regression

April 5, 2024

1 PROBLEM STATEMENT

1.0.1 Create a machine learning model which will help the company in determining the salary of newly hired employees of TechWorks Consulting using the given data.

1.0.2 Questions

1. Your views about the problem statement? Answer : The problem statement involves developing a regression model to predict the salary of newly hired employees based on various features provided in the dataset. It is a common problem in HR and talent acquisition where understanding the factors that influence salary is crucial. By creating a predictive model, TechWorks Consulting can ensure fair and competitive compensation for their employees.

2. What will be your approach to solving this task? Answer : To solve this task, we can follow these steps:

a. Load the dataset and preprocess the data by handling missing values, outliers, and categorical variables (e.g., converting college names and city types into numerical data, creating dummy variables for the "Role" feature) .

b. Splitting the data into training and testing sets.

c. Select an appropriate regression model (e.g., Linear Regression, Random Forest Regression) and make predictions on the test data.

d. Evaluate the model's performance using suitable metrics such as Mean Squared Error (MSE) and R-squared.

e. Finally, we have to provide an explanation of the selected model, its performance, and suggestions for further improvement.

3. What were the available ML model options you had to perform this task? Answer : For regression tasks, the below mentioned are the available ML models:

a. Multiple Linear Regression

b. Ridge

c. Lasso

d. K-Nearest Neighbors

e. Decision Tree

f. Bagging

g. Random Forest

h. Gradient Boosting

i. AdaBoost

j. XGBoost

4. Which model's performance is best and what could be the possible reason for that?
Answer: Among all the available ML model's Random Forest performed better with lowest MSE and high R2 score of 0.66. The reason could be of the following:

a. Handling Non-linearity: Random Forest is a tree-based ensemble model that can handle non-linear relationships between the input features and the target variable. It can capture complex interactions and non-linear patterns in the data, which can be beneficial when predicting salaries that may have non-linear relationships with the input features.

b. Robust to Outliers: Random Forest is less sensitive to outliers compared to some other models like Linear Regression. Outliers in the data can significantly impact the performance of linear models, but Random Forest can handle outliers more effectively by averaging predictions from multiple trees.

c. Handling Feature Interactions: Random Forest can capture feature interactions and identify important features in the dataset. It considers random subsets of features at each split, allowing it to find useful feature interactions that can be missed by other models. This can be advantageous when there are complex relationships and interactions among the input features that affect employee salaries.

d. Resistant to Overfitting: Random Forest uses bootstrapping and feature randomization techniques, which help to reduce overfitting. It builds multiple decision trees on different subsets of the data and combines their predictions through averaging or voting. This ensemble approach reduces the model's tendency to overfit the training data and improves its generalization ability.

e. Robust to Irrelevant Features: Random Forest can handle datasets with a large number of features, including irrelevant ones. It automatically assesses the importance of each feature based on its contribution to the overall performance of the model. This allows Random Forest to effectively handle datasets with high-dimensional feature spaces, such as employee data with various attributes.

f. Hyperparameter Tuning: The performance of Random Forest can heavily depend on their hyperparameters. It's possible that the hyperparameters of Random Forest were tuned more effectively suited for the dataset in question, leading to better performance.

5. What steps can you take to improve this selected model's performance even further?
Answer:To improve the performance of Random Forest model, we can consider the following steps:

a.Collect more data: Increasing the size of the dataset can often lead to improved model performance. Adding more data to the existing features can help the Random Forest model capture a wider range of patterns and generalize better to unseen instances.

b. Feature Engineering: We can explore the possibility of creating new features that might better capture the relationship with the target variable.

c. Feature selection: Random Forest models are robust to noisy and irrelevant features, but including too many irrelevant features can still degrade performance. Conducting feature selection techniques can help improve the model's performance by focusing on the most informative features.

d. Tune Hyperparameters: Experiment with different values for the hyperparameters of the Random Forest model. Grid search can be employed to systematically explore different combinations of hyperparameters and find the optimal values that improve the model's performance.

e.Cross-validation: Using Cross-validation it will help to assess the model's generalization ability and provides a more reliable estimate of its performance. It helps detect overfitting and ensures that the model performs well on unseen data.

2 IMPORT NECESSARY LIBRARY

[358]:
```
import pandas as pd
import xgboost as xgb
import seaborn as sns
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import Lasso
from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import train_test_split, GridSearchCV
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error, r2_score
```

3 LOAD DATASET

[359]:
```
employee_data = pd.read_csv('C:\\Users\\ntpc\\Downloads\\Employee.csv')
colleges = pd.read_csv('C:\\Users\\ntpc\\Downloads\\Colleges.csv')
cities = pd.read_csv('C:\\Users\\ntpc\\Downloads\\cities.csv')
```

4 DATA PREPROCESSING

4.0.1 Handling Categorical Values

[360]:
```
# Converting cities dataset to numerical mapping in employee_data['City']
# First Converting values of cities dataset to list
city_mapping= {}
metro_city=cities['Metrio City'].tolist()
non_metro_city=cities['non-metro cities'].tolist()
```

[361]:
```
# Assigning metro_city as 1 and non_metro_city as 0 and then mapping in␣
↪employee_data['City']
for city in metro_city:
    city_mapping[city] = 1

for city in non_metro_city:
    city_mapping[city] = 0

employee_data['City'] = employee_data['City'].map(city_mapping)
```

[362]:
```
# Converting colleges dataset to numerical mapping in employee_data['College']
# First Converting values of colleges dataset to list
college_mapping = {}
tier1_colleges = colleges['Tier 1'].tolist()
tier2_colleges = colleges['Tier 2'].tolist()
tier3_colleges = colleges['Tier 3'].tolist()
```

[363]:
```
# Assigning tier1_colleges as 1 , tier2_colleges as 2 , tier3_colleges as 3 and␣
↪then mapping in employee_data['College']
for college in tier1_colleges:
    college_mapping[college] = 1

for college in tier2_colleges:
    college_mapping[college] = 2

for college in tier3_colleges:
    college_mapping[college] = 3

employee_data['College'] = employee_data['College'].map(college_mapping)
```

[364]:
```
# Creating dummy variable for Role Column in employee_data
employee_data = pd.get_dummies(employee_data, columns=['Role'], drop_first=True)
```

[365]:
```
employee_data.head(10)
```

[365]:
```
   College  City  Previous CTC  Previous job change  Graduation Marks  \
0        2     0       55523.0                    3                66
```

```
1        2    0      57081.0                          1               84
2        3    0      60347.0                          2               52
3        3    0      49010.0                          2               81
4        1    0      57879.0                          4               74
5        2    0      54340.0                          4               73
6        3    1      60298.0                          1               42
7        2    1      49944.0                          2               56
8        3    1      53124.0                          4               40
9        1    0      51141.0                          1               47

   EXP (Month)       CTC  Role_Manager
0           19  71406.58             1
1           18  68005.87             0
2           28  76764.02             0
3           33  82092.39             0
4           32  73878.10             0
5           31  59950.89             0
6           46  66602.34             0
7           37  57768.44             0
8           37  70083.30             0
9           60  85648.48             0
```

[366]:
```python
# Shape of employee_data
employee_data.shape
```

[366]:
```
(1589, 8)
```

Since shape of employee_data doesn't change post preprocessing it suggest that there are no duplicated values

[367]:
```python
employee_data.describe()
```

[367]:
```
           College         City  Previous CTC  Previous job change  \
count  1589.000000  1589.000000   1589.000000          1589.000000
mean      1.975456     0.514160  55518.453744             2.528634
std       0.838330     0.499957   6655.218445             1.123918
min       1.000000     0.000000  36990.000000             1.000000
25%       1.000000     0.000000  50518.000000             2.000000
50%       2.000000     1.000000  55291.000000             3.000000
75%       3.000000     1.000000  60109.000000             4.000000
max       3.000000     1.000000  77911.000000             4.000000

       Graduation Marks  EXP (Month)           CTC  Role_Manager
count       1589.000000  1589.000000   1589.000000   1589.000000
mean          59.855255    39.044682  75353.278798      0.206419
std           14.935139    14.108875  12587.288237      0.404862
min           35.000000    18.000000  53020.320000      0.000000
```

```
25%          46.000000    26.000000    66902.350000       0.000000
50%          60.000000    39.000000    73028.670000       0.000000
75%          73.000000    51.000000    80588.670000       0.000000
max          85.000000    64.000000   123416.990000       1.000000
```

4.1 Checking Null Values

[368]:
```
# Checking Null Values
employee_data.isnull().sum()
```

[368]:
```
College                0
City                   0
Previous CTC           0
Previous job change    0
Graduation Marks       0
EXP (Month)            0
CTC                    0
Role_Manager           0
dtype: int64
```

No Null Values Detected

[369]:
```
# Coverting Role_Manager data Type into integer data type
employee_data['Role_Manager'] = employee_data['Role_Manager'].astype(int)
```

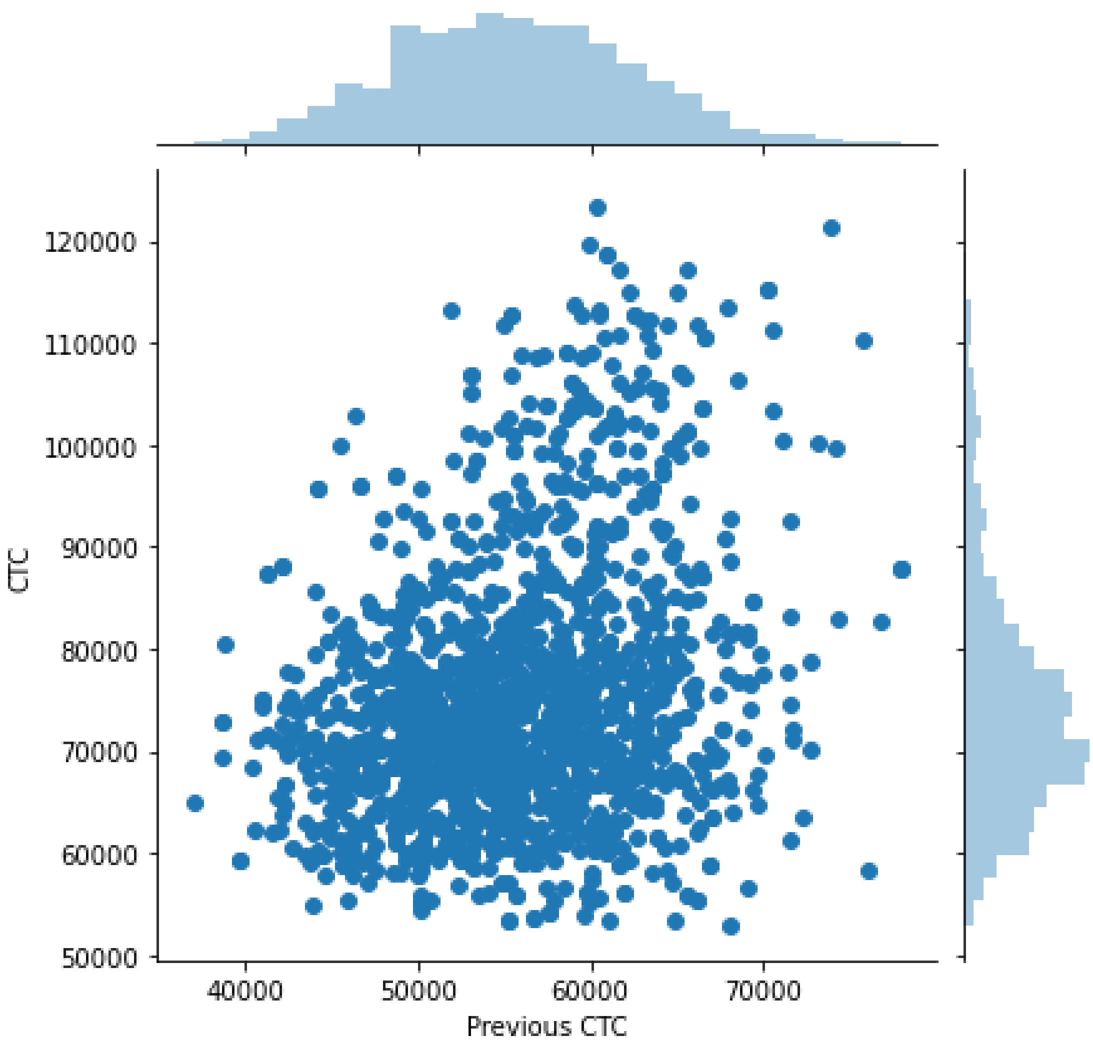
[370]:
```
employee_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1589 entries, 0 to 1588
Data columns (total 8 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   College              1589 non-null   int64  
 1   City                 1589 non-null   int64  
 2   Previous CTC         1589 non-null   float64
 3   Previous job change  1589 non-null   int64  
 4   Graduation Marks     1589 non-null   int64  
 5   EXP (Month)          1589 non-null   int64  
 6   CTC                  1589 non-null   float64
 7   Role_Manager         1589 non-null   int32  
dtypes: float64(2), int32(1), int64(5)
memory usage: 93.2 KB
```

4.2 Checking Outliers

[371]:
```
# Checking outliers for Previous CTC w.r.t target variable CTC
sns.jointplot(x='Previous CTC',y='CTC',data=employee_data)
```

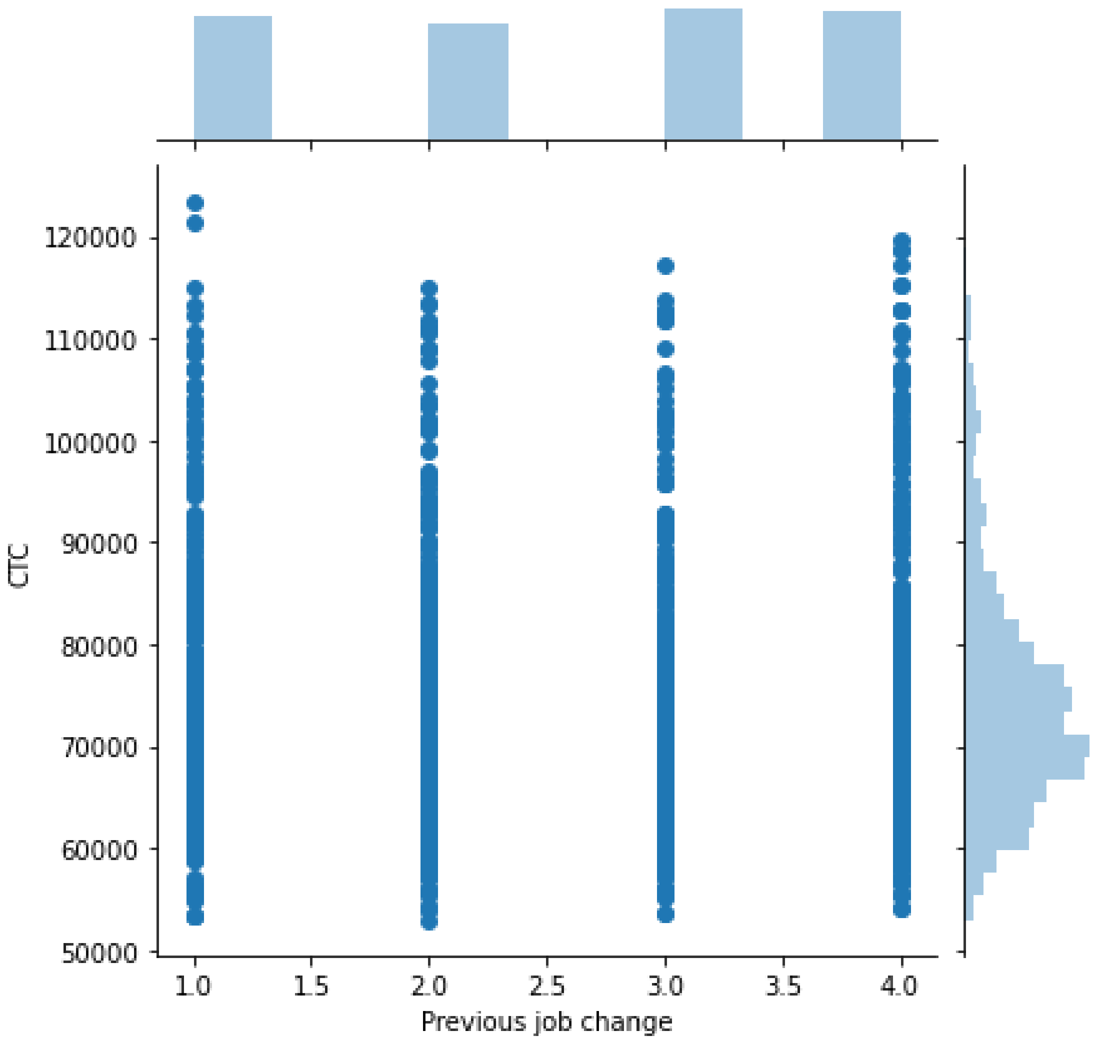
[371]: <seaborn.axisgrid.JointGrid at 0x23888a8bc10>



No outliers detected as there are no such data points which shows unusual observation

[372]:
```
# Checking outliers for Previous job change w.r.t target variable CTC
sns.jointplot(x='Previous job change',y='CTC',data=employee_data)
```

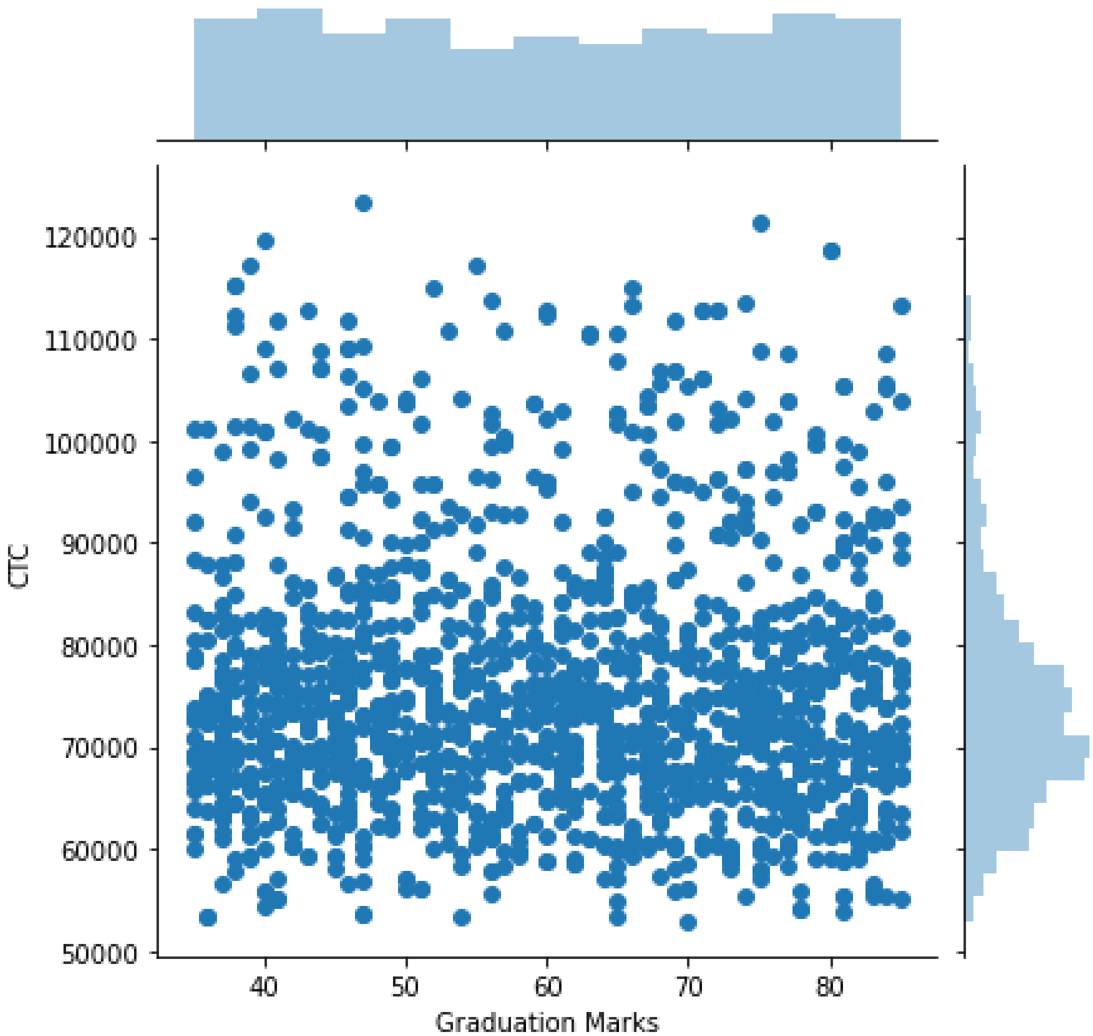
[372]: <seaborn.axisgrid.JointGrid at 0x23888c143d0>



No outliers detected as there are no such data points which shows unusual observation

[373]:
```
# Checking outliers for Graduation Marks w.r.t target variable CTC
sns.jointplot(x='Graduation Marks',y='CTC',data=employee_data)
```

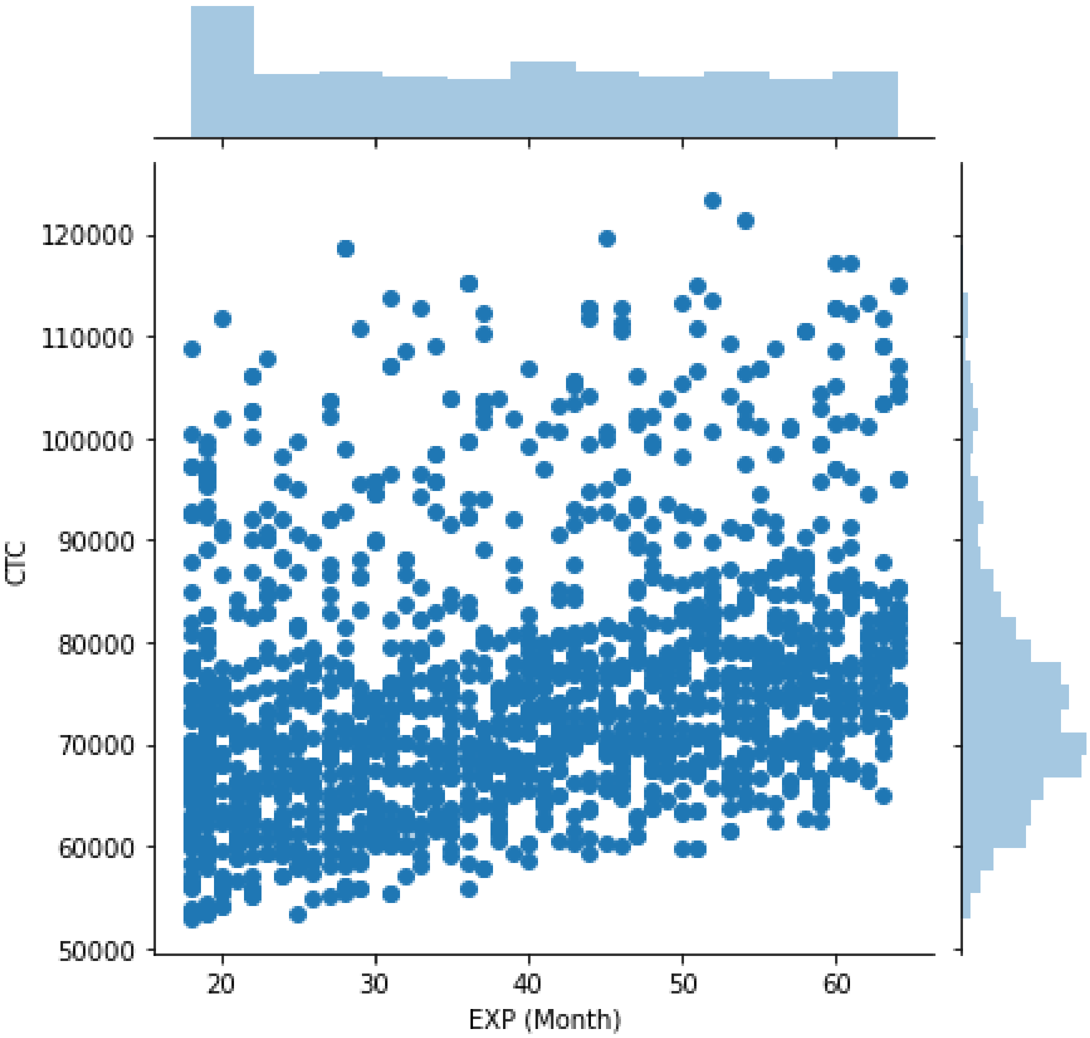
[373]:
```
<seaborn.axisgrid.JointGrid at 0x238888c3940>
```



No outliers detected as there are no such data points which shows unusual observation

[374]:
```
# Checking outliers for EXP (Month) w.r.t target variable CTC
sns.jointplot(x='EXP (Month)',y='CTC',data=employee_data)
```

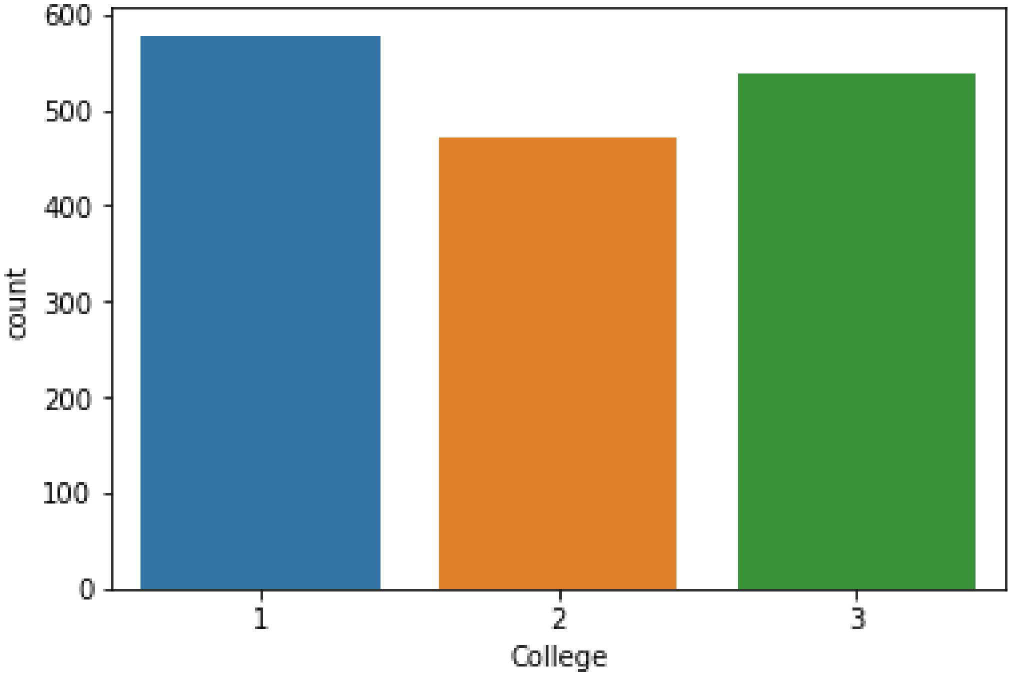
[374]: `<seaborn.axisgrid.JointGrid at 0x23888dda160>`



No outliers detected as there are no such data points which shows unusual observation

[375]:
```
# Checking outliers for College w.r.t target variable CTC
sns.countplot(x='College',data=employee_data)
```

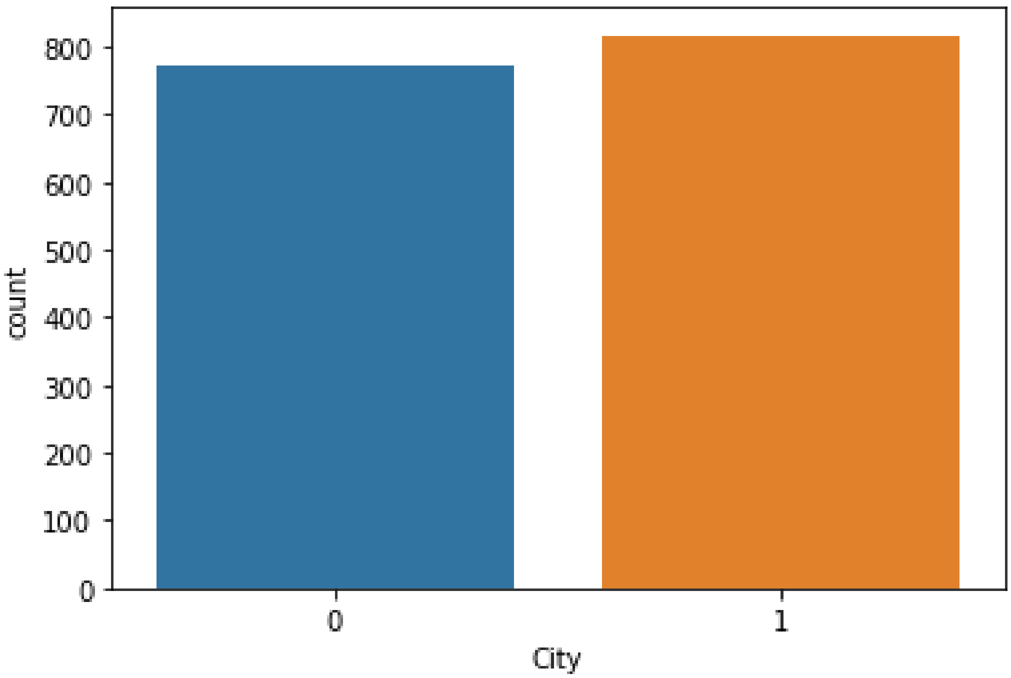
[375]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x23888faca60>
```



No outliers detected

[376]:
```
# Checking outliers for City w.r.t target variable CTC
sns.countplot(x='City',data=employee_data)
```

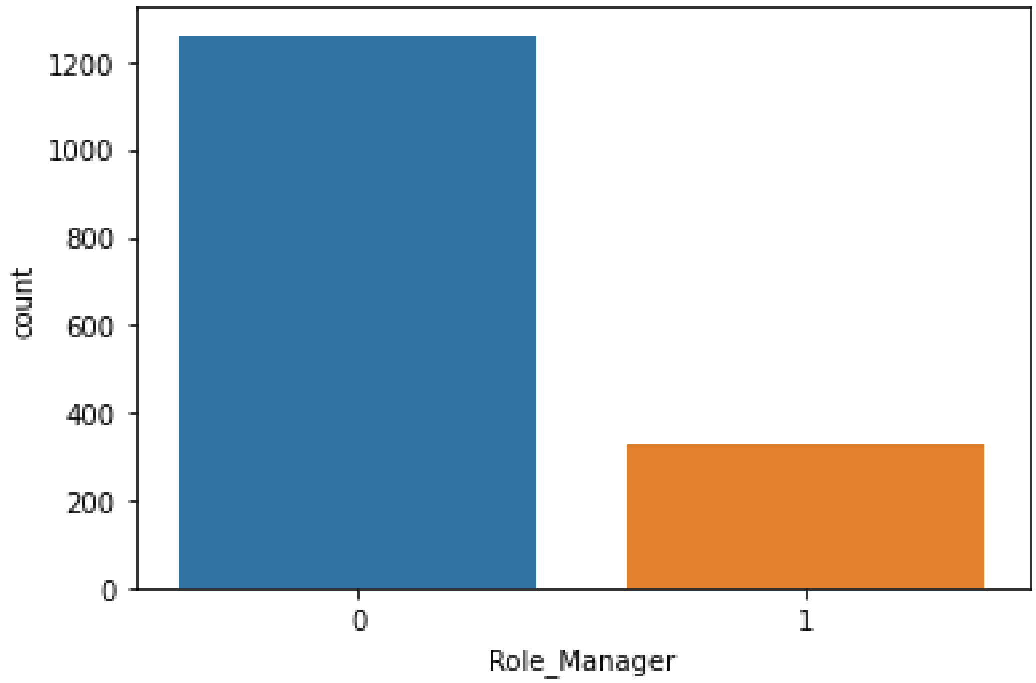
[376]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x23889000c70>
```



No outliers detected

[377]:
```
# Checking outliers for Role_Manager w.r.t target variable CTC
sns.countplot(x='Role_Manager',data=employee_data)
```

[377]: <matplotlib.axes._subplots.AxesSubplot at 0x23889056b80>



No outliers detected

4.3 Implementing Feature Selection Using Correlation

[378]:
```
correlation=employee_data.corr()
correlation
```

[378]:
```
                      College      City  Previous CTC  Previous job change  \
College              1.000000 -0.014946      0.041979            -0.055060
City                -0.014946  1.000000      0.004644             0.051670
Previous CTC         0.041979  0.004644      1.000000             0.005756
Previous job change -0.055060  0.051670      0.005756             1.000000
Graduation Marks     0.003539 -0.018616     -0.032976             0.019267
EXP (Month)          0.011752 -0.023613      0.119163             0.023488
CTC                 -0.029592 -0.020365      0.258000             0.011370
Role_Manager        -0.014749 -0.048671      0.012321            -0.017150

                     Graduation Marks  EXP (Month)       CTC  Role_Manager
College                      0.003539     0.011752 -0.029592     -0.014749
City                        -0.018616    -0.023613 -0.020365     -0.048671
Previous CTC                -0.032976     0.119163  0.258000      0.012321
Previous job change          0.019267     0.023488  0.011370     -0.017150
Graduation Marks             1.000000    -0.057061 -0.005450      0.017858
EXP (Month)                 -0.057061     1.000000  0.301115     -0.026751
CTC                         -0.005450     0.301115  1.000000      0.621311
```

```
Role_Manager                    0.017858    -0.026751   0.621311      1.000000
```

From the above observation it is noted that Previous CTC , Exp(Month) and Role_Manager are highly correlated . Also considering threshold =0.5 there are no such independent variables which shows multicollinearity among themselves.Since the dataset is small and no such multicollinearity present we are not going delete any variable to predict CTC

4.4 Steps Performing In Training the Model

a. Taking all independent features or variables into X

b. Taking only Target feature or variable in y

c. Splitting Train-Test data into 70:30 ratio

d. Implementing the available Regression model's , making prediction on the test data and then evaluating the model's performance using suitable metrics such as Mean Squared Error (MSE) and R-squared

4.5 X-y split

[379]:
```python
X = employee_data.drop(['CTC'] , axis=1)
y = employee_data['CTC']
```

[380]:
```python
X.head()
```

[380]:
```
   College  City  Previous CTC  Previous job change  Graduation Marks  \
0        2     0       55523.0                    3                66
1        2     0       57081.0                    1                84
2        3     0       60347.0                    2                52
3        3     0       49010.0                    2                81
4        1     0       57879.0                    4                74

   EXP (Month)  Role_Manager
0           19             1
1           18             0
2           28             0
3           33             0
4           32             0
```

[381]:
```python
X.shape
```

[381]:
```
(1589, 7)
```

[382]:
```python
y.head()
```

[382]:
```
0    71406.58
1    68005.87
2    76764.02
3    82092.39
4    73878.10
Name: CTC, dtype: float64
```

[383]:
```
y.shape
```

[383]:
```
(1589,)
```

4.6 Test-Train Split

Applying Multiple Linear Regression Model

[384]:
```
# Splitting Train-Test data into 70:30 ratio
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
  ↪random_state=0)
# Applying Multiple Linear Regression Model
model = LinearRegression()
```

[385]:
```
# Fitting the model
model.fit(X_train, y_train)

# Making predictions on the test data
y_pred = model.predict(X_test)

# Calculating the mean squared error and R-squared score
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Printing the evaluation metrics
print('Mean Squared Error:', mse)
```

```
Mean Squared Error: 71970784.43482201
```

[386]:
```
print('R-squared:', r2)
```

```
R-squared: 0.5467294464871
```

4.7 Applying Ridge Regression

[387]:
```
# Since Ridge needs scaled values we implement StandardScaler to standardize␣
  ↪the data
from sklearn.preprocessing import StandardScaler
scalar1 = StandardScaler().fit(X_train)
X_train_s = scalar1.transform(X_train)
```

[388]:
```
from sklearn.preprocessing import StandardScaler
scalar2 = StandardScaler().fit(X_test)
X_test_s = scalar2.transform(X_test)
```

[389]:
```
# Applying Ridge Regression Model
lm_r=Ridge(alpha=0.5)
# Fitting the model
lm_r.fit(X_train_s,y_train)
```

[389]:
```
Ridge(alpha=0.5)
```

[390]:
```
# Making predictions on the test data
y_pred = lm_r.predict(X_test_s)

# Calculating the mean squared error and R-squared score
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Printing the evaluation metrics
print("Mean Squared Error (MSE):", mse)
print("R-squared:", r2)
```

```
Mean Squared Error (MSE): 71866792.63357721
R-squared: 0.5473843847607507
```

[391]:
```
# Using validation curve to fetch optimal value of alpha for better efficiency
from sklearn.model_selection import validation_curve
```

[392]:
```
import numpy as np
param_range=np.logspace(-2,8,100)
```

[393]:
```
param_range
```

[393]:
```
array([1.00000000e-02, 1.26185688e-02, 1.59228279e-02, 2.00923300e-02,
       2.53536449e-02, 3.19926714e-02, 4.03701726e-02, 5.09413801e-02,
       6.42807312e-02, 8.11130831e-02, 1.02353102e-01, 1.29154967e-01,
       1.62975083e-01, 2.05651231e-01, 2.59502421e-01, 3.27454916e-01,
       4.13201240e-01, 5.21400829e-01, 6.57933225e-01, 8.30217568e-01,
       1.04761575e+00, 1.32194115e+00, 1.66810054e+00, 2.10490414e+00,
       2.65608778e+00, 3.35160265e+00, 4.22924287e+00, 5.33669923e+00,
       6.73415066e+00, 8.49753436e+00, 1.07226722e+01, 1.35304777e+01,
       1.70735265e+01, 2.15443469e+01, 2.71858824e+01, 3.43046929e+01,
       4.32876128e+01, 5.46227722e+01, 6.89261210e+01, 8.69749003e+01,
       1.09749877e+02, 1.38488637e+02, 1.74752840e+02, 2.20513074e+02,
       2.78255940e+02, 3.51119173e+02, 4.43062146e+02, 5.59081018e+02,
       7.05480231e+02, 8.90215085e+02, 1.12332403e+03, 1.41747416e+03,
       1.78864953e+03, 2.25701972e+03, 2.84803587e+03, 3.59381366e+03,
```

```
       4.53487851e+03, 5.72236766e+03, 7.22080902e+03, 9.11162756e+03,
       1.14975700e+04, 1.45082878e+04, 1.83073828e+04, 2.31012970e+04,
       2.91505306e+04, 3.67837977e+04, 4.64158883e+04, 5.85702082e+04,
       7.39072203e+04, 9.32603347e+04, 1.17681195e+05, 1.48496826e+05,
       1.87381742e+05, 2.36448941e+05, 2.98364724e+05, 3.76493581e+05,
       4.75081016e+05, 5.99484250e+05, 7.56463328e+05, 9.54548457e+05,
       1.20450354e+06, 1.51991108e+06, 1.91791026e+06, 2.42012826e+06,
       3.05385551e+06, 3.85352859e+06, 4.86260158e+06, 6.13590727e+06,
       7.74263683e+06, 9.77009957e+06, 1.23284674e+07, 1.55567614e+07,
       1.96304065e+07, 2.47707636e+07, 3.12571585e+07, 3.94420606e+07,
       4.97702356e+07, 6.28029144e+07, 7.92482898e+07, 1.00000000e+08])
```

[394]:
```
train_scores,test_scores=validation_curve(␣
 ↪Ridge(),X_train_s,y_train,"alpha",param_range,scoring='r2')
```

```
P:\Objects\pro1\pes\lib\site-packages\sklearn\utils\validation.py:68:
FutureWarning: Pass param_name=alpha, param_range=[1.00000000e-02 1.26185688e-02
1.59228279e-02 2.00923300e-02
 2.53536449e-02 3.19926714e-02 4.03701726e-02 5.09413801e-02
 6.42807312e-02 8.11130831e-02 1.02353102e-01 1.29154967e-01
 1.62975083e-01 2.05651231e-01 2.59502421e-01 3.27454916e-01
 4.13201240e-01 5.21400829e-01 6.57933225e-01 8.30217568e-01
 1.04761575e+00 1.32194115e+00 1.66810054e+00 2.10490414e+00
 2.65608778e+00 3.35160265e+00 4.22924287e+00 5.33669923e+00
 6.73415066e+00 8.49753436e+00 1.07226722e+01 1.35304777e+01
 1.70735265e+01 2.15443469e+01 2.71858824e+01 3.43046929e+01
 4.32876128e+01 5.46227722e+01 6.89261210e+01 8.69749003e+01
 1.09749877e+02 1.38488637e+02 1.74752840e+02 2.20513074e+02
 2.78255940e+02 3.51119173e+02 4.43062146e+02 5.59081018e+02
 7.05480231e+02 8.90215085e+02 1.12332403e+03 1.41747416e+03
 1.78864953e+03 2.25701972e+03 2.84803587e+03 3.59381366e+03
 4.53487851e+03 5.72236766e+03 7.22080902e+03 9.11162756e+03
 1.14975700e+04 1.45082878e+04 1.83073828e+04 2.31012970e+04
 2.91505306e+04 3.67837977e+04 4.64158883e+04 5.85702082e+04
 7.39072203e+04 9.32603347e+04 1.17681195e+05 1.48496826e+05
 1.87381742e+05 2.36448941e+05 2.98364724e+05 3.76493581e+05
 4.75081016e+05 5.99484250e+05 7.56463328e+05 9.54548457e+05
 1.20450354e+06 1.51991108e+06 1.91791026e+06 2.42012826e+06
 3.05385551e+06 3.85352859e+06 4.86260158e+06 6.13590727e+06
 7.74263683e+06 9.77009957e+06 1.23284674e+07 1.55567614e+07
 1.96304065e+07 2.47707636e+07 3.12571585e+07 3.94420606e+07
 4.97702356e+07 6.28029144e+07 7.92482898e+07 1.00000000e+08] as keyword args.
From version 0.25 passing these as positional arguments will result in an error
  warnings.warn("Pass {} as keyword args. From version 0.25 "
```

[395]:
```
train_mean=np.mean(train_scores,axis=1)
```

[396]:
```
test_mean=np.mean(test_scores,axis=1)
```

[397]:
```
max(test_mean)
```

[397]: 0.516252885106533

[398]:
```
np.where(test_mean==max(test_mean))
```

[398]: (array([29], dtype=int64),)

[399]:
```
param_range[29]
```

[399]: 8.497534359086439

[400]:
```
lm_r_best=Ridge(alpha=param_range[29])
```

[401]:
```
lm_r_best.fit(X_train_s,y_train)
```

[401]: Ridge(alpha=8.497534359086439)

[402]:
```
r2 = r2_score(y_test, lm_r_best.predict(X_test_s))
```

[403]:
```
r2
```

[403]: 0.5471298585640656

4.8 Applying Lasso

[404]:
```
# Since Lasso needs scaled values we implement StandardScaler to standardize␣
↪the data
from sklearn.preprocessing import StandardScaler
scalar1 = StandardScaler().fit(X_train)
X_train_s = scalar1.transform(X_train)
```

[405]:
```
from sklearn.preprocessing import StandardScaler
scalar2 = StandardScaler().fit(X_test)
X_test_s = scalar2.transform(X_test)
```

[406]:
```
# Applying Lasso Regression Model
lm_r=Lasso(alpha=0.4)
# Fitting the model
lm_r.fit(X_train_s,y_train)
```

[406]: Lasso(alpha=0.4)

[407]:
```
# Making predictions on the test data
y_pred = lm_r.predict(X_test_s)

# Calculating the mean squared error and R-squared score
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Printing the evaluation metrics
print("Mean Squared Error (MSE):", mse)
print("R-squared:", r2)
```

```
Mean Squared Error (MSE): 71863742.36377937
R-squared: 0.5474035952986167
```

[408]:
```
import numpy as np
param_range=np.logspace(-2,8,100)
```

[409]:
```
# using validation curve to get optimal value of alpha for better efficiency
train_scores,test_scores=validation_curve(␣
↪Lasso(),X_train_s,y_train,"alpha",param_range,scoring='r2')
```

```
P:\Objects\pro1\pes\lib\site-packages\sklearn\utils\validation.py:68:
FutureWarning: Pass param_name=alpha, param_range=[1.00000000e-02 1.26185688e-02
1.59228279e-02 2.00923300e-02
 2.53536449e-02 3.19926714e-02 4.03701726e-02 5.09413801e-02
 6.42807312e-02 8.11130831e-02 1.02353102e-01 1.29154967e-01
 1.62975083e-01 2.05651231e-01 2.59502421e-01 3.27454916e-01
 4.13201240e-01 5.21400829e-01 6.57933225e-01 8.30217568e-01
 1.04761575e+00 1.32194115e+00 1.66810054e+00 2.10490414e+00
 2.65608778e+00 3.35160265e+00 4.22924287e+00 5.33669923e+00
 6.73415066e+00 8.49753436e+00 1.07226722e+01 1.35304777e+01
 1.70735265e+01 2.15443469e+01 2.71858824e+01 3.43046929e+01
 4.32876128e+01 5.46227722e+01 6.89261210e+01 8.69749003e+01
 1.09749877e+02 1.38488637e+02 1.74752840e+02 2.20513074e+02
 2.78255940e+02 3.51119173e+02 4.43062146e+02 5.59081018e+02
 7.05480231e+02 8.90215085e+02 1.12332403e+03 1.41747416e+03
 1.78864953e+03 2.25701972e+03 2.84803587e+03 3.59381366e+03
 4.53487851e+03 5.72236766e+03 7.22080902e+03 9.11162756e+03
 1.14975700e+04 1.45082878e+04 1.83073828e+04 2.31012970e+04
 2.91505306e+04 3.67837977e+04 4.64158883e+04 5.85702082e+04
 7.39072203e+04 9.32603347e+04 1.17681195e+05 1.48496826e+05
 1.87381742e+05 2.36448941e+05 2.98364724e+05 3.76493581e+05
 4.75081016e+05 5.99484250e+05 7.56463328e+05 9.54548457e+05
 1.20450354e+06 1.51991108e+06 1.91791026e+06 2.42012826e+06
 3.05385551e+06 3.85352859e+06 4.86260158e+06 6.13590727e+06
 7.74263683e+06 9.77009957e+06 1.23284674e+07 1.55567614e+07
 1.96304065e+07 2.47707636e+07 3.12571585e+07 3.94420606e+07
 4.97702356e+07 6.28029144e+07 7.92482898e+07 1.00000000e+08] as keyword args.
```

```
From version 0.25 passing these as positional arguments will result in an error
  warnings.warn("Pass {} as keyword args. From version 0.25 "
```

[410]:
```
train_mean=np.mean(train_scores,axis=1)
```

[411]:
```
test_mean=np.mean(test_scores,axis=1)
```

[412]:
```
max(test_mean)
```

[412]:
```
0.5164390233754533
```

[413]:
```
np.where(test_mean==max(test_mean))
```

[413]:
```
(array([38], dtype=int64),)
```

[414]:
```
param_range[38]
```

[414]:
```
68.92612104349695
```

[415]:
```
lm_r_best=Lasso(alpha=param_range[38])
```

[416]:
```
lm_r_best.fit(X_train_s,y_train)
```

[416]:
```
Lasso(alpha=68.92612104349695)
```

[417]:
```
r2 = r2_score(y_test, lm_r_best.predict(X_test_s))
```

[418]:
```
r2
```

[418]:
```
0.5480529569555246
```

4.8.1 Applying KNN Model Using GridSearch

[419]:
```
# Since KNN needs scaled values we implement StandardScaler to standardize the␣
 ↪data
from sklearn.preprocessing import StandardScaler
scalar1 = StandardScaler().fit(X_train)
X_train_s = scalar1.transform(X_train)
```

[420]:
```
from sklearn.preprocessing import StandardScaler
scalar2 = StandardScaler().fit(X_test)
X_test_s = scalar2.transform(X_test)
```

[421]:
```
# Defining the parameter grid for grid search
params = {'n_neighbors': [1,2,3,4,5,6,7,8,9,10]}

# Create the KNN model
```

```
knn_model = KNeighborsRegressor()

# Performing grid search using cross-validation
grid_search = GridSearchCV(knn_model, params)
grid_search.fit(X_train_s, y_train)

grid_search.best_params_

# Retrieving the best model
best_knn_model = grid_search.best_estimator_

# Making predictions on the testing set using the best model
y_pred = best_knn_model.predict(X_test_s)

# Evaluating the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Printing the evaluation metrics
print("Best Parameters:", grid_search.best_params_)
print("Mean Squared Error (MSE):", mse)
print("R-squared:", r2)
```

```
Best Parameters: {'n_neighbors': 10}
Mean Squared Error (MSE): 70615542.41214117
R-squared: 0.5552647335009686
```

4.9 Applying Decision Tree

[422]:
```
# Implementing Decision Tree
from sklearn import tree
regtree=tree.DecisionTreeRegressor(max_depth=3)
```

[423]:
```
# Fitting the model
regtree.fit(X_train,y_train)
```

[423]:
```
DecisionTreeRegressor(max_depth=3)
```

[424]:
```
# Predicting the model on the test data
y_pred = regtree.predict(X_test)

# Evaluating the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Printing the evaluation metrics
print("Mean Squared Error (MSE):", mse)
```

```
print("R-squared:", r2)
```

```
Mean Squared Error (MSE): 63547766.31545223
R-squared: 0.5997774452715718
```

4.10 Applying Bagging

[425]:
```
# Implementing Bagging
from sklearn.ensemble import BaggingRegressor
```

[426]:
```
bag_reg=BaggingRegressor()
```

[427]:
```
# Fitting the model
bag_reg.fit(X_train,y_train)
```

[427]: BaggingRegressor()

[428]:
```
# Predicting the model on the test data
y_pred = bag_reg.predict(X_test)

# Evaluating the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Printing the evaluation metrics
print("Mean Squared Error (MSE):", mse)
print("R-squared:", r2)
```

```
Mean Squared Error (MSE): 58493799.35302389
R-squared: 0.6316072275990162
```

4.11 Random Forest

[429]:
```
# Implementing Random Forest
rf_regressor = RandomForestRegressor(n_estimators=1000,n_jobs=-1,␣
 ↪random_state=0)

# Fitting the model
rf_regressor.fit(X_train, y_train)

# Predicting the model on the test data
y_pred = rf_regressor.predict(X_test)

# Evaluating the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

```
# Printing the evaluation metrics
print("Mean Squared Error (MSE):", mse)
print("R-squared:", r2)
```

```
Mean Squared Error (MSE): 52521181.36020534
R-squared: 0.6692226556478471
```

4.12 Gradient Boosting

[430]:
```
from sklearn.ensemble import GradientBoostingRegressor
```

[431]:
```
# Implementing Gradient Boosting
gbr_reg=GradientBoostingRegressor()
# Fitting the model
gbr_reg.fit(X_train,y_train)
```

[431]:
```
GradientBoostingRegressor()
```

[432]:
```
# Predicting the model on the test data
y_pred = gbr_reg.predict(X_test)

# Evaluating the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Printing the evaluation metrics
print("Mean Squared Error (MSE):", mse)
print("R-squared:", r2)
```

```
Mean Squared Error (MSE): 58952193.219912946
R-squared: 0.6287202722406251
```

4.13 Ada Boost

[433]:
```
from sklearn.ensemble import AdaBoostRegressor
```

[434]:
```
# Implementing Ada Boost
ada_reg=AdaBoostRegressor(n_estimators=500)
# Fitting the model
ada_reg.fit(X_train,y_train)
```

[434]:
```
AdaBoostRegressor(n_estimators=500)
```

[435]:
```
# Predicting the model on the test data
y_pred = ada_reg.predict(X_test)

# Evaluating the model
```

```
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Printing the evaluation metrics
print("Mean Squared Error (MSE):", mse)
print("R-squared:", r2)
```

```
Mean Squared Error (MSE): 62655485.96642399
R-squared: 0.6053970089718812
```

4.14 XG Boost

[436]:
```
# Implementing XG Boost
xgb_reg=xgb.XGBRegressor(max_depth=3,n_estimators=100,n_jobs=-1)
# Fitting the model
xgb_reg.fit(X_train,y_train)
# Predicting the model on the test data
y_pred = xgb_reg.predict(X_test)

# Evaluating the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Printing the evaluation metrics
print("Mean Squared Error (MSE):", mse)
print("R-squared:", r2)
```

```
Mean Squared Error (MSE): 58538243.84358566
R-squared: 0.6313273170909436
```