```
import numpy as np
import pandas as pd
import re
import seaborn as sns
from matplotlib import pyplot as plt

#Reading csv data
data = pd.read_csv('Scaler_Kmeans.csv')

print("Dimensions of dataset ",data.shape)

data.head()
```

```
Dimensions of dataset  (206923, 8)
```

```
   Unnamed: 0                                        email_hash  \
0           0  6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...
1           1  b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...
2           2  4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...
3           3  effdede7a2e7c2af664c8a31d9346385016128d66bbc58...
4           4  6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...

                     company        normalized_company_name  orgyear
ctc  \
0             Deloitte India                      Deloitte   2016.0
1100000
1  Reliance Infocomm Limited  Reliance Jio Infocomm Limited   2018.0
449999
2              Synctactic AI                            NaN   2015.0
2000000
3                  Tokopedia                     Tokopedia   2017.0
700000
4                 RIFT Group                            NaN   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
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 206923 entries, 0 to 206922
Data columns (total 8 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   Unnamed: 0              206923 non-null  int64
 1   email_hash              206923 non-null  object
```

```
 2   company                   205215 non-null  object
 3   normalized_company_name  121425 non-null  object
 4   orgyear                   206837 non-null  float64
 5   ctc                       206923 non-null  int64
 6   job_position              153342 non-null  object
 7   ctc_updated_year          206923 non-null  float64
dtypes: float64(2), int64(2), object(4)
memory usage: 12.6+ MB
```

Checking for Null Values in dataset

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

```
Unnamed: 0                     0
email_hash                     0
company                     1708
normalized_company_name    85498
orgyear                       86
ctc                            0
job_position               53581
ctc_updated_year               0
dtype: int64
```

Data contains null values in 4 columns [company, normalized_company_name, orgyear, job_position].

Checking for Duplicate Rows in dataset

```
len(data[data.duplicated()])
```

```
0
```

Data doesn't contain any duplicate rows.

Data Preprocessing

Checking duplicated PII ids in column email_hash

```
data['email_hash'].value_counts().head(10)
```

```
bbace3cc586400bbc65765bc6a16b77d8913836cfc98b77c05488f02f5714a4b    10
6842660273f70e9aa239026ba33bfe82275d6ab0d20124021b952b5bc3d07e6c     9
3e5e49daa5527a6d5a33599b238bf9bf31e85b9efa9a94f1c88c5e15a6f31378     9
298528ce3160cc761e4dc37a07337ee2e0589df251d73645aae209b010210eee     9
b4d5afa09bec8689017d8b29701b80d664ca37b83cb883376b2e95191320da66     8
d598d6f1fb21b45593c2afc1c2f76ae9f4cb7167156cdf93246d4192a89d8065     8
faf40195f8c58d5c7edc758cc725a762d51920da996410b80ac4a4d85c803da0     8
4818edfd67ed8563dde5d083306485d91d19f4f1c95d193a1700e79dd245b75c     8
d15041f58bb01c8ee29f72e33b136e26bc32f3169a40b53d75fe7ae9cbb9a551     8
```

```
c0eb129061675da412b0deb15871dd06ef0d7cd86eb5f7e8cc6a20b0d1938183     8
Name: email_hash, dtype: int64

display(data[data['email_hash'] ==
'bbace3cc586400bbc65765bc6a16b77d8913836cfc98b77c05488f02f5714a4b'])
display(data[data['email_hash'] ==
'6842660273f70e9aa239026ba33bfe82275d6ab0d20124021b952b5bc3d07e6c'])

        Unnamed: 0                                         email_hash
\
24129        24129  bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...

46038        46038  bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...

72415        72415  bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...

103145      103145  bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...

118076      118076  bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...

121825      121825  bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...

124840      124840  bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...

145021      145021  bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...

153402      153402  bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...

160472      160472  bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...


                           company normalized_company_name  orgyear
ctc  \
24129   Sify Technologies Limited.       Sify Technologies   2018.0
720000
46038   Sify Technologies Limited.       Sify Technologies   2018.0
720000
72415   Sify Technologies Limited.       Sify Technologies   2018.0
720000
103145  Sify Technologies Limited.       Sify Technologies   2018.0
720000
118076  Sify Technologies Limited.       Sify Technologies   2018.0
720000
121825  Sify Technologies Limited.       Sify Technologies   2018.0
660000
124840  Sify Technologies Limited.       Sify Technologies   2018.0
660000
145021  Sify Technologies Limited.       Sify Technologies   2018.0
660000
153402  Sify Technologies Limited.       Sify Technologies   2018.0
660000
```

```
160472  Sify Technologies Limited.       Sify Technologies   2018.0
660000

              job_position  ctc_updated_year
24129                  NaN            2020.0
46038     Support Engineer            2020.0
72415                Other            2020.0
103145  FullStack Engineer            2020.0
118076        Data Analyst            2020.0
121825                Other            2019.0
124840    Support Engineer            2019.0
145021  FullStack Engineer            2019.0
153402     Devops Engineer            2019.0
160472                  NaN            2019.0

        Unnamed: 0                                          email_hash
\
9859          9859  6842660273f70e9aa239026ba33bfe82275d6ab0d20124...

10006        10006  6842660273f70e9aa239026ba33bfe82275d6ab0d20124...

10587        10587  6842660273f70e9aa239026ba33bfe82275d6ab0d20124...

12793        12793  6842660273f70e9aa239026ba33bfe82275d6ab0d20124...

20729        20729  6842660273f70e9aa239026ba33bfe82275d6ab0d20124...

138731      138731  6842660273f70e9aa239026ba33bfe82275d6ab0d20124...

159887      159887  6842660273f70e9aa239026ba33bfe82275d6ab0d20124...

166040      166040  6842660273f70e9aa239026ba33bfe82275d6ab0d20124...

179593      179593  6842660273f70e9aa239026ba33bfe82275d6ab0d20124...


         company normalized_company_name  orgyear      ctc
job_position  \
9859    Qualcomm                Qualcomm   2017.0  2400000       QA
Engineer
10006   Qualcomm                Qualcomm   2017.0  2400000   Devops
Engineer
10587   Qualcomm                Qualcomm   2017.0  2400000  Backend
Engineer
12793   Qualcomm                Qualcomm   2017.0  2400000
Other
20729   Qualcomm                Qualcomm   2017.0  2400000
SDET
138731  Qualcomm                Qualcomm   2017.0  2000000
SDET
159887  Qualcomm                Qualcomm   2017.0  2000000   Devops
```

```
Engineer
166040  Qualcomm                  Qualcomm   2017.0  2000000
Other
179593  Qualcomm                  Qualcomm   2017.0  2000000  Backend
Engineer

        ctc_updated_year
9859              2020.0
10006             2020.0
10587             2020.0
12793             2020.0
20729             2020.0
138731            2020.0
159887            2020.0
166040            2020.0
179593            2020.0
```

Apparently for single Anonymised Personal Identifiable Information (PII) id there exists multiple rows with same joining dates and company but different job positions, this couldn't be possible. We will take the first row in case of duplicated PII ids.

```
data = data.groupby('email_hash').first().reset_index()
```

Creating null value indicator columns (Feature Engineering)

```
for i in
['orgyear','ctc_updated_year','normalized_company_name','company','job
_position']:
    data[i+'_na'] = data[i].isna()
```

Cleaning text columns

```
text_cols = ['normalized_company_name','company']
for i in text_cols:
    data[i] = data[i].fillna('Not Available').apply(lambda x:
re.sub('[^A-Za-z0-9 ]+', '', str(x).title()))
```

Creating new columns (Feature Engineering)

```
data['YoE'] = data['ctc_updated_year'] - data['orgyear']
```

Frequency mean encoding

```
feat = 'company'
data[feat] = data[feat].fillna('na')
enc_nom = (data.groupby(feat).size()) / len(data)
data[feat+'_encode'] = data[feat].apply(lambda x : enc_nom[x])
```

```
feat = 'job_position'
data[feat] = data[feat].fillna('na')
enc_nom = (data.groupby(feat).size()) / len(data)*10000
data[feat+'_encode'] = data[feat].apply(lambda x : enc_nom[x])
```

Reemoving Outliers from Orgyear column

```
sorted(data['orgyear'].fillna(0).astype(int).unique())
```

```
[0,
 1,
 2,
 3,
 4,
 5,
 6,
 38,
 83,
 91,
 200,
 201,
 206,
 208,
 209,
 1900,
 1970,
 1971,
 1972,
 1973,
 1976,
 1977,
 1979,
 1981,
 1982,
 1984,
 1985,
 1986,
 1987,
 1988,
 1989,
 1990,
 1991,
 1992,
 1993,
 1994,
 1995,
 1996,
 1997,
 1998,
```

```
 1999,
 2000,
 2001,
 2002,
 2003,
 2004,
 2005,
 2006,
 2007,
 2008,
 2009,
 2010,
 2011,
 2012,
 2013,
 2014,
 2015,
 2016,
 2017,
 2018,
 2019,
 2020,
 2021,
 2022,
 2023,
 2024,
 2025,
 2026,
 2027,
 2028,
 2029,
 2031,
 2101,
 2106,
 2107,
 2204,
 20165]
```

Removing future years, as this case is impossible to happen, also removing single digit years.

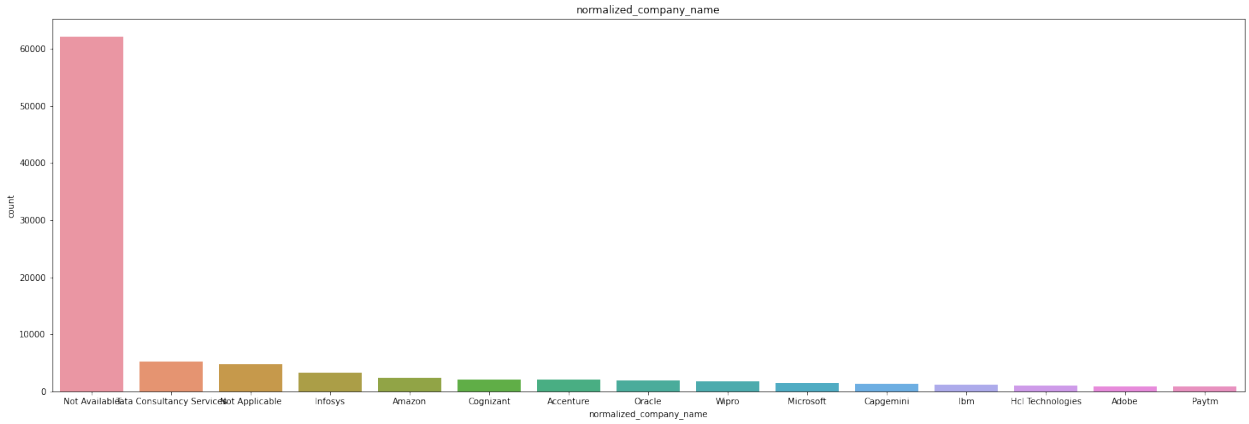
```
data = data[~data['orgyear'].isin([0,
 1,
 2,
 3,
 4,
 5,
 6,
 38,
 83,
```

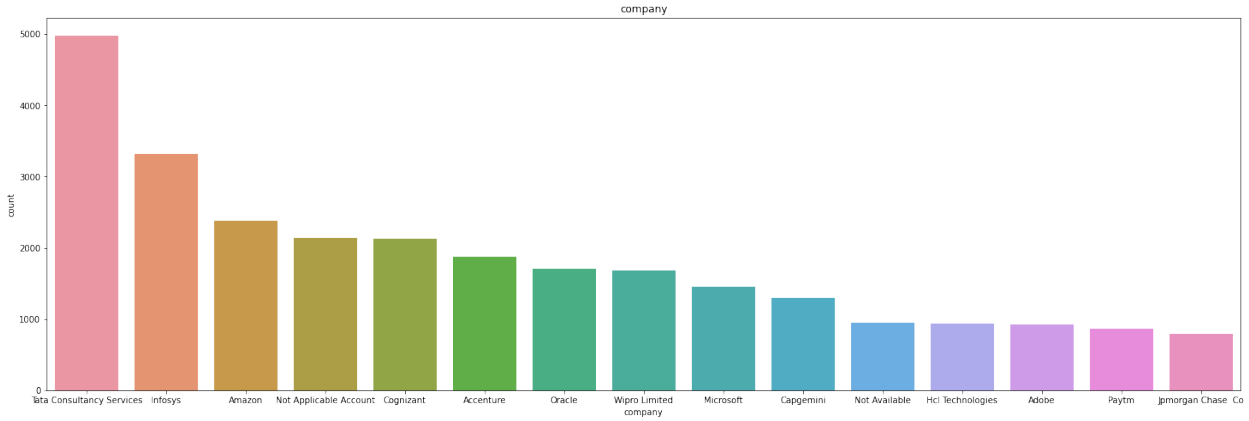
```
 91,
 200,
 201,
 206,
 208,
 209,
 1900, 2023,
 2024,
 2025,
 2026,
 2027,
 2028,
 2029,
 2031,
 2101,
 2106,
 2107,
 2204,
 20165])]

data = data[~(data['YoE']<0)]
```

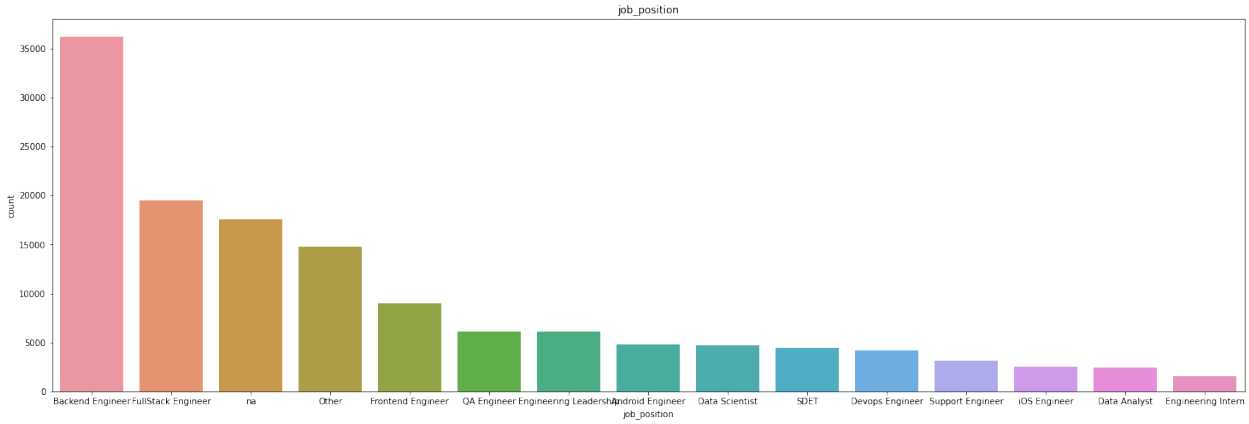
Univariate Analysis

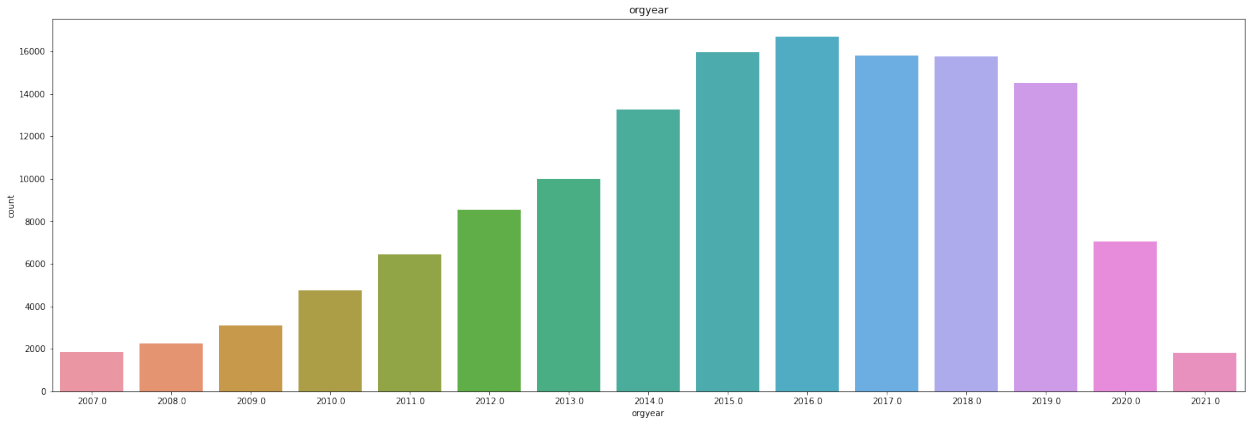
Plotting Categorical Features

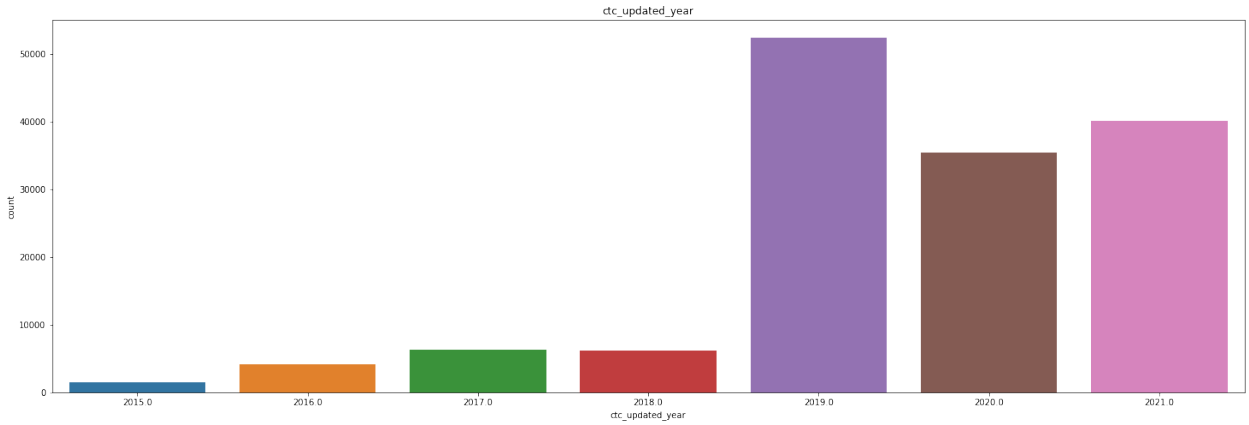
```
categroical_columns = [
'normalized_company_name','company','job_position','orgyear','ctc_upda
ted_year']

for i in categroical_columns:
    tmp = data.copy()
    tmp['count'] = 1
    tmp = tmp.groupby(i).sum()
['count'].reset_index().sort_values('count',ascending=False).head(15)
    plt.figure(figsize=(25,8))
    sns.barplot(data=tmp,y='count',x=i).set(title=i)

    plt.show()
```


normalized_company_name
count
0
10000
20000
30000
40000
50000
60000
Not Available
Tata Consultancy Services
Not Applicable
Infosys
Amazon
Cognizant
Accenture
Oracle
Wipro
Microsoft
Capgemini
Ibm
Hcl Technologies
Adobe
Paytm
normalized_company_name


company
count
0
1000
2000
3000
4000
5000
Tata Consultancy Services
Infosys
Amazon
Not Applicable Account
Cognizant
Accenture
Oracle
Wipro Limited
Microsoft
Capgemini
Not Available
Hcl Technologies
Adobe
Paytm
Jpmorgan Chase Co
company

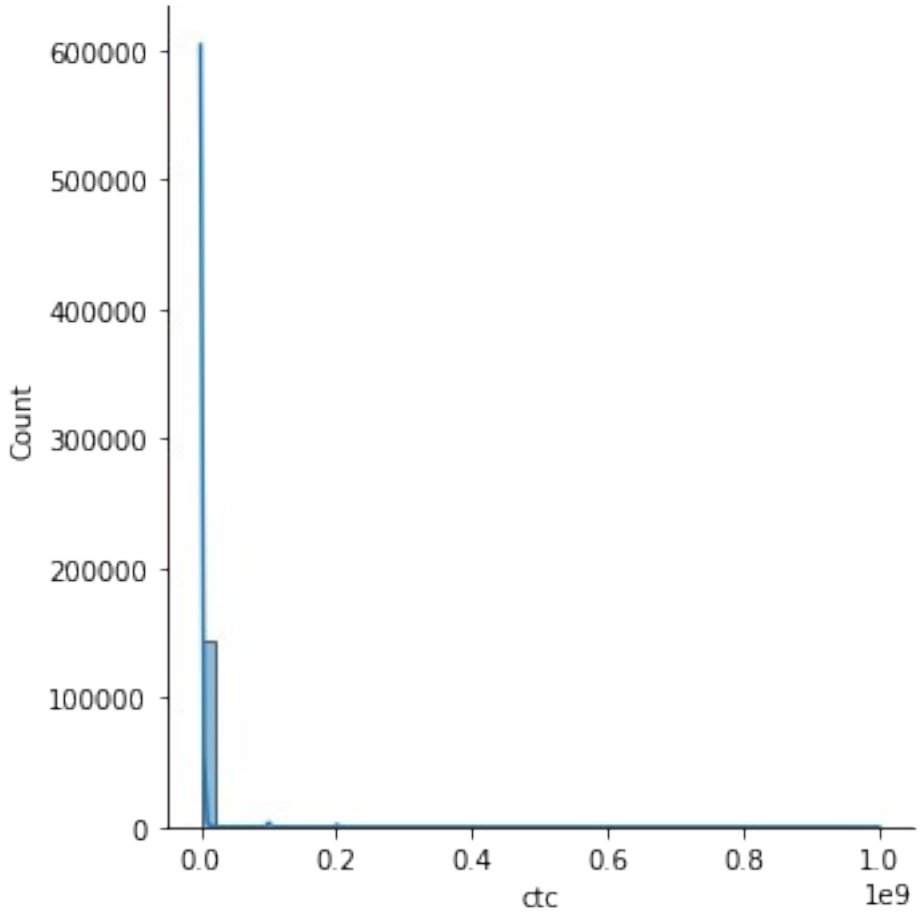

job_position
count
0
5000
10000
15000
20000
25000
30000
35000
Backend Engineer
FullStack Engineer
na
Other
Frontend Engineer
QA Engineer
Engineering Leadership
Android Engineer
Data Scientist
SDET
Devops Engineer
Support Engineer
iOS Engineer
Data Analyst
Engineering Intern
job_position





Plotting Continuous Features

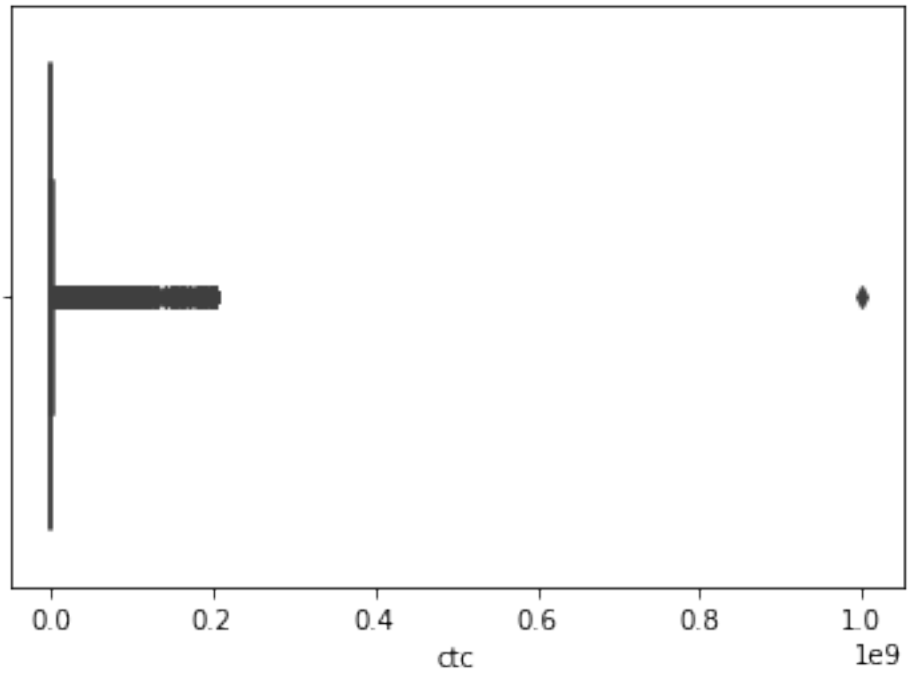
```
sns.displot(data['ctc'],kde=True,bins=50)
plt.show()
```



The plot seems to be having large range of values, let's try to scale column for visualizing.

```
v = data['ctc']
#v = (v-v.mean())/v.std()
sns.boxplot(v)
plt.show()
```

```
/opt/conda/lib/python3.7/site-packages/seaborn/_decorators.py:43:
FutureWarning: Pass the following variable as a keyword arg: x. From
version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an
error or misinterpretation.
  FutureWarning
```




```
data.sort_values(['ctc']).iloc[1000:1020,:]
```

	email_hash	Unnamed: 0
40428	439134c4b243fe33a240265f94d0c9d6e120f31cb6e2cc...	98842
30954	3394eeca520d9029ce6bd56e83faa5d4d82c396f453e2a...	97003
78889	83d1ece927b7d7e944454483a4a8a3b08a18ed846890ee...	88544
90663	975e224e718de0d75c2d33d2bf24e75c4b7559664763b1...	125784
74910	7d43b749f1651cba0a16743d6235f5f32a9a58837ee081...	24380
38801	40bf699c6ab3273acfdda2c7922b30dbc5f8cedea903f4...	93058
25247	29e7d12a6225aeff7b5d92947f949e6646ec58111e5a5a...	4290
117820	c4a7229bb63eade33516411b68d8501420e15987d116eb...	135189
73669	7b3b93e56fd67d3ddfeb41f68a88a61d01c397aab9bbe1...	151028
71300	774a4a75a15f53e19bbf4ef85a5c6dc3da689e4291f773...	77722
120930	c9f0c1b5a2a71b0b754abcf68bc68c55188763ed0c8837...	99951
5376	08bac5026bf379045813ce0e99e8df5601a56d913424fe...	84968
49442	52cad1776d3a469cc3f056fb9568b0d6f8a2f901d4f857...	164185

```
36095   3c29ecc4a921bdf1f8ed0e3143069c47f836de0ad831fc...      100559
23539   270481314e2a3f52a67719a20b7b241090d1175067c527...      107733
18584   1eb23fa16469ad4ec4bfd9c02a4878bee17986453eb87a...       81272
139896  e9867fcd4ad217d5b3eb4be37e1770de27b9b1055e2a4c...       50112
35678   3b71a41715519c7a82a0eee25b9e90edd749d77852fe55...       46366
131924  dc43256af03d641e65dc34d57ea0872500935062f7f20a...      142496
107673  b3a96ff0081272c4627cdaa0c85b4b4f24b5c46792b035...      166905


                              company normalized_company_name
orgyear  \
40428                         Elinext           Not Available
2019.0
30954                         Blabber           Not Available
2011.0
78889           Simon Fraser University           Not Available
2016.0
90663            Covalense Technologies           Not Available
2016.0
74910                             Sap                     Sap
2008.0
38801                            None          Not Applicable
2008.0
25247                 Areena Multimedia           Not Available
2001.0
117820                      Pharmeasy              Pharmeasy
2012.0
73669                        Marisoft           Not Available
2017.0
71300   Lifestyle International Pvt Ltd           Not Available
2010.0
120930                     Celigo Inc           Not Available
2009.0
5376            Prescriber360 Solutions           Not Available
2013.0
49442                   Sportradar Ag           Not Available
2008.0
36095       Integrated Technology Group           Not Available
2016.0
23539                        ImplexMe           Not Available
2013.0
18584                          Orange           Not Available
2018.0
139896                   Epam Systems             Epam Systems
```

```
2008.0
35678                          Softcare           Not Available
2004.0
131924                           Amazon                  Amazon
2014.0
107673                Businesscode Gmbh           Not Available
2015.0

          ctc        job_position  ctc_updated_year  orgyear_na  \
40428   20000         QA Engineer            2019.0       False
30954   20000    Android Engineer            2019.0       False
78889   20000               Other            2017.0       False
90663   20000    Backend Engineer            2019.0       False
74910   20000         QA Engineer            2019.0       False
38801   20000  FullStack Engineer            2019.0       False
25247   20000               Other            2021.0       False
117820  20000    Backend Engineer            2019.0       False
73669   20000                  na            2019.0       False
71300   20000               Other            2016.0       False
120930  20000    Backend Engineer            2019.0       False
5376    20000  FullStack Engineer            2019.0       False
49442   20000                  na            2016.0       False
36095   20000    Android Engineer            2019.0       False
23539   20000    Backend Engineer            2020.0       False
18584   20000  FullStack Engineer            2019.0       False
139896  20000    Backend Engineer            2016.0       False
35678   20000    Backend Engineer            2017.0       False
131924  20000               Other            2017.0       False
107673  20000      Data Scientist            2019.0       False

        ctc_updated_year_na  normalized_company_name_na  company_na  \
40428                 False                        True       False
30954                 False                        True       False
78889                 False                        True       False
90663                 False                        True       False
74910                 False                       False       False
38801                 False                       False       False
25247                 False                        True       False
117820                False                       False       False
73669                 False                        True       False
71300                 False                        True       False
120930                False                        True       False
5376                  False                        True       False
49442                 False                        True       False
36095                 False                        True       False
23539                 False                        True       False
18584                 False                        True       False
139896                False                       False       False
35678                 False                        True       False
```

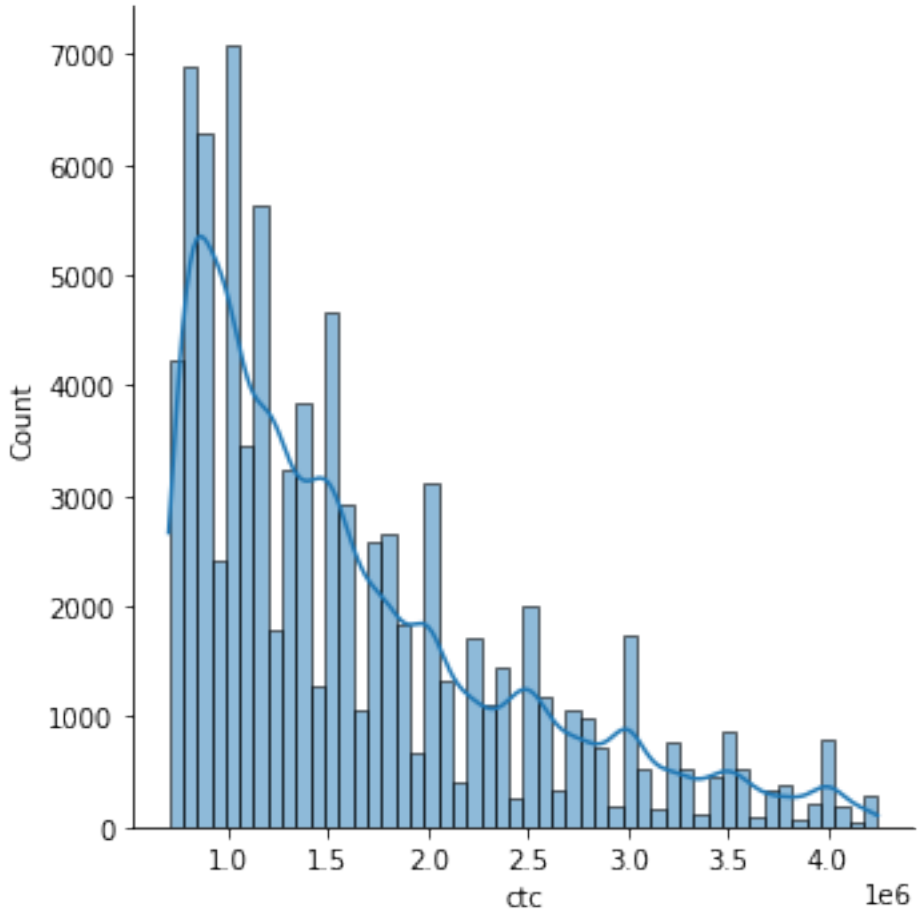
```
131924                False                          False       False
107673                False                           True       False

        job_position_na   YoE  company_encode  job_position_encode
40428             False   0.0        0.000007           401.973371
30954             False   8.0        0.000007           317.968236
78889             False   1.0        0.000026          1026.830810
90663             False   3.0        0.000020          2431.717315
74910             False  11.0        0.004112           401.973371
38801             False  11.0        0.003115          1319.056588
25247             False  20.0        0.000007          1026.830810
117820            False   7.0        0.000398          2431.717315
73669              True   2.0        0.000007          1318.013855
71300             False   6.0        0.000007          1026.830810
120930            False  10.0        0.000098          2431.717315
5376              False   6.0        0.000007          1319.056588
49442              True   8.0        0.000007          1318.013855
36095             False   3.0        0.000007           317.968236
23539             False   7.0        0.000007          2431.717315
18584             False   1.0        0.000111          1319.056588
139896            False   8.0        0.001375          2431.717315
35678             False  13.0        0.000007          2431.717315
131924            False   3.0        0.016566          1026.830810
107673            False   4.0        0.000007           319.141310

data = data[data['ctc'] >702475]
```

Outlier Removal using IQR

```
dftmp = data.copy()
print(dftmp.shape)
cols = ['ctc'] # one or more

Q1 = dftmp[cols].quantile(0.25)
Q3 = dftmp[cols].quantile(0.75)
IQR = Q3 - Q1

dftmp = dftmp[~((dftmp[cols] < (Q1 - 1.5 * IQR)) |(dftmp[cols] > (Q3 +
1.5 * IQR))).any(axis=1)]
print(dftmp.shape)
```

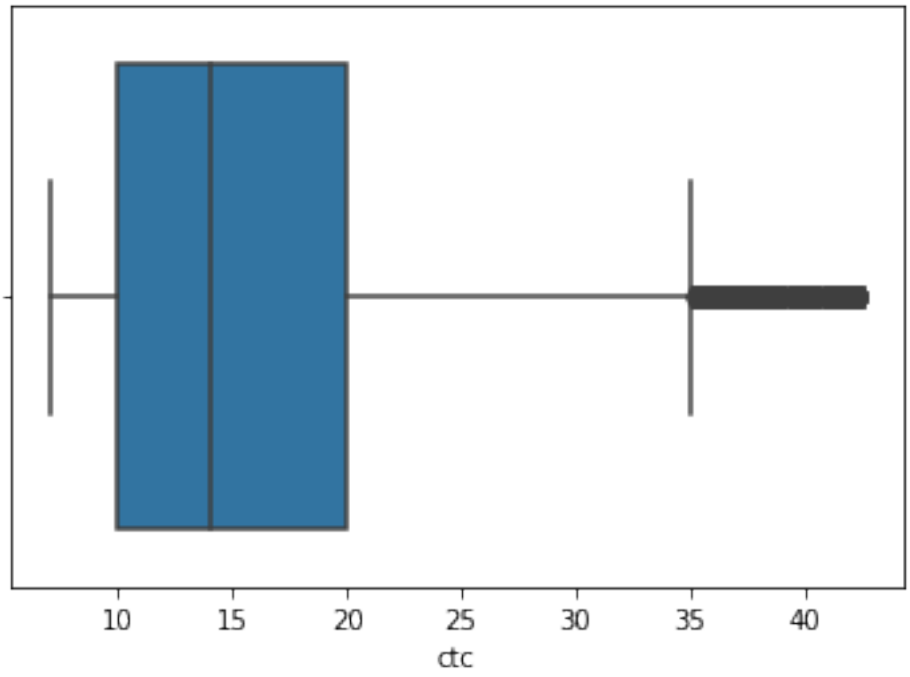
```
(92558, 16)
(86464, 16)
```

```
#dftmp = dftmp[dftmp['ctc']>300000]

v = dftmp['ctc']
sns.displot(v,kde=True,bins=50)
plt.show()
```

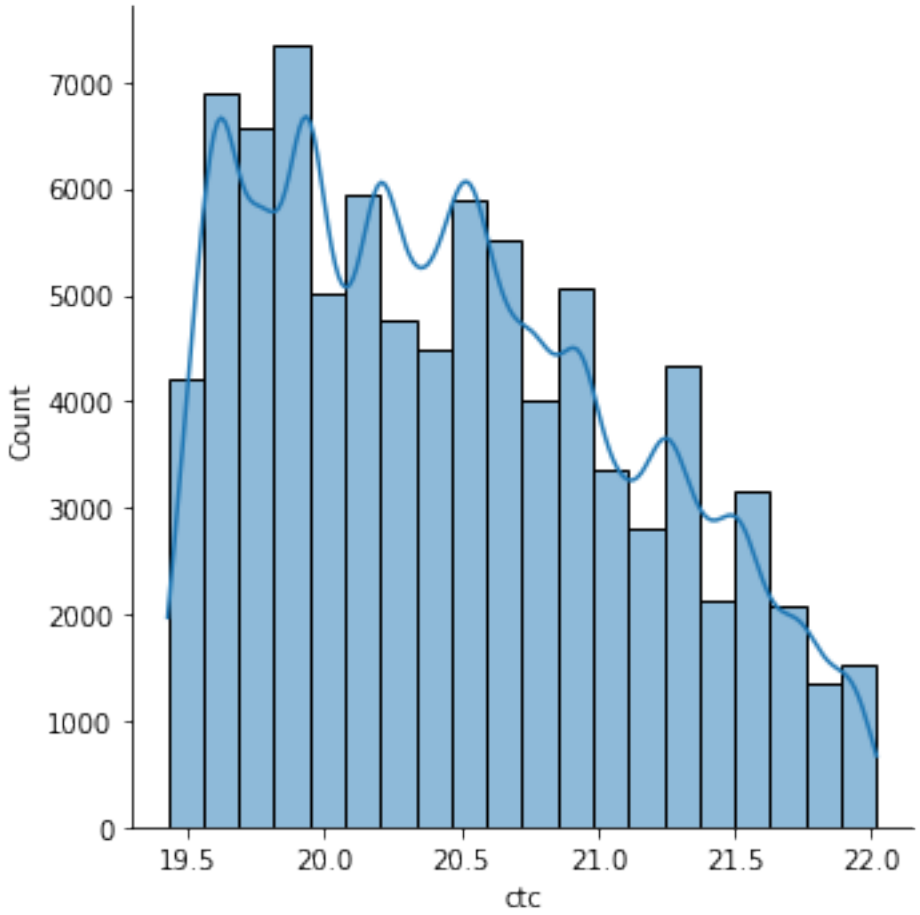



```
v = dftmp['ctc']/100000
#v = (v-v.mean())/v.std()
sns.boxplot(v)
plt.show()
```

```
/opt/conda/lib/python3.7/site-packages/seaborn/_decorators.py:43:
FutureWarning: Pass the following variable as a keyword arg: x. From
version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an
error or misinterpretation.
  FutureWarning
```



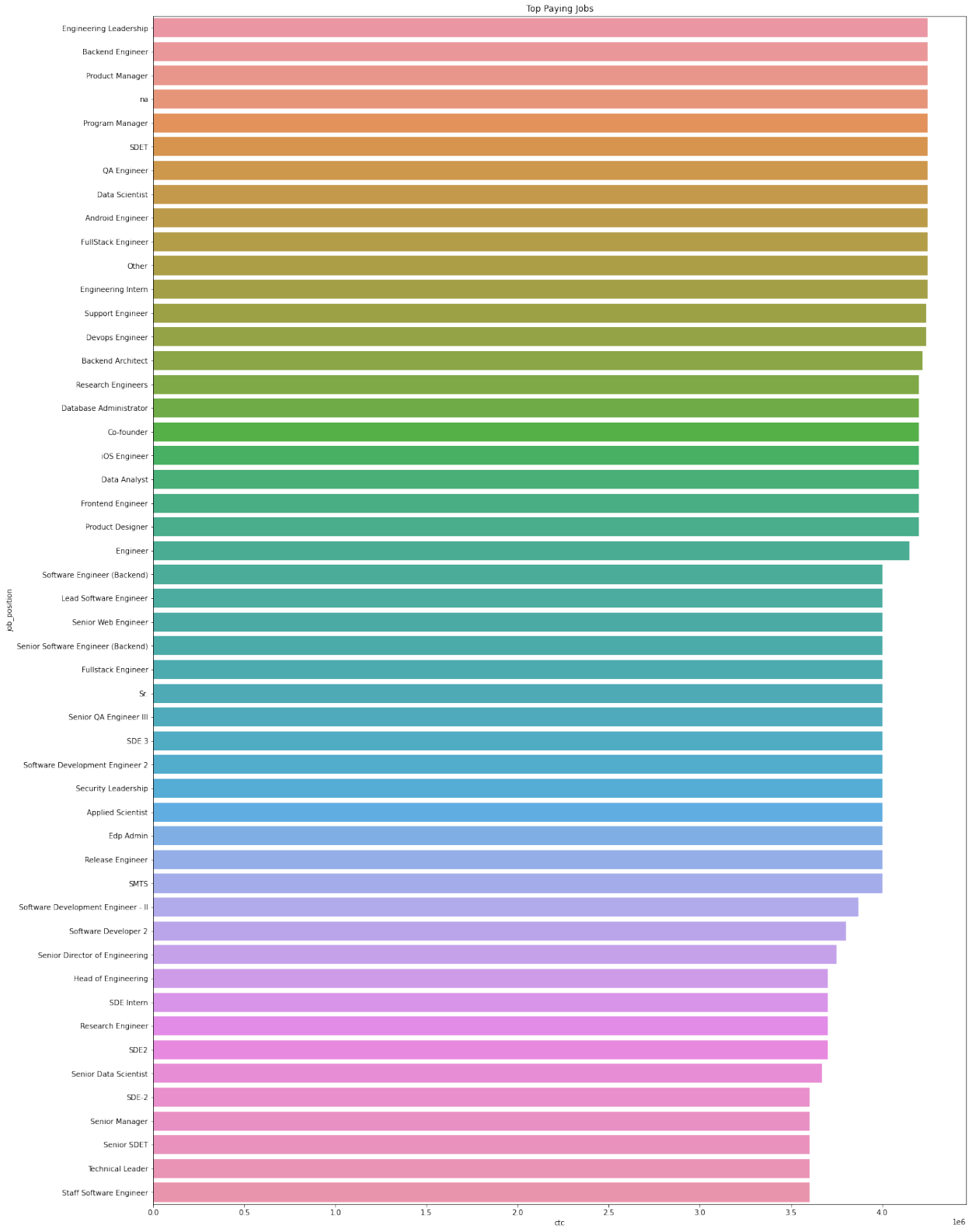

```
v = np.log2(dftmp['ctc'])
sns.displot(v,kde=True,bins=20)
plt.show()
```




```
dateda = dftmp.copy()
```

Multivariate Analysis

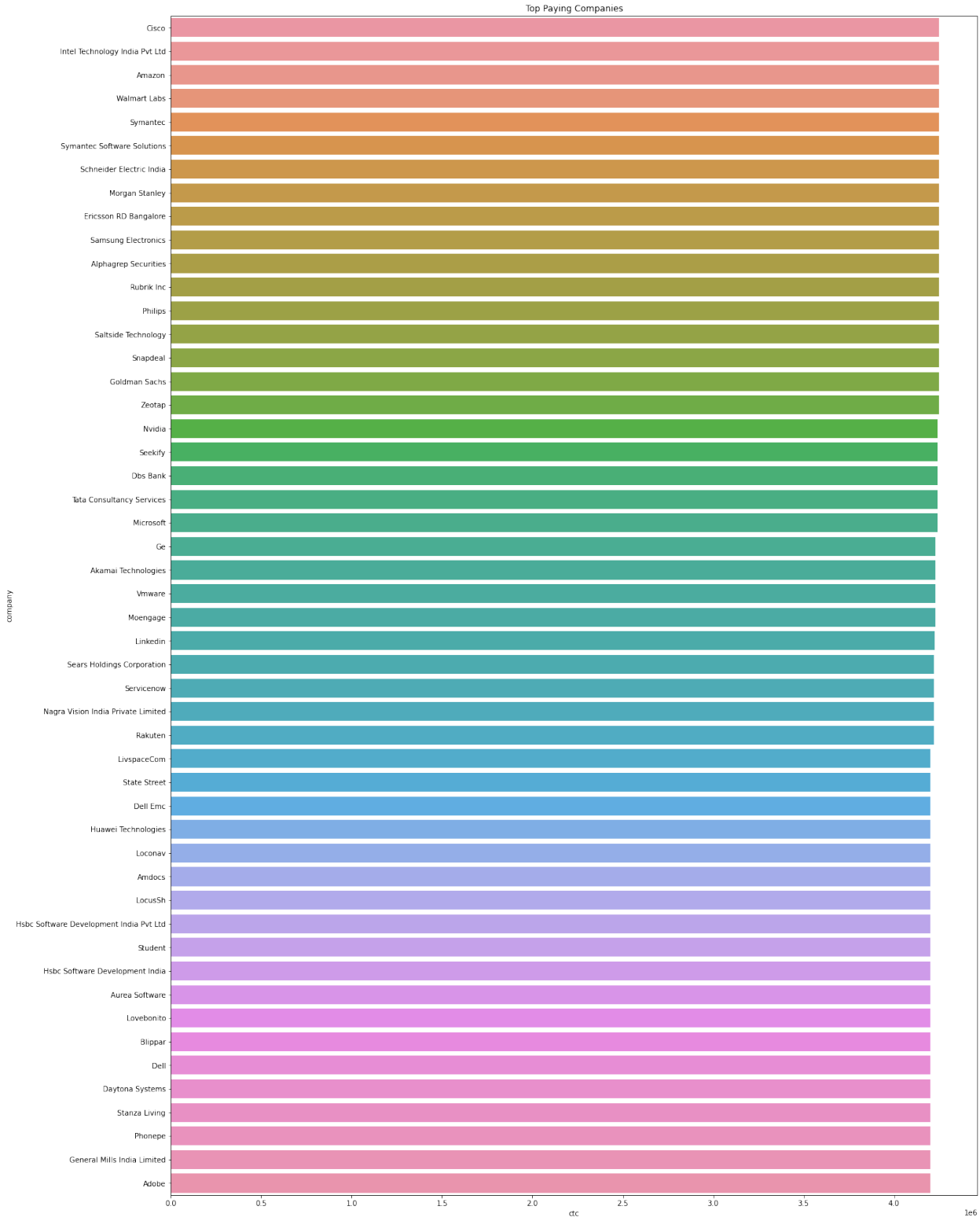
```
tmp = dftmp.copy()
tmp = tmp.groupby(['job_position']).max()
['ctc'].reset_index().sort_values('ctc',ascending=False).head(50)
plt.figure(figsize=(20,30))
sns.barplot(data=tmp,x='ctc',y='job_position').set(title="Top Paying
Jobs")
plt.show()
list(tmp['job_position'])
```




```
['Engineering Leadership',
 'Backend Engineer',
```

```
 'Product Manager',
 'na',
 'Program Manager',
 'SDET',
 'QA Engineer',
 'Data Scientist',
 'Android Engineer',
 'FullStack Engineer',
 'Other',
 'Engineering Intern',
 'Support Engineer',
 'Devops Engineer',
 'Backend Architect',
 'Research Engineers',
 'Database Administrator',
 'Co-founder',
 'iOS Engineer',
 'Data Analyst',
 'Frontend Engineer',
 'Product Designer',
 'Engineer',
 'Software Engineer (Backend)',
 'Lead Software Engineer',
 'Senior Web Engineer',
 'Senior Software Engineer (Backend)',
 'Fullstack Engineer',
 'Sr.',
 'Senior QA Engineer III',
 'SDE 3',
 'Software Development Engineer 2',
 'Security Leadership',
 'Applied Scientist',
 'Edp Admin',
 'Release Engineer',
 'SMTS',
 'Software Development Engineer - II',
 'Software Developer 2',
 'Senior Director of Engineering',
 'Head of Engineering',
 'SDE Intern',
 'Research Engineer',
 'SDE2',
 'Senior Data Scientist',
 'SDE-2',
 'Senior Manager',
 'Senior SDET',
 'Technical Leader',
 'Staff Software Engineer']
```

```
tmp = dftmp.copy()
tmp = tmp.groupby(['company']).max()
['ctc'].reset_index().sort_values('ctc',ascending=False).head(50)
plt.figure(figsize=(20,30))
sns.barplot(data=tmp,x='ctc',y='company').set(title="Top Paying
Companies")
plt.show()

list(tmp['company'])
```

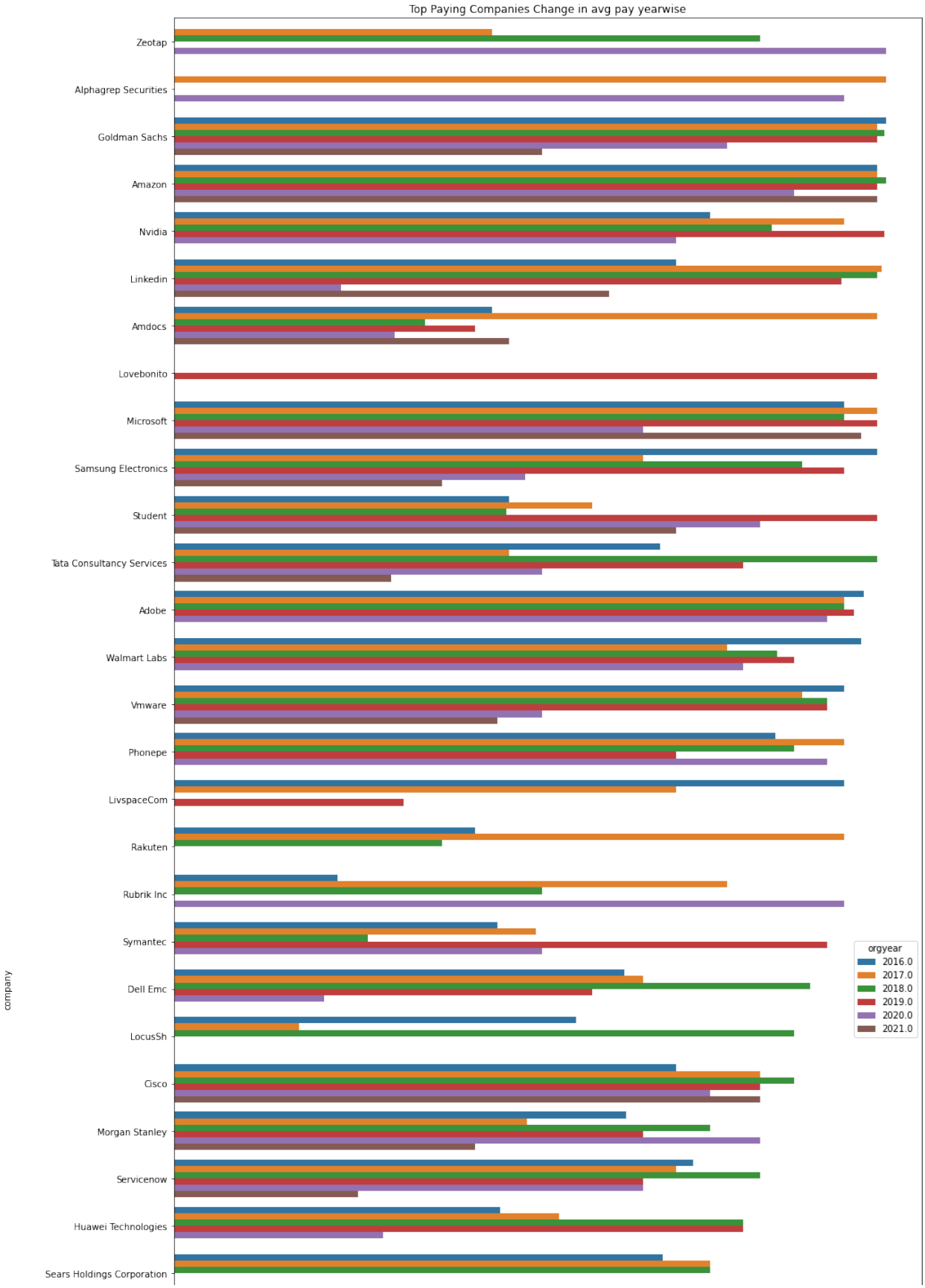



```
['Cisco',
 'Intel Technology India Pvt Ltd',
 'Amazon',
```

```
 'Walmart Labs',
 'Symantec',
 'Symantec Software Solutions',
 'Schneider Electric India',
 'Morgan Stanley',
 'Ericsson RD Bangalore',
 'Samsung Electronics',
 'Alphagrep Securities',
 'Rubrik Inc',
 'Philips',
 'Saltside Technology',
 'Snapdeal',
 'Goldman Sachs',
 'Zeotap',
 'Nvidia',
 'Seekify',
 'Dbs Bank',
 'Tata Consultancy Services',
 'Microsoft',
 'Ge',
 'Akamai Technologies',
 'Vmware',
 'Moengage',
 'Linkedin',
 'Sears Holdings Corporation',
 'Servicenow',
 'Nagra Vision India Private Limited',
 'Rakuten',
 'LivspaceCom',
 'State Street',
 'Dell Emc',
 'Huawei Technologies',
 'Loconav',
 'Amdocs',
 'LocusSh',
 'Hsbc Software Development India Pvt Ltd',
 'Student',
 'Hsbc Software Development India',
 'Aurea Software',
 'Lovebonito',
 'Blippar',
 'Dell',
 'Daytona Systems',
 'Stanza Living',
 'Phonepe',
 'General Mills India Limited',
 'Adobe']

tmp = dftmp.copy()
tmp = tmp[tmp['company'].isin(['Cisco',
```

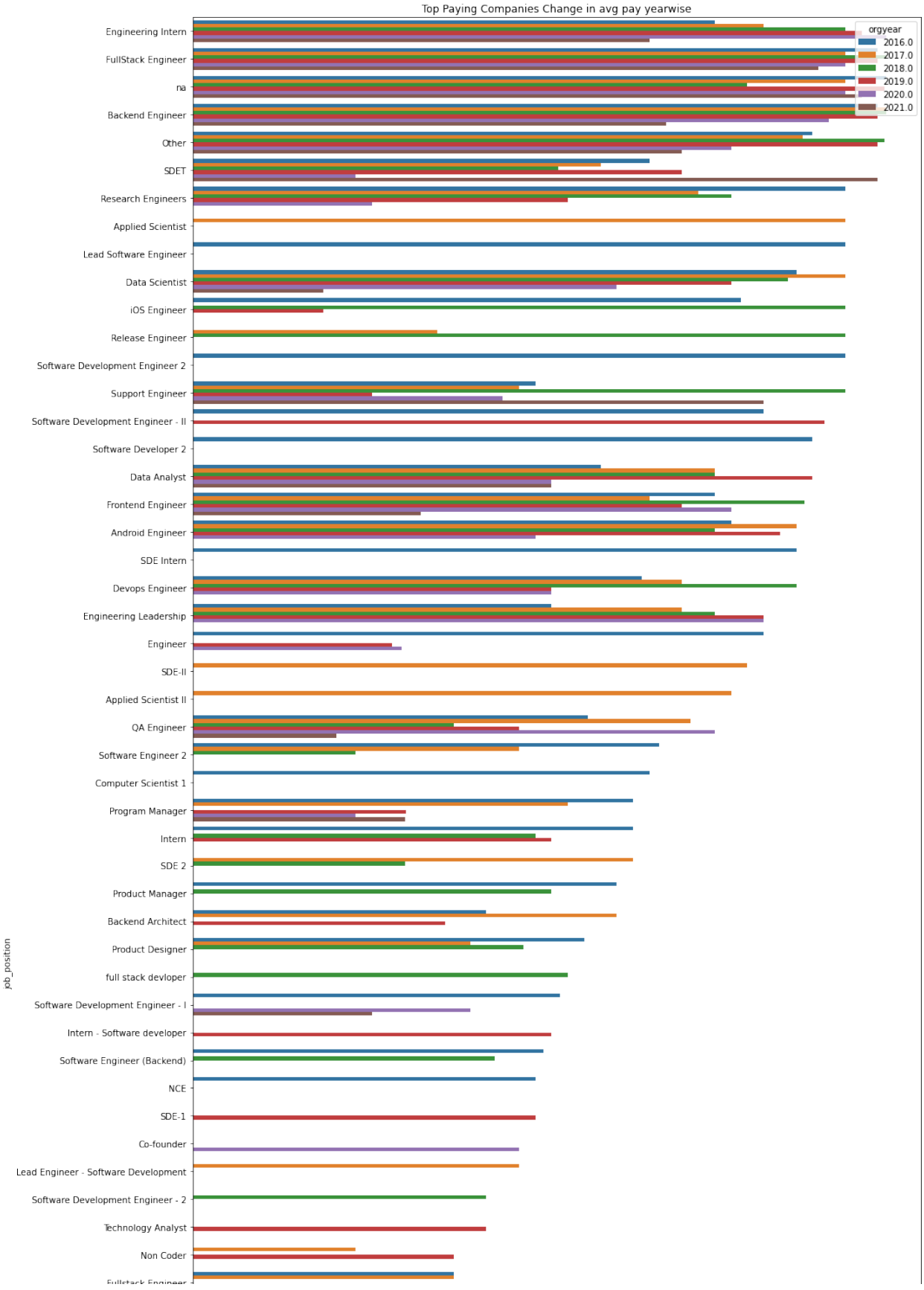
```
'Intel Technology India Pvt Ltd',
'Amazon',
'Walmart Labs',
'Symantec',
'Symantec Software Solutions',
'Schneider Electric India',
'Morgan Stanley',
'Ericsson RD Bangalore',
'Samsung Electronics',
'Alphagrep Securities',
'Rubrik Inc',
'Philips',
'Saltside Technology',
'Snapdeal',
'Goldman Sachs',
'Zeotap',
'Nvidia',
'Seekify',
'Dbs Bank',
'Tata Consultancy Services',
'Microsoft',
'Ge',
'Akamai Technologies',
'Vmware',
'Moengage',
'Linkedin',
'Sears Holdings Corporation',
'Servicenow',
'Nagra Vision India Private Limited',
'Rakuten',
'LivspaceCom',
'State Street',
'Dell Emc',
'Huawei Technologies',
'Loconav',
'Amdocs',
'LocusSh',
'Hsbc Software Development India Pvt Ltd',
'Student',
'Hsbc Software Development India',
'Aurea Software',
'Lovebonito',
'Blippar',
'Dell',
'Daytona Systems',
'Stanza Living',
'Phonepe',
'General Mills India Limited',
'Adobe'])]
```

```
tmp = tmp[tmp['orgyear'] >= 2016]
tmp = tmp.groupby(['company','orgyear']).max()
['ctc'].reset_index().sort_values('ctc',ascending=False)
plt.figure(figsize=(15,40))
sns.barplot(data=tmp,x='ctc',y='company',hue='orgyear').set(title="Top
Paying Companies Change in avg pay yearwise")
plt.show()
```

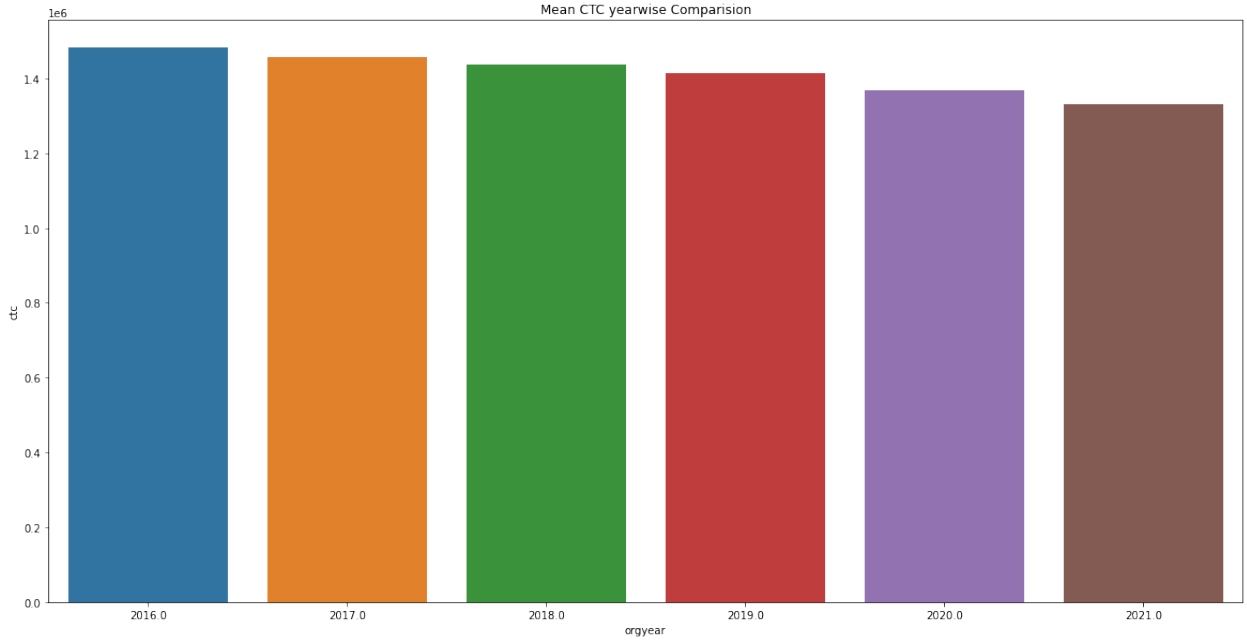

Top Paying Companies Change in avg pay yearwise
company
Zeotap
Alphagrep Securities
Goldman Sachs
Amazon
Nvidia
Linkedin
Amdocs
Lovebonito
Microsoft
Samsung Electronics
Student
Tata Consultancy Services
Adobe
Walmart Labs
Vmware
Phonepe
LivspaceCom
Rakuten
Rubrik Inc
Symantec
Dell Emc
LocusSh
Cisco
Morgan Stanley
Servicenow
Huawei Technologies
Sears Holdings Corporation
orgyear
2016.0
2017.0
2018.0
2019.0
2020.0
2021.0

```
tmp = dftmp.copy()
tmp = tmp[tmp['company'].isin(['Cisco',
 'Intel Technology India Pvt Ltd',
 'Amazon',
 'Walmart Labs',
 'Symantec',
 'Symantec Software Solutions',
 'Schneider Electric India',
 'Morgan Stanley',
 'Ericsson RD Bangalore',
 'Samsung Electronics',
 'Alphagrep Securities',
 'Rubrik Inc',
 'Philips',
 'Saltside Technology',
 'Snapdeal',
 'Goldman Sachs',
 'Zeotap',
 'Nvidia',
 'Seekify',
 'Dbs Bank',
 'Tata Consultancy Services',
 'Microsoft',
 'Ge',
 'Akamai Technologies',
 'Vmware',
 'Moengage',
 'Linkedin',
 'Sears Holdings Corporation',
 'Servicenow',
 'Nagra Vision India Private Limited',
 'Rakuten',
 'LivspaceCom',
 'State Street',
 'Dell Emc',
 'Huawei Technologies',
 'Loconav',
 'Amdocs',
 'LocusSh',
 'Hsbc Software Development India Pvt Ltd',
 'Student',
 'Hsbc Software Development India',
 'Aurea Software',
 'Lovebonito',
 'Blippar',
 'Dell',
 'Daytona Systems',
 'Stanza Living',
 'Phonepe',
 'General Mills India Limited',
```

```
 'Adobe'])]
tmp = tmp[tmp['orgyear'] >= 2016]
tmp = tmp.groupby(['job_position','orgyear']).max()
['ctc'].reset_index().sort_values('ctc',ascending=False)
plt.figure(figsize=(15,40))
sns.barplot(data=tmp,x='ctc',y='job_position',hue='orgyear').set(title
="Top Paying Companies Change in avg pay yearwise")
plt.show()
```


Top Paying Companies Change in avg pay yearwise
orgyear
2016.0
2017.0
2018.0
2019.0
2020.0
2021.0
job_position
Engineering Intern
FullStack Engineer
na
Backend Engineer
Other
SDET
Research Engineers
Applied Scientist
Lead Software Engineer
Data Scientist
iOS Engineer
Release Engineer
Software Development Engineer 2
Support Engineer
Software Development Engineer - II
Software Developer 2
Data Analyst
Frontend Engineer
Android Engineer
SDE Intern
Devops Engineer
Engineering Leadership
Engineer
SDE-II
Applied Scientist II
QA Engineer
Software Engineer 2
Computer Scientist 1
Program Manager
Intern
SDE 2
Product Manager
Backend Architect
Product Designer
full stack devloper
Software Development Engineer - I
Intern - Software developer
Software Engineer (Backend)
NCE
SDE-1
Co-founder
Lead Engineer - Software Development
Software Development Engineer - 2
Technology Analyst
Non Coder
Fullstack Engineer

```
tmp = dftmp.copy()

tmp = tmp[tmp['orgyear'] >= 2016]
tmp = tmp.groupby(['orgyear']).mean()
['ctc'].reset_index().sort_values('ctc',ascending=False).head(50)
plt.figure(figsize=(20,10))
sns.barplot(data=tmp,y='ctc',x='orgyear').set(title="Mean CTC yearwise
Comparision")
plt.show()
```



Manual Clustering

```
grp = ['company','job_position','YoE']
data_tmp1 = dateda.groupby(grp).agg({'ctc':
['mean','median','min','max','count']}).reset_index()
data_tmp1.columns  = ["{} {}".format(b_, a_) if a_ not in grp else
"{}".format(a_) for a_, b_ in zip(data_tmp1.columns.droplevel(1),
data_tmp1.columns.droplevel(0))  ]
data_tmp1.head(100).tail(50)

datatmp = dateda.merge(data_tmp1[['company', 'job_position', 'YoE',
'mean ctc']],on=['company', 'job_position', 'YoE'],how='left')



col1 = 'ctc'
col2 = 'mean ctc'
conditions  = [ datatmp[col1] > datatmp[col2], datatmp[col1] ==
datatmp[col2], datatmp[col1] < datatmp[col2] ]
```

```
choices     = [ 1, 2, 3 ]

datatmp['Designation'] = np.select(conditions, choices,
default=np.nan)

grp = ['company','job_position']
data_tmp1 = datatmp.groupby(grp).agg({'ctc':
[('mean2','mean'),'median','min','max','count']}).reset_index()
data_tmp1.columns  = ["{} {}".format(b_, a_) if a_ not in grp else
"{}".format(a_) for a_, b_ in zip(data_tmp1.columns.droplevel(1),
data_tmp1.columns.droplevel(0))  ]
data_tmp1.head(100).tail(50)


datatmp = datatmp.merge(data_tmp1[grp + ['mean2
ctc']],on=grp,how='left')


col1 = 'ctc'
col2 = 'mean2 ctc'
conditions  = [ datatmp[col1] > datatmp[col2], datatmp[col1] ==
datatmp[col2], datatmp[col1] < datatmp[col2] ]
choices     = [ 1, 2, 3 ]

datatmp['Class'] = np.select(conditions, choices, default=np.nan)

grp = ['company']
data_tmp1 = datatmp.groupby(grp).agg({'ctc':
[('mean3','mean'),'median','min','max','count']}).reset_index()
data_tmp1.columns  = ["{} {}".format(b_, a_) if a_ not in grp else
"{}".format(a_) for a_, b_ in zip(data_tmp1.columns.droplevel(1),
data_tmp1.columns.droplevel(0))  ]
data_tmp1.head(100).tail(50)


datatmp = datatmp.merge(data_tmp1[grp + ['mean3
ctc']],on=grp,how='left')


col1 = 'ctc'
col2 = 'mean3 ctc'
conditions  = [ datatmp[col1] > datatmp[col2], datatmp[col1] ==
datatmp[col2], datatmp[col1] < datatmp[col2] ]
choices     = [ 1, 2, 3 ]

datatmp['Tier'] = np.select(conditions, choices, default=np.nan)

datatmp['diff_desig'] = datatmp['ctc'] - datatmp['mean ctc']
datatmp['diff_class'] = datatmp['ctc'] - datatmp['mean2 ctc']
datatmp['diff_tier'] = datatmp['ctc'] - datatmp['mean3 ctc']
```

Answering question based on manual clustering

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

```
datatmp[datatmp['Tier'] ==
1].sort_values('diff_tier',ascending=False).head(10)
[['email_hash','ctc','mean3 ctc']]
```

```
                                                email_hash      ctc  \
76180  e15abfd41c005995728191e49ef001e83e813cd3ed5104...  4240000
49030  90d5114ca752c55babef2c517ac8b17aaee3d9ff5740de...  4200000
59575  b022b84623593cc38a3c1d39d4545b368a7b5f286be1c7...  4200000
54761  a1c1c8919e2918b24241a40271e02381daf199c61d7a3b...  4200000
70667  d13d7376e9ced16b4e250d0643f9139f8b36a62847f71b...  4200000
14808  2b10e1d996c6ab5e175eea35ca25ea7afbaacd1237ab64...  4200000
31649  5d872e52cb535a71fc75a5a97e779bb4c1554d0baa920d...  4200000
47727  8d0ed00904247626f5557f5983feeb5a0567d7726eea39...  4200000
31826  5dff6a65d548553262b6a289f014b2b72a5d47ff6dfa5c...  4170000
45627  86b90dd64ddb663ea35be98422947a01ba9ab837fb76df...  4000000

          mean3 ctc
76180  1.051315e+06
49030  1.051315e+06
59575  1.051315e+06
54761  1.144189e+06
70667  1.147773e+06
14808  1.157302e+06
31649  1.157302e+06
47727  1.176534e+06
31826  1.165011e+06
45627  1.051315e+06
```

Top 10 employees of data science in Amazon / TCS etc earning more than their peers - Class 1

```
datatmp[(datatmp['Tier'] == 1)&(datatmp['Class'] ==
1)&(datatmp['job_position'].isin(['Data Science Analyst','Data
Scientist','Data Scientist II','Associate Data Scientist','Senior Data
Scientist']))].sort_values('diff_class',ascending=False).head(10)
[['email_hash','ctc','mean2 ctc']]
```

```
                                                email_hash      ctc  \
81289  f04a0228e5af6f8f6ecc33e089892e80d85b3c749b3244...  4000000
56231  a63f3f44de7586430615a8a9bd13d41e7b0d541ca0f690...  4200000
16846  31616edfc502824631b11793313d35d5bb2288319dcb25...  3800000
21441  3efbb8c4d67b4a4c6ba4c639cd84e9ff98b85d5f57d82f...  3979999
33512  62f705ba342cb9e51117446a5522c2e42c14db27b9b20e...  4250000
83396  f67ae342b7431f7ab05eca998d904647b02711538aa839...  3750000
83524  f6e8c41a40ec308c996d498e22729359d2b564cae037a0...  3500000
191    009ded427ebcb5c2fb1970017a683693a7abef0fa96f5e...  3900000
79529  eb35a5d34977c6135372e46d6cc4f85332f1a4f9578bd5...  4080000
```

```
36086  6aa8cfeb5b98da66158e0af4ca8869362174abdba84a02...  3200000

          mean2 ctc
81289  1.533750e+06
56231  1.862000e+06
16846  1.513842e+06
21441  1.716000e+06
33512  2.025000e+06
83396  1.565556e+06
83524  1.410000e+06
191    1.834333e+06
79529  2.020000e+06
36086  1.233235e+06
```

Bottom 10 employees of data science in Amazon / TCS etc earning less than their peers - Class 3

```
datatmp[(datatmp['Tier'] == 1)&(datatmp['Class'] ==
3)&(datatmp['job_position'].isin(['Data Science Analyst','Data
Scientist','Data Scientist II','Associate Data Scientist','Senior Data
Scientist']))].sort_values('diff_class',ascending=True).head(10)
[['email_hash','ctc','mean2 ctc']]
```

```
                                              email_hash      ctc
mean2 ctc
14514  2a3136f6e2d03a3dbfa3f683e4ae1b744b4815a8e0177c...  1700000
3125000.0
55794  a4f1770283497277f8cd3b7cb04e9b5c3135815eebb4cf...  2300000
3292500.0
48870  9069f6772b1e7959734a115bf49b2168a888608496af50...  1900000
2850000.0
82770  f49bd18e7fe914929f6cc23bb4e7979d58290119f2adcf...  1600000
2500000.0
51648  987a063524741381c302a096e4b019f46088e519f59f4a...  2000000
2750000.0
65945  c371eff30d6983ab69401441f359fed64397f7699c7aff...  1630000
2350000.0
79574  eb5552cf683e3072a7e2e2c6e63ebb46183a716b2bd2a1...  1780000
2496000.0
2812   080c3b2cc8fe9e7743520a3771a3b4db72e49ef2542ebf...  1400000
1986000.0
26908  4fcbc73fbd3da62f8750d69c13846ada4d1302f4817865...  1700000
2250000.0
61631  b63f00fbd2f8774eccde057bbf3f99ae1742adf496b2cc...  1600000
2102500.0
```

Bottom 10 employees (earning less than most of the employees in the company)- Tier 3

```
datatmp[datatmp['Tier'] ==
3].sort_values('diff_tier',ascending=True).head(10)
[['email_hash','ctc','mean3 ctc']]
```

```
                                                email_hash      ctc  \
12121  2322345290a1926df62347d45f06b68932e219cb010bf8...   850000
64065  bda6e0f742115289a27f304078935331a5563d90c91461...   750000
15908  2e7e946b56a245338d8da1daf60ef851031c9964cffd25...   950000
4334   0c535bb44414d62cab133425339bd7e156ec79823899ae...   810000
49904  935480e039d80833292d858a553a4bc0f628b9b97ce9ec...   900000
73476  d96a6540ff59456abe30f51f68e954388b1f6922c4bb0c...   900000
19346  38d71a484d7663f7c14df8432620bbbab718933173a295...  1368000
70292  d034e386dbce817ee1ea099b161379d3341af0a16573d8...   800000
36006  6a6d1a4452505b678e264700fd0c28f247c4522d27f112...   770000
2612   077fd3f95d8dbf89c112a8eca6601db3729f51b53b57a0...   720000

          mean3 ctc
12121  3.262923e+06
64065  2.929000e+06
15908  2.950000e+06
4334   2.770000e+06
49904  2.840543e+06
73476  2.840543e+06
19346  3.262923e+06
70292  2.683125e+06
36006  2.637273e+06
2612   2.577054e+06
```

Top 10 employees in Amazon- X department - having 5/6/7 years of experience earning more than their peers - Tier X

```
datatmp[(datatmp['YoE'].isin([5,6,7]))&(datatmp['company'].isin(['Amaz
on']))].sort_values('diff_desig',ascending=False).head(10)
[['email_hash','ctc','mean ctc']]
```

```
                                                email_hash      ctc  \
54832  a1f32c1afc78650a5701dd0b32c15590d383a02520a755...  4000000
9990   1cbc2f4ff908528b918606b070f93b1e644cb956b83e79...  3900000
7700   1608ef4352eecde96660f30db82a3c098ee7f3d16f9542...  4000000
23513  4577592747a85357070e2ad539e2db011569fb8493d4d1...  4100000
71060  d25e73e85f498e7d413fed50097d205a014afb1d9d38db...  4000000
22521  4251a130b4dd3ddec21971f642621a5517878a391881ad...  4000000
77567  e5893568ff7c6553adda50493f2ffa9005bb410ee98fb4...  4000000
72912  d7b4d80f4a290bf75642ee81b60de7bc9f8d99ac02a611...  4220000
23699  461034625aaa1bbb5cbc54dc9e9af65673114423d1f51e...  4200000
38490  71c17d7d2d6b012855c1034f6220c507d2ff19a5e37140...  4200000

           mean ctc
54832  1.494364e+06
9990   1.494364e+06
```

```
7700   2.188000e+06
23513  2.400000e+06
71060  2.330882e+06
22521  2.330882e+06
77567  2.330882e+06
72912  2.658768e+06
23699  2.658768e+06
38490  2.658768e+06
```

Top 10 companies (based on their CTC)

```
datatmp.groupby('company').mean()
['ctc'].reset_index().sort_values('ctc',ascending=False).head(10)
[['company','ctc']]
```

	company	ctc
15171	Saltside Technology	4250000.0
5820	Ericsson RD Bangalore	4250000.0
11897	Nagra Vision India Private Limited	4220000.0
1034	Alyosha Technology Consultancy Service	4200000.0
9549	Jiffle Technologies	4200000.0
13690	Playgames 247	4200000.0
7959	Hpe India	4200000.0
8267	Idfc Bank Ltd	4200000.0
1218	Antbrains	4200000.0
19125	Walmart Global Technology Solutions	4200000.0

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

```
tmp = datatmp[datatmp['job_position'] != 'na']
tmp =
tmp.groupby(['company','job_position']).mean().sort_values(['company',
'ctc']).reset_index()
tmp = tmp.groupby('company').head(2)[['company','job_position']]
tmp
```

	company	job_position
0		Data Scientist
1		Backend Engineer
5	Aavenir India	FullStack Engineer
6	Accolite Software	Fullstack Engineer
7	Arcadis Hyderabad Gec India	Data Scientist
...	...	...
32715	Zynga	iOS Engineer
32720	Zynga Game India Pvt Limited	Fullstack Engineer
32721	Zynga Game Network	Product Manager
32722	Zyudly Labs	Data Scientist
32723	Zzz	Backend Engineer

```
[23026 rows x 2 columns]
```

Top 2 positions in top Paying companies

```
tmp[tmp['company'].isin(['Cisco',
 'Intel Technology India Pvt Ltd',
 'Amazon',
 'Walmart Labs',
 'Symantec',
 'Symantec Software Solutions',
 'Schneider Electric India',
 'Morgan Stanley',
 'Ericsson RD Bangalore',
 'Samsung Electronics',
 'Alphagrep Securities',
 'Rubrik Inc',
 'Philips',
 'Saltside Technology',
 'Snapdeal',
 'Goldman Sachs',
 'Zeotap',
 'Nvidia',
 'Seekify',
 'Dbs Bank',
 'Tata Consultancy Services',
 'Microsoft',
 'Ge',])]
```

	company	job_position
1463	Alphagrep Securities	Other
1464	Alphagrep Securities	Backend Engineer
1663	Amazon	Medical field
1664	Amazon	Compliance operation
5468	Cisco	Product Designer
5469	Cisco	SE(R&D)
7337	Dbs Bank	Data Analyst
7338	Dbs Bank	SDET
9261	Ericsson RD Bangalore	Engineering Leadership
10982	Ge	Support Engineer
10983	Ge	QA Engineer
11531	Goldman Sachs	Associate software engineer
11532	Goldman Sachs	SDET
14666	Intel Technology India Pvt Ltd	SDET
14667	Intel Technology India Pvt Ltd	Database Administrator
18307	Microsoft	Technical Engineer
18308	Microsoft	SDE2
18911	Morgan Stanley	Associate Software developer
18912	Morgan Stanley	Machine learning engineer

```
20694                          Nvidia                      QA Engineer
20695                          Nvidia                 Android Engineer
22166                         Philips              Engineering Intern
22167                         Philips                            SDET
24528                     Rubrik Inc                Frontend Engineer
24529                     Rubrik Inc                 Support Engineer
24769            Saltside Technology                 Android Engineer
24797            Samsung Electronics                            SDET
24798            Samsung Electronics                    Data Analyst
25339       Schneider Electric India                 Program Manager
25340       Schneider Electric India                      QA Engineer
25536                         Seekify              FullStack Engineer
26431                        Snapdeal                      QA Engineer
26432                        Snapdeal                           Other
27565                        Symantec                 Devops Engineer
27566                        Symantec                    Data Analyst
27586    Symantec Software Solutions                    iOS Engineer
27587    Symantec Software Solutions                 Android Engineer
28020      Tata Consultancy Services                 Product Designer
28021      Tata Consultancy Services        Automation Test Engineer
31276                  Walmart Labs                 Support Engineer
31277                  Walmart Labs              Research Engineers
32427                       Zeotap                Frontend Engineer
32428                       Zeotap                            Other
```

Preparing data for training model(Imputation/Scaling)

```
data = dateda.copy()
data
```

```
                                                email_hash  Unnamed: 0
\
0       00003288036a44374976948c327f246fdbdf0778546904...       84782

3       000120d0c8aa304fcf12ab4b85e21feb80a342cfea03d4...       53905

4       00014d71a389170e668ba96ae8e1f9d991591acc899025...      138707

6       00022dc29c7f77032275182b883d4f273ea1007aefc437...        7782

7       00036c2c5212d88d07acdc5bda7eef5653f8b09bbe30b7...       30543

...                                                   ...         ...

153432  fffa3a7b849802580a1972f11d192b43ff1c871bb43002...       79890

153438  fffc254e627e4bd1bc0ed7f01f9aebbba7c3cc56ac914e...       39683

153439  fffcf97db1e9c13898f4eb4cd1c2fe862358480e104535...      186656
```

```
153440  fffe7552892f8ca5fb8647d49ca805b72ea0e9538b6b01...      148878

153442  ffffa3eb3575f43b86d986911463dce7bcadcea227e5a4...      117170


                                    company    normalized_company_name
orgyear  \
0                                 Microsoft                   Microsoft
2012.0
3                     Microsemi Corporation      Microsemi Corporation
2004.0
4                             Walmart Labs                     Walmart
2009.0
6                   Infracloud Technologies               Not Available
2016.0
7                           Svp Itqan Oman               Not Available
2011.0
...                                    ...                         ...
...
153432          Tata Consultancy Services  Tata Consultancy Services
2014.0
153438           Ericsson Software Campus               Not Available
2004.0
153439                            Eltravo               Not Available
2015.0
153440  Ntt Data Global Delivery Services               Not Available
2014.0
153442                       Goldman Sachs               Goldman Sachs
2018.0

            ctc        job_position  ctc_updated_year  orgyear_na  \
0       3500000    Backend Engineer            2019.0       False
3       2000000  FullStack Engineer            2021.0       False
4       3400000                  na            2018.0       False
6        750000   Frontend Engineer            2019.0       False
7       2300000               Other            2021.0       False
...         ...                 ...               ...         ...
153432  1800000    Backend Engineer            2019.0       False
153438  3529999         QA Engineer            2019.0       False
153439  1600000                  na            2018.0       False
153440   900000     Devops Engineer            2019.0       False
153442  1500000  FullStack Engineer            2021.0       False

        ctc_updated_year_na  normalized_company_name_na  company_na  \
0                     False                       False       False
3                     False                       False       False
4                     False                       False       False
6                     False                        True       False
7                     False                        True       False
...                     ...                         ...         ...
```

```
153432                False                          False       False
153438                False                           True       False
153439                False                           True       False
153440                False                           True       False
153442                False                          False       False

        job_position_na   YoE  company_encode  job_position_encode
0                 False   7.0        0.010160          2431.717315
3                 False  17.0        0.000072          1319.056588
4                  True   9.0        0.003767          1318.013855
6                 False   3.0        0.000026           604.263472
7                 False  10.0        0.000007          1026.830810
...                 ...   ...             ...                 ...
153432            False   5.0        0.034228          2431.717315
153438            False  15.0        0.000007           401.973371
153439             True   3.0        0.000007          1318.013855
153440            False   5.0        0.000124           279.908500
153442            False   3.0        0.003793          1319.056588

[86464 rows x 16 columns]
```

Transforming ctc feature using log function

```
data['ctc_log'] = np.log2(data['ctc'])
```

Columns like ['normalized_company_name','job_position','email_hash','Unnamed: 0','company'] are text. We can't use them during imputation, so we'll remove these columns

```
drop_cols =
['normalized_company_name','job_position','email_hash','Unnamed:
0','company']
for i in drop_cols:
    try:
        data.drop([i],axis=1,inplace=True)
    except:
        print('no')

data.columns
```

```
Index(['orgyear', 'ctc', 'ctc_updated_year', 'orgyear_na',
       'ctc_updated_year_na', 'normalized_company_name_na',
'company_na',
       'job_position_na', 'YoE', 'company_encode',
'job_position_encode',
       'ctc_log'],
      dtype='object')
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 86464 entries, 0 to 153442
Data columns (total 12 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   orgyear                      86424 non-null  float64
 1   ctc                          86464 non-null  int64  
 2   ctc_updated_year             86464 non-null  float64
 3   orgyear_na                   86464 non-null  bool   
 4   ctc_updated_year_na          86464 non-null  bool   
 5   normalized_company_name_na   86464 non-null  bool   
 6   company_na                   86464 non-null  bool   
 7   job_position_na              86464 non-null  bool   
 8   YoE                          86424 non-null  float64
 9   company_encode               86464 non-null  float64
 10  job_position_encode          86464 non-null  float64
 11  ctc_log                      86464 non-null  float64
dtypes: bool(5), float64(6), int64(1)
memory usage: 5.7 MB
```

Summary Statistics

```
data.describe()
```

```
            orgyear           ctc  ctc_updated_year           YoE  \
count  86424.000000  8.646400e+04      86464.000000  86424.000000   
mean    2013.804626  1.626541e+06       2019.441432      5.636906   
std        4.354664  8.080584e+05          1.283791      4.225522   
min     1970.000000  7.040000e+05       2015.000000      0.000000   
25%     2012.000000  1.000000e+06       2019.000000      3.000000   
50%     2015.000000  1.400000e+06       2019.000000      5.000000   
75%     2017.000000  2.000000e+06       2020.000000      8.000000   
max     2021.000000  4.250000e+06       2021.000000     51.000000   

       company_encode  job_position_encode       ctc_log  
count    86464.000000         86464.000000  86464.000000  
mean         0.002627          1209.710671     20.474913  
std          0.005556           878.503304      0.662649  
min          0.000007             0.065171     19.425216  
25%          0.000033           319.141310     19.931569  
50%          0.000365          1318.013855     20.416995  
75%          0.002098          2431.717315     20.931569  
max          0.034228          2431.717315     22.019031  
```

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

```
orgyear                      40
ctc                           0
ctc_updated_year              0
orgyear_na                    0
```

```
ctc_updated_year_na             0
normalized_company_name_na      0
company_na                      0
job_position_na                 0
YoE                            40
company_encode                  0
job_position_encode             0
ctc_log                         0
dtype: int64
```

```
from sklearn.impute import KNNImputer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.cluster import MiniBatchKMeans, KMeans
from sklearn.metrics import silhouette_score
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
```

Kmeans clustering

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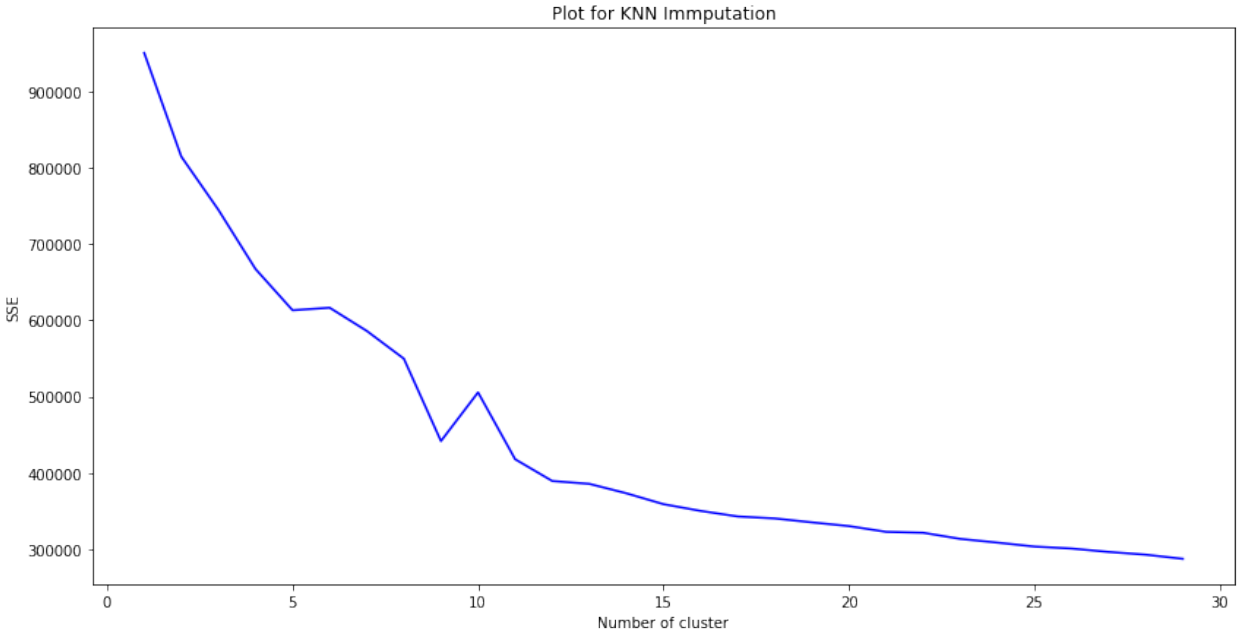
So we will be training a model with unscaled features too.

```
pipe_knn = Pipeline([('scaler', StandardScaler()), ('knn_imputer',
KNNImputer(n_neighbors=2, weights="uniform"))])
pipe_knn_5 = Pipeline([('scaler', StandardScaler()), ('knn_imputer',
KNNImputer(n_neighbors=5, weights="uniform"))])
pipe = Pipeline([('scaler', StandardScaler()), ('simple_imputer',
SimpleImputer(missing_values=np.nan, strategy='mean'))])
pipe_knn_pca = Pipeline([('scaler', StandardScaler()), ('knn_imputer',
KNNImputer(n_neighbors=2, weights="uniform")),
('pca',PCA(n_components=8))])
pipe_unscaled = Pipeline([('knn_imputer',  KNNImputer(n_neighbors=5,
weights="uniform"))])
```

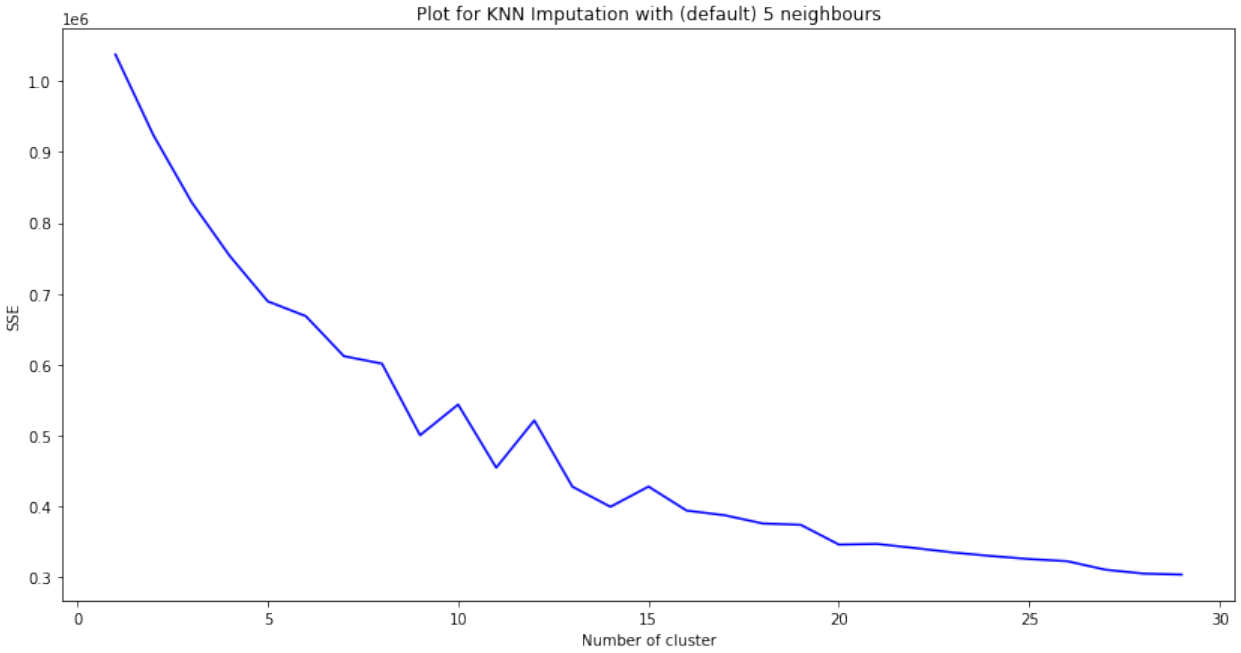
Finding optimal num of clusters using Elbow method

```
for name,pipeline in [('KNN Immputation',pipe_knn),('KNN Imputation
with (default) 5 neighbours',pipe_knn_5),('Mean Imputation ',pipe),
                      ('KNN Immputation + PCA', pipe_knn_pca),('KNN
Imputation Unscaled data',pipe_unscaled )]:

    X = pipeline.fit_transform(data)
    X = pd.DataFrame(X)
    if "PCA" not in name :
        X.columns= data.columns
```

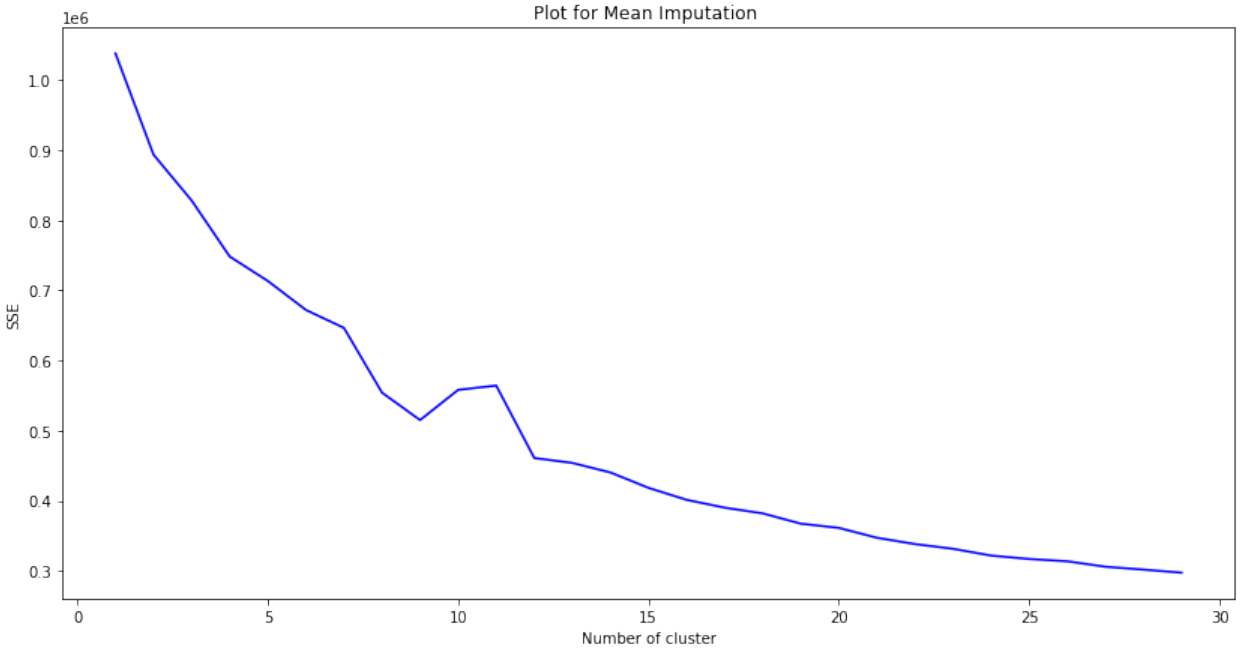
```
    sse = {}
    #sil_score = {}
    print("Running for ",name)
    for k in range(1, 30):
        #print('K :',k)
        kmeans = MiniBatchKMeans(init="k-means++",n_clusters=k,
                                 random_state=0).fit(X)
        label = kmeans.labels_
        data["clusters"] = label
        #print(data["clusters"])
        sse[k] = kmeans.inertia_

        #sil_score[k] = silhouette_score(X, label, metric='euclidean')

    plt.figure(figsize=(14,7))
    plt.plot(list(sse.keys()), list(sse.values()),'b-',label='Sum of
squared error')
    plt.xlabel("Number of cluster")
    plt.ylabel("SSE")
    plt.title("Plot for "+name)
    plt.show()


Running for  KNN Immputation
```



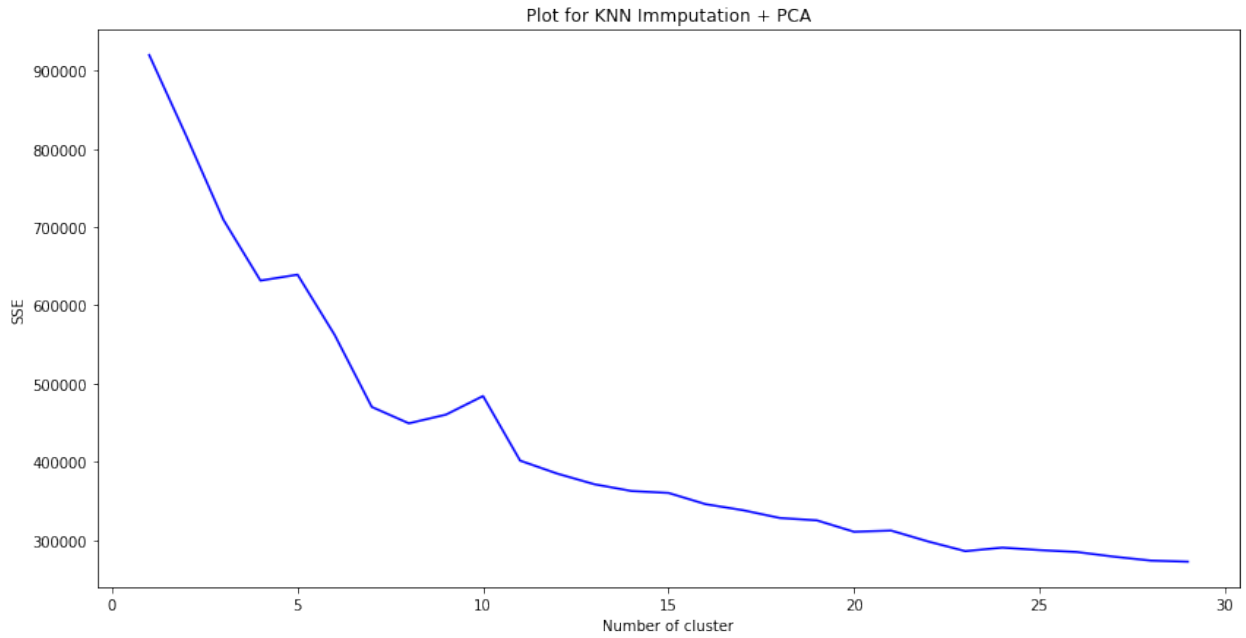

```
Running for  KNN Imputation with (default) 5 neighbours
```



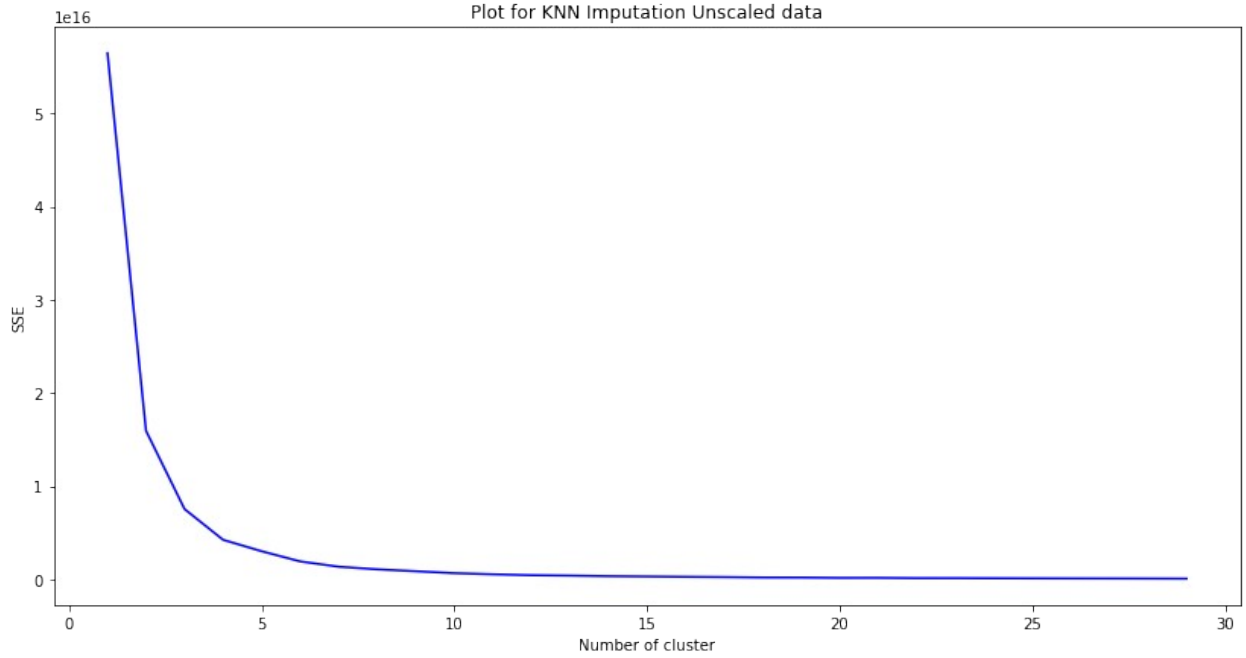

```
Running for  Mean Imputation
```




```
Running for  KNN Immputation + PCA
```




```
Running for  KNN Imputation Unscaled data
```



Number of clusters is around 16-20 for scaled data, while around 5 for unscaled data

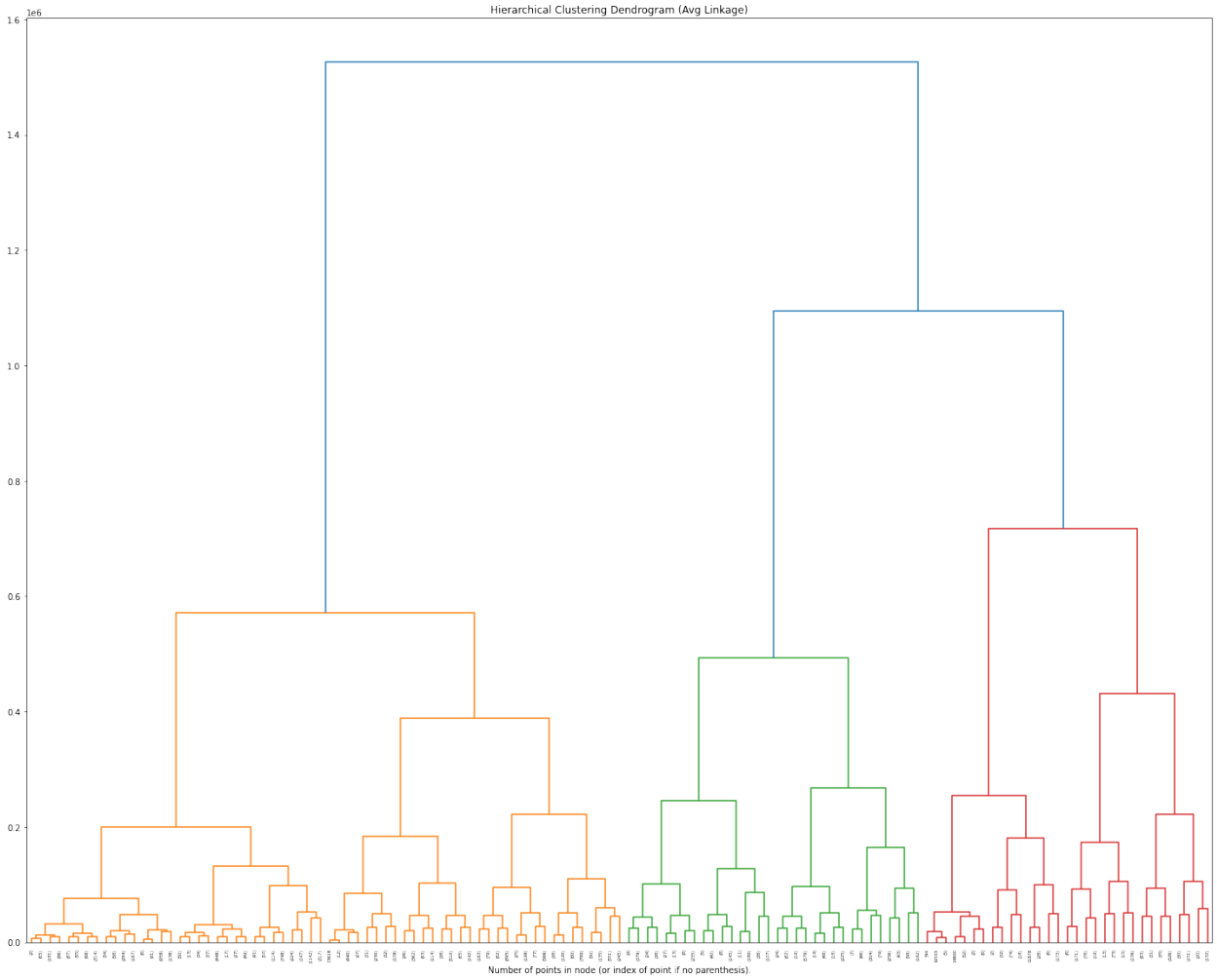
```
from sklearn.cluster import AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram
```

Agglomerative Clustering

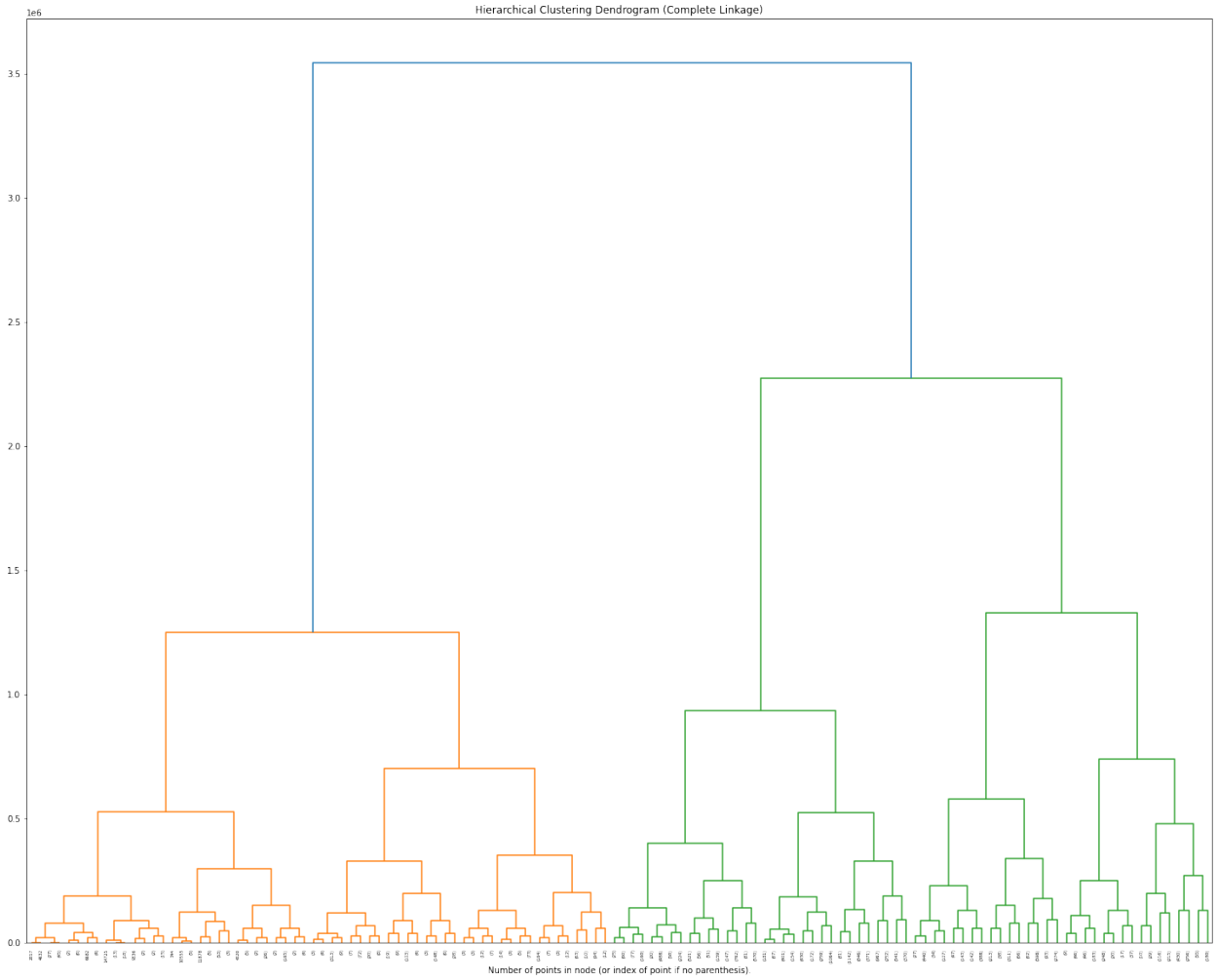
```
tmp = X.sample(frac=0.2)

tmp.shape
```

```
(17293, 13)
```

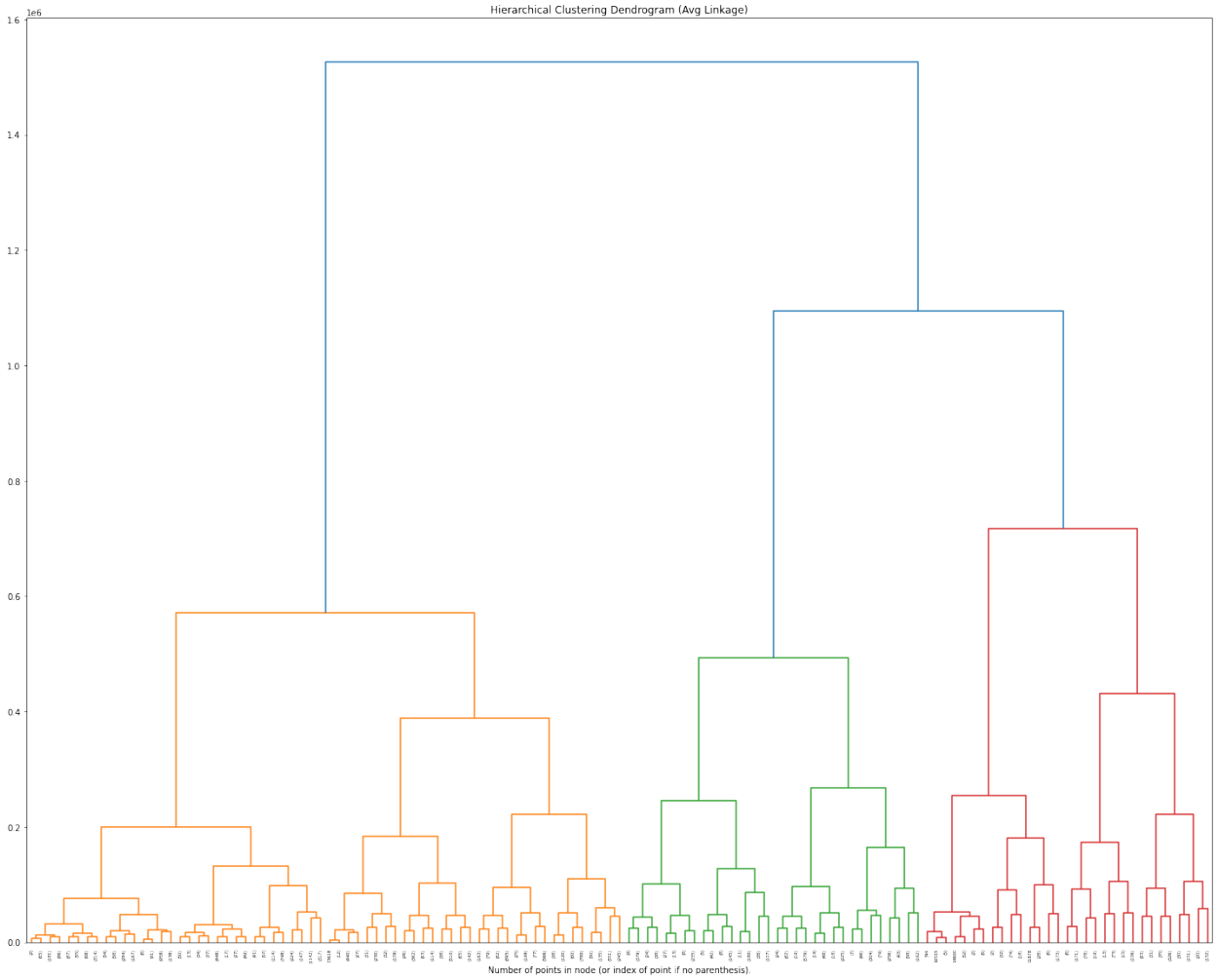
```
def plot_dendrogram(model, **kwargs):
    # Create linkage matrix and then plot the dendrogram

    # create the counts of samples under each node
    counts = np.zeros(model.children_.shape[0])
    n_samples = len(model.labels_)
    for i, merge in enumerate(model.children_):
        current_count = 0
        for child_idx in merge:
            if child_idx < n_samples:
                current_count += 1  # leaf node
            else:
                current_count += counts[child_idx - n_samples]
        counts[i] = current_count

    linkage_matrix = np.column_stack(
        [model.children_, model.distances_, counts]
    ).astype(float)

    # Plot the corresponding dendrogram

    dendrogram(linkage_matrix, **kwargs)


model = AgglomerativeClustering(distance_threshold =0,
n_clusters=None, compute_distances=True,linkage='average').fit(tmp)

plt.figure(figsize=(25,20))
plt.title("Hierarchical Clustering Dendrogram (Avg Linkage)")
plot_dendrogram(model, truncate_mode="level", p=6)
plt.xlabel("Number of points in node (or index of point if no
parenthesis).")
plt.show()
```



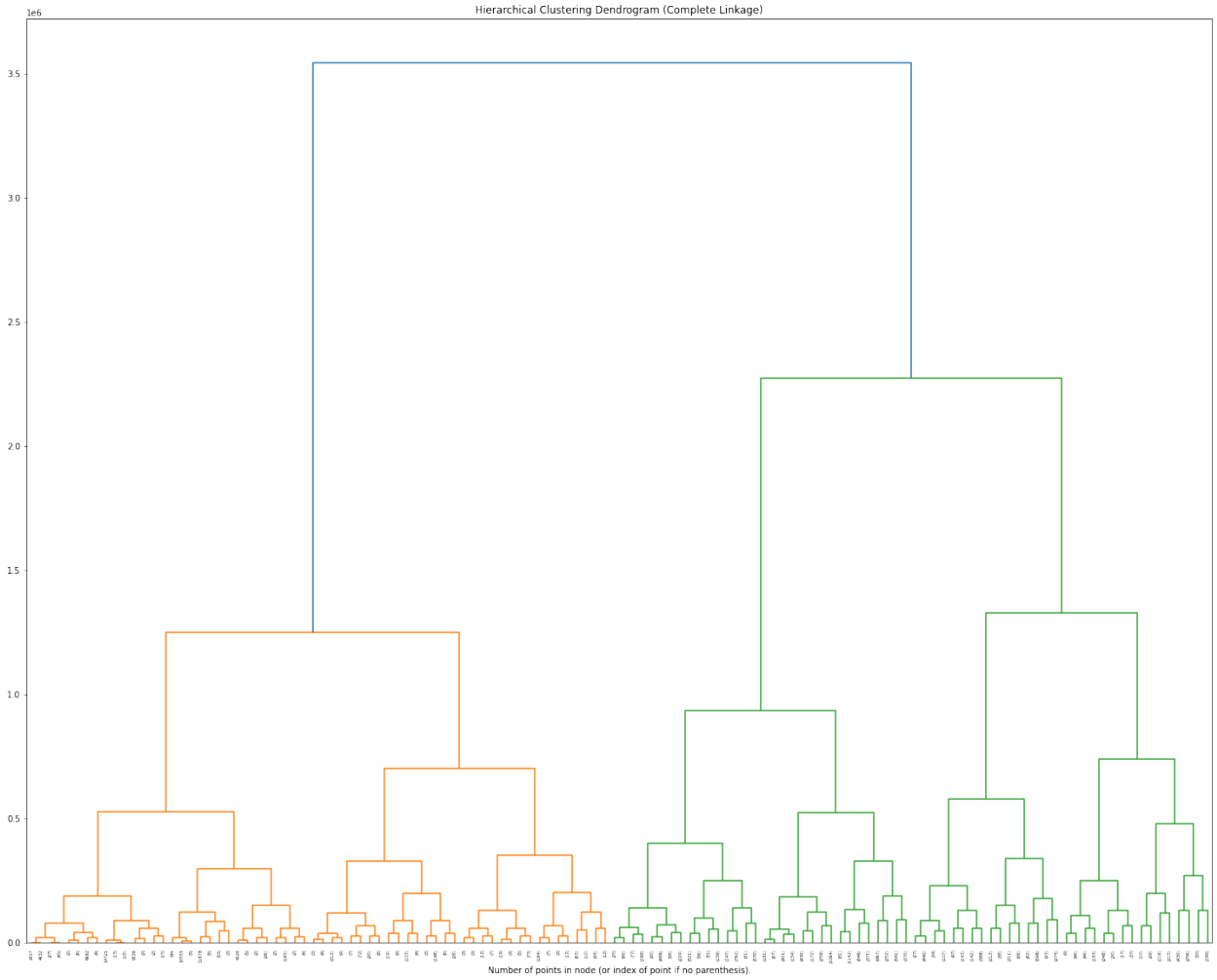

```
model = AgglomerativeClustering(distance_threshold =0,
n_clusters=None, compute_distances=True,linkage='complete').fit(tmp)

plt.figure(figsize=(25,20))
plt.title("Hierarchical Clustering Dendrogram (Complete Linkage)")
plot_dendrogram(model, truncate_mode="level", p=6)
plt.xlabel("Number of points in node (or index of point if no
parenthesis).")
plt.show()
```



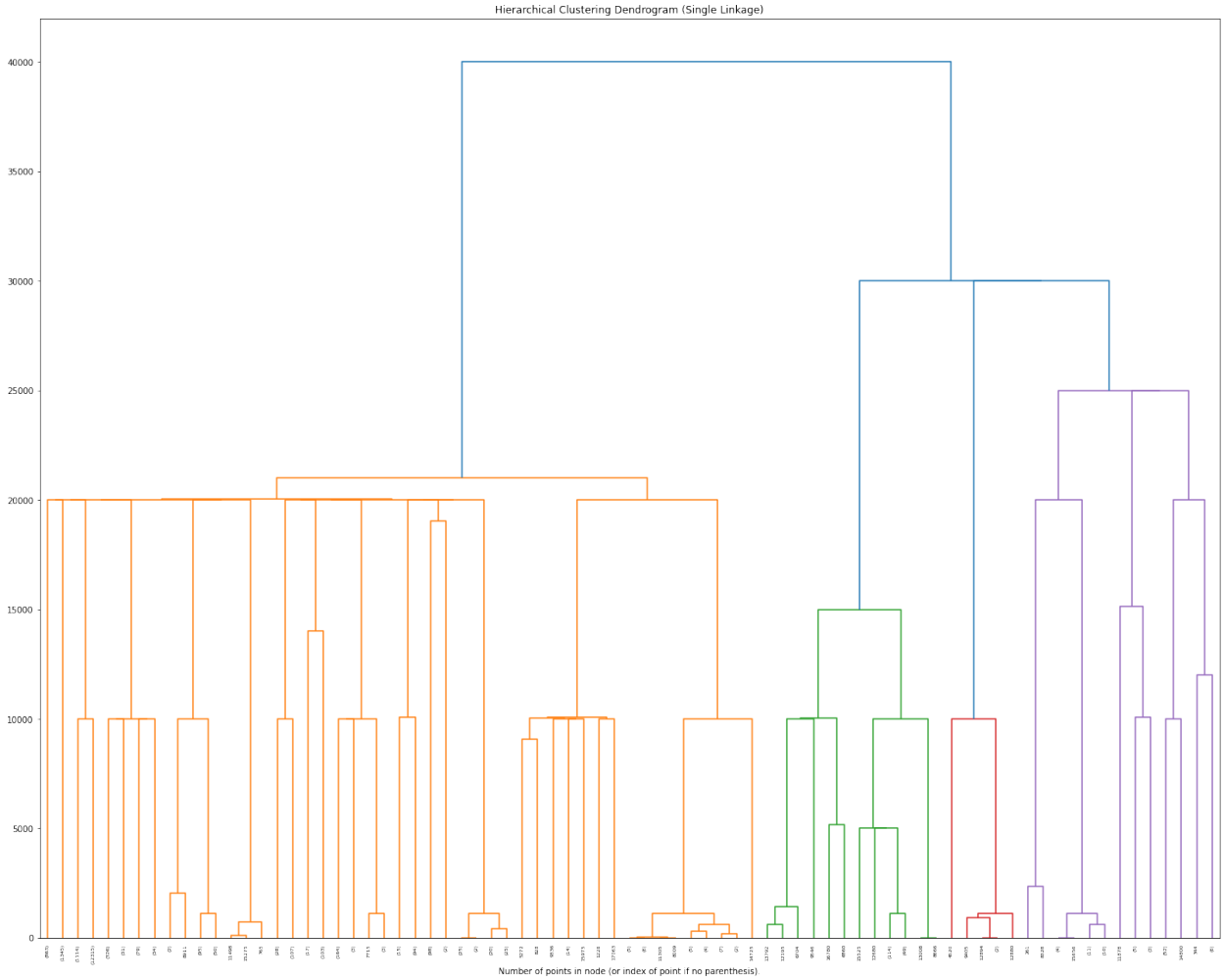

```
model = AgglomerativeClustering(n_clusters=17,
compute_distances=True,linkage='average').fit(tmp)

plt.figure(figsize=(25,20))
plt.title("Hierarchical Clustering Dendrogram (Avg Linkage)")
plot_dendrogram(model, truncate_mode="level", p=6)
plt.xlabel("Number of points in node (or index of point if no
parenthesis).")
plt.show()
```




```
model = AgglomerativeClustering(n_clusters=17,
compute_distances=True,linkage='complete').fit(tmp)

plt.figure(figsize=(25,20))
plt.title("Hierarchical Clustering Dendrogram (Complete Linkage)")
plot_dendrogram(model, truncate_mode="level", p=6)
plt.xlabel("Number of points in node (or index of point if no
parenthesis).")
plt.show()
```




```
model = AgglomerativeClustering(n_clusters=5,
compute_distances=True,linkage='single').fit(tmp)

plt.figure(figsize=(25,20))
plt.title("Hierarchical Clustering Dendrogram (Single Linkage)")
plot_dendrogram(model, truncate_mode="level", p=6)
plt.xlabel("Number of points in node (or index of point if no
parenthesis).")
plt.show()
```



Number of clusters around 2 seems optimal in most cases, while in last plot(with single linkage) number of clusters around 16 is optimal

Insights/ Recommendations

Insights

Recommendations