutureWarning)
```

```
[54]: (0.0, 2332.700029085593)
```

