Scaler Case Study

Introduction

- Scaler, as an emerging tech-versity, endeavors to provide world-class education

in computer science & data science domains

- A significant challenge for Scaler is understanding the diverse backgrounds of its

learners, especially in terms of their current roles, companies, and experience Clustering similar learners helps in customizing the learning experience, there y increasing retention and satisfact.

- Analyzing the vast data of learners can uncover patterns in their professional

backgrounds and preferences. This allows Scaler to make tailored conten recommendations and provide specialized mentorshi

- By leveraging data science and unsupervised learning, particularly clustering

techniques, Scaler can group learners with similar profiles, aiding in delivering
more personalized learning journe

What is Expected?

Assuming you're a data scientist at Scaler, you're tasked with the responsibility of analyzing the dataset to profile the best companies and job positions from Scaler' database. Your primary goal is to execute clustering techniques, evaluate t e coherence of your clusters, and provide actionable insights for enhanced lear er profiling and course tailoring.y.p.on.er churn.

1. Data

The analysis was done on the data located at - https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/002/856/original/scaler_clustering.csv

2. Libraries

Below are the libraries required

In [1]:
```
# Libraries to analyze data
import numpy as np
import pandas as pd

# Libraries to visualize data
import matplotlib.pyplot as plt
import seaborn as sns

from random import sample
from numpy.random import uniform

import re

from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler
from sklearn.impute import KNNImputer
from sklearn.neighbors import NearestNeighbors
from sklearn.cluster import KMeans, AgglomerativeClustering
from sklearn.metrics import silhouette_score
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE

import scipy.cluster.hierarchy as sch
from scipy.cluster.hierarchy import dendrogram

import umap
```

3. Data Loading

Loading the data into Pandas dataframe for easily handling of data

In [2]:
```
# read the file into a pandas dataframe
df = pd.read_csv('scaler_clustering.csv')
# Look at the datatypes of the columns
print('*************************************************')
print(df.info())
print('*************************************************\n')
print('*************************************************')
print(f'Shape of the dataset is {df.shape}')
print('*************************************************\n')
print('*************************************************')
print(f'Number of nan/null values in each column: \n{df.isna().sum()}')
print('*************************************************\n')
print('*************************************************')
print(f'Number of unique values in each column: \n{df.nunique()}')
print('*************************************************\n')
print('*************************************************')
print(f'Duplicate entries: \n{df.duplicated().value_counts()}')
```

```
*************************************************
<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      153279 non-null  object 
 6   ctc_updated_year  205843 non-null  float64
dtypes: float64(2), int64(2), object(3)
memory usage: 11.0+ MB
None
*************************************************

*************************************************
Shape of the dataset is (205843, 7)
*************************************************

*************************************************
Number of nan/null values in each column:
Unnamed: 0              0
company_hash           44
email_hash              0
orgyear                86
ctc                     0
job_position        52564
ctc_updated_year        0
dtype: int64
*************************************************

*************************************************
Number of unique values in each column:
Unnamed: 0          205843
company_hash         37299
email_hash          153443
orgyear                 77
ctc                   3360
job_position          1016
ctc_updated_year         7
dtype: int64
*************************************************

*************************************************
Duplicate entries:
False    205843
Name: count, dtype: int64
```

In [3]:
```
# look at the top 20 rows
df.head(5)
```

Out[3]:

	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 [4]:
```
df.describe()
```

Out[4]:

	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 [5]:
```
df.describe(include='object')
```

Out[5]:

	company_hash	email_hash	job_position
count	205799	205843	153279
unique	37299	153443	1016
top	nvnv wgzohrnvzwj otqcxwto	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	Backend Engineer
freq	8337	10	43554

Insight

- There are **205843** entries with 7 columns
- There are 44 null/missing values in *company_hash*, 86 in *orgyear* and 52564 in *job_position*
- There are no **duplicates**
- There are **1016** unique **job_position**
- The column **Unnamed: 0** can be dropped as it doesnt provide any new information

In [6]:
```
# Drop "Unnamed: 0" column
df.drop(columns=['Unnamed: 0'], inplace=True)

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

# Normalize the string
df["company_hash"] = df["company_hash"].apply(lambda x: preprocess_string(str(x)))
df["job_position"] = df["job_position"].apply(lambda x: preprocess_string(str(x)))

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205843 entries, 0 to 205842
Data columns (total 6 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   company_hash      205843 non-null  object 
 1   email_hash        205843 non-null  object 
 2   orgyear           205757 non-null  float64
 3   ctc               205843 non-null  int64  
 4   job_position      205843 non-null  object 
 5   ctc_updated_year  205843 non-null  float64
dtypes: float64(2), int64(1), object(3)
memory usage: 9.4+ MB
```

In [7]:
```
# look at the top 5 rows
df.head(10)
```

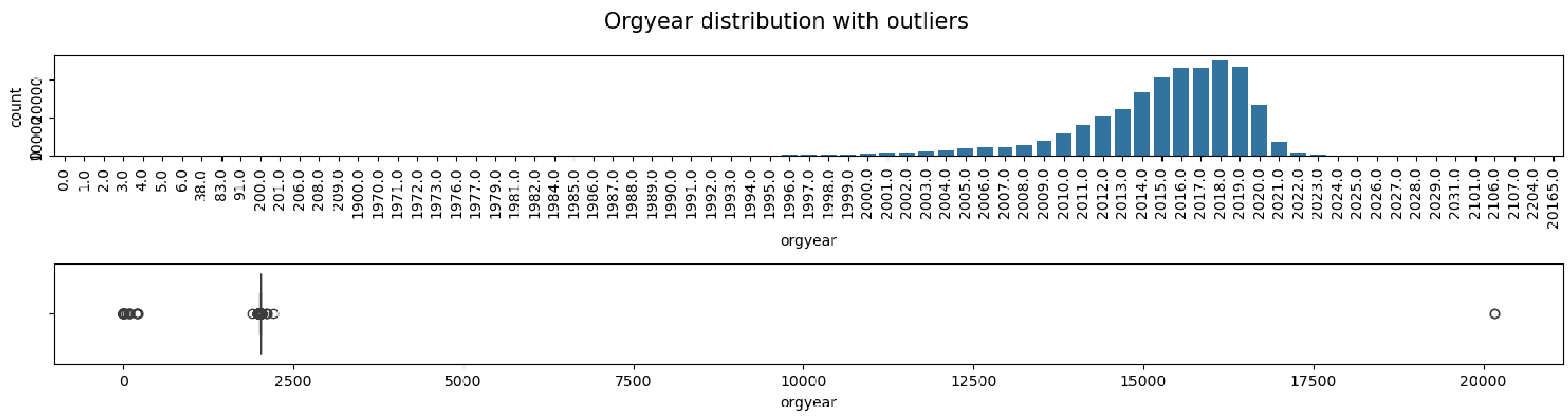
Out[7]:

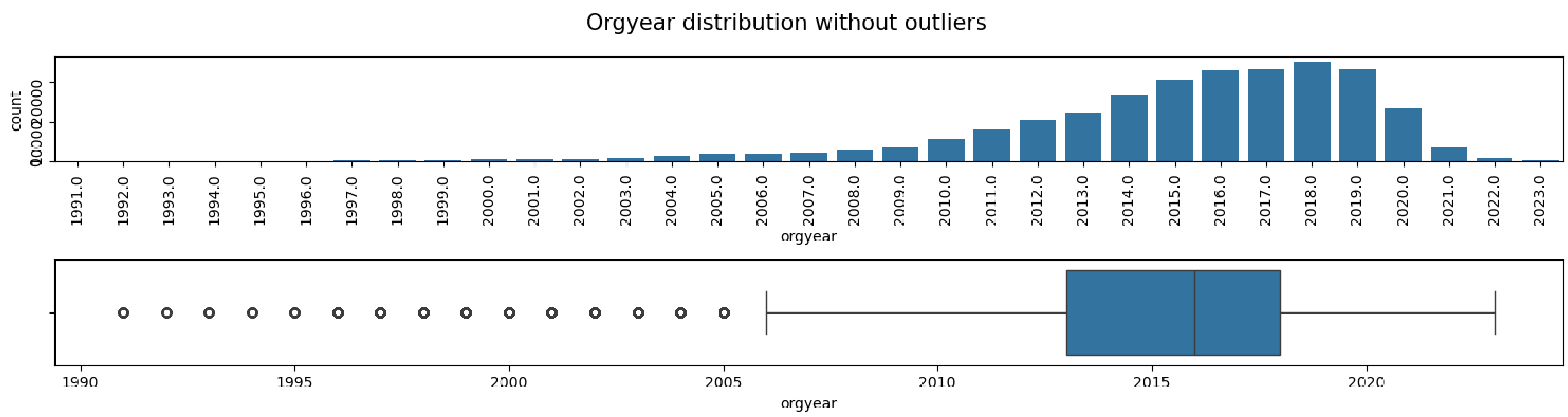
	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000	other	2020.0
1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999	fullstack engineer	2019.0
2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	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
5	yvuuxrj hzbvqqxta bvqptnxzs ucn rna	18f2c4aa2ac9dd3ae8ff74f32d30413f5165565b90d8f2...	2018.0	700000	fullstack engineer	2020.0
6	lubgqsvz wyvot wg	9bf128ae3f4ea26c7a38b9cdc58cf2acbb8592100c4128...	2018.0	1500000	fullstack engineer	2019.0
7	vwwtznhqt ntwyzgrgsj	756d35a7f6bb8ffeaffc8fcca9ddbb78e7450fa0de2be0...	2019.0	400000	backend engineer	2019.0
8	utqoxontzn ojontbo	e245da546bf50eba09cb7c9976926bd56557d1ac9a17fb...	2020.0	450000	nan	2019.0
9	xrbhd	b2dc928f4c22a9860b4a427efb8ab761e1ce0015fba1a5...	2019.0	360000	nan	2019.0

4. Exploratory Data Analysis

4.1. Univariate analysis

In [8]:
```
data = df['orgyear']
fig, axs = plt.subplots(2,1,figsize=(15,4))
sns.countplot(ax = axs[0], x=data)
axs[0].tick_params(labelrotation=90)
sns.boxplot(ax = axs[1], x=data)
fig.suptitle('Orgyear distribution with outliers', fontsize=15)
plt.tight_layout()
plt.show()

lower_bound = df['orgyear'].quantile(0.001)
upper_bound = df['orgyear'].quantile(0.999)
data = data[(data >= lower_bound) & (data <= upper_bound)]
fig, axs = plt.subplots(2,1,figsize=(15,4))
sns.countplot(ax = axs[0], x=data)
axs[0].tick_params(labelrotation=90)
sns.boxplot(ax = axs[1], x=data)
fig.suptitle('Orgyear distribution without outliers', fontsize=15)
plt.tight_layout()
plt.show()
```





Insight

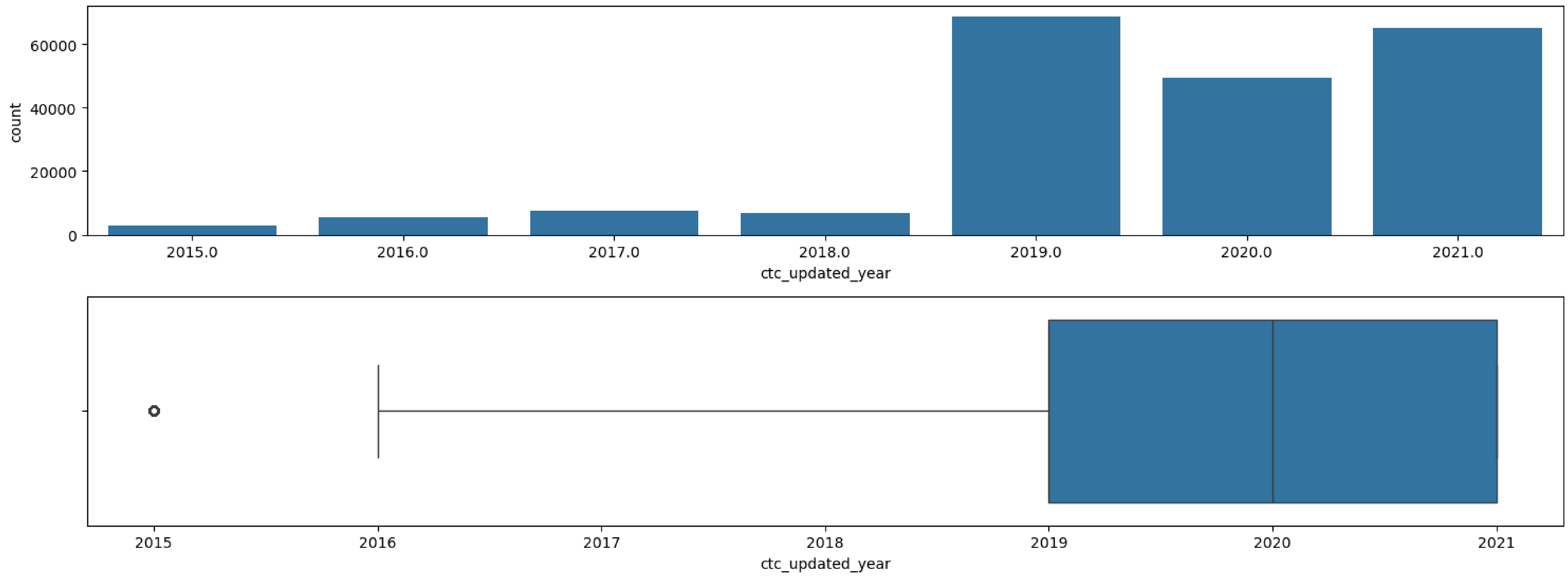
- The column **orgyear** has a lot of errors. The years close to 0 and the years greater than the current year are all outliers
- Maximum number of learners began their employment at the current company in the year 2018
- The distribution is left skewed, which is obvious as there are learners who have been working from long time too

In [9]:
```
df = df[(df['orgyear'] >= lower_bound) & (df['orgyear'] <= upper_bound)]
df.reset_index(drop=True, inplace=True)
```

In [10]:
```
data = df['ctc_updated_year']
fig, axs = plt.subplots(2,1,figsize=(15,6))
sns.countplot(ax = axs[0], x=data)
sns.boxplot(ax = axs[1], x=data)
fig.suptitle('CTC Updated Year distribution', fontsize=15)
```

```
plt.tight_layout()
plt.show()
```

CTC Updated Year distribution

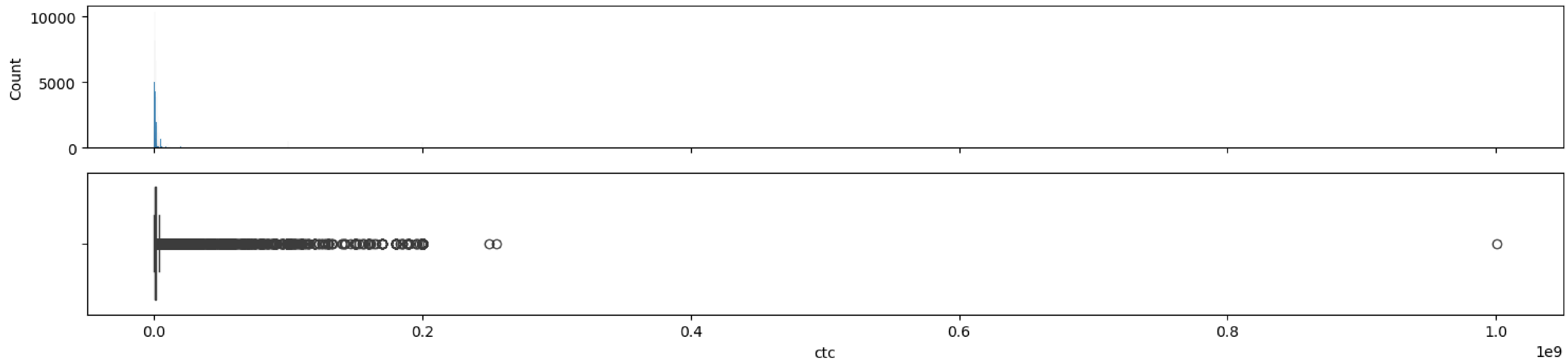


Insight

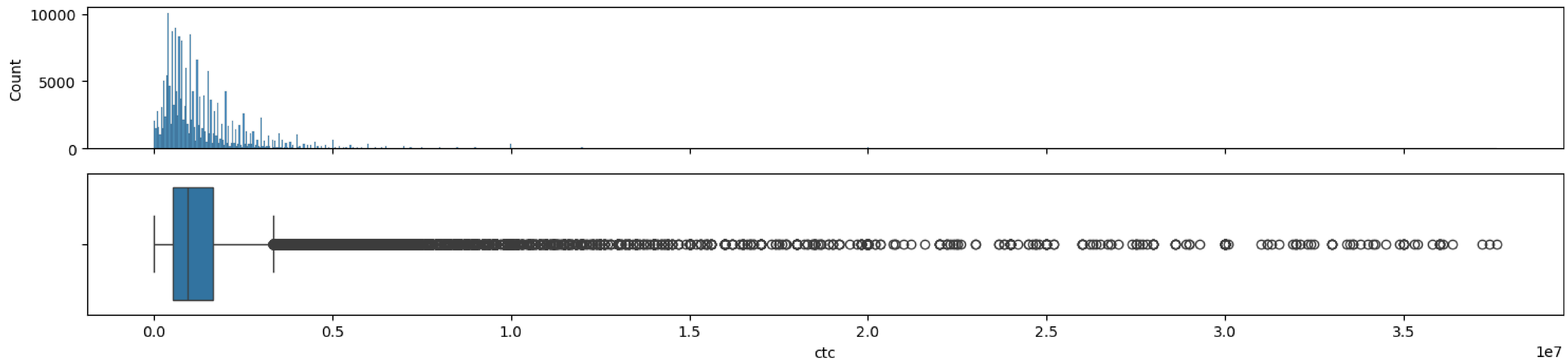
- Maximum learners got their **CTC updated** in the year **2019, 2020 and 2021**

In [11]:
```
data = df['ctc']
fig, axs = plt.subplots(2,1,figsize=(15,4), sharex=True)
sns.histplot(ax = axs[0], x=data)
sns.boxplot(ax = axs[1], x=data)
fig.suptitle('CTC distribution with outliers', fontsize=15)
plt.tight_layout()
plt.show()

mean = data.mean()
std = data.std()
lower_bound = mean - (3*std)
upper_bound = mean + (3*std)
data = data[(data > lower_bound) & (data < upper_bound)]
fig, axs = plt.subplots(2,1,figsize=(15,4), sharex=True)
sns.histplot(ax = axs[0], x=data)
sns.boxplot(ax = axs[1], x=data)
fig.suptitle('CTC distribution without outliers', fontsize=15)
plt.tight_layout()
plt.show()
```

CTC distribution with outliers



CTC distribution without outliers



Insight

- The distribution of CTC is extremely right skewed with an obvious outlier being at CTC around 1.0E9
- Without the outlier also, the CTC is right skewed as there are good number of learners with higher CTC

In [12]:
```
df = df[(df['ctc'] >= lower_bound) & (df['ctc'] <= upper_bound)]
df.reset_index(drop=True, inplace=True)
```

In [13]:
```
df['company_hash'].value_counts()[:10]
```

Out[13]:
```
company_hash
nvnv wgzohrnvzwj otqcxwto    8266
xzegojo                      5348
vbvkgz                       3446
zgn vuurxwvmrt vwwghzn       3356
wgszxkvzn                    3212
vwwtznhqt                    2833
fxuqg rxbxnta                2622
gqvwrt                       2496
bxwqgogen                    2121
wvustbxzx                    2026
Name: count, dtype: int64
```

Insight

- Maximum number of learners have their **current employer** whose company hash is **nvnv wgzohrnvzwj otqcxwto**

In [14]:
```
df['email_hash'].value_counts()[:10]
```

Out[14]:
```
email_hash
bbace3cc586400bbc65765bc6a16b77d8913836cfc98b77c05488f02f5714a4b    10
298528ce3160cc761e4dc37a07337ee2e0589df251d73645aae209b010210eee     9
6842660273f70e9aa239026ba33bfe82275d6ab0d20124021b952b5bc3d07e6c     9
3e5e49daa5527a6d5a33599b238bf9bf31e85b9efa9a94f1c88c5e15a6f31378     9
d598d6f1fb21b45593c2afc1c2f76ae9f4cb7167156cdf93246d4192a89d8065     8
4818edfd67ed8563dde5d083306485d91d19f4f1c95d193a1700e79dd245b75c     8
d15041f58bb01c8ee29f72e33b136e26bc32f3169a40b53d75fe7ae9cbb9a551     8
faf40195f8c58d5c7edc758cc725a762d51920da996410b80ac4a4d85c803da0     8
c0eb129061675da412b0deb15871dd06ef0d7cd86eb5f7e8cc6a20b0d1938183     8
b4d5afa09bec8689017d8b29701b80d664ca37b83cb883376b2e95191320da66     8
Name: count, dtype: int64
```

Insight

- It is suprising to see that many learners have the same email id, with maximum(10) learners having **email** with hash **bbace3cc586400bbc65765bc6a16b77d8913836cfc98b77c05488f02f5714a4b**

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

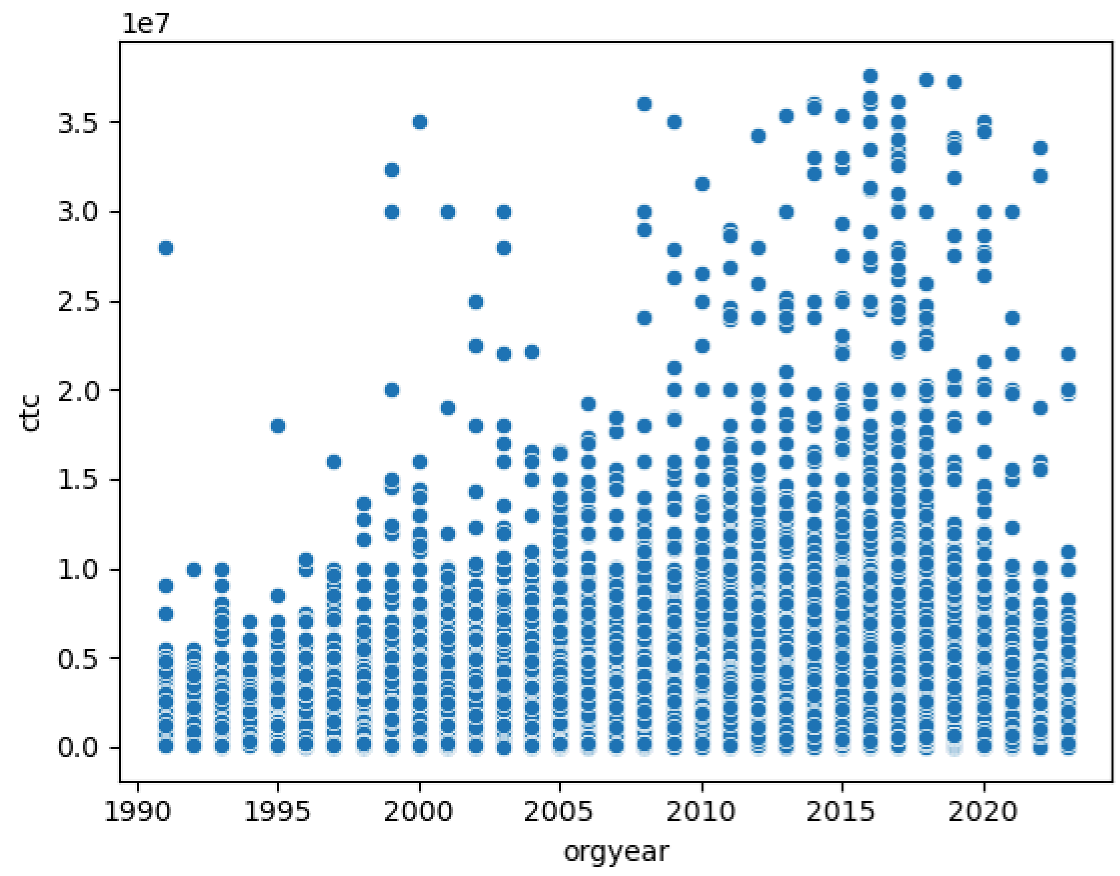
Out[15]:
```
job_position
nan                   52166
backend engineer      43336
fullstack engineer    25826
other                 17628
frontend engineer     10341
                      ...
traineeintern             1
staff consultant          1
java devloper             1
associate 1               1
azure data factory        1
Name: count, Length: 848, dtype: int64
```

Insight

- Maximum number of learners are Backend Engineers

4.2. Bivariate analysis

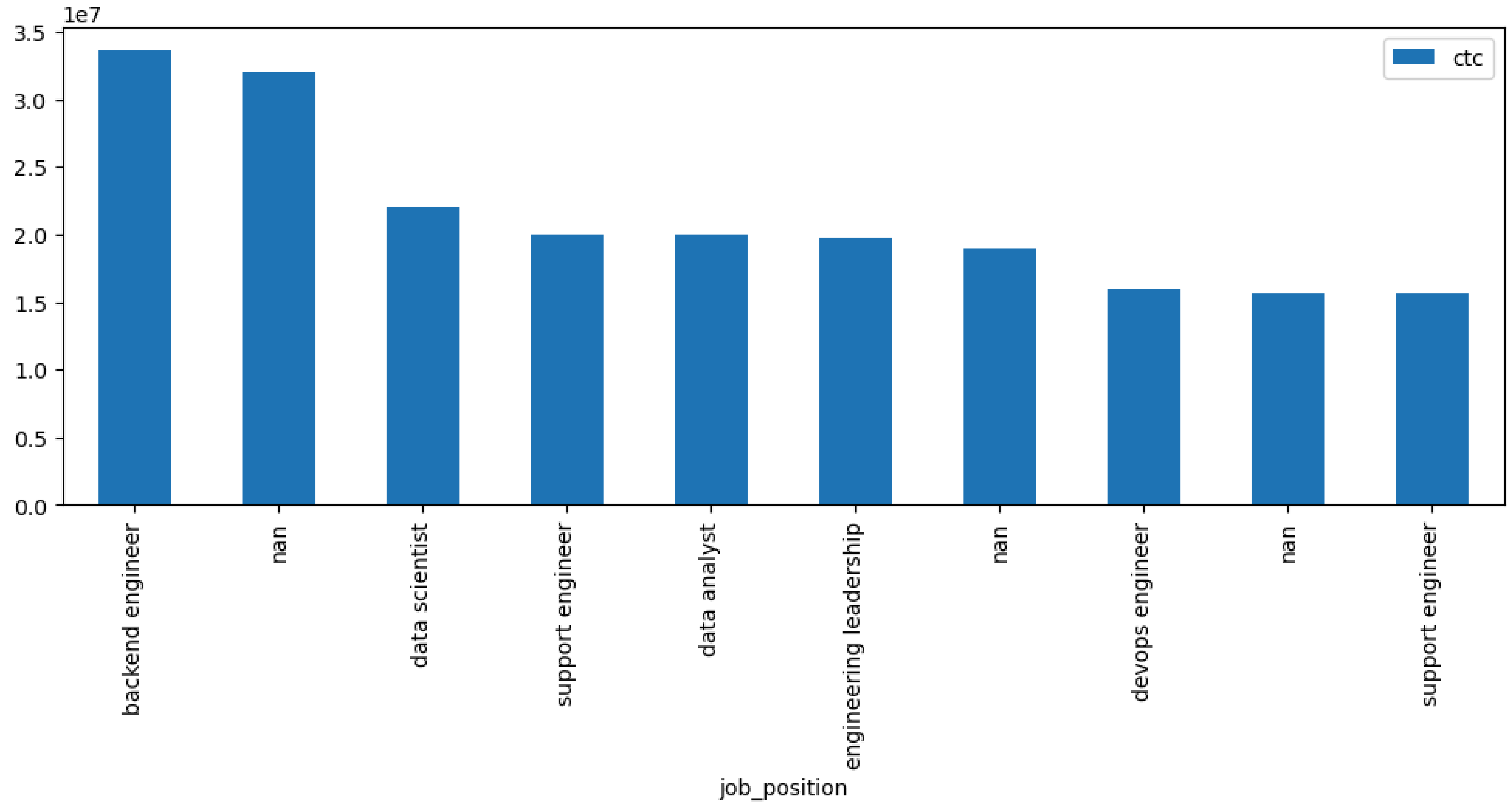
In [16]:
```
sns.scatterplot(data=df, x='orgyear', y='ctc')
plt.show()
```



Insight

- It is obvious that the learners who joined/changed company recently have a higher CTC

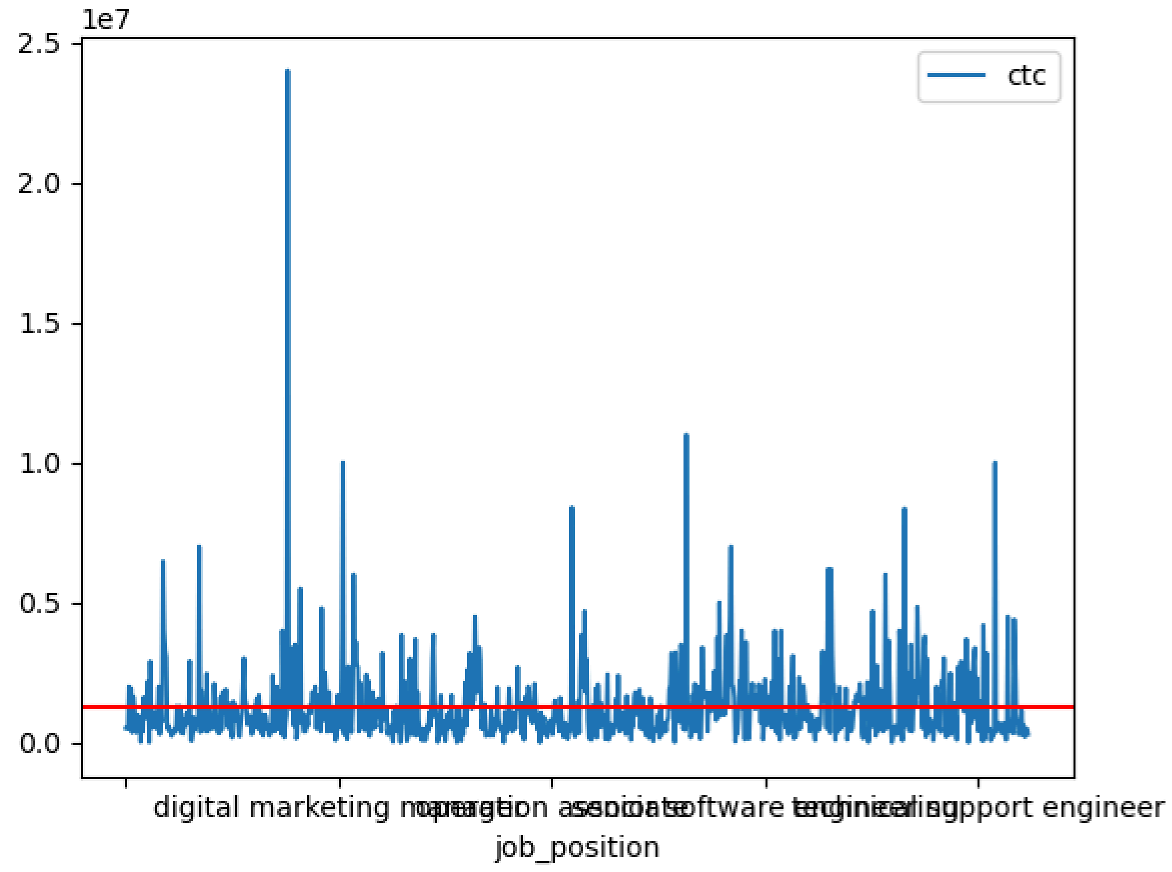
In [17]:
```
df[(df['job_position'] != 'other') &
(~df['job_position'].isna()) &
(df['orgyear'] > 2021)][['ctc', 'job_position']].sort_values(by='ctc', ascending=False).head(10).plot(kind='bar', x = 'job_position', y='ctc', figsize=(12,4))
plt.show()
```



Insight

- Above plot shows few of the positions with top CTCs
- It has a mix of software developers, data analysts/scients, leadership etc

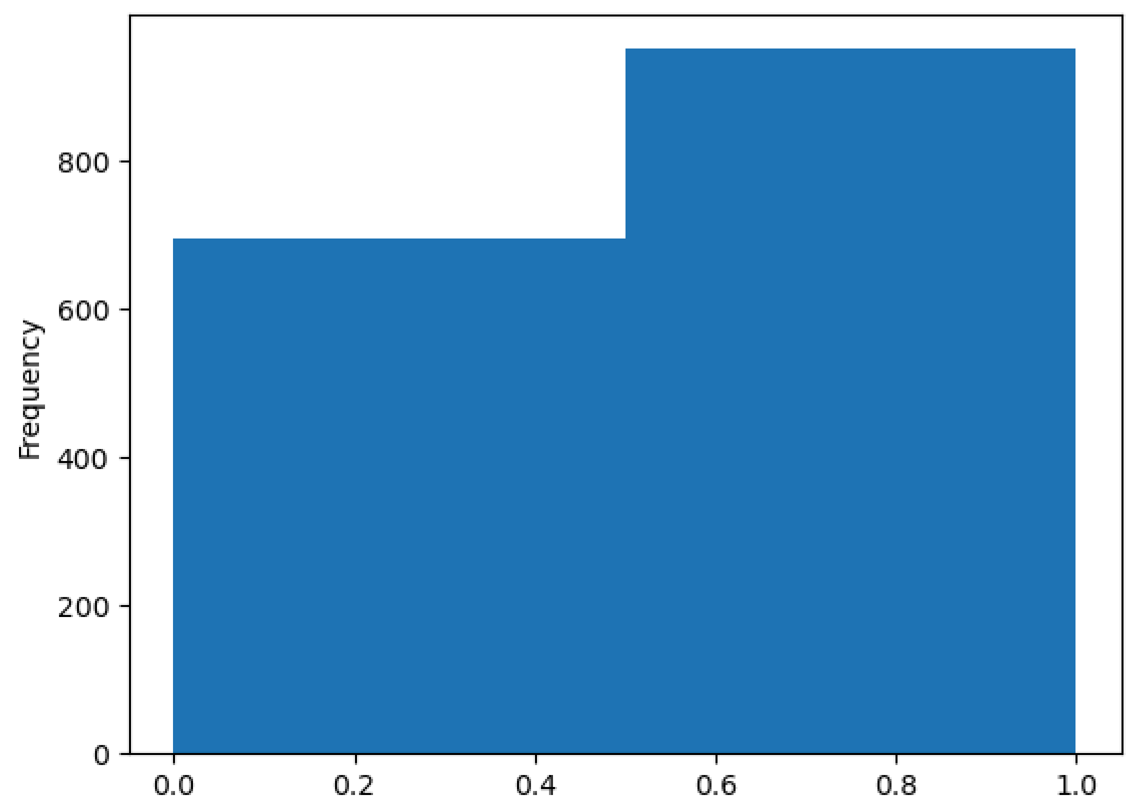
In [18]:
```
temp_df = df.groupby(['job_position']).agg({'ctc':'mean'})
temp_df.plot(kind='line')
ctc_mean = round(temp_df['ctc'].mean(),2)
plt.axhline(y = ctc_mean, color = 'r', linestyle = '-')
plt.show()
print(f'Insight: Average CTC across different job positions is {ctc_mean}')
```




```
Insight: Average CTC across different job positions is 1268701.92
```

4.3. Multivariate analysis

In [19]:
```
temp_df = df[~df['job_position'].isna()]
temp_df = temp_df.groupby(['company_hash', 'job_position']).agg({'ctc':'mean'}).reset_index()
temp_df_da = temp_df[[True if ('data' and 'scientist' in x) else False for x in temp_df['job_position']]]
temp_df_da = temp_df_da.drop(columns=['job_position']).rename(columns={'ctc':'ctc_ds'}).reset_index(drop=True)
temp_df_others = temp_df[[True if ('data' and 'scientist' not in x) else False for x in temp_df['job_position']]]
temp_df_others = temp_df_others.drop(columns=['job_position']).rename(columns={'ctc':'ctc_others'}).reset_index(drop=True)
temp_df_common = temp_df_da.merge(temp_df_others, on = 'company_hash', how='inner')
temp_df_common['ctc_ds_gt_ctc_others'] = temp_df_common['ctc_ds'] > temp_df_common['ctc_others']
temp_df_common.groupby(['company_hash']).agg({'ctc_ds_gt_ctc_others':'mean'}).reset_index()['ctc_ds_gt_ctc_others'].plot(kind='hist', bins=2)
plt.show()
```



Insight

- There are around 900+ companies in which more than 50% of the times the avergae CTC of a Data Scientist is greater than that of other roles

5. Data Preprocessing

In [20]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 203956 entries, 0 to 203955
Data columns (total 6 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   company_hash      203956 non-null  object 
 1   email_hash        203956 non-null  object 
 2   orgyear           203956 non-null  float64
 3   ctc               203956 non-null  int64  
 4   job_position      203956 non-null  object 
 5   ctc_updated_year  203956 non-null  float64
dtypes: float64(2), int64(1), object(3)
memory usage: 9.3+ MB
```

5.1. Handling duplicate values

In [21]:
```
df[df['email_hash'] == 'bbace3cc586400bbc65765bc6a16b77d8913836cfc98b77c05488f02f5714a4b']
```

Out[21]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
23498	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	720000	nan	2020.0
45062	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	720000	support engineer	2020.0
71181	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	720000	other	2020.0
101498	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	720000	fullstack engineer	2020.0
116226	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	720000	data analyst	2020.0
119910	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	660000	other	2019.0
122888	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	660000	support engineer	2019.0
142804	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	660000	fullstack engineer	2019.0
151096	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	660000	devops engineer	2019.0
158105	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	660000	nan	2019.0

There should be a unique entry for a combination of employee's e-mail and CTC. I will remove all the duplicates by keeping only the first entry as the first entry seems to be the latest entry

In [22]:
```
df = df.drop_duplicates(subset=['email_hash', 'ctc'])
df.reset_index(drop=True, inplace=True)
```

In [23]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 162004 entries, 0 to 162003
Data columns (total 6 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   company_hash      162004 non-null  object 
 1   email_hash        162004 non-null  object 
 2   orgyear           162004 non-null  float64
 3   ctc               162004 non-null  int64  
 4   job_position      162004 non-null  object 
 5   ctc_updated_year  162004 non-null  float64
dtypes: float64(2), int64(1), object(3)
memory usage: 7.4+ MB
```

In [24]:
```
df['email_hash'].value_counts()[:10]
```

Out[24]:
```
email_hash
58ae1bae06ebf94f022cc06962029090b67e1e0a19c9b367426a0478ed349a41    2
f33f83536090140ab11955aea0c1940d24e52944e22d6b1ac83c07f77da04b45    2
ffa1726ba8fbf5c3824d00f6d311384f3b6873a82ba4c299392e956a0af14f88    2
02ba5874e4bdd9952a6b1a518d15628946cb7c1d72861adbd4f513b8da1fd52f    2
bb318b24ecb7b28951bc201e00cceb3b4de49c47539b4e70cff4d66b7d0e3951    2
85b377da8855513ddc45b010a6eaf02bd1581605d4533a1d8bbe9025aedf005c    2
79a18f18303458d0a393607f951ed8088a696e540812350fb98686c558c6bd73    2
9ce698befbf7aa7fc6fc468e8c7d98c3e069b9f5c176eec471f6d2b3e621fe28    2
7f334761242f8e2bd159707e166fbf0a380700a9fbef62e70c09f4a9e878690c    2
902b1c1a83fbffd623ae728394e826ca6b72c6b2a8e3b1f5bee13761dcca1cf5    2
Name: count, dtype: int64
```

In [25]:
```
df[df['email_hash'] == 'bd126a265ff5985a859b2226e38d99eaa786771b2f3e0564adccef4772964497']
```

Out[25]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
77199	vbvkgz	bd126a265ff5985a859b2226e38d99eaa786771b2f3e05...	2018.0	320000	nan	2020.0
78210	vbvkgz	bd126a265ff5985a859b2226e38d99eaa786771b2f3e05...	2018.0	235999	other	2019.0

5.2. Handling null values

In [26]:
```
df.isna().sum()
```

Out[26]:
```
company_hash        0
email_hash          0
orgyear             0
ctc                 0
job_position        0
ctc_updated_year    0
dtype: int64
```

In [27]:
```
print(f'Number of empty company hash is {(df["company_hash"] == "").sum()}')
print(f'Number of company hash with "nan" values is {(df["company_hash"] == "nan").sum()}')
print(f'Number of empty job position is {(df["job_position"] == "").sum()}')
print(f'Number of job position with "nan" values is {(df["job_position"] == "nan").sum()}')
```

```
Number of empty company hash is 64
Number of company hash with "nan" values is 37
Number of empty job position is 6
Number of job position with "nan" values is 35841
```

Insight

- I will remove records where company hash is empty or "nan"
- I will remove records where job position is empty
- I will use imputation for job position with "nan" values

In [28]:
```
df = df[~((df["company_hash"] == "") | (df["company_hash"] == "nan") | (df["job_position"] == ""))]
df.reset_index(drop=True, inplace=True)

print(f'Number of empty company hash is {(df["company_hash"] == "").sum()}')
print(f'Number of company hash with "nan" values is {(df["company_hash"] == "nan").sum()}')
print(f'Number of empty job position is {(df["job_position"] == "").sum()}')
print(f'Number of job position with "nan" values is {(df["job_position"] == "nan").sum()}')

df.loc[df['job_position']=='nan', 'job_position']=np.nan
df.isna().sum()
```

```
Number of empty company hash is 0
Number of company hash with "nan" values is 0
Number of empty job position is 0
Number of job position with "nan" values is 35787
```

Out[28]:
```
company_hash            0
email_hash              0
orgyear                 0
ctc                     0
job_position        35787
ctc_updated_year        0
dtype: int64
```

In [29]:
```
temp_df = df[['company_hash', 'orgyear', 'ctc', 'job_position', 'ctc_updated_year']].copy()
encoders = dict()
columns_to_encode = ['company_hash', 'job_position']
for col in columns_to_encode:
    series = temp_df[col]
    encoder = LabelEncoder()
    temp_df[col] = pd.Series(encoder.fit_transform(series[series.notnull()]),
                        index = series[series.notnull()].index)
    encoders[col] = encoder

imputer = KNNImputer(n_neighbors=1)
temp_df = pd.DataFrame(imputer.fit_transform(temp_df), columns=temp_df.columns)
temp_df['job_position'] = encoders['job_position'].inverse_transform(temp_df['job_position'].astype('int32'))
```

In [30]:
```
df['job_position'] = temp_df['job_position']

print(f'Number of empty company hash is {(df["company_hash"] == "").sum()}')
print(f'Number of company hash with "nan" values is {(df["company_hash"] == "nan").sum()}')
print(f'Number of empty job position is {(df["job_position"] == "").sum()}')
print(f'Number of job position with "nan" values is {(df["job_position"] == "nan").sum()}')

df.isna().sum()
```

```
Number of empty company hash is 0
Number of company hash with "nan" values is 0
Number of empty job position is 0
Number of job position with "nan" values is 0
```

Out[30]:
```
company_hash        0
email_hash          0
orgyear             0
ctc                 0
job_position        0
ctc_updated_year    0
dtype: int64
```

5.3. Outlier Treatment

Outlier have already been taken care of

5.4. Feature Engineering

Handle entries having ctc_updated_year less than orgyear

In [31]:
```
value = (df['orgyear'] > df['ctc_updated_year']).sum()
print(f'Before -> Number of entries where ctc_updated_year is less than orgyear: {value}')
df['ctc_updated_year'] = df[["ctc_updated_year","orgyear"]].max(axis = 1)
value = (df['orgyear'] > df['ctc_updated_year']).sum()
print(f'After -> Number of entries where ctc_updated_year is less than orgyear: {value}')
```

```
Before -> Number of entries where ctc_updated_year is less than orgyear: 7331
After -> Number of entries where ctc_updated_year is less than orgyear: 0
```

Extract years of experience and years since increment values

In [32]:
```
current_year = 2023
df['years_of_experience'] = current_year - df['orgyear']
df['years_since_increment'] = current_year - df['ctc_updated_year']
```

Calculate CTC rank by comparing the CTC seperately against average CTC per company, average CTC per job position and average CTC per years of experience

Value 1 - CTC is greater than all three average CTCs

Value 2 - CTC is greater than at least 2 of the average CTCs

Value 3 - CTC is greater than at least 1 of average CTCs

Va;ue 4 - CTC is less than all the three average CTCs

In [33]:
```
df1 = df.groupby(['company_hash']).agg({'ctc':'mean'}).reset_index().rename(columns = {'ctc':'avg_ctc_per_C'})
df2 = df.groupby(['job_position']).agg({'ctc':'mean'}).reset_index().rename(columns = {'ctc':'avg_ctc_per_J'})
df3 = df.groupby(['years_of_experience']).agg({'ctc':'mean'}).reset_index().rename(columns = {'ctc':'avg_ctc_per_E'})
df = df.merge(df1, on='company_hash', how='left')
df = df.merge(df2, on='job_position', how='left')
df = df.merge(df3, on='years_of_experience', how='left')
def calculate_ctc_rnk(ctc, acpc, acpj, acpe):
    if ctc > acpc and ctc > acpj and ctc > acpe:
        return 1
    elif (ctc > acpc and ctc > acpj) or (ctc > acpc and ctc > acpe) or (ctc > acpj and ctc > acpe):
        return 2
    elif ctc > acpc or ctc > acpj or ctc > acpe:
        return 3
    else:
        return 4
df['ctc_rnk'] = df.apply(lambda x: calculate_ctc_rnk(x['ctc'],
                                                        x['avg_ctc_per_C'],
                                                        x['avg_ctc_per_J'],
                                                        x['avg_ctc_per_E']),
                           axis=1)
df.drop(columns=['avg_ctc_per_C', 'avg_ctc_per_J', 'avg_ctc_per_E'], inplace=True)
```

In [34]:
```
df.head()
```

Out[34]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	years_since_increment	ctc_rnk
0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000	other	2020.0	7.0	3.0	3
1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999	fullstack engineer	2019.0	5.0	4.0	4
2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015.0	2000000	backend engineer	2020.0	8.0	3.0	2
3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	700000	backend engineer	2019.0	6.0	4.0	4
4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017.0	1400000	fullstack engineer	2019.0	6.0	4.0	1

Calculate designation, class and tier values based on CTC statistics on company-experience level, company-position level and company level

Value 1 - CTC is greater than 75% of the population of the group

Value 2 - CTC is between 50% and 75% of the population of the group

Value 2 - CTC is less than 50% of the population of the group

In [35]:
```
def group_ctc(x,x50,x75):
    if x < x50:
```

```
        return 3
    elif x >= x50 and x <= x75:
        return 2
    elif  x > x75:
        return 1
```

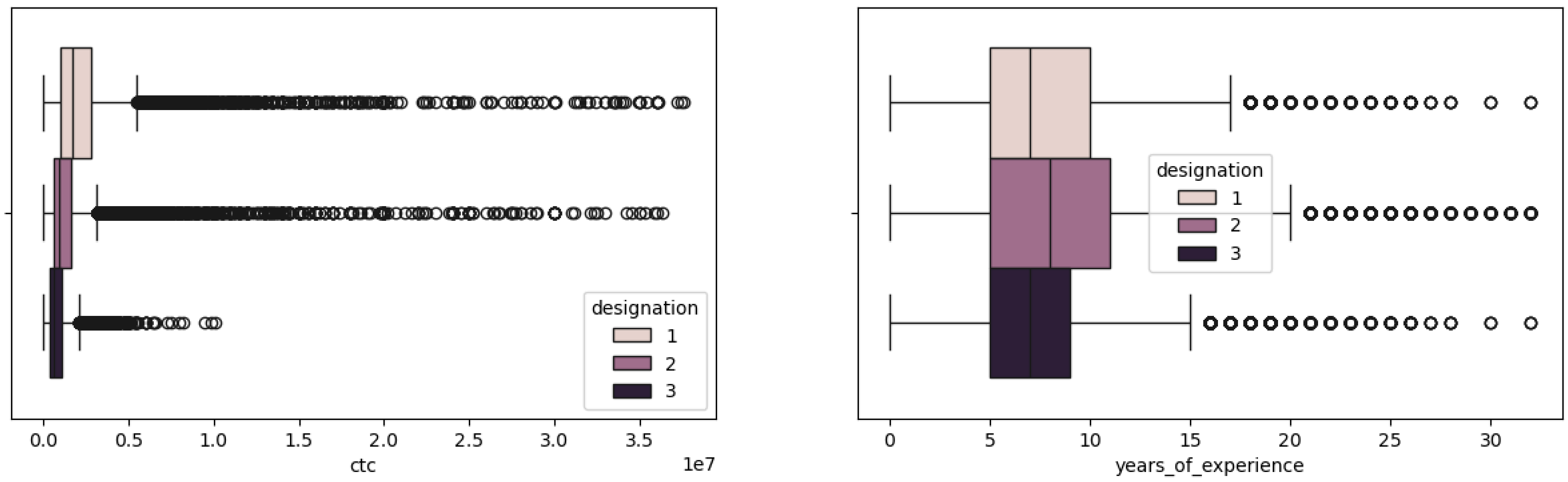
In [36]:
```
temp_df_CE = df.groupby(['company_hash', 'years_of_experience'])['ctc'].describe()
df_CE = df.merge(temp_df_CE, on=['company_hash', 'years_of_experience'], how='left')
temp_df_CJ = df.groupby(['company_hash', 'job_position'])['ctc'].describe()
df_CJ = df.merge(temp_df_CJ, on=['company_hash', 'job_position'], how='left')
temp_df_C = df.groupby(['company_hash'])['ctc'].describe()
df_C = df.merge(temp_df_C, on=['company_hash'], how='left')
```

In [37]:
```
df['designation'] = df_CE.apply(lambda x: group_ctc(x['ctc'], x["50%"], x["75%"]), axis=1)
df['class'] = df_CJ.apply(lambda x: group_ctc(x['ctc'], x["50%"], x["75%"]), axis=1)
df['tier'] = df_C.apply(lambda x: group_ctc(x['ctc'], x["50%"], x["75%"]), axis=1)
df.head()
```

Out[37]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	years_since_increment	ctc_rnk	designation	class	tier
0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000	other	2020.0	7.0	3.0	3	2	1	2
1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999	fullstack engineer	2019.0	5.0	4.0	4	3	3	3
2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015.0	2000000	backend engineer	2020.0	8.0	3.0	2	2	2	2
3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	700000	backend engineer	2019.0	6.0	4.0	4	3	3	3
4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017.0	1400000	fullstack engineer	2019.0	6.0	4.0	1	2	1	1

In [38]:
```
fig, axs = plt.subplots(1,2,figsize=(15,4))
sns.boxplot(ax=axs[0], data=df, x='ctc', hue='designation')
sns.boxplot(ax=axs[1], data=df, x='years_of_experience', hue='designation')
plt.show()
position_counts = df.groupby(['designation', 'job_position']).size().reset_index(name='count')
top_positions = position_counts.groupby('designation').apply(lambda x: x.nlargest(4, 'count')).reset_index(drop=True)
print(top_positions)
```



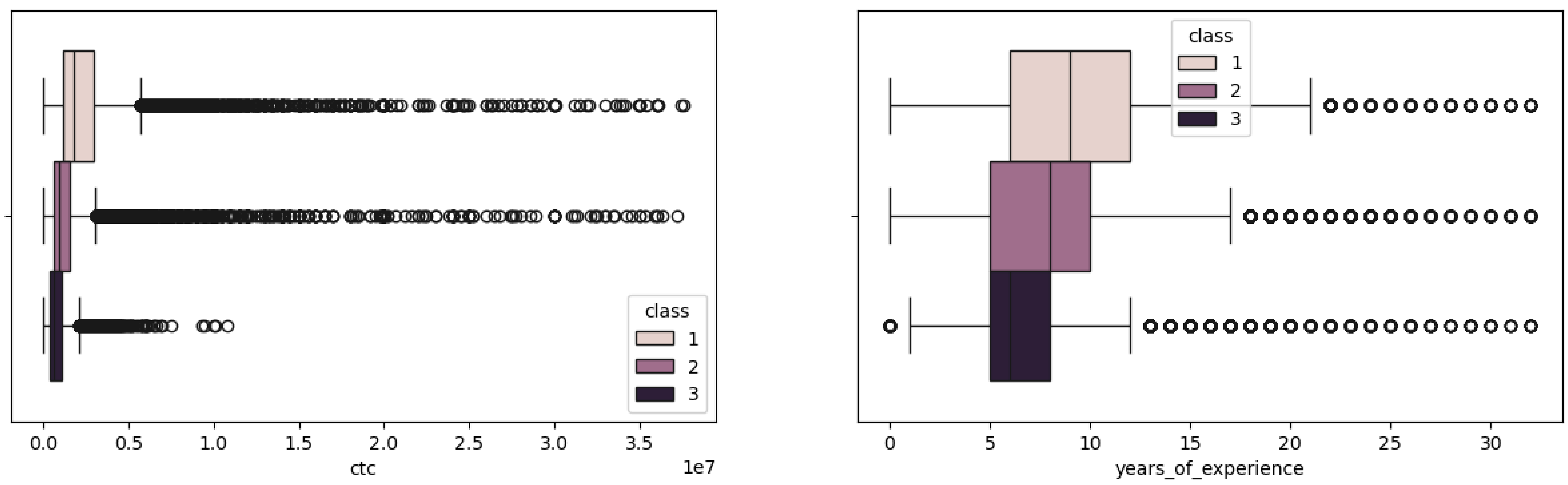

```
    designation        job_position  count
0             1    backend engineer  10657
1             1  fullstack engineer   5413
2             1               other   2969
3             1   frontend engineer   1864
4             2    backend engineer  20927
5             2  fullstack engineer  13122
6             2               other   8742
7             2   frontend engineer   5797
8             3    backend engineer  14631
9             3  fullstack engineer   7567
10            3               other   7473
11            3   frontend engineer   3422
```

```
C:\Users\dz31jl\AppData\Local\Temp\ipykernel_4344\2370918427.py:6: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is deprecated, and in a future version of pandas the grouping columns will be excluded from the operation. Either pass `include_groups=False` to exclude the groupings or explicitly select the grouping columns after groupby to silence this warning.
  top_positions = position_counts.groupby('designation').apply(lambda x: x.nlargest(4, 'count')).reset_index(drop=True)
```

Insight

- The mean CTC of designation 1 > 2 > 3
- The mean years of experience of designation 2 > 1 ~= 3
- The top 4 position of all the designations are backend engineer, fullstack engineer, other and frontend engineer
- The **clustering** based on **designation** is **able to differentiate** between **CTCs** but **not years of experience or job position**

In [39]:
```
fig, axs = plt.subplots(1,2,figsize=(15,4))
sns.boxplot(ax=axs[0], data=df, x='ctc', hue='class')
sns.boxplot(ax=axs[1], data=df, x='years_of_experience', hue='class')
plt.show()
position_counts = df.groupby(['class', 'job_position']).size().reset_index(name='count')
top_positions = position_counts.groupby('class').apply(lambda x: x.nlargest(4, 'count')).reset_index(drop=True)
print(top_positions)
```



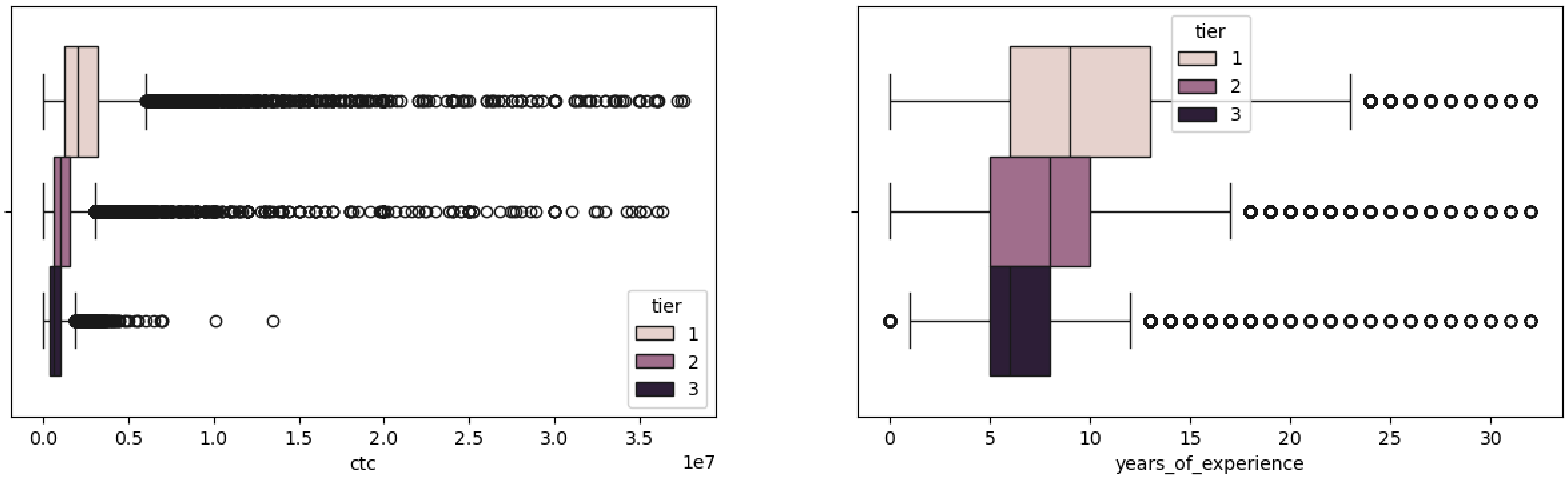
```
    class        job_position  count
0       1    backend engineer  10005
1       1  fullstack engineer   5115
2       1               other   3680
3       1   frontend engineer   1905
4       2    backend engineer  18165
5       2  fullstack engineer  12066
6       2               other   9046
7       2   frontend engineer   6051
8       3    backend engineer  18045
9       3  fullstack engineer   8921
10      3               other   6458
11      3   frontend engineer   3127
```

```
C:\Users\dz31jl\AppData\Local\Temp\ipykernel_4344\1484596224.py:6: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is deprecated, and in a future version of pandas the grouping columns will be excluded from the operation. Either pass `include_groups=False` to exclude the groupings or explicitly select the grouping columns after groupby to silence this warning.
  top_positions = position_counts.groupby('class').apply(lambda x: x.nlargest(4, 'count')).reset_index(drop=True)
```

Insight

- The mean CTC of class 1 > 2 > 3
- The mean years of experience of class 1 > 2 > 3
- The top 4 position of all the class are backend engineer, fullstack engineer, other and frontend engineer
- The **clustering** based on **class** is **able to differentiate** between **CTCs**, between **years of experience** but **not job position**

In [40]:
```python
fig, axs = plt.subplots(1,2,figsize=(15,4))
sns.boxplot(ax=axs[0], data=df, x='ctc', hue='tier')
sns.boxplot(ax=axs[1], data=df, x='years_of_experience', hue='tier')
plt.show()
position_counts = df.groupby(['tier', 'job_position']).size().reset_index(name='count')
top_positions = position_counts.groupby('tier').apply(lambda x: x.nlargest(4, 'count')).reset_index(drop=True)
print(top_positions)
```




```
    tier          job_position  count
0      1      backend engineer  10498
1      1    fullstack engineer   5236
2      1  engineering leadership  3876
3      1                 other   3148
4      2      backend engineer  17343
5      2    fullstack engineer  10711
6      2                 other   6898
7      2     frontend engineer   4705
8      3      backend engineer  18374
9      3    fullstack engineer  10155
10     3                 other   9138
11     3     frontend engineer   4317
```

```
C:\Users\dz31jl\AppData\Local\Temp\ipykernel_4344\1903124631.py:6: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is deprecated, and in a future version of pandas the grouping columns will be excluded from the operation. Either pass `include_groups=False` to exclude the groupings or explicitly select the grouping columns after groupby to silence this warning.
  top_positions = position_counts.groupby('tier').apply(lambda x: x.nlargest(4, 'count')).reset_index(drop=True)
```

Insight

- The mean CTC of tier 1 > 2 > 3
- The mean years of experience of tier 1 > 2 > 3
- The top 4 position of tier 1 are backend engineer, fullstack engineer, engineering leadership and other while for all the other tiers are backend engineer, fullstack engineer, other and frontend engineer
- The **clustering** based on **tier** is **able to differentiate** between **CTCs**, between **years of experience** and **partially** between **job position**

In [41]:
```python
temp_df = df[df['tier'] == 1].sort_values(by='ctc', ascending=False)[['company_hash', 'email_hash', 'ctc', 'job_position', 'years_of_experience']]
temp_df.head(10)
```

Out[41]:

	company_hash	email_hash	ctc	job_position	years_of_experience
25231	onvnt onqttn	fb8410d957fcc2e98cc419e9354dbb3acea2309b0898e2...	37600000	other	7.0
1652	mxsmvoptnwgb	89e0bd3c55896b4b09bb31fa4a736dd6c6d9c3622049e0...	37400000	other	5.0
12240	stztojo	a6e0d878386ba7ef29d50a698c5037864d3eb2cf4de9cb...	37200000	other	4.0
57410	xmb	46dece7d152edae30f51b0ceab430cbc9681fdd0100e72...	36100000	database administrator	6.0
16073	oytrr xzaxv bvqptno rxbxnta	109ea0d2fea7028684f062eccdc53638489ff2e662ea86...	36000000	other	7.0
49297	zgn vuurxwvmrt	2c5f9aefb73259d3a6df5fe503c48587d8fc61eefacc8e...	36000000	other	9.0
65885	ofxssj	4d287c2dd88a8b8008781f9081581d3cd7a36d0cc88c8d...	36000000	other	9.0
66457	jvygg xzw	2e67d726c283087bbfaef033b250dc4ea395fa2b2d88cd...	36000000	backend engineer	15.0
112601	vuuajzvbxwo	4015c0491e4d40f288ee1e0d5d852997bff5535c03bed6...	35820000	other	9.0
8870	nvnv wgzohrnvzwj otqcxwto	914f81589b8d14a404eeee60384fc8e9260f1023ca6636...	35400000	other	8.0

In [42]:
```python
temp_df['job_position'].value_counts()[:10]
```

Out[42]:
```
job_position
backend engineer          10498
fullstack engineer         5236
engineering leadership     3876
other                      3148
frontend engineer          2061
data scientist             1637
android engineer           1011
qa engineer                 983
devops engineer             959
backend architect           736
Name: count, dtype: int64
```

Insight

- Above are the top 10 employees earning more than most of the employees in the company
- The top employees belong to companies which provide software developer roles

In [43]:
```
df[df['tier'] == 3].sort_values(by='ctc', ascending=True).head(10)[['company_hash', 'email_hash', 'ctc']]
```

Out[43]:

	company_hash	email_hash	ctc
107027	xzntqcxtfmxn	3505b02549ebe2c95840ac6f0a35561a3b4cbe4b79cdb1...	2
93403	xzntqcxtfmxn	f2b58aeed3c074652de2cfd3c0717a5d21d6fbcf342a78...	6
90133	xzntqcxtfmxn	23ad96d6b6f1ecf554a52f6e9b61677c7d73d8a409a143...	14
145643	xm	b8a0bb340583936b5a7923947e9aec21add5ebc50cd60b...	15
92572	hzxctqoxnj ge fvoyxzsngz	f7e5e788676100d7c4146740ada9e2f8974defc01f571d...	200
134689	nvnv wgzohrnvzwj otqcxwto	80ba0259f9f59034c4927cf3bd38dc9ce2eb60ff18135b...	600
118958	zvz	9af3dca6c9d705d8d42585ccfce2627f00e1629130d14e...	600
79494	gjg	b995d7a2ae5c6f8497762ce04dc5c04ad6ec734d70802a...	600
61224	vwwtznhqt	f0f2005505c707dbdd2c86ca1587c26f822a004e86a8ec...	1000
74368	zvz	4ea8ce7809d8c69147d243bad53d88d016a1151690b8b6...	1000

Insight

- Above are the bottom 10 employees earning less than most of the employees in the company

In [44]:
```
temp_df = df[df['tier'] == 3].groupby(['company_hash']).agg({'ctc':'mean',
                                                    'years_of_experience':'mean',
                                                    'ctc_rnk':'mean',
                                                    'designation':'mean',
                                                    'class':'mean'}).reset_index()
temp_df.describe()
```

Out[44]:

	ctc	years_of_experience	ctc_rnk	designation	class
count	8.956000e+03	8956.000000	8956.000000	8956.000000	8956.000000
mean	7.456474e+05	7.430224	3.748434	2.303444	2.350800
std	5.655440e+05	3.170351	0.545134	0.383568	0.398012
min	1.500000e+01	0.000000	1.500000	1.666667	1.666667
25%	4.000000e+05	5.166667	4.000000	2.000000	2.000000
50%	6.250000e+05	7.000000	4.000000	2.000000	2.000000
75%	9.414534e+05	9.000000	4.000000	2.574495	2.666667
max	1.350000e+07	32.000000	4.000000	3.000000	3.000000

In [45]:
```
df[((df['class'] == 1) & (df['job_position'] == 'data scientist'))].sort_values(by='ctc', ascending=False).head(10)[['company_hash', 'email_hash', 'ctc']]
```

Out[45]:

	company_hash	email_hash	ctc
136197	wxnx	f7b7c771ccdbbca7248002ba83f7a176baa974c2c7bb8f...	24200000
61817	bxwqgogen	599e489c815ba51967965c5d6adefd7a76a99ffaa129bd...	22500000
9238	sggsrt	3e290b892b73283b96293c53e4ce4dce2cc6a22399b95c...	22000000
57337	zvz	80f1ae60373f0ada3b75ce19eb585f8cf112de3cfa6ea7...	20000000
21231	xmb	b5dc6ad6d8d8f04312c34285a3c45fd9ffdc73ff3f1205...	20000000
90828	xmb xzaxv uqxcvnt rxbxnta	4beee431866cc493f7cc6689c2f00023683575a29e3174...	20000000
98676	nyghsynfgqpo	aa1d9bece779ff63a54bd6d32452e3f938a0afc6a52c6b...	20000000
149152	onvnt onqttn	9fdab215a86b0e2f18ee6c3d7653442cd7ad8b9cc4cf91...	18000000
103726	sgltp	24d6a653ce21e80d3f03eaab9b7600f4bbb0888cf7bccd...	12000000
21809	exwg	d1290b7e2d85c75902b863ccc3e4aafdd6e6eb07a10a00...	12000000

Insight

- Above are the top 10 employees of data scientist role earning more than their peers

In [46]:
```
df[((df['class'] == 3) & (df['job_position'] == 'data scientist'))].sort_values(by='ctc', ascending=True).head(10)[['company_hash', 'email_hash', 'ctc']]
```

Out[46]:

	company_hash	email_hash	ctc
92778	ovbohzs trtwnqgzxwo	3711220da929dcc0f6ca1f150b31ec7ac9302e8e59b118...	3500
8145	bxyhu wgbbhzxwvnxgz	690f6fdab1ab7514a6a9325ebd6cfe910dbf12d46b6fde...	4000
36359	cgavegzt oyvqta otqcxwto rxbxnta	c5335f1ab2b6b60e4c7bf52a9dd2f22b87e07208ecbb0e...	4000
10011	srgmvrtast xzntrrxstzwt ge nyxzso	8001bc017fbe95541d23f5780c3edb988b7d9b2225e39e...	4000
48692	onvnt onqttn	210022464f7fc73ab22c22b9b2fcb8dc4fd8e3fe69ac1a...	6000
40873	onhatzn	bd9c04a574090e05b366a81cdb2f3f565d0c60fa8b1647...	6000
108429	ovbohzs trtwnqg btwyvzxwo	e374eea75640881206a21894f69190138c2c0535277dc1...	7000
8770	nvnv wgzohrnvzwj otqcxwto	3175d03fd4618eb293d6f5a1d13d42a0c79f68e9acaaa3...	7500
20257	vqxosrgmvr	3675f79c7e05de96ccf189c818b84b487cb1aa3f6b80e8...	8800
25625	sggsrt	fb64af615420e06d46a1965f59068b34460fb3cbe70541...	10000

Insight

- Above are the bottom 10 employees of data scientist role earning less than their peers

In [47]:
```
df[(df['tier'] == 1) & ((df['years_of_experience'] >= 5) & (df['years_of_experience'] <= 7))].sort_values(by='ctc', ascending=False).head(10)[['company_hash', 'email_hash', 'ctc']]
```

Out[47]:

	company_hash	email_hash	ctc
25231	onvnt onqttn	fb8410d957fcc2e98cc419e9354dbb3acea2309b0898e2...	37600000
1652	mxsmvoptnwgb	89e0bd3c55896b4b09bb31fa4a736dd6c6d9c3622049e0...	37400000
57410	xmb	46dece7d152edae30f51b0ceab430cbc9681fdd0100e72...	36100000
16073	oytrr xzaxv bvqptno rxbxnta	109ea0d2fea7028684f062eccdc53638489ff2e662ea86...	36000000
70443	stzuvwn	351256c3e18d5d9520baa0f6d7060799d2d81b2cc5c44a...	35000000
22238	vwwtznhqt	fe6af782581bf996a3daacc23387526b8f65435d3c7bd4...	34890000
103184	vnnqv	596b127f7d32653e454c6f42bf74f97af8f8e71d32d352...	34000000
11165	ihtoo wgqu	fce813324a073acc850322b38f11b48e3771c6558bc21e...	33500000
29263	xzaxsg vxqrxzt	14df647edb4209bf283db88e2fea7d52f2e321481dcc4e...	33400000
33201	yvuuxton bxzao ntwyzgrgsxto	59216d0595d84ec308c8ab6107a8e071af0aaa11bff208...	33000000

Insight

- Above are the top 10 employees with 5,6 or 7 years of experience earning more than most of the employees in the company

In [48]:
```
df.groupby(['company_hash']).agg({'ctc':'max'}).sort_values(by='ctc', ascending=False).head(10)
```

Out[48]:

company_hash	ctc
onvnt onqttn	37600000
mxsmvoptnwgb	37400000
stztojo	37200000
bgngktz ehtr ojontb	36360000
xmb	36100000
srgmvr ogenfvqt	36000000
jvygg xzw	36000000
zgn vuurxwvmrt	36000000
ofxssj	36000000
oytrr xzaxv bvqptno rxbxnta	36000000

Insight

- Above are the top 10 companies based on their CTC

In [49]:
```
temp_df = df[['company_hash', 'job_position', 'ctc']].groupby('company_hash').apply(lambda x: x.nlargest(2, 'ctc')).reset_index(drop=True).sort_values(by='ctc', ascending=False)
temp_df['job_position'].value_counts()
```

```
C:\Users\dz31jl\AppData\Local\Temp\ipykernel_4344\1812531026.py:1: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is deprecated, and in a future ver
sion of pandas the grouping columns will be excluded from the operation. Either pass `include_groups=False` to exclude the groupings or explicitly select the grouping columns after groupby to
silence this warning.
  temp_df = df[['company_hash', 'job_position', 'ctc']].groupby('company_hash').apply(lambda x: x.nlargest(2, 'ctc')).reset_index(drop=True).sort_values(by='ctc', ascending=False)
```

Out[49]:
```
job_position
backend engineer          9470
fullstack engineer        7214
other                     4869
frontend engineer         3610
engineering leadership    3183
                          ...
software qa engineer         1
credit risk                  1
assistant manager            1
web  ui designer             1
fullstack web developer      1
Name: count, Length: 255, dtype: int64
```

Insight

- **backend engineer** and **fullstack engineer** are the top 2 job positions in most of the company with high CTC

5.5. Data preparation for modelling

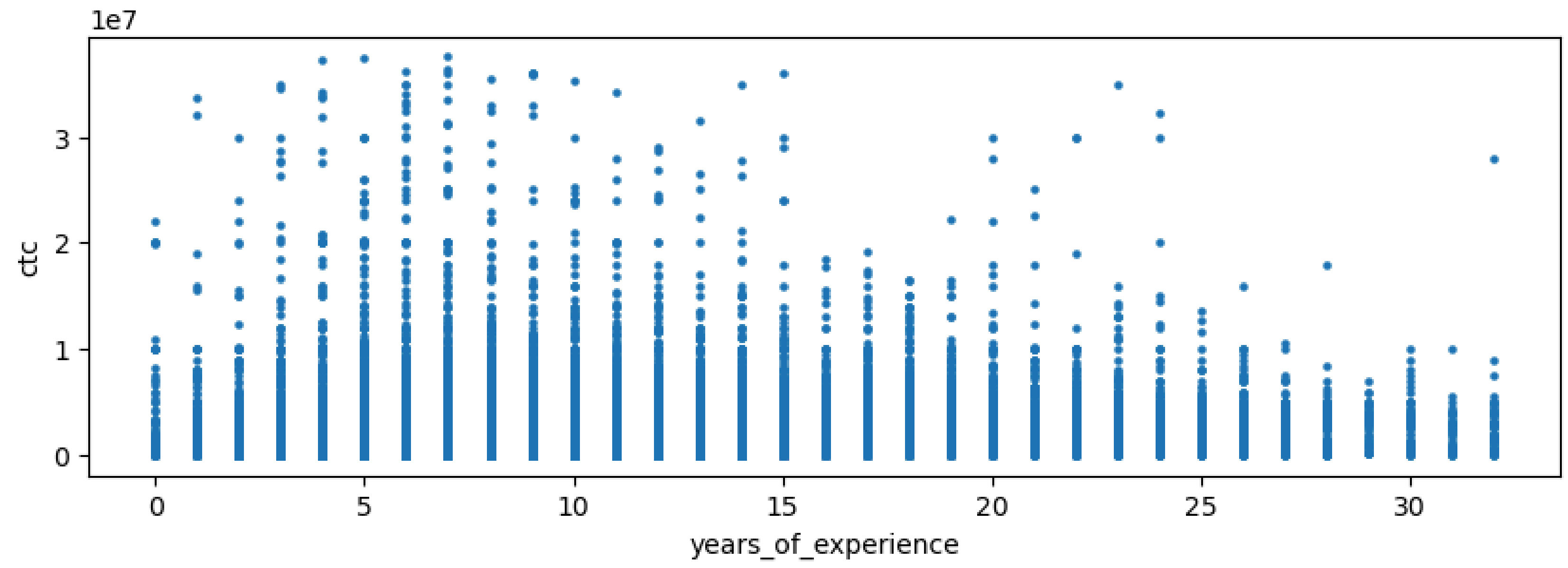
In [50]:
```
X = df.drop(columns=['company_hash', 'email_hash', 'orgyear', 'job_position', 'ctc_updated_year'])
```

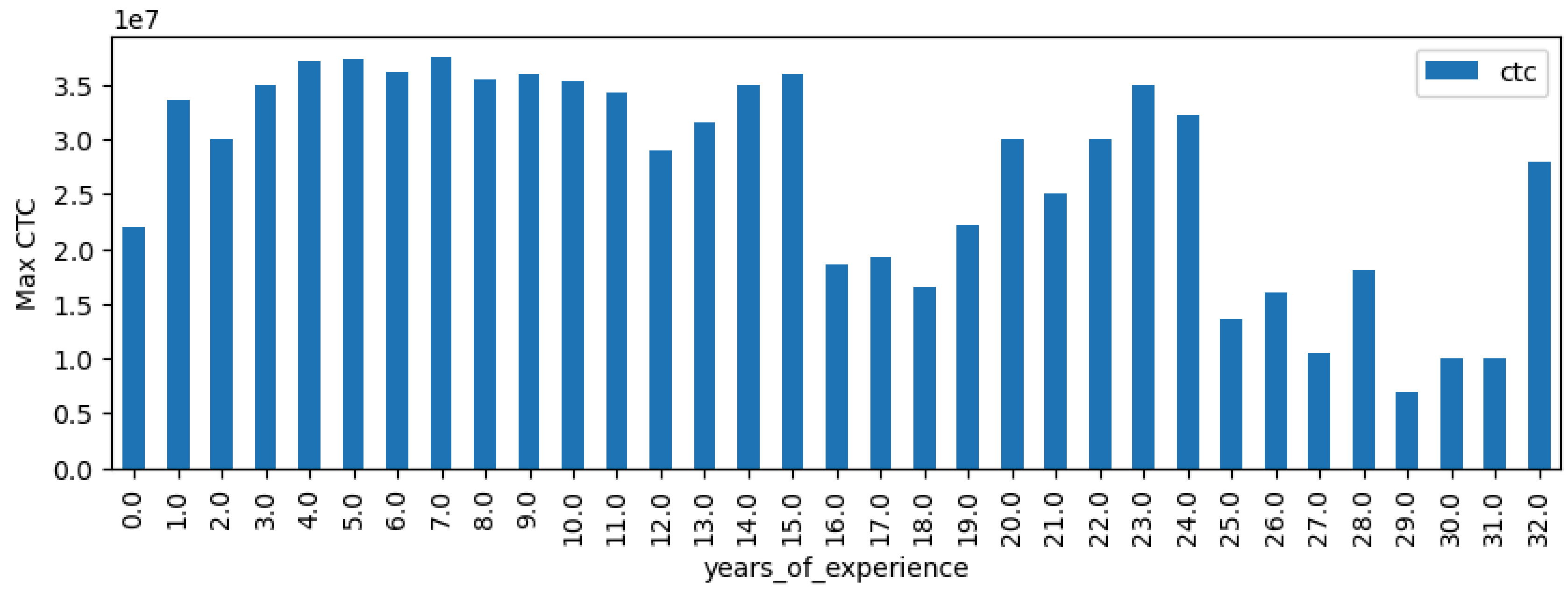
In [51]:
```
X.head()
```

Out[51]:

	ctc	years_of_experience	years_since_increment	ctc_rnk	designation	class	tier
0	1100000	7.0	3.0	3	2	1	2
1	449999	5.0	4.0	4	3	3	3
2	2000000	8.0	3.0	2	2	2	2
3	700000	6.0	4.0	4	3	3	3
4	1400000	6.0	4.0	1	2	1	1

In [52]:
```
X.plot.scatter(x='years_of_experience', y='ctc', s=5, figsize=(10,3))
plt.show()
X.groupby(['years_of_experience']).agg({'ctc':'max'}).plot(kind='bar', figsize=(10,3))
plt.ylabel('Max CTC')
plt.show()
```





Scale the data

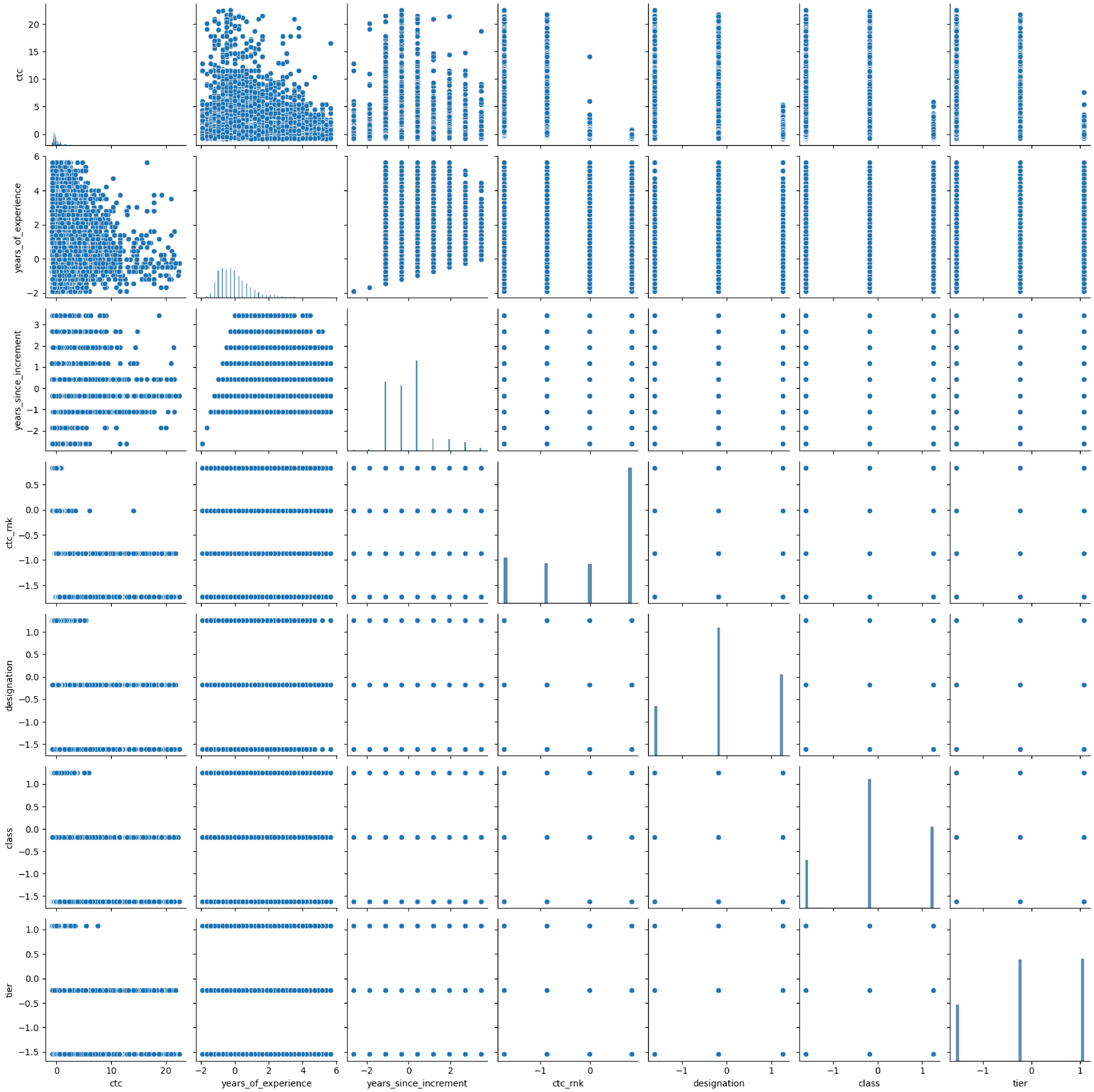
In [53]:
```
X_scaled = pd.DataFrame(StandardScaler().fit_transform(X), columns=X.columns)
```

In [54]:
```
X_scaled.head()
```

Out[54]:

	ctc	years_of_experience	years_since_increment	ctc_rnk	designation	class	tier
0	-0.166324	-0.252893	-0.351471	-0.018477	-0.176573	-1.625672	-0.234119
1	-0.570941	-0.723569	0.408135	0.834988	1.252976	1.250485	1.082146
2	0.393913	-0.017555	-0.351471	-0.871942	-0.176573	-0.187593	-0.234119
3	-0.415318	-0.488231	0.408135	0.834988	1.252976	1.250485	1.082146
4	0.020422	-0.488231	0.408135	-1.725407	-0.176573	-1.625672	-1.550384

In [55]:
```
sns.pairplot(X_scaled)
plt.show()
```



6. Model building

6.1. Check Clustering Tendency

In [56]:
```
# function to compute hopkins's statistic for the dataframe X
def hopkins_statistic(X):

    X=X.values  #convert dataframe to a numpy array
    sample_size = int(X.shape[0]*0.05) #0.05 (5%) based on paper by Lawson and Jures

    #a uniform random sample in the original data space
    X_uniform_random_sample = uniform(X.min(axis=0), X.max(axis=0) ,(sample_size , X.shape[1]))

    #a random sample of size sample_size from the original data X
    random_indices=sample(range(0, X.shape[0], 1), sample_size)
    X_sample = X[random_indices]

    #initialise unsupervised learner for implementing neighbor searches
    neigh = NearestNeighbors(n_neighbors=2)
    nbrs=neigh.fit(X)

    #u_distances = nearest neighbour distances from uniform random sample
    u_distances , u_indices = nbrs.kneighbors(X_uniform_random_sample , n_neighbors=2)
    u_distances = u_distances[: , 0] #distance to the first (nearest) neighbour

    #w_distances = nearest neighbour distances from a sample of points from original data X
    w_distances , w_indices = nbrs.kneighbors(X_sample , n_neighbors=2)
    #distance to the second nearest neighbour (as the first neighbour will be the point itself, with distance = 0)
    w_distances = w_distances[: , 1]

    u_sum = np.sum(u_distances)
    w_sum = np.sum(w_distances)

    #compute and return hopkins' statistic
    H = u_sum/ (u_sum + w_sum)
    return H
```

In [57]:
```
l = [] #list to hold values for each call
for i in range(5):
    H=hopkins_statistic(X_scaled)
    l.append(H)
#print average value:
np.mean(l)
```

Out[57]: 0.9875647762150388

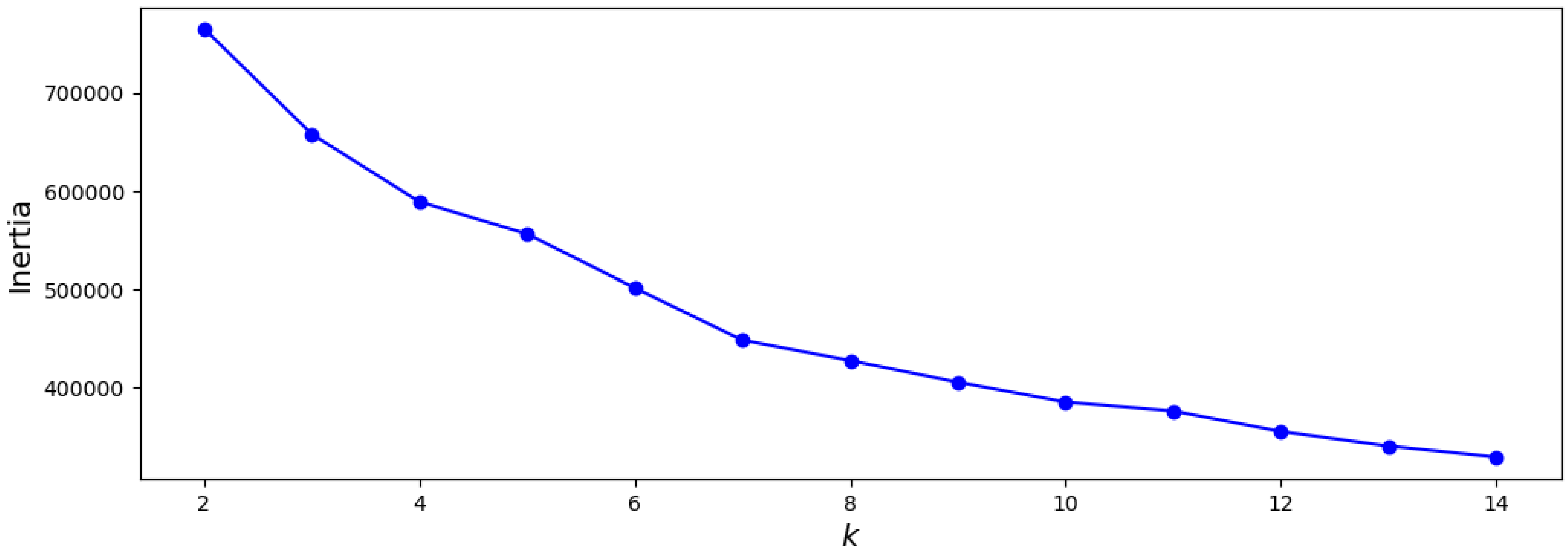
As per Hopkins statistics, with the value of ~0.98, the dataset exhibits very good clustering tendency

6.2. Selecting Optimal Number of Clusters

6.2.1. Using the KMeans inertia and Elbow Method

In [58]:
```
min_num_of_clusters = 2
max_num_of_clusters = 15
kmeans_per_k = [KMeans(n_clusters=k, random_state=42).fit(X_scaled)
                for k in range(min_num_of_clusters, max_num_of_clusters)]
```

In [59]:
```
inertias = [model.inertia_ for model in kmeans_per_k]
#print(inertias)
plt.figure(figsize=(12, 4))
plt.plot(range(min_num_of_clusters, max_num_of_clusters, 1), inertias, "bo-")
plt.xlabel("$k$", fontsize=14)
plt.ylabel("Inertia", fontsize=14)
plt.show()
```



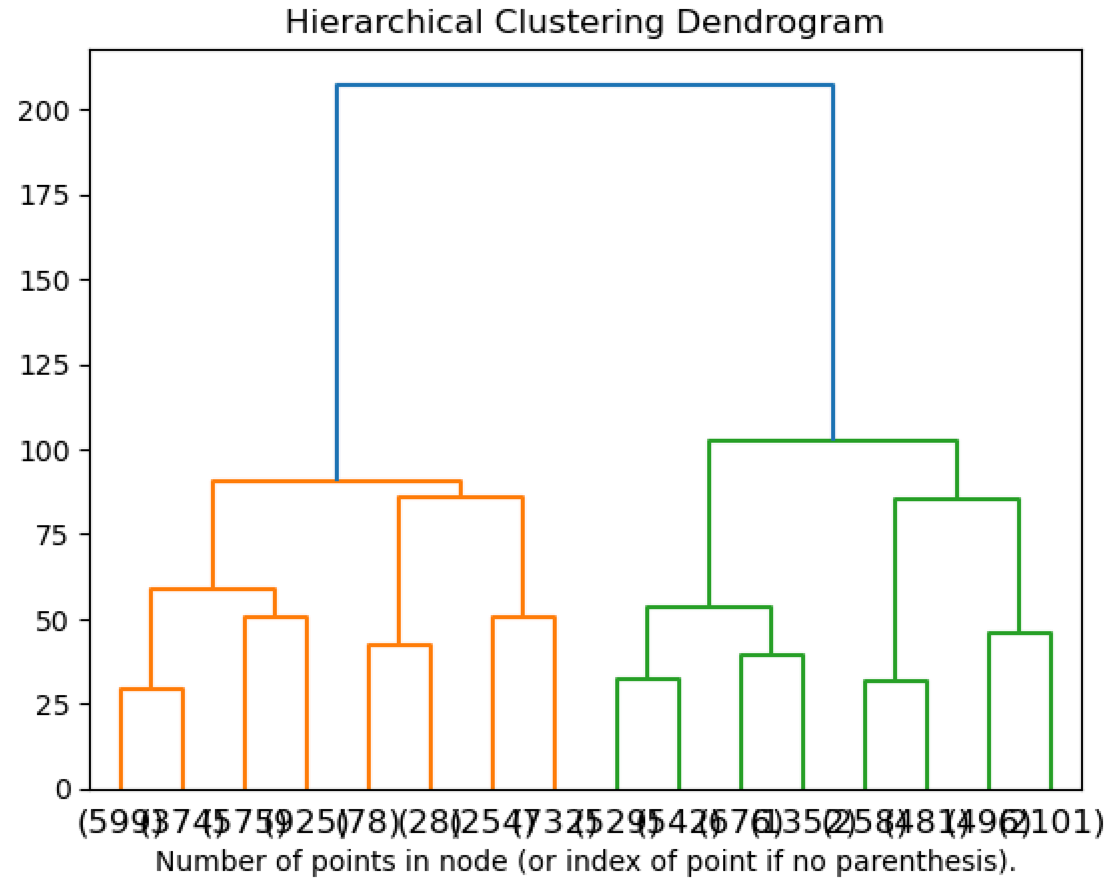
As per the above WCSS, an elbow is created at value 4 and also at 7

6.2.2. Using the Hierarchical Clustering Dendrogram

In [60]:
```
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)
```

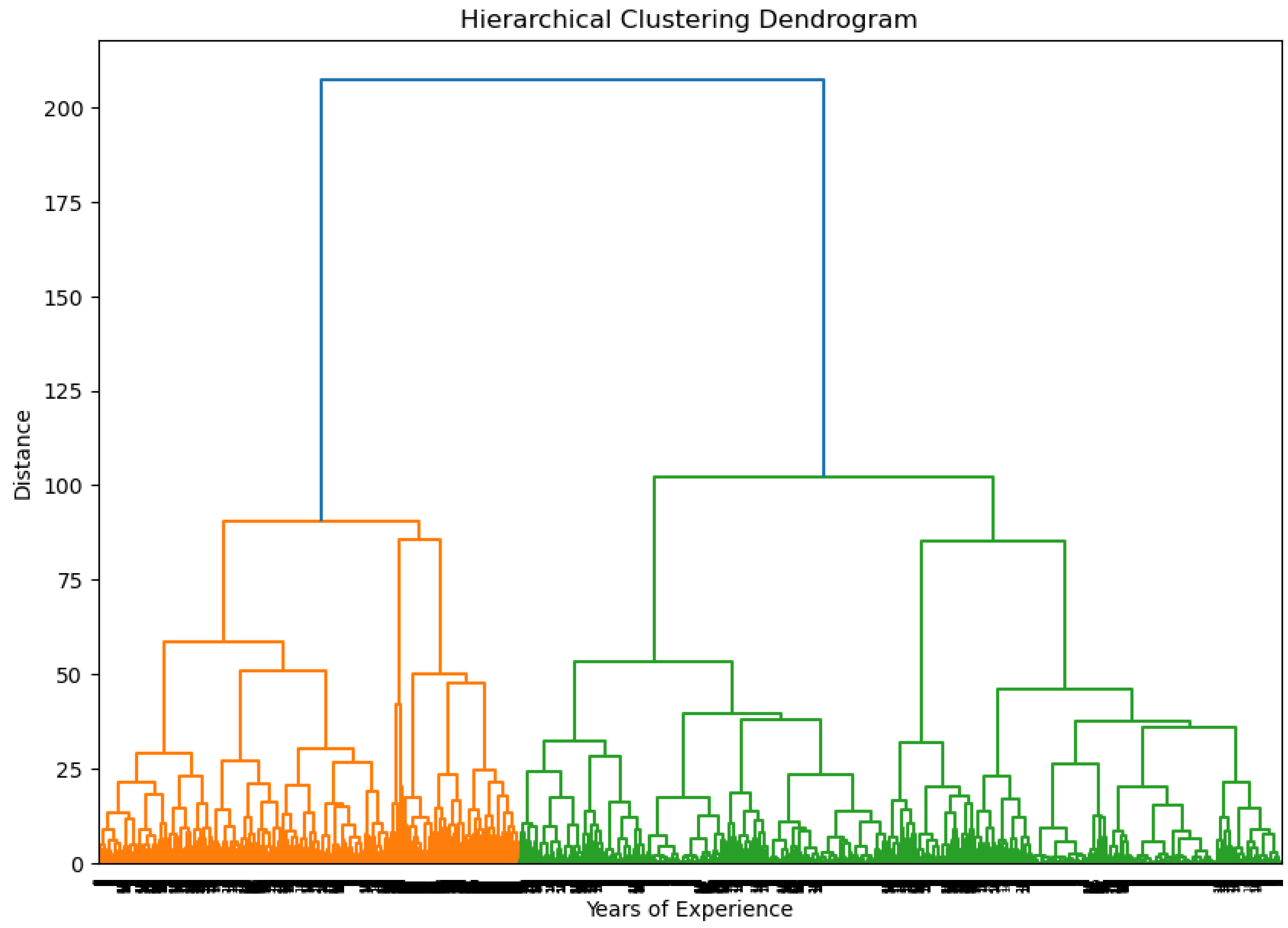
In [62]:
```
X_scaled_sample = X_scaled.sample(10000)
X_sample = X.iloc[X_scaled_sample.index]
model = AgglomerativeClustering(distance_threshold=0, n_clusters=None)
model = model.fit(X_scaled_sample)
```

In [63]:
```
plt.title("Hierarchical Clustering Dendrogram")
# plot the top three levels of the dendrogram
plot_dendrogram(model, truncate_mode="level", p=3)
plt.xlabel("Number of points in node (or index of point if no parenthesis).")
plt.show()
```



As per the dendrogram plot, number of clusters could be 4

In [64]:
```
linkage_matrix = sch.linkage(X_scaled_sample, method='ward')
plt.figure(figsize=(10, 7))
sch.dendrogram(linkage_matrix, labels=X_sample['years_of_experience'].values.astype(int))
plt.title('Hierarchical Clustering Dendrogram')
plt.xlabel('Years of Experience')
plt.ylabel('Distance')
plt.show()
```



Insight

- From the above we can see a clear pattern that the low number of years of experience are grouped together on the extreme left, medium number of years of experience are grouped together in the middle and high number of years of experience are grouped together at the extreme right

6.3. K-means Clustering using the optimal number of clusters

In [65]:
```
final_num_clusters = 4
kM = KMeans(n_clusters=final_num_clusters, random_state=42)
y_pred = kM.fit_predict(X_scaled)
clusters = pd.DataFrame(X, columns=X.columns)
clusters['label'] = kM.labels_
```

In [66]:
```
clusters.head()
```

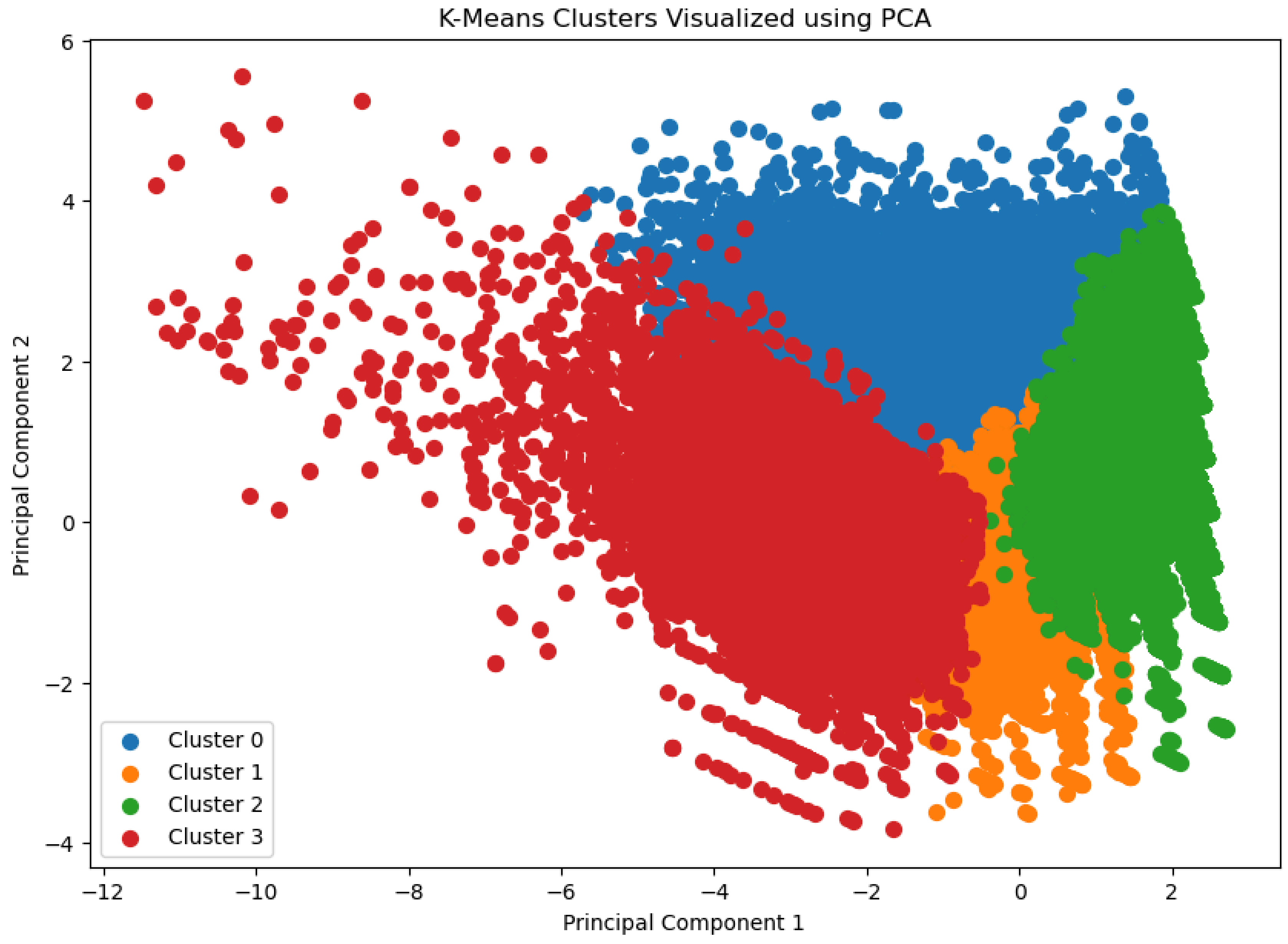
Out[66]:

	ctc	years_of_experience	years_since_increment	ctc_rnk	designation	class	tier	label
0	1100000	7.0	3.0	3	2	1	2	1
1	449999	5.0	4.0	4	3	3	3	2
2	2000000	8.0	3.0	2	2	2	2	1
3	700000	6.0	4.0	4	3	3	3	2
4	1400000	6.0	4.0	1	2	1	1	3

6.3.1 Visualizing clusters using PCA

In [67]:
```
pca = PCA(n_components=2)
pca_components = pca.fit_transform(X_scaled)
df_pca = pd.DataFrame(data=pca_components, columns=['PC1', 'PC2'])
df_pca['cluster'] = kM.labels_
# Plot the clusters
plt.figure(figsize=(10, 7))
for cluster in range(final_num_clusters):
    clustered_data = df_pca[df_pca['cluster'] == cluster]
    plt.scatter(clustered_data['PC1'], clustered_data['PC2'], label=f'Cluster {cluster}', s=50)

plt.title('K-Means Clusters Visualized using PCA')
```

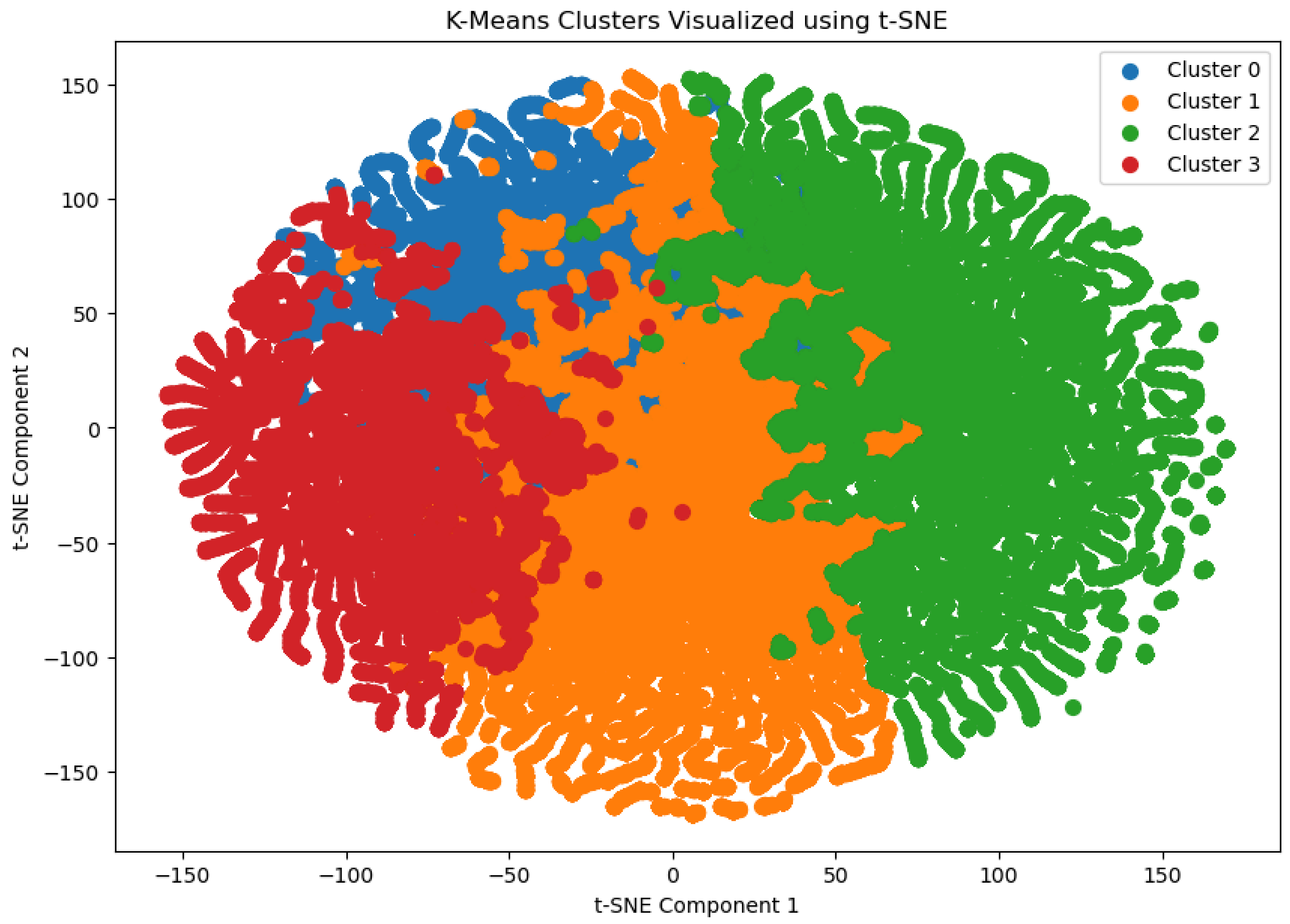
```
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend()
plt.show()
```



6.3.2 Visualizing clusters using TSNE

In [68]:

```
# Perform t-SNE to reduce to 2 components
tsne = TSNE(n_components=2, random_state=42)
tsne_components = tsne.fit_transform(X_scaled)

# Create a DataFrame with the t-SNE components and cluster labels
df_tsne = pd.DataFrame(data=tsne_components, columns=['TSNE1', 'TSNE2'])
df_tsne['cluster'] = kM.labels_

# Plot the clusters
plt.figure(figsize=(10, 7))
for cluster in range(final_num_clusters):
    clustered_data = df_tsne[df_tsne['cluster'] == cluster]
    plt.scatter(clustered_data['TSNE1'], clustered_data['TSNE2'], label=f'Cluster {cluster}', s=50)

plt.title('K-Means Clusters Visualized using t-SNE')
plt.xlabel('t-SNE Component 1')
plt.ylabel('t-SNE Component 2')
plt.legend()
plt.show()
```

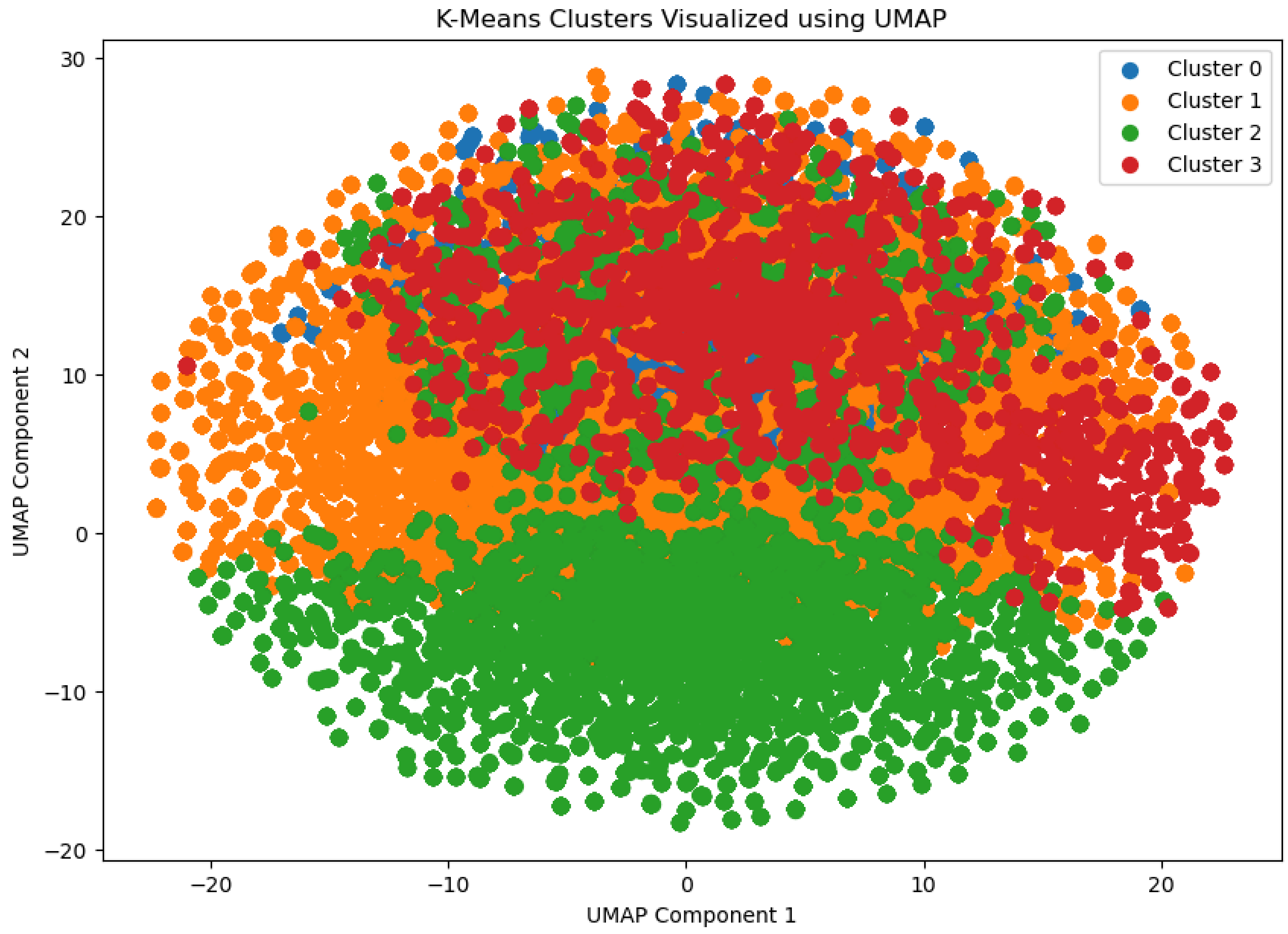


6.3.3 Visualizing clusters using UMAP

In [69]:

```
# Perform UMAP to reduce to 2 components
umap_reducer = umap.UMAP(n_components=2, random_state=42)
umap_components = umap_reducer.fit_transform(X_scaled)

# Create a DataFrame with the UMAP components and cluster labels
df_umap = pd.DataFrame(data=umap_components, columns=['UMAP1', 'UMAP2'])
df_umap['cluster'] = kM.labels_

# Plot the clusters
plt.figure(figsize=(10, 7))
for cluster in range(final_num_clusters):
    clustered_data = df_umap[df_umap['cluster'] == cluster]
    plt.scatter(clustered_data['UMAP1'], clustered_data['UMAP2'], label=f'Cluster {cluster}', s=50)

plt.title('K-Means Clusters Visualized using UMAP')
plt.xlabel('UMAP Component 1')
plt.ylabel('UMAP Component 2')
plt.legend()
plt.show()
```

```
C:\ProgramData\anaconda3\Lib\site-packages\umap\umap_.py:1945: UserWarning: n_jobs value 1 overridden to 1 by setting random_state. Use no seed for parallelism.
  warn(f"n_jobs value {self.n_jobs} overridden to 1 by setting random_state. Use no seed for parallelism.")
C:\ProgramData\anaconda3\Lib\site-packages\umap\spectral.py:550: UserWarning: Spectral initialisation failed! The eigenvector solver
failed. This is likely due to too small an eigengap. Consider
adding some noise or jitter to your data.

Falling back to random initialisation!
  warn(
```



PCA does a better job at visualizing the clusters in my dataset

In [70]:
```
clusters.head()
```

Out[70]:

	ctc	years_of_experience	years_since_increment	ctc_rnk	designation	class	tier	label
0	1100000	7.0	3.0	3	2	1	2	1
1	449999	5.0	4.0	4	3	3	3	2
2	2000000	8.0	3.0	2	2	2	2	1
3	700000	6.0	4.0	4	3	3	3	2
4	1400000	6.0	4.0	1	2	1	1	3

In [71]:
```
unique_labels = clusters['label'].nunique()
colors = sns.color_palette("tab10")[:unique_labels]
```

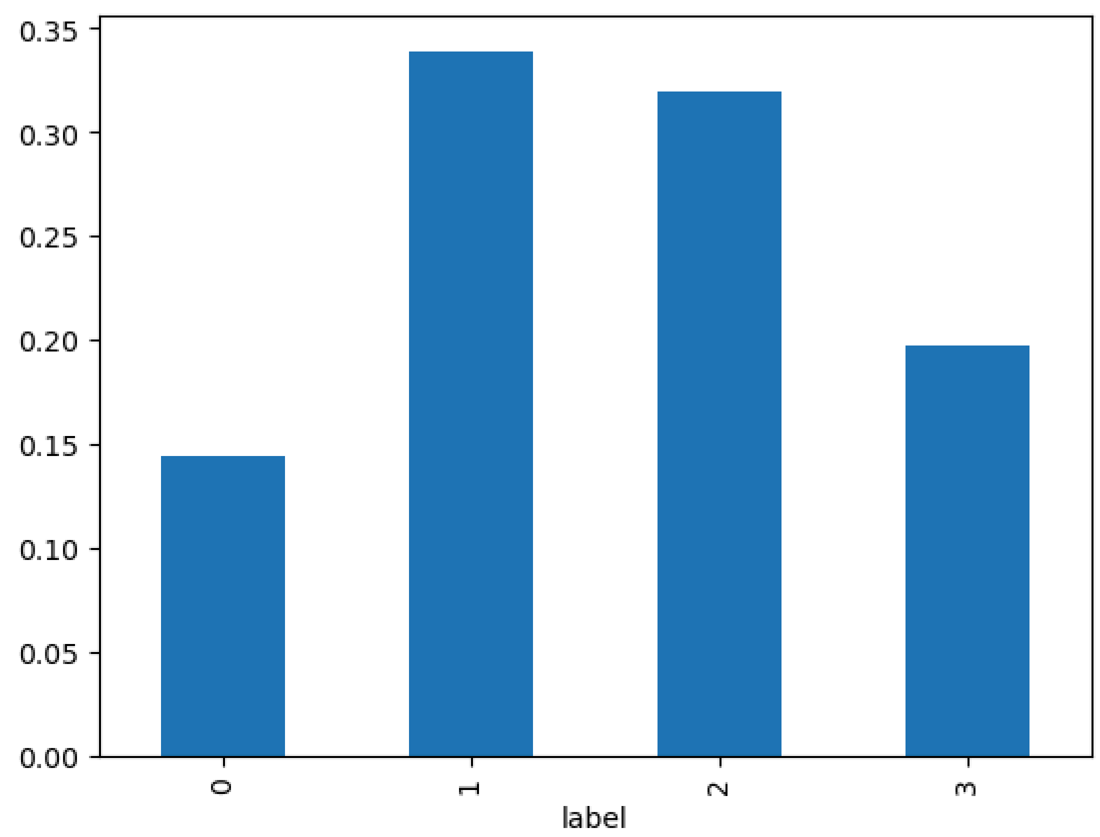
In [72]:
```
clusters.groupby(['label']).agg({'ctc':'mean',
                                 'years_of_experience':'mean',
                                 'years_since_increment':'mean',
                                 'ctc_rnk':pd.Series.mode,
                                 'designation':pd.Series.mode,
                                 'class':pd.Series.mode,
                                 'tier':pd.Series.mode,}).reset_index()
```

Out[72]:

	label	ctc	years_of_experience	years_since_increment	ctc_rnk	designation	class	tier
0	0	1.990055e+06	14.549212	4.590624	2	2	2	2
1	1	8.236399e+05	6.709576	3.164938	4	2	2	2
2	2	7.241013e+05	6.577885	3.492236	4	3	3	3
3	3	2.887250e+06	8.099743	3.099837	1	1	1	1

In [73]:
```
temp_df = clusters.groupby(['label'])['label'].value_counts()/clusters.shape[0]
print(temp_df)
temp_df.plot(kind='bar')
plt.show()
```

```
label
0    0.144530
1    0.338950
2    0.319407
3    0.197113
Name: count, dtype: float64
```



7. Insights

- **4 clusters** were created based on the elbow method and dendrogram chart
- **Cluster 3** has the highest mean CTC, highest CTC rank, highest designation, highest class and highest tier. It also has the second highest years of experience
- **Cluster 2** has lowest mean CTC, lowest CTC rank, lowest designation, lowest class and lowest tier. It also has the lowest years of experience
- **Cluster 1** is similar to Cluster 2 with slighly better CTC, designation, class and tier
- **Cluster 0** has good CTC, CTC rank, designation, class and tier. It has the highest years of experience
- From these observation, it looks like **Cluster 0** comprises of **highly experienced** people with **good CTC**, **Cluster 1** and **Cluster 2** comprises of **entry level to mid-senior** level people with **average CTC** and **Cluster 3** comprise of **senior** level people with **great CTC**
- **Maximum** learners belong to **Cluster 1** followed by Cluster 2.

8. Recommendation

- Scaler has a lot of learners belonging to junior/mid-senior roles and hence should design more courses which will help these learners enhance their skills and move up the career ladder.
- Scaler can attract more people to their learning platform by running ads of how Software Development and Data Analyst/Scientist roles get high salary
- Scaler should make efforts to pull in more people from Academia(both students and teachers) to increase their learners base as well as make the students industry ready and employable with high salaries.
- The clustering algorithm can be bettered by asking the learners to mention their job position more precisely and specifically instead of just mentioning "Others"
- Scaler should also ask the learners to mention their domain of study/work which again will be helpful in improving the clustering algorithm

9. Questionnaire

1. What percentage of users fall into the largest cluster?

Ans: Around 34% of learners fall into the largest cluster, 1

2. Comment on the characteristics that differentiate the primary clusters from each other.

Ans: CTC, Years of experience, CTC rank, Designation, Class and Tier are the most important characteristics that differentiate the clusters

3. Is it always true that with an increase in years of experience, the CTC increases? Provide a case where this isn't true.

Ans: No, it is not true that CTC increases with increase in experience. The maximum CTC belongs to a learner with 7 years of experience and the minimum CTC belongs to a 29 year experienced learner

4. Name a job position that is commonly considered entry-level but has a few learners with unusually high CTCs in the dataset.

Ans: Data Analysts is usually considered a entry-level job and there is a learner with Data Analyst job position with a CTC higher than that of a learner with engineering leadership job position

5. What is the average CTC of learners across different job positions?

Ans: Average CTC across different job positions is 1268701.92

6. For a given company, how does the average CTC of a Data Scientist compare with other roles?

Ans: There are around 900+ companies in which more than 50% of the times the avergae CTC of a Data Scientist is greater than that of other roles

7. Discuss the distribution of learners based on the Tier flag:

- **7.1. Which companies dominate in Tier 1 and why might this be the case?**
- **Ans:** The companies which offer Software Developer roles are the companies which dominate Tier 1 as Software Developers are in high demand due to the exponential growth of AI
- **7.2. Are there any notable patterns or insights when comparing learners from Tier 3 across different companies**
- **Ans** The learners have a mean of 7 years of experience with CTC being on the lower end.

8. After performing unsupervised clustering:

- **8.1. How many clusters have been identified using the Elbow method?**
- **Ans:** The elbow method gave two elbows, one at 4 and another at 7
- **8.2. Do the clusters formed align or differ significantly from the manual clustering efforts? If so, in what way**
- **Ans:** The clusters formed are slightly better than the manual clustering. The manual clustering was able to differentiate between CTCs and years of experience clearly and job_position partially. The clusters formed due to kMeans are able to differentaie CTC, years of experience and job position(encoded in **class** column) clearly.

9. From the Hierarchical Clustering results:

- **9.1. Are there any clear hierarchies or patterns formed that could suggest the different levels of seniority or roles within a company?**
- **Ans:** Yes
- **9.2 How does the dendrogram representation correlate with the 'Years of Experience' feature?**
- **Ans:** We can see a clear pattern that the low number of years of experience are grouped together on the extreme left of the dendrogram, medium number of years of experience are grouped together in the middle and high number of years of experience are grouped together at the extreme right?.s.