# Machine Learning Internship in collaboration with Start Tech Academy

## TASK 1: Build a Linear Regression Model to calculate the expected CTC of an employee using Python

Step 1: Importing necessary libraries

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
```

Step 2: Importing the dataset

In [3]:
```
dataset=pd.read_csv("Data_file.xlsx - Data - Copy feature naming.csv")
```

Step 3: Analysing and understanding the dataset

In [4]:
```
dataset.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype 
---  ------                --------------  ----- 
 0   S.No.                 1338 non-null   int64 
 1   College               1338 non-null   object
 2   Role                  1338 non-null   object
 3   City type             1338 non-null   object
 4   Previous CTC          1338 non-null   object
 5   Previous job changes  1338 non-null   int64 
 6   Graduation marks      1338 non-null   int64 
 7   Exp (Months)          1338 non-null   int64 
 8   CTC                   1338 non-null   object
dtypes: int64(4), object(5)
memory usage: 94.2+ KB
```

NOTE: dtypes: int64(4), object(5)

In [5]:
```
dataset.describe()
```

Out[5]:

| | S.No. | Previous job changes | Graduation marks | Exp (Months) |
|---|---|---|---|---|
| count | 1338.000000 | 1338.000000 | 1338.000000 | 1338.000000 |
| mean | 669.500000 | 2.525411 | 59.890882 | 39.207025 |
| std | 386.391641 | 1.123502 | 14.894696 | 14.049960 |
| min | 1.000000 | 1.000000 | 35.000000 | 18.000000 |
| 25% | 335.250000 | 2.000000 | 47.000000 | 27.000000 |
| 50% | 669.500000 | 3.000000 | 60.000000 | 39.000000 |
| 75% | 1003.750000 | 4.000000 | 73.000000 | 51.000000 |
| max | 1338.000000 | 4.000000 | 85.000000 | 64.000000 |

In [6]:
```
dataset.head()
```

Out[6]:

| | S.No. | College | Role | City type | Previous CTC | Previous job changes | Graduation marks | Exp (Months) | CTC |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | Tier 1 | Manager | Non-Metro | 55,523.00 | 3 | 66 | 19 | 71,406.58 |
| 1 | 2 | Tier 2 | Executive | Metro | 57,081.00 | 1 | 84 | 18 | 68,005.87 |
| 2 | 3 | Tier 2 | Executive | Metro | 60,347.00 | 2 | 52 | 28 | 76,764.02 |
| 3 | 4 | Tier 3 | Executive | Metro | 49,010.00 | 2 | 81 | 33 | 82,092.39 |
| 4 | 5 | Tier 3 | Executive | Metro | 57,879.00 | 4 | 74 | 32 | 73,878.10 |

In [7]:
```
dataset.shape
```

Out[7]: (1338, 9)

In [8]:
```
dataset.tail()
```

Out[8]:

| | S.No. | College | Role | City type | Previous CTC | Previous job changes | Graduation marks | Exp (Months) | CTC |
|---|---|---|---|---|---|---|---|---|---|
| 1333 | 1334 | Tier 3 | Executive | Metro | 59,661.00 | 4 | 68 | 50 | 69,712.40 |
| 1334 | 1335 | Tier 1 | Executive | Non-Metro | 53,714.00 | 1 | 67 | 18 | 69,298.75 |
| 1335 | 1336 | Tier 2 | Executive | Non-Metro | 61,957.00 | 1 | 47 | 18 | 66,397.77 |
| 1336 | 1337 | Tier 1 | Executive | Non-Metro | 53,203.00 | 3 | 69 | 21 | 64,044.38 |
| 1337 | 1338 | Tier 3 | Manager | Non-Metro | 51,820.00 | 1 | 47 | 61 | 83,346.06 |

Inference:

- The given dataset has 1338 rows and 9 columns
- For regression analysis, we will consider numeric values
- There are 4 features which are of integer data type namely S.No.,Previous job changes,Graduation marks,Exp (Months)
- The CTC feature is of object datatype

In [ ]:
```
#dataset['CTC'].astype(str).astype(int)
#raises error because of conversion from comma seperated values to pure integer
#eg: 70,000  ->  70000
```

In [9]:
```
# dataset['new']=dataset['CTC'].replace(',','')
dataset.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype 
---  ------                --------------  ----- 
 0   S.No.                 1338 non-null   int64 
 1   College               1338 non-null   object
 2   Role                  1338 non-null   object
 3   City type             1338 non-null   object
 4   Previous CTC          1338 non-null   object
 5   Previous job changes  1338 non-null   int64 
 6   Graduation marks      1338 non-null   int64 
 7   Exp (Months)          1338 non-null   int64 
 8   CTC                   1338 non-null   object
dtypes: int64(4), object(5)
memory usage: 94.2+ KB
```

In [10]:
```
dataset['CTC']=dataset.CTC.str.replace(',','').astype(float)
```

In [11]:
```
dataset.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   S.No.                 1338 non-null   int64  
 1   College               1338 non-null   object 
 2   Role                  1338 non-null   object 
 3   City type             1338 non-null   object 
 4   Previous CTC          1338 non-null   object 
 5   Previous job changes  1338 non-null   int64  
 6   Graduation marks      1338 non-null   int64  
 7   Exp (Months)          1338 non-null   int64  
 8   CTC                   1338 non-null   float64
dtypes: float64(1), int64(4), object(4)
memory usage: 94.2+ KB
```

In [12]:
```
dataset.head()
```

Out[12]:

| | S.No. | College | Role | City type | Previous CTC | Previous job changes | Graduation marks | Exp (Months) | CTC |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | Tier 1 | Manager | Non-Metro | 55,523.00 | 3 | 66 | 19 | 71406.58 |
| 1 | 2 | Tier 2 | Executive | Metro | 57,081.00 | 1 | 84 | 18 | 68005.87 |
| 2 | 3 | Tier 2 | Executive | Metro | 60,347.00 | 2 | 52 | 28 | 76764.02 |
| 3 | 4 | Tier 3 | Executive | Metro | 49,010.00 | 2 | 81 | 33 | 82092.39 |
| 4 | 5 | Tier 3 | Executive | Metro | 57,879.00 | 4 | 74 | 32 | 73878.10 |

Deleting the useless columns which are created as an experiment

In [ ]:
```
del dataset['newCTC']
del dataset['new']
#this cell may raise error
```

In [13]:
```
dataset.head()
```

Out[13]:

| | S.No. | College | Role | City type | Previous CTC | Previous job changes | Graduation marks | Exp (Months) | CTC |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | Tier 1 | Manager | Non-Metro | 55,523.00 | 3 | 66 | 19 | 71406.58 |
| 1 | 2 | Tier 2 | Executive | Metro | 57,081.00 | 1 | 84 | 18 | 68005.87 |
| 2 | 3 | Tier 2 | Executive | Metro | 60,347.00 | 2 | 52 | 28 | 76764.02 |
| 3 | 4 | Tier 3 | Executive | Metro | 49,010.00 | 2 | 81 | 33 | 82092.39 |
| 4 | 5 | Tier 3 | Executive | Metro | 57,879.00 | 4 | 74 | 32 | 73878.10 |

NOTE: dtypes: float64(1), int64(4), object(4)

Step 4: removing extra spaces from column names

In [14]:
```
dataset.rename(columns = {'City type':'City_type',
                          'Previous CTC':'Previous_CTC',
                          'Previous job changes':'Previous_job_changes',
                          'Graduation marks':'Graduation_marks',
                          'Exp (Months)':'Exp_(Months)'}, inplace = True)
```

Step 5: finding unique values in those columns which hold discrete information

In [15]:
```
dataset.College.unique()
```

Out[15]: array(['Tier 1', 'Tier 2', 'Tier 3'], dtype=object)

In [16]:
```
dataset.Role.unique()
```

Out[16]: array(['Manager', 'Executive'], dtype=object)

In [17]:
```
dataset.City_type.unique()
```

Out[17]: array(['Non-Metro', 'Metro'], dtype=object)

Step 6: Checking for Nan values in the dataset

In [18]:
```
dataset.isnull().values.any()
```

Out[18]: False

In [19]:
```
dataset.isnull().sum()
```

Out[19]:
```
S.No.                   0
College                 0
Role                    0
City_type               0
Previous_CTC            0
Previous_job_changes    0
Graduation_marks        0
Exp_(Months)            0
CTC                     0
dtype: int64
```

Checking the distribution of categorial features

In [20]:
```
dataset.College.value_counts()
```

Out[20]:
```
Tier 1    649
Tier 2    364
Tier 3    325
Name: College, dtype: int64
```

In [21]:
```
dataset.Role.value_counts()
```

Out[21]:
```
Executive    1064
Manager       274
Name: Role, dtype: int64
```

In [22]:
```
dataset.City_type.value_counts()
```

Out[22]:
```
Metro        676
Non-Metro    662
Name: City_type, dtype: int64
```

In [23]:
```
dataset.Previous_job_changes.value_counts()
```

Out[23]:
```
3    348
4    344
1    333
2    313
Name: Previous_job_changes, dtype: int64
```

In [15]:
```
dataset['Previous_CTC']=dataset.Previous_CTC.str.replace(',','').astype(float)
#since the column name was Previous CTC, the space between the 2 words cause syntax error:
#...dataset.Previous CTC.str.replace...
#So, after changing the column name, we are implementing this
dataset.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 9 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   S.No.                 1338 non-null   int64  
 1   College               1338 non-null   object 
 2   Role                  1338 non-null   object 
 3   City_type             1338 non-null   object 
 4   Previous_CTC          1338 non-null   float64
 5   Previous_job_changes  1338 non-null   int64  
 6   Graduation_marks      1338 non-null   int64  
 7   Exp_(Months)          1338 non-null   int64  
 8   CTC                   1338 non-null   float64
dtypes: float64(2), int64(4), object(3)
memory usage: 94.2+ KB
```

Step 7: Encoding the Data

The categorial values (as text) should be converted into numerical values

In [16]:
```
dataset.head()
```

Out[16]:

| | S.No. | College | Role | City_type | Previous_CTC | Previous_job_changes | Graduation_marks | Exp_(Months) | CTC |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | Tier 1 | Manager | Non-Metro | 55523.0 | 3 | 66 | 19 | 71406.58 |
| 1 | 2 | Tier 2 | Executive | Metro | 57081.0 | 1 | 84 | 18 | 68005.87 |
| 2 | 3 | Tier 2 | Executive | Metro | 60347.0 | 2 | 52 | 28 | 76764.02 |
| 3 | 4 | Tier 3 | Executive | Metro | 49010.0 | 2 | 81 | 33 | 82092.39 |
| 4 | 5 | Tier 3 | Executive | Metro | 57879.0 | 4 | 74 | 32 | 73878.10 |

In [17]:
```
dataset.replace({'College':{'Tier 1':1,'Tier 2':2,'Tier 3':3}},inplace=True)
dataset.replace({'Role':{'Manager':0,'Executive':1}},inplace=True)
dataset.replace({'City_type':{'Metro':0,'Non-Metro':1}},inplace=True)
```

In [18]:
```
dataset.head()
```

Out[18]:

| | S.No. | College | Role | City_type | Previous_CTC | Previous_job_changes | Graduation_marks | Exp_(Months) | CTC |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 1 | 0 | 1 | 55523.0 | 3 | 66 | 19 | 71406.58 |
| 1 | 2 | 2 | 1 | 0 | 57081.0 | 1 | 84 | 18 | 68005.87 |
| 2 | 3 | 2 | 1 | 0 | 60347.0 | 2 | 52 | 28 | 76764.02 |
| 3 | 4 | 3 | 1 | 0 | 49010.0 | 2 | 81 | 33 | 82092.39 |
| 4 | 5 | 3 | 1 | 0 | 57879.0 | 4 | 74 | 32 | 73878.10 |

The Dataset is ready for implementing machine learning algorithms

Naive Assumptions:

- Manager role may have higher CTC than executive role
- Tier 1 college candidates may get higher CTC than Tier 3 college candidates
- More experienced candidates may get higher CTC than less experienced candidates
- Metro cities may offer more CTC than Non Metro cities
- Higher Graduation marks may indicate that candidates are worthy for higher CTC
- Expected CTC may be higher than Previous CTC

Step 8: Splitting the data and target

We create two variables X and Y

X stores the trainning data, Y stores the Target data

In [19]:
```
X=dataset.drop(['S.No.','CTC'],axis=1)
#axis=1 means vertical data
#axis=0 means horizontal data
Y=dataset['CTC']
```

Step 9: Spliting for training and testing

In [20]:
```
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.1)
#10% is used for testing, 90% of the data is used for training.
```

Step 10: Training the Model

We are told to use Linear Regression Algorithm

In [21]:
```
lg_model=LinearRegression()
lg_model.fit(X_train,Y_train)
```

Out[21]: LinearRegression()

Step 11: Model Evaluation

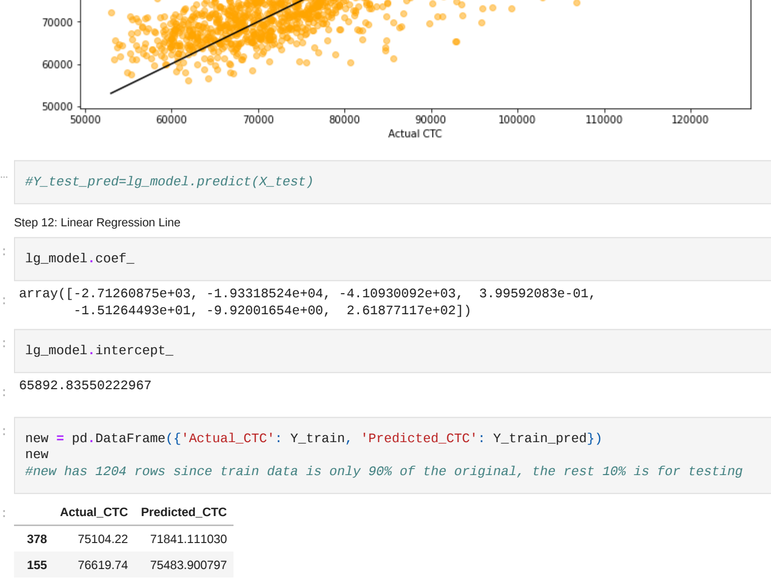
In [22]:
```
Y_train_pred=lg_model.predict(X_train)
```

Mean Squared Error:

In [23]:
```
mean_squared_error(Y_train,Y_train_pred)
#or
np.square(Y_train-Y_train_pred).mean()
```

Out[23]: 63346014.58166719

In [24]:
```
plt.figure(figsize=(12,6))
plt.scatter(Y_train,Y_train_pred,color='orange',alpha=0.5)
plt.xlabel("Actual CTC")
plt.ylabel("Predictied CTC")
plt.title("Predicted CTC vs Actual CTC on training dataset")
p1 = max(max(Y_train), max(Y_train_pred))
p2 = min(min(Y_train), min(Y_train_pred))
plt.plot([p1, p2], [p1, p2], color='black')
plt.show()
```




In [107…
```
#Y_test_pred=lg_model.predict(X_test)
```

Step 12: Linear Regression Line

In [25]:
```
lg_model.coef_
```

Out[25]:
```
array([-2.71260875e+03, -1.93318524e+04, -4.10930092e+03,  3.99592083e-01,
       -1.51264493e+01, -9.92001654e+00,  2.61877117e+02])
```

In [26]:
```
lg_model.intercept_
```

Out[26]: 65892.83550222967

In [27]:
```
new = pd.DataFrame({'Actual_CTC': Y_train, 'Predicted_CTC': Y_train_pred})
new
#new has 1204 rows since train data is only 90% of the original, the rest 10% is for testing
```

Out[27]:

| | Actual_CTC | Predicted_CTC |
|---|---|---|
| 378 | 75104.22 | 71841.111030 |
| 155 | 76619.74 | 75483.900797 |
| 722 | 77770.17 | 83821.894210 |
| 1118 | 94368.83 | 94797.395309 |
| 321 | 79572.91 | 68236.546329 |
| ... | ... | ... |
| 950 | 74893.91 | 75482.216034 |
| 907 | 70973.39 | 70778.102706 |
| 986 | 66304.02 | 69467.185740 |
| 20 | 73487.13 | 78829.754727 |
| 700 | 62927.79 | 66199.131976 |

1204 rows × 2 columns

Equation of Line: Predicted CTC vs Actual CTC

y=mx+c

y=2.587629x + 65678.3627916

In [36]:
```
accuracy=100-abs((new['Predicted_CTC']-new['Actual_CTC'])*100/new['Actual_CTC'])
#accuracy=(numerator/new['Actual_CTC'])*100
#accuracy
accuracy
```

Out[36]:
```
378     95.655226
155     98.517563
722     92.218451
1118    99.545861
321     85.753489
          ...    
950     99.214481
907     99.724844
986     95.229300
20      92.729850
700     94.801435
Length: 1204, dtype: float64
```

In [37]:
```
accuracy.describe()
```

Out[37]:
```
count    1204.000000
mean       91.783861
std         6.202065
min        61.416422
25%        88.748060
50%        93.099073
75%        96.530036
max        99.988826
dtype: float64
```

The Accuracy of the model is 91.783%

In [ ]: