Introduction

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.

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. 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.

Know your Data

In [3]:

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

In [4]:

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

In [5]:

```
df
```

Out[5]:

	Unnamed: 0	company_hash	ema
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d51
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79
...	...	...	
205838	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc2
205839	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c847
205840	206920	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d
205841	206921	zgn vuurxwvmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee5
205842	206922	bgqsvz onvzrtj	0bcfc1d05f2e8dc4147743a1313aa70a119b41b30

205843 rows × 7 columns

In [6]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205843 entries, 0 to 205842
Data columns (total 7 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   Unnamed: 0        205843 non-null  int64  
 1   company_hash      205799 non-null  object 
 2   email_hash        205843 non-null  object 
 3   orgyear           205757 non-null  float64
 4   ctc               205843 non-null  int64  
 5   job_position      153279 non-null  object 
 6   ctc_updated_year  205843 non-null  float64
dtypes: float64(2), int64(2), object(3)
memory usage: 11.0+ MB
```

Data Dictionary:

1. ‘Unnamed 0’ - Index of the dataset
2. Email_hash - Anonymised Personal Identifiable Information (PII)
3. Company_hash - This represents an anonymized identifier for the company, which is the current employer of the learner.

4. orgyear - Employment start date
5. CTC - Current CTC
6. Job_position - Job profile in the company
7. CTC_updated_year - Year in which CTC got updated (Yearly increments, Promotions)

In [7]:
```
df.describe(exclude=['float64','int64']).T
```

Out[7]:

	count	unique	t
company_hash	205799	37299	nvnv wgzohrnvzwj otqcxv
email_hash	205843	153443	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b
job_position	153279	1016	Backend Engin

Observations:

- There are 205843 rows and 7 columns
- Null Values observed in 3 columns
- Backend Engineer is the most frequent Job Position in the dataset.
- Further analysis can be better performed post EDA, handling null, duplicates and outliers

Data Preprocessing

- Data Cleaning
- Checking Duplicates and Treatment
- Checking Outliers and Treatment using Capping
- Checking Null Values and Treatment using KNN imputation for Numerical attributes
- Remove Special characters using Regex
- Feature Engineering

In [8]:
```
df1=df.copy()
```

Regex for Cleaning Company Names

In [9]:
```
import re
```

In [10]:
```
# Function to clean special characters
def clean_string(s):
    if not isinstance(s, str):
```

```
        s = str(s)
    return re.sub('[^A-Za-z0-9 ]+', '', s)

# Apply the function to the 'company_hash' column
df1['company_hash'] = df1['company_hash'].apply(clean_string)
```

Check Duplicates

In [11]:
```
df1.duplicated().any()
```

Out[11]:
```
np.False_
```

- No Duplicate rows observed overall in the dataset

Check Duplicates based on Email_hash and remove them to ensure uniqueness of each learner's data

In [12]:
```
combined_duplicates = df[df.duplicated(subset=['email_hash'], keep=False)]
print(f"Number of duplicate rows based on 'email_hash': {combined_duplicates.s

# Display the duplicate rows
print(combined_duplicates)
```

```
Number of duplicate rows based on 'email_hash': 93616
        Unnamed: 0                        company_hash  \
0                0                      atrgxnnt xzaxv
1                1           qtrxvzwt xzegwgbb rxbxnta
2                2                       ojzwnvwnxw vx
4                4                          qxen sqghu
5                5  yvuuxrj hzbvqqxta bvqptnxzs ucn rna
...            ...                                 ...
205827      206907                            btaxvztn
205830      206910                      zgn vuurxwvmrt
205831      206911            tcxct ogenfvqt vzvrjnxwo
205837      206917                      zgn vuurxwvmrt
205838      206918                           vuurt xzw

                                               email_hash  orgyear      ctc  \
0       6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...   2016.0  1100000
1       b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...   2018.0   449999
2       4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...   2015.0  2000000
4       6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...   2017.0  1400000
5       18f2c4aa2ac9dd3ae8ff74f32d30413f5165565b90d8f2...   2018.0   700000
...                                                   ...      ...      ...
205827  41a149cbd1b74bfc092e43aebb2f6ff574c2ffe45ff5b4...   2018.0  1200000
205830  586e06d65892218f96debd87457bc127de3cae87dd0edf...   2019.0   700000
205831  5b5763bd9c93e9afd38452cc267e3c547497d76747eb89...   2018.0   550000
205837  fe34477c3f64e6ed4301417c8fb9d5e2608722a10f1f4e...   2021.0   800000
205838  70027b728c8ee901fe979533ed94ffda97be08fc23f33b...   2008.0   220000

              job_position  ctc_updated_year
0                    Other            2020.0
1        FullStack Engineer            2019.0
2         Backend Engineer            2020.0
4        FullStack Engineer            2019.0
5        FullStack Engineer            2020.0
...                    ...               ...
205827                 NaN            2020.0
205830                 NaN            2019.0
205831                 NaN            2019.0
205837                 NaN            2021.0
205838                 NaN            2019.0

[93616 rows x 7 columns]
```

In [13]:
```python
df1= df1.drop_duplicates(subset=['email_hash'], keep='last')
```

- Removed Duplicates based on Email_hash
- Multiple individuals can be associated with the same company, so using company_hash alone may not ensure the uniqueness of learners
- Could have considered both Email and Company for duplicate. This would have ensured that we don't remove valid records where the same individual is associated with multiple companies. But with limited

information currently going ahead with removing duplicates based on Email_hash to ensure uniqueness of each learner's data

Check Null Values

In [14]:
```
df1.isna().sum()
```

Out[14]:

	0
Unnamed: 0	0
company_hash	0
email_hash	0
orgyear	79
ctc	0
job_position	34191
ctc_updated_year	0

dtype: int64

- job_position has high number of null values
- company_hash and orgyear have got few null values
- Will treat null values upon further analysis

Check Unique Values for Each Feature and Convert Data type if needed

In [15]:
```
# Non-numeric columns
obj_cols = df1.select_dtypes(include='object').columns
obj_cols
```

Out[15]:
```
Index(['company_hash', 'email_hash', 'job_position'], dtype='object')
```

In [16]:
```
for _ in obj_cols:
    print()
    print(f'Total Unique Values in {_} column are :- {df1[_].nunique()}')
    print(f'Value counts in {_} column are :-\n {df1[_].value_counts()}')
    print()
    print('-'*120)
```

```
Total Unique Values in company_hash column are :- 36366
Value counts in company_hash column are :-
 company_hash
nvnv wgzohrnvzwj otqcxwto                  5336
xzegojo                                    3526
vbvkgz                                     2440
wgszxkvzn                                  2199
zgn vuurxwvmrt vwwghzn                     2192
                                           ...
nqvzoftm srgmvr xzwgqugqvnxgz                 1
uqguqgeowgb                                   1
txrjoxo                                       1
vbzo                                          1
ftvnytq qxop bvzvstbtzn otqcxwto ucn rna      1
Name: count, Length: 36366, dtype: int64

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

Total Unique Values in email_hash column are :- 153443
Value counts in email_hash column are :-
 email_hash
0bcfc1d05f2e8dc4147743a1313aa70a119b41b30d4a1f7e738a6a87d3712c31    1
effdede7a2e7c2af664c8a31d9346385016128d66bbc58a44274d5d6876dfec7    1
756d35a7f6bb8ffeaffc8fcca9ddbb78e7450fa0de2be0a5e9c8d98eb87f97f9    1
3467ccdf01adc36d8250a2a5edc99dfa5af05c102ccb19cecbd1c0930ee7727f    1
95023bca0172ad67bfc3453550c5cf056557bc2c8c7169c45d544526834d19a4    1
                                                                   ..
be9363f1468f242f655953b2f088922cb6cad80e62c493335d2e28dcb22fd47e    1
26b502eb6439ac80bd618a6f7c2b1c640b84c1e64c472cf0510b0b36c2d3c247    1
26ec792de0792706df9beb9a8d37f45d732982e7ea21e2dcf2a6c2167785ac08    1
ebcaf397ef5084e05889a6e9a0c3f96a5c8fb0b16749cef5ee3ce31a0271c12b    1
134cc4a76a119493d523f1855a3b7106f64287455d5cd4bb14f4ad0659fe8a5f    1
Name: count, Length: 153443, dtype: int64

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

Total Unique Values in job_position column are :- 651
Value counts in job_position column are :-
 job_position
Backend Engineer             33154
FullStack Engineer           17460
Other                        13747
Frontend Engineer             8154
Engineering Leadership        5987
                             ...
system software engineer         1
Pop engineer                     1
Senior Web Developer             1
Full stack web developer         1
Machine learning engineer        1
Name: count, Length: 651, dtype: int64
```

- Since company and email are hashed so not much information can be inferred. However, we can conveniently identify contribution of each element to the Feature
- Since email_hash is unique for every learner so it is correctly showing frequency as 1 for each email
- Backend Engineer is the most frequent with 33154 value counts followed by FullStack Engineer and Other

In [17]:
```
# Numeric columns
num_cols = df1.select_dtypes(include='number').columns
num_cols
```

Out[17]:
```
Index(['Unnamed: 0', 'orgyear', 'ctc', 'ctc_updated_year'], dtype='object')
```

In [18]:
```
for _ in num_cols:
    print()
    print(f'Total Unique Values in {_} column are :- {df1[_].nunique()}')
    print(f'Value counts in {_} column are :-\n {df1[_].value_counts(normalize
    print()
    print('-'*120)
```

```
Total Unique Values in Unnamed: 0 column are :- 153443
Value counts in Unnamed: 0 column are :-
 Unnamed: 0
206922    0.000007
3         0.000007
7         0.000007
206906    0.000007
206905    0.000007
            ...
21        0.000007
17        0.000007
16        0.000007
14        0.000007
13        0.000007
Name: proportion, Length: 153443, dtype: float64

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

Total Unique Values in orgyear column are :- 76
Value counts in orgyear column are :-
 orgyear
2016.0    0.112993
2018.0    0.109661
2017.0    0.107985
2015.0    0.104249
2019.0    0.098022
            ...
2204.0    0.000007
201.0     0.000007
1900.0    0.000007
38.0      0.000007
200.0     0.000007
Name: proportion, Length: 76, dtype: float64

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

Total Unique Values in ctc column are :- 3299
Value counts in ctc column are :-
 ctc
600000       0.036300
1000000      0.033830
400000       0.032422
800000       0.030637
500000       0.030448
               ...
791000       0.000007
147500       0.000007
1066000      0.000007
111800000    0.000007
1237000      0.000007
Name: proportion, Length: 3299, dtype: float64
```

```
----------------------------------------------------------------------------------------------------------------------

Total Unique Values in ctc_updated_year column are :- 7
Value counts in ctc_updated_year column are :-
 ctc_updated_year
2019.0    0.376166
2021.0    0.245335
2020.0    0.237652
2017.0    0.046825
2018.0    0.043228
2016.0    0.033452
2015.0    0.017342
Name: proportion, dtype: float64

----------------------------------------------------------------------------------------------------------------------
```

- Unnamed: 0 do not provide any useful information, will drop this column
- ctc_updated_year to be converted to datetime datatype for further analysis
- orgyear is the starting year of employment. We could identify many invalid entries like 200,208,2107 ..which are not valid years. This column will undergo treatment
- Maximum Learners have got CTC of 6 Lac followed by 10 Lac and 4 Lac

Removing column 'Unnamed: 0' as it does not have any useful information

In [19]:
```
df1 = df1.drop(columns=['Unnamed: 0'])
```

Convert Required Columns to Datetime datatype

In [20]:
```
df1['ctc_updated_year'] = pd.to_datetime(df1['ctc_updated_year'], format='%Y')
df1['ctc_updated_year'] = df1['ctc_updated_year'].dt.year
```

Treatment of column 'orgyear'

orgyear is the starting year of employment. We could identify many invalid entries like 200,208,2107 ..which are not valid years.

In [21]:
```
# Define the range of valid years (e.g., 1900 to 2023)
valid_years = range(1900, 2024)

# Replace invalid years with NaN
df1['orgyear'] = df1['orgyear'].apply(lambda x: x if x in valid_years else np.

# Convert valid years to datetime
```

```
df1['orgyear'] = pd.to_datetime(df1['orgyear'].dropna().astype(int), format='%
df1['orgyear'] = df1['orgyear'].dt.year
df1['orgyear']=df1['orgyear'].astype('Int64')
```

Treatment of Null Values

In [22]:
```
df1.isna().sum()
```

Out[22]:

	0
company_hash	0
email_hash	0
orgyear	186
ctc	0
job_position	34191
ctc_updated_year	0

dtype: int64

In [23]:
```
from sklearn.impute import KNNImputer
```

KNN Imputation for Numerical Column

In [24]:
```
# Impute missing values in Job Position column with 'Other'
df1['job_position'].fillna('unknown', inplace=True)

# Impute missing values in numerical columns using KNN
knn_imputer = KNNImputer(n_neighbors=3)

# Select only numerical columns for KNN imputation
numerical_cols = ['orgyear']

# Fit and transform the KNN imputer on the numerical columns
df1[numerical_cols] = knn_imputer.fit_transform(df1[numerical_cols])
```

```
/tmp/ipython-input-2113973626.py:2: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work bec
ause the intermediate object on which we are setting values always behaves as a
copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.me
thod({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, t
o perform the operation inplace on the original object.


  df1['job_position'].fillna('unknown', inplace=True)
```

In [25]:
```
# Convert orgyear back to int
df1['orgyear'] = df1['orgyear'].astype(int)
```

- For job_position, filled missing values with the string 'unknown'. This ensures that the analysis considers these entries as a separate category rather than skewing the distribution of existing categories. This approach maintains the integrity of the categorical data while addressing missing values in a straightforward and non-biased manner.
- Applied KNN imputation to fill missing values in the orgyear column. This leverages the relationships between existing data points to predict the missing values.

Feature Engineering

Creating new feature 'YOE' Years of Experience

In [26]:
```
from datetime import datetime
```

In [27]:
```
# Get the current year
current_year = datetime.now().year

# Create the YOE column by subtracting orgyear from current_year
df1['YOE'] = current_year - df1['orgyear']
```

In [28]:
```
df1.head()
```

Out[28]:

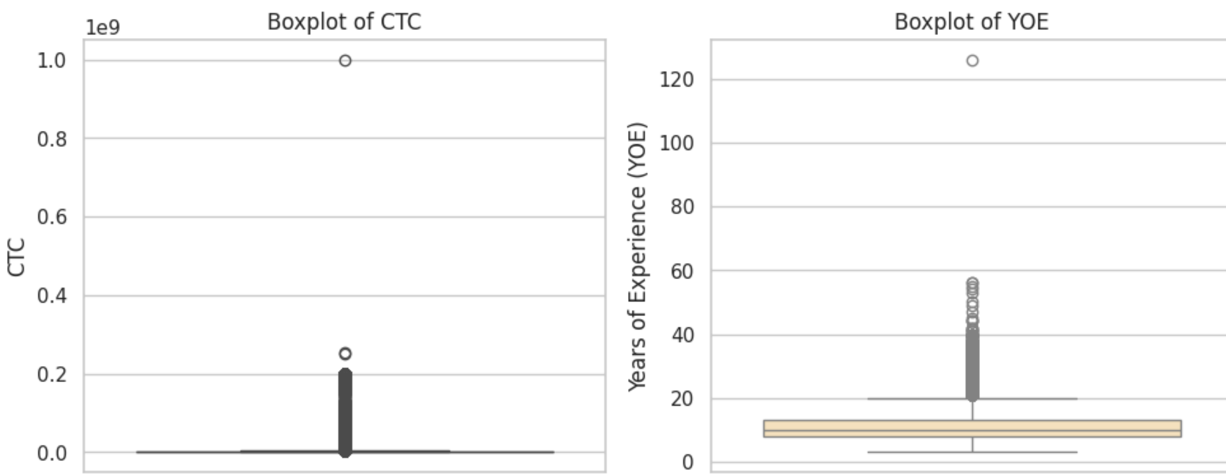
	company_hash	email_hash	orgyear
3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017
7	vwwtznhqt ntwyzgrgsj	756d35a7f6bb8ffeaffc8fcca9ddbb78e7450fa0de2be0...	2019
9	xrbhd	b2dc928f4c22a9860b4a427efb8ab761e1ce0015fba1a5...	2019
13	wgszxkvzn	134cc4a76a119493d523f1855a3b7106f64287455d5cd4...	2016
14	xznhxn	ebcaf397ef5084e05889a6e9a0c3f96a5c8fb0b16749ce...	2016

Checking Outliers

In [29]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

In [30]:
```
df2=df1.copy()
```

In [31]:
```python
# Set the style of seaborn
sns.set(style="whitegrid")

# Create a figure with two subplots for CTC and YOE
fig, ax = plt.subplots(1, 2, figsize=(10, 4))

# Boxplot for CTC
sns.boxplot(data=df2, y='ctc', ax=ax[0])
ax[0].set_title('Boxplot of CTC')
ax[0].set_ylabel('CTC')

# Boxplot for YOE
sns.boxplot(data=df2, y='YOE', ax=ax[1],color='moccasin')
ax[1].set_title('Boxplot of YOE')
ax[1].set_ylabel('Years of Experience (YOE)')

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



- We can clearly observe outliers in ctc and YOE
- Outliers can significantly impact the performance and results of clustering algorithms like K-means and hierarchical clustering

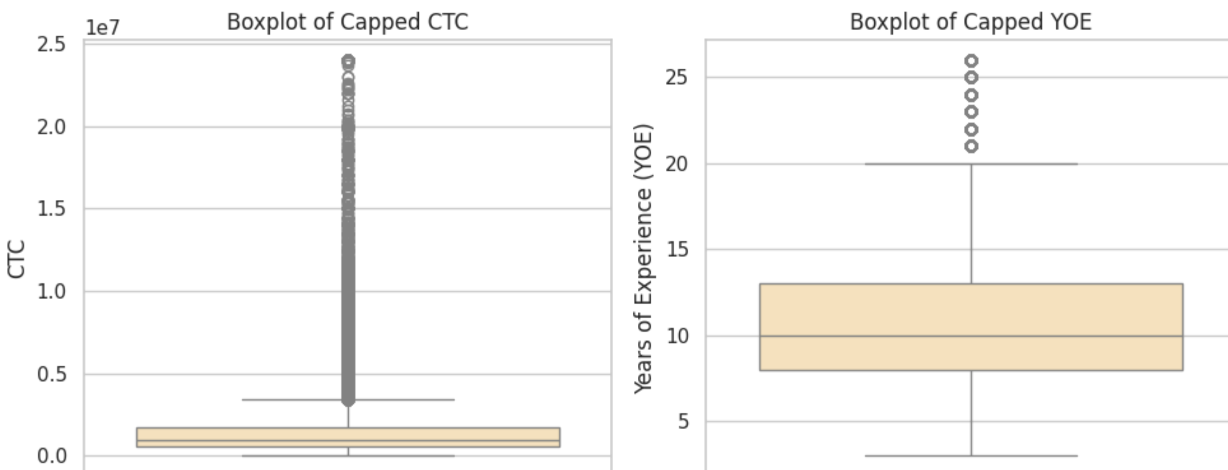
Treatment of Outliers

Used Capping method to treat outliers. This approach reduces the impact of extreme outliers without completely removing data points.

In [32]:
```python
# Calculate upper bound for ctc using 99th percentile
ctc_upper_bound = df2['ctc'].quantile(0.99)

# Apply clipping to ctc column
df2['ctc_capped'] = np.clip(df2['ctc'], df2['ctc'].min(), ctc_upper_bound)
```

In [33]:
```
# Calculate upper bound for YOE using 99th percentile
yoe_upper_bound = df2['YOE'].quantile(0.99)

# Apply clipping to YOE column
df2['YOE_capped'] = np.clip(df2['YOE'], df2['YOE'].min(), yoe_upper_bound)
```

In [34]:
```
# Set the style of seaborn
sns.set(style="whitegrid")

# Create a figure with two subplots for CTC and YOE
fig, ax = plt.subplots(1, 2, figsize=(10, 4))

# Boxplot for CTC post Capping
sns.boxplot(data=df2, y='ctc_capped', ax=ax[0],color='moccasin')
ax[0].set_title('Boxplot of Capped CTC')
ax[0].set_ylabel('CTC')

# Boxplot for YOE post Capping
sns.boxplot(data=df2, y='YOE_capped', ax=ax[1],color='moccasin')
ax[1].set_title('Boxplot of Capped YOE')
ax[1].set_ylabel('Years of Experience (YOE)')

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



- We can observe that extreme outliers have been treated with capping method.
- Setting the upper percentile to 99% is a way to include most of the data points while excluding the extreme 1% of outliers that are far from the rest of the data.
- This approach ensured that the majority of data remains intact, while the extreme values that could significantly impact the clustering results are capped.
- Created two new capped columns while keeping the original columns if

needed to refer further

In [35]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 153443 entries, 3 to 205842
Data columns (total 9 columns):
 #   Column            Non-Null Count   Dtype 
---  ------            --------------   ----- 
 0   company_hash      153443 non-null  object
 1   email_hash        153443 non-null  object
 2   orgyear           153443 non-null  int64 
 3   ctc               153443 non-null  int64 
 4   job_position      153443 non-null  object
 5   ctc_updated_year  153443 non-null  int32 
 6   YOE               153443 non-null  int64 
 7   ctc_capped        153443 non-null  int64 
 8   YOE_capped        153443 non-null  int64 
dtypes: int32(1), int64(5), object(3)
memory usage: 11.1+ MB
```

Manual Clustering

- Creating Designation Flag & Insights
- Creating Class Flag & Insights
- Creating Tier Flag & Insights

In [36]:
```
df3=df2.copy()
```

Dropping original columns ctc and YOE for capped_ctc and capped_YOE

- Analysis will be more consistent and robust when performed on a dataset where extreme values have been controlled or standardized through capping.
- Capped Feature preserves the integrity of the dataset by retaining most data points while adjusting extreme values. This ensures that the analysis reflects the general trends and patterns in the data without being overly influenced by outliers.

In [37]:
```
# Drop original ctc and YOE columns
df3.drop(['ctc', 'YOE'], axis=1, inplace=True)
```

In [38]:
```
df3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 153443 entries, 3 to 205842
Data columns (total 7 columns):
 #   Column            Non-Null Count   Dtype 
---  ------            --------------   ----- 
 0   company_hash      153443 non-null  object
 1   email_hash        153443 non-null  object
 2   orgyear           153443 non-null  int64 
 3   job_position      153443 non-null  object
 4   ctc_updated_year  153443 non-null  int32 
 5   ctc_capped        153443 non-null  int64 
 6   YOE_capped        153443 non-null  int64 
dtypes: int32(1), int64(3), object(3)
memory usage: 8.8+ MB
```

Creating Flags:

- Designation Flag: CTC on the basis of Company, Job Position and Years of Experience
- Class Flag: CTC On the basis of Company and Job Position
- Tier Flag: CTC On the basis of Company

In [39]:

```
# Step 1: Group by company, job position, and years of experience (Designation
grouped_summary_designation = df3.groupby(['company_hash', 'job_position', 'YO
grouped_summary_designation.rename(columns={'mean': 'mean_designation'}, inpla

# Group by company and years of experience (Class)
grouped_summary_class = df3.groupby(['company_hash', 'job_position'])['ctc_cap
grouped_summary_class.rename(columns={'mean': 'mean_class'}, inplace=True)

# Group by company level only (Tier)
grouped_summary_tier = df3.groupby(['company_hash'])['ctc_capped'].agg(['mean'
grouped_summary_tier.rename(columns={'mean': 'mean_tier'}, inplace=True)

# Step 2: Merge only the mean values with the original dataset
df3 = df3.merge(grouped_summary_designation[['company_hash', 'job_position', '
df3 = df3.merge(grouped_summary_class[['company_hash', 'job_position', 'mean_c
df3 = df3.merge(grouped_summary_tier[['company_hash', 'mean_tier']], on=['comp

# Step 3: Create flags for Designation, Class, and Tier based on mean values
def designation_flag(row):
    if row['ctc_capped'] > row['mean_designation']:
        return 3
    elif row['ctc_capped'] == row['mean_designation']:
        return 2
    else:
        return 1

def class_flag(row):
    if row['ctc_capped'] > row['mean_class']:
        return 3
    elif row['ctc_capped'] == row['mean_class']:
```

```
        return 2
    else:
        return 1

def tier_flag(row):
    if row['ctc_capped'] > row['mean_tier']:
        return 3
    elif row['ctc_capped'] == row['mean_tier']:
        return 2
    else:
        return 1

df3['Designation_Flag'] = df3.apply(designation_flag, axis=1)
df3['Class_Flag'] = df3.apply(class_flag, axis=1)
df3['Tier_Flag'] = df3.apply(tier_flag, axis=1)

# Step 4: Check if columns exist before attempting to drop them
columns_to_drop = ['mean_class', 'mean_designation', 'mean_tier']
df3.drop(columns=[col for col in columns_to_drop if col in df3.columns], inpla
```

In [40]:
```
grouped_summary_designation.head()
```

Out[40]:

	company_hash	job_position	YOE_capped	mean_designation	median	r
0	0	Other	6	100000.0	100000.0	100
1	0000	Other	9	300000.0	300000.0	300
2	01 ojztqsj	Android Engineer	10	270000.0	270000.0	270
3	01 ojztqsj	Frontend Engineer	15	830000.0	830000.0	830
4	05mz exzytvrny uqxcvnt rxbxnta	Backend Engineer	7	1100000.0	1100000.0	1100

In [41]:
```
grouped_summary_class.head()
```

Out[41]:

	company_hash	job_position	mean_class	median	max	min	count
0	0	Other	100000.0	100000.0	100000	100000	1
1	0000	Other	300000.0	300000.0	300000	300000	1
2	01 ojztqsj	Android Engineer	270000.0	270000.0	270000	270000	1
3	01 ojztqsj	Frontend Engineer	830000.0	830000.0	830000	830000	1
4	05mz exzytvrny uqxcvnt rxbxnta	Backend Engineer	1100000.0	1100000.0	1100000	1100000	1

In [42]:
```python
grouped_summary_tier.head()
```

Out[42]:

	company_hash	mean_tier	median	max	min	count
0	0	100000.0	100000.0	100000	100000	1
1	0000	300000.0	300000.0	300000	300000	1
2	01 ojztqsj	550000.0	550000.0	830000	270000	2
3	05mz exzytvrny uqxcvnt rxbxnta	1100000.0	1100000.0	1100000	1100000	1
4	1	175000.0	175000.0	250000	100000	2

In [43]:
```python
df3.head()
```

Out[43]:

	company_hash	email_hash	orgyear
0	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017
1	vwwtznhqt ntwyzgrgsj	756d35a7f6bb8ffeaffc8fcca9ddbb78e7450fa0de2be0...	2019
2	xrbhd	b2dc928f4c22a9860b4a427efb8ab761e1ce0015fba1a5...	2019
3	wgszxkvzn	134cc4a76a119493d523f1855a3b7106f64287455d5cd4...	2016
4	xznhxn	ebcaf397ef5084e05889a6e9a0c3f96a5c8fb0b16749ce...	2016

Three new Features / Flags have been created

We can derive many insights from each of these flags, following are few explorations

Designation Flag- Exploration

Top 10 Employees with Designation Flag 1 (Earning More Than Most of Their Peers with Same Job Position and Experience)

In [44]:
```python
top_10_designation1 = df3[df3['Designation_Flag'] == 1].nlargest(10, 'ctc_capp
top_10_designation1
```

Out[44]:

	company_hash	email_hash	org
5984	ofxssj	e6b830e44ae282c86a370685a6e3bb3aa82ec995eec5db...	
141146	vbvkgz ftm otqcxwto	0932dc8d855953b2ac63c8046c9fb33f7f554174b6c2fe...	
124808	sqvm	ed3b3231ac4758173e68bcde8eac3842497e153d9d1832...	
141694	hmtq	9885423385b89dd905f1df74a1d6e71906ccccd915c7e4...	
71127	xzntr wgqugqvnxgz	9aa54ea5c7e0b2567cc43718bd6516f3cfefb5622b6e2b...	
51532	fvrbvqn rvmo	9adf861294aa69336409395a5474ce6f9ffbfd38594ed4...	
149217	vba	f9530fc2d3629fc9a04c7e4e2ea6b8ddbe03eb3a97caff...	
2890	eqttwyvqst	28dc7d414a336ebfecf691f1db3b9cdc95b58ffede1107...	
40534	gnytq	4f4f4bac863dc79205345fd614a4e4cd4c99718533c60d...	
115313	sggsrt	97f2289a59953b4e94f8d2436f6edf621b9a359d919bbc...	

Bottom 10 Employees with Designation Flag 3 (Earning Less Than Most of Their Peers with Same Job Position and Experience)

In [45]:

```
bottom_10_designation3 = df3[df3['Designation_Flag'] == 3].nsmallest(10, 'ctc_
bottom_10_designation3
```

Out[45]:

	company_hash	email_hash	org
73575	xzntqcxtfmxn	23ad96d6b6f1ecf554a52f6e9b61677c7d73d8a409a143...	
43232	xz rgwg	66573ebeb4fcfc496d2af1548a18a62ec3a48dae59d1cc...	
59186	xmtd	792ac1d3daa5bc5fef39e3d61e0722cce004a0b81966b1...	
47719	wgbgag	87f95061ed13da965818fded3d19249bc6d88de3b73ff2...	
94108	kvrgqv sqghu	0b1eeb6d24629a06d29fcd410c02d0f1f2577a0a050c54...	
65176	ogwxn szqvrt	38e8416bc59782b9fb60b144657130662ec8dab8094a41...	
124414	cxkqn	718ad268d9c671de079ff1c55f93e91a2d06928243ad29...	
112825	zvnxgzvr wgrrtst ge xqtrvza	fb10b6e7b4fcc82e96f5a591146046c0988c23cccb8269...	
146490	wtqz	217504679c19c4738eb44eacb651c80432d3a3801f62a5...	
56743	jvzatd	2f31b0f7d87048f22a9a6eb33526325d0b3f470185652b...	

Top 10 Employees in Each Company with Designation Flag 1

In [46]:

```
top_10_each_company_designation1 = df3[df3['Designation_Flag'] == 1].groupby('
top_10_each_company_designation1
```

```
/tmp/ipython-input-633303111.py:1: DeprecationWarning: DataFrameGroupBy.apply o
perated on the grouping columns. This behavior is deprecated, and in a future v
ersion of pandas the grouping columns will be excluded from the operation. Eith
er pass `include_groups=False` to exclude the groupings or explicitly select th
e grouping columns after groupby to silence this warning.
  top_10_each_company_designation1 = df3[df3['Designation_Flag'] == 1].groupb
y('company_hash').apply(lambda x: x.nlargest(10, 'ctc_capped')).reset_index(dro
p=True)
```

Out[46]:

	company_hash	email_hash	orgye
0	1bs	9c02076a74a2b8a64a6e003fa0a2e4115fc717dacb3585...	20
1	1bs	38dfe791fc911da418b67aa989a6aa7f00b8c680c6d4e1...	20
2	1bs	c97fd1612080086b898e440529c86325ae8ddf2e9a0b60...	20
3	1bs	7c6f711001cae257c36a621abb0b6ffa249b3d92240ee4...	20
4	1bs	bde68bd40e5bf94d4af39e89c6fe8af4b0926e4286de55...	20
...	...	...	
8457	zxztrtvuo	b5628c03989a151f60c89e726351817c3a62078e7c70de...	20
8458	zxztrtvuo	41367fd92cd85ecfa2e2ce76f4ff94cde287b95df93871...	20
8459	zxztrtvuo	f09524b67053af24c9e446c0dd4d861cf053470ceaf0c9...	20
8460	zxztrtvuo	73ed57fdb578ccb723d176b1624bb29b0e840e89ab4230...	20
8461	zxztrtvuo	f861d9f1bfee791938d90e9ad91069220eec8664b32fea...	20

8462 rows × 10 columns

Class Flag- Exploration

Top 10 employees of FullStack Engineer in each company earning more than their peers - Class 1

In [47]:

```
top_10_class1_fs = df3[(df3['job_position'] == 'FullStack Engineer') & (df3['C
top_10_class1_fs = top_10_class1_fs.groupby('company_hash').apply(lambda x: x.
```

```
/tmp/ipython-input-4177404748.py:2: DeprecationWarning: DataFrameGroupBy.apply
operated on the grouping columns. This behavior is deprecated, and in a future
version of pandas the grouping columns will be excluded from the operation. Eit
her pass `include_groups=False` to exclude the groupings or explicitly select t
he grouping columns after groupby to silence this warning.
  top_10_class1_fs = top_10_class1_fs.groupby('company_hash').apply(lambda x:
x.nlargest(10, 'ctc_capped')).reset_index(drop=True)
```

In [48]:

```
top_10_class1_fs
```

Out[48]:

	company_hash	email_hash	orgy
0	1bs	4ccdf10738e25d4f5ac6b85572ca7454453e17c5b1091b...	2(
1	1bs	55824c4e7df3af153fdfe867c15a599a6e86432c33f7c6...	2(
2	1bs ntwyzgrgsxto ucn rna	4c1e4fa4b2a7ef873e1f2b7104790a2b85aa51cae54585...	2(
3	1bs ntwyzgrgsxto ucn rna	31d074dc51e6fabd2a235c23a3d9ae0e3702cf78f270e9...	2(
4	2017	03b2ac96f3c199bcf9a5b4176d63750cd522cc315537a2...	2(
...	...	...	
4004	zxzlvwvqn	e2377e7ee0d53d2e3a45b9687fdc9c08b136b1dc470806...	2(
4005	zxzlvwvqn	e38914706e3522ee5773627abe091edd8c6596b8519a80...	2(
4006	zxztrtvuo	af742fa47c46fa167ddfaf9c22a12a31cff23717582daa...	2(
4007	zxztrtvuo	b5628c03989a151f60c89e726351817c3a62078e7c70de...	2(
4008	zxztrtvuo	0228801807a4911ebde807b5f88a273a51d92b25e6c160...	2(

4009 rows × 10 columns

Bottom 10 Employees of FullStack Engineer in Each Company Earning Less Than Their Peers - Class 3

In [49]:

```
bottom_10_class3_fs = df3[(df3['job_position'] == 'FullStack Engineer') & (df3
bottom_10_class3_fs = bottom_10_class3_fs.groupby('company_hash').apply(lambda
```

```
/tmp/ipython-input-2299531944.py:2: DeprecationWarning: DataFrameGroupBy.apply
operated on the grouping columns. This behavior is deprecated, and in a future
version of pandas the grouping columns will be excluded from the operation. Eit
her pass `include_groups=False` to exclude the groupings or explicitly select t
he grouping columns after groupby to silence this warning.
  bottom_10_class3_fs = bottom_10_class3_fs.groupby('company_hash').apply(lambd
a x: x.nsmallest(10, 'ctc_capped')).reset_index(drop=True)
```

In [50]:

```
bottom_10_class3_fs
```

Out[50]:

	company_hash	email_hash	orgye
0	1bs	a58fadbfbc00c007dfe6e5d5891f2dda013eb5cc66552a...	20
1	1bs ntwyzgrgsxto ucn rna	70ba4ee689ae53a942d5a9dffe2ceae1d776ca5736e69e...	20
2	2017	59e55425c5c878bc984e046f7664ca70e4d0df93bb21f0...	20
3	247 xrvm	e959c3dae7a03c57d6bf03d299e623be9f7e736184788b...	20
4	247vx	f8b27f9ca749c05db8ed076d13534413b63f2a2185234d...	20
...	...	...	
3226	zxxn ntwyzgrgsxto rxbxnta	58e652d3e06d4228be0a8ac9ef8228928628299d93795f...	20
3227	zxzlvwvqn	9002b19d0e582e7a807b96851505b9937bf8b696eaaa50...	20
3228	zxztrtvuo	650fd4e2b40bbc033df1c93c07f9b778ce8aa5d98e8292...	20
3229	zxztrtvuo	077a6b1aa5195410e497d0fb91fe2627db85d9b9879ec7...	20
3230	zxztrtvuo	3879b9a1e356ed20363fffd6871207eb908b38c864a2db...	20

3231 rows × 10 columns

Tier Flag- Exploration

Top 10 Employees Earning More Than Most of the Employees in the Company - Tier 1

In [51]:
```
top_10_tier1 = df3[df3['Tier_Flag'] == 1].nlargest(10, 'ctc_capped')
```

In [52]:
```
top_10_tier1
```

Out[52]:

	company_hash	email_hash	orgy
63104	mvmjrgz ytvrny	c5e7360dd9c5dd31b9b4927ccccc2f3be8f6f6a5a84963...	2
69295	aggqavoy	68f1fea4dbfb7ae2209664b93d5f57fb86912dbe516b37...	2
3393	ho mvzp	7ffb1e475e90f5bcb65de6664f24820a0049992f50cddd...	2
13674	fvqsvbxzs	299864b7e8f632bfd7079ac1f97a18371f413dfb06a2dd...	2
82719	bvqptnxzs	a53d6b54b56d30daedbfaf860cbdbbb6cc376c60832c57...	2
74545	wvqttb	01a83f323a2e7dfe7561157dce0b3dd718d68511127512...	2
50199	zxbmrt ongqvst	b6c269b356f1f7fd8d0aa23957f42d832a1de3d6c58ed3...	2
68395	wvqttb	0485990d28fdbb10e494793b31dd97f94c326a93c07a2d...	2
70600	zvnxgzvr vhonqvrxv mvzp	2ddbc233754a1bf09fa7e92d61a5fb8fd46f3fe7908318...	2
75025	bsb qtogqno xzntqzvnxgzvr	420388fd953332be671e1b0761f9af06d323382d075ecf...	2

Above List shows Top 10 employees details earning more than most of the employees of the company

Top 10 Companies Based on Their CTC

In [53]:

```
top_10_companies = df3.groupby('company_hash')['ctc_capped'].mean().nlargest(1
```

In [54]:

```
top_10_companies
```

Out[54]:

	company_hash	ctc_capped
0	2jghqaggq mrxav1 hzxctqoxnj	24000000.0
1	32255407428	24000000.0
2	3ow ogrhnxgz	24000000.0
3	99 mvkvq	24000000.0
4	agbtonxiht	24000000.0
5	aggovz mgmwvn xzaxv uqxcvnt rxbxnta	24000000.0
6	agyv tdnqvwg	24000000.0
7	ajzvbxnt vootno bvzvstbtzn	24000000.0
8	ajzvbxw oxszvr	24000000.0
9	al	24000000.0

Above is the list of Top 10 Companies with highest CTC

Top 2 Positions in Every Company Based on Their CTC

In [55]:

```
top_2_positions_per_company = df3.groupby(['company_hash', 'job_position'])['c
top_2_positions_per_company = top_2_positions_per_company.groupby('company_has
```

```
/tmp/ipython-input-266804086.py:2: DeprecationWarning: DataFrameGroupBy.apply o
perated on the grouping columns. This behavior is deprecated, and in a future v
ersion of pandas the grouping columns will be excluded from the operation. Eith
er pass `include_groups=False` to exclude the groupings or explicitly select th
e grouping columns after groupby to silence this warning.
  top_2_positions_per_company = top_2_positions_per_company.groupby('company_ha
sh').apply(lambda x: x.nlargest(2, 'ctc_capped')).reset_index(drop=True)
```

In [56]:

```
top_2_positions_per_company
```

Out[56]:

	company_hash	job_position	ctc_capped
0	0	Other	100000.0
1	0000	Other	300000.0
2	01 ojztqsj	Frontend Engineer	830000.0
3	01 ojztqsj	Android Engineer	270000.0
4	05mz exzytvrny uqxcvnt rxbxnta	Backend Engineer	1100000.0
...	...	...	...
44121	zyvzwt wgzohrnxzs tzsxzttqo	Frontend Engineer	940000.0
44122	zz	Other	1370000.0
44123	zz	unknown	500000.0
44124	zzb ztdnstz vacxogqj ucn rna	unknown	600000.0
44125	zzgato	unknown	130000.0

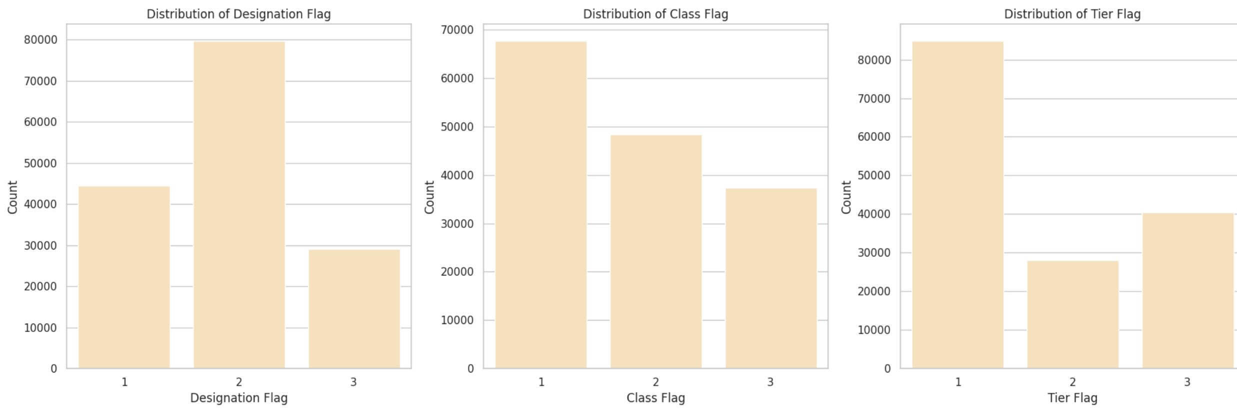
44126 rows × 3 columns

INSIGHTS

Distribution Analysis

In [57]:

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

# Plot the distribution of Designation_Flag
sns.countplot(x='Designation_Flag', data=df3, ax=axes[0],color='moccasin')
axes[0].set_title('Distribution of Designation Flag')
axes[0].set_xlabel('Designation Flag')
axes[0].set_ylabel('Count')

# Plot the distribution of Class_Flag
sns.countplot(x='Class_Flag', data=df3, ax=axes[1],color='moccasin')
axes[1].set_title('Distribution of Class Flag')
axes[1].set_xlabel('Class Flag')
axes[1].set_ylabel('Count')

# Plot the distribution of Tier_Flag
sns.countplot(x='Tier_Flag', data=df3, ax=axes[2],color='moccasin')
axes[2].set_title('Distribution of Tier Flag')
axes[2].set_xlabel('Tier Flag')
axes[2].set_ylabel('Count')

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



- Class Flag distribution looks more balanced as compared to Designation and Tier Flag

Q. Discuss the distribution of learners based on the Tier flag:

1. Which companies dominate in Tier 1 and why might this be the case?
2. Are there any notable patterns or insights when comparing learners from Tier 3 across different companies?

In [58]:
```
# Filter for Tier 1 learners
tier_1_learners = df3[df3['Tier_Flag'] == 1]

# Count learners in Tier 1 for each company
tier_1_company_counts = tier_1_learners['company_hash'].value_counts().reset_i
tier_1_company_counts.columns = ['company_hash', 'count']

# Top companies in Tier 1
top_tier_1_companies = tier_1_company_counts.head(10)
print(top_tier_1_companies)
```

```
               company_hash  count
0  nvnv wgzohrnvzwj otqcxwto   4642
1                   xzegojo   2947
2     zgn vuurxwvmrt vwwghzn   1804
3                 wgszxkvzn   1783
4                 vwwtznhqt   1660
5                   vbvkgz   1564
6              fxuqg rxbxnta   1513
7                   gqvwrt   1136
8                 wvustbxzx   1039
9                      zvz    983
```

In [59]:
```
# Filter for Tier 3 learners
tier_3_learners = df3[df3['Tier_Flag'] == 3]

# Count learners in Tier 3 for each company
tier_3_company_counts = tier_3_learners['company_hash'].value_counts().reset_i
tier_3_company_counts.columns = ['company_hash', 'count']
```

```python
# Top companies in Tier 3
top_tier_3_companies = tier_3_company_counts.head(10)
print(top_tier_3_companies)
```

```
                company_hash  count
0                     vbvkgz    876
1  nvnv wgzohrnvzwj otqcxwto    694
2                     gqvwrt    611
3                  bxwqgogen    592
4                    xzegojo    579
5                        zvz    416
6                  wgszxkvzn    416
7     zgn vuurxwvmrt vwwghzn    388
8                      vagmt    366
9                  wvustbxzx    336
```

1. Companies Dominating in Tier 1

Common Factors: Companies dominating Tier 1 might have a large number of entry-level positions or companies that offer lower-than-average compensation.

Possible Reasons: Large enterprises with many junior or mid-level positions. Companies in traditional industries or smaller firms with limited budgets. 2. Patterns in Tier 3 Across Different Companies

High CTC Companies: Companies with a high number of Tier 3 learners might be in tech, finance, or other high-paying sectors.

Career Progression: These companies might offer better career progression and compensation growth.

Retention Strategy: Higher compensation could be a strategy to retain top talent.

Summary Statistics

In [60]:
```python
designation_summary = df3.groupby('Designation_Flag')['ctc_capped'].describe()
class_summary = df3.groupby('Class_Flag')['ctc_capped'].describe()
tier_summary = df3.groupby('Tier_Flag')['ctc_capped'].describe()
```

In [61]:
```python
designation_summary
```

Out[61]:

Designation_Flag	count	mean	std	min	25%	50
1	44536.0	8.964837e+05	7.123766e+05	2.0	400000.0	697000
2	79743.0	1.606745e+06	2.846606e+06	15.0	550000.0	950000
3	29164.0	2.508838e+06	3.605452e+06	14.0	1000000.0	1600000

In [62]:
```
class_summary
```

Out[62]:

Class_Flag	count	mean	std	min	25%	50%	
1	67733.0	9.048573e+05	6.766357e+05	2.0	450000.0	710000.0	120
2	48358.0	1.520279e+06	3.011210e+06	24.0	490000.0	810000.0	150
3	37352.0	2.848947e+06	3.778324e+06	16.0	1200000.0	1900000.0	300

In [63]:
```
tier_summary
```

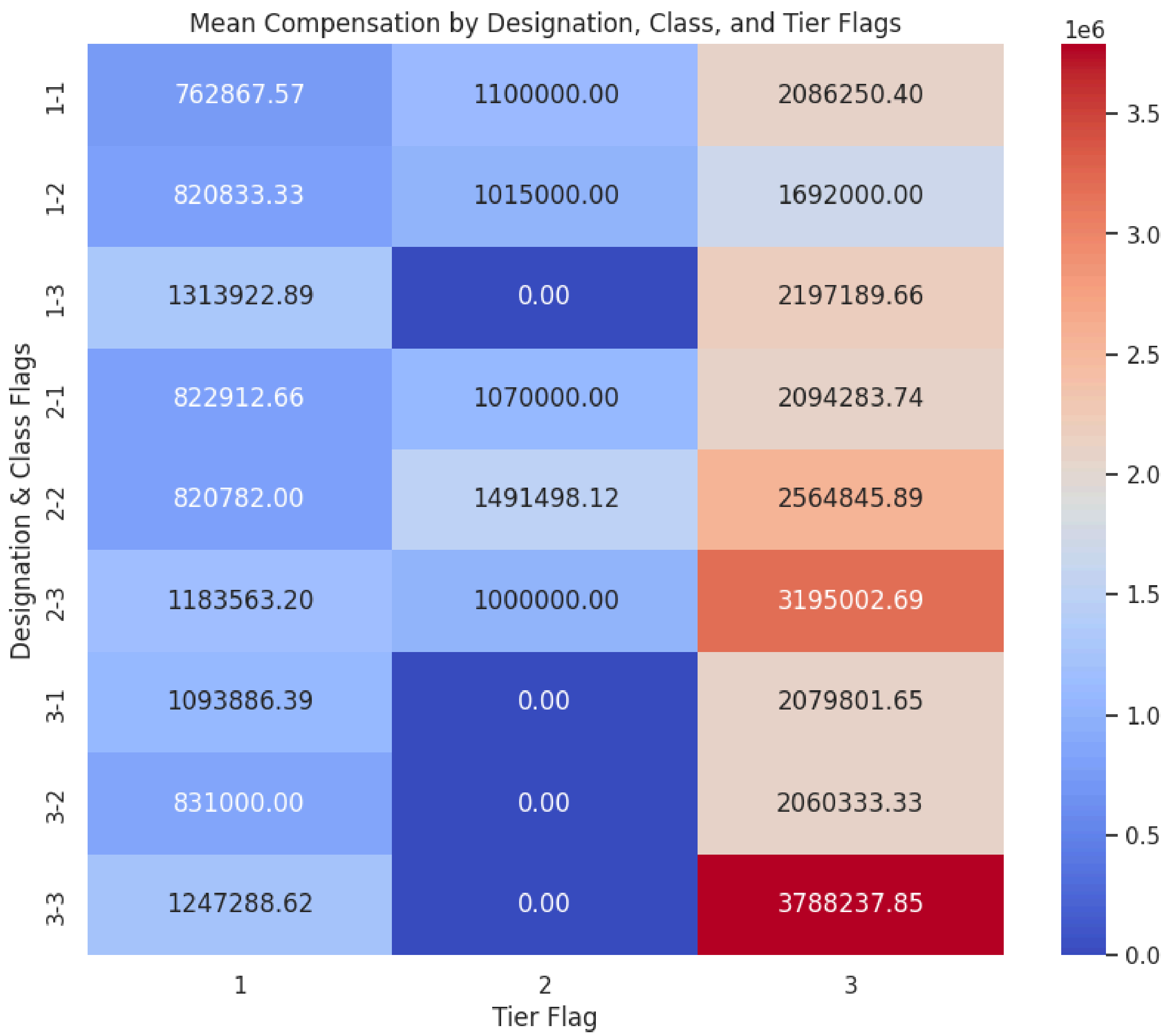
Out[63]:

Tier_Flag	count	mean	std	min	25%	50%	
1	84894.0	8.710126e+05	5.787411e+05	2.0	450000.0	730000.0	1150
2	28069.0	1.491308e+06	3.280566e+06	24.0	400000.0	730000.0	1310
3	40480.0	3.098245e+06	3.936230e+06	16.0	1400000.0	2100000.0	3200

- Mean CTC in all the categories and under each flag is similar
- Maximum CTC in flags 2 and 3 of all the categories is same

Visualizing Mean Compensation

In [64]:
```
# Mean compensation by flags
mean_compensation_flags = df3.groupby(['Designation_Flag', 'Class_Flag', 'Tier

# Plot the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(mean_compensation_flags, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Mean Compensation by Designation, Class, and Tier Flags')
plt.xlabel('Tier Flag')
plt.ylabel('Designation & Class Flags')
plt.show()
```



- Mean CTC in Designation Flag 3 , Class Flag 3 and Tier Flag 3 are highly correlated
- Followed by mean CTC of D2, C3 and T3
- Tier 2 ctc is not correlated to D3 and any of the flag of Class

Cross-Tabulation Analysis

Examining the relationship between these flags can reveal if there are patterns or dependencies among them.

In [65]:
```
designation_class_ct = pd.crosstab(df3['Designation_Flag'], df3['Class_Flag'],
designation_tier_ct = pd.crosstab(df3['Designation_Flag'], df3['Tier_Flag'], n
class_tier_ct = pd.crosstab(df3['Class_Flag'], df3['Tier_Flag'], normalize='in

print("Cross-Tabulation between Designation Flag and Class Flag:\n", designati
print("\nCross-Tabulation between Designation Flag and Tier Flag:\n", designat
print("\nCross-Tabulation between Class Flag and Tier Flag:\n", class_tier_ct)
```

```
Cross-Tabulation between Designation Flag and Class Flag:
 Class_Flag               1         2         3
Designation_Flag
1                 0.911892  0.000427  0.087682
2                 0.211367  0.605947  0.182687
3                 0.352009  0.000651  0.647339

Cross-Tabulation between Designation Flag and Tier Flag:
 Tier_Flag                1         2         3
Designation_Flag
1                 0.916966  0.000067  0.082967
2                 0.384071  0.351956  0.263973
3                 0.460465  0.000000  0.539535

Cross-Tabulation between Class Flag and Tier Flag:
 Tier_Flag          1         2         3
Class_Flag
1           0.936781  0.000103  0.063115
2           0.241718  0.580235  0.178047
3           0.261137  0.000080  0.738782
```

Cross-Tabulation between Designation_Flag and Class_Flag:

- Designation_Flag 1: 91.2% of these employees are also in Class_Flag 1, indicating a strong overlap where lower designations coincide with lower class levels.
- Designation_Flag 2: Majority (60.6%) are in Class_Flag 2, meaning median designation levels align with median class levels.
- Designation_Flag 3: 64.7% are in Class_Flag 3, showing higher designations are often associated with higher class levels.

Cross-Tabulation between Designation_Flag and Tier_Flag:

- Designation_Flag 1: 91.7% are in Tier_Flag 1, showing low designation levels are mostly in lower tier companies.
- Designation_Flag 2: Distribution is more spread with notable percentages in all tiers.
- Designation_Flag 3: 53.9% in Tier_Flag 3, indicating higher designations are more common in higher tier companies.

Cross-Tabulation between Class_Flag and Tier_Flag:

- Class_Flag 1: 93.7% are in Tier_Flag 1, indicating lower class levels are predominantly in lower tier companies.
- Class_Flag 2: 58% in Tier_Flag 2, showing median class levels align with median tier companies.
- Class_Flag 3: 73.9% in Tier_Flag 3, indicating higher class levels are mostly in higher tier companies.

General Insights:

1. Alignment within Categories: There is a noticeable alignment within the categories where higher flags in one dimension (e.g., Designation_Flag) often coincide with higher flags in another dimension (e.g., Class_Flag and Tier_Flag). This suggests that performance, role importance, and company tier are interconnected.

2. Disparities at Median Levels: Employees with median flags (Flag 2) in one category tend to have a more spread distribution across other categories. This indicates that employees at the median level in terms of designation, class, or tier are not strictly confined to the median level in the other categories.

3. Low-End and High-End Correlation: Employees at the low end (Flag 1) in one category are predominantly at the low end in others, and similarly for the high end (Flag 3). This can be used to target interventions or identify opportunities for improvement for lower-tier employees.

Recommendations:

1. Cluster Characterization:

- A cluster with Designation_Flag 3, Class_Flag 3, and Tier_Flag 3 would represent high-performing individuals in top companies with high compensation.

2. Targeted Recommendations:

- Provide personalized course recommendations or career advice based on the clusters. -Lower-tier clusters might benefit from upskilling programs targeting higher-tier company requirements.

3. Identifying Opportunities:

- Recognize gaps where there are inconsistencies, such as Designation_Flag 3 individuals in Tier_Flag 1 companies, and investigate the reasons.

4. Company and Job Position Profiling:

- Profile companies and job positions based on the prevalence of higher flags.
- Use these profiles to guide learners towards roles and companies that

align with their career aspirations and skills.

5. Retention Strategies:

- For clusters with high Designation_Flag, Class_Flag, and Tier_Flag, develop retention strategies to maintain engagement and satisfaction.

Exploratory Data Analysis

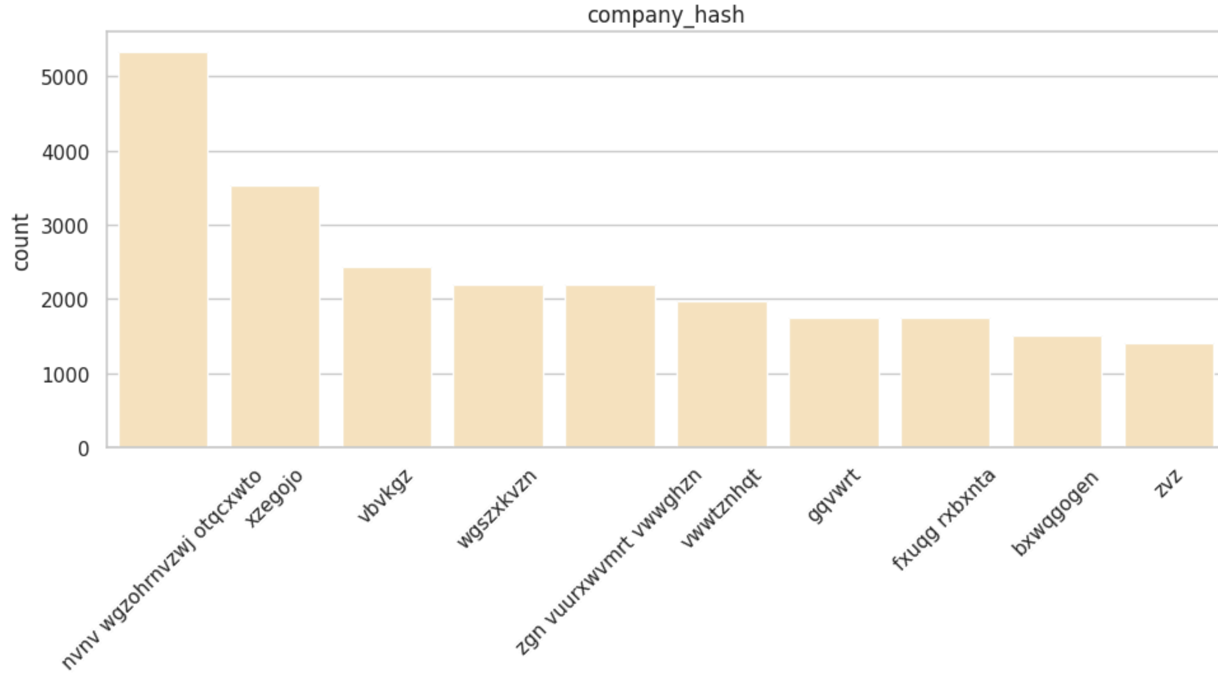
- UniVariate Analysis
- BiVariate Analysis
- Statistical Summary

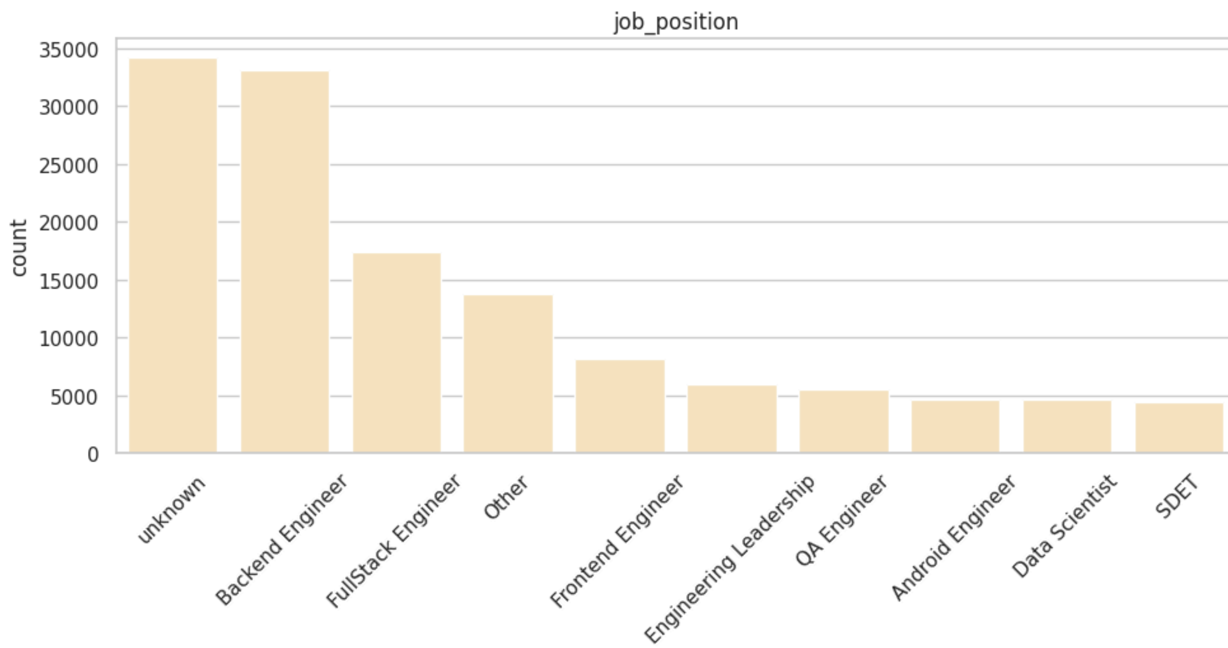
Categorical Feature Distribution

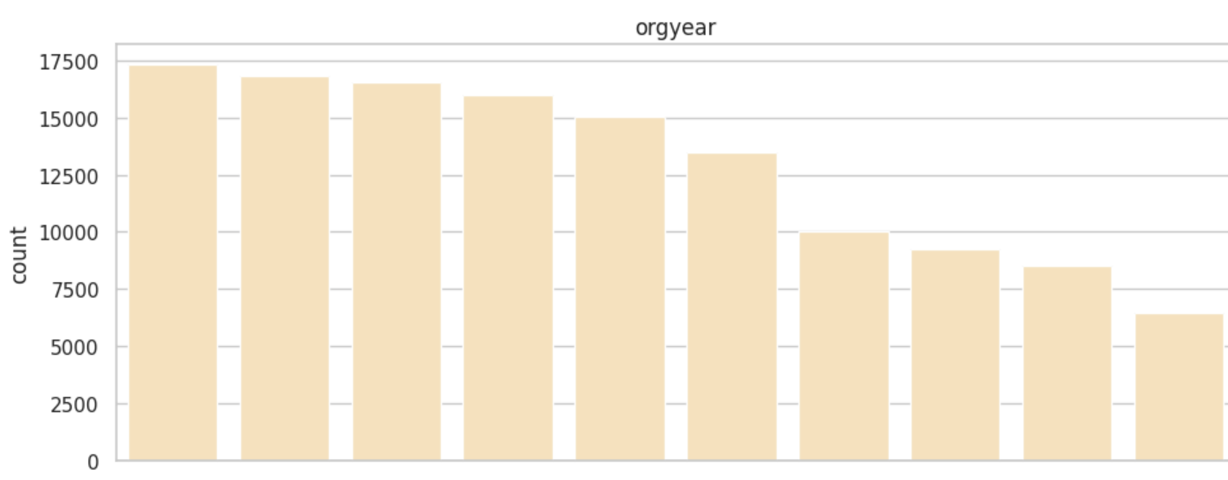
In [66]:
```
obj_cols= ['company_hash', 'job_position','orgyear']
```

In [67]:
```
num_cols= ['ctc_capped','YOE_capped']
```

In [68]:
```
plt.figure(figsize=(10, 15))

i = 1
for col in obj_cols:
    # Get the top 10 values for the column
    top_10 = df3[col].value_counts().nlargest(10)
    top_10_index = top_10.index

    ax = plt.subplot(3, 1, i)
    sns.countplot(x=df3[col], order=top_10_index, color='moccasin')
    plt.title(f'{col}')
    if i <= 2:
        plt.xticks(rotation=45)

    ax.set_xlabel('')
    i += 1

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


company_hash
count
0
1000
2000
3000
4000
5000
nvnv wgzohrnvzwj otqcxwto
xzegojo
vbvkgz
wgszxkvzn
zgn vuurxwvmrt vwwghzn
vwwtznhqt
gqvwrt
fxuqg rxbxnta
bxwqgogen
zvz


job_position
count
0
5000
10000
15000
20000
25000
30000
35000
unknown
Backend Engineer
FullStack Engineer
Other
Frontend Engineer
Engineering Leadership
QA Engineer
Android Engineer
Data Scientist
SDET

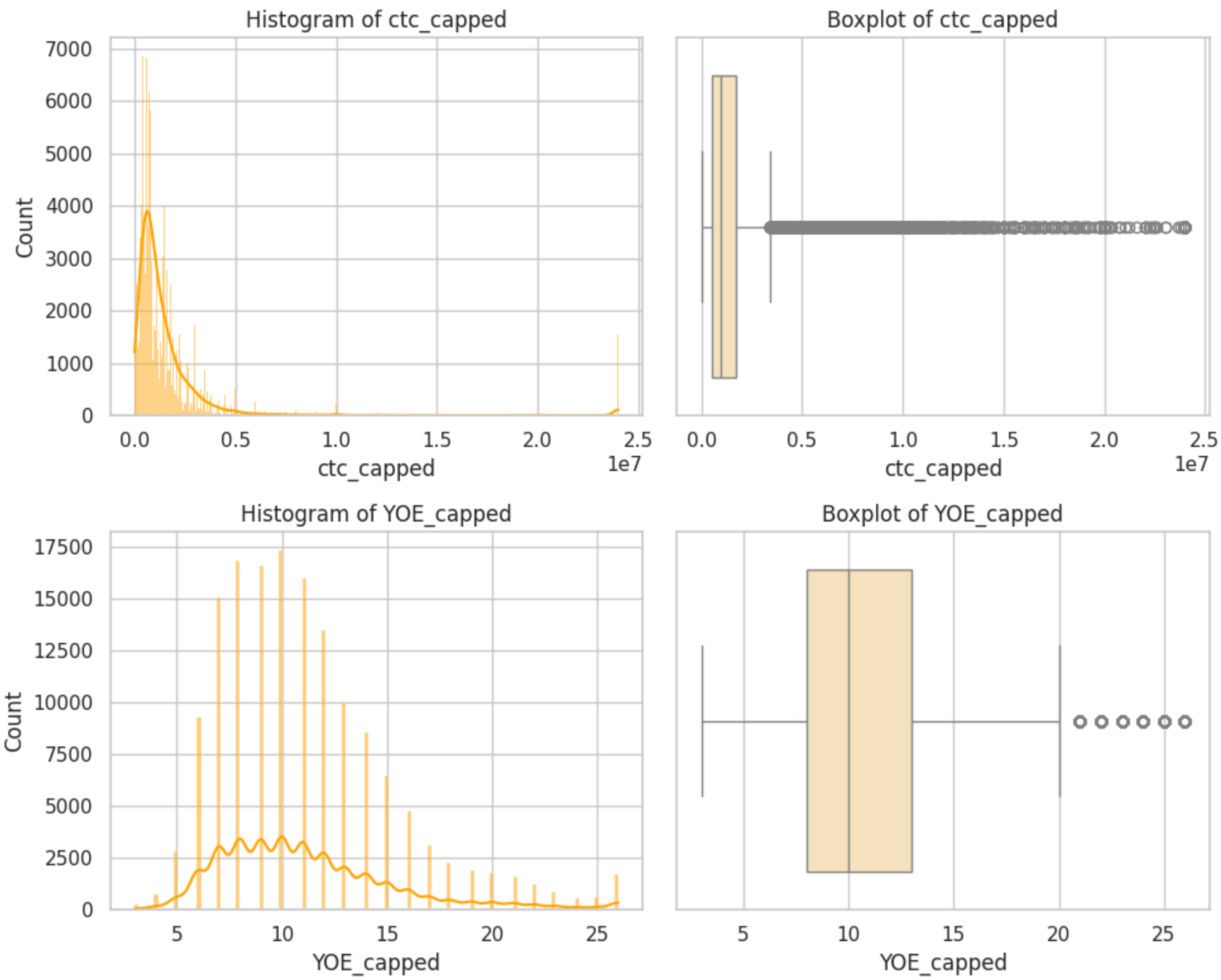

orgyear
count
0
2500
5000
7500
10000
12500
15000
17500

Highlights:

- We can easily find top 10 companies in terms of count in the dataset
- Top job position is 'unknown' followed by 'Backend Engineer' and 'FullStack Engineer'
- Most of the employees started working in the year 2016 followed by 2018 and 2017

Numerical Feature Distribution

In [69]:
```
plt.figure(figsize=(10, 8))

# Loop through each numerical column and plot histogram and boxplot
for i, col in enumerate(num_cols):
    # Histogram
    ax1 = plt.subplot(2, 2, 2*i + 1)
    sns.histplot(df3[col], kde=True, color='orange')
    plt.title(f'Histogram of {col}')

    # Boxplot
    ax2 = plt.subplot(2, 2, 2*i + 2)
    sns.boxplot(x=df3[col], color='moccasin')
    plt.title(f'Boxplot of {col}')

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



- Distribution of CTC is right skewed
- Most of the ctc is around 10 Lac
- Distribution of YOE is almost normal with most of the YOE lying around 6-9 years

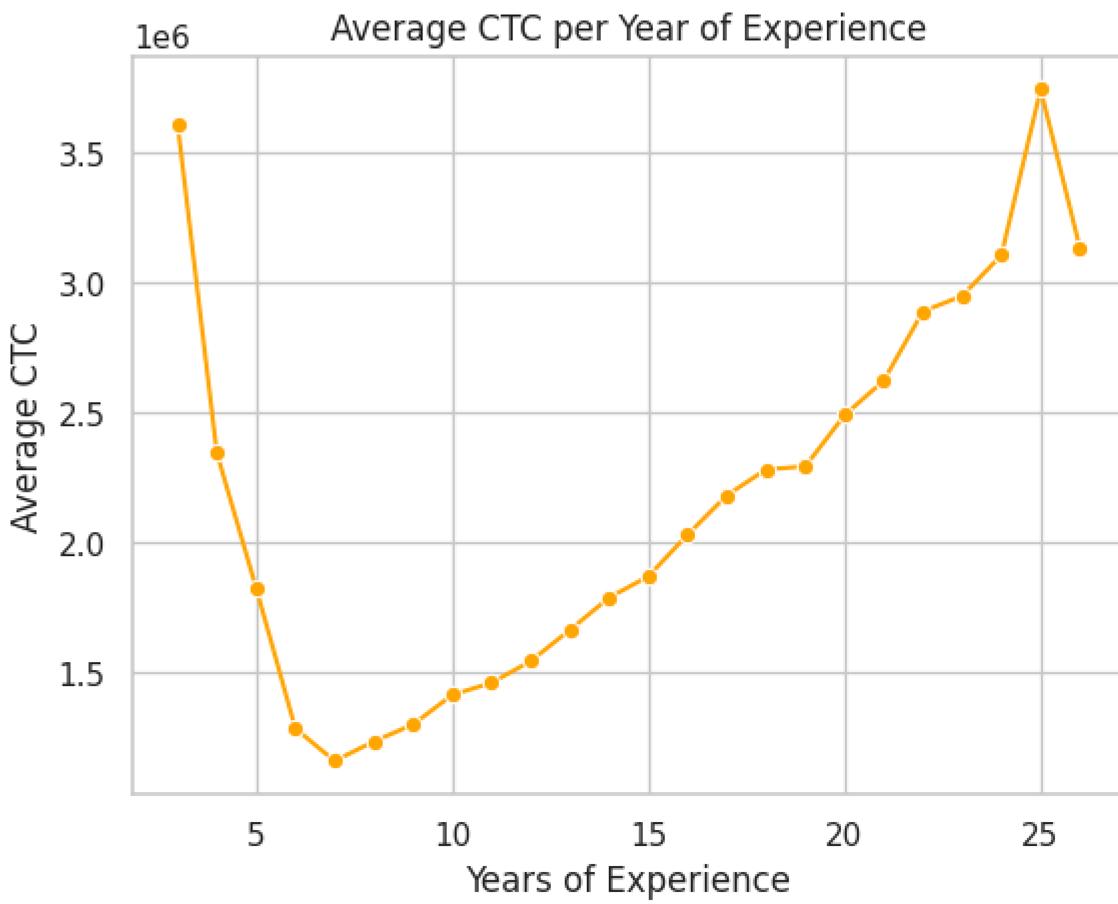
CTC vs Years of Experience

In [70]:
```
sns.scatterplot(x='YOE_capped', y='ctc_capped', data=df3, color='moccasin')
plt.title('CTC vs. Years of Experience')
plt.show()
```

There is no linear relationship or any specific pattern between Years of Experience and CTC

Years of Experience vs Avg. CTC

In [71]:
```
# Calculate average CTC per year of experience
avg_ctc_per_yoe = df3.groupby('YOE_capped')['ctc_capped'].mean().reset_index()

# Line plot with markers
sns.lineplot(x='YOE_capped', y='ctc_capped', data=avg_ctc_per_yoe, marker='o',
plt.title('Average CTC per Year of Experience')
plt.xlabel('Years of Experience')
plt.ylabel('Average CTC')

plt.show()
```



- Avg. CTC is decreasing from 1 to 5 years of Experience. There might be a slight decrease in CTC with increasing experience, possibly due to industry-specific factors or career shifts.
- From 5 to 23 years it is showing natural increase in CTC, then again a drop from 23 to 24 years

Q. Name job position that is commonly considered entry-level but has a few learners with unusually high CTCs in the dataset.

In [72]:
```
# Identify common entry-level job positions (this is a subjective list, you ca
entry_level_positions = ['Junior Engineer', 'Intern', 'Trainee', 'Associate', 

# Filter the dataframe for these positions
entry_level_df = df3[df3['job_position'].isin(entry_level_positions)]

# Group by job position and calculate statistics
grouped_positions = entry_level_df.groupby('job_position')['ctc_capped'].agg([

# Calculate the threshold to identify unusually high CTCs (e.g., 2 times the m
grouped_positions['high_ctc_threshold'] = grouped_positions['mean'] * 2

# Find job positions where the max CTC is greater than the high CTC threshold
```

```
unusually_high_ctcs = grouped_positions[grouped_positions['max'] > grouped_pos

# Output the results
print(unusually_high_ctcs)
```

```
  job_position      mean      max  high_ctc_threshold
0    Associate  646000.0  1500000           1292000.0
```

Associate is one job position considered as entry level but maximum CTC going beyond set threshold

Q. What is the average CTC of learners across different job positions?

In [73]:
```
# Group by job position and calculate the average CTC
average_ctc_by_position = df3.groupby('job_position')['ctc_capped'].mean().res

# Rename the columns for clarity
average_ctc_by_position.columns = ['job_position', 'average_ctc']

# Sort the result by average CTC in descending order
average_ctc_by_position = average_ctc_by_position.sort_values(by='average_ctc'

# Print the result
print(average_ctc_by_position)
```

```
                                          job_position  average_ctc
382                                          Seleceman   24000000.0
101                                       Business Man   24000000.0
425                             Senior System Engineer   24000000.0
143                                         Data entry   24000000.0
342                                           Reseller   24000000.0
..                                                 ...          ...
526  Some data entry operator like some copy's writ...      10000.0
223                                  Junior consultant      10000.0
641                                   project engineer       7900.0
189                            Full-stack web developer       7500.0
273                                      New graduate       2000.0

[652 rows x 2 columns]
```

Q.For a given company, how does the average CTC of a Data Scientist compare with other roles?

In [74]:
```
# Filter the dataframe for rows where job_position is 'Data Scientist'
data_scientist_df = df3[df3['job_position'] == 'Data Scientist']

# Get the unique companies that have the job position 'Data Scientist'
companies_with_data_scientist = data_scientist_df['company_hash'].unique()

# Print the result
print("Companies with 'Data Scientist' job position:")
print(companies_with_data_scientist)
```

```
Companies with 'Data Scientist' job position:
['ihvznuyx' 'tqxwoogz' 'vrsgzgd ucn rna' ... 'ohbjvs xzoxsyno rrw'
 'yjhzavx bgmxo' 'wgbuzgcv wgznqvwn']
```

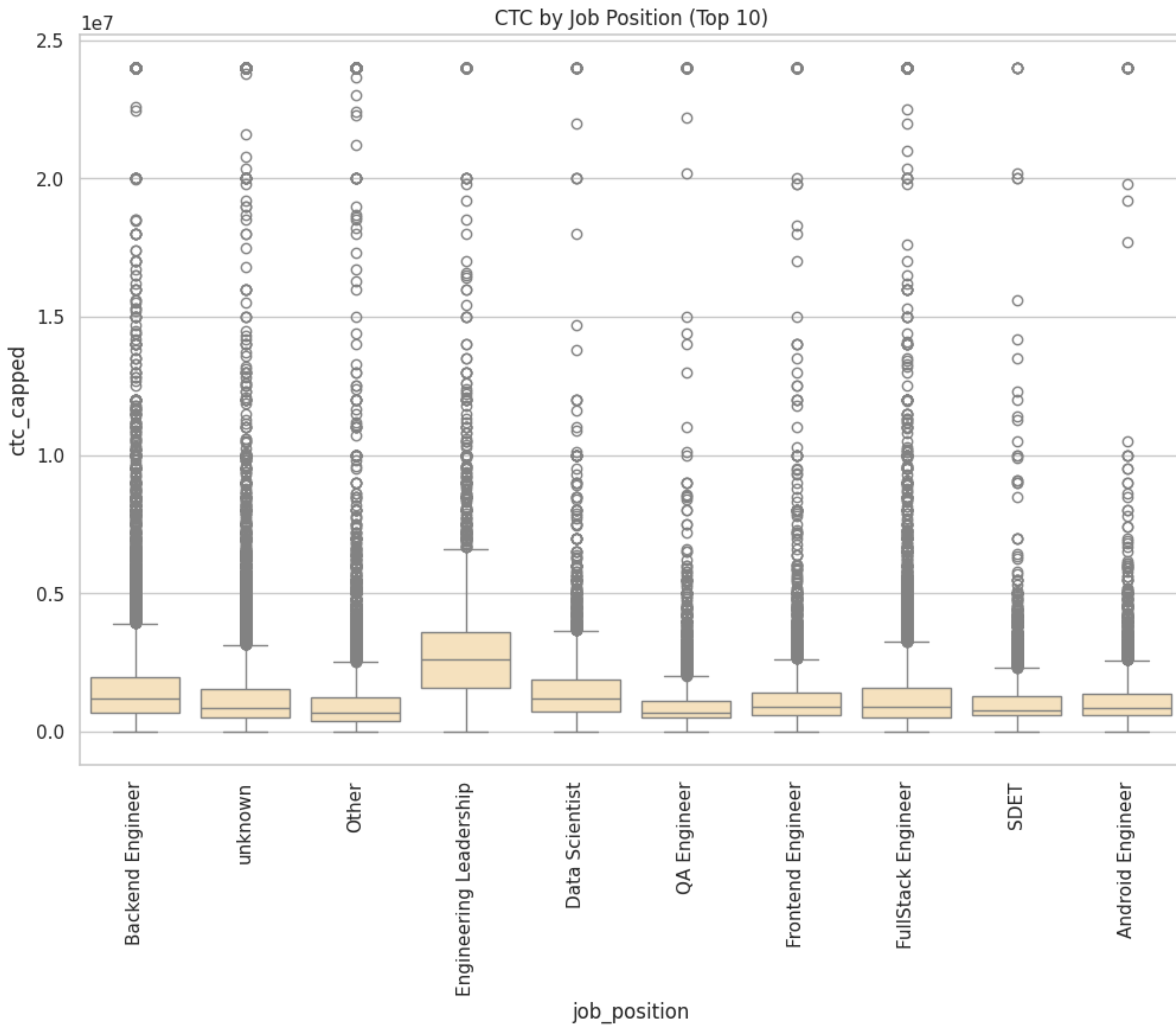
In [75]:
```python
company_hash_given = 'xznhxn'  # Replace with the actual company_hash

# Filter the dataframe for the given company
df_company = df3[df3['company_hash'] == company_hash_given]

# Calculate the average CTC for Data Scientist role
data_scientist_ctc = df_company[df_company['job_position'] == 'Data Scientist'

# Calculate the average CTC for all other roles
other_roles_ctc = df_company[df_company['job_position'] != 'Data Scientist']['

# Print the result
print(f"Average CTC for Data Scientist in company {company_hash_given}: {data_
print(f"Average CTC for all other roles in company {company_hash_given}: {othe

# Compare the two values
if not pd.isna(data_scientist_ctc) and not pd.isna(other_roles_ctc):
    if data_scientist_ctc > other_roles_ctc:
        print("Data Scientists have a higher average CTC compared to other rol
    elif data_scientist_ctc < other_roles_ctc:
        print("Data Scientists have a lower average CTC compared to other role
    else:
        print("Data Scientists have the same average CTC as other roles.")
else:
    print("Data Scientist role or other roles not found in the given company."
```

```
Average CTC for Data Scientist in company xznhxn: 4833333.333333333
Average CTC for all other roles in company xznhxn: 2816223.105527638
Data Scientists have a higher average CTC compared to other roles.
```

We can get same information for any given company or all the companies

CTC by Job Position

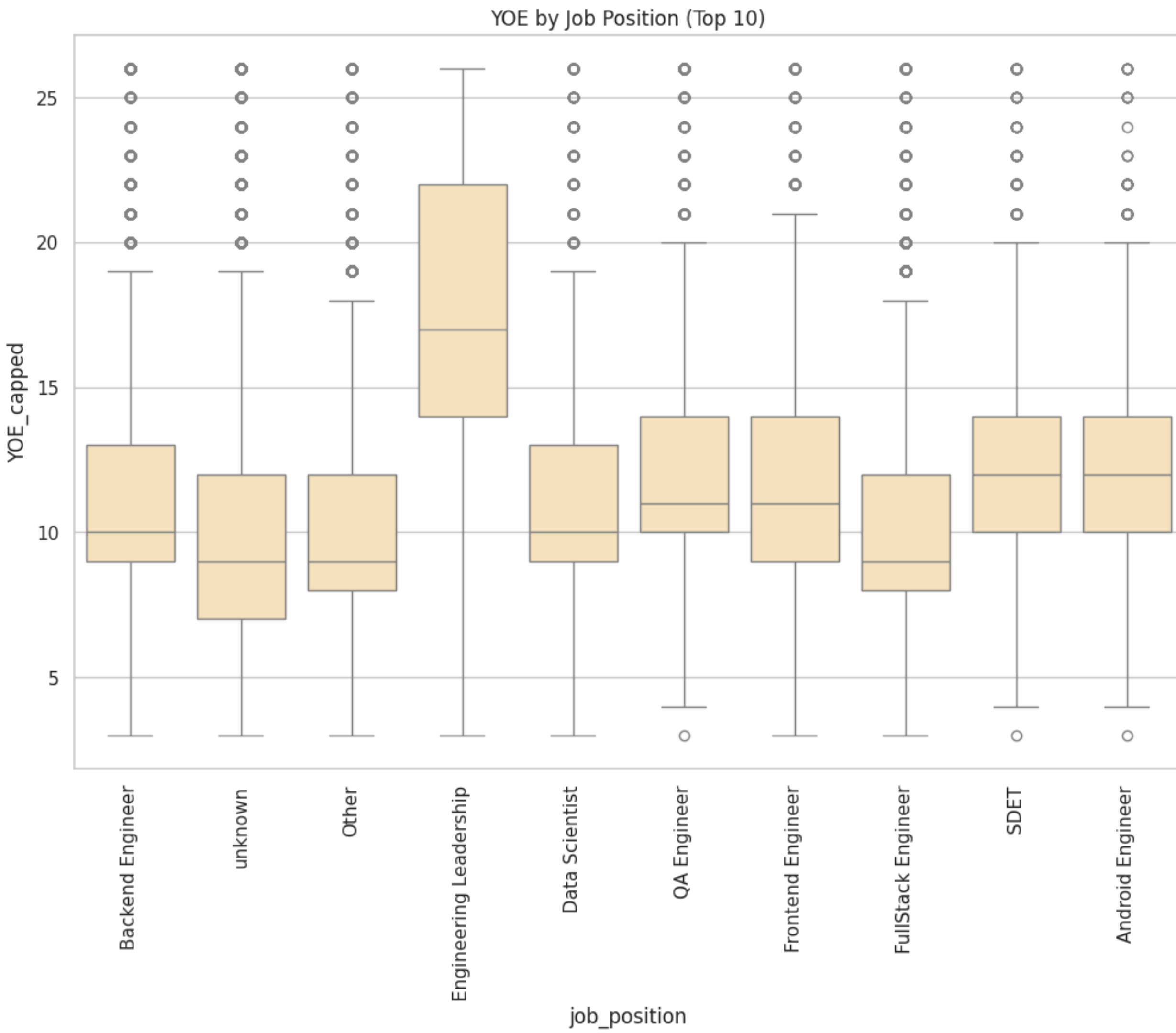
In [76]:
```python
# Get the top 10 job positions by count
top_10_job_positions = df3['job_position'].value_counts().nlargest(10).index

# Filter the dataset to include only the top 10 job positions
df_top_10 = df3[df3['job_position'].isin(top_10_job_positions)]

# Plot the box plot for CTC by Job Position
plt.figure(figsize=(12, 8))
sns.boxplot(x='job_position', y='ctc_capped', data=df_top_10, color='moccasin'
plt.xticks(rotation=90)
plt.title('CTC by Job Position (Top 10)')
plt.show()
```



CTC is highest for Engineering Leadership followed by Backend Engineer and Data Scientist

Years of Experience by Job Position

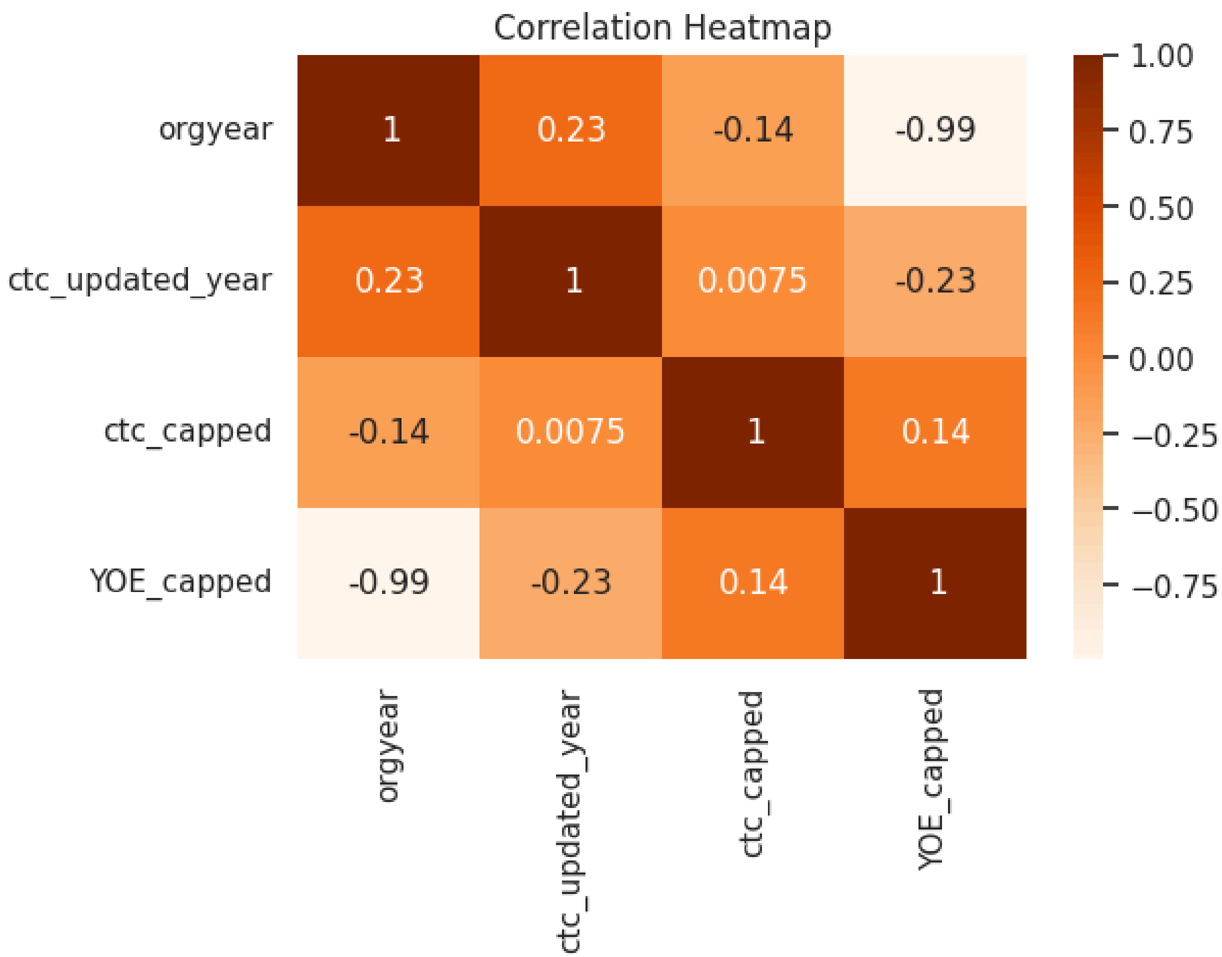
In [77]:
```
# Get the top 10 job positions by count
top_10_job_positions = df3['job_position'].value_counts().nlargest(10).index

# Filter the dataset to include only the top 10 job positions
df_top_10 = df3[df3['job_position'].isin(top_10_job_positions)]

# Plot the box plot for YOE by Job Position
plt.figure(figsize=(12, 8))
sns.boxplot(x='job_position', y='YOE_capped', data=df_top_10,color='moccasin')
plt.xticks(rotation=90)
plt.title('YOE by Job Position (Top 10)')
plt.show()
```



Years of Experience is highest for Engineering Leadership followed by Android Engineer and SDET

Correlation Heatmap

In [78]:
```
plt.figure(figsize=(6, 4))
sns.heatmap(df3[['orgyear', 'ctc_updated_year', 'ctc_capped', 'YOE_capped']].c
plt.title('Correlation Heatmap')
plt.show()
```



- orgyear and ctc_updated_year shown weak positive correlation
- Years of Experience and orgyear show strong negative correlation
- Years of Experience and CTC show weak positive correaltion

Statistical Summary

In [79]:
```
df2.describe(include='object')
```

Out[79]:

	company_hash	email_hash	job_p
count	153443	153443	
unique	36366	153443	
top	nvnv wgzohrnvzwj otqcxwto	0bcfc1d05f2e8dc4147743a1313aa70a119b41b30d4a1f...	u
freq	5336	1	

In [80]:
```
df2.describe()
```

Out[80]:

	orgyear	ctc	ctc_updated_year	YOE	ctc_cap
count	153443.000000	1.534430e+05	153443.00000	153443.000000	1.534430e
mean	2014.811467	2.501398e+06	2019.42172	11.188533	1.572051e
std	4.369586	1.307523e+07	1.36023	4.369586	2.670005e
min	1900.000000	2.000000e+00	2015.00000	3.000000	2.000000e
25%	2013.000000	5.500000e+05	2019.00000	8.000000	5.500000e
50%	2016.000000	9.500000e+05	2019.00000	10.000000	9.500000e
75%	2018.000000	1.700000e+06	2020.00000	13.000000	1.700000e
max	2023.000000	1.000150e+09	2021.00000	126.000000	2.400000e

- Dataset have got 36366 unique companies
- There are 153443 unique learners
- And 652 unique job positions
- Minimum year of Employment starting date is 1900 and maximum is 2023
- Minimum CTC is 2 and maximum 2.4 cr after capping
- Minimum Years of experience is 1 and maximum is 24 after capping

Data Processing for Unsupervised Learning

- Encoding
- Scaling
- Feature Engineering
- Log Transformation

In [81]:
```
df4=df3.drop(['Designation_Flag', 'Class_Flag', 'Tier_Flag'], axis=1)
```

Removing these flags from the prepared data since they were meant for Manual Clustering

In [82]:
```
dfcopy=df.copy()
```

In [83]:
```
# Calculate frequency of email_hash in dfcopy
email_hash_freq = dfcopy['email_hash'].value_counts().reset_index()
email_hash_freq.columns = ['email_hash', 'no_of_ctc_update']

# Merge with df4 on email_hash
```

```
df4_merged = pd.merge(df4, email_hash_freq, on='email_hash', how='left')
```

Created a new feature 'no_of_ctc_update' signifying the number of times CTC got updated of a learner which is derived from frequency of email_hash in the dataset

In [84]:
```
df4_merged=df4_merged.drop(['email_hash', 'orgyear', 'ctc_updated_year'], axis
```

Removing followng columns:

- email_hash: It is unique for each row and do not provide useful information for clustering
- orgyear: We have got Years of Experience derived from this feature which is more relevant then just the year of joining for clustering algorithm
- ctc_updated_year: We have derived a feature no. of ctc update signifying number of times ctc got updated of a learner which is more relevant to clustering algorithm than mere year as a timeline or int

In [85]:
```
df4_merged.head()
```

Out[85]:

	company_hash	job_position	ctc_capped	YOE_capped	no_of_ctc_update
0	ngpgutaxv	Backend Engineer	700000	9	1
1	vwwtznhqt ntwyzgrgsj	Backend Engineer	400000	7	1
2	xrbhd	unknown	360000	7	1
3	wgszxkvzn	Data Analyst	440000	10	1
4	xznhxn	Backend Engineer	440000	10	1

In [86]:
```
df5=df4_merged.copy()
```

Encoding non-numerical columns

Frequency Encoding replaces each categorical value with its frequency in the dataset. A good compromise between simplicity and capturing categorical variable importance.

In [87]:
```
# Frequency encoding for company_hash
company_hash_freq = df4_merged['company_hash'].value_counts().to_dict()
df4_merged['company_hash_encoded'] = df4_merged['company_hash'].map(company_ha

# Frequency encoding for job_position
job_position_freq = df4_merged['job_position'].value_counts().to_dict()
```

```
df4_merged['job_position_encoded'] = df4_merged['job_position'].map(job_positi
```

In [88]:
```
df4_merged=df4_merged.drop(['company_hash', 'job_position'], axis=1)
```

In [89]:
```
df4_merged.head()
```

Out[89]:

	ctc_capped	YOE_capped	no_of_ctc_update	company_hash_encoded	job_posit
0	700000	9	1	53	
1	400000	7	1	15	
2	360000	7	1	1	
3	440000	10	1	2199	
4	440000	10	1	202	

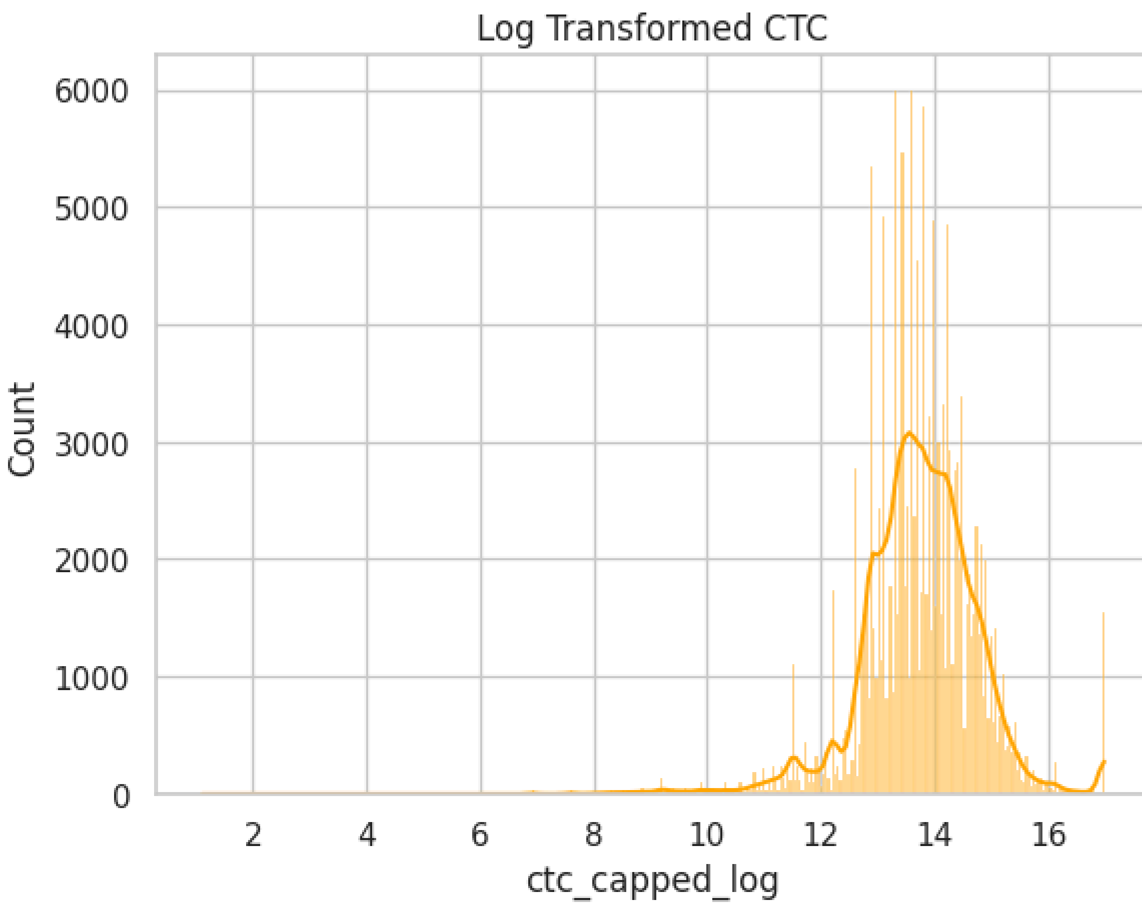
Log Transformation

Applying Log Transformation on ctc_capped column since it is right skewed. Since skewness can affect performance of clustering algorithms

In [90]:
```
df4_merged['ctc_capped_log'] = np.log1p(df4_merged['ctc_capped'])
```

In [91]:
```
df4_merged=df4_merged.drop(['ctc_capped'], axis=1)
```

In [92]:
```
sns.histplot(df4_merged['ctc_capped_log'], kde=True,color='orange')
plt.title('Log Transformed CTC')
plt.show()
```



After applying log transformation, the feature shows normal distribution

In [93]:
```
df4_merged.head()
```

Out[93]:

	YOE_capped	no_of_ctc_update	company_hash_encoded	job_position_encoded
0	9	1	53	33154
1	7	1	15	33154
2	7	1	1	34191
3	10	1	2199	2222
4	10	1	202	33154

Standard Scaling

In [94]:
```
from sklearn.preprocessing import StandardScaler
```

In [95]:
```
# Initialize the StandardScaler
scaler = StandardScaler()

# Fit and transform the data
scaled_features = scaler.fit_transform(df4_merged[['YOE_capped', 'no_of_ctc_up
```

```
# Convert the scaled features back to a DataFrame
df_scaled = pd.DataFrame(scaled_features, columns=['YOE_capped', 'no_of_ctc_up
```

In [96]:
```
df_scaled.head()
```

Out[96]:

	YOE_capped	no_of_ctc_update	company_hash_encoded	job_position_encoded
0	-0.511243	-0.530558	-0.453490	1.025669
1	-0.985991	-0.530558	-0.485592	1.025669
2	-0.985991	-0.530558	-0.497419	1.103940
3	-0.273869	-0.530558	1.359455	-1.309018
4	-0.273869	-0.530558	-0.327614	1.025669

Model Building

- K-means Clustering
- Hierarchical Clustering

Checking Clustering Tendency- Hopkins Statistics

In [97]:
```
from sklearn.neighbors import NearestNeighbors
```

In [98]:
```
def hopkins_statistic(X):
    X = np.array(X)  # Ensure X is a numpy array
    d = X.shape[1]  # Number of dimensions
    n = len(X)  # Number of data points
    m = int(0.1 * n)  # Subset size (10% of the data points)

    nbrs = NearestNeighbors(n_neighbors=1).fit(X)
    rand_X = np.random.random((m, d)) * np.amax(X, axis=0)
    u_distances, _ = nbrs.kneighbors(rand_X, 2, return_distance=True)

    w_distances, _ = nbrs.kneighbors(X[np.random.choice(n, m, replace=False)],

    u_distances = u_distances[:, 1]
    w_distances = w_distances[:, 1]

    H = (np.sum(u_distances) / (np.sum(u_distances) + np.sum(w_distances)))
    return H

hopkins_score = hopkins_statistic(df_scaled)
print(f"Hopkins Statistic: {hopkins_score}")
```

```
Hopkins Statistic: 0.9825005448878481
```

The value is very close to 1, which means that the dataset has a very strong clustering structure. It is likely to form well defined clusters

Elbow Method- To select optimal number of clusters

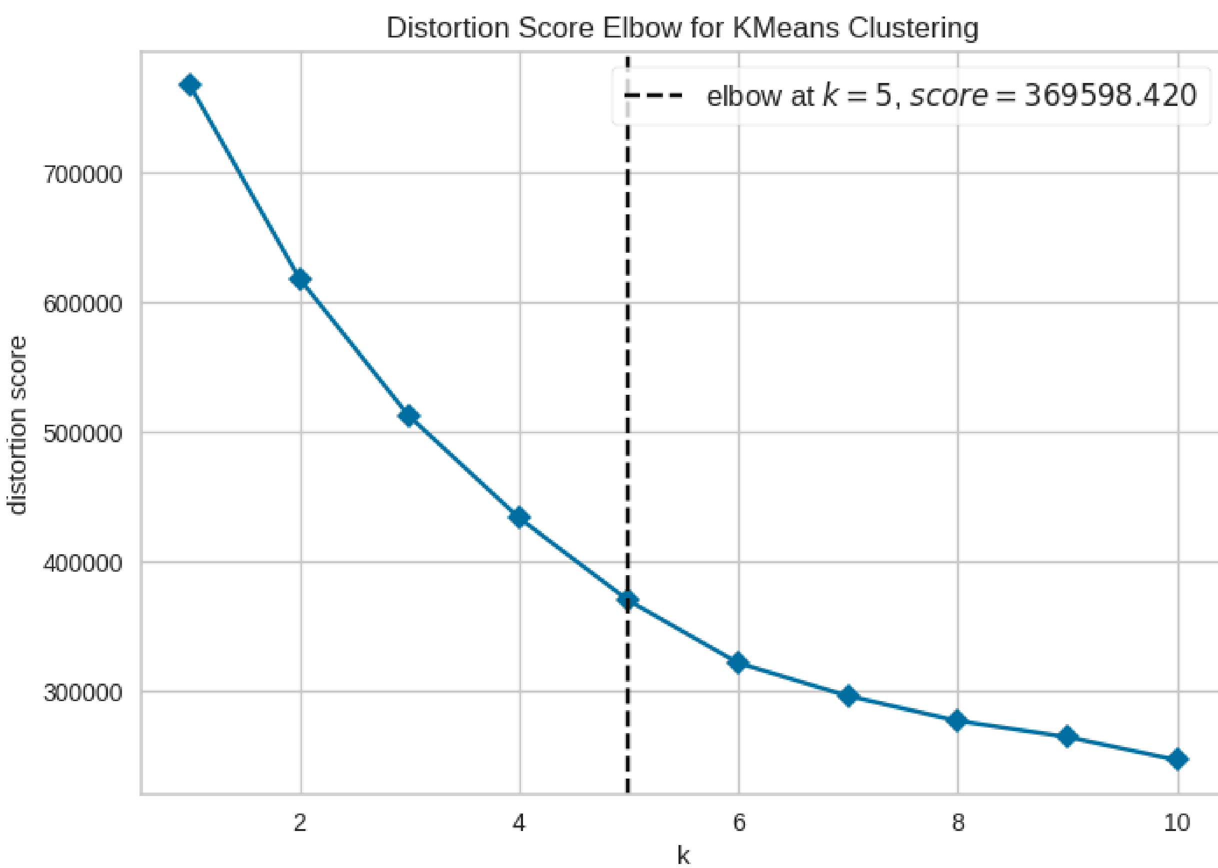
Inertia

Within Cluster Sum of Squares. This metric measures how tightly the clusters are packed. Lower inertia values indicate better-defined clusters.

In [99]:
```
from sklearn.cluster import KMeans
import warnings
warnings.filterwarnings('ignore')
```

In [100…
```
from yellowbrick.cluster import KElbowVisualizer
```

In [101…
```
model = KMeans()
# k is range of number of clusters.
visualizer = KElbowVisualizer(model, k=(1,11), timings= False)
visualizer.fit(df_scaled)        # Fit data to visualizer
visualizer.show()        # Finalize and render figure
```



Out[101…
```
<Axes: title={'center': 'Distortion Score Elbow for KMeans Clustering'}, xlab
el='k', ylabel='distortion score'>
```

The elbow point suggests that 5 clusters is a good choice for our data. This is where the inertia starts to decrease at a slower rate, indicating that additional clusters beyond this point don't significantly improve the clustering quality.

K-Means Clustering

In [102…
```
optimal_clusters = 5  # Set the optimal number of clusters as found above
kmeans = KMeans(n_clusters=optimal_clusters, random_state=42)
kmeans.fit(df_scaled)

# Adding cluster labels to the DataFrame
df5['kmeans_cluster'] = kmeans.labels_
```

In [103…
```
df5.head()
```

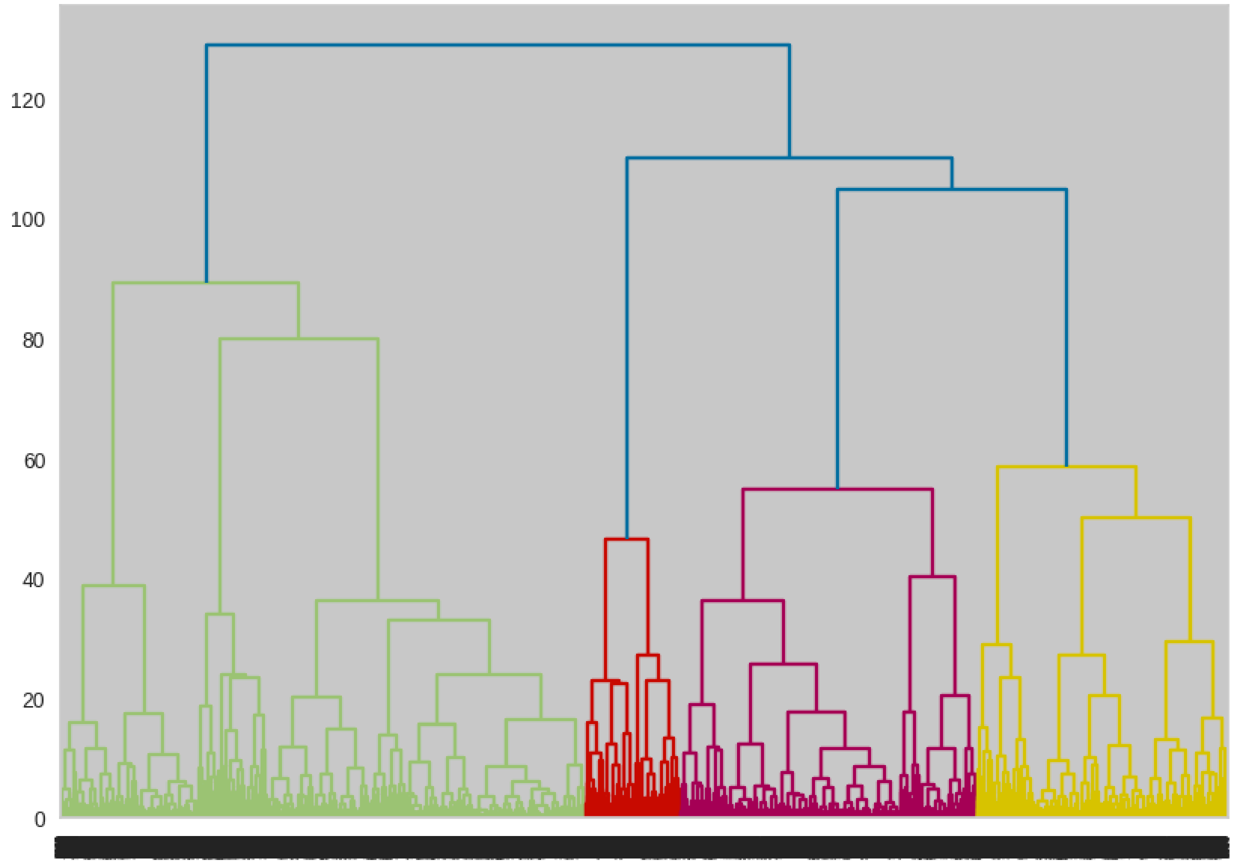
Out[103…

	company_hash	job_position	ctc_capped	YOE_capped	no_of_ctc_update	kme
0	ngpgutaxv	Backend Engineer	700000	9	1	
1	vwwtznhqt ntwyzgrgsj	Backend Engineer	400000	7	1	
2	xrbhd	unknown	360000	7	1	
3	wgszxkvzn	Data Analyst	440000	10	1	
4	xznhxn	Backend Engineer	440000	10	1	

Hierarchical Clustering

In [104…
```
from scipy.cluster.hierarchy import dendrogram, linkage, fcluster
import matplotlib.pyplot as plt
```

In [105…
```
# Sample a subset of the data
df_sampled = df_scaled.sample(n=10000, random_state=42)

# Perform hierarchical clustering
Z = linkage(df_sampled, method='ward')

# Plot the dendrogram
plt.figure(figsize=(10, 7))
dendrogram(Z)
plt.show()
```



- Used Representative subset of data to avoid running out of memory.
- Dendogram is showing 5 different colored branches at the end representing 5 clusters

Both Elbow Method and Dendogram are suggesting 5 clusters for the given dataset

Evaluation of K-means Clustering

Within-Cluster Sum of Squares (WCSS)

The Within-Cluster Sum of Squares (WCSS) is a measure of the compactness of the clusters formed by the K-means algorithm. It represents the sum of squared distances between each data point and its corresponding cluster centroid. A lower WCSS value indicates tighter clusters, meaning that the data points within each cluster are closer to their respective centroid.

In [106…
```
wcss = kmeans.inertia_
print(f'Within-Cluster Sum of Squares (WCSS): {wcss}')
```

```
Within-Cluster Sum of Squares (WCSS): 362131.63471221185
```

WCSS Value Consistency: The WCSS value remains consistent at 362126.90999960434 for k=5. This value represents the total within-cluster variance for the five clusters formed by K-means.

Optimal Number of Clusters:

- The elbow method helps identify the optimal number of clusters by plotting WCSS values for different k values and looking for a point where the decrease in WCSS slows down.
- If k=5 is identified as the elbow point, it suggests that adding more clusters beyond this number does not significantly reduce the WCSS, indicating diminishing returns in terms of cluster compactness.

Between-Cluster Sum of Squares (BCSS)

This value represents the total squared distance between each cluster centroid and the overall mean of the data, weighted by the number of points in each cluster. A higher BCSS indicates that the cluster centroids are far from the overall mean, suggesting well-separated clusters.

In [107…

```
# Assuming df_scaled is your scaled dataframe
df_scaled_copy = df_scaled.copy()

# Adding cluster labels to the DataFrame
df_scaled_copy['kmeans_cluster'] = kmeans.labels_

# Between-Cluster Sum of Squares (BCSS)
def calculate_bcss(df, kmeans):
    cluster_centers = kmeans.cluster_centers_
    overall_mean = df.drop(columns='kmeans_cluster').mean(axis=0)
    bcss = 0
    for i, center in enumerate(cluster_centers):
        size = len(df[df['kmeans_cluster'] == i])
        bcss += size * np.sum((center - overall_mean) ** 2)
    return bcss

bcss = calculate_bcss(df_scaled_copy, kmeans)
print(f'Between-Cluster Sum of Squares (BCSS): {bcss}')
```

```
Between-Cluster Sum of Squares (BCSS): 405340.05670200626
```

High BCSS and Low WCSS: The combination of a relatively high BCSS and a relatively low WCSS is desirable. It means that the clusters are well-separated and compact.

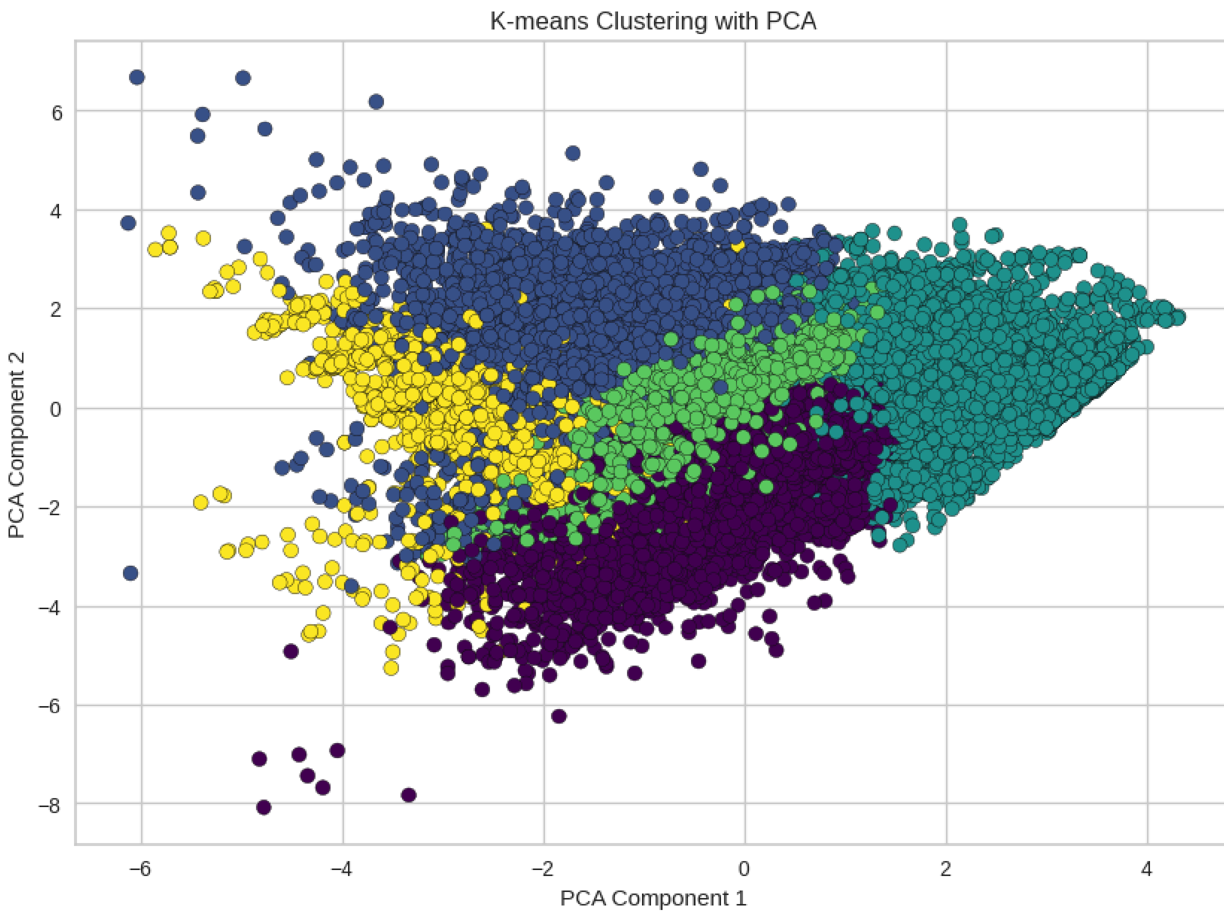
Visual Inspection- PCA

In [108…

```
from sklearn.decomposition import PCA
```

In [109…

```
#Visual Inspection using PCA
pca = PCA(n_components=2)
pca_result = pca.fit_transform(df_scaled_copy.drop(columns='kmeans_cluster'))

df_scaled_copy['pca_one'] = pca_result[:, 0]
df_scaled_copy['pca_two'] = pca_result[:, 1]

plt.figure(figsize=(10, 7))
plt.scatter(df_scaled_copy['pca_one'], df_scaled_copy['pca_two'], c=df_scaled_
plt.title('K-means Clustering with PCA')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.show()
```



Above we can visualize 5 clusters

Cluster Profile and Key Characteristics

Cluster Size and Distribution

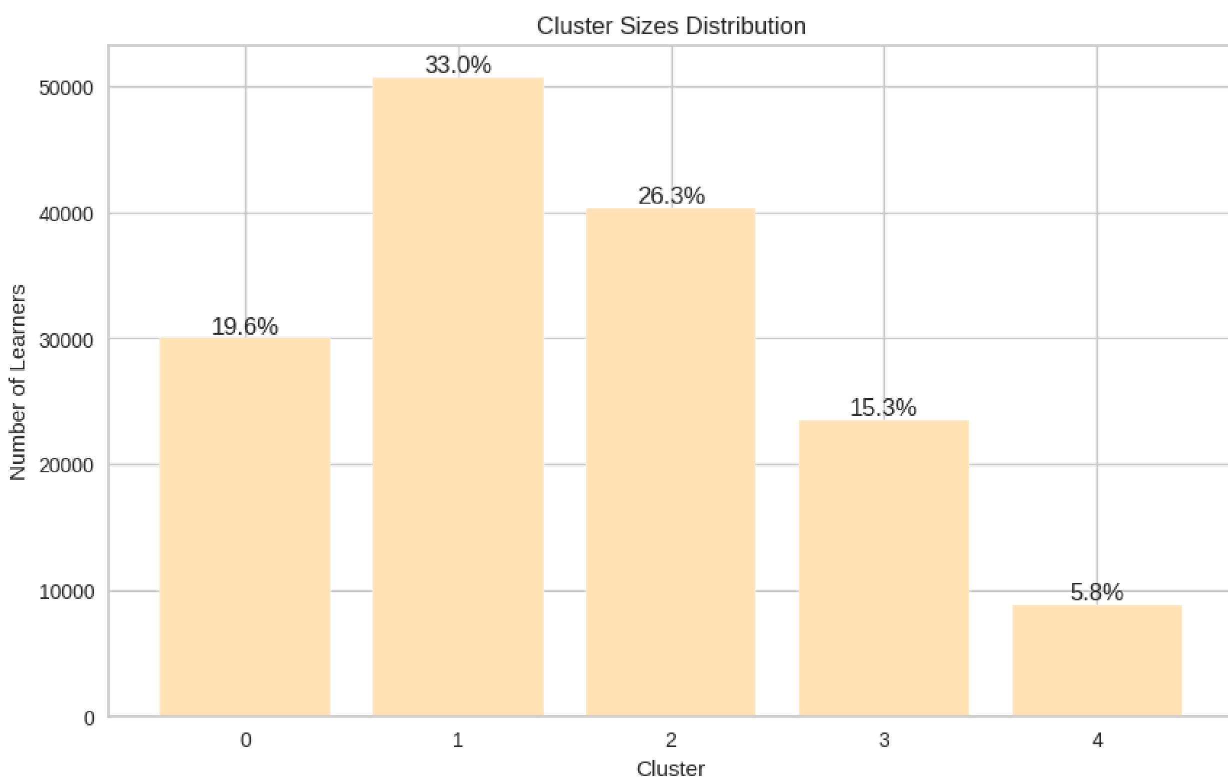
In [110…

```
cluster_sizes = df5['kmeans_cluster'].value_counts().sort_index()
print(f'Cluster Sizes:\n{cluster_sizes}')
```

```
Cluster Sizes:
kmeans_cluster
0    51233
1    30007
2    23193
3    40150
4     8860
Name: count, dtype: int64
```

In [111…

```python
# Assuming cluster sizes are stored in a dictionary
cluster_sizes = {0: 30030, 1: 50706, 2: 40326, 3: 23525, 4: 8856}

# Calculate the total number of learners
total_learners = sum(cluster_sizes.values())

# Create a bar chart
plt.figure(figsize=(10, 6))
bars = plt.bar(cluster_sizes.keys(), cluster_sizes.values(), color='moccasin')

# Add percentage labels above the bars
for bar in bars:
    height = bar.get_height()
    percentage = (height / total_learners) * 100
    plt.text(bar.get_x() + bar.get_width() / 2, height, f'{percentage:.1f}%',

# Add labels and title
plt.xlabel('Cluster')
plt.ylabel('Number of Learners')
plt.title('Cluster Sizes Distribution')
plt.show()
```



The clustering analysis resulted in 5 distinct clusters with the following sizes:

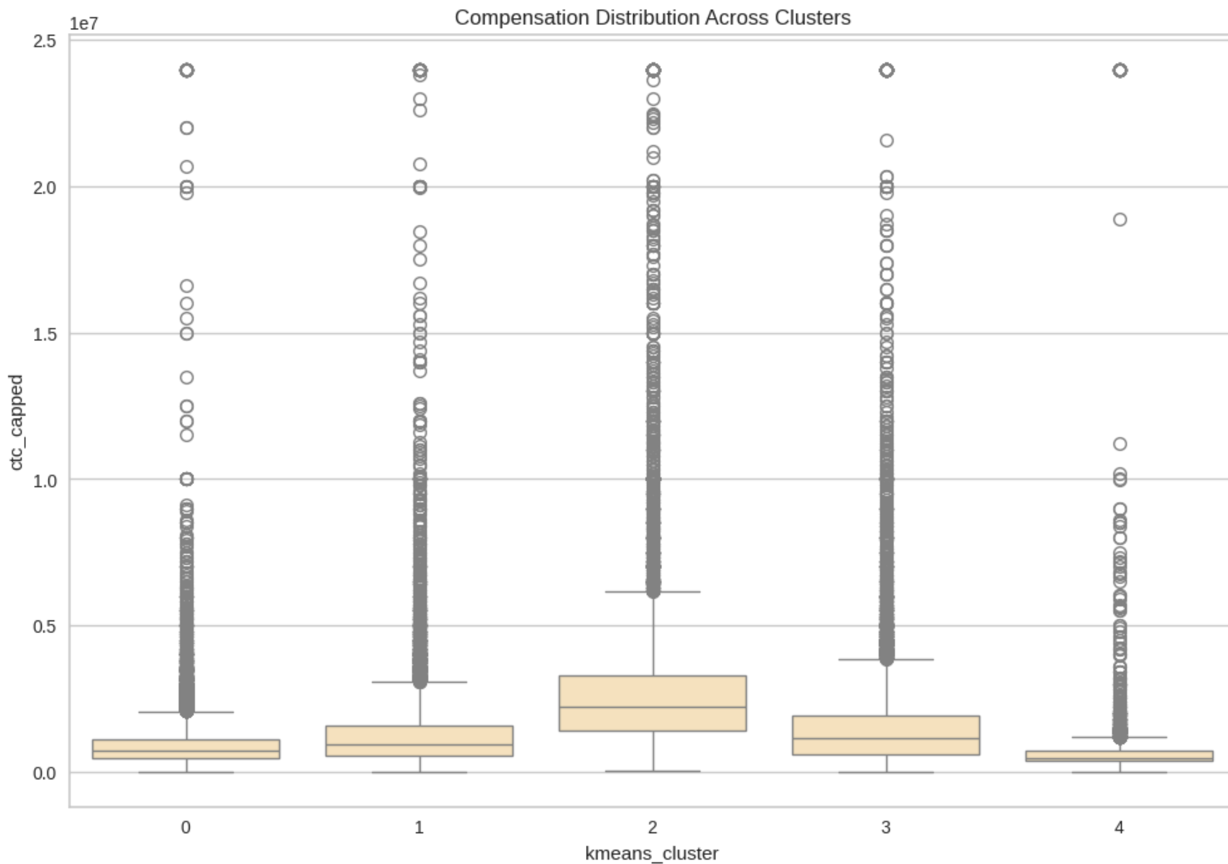
- Cluster 0: 30,030 learners (19.6%)
- Cluster 1: 50,706 learners (33.1%)
- Cluster 2: 40,326 learners (26.3%)
- Cluster 3: 23,525 learners (15.3%)
- Cluster 4: 8,856 learners (5.8%)

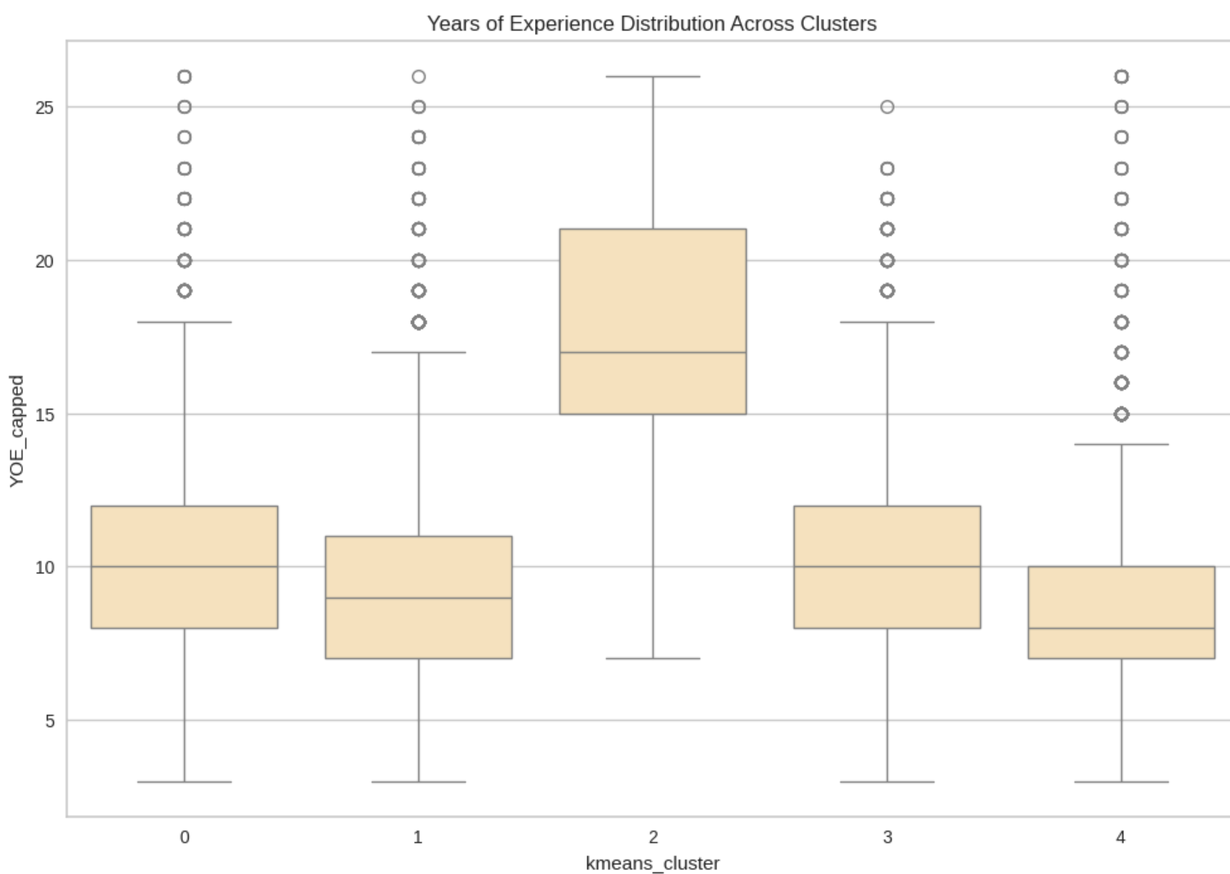
This distribution indicates that Cluster 1 is the largest segment, representing a significant portion of our learner base.

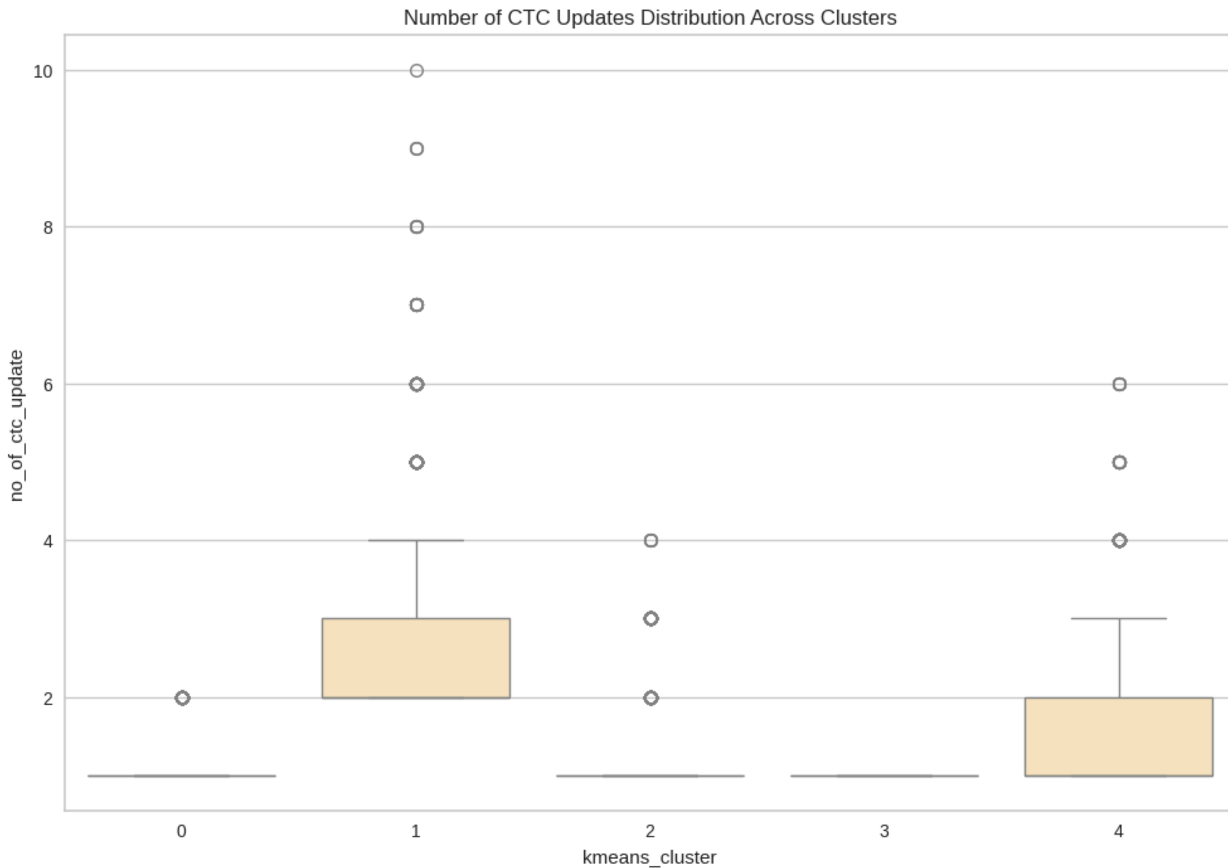
CTC / Years of Exp / CTC_updates distribution across Clusters

In [112…

```
plt.figure(figsize=(12, 8))
sns.boxplot(x='kmeans_cluster', y='ctc_capped', data=df5,color='moccasin')
plt.title('Compensation Distribution Across Clusters')
plt.show()

plt.figure(figsize=(12, 8))
sns.boxplot(x='kmeans_cluster', y='YOE_capped', data=df5,color='moccasin')
plt.title('Years of Experience Distribution Across Clusters')
plt.show()

plt.figure(figsize=(12, 8))
sns.boxplot(x='kmeans_cluster', y='no_of_ctc_update', data=df5, color='moccasi
plt.title('Number of CTC Updates Distribution Across Clusters')
plt.show()
```


Compensation Distribution Across Clusters
1e7
2.5
2.0
1.5
1.0
0.5
0.0
ctc_capped
0
1
2
3
4
kmeans_cluster

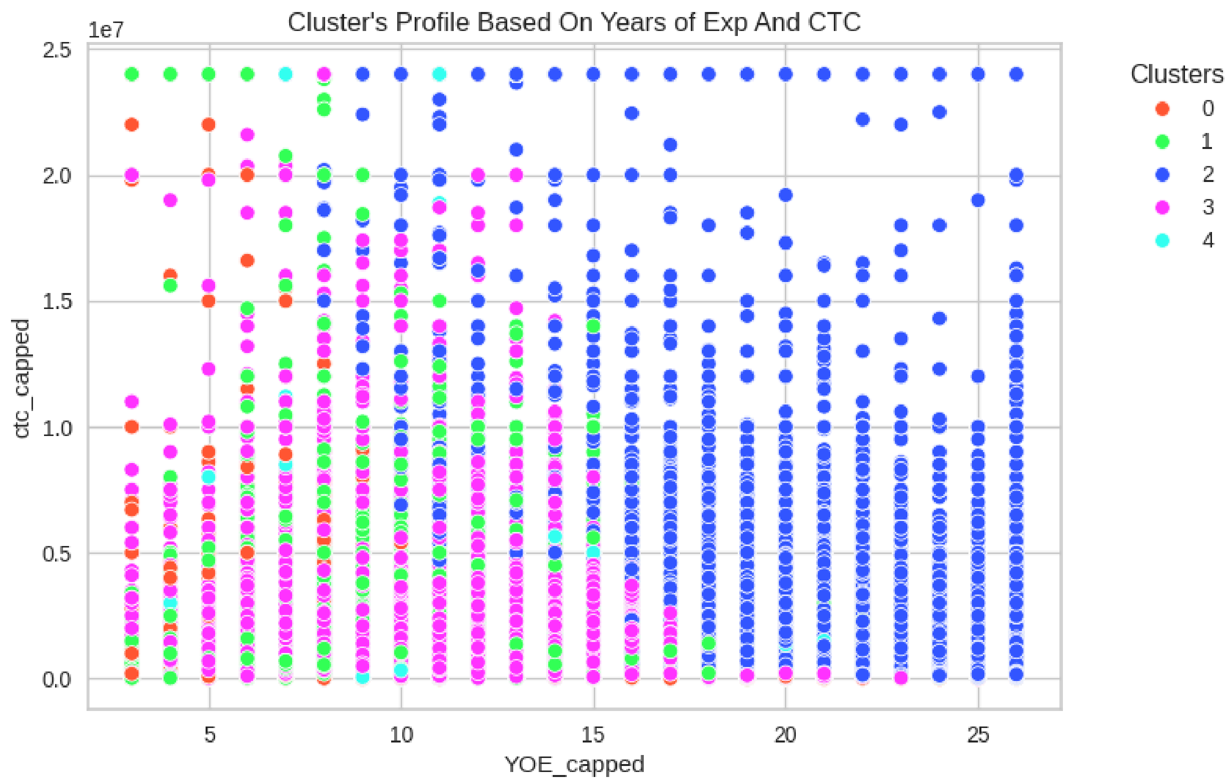

Years of Experience Distribution Across Clusters
25
20
15
10
5
YOE_capped
0
1
2
3
4
kmeans_cluster



- Compensation is high for cluster 3 followed by cluster 2
- Years of Experience is highest for cluster 3 followed by 2 and 1
- CTC_updates is high for cluster 0 followed by 4
- Compensation and Years of Exp is relatively higher for cluster 3

In [113…

```
# Define a custom color palette with distinct colors
custom_palette = sns.color_palette(["#FF5733", "#33FF57", "#3357FF", "#FF33FF"

# Create the scatter plot with the custom palette
pl = sns.scatterplot(data=df5, x="YOE_capped", y="ctc_capped", hue="kmeans_clu

# Set the title
pl.set_title("Cluster's Profile Based On Years of Exp And CTC")

# Place the legend outside the plot
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', title='Clusters')

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



- Cluster 3 has relatively higher years of experience and compensation which was reflected from above box plots too
- Cluster 1 has lesser years of experience and w.r.t cluster 3 and most of the compensation is lower

Cluster Profiling

In [114…

```
# Select only numeric columns for aggregation
numeric_columns = ['ctc_capped', 'YOE_capped', 'no_of_ctc_update']

# Calculate mean values for each cluster
cluster_averages = df5.groupby('kmeans_cluster')[numeric_columns].mean()

# Display the average values for each cluste
print(cluster_averages)
```

```
                  ctc_capped  YOE_capped  no_of_ctc_update
kmeans_cluster
0               9.197125e+05   10.047255          1.091172
1               1.310774e+06    9.611591          2.335655
2               3.445561e+06   18.030613          1.122149
3               1.684767e+06   10.215243          1.000000
4               8.139841e+05    9.026185          1.543679
```

In [115…

```
from collections import Counter

# Function to get the most common job positions and companies in each cluster
```

```python
def get_common_entries(df, cluster_label, column_name, top_n=3):
    cluster_data = df[df['kmeans_cluster'] == cluster_label]
    most_common_entries = Counter(cluster_data[column_name]).most_common(top_n
    return most_common_entries

# Get profiles for each cluster
cluster_profiles = {}

for cluster in range(5):
    job_positions = get_common_entries(df5, cluster, 'job_position')
    companies = get_common_entries(df5, cluster, 'company_hash')

    cluster_profiles[cluster] = {
        'average_ctc': cluster_averages.loc[cluster, 'ctc_capped'],
        'average_yoe': cluster_averages.loc[cluster, 'YOE_capped'],
        'average_ctc_updates': cluster_averages.loc[cluster, 'no_of_ctc_update
        'common_job_positions': job_positions,
        'common_companies': companies
    }

# Display the profiles
for cluster, profile in cluster_profiles.items():
    print(f"Cluster {cluster}:")
    print(f"  Average Compensation (CTC): {profile['average_ctc']}")
    print(f"  Average Years of Experience: {profile['average_yoe']} years")
    print(f"  Average Number of CTC Updates: {profile['average_ctc_updates']}"
    print("  Common Job Positions:")
    for job, count in profile['common_job_positions']:
        print(f"    - {job}: {count} occurrences")
    print("  Common Companies:")
    for company, count in profile['common_companies']:
        print(f"    - {company}: {count} occurrences")
    print()
```

```
Cluster 0:
  Average Compensation (CTC): 919712.4957546893
  Average Years of Experience: 10.047254699119708 years
  Average Number of CTC Updates: 1.091171705736537
  Common Job Positions:
    - FullStack Engineer: 8540 occurrences
    - Other: 8013 occurrences
    - Frontend Engineer: 5328 occurrences
  Common Companies:
    - wgszxkvzn: 862 occurrences
    - vwwtznhqt: 711 occurrences
    - zgn vuurxwvmrt vwwghzn: 701 occurrences

Cluster 1:
  Average Compensation (CTC): 1310773.8996900723
  Average Years of Experience: 9.611590628853268 years
  Average Number of CTC Updates: 2.3356550138301064
  Common Job Positions:
    - unknown: 12848 occurrences
    - Backend Engineer: 7466 occurrences
    - FullStack Engineer: 5085 occurrences
  Common Companies:
    - zgn vuurxwvmrt vwwghzn: 771 occurrences
    - wgszxkvzn: 673 occurrences
    - vwwtznhqt: 604 occurrences

Cluster 2:
  Average Compensation (CTC): 3445561.4628982884
  Average Years of Experience: 18.03061268486181 years
  Average Number of CTC Updates: 1.122148924244384
  Common Job Positions:
    - Engineering Leadership: 4583 occurrences
    - FullStack Engineer: 1951 occurrences
    - Other: 1892 occurrences
  Common Companies:
    - gqvwrt: 341 occurrences
    - bxwqgogen: 293 occurrences
    - lubgqsvz wyvot  wg: 251 occurrences

Cluster 3:
  Average Compensation (CTC): 1684766.825180573
  Average Years of Experience: 10.21524283935243 years
  Average Number of CTC Updates: 1.0
  Common Job Positions:
    - Backend Engineer: 22411 occurrences
    - unknown: 16829 occurrences
    - FullStack Engineer: 825 occurrences
  Common Companies:
    - vbvkgz: 1116 occurrences
    - zgn vuurxwvmrt: 803 occurrences
    - zvz: 678 occurrences

Cluster 4:
  Average Compensation (CTC): 813984.141309255
```

```
Average Years of Experience: 9.026185101580136 years
Average Number of CTC Updates: 1.5436794582392777
Common Job Positions:
  - unknown: 2938 occurrences
  - Backend Engineer: 1476 occurrences
  - Other: 1329 occurrences
Common Companies:
  - nvnv wgzohrnvzwj otqcxwto: 5335 occurrences
  - xzegojo: 3392 occurrences
  - vbvkgz: 100 occurrences
```

Detailed Insights of Profiling are shared in next section

Q.Do the clusters formed align or differ significantly from the manual clustering efforts? If so, in what way?

In [116…
```
df8=df3.copy()
```

In [117…
```
kmeans = KMeans(n_clusters=5)
df8['Cluster'] = kmeans.fit_predict(df8[['ctc_capped', 'YOE_capped', 'Designat
```

In [118…
```
from sklearn.metrics import adjusted_rand_score, normalized_mutual_info_score
```

In [119…
```
# Create a unique identifier for each combination of manual flags
df8['Manual_Cluster'] = df8['Designation_Flag'].astype(str) + df8['Class_Flag'

# Convert the combined string to a categorical variable and then to integer co
df8['Manual_Cluster'] = pd.Categorical(df8['Manual_Cluster']).codes
```

In [120…
```
# Adjusted Rand Index
ari = adjusted_rand_score(df8['Manual_Cluster'], df8['Cluster'])

# Normalized Mutual Information
nmi = normalized_mutual_info_score(df8['Manual_Cluster'], df8['Cluster'])

print(f'Adjusted Rand Index: {ari}')
print(f'Normalized Mutual Information: {nmi}')
```

```
Adjusted Rand Index: 0.0950667409414119
Normalized Mutual Information: 0.1258669146589949
```

The values of Adjusted Rand Index (ARI) and Normalized Mutual Information (NMI) provide insights into how similar the manual clustering is to the clusters obtained through unsupervised clustering:

Adjusted Rand Index (ARI):

Value: 0.096

Interpretation: ARI ranges from -1 to 1, where 1 indicates perfect agreement between the two clusterings, 0 indicates random agreement, and negative values indicate less than random agreement. An ARI of 0.096 suggests that there is a low level of agreement between the manual clustering and the unsupervised clustering. This means the clusters formed by the two methods are not very similar.

Normalized Mutual Information (NMI):

Value: 0.125

Interpretation: NMI ranges from 0 to 1, where 1 indicates perfect agreement and 0 indicates no agreement. An NMI of 0.125 indicates a low level of shared information between the manual clustering and the unsupervised clustering. This also suggests that the clusters formed by the two methods do not align well.

Implications:

Low Similarity: Both ARI and NMI values are quite low, indicating that the clusters formed by your manual clustering (using flags) and the clusters formed by the unsupervised method (e.g., KMeans) are significantly different.

Potential Reasons: This difference could be due to various factors, such as the criteria used for manual clustering not capturing the underlying structure of the data as effectively as the unsupervised method, or the unsupervised method uncovering patterns not evident through the manual criteria.

Insights

Cluster 0:

- This cluster consists of individuals with mid-level experience (around 7.6 years).
- They have a moderately high average compensation.
- Backend and FullStack Engineers are prominent roles apart from 'unknown'.
- Common employers include companies like zgn vuurxwvmrt, vwwghzn and wgszxkvzn.

Cluster 1:

- Individuals in this cluster have slightly more experience on average compared to Cluster 0.
- The average compensation is lower than Cluster 0.

- FullStack and Frontend Engineers are prevalent.
- The "Other" category indicates a diverse range of job positions.
- The companies overlap with those in Cluster 0, suggesting similar employer bases.

Cluster 2:

- This cluster has individuals with high compensation and above-average experience.
- Backend Engineers dominate this cluster, indicating a specialized skill set.
- There's a significant number of "unknown" job positions.
- Key employers include vbvkgz and zgn vuurxwvmrt.

Cluster 3:

- This cluster represents highly experienced professionals with significantly high compensation.
- The predominant role is in Engineering Leadership, indicating senior positions.
- The diversity in job positions (FullStack Engineer and Other) suggests a variety of responsibilities even among senior staff.
- The companies are distinct from those in other clusters, likely top-tier employers or specialized firms.

Cluster 4:

- Individuals in this cluster have lower compensation and slightly less experience compared to other clusters.
- Backend Engineers are common, but there's also a significant "Other" category.
- The most frequent employers are nvnv wgzohrnvzwj, otqcxwto and xzegojo, which are distinct from those in other clusters.

Central Tendencies (Mean/Median) of Features

By examining the mean and median of features within each cluster, we gain a deeper understanding of the dominant characteristics:

Cluster 0:

- Mid-level experience and moderately high compensation.
- Diverse job positions, predominantly in tech roles.

Cluster 1:

- Similar experience to Cluster 0 but with lower compensation.
- High prevalence of FullStack and Frontend Engineers.

Cluster 2:

- High compensation and specialized in Backend Engineering.
- Above-average experience, indicating skilled professionals.

Cluster 3:

- Very high compensation and extensive experience.
- Leadership roles dominate, with a focus on senior positions.

Cluster 4:

- Lower compensation and slightly less experience.
- Backend Engineers are common, with significant data inconsistencies in job positions.

Let's Answer Few Specific Questions

1. What percentage of users fall into the largest cluster?

Ans: 33% of the learners fall into largest cluster 1.

2. Comment on the characteristics that differentiate the primary clusters from each other.

Ans:

Compensation:

Cluster 3 has the highest average CTC, followed by Cluster 2, Cluster 0, Cluster 1, and Cluster 4.

Experience:

Cluster 3 members have the most experience, significantly higher than other clusters.

Job Positions:

Cluster 3 is dominated by leadership roles.

Cluster 2 mainly comprises backend engineers.

Cluster 1 has a mix of FullStack and Frontend engineers.

Cluster 0 and Cluster 4 have a varied mix of job positions.

CTC Updates:

Cluster 0 has the highest number of CTC updates, indicating more job movement or salary revisions.

Cluster 2 and Cluster 3 have fewer CTC updates, indicating stability in roles. 3. Is it always true that with an increase in years of experience, the CTC increases? Provide a case where this isn't true.

Ans: No its not always true as shown in the plot earlier above. Avg. CTC is decreasing from 1 to 5 years of Experience. There might be a slight decrease in CTC with increasing experience, possibly due to industry-specific factors or career shifts.

4. Name a job position that is commonly considered entry-level but has a few learners with unusually high CTCs in the dataset.

Ans: Associate is the job position considered as entry level but maximum CTC going beyond set threshold

5. What is the average CTC of learners across different job positions?

Ans: job_position average_ctc

372 Safety officer 24000000.0

342 Reseller 24000000.0

288 Owner 24000000.0

593 Telar 24000000.0

.. ..

24 Any technical 10000.0

257 Matlab programmer 10000.0

641 project engineer 7900.0

189 Full-stack web developer 7500.0

273 New graduate 2000.0

[652 rows x 2 columns]

6. For a given company, how does the average CTC of a Data Scientist compare with other roles?

Ans:

Average CTC for Data Scientist in company xznhxn: 4833333.333333333 Average CTC for all other roles in company xznhxn: 2816223.105527638 Data Scientists have a higher average CTC compared to other roles.

Similarly we can find for any company or all the companies.

7. Discuss the distribution of learners based on the Tier flag:

- Which companies dominate in Tier 1 and why might this be the case?
- Are there any notable patterns or insights when comparing learners from Tier 3 across different companies?

Ans:

- Companies Dominating in Tier 1

  Common Factors: Companies dominating Tier 1 might have a large number of entry-level positions or companies that offer lower-than-average compensation.

  Possible Reasons: Large enterprises with many junior or mid-level positions. Companies in traditional industries or smaller firms with limited budgets.

- Patterns in Tier 3 Across Different Companies

  High CTC Companies: Companies with a high number of Tier 3 learners might be in tech, finance, or other high-paying sectors.

  Career Progression: These companies might offer better career progression and compensation growth.

  Retention Strategy: Higher compensation could be a strategy to retain top talent.

8. After performing unsupervised clustering:

- How many clusters have been identified using the Elbow method?
- Do the clusters formed align or differ significantly from the manual clustering efforts? If so, in what way?

Ans: 5 clusters were identified using Elbow method. It differs w.r.t no. of clusters and tried statistical comparison as below.

The values of Adjusted Rand Index (ARI) and Normalized Mutual Information (NMI) provide insights into how similar the manual clustering is to the clusters obtained through unsupervised clustering:

Adjusted Rand Index (ARI):

Value: 0.096

Interpretation: ARI ranges from -1 to 1, where 1 indicates perfect agreement between the two clusterings, 0 indicates random agreement, and negative values indicate less than random agreement. An ARI of 0.096 suggests that there is a low level of agreement between the manual clustering and the unsupervised clustering. This means the clusters formed by the two methods are not very similar.

Normalized Mutual Information (NMI):

Value: 0.125

Interpretation: NMI ranges from 0 to 1, where 1 indicates perfect agreement and 0 indicates no agreement. An NMI of 0.125 indicates a low level of shared information between the manual clustering and the unsupervised clustering. This also suggests that the clusters formed by the two methods do not align well.

Implications:

Low Similarity: Both ARI and NMI values are quite low, indicating that the clusters formed by your manual clustering (using flags) and the clusters formed by the unsupervised method (e.g., KMeans) are significantly different.

Potential Reasons: This difference could be due to various factors, such as the criteria used for manual clustering not capturing the underlying structure of the data as effectively as the unsupervised method, or the unsupervised method uncovering patterns not evident through the manual criteria.

9. From the Hierarchical Clustering results:

- Are there any clear hierarchies or patterns formed that could suggest

- the different levels of seniority or roles within a company?
- How does the dendrogram representation correlate with the 'Years of Experience' feature?

Ans:

From the detailed analysis in previous section following is the summarized answer.

Cluster 0: Mid-level experience and moderately high compensation. Diverse job positions, predominantly in tech roles.

Cluster 1: Similar experience to Cluster 0 but with lower compensation. High prevalence of FullStack and Frontend Engineers.

Cluster 2: High compensation and specialized in Backend Engineering. Above-average experience, indicating skilled professionals.

Cluster 3: Very high compensation and extensive experience. Leadership roles dominate, with a focus on senior positions.

Cluster 4: Lower compensation and slightly less experience. Backend Engineers are common, with significant data inconsistencies in job positions

Trade-Off Analysis

Cluster 0

Targeting Cost vs. ROI:

- Cost: Mid-level professionals might require moderate investment in upskilling and career advancement programs.
- ROI: Higher than average CTC and significant experience make them valuable. Potentially high engagement and retention due to relevant job positions.

Tailored vs. Generalized Approach:

- Tailored: Customized learning paths focusing on backend and fullstack development could lead to higher satisfaction and outcomes.
- Generalized: A broader approach might dilute the impact but could still attract professionals due to the moderately high compensation and experience levels.

Cluster 1

Targeting Cost vs. ROI:

- Cost: Targeting might involve moderate investment, particularly in frontend and fullstack development courses.
- ROI: Lower average compensation might mean lower direct returns, but the significant number of FullStack Engineers suggests high demand for relevant skills.

Tailored vs. Generalized Approach:

- Tailored: Programs focused on FullStack and frontend technologies could be very effective.
- Generalized: This cluster may benefit from a combination of specific and broad content due to their versatile job roles.

Cluster 2

Targeting Cost vs. ROI:

- Cost: Investment might be higher due to specialized backend development needs.
- ROI: High compensation indicates a potentially lucrative return on investment. Experienced professionals may value advanced and specialized courses.

Tailored vs. Generalized Approach:

- Tailored: Focusing on backend engineering and advanced development skills could yield high engagement.
- Generalized: Less effective for this cluster due to their specialized nature and higher expectations.

Cluster 3

Targeting Cost vs. ROI:

- Cost: High, due to the need for leadership and executive-level training programs.
- ROI: Very high, given the substantial compensation and seniority of this

cluster. High potential for influencing strategic decisions within their companies.

Tailored vs. Generalized Approach:

- Tailored: Essential. Executive leadership programs and high-level technical courses would be necessary to cater to their needs.

- Generalized: Likely ineffective, as this cluster requires very specific and advanced content.

Cluster 4

Targeting Cost vs. ROI:

- Cost: Lower, as they might benefit from general upskilling and career advancement programs.

- ROI: Moderate, due to the lower average compensation and diverse job positions.

Tailored vs. Generalized Approach:

- Tailored: Focus on foundational and intermediate backend engineering skills could be beneficial.

- Generalized: Could be effective, as the cluster has varied job positions and lower compensation, making them receptive to broader programs.

Recommendations

Cluster 0:

- Average Compensation (CTC): ₹1,313,574.27
- Average Years of Experience: 7.62 years
- Common Job Positions: Backend Engineer, FullStack Engineer
- Common Companies: zgn vuurxwvmrt vwwghzn, wgszxkvzn

Recommendations:

1. Increase Purchase Frequency:

- Strategy: Offer advanced courses or certifications that build on existing

skills. Introduce subscription-based learning models with new content released periodically to encourage ongoing participation.
- Example: Monthly or quarterly advanced backend or fullstack engineering workshops.

2. Retention Strategies:

- Strategy: Implement a mentorship program connecting mid-level professionals with more experienced mentors. Offer personalized career coaching sessions to help them navigate career growth.
- Example: Bi-monthly career coaching and mentoring sessions.

3. Targeted Marketing:

- Strategy: Focus marketing efforts on backend and fullstack engineering courses. Highlight success stories and case studies from learners in similar roles.
- Example: Email campaigns featuring testimonials from successful backend and fullstack engineers.

Cluster 1:

- Average Compensation (CTC): ₹903,513.06
- Average Years of Experience: 8.02 years
- Common Job Positions: FullStack Engineer, Frontend Engineer
- Common Companies: wgszxkvzn, vwwtznhqt

Recommendations:

1. Increase Purchase Frequency:

- Strategy: Introduce micro-credentials or nano-degrees for specific frontend and fullstack technologies. Offer bundle discounts for multiple courses.
- Example: "Frontend Developer Toolkit" package including courses on React, Angular, and Vue.js.

2. Retention Strategies:

- Strategy: Develop a points-based loyalty program where learners earn points for completing courses, which can be redeemed for additional courses or exclusive content.
- Example: Points system where 100 points can be redeemed for a free

advanced course.

3. Targeted Marketing:

- Strategy: Highlight course bundles for fullstack and frontend technologies. Promote content that addresses common challenges and trends in these fields.
- Example: Blog posts and webinars on "The Future of Frontend Development".

Cluster 2:

- Average Compensation (CTC): ₹1,698,640.88
- Average Years of Experience: 8.22 years
- Common Job Positions: Backend Engineer, FullStack Engineer
- Common Companies: vbvkgz, zgn vuurxwvmrt

Recommendations:

1. Increase Purchase Frequency:

- Strategy: Offer specialization tracks in advanced backend technologies, such as microservices, cloud computing, and big data. Create exclusive content available only to frequent learners.
- Example: "Mastering Microservices" specialization track.

2. Retention Strategies:

- Strategy: Provide access to exclusive webinars, industry talks, and networking events. Create a premium membership tier with added benefits.
- Example: Premium membership that includes quarterly industry webinars and access to an exclusive online community.

3. Targeted Marketing:

- Strategy: Emphasize advanced backend engineering content in marketing materials. Showcase the career advancement of learners who have completed these tracks.
- Example: Success stories of learners who transitioned to senior backend roles after completing advanced courses.

Cluster 3:

- Average Compensation (CTC): ₹3,411,238.72
- Average Years of Experience: 15.95 years
- Common Job Positions: Engineering Leadership, FullStack Engineer
- Common Companies: gqvwrt, bxwqgogen

Recommendations:

1. Increase Purchase Frequency:

- Strategy: Introduce executive education programs and leadership workshops tailored for senior professionals. Offer continuous learning subscriptions for leadership content.
- Example: Annual subscription to "Executive Leadership Series".

2. Retention Strategies:

- Strategy: Implement an executive coaching program. Provide access to exclusive leadership forums and roundtable discussions with industry leaders.
- Example: Monthly executive coaching sessions and leadership roundtables.

3. Targeted Marketing:

- Strategy: Focus on leadership development programs and high-impact management courses. Highlight the ROI of these programs through case studies and testimonials.
- Example: Marketing campaigns showcasing leaders who achieved significant career milestones after completing Scaler's leadership programs.

Cluster 4:

- Average Compensation (CTC): ₹814,280.20
- Average Years of Experience: 7.03 years
- Common Job Positions: Backend Engineer, Other
- Common Companies: nvnv wgzohrnvzwj otqcxwto, xzegojo

Recommendations:

1. Increase Purchase Frequency:

- Strategy: Offer foundational and intermediate courses in various backend technologies. Provide frequent learners with incentives such as

discounts on advanced courses.
- Example: Discounted rates for advanced courses upon completion of foundational courses.

2. Retention Strategies:

- Strategy: Develop a comprehensive career pathing tool that helps learners identify and achieve their career goals. Implement a regular feedback loop to improve course offerings based on learner input.
- Example: Personalized career pathing tool and quarterly feedback surveys with actionable improvements.

3. Targeted Marketing:

- Strategy: Promote a wide range of backend engineering courses, emphasizing career growth and skill enhancement. Use targeted ads on platforms frequented by mid-level professionals.
- Example: Ads on LinkedIn targeting backend engineers looking for career advancement.

Overall Recommendations

- Personalized Learning Paths: Implement personalized learning paths based on the cluster profiles. Utilize data to recommend courses that align with individual career goals and current industry trends.

- Exclusive Content and Membership Tiers: Develop exclusive content and membership tiers for high-value clusters, providing advanced learning opportunities and industry insights.

- Loyalty Programs and Incentives: Create loyalty programs to encourage continued learning and engagement. Offer incentives such as discounts, exclusive access, and career coaching.

- Targeted Marketing Campaigns: Design marketing campaigns that address the specific needs and preferences of each cluster. Use success stories, testimonials, and case studies to highlight the benefits of Scaler’s programs.

By implementing these recommendations, Scaler can enhance its engagement with learners, improve retention rates, and maximize the ROI of its educational programs.

Feedback Loop for Periodic Clustering

To ensure that the clustering remains relevant and effective, it's crucial to periodically re-run the clustering process and continuously collect and analyze data. Here are detailed recommendations:

a. Regular Re-run of Clustering Process

1. Frequency of Re-run:

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- Quarterly Re-run: Given the fast-paced changes in the tech
industry and learner behavior, it is recommended to re-run the
clustering process every quarter. This allows for timely
adjustments to changing trends and ensures that the clustering
remains accurate.
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2. Update with New Data:

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- Incorporate Latest Data: Each re-run should include the most
recent data to capture new trends, behaviors, and any shifts in
the demographics of learners. This includes new enrollments,
course completions, updated CTC, and job transitions.
```

3. Review and Validate Clusters:

```
- Validation Metrics: Use metrics like silhouette score,
Davies-Bouldin index, and within-cluster sum of squares (WCSS)
to validate the quality of the clusters. This ensures that the
clusters are well-defined and meaningful.
- Comparison with Previous Clusters: Compare the new clusters
with previous ones to identify shifts or trends. This can help
in understanding how learner profiles are evolving over time.
```

4. Adapt to Business Changes:

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- Align with Business Strategy: Ensure that the clustering
process aligns with Scaler's current business strategy and
objectives. If there are significant changes in course
offerings or target demographics, adjust the clustering
parameters accordingly.
```

b. Channels for Continuous Data Collection

1. Feedback Collection Mechanisms:

- Surveys and Questionnaires: Regularly distribute surveys to gather feedback on courses, learning experience, and future needs. Ensure surveys are short and targeted to increase response rates.
- Post-Course Feedback: Collect feedback after each course or module to understand learner satisfaction and areas for improvement.
- Net Promoter Score (NPS): Use NPS to gauge overall learner satisfaction and willingness to recommend Scaler to others.

2. Behavioral Data Collection:

- Learning Management System (LMS) Analytics: Utilize LMS data to track learner engagement, course completion rates, time spent on modules, and interaction with course materials.
- Website and App Analytics: Use tools like Google Analytics to monitor how learners interact with the Scaler website and app. Track metrics such as page views, session duration, and navigation patterns.

3. Preference and Interaction Tracking:

- Course Enrollment Patterns: Analyze which courses are most popular and how learners progress through different learning paths. This can provide insights into learner preferences and trending topics.
- Support and Interaction Logs: Monitor interactions with customer support, chatbots, and community forums to identify common issues, questions, and areas where learners seek additional help.

4. Social Media and Community Insights:

- Social Media Monitoring: Track mentions, comments, and reviews on social media platforms to understand public perception and gather unfiltered feedback.
- Community Engagement: Leverage platforms like Slack, Discord, or proprietary forums where learners can discuss courses, share experiences, and provide feedback.

5. Periodic Reviews and Workshops:

- Focus Groups and Workshops: Conduct periodic focus groups or workshops with learners to gather in-depth insights into their experiences and expectations.
- Advisory Panels: Establish advisory panels consisting of top learners and industry experts to provide ongoing feedback and

`strategic direction.`

Implementation Plan

1. Set Up Automated Data Pipelines:

- Develop automated processes to regularly collect, process, and store feedback and behavioral data from all the mentioned channels.

2. Regular Review Meetings:

- Schedule quarterly review meetings to analyze collected data, assess the current clustering, and determine if re-clustering is necessary.

3. Action Plans Based on Insights:

- Create action plans based on the insights derived from feedback and behavioral data. Implement changes in course offerings, support mechanisms, and marketing strategies accordingly.

4. Communication with Learners:

- Keep learners informed about the steps being taken based on their feedback. This enhances transparency and builds trust in Scaler’s commitment to continuous improvement.

By following these recommendations, Scaler can maintain up-to-date and relevant clustering, leading to more effective and personalized learning experiences for its users.