```
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from matplotlib import pyplot as plt
plt.rcParams["figure.figsize"] = (18,10)
import re
import seaborn as sns
```

Problem Statement - To cluster or group CTC that company provides based on features of its employees like orgyear, CTC, job_position & ctc_updated_year

```
pd.set_option('display.max_columns', None)
pd.set_option('display.max_colwidth', None)
```

```
df = pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/002/856/original/scaler_clustering.csv')
```

```
df
```

	Unnamed: 0	company_hash	email_hash	orgyear	ctc	job_position
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618caea697c87af	2016.0	1100000	Other
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a92bdcc0407b	2018.0	449999	FullStack Engineer
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9df6b37b9059	2015.0	2000000	Backend Engineer
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58a44274d5d6876dfec7	2017.0	700000	Backend Engineer
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520214b31b95211adb095	2017.0	1400000	FullStack Engineer
...	...	...	...	...	...	...
205838	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b6e8d7cb06af04e0c05	2008.0	220000	NaN
205839	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b4264c8e881b4a61cdb53	2017.0	500000	NaN
205840	206920	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c8852b58da2fde5e00c	2021.0	700000	NaN

EDA

```
df.columns
```

```
Index(['Unnamed: 0', 'company_hash', 'email_hash', 'orgyear', 'ctc',
       'job_position', 'ctc_updated_year'],
      dtype='object')
```

```
df = df.rename(columns={'Unnamed: 0': 'id'})
```

```
df.describe()
```

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

```
num_cols = df.select_dtypes(include=['float64', 'int64']).columns.tolist()
num_cols
```

```
['id', 'orgyear', 'ctc', 'ctc_updated_year']
```

```
['id', 'orgyear', 'ctc', 'ctc_updated_year']
```

```
# Create histograms for numeric feature columns
df['orgyear'].value_counts()
```

```
2018.0    25256
2019.0    23427
2017.0    23239
2016.0    23043
2015.0    20610
          ...
2107.0        1
1972.0        1
2101.0        1
208.0         1
200.0         1
Name: orgyear, Length: 77, dtype: int64
```

```
# Data cleaning
# we see max orgyear 20165 which is wrong year so need to replace it to max year
maxYear = df['orgyear'].max()
print(maxYear)
maxYearCTC = df['ctc_updated_year'].max()
print(maxYearCTC)
```

```
20165.0
2021.0
```

```
df.shape
```

```
(205843, 7)
```

```
# lets remove this filtered data as it pollutes Employment start date cannot be <1980 and >2023
df_range = df[(df['orgyear']>=1980) & (df['orgyear']<=2023)]
df_range
```

	id	company_hash	email_hash	orgyear	ctc	job_position	c
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618caea697c87af	2016.0	1100000	Other	
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a92bdcc0407b	2018.0	449999	FullStack Engineer	
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9df6b37b9059	2015.0	2000000	Backend Engineer	
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58a44274d5d6876dfec7	2017.0	700000	Backend Engineer	
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520214b31b95211adb095	2017.0	1400000	FullStack Engineer	
...	...	...	...	...	...	...	
205838	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b6e8d7cb06af04e0c05	2008.0	220000	NaN	
205839	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b4264c8e881b4a61cdb53	2017.0	500000	NaN	
205840	206920	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c8852b58da2fde5e00c	2021.0	700000	NaN	
205841	206921	zqn vuurxwwmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c819ec41f6af222a8699	2019.0	5100000	NaN	

```
df = df_range.copy()
```

```
# df.drop('Unnamed: 0', axis=1, inplace=True)
```

```
df.isna().sum()
```

```
id                     0
company_hash          44
email_hash             0
orgyear                0
ctc                    0
job_position       52497
ctc_updated_year       0
dtype: int64
```

```
df[df['company_hash'].isna()]
```

	id	company_hash	email_hash	orgyear	ctc	job_position
1115	1115	NaN	8fe09b732fe2e5b66c14904fd02ff89fb54f458465ac1e5b04468e11db641e01	2022.0	66600000	NaN
2400	2400	NaN	1074b55f02e6fc88596db85854e057c98cb53c038e0d7f3d5e353e0c1d1a977b	2018.0	250000	Other
3277	3277	NaN	66263f4942b046c67ae6e2570e7825c03792631a0b13f1b5fed1fe3eafc396db	2018.0	500000	Other
4205	4205	NaN	6eb55d779699a2ea94f340ab7a58c8ec505e38bbb41214278e72b5f03d2af064	2018.0	600000	NaN
4596	4597	NaN	18813fe2a50a45cc02c5b3871c676bd147c80ff0327ee9e7bd8d9c121d9fa6d3	2020.0	300000	NaN
11753	11761	NaN	ea4f735b9357e8086a42bacc1f64b18e98c3dd1ad81f60140c0f4e6be8616830	2018.0	300000	NaN
14739	14748	NaN	b4a56d1199bc569aabd30cba8ea7a86fbddc85211453bac05e92b44a8e82e090	2013.0	1600000	NaN
18853	18865	NaN	07a60d6e853852471b0963b78a0a3074532572a258086431b4a14a2a1e2aaecc	2017.0	700000	FullStack Engineer
19466	19478	NaN	07a60d6e853852471b0963b78a0a3074532572a258086431b4a14a2a1e2aaecc	2017.0	700000	NaN
22846	22864	NaN	bdce6736cc1d55a909a46aed9e0bfdcd7cd523bfcf9b63ffa17c618a9a6424e5	2010.0	2000000	NaN
31489	31521	NaN	8e70184e76f9a29078e8ddd928d24582e096f5b1a63197a6e3803966b40bff31	2018.0	229999	NaN
40272	40319	NaN	4baf80fe2b9513f2f1d17d90f26071bd21f4a89d865fa1d16a18143c7b94e972	2012.0	2000000	NaN
45630	45684	NaN	b17c74b195c1fa8038bf82c674716ae81b41b995a3b4349fb7ae7d07e0873599	2020.0	600000	NaN
48583	48638	NaN	d9d7be8e4e4e5b6eb1092772d366c6bb21c8502e0e8253871fd6605da409e721	2011.0	910000	Data Scientist
62974	63058	NaN	8420dc8fe52b5acaf629914b3917fbc37111924b9654042f659f342abb9ea48f	2018.0	300000	NaN
68706	68803	NaN	8fe09b732fe2e5b66c14904fd02ff89fb54f458465ac1e5b04468e11db641e01	2022.0	66600000	Database Administrator
71138	71237	NaN	8ce727669517d613c973b752e211e50f0bad3cab50d7cb1e03517b100bdb0473	2019.0	200000	NaN
76614	76723	NaN	c83f98e2b2fb365515f48002f40db363a9de3319069f383a64f16d8b94d6bcc9	2014.0	1000000	NaN
79347	79461	NaN	1a5f329f97cdac513d7e33b5f8705e46053595ef6254c90ff68ba3d711588542	2015.0	2200000	NaN
80516	80639	NaN	cd6bc6ddf180c00306ad009a187cc5eb2a4b62af4ad58427f058a459a1ed8287	2017.0	300000	NaN
82680	82815	NaN	5ef6071f5c390f317dfa60f7aadb9ee7a1abc92aaa02fc68c4b479578b52eca8	2014.0	600000	NaN
85037	85181	NaN	a80b0711a63a65c0b70c3ed3f825043a8fc2b6871c3b0e53aad5dff78929c197	2019.0	1200000	FullStack Engineer
93712	93891	NaN	50f183667fd8a115dda5aa345988b314e1d98a3d937ea047ad82db9148caddbc	2019.0	500000	Database Administrator
103107	103338	NaN	98177023d0d95876047a39ed525d4c7eb44af739502aca75a9b78373ef88eb29	2011.0	1200000	NaN
103299	103530	NaN	87f640fc89281c082d94d1ee7fd6ee7391a8e30ad6182ba292ddd14aa502ba59	2013.0	400000	NaN
108479	108738	NaN	50f183667fd8a115dda5aa345988b314e1d98a3d937ea047ad82db9148caddbc	2019.0	500000	NaN
117021	117331	NaN	1606fcb8a2b3e4b242df4ee71190194fc556cf0d54861633038209d41757b52a	2016.0	700000	NaN
117915	118227	NaN	f4bb477609fc559301e37c73a5b17428afe18c53c0fa27f4993cba5efb3f425b	2015.0	600000	NaN
125509	125889	NaN	9f9ba6d4e58f4f175f348d6d188be8ee8d5aa3537a0187ae5c6b7b067f01e051	2017.0	400000	NaN
130031	130449	NaN	d7f39bfaa3be4957fa36a97fabb5ab7a39f6d55f377f334ece6bd1b3c8f6558a	2015.0	800000	Backend Engineer
141214	141719	NaN	cd281f18ef3d9042fab48860b4a7f80ec1d559c3fc2f857c266fc367b05a4e4d	2006.0	1000000	NaN
141355	141860	NaN	a51106f9193e46db561f27b02db413396e651be5394ca5e008ce4bdc1fc9ae75	2015.0	110000	NaN
142613	143135	NaN	ce803383ed3dda0838959afb466eb1cffff964c94cb1ea7cc5dec8e6293e61d4	2018.0	2000000	Data Analyst
142955	143477	NaN	f47fbe35140825c07caf830b18058e737a3c6f18c50f503c535e5efdfbe5ac50	2019.0	2700000	FullStack Engineer
146191	146743	NaN	f47fbe35140825c07caf830b18058e737a3c6f18c50f503c535e5efdfbe5ac50	2019.0	2700000	NaN
156511	157132	NaN	c9af26980cf32f393089c1b33d3e138450e506b2d044a359a23d117e36362ff5	2021.0	900000	NaN
162073	162746	NaN	d000a77f0045504e2ee51a667ac0ad2671795b3f70ce33f16f9c06ba4ca20aa1	2020.0	800000	NaN
171527	172311	NaN	824c00340acc623b57c75ca41535bf9d52fdee81d006bf7991990f47b1a62d99	2012.0	2100000	Other
175270	176096	NaN	aae19078f349d6403856abf2c28ee731a32c0dbeb8de76587828b494a7774454a	2018.0	956000	NaN

```
df.describe(include='object')
```

	company_hash	email_hash	job_position
count	205575	205619	153122
unique	37238	153253	1017
top	nvnv wgzohrnvzwj otqcxwto	bbace3cc586400bbc65765bc6a16b77d8913836cfc98b77c05488f02f5714a4b	Backend Engineer
freq	8335	10	43522

```
company_group = df[df['company_hash']=='qtrxvzwt xzegwgbb rxbxnta']
company_group
```

	id	company_hash	email_hash	orgyear	ctc	job_position	c
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a92bdcc0407b	2018.0	449999	FullStack Engineer	
697	697	qtrxvzwt xzegwgbb rxbxnta	8dcec4009f7a5bdd8c6a2af379b5763816563e25d814d018daa334db7843efff	2018.0	700000	Backend Engineer	
739	739	qtrxvzwt xzegwgbb rxbxnta	f4fa64972185ac2b73e99c0cc10d1bf50d6dbfbc9a2cbad8d14714cad5df925f	2018.0	620000	FullStack Engineer	
1389	1389	qtrxvzwt xzegwgbb rxbxnta	97f1a965db57f2baacbbacf36b9572819e8a90007e3c86d090ddc96ab8fc7fd7	2020.0	1100000	NaN	
3118	3118	qtrxvzwt xzegwgbb rxbxnta	fe8010b8aa29f7bd16d111ab332881cdfc819fbcc82b5d9b690ffe16310c2d44	2019.0	630000	Backend Engineer	
...	...	...	...	...	...	...	...
		qtrxvzwt					

```
# Checking unique emails and frequency of occurrence of the same email hash in the data.
# Recording observation and inference, wherever necessary.
email_counts = df['email_hash'].value_counts()
email_counts
```

```
bbace3cc586400bbc65765bc6a16b77d8913836cfc98b77c05488f02f5714a4b    10
6842660273f70e9aa239026ba33bfe82275d6ab0d20124021b952b5bc3d07e6c     9
298528ce3160cc761e4dc37a07337ee2e0589df251d73645aae209b010210eee     9
3e5e49daa5527a6d5a33599b238bf9bf31e85b9efa9a94f1c88c5e15a6f31378     9
b4d5afa09bec8689017d8b29701b80d664ca37b83cb883376b2e95191320da66     8
                                                                    ..
1bf133f4545f330347ce99d4ef23e10d08c72a6d2a71d1fff92426adebbafe7a     1
352332d97ee4a09346cd4b539c096843c97f6e88352adeaeb132e52c7fe15143     1
ce7b0b9c2d37b0df8fc9f9436961ece9086226b6450ace168bb475017bdd87c6     1
6ed7767a6ba36e8ab4f4d2397a4d32f26f34387720645906bf51a05c2152fd56     1
0bcfc1d05f2e8dc4147743a1313aa70a119b41b30d4a1f7e738a6a87d3712c31     1
Name: email_hash, Length: 153253, dtype: int64
```

```
email_group = df[df['email_hash']=='b4d5afa09bec8689017d8b29701b80d664ca37b83cb883376b2e95191320da66']
email_group
```

	id	company_hash	email_hash	orgyear	ctc	job_position	c
37734	37778	bvi ogenfvqt	b4d5afa09bec8689017d8b29701b80d664ca37b83cb883376b2e95191320da66	2020.0	900000	Engineering Leadership	
45982	46036	bvi ogenfvqt	b4d5afa09bec8689017d8b29701b80d664ca37b83cb883376b2e95191320da66	2020.0	900000	Engineering Intern	
144760	145307	bvi ogenfvqt	b4d5afa09bec8689017d8b29701b80d664ca37b83cb883376b2e95191320da66	2020.0	900000	Data Analyst	
151714	152309	bvi ogenfvqt	b4d5afa09bec8689017d8b29701b80d664ca37b83cb883376b2e95191320da66	2020.0	900000	Data Scientist	
153866	154474	bvi ogenfvqt	b4d5afa09bec8689017d8b29701b80d664ca37b83cb883376b2e95191320da66	2020.0	900000	NaN	
154644	155256	bvi ogenfvqt	b4d5afa09bec8689017d8b29701b80d664ca37b83cb883376b2e95191320da66	2020.0	900000	Software Engineer 1	
						Engineering	

We notice that for every email hash repetition only 1 unique company_hash exists.

```
# remove special characters from the dataset by using Regex for cleaning company names
df['company_hash'] = df['company_hash'].str.replace('[^A-Za-z0-9 ]+', '', regex=True)
df
```

	id	company_hash	email_hash	orgyear	ctc	job_position	c
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618caea697c87af	2016.0	1100000	Other	
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a92bdcc0407b	2018.0	449999	FullStack Engineer	
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9df6b37b9059	2015.0	2000000	Backend Engineer	
3	3	[illegible]	[illegible]	[illegible]	[illegible]	Backend	
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520214b31b95211adb095	2017.0	1400000	FullStack	

Handling null values in dataset

```
# replace NA in company_hash to first value of email_hash (just for uniqueness, we will do label encoding later)
grouped = df.groupby('company_hash')

# Define a function to fill NA values with the first 'email_hash' value in the group
def fill_na_with_first(group):
    first_email_hash = group['email_hash'].dropna().iloc[0]  # Get the first non-NA value
    group['company_hash'].fillna(first_email_hash, inplace=True)
    return group

# Apply the function to each group within the DataFrame
df_filled = grouped.apply(fill_na_with_first).reset_index(drop=True)
df_filled
```

```
<ipython-input-207-599f3a77d0e6>:11: FutureWarning: Not prepending group keys
To preserve the previous behavior, use

        >>> .groupby(..., group_keys=False)

To adopt the future behavior and silence this warning, use

        >>> .groupby(..., group_keys=True)
  df_filled = grouped.apply(fill_na_with_first).reset_index(drop=True)
```

	id	company_hash	
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618c
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58a44274d
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520214b31b
...	...	...	
205570	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b6e8d7cb
205571	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b4264c8e88
205572	206920	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c8852b58
205573	206921	zgn vuurxwvmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c819ec41f

```
df_filled.isna().sum()
```

```
id                      0
company_hash            0
email_hash              0
orgyear                 0
ctc                     0
job_position        52466
ctc_updated_year        0
dtype: int64
```

```
# replace NA in orgyear to ctc_updated_year
df_filled['orgyear'].fillna(df_filled['ctc_updated_year'], inplace=True)
df_filled
```

	id	company_hash	email_hash	orgyear	ctc	job_position	c
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618caea697c87af	2016.0	1100000	Other	
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a92bdcc0407b	2018.0	449999	FullStack Engineer	
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9df6b37b9059	2015.0	2000000	Backend Engineer	
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58a44274d5d6876dfec7	2017.0	700000	Backend Engineer	
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520214b31b95211adb095	2017.0	1400000	FullStack Engineer	

```
df_filled.isna().sum()
```

```
id                    0
company_hash          0
email_hash            0
orgyear               0
ctc                   0
job_position      52466
ctc_updated_year      0
dtype: int64
```

```
df[df['job_position'].isna()]
```

	id	company_hash	email_hash	orgyear	ctc	job_position	ct
8	8	utqoxontzn ojontbo	e245da546bf50eba09cb7c9976926bd56557d1ac9a17fb019e8de1fdb83fc0d6	2020.0	450000	NaN	
9	9	xrbhd	b2dc928f4c22a9860b4a427efb8ab761e1ce0015fba1a5e804e1dc27e305b06b	2019.0	360000	NaN	
12	12	mvqwrvjo wgqugqvnt mvzpxzs	7f24d2f5171ea469482a9966832237bc023678883ecd0c5142677b75a138b2fa	2020.0	800000	NaN	
17	17	puxn	26b502eb6439ac80bd618a6f7c2b1c640b84c1e64c472cf0510b0b36c2d3c247	2020.0	1400000	NaN	
18	18	mvlvl exzotqc	62d2e04b44c8bf2f6ec15d5b4c259c06199f598dc51816b1e32a84bc3ed980ea	2018.0	100000	NaN	
...	...	...	...	...	...	...	...
205838	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b6e8d7cb06af04e0c05	2008.0	220000	NaN	
205839	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b4264c8e881b4a61cdb53	2017.0	500000	NaN	
205840	206920	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c8852b58da2fde5e00c	2021.0	700000	NaN	
205841	206921	zgn vuurxwvmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c819ec41f6af222a8699	2019.0	5100000	NaN	
205842	206922	bqqsvz onvzrti	0bcfc1d05f2e8dc4147743a1313aa70a119b41b30d4a1f7e738a6a87d3712c31	2014.0	1240000	NaN	

```
# replace NA in job_position to Unknown
df_filled['job_position'].fillna("Unknown", inplace=True)
df_filled
```

	id	company_hash	email_hash	orgyear	ctc	job_position	c
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618caea697c87af	2016.0	1100000	Other	
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a92bdcc0407b	2018.0	449999	FullStack Engineer	
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9df6b37b9059	2015.0	2000000	Backend Engineer	
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58a44274d5d6876dfec7	2017.0	700000	Backend Engineer	
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520214b31b95211adb095	2017.0	1400000	FullStack Engineer	
...	...	...	...	...	...	...	...
205570	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b6e8d7cb06af04e0c05	2008.0	220000	Unknown	
205571	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b4264c8e881b4a61cdb53	2017.0	500000	Unknown	
205572	206920	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c8852b58da2fde5e00c	2021.0	700000	Unknown	
205573	206921	zgn vuurxwvmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c819ec41f6af222a8699	2019.0	5100000	Unknown	

```
df_filled.isna().sum()
```

```
id                0
company_hash      0
```

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

All missing values are handled in df_filled

```
df_filled.shape
```

```
(205575, 7)
```

```
df = df_filled.copy()
```

```
# Check for duplicates and drop them
df = df.drop_duplicates()
```

```
df.shape
```

```
(205575, 7)
```

Making some new features like adding 'Years of Experience' column by subtracting orgyear from current year

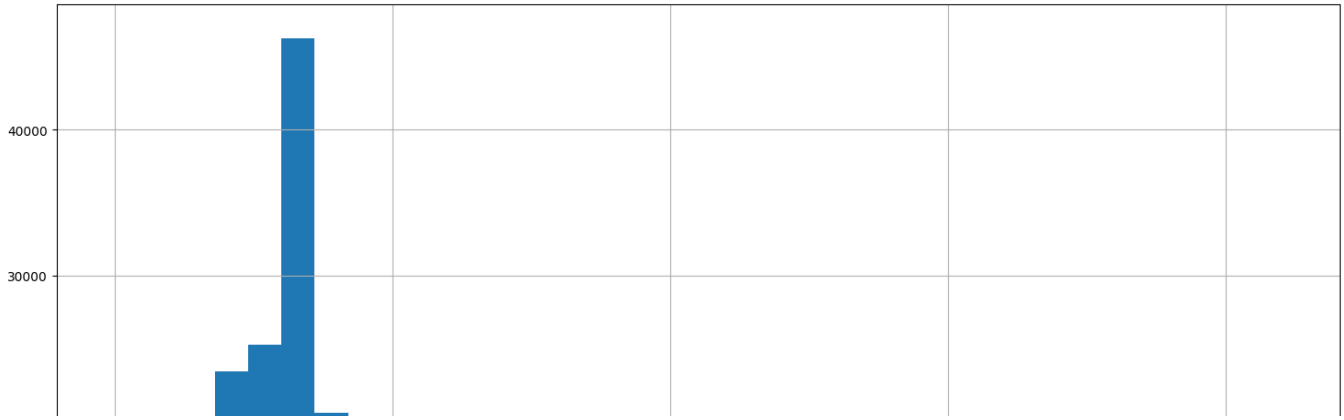
```
df['YOE'] = 2023 - df['orgyear']
df
```

	id	company_hash	email_hash	orgyear	ctc	job_position	c
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618caea697c87af	2016.0	1100000	Other	
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a92bdcc0407b	2018.0	449999	FullStack Engineer	
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9df6b37b9059	2015.0	2000000	Backend Engineer	
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58a44274d5d6876dfec7	2017.0	700000	Backend Engineer	
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520214b31b95211adb095	2017.0	1400000	FullStack Engineer	
...	...	...	...	...	...	...	...
205570	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b6e8d7cb06af04e0c05	2008.0	220000	Unknown	
205571	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b4264c8e881b4a61cdb53	2017.0	500000	Unknown	
205572	206920	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c8852b58da2fde5e00c	2021.0	700000	Unknown	
205573	206921	zqn vuurxwvmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c819ec41f6af222a8699	2019.0	5100000	Unknown	

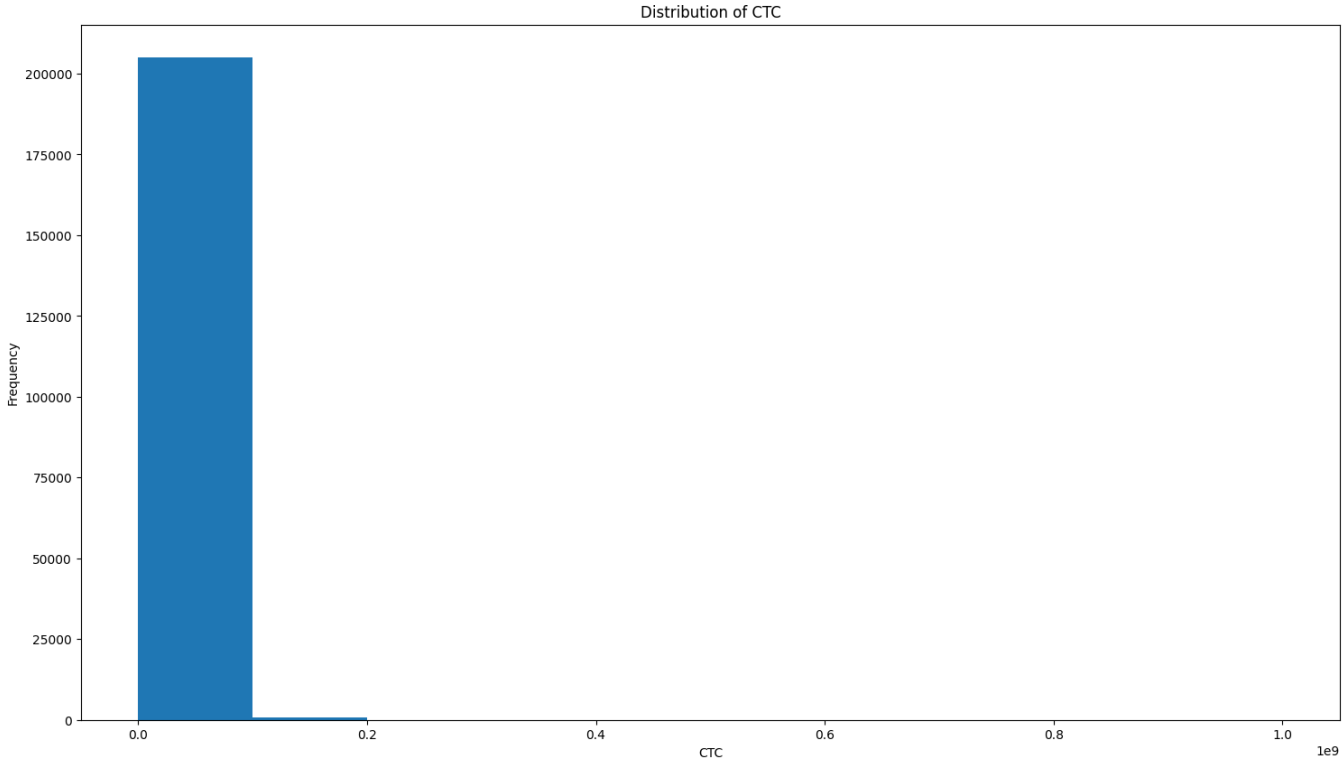
Univariate Analysis

```
df['YOE'].hist(bins=35)
```

```
<Axes: >
```

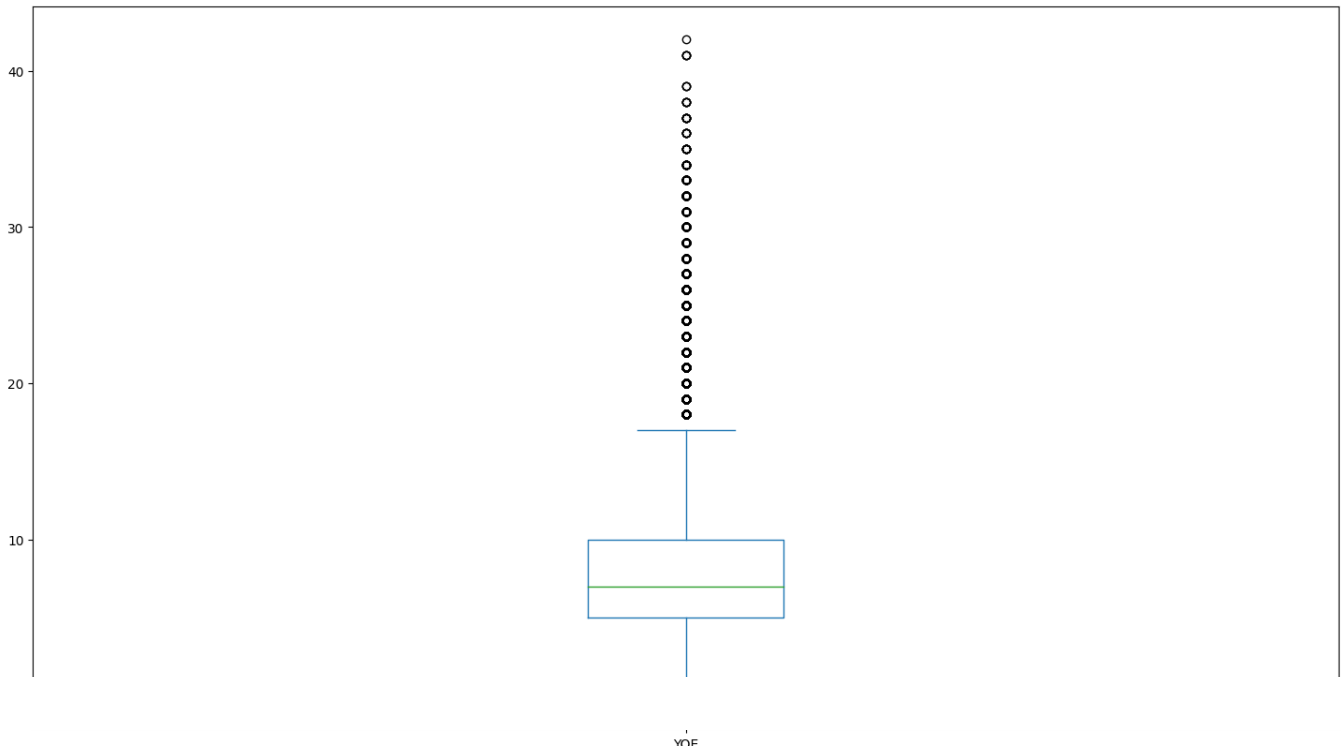



```
import matplotlib.pyplot as plt
df['ctc'].plot.hist()
plt.title('Distribution of CTC')
plt.xlabel('CTC')
plt.ylabel('Frequency')
plt.show()
```




```
df[['YOE']].plot(kind='box', subplots=True)
```

```
YOE    Axes(0.125,0.11;0.775x0.77)
dtype: object
```

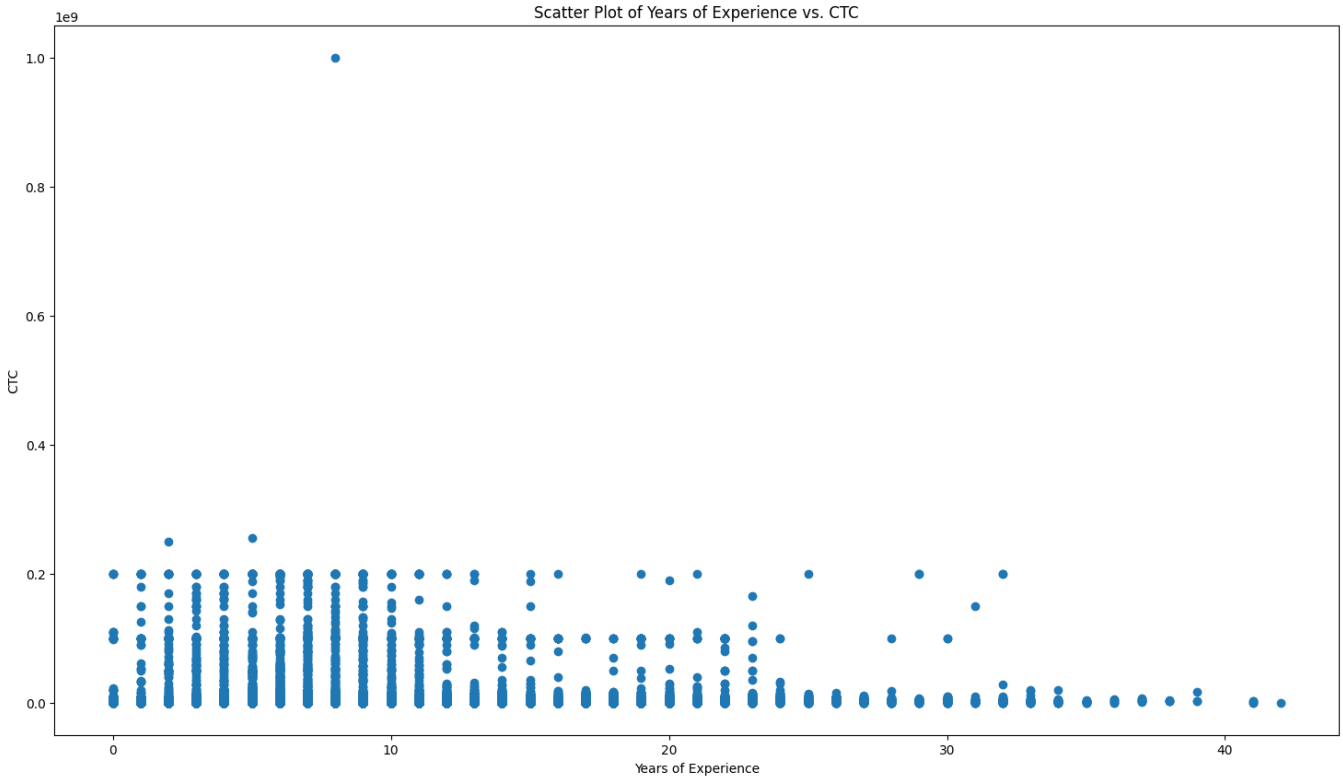


Bivariate Analysis

```
import seaborn as sns
correlation_matrix = df[['ctc', 'ctc_updated_year', 'YOE']].corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
```

```
<Axes: >
```

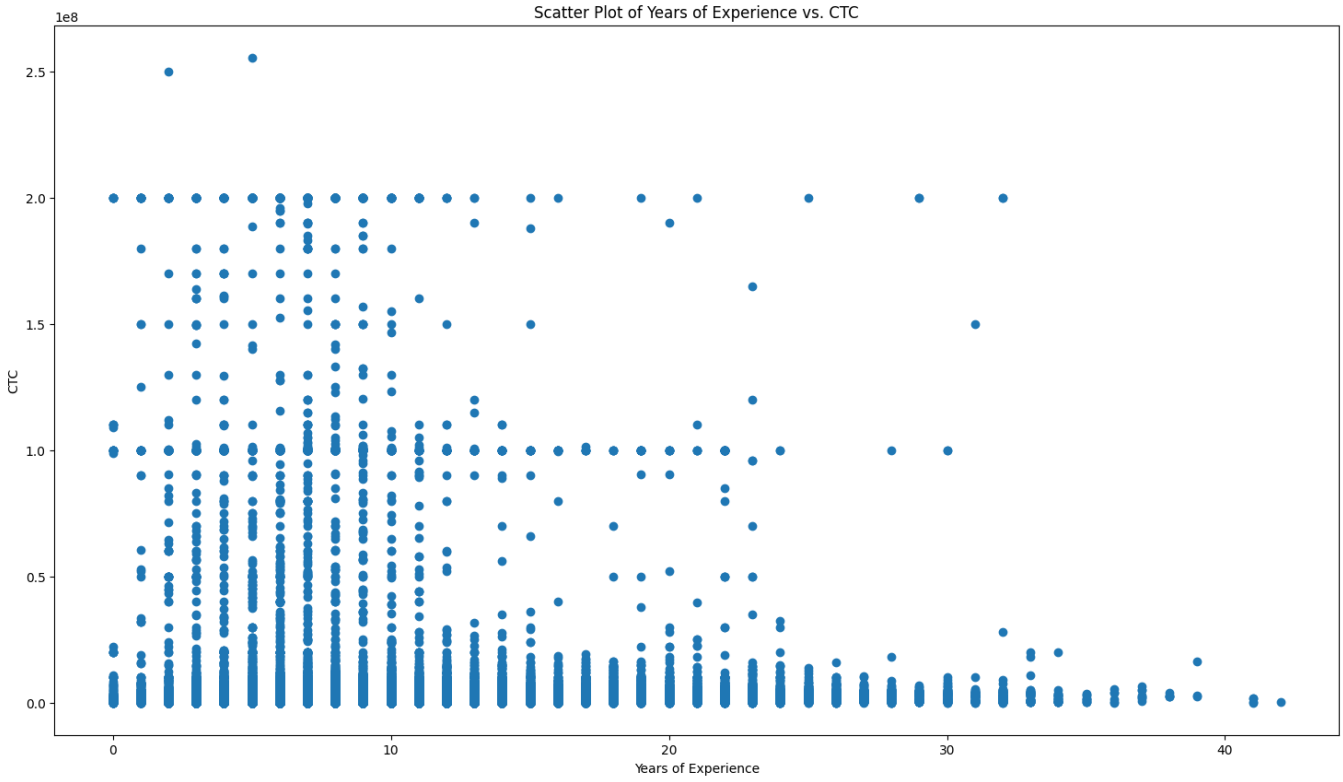
```
plt.scatter(df['YOE'], df['ctc'])
plt.title('Scatter Plot of Years of Experience vs. CTC')
plt.xlabel('Years of Experience')
plt.ylabel('CTC')
plt.show()
```




```
# remove 1 outlier and see plot again
df = df[df['ctc']<0.8*1e9]
df
```

	id	company_hash	email_hash	orgyear	ctc	job_position	c
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618caea697c87af	2016.0	1100000	Other	
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a92bdcc0407b	2018.0	449999	FullStack Engineer	
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9df6b37b9059	2015.0	2000000	Backend Engineer	
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58a44274d5d6876dfec7	2017.0	700000	Backend Engineer	
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520214b31b95211adb095	2017.0	1400000	FullStack Engineer	
...	...	...	...	...	...	...	...
205570	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b6e8d7cb06af04e0c05	2008.0	220000	Unknown	
205571	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b4264c8e881b4a61cdb53	2017.0	500000	Unknown	
205572	206920	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c8852b58da2fde5e00c	2021.0	700000	Unknown	
205573	206921	zqn vuurxwvmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c819ec41f6af222a8699	2019.0	5100000	Unknown	

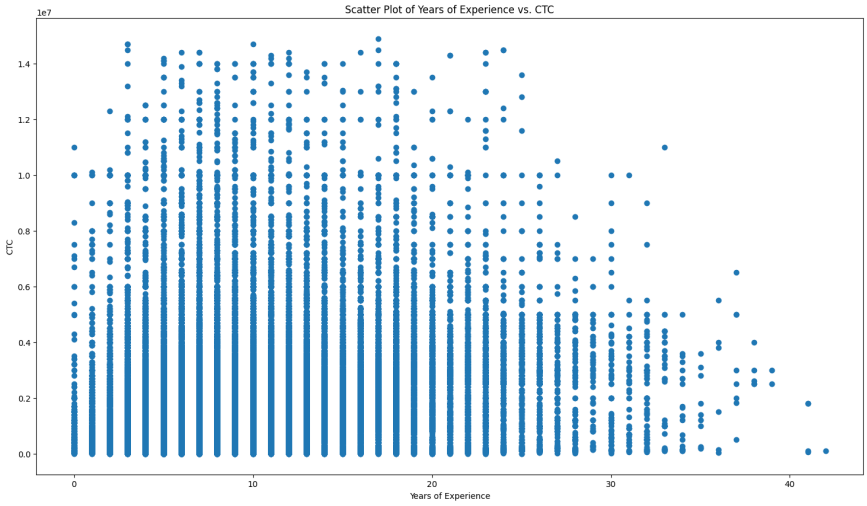
```
plt.scatter(df['YOE'], df['ctc'])
plt.title('Scatter Plot of Years of Experience vs. CTC')
plt.xlabel('Years of Experience')
plt.ylabel('CTC')
plt.show()
```




```
# remove ctc more than 15 Lakhs and see plot again
dfless15lac_ctc = df[df['ctc']<0.15*1e8]
dfless15lac_ctc
```

	id	company_hash	
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618c
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58a44274d
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520214b31b
...	...	...	
205570	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b6e8d7cb
205571	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b4264c8e88
205572	206920	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c8852b58
205573	206921	zqn vuurxwvmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c819ec41f

```
plt.scatter(dfless15lac_ctc['YOE'], dfless15lac_ctc['ctc'])
plt.title('Scatter Plot of Years of Experience vs. CTC')
plt.xlabel('Years of Experience')
plt.ylabel('CTC')
plt.show()
```




```
crosstab = pd.crosstab(df['orgyear'], df['ctc_updated_year'])
crosstab.plot(kind='bar', stacked=True)
```

Insights based on EDA:

1. The org year & ctc updated year were having few outliers that doesnot make sense like max year 20165 & min year so removed those values.
2. We handled null values in dataset, there were lot of null values in company_id & on analysis we saw for every email_id there exists unique company_id, so we can replace company_id to first email_id of that company.
3. Mostly dataset contains data with people having 3-12 years of experience.
4. Mostly people got increment (ctc updated) in years 2019 to 2021. Although, people have been working from 2009-2021 (orgyear).
5. With YOE 8-12 years, CTC has big range with 8 years work experience having most of it. According to data, it doesnot matter on YOE for CTC, CTC ranges depend on other things also. Data for 8-12 YOE is also more.
6. There is negative correlation between CTC updated year & YOE.

Manual Clustering

```
Manual Clustering on the basis of learner's company, job position and years of experience
Getting the 5 point summary of CTC (mean, median, max, min, count etc) on the basis of Company, Job Position, Years of Experience
Merging the same with original dataset carefully and creating some flags showing learners with CTC greater than the Average of their
Doing above analysis at Company & Job Position level. Name that flag Class with values [1,2,3]
Repeating the same analysis at the Company level. Name that flag Tier with values [1,2,3]
```

```
df
```

	id	company_hash	
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618c
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58a44274d
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520214b31b
...	...	...	
205570	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b6e8d7cb
205571	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b4264c8e88
205572	206920	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c8852b58
205573	206921	zgn vuurxwvmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c819ec41f

```
agg_data = df.groupby(['company_hash', 'job_position','YOE']).agg({
    'ctc':['mean','median','max','min']
})
agg_data
```

				ctc			
				mean	median	max	min
	company_hash	job_position	YOE				
	0	Other	3.0	100000.0	100000.0	100000	100000
		Unknown	3.0	100000.0	100000.0	100000	100000

```
agg_data = agg_data.reset_index()
agg_data
```

	company_hash	job_position	YOE	ctc			
				mean	median	max	min
0	0	Other	3.0	100000.0	100000.0	100000	100000
1	0	Unknown	3.0	100000.0	100000.0	100000	100000
2	0000	Other	6.0	300000.0	300000.0	300000	300000
3	01 ojztqsj	Android Engineer	7.0	270000.0	270000.0	270000	270000
4	01 ojztqsj	Frontend Engineer	12.0	830000.0	830000.0	830000	830000
...	...	...	...	...	...	...	...
113289	zz	Unknown	14.0	500000.0	500000.0	500000	500000
113290	zzb ztdnstz vacxogqj ucn rna	FullStack Engineer	6.0	600000.0	600000.0	600000	600000
113291	zzb ztdnstz vacxogqj ucn rna	Unknown	6.0	600000.0	600000.0	600000	600000
113292	zzgato	Unknown	9.0	130000.0	130000.0	130000	130000

```
agg_data.columns = [' '.join(col).strip() for col in agg_data.columns.values]
agg_data
```

	company_hash	job_position	YOE	ctc mean	ctc median	ctc max	ctc min
0	0	Other	3.0	100000.0	100000.0	100000	100000
1	0	Unknown	3.0	100000.0	100000.0	100000	100000
2	0000	Other	6.0	300000.0	300000.0	300000	300000
3	01 ojztqsj	Android Engineer	7.0	270000.0	270000.0	270000	270000
4	01 ojztqsj	Frontend Engineer	12.0	830000.0	830000.0	830000	830000
...	...	...	...	...	...	...	...
113289	zz	Unknown	14.0	500000.0	500000.0	500000	500000
113290	zzb ztdnstz vacxogqj ucn rna	FullStack Engineer	6.0	600000.0	600000.0	600000	600000
113291	zzb ztdnstz vacxogqj ucn rna	Unknown	6.0	600000.0	600000.0	600000	600000
113292	zzgato	Unknown	9.0	130000.0	130000.0	130000	130000

```
# data with varying mean median max min
agg_data[agg_data['ctc mean']!=agg_data['ctc median']]
```

	company_hash	job_position	YOE	ctc mean	ctc median	ctc max	ctc min
50	1bs	Backend Engineer	4.0	1.116667e+06	1000000.0	1350000	1000000
51	1bs	Backend Engineer	5.0	9.333333e+05	900000.0	1100000	800000

```
# merge these values with df
df_merged = df.merge(agg_data, on=['company_hash', 'job_position', 'YOE'], how='left')
df_merged
```

	id	company_hash	
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618c
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58a44274d
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520214b31b
...	...	...	
205569	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b6e8d7cb
205570	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b4264c8e88
205571	206920	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c8852b58
205572	206921	zgn vuurxwvmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c819ec41f
205573	206922	bgqsvz onvzrtj	0bcfc1d05f2e8dc4147743a1313aa70a119b41b30d4a1f7e738a6

205574 rows × 12 columns

```
df_comparison=df_merged.copy()
```

```
# Define a function to categorize the 'ctc' values
def categorize_ctc(row, comparison_column):
    if row['ctc'] < 0.5 * row[comparison_column]:
        return 3  # Less than 50% of mean_ctc -> Underpaid
    elif row['ctc'] > 1.5 * row[comparison_column]:
        return 1  # More than 150% of mean_ctc -> Cream employees
    else:
        return 2  # Within the range
```

Flag Designation calculation

```
df_comparison['ctc_flag_mean'] = df_comparison.apply(categorize_ctc, args=('ctc mean',), axis=1)
df_comparison['ctc_flag_median'] = df_comparison.apply(categorize_ctc, args=('ctc median',), axis=1)
df_comparison
```

	id	company_hash	email_hash	orgyear	ctc	job_position	c
0	0	atrgxnnt xzaxv qtrxvzwt	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618caea697c87af	2016.0	1100000	Other	

```
df_comparison[df_comparison['ctc_flag_mean']!=df_comparison['ctc_flag_median']]
# maybe many outliers
```

	id	company_hash	email_hash	orgyear	ctc	job_position
81	81	nv axsxnvr	d1829ec6261f538309e4496ff0c97a87ecd782067343d5a323f818ea0d7d46a1	2020.0	910000	Unknown
83	83	wgszxkvzn	985f3ffced0e16713147c7c36ec70c5414cc9d6c79fe9d940fa55672c4e3da07	2015.0	750000	Other
116	116	mvqwrvjo wgqugqvnt mvzpxzs	3e2e7e6242f662ccd27dbd41ace1a029d19b9dedd7e4f7b49b507ddb1bdb01db	2019.0	800000	Engineering Intern
185	185	ntwy bvyxzaqv	2ee09b45e4335aa9aeb6ac2b36ddd79dcbe5f7b954d2587f2a722800dd9d5ded	2017.0	250000	Support Engineer
201	201	fxuqg rxbxnta	e4ad74a458078a292a1de28d2039c36b415e7e12682e94e98c3555be1858d865	2016.0	720000	Unknown
...	...	...	...	...	...	...
205556	206905	vbvkgz	95023bca0172ad67bfc3453550c5cf056557bc2c8c7169c45d544526834d19a4	2016.0	4800000	Unknown
205561	206910	zgn vuurxwvmrt	586e06d65892218f96debd87457bc127de3cae87dd0edf32f1ec3b50bc2c1321	2019.0	700000	Unknown
205564	206913	vbvkgz	f4415be48a1ef885e086dcd72181f667a289641e66f828159d7154228a9b9a95	2014.0	3800000	Unknown
205568	206917	zgn vuurxwvmrt	fe34477c3f64e6ed4301417c8fb9d5e2608722a10f1f4e5cf7872038bbb98b31	2021.0	800000	Unknown
205572	206921	zgn vuurxwvmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c819ec41f6af222a8699	2019.0	5100000	Unknown

21136 rows × 14 columns

```
agg_data_company_job = df.groupby(['company_hash', 'job_position']).agg({
    'ctc':['mean','median','max','min']
})
agg_data_company_job = agg_data_company_job.reset_index()
agg_data_company_job.columns = [' '.join(col).strip() for col in agg_data_company_job.columns.values]
agg_data_company_job
```

	company_hash	job_position	ctc mean	ctc median	ctc max	ctc min
0	0	Other	100000.0	100000.0	100000	100000
1	0	Unknown	100000.0	100000.0	100000	100000
2	0000	Other	300000.0	300000.0	300000	300000
3	01 ojztqsj	Android Engineer	270000.0	270000.0	270000	270000
4	01 ojztqsj	Frontend Engineer	830000.0	830000.0	830000	830000
...	...	...	...	...	...	...
71201	zz	Unknown	500000.0	500000.0	500000	500000
71202	zzb ztdnstz vacxogqj ucn rna	FullStack Engineer	600000.0	600000.0	600000	600000
71203	zzb ztdnstz vacxogqj ucn rna	Unknown	600000.0	600000.0	600000	600000
71204	zzgato	Unknown	130000.0	130000.0	130000	130000
71205	zzzbzb	Other	720000.0	720000.0	720000	720000

71206 rows × 6 columns

```
# merge these values with df_comparison
df_comparison2 = df_comparison.merge(agg_data_company_job, on=['company_hash','job_position'], how='left')
df_comparison2
```

	id	company_hash	email_hash	orgyear	ctc	job_position	c
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618caea697c87af	2016.0	1100000	Other	
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a92bdcc0407b	2018.0	449999	FullStack Engineer	
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9df6b37b9059	2015.0	2000000	Backend Engineer	
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58a44274d5d6876dfec7	2017.0	700000	Backend Engineer	
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520214b31b95211adb095	2017.0	1400000	FullStack Engineer	
...	...	...	...	...	...	...	
205569	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b6e8d7cb06af04e0c05	2008.0	220000	Unknown	
205570	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b4264c8e881b4a61cdb53	2017.0	500000	Unknown	

Flag Class calculation

```
df_comparison2['ctc_flag_mean_job'] = df_comparison2.apply(categorize_ctc, args=('ctc mean_y',), axis=1)
df_comparison2['ctc_flag_median_company'] = df_comparison2.apply(categorize_ctc, args=('ctc median_y',), axis=1)
df_comparison2
```

	id	company_hash	email_hash	orgyear	ctc	job_position	c
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618caea697c87af	2016.0	1100000	Other	
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a92bdcc0407b	2018.0	449999	FullStack Engineer	
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9df6b37b9059	2015.0	2000000	Backend Engineer	
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58a44274d5d6876dfec7	2017.0	700000	Backend Engineer	
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520214b31b95211adb095	2017.0	1400000	FullStack Engineer	
...	...	...	...	...	...	...	
205569	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b6e8d7cb06af04e0c05	2008.0	220000	Unknown	
205570	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b4264c8e881b4a61cdb53	2017.0	500000	Unknown	
205571	206920	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c8852b58da2fde5e00c	2021.0	700000	Unknown	
205572	206921	zgn vuurxwvmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c819ec41f6af222a8699	2019.0	5100000	Unknown	
205573	206922	bgqsvz onvzrtj	0bcfc1d05f2e8dc4147743a1313aa70a119b41b30d4a1f7e738a6a87d3712c31	2014.0	1240000	Unknown	

205574 rows × 20 columns

```
# aggregating based on only company
agg_data_company = df.groupby(['company_hash']).agg({
    'ctc':['mean','median','max','min']
})
agg_data_company = agg_data_company.reset_index()
agg_data_company.columns = [' '.join(col).strip() for col in agg_data_company.columns.values]
agg_data_company
```

	company_hash	ctc mean	ctc median	ctc max	ctc min
0	0	100000.0	100000.0	100000	100000
1	0000	300000.0	300000.0	300000	300000

```
# merge these values with df_comparison
df_manual_clustering = df_comparison2.merge(agg_data_company, on=['company_hash'], how='left')
df_manual_clustering
```

	id	company_hash	
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618c
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58a44274d
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520214b31b
...	...	...	
205569	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b6e8d7cb
205570	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b4264c8e88
205571	206920	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c8852b58
205572	206921	zgn vuurxwvmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c819ec41f
205573	206922	bgqsvz onvzrtj	0bcfc1d05f2e8dc4147743a1313aa70a119b41b30d4a1f7e738a6

205574 rows × 24 columns

Flag Tier calculation

```
df_manual_clustering['ctc_flag_mean_company'] = df_manual_clustering.apply(categorize_ctc, args=('ctc mean',), axis=1)
df_manual_clustering['ctc_flag_median_company'] = df_manual_clustering.apply(categorize_ctc, args=('ctc median',), axis=1)
df_manual_clustering['CTC_updated_in_years'] = df_manual_clustering['ctc_updated_year'] - df_manual_clustering['orgyear']
df_manual_clustering
```

	id	company_hash	
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618c
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58a44274d
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520214b31b
...	...	...	
205569	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b6e8d7cb
205570	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b4264c8e88
205571	206920	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c8852b58
205572	206921	zgn vuurxwvmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c819ec41f
205573	206922	bgqsvz onvzrtj	0bcfc1d05f2e8dc4147743a1313aa70a119b41b30d4a1f7e738a6

205574 rows × 26 columns

```
Based on the manual clustering done so far, answering few questions like:
Top 10 employees (earning more than most of the employees in the company) - Tier 1
Top 10 employees of data science in Amazon / TCS etc earning more than their peers - Class 1
Bottom 10 employees of data science in Amazon / TCS etc earning less than their peers - Class 3
```

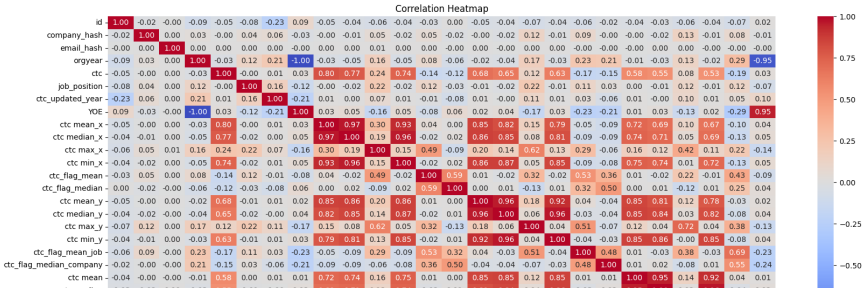
```
Bottom 10 employees (earning less than most of the employees in the company)- Tier 3
Top 10 employees in Amazon- X department - having 5/6/7 years of experience earning more than their peers - Tier X
Top 10 companies (based on their CTC)
Top 2 positions in every company (based on their CTC)
```

```
df_manual_clustering
```

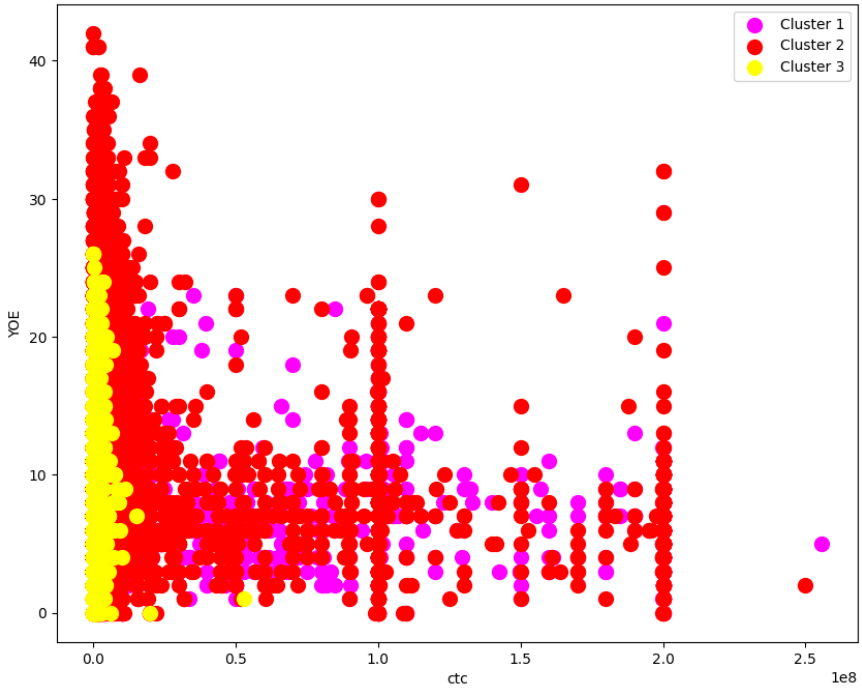
	id	company_hash	
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618c
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e90fd66c9
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58a44274d
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520214b31b
...	...	...	
205569	206918	vuurt xzw	70027b728c8ee901fe979533ed94ffda97be08fc23f33b6e8d7cb
205570	206919	husqvawgb	7f7292ffad724ebbe9ca860f515245368d714c84705b4264c8e88
205571	206920	vwwgrxnt	cb25cc7304e9a24facda7f5567c7922ffc48e3d5d6018c8852b58
205572	206921	zgn vuurxwvmrt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c819ec41f
205573	206922	bgqsvz onvzrtj	0bcfc1d05f2e8dc4147743a1313aa70a119b41b30d4a1f7e738a6

205574 rows × 26 columns

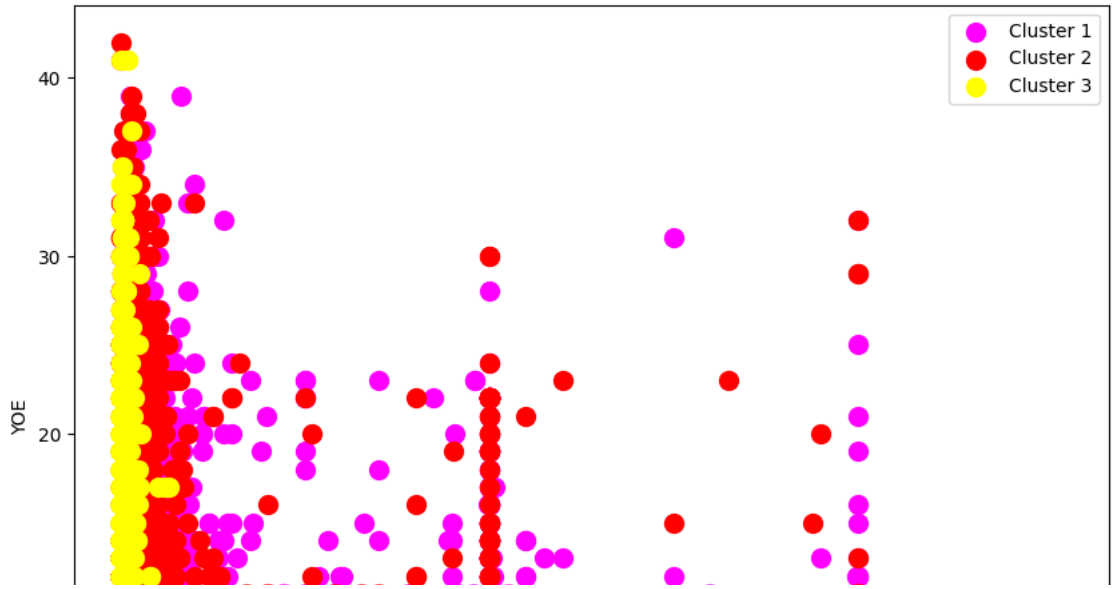
```
# labeling

label_encoder = LabelEncoder()
df_manual_clustering_scaled = df_manual_clustering.copy()

# Fit the encoder on the categorical data and transform the data
df_manual_clustering_scaled['company_hash'] = label_encoder.fit_transform(df_manual_clustering_scaled['company_hash'])
df_manual_clustering_scaled['email_hash'] = label_encoder.fit_transform(df_manual_clustering_scaled['email_hash'])
df_manual_clustering_scaled['job_position'] = label_encoder.fit_transform(df_manual_clustering_scaled['job_position'])


correlation_matrix = df_manual_clustering_scaled.corr()


plt.figure(figsize=(20, 8))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()
```



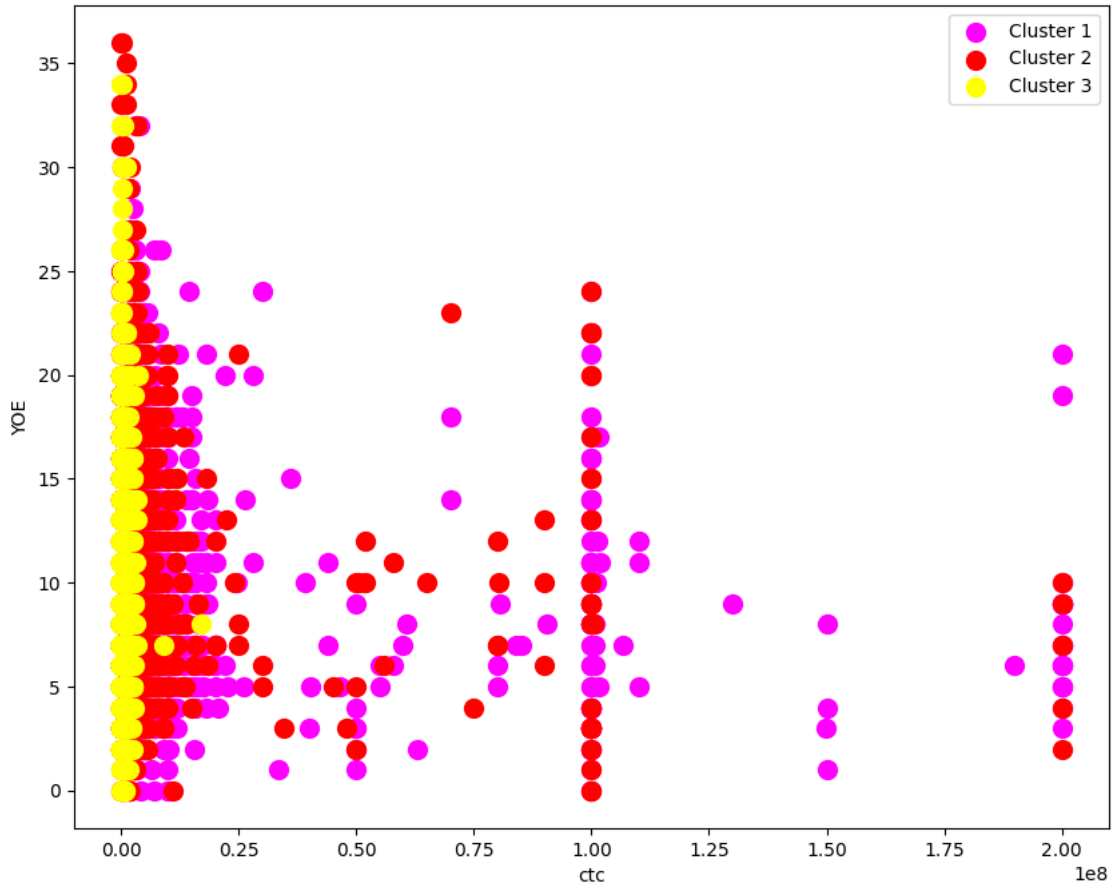

```
fig, ax = plt.subplots(figsize=(10,8))
plt.scatter(df_manual_clustering_scaled[df_manual_clustering_scaled['ctc_flag_mean'] == 1]['ctc'], df_manual_clustering_scale
plt.scatter(df_manual_clustering_scaled[df_manual_clustering_scaled['ctc_flag_mean'] == 2]['ctc'], df_manual_clustering_scale
plt.scatter(df_manual_clustering_scaled[df_manual_clustering_scaled['ctc_flag_mean'] == 3]['ctc'], df_manual_clustering_scale

plt.xlabel('ctc')
plt.ylabel('YOE')
plt.legend()
plt.show()
```




```
fig, ax = plt.subplots(figsize=(10,8))
plt.scatter(df_manual_clustering_scaled[df_manual_clustering_scaled['ctc_flag_mean_company'] == 1]['ctc'], df_manual_clusteri
plt.scatter(df_manual_clustering_scaled[df_manual_clustering_scaled['ctc_flag_mean_company'] == 2]['ctc'], df_manual_clusteri
plt.scatter(df_manual_clustering_scaled[df_manual_clustering_scaled['ctc_flag_mean_company'] == 3]['ctc'], df_manual_clusteri

plt.xlabel('ctc')
plt.ylabel('YOE')
plt.legend()
plt.show()
```




```
# also lets see for any particular job position
df_job = df_manual_clustering_scaled[df_manual_clustering_scaled['job_position']==140]
fig, ax = plt.subplots(figsize=(10,8))
plt.scatter(df_job[df_job['ctc_flag_mean_job'] == 1]['ctc'], df_job[df_job['ctc_flag_mean_job'] == 1]['YOE'], s=100, c='Magen
plt.scatter(df_job[df_job['ctc_flag_mean_job'] == 2]['ctc'], df_job[df_job['ctc_flag_mean_job'] == 2]['YOE'], s=100, c='Red',
plt.scatter(df_job[df_job['ctc_flag_mean_job'] == 3]['ctc'], df_job[df_job['ctc_flag_mean_job'] == 3]['YOE'], s=100, c='Yello

plt.xlabel('ctc')
plt.ylabel('YOE')
plt.legend()
plt.show()
```



- Manual clustering doesnot create clean clusters.

  We had used mean/median of CTC in company / company & job role / company, job role & YOE to create 3 flags used as prediction label to cluster above.

  We also see strong correlation between CTC updation in years & Years of Experience. Also between CTC & CTC mean in company.

```
# get top 10 companies
top_10_companies = df_manual_clustering.nlargest(10, 'ctc mean_y')['company_hash']
top_10_companies.values
```

```
array(['aveegaxr xzntqzvnxgzvr hzxctqoxnj', 'oxburjyq ogrhnxgzo rru',
       'ihvrxnvo srgmvr rru', 'uvqp wgbuhntq ojontb xzw',
       'xfgqp ntwyzgrgsxto', 'outwnqt vzvrjnxwv', 'twgbtduqtoo',
       'ofvr xzegntwy ucn rna', 'nvrtzn ouvwt xzw', 'zxoyvzn wgbuhntqo'],
      dtype=object)
```

```
filtered_df = df_manual_clustering[df_manual_clustering['ctc_flag_mean_company'] == 1]
distinct_values = filtered_df['company_hash'].unique()
print(distinct_values)
```

```
['bgsrxd' 'nxbto xzntqztn' 'qxenxg' ... 'ujut ntwyzgrgsxto' 'nvqvbo'
 'oyguwg']
```

```
# get top 2 job positions
top_2_positions = df_manual_clustering.nlargest(3, 'ctc mean_y')['job_position']
distinct_positions = top_2_positions.unique()
distinct_positions
```

```
array(['Unknown', 'Support Engineer', 'QA Engineer'], dtype=object)
```

```
filtered_df = df_manual_clustering[df_manual_clustering['ctc_flag_mean_job'] == 1]
distinct_values = filtered_df['job_position'].unique()
print(distinct_values)
```

```
['FullStack Engineer' 'Backend Engineer' 'Unknown' 'Frontend Engineer'
 'Android Engineer' 'QA Engineer' 'Other' 'Data Scientist'
 'Support Engineer' 'Data Analyst' 'SDET' 'Engineering Leadership'
 'Engineering Intern' 'Devops Engineer' 'Research Engineers'
 'iOS Engineer' 'Database Administrator' 'Product Manager' 'Co-founder'
 'Student' 'Program Manager' 'Backend Architect' 'Release Engineer'
 'Product Designer' 'Software Development Engineer - II' 'Non Coder'
 'Engineer' 'Security Leadership' 'Associate' 'Project Engineer'
 'System Engineer' 'project engineer' 'SDE II'
 'Business Technology Analyst' 'Software Engineer (Backend)' 'SDE 1'
 'SDE 2' 'Software Engineer 2' 'SDE-1' 'Fullstack Engineer' 'Na' 'None'
 'Software Development Engineer - I'
 'Application development senior analyst'
 'Assistant System Engineer Trainee' 'SDE2' 'Associate Consultant'
 'Software Development Engineer Intern' 'Senior  Software Engineer'
 'MTS-2' 'Teaching Assistant' 'Sr Software Engineer']
```

```
## Get the top 10 employees
sorted_df = df_manual_clustering.sort_values(by='ctc', ascending=False)
top_10_employees = sorted_df['id'].head(10)
top_10_employees.values
```

```
array([117948,   3301,   9763, 103894,  16603,  20196,  90189,  10405,
        60429,    836])
```

```
filtered_df = df_manual_clustering[df_manual_clustering['ctc_flag_mean'] == 1]
distinct_values = filtered_df['id'].unique()
print(distinct_values)
```

```
[    17     25     38 ... 206887 206900 206916]
```

```
## Get the bottom 10 employees
sorted_df = df_manual_clustering.sort_values(by='ctc', ascending=True)
bottom_10_employees = sorted_df['id'].head(10)
bottom_10_employees.values
```

```
array([135886, 118549, 114452, 185851, 184706,  54885,  91723, 117256,
       167115,  82161])
```

```
filtered_df = df_manual_clustering[df_manual_clustering['ctc_flag_mean'] == 3]
distinct_values = filtered_df['id'].unique()
print(distinct_values)
```

```
[    14     20     59 ... 206910 206917 206919]
```

```
## Get the top 10 employees by job position
sorted_df = df_manual_clustering.sort_values(by='ctc mean_x', ascending=False)
top_10_employees = sorted_df['id'].head(10)
top_10_employees.values
```

```
array([ 3301, 23067, 12612,  2824, 20196, 29753,   361, 20184,  2793,
       22640])
```

```
filtered_df = df_manual_clustering[df_manual_clustering['ctc_flag_mean_job'] == 1]
distinct_values = filtered_df['id'].unique()
print(distinct_values)
```

```
[     4     15     17 ... 206876 206887 206903]
```

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

df_filtered = df_manual_clustering[(df_manual_clustering['YOE'] >= 5) & (df_manual_clustering['YOE'] <= 7) & (df_manual_clust

df_sorted = df_filtered.sort_values(by=['ctc', 'job_position'], ascending=[False, True])

top_10_employees = df_filtered.groupby(['company_hash'], group_keys=True).apply(
    lambda x: x.nlargest(10, 'ctc')
)

top_10_employees
```

		id	company_hash	email_hash	orgyear	ctc	jo
company_hash							
01 ojztqsj	**74315**	74535	01 ojztqsj	819789ff4068fd5c8facf8a5074cdd2e1ff989c95ae02c02b81ac1447cbd6386	2016.0	270000	
1bs	**128317**	128911	1bs	9977fcf096a81795abeb0829760e399a0a7a727ebf8bbb2f975a66dbac3c5326	2017.0	700000	
	138145	138817	1bs	9977fcf096a81795abeb0829760e399a0a7a727ebf8bbb2f975a66dbac3c5326	2017.0	700000	
	167432	168383	1bs	d0d06e9bb510f55e1e26e25cc8e1f6dfbe31384d3864a5bbb5bf7e3c3a21ebc7	2017.0	700000	
	205082	206430	1bs	6eb6cb9918e8eceb347c37797a75e08f94c2050b857258f10609799502151a83	2018.0	700000	
...	**...**	...	...	...	...	...	
zxzlvwvqn	**33776**	33885	zxzlvwvqn	4b083429e503553fb88ede06604aceccef192b2501226318f00d9eebdcde748b	2017.0	600000	
	57419	57586	zxzlvwvqn	4b083429e503553fb88ede06604aceccef192b2501226318f00d9eebdcde748b	2017.0	600000	
	56282	56447	zxzlvwvqn	d22eddf77b769126fdb8f25fe69489204d7f1b8fe18bb12b8ffbd0522c3e24c5	2017.0	500000	
zxztrtvuo	**196545**	197815	zxztrtvuo	b5628c03989a151f60c89e726351817c3a62078e7c70deb9351e3b51c69c012f	2016.0	575000	
	17377	17423	zxztrtvuo	41367fd92cd85ecfa2e2ce76f4ff94cde287b95df93871713fe4f52c7c61c000	2018.0	570000	

7771 rows × 21 columns

Clustering using KMeans, GMM & Hierarchical methods

```
df = df_manual_clustering.copy()
df
```

	id	company_hash	
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c050c0618c
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c100a9661a

```
# Create a LabelEncoder object
label_encoder = LabelEncoder()

# Fit the encoder on the categorical data and transform the data
df['company_hash'] = label_encoder.fit_transform(df['company_hash'])
df['email_hash'] = label_encoder.fit_transform(df['email_hash'])
df['job_position'] = label_encoder.fit_transform(df['job_position'])
df
```

	id	company_hash	email_hash	orgyear	ctc	job_position	ctc_up
0	0	967	65689	2016.0	1100000	458	
1	1	19690	105755	2018.0	449999	292	
2	2	15482	43239	2015.0	2000000	140	
3	3	12085	143658	2017.0	700000	140	
4	4	20186	66892	2017.0	1400000	292	
...	...	...	...	...	...	...	
205569	206918	28705	66934	2008.0	220000	954	
205570	206919	8491	76135	2017.0	500000	954	
205571	206920	29038	121480	2021.0	700000	954	
205572	206921	35968	150460	2019.0	5100000	954	
205573	206922	2164	7274	2014.0	1240000	954	

205574 rows × 21 columns

```
df.columns
```

```
Index(['id', 'company_hash', 'email_hash', 'orgyear', 'ctc', 'job_position',
       'ctc_updated_year', 'YOE', 'ctc mean_x', 'ctc median_x', 'ctc max_x',
       'ctc min_x', 'ctc_flag_mean', 'ctc_flag_median', 'ctc mean_y',
       'ctc median_y', 'ctc max_y', 'ctc min_y', 'ctc_flag_mean_company',
       'ctc_flag_median_company', 'CTC_updated_in_years'],
      dtype='object')
```

PCA

```
df_cluster_pca = df[['job_position', 'ctc', 'YOE', 'ctc mean_x', 'ctc mean_y', 'CTC_updated_in_years']] # we will cluster bas
df_cluster_pca
```

	job_position	ctc	YOE	ctc mean_x	ctc mean_y	CTC_updated_in_years
0	458	1100000	7.0	1.100000e+06	1.115667e+06	4.0
1	292	449999	5.0	7.742856e+05	2.197334e+06	1.0
2	140	2000000	8.0	2.000000e+06	2.000000e+06	5.0
3	140	700000	6.0	1.158571e+06	1.713929e+06	2.0
4	292	1400000	6.0	1.400000e+06	9.400000e+05	2.0
...	...	...	...	...	...	...
205569	954	220000	15.0	2.200000e+05	1.681941e+06	11.0
205570	954	500000	6.0	1.150000e+06	2.119245e+06	3.0
205571	954	700000	2.0	6.666667e+05	1.404485e+06	0.0
205572	954	5100000	4.0	5.920732e+06	5.477717e+06	0.0
205573	954	1240000	9.0	1.693333e+06	2.413205e+06	2.0

205574 rows × 6 columns

```
scaler = StandardScaler()
X_cluster_pca = scaler.fit_transform(df_cluster_pca)
X_cluster_pca
```

```
array([[-0.03633311, -0.10041986, -0.20925941, -0.12594359, -0.17140339,
        -0.12336313],
       [-0.54040269, -0.15657538, -0.68269025, -0.16123523, -0.00972009,
        -0.84614513],
       [-1.00196037, -0.02266618,  0.02745601, -0.02842725, -0.03921674,
         0.1175642 ],
       ...,
       [ 1.46980251, -0.13497705, -1.39283651, -0.1728959 , -0.12823194,
        -1.08707246],
       [ 1.46980251,  0.24515205, -0.91940567,  0.39638993,  0.4806186 ,
        -1.08707246],
       [ 1.46980251, -0.08832484,  0.26417143, -0.06165504,  0.0225475 ,
        -0.60521779]])
```

```
cov_X_st = np.matmul(X_cluster_pca.T, X_cluster_pca)/(len(X_cluster_pca)-1)
```

```
eigenvalues, eigenvectors = np.linalg.eig(cov_X_st)
print(eigenvalues)
print(eigenvectors)
```

```
[2.41261484 1.96065299 0.98237182 0.42782339 0.048669   0.16789715]
[[-0.01453905  0.1379314   0.9896253  -0.00891342 -0.03631253  0.00269483]
 [ 0.56692195  0.07530792 -0.00638234 -0.62166935 -0.00199121 -0.53517357]
 [ 0.0955654  -0.69547896  0.07244463  0.0093261  -0.70838454 -0.0056926 ]
 [ 0.60361524  0.0773669  -0.00520254 -0.11587351 -0.00289174  0.78498465]
 [ 0.54332995  0.08680309  0.00375237  0.77453531  0.00116475 -0.31198942]
 [ 0.09847122 -0.69144215  0.12374029  0.00540191  0.7048823  -0.00335797]]
```

```
(eigenvalues[0]+eigenvalues[1]+eigenvalues[2])  / eigenvalues.sum()
```

```
0.8926022665385465
```

```
eigenvectors = eigenvectors.T
X_prime = eigenvectors[0].dot(X_cluster_pca.T)
X_prime_reduced = X_prime
print(X_prime_reduced)
```

```
[-0.25769772 -0.33207685 -0.02254862 ... -0.51207817  0.4231053
 -0.1307589 ]
```

```
from sklearn import decomposition
pca = decomposition.PCA(n_components=3)
pcafit = pca.fit(X_cluster_pca)
percentExplained = pca.explained_variance_ratio_.sum()
print(percentExplained)
```

```
0.8926022665385476
```

```
principal_components = pca.fit_transform(X_cluster_pca)
principal_components
```

```
array([[-0.25769772, -0.19363789, -0.0657279 ],
       [-0.33207685, -0.96020924, -0.68715398],
       [-0.02254862,  0.24589612, -0.97488347],
       ...,
       [-0.51207817, -1.88839593,  1.22041535],
       [ 0.4231053 , -1.68465546,  1.25160966],
       [-0.1307589 , -0.4280149 ,  1.39977081]])
```

Clustering using CTC & YOE for job position

```
df = df[['job_position', 'ctc', 'YOE']] # we will cluster based on CTC & YOE
df
```

	job_position	ctc	YOE
0	458	1100000	7.0
1	292	449999	5.0
2	140	2000000	8.0
3	140	700000	6.0
4	292	1400000	6.0
...	...	...	...

```
df.isna().sum()
```

```
job_position    0
ctc             0
YOE             0
dtype: int64
```

```
X = df
```

```
# Standardisation
# lets do standard scaling now
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_scaled
```

```
array([[-0.03633311, -0.10041986, -0.20925941],
       [-0.54040269, -0.15657538, -0.68269025],
       [-1.00196037, -0.02266618,  0.02745601],
       ...,
       [ 1.46980251, -0.13497705, -1.39283651],
       [ 1.46980251,  0.24515205, -0.91940567],
       [ 1.46980251, -0.08832484,  0.26417143]])
```

Silhouette Score

```
from sklearn.metrics import silhouette_score
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
```

```
# Checking clustering tendency
silhouette_avg = silhouette_score(X, KMeans(n_clusters=4).fit_predict(X))
print(f'Silhouette Score for original data: {silhouette_avg:.2f}')
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
Silhouette Score for original data: 0.97
```

A high Silhouette Score indicates that the object is well matched to its own cluster and poorly matched to neighboring clusters. This suggests that the clustering is appropriate.

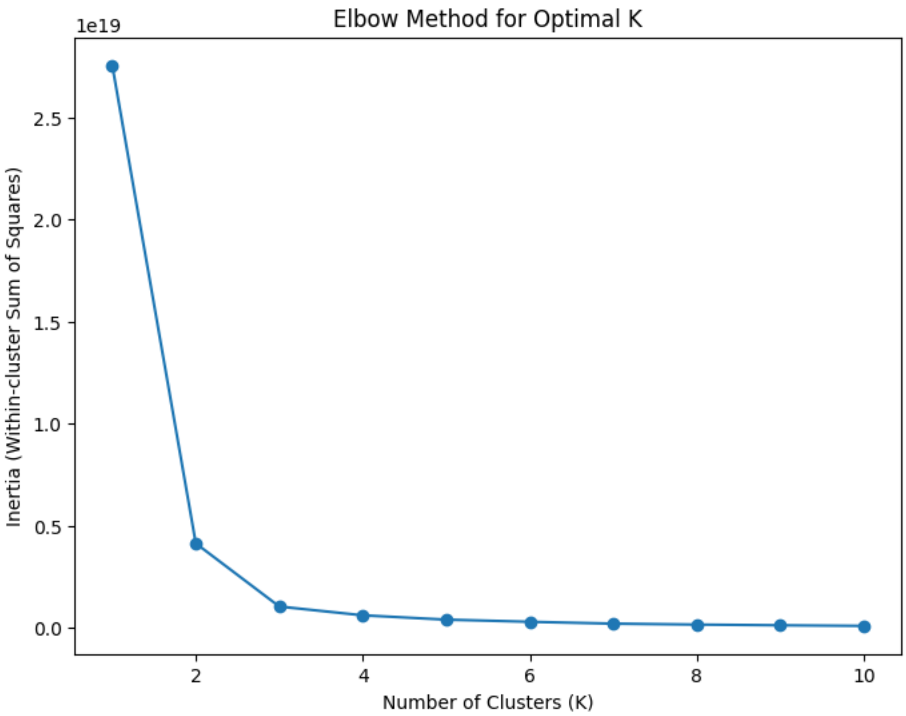
KMeans & Elbow method to find no of clusters to create

```
# Elbow method to find the optimal number of clusters
inertia = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X)
    inertia.append(kmeans.inertia_)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
```

```
# Plot the Elbow curve
plt.figure(figsize=(8, 6))
plt.plot(range(1, 11), inertia, marker='o')
plt.title('Elbow Method for Optimal K')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Inertia (Within-cluster Sum of Squares)')
plt.show()
```



Based on the Elbow method, let's choose K=4

```
from sklearn.cluster import KMeans

k = 4
kmeans = KMeans(n_clusters=k, init = 'k-means++')
y_pred = kmeans.fit_predict(X_scaled)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` wil
  warnings.warn(
```

```
# from sklearn.cluster import KMeans

# k = 4
# kmeans = KMeans(n_clusters=k, init = 'k-means++')
# y_pred = kmeans.fit_predict(principal_components)
```

On testing with PCA components, the results were not very good!!

```
df['predicted_label'] = y_pred
```

```
<ipython-input-119-60de8de49a36>:1: 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
```

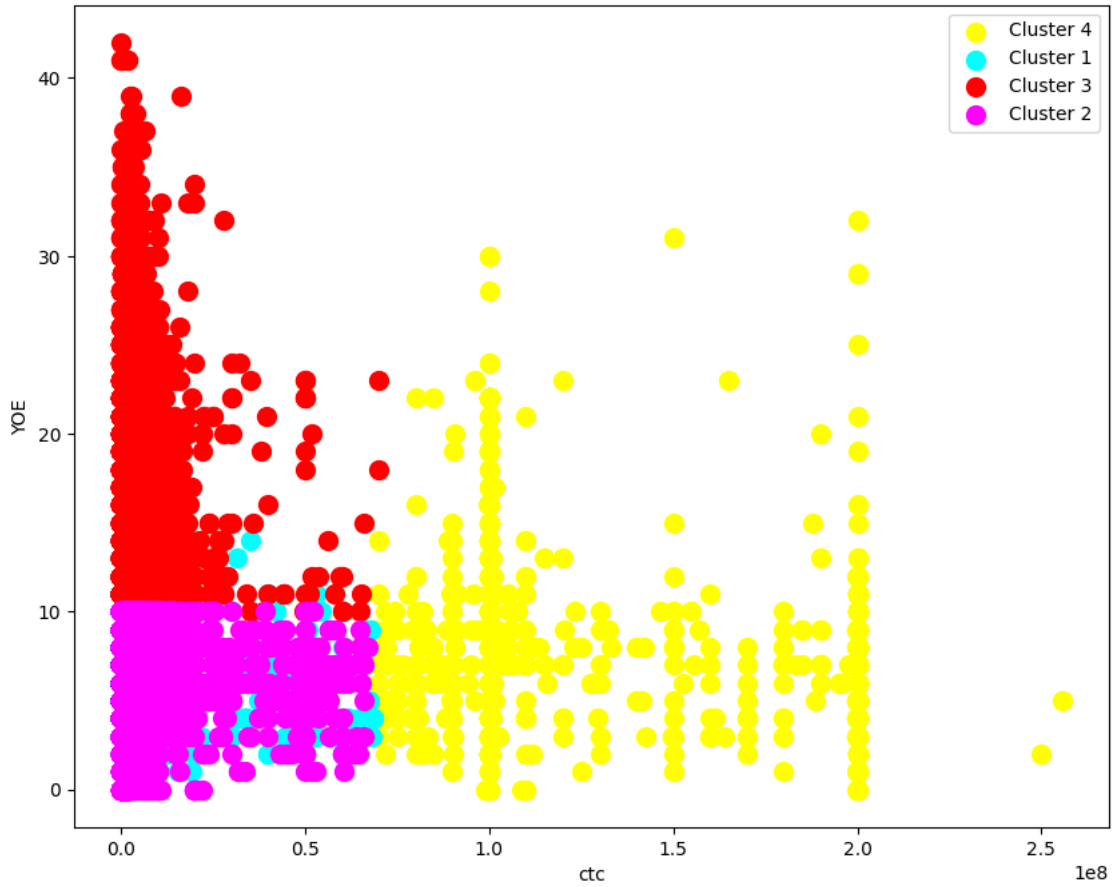
```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-
  df['predicted_label'] = y_pred
```

```
df
```

	job_position	ctc	YOE	predicted_label
0	458	1100000	7.0	1
1	292	449999	5.0	1
2	140	2000000	8.0	1
3	140	700000	6.0	1
4	292	1400000	6.0	1
...	...	...	...	...
205569	954	220000	15.0	2
205570	954	500000	6.0	0
205571	954	700000	2.0	0
205572	954	5100000	4.0	0
205573	954	1240000	9.0	0

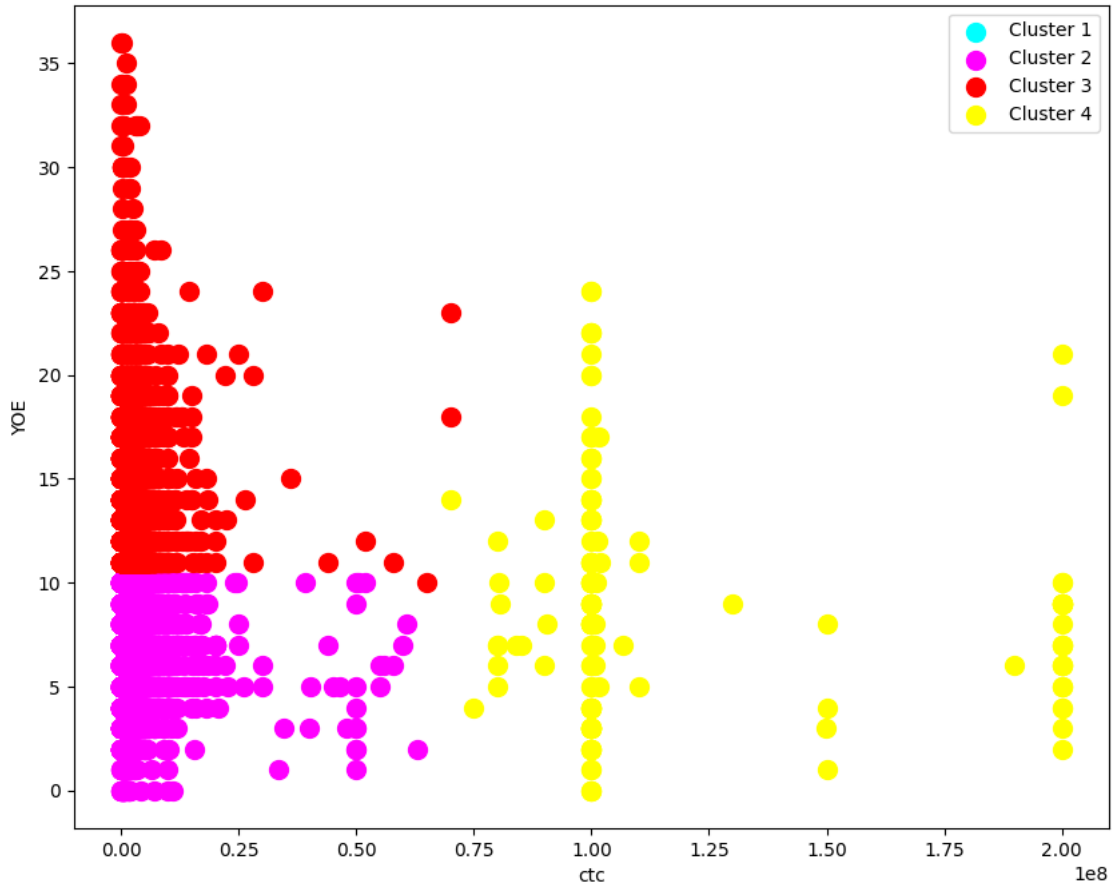
205574 rows × 4 columns

```
fig, ax = plt.subplots(figsize=(10,8))
plt.scatter(df[df['predicted_label'] == 3]['ctc'], df[df['predicted_label'] == 3]['YOE'], s=100, c='Yellow', label = 'Cluster
plt.scatter(df[df['predicted_label'] == 0]['ctc'], df[df['predicted_label'] == 0]['YOE'], s=100, c='Cyan', label = 'Cluster 1
plt.scatter(df[df['predicted_label'] == 2]['ctc'], df[df['predicted_label'] == 2]['YOE'], s=100, c='Red', label = 'Cluster 3'
plt.scatter(df[df['predicted_label'] == 1]['ctc'], df[df['predicted_label'] == 1]['YOE'], s=100, c='Magenta', label = 'Cluste

plt.xlabel('ctc')
plt.ylabel('YOE')
plt.legend()
plt.show()
```




```
# also lets see for any particular job position
df_job = df[df['job_position']==140]
fig, ax = plt.subplots(figsize=(10,8))
plt.scatter(df_job[df_job['predicted_label'] == 0]['ctc'], df_job[df_job['predicted_label'] == 0]['YOE'], s=100, c='Cyan', la
```

```
plt.scatter(df_job[df_job['predicted_label'] == 1]['ctc'], df_job[df_job['predicted_label'] == 1]['YOE'], s=100, c='Magenta',
plt.scatter(df_job[df_job['predicted_label'] == 2]['ctc'], df_job[df_job['predicted_label'] == 2]['YOE'], s=100, c='Red', lab
plt.scatter(df_job[df_job['predicted_label'] == 3]['ctc'], df_job[df_job['predicted_label'] == 3]['YOE'], s=100, c='Yellow',

plt.xlabel('ctc')
plt.ylabel('YOE')
plt.legend()
plt.show()
```



We see clear boundary of cluster in case of particular job position (which we visualised) but a little overlap in Cluster 2 & Cluster 4

```
X.shape
```

```
(205574, 4)
```

GMM

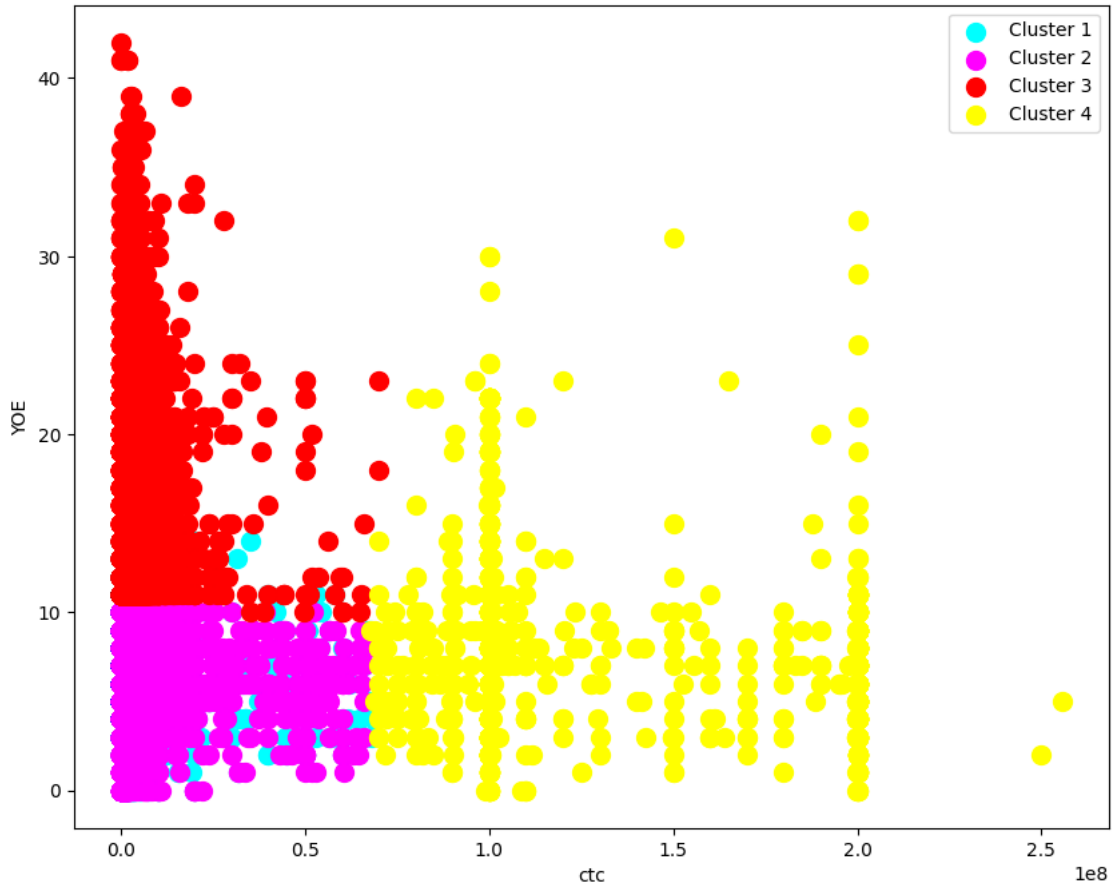
```
from sklearn.mixture import GaussianMixture
gmm = GaussianMixture(n_components=3).fit(X_scaled)
y_pred = gmm.predict(X_scaled)
```

```
df['predicted_label'] = y_pred
```

```
<ipython-input-114-60de8de49a36>:1: 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-
  df['predicted_label'] = y_pred
```

```
fig, ax = plt.subplots(figsize=(10,8))
plt.scatter(df[df['predicted_label'] == 0]['ctc'], df[df['predicted_label'] == 0]['YOE'], s=100, c='Cyan', label = 'Cluster 1
plt.scatter(df[df['predicted_label'] == 1]['ctc'], df[df['predicted_label'] == 1]['YOE'], s=100, c='Magenta', label = 'Cluste
plt.scatter(df[df['predicted_label'] == 2]['ctc'], df[df['predicted_label'] == 2]['YOE'], s=100, c='Red', label = 'Cluster 3'
plt.scatter(df[df['predicted_label'] == 3]['ctc'], df[df['predicted_label'] == 3]['YOE'], s=100, c='Yellow', label = 'Cluster

plt.xlabel('ctc')
plt.ylabel('YOE')
```

```
plt.legend()
plt.show()
```




```
# also lets see for any particular job position
df_job = df[df['job_position']==140]
fig, ax = plt.subplots(figsize=(10,8))
plt.scatter(df_job[df_job['predicted_label'] == 0]['ctc'], df_job[df_job['predicted_label'] == 0]['YOE'], s=100, c='Cyan', la
plt.scatter(df_job[df_job['predicted_label'] == 1]['ctc'], df_job[df_job['predicted_label'] == 1]['YOE'], s=100, c='Magenta',
plt.scatter(df_job[df_job['predicted_label'] == 2]['ctc'], df_job[df_job['predicted_label'] == 2]['YOE'], s=100, c='Red', lab
plt.scatter(df_job[df_job['predicted_label'] == 3]['ctc'], df_job[df_job['predicted_label'] == 3]['YOE'], s=100, c='Yellow',

plt.xlabel('ctc')
plt.ylabel('YOE')
plt.legend()
plt.show()
```

Using GMM, we see more than 10 Lakhs CTC seems to be clustered as Cluster 3 with no variation due to YOE. For other clusters we see 0-15, 15-25 & 25+ YOE cluster within 10 Lakhs CTC.

```
df_job.shape
```

```
(43521, 4)
```

```
sampled_X = df.sample(n=5000) # using 5000 columns to do Hierarchial Clustering
sampled_X
```

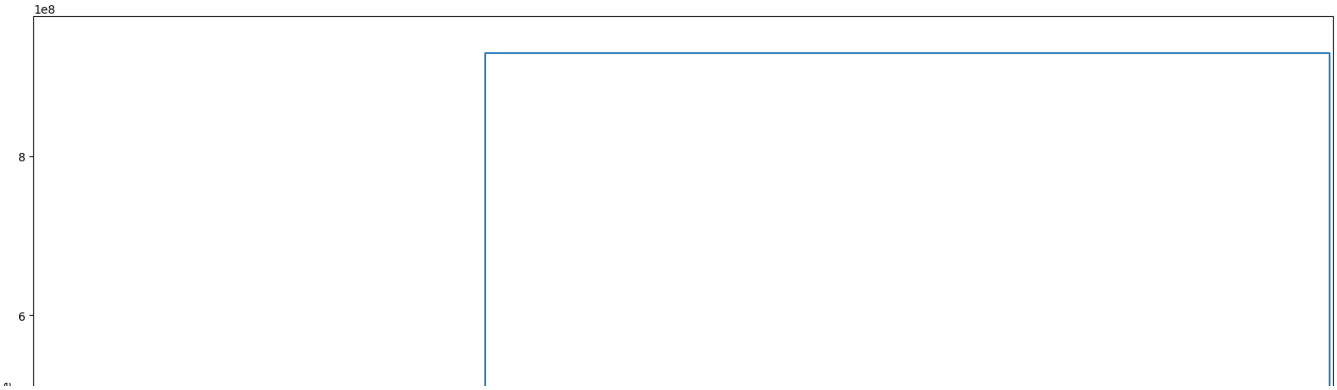
	job_position	ctc	YOE
50879	140	145000	6.0
92967	140	700000	6.0
85651	140	2400000	10.0
65467	287	930000	10.0
63279	140	1650000	7.0
...	...	...	...
85268	954	1500000	3.0
26380	954	630000	3.0
188433	292	1050000	4.0
89863	292	1350000	8.0
47638	954	850000	8.0

5000 rows × 3 columns

Hierarchical clustering

```
import scipy.cluster.hierarchy as sch
Z = sch.linkage(sampled_X, method='ward') #linkage = ward


fig, ax = plt.subplots(figsize=(20, 12))
sch.dendrogram(Z, labels=sampled_X.index, ax=ax, color_threshold=2)
plt.xticks(rotation=90)
ax.set_ylabel('distance')
```

```
Text(0, 0.5, 'distance')
```




```
# import hierarchical clustering libraries
from sklearn.cluster import AgglomerativeClustering

# create clusters
agglo = AgglomerativeClustering(n_clusters=4, linkage = 'ward')
y_pred = agglo.fit_predict(sampled_X)
y_pred
```

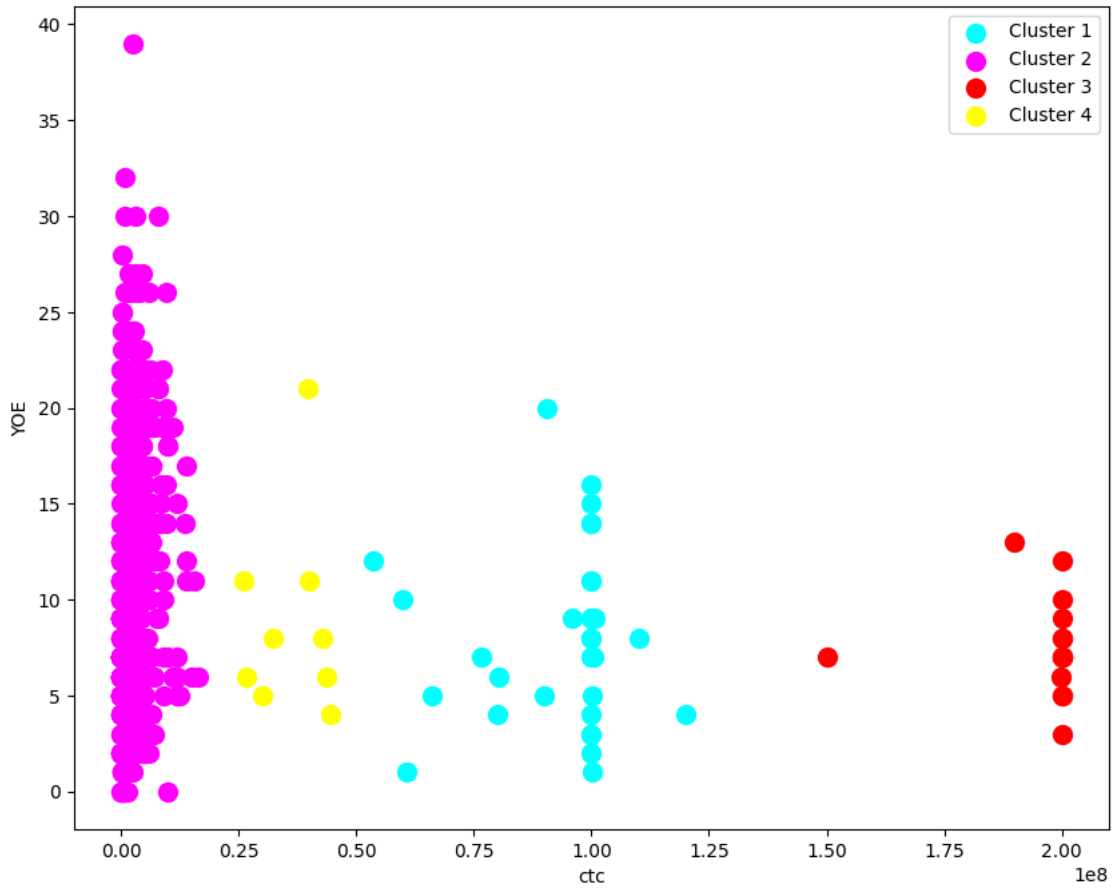
```
viz_df = sampled_X
viz_df['predicted_label'] = y_pred
```

```
#Plot a line graph to see the characteristics of the clusters
viz_df['label'] = pd.Series(y_pred, index=viz_df.index)

clustered_df = viz_df.groupby('label').mean()

labels = ['Cluster 1', 'Cluster 2', 'Cluster 3', 'Cluster 4']

plt.figure(figsize=(14,8))
plt.plot(clustered_df.T, label=labels)
plt.xticks(rotation=90)
plt.legend(labels)
```

```
<matplotlib.legend.Legend at 0x7cae69d6d2a0>
```

1e8

```
fig, ax = plt.subplots(figsize=(10,8))
plt.scatter(viz_df[viz_df['predicted_label'] == 0]['ctc'], viz_df[viz_df['predicted_label'] == 0]['YOE'], s=100, c='Cyan', la
plt.scatter(viz_df[viz_df['predicted_label'] == 1]['ctc'], viz_df[viz_df['predicted_label'] == 1]['YOE'], s=100, c='Magenta',
plt.scatter(viz_df[viz_df['predicted_label'] == 2]['ctc'], viz_df[viz_df['predicted_label'] == 2]['YOE'], s=100, c='Red', lab
plt.scatter(viz_df[viz_df['predicted_label'] == 3]['ctc'], viz_df[viz_df['predicted_label'] == 3]['YOE'], s=100, c='Yellow',

plt.xlabel('ctc')
plt.ylabel('YOE')
plt.legend()
plt.show()
```



Insights & Recommendations

1. While doing Manual clustering, we could not see any clear distinction in clusters created using mean/median of CTC. We created Designation Flag, Class Flag & Tier Flag. We were trying to cluster YOE to CTC for clusters created. Although we can use the CTC flag values for top & bottom employees based on job position, company_id and YOE to categorise & finding employees of each cluster. Flag value 1 being top & 3 being bottom.
2. With YOE 8-12 years, CTC has big range with 8 years work experience having most of it. According to data, it doesnot matter on YOE for CTC, CTC ranges depend on other things also. Data for 8-12 YOE is also more.
3. There is negative correlation between CTC updated year & YOE. It makes sense that CTC updation decreases as YOE increases. Promotion to Manager/Sr Manager takes more years.
4. Mostly people got increment (ctc updated) in years 2019 to 2021. Although, people have been working from 2009-2021 (orgyear). This may be inferred that these 3 years market was very good.
5. Mostly dataset contains data with people having 3-12 years of experience. We can try to collect data for other experience years. Also, density of data is not consistent, we can use SMOTE to tackle it but prefer to have original data as it is unssupervised learning.
6. While we did Clustering using KMeans, we found that ideal clusters value of 4 using Elbow method. We see quite good clustering and clean distinctions when K=4. We can infer:
    - Cluster 1 - Employees with less experience and fairly good CTC --> Fairly CTC receiving employees
    - Cluster 2 - Employees having Years of Experience (YOE) as less than 10 years and CTC less than 7.5 Lakhs. ---> Regular employees
    - Cluster 3 - Underpaid employees (less than 7.5 Lakhs CTC) having Years of Experience (YOE) as more than 10 years. --> Underpaid employees
    - Cluster 4 - Employees having CTC more than 7.5 Lakhs CTC. --> High CTC receiving employees

7. We saw similar cluster results while clustering using GMM. When using AgglomerativeClustering, we couldnot train on whole data so trained on 5000 samples only (due to limited RAM & session crash issue), but we see good clusters although on limited data.
8. Looking at clusters and all data, we can recommend company to hire employees based on skills and not YOE as for all clusters we see trend that CTC for each clusters varies more or less across wide range of YOE. Good companies tend to give good CTC irrespective of job position.