Problem Statement

- Profiling the best companies and job positions to work for from the Scaler database.
- Clustering the learners on the basis of their job profile, company, and other features.

Concept Used:

- Manual Clustering
- Unsupervised Clustering - K- means, Hierarchical Clustering

In [84]:
```
import re
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
#plt.rcParams["figure.figsize"] = (12,8)
```

In [2]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
df = pd.read_csv("scaler_clustering.csv",index_col=0)
```

In [4]:
```
df.sample(10)
```

Out[4]:

	company_hash	email_hash	orgyear	ctc	j
32773	zhwrtho ogenfvqt	5beab3e022fe7704954f7ce66047e9335588cd483d9d4d...	2023.0	98900000	
167665	wgszxkvzn	022dd28413ab1ebcec604b3528441b686b0174d2bbdf6e...	2008.0	103000	
94617	atrgxnnt	3bdaaf20ba7fbbcdfe80e63ba285a6760160c2bd7e6f47...	2014.0	1600000	(
115361	ywr ntwyzgrgsxto	fd3c3f85bf3e995fb7e99daa125a532eb04cd28f0c8461...	2016.0	1090000	
89262	xzntr wgqugqvnxgz	e0f3c434b906b63344eaa01cd6a14b0e15fbf471245074...	2017.0	1800000	
51990	exatrxnj xzctonbtzno	b43a9dfe14227b0c01565782479b618d476272e750effc...	2012.0	1050000	
179837	zx zvnxgzvr xzonqhbtzno	4ba864840f28b60a94e54b24ec66ceba588182cd55a24a...	2018.0	1350000	
179953	vrnvxq	0c41a4de7a6014e5dc3528b37d28f1c8574636a743499e...	2013.0	800000	
14640	uhmrxwxo ovuxtzn	25ff9ad29e16f59f205c1d42e0b1d678ba3b213efd1c32...	2018.0	550000	
127568	tdutaxv xzw	b716b89a03a6b3c75f4b21d5dff38e8f01e2929869bb03...	2012.0	2000000	

In [5]:
```
df.shape
```

Out[5]:
```
(205843, 6)
```

In [6]:
```
# 205843 learners data
```

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 205843 entries, 0 to 206922
Data columns (total 6 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   company_hash      205799 non-null  object 
 1   email_hash        205843 non-null  object 
 2   orgyear           205757 non-null  float64
 3   ctc               205843 non-null  int64  
 4   job_position      153281 non-null  object 
 5   ctc_updated_year  205843 non-null  float64
dtypes: float64(2), int64(1), object(3)
memory usage: 11.0+ MB
```

In [8]:
```
df.isna().sum()
```

Out[8]:
```
company_hash           44
email_hash              0
orgyear                86
ctc                     0
job_position        52562
ctc_updated_year        0
dtype: int64
```

In [9]:
```
(df.isna().sum()/ len(df))*100
```

Out[9]:
```
company_hash         0.021376
email_hash           0.000000
orgyear              0.041779
ctc                  0.000000
job_position        25.534995
ctc_updated_year     0.000000
dtype: float64
```

In [10]:
```
df.describe()
```

Out[10]:

	orgyear	ctc	ctc_updated_year
count	205757.000000	2.058430e+05	205843.000000
mean	2014.882750	2.271685e+06	2019.628231
std	63.571115	1.180091e+07	1.325104
min	0.000000	2.000000e+00	2015.000000
25%	2013.000000	5.300000e+05	2019.000000
50%	2016.000000	9.500000e+05	2020.000000
75%	2018.000000	1.700000e+06	2021.000000
max	20165.000000	1.000150e+09	2021.000000

In [11]:
```
# based on above information , noticing some unusual outliers in the data
```

In [12]:
```
df.describe(include="object")
```

Out[12]:

	company_hash	email_hash	job_position
count	205799	205843	153281
unique	37299	153443	1017
top	nvnv wgzohrnvzwj otqcxwto	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	Backend Engineer
freq	8337	10	43554

Using Regex to clean Company Hash

In [13]:
```
def preprocess_string(string):
    new_string= re.sub('[^A-Za-z ]+', '', string).lower().strip()
    return new_string

mystring='\tAirtel\\\\&&**() X Labs'
preprocess_string(mystring)
```

Out[13]:
```
'airtel x labs'
```

In [14]:
```
df["company_hash"].nunique()
```

Out[14]:
```
37299
```

In [15]:
```
df["company_hash"] = df["company_hash"].apply(lambda x: preprocess_string(str(x)))
df["company_hash"].nunique()
```

Out[15]:
```
37208
```

In [ ]:
```

```

In [16]:
```
df["job_position"].nunique()
# 1017 unique job positions are there in the dataset
```

Out[16]:
```
1017
```

In [17]:
```
df["job_position"] = df["job_position"].apply(lambda x: preprocess_string(str(x)))
df["job_position"].nunique()

# 857 unique job positions are there in the dataset after preprocessing strings
```

Out[17]:
```
857
```

In [18]:
```
# removing the email_hash
df.drop("email_hash",axis = 1,inplace=True)
```

In [19]:
```
df.sample(5)
```

Out[19]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year
32385	uhmrxwxo ovuxtzn	2016.0	1100000	backend engineer	2019.0
150664	gutz lhxwt ntwyzgrgsxto	2017.0	650000	fullstack engineer	2019.0
144284	vwwhqv xzahonqxto	2017.0	1200000	qa engineer	2019.0
18253	axbno	2006.0	1300000	backend engineer	2021.0
26924	zgn vuurxwvmrt vwwghzn	2021.0	10000	other	2021.0

In [20]:
```
df.duplicated().sum() # 17597 duplicated records
```

Out[20]:
```
17597
```

In [21]:
```
df.isna().sum()
```

Out[21]:
```
company_hash         0
orgyear             86
ctc                  0
job_position         0
ctc_updated_year     0
dtype: int64
```

In [22]:
```
(df["company_hash"] == "").sum()
```

Out[22]:
```
89
```

In [23]:
```
(df["company_hash"] == "nan").sum()
```

Out[23]:
```
44
```

In [24]:
```
(df["job_position"] == "").sum()
```

Out[24]:
```
9
```

In [25]:
```
(df["job_position"] == "nan").sum()
```

Out[25]:
```
52562
```

In [26]:
```
# removing the records where company or job_position reocords are not available
```

In [27]:
```
df[(df["company_hash"] == "") | (df["job_position"] == "")].sample(10)
```

Out[27]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year
86550		2021.0	100000000	nan	2019.0
198561		2017.0	300000	other	2020.0
66088		2007.0	2300000	fullstack engineer	2019.0
86758		2019.0	700000	nan	2019.0
2940		2020.0	100000	nan	2020.0
161691	yaew mvzp	2001.0	100000000		2021.0
200558		2018.0	1000000	other	2019.0
197495		2020.0	2700000	nan	2019.0
5797	seo gxr svo axcxoxgz	2011.0	700000		2021.0
87642		2016.0	500000	fullstack engineer	2018.0

In [28]:
```
len(df[(df["company_hash"] == "") | (df["job_position"] == "")])
```

Out[28]:
```
98
```

In [29]:
```
# df[((df["company_hash"] != "") & (df["job_position"] != ""))]
```

In [30]:
```
df = df[~((df["company_hash"] == "") | (df["job_position"] == ""))]
df
```

Out[30]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year
0	atrgxnnt xzaxv	2016.0	1100000	other	2020.0
1	qtrxvzwt xzegwgbb rxbxnta	2018.0	449999	fullstack engineer	2019.0
2	ojzwnvwnxw vx	2015.0	2000000	backend engineer	2020.0
3	ngpgutaxv	2017.0	700000	backend engineer	2019.0
4	qxen sqghu	2017.0	1400000	fullstack engineer	2019.0
...	...	...	...	...	...
206918	vuurt xzw	2008.0	220000	nan	2019.0
206919	husqvawgb	2017.0	500000	nan	2020.0
206920	vwwgrxnt	2021.0	700000	nan	2021.0
206921	zgn vuurxwvmrt	2019.0	5100000	nan	2019.0
206922	bgqsvz onvzrtj	2014.0	1240000	nan	2016.0

205745 rows × 5 columns

Data Preprocessing

Handling Missing values-Imputation

In [31]:
```
df["orgyear"].isna().sum()
```

Out[31]:
```
86
```

imputing Employee Start Year as per the median year as per each company.

In [32]:
```
df.groupby("company_hash")["orgyear"].transform("median")
```

Out[32]:
```
0         2014.0
1         2016.0
2         2015.0
3         2016.0
4         2017.0
           ...
206918    2018.0
206919    2017.0
206920    2016.0
206921    2020.0
206922    2015.0
Name: orgyear, Length: 205745, dtype: float64
```

In [33]:
```
#df["orgyear"].fillna(df['orgyear'].isnull().sum(),inplace=True)
```

In [34]:
```
df["orgyear"].isna().sum()
```

Out[34]:
```
0
```

In [35]:
```
df.sample(5)
```

Out[35]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year
25912	hzxexta ntwy sqghu xzw	2020.0	6000000	data analyst	2020.0
98719	wvustbxzx	2016.0	620000	fullstack engineer	2021.0
113597	nvqstn	2006.0	2250000	nan	2021.0
81678	zvz	2020.0	400000	nan	2021.0
175253	eqtoytq	2018.0	1300000	other	2019.0

Outliers Treatment :

- ### employment start year

In [40]:
```
df["orgyear"].value_counts()
```

Out[40]:
```
2018.0    25240
2019.0    23402
2017.0    23237
2016.0    23038
2015.0    20602
          ...
2107.0        1
1972.0        1
2101.0        1
208.0         1
200.0         1
Name: orgyear, Length: 78, dtype: int64
```

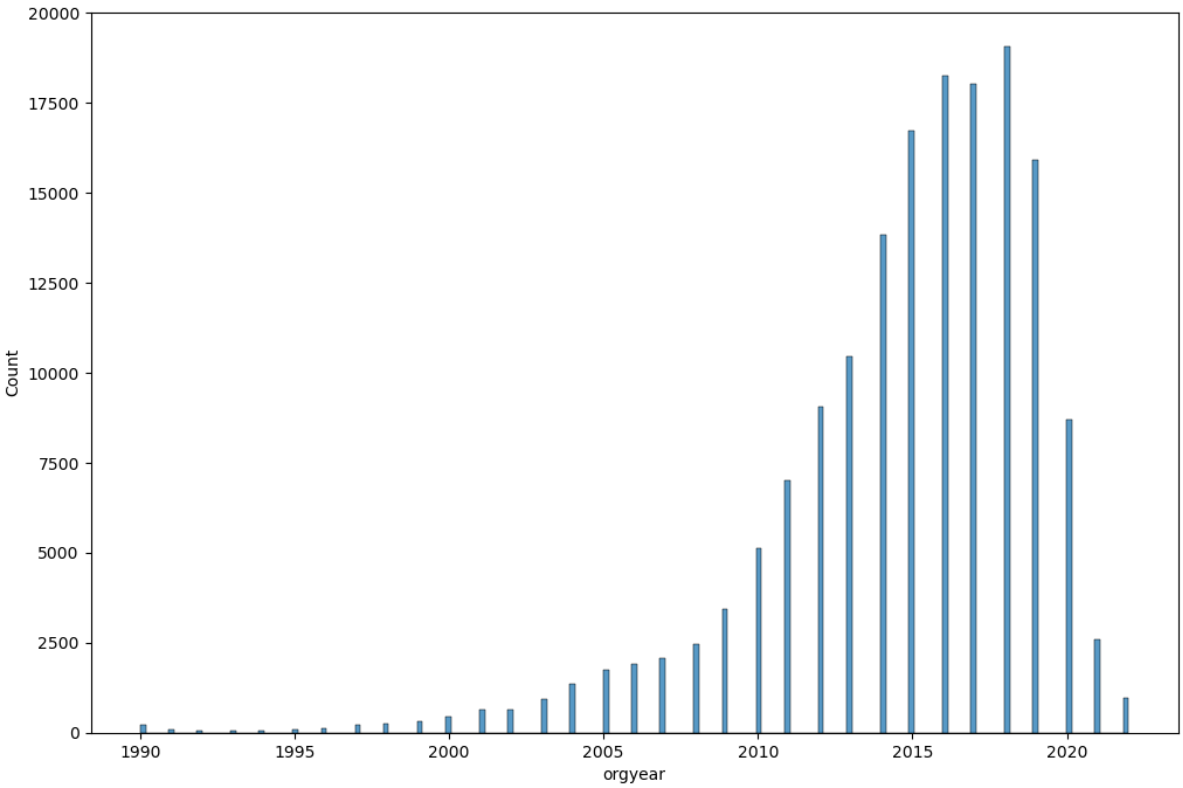
In [94]:
```
df["orgyear"]=df["orgyear"].astype('int')
```

In [51]:
```
df["orgyear"].unique()
```

Out[51]:
```
[2016.0, 2018.0, 2015.0, 2017.0, 2019.0, ..., 1995.0, 1992.0, 1991.0, 1998.0, 199
3.0]
Length: 33
Categories (33, float64): [1990.0, 1991.0, 1992.0, 1993.0, ..., 2019.0, 2020.0, 20
21.0, 2022.0]
```

In [194…
```
sns.histplot(df["orgyear"])
```

Out[194]:
```
<Axes: xlabel='orgyear', ylabel='Count'>
```



In [57]:
```
df.dtypes
```

Out[57]:
```
company_hash          object
orgyear             category
ctc                    int64
job_position          object
ctc_updated_year     float64
dtype: object
```

In [ ]:
```
# sns.histplot(np.log(df["orgyear"]))
```

In [42]:
```
df["orgyear"].quantile(0.001)
```

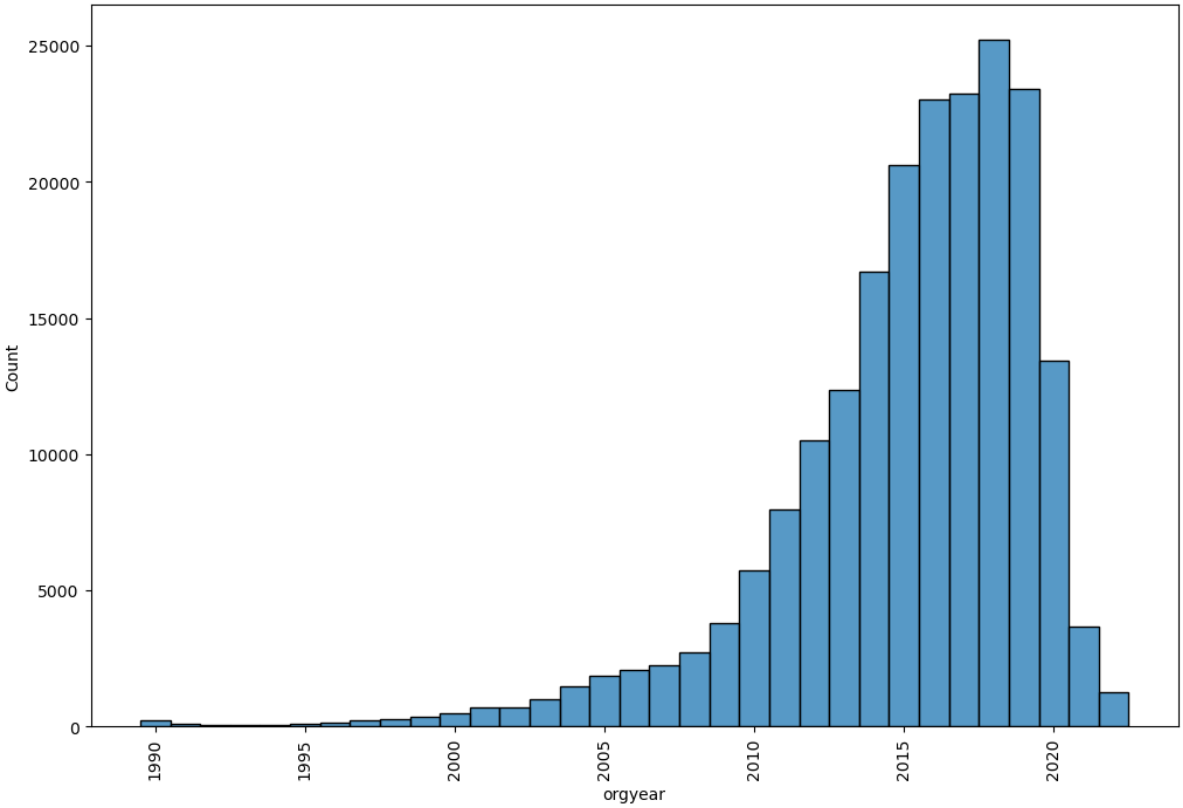
Out[42]:
```
1990.0
```

In [43]:
```
df["orgyear"].quantile(0.999)
```

Out[43]:
```
2023.0
```

In [44]:
```
df["orgyear"] = df["orgyear"].clip(1990,2022)
```

In [59]:
```
sns.histplot(df["orgyear"])
plt.xticks(rotation = 90)
plt.show()
```



- ### ctc updated_year

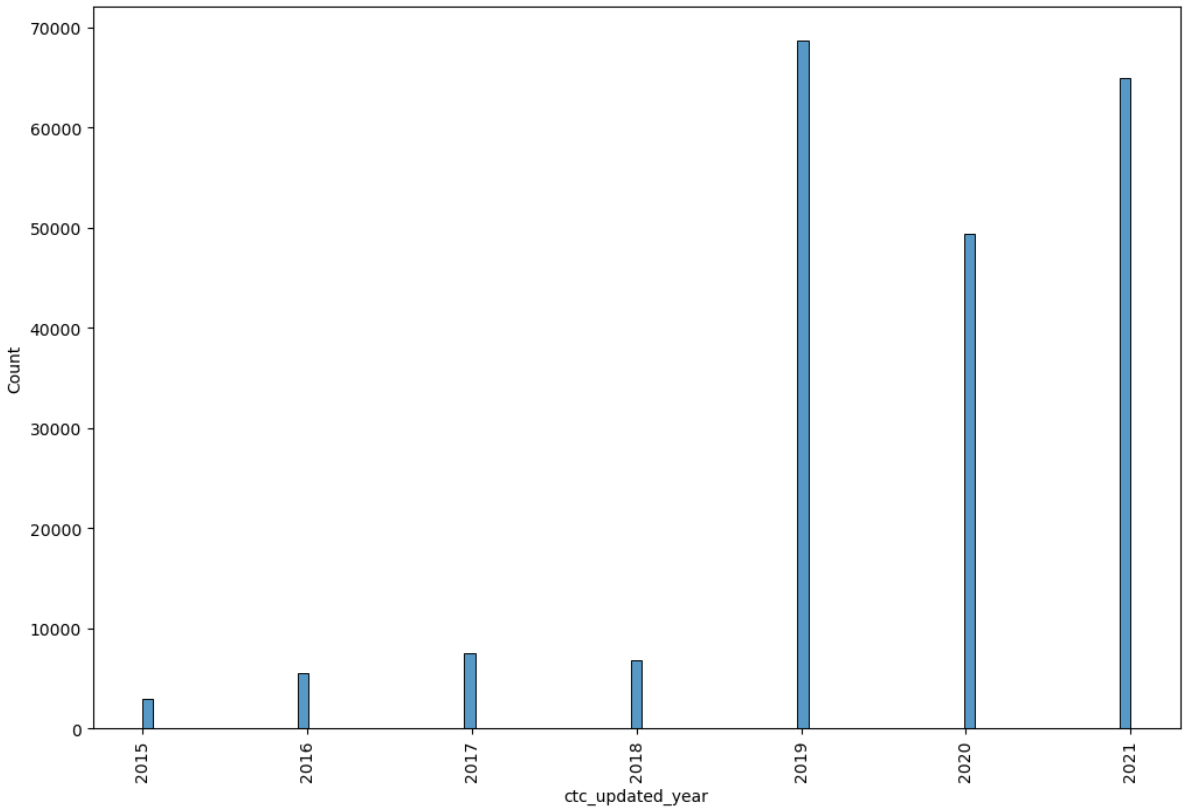
In [60]:
```
df["ctc_updated_year"].quantile(0.001)
```

Out[60]:
```
2015.0
```

In [61]:
```
df["ctc_updated_year"].quantile(0.99)
```

Out[61]:
```
2021.0
```

In [63]:
```
sns.histplot(df["ctc_updated_year"])
plt.xticks(rotation = 90)
plt.show()
```



- ### outlier treatment for CTC

In [64]:
```
df["ctc"].quantile(0.01)
```

Out[64]:
```
37000.0
```

In [65]:
```
df["ctc"].quantile(0.999)
```

Out[65]:
```
200000000.0
```

In [66]:
```
df = df.loc[((df.ctc) > df.ctc.quantile(0.01)) & ((df.ctc) < df.ctc.quantile(0.99))
```

In [67]:
```
df
```

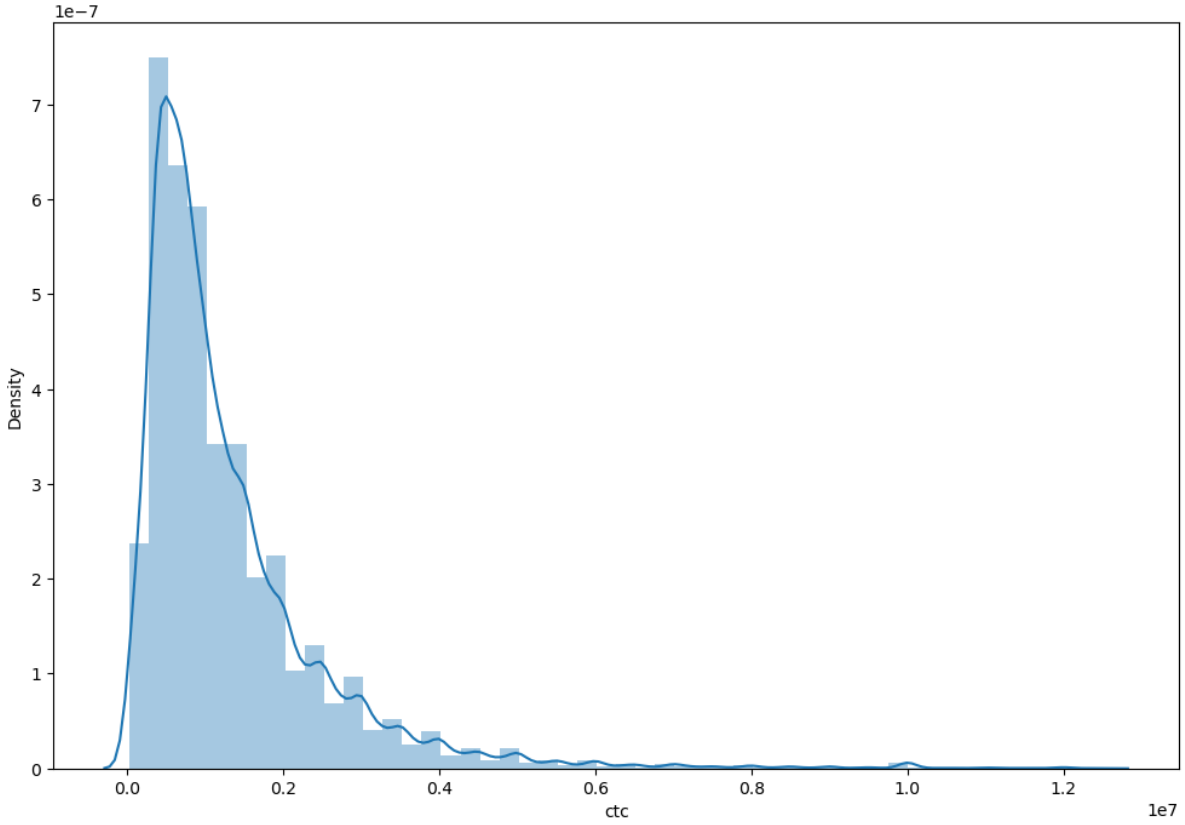
Out[67]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year
0	atrgxnnt xzaxv	2016.0	1100000	other	2020.0
1	qtrxvzwt xzegwgbb rxbxnta	2018.0	449999	fullstack engineer	2019.0
2	ojzwnvwnxw vx	2015.0	2000000	backend engineer	2020.0
3	ngpgutaxv	2017.0	700000	backend engineer	2019.0
4	qxen sqghu	2017.0	1400000	fullstack engineer	2019.0
...	...	...	...	...	...
206918	vuurt xzw	2008.0	220000	nan	2019.0
206919	husqvawgb	2017.0	500000	nan	2020.0
206920	vwwgrxnt	2021.0	700000	nan	2021.0
206921	zgn vuurxwvmrt	2019.0	5100000	nan	2019.0
206922	bgqsvz onvzrtj	2014.0	1240000	nan	2016.0

201625 rows × 5 columns

In [70]:
```
sns.distplot(df["ctc"])
```

Out[70]:
```
<Axes: xlabel='ctc', ylabel='Density'>
```



- replacing string "nan" to np.nan

In [71]:
```
df.loc[df['job_position']=='nan', 'job_position']=np.nan
```

In [72]:
```
df.loc[df["company_hash"]=="nan","company_hash"] = np.nan
```

In [73]:
```
# df.company_hash.value_counts(dropna=False)
```

In [74]:
```
# df.job_position.value_counts(dropna=False)
```

Feature Engineering

Masked company name to "Others" having count less than 5

In [75]:
```
df.loc[df.groupby("company_hash")["ctc"].transform("count") < 5,"company_hash"] = '
```

In [76]:
```
(df["company_hash"] == "Others").sum()
```

Out[76]:
```
46434
```

In [77]:
```
# df.company_hash.value_counts(dropna=False)
```

In [78]:
```
df['orgyear'].describe()
```

Out[78]:
```
count     201625.0
unique        33.0
top         2018.0
freq       24739.0
Name: orgyear, dtype: float64
```

years of experience = current year - employement start year

In [196…
```
import datetime
```

In [197…
```
# years of experience
df["years_of_experience_in_organization"] = datetime.datetime.now().year - df["orgy
```

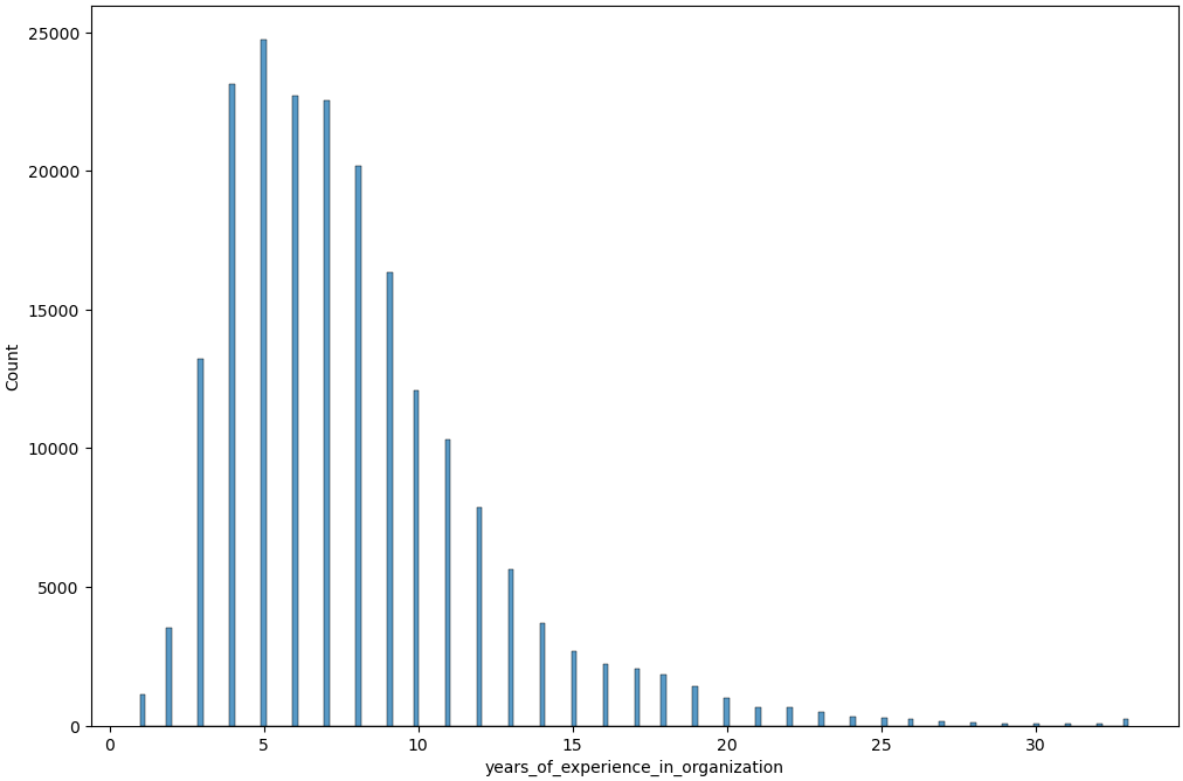
In [81]:
```
df.sample(2)
```

Out[81]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_o
192205	vcxog xzw	2015.0	1000000	backend engineer	2019.0	
180674	wqtaxncxajv	2017.0	1500000	backend engineer	2020.0	

In [86]:
```
sns.histplot(df["years_of_experience_in_organization"])
```

Out[86]:
```
<Axes: xlabel='years_of_experience_in_organization', ylabel='Count'>
```



In [87]:
```
df.duplicated().sum()
```

Out[87]:
```
37683
```

In [88]:
```
df.drop_duplicates(inplace=True)
df.shape
```

Out[88]:
```
(163942, 6)
```

In [89]:
```
df.isna().sum()
```

Out[89]:
```
company_hash                          42
orgyear                                0
ctc                                    0
job_position                       36745
ctc_updated_year                       0
years_of_experience_in_organization    0
dtype: int64
```

treating records having ctc_updated_year higher than their organization joining year

In [91]:
```
# records having ctc_updated_year higher than their organization joining year
(df["ctc_updated_year"] < df["orgyear"].astype(int)).sum()
```

Out[91]:
```
7181
```

In [92]:
```
df.ctc_updated_year = df[["ctc_updated_year","orgyear"]].max(axis = 1)
```

In [95]:
```
(df["ctc_updated_year"] < df["orgyear"]).sum()
```

Out[95]:
```
0
```

In [96]:
```
df.sample(2)
```

Out[96]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_org
26563	xmb xzaxv uqxcvnt rxbxnta	2014	450000	support engineer	2020.0	
59821	uhmrxwxo ovuxtzn	2014	550000	NaN	2019.0	

Filling null values with others -- if not done before

In [97]:
```
df['job_position'] = df['job_position'].fillna('Others')
df['company_hash'] = df['company_hash'].fillna('Others')
```

In [98]:
```
df.isna().sum()
```

Out[98]:
```
company_hash                        0
orgyear                             0
ctc                                 0
job_position                        0
ctc_updated_year                    0
years_of_experience_in_organization    0
dtype: int64
```

In [99]:
```
df.duplicated().sum()
```

Out[99]:
```
1061
```

In [100…
```
df.drop_duplicates(inplace=True)
```

In [101…
```
# glacing over data after outlier treatment and preprocessing
```

In [102…
```
df.describe()
```

Out[102]:

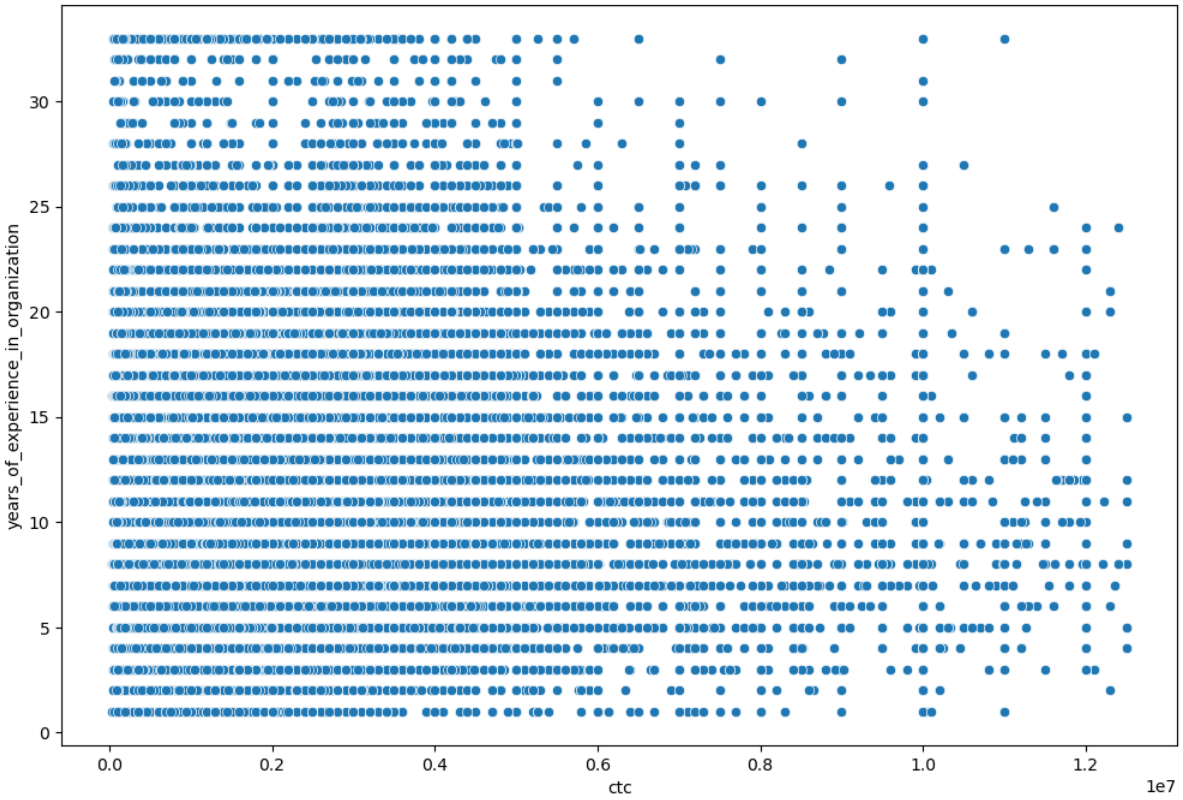
	orgyear	ctc	ctc_updated_year	years_of_experience_in_organization
count	162881.000000	1.628810e+05	162881.000000	162881.000000
mean	2014.740154	1.428152e+06	2019.594274	8.259846
std	4.396876	1.305734e+06	1.335473	4.396876
min	1990.000000	3.800000e+04	2015.000000	1.000000
25%	2013.000000	6.000000e+05	2019.000000	5.000000
50%	2016.000000	1.040000e+06	2020.000000	7.000000
75%	2018.000000	1.800000e+06	2021.000000	10.000000
max	2022.000000	1.250000e+07	2022.000000	33.000000

In [103…
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 162881 entries, 0 to 206922
Data columns (total 6 columns):
 #   Column                                  Non-Null Count   Dtype
---  ------                                  --------------   -----
 0   company_hash                            162881 non-null  object
 1   orgyear                                 162881 non-null  int32
 2   ctc                                     162881 non-null  int64
 3   job_position                            162881 non-null  object
 4   ctc_updated_year                        162881 non-null  float64
 5   years_of_experience_in_organization     162881 non-null  int32
dtypes: float64(1), int32(2), int64(1), object(2)
memory usage: 7.5+ MB
```

In [106…
```
sns.scatterplot(x='ctc', y='years_of_experience_in_organization', data=df)
```

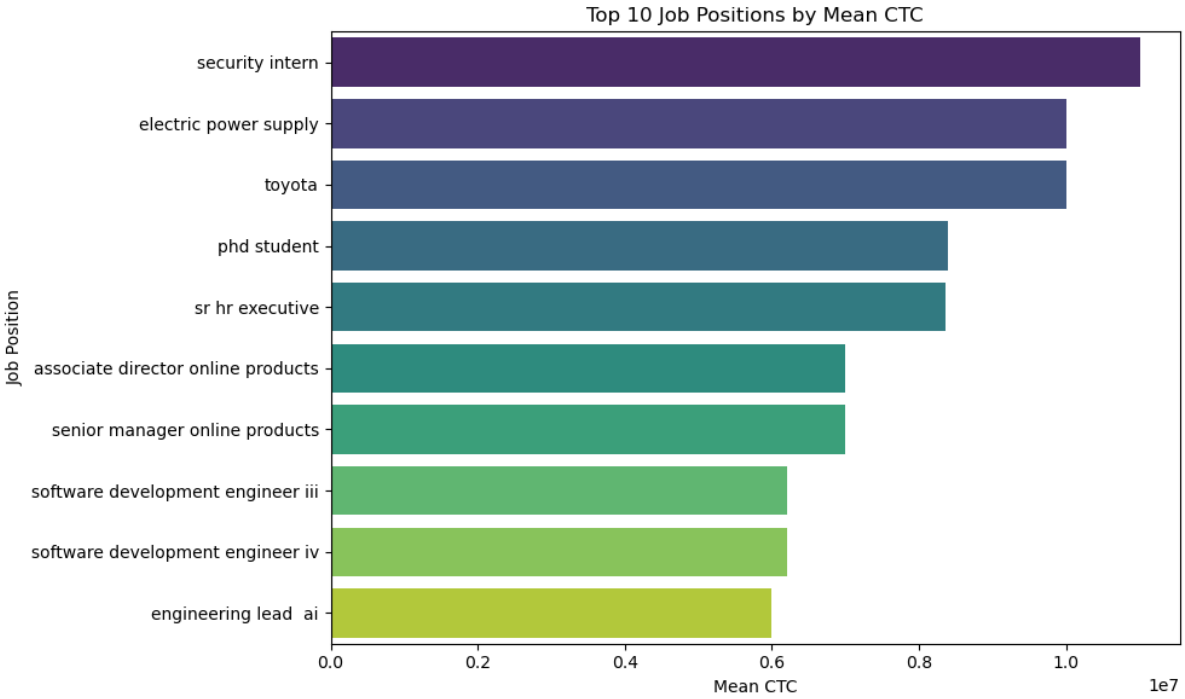
Out[106]:
```
<Axes: xlabel='ctc', ylabel='years_of_experience_in_organization'>
```



In [107…
```
df.columns
```

Out[107]:
```
Index(['company_hash', 'orgyear', 'ctc', 'job_position', 'ctc_updated_year',
       'years_of_experience_in_organization'],
      dtype='object')
```

In [201…
```
# Calculate the mean CTC for each job position
mean_ctc_by_position = df.groupby('job_position')['ctc'].mean().reset_index()

# Sort by mean CTC and select top N job positions
top_n_positions = 10  # Change this value to select top N job positions
top_n_mean_ctc = mean_ctc_by_position.nlargest(top_n_positions, 'ctc')

# Plotting
plt.figure(figsize=(10, 6))
sns.barplot(x='ctc', y='job_position', data=top_n_mean_ctc, palette='viridis')
plt.xlabel('Mean CTC')
plt.ylabel('Job Position')
plt.title(f'Top {top_n_positions} Job Positions by Mean CTC')
plt.tight_layout()
plt.show()
```



In [208…
```
mean_ctc_by_position = df.groupby('job_position')['ctc'].mean()

# Find the top job positions by mean CTC
top_job_positions = mean_ctc_by_position.nlargest(100)

# Print the top job positions
print("Top job positions by mean CTC:")
print(top_job_positions)
```

```
Top job positions by mean CTC:
job_position
security intern                 1.100000e+07
electric power supply           1.000000e+07
toyota                          1.000000e+07
phd student                     8.400000e+06
sr hr executive                 8.360000e+06
                                    ...
teaching assistant              2.482667e+06
associate principal engineer    2.462000e+06
sde intern                      2.450000e+06
escalation engineer             2.425000e+06
research assistant              2.420400e+06
Name: ctc, Length: 100, dtype: float64
```

In [203…
```
df.ctc.max()
```

Out[203]:
```
12500000
```

In [209…
```
# Filter the DataFrame for job positions containing "data scientist" (case-insensit
data_scientist_positions = df[df['job_position'].str.lower().str.contains('data sci

# Calculate the mean CTC for data scientist positions
data_scientist_mean_ctc = data_scientist_positions['ctc'].mean()

# Group the data by job position and calculate the mean CTC for each position
mean_ctc_by_position = df.groupby(df['job_position'].str.lower())['ctc'].mean()

# Find the top 10 job positions by mean CTC
top_10_job_positions = mean_ctc_by_position.nlargest(10)
```

```
# Print the mean CTC for data scientist positions
print("Mean CTC for job positions containing 'data scientist':", data_scientist_mea

# Print the top 10 job positions by mean CTC
print("\nTop 10 job positions by mean CTC:")
print(top_10_job_positions)
```

```
Mean CTC for job positions containing 'data scientist': 1556937.4285407725

Top 10 job positions by mean CTC:
job_position
security intern                         11000000.0
electric power supply                   10000000.0
toyota                                  10000000.0
phd student                              8400000.0
sr hr executive                          8360000.0
associate director online products       7000000.0
senior manager online products           7000000.0
software development engineer iii        6200000.0
software development engineer iv         6200000.0
engineering lead  ai                     6000000.0
Name: ctc, dtype: float64
```

In [211…

```
# Group the data by job position and calculate the mean CTC for each position
mean_ctc_by_position = df.groupby('job_position').agg({'ctc': 'mean', 'job_position

# Calculate the 50th percentile of the record count by job position
percentile_50 = mean_ctc_by_position['job_position'].quantile(0.25)

# Filter out positions where the count is below the 50th percentile
mean_ctc_by_position_filtered = mean_ctc_by_position[mean_ctc_by_position['job_posi

# Find the top job positions by mean CTC
top_job_positions = mean_ctc_by_position_filtered.nlargest(10, 'ctc')

# Print the top job positions
print("Top job positions by mean CTC with record count greater than 50th percentile
print(top_job_positions)
```

```
Top job positions by mean CTC with record count greater than 50th percentile:
                                        ctc  job_position
job_position
cto                             5.500000e+06             2
vice president                  4.400000e+06             3
staff software engineer         3.800000e+06             3
solutions architect             3.650000e+06             2
engineering manager ii          3.600000e+06             3
computer scientist              3.590000e+06             2
software enginner               3.444250e+06             4
sdei                            3.225000e+06             2
software development engineer   3.151429e+06            21
sr technical architect          3.150000e+06             2
```

Manual Clustering based on Company , Job position and Years of experience

Learner's "designation_in_organization" flag

In [108…

```
GROUPED_CTC = df.groupby(["years_of_experience_in_organization",
                                                        "job_position",
                                                        "company_hash"])["ctc"].de
```

In [109…
```
GROUPED_CTC
```

Out[109]:

years_of_experience_in_organization	job_position	company_hash	count	mean	st
1	Others	Others	48.0	1.649375e+06	2.198937e+0
		agzn fgqp xz vzj gqsvzxkvnxgz	1.0	1.600000e+06	Na
		atrgxnnt	1.0	1.000000e+06	Na
		atrr	1.0	1.000000e+06	Na
		atrr ntwyzgrgsxto	2.0	1.000000e+06	2.828427e+0
...	...	...	...	...	
33	qa engineer	hzxntaytvrny sqghu	1.0	5.400000e+05	Na
		tmxd ogenfvqt xzaxv ucn rna	1.0	1.220000e+06	Na
		utrvnqg ogrhnxgzo ucnrna	1.0	6.000000e+05	Na
	research engineers	ovbohzs qa xzonxnhnt xzaxv atryx	1.0	1.400000e+06	Na
	support engineer	Others	2.0	3.700000e+05	3.252691e+0

66191 rows × 8 columns

In [110…
```
df_GROUPED_CTC_BY_E_P_C = df.merge(GROUPED_CTC,
        on = ["years_of_experience_in_organization",
              "job_position",
              "company_hash"],
        how = "left")
```

In [111…
```
df_GROUPED_CTC_BY_E_P_C
```

Out[111]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_o
0	atrgxnnt xzaxv	2016	1100000	other	2020.0	
1	qtrxvzwt xzegwgbb rxbxnta	2018	449999	fullstack engineer	2019.0	
2	Others	2015	2000000	backend engineer	2020.0	
3	ngpgutaxv	2017	700000	backend engineer	2019.0	
4	qxen sqghu	2017	1400000	fullstack engineer	2019.0	
...	...	...	...	...	...	
162876	vuurt xzw	2008	220000	Others	2019.0	
162877	husqvawgb	2017	500000	Others	2020.0	
162878	vwwgrxnt	2021	700000	Others	2021.0	
162879	zgn vuurxwvmrt	2019	5100000	Others	2019.0	
162880	bgqsvz onvzrtj	2014	1240000	Others	2016.0	

162881 rows × 14 columns

In [112…

```
def classification(x,ctc_50,ctc_75):
    if x < ctc_50:
        return 3
    elif x >= ctc_50 and x <= ctc_75:
        return 2
    elif  x >= ctc_75:
        return 1
```

whichever learner has ctc compared to their years of experience , respective company , position

giving designation as 3 when ctc is < 50th percentile in his position ,experience and company

giving designation as 2 when ctc is between 50th and 75th percentile in his position ,experience and company

giving designation as 1 when ctc is > 75th percentile in his position ,experience and company

In [113…

```
df_GROUPED_CTC_BY_E_P_C["designation_in_organization"] = df_GROUPED_CTC_BY_E_P_C.ap
```

In [114…

```
df_GROUPED_CTC_BY_E_P_C
```

Out[114]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_o
0	atrgxnnt xzaxv	2016	1100000	other	2020.0	
1	qtrxvzwt xzegwgbb rxbxnta	2018	449999	fullstack engineer	2019.0	
2	Others	2015	2000000	backend engineer	2020.0	
3	ngpgutaxv	2017	700000	backend engineer	2019.0	
4	qxen sqghu	2017	1400000	fullstack engineer	2019.0	
...	...	...	...	...	...	
162876	vuurt xzw	2008	220000	Others	2019.0	
162877	husqvawgb	2017	500000	Others	2020.0	
162878	vwwgrxnt	2021	700000	Others	2021.0	
162879	zgn vuurxwvmrt	2019	5100000	Others	2019.0	
162880	bgqsvz onvzrtj	2014	1240000	Others	2016.0	

162881 rows × 15 columns

In [115…
```
df_GROUPED_CTC_BY_E_P_C.designation_in_organization.value_counts(normalize=True)
```

Out[115]:
```
2    0.456880
3    0.331101
1    0.212020
Name: designation_in_organization, dtype: float64
```

In [116…
```
df_GROUPED_CTC_BY_E_P_C
```

Out[116]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_o
0	atrgxnnt xzaxv	2016	1100000	other	2020.0	
1	qtrxvzwt xzegwgbb rxbxnta	2018	449999	fullstack engineer	2019.0	
2	Others	2015	2000000	backend engineer	2020.0	
3	ngpgutaxv	2017	700000	backend engineer	2019.0	
4	qxen sqghu	2017	1400000	fullstack engineer	2019.0	
...	...	...	...	...	...	
162876	vuurt xzw	2008	220000	Others	2019.0	
162877	husqvawgb	2017	500000	Others	2020.0	
162878	vwwgrxnt	2021	700000	Others	2021.0	
162879	zgn vuurxwvmrt	2019	5100000	Others	2019.0	
162880	bgqsvz onvzrtj	2014	1240000	Others	2016.0	

162881 rows × 15 columns

In [117…

```
df_GROUPED_CTC_BY_E_P_C.drop(columns=['count',
                                      'mean',
                                     'std',
                                     'min',
                                     '25%',
                                     '50%',
                                     '75%',
                                     'max'],axis = 1,inplace=True)
```

In [118…

```
df_GROUPED_CTC_BY_E_P_C
```

Out[118]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_o
0	atrgxnnt xzaxv	2016	1100000	other	2020.0	
1	qtrxvzwt xzegwgbb rxbxnta	2018	449999	fullstack engineer	2019.0	
2	Others	2015	2000000	backend engineer	2020.0	
3	ngpgutaxv	2017	700000	backend engineer	2019.0	
4	qxen sqghu	2017	1400000	fullstack engineer	2019.0	
...	...	...	...	...	...	
162876	vuurt xzw	2008	220000	Others	2019.0	
162877	husqvawgb	2017	500000	Others	2020.0	
162878	vwwgrxnt	2021	700000	Others	2021.0	
162879	zgn vuurxwvmrt	2019	5100000	Others	2019.0	
162880	bgqsvz onvzrtj	2014	1240000	Others	2016.0	

162881 rows × 7 columns

In [119…
```
df_GROUPED_CTC_BY_E_P_C.shape
```

Out[119]:
```
(162881, 7)
```

Manual Clustering on company and job position

grouping by each job_position and company ,

finding which class of job an individual have,

based on his ctc compared to his job_position and respective company.

In [120…
```
GROUPED_C_J=df.groupby(['job_position','company_hash'])['ctc'].describe()
GROUPED_C_J
```

Out[120]:

job_position	company_hash	count	mean	std	min	25%	50%	
Others	**Others**	3364.0	1.378793e+06	1.458746e+06	40000.0	409999.0	900000.0	18
	a ntwyzgrgsxto	6.0	1.229167e+06	1.401465e+06	350000.0	518750.0	587500.0	11
	aaqxctz avnv owxtzwto vzvrjnxwo ucn rna	1.0	5.000000e+05	NaN	500000.0	500000.0	500000.0	5
	abwavnv ojontb	1.0	7.000000e+05	NaN	700000.0	700000.0	700000.0	7
	adw ntwyzgrgsj	69.0	8.502319e+05	1.036041e+06	80000.0	380000.0	500000.0	10
...	**...**	...	...	...	...	...	...	
wordpress developer	**Others**	1.0	6.000000e+05	NaN	600000.0	600000.0	600000.0	6
worker	**zgn vuurxwvmrt vwwghzn**	1.0	2.000000e+05	NaN	200000.0	200000.0	200000.0	2
x	**Others**	1.0	4.000000e+05	NaN	400000.0	400000.0	400000.0	4
young professional ii	**sgctqzbtzn ge xzaxv**	1.0	5.000000e+05	NaN	500000.0	500000.0	500000.0	5
zomato	**kgbvng**	2.0	3.000000e+05	2.828427e+05	100000.0	200000.0	300000.0	4

25593 rows × 8 columns

In [121...
```
df_GROUPED_C_J=df.merge(GROUPED_C_J, on=['job_position','company_hash'], how='left'
```

In [122...
```
df_GROUPED_C_J.sample(5)
```

Out[122]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_o
142784	wvqo	2017	1500000	backend engineer	2020.0	
49467	vbagwo	2017	760000	Others	2019.0	
140136	vxqntr	2014	1720000	backend engineer	2019.0	
75028	athnowyt mvzp	2020	1200000	Others	2021.0	
63337	fyttrotjt	2019	300000	other	2021.0	

In [123...
```
# creating classes basis on the salary in their respective company
```

In [124...
```
df_GROUPED_C_J['classs'] = df_GROUPED_C_J.apply(lambda x: classification(x['ctc'],x
```

In [125...
```
df_GROUPED_C_J.sample(5)
```

Out[125]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_
42659	wgszxkvzn	2014	500000	other	2021.0	
113587	bvqctrr otbxwgzahwngq	2011	1250000	qa engineer	2017.0	
122447	evwnotn	2017	1500000	fullstack engineer	2019.0	
87442	vuuwxzg	2019	200000	Others	2021.0	
6354	ssp ntwy	2018	700000	backend engineer	2019.0	

In [126…
```
df_GROUPED_C_J.classs.value_counts(normalize=True)
```

Out[126]:
```
3    0.434931
2    0.320381
1    0.244688
Name: classs, dtype: float64
```

In [127…
```
df_GROUPED_C_J.drop(columns=['count',
                             'mean',
                            'std',
                            'min',
                            '25%',
                            '50%',
                            '75%',
                            'max'],axis = 1,inplace=True)
```

In [128…
```
df_GROUPED_CTC_BY_E_P_C.iloc[0]
```

Out[128]:
```
company_hash                            atrgxnnt xzaxv
orgyear                                           2016
ctc                                            1100000
job_position                                     other
ctc_updated_year                                2020.0
years_of_experience_in_organization                  7
designation_in_organization                          2
Name: 0, dtype: object
```

In [129…
```
df_GROUPED_C_J.iloc[0]
```

Out[129]:
```
company_hash                            atrgxnnt xzaxv
orgyear                                           2016
ctc                                            1100000
job_position                                     other
ctc_updated_year                                2020.0
years_of_experience_in_organization                  7
classs                                               1
Name: 0, dtype: object
```

In [130…
```
df_Grouped = df_GROUPED_CTC_BY_E_P_C.merge(df_GROUPED_C_J, on=['company_hash',
                                                               'orgyear',
                                                               'ctc',
                                                               'job_position',
                                                               'years_of_experience_in_organ
                                                               'ctc_updated_year'], how='lef
```

In [131…
```
df_Grouped.sample(5)
```

Out[131]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_o
19335	eqtjq tztqsj	2009	1050000	product manager	2020.0	
107967	atrr tbw	2018	2100000	engineering intern	2019.0	
13135	nyghsynfgqpo	2015	1000000	backend engineer	2021.0	
62119	ktgnvu	2017	100000	data scientist	2021.0	
30809	zg wgbuvzj	2018	100000	backend engineer	2018.0	

In [132…
```
df_Grouped.shape
```

Out[132]:
```
(162881, 8)
```

Manual Clustering based on comapny

Based on ctc per company , assigning company as tier 1 2 and 3 per each learner

In [133…
```
GROUPED_C = df.groupby(['company_hash'])['ctc'].describe()
df_company = df.merge(GROUPED_C, on=['company_hash'], how='left')
```

In [134…
```
df_company.sample(5)
```

Out[134]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_o
128854	tzctonztn	2018	2300000	Others	2019.0	
10400	evwtmggp	2018	1200000	devops engineer	2020.0	
152601	xzegojo	2020	720000	qa engineer	2021.0	
101944	zvsvqqg	2015	750000	frontend engineer	2019.0	
66834	rvqotz nghmqg	2016	1270000	research engineers	2020.0	

In [135…
```
df_company['tier'] =df_company.apply(lambda x: classification(x['ctc'],x['50%'],x['
```

In [170…
```
df_company.sample(5)
```

Out[170]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_o
32294	tkt ogenfvqt	2016	1000000	backend engineer	2019.0	
94150	wxnxsqghu	2020	1630000	Others	2021.0	
105592	Others	2014	950000	ios engineer	2017.0	
85050	vbvkgz	2018	2000000	fullstack engineer	2021.0	
61520	btzngq sqvuyxwo	2016	1700000	backend engineer	2019.0	

In [188…

```
df3=df_company[df_company['tier']==1].sort_values('ctc',ascending=False)
```

1.Top 10 employees (earning more than most of the employees in the company) - Tier 1

In [189…

```
df3.head(10)
```

Out[189]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_
85657	zgn vuurxwvmrt vwwghzn	2019	12500000	frontend engineer	2021.0	
13883	vrnxbtnqxp	2012	12500000	fullstack engineer	2020.0	
143898	bxwqgogen	2014	12500000	fullstack engineer	2019.0	
52121	uvjuvr	2015	12500000	backend engineer	2017.0	
52593	zvz	2019	12500000	Others	2019.0	
58259	vbvkgz	2011	12500000	other	2018.0	
65795	Others	2008	12500000	Others	2020.0	
103428	xzntr wgqugqvnxgz	2018	12500000	frontend engineer	2019.0	
94585	zgn vuurxwvmrt vwwghzn	2019	12500000	other	2021.0	
58719	wmqt	2018	12500000	frontend engineer	2020.0	

2.Bottom 10 employees (earning less than most of the employees in the company)- Tier 3

In [190…

```
df4=df_company[df_company['tier']==3].sort_values('ctc')
```

In [191…

```
df4.head(10)
```

Out[191]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_org
158843	xb v onhatzn	2022	38000	Others	2022.0	
52651	Others	2007	38000	devops engineer	2018.0	
76476	zgn vuurxwvmrt vwwghzn	2015	38000	frontend engineer	2021.0	
113786	Others	2015	38000	other	2017.0	
106607	zgzt	2017	39000	backend engineer	2017.0	
144607	bwpxzotj	2020	39000	data scientist	2021.0	
75425	Others	2017	39000	backend engineer	2020.0	
19093	rvkvav sqghu	2013	39000	backend engineer	2020.0	
123487	bwpxzotj	2020	39000	Others	2021.0	
30456	vnytzvytvrny	2007	39550	Others	2019.0	

In [137…
```
df_company.tier.value_counts(normalize=True)
```

Out[137]:
```
3    0.476931
2    0.282998
1    0.240071
Name: tier, dtype: float64
```

In [138…
```
df_company.drop(['count','mean','std','min','25%','50%','75%','max'],
                axis = 1,
                inplace=True)
```

In [139…
```
df_company.iloc[0]
```

Out[139]:
```
company_hash                              atrgxnnt xzaxv
orgyear                                             2016
ctc                                              1100000
job_position                                       other
ctc_updated_year                                2020.0
years_of_experience_in_organization                  7
tier                                                 2
Name: 0, dtype: object
```

In [140…
```
df_Grouped.iloc[0]
```

Out[140]:
```
company_hash                              atrgxnnt xzaxv
orgyear                                             2016
ctc                                              1100000
job_position                                       other
ctc_updated_year                                2020.0
years_of_experience_in_organization                  7
designation_in_organization                          2
classs                                               1
Name: 0, dtype: object
```

In [141…
```
df_Grouped = df_Grouped.merge(df_company,
                 on=['company_hash',
```

```
                    'orgyear','ctc',
                    'job_position',
                    'years_of_experience_in_organization',
                    'ctc_updated_year'
                   ])
```

In [142…
```
df_Grouped
```

Out[142]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_o
0	atrgxnnt xzaxv	2016	1100000	other	2020.0	
1	qtrxvzwt xzegwgbb rxbxnta	2018	449999	fullstack engineer	2019.0	
2	Others	2015	2000000	backend engineer	2020.0	
3	ngpgutaxv	2017	700000	backend engineer	2019.0	
4	qxen sqghu	2017	1400000	fullstack engineer	2019.0	
...	...	...	...	...	...	
162876	vuurt xzw	2008	220000	Others	2019.0	
162877	husqvawgb	2017	500000	Others	2020.0	
162878	vwwgrxnt	2021	700000	Others	2021.0	
162879	zgn vuurxwvmrt	2019	5100000	Others	2019.0	
162880	bgqsvz onvzrtj	2014	1240000	Others	2016.0	

162881 rows × 9 columns

In [143…
```
X = df_Grouped.copy()
```

In [144…
```
X.shape
```

Out[144]:
```
(162881, 9)
```

In [145…
```
X_data = X.drop(["company_hash","job_position"],axis  = 1)
```

Final data for Model :

In [146…
```
X_data
```

Out[146]:

	orgyear	ctc	ctc_updated_year	years_of_experience_in_organization	designation_in_or
0	2016	1100000	2020.0	7	
1	2018	449999	2019.0	5	
2	2015	2000000	2020.0	8	
3	2017	700000	2019.0	6	
4	2017	1400000	2019.0	6	
...	...	...	...	...	
162876	2008	220000	2019.0	15	
162877	2017	500000	2020.0	6	
162878	2021	700000	2021.0	2	
162879	2019	5100000	2019.0	4	
162880	2014	1240000	2016.0	9	

162881 rows × 7 columns

Data Processing for Unsupervised Learning

Standardization:

In [147...

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaler.fit(X_data)
X_sc = pd.DataFrame(scaler.transform(X_data), columns=X_data.columns, index=X_data.
```

In [148...

```
X_sc
```

Out[148]:

	orgyear	ctc	ctc_updated_year	years_of_experience_in_organization	designation_in
0	0.286533	-0.251317	0.303808	-0.286533	
1	0.741403	-0.749124	-0.444993	-0.741403	
2	0.059098	0.437953	0.303808	-0.059098	
3	0.513968	-0.557659	-0.444993	-0.513968	
4	0.513968	-0.021561	-0.444993	-0.513968	
...	...	...	...	...	
162876	-1.532946	-0.925270	-0.444993	1.532946	
162877	0.513968	-0.710830	0.303808	-0.513968	
162878	1.423708	-0.557659	1.052608	-1.423708	
162879	0.968838	2.812104	-0.444993	-0.968838	
162880	-0.168337	-0.144097	-2.691395	0.168337	

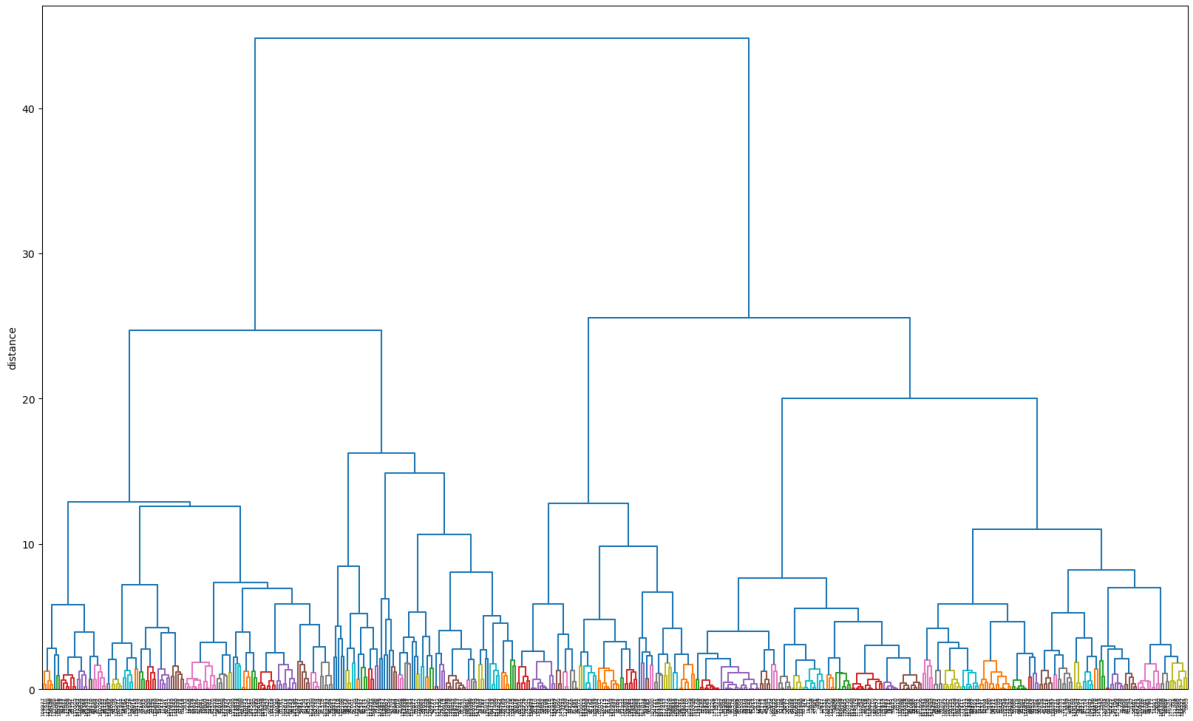
162881 rows × 7 columns

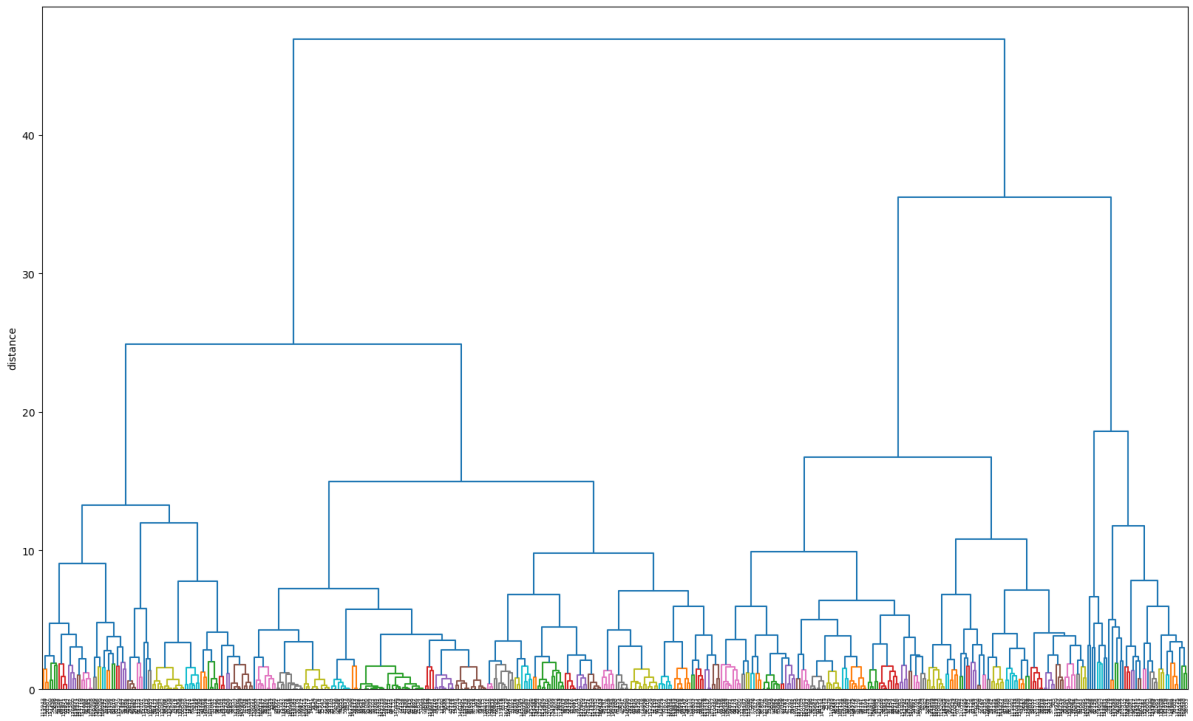
Hierarchical Clustering

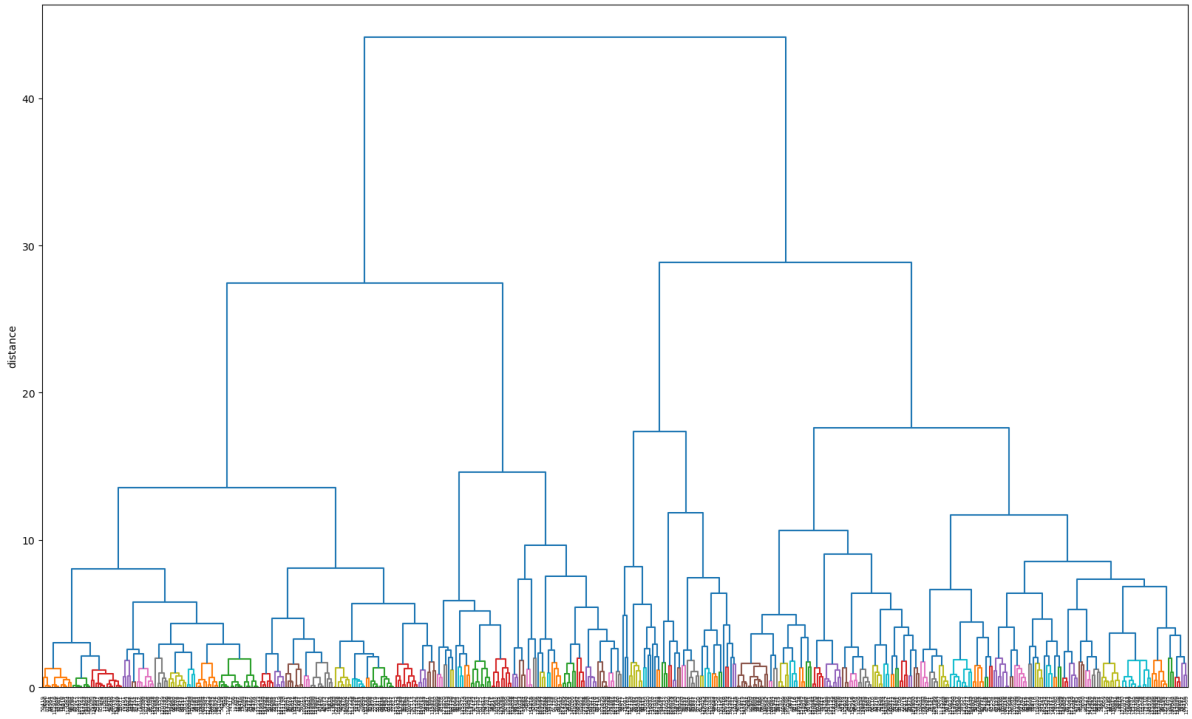
In [149…

```
import scipy.cluster.hierarchy as sch
import matplotlib.pyplot as plt

sample = X_sc.sample(500)
Z = sch.linkage(sample, method='ward')

fig, ax1 = plt.subplots(figsize=(20, 12))
sch.dendrogram(Z, labels=sample.index, ax=ax1, color_threshold=2)
plt.xticks(rotation=90)
ax1.set_ylabel('distance')
plt.show()

import scipy.cluster.hierarchy as sch
import matplotlib.pyplot as plt

sample = X_sc.sample(500)
Z = sch.linkage(sample, method='ward')

fig, ax2 = plt.subplots(figsize=(20, 12))
sch.dendrogram(Z, labels=sample.index, ax=ax2, color_threshold=2)
plt.xticks(rotation=90)
ax2.set_ylabel('distance')
plt.show()



import scipy.cluster.hierarchy as sch
import matplotlib.pyplot as plt

sample = X_sc.sample(500)
Z = sch.linkage(sample, method='ward')

fig, ax3 = plt.subplots(figsize=(20, 12))
sch.dendrogram(Z, labels=sample.index, ax=ax3, color_threshold=2)
```

```
plt.xticks(rotation=90)
ax3.set_ylabel('distance')
plt.show()
```







Based on dendrogram , we can observe there are 4 clusters in the data based on similarity

Further checking appropriate number of clusters using Elbow Method using k-Means clustering :

KMeans and Elbow method

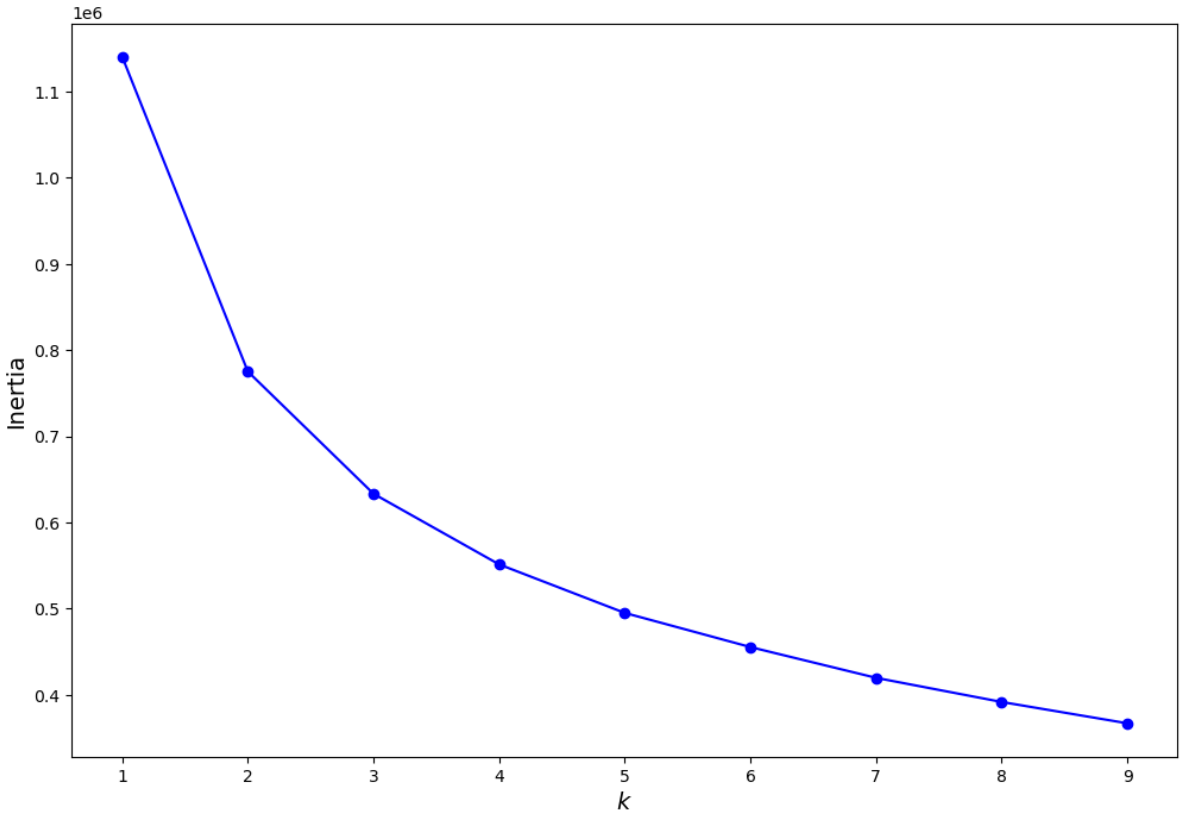
In [150…
```
for i in range(1,10):
    from sklearn.cluster import KMeans

    k = 4

    kM = KMeans(n_clusters=k,
                random_state=654)
    y_pred = kM.fit_predict(X_sc)
```

In [151…
```
kmeans_per_k = [KMeans(n_clusters=k, random_state=42).fit(X_sc)
                for k in range(1, 10)]

inertias = [model.inertia_ for model in kmeans_per_k]
inertias
```

Out[151]:
```
[1140166.9999999998,
 775054.4295111096,
 633247.7223051763,
 551271.1752209156,
 494989.60171362327,
 455370.7086296082,
 419683.5015521751,
 391674.841039793,
 366932.12750637834]
```

In [169…
```
plt.figure(figsize=(12, 8))
plt.plot(range(1, 10), inertias, "bo-")
plt.xlabel("$k$", fontsize=14)
plt.ylabel("Inertia", fontsize=14)
```

```
#plt.annotate('Elbow',
#             xy=(3, inertias[2]),
 #            xytext=(0.55, 0.55),
 #            textcoords='figure fraction',
 #            fontsize=16,
 #            arrowprops=dict(facecolor='black', shrink=0.1)
   #         )
plt.show()

# KMeans with n_clusters = 3
```



In [153…
```
from sklearn.cluster import KMeans

k = 3

kM = KMeans(n_clusters=k,
            random_state=654)
y_pred = kM.fit_predict(X_sc)
```

In [154…
```
clusters = pd.DataFrame(X, columns=X.columns)
clusters['label'] = kM.labels_
```

In [155…
```
clusters.sample(5)
```

Out[155]:

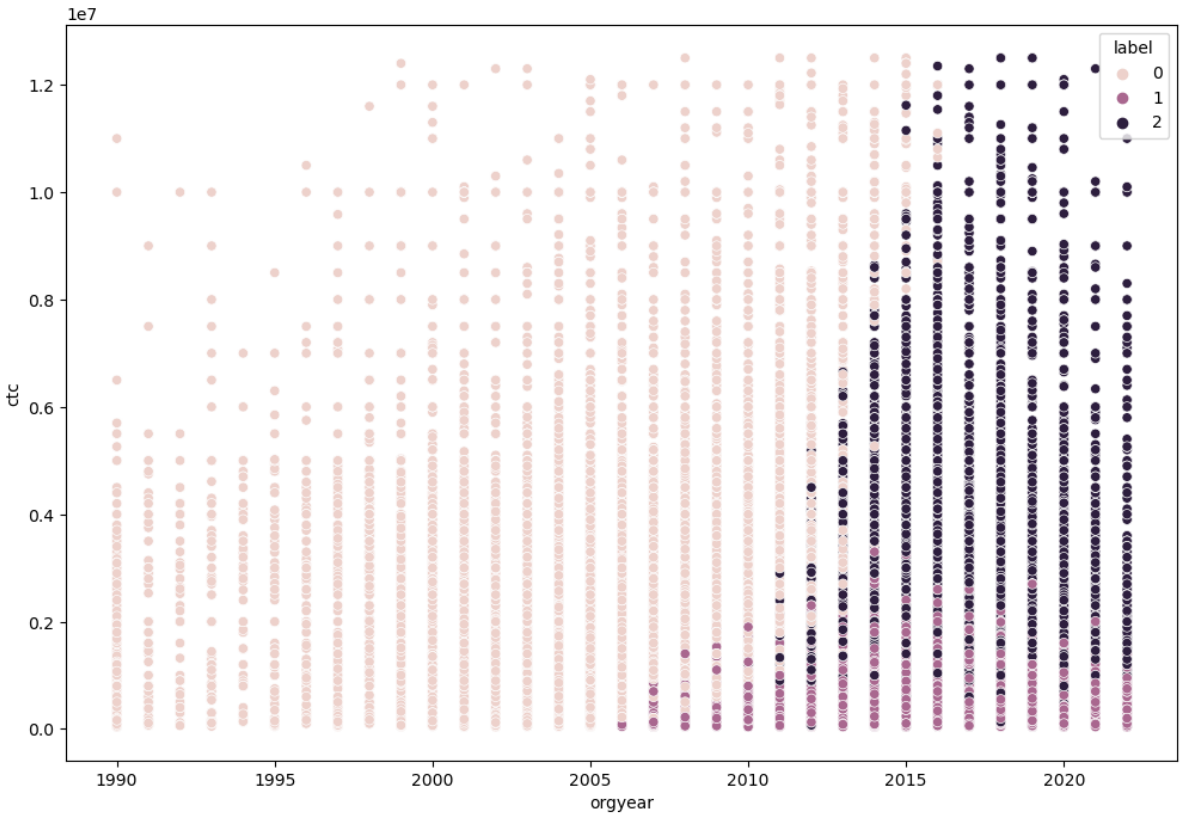
	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_o
136721	cbfvqt	2012	1150000	frontend engineer	2019.0	
49720	wxowg	2011	1600000	backend engineer	2017.0	
120021	xzzgcvwwtq	2013	1050000	devops engineer	2019.0	
46014	xmb xzaxv uqxcvnt rxbxnta	2007	850000	backend engineer	2021.0	
162600	Others	2012	1000000	Others	2015.0	

In [156…
```
clusters.shape
```

Out[156]:
```
(162881, 10)
```

Insights | EDA after Clustering :

In [158…
```
sns.scatterplot(x=clusters["orgyear"], y=clusters["ctc"], hue=clusters["label"])
plt.show()
```



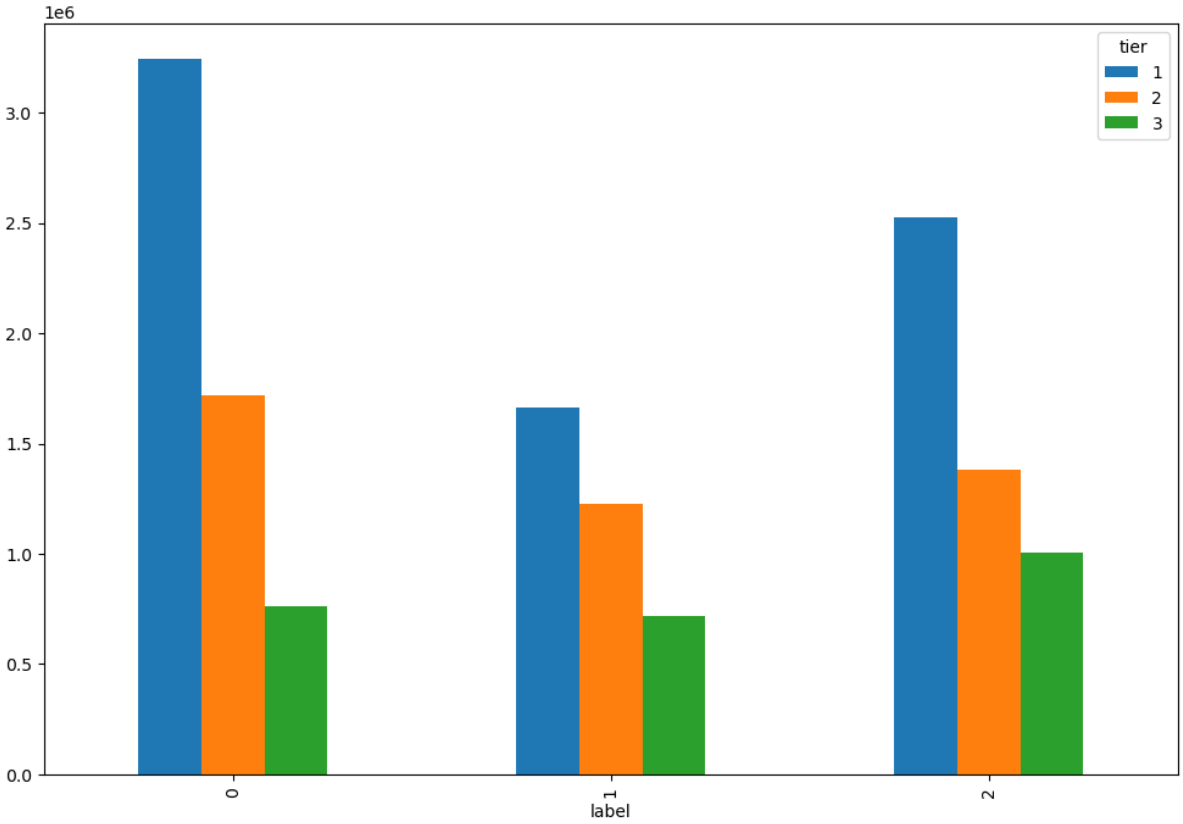
based on above scatter plot , we can observe , a cluster of learners received CTC upto 30 LPA who joined after 2006-07.

there's a group of learners who are very much experienced.

and also learners joined after 2012-13 receiving CTC between 20 LPA to upto 1.25cr.

In [159…
```
pd.crosstab(index = clusters["label"],
    columns = clusters["tier"],values=clusters["ctc"],aggfunc= np.mean
       ).plot(kind = "bar")
```

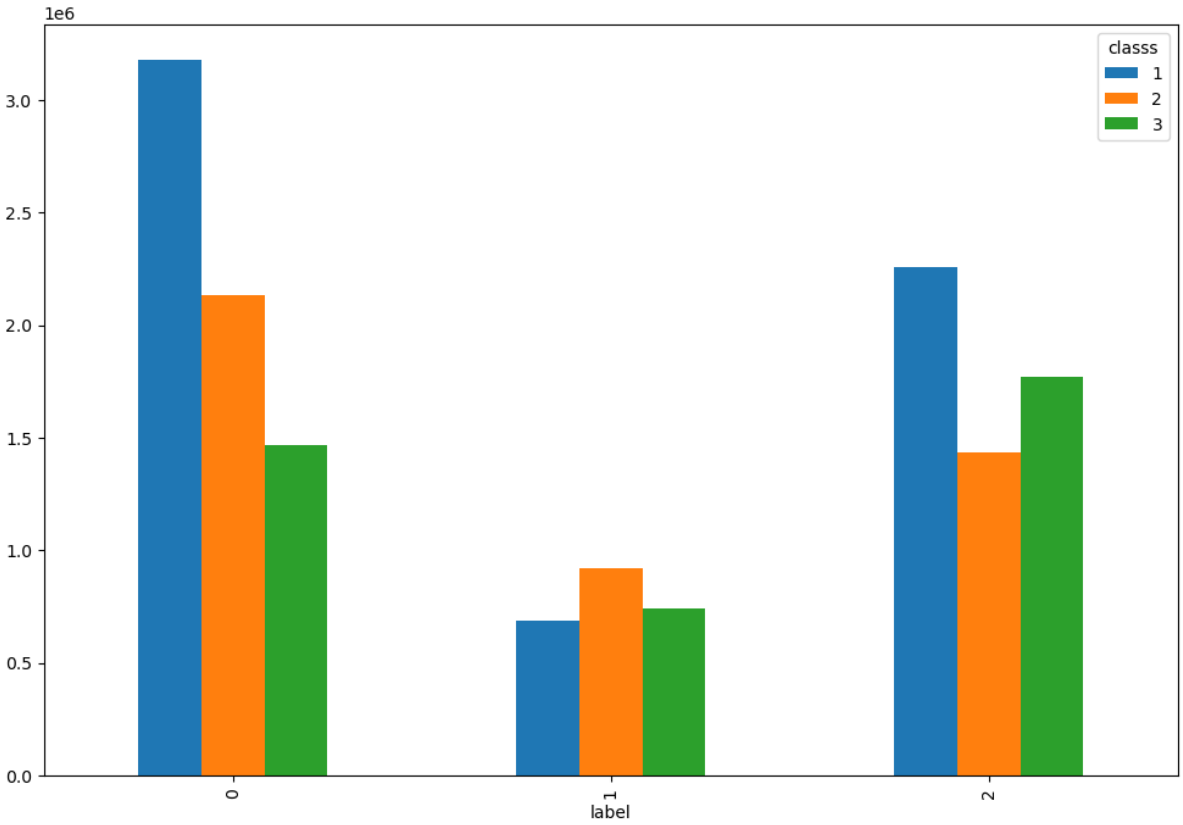
Out[159]:
```
<Axes: xlabel='label'>
```



Based on k-Means Clustering algorithm output , as well as manual clustering , learners from tier1 company receiving very high CTC.

In [160…
```
pd.crosstab(index = clusters["label"],
    columns = clusters["classs"],values=clusters["ctc"],aggfunc= np.mean
       ).plot(kind = "bar")
```

Out[160]:
```
<Axes: xlabel='label'>
```

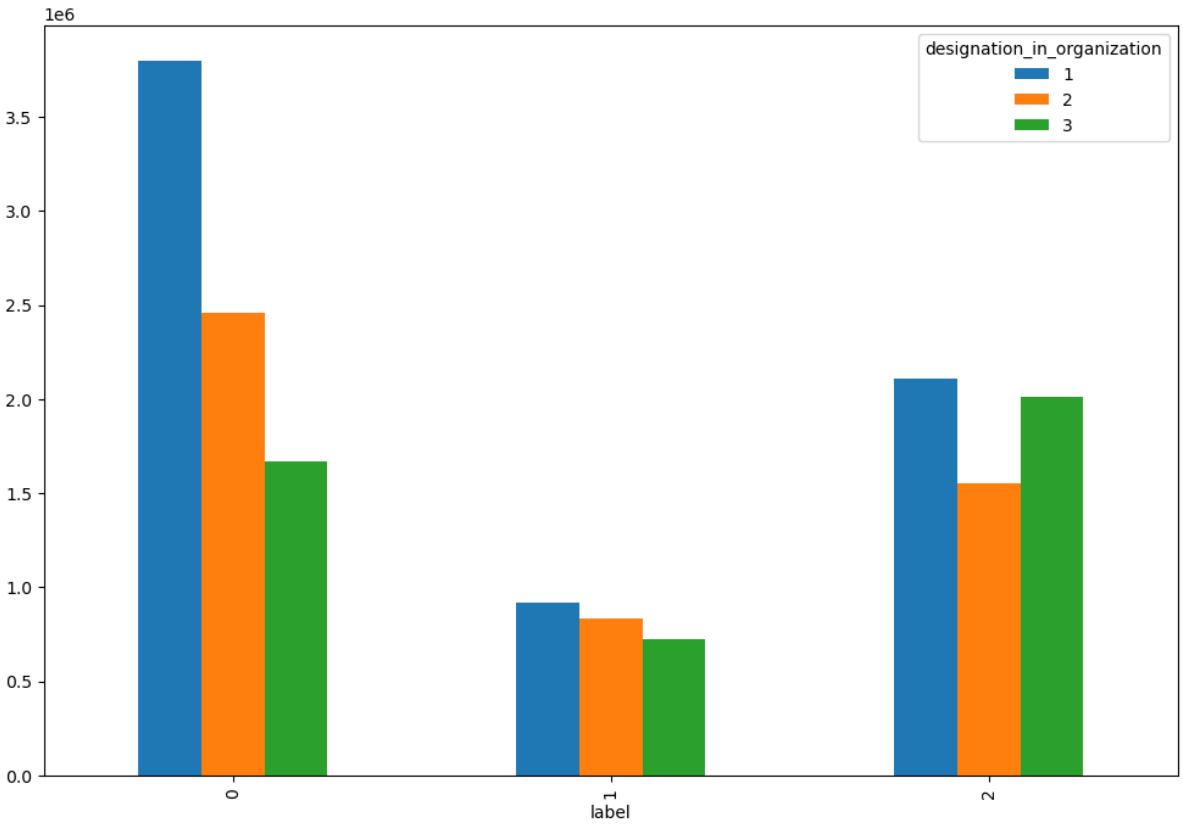


In [161…

```
pd.crosstab(index = clusters["label"],
    columns = clusters["designation_in_organization"],
            values=clusters["ctc"],aggfunc= np.mean
       ).plot(kind = "bar")
```

Out[161]:

```
<Axes: xlabel='label'>
```

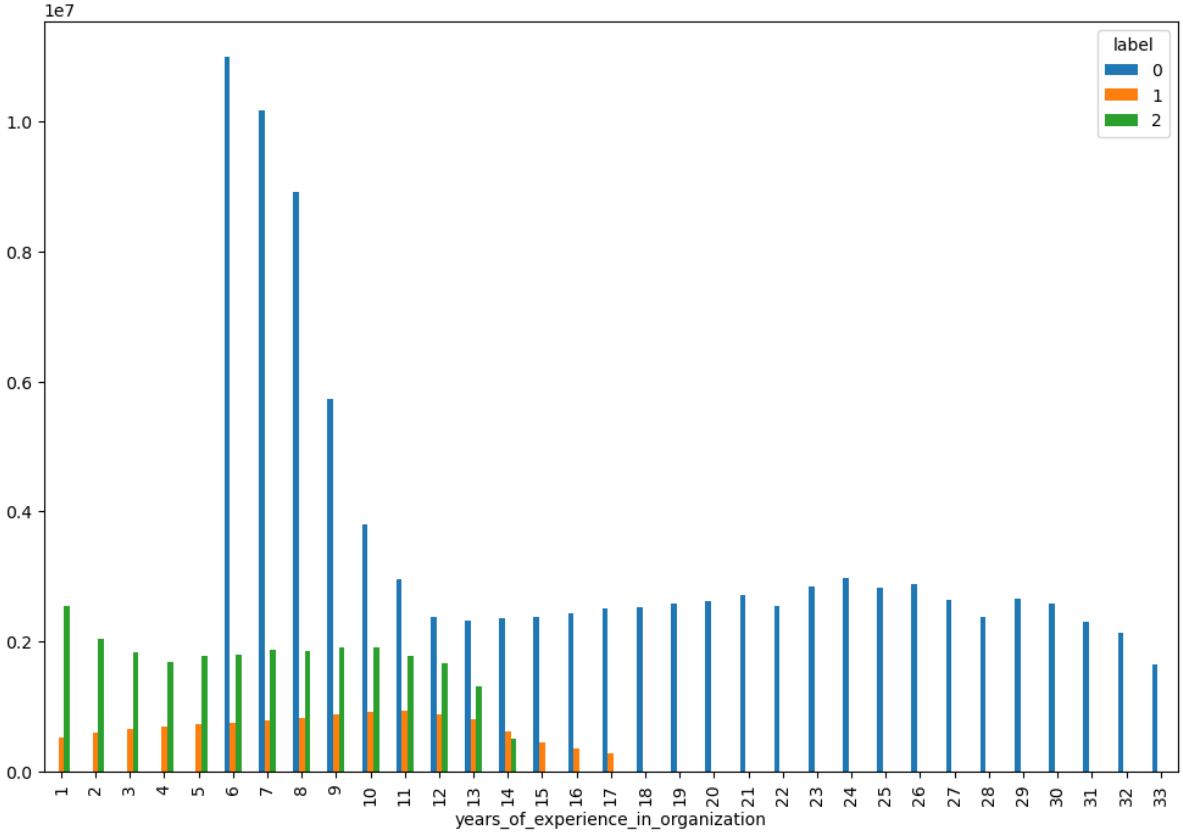


In [162…

```
pd.crosstab(columns = clusters["label"],
    index = clusters["years_of_experience_in_organization"],
```

```
            values=clusters["ctc"],aggfunc= np.mean
        ).plot(kind = "bar")
```

Out[162]: <Axes: xlabel='years_of_experience_in_organization'>



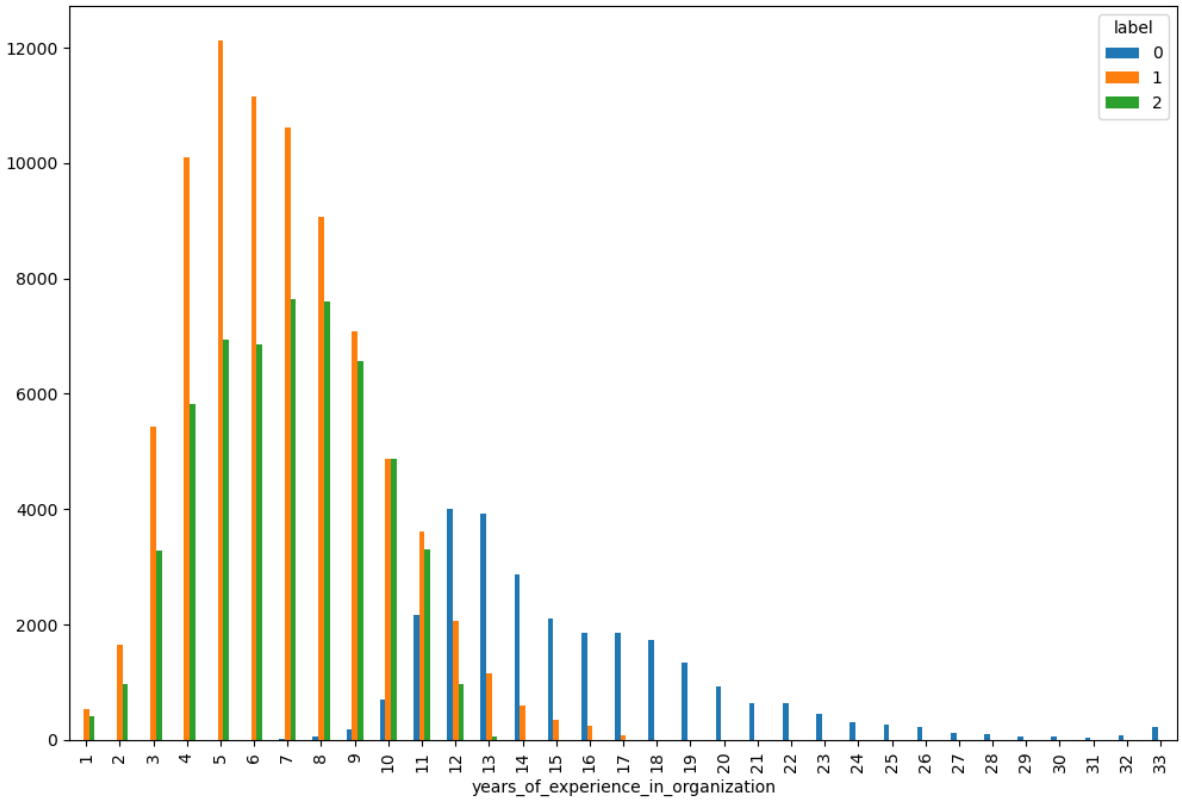
Cluster label 0 , are those learners who are very very experienced,

experienced learners between 6 to 10 years of experience, earning above 40 LPA up tp 1.5Cr.

In [163…

```
pd.crosstab(columns = clusters["label"],
    index = clusters["years_of_experience_in_organization"],

        ).plot(kind = "bar")
```

Out[163]: <Axes: xlabel='years_of_experience_in_organization'>



Majority of Learners are experienced between 1 to 15 years . (49.56%)- (Cluster 1)

there is a group of learners having 8 to upto 33 years of experience. (33.93%) - (Cluster 2)

16.52% of learners who have experiences - (cluster 0)

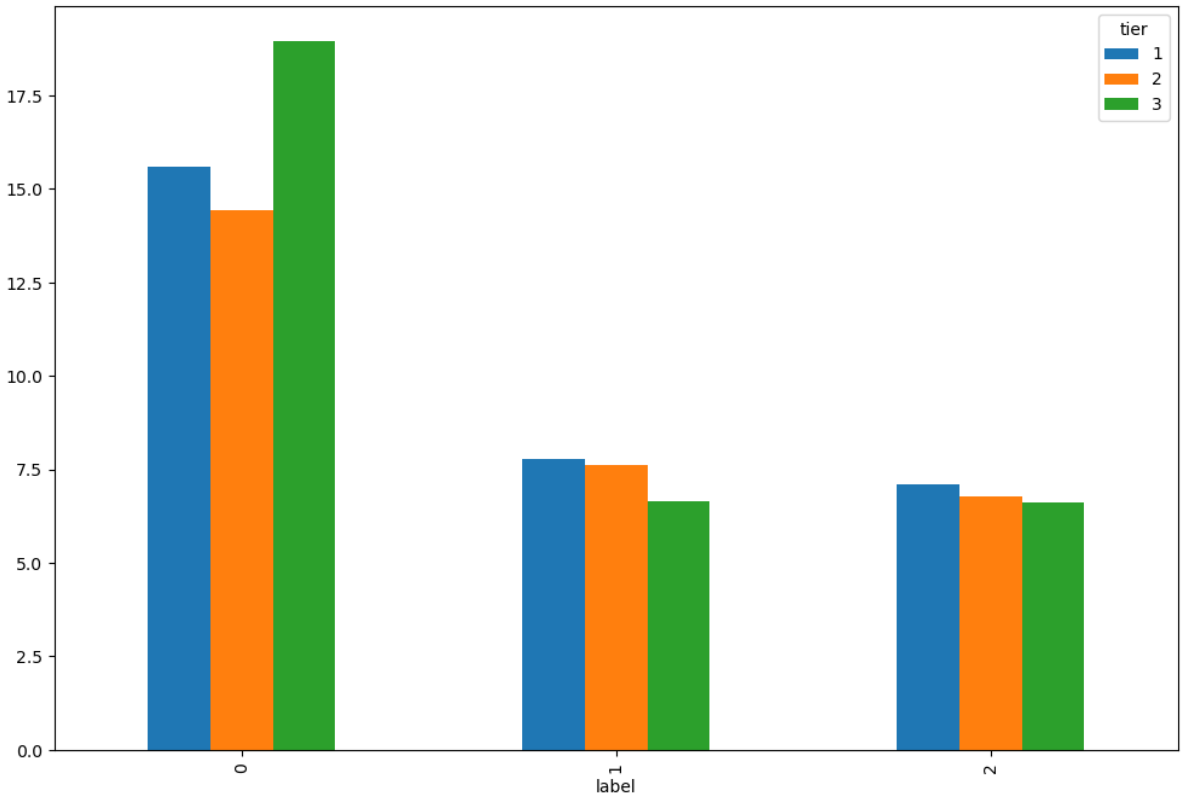
In [164…
```
clusters.label.value_counts(normalize=True)*100
```

Out[164]:
```
1    49.557039
2    33.926609
0    16.516352
Name: label, dtype: float64
```

years_of_experience_in_organization per each cluster group of learners

In [165…
```
pd.crosstab(index = clusters["label"],
    columns = clusters["tier"],
            values=clusters["years_of_experience_in_organization"],
            aggfunc=np.mean
       ).plot(kind = "bar")
```

Out[165]:
```
<Axes: xlabel='label'>
```



In [166…
```
clusters.columns
```

Out[166]:
```
Index(['company_hash', 'orgyear', 'ctc', 'job_position', 'ctc_updated_year',
       'years_of_experience_in_organization', 'designation_in_organization',
       'classs', 'tier', 'label'],
      dtype='object')
```

Statistical Summury based on Each Cluster :

In [167…
```
clusters.groupby("label").describe()[["ctc","classs","tier","years_of_experience_ir
```

Out[167]:

	label	0	1	2
ctc	count	2.690200e+04	8.071900e+04	5.526000e+04
	mean	2.567945e+06	7.721017e+05	1.831573e+06
	std	1.763374e+06	5.132420e+05	1.304987e+06
	min	4.000000e+04	3.800000e+04	6.500000e+04
	25%	1.450000e+06	4.030000e+05	1.000000e+06
	50%	2.160000e+06	6.500000e+05	1.500000e+06
	75%	3.200000e+06	1.000000e+06	2.200000e+06
	max	1.250000e+07	5.600000e+06	1.250000e+07
classs	count	2.690200e+04	8.071900e+04	5.526000e+04
	mean	1.629358e+00	2.824738e+00	1.536482e+00
	std	6.998365e-01	3.809424e-01	5.268012e-01
	min	1.000000e+00	1.000000e+00	1.000000e+00
	25%	1.000000e+00	3.000000e+00	1.000000e+00
	50%	2.000000e+00	3.000000e+00	2.000000e+00
	75%	2.000000e+00	3.000000e+00	2.000000e+00
	max	3.000000e+00	3.000000e+00	3.000000e+00
tier	count	2.690200e+04	8.071900e+04	5.526000e+04
	mean	1.475727e+00	2.896914e+00	1.643250e+00
	std	6.501709e-01	3.063866e-01	5.782173e-01
	min	1.000000e+00	1.000000e+00	1.000000e+00
	25%	1.000000e+00	3.000000e+00	1.000000e+00
	50%	1.000000e+00	3.000000e+00	2.000000e+00
	75%	2.000000e+00	3.000000e+00	2.000000e+00
	max	3.000000e+00	3.000000e+00	3.000000e+00
years_of_experience_in_organization	count	2.690200e+04	8.071900e+04	5.526000e+04
	mean	1.553535e+01	6.758483e+00	6.911003e+00
	std	4.331037e+00	2.734619e+00	2.459113e+00
	min	6.000000e+00	1.000000e+00	1.000000e+00
	25%	1.200000e+01	5.000000e+00	5.000000e+00
	50%	1.400000e+01	6.000000e+00	7.000000e+00
	75%	1.800000e+01	8.000000e+00	9.000000e+00
	max	3.300000e+01	1.700000e+01	1.400000e+01

Insights and Recommendations

Insights

- Top Paying job titles in 50th percentile include cto ,vice president, staff software engineer ,solutions architect,engineering manager ii,computer scientist ,software enginner ,sdei,software development engineer ,sr technical architect
- The largest cluster consists of almost 50% learners
- CTC increases with years of experience but after that it decreases and becomes constant
- Most employment happened in 2018 then decreased

Recommendations

Personalized Learning Paths:

Utilize cluster insights to tailor learning paths and course recommendations for learners based on their job profiles, company affiliations, and skill levels. Offer customized learning experiences that address the specific needs and career aspirations of each cluster, ensuring maximum engagement and skill acquisition.

Peer Collaboration and Networking:

Facilitate peer collaboration and networking opportunities within each cluster to encourage knowledge sharing, collaboration on projects, and mutual support. Create virtual communities or forums where learners within the same cluster can connect, exchange ideas, and build professional relationships.

Career Guidance and Mentorship:

Provide targeted career guidance and mentorship programs tailored to the career trajectories and aspirations of learners within each cluster. Match learners with mentors who have relevant industry experience and expertise in their specific job profiles and companies, offering valuable insights and advice.

Industry-Specific Skill Development:

Offer specialized courses and workshops designed to enhance skills that are particularly relevant to learners' job profiles and industries. Partner with industry leaders and subject matter experts to deliver content that reflects the latest trends and technologies in each cluster's respective fields.

Job Placement Support:

Develop job placement support services customized to the needs of each cluster, including resume assistance, interview preparation, and job matching services. Leverage insights from cluster analysis to identify high-demand job roles and companies within each cluster, guiding learners towards lucrative career opportunities.

Continuous Learning and Upskilling:

Encourage learners to engage in continuous learning and upskilling activities to stay competitive in their respective industries. Provide access to ongoing training resources, professional development opportunities, and certification programs tailored to the evolving needs of each cluster.

Feedback and Course Improvement:

Collect feedback from learners within each cluster to identify areas for course improvement, curriculum updates, and instructional enhancements. Use cluster-specific feedback to iterate

on course content, delivery methods, and learning materials, ensuring alignment with learners' preferences and learning styles.

Community Building and Engagement:

Foster a sense of community and belonging among learners within each cluster through virtual events, group projects, and social activities. Organize cluster-specific meetups, webinars, and networking events to facilitate meaningful connections and peer-to-peer support.

In [ ]: