Problem Statement

- Scaler is an online tech-versity offering intensive computer science & Data Science courses through live classes delivered by tech leaders and subject matter experts. The meticulously structured program enhances the skills of software professionals by offering a modern curriculum with exposure to the latest technologies. It is a product by InterviewBit.
- You are working as a data scientist with the analytics vertical of Scaler, focused on profiling the best companies and job positions to work for from the Scaler database. You are provided with the information for a segment of learners and tasked to cluster them on the basis of their job profile, company, and other features.

Loading dependencies and dataset

In [1]:
```
# !pip install python-Levenshtein
# !pip install fuzzywuzzy

import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from fuzzywuzzy import fuzz

# from scipy.stats import levene, f_oneway, kruskal
# from scipy.stats import ttest_ind
# from scipy.stats import chi2_contingency
# from statsmodels.graphics.gofplots import qqplot

from sklearn.pipeline import Pipeline

from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.impute import KNNImputer

from sklearn.cluster import KMeans, MiniBatchKMeans
from sklearn.decomposition import PCA

from sklearn.metrics import silhouette_score
from scipy.spatial.distance import pdist, squareform


import plotly.express as px


import scipy.cluster.hierarchy as sch
```

In [2]:
```
df = pd.read_csv('./data/scaler.csv')
df.head()
```

Out[2]:

	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

Basic checks on the data

In [3]:
```
df.shape
```

Out[3]:
```
(205843, 7)
```

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

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

In [5]:
```
# Dropping unnecessary columns
df.drop('Unnamed: 0', axis=1, inplace=True)
```

In [6]:
```
# Total duplicate rows across all columns
df.duplicated().sum()
```

Out[6]:
```
33
```

In [7]:
```python
# Checking for duplicate rows across all columns
df.loc[df.duplicated(keep='first')]
```

Out[7]:

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

In [8]:
```python
# Dropping duplicate rows
df.drop_duplicates(keep='first', inplace=True)
```

In [9]:
```python
# Missing values in dataset:
df.isna().sum()
```

Out[9]:
```
company_hash           44
email_hash              0
orgyear                86
ctc                     0
job_position        52547
ctc_updated_year        0
dtype: int64
```

In [10]:
```python
# Missing values in dataset:
100*df.isna().sum()/df.shape[0]
```

Out[10]:
```
company_hash         0.021379
email_hash           0.000000
orgyear              0.041786
ctc                  0.000000
job_position        25.531801
ctc_updated_year     0.000000
dtype: float64
```

EDA:

In [11]:
```python
# Segregating numerical and categorical columns
cat_cols = []
num_cols = []
for col in df.columns:
    if df[col].dtype=='object':
        cat_cols.append(col)
    else:
        num_cols.append(col)

print('Categorical Columns:', cat_cols)
print('Numerical Columns:', num_cols)
```

```
Categorical Columns: ['company_hash', 'email_hash', 'job_position']
Numerical Columns: ['orgyear', 'ctc', 'ctc_updated_year']
```

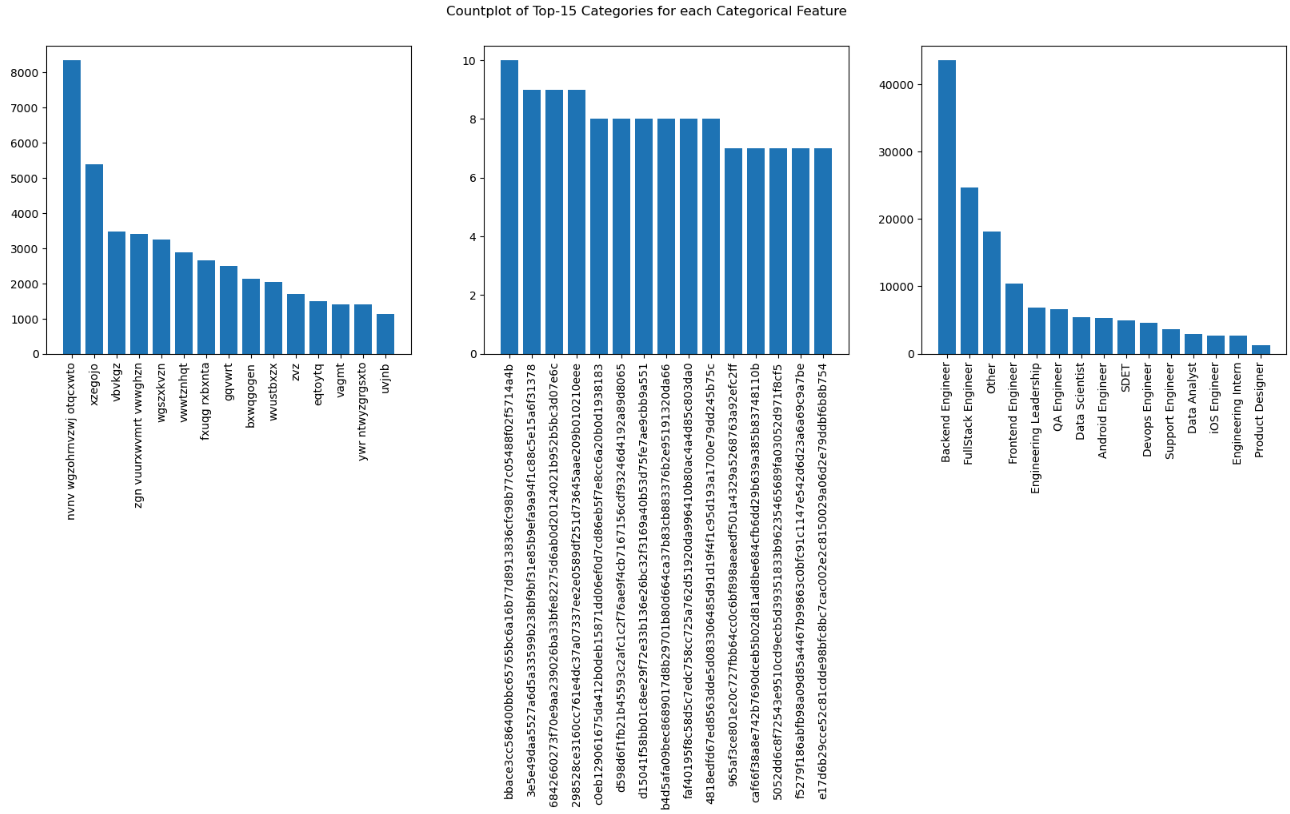
Univaritate Analysis

In [12]:
```python
df.describe(include='O')
```

Out[12]:

	company_hash	email_hash	job_position
count	205766	205810	153263
unique	37299	153443	1017
top	nvnv wgzohrnvzwj otqcxwto	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	Backend Engineer
freq	8337	10	43546

In [13]:
```python
# Countplot: Categorical features (top 15 most frequent categories)
fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(20, 5))
i = 0
for col in cat_cols:

    axs[i].bar(df[col].value_counts()[:15].index, df[col].value_counts()[:15])
    axs[i].tick_params(axis='x', rotation=90)
    # axs[i].xticks(rotation=90)
    i += 1

plt.suptitle('Countplot of Top-15 Categories for each Categorical Feature')
plt.show()
```



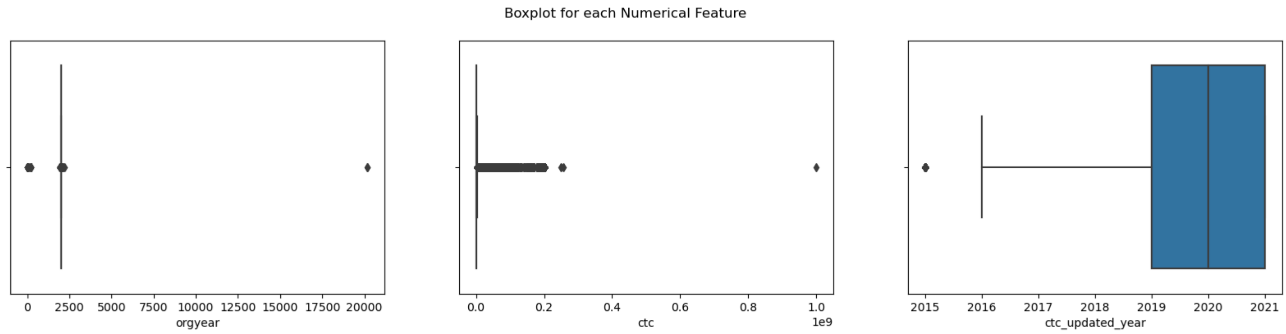
In [14]:
```python
df.describe()
```

Out[14]:

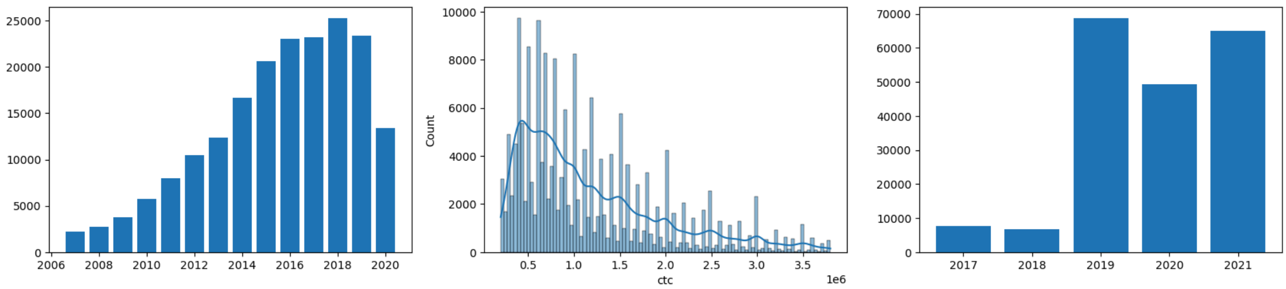
	orgyear	ctc	ctc_updated_year
count	205724.000000	2.058100e+05	205810.000000
mean	2014.882284	2.271854e+06	2019.628279
std	63.576199	1.180185e+07	1.325188
min	0.000000	2.000000e+00	2015.000000
25%	2013.000000	5.300000e+05	2019.000000
50%	2016.000000	9.500000e+05	2020.000000
75%	2018.000000	1.700000e+06	2021.000000
max	20165.000000	1.000150e+09	2021.000000

In [15]:
```python
# Distribution: Numerical features
# fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(16, 10))
# i = 0
# for col in num_cols:
#     sns.boxplot(x=df[col], ax=axs[i][0])
#     if col in ['orgyear', 'ctc_updated_year']:
#         # sns.countplot(df[col], ax=axs[i][1])
#         df[col].plot.hist(bins=50, ax=axs[i][1], color='blue')
#     df[col].plot.hist(bins=10, ax=axs[i][1])
#     i += 1

# plt.suptitle('Distribution for each Numerical Feature')


fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(20, 4))
i = 0
for col in num_cols:
    sns.boxplot(x=df[col], ax=axs[i])
    i += 1
```

```
plt.suptitle('Boxplot for each Numerical Feature')

plt.show()
```



In [16]:
```
# As seen from box-plots there are many outliers in the numerical features. We will focus on values b/w 5p and 95p and check the distribu

fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(20, 4))

i = 0
for col in num_cols:
    # only looking at the values b/w 5th and 95th percentiles
    ser_col = df.loc[((df[col]>=df[col].quantile(0.05)) & (df[col]<=df[col].quantile(0.95))), col]
    if col=='ctc':
        sns.histplot(ser_col, bins=100, ax=axs[i], kde=True)
    else:
        axs[i].bar(ser_col.value_counts().index, ser_col.value_counts().values)

    i += 1
plt.show()
```

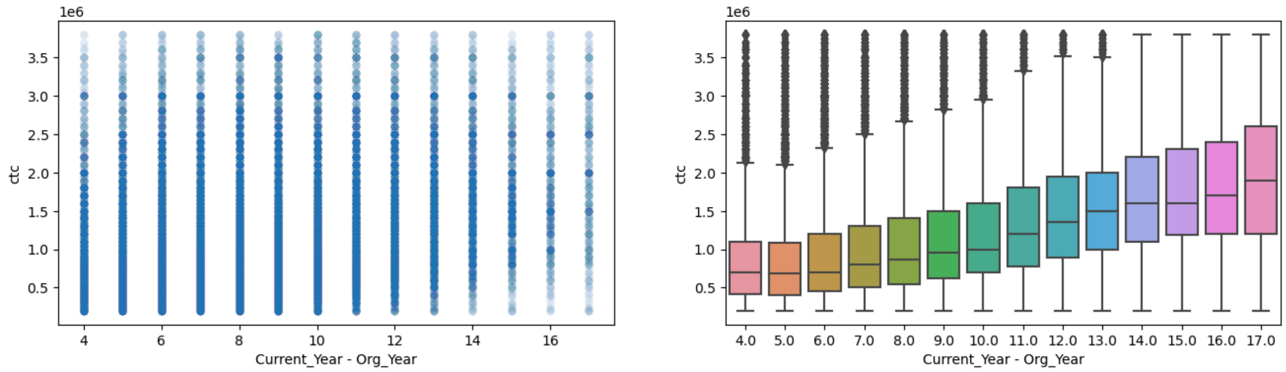


Bivariate Analysis

In [17]:
```
# We will only consider the middle 90% of data for ctc and orgyear for first cut analysis, we will treat outliers later
ctc_5p = df['ctc'].quantile(0.05)
ctc_95p = df['ctc'].quantile(0.95)

orgyr_5p = df['orgyear'].quantile(0.05)
orgyr_95p = df['orgyear'].quantile(0.95)

df_eda = df.loc[((df['ctc']>=ctc_5p) & (df['ctc']<=ctc_95p)) & ((df['orgyear']>=orgyr_5p) & (df['orgyear']<=orgyr_95p))].copy()
```

Relationship between ctc & orgyear

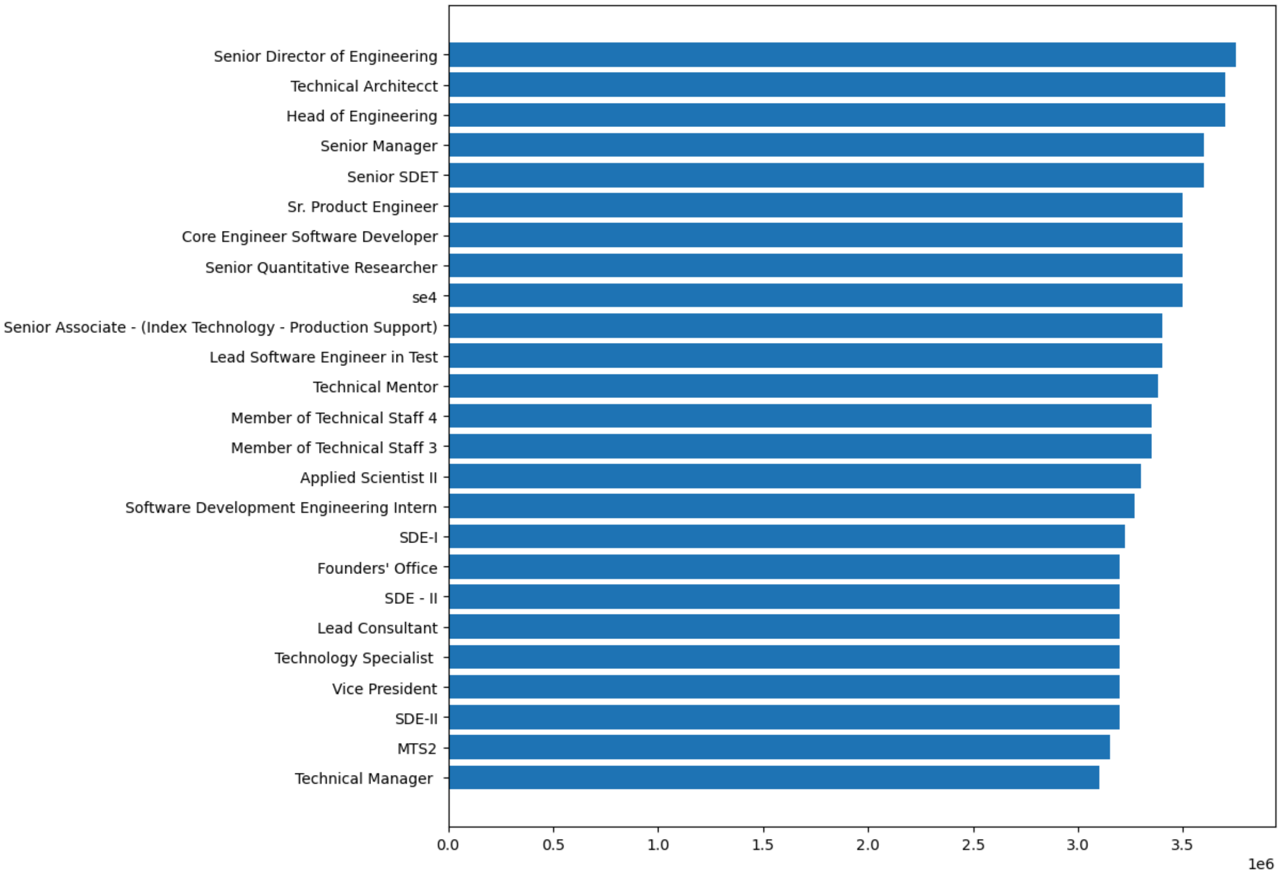
In [18]:
```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(16, 4))

sns.scatterplot(y=df_eda['ctc'], x=2024-df_eda['orgyear'], ax=axs[0], alpha=0.01)
axs[0].set_xlabel('Current_Year - Org_Year')

sns.boxplot(y=df_eda['ctc'], x=2024-df_eda['orgyear'], ax=axs[1])
axs[1].set_xlabel('Current_Year - Org_Year')
plt.show()
```



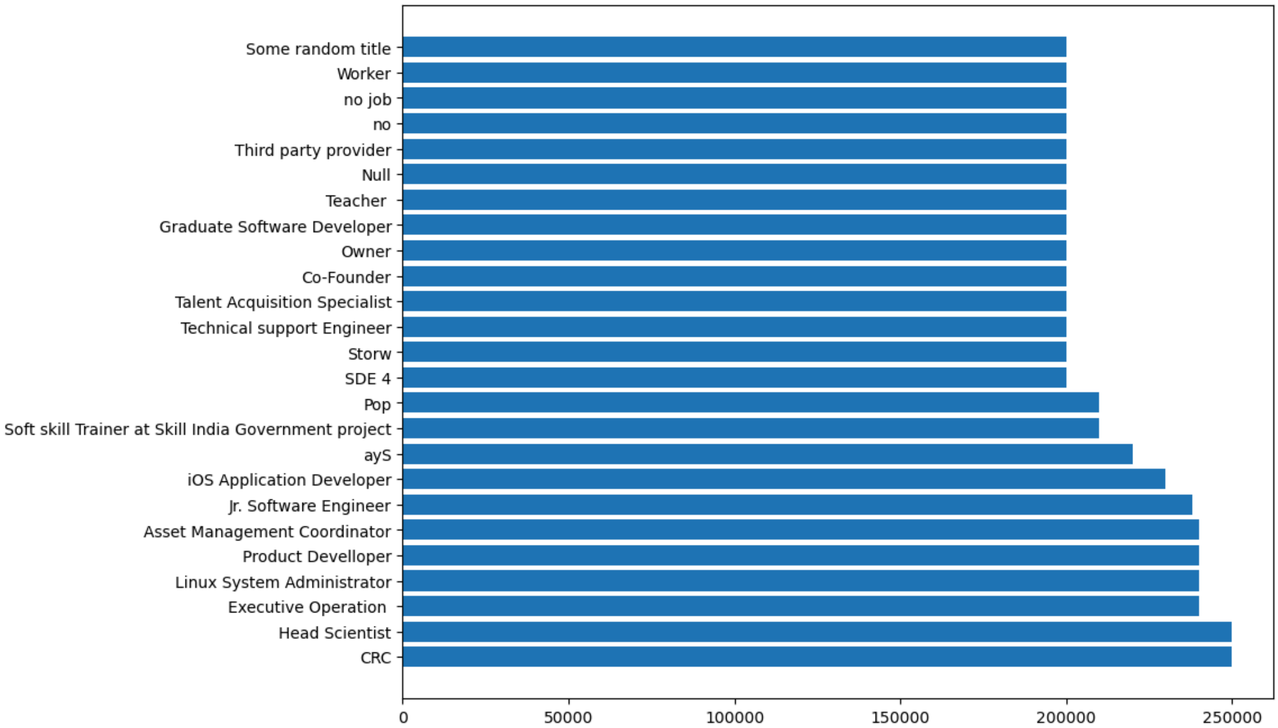
Mean CTC of Top15 and Bottom15 Job descriptions

In [19]:
```
# Top-25
plt.figure(figsize=(10, 10))
plt.barh(df_eda.groupby('job_position')['ctc'].mean().sort_values(ascending=False).iloc[:25].index[::-1],
```

```
        df_eda.groupby('job_position')['ctc'].mean().sort_values(ascending=False).iloc[:25].values[::-1])
plt.show()
```



In [20]:
```
# Bottom-25
plt.figure(figsize=(10, 8))
plt.barh(df_eda.groupby('job_position')['ctc'].mean().sort_values(ascending=True).iloc[:25].index[::-1],
        df_eda.groupby('job_position')['ctc'].mean().sort_values(ascending=True).iloc[:25].values[::-1])
plt.show()
```



Observations from EDA:

1. *ctc, oreyear have outliers and it needs to be treated. Aside from the outliers:*

- ctc follows a log-normal distribution with a heavy rhs tail
- orgyear is also a skewed distribution but skewness is less compared to ctc

1. *For any particular orgyear, the variablity in the ctc is high (as seen from the boxplot is bivariate section).*

- This is expected since orgyear as a variable which tells the joining date for a learner in current company

- For example someone with 20years of overall experience can join his current company 1 year back and thus can have a high ctc
- However the general trend can be seen if we track the median ctc across orgyear, learners with high years of expereince in current position tend to have a higher ctc

1. *There are many job positions 1017 unique job positions but many out of then are eseentially the same job position if observered closely.*

- These are showing up as unique categories due to uneven string format, spelling errors and so on.
- They can be cleaned to make the dataset proper

1. *Missing values are present in company_hash, orgyear and job_position. We will have to take of those missing values.*

- Company_hash and orgyear have <0.05% missing values (Simple Imputation techniques like mode can be a possible solution)
- Job_position has ~25% missing values (KNN Imputation may be a possible option)

Data-Preprocessing

Data Cleaning of Duplicate Values

Data Cleaning - Part 1

We will first group by the whole dataset on the below 4 features:

- email_hash
- company_hash
- orgyear
- ctc_updated_year

In [21]:
```
# Cheking m,issing values in these 4 features --> only 2 features have missing values
df[['email_hash', 'company_hash', 'orgyear', 'ctc_updated_year']].isna().sum()
```

Out[21]:
```
email_hash           0
company_hash        44
orgyear             86
ctc_updated_year     0
dtype: int64
```

In [22]:
```
print('Total missing values in 2 features:', 44 + 86)
print('Rows impacted by missing values in the above 2 features:', np.any(df[['email_hash', 'company_hash', 'orgyear', 'ctc_updated_year']
print('Rows NOT impacted by missing values:', df.shape[0]-130)
```

```
Total missing values in 2 features: 130
Rows impacted by missing values in the above 2 features: 130
Rows NOT impacted by missing values: 205680
```

Data Cleaning - Part 1 (Approach)

We only focus on 4 features of the dataset here (email_hash, company_hash, orgyear, ctc_updated_year)

- SetA: In these 205680 rows, none of the features are missing here. However we have duplicates as shown in the examples below, so we will need to drop them anyways
- SetB: In these 130 rows, either company_hash or orgyear is missing
- From SetB, we only preserve those learners who are not found in SetA and drop the rows of those learners whose records are found in SetA

SetA

In [23]:
```
df_tst1 = df.groupby(['email_hash', 'company_hash', 'orgyear', 'ctc_updated_year'])[['ctc_updated_year']].agg(count=('ctc_updated_year','
df_tst1['count'].value_counts()
```

Out[23]:
```
1    129707
2     31199
3      3735
4       450
5        83
6        18
7         3
9         2
8         1
Name: count, dtype: int64
```

In [24]:
```
# df_tst1.loc[df_tst1['ctc']==9, 'email_hash'].values
# df_tst1.loc[df_tst1['ctc']==8, 'email_hash'].values
# df_tst1.loc[df_tst1['ctc']==5, 'email_hash'].values
```

SetA: Example1 with duplicate values

In [25]:
```
df.loc[df['email_hash']=='298528ce3160cc761e4dc37a07337ee2e0589df251d73645aae209b010210eee']
```

Out[25]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
65909	cvrhtbgbtznhb	298528ce3160cc761e4dc37a07337ee2e0589df251d736...	2018.0	720000	Backend Engineer	2020.0
72799	cvrhtbgbtznhb	298528ce3160cc761e4dc37a07337ee2e0589df251d736...	2018.0	720000	Research Engineers	2020.0
82099	cvrhtbgbtznhb	298528ce3160cc761e4dc37a07337ee2e0589df251d736...	2018.0	720000	Other	2020.0
93495	cvrhtbgbtznhb	298528ce3160cc761e4dc37a07337ee2e0589df251d736...	2018.0	720000	NaN	2020.0
93783	cvrhtbgbtznhb	298528ce3160cc761e4dc37a07337ee2e0589df251d736...	2018.0	720000	Data Scientist	2020.0
190903	cvrhtbgbtznhb	298528ce3160cc761e4dc37a07337ee2e0589df251d736...	2018.0	700000	Other	2020.0
191498	cvrhtbgbtznhb	298528ce3160cc761e4dc37a07337ee2e0589df251d736...	2018.0	700000	Research Engineers	2020.0
196685	cvrhtbgbtznhb	298528ce3160cc761e4dc37a07337ee2e0589df251d736...	2018.0	700000	Data Scientist	2020.0
201587	cvrhtbgbtznhb	298528ce3160cc761e4dc37a07337ee2e0589df251d736...	2018.0	700000	Backend Engineer	2020.0

SetA: Example2 with duplicate values

In [26]:
```
df.loc[df['email_hash']=='b4d5afa09bec8689017d8b29701b80d664ca37b83cb883376b2e95191320da66']
```

Out[26]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
37734	bvi ogenfvqt	b4d5afa09bec8689017d8b29701b80d664ca37b83cb883...	2020.0	900000	Engineering Leadership	2021.0
45982	bvi ogenfvqt	b4d5afa09bec8689017d8b29701b80d664ca37b83cb883...	2020.0	900000	Engineering Intern	2021.0
144760	bvi ogenfvqt	b4d5afa09bec8689017d8b29701b80d664ca37b83cb883...	2020.0	900000	Data Analyst	2021.0
151714	bvi ogenfvqt	b4d5afa09bec8689017d8b29701b80d664ca37b83cb883...	2020.0	900000	Data Scientist	2021.0
153866	bvi ogenfvqt	b4d5afa09bec8689017d8b29701b80d664ca37b83cb883...	2020.0	900000	NaN	2021.0
154644	bvi ogenfvqt	b4d5afa09bec8689017d8b29701b80d664ca37b83cb883...	2020.0	900000	Software Engineer 1	2021.0
197145	bvi ogenfvqt	b4d5afa09bec8689017d8b29701b80d664ca37b83cb883...	2020.0	2000000	Engineering Intern	2021.0
203171	bvi ogenfvqt	b4d5afa09bec8689017d8b29701b80d664ca37b83cb883...	2020.0	2000000	Data Analyst	2021.0

SetA: Example3 with duplicate values

In [27]:
```
df.loc[df['email_hash']=='bbace3cc586400bbc65765bc6a16b77d8913836cfc98b77c05488f02f5714a4b']
```

Out[27]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
24109	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	720000	NaN	2020.0
45984	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	720000	Support Engineer	2020.0
72315	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	720000	Other	2020.0
102915	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	720000	FullStack Engineer	2020.0
117764	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	720000	Data Analyst	2020.0
121483	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	660000	Other	2019.0
124476	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	660000	Support Engineer	2019.0
144479	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	660000	FullStack Engineer	2019.0
152801	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	660000	Devops Engineer	2019.0
159835	oxej ntwyzgrgsxto rxbxnta	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	2018.0	660000	NaN	2019.0

SetB

In [28]:
```
df_miss_val = df.loc[df['company_hash'].isna() | df['orgyear'].isna(), ['email_hash']]
df_miss_val_tst1_lj = pd.merge(df_miss_val, df_tst1, on=['email_hash'], how='left', indicator=True)
df_miss_val_tst1_lj['_merge'].value_counts()
```

Out[28]:
```
left_only     117
both           13
right_only      0
Name: _merge, dtype: int64
```

In [29]:
```
# Learners who are found in both SetA and SetB
df_miss_val_tst1_lj.loc[df_miss_val_tst1_lj['_merge']=='both']
```

Out[29]:

	email_hash	company_hash	orgyear	ctc_updated_year	count	_merge
8	6eb55d779699a2ea94f340ab7a58c8ec505e38bbb41214...	hzxnta ntwyzgrgsxto	2018.0	2020.0	2.0	both
9	18813fe2a50a45cc02c5b3871c676bd147c80ff0327ee9...	xzegojo	2020.0	2021.0	1.0	both
10	0e25bf875aaa6550db1aa9f9452179ed1cd6737c079fbc...	sgrabvz ovwyo	2017.0	2021.0	1.0	both
19	b4a56d1199bc569aabd30cba8ea7a86fbddc85211453ba...	exo	2013.0	2019.0	2.0	both
26	ecf94874c8c63483c18277817848cd6507d8b78dd00474...	vbvkgz	2019.0	2020.0	2.0	both
33	d76c197d014cc42d3f7f77f278f7a313a316c3db7e96a3...	x3 wgzohrnxzs	2019.0	2020.0	1.0	both
39	5721ff19939451f5e0c6743133acd64d67f3e372229759...	nojo	2016.0	2019.0	2.0	both
43	b17c74b195c1fa8038bf82c674716ae81b41b995a3b434...	xzaho cvrrtj uvqnztqo	2020.0	2020.0	1.0	both
54	da4d1843baedd22459d7a8d08344375cc8752d1dcfe211...	wvqfvrt	2021.0	2021.0	2.0	both
89	d7f39bfaa3be4957fa36a97fabb5ab7a39f6d55f377f33...	xzzgcvnxgz urvnegqbo	2015.0	2019.0	1.0	both
105	d000a77f0045504e2ee51a667ac0ad2671795b3f70ce33...	zgn vuurxwvmrt	2020.0	2019.0	1.0	both
120	a75da322109f201148da6b4a1ab785518e6229c1379a09...	xq vacxogqj	2017.0	2021.0	1.0	both
129	3fa8de870da01d863abba8eb6a8ae3df1aa18c18946688...	vhngsqxa	2013.0	2020.0	1.0	both

In [30]:
```
# Dropping rows belonging to learners in SetB who are also found in SetA
learner_emails_to_drop = df_miss_val_tst1_lj.loc[df_miss_val_tst1_lj['_merge']=='both', 'email_hash']
df.drop(df.loc[(df['email_hash'].isin(learner_emails_to_drop)) & (df['company_hash'].isna() | df['orgyear'].isna())].index, axis=0, inpla
```

In [31]:
```
df.isna().sum()
```

Out[31]:
```
company_hash           37
email_hash              0
orgyear                80
ctc                     0
job_position        52536
ctc_updated_year        0
dtype: int64
```

Data Cleaning - Part 2 (Imputing missing values of orgyear and company_hash)

Since we are aggregating the data on the below 4 features, we want to make sure that there are no missing values in any of them:

- email_hash : No missing values
- company_hash : 37 missing values

- orgyear : 80 missing values
- ctc_updated_year : No missing values

We will impute using the following approach:

- company_hash : use mode
- orgyear : We find the median gap of (ctc_updated_year-orgyear) and subtract that value from ctc_updated_year to fill the missing value

In [32]:
```
# Imputing company_hash
df['company_hash'].mode()[0]
```
Out[32]:
```
'nvnv wgzohrnvzwj otqcxwto'
```

In [33]:
```
df['company_hash'].fillna(df['company_hash'].mode()[0], inplace=True)
```

In [34]:
```
# Imputing orgyear
(df['ctc_updated_year'] - df['orgyear']).median()
```
Out[34]:
```
4.0
```

In [35]:
```
df.loc[df['orgyear'].isna(), 'orgyear'] = df.loc[df['orgyear'].isna(), 'ctc_updated_year'] - 4
```

In [36]:
```
df.isna().sum()
```
Out[36]:
```
company_hash            0
email_hash              0
orgyear                 0
ctc                     0
job_position        52536
ctc_updated_year        0
dtype: int64
```

Data Cleaning - Part 3

- We define each tuple as unique combinations of email_hash, company_hash, orgyear, ctc_updated_year
- Since there can be only 1 occurence for each tuple, we remove the duplicates using some custom written functions

In [37]:
```
def custom_count(x):
    jd_cnt_rows = x.size
    jd_cnt_non_nulls = x.count()
    jd_cnt_non_nulls_other = ((~x.isna()) & (x=='Other')).sum()
    jd_cnt_non_nulls_non_other = ((~x.isna()) & (x!='Other')).sum()


    return jd_cnt_rows, jd_cnt_non_nulls, jd_cnt_non_nulls_other, jd_cnt_non_nulls_non_other


df_tst2 = df.groupby(['email_hash', 'company_hash', 'orgyear', 'ctc_updated_year'])[['job_position']].agg(custom_count)
df_tst2['cnt_rows'] = df_tst2['job_position'].apply(lambda x: x[0])
df_tst2['cnt_non_nulls'] = df_tst2['job_position'].apply(lambda x: x[1])
df_tst2['cnt_other'] = df_tst2['job_position'].apply(lambda x: x[2])
df_tst2['cnt_non_other'] = df_tst2['job_position'].apply(lambda x: x[3])
# # df_tst2['cnt_rows'].value_counts()
df_tst2.drop('job_position', axis=1, inplace=True)
df_tst2.reset_index(inplace=True)
df_tst2
```
Out[37]:

	email_hash	company_hash	orgyear	ctc_updated_year	cnt_rows	cnt_non_nulls	cnt_other	cnt_non_other
0	00003288036a44374976948c327f246fdbdf0778546904...	bxwqgogen	2012.0	2019.0	1	1	0	1
1	0000aaa0e6b61f7636af1954b43d294484cd151c9b3cf6...	nqsn axsxnvr	2013.0	2020.0	1	1	0	1
2	0000d58fbc18012bf6fa2605a7b0357d126ee69bc41032...	gunhb	2021.0	2019.0	2	1	0	1
3	000120d0c8aa304fcf12ab4b85e21feb80a342cfea03d4...	bxwqgotbx wgqugqvnxgz	2004.0	2021.0	1	1	0	1
4	00014d71a389170e668ba96ae8e1f9d991591acc899025...	fvrbvqn rvmo	2009.0	2018.0	1	0	0	0
...	...	...	...	...	...	...	...	...
165303	fffc254e627e4bd1bc0ed7f01f9aebbba7c3cc56ac914e...	tqxwoogz ogenfvqt wvbuho	2004.0	2019.0	1	1	0	1
165304	fffcf97db1e9c13898f4eb4cd1c2fe862358480e104535...	trnqvcg	2015.0	2018.0	1	0	0	0
165305	fffe7552892f8ca5fb8647d49ca805b72ea0e9538b6b01...	znn avnv srgmvr atrxctqj otqcxwto	2014.0	2019.0	1	1	0	1
165306	ffff49f963e4493d8bbc7cc15365423d84a767259f7200...	zwq wgqugqvnxgz	2020.0	2020.0	1	1	0	1
165307	ffffa3eb3575f43b86d986911463dce7bcadcea227e5a4...	sgrabvz ovwyo	2018.0	2021.0	1	1	0	1

165308 rows × 8 columns

In [38]:
```
df_single_rec = df_tst2.loc[df_tst2['cnt_rows']==1]
df_multiple_rec_allnull = df_tst2.loc[(df_tst2['cnt_rows']>1) & (df_tst2['cnt_non_nulls']==0)]
df_multiple_rec_other = df_tst2.loc[(df_tst2['cnt_rows']>1) & (df_tst2['cnt_non_nulls']>0) & (df_tst2['cnt_non_nulls']==df_tst2['cnt_othe
df_multiple_rec_nonother = df_tst2.loc[(df_tst2['cnt_rows']>1) & (df_tst2['cnt_non_nulls']>df_tst2['cnt_other'])]


print(df_tst2.shape)
print(df_single_rec.shape)
print(df_multiple_rec_allnull.shape)
print(df_multiple_rec_other.shape)
print(df_multiple_rec_nonother.shape)
```
```
(165308, 8)
(129810, 8)
(37, 8)
(3484, 8)
(31977, 8)
```

In [39]:
```
# Dealing with tuples with 1 occurence
df_single_rec_temp1 = pd.merge(df_single_rec, df, on=['email_hash', 'company_hash', 'orgyear', 'ctc_updated_year'])
df_single_rec_temp2 = df_single_rec_temp1[['email_hash', 'company_hash', 'orgyear',
                                           'ctc_updated_year','ctc', 'job_position']].groupby(['email_hash',
                                                                                               'company_hash',
                                                                                               'orgyear',
                                                                                               'ctc_updated_year']
                                                                                             ).first().reset_index()


# Dealing with tuples with multiple occurences where jd is null for all occurences

df_multiple_rec_allnull_temp1 = pd.merge(df_multiple_rec_allnull, df, on=['email_hash', 'company_hash', 'orgyear', 'ctc_updated_year'])
df_multiple_rec_allnull_temp2 = df_multiple_rec_allnull_temp1[['email_hash', 'company_hash', 'orgyear',
                                                               'ctc_updated_year','ctc', 'job_position']].groupby(['email_hash',
                                                                                                                   'company_hash',
                                                                                                                   'orgyear',
                                                                                                                   'ctc_updated_year']
                                                                                                                 ).first().reset_index()




# Dealing with tuples with multiple occurences where the only non-null jd is 'Other'

df_multiple_rec_other_temp1 = pd.merge(df_multiple_rec_other, df, on=['email_hash', 'company_hash', 'orgyear', 'ctc_updated_year'])
df_multiple_rec_other_temp2 = df_multiple_rec_other_temp1[['email_hash', 'company_hash', 'orgyear',
                                                           'ctc_updated_year','ctc', 'job_position']].groupby(['email_hash',
                                                                                                               'company_hash',
                                                                                                               'orgyear',
                                                                                                               'ctc_updated_year']
                                                                                                             ).first().reset_index()


# Dealing with tuples with multiple occurences where there are 1 or more non-null occurences where jds is NOT 'Other'

df_multiple_rec_nonother_temp1 = pd.merge(df_multiple_rec_nonother, df, on=['email_hash', 'company_hash', 'orgyear', 'ctc_updated_year'])
df_multiple_rec_nonother_temp1 = df_multiple_rec_nonother_temp1.loc[(~df_multiple_rec_nonother_temp1['job_position'].isna()) & (df_multip
df_multiple_rec_nonother_temp2 = df_multiple_rec_nonother_temp1[['email_hash', 'company_hash', 'orgyear',
                                                                 'ctc_updated_year','ctc', 'job_position']].groupby(['email_hash',
                                                                                                                     'company_hash',
                                                                                                                     'orgyear',
                                                                                                                     'ctc_updated_year']
                                                                                                                   ).first().reset_index(


print(df_single_rec_temp2.shape)
print(df_multiple_rec_allnull_temp2.shape)
print(df_multiple_rec_other_temp2.shape)
print(df_multiple_rec_nonother_temp2.shape)
```

```
(129810, 6)
(37, 6)
(3484, 6)
(31977, 6)
```

In [40]:
```
df_clean1 = pd.concat([df_single_rec_temp2, df_multiple_rec_allnull_temp2, df_multiple_rec_other_temp2, df_multiple_rec_nonother_temp2],
df_clean1.shape
```

Out[40]:
```
(165308, 6)
```

In [41]:
```
df_clean1.head()
```

Out[41]:

	email_hash	company_hash	orgyear	ctc_updated_year	ctc	job_position
0	00003288036a44374976948c327f246fdbdf0778546904...	bxwqgogen	2012.0	2019.0	3500000	Backend Engineer
1	0000aaa0e6b61f7636af1954b43d294484cd151c9b3cf6...	nqsn axsxnvr	2013.0	2020.0	250000	Backend Engineer
2	000120d0c8aa304fcf12ab4b85e21feb80a342cfea03d4...	bxwqgotbx wgqugqvnxgz	2004.0	2021.0	2000000	FullStack Engineer
3	00014d71a389170e668ba96ae8e1f9d991591acc899025...	fvrbvqn rvmo	2009.0	2018.0	3400000	None
4	0001b94dbb1e85477b07fb6558ead3456c3735893c81f4...	nvnv wgzohrnvzwj otqcxwto	2018.0	2020.0	380000	Database Administrator

In [42]:
```
df_clean1.isna().sum()
```

Out[42]:
```
email_hash              0
company_hash            0
orgyear                 0
ctc_updated_year        0
ctc                     0
job_position        24991
dtype: int64
```

In [43]:
```
print('Original data shape:', df.shape[0])
print('After removing duplicates data shape:', df_clean1.shape[0])
print('Duplicate rows removed:', (df.shape[0] - df_clean1.shape[0]))
```

```
Original data shape: 205797
After removing duplicates data shape: 165308
Duplicate rows removed: 40489
```

Data Cleaning - Part 4

We now focus on 2 features of the dataset here (email_hash, company_hash)

- The idea is for each unique combination of email_hash and company_hash, we only allow 1 occurence
- We define each tuple as unique combinations of email_hash, company_hash here
- Since there can be only 1 occurence for each tuple, we remove the duplicates

In [44]:
```
df_clean1.groupby(['email_hash', 'company_hash'])['company_hash'].count().value_counts()
```

Out[44]:
```
1    155300
2      5004
Name: company_hash, dtype: int64
```

In [45]:
```
df_tst3_tmp = df_clean1.groupby(['email_hash', 'company_hash'])[['company_hash']].agg(cnt = ('company_hash', 'count')).reset_index()
df_tst3 = pd.merge(df_clean1, df_tst3_tmp, on=['email_hash', 'company_hash'])
df_tst3_singlerec = df_tst3.loc[df_tst3['cnt']==1]
df_tst3_multiplerec = df_tst3.loc[df_tst3['cnt']>1]
print(df_tst3_singlerec.shape)
print(df_tst3_multiplerec.shape)
```

```
(155300, 7)
(10008, 7)
```

In [46]:
```
df_tst3_multiplerec_tmp1 = df_tst3_multiplerec.groupby(['email_hash', 'company_hash'])[['ctc_updated_year']].max().reset_index()
df_tst3_multiplerec_tmp2 = pd.merge(df_tst3_multiplerec, df_tst3_multiplerec_tmp1, on=['email_hash', 'company_hash'])
df_tst3_multiplerec_tmp3 = df_tst3_multiplerec_tmp2.loc[(df_tst3_multiplerec_tmp2['ctc_updated_year_x']==df_tst3_multiplerec_tmp2['ctc_up
df_tst3_multiplerec_tmp4 = df_tst3_multiplerec_tmp3.groupby(['email_hash', 'company_hash'])[['orgyear']].min().reset_index()
df_tst3_multiplerec_tmp5 = pd.merge(df_tst3_multiplerec_tmp3, df_tst3_multiplerec_tmp4, on=['email_hash', 'company_hash'])
df_tst3_multiplerec_final = df_tst3_multiplerec_tmp5.loc[(df_tst3_multiplerec_tmp5['orgyear_x']==df_tst3_multiplerec_tmp5['orgyear_y'])].
df_tst3_multiplerec_final['orgyear'] = df_tst3_multiplerec_final['orgyear_x']
df_tst3_multiplerec_final['ctc_updated_year'] = df_tst3_multiplerec_final['ctc_updated_year_x']
df_tst3_multiplerec_final.drop(['orgyear_x', 'orgyear_y', 'ctc_updated_year_x', 'ctc_updated_year_y'], axis=1, inplace=True)
df_tst3_multiplerec_final = df_tst3_multiplerec_final[['email_hash', 'company_hash', 'orgyear', 'ctc_updated_year', 'ctc', 'job_position'
df_tst3_multiplerec_final
```

Out[46]:

	email_hash	company_hash	orgyear	ctc_updated_year	ctc	job_position	cnt
0	0001b94dbb1e85477b07fb6558ead3456c3735893c81f4...	nvnv wgzohrnvzwj otqcxwto	2018.0	2021.0	450000	Database Administrator	2
1	003d55220da35ffe1f899341e65203efc2c7f858ec1a70...	zvsvqqg	2014.0	2021.0	1400000	FullStack Engineer	2
2	005b303d5f799bb57904a5d7baffe8b8f0ec9bc6153e2e...	mggpxzswgb	2013.0	2021.0	7500000	Backend Engineer	2
3	006de042d86e55a046169baf1d829c75276ce4707dc705...	eqtoytq	2020.0	2020.0	720000	Engineering Intern	2
4	007aabb2e1f8fab88172912705605381248e4c17361331...	xzegojo	2019.0	2021.0	500000	Other	2
...	...	...	...	...	...	...	...
5110	fddc75d7d1ee9b59093b49d775ac729d68e38fd91f7a5c...	wyvxugxzn	2018.0	2021.0	600000	FullStack Engineer	2
5111	ff0f2fc920d9764f1c465441fb9e9acd61207fc527ac95...	ktnnvmjnt unt rna	2017.0	2020.0	1100000	FullStack Engineer	2
5112	ff19647f99960883dcd214b5d9ae8f4c2398155e8c26a7...	pgqtvx	2018.0	2021.0	600000	Frontend Engineer	2
5113	ff61f226298058d2f19d249990ea9631e1e3e8538de207...	pgzj xzaxv	2019.0	2020.0	1440000	Engineering Intern	2
5114	ffa14c7b35e5040e613ceb4ac039f19c9307db362e34ab...	erxupvqn	2016.0	2021.0	5200000	Backend Engineer	2

5004 rows × 7 columns

In [47]:
```
print(df_tst3_singlerec.shape)
print(df_tst3_multiplerec_final.shape)
```

```
(155300, 7)
(5004, 7)
```

In [48]:
```
df_clean2 = pd.concat([df_tst3_singlerec, df_tst3_multiplerec_final], axis=0, ignore_index=True)
df_clean2.drop('cnt', axis=1, inplace=True)
df_clean2.shape
```

Out[48]:
```
(160304, 6)
```

In [49]:
```
df_clean2.head()
```

Out[49]:

	email_hash	company_hash	orgyear	ctc_updated_year	ctc	job_position
0	00003288036a44374976948c327f246fdbdf0778546904...	bxwqgogen	2012.0	2019.0	3500000	Backend Engineer
1	0000aaa0e6b61f7636af1954b43d294484cd151c9b3cf6...	nqsn axsxnvr	2013.0	2020.0	250000	Backend Engineer
2	000120d0c8aa304fcf12ab4b85e21feb80a342cfea03d4...	bxwqgotbx wgqugqvnxgz	2004.0	2021.0	2000000	FullStack Engineer
3	00014d71a389170e668ba96ae8e1f9d991591acc899025...	fvrbvqn rvmo	2009.0	2018.0	3400000	None
4	00022dc29c7f77032275182b883d4f273ea1007aefc437...	vqtkkgopj	2016.0	2020.0	750000	Frontend Engineer

In [50]:
```
df_clean2.isna().sum()
```

Out[50]:
```
email_hash              0
company_hash            0
orgyear                 0
ctc_updated_year        0
ctc                     0
job_position        23906
dtype: int64
```

In [51]:
```
# Sanity Checks
# df_clean2.groupby(['email_hash', 'company_hash', 'orgyear', 'ctc_updated_year'])['orgyear'].count().value_counts()
# df_clean2.groupby(['email_hash', 'company_hash'])['orgyear'].count().value_counts()
```

In [ ]:

Data Cleaning - Part 5

We now fetch those rows where orgyear > ctc_updated_year

- Since this cannot happen, we impute the org year with the median of gap
- gap is defined as the difference of ctc_updated_year and orgyear

In [52]:
```
(df_clean2['orgyear']>df_clean2['ctc_updated_year']).sum()
```

Out[52]:
```
7572
```

In [53]:
```
median_gap_ctc_up_yr_org_yr = (df['ctc_updated_year']-df['orgyear']).median()
df_clean2.loc[df_clean2['orgyear']>df_clean2['ctc_updated_year'], 'orgyear'] = df_clean2.loc[df_clean2['orgyear']>df_clean2['ctc_updated_
```

```
                                                          'ctc_updated_year'] - median_gap_ctc_up_yr_c
(df_clean2['orgyear']>df_clean2['ctc_updated_year']).sum()
```

Out[53]: 0

Outlier Treatment of Numerical Columns

- As we have seen earlier, orgyear and ctc have outliers and we will treat them one by one.

Outlier Treatment: orgyear

In [54]:
```
df_clean2['orgyear'].describe()
```

Out[54]:
```
count    160304.000000
mean       2014.131731
std          31.975879
min           0.000000
25%        2013.000000
50%        2015.000000
75%        2018.000000
max        2021.000000
Name: orgyear, dtype: float64
```

In [55]:
```
for i in range(10):
    print(f'{round(100*i*0.002, 3)} percentile of orgyear:', df_clean2['orgyear'].quantile(i*0.002))
```

```
0.0 percentile of orgyear: 0.0
0.2 percentile of orgyear: 1994.0
0.4 percentile of orgyear: 1997.0
0.6 percentile of orgyear: 1998.0
0.8 percentile of orgyear: 1999.0
1.0 percentile of orgyear: 2000.0
1.2 percentile of orgyear: 2001.0
1.4 percentile of orgyear: 2001.0
1.6 percentile of orgyear: 2002.0
1.8 percentile of orgyear: 2002.0
```

In [56]:
```
for i in range(10):
    print(f'{round(99 + 100*i*0.001, 3)} percentile of orgyear:', df_clean2['orgyear'].quantile(0.99 + i*0.001))
```

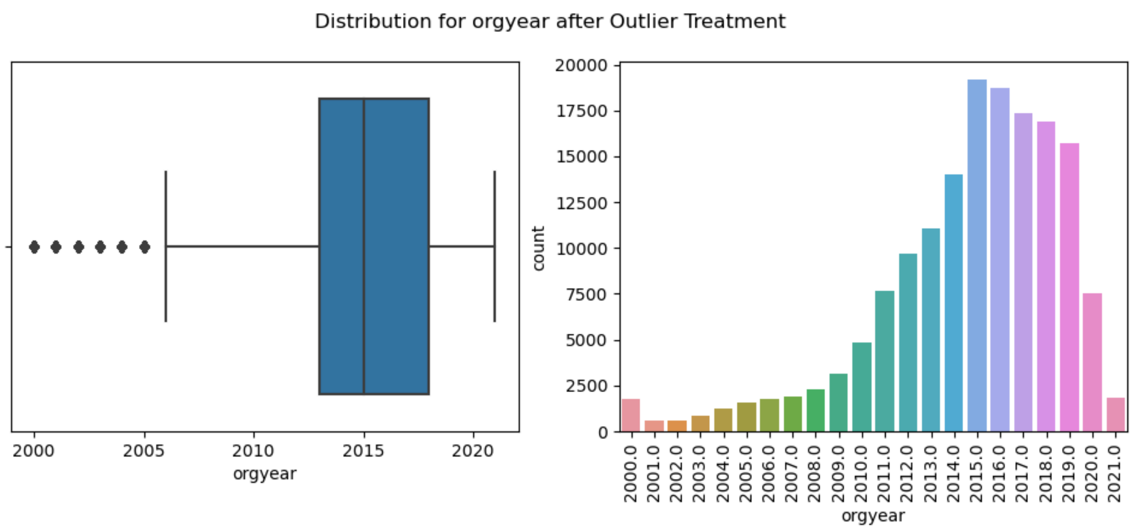
```
99.0 percentile of orgyear: 2021.0
99.1 percentile of orgyear: 2021.0
99.2 percentile of orgyear: 2021.0
99.3 percentile of orgyear: 2021.0
99.4 percentile of orgyear: 2021.0
99.5 percentile of orgyear: 2021.0
99.6 percentile of orgyear: 2021.0
99.7 percentile of orgyear: 2021.0
99.8 percentile of orgyear: 2021.0
99.9 percentile of orgyear: 2021.0
```

We will use capping to treat the outliers:

- Cap the values below 1st percentile with value at 1st percentile
- Cap the values above 99th percentile with value at 99th percentile

In [57]:
```
def out_trt_orgyear(yr):
    if yr < 2000:
        return 2000
    elif yr > 2021:
        return 2021
    return yr

df_clean2['orgyear'] = df_clean2['orgyear'].apply(lambda x: out_trt_orgyear(x))
```

In [58]:
```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(12, 4))
i = 0

sns.boxplot(x=df_clean2['orgyear'], ax=axs[0])
sns.countplot(x=df_clean2['orgyear'], ax=axs[1])
axs[1].tick_params(axis='x', rotation=90)

plt.suptitle(f'Distribution for orgyear after Outlier Treatment')
plt.show()
```



Outlier Treatment: ctc

In [59]:
```
df_clean2['ctc'].describe()
```

Out[59]:
```
count    1.603040e+05
mean     2.471383e+06
std      1.285101e+07
min      2.000000e+00
25%      5.500000e+05
50%      9.750000e+05
75%      1.700000e+06
max      1.000150e+09
Name: ctc, dtype: float64
```

In [60]:
```
# Using 1.5*IQR
iqr = df_clean2['ctc'].quantile(0.75)-df_clean2['ctc'].quantile(0.25)
Lower_whisker = df_clean2['ctc'].quantile(0.25) - 1.5*iqr
Upper_whisker = df_clean2['ctc'].quantile(0.75) + 1.5*iqr

print(f'Lower_whisker: {Lower_whisker}')
print(f'Upper_whisker: {Upper_whisker}')
```

```
Lower_whisker: -1175000.0
Upper_whisker: 3425000.0
```

In [61]:
```
for i in range(11):
    print(f'{round(10*i*0.01, 3)} percentile of ctc:', df_clean2['ctc'].quantile(i*0.01))
```

```
0.0 percentile of ctc: 2.0
0.1 percentile of ctc: 38000.0
0.2 percentile of ctc: 80000.0
0.3 percentile of ctc: 100000.0
0.4 percentile of ctc: 140000.0
0.5 percentile of ctc: 200000.0
0.6 percentile of ctc: 202000.0
0.7 percentile of ctc: 260000.0
0.8 percentile of ctc: 300000.0
0.9 percentile of ctc: 300000.0
1.0 percentile of ctc: 336000.0
```

In [62]:
```
for i in range(10):
    print(f'{round(98 + 100*i*0.002, 3)} percentile of ctc:', df_clean2['ctc'].quantile(0.98 + i*0.002))
```

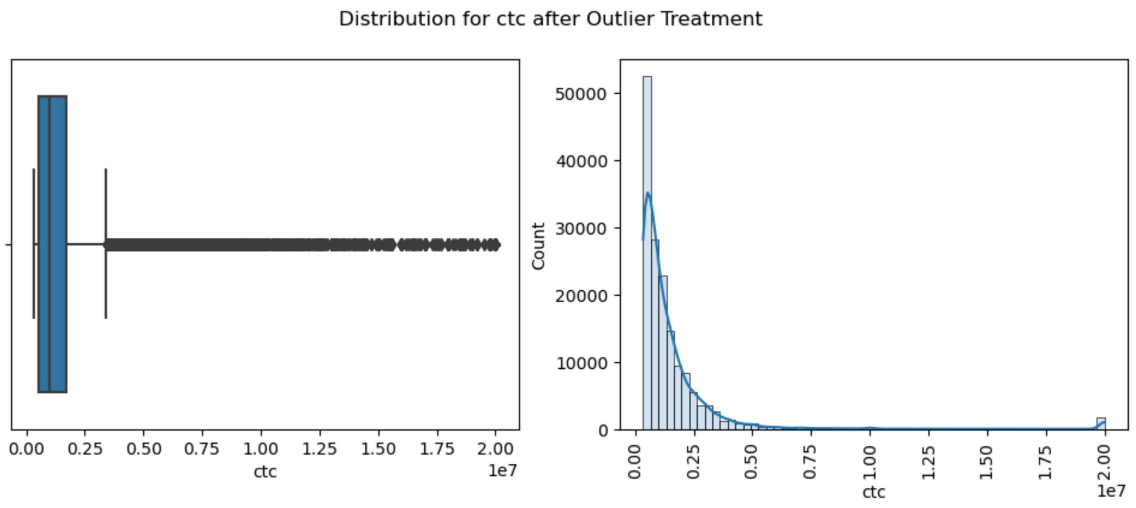
```
98.0 percentile of ctc: 6850000.0
98.2 percentile of ctc: 7500000.0
98.4 percentile of ctc: 8500000.0
98.6 percentile of ctc: 10000000.0
98.8 percentile of ctc: 12000000.0
99.0 percentile of ctc: 20000000.0
99.2 percentile of ctc: 60000000.0
99.4 percentile of ctc: 100000000.0
99.6 percentile of ctc: 100000000.0
99.8 percentile of ctc: 200000000.0
```

We will use capping to treat the outliers:

- Cap the values below 1st percentile with value at 1st percentile
- Cap the values above 99th percentile with value at 99th percentile

In [63]:
```
def out_trt_ctc(yr):
    if yr < 336000:
        return 336000
    elif yr > 20000000:
        return 20000000
    return yr

df_clean2['ctc'] = df_clean2['ctc'].apply(lambda x: out_trt_ctc(x))
```

In [64]:
```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(12, 4))
i = 0

sns.boxplot(x=df_clean2['ctc'], ax=axs[0])
sns.histplot(x=df_clean2['ctc'], ax=axs[1], bins=60, kde=True, alpha=0.2)
axs[1].tick_params(axis='x', rotation=90)

plt.suptitle(f'Distribution for ctc after Outlier Treatment')
plt.show()
```



Treatment of Categorical Columns

- Here we will explore the various categories inside each categorical feature and do some data cleaning if required

Treatment: company_hash

In [65]:
```
df_clean2['company_hash'].describe()
```

Out[65]:
```
count                       160304
unique                       37299
top       nvnv wgzohrnvzwj otqcxwto
freq                          5469
Name: company_hash, dtype: object
```

In [66]:
```
ser_company = df_clean2['company_hash'].value_counts()
print(f'#Companies with more than 1 record: {ser_company.loc[ser_company>=2].shape[0]}')
```

```
#Companies with more than 1 record: 9012
```

In [67]:
```
# Checking for empty strings as company_hash
(df_clean2['company_hash']=='').sum()
```

Out[67]:
```
0
```

Treatment: email_hash

In [68]:
```
df_clean2['email_hash'].describe()
```

Out[68]:
```
count                                                160304
unique                                               153443
top       db84980ad197f8eff08b14a3442ff57f6374ea780f2587...
freq                                                      3
Name: email_hash, dtype: object
```

In [69]:
```
ser_email = df_clean2['email_hash'].value_counts()
print(f'#Learners with more than 1 record: {ser_email.loc[ser_email>=2].shape[0]}')
print(f'Max records against a single learner: {ser_email.max()}')
```

```
#Learners with more than 1 record: 6860
Max records against a single learner: 3
```

In [70]:
```
# Checking for empty strings as email_hash
(df_clean2['email_hash']=='').sum()
```

Out[70]:
```
0
```

Treatment: job_position

In [71]:
```
df_clean2['job_position'].describe()
```

Out[71]:
```
count               136398
unique                 867
top       Backend Engineer
freq                 39053
Name: job_position, dtype: object
```

In [72]:
```
ser_job = df_clean2['job_position'].value_counts()
print(f'Total records of job_position: {df_clean2["job_position"].shape[0]}')
print(f'#Records with missing job: {df_clean2["job_position"].isna().sum()}')
print('-'*50)
print(f'Unique #jobs: {ser_job.shape[0]}')
print(f'#Jobs with more than 1 record: {ser_job.loc[ser_job>=2].shape[0]}')
print(f'#Jobs with only 1 record: {867-ser_job.loc[ser_job>=2].shape[0]}')
print(f'Max records against a single job: {ser_job.max()}')
```

```
Total records of job_position: 160304
#Records with missing job: 23906
--------------------------------------------------
Unique #jobs: 867
#Jobs with more than 1 record: 202
#Jobs with only 1 record: 665
Max records against a single job: 39053
```

In [73]:
```
non_null_jds = df_clean2.loc[~df_clean2['job_position'].isna(), 'job_position']
non_null_jds
```

Out[73]:
```
0           Backend Engineer
1           Backend Engineer
2          FullStack Engineer
4          Frontend Engineer
5          Frontend Engineer
                 ...
160299    FullStack Engineer
160300    FullStack Engineer
160301     Frontend Engineer
160302    Engineering Intern
160303      Backend Engineer
Name: job_position, Length: 136398, dtype: object
```

Approach

We wish to go through the different jobs and explore the option of grouping similar jobs manually. The approaches used are as follows:

- converting all strings to lower case, and using string functions like split(), strip()
- converting roman numbers in job designations to decimal numbers (ed: 'SDE II' to 'SDE 2')
- using Levenshtein distance to group similar strings and manually examining groups to clean further

Simple cleaning using lower(), split(), strip()

In [74]:
```
non_null_jds_sc = non_null_jds.apply(lambda x: (' ').join([item.strip(' ()-')for item in x.lower().split()]))
non_null_jds_sc
```

Out[74]:
```
0           backend engineer
1           backend engineer
2         fullstack engineer
4          frontend engineer
5          frontend engineer
                 ...
160299    fullstack engineer
160300    fullstack engineer
160301     frontend engineer
160302    engineering intern
160303      backend engineer
Name: job_position, Length: 136398, dtype: object
```

In [75]:
```
# jds = []
# for val in non_null_jds.apply(lambda x: (' ').join([item.strip(' ()-') for item in x.lower().split()])).values:
#     jds.append(val)

# jds = np.array(jds)
# np.unique(jds)
```

Converting roman numbers to decimal numbers

In [76]:
```
def roman_handling(word_lst):
    lookup_d = {'i': '1', 'ii': '2', 'iii': '3', 'iv': '4', 'v': '5'}
    for key in lookup_d:
        if key in word_lst:
            idx = word_lst.index(key)
            word_lst[idx] = lookup_d[key]
    return (' ').join(word_lst)


# roman_handling('software engineer iii'.split())
```

In [77]:
```
non_null_jds_rh = non_null_jds_sc.apply(lambda x: roman_handling(x.split()))
non_null_jds_rh
```

Out[77]:
```
0           backend engineer
1           backend engineer
2         fullstack engineer
4          frontend engineer
5          frontend engineer
                 ...
160299    fullstack engineer
160300    fullstack engineer
160301     frontend engineer
160302    engineering intern
160303      backend engineer
Name: job_position, Length: 136398, dtype: object
```

In [78]:
```
# jd_rh = []
# for val in non_null_jds_rh.values:
#     jd_rh.append(val)

# jd_rh = np.array(jd_rh)
# np.unique(jd_rh)
```

In [79]:
```
# Removing some spaces that were not removed earlier
non_null_jds_rh = non_null_jds_rh.apply(lambda x: (' ').join(x.split()))
non_null_jds_rh
```

Out[79]:
```
0           backend engineer
1           backend engineer
2         fullstack engineer
4          frontend engineer
5          frontend engineer
                 ...
160299    fullstack engineer
160300    fullstack engineer
160301     frontend engineer
160302    engineering intern
160303      backend engineer
Name: job_position, Length: 136398, dtype: object
```

Using Levenshtein distance to group similar strings

In [80]:
```
xx = np.unique(non_null_jds_rh)
xx_copy = set()

print('Pre-Run')
print(len(xx), len(xx_copy))

similar_d = {}
for i in range(len(xx)):
    if xx[i] not in xx_copy:
        xx_copy.add(xx[i])
        matches = [xx[i]]
        for j in range(i+1, len(xx)):
            if (xx[j] not in xx_copy) and (fuzz.ratio(xx[i], xx[j])>=80):
                xx_copy.add(xx[j])
                matches.append(xx[j])

        similar_d[xx[i]] = matches

print('Post-Run')
print(len(xx), len(xx_copy))
```

```
Pre-Run
763 0
Post-Run
763 763
```

Manual grouping using grops created by Levenshtein distance

In [81]:
```python
# Unique group lengths (here groups refer to those created by Lev_distance)
np.unique(np.array([len(similar_d[key]) for key in similar_d]))
```

Out[81]:
```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 11])
```

In [82]:
```python
def jd_raw_clean(jd):
    clean_d = {
        'software engineer' : ['software enginner', 'softwear engineer', 'java software engineer', 'cloud software engineer', 'software e
                               'analyst / software engineer', 'software eng', 'software', 'software engineer r&d', 'software engineering
                               'software engineer 1'],
        'software engineer 2' : ['software engineer 2b', 'software engineer l2'],
        'software engineer 3' : ['software engineer 4', 'software engineer 3 sde2'],
        'lead software engineer' : ['tech lead software engineer', 'senior software engineer lead', 'software engineering lead',
                                    'sr lead engineer', 'lead engineer 2'],



        'senior software engineer' : ['sr software engineer', 'sr. software engineer', 'senior software engineeer', 'seniorsoftwareengine
                                      'senior software engineer-l2', 'sr software engg'],
        'junior software engineer' : ['jr. software engineer'],

        'associate software developer' : ['associate developer'],
        'software developer' : ['software devloper', 'graduate software developer', 'junior developer', 'software development', 'software
        'senior software developer' : ['sr. developer', 'senior developer', 'executive software developer'],




        'senior software development engineer' : ['senior software development enggineer'],
        'software development engineer 1' : ['software development enginner', 'sde 1', 'sde-1', 'sde-i', 'software dev. engineer'],
        'software development engineer 2' : ['senior software development engineer 2', 'sde 2', 'sde-2', 'sde2', 'sde-ii', 'sdeii'],
        'software development engineer 3' : ['sde 3', 'sde-3', 'sde 4', 'software developer sde-3', 'sde3'],


        'software engineer testing' : ['software engineer in test', 'software test engineer'],
        'software engineer testing 2' : ['sdet-2', 'senior software test engineer', 'senior software development engineer in test', 'sdet
        'lead software engineer testing' : ['lead software engineer in test', 'technical test lead'],
        'automation test engineer' : ['automation test enginner', 'test automation engineer', 'automation engineer'],

        'backend engineer' : ['software engineer backend', 'backend engineering'],
        'senior backend engineer' : ['senior software engineer backend', 'senior software development engineer backend', 'software engine
                                     'senior software engineer .net backend'],

        'frontend engineer' : ['front end engineer', 'front end web developer', 'front-end developer', 'front end dev', 'front end develo
                               'software engineer frontend'],
        'senior frontend engineer' : ['senior software engineer front end', 'senior front end engineer', 'senior frontend developer'],


        'fullstack engineer' : ['full stack engineer', 'full-stack web developer', 'full stack devloper', 'full stack web developer', 'sc
                                'software engineer 2 full stack' ],




        'web developer' : ['junior web developer', 'senior web developer', 'software / web developer', 'software developer ui'],
        'senior android developer' : ['sr software engg android'],


        'software developer intern' : ['intern software developer', 'software development intern'],
        'software engineering intern' : ['software engineering intern', 'software engineer(r&d intern'],
        'intern' : ['qa intern', 'sde intern', 'student intern', 'sdet intern'],
        'machine learning engineer intern' : ['machine learning intern'],
        'trainee' : ['it trainee', 'assistant engineer trainee'],





        'consultant' : ['consultanat', 'technical consultant', 'technology consultant', 'technical consulting', 'software consultant'],
        'senior consultant' : ['sr consultant', 'senior software consultant', 'senior consulant'],
        'manager' : ['asst. manager', 'tech manager', 'team manager', 'it mmanager', 'audit manager', 'manager-cx', 'sr. technical manage
                     'technical manager', 'senior manager', 'senior manager it'],
        'executive' : ['sr. executive', 'pdp executive', 'it executive', 'sr. mis executive', 'sr hr executive'],




        'engineering leadership' : ['engineering lead ai', 'engineering team lead'],
        'member of technical staff' : ['member of technical staff', 'member of technical staff java', 'member technial staff'],
        'principal member of technical staff' : ['principle member of technical staff'],
        'technical lead' : ['technical leader', 'tecchnical lead', 'technical head'],



        'research engineer' : ['r&d engineer', 'research engineers', 'reasearch engineer', 'research engineer 2', 'rd engineer 2'],
        'research analyst' : ['reseach analyst'],
        'research assistant' : ['graduate research assistant'],



        'qa engineer' : ['software qa engineer', 'software qa'],
        'programmer analyst' : ['programmer analyst', 'programmar analyst', 'programmer analyst 2', 'software engineering analyst',
                                'software engineer analyst', 'software development analyst', 'senior software analyst', 'senior analyst p
                                'analyst programmer'],
        'programmer analyst trainee' : ['program analyst trainee'],




        'engineer' : ['engineer 1', 'engineet', 'technical engineer'],
        'embedded software engineer' : ['embedded software development engineer'],
```

```
        'assistant system engineer' : ['assisatnt system engineer', 'assistant system enginner'],
        'application development associate' : ['application developmentaassociate'],
        'technical associate' : ['associate l1', 'technology associate', 'technical associate'],



        'other' : ['others', 'pa', 'pat', 'eno', 'no'],
        'operation executive': ['sr. operation executive'] ,
        'oracle administrator' : ['oracle dba', 'oracle lead dba'],
        'solution architect' : ['sr solution architect'],
        'senior analyst': ['senior analysts', 'senior lead analyst', 'senior business operations analyst', 'senior business analyst'],
        'senior associate': ['senior chat associate'],
        'senior associate platform' : ['sr. associate platform'],
        'specialist programmer' : ['specialist programmer pp'],
        'technical architect' : ['technical architecct', 'sr technical architect', 'sr. technical architect'],
        'mts' : ['smts', 'mts2'],


        'data engineer' : ['data eingineer', 'associate data engineer'],
        'mechanical engineer' : ['mechanical engineers'],
        'associate application developer' : ['associate applications developer'],
        'application engineer 2' : ['applications engineer 2'],

        'co-founder' : ['co-founderg'],
        'associate technical lead' : ['associate tech lead'],
        'associate system engineer trainee' : ['associate system engineer-trainee'],
        'associate processor' : ['associate professor'],

        'business analyst' : ['business analysts', 'ba', 'bda'],
        'technology analyst' : ['business technology analyst', 'bta'],
        'security analyst' : ['cloud security analyst'],
        'digital marketing' : ['digital marketing manager'],
        'developer associate' : ['developer asociate'],
        'entrepreneur' : ['entrepreneurship'],
        'product developer': ['product develloper'],
        'project lead' : ['project leader'],
        'talent acquisition specialist': ['talent acquisition sspecialist'],
        'vice president' : ['voice president'],
        'web designer' : ['web / ui designer']



        # To check: trianee, intern, android, ios, backend, frontend, fullstack, web, mobile, analyst


    }

    for key in clean_d:
        if jd in clean_d[key]:
            return key

    return jd

# clean_jd('software enginner')
non_null_jds_rh_rc = non_null_jds_rh.apply(lambda x: jd_raw_clean(x))
```

In [83]:
```
# len(similar_d[key]) : [10, )

# for key in similar_d:
#     if len(similar_d[key])>=10:
#         print(f'{key}: {similar_d[key]}')
#         print('~'*50)
#         print(non_null_jds_rh.loc[(non_null_jds_rh.isin(similar_d[key]))].value_counts())
#         print('-'*150)

# -------- XX -------- || -------- XX -------- || -------- XX -------- || -------- XX --------

# len(similar_d[key]) : [7-10)

# for key in similar_d:
#     if len(similar_d[key])>=7 and len(similar_d[key])<10:
#         print(f'{key}: {similar_d[key]}')
#         print('~'*50)
#         print(non_null_jds_rh.loc[(non_null_jds_rh.isin(similar_d[key]))].value_counts())
#         print('-'*50)

# -------- XX -------- || -------- XX -------- || -------- XX -------- || -------- XX --------

# len(similar_d[key]) : [4-7)

# for key in similar_d:
#     if len(similar_d[key])>=4 and len(similar_d[key])<7:
#         print(f'{key}: {similar_d[key]}')
#         print('~'*50)
#         print(non_null_jds_rh.loc[(non_null_jds_rh.isin(similar_d[key]))].value_counts())
#         print('-'*50)

# -------- XX -------- || -------- XX -------- || -------- XX -------- || -------- XX --------

# len(similar_d[key]) : [2-4)

# for key in similar_d:
#     if len(similar_d[key])>=2 and len(similar_d[key])<4:
#         # print(f'{key}: {similar_d[key]}')
#         # print('~'*50)
#         print(non_null_jds_rh.loc[(non_null_jds_rh.isin(similar_d[key]))].value_counts())
#         print('-'*50)


# -------- XX -------- || -------- XX -------- || -------- XX -------- || -------- XX --------

# len(similar_d[key]) : [2-4)

# count = 0
# for key in similar_d:
#     # if len(similar_d[key])==1:
```

```
#     #     print(f'{key}: {similar_d[key]}')
#     #     print('~'*50)
#     #     print(non_null_jds_rh.loc[(non_null_jds_rh.isin(similar_d[key]))].value_counts())
#     #     print('-'*50)
#         count += 1
# print(count)
```

In [84]:
```
ser_job_rh_rc = non_null_jds_rh_rc.value_counts()
```

In [85]:
```
print(f'Total records of job_position: {df_clean2["job_position"].shape[0]}')
print(f'#Records with missing job: {df_clean2["job_position"].isna().sum()}')
print(f'% of Records with missing job: {round(100*df_clean2["job_position"].isna().sum()/df_clean2["job_position"].shape[0], 2)}%')
print(f'#Records with non-null jobs: {(~df_clean2["job_position"].isna()).sum()}')
print(f'% of Records with missing job: {round(100*(~df_clean2["job_position"].isna()).sum()/df_clean2["job_position"].shape[0], 2)}%')
print('-'*50)
print(f'Unique #jobs: {ser_job_rh_rc.shape[0]}')
print(f'#Jobs with more than 1 record: {ser_job_rh_rc.loc[ser_job_rh_rc>=2].shape[0]}')
print(f'#Jobs with only 1 record: {576-ser_job_rh_rc.loc[ser_job_rh_rc>=2].shape[0]}')
print(f'Max records against a single job: {ser_job_rh_rc.max()}')
```

```
Total records of job_position: 160304
#Records with missing job: 23906
% of Records with missing job: 14.91%
#Records with non-null jobs: 136398
% of Records with missing job: 85.09%
--------------------------------------------------
Unique #jobs: 575
#Jobs with more than 1 record: 173
#Jobs with only 1 record: 403
Max records against a single job: 39085
```

In [ ]:

In [86]:
```
# Top 25 job descriptions
df_top50_jds = pd.DataFrame(ser_job_rh_rc.iloc[:25])
df_top50_jds['count'] = df_top50_jds['job_position']
df_top50_jds.drop('job_position', axis=1, inplace=True)
df_top50_jds['count_pct'] = 100*df_top50_jds['count']/df_clean2.shape[0]
df_top50_jds['count_cumsum'] = df_top50_jds['count'].cumsum()
df_top50_jds['count_cumsum_pct'] = 100*df_top50_jds['count_cumsum']/df_clean2.shape[0]
df_top50_jds
```

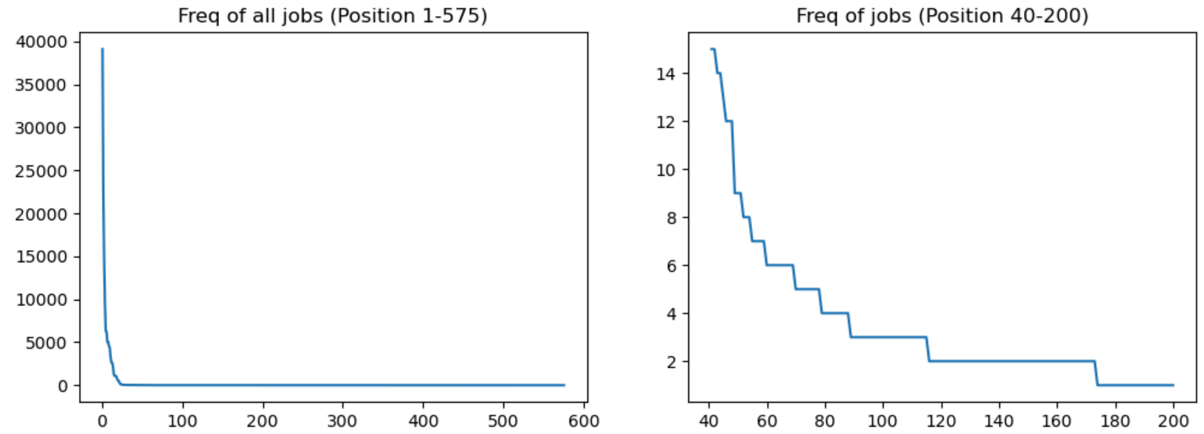
Out[86]:

	count	count_pct	count_cumsum	count_cumsum_pct
backend engineer	39085	24.381800	39085	24.381800
fullstack engineer	22419	13.985303	61504	38.367103
other	14587	9.099586	76091	47.466688
frontend engineer	9581	5.976769	85672	53.443457
engineering leadership	6316	3.940014	91988	57.383471
qa engineer	6232	3.887614	98220	61.271085
data scientist	5042	3.145274	103262	64.416359
android engineer	5029	3.137164	108291	67.553523
sdet	4567	2.848962	112858	70.402485
devops engineer	4385	2.735428	117243	73.137913
support engineer	3263	2.035508	120506	75.173421
data analyst	2666	1.663090	123172	76.836511
ios engineer	2624	1.636890	125796	78.473401
engineering intern	2202	1.373640	127998	79.847041
product designer	1283	0.800354	129281	80.647395
product manager	1096	0.683701	130377	81.331096
backend architect	1086	0.677463	131463	82.008559
research engineer	1060	0.661244	132523	82.669802
program manager	778	0.485328	133301	83.155130
non coder	560	0.349336	133861	83.504467
database administrator	523	0.326255	134384	83.830722
co-founder	342	0.213345	134726	84.044066
security leadership	142	0.088582	134868	84.132648
release engineer	119	0.074234	134987	84.206882
senior software engineer	60	0.037429	135047	84.244311

After manual cleaning of the categories in job_position, we have the below observations:

- There are 160304 records out of which missing records (23906) are ~15% (that is non-missing records (136398) account for 85%)
- There are 576 unique jobs and out of these 576 jobs, we show the top 25 most occuring job positions in the above dataframe
- The key observation is that the top 25 jobs account for 135047 records (which account for 84% of total records)
- This implies that all the other jobs except the top 25 jobs account for only (136398-135047)=1351 records accounting for only 1% of total records
- Given this insight we can go ahead an re-catogorize those jobs with freq<=5 as 'other'

In [87]:
```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(12, 4))
len_job_rh_rc = ser_job_rh_rc.shape[0]

axs[0].plot(np.linspace(1, len_job_rh_rc, len_job_rh_rc), ser_job_rh_rc.values)
axs[0].set_title(f'Freq of all jobs (Position 1-{len_job_rh_rc})')
axs[1].plot(np.linspace(1, len_job_rh_rc, len_job_rh_rc)[40:200], ser_job_rh_rc.values[40:200])
axs[1].set_title('Freq of jobs (Position 40-200)')

plt.show()
```



Re-categorizing jobs with frequency<=5 as 'other'

In [88]:
```
df_clean3 = df_clean2.copy()
df_clean3['job_position_cln'] = non_null_jds_rh_rc
```

In [89]:
```
jobs_freq_upto5 = ser_job_rh_rc.loc[ser_job_rh_rc<=5].index
jobs_freq_upto5
```

Out[89]:
```
Index(['automation test engineer', 'principal software engineer',
       'research assistant', 'na', 'product developer', 'executive',
       'programmer analyst trainee', 'assistant manager', 'web developer',
       'vice president',
       ...
       'professional services engineer', 'associate data scientist',
       'sap cpq consultant', 'back office executive admin',
       'chief people officer', 'computer scientist 2',
       'student in computer application', 'delivery project lead',
       'associate futures engineering team', 'subject matter expert'],
      dtype='object', length=506)
```

In [90]:
```
df_clean3.loc[df_clean3['job_position_cln'].isin(jobs_freq_upto5), 'job_position_cln'] = 'other'
df_clean3.drop('job_position', axis=1, inplace=True)
df_clean3['job_position_cln'].describe()
```

Out[90]:
```
count              136398
unique                 69
top       backend engineer
freq                39085
Name: job_position_cln, dtype: object
```

In [ ]:

In [ ]:

KNN Imputation of job_position

In [91]:
```
# df_clean2.isna().sum()
```

In [92]:
```
df_clean3.isna().sum()
```

Out[92]:
```
email_hash              0
company_hash            0
orgyear                 0
ctc_updated_year        0
ctc                     0
job_position_cln    23906
dtype: int64
```

In [93]:
```
# df_clean4 = df_clean2.copy()
df_clean4 = df_clean3.copy()

le = LabelEncoder()
df_clean4['company_hash_encode'] = le.fit_transform(df_clean4['company_hash'])
df_clean4['job_position_cln'].fillna('missing', inplace=True)
df_clean4['job_position_cln_encode'] = le.fit_transform(df_clean4['job_position_cln'])
```

In [94]:
```
df_clean4.loc[df_clean4['job_position_cln']=='missing'].head()
```

Out[94]:

	email_hash	company_hash	orgyear	ctc_updated_year	ctc	job_position_cln	company_hash_encode	job_positior
3	00014d71a389170e668ba96ae8e1f9d991591acc899025...	fvrbvqn rvmo	2009.0	2018.0	3400000	missing	7022	
6	000411b5d6d4e1c113bf83f1eebc0b835d77cc45bded1d...	gutzcgj	2017.0	2021.0	3500000	missing	7914	
15	000a028ed6fe3c5a2ebdcdf67b8d4f7785821b51113565...	vhnymqxast qtotvqwy otqcxwto	2016.0	2020.0	360000	missing	26987	
20	000c89400932b5cc8a3d6c5b6a854c844f0f64a53d7b8a...	evwtmggp	2015.0	2016.0	2100000	missing	6118	
22	000dbb08ff8c14f7c6d4729e0d9015c48cc57c6de27cf2...	bxwqgogen qa xzaxv uqxcvnt rna	2011.0	2015.0	1650000	missing	3808	

In [95]:
```
df_clean4.loc[df_clean4['job_position_cln']=='missing', 'job_position_cln_encode']=np.nan
df_clean4.loc[df_clean4['job_position_cln']=='missing'].head()
```

Out[95]:

	email_hash	company_hash	orgyear	ctc_updated_year	ctc	job_position_cln	company_hash_encode	job_positior
3	00014d71a389170e668ba96ae8e1f9d991591acc899025...	fvrbvqn rvmo	2009.0	2018.0	3400000	missing	7022	
6	000411b5d6d4e1c113bf83f1eebc0b835d77cc45bded1d...	gutzcgj	2017.0	2021.0	3500000	missing	7914	
15	000a028ed6fe3c5a2ebdcdf67b8d4f7785821b51113565...	vhnymqxast qtotvqwy otqcxwto	2016.0	2020.0	360000	missing	26987	
20	000c89400932b5cc8a3d6c5b6a854c844f0f64a53d7b8a...	evwtmggp	2015.0	2016.0	2100000	missing	6118	
22	000dbb08ff8c14f7c6d4729e0d9015c48cc57c6de27cf2...	bxwqgogen qa xzaxv uqxcvnt rna	2011.0	2015.0	1650000	missing	3808	

In [96]:
```
std_scaler = StandardScaler()
X_clean4 = std_scaler.fit_transform(df_clean4[['company_hash_encode', 'job_position_cln_encode', 'orgyear', 'ctc_updated_year', 'ctc']])
```

In [97]:
```
knn_imputer = KNNImputer(n_neighbors=1, weights='uniform')
X_clean_knn4 = knn_imputer.fit_transform(X_clean4)
```

In [98]:
```
x_job_pos_cln_enc_knn_unscaled = std_scaler.inverse_transform(X_clean_knn4)[:, 1]
x_job_pos_cln_enc_knn_unscaled = np.array(x_job_pos_cln_enc_knn_unscaled, dtype='int64')
```

In [99]:
```
df_clean4['job_position'] = le.inverse_transform(x_job_pos_cln_enc_knn_unscaled)
df_clean4.drop(['job_position_cln', 'company_hash_encode', 'job_position_cln_encode'], axis=1, inplace=True)
df_clean4.head()
```

Out[99]:

	email_hash	company_hash	orgyear	ctc_updated_year	ctc	job_position
0	00003288036a44374976948c327f246fdbdf0778546904...	bxwqgogen	2012.0	2019.0	3500000	backend engineer
1	0000aaa0e6b61f7636af1954b43d294484cd151c9b3cf6...	nqsn axsxnvr	2013.0	2020.0	336000	backend engineer
2	000120d0c8aa304fcf12ab4b85e21feb80a342cfea03d4...	bxwqgotbx wgqugqvnxgz	2004.0	2021.0	2000000	fullstack engineer
3	00014d71a389170e668ba96ae8e1f9d991591acc899025...	fvrbvqn rvmo	2009.0	2018.0	3400000	fullstack engineer
4	00022dc29c7f77032275182b883d4f273ea1007aefc437...	vqtkkgopj	2016.0	2020.0	750000	frontend engineer

In [100…
```
df_clean4.isna().sum()
```

Out[100]:
```
email_hash          0
company_hash        0
orgyear             0
ctc_updated_year    0
ctc                 0
job_position        0
dtype: int64
```

In [101…
```
(df_clean4['job_position']=='missing').sum()
```

Out[101]:
```
0
```

Feature Engineering1: Manual Clustering

Years of Experience in current company & current job (yoe):

In [102…
```
df_final = df_clean4.copy()
df_final['yoe'] = 2024-df_final['orgyear']
df_final.drop(['orgyear'], axis=1, inplace=True)
df_final = df_final.iloc[:, [0, 1, 4, 5, 2, 3]]
df_final.head()
```

Out[102]:

	email_hash	company_hash	job_position	yoe	ctc_updated_year	ctc
0	00003288036a44374976948c327f246fdbdf0778546904...	bxwqgogen	backend engineer	12.0	2019.0	3500000
1	0000aaa0e6b61f7636af1954b43d294484cd151c9b3cf6...	nqsn axsxnvr	backend engineer	11.0	2020.0	336000
2	000120d0c8aa304fcf12ab4b85e21feb80a342cfea03d4...	bxwqgotbx wgqugqvnxgz	fullstack engineer	20.0	2021.0	2000000
3	00014d71a389170e668ba96ae8e1f9d991591acc899025...	fvrbvqn rvmo	fullstack engineer	15.0	2018.0	3400000
4	00022dc29c7f77032275182b883d4f273ea1007aefc437...	vqtkkgopj	frontend engineer	8.0	2020.0	750000

Designation:

- How much does leaner earn compared to other learners in same company, in same job and with same yoe?
- Will bucketize learners into 3 buckets (1 denoting high earners and 3 denoting low earners)

In [103…
```
df_grp_comp_job_yoe = df_final.groupby(['company_hash', 'job_position', 'yoe'])[['ctc']].describe()
df_grp_comp_job_yoe.columns = [('_').join(tup) for tup in df_grp_comp_job_yoe.columns]
df_grp_comp_job_yoe = df_grp_comp_job_yoe.reset_index()
df_grp_comp_job_yoe.rename(columns={'ctc_count':'grp_count'}, inplace=True)
df_grp_comp_job_yoe.head()
```

Out[103]:

	company_hash	job_position	yoe	grp_count	ctc_mean	ctc_std	ctc_min	ctc_25%	ctc_50%	ctc_75%	ctc_max
0	0	other	4.0	1.0	336000.0	NaN	336000.0	336000.0	336000.0	336000.0	336000.0
1	0000	other	7.0	1.0	336000.0	NaN	336000.0	336000.0	336000.0	336000.0	336000.0
2	01 ojztqsj	android engineer	8.0	1.0	336000.0	NaN	336000.0	336000.0	336000.0	336000.0	336000.0
3	01 ojztqsj	frontend engineer	13.0	1.0	830000.0	NaN	830000.0	830000.0	830000.0	830000.0	830000.0
4	05mz exzytvrny uqxcvnt rxbxnta	backend engineer	5.0	1.0	1100000.0	NaN	1100000.0	1100000.0	1100000.0	1100000.0	1100000.0

In [104…
```
# df_grp_comp_job_yoe['grp_count'].value_counts()
```

In [105…
```
# sns.histplot(df_grp_comp_job_yoe['grp_count'].value_counts().index, bins=20)
# plt.show()
```

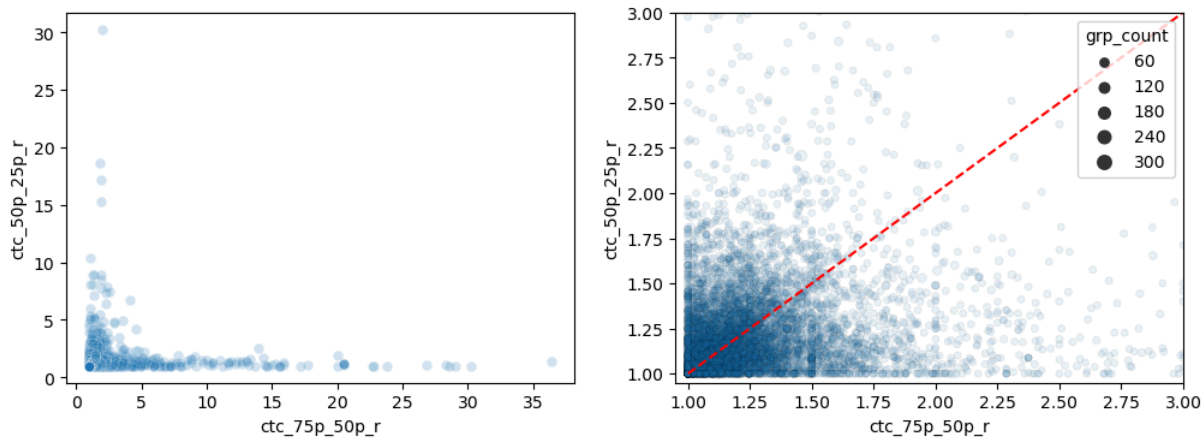
Checking percentile ratios 75p/50p & 50p/25p to understand skewness of groups created

In [106…
```
df_grp_comp_job_yoe['ctc_75p_50p_r'] = df_grp_comp_job_yoe['ctc_75%']/df_grp_comp_job_yoe['ctc_50%']
df_grp_comp_job_yoe['ctc_50p_25p_r'] = df_grp_comp_job_yoe['ctc_50%']/df_grp_comp_job_yoe['ctc_25%']
df_grp_comp_job_yoe.loc[df_grp_comp_job_yoe['grp_count']>5, ['ctc_50p_25p_r', 'ctc_75p_50p_r']].describe()
```

Out[106]:

	ctc_50p_25p_r	ctc_75p_50p_r
count	2725.000000	2725.000000
mean	1.340348	1.395893
std	0.493833	1.119090
min	1.000000	1.000000
25%	1.109890	1.125000
50%	1.217647	1.243636
75%	1.413043	1.438849
max	10.416667	36.363636

In [107…
```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(12, 4))

sns.scatterplot(x=df_grp_comp_job_yoe['ctc_75p_50p_r'], y=df_grp_comp_job_yoe['ctc_50p_25p_r'], alpha=0.2, ax=axs[0])
# axs[0].set_xlim(left=0.95, right=3)
# axs[0].set_ylim(bottom=0.95, top=3)


df_grp_comp_job_yoe_tmp = df_grp_comp_job_yoe.loc[df_grp_comp_job_yoe['grp_count']>2]

sns.scatterplot(x=df_grp_comp_job_yoe_tmp['ctc_75p_50p_r'], y=df_grp_comp_job_yoe_tmp['ctc_50p_25p_r'], alpha=0.1,
                size=df_grp_comp_job_yoe_tmp['grp_count'], edgecolor='black', ax=axs[1])
axs[1].set_xlim(left=0.95, right=3)
axs[1].set_ylim(bottom=0.95, top=3)
axs[1].plot(np.arange(1, 4), np.arange(1, 4), color='r', linestyle='--')

plt.show()
```



In [108…
```
# Joining original dataset with 25p, 50p, 75p of created groups
df_grp_comp_job_yoe_merge = pd.merge(df_final, df_grp_comp_job_yoe.iloc[:, [0,1,2,7,8,9]], on=['company_hash', 'job_position', 'yoe'], hc
df_grp_comp_job_yoe_merge.head()
```

Out[108]:

	email_hash	company_hash	job_position	yoe	ctc_updated_year	ctc	ctc_25%	ctc_50%	ctc_75%
0	00003288036a44374976948c327f246fdbdf0778546904...	bxwqgogen	backend engineer	12.0	2019.0	3500000	2045000.0	2800000.0	3500000.0
1	0000aaa0e6b61f7636af1954b43d294484cd151c9b3cf6...	nqsn axsxnvr	backend engineer	11.0	2020.0	336000	336000.0	336000.0	336000.0
2	000120d0c8aa304fcf12ab4b85e21feb80a342cfea03d4...	bxwqgotbx wgqugqvnxgz	fullstack engineer	20.0	2021.0	2000000	2000000.0	2000000.0	2000000.0
3	00014d71a389170e668ba96ae8e1f9d991591acc899025...	fvrbvqn rvmo	fullstack engineer	15.0	2018.0	3400000	3625000.0	3850000.0	4075000.0
4	00022dc29c7f77032275182b883d4f273ea1007aefc437...	vqtkkgopj	frontend engineer	8.0	2020.0	750000	750000.0	750000.0	750000.0

Logic for creating feature:

- We create a feature called 'designation'
- We bucketize all the records into 3 possible buckets: [1, 2, 3]
  - 1: if ctc is more than the median_ctc of the group which the record belongs to by 10%
  - 3: if ctc is less than the median_ctc of the group which the record belongs to by 10%
  - 2: all other cases

In [109…
```
def designation_logic(ctc, ctc_grp_median, ctc_grp_25p, ctc_grp_75p):
    if ctc > 1.1*ctc_grp_median:
        return 1
    elif ctc_grp_median > 1.1*ctc:
        return 3
```

```
    return 2

    # if ctc > ctc_grp_75p:
    #     return 1
    # elif ctc < ctc_grp_25p:
    #     return 3
    # return 2

df_grp_comp_job_yoe_merge['designation'] = df_grp_comp_job_yoe_merge[['ctc', 'ctc_50%',
                                                                       'ctc_25%', 'ctc_75%']].apply(lambda x:
                                                                                                        designation_logic(x[0],x[1],x[2],x[3]
df_grp_comp_job_yoe_merge['designation'].value_counts(normalize=True)
```

Out[109]:

```
2    0.672959
1    0.167139
3    0.159902
Name: designation, dtype: float64
```

In [ ]:

Class:

- How much does leaner earn compared to other learners in same company and in same job?
- Will bucketize learners into 3 buckets (1 denoting high earners and 3 denoting low earners)

In [110…

```
df_grp_comp_job = df_final.groupby(['company_hash', 'job_position'])[['ctc']].describe()
df_grp_comp_job.columns = ['_'.join(tup) for tup in df_grp_comp_job.columns]
df_grp_comp_job = df_grp_comp_job.reset_index()
df_grp_comp_job.rename(columns={'ctc_count':'grp_count'}, inplace=True)
df_grp_comp_job.head()
```

Out[110]:

	company_hash	job_position	grp_count	ctc_mean	ctc_std	ctc_min	ctc_25%	ctc_50%	ctc_75%	ctc_max
0	0	other	1.0	336000.0	NaN	336000.0	336000.0	336000.0	336000.0	336000.0
1	0000	other	1.0	336000.0	NaN	336000.0	336000.0	336000.0	336000.0	336000.0
2	01 ojztqsj	android engineer	1.0	336000.0	NaN	336000.0	336000.0	336000.0	336000.0	336000.0
3	01 ojztqsj	frontend engineer	1.0	830000.0	NaN	830000.0	830000.0	830000.0	830000.0	830000.0
4	05mz exzytvrny uqxcvnt rxbxnta	backend engineer	1.0	1100000.0	NaN	1100000.0	1100000.0	1100000.0	1100000.0	1100000.0

In [111…

```
# df_grp_comp_job['grp_count'].value_counts()
```

In [112…

```
# sns.histplot(df_grp_comp_job['grp_count'].value_counts().index, bins=50)
# plt.show()
```

In [113…

```
df_grp_comp_job['ctc_75p_50p_r'] = df_grp_comp_job['ctc_75%']/df_grp_comp_job['ctc_50%']
df_grp_comp_job['ctc_50p_25p_r'] = df_grp_comp_job['ctc_50%']/df_grp_comp_job['ctc_25%']
df_grp_comp_job.loc[df_grp_comp_job['grp_count']>5, ['ctc_50p_25p_r', 'ctc_75p_50p_r']].describe()
```

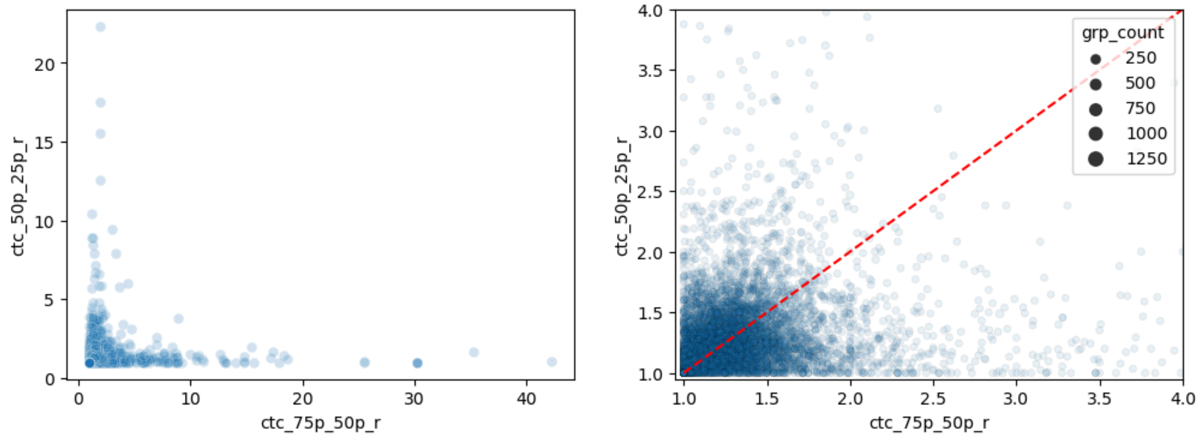
Out[113]:

	ctc_50p_25p_r	ctc_75p_50p_r
count	3320.000000	3320.000000
mean	1.393012	1.451158
std	0.499166	1.183019
min	1.000000	1.000000
25%	1.154212	1.180288
50%	1.280000	1.312500
75%	1.476374	1.500000
max	10.416667	42.164804

Checking percentile ratios 75p/50p & 50p/25p to understand skewness of groups created

In [114…

```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(12, 4))

sns.scatterplot(x=df_grp_comp_job['ctc_75p_50p_r'], y=df_grp_comp_job['ctc_50p_25p_r'], alpha=0.2, ax=axs[0])
# axs[0].set_xlim(left=0.95, right=3)
# axs[0].set_ylim(bottom=0.95, top=3)


df_grp_comp_job_tmp = df_grp_comp_job.loc[df_grp_comp_job['grp_count']>2]

sns.scatterplot(x=df_grp_comp_job_tmp['ctc_75p_50p_r'], y=df_grp_comp_job_tmp['ctc_50p_25p_r'], alpha=0.1,
                size=df_grp_comp_job_tmp['grp_count'], edgecolor='black', ax=axs[1])
axs[1].set_xlim(left=0.95, right=4)
axs[1].set_ylim(bottom=0.95, top=4)
axs[1].plot(np.arange(1, 5), np.arange(1, 5), color='r', linestyle='--')

plt.show()
```




```
In [115…: # Joining original dataset with 25p, 50p, 75p of created groups
df_grp_comp_job_merge = pd.merge(df_grp_comp_job_yoe_merge.drop(['ctc_50%','ctc_25%','ctc_75%'], axis=1), df_grp_comp_job.iloc[:, [0,1,6,
                            on=['company_hash', 'job_position'], how='left')
df_grp_comp_job_merge.head()
```

Out[115]:

	email_hash	company_hash	job_position	yoe	ctc_updated_year	ctc	designation	ctc_25%	ctc_50%	ctc_7!
0	00003288036a44374976948c327f246fdbdf0778546904...	bxwqgogen	backend engineer	12.0	2019.0	3500000	1	1900000.0	2510000.0	360000
1	0000aaa0e6b61f7636af1954b43d294484cd151c9b3cf6...	nqsn axsxnvr	backend engineer	11.0	2020.0	336000	2	336000.0	336000.0	33600
2	000120d0c8aa304fcf12ab4b85e21feb80a342cfea03d4...	bxwqgotbx wgqugqvnxgz	fullstack engineer	20.0	2021.0	2000000	2	752000.0	1168000.0	158400
3	00014d71a389170e668ba96ae8e1f9d991591acc899025...	fvrbvqn rvmo	fullstack engineer	15.0	2018.0	3400000	3	1700000.0	2400000.0	307500
4	00022dc29c7f77032275182b883d4f273ea1007aefc437...	vqtkkgopj	frontend engineer	8.0	2020.0	750000	2	750000.0	750000.0	75000

Logic for creating feature:

- We create a feature called 'class'
- We bucketize all the records into 3 possible buckets: [1, 2, 3]
    - 1: if ctc is more than the median_ctc of the group which the record belongs to by 10%
    - 3: if ctc is less than the median_ctc of the group which the record belongs to by 10%
    - 2: all other cases

```
In [116…: def class_logic(ctc, ctc_grp_median, ctc_grp_25p, ctc_grp_75p):
    if ctc > 1.1*ctc_grp_median:
        return 1
    elif ctc_grp_median > 1.1*ctc:
        return 3
    return 2

    # if ctc > ctc_grp_75p:
    #     return 1
    # elif ctc < ctc_grp_25p:
    #     return 3
    # return 2

df_grp_comp_job_merge['class'] = df_grp_comp_job_merge[['ctc', 'ctc_50%',
                                                         'ctc_25%', 'ctc_75%']].apply(lambda x: class_logic(x[0],x[1],x[2],x[3]), axis=1)
df_grp_comp_job_merge['class'].value_counts(normalize=True)
```

```
Out[116]: 2    0.468903
1    0.268696
3    0.262401
Name: class, dtype: float64
```

```
In [117…: df_grp_comp_job_merge[['designation', 'class']].apply(lambda x: f'{x[0]}_{x[1]}', axis=1).value_counts(normalize=True)
```

```
Out[117]: 2_2    0.427949
1_1    0.138113
3_3    0.129392
2_3    0.125331
2_1    0.119679
1_2    0.021347
3_2    0.019606
3_1    0.010904
1_3    0.007679
dtype: float64
```

```
In [ ]:
```

Tier:

- How much does leaner earn compared to other learners in same company?
- Will bucketize learners into 3 buckets (1 denoting high earners and 3 denoting low earners)

```
In [118…: df_grp_comp = df_final.groupby(['company_hash'])[['ctc', 'yoe']].describe()
df_grp_comp.columns = ['_'.join(tup) for tup in df_grp_comp.columns]
df_grp_comp = df_grp_comp.reset_index()
df_grp_comp.head()
```

Out[118]:

	company_hash	ctc_count	ctc_mean	ctc_std	ctc_min	ctc_25%	ctc_50%	ctc_75%	ctc_max	yoe_count	yoe_mean	yoe_std	yoe_min	yoe_25%
0	0	1.0	336000.0	NaN	336000.0	336000.0	336000.0	336000.0	336000.0	1.0	4.0	NaN	4.0	4.00
1	0000	1.0	336000.0	NaN	336000.0	336000.0	336000.0	336000.0	336000.0	1.0	7.0	NaN	7.0	7.00
2	01 ojztqsj	2.0	583000.0	349310.749906	336000.0	459500.0	583000.0	706500.0	830000.0	2.0	10.5	3.535534	8.0	9.25
3	05mz exzytvrny uqxcvnt rxbxnta	1.0	1100000.0	NaN	1100000.0	1100000.0	1100000.0	1100000.0	1100000.0	1.0	5.0	NaN	5.0	5.00
4	1	2.0	336000.0	0.000000	336000.0	336000.0	336000.0	336000.0	336000.0	2.0	7.0	0.000000	7.0	7.00

In [119…

```
df_grp_comp_merge = pd.merge(df_grp_comp_job_merge.drop(['ctc_50%','ctc_25%','ctc_75%'], axis=1), df_grp_comp.iloc[:, [0, 5, 6, 7, 13, 14
                                 on=['company_hash'], how='left')
df_grp_comp_merge.head()
```

Out[119]:

	email_hash	company_hash	job_position	yoe	ctc_updated_year	ctc	designation	class	ctc_25%	ctc_50%
0	00003288036a44374976948c327f246fdbdf0778546904...	bxwqgogen	backend engineer	12.0	2019.0	3500000	1	1	1697500.0	2500000.0
1	0000aaa0e6b61f7636af1954b43d294484cd151c9b3cf6...	nqsn axsxnvr	backend engineer	11.0	2020.0	336000	2	2	336000.0	336000.0
2	000120d0c8aa304fcf12ab4b85e21feb80a342cfea03d4...	bxwqgotbx wgqugqvnxgz	fullstack engineer	20.0	2021.0	2000000	2	1	950000.0	2000000.0
3	00014d71a389170e668ba96ae8e1f9d991591acc899025...	fvrbvqn rvmo	fullstack engineer	15.0	2018.0	3400000	3	1	1800000.0	2500000.0
4	00022dc29c7f77032275182b883d4f273ea1007aefc437...	vqtkkgopj	frontend engineer	8.0	2020.0	750000	2	2	750000.0	750000.0

Logic for creating feature:

- We create a feature called 'tier'
- We bucketize all the records into 3 possible buckets: [1, 2, 3]
  - 1: if ctc is more than the median_ctc of the group which the record belongs to by 20%
  - 3: if ctc is less than the median_ctc of the group which the record belongs to by 20%
  - 2: all other cases

In [120…

```
def tier_logic(ctc, ctc_grp_median, ctc_grp_25p, ctc_grp_75p):
    if ctc > 1.2*ctc_grp_median:
        return 1
    elif ctc_grp_median > 1.2*ctc:
        return 3
    return 2

    # if ctc > ctc_grp_75p:
    #     return 1
    # elif ctc < ctc_grp_25p:
    #     return 3
    # return 2

df_grp_comp_merge['tier'] = df_grp_comp_merge[['ctc', 'ctc_50%',
                                               'ctc_25%', 'ctc_75%']].apply(lambda x: tier_logic(x[0],x[1],x[2],x[3]), axis=1)
df_grp_comp_merge['tier'].value_counts(normalize=True)
```

Out[120]:

```
2    0.440195
1    0.285345
3    0.274460
Name: tier, dtype: float64
```

Checking distribution of records to each cluster:

- For manual clustering, we designed 3 features (designation, class, tier)
- Each of the above features can be either 1 or 2 or 3
- Thus effectively we have split the entire dataset in any of the possible 27 groups (3X3X3)
- Below we show the #records per cluster as a % of the total records
- Top 5 clusters by size are the below ones (Designation-Class-Tier):
  - 2-2-2
  - 2-2-3
  - 2-2-1
  - 1-1-1
  - 3-3-3

In [121…

```
df_final2 = df_grp_comp_merge.copy()
df_final2.drop(['ctc_25%', 'ctc_50%', 'ctc_75%', 'yoe_25%', 'yoe_50%', 'yoe_75%'], axis=1, inplace=True)
df_final2.head()
```

Out[121]:

	email_hash	company_hash	job_position	yoe	ctc_updated_year	ctc	designation	class	tier
0	00003288036a44374976948c327f246fdbdf0778546904...	bxwqgogen	backend engineer	12.0	2019.0	3500000	1	1	1
1	0000aaa0e6b61f7636af1954b43d294484cd151c9b3cf6...	nqsn axsxnvr	backend engineer	11.0	2020.0	336000	2	2	2
2	000120d0c8aa304fcf12ab4b85e21feb80a342cfea03d4...	bxwqgotbx wgqugqvnxgz	fullstack engineer	20.0	2021.0	2000000	2	1	2
3	00014d71a389170e668ba96ae8e1f9d991591acc899025...	fvrbvqn rvmo	fullstack engineer	15.0	2018.0	3400000	3	1	1
4	00022dc29c7f77032275182b883d4f273ea1007aefc437...	vqtkkgopj	frontend engineer	8.0	2020.0	750000	2	2	2

In [122…

```
df_final2[['designation', 'class', 'tier']].apply(lambda x: f'{x[0]}_{x[1]}_{x[2]}', axis=1).value_counts(normalize=True)
```

Out[122]:
```
2_2_2    0.303947
1_1_1    0.115212
3_3_3    0.108300
2_1_1    0.088002
2_3_3    0.086704
2_2_3    0.062955
2_2_1    0.061047
2_3_2    0.032189
2_1_2    0.027922
1_1_2    0.020605
3_3_2    0.019251
1_2_2    0.015502
3_2_2    0.014030
3_1_1    0.006931
2_3_1    0.006438
1_3_3    0.004161
2_1_3    0.003755
3_1_2    0.003624
3_2_3    0.003312
1_2_1    0.003219
1_3_2    0.003125
1_2_3    0.002626
1_1_3    0.002296
3_2_1    0.002264
3_3_1    0.001840
1_3_1    0.000393
3_1_3    0.000349
dtype: float64
```

Insights from Manual Clustering:

Top 10 employees (earning more than most of the employees in the company)

In [123…
```
df_final2_top10_emp_by_tier = df_final2.loc[df_final2['tier']==1, ['email_hash', 'company_hash', 'ctc']].copy()
df_final2_top10_emp_by_tier['rank'] = df_final2_top10_emp_by_tier.groupby('company_hash')[['ctc']].rank(ascending=False)
df_final2_top10_emp_by_tier = df_final2_top10_emp_by_tier.loc[df_final2_top10_emp_by_tier['rank']<=10].sort_values(by=['company_hash', 'r
```

In [124…
```
# Showing top10 earning employees for 1 company:
df_final2_top10_emp_by_tier.loc[df_final2_top10_emp_by_tier['company_hash']=='zxztrtvuo']
```

Out[124]:

	email_hash	company_hash	ctc	rank
23212	303aab779b6daea19317b430f600b0e8543f4c66ca3251...	zxztrtvuo	11950000	1.0
67440	8c7b6b29eddd85e147c7d02507735f2c250d6c40d34bb2...	zxztrtvuo	3000000	2.0
104763	da254908334157ddde0078c9bf967114ae67cc00816f4c...	zxztrtvuo	2700000	3.0
9202	12b42968b62afcbac9252406392275719b35c99d39aefb...	zxztrtvuo	2500000	5.5
17118	234f0f52e89b20231f5685551b865a08a5634189e1ffec...	zxztrtvuo	2500000	5.5
37722	4ebf56aec16de134303f4c54752d26bc12791e8b20b28b...	zxztrtvuo	2500000	5.5
49347	66a9ddfbd95e2f5fb57e5f649bd22eeeb7c1a9aec920b8...	zxztrtvuo	2500000	5.5
14010	1cd0a52ed52dae24d605d9cdc8536499c10ce62bfb070f...	zxztrtvuo	2250000	8.0
24789	3385dc93ba44f4f1cc237ef4f8e057dab2f693d8961b64...	zxztrtvuo	1800000	9.0
11149	16c227291d7c4f151b52599cc15e1ddd6f7e12a694753c...	zxztrtvuo	1780000	10.0

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

In [125…
```
df_final2_bot10_emp_by_tier = df_final2.loc[df_final2['tier']==3, ['email_hash', 'company_hash', 'ctc']].copy()
df_final2_bot10_emp_by_tier['rank'] = df_final2_bot10_emp_by_tier.groupby('company_hash')[['ctc']].rank(ascending=True)
df_final2_bot10_emp_by_tier = df_final2_bot10_emp_by_tier.loc[df_final2_bot10_emp_by_tier['rank']<=10].sort_values(by=['company_hash', 'r
```

In [126…
```
# Showing top10 earning employees for 1 company:
df_final2_bot10_emp_by_tier.loc[df_final2_bot10_emp_by_tier['company_hash']=='zxztrtvuo']
```

Out[126]:

	email_hash	company_hash	ctc	rank
98488	cd2e14f599f7749ac2be21c9ee219f10e46df8bac74b6d...	zxztrtvuo	400000	1.5
157399	798f312433ee4125ee5dd5887250701eb533249e8fbad6...	zxztrtvuo	400000	1.5
24023	31f3aea195401c4f20d0e910d2ac18d0f85d9664165afa...	zxztrtvuo	450000	5.0
65414	88534a8bc32c10480086fe9dac0375caeb489539561eee...	zxztrtvuo	450000	5.0
125303	aeb0d8dd3adcfd03520f22cb10f36295a2cc985d43c267...	zxztrtvuo	450000	5.0
125951	e2d27a8acde6484d35b69a75d9ecbc8b1f541223b3a296...	zxztrtvuo	450000	5.0
159503	f230cabdfbe43c7fe4ba66629b0fa9e058b1fd613dc232...	zxztrtvuo	450000	5.0
936	01f98ed38bb3f6013cef8ebed0b0db568c586824b8e219...	zxztrtvuo	500000	10.0
1042	0228801807a4911ebde807b5f88a273a51d92b25e6c160...	zxztrtvuo	500000	10.0
112571	ea8082622619d930daedcb37053f8514d798d65b68f520...	zxztrtvuo	500000	10.0
150564	d5b98d92628266c2037e78a367db956c140585fa027171...	zxztrtvuo	500000	10.0
159609	f861d9f1bfee791938d90e9ad91069220eec8664b32fea...	zxztrtvuo	500000	10.0

Top 10 employees of data science in each company earning more than their peers

In [127…
```
df_final2_top10_ds_emp_by_class = df_final2.loc[(df_final2['job_position'].isin(['data scientist', 'machine learning engineer'])) & (df_f
df_final2_top10_ds_emp_by_class['rank'] = df_final2_top10_ds_emp_by_class.groupby('company_hash')[['ctc']].rank(ascending=False)
df_final2_top10_ds_emp_by_class = df_final2_top10_ds_emp_by_class.loc[df_final2_top10_ds_emp_by_class['rank']<=10].sort_values(by=['compa
```

In [128…
```
# Showing top10 earning employees in DS earning more than their peers for 1 company:
df_final2_top10_ds_emp_by_class.loc[df_final2_top10_ds_emp_by_class['company_hash']=='247vx']
```

Out[128]:

	email_hash	company_hash	job_position	yoe	ctc_updated_year	ctc	designation	class	tier	rank
75537	9d2537610d57179230806bb77258f63c3134b8fde9aa3a...	247vx	data scientist	14.0	2015.0	2600000	2	1	1	1.0
106496	ddd9683a58865398ed934ee7faeb0825e515f2fe3cdaad...	247vx	data scientist	16.0	2019.0	2500000	2	1	1	2.0
93785	c35054c043f6a02da3e6f142fbcb095f8145eb521137ff...	247vx	data scientist	10.0	2018.0	2150000	1	1	1	3.0

Bottom 10 employees of data science in each company earning less than their peers

In [129…
```
df_final2_bot10_ds_emp_by_class = df_final2.loc[(df_final2['job_position'].isin(['data scientist', 'machine learning engineer'])) & (df_f
df_final2_bot10_ds_emp_by_class['rank'] = df_final2_bot10_ds_emp_by_class.groupby('company_hash')[['ctc']].rank(ascending=True)
df_final2_bot10_ds_emp_by_class = df_final2_bot10_ds_emp_by_class.loc[df_final2_bot10_ds_emp_by_class['rank']<=10].sort_values(by=['compa
```

In [130…
```
# Showing bot10 earning employees in DS earning less than their peers for 1 company:
df_final2_bot10_ds_emp_by_class.loc[df_final2_bot10_ds_emp_by_class['company_hash']=='247vx']
```

Out[130]:

	email_hash	company_hash	job_position	yoe	ctc_updated_year	ctc	designation	class	tier	rank
30475	3f44f5ecd242ab4739b45e8f861e5c73e3335ae012c25d...	247vx	data scientist	9.0	2019.0	1300000	2	3	2	1.0
86901	b4dcb89cf2df6baf43f009d277a3f38a191c840f17ba46...	247vx	data scientist	10.0	2019.0	1400000	3	3	2	2.0
45807	5f4b52a1c2539fe2e4b29a8470bc57dbace331b819a0af...	247vx	data scientist	22.0	2019.0	1440000	2	3	2	3.0

Top 10 employees in each company having 5/6/7 years of experience earning more than their peers

In [131…
```
df_final2_top10_emp_by_tier_yoe = df_final2.loc[(df_final2['tier']==1) & (df_final2['yoe']>=5) & (df_final2['yoe']<=7),
                                                ['email_hash', 'company_hash', 'yoe', 'ctc']].copy()
df_final2_top10_emp_by_tier_yoe['rank'] = df_final2_top10_emp_by_tier_yoe.groupby('company_hash')[['ctc']].rank(ascending=False)
df_final2_top10_emp_by_tier_yoe = df_final2_top10_emp_by_tier_yoe.loc[df_final2_top10_emp_by_tier_yoe['rank']<=10].sort_values(by=['compa
```

In [132…
```
# Showing top10 earning employees with yoe b/w [5-7] for 1 company:
df_final2_top10_emp_by_tier_yoe.loc[df_final2_top10_emp_by_tier_yoe['company_hash']=='athnowyt mvzp']
```

Out[132]:

	email_hash	company_hash	yoe	ctc	rank
37204	4dba76a8b2372102e23533ced4b205cbd4bc9316fcaebf...	athnowyt mvzp	5.0	6000000	1.0
156362	3da00100b5c5a530d8bf1f4b70ef15648dbadba677fb8a...	athnowyt mvzp	6.0	4000000	2.0
23918	31b7ca88a8b5c06857f2892e4ab089f36faf8f1cf2952b...	athnowyt mvzp	6.0	2800000	3.5
118766	f70de41b2d0ed960460421087693c8d1dc7383c603f833...	athnowyt mvzp	5.0	2800000	3.5
11214	16ea252388d98640b6f24c79b58888295cfa4ce3a2eeae...	athnowyt mvzp	5.0	2650000	6.0
82374	ab84b1e23720d03b27aebb266a2e139783e137ed0490ca...	athnowyt mvzp	6.0	2650000	6.0
150687	d6c7ee6d4803cafb7edf7c78a1e4ad46bd4503a37c7e48...	athnowyt mvzp	5.0	2650000	6.0
98596	cd686792b19fa4d61e86695237988bacfff58c1c35b478...	athnowyt mvzp	6.0	2500000	8.0
19016	274154a1ba46fea8988df17723bf26fcfcf7dbce168522...	athnowyt mvzp	5.0	2000000	9.0
9060	1262016b0b910d514f295cf67497f3bcfeec46e49fc6f0...	athnowyt mvzp	6.0	1900000	10.0

Top 10 companies (based on their CTC) : using Median CTC

In [133…
```
df_final2.groupby('company_hash')['ctc'].median().sort_values(ascending=False).iloc[:10]
```

Out[133]:
```
company_hash
pvbqhu wgrrtst ge cgwvnxgzvr nqvxzxzs     20000000.0
xzntqvwnxctmttoucn                        20000000.0
mvwytrgq                                  20000000.0
tduqtoo qgvafvjo                          20000000.0
otwr                                      20000000.0
nyt vpoyvjvuvnqv eghzavnxgz               20000000.0
hwow                                      20000000.0
tdutaxngqo                                20000000.0
bgmxuvj                                   20000000.0
wo ogen ogrhnxgzo                         20000000.0
Name: ctc, dtype: float64
```

Top 2 positions in every company (based on their CTC) : using Median CTC

In [134…
```
df_final2_median_ctc_by_comp_job = df_final2.groupby(['company_hash', 'job_position'])[['ctc']].median().reset_index().copy()
df_final2_median_ctc_by_comp_job['job_rk_within_comp'] = df_final2_median_ctc_by_comp_job.groupby('company_hash')[['ctc']].rank(ascending
df_final2_median_ctc_by_comp_job = df_final2_median_ctc_by_comp_job.loc[df_final2_median_ctc_by_comp_job['job_rk_within_comp']<=2]
```

In [135…
```
# Showing top2 job positions for 1 company:
df_final2_median_ctc_by_comp_job.loc[df_final2_median_ctc_by_comp_job['company_hash']=='zxztrtvuo']
```

Out[135]:

	company_hash	job_position	ctc	job_rk_within_comp
61432	zxztrtvuo	backend architect	3000000.0	1.0
61435	zxztrtvuo	devops engineer	2700000.0	2.0

Feature Engineering2:

Seniority within company (seniority_comp)

- What is learner's yoe in current company with respect to median yoe across all learners in same company?
- Like before, will bucketize learners into 3 buckets

In [136…
```
def seniority_in_comp_logic(yoe, yoe_grp_median, yoe_grp_25p, yoe_grp_75p):
    if yoe > 1.1*yoe_grp_median:
```

```
        return 1
    elif yoe_grp_median > 1.1*yoe:
        return 3
    return 2

    # if yoe > yoe_grp_75p:
    #     return 1
    # elif yoe < yoe_grp_25p:
    #     return 3
    # return 2

df_grp_comp_merge['seniority_comp'] = df_grp_comp_merge[['yoe', 'yoe_50%',
                                                         'yoe_25%', 'yoe_75%']].apply(lambda x: seniority_in_comp_logic(x[0],x[1],x[2],x[
df_grp_comp_merge['seniority_comp'].value_counts(normalize=True)
```

Out[136]:
```
2    0.359723
1    0.320479
3    0.319799
Name: seniority_comp, dtype: float64
```

Tier within job (tier_job) & seniority within job (seniority_job)

- Tier_job:
  - How much does leaner earn compared to other learners in same job?
- Seniority_job
  - What is learner's yoe in current job with respect to median yoe across all learners in same job?
- Like before, will bucketize learners into 3 buckets

In [137…
```
df_grp_job = df_final.groupby(['job_position'])[['ctc', 'yoe']].describe()
df_grp_job.columns = [('_').join(tup) for tup in df_grp_job.columns]
df_grp_job = df_grp_job.reset_index()
df_grp_job.head()
```

Out[137]:

	job_position	ctc_count	ctc_mean	ctc_std	ctc_min	ctc_25%	ctc_50%	ctc_75%	ctc_max	yoe_count	yoe_mean	yoe_std	yoe_min	yoe_25%
0	android engineer	5652.0	1.251997e+06	1.653556e+06	336000.0	600000.0	869999.0	1400000.0	20000000.0	5652.0	9.887473	2.897727	3.0	8.0
1	application engineer	6.0	1.312000e+06	1.607329e+06	336000.0	359500.0	750000.0	1167500.0	4500000.0	6.0	8.666667	5.085928	3.0	5.5
2	assistant professor	8.0	5.901250e+05	1.444007e+05	400000.0	450000.0	600000.0	712500.0	771000.0	8.0	13.000000	4.242641	8.0	9.5
3	assistant system engineer	21.0	4.318571e+05	1.017380e+05	336000.0	360000.0	380000.0	470000.0	600000.0	21.0	7.000000	2.428992	3.0	5.0
4	associate	8.0	7.152500e+05	4.637782e+05	336000.0	384000.0	550000.0	862500.0	1500000.0	8.0	10.125000	4.703722	3.0	7.5

In [138…
```
df_grp_job_merge = pd.merge(df_grp_comp_merge.drop(['ctc_25%','ctc_50%','ctc_75%','yoe_25%','yoe_50%','yoe_75%'], axis=1),
                            df_grp_job.iloc[:, [0, 5, 6, 7, 13, 14, 15]], on=['job_position'], how='left')
df_grp_job_merge.head()
```

Out[138]:

	email_hash	company_hash	job_position	yoe	ctc_updated_year	ctc	designation	class	tier	seniority_comp	ct
0	00003288036a44374976948c327f246fdbdf0778546904...	bxwqgogen	backend engineer	12.0	2019.0	3500000	1	1	1	1	68
1	0000aaa0e6b61f7636af1954b43d294484cd151c9b3cf6...	nqsn axsxnvr	backend engineer	11.0	2020.0	336000	2	2	2	2	68
2	000120d0c8aa304fcf12ab4b85e21feb80a342cfea03d4...	bxwqgotbx wgqugqvnxgz	fullstack engineer	20.0	2021.0	2000000	2	1	2	1	52
3	00014d71a389170e668ba96ae8e1f9d991591acc899025...	fvrbvqn rvmo	fullstack engineer	15.0	2018.0	3400000	3	1	1	1	52
4	00022dc29c7f77032275182b883d4f273ea1007aefc437...	vqtkkgopj	frontend engineer	8.0	2020.0	750000	2	2	2	2	50

In [139…
```
def tier_job_logic(ctc, ctc_grp_median, ctc_grp_25p, ctc_grp_75p):
    if ctc > 1.3*ctc_grp_median:
        return 1
    elif ctc_grp_median > 1.3*ctc:
        return 3
    return 2

    # if ctc > ctc_grp_75p:
    #     return 1
    # elif ctc < ctc_grp_25p:
    #     return 3
    # return 2

df_grp_job_merge['tier_job'] = df_grp_job_merge[['ctc', 'ctc_50%',
                                                 'ctc_25%', 'ctc_75%']].apply(lambda x: tier_job_logic(x[0],x[1],x[2],x[3]), axis=1)
df_grp_job_merge['tier_job'].value_counts(normalize=True)
```

Out[139]:
```
1    0.354065
3    0.347209
2    0.298726
Name: tier_job, dtype: float64
```

In [140…
```
def seniority_in_job_logic(ctc, ctc_grp_median, ctc_grp_25p, ctc_grp_75p):
    if ctc > 1.3*ctc_grp_median:
        return 1
    elif ctc_grp_median > 1.3*ctc:
        return 3
    return 2

    # if ctc > ctc_grp_75p:
    #     return 1
    # elif ctc < ctc_grp_25p:
    #     return 3
```

```
    # return 2

df_grp_job_merge['seniority_job'] = df_grp_job_merge[['yoe', 'yoe_50%',
                                                       'yoe_25%', 'yoe_75%']].apply(lambda x: seniority_in_job_logic(x[0],x[1],x[2],x[3]),
df_grp_job_merge['seniority_job'].value_counts(normalize=True)
```

Out[140]:
```
2    0.500075
3    0.265726
1    0.234199
Name: seniority_job, dtype: float64
```

Tier within yoe (tier_yoe)

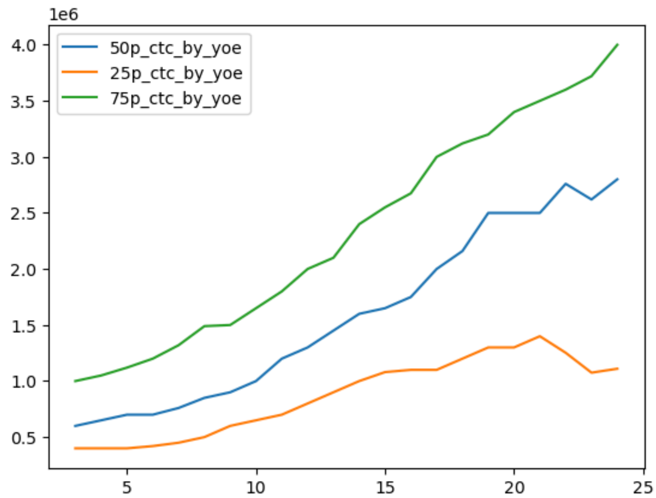
- How much does leaner earn compared to other learners with same yoe?
- Like before, will bucketize learners into 3 buckets

In [141…
```
df_grp_yoe = df_final.groupby(['yoe'])[['ctc']].describe()
df_grp_yoe.columns = [('_').join(tup) for tup in df_grp_yoe.columns]
df_grp_yoe = df_grp_yoe.reset_index()
df_grp_yoe.head()
```

Out[141]:

	yoe	ctc_count	ctc_mean	ctc_std	ctc_min	ctc_25%	ctc_50%	ctc_75%	ctc_max
0	3.0	1846.0	1.371897e+06	3.154587e+06	336000.0	400000.0	600000.0	1000000.0	20000000.0
1	4.0	7518.0	1.159139e+06	2.359417e+06	336000.0	400000.0	650000.0	1050000.0	20000000.0
2	5.0	15697.0	1.105782e+06	1.953012e+06	336000.0	400000.0	700000.0	1120000.0	20000000.0
3	6.0	16897.0	1.191728e+06	2.103050e+06	336000.0	420000.0	700000.0	1200000.0	20000000.0
4	7.0	17327.0	1.304397e+06	2.308352e+06	336000.0	450000.0	760000.0	1320000.0	20000000.0

In [142…
```
plt.plot(df_grp_yoe['yoe'].values, df_grp_yoe['ctc_50%'].values, label='50p_ctc_by_yoe')
plt.plot(df_grp_yoe['yoe'].values, df_grp_yoe['ctc_25%'].values, label='25p_ctc_by_yoe')
plt.plot(df_grp_yoe['yoe'].values, df_grp_yoe['ctc_75%'].values, label='75p_ctc_by_yoe')
plt.legend()
plt.show()
```



In [143…
```
df_grp_yoe_merge = pd.merge(df_grp_job_merge.drop(['ctc_25%','ctc_50%','ctc_75%','yoe_25%','yoe_50%','yoe_75%'], axis=1),
                            df_grp_yoe.iloc[:, [0, 5, 6, 7]], on=['yoe'], how='left')
df_grp_yoe_merge.head()
```

Out[143]:

	email_hash	company_hash	job_position	yoe	ctc_updated_year	ctc	designation	class	tier	seniority_comp	tie
0	00003288036a44374976948c327f246fdbdf0778546904...	bxwqgogen	backend engineer	12.0	2019.0	3500000	1	1	1	1	
1	0000aaa0e6b61f7636af1954b43d294484cd151c9b3cf6...	nqsn axsxnvr	backend engineer	11.0	2020.0	336000	2	2	2	2	
2	000120d0c8aa304fcf12ab4b85e21feb80a342cfea03d4...	bxwqgotbx wgqugqvnxgz	fullstack engineer	20.0	2021.0	2000000	2	1	2	1	
3	00014d71a389170e668ba96ae8e1f9d991591acc899025...	fvrbvqn rvmo	fullstack engineer	15.0	2018.0	3400000	3	1	1	1	
4	00022dc29c7f77032275182b883d4f273ea1007aefc437...	vqtkkgopj	frontend engineer	8.0	2020.0	750000	2	2	2	2	

In [144…
```
def tier_yoe_logic(ctc, ctc_grp_median, ctc_grp_25p, ctc_grp_75p):
    if ctc > 1.3*ctc_grp_median:
        return 1
    elif ctc_grp_median > 1.3*ctc:
        return 3
    return 2

    # if ctc > ctc_grp_75p:
    #     return 1
    # elif ctc < ctc_grp_25p:
    #     return 3
    # return 2

df_grp_yoe_merge['tier_yoe'] = df_grp_yoe_merge[['ctc', 'ctc_50%',
                                                 'ctc_25%', 'ctc_75%']].apply(lambda x: tier_yoe_logic(x[0],x[1],x[2],x[3]), axis=1)
df_grp_yoe_merge['tier_yoe'].value_counts(normalize=True)
```

Out[144]:
```
3    0.354982
1    0.350054
2    0.294965
Name: tier_yoe, dtype: float64
```

In [145…
```
df_final3 = df_grp_yoe_merge.copy()
df_final3.drop(['ctc_25%','ctc_50%','ctc_75%'], axis=1, inplace=True)
df_final3.head()
```

Out[145]:

	email_hash	company_hash	job_position	yoe	ctc_updated_year	ctc	designation	class	tier	seniority_comp	tie
0	00003288036a44374976948c327f246fdbdf0778546904...	bxwqgogen	backend engineer	12.0	2019.0	3500000	1	1	1	1	
1	0000aaa0e6b61f7636af1954b43d294484cd151c9b3cf6...	nqsn axsxnvr	backend engineer	11.0	2020.0	336000	2	2	2	2	
2	000120d0c8aa304fcf12ab4b85e21feb80a342cfea03d4...	bxwqgotbx wgqugqvnxgz	fullstack engineer	20.0	2021.0	2000000	2	1	2	1	
3	00014d71a389170e668ba96ae8e1f9d991591acc899025...	fvrbvqn rvmo	fullstack engineer	15.0	2018.0	3400000	3	1	1	1	
4	00022dc29c7f77032275182b883d4f273ea1007aefc437...	vqtkkgopj	frontend engineer	8.0	2020.0	750000	2	2	2	2	

Job Band

- A DS role in a service based company will pay quite differently for the same DS role in a top-product company
- Similarly DS role in a product company will be pying differently from a Test Engineer in the same product company
- Here we want to essentially capture the job_band for each learner
- Job_band is found out as follows:
  - We form groups depending on the company and job role
  - For each group we find the median ctc offered
  - We split all the groups into 4 bands (as per the quartiles)

In [146…
```
df_grp_comp_job_band = df_grp_comp_job[['company_hash', 'job_position', 'ctc_50%']].copy()
job_band_min = df_grp_comp_job_band['ctc_50%'].describe()['min']
job_band_max = df_grp_comp_job_band['ctc_50%'].describe()['max']
job_band_25p = df_grp_comp_job_band['ctc_50%'].describe()['25%']
job_band_50p = df_grp_comp_job_band['ctc_50%'].describe()['50%']
job_band_75p = df_grp_comp_job_band['ctc_50%'].describe()['75%']
print(job_band_min, job_band_25p, job_band_50p, job_band_75p, job_band_max)
```

```
336000.0 520000.0 900000.0 1535000.0 20000000.0
```

In [147…
```
df_grp_comp_job_band['ctc_50%'].describe()
```

Out[147]:
```
count    6.145500e+04
mean     1.482477e+06
std      2.385213e+06
min      3.360000e+05
25%      5.200000e+05
50%      9.000000e+05
75%      1.535000e+06
max      2.000000e+07
Name: ctc_50%, dtype: float64
```

In [148…
```
job_band_bins = [job_band_min-100, job_band_25p, job_band_50p, job_band_75p, job_band_max+100]
job_band_labels=[4, 3, 2, 1]
df_grp_comp_job_band['job_band'] = pd.cut(df_grp_comp_job_band['ctc_50%'], bins=job_band_bins, labels=job_band_labels)
# df_grp_comp_job_band['job_band'].value_counts()
df_grp_comp_job_band.head()
```

Out[148]:

	company_hash	job_position	ctc_50%	job_band
0	0	other	336000.0	4
1	0000	other	336000.0	4
2	01 ojztqsj	android engineer	336000.0	4
3	01 ojztqsj	frontend engineer	830000.0	3
4	05mz exzytvrny uqxcvnt rxbxnta	backend engineer	1100000.0	2

In [149…
```
df_final4 = pd.merge(df_final3, df_grp_comp_job_band.iloc[:, [0, 1, 3]], on=['company_hash', 'job_position'], how='left')
df_final4.head()
```

Out[149]:

	email_hash	company_hash	job_position	yoe	ctc_updated_year	ctc	designation	class	tier	seniority_comp	tie
0	00003288036a44374976948c327f246fdbdf0778546904...	bxwqgogen	backend engineer	12.0	2019.0	3500000	1	1	1	1	
1	0000aaa0e6b61f7636af1954b43d294484cd151c9b3cf6...	nqsn axsxnvr	backend engineer	11.0	2020.0	336000	2	2	2	2	
2	000120d0c8aa304fcf12ab4b85e21feb80a342cfea03d4...	bxwqgotbx wgqugqvnxgz	fullstack engineer	20.0	2021.0	2000000	2	1	2	1	
3	00014d71a389170e668ba96ae8e1f9d991591acc899025...	fvrbvqn rvmo	fullstack engineer	15.0	2018.0	3400000	3	1	1	1	
4	00022dc29c7f77032275182b883d4f273ea1007aefc437...	vqtkkgopj	frontend engineer	8.0	2020.0	750000	2	2	2	2	

In [152…
```
# Saving data (cleaned + feature_engg done, different versions)
# df_final2.to_csv('./data/df_final2.csv')
# df_final3.to_csv('./data/df_final3.csv')
# df_final4.to_csv('./data/df_final4.csv')
```

In [153…
```
# Loading data (cleaned + feature_engg done, different versions)
# df_final2 = pd.read_csv('./data/df_final2.csv')
```

```
# df_final3 = pd.read_csv('./data/df_final3.csv')
# df_final4 = pd.read_csv('./data/df_final4.csv')
```

KMeans:

In [154…
```
pipe_stdscl = Pipeline([('std_scaler', StandardScaler())])
```

In [155…
```
# Function computes dunn_index
def compute_dunn_index(X, label, centroids):

    # Calculates pairwise distance b/w cluster centroids
    inter_cluster_arr = pdist(centroids)

    # Below array will store the maximum intra_cluster distance fr each cluster
    intra_cluster_arr = np.zeros(len(centroids))
    for i in range(len(centroids)):
        cluster_pts = X[label==i]
        if len(cluster_pts)>1:
            intra_cluster_arr[i] = np.max(pdist(cluster_pts))



    wc_inter_cluster_dis = np.min(inter_cluster_arr)
    wc_intra_cluster_dis = np.max(intra_cluster_arr)
    dunn_index = wc_inter_cluster_dis/wc_intra_cluster_dis
    return np.round(dunn_index, 4)
```

KMeans: Trial1

- ctc_log can be removed since it seems like a redundant variable (we can infer about ctc by looking at other variables)
- In next trail (Trail2), we add some extra features while performing clustering for better interpretation of results

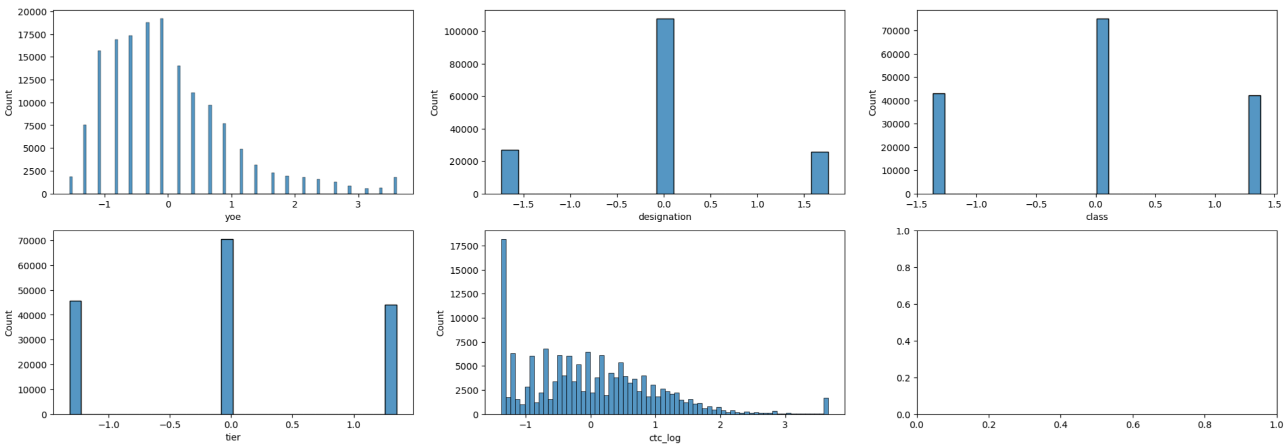
In [156…
```
df_final_ml2 = df_final2.copy()

df_final_ml2['ctc_log'] = np.log(df_final_ml2['ctc'])
df_final_ml2.drop(['email_hash', 'company_hash', 'job_position', 'ctc_updated_year', 'ctc'], axis=1, inplace=True)

df_final_ml2.head()
```

Out[156]:

	yoe	designation	class	tier	ctc_log
0	12.0	1	1	1	15.068274
1	11.0	2	2	2	12.724866
2	20.0	2	1	2	14.508658
3	15.0	3	1	1	15.039286
4	8.0	2	2	2	13.527828

In [157…
```
X_scaled2 = pipe_stdscl.fit_transform(df_final_ml2)
```

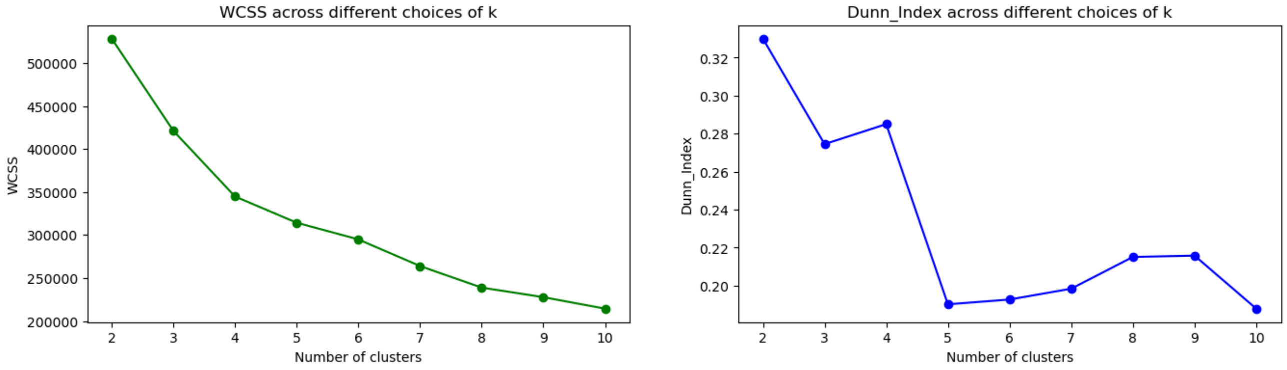
In [158…
```
df_final_ml_scl2 = pd.DataFrame(X_scaled2, columns=df_final_ml2.columns)

fig, axs = plt.subplots(nrows=2, ncols=3, figsize=(24, 8))

i = 0
for col in df_final_ml_scl2.columns[:3]:
    if col=='ctc_log':
        sns.histplot(df_final_ml_scl2[col], ax=axs[0][i], bins=70)
    else:
        sns.histplot(df_final_ml_scl2[col], ax=axs[0][i])
    i += 1

i = 0
for col in df_final_ml_scl2.columns[3:]:
    if col=='ctc_log':
        sns.histplot(df_final_ml_scl2[col], ax=axs[1][i], bins=70)
    else:
        sns.histplot(df_final_ml_scl2[col], ax=axs[1][i])
    i += 1
```



In [159…
```
wcss2 = {}
dn_idx2 = {}
for k in range(2, 11):
    kmeans = MiniBatchKMeans(n_clusters=k, init='k-means++', random_state=42, n_init='auto')
    kmeans.fit(X_scaled2)
```

```
    wcss2[k] = kmeans.inertia_
    dn_idx2[k]=compute_dunn_index(X_scaled2, kmeans.labels_, kmeans.cluster_centers_)
```

In [160…
```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(16,4))

axs[0].plot(list(wcss2.keys()), list(wcss2.values()), c='g', marker='o', label='wcss')
axs[0].set_xlabel("Number of clusters")
axs[0].set_ylabel("WCSS")
axs[0].set_title("WCSS across different choices of k")

axs[1].plot(list(dn_idx2.keys()), list(dn_idx2.values()), c='b', marker='o', label='wcss')
axs[1].set_xlabel("Number of clusters")
axs[1].set_ylabel("Dunn_Index")
axs[1].set_title("Dunn_Index across different choices of k")
plt.show()
```



In [161…
```
kmeans2 = KMeans(n_clusters=4, init='k-means++', random_state=42, n_init='auto')
kmeans2.fit(X_scaled2)
```

Out[161]:
```
▾ KMeans
KMeans(n_clusters=4, n_init='auto', random_state=42)
```

In [162…
```
pd.Series(kmeans2.labels_).value_counts(normalize=True)
```

Out[162]:
```
1    0.409746
2    0.216695
0    0.193757
3    0.179802
dtype: float64
```

In [163…
```
df_final_ml_scl2['labels'] = kmeans2.labels_
df_final_ml_scl2.head()
```

Out[163]:

	yoe	designation	class	tier	ctc_log	labels
0	0.655225	-1.736119	-1.363600	-1.322130	1.515773	0
1	0.409664	0.012655	0.008637	0.014551	-1.374357	1
2	2.619718	0.012655	-1.363600	0.014551	0.825597	3
3	1.391910	1.761428	-1.363600	-1.322130	1.480022	3
4	-0.327021	0.012655	0.008637	0.014551	-0.384062	1

In [164…
```
polar2 = df_final_ml_scl2.groupby('labels').mean()
polar2 = polar2.reset_index()
polar2 = pd.melt(polar2, id_vars=['labels'])
polar2.head()
```

Out[164]:

	labels	variable	value
0	0	yoe	-0.271773
1	1	yoe	-0.317424
2	2	yoe	-0.357814
3	3	yoe	1.447467
4	0	designation	-1.263680

In [165…
```
fig = px.line_polar(polar2, r="value", theta="variable", color="labels", line_close=True,height=700,width=800)
fig.show()
```

KMeans: Trial2

- Experiemnts showed that yoe, seniority_comp, senirity_yoe tend to give the same insights, hence we keep only 1 feature among those
- Designation feature does not seem to be well seperated amongst the different clusters formed, hence dropping it.
- In next trail (Trail3) we add job_band to better infer the results of clustering

In [166…

```
df_final_ml3 = df_final3.copy()

df_final_ml3['ctc_log'] = np.log(df_final_ml3['ctc'])
df_final_ml3.drop(['email_hash', 'company_hash', 'job_position', 'ctc_updated_year', 'ctc'], axis=1, inplace=True)
df_final_ml3.drop(['designation', 'seniority_comp', 'seniority_job', 'ctc_log'], axis=1, inplace=True)

df_final_ml3.head()
```

Out[166]:

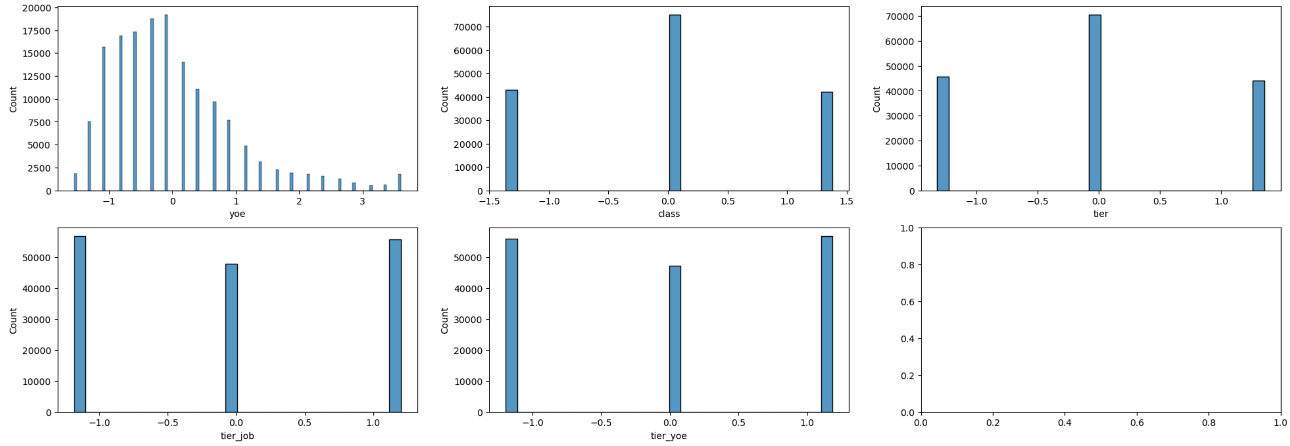
	yoe	class	tier	tier_job	tier_yoe
0	12.0	1	1	1	1
1	11.0	2	2	3	3
2	20.0	1	2	1	2
3	15.0	1	1	1	1
4	8.0	2	2	2	2

In [167…

```
X_scaled3 = pipe_stdscl.fit_transform(df_final_ml3)
```

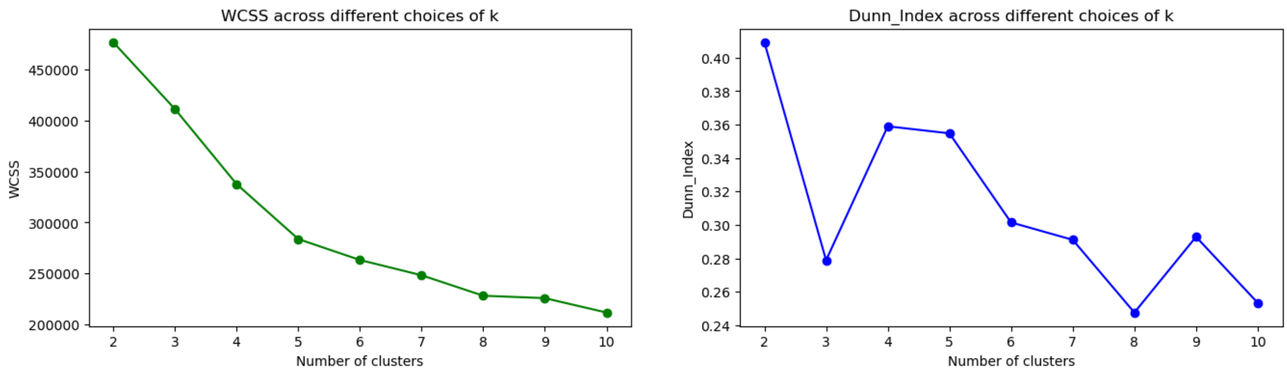
In [168…

```
df_final_ml_scl3 = pd.DataFrame(X_scaled3, columns=df_final_ml3.columns)

fig, axs = plt.subplots(nrows=2, ncols=3, figsize=(24, 8))

i = 0
for col in df_final_ml_scl3.columns[:3]:
    if col=='ctc_log':
        sns.histplot(df_final_ml_scl3[col], ax=axs[0][i], bins=70)
    else:
        sns.histplot(df_final_ml_scl3[col], ax=axs[0][i])
    i += 1

i = 0
for col in df_final_ml_scl3.columns[3:]:
    if col=='ctc_log':
        sns.histplot(df_final_ml_scl3[col], ax=axs[1][i], bins=70)
    else:
        sns.histplot(df_final_ml_scl3[col], ax=axs[1][i])
    i += 1
```



In [169…
```python
wcss3 = {}
dn_idx3 = {}
for k in range(2, 11):
    kmeans = MiniBatchKMeans(n_clusters=k, init='k-means++', random_state=42, n_init='auto')
    kmeans.fit(X_scaled3)
    wcss3[k] = kmeans.inertia_
    dn_idx3[k]=compute_dunn_index(X_scaled3, kmeans.labels_, kmeans.cluster_centers_)
```

In [170…
```python
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(16,4))

axs[0].plot(list(wcss3.keys()), list(wcss3.values()), c='g', marker='o', label='wcss')
axs[0].set_xlabel("Number of clusters")
axs[0].set_ylabel("WCSS")
axs[0].set_title("WCSS across different choices of k")

axs[1].plot(list(dn_idx3.keys()), list(dn_idx3.values()), c='b', marker='o', label='wcss')
axs[1].set_xlabel("Number of clusters")
axs[1].set_ylabel("Dunn_Index")
axs[1].set_title("Dunn_Index across different choices of k")
plt.show()
```



In [171…
```python
kmeans3 = KMeans(n_clusters=5, init='k-means++', random_state=42, n_init='auto')
kmeans3.fit(X_scaled3)
```

Out[171]:
```
▾ KMeans
KMeans(n_clusters=5, n_init='auto', random_state=42)
```

In [172…
```python
pd.Series(kmeans3.labels_).value_counts(normalize=True)
```

Out[172]:
```
1    0.237723
3    0.234779
0    0.221698
4    0.201342
2    0.104458
dtype: float64
```

In [173…
```python
df_final_ml_scl3['labels'] = kmeans3.labels_
df_final_ml_scl3.head()
```

Out[173]:

	yoe	class	tier	tier_job	tier_yoe	labels
0	0.655225	-1.363600	-1.322130	-1.185996	-1.196843	0
1	0.409664	0.008637	0.014551	1.202370	1.185104	4
2	2.619718	-1.363600	0.014551	-1.185996	-0.005869	2
3	1.391910	-1.363600	-1.322130	-1.185996	-1.196843	0
4	-0.327021	0.008637	0.014551	0.008187	-0.005869	3

In [174…
```python
polar3 = df_final_ml_scl3.groupby('labels').mean()
polar3 = polar3.reset_index()
polar3 = pd.melt(polar3, id_vars=['labels'])
polar3.head()
```

Out[174]:

	labels	variable	value
0	0	yoe	-0.087484
1	1	yoe	-0.377946
2	2	yoe	2.055593
3	3	yoe	-0.279606
4	4	yoe	-0.197849

In [175…

```
fig = px.line_polar(polar3, r="value", theta="variable", color="labels", line_close=True,height=700,width=800)
fig.show()
```

KMeans: Trial3

- We achieve results which are interpretable and are making intuitive sense with the below features
- We aimed for 5 clusters to keep things simple and to make it easy for result interpretation
- With 5 clusters, we achieved relatively uniform split amongst different clusters without too much skew in any 1 of them

In [176…

```
df_final_ml4 = df_final4.copy()

df_final_ml4['ctc_log'] = np.log(df_final_ml4['ctc'])
df_final_ml4.drop(['email_hash', 'company_hash', 'job_position', 'ctc_updated_year', 'ctc'], axis=1, inplace=True)
df_final_ml4.drop(['designation', 'seniority_comp', 'seniority_job', 'ctc_log'], axis=1, inplace=True)

df_final_ml4.head()
```

Out[176]:

	yoe	class	tier	tier_job	tier_yoe	job_band
0	12.0	1	1	1	1	1
1	11.0	2	2	3	3	4
2	20.0	1	2	1	2	2
3	15.0	1	1	1	1	1
4	8.0	2	2	2	2	3

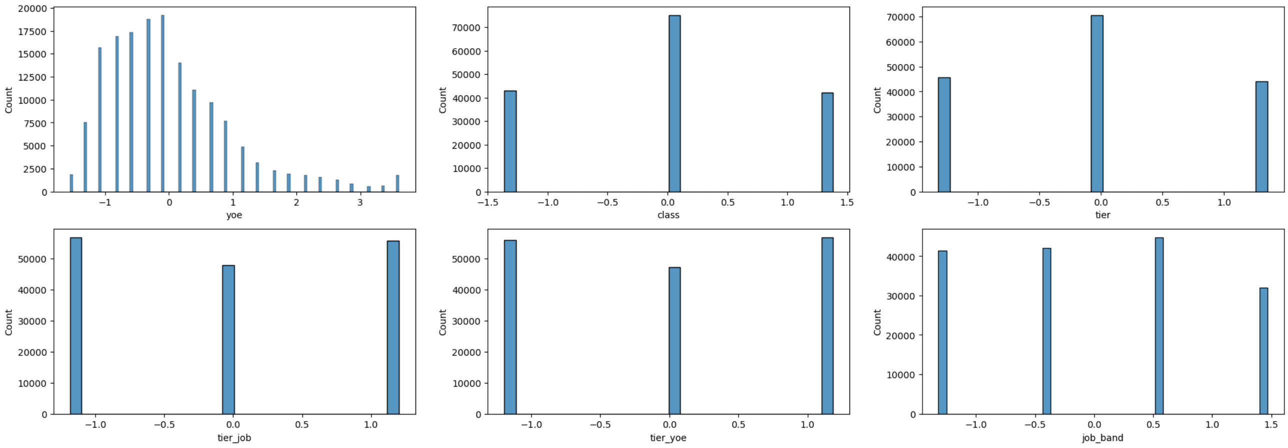
In [177…

```
X_scaled4 = pipe_stdscl.fit_transform(df_final_ml4)
```

In [178…

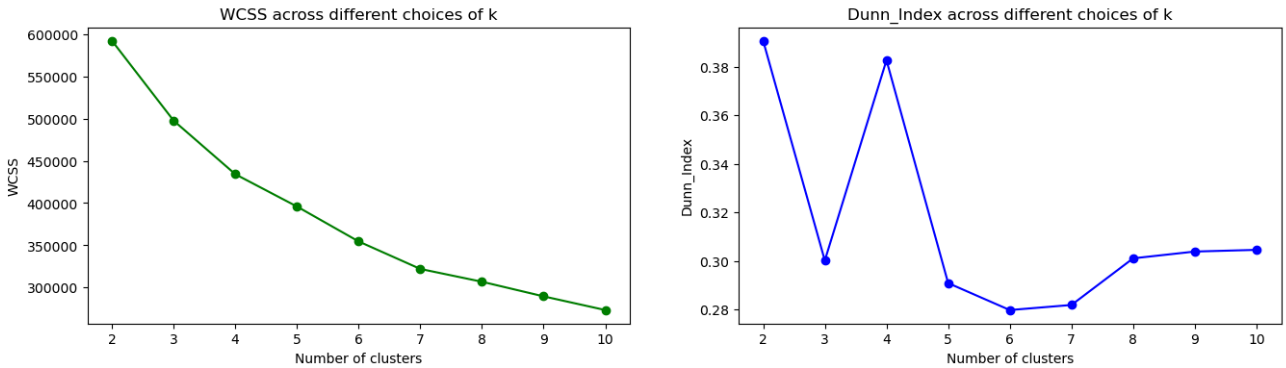
```
df_final_ml_scl4 = pd.DataFrame(X_scaled4, columns=df_final_ml4.columns)

fig, axs = plt.subplots(nrows=2, ncols=3, figsize=(24, 8))

i = 0
for col in df_final_ml_scl4.columns[:3]:
    if col=='ctc_log':
        sns.histplot(df_final_ml_scl4[col], ax=axs[0][i], bins=70)
    else:
        sns.histplot(df_final_ml_scl4[col], ax=axs[0][i])
    i += 1

i = 0
for col in df_final_ml_scl4.columns[3:]:
    if col=='ctc_log':
        sns.histplot(df_final_ml_scl4[col], ax=axs[1][i], bins=70)
    else:
```

```
        sns.histplot(df_final_ml_scl4[col], ax=axs[1][i])
    i += 1
```



In [179…
```
wcss4 = {}
dn_idx4 = {}
for k in range(2, 11):
    kmeans = MiniBatchKMeans(n_clusters=k, init='k-means++', random_state=42, n_init='auto')
    kmeans.fit(X_scaled4)
    wcss4[k] = kmeans.inertia_
    dn_idx4[k]=compute_dunn_index(X_scaled4, kmeans.labels_, kmeans.cluster_centers_)
```

In [180…
```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(16,4))

axs[0].plot(list(wcss4.keys()), list(wcss4.values()), c='g', marker='o', label='wcss')
axs[0].set_xlabel("Number of clusters")
axs[0].set_ylabel("WCSS")
axs[0].set_title("WCSS across different choices of k")

axs[1].plot(list(dn_idx4.keys()), list(dn_idx4.values()), c='b', marker='o', label='wcss')
axs[1].set_xlabel("Number of clusters")
axs[1].set_ylabel("Dunn_Index")
axs[1].set_title("Dunn_Index across different choices of k")
plt.show()
```



In [ ]:

In [181…
```
kmeans4 = KMeans(n_clusters=5, init='k-means++', random_state=42, n_init='auto')
kmeans4.fit(X_scaled4)
```

Out[181]:
```
KMeans
KMeans(n_clusters=5, n_init='auto', random_state=42)
```

In [182…
```
pd.Series(kmeans4.labels_).value_counts(normalize=True)
```

Out[182]:
```
0    0.258297
4    0.248584
3    0.207082
1    0.165479
2    0.120558
dtype: float64
```

In [183…
```
df_final_ml_scl4['labels'] = kmeans4.labels_
df_final_ml_scl4.head()
```

Out[183]:

	yoe	class	tier	tier_job	tier_yoe	job_band	labels
0	0.655225	-1.363600	-1.322130	-1.185996	-1.196843	-1.318077	0
1	0.409664	0.008637	0.014551	1.202370	1.185104	1.466528	4
2	2.619718	-1.363600	0.014551	-1.185996	-0.005869	-0.389875	2
3	1.391910	-1.363600	-1.322130	-1.185996	-1.196843	-1.318077	2
4	-0.327021	0.008637	0.014551	0.008187	-0.005869	0.538326	4

In [184…
```
polar4 = df_final_ml_scl4.groupby('labels').mean()
polar4 = polar4.reset_index()
polar4 = pd.melt(polar4, id_vars=['labels'])
polar4.head()
```

Out[184]:

	labels	variable	value
0	0	yoe	-0.160437
1	1	yoe	-0.270192
2	2	yoe	1.885015
3	3	yoe	-0.391303
4	4	yoe	-0.241654

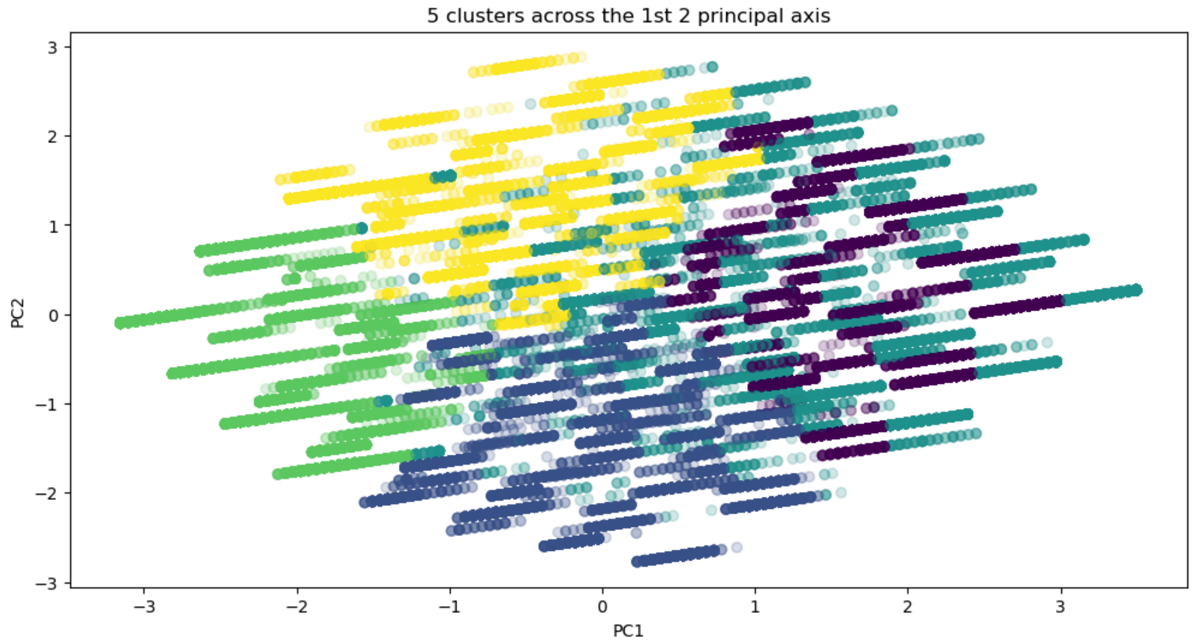
In [185…

```
fig = px.line_polar(polar4, r="value", theta="variable", color="labels", line_close=True,height=700,width=800)
fig.show()
```

In [186…

```
pca = PCA(n_components=2)
pca.fit(X_scaled4)
print(f'Explained Variance Ratio: {pca.explained_variance_ratio_}')

X_scaled4_pca2 = pca.transform(X_scaled4)
X_scaled4_pca2


df_scaled4_pca2 = pd.DataFrame(X_scaled4_pca2, columns=['pc1', 'pc2'])
df_scaled4_pca2['labels'] = kmeans4.labels_
df_scaled4_pca2.head()


plt.figure(figsize=(12,6))
plt.scatter(df_scaled4_pca2['pc1'].values, df_scaled4_pca2['pc2'].values, alpha=0.2, c=df_scaled4_pca2['labels'])
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.title('5 clusters across the 1st 2 principal axis')
plt.show()
```

```
Explained Variance Ratio: [0.50348877 0.21423317]
```



In [188…
```
polar4_cp = polar4.copy()
polar4_cp['rank'] = polar4_cp.groupby(['variable'])['value'].rank()
polar4_cp = pd.pivot(polar4_cp.iloc[:, [0, 1, 3]], index='labels', columns='variable')
polar4_cp.columns = [('_').join(tup) for tup in polar4_cp.columns]
learner_persona = {0:'champions', 1:'stable', 2:'pre-champions', 3:'weaklings', 4:'aspirers'}
polar4_cp['learner_persona'] = learner_persona
polar4_cp
```

Out[188]:

labels	rank_class	rank_job_band	rank_tier	rank_tier_job	rank_tier_yoe	rank_yoe	learner_persona
0	1.0	3.0	1.0	1.0	1.0	4.0	champions
1	4.0	2.0	4.0	3.0	2.0	2.0	stable
2	2.0	1.0	2.0	2.0	3.0	5.0	pre-champions
3	5.0	4.0	5.0	5.0	5.0	1.0	weaklings
4	3.0	5.0	3.0	4.0	4.0	3.0	aspirers

BEST companies, job_positions and jobs (company+job_position combinations):

- We zoom into the learners who are identified as champions
- After isolating the champions, we can identify the best companies and job positions to work for from the Scaler database

In [189…
```
df_final4['labels'] = kmeans4.labels_
df_final4_champions = df_final4.loc[df_final4['labels']==0, ['email_hash', 'company_hash', 'job_position', 'yoe', 'ctc', 'labels']].copy(
df_final4_champions.head()
```

Out[189]:

	email_hash	company_hash	job_position	yoe	ctc	labels
0	00003288036a44374976948c327f246fdbdf0778546904...	bxwqgogen	backend engineer	12.0	3500000	0
6	000411b5d6d4e1c113bf83f1eebc0b835d77cc45bded1d...	gutzcgj	backend engineer	7.0	3500000	0
7	000411b5d6d4e1c113bf83f1eebc0b835d77cc45bded1d...	sgowvrt sqghu xzw	frontend engineer	7.0	1600000	0
11	000467b0e6a1fcc95b882052b63d0d783196327087f76b...	thrtq ojontbo	backend engineer	5.0	3600000	0
20	000c89400932b5cc8a3d6c5b6a854c844f0f64a53d7b8a...	evwtmggp	fullstack engineer	9.0	2100000	0

In [190…
```
# Top20 most frequent companies where champions work at:
df_final4_champions['company_hash'].value_counts().iloc[:20]
```

Out[190]:
```
vbvkgz                                   1235
bxwqgogen                                 805
zvz                                       605
gqvwrt                                    586
zgn vuurxwvmrt vwwghzn                    527
vagmt                                     472
nvnv wgzohrnvzwj otqcxwto                 471
eqtoytq                                   431
zgn vuurxwvmrt                            427
uvjnb                                     414
erxupvqn                                  408
xzegojo                                   360
vwwtznhqt                                 349
sgrabvz ovwyo                             330
ovbohzs qa xzonxnhnt xzaxv  mvzsvrgqt     329
lubgqsvz wyvot  wg                        307
fvrbvqn rvmo                              289
wgszxkvzn                                 271
wxowg                                     255
fxuqg rxbxnta                             245
Name: company_hash, dtype: int64
```

In [191…
```
# Top20 most frequent job_positions where champions work at:
df_final4_champions['job_position'].value_counts().iloc[:20]
```

Out[191]:
```
backend engineer          14615
fullstack engineer         7911
other                      4446
frontend engineer          2644
data scientist             1892
android engineer           1240
engineering leadership     1027
qa engineer                 950
engineering intern          922
devops engineer             910
sdet                        810
support engineer            799
data analyst                702
ios engineer                599
research engineer           451
product manager             388
product designer            207
backend architect           150
database administrator      119
co-founder                  116
Name: job_position, dtype: int64
```

In [192…
```
# Top20 most frequent (company+job_positions) combinations where champions work at:
df_final4_champions.groupby(['company_hash', 'job_position'])['email_hash'].count().sort_values(ascending=False).iloc[:20]
```

Out[192]:
```
company_hash                        job_position
vbvkgz                              backend engineer      637
bxwqgogen                           backend engineer      406
gqvwrt                              backend engineer      285
erxupvqn                            backend engineer      282
vbvkgz                              fullstack engineer    268
eqtoytq                             other                 253
vagmt                               backend engineer      233
uvjnb                               backend engineer      228
bxwqgogen                           fullstack engineer    210
zvz                                 backend engineer      175
fvrbvqn rvmo                        backend engineer      168
sgrabvz ovwyo                       backend engineer      165
gqvwrt                              fullstack engineer    159
ovbohzs qa xzonxnhnt xzaxv  mvzsvrgqt backend engineer    150
zvz                                 fullstack engineer    144
lubgqsvz wyvot  wg                  backend engineer      142
zgn vuurxwvmrt vwwghzn              backend engineer      132
zgn vuurxwvmrt                      backend engineer      120
bgqsvz onvzrtj                      backend engineer      115
wxowg                               backend engineer      113
Name: email_hash, dtype: int64
```

Hierarchical Clustering: Experimental

- Due to compute constraints, we take a random sample from the dataset (25%) and perform hierarchical clustering on it
- From the below dendrogram, the optimal #clusters seems to be anywhere between 3-6

In [193…
```
df_final_ml5 = df_final4.copy()
df_final_ml5.drop(['email_hash', 'company_hash', 'job_position', 'ctc_updated_year', 'ctc',
                   'designation', 'seniority_comp', 'seniority_job', 'labels'], axis=1, inplace=True)
df_final_ml5.head()
```

Out[193]:

	yoe	class	tier	tier_job	tier_yoe	job_band
0	12.0	1	1	1	1	1
1	11.0	2	2	3	3	4
2	20.0	1	2	1	2	2
3	15.0	1	1	1	1	1
4	8.0	2	2	2	2	3

In [194…
```
retain_sample_pct = 0.25
rows_to_retain = round(retain_sample_pct*df_final_ml5.shape[0])
# rows_to_retain
df_final_ml5_sample = df_final_ml5.sample(rows_to_retain).copy()
df_final_ml5_sample.shape
```

Out[194]:
```
(40076, 6)
```

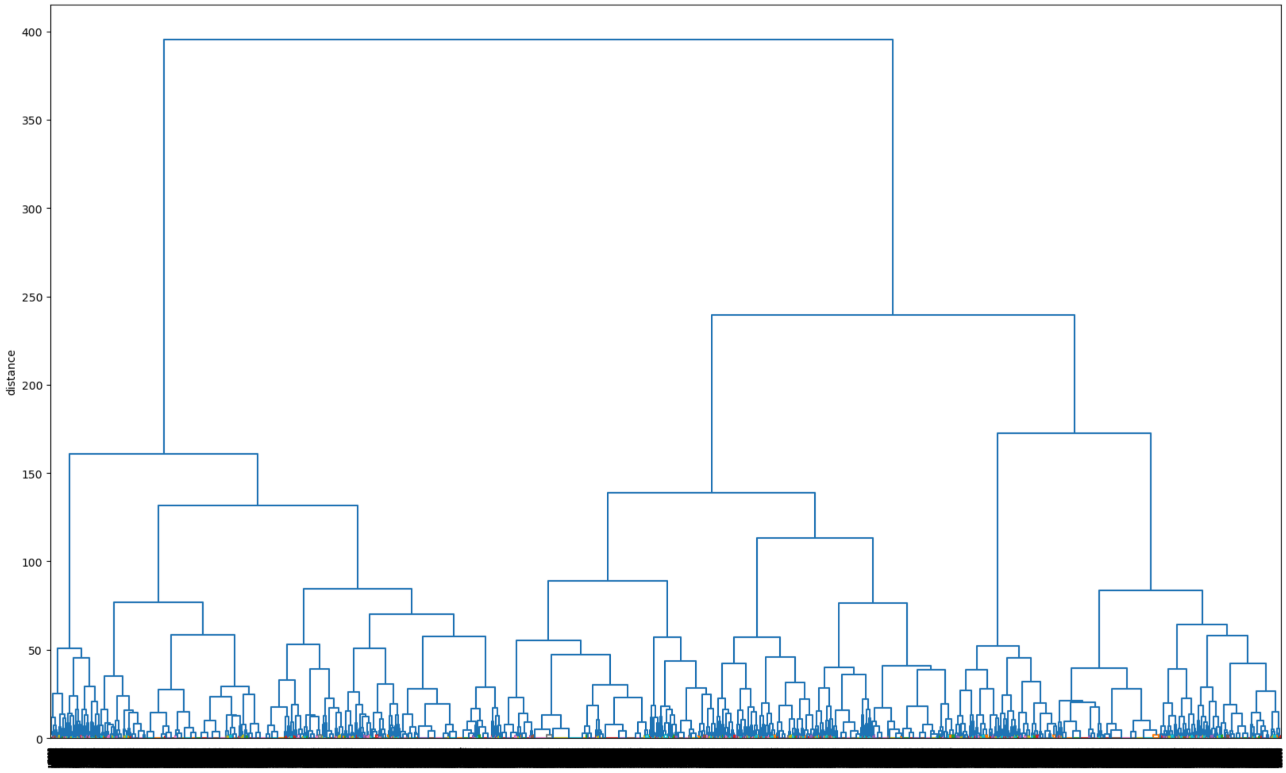
In [195…
```
X_scaled5 = pipe_stdscl.fit_transform(df_final_ml5_sample)
X_scaled5.shape
```

Out[195]:
```
(40076, 6)
```

In [196…
```
Z1 = sch.linkage(X_scaled5, method='ward') #linkage = ward
Z1.shape
```

Out[196]:
```
(40075, 4)
```

In [197…
```
fig, ax = plt.subplots(figsize=(20, 12))
sch.dendrogram(Z1, labels=df_final_ml5_sample.index, ax=ax, color_threshold=2)
plt.xticks(rotation=90)
ax.set_ylabel('distance')
plt.show()
```



Insights & Recommendations:

Below are the different learner personas identified:

1. CHAMPIONS: (Cluster0): 26% of learners:

- Are learners who are mostly working in jobs in the top job_band.
  - Top job_bands are those (company,job) combinations which pay better across the entire population
- High earners compared to people:
  - in same company (tier)
  - with same job position (tier_job)
  - with same years of experience in current company and job (tier_yoe)
  - in same company & same job position (class)

2. PRE-CHAMPIONS: (Cluster2): 12% of learners:

- Are learners who are mostly working in jobs in the top job_band.
  - Top job_bands are those (company,job) combinations which pay better across the entire population
- They are moderately high earners compared to people:
  - in the same company (tier)
  - with same job position (tier_job)
  - in same company & same job position (class)
- The are average earners compared to people:
  - with same years of experience in current company and job (tier_yoe)
- Also this group mostly consists of learners with high years of experience in their current company and job, significantly greater than the rest of the population.

3. STABLE: (Cluster1): 16% of learners:

- Are learners who are mostly working in jobs in the top job_band.
  - Top job_bands are those (company,job) combinations which pay better across the entire population
- They are moderately high earners compared to people:
  - with same job position (tier_job)
  - with same years of experience in current company and job (tier_yoe)
- The are average to moderately low earners compared to people:
  - in the same company (tier)
  - in same company & same job position (class)
- These learners are mostly working in high paying companies (like FAANG) where the ctc offered for any job position is industry leading.

4. ASPIRERS: (Cluster4): 25% of learners:

- Are learners who are mostly working in jobs in the low job_band.
  - Low job_bands are those (company,job) combinations which pay lesser across the entire population
- They are low earners compared to people
  - with same job position (tier_job)
  - with same years of experience in current company and job (tier_yoe)
- The are moderately high to average earners compared to people:
  - in the same company (tier)
  - in same company & same job position (class)
- These learners are above-average earners within the same tier/class, but low earners within same tier_job/tier_yoe. These learners can benefit the most by changing their companies to other companies which pay better for same job positions.

5. WEAKLINGS: (Cluster3): 21% of learners:

- Are learners who are mostly working in jobs in the low job_band.
  - Low job_bands are those (company,job) combinations which pay lesser across the entire population
- Low earners compared to people:
  - in same company (tier)
  - with same job position (tier_job)
  - with same years of experience in current company and job (tier_yoe)
  - in same company & same job position (class)

We have also identified the most frequent job_positions, companies where our champion learners work at.

- Top5 most frequent companies of champions: vbvkgz, bxwqgogen, zvz, gqvwrt, zgn vuurxwvmrt vwwghzn
- Top5 most frequent job_positions of champions: backend engineer, fullstack engineer, frontend engineer, data scientist, android engineer

Recommendations:

1. Learners with champion/pre-champion personas can be requested to do promotional work for Scaler (to generate leads). They can also be requested to share their insights to help other learners.

2. Learners with stable persona can be pushed to take the next big step in their career. These learners can be allocated mentors who are in senior positions who can guide them with strategies to grow in the corporate ladder.

3. Learners with aspirer persona can be provided with special bootcamps aimed specifically to improve interview performance. These learners have demonstrated high quality by being above average earners in their current organization but their current company pays lesser than the industry for their current job role. Hence making a switch seems to be the obvious decision for them.

4. Leaners with weakling persona can be explored further to understand what is stopping them from improving their carrer outcomes. Accordingly tailored pathways can be assigned to them for better results. Mentors can be allocated, remedial sessions can be conducted depending on need of the hour!

5. Since Dream jobs have been identified, Scaler placement team can work towards bringing in more of similar roles and also making sure candidates are prepared well enough to tackle interviews of dream jobs by doing the necessary market research.

In [ ]:

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In [ ]: