In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
import re
from sklearn.datasets import load_digits
from sklearn.model_selection import train_test_split
```

In [2]:

a=pd.read_csv(r"C:\Users\user\Downloads\spi_index_labelled.csv")
a

Out[2]:

	country	iso3c	date	SPI.INDEX.PIL1	SPI.INDEX.PIL2	SPI.INDEX.PIL3	SPI.INDE
0	NaN	NaN	NaN	Pillar 1 - Data Use - Score	Pillar 2 - Data Services - Score	Pillar 3 - Data Products - Score	Pillar ² Sources
1	Norway	NOR	2019.0	100	92.23333333333333	77.56875	80.6666666
2	Italy	ITA	2019.0	100	91.8666666666666	75.2875	
3	Austria	AUT	2019.0	100	91.3	74.55	
4	Poland	POL	2019.0	100	95.1	70.5375	79.7166666
3484	Virgin Islands (U.S.)	VIR	2004.0	20	NaN	NaN	
3485	West Bank and Gaza	PSE	2004.0	20	NaN	NaN	
3486	Yemen, Rep.	YEM	2004.0	20	NaN	NaN	
3487	Zambia	ZMB	2004.0	40	NaN	NaN	
3488	Zimbabwe	ZWE	2004.0	20	NaN	NaN	

In [3]:

a.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3489 entries, 0 to 3488
Data columns (total 79 columns):

#	Columns (total /9 Columns):	Non-Null Count	Dtype
0	country	3488 non-null	object
1	iso3c	3488 non-null	object
2	date	3488 non-null	float64
3	SPI.INDEX.PIL1	3489 non-null	object
4	SPI.INDEX.PIL2	693 non-null	object
5	SPI.INDEX.PIL3	3226 non-null	object
6	SPI.INDEX.PIL4	690 non-null	object
7	SPI.INDEX.PIL5	756 non-null	object
8	SPI.INDEX	690 non-null	object
9	SPI.DIM1.5.INDEX	3489 non-null	object
10	SPI.DIM2.1.INDEX	1283 non-null	object
11	SPI.DIM2.2.INDEX	840 non-null	object
12	SPI.DIM2.4.INDEX	762 non-null	object
13	SPI.DIM3.1.INDEX	3441 non-null	object
14	SPI.DIM3.2.INDEX	3441 non-null	object
15	SPI.DIM3.3.INDEX	3226 non-null	object
16	SPI.DIM3.4.INDEX	3441 non-null	object
17	SPI.DIM4.1.CEN.INDEX	755 non-null	object
18	SPI.DIM4.1.SVY.INDEX SPI.DIM4.2.INDEX	3041 non-null	object
19 20	SPI.DIM4.2.INDEX SPI.DIM4.3.INDEX	1076 non-null	object
20	SPI.DIM4.3.INDEX SPI.DIM5.1.INDEX	840 non-null 3489 non-null	object object
22	SPI.DIM5.1.INDEX	756 non-null	object
23	SPI.DIM5.5.INDEX	3489 non-null	object
24	SPI.D1.5.POV	3489 non-null	object
25	SPI.D1.5.CHLD.MORT	3489 non-null	object
26	SPI.D1.5.DT.TDS.DPPF.XP.ZS	3489 non-null	object
27	SPI.D1.5.SAFE.MAN.WATER	3489 non-null	object
28	SPI.D1.5.LFP	3489 non-null	object
29	SPI.D2.1.GDDS	1283 non-null	object
30	SPI.D2.2.Machine.readable	840 non-null	object
31	SPI.D2.2.Non.proprietary	840 non-null	object
32	SPI.D2.2.Download.options	840 non-null	object
33	SPI.D2.2.Metadata.available	840 non-null	object
34	SPI.D2.2.Terms.of.use	840 non-null	object
35	SPI.D2.2.Openness.subscore	840 non-null	object
36	SPI.D2.4.NADA	762 non-null	object
37	SPI.D3.1.POV	3441 non-null	object
38	SPI.D3.2.HNGR	3441 non-null	object
39	SPI.D3.3.HLTH	3441 non-null	object
40	SPI.D3.4.EDUC	3441 non-null	object
41	SPI.D3.5.GEND	3441 non-null	object
42	SPI.D3.6.WTRS	3441 non-null	object
43	SPI.D3.7.ENRG	3441 non-null	object
44	SPI.D3.8.WORK	3441 non-null	object
45 46	SPI.D3.9.INDY	3441 non-null 3441 non-null	object
40 47	SPI.D3.10.NEQL SPI.D3.11.CITY	3441 non-null	object object
48	SPI.D3.11.CITY SPI.D3.12.CNSP	3441 non-null	object
49	SPI.D3.15.LAND	3441 non-null	object
50	SPI.D3.16.INST	3441 non-null	object
51	SPI.D3.17.PTNS	3441 non-null	object
52	SPI.D3.13.CLMT	3226 non-null	object
53	SPI.D4.1.1.POPU	863 non-null	object
54	SPI.D4.1.2.AGRI	863 non-null	object
55	SPI.D4.1.3.BIZZ	3041 non-null	object
			J

56	SPI.D4.1.4.HOUS	3041 non-null	object
57	SPI.D4.1.5.AGSVY	3041 non-null	object
58	SPI.D4.1.6.LABR	3057 non-null	object
59	SPI.D4.1.7.HLTH	3089 non-null	object
60	SPI.D4.1.8.BZSVY	3041 non-null	object
61	SPI.D4.2.3.CRVS	1076 non-null	object
62	SPI.D4.3.GEO.first.admin.level	840 non-null	object
63	SPI.D5.1.DILG	678 non-null	object
64	SPI.D5.2.1.SNAU	863 non-null	object
65	SPI.D5.2.2.NABY	863 non-null	object
66	SPI.D5.2.3.CNIN	1181 non-null	object
67	SPI.D5.2.4.CPIBY	958 non-null	object
68	SPI.D5.2.5.HOUS	1183 non-null	object
69	SPI.D5.2.6.EMPL	1181 non-null	object
70	SPI.D5.2.7.CGOV	762 non-null	object
71	SPI.D5.2.8.FINA	1181 non-null	object
72	SPI.D5.2.9.MONY	763 non-null	object
73	SPI.D5.2.10.GSBP	1181 non-null	object
74	SPI.D5.5.DIFI	673 non-null	object
75	income	3488 non-null	object
76	region	3488 non-null	object
77	weights	3488 non-null	float64
78	population	3464 non-null	float64

dtypes: float64(3), object(76) memory usage: 2.1+ MB

In [4]:

b=a.fillna(value=104)

Out[4]:

	country	iso3c	date	SPI.INDEX.PIL1	SPI.INDEX.PIL2	SPI.INDEX.PIL3	SPI.INDE
0	104	104	104.0	Pillar 1 - Data Use - Score	Pillar 2 - Data Services - Score	Pillar 3 - Data Products - Score	Pillar ² Sources
1	Norway	NOR	2019.0	100	92.23333333333333	77.56875	80.6666666
2	Italy	ITA	2019.0	100	91.8666666666666	75.2875	
3	Austria	AUT	2019.0	100	91.3	74.55	
4	Poland	POL	2019.0	100	95.1	70.5375	79.7166666
3484	Virgin Islands (U.S.)	VIR	2004.0	20	104	104	
3485	West Bank and Gaza	PSE	2004.0	20	104	104	
3486	Yemen, Rep.	YEM	2004.0	20	104	104	
3487	Zambia	ZMB	2004.0	40	104	104	
3488	Zimbabwe	ZWE	2004.0	20	104	104	

3489 rows × 79 columns

In [5]:

a.mean()

Out[5]:

date 2.011500e+03 weights 1.000000e+00 population 3.244250e+07

dtype: float64

In [7]:

a.median()

Out[7]:

date 2011.5 weights 1.0 population 5868890.0

dtype: float64

In [8]:

a.mode()

Out[8]:

	country	iso3c	date	SPI.INDEX.PIL1	SPI.INDEX.PIL2	SPI.INDEX.PIL3	SPI.INDE
0	Afghanistan	ABW	2004.0	20	59.9	4.89375	39.9166666
1	Albania	AFG	2005.0	NaN	81.0333333333333	5.41875	53.8666666
2	Algeria	AGO	2006.0	NaN	NaN	9.8	
3	American Samoa	ALB	2007.0	NaN	NaN	NaN	
4	Andorra	AND	2008.0	NaN	NaN	NaN	
685	NaN	NaN	NaN	NaN	NaN	NaN	
686	NaN	NaN	NaN	NaN	NaN	NaN	
687	NaN	NaN	NaN	NaN	NaN	NaN	
688	NaN	NaN	NaN	NaN	NaN	NaN	
689	NaN	NaN	NaN	NaN	NaN	NaN	
	70	l					

In [9]:

a.describe()

Out[9]:

	date	weights	population
count	3488.000000	3488.0	3.464000e+03
mean	2011.500000	1.0	3.244250e+07
std	4.610433	0.0	1.293668e+08
min	2004.000000	1.0	9.828000e+03
25%	2007.750000	1.0	7.152712e+05
50%	2011.500000	1.0	5.868890e+06
75%	2015.250000	1.0	2.071792e+07
max	2019.000000	1.0	1.397715e+09

In [10]:

a.sum()

Out[10]:

date	7016
112.0	
SPI.INDEX.PIL1	Pillar 1 - Data Use - Score1001001001001
00	
SPI.DIM1.5.INDEX	Dimension 1.5: Data use by international org
an	
SPI.DIM5.1.INDEX	Dimension 5.1: Legislation and governance111
11	
SPI.DIM5.5.INDEX	Dimension 5.5: Finance1111111111111111111111
11	
SPI.D1.5.POV	Dimension 1.5: Data use by international org
an	
SPI.D1.5.CHLD.MORT	Dimension 1.5: Data use by international org
an	
SPI.D1.5.DT.TDS.DPPF.XP.ZS	Dimension 1.5: Data use by international org
an	
SPI.D1.5.SAFE.MAN.WATER	Dimension1.5: Data use by international orga
ni	
SPI.D1.5.LFP	Dimension 1.5: Data use by international org
an	
weights	3
488.0	
population	112380821
894.5	
dtype: object	

In [12]:

a.count()

Out[12]:

country 3488 iso3c 3488 3488 date SPI.INDEX.PIL1 3489 SPI.INDEX.PIL2 693 . . . SPI.D5.5.DIFI 673 income 3488 region 3488 weights 3488 population 3464 Length: 79, dtype: int64

In [13]:

a.max()

Out[13]:

dtype: object

date 2 019.0 Pillar 1 - Data Use -SPI.INDEX.PIL1 Score Dimension 1.5: Data use by international org SPI.DIM1.5.INDEX Dimension 5.1: Legislation and gover SPI.DIM5.1.INDEX nance SPI.DIM5.5.INDEX Dimension 5.5: Fi nance Dimension 1.5: Data use by international org SPI.D1.5.POV an... SPI.D1.5.CHLD.MORT Dimension 1.5: Data use by international org SPI.D1.5.DT.TDS.DPPF.XP.ZS Dimension 1.5: Data use by international org an... Dimension1.5: Data use by international orga SPI.D1.5.SAFE.MAN.WATER ni... SPI.D1.5.LFP Dimension 1.5: Data use by international org an... weights 1.0 population 1397715 000.0

In [14]:

a.dropna()

Out[14]:

	country	iso3c	date	SPI.INDEX.PIL1	SPI.INDEX.PIL2	SPI.INDEX.PIL3	SPI.IND
1	Norway	NOR	2019.0	100	92.23333333333333	77.56875	80.6666666
2	Italy	ITA	2019.0	100	91.8666666666666	75.2875	
3	Austria	AUT	2019.0	100	91.3	74.55	
4	Poland	POL	2019.0	100	95.1	70.5375	79.7166666
5	Slovenia	SVN	2019.0	100	96.9333333333333	76.28125	71.4416666
694	Belgium	BEL	2016.0	100	53.13333333333333	60.4125	66.2166666
695	Israel	ISR	2016.0	100	81.8666666666667	52.375	44.3083333
708	Iceland	ISL	2016.0	80	49.56666666666667	54.75	62.8916666
710	Luxembourg	LUX	2016.0	80	49.0666666666667	53.8875	60.5166666
722	Singapore	SGP	2016.0	100	48.03333333333333	40.94375	50.0333333
230 r	ows × 79 col	umns					
4							•

In [15]:

a.isna()

Out[15]:

	country	iso3c	date	SPI.INDEX.PIL1	SPI.INDEX.PIL2	SPI.INDEX.PIL3	SPI.INDEX.PIL4
0	True	True	True	False	False	False	False
1	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False
3484	False	False	False	False	True	True	True
3485	False	False	False	False	True	True	True
3486	False	False	False	False	True	True	True
3487	False	False	False	False	True	True	True
3488	False	False	False	False	True	True	True

In [16]:

b.columns

Out[16]:

```
Index(['country', 'iso3c', 'date', 'SPI.INDEX.PIL1', 'SPI.INDEX.PIL2',
        'SPI.INDEX.PIL3', 'SPI.INDEX.PIL4', 'SPI.INDEX.PIL5', 'SPI.INDEX',
        'SPI.DIM1.5.INDEX', 'SPI.DIM2.1.INDEX', 'SPI.DIM2.2.INDEX', 'SPI.DIM2.4.INDEX', 'SPI.DIM3.1.INDEX', 'SPI.DIM3.2.INDEX',
        'SPI.DIM3.3.INDEX', 'SPI.DIM3.4.INDEX', 'SPI.DIM4.1.CEN.INDEX',
        'SPI.DIM4.1.SVY.INDEX', 'SPI.DIM4.2.INDEX', 'SPI.DIM4.3.INDEX',
        'SPI.DIM5.1.INDEX', 'SPI.DIM5.2.INDEX', 'SPI.DIM5.5.INDEX',
        'SPI.D1.5.POV', 'SPI.D1.5.CHLD.MORT', 'SPI.D1.5.DT.TDS.DPPF.XP.ZS',
        'SPI.D1.5.SAFE.MAN.WATER', 'SPI.D1.5.LFP', 'SPI.D2.1.GDDS',
        'SPI.D2.2.Machine.readable', 'SPI.D2.2.Non.proprietary', 'SPI.D2.2.Download.options', 'SPI.D2.2.Metadata.available',
        'SPI.D2.2.Terms.of.use', 'SPI.D2.2.Openness.subscore', 'SPI.D2.4.NA
DA',
        'SPI.D3.1.POV', 'SPI.D3.2.HNGR', 'SPI.D3.3.HLTH', 'SPI.D3.4.EDUC',
        'SPI.D3.5.GEND', 'SPI.D3.6.WTRS', 'SPI.D3.7.ENRG', 'SPI.D3.8.WORK',
        'SPI.D3.9.INDY', 'SPI.D3.10.NEQL', 'SPI.D3.11.CITY', 'SPI.D3.12.CNS
        'SPI.D3.15.LAND', 'SPI.D3.16.INST', 'SPI.D3.17.PTNS', 'SPI.D3.13.CL
MT',
        'SPI.D4.1.1.POPU', 'SPI.D4.1.2.AGRI', 'SPI.D4.1.3.BIZZ',
        'SPI.D4.1.4.HOUS', 'SPI.D4.1.5.AGSVY', 'SPI.D4.1.6.LABR', 'SPI.D4.1.7.HLTH', 'SPI.D4.1.8.BZSVY', 'SPI.D4.2.3.CRVS',
        'SPI.D4.3.GEO.first.admin.level', 'SPI.D5.1.DILG', 'SPI.D5.2.1.SNA
U',
        'SPI.D5.2.2.NABY', 'SPI.D5.2.3.CNIN', 'SPI.D5.2.4.CPIBY',
        'SPI.D5.2.5.HOUS', 'SPI.D5.2.6.EMPL', 'SPI.D5.2.7.CGOV',
        'SPI.D5.2.8.FINA', 'SPI.D5.2.9.MONY', 'SPI.D5.2.10.GSBP',
        'SPI.D5.5.DIFI', 'income', 'region', 'weights', 'population'],
       dtype='object')
```

In [20]:

c=b.tail(10)
c

Out[20]:

	country	iso3c	date	SPI.INDEX.PIL1	SPI.INDEX.PIL2	SPI.INDEX.PIL3	SPI.INDEX.PI
3479	Uruguay	URY	2004.0	40	104	104	1
3480	Uzbekistan	UZB	2004.0	40	104	104	1
3481	Vanuatu	VUT	2004.0	20	104	104	1
3482	Venezuela, RB	VEN	2004.0	40	104	104	1
3483	Vietnam	VNM	2004.0	40	104	104	1
3484	Virgin Islands (U.S.)	VIR	2004.0	20	104	104	1
3485	West Bank and Gaza	PSE	2004.0	20	104	104	1
3486	Yemen, Rep.	YEM	2004.0	20	104	104	1
3487	Zambia	ZMB	2004.0	40	104	104	1
3488	Zimbabwe	ZWE	2004.0	20	104	104	1

In [21]:

Out[21]:

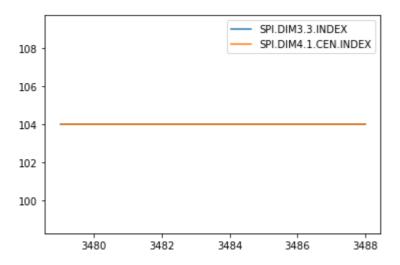
	SPI.DIM3.1.INDEX	SPI.DIM3.2.INDEX	SPI.DIM3.3.INDEX	SPI.DIM3.4.INDEX	SPI.DIM4.1
3479	0.640333333333333	0.406166666666667	104	0.2	_
3480	0.375	0.388166666666667	104	0.143	
3481	0.296166666666667	0.3168333333333333	104	0.2855	
3482	0.4828333333333333	0.3925	104	0.5355	
3483	0.443	0.353166666666667	104	0.4	
3484	0.0166666666666667	0.1708333333333333	104	0.25	
3485	0.514166666666667	0.3235	104	0.2145	
3486	0.3343333333333333	0.338333333333333	104	0.25	
3487	0.390666666666667	0.3645	104	0.4	
3488	0.3343333333333333	0.371666666666667	104	0.143	
4					>

In [22]:

```
d.plot.line()
```

Out[22]:

<AxesSubplot:>

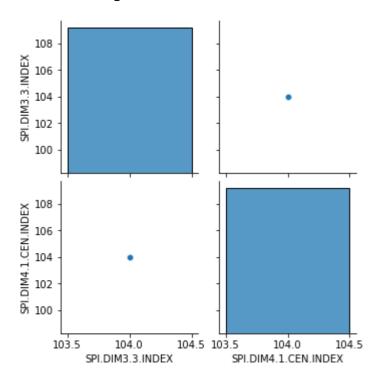


In [23]:

```
sns.pairplot(d)
```

Out[23]:

<seaborn.axisgrid.PairGrid at 0x121a25e5430>



In [24]:

In [25]:

```
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)
```

In [26]:

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

Out[26]:

LinearRegression()

In [27]:

```
print(lr.intercept_)
```

104.0

In [28]:

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

Out[28]:

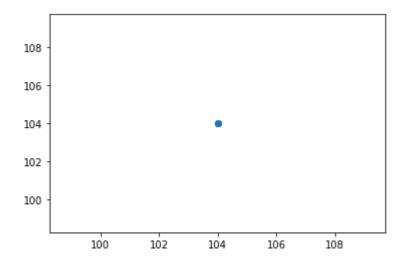
	Co-efficient
SPI.DIM3.1.INDEX	0.0
SPI.DIM3.2.INDEX	0.0
SPI.DIM3.4.INDEX	0.0
SPI.DIM4.1.CEN.INDEX	0.0
SPI.DIM4.1.SVY.INDEX	0.0

In [29]:

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

Out[29]:

<matplotlib.collections.PathCollection at 0x121a6eb7730>



In [30]:

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

1.0

In [31]:

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

In [32]:

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

Out[32]:

```
Ridge(alpha=10)
```

```
In [33]:
rr.score(x_test,y_test)
Out[33]:
1.0
In [34]:
la=Lasso(alpha=10)
la.fit(x_train,y_train)
\label{lem:c:programDataAnaconda3} Iib\site-packages\sklearn\linear\_model\_coordinat
e_descent.py:530: ConvergenceWarning: Objective did not converge. You migh
t want to increase the number of iterations. Duality gap: 0.0, tolerance:
  model = cd_fast.enet_coordinate_descent(
Out[34]:
Lasso(alpha=10)
In [35]:
la.score(x_test,y_test)
Out[35]:
1.0
```

In [39]:

a1=b.tail(500) a1

Out[39]:

;	date	SPI.INDEX.PIL1	SPI.INDEX.PIL2	SPI.INDEX.PIL3	SPI.INDEX.PIL4	SPI.INDEX.PIL5	SPI.
₹	2006.0	40	104	69.525	104	104	
-	2006.0	40	104	65.86875	104	104	
-	2006.0	40	104	42.3375	104	104	
Γ	2006.0	40	104	44.53125	104	104	
J	2006.0	20	104	19.84375	104	104	
?	2004.0	20	104	104	104	104	
Ξ	2004.0	20	104	104	104	104	
1	2004.0	20	104	104	104	104	
3	2004.0	40	104	104	104	104	
Ξ	2004.0	20	104	104	104	104	
;							