# Importing Libraries

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

# Importing Datasets

In [2]:
```
df=pd.read_csv("innovation_and_development_database.csv")
df
```

Out[2]:

| | country | code | year | eap | eca | lac | mena | sha | sa | hi | ... | y | stockpatEPO | poptotal | labor | rdexpgdp | pat |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Aruba | ABW | 1960 | 0 | 0 | 1 | 0 | 0 | 0 | 0.0 | ... | NaN | NaN | NaN | NaN | NaN | |
| **1** | Aruba | ABW | 1961 | 0 | 0 | 1 | 0 | 0 | 0 | 0.0 | ... | NaN | NaN | NaN | NaN | NaN | |
| **2** | Aruba | ABW | 1962 | 0 | 0 | 1 | 0 | 0 | 0 | 0.0 | ... | NaN | NaN | NaN | NaN | NaN | |
| **3** | Aruba | ABW | 1963 | 0 | 0 | 1 | 0 | 0 | 0 | 0.0 | ... | NaN | NaN | NaN | NaN | NaN | |
| **4** | Aruba | ABW | 1964 | 0 | 0 | 1 | 0 | 0 | 0 | 0.0 | ... | NaN | NaN | NaN | NaN | NaN | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **8290** | Zimbabwe | ZWE | 1998 | 0 | 0 | 0 | 0 | 1 | 0 | 0.0 | ... | 8.290000e+09 | 8.0 | 12153850.0 | 6236700.0 | NaN | |
| **8291** | Zimbabwe | ZWE | 1999 | 0 | 0 | 0 | 0 | 1 | 0 | 0.0 | ... | 8.230000e+09 | 8.0 | 12388320.0 | 6374300.0 | NaN | |
| **8292** | Zimbabwe | ZWE | 2000 | 0 | 0 | 0 | 0 | 1 | 0 | 0.0 | ... | 7.830000e+09 | 8.0 | 12627000.0 | 6514800.0 | NaN | |
| **8293** | Zimbabwe | ZWE | 2001 | 0 | 0 | 0 | 0 | 1 | 0 | 0.0 | ... | NaN | 8.0 | 12820650.0 | NaN | NaN | |
| **8294** | Zimbabwe | ZWE | 2002 | 0 | 0 | 0 | 0 | 1 | 0 | 0.0 | ... | NaN | NaN | NaN | NaN | NaN | |

8295 rows × 33 columns

# Data Cleaning and Data Preprocessing

In [3]:
```
df=df.fillna(1)
df
```

Out[3]:

| | country | code | year | eap | eca | lac | mena | sha | sa | hi | ... | y | stockpatEPO | poptotal | labor | rdexpgdp |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Aruba | ABW | 1960 | 0 | 0 | 1 | 0 | 0 | 0 | 0.0 | ... | 1.000000e+00 | 1.0 | 1.0 | 1.0 | 1.0 |
| **1** | Aruba | ABW | 1961 | 0 | 0 | 1 | 0 | 0 | 0 | 0.0 | ... | 1.000000e+00 | 1.0 | 1.0 | 1.0 | 1.0 |
| **2** | Aruba | ABW | 1962 | 0 | 0 | 1 | 0 | 0 | 0 | 0.0 | ... | 1.000000e+00 | 1.0 | 1.0 | 1.0 | 1.0 |
| **3** | Aruba | ABW | 1963 | 0 | 0 | 1 | 0 | 0 | 0 | 0.0 | ... | 1.000000e+00 | 1.0 | 1.0 | 1.0 | 1.0 |
| **4** | Aruba | ABW | 1964 | 0 | 0 | 1 | 0 | 0 | 0 | 0.0 | ... | 1.000000e+00 | 1.0 | 1.0 | 1.0 | 1.0 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **8290** | Zimbabwe | ZWE | 1998 | 0 | 0 | 0 | 0 | 1 | 0 | 0.0 | ... | 8.290000e+09 | 8.0 | 12153850.0 | 6236700.0 | 1.0 |
| **8291** | Zimbabwe | ZWE | 1999 | 0 | 0 | 0 | 0 | 1 | 0 | 0.0 | ... | 8.230000e+09 | 8.0 | 12388320.0 | 6374300.0 | 1.0 |
| **8292** | Zimbabwe | ZWE | 2000 | 0 | 0 | 0 | 0 | 1 | 0 | 0.0 | ... | 7.830000e+09 | 8.0 | 12627000.0 | 6514800.0 | 1.0 |
| **8293** | Zimbabwe | ZWE | 2001 | 0 | 0 | 0 | 0 | 1 | 0 | 0.0 | ... | 1.000000e+00 | 8.0 | 12820650.0 | 1.0 | 1.0 |
| **8294** | Zimbabwe | ZWE | 2002 | 0 | 0 | 0 | 0 | 1 | 0 | 0.0 | ... | 1.000000e+00 | 1.0 | 1.0 | 1.0 | 1.0 |

In [4]:
```
df.columns
```

Out[4]:
```
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')
```

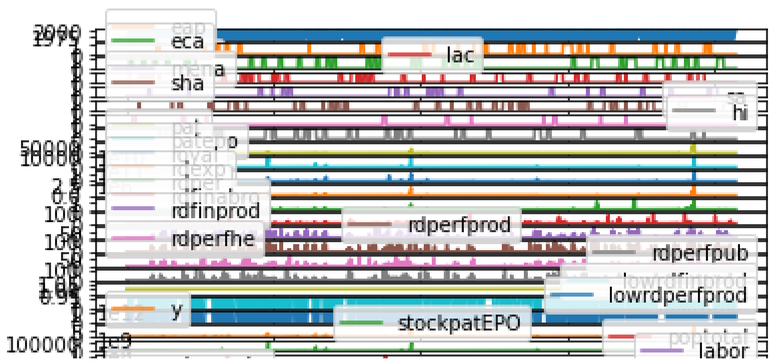
In [5]:
```
df.info()
```

```
<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

In [6]:
```
df.plot.line(subplots=True)
```

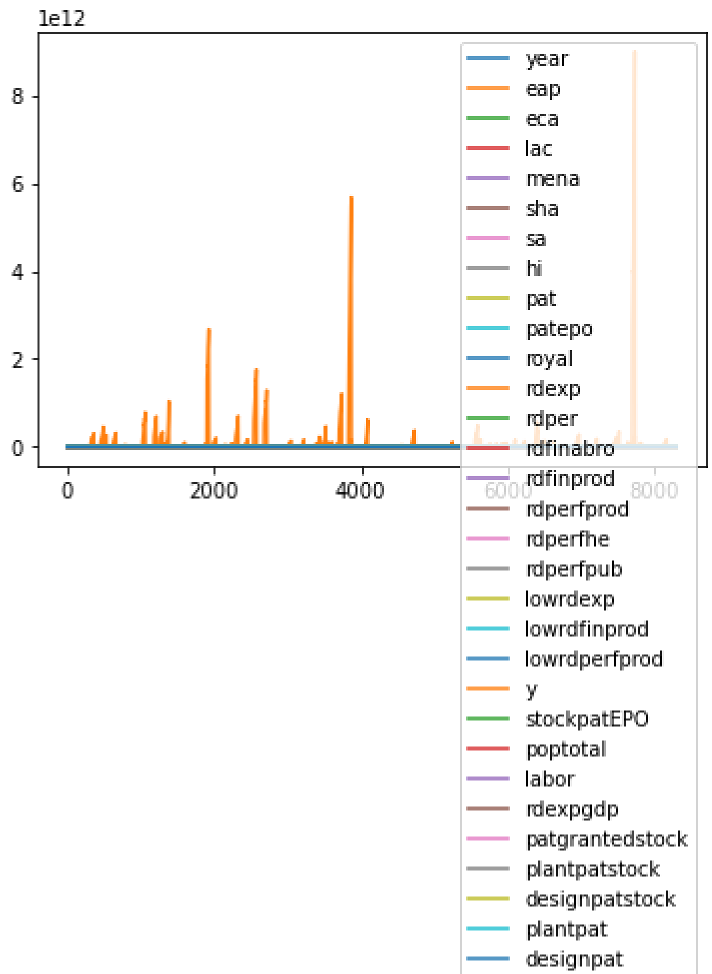
Out[6]:
```
array([<AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>,
       <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>,
       <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>,
       <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>,
       <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>,
       <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>,
       <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>,
       <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>], dtype=object)
```




# Line chart

In [7]:
```
df.plot.line()
```

Out[7]: `<AxesSubplot:>`

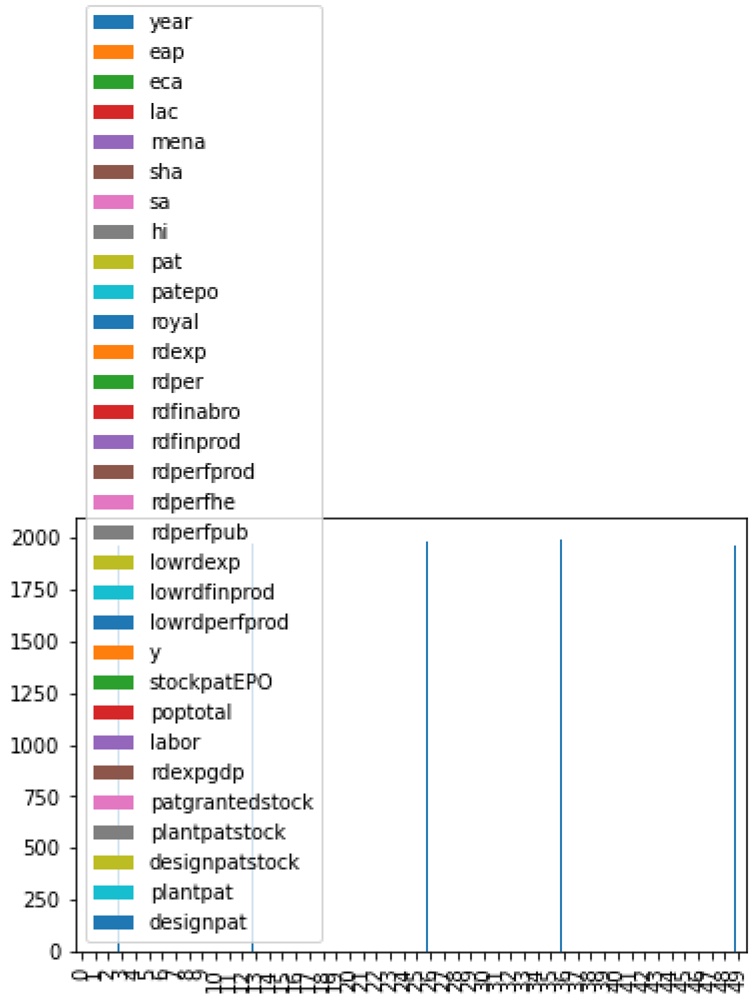



# Bar chart

In [8]:
```
b=df[0:50]
```

In [9]:
```
b.plot.bar()
```

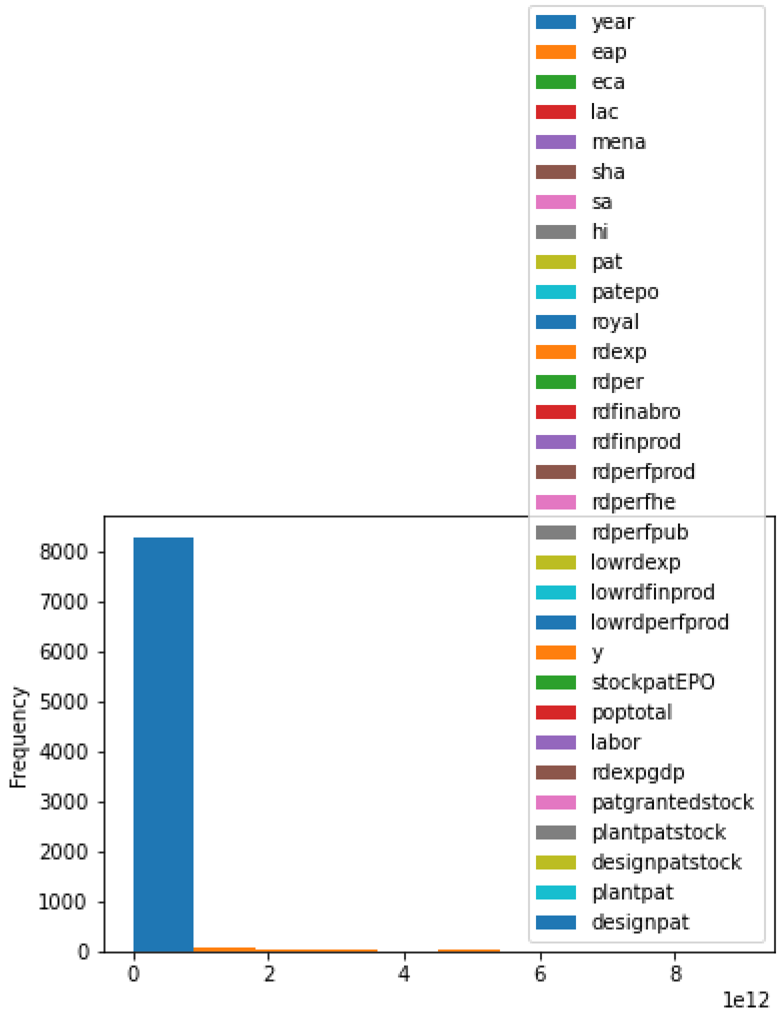
Out[9]:
```
<AxesSubplot:>
```




# Histogram

In [10]:
```
df.plot.hist()
```

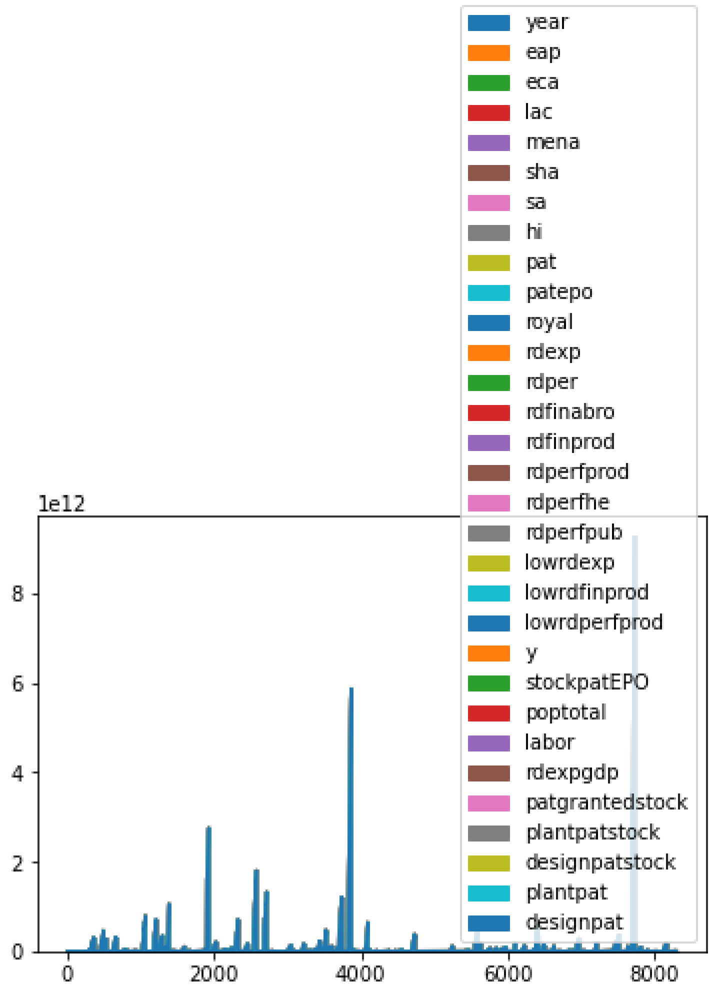
Out[10]: <AxesSubplot:ylabel='Frequency'>




# Area chart

In [11]:
```
df.plot.area()
```

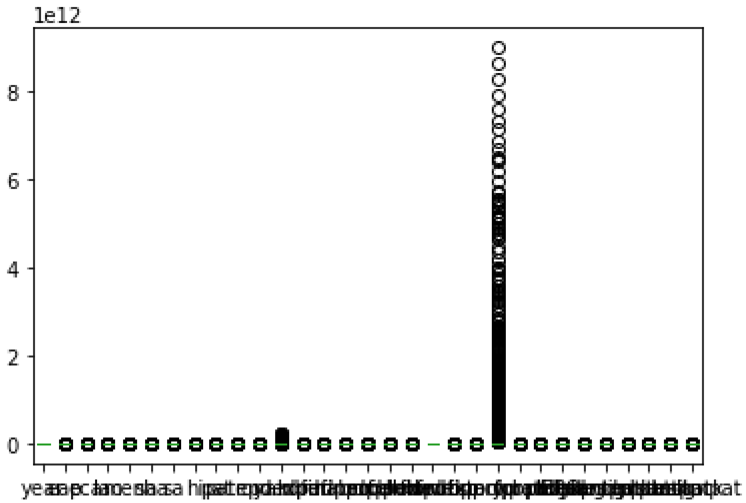
Out[11]: <AxesSubplot:>




# Box chart

In [12]:
```
df.plot.box()
```

Out[12]: <AxesSubplot:>

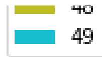



# Pie chart

In [13]:
```
b.plot.pie(y='designpat' )
```

Out[13]:
```
<AxesSubplot:ylabel='designpat'>
```

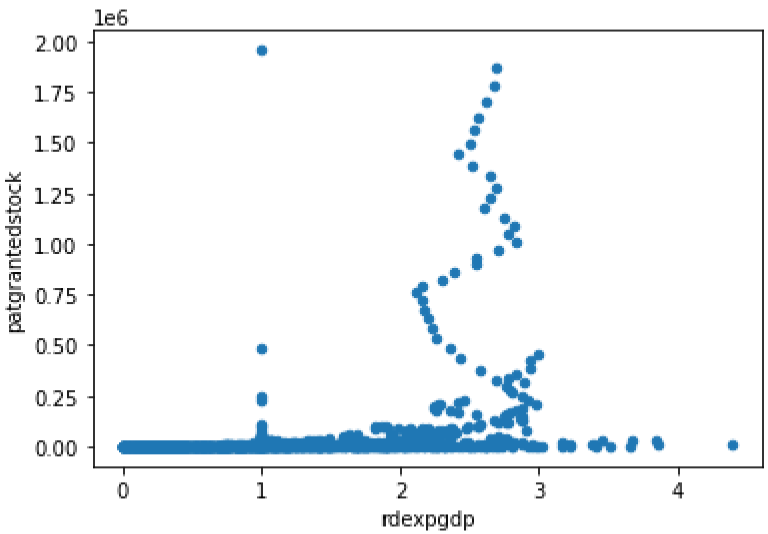

designpat
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
42
43
44
45
47
48
49
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47




# Scatter chart

In [14]:
```python
df.plot.scatter( x='rdexpgdp',y= 'patgrantedstock')
```

Out[14]: <AxesSubplot:xlabel='rdexpgdp', ylabel='patgrantedstock'>



In [15]:
```
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
```

In [16]:
```
df.describe()
```

Out[16]:

| | year | eap | eca | lac | mena | sha | sa | hi | pat | pa |
|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 8295.000000 | 8295.000000 | 8295.000000 | 8295.000000 | 8295.000000 | 8295.000000 | 8295.000000 | 8295.000000 | 8295.000000 | 8295.0 |
| **mean** | 1981.203014 | 0.094515 | 0.195901 | 0.176974 | 0.098614 | 0.150090 | 0.026522 | 0.134901 | 411.663773 | 65.7 |
| **std** | 12.421590 | 0.292561 | 0.396917 | 0.381670 | 0.298161 | 0.357182 | 0.160691 | 0.341638 | 3893.360772 | 580.3 |
| **min** | 1960.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.0 |
| **25%** | 1970.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 1.0 |
| **50%** | 1981.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 1.0 |
| **75%** | 1992.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 2.000000 | 1.0 |
| **max** | 2002.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 87607.000000 | 10300.0 |

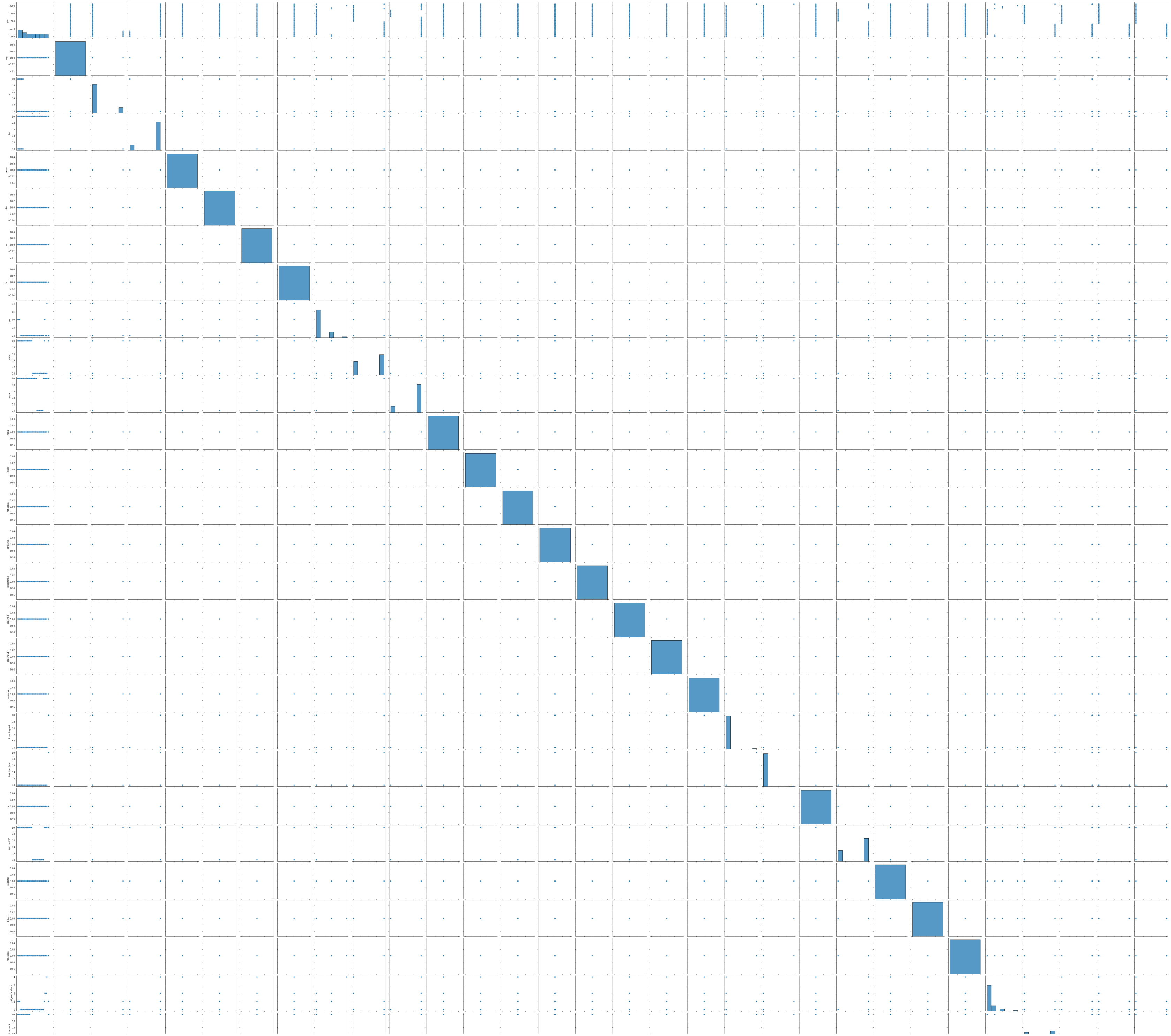
8 rows × 31 columns

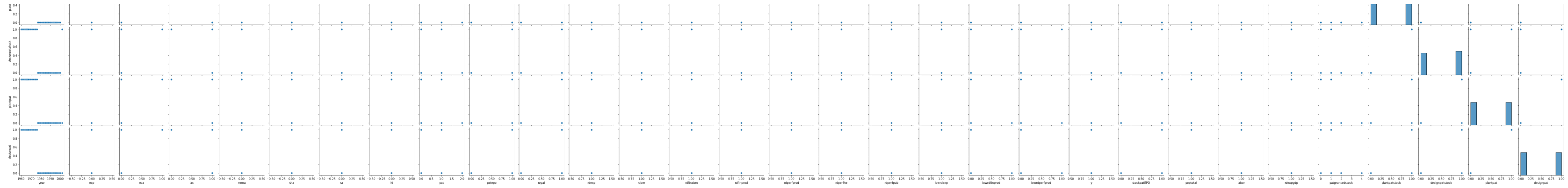
In [17]:
```
df1=df[['year', 'eap', 'eca', 'lac', 'mena', 'sha', 'sa',
       'hi', 'pat', 'patepo', 'royal', 'rdexp', 'rdper', 'rdfinabro',
       'rdfinprod', 'rdperfprod', 'rdperfhe', 'rdperfpub', 'lowrdexp',
       'lowrdfinprod', 'lowrdperfprod', 'y', 'stockpatEPO', 'poptotal',
       'labor', 'rdexpgdp', 'patgrantedstock', 'plantpatstock',
       'designpatstock', 'plantpat', 'designpat']]
```

# EDA AND VISUALIZATION

In [18]:
```
sns.pairplot(df1[0:50])
```

Out[18]: <seaborn.axisgrid.PairGrid at 0x24b293635e0>





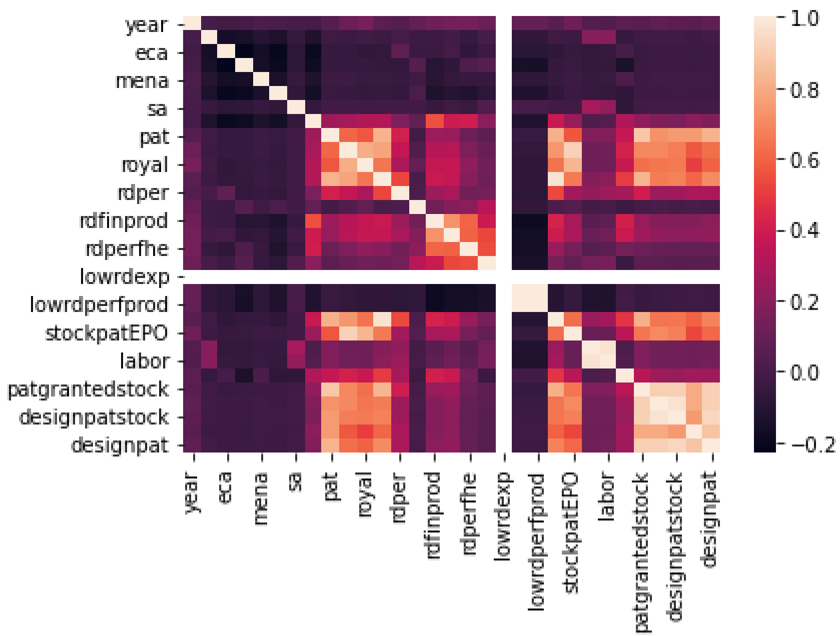
In [19]:
```
sns.distplot(df1['designpat'])
```

```
C:\Users\USER\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a de
precated 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 `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[19]:
```
<AxesSubplot:xlabel='designpat', ylabel='Density'>
```

In [20]:
```
sns.heatmap(df1.corr())
```

Out[20]: <AxesSubplot:>




# TO TRAIN THE MODEL AND MODEL BULDING

In [21]:
```
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']
```

In [22]:
```
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

In [23]:
```
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
lr.fit(x_train,y_train)
```

Out[23]:
```
LinearRegression()
```

In [24]:
```
lr.intercept_
```

Out[24]:
```
-895.707237255563
```

In [25]:
```
coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
coeff
```

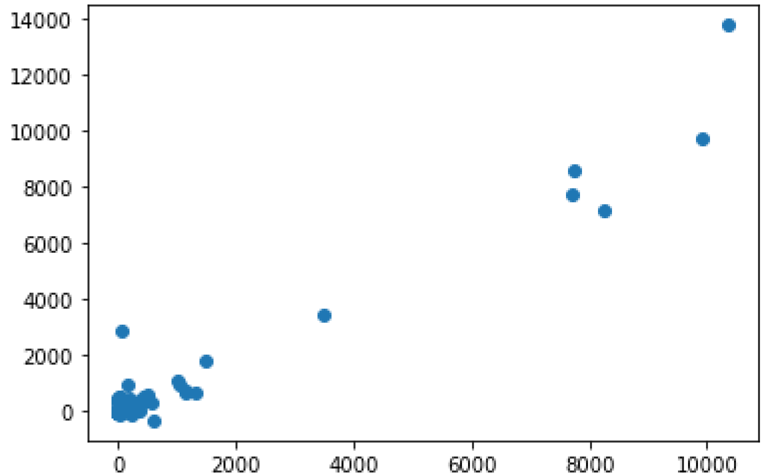
Out[25]:

| | Co-efficient |
|---|---|
| **year** | 4.478269e-01 |
| **eap** | 1.044973e+01 |
| **eca** | -4.112414e-01 |
| **lac** | 1.711691e+00 |
| **mena** | 1.505925e+00 |
| **sha** | 2.727725e+00 |
| **sa** | 2.171481e+00 |
| **hi** | -1.068480e+01 |
| **pat** | 1.077552e-02 |
| **patepo** | -2.062311e-02 |
| **royal** | -1.515536e-08 |
| **rdexp** | -2.591489e-09 |
| **rdper** | -5.410640e-05 |
| **rdfinabro** | -1.926877e-01 |
| **rdfinprod** | 3.072198e-01 |
| **rdperfprod** | 2.148397e-01 |
| **rdperfhe** | -1.150555e-01 |
| **rdperfpub** | 5.812949e-03 |
| **lowrdexp** | 5.284662e-14 |
| **lowrdfinprod** | 2.735943e+00 |
| **lowrdperfprod** | 7.338671e-01 |
| **y** | 3.814805e-11 |
| **stockpatEPO** | 9.898542e-04 |
| **poptotal** | -3.071126e-08 |
| **labor** | 3.423496e-08 |
| **rdexpgdp** | 6.661779e-01 |

| | Co-efficient |
|---|---|
| **patgrantedstock** | -6.384360e-05 |
| **plantpatstock** | -1.126773e+00 |
| **designpatstock** | 9.806644e-02 |
| **plantpat** | 1.316892e+01 |

In [26]:
```
prediction =lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[26]: <matplotlib.collections.PathCollection at 0x24b5f465730>




# ACCURACY

In [27]:
```
lr.score(x_test,y_test)
```

Out[27]: 0.9359440854000607

In [28]:
```
lr.score(x_train,y_train)
```

Out[28]: 0.9556190976958261

# Ridge and Lasso

In [29]:
```
from sklearn.linear_model import Ridge,Lasso
```

In [30]:
```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```

```
C:\Users\USER\anaconda3\lib\site-packages\sklearn\linear_model\_ridge.py:157: LinAlgWarning: Ill-conditioned
matrix (rcond=6.91987e-27): result may not be accurate.
  return linalg.solve(A, Xy, sym_pos=True, overwrite_a=True).T
```

Out[30]:
```
Ridge(alpha=10)
```

# Accuracy(Ridge)

In [31]:
```
rr.score(x_test,y_test)
```

Out[31]:
```
0.9359433503141961
```

In [32]:
```
rr.score(x_train,y_train)
```

Out[32]:
```
0.9556189968019976
```

In [33]:
```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[33]:
```
Lasso(alpha=10)
```

In [34]:
```
la.score(x_train,y_train)
```

Out[34]:
```
0.9553951543156738
```

# Accuracy(Lasso)

In [35]:
```
la.score(x_test,y_test)
```

Out[35]:
```
0.9365057709302195
```

# ElasticNet

In [36]:
```
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[36]:
```
ElasticNet()
```

In [37]:
```
en.coef_
```

Out[37]:
```
array([ 4.80389038e-01,  5.81402950e-01, -0.00000000e+00,  0.00000000e+00,
       -0.00000000e+00,  0.00000000e+00, -0.00000000e+00, -6.77890367e-01,
        1.09871047e-02, -1.95517371e-02, -1.58117666e-08, -2.30292806e-09,
       -5.39439272e-05, -1.70086963e-01,  2.00042804e-01,  2.29682240e-01,
       -1.76965155e-01,  0.00000000e+00,  0.00000000e+00,  0.00000000e+00,
        0.00000000e+00,  2.79875266e-11,  8.57046944e-04, -2.65239954e-08,
        4.22220894e-08, -0.00000000e+00, -5.45100706e-05, -1.11854094e+00,
        9.80471935e-02,  1.30136367e+01])
```

In [38]:
```
en.intercept_
```

Out[38]:
```
-957.1590613062978
```

In [39]:
```
prediction=en.predict(x_test)
```

In [40]:
```
en.score(x_test,y_test)
```

Out[40]:
```
0.9361560503753533
```

# Evaluation Metrics

In [41]:
```
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)))
```

```
13.24769486414481
10640.218004441078
103.15143239161091
```

# Logistic Regression

In [42]:
```
from sklearn.linear_model import LogisticRegression
```

In [43]:
```
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']
```

In [44]:
```
feature_matrix.shape
```

Out[44]:
```
(8295, 30)
```

In [45]:
```
target_vector.shape
```

Out[45]:
```
(8295,)
```

In [46]:
```
from sklearn.preprocessing import StandardScaler
```

In [47]:
```
fs=StandardScaler().fit_transform(feature_matrix)
```

In [48]:
```
logr=LogisticRegression(max_iter=10000)
logr.fit(fs,target_vector)
```

Out[48]:
```
LogisticRegression(max_iter=10000)
```

In [49]:
```
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]]
```

In [50]:
```
prediction=logr.predict(observation)
print(prediction)
```

```
[212.]
```

In [51]:
```
logr.classes_
```

Out[51]:
```
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])
```

In [52]:
```
logr.score(fs,target_vector)
```

Out[52]:
```
0.8764315852923448
```

In [53]:
```
logr.predict_proba(observation)[0][0]
```

Out[53]:
```
0.0
```

In [54]:
```
logr.predict_proba(observation)
```

```
Out[54]: 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, 2.45420341e-12, 5.20103815e-26, 1.31984657e-10,
6.15952510e-20, 9.20354758e-19, 5.84975126e-21, 1.31131770e-18,
8.45741933e-13, 1.03629389e-08, 1.79179668e-13, 2.82884116e-08,
1.24337025e-11, 6.93118767e-12, 2.24629133e-13, 5.49609681e-07,
6.10191031e-09, 9.96528220e-11, 3.87985456e-13, 2.53836642e-09,
1.26770832e-06, 1.24209791e-08, 3.02700348e-08, 1.53830151e-06,
2.39069364e-11, 2.79232187e-11, 2.18150800e-21, 2.44157090e-13,
1.53833366e-08, 5.51628248e-12, 1.97159115e-09]])
```

# Random Forest

In [55]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [56]:
```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

Out[56]:
```
RandomForestClassifier()
```

In [57]:
```
parameters={'max_depth':[1,2,3,4,5],
            'min_samples_leaf':[5,10,15,20,25],
            'n_estimators':[10,20,30,40,50]
}
```

In [58]:
```
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:\Users\USER\anaconda3\lib\site-packages\sklearn\model_selection\_split.py:676: UserWarning: The least popu
lated class in y has only 1 members, which is less than n_splits=2.
  warnings.warn(
```

Out[58]:
```
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')
```

In [59]:
```
grid_search.best_score_
```

Out[59]:
```
0.8815018945918016
```

In [60]:
```
rfc_best=grid_search.best_estimator_
```

In [61]:
```python
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',
'variable11', 'variable12', 'variable13', 'variable14', 'variable15', 'variable16', 'variable17', 'variable18
'variable21', 'variable22', 'variable23', 'variable24', 'variable25', 'variable26', 'variable27', 'variable28
'variable31', 'variable32', 'variable33', 'variable34', 'variable35', 'variable36', 'variable37', 'variable38
'variable41', 'variable42', 'variable43', 'variable44', 'variable45', 'variable46', 'variable47', 'variable48
'variable51', 'variable52', 'variable53', 'variable54', 'variable55', 'variable56', 'variable57', 'variable58
'variable61', 'variable62', 'variable63', 'variable64', 'variable65', 'variable66', 'variable67', 'variable68
'variable71', 'variable72', 'variable73', 'variable74', 'variable75', 'variable76', 'variable77', 'variable78
'variable81', 'variable82', 'variable83', 'variable84', 'variable85', 'variable86', 'variable87', 'variable88
'variable91', 'variable92', 'variable93', 'variable94', 'variable95', 'variable96', 'variable97', 'variable98
```

Out[61]:
```
[Text(0.5982142857142857, 0.9166666666666666, 'plantpat <= 0.5\ngini = 0.599\nsamples = 3698\nvalue = [256
9, 2631, 50, 40, 37, 20, 14, 12, 16, 8, 10\n11, 12, 5, 5, 11, 5, 8, 1, 2, 4, 3, 4, 10, 0\n5, 3, 2, 2, 3,
1, 3, 1, 5, 4, 0, 4, 0, 11\n1, 2, 2, 4, 2, 11, 2, 7, 2, 3, 0, 2, 0, 3\n2, 1, 2, 1, 5, 5, 1, 2, 1, 3, 3, 2,
3, 0\n3, 1, 1, 1, 0, 3, 2, 1, 4, 1, 1, 4, 1, 3\n1, 3, 1, 3, 2, 1, 3, 1, 0, 5, 1, 0, 2, 0\n0, 3, 3, 1, 0,
1, 2, 1, 2, 3, 4, 2, 3, 2\n2, 1, 2, 4, 1, 5, 3, 1, 3, 1, 1, 1, 1, 2\n2, 1, 0, 2, 2, 1, 0, 6, 0, 3, 1, 2,
0, 0\n3, 1, 0, 0, 1, 0, 2, 1, 1, 0, 2, 0, 2, 1\n0, 1, 3, 4, 0, 1, 1, 3, 5, 0, 2, 1, 1, 0\n0, 1, 6, 1, 0,
1, 1, 2, 1, 0, 0, 1, 0, 0\n1, 2, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1\n2, 3, 1, 1, 2, 0, 2, 0, 2, 0, 0, 2,
0, 1\n1, 1, 0, 1, 0]\nclass = variable2'),
 Text(0.3273809523809524, 0.75, 'patepo <= 1.5\ngini = 0.287\nsamples = 1947\nvalue = [2547, 145, 47, 35,
36, 10, 11, 10, 14, 8, 7, 7\n8, 3, 3, 5, 5, 8, 1, 2, 4, 3, 4, 6, 0, 3\n0, 1, 0, 3, 1, 1, 1, 5, 3, 0, 2, 0,
0, 1\n1, 2, 2, 0, 7, 0, 3, 2, 2, 0, 2, 0, 1, 2\n1, 0, 0, 5, 0, 1, 1, 0, 1, 1, 0, 2, 0, 0\n0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 3, 0\n0, 0, 0, 0, 1, 2, 0, 0, 0, 0, 0, 0, 0\n0, 3, 0, 0, 0, 0, 0, 0, 3, 3, 0, 0,
0, 0\n0, 0, 0, 0, 2, 0, 1, 1, 0, 0, 1, 1, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0\n0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 4, 0, 0, 0, 0, 3, 0, 0, 0, 0, 0\n0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0,
0, 0\n2, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0]\ncla
ss = variable1'),
 Text(0.17857142857142858, 0.5833333333333334, 'royal <= 127000000.0\ngini = 0.157\nsamples = 1666\nvalue
 = [2365, 82, 31, 30, 19, 4, 4, 3, 3, 0, 3, 4, 6\n0, 0, 2, 0, 3, 0, 1, 1, 2, 4, 0, 0, 0, 0\n0, 0, 2, 0, 0,
1, 0, 0, 0, 0, 0, 0, 0, 1\n0, 0, 0, 0, 0, 2, 0, 2, 0, 0, 0, 0, 0, 1\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
```

# Conclusion

# Accuracy

In [62]:
```
print("Linear Regression:",lr.score(x_test,y_test))
print("Ridge Regression:",rr.score(x_test,y_test))
print("Lasso Regression",la.score(x_test,y_test))
print("ElasticNet Regression:",en.score(x_test,y_test))
print("Logistic Regression:",logr.score(fs,target_vector))
print("Random Forest:",grid_search.best_score_)
```

```
Linear Regression: 0.9359440854000607
Ridge Regression: 0.9359433503141961
Lasso Regression 0.9365057709302195
ElasticNet Regression: 0.9361560503753533
Logistic Regression: 0.8764315852923448
Random Forest: 0.8815018945918016
```

# Lasso Regression is suitable for this dataset