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

Problem statement

Scaler is an online tech-versity offering intensive computer science & Data Science courses through live classes delivered by tech leaders and subject matter experts. The meticulously structured program enhances the skills of software professionals by offering a modern curriculum with exposure to the latest technologies. It is a product by InterviewBit.

You are working as a data scientist with the analytics vertical of Scaler, focused on profiling the best companies and job positions to work for from the Scaler database. You are provided with the information for a segment of learners and tasked to cluster them on the basis of their job profile, company, and other features. Ideally, these clusters should have similar characteristics.

```
data = pd.read_csv('data/scaler_clustering.csv')

data =data.sample(frac=1 , random_state=42)

data.rename(columns={'Unnamed: 0' : 'id'} , inplace=True)

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 205843 entries, 189818 to 121958
Data columns (total 7 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   id                205843 non-null  int64  
 1   company_hash      205799 non-null  object 
 2   email_hash        205843 non-null  object 
 3   orgyear           205757 non-null  float64
 4   ctc               205843 non-null  int64  
 5   job_position      153279 non-null  object 
 6   ctc_updated_year  205843 non-null  float64
dtypes: float64(2), int64(2), object(3)
memory usage: 12.6+ MB
```

```
print(data.duplicated().sum())
data.drop_duplicates(inplace=True)
print(data.duplicated().sum())
```

```
0
0
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 205843 entries, 189818 to 121958
Data columns (total 7 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   id                205843 non-null  int64  
 1   company_hash      205799 non-null  object 
 2   email_hash        205843 non-null  object 
 3   orgyear           205757 non-null  float64
 4   ctc               205843 non-null  int64  
 5   job_position      153279 non-null  object 
 6   ctc_updated_year  205843 non-null  float64
dtypes: float64(2), int64(2), object(3)
memory usage: 12.6+ MB
```

```
data.describe()
```

```
                  id        orgyear           ctc  ctc_updated_year
count  205843.000000  205757.000000  2.058430e+05     205843.000000
mean   103273.941786    2014.882750  2.271685e+06       2019.628231
std     59741.306484      63.571115  1.180091e+07          1.325104
min         0.000000       0.000000  2.000000e+00       2015.000000
25%     51518.500000    2013.000000  5.300000e+05       2019.000000
50%    103151.000000    2016.000000  9.500000e+05       2020.000000
75%    154992.500000    2018.000000  1.700000e+06       2021.000000
max    206922.000000   20165.000000  1.000150e+09       2021.000000
```

1. min org year is 0 and max is 20165 -- this seem wrong entry
2. ctc min is 2 and max is -- this seems worng entry

```
data.isna().sum()/data.shape[0]
```

```
id                  0.000000
company_hash        0.000214
email_hash          0.000000
orgyear             0.000418
ctc                 0.000000
job_position        0.255360
ctc_updated_year    0.000000
dtype: float64
```

1. job_position has almost 25% missing values

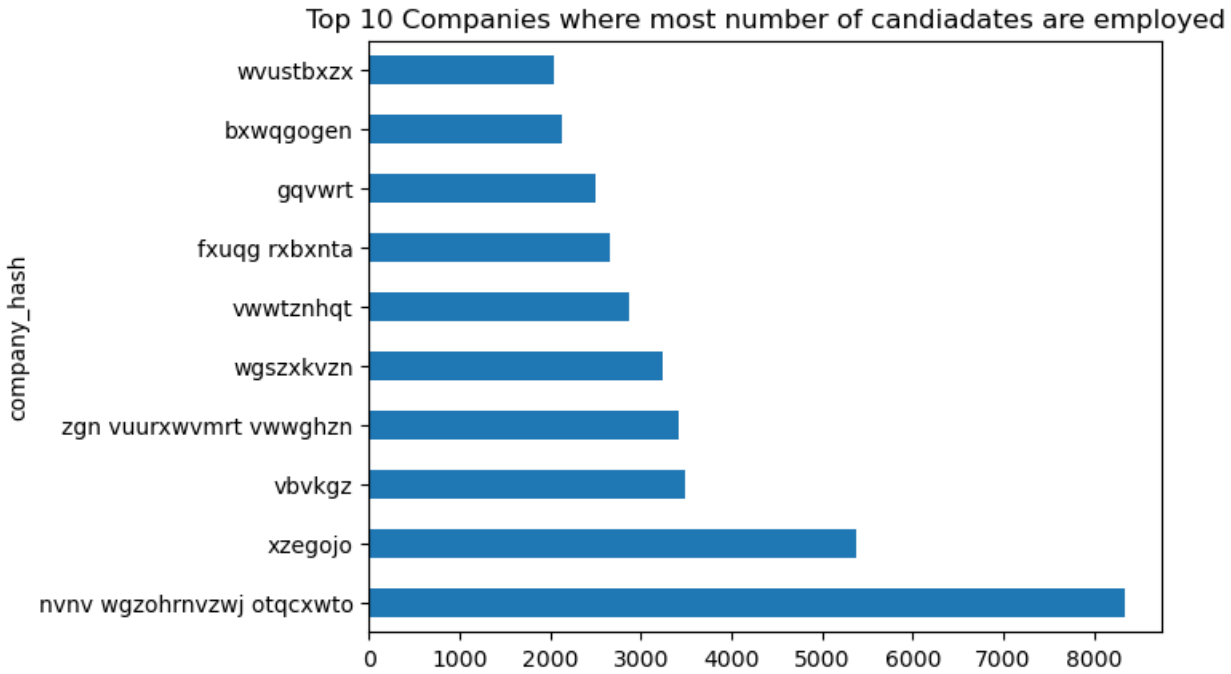
```
data.head()
```

```
            id      company_hash  \
189818  190756            vnxaxc   
126587  126989  uhmrxwxo ovuxtzn   
186392  187300          otznxtg   
57218    57290   fton vsxrt rvmo   
```

```
99723    99934           xzegojo

                                                email_hash  orgyear
ctc  \
189818  e2b961cf0e0fb48019912984ab9baab856a4ac8f19f3df...   2018.0
600000
126587  6ea566f60dd5803cc3adee080337379360a3d734c4ee8a...   2011.0
900000
186392  a99c2f235aa83ae355a0a61ee9c7b9e7f684b3284485d3...   2015.0
1150000
57218   7dfab469864858274a722ae3dc2224ceff6d4b65fbdf97...   2013.0
1600000
99723   0216365626735c67ce00310155b3a2d62a276fcf9bff70...   2018.0
600000

              job_position  ctc_updated_year
189818  FullStack Engineer            2019.0
126587    Android Engineer            2019.0
186392    Backend Engineer            2019.0
57218                  NaN            2021.0
99723   FullStack Engineer            2020.0
```

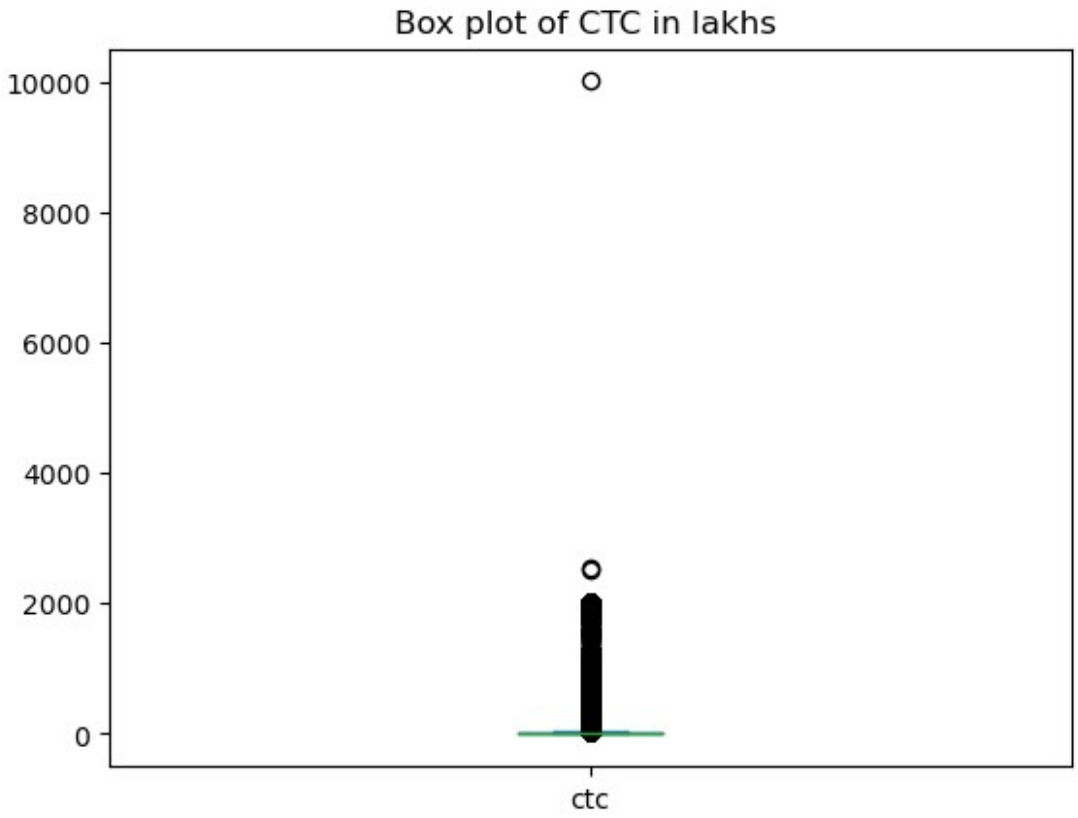
eda

```
data['company_hash'] =data['company_hash'].apply(lambda x :
x.lower().strip() if not pd.isna(x) else pd.NA )
data['email_hash'] =data['email_hash'].apply(lambda x :
x.lower().strip()  if not pd.isna(x) else pd.NA)
data['job_position'] =data['job_position'].apply(lambda x :
x.lower().strip()  if not pd.isna(x) else pd.NA )



data['company_hash'].value_counts().head(10).plot(kind='barh')
plt.title('Top 10 Companies where most number of candiadates are
employed')
plt.show()
print("Number of unique  employers : ",data['company_hash'].nunique())
```




```
Number of unique  employers :  37299
```

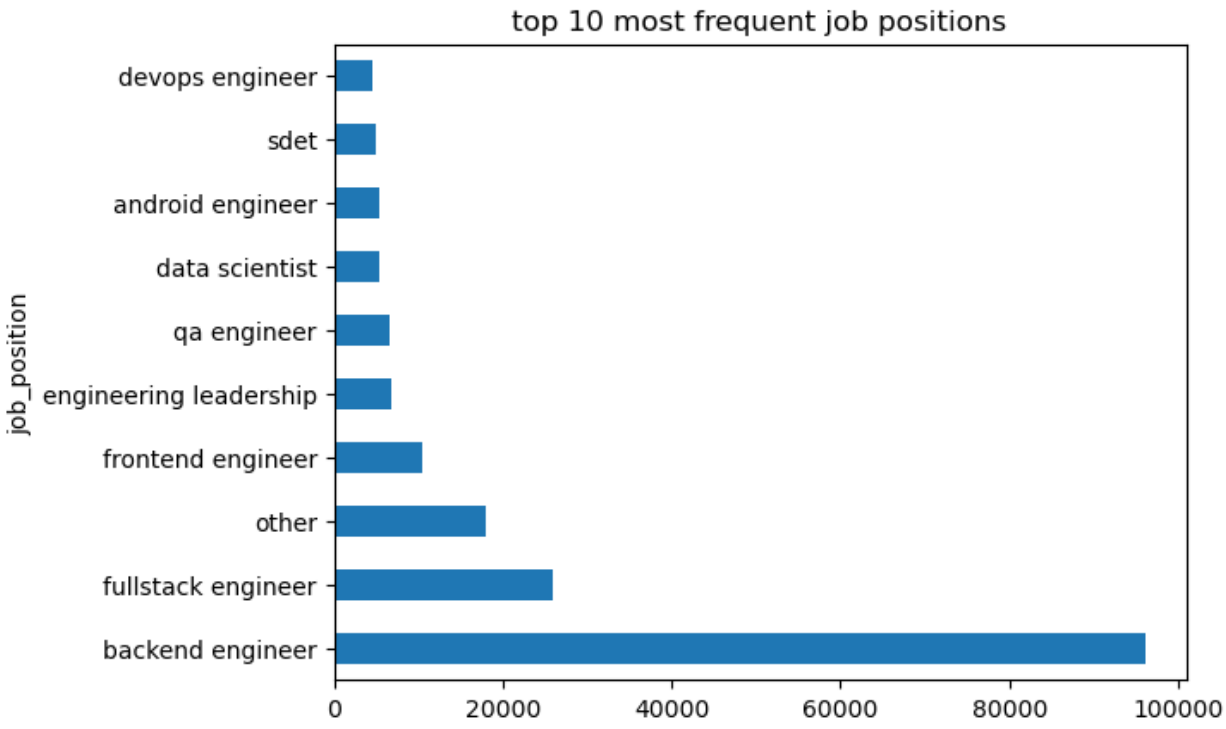
```
# ctc in lakhs
data['ctc'] = data['ctc']/100000

data.sort_values(by='ctc',  ascending=False, inplace=True)

data['ctc'].plot(kind='box')
plt.title('Box plot of CTC in lakhs ')
plt.show()
```



- People have very large salary greater than 2000 lpa which very rare
- People have very small salary less than 1 lakhs which very rare

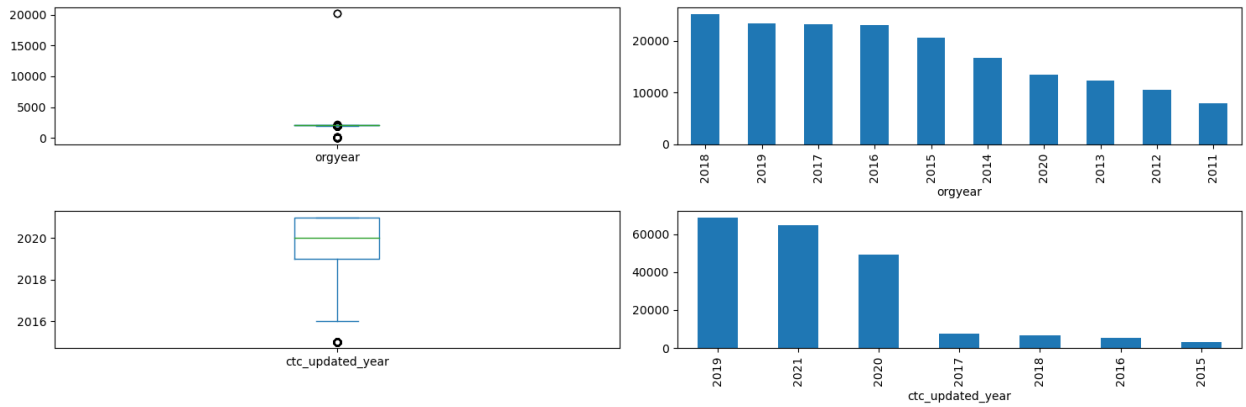
cleaning string

```
# removing special characters
# removing extra spaces
# lowercasing
# filling missing values with 'other'
# fill missing values with mode
data['job_position']
=data['job_position'].fillna(data['job_position'].mode()[0])
data['job_position'] =data['job_position'].apply(lambda x :
(re.sub('[^A-Za-z0-9 ]+', '', x).lower().strip()) if pd.isna(x)==False
else x)
data['job_position'].value_counts().head(10).plot(kind='barh')
plt.title("top 10 most frequent job positions")
plt.show()

print(" Number of unique job positions :
",data['job_position'].nunique())
print(" Number of unique email ids : ",data['email_hash'].nunique())
```



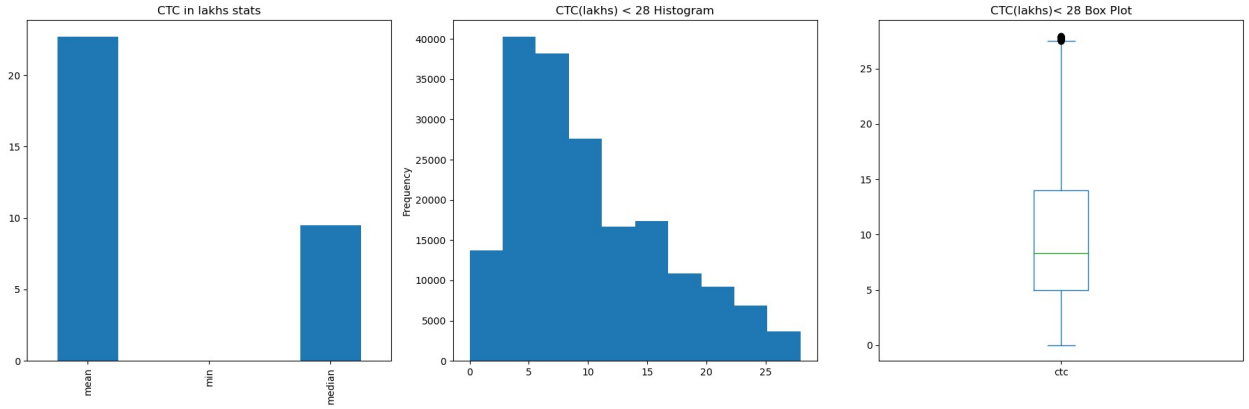

```
 Number of unique job positions :  899
 Number of unique email ids :  153443
```

```
# drop data where company_hash and orgyear is na

data.dropna(inplace=True)
data['orgyear']  =data['orgyear'].apply(lambda x : int(x))
data['ctc_updated_year']  =data['ctc_updated_year'].apply(lambda x :
int(x))

# create subplots
fig , axis  = plt.subplots(2,2,figsize=(15,5))

# plot histogram

data['orgyear'].plot(kind='box',ax=axis[0,0])
data['orgyear'].value_counts().head(10).plot(kind='bar' ,
ax=axis[0,1])
data['ctc_updated_year'].plot(kind='box',ax=axis[1,0])
data['ctc_updated_year'].value_counts().head(10).plot(kind='bar' ,
ax=axis[1,1])
plt.tight_layout()
```



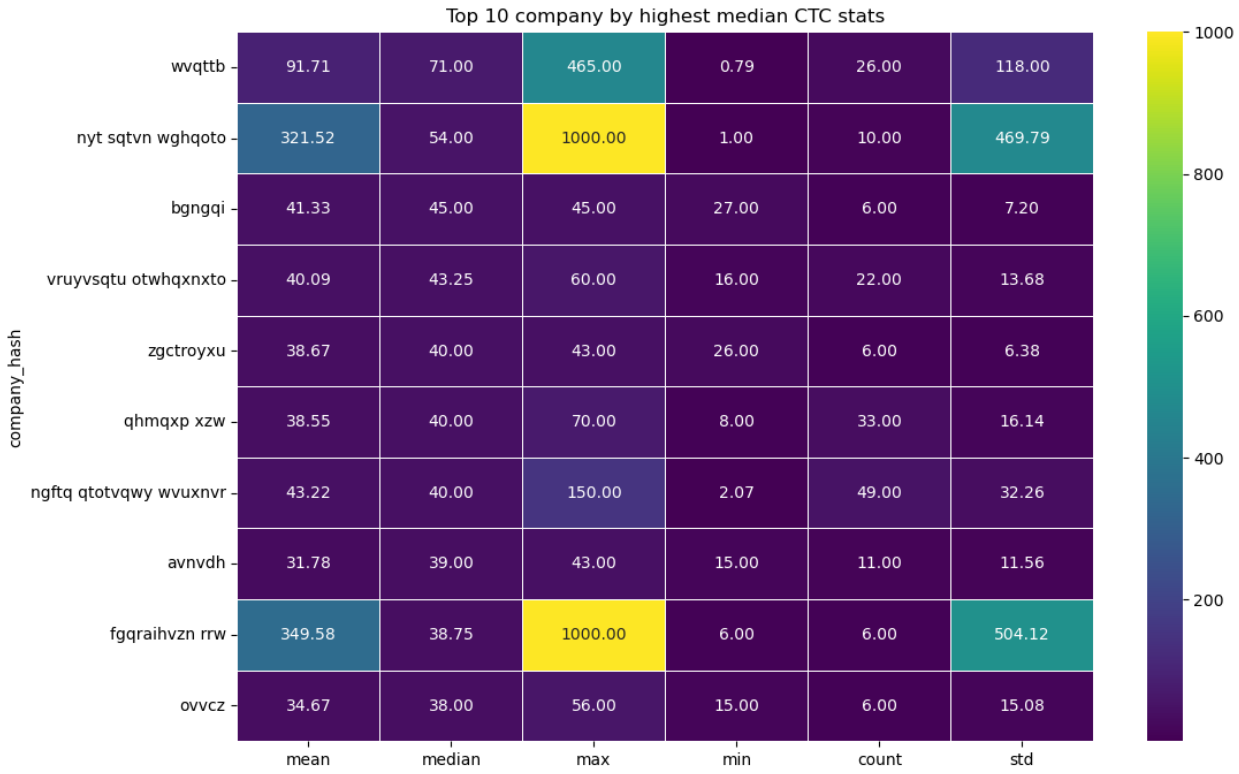
- min join date is 1986 and max is 2021
- most frequent orgyear is 2018

```
fig, axes = plt.subplots(1, 3, figsize=(18, 6))

# First subplot: Bar plot for mean, min, median
data['ctc'].agg(['mean','min', 'median']).plot(kind='bar', ax=axes[0])
axes[0].set_title("CTC in lakhs stats")

# Second subplot: Histogram for CTC < 28
data[data['ctc'] < 28]['ctc'].plot(kind='hist', ax=axes[1])
axes[1].set_title("CTC(lakhs) < 28 Histogram")

# Third subplot: Box plot for CTC < 28
data[data['ctc'] < 28]['ctc'].plot(kind='box', ax=axes[2])
axes[2].set_title("CTC(lakhs)< 28 Box Plot")

# Adjust layout to prevent overlap
plt.tight_layout()

# Display the plots
plt.show()
```



- salary is highly right skewed

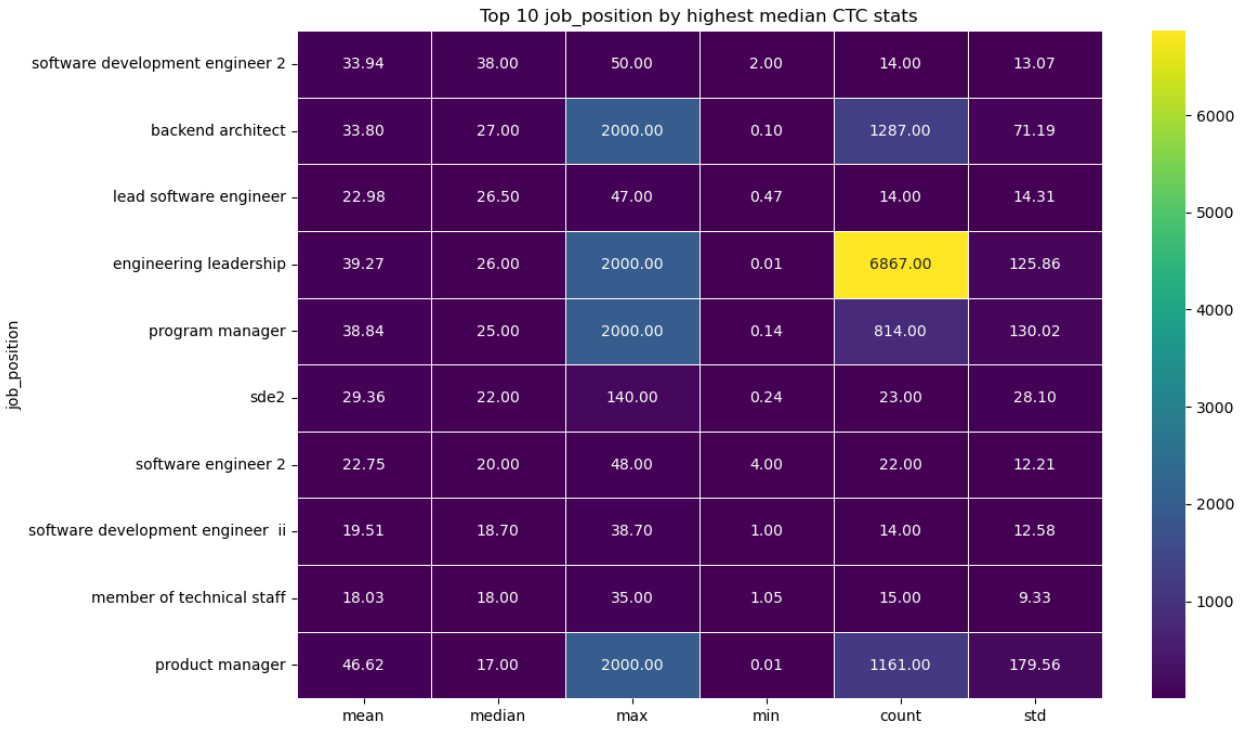
```
agg_data = data.groupby('company_hash')
['ctc'].agg(['mean','median','max','min','count' ,'std']).sort_index()
agg_data =agg_data[agg_data['count']>5].sort_values(by=['median'] ,
ascending=False).head(10 )

# Create a heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(agg_data, annot=True ,fmt=".2f", cmap='viridis',
linewidths=.5)

# Set the title
plt.title("Top 10 company by highest median CTC stats")

# Display the heatmap
plt.show()
```



- outlier are making mean very unreliable
- Large std of ctc are clear indicator large salary range

```
agg_data = data.groupby('job_position')
['ctc'].agg(['mean','median','max','min','count' ,'std']).sort_index()
agg_data =agg_data[agg_data['count']>10].sort_values(by=['median'] ,
ascending=False).head(10 )
```

```
# Create a heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(agg_data, annot=True ,fmt=".2f", cmap='viridis',
linewidths=.5)

# Set the title
plt.title("Top 10 job_position by highest median CTC stats")

# Display the heatmap
plt.show()
```



- Top earner job position is software development engineer 2 based on median salary
- There are many job position with high variation is salary example product manager , program manager , engineering leadership/

remove outliers

```
# Detect outliers
mean_ctc = data['ctc'].mean()
std_ctc = data['ctc'].std()
median_ctc = data['ctc'].median()


upper_threshold = mean_ctc + (2.5* std_ctc)
```

```
lower_threshold = mean_ctc - (.17* std_ctc)
print(f"upper_threshold :{ upper_threshold} , lower_threshold :
{ lower_threshold}")

# filling with median
data['ctc'] = np.where((data['ctc'] > upper_threshold) | (data['ctc']
<lower_threshold), median_ctc, data['ctc'])
```

```
upper_threshold :317.7353635981371 ,
lower_threshold :2.651406082804474
```

```
temp =data[data['orgyear']  > 2024]
print('how can joining date be more then current year ')
print(temp['orgyear'].value_counts().T)

# removing those data
data.drop(index =temp.index,inplace=True)

# joining date less then 1970 should be very rare removing it
temp =data[data['orgyear']<1970]

print('joining date less then 1970 should be very rare removing it ')
print(temp['orgyear'].value_counts().T)
# removing those data
data.drop(index =temp.index,inplace=True)
del temp
```

```
how can joining date be more then current year
orgyear
2025     13
2026      9
2029      5
2031      5
2028      4
20165     2
2107      1
2204      1
2101      1
2106      1
2027      1
Name: count, dtype: int64
joining date less then 1970 should be very rare removing it
orgyear
0       17
3        6
2        3
91       3
1        2
5        2
```

```
6         2
201       1
1900      1
38        1
200       1
4         1
206       1
83        1
208       1
209       1
Name: count, dtype: int64
```

```
data['Years_of_Experience']=data['ctc_updated_year']- data['orgyear']
print("since year of experience can be negative we will remove it")
temp =data[data['orgyear']  > data['ctc_updated_year']   ]

data.drop(index =temp.index,inplace=True)
print("removing year of experience  which occurance is less then 30")
x =data['Years_of_Experience'].value_counts()
yoe =x[x<30].index.values
data=data[~data['Years_of_Experience'].isin(yoe)]

del x ,yoe ,temp
```

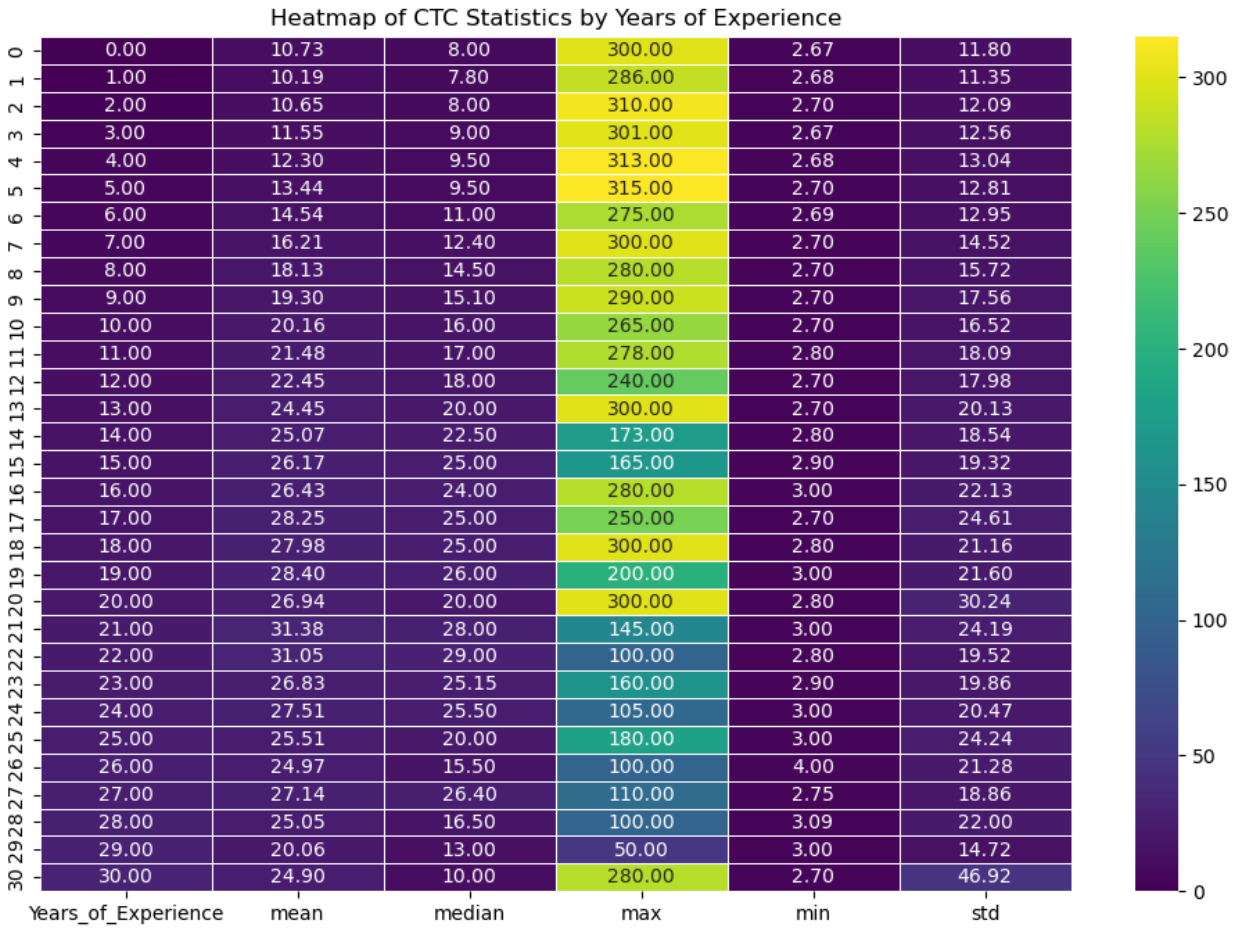
```
since year of experience can be negative we will remove it
removing year of experience  which occurance is less then 30
```

- employee start date > ctc_updated_year
- This could be erronous data -- did employee not get hike when joining.

feature engineering

```
agg_data = data.groupby('Years_of_Experience')
['ctc'].agg(['mean','median','max','min','count' ,'std']).sort_index()

agg_data =agg_data.reset_index().drop(['count'],axis=1)
plt.figure(figsize=(12, 8))
sns.heatmap(agg_data, annot=True ,fmt=".2f", cmap='viridis',
linewidths=.5)


plt.title("Heatmap of CTC Statistics by Years of Experience")


plt.show()
```

```
del agg_data
```



- All levels of Years of Experience have very high maximum CTC values.
- Individuals with 0 years of experience have an exceptionally high CTC, almost 300 LPA, which is significantly higher than that of more experienced individuals.

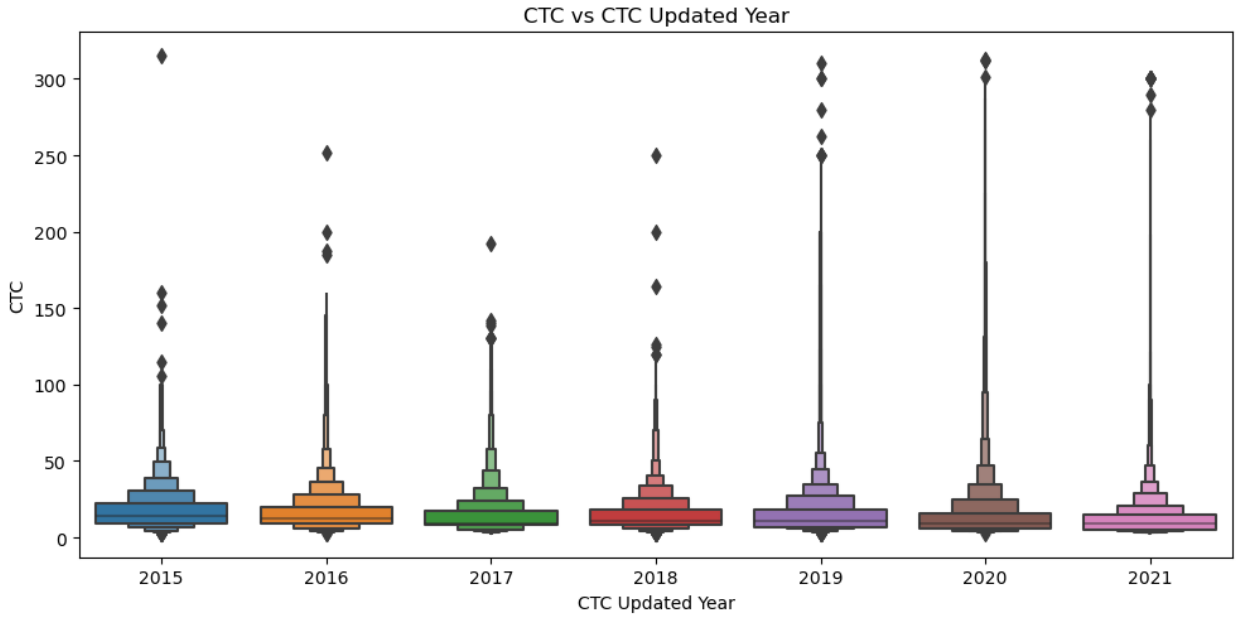
manual clustering

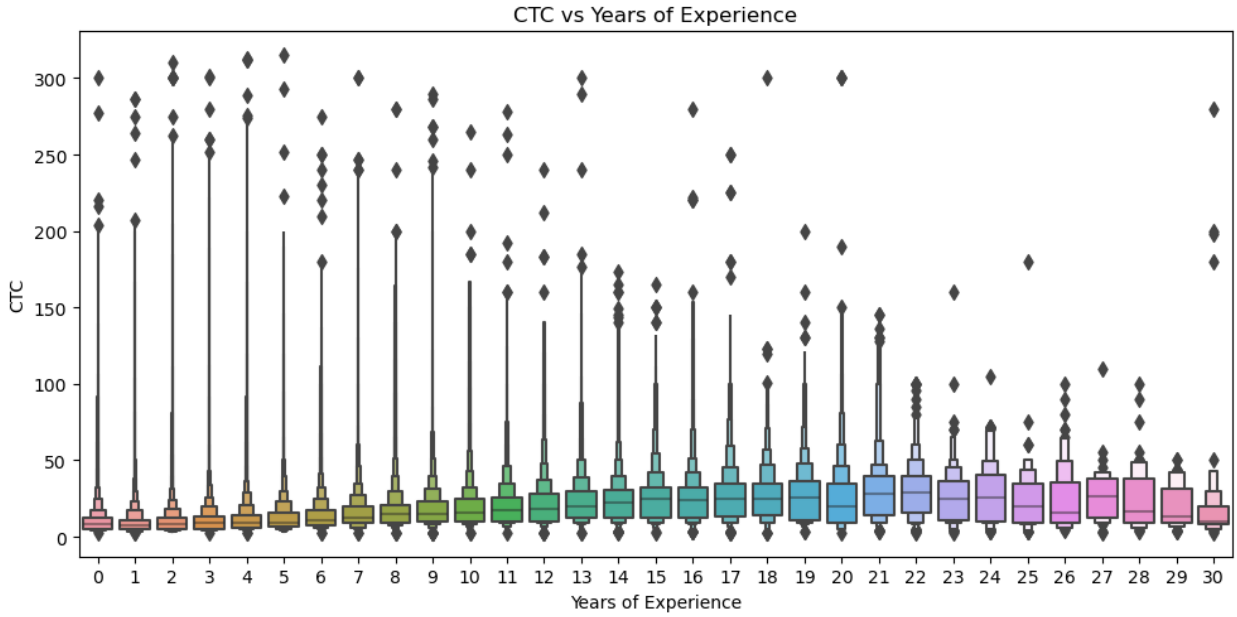
- compared to market average how there median salary faring by employee , job_position , compamy , yoe

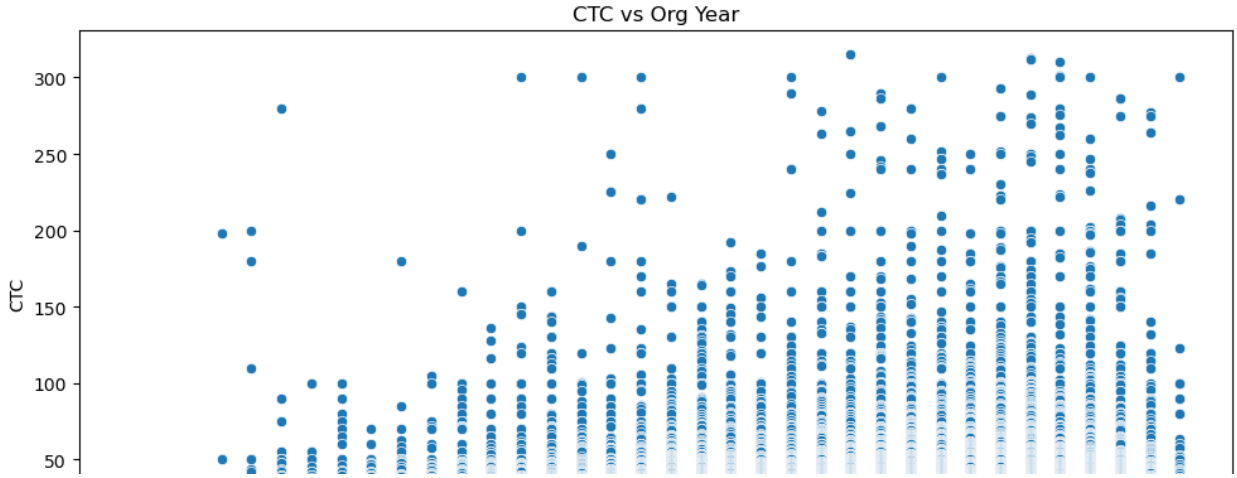
```
q1 =data['ctc'].quantile(0.25)
q3 =data['ctc'].quantile(0.75)

def bin_ctc(x ,q1 =q1 ,q9 =q3) :
    """_summary_

    Args:
```

```
        x (_type_): {high : 1 , medium : 2 , low : 3}

    Returns:
        _type_: _description_
    """
    if x>=q9:
        return "high"
    elif x>q1  and  x<q9:
        return 'medium'
    elif x<=q1:
        return 'low'




def feature_mapper( vals , group_columns , mapper):

    mapper_value =vals[group_columns]

    ctc = vals['ctc']
    if  not isinstance(mapper_value ,str ) and not
isinstance(mapper_value , int ):
        mapper_value = list(mapper_value.values)
        mapper_value.append(0.25)
        q1_k = tuple(mapper_value)
        mapper_value = list(mapper_value[:-1])
        mapper_value.append(0.75)
        q3_k = tuple(mapper_value)
        q1 =mapper.get(q1_k)
        q3 = mapper.get(q3_k)
        return bin_ctc(ctc , q1 ,q3)
    q1 =mapper.get((mapper_value,0.25))
    q3 = mapper.get((mapper_value,0.75))
    return bin_ctc(ctc , q1 ,q3)


def feature_mapper_with_respect_to_market( vals , q1 , q3 ):
    ctc = vals['ctc']
    return bin_ctc(ctc , q1 ,q3)


labels = ['0-6', '6-12', '12-18', '18-24', '24-30']
bins = [0, 6, 12, 18, 24, 30]

data['Years_of_Experience_binned'] =
pd.cut(data['Years_of_Experience'], bins=bins, labels=labels,
right=False)

import matplotlib.pyplot as plt
import seaborn as sns
```

```
fig, axes = plt.subplots(3, 1, figsize=(10, 15))


sns.boxenplot(x=data['ctc_updated_year'], y=data['ctc'], ax=axes[0])
axes[0].set_title('CTC vs CTC Updated Year')
axes[0].set_xlabel('CTC Updated Year')
axes[0].set_ylabel('CTC')


sns.boxenplot(x=data['Years_of_Experience'], y=data['ctc'],
ax=axes[1])
axes[1].set_title('CTC vs Years of Experience')
axes[1].set_xlabel('Years of Experience')
axes[1].set_ylabel('CTC')


sns.scatterplot(x=data['orgyear'], y=data['ctc'], ax=axes[2])
axes[2].set_title('CTC vs Org Year')
axes[2].set_xlabel('Org Year')
axes[2].set_ylabel('CTC')



# Adjust layout
plt.tight_layout()

# Show the plots
plt.show()
```

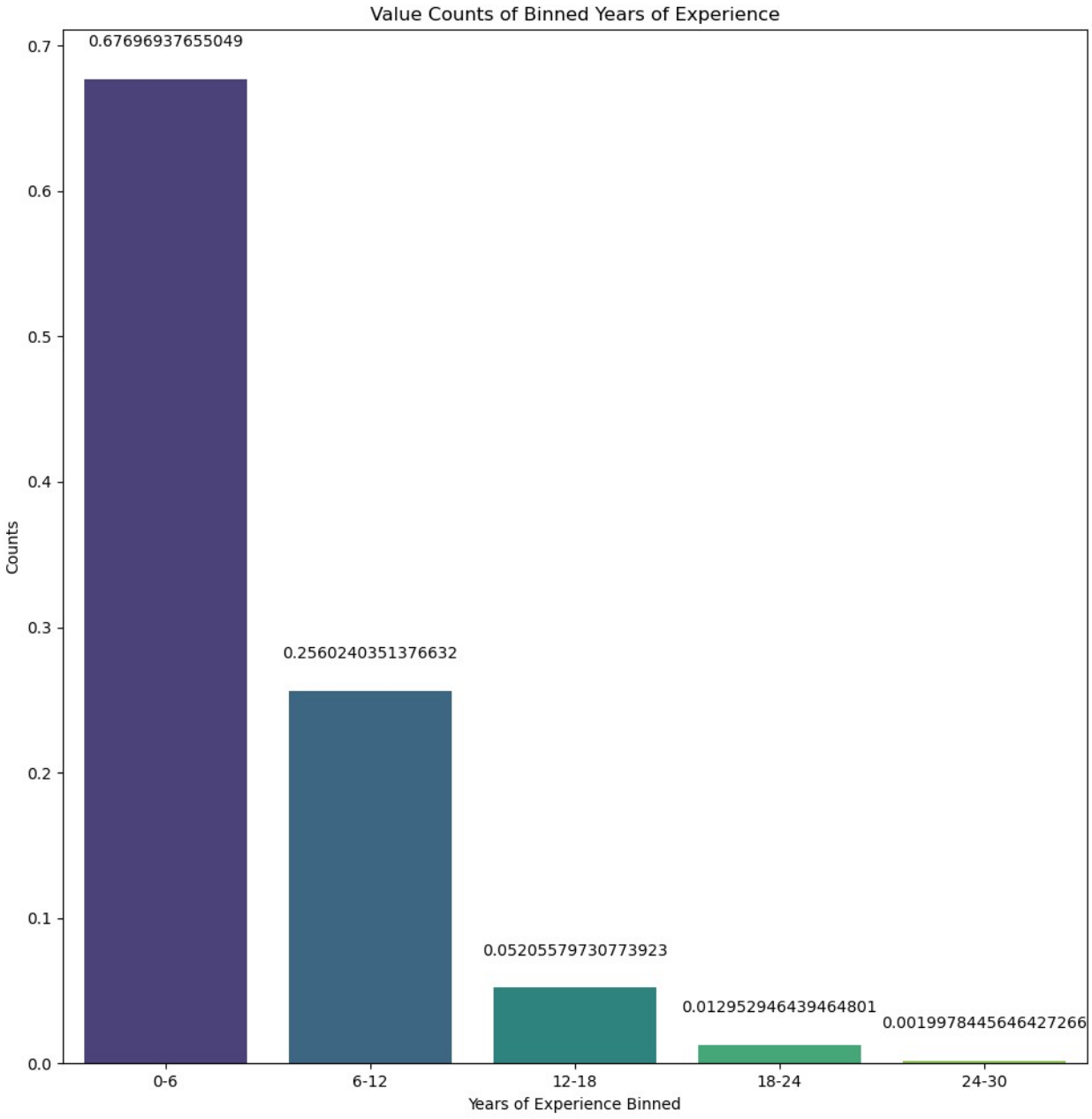

CTC vs CTC Updated Year
CTC
CTC Updated Year
0
50
100
150
200
250
300
2015
2016
2017
2018
2019
2020
2021

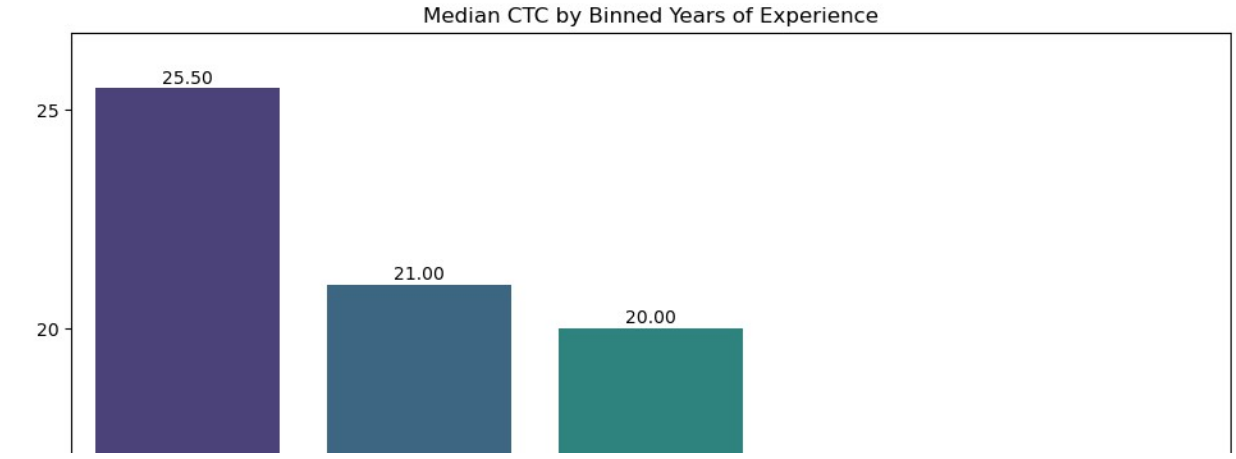

CTC vs Years of Experience
CTC
Years of Experience
0
50
100
150
200
250
300
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30


CTC vs Org Year
CTC
50
100
150
200
250
300

- There is high variablity in salaries for 0-15 years of experience , some earn very low some very high

```
import matplotlib.pyplot as plt
import seaborn as sns

value_counts =
data['Years_of_Experience_binned'].value_counts( normalize=True)
median_ctc = data.groupby('Years_of_Experience_binned')
['ctc'].median().sort_values(ascending=False)
std_ctc = data.groupby('Years_of_Experience_binned')
['ctc'].std().sort_values(ascending=False)


fig, axes = plt.subplots(2, 1, figsize=(10, 20))

sns.barplot(x=value_counts.index, y=value_counts.values, ax=axes[0],
palette="viridis" , order=value_counts.index)
axes[0].set_title('Value Counts of Binned Years of Experience')
axes[0].set_xlabel('Years of Experience Binned')
axes[0].set_ylabel('Counts')


for i, v in enumerate(value_counts.values):
    axes[0].text(i, v + 0.02, f'{v}', ha='center', va='bottom')


sns.barplot(x=median_ctc.index, y=median_ctc.values, ax=axes[1],
palette="viridis" , order=median_ctc.index)
axes[1].set_title('Median CTC by Binned Years of Experience')
axes[1].set_xlabel('Years of Experience Binned')
axes[1].set_ylabel('Median CTC')

for i, v in enumerate(median_ctc.values):
    axes[1].text(i, v + 0.02, f'{v:.2f}', ha='center', va='bottom')



plt.tight_layout()

plt.show()
```


Value Counts of Binned Years of Experience
0.67696937655049
0.2560240351376632
0.05205579730773923
0.012952946439464801
0.0019978445646427266
Counts
Years of Experience Binned
0-6
6-12
12-18
18-24
24-30


Median CTC by Binned Years of Experience
25.50
21.00
20.00

- 67% of the datapoint is in 0-6 years of experience
- less then 1% of datapoint is in 24-30 years of experience
- 18-24 years of experience has the highest median CTC
- 0-6 yoe has lowest median ctc

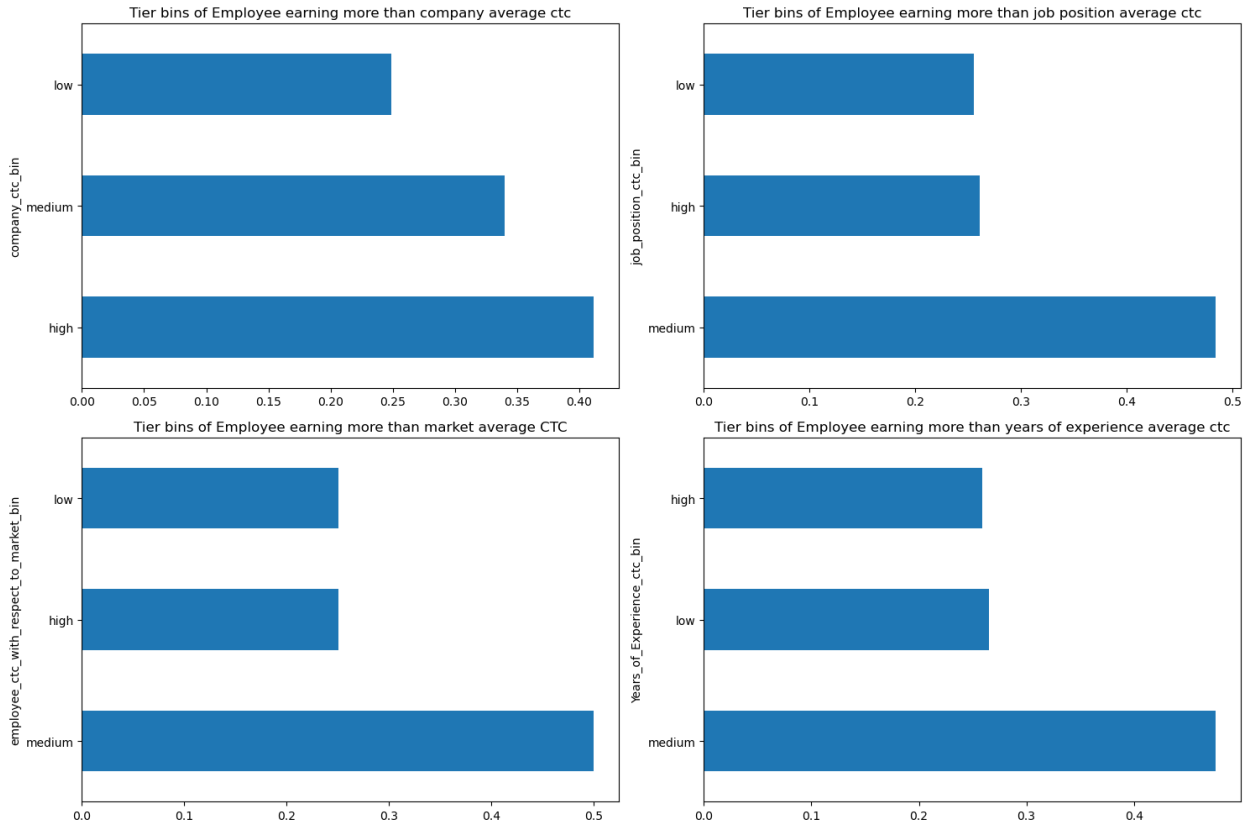
```
data.drop(columns=['Years_of_Experience_binned'],inplace=True)
```

feature defination

- company_ctc_bin -- employee earning more than company avg
- job_position_ctc_bin -- employee earning more than job position avg
- Years_of_Experience_ctc_bin -- employee earning more than years of experience avg
- employee_ctc_with_respect_to_market_bin -- employee earning more than market average ctc

```
company_ctc_bin =data.groupby('company_hash')
['ctc'].quantile([0.25,0.75]).to_dict()
data['company_ctc_bin']=data.apply(lambda vals: feature_mapper(vals,
group_columns ='company_hash' , mapper = company_ctc_bin) , axis=1)

job_position_ctc_bin =data.groupby('job_position')
['ctc'].quantile([0.25,0.75]).to_dict()
data['job_position_ctc_bin'] =data.apply(lambda vals:
feature_mapper(vals, group_columns ='job_position' , mapper =
job_position_ctc_bin) , axis=1)

data['employee_ctc_with_respect_to_market_bin'] =data.apply(lambda
vals: feature_mapper_with_respect_to_market (vals , q1, q3), axis=1)
Years_of_Experience_ctc_bin =data.groupby('Years_of_Experience')
['ctc'].quantile([0.25,0.75]).to_dict()
data['Years_of_Experience_ctc_bin'] =data.apply(lambda vals:
feature_mapper(vals, group_columns ='Years_of_Experience' , mapper =
Years_of_Experience_ctc_bin) , axis=1)

del company_ctc_bin , job_position_ctc_bin ,
Years_of_Experience_ctc_bin

binned_features =[x  for x in data.columns  if 'bin'  in x]



bin_descriptions = {
    "company_ctc_bin": "Tier bins of Employee earning more than
company average ctc",
    "job_position_ctc_bin": "Tier bins of Employee earning more than
job position average ctc",
    "Years_of_Experience_ctc_bin": "Tier bins of Employee earning more
than years of experience average ctc",
    "employee_ctc_with_respect_to_market_bin": "Tier bins of Employee
earning more than market average CTC"
```

```
}


n_features = len(binned_features)
n_cols = 2
n_rows = (n_features + 1) // n_cols

fig, axes = plt.subplots(n_rows, n_cols, figsize=(15, 10))

axes = axes.flatten()

for i, x in enumerate(binned_features):
    ax = axes[i]
    data[x].value_counts(normalize=True).plot(kind='barh', ax=ax)
    ax.set_title(bin_descriptions.get(x))


for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()
plt.show()
```



1. **Company CTC Bin**:

- **High**: 41.12% of employees earn more than the company's average CTC.
- **Medium**: 34.02% of employees earn around the company's average CTC.
- **Low**: 24.87% of employees earn less than the company's average CTC.

Insight: A significant portion of employees (41.12%) are earning well above the company average, indicating a possible skew towards higher compensation within the company.

2. **Job Position CTC Bin**:
   - **Medium**: 48.35% of employees earn around the job position's average CTC.
   - **High**: 26.11% of employees earn more than the job position's average CTC.
   - **Low**: 25.54% of employees earn less than the job position's average CTC.

   Insight: The majority of employees (48.35%) are earning around the average CTC for their job position, with relatively equal distributions among those earning more and less than the average.

3. **Employee CTC with Respect to Market Bin**:
   - **Medium**: 49.94% of employees earn around the market average CTC.
   - **High**: 25.03% of employees earn more than the market average CTC.
   - **Low**: 25.03% of employees earn less than the market average CTC.

   Insight: Nearly half of the employees (49.94%) earn around the market average, with the remaining employees evenly split between earning more and less than the market average.

4. **Years of Experience CTC Bin**:
   - **Medium**: 47.56% of employees earn around the average CTC for their years of experience.
   - **Low**: 26.54% of employees earn less than the average CTC for their years of experience.
   - **High**: 25.90% of employees earn more than the average CTC for their years of experience.

   Insight: Most employees (47.56%) earn around the average CTC for their years of experience, with the distribution of those earning more and less being relatively balanced.

General Insights:

1. **Balance in Earnings**:
   - Across all four binned features, a considerable proportion of employees are earning around the average for their respective bins (company, job position, market, and years of experience).
2. **Higher Earners**:
   - The **Company CTC Bin** stands out with a notably higher percentage of employees earning well above the company's average CTC (41.12%).
3. **Medium Tier Prevalence**:

- The **Medium** tier is the most common across all bins, especially in the **Job Position** and **Market** bins, indicating that many employees' earnings are around the average of their respective categories.

4. **Equitable Distribution**:
   - There is an equitable distribution between high and low earners in the **Job Position**, **Market**, and **Years of Experience** bins, suggesting a balanced compensation structure relative to these factors.

These insights can help identify trends and outliers in compensation, aiding in strategic decisions regarding salary adjustments, recruitment, and retention.

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

```
data[data['company_ctc_bin']=='high'].sort_values('ctc' , ascending =
False)[['email_hash' ,'ctc']].head(10)
```

	email_hash	ctc
204715	eb9df9d736e0380ae9534f2c078973472859e6688f012a...	315.0
33952	3769a3147e30ca5d7c861c491621389c3bd9d8f97c5a2e...	313.0
16828	5cfe552d41688874fb12ddec7f2421e63b8c1e7a22eec1...	312.0
6746	c9a89c9e3abebb6b84e9d4cf5f819a38cc2b2ccbaa4d26...	312.0
22887	7c3d7ee6c0b7ec05685d40328febcdf5761434cbbf9fc6...	310.0
5422	0e3fc98e0403cb26fbe66ef0d15696f30231280be85ae7...	301.0
98759	14c1588f66c0c47dc710b6c515579a2f6313a9ee7210f7...	300.0
75229	ada6b1c8fb17f731c2135a764f9d59ee210b16c8abb6d6...	300.0
2661	f0bb5f1140e4c63e3214803b44ff38e5af9cb7868366f3...	300.0
42420	f1002fcda63332a7075cc201fabd9dad0cdb1b514dc123...	300.0

- Top employess are earning around 300 lpa

Top 10 employees of data science in each company earning more than their peers - Class 1

```
index =data['job_position'][ (data['job_position'].isin(['data
analyst' ,'data scientist'])
&(data['company_ctc_bin']=='high' ))].index

temp =data.loc[index ,: ]
# company with more than 10 employees in data science
cnts =temp['company_hash'].value_counts()
index =cnts[cnts>=10].index
temp =temp[temp['company_hash'].isin(index)]

rank=temp.groupby(['company_hash'])['ctc'].rank(ascending=False)
rank =rank[rank<=10]

index =rank.index
temp =temp.loc[index ,: ]
temp
```

```
=temp[['company_hash' ,'email_hash' ,'job_position' ,'ctc']].sort_valu
es(by = ['ctc'] , ascending=False )
display(temp)

display(temp['ctc'].agg(['mean','median','max','min','count' ,'std']))

del temp,index,rank,cnts
```

```
                     company_hash  \
6413    nvnv wgzohrnvzwj otqcxwto
173187                       wxnx
72489                         zvz
25547                         xmb
137414  nvnv wgzohrnvzwj otqcxwto
...                            ...
35985                    wvustbxzx
31151                ntwy bvyxzaqv
89766                ntwy bvyxzaqv
65711                      xzegojo
204862               ntwy bvyxzaqv

                                                    email_hash
job_position  \
6413    92e74560ace875ff0046b22e57fd7138557ab6d2f29881...    data
analyst
173187  f7b7c771ccdbbca7248002ba83f7a176baa974c2c7bb8f...  data
scientist
72489   80f1ae60373f0ada3b75ce19eb585f8cf112de3cfa6ea7...  data
scientist
25547   b5dc6ad6d8d8f04312c34285a3c45fd9ffdc73ff3f1205...  data
scientist
137414  9d5cafecc23737f2a4663b0dbde9db23213992fb1fb0d8...    data
analyst
...                                                   ...
...
35985   b69ff7cff8dcfbfc2cebeccbea707783228f0f4cc1ee7f...    data
analyst
31151   d7c3d00e212a98a5dce83e1cbf48b4e8d8fb96de1dd4cf...  data
scientist
89766   3f87ed7ee11308ddbfce10d911b619bec3897b7e416de9...  data
scientist
65711   470278f7a884a0e4749956c8cd4ebeed4afd52aa950eac...  data
scientist
204862  20ea3c0ddd4d97a4960e780f3abb4fdb51344e159be258...  data
scientist

           ctc
6413    293.00
173187  242.00
72489   200.00
```

```
25547   200.00
137414  188.87
...        ...
35985    11.50
31151    11.50
89766    11.00
65711    10.80
204862   10.00

[269 rows x 4 columns]

mean       33.870223
median     23.000000
max       293.000000
min        10.000000
count     269.000000
std        34.551440
Name: ctc, dtype: float64
```

- salary of datascience job lies from 10 lpa to 242 lpa
- 50% of top 10 employee in data science company earn more than 23 lpa

Bottom 10 employees of data science in each company earning less than their peers - Class 3

```
index =data['job_position'][ (data['job_position'].isin(['data
analyst' ,'data scientist'])
&(data['company_ctc_bin']=='low' ))].index

temp =data.loc[index ,: ]
# company with more than 10 employees in data science
cnts =temp['company_hash'].value_counts()
index =cnts[cnts>=10].index
temp =temp[temp['company_hash'].isin(index)]

rank=temp.groupby(['company_hash'])['ctc'].rank(ascending=True)
rank =rank[rank<=10]

index =rank.index
temp =temp.loc[index ,: ]
temp
=temp[['company_hash' ,'email_hash' ,'job_position' ,'ctc']].sort_valu
es(by = ['company_hash'  ,'ctc'] , ascending=True )
display(temp.head(10))

display(temp['ctc'].agg(['mean','median','max','min','count' ,'std']))

del temp,index,rank,cnts
```

```
       company_hash                                          email_hash
\
170125     atrgxnnt  46dd334375d06d3ad5b21b58c63ef2446c6936097bf056...

138220     atrgxnnt  446f7f57b81e3cab0237560ce14b95f4fae9e1dbbfb037...

88212      atrgxnnt  5a94c12939034f5efee14544389805597de7d88b9f3b24...

18549      atrgxnnt  3a5f22c995b53830c1bd6abf59c2193a1a63108152664d...

24502      atrgxnnt  bd9e4252161745f7b58262433dc39371117a306612e328...

200489     atrgxnnt  89093792038328080adafb000178424094be218276d237...

204154     atrgxnnt  78312adda24a93c1b697634e075799ca4d4e8ae2cbaa1c...

133771     atrgxnnt  e0751b03bbd29ec010de79669656a2d43b62fe162d535f...

97265      atrgxnnt  435d7c9607c388814b38986cb8a6ca5dfef3623a07bdf9...

185162     atrgxnnt  1478ba0116389d3c349c2b3b397fd9eb49c94ddd2c7703...


          job_position   ctc
170125    data analyst  3.00
138220    data analyst  3.00
88212     data analyst  3.50
18549     data analyst  4.00
24502   data scientist  4.00
200489    data analyst  4.25
204154    data analyst  5.00
133771    data analyst  5.50
97265     data analyst  5.50
185162    data analyst  5.50

mean         4.873247
median       3.725000
max         12.000000
min          2.700000
count      194.000000
std          2.383457
Name: ctc, dtype: float64
```

- bottom 10 datascience employee earn anywhere from 1 lpa to 12lpa
- 50% of bottom 10 employee in data science company earn less than 3.7 lpa

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

```
temp =data[data['company_ctc_bin']=='low'].sort_values('ctc' ,
ascending = True).head(10)
display(temp)

display(temp['ctc'].agg(['mean','median','max','min','count' ,'std']))
del temp
```

```
            id        company_hash  \
71269    71368           jtowg oqr
117242  117553           vuurt xzw
161891  162554           bxwqgogen
50776    50834           bxwqgogen
169952  170728  trtwnqgzxw vqno tv
197353  198374         bxwqg egwho
74047    74152            ontqrxzs
17252    17263               uvjnb
3895      3895             stzuvwn
30725    30756           wgszxkvzn

                                                email_hash  orgyear
ctc  \
71269   65a13a171d39d52233440894fc7bd79d50a1b80946d8ed...     2019
2.67
117242  ab2f7c9f0271aa5cca079cb65d0e5bb439cf47d6764da4...     2019
2.68
161891  dad1d9e471d638f70bab93dadc110b5d0eefb18fa3eb1b...     2013
2.69
50776   dad1d9e471d638f70bab93dadc110b5d0eefb18fa3eb1b...     2013
2.69
169952  cdec71c3f343f46c91380c08b4ea25a4bc446e9fd4d4b0...     2011
2.69
197353  5aa5ad44830735f201898e872f2d1b0d003b78936829f2...     2019
2.70
74047   eab436b491ff794028c15a4de71fb039b2b47ffe1ba26e...     2013
2.70
17252   43c6b0b0a7102bada8c8071d32a1b0c8e323a9b552da4a...     2017
2.70
3895    0d16c6593cb9aa3bb26512421eaeacd41dbc354c8b63fd...     2018
2.70
30725   649e8904ff7e5165a7bb05be6171da60815276a52bf7ab...     2018
2.70

            job_position  ctc_updated_year  Years_of_Experience  \
71269   backend engineer              2019                    0
117242  backend engineer              2020                    1
```

```
161891  backend engineer              2019                      6
50776   backend engineer              2019                      6
169952  backend engineer              2015                      4
197353  backend engineer              2020                      1
74047              other              2021                      8
17252              other              2021                      4
3895         qa engineer              2020                      2
30725   support engineer              2020                      2

       company_ctc_bin job_position_ctc_bin  \
71269              low                   low
117242             low                   low
161891             low                   low
50776              low                   low
169952             low                   low
197353             low                   low
74047              low                   low
17252              low                   low
3895               low                   low
30725              low                   low

       employee_ctc_with_respect_to_market_bin
Years_of_Experience_ctc_bin
71269                                       low
low
117242                                      low
low
161891                                      low
low
50776                                       low
low
169952                                      low
low
197353                                      low
low
74047                                       low
low
17252                                       low
low
3895                                        low
low
30725                                       low
low

mean       2.692000
median     2.695000
max        2.700000
min        2.670000
count     10.000000
```

```
std        0.010328
Name: ctc, dtype: float64
```

- 50% of bottom employee earn less than 2.6 lpa

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

```
import pandas as pd

temp = data[(data['Years_of_Experience_ctc_bin'] == 'high') &
            (data['company_ctc_bin'] == 'high') &
            (data['Years_of_Experience'].isin([5, 6, 7]))]

groups = temp.groupby(['company_hash', 'Years_of_Experience'])


def get_top_10(group):
    return group.nlargest(10, 'ctc')


top_10_per_group = groups.apply(get_top_10).reset_index(drop=True)

top_10_per_group=top_10_per_group[['company_hash' ,'email_hash' ,'job_
position' ,'Years_of_Experience','ctc' ]].sort_values(by =
['company_hash' ,'job_position'  ,'ctc'] , ascending=True )
display(top_10_per_group)
```

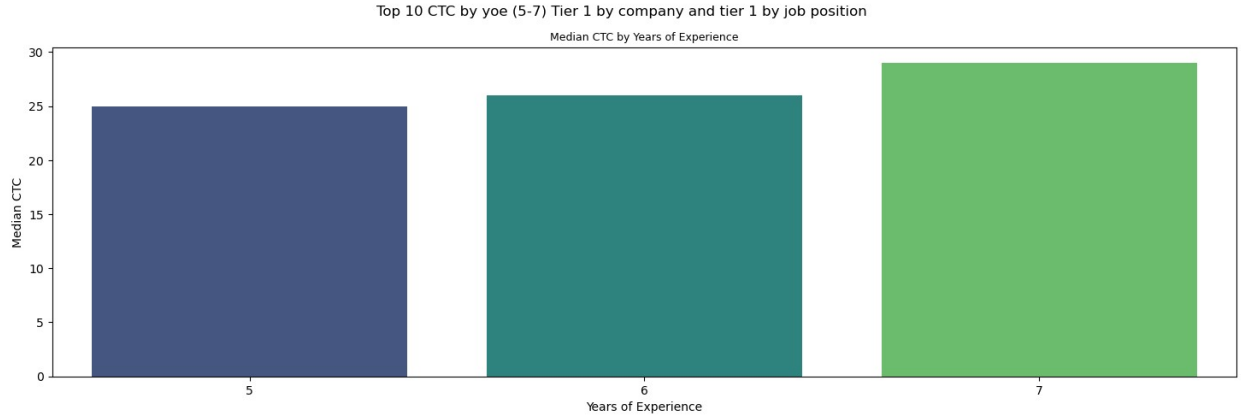
```
     company_hash
email_hash  \
2             1bs  2b50861d0780b85284d70b0d8d284c6db631fc7462870f...

3             1bs  a58fadbfbc00c007dfe6e5d5891f2dda013eb5cc66552a...

0             1bs  350df9243c5c93a9b2a330e7e665c791d9dbe0c7e20209...

1             1bs  a58fadbfbc00c007dfe6e5d5891f2dda013eb5cc66552a...

4             1bs  bead623eebed2fdb6700e498bd7ad0fe026f4d7b9a2c25...

...           ...                                               ...

6566    zxztrtvuo  da254908334157ddde0078c9bf967114ae67cc00816f4c...

6565    zxztrtvuo  3385dc93ba44f4f1cc237ef4f8e057dab2f693d8961b64...

6567    zxztrtvuo  12b42968b62afcbac9252406392275719b35c99d39aefb...

6568    zxztrtvuo  4ebf56aec16de134303f4c54752d26bc12791e8b20b28b...
```

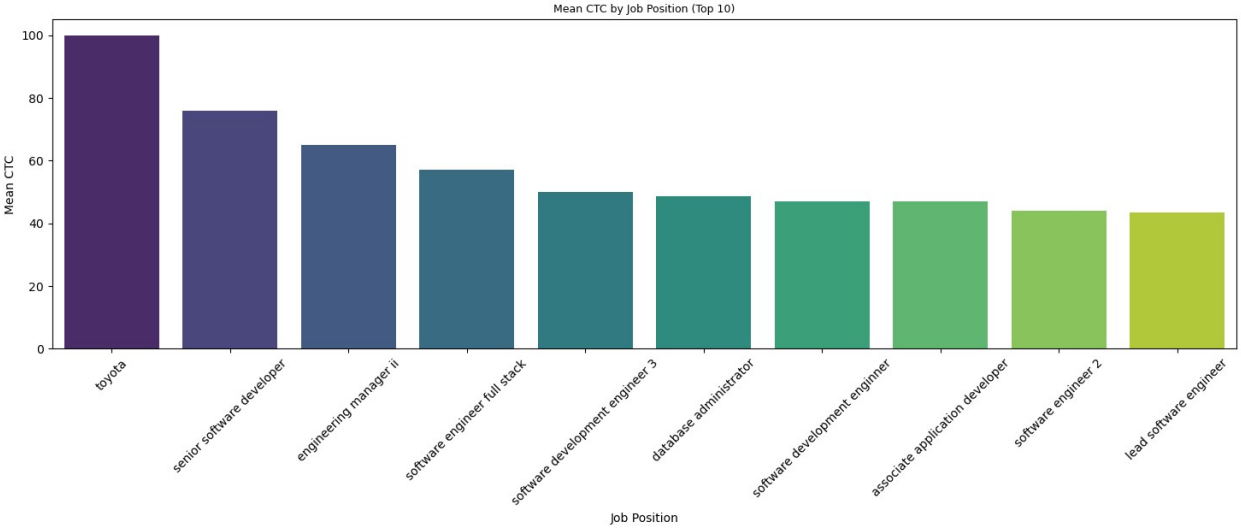
```
6569    zxztrtvuo  66a9ddfbd95e2f5fb57e5f649bd22eeeb7c1a9aec920b8...
```

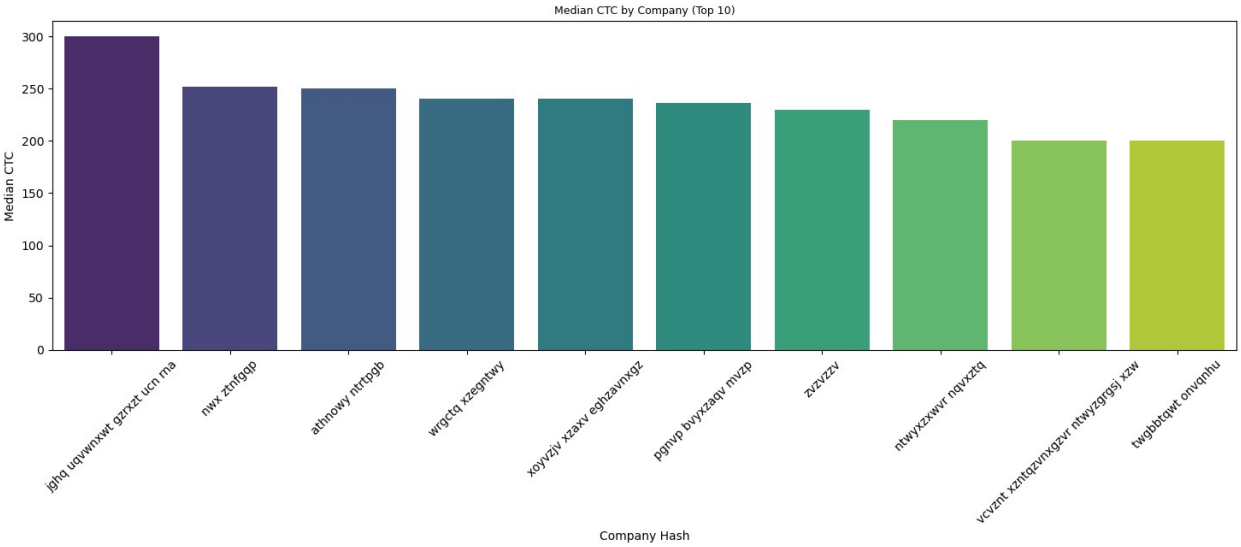
```
            job_position  Years_of_Experience   ctc
2       backend engineer                    5  16.0
3       backend engineer                    5  16.0
0       backend engineer                    5  33.0
1     fullstack engineer                    5  16.0
4           ios engineer                    7  24.0
...                  ...                  ...   ...
6566     devops engineer                    7  27.0
6565   frontend engineer                    6  18.0
6567   frontend engineer                    7  25.0
6568   frontend engineer                    7  25.0
6569   frontend engineer                    7  25.0

[6571 rows x 5 columns]
```

```
fig, axes = plt.subplots(3, 1, figsize=(15, 20))


sns.barplot(x=temp.groupby('Years_of_Experience')
['ctc'].median().index,
            y=temp.groupby('Years_of_Experience')
['ctc'].median().values,
            ax=axes[0], palette="viridis")
axes[0].set_title(fontsize =9 , label ='Median CTC by Years of
Experience')
axes[0].set_xlabel('Years of Experience')
axes[0].set_ylabel('Median CTC')

# Second subplot: Mean CTC by Job Position (Top 10)
sns.barplot(x=temp.groupby('job_position')
['ctc'].mean().sort_values(ascending=False).head(10).index,
            y=temp.groupby('job_position')
['ctc'].mean().sort_values(ascending=False).head(10).values,
            ax=axes[1], palette="viridis")
axes[1].set_title(fontsize =9 , label ='Mean CTC by Job Position (Top
10)')
axes[1].set_xlabel('Job Position')
axes[1].set_ylabel('Mean CTC')
axes[1].tick_params(axis='x', rotation=45)

# Third subplot: Median CTC by Company (Top 10)
sns.barplot(x=temp.groupby('company_hash')
['ctc'].median().sort_values(ascending=False).head(10).index,
            y=temp.groupby('company_hash')
```

```
['ctc'].median().sort_values(ascending=False).head(10).values,
            ax=axes[2], palette="viridis")
axes[2].set_title(fontsize =9 , label ='Median CTC by Company (Top
10)')
axes[2].set_xlabel('Company Hash')
axes[2].set_ylabel('Median CTC')
axes[2].tick_params(axis='x', rotation=45)
plt.suptitle("Top 10 CTC by yoe (5-7) Tier 1 by company and tier 1 by
job position")
# Adjust layout
plt.tight_layout(pad =2)



# Show the plots
plt.show()

del temp,groups,top_10_per_group
```







- based on yoe median salary is increasing +vely

- most the top 10 earners are senior developers earning on an avg 57 lpa

Top 10 companies (based on their CTC)

```
temp =data[data['company_ctc_bin']=='high']
display(temp.groupby('company_hash')
['ctc'].mean().sort_values(ascending = False).head(10))
del temp
```

```
company_hash
qvxatq avnv otqcxwt ucn rna     310.0
jghq uqvwnxwt gzrxzt ucn rna    300.0
vr zvootq wgbuvzj               300.0
vo                              300.0
xxblgmowgb                      300.0
srgfonvq                        300.0
mqvybvzx stbo                   300.0
xzehbxz ntwyzgrgsj rru          300.0
tdurtg                          290.0
ntrtutqegqbvzwt lvxuhq          289.0
Name: ctc, dtype: float64
```

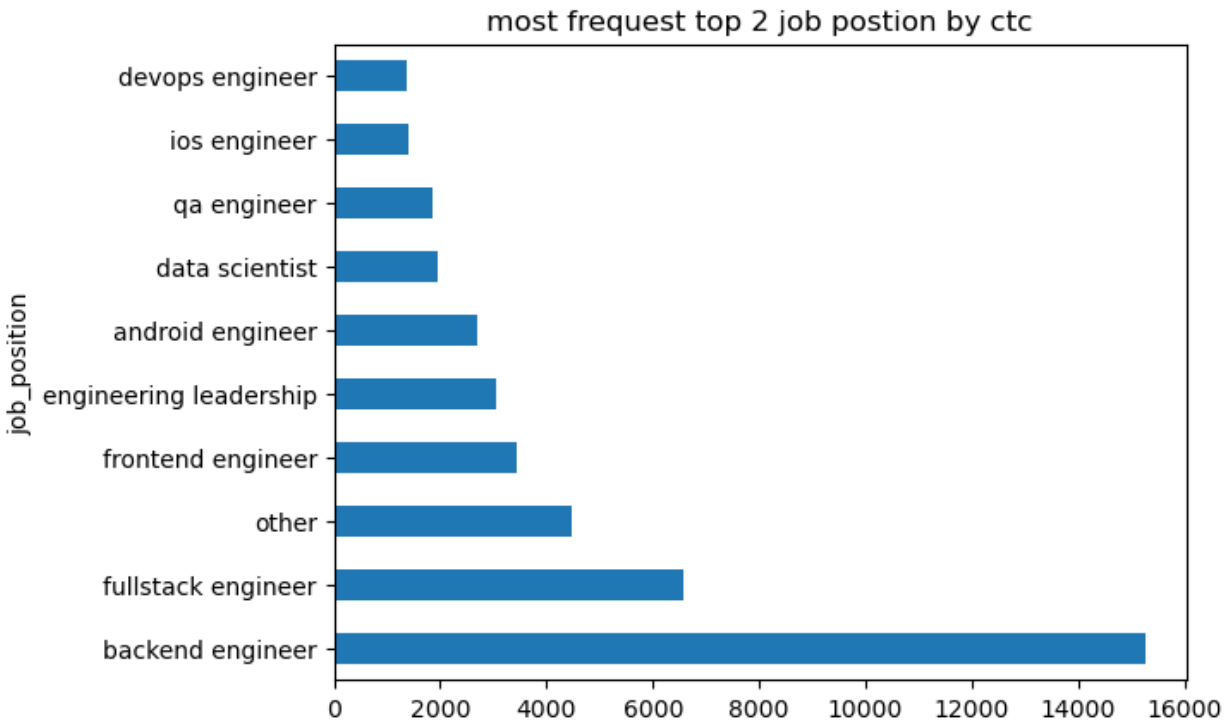
- top tier company pay on an avg 300 lpa

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

```
average_ctc = data.groupby(['company_hash', 'job_position'])
['ctc'].mean().reset_index()

average_ctc_sorted = average_ctc.sort_values(by=['company_hash',
'ctc'], ascending=[True, False])


average_ctc_sorted['rank'] =
average_ctc_sorted.groupby('company_hash')['ctc'].rank(method='dense',
ascending=False)

top_positions = average_ctc_sorted[average_ctc_sorted['rank'] <= 2]

display(top_positions.sort_values(by =[  'ctc'  ], ascending=[False]))


top_positions['job_position'].value_counts().head(10).plot(kind='barh'
)
```

```
plt.title(' most frequest top 2 job postion by ctc ')
del average_ctc,average_ctc_sorted,top_positions
```

```
                            company_hash             job_position
ctc  rank
44365                           uvrvaxgz                    other
313.00   1.0
31525                             pgnvp  database administrator
312.00   1.0
34723       qvxatq avnv otqcxwt ucn rna                    other
310.00   1.0
16054       jghq uqvwnxwt gzrxzt ucn rna                    other
300.00   1.0
16053       jghq uqvwnxwt gzrxzt ucn rna        backend engineer
300.00   1.0
...                                  ...                     ...     ..
.   ...
52657                  wjmtq vhngbgmxrto                    other
2.70   2.0
30265                       owxx nhbphq      fullstack engineer
2.70   1.0
34071         qtshq ntwyzgrgsj ogrhnxgz      fullstack engineer
2.69   1.0
49599  vuxagq vmqvoxct uqgahwno ucn rna                    other
2.68   1.0
59193          xzntrrgmgno ntwyzgrgsxto       frontend engineer
2.67   1.0

[49220 rows x 4 columns]
```



Feature engineering/encoding

```
def transform_features_range(data  , group_by = 'company_hash' ,
agg_col = 'orgyear' , feature_name='company_exp_range'):
    mapper =data.groupby(group_by)
[agg_col].agg(['min','max']).apply(lambda x : x['max']-x['min'] , axis
=1).fillna(0).to_dict()
    data[feature_name] = data[group_by].map(mapper)
    return data


def transform_features_min(data  , group_by = 'company_hash' , agg_col
= 'orgyear' , feature_name='company_min_exp'):
    mapper = data.groupby('company_hash')
[agg_col].min().fillna(0).to_dict()
    data[feature_name] = data[group_by].map(mapper)
    return data

def transform_features_max(data  , group_by = 'company_hash' , agg_col
= 'orgyear' , feature_name='company_max_exp'):
    mapper = data.groupby('company_hash')
[agg_col].max().fillna(0).to_dict()
    data[feature_name] = data[group_by].map(mapper)
    return data


def transform_features_std(data  , group_by = 'company_hash' , agg_col
= 'orgyear' , feature_name='company_exp_std'):
```

```
    mapper = data.groupby('company_hash')
[agg_col].std().fillna(0).to_dict()
    data[feature_name] = data[group_by].map(mapper)
    return data



# Add range features

data = transform_features_range(data=data, group_by='company_hash',
agg_col='ctc', feature_name='company_ctc_range')

data = transform_features_range(data=data, group_by='company_hash',
agg_col='Years_of_Experience',
feature_name='company_Years_of_Experience_range')

# Add minimum features
data = transform_features_min(data=data, group_by='company_hash',
agg_col='ctc', feature_name='company_min_ctc')
data = transform_features_min(data=data, group_by='company_hash',
agg_col='Years_of_Experience',
feature_name='company_min_Years_of_Experience')

# Add maximum features

data = transform_features_max(data=data, group_by='company_hash',
agg_col='ctc_updated_year',
feature_name='company_max_ctc_updated_year')


# Add standard deviation features

data = transform_features_std(data=data, group_by='company_hash',
agg_col='ctc', feature_name='company_std_ctc')
```

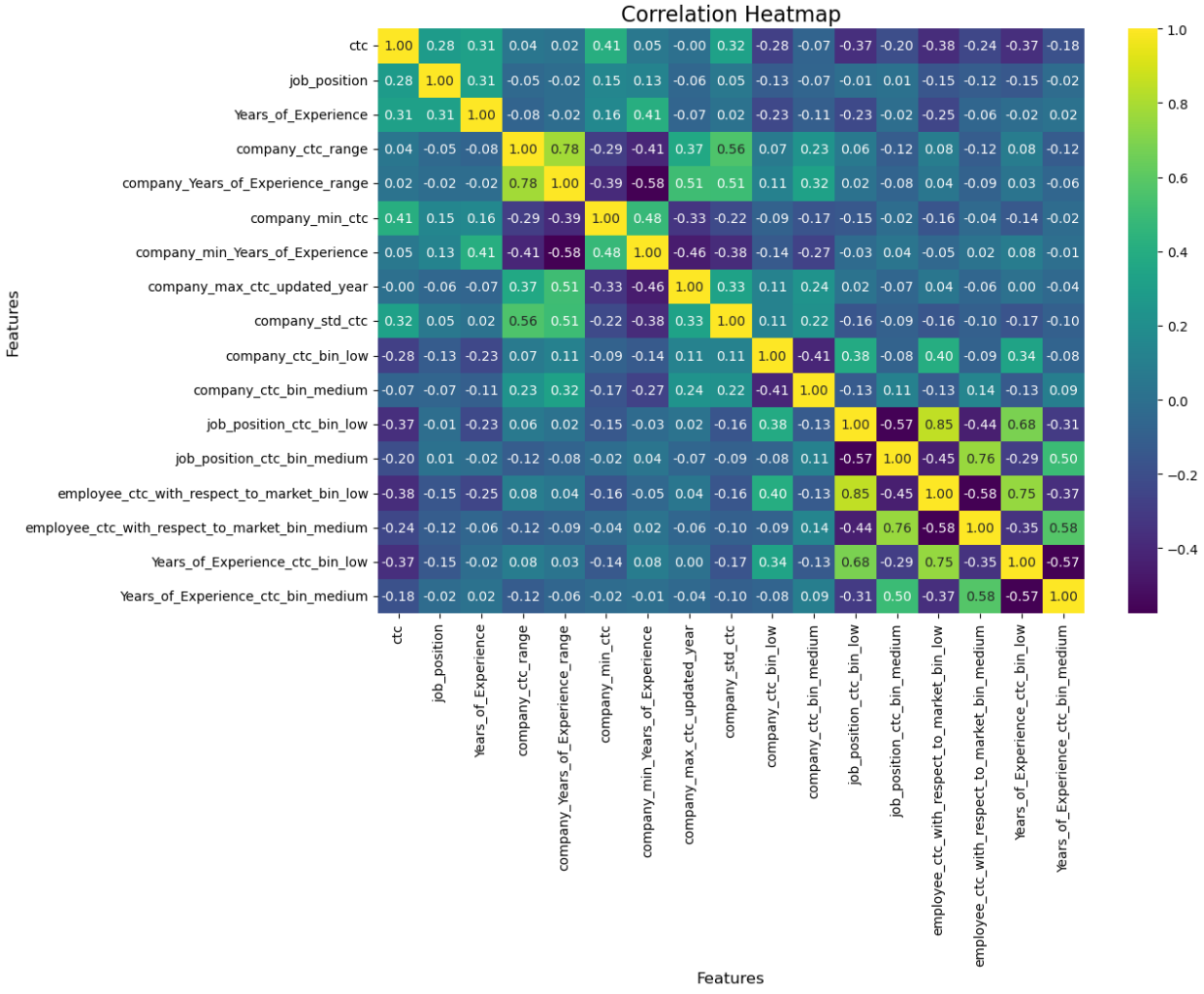
selecting subset of data for faster training

```
data =data.sample(frac = 0.08, random_state = 42)

# keeping a copy of orignal data



orignal_data =data[[ 'company_hash' , 'email_hash' , 'job_position' ,
'ctc' ,'orgyear' ,'ctc_updated_year' ,'Years_of_Experience'] ].copy(de
ep=True)
orignal_data
```

```
mapper =data.groupby('job_position')['ctc'].mean().fillna(0).to_dict()

data['job_position']=data['job_position'].map(mapper )

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

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

ohe

```
# one hot encoding all these features

ohe_cols =data.select_dtypes(include='object').columns

ohe_data =pd.get_dummies(data[ohe_cols],drop_first=True ,dtype=float)

data =pd.concat([data,ohe_data],axis=1)
data.drop(columns=ohe_cols,inplace=True)

# standard scaling all these features
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
std_data = scaler.fit_transform(data)
std_data=pd.DataFrame(std_data, columns= data.columns)
del data


plt.figure(figsize=(12, 8))


sns.heatmap(std_data.corr(), cmap='viridis', annot=True, fmt=".2f",
annot_kws={"size": 10})

# Set title and labels
plt.title('Correlation Heatmap', fontsize=16)
plt.xlabel('Features', fontsize=12)
plt.ylabel('Features', fontsize=12)

# Show the plot
plt.show()
```



clustering

```
# visualisation purpuse
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
pca.fit(std_data)
std_2d = pca.transform(std_data)

from sklearn.metrics import silhouette_score
from sklearn.cluster import KMeans
from sklearn.cluster import AgglomerativeClustering
```

kmeans

```
# finding the best number of clusters
wcss = []
silhouettes = []
for i in range(2, 20):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 
42)
    kmeans.fit(std_data)
    labels = kmeans.fit_predict(std_data)
    wcss.append(kmeans.inertia_)
    silhouette_avg = silhouette_score(std_data, labels)
    silhouettes.append(silhouette_avg)

plt.plot(range(2, 20), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()

plt.plot(range(2, 20), silhouettes)
plt.title('silhouettes vs number of clusters')
plt.xlabel('Number of clusters')
plt.ylabel('silhouette avg ')
plt.show()
```

```
/Users/aditya/miniconda3/envs/pytorch/lib/python3.10/site-packages/
sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of
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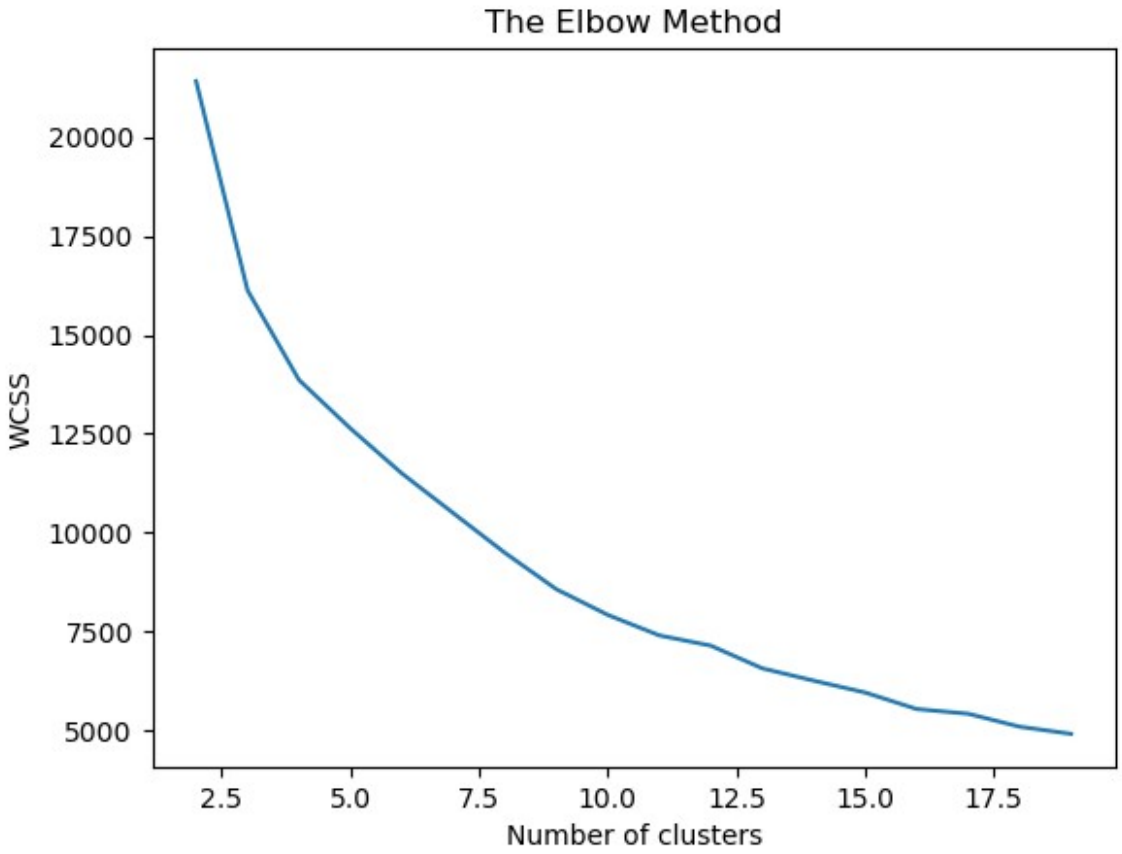

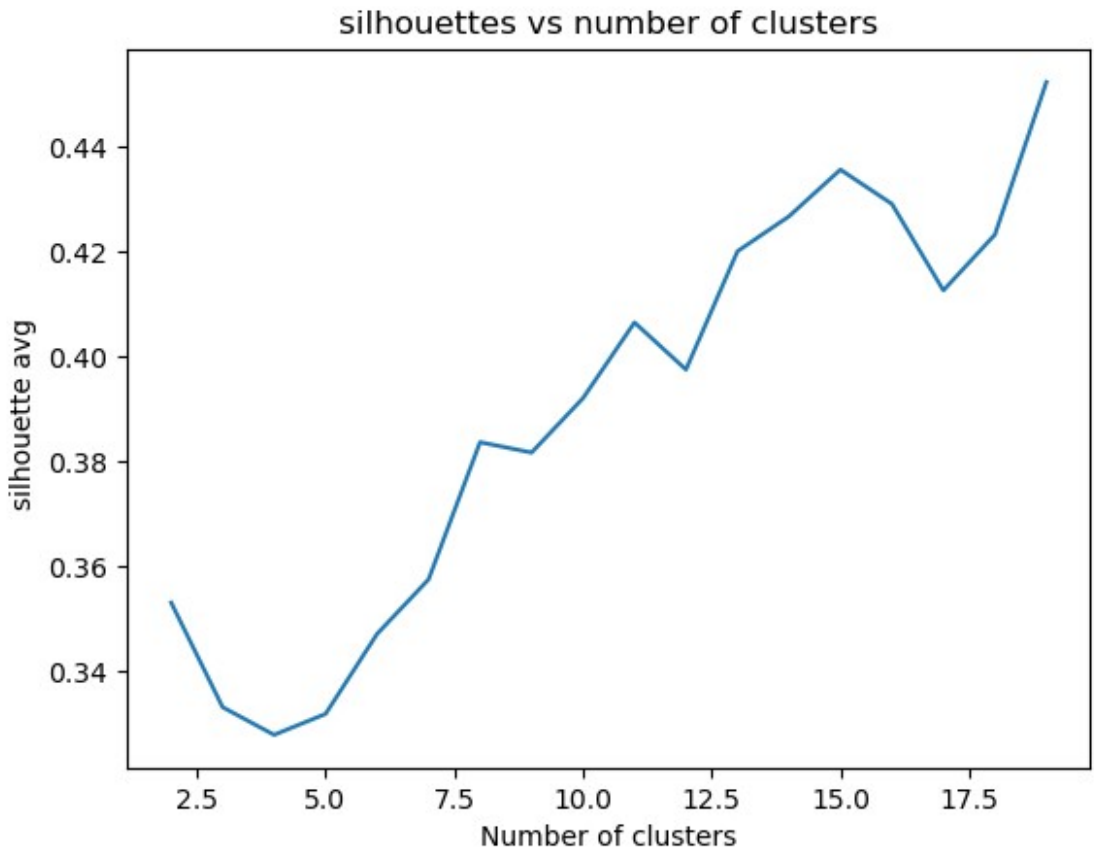

- cant decide no of clusters based on elbow plot
- from silhouette score fixing no of cluster to 18

AgglomerativeClustering

```
# # finding the best number of clusters

silhouettes = []
for i in range(2, 20):
    hc = AgglomerativeClustering(n_clusters = i, affinity =
'euclidean', linkage = 'ward' )
    labels = hc.fit_predict(std_data)

    silhouette_avg = silhouette_score(std_data, labels)
    silhouettes.append(silhouette_avg)


plt.plot(range(2, 20), silhouettes)
plt.title('silhouettes vs number of clusters')
plt.xlabel('Number of clusters')
plt.ylabel('silhouette avg ')
```

```
plt.show()
```

```
/Users/aditya/miniconda3/envs/pytorch/lib/python3.10/site-packages/
sklearn/cluster/_agglomerative.py:983: FutureWarning: Attribute
`affinity` was deprecated in version 1.2 and will be removed in 1.4.
Use `metric` instead
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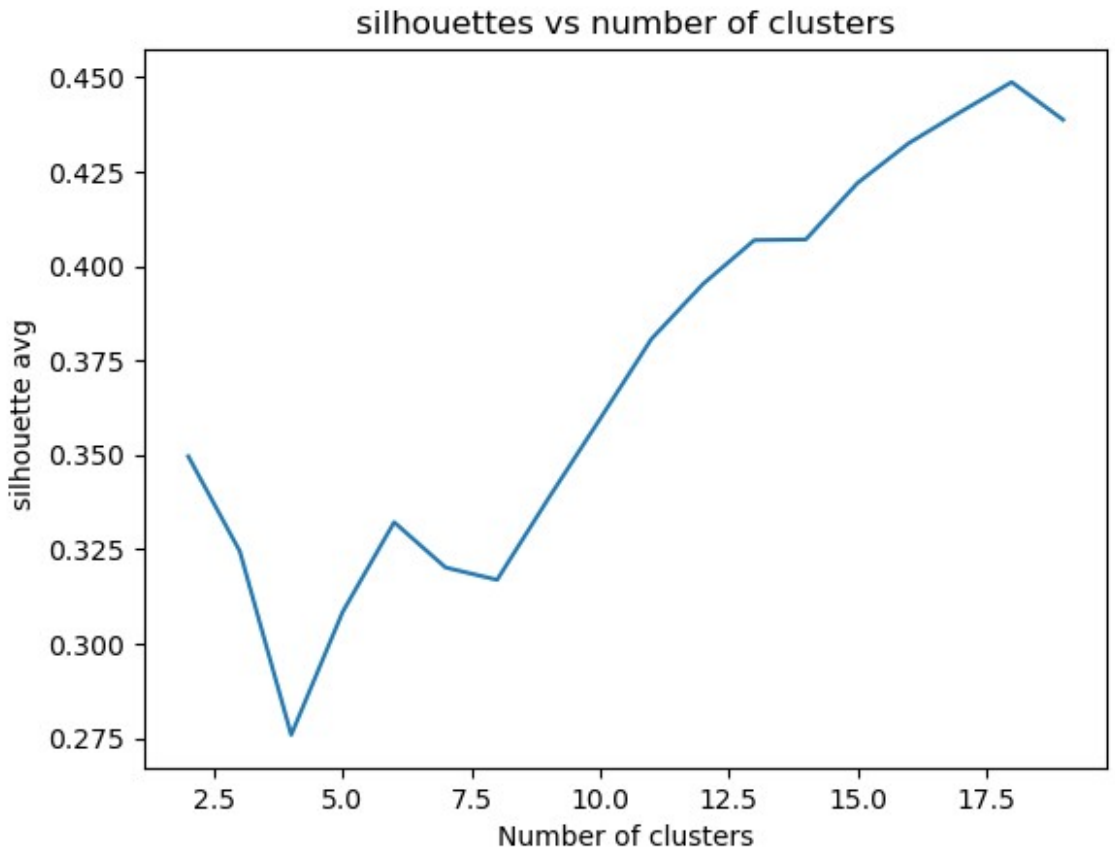

- its look 18 is good cluster number to choose based on silhouette score

```
kmeans = KMeans(n_clusters = 18, init = 'k-means++', random_state =
42)
kmeans.fit(std_data)
labels = kmeans.fit_predict(std_data)
silhouette_avg = round(silhouette_score(std_data, labels),3)
print(silhouette_avg)
orignal_data['labels']=labels




temp = orignal_data.groupby('labels')
['ctc'].mean().sort_values(ascending=False)


plt.figure(figsize=(10, 6))
ax = sns.barplot(x=temp.index, y=temp.values, order=temp.index,
palette="viridis")


for i, v in enumerate(temp.values):
    ax.text(i, v + 0.02, f'{v:.2f}', ha='center', va='bottom')
```

```
plt.title('Mean CTC by Labels kmmeans')
plt.xlabel('Labels')
plt.ylabel('Mean CTC')


plt.tight_layout()
plt.show()
```

```
/Users/aditya/miniconda3/envs/pytorch/lib/python3.10/site-packages/
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```
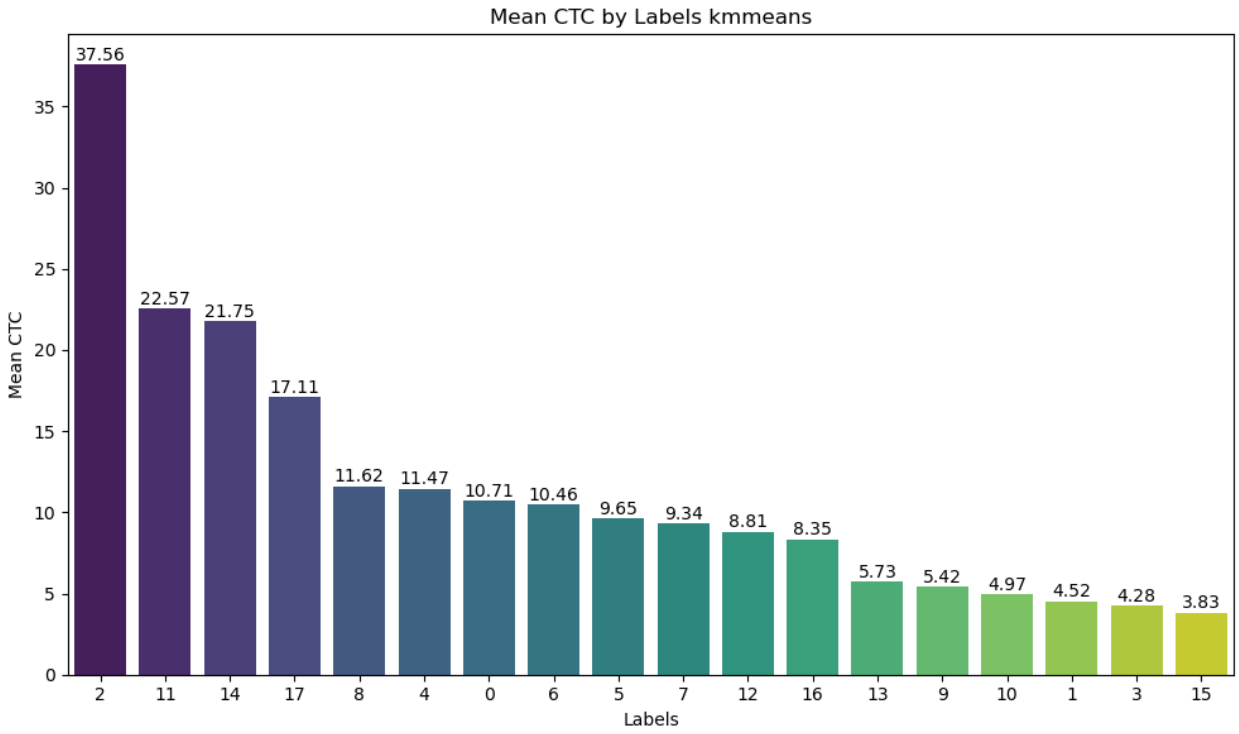

```
0.423
```



- cluster 2 are highest earner
- cluster [11 , 14 ,17] are above average earner
- cluster [8,4,0,6,7,12,16] are medium earner
- cluster 15 are bottom earner

```
hc = AgglomerativeClustering(n_clusters = 18, affinity = 'euclidean',
linkage = 'ward' )
labels = hc.fit_predict(std_data)
silhouette_avg = round(silhouette_score(std_data, labels),3)
orignal_data['labels']=labels
```

```
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for i, v in enumerate(temp.values):
    ax.text(i, v + 0.02, f'{v:.2f}', ha='center', va='bottom')


plt.title('Mean CTC by Labels AgglomerativeClustering')
plt.xlabel('Labels')
plt.ylabel('Mean CTC')


plt.tight_layout()
plt.show()
```

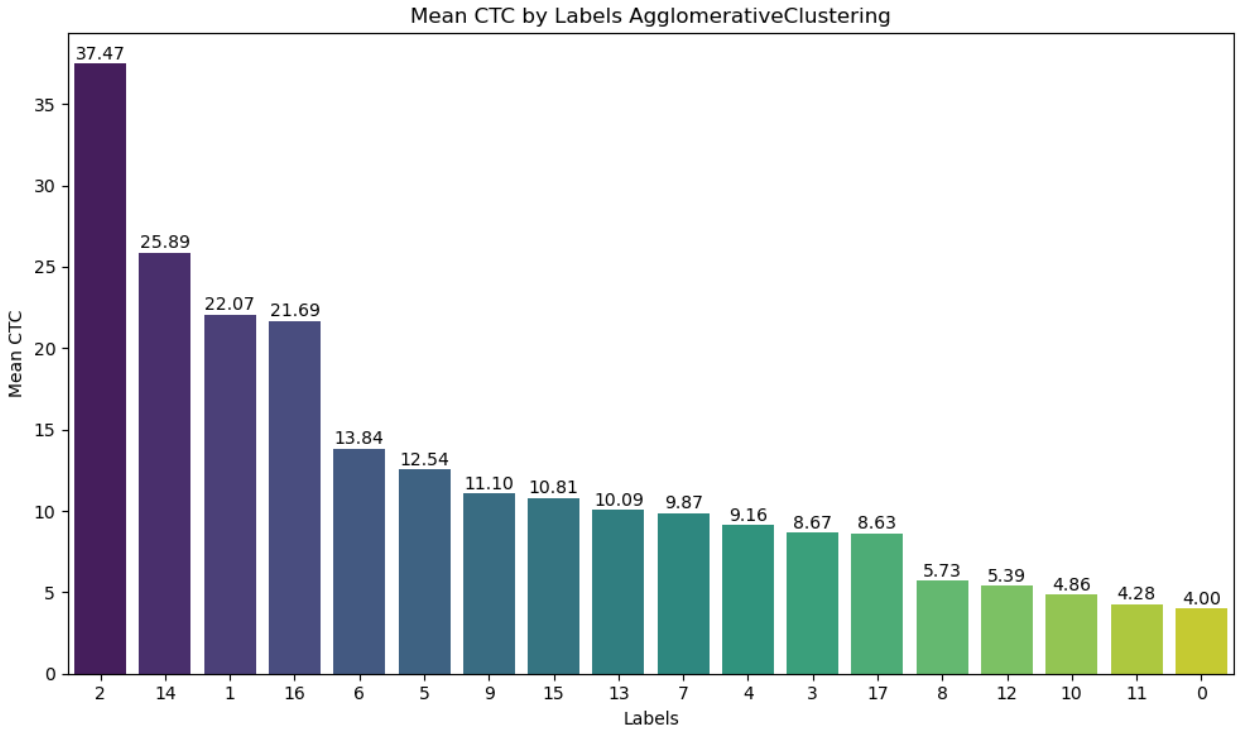

- cluster 2 are highest earner
- cluster [14 ,1 ,16] are above average earner
- cluster [6, 7, 1, 15, 13,17, 4, 5] are medium earner
- cluster 0 are bottom earner

Insight:

- Salary ranges widely from hundreds to 2000 lakhs per annum, with a highly right-skewed distribution.
- The median salary is around 10 LPA.
- Software engineering jobs typically pay the most.
- Experienced professionals generally have higher median salaries.
- For each experience range (0-14 years), the average maximum salary is 300 LPA.
- The median salary increases with experience, but after 25 years, it falls.
- There are very few individuals with more than 25 years of experience.
- There is high variability in salaries for 0-15 years of experience; some earn very low, some very high.
- 93% of the workforce has 0-12 years of experience, only 7% have more than that.
- Salary for data science jobs ranges from 10 LPA to 242 LPA.
- 50% of the top 10 employees in data science companies earn more than 23 LPA.
- The bottom 10 data science employees earn anywhere from 1 LPA to 12 LPA.
- 50% of the bottom 10 employees in data science companies earn less than 3.7 LPA.

Company CTC Bin:

- **High**: 41.12% of employees earn more than the company's average CTC.

- **Medium**: 34.02% of employees earn around the company's average CTC.
- **Low**: 24.87% of employees earn less than the company's average CTC.

Job Position CTC Bin:

- **Medium**: 48.35% of employees earn around the job position's average CTC.
- **High**: 26.11% of employees earn more than the job position's average CTC.
- **Low**: 25.54% of employees earn less than the job position's average CTC.

Employee CTC with Respect to Market Bin:

- **Medium**: 49.94% of employees earn around the market average CTC.
- **High**: 25.03% of employees earn more than the market average CTC.
- **Low**: 25.03% of employees earn less than the market average CTC.

Years of Experience CTC Bin:

- **Medium**: 47.56% of employees earn around the average CTC for their years of experience.
- **Low**: 26.54% of employees earn less than the average CTC for their years of experience.
- **High**: 25.90% of employees earn more than the average CTC for their years of experience.