In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [3]:
```
data=pd.read_csv(r"C:\Users\user\Downloads\stations.csv")
data
```

Out[3]:

	id	name	address	lon	lat	elevation
0	28079004	Pza. de España	Plaza de España	-3.712247	40.423853	635
1	28079008	Escuelas Aguirre	Entre C/ Alcalá y C/ O' Donell	-3.682319	40.421564	670
2	28079011	Avda. Ramón y Cajal	Avda. Ramón y Cajal esq. C/ Príncipe de Vergara	-3.677356	40.451475	708
3	28079016	Arturo Soria	C/ Arturo Soria esq. C/ Vizconde de los Asilos	-3.639233	40.440047	693
4	28079017	Villaverde	C/. Juan Peñalver	-3.713322	40.347139	604
5	28079018	Farolillo	Calle Farolillo - C/Ervigio	-3.731853	40.394781	630
6	28079024	Casa de Campo	Casa de Campo (Terminal del Teleférico)	-3.747347	40.419356	642
7	28079027	Barajas Pueblo	C/. Júpiter, 21 (Barajas)	-3.580031	40.476928	621
8	28079035	Pza. del Carmen	Plaza del Carmen esq. Tres Cruces.	-3.703172	40.419208	659
9	28079036	Moratalaz	Avd. Moratalaz esq. Camino de los Vinateros	-3.645306	40.407947	685
10	28079038	Cuatro Caminos	Avda. Pablo Iglesias esq. C/ Marqués de Lema	-3.707128	40.445544	698
11	28079039	Barrio del Pilar	Avd. Betanzos esq. C/ Monforte de Lemos	-3.711542	40.478228	674
12	28079040	Vallecas	C/ Arroyo del Olivar esq. C/ Río Grande.	-3.651522	40.388153	677
13	28079047	Mendez Alvaro	C/ Juan de Mariana / Pza. Amanecer Mendez Alvaro	-3.686825	40.398114	599
14	28079048	Castellana	C/ Jose Gutierrez Abascal	-3.690367	40.439897	676
15	28079049	Parque del Retiro	Paseo Venezuela- Casa de Vacas	-3.682583	40.414444	662
16	28079050	Plaza Castilla	Plaza Castilla (Canal)	-3.688769	40.465572	728
17	28079054	Ensanche de Vallecas	Avda La Gavia / Avda. Las Suertes	-3.612117	40.372933	627
18	28079055	Urb. Embajada	C/ Riaño (Barajas)	-3.580747	40.462531	618
19	28079056	Pza. Fernández Ladreda	Pza. Fernández Ladreda - Avda. Oporto	-3.718728	40.384964	604
20	28079057	Sanchinarro	C/ Princesa de Eboli esq C/ Maria Tudor	-3.660503	40.494208	700
21	28079058	El Pardo	Avda. La Guardia	-3.774611	40.518058	615
22	28079059	Juan Carlos I	Parque Juan Carlos I (frente oficinas mantenim...	-3.609072	40.465250	660
23	28079060	Tres Olivos	Plaza Tres Olivos	-3.689761	40.500589	715

In [4]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 24 entries, 0 to 23
Data columns (total 6 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   id         24 non-null     int64  
 1   name       24 non-null     object 
 2   address    24 non-null     object 
 3   lon        24 non-null     float64
 4   lat        24 non-null     float64
 5   elevation  24 non-null     int64  
dtypes: float64(2), int64(2), object(2)
memory usage: 1.2+ KB
```

In [5]:
```
df=data.fillna(value=0)
df
```

Out[5]:

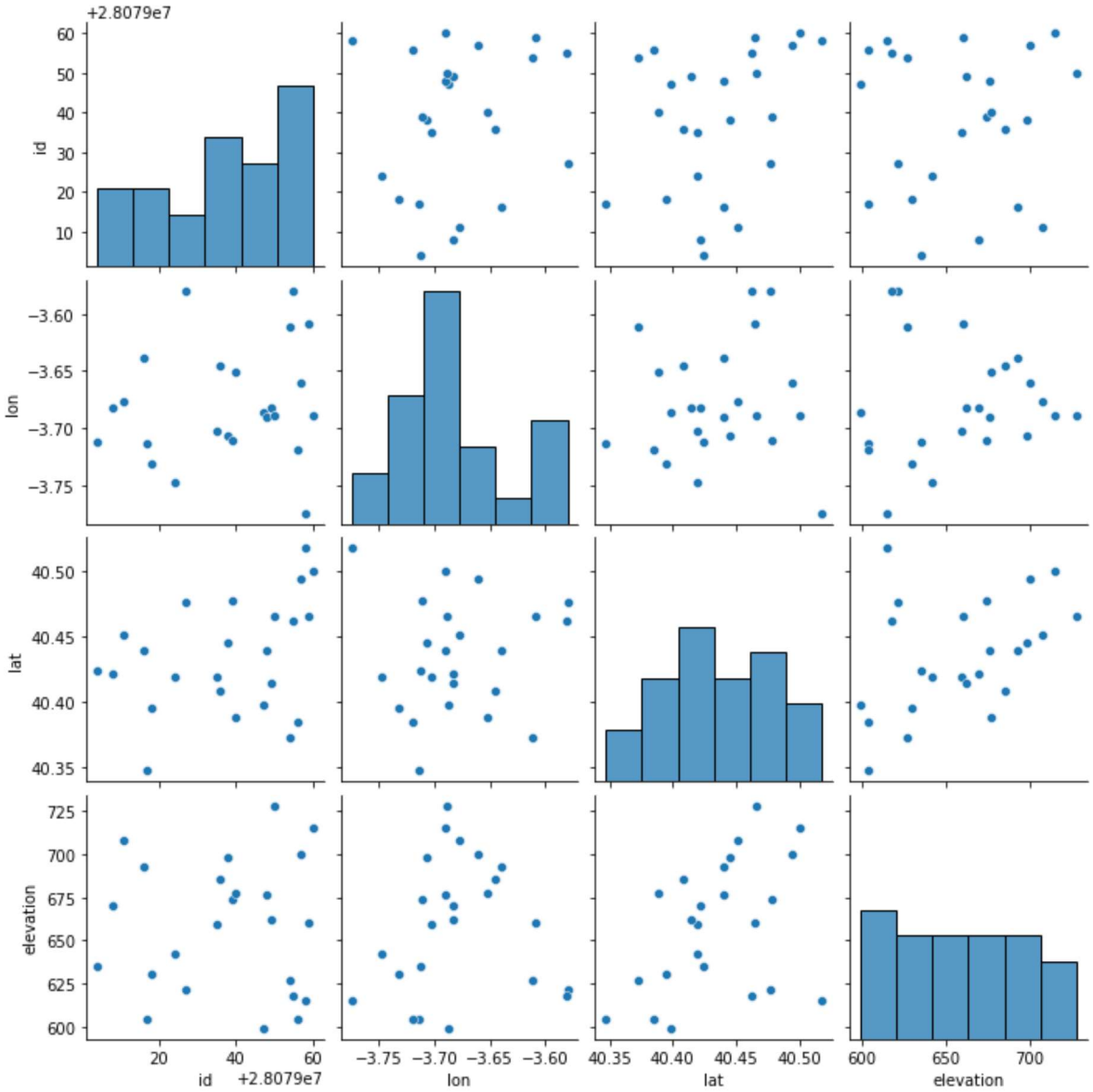
	id	name	address	lon	lat	elevation
0	28079004	Pza. de España	Plaza de España	-3.712247	40.423853	635
1	28079008	Escuelas Aguirre	Entre C/ Alcalá y C/ O' Donell	-3.682319	40.421564	670
2	28079011	Avda. Ramón y Cajal	Avda. Ramón y Cajal esq. C/ Príncipe de Vergara	-3.677356	40.451475	708
3	28079016	Arturo Soria	C/ Arturo Soria esq. C/ Vizconde de los Asilos	-3.639233	40.440047	693
4	28079017	Villaverde	C/. Juan Peñalver	-3.713322	40.347139	604
5	28079018	Farolillo	Calle Farolillo - C/Ervigio	-3.731853	40.394781	630
6	28079024	Casa de Campo	Casa de Campo (Terminal del Teleférico)	-3.747347	40.419356	642
7	28079027	Barajas Pueblo	C/. Júpiter, 21 (Barajas)	-3.580031	40.476928	621
8	28079035	Pza. del Carmen	Plaza del Carmen esq. Tres Cruces.	-3.703172	40.419208	659
9	28079036	Moratalaz	Avd. Moratalaz esq. Camino de los Vinateros	-3.645306	40.407947	685
10	28079038	Cuatro Caminos	Avda. Pablo Iglesias esq. C/ Marqués de Lema	-3.707128	40.445544	698
11	28079039	Barrio del Pilar	Avd. Betanzos esq. C/ Monforte de Lemos	-3.711542	40.478228	674
12	28079040	Vallecas	C/ Arroyo del Olivar esq. C/ Río Grande.	-3.651522	40.388153	677
13	28079047	Mendez Alvaro	C/ Juan de Mariana / Pza. Amanecer Mendez Alvaro	-3.686825	40.398114	599
14	28079048	Castellana	C/ Jose Gutierrez Abascal	-3.690367	40.439897	676
15	28079049	Parque del Retiro	Paseo Venezuela- Casa de Vacas	-3.682583	40.414444	662
16	28079050	Plaza Castilla	Plaza Castilla (Canal)	-3.688769	40.465572	728
17	28079054	Ensanche de Vallecas	Avda La Gavia / Avda. Las Suertes	-3.612117	40.372933	627
18	28079055	Urb. Embajada	C/ Riaño (Barajas)	-3.580747	40.462531	618
19	28079056	Pza. Fernández Ladreda	Pza. Fernández Ladreda - Avda. Oporto	-3.718728	40.384964	604
20	28079057	Sanchinarro	C/ Princesa de Eboli esq C/ Maria Tudor	-3.660503	40.494208	700
21	28079058	El Pardo	Avda. La Guardia	-3.774611	40.518058	615
22	28079059	Juan Carlos I	Parque Juan Carlos I (frente oficinas mantenim...	-3.609072	40.465250	660
23	28079060	Tres Olivos	Plaza Tres Olivos	-3.689761	40.500589	715

In [6]:
```
df.columns
```

Out[6]:
```
Index(['id', 'name', 'address', 'lon', 'lat', 'elevation'], dtype='object')
```

In [7]:
```
sns.pairplot(df)
```

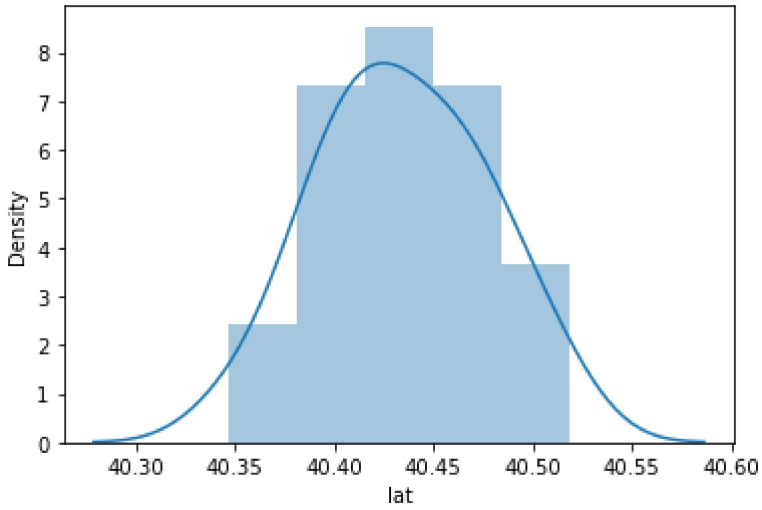
Out[7]:
```
<seaborn.axisgrid.PairGrid at 0x14559a0ec70>
```



In [9]:
```
sns.distplot(data["lat"])
```

```
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 fu
nction with similar flexibility) or `histplot` (an axes-level function for hi
stograms).
  warnings.warn(msg, FutureWarning)
```

Out[9]:
```
<AxesSubplot:xlabel='lat', ylabel='Density'>
```



MODEL BUILDING

Linear Regression

In [33]:
```
df1=df[['id', 'lon', 'lat', 'elevation']]
```

In [34]:
```
x=df1[['id', 'lon', 'lat', 'elevation']]
y=df1[['lat']]
```

In [35]:
```
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 [36]:
```
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
lr.fit(x_train,y_train)
```

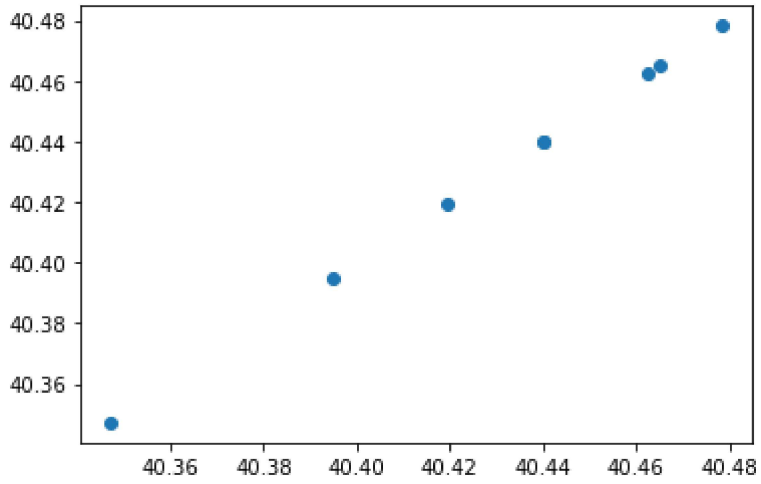
Out[36]:
```
LinearRegression()
```

In [37]:
```
print(lr.intercept_)
```

```
[-4.86011231e-12]
```

In [38]:
```
prediction=lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[38]: <matplotlib.collections.PathCollection at 0x14560595fa0>



In [39]:
```
print(lr.score(x_test,y_test))
```

```
1.0
```

Ridge Regression

In [40]:
```
from sklearn.linear_model import Ridge
```

In [41]:
```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```

Out[41]: Ridge(alpha=10)

In [42]:
```
rr.score(x_test,y_test)
```

Out[42]: 0.4710143619948185

Lasso Regression

In [43]:
```
from sklearn.linear_model import Lasso
```

In [44]:
```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[44]: Lasso(alpha=10)

In [45]:
```
la.score(x_test,y_test)
```

Out[45]:
```
-0.019026938268361437
```

Elastic Regression

In [46]:
```
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[46]:
```
ElasticNet()
```

In [47]:
```
print(en.coef_)
```

```
[ 0.00000000e+00 -0.00000000e+00  0.00000000e+00  5.98092198e-05]
```

In [48]:
```
print(en.predict(x_test))
```

```
[40.43631148 40.43726843 40.43451721 40.4337995  40.43296217 40.43523492
 40.43828519 40.43714881]
```

In [49]:
```
print(en.score(x_test,y_test))
```

```
0.03693354444817687
```

Logistic Regression

In [50]:
```
from sklearn.linear_model import LogisticRegression
```

In [92]:
```
feature_matrix=df1.iloc[:,0:6]
target_vector=df1.iloc[:,-1]
```

In [93]:
```
feature_matrix.shape
```

Out[93]:
```
(24, 3)
```

In [94]:
```
target_vector.shape
```

Out[94]:
```
(24,)
```

In [95]:
```
from sklearn.preprocessing import StandardScaler
```

In [96]:
```
fs=StandardScaler().fit_transform(feature_matrix)
```

In [97]:
```
logr=LogisticRegression()
logr.fit(fs,target_vector)
```

Out[97]:
```
LogisticRegression()
```

In [102]:
```
observation=[[1,2,3]]
```

In [103]:
```
prediction=logr.predict(observation)
print(observation)
```

```
[[1, 2, 3]]
```

In [104]:
```
logr.classes_
```

Out[104]:
```
array([599, 604, 615, 618, 621, 627, 630, 635, 642, 659, 660, 662, 670,
       674, 676, 677, 685, 693, 698, 700, 708, 715, 728], dtype=int64)
```

In [105]:
```
logr.score(fs,target_vector)
```

Out[105]:
```
0.5416666666666666
```

Result

The best model is Ridge Regression 0.4710143619948185