

Unemployment dataset

```
In [1]: import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression, LogisticRegression, Lasso, Rid
```

```
In [2]: df=pd.read_csv(r"C:\Users\USER\Desktop\Unemployment Rate, seas. adj..csv")
df.fillna(0,inplace=True)
```

Out[2]:

	Unnamed: 0	Advanced Economies	Argentina	Australia	Austria	Belgium	Bulgaria	Bahrain	Belarus
0	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.000000
1	1994.0	7.818759	0.000000	9.703104	6.545480	9.753783	14.065830	0.0	0.000000
2	1995.0	7.352965	0.000000	8.467310	6.589767	9.673502	11.385830	0.0	0.000000
3	1996.0	7.321421	0.000000	8.512719	7.033851	9.544409	11.061670	0.0	0.000000
4	1997.0	7.022442	0.000000	8.358484	7.103283	9.212289	14.045830	0.0	0.000000
5	1998.0	6.646781	0.000000	7.677949	7.184796	9.340881	12.203330	0.0	0.000000
6	1999.0	6.324369	0.000000	6.867747	6.645249	8.411080	13.782500	0.0	0.000000
7	2000.0	5.844973	0.000000	6.275520	5.803798	6.875592	18.129170	0.0	0.000000
8	2001.0	5.991557	0.000000	6.757151	6.094126	6.589738	17.508330	0.0	0.000000
9	2002.0	6.550974	22.425370	6.361517	6.871619	7.526965	17.426670	0.0	0.000000
10	2003.0	6.762680	17.216580	5.927986	7.014325	8.182808	14.259170	0.0	0.000000
11	2004.0	6.526365	13.622010	5.394249	7.067989	8.390290	12.670000	0.0	0.000000
12	2005.0	6.196061	11.560380	5.034545	7.272197	8.441850	11.450830	0.0	0.000000
13	2006.0	5.748805	10.150660	4.775160	6.779983	8.259000	9.602500	16.0	0.000000
14	2007.0	5.506039	8.445448	4.373901	6.212382	7.488009	7.736667	5.6	0.000000
15	2008.0	5.913973	7.856474	4.238160	5.900164	6.964916	6.302500	3.7	0.000000
16	2009.0	8.137286	8.667093	5.565805	7.277309	7.986718	7.584167	4.0	0.000000
17	2010.0	8.446151	7.745606	5.203839	6.924717	8.371833	9.474167	3.6	0.000000
18	2011.0	8.157150	7.154081	5.081351	6.724666	7.208788	9.595000	4.0	0.000000
19	2012.0	8.281009	7.214789	5.221220	6.980560	7.632016	11.089170	3.7	0.000000
20	2013.0	8.234926	7.075874	5.665686	7.614778	8.554433	11.312500	4.3	0.000000
21	2014.0	7.600729	7.268765	6.080297	8.365268	8.662285	11.160000	3.8	0.000000
22	2015.0	6.986622	6.607571	6.053246	9.102619	8.655595	10.059170	3.5	0.000000
23	2016.0	6.510643	8.462791	5.710455	9.063808	7.850004	8.687500	4.3	0.000000
24	2017.0	5.903856	8.337106	5.589480	8.516667	7.096994	7.199167	4.1	5.6727
25	2018.0	5.352979	9.207210	5.298026	7.713245	5.958490	6.175000	4.3	4.8274
26	2019.0	5.033913	9.798736	5.167842	7.355347	5.365955	5.650833	4.7	4.2248
27	2020.0	6.885005	11.520220	6.489594	10.002220	5.528885	7.359167	5.9	4.1033
28	2021.0	5.816167	8.719054	5.089850	7.990778	6.273146	5.524167	0.0	3.9251
29	2022.0	4.636630	6.827820	3.695052	6.301216	5.579375	4.497500	0.0	3.5998
30	2023.0	0.000000	0.000000	0.000000	6.176443	0.000000	0.000000	0.0	0.000000

21 rows x 80 columns

In [3]:

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 31 entries, 0 to 30

Data columns (total 80 columns):

#	Column	Non-Null Count	Dtype
0	Unnamed: 0	31 non-null	float64
4			
1	Advanced Economies	31 non-null	float64
4			
2	Argentina	31 non-null	float64
4			
3	Australia	31 non-null	float64
4			
4	Austria	31 non-null	float64
4			
5	Belgium	31 non-null	float64
4			
6	Bulgaria	31 non-null	float64
4			
7	Bahrain	31 non-null	float64
4			
8	Belarus	31 non-null	float64
4			
9	Brazil	31 non-null	float64
4			
10	Canada	31 non-null	float64
4			
11	Switzerland	31 non-null	float64
4			
12	Chile	31 non-null	float64
4			
13	Colombia	31 non-null	float64
4			
14	Cyprus	31 non-null	float64
4			
15	Czech Republic	31 non-null	float64
4			
16	Germany	31 non-null	float64
4			
17	Denmark	31 non-null	float64
4			
18	Dominican Republic	31 non-null	float64
4			
19	Algeria	31 non-null	float64
4			
20	EMDE East Asia & Pacific	31 non-null	float64
4			
21	EMDE Europe & Central Asia	31 non-null	float64
4			
22	Ecuador	31 non-null	float64
4			
23	Egypt, Arab Rep.	31 non-null	float64
4			
24	Emerging Market and Developing Economies (EMDEs)	31 non-null	float64

4			
25	Spain	31 non-null	float64
4			
26	Estonia	31 non-null	float64
4			
27	Finland	31 non-null	float64
4			
28	France	31 non-null	float64
4			
29	United Kingdom	31 non-null	float64
4			
30	Greece	31 non-null	float64
4			
31	High Income Countries	31 non-null	float64
4			
32	Hong Kong SAR, China	31 non-null	float64
4			
33	Croatia	31 non-null	float64
4			
34	Hungary	31 non-null	float64
4			
35	Ireland	31 non-null	float64
4			
36	Iceland	31 non-null	float64
4			
37	Israel	31 non-null	float64
4			
38	Italy	31 non-null	float64
4			
39	Japan	31 non-null	float64
4			
40	Korea, Rep.	31 non-null	float64
4			
41	EMDE Latin America & Caribbean	31 non-null	float64
4			
42	Low-Income Countries (LIC)	31 non-null	float64
4			
43	Sri Lanka	31 non-null	float64
4			
44	Lithuania	31 non-null	float64
4			
45	Luxembourg	31 non-null	float64
4			
46	Latvia	31 non-null	float64
4			
47	Morocco	31 non-null	float64
4			
48	Mexico	31 non-null	float64
4			
49	Middle-Income Countries (MIC)	31 non-null	float64
4			
50	North Macedonia	31 non-null	float64
4			
51	Malta	31 non-null	float64
4			
52	EMDE Middle East & N. Africa	31 non-null	float64

```
4
53 Netherlands 31 non-null float64
4
54 Norway 31 non-null float64
4
55 New Zealand 31 non-null float64
4
56 Pakistan 31 non-null float64
4
57 Peru 31 non-null float64
4
58 Philippines 31 non-null float64
4
59 Poland 31 non-null float64
4
60 Portugal 31 non-null float64
4
61 Romania 31 non-null float64
4
62 Russian Federation 31 non-null float64
4
63 EMDE South Asia 31 non-null float64
4
64 Saudi Arabia 31 non-null float64
4
65 Singapore 31 non-null float64
4
66 EMDE Sub-Saharan Africa 31 non-null float64
4
67 Slovakia 31 non-null float64
4
68 Slovenia 31 non-null float64
4
69 Sweden 31 non-null float64
4
70 Thailand 31 non-null float64
4
71 Tunisia 31 non-null float64
4
72 Turkey 31 non-null float64
4
73 Taiwan, China 31 non-null float64
4
74 Uruguay 31 non-null float64
4
75 United States 31 non-null float64
4
76 Venezuela, RB 31 non-null float64
4
77 Vietnam 31 non-null float64
4
78 World (WBG members) 31 non-null float64
4
79 South Africa 31 non-null float64
4
dtypes: float64(80)
```

memory usage: 10.5 MB

```
In [4]: df1=df.dropna()
```

```
Out[4]:
```

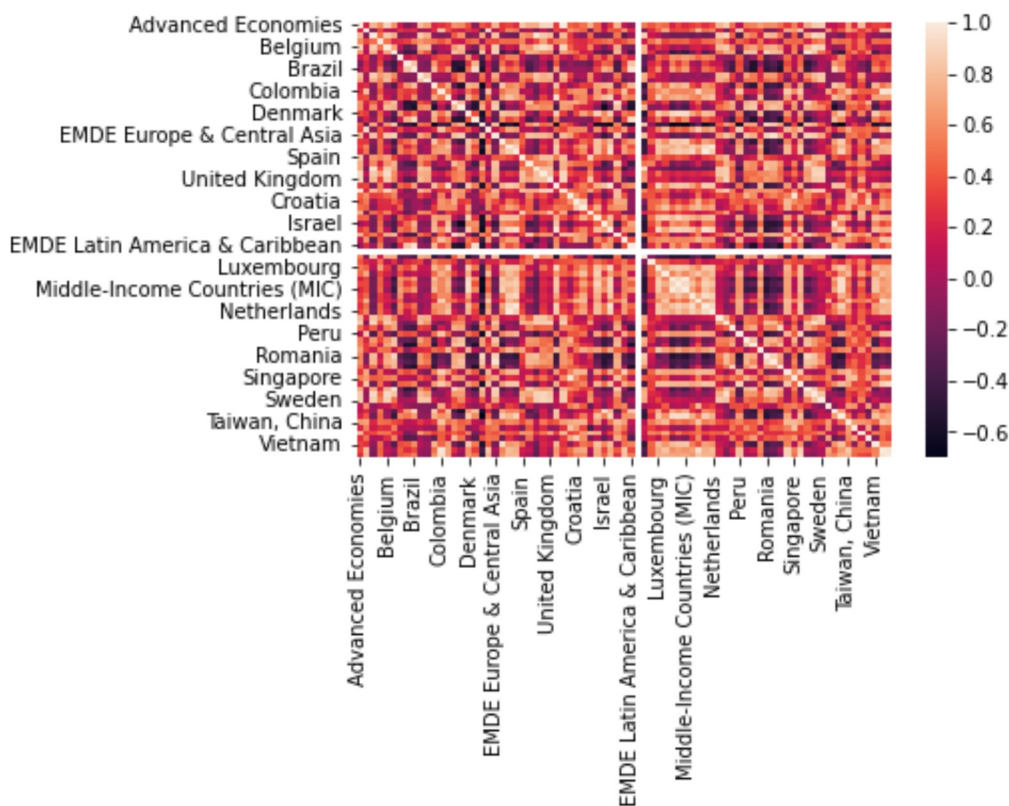
	Unnamed: 0	Advanced Economies	Argentina	Australia	Austria	Belgium	Bulgaria	Bahrain	Belar
0	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0000
1	1994.0	7.818759	0.000000	9.703104	6.545480	9.753783	14.065830	0.0	0.0000
2	1995.0	7.352965	0.000000	8.467310	6.589767	9.673502	11.385830	0.0	0.0000
3	1996.0	7.321421	0.000000	8.512719	7.033851	9.544409	11.061670	0.0	0.0000
4	1997.0	7.022442	0.000000	8.358484	7.103283	9.212289	14.045830	0.0	0.0000
5	1998.0	6.646781	0.000000	7.677949	7.184796	9.340881	12.203330	0.0	0.0000
6	1999.0	6.324369	0.000000	6.867747	6.645249	8.411080	13.782500	0.0	0.0000
7	2000.0	5.844973	0.000000	6.275520	5.803798	6.875592	18.129170	0.0	0.0000
8	2001.0	5.991557	0.000000	6.757151	6.094126	6.589738	17.508330	0.0	0.0000
9	2002.0	6.550974	22.425370	6.361517	6.871619	7.526965	17.426670	0.0	0.0000
10	2003.0	6.762680	17.216580	5.927986	7.014325	8.182808	14.259170	0.0	0.0000
11	2004.0	6.526365	13.622010	5.394249	7.067989	8.390290	12.670000	0.0	0.0000
12	2005.0	6.196061	11.560380	5.034545	7.272197	8.441850	11.450830	0.0	0.0000
13	2006.0	5.748805	10.150660	4.775160	6.779983	8.259000	9.602500	16.0	0.0000
14	2007.0	5.506039	8.445448	4.373901	6.212382	7.488009	7.736667	5.6	0.0000
15	2008.0	5.913973	7.856474	4.238160	5.900164	6.964916	6.302500	3.7	0.0000
16	2009.0	8.137286	8.667093	5.565805	7.277309	7.986718	7.584167	4.0	0.0000
17	2010.0	8.446151	7.745606	5.203839	6.924717	8.371833	9.474167	3.6	0.0000
18	2011.0	8.157150	7.154081	5.081351	6.724666	7.208788	9.595000	4.0	0.0000
19	2012.0	8.281009	7.214789	5.221220	6.980560	7.632016	11.089170	3.7	0.0000
20	2013.0	8.234926	7.075874	5.665686	7.614778	8.554433	11.312500	4.3	0.0000
21	2014.0	7.600729	7.268765	6.080297	8.365268	8.662285	11.160000	3.8	0.0000
22	2015.0	6.986622	6.607571	6.053246	9.102619	8.655595	10.059170	3.5	0.0000
23	2016.0	6.510643	8.462791	5.710455	9.063808	7.850004	8.687500	4.3	0.0000
24	2017.0	5.903856	8.337106	5.589480	8.516667	7.096994	7.199167	4.1	5.6727
25	2018.0	5.352979	9.207210	5.298026	7.713245	5.958490	6.175000	4.3	4.8274
26	2019.0	5.033913	9.798736	5.167842	7.355347	5.365955	5.650833	4.7	4.2248
27	2020.0	6.885005	11.520220	6.489594	10.002220	5.528885	7.359167	5.9	4.1033
28	2021.0	5.816167	8.719054	5.089850	7.990778	6.273146	5.524167	0.0	3.9251
29	2022.0	4.636630	6.827820	3.695052	6.301216	5.579375	4.497500	0.0	3.5998
30	2023.0	0.000000	0.000000	0.000000	6.176443	0.000000	0.000000	0.0	0.0000

31 rows × 80 columns

In [5]:

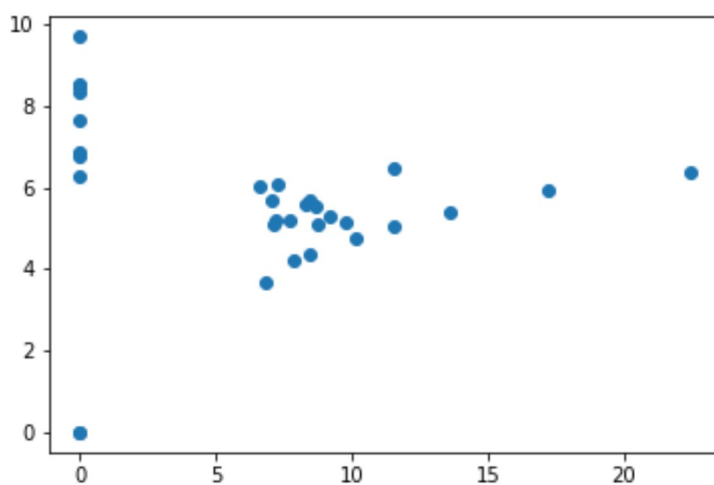
In [6]:

Out[6]: <AxesSubplot:>



In [8]:

Out[8]: [<matplotlib.lines.Line2D at 0x18129dfcb20>]



In []:

```
In [9]: x=df1.drop(["Australia"],axis=1)
        y=df1["Australia"]
```

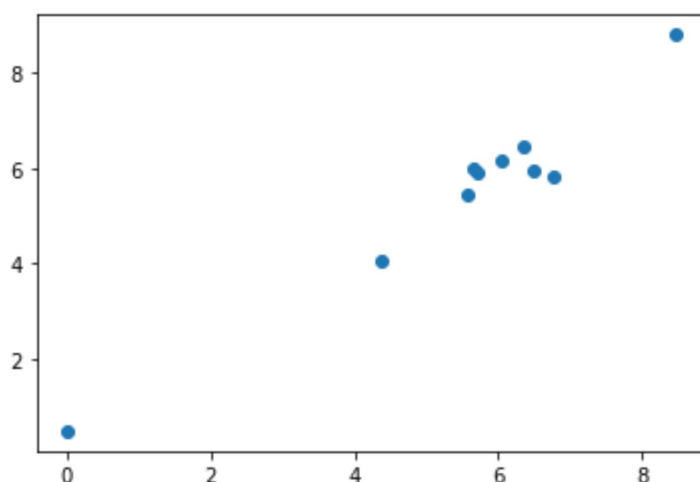
Linear

In [10]: `li=LinearRegression()`

Out[10]: `LinearRegression()`

In [11]: `prediction=li.predict(x_test)`

Out[11]: `<matplotlib.collections.PathCollection at 0x1812a1c2f70>`



In [12]: `print('R-squared: %.4f' % r2)`

In [13]: `print('Adjusted R-squared: %.4f' % adj_r2)`

Out[13]:

0.000000	10
22.425370	1
8.719054	1
11.520220	1
9.798736	1
9.207210	1
8.337106	1
8.462791	1
6.607571	1
7.268765	1
7.075874	1
7.214789	1
7.154081	1
7.745606	1
8.667093	1
7.856474	1
8.445448	1
10.150660	1
11.560380	1
13.622010	1
17.216580	1
6.827820	1

Name: Argentina, dtype: int64

```
In [14]: df1.loc[df1["Argentina"]<1.40,"Argentina"]=1  
df1.loc[df1["Argentina"]>1.40,"Argentina"]=2
```

```
Out[14]: 2.0    21  
1.0    10  
Name: Argentina, dtype: int64
```

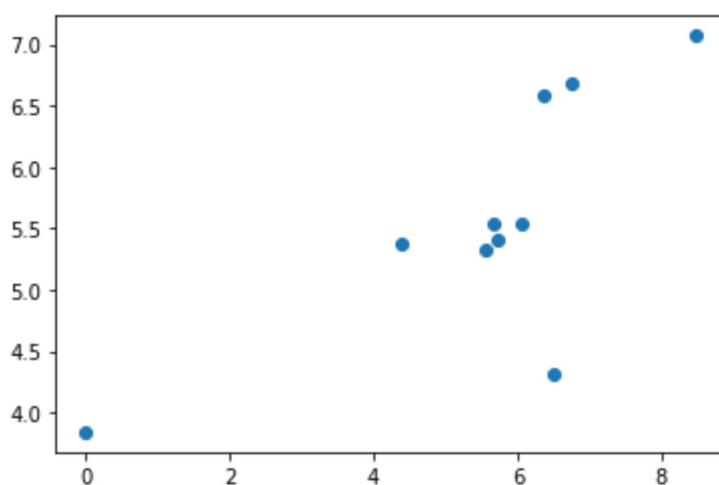
Lasso

```
In [15]: la=Lasso(alpha=5)
```

```
Out[15]: Lasso(alpha=5)
```

```
In [16]: prediction1=la.predict(x_test)
```

```
Out[16]: <matplotlib.collections.PathCollection at 0x1812a22cbe0>
```



```
In [17]:
```

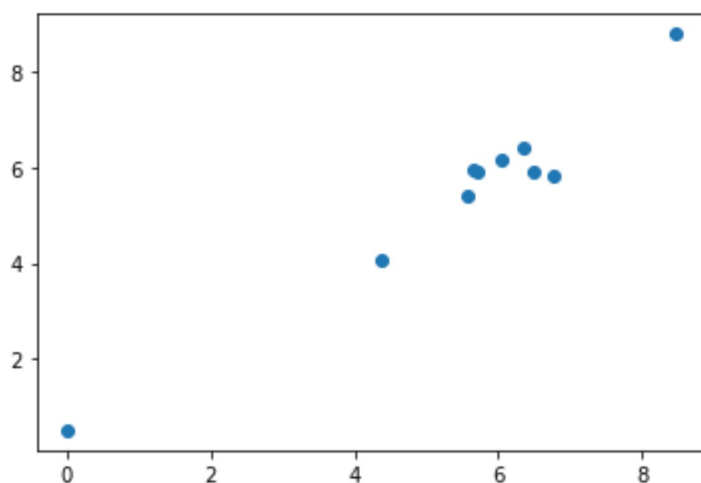
Ridge

```
In [18]: rr=Ridge(alpha=1)
```

```
Out[18]: Ridge(alpha=1)
```

```
In [19]: prediction2=rr.predict(x_test)
```

```
Out[19]: <matplotlib.collections.PathCollection at 0x1812a28b100>
```



```
In [20]:
```

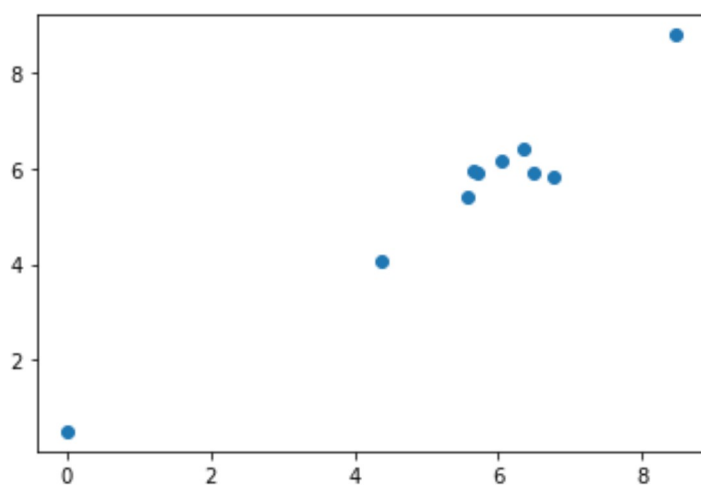
ElasticNet

```
In [21]: en=ElasticNet()  
en.fit(x_train,y_train)
```

```
Out[21]: ElasticNet()
```

```
In [22]: prediction2=rr.predict(x_test)
```

```
Out[22]: <matplotlib.collections.PathCollection at 0x1812b33c820>
```



```
In [23]:
```

```
In [24]: print(rr.score(x_test,y_test))
```

```
0.9589303894434331
```

```
Out[24]: 0.9999909096616653
```

Logistic

```
In [25]: g={"Argentina":{1.0:"Low",2.0:"High"}}
df1=df1.replace(g)
```

```
Out[25]: High      21
Low         10
Name: Argentina, dtype: int64
```

```
In [26]: x=df1.drop(["Argentina"],axis=1)
y=df1["Argentina"]
```

```
In [27]: lo=LogisticRegression()
```

```
Out[27]: LogisticRegression()
```

```
In [28]: prediction3=lo.predict(x_test)
```

```
Out[28]: <matplotlib.collections.PathCollection at 0x1812b3bc340>
```



```
In [29]:
```

Random Forest

```
In [30]: from sklearn.ensemble import RandomForestClassifier
```

```
In [31]: g1={"Argentina":{"Low":1.0,"High":2.0}}
df1=df1.replace(g1)
```

```
In [32]: x=df1.drop(["Argentina"],axis=1)
        y=df1["Argentina"]
```

```
In [33]: rfc=RandomForestClassifier()
```

```
Out[33]: RandomForestClassifier()
```

```
In [34]: parameter={
        'max_depth':[1,2,4,5,6],
        'min_samples_leaf':[5,10,15,20,25],
        'n_estimators':[10,20,30,40,50]
```

```
In [35]: grid_search=GridSearchCV(estimator=rfc,param_grid=parameter,cv=2,scoring="accu
```

```
Out[35]: GridSearchCV(cv=2, estimator=RandomForestClassifier(),
        param_grid={'max_depth': [1, 2, 4, 5, 6],
        'min_samples_leaf': [5, 10, 15, 20, 25],
        'n_estimators': [10, 20, 30, 40, 50]},
        scoring='accuracy')
```

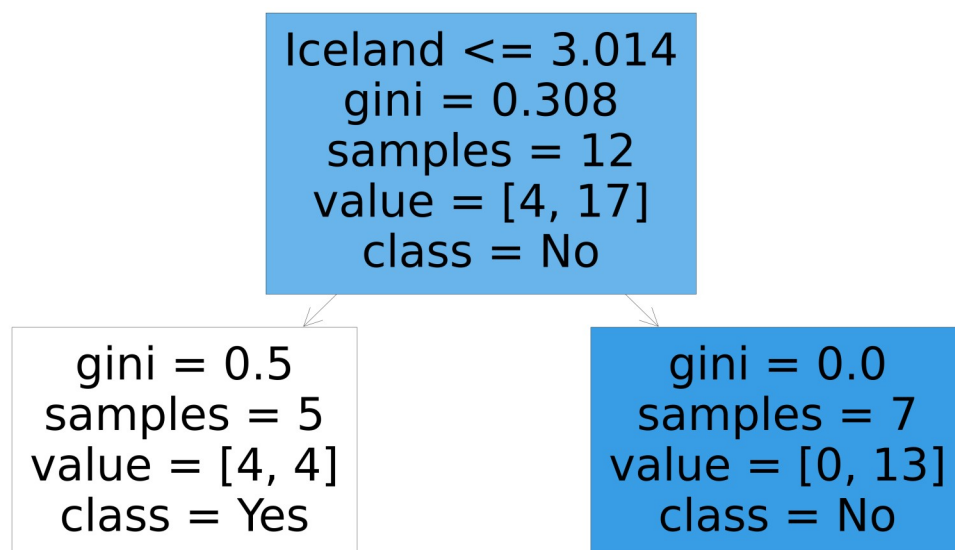
```
In [36]:
```

```
In [37]:
```

```
In [38]: from sklearn.tree import plot_tree
```

```
plt.figure(figsize=(80,40))
```

```
Out[38]: [Text(0.5, 0.75, 'Iceland <= 3.014\ngini = 0.308\nsamples = 12\nvalue = [4, 17]\nnclass = No'),
        Text(0.25, 0.25, 'gini = 0.5\nsamples = 5\nvalue = [4, 4]\nnclass = Yes'),
        Text(0.75, 0.25, 'gini = 0.0\nsamples = 7\nvalue = [0, 13]\nnclass = No')]
```



```
In [39]: print("Linear:", lis)
          print("Lasso:", las)
          print("Ridge:", rrs)
          print("ElasticNet:", ens)
          print("Logistic:", los)
```

```
Linear: 0.9594602355290545
Lasso: 0.4787865444920507
Ridge: 0.9589303894434331
ElasticNet: 0.8913730112352303
Logistic: 0.9
Random Forest: 0.7136363636363636
```