### In [47]: import numpy as np import pandas as pd import seaborn as sns import matplotlib %matplotlib inline from matplotlib import pyplot as plt import statsmodels from sklearn.model\_selection import train\_test split from sklearn.linear\_model import LinearRegression from sklearn import metrics import statsmodels.formula.api as smf from sklearn import tree from sklearn.ensemble import RandomForestRegressor from sklearn.neural\_network import MLPRegressor from sklearn.metrics import mean\_squared\_error from sklearn.metrics import mean absolute error

### In [48]: # Importing the data:

expected\_ctc= pd.read\_csv('expected\_ctc.csv')
expected ctc.head(10)

### Out [48]:

	IDX	( Applicant_ID Total_Experience Total_Experience_in_field_applied		Department		
0	1	22753	0	0	NaN	
1	2	51087	23	14	HR	Cons
2	3	38413	21	12	Top Management	Cons
3	4	11501	15	8	Banking	Fina Ar
4	5	58941	10	5	Sales	P Ma
5	6	30564	16	3	Top Management	Area Ma
6	7	27267	1	1	Engineering	
7	8	36521	19	11	Others	Aı
8	9	11616	8	7	Analytics/BI	С
9	10	43886	15	15	Analytics/BI	

### In [49]: # Accomodating all columns on screen:

pd.options.display.max\_columns = None

In [4]: expected\_ctc.head(10)

Out[4]:

	IDX	Applicant_ID	Total_Experience	Total_Experience_in_field_applied	Department	
0	1	22753	0	0	NaN	
1	2	51087	23	14	HR	Cons
2	3	38413	21	12	Top Management	Cons
3	4	11501	15	8	Banking	Fina Ar
4	5	58941	10	5	Sales	P Ma
5	6	30564	16	3	Top Management	Area Ma
6	7	27267	1	1	Engineering	
7	8	36521	19	11	Others	Aı
8	9	11616	8	7	Analytics/BI	С
9	10	43886	15	15	Analytics/BI	

In [5]: ### Detailed EDA has already been done in Project Notes-1, however,

In [5]: # Checking the total entries:

expected\_ctc.size

Out[5]: 725000

In [50]: # Checking the data structure:

expected\_ctc.shape

Out[50]: (25000, 29)

### In [6]: # Checking the data types:

expected\_ctc.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25000 entries, 0 to 24999
Data columns (total 29 columns):

Data #	columns (total 29 columns): Column	Non-N	ull Count	Dtype
0	IDX	25000	non-null	 int64
1	Applicant_ID	25000	non-null	int64
2	Total_Experience	25000	non-null	int64
3	Total_Experience_in_field_applied	25000	non-null	int64
4	Department	22222	non-null	object
5	Role	24037	non-null	object
6	Industry	24092	non-null	object
7	Organization	24092	non-null	object
8	Designation	21871	non-null	object
9	Education		non-null	object
10	Graduation_Specialization	18820	non-null	object
11	University_Grad		non-null	object
12	Passing_Year_Of_Graduation		non-null	float64
13	PG_Specialization		non-null	object
14	University_PG		non-null	object
15	Passing_Year_Of_PG		non-null	float64
16	PHD_Specialization		non-null	object
17	University_PHD		non-null	object
18	Passing_Year_Of_PHD		non-null	float64
19	Curent_Location		non-null	object
20	Preferred_location		non-null	object
21	Current_CTC		non-null	int64
22	Inhand_Offer		non-null	object
23	Last_Appraisal_Rating		non-null	object
24	No_Of_Companies_worked		non-null	int64
25	Number_of_Publications		non-null	int64
26	Certifications		non-null	int64
27	International_degree_any		non-null	int64
28	Expected_CTC		non-null	int64
	es: float64(3), int64(10), object(1	6)		
memo	ry usage: 5.5+ MB			

## In [51]: #Dropping unnecessary columns that are unique identifiers and do no

expected\_ctc=expected\_ctc.drop(columns=["IDX","Applicant\_ID"])

In [8]: expected\_ctc.head()

Out[8]:

	Total_Experience	Total_Experience_in_field_applied	Department	Role	Industry	Oı
0	0	0	NaN	NaN	NaN	
1	23	14	HR	Consultant	Analytics	
2	21	12	Top Management	Consultant	Training	
3	15	8	Banking	Financial Analyst	Aviation	
4	10	5	Sales	Project Manager	Insurance	

In [52]: expected\_ctc.shape

Out[52]: (25000, 27)

### In [53]: # Converting year\_of\_passing variables to categorical type:

expected\_ctc['Passing\_Year\_Of\_Graduation'] = expected\_ctc['Passing\_Year\_Of\_PG'] = expected\_ctc['Passing\_Year\_Of\_PG'] = expected\_ctc['Passing\_Year\_Of\_PG'] = expected\_ctc['Passing\_Year\_Of\_PHD'] = expected\_ctc['Passing\_Year\_Of\_PG'] = expected\_ctc['Passing\_Year\_Of\_PG']

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25000 entries, 0 to 24999
Data columns (total 27 columns):

#	Column	Non-Null Count	Dtype
0	Total_Experience	25000 non-null	 int64
1	Total_Experience_in_field_applied	25000 non-null	int64
2	Department	22222 non-null	object
3	Role	24037 non-null	object
4	Industry	24092 non-null	object
5	Organization	24092 non-null	object
6	Designation	21871 non-null	object
7	Education	25000 non-null	object
8	Graduation_Specialization	18820 non-null	object
9	University_Grad	18820 non-null	object
10	Passing_Year_Of_Graduation	18820 non-null	object
11	PG_Specialization	17308 non-null	object
12	University_PG	17308 non-null	object
13	Passing_Year_Of_PG	17308 non-null	object
14	PHD_Specialization	13119 non-null	object
15	University_PHD	13119 non-null	object
16	Passing_Year_Of_PHD	13119 non-null	object
17	Curent_Location	25000 non-null	object
18	Preferred_location	25000 non-null	object
19	Current_CTC	25000 non-null	int64
20	Inhand_Offer	25000 non-null	object
21	Last_Appraisal_Rating	24092 non-null	object
22	No_Of_Companies_worked	25000 non-null	int64
23	Number_of_Publications	25000 non-null	int64
24	Certifications	25000 non-null	int64
25	International_degree_any	25000 non-null	int64
26	Expected_CTC	25000 non-null	int64
	es: int64(8), object(19)		
memo	ry usage: 5.1+ MB		

```
In [54]: # Since 'Total_Experience_in_field_applied' showed presence of utli
```

```
def remove_outlier(col):
    sorted(col)
    Q1,Q3=np.percentile(col,[25,75])
    IQR=Q3-Q1
    lower_range= Q1-(1.5 * IQR)
    upper_range= Q3+(1.5 * IQR)
    return lower_range, upper_range
```

```
In [56]: ## NaN value treatments:
    # In columns - ""Industry","Last_Appraisal_Rating","Organization","I
    cat=["Industry","Last_Appraisal_Rating","Organization","Department"
    for column in expected_ctc[cat]:
        expected_ctc[column]=expected_ctc[column].fillna("None")
```

In [14]: # Checking if NaN are replaced correctly:

expected\_ctc.head(20)

Out[14]:

	Total_Experience	Total_Experience_in_field_applied	Department	Role	Industry
0	0	0.0	None	None	None
1	23	14.0	HR	Consultant	Analytics
2	21	12.0	Top Management	Consultant	Training
3	15	8.0	Banking	Financial Analyst	Aviation
4	10	5.0	Sales	Project Manager	Insurance
5	16	3.0	Top Management	Area Sales Manager	Retail
6	1	1.0	Engineering	Team Lead	FMCG
7	19	11.0	Others	Analyst	Others
8	8	7.0	Analytics/BI	Others	Telecom
9	15	15.0	Analytics/BI	CEO	Telecom
10	13	10.0	Education	Business Analyst	Automobile
11	7	1.0	Marketing	Sales Manager	FMCG
12	10	10.0	Others	Bio statistician	Automobile
13	0	0.0	None	None	None
14	12	9.0	Banking	Bio statistician	Telecom
15	20	15.0	Healthcare	Analyst	IT
16	4	4.0	Analytics/BI	Scientist	Analytics
17	21	7.0	Healthcare	Research Scientist	BFSI
18	14	9.0	Sales	Business Analyst	Telecom
19	8	3.0	Engineering	Consultant	Telecom

In [18]: ### Converting discrete categorical to discrete numerical variables

#### Out[61]:

	Total_Experience	Total_Experience_in_field_applied	Department	Role	Industry
0	0	0.0	None	None	None
1	23	14.0	HR	Consultant	Analytics
2	21	12.0	Top Management	Consultant	Training
3	15	8.0	Banking	Financial Analyst	Aviation
4	10	5.0	Sales	Project Manager	Insurance
5	16	3.0	Top Management	Area Sales Manager	Retail
6	1	1.0	Engineering	Team Lead	FMCG
7	19	11.0	Others	Analyst	Others
8	8	7.0	Analytics/BI	Others	Telecom
9	15	15.0	Analytics/BI	CEO	Telecom
10	13	10.0	Education	Business Analyst	Automobile
11	7	1.0	Marketing	Sales Manager	FMCG

12	10	10.0	Others	Bio statistician	Automobile
13	0	0.0	None	None	None
14	12	9.0	Banking	Bio statistician	Telecom
15	20	15.0	Healthcare	Analyst	IT
16	4	4.0	Analytics/BI	Scientist	Analytics
17	21	7.0	Healthcare	Research Scientist	BFSI
18	14	9.0	Sales	Business Analyst	Telecom
19	8	3.0	Engineering	Consultant	Telecom
20	17	12.0	HR	Others	Training
21	7	6.0	Banking	Analyst	Training
22	22	6.0	Top Management	Consultant	BFSI
23	15	10.0	Sales	Head	Insurance
24	3	2.0	Banking	Associate	Aviation

In [20]: expected\_ctc.head()

Out [20]:

	Total_Experience	Total_Experience_in_field_applied	Department	Role	Industry	Oı
0	0	0.0	None	None	None	
1	23	14.0	HR	Consultant	Analytics	
2	21	12.0	Top Management	Consultant	Training	
3	15	8.0	Banking	Financial Analyst	Aviation	
4	10	5.0	Sales	Project Manager	Insurance	

In [63]: expected\_ctc['Edu\_qualification'].unique()

In [64]: # Ordinal encoding for 'Edu\_qualification', since EDA has shown a d.
scores={"Under\_Grad":0,"Graduate":1,"Post\_Grad":2,"Doctorate":3}
expected\_ctc['Edu\_qualification']=expected\_ctc['Edu\_qualification']

In [65]: expected\_ctc['Edu\_qualification'].unique()

Out[65]: array([1, 3, 0, 2])

In [24]: expected\_ctc.head(10)

Out [24]:

	Total_Experience	Total_Experience_in_field_applied	Department	Role	Industry	0
0	0	0.0	None	None	None	
1	23	14.0	HR	Consultant	Analytics	
2	21	12.0	Top Management	Consultant	Training	
3	15	8.0	Banking	Financial Analyst	Aviation	
4	10	5.0	Sales	Project Manager	Insurance	
5	16	3.0	Top Management	Area Sales Manager	Retail	
6	1	1.0	Engineering	Team Lead	FMCG	
7	19	11.0	Others	Analyst	Others	
8	8	7.0	Analytics/BI	Others	Telecom	
9	15	15.0	Analytics/BI	CEO	Telecom	

### In [25]: expected\_ctc.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 25000 entries, 0 to 24999 Data columns (total 27 columns):

#	Column		ull Count	Dtype	
0	Total_Experience	25000	non-null	int64	
1	Total_Experience_in_field_applied	25000	non-null	float64	
2	Department	25000	non-null	object	
3	Role	25000	non-null	object	
4	Industry	25000	non-null	object	
5	Organization	25000	non-null	object	
6	Designation	25000	non-null	object	
7	Graduation_Specialization	25000	non-null	object	
8	University_Grad	25000	non-null	object	
9	Passing_Year_Of_Graduation	18820	non-null	object	
10	PG_Specialization	25000	non-null	object	
11	University_PG	25000	non-null	object	
12	Passing_Year_Of_PG	17308	non-null	object	
13	PHD_Specialization	25000	non-null	object	
14	University_PHD	25000	non-null	object	
15	Passing_Year_Of_PHD	13119	non-null	object	
16	Curent_Location	25000	non-null	object	
17	Preferred_location	25000	non-null	object	
18	Current_CTC	25000	non-null	int64	
19	Inhand_Offer	25000	non-null	int64	
20	Last_Appraisal_Rating	25000	non-null	object	
21	No_Of_Companies_worked	25000	non-null	int64	
22	Number_of_Publications	25000	non-null	int64	
23	Certifications	25000	non-null	int64	
24	<pre>International_degree_any</pre>	25000	non-null	int64	
25	Expected_CTC	25000	non-null	int64	
26	Edu_qualification		non-null	int64	
	es: float64(1), int64(9), object(17	)			
memo	ry usage: 5.1+ MB				

memory usage: 5.1+ MB

In [31]: # For data preprocessing, dummy encoding of catrgorical variables w

In [66]: ## Changing city names to tiers to reduce dimensionality post encod expected\_ctc.replace(dict.fromkeys(['Bangalore','Chennai','Hyderaba

In [67]: expected\_ctc.replace(dict.fromkeys(['Mangalore','Jaipur','Bhubanesw

## In [28]: expected\_ctc.head(10)

Out[28]:

	Total_Experience	Total_Experience_in_field_applied	Department	Role	Industry	0
0	0	0.0	None	None	None	
1	23	14.0	HR	Consultant	Analytics	
2	21	12.0	Top Management	Consultant	Training	
3	15	8.0	Banking	Financial Analyst	Aviation	
4	10	5.0	Sales	Project Manager	Insurance	
5	16	3.0	Top Management	Area Sales Manager	Retail	
6	1	1.0	Engineering	Team Lead	FMCG	
7	19	11.0	Others	Analyst	Others	
8	8	7.0	Analytics/BI	Others	Telecom	
9	15	15.0	Analytics/BI	CEO	Telecom	

```
In [68]: # Checking for unique values:
         columns=["Curent_Location","Preferred_location","University_PHD","U
         for column in expected_ctc[columns]:
             print(column.upper(),': ',expected_ctc[column].nunique())
             print(expected_ctc[column].value_counts().sort_values(ascending)
             print('\n')
         CURENT_LOCATION :
                            2
         Tier-2
                   16631
         Tier-1
                    8369
         Name: Curent_Location, dtype: int64
         PREFERRED LOCATION:
         Tier-2
                   16745
         Tier-1
                    8255
         Name: Preferred_location, dtype: int64
         UNIVERSITY_PHD :
         Not Applicable
                            11881
         Tier-2
                             8946
         Tier-1
                             4173
         Name: University_PHD, dtype: int64
         UNIVERSITY_PG :
         Tier-2
                            11981
         Not_Applicable
                             7692
         Tier-1
                             5327
         Name: University_PG, dtype: int64
```

UNIVERSITY\_GRAD :

Not\_Applicable

Tier-2

Tier-1

3

Name: University\_Grad, dtype: int64

13020

6180

5800

```
In [30]: # Classifying years of graduation, PG and PHD into intervals so as
          columns=["Passing Year Of Graduation","Passing Year Of PG","Passing
          for column in expected_ctc[columns]:
              print(column.upper(),': ',expected_ctc[column].nunique())
              print(expected ctc[column].value counts())
              print('\n')
          2013.0
                     435
          1988.0
                     372
                     328
          2014.0
          1987.0
                     252
                     239
          2019.0
                     223
          2015.0
          2018.0
                     218
                     217
          2020.0
          2016.0
                     210
          2017.0
                     204
          1986.0
                     146
          Name: Passing Year Of Graduation, dtype: int64
          PASSING_YEAR_OF_PG:
                                  36
          2011.0
                     816
          2013.0
                     815
          2010.0
                     774
          2012.0
                     766
          2009.0
                     759
In [69]: bins=[1980,1985,1990,1995,2000,2005,2010,2015,2020,2025]
          expected_ctc['Year_Graduation_bin']=pd.cut(x=expected_ctc['Passing_
          expected ctc['Year PG bin']=pd.cut(x=expected ctc['Passing Year Of
          expected ctc['Year PHD bin']=pd.cut(x=expected ctc['Passing Year Of
In [32]: expected ctc.head()
Out[32]:
             Total_Experience Total_Experience_in_field_applied
                                                      Department
                                                                    Role
                                                                          Industry O
          0
                        0
                                                  0.0
                                                           None
                                                                    None
                                                                            None
           1
                        23
                                                 14.0
                                                                Consultant
                                                                          Analytics
                                                            Top
          2
                        21
                                                 12.0
                                                                Consultant
                                                                           Training
                                                     Management
```

15

10

Aviation

Insurance

Financial

Analyst

**Project** 

Manager

8.0

5.0

Banking

Sales

# In [70]: check\_nan\_in\_data=expected\_ctc.isnull().sum() print(check\_nan\_in\_data)

Total_Experience	0
Total_Experience_in_field_applied	0
Department	0
Role	0
Industry	0
Organization	0
Designation	0
Graduation_Specialization	0
University_Grad	0
Passing_Year_Of_Graduation	6180
PG_Specialization	0
University_PG	0
Passing_Year_Of_PG	7692
PHD_Specialization	0
University_PHD	0
Passing_Year_Of_PHD	11881
Curent_Location	0
Preferred_location	0
Current_CTC	0
Inhand_Offer	0
Last_Appraisal_Rating	0
No_Of_Companies_worked	0
Number_of_Publications	0
Certifications	0
<pre>International_degree_any</pre>	0
Expected_CTC	0
Edu_qualification	0
Year_Graduation_bin	6180
Year_PG_bin	7692
Year_PHD_bin	11881
dtype: int64	

## In [71]: # Replacing NaN values with 'Not Applicable', since here imputation

cat=['Passing\_Year\_Of\_Graduation','Passing\_Year\_Of\_PG','Passing\_Yea
for column in expected\_ctc[cat]:
 expected\_ctc[column]=expected\_ctc[column].fillna("Not\_Applicable

In [35]: expected\_ctc.head()

Out[35]:

	Total_Experience	Total_Experience_in_field_applied	Department	Role	Industry	Oı
0	0	0.0	None	None	None	
1	23	14.0	HR	Consultant	Analytics	
2	21	12.0	Top Management	Consultant	Training	
3	15	8.0	Banking	Financial Analyst	Aviation	
4	10	5.0	Sales	Project Manager	Insurance	

### In [72]: # Converting year\_bin variables to categorical type:

expected\_ctc['Year\_Graduation\_bin']=expected\_ctc['Year\_Graduation\_b
expected\_ctc['Year\_PG\_bin']=expected\_ctc['Year\_PG\_bin'].astype("objected\_ctc['Year\_PHD\_bin']=expected\_ctc['Year\_PHD\_bin'].astype("olevated\_ctc.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25000 entries, 0 to 24999
Data columns (total 30 columns):

#	Column	Non-N	ull Count	Dtype
0	Total_Experience	25000	non-null	int64
1	Total_Experience_in_field_applied	25000	non-null	float64
2	Department	25000	non-null	object
3	Role	25000	non-null	object
4	Industry	25000	non-null	object
5	Organization	25000	non-null	object
6	Designation	25000	non-null	object
7	Graduation_Specialization	25000	non-null	object
8	University_Grad	25000	non-null	object
9	Passing_Year_Of_Graduation	25000	non-null	object
10	PG_Specialization	25000	non-null	object
11	University_PG	25000	non-null	object
12	Passing_Year_Of_PG	25000	non-null	object
13	PHD_Specialization	25000	non-null	object
14	University_PHD	25000	non-null	object
15	Passing_Year_Of_PHD	25000	non-null	object
16	Curent_Location	25000	non-null	object
17	Preferred_location	25000	non-null	object
18	Current_CTC	25000	non-null	int64
19	Inhand_Offer	25000	non-null	int64
20	Last_Appraisal_Rating	25000	non-null	object
21	No_Of_Companies_worked	25000	non-null	int64
22	Number_of_Publications	25000	non-null	int64
23	Certifications	25000	non-null	int64
24	<pre>International_degree_any</pre>	25000	non-null	int64
25	Expected_CTC	25000	non-null	int64
26	Edu_qualification	25000	non-null	int64
27	Year_Graduation_bin	18820	non-null	object
28	Year_PG_bin		non-null	object
29	Year_PHD_bin		non-null	object
	es: float64(1), int64(9), object(20	)		
memo	ry usage: 5.7+ MB			

## In [44]: expected\_ctc.head(10)

### Out [44]:

	Total_Experience	Total_Experience_in_field_applied	Department	Role	Industry	0
0	0	0.0	None	None	None	
1	23	14.0	HR	Consultant	Analytics	
2	21	12.0	Top Management	Consultant	Training	
3	15	8.0	Banking	Financial Analyst	Aviation	
4	10	5.0	Sales	Project Manager	Insurance	
5	16	3.0	Top Management	Area Sales Manager	Retail	
6	1	1.0	Engineering	Team Lead	FMCG	
7	19	11.0	Others	Analyst	Others	
8	8	7.0	Analytics/BI	Others	Telecom	
9	15	15.0	Analytics/BI	CEO	Telecom	

# In [74]: check\_nan\_in\_data=expected\_ctc.isnull().sum() print(check\_nan\_in\_data)

Total_Experience	0
Total_Experience_in_field_applied	0
Department	0
Role	0
Industry	0
Organization	0
Designation	0
Graduation_Specialization	0
University_Grad	0
Passing_Year_Of_Graduation	0
PG_Specialization	0
University_PG	0
Passing_Year_Of_PG	0
PHD_Specialization	0
University_PHD	0
Passing_Year_Of_PHD	0
Curent_Location	0
Preferred_location	0
Current_CTC	0
Inhand_Offer	0
Last_Appraisal_Rating	0
No_Of_Companies_worked	0
Number_of_Publications	0
Certifications	0
<pre>International_degree_any</pre>	0
Expected_CTC	0
Edu_qualification	0
Year_Graduation_bin	0
Year_PG_bin	0
Year_PHD_bin	0
dtype: int64	

### In [75]: ## Changing education specialization names to subject categories in

```
expected_ctc.replace(dict.fromkeys(['Chemistry','Zoology','Botony']
expected_ctc.replace(dict.fromkeys(['Mathematics','Statistics'],'Mathematics','Psychology','Sociology'
```

Not\_Applicable 6180
Pure\_sciences 5189
Arts\_Humanities 5123
Maths\_Stats 3413
Economics 1774
Engineering 1661
Others 1660

Name: Graduation\_Specialization, dtype: int64

PG\_SPECIALIZATION: 7
Not\_Applicable 7692
Pure\_sciences 4591
Arts\_Humanities 4220
Maths\_Stats 3439
Economics 1755
Engineering 1674
Others 1629

Name: PG\_Specialization, dtype: int64

PHD SPECIALIZATION: 7 Not\_Applicable 11881 Pure sciences 3445 Arts\_Humanities 2913 Maths\_Stats 2614 0thers 1545 **Economics** 1343 1259 Engineering

Name: PHD\_Specialization, dtype: int64

```
In [31]: # Finally checking for unique categorical values: (to check data hy
categorical=['Department','Role','Industry','Organization','Designar

for column in expected_ctc[categorical]:
    print(column.upper(),': ',expected_ctc[column].nunique())
    print(expected_ctc[column].value_counts().sort_values(ascending:
    print('\n')
```

None 2778 2379 Marketing Analytics/BI 2096 Healthcare 2062 0thers 2041 Sales 1991 HR 1988 1952 Banking Education 1948 Engineering 1937 Top Management 1632 Accounts 1118 IT-Software 1078

Name: Department, dtype: int64

ROLE : 25

Others 2248
Bio statistician 1913
Analyst 1802

### In [ ]:

In [77]: expected\_ctc= pd.get\_dummies(expected\_ctc, columns=['Department','Re

In [43]: expected\_ctc.head(10)

Out[43]:

	Total_Experience	Total_Experience_in_field_applied	Passing_Year_Of_Graduation	Passing_
0	0	0.0	2020.0	Nc
1	23	14.0	1988.0	
2	21	12.0	1990.0	
3	15	8.0	1997.0	
4	10	5.0	2004.0	
5	16	3.0	1998.0	
6	1	1.0	2011.0	
7	19	11.0	2001.0	Nc
8	8	7.0	2003.0	
9	15	15.0	1998.0	

In [78]: # Columns 'Passing\_Year\_Of\_Graduation', 'Passing\_Year\_Of\_PG', 'Passing
expected\_ctc=expected\_ctc.drop(columns=['Passing\_Year\_Of\_Graduation]

In [79]: expected\_ctc.shape

Out[79]: (25000, 143)

In [80]: expected\_ctc.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25000 entries, 0 to 24999

Columns: 143 entries, Total\_Experience to Year\_PHD\_bin\_Not\_Applica

ble

dtypes: float64(1), int64(9), uint8(133)

memory usage: 5.1 MB

In [54]: ### Model building:

```
In [81]: #Extracting the target column to create separate vectors for splitt.

x = expected_ctc.drop("Expected_CTC", axis=1)
y = expected_ctc.pop("Expected_CTC")

x.head()
```

### Out[81]:

Total_Experience To	otal_Experience_i	in_field_applied	Current_CTC	Inhand_Offer	No_Of_Co
---------------------	-------------------	------------------	-------------	--------------	----------

0	0	0.0	0	0	
1	23	14.0	2702664	1	
2	21	12.0	2236661	1	
3	15	8.0	2100510	0	
4	10	5.0	1931644	0	

```
In [82]: #Splitting the data into Training & Testing sets:
    from sklearn.model_selection import train_test_split
    x train, x test, y train, y test = train_test_split(x, y, test_size)
```

```
In [83]: #checking the dimensions of the two sets:
```

```
print('x_train',x_train.shape)
print('x_test',x_test.shape)
print('y_train',y_train.shape)
print('y_test',y_test.shape)
```

```
x_train (17500, 142)
x_test (7500, 142)
y_train (17500,)
y_test (7500,)
```

### In [37]: # Building a LinearRegression model and finding the bestfit model o

```
from sklearn.linear_model import LinearRegression
regression model = LinearRegression()
```

regression\_model.fit(x\_train, y\_train)

Out[37]: LinearRegression()

```
In [59]: #Checking the coefficients for each feature:
         from sklearn import metrics
         for idx, col_name in enumerate(x_train.columns):
             print("The coefficient for {} is {}".format(col_name, regression)
         The coefficient for Role_Lab Executuve is 32775.6447403629
         The coefficient for Role_None is 3753.644029711022
         The coefficient for Role Others is -56.60079629758957
         The coefficient for Role_Principal Analyst is 6415.09437098778
         The coefficient for Role Professor is -909.9381943583301
         The coefficient for Role_Project Manager is -2288.1258282706535
         The coefficient for Role_Research Scientist is 85909.96521027279
         The coefficient for Role_Researcher is -20012.551614403987
         The coefficient for Role_Sales Execituve is 1307.9036347681822
         The coefficient for Role Sales Manager is -520.8415145142062
         The coefficient for Role_Scientist is 5298.277142100883
         The coefficient for Role Senior Analyst is 13093.274674785851
         The coefficient for Role_Senior Researcher is -1059.3391745529116
         The coefficient for Role_Sr. Business Analyst is 9567.016430777692
         The coefficient for Role_Team Lead is -460.2775162408675
         The coefficient for Industry_Automobile is 3835.229465967636
         The coefficient for Industry Aviation is 2307.804833008578
         The coefficient for Industry_BFSI is 5590.428636728054
         The coefficient for Industry_FMCG is 1904.15105151379
         The coefficient for Industry IT is
In [51]: #Finding the intercept value:
         intercept = regression_model.intercept_
         print("The intercept for our model is {}".format(intercept))
         The intercept for our model is 83923.89081323612
In [52]: # Calculating R2:
         r2_train=regression_model.score(x_train, y_train)
         print("R2 on training data is {}".format(r2_train))
         #93% of variation in price is explained by predictors in training s
         #Calculating R2 on test data:
         r2_test=regression_model.score(x_test, y_test)
         print("R2 on test data is {}".format(r2_test))
         R2 on training data is 0.9928744656374558
         R2 on test data is 0.9930025402502967
```

In [84]: **from** sklearn **import** metrics

### In [55]: # Calculating RSME:

predicted\_train=regression\_model.fit(x\_train, y\_train).predict(x\_train)
rsme\_train=np.sqrt(metrics.mean\_squared\_error(y\_train,predicted\_train)
print("RSME on training data is {}".format(rsme\_train))

predicted\_test=regression\_model.fit(x\_train, y\_train).predict(x\_testing)
rsme\_test=np.sqrt(metrics.mean\_squared\_error(y\_test,predicted\_test)
print("RSME on test data is {}".format(rsme\_test))

RSME on training data is 97582.27324718762 RSME on test data is 97934.3355324096

### In [ ]:

data\_train = pd.concat([x\_train, y\_train], axis=1)
data\_test=pd.concat([x\_test,y\_test],axis=1)
data\_train.head()

#### Out[85]:

### Total\_Experience Total\_Experience\_in\_field\_applied Current\_CTC Inhand\_Offer No\_C

16	6.0	2599539	0
12	11.0	1590046	1
25	13.0	3641226	0
14	0.0	1567804	0
20	17.0	3344366	0
	12 25 14	12 11.0 25 13.0 14 0.0	12     11.0     1590046       25     13.0     3641226       14     0.0     1567804

In [41]: data\_train.shape

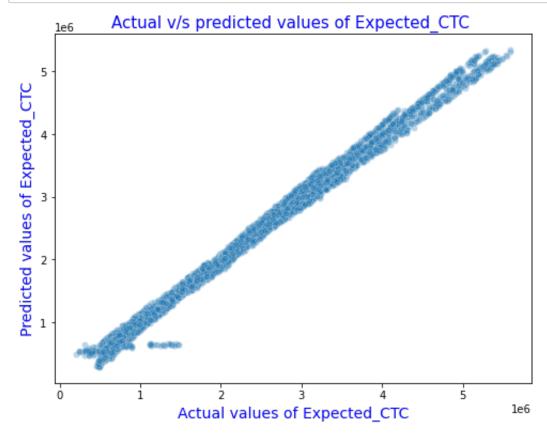
Out[41]: (17500, 143)

```
In [65]: data_train.columns
Out[65]: Index(['Total Experience', 'Total Experience in field applied', 'C
          urrent CTC',
                   'Inhand_Offer', 'No_Of_Companies_worked', 'Number_of_Public
          ations',
                   'Certifications', 'International_degree_any', 'Edu_qualific
          ation',
                   'Department Analytics/BI',
                   'Year_PG_bin_(2015, 2020]', 'Year_PG_bin_(2020, 2025]',
                   'Year_PG_bin_Not_Applicable', 'Year_PHD_bin_(1995, 2000]', 'Year_PHD_bin_(2000, 2005]', 'Year_PHD_bin_(2005, 2010]', 'Year_PHD_bin_(2010, 2015]', 'Year_PHD_bin_(2015, 2020]', 'Year_PHD_bin_Not_Applicable', 'Expected_CTC'],
                  dtype='object', length=143)
In [86]: data train.rename(columns = {'Department Analytics/BI':'Department
In [67]: import statsmodels.formula.api as smf
           lm1 = smf.ols(formula= 'Expected_CTC ~ Total_Experience + Total_Exp
           print(lm1.summary())
                                           OLS Regression Results
           Dep. Variable:
                                        Expected CTC
                                                         R-squared:
           0.993
          Model:
                                                  0LS
                                                         Adj. R-squared:
           0.993
          Method:
                                       Least Squares
                                                         F-statistic:
           1.819e+04
          Date:
                                   Sat, 14 May 2022
                                                         Prob (F-statistic):
           0.00
          Time:
                                             11:11:11
                                                         Log-Likelihood:
           -2.2588e+05
          No. Observations:
                                                17500
                                                         AIC:
           4.520e+05
          Df Residuals:
                                                17366
                                                         BIC:
           4.531e+05
           Df Model:
                                                   133
           Covariance Type:
                                           nonrobust
In [70]: # Let us check the sum of squared errors by predicting value of y f
          # subtracting from the actual y for the test cases
          mse = np.mean((regression model.predict(x test)-y test)**2)
```

In [71]: # underroot of mean\_sq\_error is standard deviation i.e. avg variance
import math
math.sqrt(mse)
# so there is avg of 97934.335 (roundoff) mpg difference from real

Out[71]: 97934.3355324097

In [89]: plt.figure(figsize=(8,6))
 sns.scatterplot(x=y\_test, y=predicted\_test, data=data\_test, alpha=0
 plt.title("Actual v/s predicted values of Expected\_CTC ",color="blue"
 plt.xlabel("Actual values of Expected\_CTC", color="blue",size=14)
 plt.ylabel("Predicted values of Expected\_CTC",color="blue",size=14)
 plt.show()



In []: # Caculating VIF (Variable inflation Factor) to determine multicoll

```
In [68]: def vif_cal(input_data):
             vars=input data
             var names=input data.columns
             for i in range(0,var_names.shape[0]):
                 y=vars[var_names[i]]
                 x=vars[var_names.drop(var_names[i])]
                 rsq=smf.ols(formula="y~x", data=vars).fit().rsquared
                 vif=round(1/(1-rsq),2)
                 print (var_names[i], " VIF = " , vif)
In [ ]:
In [69]: vif cal(input data=data train.drop('Expected CTC',axis=1))
         Total Experience VIF = 7.48
         Total_Experience_in_field_applied VIF = 1.74
         Current_CTC VIF = 5.42
         Inhand Offer VIF = 1.62
         No Of_Companies_worked VIF = 1.37
         Number of Publications VIF = 2.07
         Certifications VIF = 1.48
         International_degree_any VIF = 1.88
         <ipython-input-68-006ae825bd87>:8: RuntimeWarning: divide by zero
         encountered in double_scalars
           vif=round(1/(1-rsq),2)
         Edu_qualification VIF = inf
         Department Analytics BI VIF = 3.03
         Department_Banking VIF = 2.68
         Department_Education VIF = 2.68
         Department_Engineering VIF = 2.62
         Department HR VIF = 2.68
         Department Healthcare VIF = 2.82
 In [ ]: ### Iteration-2 --> dropping variable 'Total_Expeerience' which has
```

```
In [101]: vif_cal(input_data=data_train.drop(['Expected_CTC','Total_Experienc
          Total Experience in field applied VIF = 1.57
          Current CTC VIF = 3.57
          Inhand Offer VIF = 1.62
          No_Of_Companies_worked VIF =
         Number of Publications VIF = 2.07
          Certifications VIF = 1.48
          International degree any VIF = 1.88
          <ipython-input-68-006ae825bd87>:8: RuntimeWarning: divide by zero
          encountered in double scalars
           vif=round(1/(1-rsq),2)
          Edu qualification VIF = inf
          Department_Analytics_BI VIF = 3.02
          Department_Banking VIF = 2.67
          Department_Education VIF = 2.68
          Department_Engineering VIF = 2.61
          Department HR VIF = 2.67
          Department Healthcare VIF = 2.81
          Department IT Software VIF = 1.93
In [103]: lm2 = smf.ols(formula= 'Expected_CTC ~ Total_Experience_in_field_ap)
          print(lm2.summary())
```

# OLS Regression Results

```
Dep. Variable: Expected_CTC R-squared: 0.992
Model: OLS Adj. R-squared:
```

0.992
Method: Least Squares F-statistic:

1.726e+04

Date: Sat, 14 May 2022 Prob (F-statistic):

0.00
Time: 13:45:08 Log-Likelihood:

-2.2640e+05 No. Observations: 17500 AIC:

4.531e+05
Df Residuals: 17367 BIC:

UT RESIDUALS: 1/36/ BIC: 4.541e+05

Df Model: 132 Covariance Type: nonrobust

In [ ]: # In the 2nd model also,  $r^2$  and adjussred  $R^2$  is showing very mini

```
In [87]: ### Building other models (ANN, Decision tree and Random Forest) al
    #As a prerequisite for ANN model, data will be scaled before model
    from sklearn.preprocessing import StandardScaler
    ss=StandardScaler()
    x_train_scaled=ss.fit_transform(x_train)
    x_test_scaled=ss.transform(x_test)
```

```
In [78]: from sklearn import tree
         from sklearn.ensemble import RandomForestRegressor
         from sklearn.neural network import MLPRegressor
         from sklearn.metrics import mean squared error
         from sklearn.metrics import mean_absolute_error
         ann = MLPRegressor(hidden_layer_sizes=(300),random_state=123, max_i
         rf = RandomForestRegressor(random state=123)
         dt = tree.DecisionTreeRegressor(criterion='gini', random state=123)
         lr = LinearRegression()
         models=[lr,dt,rf,ann]
         rmse_train=[]
         rmse test=[]
         scores_train=[]
         scores test=[]
         for i in models:
             if (i != ann) :
                 i.fit(x_train,y_train)
                 scores_train.append(i.score(x_train, y_train))
                 scores test.append(i.score(x test, y test))
                 rmse train.append(np.sgrt(mean squared error(y train,i.pred
                 rmse_test.append(np.sqrt(mean_squared_error(y_test,i.predic
             else:
                 i.fit(x_train_scaled,y_train)
                 scores train.append(i.score(x train scaled, y train))
                 scores test.append(i.score(x test scaled, y test))
                 rmse train.append(np.sgrt(mean squared error(y train,i.pred)
                 rmse test.append(np.sqrt(mean squared error(y test,i.predic
         print(pd.DataFrame({'Train RMSE': rmse_train,'Test RMSE': rmse_test
                     index=['Linear Regression','Decision Tree Regressor','R
```

/Users/sabita/opt/anaconda3/lib/python3.8/site-packages/sklearn/ne ural\_network/\_multilayer\_perceptron.py:582: ConvergenceWarning: St ochastic Optimizer: Maximum iterations (5000) reached and the opti mization hasn't converged yet.

warnings.warn(

Train RMSE Test RMSE Training Scor

e \

```
Linear Regression
                                   97582.273247
                                                 97934.335532
                                                                      0.99287
         Decision Tree Regressor
                                   10608.936386
                                                 93445.970082
                                                                      0.99991
         Random Forest Regressor
                                  28114.073619
                                                 69852.484628
                                                                      0.99940
                                                                      0.99645
         ANN Regressor
                                   68880.980429
                                                 82933.139529
                                   Test Score
         Linear Regression
                                     0.993003
         Decision Tree Regressor
                                     0.993629
         Random Forest Regressor
                                     0.996440
                                     0.994982
         ANN Regressor
In [79]: ### Tuning the models with grid search to find the best parameters
In [42]: from sklearn.model_selection import GridSearchCV
In [59]: # Grid search CV for Decision Tree regressor:
         param_grid = {
              'max_depth': [10,15,20,25,30],
             'min_samples_leaf': [3, 10,20],
             'min_samples_split': [10,25,30,40,50],
         }
         dtr=tree.DecisionTreeRegressor(random_state=123)
         grid_search = GridSearchCV(estimator = dtr, param_grid = param_grid
         grid_search.fit(x_train,y_train)
         print(grid_search.best_params_)
         {'max_depth': 20, 'min_samples_leaf': 10, 'min_samples_split': 10}
In [60]:
         best_grid = grid_search.best_estimator_
         best_grid
Out[60]: DecisionTreeRegressor(max_depth=20, min_samples_leaf=10, min_sampl
         es split=10,
                                random state=123)
```

```
In [70]: # Generating the decision tree:
         train char label = ['no', 'yes']
         tree_regularized = open('tree_regularized.doc','w')
         doc_data = tree.export_graphviz(best_grid, out_file= tree_regulariz
         tree regularized.close()
         doc data
In [62]: # Genrating the decision tree on the site http://webgraphviz.com/
In [65]: # Understanding feature importance:
         pd.options.display.max rows = None
         print (pd.DataFrame(best grid.feature importances , columns = ["Imp"]
                                                              Imp
         Current_CTC
                                                     9.878782e-01
         Last_Appraisal_Rating_D
                                                     4.387552e-03
         Last_Appraisal_Rating_C
                                                     4.159063e-03
         Total Experience
                                                     8.723766e-04
         Edu_qualification
                                                     6.599851e-04
         Inhand Offer
                                                     6.560692e-04
         Certifications
                                                     3.051328e-04
         Year_Graduation_bin_Not_Applicable
                                                     1.897096e-04
         Graduation Specialization Not Applicable
                                                    1.595508e-04
         Number_of_Publications
                                                     8.353873e-05
         Last Appraisal Rating B
                                                     7.445832e-05
         PHD_Specialization_Engineering
                                                     6.221591e-05
         Total_Experience_in_field_applied
                                                     5.553028e-05
         No_Of_Companies_worked
                                                     4.361974e-05
         PHD Specialization Maths Stats
                                                     4.161556e-05
         PG Specialization Pure sciences
                                                     3.716847e-05
         PG_Specialization_Maths_Stats
                                                     3.603037e-05
         Last_Appraisal_Rating_Key_Performer
                                                     3.018223e-05
         DC Charialization Othora
                                                     2 EEA0724 AE
```

# In [66]:

```
In [83]: # Grid search CV for Random Forest regressor:
         param grid = {
             'max_depth': [10,15],
             'max_features': [15, 20],
             'min_samples_leaf': [5, 15,30],
             'min_samples_split': [20,40,60],
             'n_estimators': [200, 300]
         }
         rfr = RandomForestRegressor(random_state=123)
         grid_search = GridSearchCV(estimator = rfr, param_grid = param_grid
         grid search.fit(x train,y train)
Out[83]: GridSearchCV(cv=3, estimator=RandomForestRegressor(random_state=12
         3),
                      param_grid={'max_depth': [10, 15], 'max_features': [1
         5, 20],
                                   'min_samples_leaf': [5, 15, 30],
                                   'min_samples_split': [20, 40, 60],
                                   'n_estimators': [200, 300]})
In [84]: |print(grid_search.best_params_)
         {'max_depth': 15, 'max_features': 20, 'min_samples_leaf': 5, 'min_
         samples_split': 20, 'n_estimators': 300}
 In [ ]:
In [68]: # Grid search CV for Artificial Neural Network regressor:
         #from sklearn.neural_network import MLPRegressor
         #param grid = {
             'hidden_layer_sizes': [50,100],
             'max_iter': [5500,7000],
             'solver': ['adam', 'sgd'],
             'tol': [0.01],
         #nnr = MLPRegressor(random_state=1)
         #grid_search = GridSearchCV(estimator = nnr, param_grid = param_gri
In [43]: #grid search.fit(x train scaled, y train)
         #grid_search.best_params_
 In [ ]: |#best_grid = grid_search.best_estimator_
         #best grid
```

```
In [38]: | ### Creating regularised models using Lasso & Ridge:
In [45]: from sklearn.linear model import Ridge
         from sklearn.linear_model import Lasso
         from sklearn.metrics import r2 score
In [58]:
        ridge = Ridge(alpha=50)
         ridge.fit(x_train,y_train)
         print ("Ridge model:", (ridge.coef_))
         Ridge model: [-8.48413668e+03
                                        1.18324315e+02
                                                        1.34308566e+00
         0663881e+04
          -6.20445524e+02
                          4.86656852e+02 -1.47168253e+04
                                                            8.17013395e+02
           9.82274079e+03 -1.36352392e+04 -1.55319171e+04
                                                            6.94969917e+03
          -1.41885568e+04 -1.44267457e+04 -1.18579162e+04 -1.02480824e+04
          -1.44679356e+04 -1.02068394e+04 -1.21891835e+04 -1.15131721e+04
          -2.04921908e+04 4.36571160e+03 -4.94057049e+03 -2.75344995e+03
           4.66309185e+02 -1.75912174e+03
                                           1.52884180e+03
                                                            1.42080801e+03
           2.28774043e+03 -7.74967612e+03
                                           7.83965976e+03
                                                            7.87113278e+04
          -3.15447730e+03
                           3.17903775e+03 -1.36268762e+03 -5.38419583e+03
           2.57190989e+04 -1.48431265e+04 -1.88324706e+03 -3.19135348e+03
           2.02501915e+03 5.30110379e+03 -4.78787825e+03
                                                           2.17277089e+03
          -3.66228802e+03 -1.40030036e+02 -1.99242847e+03
                                                            1.62049931e+03
          -2.02642127e+03 -3.75139161e+03 -2.05898446e+02
                                                            1.39019696e+05
           1.97135359e+03
                           1.75590808e+02 -2.51455781e+03 -1.75455199e+03
          -9.61802025e+03 -6.68355677e+03 -1.33553264e+03 -8.55296351e+03
          -1.36646873e+03 -8.77890010e+03 -8.85088236e+03 -2.87653623e+03
          -6.03578600e+03 -3.70486502e+03 -5.80906521e+03 -2.13598257e+03
          -4.08469731e+03
                          1.39019696e+05 -7.75075952e+03 -5.71812197e+03
                                           2.02324184e+03 -8.10970177e+03
          -9.24717647e+03 -3.14967224e+03
          -9.05696113e+03 -1.92864467e+02 -6.08015705e+03 -1.33394790e+03
                           2.65067562e+03 -8.08967473e+03 -4.46415338e+03
          -4.68991147e+03
                                           2.76321551e+01 -1.38090396e+03
           5.00424703e+03 -1.29942936e+04
          -2.71206812e+03 -3.00507037e+03 -2.56735707e+04 -1.98642221e+05
          -2.02526376e+05
                           1.69275460e+04
                                           1.39019696e+05
                                                            5.50676700e+03
           1.17560046e+04 -7.81363170e+03 -5.87059083e+03
                                                           2.83805714e+03
           3.64364099e+03
                           8.54772689e+02
                                           5.01581815e+03 -6.10039414e+02
          -3.31511917e+03 -1.27388522e+03 -3.97741869e+02 -1.57484449e+03
           2.28790666e+03
                           2.02983396e+03 -1.63209209e+03
                                                          4.03268256e+03
                           2.50125802e+04 -3.55440809e+03 -1.46912168e+03
           7.78745260e+03
          -8.40883732e+03
                           1.08594024e+03
                                          2.46846785e+03 -4.30627471e+03
           2.43380266e+02 -3.50437147e+03 -4.71828944e+03 -3.00396208e+04
                           1.73528126e+04 -3.27481548e+04 -5.87059083e+03
          -3.17941331e+04
          -6.41463863e+03 -1.56960068e+04 -8.67543964e+03 -4.38040784e+03
          -1.02788521e+04 8.55604483e+03 -2.74297101e+03 -3.97741869e+02
          -6.60918586e+03 -3.25725688e+04 -2.79599353e+04 1.11765836e+04
           1.20119366e+04 -3.55440809e+03]
```

```
In [59]: print(ridge.score(x_train, y_train))
         print(ridge.score(x_test, y_test))
         0.9928388928789039
         0.9929874356258246
In [62]: lasso = Lasso(alpha=50)
         lasso.fit(x_train,y_train)
         print ("Lasso model:", (lasso.coef_))
         Lasso model: [-8.63276030e+03
                                         1.14033545e+02
                                                                          5.8
                                                         1.34377050e+00
         3630625e+04
          -2.16567618e+02 4.40031297e+02 -1.45930789e+04
                                                            5.72122516e+02
           1.05844671e+04 -1.07437085e+04 -1.33487190e+04
                                                            8.64634187e+03
          -1.20660228e+04 -1.22718770e+04 -9.70871011e+03 -7.98585900e+03
          -1.01044662e+04 -1.25643441e+04 -9.91593140e+03 -9.28177588e+03
          -1.75540171e+04
                            0.00000000e+00 -8.54022699e+02 -3.40032526e+02
                                           2.86829378e+03
                                                            0.00000000e+00
           1.65058236e+03 -0.00000000e+00
           3.30834079e+03 -4.96638459e+03
                                            0.00000000e+00
                                                            1.62188766e+03
          -7.23085316e+02
                           9.23458697e+02 -0.00000000e+00 -2.81086299e+03
                                            0.00000000e+00 -5.63465059e+02
           4.63864094e+04 -1.08508406e+04
           2.93326274e+03
                            0.000000000e+00 -1.69495933e+03
                                                            0.00000000e+00
                            1.17156847e+03
                                                            2.78275308e+03
          -1.03966896e+03
                                            0.00000000e+00
          -0.000000000e+00 -1.56852947e+03
                                            1.18637133e+03
                                                            5.17320602e+05
           3.28798525e+03
                            1.68197412e+03 -5.37698968e+01
                                                            0.00000000e+00
          -4.59018182e+03 -1.17892134e+03
                                            2.37076936e+03
                                                           -3.30557545e+03
           2.52737926e+03 -3.43107261e+03 -3.68325573e+03
                                                            1.03744814e+03
          -6.23029363e+02
                            1.84430765e+02 -1.06744196e+02
                                                            1.91889329e+03
           0.00000000e+00
                           2.42606339e+03 -2.37828675e+03 -1.95036731e+02
          -5.94302994e+03 -3.67179255e+02
                                            3.11403344e+03
                                                           -4.96436996e+03
                            1.12724660e+03 -3.65604135e+03
          -6.80689771e+03
                                                            0.00000000e+00
                            0.00000000e+00 -5.42786655e+03
                                                           -2.18561448e+03
          -1.32757800e+03
           6.25017124e+03 -1.12818294e+04
                                            0.00000000e+00
                                                            0.00000000e+00
          -3.12373026e+02 -0.000000000e+00 -2.92649999e+04 -2.05061747e+05
          -2.09059182e+05
                            1.20626134e+04
                                            1.03025072e+01
                                                            2.58795306e+03
           6.69946841e+03 -1.06388973e+04 -0.00000000e+00
                                                            0.00000000e+00
           2.73588597e+03 -0.00000000e+00
                                            1.96865541e+03
                                                            0.00000000e+00
          -0.00000000e+00 -0.00000000e+00
                                            0.00000000e+00 -4.68112348e+02
           1.40213768e+03
                           0.00000000e+00 -1.48708134e+03
                                                            4.01166144e+03
           7.89282724e+03
                            2.52382443e+04 -0.00000000e+00 -0.00000000e+00
          -6.88010324e+03 -0.00000000e+00
                                            1.35723211e+03 -4.15074925e+03
           7.52038017e+01 -3.26271396e+03 -5.11703465e+03 -3.19194221e+04
          -3.31539324e+04
                           1.41612351e+04 -3.74293219e+04 -1.51753341e+04
          -3.21113356e+03 -9.90070514e+03 -1.58403485e+03 -0.00000000e+00
                           9.52560118e+03 -0.00000000e+00
          -6.75833911e+03
                                                            0.00000000e+00
          -1.08014766e+04 -4.07542547e+04 -3.62198104e+04
                                                            5.59384698e+03
           6.21328514e+03 -8.92182513e+031
```

```
In [63]: print(lasso.score(x_train, y_train))
         print(lasso.score(x_test, y_test))
         0.992858570356946
         0.9930037340269746
 In [ ]: | ### Using polynomial feature expansion for further checking:
In [46]: from sklearn import preprocessing
         from sklearn.preprocessing import PolynomialFeatures
In [47]: # Scaling all the columns before polynomial feature processing:
         x_scaled = preprocessing.scale(x)
         y_scaled = preprocessing.scale(y)
         x_train_scaled, x_test_scaled, y_train_scaled, y_test_scaled = trail
In [48]: poly = PolynomialFeatures(degree = 2, interaction_only=True)
In [49]: | x_poly = poly.fit_transform(x_scaled)
         x_poly_train, x_poly_test, y_poly_train, y_poly_test = train_test_s
         x_poly_train.shape
Out[49]: (17500, 10154)
In [50]: # Fitting a simple non-regularized linear model on poly features:
         regression_model = LinearRegression()
         regression model.fit(x poly train, y poly train)
Out[50]: LinearRegression()
In [51]: ridge = Ridge(alpha=50)
         ridge.fit(x_poly_train,y_poly_train)
Out[51]: Ridge(alpha=50)
In [52]: print(ridge.score(x_poly_train, y_poly_train))
         print(ridge.score(x_poly_test, y_poly_test))
         0.997468003090859
         0.9904693141999761
```

```
In [53]: lasso = Lasso(alpha=50)
         lasso.fit(x_poly_train,y_poly_train)
         /Users/sabita/opt/anaconda3/lib/python3.8/site-packages/sklearn/li
         near_model/_coordinate_descent.py:529: ConvergenceWarning: Objecti
         ve did not converge. You might want to increase the number of iter
         ations. Duality gap: 9789786430576.95, tolerance: 2338635145561.99
           model = cd_fast.enet_coordinate_descent(
Out[53]: Lasso(alpha=50)
In [54]: print(lasso.score(x_poly_train, y_poly_train))
         print(lasso.score(x_poly_test, y_poly_test))
         0.9973917653305221
         0.9944631786604274
In [57]: lasso = Lasso(alpha=200)
         lasso.fit(x_poly_train,y_poly_train)
         /Users/sabita/opt/anaconda3/lib/python3.8/site-packages/sklearn/li
         near model/_coordinate_descent.py:529: ConvergenceWarning: Objecti
         ve did not converge. You might want to increase the number of iter
         ations. Duality gap: 3443908380766.547, tolerance: 2338635145561.9
         91
           model = cd_fast.enet_coordinate_descent(
Out[57]: Lasso(alpha=200)
In [58]: print(lasso.score(x_poly_train, y_poly_train))
         print(lasso.score(x_poly_test, y_poly_test))
         0.9969722884295543
         0.9953317792133534
 In []: ### Generating additional ensemble models:
In [72]: # Creating model using Gradient Boosting (GB):
         from sklearn.ensemble import GradientBoostingRegressor
         gb = GradientBoostingRegressor(n_estimators = 50, random_state=1)
         gb = gb.fit(x_train, y_train)
```

```
In [74]: y_predict = gb.predict(x_test)
print(gb.score(x_train, y_train))
print(gb.score(x_test, y_test))
```

0.9942524461191704

0.9942424756733194

### In [44]: pip install -U xgboost --upgrade

Collecting xgboost

Downloading xgboost-1.6.1-py3-none-macosx\_10\_15\_x86\_64.macosx\_11\_0\_x86\_64.macosx\_12\_0\_x86\_64.whl (1.7 MB)

| 1.7 MB 2.6 MB/s eta 0:00:0

Requirement already satisfied, skipping upgrade: numpy in /Users/s abita/opt/anaconda3/lib/python3.8/site-packages (from xgboost) (1. 22.3)

Requirement already satisfied, skipping upgrade: scipy in /Users/s abita/opt/anaconda3/lib/python3.8/site-packages (from xgboost) (1.5.0)

Installing collected packages: xgboost

Successfully installed xgboost-1.6.1

Note: you may need to restart the kernel to use updated packages.

### In [90]: # Renaming the variables again to enable XGBoosting:

x\_train.rename(columns = {'Department\_Analytics/BI':'Department\_Ana

<ipython-input-90-8bcfd763a787>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy)

x\_train.rename(columns = {'Department\_Analytics/BI':'Department\_ Analytics\_BI','Department\_IT\_Software':'Department\_IT\_Software','D epartment\_Top Management':'Department\_Top\_Management','Role\_Area S ales Manager':'Role\_Area\_Sales\_Manager','Role\_Bio statistician':'R ole\_Bio\_statistician','Role\_Business Analyst':'Role\_Business\_Analy st','Role\_Data scientist':'Role\_Data\_scientist','Role\_Financial An alyst':'Role\_Financial\_Analyst','Role\_Lab Executuve':'Role\_Lab\_Exe cutuve','Role\_Principal Analyst':'Role\_Principal\_Analyst','Role\_Pr oject Manager':'Role\_Project\_Manager','Role\_Research Scientist':'R ole\_Research\_Scientist','Role\_Sales Execituve':'Role\_Sales\_Execitu ve','Role\_Sales Manager':'Role\_Sales\_Manager','Role\_Senior Analyst ':'Role\_Senior\_Analyst','Role\_Senior Researcher':'Role\_Senior\_Rese archer','Role\_Sr. Business Analyst':'Role\_Sr\_Business\_Analyst','Ro le\_Team Lead':'Role\_Team\_Lead','Designation\_Data Analyst':'Designation\_Marketing Manager':'Designation\_Ma

rketing\_Manager', 'Designation\_Medical Officer': 'Designation Medica l Officer', 'Designation Network Engineer': 'Designation Network Eng ineer','Designation\_Product Manager':'Designation\_Product\_Manager' , 'Designation\_Research Analyst': 'Designation\_Research\_Analyst', 'De signation\_Research\_Scientist':'Designation\_Research\_Scientist','De signation Software Developer': 'Designation Software Developer', 'De signation\_Sr.Manager':'Designation\_Sr\_Manager','Designation\_Web De signer': 'Designation\_Web\_Designer', 'University\_Grad\_Tier-1': 'Unive rsity\_Grad\_Tier\_1','University\_Grad\_Tier-2':'University\_Grad\_Tier\_ 2', 'University\_PG\_Tier-1': 'University\_PG\_Tier\_1', 'University\_PG\_Ti er-2':'University\_PG\_Tier\_2','University\_PHD\_Tier-1':'University\_P HD\_Tier\_1', 'University\_PHD\_Tier-2': 'University\_PHD\_Tier\_2', 'Curent \_Location\_Tier-2':'Curent\_Location\_Tier\_2','Preferred\_location\_Tie r-2':'Preferred location Tier 2','Year Graduation bin (1990, 1995] ':'Year\_Graduation\_bin\_1990\_1995','Year\_Graduation\_bin\_(1995, 2000 ]':'Year\_Graduation\_bin\_1995\_2000','Year\_Graduation\_bin\_(2000, 200 5]':'Year\_Graduation\_bin\_2000\_2005','Year\_Graduation\_bin\_(2005, 20 10]':'Year\_Graduation\_bin\_2005\_2010','Year\_Graduation\_bin\_(2010, 2 015]':'Year\_Graduation\_bin\_2010\_2015','Year\_Graduation\_bin\_(2015, 2020]':'Year\_Graduation\_bin\_2015\_2020','Year\_PG\_bin\_(1990, 1995]': 'Year\_PG\_bin\_1990\_1995','Year\_PG\_bin\_(1995, 2000]':'Year\_PG\_bin\_19 95 2000', 'Year PG bin (2000, 2005]': 'Year PG bin 2000 2005', 'Year PG\_bin\_(2005, 2010]':'Year\_PG\_bin\_2005\_2010','Year\_PG\_bin\_(2010, 2 015]':'Year\_PG\_bin\_2010\_2015','Year\_PG\_bin\_(2015, 2020]':'Year\_PG\_ bin\_2015\_2020','Year\_PG\_bin\_(2020, 2025]':'Year\_PG\_bin\_2020\_2025', 'Year PHD\_bin\_(1995, 2000]':'Year\_PHD\_bin\_1995\_2000','Year\_PHD\_bin \_(2000, 2005]':'Year\_PHD\_bin\_2000\_2005','Year\_PHD\_bin\_(2005, 2010] ':'Year\_PHD\_bin\_2005\_2010','Year\_PHD\_bin\_(2010, 2015]':'Year\_PHD\_b in\_2010\_2015','Year\_PHD\_bin\_(2015, 2020]':'Year\_PHD\_bin\_2015\_2020' }.inplace=True)

```
In [98]: # Creating model using Xtreme Gradient Boosting (XGB):
         import xqboost as xqb
         model=xgb.XGBRegressor(n_estimators=500, max_depth=7, eta=0.1, subs
         model.fit(x_train, y_train)
Out[98]: XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
                      colsample_bylevel=1, colsample_bynode=1, colsample_by
         tree=0.8,
                      early_stopping_rounds=None, enable_categorical=False,
         eta=0.1,
                      eval_metric=None, gamma=0, gpu_id=-1, grow_policy='de
         pthwise',
                      importance type=None, interaction constraints='',
                      learning rate=0.100000001, max bin=256, max cat to on
         ehot=4,
                      max_delta_step=0, max_depth=7, max_leaves=0, min_chil
         d_weight=1,
                      missing=nan, monotone_constraints='()', n_estimators=
         500, n_jobs=0,
                      num parallel tree=1, predictor='auto', random state=0
         , reg_alpha=0, ...)
In [99]:
         y pred=model.predict(x test)
         model_score_train=model.score(x_train,y_train)
         model_score_test=model.score(x_test,y_test)
         print(model score train)
         print(model_score_test)
```

0.99635932877079

0.999474549736053

In [101]: ### The End