In [6]: 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

In [10]: a=pd.read_csv(r"C:\Users\user\Downloads\spi_index_labelled.csv")

Out[10]: SPI.INDEX.PIL2 SPI.INDEX.PIL3 country iso3c date SPI.INDEX.PIL1 SPI.INDEX.F Pillar 3 - Data Pillar 1 - Data Pillar 2 - Data Pillar 4 - [0 NaN NaN NaN Products -Use - Score Services - Score Sources - So Score 1 Norway NOR 2019.0 100 92.2333333333333 77.56875 80.666666666 2 81. Italy ITA 2019.0 100 91.866666666666 75.2875 3 100 91.3 79 Austria AUT 2019.0 74.55 4 Poland POL 2019.0 100 95.1 70.5375 79.7166666666 Virgin I 3484 Islands VIR 2004.0 20 NaN NaN (U.S.) West 3485 Bank and PSE 2004.0 20 NaN NaN Gaza Yemen, 3486 YEM 2004.0 20 NaN NaN ı Rep.

3489 rows × 79 columns

3488 Zimbabwe

Zambia

ZMB 2004.0

ZWE 2004.0

3487

1 of 12 08-08-2023, 14:31

40

20

NaN

NaN

NaN

NaN

ı

In [12]: b=a.fillna(value=221)

Out[12]:

	country	iso3c	date	SPI.INDEX.PIL1	SPI.INDEX.PIL2	SPI.INDEX.PIL3	SPI.INDEX.F
0	221	221	221.0	Pillar 1 - Data Use - Score	Pillar 2 - Data Services - Score	Pillar 3 - Data Products - Score	Pillar 4 - [Sources - S
1	Norway	NOR	2019.0	100	92.23333333333333	77.56875	80.666666666
2	Italy	ITA	2019.0	100	91.8666666666666	75.2875	81.
3	Austria	AUT	2019.0	100	91.3	74.55	7!
4	Poland	POL	2019.0	100	95.1	70.5375	79.7166666666
3484	Virgin Islands (U.S.)	VIR	2004.0	20	221	221	
3485	West Bank and Gaza	PSE	2004.0	20	221	221	
3486	Yemen, Rep.	YEM	2004.0	20	221	221	
3487	Zambia	ZMB	2004.0	40	221	221	
3488	Zimbabwe	ZWE	2004.0	20	221	221	

3489 rows × 79 columns

In [24]: c=b.head(400)

Out[24]:

	country	iso3c	date	SPI.INDEX.PIL1	SPI.INDEX.PIL2	SPI.INDEX.PIL3	SPI.INDEX.PII
0	221	221	221.0	Pillar 1 - Data Use - Score	Pillar 2 - Data Services - Score	Pillar 3 - Data Products - Score	Pillar 4 - Da Sources - Sco
1	Norway	NOR	2019.0	100	92.23333333333333	77.56875	80.66666666666
2	Italy	ITA	2019.0	100	91.8666666666666	75.2875	81.82
3	Austria	AUT	2019.0	100	91.3	74.55	79.7
4	Poland	POL	2019.0	100	95.1	70.5375	79.716666666666
395	Antigua and Barbuda	ATG	2018.0	20	221	52.06875	24
396	Aruba	ABW	2018.0	60	221	18.45	2:
397	Barbados	BRB	2018.0	80	221	50.425	2:
398	Bermuda	BMU	2018.0	60	221	16.2125	2:
399	British Virgin Islands	VGB	2018.0	40	221	15.69375	27

400 rows × 79 columns

In [25]: e=c.tail(399)

Out[25]:

	country	iso3c	date	SPI.INDEX.PIL1	SPI.INDEX.PIL2	SPI.INDEX.PIL3	SPI.INDEX.PII
1	Norway	NOR	2019.0	100	92.233333333333333	77.56875	80.66666666666
2	Italy	ITA	2019.0	100	91.866666666666	75.2875	81.82
3	Austria	AUT	2019.0	100	91.3	74.55	79.7
4	Poland	POL	2019.0	100	95.1	70.5375	79.716666666666
5	Slovenia	SVN	2019.0	100	96.9333333333333	76.28125	71.441666666666
395	Antigua and Barbuda	ATG	2018.0	20	221	52.06875	21
396	Aruba	ABW	2018.0	60	221	18.45	2;
397	Barbados	BRB	2018.0	80	221	50.425	27
398	Bermuda	BMU	2018.0	60	221	16.2125	22
399	British Virgin Islands	VGB	2018.0	40	221	15.69375	2:

399 rows × 79 columns

```
In [26]:
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 399 entries, 1 to 399
Data columns (total 79 columns):

	columns (total /9 columns):	Non Null Count	Dtura
#	Column	Non-Null Count	Dtype
0	country	399 non-null	object
1	iso3c	399 non-null	object
2	date	399 non-null	float64
3	SPI.INDEX.PIL1	399 non-null	object
4	SPI.INDEX.PIL2	399 non-null	object
5	SPI.INDEX.PIL3	399 non-null	object
6	SPI.INDEX.PIL4	399 non-null	object
7	SPI.INDEX.PIL5	399 non-null	object
8	SPI.INDEX	399 non-null	object
9	SPI.DIM1.5.INDEX	399 non-null	object
10	SPI.DIM2.1.INDEX	399 non-null	object
11	SPI.DIM2.2.INDEX	399 non-null	object
12	SPI.DIM2.4.INDEX	399 non-null	object
13	SPI.DIM3.1.INDEX	399 non-null	object
14	SPI.DIM3.2.INDEX	399 non-null	object
15	SPI.DIM3.3.INDEX	399 non-null	object
16	SPI.DIM3.4.INDEX	399 non-null	object
17	SPI.DIM4.1.CEN.INDEX	399 non-null	object
18	SPI.DIM4.1.SVY.INDEX	399 non-null	object
19	SPI.DIM4.2.INDEX	399 non-null	object
20	SPI.DIM4.3.INDEX	399 non-null	object
21	SPI.DIM5.1.INDEX	399 non-null	object
22	SPI.DIM5.2.INDEX	399 non-null	object
23	SPI.DIM5.5.INDEX	399 non-null	object
24	SPI.D1.5.POV	399 non-null	object
25	SPI.D1.5.CHLD.MORT	399 non-null	object
26	SPI.D1.5.DT.TDS.DPPF.XP.ZS	399 non-null	object
27	SPI.D1.5.SAFE.MAN.WATER	399 non-null	object
28	SPI.D1.5.LFP	399 non-null	object
29	SPI.D2.1.GDDS	399 non-null	object
30	SPI.D2.2.Machine.readable	399 non-null	object
31	SPI.D2.2.Non.proprietary	399 non-null	object
32	SPI.D2.2.Download.options	399 non-null	object
33	SPI.D2.2.Metadata.available	399 non-null	object
34	SPI.D2.2.Terms.of.use	399 non-null	object
35	SPI.D2.2.Openness.subscore	399 non-null	object
36	SPI.D2.4.NADA	399 non-null	object
37	SPI.D3.1.POV	399 non-null	object
38	SPI.D3.2.HNGR	399 non-null	object
39	SPI.D3.3.HLTH	399 non-null	object
40	SPI.D3.4.EDUC	399 non-null	object
41	SPI.D3.5.GEND	399 non-null	object
42	SPI.D3.6.WTRS	399 non-null	object
43	SPI.D3.7.ENRG	399 non-null	object
44	SPI.D3.8.WORK	399 non-null	object
45	SPI.D3.9.INDY	399 non-null	object
46	SPI.D3.10.NEQL	399 non-null	object
47	SPI.D3.11.CITY	399 non-null	object
48	SPI.D3.12.CNSP	399 non-null	object

49	SPI.D3.15.LAND	399 non-null	object
50	SPI.D3.16.INST	399 non-null	object
51	SPI.D3.17.PTNS	399 non-null	object
52	SPI.D3.13.CLMT	399 non-null	object
53	SPI.D4.1.1.POPU	399 non-null	object
54	SPI.D4.1.2.AGRI	399 non-null	object
55	SPI.D4.1.3.BIZZ	399 non-null	object
56	SPI.D4.1.4.HOUS	399 non-null	object
57	SPI.D4.1.5.AGSVY	399 non-null	object
58	SPI.D4.1.6.LABR	399 non-null	object
59	SPI.D4.1.7.HLTH	399 non-null	object
60	SPI.D4.1.8.BZSVY	399 non-null	object
61	SPI.D4.2.3.CRVS	399 non-null	object
62	SPI.D4.3.GEO.first.admin.level	399 non-null	object
63	SPI.D5.1.DILG	399 non-null	object
64	SPI.D5.2.1.SNAU	399 non-null	object
65	SPI.D5.2.2.NABY	399 non-null	object
66	SPI.D5.2.3.CNIN	399 non-null	object
67	SPI.D5.2.4.CPIBY	399 non-null	object
68	SPI.D5.2.5.HOUS	399 non-null	object
69	SPI.D5.2.6.EMPL	399 non-null	object
70	SPI.D5.2.7.CGOV	399 non-null	object
71	SPI.D5.2.8.FINA	399 non-null	object
72	SPI.D5.2.9.MONY	399 non-null	object
73	SPI.D5.2.10.GSBP	399 non-null	object
74	SPI.D5.5.DIFI	399 non-null	object
75	income	399 non-null	object
76	region	399 non-null	object
77	weights	399 non-null	float64
78	population	399 non-null	float64
	67		

dtypes: float64(3), object(76)

memory usage: 246.4+ KB

```
In [27]:
Out[27]: 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.NADA
                    '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.CNSP',
                    'SPI.D3.15.LAND', 'SPI.D3.16.INST', 'SPI.D3.17.PTNS', 'SPI.D3.13.CLMT
                    '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.SNAU',
                    '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')
```

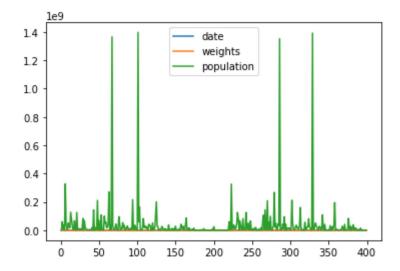
In [28]:

Out[28]:

	date	weights	population
count	399.000000	399.0	3.990000e+02
mean	2018.546366	1.0	3.797507e+07
std	0.498471	0.0	1.425263e+08
min	2018.000000	1.0	2.210000e+02
25%	2018.000000	1.0	1.341288e+06
50%	2019.000000	1.0	7.650154e+06
75%	2019.000000	1.0	2.752859e+07
max	2019.000000	1.0	1.397715e+09

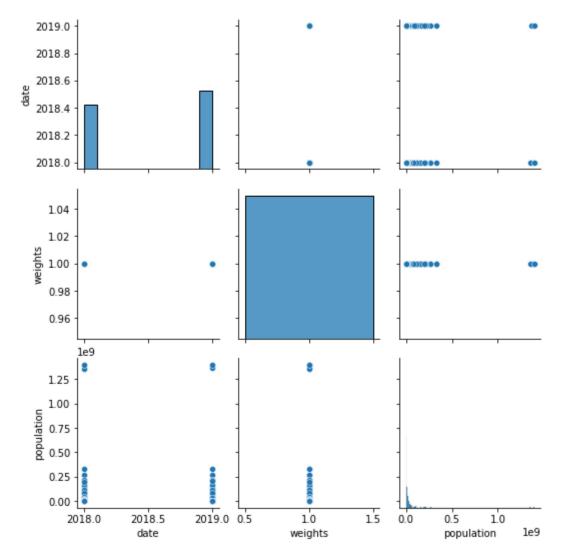
In [78]:

Out[78]: <AxesSubplot:>



In [29]:

Out[29]: <seaborn.axisgrid.PairGrid at 0x2230b8c3e80>

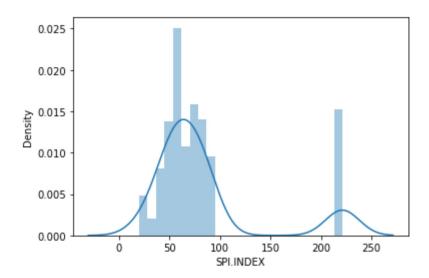


```
In [30]:
```

C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: Fut ureWarning: `distplot` is a deprecated function and will be removed in a futu re 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)

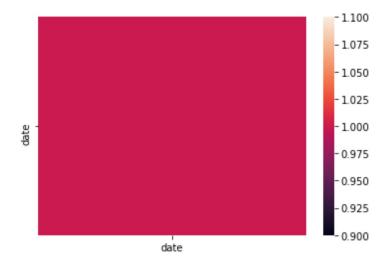
Out[30]: <AxesSubplot:xlabel='SPI.INDEX', ylabel='Density'>



```
In [32]: x1=e[['country', 'iso3c', 'date', 'SPI.INDEX.PIL1', 'SPI.INDEX.PIL2',
```

In [33]:

Out[33]: <AxesSubplot:>



```
In [49]: x=x1[['SPI.INDEX.PIL1','SPI.INDEX.PIL2','SPI.INDEX.PIL3','SPI.INDEX.PIL4','SPI
```

In [50]: 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 [51]: from sklearn.linear_model import LinearRegression
        lr=LinearRegression()
Out[51]: LinearRegression()
In [52]:
         -2.842170943040401e-14
In [53]: coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
Out[53]:
                       Co-efficient
         SPI.INDEX.PIL1 1.000000e+00
         SPI.INDEX.PIL2 7.452565e-17
         SPI.INDEX.PIL3 4.042679e-16
         SPI.INDEX.PIL4 8.949258e-17
         SPI.INDEX.PIL5 -2.947899e-17
In [54]: | prediction=lr.predict(x_test)
Out[54]: <matplotlib.collections.PathCollection at 0x2230e0f8b20>
         100
          80
          60
          40
          20
             100 26.6 90 60 20 80 70 10 40 53.4 30 56.6 83.4 86.6
In [55]:
Out[55]: 1.0
In [56]:
Out[56]: 1.0
In [57]:
```

```
In [58]: rr=Ridge(alpha=10)
         rr.fit(x_train,y_train)
Out[58]: 0.999999944915434
In [59]: la=Lasso(alpha=10)
Out[59]: Lasso(alpha=10)
In [60]: -
Out[60]: 0.999673531532171
In [61]: from sklearn.linear model import ElasticNet
         en=ElasticNet()
Out[61]: ElasticNet()
In [62]:
Out[62]: array([ 9.98172414e-01, -0.00000000e+00, 0.00000000e+00, -3.78564879e-05,
                 0.00000000e+001)
In [63]:
Out[63]: array([99.96020021, 99.96036583, 26.69635521, 89.97893508, 89.97974679,
                99.96112391, 99.96061285, 60.02761919, 89.97996099, 99.9601775,
                99.96007812, 60.03529743, 99.96077752, 99.96028539, 20.10850088,
                99.96190502, 79.99694532, 70.0169916, 89.97939882, 26.69635521,
                89.97829531, 20.10072263, 99.96035921, 99.95986297, 20.10072263,
                99.9601368 , 99.96006298 , 99.96030621 , 20.10072263 , 60.03521194 ,
                20.10072263, 89.97957013, 60.03478763, 99.96035921, 99.96016141,
                99.96184161, 10.11899849, 99.96057594, 60.0353132 , 40.07192928,
                60.02761919, 89.97957013, 89.97962344, 99.96014816, 53.44715413,
                40.07049799, 99.96049076, 79.99106747, 99.96030621, 30.089978 ,
                70.0164777 , 40.07170214, 99.95982827, 99.96027214, 89.97927232,
                89.97879659, 70.01691809, 89.97945687, 79.99718918, 60.02761919,
                56.64140775, 70.01600796, 99.96045038, 79.99812297, 83.39075171,
                60.02761919, 20.10845356, 89.97975089, 89.97996099, 60.02761919,
                99.96014816, 79.99827408, 99.96049234, 60.02761919, 89.98015532,
                79.99737373, 79.99106747, 89.97976446, 79.99792265, 60.02761919,
                99.95984688, 79.99682638, 99.9608545, 79.99688885, 99.96038666,
                99.96122423, 70.01650672, 79.99767721, 40.07049799, 79.99709927,
                79.99839806, 86.58478987, 99.95976265, 99.9601775, 79.99718918,
                99.96086302, 60.02761919, 60.0339368 , 89.97836156, 89.97960483,
                99.96046142, 79.996945 , 79.99701598, 79.99866085, 89.97927232,
                89.97984522, 99.96006298, 79.99734817, 99.96010683, 89.97983985,
                79.99701598, 83.39183378, 40.06417091, 70.0164777 , 99.9603693 ,
                60.03490561, 60.0353132, 99.96058162, 99.96122423, 99.95966328])
In [64]:
Out[64]: 0.1456406343489931
```

