20104154

Santhosh Gopi B

Importing Libraries

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

Importing Datasets

```
df=pd.read_csv(C:\Users\user\Downloads\154)
df
```

	country	code	year	eap	eca	lac	mena	sha	sa	hi	...	y	stockpa
0	Aruba	ABW	1960	0	0	1	0	0	0	0.0	...	NaN	
1	Aruba	ABW	1961	0	0	1	0	0	0	0.0	...	NaN	
2	Aruba	ABW	1962	0	0	1	0	0	0	0.0	...	NaN	
3	Aruba	ABW	1963	0	0	1	0	0	0	0.0	...	NaN	
4	Aruba	ABW	1964	0	0	1	0	0	0	0.0	...	NaN	
...	...	...	...	...	...	...	...	...	...	...	...	...	
8290	Zimbabwe	ZWE	1998	0	0	0	0	1	0	0.0	...	8.290000e+09	
8291	Zimbabwe	ZWE	1999	0	0	0	0	1	0	0.0	...	8.230000e+09	
8292	Zimbabwe	ZWE	2000	0	0	0	0	1	0	0.0	...	7.830000e+09	
8293	Zimbabwe	ZWE	2001	0	0	0	0	1	0	0.0	...	NaN	
8294	Zimbabwe	ZWE	2002	0	0	0	0	1	0	0.0	...	NaN	

8295 rows × 33 columns

Data Cleaning and Data Preprocessing

```
df=df.fillna(1)
df
```

	country	code	year	eap	eca	lac	mena	sha	sa	hi	...	y	st
0	Aruba	ABW	1960	0	0	1	0	0	0	0.0	...	1.000000e+00	

```
df.columns
```

```
Index(['country', 'code', 'year', 'eap', 'eca', 'lac', 'mena', 'sha', 'sa',
       'hi', 'pat', 'patepo', 'royal', 'rdexp', 'rdper', 'rdfinabro',
       'rdfinprod', 'rdperfprod', 'rdperfhe', 'rdperfpub', 'lowrdexp',
       'lowrdfinprod', 'lowrdperfprod', 'y', 'stockpatEPO', 'poptotal',
       'labor', 'rdexpgdp', 'patgrantedstock', 'plantpatstock',
       'designpatstock', 'plantpat', 'designpat'],
      dtype='object')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8295 entries, 0 to 8294
Data columns (total 33 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   country          8295 non-null   object 
 1   code             8295 non-null   object 
 2   year             8295 non-null   int64  
 3   eap              8295 non-null   int64  
 4   eca              8295 non-null   int64  
 5   lac              8295 non-null   int64  
 6   mena             8295 non-null   int64  
 7   sha              8295 non-null   int64  
 8   sa               8295 non-null   int64  
 9   hi               8295 non-null   float64
 10  pat              8295 non-null   float64
 11  patepo           8295 non-null   float64
 12  royal            8295 non-null   float64
 13  rdexp            8295 non-null   float64
 14  rdper            8295 non-null   float64
 15  rdfinabro        8295 non-null   float64
 16  rdfinprod        8295 non-null   float64
 17  rdperfprod       8295 non-null   float64
 18  rdperfhe         8295 non-null   float64
 19  rdperfpub        8295 non-null   float64
 20  lowrdexp         8295 non-null   float64
 21  lowrdfinprod     8295 non-null   float64
 22  lowrdperfprod    8295 non-null   float64
 23  y                8295 non-null   float64
 24  stockpatEPO      8295 non-null   float64
 25  poptotal         8295 non-null   float64
 26  labor            8295 non-null   float64
 27  rdexpgdp         8295 non-null   float64
 28  patgrantedstock  8295 non-null   float64
 29  plantpatstock    8295 non-null   float64
 30  designpatstock   8295 non-null   float64
 31  plantpat         8295 non-null   float64
 32  designpat        8295 non-null   float64
dtypes: float64(24), int64(7), object(2)
memory usage: 2.1+ MB
```

Line chart

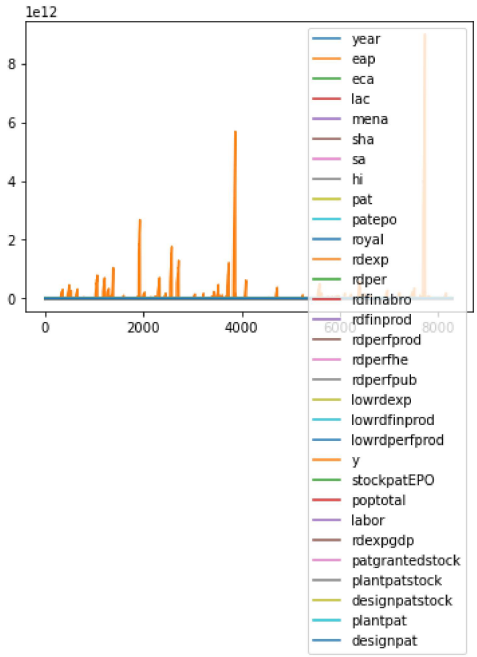
```
df.plot.line(subplots=True)
```

```
array([<AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>,
       <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>,
       <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>,
       <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>,
       <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>,
       <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>,
```

Line chart

```
df.plot.line()
```

```
<AxesSubplot:>
```



Bar chart

```
b=df[0:50]
```

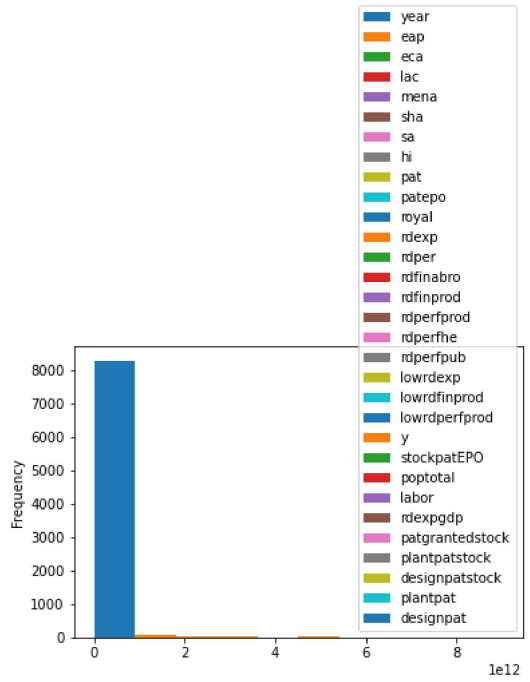
```
b.plot.bar()
```

```
<AxesSubplot:>
```

Histogram

```
df.plot.hist()
```

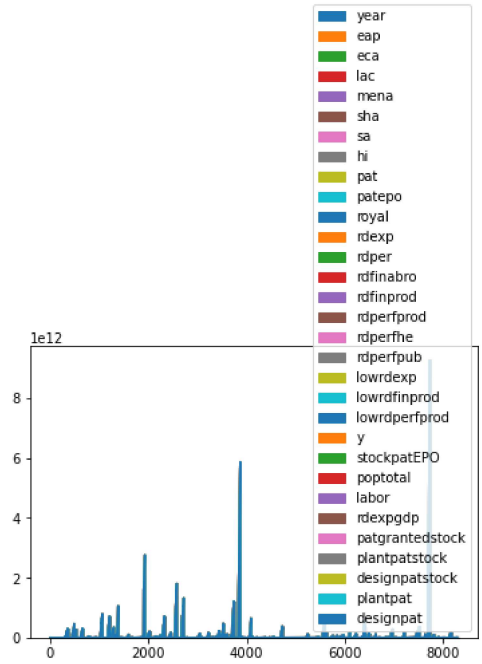
```
<AxesSubplot:ylabel='Frequency'>
```



Area chart

```
df.plot.area()
```

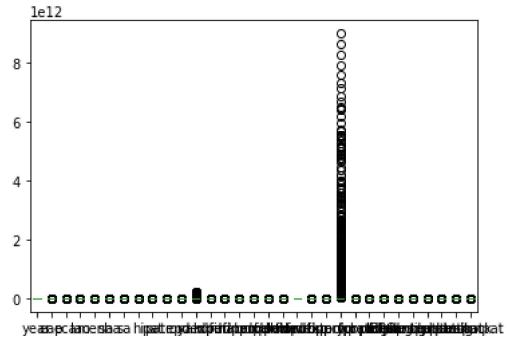
```
<AxesSubplot:>
```



Box chart

```
df.plot.box()
```

```
<AxesSubplot:>
```



Pie chart

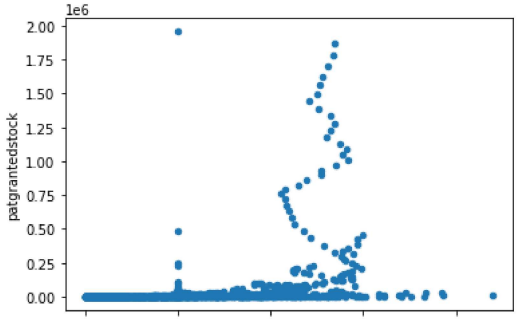
```
b.plot.pie(y='designpat' )
```

```
<AxesSubplot:ylabel='designpat'>
```

Scatter chart

```
df.plot.scatter( x='rdexpgdp',y= 'patgrantedstock')
```

```
<AxesSubplot:xlabel='rdexpgdp', ylabel='patgrantedstock'>
```




```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8295 entries, 0 to 8294
Data columns (total 33 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   country          8295 non-null   object 
 1   code             8295 non-null   object 
 2   year             8295 non-null   int64  
 3   eap              8295 non-null   int64  
 4   eca              8295 non-null   int64  
 5   lac              8295 non-null   int64  
 6   mena             8295 non-null   int64  
 7   sha              8295 non-null   int64  
 8   sa               8295 non-null   int64  
 9   hi               8295 non-null   float64
 10  pat              8295 non-null   float64
 11  patepo           8295 non-null   float64
 12  royal            8295 non-null   float64
 13  rdexp            8295 non-null   float64
 14  rdper            8295 non-null   float64
 15  rdfinabro        8295 non-null   float64
 16  rdfinprod        8295 non-null   float64
 17  rdperfprod       8295 non-null   float64
 18  rdperfhe         8295 non-null   float64
 19  rdperfpub        8295 non-null   float64
 20  lowrdexp         8295 non-null   float64
 21  lowrdfinprod     8295 non-null   float64
 22  lowrdperfprod    8295 non-null   float64
 23  y                8295 non-null   float64
 24  stockpatEPO      8295 non-null   float64
 25  poptotal         8295 non-null   float64
 26  labor            8295 non-null   float64
 27  rdexpgdp         8295 non-null   float64
 28  patgrantedstock  8295 non-null   float64
 29  plantpatstock    8295 non-null   float64
 30  designpatstock   8295 non-null   float64
 31  plantpat         8295 non-null   float64
 32  designpat        8295 non-null   float64
dtypes: float64(24), int64(7), object(2)
memory usage: 2.1+ MB
```

```
df.describe()
```

	year	eap	eca	lac	mena	sha	
count	8295.000000	8295.000000	8295.000000	8295.000000	8295.000000	8295.000000	8295.(
mean	1981.203014	0.094515	0.195901	0.176974	0.098614	0.150090	0.(
std	12.421590	0.292561	0.396917	0.381670	0.298161	0.357182	0.'
min	1960.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.(
25%	1970.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.(
50%	1981.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.(
75%	1992.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.(
max	2002.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.(

8 rows × 31 columns

```
df1=df[['year', 'eap', 'eca', 'lac', 'mena', 'sha', 'sa',
       'hi', 'pat', 'patepo', 'royal', 'rdexp', 'rdper', 'rdfinabro',
       'rdfinprod', 'rdperfprod', 'rdperfhe', 'rdperfpub', 'lowrdexp',
       'lowrdfinprod', 'lowrdperfprod', 'y', 'stockpatEPO', 'poptotal',
       'labor', 'rdexpgdp', 'patgrantedstock', 'plantpatstock',
       'designpatstock', 'plantpat', 'designpat']]
```

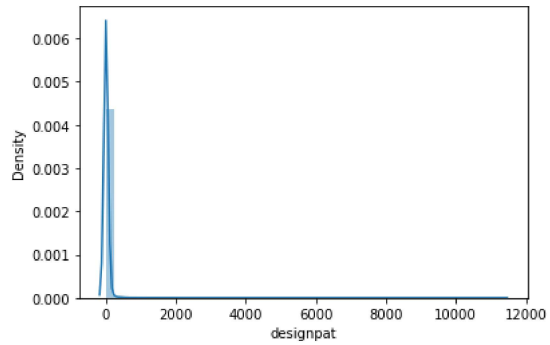
EDA AND VISUALIZATION

```
sns.pairplot(df1[0:50])
```

```
<seaborn.axisgrid.PairGrid at 0x16183092580>
```

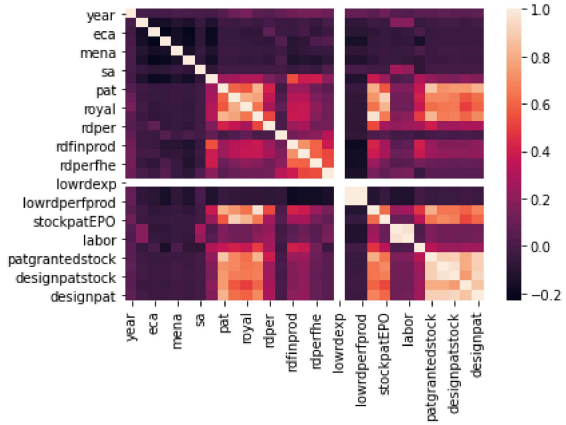
```
sns.distplot(df1['designpat'])
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning
  warnings.warn(msg, FutureWarning)
<AxesSubplot:xlabel='designpat', ylabel='Density'>
```



```
sns.heatmap(df1.corr())
```

```
<AxesSubplot:>
```



TO TRAIN THE MODEL AND MODEL BULDING

```
x=df[['year', 'eap', 'eca', 'lac', 'mena', 'sha', 'sa',
       'hi', 'pat', 'patepo', 'royal', 'rdexp', 'rdper', 'rdfinabro',
       'rdfinprod', 'rdperfprod', 'rdperfhe', 'rdperfpub', 'lowrdexp',
       'lowrdfinprod', 'lowrdperfprod', 'y', 'stockpatEPO', 'poptotal',
       'labor', 'rdexpgdp', 'patgrantedstock', 'plantpatstock',
       'designpatstock', 'plantpat']]
y=df['designpat']
```

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

Linear Regression

```
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
lr.fit(x_train,y_train)
```

```
LinearRegression()
```

```
lr.intercept_
```

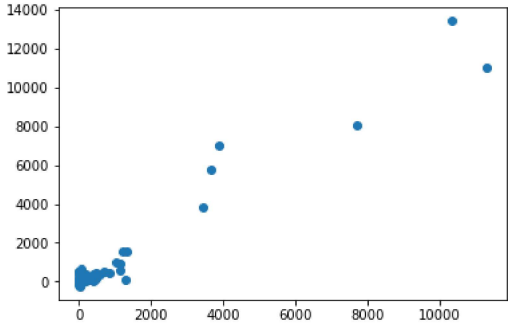
```
-764.4487900938358
```

```
coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
coeff
```

	Co-efficient
year	3.912868e-01
eap	5.333837e+00
eca	-5.922969e+00
lac	-3.187443e+00
mena	-2.360544e+00
sha	-2.628649e+00
sa	-2.353376e+00
hi	-1.965513e+01
pat	9.872656e-03
patepo	-5.267820e-03
royal	-3.015520e-08
rdexp	6.506588e-10
rdper	-1.735738e-05
rdfinabro	-1.350879e-01
rdfinprod	4.810888e-01
rdperfprod	1.392027e-01
rdperfhe	-1.862709e-02
rdperfpub	-1.106904e-01
lowrdexp	-6.039613e-14
lowrdfinprod	-2.905639e-01
lowrdperfprod	-1.879814e+00
y	-1.845861e-11
stockpatEPO	-3.208420e-04
poptotal	-1.301376e-08
labor	2.067889e-08
rdexpgdp	-1.324317e+01
patgrantedstock	1.005447e-04
plantpatstock	-8.437710e-01
designpatstock	8.631382e-02
plantpat	1.307181e+01

```
prediction =lr.predict(x_test)
plt.scatter(y_test,prediction)
```

```
<matplotlib.collections.PathCollection at 0x161b3d09940>
```



ACCURACY

```
lr.score(x_test,y_test)
```

```
0.9162096408969369
```

```
lr.score(x_train,y_train)
```

```
0.9634754764411437
```

Ridge and Lasso

```
from sklearn.linear_model import Ridge,Lasso
```

```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_ridge.py:147: LinAlgWarning: Ill-conditioned matrix (rcond=6.86535e-27)
  return linalg.solve(A, Xy, sym_pos=True,
Ridge(alpha=10)
```

Accuracy(Ridge)

```
rr.score(x_test,y_test)
```

```
0.9162124778768015
```

```
rr.score(x_train,y_train)
```

```
0.9634750582706163
```

```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

```
Lasso(alpha=10)
```

```
la.score(x_train,y_train)
```

```
0.9631243502492564
```

Accuracy(Lasso)

```
la.score(x_test,y_test)
```

```
0.9165661481463434
```

ElasticNet

```
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
```

```
ElasticNet()
```

```
en.coef_
```

```
array([ 4.07138505e-01,  6.08336385e-01, -0.00000000e+00,  0.00000000e+00,
        0.00000000e+00,  0.00000000e+00,  0.00000000e+00, -1.25164599e+00,
```

```
             1.00103255e-02, -4.76758743e-03, -3.15108699e-08,  7.17148629e-10,
            -1.63658098e-05, -4.86910773e-02,  2.68159282e-01,  1.00464920e-01,
            -7.91213036e-03, -0.00000000e+00,  0.00000000e+00, -0.00000000e+00,
            -0.00000000e+00, -2.76853805e-11, -3.73949002e-04,  7.78322034e-10,
             2.11411623e-08, -6.83653979e-01,  1.15933568e-04, -8.48042740e-01,
             8.70159523e-02,  1.28954823e+01])
```

```
en.intercept_
```

```
-811.8228637770986
```

```
prediction=en.predict(x_test)
```

```
en.score(x_test,y_test)
```

```
0.9162648062418464
```

Evaluation Metrics

```
from sklearn import metrics
print(metrics.mean_absolute_error(y_test,prediction))
print(metrics.mean_squared_error(y_test,prediction))
print(np.sqrt(metrics.mean_squared_error(y_test,prediction)))
```

```
13.73174811011863
11614.398900657516
107.7701206302448
```

Logistic Regression

```
from sklearn.linear_model import LogisticRegression
```

```
feature_matrix=df[['year', 'eap', 'eca', 'lac', 'mena', 'sha', 'sa',
       'hi', 'pat', 'patepo', 'royal', 'rdexp', 'rdper', 'rdfinabro',
       'rdfinprod', 'rdperfprod', 'rdperfhe', 'rdperfpub', 'lowrdexp',
       'lowrdfinprod', 'lowrdperfprod', 'y', 'stockpatEPO', 'poptotal',
       'labor', 'rdexpgdp', 'patgrantedstock', 'plantpatstock',
       'designpatstock', 'plantpat']]
target_vector=df[ 'designpat']
```

```
feature_matrix.shape
```

```
(8295, 30)
```

```
target_vector.shape
```

```
(8295,)
```

```
from sklearn.preprocessing import StandardScaler
```

```
fs=StandardScaler().fit_transform(feature_matrix)
```

```
logr=LogisticRegression(max_iter=10000)
logr.fit(fs,target_vector)
```

```
LogisticRegression(max_iter=10000)
```

```
observation=[[1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30]]
```

```
prediction=logr.predict(observation)
print(prediction)
```

```
[212.]
```

```
logr.classes_
```

```
array([0.0000e+00, 1.0000e+00, 2.0000e+00, 3.0000e+00, 4.0000e+00,
       5.0000e+00, 6.0000e+00, 7.0000e+00, 8.0000e+00, 9.0000e+00,
       1.0000e+01, 1.1000e+01, 1.2000e+01, 1.3000e+01, 1.4000e+01,
       1.5000e+01, 1.6000e+01, 1.7000e+01, 1.8000e+01, 1.9000e+01,
       2.0000e+01, 2.1000e+01, 2.2000e+01, 2.3000e+01, 2.4000e+01,
       2.5000e+01, 2.6000e+01, 2.7000e+01, 2.8000e+01, 2.9000e+01,
       3.0000e+01, 3.2000e+01, 3.3000e+01, 3.4000e+01, 3.7000e+01,
       3.8000e+01, 3.9000e+01, 4.0000e+01, 4.1000e+01, 4.2000e+01,
       4.3000e+01, 4.4000e+01, 4.5000e+01, 4.6000e+01, 4.7000e+01,
       4.8000e+01, 4.9000e+01, 5.0000e+01, 5.4000e+01, 5.5000e+01,
       5.6000e+01, 5.7000e+01, 5.8000e+01, 5.9000e+01, 6.0000e+01,
       6.1000e+01, 6.2000e+01, 6.3000e+01, 6.4000e+01, 6.5000e+01,
       6.6000e+01, 6.7000e+01, 6.9000e+01, 7.0000e+01, 7.1000e+01,
       7.2000e+01, 7.3000e+01, 7.4000e+01, 7.6000e+01, 7.7000e+01,
       7.8000e+01, 8.0000e+01, 8.1000e+01, 8.2000e+01, 8.3000e+01,
       8.4000e+01, 8.5000e+01, 8.6000e+01, 8.7000e+01, 8.8000e+01,
       8.9000e+01, 9.0000e+01, 9.1000e+01, 9.3000e+01, 9.4000e+01,
       9.5000e+01, 9.6000e+01, 9.7000e+01, 9.8000e+01, 9.9000e+01,
       1.0000e+02, 1.0100e+02, 1.0200e+02, 1.0300e+02, 1.0500e+02,
       1.0600e+02, 1.0700e+02, 1.0900e+02, 1.1000e+02, 1.1200e+02,
       1.1300e+02, 1.1400e+02, 1.1500e+02, 1.1700e+02, 1.1800e+02,
       1.1900e+02, 1.2000e+02, 1.2100e+02, 1.2300e+02, 1.2400e+02,
       1.2500e+02, 1.2600e+02, 1.2700e+02, 1.2900e+02, 1.3200e+02,
       1.3300e+02, 1.3400e+02, 1.3600e+02, 1.3800e+02, 1.3900e+02,
       1.4200e+02, 1.4300e+02, 1.4400e+02, 1.4700e+02, 1.5000e+02,
       1.5200e+02, 1.5300e+02, 1.5600e+02, 1.5900e+02, 1.6000e+02,
       1.6200e+02, 1.6300e+02, 1.6500e+02, 1.6900e+02, 1.7200e+02,
       1.7300e+02, 1.7600e+02, 1.7900e+02, 1.8000e+02, 1.8100e+02,
       1.8200e+02, 1.8400e+02, 1.8500e+02, 1.8600e+02, 1.9000e+02,
       1.9300e+02, 1.9500e+02, 1.9600e+02, 1.9700e+02, 2.0100e+02,
       2.0200e+02, 2.0500e+02, 2.0800e+02, 2.1100e+02, 2.1200e+02,
       2.1300e+02, 2.1500e+02, 2.1600e+02, 2.2100e+02, 2.2200e+02,
       2.2700e+02, 2.2800e+02, 2.3000e+02, 2.3100e+02, 2.3400e+02,
       2.3700e+02, 2.3900e+02, 2.4000e+02, 2.4300e+02, 2.4700e+02,
       2.5000e+02, 2.5300e+02, 2.5400e+02, 2.5700e+02, 2.5800e+02,
       2.6000e+02, 2.6500e+02, 2.7500e+02, 2.8200e+02, 3.0000e+02,
       3.0600e+02, 3.2000e+02, 3.3000e+02, 3.3800e+02, 3.4100e+02,
       3.5000e+02, 3.5600e+02, 3.6000e+02, 3.6800e+02, 3.7000e+02,
       3.7200e+02, 3.8200e+02, 3.9000e+02, 3.9600e+02, 4.0100e+02,
       4.1000e+02, 4.1800e+02, 4.3800e+02, 4.3900e+02, 4.6600e+02,
       4.8200e+02, 4.8400e+02, 4.8500e+02, 5.0300e+02, 5.0500e+02,
       5.0900e+02, 5.2200e+02, 5.3900e+02, 5.4700e+02, 5.7600e+02,
       5.8800e+02, 6.2000e+02, 6.9800e+02, 7.0500e+02, 7.9500e+02,
       8.3300e+02, 8.6100e+02, 9.3600e+02, 9.4800e+02, 1.0260e+03,
       1.0370e+03, 1.0560e+03, 1.1350e+03, 1.1370e+03, 1.1490e+03,
       1.1680e+03, 1.2070e+03, 1.2940e+03, 1.3070e+03, 1.3100e+03,
       1.3640e+03, 1.4970e+03, 1.5460e+03, 2.4690e+03, 3.0520e+03,
       3.0550e+03, 3.0650e+03, 3.2780e+03, 3.4280e+03, 3.4460e+03,
       3.4750e+03, 3.5460e+03, 3.5700e+03, 3.6450e+03, 3.8830e+03,
       3.9020e+03, 5.0690e+03, 6.0130e+03, 6.0750e+03, 7.4160e+03,
       7.6970e+03, 7.7470e+03, 7.8630e+03, 8.2510e+03, 9.3250e+03,
       9.6540e+03, 9.9130e+03, 1.0346e+04, 1.1285e+04])
```

```
logr.score(fs,target_vector)
```

```
0.8764315852923448
```

```
logr.predict_proba(observation)[0][0]
```

```
0.0
```

```
logr.predict_proba(observation)
```

```
array([[0.00000000e+00, 6.46875839e-85, 4.18064698e-86, 4.97640492e-80,
        8.59945817e-83, 2.37734566e-56, 3.98520696e-68, 2.90827307e-74,
        3.93470301e-68, 7.84564082e-60, 4.43221229e-85, 6.56263221e-55,
        1.03039805e-73, 1.08013371e-59, 1.08112169e-50, 7.94176532e-68,
        1.81569452e-50, 2.60212594e-61, 4.31128405e-50, 7.36175743e-49,
        3.51381920e-52, 8.03683141e-50, 4.61455481e-44, 9.29966791e-71,
        2.15616849e-32, 1.47123590e-51, 3.22397464e-25, 1.13656197e-42,
        3.84756439e-36, 3.92528441e-58, 2.57777087e-38, 4.08345965e-33,
        4.43714065e-49, 1.95954619e-43, 1.45852110e-54, 1.32840786e-50,
        1.61612437e-22, 2.16834024e-29, 1.26908838e-34, 8.98132380e-30,
        2.17424290e-44, 4.15451744e-15, 6.05958093e-36, 3.76411606e-12,
        1.64039866e-26, 5.78586665e-31, 1.98698848e-18, 1.60937793e-35,
        3.86587379e-25, 7.65725299e-09, 1.68641093e-36, 7.44871984e-19,
        9.91118520e-31, 3.27302787e-26, 4.54761528e-32, 3.46546939e-26,
        3.43068716e-38, 2.09551086e-46, 1.47074020e-24, 5.60652672e-29,
        4.46188339e-14, 5.23448116e-35, 4.90515430e-13, 4.19574969e-43,
```

```
1.88139168e-38, 5.87960896e-41, 1.68589460e-22, 1.06641334e-28,
4.31086801e-32, 2.11026858e-21, 1.36350787e-13, 2.68466590e-17,
2.06256309e-27, 4.64149327e-37, 6.11020490e-11, 1.77915082e-04,
1.04327068e-33, 9.27239443e-25, 1.64059124e-19, 1.41867503e-26,
3.45576309e-25, 3.78644588e-25, 5.53565304e-21, 1.10810312e-32,
4.17326226e-30, 2.85198531e-14, 1.70870740e-16, 2.37696717e-31,
4.57363954e-20, 1.10518235e-31, 7.04942289e-18, 7.09899878e-15,
6.18243195e-20, 5.14010433e-12, 1.30131822e-26, 2.75215467e-28,
3.56175114e-23, 1.43488680e-20, 1.49026166e-35, 2.31955497e-19,
2.80943383e-28, 3.26844661e-25, 1.98767004e-25, 2.90381563e-47,
4.16144030e-38, 2.15517707e-26, 5.16987221e-29, 3.01843396e-43,
2.43209628e-24, 1.67542453e-22, 1.49536949e-44, 4.37752030e-24,
1.19030241e-27, 1.26335802e-12, 3.25590978e-18, 1.46940286e-36,
6.21194731e-25, 1.02987622e-16, 2.55264374e-31, 3.08002770e-28,
2.73592092e-19, 1.09563396e-20, 7.28661834e-15, 8.63266119e-24,
6.55186889e-19, 3.67493263e-23, 5.37165816e-11, 1.42090765e-29,
1.96504387e-26, 3.15806890e-35, 4.67423646e-41, 1.03249746e-42,
2.06352084e-18, 4.80872013e-11, 2.38144854e-22, 1.44623746e-19,
1.12561121e-23, 1.27398771e-17, 5.88348615e-41, 9.14398660e-13,
2.69631717e-12, 3.53809810e-06, 1.35670563e-37, 4.00635816e-07,
3.66333929e-26, 3.21990721e-11, 4.34472713e-18, 3.82940747e-11,
4.48980290e-12, 3.70126759e-10, 3.42435599e-16, 2.23506481e-29,
2.06547055e-22, 1.65143853e-23, 9.99292856e-01, 1.89931562e-40,
9.95178307e-09, 4.04014787e-33, 6.45046777e-19, 6.39481242e-17,
1.65711204e-21, 1.66902668e-13, 5.85102749e-09, 3.58553149e-20,
7.63863608e-14, 2.16528932e-16, 2.31182283e-19, 5.19372698e-10,
2.85136582e-18, 2.20030544e-23, 8.40363376e-15, 1.52062520e-10,
2.11702071e-34, 9.43588493e-11, 2.38638165e-34, 6.84723725e-16,
7.27402502e-24, 1.34617982e-10, 7.45356898e-05, 2.01297770e-13,
6.90786546e-16, 2.47182409e-26, 4.93804370e-15, 1.42551905e-13,
2.26831073e-18, 4.95819552e-17, 2.54256226e-26, 3.33888563e-11,
1.20758731e-31, 2.15710411e-24, 4.34686023e-07, 1.48682527e-40,
1.80994770e-16, 1.56738491e-25, 5.46790333e-18, 3.54425763e-04,
1.27586197e-10, 3.05700233e-12, 1.93730817e-21, 5.51384567e-23,
2.69380119e-17, 3.77031259e-10, 1.01278030e-07, 5.00823656e-20,
9.23034863e-05, 1.50877311e-19, 3.49094704e-21, 2.04317551e-20,
6.66023049e-12, 2.20980382e-22, 5.86801028e-22, 8.35022702e-20,
5.26476071e-19, 2.53780151e-18, 6.88038395e-17, 1.31007494e-15,
3.18385328e-17, 1.42025828e-18, 3.67892414e-17, 2.01043312e-14,
6.10377056e-18, 5.68120253e-21, 2.01399099e-13, 7.29833544e-15,
3.86518040e-15, 6.63952897e-26, 9.64773366e-12, 1.62949403e-24,
9.21556898e-19, 2.45429341e-12, 5.20193815e-26, 1.31984657e-10
```

Random Forest

```
from sklearn.ensemble import RandomForestClassifier
```

```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

```
RandomForestClassifier()
```

```
parameters={'max_depth':[1,2,3,4,5],
            'min_samples_leaf':[5,10,15,20,25],
            'n_estimators':[10,20,30,40,50]
}
```

```
from sklearn.model_selection import GridSearchCV
grid_search =GridSearchCV(estimator=rfc,param_grid=parameters,cv=2,scoring="accuracy")
grid_search.fit(x_train,y_train)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\model_selection\_split.py:666: UserWarning: The least populated class in y has only 1
  warnings.warn(("The least populated class in y has only %d"
GridSearchCV(cv=2, estimator=RandomForestClassifier(),
             param_grid={'max_depth': [1, 2, 3, 4, 5],
                         'min_samples_leaf': [5, 10, 15, 20, 25],
                         'n_estimators': [10, 20, 30, 40, 50]},
             scoring='accuracy')
```

```
grid_search.best_score_
```

```
0.8825353083017569
```

```
rfc_best=grid_search.best_estimator_
```

```
from sklearn.tree import plot_tree

plt.figure(figsize=(80,40))
plot_tree(rfc_best.estimators_[5],feature_names=x.columns,class_names=['variable1', 'variable2', 'variable3', 'variable4', 'variable5', 'vari
'variable11', 'variable12', 'variable13', 'variable14', 'variable15', 'variable16', 'variable17', 'variable18', 'variable19', 'variable20',
'variable21', 'variable22', 'variable23', 'variable24', 'variable25', 'variable26', 'variable27', 'variable28', 'variable29', 'variable30',
'variable31', 'variable32', 'variable33', 'variable34', 'variable35', 'variable36', 'variable37', 'variable38', 'variable39', 'variable40',
'variable41', 'variable42', 'variable43', 'variable44', 'variable45', 'variable46', 'variable47', 'variable48', 'variable49', 'variable50',
'variable51', 'variable52', 'variable53', 'variable54', 'variable55', 'variable56', 'variable57', 'variable58', 'variable59', 'variable60',
'variable61', 'variable62', 'variable63', 'variable64', 'variable65', 'variable66', 'variable67', 'variable68', 'variable69', 'variable70',
'variable71', 'variable72', 'variable73', 'variable74', 'variable75', 'variable76', 'variable77', 'variable78', 'variable79', 'variable80',
'variable81', 'variable82', 'variable83', 'variable84', 'variable85', 'variable86', 'variable87', 'variable88', 'variable89', 'variable90',
'variable91', 'variable92', 'variable93', 'variable94', 'variable95', 'variable96', 'variable97', 'variable98', 'variable99', 'variable100','
```

```
[Text(1906.5, 1993.2, 'stockpatEPO <= 0.5\ngini = 0.591\nsamples = 3662\nvalue
= [2635, 2615, 45, 37, 30, 19, 25, 11, 16, 16, 6, 5\n10, 5, 0, 3, 5, 11, 2, 5,
4, 6, 2, 2, 3, 5\n6, 8, 2, 5, 1, 3, 1, 1, 4, 0, 3, 3, 4, 1\n1, 1, 7, 3, 1, 4,
5, 3, 1, 3, 0, 0, 3, 0\n1, 1, 1, 0, 1, 3, 4, 1, 0, 2, 2, 2, 0, 0\n3, 3, 2, 3,
5, 2, 0, 1, 1, 0, 4, 4, 5, 3\n1, 2, 4, 3, 3, 2, 1, 2, 2, 2, 4, 1, 0, 1\n0, 2,
0, 0, 0, 1, 3, 2, 0, 2, 3, 3, 2, 0\n0, 1, 0, 3, 2, 2, 2, 3, 0, 2, 2, 1, 2,
1\n1, 1, 2, 1, 1, 0, 1, 1, 2, 1, 1, 0, 1, 2\n1, 2, 1, 1, 1, 2, 0, 2, 1, 3, 1,
4, 0, 1\n0, 0, 1, 1, 0, 2, 2, 1, 3, 2, 0, 0, 0, 0\n1, 1, 1, 0, 3, 1, 2, 0, 0,
1, 2, 1, 0, 1\n0, 0, 1, 1, 0, 1, 0, 0, 2, 0, 1, 1, 1, 1\n0, 2, 3, 2, 1, 0, 2,
1, 4, 0, 2, 1, 0, 0\n0]\nclass = variable1'),
 Text(837.0, 1630.8000000000002, 'pat <= 42.0\ngini = 0.145\nsamples =
634\nvalue = [946, 52, 6, 8, 2, 0, 6, 1, 1, 0, 0, 1, 0, 0\n0, 0, 0, 0, 0, 0, 0,
0, 2, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0]\nclass = variable1'),
 Text(744.0, 1268.4, 'royal <= 29397300.0\ngini = 0.124\nsamples = 626\nvalue =
[945, 52, 6, 3, 2, 0, 0, 0, 1, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 2, 0, 0,
0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0,
0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0]\nclass = variable1'),
 Text(372.0, 906.0, 'eca <= 0.5\ngini = 0.087\nsamples = 589\nvalue = [910, 31,
6, 2, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0,
0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0]\nclass = variable1'),
 Text(186.0, 543.5999999999999, 'pat <= 8.5\ngini = 0.063\nsamples = 498\nvalue
= [780, 14, 6, 2, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 2, 0,
0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0,
0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0]\nclass = variable1'),
 Text(93.0, 181.19999999999982, 'gini = 0.049\nsamples = 491\nvalue = [774, 14,
2, 2, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0,
```