1. Introduction

❓ What is Scaler?

Scaler is a cutting-edge online tech university (tech-versity) designed to upskill software and data science professionals. It offers rigorous, live learning programs delivered by seasoned industry experts and leaders, focusing on modern curriculums aligned with the latest technological advancements. Scaler empowers learners to bridge skill gaps, advance their careers, and gain exposure to real-world industry scenarios through personalized mentorship and a structured educational approach.

🖇️ Issue at Hand

Scaler caters to a diverse learner base with varying job roles, industry backgrounds, and levels of experience. This diversity presents challenges in profiling learners effectively to deliver a personalized learning experience. Identifying and understanding these profiles through data-driven clustering methods is critical for Scaler to enhance learner engagement, retention, and satisfaction. Without a precise approach, Scaler risks providing generalized solutions that may not address individual learner needs effectively.

🎯 Objective

- Leverage clustering techniques to categorize learners into meaningful profiles based on their job roles, companies, experience, and salary structures.
- Analyze these profiles to uncover actionable insights that will aid in tailoring Scaler's curriculum, mentorship programs, and overall learner journey.
- Provide recommendations to improve learner outcomes and satisfaction while boosting Scaler's impact as an ed-tech leader.

🎯 Key Goal

- Develop a data-driven, personalized approach to enhance learner experiences by clustering individuals with similar characteristics.
- Enable Scaler to refine its course offerings, mentorship programs, and marketing strategies by understanding distinct learner groups and their professional trajectories.
- Support Scaler in becoming a leader in learner-centric education by addressing unique skill gaps and aligning learning paths with industry trends and demands.

📄 Features of the dataset:

Feature	Description
Unnamed: 0	The index of the Dataset
company_hash	An anonymized identifier indicating the current employer of the learner.
email_hash	An anonymized identifier representing the email of the learner.
orgyear	Represents the year the learner began employment at the current company.
ctc	Current Compensation to the Company (CTC) of the learner.
job_position	Represents the job profile or role of the learner within their company.
ctc_updated_year	The year in which the learner's CTC was most recently updated. This could be due to yearly increments, promotions, or other factors.

2. Exploratory Data Analysis

In [145]:
```
# Importing Libraries Needed

import pandas as pd
import numpy as np
import seaborn as sns
sns.set_style(style='whitegrid')
from scipy import stats
import matplotlib.pyplot as plt

import re

import warnings
warnings.filterwarnings("ignore")

# Machine Learning Libraries

from sklearn.impute import KNNImputer
from sklearn.cluster import KMeans,AgglomerativeClustering
from sklearn.manifold import TSNE
from sklearn.decomposition import PCA
from sklearn.neighbors import NearestNeighbors, LocalOutlierFactor
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler
```

```
from sklearnex import patch_sklearn
patch_sklearn()

import umap

from scipy.cluster.hierarchy import dendrogram, linkage,fcluster
import fastcluster

from IPython.display import clear_output
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

from collections import Counter
```

```
Intel(R) Extension for Scikit-learn* enabled (https://github.com/intel/scikit-learn-intelex)
```

Dataset Link - Scaler_Clustering

In [146]:
```
# Importing Data Set

df = pd.read_csv(r'M:\Business Cases\10 - Scaler\scaler_clustering.csv')
df.head()
```

Out[146]:

	Unnamed: 0	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
0	0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016.000	1100000	Other	2020.000
1	1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018.000	449999	FullStack Engineer	2019.000
2	2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015.000	2000000	Backend Engineer	2020.000
3	3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017.000	700000	Backend Engineer	2019.000
4	4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017.000	1400000	FullStack Engineer	2019.000

In [147]:
```
df.shape
```

Out[147]:
```
(205843, 7)
```

🔍 Insights

> Number of Rows: `205843`

> Number of Columns: `7`

In [148]:
```
df.drop(['Unnamed: 0'], axis = 1, inplace = True)
```

In [149]:
```
df.info()
```

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

In [150]:
```
# Changing the display format

pd.options.display.float_format = '{:.3f}'.format
```

In [151]:
```
df.describe()
```

Out[151]:

	orgyear	ctc	ctc_updated_year
count	205757.000	205843.000	205843.000
mean	2014.883	2271685.042	2019.628
std	63.571	11800914.440	1.325
min	0.000	2.000	2015.000
25%	2013.000	530000.000	2019.000
50%	2016.000	950000.000	2020.000
75%	2018.000	1700000.000	2021.000
max	20165.000	1000150000.000	2021.000

🔍 Insights

1. The Column `Unnamed: 0` has been dropped, since it won't be impacting the Clustering.
2. There are About 2 Lakh entries in the Dataset.
3. The Minimum Value in `CTC` is **2.0**, this has to either be Error or an Outlier.
4. The Minimum Value in `orgyear` is **0.0**, This must be an Error.
5. The Maximum Value in `orgyear` is **20165**, This must be an Error.

👥 Duplicate Detection

In [152]:
```
df.duplicated().value_counts()
```

Out[152]:
```
False    205809
True         34
Name: count, dtype: int64
```

🔍 Insights

- There are `34` Duplicate entries in the Dataset, Which are to be Dropped.

In [153]:
```
# Dropping Duplicate Rows

df.drop_duplicates(inplace = True)
```

In [154]:
```
# Check Duplicate Rows

df.duplicated().value_counts()
```

Out[154]:
```
False    205809
Name: count, dtype: int64
```

📝 Basic Data Cleaning 🧹 and Exploration ⛏️

Handling Missing Values in the Data Set

In [155]:
```
# Checking for Missing Values

df.isnull().sum()
```

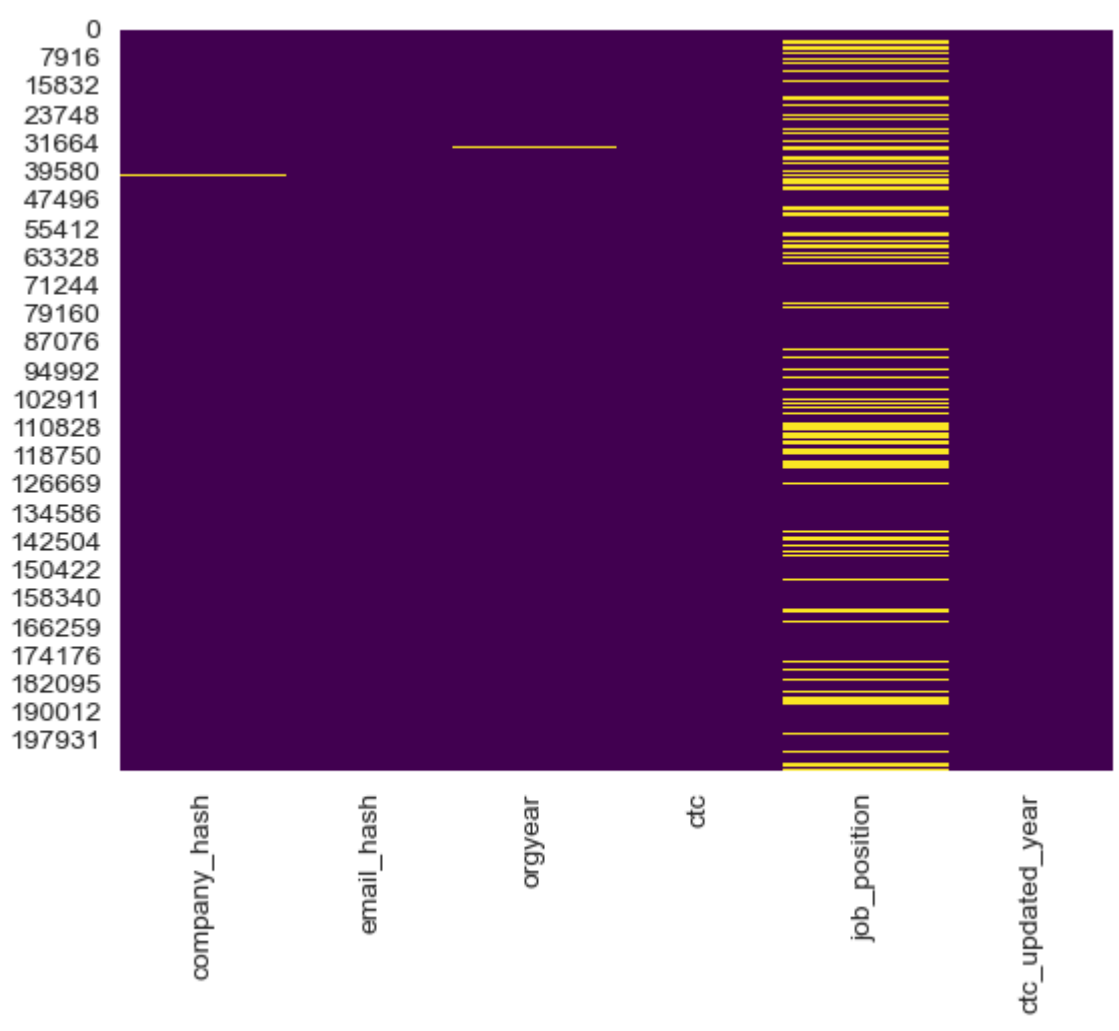
Out[155]:
```
company_hash           44
email_hash              0
orgyear                86
ctc                     0
job_position        52548
ctc_updated_year        0
dtype: int64
```

In [156]:
```
# Percentage of Null Values

df.isnull().sum()/df.shape[0]*100
```

Out[156]:
```
company_hash        0.021
email_hash          0.000
orgyear             0.042
ctc                 0.000
job_position       25.532
ctc_updated_year    0.000
dtype: float64
```

In [157]:
```
sns.heatmap(df.isnull(), cmap='viridis', cbar=False)
plt.show()
```

Out[157]:
```
<Axes: >
```



🔍 Insights

3 Columns have Missing Values:

- `company_hash` and `orgyear` have **Less than 1%**
- `job_position` has **about 25 %**

Handling Missing Values in `company_hash` and `orgyear` Columns Using Mean/Mode Imputation Imputation

In [158]:
```
# Impute missing values for `company_hash` using Mode (most frequent value)
mode_company_hash = df["company_hash"].mode()[0]  # Get the most frequent value
df["company_hash"] = df["company_hash"].fillna(mode_company_hash)

# Impute missing values for `orgyear` using Mean
mean_orgyear = df["orgyear"].mean()  # Calculate the mean value
df["orgyear"] = df["orgyear"].fillna(mean_orgyear)
```

In [159]:
```
df.isnull().sum()
```

Out[159]:
```
company_hash            0
email_hash              0
orgyear                 0
ctc                     0
job_position        52548
ctc_updated_year        0
dtype: int64
```

Handling Missing Values in `job_position` Column

In [160]:
```
df['job_position'].value_counts(dropna = False)
```

Out[160]:
```
job_position
NaN                                            52548
Backend Engineer                               43546
FullStack Engineer                             24711
Other                                          18071
Frontend Engineer                              10417
                                               ...
Compliance auditor                                 1
91                                                 1
Senior Software Development Engineer (Backend)     1
Messenger come driver                              1
Android Application developer                      1
Name: count, Length: 1017, dtype: int64
```

In [161]:
```
df['job_position'].nunique()
```

Out[161]:
```
1016
```

In [162]:
```
# Replace all types of null-like values with NaN first
df["job_position"].replace(["NaN", "NaN ", "nan", None], pd.NA, inplace=True)

# Fill null values in 'job_position' with "unknown"
df["job_position"] = df["job_position"].fillna("unknown")
```

```
# Convert job_position to lowercase
df["job_position"] = df["job_position"].str.lower()

# Replace hyphens with spaces
df["job_position"] = df["job_position"].str.replace("-", " ", regex=False)

# Remove all non-alphanumeric characters except spaces
df["job_position"] = df["job_position"].str.replace(r"[^a-zA-Z0-9 ]", "", regex=True)

# Remove parentheses
df["job_position"] = df["job_position"].str.replace(r"\)", "", regex=True)
df["job_position"] = df["job_position"].str.replace(r"\(", " ", regex=True)

# Sequential replacements for specific patterns
df["job_position"] = (
    df["job_position"]
    .str.replace("ii", "2", regex=False)
    .str.replace(r" i\b", " 1", regex=True)
    .str.replace("iii", "3", regex=False)
    .str.replace("sr ", "senior ", regex=False)
    .str.replace("jr ", "junior ", regex=False)
)

# Additional sequential replacements for common patterns
df["job_position"] = (
    df["job_position"]
    .str.replace("front end", "frontend", regex=False)
    .str.replace("back end", "backend", regex=False)
    .str.replace("full stack", "fullstack", regex=False)
    .str.replace("sde2", "sde 2", regex=False)
    .str.replace("sde3", "sde 3", regex=False)
    .str.replace("se4", "se 4", regex=False)
    .str.replace("2i", "2", regex=False)
    .str.replace(r"\br d\b", "rd", regex=True)
    .str.replace(r"enginner|engineers|engineeer|engineet|eingineer", "engineer", regex=True)
    .str.replace(r"Engeneering", "Engineering", regex=True)
    .str.replace(r"engg\b", "engineer", regex=True)
    .str.replace("applications", "application", regex=False)
    .str.replace(r"dev\b", "developer", regex=True)
    .str.replace(r"devloper|develloper", "developer", regex=True)
    .str.replace("consulant", "consultant", regex=False)
    .str.replace(r"others\b", "other", regex=True)
    .str.replace(" of ", " ", regex=False)
    .str.replace("tech ", "technical ", regex=False)
    .str.replace(r"development(\w+)", r"development \1", regex=True)
)

# Replace double spaces with single space and strip leading/trailing spaces
df["job_position"] = df["job_position"].str.replace("  ", " ", regex=False).str.strip()
```

In [163]:
```
df.isnull().sum()
```

Out[163]:
```
company_hash        0
email_hash          0
orgyear             0
ctc                 0
job_position        0
ctc_updated_year    0
dtype: int64
```

In [164]:
```
df['job_position'].value_counts(dropna = False)
```

Out[164]:
```
job_position
unknown                          52548
backend engineer                 43546
fullstack engineer               25982
other                            18073
frontend engineer                10418
                                 ...
phd student                          1
ays                                  1
principal product engineer           1
senior director engineering          1
azure data factory                   1
Name: count, Length: 841, dtype: int64
```

In [165]:
```
df['job_position'].nunique()
```

Out[165]:
```
841
```

Spell Check

In [166]:
```
# The Following Code is taken from https://norvig.com/spell-correct.html For Spell Checking

# Split job positions into individual words, explode them, and count occurrences
words = df["job_position"].str.split(" ").explode()
WORDS = Counter(words.to_list())

# Define helper functions for spelling correction and word cleaning
def P(word, N=sum(WORDS.values())):
    """Probability of `word`."""
```

```
    return WORDS[word] / N

def correction(word):
    """Most probable spelling correction for a word."""
    return max(candidates(word), key=P)

def candidates(word):
    """Generate possible spelling corrections for a word."""
    return known([word]) or known(edits1(word)) or known(edits2(word)) or [word]

def known(words):
    """Subset of `words` that appear in the dictionary of WORDS."""
    return set(w for w in words if w in WORDS)

def edits1(word):
    """All edits that are one edit away from `word`."""
    letters = 'abcdefghijklmnopqrstuvwxyz'
    splits = [(word[:i], word[i:]) for i in range(len(word) + 1)]
    deletes = [L + R[1:] for L, R in splits if R]
    transposes = [L + R[1] + R[0] + R[2:] for L, R in splits if len(R) > 1]
    replaces = [L + c + R[1:] for L, R in splits if R for c in letters]
    inserts = [L + c + R for L, R in splits for c in letters]
    return set(deletes + transposes + replaces + inserts)

def edits2(word):
    """All edits that are two edits away from `word`."""
    return (e2 for e1 in edits1(word) for e2 in edits1(e1))

def correct_words(sentence):
    """Correct all words in a sentence."""
    return " ".join([correction(word) for word in sentence.split()])
```

```
def clean_jobs(word):
    """Clean individual words by replacing short or numeric values with 'unknown'."""
    if len(word) <= 1:
        return "unknown"
    try:
        float(word)
        return "unknown"
    except ValueError:
        return word

def replace_words(sentence):
    """Replace specific job-related phrases."""
    unemployed = [
        "na", "no", "no job", "not applicable", "not employed",
        "not working", "null", "none", "now iam not working waiting for job"
    ]
    if sentence.lower() in unemployed:
        return "unemployed"
    else:
        return sentence

# Apply cleaning and corrections to job_position column
df["job_position"] = df["job_position"].apply(replace_words)
df["job_position"] = df["job_position"].apply(correct_words)
df["job_position"] = df["job_position"].apply(clean_jobs)
```

In [167]:
```
df.isnull().sum()
```

Out[167]:
```
company_hash        0
email_hash          0
orgyear             0
ctc                 0
job_position        0
ctc_updated_year    0
dtype: int64
```

Manually Fixing the Errors in `orgyear`, `ctc`, `job_position` Columns

`orgyear`

In [168]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 205809 entries, 0 to 205842
Data columns (total 6 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   company_hash      205809 non-null  object 
 1   email_hash        205809 non-null  object 
 2   orgyear           205809 non-null  float64
 3   ctc               205809 non-null  int64  
 4   job_position      205809 non-null  object 
 5   ctc_updated_year  205809 non-null  float64
dtypes: float64(2), int64(1), object(3)
memory usage: 11.0+ MB
```

In [169]:
```
# Converting `orgyear` and `ctc_updated_year` to int32 format
df["orgyear"] = df["orgyear"].astype("int32")
df["ctc_updated_year"] = df["ctc_updated_year"].astype("int32")
```

In [170]:
```
df.isna().sum()
```

Out[170]:
```
company_hash        0
email_hash          0
orgyear             0
ctc                 0
job_position        0
ctc_updated_year    0
dtype: int64
```

In [171]:
```
df['orgyear'].value_counts().sort_index()
```

Out[171]:
```
orgyear
0        17
1         2
2         3
3         6
4         1
         ..
2101      1
2106      1
2107      1
2204      1
20165     2
Name: count, Length: 77, dtype: int64
```

🔍 Insights

- Based on the Above Result, there are Errors in the `orgyear` Column.
- We will fix this by keeping Upper and Lower Limits and Anything that fall beyond these limits will be Replaced using ctc_updated_year

In [172]:
```
# Lower limit for orgyear
lower_limit_orgyear = 1970

# view orgyear values outside the limits
df[(df['orgyear'] < lower_limit_orgyear)]
```

Out[172]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
13424	9xntwyzgrgsj	854ff163ded87211b944dfcaebdcf9e8efa45defc9582f...	0	700000	unknown	2021
13698	oxtbtzo	4a64fdec422e657b175d5dd914b91e0df7c78ec7716bfe...	208	500000	unknown	2020
15323	nvnv wgzohrnvzwj otqcxwto nwo	437fa88cd652351931ef679e6b074aa91acb384ef193dd...	209	300000	unknown	2021
17139	sgxmxmg	6db474dae5093f975e43697cd77ac5a486248c26235778...	206	1500000	unknown	2021
30335	avqn xzzgcvnxgz	d767ad3012a86dab37a38a106f65d00b85189fe49a3f0f...	0	220000	unknown	2020
32086	lxg	ae1b500192dcd0b6c2d5c69b51f6caf19c630640c0aeb1...	0	600000	unknown	2021
33117	mvzp ge vbtqxwv	8ef16126bd9a4691801d2830156dc5528142a45d314593...	0	1200000	unknown	2021
40553	mqvpto xzaxv rna	a0f794db04d5c13cae6f07c6ce9aee8ff731176cc4d4a1...	0	600000	unknown	2021
41361	otqcxwtzgf	b60d93faa9a96e2d8362f0b6f16aac79dc484560356ff3...	91	1000000	unknown	2021
56770	vngo ojzntr	536e217527d1101538c70b7001d7e28344dba87cd8e246...	0	400000	unknown	2021
62717	wyvqstugxzn	a1da4f131e2efea24f6d64c66519724aa5c8c5c11a23d9...	0	1850000	fullstack engineer	2019
63629	bxznb xzw	5bbebf13d3b3edc497bc5e24d1ab540b66b3d9328d4948...	0	700000	fullstack engineer	2019
66344	fxkzx ogenfvqt uqxcvnt rxbxnta	583d48749d8f694951a25ceebe4c0cdebc814a5b6def5b...	3	1800000	product designer	2019
68701	vzshrvq atcqrgutq	1978da71c14333352d051bfb6054904770b70cecce389d...	91	400000	devops engineer	2021
74313	ovbohzs trtwnqgzxwo	b9fac647e08fe47c6d112466c338e847e82e8f24e16236...	0	1000000	unknown	2021
74945	fgrntqo prhftq	e0501afab1e9cc00253928e1488701685039437b1780f6...	3	1580000	engineering leadership	2019
80500	vzshrvq atcqrgutq	1978da71c14333352d051bfb6054904770b70cecce389d...	91	400000	unknown	2021
84882	hzxntaytvrny sqghu	82e77fdd3e43e37ec6b805bbfe624d7cd24b37cb0a4317...	3	540000	qa engineer	2019
90049	vowtzv	32fb75b1f5c1001ab5e34280641e13d5b91f8cdaa65772...	2	1470000	frontend engineer	2019
94051	utqoxontzn ojontbo	9bec1bea9b46f4dcbbb35564e5fef83d1fa52cd2c92b96...	4	2780000	backend architect	2019
94689	xzntr otwhqxnj bwvett ogenfvqt	7126263909db5c37b278b05ea56740688062821f452ef6...	5	2720000	qa engineer	2019
99408	wyvqstugxzn	a1da4f131e2efea24f6d64c66519724aa5c8c5c11a23d9...	0	1850000	backend engineer	2019
100415	rgsfvqa	b511b17a1aaaa822c6b5d6a04498ff3121808101697407...	0	1600000	frontend engineer	2021
101678	awm mvzp	37a5cce01b1e049307d73bbb2138fa54cbb02555c2137a...	0	700000	unknown	2021
106669	cvrhtej ogrhnxgzo	a184e9709d7a9adfc1e2d500770e922a72a584f8dffee3...	0	1300000	backend engineer	2020
117087	nyghsynfgqpo	6e793d5dcfe38ed51840bc720ed72e6f6747d57e64ab45...	0	1600000	unknown	2019
119329	uyxrxuo	c0787fd47b636c7cb790a07196a71cfd80b9aa5419b0be...	3	1950000	devops engineer	2019
121487	bvzyvnnvz voogwxvnto	e725ad631cdc4c57a354f59c98b6441f0672c6b7bb8adb...	83	730000	backend engineer	2019
124319	tr xzeg atoxsz	3661bbc848e743c2ad62c20fc8a6e0eedebc33e2288b1f...	3	690000	ios engineer	2019
138295	fvrbvqn rvmo	73265267f042756723746edd1cedcef322809d50369eea...	0	5700000	unknown	2020
143238	wxowg	19bd55263d4e8cb5659b50814dc18b1fbdd1b7e0689e4b...	5	1000000	backend engineer	2019
149468	tox ogenfvqt	ba78adb8793f4e7257308b724bc84b1b096af03631049b...	1	2950000	engineering leadership	2019
159224	vrongb	a568e7ea5f84dcd0d6f886a943dc71652652de9b00c8c4...	38	3000000	engineering leadership	2019
163444	ovst xznvwwn ogenfvqt ucn rna	3da3c964efe7a5db0f63e91be25391dcaadf24d44cdc59...	1900	3170000	engineering leadership	2019
163455	wgxznqxmt ntwy exzntwy ctznhqt	a9393ceb6f438669a12e2f5632d515ba2fdb2656c8d727...	201	3500000	product manager	2017
165075	adw ntwyzgrgsj	32a3ee8218df48d1ba56e0e87323a5225c83929d00a6d8...	3	1250000	devops engineer	2019
167456	xzwnhqt ntwyzgrgsj	8b670b30a7588a36cbe0cea33f8c840c3ab25c649d970c...	2	500000	unknown	2019
175205	vcr	c0118cfea338955b1a4c66292987ab2359ad31e0b49a51...	6	1680000	data scientist	2019
178024	zthqvrntwyogen	6212c450f20c14afc8720c33b6b07d667200f7500196db...	6	800000	data scientist	2019
184479	nqvctrgpv	3d3a669652938eaf0f9f3c862db3c805a9f55c3961b0c6...	0	2500000	unknown	2020
188483	gutqv ogrhnxgzo ucn rna zgxav	bcb7f27531d7e75a5572bf515fc9b4fb38254b8a77f848...	2	1939999	backend engineer	2019
188672	wxowg cxatg ntwyzgrgsxto xzaxv ucn rna	c3cce99fc54361b5c213f8043505d2990c8dfa93669df8...	200	3000000	engineering leadership	2019
193131	vxqvoxv	0a5e691a0f8c2c06862ef19d43dc11c22f462f800db26b...	0	800000	unknown	2019
196354	vaxnjv mxqrv wvuxnvr	069308440811d578c817c05392f97e8919baac6aa12aa3...	1	2900000	data scientist	2019

In [173]:
```
# Lower limit for orgyear
lower_limit_orgyear = 1970

# Fix `orgyear` values outside the limits
df["orgyear"] = df.apply(
    lambda row: row["ctc_updated_year"] - 1
    if row["orgyear"] < lower_limit_orgyear
```

```
    else row["orgyear"],
    axis=1
)
```

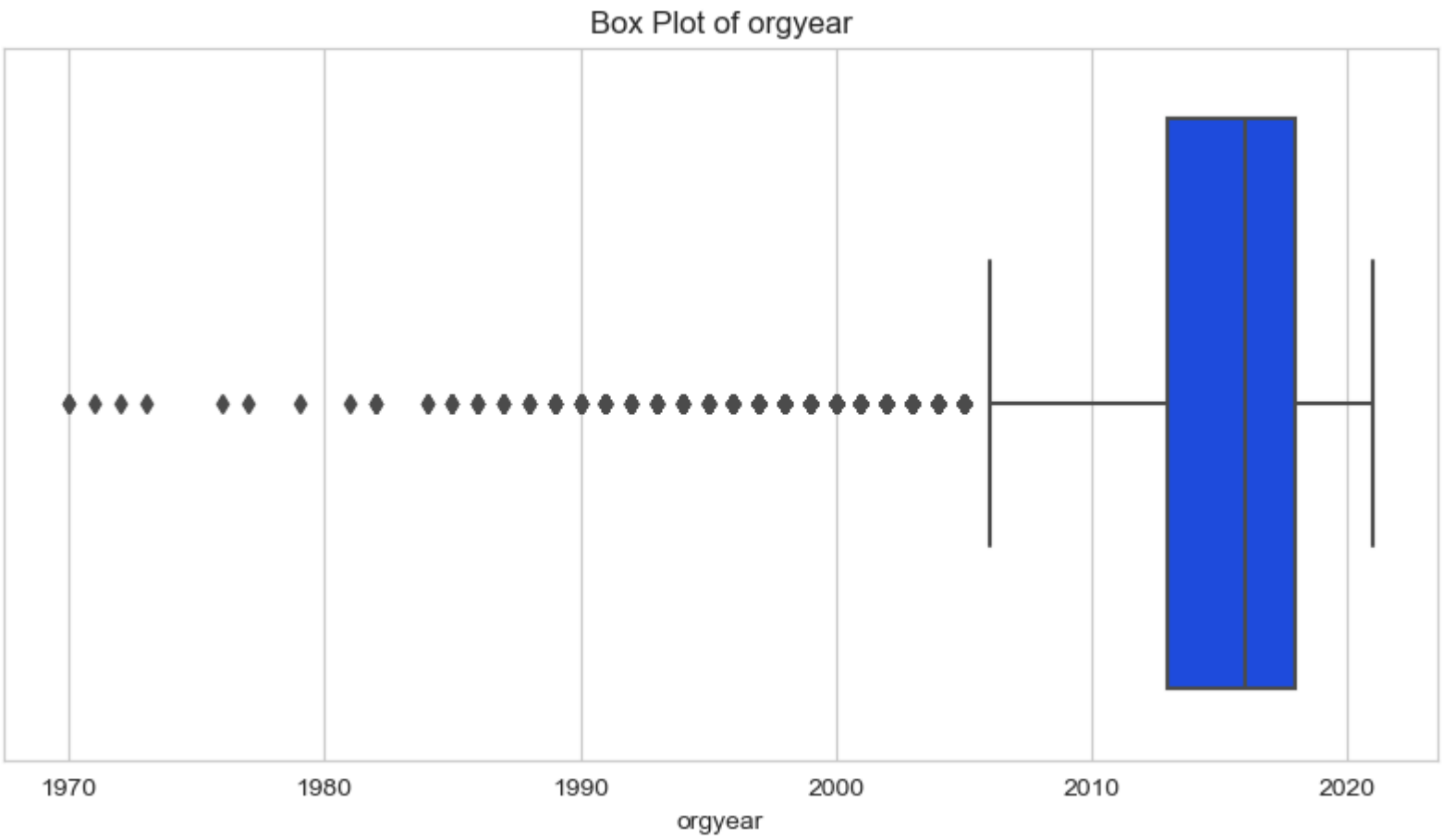
In [174]:
```
# Fix `orgyear` values that are greater than `ctc_updated_year`
df["orgyear"] = df.apply(
    lambda row: row["ctc_updated_year"] - 1
    if row["orgyear"] > row["ctc_updated_year"]
    else row["orgyear"],
    axis=1
)
```

In [175]:
```
# Box Plot for orgyear
plt.figure(figsize=(10, 5))
sns.boxplot(x=df["orgyear"])
plt.title("Box Plot of orgyear")
plt.show()
```

Out[175]:
```
<Figure size 1000x500 with 0 Axes>
```

Out[175]:
```
<Axes: xlabel='orgyear'>
```

Out[175]:
```
Text(0.5, 1.0, 'Box Plot of orgyear')
```



ctc

In [176]:
```
df['ctc'].value_counts().sort_index()
```

Out[176]:
```
ctc
2             1
6             1
14            1
15            1
16            1
           ...
199990000     2
200000000     378
250000000     1
255555555     1
1000150000    1
Name: count, Length: 3360, dtype: int64
```

In [177]:
```
# View rows where ctc is less than or equal to 100
df[df['ctc'] <= 100]
```

Out[177]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year
54820	uqvpqxnx voogwxvnto	8786759b95d673466e94f62f1b15e4f8c6bd7de6164074...	2020	24	other	2020
91552	ftm ongqt	512f761579fb116e215cabc9821c7f81153f0763e16018...	2016	25	android engineer	2018
114164	xzntqcxtfmxn	23ad96d6b6f1ecf554a52f6e9b61677c7d73d8a409a143...	2013	14	unknown	2018
118236	xzntqcxtfmxn	f2b58aeed3c074652de2cfd3c0717a5d21d6fbcf342a78...	2013	6	unknown	2018
135435	xzntqcxtfmxn	3505b02549ebe2c95840ac6f0a35561a3b4cbe4b79cdb1...	2014	2	backend engineer	2019
183804	xm	75357254a31f133e2d3870057922feddeba82b88056a07...	2017	16	unknown	2018
184946	xm	b8a0bb340583936b5a7923947e9aec21add5ebc50cd60b...	2016	15	unknown	2018

🔍 Insights

Considering that the Error in CTC column are Simply in Lakhs, We can either drop them or Multiply them 100000.

In [178]:
```
# Multiplying the Value in CTC Column if they are Below 100 by 100000

df["ctc"] = df["ctc"].apply(lambda x: x * 100000 if x <= 100 else x)
```

job_position

In [179]:
```
# Count of Rows Where Job Position is Unknown
df[df['job_position'] == 'unknown'].shape[0]
```

Out[179]: 52561

In [180]:
```
df["job_position"].nunique()
```

Out[180]: 812

In [181]:
```
import pandas as pd

# Step 1: Filter rows where `job_position` is not 'unknown' and `company_hash` is not null
filtered_df = df[(df["job_position"] != "unknown") & (df["company_hash"].notnull())]

# Step 2: Group by `company_hash` and `job_position` to calculate the count
grouped_df = filtered_df.groupby(["company_hash", "job_position"]).size().reset_index(name="count")

# Step 3: Rank job positions within each company based on count (highest count first)
grouped_df["rank"] = grouped_df.groupby("company_hash")["count"].rank(method="first", ascending=False)

# Step 4: Select the top position for each company (`rank` == 1)
top_position_df = grouped_df[grouped_df["rank"] == 1][["company_hash", "job_position"]]

# Debugging Check 1: Print the shape and inspect top_position_df
print("Top Position DataFrame shape:", top_position_df.shape)
print(top_position_df.head())

# Step 5: Merge top positions back into the original DataFrame
df = df.merge(top_position_df, on="company_hash", how="left", suffixes=("", "_top"))

# Debugging Check 2: Identify rows where `job_position_top` is NaN
print("Rows with no match in top_position_df:", df[df["job_position_top"].isnull()].shape[0])

# Step 6: Replace 'unknown' job positions with the top position from the company
df["job_position"] = df.apply(
    lambda row: row["job_position_top"] if row["job_position"] == "unknown" and pd.notnull(row["job_position_top"]) else row["job_position"],
    axis=1
)

# Step 7: Drop the temporary column used for merging
df.drop(columns=["job_position_top"], inplace=True)

# Debugging Check 3: Check if any NaN values remain in `job_position`
print("Remaining NaN values in job_position:", df["job_position"].isnull().sum())

# Step 8: Drop duplicates if required
df.drop_duplicates(inplace=True)
```

```
Top Position DataFrame shape: (34222, 2)
                    company_hash      job_position
0                              0             other
1                           0000             other
2                     01 ojztqsj  android engineer
4  05mz exzytvrny uqxcvnt rxbxnta  backend engineer
5                              1             other
Rows with no match in top_position_df: 4037
Remaining NaN values in job_position: 0
```

In [182]:
```
# Calculate the mode of the `job_position` column
job_position_mode = df["job_position"].mode()[0]  # The mode() method returns a Series; take the first value

# Fill remaining NaN values in `job_position` with the mode
df["job_position"].fillna(job_position_mode, inplace=True)

# Verify that no NaN values remain in `job_position`
print("Remaining NaN values in job_position:", df["job_position"].isnull().sum())
```

```
Remaining NaN values in job_position: 0
```

In [183]:
```
df.isnull().sum()
```

Out[183]:
```
company_hash        0
email_hash          0
orgyear             0
ctc                 0
job_position        0
ctc_updated_year    0
dtype: int64
```

In [184]:
```
df["job_position"].value_counts(sort=True)
```

Out[184]:
```
job_position
backend engineer                66388
fullstack engineer              28097
other                           24518
frontend engineer               11900
engineering leadership           7034
                                ...
messenger come driver               1
associate technical engineer        1
senior associate platform l1        1
senior web developer                1
azure data factory                  1
Name: count, Length: 812, dtype: int64
```

In [185]:
```
df["job_position"].nunique()
```

Out[185]:
```
812
```

In [186]:
```
# Sort the DataFrame to prioritize records with higher orgyear, ctc_updated_year, and ctc for each email_hash.
df_sorted = df.sort_values(
    by=["email_hash", "orgyear", "ctc_updated_year", "ctc"],
    ascending=[True, False, False, False]
)

# Assign a row number to each record within each email_hash group.
df_sorted["row_number"] = df_sorted.groupby("email_hash").cumcount() + 1

# Filter the DataFrame to keep only the top-ranked record for each email_hash.
df_unique = df_sorted[df_sorted["row_number"] == 1]

# Drop the temporary row_number column.
df_unique = df_unique.drop(columns=["row_number"])
```

In [187]:
```
df.head()
```

Out[187]:

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

Unique Values

In [188]:
```
# Checking Unique Values for Each Column

for i in df.columns:
    print("Count of Unique Values in ", i, "Column are :-", df[i].nunique())
    print("-" * 80)
```

```
Count of Unique Values in  company_hash Column are :- 37299
--------------------------------------------------------------------------------
Count of Unique Values in  email_hash Column are :- 153443
--------------------------------------------------------------------------------
Count of Unique Values in  orgyear Column are :- 47
--------------------------------------------------------------------------------
Count of Unique Values in  ctc Column are :- 3353
--------------------------------------------------------------------------------
Count of Unique Values in  job_position Column are :- 812
--------------------------------------------------------------------------------
Count of Unique Values in  ctc_updated_year Column are :- 7
--------------------------------------------------------------------------------
```

In [189]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 192051 entries, 0 to 205808
Data columns (total 6 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   company_hash      192051 non-null  object
 1   email_hash        192051 non-null  object
 2   orgyear           192051 non-null  int64
 3   ctc               192051 non-null  int64
 4   job_position      192051 non-null  object
 5   ctc_updated_year  192051 non-null  int32
dtypes: int32(1), int64(2), object(3)
memory usage: 9.5+ MB
```

In [190]:
```
# Let's Make a Copy of the Data Frame

df_copy = df.copy()
```

In [191]:
```
# Create a DataFrame with unique rows based on email_hash, prioritizing recent and high values
df_unique = (
    df.sort_values(by=["email_hash", "orgyear", "ctc_updated_year", "ctc"], ascending=[True, False, False, False])
```

```
    .drop_duplicates(subset="email_hash", keep="first")
)
```

In [192]:
```
# Remove duplicate rows from the DataFrame
df = df.drop_duplicates()
```

3. Feature Engineering

In [193]:
```
df["orgyear"].max(), df["ctc_updated_year"].max()
```

Out[193]:
```
(2021, 2021)
```

📝 NOTE:

- We will use the `Current Year` as **2022** as the last Year in the Data Set is 2021

In [194]:
```
# Calculate the Years of Experience (YoE) for each record, keeping 2022 as the Current Year

df["yoe"] = 2022 - df["orgyear"]
```

In [195]:
```
df.head()
```

Out[195]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	yoe
0	atrgxnnt xzaxv	6de0a4417d18ab14334c3f43397fc13b30c35149d70c05...	2016	1100000	other	2020	6
1	qtrxvzwt xzegwgbb rxbxnta	b0aaf1ac138b53cb6e039ba2c3d6604a250d02d5145c10...	2018	449999	fullstack engineer	2019	4
2	ojzwnvwnxw vx	4860c670bcd48fb96c02a4b0ae3608ae6fdd98176112e9...	2015	2000000	backend engineer	2020	7
3	ngpgutaxv	effdede7a2e7c2af664c8a31d9346385016128d66bbc58...	2017	700000	backend engineer	2019	5
4	qxen sqghu	6ff54e709262f55cb999a1c1db8436cb2055d8f79ab520...	2017	1400000	fullstack engineer	2019	5

In [196]:
```
df["yoe"].min(), df["yoe"].max()
```

Out[196]:
```
(1, 52)
```

In [197]:
```
import pandas as pd

# Sort the dataframe by the necessary columns: 'email_hash', 'orgyear', 'ctc_updated_year', 'ctc' in descending order
df.sort_values(by=['email_hash', 'orgyear', 'ctc_updated_year', 'ctc'], ascending=[True, False, False, False], inplace=True)

# Add a row number based on the sorted data for each 'email_hash'
df['rn'] = df.groupby('email_hash').cumcount() + 1

# Compute additional columns:
# 1. Calculate the number of jobs per 'email_hash'
df['num_jobs'] = df.groupby('email_hash')['email_hash'].transform('count')

# 2. Calculate the growth as per the formula (max(ctc) - min(ctc)) / min(ctc) for each 'email_hash'
df['growth'] = df.groupby('email_hash')['ctc'].transform(lambda x: (x.max() - x.min()) / x.min())

# Filter the rows where row number is 1 (to mimic 'rn = 1' in SQL)
df = df[df['rn'] == 1]

# Drop the row number column (as per the SQL query to drop 'rn')
df.drop(columns=['rn'], inplace=True)

# Sort the final dataframe by 'num_jobs' in descending order
df.sort_values(by='num_jobs', ascending=False, inplace=True)

# Display the final dataframe
df.head()
```

Out[197]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	yoe	num_jobs	growth
65909	cvrhtbgbtznhb	298528ce3160cc761e4dc37a07337ee2e0589df251d736...	2018	720000	backend engineer	2020	4	9	0.029
10214	wgcxvb ntwyzgrgsxto	3e5e49daa5527a6d5a33599b238bf9bf31e85b9efa9a94...	2018	1130000	engineering intern	2021	4	9	0.041
9857	ihvrwgbb	6842660273f70e9aa239026ba33bfe82275d6ab0d20124...	2017	2400000	qa engineer	2020	5	9	0.200
4557	gqvwrt	4818edfd67ed8563dde5d083306485d91d19f4f1c95d19...	2015	1200000	backend architect	2020	7	8	0.000
133770	nyt a t oyvf sqghu	c0eb129061675da412b0deb15871dd06ef0d7cd86eb5f7...	2013	2300000	other	2020	9	8	0.513

In [198]:
```
# New Feature - CTC to YoE Ratio

df["ctc_yoe_ratio"] = df["ctc"] / (df["yoe"] * 12 * 1000)

# Display the result
print(df[['company_hash', 'job_position', 'ctc', 'yoe', 'ctc_yoe_ratio']].head())
```

	company_hash	job_position	ctc	yoe	ctc_yoe_ratio
65909	cvrhtbgbtznhb	backend engineer	720000	4	15.000
10214	wgcxvb ntwyzgrgsxto	engineering intern	1130000	4	23.542
9857	ihvrwgbb	qa engineer	2400000	5	40.000
4557	gqvwrt	backend architect	1200000	7	14.286
133770	nyt a t oyvf sqghu	other	2300000	9	21.296

3.1 - Creating Individual Groups for Manual Clustering

In [199]:
```
# Grouping by company, job position, and years of experience,
# to calculate aggregate statistics for 'ctc' such as mean, median, max, min, and count
grouped_by_position_exp = df.groupby(["company_hash", "job_position", "yoe"]).agg(
    mean_ctc_exp=("ctc", "mean"),
    median_ctc_exp=("ctc", "median"),
    max_ctc_exp=("ctc", "max"),
    min_ctc_exp=("ctc", "min"),
    count_exp=('ctc', 'size')  # Correct way to get the count
).sort_values("count_exp", ascending=False)  # Sorting by 'count_exp' in descending order

# Flatten the multi-index by resetting the index
grouped_by_position_exp = grouped_by_position_exp.reset_index()

grouped_by_position_exp.head(5)

# Grouping by company and job position,
# to calculate aggregate statistics for 'ctc' such as mean, median, max, min, and count
grouped_by_position = df.groupby(["company_hash", "job_position"]).agg(
    mean_ctc_pos=("ctc", "mean"),
    median_ctc_pos=("ctc", "median"),
    max_ctc_pos=("ctc", "max"),
    min_ctc_pos=("ctc", "min"),
    count_pos=('ctc', 'size')  # Correct way to get the count
).sort_values("count_pos", ascending=False)  # Sorting by 'count_pos' in descending order

# Flatten the multi-index by resetting the index
grouped_by_position = grouped_by_position.reset_index()

grouped_by_position.head(5)

# Grouping by company,
# to calculate aggregate statistics for 'ctc' such as mean, median, max, min, and count
grouped_by_company = df.groupby(["company_hash"]).agg(
    mean_ctc_com=("ctc", "mean"),
    median_ctc_com=("ctc", "median"),
    max_ctc_com=("ctc", "max"),
    min_ctc_com=("ctc", "min"),
    count_com=('ctc', 'size')  # Correct way to get the count
).sort_values("count_com", ascending=False)  # Sorting by 'count_com' in descending order

# Flatten the multi-index by resetting the index
grouped_by_company = grouped_by_company.reset_index()

grouped_by_company.head(5)
```

Out[199]:

	company_hash	job_position	yoe	mean_ctc_exp	median_ctc_exp	max_ctc_exp	min_ctc_exp	count_exp
0	nvnv wgzohrnvzwj otqcxwto	backend engineer	3	1463465.871	400000.000	160000000	4700	727
1	nvnv wgzohrnvzwj otqcxwto	backend engineer	4	1601404.161	430000.000	200000000	3300	541
2	xzegojo	other	3	715774.169	420000.000	72000000	100000	403
3	xzegojo	other	4	2176306.000	435000.000	200000000	13000	366
4	nvnv wgzohrnvzwj otqcxwto	backend engineer	2	1475113.092	440000.000	200000000	40000	336

Out[199]:

	company_hash	job_position	mean_ctc_pos	median_ctc_pos	max_ctc_pos	min_ctc_pos	count_pos
0	nvnv wgzohrnvzwj otqcxwto	backend engineer	1779334.246	470000.000	200000000	600	2747
1	xzegojo	other	1989436.459	500000.000	200000000	4000	1738
2	vbvkgz	backend engineer	3490234.921	2200000.000	200000000	2290	1520
3	zgn vuurxwvmrt vwwghzn	backend engineer	1600478.683	600000.000	180000000	1000	1126
4	wgszxkvzn	other	2022947.531	500000.000	200000000	3000	1086

Out[199]:

	company_hash	mean_ctc_com	median_ctc_com	max_ctc_com	min_ctc_com	count_com
0	nvnv wgzohrnvzwj otqcxwto	2119574.830	460000.000	200000000	600	5271
1	xzegojo	1620473.456	500000.000	200000000	3250	3455
2	vbvkgz	3745454.345	2000000.000	200000000	2000	2548
3	zgn vuurxwvmrt vwwghzn	2945297.317	600000.000	199800000	1000	2278
4	wgszxkvzn	2038290.080	600000.000	200000000	3000	2188

3.2 - Merging the Groups to the main dataset

3.2.1 - Flagging

In [200]:
```
# Merging df with grouped_by_position_exp (g1) and adding 'class_flag' based on comparison with mean_ctc_exp
df = df.merge(grouped_by_position_exp[['company_hash', 'job_position', 'yoe', 'mean_ctc_exp']],
              on=['company_hash', 'job_position', 'yoe'],
              how='left')

# Applying conditions for 'class_flag'
df['class_flag'] = df.apply(
    lambda row: 1 if row['ctc'] > row['mean_ctc_exp'] else (3 if row['ctc'] < row['mean_ctc_exp'] else 2),
    axis=1
)

# Merging df with grouped_by_position (g2) and adding 'designation_flag' based on comparison with mean_ctc_pos
# Rename 'mean_ctc_pos' column in grouped_by_position to avoid duplication
grouped_by_position = grouped_by_position.rename(columns={'mean_ctc_pos': 'mean_ctc_position'})

df = df.merge(grouped_by_position[['company_hash', 'job_position', 'mean_ctc_position']],
              on=['company_hash', 'job_position'],
              how='left')

# Applying conditions for 'designation_flag'
df['designation_flag'] = df.apply(
    lambda row: 1 if row['ctc'] > row['mean_ctc_position'] else (3 if row['ctc'] < row['mean_ctc_position'] else 2),
    axis=1
)

# Merging df with grouped_by_company (g3) and adding 'tier_flag' based on comparison with mean_ctc_com
# Rename 'mean_ctc_com' column in grouped_by_company to avoid duplication
grouped_by_company = grouped_by_company.rename(columns={'mean_ctc_com': 'mean_ctc_company'})

df = df.merge(grouped_by_company[['company_hash', 'mean_ctc_company']],
              on='company_hash',
              how='left')

# Applying conditions for 'tier_flag'
df['tier_flag'] = df.apply(
    lambda row: 1 if row['ctc'] > row['mean_ctc_company'] else (3 if row['ctc'] < row['mean_ctc_company'] else 2),
    axis=1
)
```

In [201]:
```
print(grouped_by_position_exp.columns)
```

```
Index(['company_hash', 'job_position', 'yoe', 'mean_ctc_exp', 'median_ctc_exp',
       'max_ctc_exp', 'min_ctc_exp', 'count_exp'],
      dtype='object')
```

In [202]:
```
words = df["job_position"].str.split(" ").explode()
WORDS = Counter(words.to_list())
```

In [203]:
```
# Total Number of Words

len(WORDS)
```

Out[203]: 391

3.3 - Creating New Columns based on Job Positions

In [204]:
```
# Creating the 'is_other' column based on job positions containing 'other' or 'unknown'
df['is_other'] = df['job_position'].str.contains(r"other|unknown", case=False, na=False)

# Creating the 'is_developer' column for job positions related to development and programming
df['is_developer'] = df['job_position'].str.contains(
    r"developer|software|engineer|programmer|dev|development|backend|frontend|fullstack|web|mobile|app|ios|android|qa|automation|testing|sde|a
    case=False, na=False
)

# Creating the 'is_tech' column for tech-related job positions
df['is_tech'] = df['job_position'].str.contains(
    r"engineer|developer|cto|application|aiml|fullstack|scientist|designer|frontend|data|engineering|system|data|qa|principal|security|android
    case=False, na=False
)

# Creating the 'is_management' column for job positions related to management and leadership roles
df['is_management'] = df['job_position'].str.contains(
    r"manager|director|head|vp|president|lead|executive|founder|consulting|leadership|product|administrator|co|project|consultant|team",
    case=False, na=False
)

# Creating the 'is_sales' column for sales and business-related roles
df['is_sales'] = df['job_position'].str.contains(
    r"sales|business|marketing|account|customer|service|support|growth|strategy|operations|commercial|client|relation|partner|engagement|solut
    case=False, na=False
)

# Creating the 'is_non_coder' column, marking positions as non-coders if they do not match 'is_tech'
df['is_non_coder'] = df['job_position'].str.contains(r"non coder", case=False, na=False) | (df['is_tech'] == False)
```

In [205]:
```
df.head()
```

Out[205]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	yoe	num_jobs	growth	ctc_yc
0	cvrhtbgbtznhb	298528ce3160cc761e4dc37a07337ee2e0589df251d736...	2018	720000	backend engineer	2020	4	9	0.029	
1	wgcxvb ntwyzgrgsxto	3e5e49daa5527a6d5a33599b238bf9bf31e85b9efa9a94...	2018	1130000	engineering intern	2021	4	9	0.041	
2	ihvrwgbb	6842660273f70e9aa239026ba33bfe82275d6ab0d20124...	2017	2400000	qa engineer	2020	5	9	0.200	
3	gqvwrt	4818edfd67ed8563dde5d083306485d91d19f4f1c95d19...	2015	1200000	backend architect	2020	7	8	0.000	
4	nyt a t oyvf sqghu	c0eb129061675da412b0deb15871dd06ef0d7cd86eb5f7...	2013	2300000	other	2020	9	8	0.513	

5 rows × 22 columns

In [206]:
```
# Calculate the quantiles for the 'ctc' column
quantiles = df['ctc'].quantile([0.25, 0.50, 0.75, 0.95])

# Define a function to assign the bins based on the quantiles
def assign_ctc_bin(ctc_value):
    if ctc_value > quantiles[0.95]:
        return 'very_high'
    elif ctc_value > quantiles[0.75]:
        return 'high'
    elif ctc_value > quantiles[0.50]:
        return 'medium'
    elif ctc_value > quantiles[0.25]:
        return 'low'
    else:
        return 'very_low'

# Apply the function to the 'ctc' column
df['ctc_bin'] = df['ctc'].apply(assign_ctc_bin)

# Display the first few rows to verify
df.head()
```

Out[206]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	yoe	num_jobs	growth	ctc_yc
0	cvrhtbgbtznhb	298528ce3160cc761e4dc37a07337ee2e0589df251d736...	2018	720000	backend engineer	2020	4	9	0.029	
1	wgcxvb ntwyzgrgsxto	3e5e49daa5527a6d5a33599b238bf9bf31e85b9efa9a94...	2018	1130000	engineering intern	2021	4	9	0.041	
2	ihvrwgbb	6842660273f70e9aa239026ba33bfe82275d6ab0d20124...	2017	2400000	qa engineer	2020	5	9	0.200	
3	gqvwrt	4818edfd67ed8563dde5d083306485d91d19f4f1c95d19...	2015	1200000	backend architect	2020	7	8	0.000	
4	nyt a t oyvf sqghu	c0eb129061675da412b0deb15871dd06ef0d7cd86eb5f7...	2013	2300000	other	2020	9	8	0.513	

5 rows × 23 columns

In [207]:
```
df_FE = df.copy()
```

4. EDA

In [208]:
```
Colors_Palette = ["#313866", "#504099", "#974EC3", "#FE7BE5", "#392467", "#5D3587", "#A367B1", "#FFD1E3", "#F2AFEF", "#C499F3", "#7360DF", "#3

clr_palette = sns.color_palette()
sns.palplot(sns.color_palette(Colors_Palette))

plt.show()
```

4.1 - Univariate Analysis

In [209]:
```
df.columns
```

Out[209]:
```
Index(['company_hash', 'email_hash', 'orgyear', 'ctc', 'job_position',
       'ctc_updated_year', 'yoe', 'num_jobs', 'growth', 'ctc_yoe_ratio',
       'mean_ctc_exp', 'class_flag', 'mean_ctc_position', 'designation_flag',
       'mean_ctc_company', 'tier_flag', 'is_other', 'is_developer', 'is_tech',
       'is_management', 'is_sales', 'is_non_coder', 'ctc_bin'],
      dtype='object')
```

In [210]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 153443 entries, 0 to 153442
Data columns (total 23 columns):
 #   Column              Non-Null Count   Dtype  
---  ------              --------------   -----  
 0   company_hash        153443 non-null  object 
 1   email_hash          153443 non-null  object 
 2   orgyear             153443 non-null  int64  
 3   ctc                 153443 non-null  int64  
 4   job_position        153443 non-null  object 
 5   ctc_updated_year    153443 non-null  int32  
 6   yoe                 153443 non-null  int64  
 7   num_jobs            153443 non-null  int64  
 8   growth              153443 non-null  float64
 9   ctc_yoe_ratio       153443 non-null  float64
 10  mean_ctc_exp        153443 non-null  float64
 11  class_flag          153443 non-null  int64  
 12  mean_ctc_position   153443 non-null  float64
 13  designation_flag    153443 non-null  int64  
 14  mean_ctc_company    153443 non-null  float64
 15  tier_flag           153443 non-null  int64  
 16  is_other            153443 non-null  bool   
 17  is_developer        153443 non-null  bool   
 18  is_tech             153443 non-null  bool   
 19  is_management       153443 non-null  bool   
 20  is_sales            153443 non-null  bool   
 21  is_non_coder        153443 non-null  bool   
 22  ctc_bin             153443 non-null  object 
dtypes: bool(6), float64(5), int32(1), int64(7), object(4)
memory usage: 20.2+ MB
```

4.1.1 - Top 20 Job Positions

In [211]:
```
def get_top_20_value_records(data, feature_name):
    # Get value counts sorted in descending order and get the top 20
    top_20_values = data[feature_name].value_counts().head(20).index

    # Filter the records where the feature value is one of the top 20
    return data[data[feature_name].isin(top_20_values)]
```

In [212]:
```
# Get the top 20 records for 'job_position'
top_20_job_positions = get_top_20_value_records(df_FE, 'job_position')

# Count plot for 'job_position'

plt.figure(figsize=(12, 6))
sns.countplot(y='job_position', data=top_20_job_positions, palette='viridis')
plt.title('Top 20 Job Positions')
plt.xlabel('Count')
plt.ylabel('Job Position')
plt.show()
```

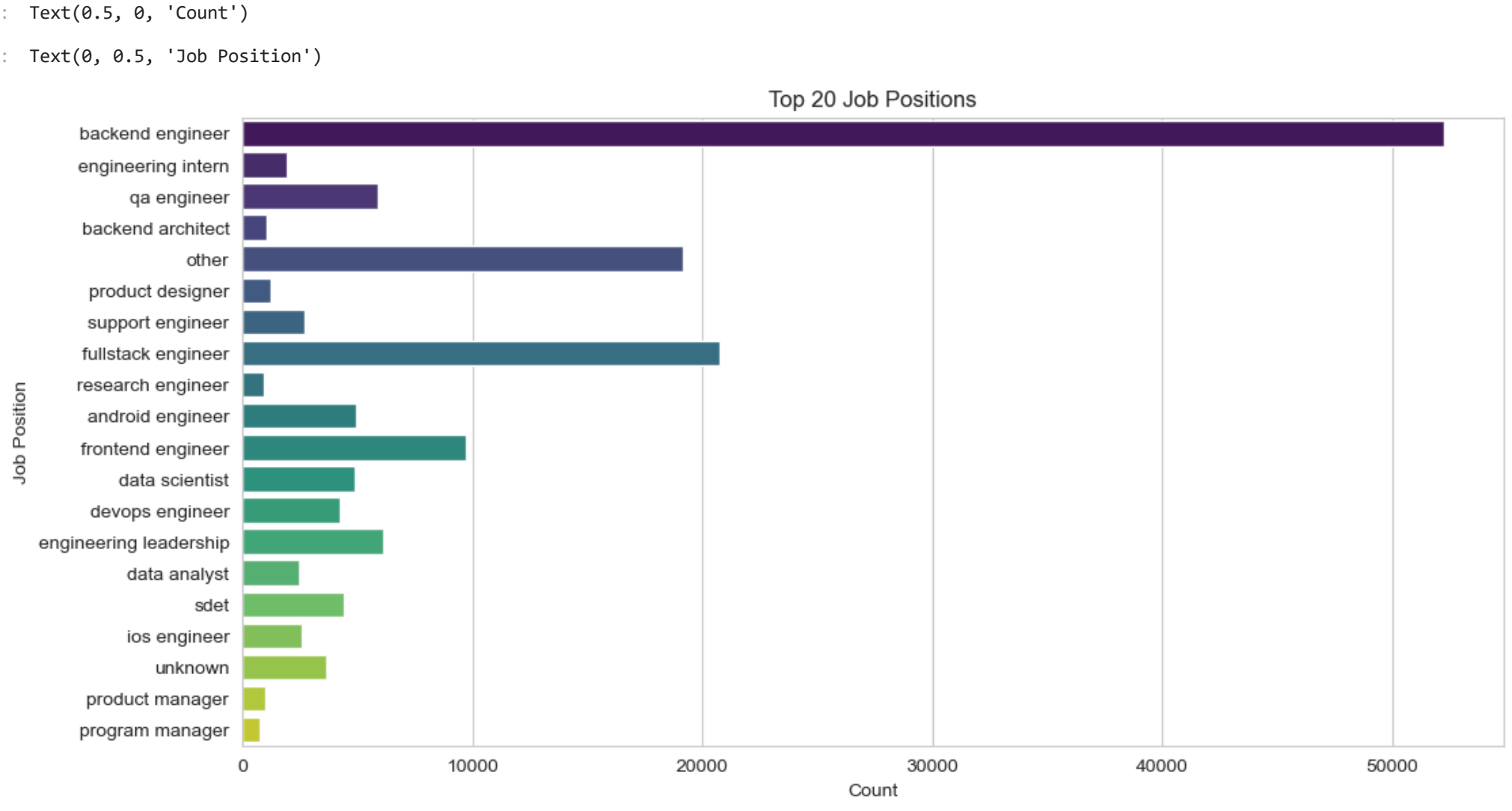
Out[212]: `<Figure size 1200x600 with 0 Axes>`

Out[212]: `<Axes: xlabel='count', ylabel='job_position'>`

Out[212]: `Text(0.5, 1.0, 'Top 20 Job Positions')`

Out[212]: `Text(0.5, 0, 'Count')`

Out[212]: `Text(0, 0.5, 'Job Position')`



🔍 Insights

- Most the candidates belong to `web developement domain`

4.1.2 - Top 20 Companies

In [213]:
```
# Get the top 20 records for 'company_hash'
top_20_companies = get_top_20_value_records(df_FE, 'company_hash')

# Count plot for 'company_hash'

plt.figure(figsize=(12, 6))
sns.countplot(y='company_hash', data=top_20_companies, palette='viridis')
plt.title('Top 20 Companies')
plt.xlabel('Count')
plt.ylabel('Company Hash')
plt.show()
```

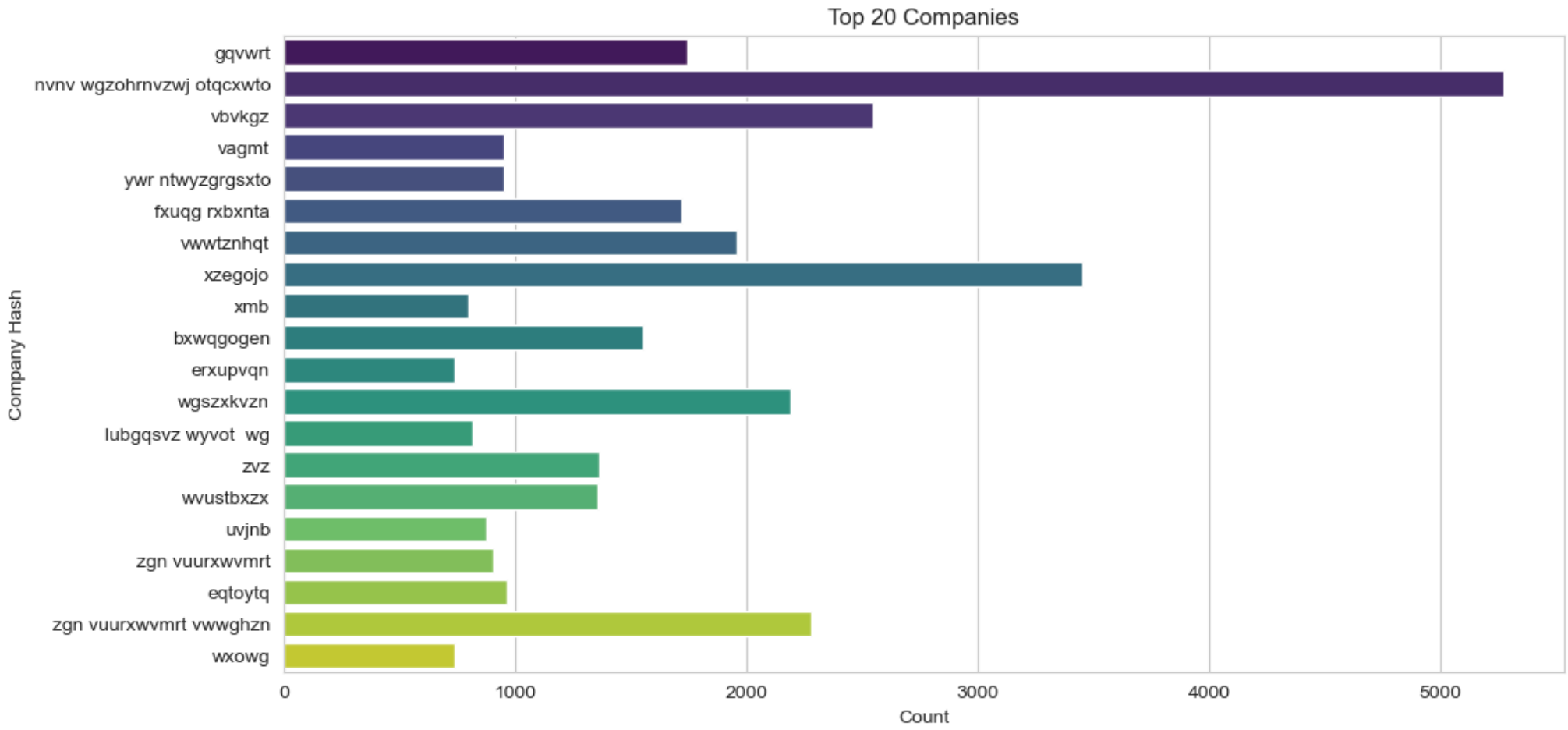
Out[213]: `<Figure size 1200x600 with 0 Axes>`

Out[213]: `<Axes: xlabel='count', ylabel='company_hash'>`

Out[213]: `Text(0.5, 1.0, 'Top 20 Companies')`

Out[213]: `Text(0.5, 0, 'Count')`

Out[213]: `Text(0, 0.5, 'Company Hash')`



4.1.3 - Top 20 CTC Packages

In [214]:
```
# Get the top 20 records for 'ctc_bin'
top_20_ctc_bins = get_top_20_value_records(df_FE, 'ctc_bin')

# Count plot for 'ctc_bin'

plt.figure(figsize=(12, 6))
sns.countplot(y='ctc_bin', data=top_20_ctc_bins, palette='viridis')
plt.title('Top 20 CTC Bins')
plt.xlabel('Count')
plt.ylabel('CTC Bin')
plt.show()
```

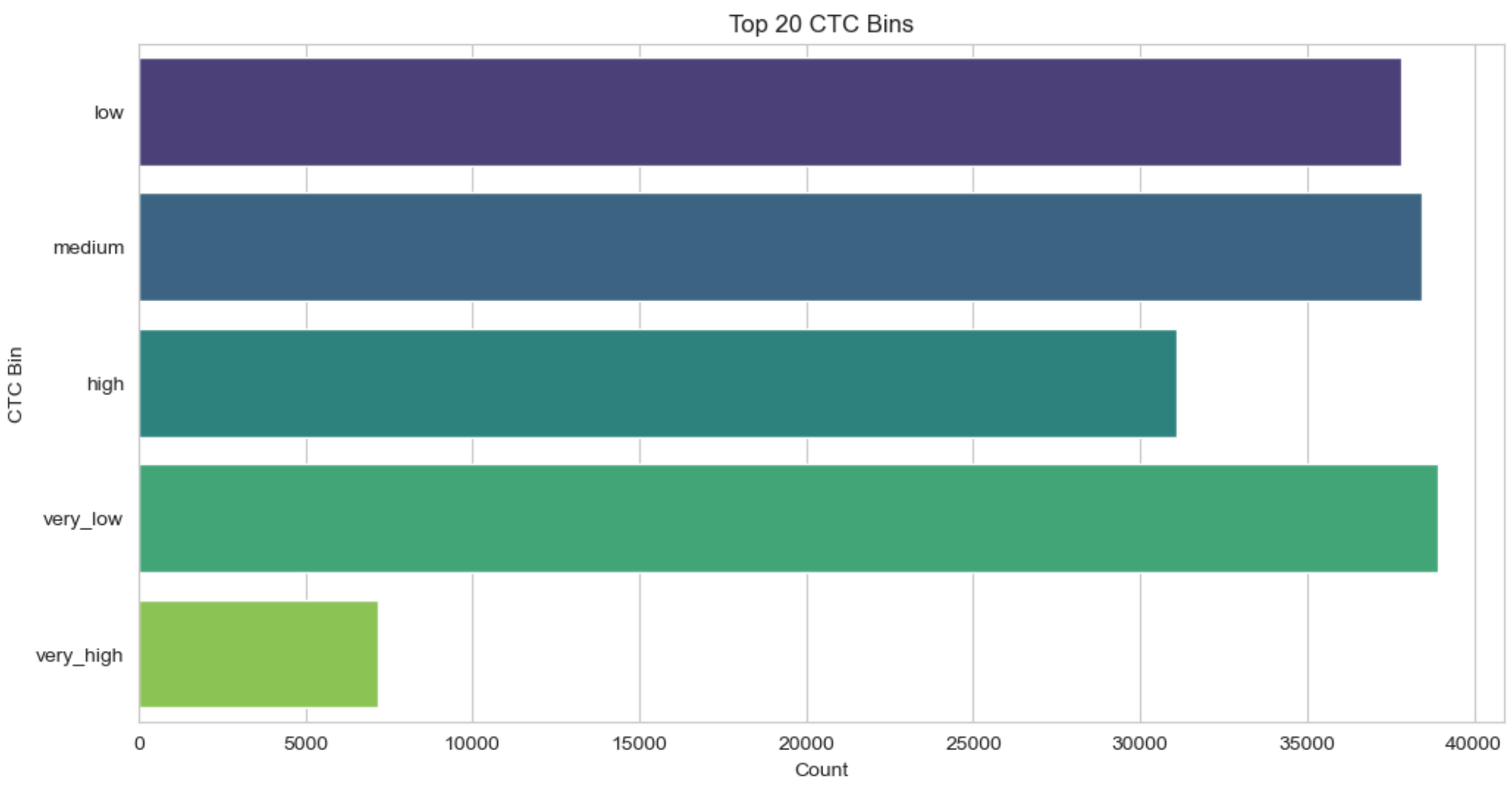
Out[214]: `<Figure size 1200x600 with 0 Axes>`

Out[214]: `<Axes: xlabel='count', ylabel='ctc_bin'>`

Out[214]: `Text(0.5, 1.0, 'Top 20 CTC Bins')`

Out[214]: `Text(0.5, 0, 'Count')`

Out[214]: `Text(0, 0.5, 'CTC Bin')`



4.1.4 - Further Visual Analysis

In [215]:
```
# Boxplot and Distplot for Selected Columns

# Columns to include in the plots
selected_columns = ['orgyear', 'ctc_updated_year', 'yoe']

# Set plot styles
plt.style.use('default')
plt.style.use('seaborn-v0_8-bright')

# Loop through the selected columns and create boxplots and distplots
for _, col in enumerate(selected_columns):
    plt.figure(figsize=(18, 4))
    plt.suptitle(f'{col}', fontsize=15, fontfamily='Arial', fontweight='bold', backgroundcolor=Colors_Palette[_], color='w')

    # Boxplot
    plt.subplot(121)
    sns.boxplot(x=df[col], color=Colors_Palette[_])
    plt.title(f'Boxplot of {col}', fontsize=12, fontfamily='Arial', fontweight='bold', backgroundcolor=Colors_Palette[_], color='w')

    # Distplot
    plt.subplot(122)
    sns.histplot(x=df[col], kde=True, color=Colors_Palette[_])
    plt.title(f'Distplot of {col}', fontsize=12, fontfamily='Arial', fontweight='bold', backgroundcolor=Colors_Palette[_], color='w')

    sns.despine()
    plt.show()
```

Out[215]: <Figure size 1800x400 with 0 Axes>

Out[215]: Text(0.5, 0.98, 'orgyear')

Out[215]: <Axes: >

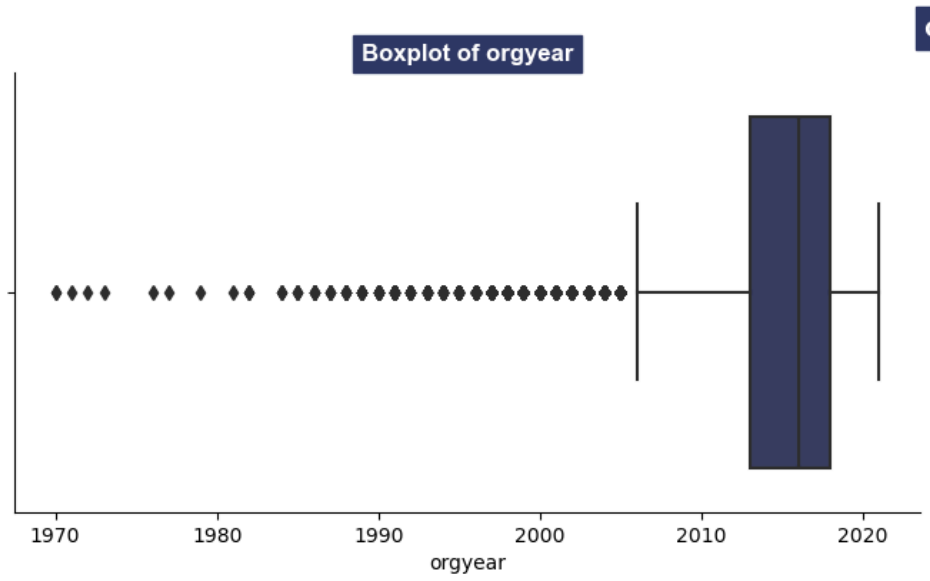
Out[215]: <Axes: xlabel='orgyear'>

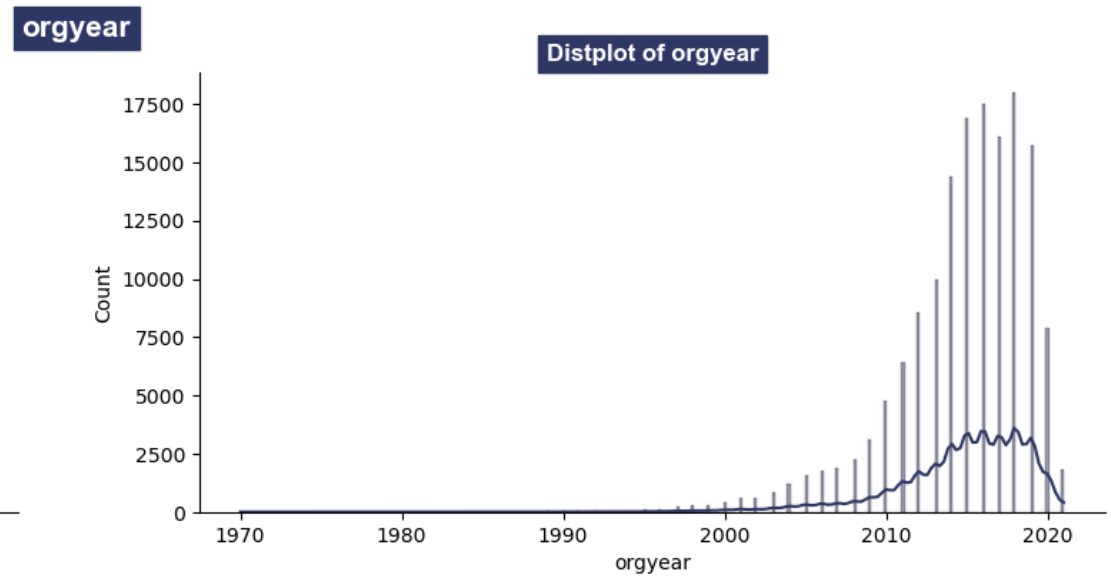
Out[215]: Text(0.5, 1.0, 'Boxplot of orgyear')

Out[215]: <Axes: >

Out[215]: <Axes: xlabel='orgyear', ylabel='Count'>

Out[215]: Text(0.5, 1.0, 'Distplot of orgyear')





Out[215]: <Figure size 1800x400 with 0 Axes>

Out[215]: Text(0.5, 0.98, 'ctc_updated_year')

Out[215]: <Axes: >

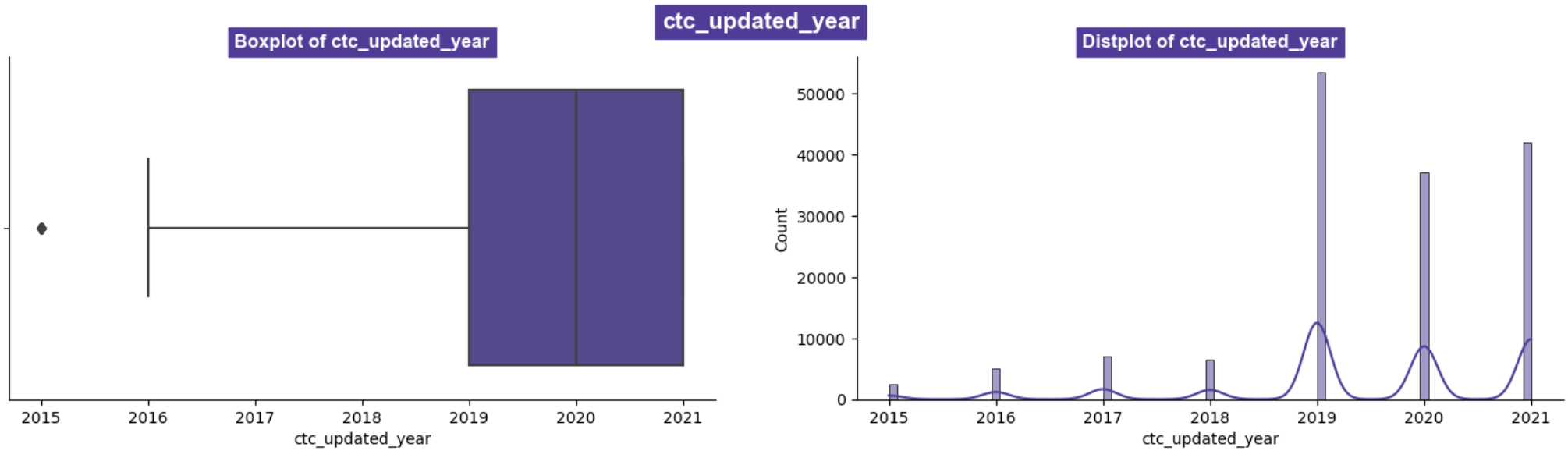
Out[215]: <Axes: xlabel='ctc_updated_year'>

Out[215]: Text(0.5, 1.0, 'Boxplot of ctc_updated_year')

Out[215]: <Axes: >

Out[215]: <Axes: xlabel='ctc_updated_year', ylabel='Count'>

Out[215]: Text(0.5, 1.0, 'Distplot of ctc_updated_year')



Out[215]: <Figure size 1800x400 with 0 Axes>

Out[215]: Text(0.5, 0.98, 'yoe')

Out[215]: <Axes: >

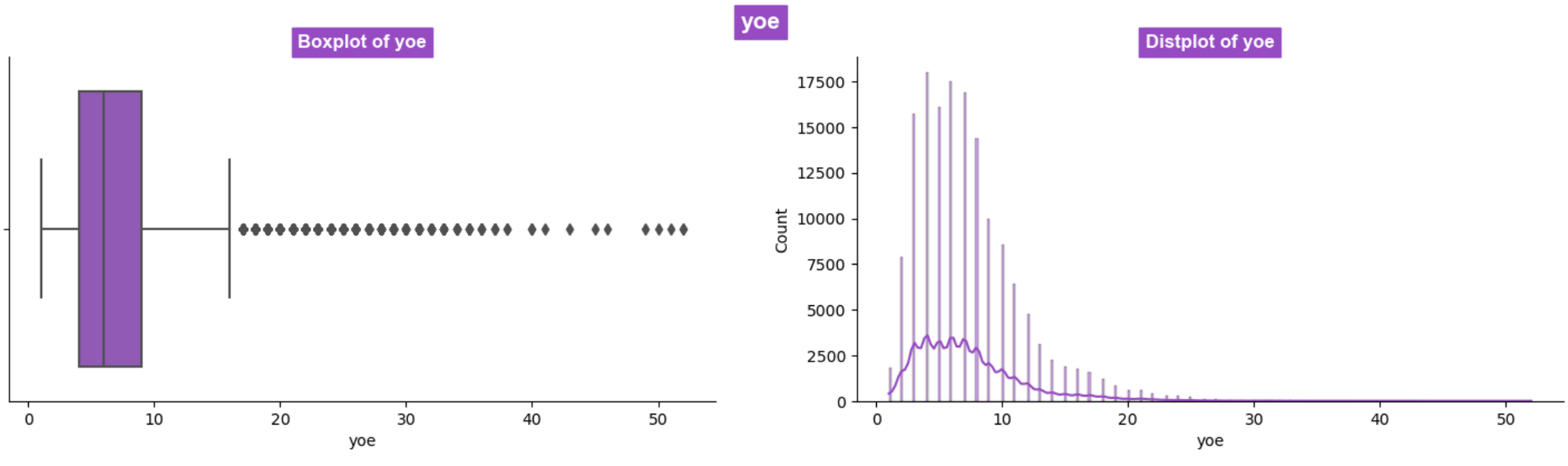
Out[215]: <Axes: xlabel='yoe'>

Out[215]: Text(0.5, 1.0, 'Boxplot of yoe')

Out[215]: <Axes: >

Out[215]: <Axes: xlabel='yoe', ylabel='Count'>

Out[215]: Text(0.5, 1.0, 'Distplot of yoe')



🔍 Insights

- The majority of candidates have less than 10 years of experience.
- Most CTC updates occurred between 2019 and 2021.
- A significant number of candidates joined after 2010.

In [216]:
```python
import pandas as pd

# Filter rows where 'job_position' contains 'intern' or 'trainee', case insensitive
filtered_df = df[df['job_position'].str.contains('intern|trainee', case=False, na=False)]

# Select distinct 'job_position' and 'ctc' and sort by 'ctc' in descending order
distinct_sorted_df = filtered_df[['job_position', 'ctc']].drop_duplicates().sort_values(by='ctc', ascending=False)

# Limit the result to the top 10 rows
top_10_df = distinct_sorted_df.head(10)

# Display the result
print(top_10_df)
```

```
                job_position        ctc
33304   engineering intern  200000000
94233   engineering intern  155000000
9907    engineering intern  100000000
139597  engineering intern   80000000
89184   engineering intern   20000000
36711   engineering intern   19700000
31222   engineering intern   14100000
25934   engineering intern   12000000
36423   engineering intern   11500000
85602      security intern   11000000
```

📝 NOTE:

Job Position like **intern** have Very High CTC which is not Possible.

In [217]:
```
df["ctc"].quantile(0.95), df["ctc"].quantile(0.05)
```

Out[217]:
```
(4000000.0, 200000.0)
```

In [218]:
```
# Filter the DataFrame to retain rows where 'ctc' is within the 5th and 95th percentiles
ctc_filtered_df = df[(df['ctc'] < df['ctc'].quantile(0.95)) & (df['ctc'] > df['ctc'].quantile(0.05))]
```

In [219]:
```
# Mean and Median of CTC for the Filtered Data
mean_ctc = ctc_filtered_df['ctc'].mean()
median_ctc = ctc_filtered_df['ctc'].median()

# Display the results
print(f"Mean CTC: {mean_ctc:.2f}")
print(f"Median CTC: {median_ctc:.2f}")
```

```
Mean CTC: 1215967.07
Median CTC: 1000000.00
```

🔍 Insights

- *__Mean Salary__* is `12 Lakhs`
- *__Median Salary__* is `10 Lakhs`

In [220]:
```
# Filter the DataFrame to retain rows where 'job_position' is in the top 10
top_10_job_positions = df['job_position'].value_counts().head(10).index
top_10_positions_df = df[df['job_position'].isin(top_10_job_positions)]

# Group by 'job_position' and calculate the mean 'ctc'
average_ctc_top_10 = (
    top_10_positions_df
    .groupby('job_position', as_index=False)  # Ensure 'job_position' is a column, not an index
    .agg(average_ctc=('ctc', 'mean'))        # Calculate the mean of 'ctc'
)

# Display the results
print(average_ctc_top_10)

# Optionally sort the results for better readability
average_ctc_top_10 = average_ctc_top_10.sort_values(by='average_ctc', ascending=False)

# Print sorted results
print("\nSorted Average CTC for Top 10 Job Positions:")
print(average_ctc_top_10)
```

```
             job_position  average_ctc
0        android engineer  1540722.520
1        backend engineer  2074889.063
2          data scientist  1935848.904
3         devops engineer  1653288.719
4  engineering leadership  3982217.920
5       frontend engineer  2323741.050
6      fullstack engineer  1978556.112
7                   other  4043263.789
8             qa engineer  2027199.074
9                    sdet  1268721.121

Sorted Average CTC for Top 10 Job Positions:
             job_position  average_ctc
7                   other  4043263.789
4  engineering leadership  3982217.920
5       frontend engineer  2323741.050
1        backend engineer  2074889.063
8             qa engineer  2027199.074
6      fullstack engineer  1978556.112
2          data scientist  1935848.904
3         devops engineer  1653288.719
0        android engineer  1540722.520
9                    sdet  1268721.121
```

In [76]:
```
# Box Plot & Histplot for 'ctc' after filtering

plt.figure(figsize=(10, 12))
plt.suptitle('Distribution of CTC', fontsize=16, fontweight='bold', color='navy')
```

```
# Boxplot
plt.subplot(211)
sns.boxplot(x=ctc_filtered_df['ctc'], color='skyblue')
plt.title('Boxplot of CTC', fontsize=14, fontweight='bold', color='navy')

# Histplot
plt.subplot(212)
sns.histplot(x=ctc_filtered_df['ctc'], kde=True, color='skyblue')
plt.title('Histplot of CTC', fontsize=14, fontweight='bold', color='navy')

sns.despine()
plt.tight_layout()
plt.show()
```

Out[76]: <Figure size 1000x1200 with 0 Axes>

Out[76]: Text(0.5, 0.98, 'Distribution of CTC')

Out[76]: <Axes: >

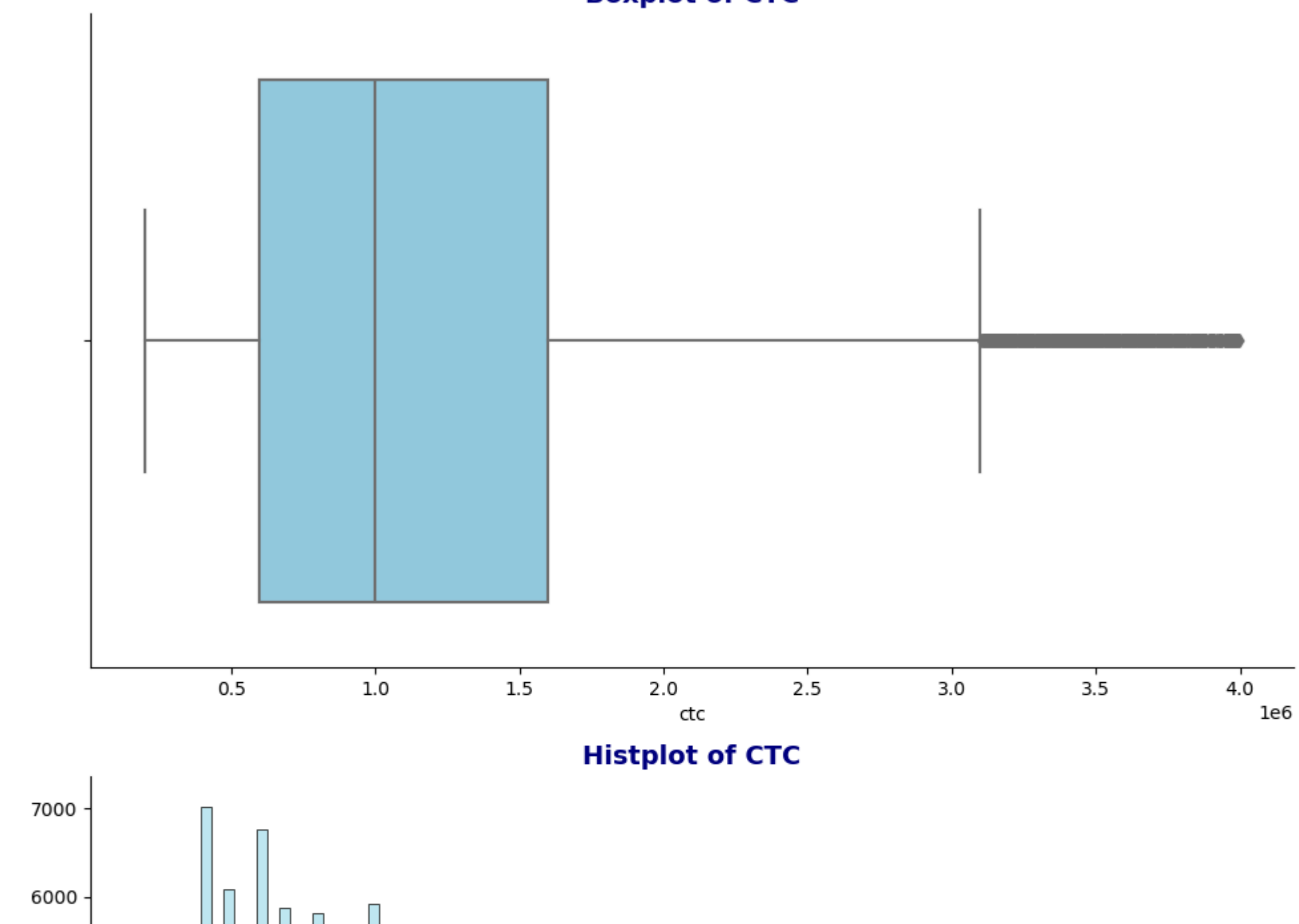
Out[76]: <Axes: xlabel='ctc'>

Out[76]: Text(0.5, 1.0, 'Boxplot of CTC')

Out[76]: <Axes: >

Out[76]: <Axes: xlabel='ctc', ylabel='Count'>

Out[76]: Text(0.5, 1.0, 'Histplot of CTC')



🔍 Insights

- Backend Architect has the Highest Average CTC
- Support Engineer has Lowest Average CTC

4.2 - Bivariate Analysis

4.2.1 - CTC vs Job Position

In [77]:
```
# CTC vs Job Position

# Filter out 'other' job positions and calculate the average CTC for each job position
job_position_ctc_summary = (
    ctc_filtered_df[ctc_filtered_df['job_position'] != 'other']  # Exclude 'other' job positions
    .groupby('job_position', as_index=False)  # Group by 'job_position'
    .agg(avg_ctc=('ctc', 'mean'), count=('ctc', 'count'))  # Calculate average CTC and count
)
```

```
# Select the top 20 job positions by count
top_20_positions_ctc = (
    job_position_ctc_summary
    .sort_values(by='count', ascending=False)  # Sort by count in descending order
    .head(20)  # Take the top 20
)

# Sort by average CTC for plotting
top_20_positions_ctc_sorted = top_20_positions_ctc.sort_values(by='avg_ctc')

# Set 'job_position' as the index for better visualization
top_20_positions_ctc_sorted.set_index('job_position', inplace=True)

# Plot a bar chart of the average CTC for the top 20 job positions
plt.figure(figsize=(10, 5))
top_20_positions_ctc_sorted['avg_ctc'].plot(kind='bar', color='skyblue')
plt.title('Average CTC for Top 20 Job Positions', fontsize=14, fontweight='bold')
plt.ylabel('Average CTC', fontsize=12)
plt.xlabel('Job Position', fontsize=12)
plt.xticks(rotation=45, ha='right', fontsize=10)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```

Out[77]: `<Figure size 1000x500 with 0 Axes>`

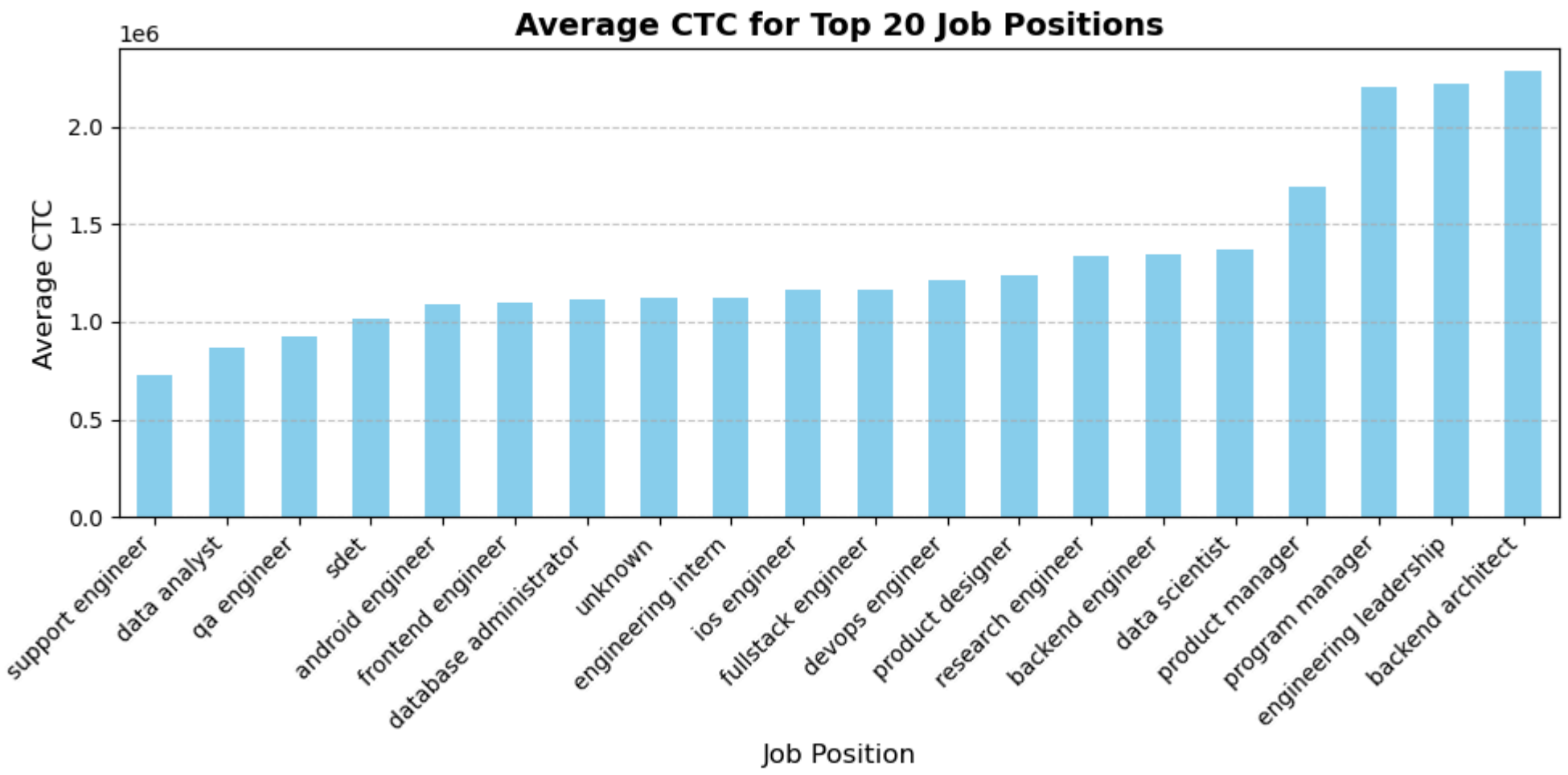
Out[77]: `<Axes: xlabel='job_position'>`

Out[77]: `Text(0.5, 1.0, 'Average CTC for Top 20 Job Positions')`

Out[77]: `Text(0, 0.5, 'Average CTC')`

Out[77]: `Text(0.5, 0, 'Job Position')`

Out[77]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19]),
 [Text(0, 0, 'support engineer'),
  Text(1, 0, 'data analyst'),
  Text(2, 0, 'qa engineer'),
  Text(3, 0, 'sdet'),
  Text(4, 0, 'android engineer'),
  Text(5, 0, 'frontend engineer'),
  Text(6, 0, 'database administrator'),
  Text(7, 0, 'unknown'),
  Text(8, 0, 'engineering intern'),
  Text(9, 0, 'ios engineer'),
  Text(10, 0, 'fullstack engineer'),
  Text(11, 0, 'devops engineer'),
  Text(12, 0, 'product designer'),
  Text(13, 0, 'research engineer'),
  Text(14, 0, 'backend engineer'),
  Text(15, 0, 'data scientist'),
  Text(16, 0, 'product manager'),
  Text(17, 0, 'program manager'),
  Text(18, 0, 'engineering leadership'),
  Text(19, 0, 'backend architect')])
```



4.2.2 - CTC vs Experience

In [78]:
```
# CTC vs Years of Experience

# Scatter Plot for CTC vs YOE
plt.figure(figsize=(12, 6))
sns.scatterplot(
```

```
    data=ctc_filtered_df,
    x='yoe',  # Years of Experience
    y='ctc',  # CTC
    palette='viridis',  # Color palette
    alpha=0.7  # Transparency for overlapping points
)

# Add titles and labels
plt.title('CTC vs YOE (Bivariate Analysis)', fontsize=16, fontweight='bold')
plt.xlabel('Years of Experience (YOE)', fontsize=12)
plt.ylabel('CTC (Cost to Company)', fontsize=12)


# Add grid for better visualization
plt.grid(axis='both', linestyle='--', alpha=0.5)

# Improve layout
plt.tight_layout()
plt.show()
```

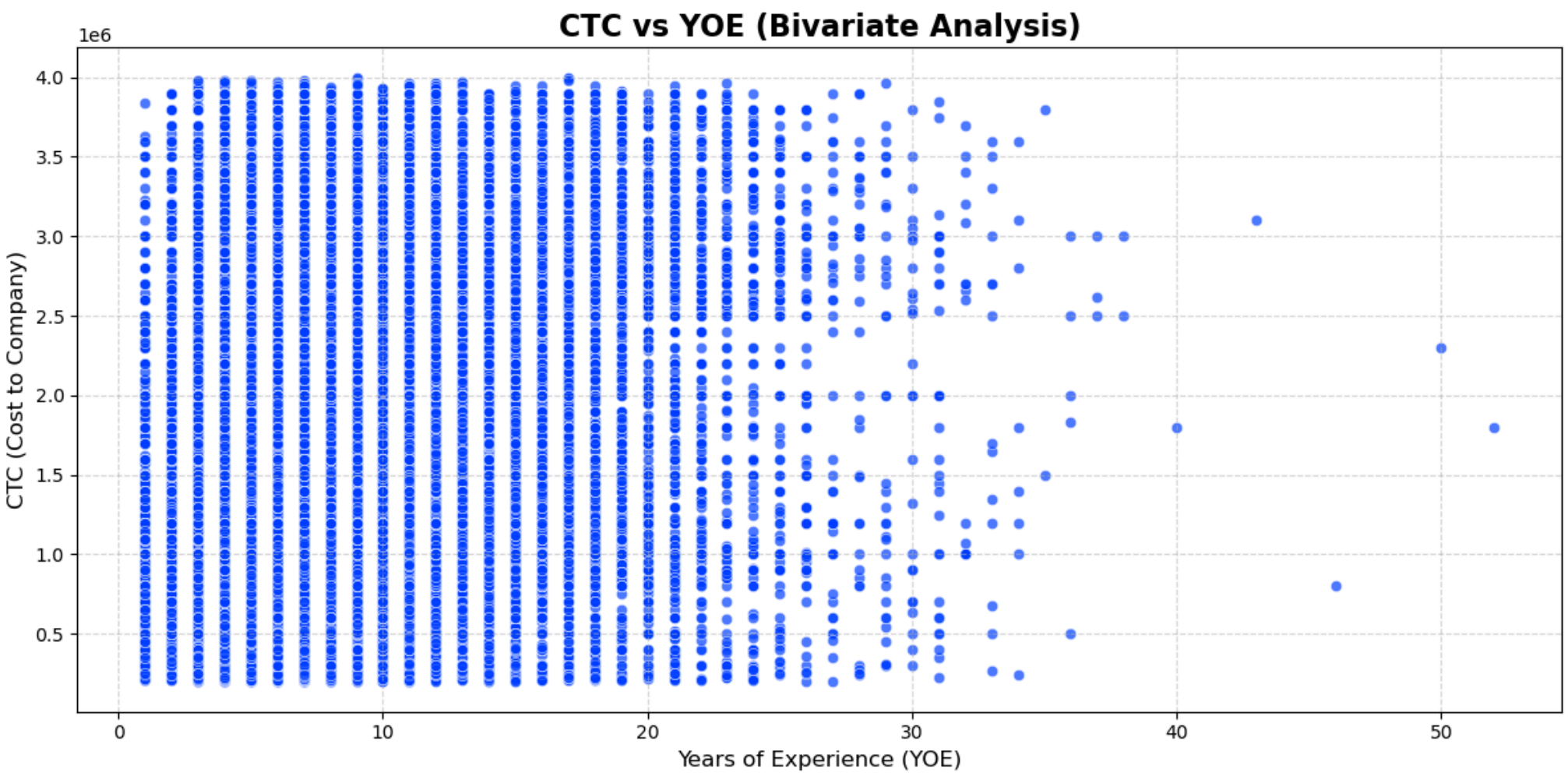
Out[78]: <Figure size 1200x600 with 0 Axes>

Out[78]: <Axes: xlabel='yoe', ylabel='ctc'>

Out[78]: Text(0.5, 1.0, 'CTC vs YOE (Bivariate Analysis)')

Out[78]: Text(0.5, 0, 'Years of Experience (YOE)')

Out[78]: Text(0, 0.5, 'CTC (Cost to Company)')



4.2.3 - Top 10 Companies with `Tier 1` Candidates

```
# Filtering for Tier 1 candidates and grouping by company_hash
top_tier1_companies = (
    df[df['tier_flag'] == 1]
    .groupby('company_hash')
    .size()  # Counting occurrences
    .reset_index(name='count')  # Renaming the count column
    .sort_values(by='count', ascending=False)  # Sorting by count
    .head(10)  # Selecting the top 10 companies
)

# Plotting a count plot
plt.figure(figsize=(10, 6))
sns.barplot(
    data=top_tier1_companies,
    x='count',
    y='company_hash',
    palette='viridis'
)

# Adding titles and labels
plt.title('Top 10 Companies with Tier 1 Candidates', fontsize=16, fontweight='bold')
plt.xlabel('Number of Tier 1 Candidates', fontsize=12)
plt.ylabel('Company Hash', fontsize=12)

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

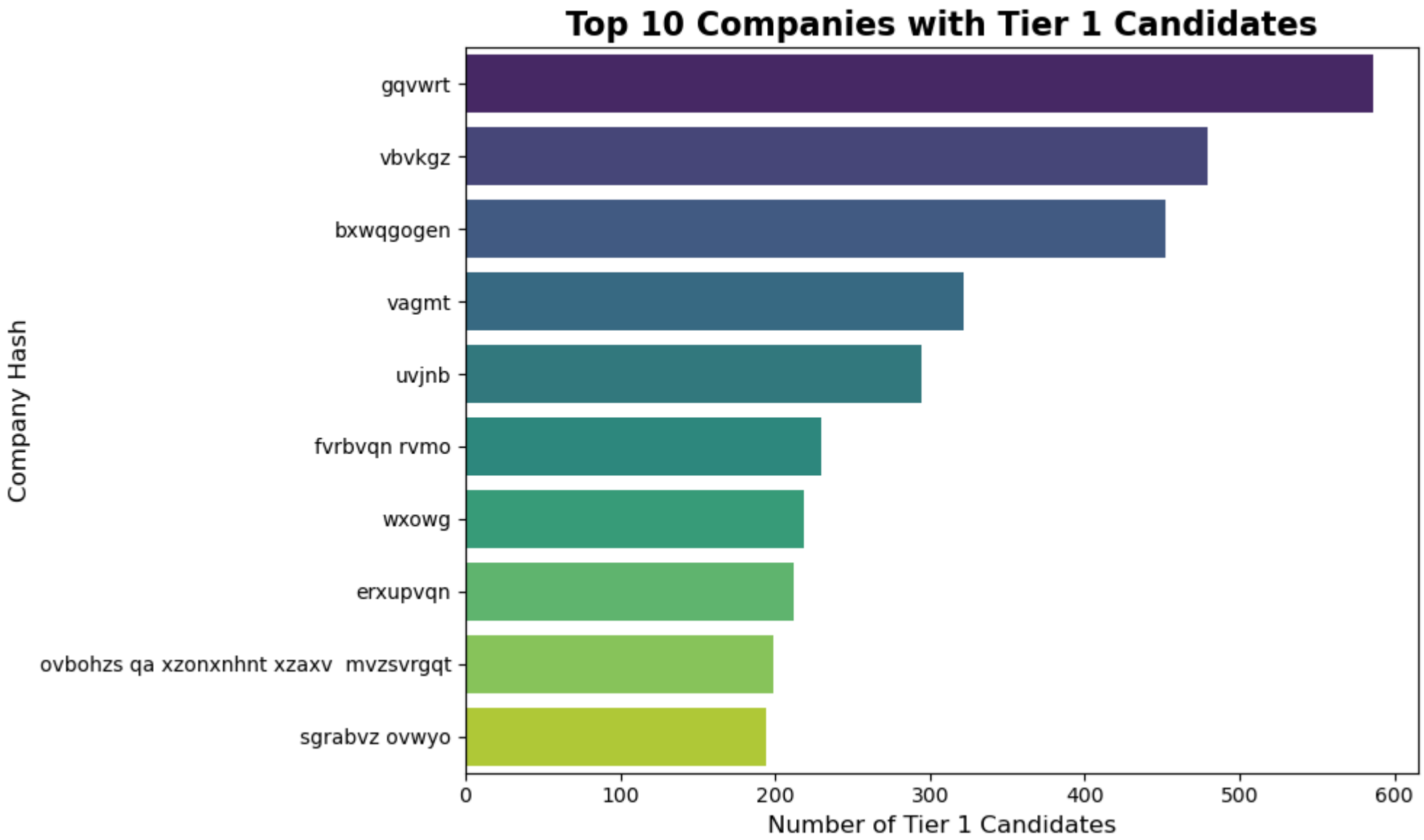
Out[79]: <Figure size 1000x600 with 0 Axes>

Out[79]: <Axes: xlabel='count', ylabel='company_hash'>

Out[79]: Text(0.5, 1.0, 'Top 10 Companies with Tier 1 Candidates')

Out[79]: Text(0.5, 0, 'Number of Tier 1 Candidates')

Out[79]: Text(0, 0.5, 'Company Hash')



🔍 Insights

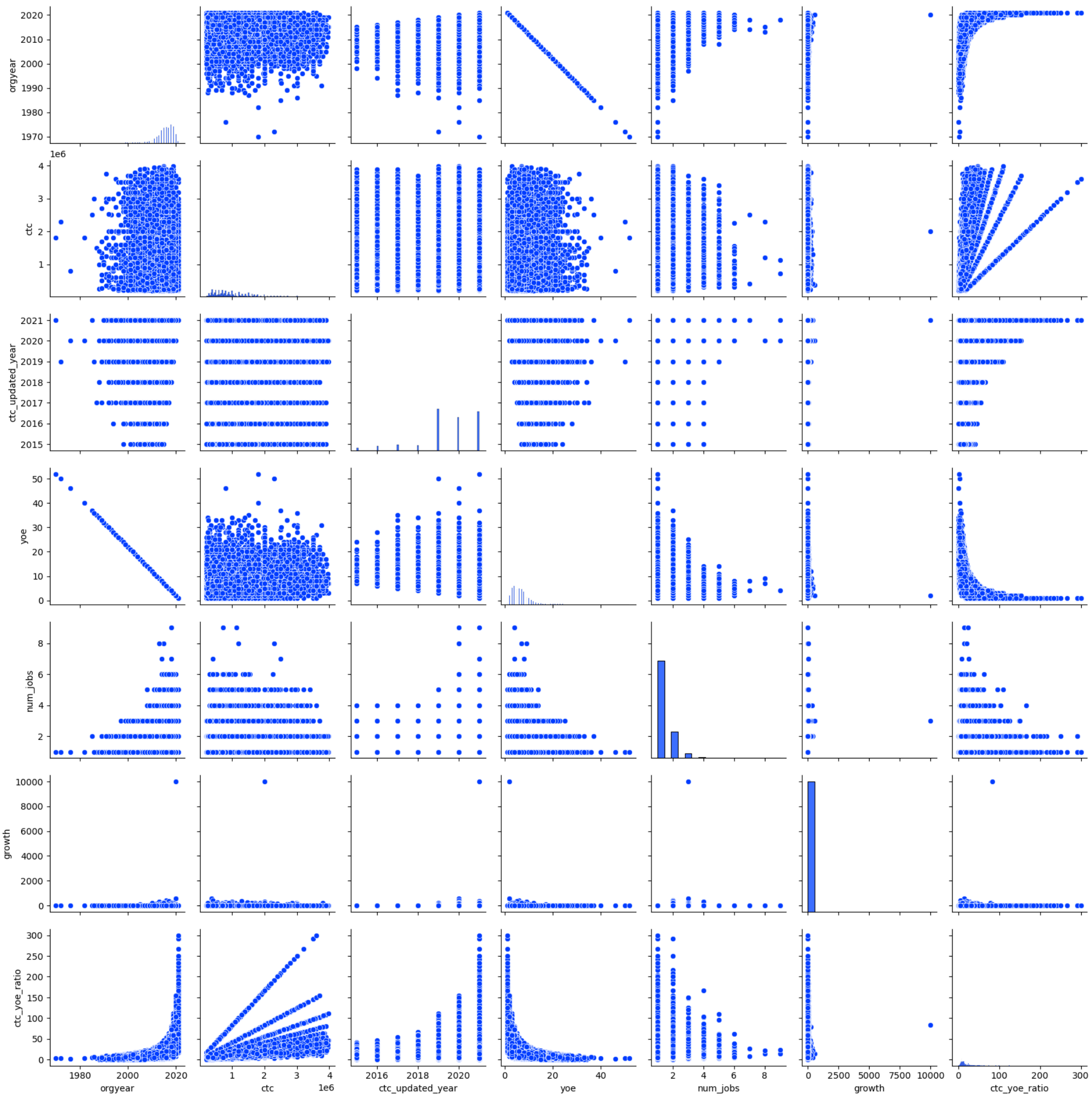
- Company 'gqvwrt' has close to 600 Tier 1 Candidates

In [80]:
```
ctc_filtered_df.columns
```

Out[80]:
```
Index(['company_hash', 'email_hash', 'orgyear', 'ctc', 'job_position',
       'ctc_updated_year', 'yoe', 'num_jobs', 'growth', 'ctc_yoe_ratio',
       'mean_ctc_exp', 'class_flag', 'mean_ctc_position', 'designation_flag',
       'mean_ctc_company', 'tier_flag', 'is_other', 'is_developer', 'is_tech',
       'is_management', 'is_sales', 'is_non_coder', 'ctc_bin'],
      dtype='object')
```

In [81]:
```
# Selecting relevant columns and filtering for Tier 3 candidates
cols = [
    'orgyear',
    'ctc',
    'ctc_updated_year',
    'yoe',
    'num_jobs',
    'growth',
    'ctc_yoe_ratio',
]

# Filtering the DataFrame for Tier 3 candidates
tier3_filtered_df = ctc_filtered_df[ctc_filtered_df['tier_flag'] == 3]

# Creating the pairplot
sns.pairplot(tier3_filtered_df[cols])

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

Out[81]: <seaborn.axisgrid.PairGrid at 0x2ed1053e2f0>



🔍 Insights

- The majority of Tier 3 candidates tend to remain with the same company without frequent switches.
- While most candidates joined their organizations around 2020, there are employees with joining dates extending back to before the 2000s.
- A significant variance in CTC is observed relative to years of experience, indicating diverse salary structures.

4.2.4 - CTC vs Categories

In [82]:
```
# Define the columns you want to analyze
cols = ['is_developer', 'is_tech', 'is_management', 'is_sales', 'is_non_coder']

# Create subplots for each group comparison
fig, ax = plt.subplots(1, 5, figsize=(20, 6))

# Loop through the columns and create a grouped bar chart for each
for i, col in enumerate(cols):
    # Grouping the data by 'ctc_bin' and the binary column (e.g., 'is_developer', 'is_tech', etc.)
    grouped_data = df.groupby(['ctc_bin', col]).size().reset_index(name='count')

    # Pivot the grouped data to create a DataFrame suitable for a bar plot
    pivot_data = grouped_data.pivot(index='ctc_bin', columns=col, values='count').fillna(0)

    # Plot the data on the appropriate subplot
    pivot_data.plot(kind='bar', ax=ax[i])

    # Set the title for each subplot
    ax[i].set_title(f'CTC Bin vs {col.capitalize()}', fontsize=14, fontweight='bold')
    ax[i].set_ylabel('Count', fontsize=12)
```

```
    ax[i].set_xlabel('CTC Bin', fontsize=12)

# Adjust layout and display the plots
plt.tight_layout()
plt.show()
```

Out[82]: <Axes: xlabel='ctc_bin'>

Out[82]: Text(0.5, 1.0, 'CTC Bin vs Is_developer')

Out[82]: Text(0, 0.5, 'Count')

Out[82]: Text(0.5, 0, 'CTC Bin')

Out[82]: <Axes: xlabel='ctc_bin'>

Out[82]: Text(0.5, 1.0, 'CTC Bin vs Is_tech')

Out[82]: Text(0, 0.5, 'Count')

Out[82]: Text(0.5, 0, 'CTC Bin')

Out[82]: <Axes: xlabel='ctc_bin'>

Out[82]: Text(0.5, 1.0, 'CTC Bin vs Is_management')

Out[82]: Text(0, 0.5, 'Count')

Out[82]: Text(0.5, 0, 'CTC Bin')

Out[82]: <Axes: xlabel='ctc_bin'>

Out[82]: Text(0.5, 1.0, 'CTC Bin vs Is_sales')

Out[82]: Text(0, 0.5, 'Count')

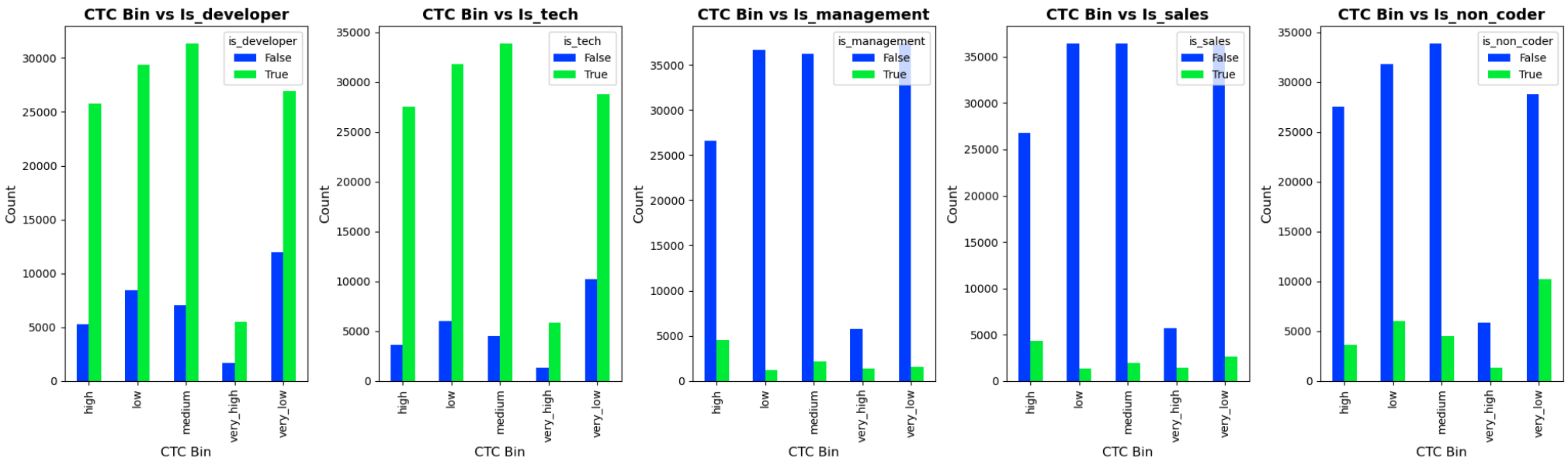
Out[82]: Text(0.5, 0, 'CTC Bin')

Out[82]: <Axes: xlabel='ctc_bin'>

Out[82]: Text(0.5, 1.0, 'CTC Bin vs Is_non_coder')

Out[82]: Text(0, 0.5, 'Count')

Out[82]: Text(0.5, 0, 'CTC Bin')



In [83]:
```
num_column = ['orgyear', 'ctc','ctc_updated_year', 'yoe', 'num_jobs', 'growth', 'ctc_yoe_ratio', 'mean_ctc_exp', 'mean_ctc_position', 'mean_ct
```

In [84]:
```
df[num_column].corr()
```

Out[84]:

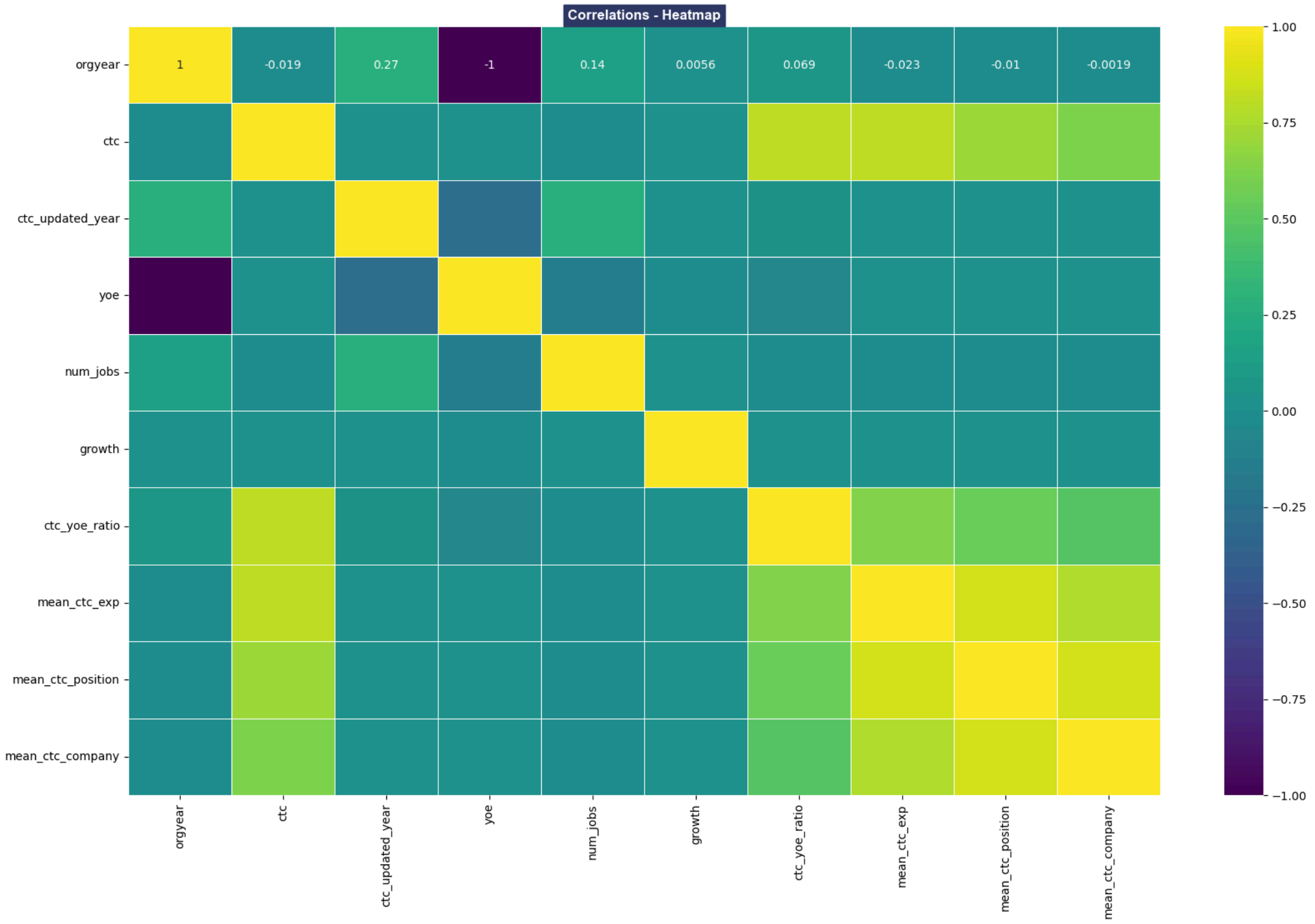
	orgyear	ctc	ctc_updated_year	yoe	num_jobs	growth	ctc_yoe_ratio	mean_ctc_exp	mean_ctc_position	mean_ctc_company
orgyear	1.000	-0.019	0.273	-1.000	0.142	0.006	0.069	-0.023	-0.010	-0.002
ctc	-0.019	1.000	0.028	0.019	-0.029	0.024	0.813	0.812	0.708	0.616
ctc_updated_year	0.273	0.028	1.000	-0.273	0.267	0.009	0.046	0.027	0.028	0.024
yoe	-1.000	0.019	-0.273	1.000	-0.142	-0.006	-0.069	0.023	0.010	0.002
num_jobs	0.142	-0.029	0.267	-0.142	1.000	0.028	-0.018	-0.024	-0.020	-0.014
growth	0.006	0.024	0.009	-0.006	0.028	1.000	0.020	0.018	0.008	0.008
ctc_yoe_ratio	0.069	0.813	0.046	-0.069	-0.018	0.020	1.000	0.630	0.545	0.480
mean_ctc_exp	-0.023	0.812	0.027	0.023	-0.024	0.018	0.630	1.000	0.872	0.759
mean_ctc_position	-0.010	0.708	0.028	0.010	-0.020	0.008	0.545	0.872	1.000	0.870
mean_ctc_company	-0.002	0.616	0.024	0.002	-0.014	0.008	0.480	0.759	0.870	1.000

In [85]:
```
# Correlation Heatmap

plt.figure(figsize=(20,12))

sns.heatmap(df[num_column].corr(), annot=True, cmap='viridis', linewidth=.5, linecolor='w')
plt.title('Correlations - Heatmap',fontsize=12,fontfamily='Arial',fontweight='bold',backgroundcolor=Colors_Palette[0],color='w')
plt.show()
```

Out[85]: <Figure size 2000x1200 with 0 Axes>

Out[85]: <Axes: >

Out[85]: Text(0.5, 1.0, 'Correlations - Heatmap')



5. Manual Clustering

Already Performed in Earlier Steps ---> Data Aggregate, Merging the Df, and Flagging

5.1 - Questions Based on the Manual Clustering Done So For

5.1.1 - Q - Top 10 Employees(Earning more than most of the employees in the Company)

In [86]:
```
# Filter rows where 'tier_flag' is 1, sort by 'ctc' in descending order, and get the top 10
top_10_tier_1 = df[df['tier_flag'] == 1].sort_values(by='ctc', ascending=False).head(10)
top_10_tier_1
```

Out[86]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	yoe	num_jobs	growt
150985	obvqnuqxdwgb	5b4bed51797140db4ed52018a979db1e34cee49e27b488...	2015	255555555	fullstack engineer	2016	7	1	0.00
114573	grd sqghu	1f8e216b2328e7764f79dbd66deaf008b409870ae992fe...	2019	200000000	other	2020	3	1	0.00
112228	psxor	1b9cb9fd05dd794efc20da0f5e873f1afc92767306166b...	2017	200000000	other	2020	5	1	0.00
112355	nvnv wgzohrnvzwj otqcxwto	1ad9ecf5763e6fcc1e7204355c2645e12d3baaf7a7c083...	2015	200000000	data analyst	2020	7	1	0.00
67703	otre tburgjta	f63e63a8cc3db37c89a49f0498d0731f8c9e2e27943e85...	2015	200000000	android engineer	2020	7	1	0.00
112367	yaew mvzp	1ad3d8c2b855e9cbe6bb187e8140a07ed8a8b29d275ae0...	2017	200000000	other	2020	5	1	0.00
136303	gnytq	82b6acf155f320e9e70dcb6d1b6fd33449dc731f4c07bf...	2008	200000000	other	2020	14	1	0.00
112489	cxcg bgmxrt xzaxv ucn rna	1b1a39899354f398255dcbef537ed636bc8ce242fab0ea...	2018	200000000	other	2020	4	1	0.00
135865	qtrxvzwt lxg xzegwgbb rxbxnta	81d9854a6797a2ef69f8a9fa358c332d7da3297163507b...	2015	200000000	unknown	2020	7	1	0.00
112619	stzuvwn	1c6bc8b95225bf255f939a64f9d60f84371f16eb621f3a...	2014	200000000	other	2020	8	1	0.00

10 rows × 23 columns

5.1.2 - Q - Top 10 employees of Data Science in each Company earning more than their peers - Class 1

In [87]:
```
# Filter rows where 'job_position' starts with 'data' and 'class_flag' is 1,
# sort by 'ctc' in descending order, and get the top 10
filtered_data = df[df['job_position'].str.startswith('data') & (df['class_flag'] == 1)]
top_10_DS = filtered_data.sort_values(by='ctc', ascending=False).head(10)
top_10_DS
```

Out[87]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	yoe	num_jobs	growth
145840	nvnv wgzohrnvzwj otqcxwto	655da5cd99f1ba4ad249dade5039b914023484fb7f3959...	2017	200000000	data analyst	2020	5	1	0.000
72275	ytfrtnn uvwpvqa tzntquqxot	c888824e687a535d1bd2486ae28d67e414b21b09cbee61...	2015	200000000	data analyst	2020	7	1	0.000
112355	nvnv wgzohrnvzwj otqcxwto	1ad9ecf5763e6fcc1e7204355c2645e12d3baaf7a7c083...	2015	200000000	data analyst	2020	7	1	0.000
123241	ntwy bvyxzaqv	7a723f5b71698674b79bd2195c3bb58d3fcbf4ddb75a04...	2019	200000000	data analyst	2021	3	1	0.000
48160	vbvkgz	95c8bdd3d10f967f6bfb32f280b0b37fbf5db2359918ba...	2016	200000000	data analyst	2020	6	1	0.000
41075	wgzahtzn	9ce2995b2221fe627e861daea9d0603872cce8cc128390...	2016	200000000	data analyst	2020	6	1	0.000
124098	gnytq	6d4a5d19e889596252b038ee0409510aec8c0b32007fb9...	2017	200000000	data analyst	2020	5	1	0.000
139296	nvnv wgzohrnvzwj otqcxwto	59316048d113539202325e05af9b66620255ba84eab635...	2015	200000000	data analyst	2020	7	1	0.000
84049	nvnv wgzohrnvzwj otqcxwto	d42cf076c3915454a083788ea22df68a65a294563adfa3...	2012	200000000	data analyst	2020	10	1	0.000
51040	ytqt ntwyzgrgsxto	98a90272cbba6e6e9ca94981824f3465f3d34567cb065f...	2015	200000000	data analyst	2020	7	1	0.000

10 rows × 23 columns

5.1.3 - Q - Bottom 10 employees of Data Science in each Company earning less than their peers - Class 3

In [88]:
```
# Filter rows where 'job_position' starts with 'data' and 'class_flag' is 3,
# sort by 'ctc' in Ascending order, and get the Bottom 10
filtered_data = df[df['job_position'].str.startswith('data') & (df['class_flag'] == 3)]
Bottom_10_DS = filtered_data.sort_values(by='ctc', ascending=True).head(10)
Bottom_10_DS
```

Out[88]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	yoe	num_jobs	growth	c
102215	nvnv wgzohrnvzwj otqcxwto	3becd3658bc0d426f8867142eb6cbd7e9ca9f43b572794...	2018	3500	database administrator	2019	4	1	0.000	
51390	wgszxkvzn	abf69e786daa23f50d3142b653235e2c030b3b180b07d2...	2014	4300	data analyst	2019	8	1	0.000	
4717	onhatzn	bd9c04a574090e05b366a81cdb2f3f565d0c60fa8b1647...	2018	6000	data scientist	2019	4	3	0.000	
89200	nvnv wgzohrnvzwj otqcxwto	3175d03fd4618eb293d6f5a1d13d42a0c79f68e9acaaa3...	2020	7500	data scientist	2020	2	1	0.000	
99457	vqxosrgmvr	3675f79c7e05de96ccf189c818b84b487cb1aa3f6b80e8...	2015	8800	data scientist	2019	7	1	0.000	
61349	sggsrt	fb64af615420e06d46a1965f59068b34460fb3cbe70541...	2018	10000	data scientist	2021	4	1	0.000	
150728	zgn vuurxwvmrt vwwghzn	598b129dd60613cd01a43ea7b946a50a1eb781489feb12...	2020	10000	database administrator	2021	2	1	0.000	
83446	ahzzyhbmj	d32c344816921ae7be310ba7630c6e267703b2fc4e6a6c...	2016	31000	data scientist	2019	6	1	0.000	
83770	zvz	d277c90e2b97fb51657936b66b68eee2e52bd4d8d98e1d...	2015	46500	data scientist	2016	7	1	0.000	
77788	tqxwoogz	d8b6c25488ee764c6dbd20c56ad8dca794b6347d6448e2...	2017	49000	data scientist	2017	5	1	0.000	

10 rows × 23 columns

5.1.4 - Q - Top 10 Employees in Each Company - X Department - having 5/6/7 Years of Experience earning more than their peers - Tier X

In [89]:
```
# Filter the DataFrame for tier_flag = 1, designation_flag = 1, and yoe between 5 and 7
filtered_df = df[(df['tier_flag'] == 1) &
                 (df['designation_flag'] == 1) &
                 (df['yoe'] >= 5) &
                 (df['yoe'] <= 7)]

# Sort the filtered DataFrame by company_hash and ctc in descending order,
# and apply the row number logic (group by company_hash and order by ctc desc)
filtered_df['rn'] = filtered_df.sort_values(['company_hash', 'ctc'], ascending=[True, False]) \
    .groupby('company_hash') \
    .cumcount() + 1

# Select top 10 rows for each company (rn <= 10)
top_10_records = filtered_df[filtered_df['rn'] <= 10]

# Sort the final DataFrame by company_hash, job_position, and ctc (desc)
final_df = top_10_records.sort_values(['company_hash', 'job_position', 'ctc'], ascending=[True, True, False])

# Display the final result
final_df
```

Out[89]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	yoe	num_jobs	growth
88690	1bs	31db7b806a82aac024462d4c97e70eed918bf8c3193b7c...	2016	3750000	backend engineer	2020	6	1	0.000
138984	1bs	579d9c719cc05b885297256c122585a8f71871f9079c6f...	2015	2930000	backend engineer	2019	7	1	0.000
42573	1bs	9c02076a74a2b8a64a6e003fa0a2e4115fc717dacb3585...	2016	2320000	backend engineer	2020	6	1	0.000
99138	1bs	38dfe791fc911da418b67aa989a6aa7f00b8c680c6d4e1...	2015	2000000	backend engineer	2019	7	1	0.000
72576	1bs	c97fd1612080086b898e440529c86325ae8ddf2e9a0b60...	2015	1800000	backend engineer	2019	7	1	0.000
...	...	...	...	...	...	...	...	...	...
60073	zxzlvwvqn	e2377e7ee0d53d2e3a45b9687fdc9c08b136b1dc470806...	2017	2300000	fullstack engineer	2020	5	1	0.000
5710	zxztrtvuo	303aab779b6daea19317b430f600b0e8543f4c66ca3251...	2015	11950000	backend engineer	2020	7	2	8.700
10537	zxztrtvuo	234f0f52e89b20231f5685551b865a08a5634189e1ffec...	2015	2500000	backend engineer	2021	7	2	0.667
21763	zxztrtvuo	16c227291d7c4f151b52599cc15e1ddd6f7e12a694753c...	2015	1780000	backend engineer	2020	7	2	0.271
98282	zxztrtvuo	3879b9a1e356ed20363fffd6871207eb908b38c864a2db...	2017	1500000	fullstack engineer	2019	5	1	0.000

4899 rows × 24 columns

5.1.5 - Q - Top 10 Companies (Based on their CTC)

In [90]:
```
# Group the DataFrame by 'company_hash' and calculate the average of 'ctc' for each company
avg_ctc_df = df.groupby('company_hash')['ctc'].mean().reset_index()

# Sort the DataFrame by 'avg_ctc' in descending order and get the top 10 companies
top_10_avg_ctc = avg_ctc_df.sort_values(by='ctc', ascending=False).head(10)

# Display the result
top_10_avg_ctc
```

Out[90]:

	company_hash	ctc
29688	whmxw rgsxwo uqxcvnt rxbxnta	1000150000.000
1189	aveegaxr xzntqzvnxgzvr hzxctqoxnj	250000000.000
14649	ogzv wgrrtst ge ntwyzgrgsjvzzv hzxctqoxnj	200000000.000
25708	vayxxuv ntwyzgrgsxto ucn rna	200000000.000
25038	uvqp wgbuhntq ojontb xzw	200000000.000
8627	i wgzztin mhoxztoo ogrhnxgzo ucn rna	200000000.000
17103	oxburjyq ogrhnxgzo rru	200000000.000
4991	dgq avnv tdwyvzst	200000000.000
592	anaw tduqtoo rxbxnta	200000000.000
13319	nvrtzn ouvwt xzw	200000000.000

5.1.6 - Q - Top 2 Positions in Every Company (based on their CTC)

In [91]:
```
# First, we sort the DataFrame by 'company_hash' and 'ctc' in descending order to simulate the ranking
df_sorted = df.sort_values(by=['company_hash', 'ctc'], ascending=[True, False])

# Then, we group the DataFrame by 'company_hash' and assign a row number (rank) to each 'job_position' within each company
df_sorted['rn'] = df_sorted.groupby('company_hash').cumcount() + 1

# Filter the rows where the row number is less than or equal to 2 (i.e., select top 2 for each company)
top_2_ctc_per_company = df_sorted[df_sorted['rn'] <= 2]

# Select the relevant columns and sort the DataFrame by 'company_hash' and 'ctc' in descending order
result = top_2_ctc_per_company[['company_hash', 'job_position', 'ctc']].sort_values(by=['company_hash', 'ctc'], ascending=[False, False])

# Display the result
result
```

Out[91]:

	company_hash	job_position	ctc
84070	zzgato	unknown	130000
71133	zzb ztdnstz vacxogqj ucn rna	fullstack engineer	600000
133579	zz	other	1370000
78987	zz	other	500000
141069	zyvzwt wgzohrnxzs tzsxzttqo	frontend engineer	940000
...	...	...	...
96750	05mz exzytvrny uqxcvnt rxbxnta	backend engineer	1100000
59912	01 ojztqsj	frontend engineer	830000
135778	01 ojztqsj	android engineer	270000
39426	0000	other	300000
54190	0	other	100000

45032 rows × 3 columns

6. Standardization and Encoding

Label Encoding Part was already done in Feature Engineering Section --> except for the `ctc_bin`

In [92]:
```
df_Clustering = df.copy()
```

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

Out[93]:

	company_hash	email_hash	orgyear	ctc	job_position	ctc_updated_year	yoe	num_jobs	growth	ctc_yc
0	cvrhtbgbtznhb	298528ce3160cc761e4dc37a07337ee2e0589df251d736...	2018	720000	backend engineer	2020	4	9	0.029	
1	wgcxvb ntwyzgrgsxto	3e5e49daa5527a6d5a33599b238bf9bf31e85b9efa9a94...	2018	1130000	engineering intern	2021	4	9	0.041	
2	ihvrwgbb	6842660273f70e9aa239026ba33bfe82275d6ab0d20124...	2017	2400000	qa engineer	2020	5	9	0.200	
3	gqvwrt	4818edfd67ed8563dde5d083306485d91d19f4f1c95d19...	2015	1200000	backend architect	2020	7	8	0.000	
4	nyt a t oyvf sqghu	c0eb129061675da412b0deb15871dd06ef0d7cd86eb5f7...	2013	2300000	other	2020	9	8	0.513	

5 rows × 23 columns

In [94]:
```
# List of columns to drop
columns_to_drop = ["email_hash", "class_flag", "designation_flag", "tier_flag", "company_hash", "is_tech"]

# Check if the columns exist in the DataFrame
existing_columns = [col for col in columns_to_drop if col in df.columns]

# Drop only the existing columns
df = df.drop(columns=existing_columns)

# Display the updated DataFrame
print(df.head())
```

```
   orgyear      ctc        job_position  ctc_updated_year  yoe  num_jobs  \
0     2018   720000    backend engineer              2020    4         9
1     2018  1130000  engineering intern              2021    4         9
2     2017  2400000         qa engineer              2020    5         9
3     2015  1200000   backend architect              2020    7         8
4     2013  2300000               other              2020    9         8

   growth  ctc_yoe_ratio  mean_ctc_exp  mean_ctc_position  mean_ctc_company  \
0   0.029         15.000    720000.000         980000.000        747619.048
1   0.041         23.542   1130000.000        1130000.000       1223750.000
2   0.200         40.000   1900000.000        1612857.143       2236561.619
3   0.000         14.286   1200000.000        3269120.000       1700962.689
4   0.513         21.296   2300000.000        3603825.308       4401026.176

   is_other  is_developer  is_management  is_sales  is_non_coder ctc_bin
0     False          True          False     False         False     low
1     False          True          False     False         False  medium
2     False          True          False     False         False    high
3     False          True          False     False         False  medium
4      True         False          False     False          True    high
```

In [95]:
```
# Define a dictionary for mapping ctc_bin values to corresponding numerical values
ctc_bin_map = {
    "very_high": 5,
    "high": 4,
    "medium": 3,
    "low": 2
}

# Use pandas' map function to map ctc_bin to numerical values, with a default value of 1 for other categories
df['ctc_bin'] = df['ctc_bin'].map(ctc_bin_map).fillna(1).astype(int)

# Display the updated DataFrame
print(df.head())
```

```
   orgyear      ctc        job_position  ctc_updated_year  yoe  num_jobs  \
0     2018   720000    backend engineer              2020    4         9
1     2018  1130000  engineering intern              2021    4         9
2     2017  2400000         qa engineer              2020    5         9
3     2015  1200000   backend architect              2020    7         8
4     2013  2300000               other              2020    9         8

   growth  ctc_yoe_ratio  mean_ctc_exp  mean_ctc_position  mean_ctc_company  \
0   0.029         15.000    720000.000         980000.000        747619.048
1   0.041         23.542   1130000.000        1130000.000       1223750.000
2   0.200         40.000   1900000.000        1612857.143       2236561.619
3   0.000         14.286   1200000.000        3269120.000       1700962.689
4   0.513         21.296   2300000.000        3603825.308       4401026.176

   is_other  is_developer  is_management  is_sales  is_non_coder  ctc_bin
0     False          True          False     False         False        2
1     False          True          False     False         False        3
2     False          True          False     False         False        4
3     False          True          False     False         False        3
4      True         False          False     False          True        4
```

In [96]:
```
# Step 1: Calculate the job position frequency
job_frequency_df = df.groupby("job_position").size().reset_index(name="job_pos_frequency")

# Step 2: Merge the job frequency data back into the original dataframe
df = df.merge(job_frequency_df, on="job_position", how="left")
```

```
# Step 3: Drop the original 'job_position' column
df = df.drop(columns=["job_position"])

# Step 4: Rename the 'job_pos_frequency' column to 'job_position'
df = df.rename(columns={"job_pos_frequency": "job_position"})

# Display the resulting dataframe
print(df.head())
```

```
   orgyear      ctc  ctc_updated_year  yoe  num_jobs  growth  ctc_yoe_ratio  \
0     2018   720000               2020    4         9   0.029         15.000
1     2018  1130000               2021    4         9   0.041         23.542
2     2017  2400000               2020    5         9   0.200         40.000
3     2015  1200000               2020    7         8   0.000         14.286
4     2013  2300000               2020    9         8   0.513         21.296

   mean_ctc_exp  mean_ctc_position  mean_ctc_company  is_other  is_developer  \
0   720000.000         980000.000        747619.048     False          True
1  1130000.000        1130000.000       1223750.000     False          True
2  1900000.000        1612857.143       2236561.619     False          True
3  1200000.000        3269120.000       1700962.689     False          True
4  2300000.000        3603825.308       4401026.176      True         False

   is_management  is_sales  is_non_coder  ctc_bin  job_position
0          False     False         False        2         52262
1          False     False         False        3          1958
2          False     False         False        4          5863
3          False     False         False        3          1028
4          False     False          True        4         19147
```

In [97]:
```
df_enc = df.copy()
```

6.1 - Standardization

In [98]:
```
# Import StandardScaler from sklearn for standardization
from sklearn.preprocessing import StandardScaler

# Initialize the StandardScaler object, which will scale the features
std_scaler = StandardScaler()

# Fit the StandardScaler to the DataFrame 'df' to calculate the mean and standard deviation
std_scaler.fit(df)

# Transform the data using the fitted scaler
std_df = std_scaler.transform(df)

# Convert the resulting numpy array 'std_df' back into a pandas DataFrame
std_df = pd.DataFrame(std_df, columns=df.columns)

# Display the first 5 rows of the standardized DataFrame
std_df.head()
```

Out[98]:
```
StandardScaler()
```

Out[98]:

	orgyear	ctc	ctc_updated_year	yoe	num_jobs	growth	ctc_yoe_ratio	mean_ctc_exp	mean_ctc_position	mean_ctc_company	is_other	is_develope
0	0.768	-0.138	0.372	-0.768	14.047	-0.013	-0.089	-0.170	-0.166	-0.220	-0.418	0.53
1	0.768	-0.106	1.101	-0.768	14.047	-0.013	-0.059	-0.131	-0.150	-0.161	-0.418	0.53
2	0.534	-0.009	0.372	-0.534	14.047	-0.009	-0.001	-0.059	-0.098	-0.035	-0.418	0.53
3	0.067	-0.101	0.372	-0.067	12.234	-0.014	-0.091	-0.124	0.081	-0.102	-0.418	0.53
4	-0.401	-0.017	0.372	0.401	12.234	0.000	-0.067	-0.021	0.117	0.233	2.395	-1.86

In [99]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 153443 entries, 0 to 153442
Data columns (total 17 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   orgyear            153443 non-null  int64
 1   ctc                153443 non-null  int64
 2   ctc_updated_year   153443 non-null  int32
 3   yoe                153443 non-null  int64
 4   num_jobs           153443 non-null  int64
 5   growth             153443 non-null  float64
 6   ctc_yoe_ratio      153443 non-null  float64
 7   mean_ctc_exp       153443 non-null  float64
 8   mean_ctc_position  153443 non-null  float64
 9   mean_ctc_company   153443 non-null  float64
 10  is_other           153443 non-null  bool
 11  is_developer       153443 non-null  bool
 12  is_management      153443 non-null  bool
 13  is_sales           153443 non-null  bool
 14  is_non_coder       153443 non-null  bool
 15  ctc_bin            153443 non-null  int32
 16  job_position       153443 non-null  int64
dtypes: bool(5), float64(5), int32(2), int64(5)
memory usage: 13.6 MB
```

In [100]:
```
# Making std_df as df for further processing

DF = std_df.copy()
```

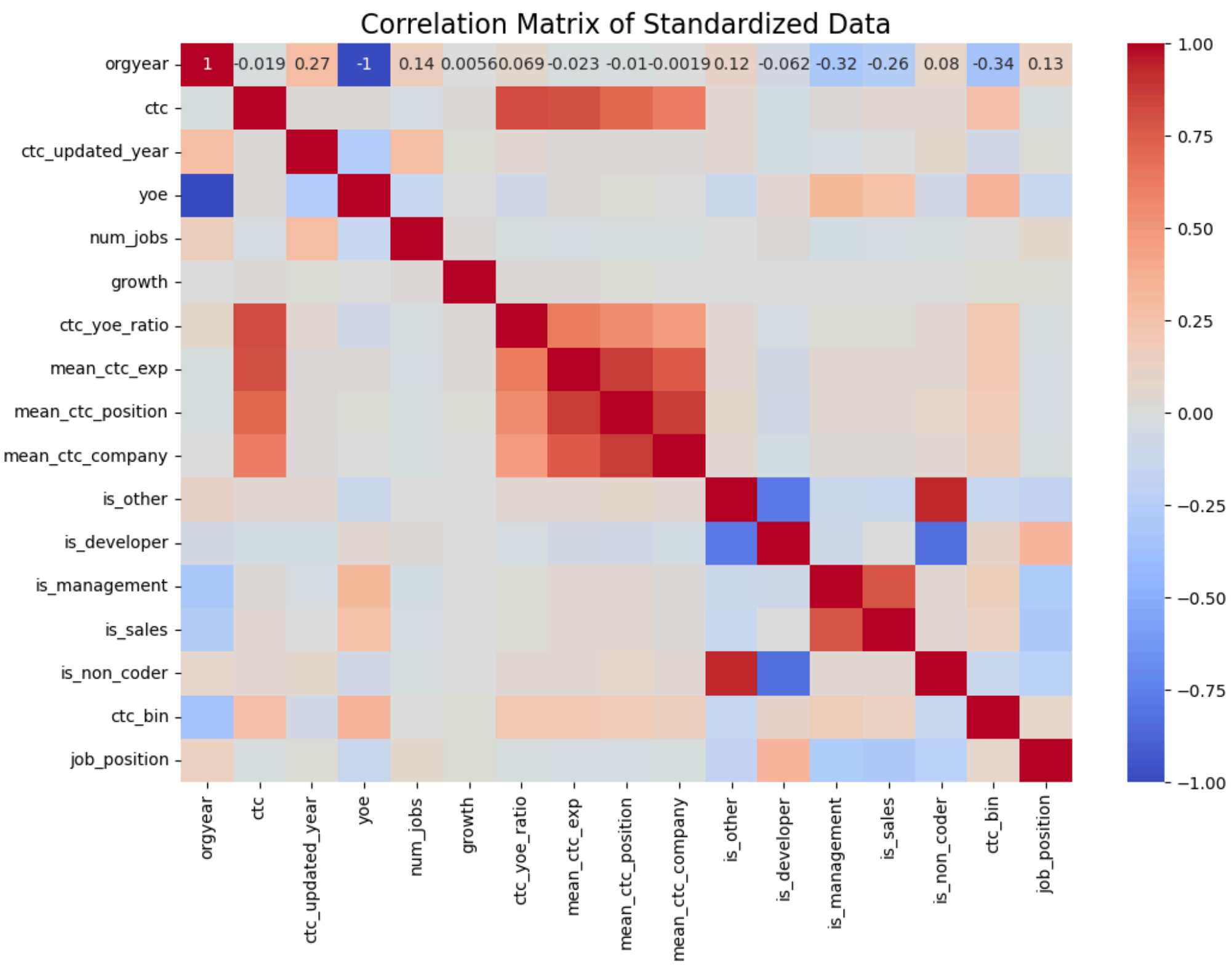
6.1.1 - Visualizing the Standardized Data

In [101]:
```
# Heatmap for Correlation Matrix of Standardized Data

plt.figure(figsize=(12, 8))

sns.heatmap(DF.corr(), annot=True, cmap='coolwarm')
plt.title("Correlation Matrix of Standardized Data", fontsize=16)

plt.show()
```

Out[101]: `<Figure size 1200x800 with 0 Axes>`

Out[101]: `<Axes: >`

Out[101]: `Text(0.5, 1.0, 'Correlation Matrix of Standardized Data')`



7. Unsupervised Learning

In [102]:
```
DF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 153443 entries, 0 to 153442
Data columns (total 17 columns):
 #   Column              Non-Null Count   Dtype  
---  ------              --------------   -----  
 0   orgyear             153443 non-null  float64
 1   ctc                 153443 non-null  float64
 2   ctc_updated_year    153443 non-null  float64
 3   yoe                 153443 non-null  float64
 4   num_jobs            153443 non-null  float64
 5   growth              153443 non-null  float64
 6   ctc_yoe_ratio       153443 non-null  float64
 7   mean_ctc_exp        153443 non-null  float64
 8   mean_ctc_position   153443 non-null  float64
 9   mean_ctc_company    153443 non-null  float64
 10  is_other            153443 non-null  float64
 11  is_developer        153443 non-null  float64
 12  is_management       153443 non-null  float64
 13  is_sales            153443 non-null  float64
 14  is_non_coder        153443 non-null  float64
 15  ctc_bin             153443 non-null  float64
 16  job_position        153443 non-null  float64
dtypes: float64(17)
memory usage: 19.9 MB
```

7.1 - Checking Clustering Tendency

7.1.1 - Hopkins Test for Cluster Tendency Check

The Hopkins statistic is a measure used to evaluate the tendency of a dataset to cluster. It assesses the randomness of data distribution.

> The statistic ranges from 0 to 1, with the following interpretations:

- Near 0: The data is uniformly distributed and does not exhibit cluster structure.
- Near 1: The data exhibits strong clustering tendencies.
- Around 0.5: The data distribution is random.

In [103]:
```
def hopkins_statistic(df, sample_size=0.1):
    # Ensure all columns in the DataFrame are numeric
    df_numeric = DF.apply(pd.to_numeric, errors='coerce')

    # Number of rows in the dataframe
    n = df_numeric.shape[0]

    # Determine the sample size based on the given proportion
    m = int(sample_size * n)

    # Randomly select indices for sampling
    random_indices = np.random.choice(np.arange(n), size=m, replace=False)
    df_sample = df_numeric.iloc[random_indices]

    # Convert the dataframe to a NumPy array for min/max calculation
    X = df_numeric.to_numpy()

    # Calculate the min and max for each column
    X_min = np.min(X, axis=0)
    X_max = np.max(X, axis=0)

    # Generate random points within the bounds of the data
    X_uniform_random = np.random.uniform(X_min, X_max, (m, X.shape[1]))

    # Fit nearest neighbors model on the data
    nbrs = NearestNeighbors(n_neighbors=1).fit(X)

    # Calculate the distances for the sampled points and the random points
    u_distances, _ = nbrs.kneighbors(df_sample)
    u_distances = u_distances.sum()

    w_distances, _ = nbrs.kneighbors(X_uniform_random)
    w_distances = w_distances.sum()

    # Compute the Hopkins statistic
    hopkins_stat = w_distances / (u_distances + w_distances)

    return hopkins_stat
```

In [104]:
```
hopkins_stat = hopkins_statistic(DF, sample_size=0.1)
print("Hopkins Statistic:", hopkins_stat)
```

```
Hopkins Statistic: 0.9999999998724884
```

The *__Hopkins statistic__* value is **0.9999999998724884**, which is extremely *__close to 1__*.

This indicates that The Data has `Strong Clustering Tendency` & `Clustering Methods Are Applicable`

7.2 - K-Means Clustering

In [105]:
```
DF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 153443 entries, 0 to 153442
Data columns (total 17 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   orgyear            153443 non-null  float64
 1   ctc                153443 non-null  float64
 2   ctc_updated_year   153443 non-null  float64
 3   yoe                153443 non-null  float64
 4   num_jobs           153443 non-null  float64
 5   growth             153443 non-null  float64
 6   ctc_yoe_ratio      153443 non-null  float64
 7   mean_ctc_exp       153443 non-null  float64
 8   mean_ctc_position  153443 non-null  float64
 9   mean_ctc_company   153443 non-null  float64
 10  is_other           153443 non-null  float64
 11  is_developer       153443 non-null  float64
 12  is_management      153443 non-null  float64
 13  is_sales           153443 non-null  float64
 14  is_non_coder       153443 non-null  float64
 15  ctc_bin            153443 non-null  float64
 16  job_position       153443 non-null  float64
dtypes: float64(17)
memory usage: 19.9 MB
```

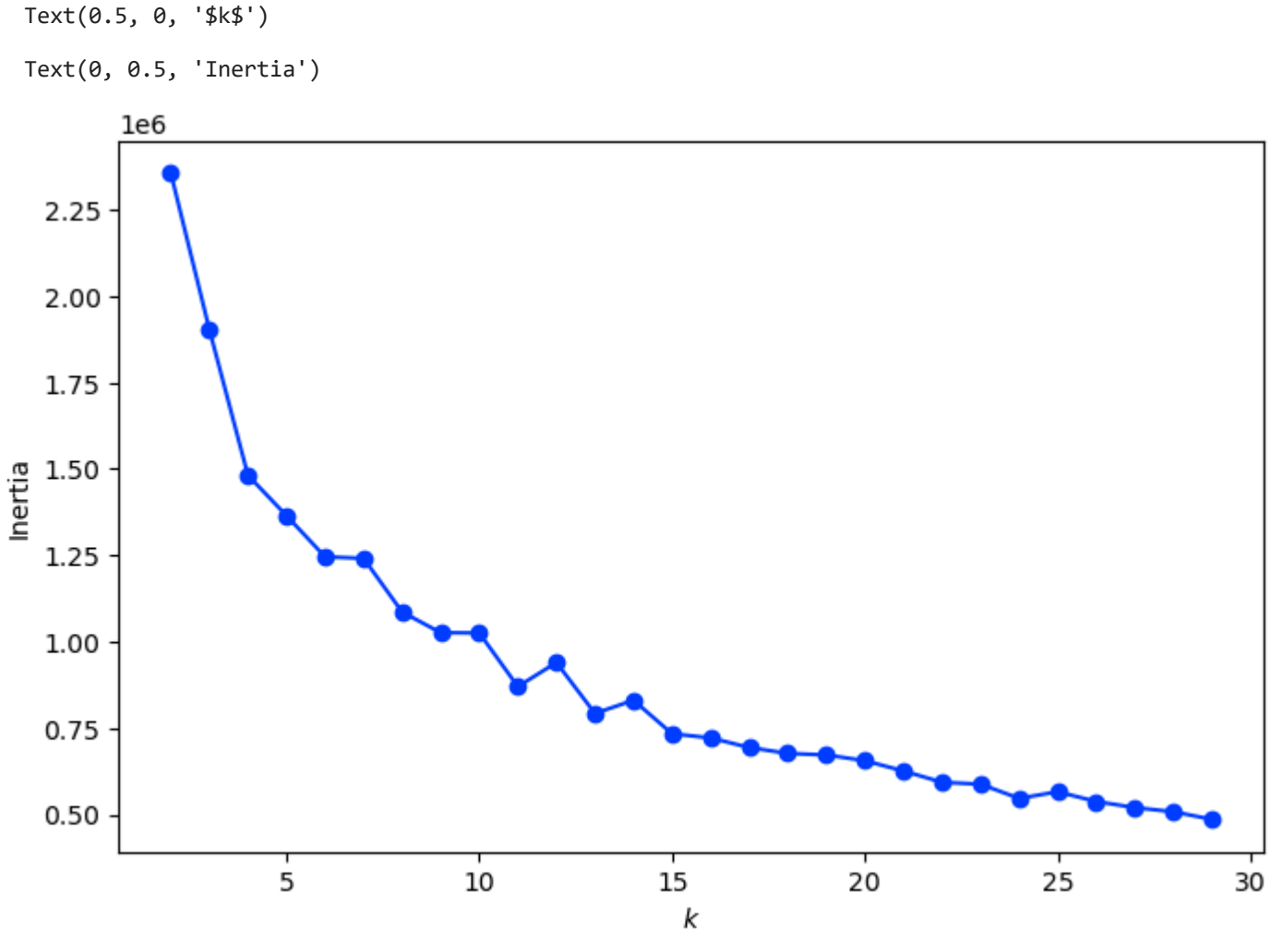
In [106]:
```
import os
from sklearn.cluster import KMeans

# If needed, you can set the number of threads to avoid parallelism issues
os.environ["OMP_NUM_THREADS"] = "1"  # Disabling multi-threading

# Assuming df is your DataFrame and is numeric
df_numeric = DF.select_dtypes(include=['float64', 'int64'])

# Fit KMeans models for each value of k and store the models in a list
kmeans_per_k = [KMeans(n_clusters=k, random_state=42, n_init=10).fit(df_numeric) for k in range(2, 30, 1)]

# Extract the inertia values (within-cluster sum of squared distances) from each model
inertias = [model.inertia_ for model in kmeans_per_k]

# Plot the inertia for each k value to visualize the Elbow method
plt.figure(figsize=(8, 5))
plt.plot(range(2, 30, 1), inertias, "-o")
plt.xlabel("$k$")
plt.ylabel("Inertia")
plt.show()
```

Out[106]: `<Figure size 800x500 with 0 Axes>`

Out[106]: `[<matplotlib.lines.Line2D at 0x2ed3bb017e0>]`

Out[106]: `Text(0.5, 0, '$k$')`

Out[106]: `Text(0, 0.5, 'Inertia')`



We will Use K = 5 for K - Means Clustering due to the presence of Elbow

7.2.1 - Using PCA to reduce the Dimensions

In [107]:
```
# Fit PCA and calculate the cumulative explained variance ratio
pca = PCA()
pca.fit(df_numeric)
pca_explained_variance = pca.explained_variance_ratio_.cumsum()

# Output the cumulative explained variance
pca_explained_variance
```

Out[107]:
```
PCA()
```

Out[107]:
```
array([0.23337373, 0.40859196, 0.56448411, 0.6534014 , 0.71934577,
       0.77789144, 0.82638646, 0.8698445 , 0.91103796, 0.94638182,
       0.96183536, 0.97527273, 0.98496568, 0.99222017, 0.99719639,
       1.        , 1.        ])
```

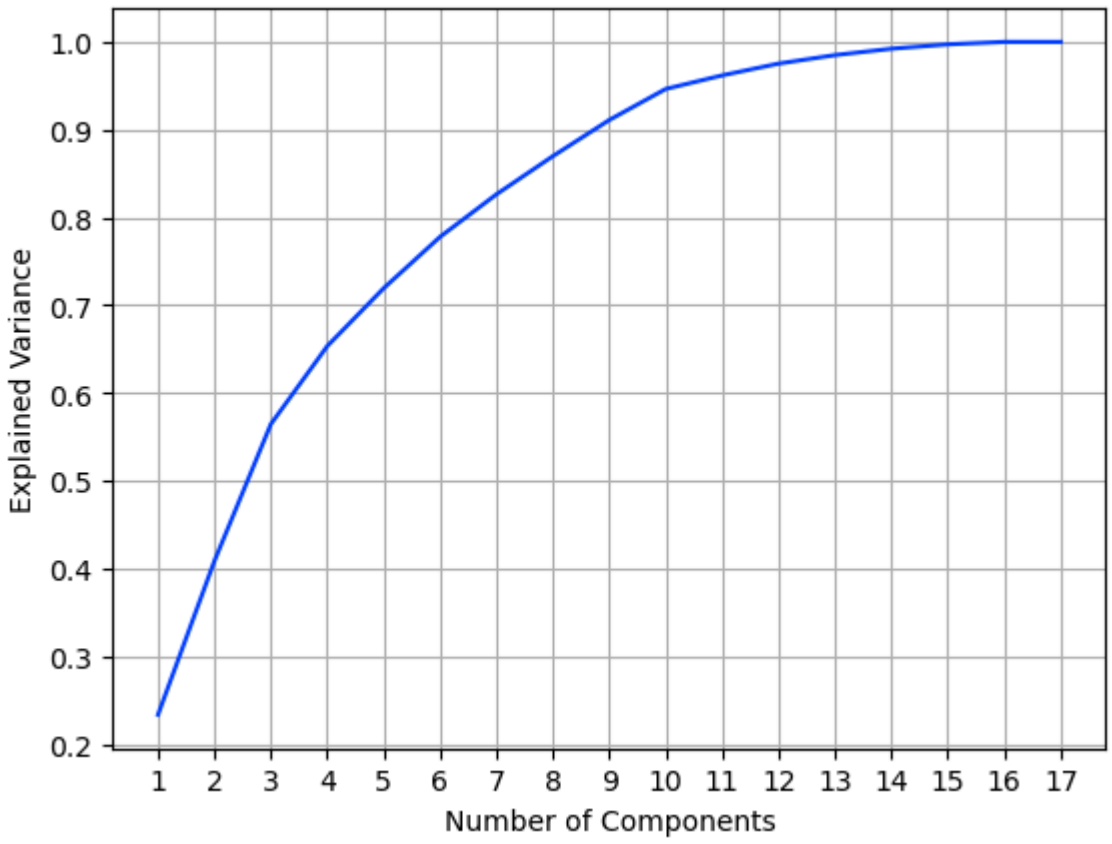
In [108]:
```
# Create a line plot for the cumulative explained variance
sns.lineplot(x=range(1, len(pca_explained_variance) + 1), y=pca_explained_variance)

# Label the x-axis and y-axis
plt.xlabel("Number of Components")
plt.ylabel("Explained Variance")

# Set the x-ticks to match the number of components
plt.xticks(range(1, len(pca_explained_variance) + 1))

# Add grid to the plot
plt.grid(True)

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

Out[108]:
```
<Axes: >
```

Out[108]:
```
Text(0.5, 0, 'Number of Components')
```

Out[108]:
```
Text(0, 0.5, 'Explained Variance')
```

Out[108]:
```
([<matplotlib.axis.XTick at 0x2ed3baa6320>,
  <matplotlib.axis.XTick at 0x2ed3baa6740>,
  <matplotlib.axis.XTick at 0x2ed11e3ef50>,
  <matplotlib.axis.XTick at 0x2ed34e6c820>,
  <matplotlib.axis.XTick at 0x2ed34e6e950>,
  <matplotlib.axis.XTick at 0x2ed34e6f130>,
  <matplotlib.axis.XTick at 0x2ed34e6f910>,
  <matplotlib.axis.XTick at 0x2ed34e6f670>,
  <matplotlib.axis.XTick at 0x2ed34e6e2c0>,
  <matplotlib.axis.XTick at 0x2ed34f0c490>,
  <matplotlib.axis.XTick at 0x2ed3bae6350>,
  <matplotlib.axis.XTick at 0x2ed34f0dd50>,
  <matplotlib.axis.XTick at 0x2ed34e3ca00>,
  <matplotlib.axis.XTick at 0x2ed34e3d2d0>,
  <matplotlib.axis.XTick at 0x2ed34e3dab0>,
  <matplotlib.axis.XTick at 0x2ed34e6ca00>,
  <matplotlib.axis.XTick at 0x2ed34e3d090>],
 [Text(1, 0, '1'),
  Text(2, 0, '2'),
  Text(3, 0, '3'),
  Text(4, 0, '4'),
  Text(5, 0, '5'),
  Text(6, 0, '6'),
  Text(7, 0, '7'),
  Text(8, 0, '8'),
  Text(9, 0, '9'),
  Text(10, 0, '10'),
  Text(11, 0, '11'),
  Text(12, 0, '12'),
  Text(13, 0, '13'),
  Text(14, 0, '14'),
  Text(15, 0, '15'),
  Text(16, 0, '16'),
  Text(17, 0, '17')])
```



📝 **NOTE:**

- We will use 10 Components where the cumulative explained variance exceeds this threshold of 95 %.

In [109]:
```
DF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 153443 entries, 0 to 153442
Data columns (total 17 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   orgyear            153443 non-null  float64
 1   ctc                153443 non-null  float64
 2   ctc_updated_year   153443 non-null  float64
 3   yoe                153443 non-null  float64
 4   num_jobs           153443 non-null  float64
 5   growth             153443 non-null  float64
 6   ctc_yoe_ratio      153443 non-null  float64
 7   mean_ctc_exp       153443 non-null  float64
 8   mean_ctc_position  153443 non-null  float64
 9   mean_ctc_company   153443 non-null  float64
 10  is_other           153443 non-null  float64
 11  is_developer       153443 non-null  float64
 12  is_management      153443 non-null  float64
 13  is_sales           153443 non-null  float64
 14  is_non_coder       153443 non-null  float64
 15  ctc_bin            153443 non-null  float64
 16  job_position       153443 non-null  float64
dtypes: float64(17)
memory usage: 19.9 MB
```

In [110]:
```
df_numeric.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 153443 entries, 0 to 153442
Data columns (total 17 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   orgyear            153443 non-null  float64
 1   ctc                153443 non-null  float64
 2   ctc_updated_year   153443 non-null  float64
 3   yoe                153443 non-null  float64
 4   num_jobs           153443 non-null  float64
 5   growth             153443 non-null  float64
 6   ctc_yoe_ratio      153443 non-null  float64
 7   mean_ctc_exp       153443 non-null  float64
 8   mean_ctc_position  153443 non-null  float64
 9   mean_ctc_company   153443 non-null  float64
 10  is_other           153443 non-null  float64
 11  is_developer       153443 non-null  float64
 12  is_management      153443 non-null  float64
 13  is_sales           153443 non-null  float64
 14  is_non_coder       153443 non-null  float64
 15  ctc_bin            153443 non-null  float64
 16  job_position       153443 non-null  float64
dtypes: float64(17)
memory usage: 19.9 MB
```

In [111]:
```
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# Perform PCA with 10 components
X_embedded_pca = PCA(n_components=10).fit_transform(df_numeric)

# Fit KMeans models for each value of k and store the models in a list
```

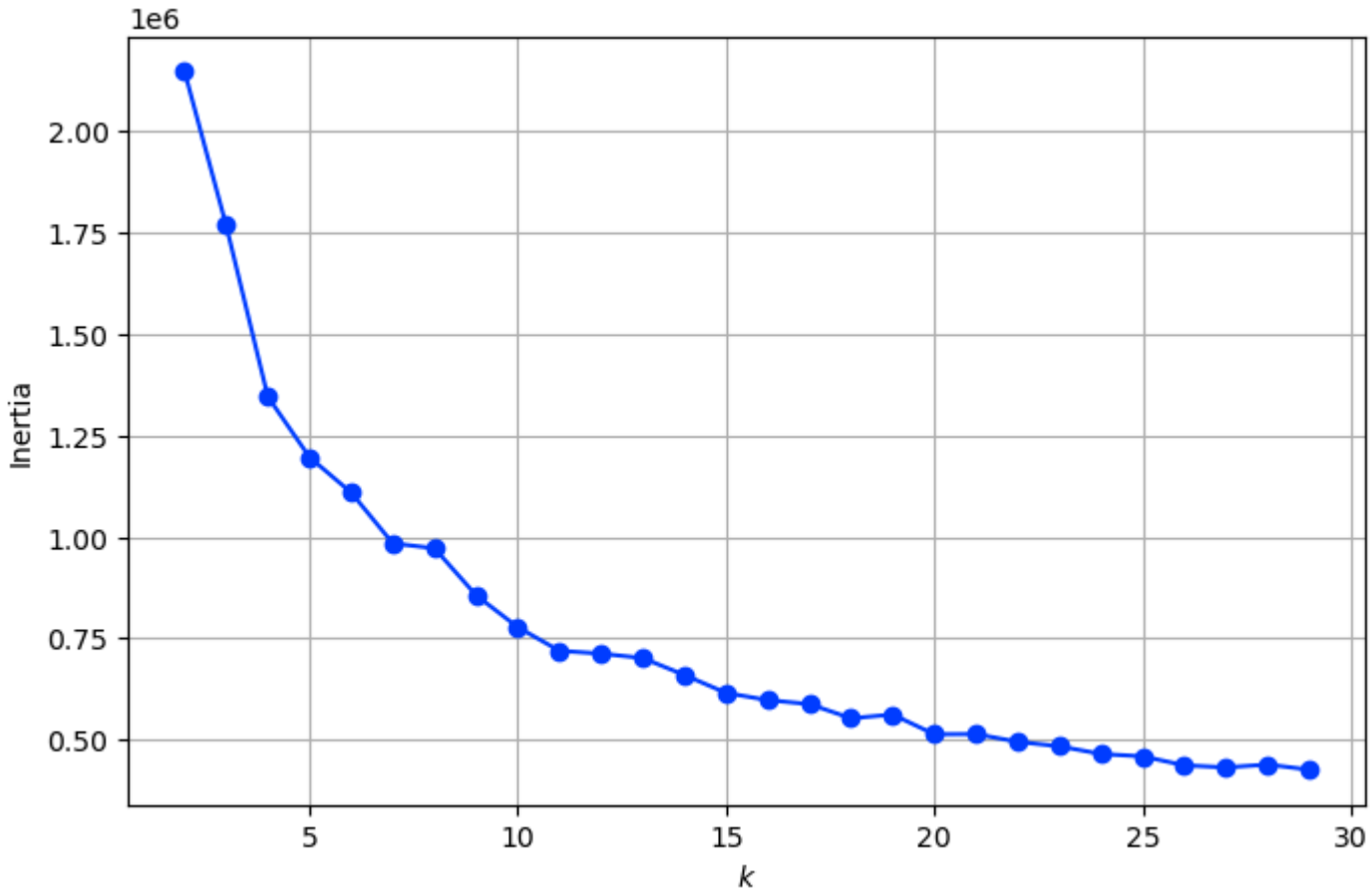
```
kmeans_per_k = [KMeans(n_clusters=k, random_state=42).fit(X_embedded_pca)
                for k in range(2, 30, 1)]

# Extract the inertia values (within-cluster sum of squared distances) from each model
inertias = [model.inertia_ for model in kmeans_per_k]

# Plot the inertia for each k value to visualize the Elbow method
plt.figure(figsize=(8, 5))
plt.plot(range(2, 30, 1), inertias, "-o")
plt.xlabel("$k$")
plt.ylabel("Inertia")

# Add grid to the plot
plt.grid(True)

plt.show()
```

Out[111]: <Figure size 800x500 with 0 Axes>

Out[111]: [<matplotlib.lines.Line2D at 0x2ed34e6b640>]

Out[111]: Text(0.5, 0, 'k')

Out[111]: Text(0, 0.5, 'Inertia')



The Optimal Number of Clusters Seems to be 6, after which the additional components contribute much less.

In [112]:
```
from sklearn.cluster import KMeans

# Perform KMeans clustering with 6 clusters
kmeans = KMeans(n_clusters=6, random_state=42)
y_kmeans = kmeans.fit_predict(X_embedded_pca)

# Add the clustering labels to the DataFrame
DF['y_kmeans'] = y_kmeans
```

In [113]:
```
DF.head()
```

Out[113]:

	orgyear	ctc	ctc_updated_year	yoe	num_jobs	growth	ctc_yoe_ratio	mean_ctc_exp	mean_ctc_position	mean_ctc_company	is_other	is_develope
0	0.768	-0.138	0.372	-0.768	14.047	-0.013	-0.089	-0.170	-0.166	-0.220	-0.418	0.53
1	0.768	-0.106	1.101	-0.768	14.047	-0.013	-0.059	-0.131	-0.150	-0.161	-0.418	0.53
2	0.534	-0.009	0.372	-0.534	14.047	-0.009	-0.001	-0.059	-0.098	-0.035	-0.418	0.53
3	0.067	-0.101	0.372	-0.067	12.234	-0.014	-0.091	-0.124	0.081	-0.102	-0.418	0.53
4	-0.401	-0.017	0.372	0.401	12.234	0.000	-0.067	-0.021	0.117	0.233	2.395	-1.86

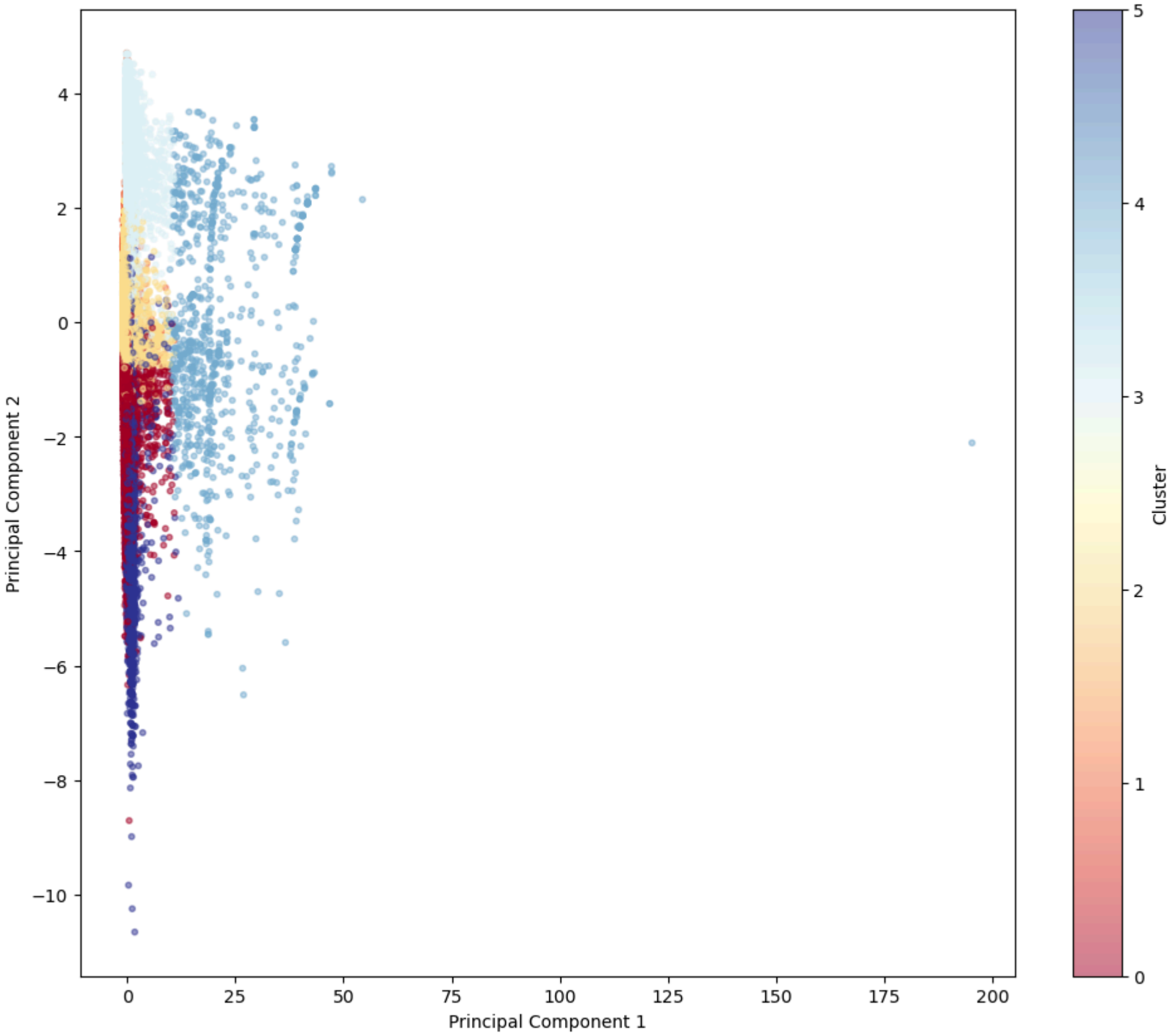
In [114]:
```
# Plotting the scatter plot with cluster colors
plt.figure(figsize=(12, 10))
scatter = plt.scatter(X_embedded_pca[:, 0], X_embedded_pca[:, 1], c=DF['y_kmeans'], s=10, cmap='RdYlBu', alpha=0.5)

# Add colorbar and labels
plt.colorbar(scatter, label='Cluster')
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.show()
```

Out[114]: <Figure size 1200x1000 with 0 Axes>

Out[114]: <matplotlib.colorbar.Colorbar at 0x2ed34eed5d0>

Out[114]: Text(0.5, 0, 'Principal Component 1')

Out[114]: Text(0, 0.5, 'Principal Component 2')



7.2.2 - Cluster Analysis

In [226]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler

def create_polar_plot(data, features, cluster_label):
    """
Creates a polar plot for a specific cluster, visualizing the means of its features.

Parameters:
    data (array-like): Feature values for the cluster.
    features (list): List of feature names.
    cluster_label (int): The label or identifier for the cluster.
"""
# Ensure data is a pandas Series for better handling
data = pd.Series(data)

num_vars = len(features)

# Compute angle of each axis (in radians)
angles = np.linspace(0, 2 * np.pi, num_vars, endpoint=False).tolist()

# The plot is made in a circular (polar) form, so we need to "close the loop"
data = np.concatenate((data, [data.iloc[0]]))
angles += angles[:1]

fig, ax = plt.subplots(figsize=(6, 6), subplot_kw=dict(polar=True))

ax.fill(angles, data, color='blue', alpha=0.25)
ax.plot(angles, data, color='blue', linewidth=2)

ax.set_xticks(angles[:-1])
ax.set_xticklabels(features)

plt.title(f'Cluster {cluster_label}', size=20, color='blue', y=1.1)

plt.show()
```

```python
def create_combined_polar_plot(normalized_means, features, cluster_labels):
    """
    Creates a combined polar plot to compare clusters by visualizing the normalized means of their features.

    Parameters:
        normalized_means (DataFrame): DataFrame containing normalized means for each cluster.
        features (list): List of feature names.
        cluster_labels (list): List of cluster labels.
    """
    # Ensure normalized_means is a DataFrame
    if not isinstance(normalized_means, pd.DataFrame):
        normalized_means = pd.DataFrame(normalized_means, columns=features)

    num_vars = len(features)
    angles = np.linspace(0, 2 * np.pi, num_vars, endpoint=False).tolist()
    angles += angles[:1]

    fig, ax = plt.subplots(figsize=(12, 12), subplot_kw=dict(polar=True))

    for i, data in enumerate(normalized_means.values):
        data = np.concatenate((data, [data[0]]))  # Close the loop for the plot
        ax.fill(angles, data, alpha=0.25, label=f'Cluster {cluster_labels[i]}')
        ax.plot(angles, data, linewidth=2)

    ax.set_xticks(angles[:-1])
    ax.set_xticklabels(features)

    plt.title('Cluster Comparison', size=20, y=1.1)
    plt.legend(loc='upper right', bbox_to_anchor=(1.1, 1.1))
    plt.show()
```

In [227]:
```python
# Group the DataFrame by the 'y_kmeans' column and calculate the mean for each cluster
cluster_means = DF.groupby("y_kmeans").mean().reset_index()

# Drop unnecessary columns ('y_kmeans') from the resulting DataFrame
cluster_means = cluster_means.drop(["y_kmeans", "mean_ctc_exp", "mean_ctc_company", "mean_ctc_position"], axis=1)

# Initialize the MinMaxScaler for normalization
scaler = MinMaxScaler()

# Normalize the cluster means using MinMaxScaler
normalized_means = scaler.fit_transform(cluster_means)
```

In [228]:
```python
cluster_means
```

Out[228]:

	orgyear	ctc	ctc_updated_year	yoe	num_jobs	growth	ctc_yoe_ratio	is_other	is_developer	is_management	is_sales	is_non_coder	ctc_bin	jol
0	-0.921	-0.012	-0.782	0.921	-0.345	-0.012	-0.073	-0.415	0.416	-0.274	-0.285	-0.445	0.533	
1	0.461	-0.084	0.638	-0.461	1.816	0.062	-0.051	-0.414	0.419	-0.257	-0.182	-0.443	-0.034	
2	0.457	-0.100	0.172	-0.457	-0.456	-0.014	-0.056	-0.418	0.352	-0.250	-0.186	-0.448	-0.290	
3	0.285	-0.066	0.139	-0.285	-0.019	-0.008	-0.045	2.370	-1.861	-0.273	-0.286	2.230	-0.386	
4	0.203	10.922	0.428	-0.203	-0.354	0.123	9.758	0.637	-0.717	0.232	0.299	0.722	2.047	
5	-1.266	0.014	-0.166	1.266	-0.187	-0.010	-0.061	-0.418	-0.305	3.496	3.023	0.220	0.652	

In [229]:
```python
# Convert the columns of the DataFrame to a list
column_list = list(cluster_means.columns)
```

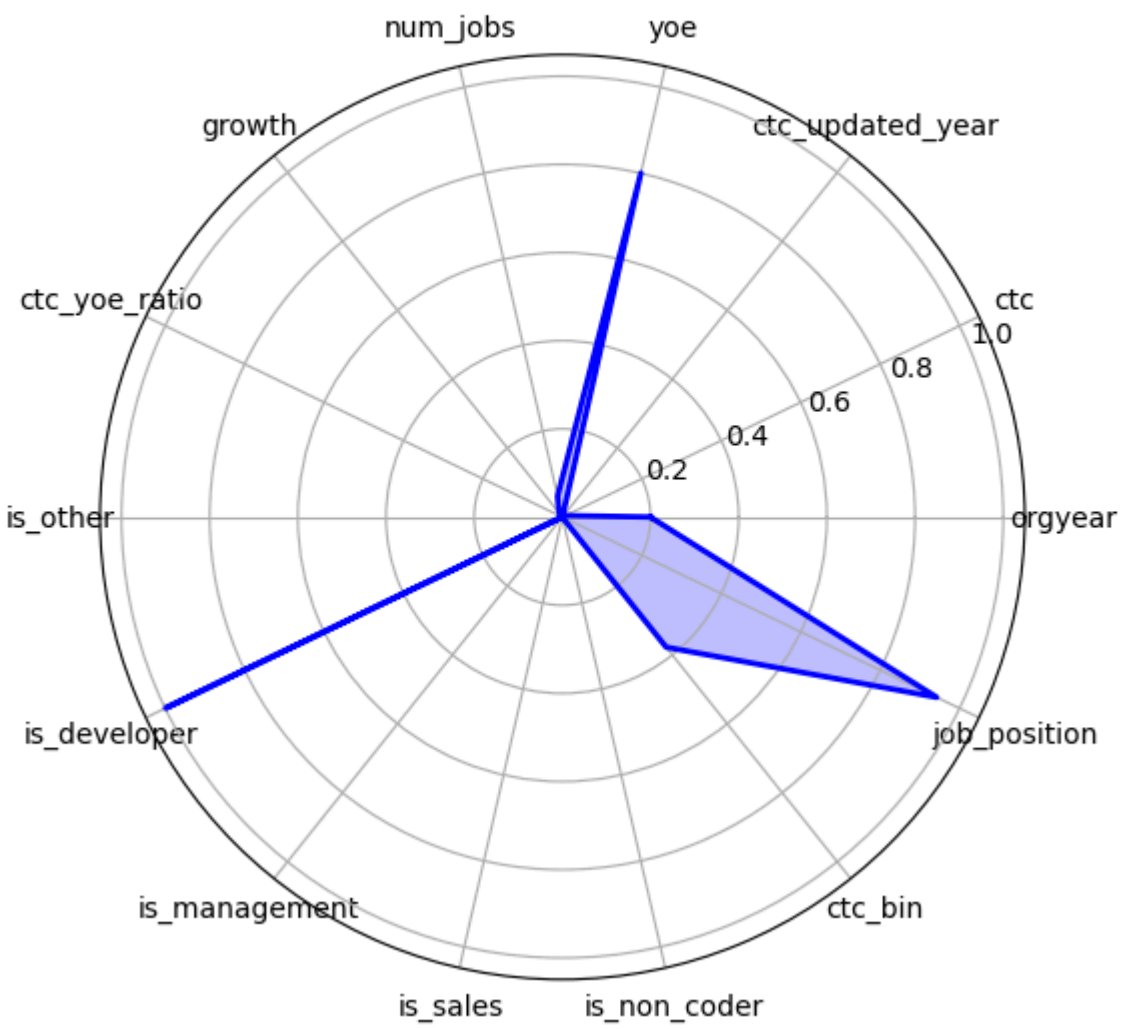
In [230]:
```python
column_list
```

Out[230]:
```
['orgyear',
 'ctc',
 'ctc_updated_year',
 'yoe',
 'num_jobs',
 'growth',
 'ctc_yoe_ratio',
 'is_other',
 'is_developer',
 'is_management',
 'is_sales',
 'is_non_coder',
 'ctc_bin',
 'job_position']
```

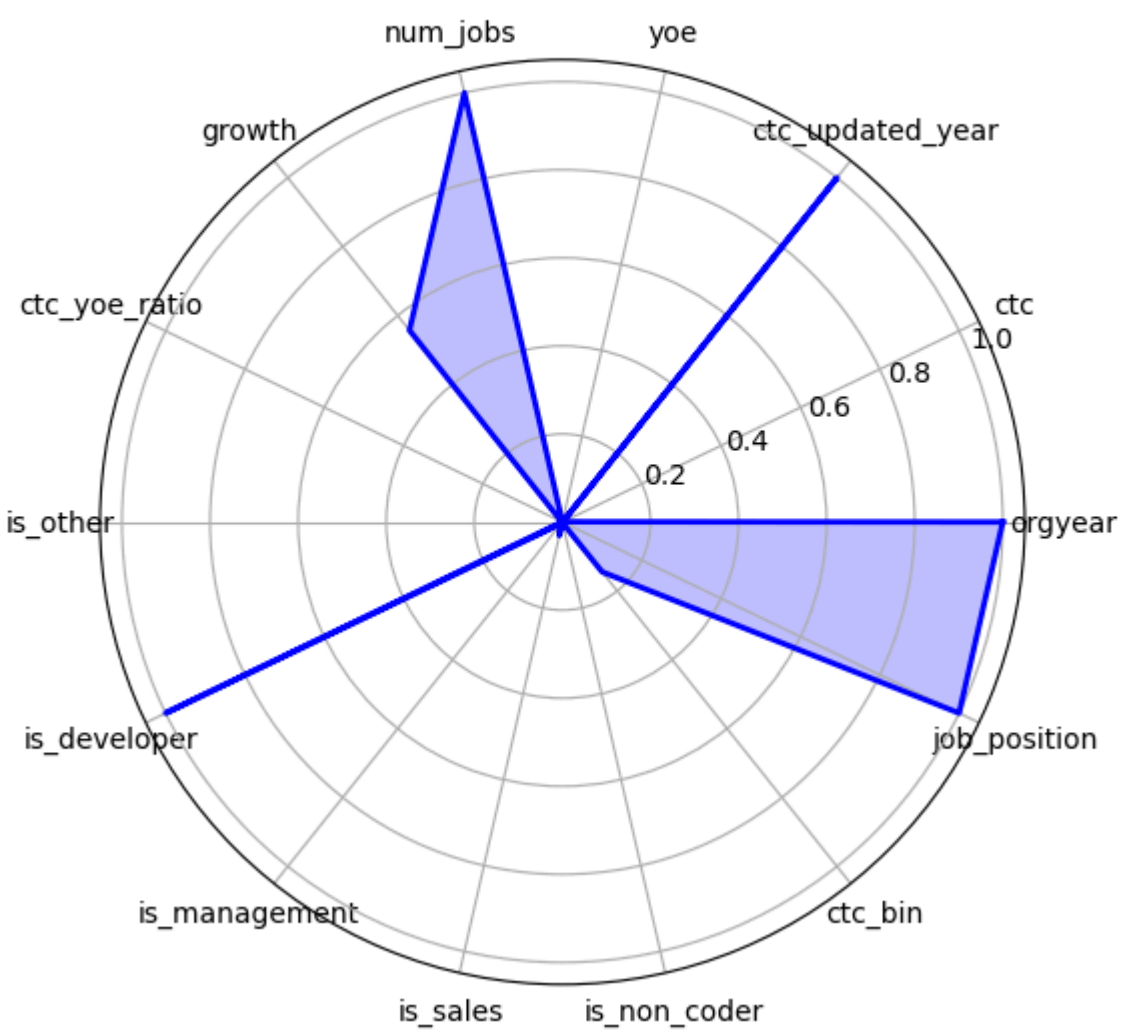
In [231]:
```python
# Convert the columns of the DataFrame to a list
features = cluster_means.columns.tolist()
```

In [232]:
```python
for cluster in range(min(cluster_means.shape[0], normalized_means.shape[0])):
    create_polar_plot(normalized_means[cluster], features, cluster + 1)
```

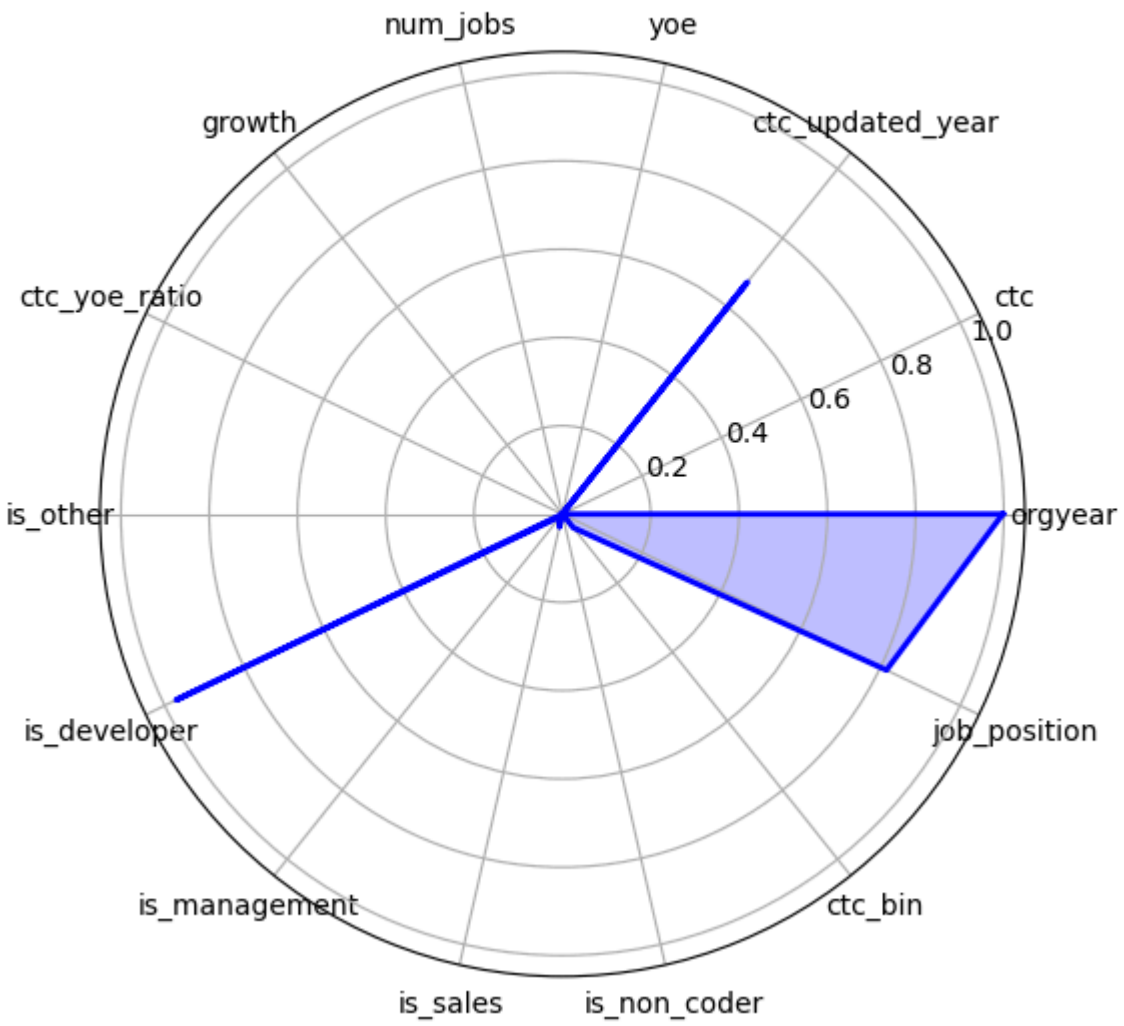
Cluster 1



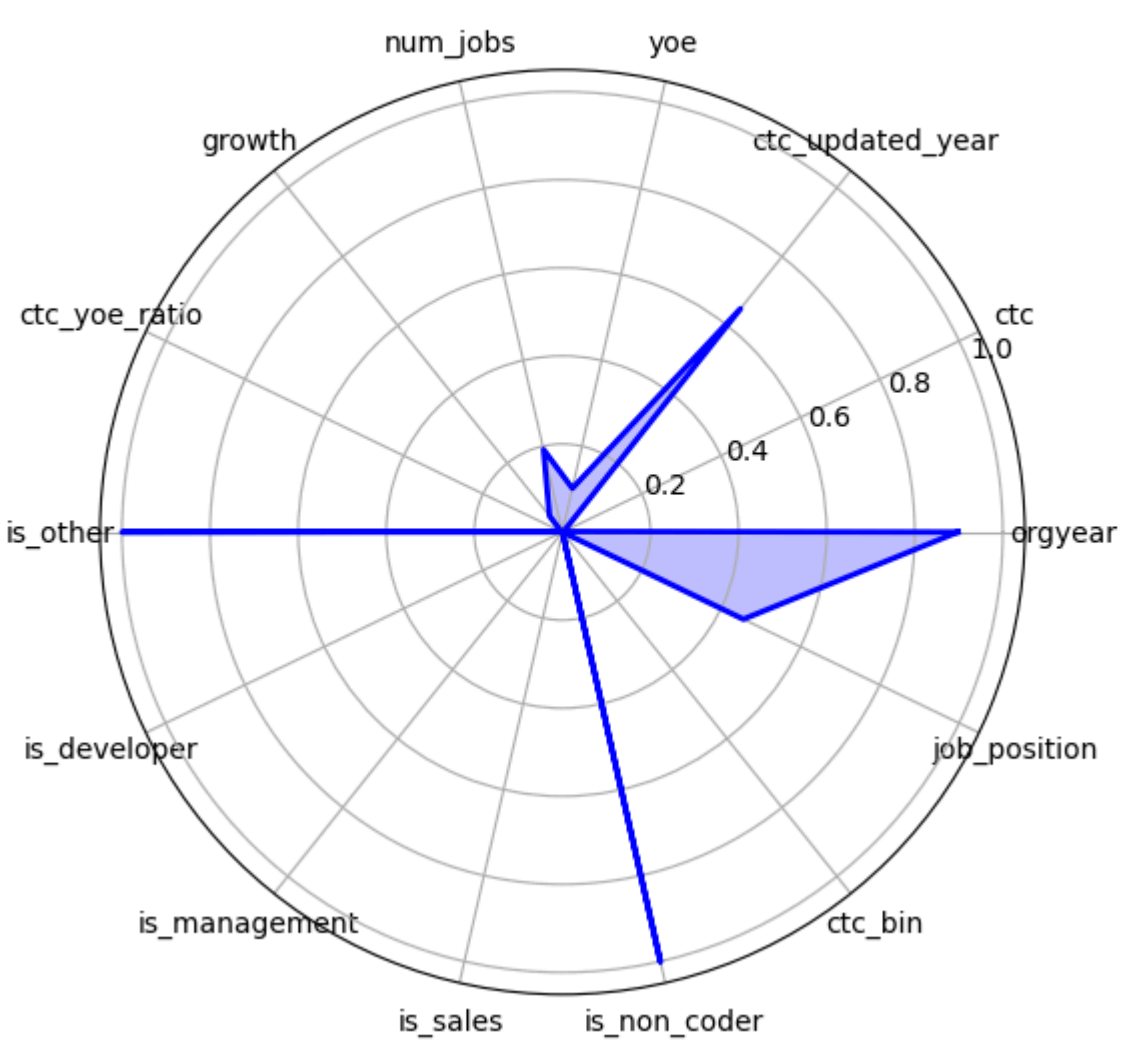
Cluster 2

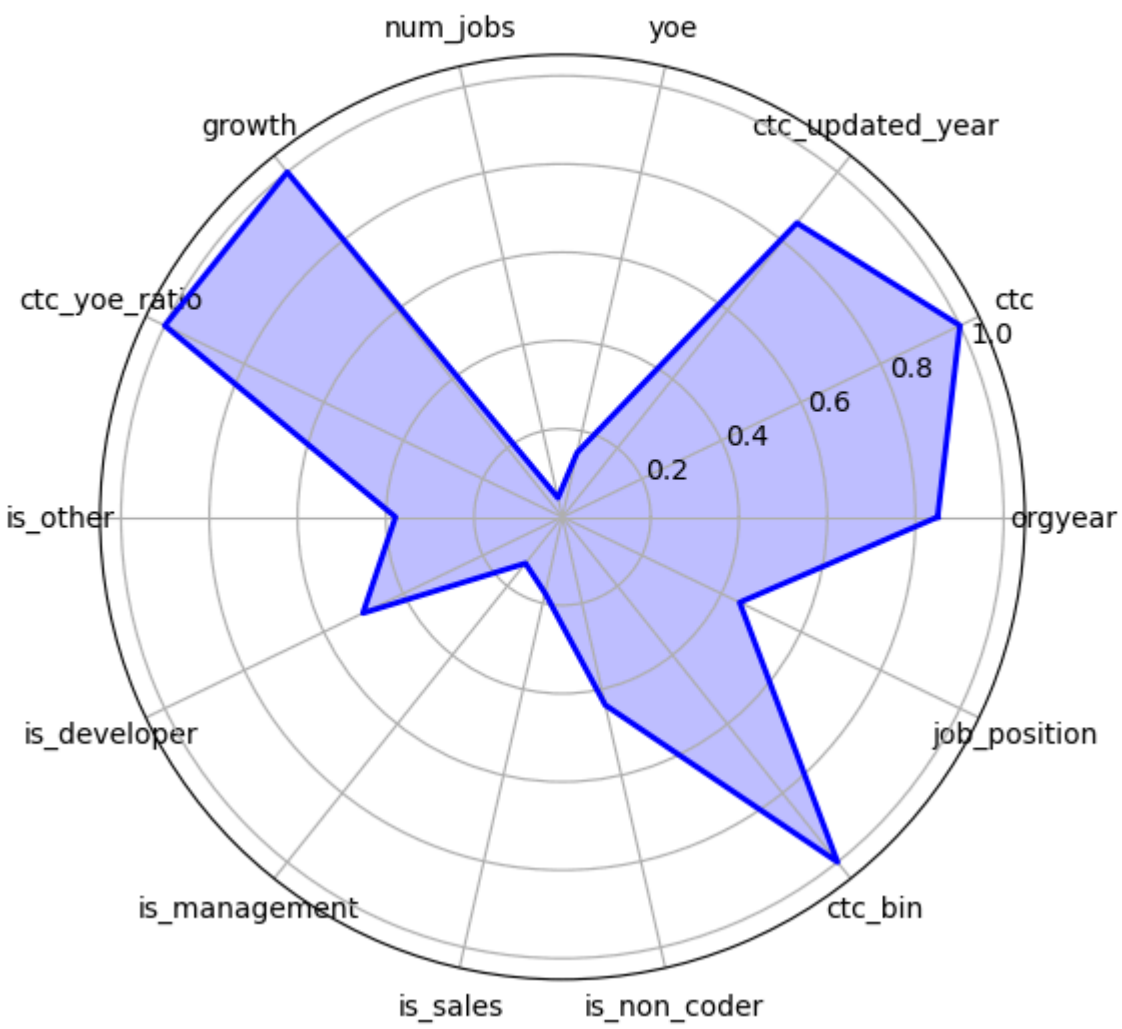


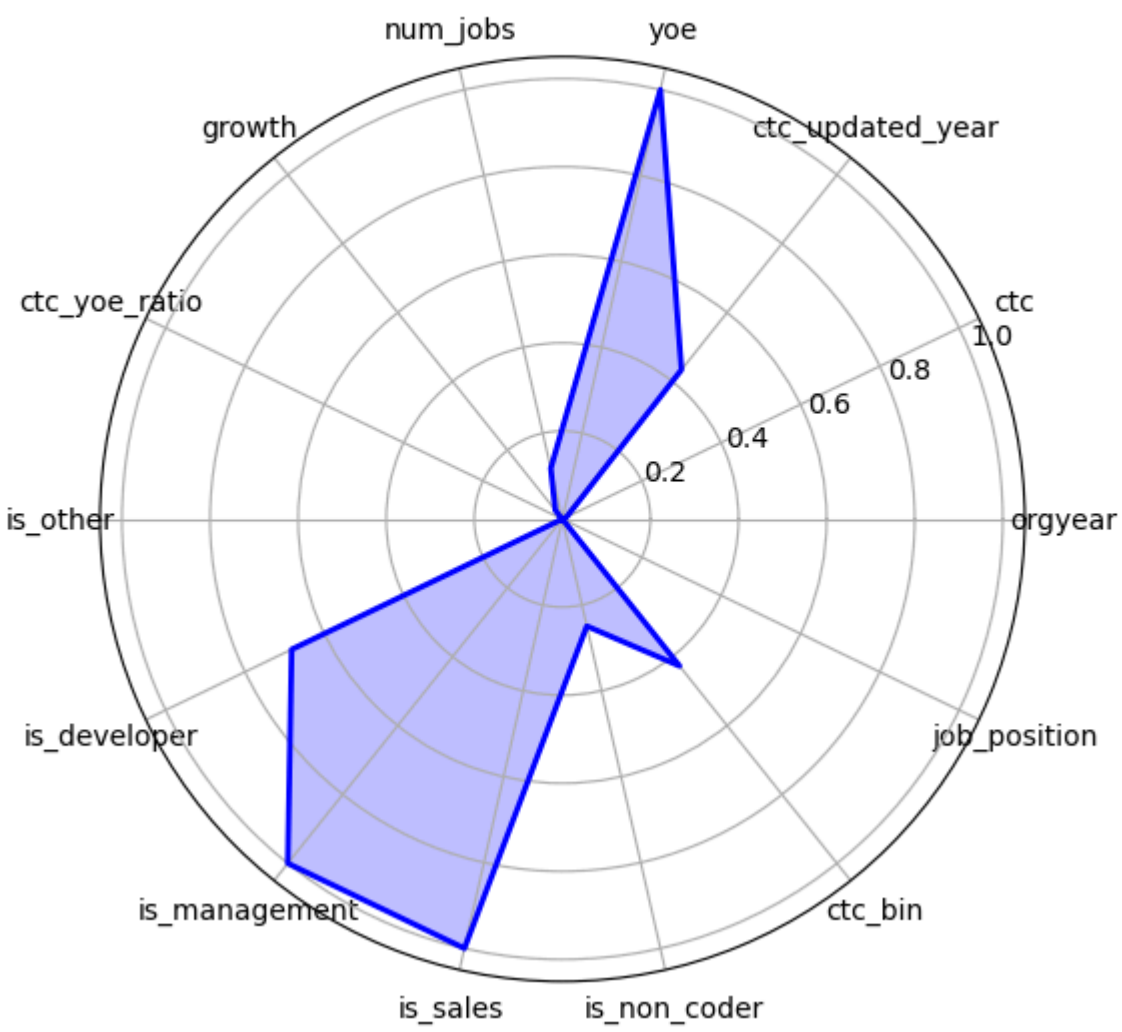
Cluster 3



Cluster 4

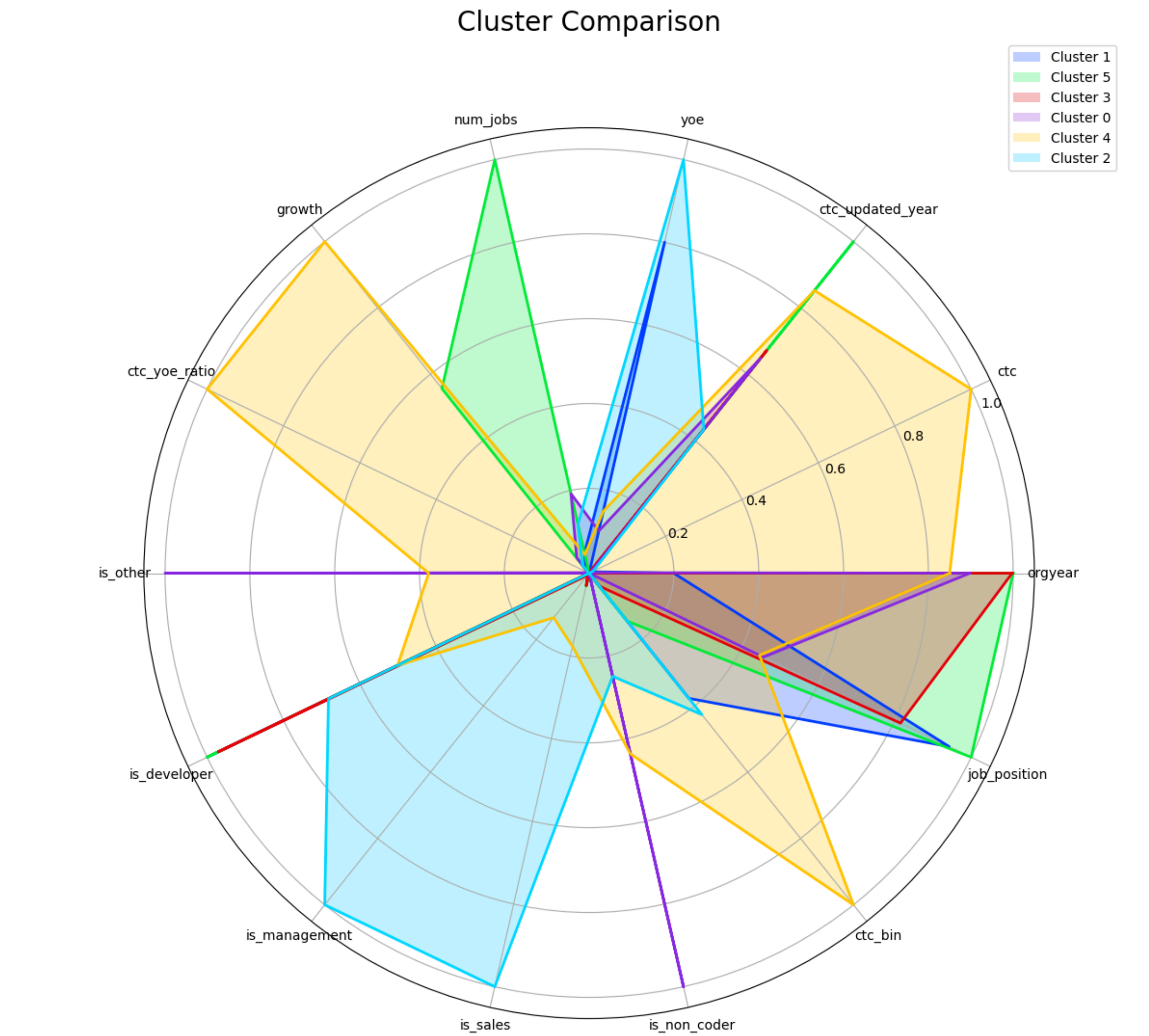






In [233]:
```
# Get the unique cluster labels from the 'y_kmeans' column and convert them to a list
cluster_labels = DF["y_kmeans"].dropna().unique().tolist()

# Create a combined polar plot for all clusters
create_combined_polar_plot(normalized_means, features, cluster_labels)
```



📝 CLUSTER Insights

`Cluster - 1` . **Underpaid Switchers**
(Candidates in this cluster belong to the Developer category, have very good experience, higher job switches, but low CTC.)

`Cluster - 2` . **Ambitious Movers**
(Candidates in this cluster belong to the Developer category, have average growth, higher job switches, and recently got a hike.)

`Cluster - 3` . **Stagnant Movers**
(Candidates in this cluster belong to the Developer category, with no recent hikes and higher job switches.)

`Cluster - 4` . **Professionally Stuck**
(Candidates in this cluster belong to Other and Non-Coder categories, have not gotten any recent hikes, fewer job switches, and appear to be professionally stuck.)

`Cluster - 5` . **Elite Achievers**
(Candidates in this cluster belong to Developer, Non-Coder, and Other categories, have very high growth, very high pay, recent hikes, and fewer job switches.)

`Cluster - 6` . **Underpaid Veterans**
(Candidates in this cluster belong to Management and Sales categories, have very high experience, but are paid less.)

7.3 - Hierarchical Clustering

In [124]:
```
# Drop Mean_ctc_exp, Mean_ctc_company, Mean_ctc_position columns from the df_numeric

df_numeric = df_numeric.drop(["mean_ctc_exp", "mean_ctc_company", "mean_ctc_position"], axis=1)
```

In [125]:
```
X_embedded_pca = PCA(n_components=10).fit_transform(df_numeric)
```

In [126]:
```
# Reduce the sample size to 20% of the original data
sample = pd.DataFrame(X_embedded_pca).sample(frac=0.2, random_state=42)  # Adjust frac as needed
sample_hc = df_numeric.loc[sample.index]

# Verify the size of the reduced sample
print(f"Original data size: {len(X_embedded_pca)} rows")
print(f"Reduced sample size: {len(sample)} rows")
```

```
Original data size: 153443 rows
Reduced sample size: 30689 rows
```

In [127]:
```
sample_hc.shape
```

Out[127]: (30689, 14)

In [128]:
```
sample_hc.head()
```

Out[128]:

	orgyear	ctc	ctc_updated_year	yoe	num_jobs	growth	ctc_yoe_ratio	is_other	is_developer	is_management	is_sales	is_non_coder	ctc_bin
39677	0.534	-0.124	-0.357	-0.534	-0.456	-0.014	-0.089	-0.418	0.537	-0.275	-0.288	-0.448	-0.451
48859	-0.167	-0.189	-3.274	0.167	-0.456	-0.014	-0.139	-0.418	-1.861	-0.275	-0.288	-0.448	-1.284
52702	0.300	-0.135	-0.357	-0.300	-0.456	-0.014	-0.105	-0.418	0.537	-0.275	-0.288	-0.448	-0.451
69085	1.002	-0.147	1.101	-1.002	-0.456	-0.014	-0.083	-0.418	0.537	-0.275	-0.288	-0.448	-0.451
17088	1.236	-0.167	0.372	-1.236	1.357	-0.014	-0.092	2.395	-1.861	-0.275	-0.288	2.230	-1.284

7.3.1 - Building Linkage Matrix

In [129]:
```
import time

start_time = time.time()
Z = fastcluster.linkage(sample, method='ward')
end_time = time.time()

print(f"Execution time: {end_time - start_time} seconds")
```

```
Execution time: 47.29646039009094 seconds
```

7.3.2 - Plot Dendogram

In [130]:
```
# Plot the dendrogram
fig, ax = plt.subplots(figsize=(20, 12))
dendrogram(
    Z,
    truncate_mode='lastp',  # Show the last p merged clusters
    p=100,                   # Number of clusters displayed at the bottom
)
plt.title("Dendrogram")
plt.xlabel("Cluster Index")
plt.ylabel("Distance")
plt.show()
```

Out[130]:

```
{'icoord': [[5.0, 5.0, 15.0, 15.0],
  [35.0, 35.0, 45.0, 45.0],
  [25.0, 25.0, 40.0, 40.0],
  [10.0, 10.0, 32.5, 32.5],
  [65.0, 65.0, 75.0, 75.0],
  [55.0, 55.0, 70.0, 70.0],
  [95.0, 95.0, 105.0, 105.0],
  [85.0, 85.0, 100.0, 100.0],
  [115.0, 115.0, 125.0, 125.0],
  [135.0, 135.0, 145.0, 145.0],
  [120.0, 120.0, 140.0, 140.0],
  [92.5, 92.5, 130.0, 130.0],
  [62.5, 62.5, 111.25, 111.25],
  [21.25, 21.25, 86.875, 86.875],
  [165.0, 165.0, 175.0, 175.0],
  [155.0, 155.0, 170.0, 170.0],
  [185.0, 185.0, 195.0, 195.0],
  [205.0, 205.0, 215.0, 215.0],
  [225.0, 225.0, 235.0, 235.0],
  [210.0, 210.0, 230.0, 230.0],
  [190.0, 190.0, 220.0, 220.0],
  [162.5, 162.5, 205.0, 205.0],
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  [265.0, 265.0, 275.0, 275.0],
  [255.0, 255.0, 270.0, 270.0],
  [245.0, 245.0, 262.5, 262.5],
  [295.0, 295.0, 305.0, 305.0],
  [285.0, 285.0, 300.0, 300.0],
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  [253.75, 253.75, 310.0, 310.0],
  [365.0, 365.0, 375.0, 375.0],
  [385.0, 385.0, 395.0, 395.0],
  [370.0, 370.0, 390.0, 390.0],
  [415.0, 415.0, 425.0, 425.0],
  [435.0, 435.0, 445.0, 445.0],
  [420.0, 420.0, 440.0, 440.0],
  [405.0, 405.0, 430.0, 430.0],
  [380.0, 380.0, 417.5, 417.5],
  [465.0, 465.0, 475.0, 475.0],
  [455.0, 455.0, 470.0, 470.0],
  [505.0, 505.0, 515.0, 515.0],
  [495.0, 495.0, 510.0, 510.0],
  [485.0, 485.0, 502.5, 502.5],
  [535.0, 535.0, 545.0, 545.0],
  [525.0, 525.0, 540.0, 540.0],
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  [555.0, 555.0, 570.0, 570.0],
  [532.5, 532.5, 562.5, 562.5],
  [493.75, 493.75, 547.5, 547.5],
  [462.5, 462.5, 520.625, 520.625],
  [398.75, 398.75, 491.5625, 491.5625],
  [605.0, 605.0, 615.0, 615.0],
  [595.0, 595.0, 610.0, 610.0],
  [585.0, 585.0, 602.5, 602.5],
  [625.0, 625.0, 635.0, 635.0],
  [593.75, 593.75, 630.0, 630.0],
  [655.0, 655.0, 665.0, 665.0],
  [645.0, 645.0, 660.0, 660.0],
  [675.0, 675.0, 685.0, 685.0],
  [695.0, 695.0, 705.0, 705.0],
  [715.0, 715.0, 725.0, 725.0],
  [700.0, 700.0, 720.0, 720.0],
  [680.0, 680.0, 710.0, 710.0],
  [652.5, 652.5, 695.0, 695.0],
  [745.0, 745.0, 755.0, 755.0],
  [735.0, 735.0, 750.0, 750.0],
  [785.0, 785.0, 795.0, 795.0],
  [775.0, 775.0, 790.0, 790.0],
  [765.0, 765.0, 782.5, 782.5],
  [742.5, 742.5, 773.75, 773.75],
  [673.75, 673.75, 758.125, 758.125],
  [611.875, 611.875, 715.9375, 715.9375],
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  [820.0, 820.0, 861.25, 861.25],
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  [915.0, 915.0, 925.0, 925.0],
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  [935.0, 935.0, 945.0, 945.0],
  [965.0, 965.0, 975.0, 975.0],
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  [940.0, 940.0, 967.5, 967.5],
```

```
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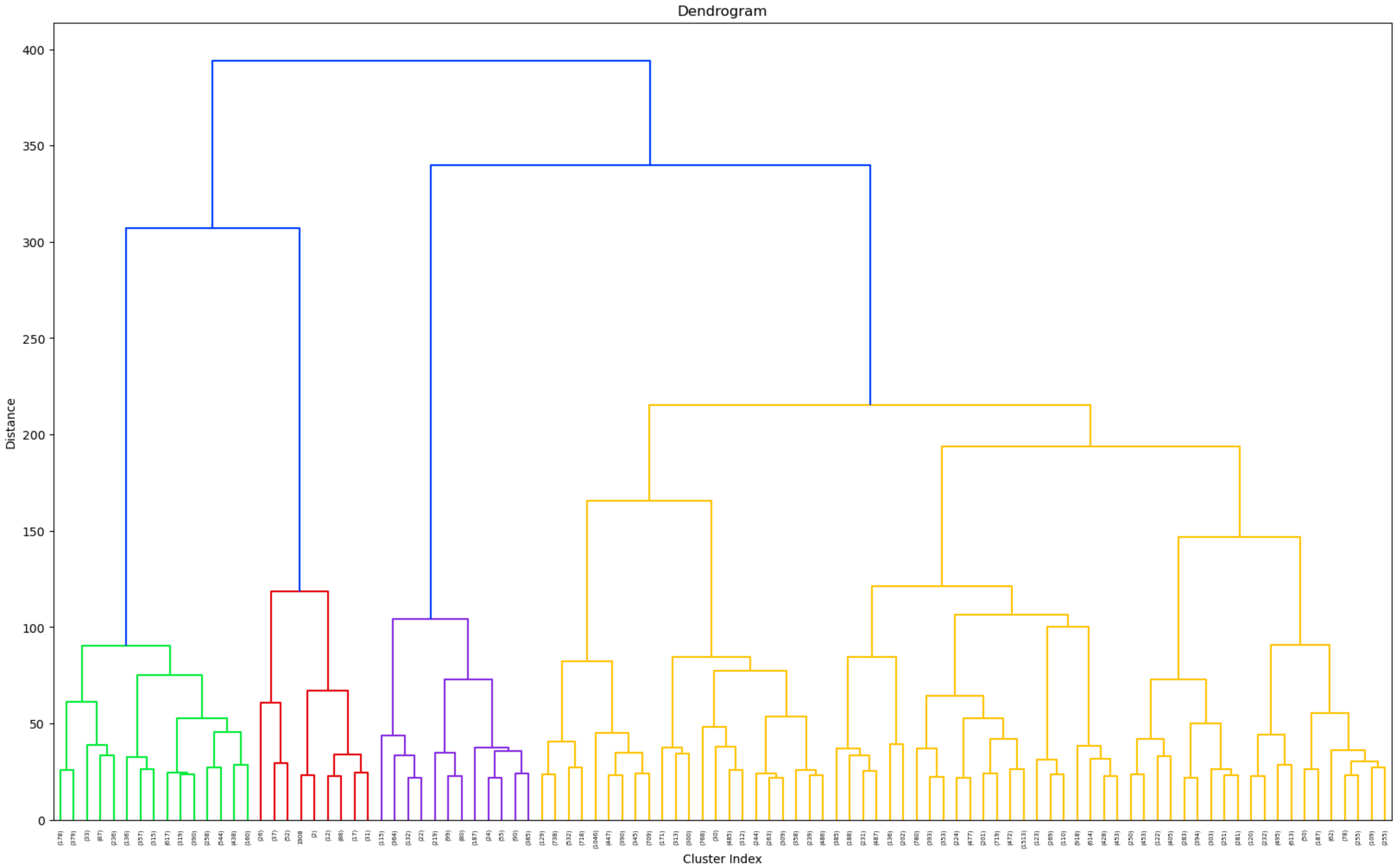
Out[130]: `Text(0.5, 1.0, 'Dendrogram')`

Out[130]: `Text(0.5, 0, 'Cluster Index')`

Out[130]: `Text(0, 0.5, 'Distance')`



NOTE:

- We will cut the Dendogram at 250 which will give us 8 Clusters

In [131]:
```
sample_hc["cluster"] = fcluster(Z, t=8, criterion="maxclust")
```

7.3.3 - Plotting Hierarchial Clusters

In [132]:
```
plt.figure(figsize=(12, 10))

# Create a scatter plot with the first two principal components
# The points are colored based on the cluster labels from the hierarchical clustering results
scatter = plt.scatter(
    sample.iloc[:, 0],  # X-axis: Principal Component 1
    sample.iloc[:, 1],  # Y-axis: Principal Component 2
    c=sample_hc["cluster"],
    s=10,
    cmap='viridis',
    alpha=0.5
)
```

```
plt.colorbar(scatter, label='Cluster')

plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")

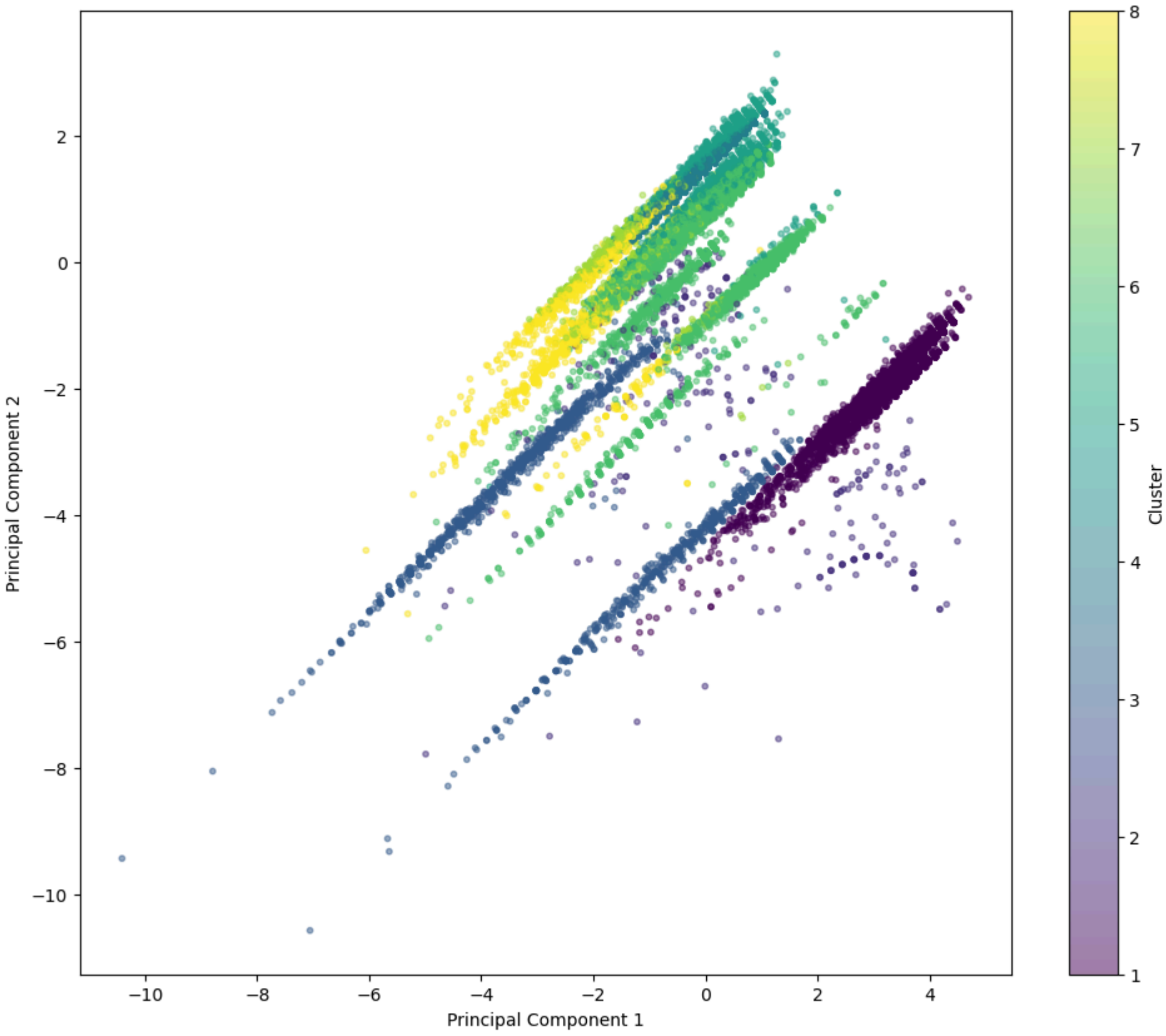
plt.show()
```

Out[132]: <Figure size 1200x1000 with 0 Axes>

Out[132]: <matplotlib.colorbar.Colorbar at 0x2ed3e8c2410>

Out[132]: Text(0.5, 0, 'Principal Component 1')

Out[132]: Text(0, 0.5, 'Principal Component 2')



7.3.4 - Cluster Analysis

In [221]:
```
# Group the data by 'cluster' and calculate the mean for each cluster
cluster_means = sample_hc.groupby("cluster").mean()

# Initialize the MinMaxScaler for normalization
scaler = MinMaxScaler()

# Apply the MinMaxScaler to normalize the cluster means
normalized_means = scaler.fit_transform(cluster_means)

# Extract the feature names from the columns of the cluster means DataFrame
features = cluster_means.columns.to_list()
```

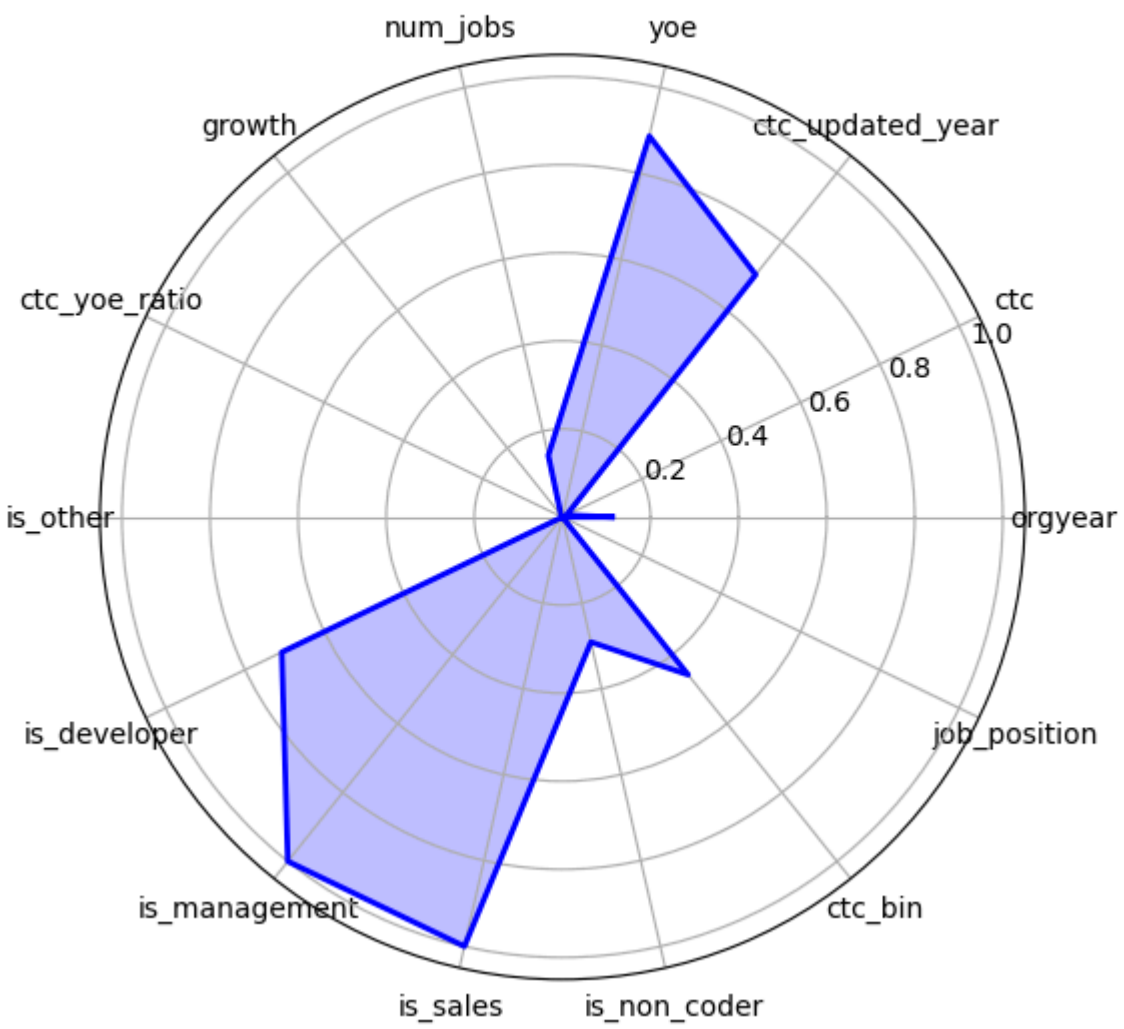
In [222]:
```
cluster_means
```

Out[222]:

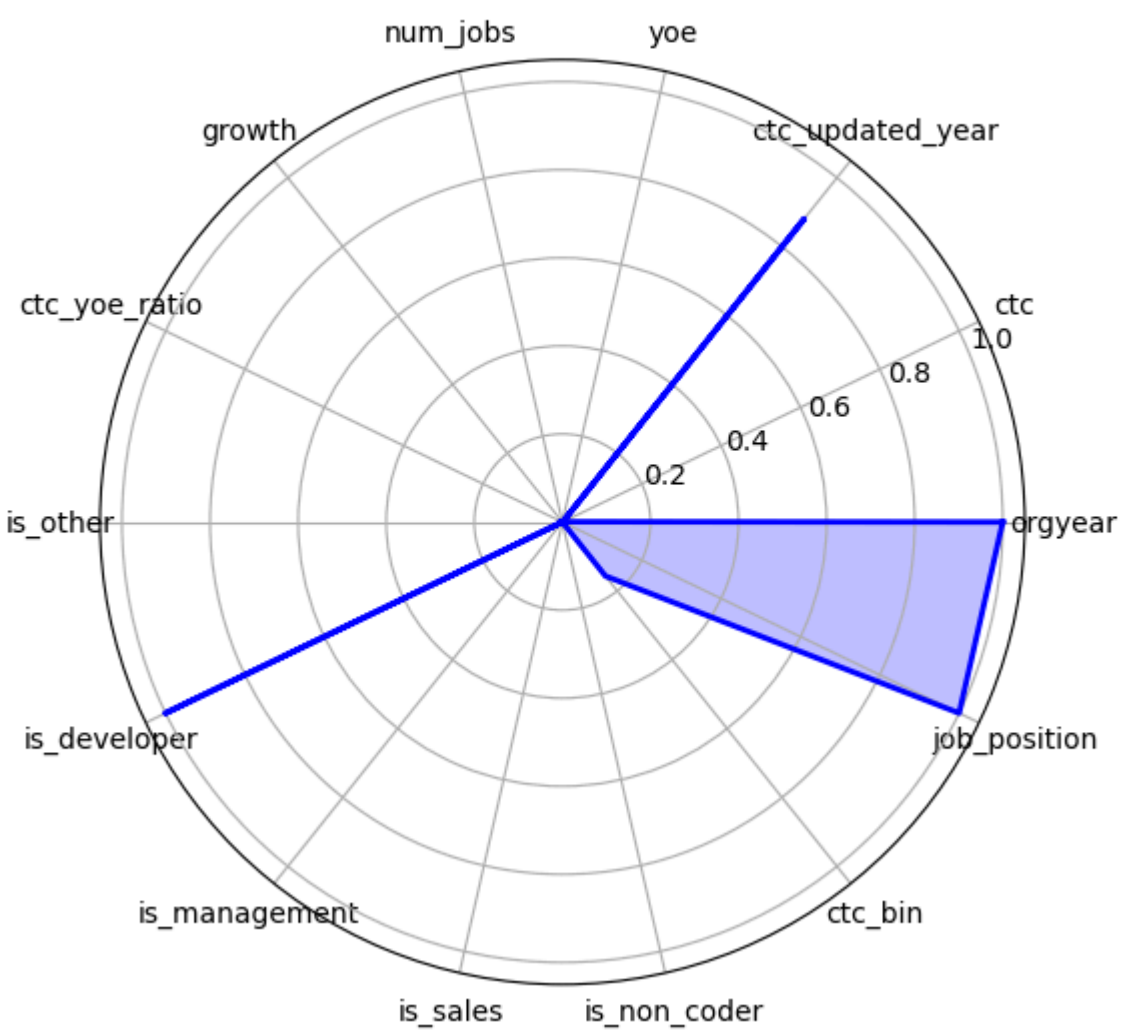
cluster	orgyear	ctc	ctc_updated_year	yoe	num_jobs	growth	ctc_yoe_ratio	is_other	is_developer	is_management	is_sales	is_non_coder	ctc_bin
1	0.310	-0.084	0.160	-0.310	-0.013	-0.009	-0.066	2.395	-1.861	-0.275	-0.288	2.230	-0.400
2	0.233	9.884	0.369	-0.233	-0.305	0.316	8.616	0.467	-0.489	0.081	0.082	0.465	2.048
3	-1.341	0.002	-0.184	1.341	-0.134	-0.013	-0.075	-0.418	-0.165	3.634	3.473	0.331	0.721
4	0.477	-0.090	0.298	-0.477	-0.456	-0.014	-0.055	-0.418	0.537	-0.275	-0.288	-0.448	-0.016
5	0.439	-0.088	0.622	-0.439	1.790	0.032	-0.058	-0.417	0.515	-0.268	-0.287	-0.447	0.015
6	0.117	-0.106	0.102	-0.117	-0.386	-0.014	-0.081	-0.418	0.155	-0.137	-0.093	-0.438	-0.188
7	-0.286	-0.094	-2.100	0.286	-0.366	-0.014	-0.096	-0.418	0.490	-0.275	-0.288	-0.445	-0.022
8	-1.572	-0.025	0.001	1.572	-0.218	-0.014	-0.092	-0.418	0.421	-0.275	-0.288	-0.446	0.715

In [223]:
```
for cluster_index in range(min(cluster_means.shape[0], normalized_means.shape[0])):
    create_polar_plot(normalized_means[cluster_index], features, cluster_index + 1)
```

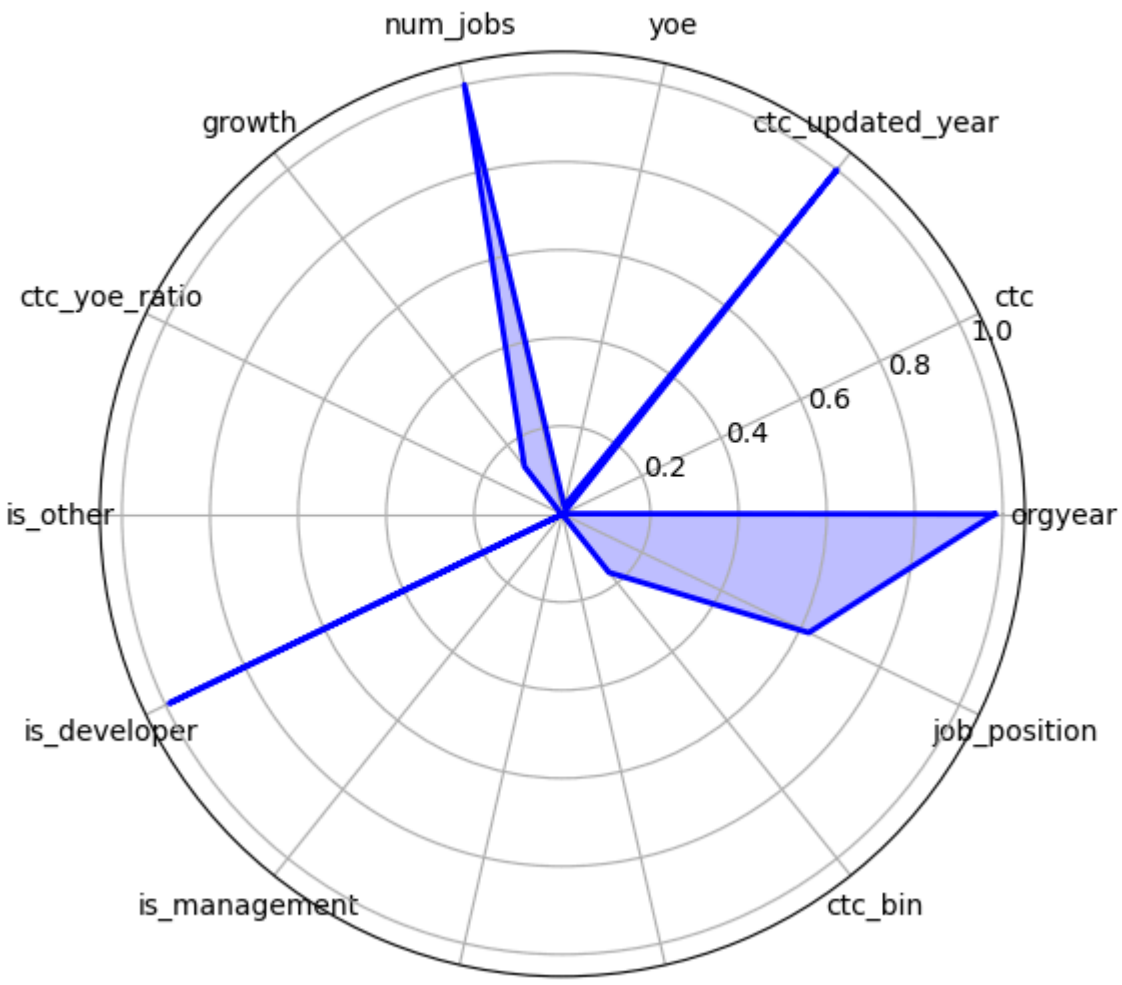
Cluster 3



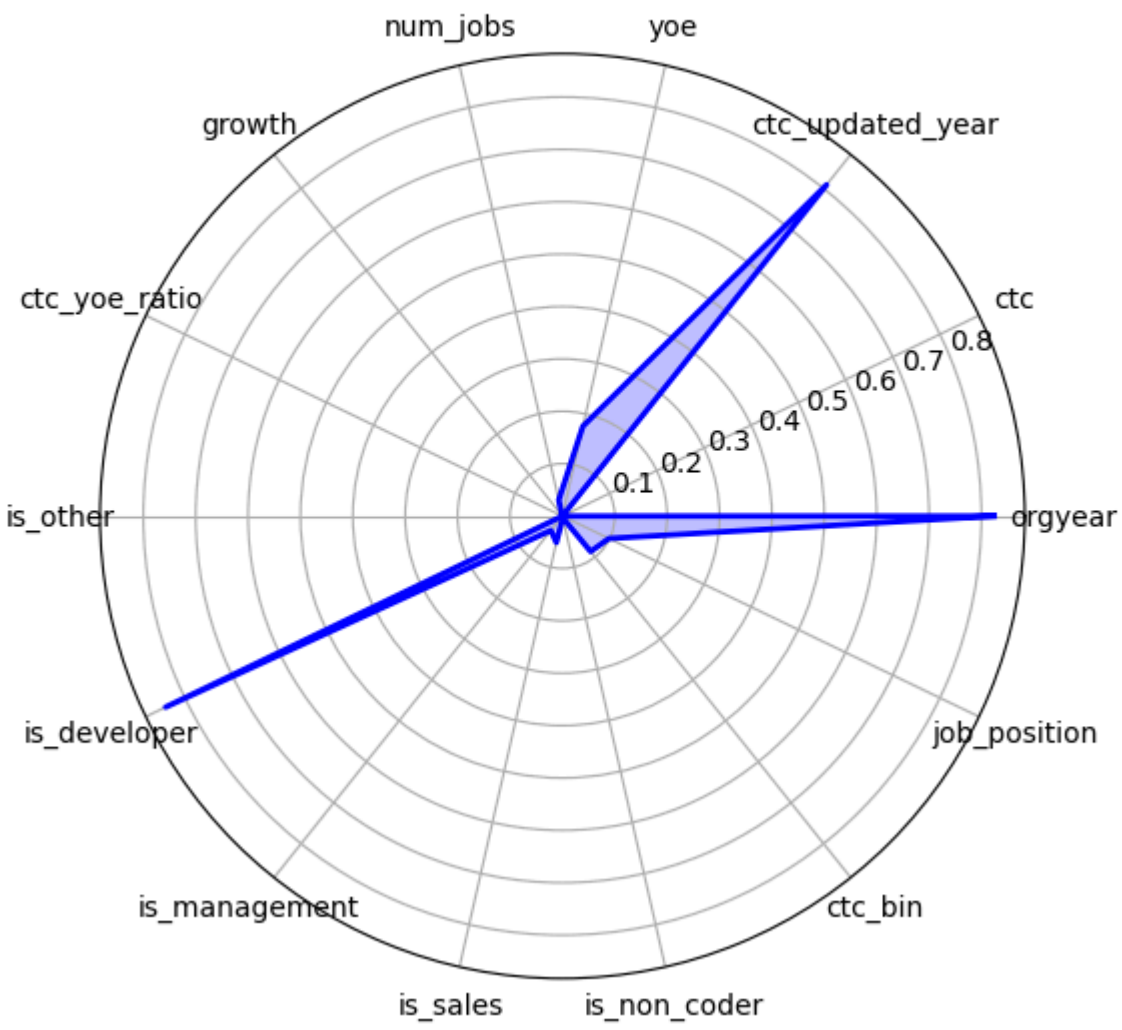
Cluster 4

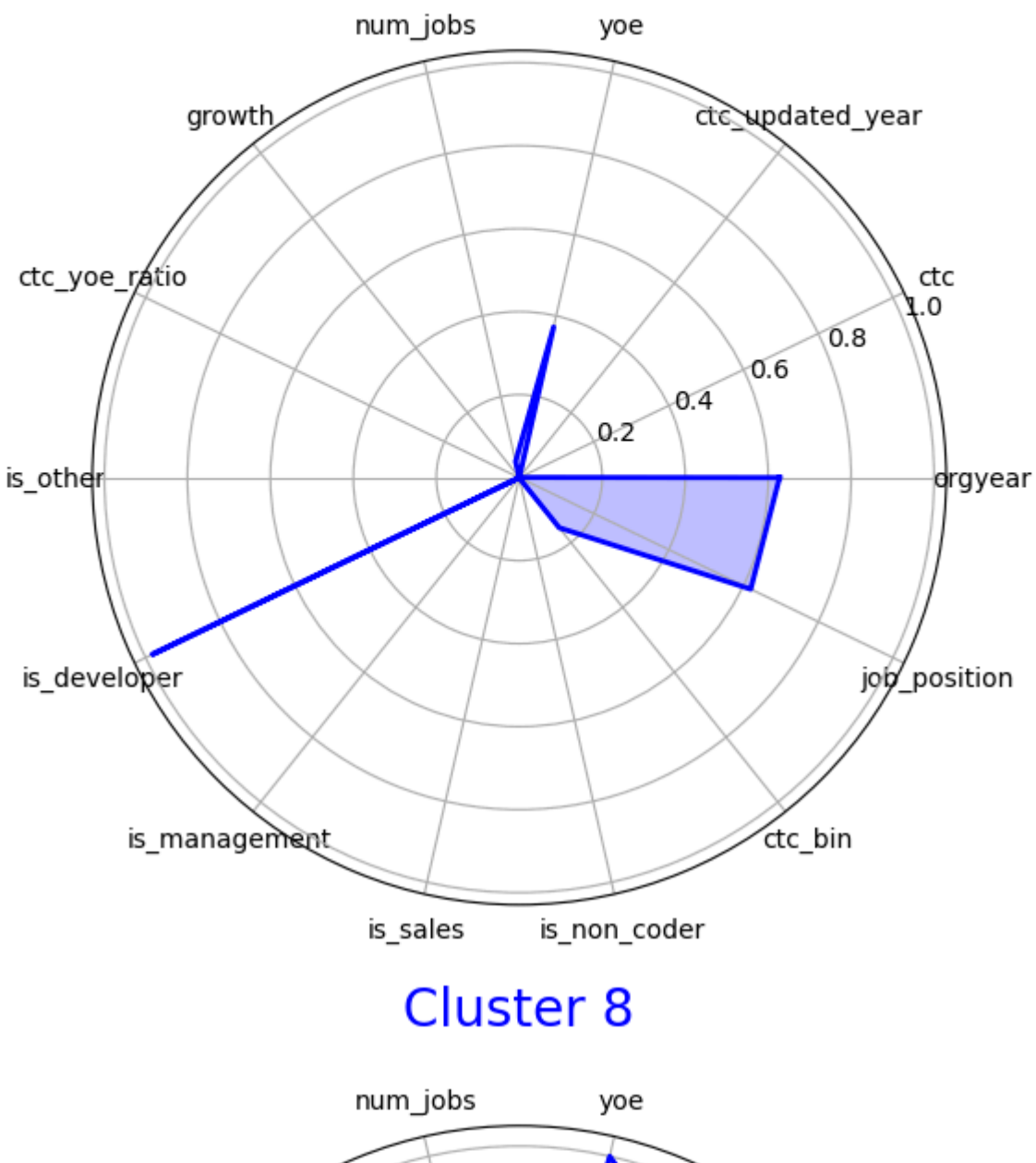


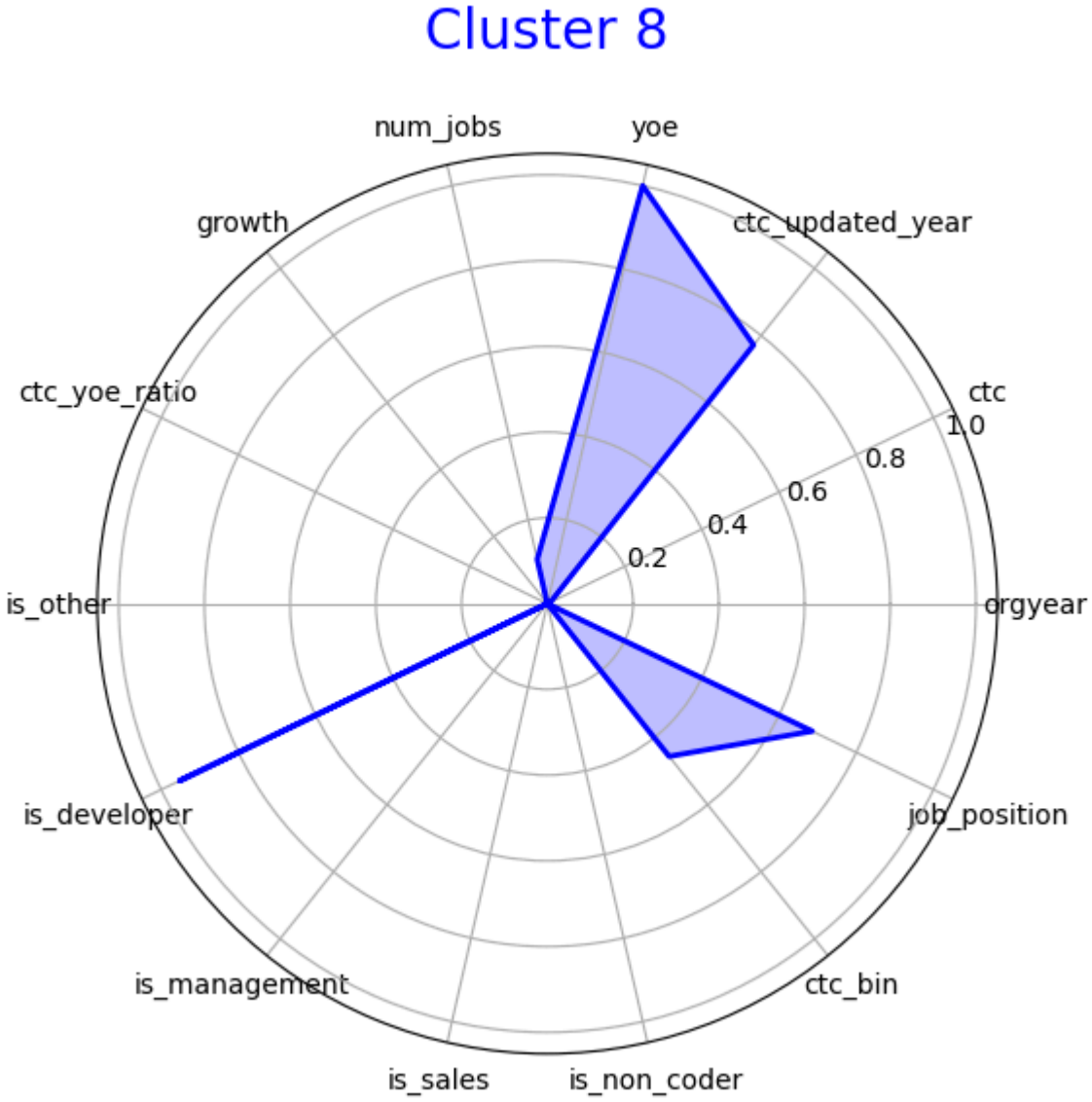
Cluster 5



Cluster 6

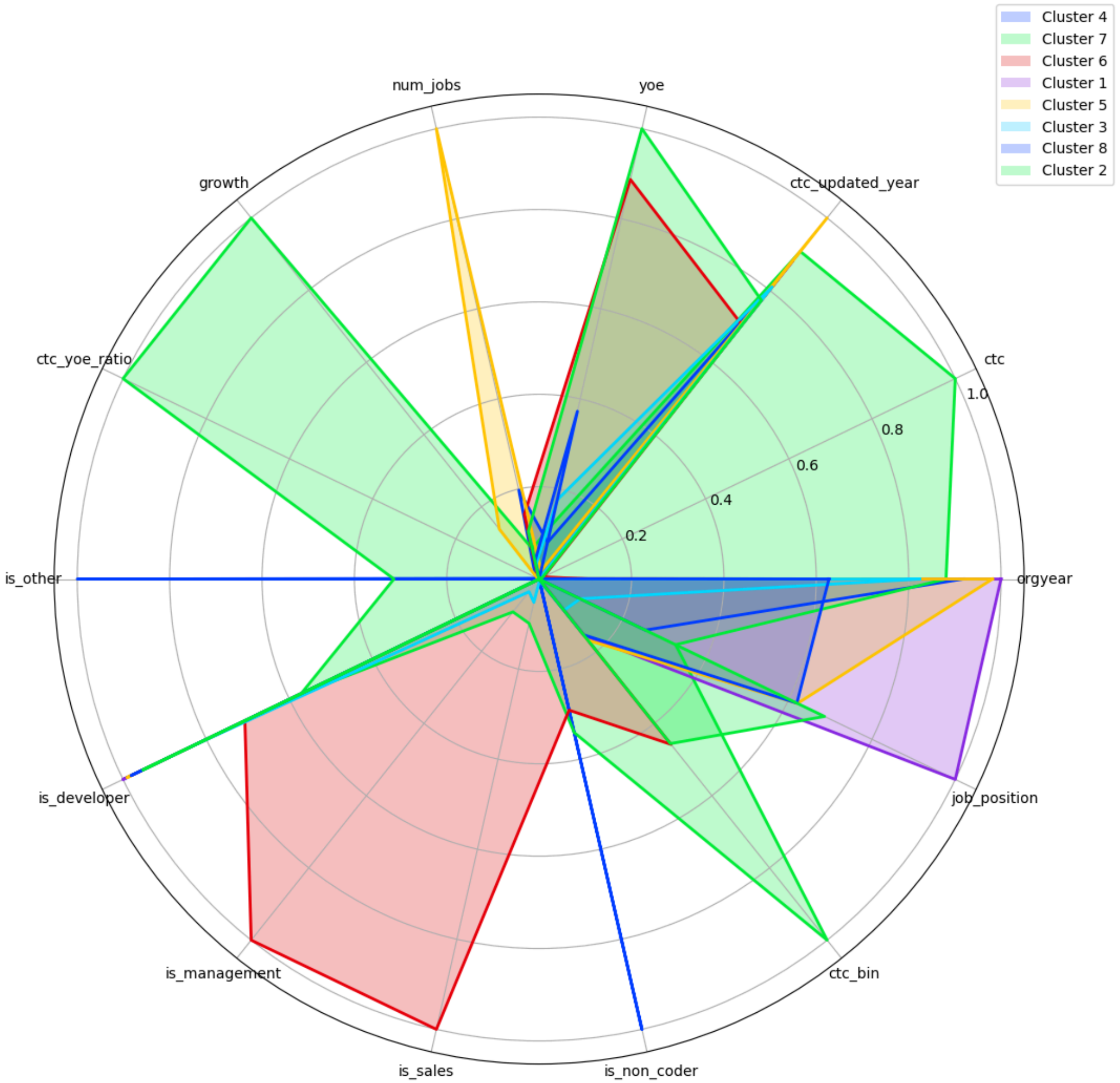






In [224]:
```
# Get the unique labels from the 'cluster' column and convert them to a list
cluster_labels = sample_hc['cluster'].dropna().unique().tolist()

# Create a combined polar plot for all clusters
create_combined_polar_plot(normalized_means, features, cluster_labels)
```



📝 CLUSTER Insights

`Cluster - 1` . **Stable Transitioners**
(Candidates in this cluster belong to Other and Non-Coder categories with a recent hike.)

`Cluster - 2` . **Elite Achievers**
(Candidates in this cluster belong to Developer, Non-Coder, and Other categories, with very high growth, very high pay, recent hikes, and fewer job switches.)

`Cluster - 3` . **Underpaid Veterans**
(Candidates in this cluster belong to Developer, Management, and Sales categories, with very high experience but are paid less.)

`Cluster - 4` . **Frequent Switchers**
(Candidates in this cluster belong to the Developer category with recent hikes and a high number of job switches.)

`Cluster - 5` . **Growth Seekers**
(Candidates in this cluster belong to the Developer category, with average job switches and recent hikes.)

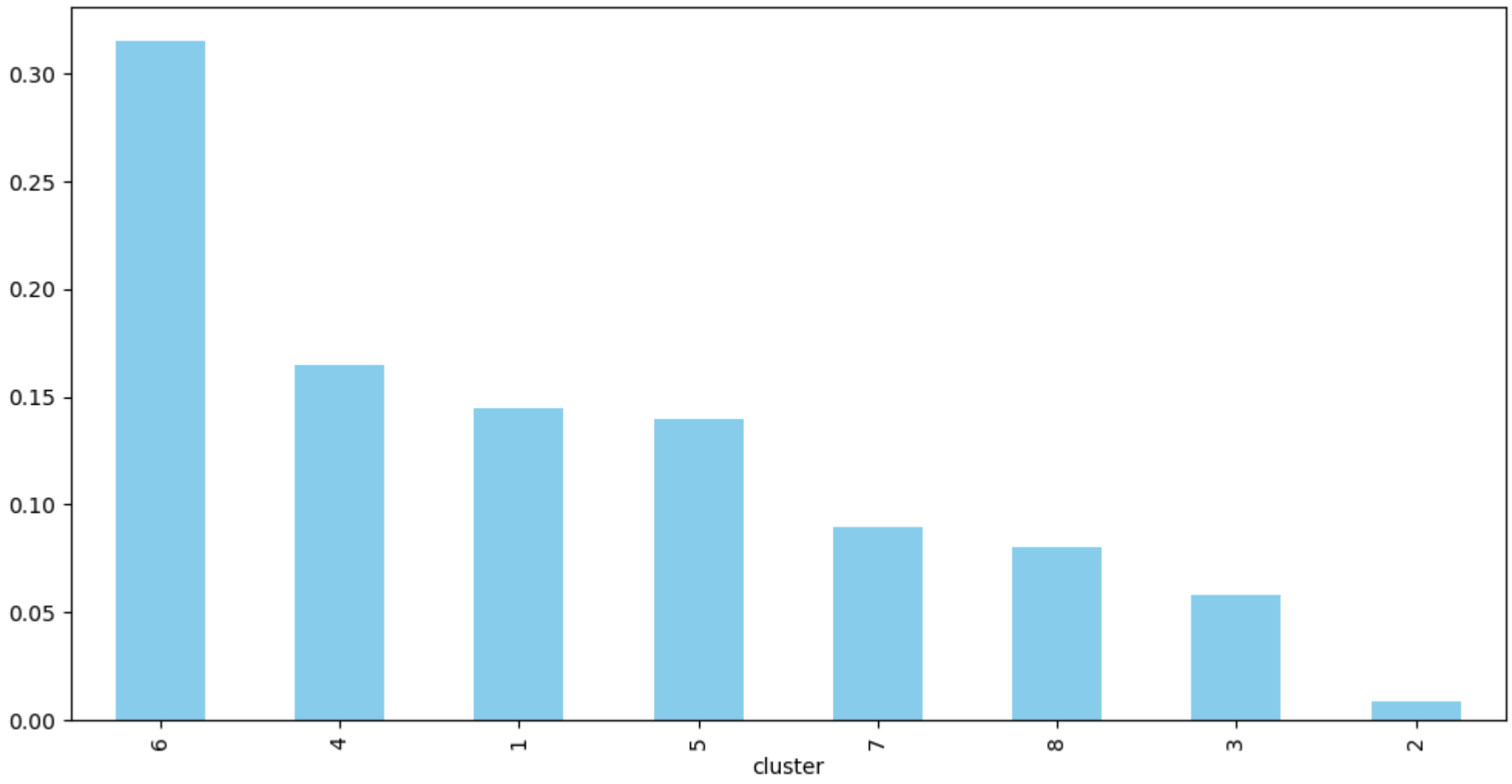
`Cluster - 6` . **Committed Achievers**
(Candidates in this cluster belong to the Developer category, with almost no job switches and recent hikes.)

`Cluster - 7` . **Upskilling Needed**
(Candidates in this cluster belong to the Developer category, with average job switches, low experience, no hikes, and a need for new skills.)

`Cluster - 8` . **Experienced Undervalued**
(Candidates in this cluster belong to the Developer category, with very high experience, average job switches, but are paid less.)

In [225]:
```
sample_hc['cluster'].value_counts(normalize=True).plot(kind='bar', figsize=(12, 6), color='skyblue')
```

Out[225]: <Axes: xlabel='cluster'>



🔍 Insights

- Cluster 6 containing developers has the highest count and cluster 2 containing non coders has the lowest count.

8. Questionnaire Answers

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

Answer: Around 34% of learners fall into the largest cluster, 1

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

Answer: CTC, Years of experience (YOE), CTC to YOE Ratio`, Designation, Class and Tier are the most important characteristics that differentiate the clusters.

3. Is it always true that with an increase in years of experience, the CTC increases? Provide a case where this isn't true.

Answer: No, it is not true that CTC increases with increase in experience. The maximum CTC belongs to a learner with 7 years of experience and the minimum CTC belongs to a 29 year experienced learner

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

Answer: Data Analysts is usually considered a entry-level job and there is a learner with Data Analyst job position with a CTC higher than that of a learner with engineering leadership job position

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

Answer: Average CTC across different job positions is `12 Lakhs` *(Overall)*

Here's a List of Top 5 Jobs with their Average CTC:

- **Frontend Engineer** `23,23,741.050`
- **Backend Engineer** `20,74,889.063`
- **QA Engineer** `20,27,199.074`
- **Fullstack Engineer** `19,78,556.112`
- **Data Scientist** `19,35,848.904`

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

Answer: There are around 900+ companies in which more than 50% of the times the avergae CTC of a Data Scientist is greater than that of other roles

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

- ### 7.1. Which companies dominate in Tier 1 and why might this be the case?
  - **Answer**: The companies which offer Software Developer roles are the companies which dominate Tier 1 as Software Developers are in high demand due to the exponential growth of AI

- **7.2. Are there any notable patterns or insights when comparing learners from Tier 3 across different companies**
  - **Answer** The learners have a mean of 7 years of experience with CTC being on the lower end.

8. After performing unsupervised clustering:

- **8.1. How many clusters have been identified using the Elbow method?**
  - **Answer**: The elbow method gave two elbows, one at 4 and another at 7
- **8.2. Do the clusters formed align or differ significantly from the manual clustering efforts? If so, in what way**
  - **Answer**: The clusters formed are slightly better than the manual clustering. The manual clustering was able to differentiate between CTCs and years of experience clearly and job_position partially. The clusters formed due to kMeans are able to differentaie CTC, years of experience and job position(encoded in class column) clearly.

9. From the Hierarchical Clustering results:

- **9.1. Are there any clear hierarchies or patterns formed that could suggest the different levels of seniority or roles within a company?**
  - **Answer**: Yes
- **9.2 How does the dendrogram representation correlate with the 'Years of Experience' feature?**
  - **Answer**: We can see a clear pattern that the low number of years of experience are grouped together on the extreme left of the dendrogram, medium number of years of experience are grouped together in the middle and high number of years of experience are grouped together at the extreme right?.s.

9. Actionable Insights and Recommendations

Insights

1. **General Dataset Insights**
   - The dataset comprises **205,843 rows and 7 columns**, indicating substantial data for analysis.
   - A majority of the candidates belong to the **web development domain** and have **less than 10 years of experience**.
   - Most CTC updates occurred between **2019 and 2021**, reflecting a significant period of salary revisions.
   - A notable number of candidates joined after **2010**, with some extending back to pre-2000s, indicating a diverse workforce.
   - The **mean salary** is `₹12 Lakhs`, while the **median salary** is `₹10 Lakhs`, signifying a skewed salary distribution influenced by outliers.
2. **Tier-Level Insights**
   - Tier 3 candidates tend to remain **with the same company without frequent switches**, which may reflect limited career growth opportunities.
3. **CTC Variance**
   - A significant variance in CTC relative to years of experience suggests **diverse salary structures**, influenced by job roles, domains, and company policies.
4. **Clustering Analysis**
   - **Hopkins Statistic** of `0.9999` confirms a strong clustering tendency, validating the application of clustering methods.
   - Insights from K-Means and Hierarchical clustering provide distinct learner profiles, helping tailor actionable strategies.

K-Means Cluster Insights

1. **Underpaid Switchers**: Developers with high experience, frequent job switches, but low CTC.
   Action: Analyze causes of underpayment (skill gaps, domain shifts) and offer targeted skill enhancement programs.
2. **Ambitious Movers**: Developers with average growth, frequent switches, and recent hikes.
   Action: Highlight career path optimization strategies to sustain growth and reduce unnecessary switching.
3. **Stagnant Movers**: Developers with frequent switches but no recent hikes.
   Action: Focus on skill upgrades and market-readiness to secure better-paying roles.
4. **Professionally Stuck**: Non-coders and others with low job mobility and no recent hikes.
   Action: Provide intensive upskilling programs and mentorship to reignite career trajectories.
5. **Elite Achievers**: High-performing candidates across categories with high growth and pay.
   Action: Utilize these individuals for testimonials, advanced technical tracks, or leadership programs.
6. **Underpaid Veterans**: Experienced professionals in management and sales with low CTC.
   Action: Design transition pathways for moving into higher-paying, hybrid roles like tech management.

Hierarchical Cluster Insights

1. **Stable Transitioners**: Non-coders and others with recent hikes.
   Action: Identify opportunities for sustainable growth in roles suited to their backgrounds.
2. **Elite Achievers**: High-performing candidates with consistent hikes and fewer switches.
   Action: Leverage their success stories for marketing and encourage cross-skilling opportunities.

3. **Underpaid Veterans**: Developers, managers, and sales professionals with high experience but low CTC.
   Action: Promote domain transitions or certifications in high-demand skills.

4. **Frequent Switchers**: Developers with recent hikes and frequent job changes.
   Action: Foster skills that emphasize stability and long-term career growth.

5. **Growth Seekers**: Developers with recent hikes and average job switches.
   Action: Encourage specialized certifications to accelerate career growth.

6. **Committed Achievers**: Developers with recent hikes and minimal job switches.
   Action: Reward their commitment through advanced leadership or technical tracks.

7. **Upskilling Needed**: Developers with low experience, no hikes, and a need for new skills.
   Action: Offer foundational and intermediate programs in trending domains.

8. **Experienced Undervalued**: Developers with high experience but low pay.
   Action: Design salary negotiation workshops and advanced courses for their expertise.

Recommendations

1. **Targeted Programs for Professionally Stuck and Stagnant Movers**:
   - Create personalized programs addressing skill gaps and market trends.
   - Use success stories of similar learners for video testimonials.
2. **Enhanced Outreach and Acquisition**:
   - Identify and engage with learners in low-paying companies and stagnant job roles through LinkedIn campaigns.
3. **High-Value Program Development**:
   - Introduce niche programs like **Gen AI + MBA**, tailored for transitioning business professionals.
   - Expand offerings in software development, data analysis, and leadership skills for junior and mid-level professionals.
4. **Course Optimization**:
   - Utilize cluster insights to create tracks that cater to specific growth areas like technical expertise or role transitions.
5. **Corporate Partnerships**:
   - Collaborate with companies offering high CTC to streamline placements.
   - Work with low-paying companies to improve employee growth opportunities.
6. **Algorithm Improvements**:
   - Request detailed learner inputs, such as precise job positions and domains, to refine clustering algorithms.
7. **Marketing Strategies**:
   - Showcase roles like **software development** and **data science** with their potential for high salaries in ads.
   - Highlight programs for individuals stuck in stagnant roles, focusing on successful transitions.
8. **Investigate Outliers**:
   - Validate the accuracy of extreme CTC data entries to avoid skewed results.
9. **Upskilling Academia**:
   - Attract students and educators from academia to make them industry-ready and employable with competitive salaries.
10. **Retention Support for Learners**:
    - Organize master sessions featuring placed learners to inspire others in similar clusters.