In [1]:

```
import pandas as pd
import numpy as np
import datetime
from sklearn.impute import KNNImputer
```

In [2]:

```
df = pd.read_csv('scaler_clustering.csv')
```

EDA

In [3]:

```
df.shape
```

Out[3]:

```
(205843, 7)
```

In [4]:

```
df.isnull().sum()
```

Out[4]:

```
Unnamed: 0              0
company_hash           44
email_hash              0
orgyear                86
ctc                     0
job_position        52562
ctc_updated_year        0
dtype: int64
```

In [5]:

```
df.nunique()
```

Out[5]:

```
Unnamed: 0          205843
company_hash         37299
email_hash          153443
orgyear                 77
ctc                   3360
job_position          1017
ctc_updated_year         7
dtype: int64
```

In [6]:

```
df.head()
```

Out[6]:

	Unnamed: 0	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000	Other	2020.0
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999	FullStack Engineer	2019.0
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015.0	2000000	Backend Engineer	2020.0
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	700000	Backend Engineer	2019.0
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017.0	1400000	FullStack Engineer	2019.0

Null Values

In [7]:

```
df.info()
```

```
<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
```

In [8]:

```
df.describe()
```

Out[8]:

	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

```
Removing index column
```

In [9]:

```
df.drop(columns=['Unnamed: 0'],axis = 1,inplace = True)
```

In [10]:

```
df.head()
```

Out[10]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000	Other	2020.0
1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999	FullStack Engineer	2019.0
2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015.0	2000000	Backend Engineer	2020.0
3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	700000	Backend Engineer	2019.0
4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017.0	1400000	FullStack Engineer	2019.0

In [11]:

```
df.nunique().reset_index()
```

Out[11]:

	index	0
0	company_hash	37299
1	email_hash	153443
2	orgyear	77
3	ctc	3360
4	job_position	1017
5	ctc_updated_year	7

In [12]:

```
pd.DataFrame(df.ctc.unique(),columns=['ctc']).sort_values(by=['ctc'])
```

	ctc
2627	2
2417	6
2341	14
3165	15
3143	16
...	...
315	199990000
61	200000000
361	250000000
2413	255555555
1772	1000150000

Duplicates

In [13]:

```
df[df.duplicated()]
```

Out[13]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
97138	wtqtzwt xzw	bb8e4b09544daf1bfc8c7bb9a9ae1fee35490cf3f321b8...	2014.0	1000000	FullStack Engineer	2019.0
98085	2020	6ad3e6ab27462c2c7428fa5d51405933335341d4d969b5...	2020.0	720000	NaN	2019.0
102600	voxvz uvxzno	c7fac937a34f7ae432ff1d77466eb7ea6cf25dfd5ebcca...	2020.0	1280000	NaN	2019.0
109324	wgbwvon mhoxztoo	0442a51ef5080d7d40721c007131a1d5bdeabae2c1b153...	2016.0	700000	NaN	2019.0
111354	uyxrxuo xzzgcvnxgz wvbuho	704d69965035d1c341b06fc5d83bf1b714f1625c0cf271...	2017.0	850000	iOS Engineer	2019.0
111521	aqggb ntwyzgrgsj	df81dac132d66a42a0c71a4799e1040731738e542c81ff...	2017.0	1270000	FullStack Engineer	2019.0
115241	rgfto wgbuvzxto xzw	ea363e930dabe0fbb63438e07775af3cb3b32639947c47...	2017.0	1100000	Backend Engineer	2019.0
117246	xatbxv	f451ceee50b1bfa3dc749c6aa8634ab3851a4ab961b003...	2019.0	640000	NaN	2019.0
117549	exzdtqv	e7df851527dd6f8ec95d5e13d9fb2a7255380245b808e3...	2020.0	1500000	NaN	2020.0
120371	avnvbtnxwv ogrhnxgzo uqxcvnt rxbxnta	15d7dd6801fb7cb980e77c420dd9bef5773e7ef57f510c...	2016.0	1300000	Backend Engineer	2020.0
121946	oguqv ontqxv	f48d4cd35091adb89c8e82b8bc39b68416e2e954e406fd...	2016.0	1250000	Data Scientist	2019.0
122316	eqtoytq	567e7ff3ad74ce235a75b1feea224204d35cd698922e59...	2018.0	900000	Backend Engineer	2019.0
130495	xatbxv	80a04f3eb89aa385e32b6e1c9a0b564730274632fad4c4...	2017.0	409999	Backend Engineer	2020.0
138371	xicxv	d0e72d551c69a2f9d96914515aeef797f4989b54c90ef0...	2014.0	1200000	FullStack Engineer	2019.0
141686	uhmrxwxo ovuxtzn	f27a6a759a02e90ebd17041fb26b72d13420d53edcdc99...	2020.0	940000	NaN	2019.0
143061	vwwtznhqt ogrhnxgzo uqxcvnt rxbxnta	bf09ce2b61e3bba0846412cf76b2e408c92384b373f709...	2014.0	800000	Android Engineer	2019.0
146097	axvouvqp xzw	8e5fe3154be66d7cd8730224318d913ecd10ec5197e20a...	2017.0	1000000	Backend Engineer	2021.0
151473	rgfto wgbuvzxto xzw	f67d3be9653bca997a75c81a88e851bcf0368fd83255aa...	2017.0	1265000	Backend Engineer	2019.0
157950	ti ntwyzgrgsxw	843a5216e56e06b9d31d35e0c3820beec3af19dc4978af...	2019.0	850000	FullStack Engineer	2020.0
161251	avnvftvct ucn rna	5083a995fa1623fd7d329766f8e7adbe5497a8c3c826f9...	2018.0	800000	Backend Engineer	2019.0
164554	ng nyt ztf	7b47ee99ce695d48d18dea36d3c6cc73e3b5b40ed477cf...	2019.0	450000	NaN	2020.0
165326	uhmrxwxo ovuxtzn	d40b483baf912b9f21cd1952e8b79388ce88ed5222d3d8...	2019.0	1200000	NaN	2019.0
171421	fyvnexd	7e2ac7c6b9051177ea51af3f7c8e934d6d3ce15a5cb587...	2020.0	1300000	FullStack Engineer	2020.0
175942	tdnqvbvqpo	82b93606127fa5ed0d28cb32469d7ba177b8e70088608c...	2019.0	350000	NaN	2020.0
179858	buyvoxo rna	bd443574985b2f72a4a382b6be392db2358158761f38de...	2016.0	750000	FullStack Engineer	2020.0
180630	uhmrxwxo ovuxtzn	59e67f9f149ede96889afacb1a70645fd3f309e3a1fa43...	2019.0	1620000	NaN	2019.0
182531	xznqvrxzp	c2c34a82a91169e2523727f7f15a4cc64f973ccb895b69...	2016.0	6730000	Backend Engineer	2019.0
195375	souvzz ntwyzgrgsxto xzw	31fefa78a0f32b56c8f0d60d2355d92c480b4ba95fcd83...	2018.0	600000	Support Engineer	2020.0
196492	2020	b6a63b76c3a1a395f7c3d509f2760d83aeb6e8c53db2b1...	2020.0	2700000	NaN	2019.0
196971	2020	77a5cecd2ed9bb764df8bf6da78a0ae2aef97fc87e913e...	2020.0	1000000	NaN	2019.0
201165	xzzgcvwwtq	5d00f5560a82d5ed91708273f9190499a6405abff35ab1...	2020.0	1300000	NaN	2019.0
203257	uhmrxwxo ovuxtzn	9efbaf1f3740b6661adb699ed5ee03ba10c51f6185e681...	2015.0	1500000	NaN	2019.0
205733	uhmrxwxo ovuxtzn	da614aea4d5dfacac3a2a6523e7e94b485fa3ba803db79...	2020.0	990000	NaN	2019.0

Drop Duplicates

In [14]:

```
df = df.drop_duplicates(keep='first')
```

In [15]:

```
df.duplicated().sum()
```

Out[15]:

```
0
```

In [16]:

```
df.isnull().sum()
```

Out[16]:

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

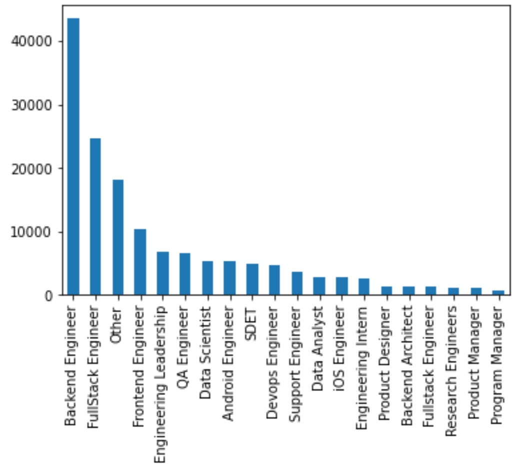
```
Univariate Analysis and BiVariate Analysis
```

In [17]:

```
df["job_position"].value_counts()[:20,].sort_values(ascending=False).plot(kind="bar")
```

Out[17]:

```
<AxesSubplot:>
```

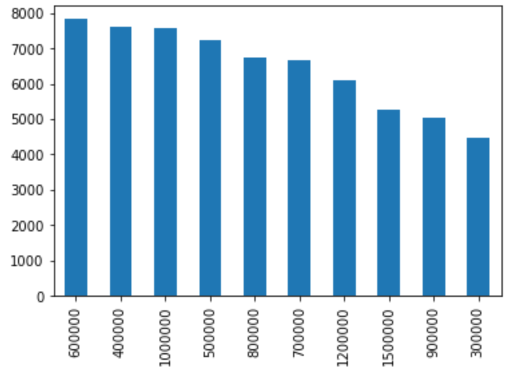


In [18]:

```
df["ctc"].value_counts()[:10,].sort_values(ascending=False).plot(kind="bar")
```

Out[18]:

```
<AxesSubplot:>
```

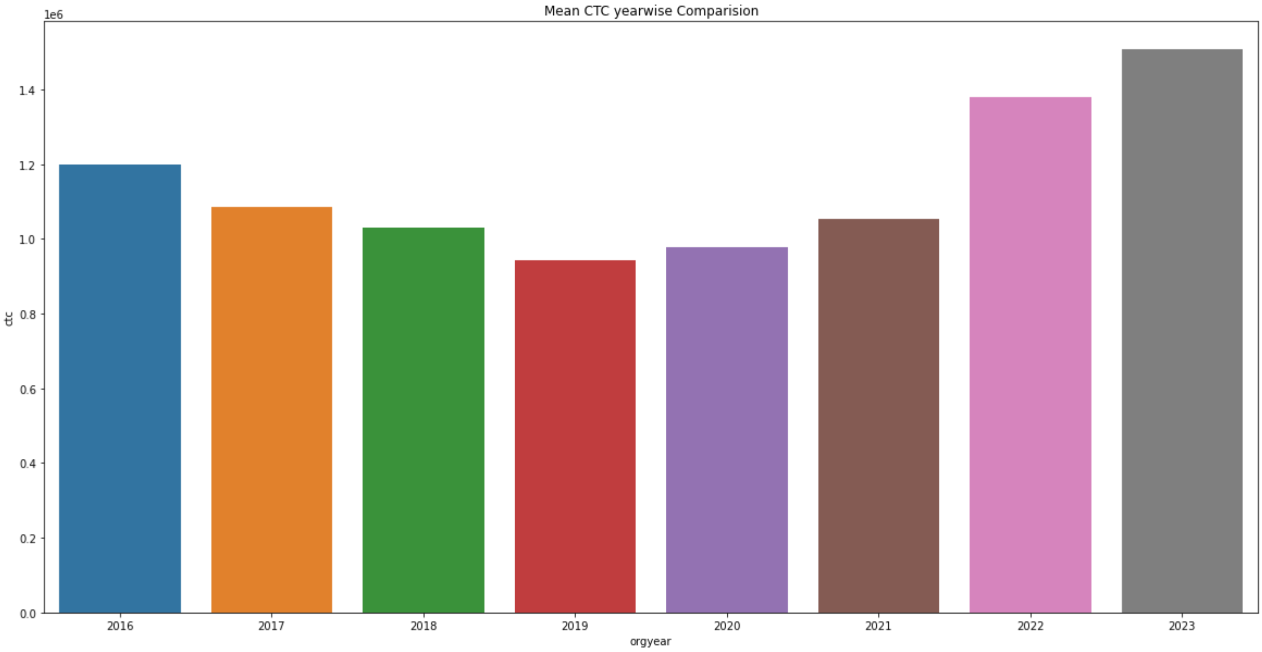


In [123]:

```
import seaborn as sns
```

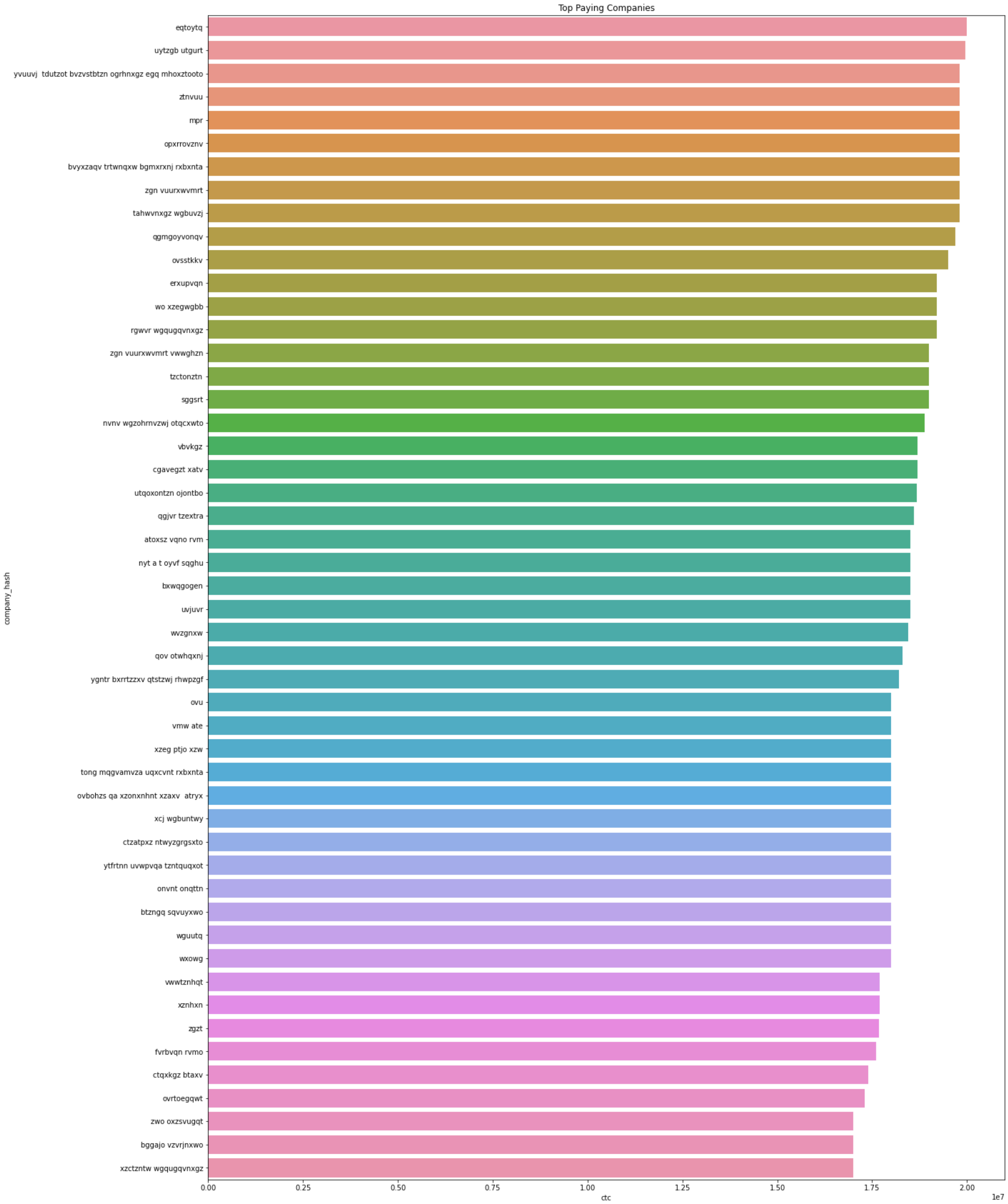
In [124]:

```
tmp = df[df['orgyear'] >= 2016]
tmp = tmp.groupby(['orgyear']).mean()['ctc'].reset_index().sort_values('ctc',ascending=False).head(50)
plt.figure(figsize=(20,10))
sns.barplot(data=tmp,y='ctc',x='orgyear').set(title="Mean CTC yearwise Comparision")
plt.show()
```



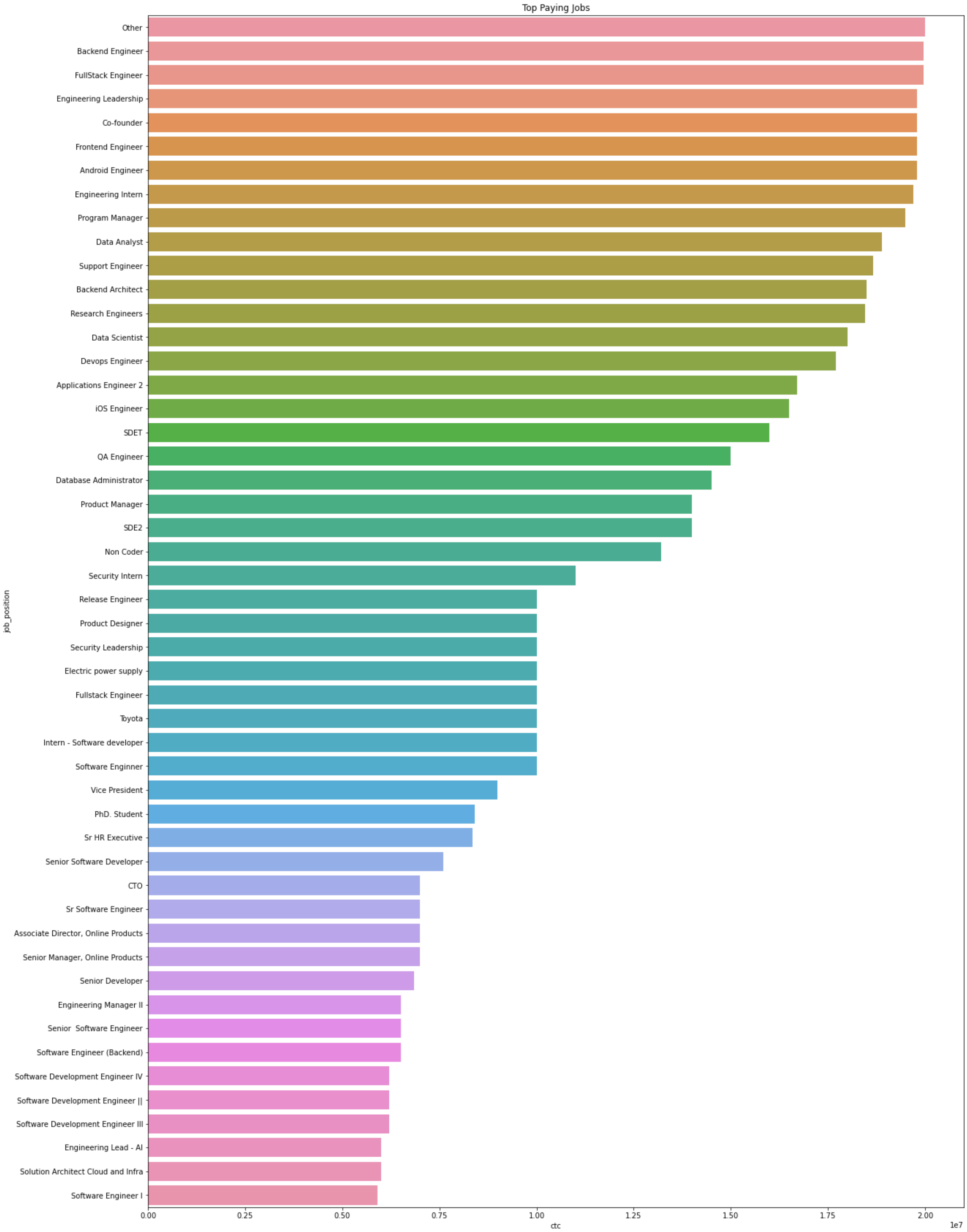
In [125]:

```
tmp = df.groupby(['company_hash']).max()['ctc'].reset_index().sort_values('ctc',ascending=False).head(50)
plt.figure(figsize=(20,30))
sns.barplot(data=tmp,x='ctc',y='company_hash').set(title="Top Paying Companies")
plt.show()
```



In [126]:

```
tmp = df.groupby(['job_position']).max()['ctc'].reset_index().sort_values('ctc',ascending=False).head(50)
plt.figure(figsize=(20,30))
sns.barplot(data=tmp,x='ctc',y='job_position').set(title="Top Paying Jobs")
plt.show()
```



In [19]:

```
df["orgyear"].describe()
```

Out[19]:

```
count    205724.000000
mean       2014.882284
std          63.576199
min           0.000000
25%        2013.000000
50%        2016.000000
75%        2018.000000
max       20165.000000
Name: orgyear, dtype: float64
```

In [20]:

```
df.shape
```

Out[20]:

```
(205810, 6)
```

```
Removing invalid years
```

In [22]:

```
df = df[(df['orgyear']>1900) & (df['orgyear']<=2023)]
```

In [23]:

```
df.shape
```

Out[23]:

```
(205594, 6)
```

In [24]:

```
df["orgyear"].describe()
```

Out[24]:

```
count    205594.000000
mean       2015.114230
std           4.232484
min        1970.000000
25%        2013.000000
50%        2016.000000
75%        2018.000000
max        2023.000000
Name: orgyear, dtype: float64
```

In [25]:

```
df.isnull().sum()
```

Out[25]:

```
company_hash           44
email_hash              0
orgyear                 0
ctc                     0
job_position        52483
ctc_updated_year        0
dtype: int64
```

In [26]:

```
df["ctc"].describe()
```

Out[26]:

```
count    2.055940e+05
mean     2.267724e+06
std      1.178357e+07
min      2.000000e+00
25%      5.300000e+05
50%      9.500000e+05
75%      1.700000e+06
max      1.000150e+09
Name: ctc, dtype: float64
```

In [27]:

```
df[(df['ctc']>20000000)].value_counts().reset_index()
```

Out[27]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	0
0	247 xrvm	a2f5b06ce7047c4b6c009d225b3cdf7ca9e4fbd7dd7b9a...	2013.0	100000000	SDET	2020.0	1
1	vbvkgz	a24cb4320f2cc9b75880d1ce3e6178fa643206f85e080f...	2020.0	100000000	Product Designer	2021.0	1
2	vbvkgz	fac2d01e4a347175bc91492927b5debbe2926b7b42e7f2...	2020.0	100000000	Support Engineer	2020.0	1
3	vbvkgz	e229403209e6c5c8ade0f6905474cecba91b2f223345ba...	2018.0	100000000	Other	2021.0	1
4	vbvkgz	d4a907191bd1b53c6f4b69a515be05c3d900650b823c78...	2010.0	100000000	Backend Engineer	2020.0	1
...	...	...	...	...	...	...	...
1366	nvnv wgzohrnvzwj otqcxwto	82fbacc015757ee74efe763c3623dc751812af48c741ff...	2015.0	200000000	Data Analyst	2020.0	1
1367	nvnv wgzohrnvzwj otqcxwto	8212e1a25405440bf29178cd87f89bb1ad33108e3cbc04...	2020.0	100000000	Data Analyst	2020.0	1
1368	nvnv wgzohrnvzwj otqcxwto	7794dcb7f5649076573e653610bd3f652ca5aa9d5b1671...	2021.0	100000000	Other	2020.0	1
1369	nvnv wgzohrnvzwj otqcxwto	71816854137816ffdc94fc2b283803af8e38979e2d0992...	2014.0	200000000	Backend Engineer	2020.0	1
1370	zxxn ntwyzgrgsxto rxbxnta	b9be7817ffdf6548c76b9514e878d11d3c029c7a96ec52...	2021.0	100000000	Backend Engineer	2020.0	1

1371 rows × 7 columns

In [28]:

```
df.shape
```

Out[28]:

```
(205594, 6)
```

```
removing outliers for CTC
```

In [29]:

```
df=df.loc[(df['ctc']>50000) & (df['ctc']<20000000)]
```

In [30]:

```
df.shape
```

Out[30]:

```
(201300, 6)
```

In [31]:

```
df.isnull().sum()/len(df)*100
```

Out[31]:

```
company_hash         0.020864
email_hash           0.000000
orgyear              0.000000
ctc                  0.000000
job_position        25.646796
ctc_updated_year     0.000000
dtype: float64
```

```
Removing outliers such as invalid orgyear,outside the range of 1900-2023
```

In [32]:

```
df.isnull().sum()
```

Out[32]:

```
company_hash           42
email_hash              0
orgyear                 0
ctc                     0
job_position        51627
ctc_updated_year        0
dtype: int64
```

In [33]:

```
# x.rename({0:'orgyear_impute'},axis=1,inplace = True)

# df = pd.concat([df, x], axis=1, join='inner')

# df.isnull().sum()

# df.head()

# df['orgyear_impute'].min(), df['orgyear_impute'].max()
```

In [34]:

```
current_year = datetime.datetime.now().year #get current year

df['Current Year'] = datetime.datetime.now().year
#   # substract to get the year delta
```

In [ ]:

```

```

In [35]:

```
df['orgyear']=df['orgyear'].astype('int64')
```

```
Experience Feature:
```

In [36]:

```
df["experience"] = df['Current Year'] - df['orgyear']
```

In [37]:

```
df.groupby("job_position")["ctc"].describe()
```

Out[37]:

job_position	count	mean	std	min	25%	50%	75%	max
SDE 2	1.0	1200000.0	NaN	1200000.0	1200000.0	1200000.0	1200000.0	1200000.0
.	1.0	700000.0	NaN	700000.0	700000.0	700000.0	700000.0	700000.0
..	1.0	600000.0	NaN	600000.0	600000.0	600000.0	600000.0	600000.0
.7	1.0	470000.0	NaN	470000.0	470000.0	470000.0	470000.0	470000.0
7	1.0	420000.0	NaN	420000.0	420000.0	420000.0	420000.0	420000.0
...	...	...	...	...	...	...	...	...
student	2.0	1715000.0	968736.290226	1030000.0	1372500.0	1715000.0	2057500.0	2400000.0
support escalation engineer	1.0	2000000.0	NaN	2000000.0	2000000.0	2000000.0	2000000.0	2000000.0
system engineer	1.0	500000.0	NaN	500000.0	500000.0	500000.0	500000.0	500000.0
system software engineer	1.0	610000.0	NaN	610000.0	610000.0	610000.0	610000.0	610000.0
technology analyst	1.0	82000.0	NaN	82000.0	82000.0	82000.0	82000.0	82000.0

991 rows × 8 columns

In [38]:

```
df.head()
```

Out[38]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Current Year	experience
0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016	1100000	Other	2020.0	2023	7
1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018	449999	FullStack Engineer	2019.0	2023	5
2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015	2000000	Backend Engineer	2020.0	2023	8
3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017	700000	Backend Engineer	2019.0	2023	6
4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017	1400000	FullStack Engineer	2019.0	2023	6

Duplicates

In [39]:

```
# dup_email = df['email_hash'].value_counts().reset_index()

# dup_email[dup_email['email_hash']>2].iloc[:1]

# df.groupby(df['email_hash'])

# df.groupby('email_hash').apply(lambda x : x.sort_values(by = 'job_position', ascending = False).head(2).reset_index(drop = True))
```

Replace special characters from company hash

In [40]:

```
df.experience.min(),df.experience.max()
```

Out[40]:

```
(0, 53)
```

In [41]:

```
df.shape
```

Out[41]:

```
(201300, 8)
```

In [42]:

```
#Assuming that people who has more than 20 years of experience will be having CTC greater than 10LPA and removing the records
df = df[~((df['experience']>20) &(df['ctc']<1000000))]
```

In [43]:

```
df.shape
```

Out[43]:

```
(200647, 8)
```

Handling the case where there are more than one record for an user by sorting it by year and taking the latest values

In [44]:

```
email_dup = df.groupby(df['email_hash']).count()['ctc'].reset_index()
```

In [45]:

```
email_dup[email_dup['ctc']>1].sort_values(by = 'ctc', ascending = False)
```

Out[45]:

	email_hash	ctc
109369	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	10
24397	298528ce3160cc761e4dc37a07337ee2e0589df251d736...	9
60776	6842660273f70e9aa239026ba33bfe82275d6ab0d20124...	9
36407	3e5e49daa5527a6d5a33599b238bf9bf31e85b9efa9a94...	9
121994	d15041f58bb01c8ee29f72e33b136e26bc32f3169a40b5...	8
...	...	...
55473	5f24d4cde7984dbab5a2d56c60b60de4ca8dc7c508b288...	2
55456	5f1dbd52a4c170334d7b9ded2a76280f604c1548828470...	2
55445	5f1ac892681e388456df5f82576efc9b0ea759f3542570...	2
55443	5f1a0dd38dc5b8d2dbd855ee80338174f1de81aadd7dae...	2
149243	fffbf480e0003fe636e4d73543eaa472305e1a720c1fd3...	2

40426 rows × 2 columns

In [46]:

```
df.columns
```

Out[46]:

```
Index(['company_hash', 'email_hash', 'orgyear', 'ctc', 'job_position',
       'ctc_updated_year', 'Current Year', 'experience'],
      dtype='object')
```

In [47]:

```
df['job_position'] = df['job_position'].fillna('Other') # filled null values with 'Other'
df['job_position'].isna().sum()
```

Out[47]:

0

In [48]:

```
# removing duplicates
df.duplicated().sum()
```

Out[48]:

4261

In [49]:

```
df.drop_duplicates(keep='first',inplace=True)
```

In [50]:

```
df.duplicated().sum()
```

Out[50]:

0

In [51]:

```
email_dup = df.groupby(df['email_hash']).count()['ctc'].reset_index()
```

In [52]:

```
email_dup[email_dup['ctc']>1].sort_values(by = 'ctc', ascending = False)
```

Out[52]:

	email_hash	ctc
36407	3e5e49daa5527a6d5a33599b238bf9bf31e85b9efa9a94...	9
60776	6842660273f70e9aa239026ba33bfe82275d6ab0d20124...	9
112412	c0eb129061675da412b0deb15871dd06ef0d7cd86eb5f7...	8
105449	b4d5afa09bec8689017d8b29701b80d664ca37b83cb883...	8
41984	4818edfd67ed8563dde5d083306485d91d19f4f1c95d19...	8
...	...	...
55425	5f10a84435767459749b0842b8d7de0b8bd66d5b9f0b69...	2
55424	5f10a445e04c184991a62ff9c7a144742df1ac21127065...	2
55419	5f0e7d02a3af66bc35efd0cf9dad1dc67ad31794e7e03a...	2
55418	5f0da43d019faea71763de3cae69f9172997c5f6231b4d...	2
149237	fff9d3463b21cf1b552a5deb4d7d8af2c5ce7ebcb1f37e...	2

37439 rows × 2 columns

In [53]:

```
df.columns
```

Out[53]:

```
Index(['company_hash', 'email_hash', 'orgyear', 'ctc', 'job_position',
       'ctc_updated_year', 'Current Year', 'experience'],
      dtype='object')
```

In [54]:

```
df.shape
```

Out[54]:

(196386, 8)

In [55]:

```
df.sort_values(by='ctc_updated_year',ascending=True,inplace=True)
```

In [56]:

```
df_grouped = df.groupby(['email_hash']).aggregate(orgyear =('orgyear', 'min'),
                                      ctc = ('ctc','max'),
                                      ctc_updated_year = ('ctc_updated_year','max'),
                                        experience = ('experience','max'),
                                        job_position = ('job_position','last'),
                                        company_hash=('company_hash','last')).reset_index()
```

In [57]:

```
email_dup = df_grouped.groupby(df_grouped['email_hash']).count()['ctc'].reset_index()
```

In [58]:

```
email_dup[email_dup['ctc']>1].sort_values(by = 'ctc', ascending = False)
```

Out[58]:

email_hash	ctc

```
Manual Clustering on the basis of learner's company, job position and years of experience
-->Getting the 5 point summary of CTC (mean, median, max, min, count etc) on the basis of Company, Job Position, Years of Experience
-->Merging the same with original dataset carefully and creating some flags showing learners with CTC greater than the Average of their
Company's department having same Years of Experience - Call that flag designation with values [1,2,3]
-->Doing above analysis at Company & Job Position level. Name that flag Class with values [1,2,3]
-->Repeating the same analysis at the Company level. Name that flag Tier with values [1,2,3]
```

In [59]:

```
company_details = df.groupby('company_hash').aggregate(company_mean=('ctc','mean'),
                                     company_median=('ctc','median'),
                                    company_max=('ctc','max'),
                                    company_min=('ctc','min'),
                                    company_count=('ctc','count')).reset_index()
```

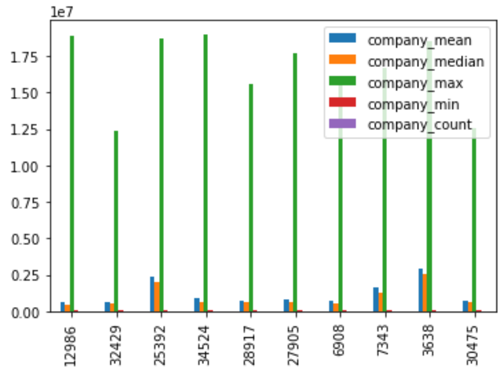
```
all companies almost have the same statistics
```

In [60]:

```
company_details.sort_values(by='company_count',ascending=False).head(10).plot(kind='bar')
```

Out[60]:

<AxesSubplot:>



In [61]:

```
company_details[company_details['company_count']>=100].round(2)
```

Out[61]:

	company_hash	company_mean	company_median	company_max	company_min	company_count
312	adw ntwyzgrgsj	920565.97	600000.0	8000000	56000	288
323	adw ntwyzgrgsxto	940614.79	670000.0	12000000	100000	135
562	amo mvzp	1493992.74	1200000.0	10000000	75000	193
839	athnowyt mvzp	1711856.51	1500000.0	6000000	70000	230
911	atrgxnnt	1084197.35	900000.0	10000000	60000	646
...	...	...	...	...	...	...
35152	ztnvuu	2416521.18	2000000.0	19800000	105000	165
35472	zvsvqqg	1169893.58	1000000.0	11400000	68000	780
35494	zvz	1263444.46	953999.0	12500000	51000	1619
35520	zwq wgqugqvnxgz	1159296.08	800000.0	5500000	100000	179
35708	zxxn ntwyzgrgsxto rxbxnta	903118.10	700000.0	3400000	100000	127

229 rows × 6 columns

In [62]:

```
# Job_position
```

In [63]:

```
job_position_details = df.groupby('job_position').aggregate(job_position_mean=('ctc','mean'),
                                     job_position_median=('ctc','median'),
                                    job_position_max=('ctc','max'),
                                    job_position_min=('ctc','min'),
                                    job_position_count=('ctc','count')).reset_index()
```

In [64]:

```
job_position_details.sort_values(by='job_position_count',ascending=False)
```

Out[64]:

	job_position	job_position_mean	job_position_median	job_position_max	job_position_min	job_position_count
441	Other	1.179907e+06	800000.0	19998000	51000	64463
137	Backend Engineer	1.547486e+06	1200000.0	19959000	51000	42599
281	FullStack Engineer	1.287284e+06	950000.0	19959000	51000	24036
277	Frontend Engineer	1.149396e+06	900000.0	19800000	52000	10194
246	Engineering Leadership	2.836434e+06	2600000.0	19800000	52000	6656
...	...	...	...	...	...	...
366	MTS-3	1.100000e+06	1100000.0	1100000	1100000	1
368	Machine Learning Data Associate	3.600000e+05	360000.0	360000	360000	1
369	Machine Learning Developer	2.500000e+05	250000.0	250000	250000	1
371	Machine Learning Engineer Intern	7.000000e+05	700000.0	700000	700000	1
976	technology analyst	8.200000e+04	82000.0	82000	82000	1

977 rows × 6 columns

In [65]:

```
job_position_details[job_position_details['job_position_count']<=5]
```

Out[65]:

	job_position	job_position_mean	job_position_median	job_position_max	job_position_min	job_position_count
0	SDE 2	1200000.0	1200000.0	1200000	1200000	1
1	.	700000.0	700000.0	700000	700000	1
2	..	600000.0	600000.0	600000	600000	1
3	.7	470000.0	470000.0	470000	470000	1
4	7	420000.0	420000.0	420000	420000	1
...	...	...	...	...	...	...
972	student	1715000.0	1715000.0	2400000	1030000	2
973	support escalation engineer	2000000.0	2000000.0	2000000	2000000	1
974	system engineer	500000.0	500000.0	500000	500000	1
975	system software engineer	610000.0	610000.0	610000	610000	1
976	technology analyst	82000.0	82000.0	82000	82000	1

899 rows × 6 columns

YOE

In [66]:

```
yoe_details = df.groupby('experience').aggregate(yoe_mean=('ctc','mean'),
                                                  yoe_median=('ctc','median'),
                                                 yoe_max=('ctc','max'),
                                                 yoe_min=('ctc','min'),
                                                 yoe_count=('ctc','count')).reset_index()
```

In [67]:

```
yoe_details.head(10)
```

Out[67]:

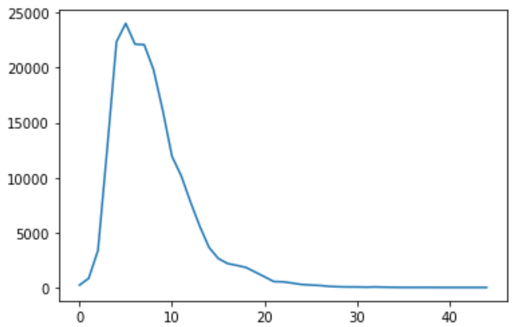
	experience	yoe_mean	yoe_median	yoe_max	yoe_min	yoe_count
0	0	1.508037e+06	720000.0	19800000	80000	214
1	1	1.381448e+06	860000.0	19000000	60000	834
2	2	1.054513e+06	700000.0	19800000	58000	3378
3	3	9.787543e+05	700000.0	18500000	51000	12670
4	4	9.434998e+05	700000.0	18500000	55000	22373
5	5	1.030918e+06	714000.0	19800000	51000	24045
6	6	1.086802e+06	800000.0	19998000	51000	22151
7	7	1.198410e+06	869999.0	19500000	51000	22102
8	8	1.279824e+06	960000.0	19800000	52000	19839
9	9	1.383307e+06	1036999.0	19800000	52000	16121

In [68]:

```
yoe_details.sort_values(by='experience')['yoe_count'].plot()
```

Out[68]:

```
<AxesSubplot:>
```




```
Most of the students are with experience around 4-9 YOE
```

In [69]:

```
company_details=company_details.round(2)
job_position_details=job_position_details.round(2)
yoe_details=yoe_details.round(2)
```

In [70]:

```
df = df.merge(right=company_details[['company_hash','company_mean']], on='company_hash',how='inner')
```

In [71]:

```
df = df.merge(right=job_position_details[['job_position','job_position_mean']], on='job_position',how='inner')
```

In [72]:

```
df = df.merge(right=yoe_details[['experience','yoe_mean']], on='experience',how='inner')
```

In [73]:

```
df.reset_index(inplace=True)
```

In [74]:

```
df.shape
```

Out[74]:

```
(196345, 12)
```

```
Relative Values
```

In [75]:

```
def company_relative_change(df):
    return (df['ctc'] - df['company_mean']) / df['company_mean']

def job_position_relative_change(df):
    return (df['ctc'] - df['job_position_mean']) / df['job_position_mean']

def yoe_relative_change(df):
    return (df['ctc'] - df['yoe_mean']) / df['yoe_mean']
```

In [76]:

```
company_rel = pd.DataFrame(company_relative_change(df)).reset_index().rename(columns={'0':'company_rel'})
job_position_rel = pd.DataFrame(job_position_relative_change(df)).reset_index().rename(columns={'0':'job_position_rel'})
yoe_rel = pd.DataFrame(yoe_relative_change(df)).reset_index().rename(columns={'0':'yoe_rel'})
```

In [77]:

```
company_rel.head()
```

Out[77]:

	index	0
0	0	0.034625
1	1	0.114212
2	2	0.273385
3	3	1.586563
4	4	-0.840333

In [78]:

```
df = df.merge(right=company_rel, on='index',how='inner')
df = df.merge(right=job_position_rel, on='index',how='inner')
df = df.merge(right=yoe_rel, on='index',how='inner')
```

```
# Dividing classes bases on below values
>= 0.2 -- class 1
>= -0.2 and < 0.2 -- class 2
< 0.2 -- class 3
```

In [79]:

```
df.head()
```

Out[79]:

	index	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Current Year	experience	com
0	0	bxzanxwprt	945a580970d17b4b9bea9945f72709bb47a030bc70d490...	2015	2600000	Backend Engineer	2015.0	2023	8	
1	1	bxzanxwprt	8e941fac74044e63964754e63d7d21cfa986267f89e4f7...	2015	2800000	Backend Engineer	2019.0	2023	8	
2	2	bxzanxwprt	5913d933b27bd607936925ff67ad94e1c1b83ffc9f5191...	2015	3200000	Backend Engineer	2019.0	2023	8	
3	3	bxzanxwprt	5bd4f708f6ab38c3d00de65b88677c8789b69255e40c07...	2015	6500000	Backend Engineer	2020.0	2023	8	
4	4	jvygg xzw	63a28c8f24f178b07c8ad560025a9305b5b978b8f38b7c...	2015	135000	Backend Engineer	2017.0	2023	8	

In [80]:

```
df.rename(columns={'0_x':'company_rel','0_y':'job_position_rel',0:'yoe_rel'},inplace=True)
```

In [81]:

```
df.head()
```

Out[81]:

	index	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Current Year	experience	com
0	0	bxzanxwprt	945a580970d17b4b9bea9945f72709bb47a030bc70d490...	2015	2600000	Backend Engineer	2015.0	2023	8	
1	1	bxzanxwprt	8e941fac74044e63964754e63d7d21cfa986267f89e4f7...	2015	2800000	Backend Engineer	2019.0	2023	8	
2	2	bxzanxwprt	5913d933b27bd607936925ff67ad94e1c1b83ffc9f5191...	2015	3200000	Backend Engineer	2019.0	2023	8	
3	3	bxzanxwprt	5bd4f708f6ab38c3d00de65b88677c8789b69255e40c07...	2015	6500000	Backend Engineer	2020.0	2023	8	
4	4	jvygg xzw	63a28c8f24f178b07c8ad560025a9305b5b978b8f38b7c...	2015	135000	Backend Engineer	2017.0	2023	8	

In [82]:

```
col = ['company_rel','job_position_rel','yoe_rel']
for i in col:
    conditions = [df[i] >= 0.2, (df[i] > -0.2) & (df[i] <= 0.2), df[i] < -0.2]
    choices = [1, 2, 3]
    df[i + '_class'] = np.select(conditions, choices, default='null')
```

In [83]:

```
df.head()
```

Out[83]:

	index	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Current Year	experience	com
0	0	bxzanxwprt	945a580970d17b4b9bea9945f72709bb47a030bc70d490...	2015	2600000	Backend Engineer	2015.0	2023	8	
1	1	bxzanxwprt	8e941fac74044e63964754e63d7d21cfa986267f89e4f7...	2015	2800000	Backend Engineer	2019.0	2023	8	
2	2	bxzanxwprt	5913d933b27bd607936925ff67ad94e1c1b83ffc9f5191...	2015	3200000	Backend Engineer	2019.0	2023	8	
3	3	bxzanxwprt	5bd4f708f6ab38c3d00de65b88677c8789b69255e40c07...	2015	6500000	Backend Engineer	2020.0	2023	8	
4	4	jvygg xzw	63a28c8f24f178b07c8ad560025a9305b5b978b8f38b7c...	2015	135000	Backend Engineer	2017.0	2023	8	

In [84]:

```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
le.fit_transform(df['job_position'])
```

Out[84]:

```
array([137, 137, 137, ..., 246, 246, 246])
```

```
Based on the manual clustering done so far, answering few questions like:
--Top 10 employees (earning more than most of the employees in the company) - Tier 1
--Top 10 employees of data science in Amazon / TCS etc earning more than their peers - Class 1
--Bottom 10 employees of data science in Amazon / TCS etc earning less than their peers - Class 3
--Bottom 10 employees (earning less than most of the employees in the company)- Tier 3
--Top 10 employees in Amazon- X department - having 5/6/7 years of experience earning more than their peers - Tier X
--Top 10 companies (based on their CTC)
--Top 2 positions in every company (based on their CTC)
```

In [85]:

```python
df[df['company_rel_class']=='1'].sort_values(by='ctc',ascending=False).head(10)
```

Out[85]:

	index	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Current Year	experien
122804	122804	eqtoytq	db6866f146f012adb03831a251f892277cf076938cc1fc...	2017	19998000	Other	2019.0	2023	
119191	119191	uytzgb utgurt	bdedd1d96b39018c1ae020c90ae326b6ad4e160c2ab44a...	2017	19959000	FullStack Engineer	2020.0	2023	
114869	114869	uytzgb utgurt	bdedd1d96b39018c1ae020c90ae326b6ad4e160c2ab44a...	2017	19959000	Backend Engineer	2020.0	2023	
191485	191485	zgn vuurxwvmrt	e5ef043e885543843a2ffc11e18ba1662194512592b442...	2021	19800000	Other	2019.0	2023	
106940	106940	yvuuvj tdutzot bvzvstbtzn ogrhnxgz egq mhoxzt...	83fd708a1cdbc3b7f2cd28289e9d37ce6009bb9bd87621...	2018	19800000	Frontend Engineer	2020.0	2023	
18074	18074	bvyxzaqv trtwnqxw bgmxrxnj rxbxnta	a60507e926b9532ac5502d3821355e0c0861b4f97c6f9b...	2015	19800000	Android Engineer	2020.0	2023	
193729	193729	tahwvnxgz wgbuvzj	ee4e1a59a6613a15c0e16866c32f5af4c65e46a38d23e4...	2023	19800000	Engineering Leadership	2020.0	2023	
196219	196219	ztnvuu	0439e2628e7ba75f1a2cca142ec8ca9a7f0fdc042b92dc...	1989	19800000	FullStack Engineer	2019.0	2023	
25575	25575	ovsstkkv	61a2723ab9dbce9ef7bb18bf6db751b103b5b6bfca2f86...	2016	19500000	Program Manager	2021.0	2023	
37465	37465	rgwvr wgqugqvnxgz	b0f097f96176973f41c7ae71dd6d0763deab45ea407189...	2016	19200000	Engineering Leadership	2020.0	2023	

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

In [86]:

```python
df[(df['company_rel_class'] == '1')&(df['job_position_rel_class'] == '3')&(df['job_position'].isin(['Data Science Analyst','Data Scientist
```

Out[86]:

	index	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Current Year	experienc
54909	54909	btnxo	87928a88e94e306901e85de2b3ce1d861c616a7ad0854e...	2014	120000	Data Scientist	2020.0	2023	
131021	131021	wgbowgqt xzw	b43515409964a2090dc9efe1bf4a290cf542fbc7324c79...	2017	160000	Data Scientist	2017.0	2023	
108741	108741	xzatrrxtzn	cafbe82bdd822f80cdf232311a09fb8d8c6ccdac5786f2...	2018	180000	Data Scientist	2019.0	2023	
131340	131340	utzz onvnt hzxctqoxnj	eb8283b0eb3fc5fd386cb31567f0a0fe85d1148d50095d...	2017	200000	Data Scientist	2020.0	2023	
131343	131343	ovmuvxov	5314798d405114516dfccb1dddd6f13eafb25acb9fc824...	2017	400000	Data Scientist	2020.0	2023	
108909	108909	xzthqgzvx	2ac23890a2d35956df1f5b0a78a28e2df4ef32554d6a9b...	2018	400000	Data Scientist	2021.0	2023	
39030	39030	wxurv rxbxnta	b29a1831396dbdbefc88da4afe5c025b8e92f28735e1c5...	2016	500000	Data Scientist	2021.0	2023	
153595	153595	cxaggrj	4e24a4e775bbc933e5eff9535be540dc876327d5a4e0d2...	2019	600000	Data Scientist	2018.0	2023	
55071	55071	tdwtrq ogrhnxgzo	08f3ec5664b9cd9fd33d3eafa0b17fb1aff65ab301d59d...	2014	600000	Data Scientist	2019.0	2023	
16578	16578	tdwtrq ogrhnxgzo	e70f8f2442c035983ef6258fb1f3afd163934c89cdab41...	2015	600000	Data Scientist	2019.0	2023	

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

In [87]:

```
df[(df['company_rel_class'] == '3')&(df['job_position_rel_class'] == '3')&(df['job_position'].isin(['Data Science Analyst','Data Scientist
```

Out[87]:

	index	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Current Year	experience
108370	108370	ogwxn szqvrt	ae4d247f28622b8d6475c16a8ae1aa92fc048f0cab908d...	2018	52000	Data Scientist	2015.0	2023	5
108371	108371	ogwxn szqvrt	38e8416bc59782b9fb60b144657130662ec8dab8094a41...	2018	55000	Data Scientist	2021.0	2023	5
108661	108661	sep	9058729fee37abcc3765b85d534aedc471efaed55099b4...	2018	57000	Data Scientist	2018.0	2023	5
153646	153646	zgztonhatzn	47918c521b052ed32c8f3746f5fbf9bfb38257c5dff4a7...	2019	60000	Data Scientist	2019.0	2023	4
16121	16121	xzntr wgqugqvnxgz	6344f65bdb7dc5da9abb8bdb0f90b92718ac2f85556746...	2015	60000	Data Scientist	2017.0	2023	8
171033	171033	utnqgmqvo	b4add3288ba46af8a5fa13ffd9893c7951588ccd366dbf...	2009	61000	Data Scientist	2017.0	2023	14
39012	39012	uhmrxwxo sqghut	3fc3a28959041dabfb504174589fcd911eeddc67884006...	2016	65000	Data Scientist	2020.0	2023	7
16376	16376	uvzvogzxw	97b533796260439b294fa38d0577f9f3e420389c074a9b...	2015	65000	Data Scientist	2017.0	2023	8
38693	38693	bvqptnxzs rgsxw rna	c9121af74bc3e3a7e130109b476df6e841f3f40542ba90...	2016	66000	Data Scientist	2017.0	2023	7
75451	75451	evhqtwxv	336f5ac8956134a41a14264ed9bf6122f7dfb1a76abf74...	2013	70000	Data Scientist	2019.0	2023	10

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

In [88]:

```
df[(df['job_position_rel_class'] == '3')&(df['job_position_rel_class'] == '3')].sort_values('ctc',ascending=True).head(10)
```

Out[88]:

	index	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Current Year	experience
33176	33176	tuer wgrt ugrjntwyzxiht eaqvrt at rvhovzzt	45ce8e6080f2d92861eb76cfd731d30f9dca8938e24e1d...	2016	51000	Other	2018.0	2023	7
101059	101059	xmb	c5d944aabae3c48c0221c9a5f39daf5574ba81eb2a5b10...	2018	51000	Other	2017.0	2023	5
161153	161153	bvzvstbtzn btzngqo xzw	ccc1cff7fe4feeea1f51c72e8cd053fe14cdf1d16c89ae...	2010	51000	Backend Engineer	2017.0	2023	13
21536	21536	onhatzn	1475beb0a6731388fca2c52ca7e7ed1f5c4591b9cbc665...	2016	51000	Backend Engineer	2016.0	2023	7
112161	112161	vbvkgz	a03be8e38fc9de30a5a47418ac4f5e130e171b3215fbe1...	2017	51000	Backend Engineer	2020.0	2023	6
95310	95310	zvz	2b946b6501a6f75c785688cb767491d4476dda233258f1...	2018	51000	FullStack Engineer	2018.0	2023	5
62092	62092	xwrtx	01fb1186d250f2e3eb6fa810a09f3f59fcfcf1d597cacc...	2011	51000	Other	2018.0	2023	12
125580	125580	pxdtjt	9f9e73368e4ec8c576748588ea8e916159ac9ad2575a76...	2017	51000	Other	2017.0	2023	6
82407	82407	hzxmtn	0ff231a0490001ec15bb409791267f3bf52972f00860b6...	2012	51000	Other	2015.0	2023	11
173256	173256	svqcxovx	cf2d3d3256e8f752675963c21e1e90175254f6563044be...	2020	51000	Backend Engineer	2020.0	2023	3

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

In [89]:

```
df[(df['experience'].isin([5,6,7]))&(df['company_hash'].isin(['vbvkgz']))].sort_values('ctc',ascending=False).head(10)
```

Out[89]:

	index	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Current Year	experien
28737	28737	vbvkgz	bdb98168d0e0807cf9f2d70a7d9fa8e26c8be875b4b061...	2016	16000000	Other	2020.0	2023	
20097	20097	vbvkgz	89786e81708a0764cd0a336ff3aaff4c4cb4e76a31d3c2...	2016	14000000	Backend Engineer	2021.0	2023	
25722	25722	vbvkgz	89786e81708a0764cd0a336ff3aaff4c4cb4e76a31d3c2...	2016	14000000	FullStack Engineer	2021.0	2023	
93772	93772	vbvkgz	dfd6d48535b4cce3731acca53451cfb480abf10d6b8640...	2018	10000000	FullStack Engineer	2020.0	2023	
109083	109083	vbvkgz	bac2f8d27706e13bc320d87ead38a56229287160d49042...	2018	10000000	Engineering Intern	2019.0	2023	
88085	88085	vbvkgz	dfd6d48535b4cce3731acca53451cfb480abf10d6b8640...	2018	10000000	Backend Engineer	2020.0	2023	
88046	88046	vbvkgz	bac2f8d27706e13bc320d87ead38a56229287160d49042...	2018	10000000	Backend Engineer	2019.0	2023	
112109	112109	vbvkgz	df95a1315bd57c9060b239cddc3d7ab6e57fbc5832ef4f...	2017	10000000	Backend Engineer	2019.0	2023	
93798	93798	vbvkgz	77a2d67037afa3814539d45ce6af181ab029731bbec8a8...	2018	9800000	FullStack Engineer	2021.0	2023	
88010	88010	vbvkgz	8a08a9adba36d92b292d78302be2bcf69530e6d1a13ef7...	2018	9000000	Backend Engineer	2016.0	2023	

```
--Top 10 companies (based on their CTC)
```

In [90]:

```
df.groupby('company_hash').mean()['ctc'].reset_index().sort_values('ctc',ascending=False).head(10)[['company_hash','ctc']]
```

Out[90]:

	company_hash	ctc
15402	opxrrovznv	19800000.0
10327	mpr	19800000.0
18365	qgmgoyvonqv	19700000.0
29413	wo xzegwgbb	19200000.0
30558	wvzgnxw	18450000.0
33409	ygntr bxrrtzzxv qtstzwj rhwpzgf	18200000.0
32357	xzeg ptjo xzw	18000000.0
4324	ctzatpxz ntwyzgrgsxto	18000000.0
28949	wguutq	18000000.0
22469	tong mqgvamvza uqxcvnt rxbxnta	18000000.0

```
--Top 2 positions in every company (based on their CTC)
```

In [91]:

```
tmp = df.groupby(['company_hash','job_position']).mean().sort_values(['company_hash','ctc']).reset_index()
tmp = tmp.groupby('company_hash').head(2)[['company_hash','job_position']]
tmp
```

Out[91]:

	company_hash	job_position
0	0	Other
1	0000	Other
2	01 ojztqsj	Android Engineer
3	01 ojztqsj	Frontend Engineer
4	05mz exzytvrny uqxcvnt rxbxnta	Backend Engineer
...	...	...
66257	zyvzwt wgzohrnxzs tzsxzttqo	Frontend Engineer
66258	zz	Other
66259	zzb ztdnstz vacxogqj ucn rna	FullStack Engineer
66260	zzb ztdnstz vacxogqj ucn rna	Other
66261	zzgato	Other

47715 rows × 2 columns

In [ ]:

In [92]:

```
## Clustering
```

In [93]:

```
data = df.copy(deep=True)
```

In [94]:

```
feat = 'job_position'
data[feat] = data[feat].fillna('na')
enc_nom = (data.groupby(feat).size()) / len(data)
data[feat+'_encode'] = data[feat].apply(lambda x : enc_nom[x])
```

In [95]:

```
feat = 'company_hash'
data[feat] = data[feat].fillna('na')
enc_nom = (data.groupby(feat).size()) / len(data)
data[feat+'_encode'] = data[feat].apply(lambda x : enc_nom[x])
```

In [96]:

```
data.isna().sum()
```

Out[96]:

```
index                    0
company_hash             0
email_hash               0
orgyear                  0
ctc                      0
job_position             0
ctc_updated_year         0
Current Year             0
experience               0
company_mean             0
job_position_mean        0
yoe_mean                 0
company_rel              0
job_position_rel         0
yoe_rel                  0
company_rel_class        0
job_position_rel_class   0
yoe_rel_class            0
job_position_encode      0
company_hash_encode      0
dtype: int64
```

In [97]:

```
data['ctc'] = np.log2(data['ctc'])
```

In [98]:

```
data['ctc']=data['ctc'].round(2)
```

In [99]:

```
data.head()
```

Out[99]:

	index	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Current Year	experience	compa
0	0	bxzanxwprt	945a580970d17b4b9bea9945f72709bb47a030bc70d490...	2015	21.31	Backend Engineer	2015.0	2023	8	2ε
1	1	bxzanxwprt	8e941fac74044e63964754e63d7d21cfa986267f89e4f7...	2015	21.42	Backend Engineer	2019.0	2023	8	2ε
2	2	bxzanxwprt	5913d933b27bd607936925ff67ad94e1c1b83ffc9f5191...	2015	21.61	Backend Engineer	2019.0	2023	8	2ε
3	3	bxzanxwprt	5bd4f708f6ab38c3d00de65b88677c8789b69255e40c07...	2015	22.63	Backend Engineer	2020.0	2023	8	2ε
4	4	jvygg xzw	63a28c8f24f178b07c8ad560025a9305b5b978b8f38b7c...	2015	17.04	Backend Engineer	2017.0	2023	8	ε

In [100]:

```
X = data[['ctc','experience','company_rel_class','job_position_rel_class','yoe_rel_class','company_hash_encode','job_position_encode']]
```

In [101]:

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 196345 entries, 0 to 196344
Data columns (total 7 columns):
 #   Column                  Non-Null Count   Dtype  
---  ------                  --------------   -----  
 0   ctc                     196345 non-null  float64
 1   experience              196345 non-null  int64  
 2   company_rel_class       196345 non-null  object 
 3   job_position_rel_class  196345 non-null  object 
 4   yoe_rel_class           196345 non-null  object 
 5   company_hash_encode     196345 non-null  float64
 6   job_position_encode     196345 non-null  float64
dtypes: float64(3), int64(1), object(3)
memory usage: 12.0+ MB
```

In [102]:

```
X.columns
```

Out[102]:

```
Index(['ctc', 'experience', 'company_rel_class', 'job_position_rel_class',
       'yoe_rel_class', 'company_hash_encode', 'job_position_encode'],
      dtype='object')
```

In [103]:

```
X = X[X['company_rel_class']!='null']
```

In [104]:

```
X.head()
```

Out[104]:

	ctc	experience	company_rel_class	job_position_rel_class	yoe_rel_class	company_hash_encode	job_position_encode
0	21.31	8	2	1	1	0.000413	0.216955
1	21.42	8	2	1	1	0.000413	0.216955
2	21.61	8	1	1	1	0.000413	0.216955
3	22.63	8	1	1	1	0.000413	0.216955
4	17.04	8	3	3	3	0.000219	0.216955

In [105]:

```
X['company_rel_class'].unique()
```

Out[105]:

```
array(['2', '1', '3'], dtype=object)
```

In [106]:

```
X.isna().sum()
```

Out[106]:

```
ctc                     0
experience              0
company_rel_class       0
job_position_rel_class  0
yoe_rel_class           0
company_hash_encode     0
job_position_encode     0
dtype: int64
```

In [107]:

```
# X = df[['company_rel_class','job_position_rel_class','yoe_rel_class']]
```

In [108]:

```
from sklearn.cluster import KMeans
```

In [109]:

```
# # from sklearn.preprocessing import MinMaxScaler

# # scaler = MinMaxScaler()
# # scaler.fit(X)
# # X=scaler.transform(X)

# X = df[['company_rel','job_position_rel','yoe_rel']]

# # from sklearn.preprocessing import MinMaxScaler

# # scaler = MinMaxScaler()
# # scaler.fit(X)
# # X=scaler.transform(X)

# # from sklearn.cluster import KMeans

# # k = 3
# # kmeans = KMeans(n_clusters=k)
# # kmeans.fit(X)
# # labels = kmeans.labels_

# pd.Series(labels).value_counts()

# clusters = pd.DataFrame(X, columns=['company_rel','job_position_rel','yoe_rel'])
# clusters['kmeans'] = labels

# import plotly.express as px

# fig = px.scatter_3d(clusters, x='company_rel', y='job_position_rel', z='yoe_rel', color='kmeans', width=600, height=600)
# fig.update_traces(marker=dict(size=2), selector=dict(mode='markers'))
# fig.show()
```

In [110]:

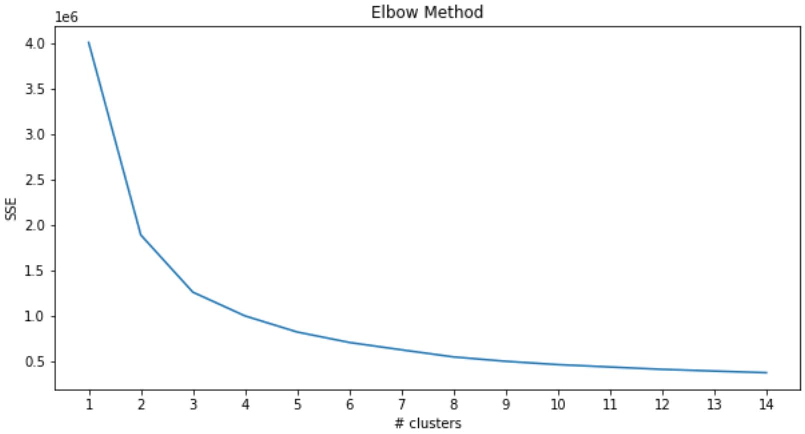
```
sse=[]
k=3
for k in range(1,15):
    kmeans = KMeans(n_clusters = k,random_state=20)
    kmeans.fit(X)
    sse.append(kmeans.inertia_)
```

In [111]:

```
import matplotlib.pyplot as plt
```

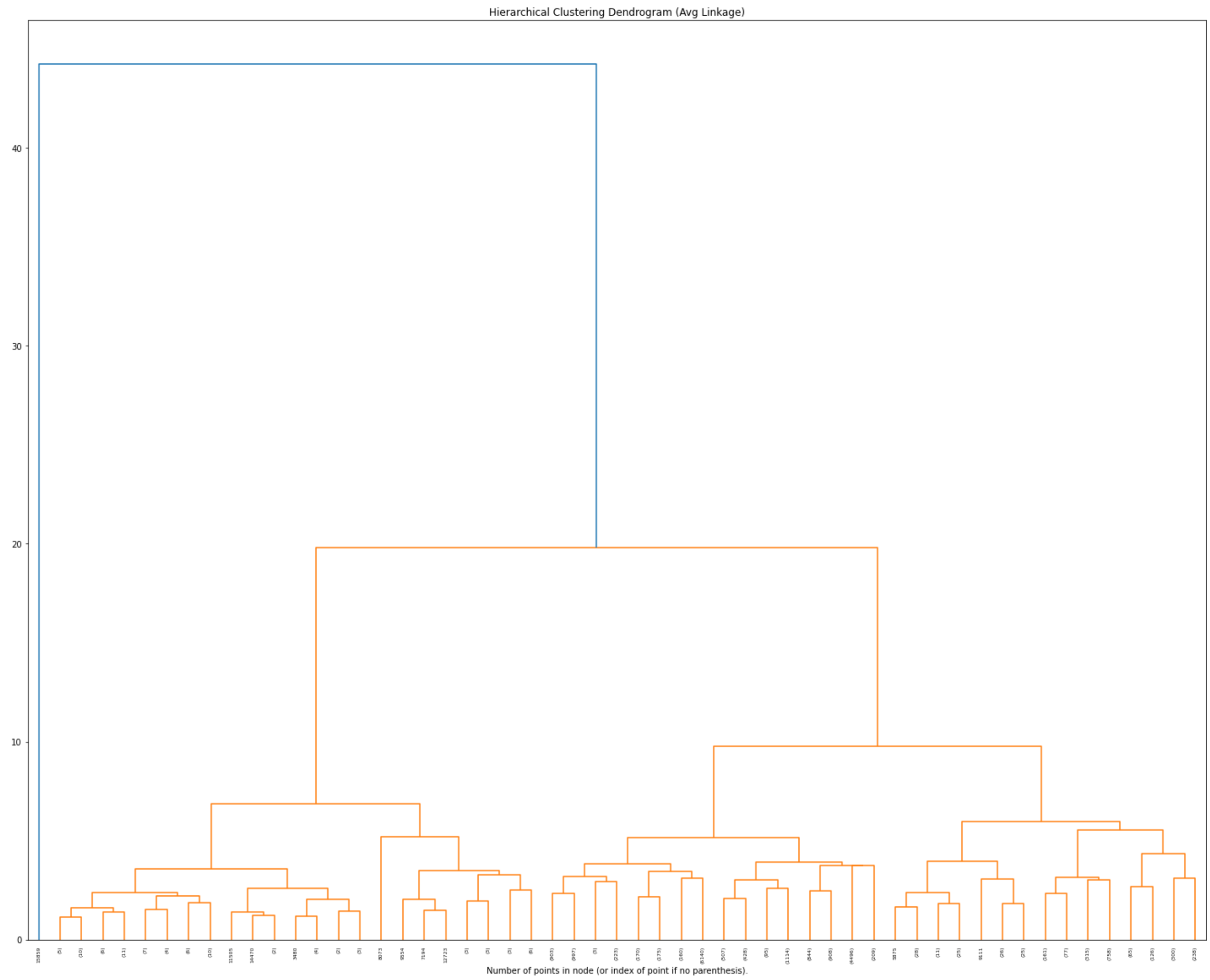
In [112]:

```
plt.figure(figsize=(10,5))
plt.plot(range(1,15),sse)
plt.xticks(range(1,15))
plt.xlabel('# clusters')
plt.ylabel('SSE')
plt.title('Elbow Method')
plt.show()
```



In [113]:

```
from sklearn.cluster import AgglomerativeClustering
from sklearn.utils import shuffle
from scipy.cluster.hierarchy import dendrogram

tmp = shuffle(X).sample(frac=0.1)
# tmp = X.sample(frac=0.2)

def plot_dendrogram(model, **kwargs):
    # Create linkage matrix and then plot the dendrogram

    # create the counts of samples under each node
    counts = np.zeros(model.children_.shape[0])
    n_samples = len(model.labels_)
    for i, merge in enumerate(model.children_):
        current_count = 0
        for child_idx in merge:
            if child_idx < n_samples:
                current_count += 1  # leaf node
            else:
                current_count += counts[child_idx - n_samples]
        counts[i] = current_count

    linkage_matrix = np.column_stack(
        [model.children_, model.distances_, counts]
    ).astype(float)

    # Plot the corresponding dendrogram

    dendrogram(linkage_matrix, **kwargs)


model = AgglomerativeClustering(distance_threshold =0, n_clusters=None, compute_distances=True,linkage='average').fit(tmp)

plt.figure(figsize=(25,20))
plt.title("Hierarchical Clustering Dendrogram (Avg Linkage)")
plot_dendrogram(model, truncate_mode="level", p=6)
plt.xlabel("Number of points in node (or index of point if no parenthesis).")
plt.show()
```



In [114]:

```
# From above we can see that we can go with 3 clusters
```

In [115]:

```
from sklearn.cluster import KMeans

k = 3
kmeans = KMeans(n_clusters=k)
kmeans.fit(X)
labels = kmeans.labels_
```

In [116]:

```
pd.Series(labels).value_counts()
```

Out[116]:

```
0    103659
2     75370
1     17196
dtype: int64
```

In [117]:

```
clusters = pd.DataFrame(X, columns=['ctc','experience','company_rel_class','job_position_rel_class','yoe_rel_class','company_hash_encode'
clusters['kmeans'] = labels
```

In [118]:

```
### GMM
```

In [119]:

```
from sklearn.mixture import GaussianMixture
gmm = GaussianMixture(n_components=3).fit(X)
```

In [120]:

```
clusters = pd.DataFrame(X, columns=df.columns)
clusters['label'] = gmm.predict(X)
```

In [121]:

```
clusters['label'].value_counts()
```

Out[121]:

```
1    149260
0     36084
2     10881
Name: label, dtype: int64
```

Insights:

- Top Paying job titles include 'Engineering Leadership', 'Backend Engineer', 'Product Manager', 'Program Manager', 'SDET', 'QA Engineer', 'Data Scientist', 'Android Engineer' and 'FullStack Engineer'.
- Top paying companies include 'Cisco', 'Intel Technology India Pvt Ltd', 'Amazon', 'Walmart Labs', 'Symantec', 'Schneider Electric India', 'Morgan Stanley', 'Ericsson RD Bangalore' and 'Samsung Electronics'.
- 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 devlopement 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.

Recommendations

- Freshers who want to work on technical side should look for roles related to Backend Engineer, SDET, QA engineer, Dataa Scientist, Android Engineer,Full stack engineer to get good salaries as expirience 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'.