```
In [29]: import pandas as pd
          import pickle
In [35]: data=pd.read csv("/home/manu/Desktop/online/fiat500.csv")
In [36]: data.head()
Out[36]:
             ID model engine_power age_in_days
                                                 km previous_owners
                                                                                 lon price
                                                                         lat
          0 1 lounge
                                51
                                          882
                                               25000
                                                                 1 44.907242
                                                                             8.611560 8900
              2
                                51
                                         1186
                                               32500
                                                                 1 45.666359 12.241890 8800
                   pop
              3
                                74
                                         4658 142228
                                                                 1 45.503300 11.417840 4200
                 sport
                lounge
                                51
                                         2739
                                             160000
                                                                 1 40.633171 17.634609 6000
                               73
                                         3074 106880
                                                                 1 41.903221 12.495650 5700
           4 5
                   pop
In [32]: #data.describe()
          list(data)
Out[32]: ['ID',
            'model',
            'engine power',
            'age in days',
            'km',
            'previous owners',
           'lat',
            'lon',
           'price']
In [33]: data1['model'] = data['model'].map({'lounge':1,'pop':2,'sport':3})
```

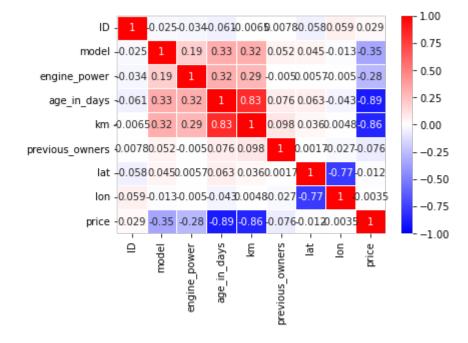
In [38]: cor=data1.corr() cor

Out[38]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon	price
ID	1.000000	-0.024740	-0.034059	-0.060753	-0.006537	0.007803	-0.058207	0.058941	0.028516
model	-0.024740	1.000000	0.189906	0.326508	0.319580	0.052480	0.044901	-0.013200	-0.349885
engine_power	-0.034059	0.189906	1.000000	0.319190	0.285495	-0.005030	0.005721	-0.005032	-0.277235
age_in_days	-0.060753	0.326508	0.319190	1.000000	0.833890	0.075775	0.062982	-0.042667	-0.893328
km	-0.006537	0.319580	0.285495	0.833890	1.000000	0.097539	0.035519	0.004839	-0.859373
previous_owners	0.007803	0.052480	-0.005030	0.075775	0.097539	1.000000	0.001697	-0.026836	-0.076274
lat	-0.058207	0.044901	0.005721	0.062982	0.035519	0.001697	1.000000	-0.766646	-0.011733
lon	0.058941	-0.013200	-0.005032	-0.042667	0.004839	-0.026836	-0.766646	1.000000	-0.003541
price	0.028516	-0.349885	-0.277235	-0.893328	-0.859373	-0.076274	-0.011733	-0.003541	1.000000

In [40]: import seaborn as sns
sns.heatmap(cor,vmax=1,vmin=-1,annot=True,linewidths=.5,cmap='bwr')

Out[40]: <AxesSubplot:>



In [5]: data1=data.drop(['model'],axis=1)

Out[28]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon	price
960	961	pop	51	4414	201000	1	45.141140	9.108080	2500
1330	1331	lounge	51	4627	171150	1	45.830688	12.033340	2900
268	269	lounge	51	4383	135762	1	43.879860	10.782810	3390
928	929	рор	51	4627	148000	1	45.356602	9.203450	3500
935	936	pop	73	4658	165000	2	45.584091	9.270960	3600
745	746	lounge	51	425	11416	1	41.903221	12.495650	11000
272	273	lounge	51	366	14816	2	38.122070	13.361120	11000
154	155	lounge	51	701	21580	1	41.125870	16.866659	11090
491	492	рор	51	670	9000	1	44.988739	9.010500	11090
675	676	lounge	51	487	17800	1	45.351528	10.844090	11100

1538 rows × 9 columns

In [6]: cor=data1.corr()
cor

Out[6]:

	ID	engine_power	age_in_days	km	previous_owners	lat	lon	price
ID	1.000000	-0.034059	-0.060753	-0.006537	0.007803	-0.058207	0.058941	0.028516
engine_power	-0.034059	1.000000	0.319190	0.285495	-0.005030	0.005721	-0.005032	-0.277235
age_in_days	-0.060753	0.319190	1.000000	0.833890	0.075775	0.062982	-0.042667	-0.893328
km	-0.006537	0.285495	0.833890	1.000000	0.097539	0.035519	0.004839	-0.859373
previous_owners	0.007803	-0.005030	0.075775	0.097539	1.000000	0.001697	-0.026836	-0.076274
lat	-0.058207	0.005721	0.062982	0.035519	0.001697	1.000000	-0.766646	-0.011733
lon	0.058941	-0.005032	-0.042667	0.004839	-0.026836	-0.766646	1.000000	-0.003541
price	0.028516	-0.277235	-0.893328	-0.859373	-0.076274	-0.011733	-0.003541	1.000000

In [7]: data2=data.loc[(data.model=='lounge')&(data.previous\_owners==1)]

```
In [12]: #data['previous owners'].unique()
         AttributeError
                                                    Traceback (most recent call last)
         <ipython-input-12-5097fa9a2cba> in <module>
               1 #data['previous owners'].unique()
         ----> 2 data['price'].sort()
         ~/.local/lib/python3.8/site-packages/pandas/core/generic.py in getattr (self, name)
            5485
                         ):
            5486
                              return self[name]
                         return object. getattribute (self, name)
         -> 5487
            5488
            5489
                     def setattr (self, name: str, value) -> None:
         AttributeError: 'Series' object has no attribute 'sort'
 In [6]: list(data.columns)
 Out[6]: ['ID',
           'model',
           'engine power',
           'age in days',
           'km',
          'previous owners',
          'lat',
          'lon',
           'price']
```

```
In [8]: data.groupby(['model']).count()
 Out[8]:
                    ID engine_power age_in_days
                                               km previous_owners
                                                                   lat Ion price
           model
           lounge 1094
                              1094
                                         1094 1094
                                                             1094 1094
                                                                       1094
                                                                            1094
                  358
                               358
                                          358
                                               358
                                                              358
                                                                   358
                                                                        358
                                                                             358
             pop
                                                                              86
            sport
                   86
                                86
                                           86
                                                86
                                                              86
                                                                   86
                                                                         86
 In [9]: data.groupby(['previous owners']).count()
 Out[9]:
                           ID model engine_power age_in_days
                                                             km
                                                                   lat
                                                                       Ion price
           previous_owners
                       1 1389
                               1389
                                            1389
                                                       1389 1389
                                                                 1389
                                                                      1389
                                                                            1389
                          117
                                 117
                                             117
                                                        117
                                                             117
                                                                  117
                                                                       117
                                                                            117
                           23
                                 23
                                              23
                                                         23
                                                              23
                                                                   23
                                                                        23
                                                                              23
                            9
                                  9
                                                          9
                                                                    9
                                                                         9
                                                                              9
In [10]: data['model'].unique()
Out[10]: array(['lounge', 'pop', 'sport'], dtype=object)
In [11]: data1=data.drop(['lat','ID'],axis=1)
In [12]: #2-3
          data2=data1.drop('lon',axis=1)
In [13]: #
          data2['model'] = data['model'].map({'lounge':1,'pop':2,'sport':3})
```

In [14]: data2

Out[14]:

	model	engine_power	age_in_days	km	previous_owners	price
0	1	51	882	25000	1	8900
1	2	51	1186	32500	1	8800
2	3	74	4658	142228	1	4200
3	1	51	2739	160000	1	6000
4	2	73	3074	106880	1	5700
1533	3	51	3712	115280	1	5200
1534	1	74	3835	112000	1	4600
1535	2	51	2223	60457	1	7500
1536	1	51	2557	80750	1	5990
1537	2	51	1766	54276	1	7900

1538 rows × 6 columns

In [16]: #data2.groupby(['previous\_owners'])

In [17]: data2

Out[17]:

	model	engine_power	age_in_days	km	previous_owners	price
0	1	51	882	25000	1	8900
1	2	51	1186	32500	1	8800
2	3	74	4658	142228	1	4200
3	1	51	2739	160000	1	6000
4	2	73	3074	106880	1	5700
1533	3	51	3712	115280	1	5200
1534	1	74	3835	112000	1	4600
1535	2	51	2223	60457	1	7500
1536	1	51	2557	80750	1	5990
1537	2	51	1766	54276	1	7900

1538 rows × 6 columns

In [14]: y=data2['price'] X=data2.drop('price',axis=1)

```
In [15]: y
Out[15]: 0
                 8900
                 8800
                 4200
         3
                 6000
                 5700
         1533
                 5200
         1534
                 4600
         1535
                 7500
         1536
                 5990
         1537
                 7900
         Name: price, Length: 1538, dtype: int64
In [16]: from sklearn.model selection import train test split
         X train, X test, y train, y test = train test split(X, y, test size=0.33, random state=42) #0.67 data will be
In [17]: X test.head(5)
Out[17]:
```

	model	engine_power	age_in_days	km	previous_owners
481	2	51	3197	120000	2
76	2	62	2101	103000	1
1502	1	51	670	32473	1
669	1	51	913	29000	1
1409	1	51	762	18800	1

In [18]: X train.shape

Out[18]: (1030, 5)

```
In [19]: y train
Out[19]: 527
                  9990
         129
                  9500
         602
                  7590
         331
                  8750
         323
                  9100
                  . . .
         1130
                 10990
         1294
                  9800
         860
                  5500
         1459
                  9990
         1126
                  8900
         Name: price, Length: 1030, dtype: int64
In [20]:
         from sklearn.linear model import LinearRegression
         reg = LinearRegression() #creating object of LinearRegression
         reg.fit(X train,y train) #training and fitting LR object using training data
Out[20]: LinearRegression()
In [21]: #X test=[[1,51,1000,28800,3],[1,51,780,18800,1]]
In [22]: #above line to actual
In [23]: ypred=reg.predict(X test)
```

```
In [24]: ypred
Out[24]: array([ 5994.51703157,
                                  7263.58726658,
                                                   9841.90754881,
                                                                   9699.31627673,
                                  9630.58715835,
                 10014.19892635,
                                                   9649.4499026 , 10092.9819664 ,
                 9879.19498711,
                                  9329.19347948, 10407.2964056,
                                                                   7716.91706011,
                  7682.89152522,
                                  6673.95810983.
                                                   9639.42618839, 10346.53679153,
                  9366.53363673,
                                  7707.90063494,
                                                   4727.33552438, 10428.17092937,
                                                                   9927.58506055,
                 10359.87663878, 10364.84674179,
                                                   7680.16157493,
                  7127.7284177 ,
                                  9097.51161986,
                                                   4929.31229715,
                                                                    6940.60225317,
                  7794.35120591,
                                  9600.43942019.
                                                   7319.85877519,
                                                                    5224.05298205,
                  5559.52039134,
                                  5201.35403287,
                                                   8960.11762682,
                                                                   5659.72968338,
                                  8255.93615893,
                  9915.79926869,
                                                   6270.40332834,
                                                                   8556.73835062,
                  9749.72882426,
                                  6873.76758364,
                                                   8951.72659758, 10301.95669828,
                  8674.89268564, 10301.93257222,
                                                   9165.73586068,
                                                                   8846.92420399,
                                  9052.4031418 ,
                                                   9390.75738772, 10267.3912561
                  7044.68964545.
                 10046.90924744,
                                  6855.71260655,
                                                   9761.93338967,
                                                                    9450.05744337,
                  9274.98388541, 10416.00474283,
                                                   9771.10646661,
                                                                   7302.96566423,
                                  6996.96553454,
                                                                    7134.21944391,
                 10082.61483093,
                                                   9829.40534825,
                  6407.26222178,
                                                                   8614.84049875,
                                  9971.82132188,
                                                   9757.01618446,
                                  6489.24658616,
                                                   7752.65456507,
                  8437.92452169,
                                                                    6626.60510856,
                  8329.88998217, 10412.00324329,
                                                   7342.77348105
                                                                    8543.63624413,
In [25]: filename='pricemodel'
         pickle.dump(reg,open(filename,'wb'))
In [ ]:
In [26]: #savedmodel=pickle.load(open(filename, 'rb'))
         #X test=[[1,75,1062,8000,1]]
         #savedmodel.predict(X test)
In [27]: from sklearn.metrics import r2 score
         r2 score(y test,ypred)
Out[27]: 0.8383895235218546
```

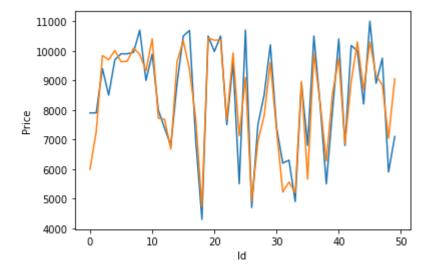
```
In [ ]:
In [28]: from sklearn.metrics import mean squared error #calculating MSE
         mean squared error(ypred,y test)
Out[28]: 593504.2888137395
In [29]: #from sklearn.metrics import accuracy score
         #accuracy score(y test,ypred)
In [35]: #Results= pd.DataFrame(columns=['Actual', 'Predicted'])
         #Results['Actual']=y test
         Results= pd.DataFrame(columns=['Price', 'Predicted'])
         Results['Price']=y test
         Results['Predicted']=ypred
         #Results['km']=X test['km']
         Results=Results.reset index()
         Results['Id']=Results.index
         Results.head(10)
```

Out[35]:

	index	Price	Predicted	ld
0	481	7900	5994.517032	0
1	76	7900	7263.587267	1
2	1502	9400	9841.907549	2
3	669	8500	9699.316277	3
4	1409	9700	10014.198926	4
5	1414	9900	9630.587158	5
6	1089	9900	9649.449903	6
7	1507	9950	10092.981966	7
8	970	10700	9879.194987	8
9	1198	8999	9329.193479	9

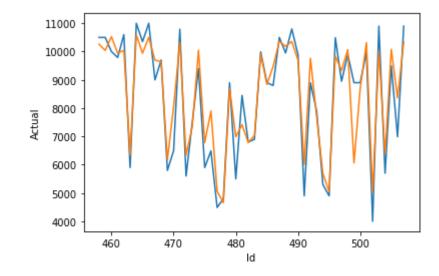


## Out[37]: []



```
In [32]: sns.lineplot(x='Id',y='Actual',data=Results.tail(50))
sns.lineplot(x='Id',y='Predicted',data=Results.tail(50))
plt.plot()
```

Out[32]: []



```
In [ ]:
In [ ]:
```

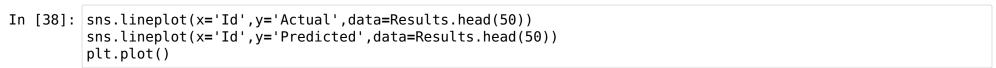
In [30]: # ridge regression

```
In [31]: from sklearn.model selection import GridSearchCV
         from sklearn.linear model import Ridge
         alpha = [1e-15, 1e-10, 1e-8, 1e-4, 1e-3,1e-2, 1, 5, 10, 20,30]
         ridge = Ridge()
         parameters = {'alpha': alpha}
         ridge regressor = GridSearchCV(ridge, parameters)
         ridge regressor.fit(X train, y train)
Out[31]: GridSearchCV(estimator=Ridge(),
                      param grid={'alpha': [1e-15, 1e-10, 1e-08, 0.0001, 0.001, 0.01, 1,
                                            5, 10, 20, 30]})
In [32]: ridge regressor.best params
Out[32]: {'alpha': 30}
In [33]: #X train=[2]
In [34]: | ridge=Ridge(alpha=30)
         ridge.fit(X train,y train)
         y pred ridge=ridge.predict(X_test)
In [35]: Ridge Error=mean squared error(y pred ridge,y test)
         Ridge Error
Out[35]: 590569.9121697355
In [36]: from sklearn.metrics import r2 score
         r2 score(y test,y pred ridge)
Out[36]: 0.8391885506165899
```

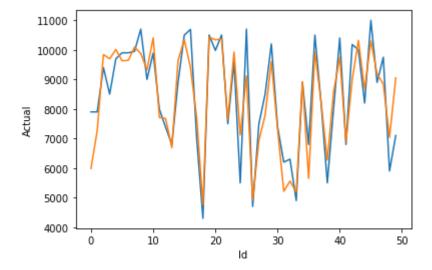
In [37]: Results= pd.DataFrame(columns=['Actual','Predicted'])
 Results['Actual']=y\_test
 Results['Predicted']=y\_pred\_ridge
 #Results['km']=X\_test['km']
 Results=Results.reset\_index()
 Results['Id']=Results.index
 Results.head(10)

## Out[37]:

	index	Actual	Predicted	ld
0	481	7900	5987.682984	0
1	76	7900	7272.490419	1
2	1502	9400	9839.847697	2
3	669	8500	9696.775405	3
4	1409	9700	10012.040862	4
5	1414	9900	9628.286853	5
6	1089	9900	9646.945160	6
7	1507	9950	10090.960592	7
8	970	10700	9877.094341	8
9	1198	8999	9326.088982	9

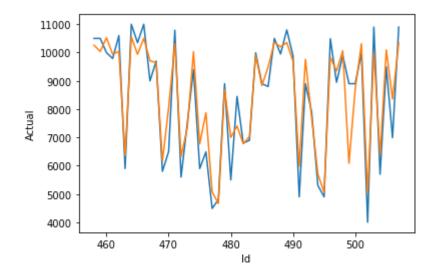


Out[38]: []



```
In [39]: sns.lineplot(x='Id',y='Actual',data=Results.tail(50))
sns.lineplot(x='Id',y='Predicted',data=Results.tail(50))
plt.plot()
```

Out[39]: []



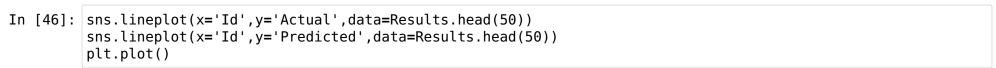
In [40]: #elastic

```
In [41]: from sklearn.linear model import ElasticNet
         elastic = ElasticNet()
         parameters = {'alpha': [1e-15, 1e-10, 1e-8, 1e-4, 1e-3,1e-2, 1, 5, 10, 20]}
         elastic regressor = GridSearchCV(elastic, parameters)
         elastic regressor.fit(X train, y train)
         /home/manu/.local/lib/python3.8/site-packages/sklearn/linear model/ coordinate descent.py:647: Convergence
         Warning: Objective did not converge. You might want to increase the number of iterations, check the scale
         of the features or consider increasing regularisation. Duality gap: 2.379e+08, tolerance: 3.149e+05
           model = cd fast.enet coordinate descent(
         /home/manu/.local/lib/python3.8/site-packages/sklearn/linear model/ coordinate descent.py:647: Convergence
         Warning: Objective did not converge. You might want to increase the number of iterations, check the scale
         of the features or consider increasing regularisation. Duality gap: 2.378e+08, tolerance: 3.129e+05
           model = cd fast.enet coordinate descent(
         /home/manu/.local/lib/python3.8/site-packages/sklearn/linear model/ coordinate descent.py:647: Convergence
         Warning: Objective did not converge. You might want to increase the number of iterations, check the scale
         of the features or consider increasing regularisation. Duality gap: 2.443e+08, tolerance: 3.204e+05
           model = cd fast.enet coordinate descent(
         /home/manu/.local/lib/python3.8/site-packages/sklearn/linear model/ coordinate descent.py:647: Convergence
         Warning: Objective did not converge. You might want to increase the number of iterations, check the scale
         of the features or consider increasing regularisation. Duality gap: 2.433e+08, tolerance: 3.065e+05
           model = cd fast.enet coordinate descent(
         /home/manu/.local/lib/python3.8/site-packages/sklearn/linear model/ coordinate descent.py:647: Convergence
         Warning: Objective did not converge. You might want to increase the number of iterations, check the scale
         of the features or consider increasing regularisation. Duality gap: 2.493e+08, tolerance: 3.114e+05
           model = cd fast.enet coordinate descent(
         /home/manu/.local/lib/python3.8/site-packages/sklearn/linear model/ coordinate descent.py:647: Convergence
         Warning: Objective did not converge. You might want to increase the number of iterations, check the scale
         of the features or consider increasing regularisation. Duality gap: 2.318e+08, tolerance: 3.149e+05
           model = cd fast.enet coordinate descent(
         /home/manu/.local/lib/python3.8/site-packages/sklearn/linear model/ coordinate descent.py:647: Convergence
         Warning: Objective did not converge. You might want to increase the number of iterations, check the scale
         of the features or consider increasing regularisation. Duality gap: 2.316e+08, tolerance: 3.129e+05
           model = cd fast.enet coordinate descent(
         /home/manu/.local/lib/python3.8/site-packages/sklearn/linear model/ coordinate descent.py:647: Convergence
         Warning: Objective did not converge. You might want to increase the number of iterations, check the scale
```

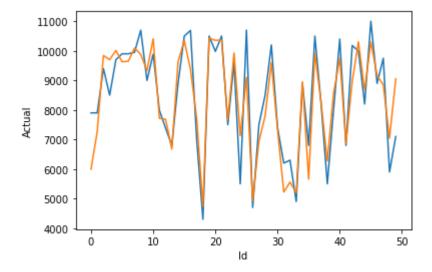
In [45]: Results= pd.DataFrame(columns=['Actual','Predicted'])
 Results['Actual']=y\_test
 Results['Predicted']=y\_pred\_elastic
 #Results['km']=X\_test['km']
 Results=Results.reset\_index()
 Results['Id']=Results.index
 Results.head(10)

## Out[45]:

	index	Actual	Predicted	ld
0	481	7900	5993.053059	0
1	76	7900	7265.275818	1
2	1502	9400	9841.546147	2
3	669	8500	9698.864284	3
4	1409	9700	10013.815854	4
5	1414	9900	9630.182678	5
6	1089	9900	9649.005668	6
7	1507	9950	10092.624034	7
8	970	10700	9878.825124	8
9	1198	8999	9328.638538	9



Out[46]: []



```
In [47]: from sklearn.model selection import GridSearchCV #GridSearchCV is for parameter tuning
         from sklearn.ensemble import RandomForestRegressor
         reg=RandomForestRegressor()
         n estimators=[25,50,75,100,125,150,175,200] #number of decision trees in the forest, default = 100
         criterion=['mse'] #criteria for choosing nodes default = 'gini'
         max depth=[3,5,10] #maximum number of nodes in a tree default = None (it will go till all possible nodes)
         parameters={'n estimators': n estimators, 'criterion':criterion, 'max depth':max depth}
         RFC reg = GridSearchCV(reg, parameters)
         RFC req.fit(X train,y train)
         /home/manu/.local/lib/python3.8/site-packages/sklearn/ensemble/ forest.py:396: FutureWarning: Criterion 'm
         se' was deprecated in v1.0 and will be removed in version 1.2. Use `criterion='squared error'` which is eq
         uivalent.
           warn(
         /home/manu/.local/lib/python3.8/site-packages/sklearn/ensemble/ forest.py:396: FutureWarning: Criterion 'm
         se' was deprecated in v1.0 and will be removed in version 1.2. Use `criterion='squared error'` which is eq
         uivalent.
           warn(
         /home/manu/.local/lib/python3.8/site-packages/sklearn/ensemble/ forest.py:396: FutureWarning: Criterion 'm
         se' was deprecated in v1.0 and will be removed in version 1.2. Use `criterion='squared error'` which is eq
         uivalent.
           warn(
         /home/manu/.local/lib/python3.8/site-packages/sklearn/ensemble/ forest.py:396: FutureWarning: Criterion 'm
         se' was deprecated in v1.0 and will be removed in version 1.2. Use `criterion='squared error'` which is eq
         uivalent.
           warn(
         /home/manu/.local/lib/python3.8/site-packages/sklearn/ensemble/ forest.py:396: FutureWarning: Criterion 'm
         se' was deprecated in v1.0 and will be removed in version 1.2. Use `criterion='squared error'` which is eq
         uivalent.
In [48]: RFC reg.best params
Out[48]: {'criterion': 'mse', 'max depth': 5, 'n estimators': 50}
In [49]: reg=RandomForestRegressor(n estimators=200,criterion='mse',max depth=5)
```

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```
In [50]: req.fit(X train,y train)
         /home/manu/.local/lib/python3.8/site-packages/sklearn/ensemble/ forest.py:396: FutureWarning: Criterion 'm
         se' was deprecated in v1.0 and will be removed in version 1.2. Use `criterion='squared error'` which is eq
         uivalent.
           warn(
Out[50]: RandomForestRegressor(criterion='mse', max depth=5, n estimators=200)
In [51]: y pred=req.predict(X test)
In [52]: y pred
Out[52]: array([ 6031.71790936,
                                  7116.79209995,
                                                  9786.74546584,
                                                                   9744.44315157,
                                  9629.47656637,
                                                  9725.30622265, 10083.32622577,
                 10033.01250991,
                  9827.68047728,
                                  9330.60138407, 10367.59658403, 7776.14165353,
                  7384.25358129,
                                  7057.94718176,
                                                  9573.13965395, 10437.15931229,
                  9678.2146621 ,
                                  7890.07808152.
                                                  4921.57201206, 10371.87480021,
                10149.95253005, 10438.95859904,
                                                  7411.75186534,
                                                                   9776.33154619,
                  7363.96619937,
                                  9150.34665672,
                                                  4884.67714928,
                                                                   7090.87523082,
                  7704.96174077,
                                  9569.82401695.
                                                  7110.47574762,
                                                                   5086.30321792,
                  5488.87441171,
                                  5012.2235297 ,
                                                  8641.03163094,
                                                                   5482.95639145,
                 10169.37188844,
                                  7404.16352977,
                                                  6476.53303213,
                                                                   8907.65724998,
                                  6801.17841555,
                                                  9327.81059815, 10327.15347559,
                  9769.02088768,
                  8145.43902011, 10441.5870099 ,
                                                   9314.92162897,
                                                                   8780.43960011,
                  6440.29706047,
                                                  9511.33728003, 10381.25986813,
                                  8844.26830125,
                 10077.86068832,
                                  7106.74880617,
                                                  9604.98221304,
                                                                   9520.27757383,
                  9633.45262024, 10433.98572582,
                                                   9759.20637029,
                                                                   7044.17220871,
                                  7123.88648829,
                                                  9761.37201648,
                                                                   7118.30123321,
                 10076.01099585,
                                  9705.80426611,
                                                  9776.2797593
                                                                   9031.53378045,
                  5816.32448799,
                  8591.03060791,
                                  6255.9528851 ,
                                                  7696.31655256,
                                                                   7126.46326613,
                  8672.93278744, 10393.24148915,
                                                   7102.24576057,
                                                                   8474.71360635,
In [53]: from sklearn.metrics import r2 score
         r2 score(y test,y pred)
Out[53]: 0.8458159519560708
```

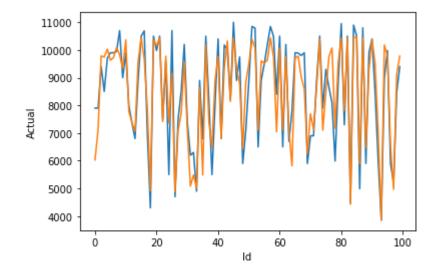
In [54]: Results= pd.DataFrame(columns=['Actual', 'Predicted'])
 Results['Actual']=y\_test
 Results['Predicted']=y\_pred
 #Results['km']=X\_test['km']
 Results=Results.reset\_index()
 Results['Id']=Results.index
 Results.head(10)

## Out[54]:

	index	Actual	Predicted	ld
0	481	7900	6031.717909	0
1	76	7900	7116.792100	1
2	1502	9400	9786.745466	2
3	669	8500	9744.443152	3
4	1409	9700	10033.012510	4
5	1414	9900	9629.476566	5
6	1089	9900	9725.306223	6
7	1507	9950	10083.326226	7
8	970	10700	9827.680477	8
9	1198	8999	9330.601384	9

```
In [55]: sns.lineplot(x='Id',y='Actual',data=Results.head(100))
sns.lineplot(x='Id',y='Predicted',data=Results.head(100))
plt.plot()
```

Out[55]: []



```
In [ ]:

In [ ]:
```