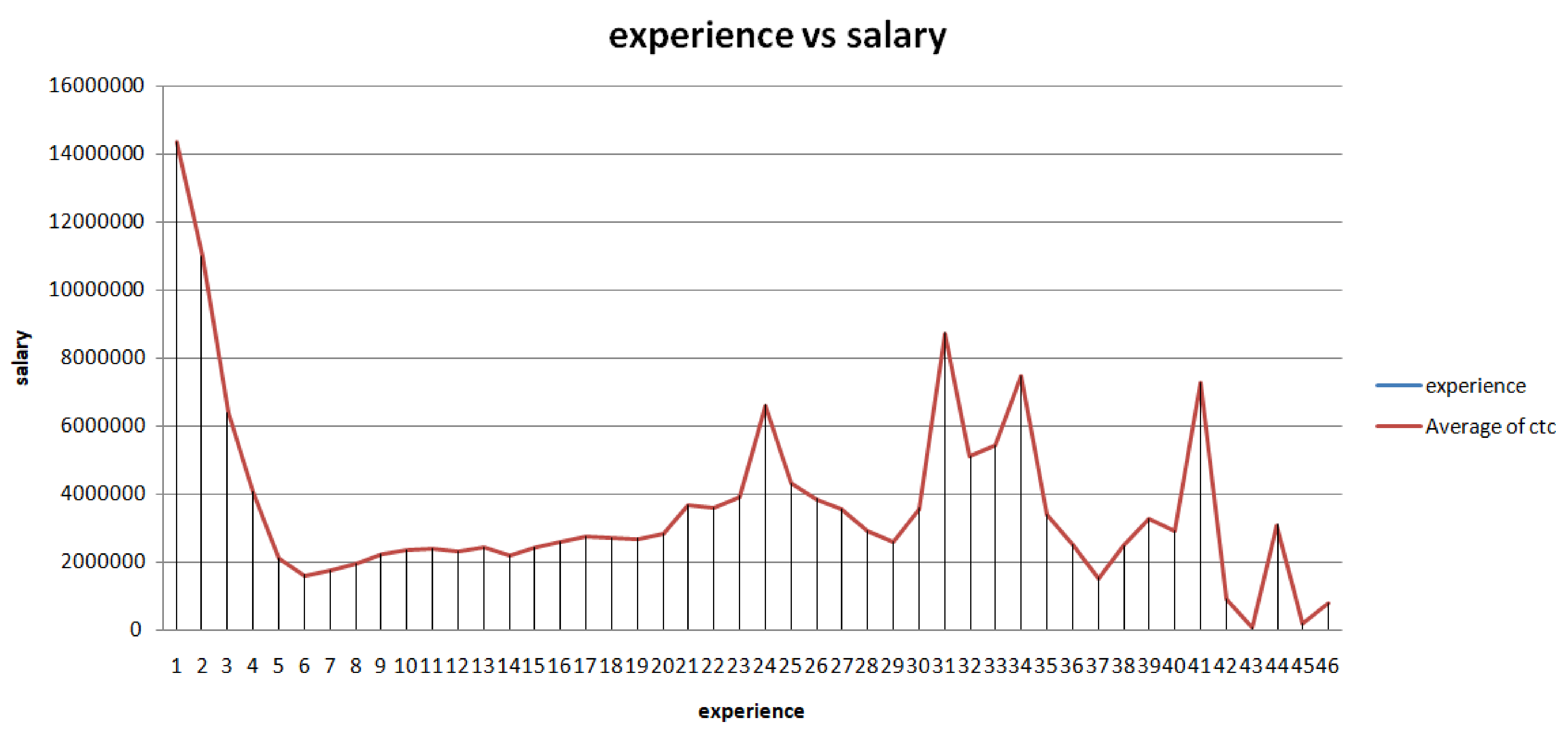
Purpose:

To help an online tech-varsity in learner segmentation which may help them in planning appropriate strategies

Approach:

1. Initially very basic steps were applied and a basic kmeans clustering model was created. It was observed that there were unusual (not plausible) values in "Years of experience". after looking into the data deeply, the reason for this was found in the "orgyear" column where some future years were appearing and also very old years were appearing. these unusual records were dropped from the data set and further data preprocessing was done.
2. manual clustering steps were performed.
3. most of teh questions (as per the business case guidelines) are answered.
4. subsequently Kmeans clustering was done. Elbow method was used for identifying appropriate value for K.
5. Hierarchical clustering was done on a downsized data (that was done on colab as memory resources on my laptop were not sufficient. Link of teh colab notebook will be shared.
6. Data looks awkward (as seen in the excel line chart of experience vs salary.
7. PCA, tsne were not done as laptop resources were not sufficient and even colab was giving error message saying that allocated memory is consumed and crashed multiple times...
8. Not many insights are drawn out from teh analysis. very basic insights were observed and recorder in teh relevant cells.



```
# from google.colab import drive
# drive.mount('/content/drive')
```

```
# file_path = '/content/drive/My Drive/scaler_clustering.csv'
```

```
# Import necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import re
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.impute import KNNImputer
from scipy.cluster.hierarchy import dendrogram, linkage
```

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

```
# Check the first few rows of the dataset
print(df.head())
```

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

                                          email_hash  orgyear      ctc  \
0  6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...   2016.0  1100000
1  b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...   2018.0   449999
2  4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...   2015.0  2000000
3  effdede7a2e7c2af664c8a31d9346385016128d66bbc58...   2017.0   700000
4  6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...   2017.0  1400000

        job_position  ctc_updated_year
0              Other              2020
1  FullStack Engineer              2019
2    Backend Engineer              2020
3    Backend Engineer              2019
4  FullStack Engineer              2019
```

```
# Checking the shape, data types, and missing values
print(df.shape)
```

```
(205843, 7)
```

```
# Check for duplicates
duplicates = df.duplicated()
```

```
# Count the number of duplicate rows
num_duplicates = duplicates.sum()
print(f"Number of duplicate rows: {num_duplicates}")
```

```
Number of duplicate rows: 0
```

```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205843 entries, 0 to 205842
Data columns (total 7 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   index             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  int64
dtypes: float64(1), int64(3), object(3)
memory usage: 11.0+ MB
None
```

I see that orgyear (which is "employment start year",) has afew values which are future years and a few values which lead to more than 50 years of experience, which is not plausible. I would like to remove these rows from the dataset.

```
# Set the current year
current_year = 2024
```

```
# Detect and eliminate rows where 'orgyear' is in the future or leads to more than 50 years of experience
# Define a valid range for 'orgyear': should be less than or equal to the current year, and not more than 50 years old
valid_orgyear = (df['orgyear'] <= current_year) & (df['orgyear'] >= current_year - 50)
```

```
# Filter the dataset to keep only the valid records
df_cleaned = df[valid_orgyear]
```

```
# Check the shape of the cleaned dataframe and number of rows removed
print(f"Original dataset size: {df.shape}")
print(f"Cleaned dataset size: {df_cleaned.shape}")
print(f"Number of invalid records removed: {df.shape[0] - df_cleaned.shape[0]}")
```

```
Original dataset size: (205843, 7)
Cleaned dataset size: (205665, 7)
```

```
Number of invalid records removed: 178
```

```
# Get the invalid rows that were removed
invalid_rows = df[~valid_orgyear]
```

```
# Display the invalid rows
print(invalid_rows)
```

```
         index                  company_hash  \
2211      2211                        phrxkv
2333      2333    xgmgn ntwyzgrgsxto ucn rna
2562      2562                            tj
3122      3122                     ft tdwtr
3365      3365                  fyxntyvn lq
...        ...                           ...
196354  197352          vaxnjv mxqrv wvuxnvr
198187  199212                 xb  v onhatzn
202210  203276                    mqvmtzatq
203992  205068  xatv ouvqp ogrhnxgzo ucn rna
205435  206515                      vhngsqxa

                                               email_hash  orgyear      ctc  \
2211    3394674bb6bb1de6289e931853fa0bd131c811e0054a92...   2031.0  1500000
2333    c737ceb66c7f0ce37c2fce087003aa129632a3a2fa4f6c...      NaN   170000
2562    25edac17c77f6f0edeafb86f7a7844d96dc899e193c87e...      NaN   860000
3122    c402eba160abf4e5b5f72af775fc98dbd346f1a081112e...      NaN   600000
3365    38bd913564fa983cd4fb7799e4027d8ed2b0fd6263e15a...      NaN   800000
...                                                   ...      ...      ...
196354  069308440811d578c817c05392f97e8919baac6aa12aa3...      1.0  2900000
198187  9429a19771ae913f169917d380c94f003115aaaf904388...   2025.0   300000
202210  d66f939c4318c1958be5bc9e7b70b741aa61be7493ff58...   2028.0  1300000
203992  7191da2e57dcb0c1301711e889ea72d5cc801e039359b1...  20165.0   850000
205435  3fa8de870da01d863abba8eb6a8ae3df1aa18c18946688...      NaN  2400000

            job_position  ctc_updated_year
2211    Backend Engineer              2020
2333               Other              2020
2562        Data Analyst              2020
3122    Support Engineer              2020
3365                 NaN              2021
...                  ...               ...
196354    Data Scientist              2019
198187             Other              2021
202210  Backend Engineer              2021
203992               NaN              2019
205435               NaN              2020

[178 rows x 7 columns]
```

```
print(df_cleaned.isnull().sum())
```

```
index                  0
company_hash          44
email_hash             0
orgyear                0
```

```
ctc                  0
job_position     52508
ctc_updated_year     0
dtype: int64
```

```
# Mode imputation for company_hash
df_cleaned['company_hash'].fillna(df_cleaned['company_hash'].mode()[0], inplace=True)
```

```
C:\Users\Dell\AppData\Local\Temp\ipykernel_22336\2994647386.py:2: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace
The behavior will change in pandas 3.0. This inplace method will never work because 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.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplac


  df_cleaned['company_hash'].fillna(df_cleaned['company_hash'].mode()[0], inplace=True)
C:\Users\Dell\AppData\Local\Temp\ipykernel_22336\2994647386.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_cleaned['company_hash'].fillna(df_cleaned['company_hash'].mode()[0], inplace=True)
```

```
print(df_cleaned.isnull().sum())
```

```
index                0
company_hash         0
email_hash           0
orgyear              0
ctc                  0
job_position     52508
ctc_updated_year     0
dtype: int64
```

```
# Fill missing values (Mean/ KNN Imputation)
# imputer = KNNImputer(n_neighbors=5)
```

```
# df_cleaned[['orgyear']] = imputer.fit_transform(df_cleaned[['orgyear']])
```

```
# print(df_cleaned.isnull().sum())
```

```
# Convert orgyear
df_cleaned['orgyear'] = df_cleaned['orgyear'].astype(int)
```

```
C:\Users\Dell\AppData\Local\Temp\ipykernel_22336\1583577424.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_cleaned['orgyear'] = df_cleaned['orgyear'].astype(int)
```

```
print(df_cleaned.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 205665 entries, 0 to 205842
Data columns (total 7 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   index             205665 non-null  int64
 1   company_hash      205665 non-null  object
 2   email_hash        205665 non-null  object
 3   orgyear           205665 non-null  int32
 4   ctc               205665 non-null  int64
 5   job_position      153157 non-null  object
 6   ctc_updated_year  205665 non-null  int64
dtypes: int32(1), int64(3), object(3)
memory usage: 11.8+ MB
None
```

```
print(df_cleaned.isnull().sum())
```

```
index                   0
company_hash            0
email_hash              0
orgyear                 0
ctc                     0
job_position        52508
ctc_updated_year        0
dtype: int64
```

```
# Group by company_hash and fill missing job_position with mode for that company
df_cleaned['job_position'] = df_cleaned.groupby('company_hash')['job_position'].transform(lambda x: x.fillna(x.mode()[0] if not x.mode().empty else 'Unknown'))
```

```
C:\Users\Dell\AppData\Local\Temp\ipykernel_22336\2546825487.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_cleaned['job_position'] = df_cleaned.groupby('company_hash')['job_position'].transform(lambda x: x.fillna(x.mode()[0] if not x.mode().empty else 'Unknown'))
```

```
print(df_cleaned.isnull().sum())
```

```
index               0
company_hash        0
email_hash          0
orgyear             0
ctc                 0
job_position        0
ctc_updated_year    0
dtype: int64
```

```
##############################################################################################
```

```
df_cleaned.head()
```

	index	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016	1100000	Other	2020
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018	449999	FullStack Engineer	2019
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015	2000000	Backend Engineer	2020
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017	700000	Backend Engineer	2019
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017	1400000	FullStack Engineer	2019

```
# Unique email hashes and frequency of occurrences
print(df_cleaned['email_hash'].value_counts())
```

```
email_hash
bbace3cc586400bbc65765bc6a16b77d8913836cfc98b77c05488f02f5714a4b    10
3e5e49daa5527a6d5a33599b238bf9bf31e85b9efa9a94f1c88c5e15a6f31378     9
6842660273f70e9aa239026ba33bfe82275d6ab0d20124021b952b5bc3d07e6c     9
298528ce3160cc761e4dc37a07337ee2e0589df251d73645aae209b010210eee     9
d15041f58bb01c8ee29f72e33b136e26bc32f3169a40b53d75fe7ae9cbb9a551     8
                                                                    ..
6ed7767a6ba36e8ab4f4d2397a4d32f26f34387720645906bf51a05c2152fd56     1
9778d2fa1bbfb721c3e90941cb3474740610d301f2ccf1429f5c6835ae5e27f4     1
9a891d279335db60cd6a45c2243bca2c56f940e31c5a812a6f642ea800832c4b     1
e96207e084f4552ba131598c704d2c5f12373999fc66285f58dea00afb9d333c     1
0bcfc1d05f2e8dc4147743a1313aa70a119b41b30d4a1f7e738a6a87d3712c31     1
Name: count, Length: 153292, dtype: int64
```

```
# Remove special characters from Company_hash
df_cleaned['company_hash_cleaned'] = df_cleaned['company_hash'].apply(lambda x: re.sub('[^A-Za-z0-9 ]+', '', str(x)))
```

```
C:\Users\Dell\AppData\Local\Temp\ipykernel_22336\1841518091.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_cleaned['company_hash_cleaned'] = df_cleaned['company_hash'].apply(lambda x: re.sub('[^A-Za-z0-9 ]+', '', str(x)))
```

```
# Unique "company_hash_cleaned" hashes and frequency of occurrences
print(df_cleaned['company_hash_cleaned'].value_counts())
```

```
company_hash_cleaned
nvnv wgzohrnvzwj otqcxwto    8379
xzegojo                      5378
vbvkgz                       3480
zgn vuurxwvmrt vwwghzn       3408
wgszxkvzn                    3238
                             ...
bvpt owyggr                     1
vhngsqxa xzaxv                  1
ctavznh td kteg                 1
ihxwprgsxw ogenfvqt             1
bvptbjnqxu td vbvkgz            1
Name: count, Length: 37246, dtype: int64
```

```
# Dropping the 'company_hash' column from the DataFrame
df_cleaned.drop(columns=['company_hash'], inplace=True)
```

```
C:\Users\Dell\AppData\Local\Temp\ipykernel_22336\3049061100.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_cleaned.drop(columns=['company_hash'], inplace=True)
```

```
print(df_cleaned.shape)
```

```
(205665, 7)
```

```
# Create new feature 'Years_of_Experience'
current_year = 2024
df_cleaned['Years_of_Experience'] = current_year - df_cleaned['orgyear']
```

```
C:\Users\Dell\AppData\Local\Temp\ipykernel_22336\2370425679.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_cleaned['Years_of_Experience'] = current_year - df_cleaned['orgyear']
```

```
df_cleaned.head()
```

	index	email_hash	orgyear	ctc	job_position	ctc_updated_year	company_hash_cleaned	Years_of_Experience
0	0	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016	1100000	Other	2020	atrgxnnt xzaxv	8
1	1	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018	449999	FullStack Engineer	2019	qtrxvzwt xzegwgbb rxbxnta	6
2	2	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015	2000000	Backend Engineer	2020	ojzwnvwnxw vx	9
3	3	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017	700000	Backend Engineer	2019	ngpgutaxv	7
4	4	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017	1400000	FullStack Engineer	2019	qxen sqghu	7

```
# from google.colab import files
```

```
# # Export the cleaned DataFrame to Excel
# df_cleaned.to_excel('scaler_clustering_pre_pro_01.xlsx', index=False)
```

```
# # Download the file
# files.download('scaler_clustering_pre_pro_01.xlsx')
```

```
# Five-point summary of CTC
grouped = df_cleaned.groupby(['company_hash_cleaned', 'job_position', 'Years_of_Experience'])['ctc'].agg(['mean', 'median', 'max', 'min', 'count'])

# Merge it back to the original dataframe
df_cleaned = df_cleaned.merge(grouped, how='left', on=['company_hash_cleaned', 'job_position', 'Years_of_Experience'])
```

```
# Create flags for designation, class, and tier
df_cleaned['Designation'] = np.where(df_cleaned['ctc'] > df_cleaned['mean'], 1, 0)
df_cleaned['Class'] = pd.qcut(df_cleaned['ctc'], 3, labels=[3, 2, 1])
df_cleaned['Tier'] = pd.qcut(df_cleaned['ctc'], 3, labels=[3, 2, 1])
```

```
# # Export the cleaned DataFrame to Excel
# df_cleaned.to_excel('scaler_clustering_pre_pro_02.xlsx', index=False)
```

```
# # Download the file
# files.download('scaler_clustering_pre_pro_02.xlsx')
```

```
df_cleaned.head()
```

	index	email_hash	orgyear	ctc	job_position	ctc_updated_year	company_hash_cleaned	Years_of_Experience	mean	median	max	
0	0	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016	1100000	Other	2020	atrgxnnt xzaxv	8	1.100000e+06	1100000.0	1100000	110
1	1	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018	449999	FullStack Engineer	2019	qtrxvzwt xzegwgbb rxbxnta	6	7.742856e+05	750000.0	1200000	44
2	2	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015	2000000	Backend Engineer	2020	ojzwnvwnxw vx	9	2.000000e+06	2000000.0	2000000	200
3	3	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017	700000	Backend Engineer	2019	ngpgutaxv	7	1.436154e+06	1210000.0	3160000	70
4	4	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017	1400000	FullStack Engineer	2019	qxen sqghu	7	1.400000e+06	1400000.0	1400000	140

```
# Top 10 employees (earning more than most of the employees in the company) - Tier 1
# Filter for Tier 1 employees and sort by CTC
top_10_tier1 = df_cleaned[df_cleaned['Tier'] == 1].sort_values(by='ctc', ascending=False).head(10)
```

```
top_10_tier1
```

	index	email_hash	orgyear	ctc	job_position	ctc_updated_year	company_hash_cleaned	Years_of_Experience	mean	median
72747	72925	29a71dd13adf6d2d497571a565bb3096cf66cb46cd1ece...	2015	1000150000	Unknown	2020	whmxw rgsxwo uqxcvnt rxbxnta	9	1.000150e+09	1.000150e+09
117518	117948	5b4bed51797140db4ed52018a979db1e34cee49e27b488...	2018	255555555	FullStack Engineer	2016	obvqnuqxdwgb	6	6.531389e+07	2.300000e+06
3297	3301	06d231f167701592a69cdd7d5c825a0f5b30f0347a4078...	2021	250000000	Unknown	2020	aveegaxr xzntqzvnxgzvr hzxctqoxnj	3	2.500000e+08	2.500000e+08
82452	82674	4c19cfc1aa47a5b007004fadeacb88da76b6a59ff4271f...	1998	200000000	Security Leadership	2020	eqttwyvqst	26	2.000000e+08	2.000000e+08
13747	13776	1d8bbc3a2b8fb477f78ab3b1ca3f5a7ae0f256555e44ed...	2019	200000000	Backend Engineer	2020	vwwtznhqt	5	1.555678e+06	5.000000e+05
45914	46025	47d993914804e1a737d4af1b877ebb7f6867e39134d6d7...	2019	200000000	Backend Engineer	2019	ntwywg egqbtqrj ntwy wgwpnvxr	5	2.000000e+08	2.000000e+08
9064	9078	4d899e4af4f98d23848a8e21455489231fc2cbf2ca9668...	2018	200000000	Research Engineers	2020	boo	6	2.000000e+08	2.000000e+08
82412	82634	f195ae4e02da9f187009f8545061a65f8a22a99c0e7aeb...	2018	200000000	Other	2020	ytfrtnn uvwpvqa tzntquqxot	6	6.771667e+07	2.500000e+06
36674	36767	4b5f9d4a42d8656a5230e5fcd3666777bdcd58f0c604d1...	2012	200000000	Other	2019	wgszxkvzn	12	1.252886e+07	9.000000e+05
20048	20087	ef9987c98edad9756ad357f551c5c861f46f8e493b358c...	2016	200000000	Other	2020	erxupvqn	8	3.006000e+07	1.390000e+06

```
# Top 10 employees of data science in each company earning more than their peers - Class 1
# Filter for Data Science employees who belong to Class 1
df_data_science_class1 = df_cleaned[(df_cleaned['job_position'] == 'Data Scientist') & (df_cleaned['Class'] == 1)]
```

```
# Group by company and get the top 10 earners in each company
top_10_ds_class1 = df_data_science_class1.groupby('company_hash_cleaned').apply(lambda x: x.sort_values(by='ctc', ascending=False).head(10))
```

```
C:\Users\Dell\AppData\Local\Temp\ipykernel_22336\2078019100.py:2: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is deprecated, and in a future
  top_10_ds_class1 = df_data_science_class1.groupby('company_hash_cleaned').apply(lambda x: x.sort_values(by='ctc', ascending=False).head(10))
```

```
top_10_ds_class1
```

company_hash_cleaned		index	email_hash	orgyear	ctc	job_position	ctc_updated_year	company_hash_cleaned	Years_of_Experience	
1t xzegojontbo	**119686**	120124	c659650daaf7f10c6c6627b33627b4c7749892cfd941d0...	2008	3300000	Data Scientist	2019	1t xzegojontbo	16	3.300000e
2020	**45577**	45687	b6a63b76c3a1a395f7c3d509f2760d83aeb6e8c53db2b1...	2020	2700000	Data Scientist	2019	2020	4	1.526667e
	196318	197495	b6a63b76c3a1a395f7c3d509f2760d83aeb6e8c53db2b1...	2020	2700000	Data Scientist	2019	2020	4	1.526667e
	84060	84290	4c94852800fd33ec5e6b0133231e282998bbf0390ca793...	2020	2100000	Data Scientist	2019	2020	4	1.526667e
	124514	125001	4c94852800fd33ec5e6b0133231e282998bbf0390ca793...	2020	2100000	Data Scientist	2019	2020	4	1.526667e
...	**...**	...	...	...	...	...	...	...	...	
zxxn ntwyzgrgsxto	**148863**	149562	1aa2717970a46b5d12b90932799227774dd418c842fa18...	2012	2200000	Data Scientist	2019	zxxn ntwyzgrgsxto	12	2.200000e
	174322	175301	6e4b185d9b1fa901e6c408dd226e24dd3eb4d24695084b...	2018	1500000	Data Scientist	2019	zxxn ntwyzgrgsxto	6	1.500000e
zxxn ntwyzgrgsxto rxbxnta	**71103**	71278	9be05cb8d1f11aa76fb01b9e33ff5633efb82fb22e085f...	2015	1500000	Data Scientist	2020	zxxn ntwyzgrgsxto rxbxnta	9	1.500000e
zxzlvwvqn	**39126**	39222	2937acfa6802f83ff11ddbd3de1997b686107dad0c2b5d...	2019	1900000	Data Scientist	2020	zxzlvwvqn	5	1.900000e
zxztrtvuo	**158857**	159631	1cd0a52ed52dae24d605d9cdc8536499c10ce62bfb070f...	2014	2250000	Data Scientist	2021	zxztrtvuo	10	2.250000e

2081 rows × 17 columns

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

```
# Filter for Data Science employees who belong to Class 3
df_data_science_class3 = df_cleaned[(df_cleaned['job_position'] == 'Data Scientist') & (df_cleaned['Class'] == 3)]
```

```
# Group by company and get the bottom 10 earners in each company
bottom_10_ds_class3 = df_data_science_class3.groupby('company_hash_cleaned').apply(lambda x: x.sort_values(by='ctc').head(10))
```

```
C:\Users\Dell\AppData\Local\Temp\ipykernel_22336\3317353462.py:2: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is deprecated, and in a future
  bottom_10_ds_class3 = df_data_science_class3.groupby('company_hash_cleaned').apply(lambda x: x.sort_values(by='ctc').head(10))
```

```
bottom_10_ds_class3
```

		index	email_hash	orgyear	ctc	job_position	ctc_updated_year	company_hash_cleaned	Years_of_Experience	
company_hash_cleaned										
10dvx rtvqzxzs	**116655**	117081	48be30753b1dbf2c2fccf43b7f45c51d68bb5725f4ae76...	2020	400000	Data Scientist	2020	10dvx rtvqzxzs	4	400000.00
1stz	**188684**	189781	3dddd88f7d7ac6ace0dfd4927d881a9d452a3666c692bf...	2017	400000	Data Scientist	2019	1stz	7	400000.00
1stz urvnegqb ogrhnxgzo ucn rna	**202852**	204098	4f4d3137aebfdc15fc4626314308ef082fd2dde54ef9f1...	2017	500000	Data Scientist	2019	1stz urvnegqb ogrhnxgzo ucn rna	7	500000.00
3rgi	**134715**	135293	24db964005796c656431df0b035768e8b9cee21f8cf425...	2015	600000	Data Scientist	2020	3rgi	9	600000.00
6ny tztqsj ntwyzgrgsxto	**196537**	197717	d15ed3db039ea786a3eefa496465a74e58d8e969cc7e94...	2016	500000	Data Scientist	2019	6ny tztqsj ntwyzgrgsxto	8	500000.00
...	**...**	...	...	...	...	...	...	...	...	
zxtrotz	**98551**	98857	c4c6477b89d69e801d35ade03de9d455a090d39294e2d0...	2016	600000	Data Scientist	2019	zxtrotz	8	600000.00
	98288	98593	d5d7fa93cf62d046654e21716c7bdd613e5f559b47bc21...	2017	650000	Data Scientist	2019	zxtrotz	7	566666.66
	168400	169279	01717d934c1c75cacd31e29f8adcb5c109c627f7f26214...	2015	650000	Data Scientist	2019	zxtrotz	9	902500.00
	197733	198930	af256544a43a5902d769859c21e05df919f05b490a227a...	2015	650000	Data Scientist	2019	zxtrotz	9	902500.00
zxtrotz xzaxv	**90539**	90804	515862ad8c8c33263846231044741bfc177af2cddcf00f...	2018	600000	Data Scientist	2020	zxtrotz xzaxv	6	600000.00

1227 rows × 17 columns

```
# Bottom 10 employees (earning less than most of the employees in the company) - Tier 3
# Filter for Tier 3 employees and sort by CTC
bottom_10_tier3 = df_cleaned[df_cleaned['Tier'] == 3].sort_values(by='ctc').head(10)
```

```
bottom_10_tier3
```

	index	email_hash	orgyear	ctc	job_position	ctc_updated_year	company_hash_cleaned	Years_of_Experience	mean	median	max	min
135308	135886	3505b02549ebe2c95840ac6f0a35561a3b4cbe4b79cdb1...	2014	2	Backend Engineer	2019	xzntqcxtfmxn	10	1650000.5	2000000.0	2600000	2
118118	118549	f2b58aeed3c074652de2cfd3c0717a5d21d6fbcf342a78...	2013	6	Backend Engineer	2018	xzntqcxtfmxn	11	223340.0	14.0	670000	6
114048	114452	23ad96d6b6f1ecf554a52f6e9b61677c7d73d8a409a143...	2013	14	Backend Engineer	2018	xzntqcxtfmxn	11	223340.0	14.0	670000	6
184777	185851	b8a0bb340583936b5a7923947e9aec21add5ebc50cd60b...	2016	15	Unknown	2018	xm	8	15.0	15.0	15	15
183637	184706	75357254a31f133e2d3870057922feddeba82b88056a07...	2019	16	Unknown	2018	xm	5	16.0	16.0	16	16
54755	54885	8786759b95d673466e94f62f1b15e4f8c6bd7de6164074...	2020	24	Other	2020	uqvpqxnx voogwxvnto	4	24.0	24.0	24	24
91457	91723	512f761579fb116e215cabc9821c7f81153f0763e16018...	2016	25	Android Engineer	2018	ftm ongqt	8	25.0	25.0	25	25
116830	117256	f7e5e788676100d7c4146740ada9e2f8974defc01f571d...	2022	200	Engineering Leadership	2021	hzxctqoxnj ge fvoyxzsngz	2	200.0	200.0	200	200
166251	167115	c411a6917058b50f44d7c62751be9b232155b23211de4c...	2013	300	Database Administrator	2019	vcvzn sqghu	11	300.0	300.0	300	300
81942	82161	edcfb902656b736e1f35863298706d9d34ee795b7ed85a...	2018	500	Co-founder	2019	uqgmrtb ogrcxzs	6	500.0	500.0	500	500

```
# Top 10 employees in each company - X department - having 5/6/7 years of experience earning more than their peers - Tier X
# Filter for employees in Tier X with 5, 6, or 7 years of experience
df_tier_x = df_cleaned[(df_cleaned['Years_of_Experience'].isin([5, 6, 7]))]
```

```
# Group by company and job position, and get the top 10 earners for each combination
top_10_tier_x = df_tier_x.groupby(['company_hash_cleaned', 'job_position']).apply(lambda x: x.sort_values(by='ctc', ascending=False).head(10))
```

```
C:\Users\Dell\AppData\Local\Temp\ipykernel_22336\31217106.py:2: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is deprecated, and in a future ve
  top_10_tier_x = df_tier_x.groupby(['company_hash_cleaned', 'job_position']).apply(lambda x: x.sort_values(by='ctc', ascending=False).head(10))
```

```
top_10_tier_x
```

company_hash_cleaned	job_position		index	email_hash	orgyear	ctc	job_position	ctc_updated_year	company_hash_cleaned	Years_of_Experi
0	**Other**	**197366**	198561	b3f3bb98cbca4b1ce5dfd5abb4e500ce6f6b66288a5202...	2017	300000	Other	2020	0	
05mz exzytvrny uqxcvnt rxbxnta	**Backend Engineer**	**97159**	97457	4702229ffb6968c87b16fc57e730769e554184e322e111...	2019	1100000	Backend Engineer	2021	05mz exzytvrny uqxcvnt rxbxnta	
		139735	140366	4702229ffb6968c87b16fc57e730769e554184e322e111...	2019	1100000	Backend Engineer	2021	05mz exzytvrny uqxcvnt rxbxnta	
1	**Other**	**2208**	2208	8cc7aba49e96a0a80f7ed6c2ed79bc1d1e81171a28445c...	2017	100000	Other	2020	1	
1 axsxnvro	**Backend Engineer**	**163810**	164649	70459269ec53bd863dc3bad03772c608842ce6182710e1...	2018	350000	Backend Engineer	2020	1 axsxnvro	
...	**...**	**...**	...	...	...	...	...	...	...	
zxztrtvuo	**FullStack Engineer**	**166724**	167591	0228801807a4911ebde807b5f88a273a51d92b25e6c160...	2019	500000	FullStack Engineer	2021	zxztrtvuo	
	Other	**186279**	187356	e2d27a8acde6484d35b69a75d9ecbc8b1f541223b3a296...	2019	450000	Other	2020	zxztrtvuo	
zxzvnxgzvr xzonqhbtzno	**Devops Engineer**	**58518**	58661	5ece45aea666b6252a7dd88f3da824efd44dab8c28f990...	2019	650000	Devops Engineer	2021	zxzvnxgzvr xzonqhbtzno	
zzb ztdnstz vacxogqj ucn rna	**FullStack Engineer**	**72906**	73084	ca8935e2314a1bac3947e60bbd2ee10524112898da29eb...	2017	600000	FullStack Engineer	2021	zzb ztdnstz vacxogqj ucn rna	
		146497	147181	ca8935e2314a1bac3947e60bbd2ee10524112898da29eb...	2017	600000	FullStack Engineer	2021	zzb ztdnstz vacxogqj ucn rna	

42822 rows × 17 columns

```
# Top 10 companies (based on their CTC)
# Group by company and calculate the average CTC
top_10_companies = df_cleaned.groupby('company_hash_cleaned')['ctc'].mean().sort_values(ascending=False).head(10)
```

```
top_10_companies
```

```
company_hash_cleaned
whmxw rgsxwo uqxcvnt rxbxnta        1.000150e+09
aveegaxr xzntqzvnxgzvr hzxctqoxnj   2.500000e+08
wrghawytqqj  wxowg wgbuvzj          2.000000e+08
ztnwrgha ojontbo uqxcvnt rxbxnta    2.000000e+08
twgbtduqtoo                         2.000000e+08
xfgqp ntwyzgrgsxto                  2.000000e+08
qvaxwvr bxzao ntwyzgrgsj ucn rna    2.000000e+08
pvnvqxv mhxrntwp ucn rna            2.000000e+08
gqmxn ogenfvqt xzw                  2.000000e+08
ngfvqao xzaxv                       2.000000e+08
Name: ctc, dtype: float64
```

```
# Top 2 positions in every company (based on their CTC)
# Group by company and job position, and calculate the mean CTC
top_positions_per_company = df_cleaned.groupby(['company_hash_cleaned', 'job_position'])['ctc'].mean()
```

```
# Get the top 2 positions in each company
top_2_positions = top_positions_per_company.groupby('company_hash_cleaned').nlargest(2).reset_index(level=0, drop=True)
```

```
top_2_positions
```

```
company_hash_cleaned           job_position
0                              Other                 1.666667e+05
01 ojztqsj                     Frontend Engineer     8.300000e+05
                               Android Engineer      2.700000e+05
05mz exzytvrny uqxcvnt rxbxnta Backend Engineer      1.100000e+06
1                              Other                 1.750000e+05
                                                         ...
zyvzwt wgzohrnxzs tzsxzttqo    Frontend Engineer     9.400000e+05
zz                             Other                 9.350000e+05
zzb ztdnstz vacxogqj ucn rna   FullStack Engineer    6.000000e+05
zzgato                         Unknown               1.300000e+05
zzzbzb                         Other                 7.200000e+05
Name: ctc, Length: 45552, dtype: float64
```

```
#
```

Start coding or generate with AI.

Start coding or generate with AI.

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```
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```
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```
Start coding or generate with AI.
```

```
df1=df_cleaned.copy()  # used for downsizing for hierarchical clustering at later steps
```

```
df_cleaned.head()
```

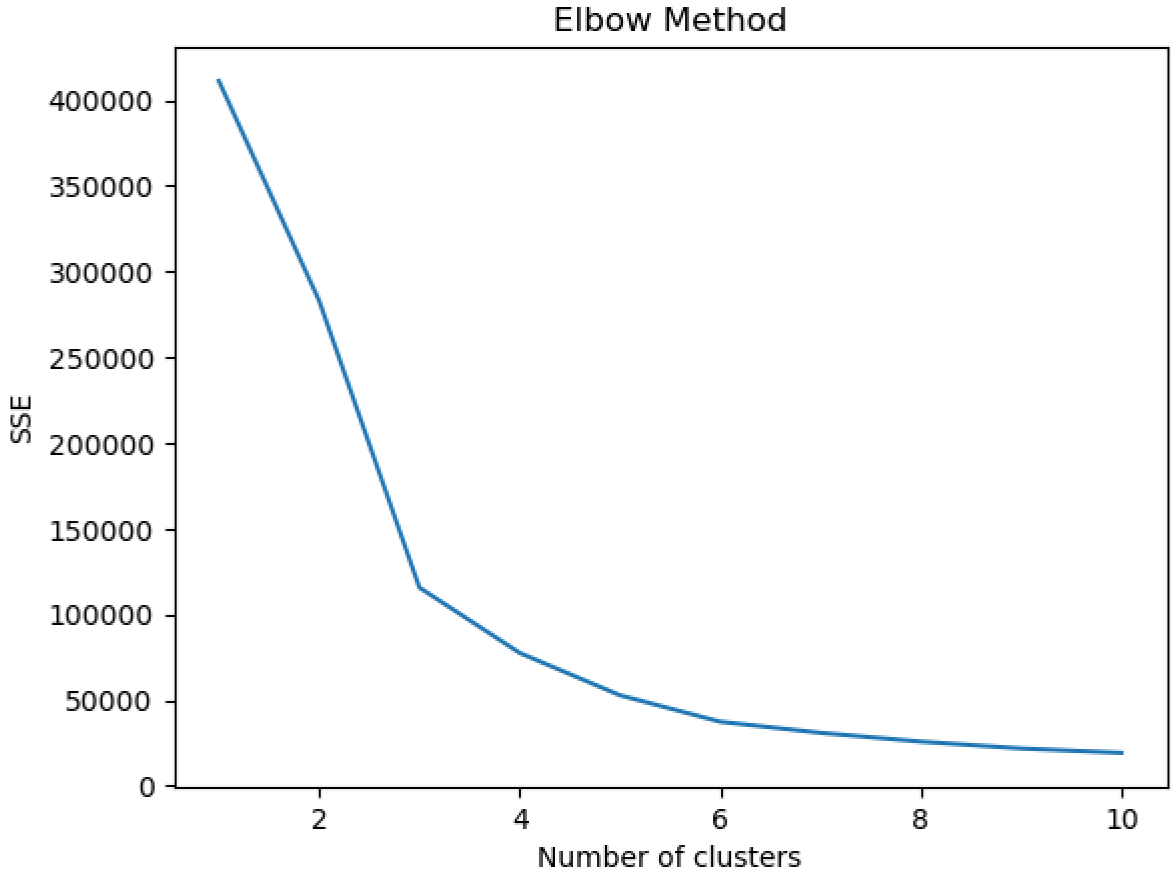
	index	email_hash	orgyear	ctc	job_position	ctc_updated_year	company_hash_cleaned	Years_of_Experience	mean	median	max	
0	0	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016	1100000	Other	2020	atrgxnnt xzaxv	8	1.100000e+06	1100000.0	1100000	110(
1	1	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018	449999	FullStack Engineer	2019	qtrxvzwt xzegwgbb rxbxnta	6	7.742856e+05	750000.0	1200000	44(
2	2	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015	2000000	Backend Engineer	2020	ojzwnvwnxw vx	9	2.000000e+06	2000000.0	2000000	200(
3	3	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017	700000	Backend Engineer	2019	ngpgutaxv	7	1.436154e+06	1210000.0	3160000	70(
4	4	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017	1400000	FullStack Engineer	2019	qxen sqghu	7	1.400000e+06	1400000.0	1400000	140(

```
Start coding or generate with AI.
```

```
# Standardize the numeric columns for clustering
scaler = StandardScaler()
df_scaled = scaler.fit_transform(df_cleaned[['ctc', 'Years_of_Experience']])
```

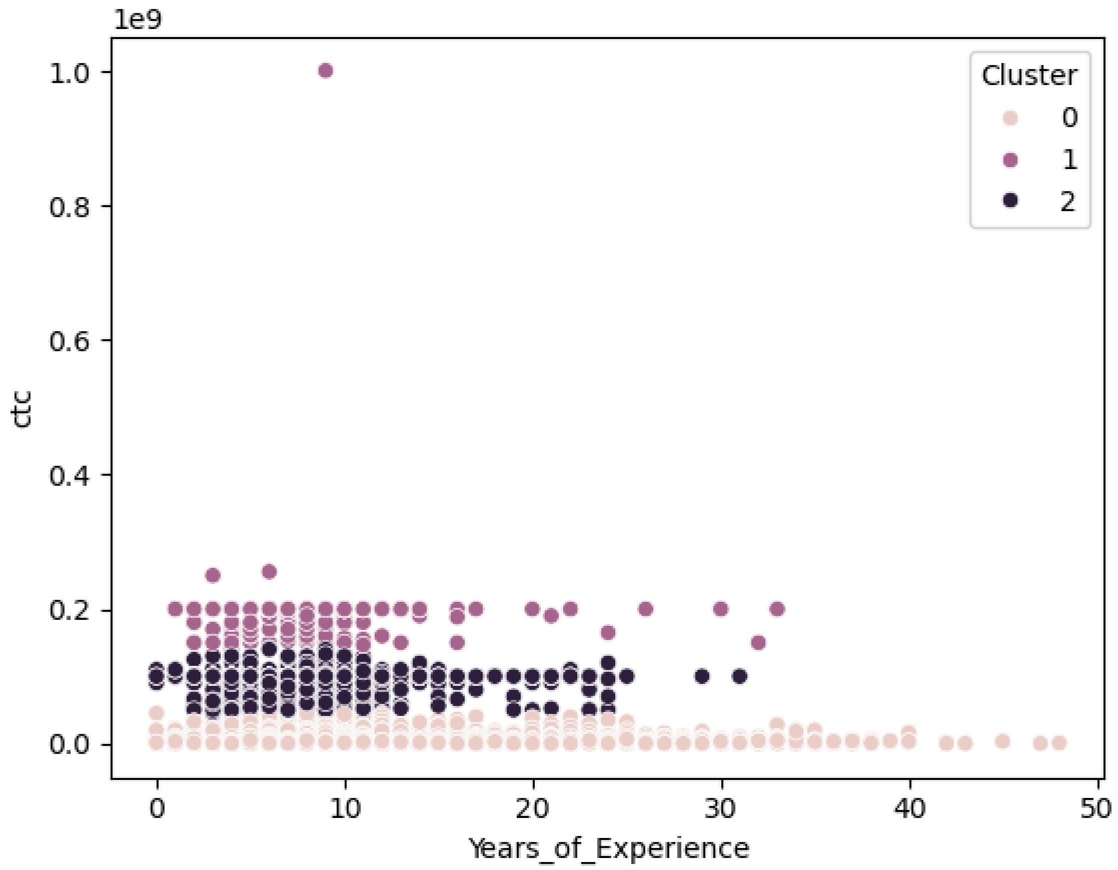
```
# Elbow method to find the optimal number of clusters
sse = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k)
    kmeans.fit(df_scaled)
    sse.append(kmeans.inertia_)

# Plot the Elbow graph
plt.plot(range(1, 11), sse)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('SSE')
plt.show()
```



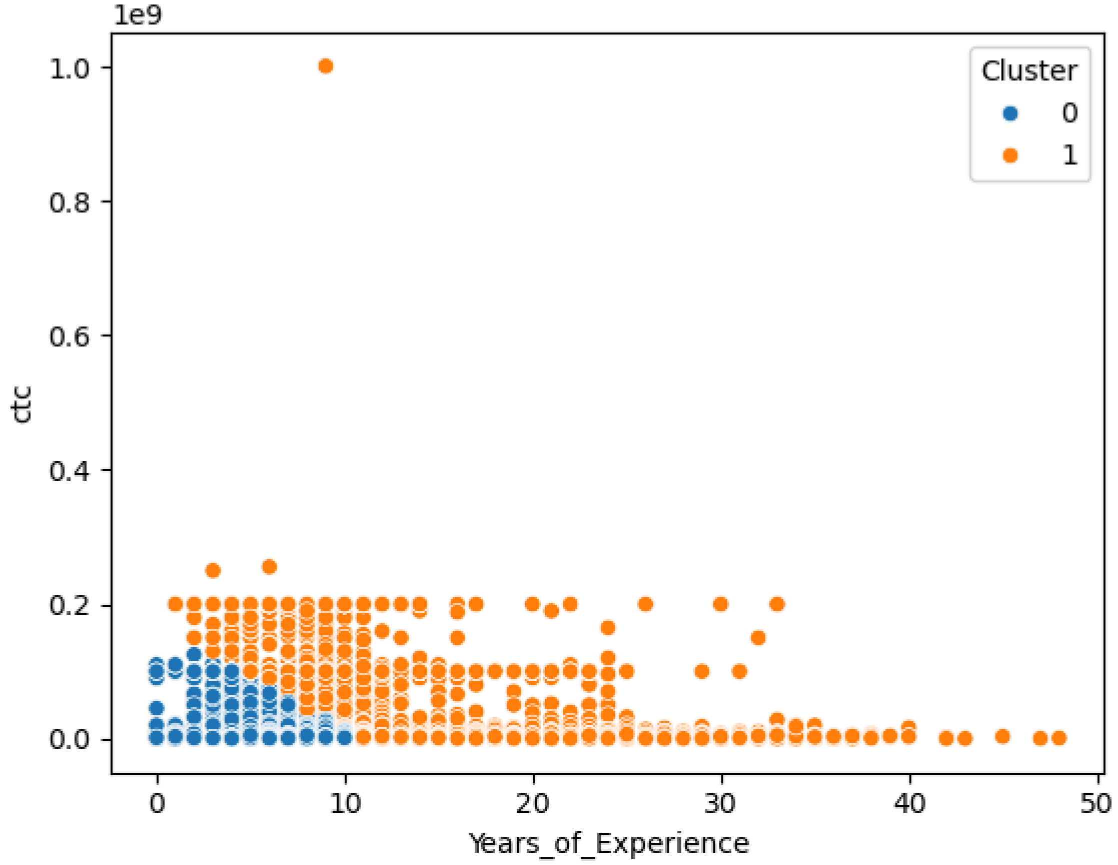

```
# Applying KMeans
kmeans = KMeans(n_clusters=3)
df_cleaned['Cluster'] = kmeans.fit_predict(df_scaled)

# Visualize the clusters
sns.scatterplot(x='Years_of_Experience', y='ctc', hue='Cluster', data=df_cleaned)
plt.show()
```



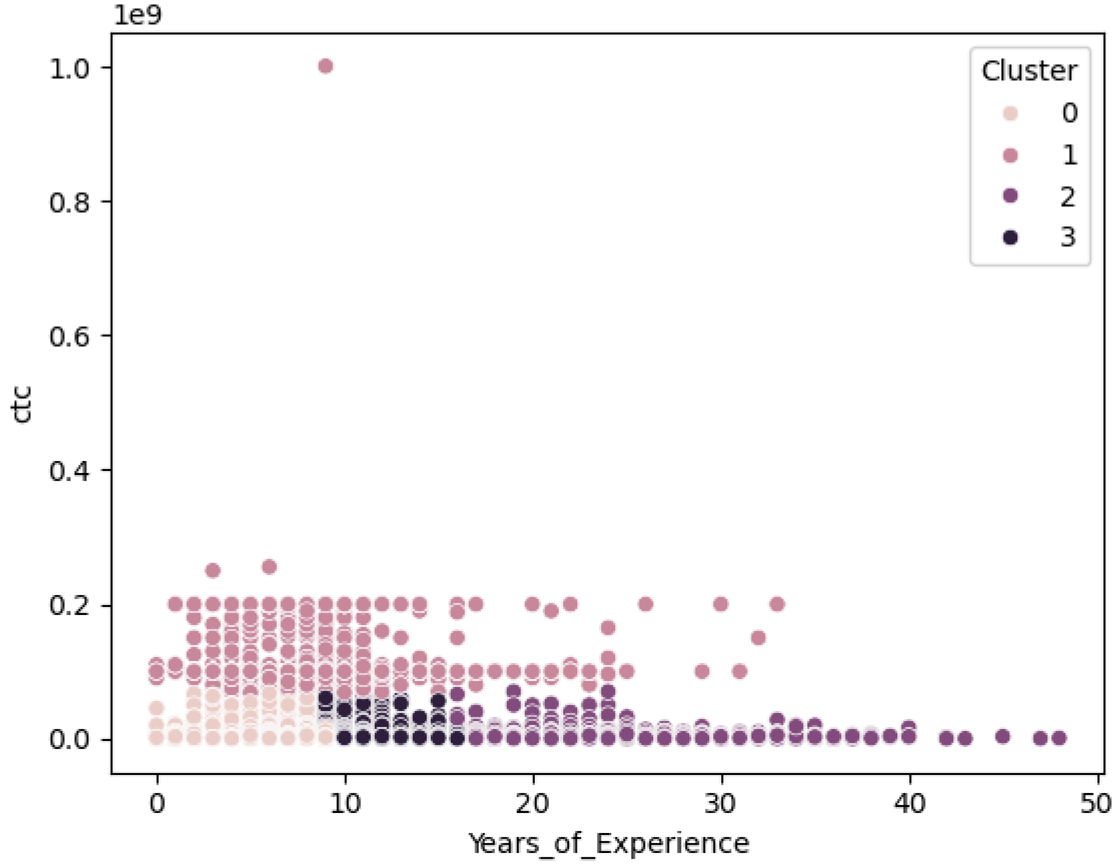

```
# Applying KMeans
kmeans = KMeans(n_clusters=2)
df_cleaned['Cluster'] = kmeans.fit_predict(df_scaled)

# Visualize the clusters
sns.scatterplot(x='Years_of_Experience', y='ctc', hue='Cluster', data=df_cleaned)
plt.show()
```



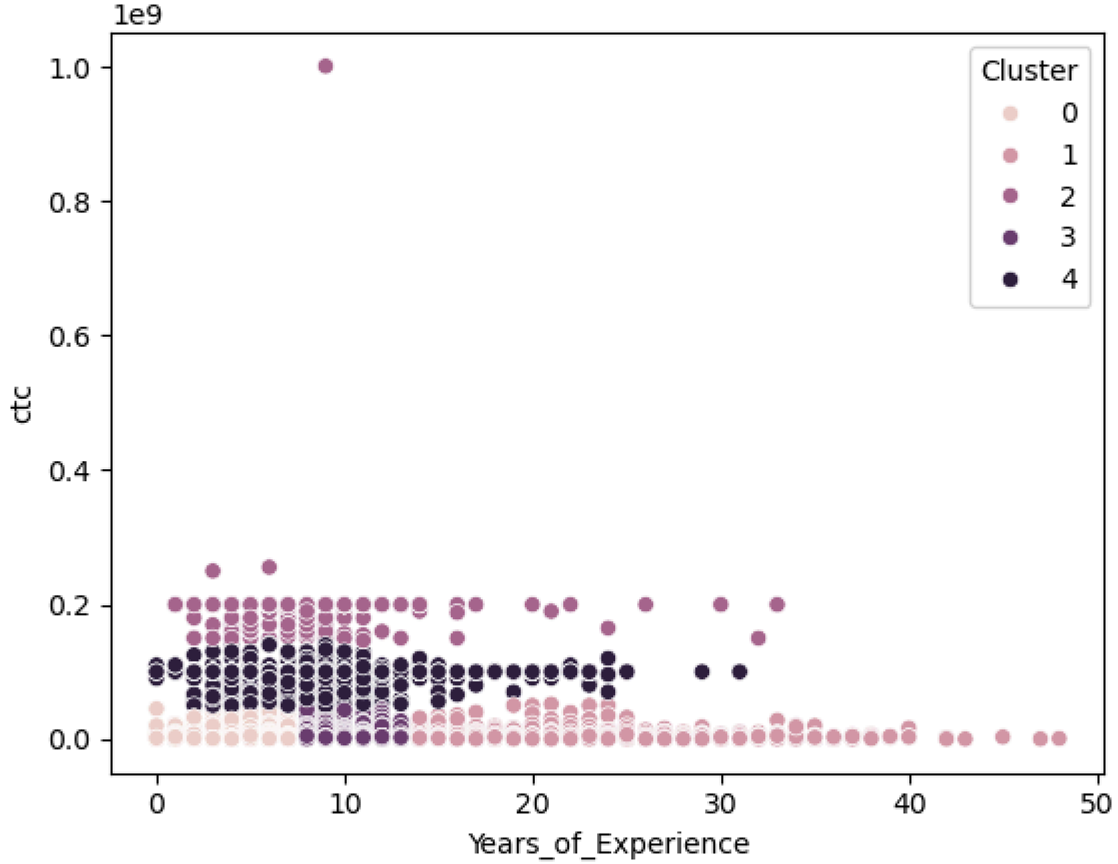

```
# Applying KMeans
kmeans = KMeans(n_clusters=4)
df_cleaned['Cluster'] = kmeans.fit_predict(df_scaled)

# Visualize the clusters
sns.scatterplot(x='Years_of_Experience', y='ctc', hue='Cluster', data=df_cleaned)
plt.show()
```



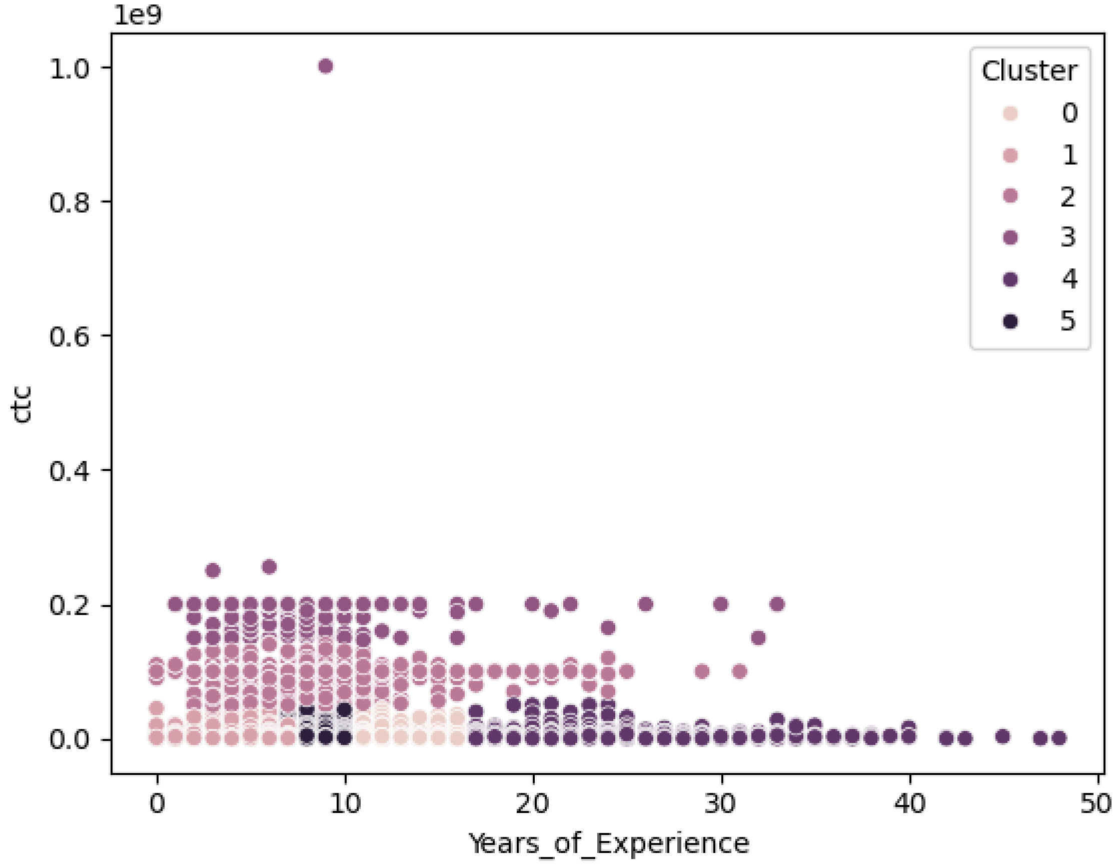

```
# Applying KMeans
kmeans = KMeans(n_clusters=5)
df_cleaned['Cluster'] = kmeans.fit_predict(df_scaled)

# Visualize the clusters
sns.scatterplot(x='Years_of_Experience', y='ctc', hue='Cluster', data=df_cleaned)
plt.show()
```




```
# Applying KMeans
kmeans = KMeans(n_clusters=6)
df_cleaned['Cluster'] = kmeans.fit_predict(df_scaled)

# Visualize the clusters
sns.scatterplot(x='Years_of_Experience', y='ctc', hue='Cluster', data=df_cleaned)
plt.show()
```




```
# Check the summary statistics of orgyear
print(df_cleaned['orgyear'].describe())
```

```
count    205665.000000
mean       2015.117584
std           4.228364
min        1976.000000
25%        2013.000000
50%        2016.000000
75%        2018.000000
max        2024.000000
Name: orgyear, dtype: float64
```

```
# Check for any unusual values (e.g., future years or very old years)
print(df_cleaned['orgyear'].value_counts().sort_index())
```

```
orgyear
1976        1
1977        1
1979        1
1981        1
1982        4
1984        3
1985        5
1986        8
1987        6
1988       10
1989       22
1990       38
1991       79
1992       47
```

```
1993       74
1994       65
1995       94
1996      134
1997      234
1998      279
1999      340
2000      495
2001      713
2002      685
2003     1018
2004     1455
2005     1873
2006     2075
2007     2257
2008     2728
2009     3777
2010     5751
2011     7970
2012    10493
2013    12351
2014    16696
2015    20610
2016    23043
2017    23239
2018    25256
2019    23427
2020    13431
2021     3670
2022      911
2023      252
2024       43
Name: count, dtype: int64
```

```
# Check the summary statistics of orgyear
print(df_cleaned['Years_of_Experience'].describe())
```

```
count    205665.000000
mean          8.882416
std           4.228364
min           0.000000
25%           6.000000
50%           8.000000
75%          11.000000
max          48.000000
Name: Years_of_Experience, dtype: float64
```

```
# Check for any unusual values (e.g., future years or very old years)
print(df_cleaned['Years_of_Experience'].value_counts().sort_index())
```

```
Years_of_Experience
0        43
1       252
2       911
3      3670
4     13431
5     23427
6     25256
```

```
7     23239
8     23043
9     20610
10    16696
11    12351
12    10493
13     7970
14     5751
15     3777
16     2728
17     2257
18     2075
19     1873
20     1455
21     1018
22      685
23      713
24      495
25      340
26      279
27      234
28      134
29       94
30       65
31       74
32       47
33       79
34       38
35       22
36       10
37        6
38        8
39        5
40        3
42        4
43        1
45        1
47        1
48        1
Name: count, dtype: int64
```

```
# # Perform hierarchical clustering
# Z = linkage(df_scaled, 'ward')
# dendrogram(Z)
# plt.show()
```

Try adding other features

```
# One-Hot Encode the categorical features
df_encoded = pd.get_dummies(df_cleaned, columns=['job_position', 'company_hash_cleaned'])
```

```
df_encoded.shape
```

```
(205665, 38278)
```

```
df_encoded.head()
```

	index	email_hash	orgyear	ctc	ctc_updated_year	Years_of_Experience	mean	median	max	min	...	company_hash_cleaned_zxzv xzonql
0	0	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016	1100000	2020	8	1.100000e+06	1100000.0	1100000	1100000	...	
1	1	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018	449999	2019	6	7.742856e+05	750000.0	1200000	449999	...	
2	2	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015	2000000	2020	9	2.000000e+06	2000000.0	2000000	2000000	...	
3	3	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017	700000	2019	7	1.436154e+06	1210000.0	3160000	700000	...	
4	4	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017	1400000	2019	7	1.400000e+06	1400000.0	1400000	1400000	...	

5 rows × 38278 columns

```
# Dropping specified columns from the df_encoded dataframe
df_encoded = df_encoded.drop(columns=['email_hash', 'mean', 'median', 'max', 'min', 'count'])
```

```
df_encoded.head()
```

	index	orgyear	ctc	ctc_updated_year	Years_of_Experience	Designation	Class	Tier	Cluster	job_position_ SDE 2	...	company_hash_cleaned_zxzvnxgzvr xzonqhbtzno	company_hash_cleaned_zxzvzxjv sqghu	com
0	0	2016	1100000	2020	8	0	2	2	5	False	...	False	False	
1	1	2018	449999	2019	6	0	3	3	1	False	...	False	False	
2	2	2015	2000000	2020	9	0	1	1	5	False	...	False	False	
3	3	2017	700000	2019	7	0	2	2	1	False	...	False	False	
4	4	2017	1400000	2019	7	0	2	2	1	False	...	False	False	

5 rows × 38272 columns

```
# Dimensionality Reduction with PCA before t-SNE
```

```
Start coding or generate with AI.
```

```
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt

# Apply PCA to reduce the dimensionality of the data to, say, 50 components
pca = PCA(n_components=50)
df_pca = pca.fit_transform(df_encoded)
```