Business 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. Ideally, these clusters should have similar characteristics.

Data Dictionary:

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

```
# Importing required libraries -
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Loading data into Dataframe:

```
!wget https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/002/856/original/scaler_clustering.csv -O scaler_clustering.csv
```

```
--2023-10-27 16:47:35--  https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/002/856/original/scaler_clustering.csv
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)... 13.35.37.159, 13.35.37.7, 13.35.37.31, ...
Connecting to d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)|13.35.37.159|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 24735965 (24M) [text/plain]
Saving to: 'scaler_clustering.csv'

scaler_clustering.c 100%[===================>]  23.59M  82.4MB/s    in 0.3s

2023-10-27 16:47:35 (82.4 MB/s) - 'scaler_clustering.csv' saved [24735965/24735965]
```

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

	Unnamed: 0	company_hash	email_hash	orgyear	ctc	job_position	ctc_
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000	Other	
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999	FullStack Engineer	
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015.0	2000000	Backend Engineer	
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	700000	Backend Engineer	
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017.0	1400000	FullStack Engineer	
...	...	...	...	...	...	...	
205838	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b...	2008.0	220000	NaN	
205839	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b42...	2017.0	500000	NaN	
205840	206920	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c...	2021.0	700000	NaN	
205841	206921	zgn vuurxwvmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c8...	2019.0	5100000	NaN	
205842	206922	bgqsvz onvzrtj	0bcfc1d05f2e8dc4147743a1313aa70a119b41b30d4a1f...	2014.0	1240000	NaN	

205843 rows × 7 columns

- We have 205843 data points, and 7 features
- We can drop the column Unnamed: 0 as it's the row Sr. No.

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

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	1100000	Other	2020.0
1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999	FullStack Engineer	2019.0
2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015.0	2000000	Backend Engineer	2020.0
3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	700000	Backend Engineer	2019.0
4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017.0	1400000	FullStack Engineer	2019.0
...	...	...	...	...	...	...
205838	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b...	2008.0	220000	NaN	2019.0
205839	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b42...	2017.0	500000	NaN	2020.0
205840	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c...	2021.0	700000	NaN	2021.0
205841	zgn vuurxwvmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c8...	2019.0	5100000	NaN	2019.0

Exploratory Data Analysis

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205843 entries, 0 to 205842
Data columns (total 6 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   company_hash      205799 non-null  object 
 1   email_hash        205843 non-null  object 
 2   orgyear           205757 non-null  float64
 3   ctc               205843 non-null  int64  
 4   job_position      153281 non-null  object 
 5   ctc_updated_year  205843 non-null  float64
dtypes: float64(2), int64(1), object(3)
memory usage: 9.4+ MB
```

```
df.describe(include="all")
```

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
count	205799	205843	205757.000000	2.058430e+05	153281	205843.000000
unique	37299	153443	NaN	NaN	1017	NaN
top	nvnv wgzohrnvzwj otqcxwto	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	NaN	NaN	Backend Engineer	NaN
freq	8337	10	NaN	NaN	43554	NaN
mean	NaN	NaN	2014.882750	2.271685e+06	NaN	2019.628231
std	NaN	NaN	63.571115	1.180091e+07	NaN	1.325104
min	NaN	NaN	0.000000	2.000000e+00	NaN	2015.000000
25%	NaN	NaN	2013.000000	5.300000e+05	NaN	2019.000000
50%	NaN	NaN	2016.000000	9.500000e+05	NaN	2020.000000
75%	NaN	NaN	2018.000000	1.700000e+06	NaN	2021.000000

```
# Checking for null values
df.isna().sum()
```

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

```
#DUPLICATE VALUE CHECK
df.duplicated().value_counts()
```

```
False    205810
True         33
dtype: int64
```

```
df.drop_duplicates(inplace=True)
df.shape
```

```
(205810, 6)
```

```
#DUPLICATE VALUE CHECK
df.duplicated().value_counts()
```

```
False    205810
dtype: int64
```

```
num_cols = df.dtypes !='object'
num_cols = list(num_cols[num_cols].index)
cat_cols = df.dtypes =='object'
cat_cols = list(cat_cols[cat_cols].index)
```

```
print("Numerical features - ",len(num_cols),"\n")
i = 1
for col in num_cols:
  print(i,":", col, " -", df[col].nunique(),"unique values. They are", df[col].unique())
  i = i + 1
```

```
Numerical features -  3

1 : orgyear  - 77 unique values. They are [2.0160e+03 2.0180e+03 2.0150e+03 2.0170e+03 2.0190e+03 2.0200e+03
 2.0120e+03 2.0130e+03 2.0030e+03 2.0060e+03 2.0140e+03 2.0110e+03
 2.0210e+03 2.0080e+03 2.0040e+03 2.0220e+03 2.0090e+03 2.0050e+03
 2.0100e+03 2.0070e+03 2.0000e+03 2.0020e+03 2.0230e+03 2.0010e+03
 1.9810e+03 2.0310e+03        nan 2.0240e+03 1.9960e+03 1.9990e+03
 2.1060e+03 1.9970e+03 1.9940e+03 1.9950e+03 1.9920e+03 1.9730e+03
 1.9910e+03 1.9980e+03 1.9900e+03 1.9930e+03 1.9880e+03 2.0250e+03
 2.0290e+03 0.0000e+00 2.0800e+02 1.9850e+03 2.0900e+02 2.0600e+02
 1.9820e+03 2.0260e+03 1.9700e+03 2.1010e+03 1.9720e+03 2.1070e+03
 1.9860e+03 1.9890e+03 9.1000e+01 1.9870e+03 3.0000e+00 2.0270e+03
 2.0000e+00 1.9760e+03 4.0000e+00 5.0000e+00 1.9710e+03 1.9770e+03
 1.9840e+03 8.3000e+01 1.0000e+00 1.9790e+03 2.0280e+03 2.2040e+03
 3.8000e+01 1.9000e+03 2.0100e+02 6.0000e+00 2.0165e+04 2.0000e+02]
2 : ctc  - 3360 unique values. They are [1100000  449999 2000000 ... 5266000  234000 3327000]
3 : ctc_updated_year  - 7 unique values. They are [2020. 2019. 2021. 2017. 2016. 2015. 2018.]
```

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

```
print("Categorical features - ",len(cat_cols),"\n")
i = 1
for col in cat_cols:
  print(i,":", col, " -", df[col].nunique(),"unique values. They are", df[col].unique())
  i = i + 1
```

```
Categorical features -  3

1 : company_hash  - 37299 unique values. They are ['atrgxnnt xzaxv' 'qtrxvzwt xzegwgbb rxbxnta' 'ojzwnvwnxw vx' ...
 'ztdnowb xzwqtee' 'mrht onvnt axsxnvr' 'bvptbjnqxu td vbvkgz']
2 : email_hash  - 153443 unique values. They are ['6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618caea697c87af'
 'b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a92bdcc0407b'
 '4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9df6b37b9059' ...
 'cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c8852b58da2fde5e00c'
 'fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c819ec41f6af222a8699'
 '0bcfc1d05f2e8dc4147743a1313aa70a119b41b30d4a1f7e738a6a87d3712c31']
3 : job_position  - 1017 unique values. They are ['Other' 'FullStack Engineer' 'Backend Engineer' ... 'Web / UI Designer'
 'Azure data Factory' 'Android Application developer']
```

```
print("Unique values : ", df["email_hash"].nunique())
print("Value counts : ")
print(df["email_hash"].value_counts())
```

```
Unique values :  153443
Value counts :
bbace3cc586400bbc65765bc6a16b77d8913836cfc98b77c05488f02f5714a4b    10
3e5e49daa5527a6d5a33599b238bf9bf31e85b9efa9a94f1c88c5e15a6f31378     9
6842660273f70e9aa239026ba33bfe82275d6ab0d20124021b952b5bc3d07e6c     9
298528ce3160cc761e4dc37a07337ee2e0589df251d73645aae209b010210eee     9
c0eb129061675da412b0deb15871dd06ef0d7cd86eb5f7e8cc6a20b0d1938183     8
                                                                    ..
```

```
63933d31becd1487d93d56844919896334e3ae39c4095979816c6fbb8816153a      1
23bcc14067e0fec60b8772b3e20abbb8fa9f2146738d37056e0d20d33a97c690      1
5a1c9d9a745d6ee95136047698dba8f68f00bac522de6d83d18cf062f7286e22      1
062597458dc597d35b2dbf3e417ac160244dc8c3dd50fce716837dc1e6fc7a10      1
0bcfc1d05f2e8dc4147743a1313aa70a119b41b30d4a1f7e738a6a87d3712c31      1
Name: email_hash, Length: 153443, dtype: int64
```

```
# Using a regex function for removing special characters

import re
def remove_special (string):
    new_string=re.sub('[^A-Za-z ]+', '', string)
    return new_string
```

```
for col in cat_cols:
 print(col)
```

```
company_hash
email_hash
job_position
```

```
# Data Cleaning on company_hash

df.company_hash=df.company_hash.apply(lambda x: remove_special(str(x)))
df.company_hash=df.company_hash.apply(lambda x: x.lower())
df.company_hash=df.company_hash.apply(lambda x: x.strip())
```

```
# Data Cleaning on email_hash

df.email_hash=df.email_hash.apply(lambda x: remove_special(str(x)))
df.email_hash=df.email_hash.apply(lambda x: x.lower())
df.email_hash=df.email_hash.apply(lambda x: x.strip())
```

```
# Data Cleaning on job_position

df.job_position=df.job_position.apply(lambda x: remove_special(str(x)))
df.job_position=df.job_position.apply(lambda x: x.lower())
df.job_position=df.job_position.apply(lambda x: x.strip())
```

```
df
```

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
0	atrgxnnt xzaxv	deadabcffcbcdcccaeacaf	2016.0	1100000	other	2020.0
1	qtrxvzwt xzegwgbb rxbxnta	baafacbcbebacdaddcaabdccb	2018.0	449999	fullstack engineer	2019.0
2	ojzwnvwnxw vx	cbcdfbcabaeaefddefdcdfbb	2015.0	2000000	backend engineer	2020.0
3	ngpgutaxv	effdedeaecafcaddbbcadddfec	2017.0	700000	backend engineer	2019.0
4	qxen sqghu	ffefcbacdbcbdfabbbadb	2017.0	1400000	fullstack engineer	2019.0
...	...	...	...	...	...	...
205838	vuurt xzw	bceefeedffdabefcfbedcbafec	2008.0	220000	nan	2019.0
205839	husqvawgb	fffadebbecafdcbcebacdb	2017.0	500000	nan	2020.0
205840	vwwgrxnt	cbcceafacdafcffceddcbdafdeec	2021.0	700000	nan	2021.0
205841	zgn vuurxwvmrt	fbaaffcefdefeefcecfafa	2019.0	5100000	nan	2019.0
205842	bgqsvz onvzrtj	bcfcdfedcaaaabbdafeaadc	2014.0	1240000	nan	2016.0

205810 rows × 6 columns

```
print("Unique values : ", df["email_hash"].nunique())
print("Value counts : ")
print(df["email_hash"].value_counts())
```

```
Unique values :  153443
Value counts : 
bbaceccbbcbcabdcfcbcffab      10
eedaaadabbfbfebefaafcceaf      9
feaababfedabdbbbcdec           9
ceccedcaeeedfdaaebeee          9
cebdabdebddefdcdebfeccabd      8
                              ..
dbecdddeaeccfbba               1
bccefecbbeabbbfafdeddac        1
acdadeedbaffbacdeddcffe        1
dcdbdbfeacdccddfcedcefca       1
```

```
    bcfcdfedcaaaabbdafeaadc       1
    Name: email_hash, Length: 153443, dtype: int64
```

```
df.drop_duplicates(inplace=True)
df.shape
```

```
    (205698, 6)
```

```
# Checking for null values
df.isna().sum()
```

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

```
#removing rows where company or job_position is not available

df=df[ ~((df['company_hash']=='') | (df['job_position']==''))]
```

```
df.shape
```

```
    (205603, 6)
```

```
company_median_org_year=df.groupby('company_hash')['orgyear'].median()
company_median_org_year
```

```
    company_hash
    a                                           2017.0
    a b onttr wgqu                              2019.0
    a j uvnxr owyggr ge tzsxzttqxzs vwvatbj vbmx    2015.0
    a ntwy ogrhnxgzo ucn rna                    2013.0
    a ntwyzgrgsxto                              2015.0
                                                 ...
    zz                                          2011.0
    zz wgzztwn mya                              2009.0
    zzb ztdnstz vacxogqj ucn rna                2017.0
    zzgato                                      2014.0
    zzzbzb                                      1990.0
    Name: orgyear, Length: 37205, dtype: float64
```

```
#Code to impute
def null_imputation(table_from_which_we_need_to_fill, main_col, null_col):
    if np.isnan(null_col):
        return table_from_which_we_need_to_fill[main_col]
    else:
        return null_col
```

```
# Filling Null values using Median Target Imputation for Orgyear

df['orgyear']=df.apply(lambda x: null_imputation(company_median_org_year,x['company_hash'],x['orgyear'] ), axis=1)
df['orgyear']
```

```
    <ipython-input-327-a6bd3b594005>:3: SettingWithCopyWarning:
    A value is trying to be set on a copy of a slice from a DataFrame.
    Try using .loc[row_indexer,col_indexer] = value instead

    See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus
      df['orgyear']=df.apply(lambda x: null_imputation(company_median_org_year,x['company_hash'],x['orgyear'] ), axis=1)
    0         2016.0
    1         2018.0
    2         2015.0
    3         2017.0
    4         2017.0
               ...
    205838    2008.0
    205839    2017.0
    205840    2021.0
    205841    2019.0
    205842    2014.0
    Name: orgyear, Length: 205603, dtype: float64
```

```
#if we still have null values, we'll drop it

len(df[df['orgyear'].isnull()])
```

```
26
```

```
#dropping remaining null values
df=df[~df['orgyear'].isnull()]
```

```
# Checking for null values -No missing values
df.isna().sum()
```

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

Outlier Detection and Treatment

```
#simple understanding
df.orgyear.value_counts().sort_values(ascending=True)
#There are outlier in the values
```

```
200.0         1
1981.0        1
206.0         1
2011.5        1
208.0         1
          ...
2015.0    20584
2016.0    23021
2017.0    23225
2019.0    23396
2018.0    25241
Name: orgyear, Length: 80, dtype: int64
```

```
#removing outliers from orgyear using IQR

q1=df.orgyear.quantile(0.25)
q3=df.orgyear.quantile(0.75)
iqr=q3-q1
df=df.loc[(df.orgyear>=q1-1.5*iqr) & (df.orgyear<=q3+1.5*iqr)]
```

```
#simple understanding
df.ctc.value_counts().sort_values(ascending=True)
#There are outlier in the values
```

```
3327000       1
3652781       1
2365000       1
1699999       1
537000        1
           ...
800000     6670
500000     7174
1000000    7375
400000     7543
600000     7761
Name: ctc, Length: 3296, dtype: int64
```

```
#removing outliers from ctc using IQR

q1=df.ctc.quantile(0.25)
q3=df.ctc.quantile(0.75)
iqr=q3-q1
df=df.loc[(df.ctc>=q1-1.5*iqr) & (df.ctc<=q3+1.5*iqr)]
```

```
df.orgyear.value_counts().sort_index(ascending=True)
```

```
2008.0     2045
2009.0     2880
2010.0     4569
2011.0     6614
2011.5        1
2012.0     8958
2013.0    10757
2014.0    15000
2014.5        2
```

```
2015.0    18738
2016.0    21108
2017.0    21687
2018.0    23749
2018.5        1
2019.0    22258
2020.0    12603
2021.0     3319
2022.0      775
2023.0      201
2024.0       32
Name: orgyear, dtype: int64
```

```
#simple understanding
df.ctc.value_counts().sort_values(ascending=True)
```

```
234000        1
911000        1
1033000       1
813000        1
1091000       1
           ...
800000     6670
500000     7174
1000000    7375
400000     7543
600000     7761
Name: ctc, Length: 2358, dtype: int64
```

```
df
```

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
0	atrgxnnt xzaxv	deadabcffcbcdcccaeacaf	2016.0	1100000	other	2020.0
1	qtrxvzwt xzegwgbb rxbxnta	baafacbcbebacdaddcaabdccb	2018.0	449999	fullstack engineer	2019.0
2	ojzwnvwnxw vx	cbcdfbcabaeaefddefdcdfbb	2015.0	2000000	backend engineer	2020.0
3	ngpgutaxv	effdedeaecafcaddbbcadddfec	2017.0	700000	backend engineer	2019.0
4	qxen sqghu	ffefcbacdbcbdfabbbadb	2017.0	1400000	fullstack engineer	2019.0
...	...	...	...	...	...	...
205837	zgn vuurxwvmrt	fecfeedcfbdeaffecfbbbb	2021.0	800000	nan	2021.0
205838	vuurt xzw	bceefeedffdabefcfbedcbafec	2008.0	220000	nan	2019.0
205839	husqvawgb	fffadebbecafdcbcebacdb	2017.0	500000	nan	2020.0
205840	vwwgrxnt	cbcceafacdafcffceddcbdafdeec	2021.0	700000	nan	2021.0
205842	bgqsvz onvzrtj	bcfcdfedcaaaabbdafeaadc	2014.0	1240000	nan	2016.0

185466 rows × 6 columns

There are nan value in the job_position

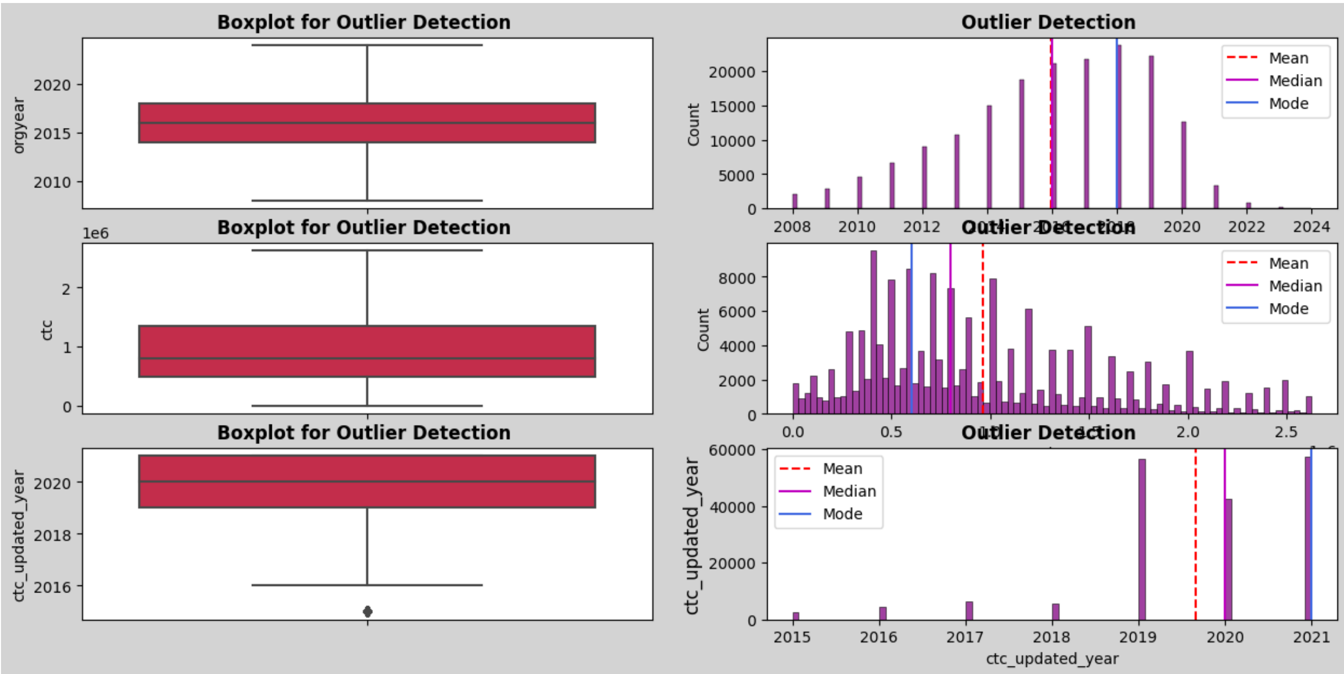
```
df.loc[df['job_position']=='nan','job_position']=np.nan
```

```
df
```

```
def numerical_feat(df,colname,nrows=2,mcols=2,width=15,height=15):
    fig , ax = plt.subplots(nrows,mcols,figsize=(width,height))
    fig.set_facecolor("lightgrey")
    rows = 0
    for var in colname:
        ax[rows][0].set_title("Boxplot for Outlier Detection ", fontweight="bold")
        plt.ylabel(var, fontsize=12)
        sns.boxplot(y = df[var],color='crimson',ax=ax[rows][0])

        # plt.subplot(nrows,mcols,pltcounter+1)
        sns.histplot(df[var],color='purple',ax=ax[rows][1])
        ax[rows][1].axvline(df[var].mean(), color='r', linestyle='--', label="Mean")
        ax[rows][1].axvline(df[var].median(), color='m', linestyle='-', label="Median")
        ax[rows][1].axvline(df[var].mode()[0], color='royalblue', linestyle='-', label="Mode")
        ax[rows][1].set_title("Outlier Detection ", fontweight="bold")
        ax[rows][1].legend({'Mean':df[var].mean(),'Median':df[var].median(),'Mode':df[var].mode()})
        rows += 1
    plt.show()
```

```
numerical_feat(df,num_cols,len(num_cols),2,15,7)
```



Data Pre-processing:

```
df=df.apply(lambda x: x.mask(x.map(x.value_counts())<=5,'Others') if x.name=='company_hash' else x)
df
```

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
0	atrgxnnt xzaxv	deadabcffcbcdcccaeacaf	2016.0	1100000	other	2020.0

Creating Years of Experience Columns

```
df.drop_duplicates(inplace=True)
df.shape
```

```
(175219, 6)
```

```
#orgyear check
df['orgyear'] = df.apply(lambda x: x['orgyear'] if x['orgyear'] <= 2023 else 2023, axis=1)
```

```
df['years_of_experience']=2022-df['orgyear']
```

```
df
```

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience
0	atrgxnnt xzaxv	deadabcffcbcdcccaeacaf	2016.0	1100000	other	2020.0	6.0
1	qtrxvzwt xzegwgbb rxbxnta	baafacbcbebacdaddcaabdccb	2018.0	449999	fullstack engineer	2019.0	4.0
2	Others	cbcdfbcabaeaefddefdcdfbb	2015.0	2000000	backend engineer	2020.0	7.0
3	ngpgutaxv	effdedeaecafcaddbbcadddfec	2017.0	700000	backend engineer	2019.0	5.0
4	qxen sqghu	ffefcbacdbcbdfabbbadb	2017.0	1400000	fullstack engineer	2019.0	5.0
...	...	...	...	...	...	...	...
205837	zgn vuurxwvmrt	fecfeedcfbdeaffecfbbbb	2021.0	800000	NaN	2021.0	1.0
205838	vuurt xzw	bceefeedffdabefcfbedcbafec	2008.0	220000	NaN	2019.0	14.0
205839	husqvawgb	fffadebbecafdcbcebacdb	2017.0	500000	NaN	2020.0	5.0
205840	vwwgrxnt	cbcceafacdafcffceddcbdafdeec	2021.0	700000	NaN	2021.0	1.0

```
#ctc_updated_year_check
df['ctc_updated_year'] = df.apply(lambda x: x['orgyear'] if x['ctc_updated_year'] < x['orgyear'] else x['ctc_updated_year'], axis=1)
df
```

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience
0	atrgxnnt xzaxv	deadabcffcbcdcccaeacaf	2016.0	1100000	other	2020.0	6.0
1	qtrxvzwt xzegwgbb rxbxnta	baafacbcbebacdaddcaabdccb	2018.0	449999	fullstack engineer	2019.0	4.0
2	Others	cbcdfbcabaeaefddefdcdfbb	2015.0	2000000	backend engineer	2020.0	7.0
3	ngpgutaxv	effdedeaecafcaddbbcadddfec	2017.0	700000	backend engineer	2019.0	5.0
4	qxen sqghu	ffefcbacdbcbdfabbbadb	2017.0	1400000	fullstack engineer	2019.0	5.0
...	...	...	...	...	...	...	...
205837	zgn vuurxwvmrt	fecfeedcfbdeaffecfbbbb	2021.0	800000	NaN	2021.0	1.0
205838	vuurt xzw	bceefeedffdabefcfbedcbafec	2008.0	220000	NaN	2019.0	14.0
205839	husqvawgb	fffadebbecafdcbcebacdb	2017.0	500000	NaN	2020.0	5.0
205840	vwwgrxnt	cbcceafacdafcffceddcbdafdeec	2021.0	700000	NaN	2021.0	1.0

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

```
# Checking for null values
df.isna().sum()
```

```
company_hash        0
email_hash          0
orgyear             0
```

```
ctc                    0
job_position           0
ctc_updated_year       0
years_of_experience    0
dtype: int64
```

```
df.drop(columns=["email_hash"],inplace=True)
```

Manual Clustering on the basis of learner's company, job position and years of experience

```
yoe_jp_ch=df.groupby(['years_of_experience','job_position','company_hash'])['ctc'].describe()
yoe_jp_ch
```

years_of_experience	job_position	company_hash	count	mean	std	min	25%	50%	75%	max
-1.0	**Others**	**Others**	10.0	765400.0	652893.082961	14000.0	182500.0	690000.0	1327500.0	1760000.0
		atrr	1.0	1000000.0	NaN	1000000.0	1000000.0	1000000.0	1000000.0	1000000.0
		eqtoytq	1.0	1400000.0	NaN	1400000.0	1400000.0	1400000.0	1400000.0	1400000.0
		eqttrvzwtq	1.0	900000.0	NaN	900000.0	900000.0	900000.0	900000.0	900000.0
		gjg qggbo	1.0	1150000.0	NaN	1150000.0	1150000.0	1150000.0	1150000.0	1150000.0
...	**...**	**...**	...	...	...	...	...	...	...	...
14.0	**support engineer**	**wxowg**	1.0	1000000.0	NaN	1000000.0	1000000.0	1000000.0	1000000.0	1000000.0
		xzegojo	1.0	1200000.0	NaN	1200000.0	1200000.0	1200000.0	1200000.0	1200000.0
		zgpxv	1.0	2400000.0	NaN	2400000.0	2400000.0	2400000.0	2400000.0	2400000.0
	technology analyst	**xzegojo**	1.0	656000.0	NaN	656000.0	656000.0	656000.0	656000.0	656000.0
	web ui designer	**vrgyv ntwyzgrgsj**	1.0	1019999.0	NaN	1019999.0	1019999.0	1019999.0	1019999.0	1019999.0

```
df_cjy=df.merge(yoe_jp_ch, on=['years_of_experience','job_position','company_hash'], how = 'left')
df_cjy.sort_values(['years_of_experience','job_position','company_hash'])
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	count	mean	std	m
9238	Others	2023.0	680000	Others	2023.0	-1.0	10.0	765400.0	652893.082961	1400(
44359	Others	2023.0	110000	Others	2023.0	-1.0	10.0	765400.0	652893.082961	1400(
48088	Others	2023.0	80000	Others	2023.0	-1.0	10.0	765400.0	652893.082961	1400(
63204	Others	2023.0	700000	Others	2023.0	-1.0	10.0	765400.0	652893.082961	1400(
90070	Others	2023.0	400000	Others	2023.0	-1.0	10.0	765400.0	652893.082961	1400(
...	...	...	...	...	...	...	...	...	...	
30257	wxowg	2008.0	1000000	support engineer	2021.0	14.0	1.0	1000000.0	NaN	100000(
42895	xzegojo	2008.0	1200000	support engineer	2021.0	14.0	1.0	1200000.0	NaN	120000(
29085	zgpxv	2008.0	2400000	support engineer	2021.0	14.0	1.0	2400000.0	NaN	240000(
135673	xzegojo	2008.0	656000	technology analyst	2016.0	14.0	1.0	656000.0	NaN	65600(
164235	vrgyv ntwyzgrgsj	2008.0	1019999	web ui designer	2019.0	14.0	1.0	1019999.0	NaN	101999(

175219 rows × 14 columns

```
#Creating Designation basis on the salary they are getting in their respective company
def condition_designation(a,b_50):
    if a<b_50:
        return 3
    elif a>b_50:
        return 1
    else:
        return 2
```

```
df_cjy['designation'] =df_cjy.apply(lambda x: condition_designation(x['ctc'],x['50%']),axis = 1)
df_cjy.head()
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	count	mean	std	min
0	atrgxnnt xzaxv	2016.0	1100000	other	2020.0	6.0	1.0	1.100000e+06	NaN	1100000.0
1	qtrxvzwt xzegwgbb rxbxnta	2018.0	449999	fullstack engineer	2019.0	4.0	7.0	7.742856e+05	250922.324350	449999.0
2	Others	2015.0	2000000	backend engineer	2020.0	7.0	889.0	9.584183e+05	630080.801120	1000.0
3	ngpgutaxv	2017.0	700000	backend engineer	2019.0	5.0	7.0	1.158571e+06	404780.951933	700000.0
4	qxen sqghu	2017.0	1400000	fullstack engineer	2019.0	5.0	1.0	1.400000e+06	NaN	1400000.0

```
df_cjy.designation.value_counts(normalize=True)*100
```

```
1    36.478350
3    36.093118
2    27.428532
Name: designation, dtype: float64
```

```
#designation == 3(CTC > average)
df_cjy[df_cjy['designation']==3]
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	count	mean	std	
1	qtrxvzwt xzegwgbb rxbxnta	2018.0	449999	fullstack engineer	2019.0	4.0	7.0	7.742856e+05	250922.324350	44
3	ngpgutaxv	2017.0	700000	backend engineer	2019.0	5.0	7.0	1.158571e+06	404780.951933	70
6	lubgqsvz wyvot wg	2018.0	1500000	fullstack engineer	2019.0	4.0	38.0	1.587368e+06	483592.603896	11
7	vwwtznhqt ntwyzgrgsj	2019.0	400000	backend engineer	2019.0	3.0	2.0	4.250000e+05	35355.339059	40
9	Others	2019.0	360000	Others	2019.0	3.0	1502.0	6.581985e+05	472175.568851	
...	...	...	...	...	...	...	...	...	...	
175209	tcxct ogenfvqt vzvrjnxwo	2018.0	550000	Others	2019.0	4.0	2.0	6.100000e+05	84852.813742	55
175211	Others	2020.0	100000	Others	2020.0	2.0	859.0	7.024824e+05	506529.210579	
175214	zgn vuurxwvmrt	2021.0	800000	Others	2021.0	1.0	168.0	9.198065e+05	619721.266215	1
175216	husqvawgb	2017.0	500000	Others	2020.0	5.0	4.0	1.202500e+06	471902.179129	50
175218	bgqsvz onvzrtj	2014.0	1240000	Others	2016.0	8.0	9.0	1.693333e+06	348425.027804	120

63242 rows × 15 columns

```
#designation == 2(CTC = average)
df_cjy[df_cjy['designation']==2]
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	count	mean	std	
0	atrgxnnt xzaxv	2016.0	1100000	other	2020.0	6.0	1.0	1.100000e+06	NaN	1100(
4	qxen sqghu	2017.0	1400000	fullstack engineer	2019.0	5.0	1.0	1.400000e+06	NaN	1400(
5	yvuuxrj hzbvqqxta bvqptnxzs ucn rna	2018.0	700000	fullstack engineer	2020.0	4.0	1.0	7.000000e+05	NaN	700(

```
#designation == 1(CTC < average)
df_cjy[df_cjy['designation']==1]
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	count	mean	std	
2	Others	2015.0	2000000	backend engineer	2020.0	7.0	889.0	9.584183e+05	630080.801120	1
16	Others	2013.0	800000	other	2020.0	9.0	242.0	8.148946e+05	567705.535602	7
17	puxn	2020.0	1400000	Others	2020.0	2.0	3.0	8.333333e+05	513160.143945	40(
20	Others	2018.0	1350000	data scientist	2019.0	4.0	253.0	8.392374e+05	557512.763496	25
21	owyrhbmtqstq	2018.0	1820000	backend engineer	2019.0	4.0	4.0	1.457500e+06	866732.369304	20(
...	...	...	...	...	...	...	...	...	...	
175204	vagmt	2017.0	2100000	Others	2018.0	5.0	20.0	1.397500e+06	640615.452432	20(
175205	btaxvztn	2018.0	1200000	Others	2020.0	4.0	7.0	9.857143e+05	592814.112036	40(
175208	zgn vuurxwvmrt	2019.0	700000	Others	2019.0	3.0	162.0	7.756735e+05	567304.677065	7
175212	xgz	2013.0	2280000	Others	2019.0	9.0	7.0	2.024286e+06	341167.463418	154(
175213	mvqwrvjo	2011.0	2250000	Others	2019.0	11.0	11.0	1.427273e+06	468638.192678	53(

63917 rows × 15 columns

Manual Clustering based on company and job position

```
grouped_c_j=df.groupby(['job_position','company_hash'])['ctc'].describe()
```

```
grouped_c_j
```

job_position	company_hash	count	mean	std	min	25%	50%	75%	max
Others	**Others**	9471.0	803641.635836	574994.252906	15.0	400000.0	605600.0	1100000.0	2600000.0
	a ntwyzgrgsxto	5.0	675000.000000	389711.431703	350000.0	500000.0	575000.0	600000.0	1350000.0
	aaqxctz avnv owxtzwto vzvrjnxwo ucn rna	1.0	500000.000000	NaN	500000.0	500000.0	500000.0	500000.0	500000.0
	adw ntwyzgrgsj	63.0	551682.539683	317749.385187	80000.0	374000.0	423000.0	677500.0	1500000.0
	adw ntwyzgrgsxto	36.0	611138.888889	319734.457036	100000.0	400000.0	512500.0	792500.0	1500000.0
...	**...**	...	...	...	...	...	...	...	...
wordpress developer	**Others**	1.0	600000.000000	NaN	600000.0	600000.0	600000.0	600000.0	600000.0
worker	**zgn vuurxwvmrt vwwghzn**	1.0	200000.000000	NaN	200000.0	200000.0	200000.0	200000.0	200000.0
x	**Others**	1.0	400000.000000	NaN	400000.0	400000.0	400000.0	400000.0	400000.0
young professional ii	**sgctqzbtzn ge xzaxv**	1.0	500000.000000	NaN	500000.0	500000.0	500000.0	500000.0	500000.0

```
df_cj=df.merge(grouped_c_j, on=['job_position','company_hash'], how='left')
df_cj
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	count	mean	std	
0	atrgxnnt xzaxv	2016.0	1100000	other	2020.0	6.0	2.0	1.085000e+06	2.121320e+04	1070
1	qtrxvzwt xzegwgbb rxbxnta	2018.0	449999	fullstack engineer	2019.0	4.0	23.0	9.371739e+05	4.730915e+05	300
2	Others	2015.0	2000000	backend engineer	2020.0	7.0	7351.0	9.290671e+05	6.289638e+05	1
3	ngpgutaxv	2017.0	700000	backend engineer	2019.0	5.0	24.0	1.416667e+06	5.453413e+05	520
4	qxen sqghu	2017.0	1400000	fullstack engineer	2019.0	5.0	3.0	8.466667e+05	4.801389e+05	540
...	...	...	...	...	...	...	...	...	...	
175214	zgn vuurxwvmrt	2021.0	800000	Others	2021.0	1.0	898.0	8.286783e+05	6.183447e+05	7
175215	vuurt xzw	2008.0	220000	Others	2019.0	14.0	12.0	1.125250e+06	1.098929e+06	60
175216	husqvawgb	2017.0	500000	Others	2020.0	5.0	13.0	1.000769e+06	3.300369e+05	500
175217	vwwgrxnt	2021.0	700000	Others	2021.0	1.0	35.0	1.151800e+06	5.001657e+05	300

```
df_cj.sort_values(['company_hash','job_position','years_of_experience'])
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	count	mean	std	
9238	Others	2023.0	680000	Others	2023.0	-1.0	9471.0	8.036416e+05	574994.252906	
44359	Others	2023.0	110000	Others	2023.0	-1.0	9471.0	8.036416e+05	574994.252906	
48088	Others	2023.0	80000	Others	2023.0	-1.0	9471.0	8.036416e+05	574994.252906	
63204	Others	2023.0	700000	Others	2023.0	-1.0	9471.0	8.036416e+05	574994.252906	
90070	Others	2023.0	400000	Others	2023.0	-1.0	9471.0	8.036416e+05	574994.252906	
...	...	...	...	...	...	...	...	...	...	
146037	zxztrtvuo	2013.0	1200000	ios engineer	2017.0	9.0	1.0	1.200000e+06	NaN	120
62581	zxztrtvuo	2016.0	1200000	member of technical staff at nineleaps	2020.0	6.0	1.0	1.200000e+06	NaN	120
9685	zxztrtvuo	2020.0	450000	other	2020.0	2.0	2.0	4.500000e+05	0.000000	45
159277	zxztrtvuo	2019.0	450000	other	2020.0	3.0	2.0	4.500000e+05	0.000000	45
43288	zxztrtvuo	2016.0	1200000	software developer intern	2020.0	6.0	1.0	1.200000e+06	NaN	120

175219 rows × 14 columns

```
#Creating Class basis on the salary they are getting in their respective company
def condition_classs(a,b_50):
    if a<b_50:
        return 3
    elif a>b_50:
        return 1
    else:
        return 2
```

```
df_cj['classes'] =df_cj.apply(lambda x: condition_classs(x['ctc'],x['50%']),axis = 1)
df_cj
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	count	mean	std	
0	atrgxnnt xzaxv	2016.0	1100000	other	2020.0	6.0	2.0	1.085000e+06	2.121320e+04	1070
1	qtrxvzwt xzegwgbb rxbxnta	2018.0	449999	fullstack engineer	2019.0	4.0	23.0	9.371739e+05	4.730915e+05	300
2	Others	2015.0	2000000	backend engineer	2020.0	7.0	7351.0	9.290671e+05	6.289638e+05	1
3	ngpgutaxv	2017.0	700000	backend engineer	2019.0	5.0	24.0	1.416667e+06	5.453413e+05	520
4	qxen sqghu	2017.0	1400000	fullstack engineer	2019.0	5.0	3.0	8.466667e+05	4.801389e+05	540
175216	husqvawgb	2017.0	500000	Others	2020.0	5.0	13.0	1.000769e+06	3.300369e+05	500

```
df_cj.classes.value_counts(normalize=True)*100
```

```
1    44.346218
3    44.003790
2    11.649992
Name: classes, dtype: float64
```

```
# job position that has the highest class
df_cj[df_cj['classes']==1][['job_position','ctc']].groupby('job_position')['ctc'].describe()
```

job_position	count	mean	std	min	25%	50%	75%	max
Others	21738.0	1.309807e+06	563512.636506	77000.0	800000.0	1200000.0	1700000.0	2620000.0
android engineer	2128.0	1.289601e+06	500853.875156	14000.0	880000.0	1150000.0	1600000.0	2600000.0
application developer	1.0	1.150000e+06	NaN	1150000.0	1150000.0	1150000.0	1150000.0	1150000.0
application developer analyst	2.0	5.600000e+05	56568.542495	520000.0	540000.0	560000.0	580000.0	600000.0
application development analyst	3.0	7.400000e+05	210000.000000	590000.0	620000.0	650000.0	815000.0	980000.0
...	...	...	...	...	...	...	...	...
support engineer	1434.0	8.708633e+05	425081.723238	350000.0	560000.0	740000.0	1000000.0	2600000.0
system engineer	17.0	7.023529e+05	330047.902049	400000.0	500000.0	500000.0	790000.0	1500000.0
teaching assistant	1.0	1.800000e+06	NaN	1800000.0	1800000.0	1800000.0	1800000.0	1800000.0
team lead	3.0	1.700000e+06	435889.894354	1400000.0	1450000.0	1500000.0	1850000.0	2200000.0
technology analyst	4.0	8.365000e+05	310862.777873	656000.0	659000.0	695000.0	872500.0	1300000.0

105 rows × 8 columns

```
df_cj.shape
```

```
(175219, 15)
```

```
df_cjy.shape
```

```
(175219, 15)
```

```
df_cj.drop(columns=['count','mean','std','min','25%','50%','75%','max'],inplace=True)
df_cjy.drop(columns=['count','mean','std','min','25%','50%','75%','max'],inplace=True)
```

```
df_cj.drop_duplicates().shape
```

```
(135737, 7)
```

```
df_cjy.drop_duplicates().shape
```

```
(135737, 7)
```

```
df_cjy_cj=df_cj.merge(df_cjy, on=['company_hash','orgyear','ctc','job_position','years_of_experience','ctc_updated_year'], how = 'right')
```

```
df_cjy_cj.drop_duplicates().shape
```

```
(135737, 8)
```

Manual Clustering based on company

```
grouped_c=df.groupby(['company_hash'])['ctc'].describe()
```

```
df_c=df.merge(grouped_c, on=['company_hash'], how='left')
```

```
df_c
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	count	mean	std	
0	atrgxnnt xzaxv	2016.0	1100000	other	2020.0	6.0	9.0	1.115667e+06	4.581119e+05	500
1	qtrxvzwt xzegwgbb rxbxnta	2018.0	449999	fullstack engineer	2019.0	4.0	387.0	1.004286e+06	5.913183e+05	10
2	Others	2015.0	2000000	backend engineer	2020.0	7.0	44980.0	8.328390e+05	5.723869e+05	
3	ngpgutaxv	2017.0	700000	backend engineer	2019.0	5.0	59.0	1.375169e+06	5.544498e+05	200
4	qxen sqghu	2017.0	1400000	fullstack engineer	2019.0	5.0	6.0	9.400000e+05	3.898718e+05	540
...	...	...	...	...	...	...	...	...	...	
175214	zgn vuurxwvmrt	2021.0	800000	Others	2021.0	1.0	907.0	8.252295e+05	6.173500e+05	7
175215	vuurt xzw	2008.0	220000	Others	2019.0	14.0	12.0	1.125250e+06	1.098929e+06	60
175216	husqvawgb	2017.0	500000	Others	2020.0	5.0	100.0	1.248600e+06	5.539099e+05	200
175217	vwwgrxnt	2021.0	700000	Others	2021.0	1.0	153.0	1.268288e+06	4.817656e+05	200
175218	bgqsvz onvzrtj	2014.0	1240000	Others	2016.0	8.0	429.0	1.675214e+06	5.744298e+05	1

175219 rows × 14 columns

```
#Creating Tier basis on the salary in the companies
def condition_tier(a,b_50):
    if a<b_50:
        return 3
    elif a>b_50:
        return 1
    else:
        return 2
```

```
df_c['tier'] =df_c.apply(lambda x: condition_tier(x['ctc'],x['50%']),axis = 1)
df_c
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	count	mean	std	
0	atrgxnnt xzaxv	2016.0	1100000	other	2020.0	6.0	9.0	1.115667e+06	4.581119e+05	500
1	qtrxvzwt xzegwgbb rxbxnta	2018.0	449999	fullstack engineer	2019.0	4.0	387.0	1.004286e+06	5.913183e+05	10
2	Others	2015.0	2000000	backend engineer	2020.0	7.0	44980.0	8.328390e+05	5.723869e+05	
3	ngpgutaxv	2017.0	700000	backend engineer	2019.0	5.0	59.0	1.375169e+06	5.544498e+05	200
4	qxen sqghu	2017.0	1400000	fullstack engineer	2019.0	5.0	6.0	9.400000e+05	3.898718e+05	540
...	...	...	...	...	...	...	...	...	...	
175214	zgn vuurxwvmrt	2021.0	800000	Others	2021.0	1.0	907.0	8.252295e+05	6.173500e+05	7
175215	vuurt xzw	2008.0	220000	Others	2019.0	14.0	12.0	1.125250e+06	1.098929e+06	60
175216	husqvawgb	2017.0	500000	Others	2020.0	5.0	100.0	1.248600e+06	5.539099e+05	200
175217	vwwgrxnt	2021.0	700000	Others	2021.0	1.0	153.0	1.268288e+06	4.817656e+05	200
175218	bgqsvz onvzrtj	2014.0	1240000	Others	2016.0	8.0	429.0	1.675214e+06	5.744298e+05	1

175219 rows × 15 columns

```
df_c.tier.value_counts(normalize=True)*100
```

```
3    47.240881
1    47.198078
2     5.561041
Name: tier, dtype: float64
```

```
df_c.shape
```

```
(175219, 15)
```

```
df_c.drop(columns=['count','mean','std','min','25%','50%','75%','max'],inplace=True)
```

```
df_cjy_cj_c=df_cjy_cj.merge(df_c, on=['company_hash','orgyear','ctc','job_position','ctc_updated_year','years_of_experience'], how = 'lef
```

```
df_cjy_cj_c.drop_duplicates(inplace=True)
```

```
df_cjy_cj_c.shape
```

```
(135737, 9)
```

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

```
df_cjy_cj_c[df_cjy_cj_c['tier']==1].sort_values(by=['ctc'], ascending=False).head(10)
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	classes	designation	tier
14946958	lav ogenfvqt	2009.0	2625000	fullstack engineer	2021.0	13.0	1	2	1
11299044	mrht jgzatq sbmy	2014.0	2625000	backend engineer	2021.0	8.0	1	2	1
8721837	sgrabvz ovwyo	2016.0	2623000	backend engineer	2020.0	6.0	1	1	1
14546543	gunhb	2013.0	2620000	other	2021.0	9.0	1	2	1
13257546	uvjovet sqghu	2014.0	2620000	backend engineer	2020.0	8.0	1	1	1
5531398	utqoxontzn ojontbo	2008.0	2620000	engineering leadership	2019.0	14.0	1	2	1
9870326	urvzygu	2014.0	2620000	backend architect	2019.0	8.0	2	2	1
15003860	ofxssj	2017.0	2620000	backend engineer	2021.0	5.0	1	1	1
8767868	Others	2009.0	2620000	engineering leadership	2019.0	13.0	1	1	1

```
#Top 10 employees of data science in Amazon / TCS etc earning more than their peers - Class 1 and Tier 1
df_cjy_cj_c[(df_cjy_cj_c['tier']==1) & (df_cjy_cj_c['classes']==1) ].sort_values(by=['ctc'], ascending=False).head(10)
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	classes	designation	tier
14946958	lav ogenfvqt	2009.0	2625000	fullstack engineer	2021.0	13.0	1	2	1
11299044	mrht jgzatq sbmy	2014.0	2625000	backend engineer	2021.0	8.0	1	2	1
8721837	sgrabvz ovwyo	2016.0	2623000	backend engineer	2020.0	6.0	1	1	1
13257546	uvjovet sqghu	2014.0	2620000	backend engineer	2020.0	8.0	1	1	1
15003860	ofxssj	2017.0	2620000	backend engineer	2021.0	5.0	1	1	1
9112789	eqtoytq	2019.0	2620000	other	2021.0	3.0	1	1	1
8767868	Others	2009.0	2620000	engineering leadership	2019.0	13.0	1	1	1
14546543	gunhb	2013.0	2620000	other	2021.0	9.0	1	2	1
8172827	xnw xzegntwy	2014.0	2620000	fullstack engineer	2021.0	8.0	1	1	1

```
#Bottom 10 employees of data science in Amazon / TCS etc earning less than their peers - Class 3 and Tier 1
df_cjy_cj_c[(df_cjy_cj_c['tier']==1) & (df_cjy_cj_c['classes']==3) ].sort_values(by=['ctc']).head(10)
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	classes	designation	tier
4462487	jvzatd	2016.0	85000	fullstack engineer	2018.0	6.0	3	2	1
9618016	tuxw	2015.0	116000	Others	2019.0	7.0	3	2	1
11586418	rvkvav sqghu	2011.0	120000	sdet	2019.0	11.0	3	2	1
8034446	zgqaonqgb	2019.0	120000	fullstack engineer	2019.0	3.0	3	2	1
7157420	mqgpxzswgb	2019.0	130000	Others	2019.0	3.0	3	2	1

```
#Bottom 10 employees (earning less than most of the employees in the company)- Tier 3
df_cjy_cj_c[(df_cjy_cj_c['tier']==3)].sort_values(by=['ctc']).head(10)
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	classes	designation	tier
12371063	xzntqcxtfmxn	2014.0	2	backend engineer	2019.0	8.0	3	3	3
11458859	xzntqcxtfmxn	2013.0	6	Others	2018.0	9.0	3	3	3
11184342	xzntqcxtfmxn	2013.0	14	Others	2018.0	9.0	3	1	3
14542568	Others	2016.0	15	Others	2018.0	6.0	3	3	3
14527644	Others	2019.0	16	Others	2019.0	3.0	3	3	3
5972217	Others	2020.0	24	other	2020.0	2.0	3	3	3
9168559	Others	2016.0	25	android engineer	2018.0	6.0	3	3	3
11299761	Others	2022.0	200	Others	2022.0	0.0	3	3	3
14082893	Others	2013.0	300	database administrator	2019.0	9.0	3	3	3
8628205	Others	2018.0	500	cofounder	2019.0	4.0	3	3	3

```
#Top 10 employees in Amazon- X department - having 5/6/7 years of experience earning more than their peers - Tier 1
df_cjy_cj_c[(df_cjy_cj_c['tier']==1) & ((df_cjy_cj_c['years_of_experience'] ==5)|(df_cjy_cj_c['years_of_experience'] ==6 )|(df_cjy_cj_c['
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	classes	designation	tier
8721837	sgrabvz ovwyo	2016.0	2623000	backend engineer	2020.0	6.0	1	1	1
1180036	erxupvqn	2017.0	2620000	fullstack engineer	2020.0	5.0	1	1	1
15003860	ofxssj	2017.0	2620000	backend engineer	2021.0	5.0	1	1	1
7688558	grd sqghu	2016.0	2610000	backend engineer	2020.0	6.0	1	1	1
14457758	nvqstn	2017.0	2610000	engineering leadership	2019.0	5.0	1	2	1
13903919	wvustbxzx	2016.0	2600000	Others	2021.0	6.0	1	1	1
112285	obvrrwvot	2016.0	2600000	android engineer	2020.0	6.0	1	2	1
14911184	ouxzzj	2015.0	2600000	Others	2020.0	7.0	1	2	1

```
#Top 10 companies (based on their CTC)
df_cjy_cj_c.groupby(['company_hash'])['ctc'].max().head(11).sort_values(ascending = False)
```

```
company_hash
Others                                      2620000
agdutq                                      2500000
aghmnzhn                                    2400000
adw ntwyzgrgsxto                            1957000
agnut                                       1800000
adw ntwyzgrgsj                              1750000
agotrtwn                                    1610000
agnoihvqto                                  1600000
aaqxctz avnv owxtzwto  vzvrjnxwo ucn rna    1400000
a ntwyzgrgsxto                              1350000
aggartmrht xzzgcvnxgzo                      1000000
Name: ctc, dtype: int64
```

Data processing for Unsupervised clustering - Label encoding/ One- hot encoding, Standardization of data

```
df_cjy_cj_c.copy(deep=True)
```

```
# Label Encoding

from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()
data['company_hash']= label_encoder.fit_transform(data['company_hash'])
len(data['company_hash'].unique())
```

```
2833
```

```
data['job_position']= label_encoder.fit_transform(data['job_position'])
len(data['job_position'].unique())
```

```
722
```

```
data
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	classes	designation	tier
0	45	2016.0	1100000	361	2020.0	6.0	1	2	1
1	1435	2018.0	449999	226	2019.0	4.0	3	3	3
2	0	2015.0	2000000	102	2020.0	7.0	1	1	1
66	904	2017.0	700000	102	2019.0	5.0	3	3	3
67	1471	2017.0	1400000	226	2019.0	5.0	1	2	1
...	...	...	...	...	...	...	...	...	...
15034049	855	2011.0	2250000	0	2019.0	11.0	1	1	1
15034131	2075	2008.0	220000	0	2019.0	14.0	3	2	3
15034132	618	2017.0	500000	0	2020.0	5.0	3	3	3
15034133	2102	2021.0	700000	0	2021.0	1.0	3	2	3
15034134	125	2014.0	1240000	0	2016.0	8.0	3	3	3

135737 rows × 9 columns

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 135737 entries, 0 to 15034134
Data columns (total 9 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   company_hash         135737 non-null  int64
 1   orgyear              135737 non-null  float64
 2   ctc                  135737 non-null  int64
 3   job_position         135737 non-null  int64
 4   ctc_updated_year     135737 non-null  float64
 5   years_of_experience  135737 non-null  float64
 6   classes              135737 non-null  int64
 7   designation          135737 non-null  int64
 8   tier                 135737 non-null  int64
dtypes: float64(3), int64(6)
memory usage: 10.4 MB
```

```
# dropping org year and cts_updated year as we already have years of experience

data.drop(columns=['orgyear'],inplace=True)
data.drop(columns=['ctc_updated_year'],inplace=True)
```

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

```
company_hash           0
ctc                    0
job_position           0
years_of_experience    0
classes                0
designation            0
tier                   0
dtype: int64
```

```
# Creating second copy after org_df

data_1 = data.copy()
```

```
from sklearn.preprocessing import MinMaxScaler

X = data_1.copy()
```

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

Clustering using Sklearn's implementation of Kmeans

```
from sklearn.cluster import KMeans

k = 3 ## arbitrary value
kmeans = KMeans(n_clusters=k)
y_pred = kmeans.fit_predict(X)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
```

```
##coordinates of the cluster centers
kmeans.cluster_centers_
```

```
array([[4.78501569e-01, 5.10481710e-01, 2.45765762e-01, 5.88016755e-01,
        2.53110003e-01, 6.24905279e-01, 6.13791361e-02],
       [4.29739441e-01, 2.29332700e-01, 2.53654498e-01, 4.35319598e-01,
        9.06058510e-01, 7.56702639e-01, 9.81633080e-01],
       [3.93390521e-01, 5.37892679e-01, 2.29004543e-01, 4.81213394e-01,
        2.86239496e-02, 2.14858671e-04, 6.14973262e-02]])
```

```
y_pred is kmeans.labels_
```

```
True
```

Visualizing Sklearn Clusters

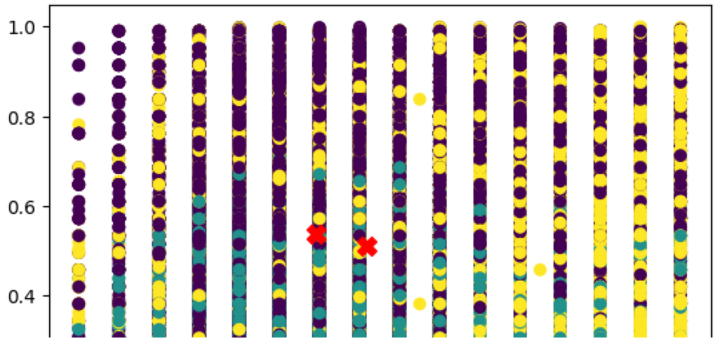
```
clusters = pd.DataFrame(X, columns=data_1.columns)
clusters['label'] = kmeans.labels_
clusters
```

	company_hash	ctc	job_position	years_of_experience	classes	designation	tier	label
0	0.015890	0.419047	0.500693	0.466667	0.0	0.5	0.0	2
1	0.506709	0.171428	0.313454	0.333333	1.0	1.0	1.0	1
2	0.000000	0.761905	0.141470	0.533333	0.0	0.0	0.0	0
3	0.319209	0.266666	0.141470	0.400000	1.0	1.0	1.0	1
4	0.519421	0.533333	0.313454	0.400000	0.0	0.5	0.0	2
...	...	...	...	...	...	...	...	...
135732	0.301907	0.857143	0.000000	0.800000	0.0	0.0	0.0	0
135733	0.732698	0.083809	0.000000	1.000000	1.0	0.5	1.0	1
135734	0.218220	0.190476	0.000000	0.400000	1.0	1.0	1.0	1
135735	0.742232	0.266666	0.000000	0.133333	1.0	0.5	1.0	1
135736	0.044138	0.472381	0.000000	0.600000	1.0	1.0	1.0	1

135737 rows × 8 columns

```
def viz_clusters(kmeans):
    plt.scatter(clusters['years_of_experience'], clusters['ctc'], c=clusters['label'])
    plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1],
                color="red",
                marker="X",
                s=100)

viz_clusters(kmeans)
```



No clarity in visualization using scatter plot

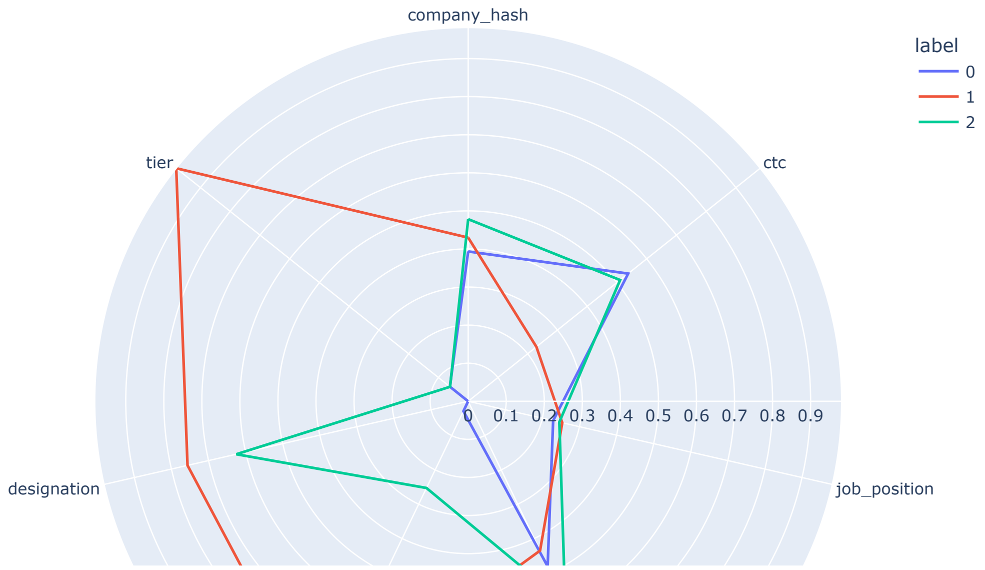
Using polar plot for better visialization

```
# Using polar plot for better visialization:
polar = clusters.groupby("label").mean().reset_index()
polar = pd.melt(polar, id_vars=["label"])
polar
```

	label	variable	value
0	0	company_hash	0.393457
1	1	company_hash	0.429823
2	2	company_hash	0.478295
3	0	ctc	0.537845
4	1	ctc	0.229339
5	2	ctc	0.510696
6	0	job_position	0.229044
7	1	job_position	0.253654
8	2	job_position	0.245712
9	0	years_of_experience	0.481254
10	1	years_of_experience	0.435346
11	2	years_of_experience	0.588022
12	0	classes	0.028882
13	1	classes	0.905870
14	2	classes	0.252789
15	0	designation	0.000155
16	1	designation	0.756672
17	2	designation	0.625083
18	0	tier	0.061489
19	1	tier	0.981550
20	2	tier	0.061001

```
import plotly.express as px

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



Feature definitions:

- Designation: Salary an employee is getting wrt salary in the same Company, Job_Position & Years of Experience
- Class: Salary an employee is getting wrt the salary in the same Company & Job_Position
- Tier: Salary an employee is getting wrt the salary in the same Company descent

Super clarity in visualizing the clusters using polar line plots:

Observations and Recommendations:

- We have three clusters mainly (label - 0, 1, 2)
- job_position , years of experience, company_hash for all the people in the three cluster is nearly same. So we can compare the other features keeping this useful info in mind.
- The students whose salaries are already high (Label 0), and who comes from a descent job role in a descent company, having slightly more amount experience, hardly care about designation , class or tier as they all are best of all !!
  - (Recomm.) Scaler should completely ignore these students for advertising/marketing their product as they don't need to upskill as they already are super skilled.
  - (Recomm.) Instead, Scaler team should identify and talk to these folks if they are interested in teaching/mentoring. This way, Scaler would be having best of the best instructors/mentors in the business.
- The students who have median salary (not too high, not too low) (Label 1), and who comes from a descent job role in a descent company, having descent amount experience, requires little upscalling.
  - (Recomm.) Scaler should advertise these set of students with some advanced courses so that they can compete with top tier students.
- The students who have least salary (Label 2), and who comes from a descent job role in a descent company, having descent amount experience, requires lots of upscalling. As these students belongs to designation - 3, class- 3, tier- 3
  - (Recomm.) These are the target audience. Scaler team should heavily focus on advertising / marketing all their tech products/ couses, free master clases, to these set of learners

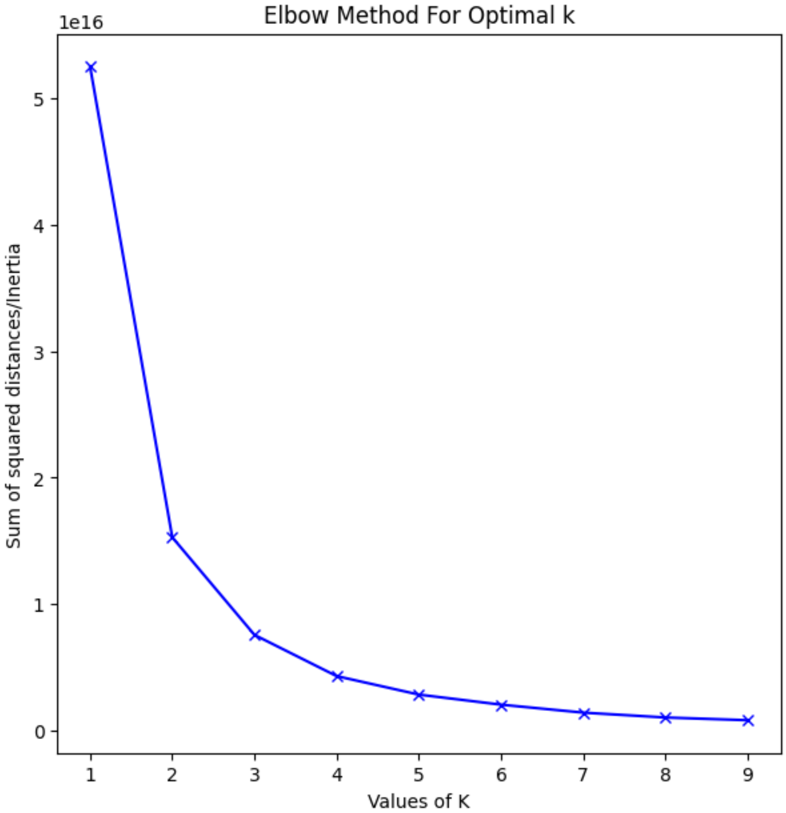
Elbow method

```
data_new = data.copy()
data_new
```

	company_hash	ctc	job_position	years_of_experience	classes	designation	tier
0	45	1100000	361	6.0	1	2	1
1	1435	449999	226	4.0	3	3	3
2	0	2000000	102	7.0	1	1	1
66	904	700000	102	5.0	3	3	3
67	1471	1400000	226	5.0	1	2	1

```
plt.figure(figsize = (7,7))
Sum_of_squared_distances = []
K = range(1,10)
for num_clusters in K :
    kmeans = KMeans(n_clusters=num_clusters)
    kmeans.fit(data_new)
    Sum_of_squared_distances.append(kmeans.inertia_)
plt.plot(K,Sum_of_squared_distances,'bx-')
plt.xlabel('Values of K')
plt.ylabel('Sum of squared distances/Inertia')
plt.title('Elbow Method For Optimal k')
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
```



From above plot, it's clear that we require 3 clusters and our earlier assumption is correct.

```
kmeans = KMeans(n_clusters=3)
kmeans.fit(data_new)
```

```
print(kmeans.cluster_centers_)
print(kmeans.cluster_centers_.shape)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
[[1.23561270e+03 5.04777019e+05 1.94292942e+02 5.49216642e+00
  2.45951364e+00 2.31887924e+00 2.55894463e+00]
 [1.22223452e+03 1.20861335e+06 1.64440108e+02 6.72251613e+00
  1.67707527e+00 1.79124731e+00 1.60619355e+00]
 [1.16018300e+03 2.05352128e+06 1.49806298e+02 7.51264966e+00
  1.20382975e+00 1.46662293e+00 1.07487289e+00]]
(3, 7)
```

```
data_new['k-m label']=kmeans.fit_predict(data_new)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
```

Hierarchical clustering

```
data_frac=data_new.sample(frac=0.0025)
#the most we could do without crashing
```

```
data_frac
```

	company_hash	ctc	job_position	years_of_experience	classes	designation	tier	k-m label
1857783	2106	740000	149	6.0	1	1	1	0
12108731	973	420000	0	6.0	3	3	3	0
14558084	2647	1600000	0	6.0	1	1	1	2
4802251	2197	600000	156	5.0	3	1	1	0
8874309	1674	2300000	102	4.0	1	1	1	1
...	...	...	...	...	...	...	...	...
2729602	0	270000	102	3.0	3	3	3	0
1444359	2197	700000	0	4.0	1	1	1	0
14793647	1263	1710000	173	4.0	1	1	1	1
999774	2064	1200000	0	1.0	1	2	1	2
14855046	78	1250000	389	4.0	2	2	1	2

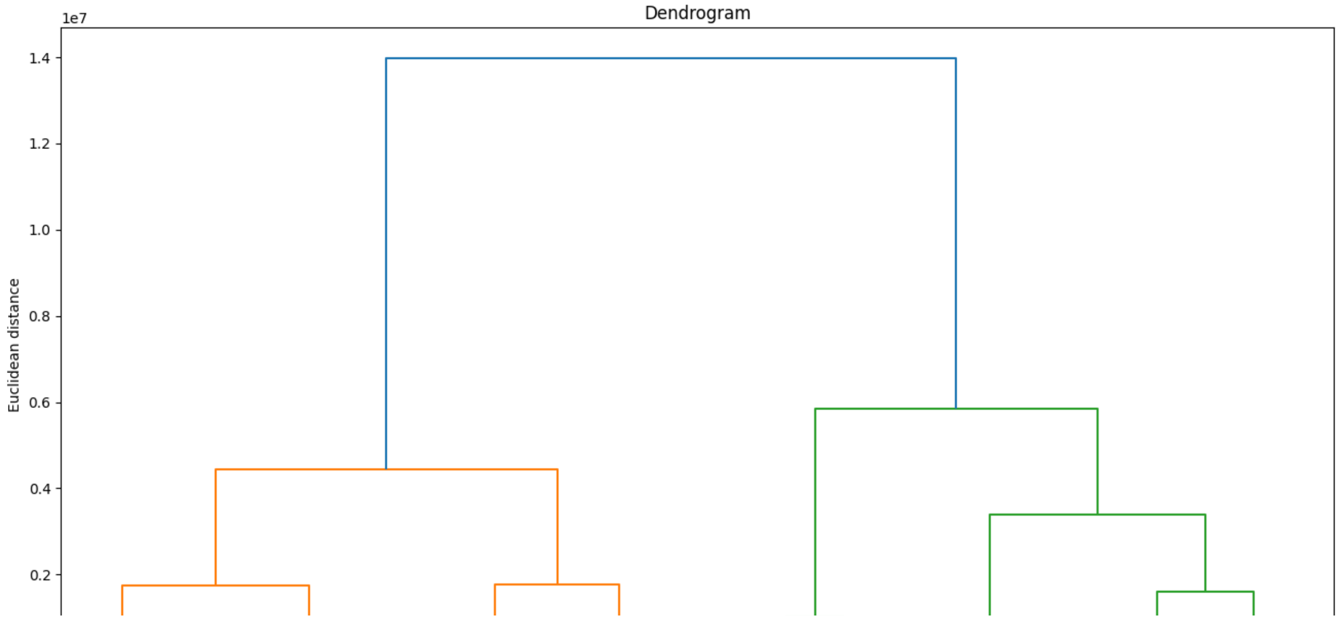
339 rows × 8 columns

```
data_frac.drop('k-m label', axis = 1, inplace = True)
```

```
import sys
sys.setrecursionlimit(100000)
```

```
# Visual representation of clusters using dendrogram

plt.figure(figsize = (16,8))
import scipy.cluster.hierarchy as sch
dendrogrm = sch.dendrogram(sch.linkage(data_frac, method = 'ward'))
plt.title('Dendrogram')
plt.xlabel('placements')
plt.ylabel('Euclidean distance')
plt.show()
```




```
from sklearn.cluster import AgglomerativeClustering
model = AgglomerativeClustering(n_clusters=3, affinity='euclidean', linkage='ward')
model.fit(data_frac)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_agglomerative.py:983: FutureWarning: Attribute `affinity` was deprecated ir
  warnings.warn(
```

```
AgglomerativeClustering
AgglomerativeClustering(affinity='euclidean', n_clusters=3)
```

```
data_frac['Aglo-label'] = model.fit_predict(data_frac)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_agglomerative.py:983: FutureWarning: Attribute `affinity` was deprecated ir
  warnings.warn(
```

```
data_frac
```

	company_hash	ctc	job_position	years_of_experience	classes	designation	tier	Aglo-label
1857783	2106	740000	149	6.0	1	1	1	0
12108731	973	420000	0	6.0	3	3	3	0
14558084	2647	1600000	0	6.0	1	1	1	1
4802251	2197	600000	156	5.0	3	1	1	0
8874309	1674	2300000	102	4.0	1	1	1	2
...	...	...	...	...	...	...	...	...
2729602	0	270000	102	3.0	3	3	3	0
1444359	2197	700000	0	4.0	1	1	1	0
14793647	1263	1710000	173	4.0	1	1	1	1
999774	2064	1200000	0	1.0	1	2	1	1
14855046	78	1250000	389	4.0	2	2	1	1

339 rows × 8 columns

```
df_cjy_cj_c
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_experience	classes	designation	tier
0	atrgxnnt xzaxv	2016.0	1100000	other	2020.0	6.0	1	2	1
1	qtrxvzwt xzegwgbb rxbxnta	2018.0	449999	fullstack engineer	2019.0	4.0	3	3	3
2	Others	2015.0	2000000	backend engineer	2020.0	7.0	1	1	1
66	ngpgutaxv	2017.0	700000	backend	2019.0	5.0	3	3	3

```
data_org = df_cjy_cj_c.copy()
final_data = pd.concat([data_org,data_new['k-m label']], axis=1)
final_data
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	years_of_ex
0	atrgxnnt xzaxv	2016.0	1100000	other	2020.0	
1	qtrxvzwt xzegwgbb rxbxnta	2018.0	449999	fullstack engineer	2019.0	
2	Others	2015.0	2000000	backend engineer	2020.0	
66	ngpgutaxv	2017.0	700000	backend engineer	2019.0	
67	qxen sqghu	2017.0	1400000	fullstack engineer	2019.0	
...	...	...	...	...	...	
15034049	mvqwrvjo	2011.0	2250000	Others	2019.0	
15034131	vuurt xzw	2008.0	220000	Others	2019.0	

Final_data is the dataset with label that used by marketing team to focus on marketing strategies