Project_10_Scaler

October 15, 2022

0.1 Problem Statement

Scaler is an online tech-versity offering intensive computer science & Data Science courses through live classes delivered by tech leaders and subject matter experts. The meticulously structured program enhances the skills of software professionals by offering a modern curriculum with exposure to the latest technologies. It is a product by InterviewBit.

You are working as a data scientist with the analytics vertical of Scaler, focused on profiling the best companies and job positions to work for from the Scaler database. You are provided with the information for a segment of learners and tasked to cluster them on the basis of their job profile, company, and other features. Ideally, these clusters should have similar characteristics.

0.2 Data Dictionary:

- 'Unnamed 0'- Index of the dataset
- Email_hash- Anonymised Personal Identifiable Information (PII)
- Company- Current employer of the learner
- orgyear- Employment start date
- CTC- Current CTC
- Job_position- Job profile in the company
- CTC_updated_year: Year in which CTC got updated (Yearly increments, Promotions)

[3]:
```
#Importing the required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
import warnings
warnings.filterwarnings('ignore')
import re
from sklearn.cluster import AgglomerativeClustering, KMeans, DBSCAN
from sklearn.mixture import GaussianMixture
from yellowbrick.cluster import SilhouetteVisualizer
from sklearn.cluster import AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram, linkage
```

[4]:
```
# Getting the Dataset.
df=pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/
↪002/856/original/scaler_clustering.csv')
```

[5]:
```
# Checking the first 5 observations.
df.head()
```

[5]:
```
   Unnamed: 0                 company_hash  \
0           0               atrgxnnt xzaxv
1           1  qtrxvzwt xzegwgbb rxbxnta
2           2                ojzwnvwnxw vx
3           3                    ngpgutaxv
4           4                   qxen sqghu

                                          email_hash  orgyear      ctc  \
0  6de0a4417d18ab14334c3f43397fc13b30c35149d70c05…   2016.0  1100000
1  b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10…   2018.0   449999
2  4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9…   2015.0  2000000
3  effdede7a2e7c2af664c8a31d9346385016128d66bbc58…   2017.0   700000
4  6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520…   2017.0  1400000

        job_position  ctc_updated_year
0              Other            2020.0
1  FullStack Engineer           2019.0
2    Backend Engineer           2020.0
3    Backend Engineer           2019.0
4  FullStack Engineer           2019.0
```

[6]:
```
# Checking the last 5 observations.
df.tail()
```

[6]:
```
        Unnamed: 0    company_hash  \
205838      206918        vuurt xzw
205839      206919        husqvawgb
205840      206920         vwwgrxnt
205841      206921   zgn vuurxwvmrt
205842      206922   bgqsvz onvzrtj

                                               email_hash  orgyear      ctc  \
205838  70027b728c8ee901fe979533ed94ffda97be08fc23f33b…   2008.0   220000
205839  7f7292ffad724ebbe9ca860f515245368d714c84705b42…   2017.0   500000
205840  cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c…   2021.0   700000
205841  fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c8…   2019.0  5100000
205842  0bcfc1d05f2e8dc4147743a1313aa70a119b41b30d4a1f…   2014.0  1240000

       job_position  ctc_updated_year
205838          NaN            2019.0
```

```
205839           NaN           2020.0
205840           NaN           2021.0
205841           NaN           2019.0
205842           NaN           2016.0
```

[7]:
```
# Checking the shape of the dataset.
df.shape

# Need to check if there are 205843 number of unique learners, otherwise we␣
↪need to remove/aggregate the duplicate records.
```

[7]:
```
(205843, 7)
```

[8]:
```
# Checking for number of duplicate values in "Unnamed: 0" column
print((df['Unnamed: 0'].duplicated()).sum())
# There are no duplicate values. All the values are unique.

# Dropping the "Unnamed: 0" column
df.drop(columns=['Unnamed: 0'],inplace=True)
```

```
0
```

[9]:
```
# Checking for number of duplicate records.
print((df.duplicated()).sum())

# There are 33 duplicate records. We can drop these observations.
df=df[~df.duplicated()]
```

```
33
```

[10]:
```
#Resetting the Index.
df.reset_index(drop=True,inplace=True)
```

[11]:
```
# Checking the shape of the dataset.
df.shape
```

[11]:
```
(205810, 6)
```

[12]:
```
# Checking for total number of unique learners using the email-Id column.
df['email_hash'].nunique()

# Total Records:205810,Total Unique Learners:153443.Need to inspect the␣
↪remaining duplicate records, and then aggregate.
```

[12]:
```
153443
```

[13]:
```
# Finding the list of email_ids for whom we have more than 1 record.
temp=df['email_hash'].value_counts()
duplicated_learners=temp[temp>1].index
```

```
# Finding the list of email_ids who have just 1 unique record.
non_duplicated_learners=temp[temp==1].index

print("Total Duplicated Learners",len(duplicated_learners))
print("Total Non-Duplicated Learners",len(non_duplicated_learners))
```

```
Total Duplicated Learners 41191
Total Non-Duplicated Learners 112252
```

[14]:
```
# Checking for missing values for every column
df.isna().sum()

# There are no missing values for "email_hash", "ctc" and "ctc_updated_year".
# Need to handle missing values for "company_hash", "orgyear" and␣
↪"job_position".
```

[14]:
```
company_hash           44
email_hash              0
orgyear                86
ctc                     0
job_position        52547
ctc_updated_year        0
dtype: int64
```

[15]:
```
# Checking the data types of the columns
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205810 entries, 0 to 205809
Data columns (total 6 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   company_hash      205766 non-null  object
 1   email_hash        205810 non-null  object
 2   orgyear           205724 non-null  float64
 3   ctc               205810 non-null  int64
 4   job_position      153263 non-null  object
 5   ctc_updated_year  205810 non-null  float64
dtypes: float64(2), int64(1), object(3)
memory usage: 9.4+ MB
```

[15]:
```
```

Lets check the duplicated records for few learners to understand how to do the aggregation.

[16]:
```
# Checking records of Learner 1
display(df[df['email_hash']==duplicated_learners[7]])
```

```
# Observation : The 8 records look almost the same except the ctc and␣
↪job_position.
```

```
        company_hash                                         email_hash  \
37734   bvi ogenfvqt  b4d5afa09bec8689017d8b29701b80d664ca37b83cb883…
45982   bvi ogenfvqt  b4d5afa09bec8689017d8b29701b80d664ca37b83cb883…
144744  bvi ogenfvqt  b4d5afa09bec8689017d8b29701b80d664ca37b83cb883…
151696  bvi ogenfvqt  b4d5afa09bec8689017d8b29701b80d664ca37b83cb883…
153848  bvi ogenfvqt  b4d5afa09bec8689017d8b29701b80d664ca37b83cb883…
154626  bvi ogenfvqt  b4d5afa09bec8689017d8b29701b80d664ca37b83cb883…
197115  bvi ogenfvqt  b4d5afa09bec8689017d8b29701b80d664ca37b83cb883…
203140  bvi ogenfvqt  b4d5afa09bec8689017d8b29701b80d664ca37b83cb883…

        orgyear      ctc            job_position  ctc_updated_year
37734    2020.0   900000  Engineering Leadership            2021.0
45982    2020.0   900000      Engineering Intern            2021.0
144744   2020.0   900000            Data Analyst            2021.0
151696   2020.0   900000          Data Scientist            2021.0
153848   2020.0   900000                     NaN            2021.0
154626   2020.0   900000     Software Engineer 1            2021.0
197115   2020.0  2000000      Engineering Intern            2021.0
203140   2020.0  2000000            Data Analyst            2021.0
```

[17]:
```
# Checking records of Learner 2
display(df[df['email_hash']==duplicated_learners[15]])

# Observation : The 7 records look almost the same except the␣
↪organisation_year, ctc and job_position.
```

```
                          company_hash  \
2396    ouxqg ogrhnxgz uqxcvnt rxbxnta
8292    ouxqg ogrhnxgz uqxcvnt rxbxnta
10927   ouxqg ogrhnxgz uqxcvnt rxbxnta
35627   ouxqg ogrhnxgz uqxcvnt rxbxnta
88098   ouxqg ogrhnxgz uqxcvnt rxbxnta
88137   ouxqg ogrhnxgz uqxcvnt rxbxnta
137341  ouxqg ogrhnxgz uqxcvnt rxbxnta

                                             email_hash  orgyear     ctc  \
2396    021ea9c97b6b287336e9345f39f9308c33ccbd15ac366d…   2020.0  300000
8292    021ea9c97b6b287336e9345f39f9308c33ccbd15ac366d…   2020.0  300000
10927   021ea9c97b6b287336e9345f39f9308c33ccbd15ac366d…   2020.0  300000
35627   021ea9c97b6b287336e9345f39f9308c33ccbd15ac366d…   2020.0  300000
88098   021ea9c97b6b287336e9345f39f9308c33ccbd15ac366d…   2022.0  420000
88137   021ea9c97b6b287336e9345f39f9308c33ccbd15ac366d…   2022.0  420000
137341  021ea9c97b6b287336e9345f39f9308c33ccbd15ac366d…   2022.0  420000
```

```
             job_position  ctc_updated_year
2396    Engineering Intern            2021.0
8292                 Other            2021.0
10927     Backend Engineer            2021.0
35627            Non Coder            2021.0
88098     Backend Engineer            2021.0
88137   Engineering Intern            2021.0
137341               Other            2021.0
```

[18]:
```
# Checking records of Learner 3
display(df[df['email_hash']==duplicated_learners[36]])

# Observation : The 6 records look almost the same except the job_position and␣
↪ctc_updated_year.
```

```
       company_hash                                        email_hash  \
8336         atigat  8b711b2bb77300ab4bfb6f8bf54d9b28cdd214d8c66e9e...
8645         atigat  8b711b2bb77300ab4bfb6f8bf54d9b28cdd214d8c66e9e...
22481        atigat  8b711b2bb77300ab4bfb6f8bf54d9b28cdd214d8c66e9e...
194677       atigat  8b711b2bb77300ab4bfb6f8bf54d9b28cdd214d8c66e9e...
196770       atigat  8b711b2bb77300ab4bfb6f8bf54d9b28cdd214d8c66e9e...
198817       atigat  8b711b2bb77300ab4bfb6f8bf54d9b28cdd214d8c66e9e...

        orgyear      ctc        job_position  ctc_updated_year
8336     2018.0  3800000  FullStack Engineer            2019.0
8645     2018.0  3800000               Other            2019.0
22481    2018.0  3800000    Backend Engineer            2019.0
194677   2018.0  3800000    Backend Engineer            2020.0
196770   2018.0  3800000  FullStack Engineer            2020.0
198817   2018.0  3800000               Other            2020.0
```

[19]:
```
# Checking records of Learner 4
display(df[df['email_hash']==duplicated_learners[41]])

# Observation : The 6 records look almost the same except the company_hash, ctc␣
↪and job_position.
```

```
                     company_hash  \
52127                 yxuug cxatg
58375                 yxuug cxatg
143785  nvnv wgzohrnvzwj otqcxwto
144053  nvnv wgzohrnvzwj otqcxwto
161826  nvnv wgzohrnvzwj otqcxwto
165732  nvnv wgzohrnvzwj otqcxwto

                                               email_hash  orgyear     ctc  \
52127   8ffe41ee60bc738df2cb50dbf5c248300b4ddf830093c7...   2019.0  750000
58375   8ffe41ee60bc738df2cb50dbf5c248300b4ddf830093c7...   2019.0  750000
143785  8ffe41ee60bc738df2cb50dbf5c248300b4ddf830093c7...   2019.0  396000
```

```
144053  8ffe41ee60bc738df2cb50dbf5c248300b4ddf830093c7…   2019.0  396000
161826  8ffe41ee60bc738df2cb50dbf5c248300b4ddf830093c7…   2019.0  396000
165732  8ffe41ee60bc738df2cb50dbf5c248300b4ddf830093c7…   2019.0  396000

             job_position  ctc_updated_year
52127   FullStack Engineer            2020.0
58375                  NaN            2020.0
143785    Support Engineer            2020.0
144053    Backend Engineer            2020.0
161826               Other            2020.0
165732                 NaN            2020.0
```

[19]:

- To aggregate the duplicate records, lets first sort the dataset according to, "email_hash", decreasing "ctc" and decreasing "ctc_updated_year".

- We can then extract the first record for every learner.

[20]:
```
df=df.
↪sort_values(by=['email_hash','ctc','ctc_updated_year'],ascending=[True,False,False])
```

[20]:

0.2.1 Creating Aggregated Dataset

[21]:
```
# Getting the first record for every learner.
df=df.groupby(by='email_hash').first().reset_index()

# We can drop the "email_hash" column from the dataset since it's of no use to␣
↪us anymore.
df.drop(columns='email_hash',inplace=True)

df.head()
```

[21]:
```
             company_hash  orgyear      ctc        job_position  \
0               bxwqgogen   2012.0  3500000    Backend Engineer
1           nqsn axsxnvr   2013.0   250000    Backend Engineer
2                   gunhb   2021.0  1300000  FullStack Engineer
3  bxwqgotbx wgqugqvnxgz   2004.0  2000000  FullStack Engineer
4           fvrbvqn rvmo   2009.0  3400000                None

   ctc_updated_year
0            2019.0
1            2020.0
2            2019.0
3            2021.0
4            2018.0
```

[22]:
```python
# Checking for missing values in Percentage.
round(100*df.isna().mean(),2)

# "company_hash" has almost 0.02% missing values.
# "orgyear" has almost 0.05% missing values.
# "job_position" has almost 13.18% missing values.
```

[22]:
```
company_hash         0.02
orgyear              0.05
ctc                  0.00
job_position        13.18
ctc_updated_year     0.00
dtype: float64
```

[23]:
```python
# Lets try to first deal with the missing values of "job_position".

# Lets look at the number of unique values of "job_position".
df['job_position'].nunique()

#There are a lot of categories for this column.Lets try doing a few data␣
↪cleaning techniques to reduce the categories.
```

[23]:
```
813
```

[24]:
```python
# First using Regex to try to reduce duplicated categories with special␣
↪characters.

def function(string):
    if string!=None:
        return re.sub('[^A-Za-z0-9 ]+', '', string)

df['job_position']=df['job_position'].apply(function)
```

[25]:
```python
# Lets convert all the "job_position" into lower-case and also removing leading␣
↪and trailing spaces.
df['job_position']=(df['job_position'].str.lower()).str.strip()
```

[26]:
```python
# Lets also remove if there are spaces between the words.
def remove_spaces(job):
    if job !=None:
        job=job.split()
        job=' '.join(job)
        return job

df['job_position']=df['job_position'].apply(remove_spaces)
```

[27]:
```python
# Lets check how many categories we have now.
df['job_position'].nunique()

# Great! We were able to remove almost 90 duplicate categories.
```

[27]:
```
721
```

[28]:
```python
# Since "job_position" is a categorical variable, lets look at its value_counts.
df['job_position'].value_counts(normalize=True,dropna=False)*100

# Observation : We do not have a clear majority mode here.
# Lets see try to look at the top 20 occuring job profiles.
(df['job_position'].value_counts(normalize=True)*100)[:20]
```

[28]:
```
backend engineer          27.981744
fullstack engineer        16.064525
other                     11.854916
frontend engineer          6.957716
engineering leadership     4.659245
qa engineer                4.616459
data scientist             3.678154
android engineer           3.672149
sdet                       3.392159
devops engineer            3.229269
support engineer           2.372785
ios engineer               1.926152
data analyst               1.909638
engineering intern         1.580105
product designer           0.957821
product manager            0.801687
backend architect          0.794932
research engineers         0.728124
program manager            0.571990
non coder                  0.399342
Name: job_position, dtype: float64
```

[29]:
```python
# We can create 1 new category "Missing" to impute the missing values.
# And we can create another new category "Combined" to combine all the␣
↪categories whose occurence is less than 1 percent.

df['job_position'].fillna('Missing',inplace=True)

temp=df['job_position'].value_counts(normalize=True)*100
jobs_to_replace=temp[temp<1].index
df.loc[df['job_position'].isin(jobs_to_replace),'job_position']='Combined'
```

[30]:
```python
# Lets check if the missing value handling was successful.
df['job_position'].isna().sum()
```

[30]: 0

[31]:
```python
# Lets check how many values are missing for "company_hash"
print('Total Missing Values',df['company_hash'].isna().sum())

# Lets check for the total number of categories in "company_hash"
print('Total Categories',df['company_hash'].nunique())

# Since there are so many companies and the number of missing values are very␣
↪less, we can drop these rows.
df=df[~df['company_hash'].isna()]


# Lets try using Regex to try to reduce duplicated categories with special␣
↪characters if present.

def function(string):
    if string!=None:
        return re.sub('[^A-Za-z0-9 ]+', '', string)
df['job_position']=df['job_position'].apply(function)

# Lets check for the total number of categories in "company_hash"
print('Total Categories after Regex',df['company_hash'].nunique())

# Resetting the Index
df.reset_index(drop=True,inplace=True)
```

```
Total Missing Values 32
Total Categories 36323
Total Categories after Regex 36323
```

[32]:
```python
# Lets check how many values are missing for "orgyear"
print('Total Missing Values:',df['orgyear'].isna().sum())
print()

# Lets check for the total number of categories in "orgyear"
print('Total Categories:',df['orgyear'].nunique())
print()

# Lets look at the possible values of "orgyear"
print(sorted(df['orgyear'].unique().tolist()))
print()

# We can see lot of illogical values such as 0,1,2,208,209,2204,20165. We can␣
↪drop such rows.
```

```
# Lets check the percentage of records that lie between 2005 and 2022. Almost␣
↪97.5%, which is a good proportion.
print(df['orgyear'].between(2005,2022).mean()*100,'%')
print()
# We can drop the other observations.

df=df[df['orgyear'].between(2005,2022)]

# Lets check whether the missing values are still present.
print('Total Missing Values:',df['orgyear'].isna().sum())

# Hurrah! The missing values were dropped as part of the previous process.
# There was no need of using KNN imputation to fill the missing values.

# Resetting the Index
df.reset_index(drop=True,inplace=True)
```

```
Total Missing Values: 78

Total Categories: 77

[1.0, 1986.0, 1989.0, 1990.0, 1991.0, 1992.0, 1993.0, 1994.0, 1995.0, 1996.0,
1997.0, 1998.0, 1999.0, 2000.0, 2001.0, 2002.0, 2003.0, 2004.0, 2005.0, 2006.0,
2007.0, 2008.0, 2009.0, 2010.0, 2011.0, 2012.0, 2013.0, 2014.0, 2015.0, 2016.0,
2017.0, 2018.0, 2019.0, 2020.0, 2021.0, 2022.0, 2023.0, nan, 0.0, 2.0, 3.0, 4.0,
5.0, 6.0, 38.0, 83.0, 91.0, 200.0, 201.0, 206.0, 208.0, 209.0, 1900.0, 1970.0,
1971.0, 1972.0, 1973.0, 1976.0, 1977.0, 1979.0, 1981.0, 1982.0, 1984.0, 1985.0,
1987.0, 1988.0, 2024.0, 2025.0, 2026.0, 2027.0, 2028.0, 2029.0, 2031.0, 2101.0,
2106.0, 2107.0, 2204.0, 20165.0]

96.47352536649915 %

Total Missing Values: 0
```

[33]:
```
# Final Check for presence of missing values.
df.isna().sum()
```

[33]:
```
company_hash        0
orgyear             0
ctc                 0
job_position        0
ctc_updated_year    0
dtype: int64
```

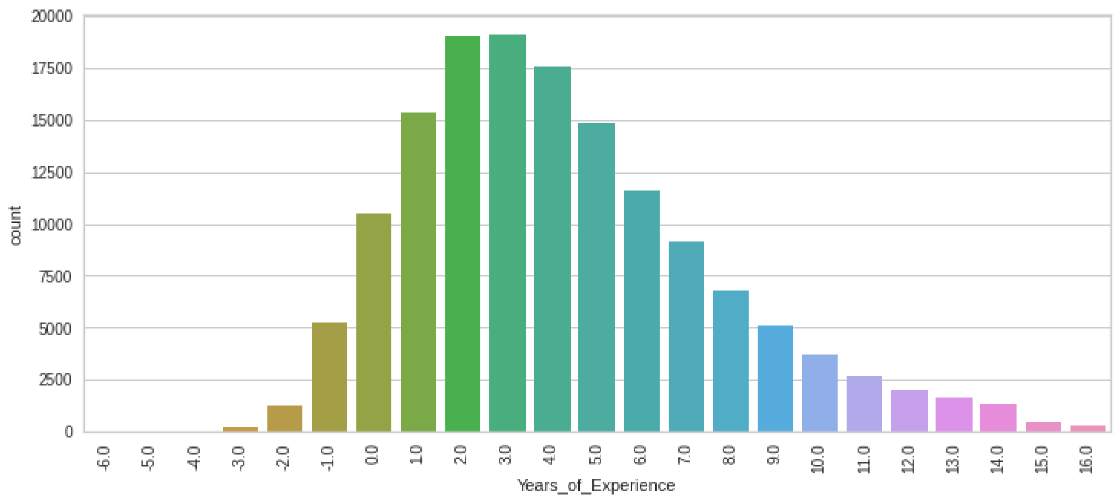
[33]:
```

```

0.3 New Features

0.3.1 1) "Years of Experience"

[34]:
```python
# We can get this new feature by subtracting "ctc_updated_year" from "orgyear".
df['Years_of_Experience']=df['ctc_updated_year']-df['orgyear']
```

[35]:
```python
# Lets check if we have only non-negative values of "Years of Experience".
plt.figure(figsize=(12,5))
sns.countplot(data=df,x='Years_of_Experience')
plt.xticks(rotation=90)
plt.show()
```



[36]:
```python
# We observed that there are negative values for "Years of Experience", which␣
↪is not possible in the real world.
# We can therefore drop those records for which "Years of Experience" has␣
↪negative values.

df=df[df['Years_of_Experience']>=0]

# Resetting the Index
df.reset_index(drop=True,inplace=True)
```

[37]:
```python
# Now we can drop the columns "orgyear" and "ctc_updated_year"
df.drop(columns=['orgyear','ctc_updated_year'],inplace=True)
```

[37]:
```python

```

[38]:
```python
# Lets take a look at our dataset.
df.head(3)
```

[38]:
```
     company_hash      ctc      job_position  Years_of_Experience
0       bxwqgogen  3500000  backend engineer                  7.0
1  nqsn axsxnvr   250000  backend engineer                  7.0
2  fvrbvqn rvmo  3400000           Missing                  9.0
```

[39]:
```python
df.shape
```

[39]:
```
(141111, 4)
```

[40]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 141111 entries, 0 to 141110
Data columns (total 4 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   company_hash         141111 non-null  object
 1   ctc                  141111 non-null  int64
 2   job_position         141111 non-null  object
 3   Years_of_Experience  141111 non-null  float64
dtypes: float64(1), int64(1), object(2)
memory usage: 4.3+ MB
```

[41]:
```python
# Descriptive Statistics for Continuous Columns
display(df[['ctc','Years_of_Experience']].describe().T)

# Observation - The max value of "ctc" is very large. And the min value is␣
↪strangely very small. Need to inspect further.
```

```
                        count          mean           std  min       25%  \
ctc                  141111.0  2.425988e+06  1.283431e+07  2.0  550000.0
Years_of_Experience  141111.0  4.471267e+00  3.266160e+00  0.0       2.0

                          50%        75%           max
ctc                  950000.0  1680000.0  1.000150e+09
Years_of_Experience       4.0        6.0  1.600000e+01
```

[42]:
```python
# Descriptive Statistics for Categorical Columns
display(df[['company_hash', 'job_position']].describe())
```

```
                    company_hash      job_position
count                     141111            141111
unique                     33953                16
top     nvnv wgzohrnvzwj otqcxwto  backend engineer
freq                        4927             35709
```

[42]:

0.4 Analysis

0.4.1 1) "ctc"

[43]:
```
df[['ctc']].describe().T
# As observed earlier, the max value is very large, and the min value is very␣
↪small. This could be a potential outlier.
```

[43]:
```
        count          mean           std  min       25%       50%        75%  \
ctc  141111.0  2.425988e+06  1.283431e+07  2.0  550000.0  950000.0  1680000.0

              max
ctc  1.000150e+09
```

[44]:
```
# Lets first look at smaller values of "ctc" columns.
# Lets check how many values are smaller than 1 lakh.

print((df['ctc']<100000).mean()*100)

# Almost 2.26 percent data is well below a logical minimum "ctc". Lets assume␣
↪these are errors and proceed to drop them.

df=df[df['ctc']>=100000]
```

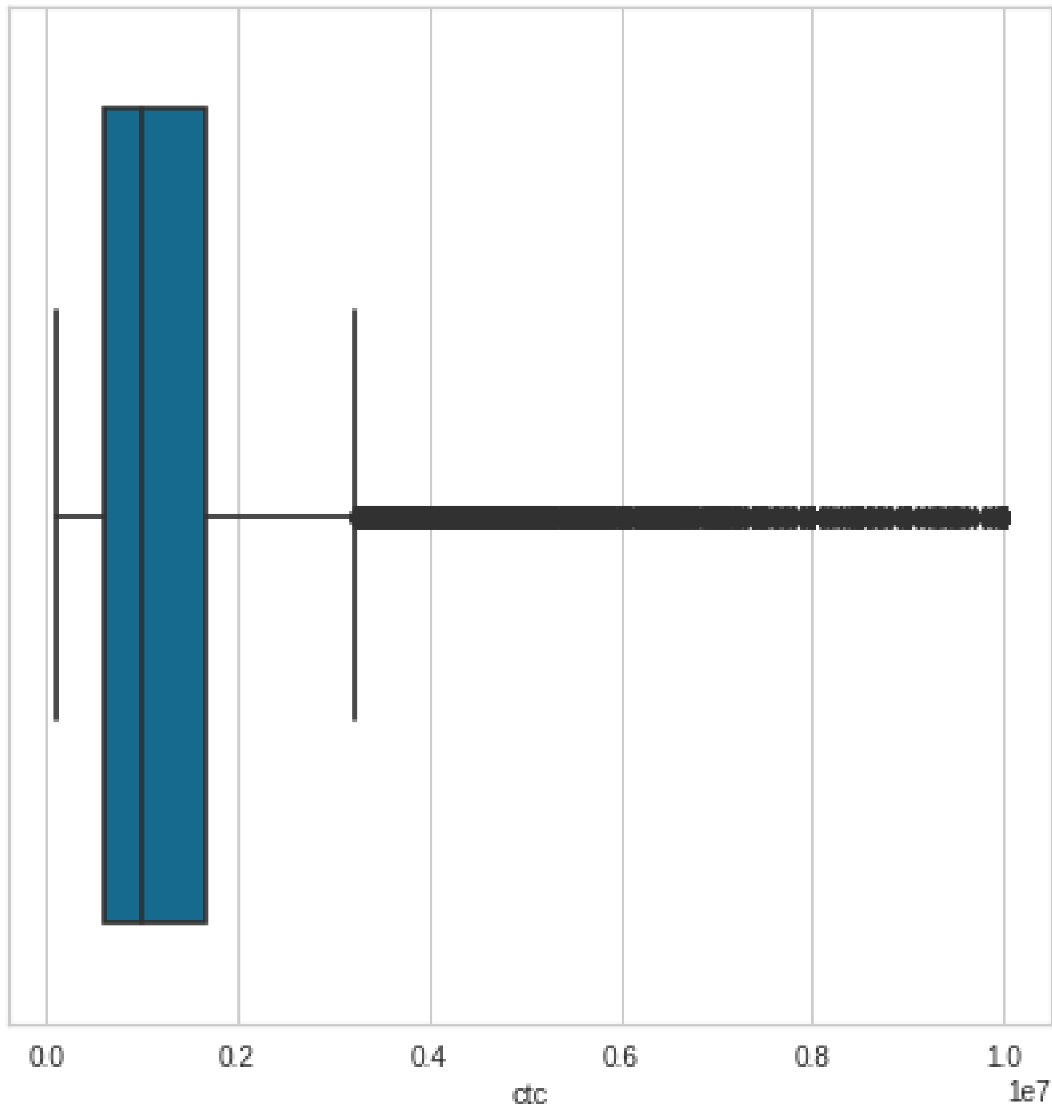
```
2.262049025235453
```

[45]:
```
# Now lets look at the larger values of "ctc" column.
# Lets check how many values are greater than 1 crore.

print((df['ctc']>10000000).mean()*100)

# Almost 1.28 percent data is greater than 1 crore. These are not very common␣
↪"ctc", so lets go ahead and drop them.

df=df[df['ctc']<=10000000]
```

```
1.2833619733321733
```

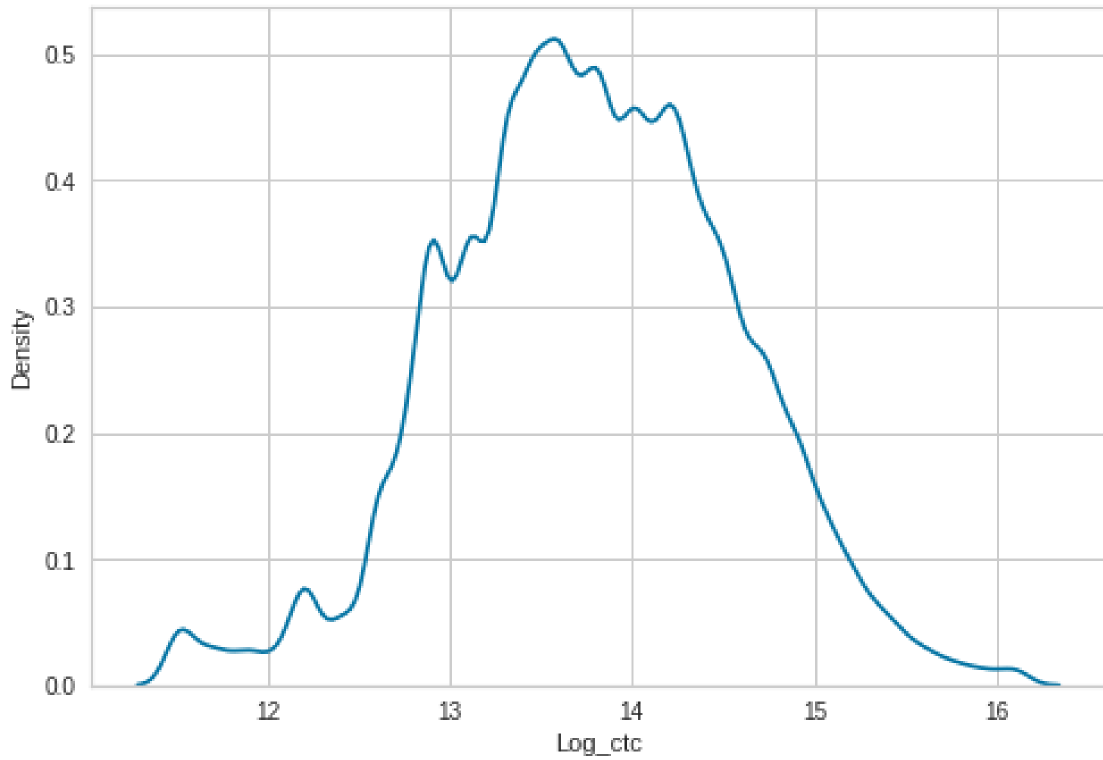
[46]:
```
# Resetting the Index.
df.reset_index(drop=True,inplace=True)
```

[47]:
```
# PLotting the boxplot.
plt.figure(figsize=(7,7))
sns.boxplot(data=df,x='ctc')
plt.show()

# There are very still big values in the "ctc" column. Lets use Log␣
↪Transformation on "ctc" colum.
df['Log_ctc']=np.log(df['ctc'])
```




```
[48]: # Lets check the distribution of "ctc" column.
      sns.kdeplot(df['Log_ctc'])

      # The distribution looks much better. We can use this column instead to find␣
       ↪the clusters.
```

```
[48]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd61a0a4d90>
```

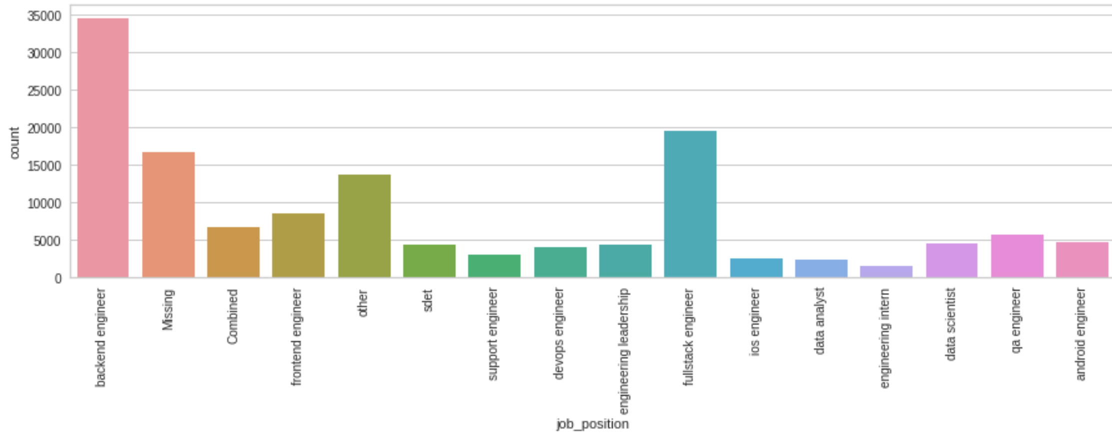


[49]:
```
df.shape
```

[49]:
```
(136149, 5)
```

0.4.2 2) "job_position"

[50]:
```
# Lets look at the occurences of each of the "job_position" categories.

plt.figure(figsize=(15,4))
sns.countplot(data=df,x='job_position')
plt.xticks(rotation=90)
plt.show()

# "Backend-Engineer" and  "Fullstack-Engineer" appear the most times.
```

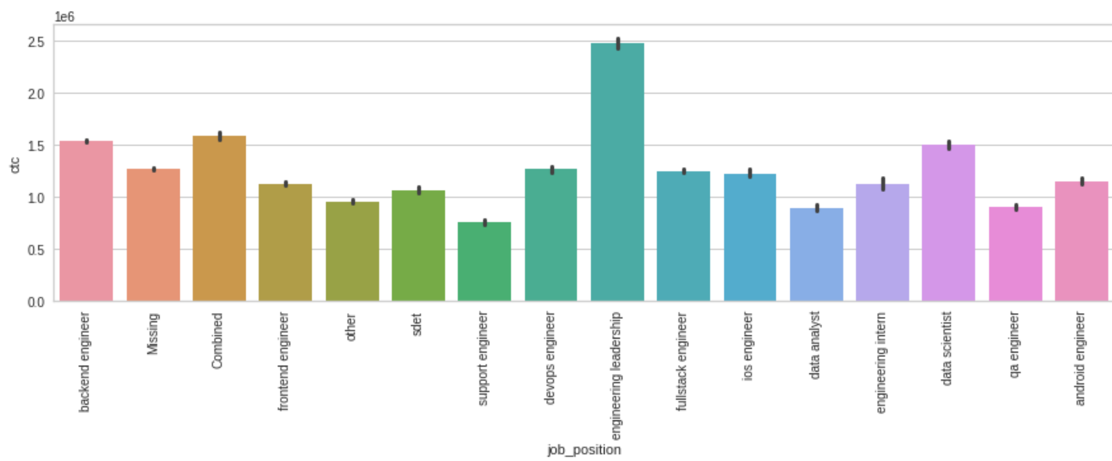


[50]:

0.4.3 3) "ctc" with "job_position"

[51]:

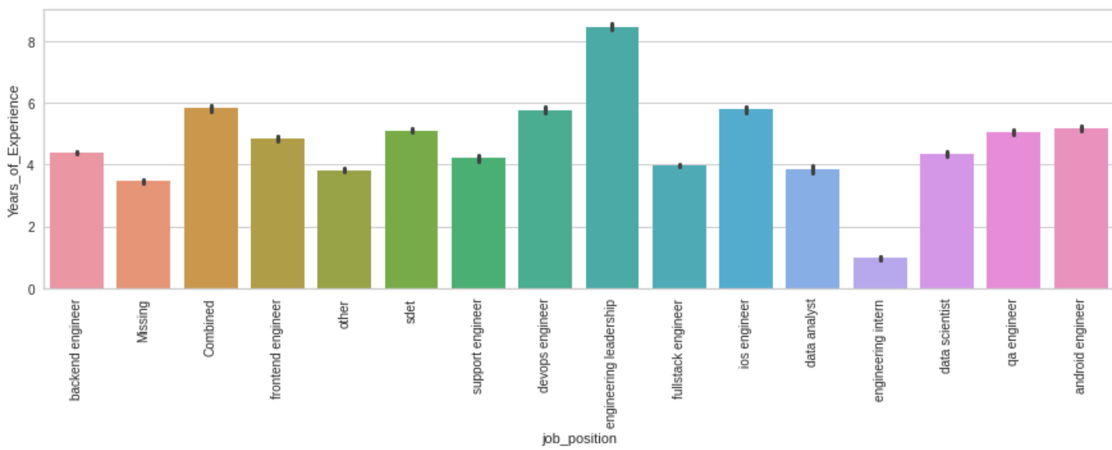
```
# Lets look at the average salary of each of the job categories.
plt.figure(figsize=(15,4))
sns.barplot(data=df,x='job_position',y='ctc')
plt.xticks(rotation=90)
plt.show()

# "Engineering Leadership" earns the highest average "ctc" among all job␣
↪categories.
# "Support Engineer" has the minimum average "ctc" among all job categories.
```



[51]:

0.4.4 4) "Years_of_Experience" with "job_position"

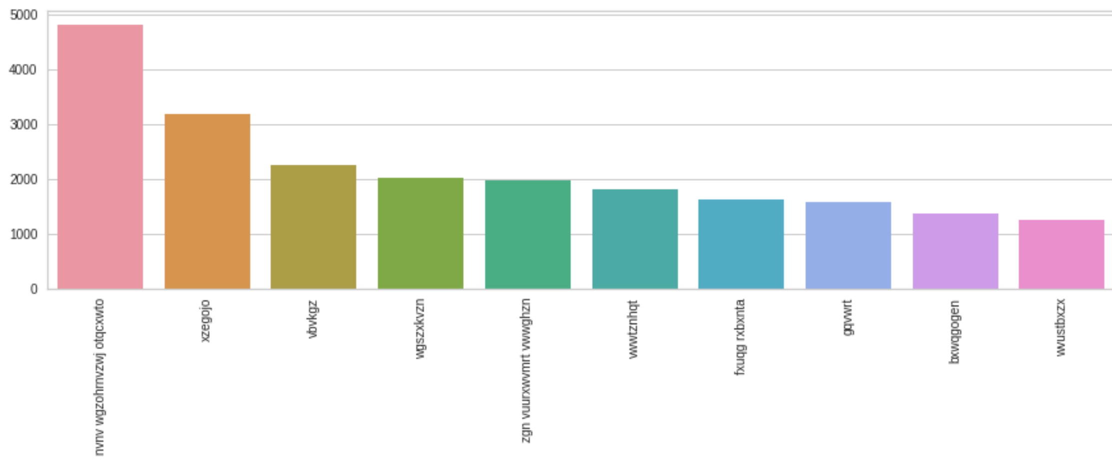
[52]:
```
# Lets look at the average salary of each of the job categories.
plt.figure(figsize=(15,4))
sns.barplot(data=df,x='job_position',y='Years_of_Experience')
plt.xticks(rotation=90)
plt.show()

# "Engineering Leadership" has the highest average "Years_of_Experience" among␣
↪all job categories.
# "Engineering Intern" has the minimum average "Years_of_Experience" among all␣
↪job categories.
```



[52]:
```
```

0.4.5 5) "company_hash"

[53]:
```
# Lets look at the top 10 companies having most number of jobs.

plt.figure(figsize=(15,4))
temp=df['company_hash'].value_counts().sort_values(ascending=False)[:10]
sns.barplot(x=temp.index,y=temp.values)
plt.xticks(rotation=90)
plt.show()
```



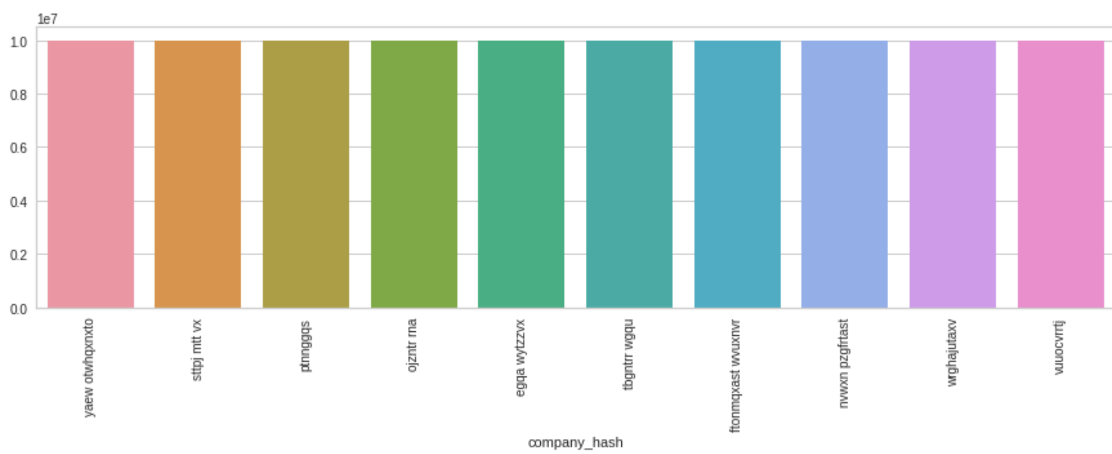
[53]:

```

```

0.4.6 6) "company_hash" with "ctc"

[54]:

```
# Lets look at the top 10 companies having average "ctc".

plt.figure(figsize=(15,4))
temp=df.groupby(by='company_hash').mean()['ctc'].sort_values(ascending=False)[:
↪10]
sns.barplot(x=temp.index,y=temp.values)
plt.xticks(rotation=90)
plt.show()

# There are many companies who pay a very big "ctc". All the top 10 "ctc" are␣
↪identical.
```



[54]:

```

```

0.5 Manual Clustering

0.5.1 1) "Designation Flag"

Creating "Designation_Flag" which shows learners with CTC greater/lower than the Average of their Company's department having same Years of Experience.

- Before we create the flag, lets specify the rules based on which the flag would be created.
- If the "ctc" is less than 75% of "average_ctc", we can flag it as 1.
- If the "ctc" is between 75% and 125% of "average_ctc", we can flag it as 2.
- If the "ctc" is grater than 125% of "average_ctc", we can flag it as 3.

[55]:

```
# Lets find the "average_ctc" as per the "company_hash","job_position" and␣
↪"Years_of_Experience". We can name it "Average_1"
temp=df.groupby(by=["company_hash","job_position","Years_of_Experience"]).
↪agg({'ctc':'mean',}).astype('int').reset_index().rename(columns={'ctc':
↪"Average_1"})

# Merging the average_ctc with the dataset.
df=pd.
↪merge(left=df,right=temp,on=["company_hash","job_position","Years_of_Experience"])
```

[56]:

```
# Lets have a look at our updated dataset.
df.head(3)
```

[56]:

```
  company_hash      ctc      job_position  Years_of_Experience    Log_ctc  \
0    bxwqgogen  3500000  backend engineer                  7.0  15.068274
1    bxwqgogen  3560000  backend engineer                  7.0  15.085271
2    bxwqgogen  5500000  backend engineer                  7.0  15.520259

   Average_1
0    3286052
1    3286052
2    3286052
```

[57]:

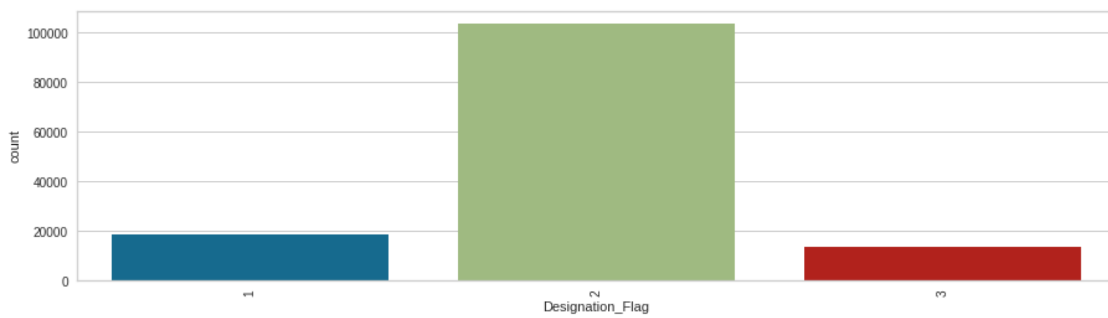
```
# Lets create a function to create the "Designation_Flag" column.
def function(arr):
    if arr[0]>(1.25*arr[1]):
        return 3
    elif arr[0]<(0.75*arr[1]):
        return 1
    else:
        return 2

# Lets get the values of "Designation_Flag"
df['Designation_Flag']=df[['ctc','Average_1']].apply(function,axis=1)
```

```
# We can now drop the "Average_1" column.
df.drop(columns=['Average_1'],inplace=True)
```

[58]:
```
# Lets have a look at our updated dataset.
df.head(3)
```

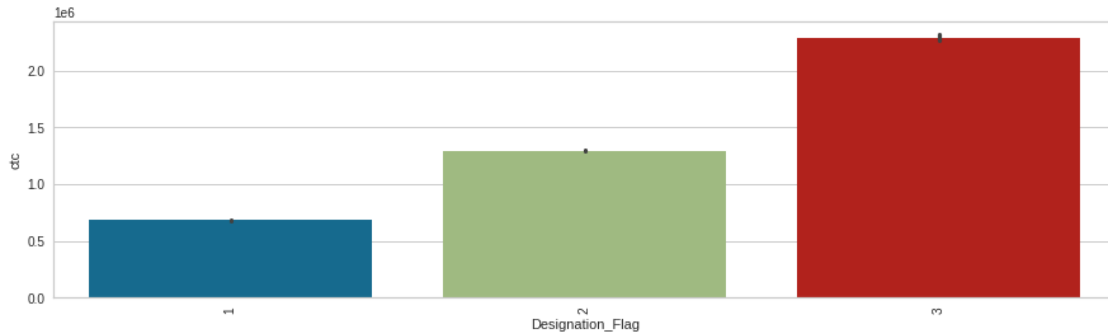
[58]:
```
  company_hash      ctc      job_position  Years_of_Experience    Log_ctc  \
0    bxwqgogen  3500000  backend engineer                  7.0  15.068274
1    bxwqgogen  3560000  backend engineer                  7.0  15.085271
2    bxwqgogen  5500000  backend engineer                  7.0  15.520259

   Designation_Flag
0                 2
1                 2
2                 3
```

[59]:
```
# Lets look at the percentage of people beloonging to each type of␣
↪"Designation_Flag".
plt.figure(figsize=(15,4))
sns.countplot(data=df,x='Designation_Flag')
plt.xticks(rotation=90)
plt.show()

# There are more people who earn almost equal to the average salary as per␣
↪their "company_hash","job_position","Years_of_Experience".
# There is a small section of learners who earn either very large or very large␣
↪ctc.
```

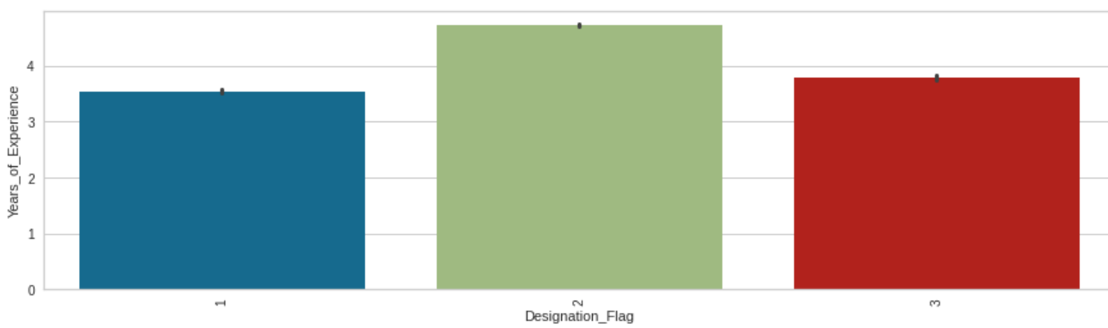


[60]:
```
# Lets look at the relationship of "Designation_Flag" with "ctc".
plt.figure(figsize=(15,4))
sns.barplot(data=df,x='Designation_Flag',y='ctc')
plt.xticks(rotation=90)
plt.show()
```

```
# We can see a good difference between the relative ctcs between flag_1, flag_2␣
↪and flag_3.
```




```
[61]: # Lets look at the relationship of "Designation_Flag" with␣
↪"Years_of_Experience".
plt.figure(figsize=(15,4))
sns.barplot(data=df,x='Designation_Flag',y='Years_of_Experience')
plt.xticks(rotation=90)
plt.show()

# This is an interesting discovery. Learners who earn the highest salaries do␣
↪not have the highest "Years_of_Experience".
```




```
[61]:
```

0.5.2 2) "Class Flag"

Creating "Class_Flag" which shows learners with CTC greater/lower than the Average of their Company's department.

- Before we create the flag, lets specify the rules based on which the flag would be created.
- If the "ctc" is less than 75% of "average_ctc", we can flag it as 1.
- If the "ctc" is between 75% and 125% of "average_ctc", we can flag it as 2.

- If the “ctc” is grater than 125% of “average_ctc”, we can flag it as 3.

[62]:
```
# Lets find the "average_ctc" as per the "company_hash" and "job_position". We␣
↪can name it "Average_2"
temp=df.groupby(by=["company_hash","job_position"]).agg({'ctc':'mean',}).
↪astype('int').reset_index().rename(columns={'ctc':"Average_2"})

# Merging the average_ctc with the dataset.
df=pd.merge(left=df,right=temp,on=["company_hash","job_position"])
```

[63]:
```
# Lets have a look at our updated dataset.
df.head(3)
```

[63]:
```
  company_hash      ctc      job_position  Years_of_Experience    Log_ctc  \
0    bxwqgogen  3500000  backend engineer                  7.0  15.068274
1    bxwqgogen  3560000  backend engineer                  7.0  15.085271
2    bxwqgogen  5500000  backend engineer                  7.0  15.520259

   Designation_Flag  Average_2
0                 2    2873402
1                 2    2873402
2                 3    2873402
```

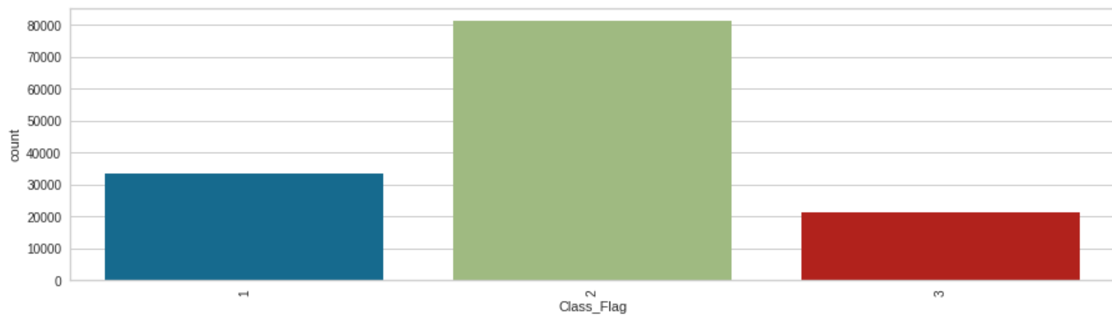
[64]:
```
# Lets get the values of "Class_Flag"
df['Class_Flag']=df[['ctc','Average_2']].apply(function,axis=1)

# We can now drop the "Average_1" column.
df.drop(columns=['Average_2'],inplace=True)
```

[65]:
```
# Lets have a look at our updated dataset.
df.head(3)
```

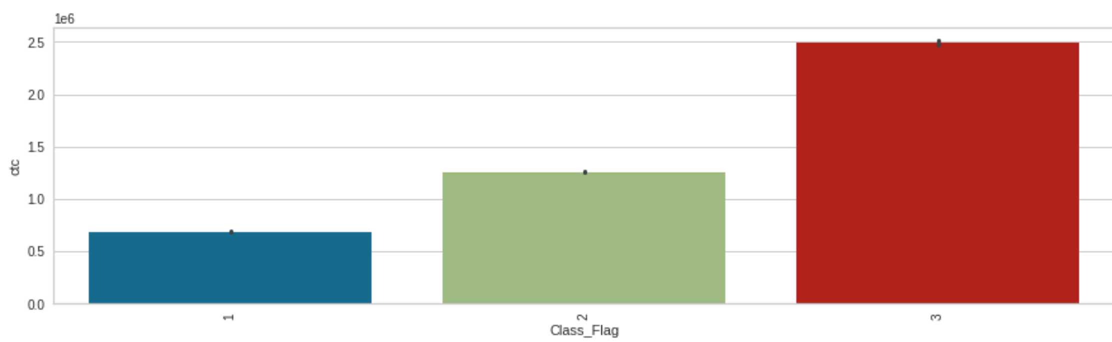
[65]:
```
  company_hash      ctc      job_position  Years_of_Experience    Log_ctc  \
0    bxwqgogen  3500000  backend engineer                  7.0  15.068274
1    bxwqgogen  3560000  backend engineer                  7.0  15.085271
2    bxwqgogen  5500000  backend engineer                  7.0  15.520259

   Designation_Flag  Class_Flag
0                 2           2
1                 2           2
2                 3           3
```

[66]:
```
# Lets look at the percentage of people beliongging to each type of "Class_Flag".
plt.figure(figsize=(15,4))
sns.countplot(data=df,x='Class_Flag')
plt.xticks(rotation=90)
plt.show()
```

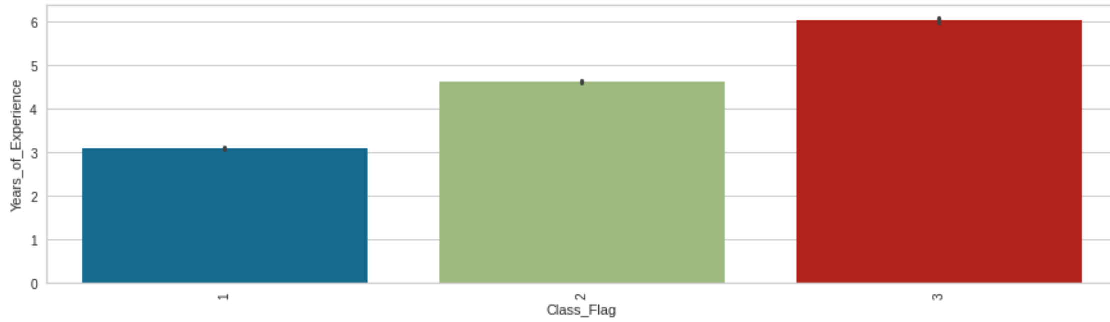
```
# There are more people who earn almost equal to the average salary as per␣
↪their "company_hash" and "job_position"
# There is a small section of learners who earn either very large or very large␣
↪ctc.
```



[67]:
```
# Lets look at the relationship of "Class_Flag" with "ctc".
plt.figure(figsize=(15,4))
sns.barplot(data=df,x='Class_Flag',y='ctc')
plt.xticks(rotation=90)
plt.show()

# We can see a good difference between the relative ctcs between flag_1, flag_2␣
↪and flag_3.
```



[68]:
```
# Lets look at the relationship of "Class_Flag" with "Years_of_Experience".
plt.figure(figsize=(15,4))
sns.barplot(data=df,x='Class_Flag',y='Years_of_Experience')
plt.xticks(rotation=90)
plt.show()

# Learners who earn the highest salaries have the highest "Years_of_Experience".
```



[68]:

```

```

0.5.3 3) "Tier Flag"

Creating "Tier_Flag" which shows learners with CTC greater/lower than the Average of their Company.

- Before we create the flag, lets specify the rules based on which the flag would be created.
- If the "ctc" is less than 75% of "average_ctc", we can flag it as 1.
- If the "ctc" is between 75% and 125% of "average_ctc", we can flag it as 2.
- If the "ctc" is grater than 125% of "average_ctc", we can flag it as 3.

[69]:

```
# Lets find the "average_ctc" as per the "company_hash". We can name it␣
↪"Average_3"
temp=df.groupby(by=["company_hash"]).agg({'ctc':'mean',}).astype('int').
↪reset_index().rename(columns={'ctc':"Average_3"})

# Merging the average_ctc with the dataset.
df=pd.merge(left=df,right=temp,on=["company_hash"])
```

[70]:

```
# Lets have a look at our updated dataset.
df.head(3)
```

[70]:

```
  company_hash      ctc      job_position  Years_of_Experience    Log_ctc  \
0    bxwqgogen  3500000  backend engineer                  7.0  15.068274
1    bxwqgogen  3560000  backend engineer                  7.0  15.085271
2    bxwqgogen  5500000  backend engineer                  7.0  15.520259

   Designation_Flag  Class_Flag  Average_3
0                 2           2    2792920
1                 2           2    2792920
2                 3           3    2792920
```

[71]:

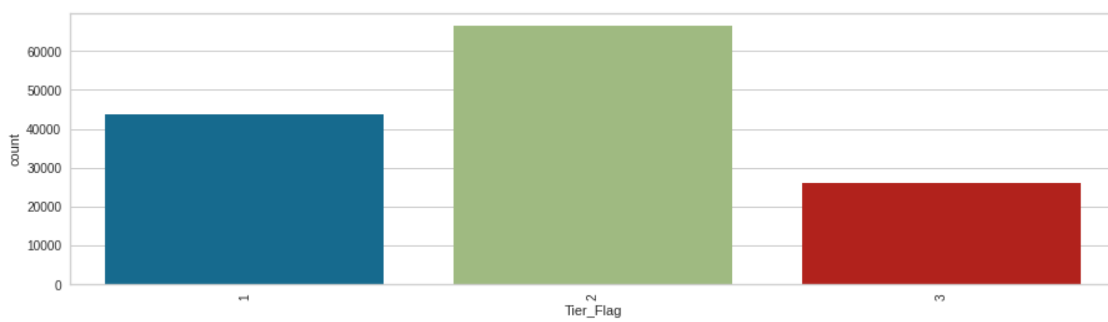
```
# Lets get the values of "Tier_Flag"
df['Tier_Flag']=df[['ctc','Average_3']].apply(function,axis=1)
```

```
# We can now drop the "Average_1" column.
df.drop(columns=['Average_3'],inplace=True)
```

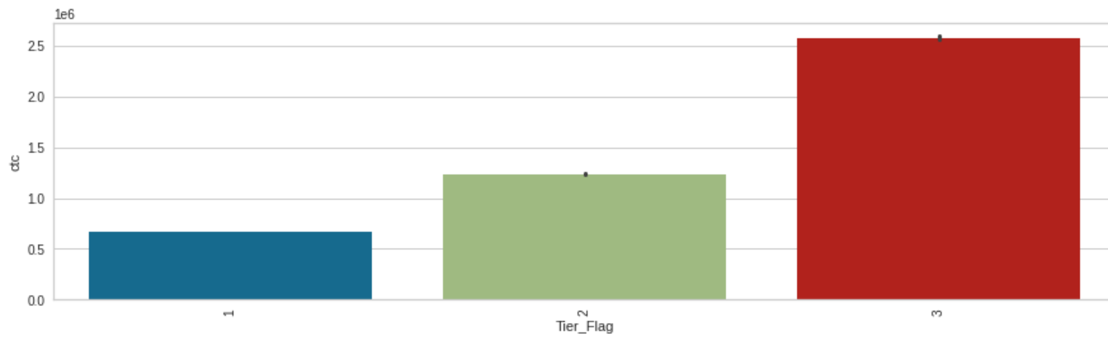
[72]:
```
# Lets have a look at our updated dataset.
df.head(3)
```

[72]:
```
  company_hash      ctc       job_position  Years_of_Experience    Log_ctc  \
0    bxwqgogen  3500000  backend engineer                  7.0  15.068274
1    bxwqgogen  3560000  backend engineer                  7.0  15.085271
2    bxwqgogen  5500000  backend engineer                  7.0  15.520259

   Designation_Flag  Class_Flag  Tier_Flag
0                 2           2          3
1                 2           2          3
2                 3           3          3
```

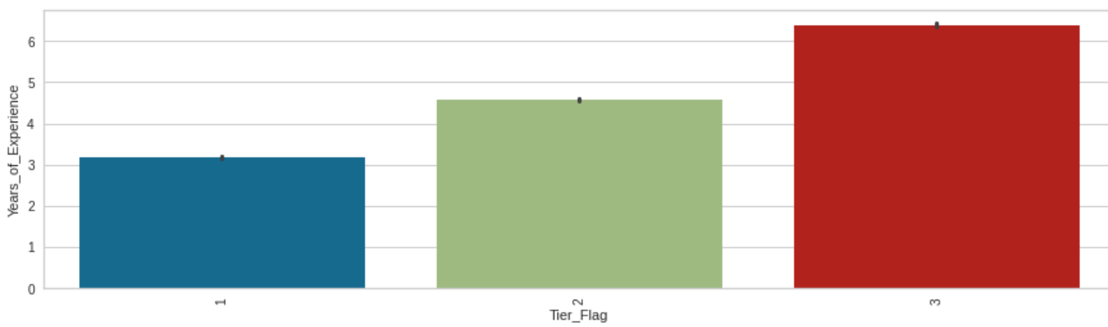
[73]:
```
# Lets look at the percentage of people beliongging to each type of "Tier_Flag".
plt.figure(figsize=(15,4))
sns.countplot(data=df,x='Tier_Flag')
plt.xticks(rotation=90)
plt.show()

# There are more people who earn almost equal to the average salary as per␣
↪their "company_hash".
# There is a small section of learners who earn either very large or very large␣
↪ctc.
```



[74]:
```
# Lets look at the relationship of "Tier_Flag" with "ctc".
plt.figure(figsize=(15,4))
sns.barplot(data=df,x='Tier_Flag',y='ctc')
plt.xticks(rotation=90)
plt.show()

# We can see a good difference between the relative ctcs between flag_1, flag_2␣
↪and flag_3.
```



[75]:
```
# Lets look at the relationship of "Tier_Flag" with "Years_of_Experience".
plt.figure(figsize=(15,4))
sns.barplot(data=df,x='Tier_Flag',y='Years_of_Experience')
plt.xticks(rotation=90)
plt.show()

# Learners who earn the highest salaries have the highest "Years_of_Experience".
```



[75]:
```
```

0.6 Encoding

[76]:
```
# Lets check which columns we need to encode.
display(df.head(2))

# Since "company_hash" has a lot of categories, we can drop it for doing␣
↪clustering.
# For doing clustering, we can also drop "Designation_Flag", "Class_Flag" and␣
↪"Tier_Flag".
# Also, we can drop "ctc" column since we have a new column - "Log_ctc".
# We need to One-Hot-Encode "job_position"
```

```
df=df[['job_position', 'Years_of_Experience', 'Log_ctc']]
encoder=OneHotEncoder(sparse=False)
temp=pd.DataFrame(data=encoder.
 ↪fit_transform(df[['job_position']]),columns=encoder.get_feature_names())
df=pd.concat((df.iloc[:,1:],temp),axis=1)
```

```
  company_hash      ctc      job_position  Years_of_Experience    Log_ctc  \
0    bxwqgogen  3500000  backend engineer                  7.0  15.068274
1    bxwqgogen  3560000  backend engineer                  7.0  15.085271

   Designation_Flag  Class_Flag  Tier_Flag
0                 2           2          3
1                 2           2          3
```

[76]:

```

```

0.7 Scaling

[77]:

```
# Lets check which columns we need to encode.
display(df.head(2))

# We need to scale "Years_of_Experience" and "Log_ctc".
scaler=StandardScaler()
temp=pd.DataFrame(data=scaler.fit_transform(df.iloc[:,[0,1]]),columns=scaler.
 ↪get_feature_names_out())
df=pd.concat((temp,df.iloc[:,2:]),axis=1)
```

```
   Years_of_Experience    Log_ctc  x0_Combined  x0_Missing  \
0                  7.0  15.068274          0.0         0.0
1                  7.0  15.085271          0.0         0.0

   x0_android engineer  x0_backend engineer  x0_data analyst  \
0                  0.0                  1.0              0.0
1                  0.0                  1.0              0.0

   x0_data scientist  x0_devops engineer  x0_engineering intern  \
0                0.0                 0.0                    0.0
1                0.0                 0.0                    0.0

   x0_engineering leadership  x0_frontend engineer  x0_fullstack engineer  \
0                        0.0                   0.0                    0.0
1                        0.0                   0.0                    0.0

   x0_ios engineer  x0_other  x0_qa engineer  x0_sdet  x0_support engineer
0              0.0       0.0             0.0      0.0                  0.0
1              0.0       0.0             0.0      0.0                  0.0
```

[78]:
```
# Final Look at our encoded and scaled dataset.
df.head(2)
```

[78]:
```
   Years_of_Experience   Log_ctc  x0_Combined  x0_Missing  \
0             0.774817  1.631987          0.0         0.0
1             0.774817  1.653532          0.0         0.0

   x0_android engineer  x0_backend engineer  x0_data analyst  \
0                  0.0                  1.0              0.0
1                  0.0                  1.0              0.0

   x0_data scientist  x0_devops engineer  x0_engineering intern  \
0                0.0                 0.0                    0.0
1                0.0                 0.0                    0.0

   x0_engineering leadership  x0_frontend engineer  x0_fullstack engineer  \
0                        0.0                   0.0                    0.0
1                        0.0                   0.0                    0.0

   x0_ios engineer  x0_other  x0_qa engineer  x0_sdet  x0_support engineer
0              0.0       0.0             0.0      0.0                  0.0
1              0.0       0.0             0.0      0.0                  0.0
```

[ ]:
```

```

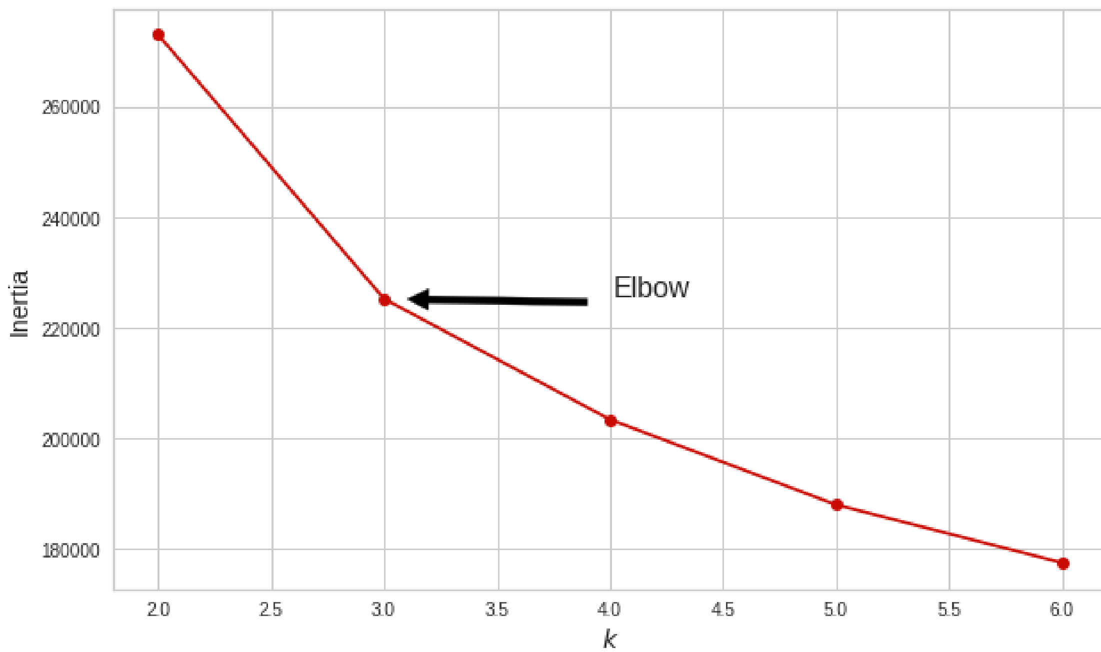
1 Unsupervised Learning - Clustering

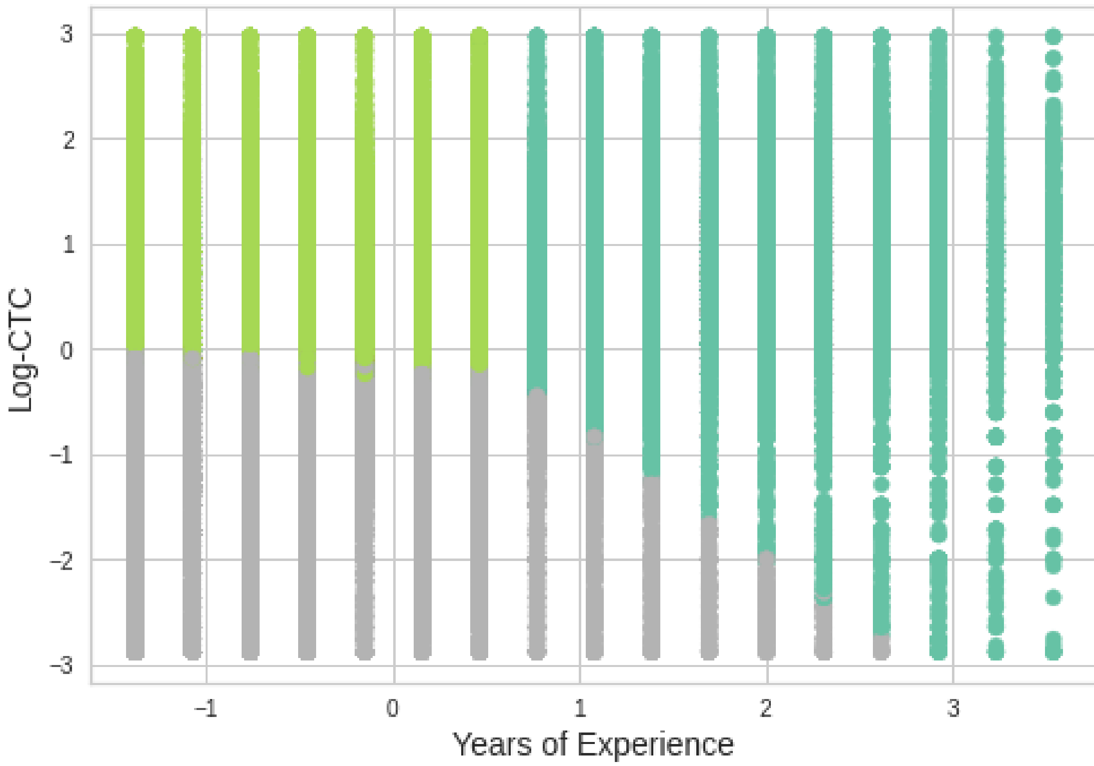
1.1 1) K-Means Clustering

[ ]:
```
# Lets use KMeans clustering to find the optimal number of clusters. Lets try␣
↪for clusters 2,3,4,5 and 6.
inertias=[]
silhouette_scores=[]
kmeans_per_k = [KMeans(n_clusters=k, random_state=42).fit(df) for k in range(2,␣
↪7)]

# Inertia and Silhouette_Scores for deciding the optimal number of clusters
inertias = [model.inertia_ for model in kmeans_per_k]
silhouette_scores = [silhouette_score(df, model.labels_) for model in␣
↪kmeans_per_k]
```

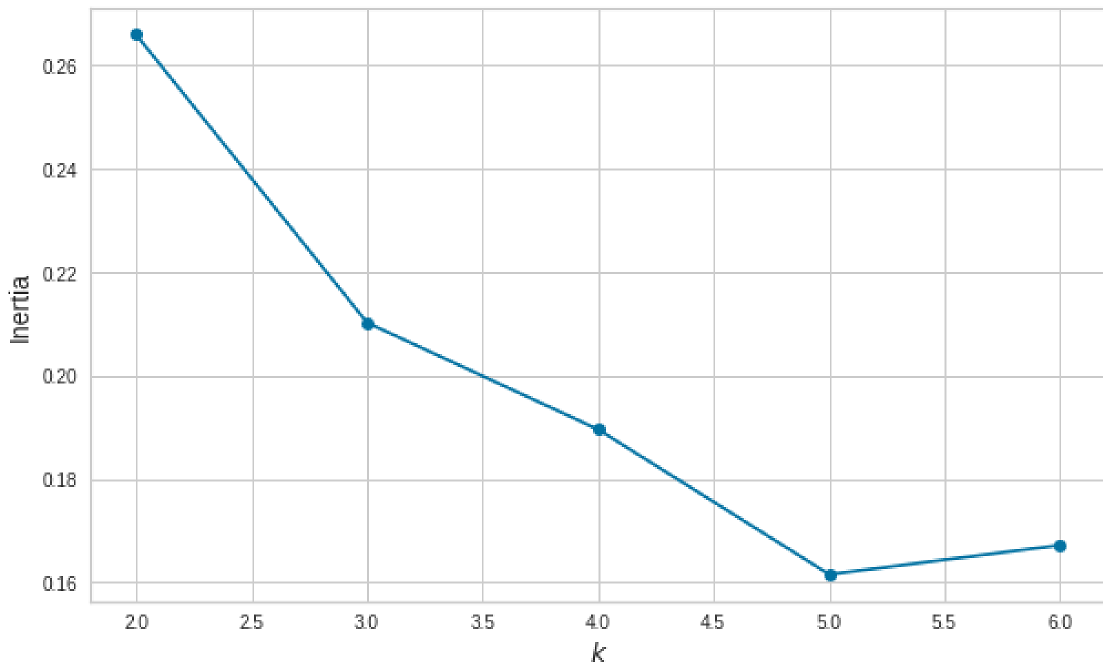
[ ]:
```
# Elbow method to determine the optimal number of clusters
plt.figure(figsize=(10, 6))
plt.plot(range(2,7), inertias, "ro-")
plt.xlabel("$k$", fontsize=14)
plt.ylabel("Inertia", fontsize=14)
```

```
plt.annotate('Elbow', xy=(3, inertias[1]), xytext=(0.55, 0.55),␣
↪textcoords='figure fraction',
             fontsize=16, arrowprops=dict(facecolor='black', shrink=0.1))
plt.show()

# From the elbow method, we can see a sharp bend for k=3. Lets look at the␣
↪segmenation for 3 clusters.
plt.scatter(x=df['Years_of_Experience'],y=df['Log_ctc'],c=kmeans_per_k[1].
↪labels_,cmap='Set2')
plt.xlabel("Years of Experience", fontsize=14)
plt.ylabel("Log-CTC", fontsize=14)
plt.show()
```

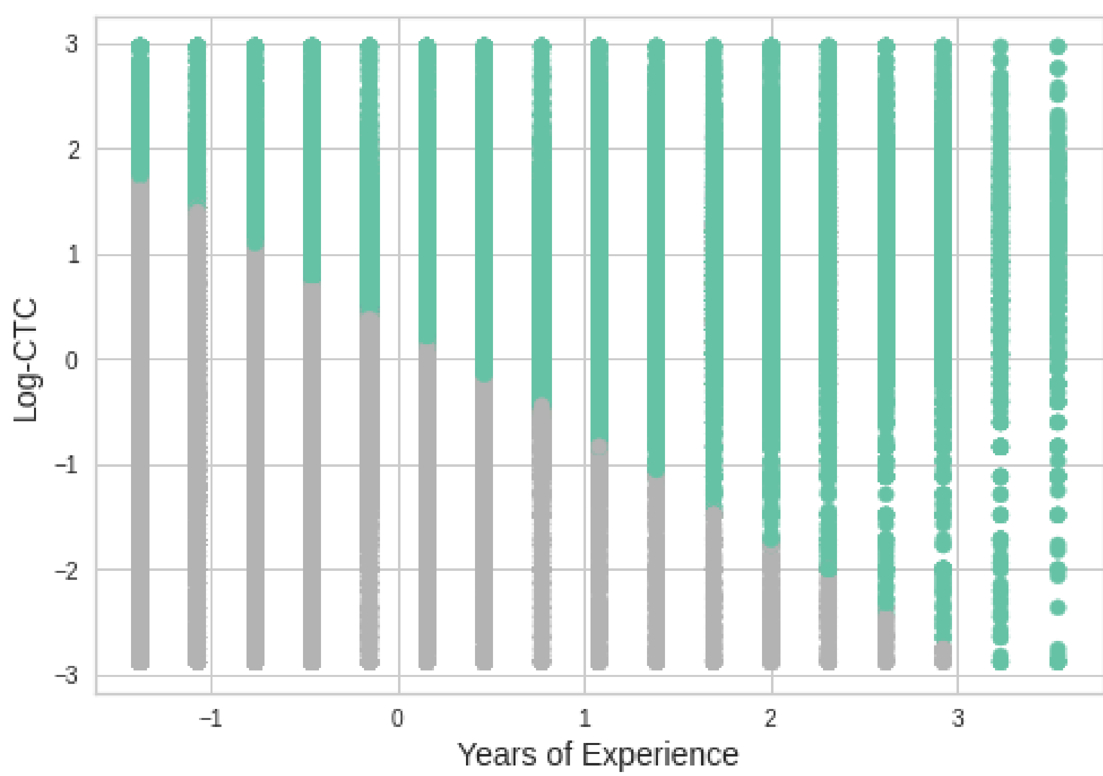




[ ]:
```python
# Silhouette_scores to determine the optimal number of clusters.
plt.figure(figsize=(10, 6))
plt.plot(range(2,7), silhouette_scores, "bo-")
plt.xlabel("$k$", fontsize=14)
plt.ylabel("Inertia", fontsize=14)
plt.show()

# From this plot, k=2 or k=3 is the right number of clusters. Lets look at the␣
 ↪segmenation for 2 clusters.
plt.scatter(x=df['Years_of_Experience'],y=df['Log_ctc'],c=kmeans_per_k[0].
 ↪labels_,cmap='Set2')
plt.xlabel("Years of Experience", fontsize=14)
plt.ylabel("Log-CTC", fontsize=14)
plt.show()
```



0.26
0.24
0.22
0.20
0.18
0.16
Inertia
2.0
2.5
3.0
3.5
4.0
4.5
5.0
5.5
6.0
k



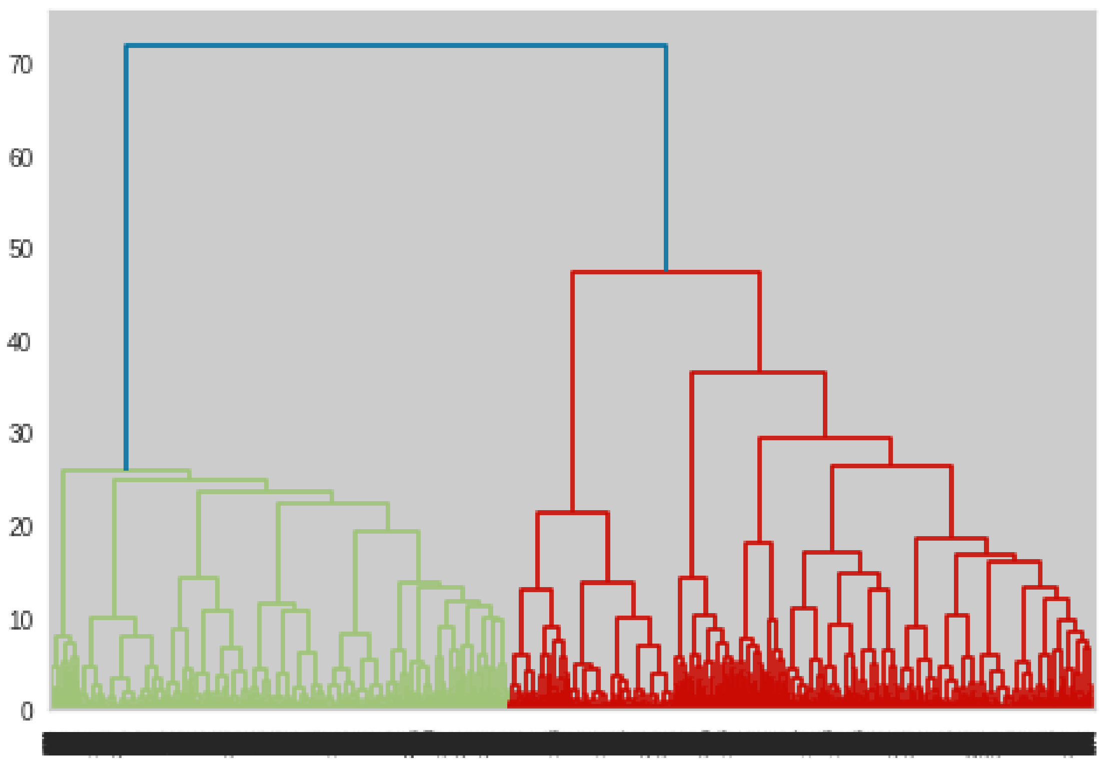
3
2
1
0
−1
−2
−3
Log-CTC
−1
0
1
2
3
Years of Experience

```
[ ]: # Observation - 3 Clusters are more suitable according to the business sense.
# - The first cluster belongs to those young learners who are probably highly skilled and have joined high paying startups and MNCs.
# - The second cluster belongs to those learner who are probably working in service based MNCs and their salary increases with experience.
# - The third cluster belongs to those learner who are probably working in top product based companies and are very skillful and experienced.
```

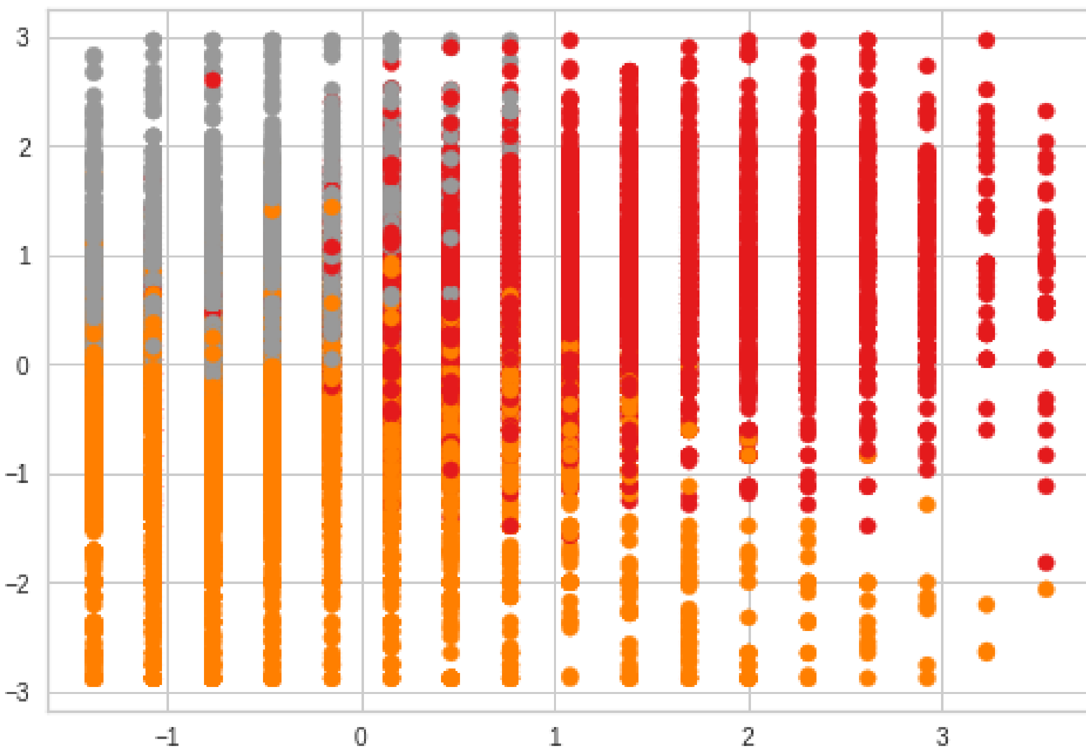
```
[ ]:
```

1.2 2) Hierarchical Clustering

```
[81]: # Lets see how many clusters "Hierarchical Clustering" on its own.
# Since it will take a lot of time to run the algorithm on the entire dataset, therefore lets take only 5,000 observations.

linkage_data = linkage(df.sample(4000), method='ward', metric='euclidean')
dendrogram(linkage_data)
plt.show()

# From the above plot we can see that the number of clusters is 3, which is also verfied by the Elbow method from K_Means.
```



[86]:
```
# Lets look at the segmentation of the 3 clusters by using␣
↪"Hierarchical_Clustering".
# Since it will take a lot of time to run the algorithm on the entire dataset,␣
↪therefore lets take only 15,000 observations.
data=df.sample(15000)

hierarchical_cluster = AgglomerativeClustering(n_clusters=3,␣
↪affinity='euclidean', linkage='ward')
labels = hierarchical_cluster.fit_predict(data)

plt.scatter(data['Years_of_Experience'], data['Log_ctc'], c=labels,cmap='Set1')
plt.show()

# The segmentation of clusters by using "Hierarchical_Clustering" is almost the␣
↪same as by using "KMeans".
```



2 Actionable Insights & Recommendations

- From the clustering analysis and also by business intuition, we finally deciced that there are 3 meaningful clusters.
- The first cluster belongs to those young learners who are probably highly skilled and have joined high paying startups and MNCs.

- The second cluster belongs to those learner who are probably working in service based MNCs and their salary increases with experience.
- The third cluster belongs to those learner who are probably working in top product based companies and are very skillful and experienced.
- For very high paying start-ups for less experienced learners, Scaler can identify, train and make them ready to crack those jobs.
- For stable MNCs, learners who are not highly skilled or who are looking to do a career transition can be placed in such companies.
- For highly experienced jobs, some learners can be identified who are both skillful and highly experieced to get those jobs.
- There are a lot of "Backend-Engineer" and "Fullstack-Engineer" jobs available, so getting learned placed for this job role would be relatively easy.
- "Engineering Leadership" earns the highest average "ctc" among all job categories, and these learners have the highest average experience. A highly experienced learner might be better suited for "Engineering Leadership" job.
- "Support Engineer" has the minimum average "ctc" among all job categories. This can be a good marketing strategy to attract learners who are looking to do a career transition.
- As expected, "Engineering Intern" has the minimum average "Years_of_Experience" among all job categories.
- "Data Scientist" and "Backend Engineer" are one of the most highly paid jobs, and Scaler's program these program for both these job profiles. So Scaler can get learner placed in such jobs easily.
- There are a few masked companies who hire a lot of people, so Scaler can also placed suitable learners in these companies based on the job fit requirement.
- There are a few companies who offer the best salaries to its employees. Scaler can shortlist such learners from its cohort and try to get learners placed in them to increase its credibility.

[ ]:

```

```