scaler notebooks

July 10, 2022

<h1 style="color:blue;"align="center"> SCALER </h1>

Unsupervised Method

0.1 Business Problem

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.

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib as mpl
import seaborn as sns
import plotly.express as px

from scipy import stats
import statsmodels.api as sm

sns.set(style="whitegrid")
%matplotlib inline
```

[2]:
```
from datetime import date
import re

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

pd.set_option('display.MAX_COLUMN',None)
```

IMPORT DATASET

[3]:
```
df = pd.read_csv("./data/scaler_clustering.csv",index_col='Unnamed: 0')
df.head()
```

[3]:
```
                 company_hash  \
0              atrgxnnt xzaxv
1  qtrxvzwt xzegwgbb rxbxnta
2               ojzwnvwnxw vx
3                   ngpgutaxv
4                  qxen sqghu

                                          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

         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
```

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 205843 entries, 0 to 206922
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: 11.0+ MB
```

[5]:
```
pd.DataFrame(
    [df.isna().sum(),(df.isna().sum() / len(df)).mul(100) ]
).T.rename(columns={0:'# of missing values',1:'percentage of NA values'})
```

[5]:
```
                  # of missing values  percentage of NA values
company_hash                     44.0                 0.021376
```

```
email_hash                    0.0          0.000000
orgyear                      86.0          0.041779
ctc                           0.0          0.000000
job_position              52562.0         25.534995
ctc_updated_year              0.0          0.000000
```

[6]:
```python
# Reduentent Records
df.duplicated().sum()
```

[6]: 33

33 reduentent records are present

[7]:
```python
duplicate_data = df.loc[df.duplicated()]

df.drop_duplicates(inplace=True)
```

[8]:
```python
df.describe(include='all').T
```

[8]:
```
                     count  unique  \
company_hash        205766   37299
email_hash          205810  153443
orgyear           205724.0     NaN
ctc               205810.0     NaN
job_position        153263    1017
ctc_updated_year  205810.0     NaN

                                                         top   freq  \
company_hash                          nvnv wgzohrnvzwj otqcxwto   8337
email_hash        bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7…     10
orgyear                                                     NaN    NaN
ctc                                                         NaN    NaN
job_position                                   Backend Engineer  43546
ctc_updated_year                                            NaN    NaN

                         mean               std     min       25%       50%  \
company_hash              NaN               NaN     NaN       NaN       NaN
email_hash                NaN               NaN     NaN       NaN       NaN
orgyear           2014.882284         63.576199     0.0    2013.0    2016.0
ctc            2271853.647053  11801845.290045     2.0  530000.0  950000.0
job_position              NaN               NaN     NaN       NaN       NaN
ctc_updated_year  2019.628279          1.325188  2015.0    2019.0    2020.0

                      75%          max
company_hash          NaN          NaN
email_hash            NaN          NaN
orgyear            2018.0      20165.0
```

```
ctc                1700000.0  1000150000.0
job_position             NaN           NaN
ctc_updated_year      2021.0        2021.0
```

[9]:
```
df.nunique()
```

[9]:
```
company_hash         37299
email_hash          153443
orgyear                 77
ctc                   3360
job_position          1017
ctc_updated_year         7
dtype: int64
```

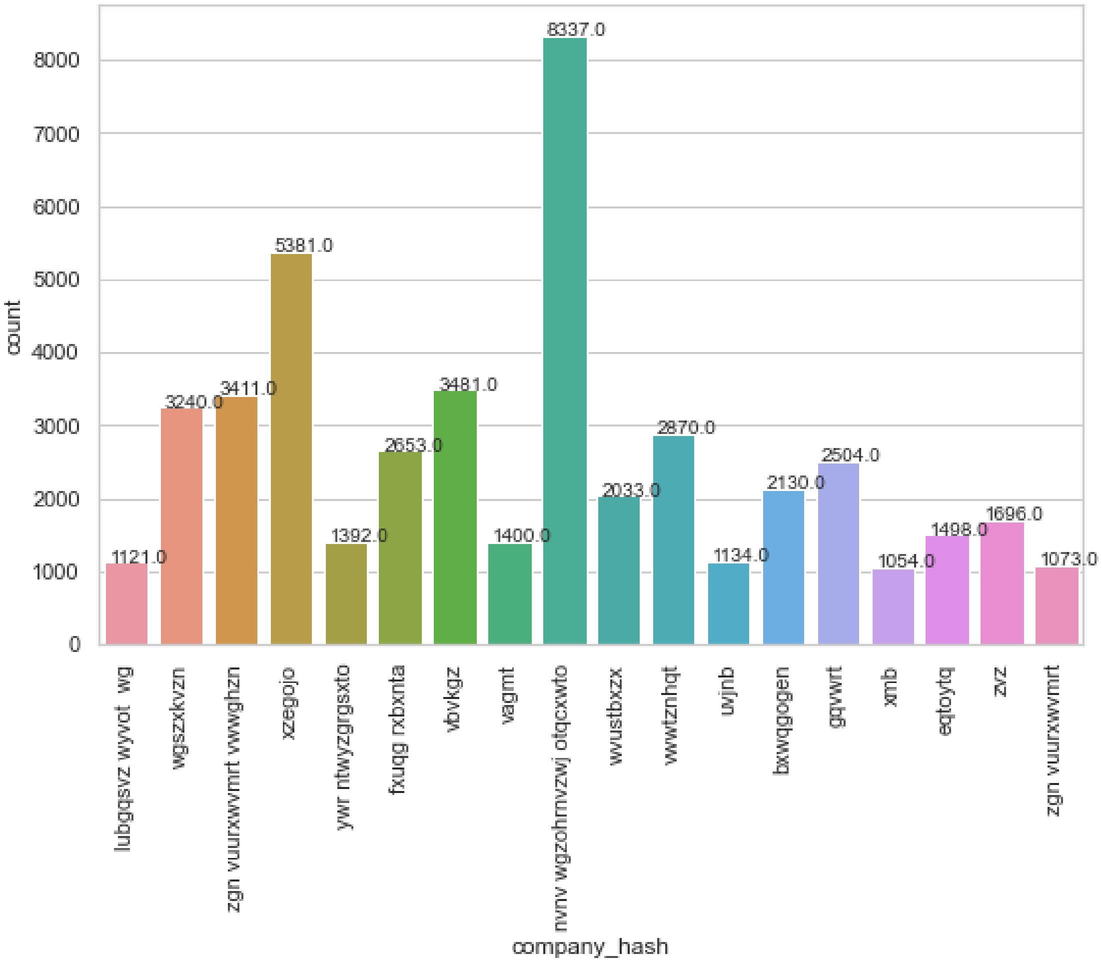
[10]:
```
df.drop('email_hash',inplace=True,axis=1)
```

email be unique to the person which tends to make every data point as cluster as unique

0.2 Data Pre-processing

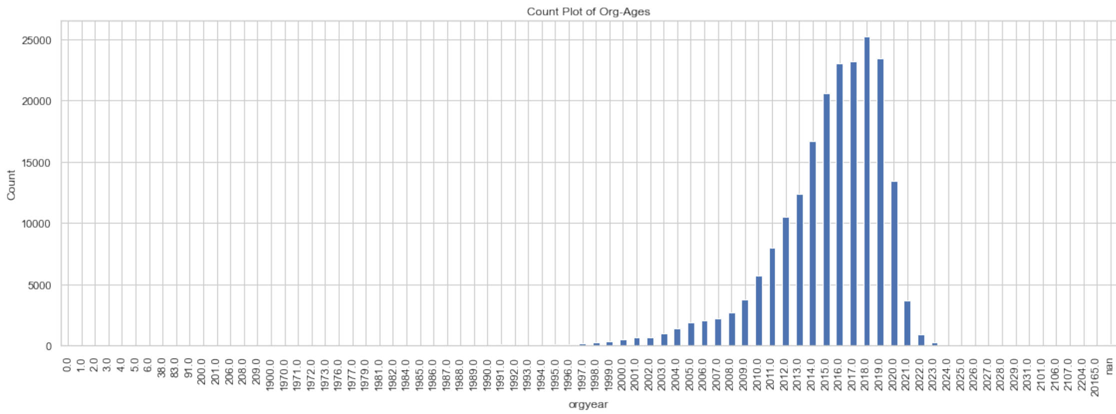
company_hash feature

[11]:
```
plt.figure(figsize=(9,6))
ax = sns.countplot(
    data = df.loc[ df.company_hash.isin(
            df.company_hash.value_counts(dropna=False)[df.company_hash.
 ↪value_counts(dropna=False).values>1000].index)],
    x='company_hash')
for p in ax.patches:
    ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.1, p.
 ↪get_height()+0.2))
plt.xticks(rotation=90)
plt.show()
```



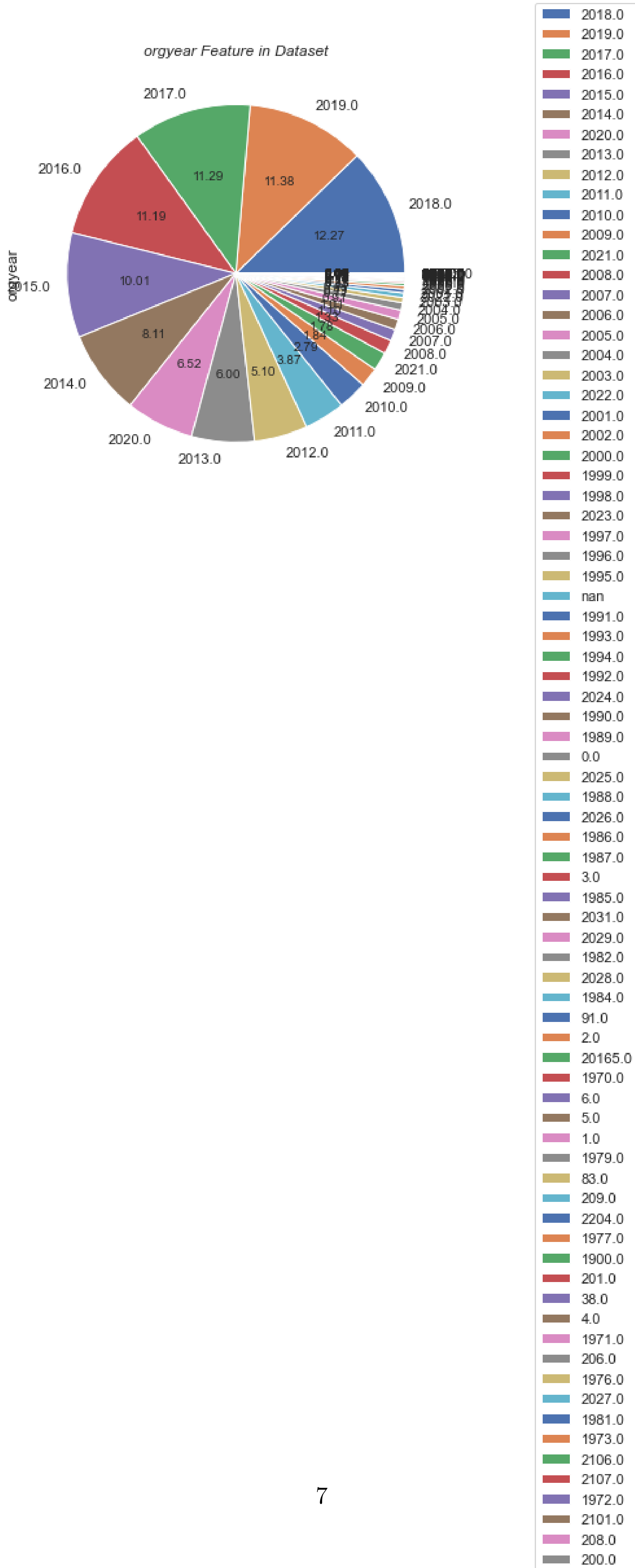
org_year

[12]:
```
plt.figure(figsize=(19,6))
df.orgyear.value_counts(dropna=False).sort_index().plot(kind="bar")
plt.xlabel("orgyear")
plt.ylabel("Count")
plt.xticks(rotation=90)
plt.title("Count Plot of Org-Ages",fontweight=15,fontsize="large")
plt.show()
```



[13]:

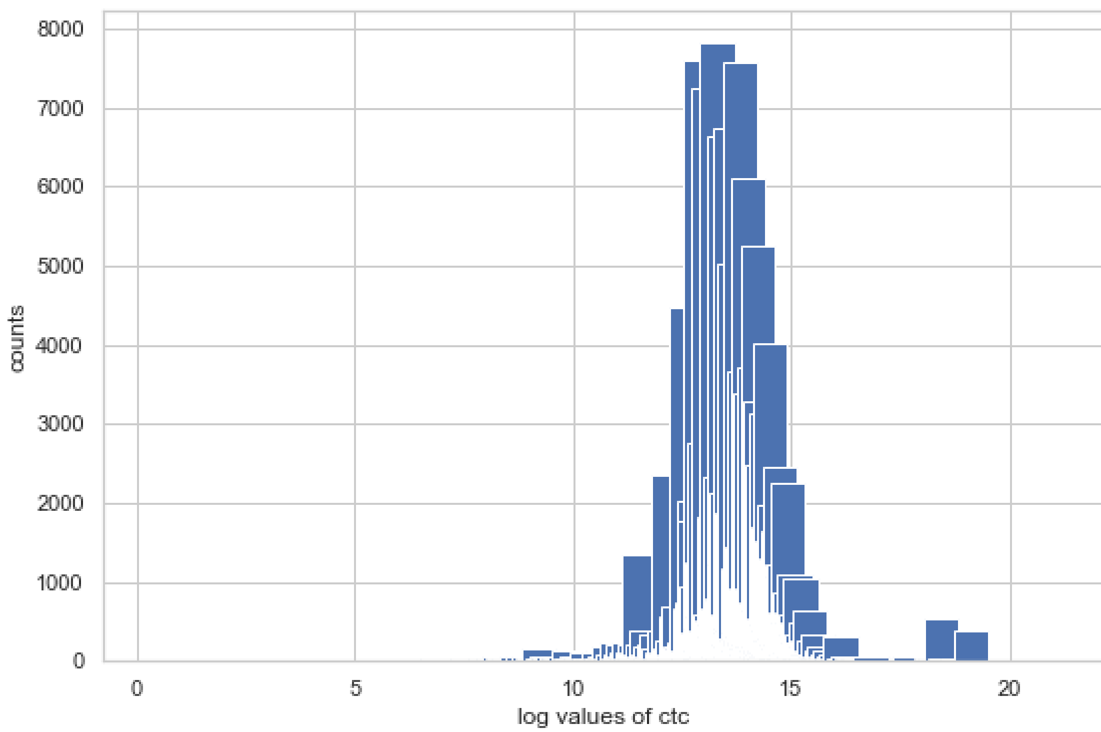
```
plt.figure(figsize=(9,6))
df['orgyear'].value_counts(dropna=False).plot(kind='pie',autopct="%0.2f")
plt.legend()
plt.title("orgyear Feature in Dataset",fontdict={"style":"italic"})
plt.legend(bbox_to_anchor=(1.0,1.0),\
    bbox_transform=plt.gcf().transFigure)
plt.show()
```


orgyear Feature in Dataset
orgyear
2018.0
2019.0
2017.0
2016.0
2015.0
2014.0
2020.0
2013.0
2012.0
2011.0
2010.0
2009.0
2021.0
2008.0
2007.0
2006.0
2005.0
2004.0
12.27
11.38
11.29
11.19
10.01
8.11
6.52
6.00
5.10
3.87
2.79
1.84
1.78
2018.0
2019.0
2017.0
2016.0
2015.0
2014.0
2020.0
2013.0
2012.0
2011.0
2010.0
2009.0
2021.0
2008.0
2007.0
2006.0
2005.0
2004.0
2003.0
2022.0
2001.0
2002.0
2000.0
1999.0
1998.0
2023.0
1997.0
1996.0
1995.0
nan
1991.0
1993.0
1994.0
1992.0
2024.0
1990.0
1989.0
0.0
2025.0
1988.0
2026.0
1986.0
1987.0
3.0
1985.0
2031.0
2029.0
1982.0
2028.0
1984.0
91.0
2.0
20165.0
1970.0
6.0
5.0
1.0
1979.0
83.0
209.0
2204.0
1977.0
1900.0
201.0
38.0
4.0
1971.0
206.0
1976.0
2027.0
1981.0
1973.0
2106.0
2107.0
1972.0
2101.0
208.0
200.0

Inference: **as you see above some orgyears are irrelevant we'll get rid in feature engineering step**

ctc feature

[14]:
```python
x_axis = df.ctc.value_counts(dropna=False).sort_index().index
y_axis = df.ctc.value_counts(dropna=False).sort_index().values


plt.figure(figsize=(9,6))
# Follows log-normall distribution
plt.bar(np.log(x_axis),y_axis)
plt.xlabel('log values of ctc')
plt.ylabel('counts')
plt.show()
```



Inference: **superprisingly salary follows log-normal distribution** or we can use box-mullar transformation

[15]:
```python
df['log_ctc'] = np.log(df.ctc)
```

[16]:
```python
df.log_ctc.describe().T
```

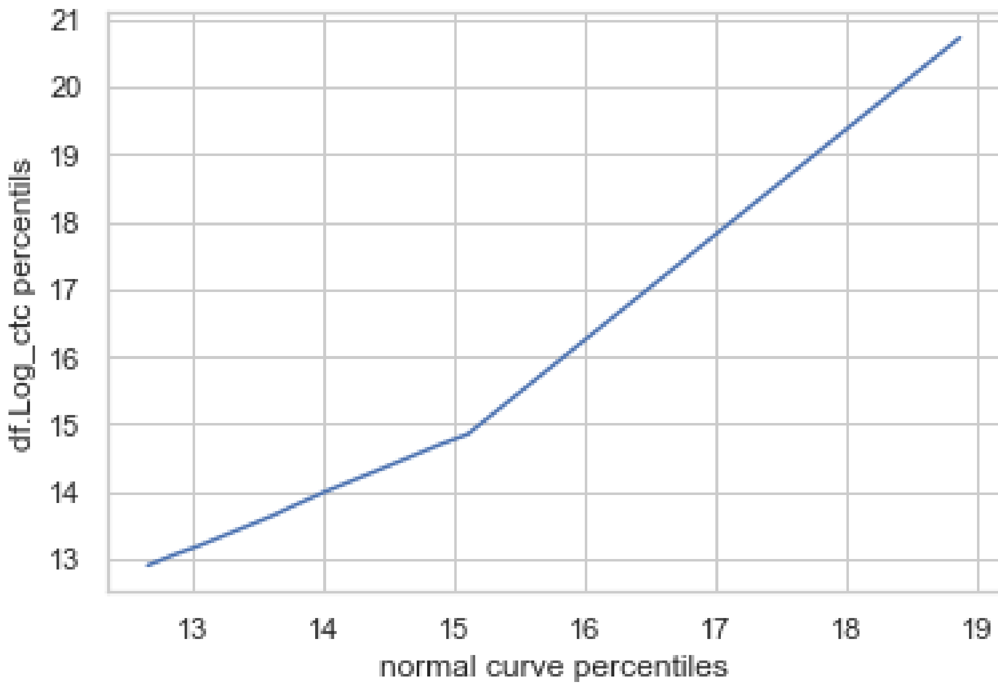
[16]:
```
count    205810.000000
mean         13.745907
std           1.055896
min           0.693147
25%          13.180632
50%          13.764217
75%          14.346139
max          20.723416
Name: log_ctc, dtype: float64
```

Inferences: **proof for normal curve**

[17]:
```
mu,sig = df.log_ctc.describe()[['mean','std']]

print(f" mean of log-normal ctc: {mu} and standard deviation of log-normal ctc:
  ↪{sig} ")
```

```
 mean of log-normal ctc: 13.745907493206696 and standard deviation of log-normal
ctc:1.0558960653149354
```

[18]:
```
log_normall = stats.norm(mu,sig)

sns.lineplot(
    x=np.percentile(log_normall.rvs(205693),[15,20,25,45,50,60,75,86,90,100]),
    y=np.percentile(df.log_ctc,[15,20,25,45,50,60,75,86,90,100])
)
# plt.plot([0,1],[0,1],'r--')
plt.xlabel('normal curve percentiles')
plt.ylabel('df.Log_ctc percentils')
plt.show()
```



Inference: It's close to striaght line so we are good to go

[19]:
```
q3, q1 = np.percentile(df.log_ctc, [75 ,25])
iqr    = q3-q1

print(f'''
quantile-1 for log-ctc {q1} and
quantile-3 for log-ctc {q3} and
interquantile of log-ctc {iqr}or {(q1- (1.5*iqr)), (q3+(1.5*iqr))}''')
```

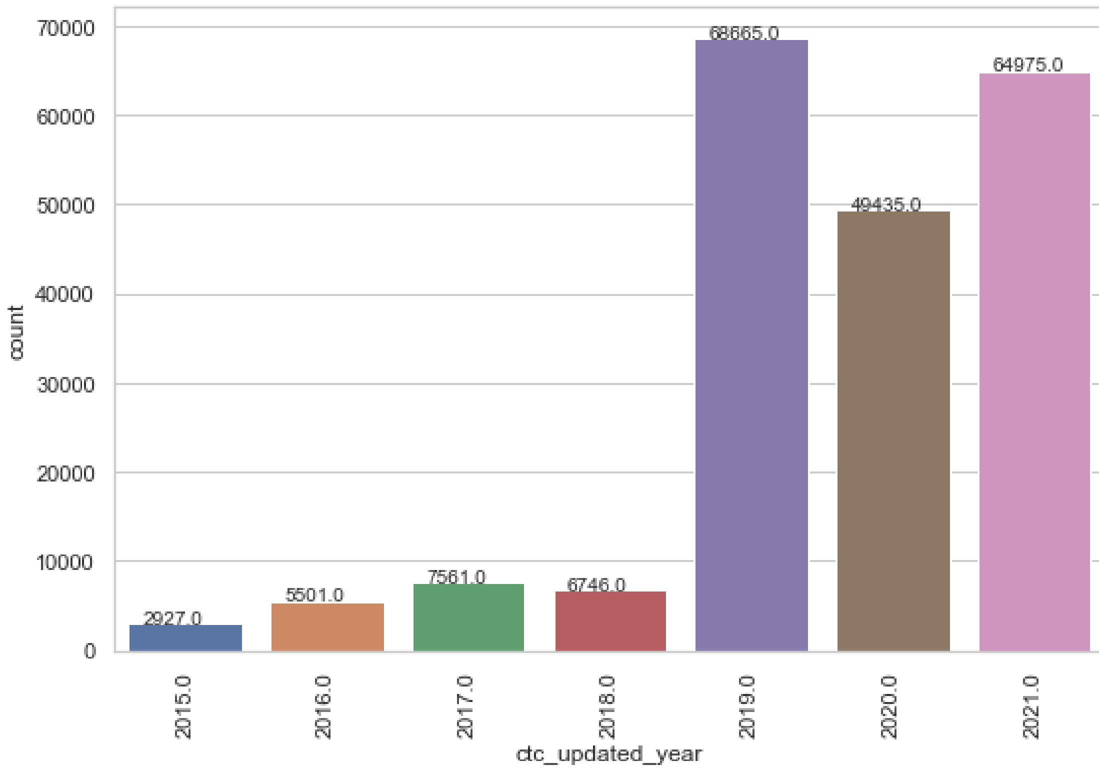
```
quantile-1 for log-ctc 13.180632285528304 and
quantile-3 for log-ctc 14.346138809026444 and
interquantile of log-ctc 1.1655065234981397or (11.432372500281094,
16.094398594273652)
```

Inference: We remove records based on Log-CTC IQR methods

ctc_updated_year

[20]:
```
plt.figure(figsize=(9,6))
ax = sns.countplot(
    x =  df['ctc_updated_year'])
for p in ax.patches:
    ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.1, p.
 ↪get_height()+0.2))
```

```
plt.xticks(rotation=90)
plt.show()
```



job_position feature

[21]:
```
df.job_position.value_counts(dropna=False)
```

[21]:
```
NaN                                  52547
Backend Engineer                     43546
FullStack Engineer                   24711
Other                                18071
Frontend Engineer                    10417
                                     …
ayS                                      1
Principal Product Engineer               1
Senior Director of Engineering           1
Seller Support Associate                 1
Android Application developer            1
Name: job_position, Length: 1018, dtype: int64
```

[22]:
```
def remove_special (string):
    new_string=re.sub('[^A-Za-z ]+', '', string)
```

```
    return new_string
```

[23]:
```
#what happens here: remove spl keyword from word
mystring='\tAirtel\\\\&&**() X */$@ Labs'
re.sub('[^A-Za-z ]+', '', mystring)
```

[23]: 'Airtel X Labs'

[24]:
```
# remove special keyword from word
df.job_position.apply(lambda x: remove_special(str(x))).str.lower().str.strip()
```

[24]:
```
0                       other
1          fullstack engineer
2            backend engineer
3            backend engineer
4          fullstack engineer
                 …
206918                    nan
206919                    nan
206920                    nan
206921                    nan
206922                    nan
Name: job_position, Length: 205810, dtype: object
```

[25]:
```
df.loc[:,'job_position'] = df.job_position.apply(lambda x:␣
 ↪remove_special(str(x))).str.lower().str.strip()
```

grouping same kind of domain into one group by keywords (bucketing people's domain)

simple Manual clustering doable by using regex :)

[26]:
```
intern_trainee_ppls = set()
android_ios_ppls    = set()
dba_ppls            = set()
testing_ppls        = set()
data_fields         = set()
sde                 = set()
application_dev     = set()

def simple_category_ppl(s):
    if( re.search('trainee|intern|student|non coder|new|junior',s) ):
        intern_trainee_ppls.add(s)
    elif( re.search('android|flutter|ios|swift|\wapp',s) ):
        android_ios_ppls.add(s)
    elif( re.
 ↪search('backend|db|database|sql|\wadmin|dba|mysql|administrator\w*|warehouse',s)␣
 ↪):
        dba_ppls.add(s)
```

```python
    elif( re.search('test|selinium',s) ):
        testing_ppls.add(s)
    elif( re.search('data|machine|matlab|pyspark',s) ):
        data_fields.add(s)
    elif( re.search('sde|software|developer',s) ):
        sde.add(s)
    elif( re.search('application',s)):
        application_dev.add(s)

_ = df.job_position.apply(lambda x: simple_category_ppl(str(x)))
```

[27]:
```python
df.job_position.value_counts()[list(testing_ppls)]
```

[27]:
```
senior software development engineer in test    1
software test engineer                          4
test automation engineer                        2
software engineer in test                       2
senior software test engineer                   1
automation test engineer                        1
test analyst                                    3
technical test lead                             1
automation test enginner                        1
senior test engineer                            1
lead software engineer in test                  1
tester                                          2
test technician specialist                      1
software development engineer in test           1
software engineer  testing                      1
manual tester                                   7
Name: job_position, dtype: int64
```

[28]:
```python
df.job_position.value_counts()[list(data_fields)]
```

[28]:
```
data engineer iii                                                     1
senior data scientist                                                 4
big data developer                                                    1
data engineer                                                        13
cloud data architect                                                  1
associate data engineer                                               1
senior member of technical staff  rd  machine learning                1
data associate                                                        1
data scientist                                                     5369
machine learning data associate                                       1
data science analyst                                                  2
dataproduct engineer                                                  1
data analyst                                                       2906
associate data scientist                                              1
```

```
data entry                                                    1
machine learning developer                                    1
data visualization engineer                                   1
azure data factory                                            1
senior data engineer                                          5
data analayst                                                 1
machine learning engineer                                     9
software developer data engineer                              2
data eingineer                                                1
some data entry operator like some copys writetype and upload 1
matlab programmer                                             1
data operations manager                                       1
data specialist                                               1
data scientist ii                                             1
Name: job_position, dtype: int64
```

[29]:
```
df.job_position.value_counts()[list(sde)]
```

[29]:
```
software                                  1
sdet                                   4971
senior mobile developer                   1
application developer analyst             5
assistant software engineer               1
                                       …
software developer automation             1
senior software engineer front end        1
assosiate software engineer               1
associate software engineer              27
software associate                        1
Name: job_position, Length: 172, dtype: int64
```

[30]:
```
df.job_position.value_counts()[list(intern_trainee_ppls)]
```

[30]:
```
engineer trainee                      1
graduate engineer  trainee            2
junior front end eng                  1
project trainee                       1
intern  software developer            5
                                     ..
student                              25
qaeintern                             1
assistant system engineer trainee     2
sdet  intern                          1
fresher student                       1
Name: job_position, Length: 64, dtype: int64
```

[31]:
```
df.job_position.value_counts()[list(android_ios_ppls)]
```

[31]:
```
ios application developer                               1
senior android developer                                2
sr software engg  android                               1
ios software developer                                  1
software developer  android                             1
android application developer                           6
mobile application engineerandroid  ios                 1
sr ios engineer                                         1
android lead                                            1
android facilitator                                     1
software developerapplication developer                 1
android developer sr executive                          1
senior mobile applications developer androidios         1
software engineer android                               4
android engineer                                     5356
software developer  ios                                 1
flutter app engineer                                    1
lead android developer                                  1
sr software engineerandroid                             1
ios engineer                                         2745
sr ios developer                                        1
team lead  android                                      1
ios  swift developer                                    1
Name: job_position, dtype: int64
```

[32]:
```
df.job_position.value_counts()[list(application_dev)]
```

[32]:
```
application development analyst           6
fusion applications engineer              1
principal application engineer            1
associate application engineer            1
applications engineer                     3
senior fusion applications engineer       1
application development associate         3
application development senior analyst    3
a group chat application                  1
senior applications engineer              1
application engineer ii                   1
principal applications engineer           1
application engineer                      6
senior application engineer               1
professional application delivery i       1
application development                   1
application developmentaassociate         1
application development team lead         1
Name: job_position, dtype: int64
```

[33]:
```
df.job_position.value_counts()[list(dba_ppls)]
```

[33]:
```
basis administrator                               1
database administrator                          552
senior software development engineer backend      1
backend architect                              1287
oracle dba                                        1
senior software engineer net backend              1
backend engineering                               1
linux administrator                               2
senior database engineer                          1
senior administrator                              2
oracle lead dba                                   1
backend engineer                              43546
database developer                                1
senior software engineer backend                 10
linux system administrator                        1
sql plsql developer                               1
software engineer  backend                        1
software engineer backend                        42
product engineer backend                          1
administrator                                     2
network administrator                             3
data warehouse developer                          1
Name: job_position, dtype: int64
```

0.3 Feature-Enginnering

[34]:
```
df.loc[df.job_position.isin(intern_trainee_ppls),"job_position"] = "Internship"
df.loc[df.job_position.isin(android_ios_ppls),'job_position']    = "Mobile␣
↪developers"
df.loc[df.job_position.isin(dba_ppls),"job_position"]            = "backend␣
↪engineer"
df.loc[df.job_position.isin(testing_ppls),'job_position']        = "Testing␣
↪Team"
df.loc[df.job_position.isin(data_fields),'job_position']         = 'Data Field'
df.loc[df.job_position.isin(sde),'job_position']                 = 'SDE Field'
df.loc[df.job_position.isin(application_dev),'job_position']     = 'Application␣
↪dev'
```

0.3.1 Data cleaning

[35]:
```
df.loc[df.job_position.isin(['','na','nan','none','not␣
↪applicable']),'job_position'] = np.nan
```

[36]:
```
df = df.loc[ ~(
    (
        ~df.orgyear.isin(range(1900,2023))
    )& (
        (df.orgyear.isna()) |(df.job_position.isna()))
)]
```

[37]:
```
df = df.loc[~(( df.log_ctc>(q1- (1.5*iqr))  ) & (   df.log_ctc< (q3+(1.5*iqr)) 
  ↪))]
```

[38]:
```
df = df.loc[~(
    (df.company_hash.isna())
    &
    (df.job_position.isna())
)]
```

[39]:
```
df = df.loc[~df.company_hash.isna()]
```

0.3.2 Filling out missing values

company_job_frequency table

[40]:
```
groupby_company = df.groupby(['company_hash'])['job_position'].agg(lambda x: pd.
  ↪Series.mode(x)).reset_index()
groupby_company
```

[40]:
```
                      company_hash                            job_position
0                             10hu                 engineering leadership
1                   11 xzntqztn ot                       backend engineer
2                         20152019                                     []
3                             2018                       backend engineer
4                             2021                                     []
…                                …                                      …
3522                      zxwt rna                       backend engineer
3523                 zxwt xzegntwy                     fullstack engineer
3524  zxxn ntwyzgrgsxto rxbxnta  [backend engineer, fullstack engineer]
3525      zxyxrtzn ntwyzgrgsxto                       Mobile developers
3526                  zxztrtvuo                        backend engineer

[3527 rows x 2 columns]
```

[41]:
```
# make empty list as np.nan values
groupby_company.job_position = groupby_company.job_position.apply(lambda x: np.
  ↪nan if(len(x)==0) else x )
```

[42]:

```
# remove records which have only one company_name and it's corresponding␣
↪job_position is NAN
df = df.loc[~(
    df.company_hash.isin(groupby_company.loc[groupby_company.job_position.
↪isna(),'company_hash'].unique())
)]
```

replacing nan values in job_position by comparing company_job_frequency _table

[43]:
```
groupby_company = df.groupby(['company_hash'])['job_position'].agg(lambda x: pd.
↪Series.mode(x)[0]).reset_index()
groupby_company.set_index('company_hash',inplace=True)                              ␣
↪                                               # To make company_hash as index to␣
↪query fast
groupby_company
```

[43]:
```
                                         job_position
company_hash
10hu                           engineering leadership
11 xzntqztn ot                       backend engineer
2018                                 backend engineer
247 xrvm                                    SDE Field
247vx                                backend engineer
…                                                   …
zxwt rna                             backend engineer
zxwt xzegntwy                      fullstack engineer
zxxn ntwyzgrgsxto rxbxnta            backend engineer
zxyxrtzn ntwyzgrgsxto               Mobile developers
zxztrtvuo                            backend engineer

[3228 rows x 1 columns]
```

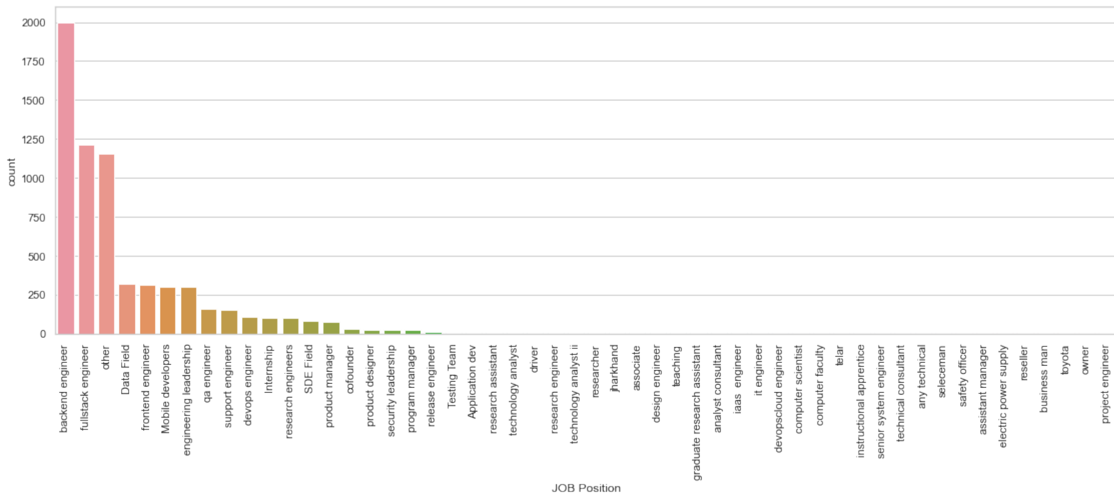
[44]:
```
# replacing nan values in job_position by number of designation mostly required␣
↪by company

for i in df.loc[df.job_position.isna(),'company_hash'].unique():
    df.loc[(
        (df.company_hash==i)& (df.job_position.isna())
    ),'job_position'] = groupby_company['job_position'][i]
```

[45]:
```
job_position_count = df.loc[
        df.job_position.isin(df.job_position.value_counts(dropna=False)[df.
↪job_position.value_counts(dropna=False).values>0].index),"job_position"
    ].value_counts(dropna=False)
job_position_count
```

```
[45]: backend engineer                1998
      fullstack engineer              1213
      other                           1156
      Data Field                       320
      frontend engineer                315
      Mobile developers                302
      engineering leadership           301
      qa engineer                      161
      support engineer                 149
      devops engineer                  104
      Internship                       102
      research engineers               100
      SDE Field                         80
      product manager                   73
      cofounder                         27
      product designer                  23
      security leadership               20
      program manager                   20
      release engineer                  11
      Testing Team                       4
      Application dev                    4
      research assistant                 3
      technology analyst                 2
      driver                             2
      research engineer                  2
      technology analyst ii              1
      researcher                         1
      jharkhand                          1
      associate                          1
      design engineer                    1
      teaching                           1
      graduate research assistant        1
      analyst consultant                 1
      iaas  engineer                     1
      it engineer                        1
      devopscloud engineer               1
      computer scientist                 1
      computer faculty                   1
      telar                              1
      instructional apprentice           1
      senior system engineer             1
      technical consultant               1
      any technical                      1
      seleceman                          1
      safety officer                     1
      assistant manager                  1
      electric power supply              1
```

```
reseller                          1
business man                      1
toyota                            1
owner                             1
project engineer                  1
Name: job_position, dtype: int64
```

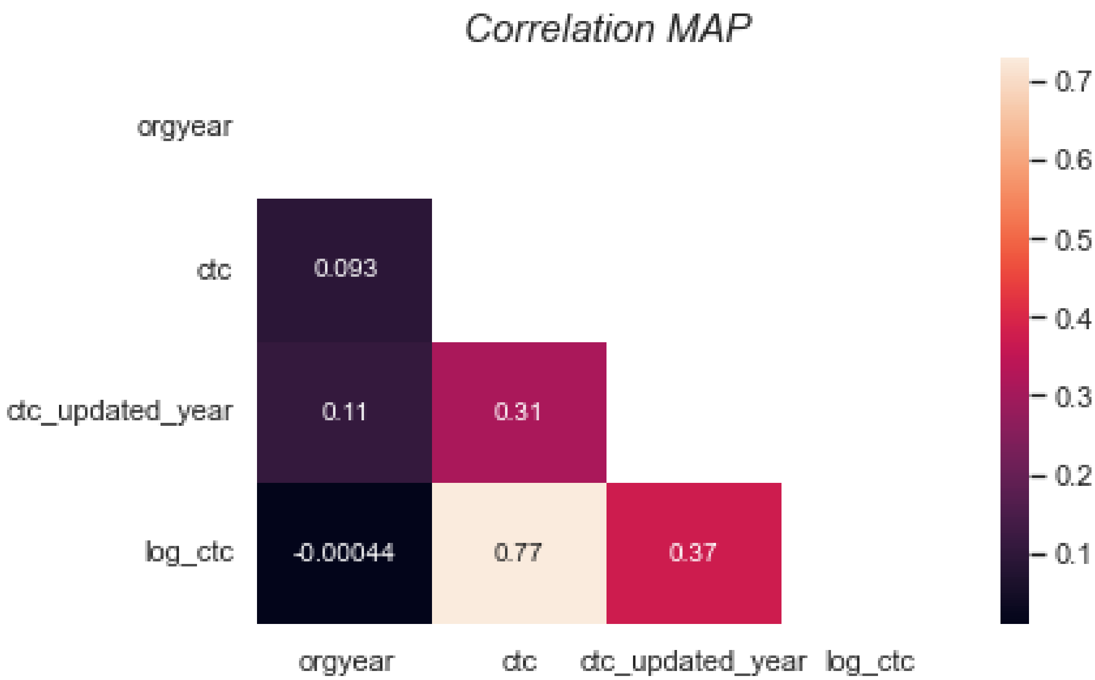
[46]:
```python
plt.figure(figsize=(19,6))
sns.barplot(x=job_position_count.index,y=job_position_count.values)
plt.xticks(rotation=90)
plt.ylabel("count")
plt.xlabel("JOB Position")
plt.show()
```



Inference:

we can put all unique (occurs only ony time in our dataset) job_position into single bucket "o

[47]:
```python
mask = np.triu(np.ones_like(df.corr()))
sns.heatmap(
    data=df.corr(),
    annot=True,
    robust=True,
    mask=mask
)
plt.title("Correlation MAP",fontsize="15",fontstyle="italic")
plt.show()
```



`Inference`: since log_ctc is derived from ctc feature obviously their correlation is more. so dropping of one feature makes our computation less

`Note`: orgyear has no correlation between ctc

[48]:
```
df.drop('log_ctc',axis=1,inplace=True)
```

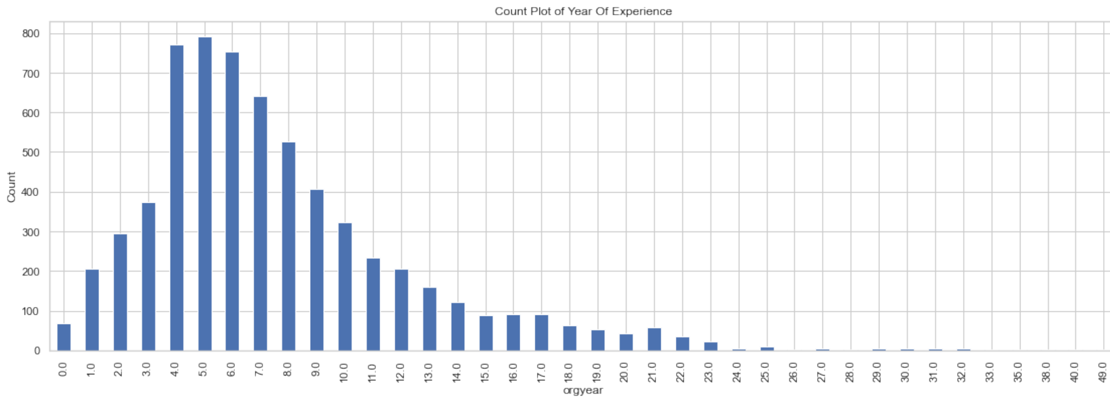
Creating NEW FEATURE called YEAR_OF_EXPERIENCE

[49]:
```
year = date.today().year
df['year_of_exp'] = year - df.orgyear
```

[50]:
```
df = df.loc[( (df.year_of_exp>-1) & (~df.year_of_exp.isna())  )]
```

`Inference`: there is **NO NULL and negative values** are present

[51]:
```
plt.figure(figsize=(19,6))
df.year_of_exp.value_counts(dropna=False).sort_index().plot(kind="bar")
plt.xlabel("orgyear")
plt.ylabel("Count")
plt.xticks(rotation=90)
plt.title("Count Plot of Year Of Experience",fontweight=15,fontsize="large")
plt.show()
```



`Inference:` most of people works on 4 to 6 years or Organization either it's might be Unicorn or Startup

0.3.3 Creation of NEW Features like class

[52]:
```
df.groupby(['job_position','company_hash'])['ctc'].describe()
```

[52]:
```
                                                 count         mean          std  \
job_position           company_hash
Application dev        fgqpavj                     1.0      85000.0          NaN
                       gqvwrt                      1.0   16700000.0          NaN
                       qvphntz                     2.0      69500.0  6363.961031
Data Field             aaw                         1.0      88555.0          NaN
                       adw ntwyzgrgsj              1.0  100000000.0          NaN
…                                                    …            …            …
technical consultant   zgn vuurxwvmrt vwwghzn      1.0       2000.0          NaN
technology analyst     xzegojo                     2.0      77500.0  6363.961031
technology analyst ii  ntrho                       1.0      60000.0          NaN
telar                  shrlvq bvzoyhqx             1.0  100000000.0          NaN
toyota                 otre tburgjta               1.0   10000000.0          NaN

                                                        min          25%  \
job_position           company_hash
Application dev        fgqpavj                      85000.0      85000.0
                       gqvwrt                    16700000.0   16700000.0
                       qvphntz                      65000.0      67250.0
Data Field             aaw                          88555.0      88555.0
                       adw ntwyzgrgsj           100000000.0  100000000.0
…                                                        …            …
technical consultant   zgn vuurxwvmrt vwwghzn        2000.0       2000.0
technology analyst     xzegojo                      73000.0      75250.0
technology analyst ii  ntrho                        60000.0      60000.0
telar                  shrlvq bvzoyhqx          100000000.0  100000000.0
```

```
toyota                   otre tburgjta         10000000.0   10000000.0

                                                      50%          75%  \
job_position             company_hash
Application dev          fgqpavj                  85000.0      85000.0
                         gqvwrt                16700000.0   16700000.0
                         qvphntz                  69500.0      71750.0
Data Field               aaw                      88555.0      88555.0
                         adw ntwyzgrgsj       100000000.0  100000000.0
…                                                     …            …
technical consultant     zgn vuurxwvmrt vwwghzn    2000.0       2000.0
technology analyst       xzegojo                  77500.0      79750.0
technology analyst ii ntrho                       60000.0      60000.0
telar                    shrlvq bvzoyhqx      100000000.0  100000000.0
toyota                   otre tburgjta         10000000.0   10000000.0

                                                      max
job_position             company_hash
Application dev          fgqpavj                  85000.0
                         gqvwrt                16700000.0
                         qvphntz                  74000.0
Data Field               aaw                      88555.0
                         adw ntwyzgrgsj       100000000.0
…                                                     …
technical consultant     zgn vuurxwvmrt vwwghzn    2000.0
technology analyst       xzegojo                  82000.0
technology analyst ii ntrho                       60000.0
telar                    shrlvq bvzoyhqx      100000000.0
toyota                   otre tburgjta         10000000.0

[4205 rows x 8 columns]
```

[53]:
```
groupby_comp_job = df.groupby(['job_position','company_hash'])['ctc'].describe()
```

[54]:
```
df = df.merge(groupby_comp_job, on=['job_position','company_hash'],how='left')
df
```

[54]:
```
                   company_hash  orgyear        ctc        job_position  \
0                    evzzxt bvt   2006.0   11800000         qa engineer
1           wqgoogctq egq fgqp   2004.0      60000   Mobile developers
2                      vqsxrad   2009.0      20000    backend engineer
3       oxburjyq ogrhnxgzo rru   2017.0  200000000    support engineer
4                   txzegwyxuo   2015.0       8000         qa engineer
…                            …        …          …                   …
6464                       zvz   2018.0   67300000    backend engineer
6465                    jvzatd   2018.0       2000    backend engineer
6466                   xzegojo   2017.0      60000  fullstack engineer
```

```
6467        ywr ntwyzgrgsxto   2008.0      55000    backend engineer
6468           ntwy bvyxzaqv   2011.0      64000    backend engineer

      ctc_updated_year  year_of_exp  count          mean           std  \
0               2019.0         16.0    1.0  1.180000e+07           NaN
1               2019.0         18.0    2.0  6.000000e+04  0.000000e+00
2               2019.0         13.0    1.0  2.000000e+04           NaN
3               2020.0          5.0    1.0  2.000000e+08           NaN
4               2019.0          7.0    2.0  8.000000e+03  0.000000e+00
…                  …           …    …            …            …
6464            2017.0          4.0   48.0  1.653691e+07  4.081696e+07
6465            2017.0          4.0   12.0  4.633333e+04  2.309795e+04
6466            2017.0          5.0   49.0  4.888164e+07  7.423453e+07
6467            2017.0         14.0   13.0  4.564641e+07  6.721278e+07
6468            2016.0         11.0    6.0  5.836017e+07  8.008065e+07

              min          25%          50%          75%          max
0      11800000.0   11800000.0   11800000.0   11800000.0   11800000.0
1         60000.0      60000.0      60000.0      60000.0      60000.0
2         20000.0      20000.0      20000.0      20000.0      20000.0
3     200000000.0  200000000.0  200000000.0  200000000.0  200000000.0
4          8000.0       8000.0       8000.0       8000.0       8000.0
…             …           …           …           …           …
6464       1000.0      33750.0      75000.0      90000.0  200000000.0
6465       2000.0      37000.0      46000.0      60250.0      80000.0
6466       3250.0       6000.0      87000.0  100000000.0  200000000.0
6467       3300.0      10000.0      85000.0  100000000.0  200000000.0
6468      40000.0      58750.0   25032000.0   87500000.0  200000000.0

[6469 rows x 14 columns]
```

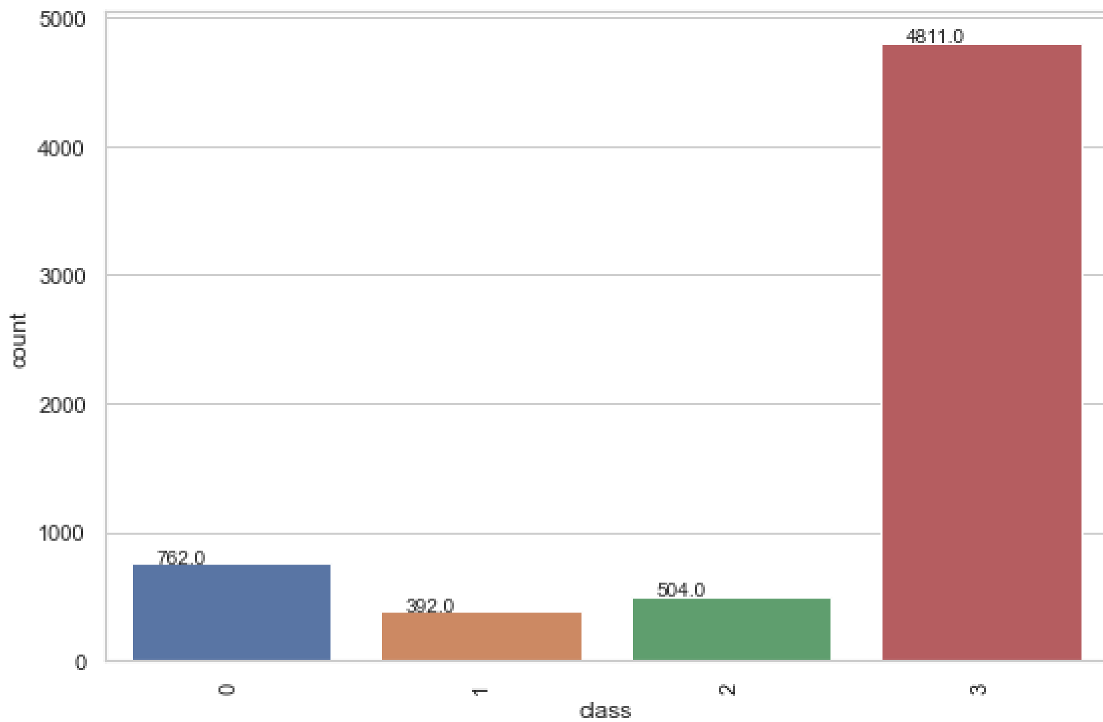
making an assumption that people works on one company is not same as other even they do same job

note: It will fail when ctc is unique and

[55]:
```python
@np.vectorize
def create_designation(ctcs,quantile1,quantile2,quantile3):
    #print(type(ctcs),type(quantile1),type(quantile2),type(quantile3))
    if(ctcs<quantile1):
        return 0
    elif(ctcs<quantile2):
        return 1
    elif(ctcs<quantile3):
        return 2
    else:
        return 3
```

[56]:
```
df['class'] = create_designation(df['ctc'],df['25%'],df['50%'],df['75%'])
```

[57]:
```
plt.figure(figsize=(9,6))
ax = sns.countplot(
    data = df,
    x='class')
for p in ax.patches:
    ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.1, p.
 ↪get_height()+0.2))
plt.xticks(rotation=90)
plt.show()
```



Inference: most of peoples are getting ctc more than quantile3

[58]:
```
df.
 ↪drop(axis=1,labels=['std','count','mean','max','min','25%','50%','75%'],inplace=True)
```

[59]:
```
#df.to_csv('clean_data.csv',index=False)
```

0.4 DATA ANALYSIS

[60]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

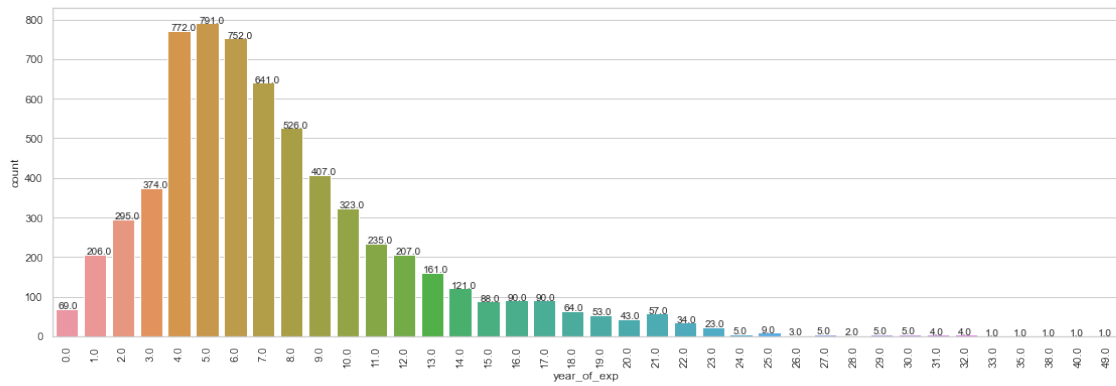
```
Int64Index: 6469 entries, 0 to 6468
Data columns (total 7 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   company_hash      6469 non-null   object
 1   orgyear           6469 non-null   float64
 2   ctc               6469 non-null   int64
 3   job_position      6469 non-null   object
 4   ctc_updated_year  6469 non-null   float64
 5   year_of_exp       6469 non-null   float64
 6   class             6469 non-null   int64
dtypes: float64(3), int64(2), object(2)
memory usage: 404.3+ KB
```

[61]:
```
df.describe(include='all').T
```

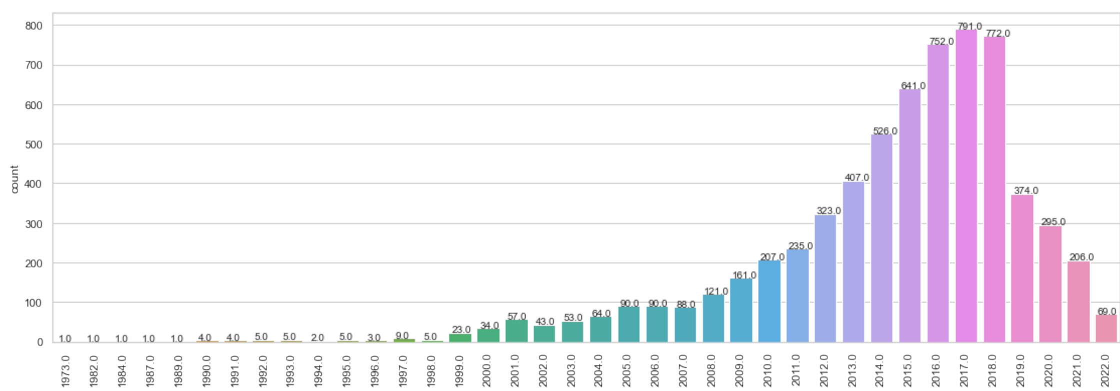
[61]:
```
                   count unique                        top  freq  \
company_hash        6469   3213  nvnv wgzohrnvzwj otqcxwto   157
orgyear           6469.0    NaN                        NaN   NaN
ctc               6469.0    NaN                        NaN   NaN
job_position        6469     52           backend engineer  1988
ctc_updated_year  6469.0    NaN                        NaN   NaN
year_of_exp       6469.0    NaN                        NaN   NaN
class             6469.0    NaN                        NaN   NaN

                          mean             std     min      25%      50%  \
company_hash               NaN             NaN     NaN      NaN      NaN
orgyear            2014.416757        4.836287  1973.0   2012.0   2016.0
ctc            29044761.460968  55447024.139376     2.0  25000.0  74000.0
job_position               NaN             NaN     NaN      NaN      NaN
ctc_updated_year   2019.095223        1.445962  2015.0   2019.0   2019.0
year_of_exp           7.583243        4.836287     0.0      4.0      6.0
class                 2.447519        1.036996     0.0      2.0      3.0

                         75%          max
company_hash             NaN          NaN
orgyear               2018.0       2022.0
ctc               19800000.0  200000000.0
job_position             NaN          NaN
ctc_updated_year      2020.0       2021.0
year_of_exp             10.0         49.0
class                    3.0          3.0
```

0.4.1 Univarient analysis

[62]:
```
plt.figure(figsize=(19,6))
ax = sns.countplot( data = df,x='year_of_exp')
for p in ax.patches: ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.
 ↪1, p.get_height()+0.2))
plt.xticks(rotation=90)
plt.show()
```

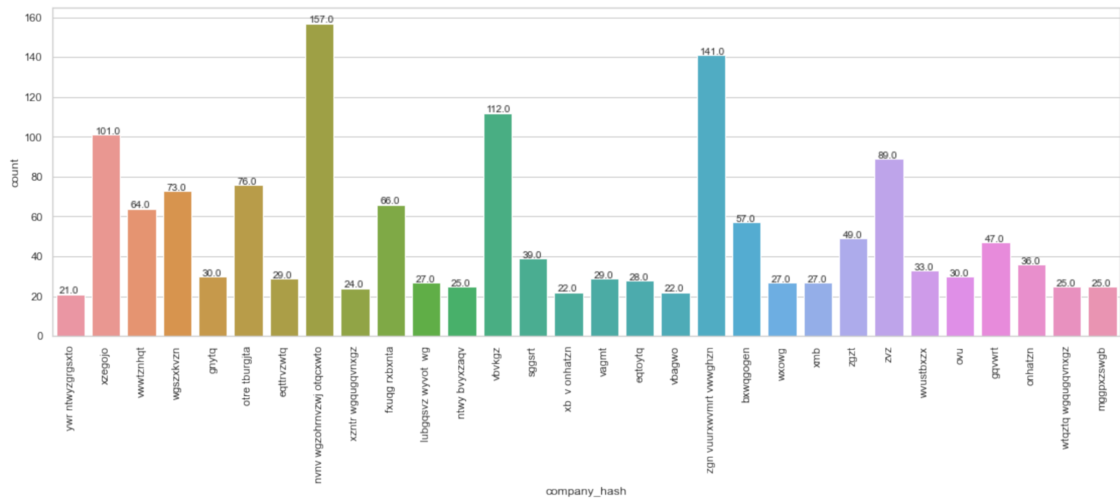


[63]:
```
plt.figure(figsize=(19,6))
ax = sns.countplot( data = df,x='orgyear')
for p in ax.patches: ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.
 ↪1, p.get_height()+0.2))
plt.xticks(rotation=90)
plt.show()
```



[64]:
```
plt.figure(figsize=(19,6))
ax = sns.countplot( data = df.loc[ df.company_hash.isin(
```

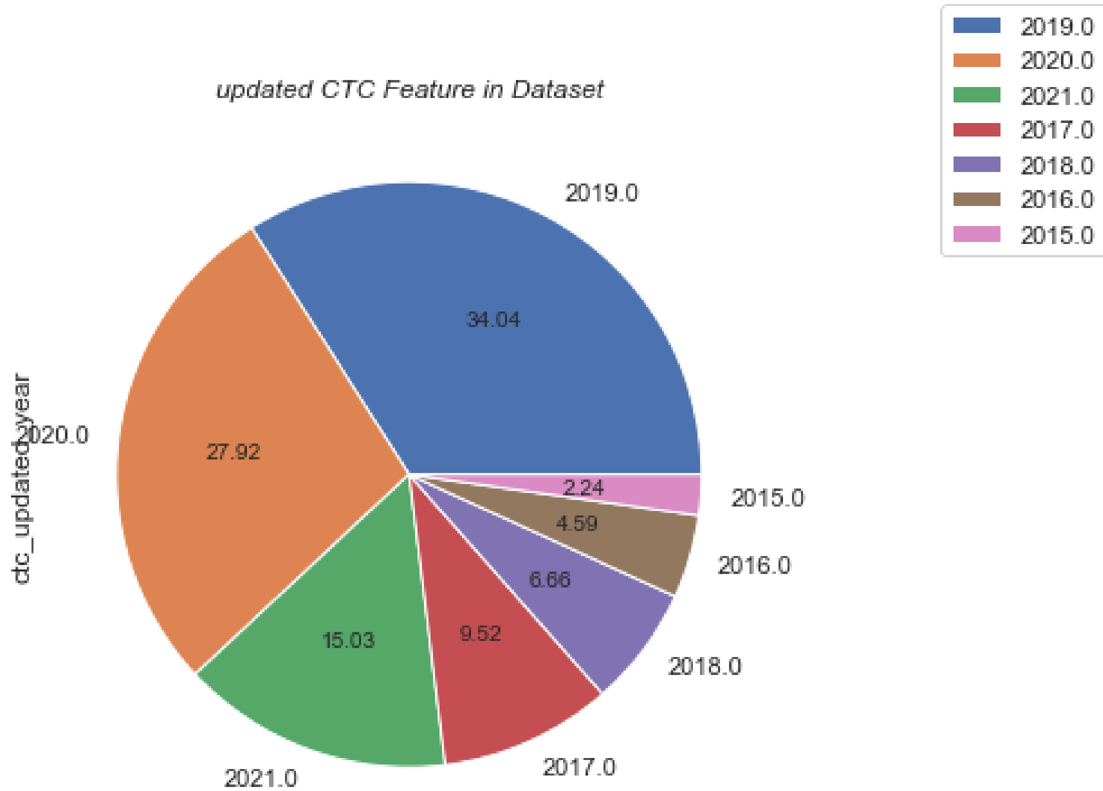
```
            df.company_hash.value_counts(dropna=False)[df.company_hash.
↪value_counts(dropna=False).values>20].index)],
        x='company_hash')
for p in ax.patches: ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.
↪1, p.get_height()+0.2))
plt.xticks(rotation=90)
plt.show()
```



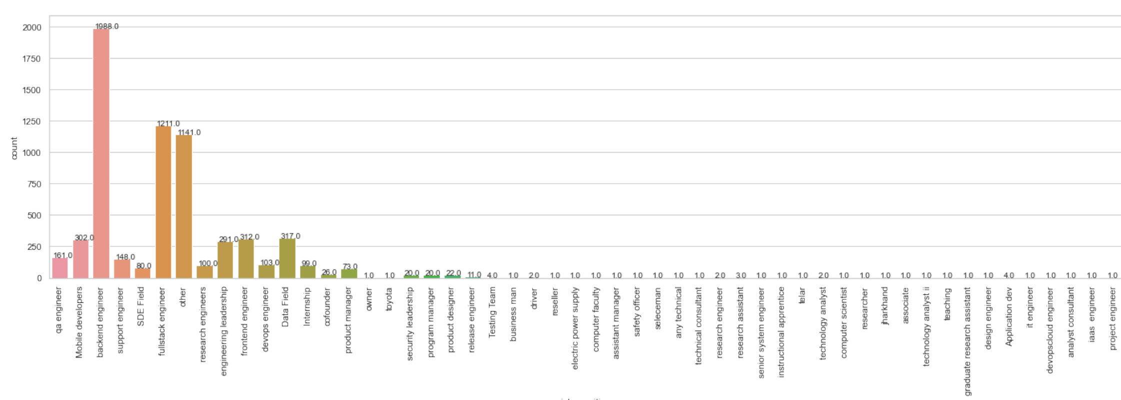
inference:

top companies listed out: nvnv wgzohrnvzwj otqcxwto,zgn vuurxwvmrt vwwghzn,vbvkgz,xzegojo

[65]:
```
plt.figure(figsize=(9,6))
df['ctc_updated_year'].value_counts(dropna=False).plot(kind='pie',autopct="%0.
↪2f")
plt.legend()
plt.title("updated CTC Feature in Dataset",fontdict={"style":"italic"})
plt.legend(bbox_to_anchor=(1.0,1.0),\
    bbox_transform=plt.gcf().transFigure)
plt.show()
```



[66]:
```python
plt.figure(figsize=(24,6))
ax = sns.countplot(df.job_position)
for p in ax.patches: ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.1, p.get_height()+0.2))
plt.xticks(rotation=90)
plt.show()
```

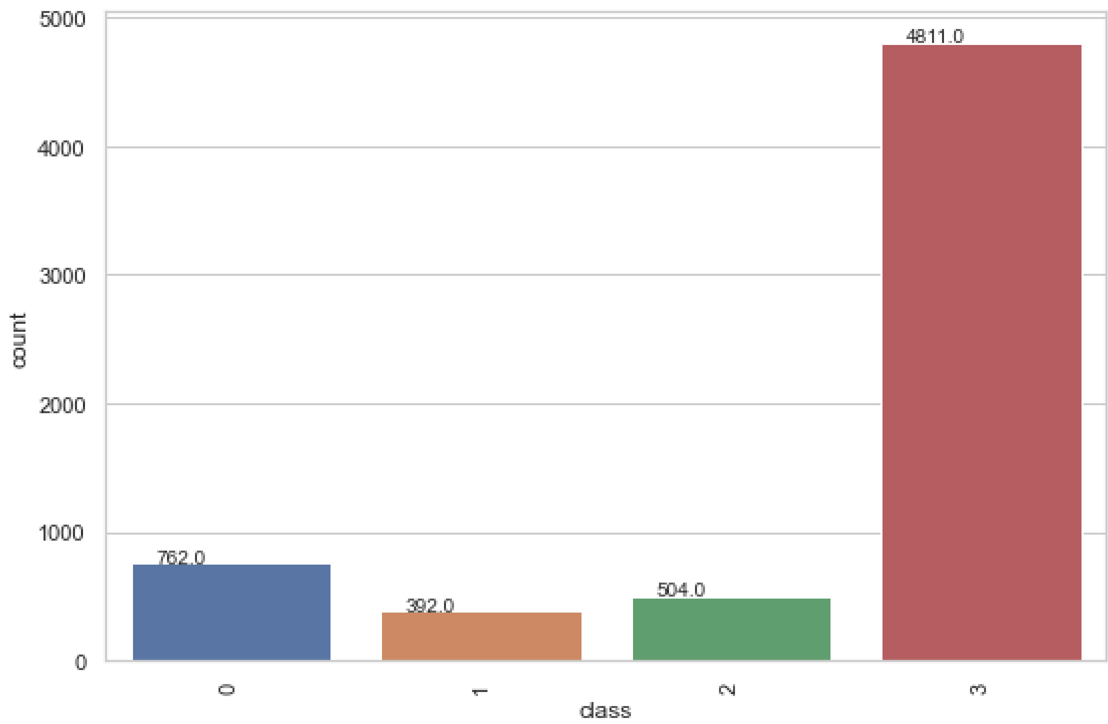


Inference:

apart from backend and fullstack enginner the Data Field and Mobile developers are going pa

since we don't have enough information to intercept Other column

[67]:
```
plt.figure(figsize=(9,6))
ax = sns.countplot(
    data = df,
    x='class')
for p in ax.patches:
    ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x()+0.1, p.
↪get_height()+0.2))
plt.xticks(rotation=90)
plt.show()
```

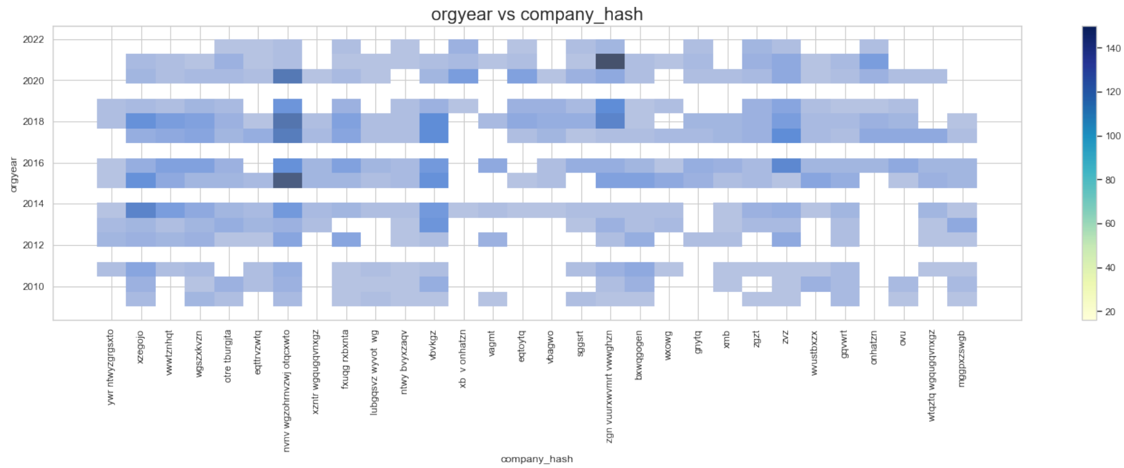


Inference:

most of the people are getting more than second quantile of ctc in their respective job and co

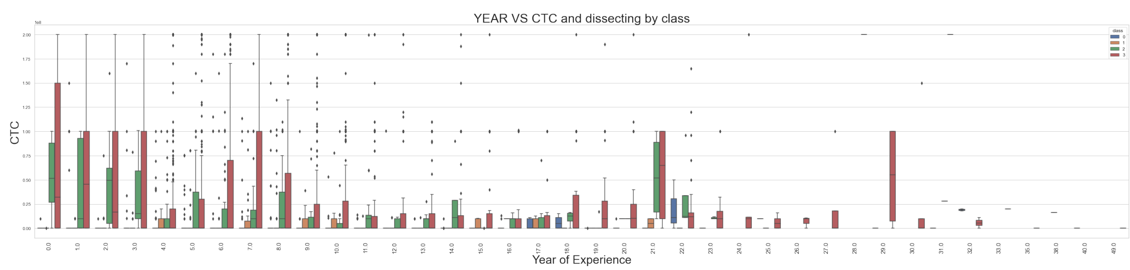
0.4.2 Bi-varient analysis

[68]:
```
plt.figure(figsize=(24,6))
sns.histplot(
    data= df.loc[(
         (df.company_hash.isin( df.company_hash.value_counts(dropna=False)[df.
 ↪company_hash.value_counts(dropna=False).values>20].index))
          &
         (df.job_position.isin(['backend engineer', 'fullstack engineer',␣
 ↪'other', 'Data Field','frontend engineer', 'Mobile developers', 'engineering␣
 ↪leadership','qa engineer', 'support engineer', 'devops engineer']))
        &
        (df.year_of_exp.isin(list(range(0,14))))
    )],
    x='company_hash',y='orgyear')



norm = mpl.colors.Normalize(
        df.loc[(
         (df.company_hash.isin( df.company_hash.value_counts(dropna=False)[df.
 ↪company_hash.value_counts(dropna=False).values>20].index))&(df.job_position.
 ↪isin(['backend engineer', 'fullstack engineer', 'other', 'Data␣
 ↪Field','frontend engineer', 'Mobile developers', 'engineering␣
 ↪leadership','qa engineer', 'support engineer', 'devops engineer']))&(df.
 ↪year_of_exp.isin(list(range(0,14))))
)].groupby('company_hash')['orgyear'].size().min(),
        df.loc[(
         (df.company_hash.isin( df.company_hash.value_counts(dropna=False)[df.
 ↪company_hash.value_counts(dropna=False).values>20].index))&(df.job_position.
 ↪isin(['backend engineer', 'fullstack engineer', 'other', 'Data␣
 ↪Field','frontend engineer', 'Mobile developers', 'engineering␣
 ↪leadership','qa engineer', 'support engineer', 'devops engineer']))&(df.
 ↪year_of_exp.isin(list(range(0,14))))
)].groupby('company_hash')['orgyear'].size().max())
plt.xticks(rotation=90)
plt.colorbar(mpl.cm.ScalarMappable(norm=norm,cmap='YlGnBu'),)

plt.xticks(rotation=90)
plt.title("orgyear vs company_hash",fontsize=20)
plt.show()
```



Inference: compare to 2010-2014 , 2017 to 2021 have more darker regions

[69]:
```
plt.figure(figsize=(50,10))
sns.boxplot(data=df,y='ctc',hue='class',x='year_of_exp')
plt.xticks(fontsize=15,rotation=90)
plt.xlabel("Year of Experience",fontsize=30)
plt.ylabel("CTC",fontsize=30)
plt.title("YEAR VS CTC and dissecting by class",fontsize=32)
plt.show()
```

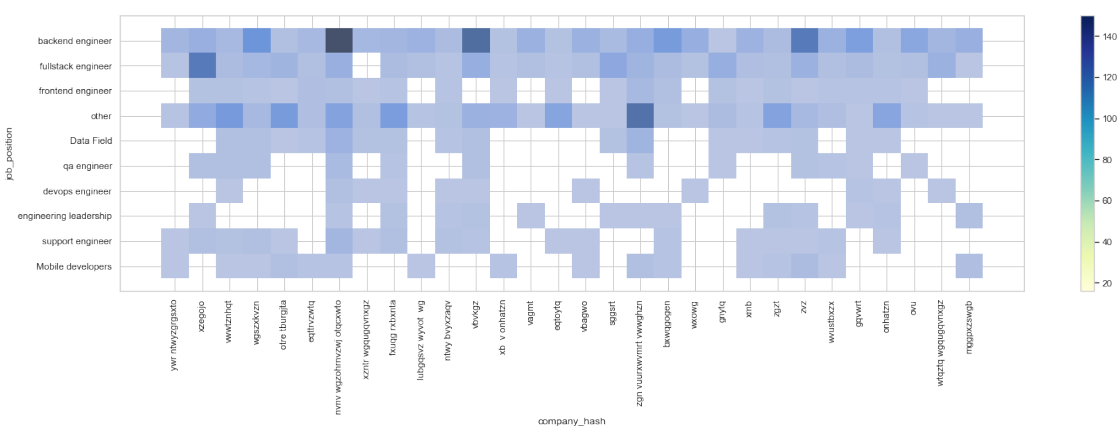


Inference:

we notice class 3 peoples are high across all year of experience

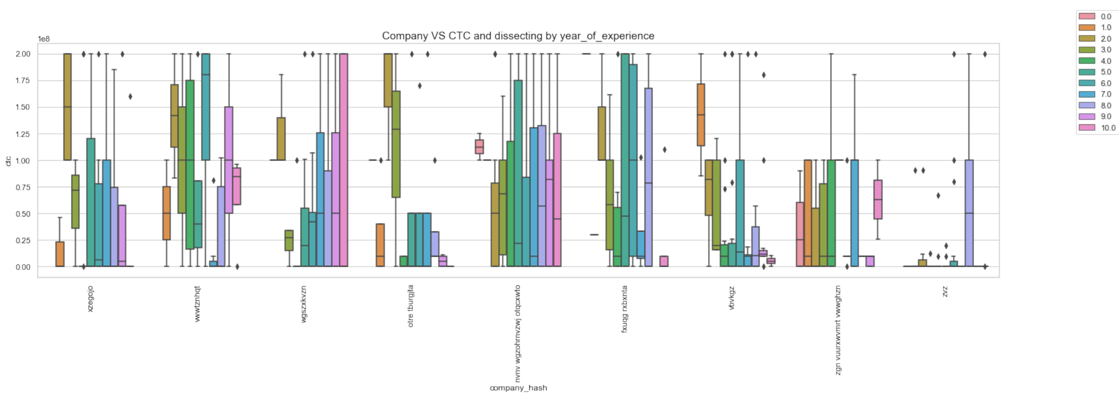
[70]:
```
plt.figure(figsize=(24,6))
sns.histplot(
    data= df.loc[(
          (df.company_hash.isin( df.company_hash.value_counts(dropna=False)[df.
↪company_hash.value_counts(dropna=False).values>20].index))
           &
```

```
        (df.job_position.isin(['backend engineer', 'fullstack engineer', 'other', 'Data Field','frontend engineer', 'Mobile developers', 'engineering leadership','qa engineer', 'support engineer', 'devops engineer']))
        &
        (df.year_of_exp.isin(list(range(0,14))))
    )],
    x='company_hash',y='job_position')
plt.xticks(rotation=90)

norm = mpl.colors.Normalize(
        df.loc[(
    (df.company_hash.isin( df.company_hash.value_counts(dropna=False)[df.company_hash.value_counts(dropna=False).values>20].index))&(df.job_position.isin(['backend engineer', 'fullstack engineer', 'other', 'Data Field','frontend engineer', 'Mobile developers', 'engineering leadership','qa engineer', 'support engineer', 'devops engineer']))&(df.year_of_exp.isin(list(range(0,14))))
)].groupby('company_hash')['job_position'].size().min(),
     df.loc[(
    (df.company_hash.isin( df.company_hash.value_counts(dropna=False)[df.company_hash.value_counts(dropna=False).values>20].index))&(df.job_position.isin(['backend engineer', 'fullstack engineer', 'other', 'Data Field','frontend engineer', 'Mobile developers', 'engineering leadership','qa engineer', 'support engineer', 'devops engineer']))&(df.year_of_exp.isin(list(range(0,14))))
)].groupby('company_hash')['job_position'].size().max())
plt.xticks(rotation=90)
plt.colorbar(mpl.cm.ScalarMappable(norm=norm,cmap='YlGnBu'),)

plt.show()
```



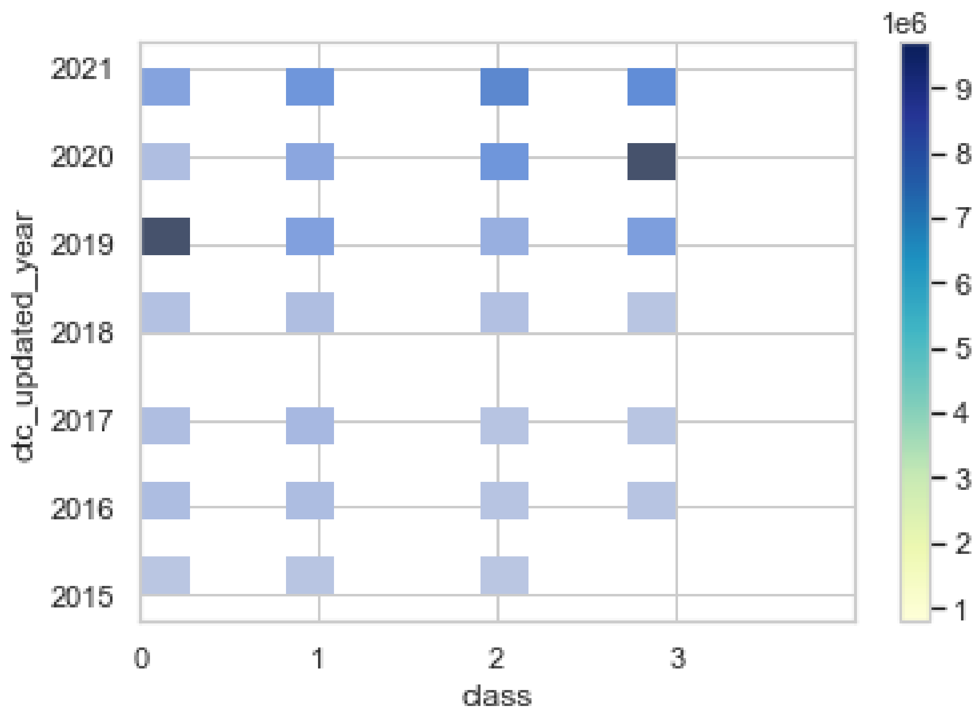
`Inference:` Hot-spot represent more jobs needs in those company

[71]:
```python
plt.figure(figsize=(24,6))
sns.boxplot(
    data= df.loc[(
         (df.company_hash.isin( df.company_hash.value_counts(dropna=False)[df.
 ↪company_hash.value_counts(dropna=False).values>60].index))
          &
         (df.job_position.isin(['backend engineer', 'fullstack engineer',␣
 ↪'other', 'Data Field','frontend engineer', 'Mobile developers', 'engineering␣
 ↪leadership','qa engineer', 'support engineer', 'devops engineer']))
          &
        (df.year_of_exp.isin(list(range(0,11))))
    )],
    x='company_hash',
    y='ctc',
    hue='year_of_exp',
)
plt.xticks(rotation=90)
plt.legend(bbox_to_anchor=(1.0,1.0),bbox_transform=plt.gcf().transFigure)
plt.title("Company VS CTC and dissecting by year_of_experience",fontsize=15)
plt.show()
```



[72]:
```python
sns.histplot(
    data=df.loc[(
         (df.company_hash.isin( df.company_hash.value_counts(dropna=False)[df.
 ↪company_hash.value_counts(dropna=False).values>60].index))
          &
         (df.job_position.isin(['backend engineer', 'fullstack engineer',␣
 ↪'other', 'Data Field','frontend engineer', 'Mobile developers', 'engineering␣
 ↪leadership','qa engineer', 'support engineer', 'devops engineer']))
          &
        (df.year_of_exp.isin(list(range(0,11))))
    )],
    x='class',
```

```
    y='ctc_updated_year',
)
plt.xlim(0,4)


norm = mpl.colors.Normalize(df.groupby('class')['ctc_updated_year'].sum().
 ↪min(), df.groupby('class')['ctc_updated_year'].sum().max())
plt.xticks(ticks=[0,1,2,3],label=[1,2,3,4])
plt.colorbar(mpl.cm.ScalarMappable(norm=norm,cmap='YlGnBu'),)

plt.show()
```

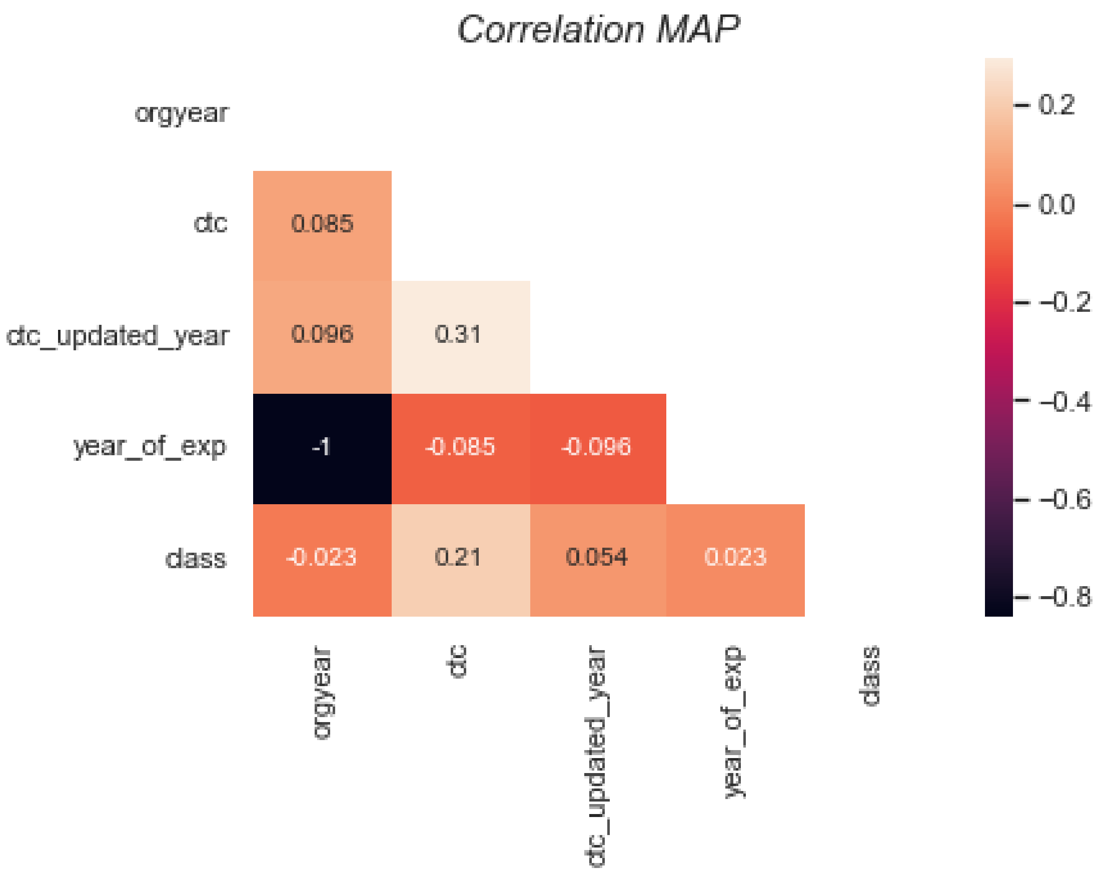


`Inference`: Plot shows number of peoples who updated ctc w.r.t class. and number of people who updated ctc before 2018 is very low

0.4.3 Multivarient analysis

[73]:
```
mask = np.triu(np.ones_like(df.corr()))
sns.heatmap(
    data=df.corr(),
    annot=True,
    robust=True,
    mask=mask
)
```

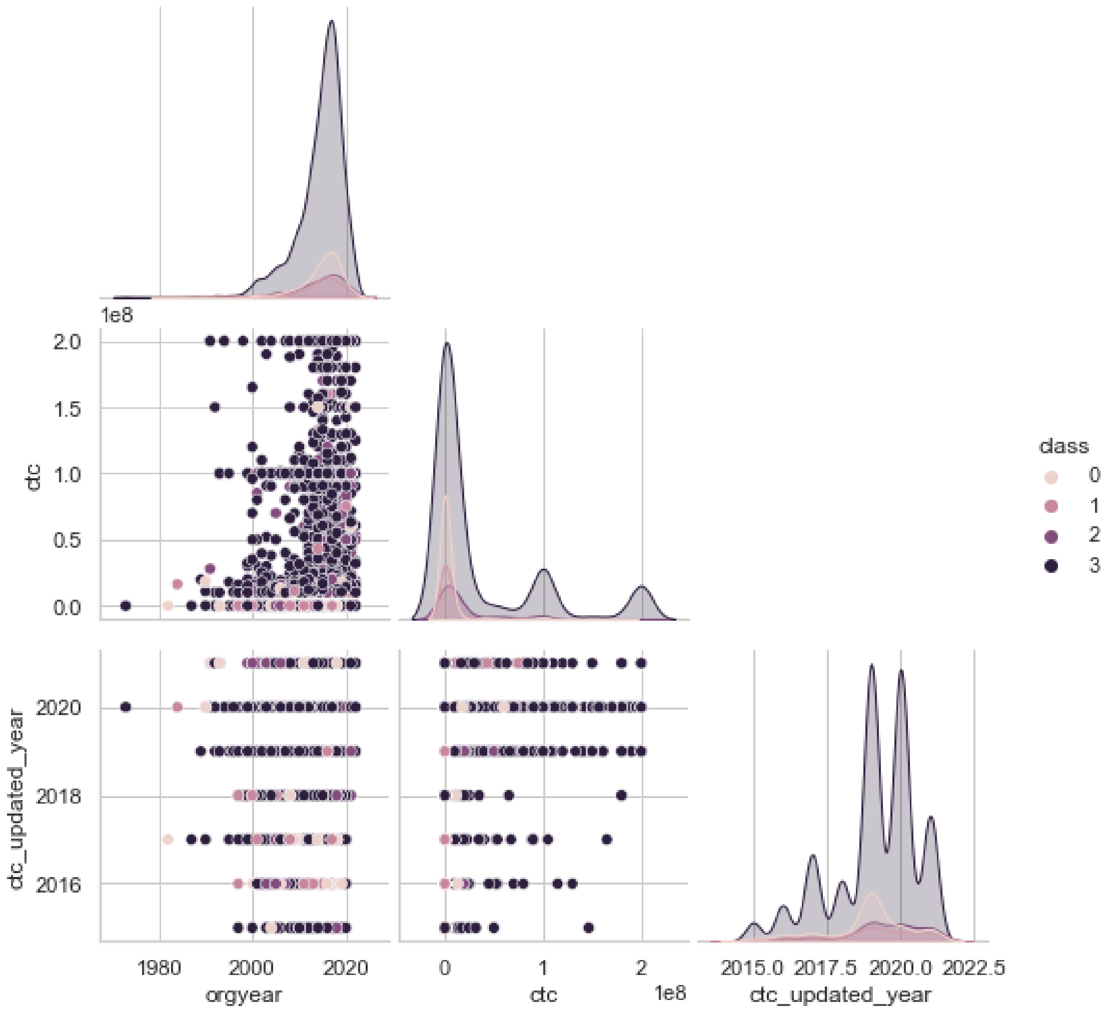
```
plt.title("Correlation MAP",fontsize="15",fontstyle="italic")
plt.show()
```



[74]:
```
df.drop('year_of_exp',axis=1,inplace=True)
```

NOTE: Correlation doesn't tell causation. but we derived year_of_exp from orgyear might be the reason as well

[75]:
```
plt.show(24,24)
sns.pairplot(df,corner=True,hue='class')
plt.show()
```



1 Modelling (Unsupervised)

1.0.1 KMeans

1. Check Clustering Tendency
2. elbow method etc for checking fair number of clusters
3. Do kmeans clustering

1.0.2 Hierarchial clustering

[76]:
```
from sklearn.model_selection import␣
↪train_test_split,GridSearchCV,RandomizedSearchCV,StratifiedKFold
from sklearn.preprocessing import StandardScaler,MinMaxScaler,LabelEncoder
#from sklearn.pipeline import make_pipeline
#from imblearn.over_sampling import SMOTE
```

```python
from category_encoders import TargetEncoder,OneHotEncoder
#from sklearn.metrics import roc_auc_score,confusion_matrix,f1_score,roc_curve,␣
↪precision_recall_curve,auc,accuracy_score,classification_report,recall_score,precision_scor

from pyclustertend import hopkins
from sklearn.cluster import KMeans
from kmodes.kmodes import KModes
from scipy.cluster import hierarchy
from sklearn.cluster import AgglomerativeClustering
```

[77]:
```python
df.info(
    memory_usage=True,
    verbose=True,
    null_counts=True
)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6469 entries, 0 to 6468
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   company_hash     6469 non-null   object
 1   orgyear          6469 non-null   float64
 2   ctc              6469 non-null   int64
 3   job_position     6469 non-null   object
 4   ctc_updated_year 6469 non-null   float64
 5   class            6469 non-null   int64
dtypes: float64(2), int64(2), object(2)
memory usage: 611.8+ KB
```

[78]:
```python
for i in df.select_dtypes(np.object_).columns: df[i]=df[i].astype('category')
```

Note: we can't pass object data-type to ML model. so somehow convert into logically relevant numbers. Pros and Cons

TargetEncoder:

It'll make sure most repetation of values get higher possibilty to occur. like normal Curve

Here I assume Target is ctc . so probabiltiy of getting new job-position is very low and questionable

[79]:
```python
Objs_df = df.select_dtypes('category')
Objs_df.sample(5)
```

[79]:
```
                company_hash        job_position
5731                    hmtq    backend engineer
4646                    cyhm   frontend engineer
3430  mrhtouxqt bvqptnxzs   frontend engineer
4909                   uvjnb               other
```

```
5141   wtqztq wgqugqvnxgz  fullstack engineer
```

[80]:
```
encoder = TargetEncoder(verbose=1)
encoder.fit(Objs_df,df['ctc'])
encoder
```

[80]:
```
TargetEncoder(cols=['company_hash', 'job_position'], verbose=1)
```

[81]:
```
encode_df = df.copy(deep=True)
encode_df[['company_hash','job_position']] = encoder.transform(Objs_df)
```

[82]:
```
scaler = StandardScaler()
scaler.fit(encode_df)

pd.DataFrame(
    [scaler.scale_,scaler.var_],
    columns=df.columns,
    index=['mean','var']
)
```

[82]:
```
      company_hash    orgyear           ctc  job_position  ctc_updated_year  \
mean  2.117487e+07   4.835914  5.544274e+07  1.596614e+07          1.445851
var   4.483752e+14  23.386060  3.073897e+15  2.549175e+14          2.090484

         class
mean  1.036916
var   1.075194
```

[83]:
```
scaled_df = scaler.transform(encode_df)

scaled_df = pd.DataFrame( scaled_df, columns=df.columns )
scaled_df.shape
```

[83]:
```
(6469, 6)
```

cluster tendency It tells data follows uniform distribution or not. returns scale between [0,1] Higher the hopkins score higher the uniform distribution of data.

If Hopkins score is closer to 0, it means good clustering can be achieved with the dataset.

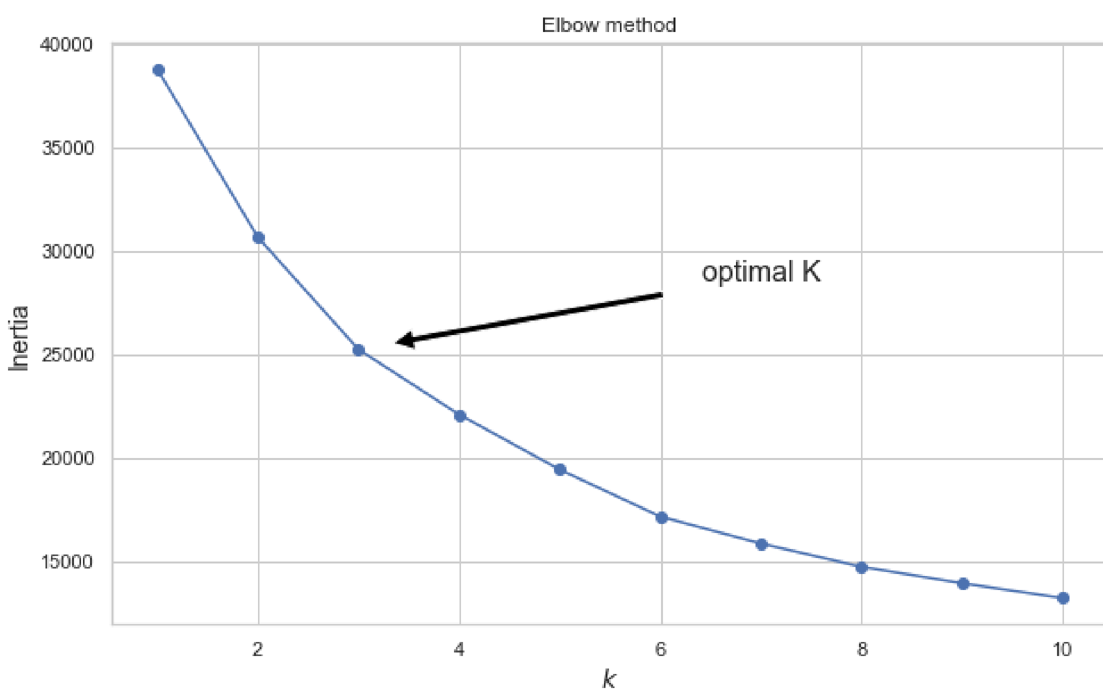
[84]:
```
hops=hopkins(scaled_df,6000)
print(hops)
```

```
0.07716225006114316
```

$$DunnIndex = \frac{maximum - distance - SumofSquares - within - cluster}{minimum - distance - sumofsquares - between - cluster}$$

Inertia tells within cluster sum of square

[85]:
```
kmeans_per_k = [KMeans(n_clusters=k, random_state=42,verbose=0).fit(scaled_df)␣
    ↪for k in range(1,11)]
inertias = [model.inertia_ for model in kmeans_per_k]

plt.figure(figsize=(10,6))
plt.plot(range(1,11),inertias,"bo-")
plt.xlabel("$k$",fontsize=14)
plt.ylabel("Inertia",fontsize=14)
plt.annotate('optimal K',
             xy=(3,inertias[2]),
             xytext=(0.55,0.55),
             textcoords='figure fraction',
             fontsize=16,
             arrowprops=dict(facecolor='black',
             shrink=0.1))
plt.title("Elbow method")
plt.show()
```



Inference:

Higher the K Within sum-of-square distance is less. with make more affinity towards noise.

We found Inflaction point of Cluster 3

[86]:
```
kmeans = KMeans(n_clusters=3,init='k-means++',verbose=0,n_jobs=-1)
kmeans.fit(scaled_df)
kmeans
```

[86]:
```
KMeans(n_clusters=3, n_jobs=-1)
```

[87]:
```
kmeans.cluster_centers_
```

[87]:
```
array([[ 0.1364098 ,  0.04104527, -0.46937759, -0.09617824, -0.16089816,
        -2.03378752],
       [-0.32715918, -0.08928211, -0.41623807, -0.2249191 , -0.19073097,
         0.44478851],
       [ 0.86023794,  0.23155001,  1.63486882,  0.75107342,  0.70359634,
         0.38405593]])
```

we can't interept the clusters now

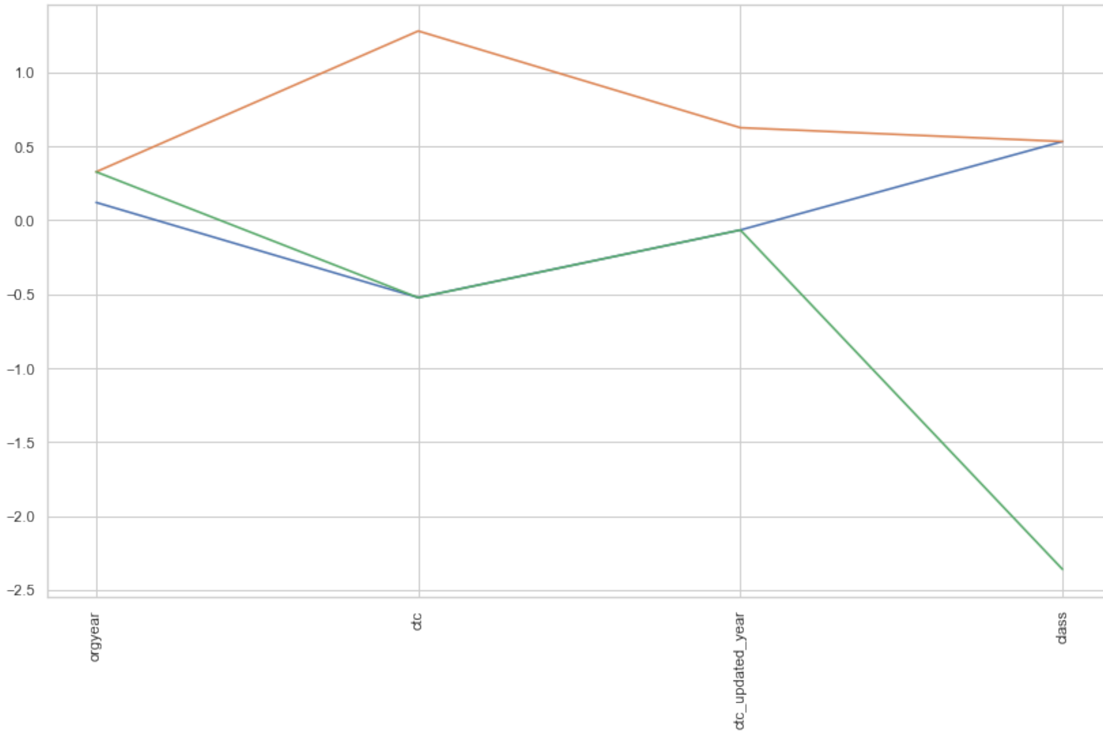
[88]:
```
scaled_df['clusters']= kmeans.fit_predict(scaled_df)
```

[89]:
```
scaled_df.groupby('clusters').median()
```

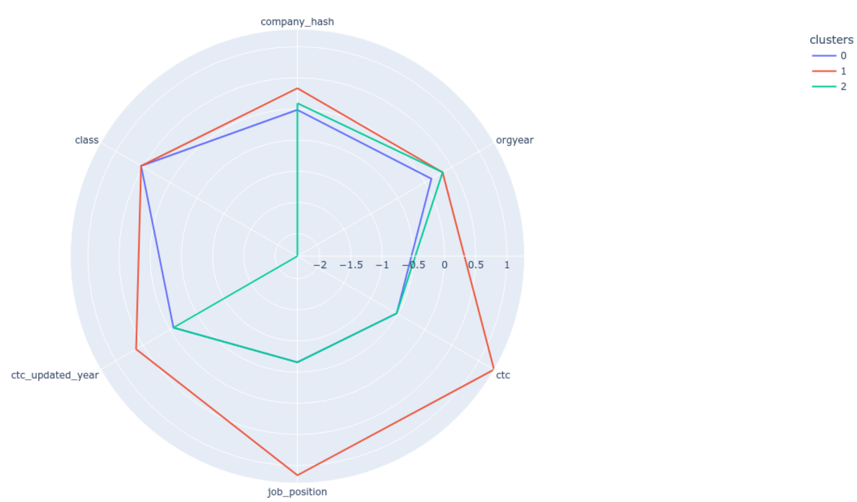
[89]:
```
          company_hash   orgyear       ctc  job_position  ctc_updated_year  \
clusters
0            -0.014486  0.120607 -0.522697     -0.658097         -0.065860
1             0.332828  0.327393  1.279793      1.153414          0.625775
2             0.091321  0.327393 -0.523419     -0.658097         -0.065860

             class
clusters
0         0.532812
1         0.532812
2        -2.360383
```

[90]:
```
melt_df = pd.melt(
    scaled_df.groupby('clusters').median().reset_index(),
    id_vars='clusters'
)
```

[91]:
```
plt.figure(figsize=(14,8))
plt.plot(scaled_df.groupby('clusters').median().
 ↪drop(['company_hash','job_position'],axis=1).T)
plt.xticks(rotation=90)
plt.show()
```



[92]:
```
fig = px.line_polar( melt_df, r="value", theta="variable",␣
    ↪color="clusters",line_close=True,width=900,height=700)
fig.show()
```



`Inference:` Three Clusters found

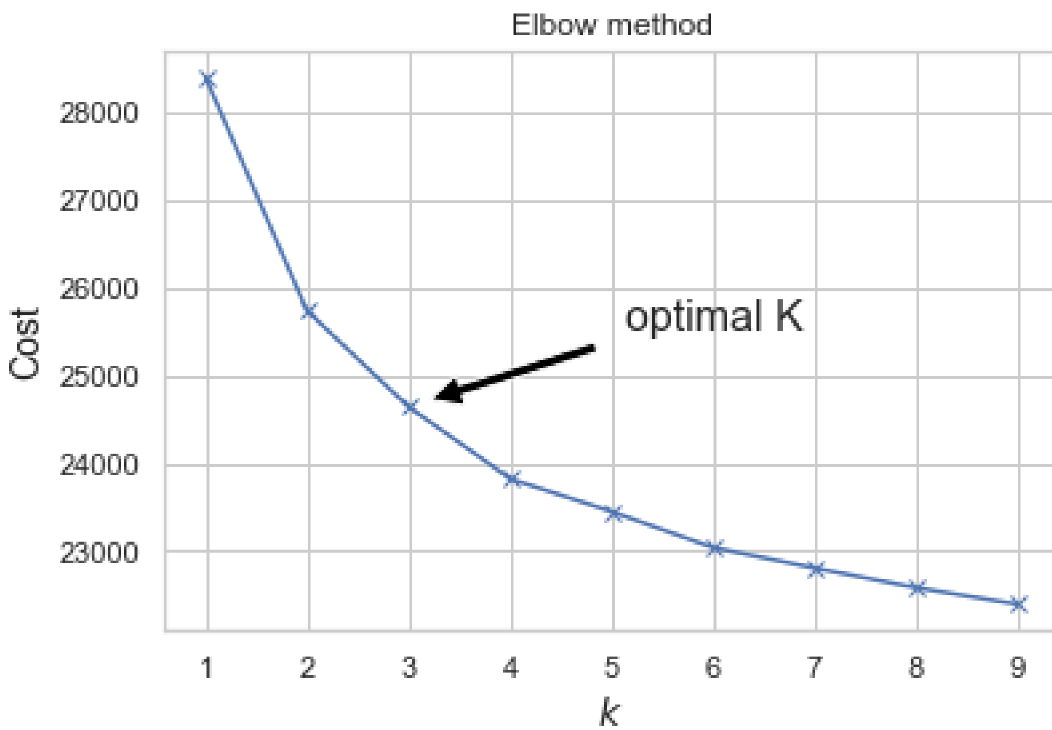
- cluster 2 might be students in scaler (high orgyear, high ctc_updated_year, low ctc and low class)
- cluster 0 graduates placed high reputed companies (high orgyear, w.r.t high ctc)
- cluster 1 graduates who placed Startups and Unicorns (less orgyear but class is same as cluster 0)

Note: company_hash and job_position has no direct interpretation

[93]:
```
cost = []
K = range(1,10)
for num_clusters in list(K):
    kmode = KModes(n_clusters=num_clusters, init = "Huang", n_init = 10,␣
 ↪verbose=0,n_jobs=-1,max_iter=100)
    kmode.fit_predict(df)
    cost.append(kmode.cost_)
```

[94]:
```
plt.plot(K, cost, 'bx-')
plt.xlabel("$k$",fontsize=14)
plt.ylabel("Cost",fontsize=14)
plt.annotate('optimal K',
            xy=(3,cost[2]),
            xytext=(0.55,0.55),
            textcoords='figure fraction',
            fontsize=16,
            arrowprops=dict(facecolor='black',
            shrink=0.1))
plt.title("Elbow method")
```

[94]:
```
Text(0.5, 1.0, 'Elbow method')
```



[95]:
```
# Huang - chooose data point as centroid
kmode = KModes(n_clusters=3, init = "Huang", n_init = 10,␣
 ↪verbose=0,n_jobs=-1,max_iter=200,random_state=1)
clusters = kmode.fit_predict(df)
```

1.0.3 Cluster Centroid

[96]:
```
centroids_ = pd.DataFrame(kmode.cluster_centroids_,columns=df.columns)
centroids_
```

[96]:
```
                company_hash orgyear        ctc        job_position  \
0     zgn vuurxwvmrt vwwghzn  2016.0  100000000               other
1                    xzegojo  2017.0      50000  fullstack engineer
2  nvnv wgzohrnvzwj otqcxwto  2018.0   10000000    backend engineer

  ctc_updated_year class
0           2020.0     3
1           2019.0     3
2           2019.0     3
```

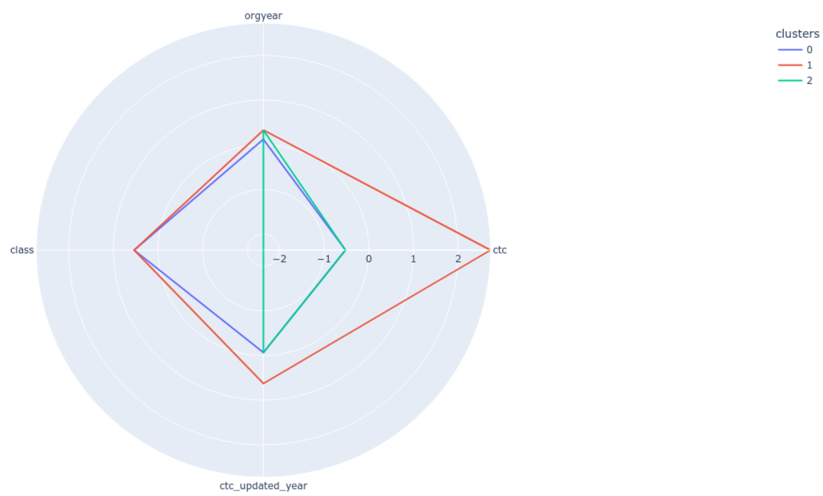
[97]:
```
agg_ = AgglomerativeClustering(n_clusters=3, affinity = 'euclidean', linkage =␣
 ↪'ward')
```

```python
y_pred = agg_.fit_predict(scaled_df.drop('clusters',axis=1))

scaled_df['clusters'] = y_pred
```

[98]:
```python
scaled_df.groupby('clusters').median()
```

[98]:
```
          company_hash   orgyear       ctc  job_position  ctc_updated_year  \
clusters
0            -0.014486  0.120607 -0.522607     -0.658097         -0.065860
1             0.444121  0.327393  2.722723      1.564227          0.625775
2             0.332828  0.327393 -0.523238     -0.658097         -0.065860

             class
clusters
0         0.532812
1         0.532812
2        -2.360383
```

[99]:
```python
melt_df = pd.melt(
    scaled_df.drop(['company_hash','job_position'],axis=1).groupby('clusters').
 ↪median().reset_index(),
    id_vars='clusters'
)

fig = px.line_polar( melt_df, r="value", theta="variable",␣
 ↪color="clusters",line_close=True,width=900,height=700)
fig.show()
```

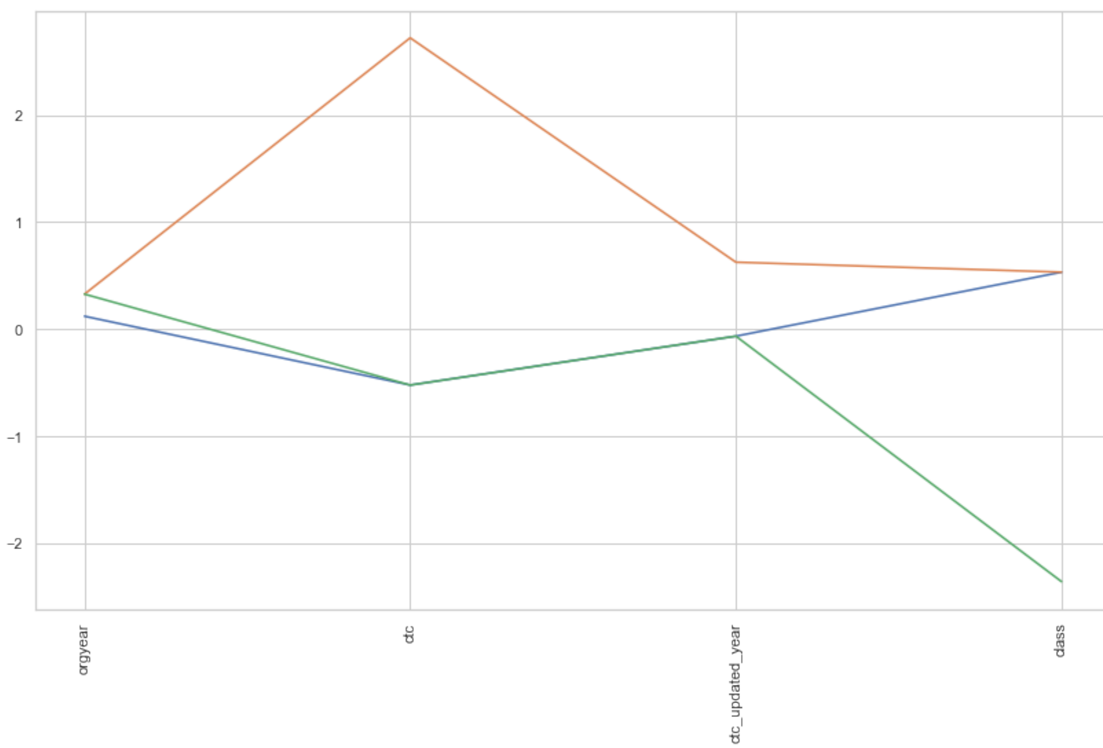


Note In hierarchy based clustering we won't do hard assignment. We pick number of cluster 3

[100]:
```
scaled_df.groupby('clusters').median().
  ↪drop(['company_hash','job_position'],axis=1)
```

[100]:
```
           orgyear       ctc  ctc_updated_year     class
clusters
0         0.120607 -0.522607         -0.065860  0.532812
1         0.327393  2.722723          0.625775  0.532812
2         0.327393 -0.523238         -0.065860 -2.360383
```

[101]:
```
plt.figure(figsize=(14,8))
plt.plot(scaled_df.groupby('clusters').median().
  ↪drop(['company_hash','job_position'],axis=1).T)
plt.xticks(rotation=90)
plt.show()
```



2 collective Inference:

- email be unique to the person which tends to make every data point as cluster as unique
- orgyear has no correlation between ctc. i.e) even startsup/unicorn also pays you decent amount and most of people works/placed on 4 to 6 years or Organization

- people are getting ctc more than above average in their respecitive company and job designation
- companies where

  ```
  nvnv wgzohrnvzwj otqcxwto especially designation for backend engineer
  xzegojo especially designation for fullstack engineer
  zgn vuurxwvmrt vwwghzn
  vbvkgz,
  ```

are recruiting scaler student more

- more placed students are backend enginner, full stack engineer, parallely mobile dev, data field are growing
- students were placed after 2016 more than students were in before 2015 year significantly increased
- class 3 peoples are highly present across all year of experience

Three Clusters found

```
cluster 2 might be students in scaler (high orgyear, high ctc_updated_year, low ctc and low cla
cluster 1 graduates who placed Startups and Unicorns (less orgyear but class is same as cluster
cluster 0 graduates placed high reputed companies (high orgyear, w.r.t high ctc)
```

[ ]:

```

```