Business Case: Scaler - Clustering

About the Dataset

- We are provided with the information for a segment of learners by Scaler, an online tech-versity.
- Working as a data scientist with the analytics vertical of Scaler, we got this dataset from the Scaler database.

Column Profiling:

1. 'Unnamed 0'- Index of the dataset
2. Email_hash- Anonymised Personal Identifiable Information (PII)
3. Company_hash- Current employer of the learner
4. orgyear- Employment start date
5. CTC- Current CTC
6. Job_position- Job profile in the company
7. CTC_updated_year: Year in which CTC got updated (Yearly increments, Promotions)

Problem Statement:

- We are tasked to cluster them on the basis of their job profile, company, and other features. We are focused on profiling the best companies and job positions to work.

Analysing basic metrics

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
from scipy import stats
import re
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
#Loading of dataset
df = pd.read_csv("../scaler/scaler_clustering.csv")
df.head()
```

Out[2]:

	Unnamed: 0	company_hash	email_hash	orgye
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	201
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	201
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	201
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	201
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	201

In [3]:
```
df.shape #to observe shape of data
```

Out[3]: (205843, 7)

- Dataset is of 205843 rows and 7 attributes.

In [4]:
```
df.info() #to observe the data type
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205843 entries, 0 to 205842
Data columns (total 7 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   Unnamed: 0        205843 non-null  int64  
 1   company_hash      205799 non-null  object 
 2   email_hash        205843 non-null  object 
 3   orgyear           205757 non-null  float64
 4   ctc               205843 non-null  int64  
 5   job_position      153281 non-null  object 
 6   ctc_updated_year  205843 non-null  float64
dtypes: float64(2), int64(2), object(3)
memory usage: 11.0+ MB
```

Check for Duplicate Values

In [5]:
```
df.duplicated().sum()
```

Out[5]: 0

- There are no duplicate instances in the data

Check for Missing Values

In [6]:
```
# Check Missing Values
df.isna().sum()
```

Out[6]:
```
Unnamed: 0              0
company_hash           44
email_hash              0
orgyear                86
ctc                     0
job_position        52562
ctc_updated_year        0
dtype: int64
```

- Data contains null values in 3 columns company_hash, orgyear, job_position.

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

Out[7]:

	Unnamed: 0	orgyear	ctc	ctc_updated_year
count	205843.000000	205757.000000	2.058430e+05	205843.000000
mean	103273.941786	2014.882750	2.271685e+06	2019.628231
std	59741.306484	63.571115	1.180091e+07	1.325104
min	0.000000	0.000000	2.000000e+00	2015.000000
25%	51518.500000	2013.000000	5.300000e+05	2019.000000
50%	103151.000000	2016.000000	9.500000e+05	2020.000000
75%	154992.500000	2018.000000	1.700000e+06	2021.000000
max	206922.000000	20165.000000	1.000150e+09	2021.000000

In [8]:
```
df.describe(include="object")
```

Out[8]:

	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

Data Preprocessing

In [9]:
```
#Drop installment
df.drop(columns=['Unnamed: 0'], inplace=True)
```

In [10]:
```
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[10]: 'airtel x labs'

In [11]:
```
df["company_hash"].nunique()
```

Out[11]: 37299

In [12]:
```
df["company_hash"] = df["company_hash"].apply(lambda x: preprocess_string(str(x)
df["company_hash"].nunique()
```

Out[12]: 37208

In [13]:
```
df["job_position"].nunique()
```

Out[13]: 1017

- 1017 unique job positions are there in the dataset.

In [14]:
```
df["job_position"] = df["job_position"].apply(lambda x: preprocess_string(str(x)
df["job_position"].nunique()
```

Out[14]: 857

- 857 unique job positions are there in the dataset after preprocessing strings.

In [15]:
```
df.isna().sum()
```

Out[15]:
```
company_hash         0
email_hash           0
orgyear             86
ctc                  0
job_position         0
ctc_updated_year     0
dtype: int64
```

In [16]:
```
(df["company_hash"] == "").sum()
```

Out[16]: 89

In [17]:
```
(df["company_hash"] == "nan").sum()
```

Out[17]: 44

In [18]:
```
(df["job_position"] == "").sum()
```

Out[18]: 9

In [19]:
```
(df["job_position"] == "nan").sum()
```

Out[19]: 52562

In [20]:
```
# removing the records where company_hash or job_position reocords are not avail
df[(df["company_hash"] == "") | (df["job_position"] == "")].sample(10)
```

Out[20]:

	company_hash	email_hash	orgyear
86378		77a5cecd2ed9bb764df8bf6da78a0ae2aef97fc87e913e...	2020.0
187995		482bf44a26d01aa6e8313253f8956ea8cc2f2206be9307...	2019.0
4151		f52c1fc6d5ee4c35ac8c7db5a8a5e0190b743d5487e288...	2020.0
131273		df0652bad1b8a46bc63394e69e1b24d70ce092dc56243c...	2020.0
156277		df0652bad1b8a46bc63394e69e1b24d70ce092dc56243c...	2020.0
173726		6f5b3ae9ce591f3eafa4bfd89ce822ed80137601492621...	2018.0
161047	yaew mvzp	0911dcca341fb4a54a729d0a5bf3adcc467c1ac0cf3322...	2001.0
4162		4793af2ce1550cdfd2e9ce20e234b321c1c180d46fe7f7...	2013.0
40476		7da9646f60f7e3e272deb8404fe92dee33909455fd83ea...	2018.0
22720		811c78a507b093aa1c736def6996fc3132fac1ad7d4840...	2019.0

In [21]:

```python
len(df[(df["company_hash"] == "") | (df["job_position"] == "")])
```

Out[21]: 98

In [22]:

```python
df = df[~((df["company_hash"] == "") | (df["job_position"] == ""))]
df.head()
```

Out[22]:

	company_hash	email_hash	orgyear	ctc
0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000
1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999
2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015.0	2000000
3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	700000
4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017.0	1400000

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

In [23]:

```python
df.groupby("company_hash")["orgyear"].transform("median")
```

Out[23]:
```
0         2014.0
1         2016.0
2         2015.0
3         2016.0
4         2017.0
           ...
205838    2018.0
205839    2017.0
205840    2016.0
205841    2020.0
205842    2015.0
Name: orgyear, Length: 205745, dtype: float64
```

In [24]:
```
df["orgyear"].fillna(df['orgyear'].isnull().sum(),inplace=True)
```

In [25]:
```
df["orgyear"].isna().sum()
```

Out[25]:
```
0
```

Non-Graphical Analysis

In [26]:
```
# unique value company_hash column(listed in %)
company_hash = df['company_hash'].value_counts(normalize=True).map(lambda calc:
company_hash.columns = ['company_hash', 'Count']
company_hash.head(10)
```

Out[26]:

	company_hash	Count
0	nvnv wgzohrnvzwj otqcxwto	4.05
1	xzegojo	2.62
2	vbvkgz	1.69
3	zgn vuurxwvmrt vwwghzn	1.66
4	wgszxkvzn	1.57
5	vwwtznhqt	1.39
6	fxuqg rxbxnta	1.29
7	gqvwrt	1.22
8	bxwqgogen	1.04
9	wvustbxzx	0.99

In [27]:
```
# unique value orgyear column(listed in %)
orgyear = df['orgyear'].value_counts(normalize=True).map(lambda calc: round(100*
orgyear.columns = ['orgyear', 'Count']
orgyear.head(10)
```

Out[27]:

	orgyear	Count
0	2018.0	12.27
1	2019.0	11.37
2	2017.0	11.29
3	2016.0	11.20
4	2015.0	10.01
5	2014.0	8.11
6	2020.0	6.52
7	2013.0	6.00
8	2012.0	5.10
9	2011.0	3.87

In [28]:

```
# unique value job_position column(listed in %)
job_position = df['job_position'].value_counts(normalize=True).map(lambda calc:
job_position.columns = ['job_position', 'Count']
job_position.head(10)
```

Out[28]:

	job_position	Count
0	nan	25.53
1	backend engineer	21.16
2	fullstack engineer	12.62
3	other	8.78
4	frontend engineer	5.06
5	engineering leadership	3.34
6	qa engineer	3.20
7	data scientist	2.61
8	android engineer	2.60
9	sdet	2.42

In [29]:

```
# unique value ctc_updated_year column(listed in %)
ctc_updated_year = df['ctc_updated_year'].value_counts(normalize=True).map(lambd
ctc_updated_year.columns = ['ctc_updated_year', 'Count']
ctc_updated_year.head(10)
```

Out[29]:

	ctc_updated_year	Count
0	2019.0	33.37
1	2021.0	31.57
2	2020.0	24.02
3	2017.0	3.67
4	2018.0	3.28
5	2016.0	2.67
6	2015.0	1.42

In [30]:

```
# Number of unique values in all columns
unique_num = ['company_hash','email_hash','orgyear','ctc','job_position','ctc_up
for col in unique_num:
  print(f"No. of unique values in {col}: {df[col].nunique()}")
```

```
No. of unique values in company_hash: 37205
No. of unique values in email_hash: 153381
No. of unique values in orgyear: 78
No. of unique values in ctc: 3360
No. of unique values in job_position: 856
No. of unique values in ctc_updated_year: 7
```

In [31]:

```
df.describe().loc[['min', 'max']]
```

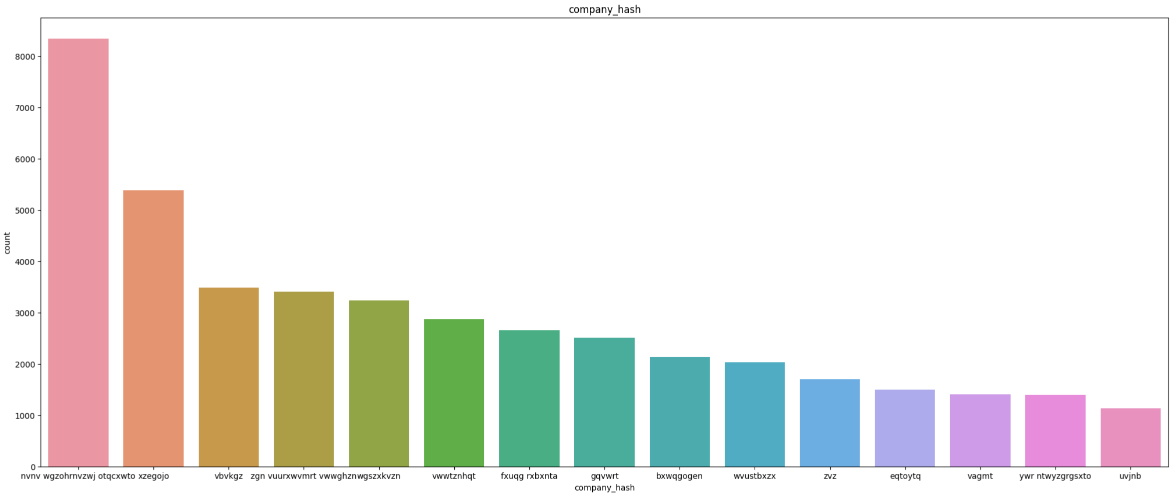
Out[31]:

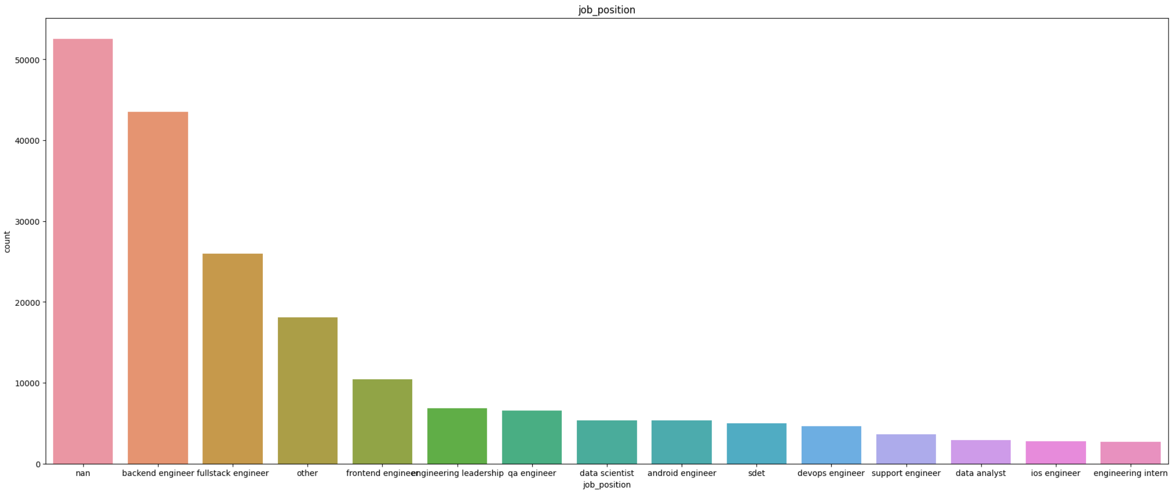
	orgyear	ctc	ctc_updated_year
min	0.0	2.000000e+00	2015.0
max	20165.0	1.000150e+09	2021.0

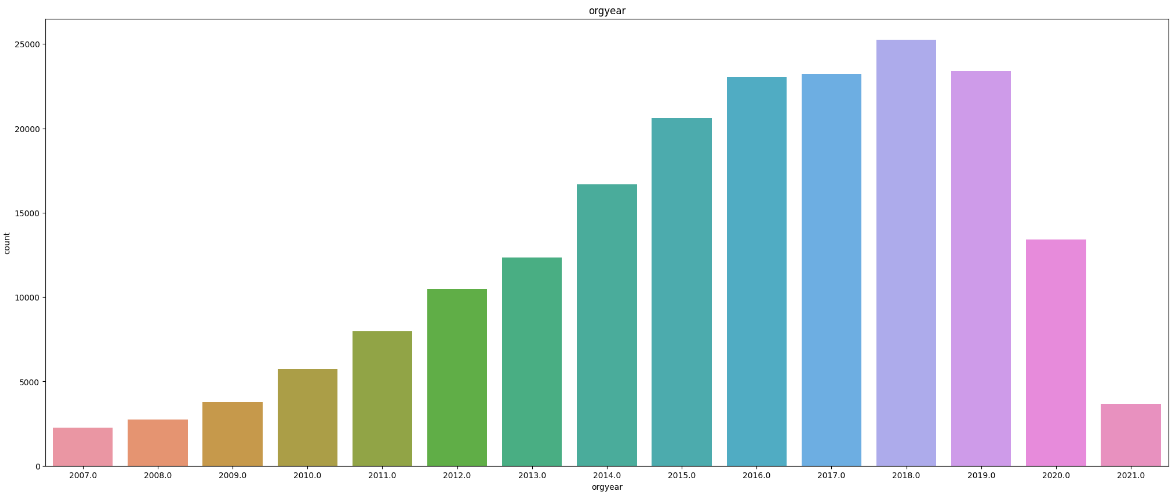
Univariate Analysis

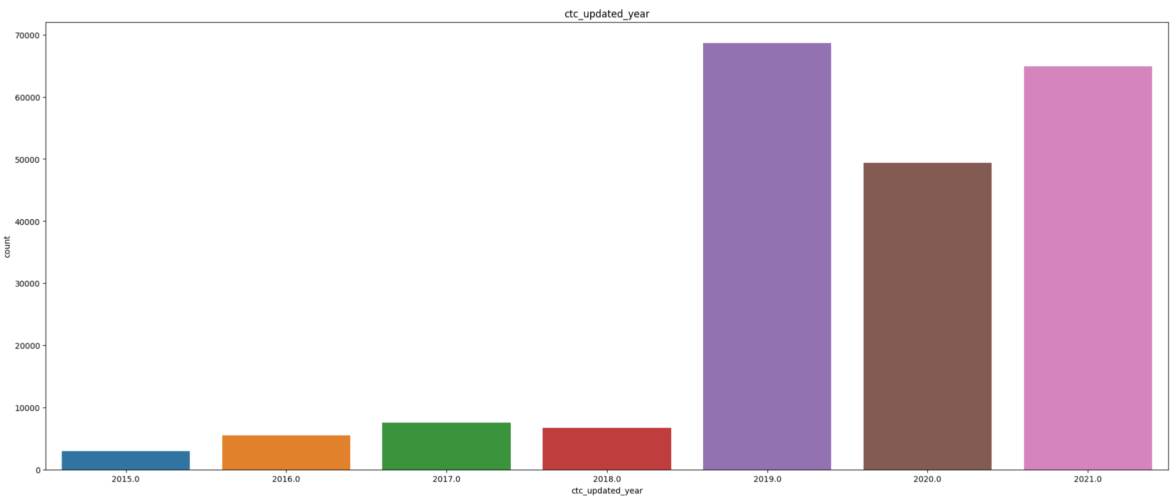
In [32]:

```
plot = ['company_hash','job_position','orgyear','ctc_updated_year']
for i in plot:
    tmp = df.copy()
    tmp['count'] = 1
    tmp = tmp.groupby(i).sum()['count'].reset_index().sort_values('count',ascend
    plt.figure(figsize=(25,10))
    sns.barplot(data=tmp,y='count',x=i).set(title=i)
    plt.show()
```


company_hash
count
8000
7000
6000
5000
4000
3000
2000
1000
0
nvnv wgzohrnvzwj otqcxwto xzegojo
vbvkgz
zgn vuurxwvmrt vwwghznwgszxkvzn
vwwtznhqt
fxuqg rxbxnta
gqvwrt
bxwqgogen
wvustbxzx
zvz
eqtoytq
vagmt
ywr ntwyzgrgsxto
uvjnb
company_hash

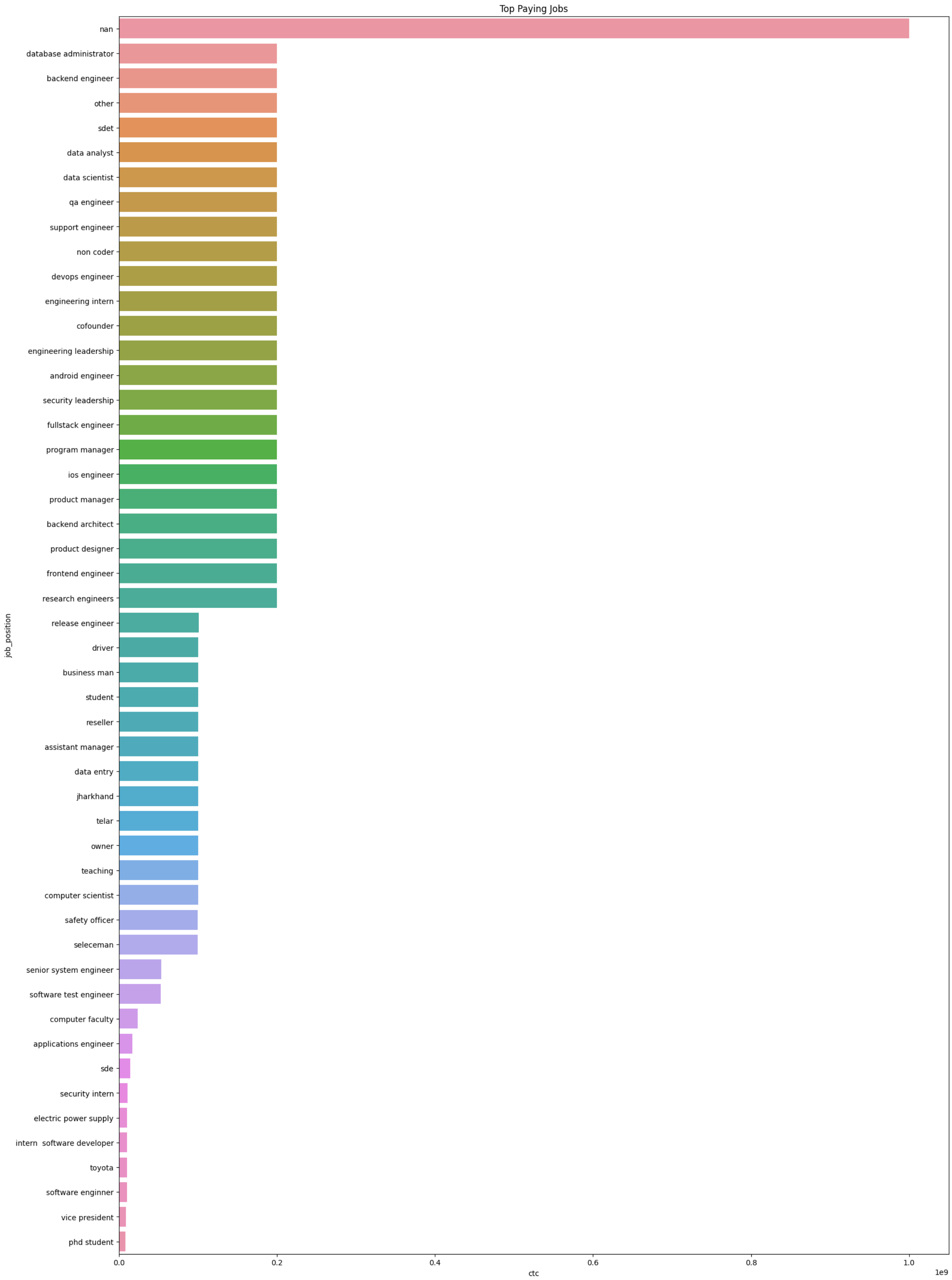

job_position
count
50000
40000
30000
20000
10000
0
nan
backend engineer
fullstack engineer
other
frontend engineer
engineering leadership
qa engineer
data scientist
android engineer
sdet
devops engineer
support engineer
data analyst
ios engineer
engineering intern
job_position


orgyear
count
25000
20000
15000
10000
5000
0
2007.0
2008.0
2009.0
2010.0
2011.0
2012.0
2013.0
2014.0
2015.0
2016.0
2017.0
2018.0
2019.0
2020.0
2021.0
orgyear


ctc_updated_year
count
70000
60000
50000
40000
30000
20000
10000
0
2015.0
2016.0
2017.0
2018.0
2019.0
2020.0
2021.0
ctc_updated_year

Bivariate Analysis & Multivariate Analysis

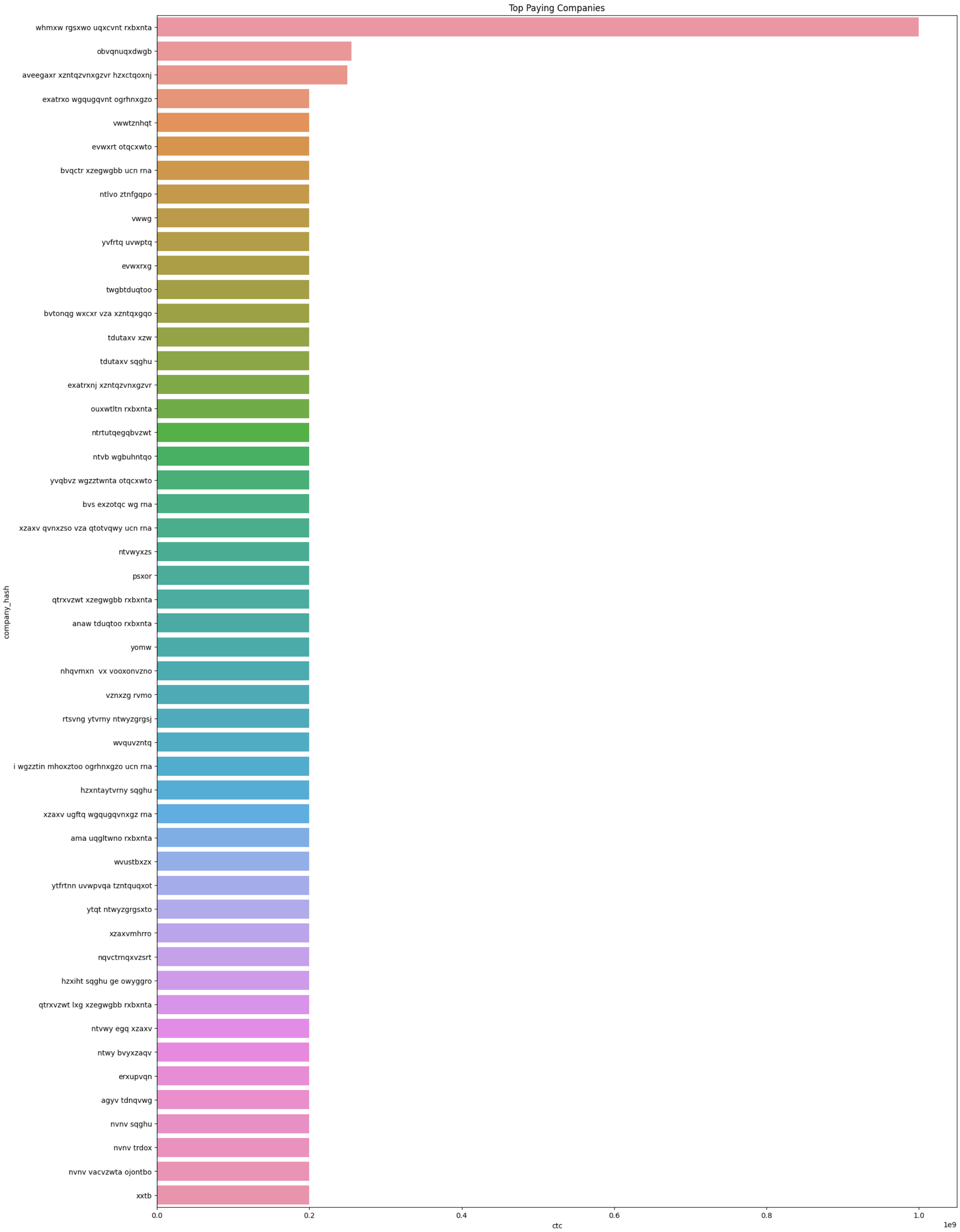
In [33]:
```
tmp = df.copy()
tmp = tmp.groupby(['job_position']).max()['ctc'].reset_index().sort_values('ctc'
plt.figure(figsize=(20,30))
sns.barplot(data=tmp,x='ctc',y='job_position').set(title="Top Paying Jobs")
plt.show()
```



In [34]:
```
list(tmp['job_position'])
```

Out[34]:
```
['nan',
 'database administrator',
 'backend engineer',
 'other',
 'sdet',
 'data analyst',
 'data scientist',
 'qa engineer',
 'support engineer',
 'non coder',
 'devops engineer',
 'engineering intern',
 'cofounder',
 'engineering leadership',
 'android engineer',
 'security leadership',
 'fullstack engineer',
 'program manager',
 'ios engineer',
 'product manager',
 'backend architect',
 'product designer',
 'frontend engineer',
 'research engineers',
 'release engineer',
 'driver',
 'business man',
 'student',
 'reseller',
 'assistant manager',
 'data entry',
 'jharkhand',
 'telar',
 'owner',
 'teaching',
 'computer scientist',
 'safety officer',
 'seleceman',
 'senior system engineer',
 'software test engineer',
 'computer faculty',
 'applications engineer',
 'sde',
 'security intern',
 'electric power supply',
 'intern  software developer',
 'toyota',
 'software enginner',
 'vice president',
 'phd student']
```

In [35]:
```
tmp = df.copy()
tmp = tmp.groupby(['company_hash']).max()['ctc'].reset_index().sort_values('ctc'
plt.figure(figsize=(20,30))
sns.barplot(data=tmp,x='ctc',y='company_hash').set(title="Top Paying Companies")
plt.show()
```



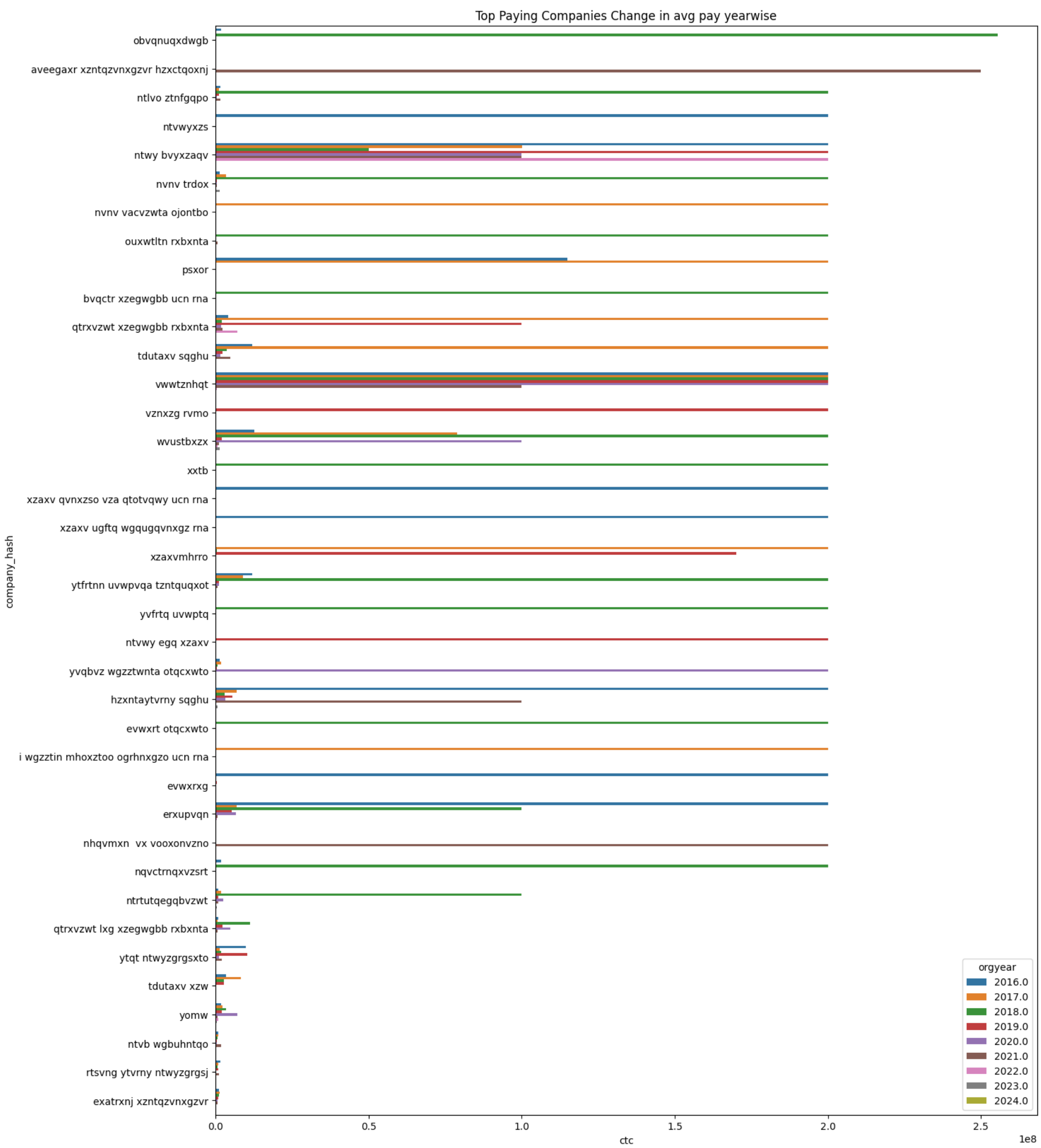
In [36]:

```
list(tmp['company_hash'])
```

Out[36]:
```
['whmxw rgsxwo uqxcvnt rxbxnta',
 'obvqnuqxdwgb',
 'aveegaxr xzntqzvnxgzvr hzxctqoxnj',
 'exatrxo wgqugqvnt ogrhnxgzo',
 'vwwtznhqt',
 'evwxrt otqcxwto',
 'bvqctr xzegwgbb ucn rna',
 'ntlvo ztnfgqpo',
 'vwwg',
 'yvfrtq uvwptq',
 'evwxrxg',
 'twgbtduqtoo',
 'bvtonqg wxcxr vza xzntqxgqo',
 'tdutaxv xzw',
 'tdutaxv sqghu',
 'exatrxnj xzntqzvnxgzvr',
 'ouxwtltn rxbxnta',
 'ntrtutqegqbvzwt',
 'ntvb wgbuhntqo',
 'yvqbvz wgzztwnta otqcxwto',
 'bvs exzotqc wg rna',
 'xzaxv qvnxzso vza qtotvqwy ucn rna',
 'ntvwyxzs',
 'psxor',
 'qtrxvzwt xzegwgbb rxbxnta',
 'anaw tduqtoo rxbxnta',
 'yomw',
 'nhqvmxn  vx vooxonvzno',
 'vznxzg rvmo',
 'rtsvng ytvrny ntwyzgrgsj',
 'wvquvzntq',
 'i wgzztin mhoxztoo ogrhnxgzo ucn rna',
 'hzxntaytvrny sqghu',
 'xzaxv ugftq wgqugqvnxgz rna',
 'ama uqgltwno rxbxnta',
 'wvustbxzx',
 'ytfrtnn uvwpvqa tzntquqxot',
 'ytqt ntwyzgrgsxto',
 'xzaxvmhrro',
 'nqvctrnqxvzsrt',
 'hzxiht sqghu ge owyggro',
 'qtrxvzwt lxg xzegwgbb rxbxnta',
 'ntvwy egq xzaxv',
 'ntwy bvyxzaqv',
 'erxupvqn',
 'agyv tdnqvwg',
 'nvnv sqghu',
 'nvnv trdox',
 'nvnv vacvzwta ojontbo',
 'xxtb']
```

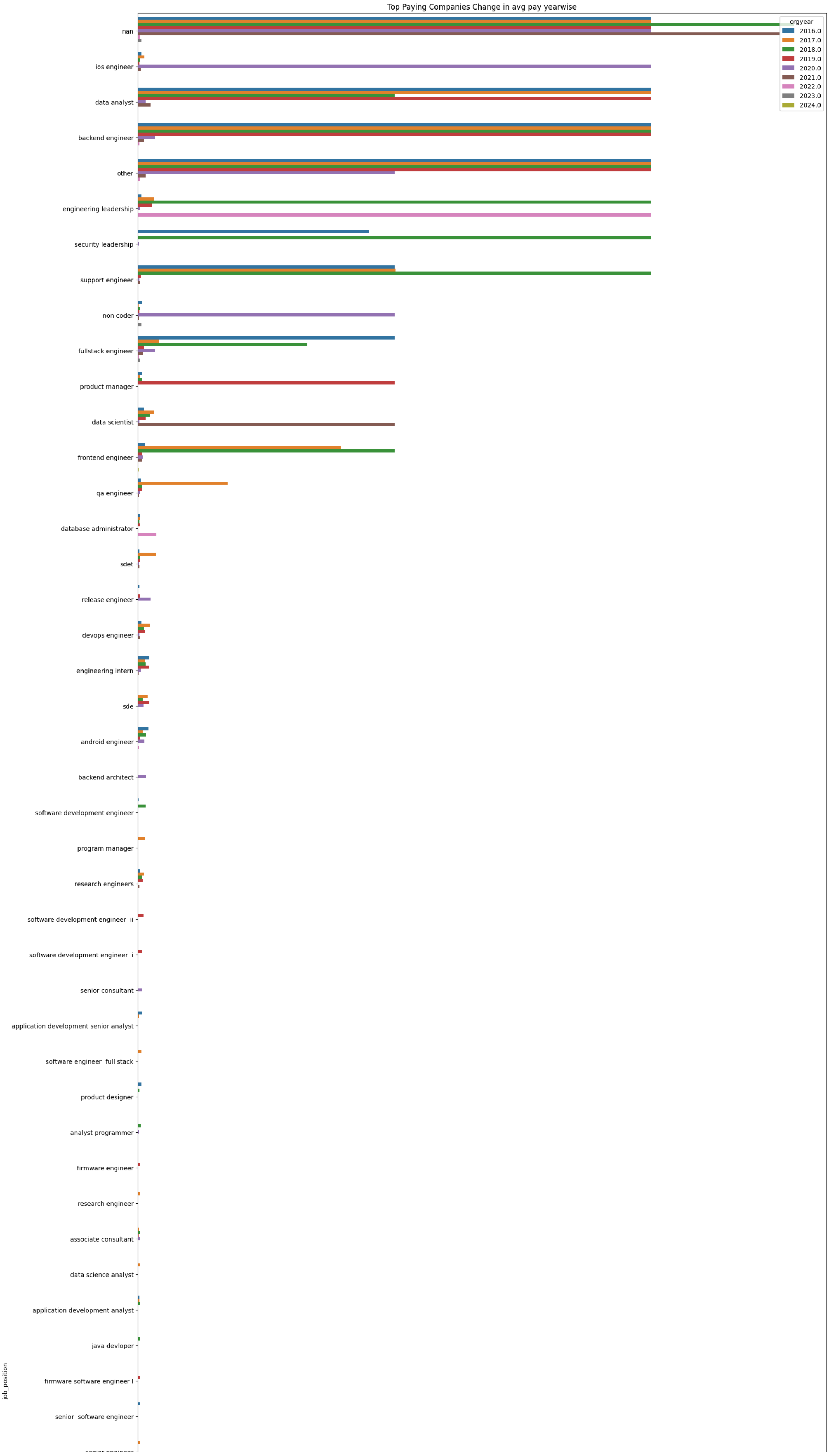
In [37]:
```
tmp = df.copy()
tmp = tmp[tmp['company_hash'].isin(['whmxw rgsxwo uqxcvnt rxbxnta',
 'obvqnuqxdwgb',
 'aveegaxr xzntqzvnxgzvr hzxctqoxnj',
 'exatrxo wgqugqvnt ogrhnxgzo',
 'vwwtznhqt',
 'evwxrt otqcxwto',
 'bvqctr xzegwgbb ucn rna',
 'ntlvo ztnfgqpo',
```

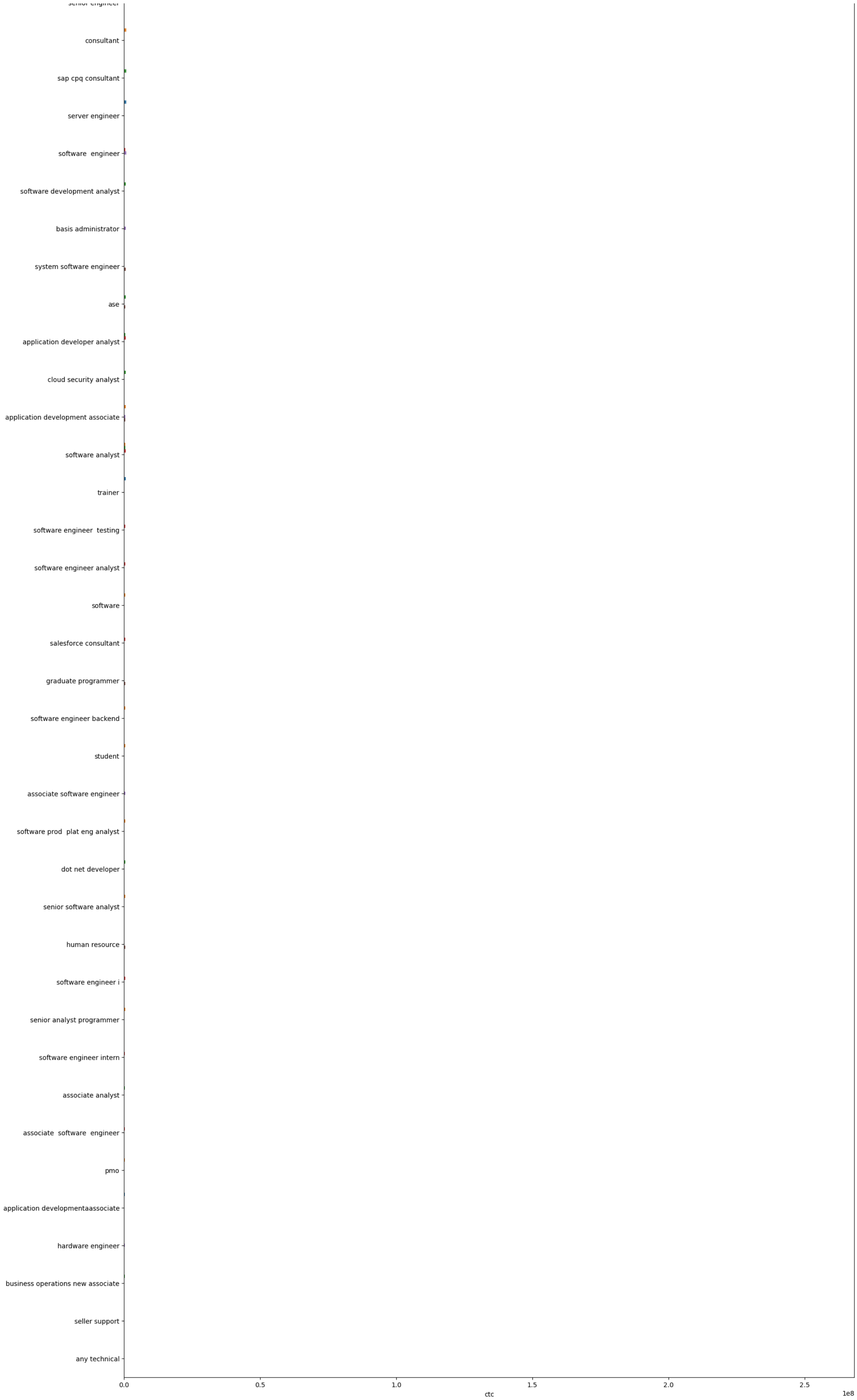
```
 'vwwg',
 'yvfrtq uvwptq',
 'evwxrxg',
 'twgbtduqtoo',
 'bvtonqg wxcxr vza xzntqxgqo',
 'tdutaxv xzw',
 'tdutaxv sqghu',
 'exatrxnj xzntqzvnxgzvr',
 'ouxwtltn rxbxnta',
 'ntrtutqegqbvzwt',
 'ntvb wgbuhntqo',
 'yvqbvz wgzztwnta otqcxwto',
 'bvs exzotqc wg rna',
 'xzaxv qvnxzso vza qtotvqwy ucn rna',
 'ntvwyxzs',
 'psxor',
 'qtrxvzwt xzegwgbb rxbxnta',
 'anaw tduqtoo rxbxnta',
 'yomw',
 'nhqvmxn  vx vooxonvzno',
 'vznxzg rvmo',
 'rtsvng ytvrny ntwyzgrgsj',
 'wvquvzntq',
 'i wgzztin mhoxztoo ogrhnxgzo ucn rna',
 'hzxntaytvrny sqghu',
 'xzaxv ugftq wgqugqvnxgz rna',
 'ama uqgltwno rxbxnta',
 'wvustbxzx',
 'ytfrtnn uvwpvqa tzntquqxot',
 'ytqt ntwyzgrgsxto',
 'xzaxvmhrro',
 'nqvctrnqxvzsrt',
 'hzxiht sqghu ge owyggro',
 'qtrxvzwt lxg xzegwgbb rxbxnta',
 'ntvwy egq xzaxv',
 'ntwy bvyxzaqv',
 'erxupvqn',
 'agyv tdnqvwg',
 'nvnv sqghu',
 'nvnv trdox',
 'nvnv vacvzwta ojontbo',
 'xxtb'])]
tmp = tmp[tmp['orgyear'] >= 2016]
tmp = tmp.groupby(['company_hash','orgyear']).max()['ctc'].reset_index().sort_va
plt.figure(figsize=(15,20))
sns.barplot(data=tmp,x='ctc',y='company_hash',hue='orgyear').set(title="Top Payi
plt.show()
```



In [38]:
```
tmp = df.copy()
tmp = tmp[tmp['company_hash'].isin(['whmxw rgsxwo uqxcvnt rxbxnta',
 'obvqnuqxdwgb',
 'aveegaxr xzntqzvnxgzvr hzxctqoxnj',
 'exatrxo wgqugqvnt ogrhnxgzo',
 'vwwtznhqt',
 'evwxrt otqcxwto',
 'bvqctr xzegwgbb ucn rna',
 'ntlvo ztnfgqpo',
 'vwwg',
 'yvfrtq uvwptq',
 'evwxrxg',
 'twgbtduqtoo',
 'bvtonqg wxcxr vza xzntqxgqo',
 'tdutaxv xzw',
 'tdutaxv sqghu',
 'exatrxnj xzntqzvnxgzvr',
 'ouxwtltn rxbxnta',
 'ntrtutqegqbvzwt',
 'ntvb wgbuhntqo',
 'yvqbvz wgzztwnta otqcxwto',
```

```python
 'bvs exzotqc wg rna',
 'xzaxv qvnxzso vza qtotvqwy ucn rna',
 'ntvwyxzs',
 'psxor',
 'qtrxvzwt xzegwgbb rxbxnta',
 'anaw tduqtoo rxbxnta',
 'yomw',
 'nhqvmxn  vx vooxonvzno',
 'vznxzg rvmo',
 'rtsvng ytvrny ntwyzgrgsj',
 'wvquvzntq',
 'i wgzztin mhoxztoo ogrhnxgzo ucn rna',
 'hzxntaytvrny sqghu',
 'xzaxv ugftq wgqugqvnxgz rna',
 'ama uqgltwno rxbxnta',
 'wvustbxzx',
 'ytfrtnn uvwpvqa tzntquqxot',
 'ytqt ntwyzgrgsxto',
 'xzaxvmhrro',
 'nqvctrnqxvzsrt',
 'hzxiht sqghu ge owyggro',
 'qtrxvzwt lxg xzegwgbb rxbxnta',
 'ntvwy egq xzaxv',
 'ntwy bvyxzaqv',
 'erxupvqn',
 'agyv tdnqvwg',
 'nvnv sqghu',
 'nvnv trdox',
 'nvnv vacvzwta ojontbo',
 'xxtb'])]
tmp = tmp[tmp['orgyear'] >= 2016]
tmp = tmp.groupby(['job_position','orgyear']).max()['ctc'].reset_index().sort_va
plt.figure(figsize=(20,80))
sns.barplot(data=tmp,x='ctc',y='job_position',hue='orgyear').set(title="Top Payi
plt.show()
```

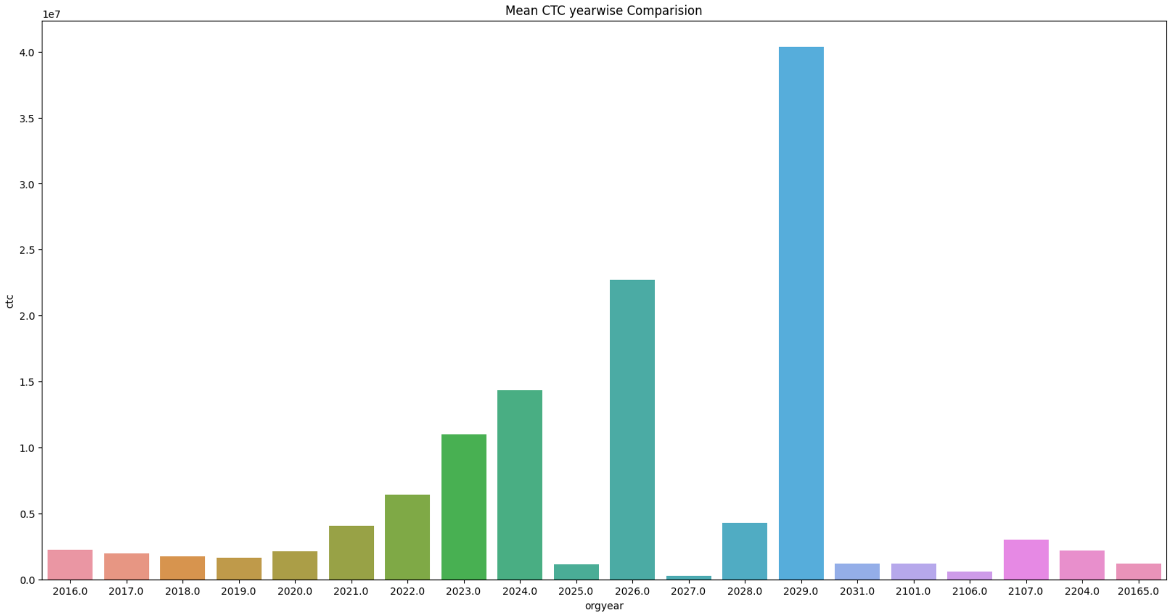

Top Paying Companies Change in avg pay yearwise
orgyear
2016.0
2017.0
2018.0
2019.0
2020.0
2021.0
2022.0
2023.0
2024.0
job_position
nan
ios engineer
data analyst
backend engineer
other
engineering leadership
security leadership
support engineer
non coder
fullstack engineer
product manager
data scientist
frontend engineer
qa engineer
database administrator
sdet
release engineer
devops engineer
engineering intern
sde
android engineer
backend architect
software development engineer
program manager
research engineers
software development engineer ii
software development engineer i
senior consultant
application development senior analyst
software engineer full stack
product designer
analyst programmer
firmware engineer
research engineer
associate consultant
data science analyst
application development analyst
java devloper
firmware software engineer l
senior software engineer



In [39]:

```
tmp = df.copy()
tmp = tmp[tmp['orgyear'] >= 2016]
tmp = tmp.groupby(['orgyear']).mean()['ctc'].reset_index().sort_values('ctc',asc
plt.figure(figsize=(20,10))
```

```
sns.barplot(data=tmp,y='ctc',x='orgyear').set(title="Mean CTC yearwise Comparisi
plt.show()
```



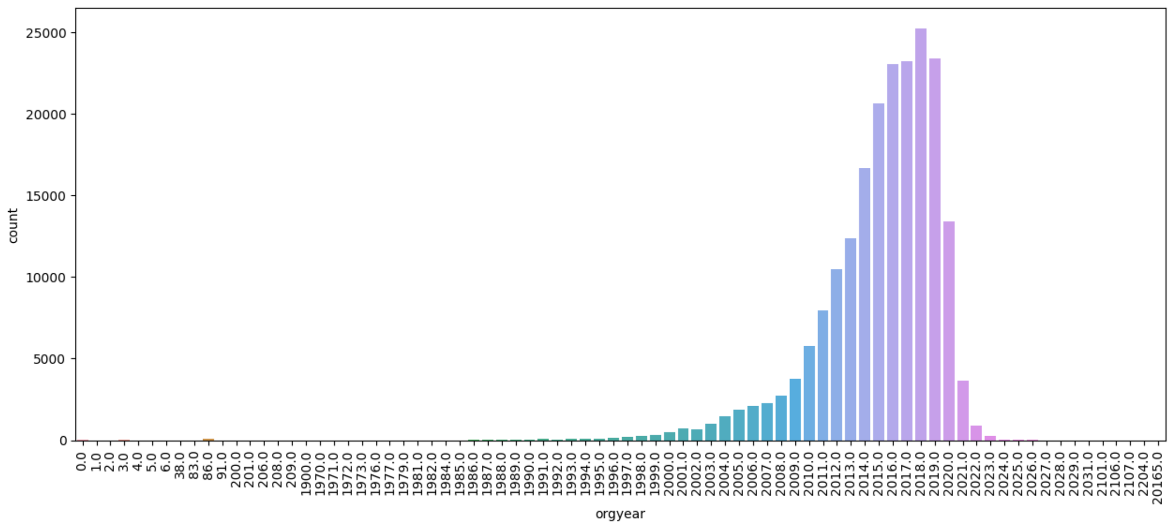
Outlier Treatment

Orgyear

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 [41]:
```
plt.figure(figsize=(15,6))
sns.countplot(x=df['orgyear'])
plt.xticks(rotation = 90)
plt.show()
```



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

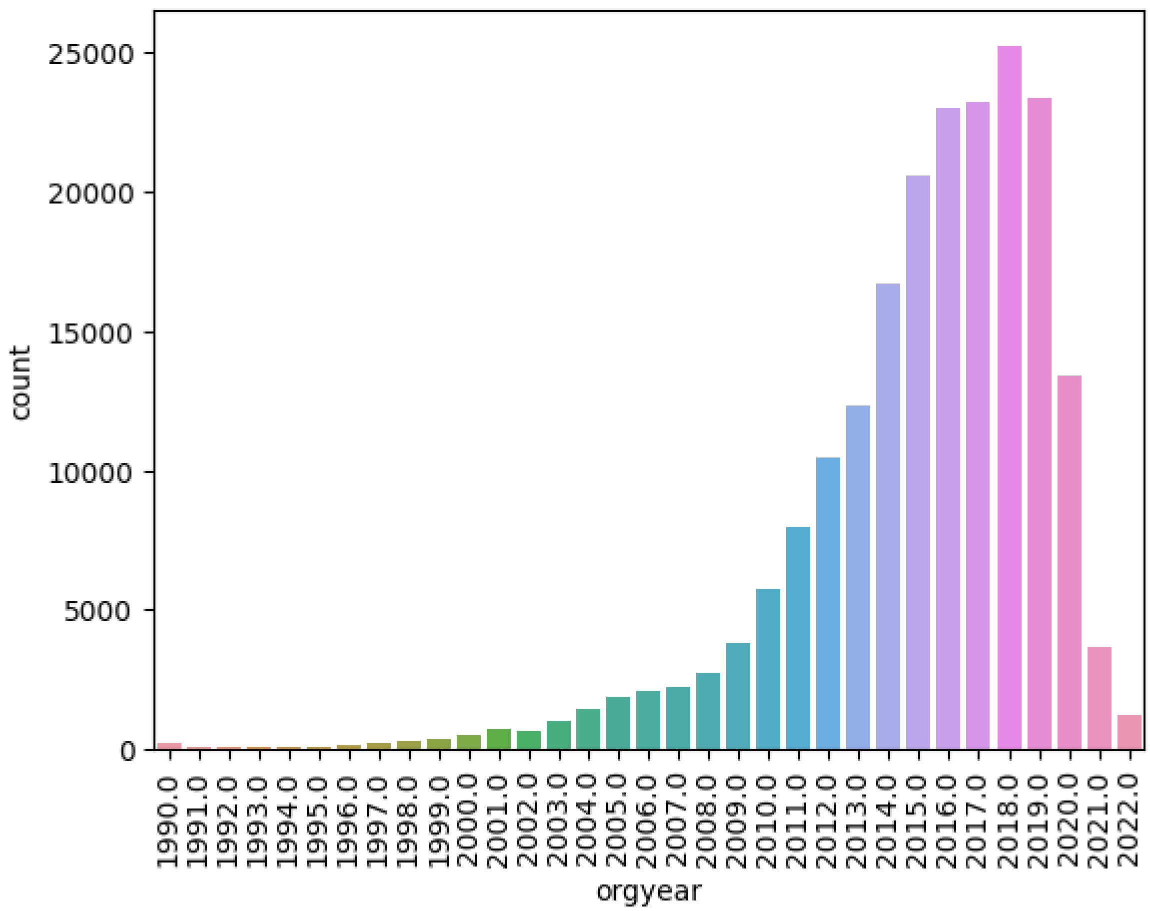
```
Out[42]: 1990.0
```

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

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

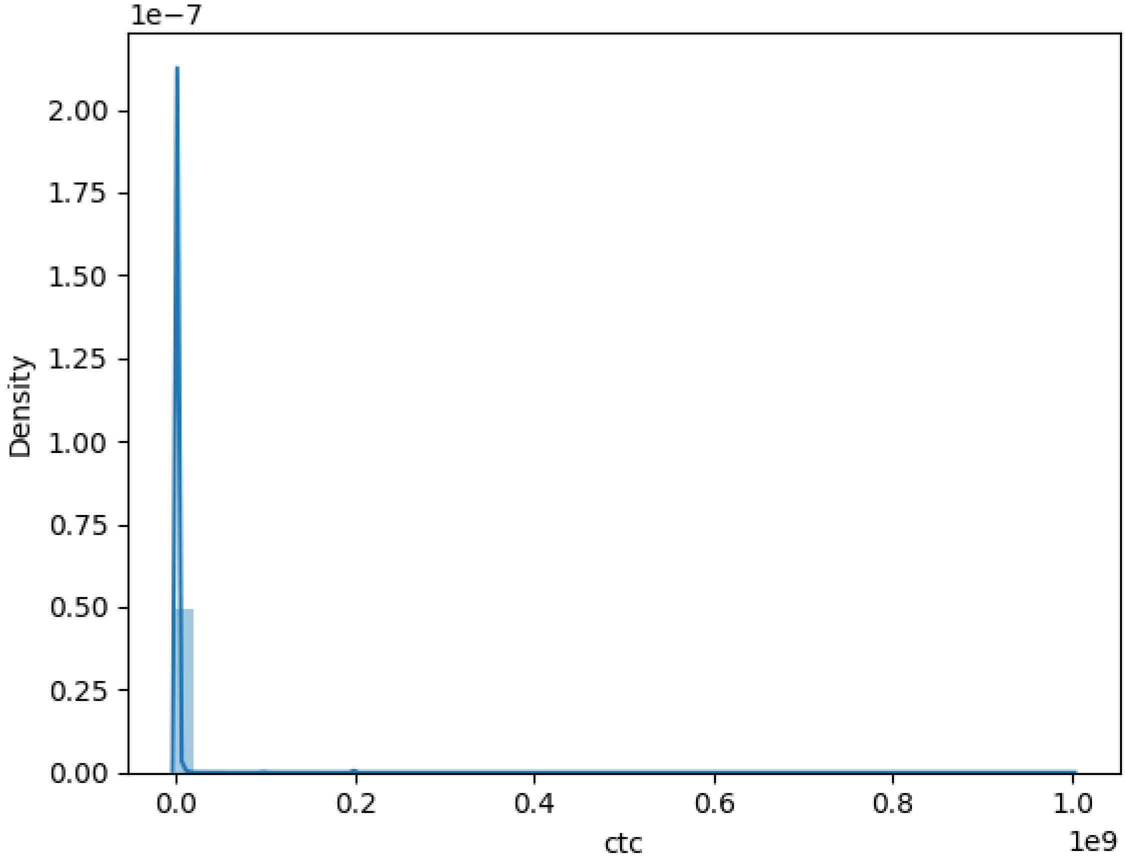
```
In [44]: df["orgyear"] = df["orgyear"].clip(1990,2022)
```

```
In [45]: sns.countplot(x=df['orgyear'])
         plt.xticks(rotation = 90)
         plt.show()
```

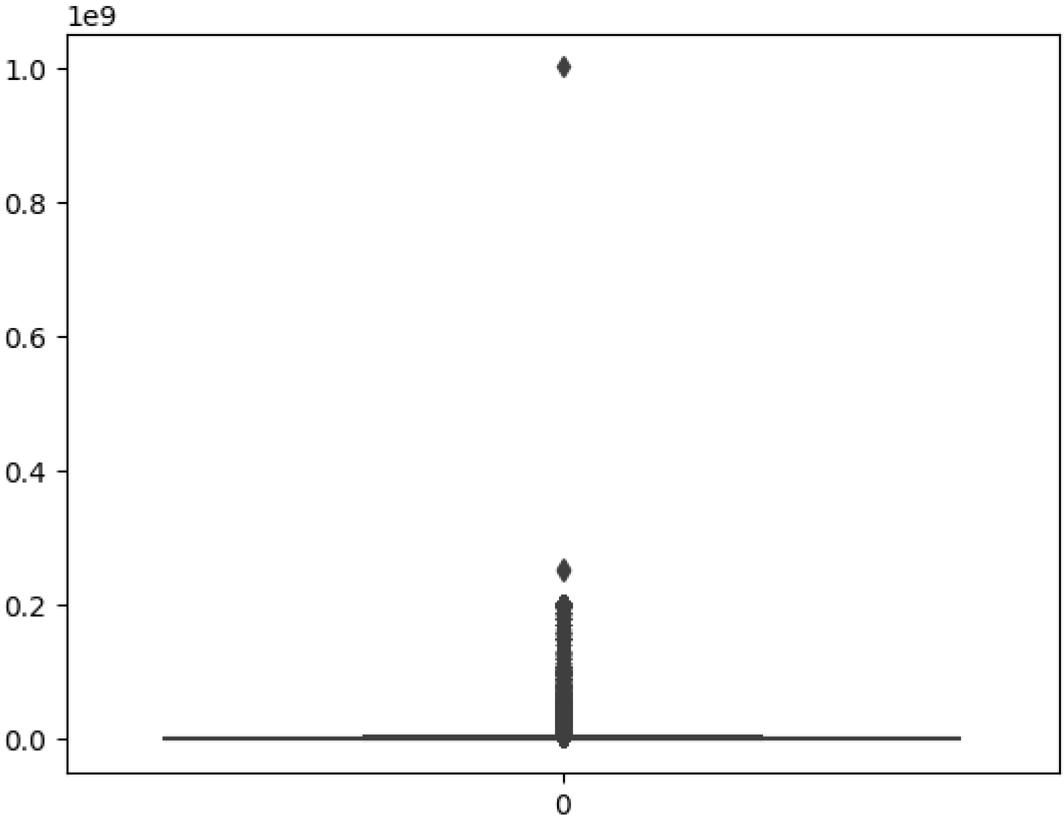


CTC

In [46]:
```
sns.distplot(df["ctc"])
plt.show()
```



In [47]:
```
sns.boxplot(df["ctc"])
plt.show()
```



In [48]:
```
df["ctc"].quantile(0.01)
```
Out[48]: 37000.0

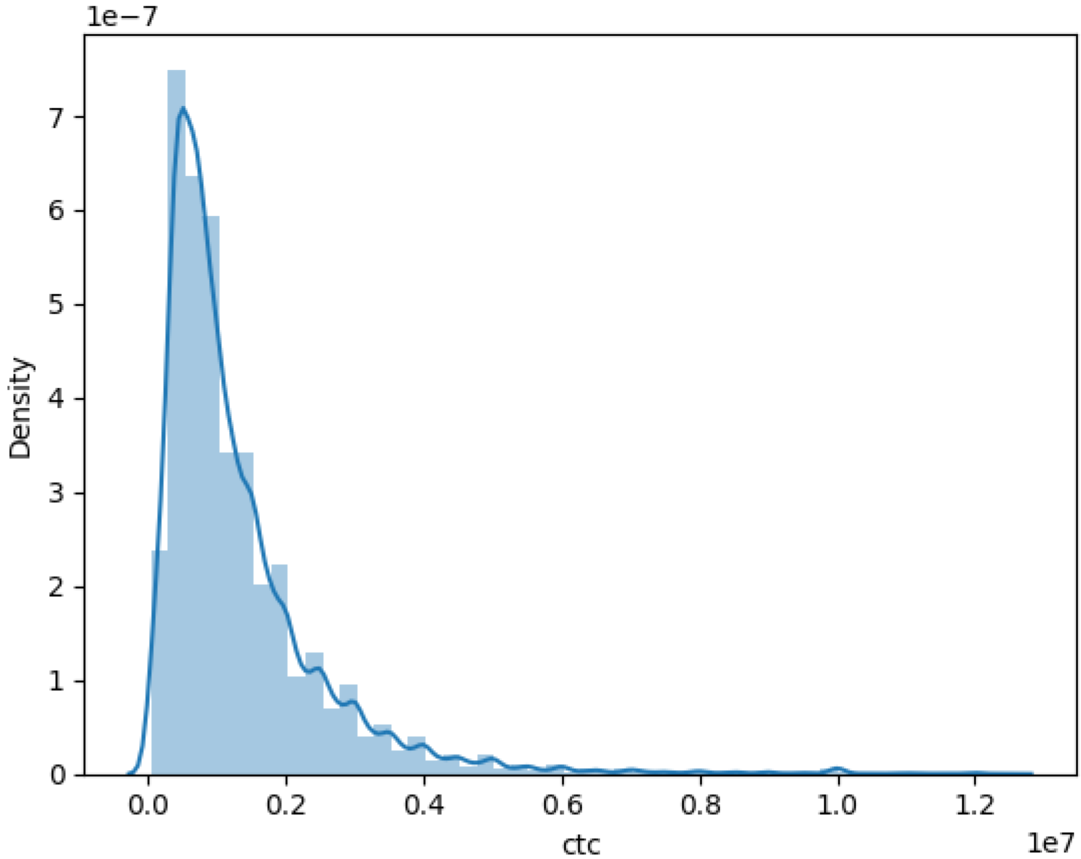
In [49]:
```
df["ctc"].quantile(0.999)
```
Out[49]: 200000000.0

In [50]:
```
df = df.loc[((df.ctc) > df.ctc.quantile(0.01)) & ((df.ctc) < df.ctc.quantile(0.9
```

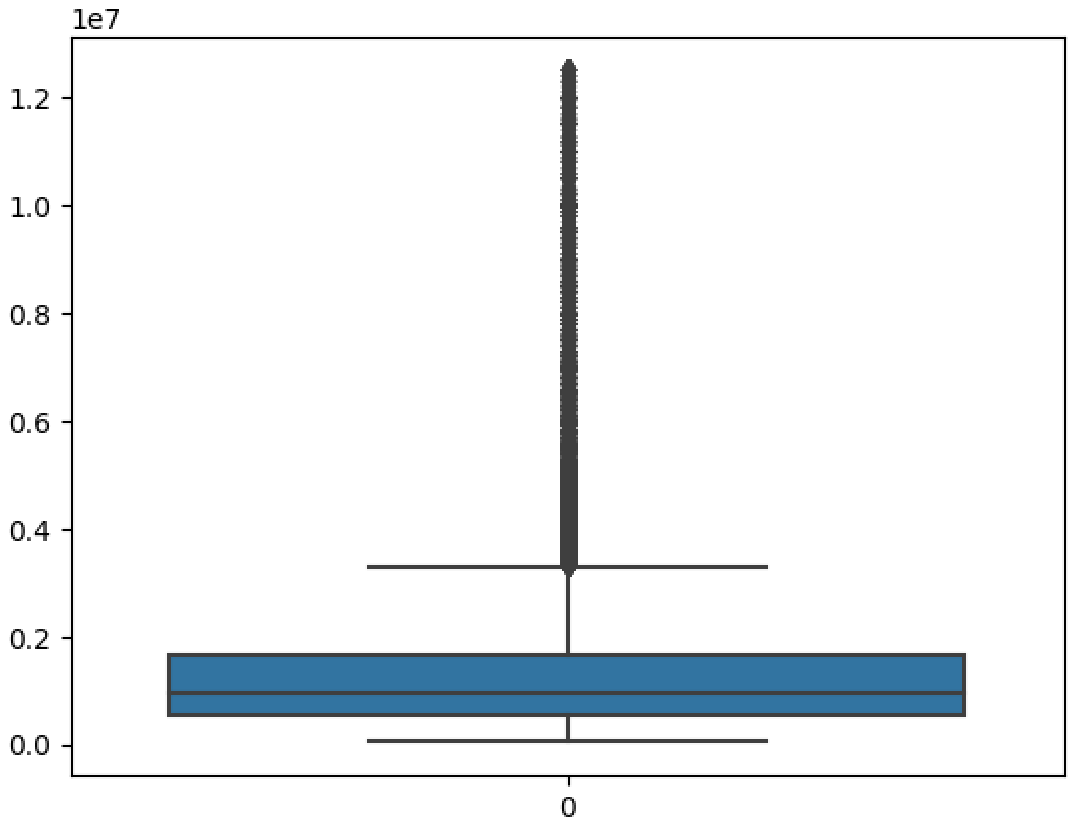
In [51]:
```
df.head()
```
Out[51]:

	company_hash	email_hash	orgyear	ctc
0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000
1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999
2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015.0	2000000
3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	700000
4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017.0	1400000

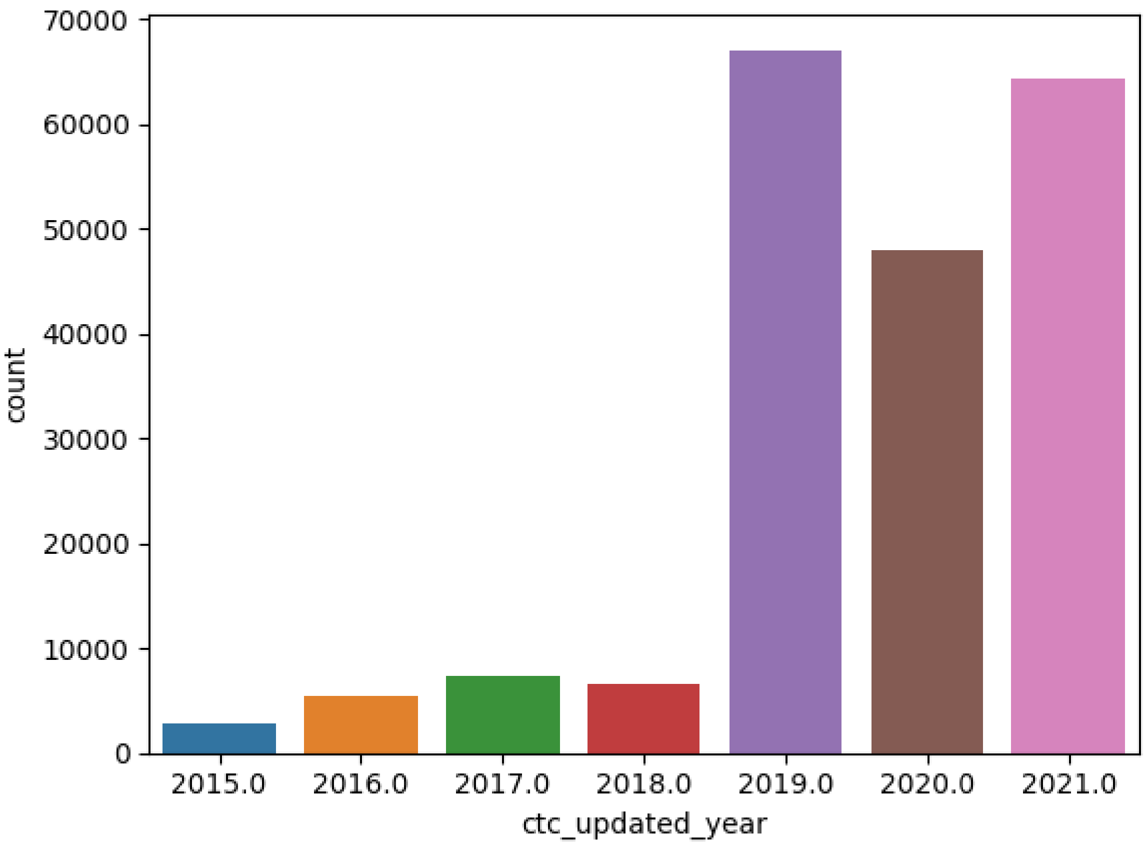
In [52]:
```
sns.distplot(df["ctc"])
plt.show()
```



In [53]:
```
sns.boxplot(df["ctc"])
plt.show()
```



ctc updated_year

In [54]:
```
df["ctc_updated_year"].quantile(0.001)
```
Out[54]:
```
2015.0
```
In [55]:
```
df["ctc_updated_year"].quantile(0.99)
```
Out[55]:
```
2021.0
```
In [56]:
```
sns.countplot(x=df['ctc_updated_year'])
plt.show()
```


In [57]:
```
df.loc[df['job_position']=='nan', 'job_position']=np.nan
```
In [58]:
```
df.loc[df["company_hash"]=="nan","company_hash"] = np.nan
```

Feature Engineering

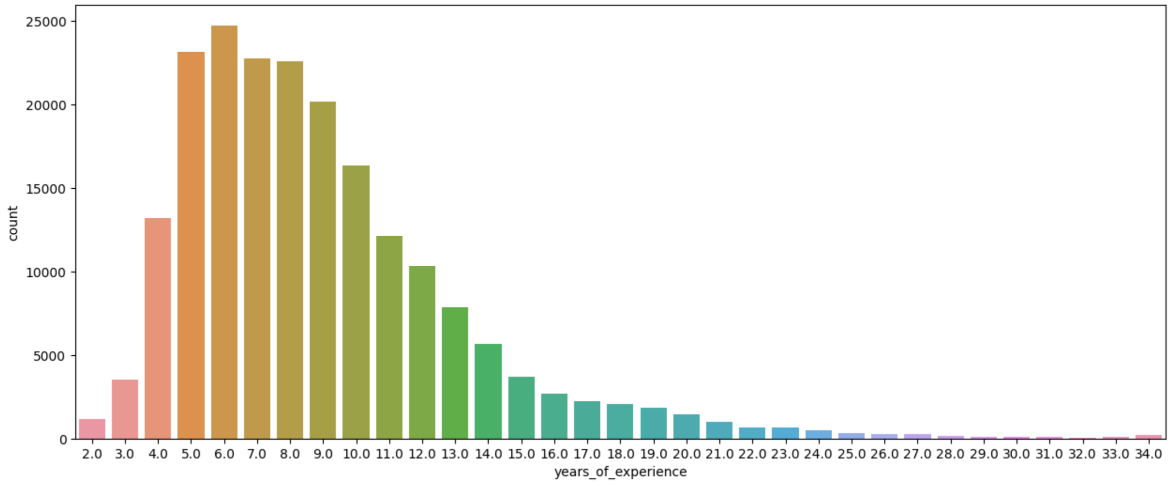
Masked company name to "Others" having count less than 5

In [59]:
```
df.loc[df.groupby("company_hash")["ctc"].transform("count") < 5,"company_hash"]
```
In [60]:
```
(df["company_hash"] == "Others").sum()
```
Out[60]:
```
46434
```
In [61]:
```
df['orgyear'].describe()
```

Out[61]:
```
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
```

In [62]:
```
# years of experience = current year - employement start year
df["years_of_experience"] = 2024 - df["orgyear"]
```

In [63]:
```
plt.figure(figsize=(15,6))
sns.countplot(x=df['years_of_experience'])
plt.show()
```



In [64]:
```
df.duplicated().sum()
```

Out[64]: 212

In [65]:
```
df.drop_duplicates(inplace=True)
```

In [66]:
```
df.isna().sum()
```

Out[66]:
```
company_hash              42
email_hash                 0
orgyear                    0
ctc                        0
job_position           51671
ctc_updated_year           0
years_of_experience        0
dtype: int64
```

In [67]:
```
# records having ctc_updated_year higher than their organization joining year
(df["ctc_updated_year"] < df["orgyear"]).sum()
```

Out[67]: 8465

In [68]:
```
df.ctc_updated_year = df[["ctc_updated_year","orgyear"]].max(axis = 1)
```

In [69]:
```
(df["ctc_updated_year"] < df["orgyear"]).sum()
```

Out[69]: 0

In [70]:
```
df.sample(2)
```

Out[70]:

	company_hash	email_hash	orgyear
11711	Others	feed3529e8360ae24b721dec3eac9124b104886d36b722...	2018.0
109030	ovbohzs qa xzonxnhnt xzaxv atryx	fc1ffb7be86e45f41c95b140b066e2a639ac54d10cf096...	2018.0

In [71]:
```
# Filling null values with others -- if not done before
df['job_position'] = df['job_position'].fillna('Others')
df['company_hash'] = df['company_hash'].fillna('Others')
```

In [72]:
```
df.isna().sum()
```

Out[72]:
```
company_hash          0
email_hash            0
orgyear               0
ctc                   0
job_position          0
ctc_updated_year      0
years_of_experience   0
dtype: int64
```

In [73]:
```
df.duplicated().sum()
```

Out[73]: 103

In [74]:
```
df.describe()
```

Out[74]:

	orgyear	ctc	ctc_updated_year	years_of_experience
count	201413.000000	2.014130e+05	201413.000000	201413.000000
mean	2015.103722	1.313212e+06	2019.687314	8.896278
std	4.257499	1.234111e+06	1.287119	4.257499
min	1990.000000	3.800000e+04	2015.000000	2.000000
25%	2013.000000	5.500000e+05	2019.000000	6.000000
50%	2016.000000	9.500000e+05	2020.000000	8.000000
75%	2018.000000	1.650000e+06	2021.000000	11.000000
max	2022.000000	1.250000e+07	2022.000000	34.000000

In [75]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 201413 entries, 0 to 205842
Data columns (total 7 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   company_hash         201413 non-null  object 
 1   email_hash           201413 non-null  object 
 2   orgyear              201413 non-null  float64
 3   ctc                  201413 non-null  int64  
 4   job_position         201413 non-null  object 
 5   ctc_updated_year     201413 non-null  float64
 6   years_of_experience  201413 non-null  float64
dtypes: float64(3), int64(1), object(3)
memory usage: 12.3+ MB
```

Manual Clustering

In [76]:
```
grp = ['company_hash','job_position','years_of_experience']
data_tmp1 = df.groupby(grp).agg({'ctc':['mean','median','min','max','count']}).r
data_tmp1.columns  = ["{} {}".format(b_, a_) if a_ not in grp else "{}".format(a
data_tmp1.head()
```

Out[76]:

	company_hash	job_position	years_of_experience	mean ctc	median ctc	min ctc	n
0	Others	Others	2.0	1.492754e+06	800000.0	60000	10(
1	Others	Others	3.0	9.209444e+05	650000.0	47000	10(
2	Others	Others	4.0	8.635434e+05	550000.0	40000	10(
3	Others	Others	5.0	7.519201e+05	500000.0	40000	104
4	Others	Others	6.0	6.756606e+05	500000.0	40000	10(

In [77]:
```
datatmp = df.merge(data_tmp1[['company_hash', 'job_position', 'years_of_experien
col1 = 'ctc'
col2 = 'mean ctc'
conditions  = [ datatmp[col1] > datatmp[col2], datatmp[col1] == datatmp[col2], d
choices     = [ 1, 2, 3 ]

datatmp['Designation'] = np.select(conditions, choices, default=np.nan)
datatmp.head()
```

Out[77]:

	company_hash	email_hash	orgyear	ctc
0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000
1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999
2	Others	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015.0	2000000
3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	700000
4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017.0	1400000

In [78]:

```
# unique value designation column(listed in %)
designation = datatmp['Designation'].value_counts(normalize=True).map(lambda cal
designation.columns = ['Designation', 'Count']
designation
```

Out[78]:

	Designation	Count
0	3.0	46.16
1	1.0	30.33
2	2.0	23.52

Manual Clustering on company_hash and job position

In [79]:

```
grp = ['company_hash','job_position']
data_tmp1 = datatmp.groupby(grp).agg({'ctc':[('mean2','mean'),'median','min','ma
data_tmp1.columns  = ["{} {}".format(b_, a_) if a_ not in grp else "{}".format(a
data_tmp1.head()
```

Out[79]:

	company_hash	job_position	mean2 ctc	median ctc	min ctc	max ctc	count ctc
0	Others	Others	9.977383e+05	700000.0	40000	12500000	9450
1	Others	a group chat application	5.000000e+05	500000.0	500000	500000	1
2	Others	abap developer	5.000000e+05	500000.0	500000	500000	1
3	Others	administrative clerk	5.000000e+05	500000.0	500000	500000	1
4	Others	administrator	1.940000e+06	1940000.0	380000	3500000	2

In [80]:

```
datatmp = datatmp.merge(data_tmp1[grp + ['mean2 ctc']],on=grp,how='left')
col1 = 'ctc'
col2 = 'mean2 ctc'
conditions  = [ datatmp[col1] > datatmp[col2], datatmp[col1] == datatmp[col2], d
```

```
choices     = [ 1, 2, 3 ]

datatmp['Class'] = np.select(conditions, choices, default=np.nan)
datatmp.head()
```

Out[80]:

	company_hash	email_hash	orgyear	ctc
0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000
1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999
2	Others	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015.0	2000000
3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	700000
4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017.0	1400000

In [81]:

```
# unique value Class column(listed in %)
Class = datatmp['Class'].value_counts(normalize=True).map(lambda calc: round(100
Class.columns = ['Class', 'Count']
Class
```

Out[81]:

	Class	Count
0	3.0	57.98
1	1.0	35.78
2	2.0	6.24

Manual Clustering based on comapny

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

In [82]:

```
grp = ['company_hash']
data_tmp1 = datatmp.groupby(grp).agg({'ctc':[('mean3','mean'),'median','min','ma
data_tmp1.columns  = ["{} {}".format(b_, a_) if a_ not in grp else "{}".format(a
data_tmp1.head()
```

Out[82]:

	company_hash	mean3 ctc	median ctc	min ctc	max ctc	count ctc
0	Others	1.108693e+06	770000.0	38000	12500000	46376
1	a ntwyzgrgsxto	1.234688e+06	600000.0	350000	4000000	16
2	aaqxctz avnv owxtzwto vzvrjnxwo ucn rna	9.850000e+05	500000.0	360000	3600000	8
3	abwavnv ojontb	7.320000e+05	700000.0	700000	780000	5
4	adw ntwyzgrgsj	9.098081e+05	600000.0	56000	8000000	297

In [83]:

```
datatmp = datatmp.merge(data_tmp1[grp + ['mean3 ctc']],on=grp,how='left')
col1 = 'ctc'
col2 = 'mean3 ctc'
conditions  = [ datatmp[col1] > datatmp[col2], datatmp[col1] == datatmp[col2], d
choices     = [ 1, 2, 3 ]

datatmp['Tier'] = np.select(conditions, choices, default=np.nan)
datatmp.head()
```

Out[83]:

	company_hash	email_hash	orgyear	ctc
0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000
1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999
2	Others	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015.0	2000000
3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	700000
4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017.0	1400000

In [84]:

```
# unique value Tier column(listed in %)
Tier = datatmp['Tier'].value_counts(normalize=True).map(lambda calc: round(100*c
Tier.columns = ['Tier', 'Count']
Tier
```

Out[84]:

	Tier	Count
0	3.0	64.08
1	1.0	35.88
2	2.0	0.04

In [85]:

```
datatmp['diff_desig'] = datatmp['ctc'] - datatmp['mean ctc']
datatmp['diff_class'] = datatmp['ctc'] - datatmp['mean2 ctc']
datatmp['diff_tier'] = datatmp['ctc'] - datatmp['mean3 ctc']
```

In [86]:
```
datatmp.head()
```

Out[86]:

	company_hash	email_hash	orgyear	ctc
0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000
1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999
2	Others	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015.0	2000000
3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	700000
4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017.0	1400000

Answering question based on manual clustering

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

In [87]:
```
datatmp[datatmp['Tier'] == 1].sort_values('diff_tier',ascending=False).head(10)[
```

Out[87]:

	email_hash	ctc	mean3 ctc
68747	85e685ccaf737be77245c7bd8d06f7007e37ae8fe9a112...	12350000	6.457040e+05
103579	b69935e9b3fb05bfca232556188524cf7e0106eebbc2c2...	12500000	9.358903e+05
114980	b69935e9b3fb05bfca232556188524cf7e0106eebbc2c2...	12500000	9.358903e+05
78717	9b543e7020439a87f759ac633f4c6f2bec139bb217934f...	12500000	1.108693e+06
62313	ab48cea6068c8b0b7fbf6d152c82cc041a3f76285bf7a9...	12500000	1.254363e+06
145513	f74fc71a9d1c32af699c8e7a5ed2ea6c6fc47413f14194...	12000000	7.547604e+05
112344	f213d7959b9f75d66d69bfa430076448295d31de469378...	12300000	1.157061e+06
2628	27e22a8ce7a77250ad179c6243cf40dc4857c3026f20d8...	12000000	9.328478e+05
62255	25dda68e55433fbc5c231e7212ad79973d1449f9f0a909...	12000000	9.527682e+05
130107	872e57a0737d0a7b5f0298586686c21c06c31fb7d5f364...	12100000	1.108693e+06

2. Top 10 employees of data science in Amazon / TCS etc earning more than their peers - Class 1

In [88]:
```
datatmp[(datatmp['Tier'] == 1)&(datatmp['Class'] == 1)&(datatmp['job_position'].
        'ios engineer', 'data analyst', 'qa engineer',
        'engineering leadership', 'data scientist', 'sdet',
        'support engineer', 'security leadership', 'devops engineer']))].sort_val
```

Out[88]:

	email_hash	ctc	mean2 ctc
145513	f74fc71a9d1c32af699c8e7a5ed2ea6c6fc47413f14194...	12000000	8.500900e+05
112745	5a004387e99e281d63b1ca7f65b56fc1cdc1d1da383b58...	12000000	1.005029e+06
84732	2bb51813fe05ab4e8ea6ba79a4c8ef631ed62f87b709ea...	12000000	1.005029e+06
148111	f7ed6c500aac4ed1d10f8e06c85557834c966f0ac2da87...	12000000	1.005029e+06
197421	05f1a6cd3688f5f5705e3d0752f65968a8aeb14af2261c...	12000000	1.005029e+06
107958	d651412f3455d6fb663a5bdb84a97a75cf062ca42e4bd5...	12000000	1.005029e+06
119289	98d1748ea1542882feb3d9075ea8a02042aaed2bfd9ecb...	12000000	1.007498e+06
62255	25dda68e55433fbc5c231e7212ad79973d1449f9f0a909...	12000000	1.093962e+06
38	69ef6838be8ee5b628375b4cc160ba54c1f7cab8c3b130...	11800000	9.192897e+05
15310	02ec75722194e07fcd31a7929843fc3c5fb3dd3a1e1d8b...	12500000	1.943600e+06

3. Bottom 10 employees of data science in Amazon / TCS etc earning less than their peers - Class 3

In [89]:
```
datatmp[(datatmp['Tier'] == 1)&(datatmp['Class'] == 3)&(datatmp['job_position'].
       'ios engineer', 'data analyst', 'qa engineer',
       'engineering leadership', 'data scientist', 'sdet',
       'support engineer', 'security leadership', 'devops engineer']))].sort_val
```

Out[89]:

	email_hash	ctc	mean2 ctc
77506	74dea008e581b2b8449afdd2d694021cb3d706c667a77d...	2500000	6.250000e+06
21889	831928c136906a9ab204fc5d793eca10d876ab2e81367a...	2500000	5.573077e+06
49652	afb0edb04b358288621e0eb3b9544173740856ff4feb60...	2300000	5.350000e+06
161094	e5925e18906ae284af8013ac1344b7fc185df5ace673a1...	1800000	4.700000e+06
167535	03b1c6a500e5ced30020aac602d4aeacbe1a6b6f9181e6...	3500000	6.300000e+06
146356	e5925e18906ae284af8013ac1344b7fc185df5ace673a1...	1800000	4.470000e+06
76994	f3b2641868f0a42de425acdc74e2cff0d03e1a70f11af4...	3000000	5.573077e+06
63042	1f0c6873153c336f38d3ff77b7de496a38e331bd8b1ff3...	3600000	6.156667e+06
123281	cbbf3f54142b858711a2719a8243304ae1d5c390e449ee...	1750000	4.262500e+06
188858	9a7894e045c744d8c5cb0b1d7281d26822183f38c62802...	3300000	5.733333e+06

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

In [90]:
```
datatmp[datatmp['Tier'] == 3].sort_values('diff_tier',ascending=True).head(10)[[
```

Out[90]:

	email_hash	ctc	mean3 ctc
58997	d4450a3ecc4f69afea7a122baaf858fa08b29196c97d79...	75000	6.337000e+06
175984	faa547efa3f271917c9429d39ee7ca1c37b48568b9ac9c...	110000	6.337000e+06
149797	aa973bb12d00382c7e6b37833249c623cf5bd5954d6a4f...	79000	6.060375e+06
162874	a45faf4d214fb83e7c9c64971deab8e7037433a140cbfd...	100000	6.060375e+06
192996	6bc12bffaad2c9c9d7b098f2c2b48e7697280c714996cb...	120000	6.060375e+06
156343	fc5ddd9f8d1bdb40fec162ffc268226a82d07527fcdb08...	120000	6.060375e+06
175322	56bf041cf16bbf23034e5111856624e9bea0e4f06b86e8...	210000	6.060375e+06
127722	56bf041cf16bbf23034e5111856624e9bea0e4f06b86e8...	210000	6.060375e+06
195322	56bf041cf16bbf23034e5111856624e9bea0e4f06b86e8...	210000	6.060375e+06
37595	e619ce4bc238af5191a8a37e484d8ca2b115c05407f2c5...	400000	4.742857e+06

5. Top 10 employees in Amazon- X department - having 5/6/7 years of experience earning more than their peers - Tier X

In [91]:
```
datatmp[(datatmp['years_of_experience'].isin([5,6,7]))&(datatmp['company_hash'].
```

Out[91]:

	email_hash	ctc	mean ctc
109834	2fab5e919a339803876fb532a618ab93c7b83c49746dd7...	3160000	1.760000e+06
85760	2fab5e919a339803876fb532a618ab93c7b83c49746dd7...	1750000	1.158571e+06
100859	5b09bddfe861cf5609982adc0a9ed3946fc08151b06cd6...	1950000	1.495000e+06
175538	c9e14b4d46b1a76974a2e06bc546886cff85bd441f21b8...	1600000	1.158571e+06
191007	4fb281fb2e423aa61d4cc18a09eb9fa7a68f948f6e880b...	1900000	1.555000e+06
153368	8b3710b3a42e17677dcfbc55e48deac378af9810efa86d...	1750000	1.446667e+06
26032	c9e14b4d46b1a76974a2e06bc546886cff85bd441f21b8...	2000000	1.760000e+06
163141	6a3ed398f74a8186b52f98a4f6b0894beb2f2032f9af2a...	1540000	1.446667e+06
177723	400aea75dc1316022b8c4436c60a0646fbea2962e26a5a...	1210000	1.158571e+06
21284	30a88256b5586ba59b25e6fe78fada76950fd65ca9f250...	1200000	1.158571e+06

6. Top 10 companies (based on their CTC)

In [92]:
```
datatmp.groupby('company_hash').mean()['ctc'].reset_index().sort_values('ctc',as
```

Out[92]:

	company_hash	ctc
362	bxwqgonqvntsj	6.337000e+06
3096	wvqttb	6.060375e+06
2814	vxqugqno vhnygqxnj ge xzaxv	4.742857e+06
1551	orxwt	4.548000e+06
592	evzvnxwo xzw	4.383000e+06
163	bgngqi	4.133333e+06
2711	vruyvsqtu otwhqxnxto	4.009091e+06
724	gqvwrt wrgha xzeqvonqhwnhqt	3.971667e+06
1207	nqvexshqv	3.960000e+06
1343	nxat	3.892000e+06

7. Top 2 positions in every company (based on their CTC)

In [93]:

```
tmp = datatmp[datatmp['job_position'] != 'na']
tmp = tmp.groupby(['company_hash','job_position']).mean().sort_values(['company_
tmp = tmp.groupby('company_hash').head(2)[['company_hash','job_position']]
tmp
```

Out[93]:

	company_hash	job_position
0	Others	research assistant
1	Others	researcher
269	a ntwyzgrgsxto	fullstack engineer
270	a ntwyzgrgsxto	frontend engineer
275	aaqxctz avnv owxtzwto vzvrjnxwo ucn rna	engineering intern
...	...	...
25563	zxyxrtzn ntwyzgrgsxto	android engineer
25569	zxzlvwvqn	other
25570	zxzlvwvqn	area operations manager
25578	zxztrtvuo	other
25579	zxztrtvuo	engineering intern

7414 rows × 2 columns

Preparing data for training model(Imputation/Scaling)

Transforming ctc feature using log function

In [94]:
```
datatmp['ctc_log'] = np.log2(datatmp['ctc'])
```

Columns like ['job_position', 'email_hash', 'company_hash'] are text.

We can't use them during imputation, so we'll remove these columns

In [95]:
```
drop_cols = ['job_position','email_hash','company_hash']
for i in drop_cols:
    try:
        datatmp.drop([i],axis=1,inplace=True)
    except:
        print('no')
```

In [96]:
```
datatmp.columns
```

Out[96]:
```
Index(['orgyear', 'ctc', 'ctc_updated_year', 'years_of_experience', 'mean ctc',
       'Designation', 'mean2 ctc', 'Class', 'mean3 ctc', 'Tier', 'diff_desig',
       'diff_class', 'diff_tier', 'ctc_log'],
      dtype='object')
```

In [97]:
```
datatmp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 201413 entries, 0 to 201412
Data columns (total 14 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   orgyear              201413 non-null  float64
 1   ctc                  201413 non-null  int64  
 2   ctc_updated_year     201413 non-null  float64
 3   years_of_experience  201413 non-null  float64
 4   mean ctc             201413 non-null  float64
 5   Designation          201413 non-null  float64
 6   mean2 ctc            201413 non-null  float64
 7   Class                201413 non-null  float64
 8   mean3 ctc            201413 non-null  float64
 9   Tier                 201413 non-null  float64
 10  diff_desig           201413 non-null  float64
 11  diff_class           201413 non-null  float64
 12  diff_tier            201413 non-null  float64
 13  ctc_log              201413 non-null  float64
dtypes: float64(13), int64(1)
memory usage: 23.0 MB
```

Statistical Summary

In [98]:
```
datatmp.describe()
```

Out[98]:

	orgyear	ctc	ctc_updated_year	years_of_experience	mean ct
count	201413.000000	2.014130e+05	201413.000000	201413.000000	2.014130e+0
mean	2015.103722	1.313212e+06	2019.687314	8.896278	1.313212e+0
std	4.257499	1.234111e+06	1.287119	4.257499	9.428384e+0
min	1990.000000	3.800000e+04	2015.000000	2.000000	3.900000e+0
25%	2013.000000	5.500000e+05	2019.000000	6.000000	7.195652e+0
50%	2016.000000	9.500000e+05	2020.000000	8.000000	1.034220e+0
75%	2018.000000	1.650000e+06	2021.000000	11.000000	1.600000e+0
max	2022.000000	1.250000e+07	2022.000000	34.000000	1.250000e+0

In [99]:

```
datatmp.isna().sum()
```

Out[99]:

```
orgyear                0
ctc                    0
ctc_updated_year       0
years_of_experience    0
mean ctc               0
Designation            0
mean2 ctc              0
Class                  0
mean3 ctc              0
Tier                   0
diff_desig             0
diff_class             0
diff_tier              0
ctc_log                0
dtype: int64
```

Training Model

In [100…

```
from sklearn.impute import KNNImputer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.cluster import MiniBatchKMeans, KMeans
from sklearn.metrics import silhouette_score
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
```

Standardization

In [101…

```
scaler = StandardScaler()
scaler.fit(datatmp)
X = pd.DataFrame(scaler.transform(datatmp), columns=datatmp.columns, index=datat
```

In [102…

```
X
```

Out[102]:

	orgyear	ctc	ctc_updated_year	years_of_experience	mean ctc	Designa
0	0.210518	-0.172766	0.242935	-0.210518	-0.226139	-0.18
1	0.680278	-0.699463	-0.533996	-0.680278	-0.571601	0.97
2	-0.024362	0.556506	0.242935	0.024362	-0.131941	-1.34
3	0.445398	-0.496887	-0.533996	-0.445398	-0.164016	0.97
4	0.445398	0.070325	-0.533996	-0.445398	0.092050	-0.18
...	...	...	...	...	...	
201408	-1.668524	-0.885832	-0.533996	1.668524	-1.159493	-0.18
201409	0.445398	-0.658947	0.242935	-0.445398	-0.173107	0.97
201410	1.384919	-0.496887	1.019866	-1.384919	-0.685745	-1.34
201411	0.915159	3.068442	-0.533996	-0.915159	-0.116674	-1.34
201412	-0.259243	-0.059324	-2.864788	0.259243	0.403168	0.97

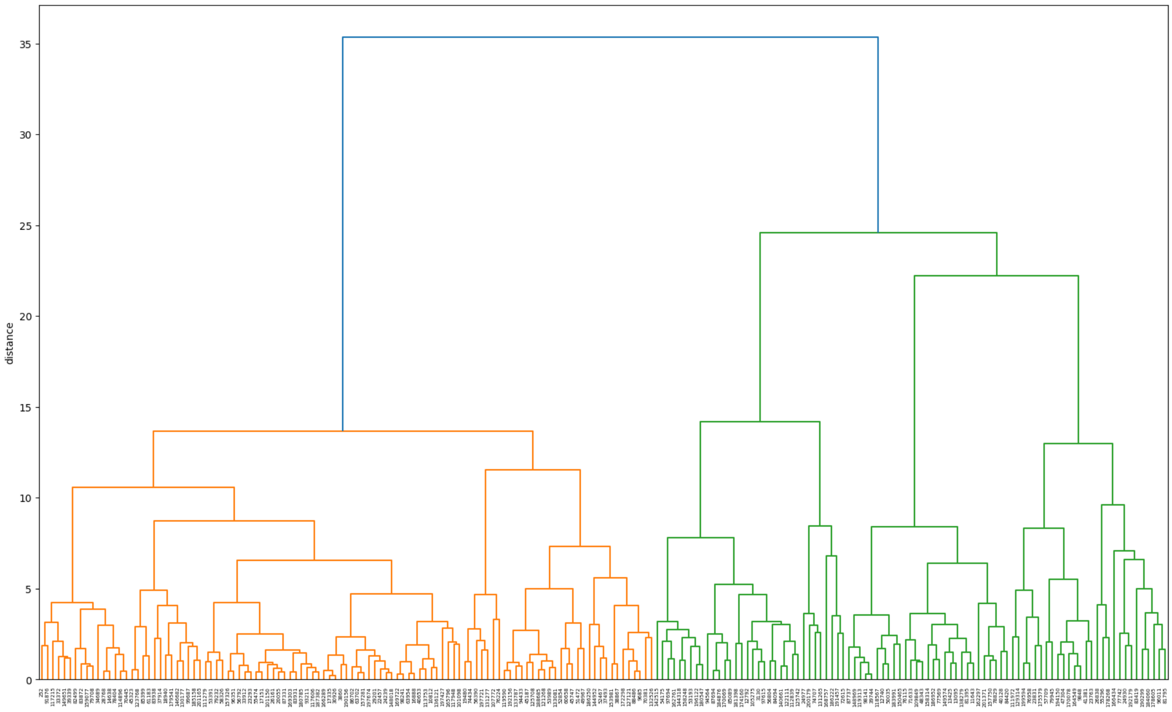
201413 rows × 14 columns

Hierarchical Clustering

Trying to get a high level idea about how many clusters we can from, by taking sample of 200 learners multiple times and forming hierarchy and visualising in dendrogram.

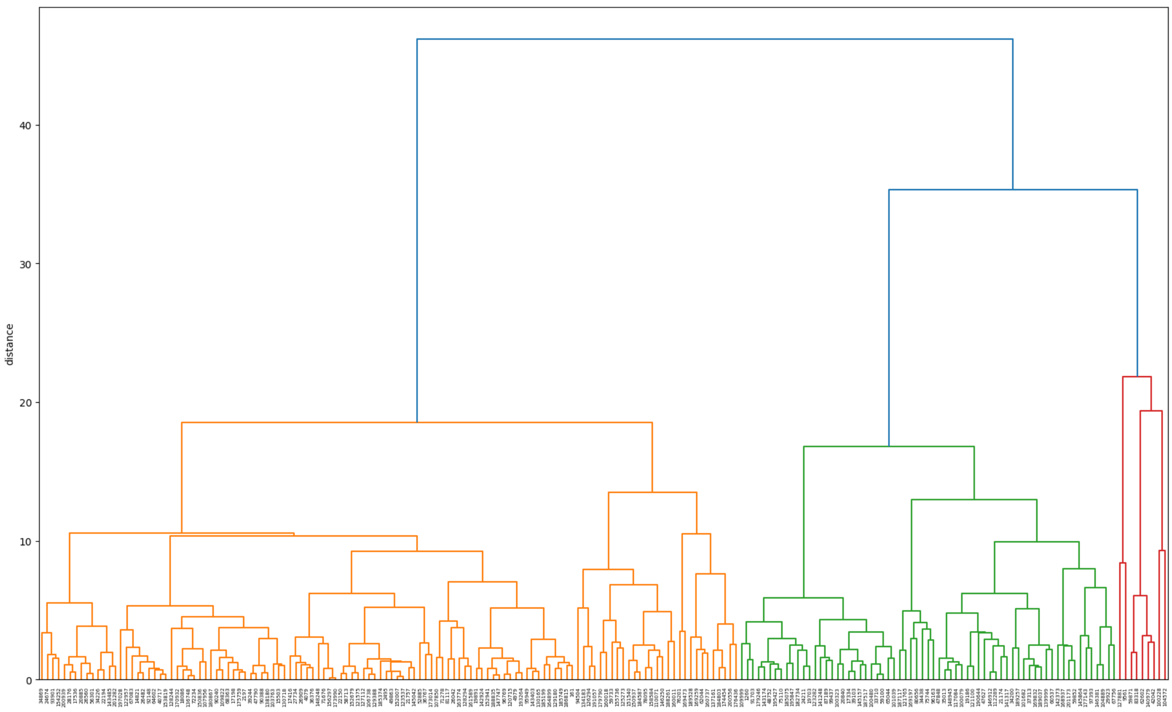
In [103…

```
import scipy.cluster.hierarchy as sch

sample = X.sample(200)
Z = sch.linkage(sample, method='ward')

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



In [104…

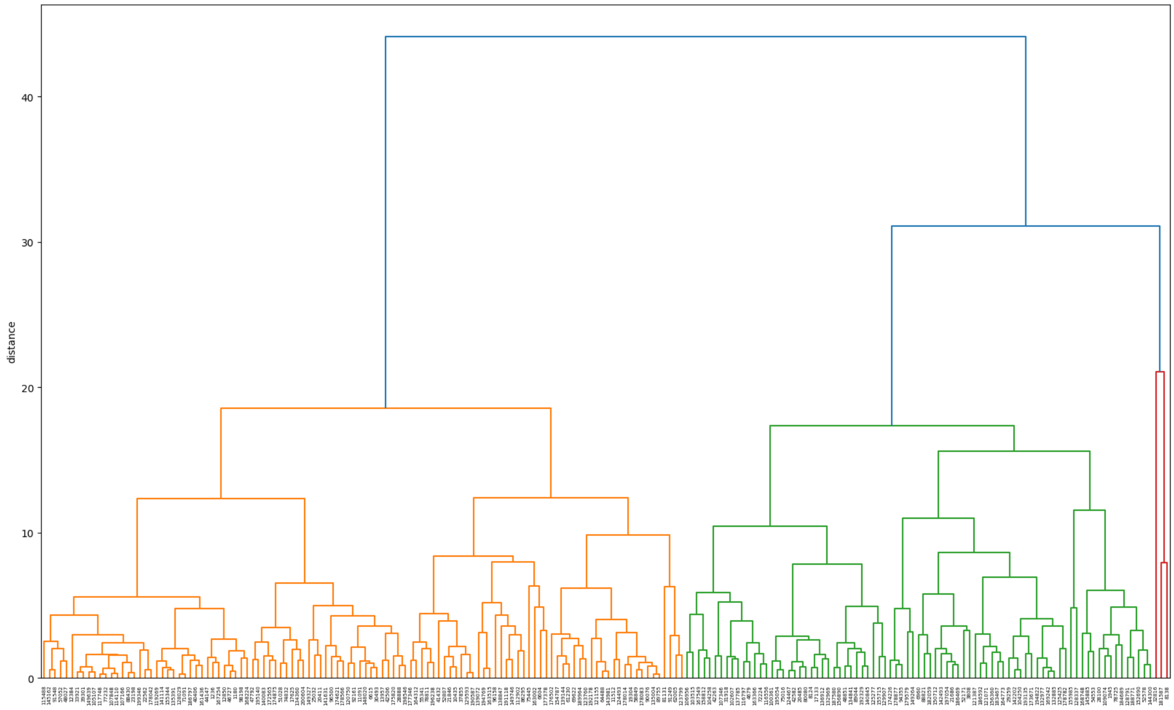
```
import scipy.cluster.hierarchy as sch

sample = X.sample(200)
Z = sch.linkage(sample, method='ward')

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



In [105…

```
import scipy.cluster.hierarchy as sch

sample = X.sample(200)
Z = sch.linkage(sample, method='ward')
```

```python
fig, ax3 = plt.subplots(figsize=(20, 12))
sch.dendrogram(Z, labels=sample.index, ax=ax3)
plt.xticks(rotation=90)
ax3.set_ylabel('distance')
plt.show()
```



- 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 :

Kmeans clustering

In [106…
```python
pipe_knn = Pipeline([('scaler', StandardScaler()), ('knn_imputer',  KNNImputer(n
```

In [107…
```python
pipe_knn_5 = Pipeline([('scaler', StandardScaler()), ('knn_imputer',  KNNImputer
```

In [108…
```python
pipe = Pipeline([('scaler', StandardScaler()), ('simple_imputer',  SimpleImputer
```

In [109…
```python
pipe_knn_pca = Pipeline([('scaler', StandardScaler()), ('knn_imputer',  KNNImput
```

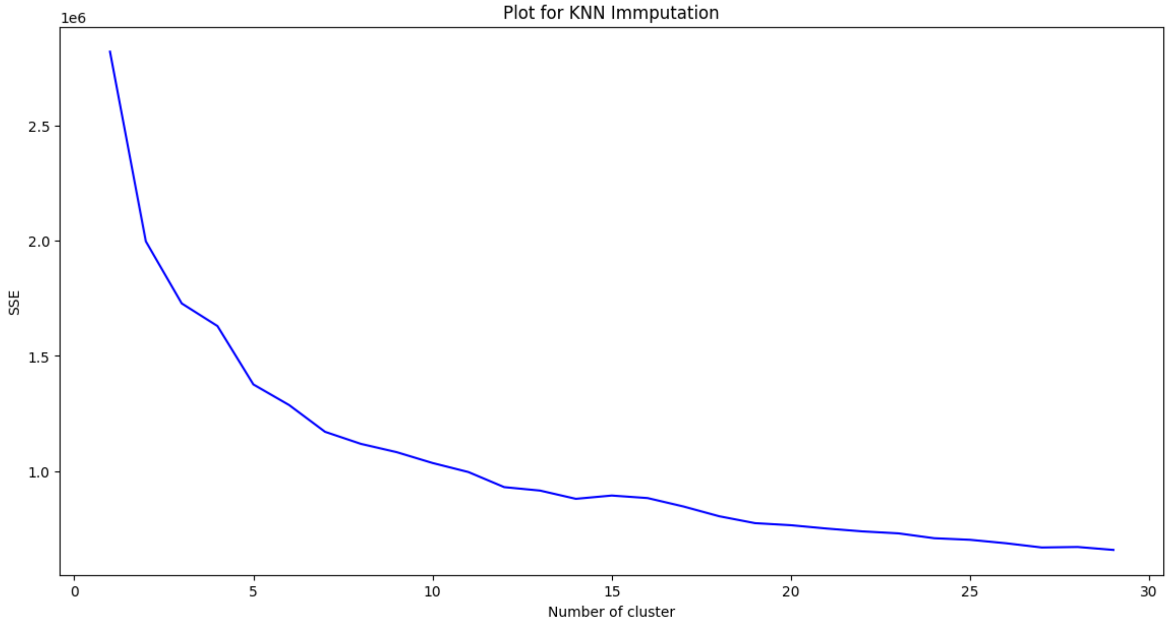
In [110…
```python
pipe_unscaled = Pipeline([('knn_imputer',  KNNImputer(n_neighbors=5, weights="un
```

Finding optimal num of clusters using Elbow method

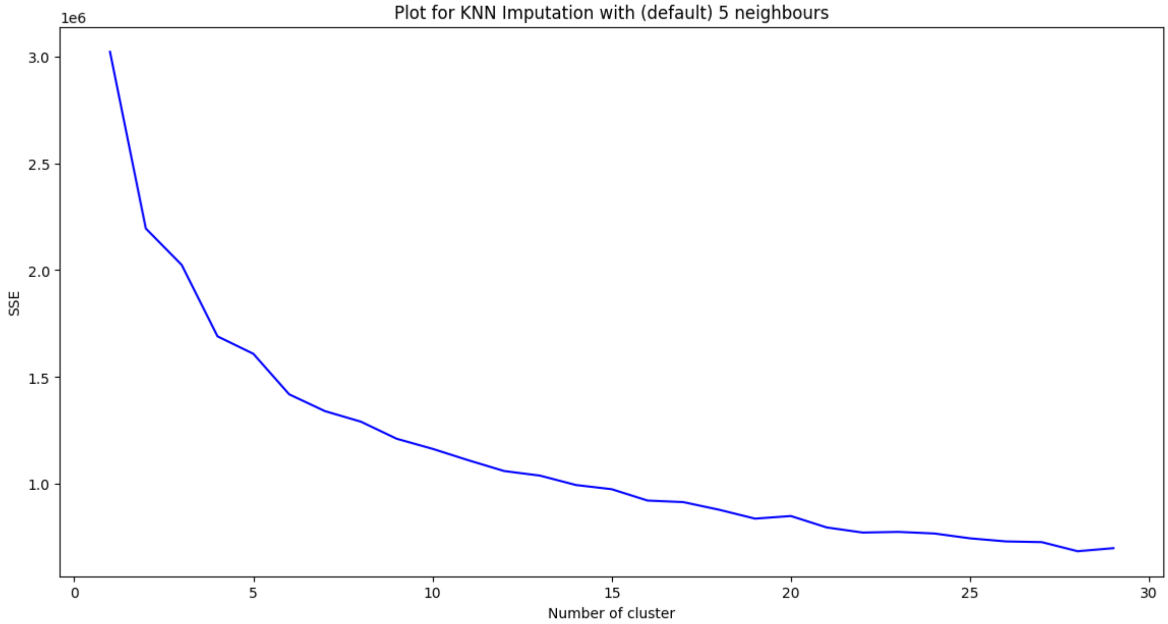
In [111…
```python
for name,pipeline in [('KNN Immputation',pipe_knn),('KNN Imputation with (defaul
                      ('KNN Immputation + PCA', pipe_knn_pca),('KNN Imputation U

    X = pipeline.fit_transform(datatmp)
    X = pd.DataFrame(X)
```

```
    if "PCA" not in name :
        X.columns= datatmp.columns

    sse = {}
    print("Running for ",name)
    for k in range(1, 30):
        kmeans = MiniBatchKMeans(init="k-means++",n_clusters=k,
                                 random_state=0).fit(X)
        label = kmeans.labels_
        datatmp["clusters"] = label
        sse[k] = kmeans.inertia_


    plt.figure(figsize=(14,7))
    plt.plot(list(sse.keys()), list(sse.values()),'b-',label='Sum of squared err
    plt.xlabel("Number of cluster")
    plt.ylabel("SSE")
    plt.title("Plot for "+name)
    plt.show()
```

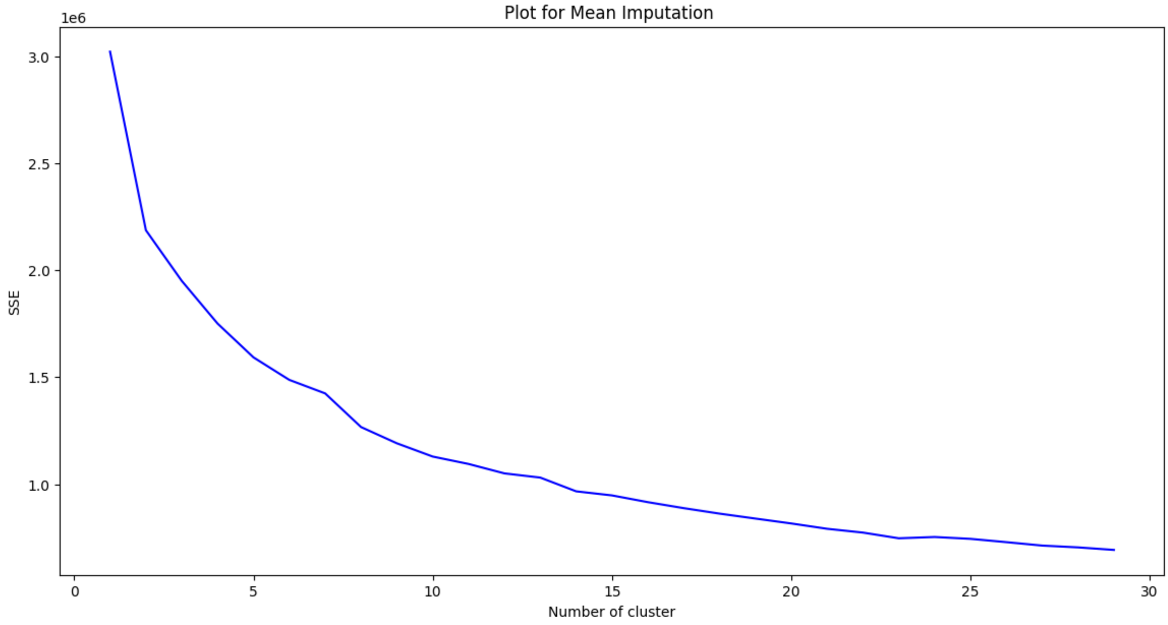
```
Running for  KNN Immputation
```



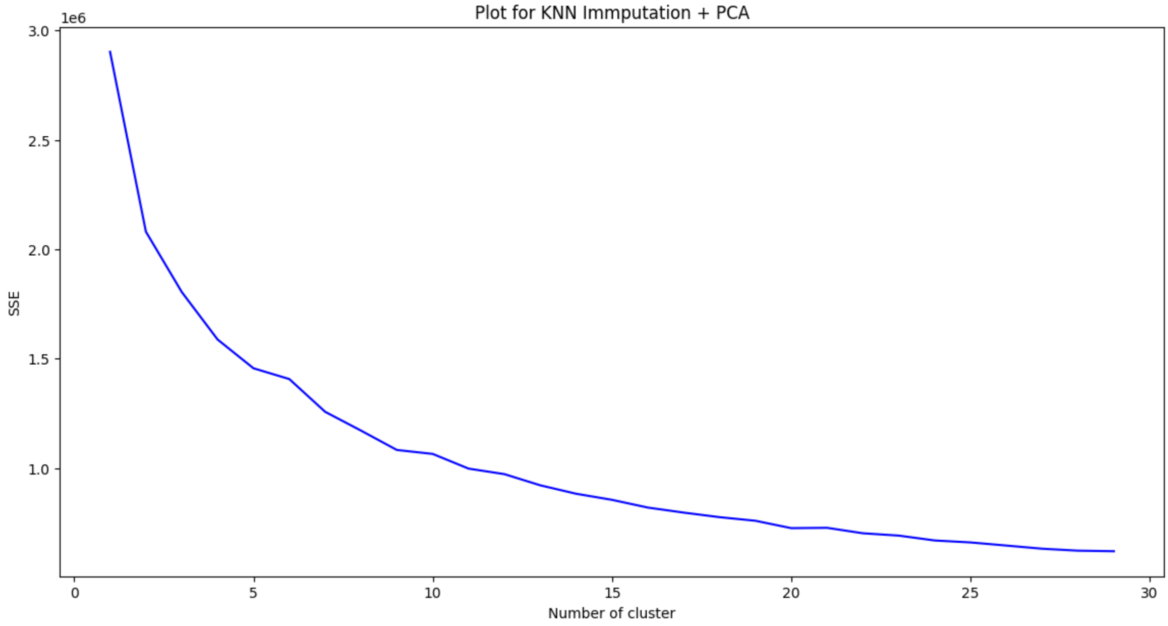

```
Running for  KNN Imputation with (default) 5 neighbours
```



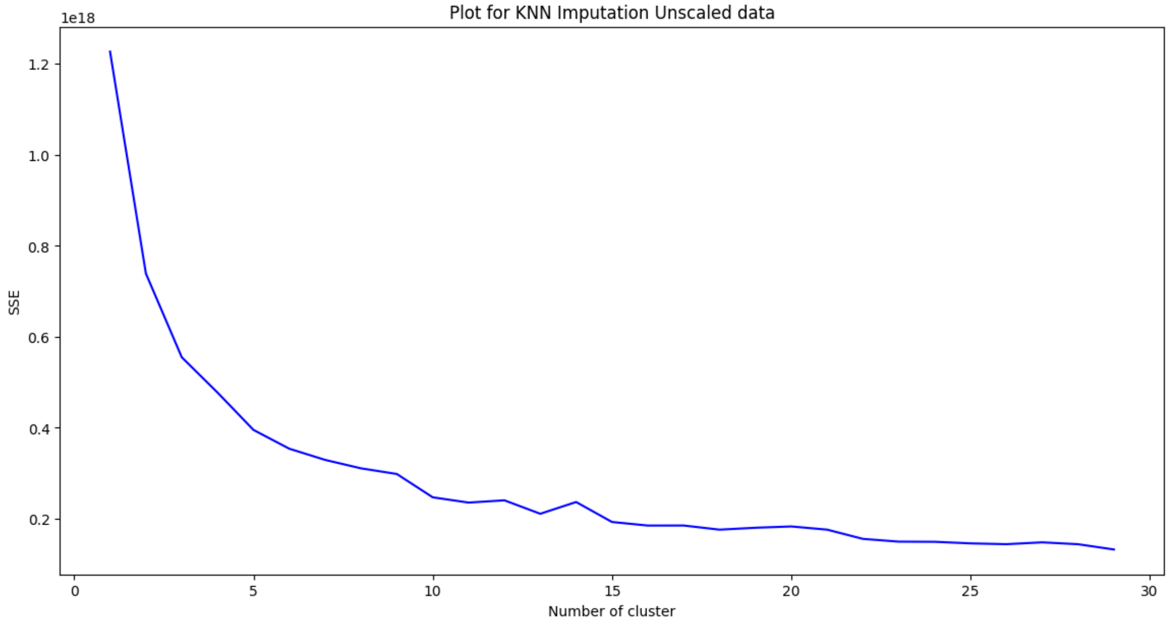
```
Running for  Mean Imputation
```




```
Running for  KNN Immputation + PCA
```




```
Running for  KNN Imputation Unscaled data
```



Model	N_clusters
KNN Immputation	16
KNN Imputation with (default) 5 neighbours	20
Mean Imputation	25
KNN Immputation + PCA	21
KNN Imputation Unscaled data	5

- Number of clusters is around 18-20 for scaled data, while around 5 for unscaled data

In [112…

```
for i in range(1,10):
    k = 4

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

In [113…

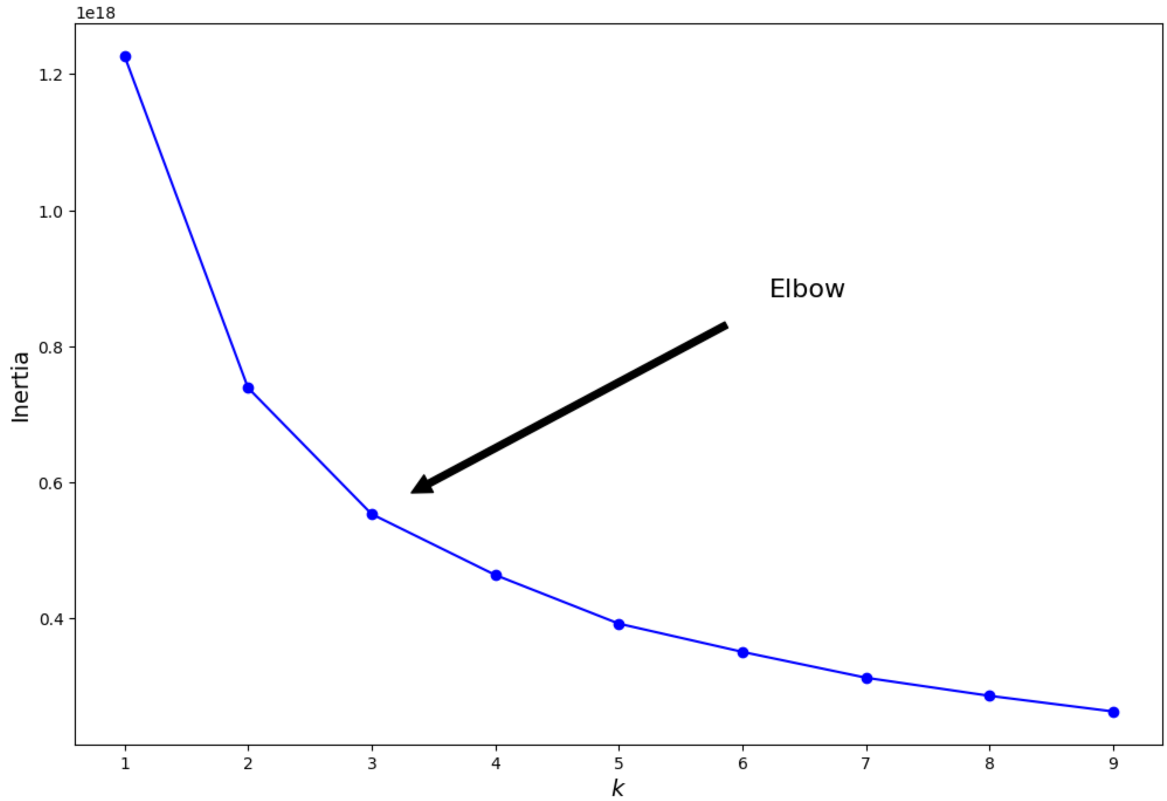
```
kmeans_per_k = [KMeans(n_clusters=k, random_state=42).fit(X)
                for k in range(1, 10)]

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

Out[113]:

```
[1.2270254261284096e+18,
 7.387574640506063e+17,
 5.532265700854374e+17,
 4.637107637866577e+17,
 3.9211306753527846e+17,
 3.5060402966441926e+17,
 3.126052869164911e+17,
 2.8600457163032083e+17,
 2.6300352325099155e+17]
```

In [114…

```
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()
```



In [115…

```
clusters = pd.DataFrame(X, columns=X.columns)
clusters['label'] = kM.labels_
clusters.sample(5)
```

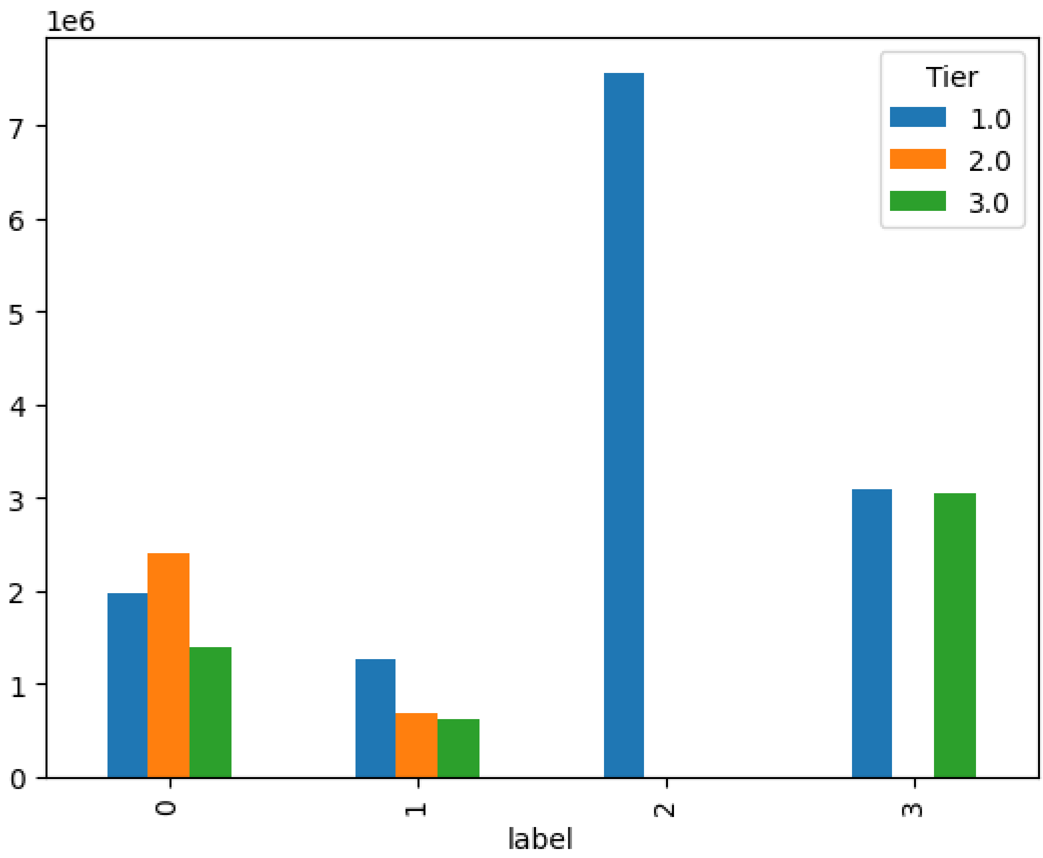
Out[115]:

	orgyear	ctc	ctc_updated_year	years_of_experience	mean ctc	Desig
171635	2012.0	742000.0	2016.0	12.0	1.794000e+06	
5086	2014.0	1000000.0	2021.0	10.0	9.300000e+05	
93005	2022.0	300000.0	2022.0	2.0	5.250000e+05	
89476	2020.0	400000.0	2021.0	4.0	4.438887e+05	
69628	2012.0	2111000.0	2017.0	12.0	2.076200e+06	

EDA after Clustering

In [116…

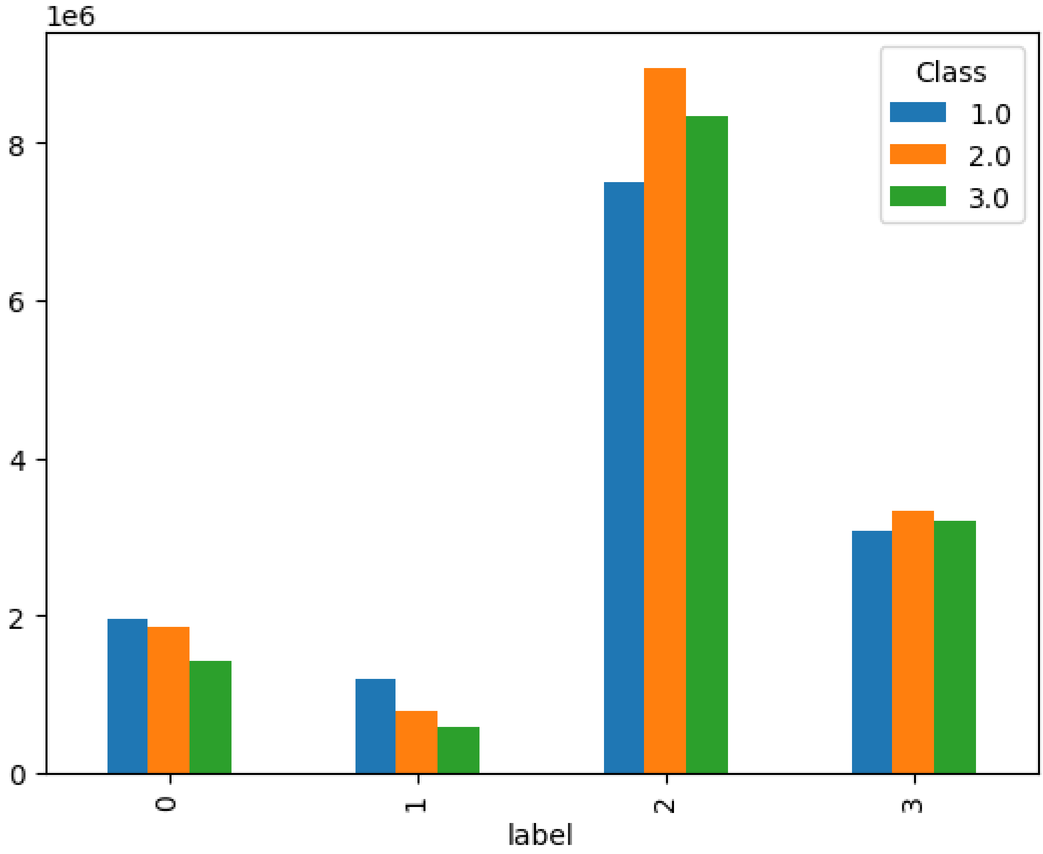
```
pd.crosstab(index = clusters["label"],
    columns = clusters["Tier"],values=clusters["ctc"],aggfunc= np.mean
       ).plot(kind = "bar")
plt.show()
```



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

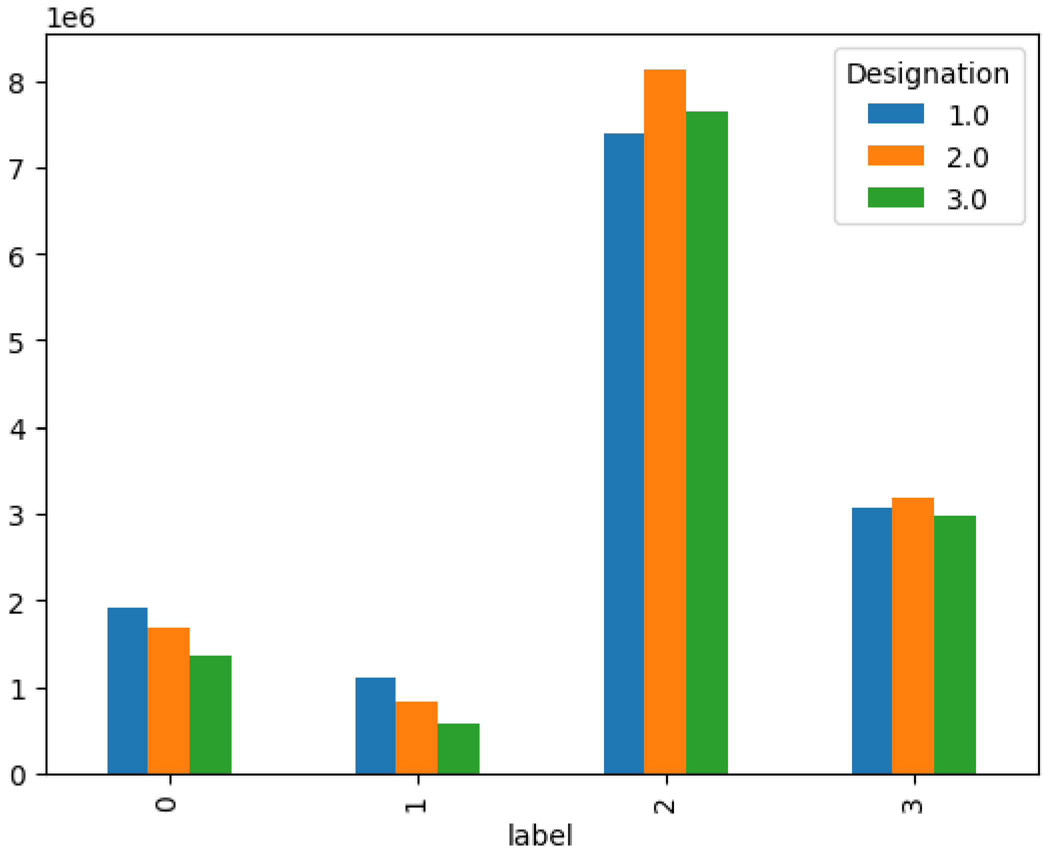
In [117…

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



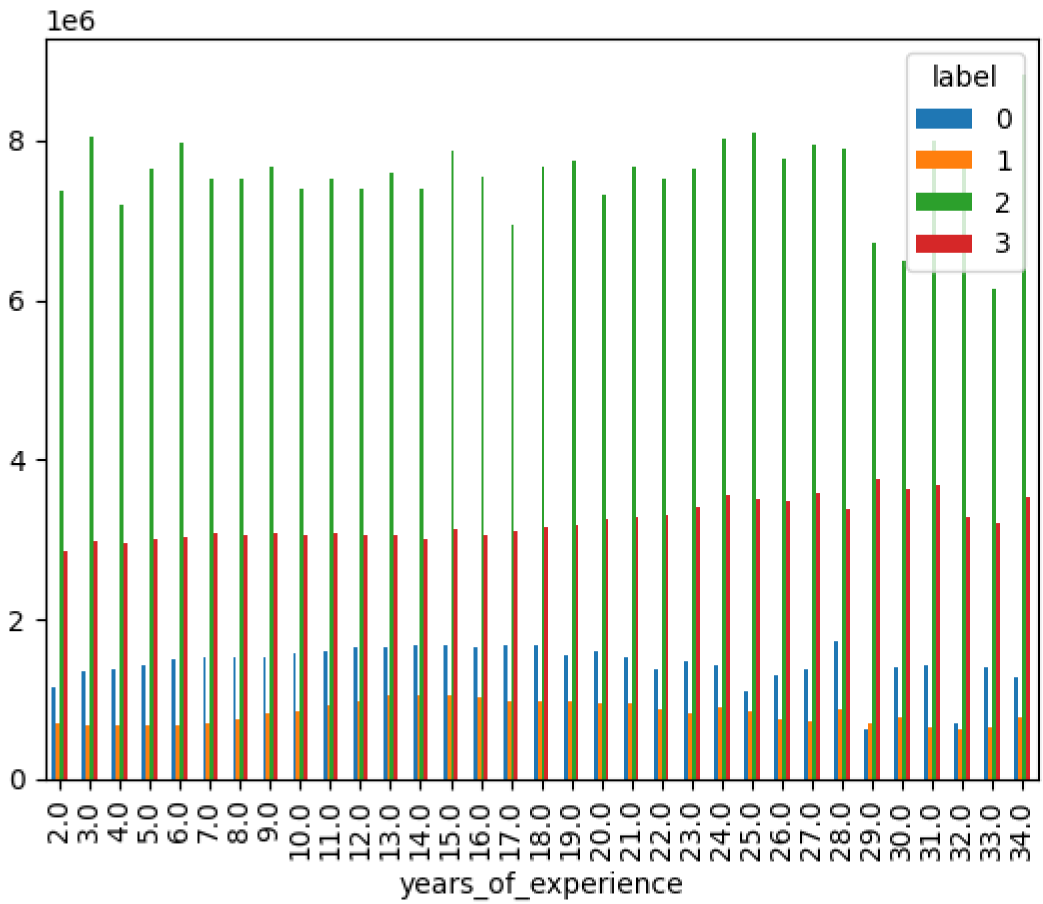
In [118…

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



In [119…

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



- Cluster label 2, are those learners who are very very experienced.

In [120…

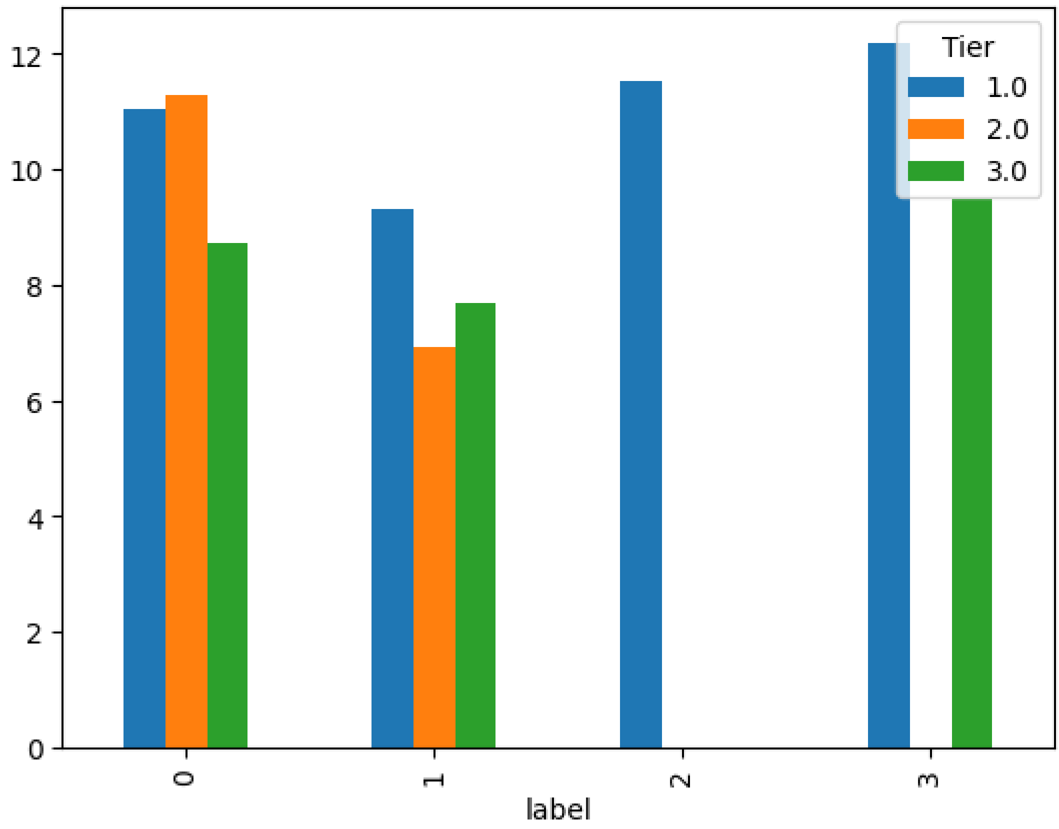
```
clusters.label.value_counts(normalize=True)*100
```

Out[120]:

```
1    68.080015
0    16.797327
3    13.748864
2     1.373794
Name: label, dtype: float64
```

In [121…

```
# years_of_experience per each cluster group of learners
pd.crosstab(index = clusters["label"],
    columns = clusters["Tier"],
            values=clusters["years_of_experience"],
            aggfunc=np.mean
        ).plot(kind = "bar")
plt.show()
```



Statistical Summury based on Each Cluster

In [122…

```
clusters.groupby("label").describe()[["ctc","Class","Tier","years_of_experience"
```

Out[122]:

	label	0	1	2	3
ctc	count	3.383200e+04	1.371220e+05	2.767000e+03	2.769200e+04
	mean	1.539786e+06	7.713451e+05	7.564227e+06	3.094949e+06
	std	6.210890e+05	4.148623e+05	1.942410e+06	8.840100e+05
	min	3.955000e+04	3.800000e+04	4.400000e+06	1.700000e+06
	25%	1.200000e+06	4.500000e+05	6.000000e+06	2.400000e+06
	50%	1.600000e+06	7.000000e+05	7.000000e+06	2.960000e+06
	75%	2.000000e+06	1.000000e+06	9.000000e+06	3.600000e+06
	max	4.000000e+06	2.200000e+06	1.250000e+07	7.500000e+06
Class	count	3.383200e+04	1.371220e+05	2.767000e+03	2.769200e+04
	mean	2.578092e+00	2.376577e+00	1.043730e+00	1.139715e+00
	std	7.785757e-01	8.921285e-01	2.114823e-01	4.376737e-01
	min	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
	25%	3.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
	50%	3.000000e+00	3.000000e+00	1.000000e+00	1.000000e+00
	75%	3.000000e+00	3.000000e+00	1.000000e+00	1.000000e+00
	max	3.000000e+00	3.000000e+00	3.000000e+00	3.000000e+00
Tier	count	3.383200e+04	1.371220e+05	2.767000e+03	2.769200e+04
	mean	2.529233e+00	2.504609e+00	1.000000e+00	1.005778e+00
	std	8.481931e-01	8.630596e-01	0.000000e+00	1.073439e-01
	min	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
	25%	3.000000e+00	3.000000e+00	1.000000e+00	1.000000e+00
	50%	3.000000e+00	3.000000e+00	1.000000e+00	1.000000e+00
	75%	3.000000e+00	3.000000e+00	1.000000e+00	1.000000e+00
	max	3.000000e+00	3.000000e+00	1.000000e+00	3.000000e+00
years_of_experience	count	3.383200e+04	1.371220e+05	2.767000e+03	2.769200e+04
	mean	9.260877e+00	8.089395e+00	1.153993e+01	1.218211e+01
	std	3.832685e+00	3.600889e+00	5.868754e+00	5.600577e+00
	min	2.000000e+00	2.000000e+00	2.000000e+00	2.000000e+00
	25%	6.000000e+00	6.000000e+00	7.000000e+00	8.000000e+00
	50%	9.000000e+00	7.000000e+00	1.000000e+01	1.100000e+01
	75%	1.100000e+01	1.000000e+01	1.500000e+01	1.500000e+01
	max	3.400000e+01	3.400000e+01	3.400000e+01	3.400000e+01

Insights

- Top Paying job titles include full stack engineer', 'iOS engineer', 'data analyst', 'qi engineer', 'engineering leadership', 'data scientist', 'sdet', 'support engineer', 'security leadership', 'devops engineer'.
- Among top paying companies, salary for these is getting lesser in recent years, Goldmaan Sachs, Tata Consultancy Services, Samsung Electronics, VMware, Dell, Dbs Bank, Hsbc software development India and GE
- Among Top paying companies mean salary for these company is increasing every year, Amazon, Microsoft and Huawei Technologies
- Avg. CTC seems to be decreasing with year.
- 1017 unique job positions are there in the dataset.
- 857 unique job positions are there in the dataset after pre-processing strings.
- Number of clusters is around 18-20 for scaled data, while around 5 for unscaled data.
- Majority number of Tier is 3.
- As compare to other Cluster label 1 is the high value.
- Based on k-Means Clustering algorithm output , as well as manual clustering , learners from tier1 company receiving very high CTC.
- Cluster label 2, are those learners who are very very experienced.
- Based on dendrogram , we can observe there are 3 clusters in the data based on similarity.

Recommendations

- Freshers who want to work on technical side should look for roles related to Backend Engineer, SDET, QA engineer, Data Scientist, Android Engineer, Full stack engineer to get good salaries as experience increases.
- Freshers who want best CTC should aim for companies like 'Cisco', 'Intel Technology India Pvt Ltd', 'Amazon', 'Walmart Labs', 'Symantec', 'Schneider Electric India', 'Morgan Stanley', 'Ericsson RD Bangalore' and 'Samsung Electronics'.