

```
import pandas as pd
```

```
data=pd.read_csv("https://d2beiqhkg929f0.cloudfront.net/public_assets/assets/000/002/856/original/scaler_clustering.csv")
```

data

	Unnamed: 0	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
0	0	atpgrnnt xzaxv	6de0a4417d18ab14334c3f43397f13b30c35149d70c05...	2016.0	1100000	Other	2020.0
1	1	qtrvxzwf xzegwgb rxbznta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999	FullStack Engineer	2019.0
2	2	oqjwmvwmx vx	4860c670bcd48fb96c02a4b0ae3608ae6fd98176112e9...	2015.0	2000000	Backend Engineer	2020.0
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	700000	Backend Engineer	2019.0
4	4	qxm sqghu	6ff54e709262f55cb999a1c1db843cb2055d8f79ab520...	2017.0	1400000	FullStack Engineer	2019.0
...	...	...	...	...	...	...	...
205838	206918	vuurt xzw	70027b728c8ee901fe979533ee94ffda97be08fc23f33b...	2008.0	220000	NaN	2019.0
205839	206919	husqvawgh	7f7292ffad724ebb9ca860f51524536a0714c84705b42...	2017.0	500000	NaN	2020.0
205840	206920	vwvgmnt	cb25cc7304e9a24fcd9a7f5567c7922ff048e3d5d6018c...	2021.0	700000	NaN	2021.0
205841	206921	zgn vuunwvmt	fb46a1a2752f5f652ce634f6178d0578ef6995ee59f6c8...	2019.0	5100000	NaN	2019.0
205842	206922	bgqvsv orvrtj	0bdcf1d05f2ebdc4147743a1313aa70a119b41b30d4a1f...	2014.0	1240000	NaN	2016.0

205843 rows × 7 columns

```
data.isna().sum()
```

Unnamed: 0	0
company_hash	44
email_hash	0
orgyear	86
ctc	0
job_position	52564
ctc_updated_year	0

dtype: int64

```
def pk(ctc):
    if ctc>1000000 and ctc<=2000000 :
        return 'A'
    elif ctc>2000000 and ctc<=3000000:
        return 'B'
    elif ctc>3000000 and ctc<=4000000:
        return 'C'
    elif ctc>4000000 and ctc<=6000000:
        return 'C'
    elif ctc>6000000 and ctc<=8000000:
        return 'D'
    elif ctc>8000000 and ctc<=10000000:
        return 'E'
    else:
        return 'F'
```

```
from sklearn.impute import SimpleImputer
```

Start coding or generate with AI.

```
s1=s.fit(data[['orgyear']])
data['orgyear']=s1.transform(data[['orgyear']])
```

```
-----
NameError: Traceback (most recent call last)
<ipython-input-11-42327284899d> in <cell line: 1>()
----> 1 s1=s.fit(data[['orgyear']])
      2 data['orgyear']=s1.transform(data[['orgyear']])
      3
      4
      5
NameError: name 's' is not defined
```

Next steps: [Explain error](#)

```
data['orgyear']
```

0	2016.0
1	2018.0
2	2015.0
3	2017.0
4	2017.0
...	...
205838	2008.0
205839	2017.0
205840	2021.0
205841	2019.0
205842	2014.0

Name: orgyear, Length: 205843, dtype: float64

```
data['job_position']=data['job_position'].fillna(data['job_position'].mode()[0])
```

# creating class

```
data.info()
```

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

dtypes: float64(2), int64(2), object(3)

memory usage: 11.0+ MB

```
data.describe()
```

	Unnamed: 0	orgyear	ctc	ctc_updated_year
count	205843.000000	205757.000000	2.058430e+05	205843.000000
mean	103273.941786	2014.882790	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

```
data.duplicated()
```

0	False
1	False
2	False
3	False
4	False
...	...
205838	False
205839	False
205840	False
205841	False
205842	False

Length: 205843, dtype: bool

```
data.head(5)
```

	Unnamed: 0	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
0	0	atpgrnnt xzaxv	6de0a4417d18ab14334c3f43397f13b30c35149d70c05...	2016.0	1100000	Other	2020.0
1	1	qtrvxzwf xzegwgb rxbznta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.0	449999	FullStack Engineer	2019.0
2	2	oqjwmvwmx vx	4860c670bcd48fb96c02a4b0ae3608ae6fd98176112e9...	2015.0	2000000	Backend Engineer	2020.0
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.0	700000	Backend Engineer	2019.0
4	4	qxm sqghu	6ff54e709262f55cb999a1c1db843cb2055d8f79ab520...	2017.0	1400000	FullStack Engineer	2019.0

```
# manual clustering
# creating designation flag and insights
data['job_position'].unique()

array(['Other', 'FullStack Engineer', 'Backend Engineer', ...,
      'Web / UI Designer', 'Azure data Factory',
      'Android Application developer'], dtype=object)

data['job_position']=data['job_position'].map({'Other':0,'FullStack Engineer':1,'FullStack Engineer':2,'Backend Engineer':3,'Web / UI Designer':4,'Azure data Factory':5,
      'Android Application developer':6,})

data.groupby('job_position')['ctc'].mean()
# thes are average ctc values

job_position
0.0    3.973584e+06
2.0    1.871618e+06
3.0    1.983635e+06
4.0    1.819999e+06
5.0    6.700000e+05
6.0    1.500000e+06
Name: ctc, dtype: float64

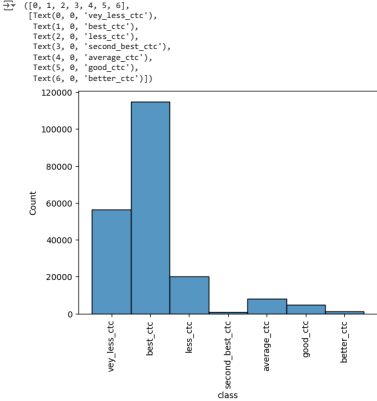
data['ctc'].unique()
array([1100000, 449999, 2000000, ..., 5266000, 234000, 3327000])
```

```
data1=data.copy()

# creating class flag and insights
def lk(ctc):
    if ctc<1000000 and ctc<=2000000 :
        return 'vey_less_ctc'
    elif ctc>2000000 and ctc<=3000000:
        return 'less_ctc'
    elif ctc>3000000 and ctc<=4000000:
        return 'average_ctc'
    elif ctc>4000000 and ctc<=6000000:
        return 'good_ctc'
    elif ctc>6000000 and ctc<=8000000:
        return 'better_ctc'
    elif ctc>8000000 and ctc<=10000000:
        return 'second_best_ctc'
    else:
        return 'best_ctc'
```

```
data['class']=data['ctc'].apply(lk)
import seaborn as sns
```

```
sns.histplot(x=data['class'],data=data)
import matplotlib.pyplot as plt
plt.xticks(rotation=90)
```



# here best ctc is more

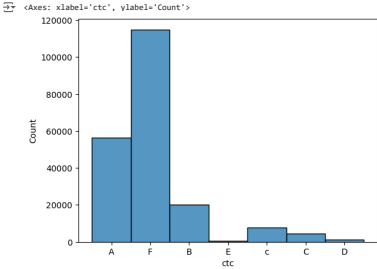
```
# creating tier flag and insights
def pk(ctc):
    if ctc<1000000 and ctc<=2000000 :
        return 'A'
    elif ctc>2000000 and ctc<=3000000:
        return 'B'
    elif ctc>3000000 and ctc<=4000000:
        return 'C'
    elif ctc>4000000 and ctc<=6000000:
        return 'D'
    elif ctc>6000000 and ctc<=8000000:
        return 'E'
    elif ctc>8000000 and ctc<=10000000:
        return 'F'
    else:
        return 'F'
```

```
data['ctc']=data['ctc'].apply(pk)
```

```
l=data['ctc'].value_counts()
l
```

```
ctc
F    114912
A    56489
B    20132
C     7984
D    4621
E    1086
F     699
Name: count, dtype: int64
```

```
import seaborn as sns
sns.histplot(x=data['ctc'])
# the frequency of occurence of f category is more means more people are having ctc greater than 10000000
```



from sklearn.preprocessing import LabelEncoder

Start coding or generate with AI.



	Unnamed: 0	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	
0	0.000000	0.025979	0.428742	0.099975	0.001100	0.000000	0.833333	
1	0.000005	0.528942	0.690261	0.100074	0.000450	0.166667	0.666667	
2	0.000010	0.415856	0.282217	0.099926	0.002000	0.333333	0.833333	
3	0.000014	0.324593	0.937612	0.100025	0.000700	0.333333	0.666667	
4	0.000019	0.542240	0.436608	0.100025	0.001400	0.166667	0.666667	
...	...	...	...	...	...	...	...	
205838	0.999981	0.770825	0.436882	0.099578	0.000220	0.333333	0.666667	
205839	0.999986	0.228103	0.496911	0.100025	0.000500	0.333333	0.833333	
205840	0.999990	0.779753	0.792899	0.100223	0.000700	0.333333	1.000000	
205841	0.999995	0.965978	0.982000	0.100124	0.005099	0.333333	0.666667	
205842	1.000000	0.058098	0.047464	0.099876	0.001240	0.333333	0.166667	

205843 rows × 7 columns

```
from sklearn.cluster import AgglomerativeClustering
```

```
ag=AgglomerativeClustering(n_clusters=3)
```

```
p=ag.fit(data1.head(1500))
```

p

	AgglomerativeClustering
	AgglomerativeClustering(n_clusters=3)

#Business Insights:  
#Talent Profiling: Gain insights into the types of learners attracted to Scalars courses based on their job profiles and company affiliations.  
#Company Preferences: Identify which companies employees are more inclined towards upskilling through Scaler's courses.  
#Course Effectiveness: Evaluate the effectiveness of Scaler's courses by examining learner performance within different clusters.  
#Market Segmentation: Segment the market of potential learners based on their characteristics, allowing for targeted marketing strategies.

# Recommendations:  
#Tailored Course Offerings: Develop specialized courses or modules tailored to the needs and preferences of specific learner clusters.  
#Strategic Partnerships: Forge partnerships with companies whose employees exhibit a high propensity for upskilling through Scaler.  
#Personalized Learning Paths: Offer personalized learning paths or recommendations based on the learner cluster they belong to, maximizing eng  
#Continuous Improvement: Continuously refine course content and delivery based on insights gained from clustering analysis to ensure relevance