

1. Treat the data to replace all missing data with median/ mode (whichever applicable), and remove all rows with outliers in column: 'Price'

```
2. import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

df = pd.read_csv('Dataset_Day6.csv')
print(df.info())
missing_value_percent = df.isna().sum() /
len(df) * 100
print(missing_value_percent)
df["Bathroom"].fillna(df["Bathroom"].median(),
inplace=True)
df["Furnishing"].fillna(df["Furnishing"].mode()
[0], inplace=True) # mode() because this is
categorical data
df["Parking"].fillna(df["Parking"].median(),
inplace=True)
df["Type"].fillna(df["Type"].mode()[0],
inplace=True)
print(df.info())
print(df[["Price"]])
OutlierData = pd.DataFrame()
temp = df[["Price"]]
for col in ["Price"]:
    Q1 = temp[col].quantile(0.25) # Gives 25th
Percentile or Q1
    Q3 = temp[col].quantile(0.75) # Gives 75th
Percentile or Q3

    IQR = Q3 - Q1

    UpperBound = Q3 + 1.5 * IQR
    LowerBound = Q1 - 1.5 * IQR

    OutlierData[col] = temp[col][(temp[col] <
LowerBound) | (temp[col] > UpperBound)]
    df_OutlierFree = df.drop(OutlierData.index,
axis=0)
print(OutlierData.index)
print(len(OutlierData))
```

```

print(df_OutlierFree[["Price"]])
print(df_OutlierFree[["Bathroom"]])
df_OutlierFree.info()

```

```

3 RangeIndex: 1259 entries, 0 to 1258
4 Data columns (total 9 columns):
5 #   Column      Non-Null Count  Dtype
6 ---  ---
7 0   Area        1259 non-null   float64
8 1   BHK         1259 non-null   int64
9 2   Bathroom    1257 non-null   float64
10 3   Furnishing  1254 non-null   object
11 4   Parking     1226 non-null   float64
12 5   Price       1259 non-null   int64
13 6   Status      1259 non-null   object
14 7   Transaction 1259 non-null   object
15 8   Type        1254 non-null   object
16 dtypes: float64(3), int64(2), object(4)
17 memory usage: 88.7+ KB
18 None
19 Area          0.000000
20 BHK           0.000000
21 Bathroom      0.158856
22 Furnishing    0.397141
23 Parking       2.621128
24 Price         0.000000
25 Status        0.000000
26 Transaction   0.000000
27 Type          0.397141
28 dtype: float64
29 <class 'pandas.core.frame.DataFrame'>
30 RangeIndex: 1259 entries, 0 to 1258
31 Data columns (total 9 columns):
32 #   Column      Non-Null Count  Dtype
33 ---  ---
34 0   Area        1259 non-null   float64
35 1   BHK         1259 non-null   int64
36 2   Bathroom    1259 non-null   float64
37 3   Furnishing  1259 non-null   object
38 4   Parking     1259 non-null   float64
39 5   Price       1259 non-null   int64
40 6   Status      1259 non-null   object
41 7   Transaction 1259 non-null   object
42 8   Type        1259 non-null   object
43 dtypes: float64(3), int64(2), object(4)
44 memory usage: 88.7+ KB
45 None
46      Price
47 0      6500000
48 1      5000000
49 2     15500000
50 3      4200000
51 4      6200000
52 ...

```

```

57 [1257 rows x 1 columns]
60 Index([ 50, 57, 94, 109, 209, 211, 215, 222, 225, 228,
61 ...
62 1213, 1216, 1219, 1221, 1223, 1224, 1226, 1227, 1232, 1245],
63 dtype='int64', length=104)
64 104
65 Price
66 0 6500000
67 1 5000000
68 2 15500000
69 3 4200000
70 4 6200000
71 ... ...
72 1254 55000000
73 1255 12500000
74 1256 17500000
75 1257 11500000
76 1258 18500000
77
78 [1155 rows x 1 columns]
79 Bathroom
80 0 2.0
81 1 2.0
82 2 2.0
83 3 2.0
84 4 2.0
85 ... ...
86 1254 5.0
87 1255 2.0
88 1256 3.0
89 1257 2.0
90 1258 3.0
91
92 [1155 rows x 1 columns]
93 <class 'pandas.core.frame.DataFrame'>
94 Index: 1155 entries, 0 to 1258
95 Data columns (total 9 columns):
96 # Column Non-Null Count Dtype
97 ---
98 0 Area 1155 non-null float64
99 1 BHK 1155 non-null int64
100 2 Bathroom 1155 non-null float64
101 3 Furnishing 1155 non-null object
102 4 Parking 1155 non-null float64
103 5 Price 1155 non-null int64
104 6 Status 1155 non-null object
105 7 Transaction 1155 non-null object
106 8 Type 1155 non-null object
107 dtypes: float64(3), int64(2), object(4)
108 memory usage: 90.2+ KB
109
110 Process finished with exit code 0

```

2. Use One Hot Encoding to encode all character variables.

```

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

```

```

import seaborn as sns

df = pd.read_csv('Dataset_Day6.csv')
print(df.info())
temp = df[["Furnishing", "Status", "Transaction",
"Type"]]
# this function converts all categorical variables
in the dataframe to one hot encoded variables
new_encoded_data = pd.get_dummies(temp)
print(new_encoded_data)

```

```

1 C:\Users\tejas\PycharmProjects\pythonProject\venv\Scripts\python.exe C:\Users\
  tejas\PycharmProjects\pythonProject\START\Day6Q2.py
2 <class 'pandas.core.frame.DataFrame'>
3 RangeIndex: 1259 entries, 0 to 1258
4 Data columns (total 9 columns):
5 #   Column      Non-Null Count  Dtype
6 ---  ---
7 0   Area        1259 non-null   float64
8 1   BHK         1259 non-null   int64
9 2   Bathroom    1257 non-null   float64
10 3   Furnishing  1254 non-null   object
11 4   Parking     1226 non-null   float64
12 5   Price       1259 non-null   int64
13 6   Status      1259 non-null   object
14 7   Transaction 1259 non-null   object
15 8   Type        1254 non-null   object
16 dtypes: float64(3), int64(2), object(4)
17 memory usage: 88.7+ KB
18 None
19      Furnishing_Furnished  ...  Type_Builder_Floor
20 0                        False  ...                True
21 1                        False  ...                False
22 2                        True   ...                False
23 3                        False  ...                True
24 4                        False  ...                True
25 ...                    ...   ...
26 1254                    False  ...                True
27 1255                    False  ...                True
28 1256                    False  ...                True
29 1257                    False  ...                True
30 1258                    False  ...                True
31
32 [1259 rows x 9 columns]
33
34 Process finished with exit code 0
35

```

3. Split the data into 80% training and 20% testing data. Then, create a multiple linear regression model with target variable as 'Price'.

a. Print the model performance metrics. R2, adjusted R2, MAE

```
2. import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import
LinearRegression
from sklearn.model_selection import
train_test_split
from sklearn.metrics import mean_squared_error,
r2_score, mean_absolute_error

df = pd.read_csv('Dataset_Day6.csv')
print(df.info())
missing_value_percent = df.isna().sum() /
len(df) * 100
print(missing_value_percent)
df["Bathroom"].fillna(df["Bathroom"].median(),
inplace=True)
df["Furnishing"].fillna(df["Furnishing"].mode()
[0], inplace=True) # mode() because this is
categorical data
df["Parking"].fillna(df["Parking"].median(),
inplace=True)
df["Type"].fillna(df["Type"].mode()[0],
inplace=True)
print(df.info())
X = df.drop('Price', axis=1) # all columns
except 'Price'
y = df['Price'] # target Variable
temp = df[["Furnishing", "Status",
"Transaction", "Type"]]
# this function converts all categorical
variables in the dataframe to one hot encoded
variables
new_encoded_data = pd.get_dummies(temp)
# Concatenate encoded categorical variables
with remaining features
X =
```

```
pd.concat([X.select_dtypes(exclude=['object']),
new_encoded_data], axis=1)
X_train, X_test, y_train, y_test =
train_test_split(X, y, test_size=0.2,
random_state=50)
lm = LinearRegression()
lm = lm.fit(X_train, y_train)
y_pred = lm.predict(X_test)
print(lm.coef_) # scale parameter
print(lm.intercept_) # intercept parameter
r2 = r2_score(y_test, y_pred)
adjusted_r2 = 1 - (1 - r2) * (len(y_test) - 1)
/ (len(y_test) - X_test.shape[1] - 1)
mae = mean_absolute_error(y_test, y_pred)
print("R2 Score:", r2)
print("Adjusted R2 Score:", adjusted_r2)
print("Mean Absolute Error (MAE):", mae)
```

```

2 <class 'pandas.core.frame.DataFrame'>
3 RangeIndex: 1259 entries, 0 to 1258
4 Data columns (total 9 columns):
5 #   Column      Non-Null Count  Dtype
6 ---  -
7 0   Area        1259 non-null   float64
8 1   BHK         1259 non-null   int64
9 2   Bathroom    1257 non-null   float64
10 3   Furnishing  1254 non-null   object
11 4   Parking     1226 non-null   float64
12 5   Price       1259 non-null   int64
13 6   Status      1259 non-null   object
14 7   Transaction 1259 non-null   object
15 8   Type        1254 non-null   object
16 dtypes: float64(3), int64(2), object(4)
17 memory usage: 88.7+ KB
18 None
19 Area          0.000000
20 BHK           0.000000
21 Bathroom     0.158856
22 Furnishing    0.397141
23 Parking      2.621128
24 Price        0.000000
25 Status       0.000000
26 Transaction   0.000000
27 Type         0.397141
28 dtype: float64
29 <class 'pandas.core.frame.DataFrame'>
30 RangeIndex: 1259 entries, 0 to 1258
31 Data columns (total 9 columns):
32 #   Column      Non-Null Count  Dtype
33 ---  -
34 0   Area        1259 non-null   float64
35 1   BHK         1259 non-null   int64
36 2   Bathroom    1259 non-null   float64
37 3   Furnishing  1259 non-null   object
38 4   Parking     1259 non-null   float64
39 5   Price       1259 non-null   int64
40 6   Status      1259 non-null   object
41 7   Transaction 1259 non-null   object
42 8   Type        1259 non-null   object
43 dtypes: float64(3), int64(2), object(4)
44 memory usage: 88.7+ KB
45 None
46 [ 5.30984492e+03  4.85967750e+05  1.30622279e+07  1.07695584e+05
47 -1.22844024e+06 -4.84332719e+05  1.71277296e+06  2.34134349e+06
48 -2.34134349e+06  2.41435659e+06 -2.41435659e+06  3.90473960e+05
49 -3.90473960e+05]
50 -18606322.05682992
51 R2 Score: 0.5046575836208773
52 Adjusted R2 Score: 0.47760106507916056
53 Mean Absolute Error (MAE): 10400538.892955128

```

4.Repeat the above process for a Ridge Regression and show from the new evaluation metrics if there is any improvement in the model performance?

```

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import
train_test_split
from sklearn.metrics import mean_squared_error,
r2_score, mean_absolute_error
from sklearn.linear_model import Ridge

df = pd.read_csv('Dataset_Day6.csv')
print(df.info())
missing_value_percent = df.isna().sum() / len(df) *
100
print(missing_value_percent)
df["Bathroom"].fillna(df["Bathroom"].median(),
inplace=True)
df["Furnishing"].fillna(df["Furnishing"].mode()[0],
inplace=True) # mode() because this is categorical
data
df["Parking"].fillna(df["Parking"].median(),
inplace=True)
df["Type"].fillna(df["Type"].mode()[0],
inplace=True)
print(df.info())
X = df.drop('Price', axis=1) # all columns except
'Price'
y = df['Price'] # target Variable
temp = df[["Furnishing", "Status", "Transaction",
"Type"]]
# this function converts all categorical variables
in the dataframe to one hot encoded variables
new_encoded_data = pd.get_dummies(temp)
# Concatenate encoded categorical variables with
remaining features
X = pd.concat([X.select_dtypes(exclude=['object']),
new_encoded_data], axis=1)
X_train, X_test, y_train, y_test =
train_test_split(X, y, test_size=0.2,
random_state=50)

```



```
alpha = [1e-50, 1e-20, 1e-15, 1e-10, 1e-8, 1e-3,
1e-2, 1, 5, 10, 20, 30, 35, 40, 45, 50, 55, 100]
print(alpha)

for param in alpha:
    ridgeModel = Ridge(alpha=param)
    ridgeModel.fit(X_train, y_train)

    y_pred = ridgeModel.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)

    r2 = r2_score(y_test, y_pred)
    print(r2)
    print("alpha = {}".format(param))
    print("mse for above alpha = {}".format(mse))
    best_r2 = 0
    best_alpha = 0
    best_mse = mse

    if r2 > best_r2:
        best_r2 = r2

    if mse < best_mse:
        best_mse = mse
        best_alpha = param

print("Best value of alpha/lambda =
{}".format(best_alpha))
print("MSE for this alpha/lambda =
{}".format(best_mse))
print("Best R square score = {}".format(best_r2))
```

```

1 C:\Users\tejas\PycharmProjects\pythonProject\venv\Scripts\python.exe C:\Users\
  tejas\PycharmProjects\pythonProject\START\Day6Q4.py
2 <class 'pandas.core.frame.DataFrame'>
3 RangeIndex: 1259 entries, 0 to 1258
4 Data columns (total 9 columns):
5 #   Column      Non-Null Count  Dtype
6 ---  -
7 0   Area        1259 non-null   float64
8 1   BHK         1259 non-null   int64
9 2   Bathroom    1257 non-null   float64
10 3   Furnishing  1254 non-null   object
11 4   Parking     1226 non-null   float64
12 5   Price       1259 non-null   int64
13 6   Status      1259 non-null   object
14 7   Transaction 1259 non-null   object
15 8   Type        1254 non-null   object
16 dtypes: float64(3), int64(2), object(4)
17 memory usage: 88.7+ KB
18 None
19 Area          0.000000
20 BHK           0.000000
21 Bathroom      0.158856
22 Furnishing    0.397141
23 Parking       2.621128
24 Price         0.000000
25 Status        0.000000
26 Transaction   0.000000
27 Type          0.397141
28 dtype: float64
29 <class 'pandas.core.frame.DataFrame'>
30 RangeIndex: 1259 entries, 0 to 1258
31 Data columns (total 9 columns):
32 #   Column      Non-Null Count  Dtype
33 ---  -
34 0   Area        1259 non-null   float64
35 1   BHK         1259 non-null   int64
36 2   Bathroom    1259 non-null   float64
37 3   Furnishing  1259 non-null   object
38 4   Parking     1259 non-null   float64
39 5   Price       1259 non-null   int64
40 6   Status      1259 non-null   object
41 7   Transaction 1259 non-null   object
42 8   Type        1259 non-null   object
43 dtypes: float64(3), int64(2), object(4)
44 memory usage: 88.7+ KB
45 None
46 [1e-50, 1e-20, 1e-15, 1e-10, 1e-08, 0.001, 0.01, 1, 5, 10, 20, 30, 35, 40, 45,
  50, 55, 100]
47 0.4541913846851654
48 alpha = 1e-50
49 mse for above alpha = 291845213565044.8
50 0.5046575836276497
51 alpha = 1e-20
52 mse for above alpha = 264860812449115.7
53 0.5046575836208771
54 alpha = 1e-15
55 mse for above alpha = 264860812452737.03
56 0.5046575836209053
57 alpha = 1e-10

```

```

58 mse for above alpha = 264860812452721.9
59 0.5046575836194864
60 alpha = 1e-08
61 mse for above alpha = 264860812453480.56
62 0.5046574403016636
63 alpha = 0.001
64 mse for above alpha = 264860889085874.16
65 0.5046561503858298
66 alpha = 0.01
67 mse for above alpha = 264861578807053.78
68 0.5045137976457408
69 alpha = 1
70 mse for above alpha = 264937695168480.0
71 0.5039298271796369
72 alpha = 5
73 mse for above alpha = 265249945617838.47
74 C:\Users\tejas\PycharmProjects\pythonProject\venv\Lib\site-packages\sklearn\
  linear_model\_ridge.py:211: LinAlgWarning: Ill-conditioned matrix (rcond=4.
    24583e-20): result may not be accurate.
75     return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
76 C:\Users\tejas\PycharmProjects\pythonProject\venv\Lib\site-packages\sklearn\
  linear_model\_ridge.py:211: LinAlgWarning: Ill-conditioned matrix (rcond=4.
    24575e-18): result may not be accurate.
77     return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
78 0.5031821241642653
79 alpha = 10
80 mse for above alpha = 265649744265352.44
81 0.5016388159162803
82 alpha = 20
83 mse for above alpha = 266474954994153.5
84 0.5000470304850191
85 alpha = 30
86 mse for above alpha = 267326086592485.3
87 0.499237469650079
88 alpha = 35
89 mse for above alpha = 267758960768776.34
90 0.498420692126058
91 alpha = 40
92 mse for above alpha = 268195693726528.5
93 0.49759787420242485
94 alpha = 45
95 mse for above alpha = 268635656500859.84
96 0.4967700333781435
97 alpha = 50
98 mse for above alpha = 269078305032563.34
99 0.49593805276367364
100 alpha = 55
101 mse for above alpha = 269523167120296.9
102 0.48836399721653057
103 alpha = 100
104 mse for above alpha = 273573033312743.28
105 Best value of alpha/lambda = 0
106 MSE for this alpha/lambda = 273573033312743.28
107 Best R square score = 0.48836399721653057
108
109 Process finished with exit code 0
110

```

5.Also do above for Lasso Regression (research code online)

(There's a convergence warning in all prevailing outputs, meaning: the alpha range must be increased from 100 to let's say 1000 or 10000 etc for the regression model to converge)

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import
train_test_split
from sklearn.metrics import mean_squared_error,
r2_score, mean_absolute_error
from sklearn.linear_model import Lasso

df = pd.read_csv('Dataset_Day6.csv')
print(df.info())
missing_value_percent = df.isna().sum() / len(df) *
100
print(missing_value_percent)
df["Bathroom"].fillna(df["Bathroom"].median(),
inplace=True)
df["Furnishing"].fillna(df["Furnishing"].mode()[0],
inplace=True) # mode() because this is categorical
data
df["Parking"].fillna(df["Parking"].median(),
inplace=True)
df["Type"].fillna(df["Type"].mode()[0],
inplace=True)
print(df.info())
X = df.drop('Price', axis=1) # all columns except
'Price'
y = df['Price'] # target Variable
temp = df[["Furnishing", "Status", "Transaction",
```

```

"Type"]])
# this function converts all categorical variables
in the dataframe to one hot encoded variables
new_encoded_data = pd.get_dummies(temp)
# Concatenate encoded categorical variables with
remaining features
X = pd.concat([X.select_dtypes(exclude=['object']),
new_encoded_data], axis=1)
X_train, X_test, y_train, y_test =
train_test_split(X, y, test_size=0.2,
random_state=50)
alpha = [1e-50, 1e-20, 1e-15, 1e-10, 1e-8, 1e-3,
1e-2, 1, 5, 10, 20, 30, 35, 40, 45, 50, 55, 100]
print(alpha)

for param in alpha:
    lassoModel = Lasso(alpha=param)
    lassoModel.fit(X_train, y_train)

    y_pred = lassoModel.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)

    r2 = r2_score(y_test, y_pred)
    print(r2)
    print("alpha = {}".format(param))
    print("mse for above alpha = {}".format(mse))
    best_r2 = 0
    best_alpha = 0
    best_mse = mse

    if r2 > best_r2:
        best_r2 = r2

    if mse < best_mse:
        best_mse = mse
        best_alpha = param

print("Best value of alpha/lambda =
{}".format(best_alpha))
print("MSE for this alpha/lambda =
{}".format(best_mse))
print("Best R square score = {}".format(best_r2))

```

```
print("In Lasso Model there's a minimal improvement  
in the performance as there's a minimal change in  
the R2 score")
```

```

tejas\PycharmProjects\pythonProject\START\Day6Q5.py
2 <class 'pandas.core.frame.DataFrame'>
3 RangeIndex: 1259 entries, 0 to 1258
4 Data columns (total 9 columns):
5 #   Column      Non-Null Count  Dtype
6 ---  ---
7 0   Area        1259 non-null   float64
8 1   BHK         1259 non-null   int64
9 2   Bathroom    1257 non-null   float64
10 3   Furnishing  1254 non-null   object
11 4   Parking     1226 non-null   float64
12 5   Price       1259 non-null   int64
13 6   Status      1259 non-null   object
14 7   Transaction 1259 non-null   object
15 8   Type        1254 non-null   object
16 dtypes: float64(3), int64(2), object(4)
17 memory usage: 88.7+ KB
18 None
19 Area        0.000000
20 BHK         0.000000
21 Bathroom    0.158856
22 Furnishing  0.397141
23 Parking     2.621128
24 Price       0.000000
25 Status      0.000000
26 Transaction 0.000000
27 Type        0.397141
28 dtype: float64
29 <class 'pandas.core.frame.DataFrame'>
30 RangeIndex: 1259 entries, 0 to 1258
31 Data columns (total 9 columns):
32 #   Column      Non-Null Count  Dtype
33 ---  ---
34 0   Area        1259 non-null   float64
35 1   BHK         1259 non-null   int64
36 2   Bathroom    1259 non-null   float64
37 3   Furnishing  1259 non-null   object
38 4   Parking     1259 non-null   float64
39 5   Price       1259 non-null   int64
40 6   Status      1259 non-null   object
41 7   Transaction 1259 non-null   object
42 8   Type        1259 non-null   object
43 dtypes: float64(3), int64(2), object(4)
44 memory usage: 88.7+ KB
45 None
46 [1e-50, 1e-20, 1e-15, 1e-10, 1e-08, 0.001, 0.01, 1, 5, 10, 20, 30, 35, 40, 45,
47 50, 55, 100]
48 C:\Users\tejas\PycharmProjects\pythonProject\venv\Lib\site-packages\sklearn\
linear_model\_coordinate_descent.py:628: ConvergenceWarning: 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: 1.372e+17,
tolerance: 6.896e+13 Linear regression models with null weight for the l1
regularization term are more efficiently fitted using one of the solvers
implemented in sklearn.linear_model.Ridge/RidgeCV instead.
48 model = cd_fast.enet_coordinate_descent(
49 0.5046575836209197
50 alpha = 1e-50
51 mse for above alpha = 264860812452714.22

```

```

52 0.5046575836209195
53 alpha = 1e-20
54 mse for above alpha = 264860812452714.34
55 C:\Users\tejas\PycharmProjects\pythonProject\venv\Lib\site-packages\sklearn\
linear_model\_coordinate_descent.py:628: ConvergenceWarning: 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: 1.
372e+17, tolerance: 6.896e+13 Linear regression models with null weight for
the l1 regularization term are more efficiently fitted using one of the
solvers implemented in sklearn.linear_model.Ridge/RidgeCV instead.
56 model = cd_fast.enet_coordinate_descent(
57 C:\Users\tejas\PycharmProjects\pythonProject\venv\Lib\site-packages\sklearn\
linear_model\_coordinate_descent.py:628: ConvergenceWarning: 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: 1.
372e+17, tolerance: 6.896e+13
58 model = cd_fast.enet_coordinate_descent(
59 0.5046575836209195
60 alpha = 1e-15
61 mse for above alpha = 264860812452714.34
62 0.5046575836209186
63 alpha = 1e-10
64 mse for above alpha = 264860812452714.84
65 C:\Users\tejas\PycharmProjects\pythonProject\venv\Lib\site-packages\sklearn\
linear_model\_coordinate_descent.py:628: ConvergenceWarning: 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: 1.
371e+17, tolerance: 6.896e+13
66 model = cd_fast.enet_coordinate_descent(
67 C:\Users\tejas\PycharmProjects\pythonProject\venv\Lib\site-packages\sklearn\
linear_model\_coordinate_descent.py:628: ConvergenceWarning: 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: 1.
368e+17, tolerance: 6.896e+13
68 model = cd_fast.enet_coordinate_descent(
69 0.504657583620919
70 alpha = 1e-08
71 mse for above alpha = 264860812452714.62
72 0.5046575836602472
73 alpha = 0.001
74 mse for above alpha = 264860812431685.72
75 0.5046575840142009
76 alpha = 0.01
77 mse for above alpha = 264860812242425.84
78 0.504657622949104
79 alpha = 1
80 mse for above alpha = 264860791423837.03
81 0.5046577802605332
82 alpha = 5
83 mse for above alpha = 264860707309027.62
84 0.5046579768981364
85 alpha = 10
86 mse for above alpha = 264860602166415.94
87 0.5046583701665819
88 alpha = 20
89 mse for above alpha = 264860391884807.62
90 0.5046587634249349
91 alpha = 30
92 mse for above alpha = 264860181608595.8

```
