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.

Data Dictionary:

- 'Unnamed 0'- Index of the dataset
- Email_hash- Anonymised Personal Identifiable Information (PII)
- Company_hash- 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)

Concept Used:

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

In [127]:
```
import re
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
plt.rcParams["figure.figsize"] = (12,8)
```

In [128]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [129]:
```
df = pd.read_csv("scaler_clustering.csv",index_col=0)
```

In [130]:
```
df.sample(10)
```

Out[130]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
17621	bvi ogenfvqt	e93abc6cafbd171f08953540ecf510f10dd3c29698fe2d...	2015.0	200000	Frontend Engineer	2021.0
43264	qfo	95359fcf297402a0fd09a5d467e90647494e1820fb4091...	2018.0	600000	NaN	2021.0
6416	zgzt	fb69e1bf6d85b39e4759ad3db8a1a55c1175c240108cca...	2016.0	450000	Devops Engineer	2020.0
35431	fyttrotjt ntwyzgrgsj	21f6b7f3bd41a215b0fff15baf9a2253a8eba2fd0127b7...	2018.0	200000	NaN	2021.0
109059	xzegojo	630b0d4ce7833b3a0f4985f36ea19b76c483523be204b6...	2020.0	525000	FullStack Engineer	2021.0
2417	qxv vacxogqj	adf6018a5bdfcd819beb86808e9c3ed2ea954a543f7dbf...	2020.0	700000	NaN	2021.0
175594	sggsrt	8e4b39577f3b328db8ef87cbc841a9fa18be0983157416...	2018.0	1950000	Frontend Engineer	2020.0
47541	hztburgjta	b4a2b543479e569cbb4591e4490f7685b0856540c08094...	2018.0	24000	NaN	2020.0
84285	ovu	08a1ffc2306b7b84edb7081c030c34df39858269cdcd2a...	2015.0	930000	Frontend Engineer	2018.0
134205	gzbgmxrt srgmvr rxbxnta	491c9b3c8df401e916538f4d9d39c8a3fee1a39d7db834...	2012.0	1700000	FullStack Engineer	2018.0

In [ ]:
```

```

In [131]:
```
df.shape
```

Out[131]:
```
(205843, 6)
```

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

In [132]:
```
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 [133]:
```
df.isna().sum()
```

Out[133]:
```
company_hash          44
email_hash             0
orgyear               86
ctc                    0
job_position       52562
ctc_updated_year       0
dtype: int64
```

In [134]:
```
(df.isna().sum()/ len(df))*100
```

Out[134]:
```
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 [ ]:

In [135]:
```
df.describe()
```

Out[135]:

	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 [136]:
```
# based on above information , noticing some unusual outliers in the data
```

In [ ]:

In [137]:
```
df.describe(include="object")
```

Out[137]:

	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

In [ ]:

In [138]:
```
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[138]:
```
'airtel x labs'
```

In [139]:
```
df["company_hash"].nunique()
```

Out[139]: 37299

In [140]:
```
df["company_hash"] = df["company_hash"].apply(lambda x: preprocess_string(str(x)))
df["company_hash"].nunique()
```

Out[140]: 37208

In [ ]:

In [141]:
```
df["job_position"].nunique()
# 1017 unique job positions are there in the dataset
```

Out[141]: 1017

In [142]:
```
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[142]: 857

In [ ]:

In [143]:
```
# removing the email_hash
df.drop("email_hash",axis = 1,inplace=True)
```

In [ ]:

In [144]:
```
df.sample(5)
```

Out[144]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year
135202	nxmwg ogenfvqt xzw	2014.0	270000	backend engineer	2016.0
8043	st	2012.0	1320000	backend engineer	2019.0
191058	vbvkgz rvm	2010.0	220000	fullstack engineer	2019.0
190577	vagmt	2016.0	2200000	devops engineer	2019.0
64059	obvqnqgz	2014.0	650000	android engineer	2019.0

In [145]:
```
df.duplicated().sum() # 17597 duplicated records
```

Out[145]: 17597

In [ ]:

In [ ]:

In [146]:
```
df.isna().sum()
```

Out[146]:
```
company_hash         0
orgyear             86
ctc                  0
job_position         0
ctc_updated_year     0
dtype: int64
```

In [147]:
```
(df["company_hash"] == "").sum()
```

Out[147]:
```
89
```

In [148]:
```
(df["company_hash"] == "nan").sum()
```

Out[148]:
```
44
```

In [149]:
```
(df["job_position"] == "").sum()
```

Out[149]:
```
9
```

In [150]:
```
(df["job_position"] == "nan").sum()
```

Out[150]:
```
52562
```

In [151]:
```
# removing the records where company or job_position reocords are not available
```

In [152]:
```
df[(df["company_hash"] == "") | (df["job_position"] == "")].sample(10)
```

Out[152]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year
167717		2018.0	1500000	backend engineer	2020.0
76907		2021.0	800000	nan	2021.0
25333		2019.0	2000000	nan	2021.0
202179		2016.0	500000	nan	2017.0
84192		2018.0	1400000	backend engineer	2019.0
197978		2020.0	1000000	nan	2019.0
50414		2020.0	720000	nan	2019.0
117571		2010.0	4500000	nan	2019.0
127679		2019.0	1400000	backend engineer	2019.0
80668		2019.0	850000	nan	2019.0

In [153]:
```
len(df[(df["company_hash"] == "") | (df["job_position"] == "")])
```

Out[153]:
```
98
```

In [154]:
```
# df[((df["company_hash"] != "") & (df["job_position"] != ""))]
```

In [155]:
```
df = df[~((df["company_hash"] == "") | (df["job_position"] == ""))]
df
```

Out[155]:

	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

In [156]:
```
df["orgyear"].isna().sum()
```

Out[156]:
```
86
```

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

In [157]:
```
df.groupby("company_hash")["orgyear"].transform("median")
```

Out[157]:
```
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 [158]:
```
df["orgyear"].fillna(df['orgyear'].isnull().sum(),inplace=True)
```

In [159]:
```
df["orgyear"].isna().sum()
```

Out[159]:
```
0
```

In [160]:
```
df.sample(5)
```

Out[160]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year
175831	bxqtrk	2013.0	2500000	fullstack engineer	2019.0
49006	wxnx	2018.0	1500000	backend engineer	2021.0
21098	tdr	2015.0	730000	other	2020.0
151312	nvnv wgzohrnvzwj otqcxwto	2020.0	700000	fullstack engineer	2020.0
153058	vwwtznhqt	2016.0	700000	nan	2021.0

In [ ]:

In [ ]:

Outliers Treatment :

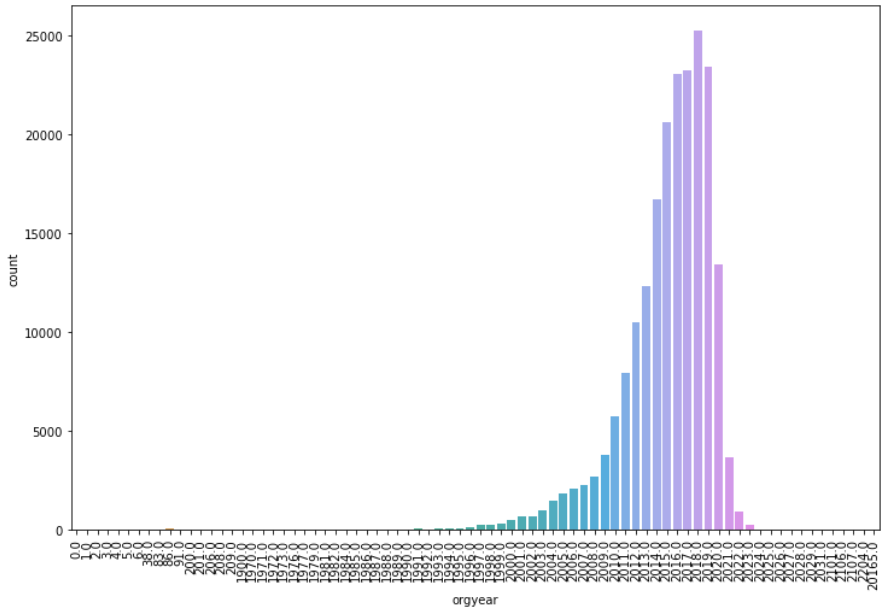
- **employement start year**

In [161]:
```
df["orgyear"].value_counts()
```

Out[161]:
```
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 [162]:
```
sns.countplot(df["orgyear"])
plt.xticks(rotation = 90)
plt.show()
```

```
<IPython.core.display.Javascript object>
```



In [163]:
```
# sns.histplot(np.log(df["orgyear"]))
```

In [164]:
```
df["orgyear"].quantile(0.001)
```

Out[164]: 1990.0

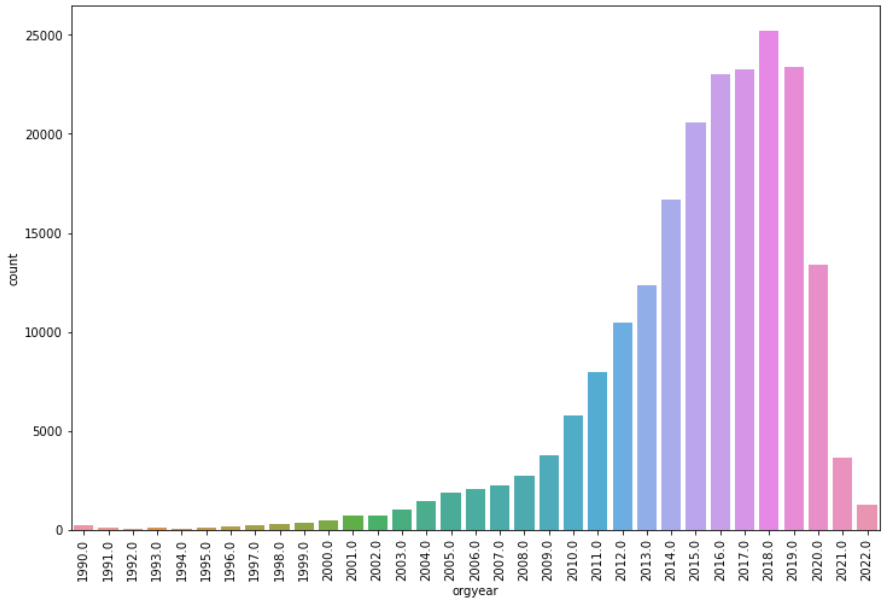
In [165]:
```
df["orgyear"].quantile(0.999)
```

Out[165]: 2023.0

In [166]:
```
df["orgyear"] = df["orgyear"].clip(1990,2022)
```

In [167]:
```
sns.countplot(df["orgyear"])
plt.xticks(rotation = 90)
plt.show()
```

```
<IPython.core.display.Javascript object>
```



In [ ]:

- **ctc updated_year**

In [168]:
```
df["ctc_updated_year"].quantile(0.001)
```

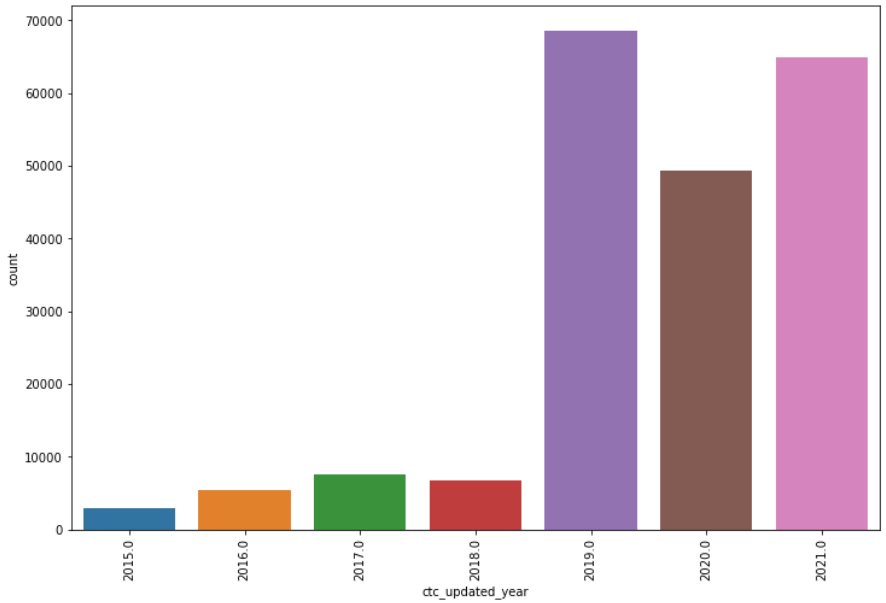
Out[168]: 2015.0

In [169]:
```
df["ctc_updated_year"].quantile(0.99)
```

Out[169]: 2021.0

In [170]:
```
sns.countplot(df["ctc_updated_year"])
plt.xticks(rotation = 90)
plt.show()
```

```
<IPython.core.display.Javascript object>
```



In [ ]:
```

```

- **outlier treatment for CTC**

In [171]:
```
df["ctc"].quantile(0.01)
```

Out[171]:
```
37000.0
```

In [172]:
```
df["ctc"].quantile(0.999)
```

Out[172]:
```
200000000.0
```

In [173]:
```
df = df.loc[((df.ctc) > df.ctc.quantile(0.01)) & ((df.ctc) < df.ctc.quantile(0.99))]
```

In [174]:
```
df
```

Out[174]:

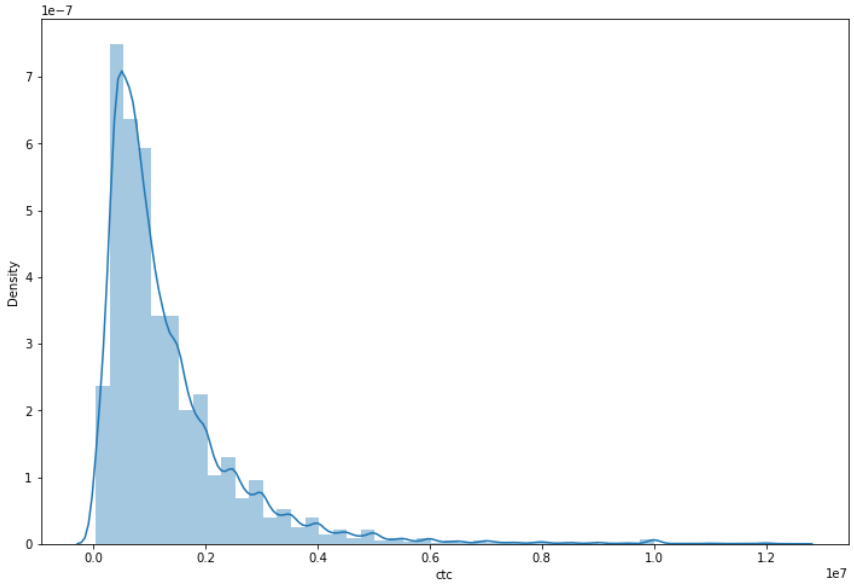
	company_hash	orgyear	ctc	job_position	ctc_updated_year
0	atrgxnnt xzaxv	2016.0	1100000	other	2020.0
1	qtrxvzwt xzegwgbb rxbxnta	2018.0	449999	fullstack engineer	2019.0
2	ojzwnvwnxw vx	2015.0	2000000	backend engineer	2020.0
3	ngpgutaxv	2017.0	700000	backend engineer	2019.0
4	qxen sqghu	2017.0	1400000	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 [175]:
```
sns.distplot(df["ctc"])
```

```
<IPython.core.display.Javascript object>
```

Out[175]:
```
<AxesSubplot:xlabel='ctc', ylabel='Density'>
```



- replacing string "nan" to np.nan

In [176]:
```
df.loc[df['job_position']=='nan', 'job_position']=np.nan
```

In [177]:
```
df.loc[df["company_hash"]=="nan","company_hash"] = np.nan
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [270]:
```
# df.company_hash.value_counts(dropna=False)
```

In [271]:
```
# df.job_position.value_counts(dropna=False)
```

Feature Engineering

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

In [180]:
```
df.loc[df.groupby("company_hash")["ctc"].transform("count") < 5,"company_hash"] = "Others"
```

In [181]:
```
(df["company_hash"] == "Others").sum()
```

Out[181]:
```
46434
```

In [272]:
```
# df.company_hash.value_counts(dropna=False)
```

In [ ]:

In [183]:
```
df['orgyear'].describe()
```

Out[183]:
```
count    201625.000000
mean       2015.104769
std           4.256063
min        1990.000000
25%        2013.000000
50%        2016.000000
75%        2018.000000
max        2022.000000
Name: orgyear, dtype: float64
```

years of experience = current year - employement start year

In [184]:
```
# years of experience
df["years_of_experience_in_organization"] = 2023 - df["orgyear"]
```

In [185]:
```
df.sample(2)
```

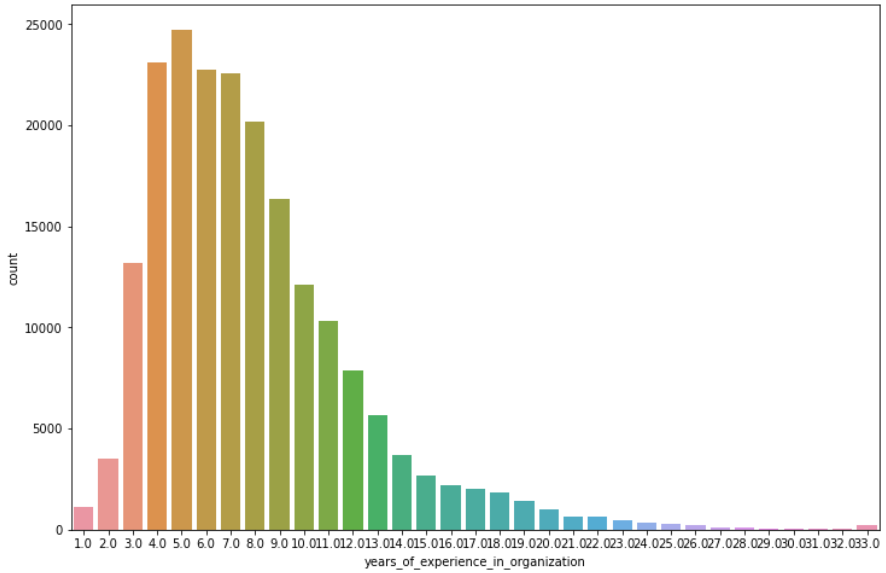
Out[185]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_organization
157723	Others	2019.0	480999	NaN	2018.0	4.0
85654	xzegojo	2018.0	900000	other	2020.0	5.0

In [186]:
```
sns.countplot(df["years_of_experience_in_organization"])
```

```
<IPython.core.display.Javascript object>
```

Out[186]:
```
<AxesSubplot:xlabel='years_of_experience_in_organization', ylabel='count'>
```



In [ ]:

In [ ]:

In [187]:
```
df.duplicated().sum()
```

Out[187]:
```
37683
```

In [188]:
```
df.drop_duplicates(inplace=True)
df.shape
```

Out[188]:
```
(163942, 6)
```

In [189]:
```
df.isna().sum()
```

Out[189]:
```
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 [190]:
```
# records having ctc_updated_year higher than their organization joining year
(df["ctc_updated_year"] < df["orgyear"]).sum()
```

Out[190]:
```
7181
```

In [191]:
```
df.ctc_updated_year = df[["ctc_updated_year","orgyear"]].max(axis = 1)
```

In [192]:
```
(df["ctc_updated_year"] < df["orgyear"]).sum()
```

Out[192]:
```
0
```

In [193]:
```
df.sample(2)
```

Out[193]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_organization
198803	bgqsvz onvzrtj	2017.0	1600000	NaN	2019.0	6.0
178348	bjznqvlvmgzs	2017.0	1970000	NaN	2017.0	6.0

Filling null values with others -- if not done before

In [194]:
```
df['job_position'] = df['job_position'].fillna('Others')
df['company_hash'] = df['company_hash'].fillna('Others')
```

In [ ]:
```

```

In [195]:
```
df.isna().sum()
```

Out[195]:
```
company_hash                         0
orgyear                              0
ctc                                  0
job_position                         0
ctc_updated_year                     0
years_of_experience_in_organization  0
dtype: int64
```

In [ ]:
```

```

In [ ]:

In [196]:
```
df.duplicated().sum()
```

Out[196]:
```
1061
```

In [197]:
```
# df.drop_duplicates(inplace=True)
```

In [273]:
```
# glacing over data after outlier treatment and preprocessing
```

In [198]:
```
df.describe()
```

Out[198]:

	orgyear	ctc	ctc_updated_year	years_of_experience_in_organization
count	163942.000000	1.639420e+05	163942.000000	163942.000000
mean	2014.772218	1.425498e+06	2019.595540	8.227782
std	4.402053	1.303985e+06	1.334962	4.402053
min	1990.000000	3.800000e+04	2015.000000	1.000000
25%	2013.000000	6.000000e+05	2019.000000	5.000000
50%	2016.000000	1.039999e+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 [ ]:

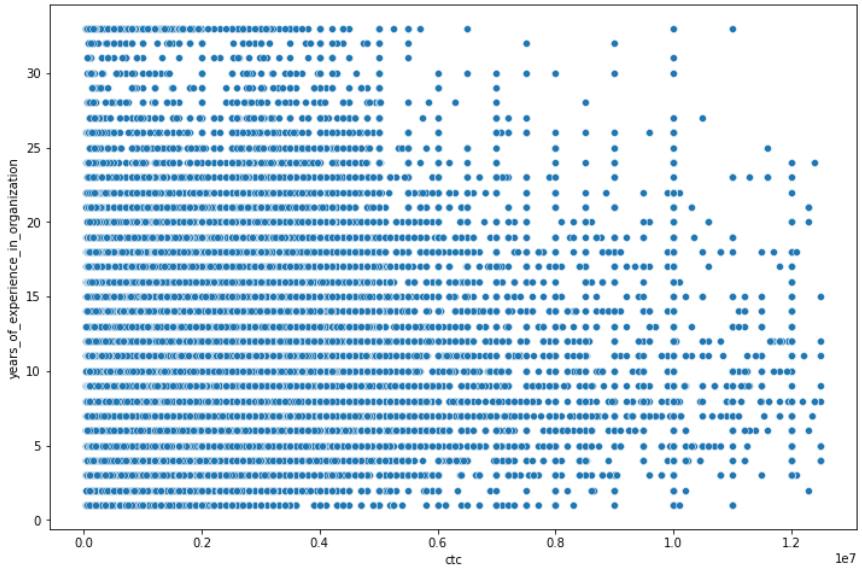
In [199]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 163942 entries, 0 to 206922
Data columns (total 6 columns):
 #   Column                             Non-Null Count   Dtype  
---  ------                             --------------   -----  
 0   company_hash                       163942 non-null  object 
 1   orgyear                            163942 non-null  float64
 2   ctc                                163942 non-null  int64  
 3   job_position                       163942 non-null  object 
 4   ctc_updated_year                   163942 non-null  float64
 5   years_of_experience_in_organization  163942 non-null  float64
dtypes: float64(3), int64(1), object(2)
memory usage: 8.8+ MB
```

In [200]:
```
sns.scatterplot(df.ctc,df.years_of_experience_in_organization)
```

```
<IPython.core.display.Javascript object>
```

Out[200]:
```
<AxesSubplot:xlabel='ctc', ylabel='years_of_experience_in_organization'>
```



In [ ]:
```

```

In [201]:
```
df.columns
```

Out[201]:
```
Index(['company_hash', 'orgyear', 'ctc', 'job_position', 'ctc_updated_year',
       'years_of_experience_in_organization'],
      dtype='object')
```

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

Learner's "designation_in_organization"

In [ ]:
```

```

In [ ]:
```

```

In [202]:
```
GROUPED_CTC = df.groupby(["years_of_experience_in_organization",
                                                "job_position",
                                                "company_hash"])["ctc"].describe()
```

In [ ]:

In [203]:
```
GROUPED_CTC
```

Out[203]:

			count	mean	std	min	25%	50%	75%	max
years_of_experience_in_organization	**job_position**	**company_hash**								
1.0	**Others**	**Others**	58.0	1.586207e+06	2.080212e+06	60000.0	407500.0	750000.0	1575000.0	10000000.0
		agzn fgqp xz vzj gqsvzxkvnxgz	1.0	1.600000e+06	NaN	1600000.0	1600000.0	1600000.0	1600000.0	1600000.0
		atrgxnnt	1.0	1.000000e+06	NaN	1000000.0	1000000.0	1000000.0	1000000.0	1000000.0
		atrr	1.0	1.000000e+06	NaN	1000000.0	1000000.0	1000000.0	1000000.0	1000000.0
		atrr ntwyzgrgsxto	2.0	1.000000e+06	2.828427e+05	800000.0	900000.0	1000000.0	1100000.0	1200000.0
...	**...**	**...**	...	...	...	...	...	...	...	...
33.0	**qa engineer**	**hzxntaytvrny sqghu**	1.0	5.400000e+05	NaN	540000.0	540000.0	540000.0	540000.0	540000.0
		tmxd ogenfvqt xzaxv ucn rna	1.0	1.220000e+06	NaN	1220000.0	1220000.0	1220000.0	1220000.0	1220000.0
		utrvnqg ogrhnxgzo ucnrna	1.0	6.000000e+05	NaN	600000.0	600000.0	600000.0	600000.0	600000.0
	research engineers	**ovbohzs qa xzonxnhnt xzaxv atryx**	1.0	1.400000e+06	NaN	1400000.0	1400000.0	1400000.0	1400000.0	1400000.0
	support engineer	**Others**	2.0	3.700000e+05	3.252691e+05	140000.0	255000.0	370000.0	485000.0	600000.0

66191 rows × 8 columns

In [ ]:

In [204]:
```
df_GROUPED_CTC_BY_E_P_C = df.merge(GROUPED_CTC,
        on = ["years_of_experience_in_organization",
              "job_position",
              "company_hash"],
        how = "left")
```

In [205]:
```
df_GROUPED_CTC_BY_E_P_C
```

Out[205]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_organization	count	mean	std	min	25%	50%	75%	max
0	atrgxnnt xzaxv	2016.0	1100000	other	2020.0	7.0	1.0	1.100000e+06	NaN	1100000.0	1100000.0	1100000.0	1100000.0	1100000.0
1	qtrxvzwt xzegwgbb rxbxnta	2018.0	449999	fullstack engineer	2019.0	5.0	7.0	7.742856e+05	2.509223e+05	449999.0	610000.0	750000.0	900000.0	1200000.0
2	Others	2015.0	2000000	backend engineer	2020.0	8.0	440.0	1.269393e+06	1.405136e+06	41000.0	400000.0	900000.0	1600000.0	10000000.0
3	ngpgutaxv	2017.0	700000	backend engineer	2019.0	6.0	7.0	1.158571e+06	4.047810e+05	700000.0	825000.0	1200000.0	1405000.0	1750000.0
4	qxen sqghu	2017.0	1400000	fullstack engineer	2019.0	6.0	1.0	1.400000e+06	NaN	1400000.0	1400000.0	1400000.0	1400000.0	1400000.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
163937	vuurt xzw	2008.0	220000	Others	2019.0	15.0	1.0	2.200000e+05	NaN	220000.0	220000.0	220000.0	220000.0	220000.0
163938	husqvawgb	2017.0	500000	Others	2020.0	6.0	3.0	1.150000e+06	5.634714e+05	500000.0	975000.0	1450000.0	1475000.0	1500000.0
163939	vwwgrxnt	2021.0	700000	Others	2021.0	2.0	3.0	6.666667e+05	3.511885e+05	300000.0	500000.0	700000.0	850000.0	1000000.0
163940	zgn vuurxwvmrt	2019.0	5100000	Others	2019.0	4.0	118.0	1.412015e+06	1.715935e+06	45000.0	400000.0	735000.0	1725250.0	10000000.0
163941	bgqsvz onvzrtj	2014.0	1240000	Others	2016.0	9.0	9.0	1.693333e+06	3.484250e+05	1200000.0	1500000.0	1700000.0	1900000.0	2200000.0

163942 rows × 14 columns

In [206]:
```
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 [207]:
```
df_GROUPED_CTC_BY_E_P_C["designation_in_organization"] = df_GROUPED_CTC_BY_E_P_C.apply(lambda x:classification(x["ctc"],x["50%"],x["75%"]),axis = 1)
```

In [208]:
```
df_GROUPED_CTC_BY_E_P_C
```

Out[208]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_organization	count	mean	std	min	25%	50%	75%	max	designation_in_organization
0	atrgxnnt xzaxv	2016.0	1100000	other	2020.0	7.0	1.0	1.100000e+06	NaN	1100000.0	1100000.0	1100000.0	1100000.0	1100000.0	2
1	qtrxvzwt xzegwgbb rxbxnta	2018.0	449999	fullstack engineer	2019.0	5.0	7.0	7.742856e+05	2.509223e+05	449999.0	610000.0	750000.0	900000.0	1200000.0	3
2	Others	2015.0	2000000	backend engineer	2020.0	8.0	440.0	1.269393e+06	1.405136e+06	41000.0	400000.0	900000.0	1600000.0	10000000.0	1
3	ngpgutaxv	2017.0	700000	backend engineer	2019.0	6.0	7.0	1.158571e+06	4.047810e+05	700000.0	825000.0	1200000.0	1405000.0	1750000.0	3
4	qxen sqghu	2017.0	1400000	fullstack engineer	2019.0	6.0	1.0	1.400000e+06	NaN	1400000.0	1400000.0	1400000.0	1400000.0	1400000.0	2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
163937	vuurt xzw	2008.0	220000	Others	2019.0	15.0	1.0	2.200000e+05	NaN	220000.0	220000.0	220000.0	220000.0	220000.0	2
163938	husqvawgb	2017.0	500000	Others	2020.0	6.0	3.0	1.150000e+06	5.634714e+05	500000.0	975000.0	1450000.0	1475000.0	1500000.0	3
163939	vwwgrxnt	2021.0	700000	Others	2021.0	2.0	3.0	6.666667e+05	3.511885e+05	300000.0	500000.0	700000.0	850000.0	1000000.0	2
163940	zgn vuurxwvmrt	2019.0	5100000	Others	2019.0	4.0	118.0	1.412015e+06	1.715935e+06	45000.0	400000.0	735000.0	1725250.0	10000000.0	1
163941	bgqsvz onvzrtj	2014.0	1240000	Others	2016.0	9.0	9.0	1.693333e+06	3.484250e+05	1200000.0	1500000.0	1700000.0	1900000.0	2200000.0	3

163942 rows × 15 columns

In [209]:
```
df_GROUPED_CTC_BY_E_P_C.designation_in_organization.value_counts(normalize=True)
```

Out[209]:
```
2    0.456393
3    0.331660
1    0.211947
Name: designation_in_organization, dtype: float64
```

In [ ]:

In [ ]:

In [211]:
```
df_GROUPED_CTC_BY_E_P_C
```

Out[211]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_organization	count	mean	std	min	25%	50%	75%	max	designation_in_organization
0	atrgxnnt xzaxv	2016.0	1100000	other	2020.0	7.0	1.0	1.100000e+06	NaN	1100000.0	1100000.0	1100000.0	1100000.0	1100000.0	2
1	qtrxvzwt xzegwgbb rxbxnta	2018.0	449999	fullstack engineer	2019.0	5.0	7.0	7.742856e+05	2.509223e+05	449999.0	610000.0	750000.0	900000.0	1200000.0	3
2	Others	2015.0	2000000	backend engineer	2020.0	8.0	440.0	1.269393e+06	1.405136e+06	41000.0	400000.0	900000.0	1600000.0	10000000.0	1
3	ngpgutaxv	2017.0	700000	backend engineer	2019.0	6.0	7.0	1.158571e+06	4.047810e+05	700000.0	825000.0	1200000.0	1405000.0	1750000.0	3
4	qxen sqghu	2017.0	1400000	fullstack engineer	2019.0	6.0	1.0	1.400000e+06	NaN	1400000.0	1400000.0	1400000.0	1400000.0	1400000.0	2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
163937	vuurt xzw	2008.0	220000	Others	2019.0	15.0	1.0	2.200000e+05	NaN	220000.0	220000.0	220000.0	220000.0	220000.0	2
163938	husqvawgb	2017.0	500000	Others	2020.0	6.0	3.0	1.150000e+06	5.634714e+05	500000.0	975000.0	1450000.0	1475000.0	1500000.0	3
163939	vwwgrxnt	2021.0	700000	Others	2021.0	2.0	3.0	6.666667e+05	3.511885e+05	300000.0	500000.0	700000.0	850000.0	1000000.0	2
163940	zgn vuurxwvmrt	2019.0	5100000	Others	2019.0	4.0	118.0	1.412015e+06	1.715935e+06	45000.0	400000.0	735000.0	1725250.0	10000000.0	1
163941	bgqsvz onvzrtj	2014.0	1240000	Others	2016.0	9.0	9.0	1.693333e+06	3.484250e+05	1200000.0	1500000.0	1700000.0	1900000.0	2200000.0	3

163942 rows × 15 columns

In [212]:
```
df_GROUPED_CTC_BY_E_P_C.drop(columns=['count',
                                      'mean',
                                     'std',
                                     'min',
                                     '25%',
                                     '50%',
                                     '75%',
                                     'max'],axis = 1,inplace=True)
```

In [213]:
```
df_GROUPED_CTC_BY_E_P_C
```

Out[213]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_organization	designation_in_organization
0	atrgxnnt xzaxv	2016.0	1100000	other	2020.0	7.0	2
1	qtrxvzwt xzegwgbb rxbxnta	2018.0	449999	fullstack engineer	2019.0	5.0	3
2	Others	2015.0	2000000	backend engineer	2020.0	8.0	1
3	ngpgutaxv	2017.0	700000	backend engineer	2019.0	6.0	3
4	qxen sqghu	2017.0	1400000	fullstack engineer	2019.0	6.0	2
...	...	...	...	...	...	...	...
163937	vuurt xzw	2008.0	220000	Others	2019.0	15.0	2
163938	husqvawgb	2017.0	500000	Others	2020.0	6.0	3
163939	vwwgrxnt	2021.0	700000	Others	2021.0	2.0	2
163940	zgn vuurxwvmrt	2019.0	5100000	Others	2019.0	4.0	1
163941	bgqsvz onvzrtj	2014.0	1240000	Others	2016.0	9.0	3

163942 rows × 7 columns

In [214]:
```
df_GROUPED_CTC_BY_E_P_C.shape
```

Out[214]:
```
(163942, 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 [215]:
```
GROUPED_C_J=df.groupby(['job_position','company_hash'])['ctc'].describe()
GROUPED_C_J
```

Out[215]:

		count	mean	std	min	25%	50%	75%	max
job_position	**company_hash**								
Others	**Others**	3520.0	1.366188e+06	1.445330e+06	40000.0	409999.0	900000.0	1842499.25	12500000.0
	a ntwyzgrgsxto	6.0	1.229167e+06	1.401465e+06	350000.0	518750.0	587500.0	1162500.00	4000000.0
	aaqxctz avnv owxtzwto vzvrjnxwo ucn rna	1.0	5.000000e+05	NaN	500000.0	500000.0	500000.0	500000.00	500000.0
	abwavnv ojontb	1.0	7.000000e+05	NaN	700000.0	700000.0	700000.0	700000.00	700000.0
	adw ntwyzgrgsj	69.0	8.502319e+05	1.036041e+06	80000.0	380000.0	500000.0	1000000.00	8000000.0
...	**...**	...	...	...	...	...	...	...	...
wordpress developer	**Others**	1.0	6.000000e+05	NaN	600000.0	600000.0	600000.0	600000.00	600000.0
worker	**zgn vuurxwvmrt vwwghzn**	1.0	2.000000e+05	NaN	200000.0	200000.0	200000.0	200000.00	200000.0
x	**Others**	1.0	4.000000e+05	NaN	400000.0	400000.0	400000.0	400000.00	400000.0
young professional ii	**sgctqzbtzn ge xzaxv**	1.0	5.000000e+05	NaN	500000.0	500000.0	500000.0	500000.00	500000.0
zomato	**kgbvng**	2.0	3.000000e+05	2.828427e+05	100000.0	200000.0	300000.0	400000.00	500000.0

25593 rows × 8 columns

In [216]:
```
df_GROUPED_C_J=df.merge(GROUPED_C_J, on=['job_position','company_hash'], how='left')
```

In [217]:
```
df_GROUPED_C_J.sample(5)
```

Out[217]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_organization	count	mean	std	min	25%	50%	75%	max
126677	zvz	2019.0	3200000	data scientist	2019.0	4.0	39.0	1.211500e+06	7.584555e+05	46500.0	647500.0	1000000.0	1650000.0	3200000.0
93215	nvnv wgzohrnvzwj otqcxwto	2012.0	850000	ios engineer	2019.0	11.0	19.0	6.852632e+05	3.520475e+05	70000.0	425000.0	600000.0	850000.0	1550000.0
29447	wvustbxzx	2013.0	910000	backend engineer	2021.0	10.0	247.0	8.295992e+05	4.891276e+05	40000.0	475000.0	700000.0	1070000.0	3000000.0
41080	znn avnv otqcxwto	2019.0	700000	Others	2019.0	4.0	62.0	1.142984e+06	1.738646e+06	300000.0	400000.0	690000.0	1275000.0	10000000.0
76917	Others	2013.0	1100000	other	2021.0	10.0	2367.0	1.117373e+06	1.423744e+06	38000.0	350000.0	700000.0	1326000.0	12000000.0

In [218]:
```
# creating classes basis on the salary in their respective company
```

In [219]:
```
df_GROUPED_C_J['classs'] = df_GROUPED_C_J.apply(lambda x: classification(x['ctc'],x['50%'],x['75%']),axis=1)
```

In [220]:
```
df_GROUPED_C_J.sample(5)
```

Out[220]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_organization	count	mean	std	min	25%	50%	75%	max	classs
79071	ohnytqrvza	2017.0	710000	data scientist	2019.0	6.0	2.0	6.155000e+06	7.700393e+06	710000.0	3432500.0	6155000.0	8877500.0	11600000.0	3
122059	Others	2019.0	130000	fullstack engineer	2020.0	4.0	3181.0	1.193104e+06	1.532888e+06	40000.0	350000.0	775000.0	1450000.0	12000000.0	3
35726	wvwnho wgbbhzxwvnxgzo	2013.0	400000	Others	2020.0	10.0	3.0	7.333333e+05	5.773503e+05	400000.0	400000.0	400000.0	900000.0	1400000.0	2
68461	vau	2015.0	819999	backend engineer	2019.0	8.0	51.0	1.124500e+06	9.053526e+05	105000.0	690000.0	820000.0	1325000.0	6000000.0	3
42240	wgszxkvzn	2015.0	800000	frontend engineer	2021.0	8.0	105.0	7.959143e+05	5.380693e+05	65000.0	450000.0	600000.0	1000000.0	4298000.0	2

In [221]:
```
df_GROUPED_C_J.classs.value_counts(normalize=True)
```

Out[221]:
```
3    0.435373
2    0.320101
1    0.244526
Name: classs, dtype: float64
```

In [222]:
```
df_GROUPED_C_J.drop(columns=['count',
                             'mean',
                            'std',
                            'min',
                            '25%',
                            '50%',
                            '75%',
                            'max'],axis = 1,inplace=True)
```

In [223]:
```
df_GROUPED_CTC_BY_E_P_C.iloc[0]
```

Out[223]:
```
company_hash                          atrgxnnt xzaxv
orgyear                                      2016.0
ctc                                         1100000
job_position                                  other
ctc_updated_year                             2020.0
years_of_experience_in_organization             7.0
designation_in_organization                       2
Name: 0, dtype: object
```

In [ ]:
```

```

In [224]:
```
df_GROUPED_C_J.iloc[0]
```

Out[224]:
```
company_hash                          atrgxnnt xzaxv
orgyear                                      2016.0
ctc                                         1100000
job_position                                  other
ctc_updated_year                             2020.0
years_of_experience_in_organization             7.0
classs                                            1
Name: 0, dtype: object
```

In [ ]:

In [225]:
```
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_organization',
                                                               'ctc_updated_year'], how='left')
```

In [226]:
```
df_Grouped.sample(5)
```

Out[226]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_organization	designation_in_organization	classs
107145	cgjrrv evoyxgzo ucn rna	2018.0	900000	fullstack engineer	2018.0	5.0	2	3
100926	ztw ntwyzgrgsxto xzaxv rna	2019.0	540000	Others	2021.0	4.0	2	3
62274	eoo	2019.0	500000	backend engineer	2021.0	4.0	2	2
10909	vqwtoxhb	2019.0	1500000	Others	2020.0	4.0	3	3
60338	bxzanqtt	2017.0	488000	support engineer	2020.0	6.0	2	3

In [227]:
```
df_Grouped.shape
```

Out[227]:
```
(166228, 8)
```

Manual Clustering based on comapny

based on ctc per company , assigning company as tier 1 2 and 3 per each learners

In [228]:
```
GROUPED_C = df.groupby(['company_hash'])['ctc'].describe()
df_company = df.merge(GROUPED_C, on=['company_hash'], how='left')
```

In [229]:
```
df_company.sample(5)
```

Out[229]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_organization	count	mean	std	min	25%	50%	75%	max
46717	Others	2012.0	700000	ios engineer	2019.0	11.0	26256.0	1.311366e+06	1.436286e+06	38000.0	440000.0	900000.0	1650000.0	12500000.0
93680	vwwgrxnt	2013.0	1900000	backend engineer	2018.0	10.0	165.0	1.414836e+06	6.917496e+05	200000.0	1000000.0	1300000.0	1500000.0	4800000.0
136812	x vb v onhatzn	2018.0	600000	other	2018.0	5.0	49.0	1.206531e+06	1.115764e+06	100000.0	500000.0	900000.0	1700000.0	6500000.0
111948	nguuq	2018.0	1600000	Others	2019.0	5.0	72.0	1.707083e+06	1.085002e+06	350000.0	900000.0	1560000.0	2070000.0	5000000.0
9856	Others	2016.0	1440000	frontend engineer	2019.0	7.0	26256.0	1.311366e+06	1.436286e+06	38000.0	440000.0	900000.0	1650000.0	12500000.0

In [230]:
```
df_company['tier'] =df_company.apply(lambda x: classification(x['ctc'],x['50%'],x['75%']),axis=1)
```

In [231]:
```
# df_company.sample(5)
```

In [232]:
```
df_company.tier.value_counts(normalize=True)
```

Out[232]:
```
3    0.477364
2    0.282911
1    0.239725
Name: tier, dtype: float64
```

In [ ]:

In [ ]:

In [ ]:

In [233]:
```
df_company.drop(['count','mean','std','min','25%','50%','75%','max'],
                axis = 1,
                inplace=True)
```

In [234]:
```
df_company.iloc[0]
```

Out[234]:
```
company_hash                          atrgxnnt xzaxv
orgyear                                      2016.0
ctc                                         1100000
job_position                                  other
ctc_updated_year                             2020.0
years_of_experience_in_organization             7.0
tier                                              2
Name: 0, dtype: object
```

In [235]:
```
df_Grouped.iloc[0]
```

Out[235]:
```
company_hash                          atrgxnnt xzaxv
orgyear                                      2016.0
ctc                                         1100000
job_position                                  other
ctc_updated_year                             2020.0
years_of_experience_in_organization             7.0
designation_in_organization                       2
classs                                            1
Name: 0, dtype: object
```

In [236]:
```
df_Grouped = df_Grouped.merge(df_company,
                 on=['company_hash',
                     'orgyear','ctc',
                     'job_position',
                     'years_of_experience_in_organization',
                     'ctc_updated_year'
                    ])
```

In [237]:
```
df_Grouped
```

Out[237]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_organization	designation_in_organization	classs	tier
0	atrgxnnt xzaxv	2016.0	1100000	other	2020.0	7.0	2	1	2
1	qtrxvzwt xzegwgbb rxbxnta	2018.0	449999	fullstack engineer	2019.0	5.0	3	3	3
2	Others	2015.0	2000000	backend engineer	2020.0	8.0	1	1	1
3	ngpgutaxv	2017.0	700000	backend engineer	2019.0	6.0	3	3	3
4	qxen sqghu	2017.0	1400000	fullstack engineer	2019.0	6.0	2	1	1
...	...	...	...	...	...	...	...	...	...
171311	vuurt xzw	2008.0	220000	Others	2019.0	15.0	2	3	3
171312	husqvawgb	2017.0	500000	Others	2020.0	6.0	3	3	3
171313	vwwgrxnt	2021.0	700000	Others	2021.0	2.0	2	3	3
171314	zgn vuurxwvmrt	2019.0	5100000	Others	2019.0	4.0	1	1	1
171315	bgqsvz onvzrtj	2014.0	1240000	Others	2016.0	9.0	3	3	3

171316 rows × 9 columns

In [238]:
```
X = df_Grouped.copy()
```

In [ ]:
```

```

In [239]:
```
X.shape
```

Out[239]:
```
(171316, 9)
```

In [240]:
```
X_data = X.drop(["company_hash","job_position"],axis  = 1)
```

Final data for Model :

In [241]:
```
X_data
```

Out[241]:

	orgyear	ctc	ctc_updated_year	years_of_experience_in_organization	designation_in_organization	classs	tier
0	2016.0	1100000	2020.0	7.0	2	1	2
1	2018.0	449999	2019.0	5.0	3	3	3
2	2015.0	2000000	2020.0	8.0	1	1	1
3	2017.0	700000	2019.0	6.0	3	3	3
4	2017.0	1400000	2019.0	6.0	2	1	1
...	...	...	...	...	...	...	...
171311	2008.0	220000	2019.0	15.0	2	3	3
171312	2017.0	500000	2020.0	6.0	3	3	3
171313	2021.0	700000	2021.0	2.0	2	3	3
171314	2019.0	5100000	2019.0	4.0	1	1	1
171315	2014.0	1240000	2016.0	9.0	3	3	3

171316 rows × 7 columns

Standardization:

In [242]:
```
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.index)
```

In [ ]:
```

```

In [243]:
```
X_sc
```

Out[243]:

	orgyear	ctc	ctc_updated_year	years_of_experience_in_organization	designation_in_organization	classs	tier
0	0.229439	-0.238430	0.298195	-0.229439	-0.175910	-1.497105	-0.300556
1	0.680950	-0.741765	-0.452799	-0.680950	1.196414	1.001707	0.933655
2	0.003683	0.458493	0.298195	-0.003683	-1.548235	-1.497105	-1.534766
3	0.455194	-0.548174	-0.452799	-0.455194	1.196414	1.001707	0.933655
4	0.455194	-0.006122	-0.452799	-0.455194	-0.175910	-1.497105	-1.534766
...	...	...	...	...	...	...	...
171311	-1.576605	-0.919866	-0.452799	1.576605	-0.175910	1.001707	0.933655
171312	0.455194	-0.703046	0.298195	-0.455194	1.196414	1.001707	0.933655
171313	1.358216	-0.548174	1.049190	-1.358216	-0.175910	1.001707	0.933655
171314	0.906705	2.859008	-0.452799	-0.906705	-1.548235	-1.497105	-1.534766
171315	-0.222072	-0.130020	-2.705782	0.222072	1.196414	1.001707	0.933655

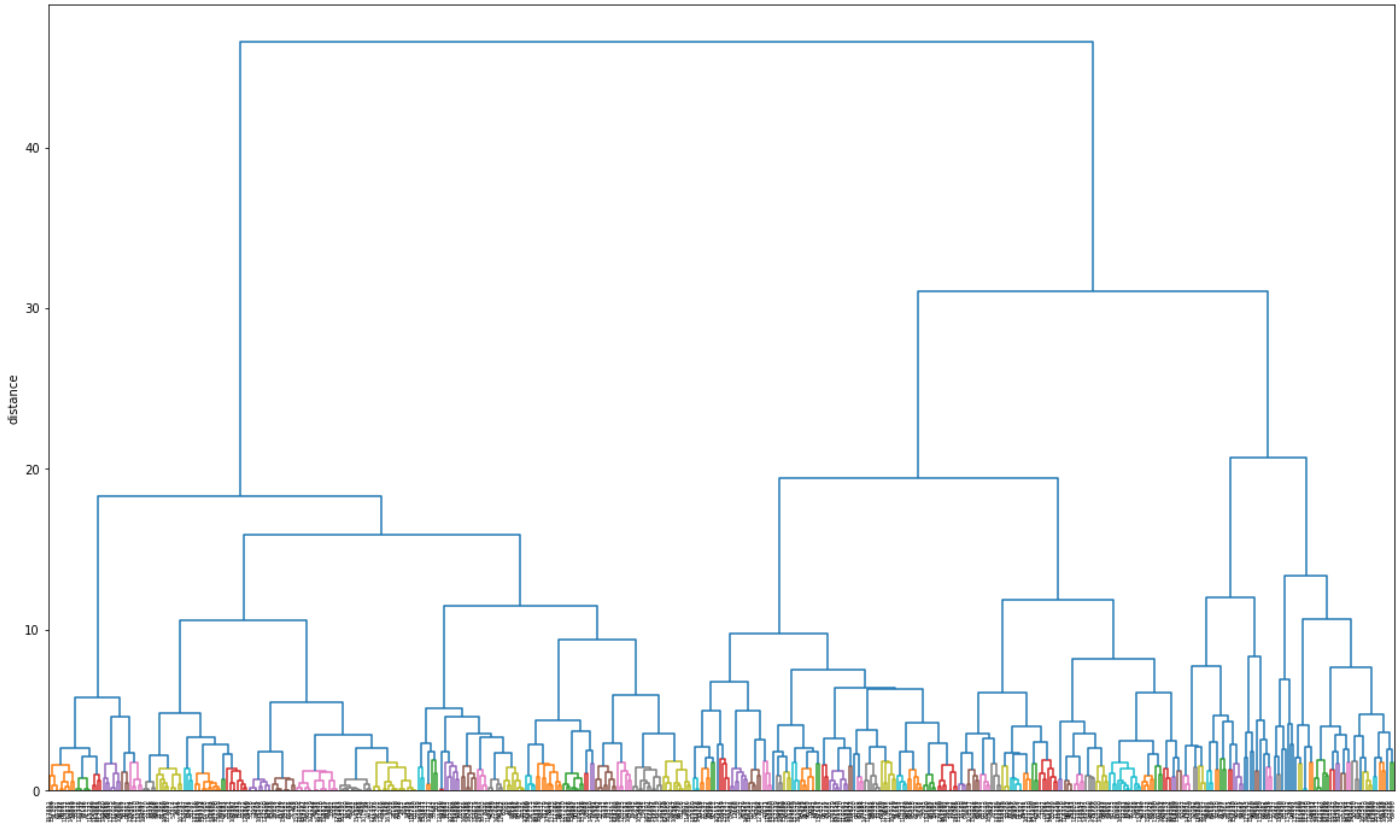
171316 rows × 7 columns

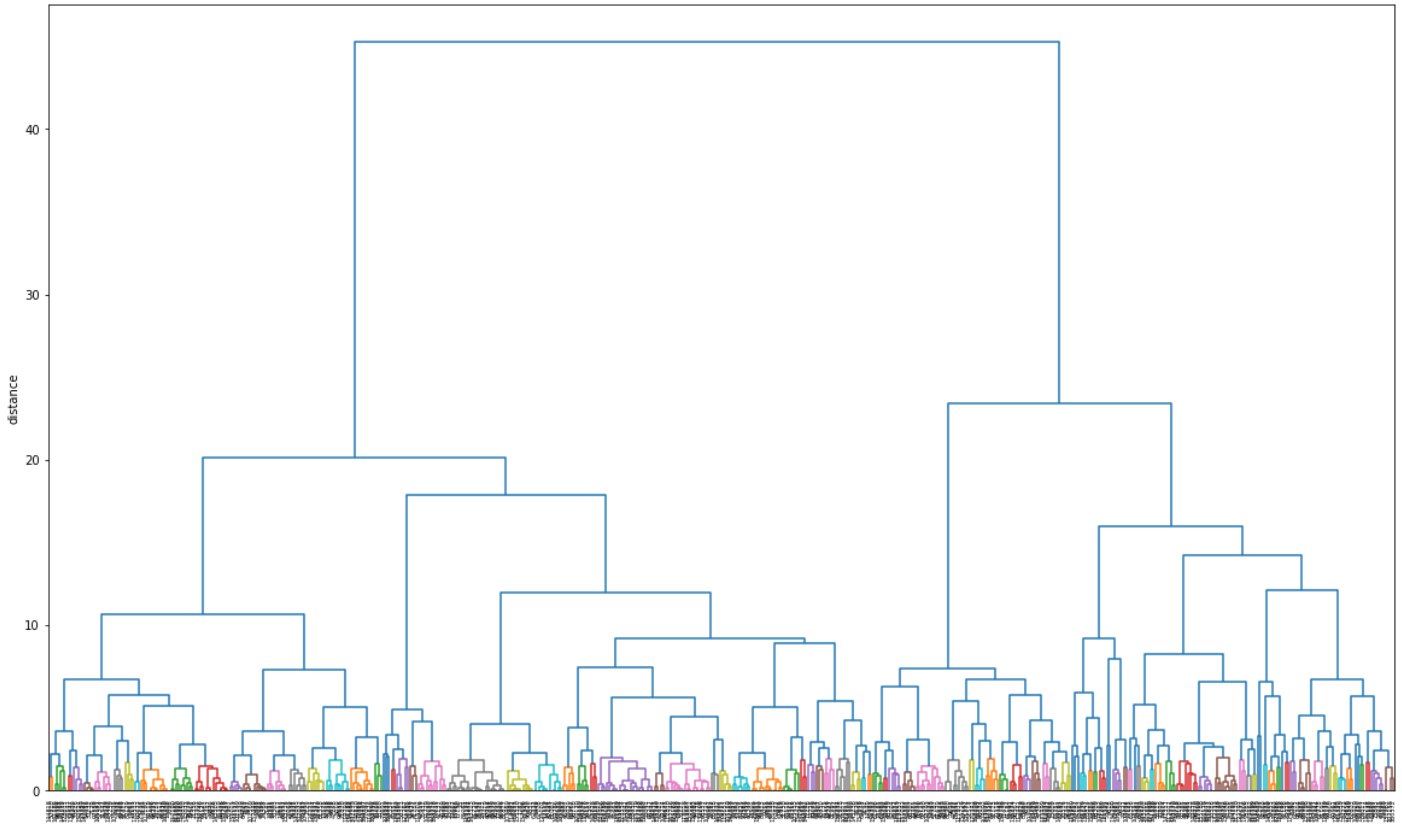
hierarchical Custering :

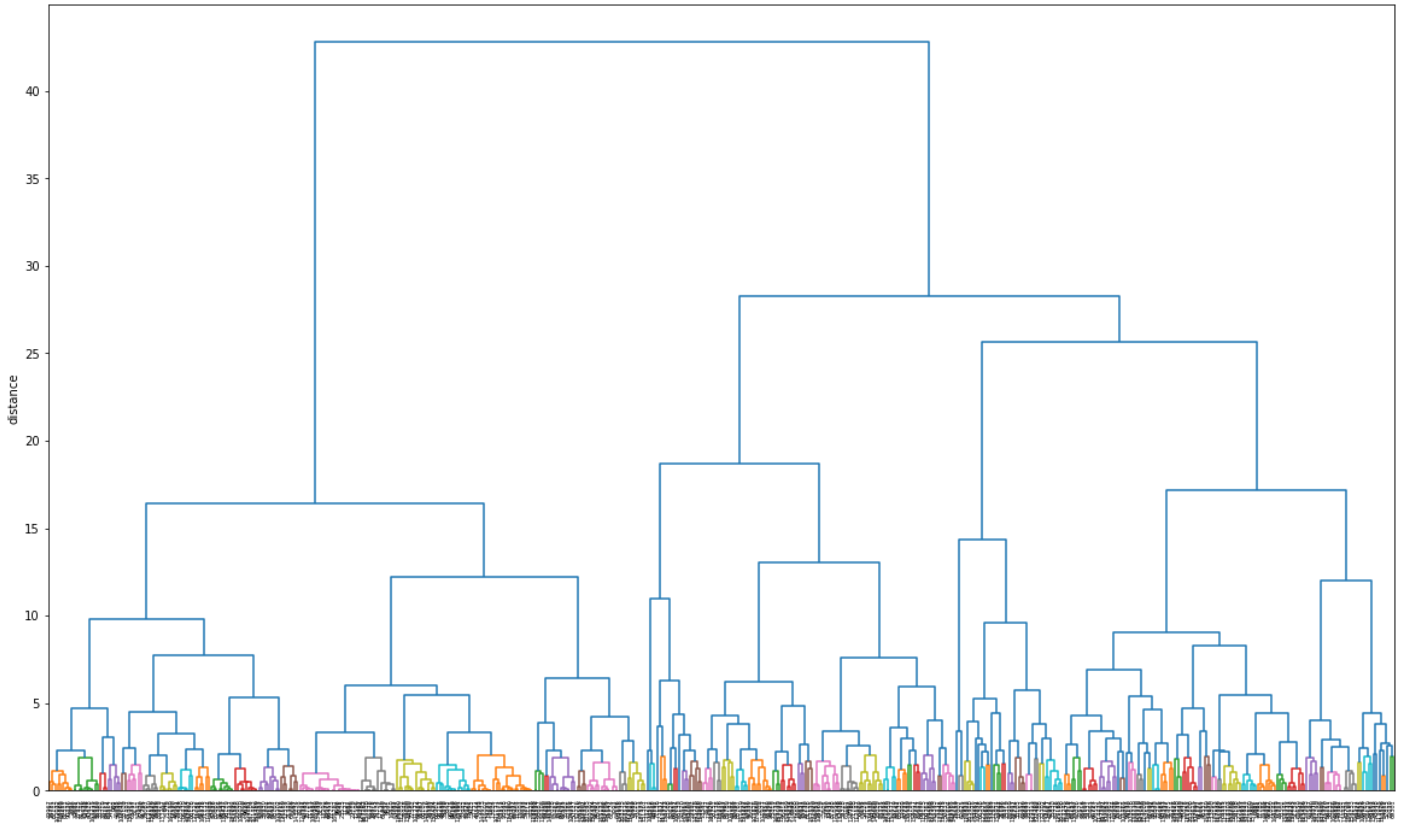
trying to get a high level idea about how many clusters we can from, by taking sample of 500 learners multiple times and forming hierarchy and visualising in dendrogram.

In [244]:

```
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()
```


distance
40
30
20
10
0


distance
40
30
20
10
0



Based on dendrogram , we can observe there are 3 clusters in the data based on similarity

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

In [ ]:

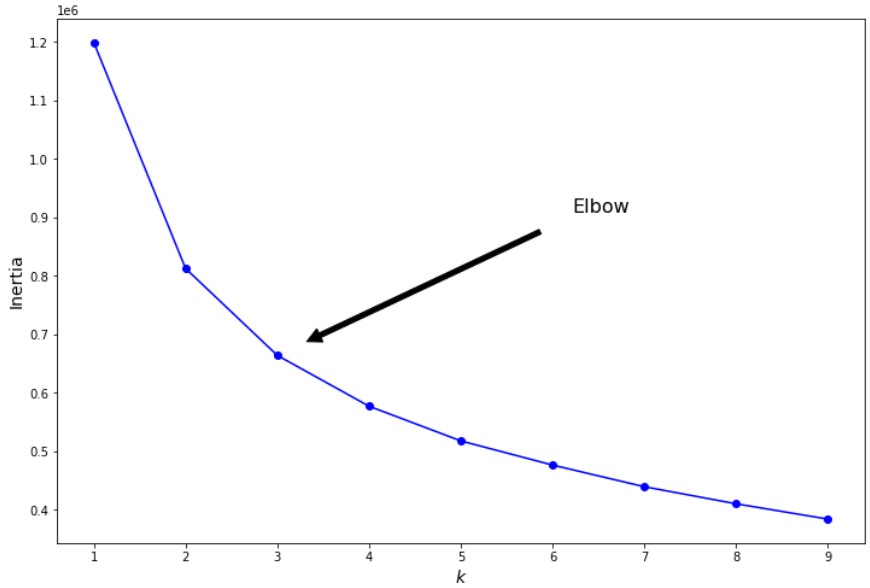
KMeans

In [ ]:
```
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 [254]:
```
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[254]:
```
[1199211.9999999972,
 812618.2236265242,
 663951.3689564556,
 577020.6292578052,
 517714.4060221886,
 476402.90178635635,
 439357.96141059144,
 410144.6171733509,
 383988.5907258121]
```

In [255]:
```
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 [256]:
```
from sklearn.cluster import KMeans

k = 3

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

In [257]:
```
clusters = pd.DataFrame(X, columns=X.columns)
clusters['label'] = kM.labels_
```

In [258]:
```
clusters.sample(5)
```

Out[258]:

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience_in_organization	designation_in_organization	classs	tier	label
69989	Others	2020.0	360000	support engineer	2020.0	3.0	3	3	3	2
160236	otvqo ygraxzso wgqugqvnxgz	2017.0	8000000	data scientist	2019.0	6.0	1	1	1	1
101242	mvqwrvjo	2001.0	3350000	Others	2019.0	22.0	1	1	1	0
136293	nvnv wgzohrnvzwj otqcxwto	2015.0	1220000	fullstack engineer	2021.0	8.0	1	1	1	1
27089	wbt sqghu	2011.0	1600000	Others	2019.0	12.0	2	3	3	2

In [259]:
```
clusters.shape
```

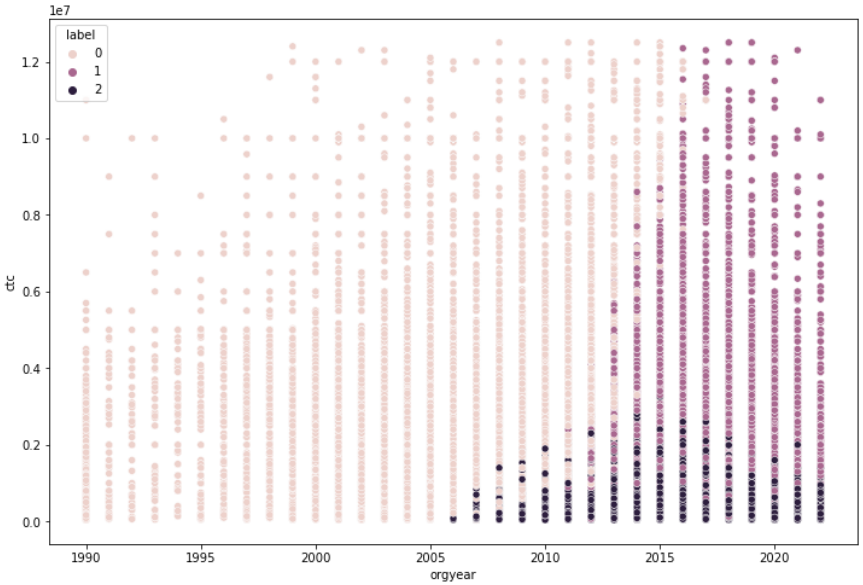
Out[259]:
```
(171316, 10)
```

Insights | EDA after Clustering :

In [260]:
```
sns.scatterplot(clusters["orgyear"],
                clusters["ctc"],
                hue = clusters["label"])
```

```
<IPython.core.display.Javascript object>
```

Out[260]:
```
<AxesSubplot:xlabel='orgyear', ylabel='ctc'>
```



In [275]:

Out[275]: 2000000.0

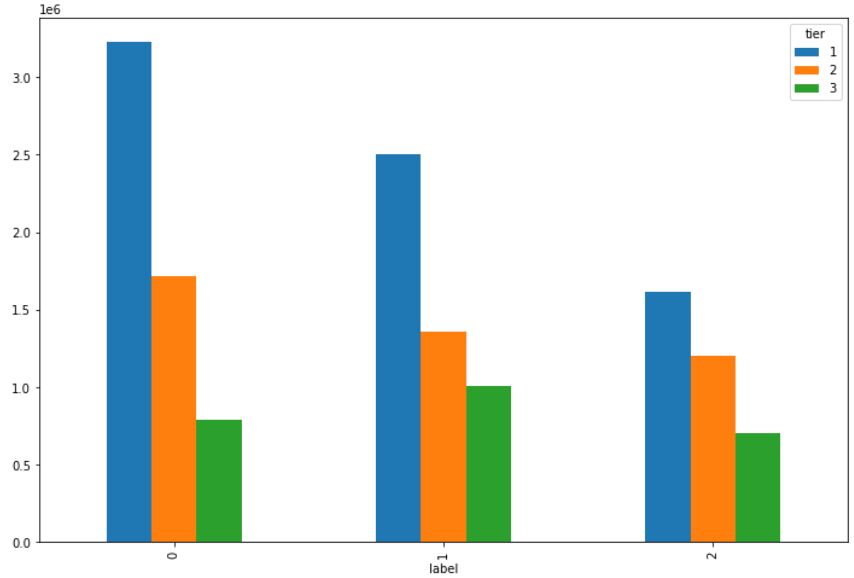
based on above scatter plot , we can observe , a cluster of learners received CTC upto 30 LPA who joined after 2006-07.

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 1.5cr.

In [261]:
```
pd.crosstab(index = clusters["label"],
    columns = clusters["tier"],values=clusters["ctc"],aggfunc= np.mean
       ).plot(kind = "bar")
```

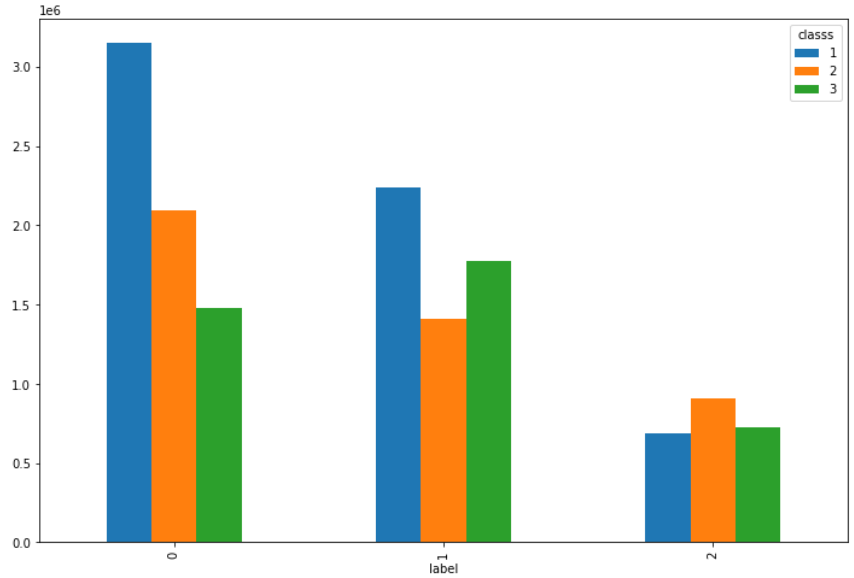
Out[261]: <AxesSubplot:xlabel='label'>



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

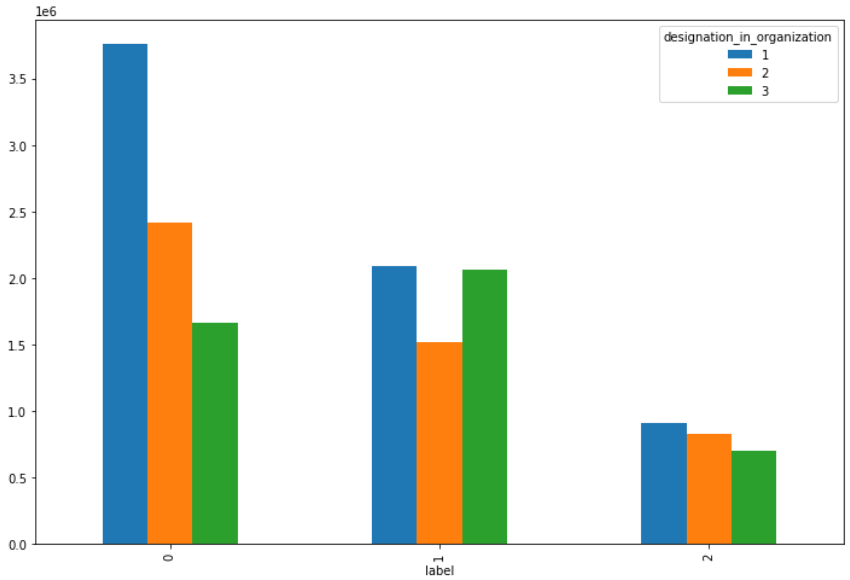
In [262]:
```
pd.crosstab(index = clusters["label"],
    columns = clusters["classs"],values=clusters["ctc"],aggfunc= np.mean
       ).plot(kind = "bar")
```

Out[262]: <AxesSubplot:xlabel='label'>



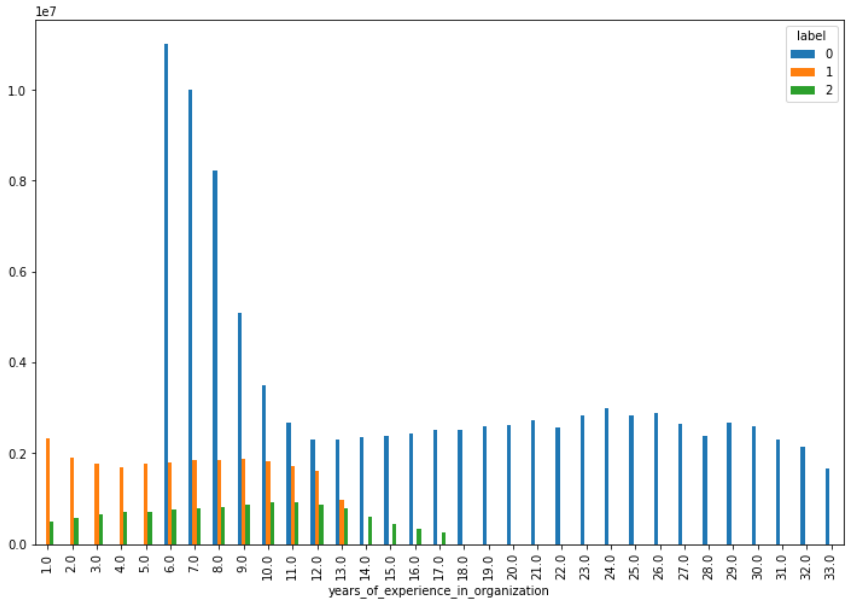
In [263]:
```
pd.crosstab(index = clusters["label"],
    columns = clusters["designation_in_organization"],
            values=clusters["ctc"],aggfunc= np.mean
       ).plot(kind = "bar")
```

Out[263]: <AxesSubplot:xlabel='label'>



In [264]:
```
pd.crosstab(columns = clusters["label"],
    index = clusters["years_of_experience_in_organization"],
            values=clusters["ctc"],aggfunc= np.mean
       ).plot(kind = "bar")
```

Out[264]: <AxesSubplot:xlabel='years_of_experience_in_organization'>

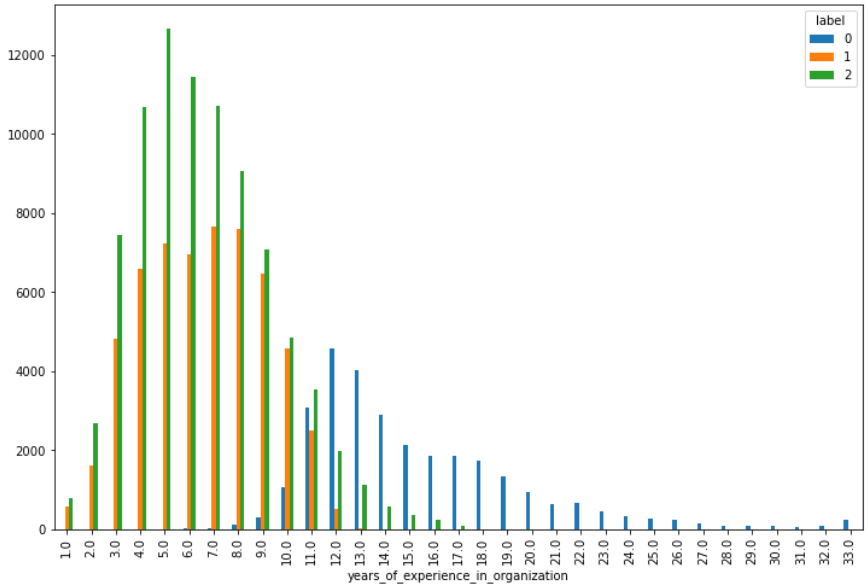


Cluster label 0 , are those learners who are very very experienced,

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

In [266]:
```
pd.crosstab(columns = clusters["label"],
    index = clusters["years_of_experience_in_organization"],

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

Out[266]: <AxesSubplot:xlabel='years_of_experience_in_organization'>



Majority of Learners are experienced between 1 to 15 years . (49.73%)- (Cluster 2)

there is a group of learners having 8 to upto 33 years of experience. (33%) - (Cluster 0)

16.95% of learners who have experiences - (cluster 1)

In [278]:
```
clusters.label.value_counts(normalize=True)*100
```

Out[278]:
```
2    49.734409
1    33.308623
0    16.956968
Name: label, dtype: float64
```

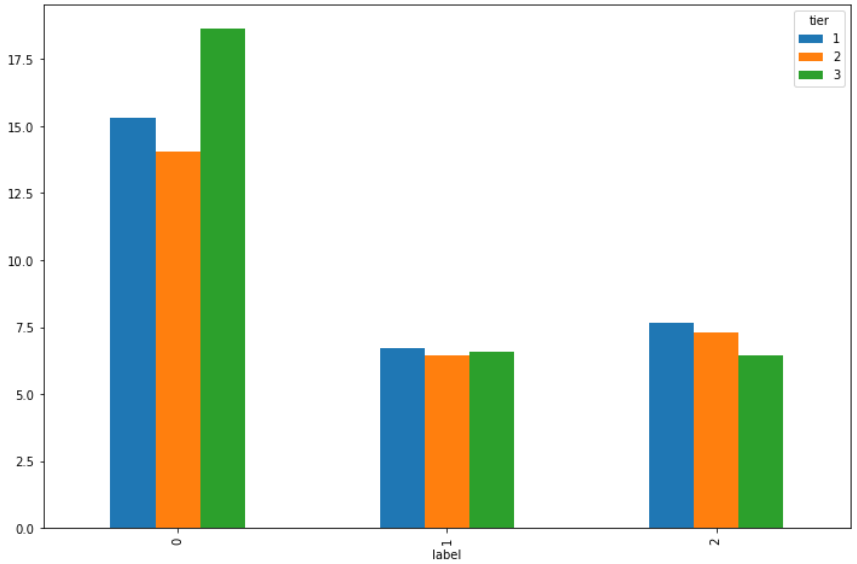
In [ ]:

In [ ]:

years_of_experience_in_organization per each cluster group of learners

In [269]:
```
pd.crosstab(index = clusters["label"],
    columns = clusters["tier"],
            values=clusters["years_of_experience_in_organization"],
            aggfunc=np.mean
       ).plot(kind = "bar")
```

Out[269]: <AxesSubplot:xlabel='label'>



In [286]:
```
clusters.columns
```

Out[286]:
```
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 [288]:
```
clusters.groupby("label").describe()[["ctc","classs","tier","years_of_experience_in_organization"]].T
```

Out[288]:

	label	0	1	2
ctc	count	2.905000e+04	5.706300e+04	8.520300e+04
	mean	2.543348e+06	1.802940e+06	7.562107e+05
	std	1.751976e+06	1.272597e+06	5.033019e+05
	min	3.955000e+04	6.500000e+04	3.800000e+04
	25%	1.420000e+06	1.000000e+06	4.000000e+05
	50%	2.100000e+06	1.500000e+06	6.300000e+05
	75%	3.147500e+06	2.200000e+06	1.000000e+06
	max	1.250000e+07	1.250000e+07	5.600000e+06
classs	count	2.905000e+04	5.706300e+04	8.520300e+04
	mean	1.625886e+00	1.544574e+00	2.831191e+00
	std	6.937293e-01	5.252113e-01	3.751798e-01
	min	1.000000e+00	1.000000e+00	1.000000e+00
	25%	1.000000e+00	1.000000e+00	3.000000e+00
	50%	2.000000e+00	2.000000e+00	3.000000e+00
	75%	2.000000e+00	2.000000e+00	3.000000e+00
	max	3.000000e+00	3.000000e+00	3.000000e+00
tier	count	2.905000e+04	5.706300e+04	8.520300e+04
	mean	1.484200e+00	1.648774e+00	2.900731e+00
	std	6.478262e-01	5.742163e-01	3.010974e-01
	min	1.000000e+00	1.000000e+00	1.000000e+00
	25%	1.000000e+00	1.000000e+00	3.000000e+00
	50%	1.000000e+00	2.000000e+00	3.000000e+00
	75%	2.000000e+00	2.000000e+00	3.000000e+00
	max	3.000000e+00	3.000000e+00	3.000000e+00
years_of_experience_in_organization	count	2.905000e+04	5.706300e+04	8.520300e+04
	mean	1.520678e+01	6.557945e+00	6.541436e+00
	std	4.339403e+00	2.474935e+00	2.775220e+00
	min	6.000000e+00	1.000000e+00	1.000000e+00
	25%	1.200000e+01	5.000000e+00	4.000000e+00
	50%	1.400000e+01	7.000000e+00	6.000000e+00
	75%	1.700000e+01	8.000000e+00	8.000000e+00
	max	3.300000e+01	1.300000e+01	1.700000e+01

In [ ]:
```

```

5. Actionable Insights & Recommendations

- Maximum users have years of experience in the range of 3-10 years. Scaler can target the audience with experience 3 to 10 because mostly they were looking for a career change or upskilling.
- In data, email_hash are repeating data and should store one email_hash for the individual users.
- Maximum users have job_positions as other and backed_engineer, so scaler can target more on these 2 job_position.
- With company_hash we can see the high-paying companies for the different job roles so the scaler can target the audience or advertise with these data insights.
- In orgyear most of the years are invalid so the system should give an error if the user enters the wrong orgyear.
- Scaler should show insights about the updated ctc and use this as a marketing strategy to bring in more audience.