

gjow0f8gh

August 9, 2023

## 1 20104169 - SUMESH R

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

## 2 Importing Datasets

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

```
[2]:
```

	country	code	year	eap	eca	lac	mena	sha	sa	hi	...	\
0	Aruba	ABW	1960	0	0	1	0	0	0	0.0	...	
1	Aruba	ABW	1961	0	0	1	0	0	0	0.0	...	
2	Aruba	ABW	1962	0	0	1	0	0	0	0.0	...	
3	Aruba	ABW	1963	0	0	1	0	0	0	0.0	...	
4	Aruba	ABW	1964	0	0	1	0	0	0	0.0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
8290	Zimbabwe	ZWE	1998	0	0	0	0	1	0	0.0	...	
8291	Zimbabwe	ZWE	1999	0	0	0	0	1	0	0.0	...	
8292	Zimbabwe	ZWE	2000	0	0	0	0	1	0	0.0	...	
8293	Zimbabwe	ZWE	2001	0	0	0	0	1	0	0.0	...	
8294	Zimbabwe	ZWE	2002	0	0	0	0	1	0	0.0	...	

	y	stockpat	EPO	poptotal	labor	rdexp	gdp	\
0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
...	...	...	...	...	...	...	...	
8290	8.290000e+09	8.0	12153850.0	6236700.0	NaN	NaN	NaN	
8291	8.230000e+09	8.0	12388320.0	6374300.0	NaN	NaN	NaN	
8292	7.830000e+09	8.0	12627000.0	6514800.0	NaN	NaN	NaN	
8293	NaN	8.0	12820650.0	NaN	NaN	NaN	NaN	

8294	NaN	NaN	NaN	NaN	NaN
	patgrantedstock	plantpatstock	designpatstock	plantpat	designpat
0	NaN	NaN	NaN	NaN	NaN
1	NaN	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN	NaN
3	0.0	NaN	NaN	NaN	NaN
4	0.0	NaN	NaN	NaN	NaN
...	...	...	...	...	...
8290	48.0	0.0	1.0	0.0	0.0
8291	48.0	0.0	1.0	0.0	0.0
8292	48.0	0.0	1.0	0.0	0.0
8293	49.0	0.0	1.0	0.0	0.0
8294	NaN	NaN	NaN	0.0	0.0

[8295 rows x 33 columns]

### 3 Data Cleaning and Data Preprocessing

```
[3]: df.fillna(1, inplace=True)
df
```

```
[3]:
```

	country	code	year	eap	eca	lac	mena	sha	sa	hi	...	\
0	Aruba	ABW	1960	0	0	1	0	0	0	0.0	...	
1	Aruba	ABW	1961	0	0	1	0	0	0	0.0	...	
2	Aruba	ABW	1962	0	0	1	0	0	0	0.0	...	
3	Aruba	ABW	1963	0	0	1	0	0	0	0.0	...	
4	Aruba	ABW	1964	0	0	1	0	0	0	0.0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
8290	Zimbabwe	ZWE	1998	0	0	0	0	1	0	0.0	...	
8291	Zimbabwe	ZWE	1999	0	0	0	0	1	0	0.0	...	
8292	Zimbabwe	ZWE	2000	0	0	0	0	1	0	0.0	...	
8293	Zimbabwe	ZWE	2001	0	0	0	0	1	0	0.0	...	
8294	Zimbabwe	ZWE	2002	0	0	0	0	1	0	0.0	...	

	y	stockpatEPO	poptotal	labor	rdexpgdp	\
0	1.000000e+00	1.0	1.0	1.0	1.0	
1	1.000000e+00	1.0	1.0	1.0	1.0	
2	1.000000e+00	1.0	1.0	1.0	1.0	
3	1.000000e+00	1.0	1.0	1.0	1.0	
4	1.000000e+00	1.0	1.0	1.0	1.0	
...	...	...	...	...	...	
8290	8.290000e+09	8.0	12153850.0	6236700.0	1.0	
8291	8.230000e+09	8.0	12388320.0	6374300.0	1.0	
8292	7.830000e+09	8.0	12627000.0	6514800.0	1.0	
8293	1.000000e+00	8.0	12820650.0	1.0	1.0	

8294	1.000000e+00	1.0	1.0	1.0	1.0
	patgrantedstock	plantpatstock	designpatstock	plantpat	designpat
0	1.0	1.0	1.0	1.0	1.0
1	1.0	1.0	1.0	1.0	1.0
2	1.0	1.0	1.0	1.0	1.0
3	0.0	1.0	1.0	1.0	1.0
4	0.0	1.0	1.0	1.0	1.0
...	...	...	...	...	...
8290	48.0	0.0	1.0	0.0	0.0
8291	48.0	0.0	1.0	0.0	0.0
8292	48.0	0.0	1.0	0.0	0.0
8293	49.0	0.0	1.0	0.0	0.0
8294	1.0	1.0	1.0	0.0	0.0

[8295 rows x 33 columns]

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

```
[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')
```

```
[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

```

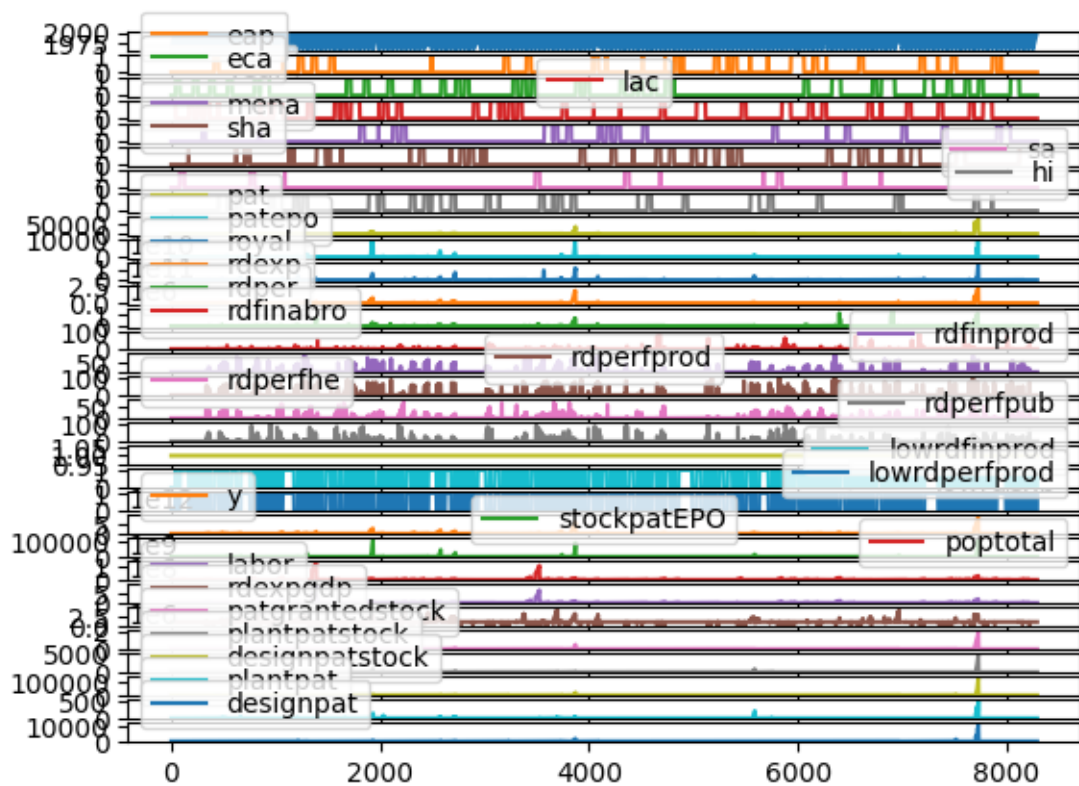
## 4 Line chart

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

```

[6]: array([<Axes: >, <Axes: >, <Axes: >, <Axes: >, <Axes: >, <Axes: >,
<Axes: >, <Axes: >, <Axes: >, <Axes: >, <Axes: >, <Axes: >,
<Axes: >, <Axes: >, <Axes: >, <Axes: >, <Axes: >, <Axes: >,
<Axes: >, <Axes: >, <Axes: >, <Axes: >, <Axes: >, <Axes: >,
<Axes: >], dtype=object)

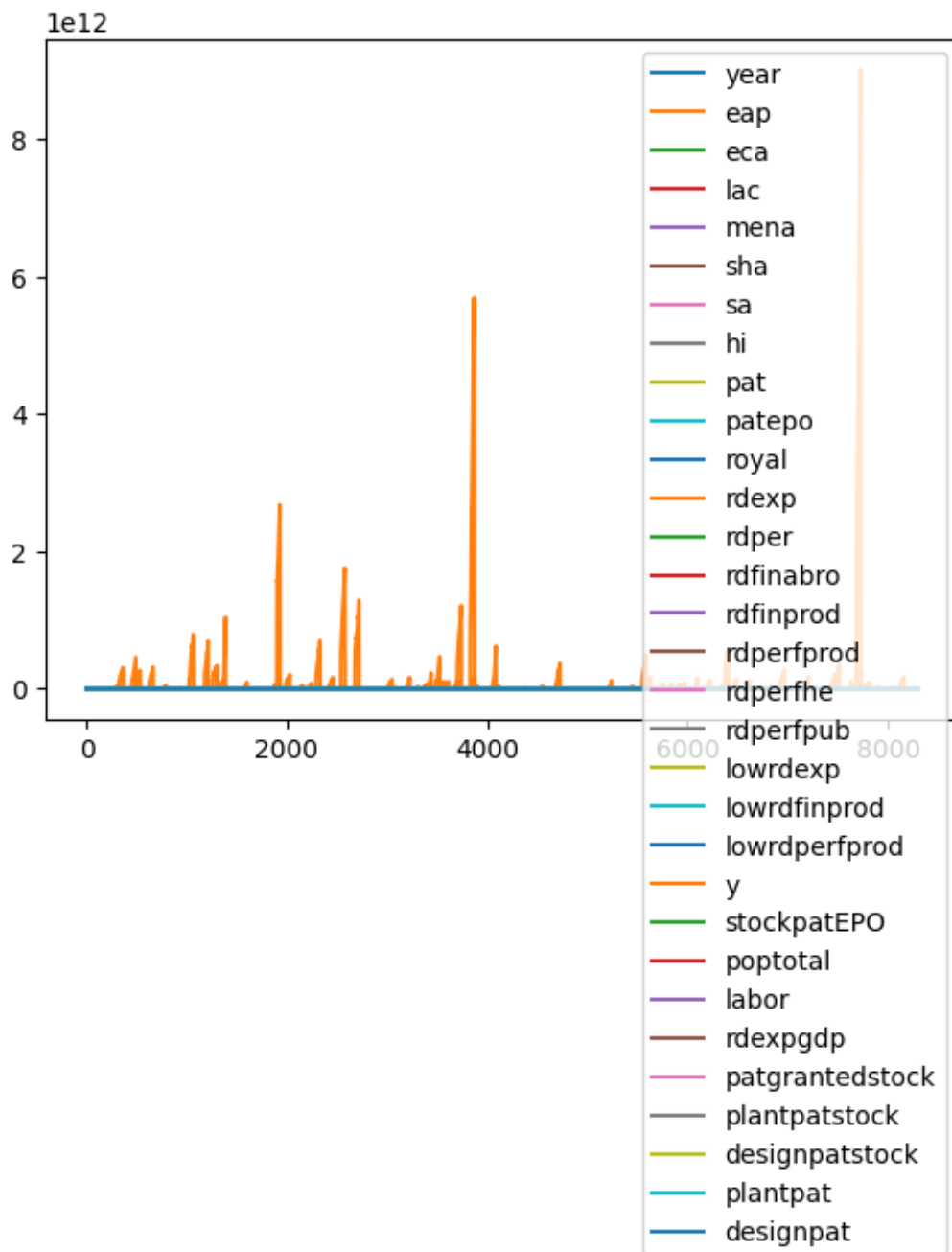
```



## 5 Line chart

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

```
[7]: <Axes: >
```

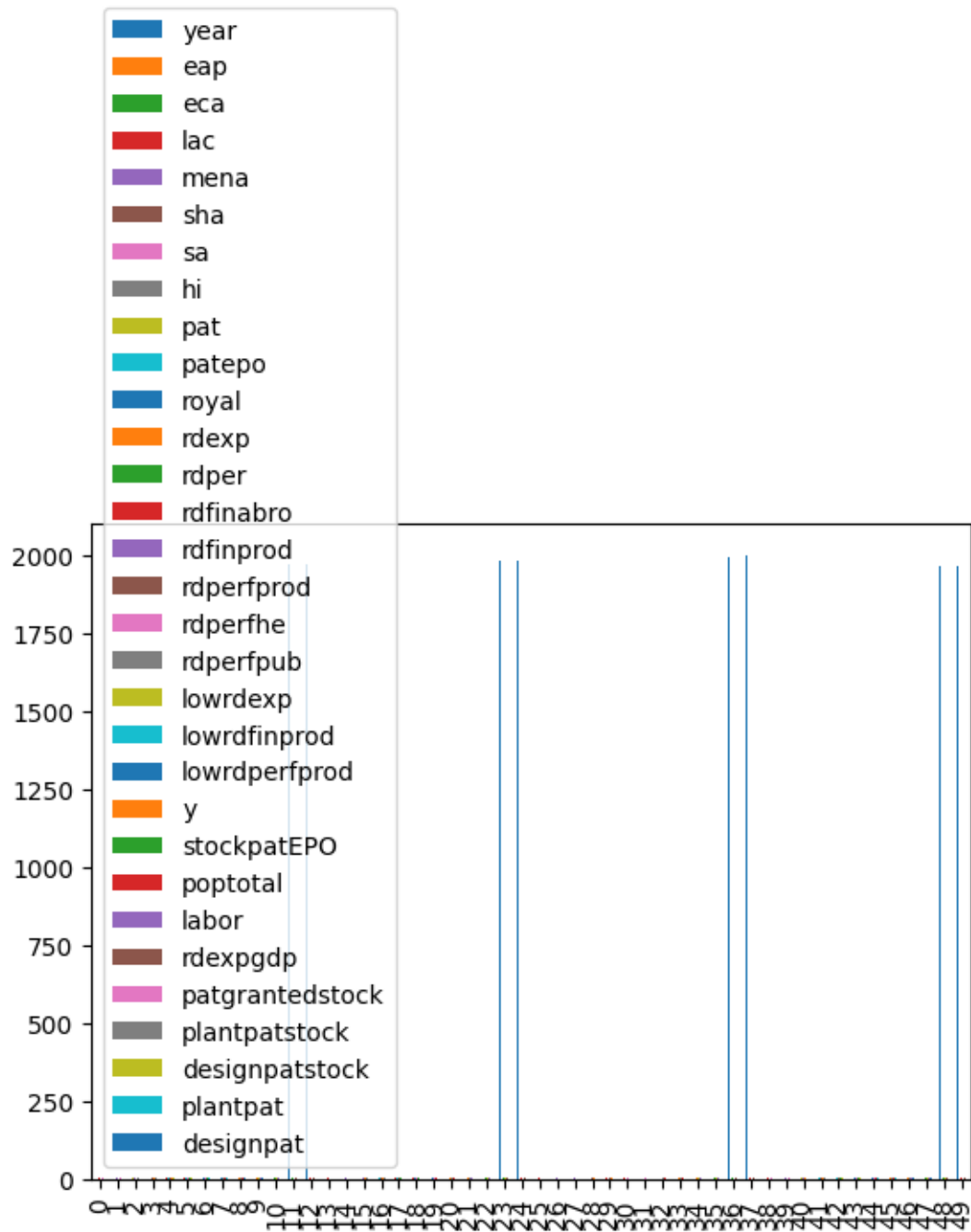


## 6 Bar chart

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

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

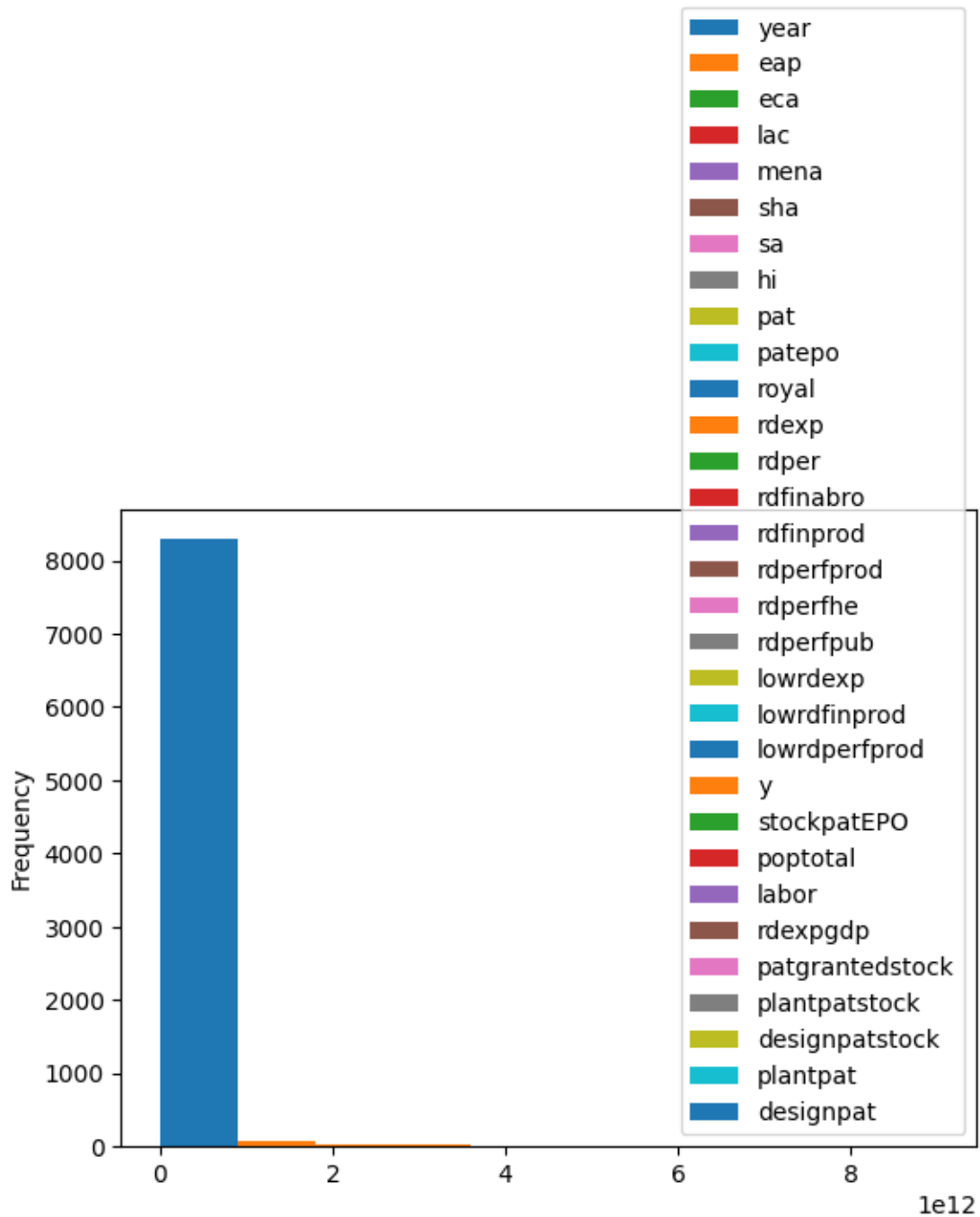
[9]: <Axes: >



## 7 Histogram

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

```
[10]: <Axes: ylabel='Frequency'>
```

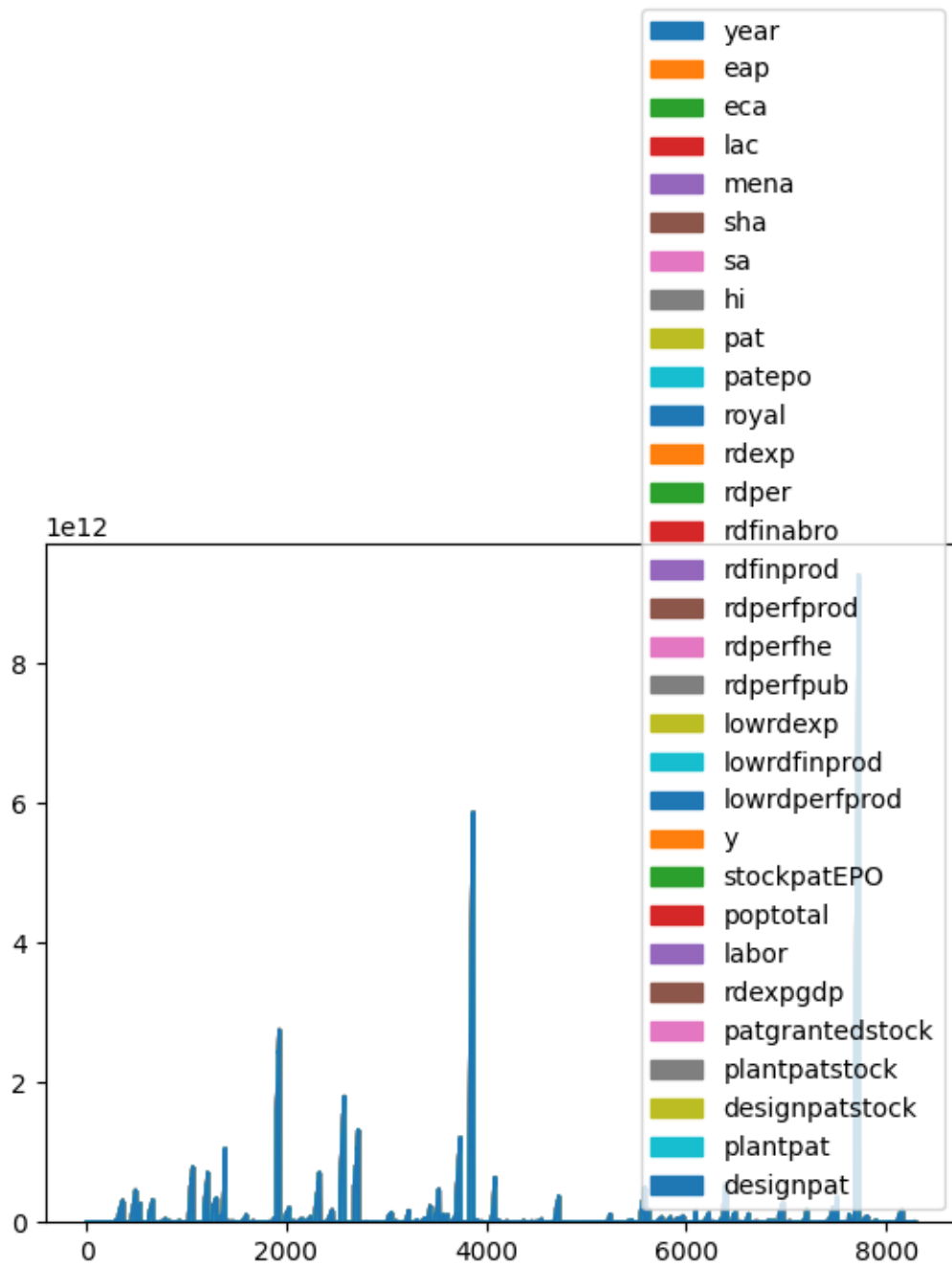




## 8 Area chart

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

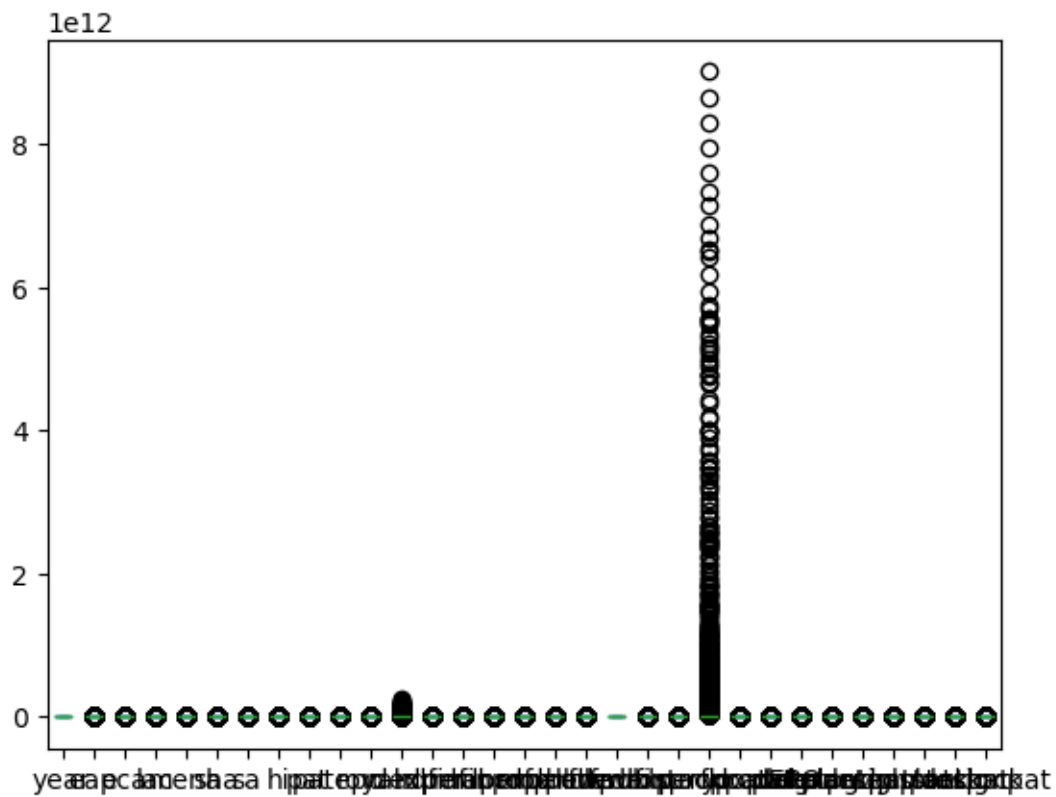
```
[11]: <Axes: >
```



## 9 Box chart

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

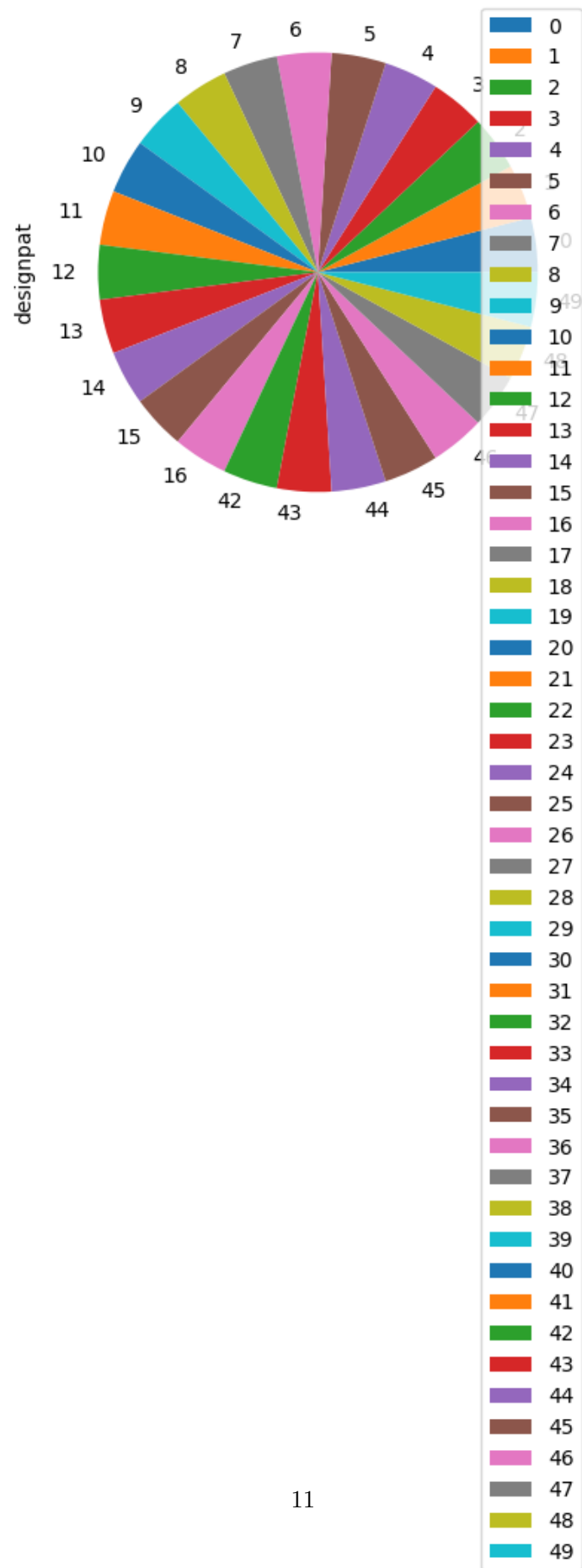
```
[12]: <Axes: >
```



## 10 Pie chart

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

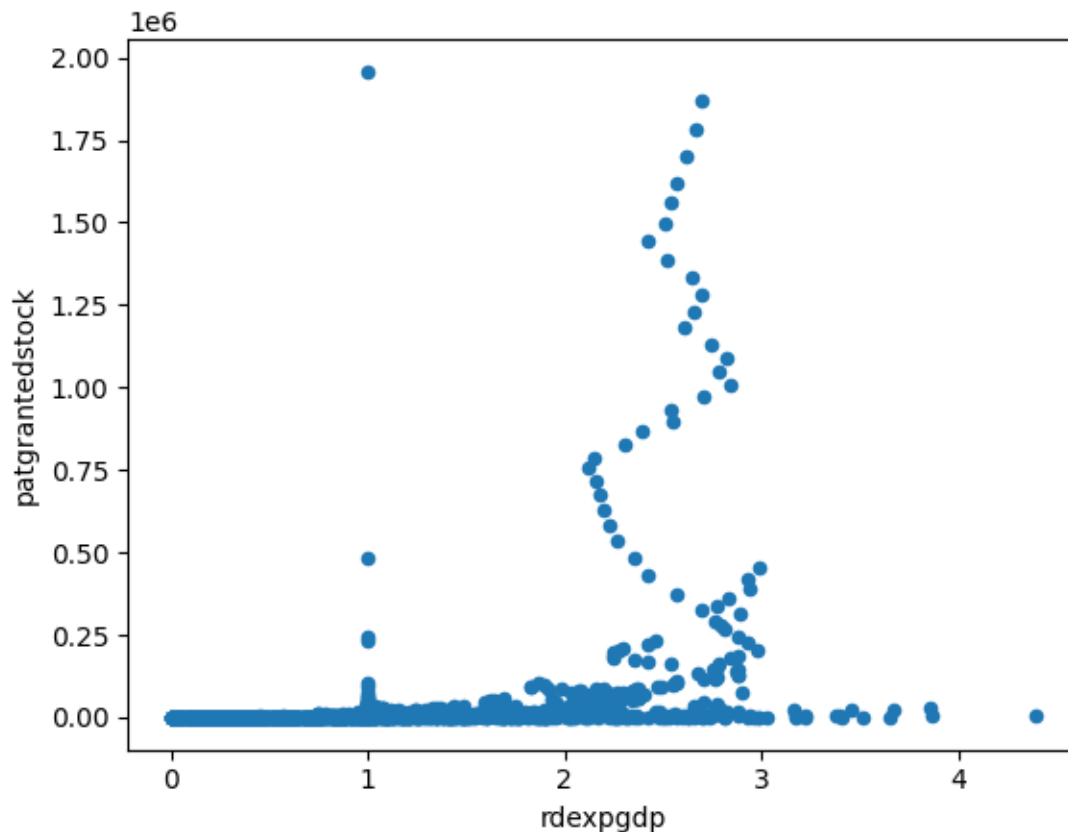
```
[13]: <Axes: ylabel='designpat'>
```



## 11 Scatter chart

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

```
[14]: <Axes: xlabel='rdexpgdp', ylabel='patgrantedstock'>
```



```
[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
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  stockpatEP0        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

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

```

[16]:
count    year    eap    eca    lac    mena  \
count  8295.000000  8295.000000  8295.000000  8295.000000  8295.000000
mean   1981.203014    0.094515    0.195901    0.176974    0.098614
std     12.421590    0.292561    0.396917    0.381670    0.298161
min     1960.000000    0.000000    0.000000    0.000000    0.000000
25%     1970.000000    0.000000    0.000000    0.000000    0.000000
50%     1981.000000    0.000000    0.000000    0.000000    0.000000
75%     1992.000000    0.000000    0.000000    0.000000    0.000000
max     2002.000000    1.000000    1.000000    1.000000    1.000000

count    sha    sa    hi    pat    patepo  ...  \
count  8295.000000  8295.000000  8295.000000  8295.000000  8295.000000  ...
mean     0.150090    0.026522    0.134901    411.663773    65.761061  ...

```

std	0.357182	0.160691	0.341638	3893.360772	580.347648	...
min	0.000000	0.000000	0.000000	0.000000	0.000000	...
25%	0.000000	0.000000	0.000000	0.000000	1.000000	...
50%	0.000000	0.000000	0.000000	0.000000	1.000000	...
75%	0.000000	0.000000	0.000000	2.000000	1.000000	...
max	1.000000	1.000000	1.000000	87607.000000	10300.000000	...

	y	stockpatEP0	poptotal	labor	rdexpgdp \
count	8.295000e+03	8295.000000	8.295000e+03	8.295000e+03	8295.000000
mean	9.342012e+10	552.738638	2.278327e+07	1.246788e+07	1.006609
std	4.884386e+11	5643.303127	9.103775e+07	5.494933e+07	0.347574
min	1.000000e+00	0.000000	1.000000e+00	1.000000e+00	0.000177
25%	1.000000e+00	1.000000	7.856450e+05	1.000000e+00	1.000000
50%	4.680000e+08	1.000000	4.375000e+06	1.773800e+06	1.000000
75%	1.800000e+10	1.000000	1.288402e+07	6.534300e+06	1.000000
max	9.010000e+12	122157.000000	1.270000e+09	8.622100e+08	4.399199

	patgrantedstock	plantpatstock	designpatstock	plantpat \
count	8.295000e+03	8295.000000	8295.000000	8295.000000
mean	6.560155e+03	10.657263	239.712719	1.561181
std	7.441335e+04	146.687532	3807.148610	13.473203
min	0.000000e+00	0.000000	0.000000	0.000000
25%	0.000000e+00	0.000000	0.000000	0.000000
50%	1.000000e+00	0.000000	1.000000	0.000000
75%	2.900000e+01	1.000000	1.000000	1.000000
max	1.957665e+06	4843.000000	141143.000000	518.000000

	designpat
count	8295.000000
mean	27.471489
std	363.622886
min	0.000000
25%	0.000000
50%	1.000000
75%	1.000000
max	11285.000000

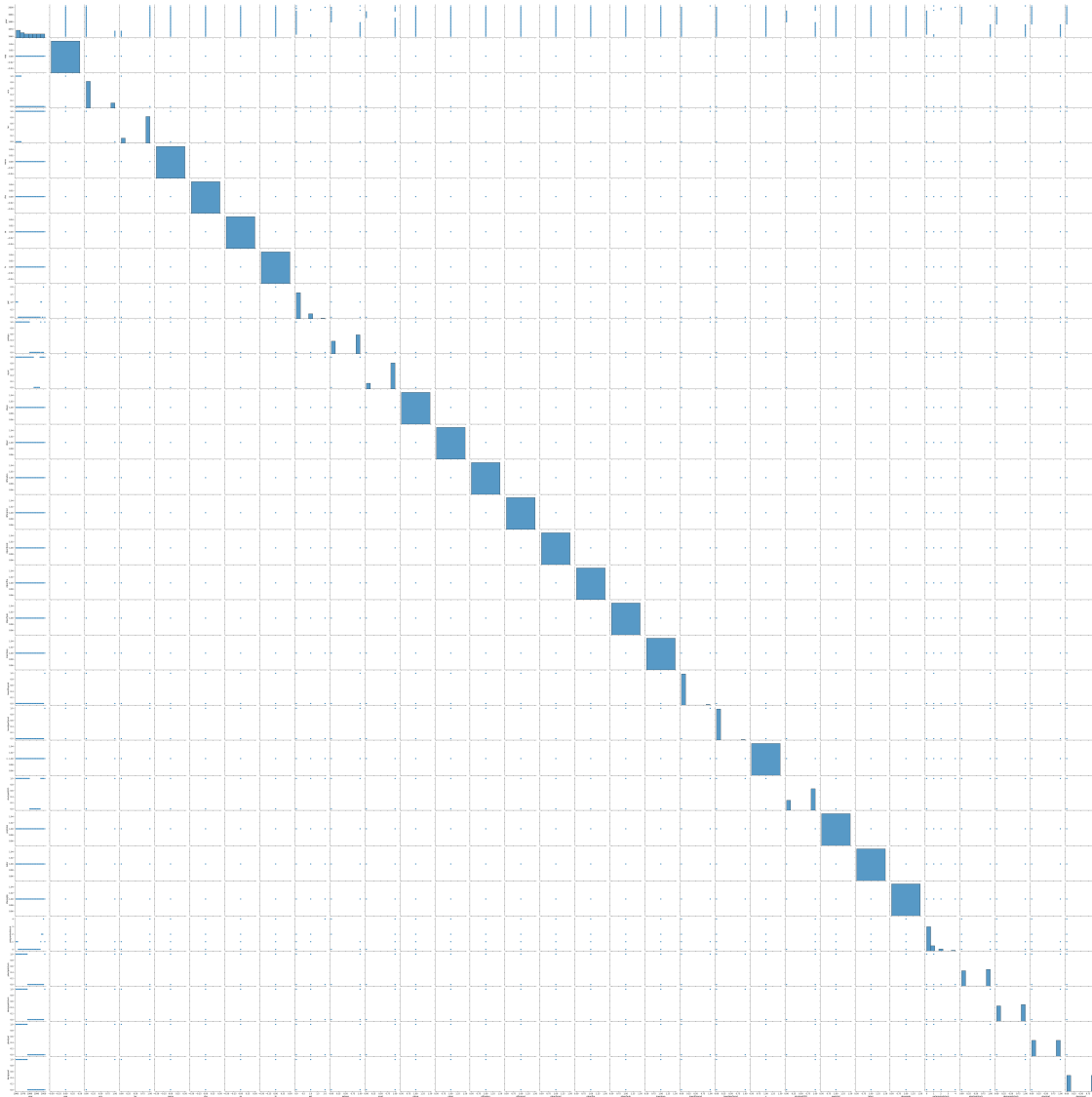
[8 rows x 31 columns]

```
[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', 'stockpatEP0', 'poptotal',
            'labor', 'rdexpgdp', 'patgrantedstock', 'plantpatstock',
            'designpatstock', 'plantpat', 'designpat']]
```

## 12 EDA AND VISUALIZATION

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

```
[18]: <seaborn.axisgrid.PairGrid at 0x793d5e09dae0>
```



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

<ipython-input-19-44d922bfa701>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

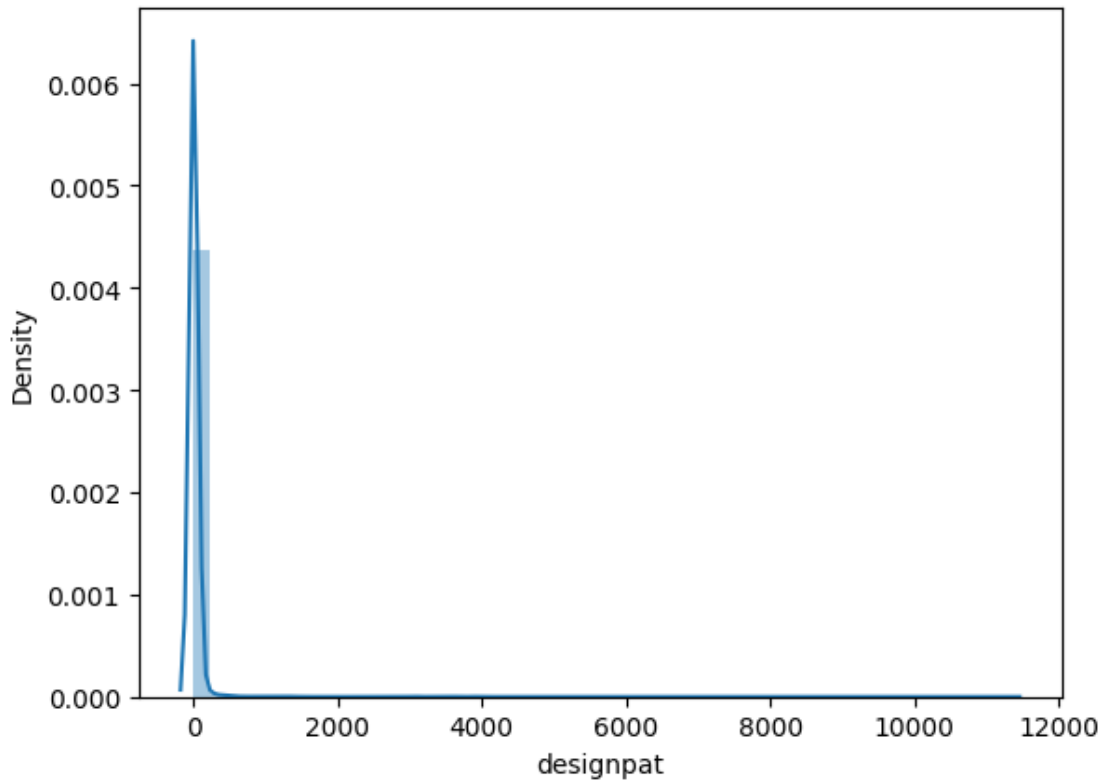
Please adapt your code to use either `displot` (a figure-level function with

similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

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

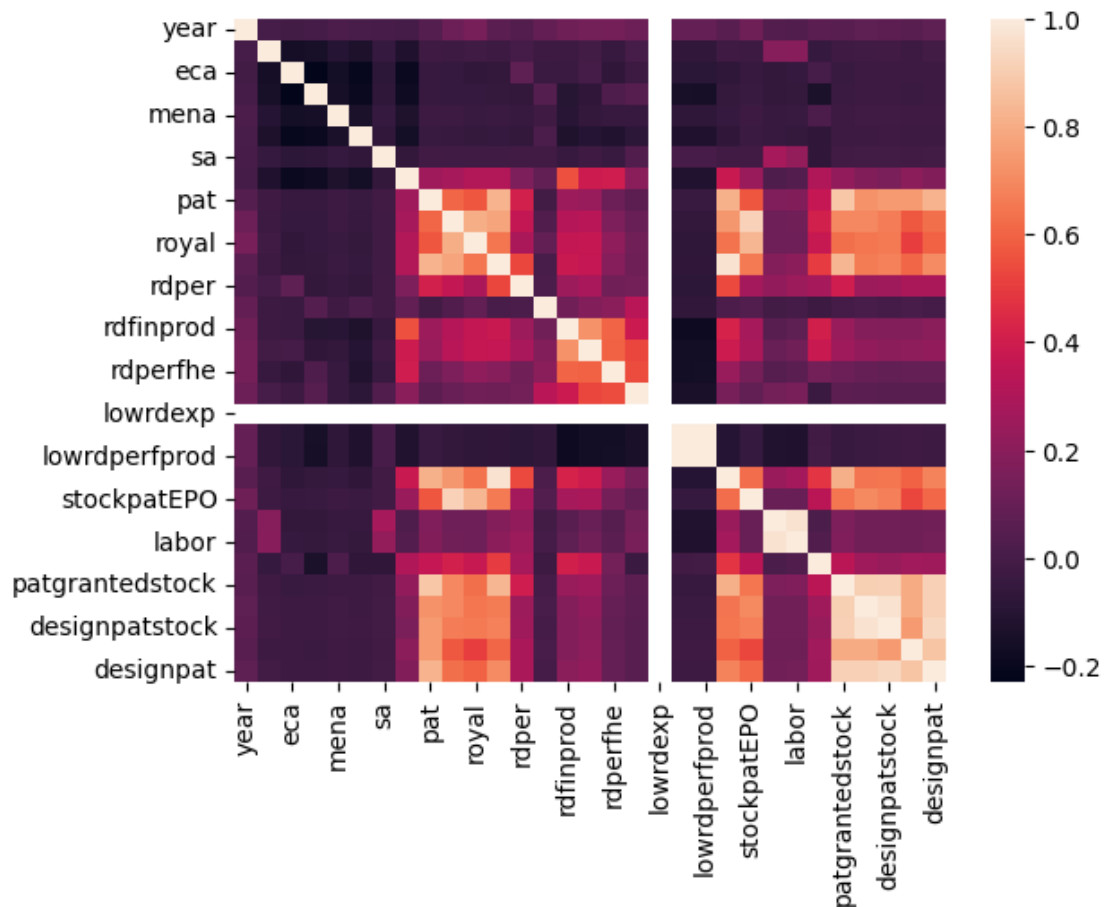
```
[19]: <Axes: xlabel='designpat', ylabel='Density'>
```



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

```
[20]: <Axes: >
```





## 13 TO TRAIN THE MODEL AND MODEL BUILDING

```
[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']
```

```
[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)
```

## 14 Linear Regression

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

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

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

```
[24]: -811.7070607736804
```

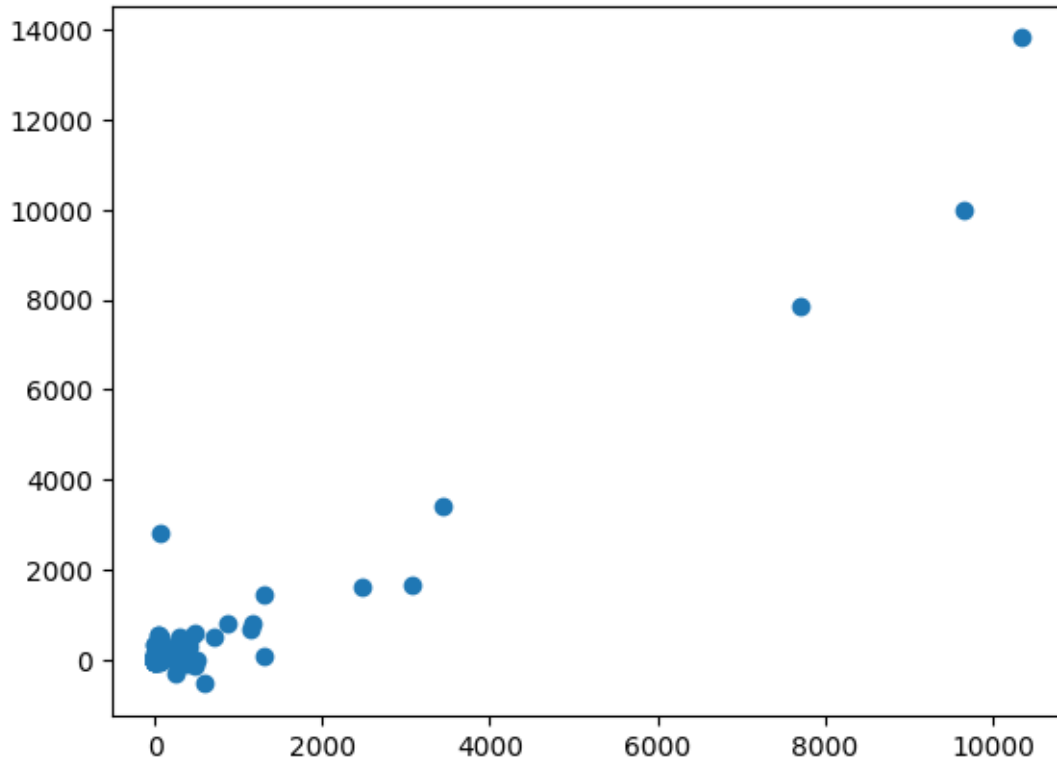
```
[25]: coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])  
coeff
```

```
[25]:
```

	Co-efficient
year	4.085833e-01
eap	6.729644e+00
eca	-1.024191e+00
lac	6.151126e-01
mena	8.012824e-02
sha	1.423315e+00
sa	1.441939e+00
hi	-1.062438e+01
pat	1.308233e-02
patepo	2.213922e-02
royal	-1.263800e-08
rdexp	-1.470649e-09
rdper	-6.015484e-05
rdfinabro	-1.542915e-01
rdfinprod	3.835362e-01
rdperfprod	1.473682e-01
rdperfhe	-4.671098e-02
rdperfpub	-4.350392e-02
lowrdexp	1.219025e-12
lowrdfinprod	3.664809e+00
lowrdperfprod	-1.420297e+00
y	1.433964e-11
stockpatEP0	-4.536374e-03
poptotal	-3.153791e-08
labor	4.954050e-08
rdexpgdp	-4.312357e+00
patgrantedstock	-5.138568e-04
plantpatstock	-1.067862e+00
designpatstock	1.039823e-01
plantpat	1.281230e+01

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

```
[26]: <matplotlib.collections.PathCollection at 0x793d26362110>
```



## 15 ACCURACY

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

```
[27]: 0.901608816724942
```

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

```
[28]: 0.9638643462783607
```

## 16 Ridge and Lasso

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

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

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_ridge.py:216:
LinAlgWarning: Ill-conditioned matrix (rcond=6.3788e-27): result may not be
accurate.
```

```
    return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
```

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

## 17 Accuracy(Ridge)

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

```
[31]: 0.9015866978331674
```

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

```
[32]: 0.9638642758073511
```

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

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

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

```
[34]: 0.9637190481323274
```

## 18 Accuracy(Lasso)

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

```
[35]: 0.9015386696202259
```

## 19 ElasticNet

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

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

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

```
[37]: array([ 4.32776819e-01,  2.10409937e-01, -0.00000000e+00,  0.00000000e+00,
          -0.00000000e+00,  0.00000000e+00,  0.00000000e+00, -5.27806342e-01,
           1.33108849e-02,  2.37960675e-02, -1.32565477e-08, -1.31479724e-09,
          -5.98300072e-05, -1.11129117e-01,  2.64049126e-01,  1.38548044e-01,
          -9.13728400e-02, -0.00000000e+00,  0.00000000e+00,  0.00000000e+00,
           0.00000000e+00,  5.58235221e-12, -4.73906817e-03, -2.49888662e-08,
           5.26849140e-08, -0.00000000e+00, -5.04583309e-04, -1.06544844e+00,
           1.04307693e-01,  1.26579078e+01])
```

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

```
[38]: -862.8941978736544
```

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

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

```
[40]: 0.9009443270496029
```

## 20 Evaluation Metrics

```
[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)))
```

```
13.878973646944198
```

```
11786.09446512705
```

```
108.56378063206462
```

## 21 Logistic Regression

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

```
[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', 'stockpatEP0', 'poptotal',
                        'labor', 'rdexpgdp', 'patgrantedstock', 'plantpatstock',
                        'designpatstock', 'plantpat']]
      target_vector=df['designpat']
```

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

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

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

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

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

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

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

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

```
[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,
```

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

```
[212.]
```

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

```
[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])

```

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

```
[52]: 0.8764315852923448
```

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

```
[53]: 0.0
```

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

```
[54]: array([[0.00000000e+00, 6.22831858e-85, 3.30126281e-86, 4.37916319e-80,
8.08978487e-83, 2.19391650e-56, 3.45360252e-68, 2.35067676e-74,
3.12474087e-68, 7.00530593e-60, 3.84182327e-85, 5.26617015e-55,
8.30126619e-74, 1.00049927e-59, 9.88115347e-51, 8.19961396e-68,
1.70214924e-50, 2.48757137e-61, 3.85665745e-50, 6.58911151e-49,
3.28745458e-52, 7.36043550e-50, 3.89824284e-44, 7.74173071e-71,
1.95066894e-32, 1.32214744e-51, 2.75073588e-25, 1.01593368e-42,
3.27258276e-36, 3.55814691e-58, 2.36763445e-38, 3.88298056e-33,
3.88973903e-49, 1.79835583e-43, 1.32011387e-54, 1.16211039e-50,

```

1.48402856e-22, 2.02686339e-29, 1.12503605e-34, 8.05018881e-30,  
 2.06211778e-44, 3.77050000e-15, 5.89102403e-36, 3.39091758e-12,  
 1.49580951e-26, 5.20083858e-31, 1.94531686e-18, 1.55476169e-35,  
 3.38716634e-25, 6.97311939e-09, 1.51131938e-36, 6.66741070e-19,  
 8.87194698e-31, 2.85516576e-26, 4.27664871e-32, 3.03165971e-26,  
 3.11504842e-38, 1.89465672e-46, 1.05480126e-24, 5.10023220e-29,  
 4.16928027e-14, 4.94838449e-35, 4.64051187e-13, 4.01650047e-43,  
 1.79621071e-38, 5.38060794e-41, 1.50270066e-22, 9.55644313e-29,  
 3.92827229e-32, 1.93117486e-21, 1.39031327e-13, 2.48784729e-17,  
 2.08444676e-27, 4.15490573e-37, 5.56550635e-11, 1.54408921e-04,  
 9.49003310e-34, 8.35342286e-25, 1.64851505e-19, 1.26156899e-26,  
 3.18807774e-25, 3.33357905e-25, 4.91381034e-21, 1.01772110e-32,  
 3.67738656e-30, 2.92804299e-14, 1.57423734e-16, 2.22846687e-31,  
 4.25260719e-20, 9.68853432e-32, 6.05637952e-18, 6.85980251e-15,  
 4.67704083e-20, 4.76743233e-12, 1.23439273e-26, 2.42556104e-28,  
 3.15864577e-23, 1.19392403e-20, 1.35266574e-35, 2.31011529e-19,  
 2.52753582e-28, 2.99437878e-25, 1.83625643e-25, 2.57831069e-47,  
 3.81262680e-38, 2.05515321e-26, 4.47801570e-29, 2.69716352e-43,  
 2.13221941e-24, 1.44493657e-22, 1.36581818e-44, 4.06002433e-24,  
 1.04833706e-27, 1.24010993e-12, 2.48811544e-18, 1.25722908e-36,  
 5.83204783e-25, 9.38344764e-17, 2.31104141e-31, 2.74893347e-28,  
 2.38534731e-19, 1.04788538e-20, 6.95969513e-15, 7.18874932e-24,  
 5.94879101e-19, 3.13523861e-23, 5.36751855e-11, 1.21265723e-29,  
 1.76098627e-26, 2.90766535e-35, 4.07407063e-41, 9.20503202e-43,  
 1.92918171e-18, 4.28752117e-11, 2.22624775e-22, 1.23538662e-19,  
 1.05125345e-23, 1.09332971e-17, 5.21741773e-41, 8.40172692e-13,  
 2.46311490e-12, 2.91424261e-06, 1.27500241e-37, 3.81946808e-07,  
 3.43144665e-26, 2.61401840e-11, 3.88867251e-18, 3.52980070e-11,  
 3.86956986e-12, 3.01234659e-10, 2.93617816e-16, 1.90031528e-29,  
 1.76198885e-22, 1.42481697e-23, 9.99406145e-01, 1.68638489e-40,  
 8.22665056e-09, 3.55184738e-33, 7.80467039e-19, 5.92058844e-17,  
 1.45246206e-21, 1.43656696e-13, 4.13492913e-09, 2.98485429e-20,  
 6.11495502e-14, 1.75771934e-16, 1.76611195e-19, 5.42847630e-10,  
 2.17063879e-18, 1.91318796e-23, 7.20968029e-15, 1.20584298e-10,  
 1.92196099e-34, 9.18547449e-11, 2.14795449e-34, 6.73999181e-16,  
 6.00762143e-24, 1.36495617e-10, 5.90061955e-05, 1.29802271e-13,  
 6.01369025e-16, 2.27236083e-26, 4.28865722e-15, 1.26930943e-13,  
 2.17198403e-18, 4.20734902e-17, 2.23147976e-26, 3.35498881e-11,  
 1.06716541e-31, 1.98362407e-24, 3.37891339e-07, 1.31396759e-40,  
 1.53264853e-16, 1.38384114e-25, 5.01563656e-18, 3.00805135e-04,  
 1.12132140e-10, 2.24379044e-12, 1.83913941e-21, 4.89982917e-23,  
 2.59982022e-17, 2.82120718e-10, 1.15442797e-07, 4.34121854e-20,  
 7.37298412e-05, 1.52036399e-19, 3.09031877e-21, 1.78697175e-20,  
 5.07391198e-12, 2.00946087e-22, 4.64104596e-22, 8.18535532e-20,  
 4.49354610e-19, 2.30232395e-18, 5.10804085e-17, 1.32081178e-15,  
 3.08588684e-17, 1.14193850e-18, 3.04511619e-17, 1.44678146e-14,  
 4.78389733e-18, 6.29368038e-21, 2.12165761e-13, 9.22257163e-15,



```

3.25794138e-15, 6.31871190e-26, 1.19641511e-11, 1.41787365e-24,
1.11373583e-18, 2.48083207e-12, 4.71046803e-26, 1.32541905e-10,
5.61521789e-20, 8.71802120e-19, 5.64128022e-21, 1.22544056e-18,
6.85909025e-13, 1.00764896e-08, 1.53370513e-13, 2.54959210e-08,
1.27111770e-11, 6.99449987e-12, 1.92054970e-13, 5.36055959e-07,
4.02202781e-09, 7.92737492e-11, 3.13523430e-13, 2.10341118e-09,
7.97160665e-07, 1.05870572e-08, 2.31446617e-08, 7.16843893e-07,
2.27223481e-11, 2.50269185e-11, 1.87794026e-21, 1.63527548e-13,
6.54465718e-09, 4.82174655e-12, 1.41529918e-09]])

```

## 22 Random Forest

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

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

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

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

```
[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)
```

```

/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_split.py:700:
UserWarning: The least populated class in y has only 1 members, which is less
than n_splits=2.
  warnings.warn(

```

```
[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')
```

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

```
[59]: 0.8837409576300379
```

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

```
[61]: 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', 'variable6', 'variable7', 'variable8', 'variable9',
    ↪'variable10',
    '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','apple', 'banana', 'cherry', 'dog', 'elephant', 'frog',
    ↪'grape', 'honey', 'icecream', 'jelly', 'kiwi', 'lemon', 'mango', 'nut',
    ↪'orange', 'pear', 'quilt', 'rabbit', 'strawberry', 'tiger', 'umbrella',
    ↪'violet', 'watermelon', 'xylophone', 'yogurt', 'zebra', 'avocado',
    ↪'broccoli', 'carrot', 'dolphin', 'eggplant', 'flamingo', 'giraffe',
    ↪'hamburger', 'iguana', 'jalapeno', 'kangaroo', 'lizard', 'muffin', 'noodle',
    ↪'ostrich', 'penguin', 'quokka', 'raccoon', 'sandwich', 'taco', 'unicorn',
    ↪'vulture', 'waffle', 'xylophone', 'yarn', 'zeppelin', 'acorn', 'butterfly',
    ↪'cactus', 'dragonfly', 'elephant', 'feather', 'gazelle', 'hedgehog',
    ↪'iguana', 'jaguar', 'koala', 'lemur', 'meerkat', 'narwhal', 'octopus',
    ↪'panda', 'quokka', 'raccoon', 'sloth', 'toucan', 'urchin', 'vulture',
    ↪'walrus', 'xenops', 'yak', 'zebra', 'alpaca', 'bison', 'cheetah', 'dolphin',
    ↪'elephant', 'flamingo', 'giraffe', 'hedgehog', 'iguana', 'jellyfish',
    ↪'kangaroo', 'lemur', 'macaw', 'narwhal', 'opossum', 'penguin', 'quokka',
    ↪'rhinoceros', 'sloth', 'tiger', 'umbrellabird', 'vulture', 'whale', 'x-ray
    ↪tetra', 'yak', 'zebra'],filled=True)
```

```
[61]: [Text(0.49107142857142855, 0.9166666666666666, 'year <= 1976.5\nngini =
0.595\nnsamples = 3639\nnvalue = [2614, 2609, 59, 30, 35, 14, 20, 15, 14, 11,
11\n9, 6, 11, 4, 16, 5, 12, 4, 6, 2, 4, 4, 6, 1\n7, 11, 2, 1, 7, 3, 2, 6, 4, 0,
2, 1, 0, 1\n1, 2, 3, 5, 1, 3, 3, 5, 1, 1, 0, 2, 2, 3\n1, 1, 6, 2, 1, 3, 2, 4, 0,
```









```

0, 0\n0, 0, 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, 0\n0, 0, 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, 0\n0, 0, 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, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0,
0]\nnclass = variable1'),
Text(0.6428571428571429, 0.25, 'rdexp <= 197500000.0\ngini = 0.232\nsamples =
49\nvalue = [66, 9, 0, 1, 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, 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, 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, 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, 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, 0, 0\n0, 0, 0,
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, 0, 0\n0, 0,
0, 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, 0, 0]\nnclass =
variable1'),
Text(0.6071428571428571, 0.08333333333333333, 'gini = 0.079\nsamples =
31\nvalue = [47, 1, 0, 1, 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, 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, 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, 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, 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, 0, 0\n0, 0, 0, 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, 0, 0\n0, 0,
0, 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, 0, 0]\nnclass =
variable1'),
Text(0.6785714285714286, 0.08333333333333333, 'gini = 0.417\nsamples =
18\nvalue = [19, 8, 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, 0\n0, 0, 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, 0\n0, 0, 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, 0\n0, 0, 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, 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, 0, 0\n0, 0, 0, 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, 0, 0]\nnclass =
variable1'),
Text(0.7142857142857143, 0.25, 'gini = 0.391\nsamples = 9\nvalue = [4, 11, 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, 0, 0\n0, 0,
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, 0, 0\n0,
0, 0, 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, 0,
0\n0, 0, 0, 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, 0, 0, 0\n0, 0, 0, 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, 0, 0, 0, 0, 0\n0, 0, 0, 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, 0, 0, 0]\nnclass = variable2'),
Text(0.8571428571428571, 0.4166666666666667, 'designpatstock <= 26.5\ngini =
0.98\nsamples = 259\nvalue = [17, 26, 21, 7, 9, 3, 19, 5, 9, 9, 6, 5, 4\n2,
11, 3, 7, 3, 3, 1, 4, 2, 4, 0, 7, 11, 2\n1, 5, 3, 2, 1, 1, 0, 2, 1, 0, 1, 1, 2,

```







```
print("Logistic Regression:",logr.score(fs,target_vector))
print("Random Forest:",grid_search.best_score_)
```

Linear Regression: 0.901608816724942  
Ridge Regression: 0.9015866978331674  
Lasso Regression 0.9015386696202259  
ElasticNet Regression: 0.9009443270496029  
Logistic Regression: 0.8764315852923448  
Random Forest: 0.8837409576300379

## 25 Linear Regression is suitable for this dataset