

Scaler_Clustering_Case_Study

June 30, 2024

1 Exploratory data analysis:

1.0.1 Importing required packages:

```
[4]: import pandas as pd
import numpy as np
import seaborn as sns
sns.set(style='whitegrid')
from scipy import stats
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
from sklearn.preprocessing import MinMaxScaler
```

1.0.2 Loading data into Dataframe:

```
[5]: df = pd.read_csv('scaler_clustering.csv')
df
```

```
[5]:      Unnamed: 0      company_hash \
0              0      atrgxmnt xzaxv
1              1  qtrxvzwt xzegwgb rxbxnta
2              2  ojzwnvwnxw vx
3              3      ngpgutaxv
4              4      qxen sqghu
...          ...          ...
205838      206918      vuurt xzw
205839      206919      husqvawgb
205840      206920      vwwgrxnt
205841      206921      zgn vuurxwvmrt
205842      206922      bgqsvz onvzrtj

      email_hash  orgyear      ctc \
0  6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...  2016.0  1100000
1  b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...  2018.0   449999
2  4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...  2015.0  2000000
3  effdede7a2e7c2af664c8a31d9346385016128d66bbc58...  2017.0   700000
```

```

4          6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...  2017.0  1400000
...
205838  70027b728c8ee901fe979533ed94ffda97be08fc23f33b...  2008.0   220000
205839  7f7292ffad724ebbe9ca860f515245368d714c84705b42...  2017.0   500000
205840  cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c...  2021.0   700000
205841  fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c8...  2019.0  5100000
205842  0bcfc1d05f2e8dc4147743a1313aa70a119b41b30d4a1f...  2014.0  1240000

```

```

          job_position  ctc_updated_year
0              Other          2020.0
1  FullStack Engineer          2019.0
2    Backend Engineer          2020.0
3    Backend Engineer          2019.0
4  FullStack Engineer          2019.0
...
205838          NaN          2019.0
205839          NaN          2020.0
205840          NaN          2021.0
205841          NaN          2019.0
205842          NaN          2016.0

```

[205843 rows x 7 columns]

Summary:

- We have 205843 data points, and 7 features. We can drop the column `Unnamed: 0` as it's the row Sr. No.
- Also, our objective is clustering, the `email_hash` won't be useful feature as we won't be looking at the granularity of the data, but more focused on groping the data into similar clusters. Hence dropping email ids will be useful

```
[6]: # Creating a copy of original dataframe
```

```
df_org = df.copy()
```

1.0.3 Identification of variables and data types:

```
[7]: df.shape
```

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

```
[8]: 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       153279 non-null  object
6    ctc_updated_year   205843 non-null  float64
dtypes: float64(2), int64(2), object(3)
memory usage: 11.0+ MB

```

```

[9]: def feature_names(df):

    print(f"Columns with category datatypes (Categorical Features) are : \
{list(df.select_dtypes('object').columns)}")
    print('-'*125)
    print('-'*125)
    print(f"Columns with integer and float datatypes (Numerical Features) are: \
{list(df.select_dtypes(['int64', 'float64']).columns)}")

```

```
[10]: feature_names(df)
```

```

Columns with category datatypes (Categorical Features) are :
['company_hash', 'email_hash', 'job_position']

```

```

-----
-----
-----

```

```

Columns with integer and float datatypes (Numerical Features) are:
['Unnamed: 0', 'orgyear', 'ctc', 'ctc_updated_year']

```

1.0.4 Analysing the basic metrics:

```
[11]: df.describe(include=[np.number]).transpose()
```

```

[11]:
count      mean      std      min      25%  \
Unnamed: 0  205843.0  1.032739e+05  5.974131e+04  0.0  51518.5
orgyear     205757.0  2.014883e+03  6.357112e+01  0.0  2013.0
ctc         205843.0  2.271685e+06  1.180091e+07  2.0  530000.0
ctc_updated_year  205843.0  2.019628e+03  1.325104e+00  2015.0  2019.0

      50%      75%      max
Unnamed: 0  103151.0  154992.5  2.069220e+05
orgyear     2016.0   2018.0  2.016500e+04
ctc         950000.0  1700000.0  1.000150e+09
ctc_updated_year  2020.0   2021.0  2.021000e+03

```

```
[12]: df.describe(include = [object]).transpose()
```

```
[12]:
```

	count	unique	\
company_hash	205799	37299	
email_hash	205843	153443	
job_position	153279	1016	

	top	freq
company_hash	nvnv wgzohrnrvzwj otqcxwto	8337
email_hash	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	10
job_position	Backend Engineer	43554

1.0.5 Missing values:

```
[13]: # Missing values:

def missingValue(df):
    #Identifying Missing data.
    total_null = df.isnull().sum().sort_values(ascending = False)
    percent = ((df.isnull().sum()/len(df))*100).sort_values(ascending = False)
    print(f"Total records in our data = {df.shape[0]} where missing values are as follows:")

    missing_data = pd.concat([total_null,percent.round(2)],axis=1,keys=['Total Missing','In Percent'])
    return missing_data

[14]: missing_df = missingValue(df)
missing_df[missing_df['Total Missing'] > 0]
```

Total records in our data = 205843 where missing values are as follows:

```
[14]:
```

	Total Missing	In Percent
job_position	52564	25.54
orgyear	86	0.04
company_hash	44	0.02

- Total 3 features has missing values (job, year, company)

2 Data Preprocessing

```
[15]: # We can drop the column `Unnamed: 0` as it's the row Sr. No.
# Also, our objective is clustering, the `email_hash` won't be useful feature
#as we won't be looking at the granularity of the data, but more focused on
    grouping the data into similar clusters.
# Hence dropping email ids will be useful

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

```
[16]: # 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
```

```
[17]: #what happens here
```

```
mystring='\tAirtel\\\\\\&&*() X Labs'
re.sub('[^A-Za-z ]+', '', mystring)
```

```
[17]: 'Airtel X Labs'
```

```
[18]: # 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.job_position
```

```
[18]: 0          other
1    fullstack engineer
2      backend engineer
3      backend engineer
4    fullstack engineer
...
205838          nan
205839          nan
205840          nan
205841          nan
205842          nan
Name: job_position, Length: 205843, dtype: object
```

```
[19]: df.shape
```

```
[19]: (205843, 5)
```

```
[20]: df.drop_duplicates(inplace=True)
df.shape
```

```
[20]: (188246, 5)
```

```
[21]: df['company_hash'].value_counts().sort_index()
```

```
[21]: company_hash
0          2
0000       1
```

```

01 ojztqsj                2
05mz exzytvrny uqxcvnt rxbxnta  2
1                            2
..
zyvzwt wgzohrnxs tsxztqo      1
zz                            2
zzb ztdnstz vacxogqj ucn rna   2
zzgato                      1
zzzbzb                      1
Name: count, Length: 37299, dtype: int64

```

[22]: *# 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())
df.company_hash

```

```

[22]: 0          atrgxmnt xzaxv
1      qtrxvzwt xzegwgb rxbxnta
2          ojzwnvwnxw vx
3          ngpgutaxv
4          qxen sqghu
...
205838          vuurt xzw
205839          husqvawgb
205840          vwwgrxnt
205841          zgn vuurxwvmt
205842          bgqsvz onvzrtj
Name: company_hash, Length: 188246, dtype: object

```

[23]: `df['company_hash'].value_counts().sort_index()`

```

[23]: company_hash
a 85
a b onttr wgqu 1
a j uvnxr owyggr ge tsxztqxs vwatbj vbm 1
a ntwy ogrhnxgzo ucn rna 2
..
zz 2
zz wgzztnw mya 1
zzb ztdnstz vacxogqj ucn rna 2
zzgato 1
zzzbzb 1
Name: count, Length: 37208, dtype: int64

```

```
[24]: print(df.shape)
      print(df.drop_duplicates().shape)
      df.drop_duplicates(inplace=True)
```

```
(188246, 5)
(188245, 5)
```

```
[25]: #removing rows where company or job_position is not available

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

```
[26]: df.shape
```

```
[26]: (188152, 5)
```

```
[27]: df['orgyear'].isnull().sum()
```

```
[27]: 86
```

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

```
[28]: company_hash
      a                                     2017.0
      a b onttr wgqu                       2019.0
      a j uvnxr owyggr ge tzsxzttxzs vwvatbj vbmj 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
```

```
[29]: #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
```

```
[30]: # 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']
```

```
[30]: 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: 188152, dtype: float64
```

```
[31]: #if we still have null values, we'll drop it

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

```
[31]: 26
```

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

```
[33]: missing_df = missingValue(df)
missing_df[missing_df['Total Missing'] > 0]
```

Total records in our data = 188126 where missing values are as follows:

```
[33]: Empty DataFrame
      Columns: [Total Missing, In Percent]
      Index: []
```

3 Outlier Detection and Treatment

- orgyear
- ctc

```
[34]: #simple understanding
df.orgyear.value_counts().sort_values(ascending=True)
```

```
[34]: orgyear
      200.0      1
      2011.5     1
```



```

1900.0      1
208.0       1
2204.0      1
...
2019.0    18550
2015.0    19613
2017.0    21320
2016.0    21477
2018.0    22157
Name: count, Length: 79, dtype: int64

```

```

[35]: #simple understanding
df.ctc.value_counts().sort_values(ascending=True)

```

```

[35]: ctc
1916000      1
2664000      1
28200        1
983000       1
516000       1
...
1200000     5623
500000      5661
800000      5917
1000000     6835
600000      6857
Name: count, Length: 3360, dtype: int64

```

```

[36]: #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)]

#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)]

```

```

[37]: df.orgyear.value_counts().sort_index(ascending=True)

```

```

[37]: orgyear
2006.0     1635
2007.0     1821

```

```

2008.0    2279
2009.0    3215
2010.0    5004
2011.0    7023
2011.5         1
2012.0    9366
2013.0   11134
2014.0   15090
2014.5         2
2015.0   18535
2016.0   20394
2017.0   20421
2018.0   21335
2019.0   17909
2020.0    9940
2021.0    2900
2022.0    739
2023.0    200
2024.0     32
2025.0     11
Name: count, dtype: int64

```

```

[38]: print(df.shape)
      print(df.drop_duplicates().shape)
      df.drop_duplicates(inplace=True)

```

```

(168986, 5)
(168985, 5)

```

```

[39]: df

```

```

[39]:
      company_hash  orgyear  ctc  job_position \
0      atrgxnt xzaxv  2016.0  1100000  other
1  qtrxvzwt xzegwbb rxbxnta  2018.0  449999  fullstack engineer
2      ojzwnvwnxw vx  2015.0  2000000  backend engineer
3      ngpgutaxv  2017.0  700000  backend engineer
4      qxen sqghu  2017.0  1400000  fullstack engineer
...
205836      mvqwrvj  2011.0  2250000  nan
205838      vuurt xzw  2008.0  220000  nan
205839      husqvawgb  2017.0  500000  nan
205840      vwwgrxnt  2021.0  700000  nan
205842      bgqsvz onvzrtj  2014.0  1240000  nan

      ctc_updated_year
0      2020.0
1      2019.0

```

```

2          2020.0
3          2019.0
4          2019.0
...
205836     2019.0
205838     2019.0
205839     2020.0
205840     2021.0
205842     2016.0

```

[168985 rows x 5 columns]

```
[40]: #We see some 'nan's in job_position
df.loc[df['job_position']=='nan','job_position']=np.nan
```

```
[41]: df
```

```
[41]:
```

	company_hash	orgyear	ctc	job_position \
0	atrgxnnt xzaxv	2016.0	1100000	other
1	qtrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer
2	ojzwnvwnxw vx	2015.0	2000000	backend engineer
3	ngpgutaxv	2017.0	700000	backend engineer
4	qxen sqghu	2017.0	1400000	fullstack engineer
...
205836	mvqwrvo	2011.0	2250000	NaN
205838	vuurt xzw	2008.0	220000	NaN
205839	husqvawgb	2017.0	500000	NaN
205840	vwwgrxnt	2021.0	700000	NaN
205842	bgqsvz onvzrtj	2014.0	1240000	NaN

```

ctc_updated_year
0          2020.0
1          2019.0
2          2020.0
3          2019.0
4          2019.0
...
205836     2019.0
205838     2019.0
205839     2020.0
205840     2021.0
205842     2016.0

```

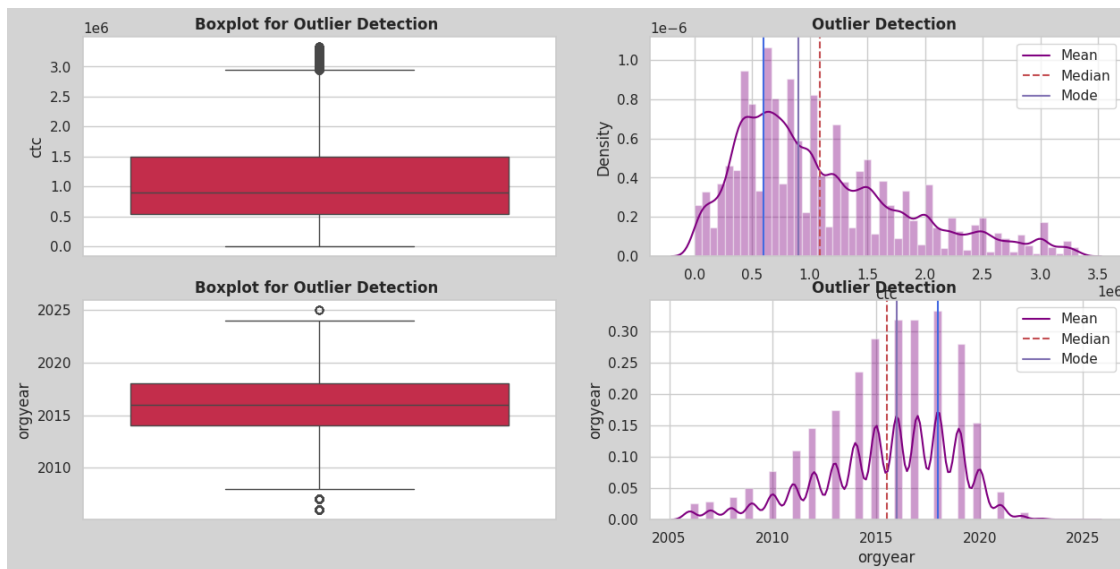
[168985 rows x 5 columns]

```
[42]: feature_names(df)
```

Columns with category datatypes (Categorical Features) are :
['company_hash', 'job_position']

Columns with integer and float datatypes (Numerical Features) are:
['orgyear', 'ctc', 'ctc_updated_year']

```
[43]: 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.distplot(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()  
  
[44]: # We won't consider 'ctc_updated_year' as numerical but instead categorical  
↪features  
  
numerical_cols = ['ctc', 'orgyear']  
  
[45]: numerical_feat(df,numerical_cols,len(numerical_cols),2,15,7)
```



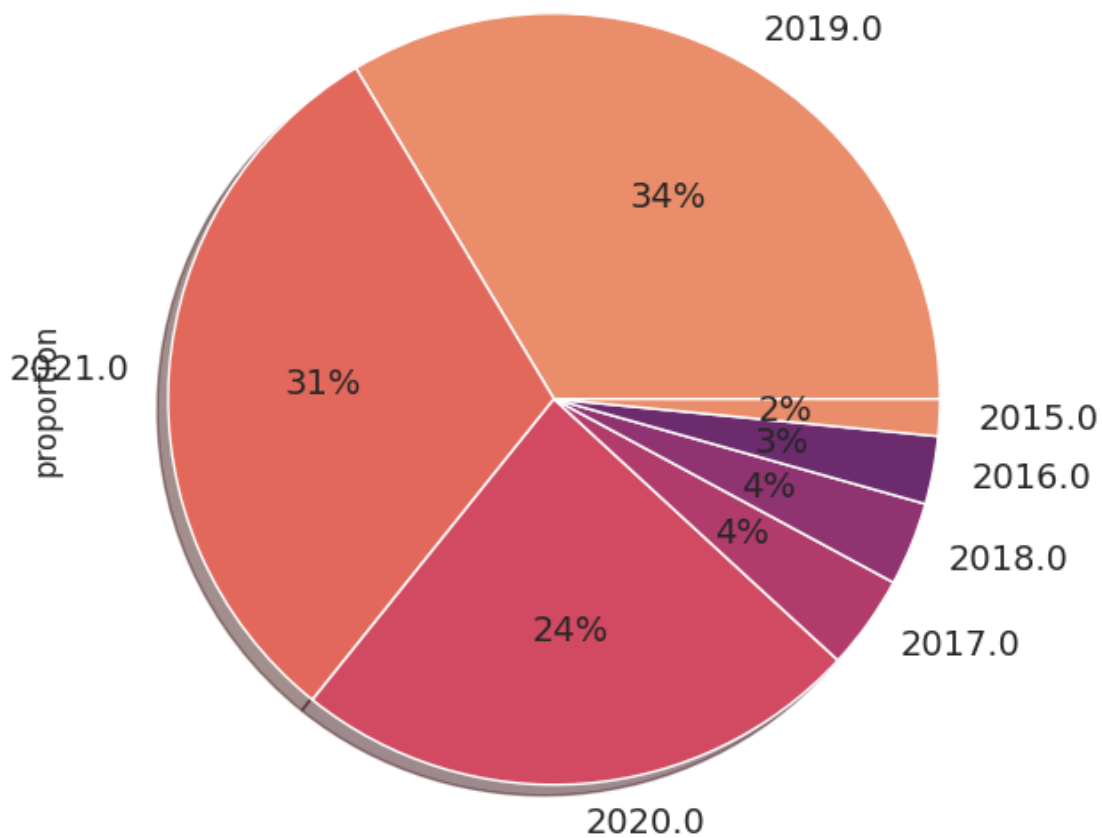
```
[46]: categorical_cols = ['company_hash', 'job_position', 'ctc_updated_year']
```

```
[47]: for i in categorical_cols:
       print(f" Unique values in {i} are {df[i].nunique()}")
```

```
Unique values in company_hash are 34008
Unique values in job_position are 761
Unique values in ctc_updated_year are 7
```

```
[48]: # categorical_cols = ['ctc_updated_year']
```

```
[49]: plt.figure(figsize = (7,8))
count = (df['ctc_updated_year'].value_counts(normalize=True)*100)
count.plot.pie(colors = sns.color_palette("flare"),autopct='%0.0f%%',
               textprops={'fontsize': 14},shadow = True)
plt.show()
```



4 Feature Engineering:

4.0.1 Definition:

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

```
[50]: # ![image.png](attachment:image.png)
      df.company_hash.value_counts()
```

```
[50]: company_hash
      nvnv wgzohrnvwj otqcxwto      4111
      xzegojo                      2910
```

```

vbvkgz                2226
wgszxxkvzn            2115
vwwtznhq             1998
...
wrjbxz ogenrvmo        1
vsxrtmgn vhnbgvnxgz uqxcvnt rxbxnta  1
whbhrho ztnfgqp        1
utznvhq ntwy           1
zzzlv cvz              1
Name: count, Length: 34008, dtype: int64

```

•

```
[51]: df.company_hash.value_counts() <= 5
```

```

[51]: company_hash
nvnv wgzohrnvwzj otqcxwto      False
xzegojo                        False
vbvkgz                        False
wgszxxkvzn                    False
vwwtznhq                      False
...
wrjbxz ogenrvmo                True
vsxrtmgn vhnbgvnxgz uqxcvnt rxbxnta  True
whbhrho ztnfgqp                True
utznvhq ntwy                   True
zzzlv cvz                      True
Name: count, Length: 34008, dtype: bool

```

```
[52]: df.company_hash.map(df.company_hash.value_counts()) <= 5
```

```

[52]: 0      False
      1      False
      2       True
      3      False
      4      False
      ...
205836  False
205838  False
205839  False
205840  False
205842  False
Name: company_hash, Length: 168985, dtype: bool

```

```
[53]: df[df.company_hash.map(df.company_hash.value_counts())<=5]
```

```
[53]:
```

	company_hash	orgyear	ctc	job_position \
2	ojzwnvwnxw vx	2015.0	2000000	backend engineer
9	xrbhd	2019.0	360000	NaN
11	ngdor ntwy	2016.0	600000	ios engineer
16	pnw xzaxv ucn rna	2013.0	800000	other
21	axgz srgmvr	2006.0	1550000	engineering leadership
...
205811	mrht onvnt axsxnv	2013.0	85000	NaN
205815	bvptbjnqxu td vbvkgz	2015.0	2400000	NaN
205816	wgat ergf ntwy rru	2019.0	2200000	NaN
205817	wxowg ojointbo	2011.0	3327000	NaN
205834	wyvqntq wgbhzhxwvnxgzo	2020.0	100000	NaN

```

ctc_updated_year
2          2020.0
9          2019.0
11         2021.0
16         2020.0
21         2019.0
...
205811     2016.0
205815     2019.0
205816     2020.0
205817     2019.0
205834     2019.0

```

```
[46749 rows x 5 columns]
```

```
[54]: df['new']=df.company_hash.mask(df.company_hash.map(df.company_hash.
↪value_counts())<=5)
df['new']
```

```
[54]: 0          atrgxnt xzaxv
1      qtrxvzwt xzegwgb rxbxnta
2              NaN
3          ngpgutaxv
4      qxen sqghu

...
205836          mvqwrvj0
205838          vuurt xzw
205839          husqvawgb
205840          vwwgrxnt
205842          bgqsvz onvzrtj
Name: new, Length: 168985, dtype: object
```

```
[55]: df
```



```
[55]:
```

	company_hash	orgyear	ctc	job_position	\
0	atrgxnnt xzaxv	2016.0	1100000	other	
1	qtrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer	
2	ojzwnvwnxw vx	2015.0	2000000	backend engineer	
3	ngpgutaxv	2017.0	700000	backend engineer	
4	qxen sqghu	2017.0	1400000	fullstack engineer	
...	
205836	mvqwrvj	2011.0	2250000		NaN
205838	vuurt xzw	2008.0	220000		NaN
205839	husqvawgb	2017.0	500000		NaN
205840	vwwgrxnt	2021.0	700000		NaN
205842	bgqsvz onvzrtj	2014.0	1240000		NaN

	ctc_updated_year	new
0	2020.0	atrgxnnt xzaxv
1	2019.0	qtrxvzwt xzegwgb rxbxnta
2	2020.0	NaN
3	2019.0	ngpgutaxv
4	2019.0	qxen sqghu
...
205836	2019.0	mvqwrvj
205838	2019.0	vuurt xzw
205839	2020.0	husqvawgb
205840	2021.0	vwwgrxnt
205842	2016.0	bgqsvz onvzrtj

[168985 rows x 6 columns]

```
[56]: df[df['new']=='Others'].company_hash.value_counts()
```

```
[56]: Series([], Name: count, dtype: int64)
```

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

```
[57]:
```

	company_hash	orgyear	ctc	job_position	\
0	atrgxnnt xzaxv	2016.0	1100000	other	
1	qtrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer	
2	Others	2015.0	2000000	backend engineer	
3	ngpgutaxv	2017.0	700000	backend engineer	
4	qxen sqghu	2017.0	1400000	fullstack engineer	
...	
205836	mvqwrvj	2011.0	2250000		NaN
205838	vuurt xzw	2008.0	220000		NaN
205839	husqvawgb	2017.0	500000		NaN
205840	vwwgrxnt	2021.0	700000		NaN

205842	bgqsvz onvzrtj	2014.0	1240000	NaN
--------	----------------	--------	---------	-----

	ctc_updated_year		new
0	2020.0	atrgxnnt xzaxv	
1	2019.0	qtrxvzwt xzegwgb rxbxnta	
2	2020.0		NaN
3	2019.0	ngpgutaxv	
4	2019.0	qxen sqghu	
...	
205836	2019.0	mvqwrvjjo	
205838	2019.0	vuurt xzw	
205839	2020.0	husqvawgb	
205840	2021.0	vwwgrxnt	
205842	2016.0	bgqsvz onvzrtj	

[168985 rows x 6 columns]

```
[58]: df.company_hash.value_counts()
```

```
[58]: company_hash
Others                                46749
nvnv wgzohrnrvzwj otqcxwto          4111
xzegojo                             2910
vbvkgz                              2226
wgszxkvzn                           2115
...
ihvrwgb b xzw                        6
lxgovvcz                             6
vrsgfgqpo ntwyzgrgsxto               6
wvbuhotvx                            6
xzntnr ntwyzgrgsj xzaxv uqxcvnt rxbxnta 6
Name: count, Length: 2943, dtype: int64
```

```
[59]: df.drop(columns='new',inplace=True)
```

•

```
[60]: df.drop_duplicates(inplace=True)
df.shape
```

```
[60]: (147139, 5)
```

```
[61]: #orgyear check
df['orgyear'] = df.apply(lambda x: x['orgyear'] if x['orgyear'] <= 2022 else_
↳2022, axis=1)
```

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

```
[63]: df.drop_duplicates(inplace=True)
df.shape
```

```
[63]: (147100, 6)
```

```
[64]: df=df[~df['years_of_experience'].isnull()]
```

```
[65]: #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
```

```
[65]:
```

	company_hash	orgyear	ctc	job_position \
0	atrgxnnt xzaxv	2016.0	1100000	other
1	qtrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer
2	Others	2015.0	2000000	backend engineer
3	ngpgutaxv	2017.0	700000	backend engineer
4	qxen sqghu	2017.0	1400000	fullstack engineer
...
205836	mvqwrvjjo	2011.0	2250000	NaN
205838	vuurt xzw	2008.0	220000	NaN
205839	husqvawgb	2017.0	500000	NaN
205840	vwwgrxnt	2021.0	700000	NaN
205842	bgqsvz onvzrtj	2014.0	1240000	NaN

	ctc_updated_year	years_of_experience
0	2020.0	6.0
1	2019.0	4.0
2	2020.0	7.0
3	2019.0	5.0
4	2019.0	5.0
...
205836	2019.0	11.0
205838	2019.0	14.0
205839	2020.0	5.0
205840	2021.0	1.0
205842	2016.0	8.0

```
[147100 rows x 6 columns]
```

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

```
[67]: missingValue(df)
```

Total records in our data = 147100 where missing values are as follows:

```
[67]:
```

	Total Missing	In Percent
company_hash	0	0.0
orgyear	0	0.0
ctc	0	0.0
job_position	0	0.0
ctc_updated_year	0	0.0
years_of_experience	0	0.0

```
[68]: df.drop_duplicates(inplace=True)
df.shape
```

```
[68]: (146052, 6)
```

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

```
[69]:
```

	orgyear	ctc	ctc_updated_year	years_of_experience
count	146052.000000	1.460520e+05	146052.000000	146052.000000
mean	2015.449384	1.129332e+06	2019.598444	6.550616
std	3.300262	7.439639e+05	1.339107	3.300262
min	2006.000000	2.000000e+00	2015.000000	0.000000
25%	2013.000000	5.700000e+05	2019.000000	4.000000
50%	2016.000000	9.600000e+05	2020.000000	6.000000
75%	2018.000000	1.560000e+06	2021.000000	9.000000
max	2022.000000	3.330000e+06	2022.000000	16.000000

4.0.2 Manual Clustering based on company, job position and years of experience

```
[70]: grouped_c_j_y=df.
      ↪groupby(['years_of_experience','job_position','company_hash'])['ctc'].
      ↪describe()
```

```
[71]: grouped_c_j_y
```

```
[71]:
```

years_of_experience	job_position	company_hash	count \
0.0	Others	Others	42.0
		agzn fgqp xz vzj gqsvzxkvnxzg	1.0
		atrgxnnt	1.0
		attr	1.0
		attr ntwyzgrgsxto	2.0
...		...	
16.0	support engineer	xzegojo	1.0

		xzegq	1.0
		ywr ntwyzgrgsxto	2.0
		zvz	1.0
	team lead	utqoxontzn ojointbo	1.0
			mean
\			
years_of_experience	job_position	company_hash	
0.0	Others	Others	7.058619e+05
		agzn fgqp xz vzj gqsvzxkvnvgz	1.600000e+06
		atrgxnnt	1.000000e+06
		attr	1.000000e+06
		attr ntwyzgrgsxto	1.000000e+06
...			...
16.0	support engineer	xzegojo	8.000000e+05
		xzegq	9.000000e+05
		ywr ntwyzgrgsxto	8.500000e+05
		zvz	4.000000e+05
	team lead	utqoxontzn ojointbo	1.600000e+06
std \			
years_of_experience	job_position	company_hash	
0.0	Others	Others	
674812.642666		agzn fgqp xz vzj gqsvzxkvnvgz	
NaN		atrgxnnt	
NaN		attr	
NaN		attr ntwyzgrgsxto	
282842.712475			
...			
...			
16.0	support engineer	xzegojo	
NaN		xzegq	
NaN		ywr ntwyzgrgsxto	
494974.746831		zvz	
NaN	team lead	utqoxontzn ojointbo	
NaN			
			min \
years_of_experience	job_position	company_hash	

0.0	Others	Others	200.0
		agzn fgqp xz vzj gqsvzxkvnxgz	1600000.0
		atrgxnnt	1000000.0
		attr	1000000.0
		attr ntwyzgrgsxto	800000.0

...			...
16.0	support engineer	xzegojo	800000.0
		xzegq	900000.0
		ywr ntwyzgrgsxto	500000.0
		zvz	400000.0
	team lead	utqoxontzn ojointbo	1600000.0

25% \

years_of_experience	job_position	company_hash	
0.0	Others	Others	227500.0
		agzn fgqp xz vzj gqsvzxkvnxgz	1600000.0
		atrgxnnt	1000000.0
		attr	1000000.0
		attr ntwyzgrgsxto	900000.0

...			...
16.0	support engineer	xzegojo	800000.0
		xzegq	900000.0
		ywr ntwyzgrgsxto	675000.0
		zvz	400000.0
	team lead	utqoxontzn ojointbo	1600000.0

50% \

years_of_experience	job_position	company_hash	
0.0	Others	Others	490000.0
		agzn fgqp xz vzj gqsvzxkvnxgz	1600000.0
		atrgxnnt	1000000.0
		attr	1000000.0
		attr ntwyzgrgsxto	1000000.0

...			...
16.0	support engineer	xzegojo	800000.0
		xzegq	900000.0
		ywr ntwyzgrgsxto	850000.0
		zvz	400000.0
	team lead	utqoxontzn ojointbo	1600000.0

75%

\			
years_of_experience	job_position	company_hash	
0.0	Others	Others	1014999.25
		agzn fgqp xz vzj gqsvzxkvnxgz	1600000.00
		atrgxnnt	1000000.00
		attr	1000000.00

		attr ntwyzgrgsxto	1100000.00
...			...
16.0	support engineer	xzegojo	800000.00
		xzegq	900000.00
		ywr ntwyzgrgsxto	1025000.00
		zvz	400000.00
	team lead	utqoxontzn ojointbo	1600000.00
			max
years_of_experience	job_position	company_hash	
0.0	Others	Others	3000000.0
		agzn fgqp xz vzj gqsvzxkvnxgz	1600000.0
		atrgxnnt	1000000.0
		attr	1000000.0
		attr ntwyzgrgsxto	1200000.0
...			...
16.0	support engineer	xzegojo	800000.0
		xzegq	900000.0
		ywr ntwyzgrgsxto	1200000.0
		zvz	400000.0
	team lead	utqoxontzn ojointbo	1600000.0

[56095 rows x 8 columns]

```
[72]: df_cjy=df.merge(grouped_c_j_y,
    on=['years_of_experience', 'job_position', 'company_hash'], how = 'left')
df_cjy
```

```
[72]:
```

	company_hash	orgyear	ctc	job_position \
0	atrgxnnt xzaxv	2016.0	1100000	other
1	qtrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer
2	Others	2015.0	2000000	backend engineer
3	ngpgutaxv	2017.0	700000	backend engineer
4	qxen sqghu	2017.0	1400000	fullstack engineer
...
146047	mvqwrvj	2011.0	2250000	Others
146048	vuurt xzw	2008.0	220000	Others
146049	husqvawgb	2017.0	500000	Others
146050	vwwgrxnt	2021.0	700000	Others
146051	bgqsvz onvzrtj	2014.0	1240000	Others

	ctc_updated_year	years_of_experience	count	mean \
0	2020.0	6.0	1.0	1.100000e+06
1	2019.0	4.0	7.0	7.742856e+05
2	2020.0	7.0	456.0	9.609559e+05
3	2019.0	5.0	7.0	1.158571e+06
4	2019.0	5.0	1.0	1.400000e+06

```

...
146047      2019.0      11.0  11.0  1.427273e+06
146048      2019.0      14.0   1.0  2.200000e+05
146049      2020.0       5.0   4.0  1.202500e+06
146050      2021.0       1.0   3.0  6.666667e+05
146051      2016.0       8.0   9.0  1.693333e+06

      std      min      25%      50%      75%      max
0      NaN  1100000.0  1100000.0  1100000.0  1100000.0  1100000.0
1  250922.324350  449999.0  610000.0  750000.0  900000.0  1200000.0
2  776546.830662   1000.0  307500.0  800000.0  1435000.0  3200000.0
3  404780.951933  700000.0  825000.0  1200000.0  1405000.0  1750000.0
4      NaN  1400000.0  1400000.0  1400000.0  1400000.0  1400000.0
...
146047  468638.192678  530000.0  1250000.0  1350000.0  1634999.5  2250000.0
146048      NaN  220000.0  220000.0  220000.0  220000.0  220000.0
146049  471902.179129  500000.0  1145000.0  1405000.0  1462500.0  1500000.0
146050  351188.458428  300000.0  500000.0  700000.0  850000.0  1000000.0
146051  348425.027804  1200000.0  1500000.0  1700000.0  1900000.0  2200000.0

```

[146052 rows x 14 columns]

```
[73]: df_cjy.sort_values(['years_of_experience', 'job_position', 'company_hash'])
```

```

[73]:      company_hash  orgyear      ctc      job_position \
896      Others    2022.0   120000      Others
2599      Others    2022.0   430000      Others
7691      Others    2022.0   570000      Others
7870      Others    2022.0   550000      Others
8789      Others    2022.0   680000      Others
...
73608      xzegq    2006.0   900000  support engineer
11355  ywr ntwyzgrgsxto    2006.0   500000  support engineer
37161  ywr ntwyzgrgsxto    2006.0  1200000  support engineer
14265      zvz    2006.0   400000  support engineer
59644  utqoxontzn ojontbo    2006.0  1600000      team lead

      ctc_updated_year  years_of_experience  count      mean \
896      2022.0      0.0   42.0  7.058619e+05
2599      2022.0      0.0   42.0  7.058619e+05
7691      2022.0      0.0   42.0  7.058619e+05
7870      2022.0      0.0   42.0  7.058619e+05
8789      2022.0      0.0   42.0  7.058619e+05
...
73608      2021.0      16.0   1.0  9.000000e+05
11355      2021.0      16.0   2.0  8.500000e+05
37161      2021.0      16.0   2.0  8.500000e+05

```


14265	2021.0		16.0	1.0	4.000000e+05	
59644	2021.0		16.0	1.0	1.600000e+06	
	std	min	25%	50%	75%	max
896	674812.642666	200.0	227500.0	490000.0	1014999.25	3000000.0
2599	674812.642666	200.0	227500.0	490000.0	1014999.25	3000000.0
7691	674812.642666	200.0	227500.0	490000.0	1014999.25	3000000.0
7870	674812.642666	200.0	227500.0	490000.0	1014999.25	3000000.0
8789	674812.642666	200.0	227500.0	490000.0	1014999.25	3000000.0
...
73608	NaN	900000.0	900000.0	900000.0	900000.00	900000.0
11355	494974.746831	500000.0	675000.0	850000.0	1025000.00	1200000.0
37161	494974.746831	500000.0	675000.0	850000.0	1025000.00	1200000.0
14265	NaN	400000.0	400000.0	400000.0	400000.00	400000.0
59644	NaN	1600000.0	1600000.0	1600000.0	1600000.00	1600000.0

[146052 rows x 14 columns]

```
[74]: df_cjy.drop_duplicates(inplace=True)
df_cjy.shape
#no change till now
```

[74]: (146052, 14)

•

```
[75]: def condition_designation(a,b_50,b_75):
    if a<b_50:
        return 3
    elif a>=b_50 and a<=b_75:
        return 2
    elif a>=b_75:
        return 1
```

```
[76]: df.head()
```

```
[76]:      company_hash  orgyear    ctc  job_position \
0      atrgxmnt xzaxv   2016.0  1100000      other
1  qtrxvzwt xzegwgb rxbxnta  2018.0   449999  fullstack engineer
2              Others   2015.0  2000000    backend engineer
3      ngpgutaxv   2017.0   700000    backend engineer
4      qxen sqghu   2017.0  1400000  fullstack engineer

      ctc_updated_year  years_of_experience
0              2020.0                6.0
```

1	2019.0	4.0
2	2020.0	7.0
3	2019.0	5.0
4	2019.0	5.0

```
[77]: df_cjy['designation'] =df_cjy.apply(lambda x:↳
↳condition_designation(x['ctc'],x['50%'],x['75%']),axis = 1)
```

```
[78]: df_cjy.head()
```

```
[78]:
```

	company_hash	orgyear	ctc	job_position	\
0	atrgxnnt xzaxv	2016.0	1100000	other	
1	qtrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer	
2	Others	2015.0	2000000	backend engineer	
3	ngpgutaxv	2017.0	700000	backend engineer	
4	qxen sqghu	2017.0	1400000	fullstack engineer	

	ctc_updated_year	years_of_experience	count	mean	std	\
0	2020.0	6.0	1.0	1.100000e+06	NaN	
1	2019.0	4.0	7.0	7.742856e+05	250922.324350	
2	2020.0	7.0	456.0	9.609559e+05	776546.830662	
3	2019.0	5.0	7.0	1.158571e+06	404780.951933	
4	2019.0	5.0	1.0	1.400000e+06	NaN	

	min	25%	50%	75%	max	designation
0	1100000.0	1100000.0	1100000.0	1100000.0	1100000.0	2
1	449999.0	610000.0	750000.0	900000.0	1200000.0	3
2	1000.0	307500.0	800000.0	1435000.0	3200000.0	1
3	700000.0	825000.0	1200000.0	1405000.0	1750000.0	3
4	1400000.0	1400000.0	1400000.0	1400000.0	1400000.0	2

```
[79]: df_cjy.shape
```

```
[79]: (146052, 15)
```

```
[80]: df_cjy.designation.value_counts(normalize=True)*100
```

```
[80]: designation
2    44.118533
3    34.180977
1    21.700490
Name: proportion, dtype: float64
```

4.0.3 Manual Clustering based on company and job position

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

```
[82]: grouped_c_j
```

```
[82]:
```

job_position	company_hash	count \
Others	Others	3159.0
	a ntwyzgrgsxto	5.0
	aaqxctz avnv owxtzwto vzvrjnxwo ucn rna	1.0
	adw ntwyzgrgsj	59.0
	adw ntwyzgrgsxto	37.0
...	...	
wordpress developer	Others	1.0
worker	zgn vuurxwvmrt vwwghzn	1.0
x	Others	1.0
young professional ii	sgctqzbtzn ge xzaxv	1.0
zomato	kgbvng	1.0
job_position	company_hash	mean \
Others	Others	1.025099e+06
	a ntwyzgrgsxto	6.750000e+05
	aaqxctz avnv owxtzwto vzvrjnxwo ucn rna	5.000000e+05
	adw ntwyzgrgsj	6.451864e+05
	adw ntwyzgrgsxto	6.230000e+05
...	...	
wordpress developer	Others	6.000000e+05
worker	zgn vuurxwvmrt vwwghzn	2.000000e+05
x	Others	4.000000e+05
young professional ii	sgctqzbtzn ge xzaxv	5.000000e+05
zomato	kgbvng	5.000000e+05
job_position	company_hash	std \
Others	Others	837191.520717
	a ntwyzgrgsxto	389711.431703
	aaqxctz avnv owxtzwto vzvrjnxwo ucn rna	NaN
	adw ntwyzgrgsj	449039.606370
	adw ntwyzgrgsxto	323412.705035
...	...	
wordpress developer	Others	NaN
worker	zgn vuurxwvmrt vwwghzn	NaN
x	Others	NaN
young professional ii	sgctqzbtzn ge xzaxv	NaN
zomato	kgbvng	NaN

		min \
job_position	company_hash	
Others	Others	15.0
	a ntwyzgrgsxto	350000.0
	aaqxctz avnv owxtzwto vzvrjnxwo ucn rna	500000.0
	adw ntwyzgrgsj	80000.0
	adw ntwyzgrgsxto	100000.0
...	...	
wordpress developer	Others	600000.0
worker	zgn vuurxwvmrt vwwghzn	200000.0
x	Others	400000.0
young professional ii	sgctqzbtzn ge xzaxv	500000.0
zomato	kgbvng	500000.0

		25% \
job_position	company_hash	
Others	Others	358500.0
	a ntwyzgrgsxto	500000.0
	aaqxctz avnv owxtzwto vzvrjnxwo ucn rna	500000.0
	adw ntwyzgrgsj	374000.0
	adw ntwyzgrgsxto	400000.0
...	...	
wordpress developer	Others	600000.0
worker	zgn vuurxwvmrt vwwghzn	200000.0
x	Others	400000.0
young professional ii	sgctqzbtzn ge xzaxv	500000.0
zomato	kgbvng	500000.0

		50% \
job_position	company_hash	
Others	Others	800000.0
	a ntwyzgrgsxto	575000.0
	aaqxctz avnv owxtzwto vzvrjnxwo ucn rna	500000.0
	adw ntwyzgrgsj	500000.0
	adw ntwyzgrgsxto	525000.0
...	...	
wordpress developer	Others	600000.0
worker	zgn vuurxwvmrt vwwghzn	200000.0
x	Others	400000.0
young professional ii	sgctqzbtzn ge xzaxv	500000.0
zomato	kgbvng	500000.0

		75% \
job_position	company_hash	
Others	Others	1525000.0
	a ntwyzgrgsxto	600000.0

	aaqxctz avnv owxtzwto vzvrjnxwo ucn rna	500000.0
	adw ntwyzgrgsj	800000.0
	adw ntwyzgrgsxto	830000.0
...	...	
wordpress developer	Others	600000.0
worker	zgn vuurxwvmrt vwwghzn	200000.0
x	Others	400000.0
young professional ii	sgctqzbtzn ge xzaxv	500000.0
zomato	kgbvng	500000.0

		max
job_position	company_hash	
Others	Others	3327000.0
	a ntwyzgrgsxto	1350000.0
	aaqxctz avnv owxtzwto vzvrjnxwo ucn rna	500000.0
	adw ntwyzgrgsj	2100000.0
	adw ntwyzgrgsxto	1500000.0
...	...	
wordpress developer	Others	600000.0
worker	zgn vuurxwvmrt vwwghzn	200000.0
x	Others	400000.0
young professional ii	sgctqzbtzn ge xzaxv	500000.0
zomato	kgbvng	500000.0

[21595 rows x 8 columns]

```
[83]: df.drop_duplicates().shape
```

```
[83]: (146052, 6)
```

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

```
[84]:
```

	company_hash	orgyear	ctc	job_position \
0	atrgxnnt xzaxv	2016.0	1100000	other
1	qtrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer
2	Others	2015.0	2000000	backend engineer
3	ngpgutaxv	2017.0	700000	backend engineer
4	qxen sqghu	2017.0	1400000	fullstack engineer
...
146047	mvqwrvo	2011.0	2250000	Others
146048	vuurt xzw	2008.0	220000	Others
146049	husqvawgb	2017.0	500000	Others
146050	vwwgrxnt	2021.0	700000	Others
146051	bgqsvz onvzrtj	2014.0	1240000	Others

ctc_updated_year	years_of_experience	count	mean \
------------------	---------------------	-------	--------

0	2020.0	6.0	2.0	1.085000e+06
1	2019.0	4.0	25.0	9.882000e+05
2	2020.0	7.0	3871.0	1.001007e+06
3	2019.0	5.0	24.0	1.416667e+06
4	2019.0	5.0	3.0	8.466667e+05
...
146047	2019.0	11.0	64.0	1.259969e+06
146048	2019.0	14.0	16.0	1.568312e+06
146049	2020.0	5.0	13.0	1.000769e+06
146050	2021.0	1.0	35.0	1.200371e+06
146051	2016.0	8.0	105.0	1.801581e+06

	std	min	25%	50%	75%	max
0	2.121320e+04	1070000.0	1077500.0	1085000.0	1092500.0	1100000.0
1	4.874998e+05	300000.0	600000.0	850000.0	1380000.0	2000000.0
2	8.124658e+05	1000.0	300000.0	830000.0	1530000.0	3300000.0
3	5.453413e+05	520000.0	1047500.0	1375000.0	1792500.0	2600000.0
4	4.801389e+05	540000.0	570000.0	600000.0	1000000.0	1400000.0
...
146047	5.777488e+05	500000.0	800000.0	1020000.0	1607500.0	3200000.0
146048	1.231984e+06	60000.0	216250.0	2275000.0	2550000.0	3000000.0
146049	3.300369e+05	500000.0	750000.0	1000000.0	1200000.0	1500000.0
146050	5.635221e+05	300000.0	771500.0	1100000.0	1400000.0	2700000.0
146051	6.903383e+05	100000.0	1450000.0	1800000.0	2300000.0	3240000.0

[146052 rows x 14 columns]

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

```
[85]:
```

	company_hash	orgyear	ctc	job_position \
896	Others	2022.0	120000	Others
2599	Others	2022.0	430000	Others
7691	Others	2022.0	570000	Others
7870	Others	2022.0	550000	Others
8789	Others	2022.0	680000	Others
...
122134	zxztrtvuo	2013.0	1200000	ios engineer
53733	zxztrtvuo	2016.0	1200000	member of technical staff at nineleaps
9189	zxztrtvuo	2020.0	450000	other
133203	zxztrtvuo	2019.0	450000	other
37242	zxztrtvuo	2016.0	1200000	software developer intern

	ctc_updated_year	years_of_experience	count	mean \
896	2022.0	0.0	3159.0	1.025099e+06
2599	2022.0	0.0	3159.0	1.025099e+06
7691	2022.0	0.0	3159.0	1.025099e+06
7870	2022.0	0.0	3159.0	1.025099e+06

8789	2022.0		0.0	3159.0	1.025099e+06	
...	
122134	2017.0		9.0	1.0	1.200000e+06	
53733	2020.0		6.0	1.0	1.200000e+06	
9189	2020.0		2.0	2.0	4.500000e+05	
133203	2020.0		3.0	2.0	4.500000e+05	
37242	2020.0		6.0	1.0	1.200000e+06	

	std	min	25%	50%	75%	max
896	837191.520717	15.0	358500.0	800000.0	1525000.0	3327000.0
2599	837191.520717	15.0	358500.0	800000.0	1525000.0	3327000.0
7691	837191.520717	15.0	358500.0	800000.0	1525000.0	3327000.0
7870	837191.520717	15.0	358500.0	800000.0	1525000.0	3327000.0
8789	837191.520717	15.0	358500.0	800000.0	1525000.0	3327000.0
...
122134	NaN	1200000.0	1200000.0	1200000.0	1200000.0	1200000.0
53733	NaN	1200000.0	1200000.0	1200000.0	1200000.0	1200000.0
9189	0.000000	450000.0	450000.0	450000.0	450000.0	450000.0
133203	0.000000	450000.0	450000.0	450000.0	450000.0	450000.0
37242	NaN	1200000.0	1200000.0	1200000.0	1200000.0	1200000.0

[146052 rows x 14 columns]

```
[86]: df_cj.shape
```

```
[86]: (146052, 14)
```

```
[87]: df_cj.drop_duplicates(inplace=True)
```

```
[88]: df_cj.shape
```

```
[88]: (146052, 14)
```

•

```
[89]: def condition_classs(a,b_50,b_75):
        if a<b_50:
            return 3
        elif a>=b_50 and a<=b_75:
            return 2

        elif a>=b_75:
            return 1
```

```
[90]: df_cj['classs'] =df_cj.apply(lambda x:
    ↪condition_classs(x['ctc'],x['50%'],x['75%']),axis = 1)
df_cj
```

```
[90]:
```

	company_hash	orgyear	ctc	job_position	\
0	atrgrxntt xzaxv	2016.0	1100000	other	
1	qtrrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer	
2	Others	2015.0	2000000	backend engineer	
3	ngpgutaxv	2017.0	700000	backend engineer	
4	qxen sqghu	2017.0	1400000	fullstack engineer	
...	
146047	mvqwrvj	2011.0	2250000	Others	
146048	vuurt xzw	2008.0	220000	Others	
146049	husqvawgb	2017.0	500000	Others	
146050	vwwgrxnt	2021.0	700000	Others	
146051	bgqsvz onvzrtj	2014.0	1240000	Others	

	ctc_updated_year	years_of_experience	count	mean	\
0	2020.0	6.0	2.0	1.085000e+06	
1	2019.0	4.0	25.0	9.882000e+05	
2	2020.0	7.0	3871.0	1.001007e+06	
3	2019.0	5.0	24.0	1.416667e+06	
4	2019.0	5.0	3.0	8.466667e+05	
...	
146047	2019.0	11.0	64.0	1.259969e+06	
146048	2019.0	14.0	16.0	1.568312e+06	
146049	2020.0	5.0	13.0	1.000769e+06	
146050	2021.0	1.0	35.0	1.200371e+06	
146051	2016.0	8.0	105.0	1.801581e+06	

	std	min	25%	50%	75%	max	\
0	2.121320e+04	1070000.0	1077500.0	1085000.0	1092500.0	1100000.0	
1	4.874998e+05	300000.0	600000.0	850000.0	1380000.0	2000000.0	
2	8.124658e+05	1000.0	300000.0	830000.0	1530000.0	3300000.0	
3	5.453413e+05	520000.0	1047500.0	1375000.0	1792500.0	2600000.0	
4	4.801389e+05	540000.0	570000.0	600000.0	1000000.0	1400000.0	
...	
146047	5.777488e+05	500000.0	800000.0	1020000.0	1607500.0	3200000.0	
146048	1.231984e+06	60000.0	216250.0	2275000.0	2550000.0	3000000.0	
146049	3.300369e+05	500000.0	750000.0	1000000.0	1200000.0	1500000.0	
146050	5.635221e+05	300000.0	771500.0	1100000.0	1400000.0	2700000.0	
146051	6.903383e+05	100000.0	1450000.0	1800000.0	2300000.0	3240000.0	

	classs
0	1
1	3
2	1


```

3          3
4          1
...
146047     1
146048     3
146049     3
146050     3
146051     3

```

[146052 rows x 15 columns]

```
[91]: df_cj.classss.value_counts(normalize=True)*100
```

```

[91]: classss
3     43.736477
2     31.831129
1     24.432394
Name: proportion, dtype: float64

```

```

[92]: # job position that has the highest class
df_cj[df_cj['classss']==1][['job_position','ctc']].
    ↳groupby('job_position')['ctc'].describe()

```

```

[92]:

```

	count	mean	std	\
job_position				
Others	8217.0	1.931143e+06	695531.136886	
android engineer	913.0	1.784897e+06	638704.770985	
application developer	1.0	1.150000e+06	NaN	
application developer analyst	1.0	6.000000e+05	NaN	
application development analyst	2.0	8.150000e+05	233345.237792	
...	
support engineer	683.0	1.190779e+06	552019.578789	
system engineer	10.0	8.420000e+05	373118.986086	
teaching assistant	1.0	1.800000e+06	NaN	
team lead	2.0	1.800000e+06	565685.424949	
technology analyst	3.0	8.966667e+05	351046.055858	

	min	25%	50%	75%	\
job_position					
Others	100000.0	1400000.0	1900000.0	2500000.0	
android engineer	14000.0	1320000.0	1700000.0	2200000.0	
application developer	1150000.0	1150000.0	1150000.0	1150000.0	
application developer analyst	600000.0	600000.0	600000.0	600000.0	
application development analyst	650000.0	732500.0	815000.0	897500.0	
...	
support engineer	350000.0	830000.0	1000000.0	1400000.0	
system engineer	400000.0	550000.0	775000.0	1100000.0	

teaching assistant	1800000.0	1800000.0	1800000.0	1800000.0
team lead	1400000.0	1600000.0	1800000.0	2000000.0
technology analyst	660000.0	695000.0	730000.0	1015000.0

	max
job_position	
Others	3330000.0
android engineer	3300000.0
application developer	1150000.0
application developer analyst	600000.0
application development analyst	980000.0
...	...
support engineer	3310000.0
system engineer	1500000.0
teaching assistant	1800000.0
team lead	2200000.0
technology analyst	1300000.0

[107 rows x 8 columns]

```
[93]: df_cjy.head()
```

```
[93]:
```

	company_hash	orgyear	ctc	job_position	\
0	atrgxnnt xzaxv	2016.0	1100000	other	
1	qtrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer	
2	Others	2015.0	2000000	backend engineer	
3	ngpgutaxv	2017.0	700000	backend engineer	
4	qxen sqghu	2017.0	1400000	fullstack engineer	

	ctc_updated_year	years_of_experience	count	mean	std	\
0	2020.0	6.0	1.0	1.100000e+06	NaN	
1	2019.0	4.0	7.0	7.742856e+05	250922.324350	
2	2020.0	7.0	456.0	9.609559e+05	776546.830662	
3	2019.0	5.0	7.0	1.158571e+06	404780.951933	
4	2019.0	5.0	1.0	1.400000e+06	NaN	

	min	25%	50%	75%	max	designation
0	1100000.0	1100000.0	1100000.0	1100000.0	1100000.0	2
1	449999.0	610000.0	750000.0	900000.0	1200000.0	3
2	1000.0	307500.0	800000.0	1435000.0	3200000.0	1
3	700000.0	825000.0	1200000.0	1405000.0	1750000.0	3
4	1400000.0	1400000.0	1400000.0	1400000.0	1400000.0	2

```
[94]: df_cj.head()
```

```
[94]:
```

	company_hash	orgyear	ctc	job_position	\
0	atrgxnnt xzaxv	2016.0	1100000	other	

```

1  qtrxvzwt xzegwbb rxbxnta  2018.0  449999  fullstack engineer
2                                Others  2015.0  2000000  backend engineer
3                                ngpgutaxv  2017.0  700000  backend engineer
4                                qxen sqghu  2017.0  1400000  fullstack engineer

```

```

      ctc_updated_year  years_of_experience  count          mean          std \
0          2020.0              6.0         2.0  1.085000e+06  21213.203436
1          2019.0              4.0        25.0  9.882000e+05  487499.789590
2          2020.0              7.0    3871.0  1.001007e+06  812465.827695
3          2019.0              5.0        24.0  1.416667e+06  545341.270627
4          2019.0              5.0         3.0  8.466667e+05  480138.868801

```

```

      min      25%      50%      75%      max  classs
0  1070000.0  1077500.0  1085000.0  1092500.0  1100000.0      1
1   300000.0   600000.0   850000.0  1380000.0  2000000.0      3
2    1000.0   300000.0   830000.0  1530000.0  3300000.0      1
3   520000.0  1047500.0  1375000.0  1792500.0  2600000.0      3
4   540000.0   570000.0   600000.0  1000000.0  1400000.0      1

```

```
[95]: df_cj.shape
```

```
[95]: (146052, 15)
```

```
[96]: df_cjy.shape
```

```
[96]: (146052, 15)
```

```

[97]: 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)

```

```
[98]: df_cj.drop_duplicates().shape
```

```
[98]: (146052, 7)
```

```
[99]: df_cjy.drop_duplicates().shape
```

```
[99]: (146052, 7)
```

```
[100]: df_cjy
```

```

[100]:      company_hash  orgyear      ctc      job_position \
0      atrgxntt xzaxv   2016.0  1100000      other
1  qtrxvzwt xzegwbb rxbxnta  2018.0  449999  fullstack engineer
2      Others  2015.0  2000000  backend engineer
3      ngpgutaxv  2017.0   700000  backend engineer

```

4	qxen sqghu	2017.0	1400000	fullstack engineer
...
146047	mvqwrvjjo	2011.0	2250000	Others
146048	vuurt xzw	2008.0	220000	Others
146049	husqvawgb	2017.0	500000	Others
146050	vwwgrxnt	2021.0	700000	Others
146051	bgqsvz onvzrtj	2014.0	1240000	Others

	ctc_updated_year	years_of_experience	designation
0	2020.0	6.0	2
1	2019.0	4.0	3
2	2020.0	7.0	1
3	2019.0	5.0	3
4	2019.0	5.0	2
...
146047	2019.0	11.0	1
146048	2019.0	14.0	2
146049	2020.0	5.0	3
146050	2021.0	1.0	2
146051	2016.0	8.0	3

[146052 rows x 7 columns]

[101]: df_cj

[101]:

	company_hash	orgyear	ctc	job_position \
0	atrgxnnt xzaxv	2016.0	1100000	other
1	qtrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer
2	Others	2015.0	2000000	backend engineer
3	ngpgutaxv	2017.0	700000	backend engineer
4	qxen sqghu	2017.0	1400000	fullstack engineer
...
146047	mvqwrvjjo	2011.0	2250000	Others
146048	vuurt xzw	2008.0	220000	Others
146049	husqvawgb	2017.0	500000	Others
146050	vwwgrxnt	2021.0	700000	Others
146051	bgqsvz onvzrtj	2014.0	1240000	Others

	ctc_updated_year	years_of_experience	classs
0	2020.0	6.0	1
1	2019.0	4.0	3
2	2020.0	7.0	1
3	2019.0	5.0	3
4	2019.0	5.0	1
...
146047	2019.0	11.0	1
146048	2019.0	14.0	3

146049	2020.0	5.0	3
146050	2021.0	1.0	3
146051	2016.0	8.0	3

[146052 rows x 7 columns]

```
[102]: 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
```

```
[102]:
```

	company_hash	orgyear	ctc	job_position \
0	atrgxnnt xzaxv	2016.0	1100000	other
1	qtrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer
2	Others	2015.0	2000000	backend engineer
3	ngpgutaxv	2017.0	700000	backend engineer
4	qxen sqghu	2017.0	1400000	fullstack engineer
...
146047	mvqwrvj	2011.0	2250000	Others
146048	vuurt xzw	2008.0	220000	Others
146049	husqvawgb	2017.0	500000	Others
146050	vwwgrxnt	2021.0	700000	Others
146051	bgqsvz onvzrtj	2014.0	1240000	Others

	ctc_updated_year	years_of_experience	classs	designation
0	2020.0	6.0	1	2
1	2019.0	4.0	3	3
2	2020.0	7.0	1	1
3	2019.0	5.0	3	3
4	2019.0	5.0	1	2
...
146047	2019.0	11.0	1	1
146048	2019.0	14.0	3	2
146049	2020.0	5.0	3	3
146050	2021.0	1.0	3	2
146051	2016.0	8.0	3	3

[146052 rows x 8 columns]

```
[103]: df_cjy_cj.shape
```

```
[103]: (146052, 8)
```

```
[104]: df_cjy_cj.drop_duplicates().shape
```

```
[104]: (146052, 8)
```

4.0.4 Manual Clustering based on company

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

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

```
[107]: df_c.head(5)
```

```
[107]:
```

	company_hash	orgyear	ctc	job_position	\
0	atrgxnnt xzaxv	2016.0	1100000	other	
1	qtrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer	
2	Others	2015.0	2000000	backend engineer	
3	ngpgutaxv	2017.0	700000	backend engineer	
4	qxen sqghu	2017.0	1400000	fullstack engineer	

	ctc_updated_year	years_of_experience	count	mean	\
0	2020.0	6.0	9.0	1.115667e+06	
1	2019.0	4.0	384.0	1.055291e+06	
2	2020.0	7.0	24489.0	9.675951e+05	
3	2019.0	5.0	59.0	1.455508e+06	
4	2019.0	5.0	6.0	9.400000e+05	

	std	min	25%	50%	75%	max
0	458111.885897	500000.0	800000.0	1070000.0	1500000.0	1771000.0
1	636095.670307	10000.0	600000.0	850000.0	1500000.0	3200000.0
2	761666.853194	15.0	390000.0	800000.0	1400000.0	3329999.0
3	655423.458086	200000.0	1075000.0	1300000.0	1850000.0	3160000.0
4	389871.773792	540000.0	625000.0	850000.0	1300000.0	1400000.0

```
[108]: #verify
df_c.sort_values(['company_hash'])
```

```
[108]:
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	\
73025	Others	2017.0	65000	Others	2019.0	
66471	Others	2017.0	1210000	backend engineer	2019.0	
66479	Others	2015.0	220000	qa engineer	2019.0	
66480	Others	2018.0	650000	qa engineer	2019.0	
66482	Others	2017.0	1140000	fullstack engineer	2019.0	
...	
68659	zxxztrtvuo	2019.0	1000000	backend engineer	2021.0	
115889	zxxztrtvuo	2017.0	1000000	backend engineer	2019.0	
23629	zxxztrtvuo	2018.0	1360000	backend engineer	2020.0	
82842	zxxztrtvuo	2018.0	710000	fullstack engineer	2020.0	
129354	zxxztrtvuo	2018.0	650000	backend engineer	2019.0	

	years_of_experience	count	mean	std	min \
73025	5.0	24489.0	967595.092940	761666.853194	15.0
66471	5.0	24489.0	967595.092940	761666.853194	15.0
66479	7.0	24489.0	967595.092940	761666.853194	15.0
66480	4.0	24489.0	967595.092940	761666.853194	15.0
66482	5.0	24489.0	967595.092940	761666.853194	15.0
...
68659	3.0	68.0	964676.455882	565370.795931	400000.0
115889	5.0	68.0	964676.455882	565370.795931	400000.0
23629	4.0	68.0	964676.455882	565370.795931	400000.0
82842	4.0	68.0	964676.455882	565370.795931	400000.0
129354	4.0	68.0	964676.455882	565370.795931	400000.0

	25%	50%	75%	max
73025	390000.0	800000.0	1400000.0	3329999.0
66471	390000.0	800000.0	1400000.0	3329999.0
66479	390000.0	800000.0	1400000.0	3329999.0
66480	390000.0	800000.0	1400000.0	3329999.0
66482	390000.0	800000.0	1400000.0	3329999.0
...
68659	515000.0	784999.5	1200000.0	2700000.0
115889	515000.0	784999.5	1200000.0	2700000.0
23629	515000.0	784999.5	1200000.0	2700000.0
82842	515000.0	784999.5	1200000.0	2700000.0
129354	515000.0	784999.5	1200000.0	2700000.0

[146052 rows x 14 columns]

```
[109]: print(df.drop_duplicates().shape)
print(df_c.shape)
print(df_c.drop_duplicates().shape)
```

```
(146052, 6)
(146052, 14)
(146052, 14)
```

•

```
[110]: def condition_tier(a,b_50,b_75):
        if a<b_50:
            return 3
        elif a>=b_50 and a<=b_75:
            return 2
        elif a>=b_75:
```

```
return 1
```

```
[111]: df_c['tier'] =df_c.apply(lambda x:
    ↳condition_tier(x['ctc'],x['50%'],x['75%']),axis = 1)
df_c
```

```
[111]:
```

	company_hash	orgyear	ctc	job_position	\
0	atrgxnnt xzaxv	2016.0	1100000	other	
1	qtrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer	
2	Others	2015.0	2000000	backend engineer	
3	ngpgutaxv	2017.0	700000	backend engineer	
4	qxen sqghu	2017.0	1400000	fullstack engineer	
...	
146047	mvqwrvjjo	2011.0	2250000	Others	
146048	vuurt xzw	2008.0	220000	Others	
146049	husqvawgb	2017.0	500000	Others	
146050	vwwgrxnt	2021.0	700000	Others	
146051	bgqsvz onvzrtj	2014.0	1240000	Others	

	ctc_updated_year	years_of_experience	count	mean	\
0	2020.0	6.0	9.0	1.115667e+06	
1	2019.0	4.0	384.0	1.055291e+06	
2	2020.0	7.0	24489.0	9.675951e+05	
3	2019.0	5.0	59.0	1.455508e+06	
4	2019.0	5.0	6.0	9.400000e+05	
...	
146047	2019.0	11.0	65.0	1.264431e+06	
146048	2019.0	14.0	16.0	1.568312e+06	
146049	2020.0	5.0	97.0	1.275361e+06	
146050	2021.0	1.0	157.0	1.344255e+06	
146051	2016.0	8.0	472.0	1.844892e+06	

	std	min	25%	50%	75%	max	\
0	4.581119e+05	500000.0	800000.0	1070000.0	1500000.0	1771000.0	
1	6.360957e+05	10000.0	600000.0	850000.0	1500000.0	3200000.0	
2	7.616669e+05	15.0	390000.0	800000.0	1400000.0	3329999.0	
3	6.554235e+05	200000.0	1075000.0	1300000.0	1850000.0	3160000.0	
4	3.898718e+05	540000.0	625000.0	850000.0	1300000.0	1400000.0	
...	
146047	5.743451e+05	500000.0	800000.0	1040000.0	1600000.0	3200000.0	
146048	1.231984e+06	60000.0	216250.0	2275000.0	2550000.0	3000000.0	
146049	5.880548e+05	200000.0	850000.0	1150000.0	1600000.0	3200000.0	
146050	5.743742e+05	200000.0	1000000.0	1300000.0	1500000.0	3000000.0	
146051	7.137398e+05	1000.0	1500000.0	1800000.0	2250000.0	3300000.0	

	tier
0	2


```

1      3
2      1
3      3
4      1
...    ...
146047  1
146048  3
146049  3
146050  3
146051  3

```

[146052 rows x 15 columns]

```
[112]: df_c.head()
```

```
[112]:
```

	company_hash	orgyear	ctc	job_position \
0	atrgxnnt xzaxv	2016.0	1100000	other
1	qtrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer
2	Others	2015.0	2000000	backend engineer
3	ngpgutaxv	2017.0	700000	backend engineer
4	qxen sqghu	2017.0	1400000	fullstack engineer

	ctc_updated_year	years_of_experience	count	mean \
0	2020.0	6.0	9.0	1.115667e+06
1	2019.0	4.0	384.0	1.055291e+06
2	2020.0	7.0	24489.0	9.675951e+05
3	2019.0	5.0	59.0	1.455508e+06
4	2019.0	5.0	6.0	9.400000e+05

	std	min	25%	50%	75%	max	tier
0	458111.885897	500000.0	800000.0	1070000.0	1500000.0	1771000.0	2
1	636095.670307	10000.0	600000.0	850000.0	1500000.0	3200000.0	3
2	761666.853194	15.0	390000.0	800000.0	1400000.0	3329999.0	1
3	655423.458086	200000.0	1075000.0	1300000.0	1850000.0	3160000.0	3
4	389871.773792	540000.0	625000.0	850000.0	1300000.0	1400000.0	1

```
[113]: df_c.tier.value_counts(normalize=True)*100
```

```
[113]: tier
3    47.952099
2    28.153671
1    23.894229
Name: proportion, dtype: float64
```

```
[114]: df_cjy_cj_c=df_cjy_cj.merge(df_c,
↳ on=['company_hash', 'orgyear', 'ctc', 'job_position']\
```

```
↳, 'ctc_updated_year', 'years_of_experience'], how = 'left')
```

```
[115]: df_cjy_cj_c.head(10)
```

```
[115]:
```

	company_hash	orgyear	ctc	job_position \
0	atrngxnt xzaxv	2016.0	1100000	other
1	qtrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer
2	Others	2015.0	2000000	backend engineer
3	ngpgutaxv	2017.0	700000	backend engineer
4	qxen sqghu	2017.0	1400000	fullstack engineer
5	yvuuxrj hzbvqqxta bvqptnxzs ucn rna	2018.0	700000	fullstack engineer
6	lubgqsvz wyvot wg	2018.0	1500000	fullstack engineer
7	vwwtznht ntwyzgrgsj	2019.0	400000	backend engineer
8	utqoxontzn ojointbo	2020.0	450000	Others
9	Others	2019.0	360000	Others

	ctc_updated_year	years_of_experience	classs	designation	count \
0	2020.0	6.0	1	2	9.0
1	2019.0	4.0	3	3	384.0
2	2020.0	7.0	1	1	24489.0
3	2019.0	5.0	3	3	59.0
4	2019.0	5.0	1	2	6.0
5	2020.0	4.0	2	2	6.0
6	2019.0	4.0	3	3	859.0
7	2019.0	3.0	3	3	24.0
8	2020.0	2.0	3	3	413.0
9	2019.0	3.0	3	3	24489.0

	mean	std	min	25%	50%	75% \
0	1.115667e+06	458111.885897	500000.0	800000.0	1070000.0	1500000.0
1	1.055291e+06	636095.670307	10000.0	600000.0	850000.0	1500000.0
2	9.675951e+05	761666.853194	15.0	390000.0	800000.0	1400000.0
3	1.455508e+06	655423.458086	200000.0	1075000.0	1300000.0	1850000.0
4	9.400000e+05	389871.773792	540000.0	625000.0	850000.0	1300000.0
5	9.066667e+05	539728.326722	620000.0	640000.0	700000.0	775000.0
6	1.706719e+06	676070.394042	11000.0	1300000.0	1675000.0	2110000.0
7	6.633333e+05	265782.956019	300000.0	422500.0	620000.0	892500.0
8	9.778668e+05	555184.830508	90000.0	550000.0	840000.0	1300000.0
9	9.675951e+05	761666.853194	15.0	390000.0	800000.0	1400000.0

	max	tier
0	1771000.0	2
1	3200000.0	3
2	3329999.0	1
3	3160000.0	3
4	1400000.0	1

```

5  2000000.0      2
6  3300000.0      3
7  1150000.0      3
8  3000000.0      3
9  3329999.0      3

```

```
[116]: df_cjy_cj_c.shape
```

```
[116]: (146052, 17)
```

```
[117]: data=df_cjy_cj_c.copy(deep=True)
```

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

```
[119]: data
```

```
[119]:
```

	company_hash	orgyear	ctc	job_position \
0	atrxxnnt xzaxv	2016.0	1100000	other
1	qtrxxvzwt xzegwbbb rxbxnta	2018.0	449999	fullstack engineer
2	Others	2015.0	2000000	backend engineer
3	ngpgutaxv	2017.0	700000	backend engineer
4	qxen sqghu	2017.0	1400000	fullstack engineer
...
146047	mvqwrjvo	2011.0	2250000	Others
146048	vuurt xzw	2008.0	220000	Others
146049	husqvawgb	2017.0	500000	Others
146050	vwwgrxnt	2021.0	700000	Others
146051	bgqsvz onvzrtj	2014.0	1240000	Others

	ctc_updated_year	years_of_experience	classs	designation	tier
0	2020.0	6.0	1	2	2
1	2019.0	4.0	3	3	3
2	2020.0	7.0	1	1	1
3	2019.0	5.0	3	3	3
4	2019.0	5.0	1	2	1
...
146047	2019.0	11.0	1	1	1
146048	2019.0	14.0	3	2	3
146049	2020.0	5.0	3	3	3
146050	2021.0	1.0	3	2	3
146051	2016.0	8.0	3	3	3

```
[146052 rows x 9 columns]
```

```
[120]: # org_data = pd.read_csv('data/scaler_clustering.csv')
        # org_data
```

```
[121]: # df_new=data.merge(org_data, on=['company_hash'], how = 'left')
# df_new

[122]: pd.set_option('display.max_rows', 20)

[123]: # Top 10 companies providing highest ctc's

data.groupby(['company_hash'])['ctc'].max().head(11).sort_values(ascending =_
↪False)
```

```
[123]: company_hash
Others                                3329999
adw ntwyzgrgsj                        3200000
a ntwyzgrgsxto                        3150000
agnut                                3000000
agdutq                               2500000
aghmznzhn                            2400000
adw ntwyzgrgsxto                      2350000
agotrtn                               1610000
agnoihvqto                           1600000
aaqxctz avnv owxtzwtv vzvrjnxwo ucn rna 1400000
aggartmrht xxxgcvnxgzo                1000000
Name: ctc, dtype: int64
```

4.0.5 Overview of what's next :

- Data processing for Unsupervised clustering - Label encoding/ One- hot encoding, Standardization of data
 - Unsupervised Learning - Clustering
 - Checking clustering tendency
 - Elbow method
 - K-means clustering
 - Hierarchical clustering (you can do this on a sample of the dataset if your process is taking time)
 - Insights from Unsupervised Clustering
 - Provide actionable Insights & Recommendations for the Business.
-
- K-Means is a distance-based algorithm. Because of that, it's really important to perform feature scaling (normalize, standardize, or choose any other option in which the distance has some comparable meaning for all the columns).
 - In this example, we use MinMaxScaler instead of StandardScaler, so as to transforming the feature values to fall within the bounded intervals (min and max), rather than making them to fall around mean as 0 with standard deviation as 1 (StandardScaler).

- MinMaxScaler is an excellent tool for this purpose. MinMaxScaler scales all the data features in the range [0, 1] or else in the range [-1, 1] if there are negative values in the dataset. This scaling compresses all the inliers in the narrow range [0, 0.005].

```
[124]: data.shape
```

```
[124]: (146052, 9)
```

```
[125]: data['company_hash'].unique()
```

```
[125]: array(['atrgxnnt xzaxv', 'qtrxvzwt xzegwgb rxbxnta', 'Others', ...,
          'srgxej', 'bh oxsbv', 'ohbngnvr ojointbo'], dtype=object)
```

```
[126]: # Label Encoding
```

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

```
[126]: array([ 45, 1497,    0, ..., 1667, 138, 1155])
```

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

```
[127]: 762
```

```
[128]: data
```

```
[128]:
```

	company_hash	orgyear	ctc	job_position	ctc_updated_year	\
0	45	2016.0	1100000	377	2020.0	
1	1497	2018.0	449999	235	2019.0	
2	0	2015.0	2000000	105	2020.0	
3	936	2017.0	700000	105	2019.0	
4	1535	2017.0	1400000	235	2019.0	
...	
146047	884	2011.0	2250000	0	2019.0	
146048	2158	2008.0	220000	0	2019.0	
146049	636	2017.0	500000	0	2020.0	
146050	2186	2021.0	700000	0	2021.0	
146051	127	2014.0	1240000	0	2016.0	

	years_of_experience	classs	designation	tier
0	6.0	1	2	2
1	4.0	3	3	3
2	7.0	1	1	1
3	5.0	3	3	3
4	5.0	1	2	1

```

...
146047      11.0      1      1      1
146048      14.0      3      2      3
146049       5.0      3      3      3
146050       1.0      3      2      3
146051       8.0      3      3      3

```

[146052 rows x 9 columns]

[129]: `data.info()`

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146052 entries, 0 to 146051
Data columns (total 9 columns):
#   Column                Non-Null Count  Dtype
---  -
0   company_hash          146052 non-null int64
1   orgyear                146052 non-null float64
2   ctc                    146052 non-null int64
3   job_position           146052 non-null int64
4   ctc_updated_year       146052 non-null float64
5   years_of_experience     146052 non-null float64
6   classs                 146052 non-null int64
7   designation            146052 non-null int64
8   tier                   146052 non-null int64
dtypes: float64(3), int64(6)
memory usage: 10.0 MB

```

[130]: *# 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)

```

[131]: `missingValue(data)`

Total records in our data = 146052 where missing values are as follows:

[131]:

	Total Missing	In Percent
company_hash	0	0.0
ctc	0	0.0
job_position	0	0.0
years_of_experience	0	0.0
classs	0	0.0
designation	0	0.0

tier	0	0.0
------	---	-----

```
[132]: data.head()
```

```
[132]:
```

	company_hash	ctc	job_position	years_of_experience	classs	\
0	45	1100000	377	6.0	1	
1	1497	449999	235	4.0	3	
2	0	2000000	105	7.0	1	
3	936	700000	105	5.0	3	
4	1535	1400000	235	5.0	1	

	designation	tier
0	2	2
1	3	3
2	1	1
3	3	3
4	2	1

```
[133]: # Creating second copy after org_df
```

```
data_1 = data.copy()
```

```
[134]: from sklearn.preprocessing import MinMaxScaler
```

```
# scaler = MinMaxScaler()
# scaler.fit(data)
# data=scaler.transform(data)

ms = MinMaxScaler()

data[['ctc']] = ms.fit_transform(data[['ctc']])
data.head()
```

```
[134]:
```

	company_hash	ctc	job_position	years_of_experience	classs	\
0	45	0.330330	377	6.0	1	
1	1497	0.135134	235	4.0	3	
2	0	0.600600	105	7.0	1	
3	936	0.210210	105	5.0	3	
4	1535	0.420420	235	5.0	1	

	designation	tier
0	2	2
1	3	3
2	1	1
3	3	3
4	2	1

5 Clustering using Sklearn's implementation of Kmeans

```
[135]: # from sklearn.cluster import KMeans
```

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

```
[136]: # ## what are learned labels(cluster #)  
# y_pred
```

```
[137]: # ##coordinates of the cluster centers  
# kmeans.cluster_centers_
```

```
[137]:
```

```
[138]: X = data_1.copy()  
scaler = MinMaxScaler()  
scaler.fit(X)  
X=scaler.transform(X)
```

```
[139]: from sklearn.cluster import KMeans
```

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

```
[140]: ##coordinates of the cluster centers  
kmeans.cluster_centers_
```

```
[140]: array([[0.42106296, 0.58222686, 0.22694486, 0.4983092 , 0.07946338,  
          0.22831217, 0.05954212],  
          [0.41462362, 0.18998503, 0.23264329, 0.35999868, 0.98794806,  
          0.86553632, 0.9793948 ],  
          [0.45047391, 0.32970016, 0.2572445 , 0.39964184, 0.52520207,  
          0.4544456 , 0.62352332]])
```

```
[141]: y_pred is kmeans.labels_
```

```
[141]: True
```


6 Visualizing Sklearn Clusters

[142]: X

```
[142]: array([[0.01529572, 0.33032993, 0.49540079, ..., 0.          , 0.5          ,
              0.5          ],
              [0.50883753, 0.13513432, 0.3088042 , ..., 1.          , 1.          ,
              1.          ],
              [0.          , 0.60060036, 0.13797635, ..., 0.          , 0.          ,
              0.          ],
              ...,
              [0.21617947, 0.15014964, 0.          , ..., 1.          , 1.          ,
              1.          ],
              [0.74303195, 0.21020974, 0.          , ..., 1.          , 0.5          ,
              1.          ],
              [0.04316791, 0.372372  , 0.          , ..., 1.          , 1.          ,
              1.          ]])
```

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

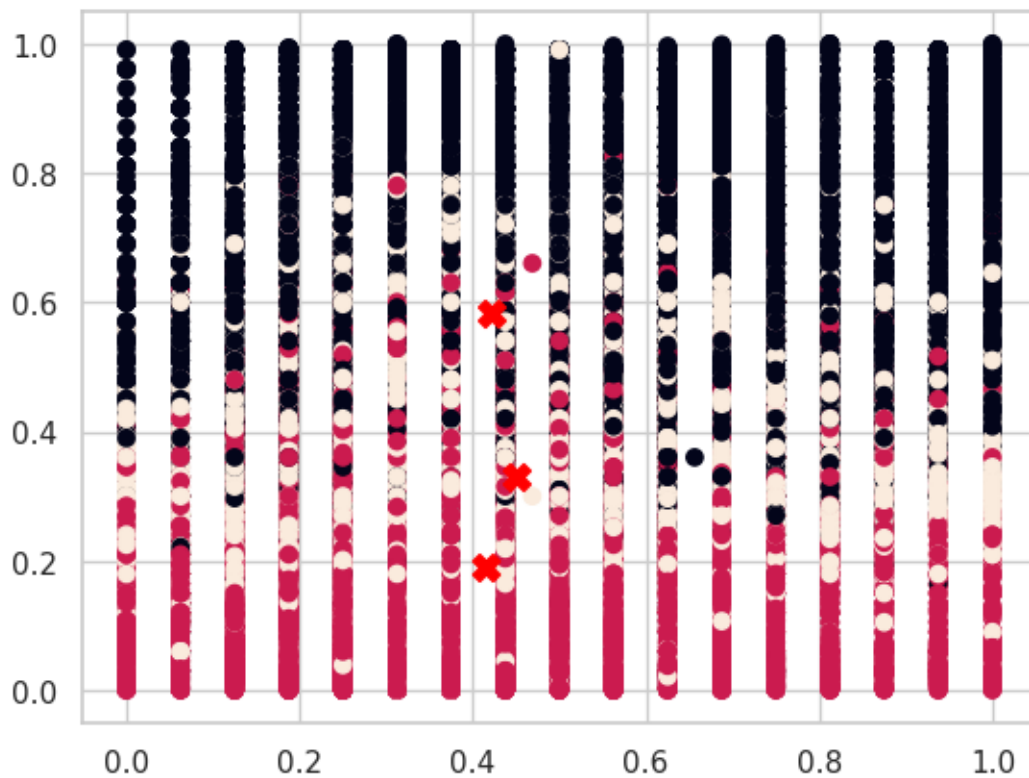
```
[143]:
```

	company_hash	ctc	job_position	years_of_experience	classs \
0	0.015296	0.330330	0.495401	0.3750	0.0
1	0.508838	0.135134	0.308804	0.2500	1.0
2	0.000000	0.600600	0.137976	0.4375	0.0
3	0.318151	0.210210	0.137976	0.3125	1.0
4	0.521754	0.420420	0.308804	0.3125	0.0
...
146047	0.300476	0.675675	0.000000	0.6875	0.0
146048	0.733515	0.066066	0.000000	0.8750	1.0
146049	0.216179	0.150150	0.000000	0.3125	1.0
146050	0.743032	0.210210	0.000000	0.0625	1.0
146051	0.043168	0.372372	0.000000	0.5000	1.0

	designation	tier	label
0	0.5	0.5	2
1	1.0	1.0	1
2	0.0	0.0	0
3	1.0	1.0	1
4	0.5	0.0	0
...
146047	0.0	0.0	0
146048	0.5	1.0	1
146049	1.0	1.0	1
146050	0.5	1.0	1
146051	1.0	1.0	1

[146052 rows x 8 columns]

```
[144]: 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)
```



6.0.1 No clarity in visualization using scatter plot

Summary: - I have tried bunch of features to visualize but I am not able to get proper result and it's not clear. - Using polar plot for better visualization:

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

```
[145]:
```

	label	variable	value
0	0	company_hash	0.421149
1	1	company_hash	0.414624
2	2	company_hash	0.450427
3	0	ctc	0.582043
4	1	ctc	0.189985
..
16	1	designation	0.865536
17	2	designation	0.454349
18	0	tier	0.059799
19	1	tier	0.979395
20	2	tier	0.623740

[21 rows x 3 columns]

```
[146]: # pip install plotly
```

```
[147]: 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()
```

6.0.2 Feature definitions:

-
- 1.
-
- 2.
-
- 3.

6.1 Super clarity in visualizing the clusters using polar line plots:

6.1.1 Observations and Recommendations:

- We have three cluster mainly (label - 0, 1, 2)
- `job_position`, `years of experience`, `comapny_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 2)**, 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 0)**, and who comes from a descent job role in a descent company, having descent amount experience, requires little upscaling.
 - (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 1)**, and who comes from a descent job role in a descent company, having descent amount experience, **requires lots of upscaling**. 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/ courses, free master clases**, to these set of learners

```
[148]: !pip install pyclustertend==1.4.9
```

```
Requirement already satisfied: pyclustertend==1.4.9 in  
/usr/local/lib/python3.10/dist-packages (1.4.9)
```

```
[149]: import matplotlib.pyplot as plt  
import seaborn as sns  
import sklearn  
from sklearn.cluster import KMeans  
from pyclustertend import hopkins  
from sklearn.preprocessing import scale
```

```
[150]: data_new = data.copy()
```

```
[151]: # data_new.drop('label', axis = 1,inplace = True)
```

```
[152]: data_new.dropna(inplace=True)
```

```
[153]: data_new
```

```
[153]:      company_hash      ctc  job_position  years_of_experience  classs  \
0              45  0.330330           377           6.0         1
1          1497  0.135134           235           4.0         3
2              0  0.600600           105           7.0         1
3           936  0.210210           105           5.0         3
4          1535  0.420420           235           5.0         1
...          ...      ...      ...      ...      ...
146047         884  0.675675            0          11.0         1
146048        2158  0.066066            0          14.0         3
146049         636  0.150150            0           5.0         3
146050        2186  0.210210            0           1.0         3
146051         127  0.372372            0           8.0         3
```

```
      designation  tier
0              2     2
1              3     3
2              1     1
3              3     3
4              2     1
...          ...   ...
146047         1     1
146048         2     3
146049         3     3
146050         2     3
146051         3     3
```

```
[146052 rows x 7 columns]
```

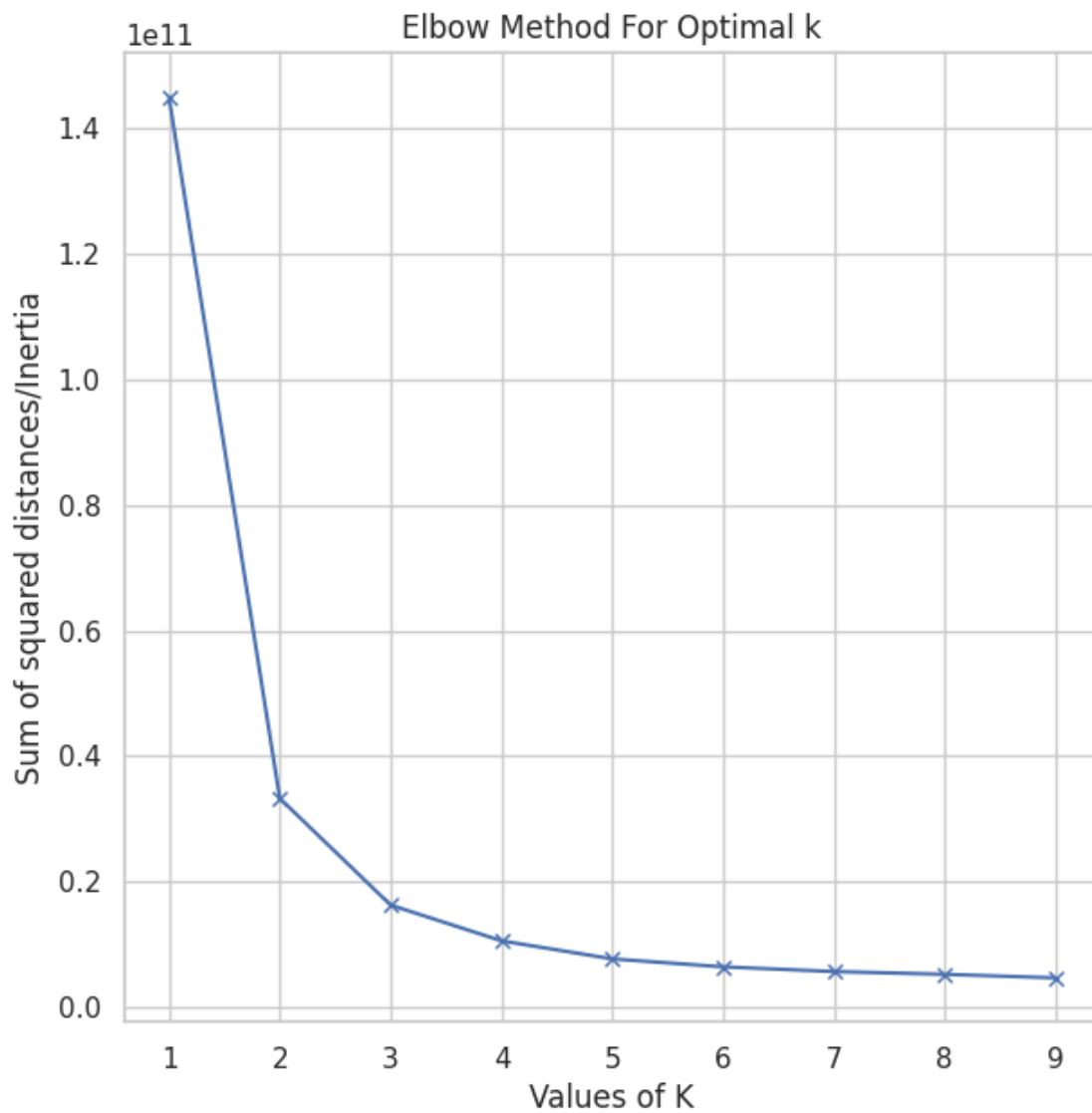
```
[154]: hop=hopkins(data_new,150)
```

```
[155]: hop
```

```
[155]: 0.057361554817738185
```

```
[156]: 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()
```



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

```
[157]: kmeans = KMeans(n_clusters=3)
kmeans.fit(data_new)
print(kmeans.cluster_centers_)
print(kmeans.cluster_centers_.shape)
```

```
[[2.20004364e+02 3.38710849e-01 1.89451912e+02 6.82628404e+00
 2.20934977e+00 2.16183802e+00 2.24353766e+00]
 [2.41601544e+03 3.28778754e-01 1.78887926e+02 6.30840606e+00
 2.19061878e+00 2.11384724e+00 2.24195741e+00]
 [1.25708218e+03 3.53266177e-01 1.75597005e+02 6.46729692e+00
 2.17258388e+00 2.08546987e+00 2.23449622e+00]]
(3, 7)
```

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

```
[159]: data_new
```

```
[159]:
```

	company_hash	ctc	job_position	years_of_experience	classs	\
0	45	0.330330	377	6.0	1	
1	1497	0.135134	235	4.0	3	
2	0	0.600600	105	7.0	1	
3	936	0.210210	105	5.0	3	
4	1535	0.420420	235	5.0	1	
...
146047	884	0.675675	0	11.0	1	
146048	2158	0.066066	0	14.0	3	
146049	636	0.150150	0	5.0	3	
146050	2186	0.210210	0	1.0	3	
146051	127	0.372372	0	8.0	3	

	designation	tier	k-m label
0	2	2	0
1	3	3	2
2	1	1	0
3	3	3	2
4	2	1	2
...
146047	1	1	2
146048	2	3	1
146049	3	3	0
146050	2	3	1
146051	3	3	0

```
[146052 rows x 8 columns]
```

```
[160]: data_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146052 entries, 0 to 146051
Data columns (total 8 columns):
#   Column                Non-Null Count  Dtype
---  -
0   company_hash          146052 non-null int64
```

```

1   ctc                146052 non-null float64
2   job_position       146052 non-null int64
3   years_of_experience 146052 non-null float64
4   classs             146052 non-null int64
5   designation        146052 non-null int64
6   tier               146052 non-null int64
7   k-m label         146052 non-null int32
dtypes: float64(2), int32(1), int64(5)
memory usage: 8.4 MB

```

```
[161]: df_cjy_cj_c
```

```

[161]:
      company_hash  orgyear    ctc  job_position \
0      atrgxmnt xzaxv  2016.0  1100000      other
1      qtrxvzwt xzegwbb rxbxnta  2018.0   449999  fullstack engineer
2              Others  2015.0  2000000  backend engineer
3      ngpgutaxv  2017.0   700000  backend engineer
4      qxen sqghu  2017.0  1400000  fullstack engineer
...
146047      mvqwrjjo  2011.0  2250000      Others
146048      vuurt xzw  2008.0   220000      Others
146049      husqvawgb  2017.0   500000      Others
146050      vwwgrxnt  2021.0   700000      Others
146051      bgqsvz onvzrtj  2014.0  1240000      Others

      ctc_updated_year  years_of_experience  classs  designation  count \
0      2020.0          6.0          1          2          9.0
1      2019.0          4.0          3          3      384.0
2      2020.0          7.0          1          1  24489.0
3      2019.0          5.0          3          3          59.0
4      2019.0          5.0          1          2          6.0
...
146047      2019.0          11.0          1          1          65.0
146048      2019.0          14.0          3          2          16.0
146049      2020.0          5.0          3          3          97.0
146050      2021.0          1.0          3          2       157.0
146051      2016.0          8.0          3          3       472.0

      mean      std      min      25%      50%      75% \
0  1.115667e+06  4.581119e+05  500000.0  800000.0  1070000.0  1500000.0
1  1.055291e+06  6.360957e+05   10000.0  600000.0   850000.0  1500000.0
2  9.675951e+05  7.616669e+05     15.0  390000.0   800000.0  1400000.0
3  1.455508e+06  6.554235e+05  200000.0  1075000.0  1300000.0  1850000.0
4  9.400000e+05  3.898718e+05  540000.0   625000.0   850000.0  1300000.0
...
146047  1.264431e+06  5.743451e+05  500000.0  800000.0  1040000.0  1600000.0
146048  1.568312e+06  1.231984e+06   60000.0  216250.0  2275000.0  2550000.0

```



```

146049  1.275361e+06  5.880548e+05  200000.0   850000.0  1150000.0  1600000.0
146050  1.344255e+06  5.743742e+05  200000.0  1000000.0  1300000.0  1500000.0
146051  1.844892e+06  7.137398e+05   1000.0   1500000.0  1800000.0  2250000.0

```

```

          max  tier
0      1771000.0    2
1      3200000.0    3
2      3329999.0    1
3      3160000.0    3
4      1400000.0    1
...
146047  3200000.0    1
146048  3000000.0    3
146049  3200000.0    3
146050  3000000.0    3
146051  3300000.0    3

```

[146052 rows x 17 columns]

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

```
[163]: data_org = df_cjy_cj_c.copy()
```

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

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146052 entries, 0 to 146051
Data columns (total 10 columns):
#   Column                Non-Null Count  Dtype
---  -
0   company_hash          146052 non-null object
1   orgyear               146052 non-null float64
2   ctc                   146052 non-null int64
3   job_position          146052 non-null object
4   ctc_updated_year      146052 non-null float64
5   years_of_experience    146052 non-null float64
6   classs                146052 non-null int64
7   designation           146052 non-null int64
8   tier                   146052 non-null int64
9   k-m label             146052 non-null int32
dtypes: float64(3), int32(1), int64(4), object(2)
memory usage: 10.6+ MB

```

```
[165]: final_data
```

```
[165]:
```

	company_hash	orgyear	ctc	job_position	\
0	atrgxnnt xzaxv	2016.0	1100000	other	
1	qtrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer	
2	Others	2015.0	2000000	backend engineer	
3	ngpgutaxv	2017.0	700000	backend engineer	
4	qxen sqghu	2017.0	1400000	fullstack engineer	
...	
146047	mvqwrvj	2011.0	2250000	Others	
146048	vuurt xzw	2008.0	220000	Others	
146049	husqvawgb	2017.0	500000	Others	
146050	vwwgrxnt	2021.0	700000	Others	
146051	bgqsvz onvzrtj	2014.0	1240000	Others	

	ctc_updated_year	years_of_experience	classs	designation	tier	\
0	2020.0	6.0	1	2	2	
1	2019.0	4.0	3	3	3	
2	2020.0	7.0	1	1	1	
3	2019.0	5.0	3	3	3	
4	2019.0	5.0	1	2	1	
...	
146047	2019.0	11.0	1	1	1	
146048	2019.0	14.0	3	2	3	
146049	2020.0	5.0	3	3	3	
146050	2021.0	1.0	3	2	3	
146051	2016.0	8.0	3	3	3	

	k-m label
0	0
1	2
2	0
3	2
4	2
...	...
146047	2
146048	1
146049	0
146050	1
146051	0

[146052 rows x 10 columns]

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

```
[167]: data_frac
```

```
[167]:
```

	company_hash	ctc	job_position	years_of_experience	classss	\
131463	1926	0.390390	0	6.0	3	
5771	569	0.750751	0	4.0	1	
86562	2309	0.162162	0	2.0	2	
28327	2191	0.135135	679	5.0	2	
142745	2918	0.630630	0	4.0	1	
...	
71366	2176	0.255255	686	9.0	3	
78411	252	0.270270	230	5.0	2	
64197	519	0.450450	235	7.0	3	
17649	2191	0.270270	0	3.0	2	
132246	1926	0.360360	0	4.0	3	

	designation	tier	k-m label
131463	3	3	1
5771	1	1	0
86562	2	2	1
28327	2	3	1
142745	1	1	1
...
71366	3	3	1
78411	1	2	0
64197	3	3	0
17649	1	2	1
132246	1	3	1

[365 rows x 8 columns]

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

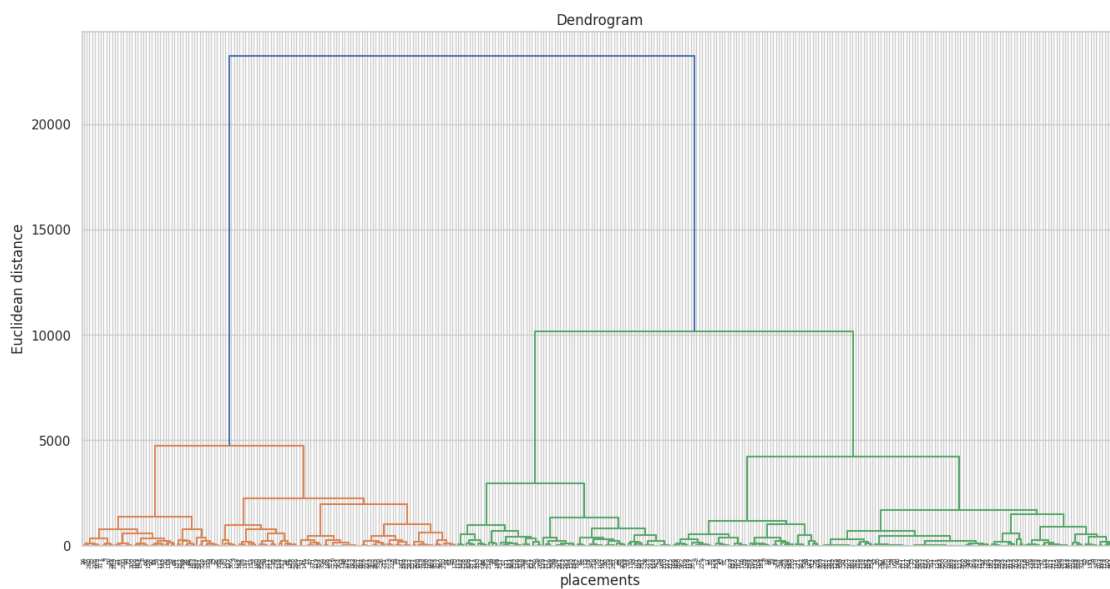
```
[169]: data_frac.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 365 entries, 131463 to 132246
Data columns (total 7 columns):
#   Column                Non-Null Count  Dtype
---  -
0   company_hash          365 non-null    int64
1   ctc                   365 non-null    float64
2   job_position          365 non-null    int64
3   years_of_experience    365 non-null    float64
4   classss               365 non-null    int64
5   designation           365 non-null    int64
6   tier                  365 non-null    int64
dtypes: float64(2), int64(5)
memory usage: 22.8 KB
```

```
[170]: import sys
sys.setrecursionlimit(100000)
```

```
[171]: # 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()
```



```
[171]:
```

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

```
[172]: AgglomerativeClustering(affinity='euclidean', n_clusters=3)
```

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

```
[174]: data_frac
```

```
[174]:
```

	company_hash	ctc	job_position	years_of_experience	classss	\
131463	1926	0.390390	0	6.0	3	
5771	569	0.750751	0	4.0	1	
86562	2309	0.162162	0	2.0	2	
28327	2191	0.135135	679	5.0	2	
142745	2918	0.630630	0	4.0	1	
...	
71366	2176	0.255255	686	9.0	3	
78411	252	0.270270	230	5.0	2	
64197	519	0.450450	235	7.0	3	
17649	2191	0.270270	0	3.0	2	
132246	1926	0.360360	0	4.0	3	

	designation	tier	Aglo-label
131463	3	3	0
5771	1	1	1
86562	2	2	0
28327	2	3	0
142745	1	1	0
...
71366	3	3	0
78411	1	2	1
64197	3	3	1
17649	1	2	0
132246	1	3	0

[365 rows x 8 columns]

```
[175]: final_data
```

```
[175]:
```

	company_hash	orgyear	ctc	job_position	\
0	atrgxnnt xzaxv	2016.0	1100000	other	
1	qtrxvzwt xzegwgb rxbxnta	2018.0	449999	fullstack engineer	
2	Others	2015.0	2000000	backend engineer	
3	ngpgutaxv	2017.0	700000	backend engineer	
4	qxen sqghu	2017.0	1400000	fullstack engineer	
...	
146047	mvqwrvjjo	2011.0	2250000	Others	
146048	vuurt xzw	2008.0	220000	Others	
146049	husqvawgb	2017.0	500000	Others	
146050	vwwgrxnt	2021.0	700000	Others	
146051	bgqsvz onvzrtj	2014.0	1240000	Others	

	ctc_updated_year	years_of_experience	classss	designation	tier	\
0	2020.0	6.0	1	2	2	
1	2019.0	4.0	3	3	3	
2	2020.0	7.0	1	1	1	

3	2019.0	5.0	3	3	3
4	2019.0	5.0	1	2	1
...
146047	2019.0	11.0	1	1	1
146048	2019.0	14.0	3	2	3
146049	2020.0	5.0	3	3	3
146050	2021.0	1.0	3	2	3
146051	2016.0	8.0	3	3	3

	k-m label
0	0
1	2
2	0
3	2
4	2
...	...
146047	2
146048	1
146049	0
146050	1
146051	0

[146052 rows x 10 columns]

6.1.2 To conclude, above is the final_data with all required features.

- We can submit this data to marketing team so that they can focus on those clusters of students who are in dire need and are willing to move forward in life.