Business Case Study: Scaler - Clustering

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.

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

In [1]:

```
# Import required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import re
from datetime import datetime
from sklearn.impute import KNNImputer, SimpleImputer
from yellowbrick.cluster import KElbowVisualizer
from sklearn.neighbors import NearestNeighbors
from scipy.cluster.hierarchy import fcluster
from collections import Counter
from sklearn.decomposition import PCA
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.cluster import KMeans, AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram, linkage
```

In [2]:

```
import warnings
warnings.filterwarnings("ignore")
```

In [3]:

```
# Load the dataset
df = pd.read_csv('scaler_clustering.csv')
df.head()
```

Out[3]:

	Unnamed: 0	company_hash	email_hash	orgyear	
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.0	110
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	44
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015.0	200
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	70
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017.0	140

In [4]:

```
# Remove unnecessary column 'Unnamed: 0'
df.drop(columns=['Unnamed: 0'], inplace=True)
```

Exploratory Data Analysis (EDA)

1. Dataset Structure and Basic Info

In [5]:

```
# Shape of the dataset
print(f'The dataset has {df.shape[0]} rows and {df.shape[1]} columns.')
```

```
The dataset has 205843 rows and 6 columns.
```

In [6]:

```
# Info about the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205843 entries, 0 to 205842
Data columns (total 6 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   company_hash      205799 non-null  object 
 1   email_hash        205843 non-null  object 
 2   orgyear           205757 non-null  float64
 3   ctc               205843 non-null  int64  
 4   job_position      153279 non-null  object 
 5   ctc_updated_year  205843 non-null  float64
dtypes: float64(2), int64(1), object(3)
memory usage: 9.4+ MB
```

Observation: Dataset Description

- **company_hash**: Anonymized identifier for the company (current employer)
- **email_hash**: Anonymized personal identifier
- **orgyear**: Employment start year
- **ctc**: Current CTC (salary)
- **job_position**: Job profile in the company
- **ctc_updated_year**: Year in which CTC was last updated

In [7]:
```python
# Check for percentage of missing values in dataset
(df.isnull().mean()*100).loc[lambda x: x > 0].sort_values(ascending=False)
```

Out[7]:
```
job_position     25.535967
orgyear           0.041779
company_hash      0.021376
dtype: float64
```

Observation:

- More than 25% of the job_position values are missing.
- orgyear and company_hash columns are missing values less than 1% which can be considered as negligible.

In [8]:
```python
# Describing the dataset
df.describe(include='object').T
```

Out[8]:

	count	unique	top	freq
company_hash	205799	37299	nvnv wgzohrnvzwj otqcxwto	8337
email_hash	205843	153443	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b7...	10
job_position	153279	1016	Backend Engineer	43554

In [9]:
```python
df.describe(include='number').round(0).astype(int)
```

Out[9]:

	orgyear	ctc	ctc_updated_year
count	205757	205843	205843
mean	2015	2271685	2020
std	64	11800914	1
min	0	2	2015
25%	2013	530000	2019
50%	2016	950000	2020
75%	2018	1700000	2021
max	20165	1000150000	2021

Observation:

- ctc column found to be right skewed as the Mean is higher than Median
- Backend Engineer is the most frequent job_position in the dataset

In [10]:
```python
# Value counts of categorical columns
for col in df.columns:
    unique_values = df[col].nunique()
    print(f'Unique values in {col}: {unique_values}\n')
    if unique_values < 10:
        print(f'Value counts for {col}:\n{df[col].value_counts()}\n')
    print(f'Percentage of unique values in {col}: {unique_values/df.shape[0]*100:.2f}%\
    print("" + "-"*50 + "\n")
```

```
Unique values in company_hash: 37299

Percentage of unique values in company_hash: 18.12%

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

Unique values in email_hash: 153443

Percentage of unique values in email_hash: 74.54%

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

Unique values in orgyear: 77

Percentage of unique values in orgyear: 0.04%

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

Unique values in ctc: 3360

Percentage of unique values in ctc: 1.63%

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

Unique values in job_position: 1016

Percentage of unique values in job_position: 0.49%

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

Unique values in ctc_updated_year: 7

Value counts for ctc_updated_year:
ctc_updated_year
2019.0    68688
2021.0    64976
2020.0    49444
2017.0     7561
2018.0     6746
2016.0     5501
2015.0     2927
Name: count, dtype: int64

Percentage of unique values in ctc_updated_year: 0.00%

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

Observation:

- Company Hash is having around 18% of unique values and Job Position is having around 0.5% of unique values.
- This indicates that those values are repeated a lot in the dataset.
- On the other hand, nearly 75% of the email hashes are unique values which indicates that the users info is not repeated much.
- orgyear is having so many invalid years which needs to be processed.
- ctc_updated_year is proper and can be converted to datatime.
- There are 1016 roles available in this dataset.

In [11]:
```
# Check for duplicates
duplicates = df.duplicated().sum()
print(f'The dataset has {duplicates} duplicate rows.')
```

```
The dataset has 34 duplicate rows.
```

2. Data Preprocessing

In [12]:
```
# Remove duplicated rows
df.drop_duplicates(inplace=True)
print(f'After removing duplicates, the dataset has {df.shape[0]} rows and {df.shape[1]}
```

```
After removing duplicates, the dataset has 205809 rows and 6 columns.
```

In [13]:
```
# Use Regex to clean company_hash column
df['company_hash'] = df['company_hash'].apply(lambda x: re.sub('[^A-Za-z0-9 ]+', '', st
```

In [14]:
```
# Treating orgyear column as it's containing invalid years
valid_year_range = range(1900, datetime.now().year + 1)
df['orgyear'] = df['orgyear'].apply(lambda x: x if x in valid_year_range else np.nan)
```

In [15]:
```
# Convert orgyear and ctc_updated_year columns to datetime year format
df['orgyear'] = pd.to_datetime(df['orgyear'], format='%Y', errors='coerce').dt.year
df['ctc_updated_year'] = pd.to_datetime(df['ctc_updated_year'], format='%Y', errors='co
```

In [16]:
```
# check for percentage of missing values again
missing_values = df.isnull().sum() / df.shape[0] * 100
print(f'Missing values in the dataset:\n{missing_values[missing_values > 0]}')
```

```
Missing values in the dataset:
orgyear          0.077256
job_position    25.532411
dtype: float64
```

Observation:

- Even after changing the invalid orgyear values, it's still low and can be considered as negligible.

In [17]:
```
# Impute missing values using KNNImputer for numerical columns
imputer = KNNImputer(n_neighbors=5)
df[['orgyear']] = imputer.fit_transform(df[['orgyear']])
```

In [18]:
```
# checking the unique values in job_position column
df['job_position'].value_counts()*100 / df.shape[0]
```

Out[18]:

```
job_position
Backend Engineer                              21.158453
FullStack Engineer                            12.006764
Other                                          8.780471
Frontend Engineer                              5.061489
Engineering Leadership                         3.338046
                                                 ...
Auditing                                       0.000486
Senior software Test Engineer                  0.000486
Front End Dev                                  0.000486
SRE                                            0.000486
Software Development Engineering Intern        0.000486
Name: count, Length: 1016, dtype: float64
```

Observation:

- Even the most frequent Job Position (Backend Engineer) is contributing to 21% in the entire dataset, imputing missing positions as "Others" will increase bias towards the dataset.

In [19]:

```
# Impute job_position by grouping by company_hash and ctc_updated_year
df['job_position'] = df.groupby(['company_hash', 'ctc'], observed=False)['job_position'
df['job_position'] = df.groupby(['ctc'], observed=False)['job_position'].transform(lamb
df['job_position'] = df.groupby(['company_hash'], observed=False)['job_position'].trans
```

In [20]:

```
# SimpleImputer for categorical columns
imputer = SimpleImputer(strategy='most_frequent')
categorical_cols = ['company_hash', 'email_hash', 'job_position']
df[categorical_cols] = imputer.fit_transform(df[categorical_cols])
```

In [21]:

```
# Check any missing values again
print(f'After imputation, the dataset has {df.isnull().sum().sum()} missing values.')
```

```
After imputation, the dataset has 0 missing values.
```

In [22]:

```
# Converting to respective data types after preprocessing
numeric_cols = ['orgyear', 'ctc_updated_year']
df[numeric_cols] = df[numeric_cols].astype('int16')
numeric_cols.append('ctc')
df['ctc'] = df['ctc'].astype('int32')
df[categorical_cols] = df[categorical_cols].astype('category')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 205809 entries, 0 to 205842
Data columns (total 6 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   company_hash      205809 non-null  category
 1   email_hash        205809 non-null  category
 2   orgyear           205809 non-null  int16
 3   ctc               205809 non-null  int32
 4   job_position      205809 non-null  category
 5   ctc_updated_year  205809 non-null  int16
dtypes: category(3), int16(2), int32(1)
memory usage: 11.6 MB
```

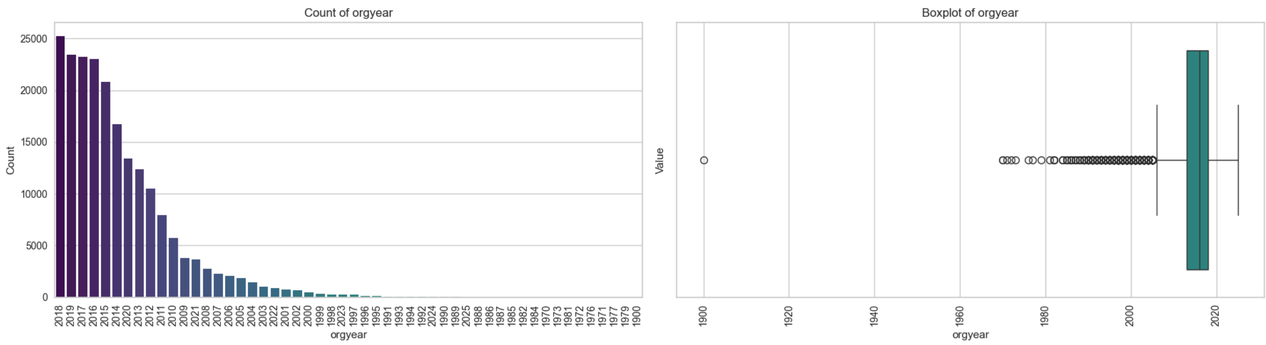
3. Outlier Treatment

In [23]:

```
# count plot for col
def plot_count(col):
```

```python
    fig, axes = plt.subplots(1, 2, figsize=(18, 5))

    # Count plot
    sns.countplot(data=df, x=col, order=df[col].value_counts().index, palette='viridis'
    axes[0].set_title(f'Count of {col}')
    axes[0].set_xlabel(col)
    axes[0].set_ylabel('Count')
    axes[0].tick_params(axis='x', rotation=90)

    # Box plot
    sns.boxplot(data=df, x=col, palette='viridis', ax=axes[1])
    axes[1].set_title(f'Boxplot of {col}')
    axes[1].set_xlabel(col)
    axes[1].set_ylabel('Value')
    axes[1].tick_params(axis='x', rotation=90)

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

In [24]:
```python
plot_count('orgyear')
```



Observation:

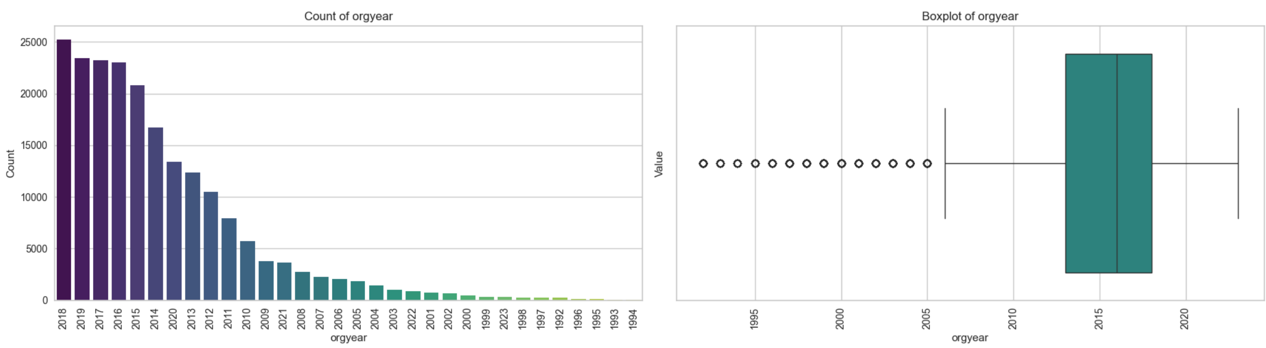
- Since all the orgyears which are invalid were imputed already, we left with the data starting from 1900 till 2018.
- Will find the 1 and 99 percentile and will clip it.

In [25]:
```python
print(f'0.1 percentile of orgyear: {df["orgyear"].quantile(0.001)} and 99.9 percentile:
```

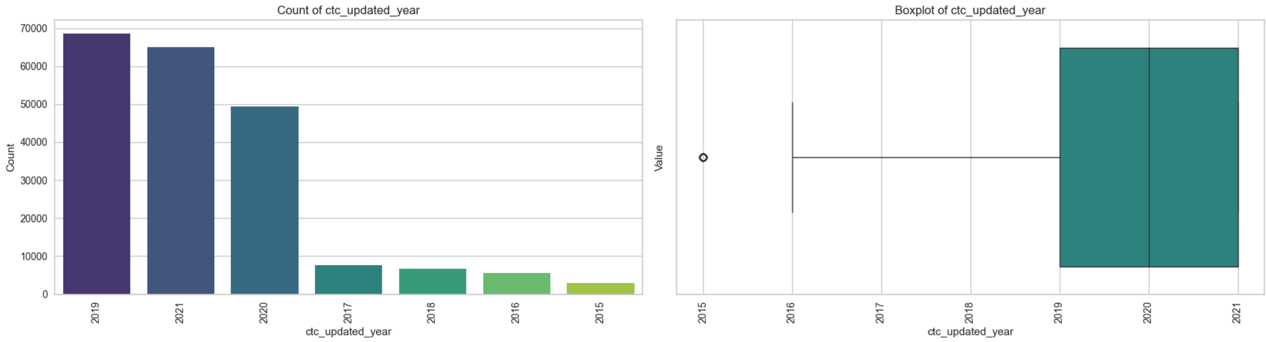
```
0.1 percentile of orgyear: 1992.0 and 99.9 percentile: 2023.0
```

In [26]:
```python
# Clip the orgyear values to remove outliers ignoring the upper limit
df['orgyear'] = df['orgyear'].clip(lower=df['orgyear'].quantile(0.001), upper=df['orgye
```

In [27]:
```python
plot_count('orgyear')
```



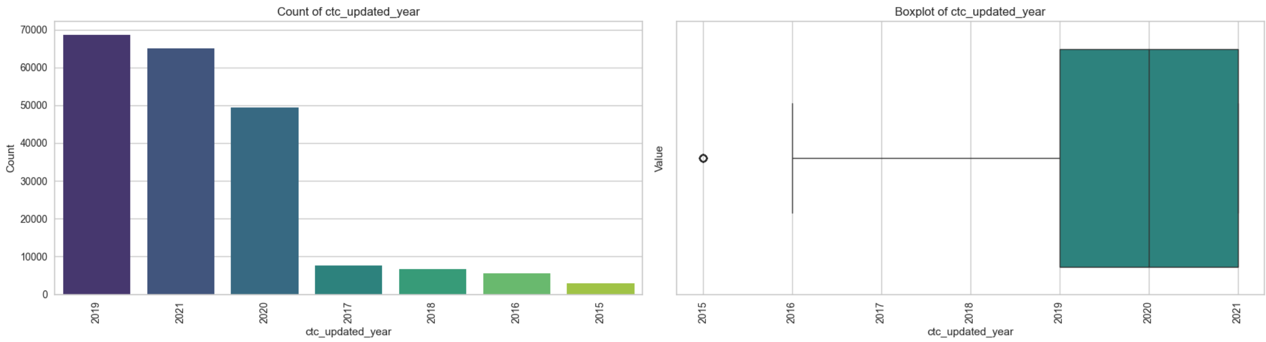
In [28]:
```python
plot_count('ctc_updated_year')
```



In [29]:
```
# Same for ctc_updated_year
print(f'0.1 percentile of ctc_updated_year: {df["ctc_updated_year"].quantile(0.001)} ar
# Clip the ctc_updated_year values to remove outliers ignoring the upper limit
df['ctc_updated_year'] = df['ctc_updated_year'].clip(lower=df['ctc_updated_year'].quant
```

```
0.1 percentile of ctc_updated_year: 2015.0 and 99.9 percentile: 2021.0
```

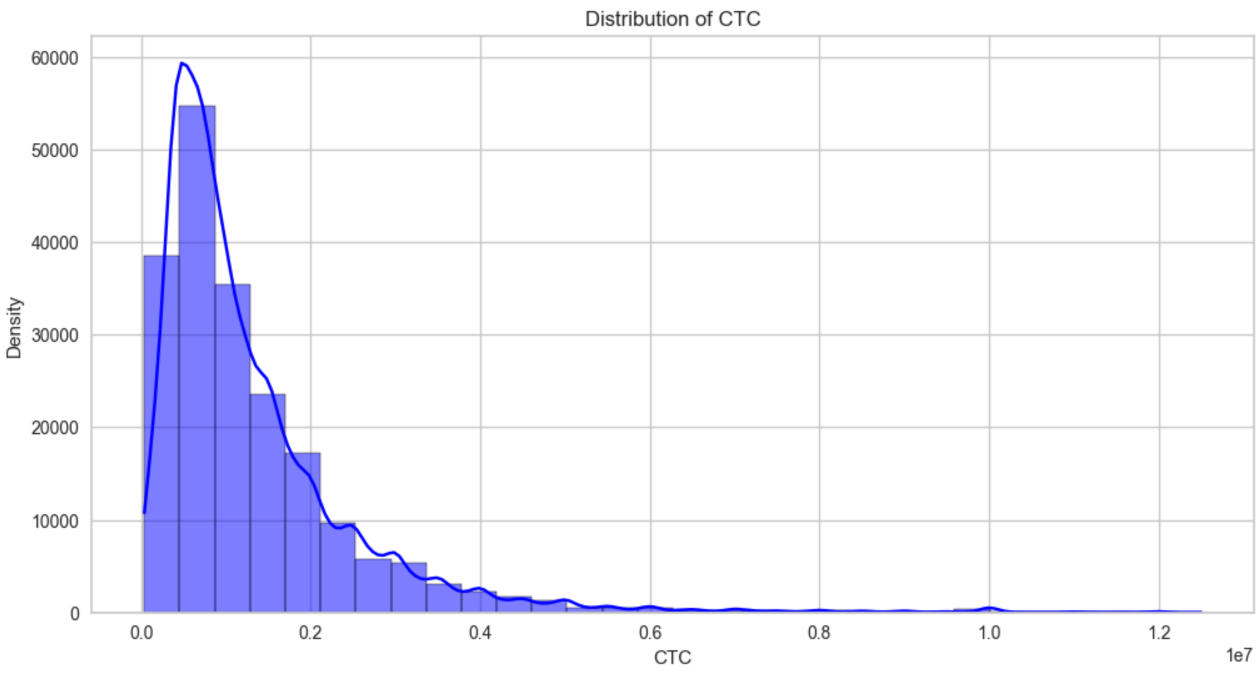
In [30]:
```
plot_count('ctc_updated_year')
```



In [31]:
```
# Same for ctc
print(f'0.1 percentile of ctc: {df["ctc"].quantile(0.001)} and 99.9 percentile: {df["ct
# Remove outliers in ctc column
df = df.loc[((df.ctc) > df.ctc.quantile(0.01)) & ((df.ctc) < df.ctc.quantile(0.99))]
```

```
0.1 percentile of ctc: 3500.0 and 99.9 percentile: 200000000.0
```

In [32]:
```
# Dist plot for ctc
plt.figure(figsize=(12, 6))
sns.histplot(df['ctc'], kde=True, bins=30, color='blue')
plt.title('Distribution of CTC')
plt.xlabel('CTC')
plt.ylabel('Density')
plt.show()
```



In [33]:
```
# Remove rows with invalid company_hash
df = df[df["company_hash"]!="nan"]
```

In [34]:
```
# Check for percentage of company_hash with less than 5 records
df[df.groupby("company_hash")["ctc"].transform("count") < 5].shape[0] / df.shape[0] * 1
```

Out[34]: 23.088558378504374

Observation:

- Since, so many companies were occured only less than 5 times, will group them into separate category
- This contributes to 23% of total datapoints

In [35]:
```
# Mask for company_hash with less than 5 records
mask = df.groupby("company_hash")["ctc"].transform("count") < 5
# Add 'less_occurred' to the categories if not present
if "less_occurred" not in df["company_hash"].cat.categories:
        df["company_hash"] = df["company_hash"].cat.add_categories(["less_occurred"])
# Replace company_hash with 'less_occurred' for those records
df.loc[mask, "company_hash"] = "less_occurred"
```

In [36]:
```
df.sample(5)
```

Out[36]:

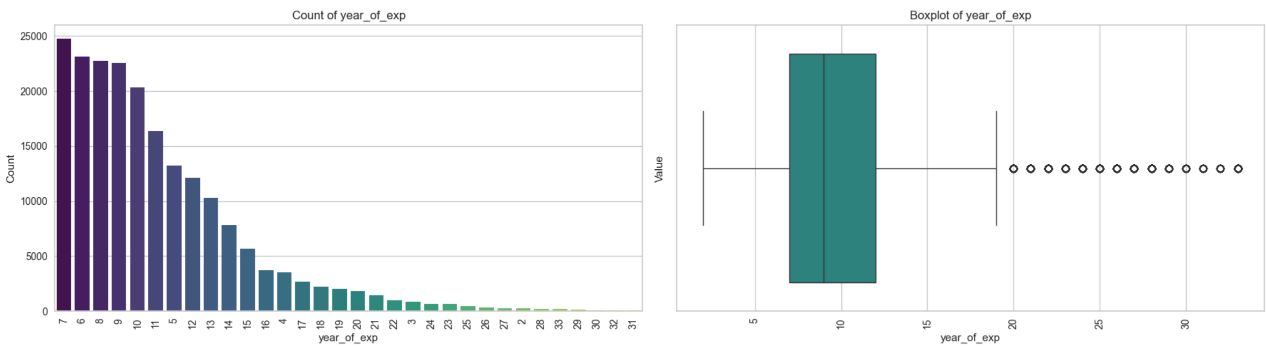
	company_hash	email_hash	orgyear	ctc
94205	less_occurred	7bddf04b4aa78319de32846ef37a33b55fc6cd839b2d64...	2008	1200000
191394	less_occurred	49d8480e68d6755e2b46ac16de3d26cfd38e1a615da68f...	2008	640000
186301	vbvkgz	debcf7ab83d26b4b8ce1981d20235eb3fb2f4617dd2820...	2012	6580000
187115	wxowg	26c42650bbd15a78272b357be2a709115b89186c53f0b3...	2004	3200000
127581	qmo xzaxv	72cf166f2d9d2c95fe5ff6e78145ce8e4fb1fa32f86be7...	2019	600000

In [37]:

```python
# Create a new column 'Year Of Experience' based on current year and orgyear
df['year_of_exp'] = datetime.now().year - df['orgyear']
```

In [38]:

```python
plot_count('year_of_exp')
```



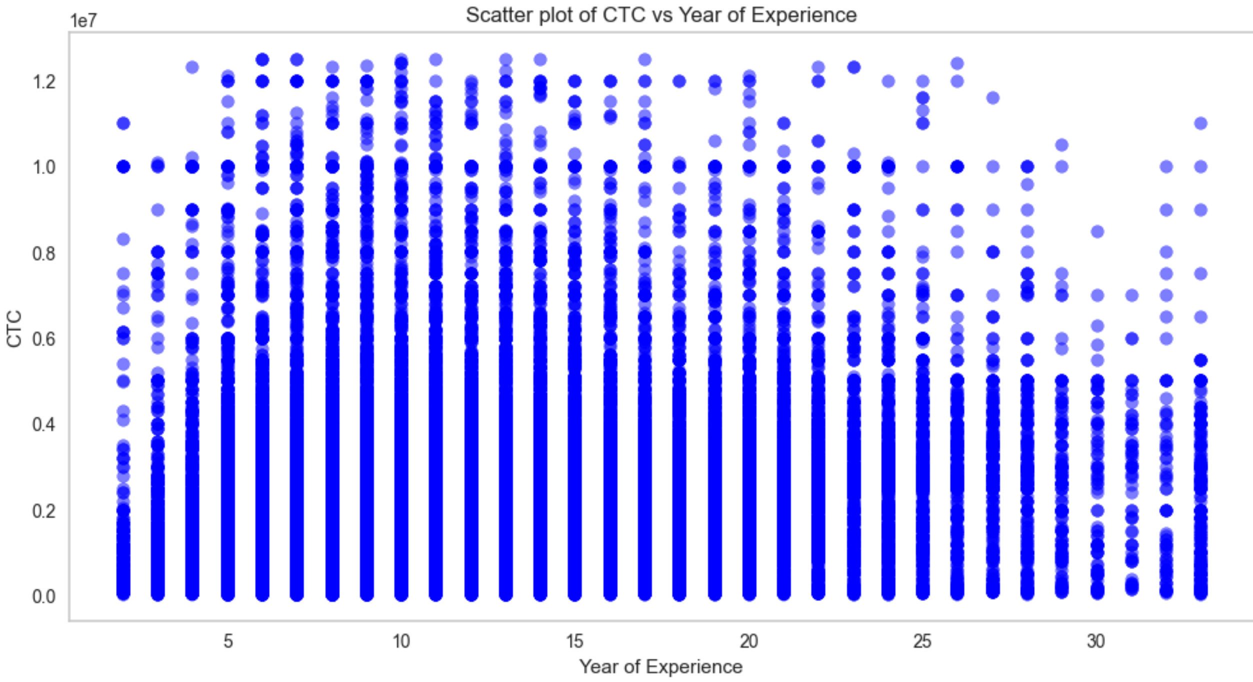
In [39]:

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 201641 entries, 0 to 205842
Data columns (total 7 columns):
 #   Column            Non-Null Count   Dtype   
---  ------            --------------   -----   
 0   company_hash      201641 non-null  category
 1   email_hash        201641 non-null  category
 2   orgyear           201641 non-null  int16   
 3   ctc               201641 non-null  int32   
 4   job_position      201641 non-null  category
 5   ctc_updated_year  201641 non-null  int16   
 6   year_of_exp       201641 non-null  int16   
dtypes: category(3), int16(3), int32(1)
memory usage: 11.9 MB
```

In [40]:

```python
# scatter plot for ctc and year_of_exp
plt.figure(figsize=(12, 6))
plt.scatter(df['year_of_exp'], df['ctc'], alpha=0.5, color='blue')
plt.title('Scatter plot of CTC vs Year of Experience')
plt.xlabel('Year of Experience')
plt.ylabel('CTC')
plt.grid()
plt.show()
```



Manual Clustering

1. Clustering based on Year of Experience, Job Position and Company Hash

In [41]:
```
grouped_ctc = df.groupby(["year_of_exp", "job_position", "company_hash"])["ctc"].descri
```

In [42]:
```
grouped_ctc.head()
```

Out[42]:

year_of_exp	job_position	company_hash	count	mean	std	min	
2	Android Engineer	yxpt btootzstq	1.0	3.000000e+05	NaN	300000.0	3000
		zgn vuurxwvmrt vwwghzn	3.0	4.253333e+06	3.250482e+06	500000.0	33150
	Backend Architect	zvz	1.0	1.500000e+05	NaN	150000.0	1500
	Backend Engineer	zgn vuurxwvmrt vwwghzn	3.0	2.462000e+06	3.227670e+06	56000.0	6280
		zvz	4.0	2.050000e+06	1.021437e+06	1200000.0	14250

In [43]:
```
df_grouped_yoe_jp_ch = df.merge(grouped_ctc, on=["year_of_exp", "job_position", "compar
```

In [44]:
```
df_grouped_yoe_jp_ch.sample(5)
```

Out[44]:

	company_hash	email_hash	orgyear	ctc
1003	bvi ogenfvqt	fcb6332a636530948581ca817fabfb0ceed7afb835e66f...	2017	980000
93791	less_occurred	328a91cff446a159c91b94893c7728e6521455bc61d560...	2016	500000
166953	xzegojo	e5ebf48289fcb710870a0abf1d0c61713699551cf52a55...	2018	390000
129111	tdr	831edf4ee86369862515dc7102cce5aab1d544d60ab959...	2018	600000
134492	less_occurred	669b43271ac1a14ccd2110117753c3359a6f9a0e28cfcd...	2015	650000

In [45]:
```
def classification_ctc(row):
    if row['ctc'] > row['mean']:
        return 3
    elif row['ctc'] == row['mean']:
        return 2
    else:
        return 1
```

In [46]:
```
df_grouped_yoe_jp_ch['designation'] = df_grouped_yoe_jp_ch.apply(classification_ctc, ax
```

In [47]:
```
df_grouped_yoe_jp_ch.sample(5)
```

Out[47]:

	company_hash	email_hash	orgyear	ctc
81647	less_occurred	ad23fe3e5e5246777803a1c80ac90fc56ade211e49ed75...	2010	6000000
95108	less_occurred	326b9962408761cf363ebc8de3f7a5f6927650571001f1...	2017	1200000
49973	bgmxrtxqgz	ff4036587f9d7fe56415a21c6ce886baa6b772c6b0b1fc...	2008	3300000
172255	onvqn hu	c4931db9b36f634b43cafa93492a86e70964b6bef51423...	2016	3300000
27600	fxuqg rxbxnta	89d26a5383944dd425632ad00ec07bc6127fe70b7c9ae6...	2020	360000

In [48]:
```
df_grouped_yoe_jp_ch['designation'].value_counts(normalize=True)
```

Out[48]:
```
designation
1    0.461781
3    0.302825
2    0.235394
Name: proportion, dtype: float64
```

Observation:

- Most of the designmation falls under mean ctc which contributes around 46%
- Around 23% were having the mean ctc
- Only around 30% is having higher than mean ctc

In [49]:
```
# drop unnecessary columns
df_grouped_yoe_jp_ch.drop(columns=['count','mean', 'std', 'min', '25%', '50%', '75%', '
```

In [50]:
```
df_grouped_yoe_jp_ch.sample(5)
```

Out[50]:

	company_hash	email_hash	orgyear	ctc
131021	zgn vuurxwvmrt vwwghzn	c9b27da8d6f37bfef3028aa8b8ade02e34863df52ef1ca...	2020	1000000
14076	ytfrtnn uvwpvqa tzntquqxot	f6e7bb3c5396b585be2b73ef57e9535e2749deba3a95ef...	2016	600000
68841	fxuqg rxbxnta	96d899fe52cd6018a1ed8af0efeb6a879c595bcf53b61d...	2010	1400000
53609	q ojontbo xzntqzvnxgzvr	6c267aaa25aff1441782e293f7e8218b83ab9033779dec...	2007	1600000
96838	eqtoytq	4c1176300b16cf537c120203914425485ba8ec2bba0c6a...	2020	800000

2. Clustering based on Company and Job Position

In [51]:
```
grouped_jp_ch = df.groupby(["job_position", "company_hash"])["ctc"].describe()
grouped_jp_ch.head()
```

Out[51]:

		count	mean	std	min	25%	50%	75
job_position	**company_hash**							
SDE 2	**bvptbjnqxuwgb**	1.0	1200000.0	NaN	1200000.0	1200000.0	1200000.0	120000(
.	**less_occurred**	1.0	700000.0	NaN	700000.0	700000.0	700000.0	70000(
..	**otre tburgjta**	1.0	600000.0	NaN	600000.0	600000.0	600000.0	60000(
.7	**wgszxkvzn**	1.0	470000.0	NaN	470000.0	470000.0	470000.0	47000(
7	**less_occurred**	1.0	420000.0	NaN	420000.0	420000.0	420000.0	42000(

In [52]:
```
df_grouped_jp_ch = df.merge(grouped_jp_ch, on=["job_position", "company_hash"], how="le
df_grouped_jp_ch.sample(5)
```

Out[52]:

	company_hash	email_hash	orgyear	ctc
157611	stzuvwn	bda94abff79f7045cc553da9a39fb9fc993e23082b2a0a...	2017	500000
111032	znn avnv otqcxwto	40c03c0099fc8b42d6f5c4674b7dc7389ab86781abe07a...	2018	500000
182314	vqxwtzn	00eab22b285848b49c08d80726f447721ebbbe01658965...	2011	3450000
188388	tcgrtzn ytvrny	c8ca2e4c14ccadb85a8fc076e784fd33e81f5dcd53b392...	2013	1800000
50242	ztdnstz ytvrnywvqt	d83d000532bf6ddf22f1526ddf73d5803d24719920368c...	2017	1630000

In [53]:

```
df_grouped_jp_ch['class'] = df_grouped_jp_ch.apply(classification_ctc, axis=1)
df_grouped_jp_ch.sample(5)
```

Out[53]:

	company_hash	email_hash	orgyear	ctc
25465	hzxojo xzaxv	005ba99ef7fa4118caa0e34c0e4d68cc671699f58eac35...	2016	1010000
59845	wxnx	8266ef332ef54cf9677e938c31cb44152beab56f713701...	2004	1900000
14686	wgszxkvzn	00ba988a37686adc250c4316904d6603f116ee4f423932...	2014	1200000
20944	ehnhqt sqghu xzaxv	32912eba013c51daf6a10d2c3148afaa8a460b7c377bbf...	2016	480000
175616	less_occurred	f893a1b4a4c5be1312cb1a01f01c645cb7a4394bc3fc85...	2005	2160000

In [54]:

```
df_grouped_jp_ch['class'].value_counts(normalize=True)
```

Out[54]:

```
class
1    0.577898
3    0.353698
2    0.068404
Name: proportion, dtype: float64
```

Observation:

- Over 57% of the data fell under mean ctc
- Only less than 1% of the data were having the same ctc
- Over 35% of data were having more the mean ctc

In [55]:

```
# Remove unnecessary columns
df_grouped_jp_ch.drop(columns=['count','mean', 'std', 'min', '25%', '50%', '75%', 'max'
df_grouped_jp_ch.sample(5)
```

Out[55]:

	company_hash	email_hash	orgyear	ctc
34660	tqxwoogz	0f12db95287402c9860d4db16b445859bac9ac4c62e62c...	2015	400000
30109	erxupvqn	7fab7be0b50c3d39ffd642552cd4be78bbfd91741a4acb...	2017	700000
172399	vwwtznhqt	8c74659276d48efa7e4d0a6912b12def83fc804655459b...	2012	130000
39375	less_occurred	a879de3dd54d6ac3dbc886f0b92e5685f8f710fb1ba9aa...	2015	300000
41812	ogwxtnt stztqvrt srgmvr ogrhnxgz wtznqt	42008cc0a5501259a93f1a253de30b7d38287915a5af51...	2016	1370000

In [56]:
```
df_grouped_yoe_jp_ch.sample(5)
```

Out[56]:

	company_hash	email_hash	orgyear	ctc
83167	mggpxzswgb	0db83e551220cdaa91b4b4de742b1b4d568b8c34b13994...	2014	8400000
57637	less_occurred	e97e04761c82a8c59c0a1da4fe414e27dd25d9894158bd...	2015	690000
178680	zgzt vn nyt bgbtzn	6a128680d3b7242f61dc7702fc218e2c0e184d21c79490...	2017	400000
146207	vouxqt ojontbo	8bff9cd1fb870e34f692e1ae0204a77d48504b8990be26...	2013	450000
51526	oyguwrhto	e8bc12a4f0a08565620a705861b7902e39dc867aa92e3d...	2014	950000

In [57]:
```
# Merge the two dataframes
df_final = df_grouped_yoe_jp_ch.merge(df_grouped_jp_ch, on=['email_hash','company_hash'
df_final.sample(5)
```

Out[57]:

	company_hash	email_hash	orgyear	ctc
2658	wsx xzegqbvnxgz ojontb vza bvzvstbtzn wgzohrnvzn	b49c5715ee4438555f047479395386d20f6ff960f3926d...	2016	700000
32581	otre tburgjta	8fff741abf56c1b285dc072da7d1fa775c05214b2c11a3...	2012	3000000
172343	vqwtoxhb	a9029bae09811b3ea7aa4a8fbf44047d8dab1139b5fafd...	2015	2200000
131908	fxuqg rxbxnta	c155e6e7f0bc598526e92cade662cf468c2595aa93c1b9...	2018	5000000
105425	less_occurred	2a6cf29a969b589741d58141ba89ce47208cdd8f9853b0...	2014	90000

3. Manual Classification by Company

In [58]:
```python
grouped_cmpny = df.groupby(["company_hash"])["ctc"].describe()
```

In [59]:
```python
grouped_cmpny.sample(5)
```

Out[59]:

company_hash	count	mean	std	min	25%	50%	75%	max
ztndwtrr rxbxnta	0.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
xzzgctwnhqt	0.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
bjxzaxvzonvj	0.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
oqx ovqvav wgrrtst egq fgbtz nxqhztrctrx	0.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
ygnovq	0.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [60]:
```python
df_grouped_cmpny = df.merge(grouped_cmpny, on=["company_hash"], how="left")
df_grouped_cmpny.sample(5)
```

Out[60]:

	company_hash	email_hash	orgyear	ctc
173881	ohnytqrvza srgmvr otqcxwto	912e8e08e2649d3f59942100d992799144164b0990dce9...	2010	1300000
84688	gutzntdn xzw	6eec69d1a296d29e9db525d144bbeea60f934987e5f621...	2014	1300000
20726	zgzt	7e32325f0858cdebf52b63bc549d62983c7a9a93dbd32e...	2021	200000
161828	kxrrxgho ogrhnxgzo	f3709c4b631a8ed183c7c40ec391a53f0bc16a84a577b3...	2018	1430000
42952	nvcvzn	a62c92a66085f9277970c47e0aebdc3aefad2c14259c74...	2015	900000

In [61]:
```python
df_grouped_cmpny['tier'] = df_grouped_cmpny.apply(classification_ctc, axis=1)
```

In [62]:
```python
df_grouped_cmpny['tier'].value_counts(normalize=True)
```

Out[62]:
```
tier
1    0.640772
3    0.358801
2    0.000427
Name: proportion, dtype: float64
```

Observation:

- Over 64% of the data lies under mean ctc
- Over 35% of the data lies above mean ctc
- only neglible (less than 1%) of data have the mean ctc

In [63]:
```python
# Drop unnecessary columns
df_grouped_cmpny.drop(columns=['count','mean', 'std', 'min', '25%', '50%', '75%', 'max'
```

In [64]:
```python
df_grouped_cmpny.head()
```

Out[64]:

	company_hash	email_hash	orgyear	ctc	job_p
0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016	1100000	
1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018	449999	Fı Eı
2	less_occurred	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015	2000000	B Eı
3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017	700000	B Eı
4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017	1400000	Fı Eı

In [65]:

```
df_final = df_final.merge(df_grouped_cmpny, on=['email_hash','company_hash', 'orgyear',
df_final.sample(5)
```

Out[65]:

	company_hash	email_hash	orgyear	ctc
83498	ntwy bvyxzaqv	dd16e34857cc5d1d1863c73fe35a7a9e5caec9eb9ebe9a...	2016	1000000
197877	less_occurred	550d34f2b99deced71f6a3d758b77fd4de642ecb58f0e3...	2018	1200000
223492	wsx	bf70bc83beeaefda9702c8bb4372a7275f9c8aa0918d00...	2017	1027999
309403	less_occurred	82192025066bc25d89c1091bfb59c8542c87639a7716b3...	2016	1300000
76939	wgszxkvzn	e61d71753ff9b6d5bc3cccda97b209477830173dd423fe...	2011	600000

Question 1:

- Top 10 employees (earning more than most of the employees in the company) - Tier 1
- Top 10 employees of data science in each company earning more than their peers - Class 1
- Bottom 10 employees of data science in each company earning less than their peers - Class 3
- Bottom 10 employees (earning less than most of the employees in the company)- Tier 3
- Top 10 employees in each company - X department - having 5/6/7 years of experience earning more than their peers - Tier X
- Top 10 companies (based on their CTC)
- Top 2 positions in every company (based on their CTC)

In [66]:

```
# Top 10 employees in each company in tier 3
top_emp_tier_3 = df_final[df_final['tier'] == 3]
top_emp_tier_3['rank'] = top_emp_tier_3.groupby('company_hash')['ctc'].rank(method='fir
top_emp_tier_3 = top_emp_tier_3[top_emp_tier_3['rank'] <= 10]
top_emp_tier_3.head(10)
```

Out[66]:

	company_hash	email_hash	orgyear	ctc	job_
4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017	1400000	
21	bgsrxd	3b99c28818530737364245236fba9a821187fc38cd6445...	2012	2030000	
22	bgsrxd	3b99c28818530737364245236fba9a821187fc38cd6445...	2012	2030000	
23	bgsrxd	3b99c28818530737364245236fba9a821187fc38cd6445...	2012	2030000	
24	bgsrxd	3b99c28818530737364245236fba9a821187fc38cd6445...	2012	2030000	
37	nxbto xzntqztn	d2668cb959e5657c3881413257b9850caa1359c7ce959a...	2015	9500000	
50	gvnx	7ed9dad40408750d848b8c1e568746be7ac2947ec098e6...	2013	780000	
51	gvnx	7ed9dad40408750d848b8c1e568746be7ac2947ec098e6...	2013	780000	
52	gvnx	7ed9dad40408750d848b8c1e568746be7ac2947ec098e6...	2013	780000	
53	gvnx	7ed9dad40408750d848b8c1e568746be7ac2947ec098e6...	2013	780000	

In [67]:

```
# Top 10 employees of data science in each company earning more than their peers - Clas
top_emp_class_3 = df_final[df_final['class'] == 3]
top_emp_class_3['rank'] = top_emp_class_3.groupby('company_hash')['ctc'].rank(method='f
top_emp_class_3 = top_emp_class_3[top_emp_class_3['rank'] <= 10]
top_emp_class_3.head(10)
```

Out[67]:

	company_hash	email_hash	orgyear	ctc	job_
0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016	1100000	
4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017	1400000	
21	bgsrxd	3b99c28818530737364245236fba9a821187fc38cd6445...	2012	2030000	
22	bgsrxd	3b99c28818530737364245236fba9a821187fc38cd6445...	2012	2030000	
23	bgsrxd	3b99c28818530737364245236fba9a821187fc38cd6445...	2012	2030000	
24	bgsrxd	3b99c28818530737364245236fba9a821187fc38cd6445...	2012	2030000	
37	nxbto xzntqztn	d2668cb959e5657c3881413257b9850caa1359c7ce959a...	2015	9500000	
50	gvnx	7ed9dad40408750d848b8c1e568746be7ac2947ec098e6...	2013	780000	
51	gvnx	7ed9dad40408750d848b8c1e568746be7ac2947ec098e6...	2013	780000	
52	gvnx	7ed9dad40408750d848b8c1e568746be7ac2947ec098e6...	2013	780000	

In [68]:

```
# Bottom 10 employees of data science in each company earning less than their peers - C
bot_emp_class_1 = df_final[df_final['class'] == 1]
bot_emp_class_1['rank'] = bot_emp_class_1.groupby('company_hash')['ctc'].rank(method='f
bot_emp_class_1 = bot_emp_class_1[bot_emp_class_1['rank'] <= 10]
bot_emp_class_1.head(10)
```

Out[68]:

	company_hash	email_hash	orgyear	ctc	job_p
7	vwwtznhqt ntwyzgrgsj	756d35a7f6bb8ffeaffc8fcca9ddbb78e7450fa0de2be0...	2019	400000	E E
27	mvlvl exzotqc	62d2e04b44c8bf2f6ec15d5b4c259c06199f598dc51816...	2018	100000	
28	mvlvl exzotqc	62d2e04b44c8bf2f6ec15d5b4c259c06199f598dc51816...	2018	100000	
29	mvlvl exzotqc	62d2e04b44c8bf2f6ec15d5b4c259c06199f598dc51816...	2018	100000	
30	mvlvl exzotqc	62d2e04b44c8bf2f6ec15d5b4c259c06199f598dc51816...	2018	100000	
32	pqgzgo xzwgqugqvnta	b7d0b9cd894ab871c547063df449d03e4138050c0463c6...	2003	600000	QA E
36	ntdvo xzonqhbtzno	85f42e6cf6ef712c9944f27d9fa607eb8c8376589400bb...	2017	900000	E E
41	vkwgb ntwyzgrgsj	f83757429132b93fd3bdceeadc0e52b52de6a78e414f5f...	2019	650000	E E
42	vkwgb ntwyzgrgsj	f83757429132b93fd3bdceeadc0e52b52de6a78e414f5f...	2019	650000	E E
43	vkwgb ntwyzgrgsj	f83757429132b93fd3bdceeadc0e52b52de6a78e414f5f...	2019	650000	E E

In [69]:

```
# Bottom 10 employees (earning less than most of the employees in the company)- Tier 1
bot_emp_tier_1 = df_final[df_final['tier'] == 1]
bot_emp_tier_1['rank'] = bot_emp_tier_1.groupby('company_hash')['ctc'].rank(method='fir
bot_emp_tier_1 = bot_emp_tier_1[bot_emp_tier_1['rank'] <= 10]
bot_emp_tier_1.head(10)
```

Out[69]:

	company_hash	email_hash	orgyear	ctc	job_
0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016	1100000	
5	yvuuxrj hzbvqqxta bvqptnxzs ucn rna	18f2c4aa2ac9dd3ae8ff74f32d30413f5165565b90d8f2...	2018	700000	
7	vwwtznhqt ntwyzgrgsj	756d35a7f6bb8ffeaffc8fcca9ddbb78e7450fa0de2be0...	2019	400000	
27	mvlvl exzotqc	62d2e04b44c8bf2f6ec15d5b4c259c06199f598dc51816...	2018	100000	
28	mvlvl exzotqc	62d2e04b44c8bf2f6ec15d5b4c259c06199f598dc51816...	2018	100000	
29	mvlvl exzotqc	62d2e04b44c8bf2f6ec15d5b4c259c06199f598dc51816...	2018	100000	
30	mvlvl exzotqc	62d2e04b44c8bf2f6ec15d5b4c259c06199f598dc51816...	2018	100000	
32	pqgzgo xzwgqugqvnta	b7d0b9cd894ab871c547063df449d03e4138050c0463c6...	2003	600000	QA
36	ntdvo xzonqhbtzno	85f42e6cf6ef712c9944f27d9fa607eb8c8376589400bb...	2017	900000	
38	nyvuvq hzxctqoxnj	9193cad13d506216fea5f0f920f16bc110a82c3d3cf52e...	2020	600000	Eng

In [70]:

```
# Top 10 employees in each company - X department - having 5/6/7 years of experience ea
top_experienced_emp = df_final[df_final['tier'] == 3]
top_experienced_emp = top_experienced_emp[(top_experienced_emp['year_of_exp'] >= 5) & (
top_experienced_emp['rank'] = top_experienced_emp.groupby(['company_hash', 'job_positio
top_experienced_emp = top_experienced_emp[top_experienced_emp['rank'] <= 10]
top_experienced_emp.head(10)
```

Out[70]:

	company_hash	email_hash	orgyear	ctc	job
26	puxn	26b502eb6439ac80bd618a6f7c2b1c640b84c1e64c472c...	2020	1400000	
75	rgfto wgbuvzxto xzw	7ce201f4f032c2af65b5d11f549de91ea3e62920834e72...	2020	3010000	
76	rgfto wgbuvzxto xzw	7ce201f4f032c2af65b5d11f549de91ea3e62920834e72...	2020	3010000	
77	rgfto wgbuvzxto xzw	7ce201f4f032c2af65b5d11f549de91ea3e62920834e72...	2020	3010000	
78	rgfto wgbuvzxto xzw	7ce201f4f032c2af65b5d11f549de91ea3e62920834e72...	2020	3010000	
86	ertdnqgzxwo	cf01b5e9c5a3eaa8dee352a8d427827c6e77ce46e143a4...	2019	1100000	
109	wtqtmqj	0b14ce548655fa4bfe8bd1f6a69d7a5d4cf5e17a6ed590...	2018	1300000	
116	cxcg bgmxrt xzaxv ucn rna	6ffc0fe7aafd0918f525ef913c3f74107aba3531b1c7b1...	2019	600000	
117	cxcg bgmxrt xzaxv ucn rna	6ffc0fe7aafd0918f525ef913c3f74107aba3531b1c7b1...	2019	600000	
118	cxcg bgmxrt xzaxv ucn rna	6ffc0fe7aafd0918f525ef913c3f74107aba3531b1c7b1...	2019	600000	

In [71]:

```
# Top 10 companies (based on their CTC)
top_companies = df_final.groupby('company_hash')['ctc'].mean().reset_index()
top_companies = top_companies.sort_values(by='ctc', ascending=False)
top_companies.head(10)
```

Out[71]:

	company_hash	ctc
3828	bxwqgonqvntsj	8.607727e+06
8618	hzxbgzx	6.876923e+06
14152	nyt sqtvn wghqoto	6.270769e+06
31715	wvqttb	6.060375e+06
24181	tzihtqg srgmvr	5.423636e+06
16209	orxwt	5.340000e+06
4261	crgwxnj	5.324444e+06
29318	vxqugqno vhnygqxnj ge xzaxv	5.252632e+06
7950	guug bgmxrto	5.164286e+06
12842	nton wgbuvzj	4.893462e+06

In [72]:

```
# Top 2 positions in every company (based on their CTC)
top_positions = df_final.groupby(['company_hash', 'job_position'])['ctc'].mean().reset_
top_positions['rank'] = top_positions.groupby('company_hash')['ctc'].rank(method='first
top_positions = top_positions[top_positions['rank'] <= 2]
```

```
top_positions = top_positions.sort_values(by=['company_hash', 'job_position'])
top_positions[['company_hash', 'job_position', 'ctc']].head(10)
```

Out[72]:

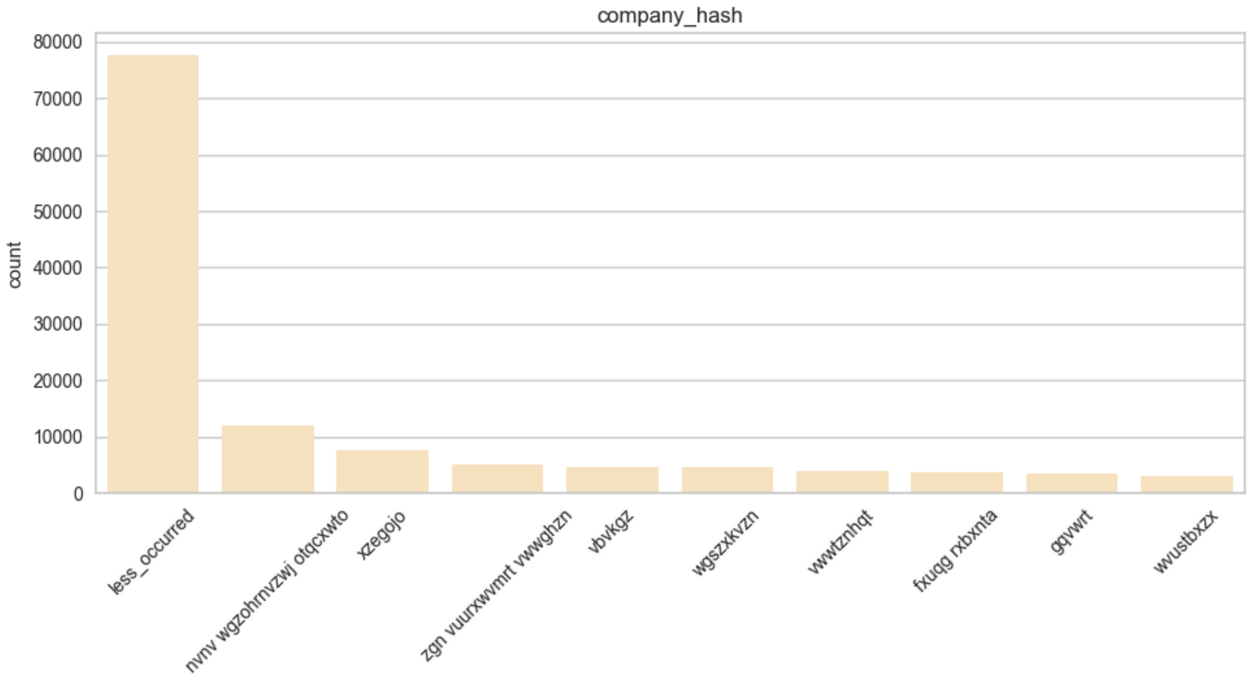
	company_hash	job_position	ctc
33783	1bs	Engineering Leadership	2.800000e+06
34515	1bs	iOS Engineer	2.700000e+06
35700	1bs ntwyzgrgsxto ucn rna	Backend Engineer	1.462281e+06
35847	1bs ntwyzgrgsxto ucn rna	Frontend Engineer	1.910000e+06
43828	1onaxmo	Backend Engineer	1.705000e+06
68212	20142018	Backend Engineer	4.222222e+05
68529	20142018	Other	5.750000e+05
71260	20152019	Backend Engineer	7.200000e+05
71321	20152019	Data Analyst	2.100000e+06
75324	2018	Backend Engineer	1.500000e+06

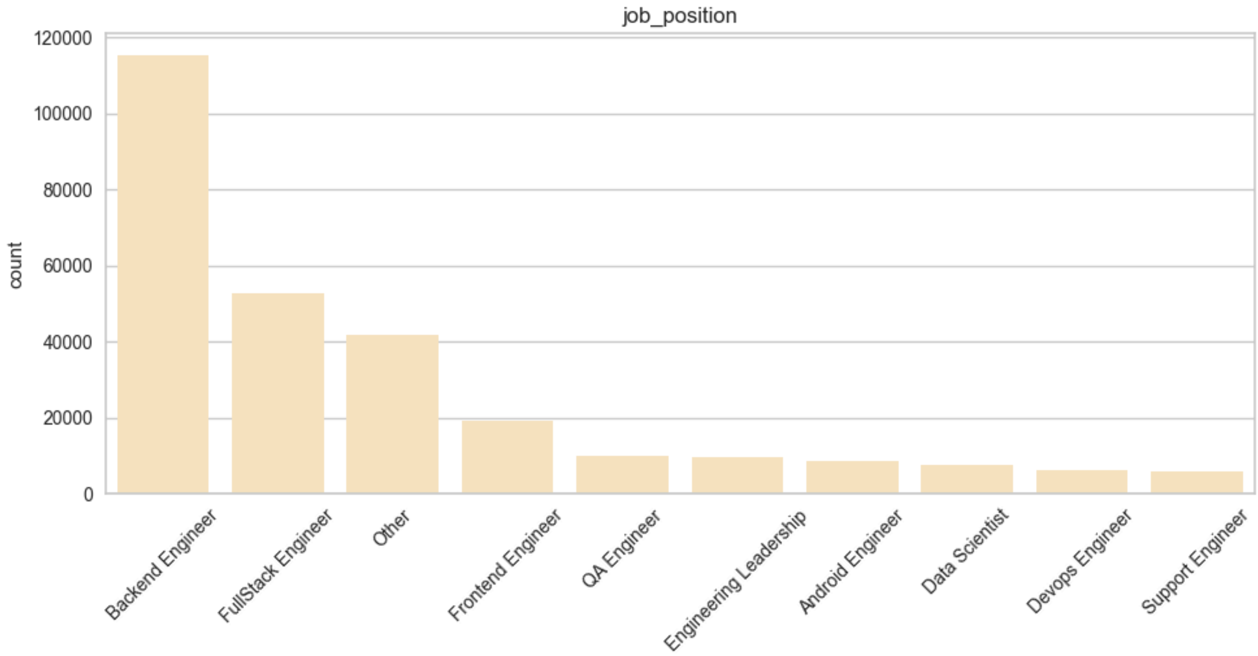
Graphical Analysis

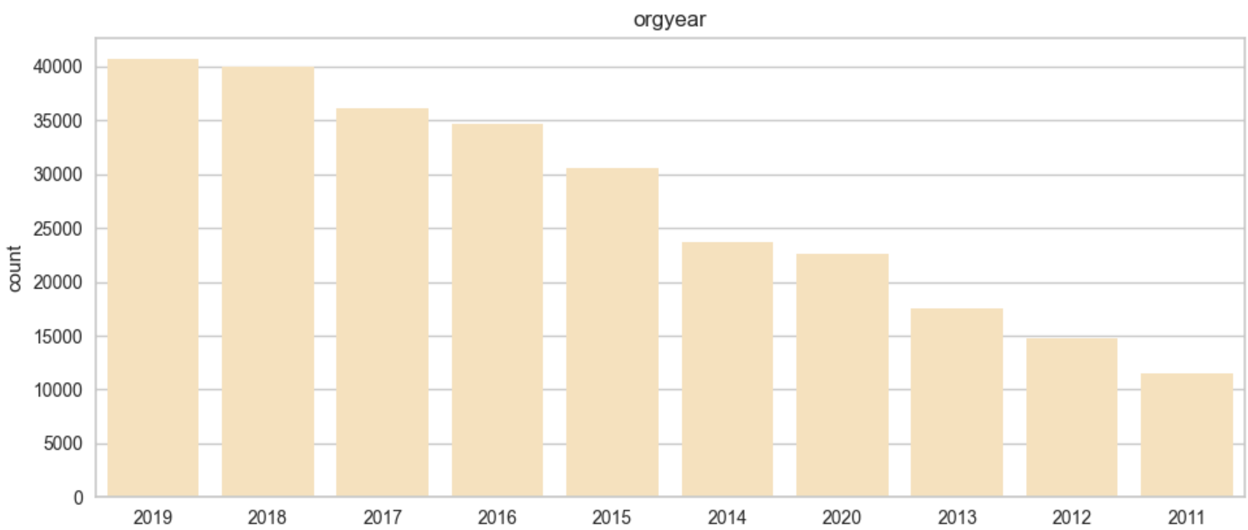
1. Univariate Analysis

In [73]:
```
obj_cols= ['company_hash', 'job_position','orgyear']
num_cols= ['ctc','year_of_exp', 'ctc_updated_year']
```

In [74]:
```
plt.figure(figsize=(10, 15))

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

    ax = plt.subplot(3, 1, i)
    sns.countplot(x=df_final[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()
```





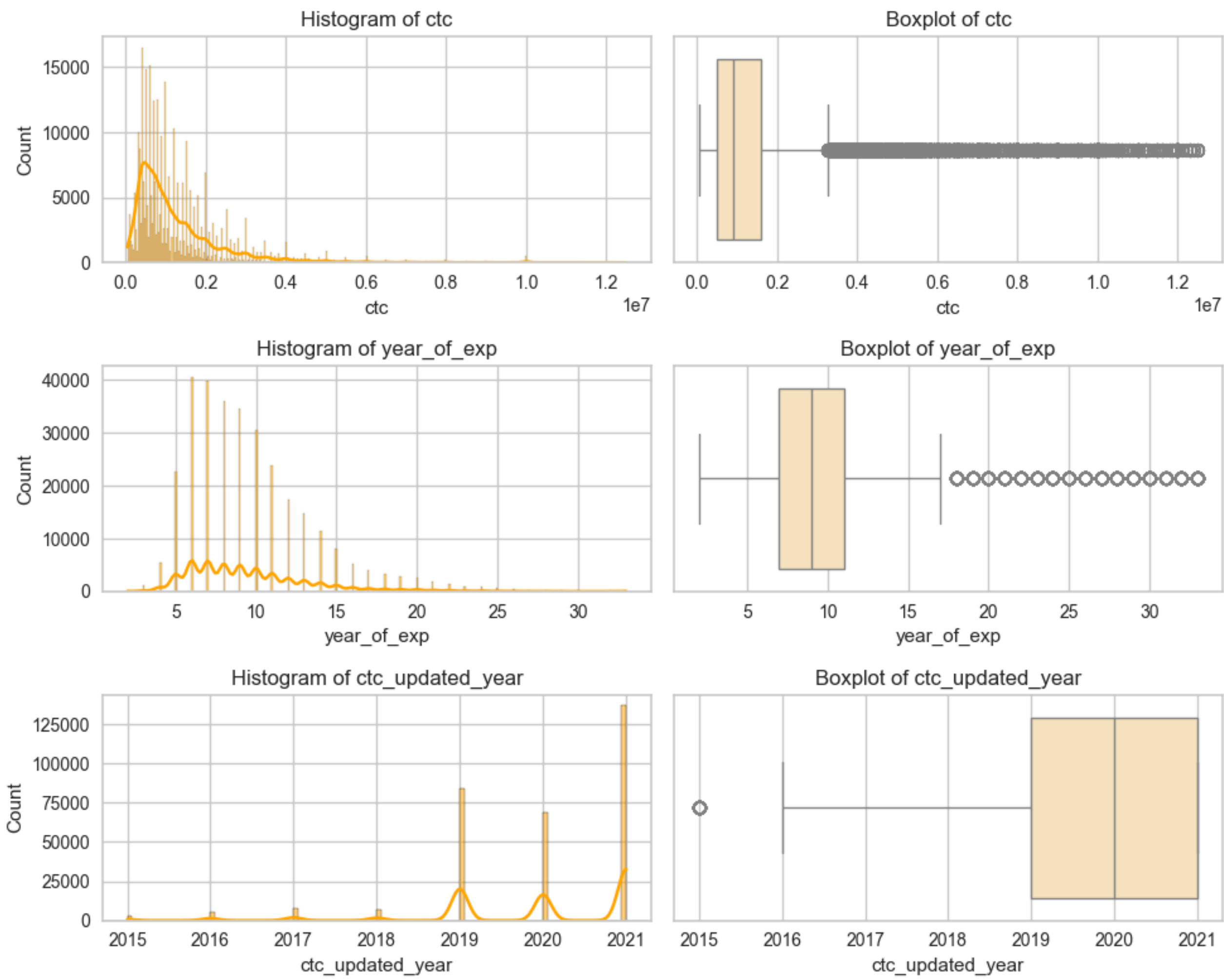


Observations:

- We can easily find top 10 companies in terms of count in the dataset

- Top job position is 'Backend Engineer' followed by 'FullStack Engineer' and 'Others'
- Most of the employees started working in the year 2019 followed by 2018 and 2017

In [75]:
```
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(3, 2, 2*i + 1)
    sns.histplot(df_final[col], kde=True, color='orange')
    plt.title(f'Histogram of {col}')

    # Boxplot
    ax2 = plt.subplot(3, 2, 2*i + 2)
    sns.boxplot(x=df_final[col], color='moccasin')
    plt.title(f'Boxplot of {col}')

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

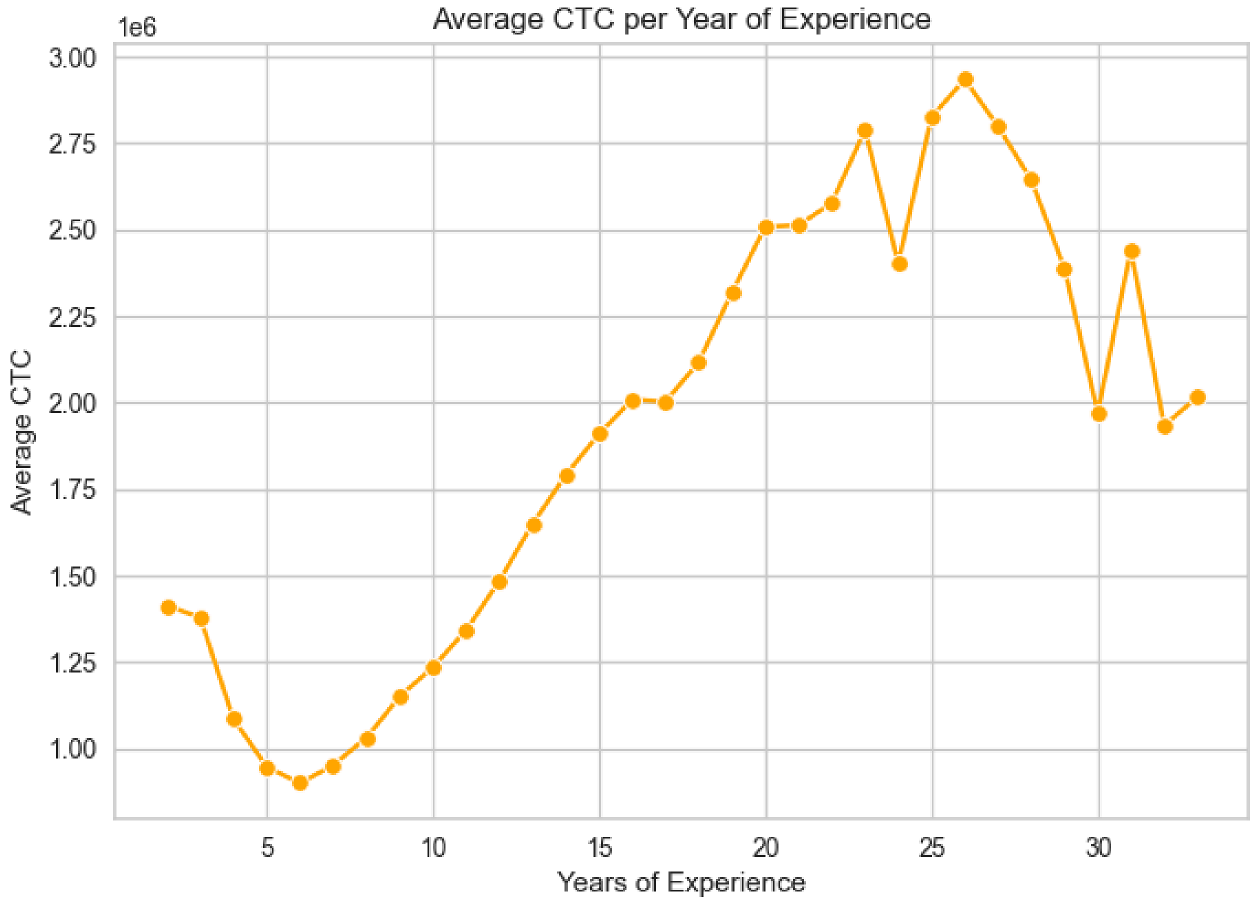


2. Bivariate Analysis

In [76]:
```
sns.scatterplot(x='year_of_exp', y='ctc', data=df_final, color='moccasin')
plt.title('CTC vs. Years of Experience')
plt.show()
```

In [77]:

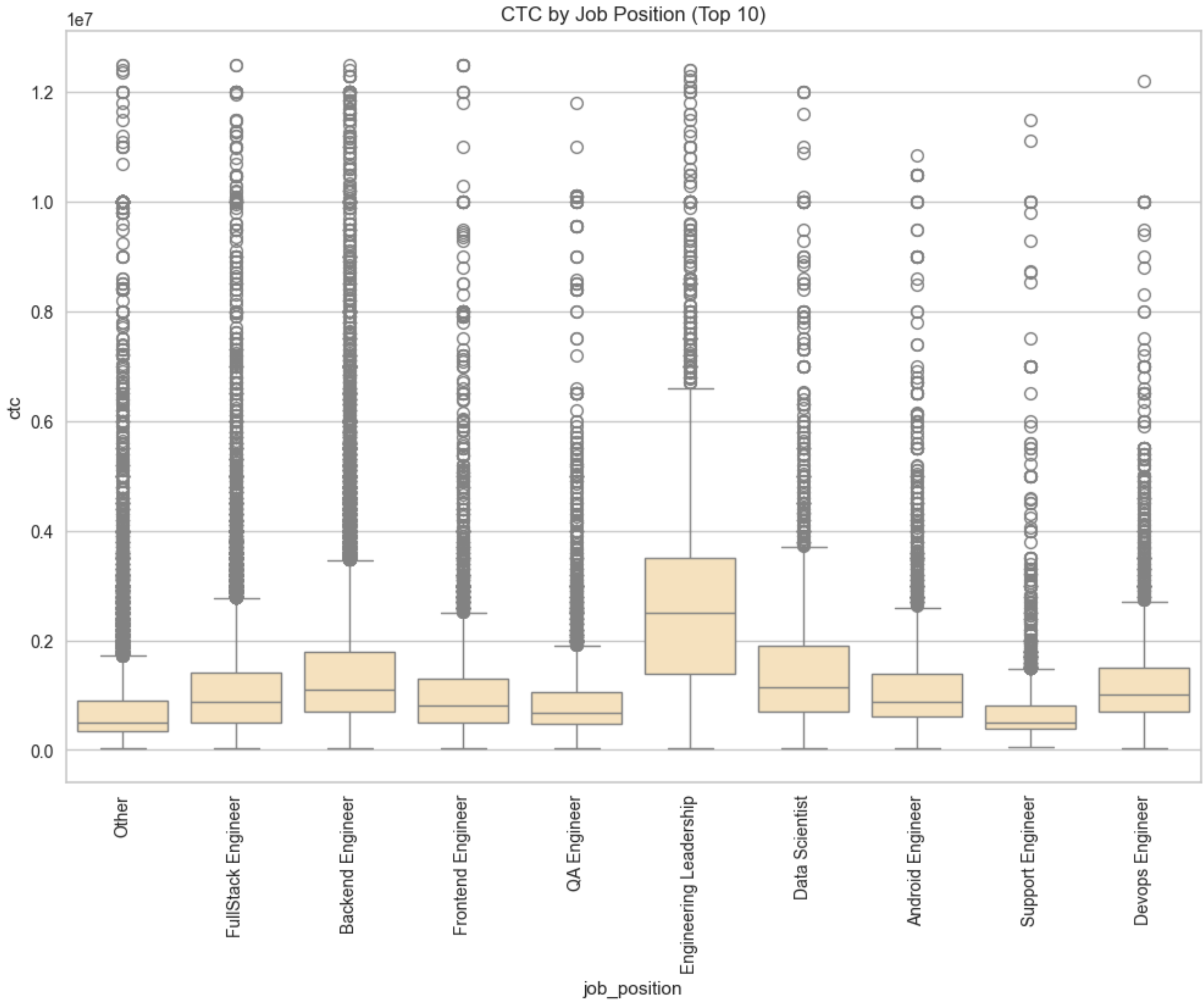
```
# Calculate average CTC per year of experience
avg_ctc_per_yoe = df_final.groupby('year_of_exp')['ctc'].mean().reset_index()

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

plt.show()
```



Observation:

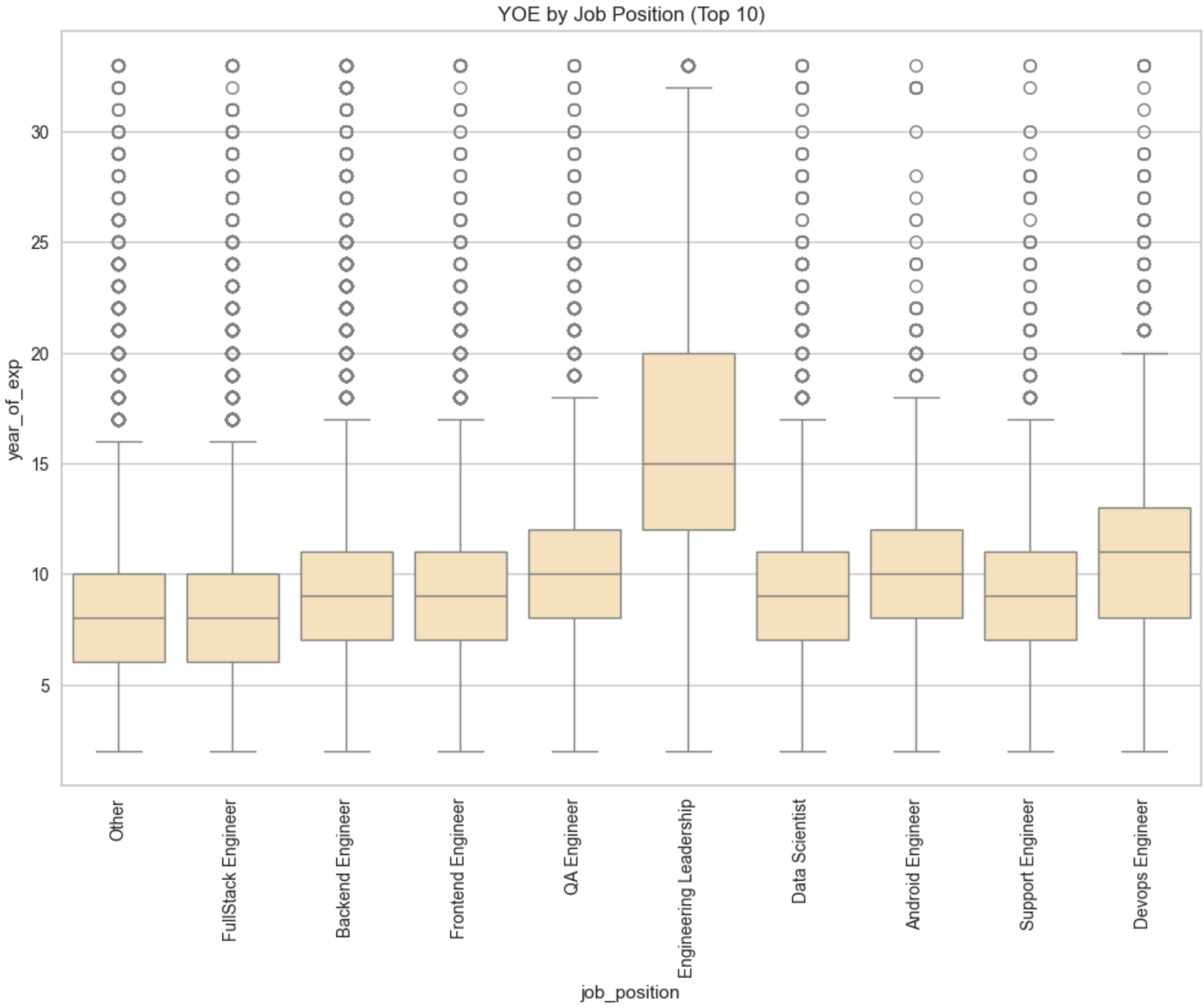
- Average CTC is increasing after 5 years of experience till 22-23 years of experience
- After that there was a drop and increase and drop again. It's because of the age of the Employer where so many layoffs will happen which also leads to ctc dropped

In [78]:
```
# Get the top 10 job positions by count
top_10_job_positions = df_final['job_position'].value_counts().nlargest(10).index

# Filter the dataset to include only the top 10 job positions
df_top_10 = df_final[df_final['job_position'].isin(top_10_job_positions)]
df_top_10["job_position"] = df_top_10['job_position'].astype('object')
# Plot the box plot for CTC by Job Position
plt.figure(figsize=(12, 8))
sns.boxplot(x='job_position', y='ctc', data=df_top_10, color='moccasin')
plt.xticks(rotation=90)
plt.title('CTC by Job Position (Top 10)')
plt.show()
```

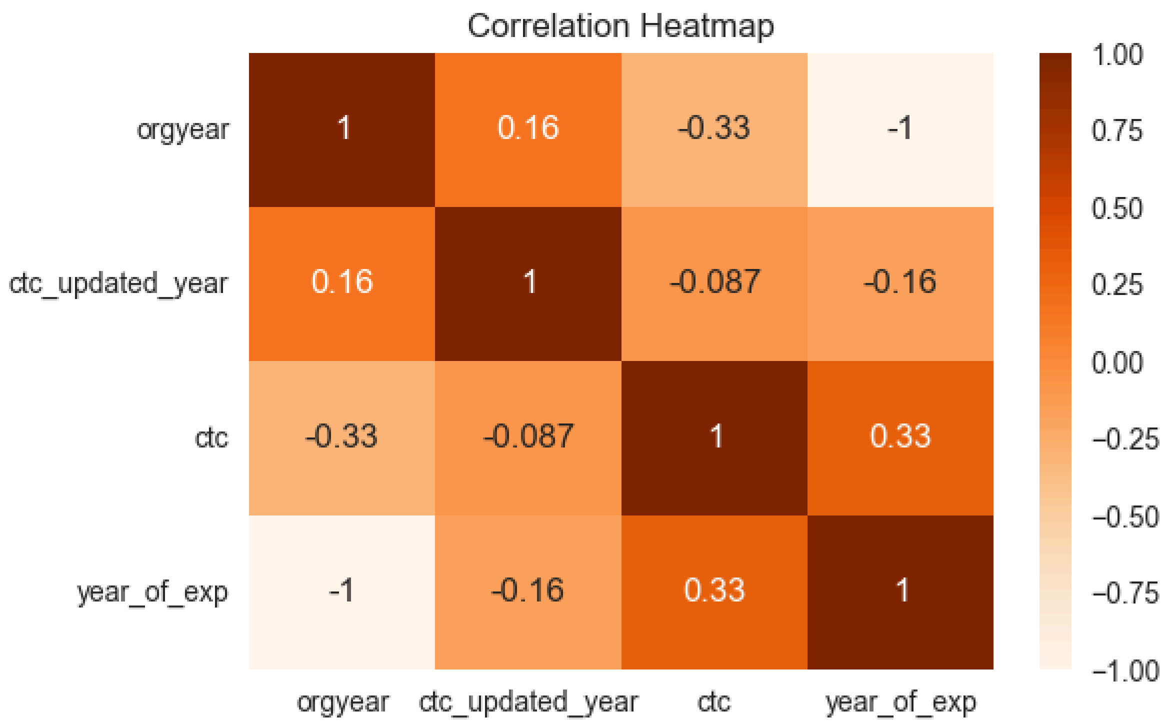


In [79]:

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

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

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



In [80]:
```
plt.figure(figsize=(6, 4))
sns.heatmap(df_final[['orgyear', 'ctc_updated_year', 'ctc', 'year_of_exp']].corr(), anr
plt.title('Correlation Heatmap')
plt.show()
```



Observation:

- 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

Data Processing for Unsupervised Learning

In [81]:
```
email_hash_freq = df['email_hash'].value_counts().reset_index()
email_hash_freq.columns = ['email_hash', 'no_of_ctc_update']

new_df = pd.merge(df, email_hash_freq, on='email_hash', how='left')
```

In [82]:
```
new_df.drop(['email_hash', 'orgyear', 'ctc_updated_year'], axis=1, inplace=True)
```

In [83]:
```
df_cluster = new_df.copy()
new_df.head()
```

Out[83]:

	company_hash	ctc	job_position	year_of_exp	no_of_ctc_update
0	atrgxnnt xzaxv	1100000	Other	9	2
1	qtrxvzwt xzegwgbb rxbxnta	449999	FullStack Engineer	7	2
2	less_occurred	2000000	Backend Engineer	10	2
3	ngpgutaxv	700000	Backend Engineer	8	1
4	qxen sqghu	1400000	FullStack Engineer	8	2

In [84]:
```
# Encoding non-numerical columns
# Frequency encoding for company_hash
company_hash_freq = new_df['company_hash'].value_counts().to_dict()
new_df['company_hash_encoded'] = new_df['company_hash'].map(company_hash_freq)

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

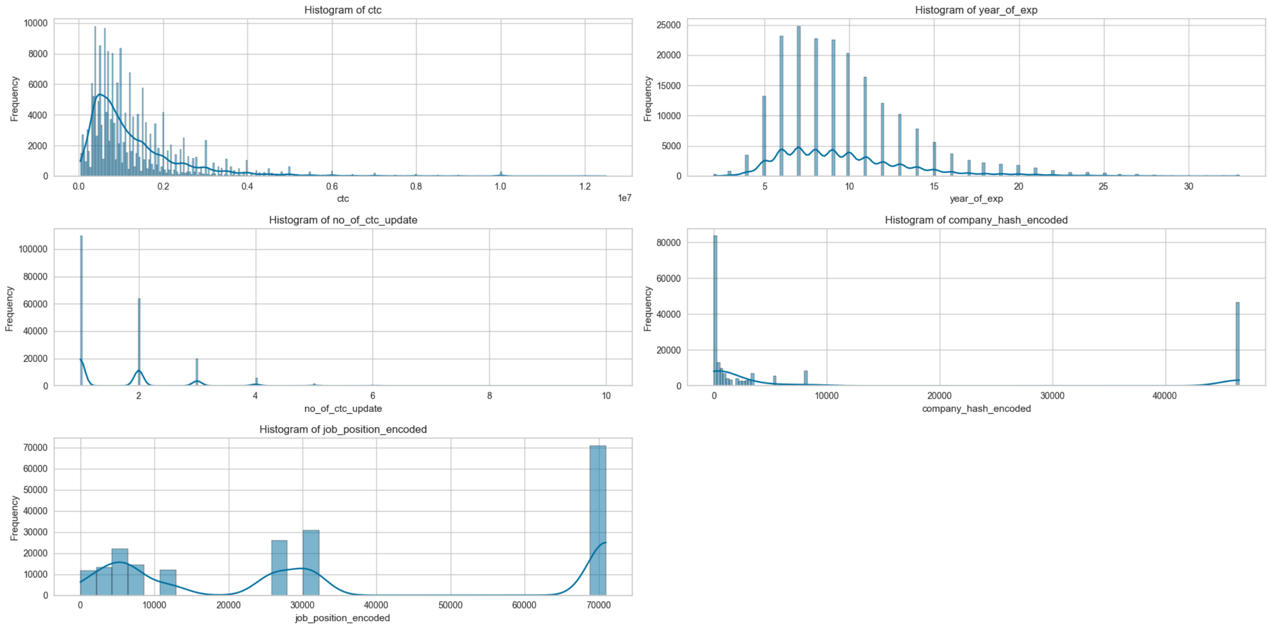
In [85]:
```
new_df.drop(['company_hash', 'job_position'], axis=1, inplace=True)
new_df.head()
```

Out[85]:

	ctc	year_of_exp	no_of_ctc_update	company_hash_encoded	job_position_encoded
0	1100000	9	2	9	26093
1	449999	7	2	421	30900
2	2000000	10	2	46556	70968
3	700000	8	1	70	70968
4	1400000	8	2	6	30900

In [86]:
```
fig, axes = plt.subplots(nrows=3, ncols=2, figsize=(20, 10))
axes = axes.flatten()

# Plot each column
for i, col in enumerate(new_df.columns):
```

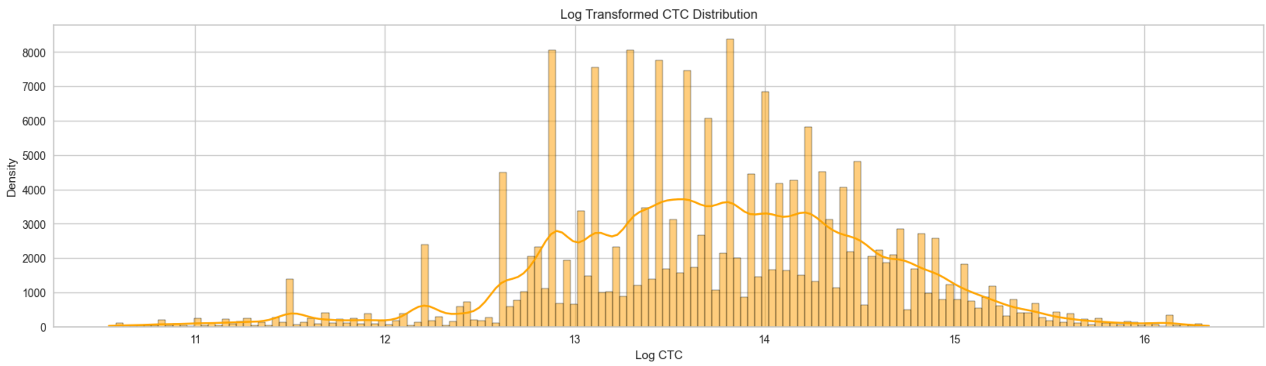
```
    sns.histplot(new_df[col], kde=True, ax=axes[i])
    axes[i].set_title(f'Histogram of {col}')
    axes[i].set_xlabel(col)
    axes[i].set_ylabel('Frequency')

# Hide the unused subplot
if len(new_df.columns) < len(axes):
    for j in range(len(new_df.columns), len(axes)):
        axes[j].set_visible(False)

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



In [87]:
```
new_df['ctc_log'] = np.log1p(new_df['ctc'])
```

In [88]:
```
new_df = new_df.drop(['ctc'], axis=1)
```

In [89]:
```
# histogram of log transformed ctc
plt.figure(figsize=(20, 5))
sns.histplot(new_df['ctc_log'], kde=True, color='orange')
plt.title('Log Transformed CTC Distribution')
plt.xlabel('Log CTC')
plt.ylabel('Density')
plt.show()
```



In [90]:
```
# Standard Scaling
# Initialize the StandardScaler
scaler = StandardScaler()

# Fit and transform the data
```

```
scaled_features = scaler.fit_transform(new_df[['year_of_exp', 'no_of_ctc_update', 'comp

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

In [91]:
```
df_scaled.head()
```

Out[91]:

	year_of_exp	no_of_ctc_update	company_hash_encoded	job_position_encoded	ctc_log
0	-0.208826	0.392346	-0.609758	-0.326032	0.192686
1	-0.684528	0.392346	-0.588279	-0.154286	-0.858981
2	0.029025	0.392346	1.816821	1.277282	0.896100
3	-0.446677	-0.736985	-0.606577	1.277282	-0.339119
4	-0.446677	0.392346	-0.609914	-0.154286	0.476437

Model Building

In [92]:
```
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)], 2, retur

    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: 0.9921965917121176
```

Observation:

- 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

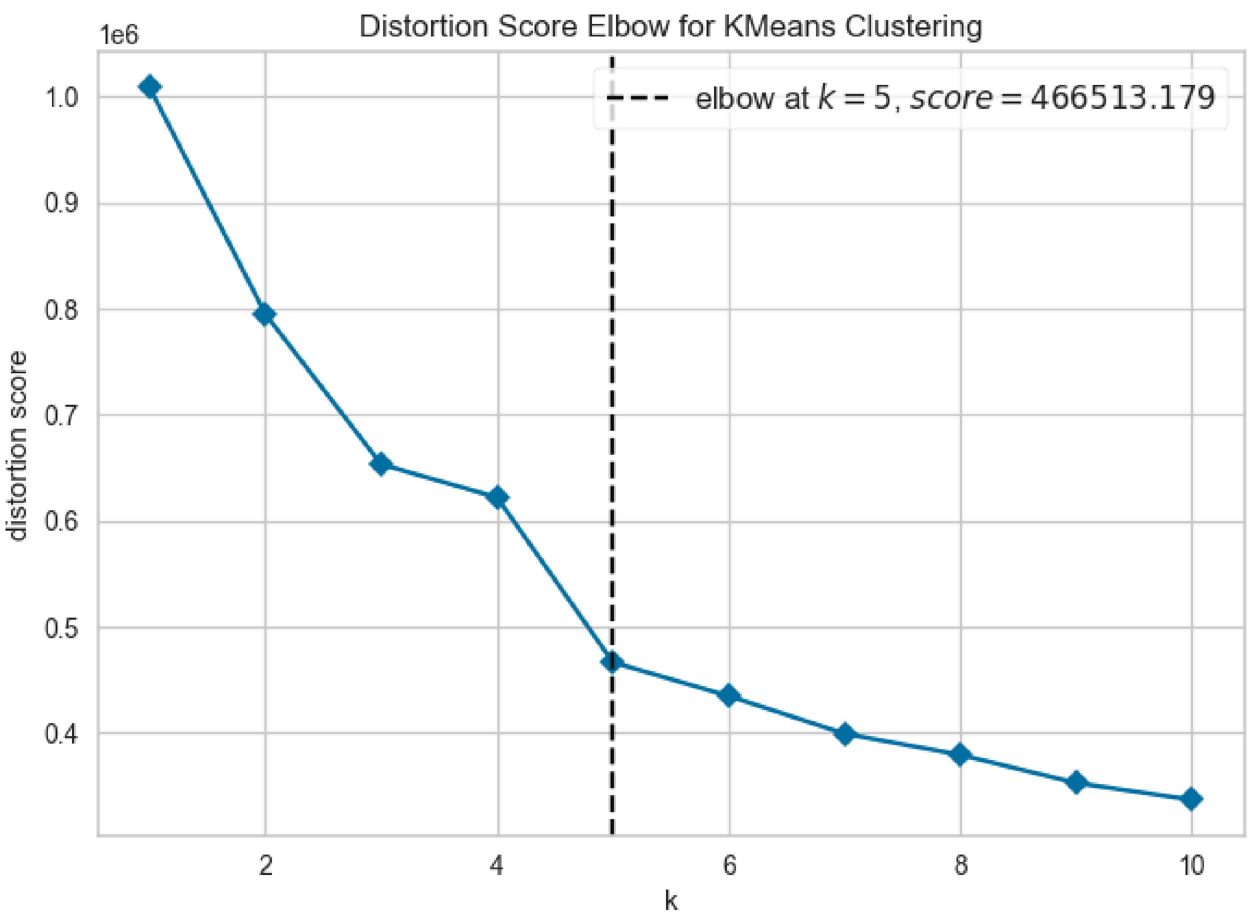
Elbow Method- To select optimal number of clusters

Inertia

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

In [93]:
```
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()
```



Out[93]: <Axes: title={'center': 'Distortion Score Elbow for KMeans Clustering'}, xlabel='k', ylabel='distortion score'>

Observation:

- 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.

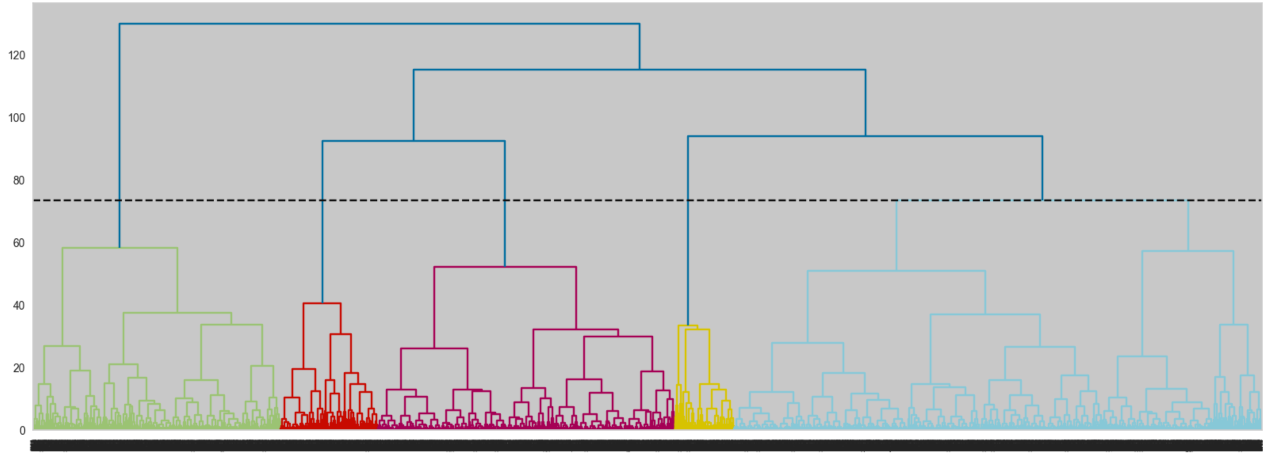
In [94]:
```
new_df.head()
```

Out[94]:

	year_of_exp	no_of_ctc_update	company_hash_encoded	job_position_encoded	ctc_log
0	9	2	9	26093	13.910822
1	7	2	421	30900	13.017003
2	10	2	46556	70968	14.508658
3	8	1	70	70968	13.458837
4	8	2	6	30900	14.151984

In [95]:
```
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
df_cluster['kmeans_cluster'] = kmeans.labels_
```

In [96]:
```
# Sample a subset of the data
df_sampled = df_scaled.sample(n=10000, random_state=0)

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

# Get cluster assignments for 5 clusters
cluster_labels = fcluster(Z, t=5, criterion='maxclust')

# Then plot with color_threshold that matches this cut
plt.figure(figsize=(20, 7))
dendrogram(Z, color_threshold=Z[-5, 2]+0.5)  # Cut at the height that gives 5 clusters
plt.axhline(Z[-5, 2], c='k', linestyle='--')  # Optional: show cut line
plt.show()
```



Observations:

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

In [97]:
```
# Within-Cluster Sum of Squares (WCSS)
wcss = kmeans.inertia_
print(f'Within-Cluster Sum of Squares (WCSS): {wcss}')
```

```
Within-Cluster Sum of Squares (WCSS): 466513.1994304687
```

Observation:

- 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.

In [98]:
```
# Between-Cluster Sum of Squares (BCSS)
# 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}')
```

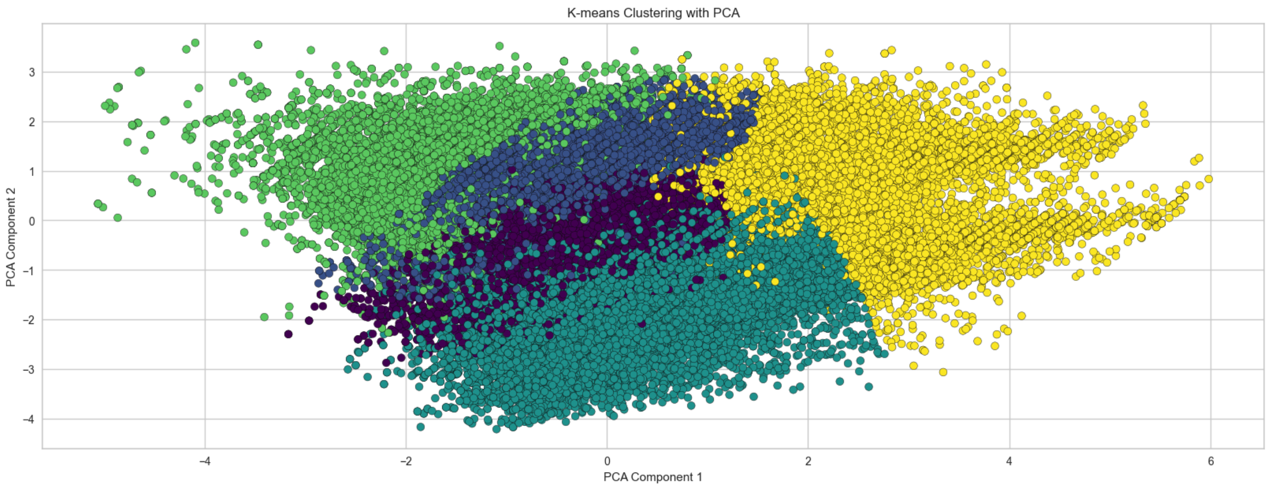
```
Between-Cluster Sum of Squares (BCSS): 541522.180778658
```

Observation:

- 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.

In [99]:

```
#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=(20, 7))
plt.scatter(df_scaled_copy['pca_one'], df_scaled_copy['pca_two'], c=df_scaled_copy['kme
plt.title('K-means Clustering with PCA')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.show()
```



In [100…

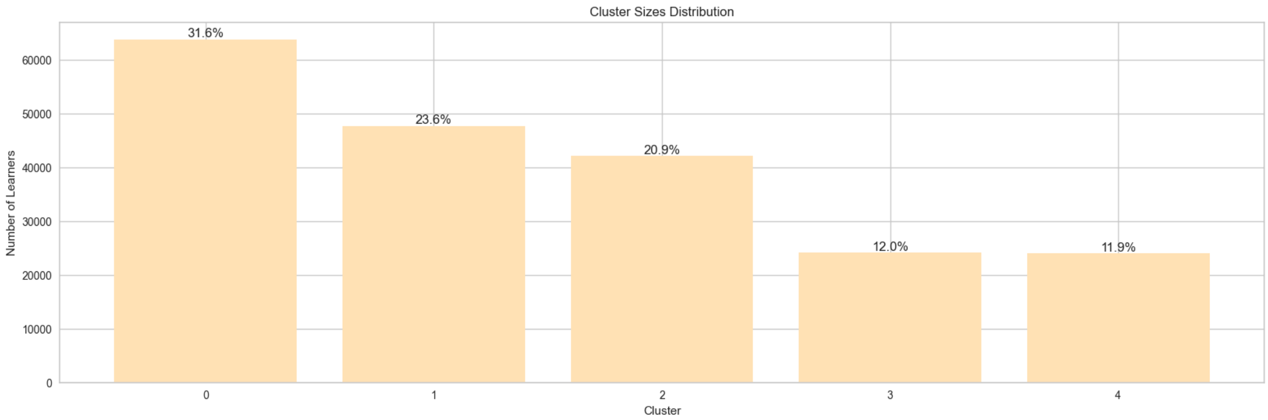
```
cluster_sizes = df_cluster['kmeans_cluster'].value_counts().sort_index()
print(f'Cluster Sizes:\n{cluster_sizes}')
```

```
Cluster Sizes:
kmeans_cluster
0    63761
1    47673
2    42068
3    24164
4    23975
Name: count, dtype: int64
```

In [101…

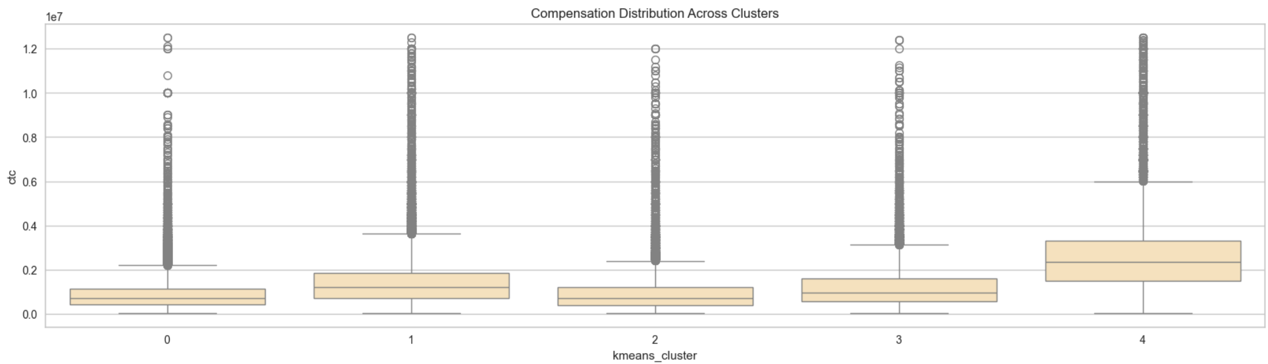
```
# Assuming cluster sizes are stored in a dictionary
cluster_sizes = {0: 63761, 1: 47673, 2: 42068, 3: 24164, 4: 23975}

# Calculate the total number of learners
```

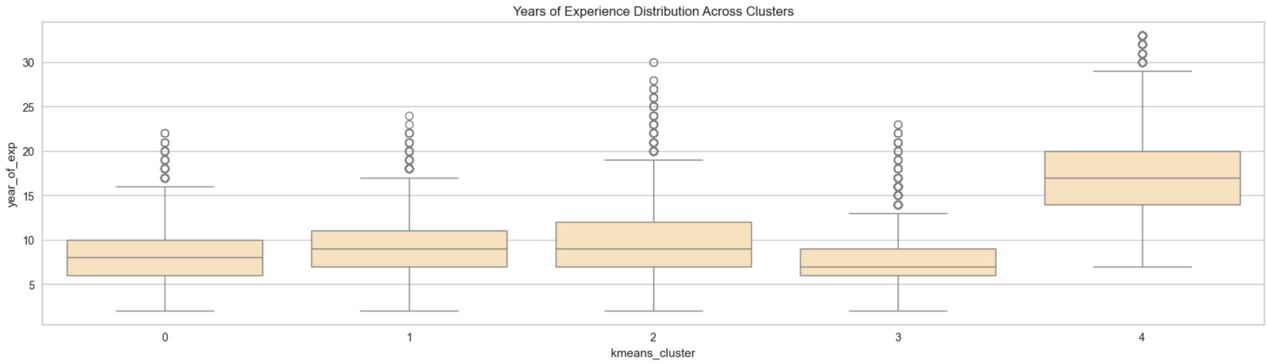
```python
total_learners = sum(cluster_sizes.values())

# Create a bar chart
plt.figure(figsize=(20, 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}%', ha='cente

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

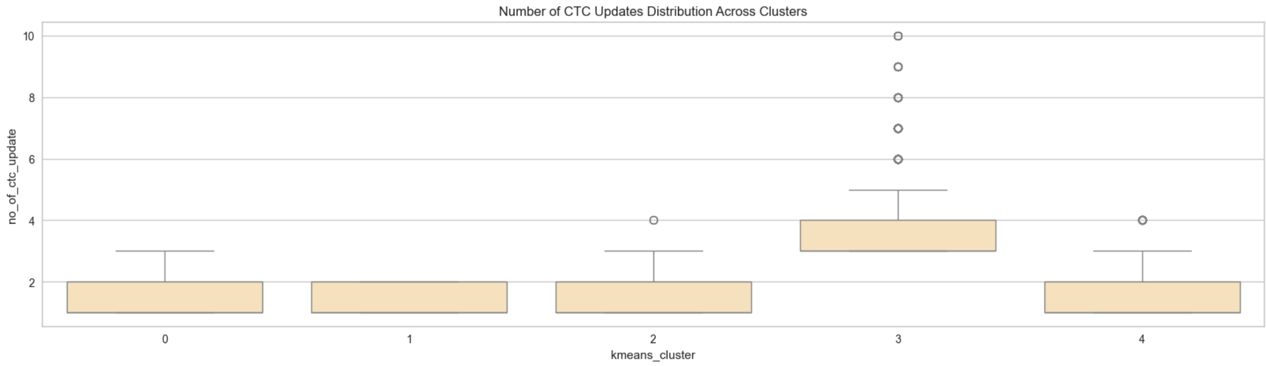


In [102…

```python
plt.figure(figsize=(20, 5))
sns.boxplot(x='kmeans_cluster', y='ctc', data=df_cluster,color='moccasin')
plt.title('Compensation Distribution Across Clusters')
plt.show()

plt.figure(figsize=(20, 5))
sns.boxplot(x='kmeans_cluster', y='year_of_exp', data=df_cluster,color='moccasin')
plt.title('Years of Experience Distribution Across Clusters')
plt.show()

plt.figure(figsize=(20, 5))
sns.boxplot(x='kmeans_cluster', y='no_of_ctc_update', data=df_cluster, color='moccasin'
plt.title('Number of CTC Updates Distribution Across Clusters')
plt.show()
```





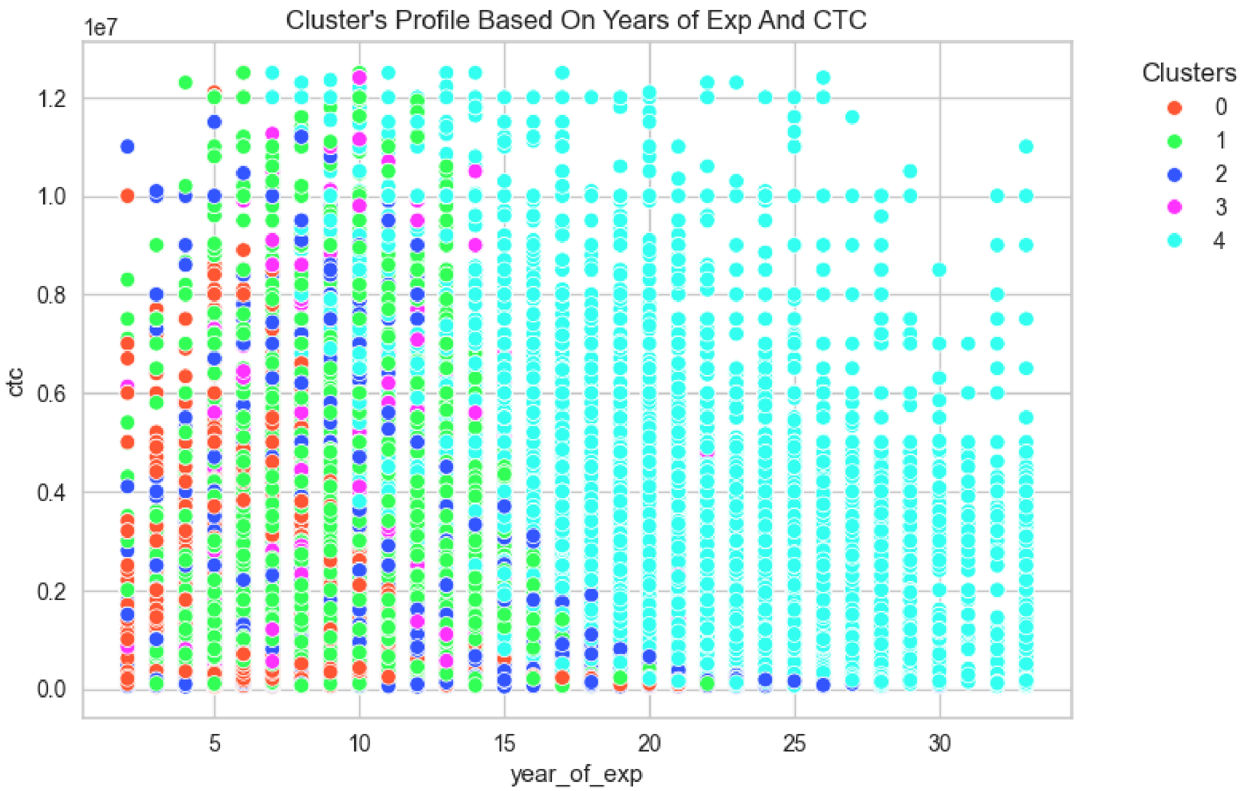


Observation:

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

In [103…

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

# Create the scatter plot with the custom palette
pl = sns.scatterplot(data=df_cluster, x="year_of_exp", y="ctc", hue="kmeans_cluster", p

# 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()
```



Observation:

- Cluster 4 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 4 and most of the compensation is lower

In [104…

```
# Select only numeric columns for aggregation
numeric_columns = ['ctc', 'year_of_exp', 'no_of_ctc_update']

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

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

```
                         ctc  year_of_exp  no_of_ctc_update
kmeans_cluster
0               9.264998e+05     8.306739          1.416242
1               1.470352e+06     9.192016          1.414952
2               9.442261e+05     9.722093          1.402420
3               1.284018e+06     8.083761          3.476784
4               2.704498e+06    17.502482          1.354035
```

In [105…

```
# Function to get the most common job positions and companies in each cluster
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(df_cluster, cluster, 'job_position')
```

```python
    companies = get_common_entries(df_cluster, cluster, 'company_hash')

    cluster_profiles[cluster] = {
        'average_ctc': cluster_averages.loc[cluster, 'ctc'],
        'average_yoe': cluster_averages.loc[cluster, 'year_of_exp'],
        '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): 926499.79399633
  Average Years of Experience: 8.306739229309452 years
  Average Number of CTC Updates: 1.416241903357852
  Common Job Positions:
    - FullStack Engineer: 16378 occurrences
    - Other: 15831 occurrences
    - Frontend Engineer: 5792 occurrences
  Common Companies:
    - nvnv wgzohrnvzwj otqcxwto: 3790 occurrences
    - xzegojo: 3080 occurrences
    - zgn vuurxwvmrt vwwghzn: 1933 occurrences

Cluster 1:
  Average Compensation (CTC): 1470351.6018920564
  Average Years of Experience: 9.192016445367399 years
  Average Number of CTC Updates: 1.4149518595431376
  Common Job Positions:
    - Backend Engineer: 47535 occurrences
    - FullStack Engineer: 120 occurrences
    - Other: 18 occurrences
  Common Companies:
    - nvnv wgzohrnvzwj otqcxwto: 2373 occurrences
    - vbvkgz: 1424 occurrences
    - xzegojo: 1046 occurrences

Cluster 2:
  Average Compensation (CTC): 944226.1393458211
  Average Years of Experience: 9.722092802129884 years
  Average Number of CTC Updates: 1.4024198916040695
  Common Job Positions:
    - Backend Engineer: 10990 occurrences
    - FullStack Engineer: 6543 occurrences
    - Other: 5227 occurrences
  Common Companies:
    - less_occurred: 42068 occurrences

Cluster 3:
  Average Compensation (CTC): 1284018.1779092865
  Average Years of Experience: 8.083760966727363 years
  Average Number of CTC Updates: 3.476783645091872
  Common Job Positions:
    - Backend Engineer: 9594 occurrences
    - FullStack Engineer: 4873 occurrences
    - Other: 3145 occurrences
  Common Companies:
    - nvnv wgzohrnvzwj otqcxwto: 1756 occurrences
    - xzegojo: 988 occurrences
    - less_occurred: 738 occurrences

Cluster 4:
  Average Compensation (CTC): 2704498.1943691345
  Average Years of Experience: 17.502481751824817 years
  Average Number of CTC Updates: 1.3540354535974974
  Common Job Positions:
    - Engineering Leadership: 4962 occurrences
    - FullStack Engineer: 2986 occurrences
    - Backend Engineer: 2832 occurrences
  Common Companies:
    - less_occurred: 3724 occurrences
    - gqvwrt: 455 occurrences
```

```
- bxwqgogen: 415 occurrences
```

Observations:

Cluster 0:

- Average CTC: ~₹9.26L
- Experience: ~8.3 years
- CTC Updates: ~1.4
- Common Roles: FullStack, Other, Frontend
- This cluster represents mid-career engineers with moderately high compensation. The presence of FullStack and Frontend roles suggests they are versatile in development, likely working in product or startup environments. The variety in job titles indicates some role fluidity.

Cluster 1:

- Average CTC: ~₹14.7L
- Experience: ~9.2 years
- CTC Updates: ~1.41
- Common Roles: Backend Engineer dominates
- Despite having only slightly more experience than Cluster 0, these professionals earn significantly higher compensation, likely due to specialization in Backend Engineering. The narrow job distribution suggests domain expertise and higher demand for backend roles in certain companies.

Cluster 2:

- Average CTC: ~₹9.44L
- Experience: ~9.7 years
- CTC Updates: ~1.4
- Common Roles: Mixed (Backend, FullStack, Other)
- This group is experienced but with modest compensation, possibly indicating a broad but non-specialized skill set. The high occurrence of “less_occurred” companies hints they might be employed in smaller or lesser-known firms, or there's some data masking/generalization.

Cluster 3:

- Average CTC: ~₹12.84L
- Experience: ~8.1 years
- CTC Updates: 3.47 (notably high)
- Common Roles: Backend and FullStack
- The standout feature here is the high number of CTC updates, suggesting a group that is either actively negotiating, switching jobs, or being promoted frequently. Their compensation is fairly high, and they likely work in dynamic or competitive environments.

Cluster 4:

- Average CTC: ~₹27.04L
- Experience: ~17.5 years

- CTC Updates: ~1.35
- Common Roles: Engineering Leadership dominates
- This cluster clearly consists of senior-level professionals or executives. Extremely high compensation and extensive experience point to leadership positions in engineering, possibly VPs, Directors, or Engineering Managers. They're typically in established firms, as seen by more structured job titles.

Insights:

Clusters 0 & 1: Both are mid-level engineers, but Cluster 1 benefits from specialization (Backend) which boosts compensation.

Cluster 2: More experienced but undercompensated, perhaps due to company type or non-core roles.

Cluster 3: Similar in experience to Cluster 0 but unusually high job/CTC mobility, possibly agile performers or job switchers.

Cluster 4: Clearly senior leadership, with matching experience and high pay.