Problem Statement

- Segmention of learners and cluster them on the basis of their job profile, company, and other features.

Import the dataset and do usual exploratory data analysis steps like checking the structure & characteristics of the dataset

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib as plt
```

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

In [3]:
```
df=pd.read_csv("")
```

In [4]:
```
df.head()
```

Out[4]:

	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

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

Out[5]:
```
(205843, 7)
```

205843 records present in the dataset

Checking datatype of each features

In [6]:
```
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
```

Dropping the unwanted column

In [7]:
```
df.drop(columns=['Unnamed: 0'],axis=1, inplace=True)
```

In [8]:
```
df.describe()
```

Out[8]:

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

In [9]:
```
lis=['company_hash','job_position']

for i in lis:
    print(i, ': ',df[i].unique())
    print()
```

```
company_hash :  ['atrgxnnt xzaxv' 'qtrxvzwt xzegwgbb rxbxnta' 'ojzwnvwnxw vx' ...
 'ztdnowb xzwqtee' 'mrht onvnt axsxnvr' 'bvptbjnqxu td vbvkgz']

job_position :  ['Other' 'FullStack Engineer' 'Backend Engineer' ... 'Web / UI Designer'
 'Azure data Factory' 'Android Application developer']
```

In [10]:
```
df['job_position'].unique()[60:70]
```

Out[10]:
```
array(['Operations Manager', 'Senior Engineer', 'Toyota',
       'Intern-data analyst', 'Senior Data Engineer', 'operation',
       'Associate  software  engineer ', 'Technical Manager ',
       'Senior SDET', 'Escalation Engineer'], dtype=object)
```

In [11]:
```
df[df['job_position']=='Data Scientist'].describe()
```

Out[11]:

	orgyear	ctc	ctc_updated_year
count	5367.000000	5.368000e+03	5368.000000
mean	2013.869014	1.992280e+06	2019.316505
std	47.778543	8.006034e+06	1.055852
min	1.000000	4.000000e+03	2015.000000
25%	2013.000000	7.000000e+05	2019.000000
50%	2016.000000	1.200000e+06	2019.000000
75%	2018.000000	1.900000e+06	2020.000000
max	2204.000000	2.000000e+08	2021.000000

In [12]:
```
df.head()
```

Out[12]:

	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

Checking unique emails and frequency of occurrence of the same email hash in the data

In [13]:
```
df['email_hash'].value_counts()[0:30]
```

Out[13]:
```
bbace3cc586400bbc65765bc6a16b77d8913836cfc98b77c05488f02f5714a4b    10
6842660273f70e9aa239026ba33bfe82275d6ab0d20124021b952b5bc3d07e6c     9
298528ce3160cc761e4dc37a07337ee2e0589df251d73645aae209b010210eee     9
3e5e49daa5527a6d5a33599b238bf9bf31e85b9efa9a94f1c88c5e15a6f31378     9
b4d5afa09bec8689017d8b29701b80d664ca37b83cb883376b2e95191320da66     8
faf40195f8c58d5c7edc758cc725a762d51920da996410b80ac4a4d85c803da0     8
4818edfd67ed8563dde5d083306485d91d19f4f1c95d193a1700e79dd245b75c     8
c0eb129061675da412b0deb15871dd06ef0d7cd86eb5f7e8cc6a20b0d1938183     8
d598d6f1fb21b45593c2afc1c2f76ae9f4cb7167156cdf93246d4192a89d8065     8
d15041f58bb01c8ee29f72e33b136e26bc32f3169a40b53d75fe7ae9cbb9a551     8
aacf9473e3cee3e3f7c322e49bb8a6d5346bb05f3ff5bb9e9ac3ae22729ab933     7
10ac4f847a1d45c7f325ececfe44c04714b739a3317878c35b818eea61d232fa     7
e17d6b29cce52c81cdde98bfc8bc7cac002e2c8150029a06d2e79ddbf6b8b754     7
b46e8caae1e78618a00f05c423afeaae37819a36b4dbb3b8b26b6ed2966bd7a3     7
c832dfd7457aeb0476d7ec66e17c91879aab7cfda8ff641dc495b86cc957d2e8     7
965af3ce801e20c727fbb64cc0c6bf898aeaedf501a4329a5268763a92efc2ff     7
94b5594a8a0757a23c4521a09b19ff3de75ec1f5da6f7ee85069364711107f07     7
5dcd62ab1a606642f3dde6f536f5a343a8e943f215c463f945dd1bad9bff1531     7
f5279f186abfb98a09d85a4467b99863c0bfc91c1147e542d6d23a6a69c9a7be     7
a7783035a9c89059383053ae533f6004e580c82eac0e657112d8275145fedf03     7
e47528ec80e00768b2a40c4e80681269eca274e47158d1e84873d362557ef72b     7
021ea9c97b6b287336e9345f39f9308c33ccbd15ac366d5f26f60032097ec26c     7
5052dd6c8f72543e9510cd9ecb5d39351833b96235465689fa03052d971f8cf5     7
caf66f38a8e742b7690dceb5b02d81ad8be684cfb6dd29b639a385b83748110b     7
f3258dc45caf3f3d09bb03a2880cadf85f277cf299c3b179834fb10a64640382     7
b4eb2cb12a7d04d2e0e0a6f40340b98bef4c669b4ef5d53722d8e7effddb7bdb     6
ca89666311f589646ffd0860db840bfcff64d90cea6aab1687ca23e49c776f6e     6
dfdf713524e5de58b10ee1700c976e18a32635e5f57867e958255aeb0f7a150a     6
8d7e516f21245bee0411f2182c621e71df968833be2dffe16190e28cf95011da     6
c224aada9ae9c447af8ef8ac31fc14fb8f8bfcc461fd3add8a6417a309b9157f     6
Name: email_hash, dtype: int64
```

More than 10 people have 8 or more job or ctc change

In [14]:
```
df['company_hash'].value_counts()
```

Out[14]:
```
nvnv wgzohrnvzwj otqcxwto         8337
xzegojo                           5381
vbvkgz                            3481
zgn vuurxwvmrt vwwghzn            3411
wgszxkvzn                         3240
                                  ...
onvqmhwpo                            1
bvsxw ogenfvqt uqxcvnt rxbxnta       1
agsbv ojontbo                        1
vnnhzt xzegwgb                       1
bvptbjnqxu td vbvkgz                 1
Name: company_hash, Length: 37299, dtype: int64
```

Most of the people are working in 'nvnv wgzohrnvzwj otqcxwto' followed by 'xzegojo' and 'vbvkgz'

In [15]:
```
df['job_position'].value_counts()
```

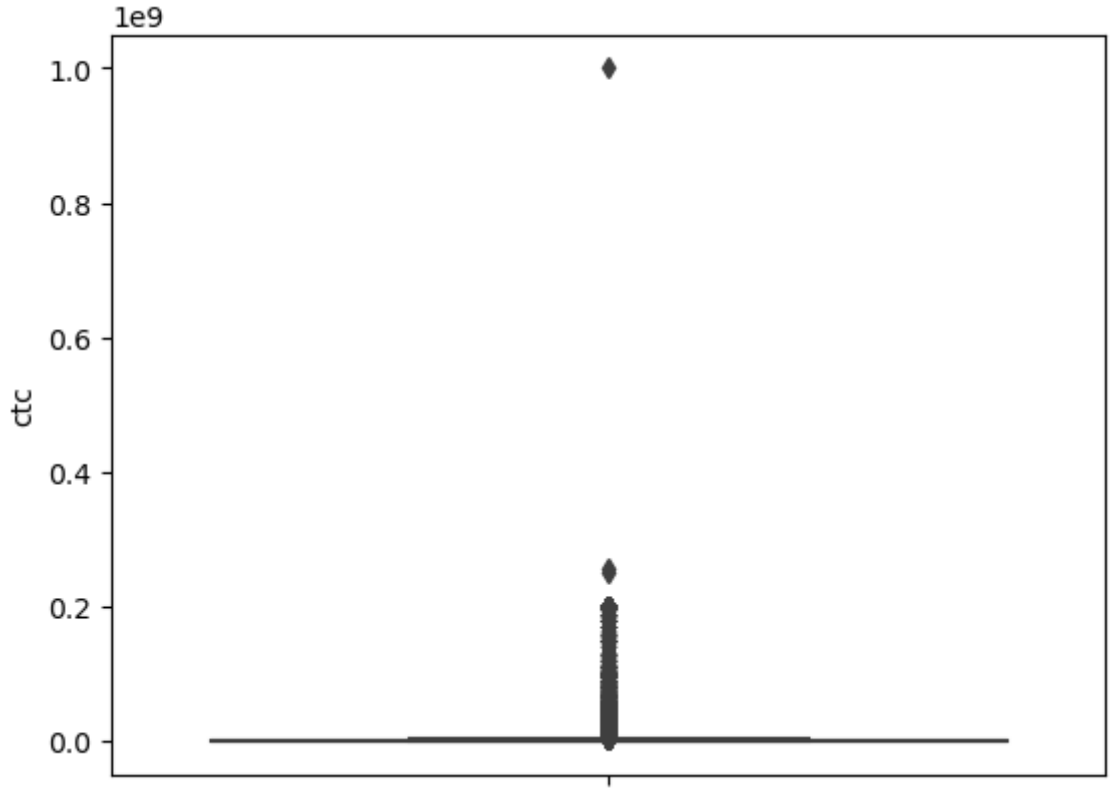
Out[15]:
```
Backend Engineer                  43554
FullStack Engineer                24717
Other                             18071
Frontend Engineer                 10417
Engineering Leadership             6870
                                  ...
ayS                                   1
Principal Product Engineer            1
Senior Director of Engineering        1
Seller Support Associate              1
Android Application developer         1
Name: job_position, Length: 1017, dtype: int64
```

Data Preprocessing

Outlier treatment

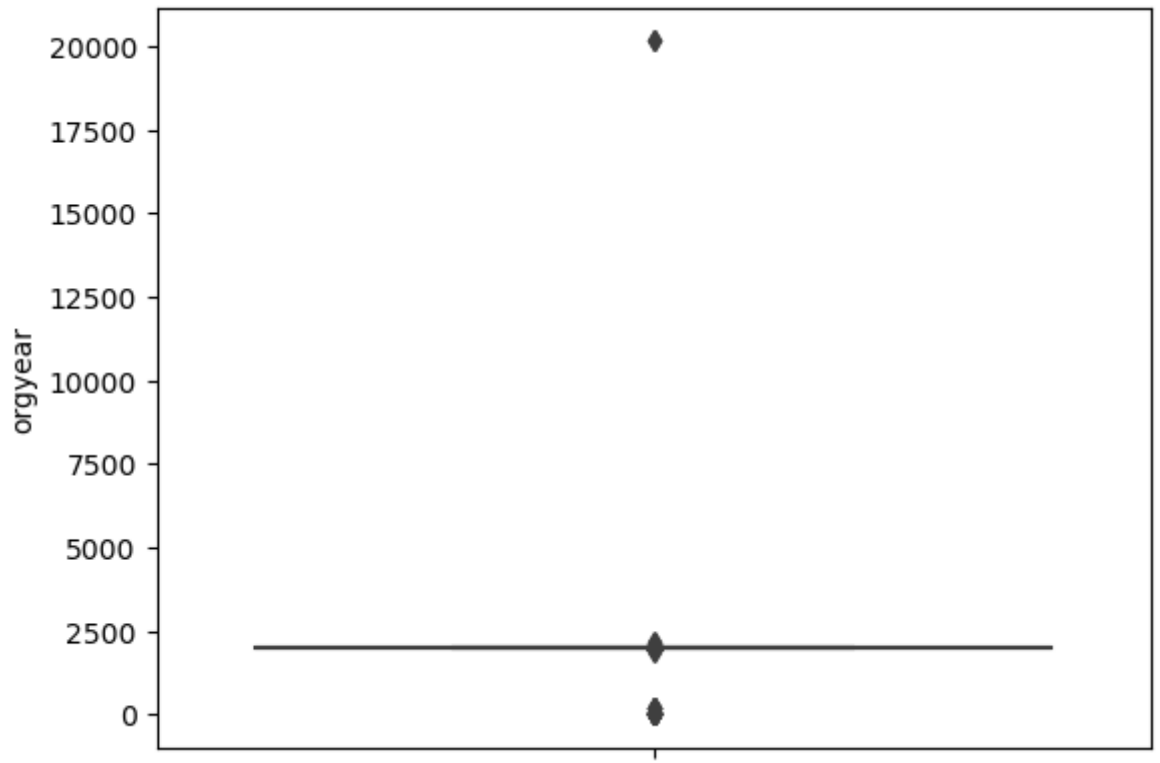
In [16]:
```
sns.boxplot(data=df,y='ctc')
```

Out[16]:
```
<AxesSubplot:ylabel='ctc'>
```



In [17]:
```
sns.boxplot(data=df,y='orgyear')
```

Out[17]: <AxesSubplot:ylabel='orgyear'>



In [18]:
```
Q1 = np.percentile(df['ctc'], 25, interpolation = 'midpoint')
Q2 = np.percentile(df['ctc'], 50, interpolation = 'midpoint')
Q3 = np.percentile(df['ctc'], 75, interpolation = 'midpoint')
IQR = Q3 - Q1
low_lim = Q1 - 1.5 * IQR
up_lim = Q3 + 1.5 * IQR

df=df[(df['ctc']>low_lim) & (df['ctc']<up_lim)]
```

In [19]:
```
# Q1 = np.percentile(df['orgyear'], 25, interpolation = 'midpoint')
# Q2 = np.percentile(df['orgyear'], 50, interpolation = 'midpoint')
# Q3 = np.percentile(df['orgyear'], 75, interpolation = 'midpoint')
# IQR = Q3 - Q1
# low_lim = Q1 - 1.5 * IQR
# up_lim = Q3 + 1.5 * IQR

# df=df[(df['orgyear']>low_lim) & (df['orgyear']<up_lim)]
```

Checking for duplicates in the dataset and drop them

In [20]:
```
df.shape
```

Out[20]:
```
(192716, 6)
```

In [21]:
```
df.drop_duplicates(inplace=True)
```

In [22]:
```
df.shape
```

Out[22]:
```
(192684, 6)
```

33 entries removed

Update cant be before jo1ning

In [23]:
```
#_Update cant be before jo1ning
df ['ctc_updated_year'] = df[['ctc_updated_year', 'orgyear']].max(axis=1)
```

Making some new features (adding 'Years of Experience' column by subtracting orgyear from current year)

In [24]:
```
df['Year of Experience']=2023-df['orgyear']
```

In [25]:
```
from sklearn.preprocessing import LabelEncoder
```

In [26]:
```
le = LabelEncoder()
df['company_hash']=le.fit_transform(df['company_hash'])
df['job_position']=le.fit_transform(df['job_position'])
```

In [27]:
```
df.head()
```

Out[27]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Year of Experience
0	921	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000	437	2020.0	7.0
1	18817	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999	276	2019.0	5.0
2	14789	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015.0	2000000	136	2020.0	8.0
3	11533	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	700000	136	2019.0	6.0
4	19288	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017.0	1400000	276	2019.0	6.0

RegX Cleaning

In [28]:
```
import re
def preprocess_string (string):
    new_string= re.sub('[A-Za-z]+', '', string).lower().strip()
    return new_string
```

In [29]:
```
df.job_position=df.job_position.apply(lambda x: preprocess_string(str(x)))
df.company_hash=df.company_hash.apply(lambda x: preprocess_string(str(x)))
```

Visual analysis

Univariate Analysis

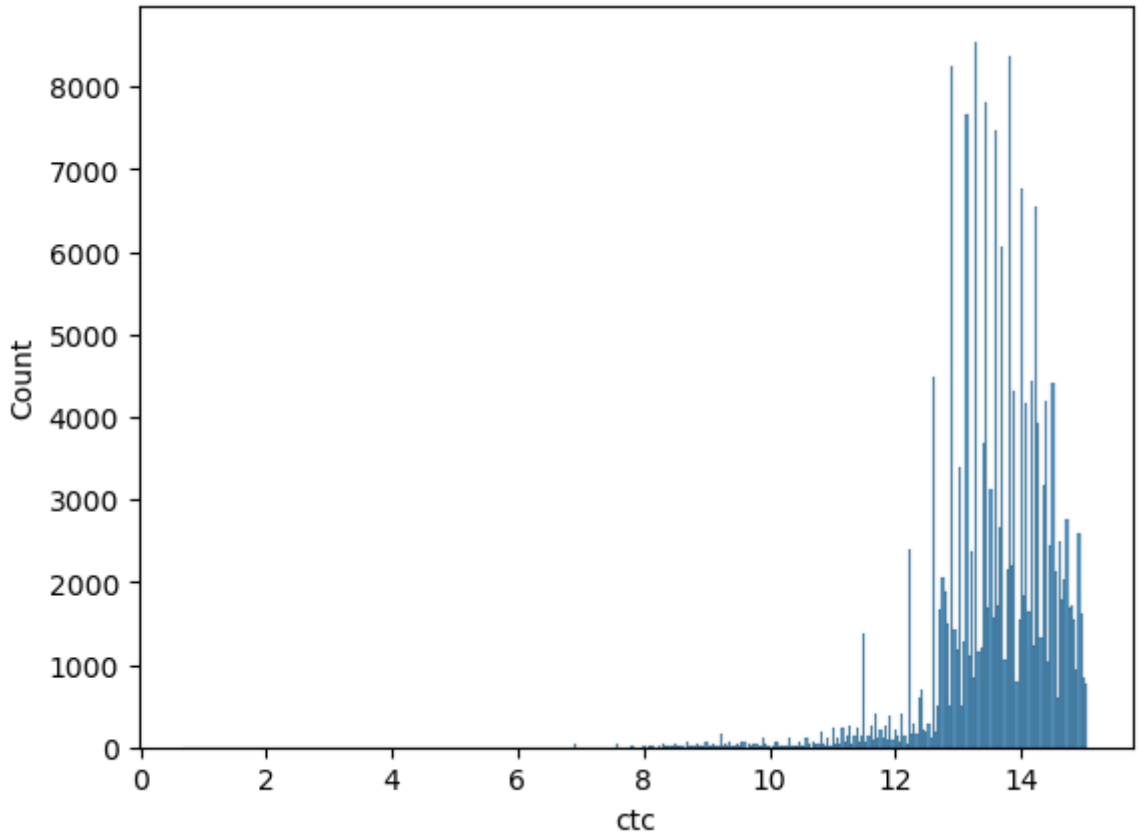
In [30]:
```
ax=sns.countplot(df['Year of Experience'])
ax.set_xticklabels(ax.get_xticklabels(), rotation=90)
```

Out[30]:
```
[Text(0, 0, '-18142.0'),
 Text(1, 0, '-181.0'),
 Text(2, 0, '-84.0'),
 Text(3, 0, '-83.0'),
 Text(4, 0, '-78.0'),
 Text(5, 0, '-8.0'),
 Text(6, 0, '-6.0'),
 Text(7, 0, '-5.0'),
 Text(8, 0, '-4.0'),
 Text(9, 0, '-3.0'),
 Text(10, 0, '-2.0'),
 Text(11, 0, '-1.0'),
 Text(12, 0, '0.0'),
 Text(13, 0, '1.0'),
 Text(14, 0, '2.0'),
 Text(15, 0, '3.0'),
 Text(16, 0, '4.0'),
 Text(17, 0, '5.0'),
 Text(18, 0, '6.0'),
```

Most of the learners are in a given range experience

In [31]:
```
sns.histplot(np.log(df['ctc']))
```

Out[31]:
```
<AxesSubplot:xlabel='ctc', ylabel='Count'>
```

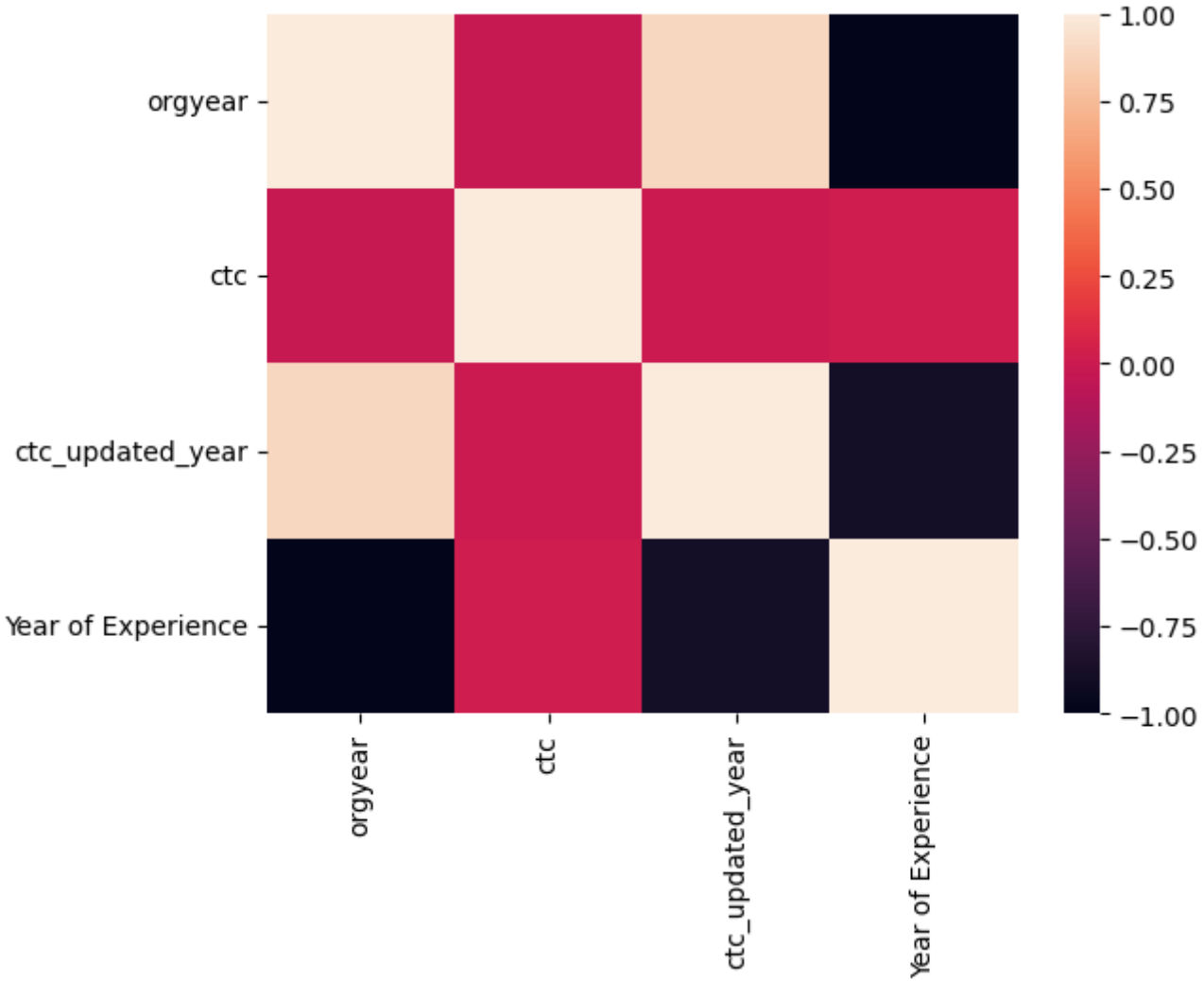


Most of the learners are in a given range of ctc. So while switching job they will look for high paying jobs

Bivariate Analysis

In [32]:
```
sns.heatmap(df.corr())
```

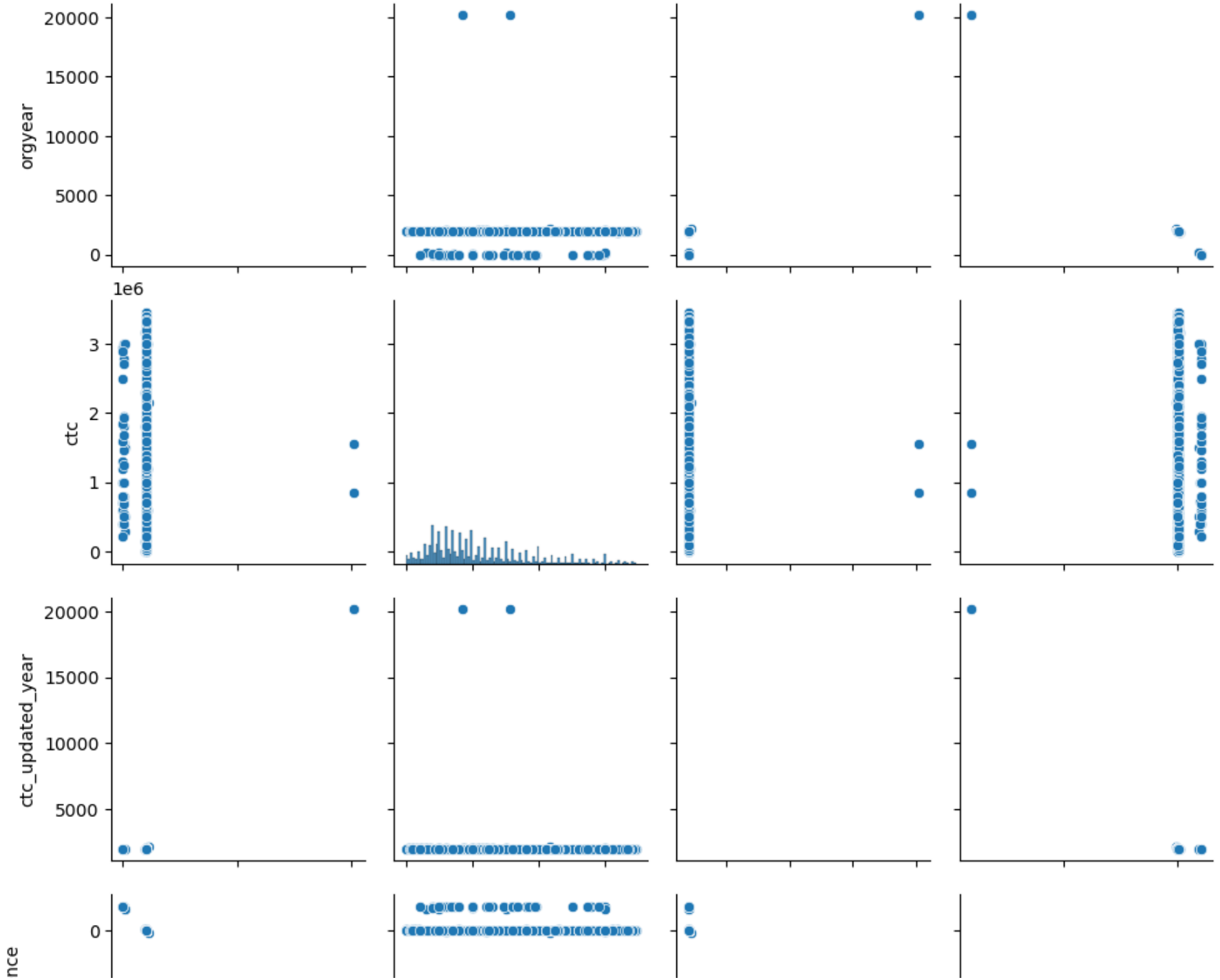
Out[32]: <AxesSubplot:>

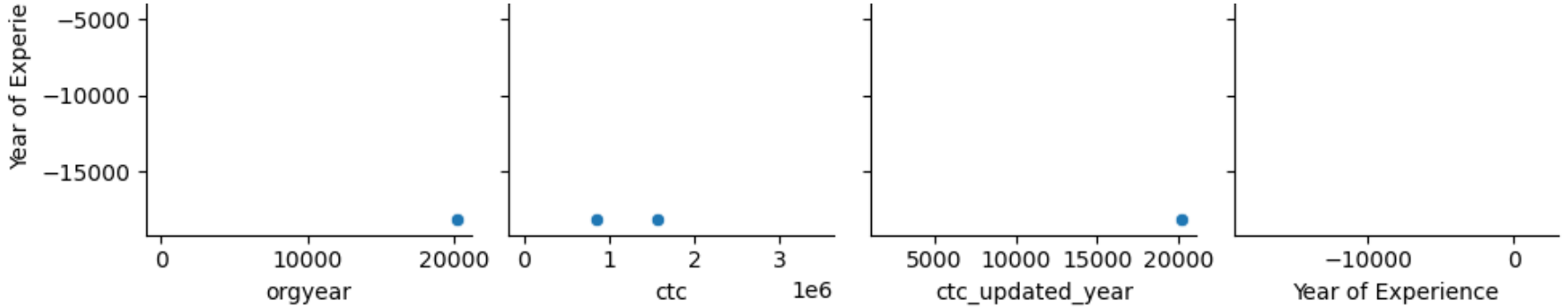


There is no significant correlation that can be noticed.

In [33]:
```
sns.pairplot(df)
```

Out[33]:
```
<seaborn.axisgrid.PairGrid at 0x2aa562953a0>
```


orgyear
20000
15000
10000
5000
0
1e6
ctc
3
2
1
0
ctc_updated_year
20000
15000
10000
5000
nce
0



In [34]:
```
grouped_ce = df.groupby(['company_hash', 'Year 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

In [35]:
```
ctc_summary_ce = grouped_ce['ctc'].describe()[['mean', '50%', 'max', 'min', 'count']]
ctc_summary_ce = ctc_summary_ce.rename(columns={'50%': 'median'})
```

In [36]:
```
merged_df_ce = df.merge(ctc_summary_ce, on=['company_hash', 'Year of Experience'])
```

In [37]:
```
merged_df_ce.head(10)
```

Out[37]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Year of Experience	me
0	921	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000	437	2020.0	7.0	1.100000e-
1	18817	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999	276	2019.0	5.0	7.433384e-
2	18817	8dcec4009f7a5bdd8c6a2af379b5763816563e25d814d0...	2018.0	700000	136	2020.0	5.0	7.433384e-
3	18817	f4fa64972185ac2b73e99c0cc10d1bf50d6dbfbc9a2cba...	2018.0	620000	276	2020.0	5.0	7.433384e-
4	18817	be3bcde831f8816f2bad9781f1282f09908f803c2fafb3...	2018.0	950000	276	2021.0	5.0	7.433384e-
5	18817	3fde2d8b375672193f1a7a7785ba20d0f47f019f01f104...	2018.0	1070000	136	2021.0	5.0	7.433384e-
6	18817	e863bbe699c9168980e7ae5643c16671ea812d2d433cbf...	2018.0	600000	136	2021.0	5.0	7.433384e-
7	18817	ddf45c7b7bd4c461890121c416b2fdff9ba34fbaea2ad4...	2018.0	750000	276	2020.0	5.0	7.433384e-
8	18817	2ab5a1559304d74d3698a203bd8d0555e67e1895244309...	2018.0	900000	136	2020.0	5.0	7.433384e-
9	18817	04b77ebfcc101c3dbb390a157b110b31646d6d7c71e650...	2018.0	500000	136	2020.0	5.0	7.433384e-

In [38]:
```
avg_ctc_ce = merged_df_ce.groupby(['company_hash', 'Year of Experience'])['mean'].transform('mean')
merged_df_ce['Class Flag'] = merged_df_ce.apply(lambda row: 0 if row['ctc'] < avg_ctc_ce[row.name] else (1 if row['ct
```

In [39]:
```
merged_df_ce.head(10)
```

Out[39]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Year of Experience	me
0	921	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000	437	2020.0	7.0	1.100000e-
1	18817	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999	276	2019.0	5.0	7.433384e-
2	18817	8dcec4009f7a5bdd8c6a2af379b5763816563e25d814d0...	2018.0	700000	136	2020.0	5.0	7.433384e-
3	18817	f4fa64972185ac2b73e99c0cc10d1bf50d6dbfbc9a2cba...	2018.0	620000	276	2020.0	5.0	7.433384e-
4	18817	be3bcde831f8816f2bad9781f1282f09908f803c2fafb3...	2018.0	950000	276	2021.0	5.0	7.433384e-
5	18817	3fde2d8b375672193f1a7a7785ba20d0f47f019f01f104...	2018.0	1070000	136	2021.0	5.0	7.433384e-
6	18817	e863bbe699c9168980e7ae5643c16671ea812d2d433cbf...	2018.0	600000	136	2021.0	5.0	7.433384e-
7	18817	ddf45c7b7bd4c461890121c416b2fdff9ba34fbaea2ad4...	2018.0	750000	276	2020.0	5.0	7.433384e-
8	18817	2ab5a1559304d74d3698a203bd8d0555e67e1895244309...	2018.0	900000	136	2020.0	5.0	7.433384e-
9	18817	04b77ebfcc101c3dbb390a157b110b31646d6d7c71e650...	2018.0	500000	136	2020.0	5.0	7.433384e-

In [40]:
```
merged_df_ce['Class Flag'].value_counts()
```

Out[40]:
```
0    75681
2    59420
1    57505
Name: Class Flag, dtype: int64
```

most people are payed less than the average salary in the same YOE and company.

Company & Job Position level

In [41]:
```
grouped_cj = df.groupby(['company_hash', 'job_position'])
```

In [42]:
```
ctc_summary_cj = grouped_cj['ctc'].describe()[['mean', '50%', 'max', 'min', 'count']]
ctc_summary_cj = ctc_summary_cj.rename(columns={'50%': 'median'})
```

In [43]:
```
merged_df_cj = df.merge(ctc_summary_cj, on=['company_hash', 'job_position'])
```

In [44]:
```
avg_ctc = merged_df_cj.groupby(['company_hash', 'job_position'])['mean'].transform('mean')
merged_df_cj['Designation Flag'] = merged_df_cj.apply(lambda row: 0 if row['ctc'] < avg_ctc[row.name] else (1 if row[
```

In [45]:
```
merged_df_cj.head(10)
```

Out[45]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Year of Experience	mea
0	921	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000	437	2020.0	7.0	1.085000e+(
1	921	696f674fbc0d337b20152f91c43082bafaa243da70932c...	2014.0	1070000	437	2018.0	9.0	1.085000e+(
2	18817	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999	276	2019.0	5.0	9.511363e+(
3	18817	f4fa64972185ac2b73e99c0cc10d1bf50d6dbfbc9a2cba...	2018.0	620000	276	2020.0	5.0	9.511363e+(
4	18817	51c50fc9fc8c8025ba1e81fd9e7eec377cbda8ba6d9be9...	2019.0	300000	276	2019.0	4.0	9.511363e+(
5	18817	a667070253210eb966557cc00fd4c6fa0b92dcdf8316b0...	2009.0	1000000	276	2021.0	14.0	9.511363e+(
6	18817	be3bcde831f8816f2bad9781f1282f09908f803c2fafb3...	2018.0	950000	276	2021.0	5.0	9.511363e+(
7	18817	1fe7524aa9dc2ae9ee2eb02f36078a9c644f987576eb59...	2016.0	600000	276	2020.0	7.0	9.511363e+(
8	18817	ddf45c7b7bd4c461890121c416b2fdff9ba34fbaea2ad4...	2018.0	750000	276	2020.0	5.0	9.511363e+(
9	18817	73e4f61b4b885458561a27990fe136e4bd9cec2425c5d9...	2019.0	470000	276	2020.0	4.0	9.511363e+(

In [46]:
```
merged_df_cj['Designation Flag'].value_counts()
```

Out[46]:
```
0    78940
2    60170
1    53574
Name: Designation Flag, dtype: int64
```

most people are payed less than the average salary in the same position and company.

Company level

In [47]:
```
grouped_c = df.groupby(['company_hash'])
```

In [48]:
```
ctc_summary_c = grouped_c['ctc'].describe()[['mean', '50%', 'max', 'min', 'count']]
ctc_summary_c = ctc_summary_c.rename(columns={'50%': 'median'})
```

In [49]:
```
merged_df_c = df.merge(ctc_summary_c, on=['company_hash'])
```

In [50]:
```
avg_ctc = merged_df_c.groupby(['company_hash'])['mean'].transform('mean')
merged_df_c['Tier Flag'] = merged_df_c.apply(lambda row: 0 if row['ctc'] < avg_ctc[row.name] else (1 if row['ctc'] ==
```

In [51]:
```
merged_df_c.head(10)
```

Out[51]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Year of Experience	mea
0	921	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000	437	2020.0	7.0	1.115667e+
1	921	a309a8c6610af7e9f0a88cfb67f9a0095b0dde63475475...	2019.0	500000	136	2020.0	4.0	1.115667e+
2	921	ffc974693a2bfd0326c707d8460d6783861a9497e538e2...	2017.0	1700000	198	2020.0	6.0	1.115667e+
3	921	b4dcd1e7ac426014a32ae303e4b527325d482e4d2c4bef...	2014.0	1000000	136	2018.0	9.0	1.115667e+
4	921	0d2f25432591093f5907a8681d600f869bbe7c2ae39cd7...	2017.0	600000	32	2021.0	6.0	1.115667e+
5	921	696f674fbc0d337b20152f91c43082bafaa243da70932c...	2014.0	1070000	437	2018.0	9.0	1.115667e+
6	921	dc8d39f3e9dd9f7576194e1a13c233bfe704bf9a72df99...	2014.0	800000	498	2019.0	9.0	1.115667e+
7	921	ab2b1b176cd5831ff3002043c82b075812a12ba212fa18...	2011.0	1771000	276	2019.0	12.0	1.115667e+
8	921	0abaddb8cb2925b7bfcda79f3d533ad76c6c7ed01dadd4...	2012.0	1500000	581	2018.0	11.0	1.115667e+
9	18817	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999	276	2019.0	5.0	1.071436e+

In [52]:
```
merged_df_c['Tier Flag'].value_counts()
```

Out[52]:
```
0    92730
2    68152
1    31802
Name: Tier Flag, dtype: int64
```

Post people in the scaler are from tire-3 companies looking upskill themself and go for better paying jobs

In [53]:
```
# merged_df = merged_df.reset_index()
# merged_df['Class'] = merged_df.groupby(['company_hash', 'job_position'])['flag_designation'].transform(lambda x: pd
```

In [54]:
```
# merged_df.head()
```

In [55]:
```
# merged_df['Tier'] = merged_df.groupby(['company_hash'])['flag_designation'].apply(lambda x: pd.factorize(x)[0]+1)
```

In [56]:
```
# merged_df.head(10)
```

Insights of manual clustering

In [57]:
```
# Top 10 employees (earning more than most of the employees in the company) - Tier 1
merged_df_c[merged_df_c['Tier Flag']==2].sort_values("ctc",ascending=False)[:11]
```

Out[57]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Year of Experience	
29246	25302	bd2b42f4aa306efb27219d09aa429f6f3166613c36c317...	2014.0	3454500	276	2015.0	9.0	1.535
28185	25302	bd2b42f4aa306efb27219d09aa429f6f3166613c36c317...	2014.0	3454500	136	2015.0	9.0	1.535
106809	8589	75fd2b1188101968e9484c4847f639d5cef5209dd2c043...	2017.0	3450000	437	2020.0	6.0	1.776
8428	8688	eef4792868a808353396cffb03423aa9104b129c38d041...	2011.0	3450000	239	2019.0	12.0	1.561
14850	7905	7b6995298e4316fdec117300a3b5c4ee41afa066e6f684...	2017.0	3450000	276	2020.0	6.0	1.931
8246	22546	b33d333397fc063e1998525575001af3333791e6dc74f8...	2013.0	3450000	239	2019.0	10.0	1.073
27119	25302	bc2eeaf42c9a587210d05557903b2d15e50914662d5e18...	2015.0	3450000	551	2015.0	8.0	1.535
92053	3624	963791cbc30c869e8914c149005c941a5ee8015c5b0a43...	2013.0	3450000	136	2019.0	10.0	1.996
133069	33269	0ca1da3746df85369fff483d0ed3ddabbe34133aa7ff94...	2017.0	3450000	136	2020.0	6.0	2.033
48423	2452	6a78c17f9caffac82f220864136182acd248ba4a824004...	2011.0	3450000	276	2020.0	12.0	1.951
48425	2452	6a78c17f9caffac82f220864136182acd248ba4a824004...	2011.0	3450000	958	2020.0	12.0	1.951

In [58]:
```
# Top 10 employees of data science in Amazon / TCS etc earning more than their peers - Class 1
merged_df_cj[(merged_df_cj['Designation Flag']==2) & ((merged_df_cj['job_position']==1017) | (merged_df_cj['job_posit
```

Out[58]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Year of Experience	mean	median	max	min	count	Designation Flag

In [59]:
```
# Bottom 10 employees of data science in Amazon / TCS etc earning less than their peers - Class 3

merged_df_cj[(merged_df_cj['Designation Flag']==0) & ((merged_df_cj['job_position']==1017) | (merged_df_cj['job_posit
```

Out[59]:

company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Year of Experience	mean	median	max	min	count	Designation Flag

In [60]:
```
# Bottom 10 employees (earning less than most of the employees in the company)- Tier 3

merged_df_c[merged_df_c['Tier Flag']==0].sort_values("ctc",ascending=True)[:11]
```

Out[60]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Year of Experience	
97894	32572	3505b02549ebe2c95840ac6f0a35561a3b4cbe4b79cdb1...	2014.0	2	136	2019.0	9.0	1.073435
97888	32572	f2b58aeed3c074652de2cfd3c0717a5d21d6fbcf342a78...	2013.0	6	958	2018.0	10.0	1.073435
97886	32572	23ad96d6b6f1ecf554a52f6e9b61677c7d73d8a409a143...	2013.0	14	958	2018.0	10.0	1.073435
189649	31288	b8a0bb340583936b5a7923947e9aec21add5ebc50cd60b...	2016.0	15	958	2018.0	7.0	1.550000
157919	8244	f7e5e788676100d7c4146740ada9e2f8974defc01f571d...	2022.0	200	958	2022.0	1.0	3.140000
44008	12918	80ba0259f9f59034c4927cf3bd38dc9ce2eb60ff18135b...	2012.0	600	136	2017.0	11.0	5.741367
66974	7149	b995d7a2ae5c6f8497762ce04dc5c04ad6ec734d70802a...	2018.0	600	276	2021.0	5.0	1.419244
103476	35338	9af3dca6c9d705d8d42585ccfce2627f00e1629130d14e...	2023.0	600	958	2023.0	0.0	1.056870
59500	21220	1694233be08738b7b50bdb7649b792f0ab8a514c01bec9...	2016.0	1000	958	2019.0	7.0	7.292778
83123	31011	4eea97c023bd58395edce18538831df9a735180f88f79d...	2020.0	1000	958	2020.0	3.0	9.843383
170096	34479	d926b36fd7c88094c8837323e378671f8354d3fe0dc488...	2011.0	1000	136	2019.0	12.0	5.550000

In [61]:
```
# Top 10 employees in Amazon- X department - having 5/6/7 years of experience earning more than their peers - Tier X

merged_df_ce[(merged_df_ce['Class Flag']==2) & (merged_df_ce['company_hash']==18817)]
```

Out[61]:

company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Year of Experience	mean	median	max	min	count	Class Flag

In [62]:
```
# Top 10 companies (based on their CTC)
merged_df_c.groupby('company_hash').agg({'ctc': 'mean'}).sort_values("ctc",ascending=False)[:11]
```

Out[62]:

company_hash	ctc
5882	3450000.0
31932	3450000.0
20536	3450000.0
8224	3450000.0
8466	3450000.0
12892	3440000.0
6823	3440000.0
8590	3440000.0
11032	3429999.0
2712	3429999.0
10954	3420000.0

In [63]:
```
# Top 2 positions in every company (based on their CTC)

company_positions_ctc_sorted=merged_df_c.groupby(['company_hash','job_position']).agg({'ctc': 'mean'}).sort_values(['
company_positions_ctc_sorted=company_positions_ctc_sorted.reset_index()
top_positions = pd.DataFrame()
for company in company_positions_ctc_sorted['company_hash'].unique():
    top_positions = top_positions.append(company_positions_ctc_sorted[company_positions_ctc_sorted['company_hash'] ==
```

In [64]:
```
top_positions
```

Out[64]:

	company_hash	job_position	ctc
0	0	437	100000.0
1	0	958	100000.0
2	1	437	300000.0
3	10	271	1650000.0
4	100	469	2500000.0
...	...	...	...
67913	9996	464	1300000.0
67914	9996	498	660000.0
67916	9997	958	220000.0
67917	9998	198	900000.0
67918	9999	437	2650000.0

48119 rows × 3 columns

In [65]:
```
company_positions_ctc_sorted
```

Out[65]:

	company_hash	job_position	ctc
0	0	437	100000.0
1	0	958	100000.0
2	1	437	300000.0
3	10	271	1650000.0
4	100	469	2500000.0
...	...	...	...
67914	9996	498	660000.0
67915	9996	136	220000.0
67916	9997	958	220000.0
67917	9998	198	900000.0
67918	9999	437	2650000.0

67919 rows × 3 columns

Unsupervised Learning - Clustering

In [66]:
```
X=df
```

In [67]:
```
X.head()
```

Out[67]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	Year of Experience
0	921	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000	437	2020.0	7.0
1	18817	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999	276	2019.0	5.0
2	14789	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015.0	2000000	136	2020.0	8.0
3	11533	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	700000	136	2019.0	6.0
4	19288	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017.0	1400000	276	2019.0	6.0

In [68]:
```
X.drop(columns=['orgyear','email_hash'],inplace=True,axis=1)
```

Normalizing data using standard scaler

In [69]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaler.fit(df)
X = scaler.transform(df)
```

In [70]:
```
scaled_df = pd.DataFrame(X, columns=df.columns, index=df.index)
```

In [71]:
```
scaled_df.head()
```

Out[71]:

	company_hash	ctc	job_position	ctc_updated_year	Year of Experience
0	-1.664776	0.020617	-0.081665	0.001995	-0.013813
1	0.002046	-0.845118	-0.565672	-0.015106	-0.044398
2	-0.373119	1.219326	-0.986547	0.001995	0.001480
3	-0.676381	-0.512142	-0.986547	-0.015106	-0.029105
4	0.045915	0.420187	-0.565672	-0.015106	-0.029105

Checking for missing values and Prepare data for KNN/ Mean Imputation.

In [72]:
```
from sklearn.impute import KNNImputer
k = 3
imputer = KNNImputer(n_neighbors=k)
imputed_data = imputer.fit_transform(scaled_df)
imputed_df = pd.DataFrame(imputed_data, columns=scaled_df.columns)
```

In [73]:
```
imputed_df.isnull().sum()
```

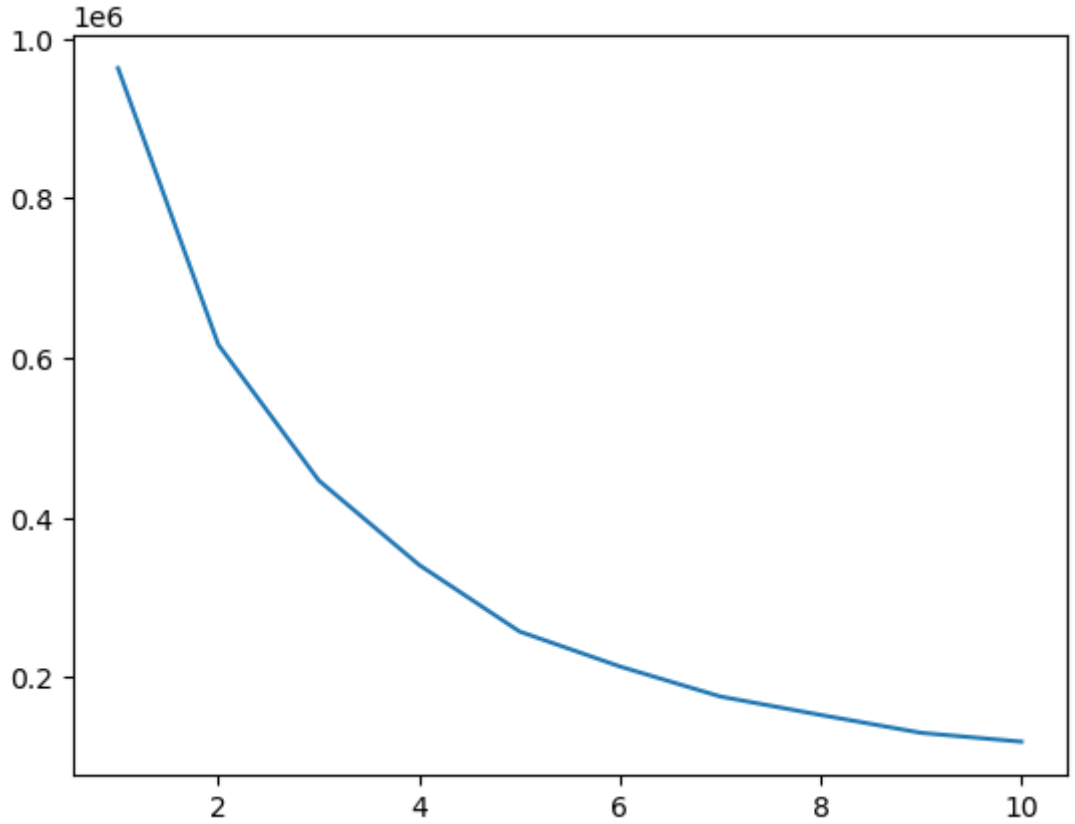
Out[73]:
```
company_hash          0
ctc                   0
job_position          0
ctc_updated_year      0
Year of Experience    0
dtype: int64
```

Elbow method

In [74]:
```
from sklearn.cluster import KMeans
wcss = []
k_range = range(1, 11)
for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(imputed_df)
    wcss.append(kmeans.inertia_)
```

In [75]:
```
sns.lineplot(k_range,wcss)
```

Out[75]: <AxesSubplot:>



2 and 5 can be the number of cluster

K-means clustering

In [87]:
```
kmeans = KMeans(n_clusters=2, random_state=0)
```

In [88]:
```
kmeans.fit(imputed_df)
labels = kmeans.labels_
imputed_df["cluster"] = labels
```

In [89]:
```
imputed_df.head()
```

Out[89]:

	company_hash	ctc	job_position	ctc_updated_year	Year of Experience	cluster
0	-1.664776	0.020617	-0.081665	0.001995	-0.013813	1
1	0.002046	-0.845118	-0.565672	-0.015106	-0.044398	1
2	-0.373119	1.219326	-0.986547	0.001995	0.001480	0
3	-0.676381	-0.512142	-0.986547	-0.015106	-0.029105	1
4	0.045915	0.420187	-0.565672	-0.015106	-0.029105	0

In [90]:
```
imputed_df.shape
```

Out[90]:
```
(192684, 6)
```

Hierarchical clustering (With sampling)

In [91]:
```
from sklearn.cluster import AgglomerativeClustering
clustering = AgglomerativeClustering(n_clusters=6)
```

In [92]:
```
imputed_df_hi=imputed_df.drop('cluster',axis=1)
```

In [93]:
```
imputed_df_hi=imputed_df_hi[:10000]
```

In [94]:
```
clustering.fit(imputed_df_hi)
```

Out[94]:
```
AgglomerativeClustering(n_clusters=6)
```

In [95]:
```
labels = clustering.labels_
imputed_df_hi["cluster"] = labels
```

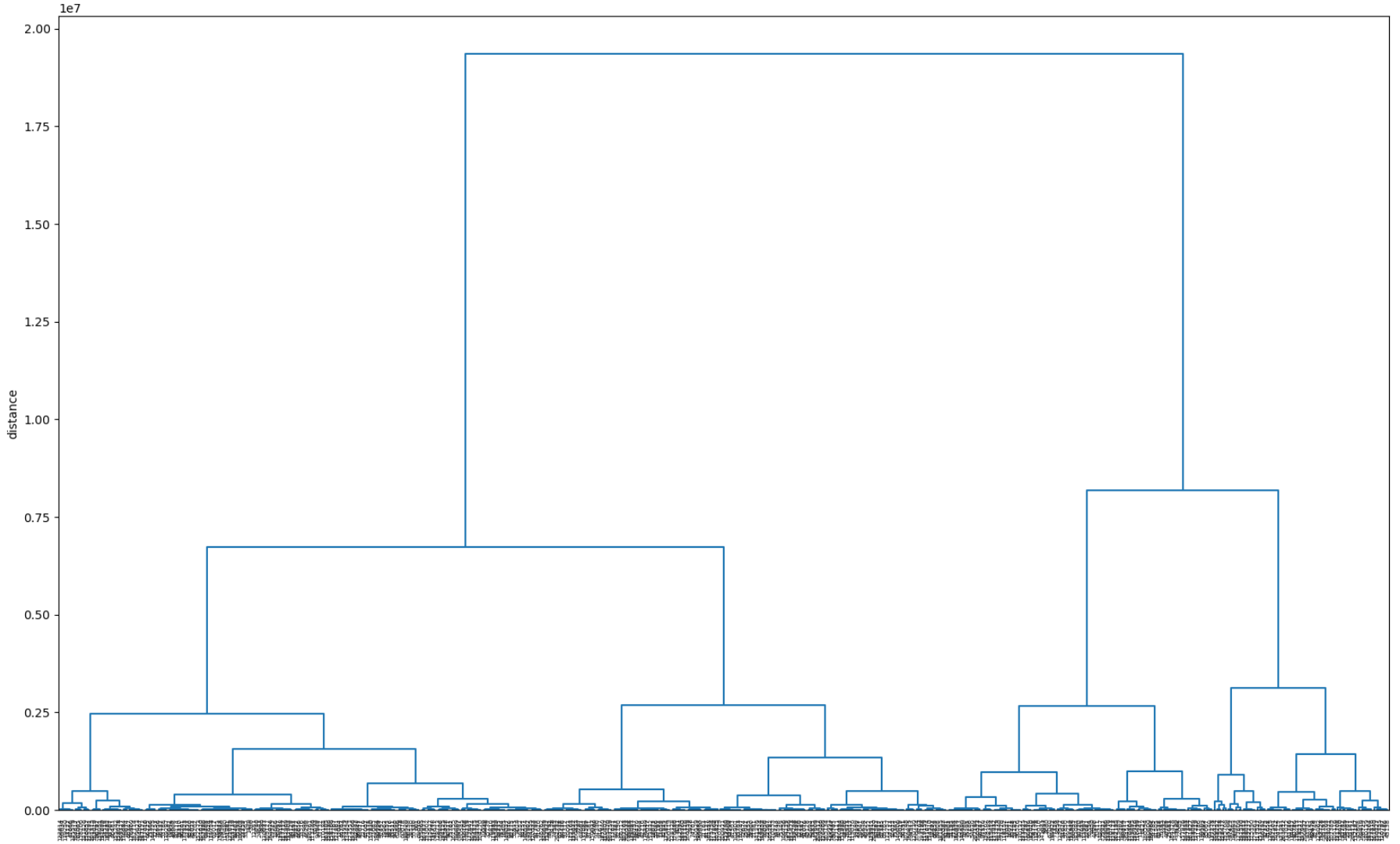
In [96]:
```
imputed_df_hi.head(10)
```

Out[96]:

	company_hash	ctc	job_position	ctc_updated_year	Year of Experience	cluster
0	-1.664776	0.020617	-0.081665	0.001995	-0.013813	0
1	0.002046	-0.845118	-0.565672	-0.015106	-0.044398	0
2	-0.373119	1.219326	-0.986547	0.001995	0.001480	1
3	-0.676381	-0.512142	-0.986547	-0.015106	-0.029105	0
4	0.045915	0.420187	-0.565672	-0.015106	-0.029105	0
5	1.410500	-0.512142	-0.565672	0.001995	-0.044398	3
6	-0.849248	0.553377	-0.565672	-0.015106	-0.044398	0
7	0.839742	-0.911712	-0.986547	-0.015106	-0.059691	3
8	0.505465	-0.845117	1.484592	0.001995	-0.074983	4
9	1.193206	-0.964988	1.484592	-0.015106	-0.059691	4

In [101]:
```
import scipy.cluster.hierarchy as sch
import matplotlib.pyplot as plt
sample = df.sample(500)
Z = sch.linkage(sample, method= 'ward')
fig, ax = plt.subplots (figsize= (20, 12))
sch.dendrogram(Z, labels=sample.index, ax=ax, color_threshold=2)
plt.xticks(rotation=90)
ax.set_ylabel('distance')
```

Out[101]:
```
Text(0, 0.5, 'distance')
```



Here dendogram indicates 2 clusters

Actionable Insights

- Start by researching industry salaries for the positions in question. This can help you determine if the company's salaries are competitive with those in the industry.
- Check for any potential biases that may be affecting salaries, such as gender or race. Take steps to address any biases that are identified.

Recommendations

- If you are currently working at a tier-1 company and looking for a new placement, it would be recommended to consider other tier-1 companies or top-tier startups within your industry. These companies typically have similar cultures, resources, and expectations, which can make for a smoother transition.
- For individuals working in tier-2 companies, which are smaller than tier-1 companies but still relatively large and successful, it may be beneficial to consider similar-sized companies within your industry, or potentially tier-1 companies if you have relevant experience and qualifications.
- For those working in tier-3 companies, which are typically smaller and less well-known, it may be helpful to seek out other companies of similar size and scope, as well as startups or mid-tier companies that can offer new opportunities for growth and development.
- Salary negotitation assistance to newly selected candidate for fair salary.
- Target people who are in initial time in there carrier, or look for people who are trying to switch thier profession

In [ ]:
```
pip uninstall matplotlib
```

In [ ]:
```
pip install matplotlib
```

In [ ]:
```

```