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,Ridg
from sklearn.model_selection import train_test_split
```

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

Out[2]:

	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 [3]:
```
df.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 [4]:
```
df1=df.dropna()
df1
```

Out[4]:

	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

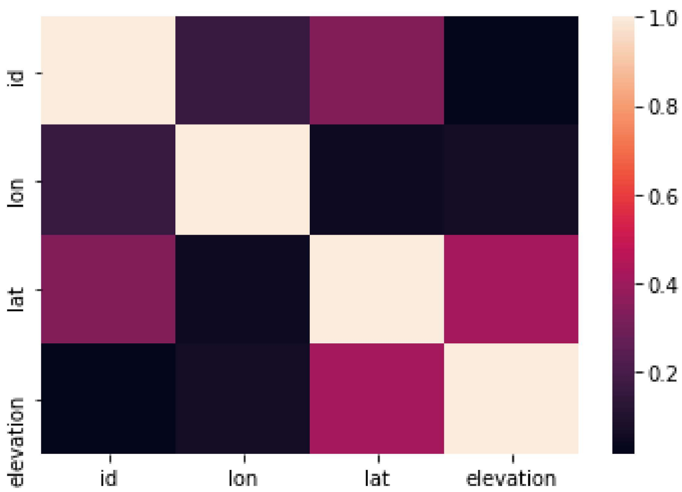
In [5]:
```
df1=df1.drop(["name","address"],axis=1)
```

In [6]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 24 entries, 0 to 23
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   id         24 non-null     int64  
 1   lon        24 non-null     float64
 2   lat        24 non-null     float64
 3   elevation  24 non-null     int64  
dtypes: float64(2), int64(2)
memory usage: 960.0 bytes
```

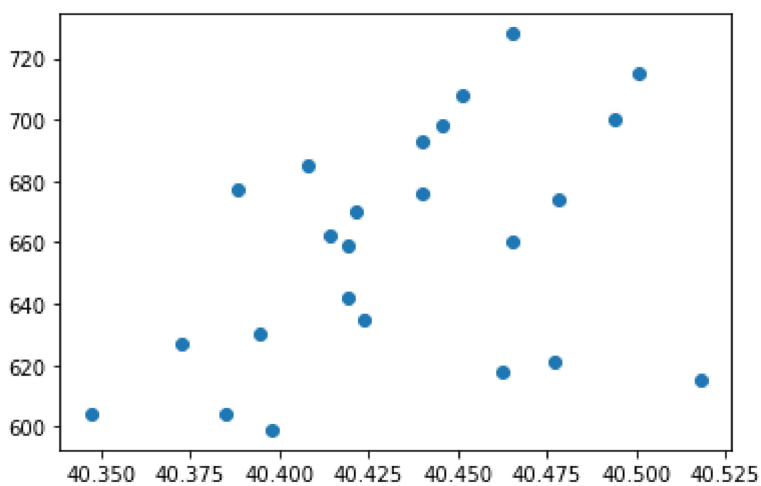
In [7]:
```
sns.heatmap(df1.corr())
```

Out[7]: <AxesSubplot:>



In [8]:
```
plt.plot(df1["lat"],df1["elevation"],"o")
```

Out[8]: [<matplotlib.lines.Line2D at 0x2a1362e2fd0>]



In [9]:
```
x=df1.drop(["elevation"],axis=1)
y=df1["elevation"]
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

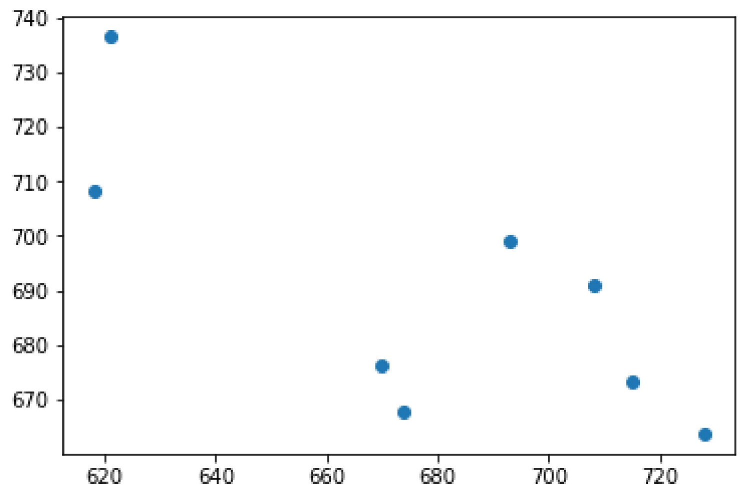
LinearRegression

In [10]:
```
li=LinearRegression()
li.fit(x_train,y_train)
```

Out[10]:
```
LinearRegression()
```

In [11]:
```
prediction=li.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[11]:
```
<matplotlib.collections.PathCollection at 0x2a1369f0820>
```



In [12]:
```
lis=li.score(x_test,y_test)
```

In [13]:
```
df1["lat"].value_counts()
```

Out[13]:
```
40.423853    1
40.462531    1
40.347139    1
40.518058    1
40.419356    1
40.388153    1
40.445544    1
40.398114    1
40.414444    1
40.384964    1
40.451475    1
40.372933    1
40.465572    1
40.394781    1
40.421564    1
40.407947    1
40.478228    1
40.476928    1
40.465250    1
40.494208    1
40.439897    1
40.419208    1
40.440047    1
40.500589    1
Name: lat, dtype: int64
```

In [14]:
```
df1.loc[df1["lat"]<40.44,"lat"]=1
df1.loc[df1["lat"]>1.40,"lat"]=2
df1["lat"].value_counts()
```

Out[14]:
```
1.0    13
2.0    11
Name: lat, dtype: int64
```

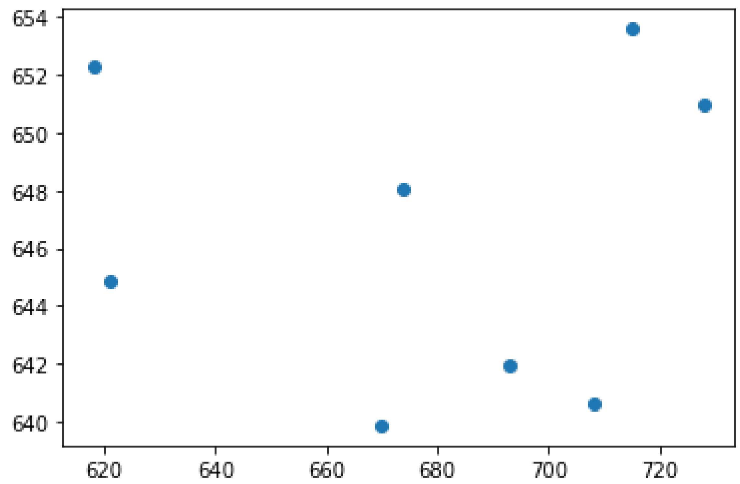
Lasso

In [15]:
```
la=Lasso(alpha=5)
la.fit(x_train,y_train)
```

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

In [16]:
```
prediction1=la.predict(x_test)
plt.scatter(y_test,prediction1)
```

Out[16]: <matplotlib.collections.PathCollection at 0x2a136a69250>



In [17]:
```
las=la.score(x_test,y_test)
```

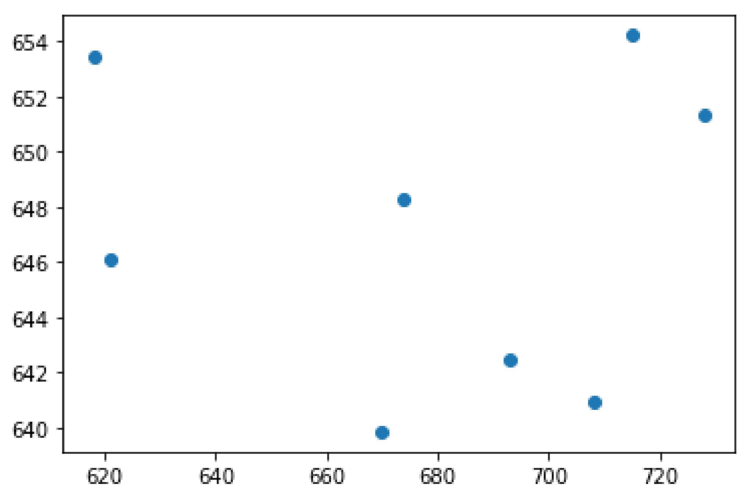
Ridge

In [18]:
```
rr=Ridge(alpha=1)
rr.fit(x_train,y_train)
```

Out[18]: Ridge(alpha=1)

In [19]:
```
prediction2=rr.predict(x_test)
plt.scatter(y_test,prediction2)
```

Out[19]: <matplotlib.collections.PathCollection at 0x2a136abe8b0>



In [20]:
```
rrs=rr.score(x_test,y_test)
```

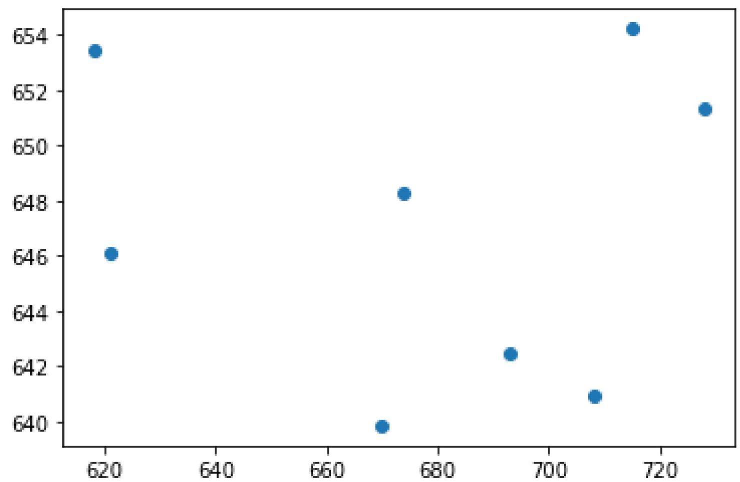
Elastic Net

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

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

In [22]:
```
prediction2=rr.predict(x_test)
plt.scatter(y_test,prediction2)
```

Out[22]:
```
<matplotlib.collections.PathCollection at 0x2a136a157c0>
```



In [23]:
```
ens=en.score(x_test,y_test)
```

LogisticRegression

In [24]:
```
g={"lat":{1.0:"Low",2.0:"High"}}
df1=df1.replace(g)
df1["lat"].value_counts()
```

Out[24]:
```
Low     13
High    11
Name: lat, dtype: int64
```

In [25]:
```
x=df1.drop(["lat"],axis=1)
y=df1["lat"]
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

In [26]:
```
lo=LogisticRegression()
lo.fit(x_train,y_train)
```

Out[26]: LogisticRegression()

In [27]:
```
prediction3=lo.predict(x_test)
plt.scatter(y_test,prediction3)
```

Out[27]: <matplotlib.collections.PathCollection at 0x2a136b5a1f0>

In [28]:
```
los=lo.score(x_test,y_test)
```

Random Forest

In [29]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
```

In [30]:
```
g1={"lat":{"Low":0,"High":1}}
df1=df1.replace(g1)
```

In [31]:
```
x=df1.drop(["lat"],axis=1)
y=df1["lat"]
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

In [32]:
```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

Out[32]: RandomForestClassifier()

In [33]:
```
parameter={
    'max_depth':[1,2,4,5,6],
    'min_samples_leaf':[5,10,15,20,25],
    'n_estimators':[10,20,30,40,50]
}
```

In [34]:
```
grid_search=GridSearchCV(estimator=rfc,param_grid=parameter,cv=2,scoring="accu
grid_search.fit(x_train,y_train)
```

Out[34]:
```
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')
```

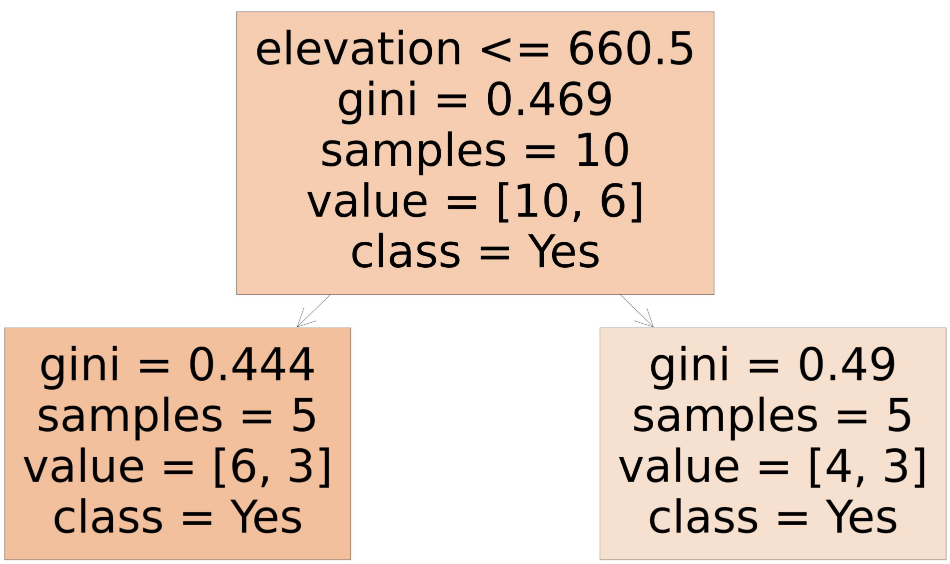
In [35]:
```
rfcs=grid_search.best_score_
```

In [36]:
```
rfc_best=grid_search.best_estimator_
```

In [37]:
```
from sklearn.tree import plot_tree

plt.figure(figsize=(80,40))
plot_tree(rfc_best.estimators_[5],feature_names=x.columns,class_names=['Yes',"
```

Out[37]:
```
[Text(2232.0, 1630.8000000000002, 'elevation <= 660.5\ngini = 0.469\nsamples
= 10\nvalue = [10, 6]\nclass = Yes'),
 Text(1116.0, 543.5999999999999, 'gini = 0.444\nsamples = 5\nvalue = [6, 3]\n
class = Yes'),
 Text(3348.0, 543.5999999999999, 'gini = 0.49\nsamples = 5\nvalue = [4, 3]\nc
lass = Yes')]
```



Best Model is Random Forest

In [ ]: