*Final Assesment *

Getting libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
```

getting data

```
df = pd.read_csv("/content/ML case Study.csv",header=0)
coll_tier = pd.read_csv("/content/Colleges.csv",header=0)
city = pd.read_csv("/content/cities.csv",header=0)
```

Preprocessing of the Data

```
df.head()
```

	College	City	Role	Previous CTC	Previous job change	Graduation Marks	EXP (Month)	CTC
0	SVNIT Surat	Asansol	Manager	55523.0	3	66	19	71406.58
1	NIT Bhopal	Ajmer	Executive	57081.0	1	84	18	68005.87
2	IEM, Kolkata	Rajpur Sonarpur	Executive	60347.0	2	52	28	76764.02
3	KIIT, Bhubaneswar	Ajmer	Executive	49010.0	2	81	33	82092.39
4	DTU	Durgapur	Executive	57879.0	4	74	32	73878.10

```
coll_tier.head()
```

	Tier 1	Tier 2	Tier 3
0	IIT Bombay	IIIT Bangalore	Ramaiah Institute of Technology, Bengaluru
1	IIT Delhi	IIIT Delhi	TIET/Thapar University
2	IIT Kharagpur	IGDTUW	Manipal Main Campus
3	IIT Madras	NIT Calicut	VIT Vellore
4	IIT Kanpur	IIITM Gwalior	SRM Main Campus

```
coll_tier.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28 entries, 0 to 27
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Tier 1  22 non-null     object
 1   Tier 2  28 non-null     object
 2   Tier 3  19 non-null     object
dtypes: object(3)
memory usage: 800.0+ bytes
```

Combining the Datasets

[ ] ↳ *9 cells hidden*

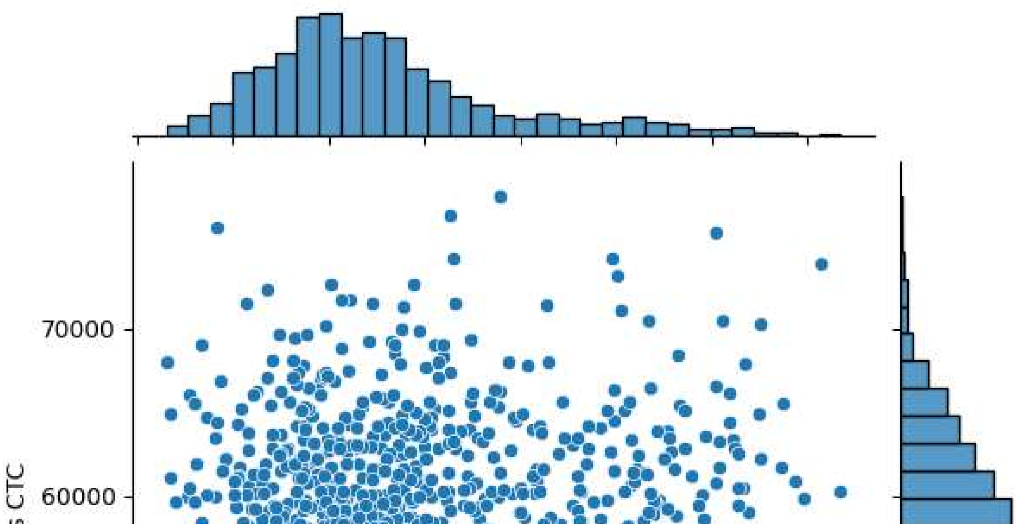
EDD

```
df.describe()
```

	City	Previous CTC	Previous job change	Graduation Marks	EXP (Month)	
count	1589.000000	1589.000000	1589.000000	1589.000000	1589.000000	1589.000
mean	0.485840	55518.453744	2.528634	59.855255	39.044682	75353.278
std	0.499957	6655.218445	1.123918	14.935139	14.108875	12587.288
min	0.000000	36990.000000	1.000000	35.000000	18.000000	53020.320
25%	0.000000	50518.000000	2.000000	46.000000	26.000000	66902.350
50%	0.000000	55291.000000	3.000000	60.000000	39.000000	73028.670
75%	1.000000	60109.000000	4.000000	73.000000	51.000000	80588.670

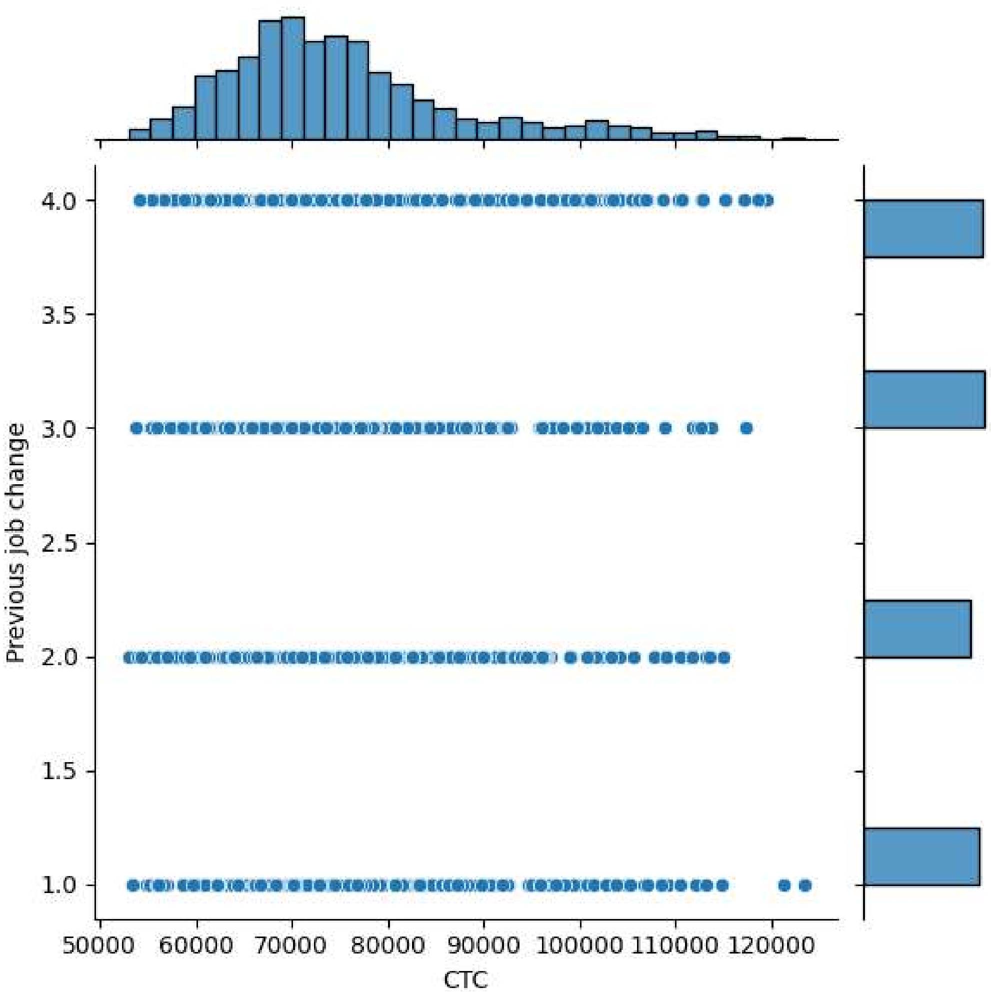
```
sns.jointplot(x='CTC', y = 'Previous CTC',data = df)
```

<seaborn.axisgrid.JointGrid at 0x7fbbce20a4a0>



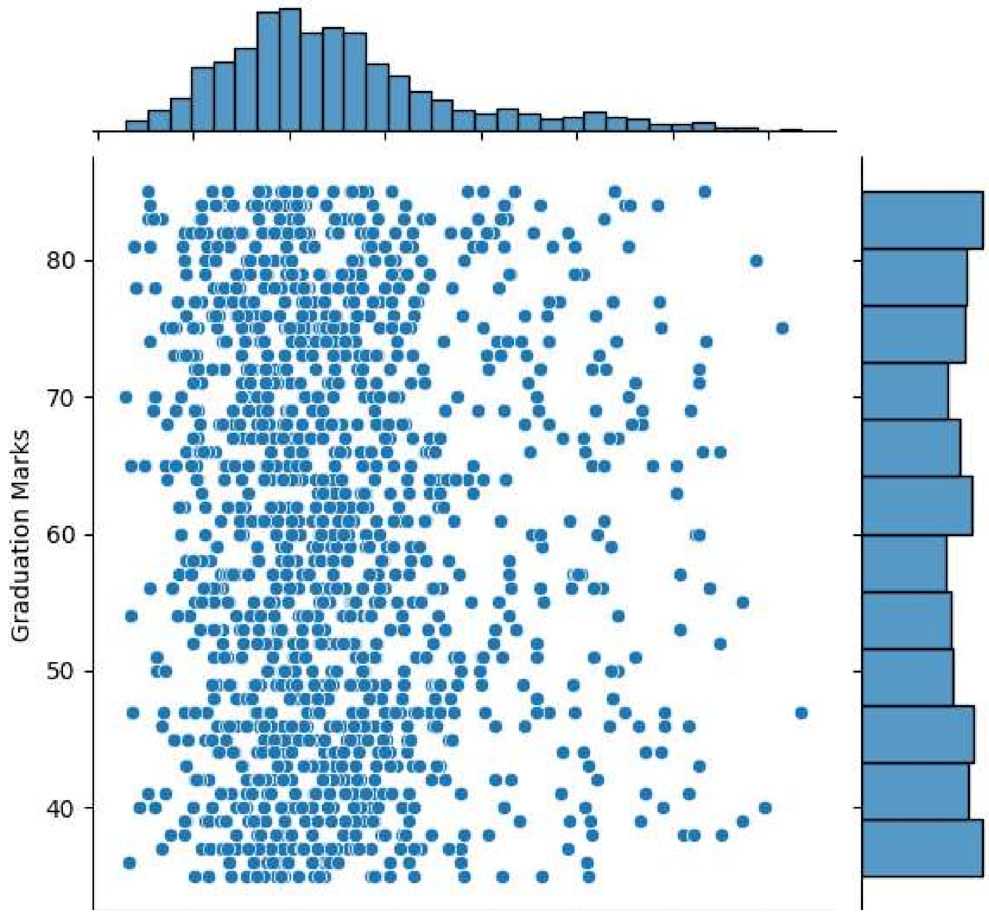

```
sns.jointplot(x='CTC', y = 'Previous job change',data = df)
```

<seaborn.axisgrid.JointGrid at 0x7fbbcbfb4a00>



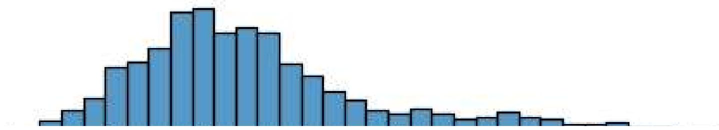

```
sns.jointplot(x='CTC', y = 'Graduation Marks',data = df)
```

```
<seaborn.axisgrid.JointGrid at 0x7fbbca19d9f0>
```



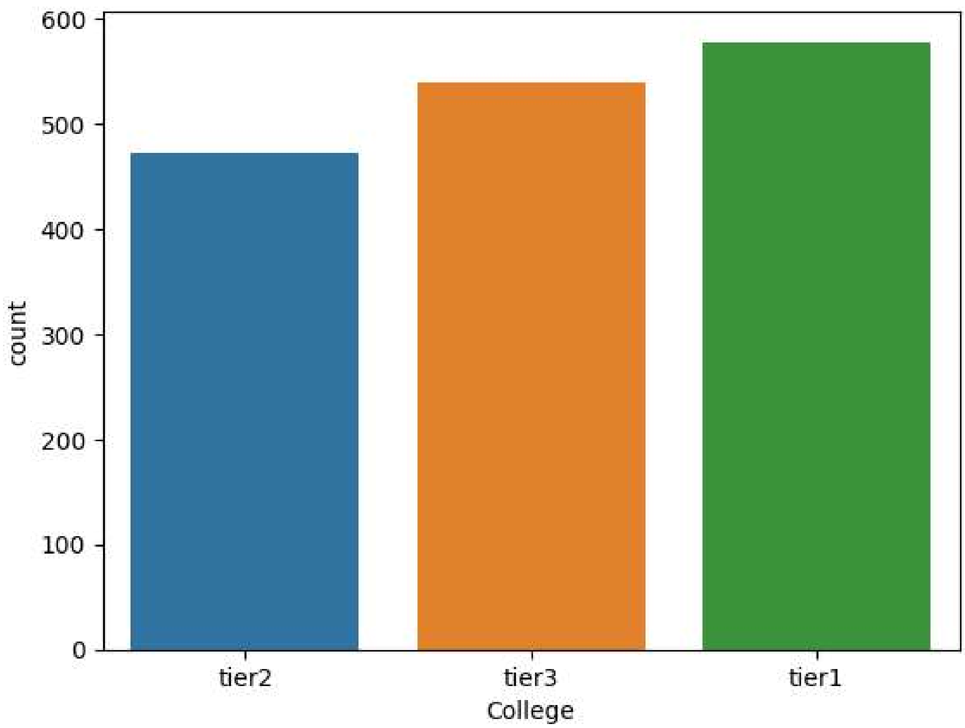

```
sns.jointplot(x='CTC', y = 'EXP (Month)',data = df)
```

```
<seaborn.axisgrid.JointGrid at 0x7fbbca13ee90>
```



```
sns.countplot(x='College',data= df)
```

```
<Axes: xlabel='College', ylabel='count'>
```

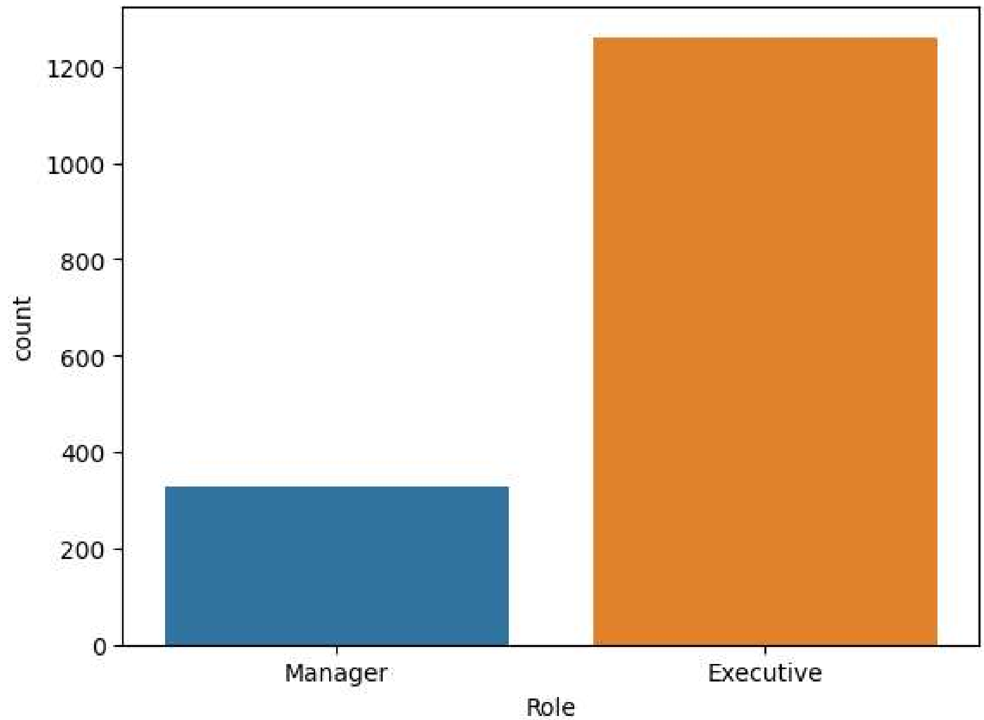



```
sns.countplot(x='City',data= df)
```

<Axes: xlabel='City', ylabel='count'>

```
sns.countplot(x='Role',data= df)
```

<Axes: xlabel='Role', ylabel='count'>




```
df = pd.get_dummies(df)
```

```
df.head()
```

	City	Previous CTC	Previous job change	Graduation Marks	EXP (Month)	CTC	College_tier1	Colleg
0	1	55523.0	3	66	19	71406.58	0	
1	1	57081.0	1	84	18	68005.87	0	
2	1	60347.0	2	52	28	76764.02	0	
3	1	49010.0	2	81	33	82092.39	0	
4	1	57879.0	4	74	32	73878.10	1	

```
del df['Role_Manager']
```

```
correlation = df.corr()
```

```
correlation
```

	City	Previous CTC	Previous job change	Graduation Marks	EXP (Month)	CTC	Co
City	1.000000	-0.004644	-0.051670	0.018616	0.023613	0.020365	
Previous CTC	-0.004644	1.000000	0.005756	-0.032976	0.119163	0.258000	
Previous job change	-0.051670	0.005756	1.000000	0.019267	0.023488	0.011370	
Graduation Marks	0.018616	-0.032976	0.019267	1.000000	-0.057061	-0.005450	
EXP (Month)	0.023613	0.119163	0.023488	-0.057061	1.000000	0.301115	
CTC	0.020365	0.258000	0.011370	-0.005450	0.301115	1.000000	
College_tier1	-0.002135	-0.031366	0.045931	0.005666	-0.003323	0.019912	
College_tier2	-0.022917	-0.010947	0.004271	-0.018419	-0.014558	0.012346	
College_tier3	0.024288	0.042438	-0.050794	0.012021	0.017427	-0.032149	
Role_Executive	-0.048671	-0.012321	0.017150	-0.017858	0.026751	-0.621311	

import necessary libraries

```
from sklearn.linear_model import LinearRegression,Ridge,Lasso,LogisticRegres
from sklearn.model_selection import train_test_split,validation_curve,GridSe
from sklearn import preprocessing
from sklearn.metrics import r2_score, mean_squared_error
from sklearn import tree
from sklearn.ensemble import BaggingRegressor,RandomForestRegressor,Gradient
```

Spliting the Data

```
x_multi = df.drop('CTC',axis=1)
y_multi = df['CTC']
x_train,x_test,y_train,y_test = train_test_split(x_multi,y_multi,test_size=0
```

Training Models

Linear Model

Linear Regression

```
lrm = LinearRegression()
lrm.fit(x_train,y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
r2_score(y_train,lrm.predict(x_train))
```

```
0.5335038205027318
```

```
r2_score(y_test,lrm.predict(x_test))
```

```
0.5366674761766204
```

preparing of Ridge and Lasso

```
scalar = preprocessing.StandardScaler().fit(x_train)
```

```
x_train_s  = scalar.transform(x_train)
```

```
x_test_s = scalar.transform(x_test)
```

Ridge

```
param_range = np.logspace(-2,8,100)
```

```
train_score,test_score = validation_curve(estimator=Ridge(),X=x_train_s,y=y_
```

```
train_mean = np.mean(train_score,axis=1)
```

```
test_mean = np.mean(test_score,axis=1)
```

```
max(test_mean)
```

```
0.5255042038246518
```

```
np.where(test_mean==max(test_mean))
```

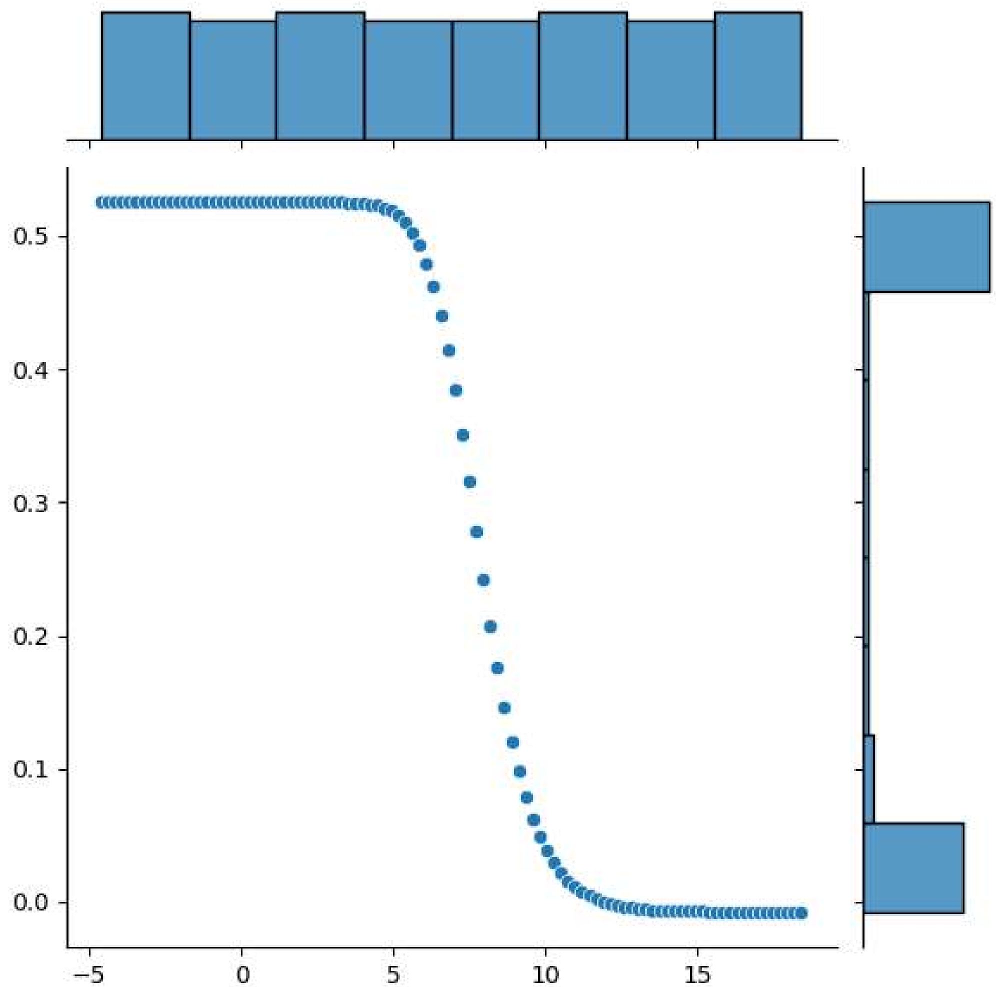
```
(array([27]),)
```

```
param_range[27]
```

```
5.336699231206307
```

```
sns.jointplot(x=np.log(param_range),y=test_mean)
```

```
<seaborn.axisgrid.JointGrid at 0x7fbbc8a17010>
```



Double-click (or enter) to edit

```
lm_r_best = Ridge(alpha=param_range[27])
```

```
lm_r_best.fit(x_train_s,y_train)
```

```
▾ Ridge
Ridge(alpha=5.336699231206307)
```

```
r2_score(y_train,lm_r_best.predict(x_train_s))
```

```
0.5334950361030206
```

```
r2_score(y_test,lm_r_best.predict(x_test_s))
```

```
0.5365159653415602
```

Lasso

```
param_range = np.logspace(-2,8,100)
```

```
train_score,test_score = validation_curve(estimator=Lasso(),X=x_train_s,y=y_
```

```
train_mean = np.mean(train_score,axis=1)
```

```
test_mean = np.mean(test_score,axis=1)
```

```
max(test_mean)
```

```
0.5256355623227839
```

```
np.where(test_mean==max(test_mean))
```

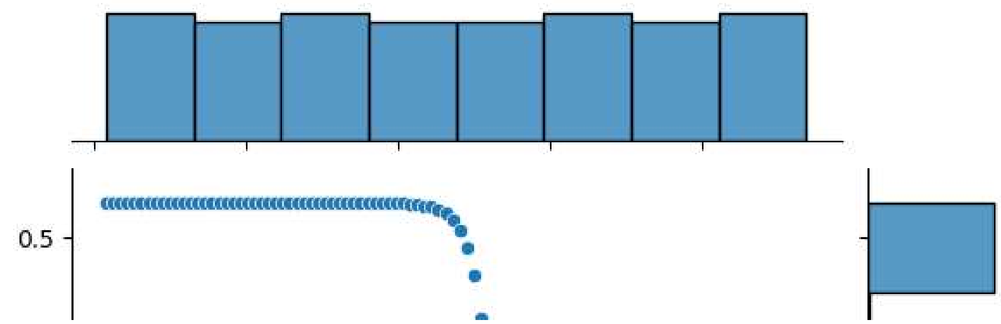
```
(array([39]),)
```

```
param_range[39]
```

```
86.97490026177834
```

```
sns.jointplot(x=np.log(param_range),y=test_mean)
```

```
<seaborn.axisgrid.JointGrid at 0x7fbbc8a15090>
```



Double-click (or enter) to edit

```
lm_r_best = Ridge(alpha=param_range[39])
```

```
lm_r_best.fit(x_train_s,y_train)
```

```
▾ Ridge
Ridge(alpha=86.97490026177834)
```

```
r2_score(y_train,lm_r_best.predict(x_train_s))
```

```
0.5314381052066899
```

```
r2_score(y_test,lm_r_best.predict(x_test_s))
```

```
0.5324961398451409
```

Decision tree

```
# regretree = tree.DecisionTreeRegressor(max_depth=4)
regretree = tree.DecisionTreeRegressor()
```

```
regretree.fit(x_train,y_train)
```

```
▾ DecisionTreeRegressor
DecisionTreeRegressor()
```

```
y_train_pred = regretree.predict(x_train)
y_test_pred = regretree.predict(x_test)
```

```
mean_squared_error(y_test,y_test_pred)
```

```
99801582.73743711
```

```
r2_score(y_train,y_train_pred)
```

```
1.0
```

```
r2_score(y_test,y_test_pred)
```

```
0.3274119454242548
```

Bagging Classifier

```
bag = BaggingRegressor(base_estimator=regretree,n_estimators=1000,
                       bootstrap=True,n_jobs=-1,random_state = 42)
```

```
bag.fit(x_train,y_train)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_base.py:166: FutureWarning: `b
  warnings.warn(
```

```
▸ BaggingRegressor
▸ base_estimator: DecisionTreeRegressor
    ▸ DecisionTreeRegressor
```

```
y_train_pred = bag.predict(x_train)
y_test_pred = bag.predict(x_test)
```

```
mean_squared_error(y_test,y_test_pred)
```

```
50802216.17354207
```

```
r2_score(y_train,y_train_pred)
```

```
0.9500288461826385
```

```
r2_score(y_test,y_test_pred)
```

```
0.6576310434455483
```

Random forest

```
rf = RandomForestRegressor(n_estimators=1000,n_jobs=-1,random_state=42)
```

```
rf.fit(x_train,y_train)
```

```
RandomForestRegressor
RandomForestRegressor(n_estimators=1000, n_jobs=-1, random_state=42)
```

```
y_train_pred = rf.predict(x_train)
y_test_pred = rf.predict(x_test)
```

```
mean_squared_error(y_test,y_test_pred)
```

```
50994949.61767761
```

```
r2_score(y_train,y_train_pred)
```

```
0.9501412879103168
```

```
r2_score(y_test,y_test_pred)
```

```
0.6563321641223232
```

Fine tuning the model with Hyper parameters

```
params_grid = {"max_features": [4,5,6,7,8,9,10],
               "min_samples_split":[2,3,10]}
```

```
grid_search = GridSearchCV(rf,params_grid,n_jobs=-1,cv=5,scoring='neg_mean_s
```

```
grid_search.fit(x_train,y_train)
```

```
/usr/local/lib/python3.10/dist-packages/joblib/externals/loky/process_executor.py:700: U
  warnings.warn(
GridSearchCV
estimator: RandomForestRegressor
RandomForestRegressor
RandomForestRegressor(n_estimators=1000, n_jobs=-1, random_state=42)
```

```
grid_search.best_params_
```

```
{'max_features': 5, 'min_samples_split': 2}
```

```
best_rf = grid_search.best_estimator_
```

```
y_train_pred = best_rf.predict(x_train)
y_test_pred = best_rf.predict(x_test)
```

```
mean_squared_error(y_test,y_test_pred)
```

```
50472155.79009371
```

```
r2_score(y_test,y_test_pred)
```

```
0.6598554036721801
```

Boosting

```
gbc = GradientBoostingRegressor(learning_rate = 0.02,n_estimators=1000,max_d
```

```
gbc.fit(x_train,y_train)
```

```
GradientBoostingRegressor
GradientBoostingRegressor(learning_rate=0.02, max_depth=5, n_estimators=1000)
```

```
y_train_pred = gbc.predict(x_train)
y_test_pred = gbc.predict(x_test)
```

```
mean_squared_error(y_test,y_test_pred)
```

```
53928979.03695529
```

```
r2_score(y_test,y_test_pred)
```

```
0.6365589993582765
```

Fine tuning the model with Hyper parameters

```
gbc = GradientBoostingRegressor()
```

```
params_grid = {"n_estimators": [500,750,1000],
               "learning_rate": [0.01,0.02,0.03,0.04,0.05,0.06,0.07,0.08,0.0
```

```
                 "max_depth":[1,2,3,4,5]
                 }
```

```
grid_search = GridSearchCV(gbc,params_grid,n_jobs=-1,cv=5,scoring='neg_mean_
```

```
grid_search.fit(x_train,y_train)
```

```
▸ GridSearchCV
▸ estimator: GradientBoostingRegressor
  ▸ GradientBoostingRegressor
```

```
grid_search.best_params_
```

```
{'learning_rate': 0.02, 'max_depth': 2, 'n_estimators': 750}
```

```
best_rf = grid_search.best_estimator_
```

```
y_train_pred = best_rf.predict(x_train)
y_test_pred = best_rf.predict(x_test)
```

```
mean_squared_error(y_test,y_test_pred)
```

```
56411263.974740624
```

```
r2_score(y_test,y_test_pred)
```

```
0.6198302546689256
```

Summary

1. Your views about the problem statement?

The company requires statistical data like MSE,Hypothesis testing (p value) along with the predicting the salary(CTC) so the direction is good,but deciding salary based on college may not be the best case as everyone have have minimum 18 months experience . More features would have been better like department they are/will be working in. So we can get more accurate things (CTC) that company need with regression Models.

---

2. What will be your approach to solving this task?

Using the best Linear Model to get the required Statistical Data based on MSE and r2 score.And decision tree for predicting the CTC For this preprocessing of the data is required

- combing the Datasets into one
- Preprocessing the dataset
- Divding the dataset into training and Testing
- Training different models on this dataset and fine tuning the models with hyper parameters
- Finding the best models and getting more details of that models

---

3. What ML model options did you have available to perform this task?

As I have discussed before all regression models can be used in this case. After Preprocessing it is clear that visibly there is no linear correlation but Since we needed statistical data we have used

- Linear_regresssion model(OLS)
- Ridge
- Lasso

In the case of Decision tree we have used

- regressionDecision
- Bagging
- Random forest
- Boosting

---

4. Which model's performance is best and what could be the possible reason for that?

It is Randomforest as Decision tree are better than linear_regression models and since Randomforest is an ensemble technique it is better than a simple DecisionTree.

Boosting reduces the bias so when comming to test data it is reducingits performance you can clearly see this as after hyper tuning we are getting higher mse for test dataset compared to randomly choosen data set. thats the reason why we are not going for adaboosting and all

Below are the results for testing Dataset

RandomForest {'max_features': 5, 'min_samples_split': 2, n_estimators:1000}

- MSE = 50472155.79
- r2 value = 0.6598554036721801

Liner_models: Linear regression

- r2 value = 0.5366674761766204

---

5. What steps can you take to improve this selected model's performance even further?

We can further tune this model by trying out different hyper parameters(maximum number of features ,number of estimators,maximum depth of the trees). Train on more higher data. Evaluate the model with a variety of metrics.

Statistic

```
import statsmodels.api as sn
# this is the reason we didnt remove the college tier_3 column to get its st
```

```
x_multi.head()
```

	City	Previous CTC	Previous job change	Graduation Marks	EXP (Month)	College_tier1	College_tier2	College_
0	1	55523.0	3	66	19	0	1	
1	1	57081.0	1	84	18	0	1	
2	1	60347.0	2	52	28	0	0	
3	1	49010.0	2	81	33	0	0	
4	1	57879.0	4	74	32	1	0	

```
x_multi_cons = sn.add_constant(x_multi)
```

```
x_multi_cons.head()
```

	const	City	Previous CTC	Previous job change	Graduation Marks	EXP (Month)	College_tier1	College_tier2	C
0	1.0	1	55523.0	3	66	19	0	1	
1	1.0	1	57081.0	1	84	18	0	1	
2	1.0	1	60347.0	2	52	28	0	0	
3	1.0	1	49010.0	2	81	33	0	0	
4	1.0	1	57879.0	4	74	32	1	0	

```
lmr_stat= sn.OLS(y_multi,x_multi_cons).fit()
```

```
lmr_stat.summary()
```

OLS Regression Results

Dep. Variable:	CTC	**R-squared:**	0.535
Model:	OLS	**Adj. R-squared:**	0.532
Method:	Least Squares	**F-statistic:**	227.1
Date:	Wed, 07 Jun 2023	**Prob (F-statistic):**	3.36e-256
Time:	04:19:28	**Log-Likelihood:**	-16647.
No. Observations:	1589	**AIC:**	3.331e+04
Df Residuals:	1580	**BIC:**	3.336e+04
Df Model:	8		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	4.297e+04	1642.824	26.154	0.000	3.97e+04	4.62e+04
City	-368.3233	433.465	-0.850	0.396	-1218.550	481.903
Previous CTC	0.4105	0.033	12.542	0.000	0.346	0.475
Previous job change	125.3208	192.846	0.650	0.516	-252.941	503.582
Graduation Marks	6.6007	14.501	0.455	0.649	-21.843	35.044
EXP (Month)	261.6302	15.458	16.925	0.000	231.309	291.951
College_tier1	1.46e+04	618.313	23.620	0.000	1.34e+04	1.58e+04

Hypothesis testing (Statistically we are sure that this features will affect our model by it value per unit)

const,previous_ctc,college_tier,Role_executibe are the most important feature

Omnibus:	48.290	**Durbin-Watson:**	2.051

Model

```
rf = RandomForestRegressor(n_estimators=1000,max_features=5, min_samples_spl
```

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
rf.fit(x_train,y_train)
```

```
RandomForestRegressor
RandomForestRegressor(max_features=5, n_estimators=1000, n_jobs=-1,
                      random_state=42)
```

```
rf.predict('your input values')
```

✓ 5s completed at 9:58 AM

Could not connect to the reCAPTCHA service. Please check your internet connection and reload to get a reCAPTCHA challenge.