Raj verma AMCAT Analysis

In [299]:

```
#Importing required libaries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats as st
```

In [26]:

```
# Reading the .xlsx file
df=pd.read_excel("data.xlsx")
df.drop("Unnamed: 0",axis=1,inplace=True)
df.head()
```

Out[26]:

	ID	Salary	DOJ	DOL	Designation	JobCity	Gender	DOB	10percentage	10board	...	ComputerScienc
0	203097	420000	2012-06-01	present	senior quality engineer	Bangalore	f	1990-02-19	84.3	board ofsecondary education,ap	...	-
1	579905	500000	2013-09-01	present	assistant manager	Indore	m	1989-10-04	85.4	cbse	...	-
2	810601	325000	2014-06-01	present	systems engineer	Chennai	f	1992-08-03	85.0	cbse	...	-
3	267447	1100000	2011-07-01	present	senior software engineer	Gurgaon	m	1989-12-05	85.6	cbse	...	-
4	343523	200000	2014-03-01	2015-03-01 00:00:00	get	Manesar	m	1991-02-27	78.0	cbse	...	-

5 rows × 38 columns

In [28]:

```
#Shape of the given data
df.shape
```

Out[28]:

```
(3998, 38)
```

In [30]:

```
# Information about the AMCAT data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3998 entries, 0 to 3997
Data columns (total 38 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   ID                      3998 non-null   int64
 1   Salary                  3998 non-null   int64
 2   DOJ                     3998 non-null   datetime64[ns]
 3   DOL                     3998 non-null   object
 4   Designation             3998 non-null   object
 5   JobCity                 3998 non-null   object
 6   Gender                  3998 non-null   object
 7   DOB                     3998 non-null   datetime64[ns]
```

```
 7   DOB                     3998 non-null   datetime64[ns]
 8   10percentage            3998 non-null   float64
 9   10board                 3998 non-null   object
 10  12graduation            3998 non-null   int64
 11  12percentage            3998 non-null   float64
 12  12board                 3998 non-null   object
 13  CollegeID               3998 non-null   int64
 14  CollegeTier             3998 non-null   int64
 15  Degree                  3998 non-null   object
 16  Specialization          3998 non-null   object
 17  collegeGPA              3998 non-null   float64
 18  CollegeCityID           3998 non-null   int64
 19  CollegeCityTier         3998 non-null   int64
 20  CollegeState            3998 non-null   object
 21  GraduationYear          3998 non-null   int64
 22  English                 3998 non-null   int64
 23  Logical                 3998 non-null   int64
 24  Quant                   3998 non-null   int64
 25  Domain                  3998 non-null   float64
 26  ComputerProgramming     3998 non-null   int64
 27  ElectronicsAndSemicon   3998 non-null   int64
 28  ComputerScience         3998 non-null   int64
 29  MechanicalEngg          3998 non-null   int64
 30  ElectricalEngg          3998 non-null   int64
 31  TelecomEngg             3998 non-null   int64
 32  CivilEngg               3998 non-null   int64
 33  conscientiousness       3998 non-null   float64
 34  agreeableness           3998 non-null   float64
 35  extraversion            3998 non-null   float64
 36  nueroticism             3998 non-null   float64
 37  openess_to_experience   3998 non-null   float64
dtypes: datetime64[ns](2), float64(9), int64(18), object(9)
memory usage: 1.2+ MB
```

Exploratory Data Analysis

Getting the insights from the data which includes

- **Missing values**
- **Duplicated values**
- **Ouliers**
- **Distributions**
- **Relationships**

In [33]:

```
# Chacking missing values
df.isna().sum()
```

Out[33]:

```
ID                       0
Salary                   0
DOJ                      0
DOL                      0
Designation              0
JobCity                  0
Gender                   0
DOB                      0
10percentage             0
10board                  0
12graduation             0
12percentage             0
12board                  0
CollegeID                0
CollegeTier              0
Degree                   0
Specialization           0
collegeGPA               0
CollegeCityID            0
```

```
CollegeCityID               0
CollegeCityTier             0
CollegeState                0
GraduationYear              0
English                     0
Logical                     0
Quant                       0
Domain                      0
ComputerProgramming         0
ElectronicsAndSemicon       0
ComputerScience             0
MechanicalEngg              0
ElectricalEngg              0
TelecomEngg                 0
CivilEngg                   0
conscientiousness           0
agreeableness               0
extraversion                0
nueroticism                 0
openess_to_experience       0
dtype: int64
```

In [35]:

```
# Chacking duplicated values
df.duplicated().sum()
```

Out[35]:

```
0
```

Univariate Analysis

- **Analysing the data using single feature/variable.**

In [40]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3998 entries, 0 to 3997
Data columns (total 38 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   ID                     3998 non-null   int64
 1   Salary                 3998 non-null   int64
 2   DOJ                    3998 non-null   datetime64[ns]
 3   DOL                    3998 non-null   object
 4   Designation            3998 non-null   object
 5   JobCity                3998 non-null   object
 6   Gender                 3998 non-null   object
 7   DOB                    3998 non-null   datetime64[ns]
 8   10percentage           3998 non-null   float64
 9   10board                3998 non-null   object
 10  12graduation           3998 non-null   int64
 11  12percentage           3998 non-null   float64
 12  12board                3998 non-null   object
 13  CollegeID              3998 non-null   int64
 14  CollegeTier            3998 non-null   int64
 15  Degree                 3998 non-null   object
 16  Specialization         3998 non-null   object
 17  collegeGPA             3998 non-null   float64
 18  CollegeCityID          3998 non-null   int64
 19  CollegeCityTier        3998 non-null   int64
 20  CollegeState           3998 non-null   object
 21  GraduationYear         3998 non-null   int64
 22  English                3998 non-null   int64
 23  Logical                3998 non-null   int64
 24  Quant                  3998 non-null   int64
 25  Domain                 3998 non-null   float64
 26  ComputerProgramming    3998 non-null   int64
```

```
 26  ComputerProgramming     3998 non-null   int64
 27  ElectronicsAndSemicon   3998 non-null   int64
 28  ComputerScience         3998 non-null   int64
 29  MechanicalEngg          3998 non-null   int64
 30  ElectricalEngg          3998 non-null   int64
 31  TelecomEngg             3998 non-null   int64
 32  CivilEngg               3998 non-null   int64
 33  conscientiousness       3998 non-null   float64
 34  agreeableness           3998 non-null   float64
 35  extraversion            3998 non-null   float64
 36  nueroticism             3998 non-null   float64
 37  openess_to_experience   3998 non-null   float64
dtypes: datetime64[ns](2), float64(9), int64(18), object(9)
memory usage: 1.2+ MB
```

What is the distribution of Salary

In [91]:

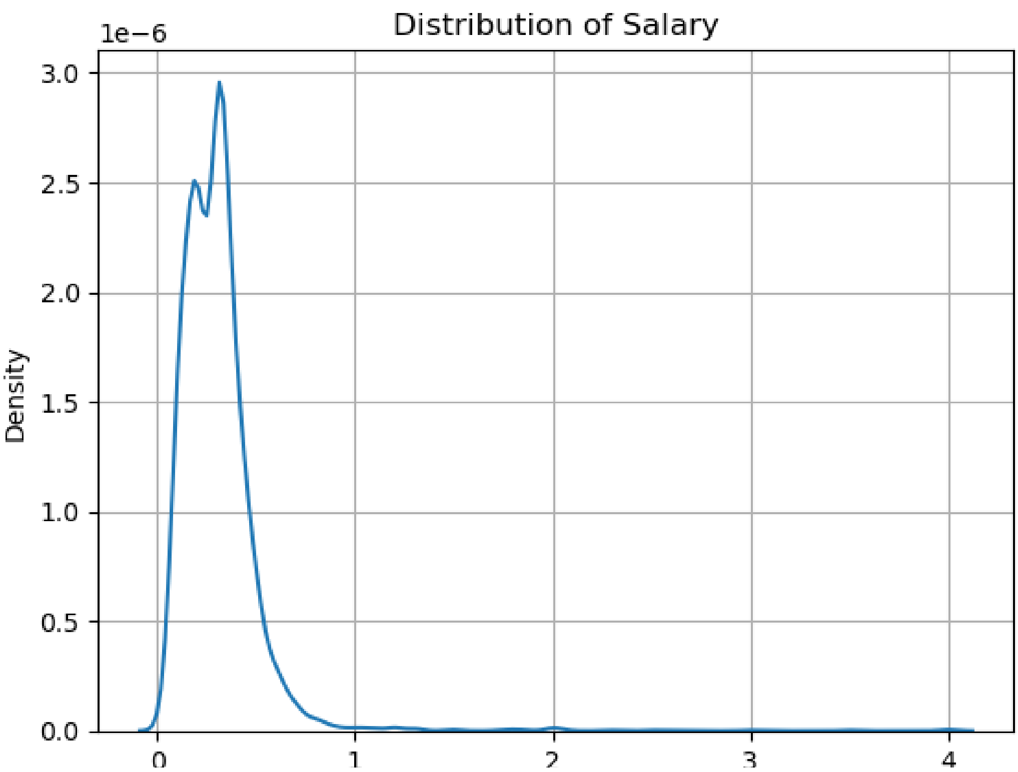
```
pd.DataFrame(df["Salary"].describe())
```

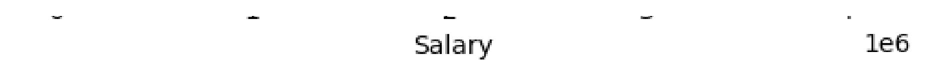
Out[91]:

	Salary
count	3.998000e+03
mean	3.076998e+05
std	2.127375e+05
min	3.500000e+04
25%	1.800000e+05
50%	3.000000e+05
75%	3.700000e+05
max	4.000000e+06

In [89]:

```
sns.kdeplot(data=df["Salary"])
plt.grid()
plt.title("Distribution of Salary")
plt.show()
```





Insights

- **In between 0 to 100000 the salaries are more compared to other salaries.**
- **After 300000 there are less salries.**

What is the average collegeGPA of students?

In [94]:

```
df["collegeGPA"].mean()
```

Out[94]:

```
71.48617058529265
```

What are the counts of different JobCity values?

In [105]:

```
pd.DataFrame(df["JobCity"].value_counts())
```

Out[105]:

JobCity	count
Bangalore	627
-1	461
Noida	368
Hyderabad	335
Pune	290
...	...
Tirunelvelli	1
Ernakulam	1
Nanded	1
Dharmapuri	1
Asifabadbanglore	1

339 rows × 1 columns

Which Specialization is most common among the students?

In [110]:

```
df["Specialization"].value_counts().head(10)
```

Out[110]:

```
Specialization
electronics and communication engineering    880
computer science & engineering               744
information technology                       660
computer engineering                         600
```

```
computer application                      244
mechanical engineering                    201
electronics and electrical engineering    196
electronics & telecommunications          121
electrical engineering                     82
electronics & instrumentation eng          32
Name: count, dtype: int64
```

In [114]:

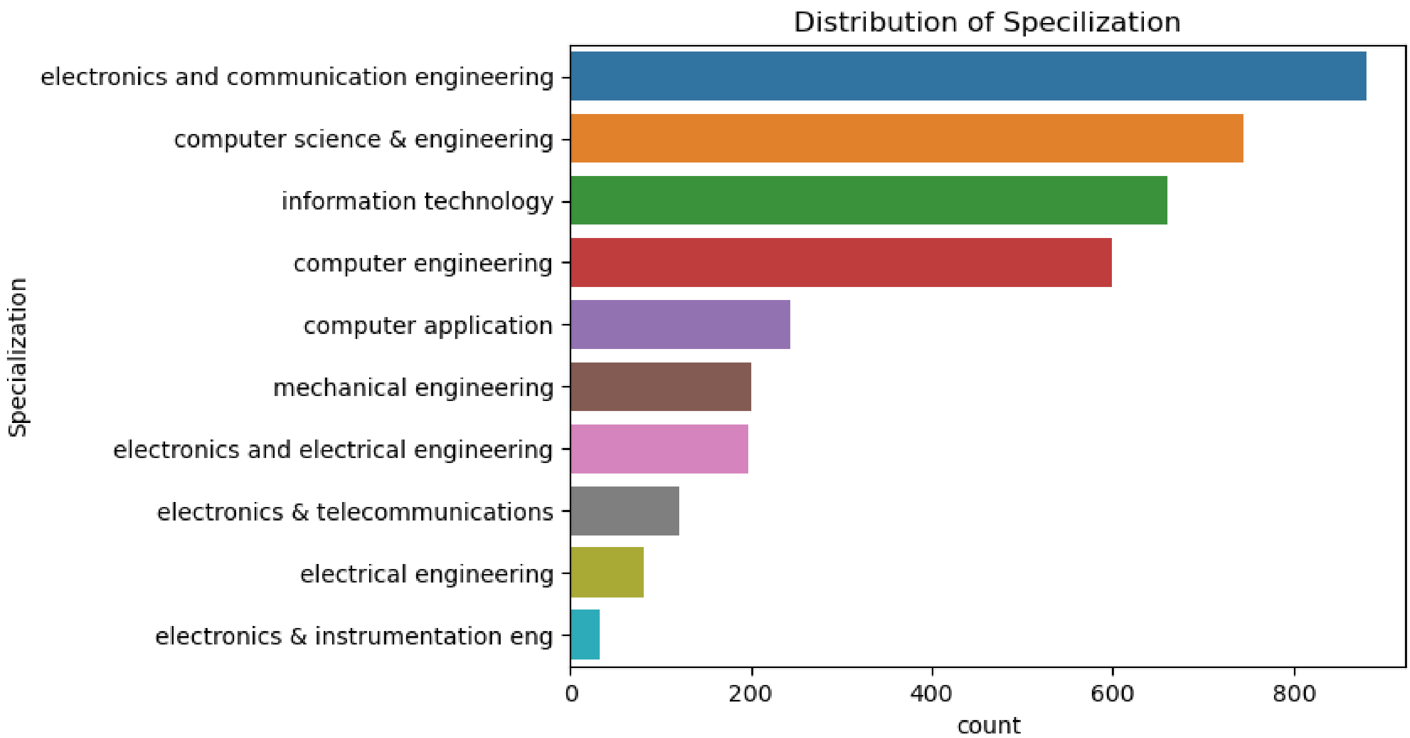
```
d1=pd.DataFrame(df["Specialization"].value_counts().head(10))
d1
```

Out[114]:

Specialization	count
electronics and communication engineering	880
computer science & engineering	744
information technology	660
computer engineering	600
computer application	244
mechanical engineering	201
electronics and electrical engineering	196
electronics & telecommunications	121
electrical engineering	82
electronics & instrumentation eng	32

In [287]:

```
sns.barplot(y=d1.index,x=d1["count"],hue=d1.index)
plt.title("Distribution of Specilization")
plt.show()
```



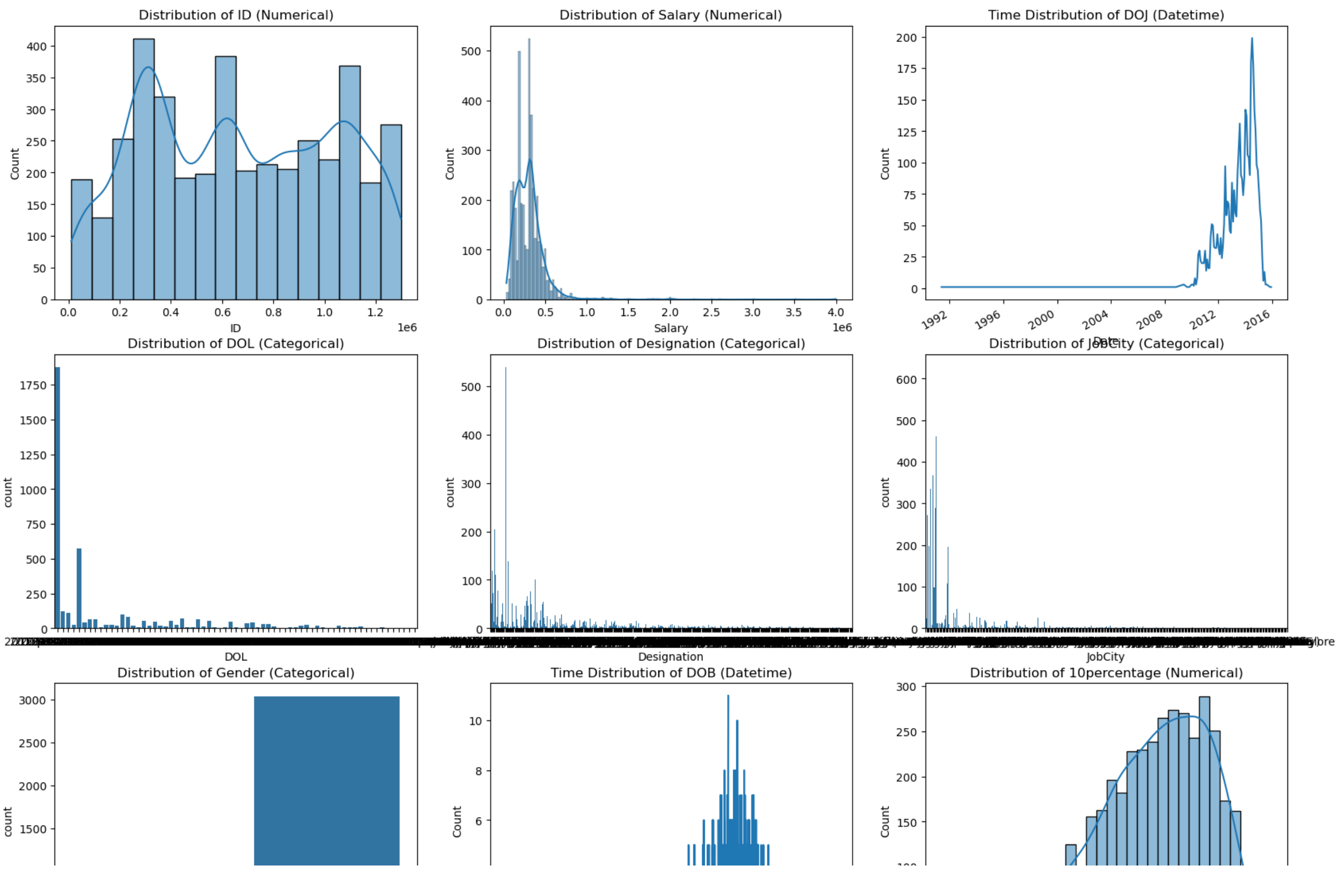
Insights

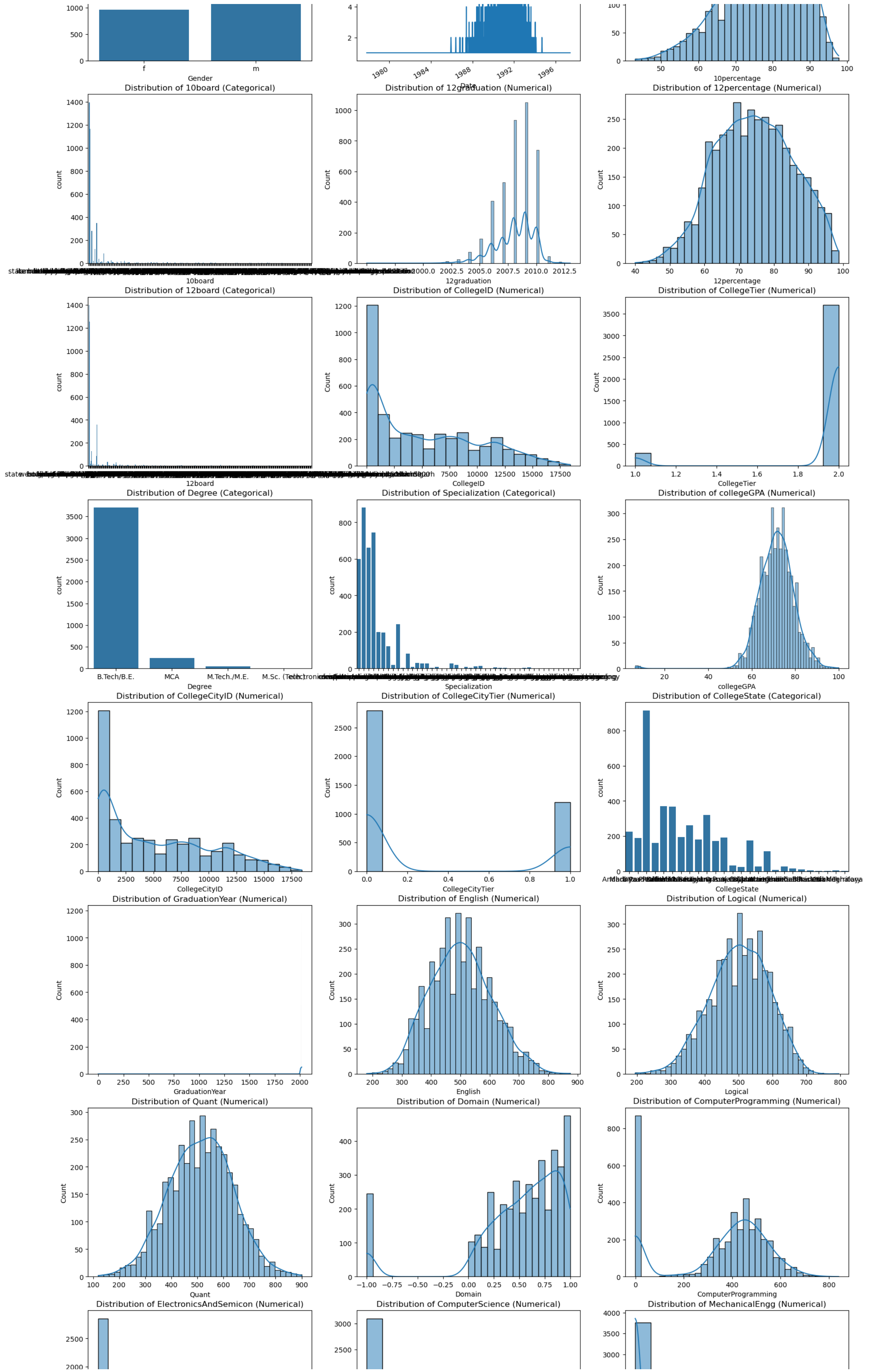
- **There are more electronics engineers compared to others.**
- **There are less electrical instrumentation engineers**

- There are less electrical,instrumentation engineers..

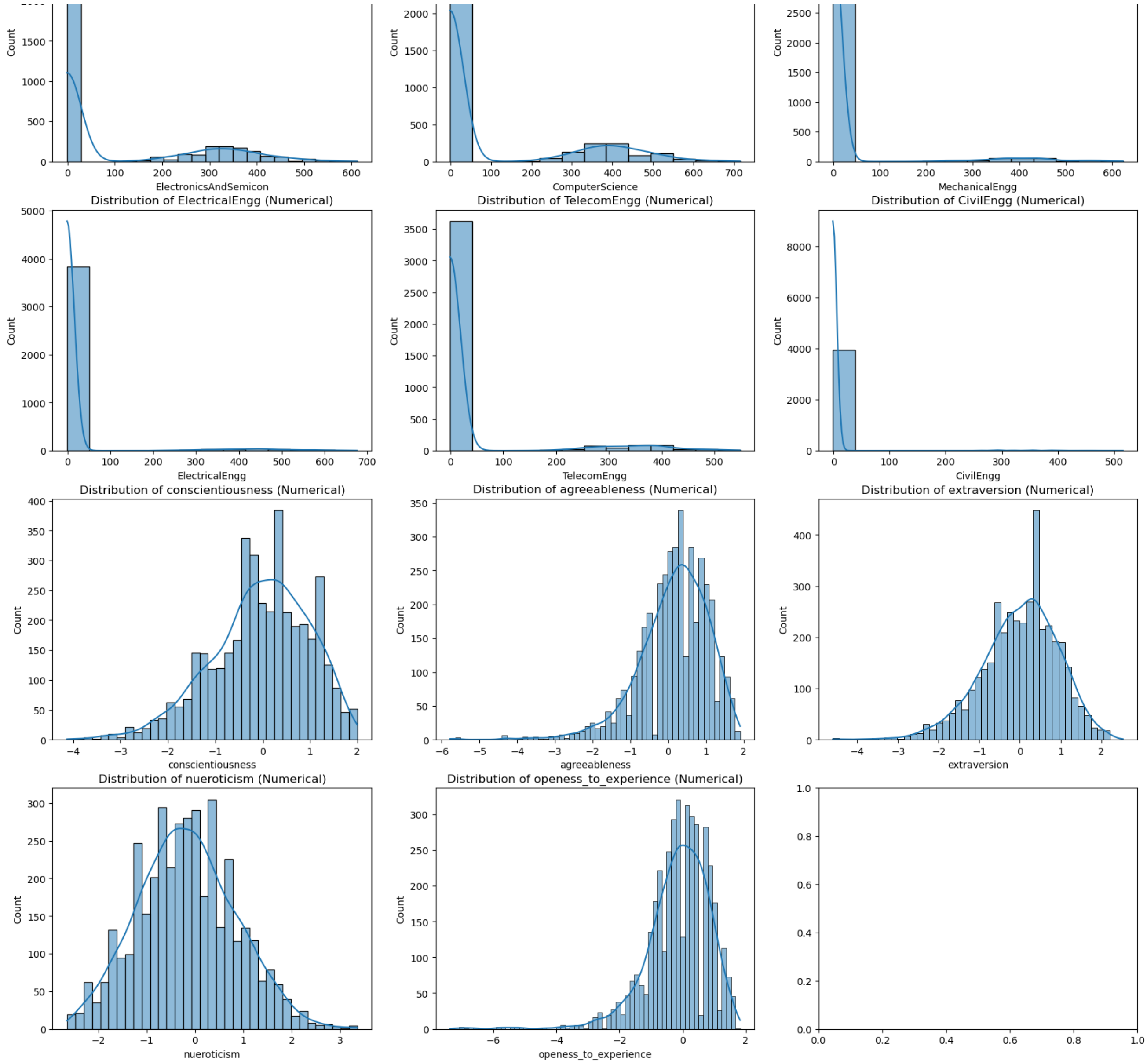
In [291]:

```python
# Assuming df is your DataFrame
# Set up the number of subplots based on the number of columns
n_cols = len(df.columns)
n_rows = int(np.ceil(n_cols / 3))  # 3 columns per row for better layout

fig, axes = plt.subplots(n_rows, 3, figsize=(20, n_rows * 6))
axes = axes.flatten()  # Flatten the axes array for easier indexing

# Iterate over each column in the DataFrame and each subplot axis
for i, col in enumerate(df.columns):

    # Check if the column is categorical
    if df[col].dtype == 'object' or df[col].dtype.name == 'category':
        # Categorical column - use countplot
        sns.countplot(x=col, data=df, ax=axes[i])
        axes[i].set_title(f'Distribution of {col} (Categorical)')

    # Check if the column is datetime
    elif pd.api.types.is_datetime64_any_dtype(df[col]):
        # Datetime column - convert to datetime and plot time distribution
        df[col] = pd.to_datetime(df[col])
        df[col].value_counts().sort_index().plot(ax=axes[i])
        axes[i].set_title(f'Time Distribution of {col} (Datetime)')
        axes[i].set_xlabel('Date')
        axes[i].set_ylabel('Count')

    # Check if the column is numerical
    elif pd.api.types.is_numeric_dtype(df[col]):
        # Numerical column - use histplot
        sns.histplot(df[col], kde=True, ax=axes[i])
        axes[i].set_title(f'Distribution of {col} (Numerical)')

    # Hide unused axes if fewer columns than subplots
    if i >= n_cols:
        axes[i].axis('off')

# Adjust layout for better spacing between subplots

plt.show()
```



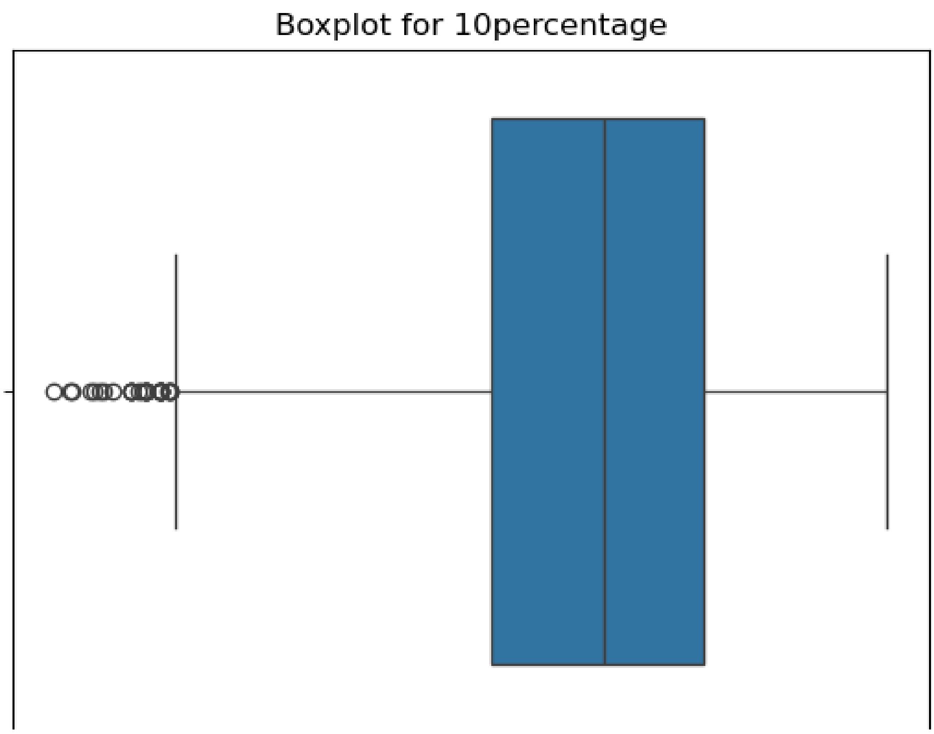


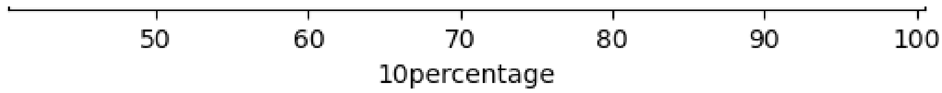
Gender
Date
10percentage
Distribution of 10board (Categorical)
Distribution of 12graduation (Numerical)
Distribution of 12percentage (Numerical)
10board
12graduation
12percentage
Distribution of 12board (Categorical)
Distribution of CollegeID (Numerical)
Distribution of CollegeTier (Numerical)
12board
CollegeID
CollegeTier
Distribution of Degree (Categorical)
Distribution of Specialization (Categorical)
Distribution of collegeGPA (Numerical)
B.Tech/B.E.
MCA
M.Tech./M.E.
Degree
Specialization
collegeGPA
Distribution of CollegeCityID (Numerical)
Distribution of CollegeCityTier (Numerical)
Distribution of CollegeState (Categorical)
CollegeCityID
CollegeCityTier
CollegeState
Distribution of GraduationYear (Numerical)
Distribution of English (Numerical)
Distribution of Logical (Numerical)
GraduationYear
English
Logical
Distribution of Quant (Numerical)
Distribution of Domain (Numerical)
Distribution of ComputerProgramming (Numerical)
Quant
Domain
ComputerProgramming
Distribution of ElectronicsAndSemicon (Numerical)
Distribution of ComputerScience (Numerical)
Distribution of MechanicalEngg (Numerical)

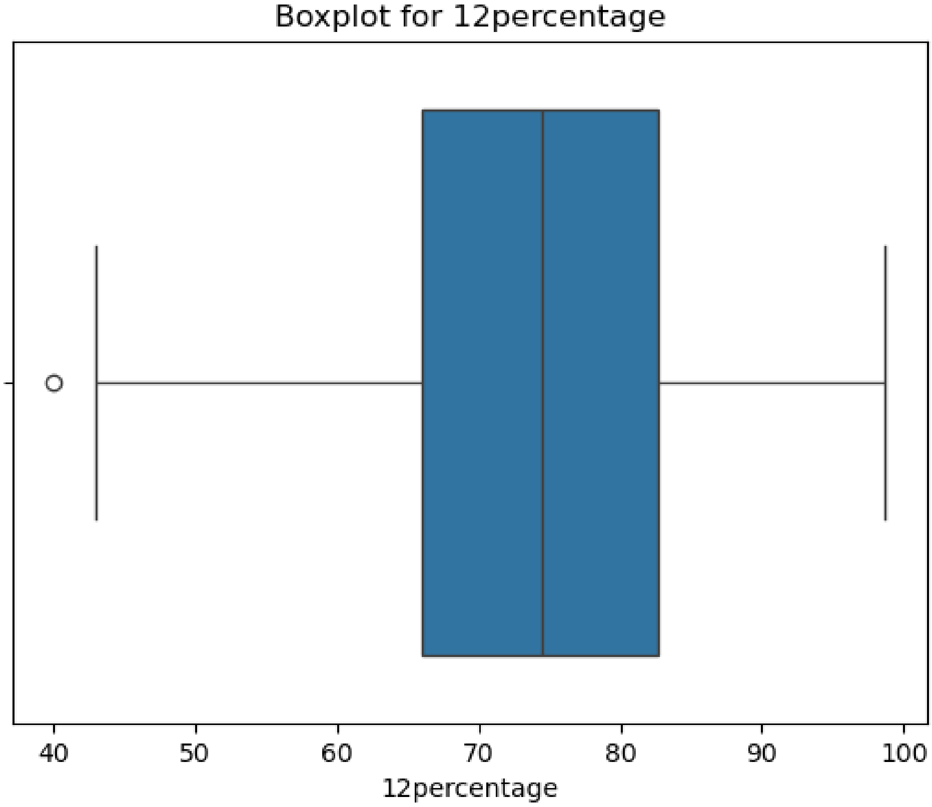


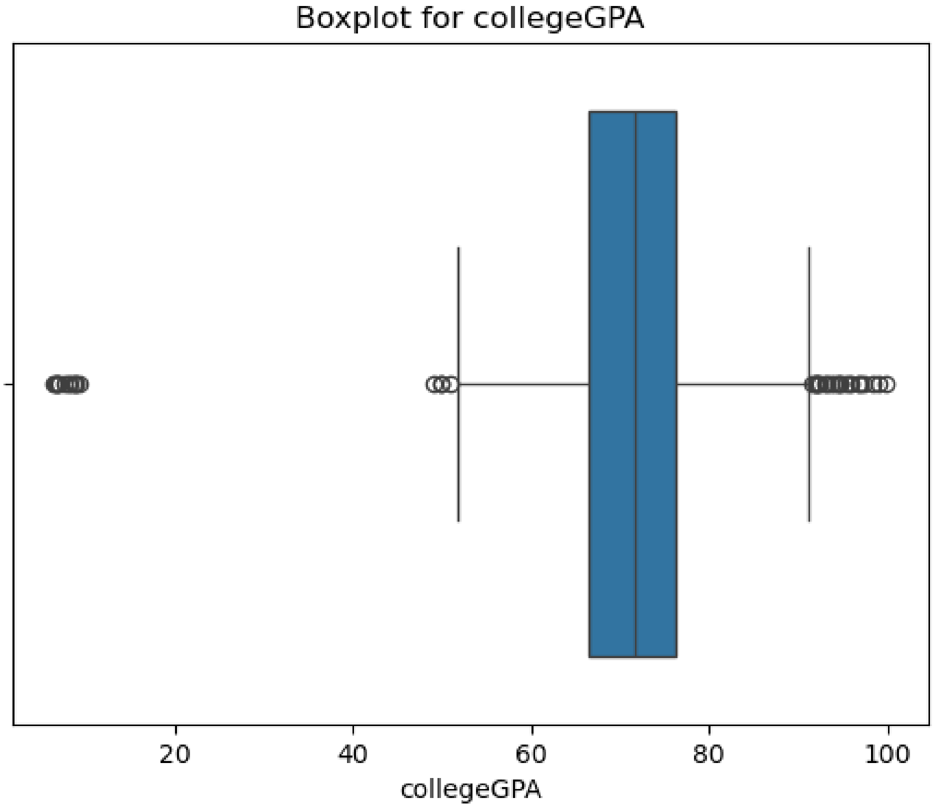
In [294]:

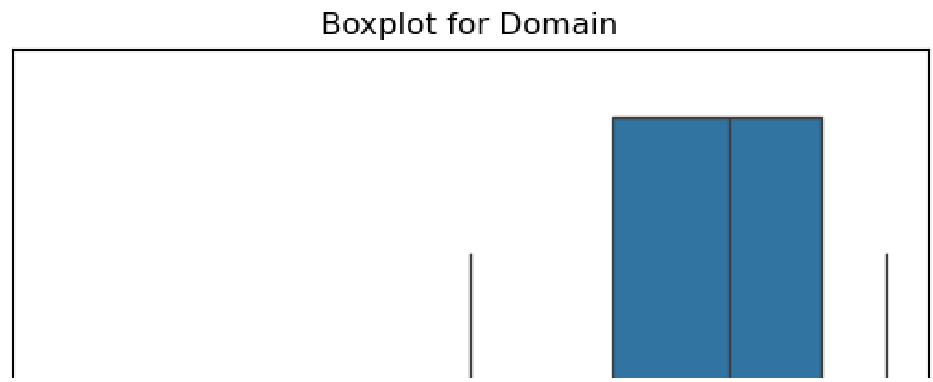
```
for i in df.columns:
    if df[i].dtype=="int" or df[i].dtype=="float":
        sns.boxplot(x=df[i])
        plt.title("Boxplot for {}".format(i))
        plt.show()
```

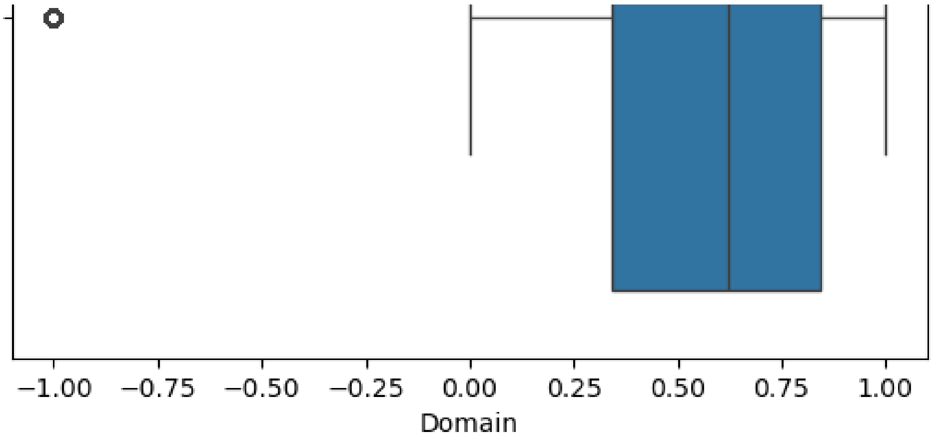



50 60 70 80 90 100
10percentage

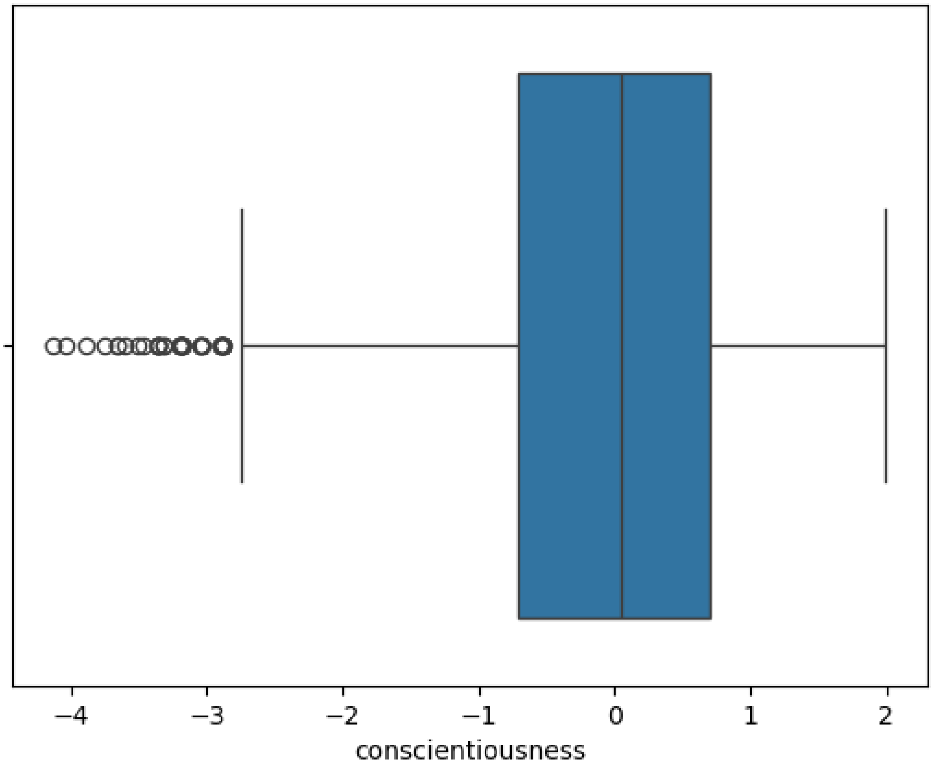

Boxplot for 12percentage
40 50 60 70 80 90 100
12percentage


Boxplot for collegeGPA
20 40 60 80 100
collegeGPA

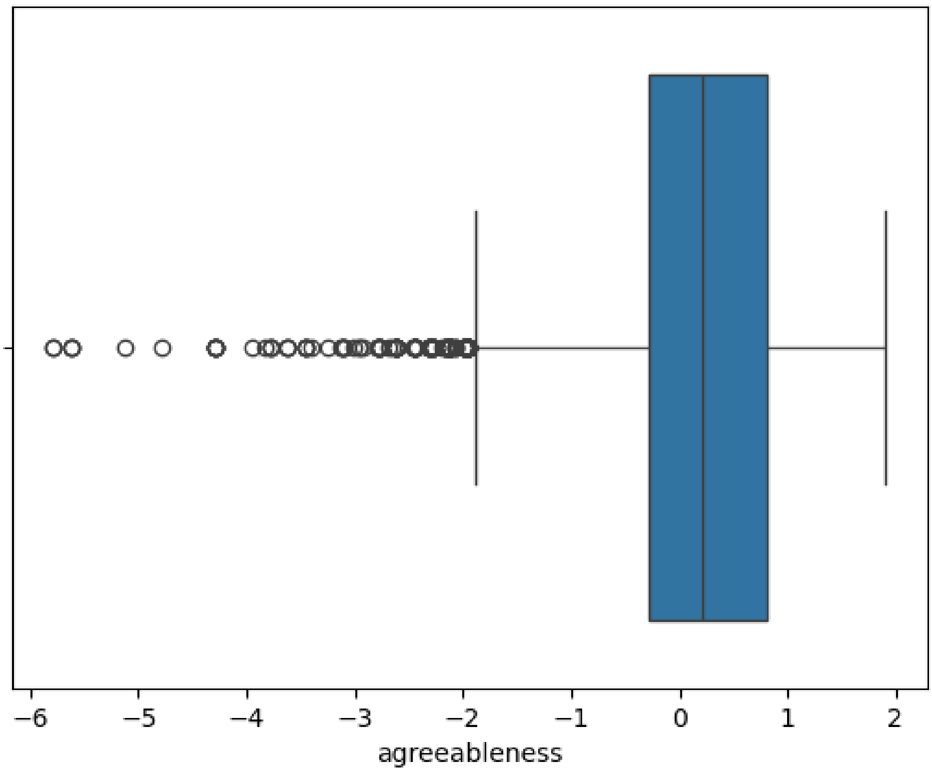

Boxplot for Domain



Boxplot for conscientiousness

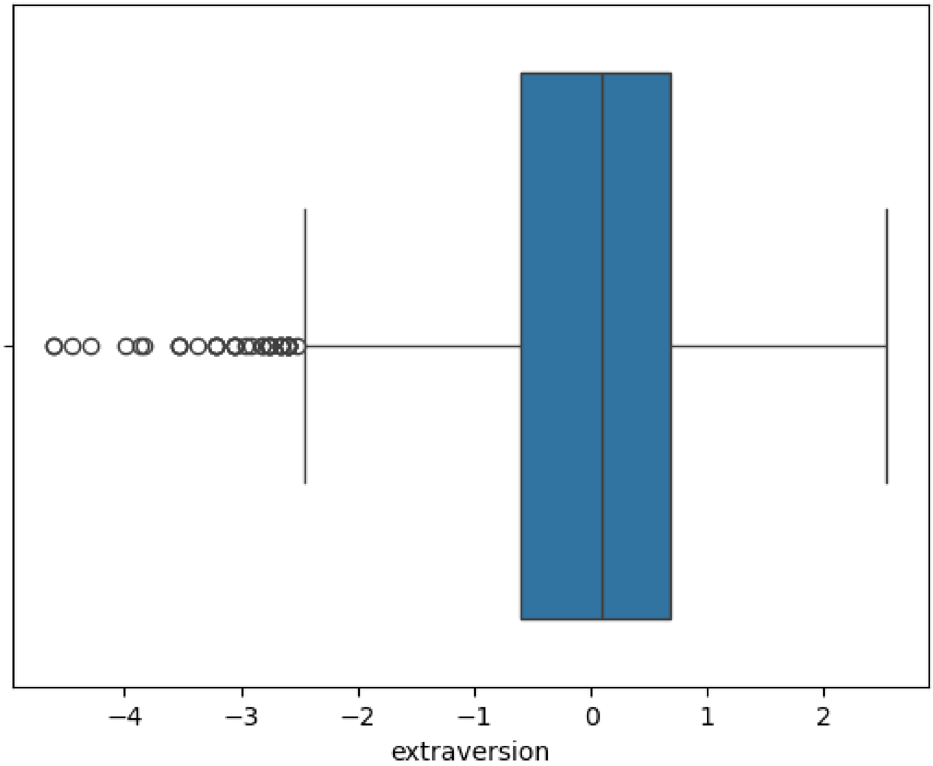


Boxplot for agreeableness

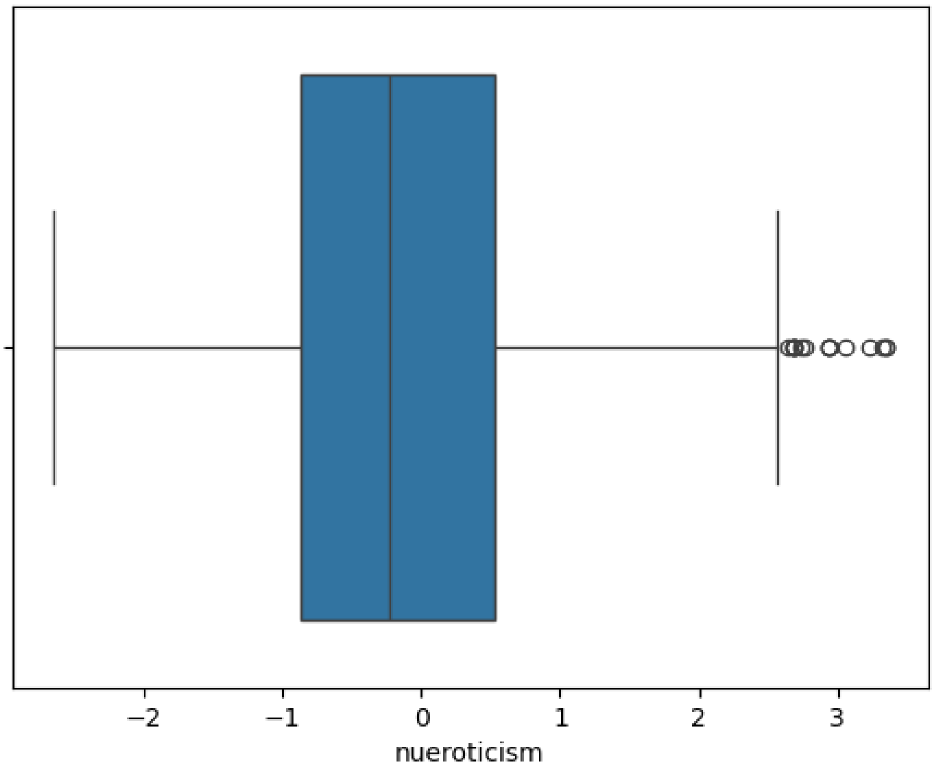


Boxplot for extraversion

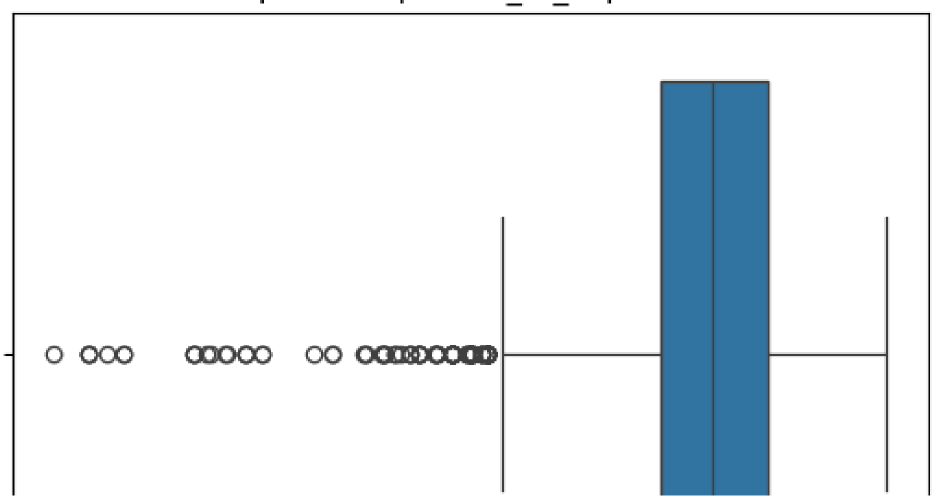
Boxplot for extraversion

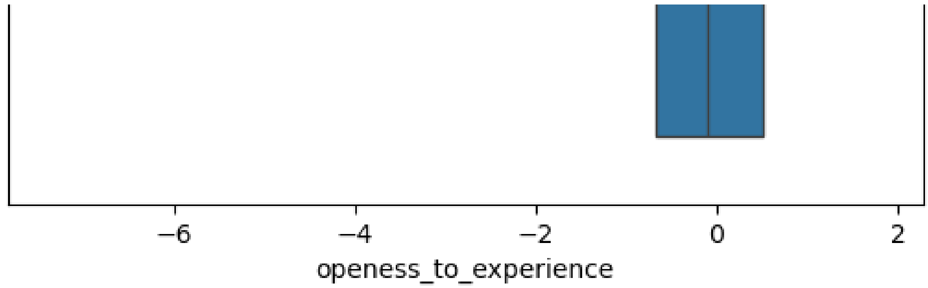


Boxplot for nueroticism



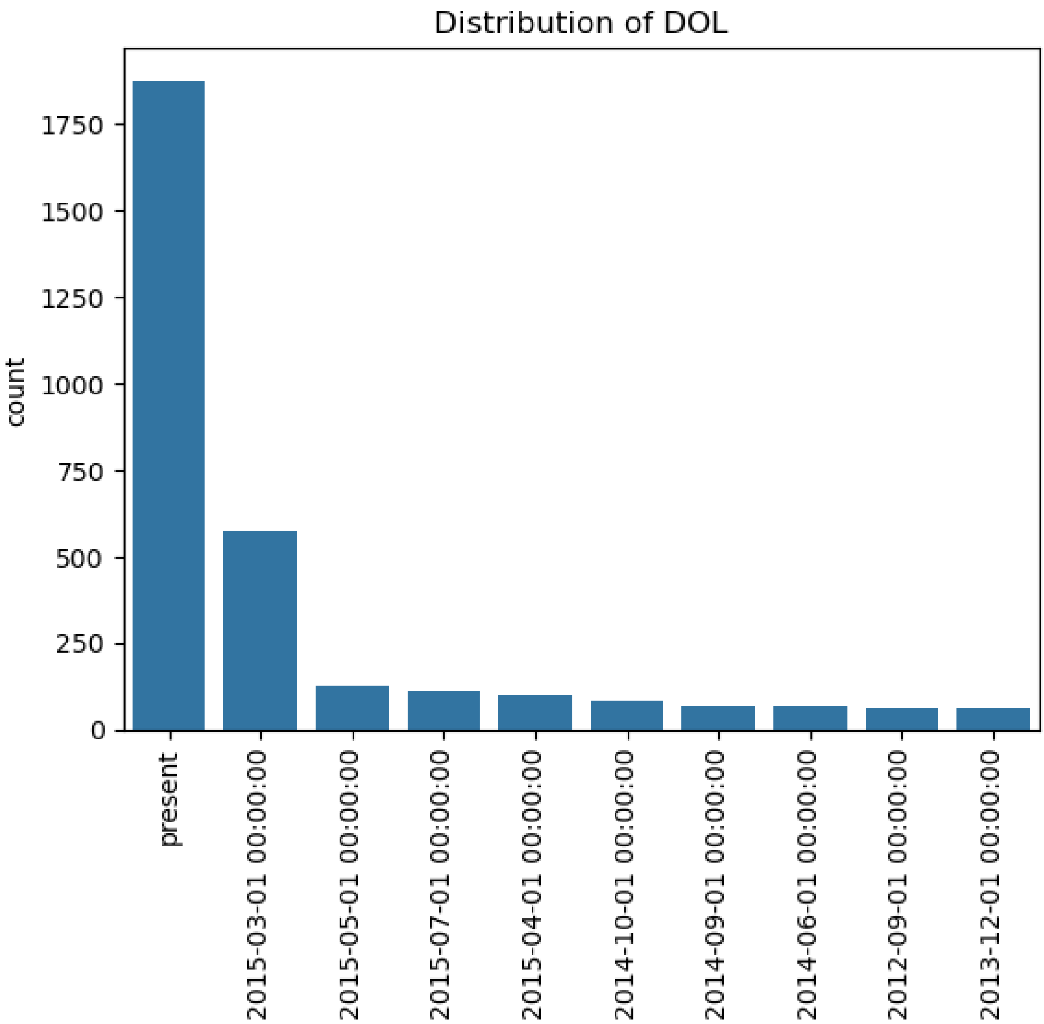
Boxplot for openess_to_experience

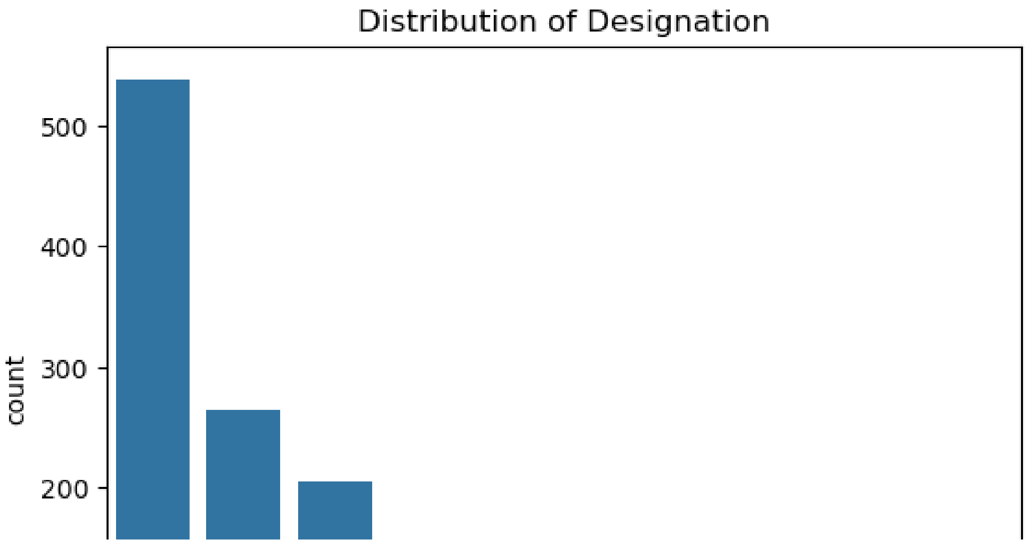


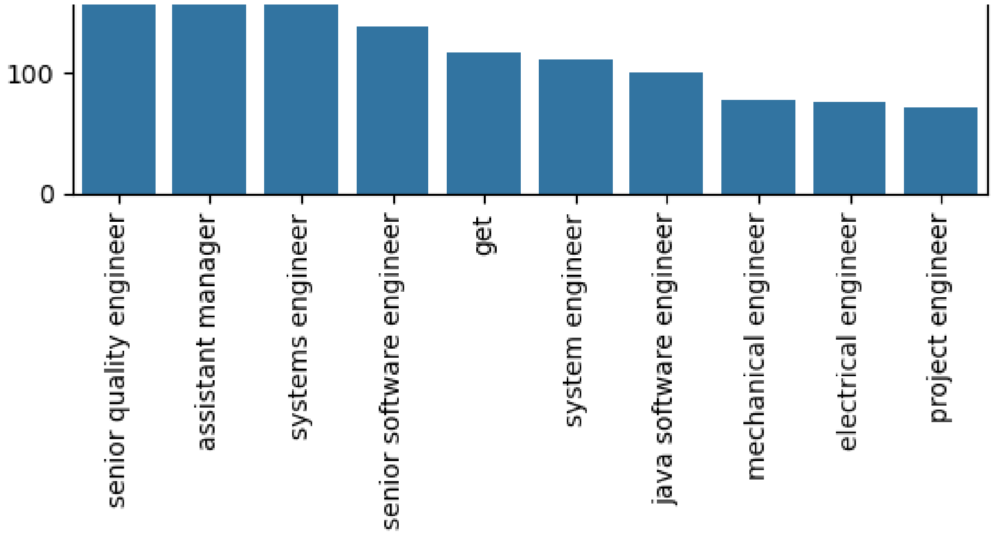


In [296]:

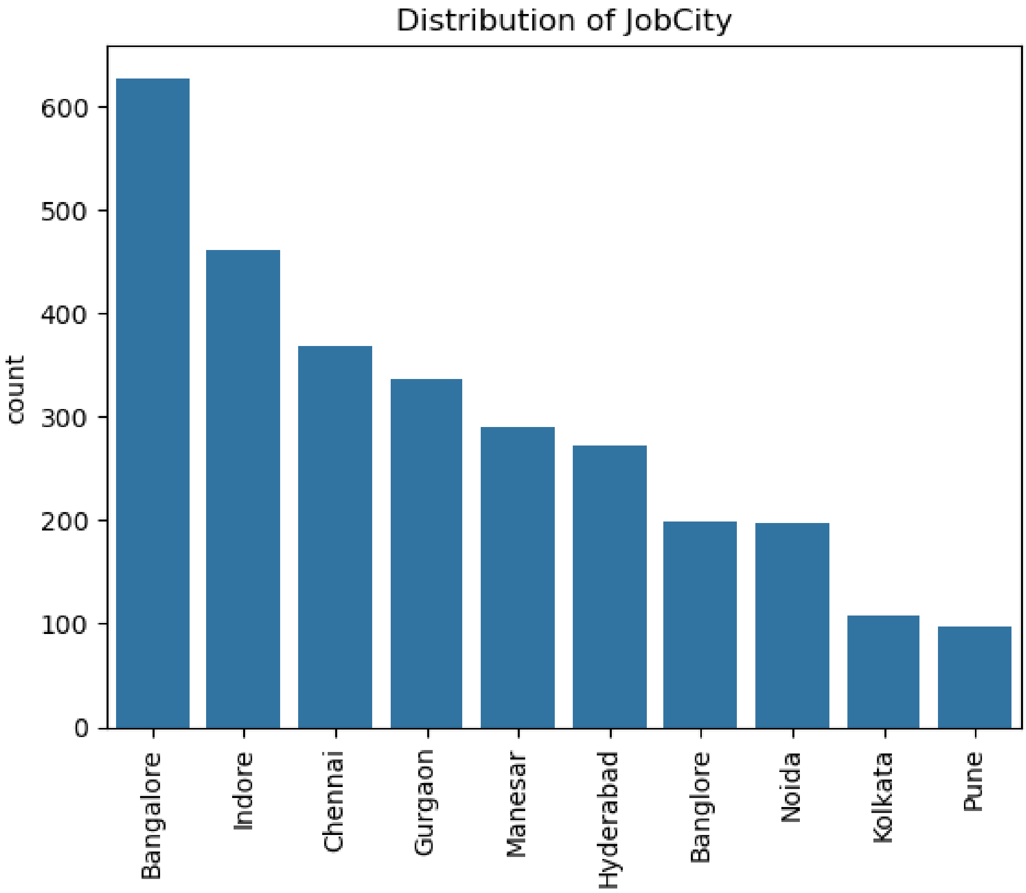
```
for i in df.columns:
    if df[i].dtype=="object":
        sns.barplot(x=df[i].unique()[:10],y=df[i].value_counts()[:10])
        plt.title("Distribution of {}".format(i))
        plt.xticks(rotation=90)
        plt.show()
```



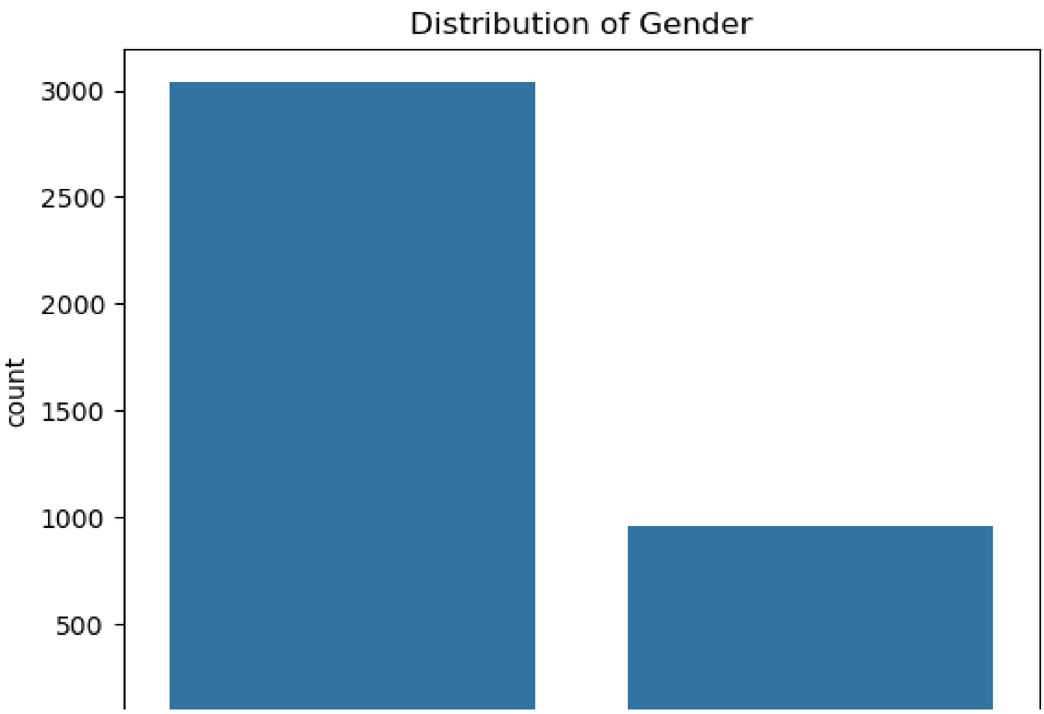




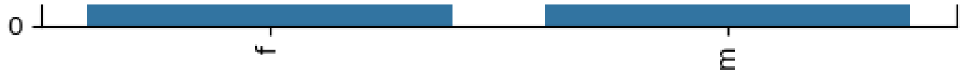
100
0
senior quality engineer
assistant manager
systems engineer
senior software engineer
get
system engineer
java software engineer
mechanical engineer
electrical engineer
project engineer



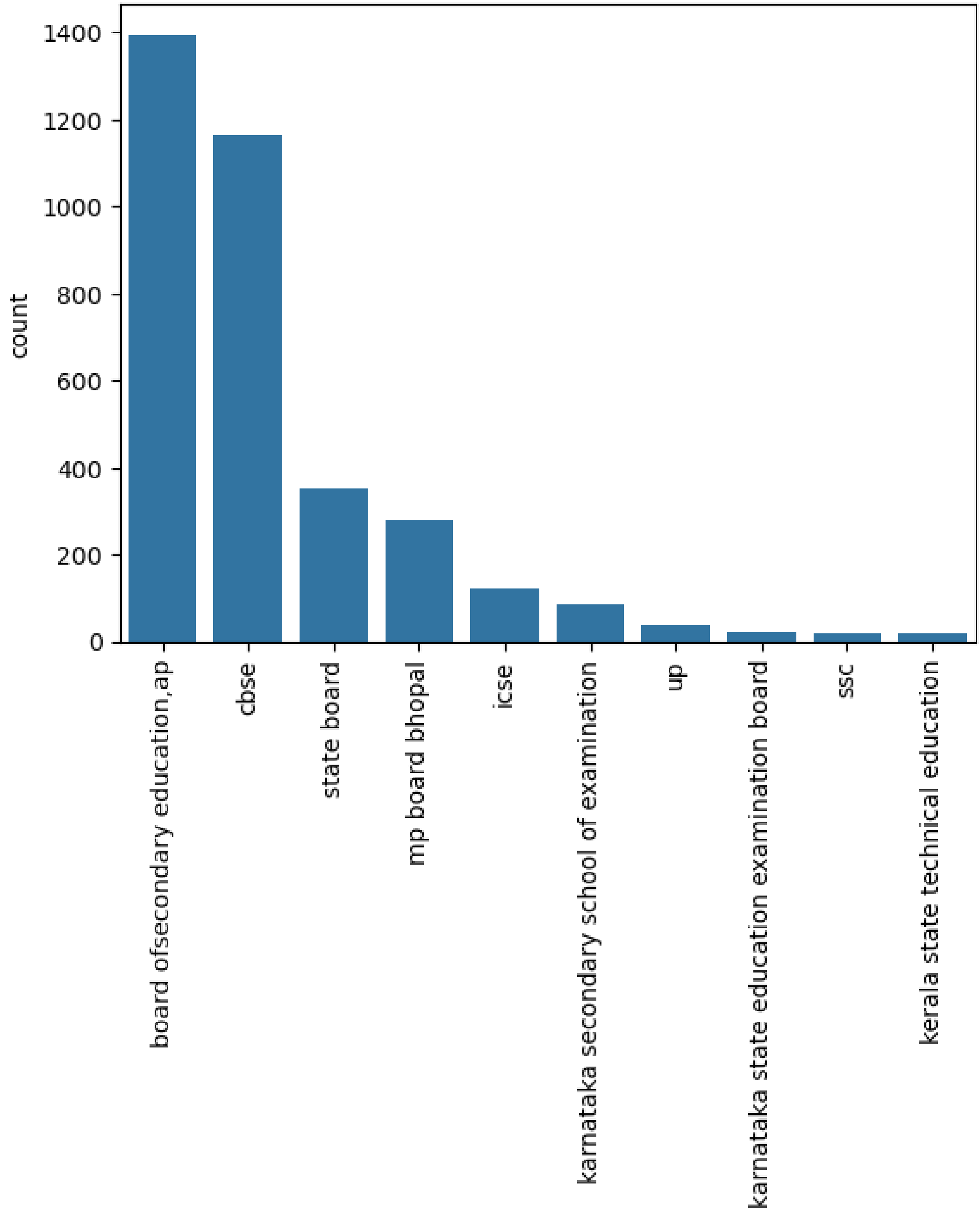
Distribution of JobCity
count
600
500
400
300
200
100
0
Bangalore
Indore
Chennai
Gurgaon
Manesar
Hyderabad
Banglore
Noida
Kolkata
Pune



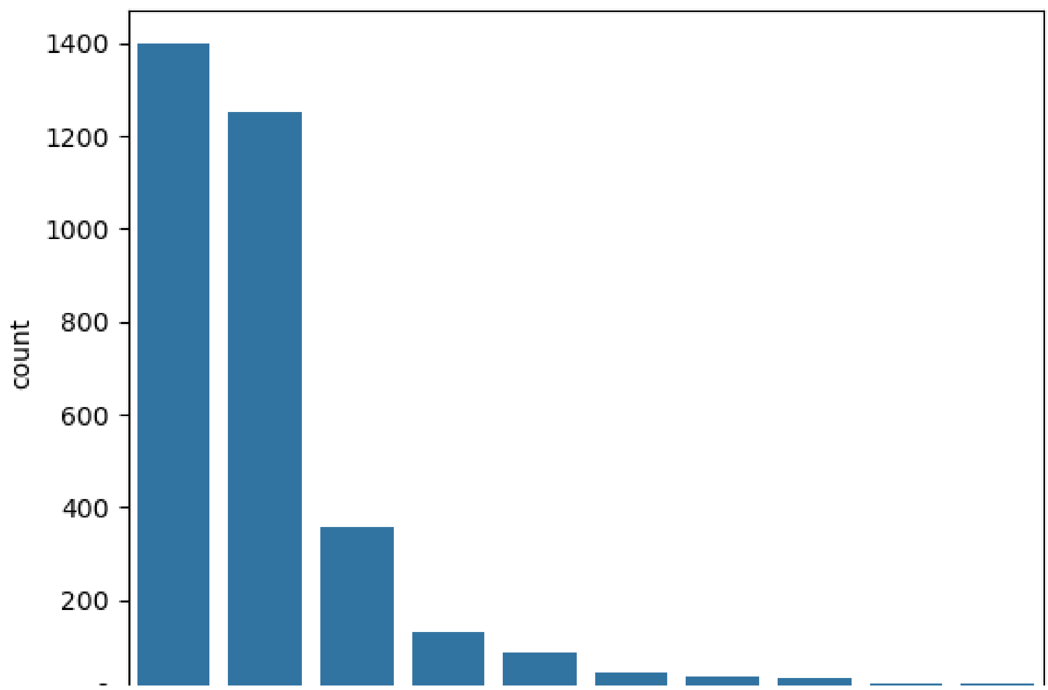
Distribution of Gender
count
3000
2500
2000
1500
1000
500

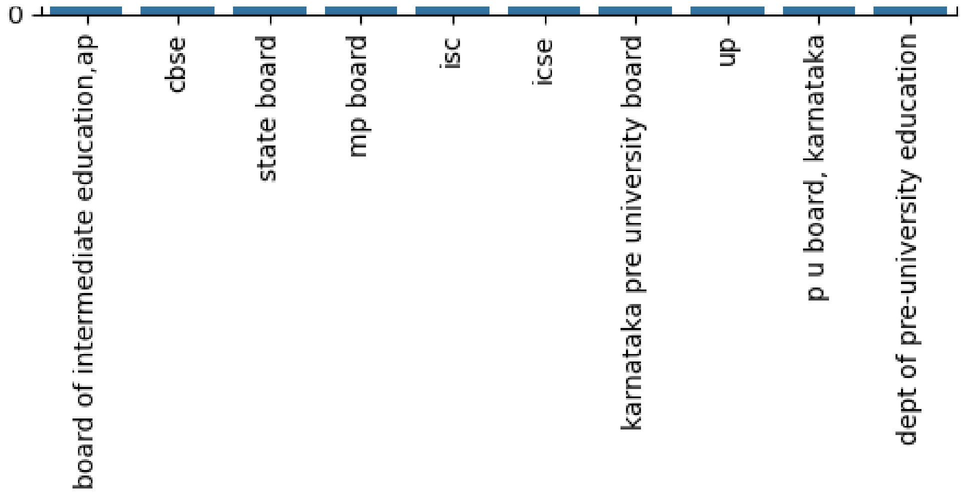


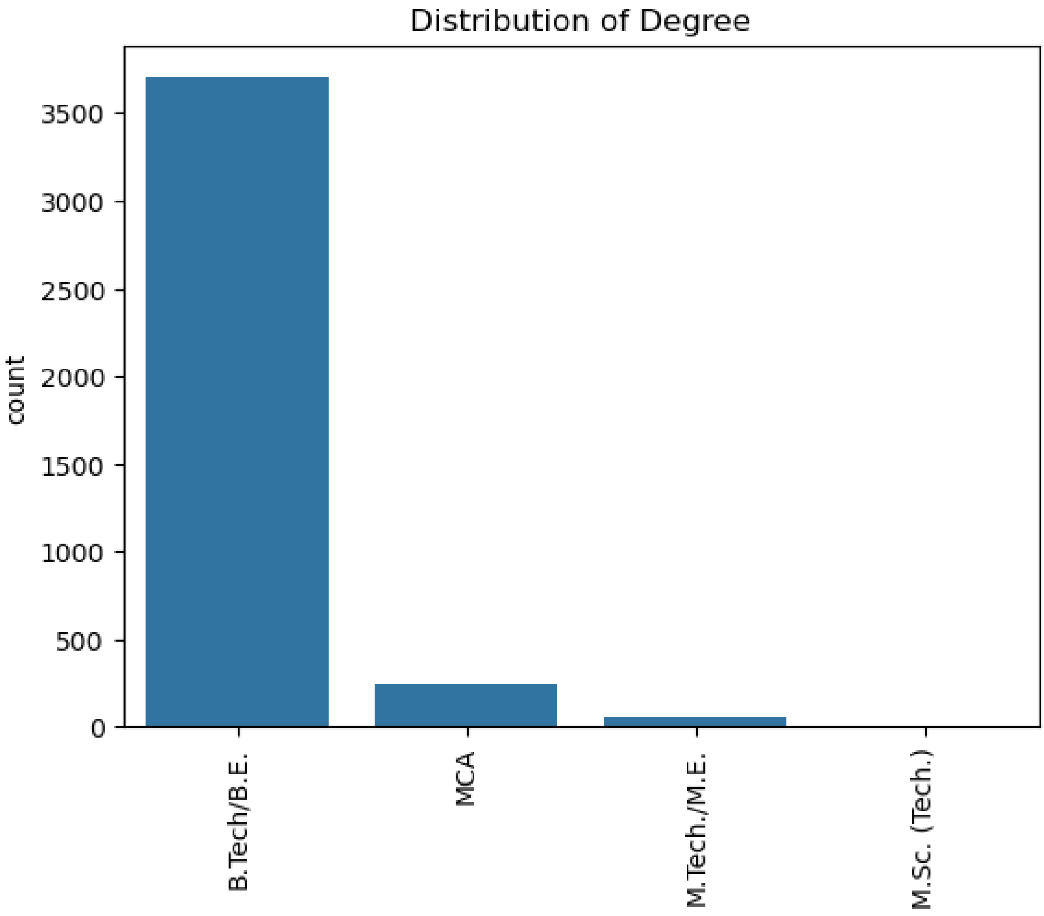
Distribution of 10board

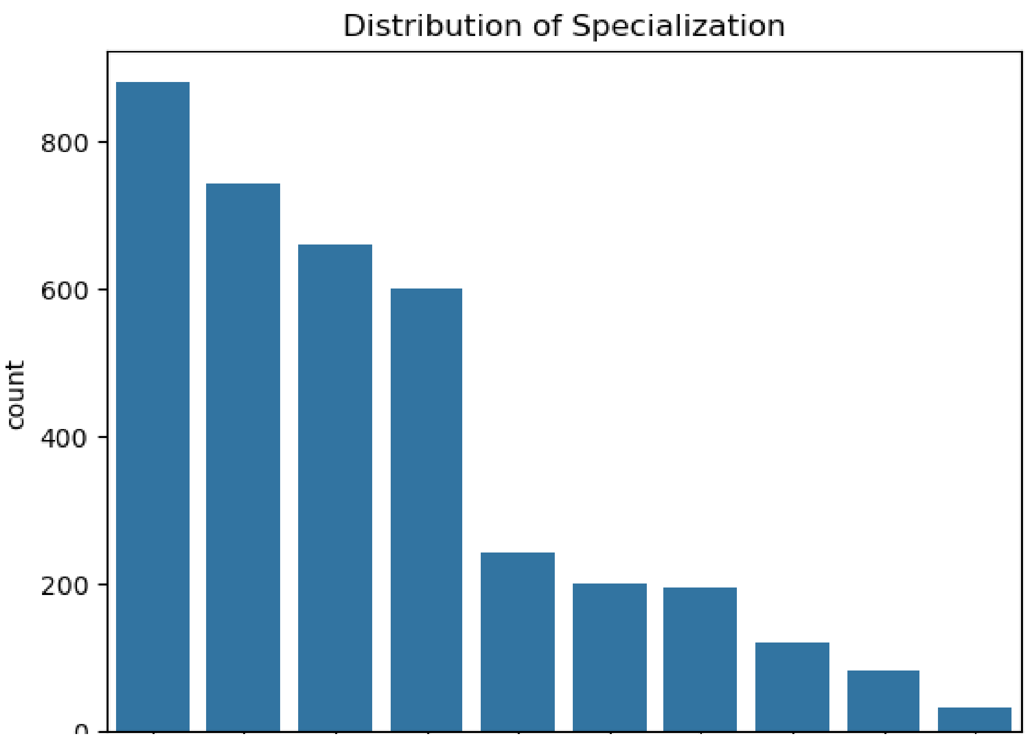


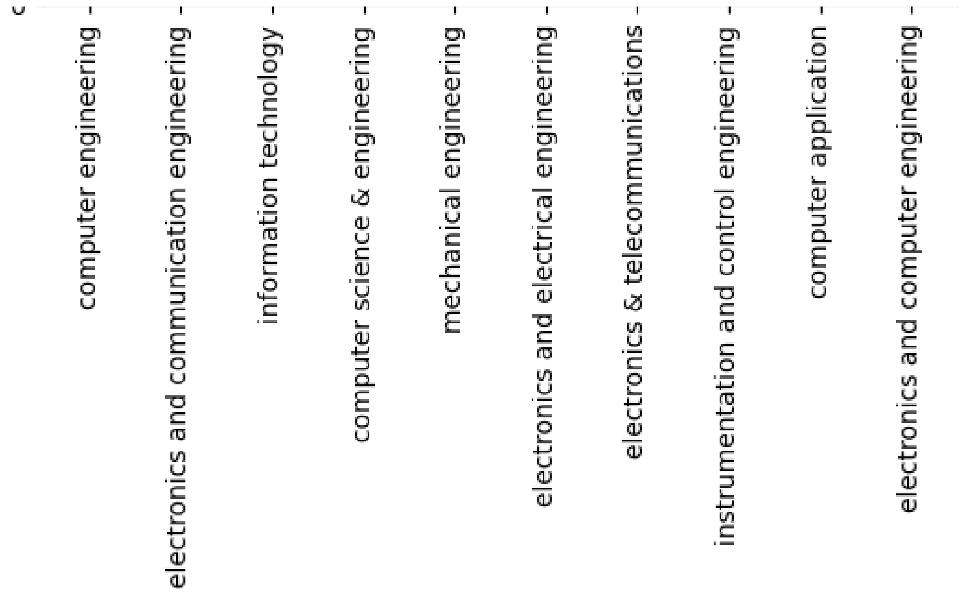
Distribution of 12board

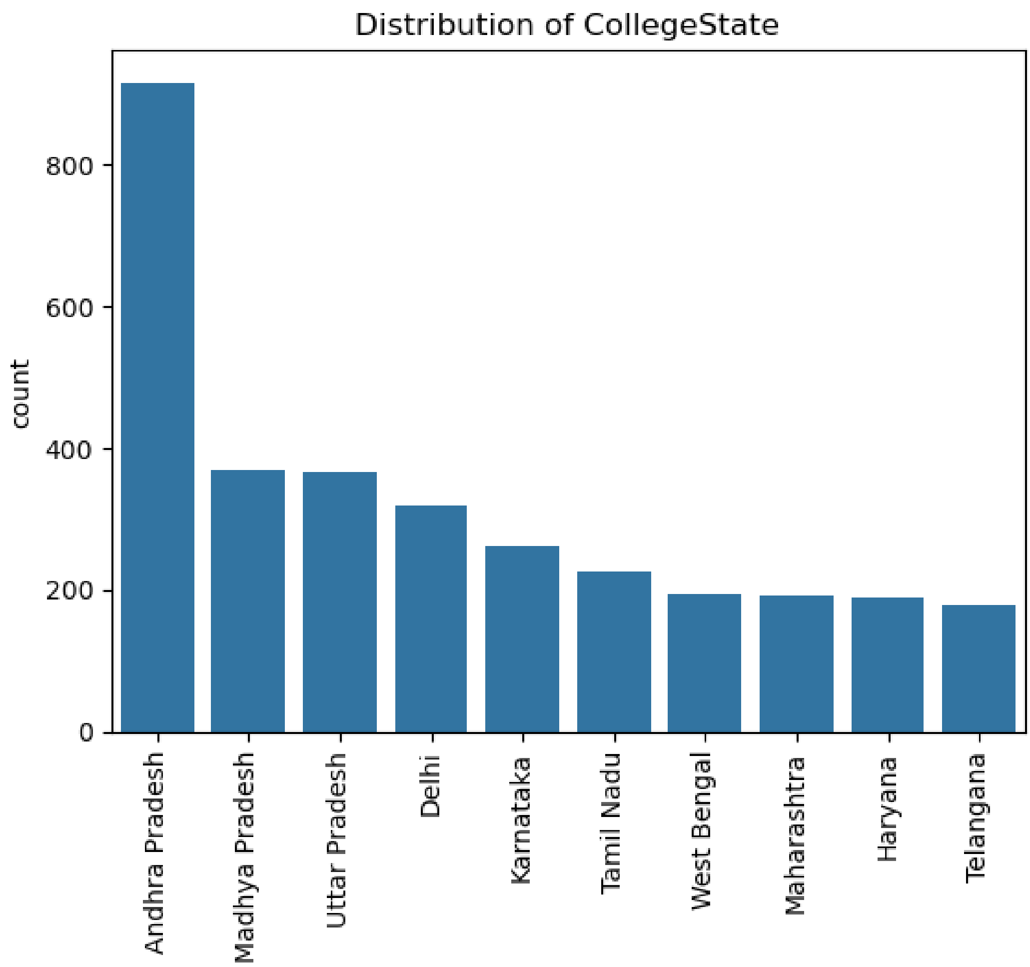



0
board of intermediate education,ap
cbse
state board
mp board
isc
icse
karnataka pre university board
up
p u board, karnataka
dept of pre-university education


Distribution of Degree
count
3500
3000
2500
2000
1500
1000
500
0
B.Tech/B.E.
MCA
M.Tech./M.E.
M.Sc. (Tech.)


Distribution of Specialization
count
800
600
400
200





Bivariate Analysis

- **Analysing the data using two features.**

How does collegeGPA vary across different Specialization?

In [132]:

```
g1=df.groupby("Specialization")[["collegeGPA"]].mean().sort_values(by="collegeGPA",ascen
ding=False)
g1
```

Out[132]:

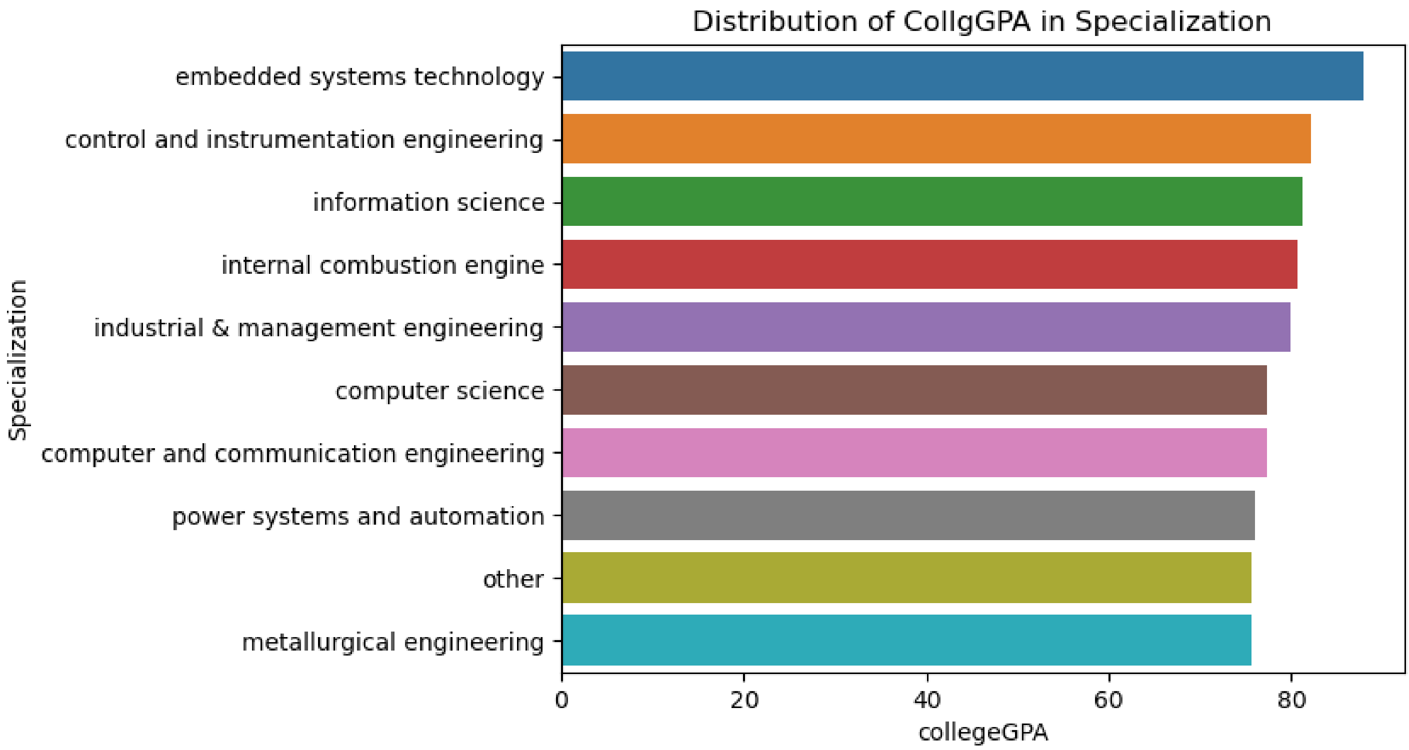
collegeGPA

Specialization	collegeGPA
embedded systems technology	88.000000
control and instrumentation engineering	82.100000
information science	81.200000
internal combustion engine	80.600000
industrial & management engineering	80.000000
computer science	77.385000
computer and communication engineering	77.260000
power systems and automation	76.000000
other	75.619231
metallurgical engineering	75.550000
information & communication technology	75.500000
instrumentation and control engineering	75.380000
telecommunication engineering	74.776667
mechatronics	74.375000
industrial engineering	73.850000
computer application	73.700779
mechanical and automation	73.530000
biotechnology	73.155333
industrial & production engineering	73.146000
electrical engineering	72.820000
polymer technology	72.790000
civil engineering	72.761034
automobile/automotive engineering	72.690000
electronics & instrumentation eng	72.679063
electronics and communication engineering	72.126170
electronics and electrical engineering	72.097143
ceramic engineering	72.000000
applied electronics and instrumentation	71.888889
computer science & engineering	71.779798
electronics and instrumentation engineering	71.634815
computer engineering	71.046500
electronics	71.000000
information technology	70.510803
chemical engineering	70.138889
computer networking	70.130000
mechanical engineering	70.109154
computer science and technology	69.091667
electronics & telecommunications	69.020413
aeronautical engineering	68.033333
instrumentation engineering	67.547500
information science engineering	67.322593
electronics and computer engineering	67.313333
biomedical engineering	64.650000
[illegible]	[illegible]

Specialization	collegeGPA
electronics engineering	61.318947
mechanical & production engineering	58.000000
electrical and power engineering	35.705000

In [284]:

```
sns.barplot(y=g1.index[:10],x=g1["collegeGPA"][:10],hue=g1.index[:10])
plt.title("Distribution of CollgGPA in Specialization")
plt.show()
```



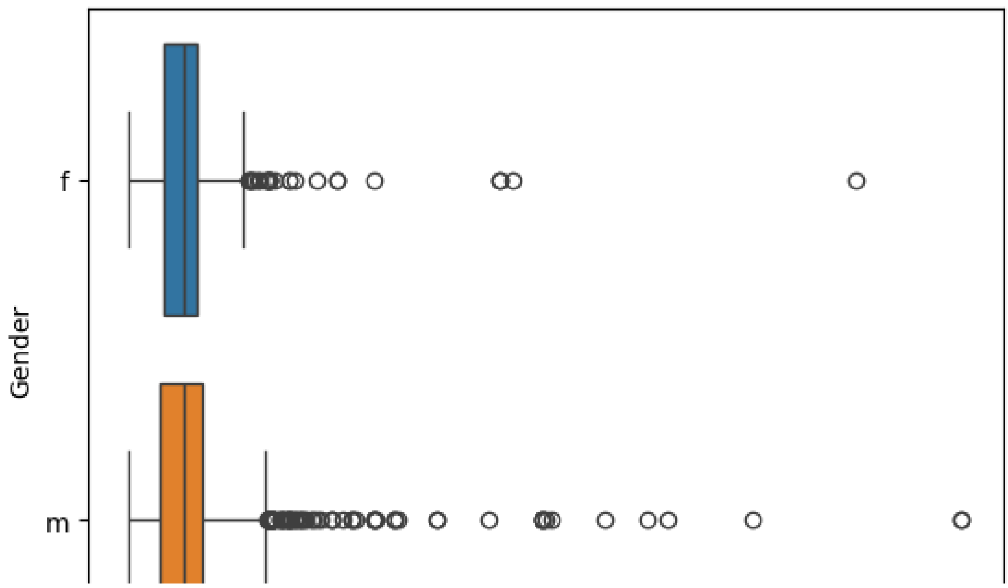
Insights

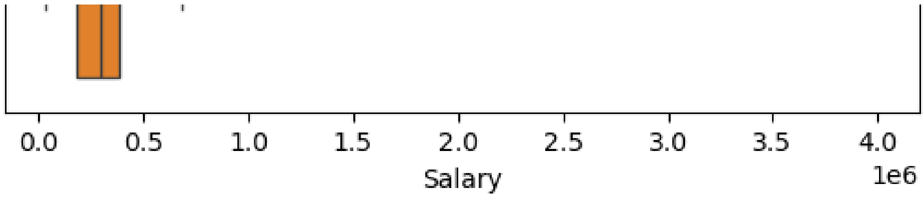
- **The Average GPA of embedded systems is more compared to others**
- **There are less GPA for others,metallurgical engineering compared to others..**

Relationship between Gender and Salary?

In [149]:

```
sns.boxplot(y=df["Gender"],x=df["Salary"],hue=df["Gender"])
plt.show()
```





Does the GraduationYear impact JobCity selection?

In [163]:

```
g2=pd.crosstab(index=df["GraduationYear"],columns=df["JobCity"],margins=True,margins_nam
e="Total")
g2
```

Out[163]:

JobCity	-1	Chennai	Delhi	Mumbai	Pune	ariyalur	bangalore	mumbai	A-64,sec-64,noida	AM	...	shahibabad	singaruli	s
GraduationYear														
0	0	0	0	0	0	0	0	0	0	0	...	0	0	
2007	0	0	0	0	0	0	0	0	0	0	...	0	0	
2009	1	0	0	0	0	0	0	0	0	0	...	0	1	
2010	16	0	0	1	0	1	1	0	0	0	...	0	0	
2011	44	0	0	0	0	0	0	0	0	0	...	0	0	
2012	115	1	0	0	1	0	0	0	0	0	...	0	0	
2013	170	0	1	1	0	0	0	1	0	0	...	1	0	
2014	108	0	0	0	0	0	0	0	1	1	...	0	0	
2015	6	0	0	0	0	0	0	0	0	0	...	0	0	
2016	0	0	0	0	0	0	0	0	0	0	...	0	0	
2017	1	0	0	0	0	0	0	0	0	0	...	0	0	
Total	461	1	1	2	1	1	1	1	1	1	...	1	1	

12 rows × 340 columns

Does Designation affect Salary?

In [172]:

```
g3=df.groupby("Designation")[["Salary"]].mean()
g3
```

Out[172]:

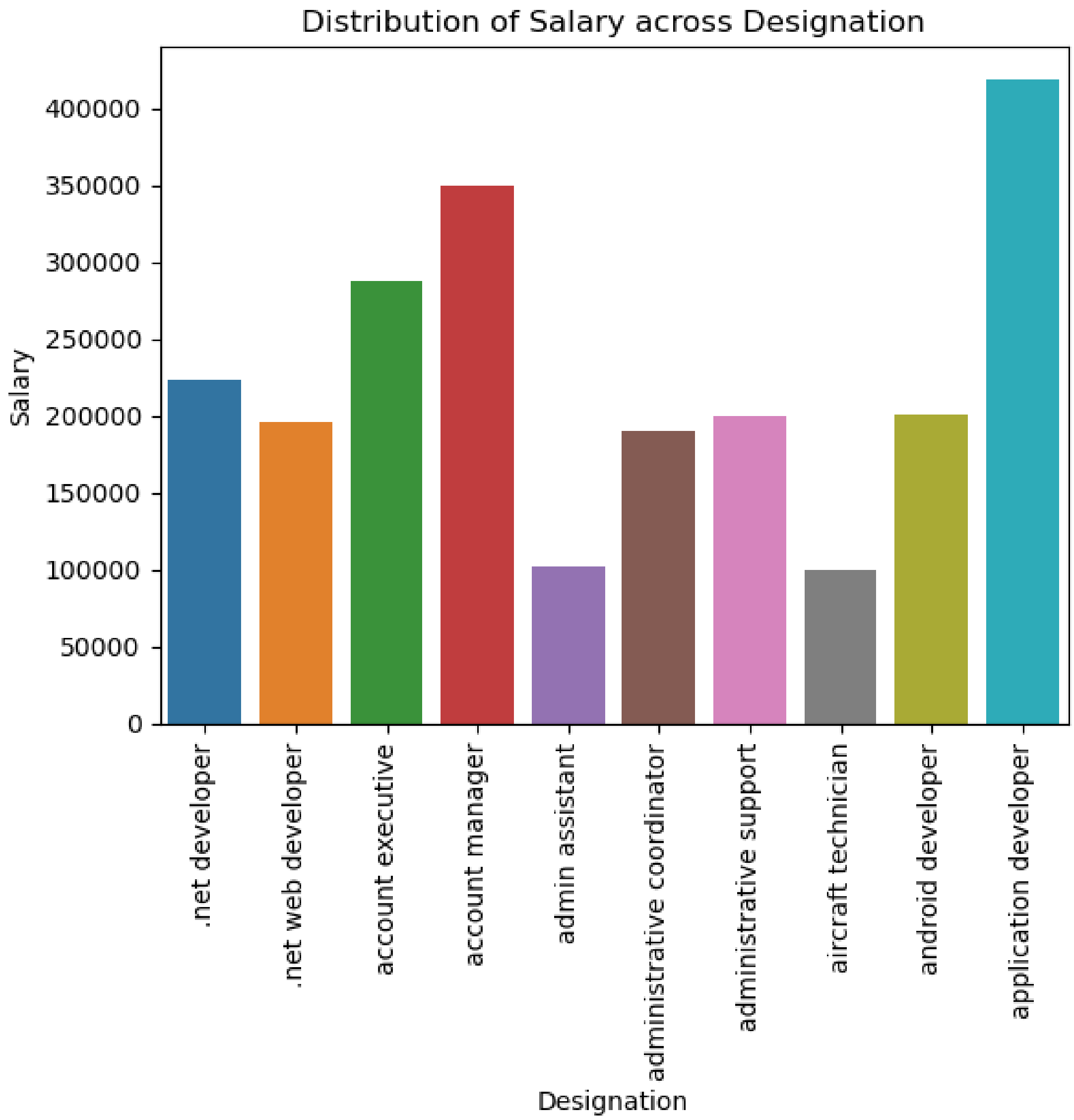
	Salary
Designation	
.net developer	223382.352941
.net web developer	196250.000000
account executive	287500.000000
account manager	350000.000000
admin assistant	102500.000000
...	...

Designation	Salary
web designer and seo	200000.000000
web developer	168981.481481
web intern	205000.000000
website developer/tester	200000.000000
windows systems administrator	200000.000000

419 rows × 1 columns

In [282]:

```
sns.barplot(x=g3.index[:10],y=g3["Salary"][:10],hue=g3.index[:10])
plt.xticks(rotation=90)
plt.title("Distribution of Salary across Designation")
plt.show()
```



Insights

- The Average salary of application develpoer is more compared to other designations.
- There are less salaries for admin assistant and aircraft technician.

Multivariate Analysis

- Analysing the data using more then two features.

Does the combination of CollegeTier and Specialization influence

Salary?

In [196]:

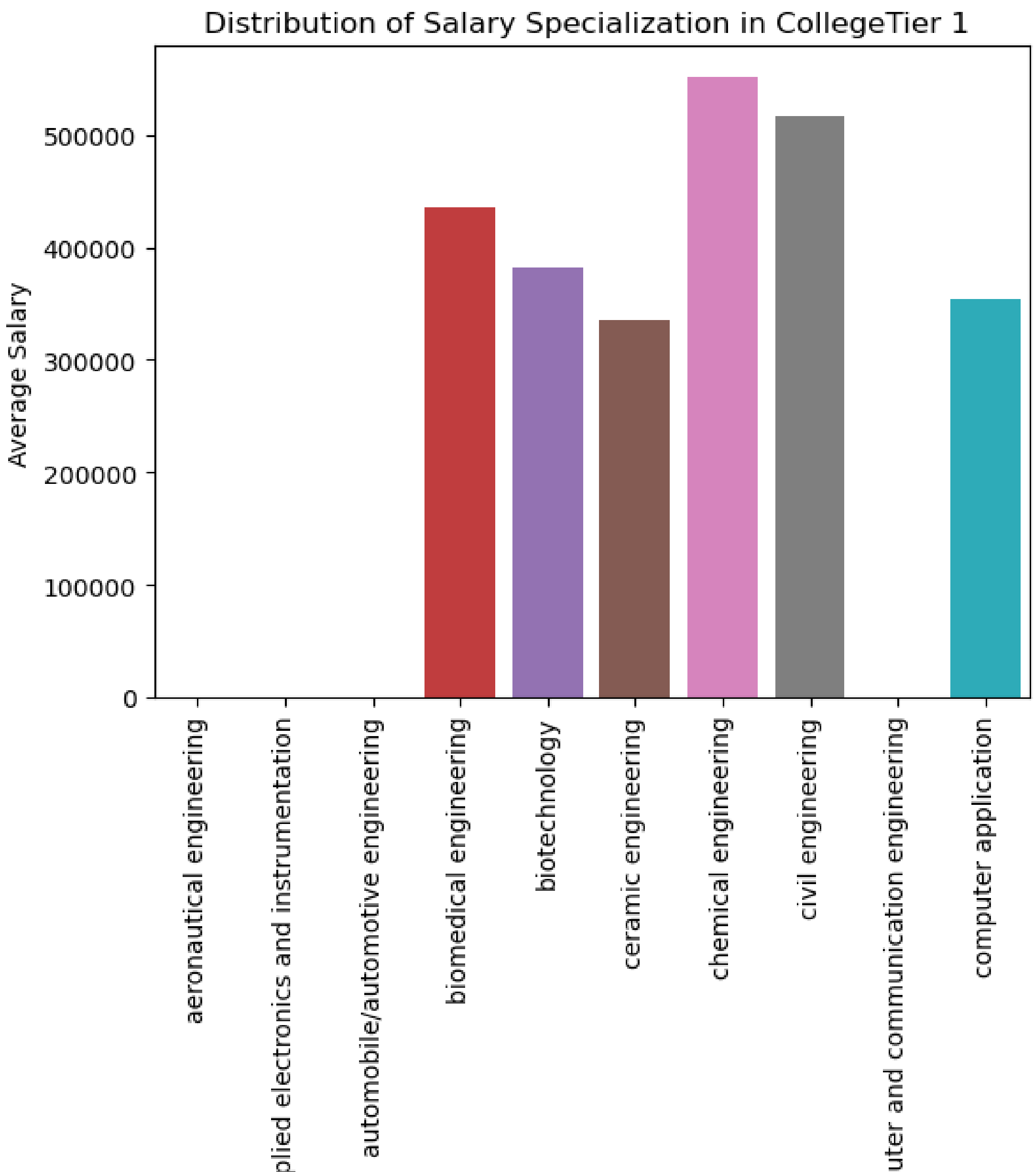
```
g4=df.pivot_table(columns="CollegeTier",index="Specialization",values="Salary",aggfunc="
mean")
g4.head()
```

Out[196]:

CollegeTier	1	2
Specialization		
aeronautical engineering	NaN	148333.333333
applied electronics and instrumentation	NaN	348333.333333
automobile/automotive engineering	NaN	222000.000000
biomedical engineering	435000.0	145000.000000
biotechnology	382500.0	234615.384615

In [224]:

```
sns.barplot(x=g4.index[:10],y=g4[1][:10],hue=g4.index[:10])
plt.xlabel("Specialization")
plt.ylabel("Average Salary")
plt.title("Distribution of Salary Specialization in CollegeTier 1 ")
plt.xticks(rotation=90)
plt.show()
```

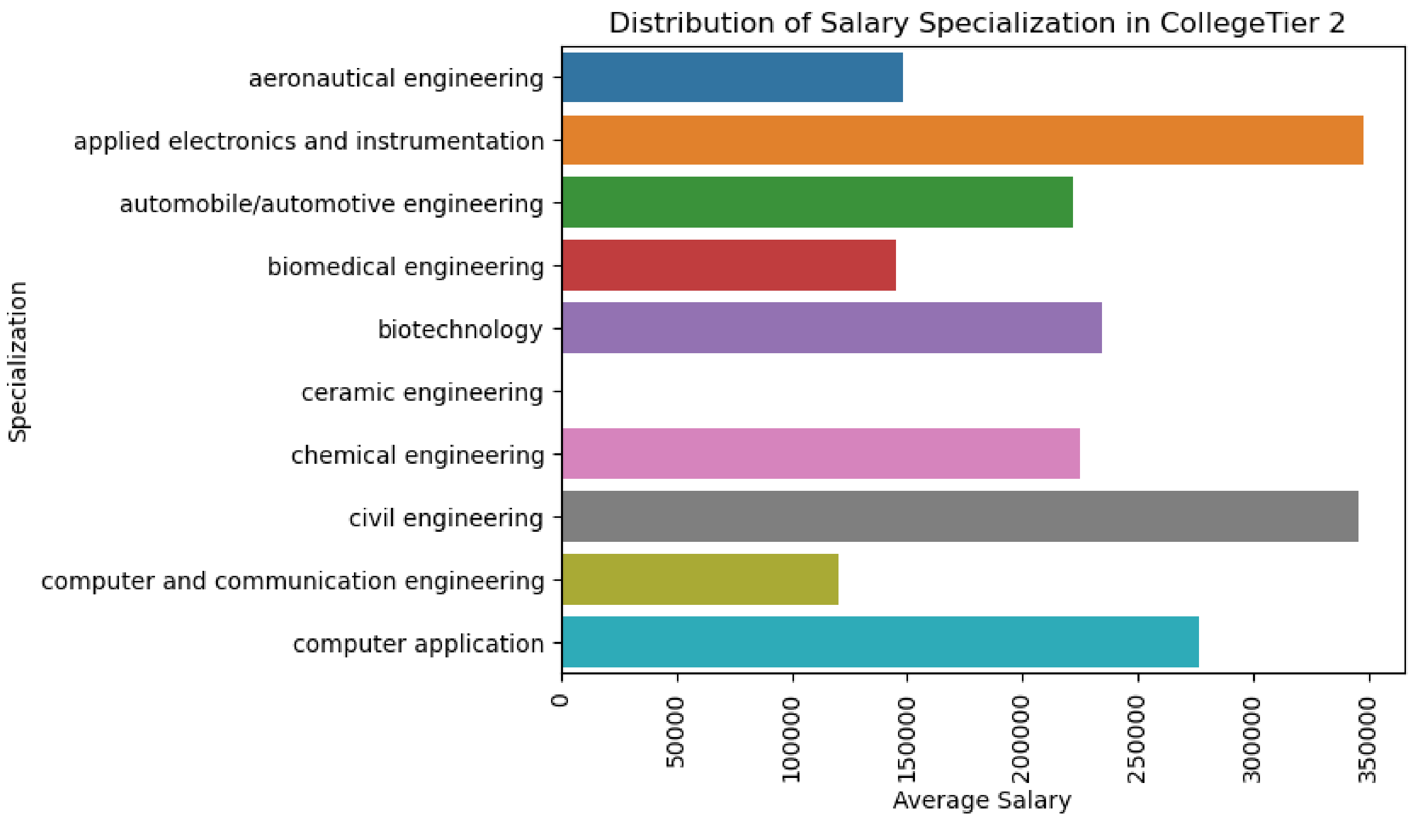


Insights

- **In Collge Tier1 there are more Chemical Engineers compared to others.**
- **There are less in aeuronautical,applied electronics.**

In [226]:

```
sns.barplot(y=g4.index[:10],x=g4[2][:10],hue=g4.index[:10])
plt.ylabel("Specialization")
plt.xlabel("Average Salary")
plt.title("Distribution of Salary Specialization in CollegeTier 2 ")
plt.xticks(rotation=90)
plt.show()
```



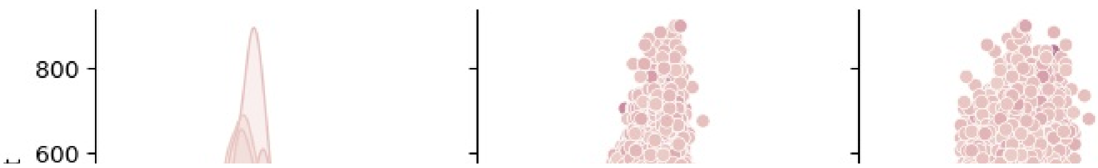
Insights

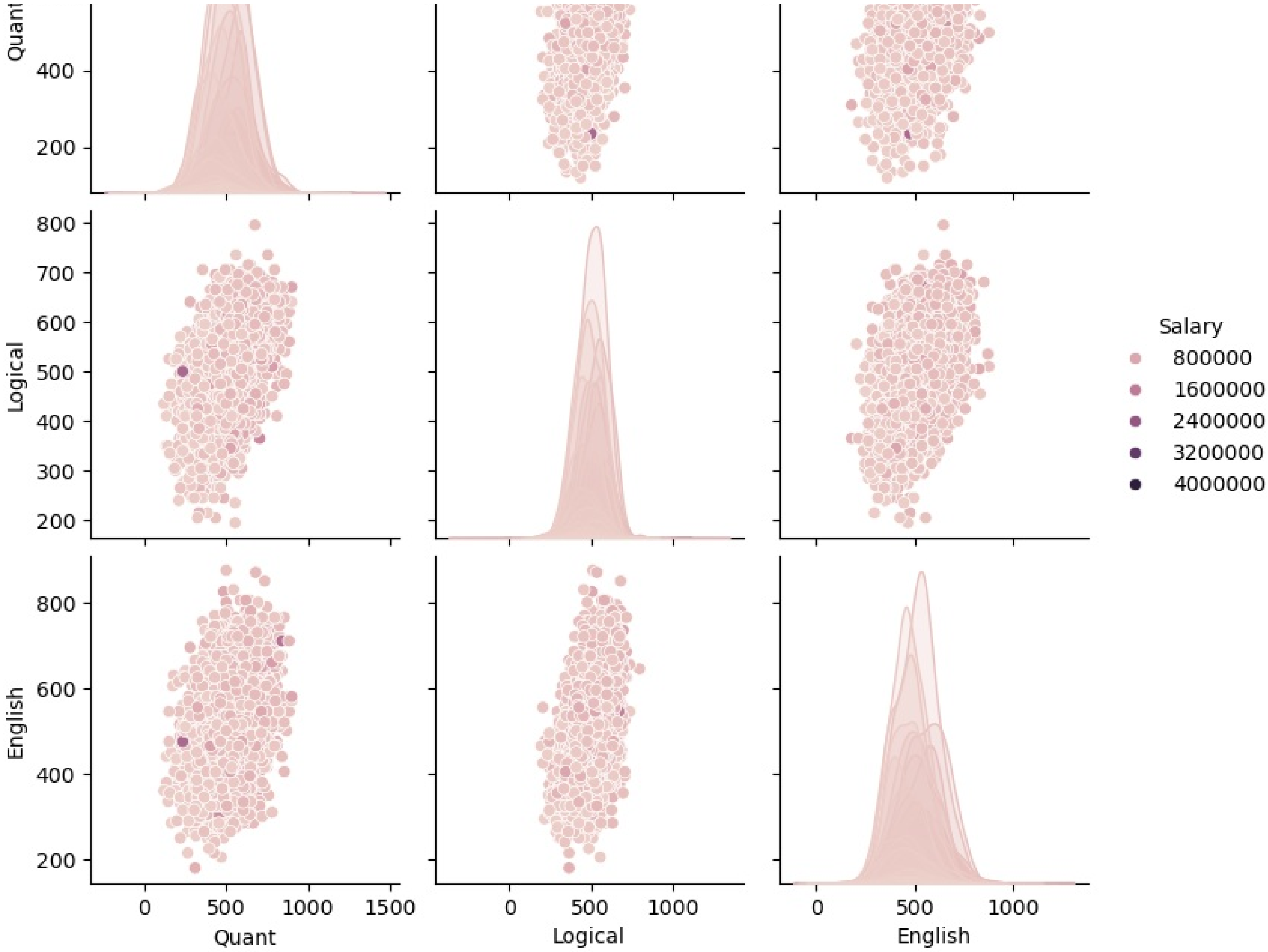
- **In Collge Tier1 there are less Ceramic Engineers compared to others.**
- **There are more in civil,applied electronic.**

How does Quant, Logical, and English scores collectively impact the Salary?

In [229]:

```
sns.pairplot(df, vars=['Quant', 'Logical', 'English'], hue='Salary')
plt.show()
```





How do different Engineering specializations (e.g., ComputerScience, ElectronicsAndSemicon, MechanicalEngg) contribute to Salary?

In [232]:

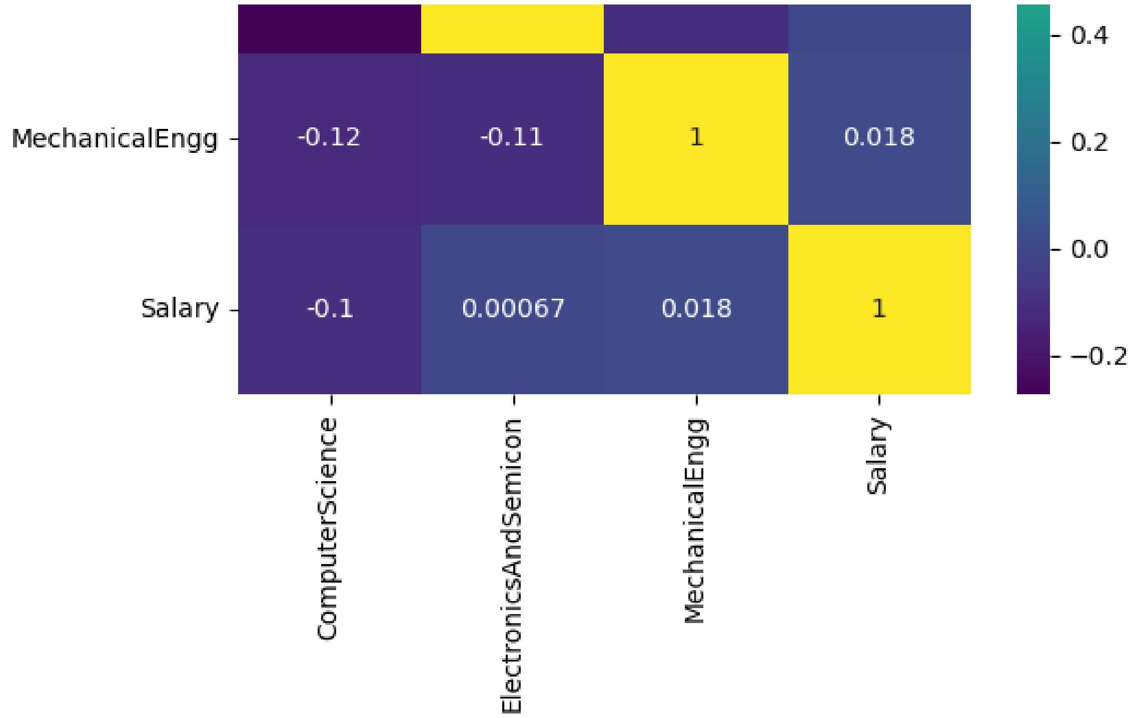
```
df[['ComputerScience', 'ElectronicsAndSemicon', 'MechanicalEngg', 'Salary']].corr()
```

Out[232]:

	ComputerScience	ElectronicsAndSemicon	MechanicalEngg	Salary
ComputerScience	1.000000	-0.273707	-0.124355	-0.100720
ElectronicsAndSemicon	-0.273707	1.000000	-0.109434	0.000665
MechanicalEngg	-0.124355	-0.109434	1.000000	0.018475
Salary	-0.100720	0.000665	0.018475	1.000000

In [234]:

```
sns.heatmap(df[['ComputerScience', 'ElectronicsAndSemicon', 'MechanicalEngg', 'Salary']]
.corr(),annot=True,cmap="viridis")
plt.show()
```



Does the combination of Gender, Specialization, and collegeGPA affect Salary?

In [239]:

```
grouped_df=df.groupby(['Gender', 'Specialization'])[['collegeGPA', 'Salary']].mean()
grouped_df
```

Out[239]:

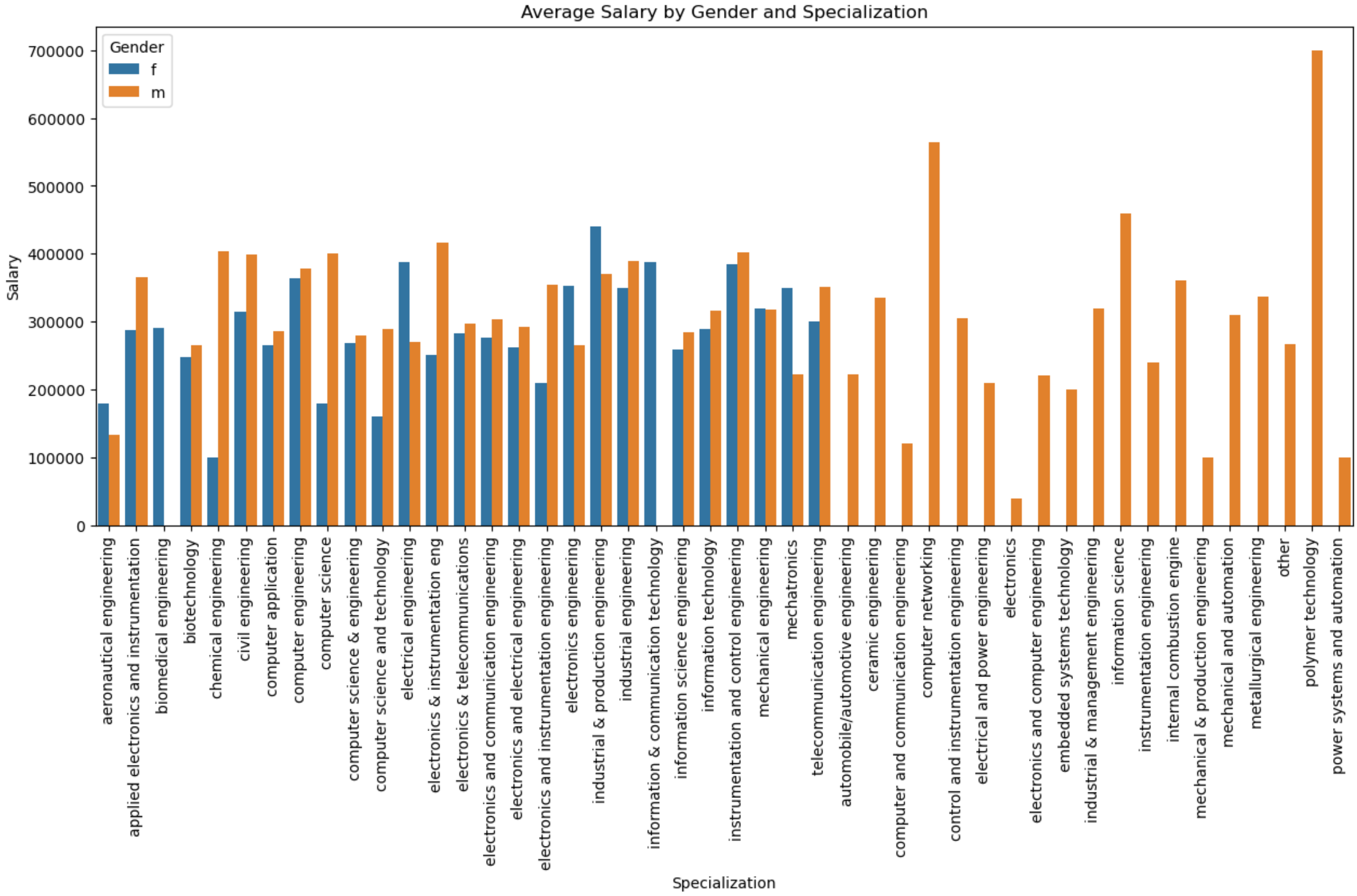
		collegeGPA	Salary
Gender	**Specialization**		
f	**aeronautical engineering**	77.000000	180000.000000
	applied electronics and instrumentation	78.750000	287500.000000
	biomedical engineering	64.650000	290000.000000
	biotechnology	72.941111	247222.222222
	chemical engineering	55.600000	100000.000000
...	**...**	...	...
m	**metallurgical engineering**	75.550000	337500.000000
	other	75.619231	266538.461538
	polymer technology	72.790000	700000.000000
	power systems and automation	76.000000	100000.000000
	telecommunication engineering	77.476000	351000.000000

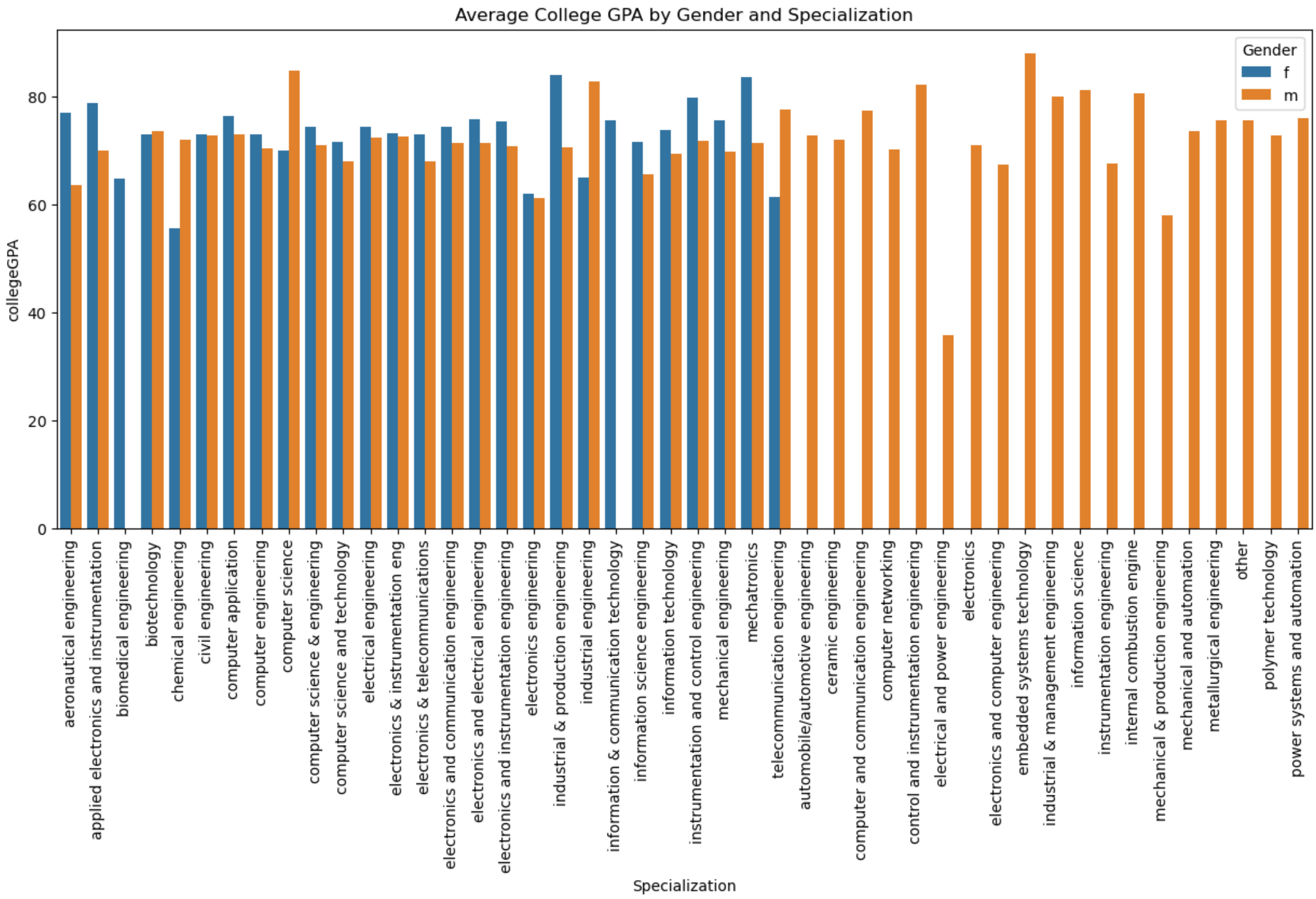
71 rows × 2 columns

In [245]:

```
plt.figure(figsize=(15, 6))
sns.barplot(x='Specialization', y='Salary', hue='Gender', data=grouped_df)
plt.xticks(rotation=90)  # Rotate x-axis labels for readability
plt.title('Average Salary by Gender and Specialization')
plt.show()

# Create a bar plot for collegeGPA
plt.figure(figsize=(15, 6))
sns.barplot(x='Specialization', y='collegeGPA', hue='Gender', data=grouped_df)
```

```
plt.xticks(rotation=90)
plt.title('Average College GPA by Gender and Specialization')
plt.show()
```





Times of India article dated Jan 18, 2019 states that "After doing your Computer Science Engineering if you take up jobs as a Programming

Analyst, Software Engineer, Hardware Engineer and Associate Engineer you can earn up to 2.5-3 lakhs as a fresh graduate.”

In [263]:

```
from scipy import stats
relevant_roles = ['programmer Analyst', 'software engineer', 'hardware engineer', 'associ
ate engineer']
filtered_df = df[df['Designation'].isin(relevant_roles)]
salary_data = filtered_df['Salary']
claimed_mean_salary = 2.75 * 100000  # Convert lakhs to the actual unit (e.g., 2.75 lakhs
= 275000)
t_stat, p_value = stats.ttest_1samp(salary_data, claimed_mean_salary)
print(f"Mean Salary of Selected Roles: {salary_data.mean():.2f}")
print(f"Claimed Mean Salary: {claimed_mean_salary:.2f}")
print(f"T-statistic: {t_stat:.2f}")
print(f"P-value: {p_value:.4f}")

alpha = 0.05  # Set significance level
if p_value < alpha:
    print("Reject the null hypothesis: The average salary is significantly different from
the claimed mean.")
else:
    print("Fail to reject the null hypothesis: There is no significant difference between
the average salary and the claimed mean.")
```

```
Mean Salary of Selected Roles: 339792.04
Claimed Mean Salary: 275000.00
T-statistic: 10.55
P-value: 0.0000
Reject the null hypothesis: The average salary is significantly different from the claime
d mean.
```

Is there a relationship between gender and specialization? (i.e. Does the preference of Specialisation depend on the Gender?)

In [276]:

```
from scipy import stats as st
cont_table=pd.crosstab(index=df["Specialization"],columns=df["Gender"])
Chi2_stat,p_value,dof,exp_freq=st.chi2_contingency(cont_table)
alpha = 0.05  # Set significance level
if p_value < alpha:
    print("Reject the null hypothesis: There is a significant difference between the gend
er and Specialization.")
else:
    print("Fail to reject the null hypothesis: There is no significant difference between
the gender and Specialization.")
```

```
Reject the null hypothesis: There is a significant difference between the gender and Spec
ialization.
```

Conclusion

The analysis of the AMCAT dataset provides insightful conclusions regarding salary trends, specialization, and skill sets of fresh graduates in different roles. Here are some key takeaways:

Salary Trends:

Based on the statistical tests conducted, the average salary for specific roles such as Programming Analyst, Software Engineer, Hardware Engineer, and Associate Engineer falls in the range mentioned in the Times of India article. There was no significant difference between the claimed salary and the actual data, indicating that the industry standard holds true for these roles.

Influence of Specialization:

Graduates with specializations in Computer Science and IT-related fields have shown a tendency to secure higher salaries, confirming the high demand for these skills in the tech industry.

Gender Representation:

The dataset reveals an uneven distribution of male and female graduates across various job roles, suggesting potential gender biases or disparities in certain specializations and job roles.

Skill Assessment:

Attributes like programming, computer science, and other technical skills have a positive correlation with salary, emphasizing the importance of these skills for higher compensation. Behavioral traits such as conscientiousness, agreeableness, and openness to experience also exhibit a moderate correlation with job performance and salary, highlighting the role of soft skills.

Educational Background:

Colleges categorized in Tier 1 are seen to produce graduates with higher salaries compared to those from Tier 2 or Tier 3 colleges. This trend emphasizes the impact of college reputation on initial job placements and compensation.