```
#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

# Reading the .xlsx file
df=pd.read_csv(r"C:\Users\saidu\Downloads\data.xlsx - Sheet1.csv")
df.drop("Unnamed: 0",axis=1,inplace=True)
df.head()
```

```
       ID   Salary        DOJ                  DOL
Designation  \
0  203097   420000 2012-06-01              present   senior quality
engineer
1  579905   500000 2013-09-01              present        assistant
manager
2  810601   325000 2014-06-01              present          systems
engineer
3  267447  1100000 2011-07-01              present  senior software
engineer
4  343523   200000 2014-03-01  2015-03-01 00:00:00
get

     JobCity Gender        DOB  10percentage
10board  \
0  Bangalore      f 1990-02-19          84.3  board ofsecondary
education,ap
1     Indore      m 1989-10-04          85.4
cbse
2    Chennai      f 1992-08-03          85.0
cbse
3    Gurgaon      m 1989-12-05          85.6
cbse
4    Manesar      m 1991-02-27          78.0
cbse

   ...  ComputerScience  MechanicalEngg ElectricalEngg  TelecomEngg  \
0  ...               -1              -1             -1           -1
1  ...               -1              -1             -1           -1
2  ...               -1              -1             -1           -1
3  ...               -1              -1             -1           -1
4  ...               -1              -1             -1           -1

   CivilEngg conscientiousness agreeableness  extraversion
nueroticism  \
0         -1            0.9737        0.8128        0.5269
1.35490
1         -1           -0.7335        0.3789        1.2396     -
```

```
0.10760
2           -1             0.2718        1.7109        0.1637      -
0.86820
3           -1             0.0464        0.3448       -0.3440      -
0.40780
4           -1            -0.8810       -0.2793       -1.0697
0.09163

   openess_to_experience
0                -0.4455
1                 0.8637
2                 0.6721
3                -0.9194
4                -0.1295

[5 rows x 38 columns]
```

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

```
(3998, 38)
```

```
# 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]
 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

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

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
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

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

0
```

Univariate Analysis

- Analysing the data using single feature/variable.

```
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
```

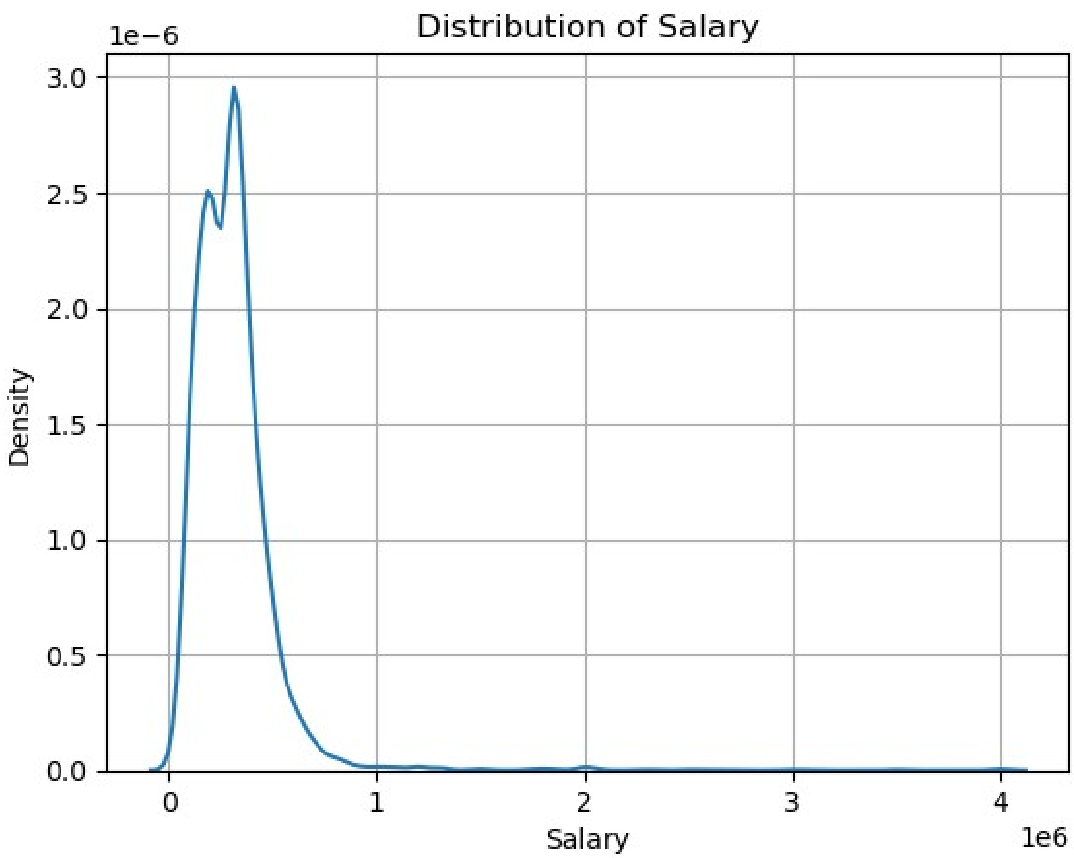
```
 6   Gender                 3998 non-null   object
 7   DOB                    3998 non-null   datetime64[ns]
 8   10percentage           3998 non-null   float64
 9   10board                3998 non-null   object
 10  12graduation           3998 non-null   int64
 11  12percentage           3998 non-null   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
 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

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

	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

```
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?

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

```
71.48617058529265
```

What are the counts of different JobCity values?

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

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

[339 rows x 1 columns]
```

Which Specialization is most common among the students?

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

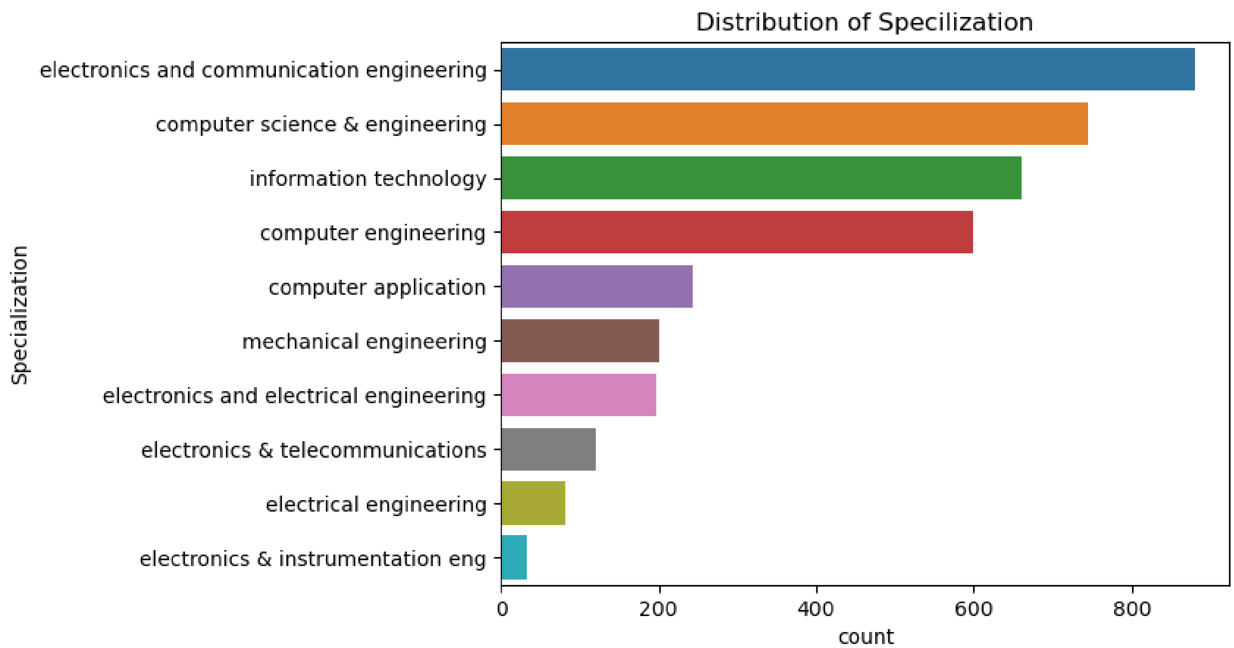
```
Specialization
electronics and communication engineering    880
computer science & engineering               744
information technology                       660
computer engineering                         600
computer application                         244
mechanical engineering                       201
electronics and electrical engineering       196
electronics & telecommunications             121
electrical engineering                        82
electronics & instrumentation eng             32
Name: count, dtype: int64
```

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

```
                                           count
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
```

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

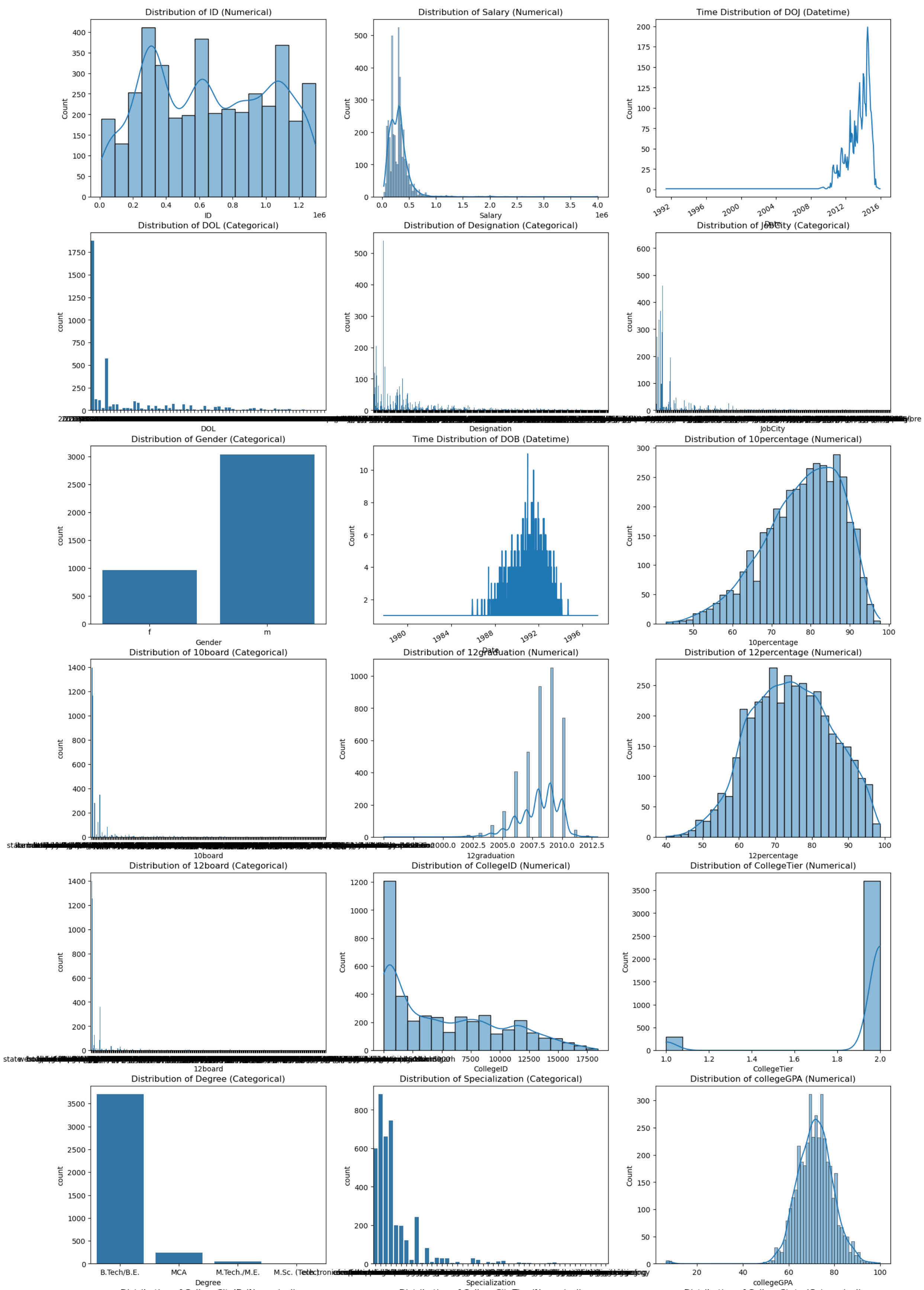


Insights

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

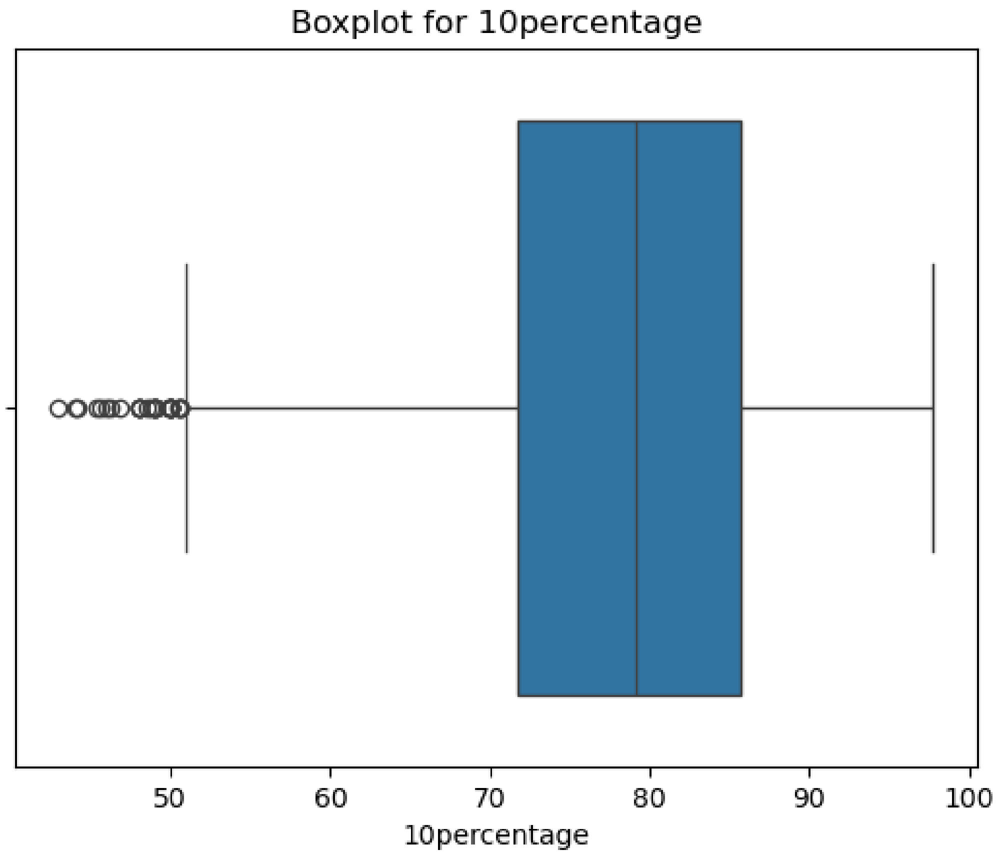
```
# Assuming df is your DataFrame
# Set up the number of subplots based on the number of columns
n_cols = len(df.columns)
n_rows = int(np.ceil(n_cols / 3))  # 3 columns per row for better 
layout

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)')
```

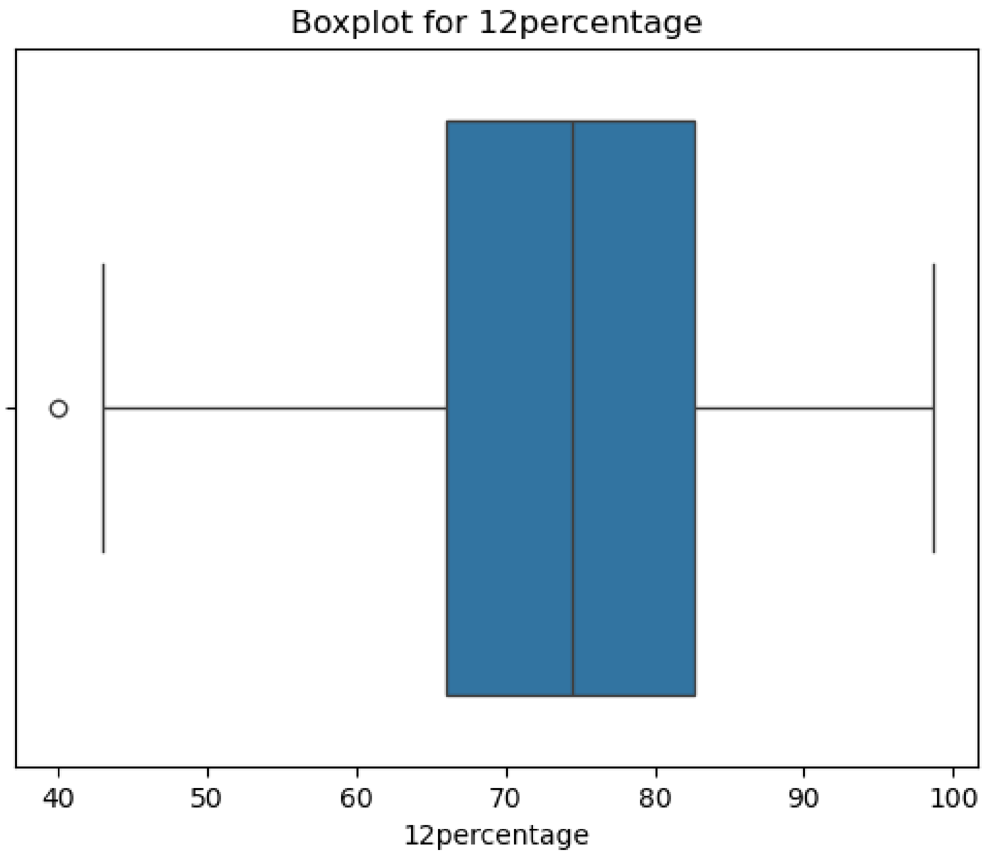
```
    # Check if the column is datetime
    elif pd.api.types.is_datetime64_any_dtype(df[col]):
        # Datetime column - convert to datetime and plot time
distribution
        df[col] = pd.to_datetime(df[col])
        df[col].value_counts().sort_index().plot(ax=axes[i])
        axes[i].set_title(f'Time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



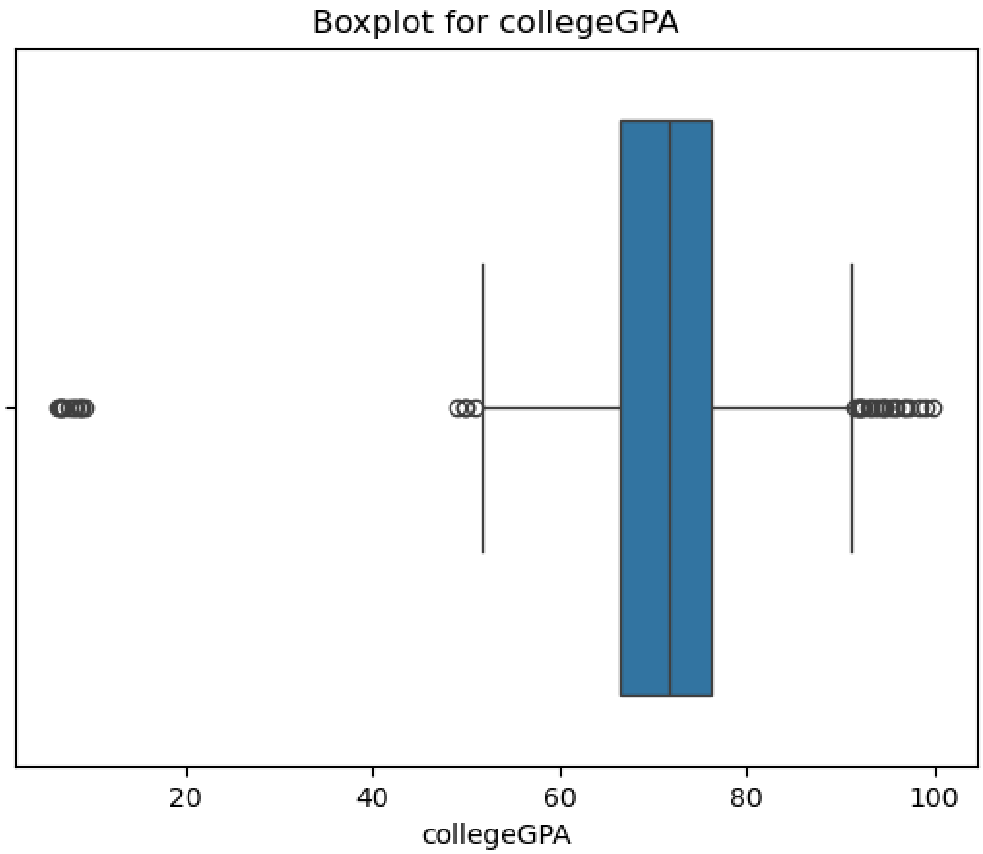
Distribution of ID (Numerical)
Distribution of Salary (Numerical)
Time Distribution of DOJ (Datetime)
Distribution of DOL (Categorical)
Distribution of Designation (Categorical)
Distribution of JobCity (Categorical)
Distribution of Gender (Categorical)
Time Distribution of DOB (Datetime)
Distribution of 10percentage (Numerical)
Distribution of 10board (Categorical)
Distribution of 12graduation (Numerical)
Distribution of 12percentage (Numerical)
Distribution of 12board (Categorical)
Distribution of CollegeID (Numerical)
Distribution of CollegeTier (Numerical)
Distribution of Degree (Categorical)
Distribution of Specialization (Categorical)
Distribution of collegeGPA (Numerical)
Count
count
ID
Salary
Date
DOL
Designation
JobCity
Gender
f
m
10percentage
10board
12graduation
12percentage
12board
CollegeID
CollegeTier
Degree
B.Tech/B.E.
MCA
M.Tech./M.E.
M.Sc. (Tech.)
Specialization
collegeGPA

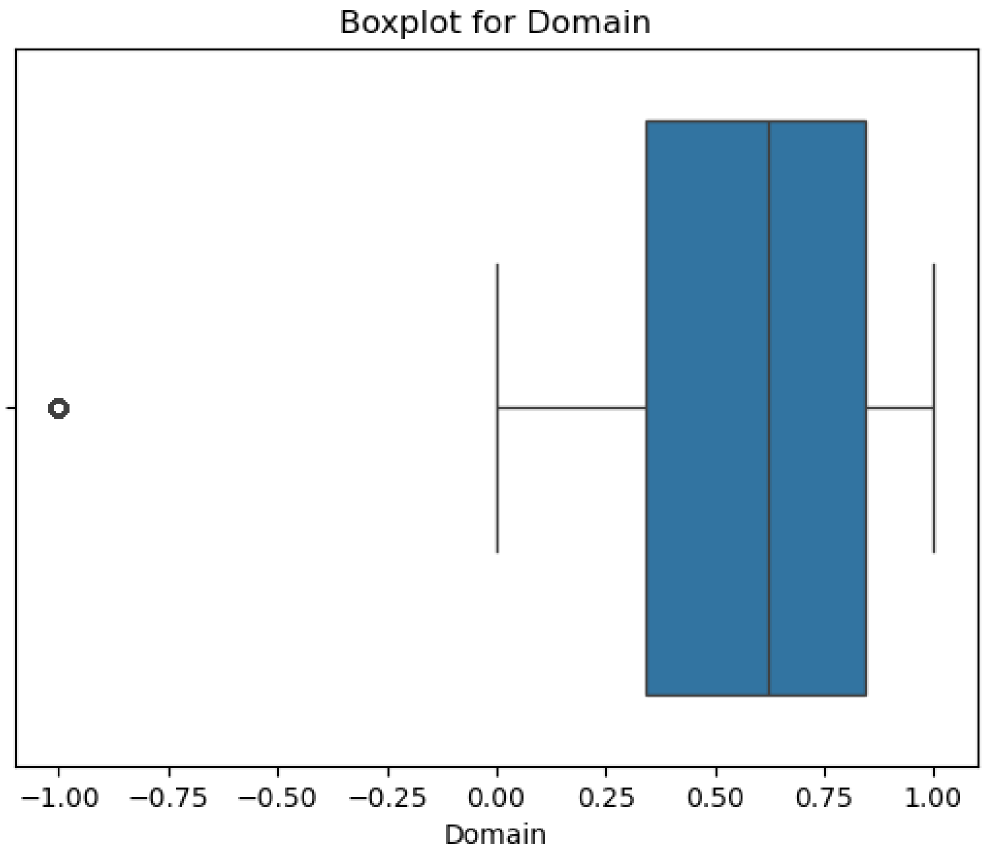
```
for i in df.columns:
    if df[i].dtype=="int" or df[i].dtype=="float":
        sns.boxplot(x=df[i])
        plt.title("Boxplot for {}".format(i))
        plt.show()
```

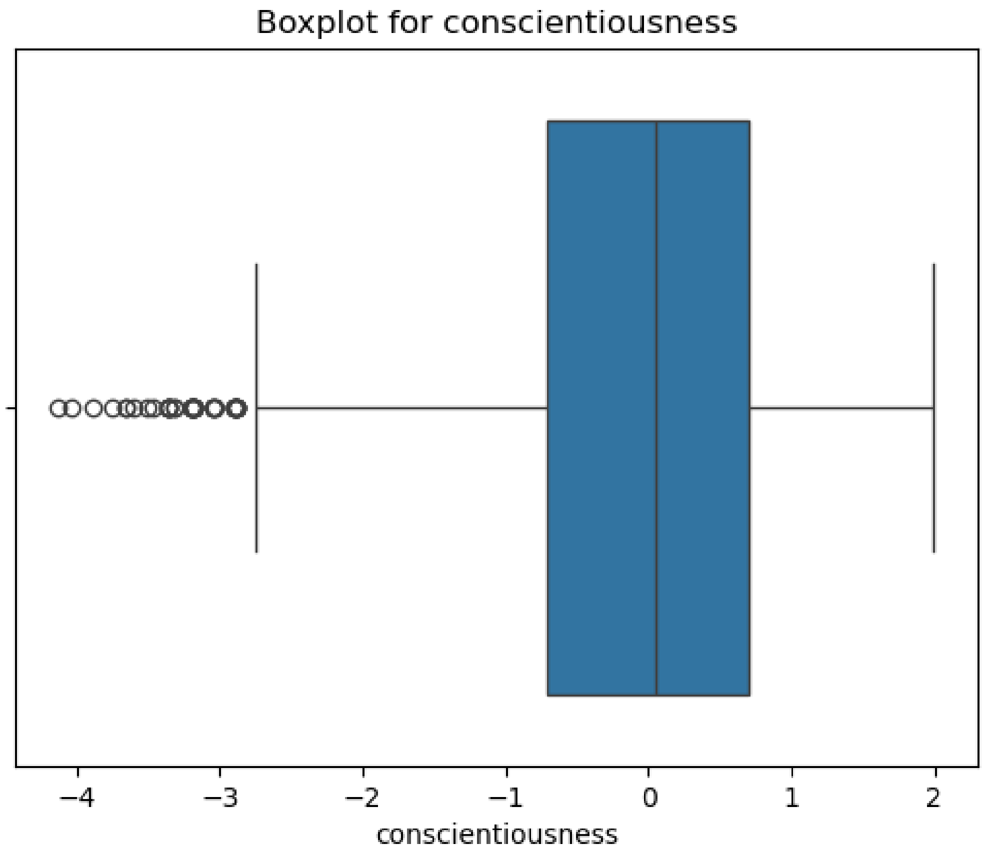


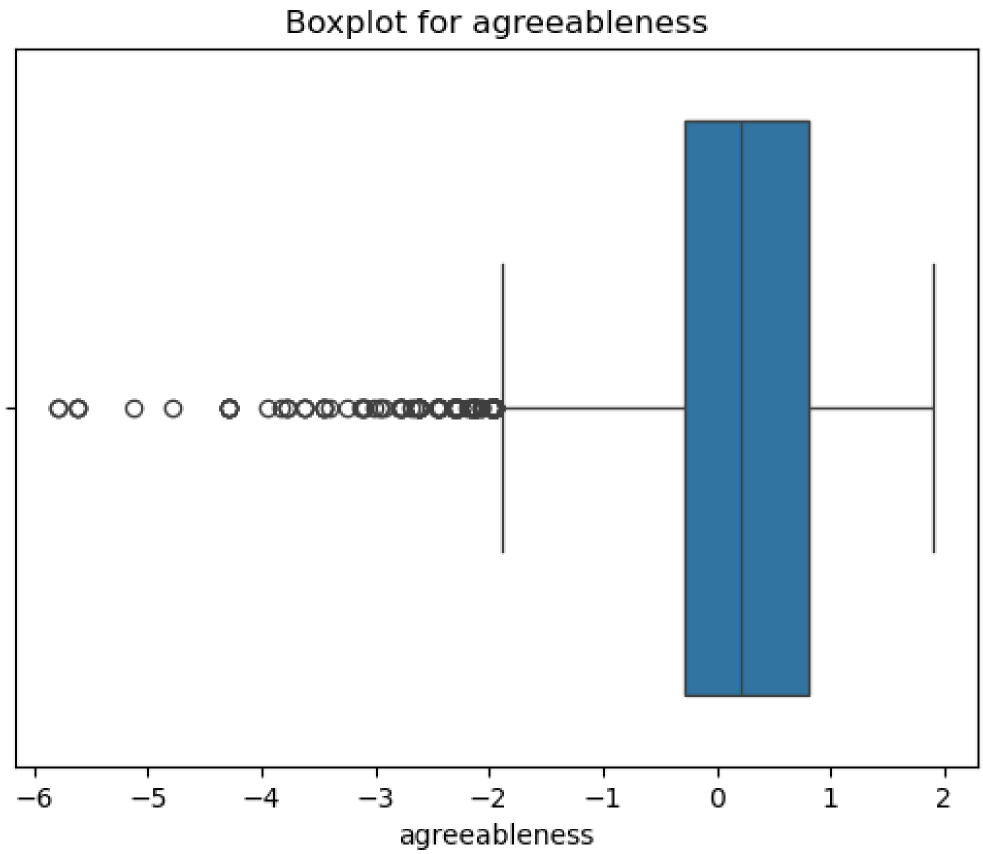


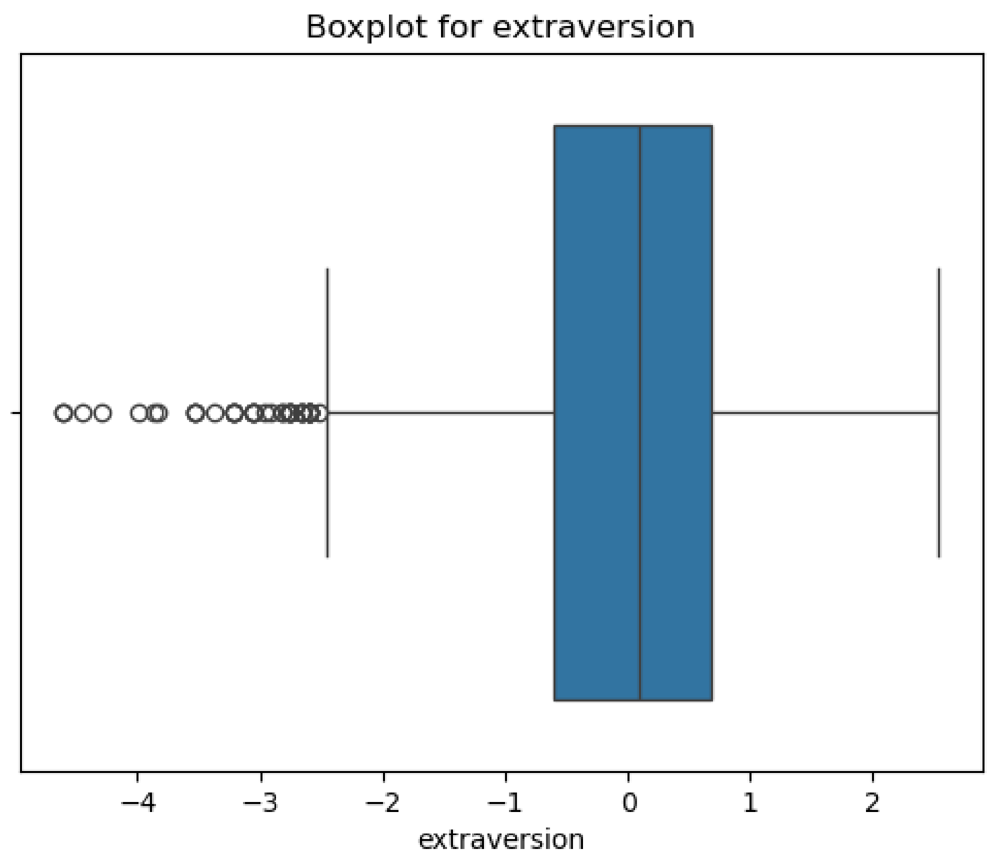
Boxplot for 12percentage
40
50
60
70
80
90
100
12percentage


Boxplot for collegeGPA
20
40
60
80
100
collegeGPA

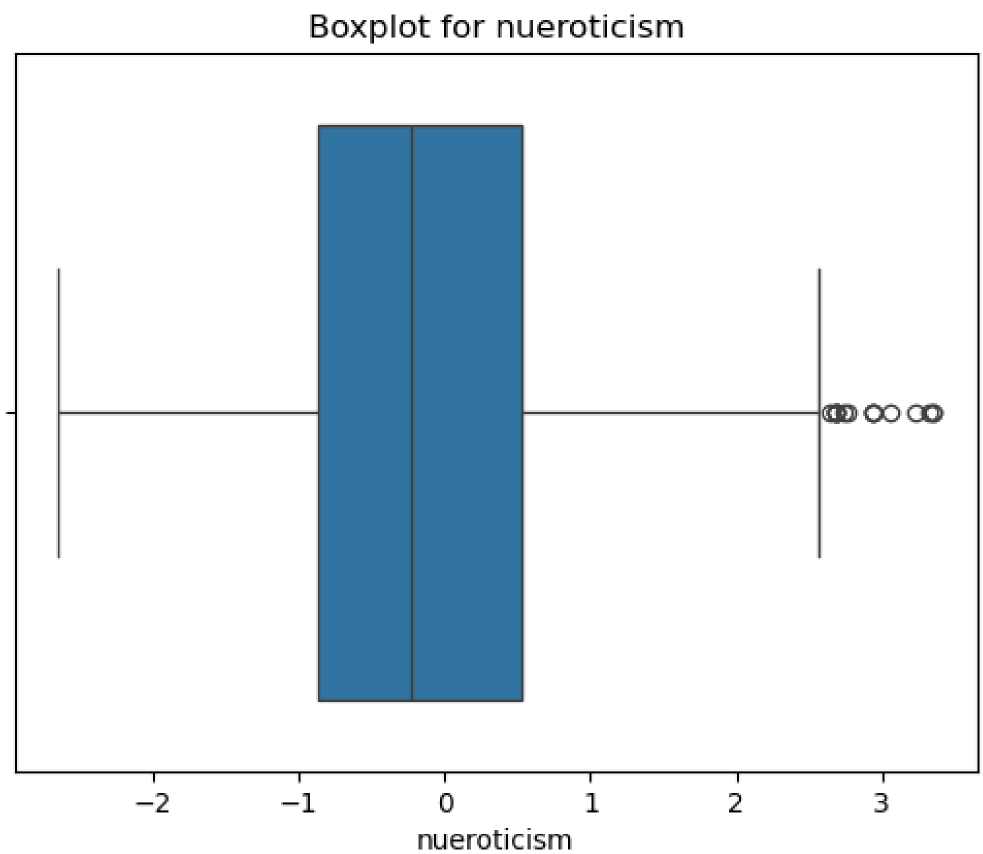

Boxplot for Domain
−1.00
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
Domain


Boxplot for conscientiousness
−4
−3
−2
−1
0
1
2
conscientiousness

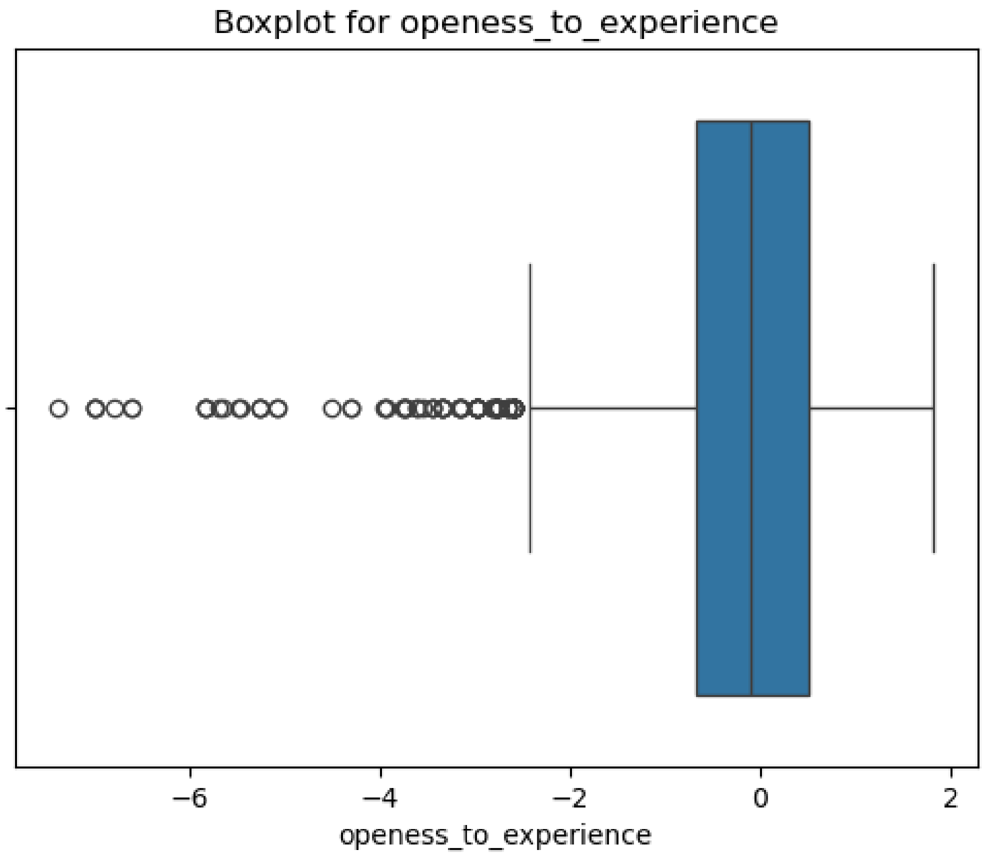

Boxplot for agreeableness
−6
−5
−4
−3
−2
−1
0
1
2
agreeableness



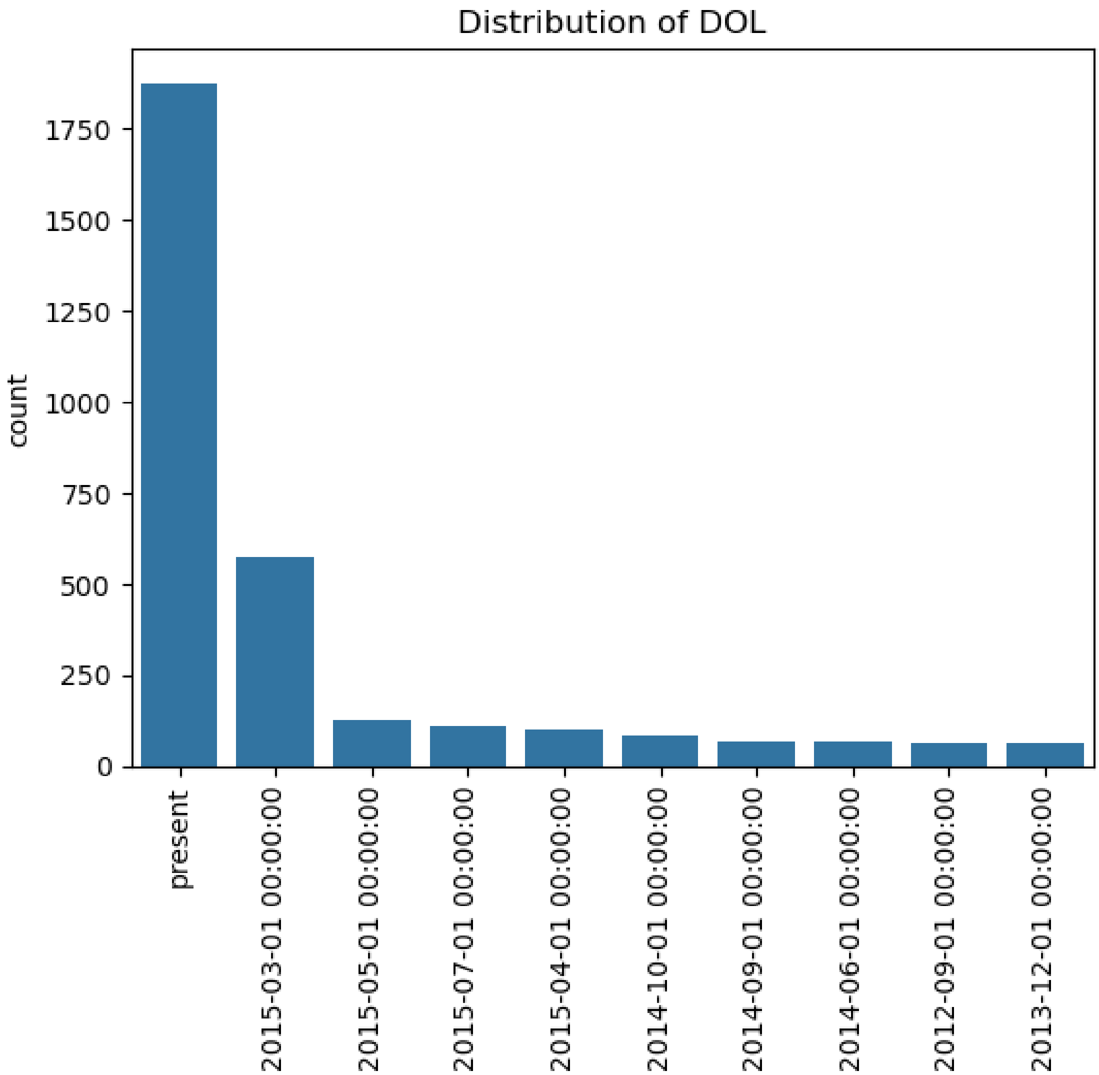
Boxplot for extraversion
−4
−3
−2
−1
0
1
2
extraversion



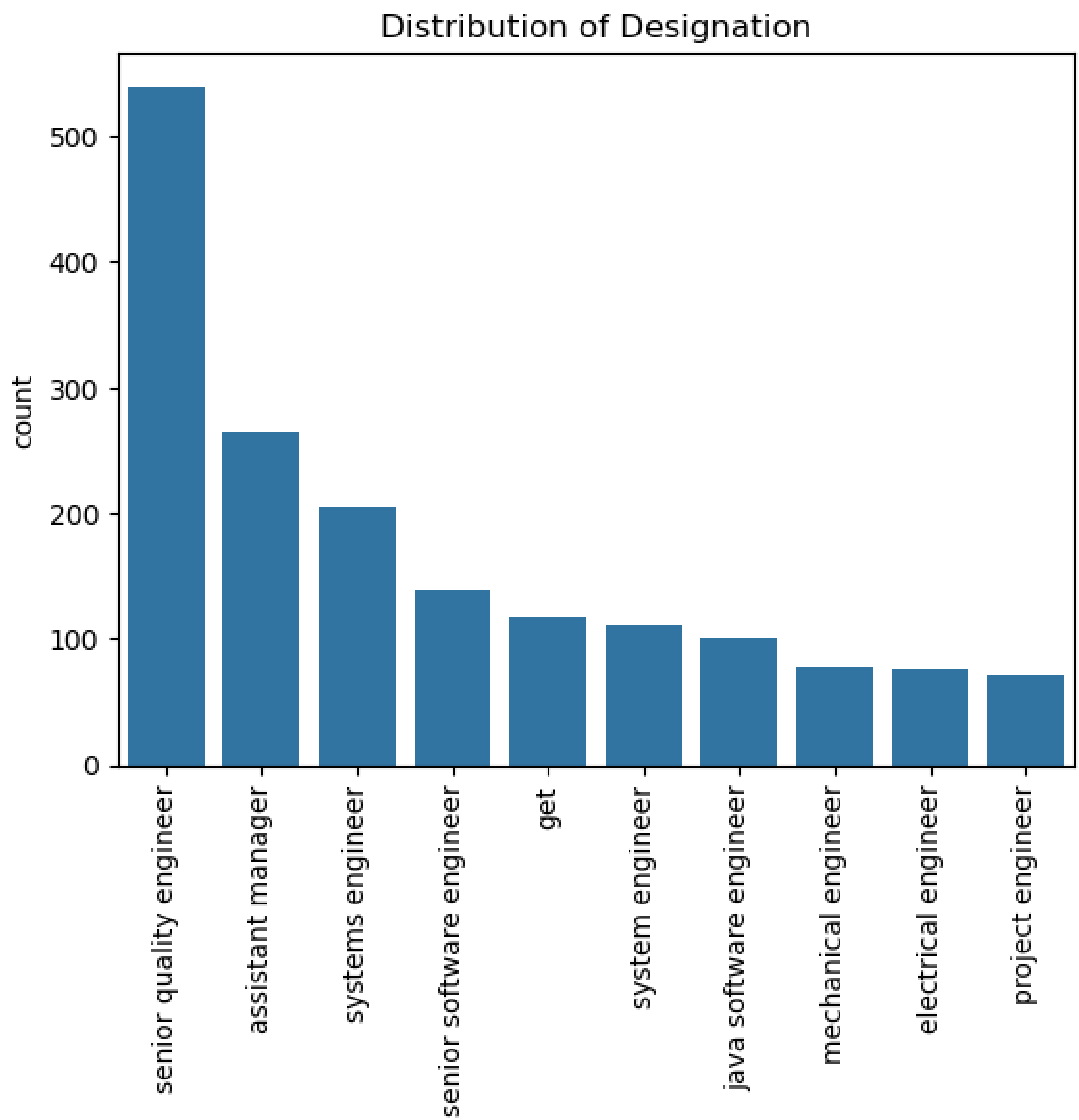
Boxplot for nueroticism
−2
−1
0
1
2
3
nueroticism



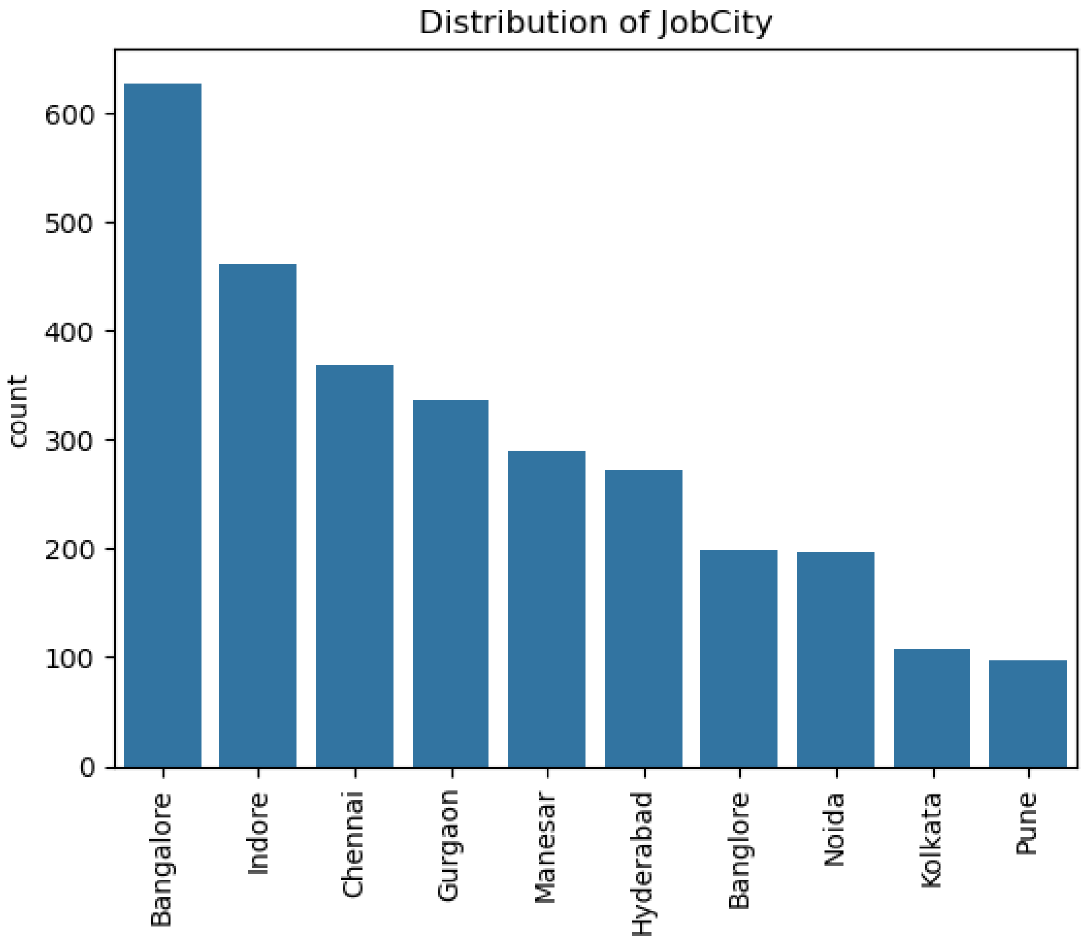

```
for i in df.columns:
    if df[i].dtype=="object":
        sns.barplot(x=df[i].unique()[:10],y=df[i].value_counts()[:10])
        plt.title("Distribution of {}".format(i))
        plt.xticks(rotation=90)
        plt.show()
```

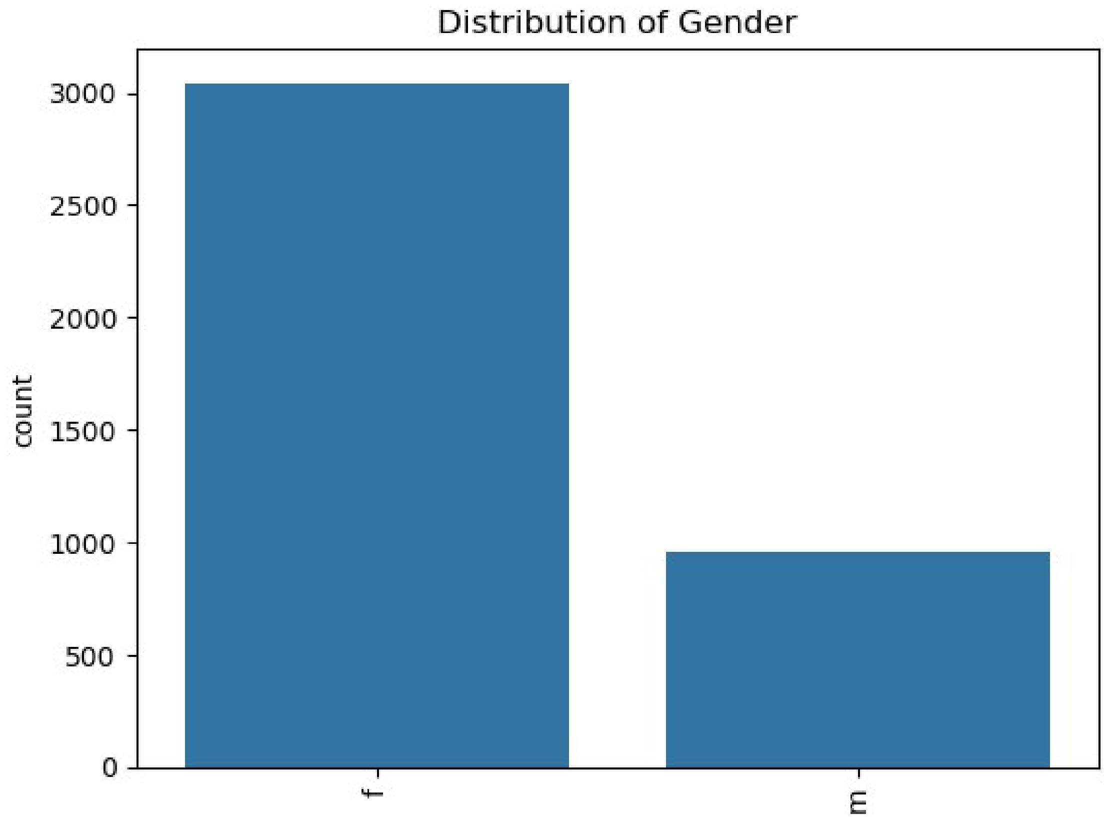


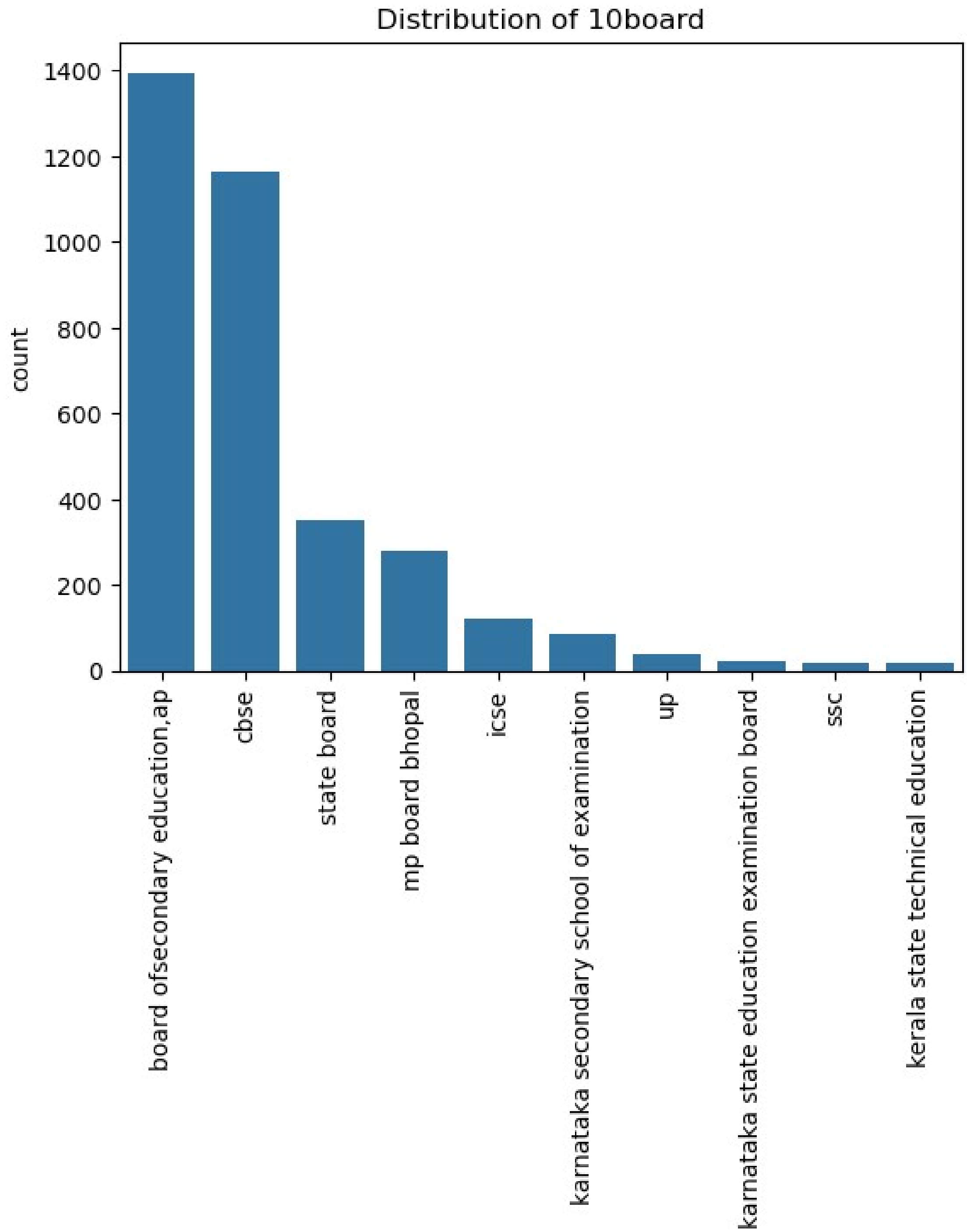
Distribution of DOL
count
0
250
500
750
1000
1250
1500
1750
present
2015-03-01 00:00:00
2015-05-01 00:00:00
2015-07-01 00:00:00
2015-04-01 00:00:00
2014-10-01 00:00:00
2014-09-01 00:00:00
2014-06-01 00:00:00
2012-09-01 00:00:00
2013-12-01 00:00:00

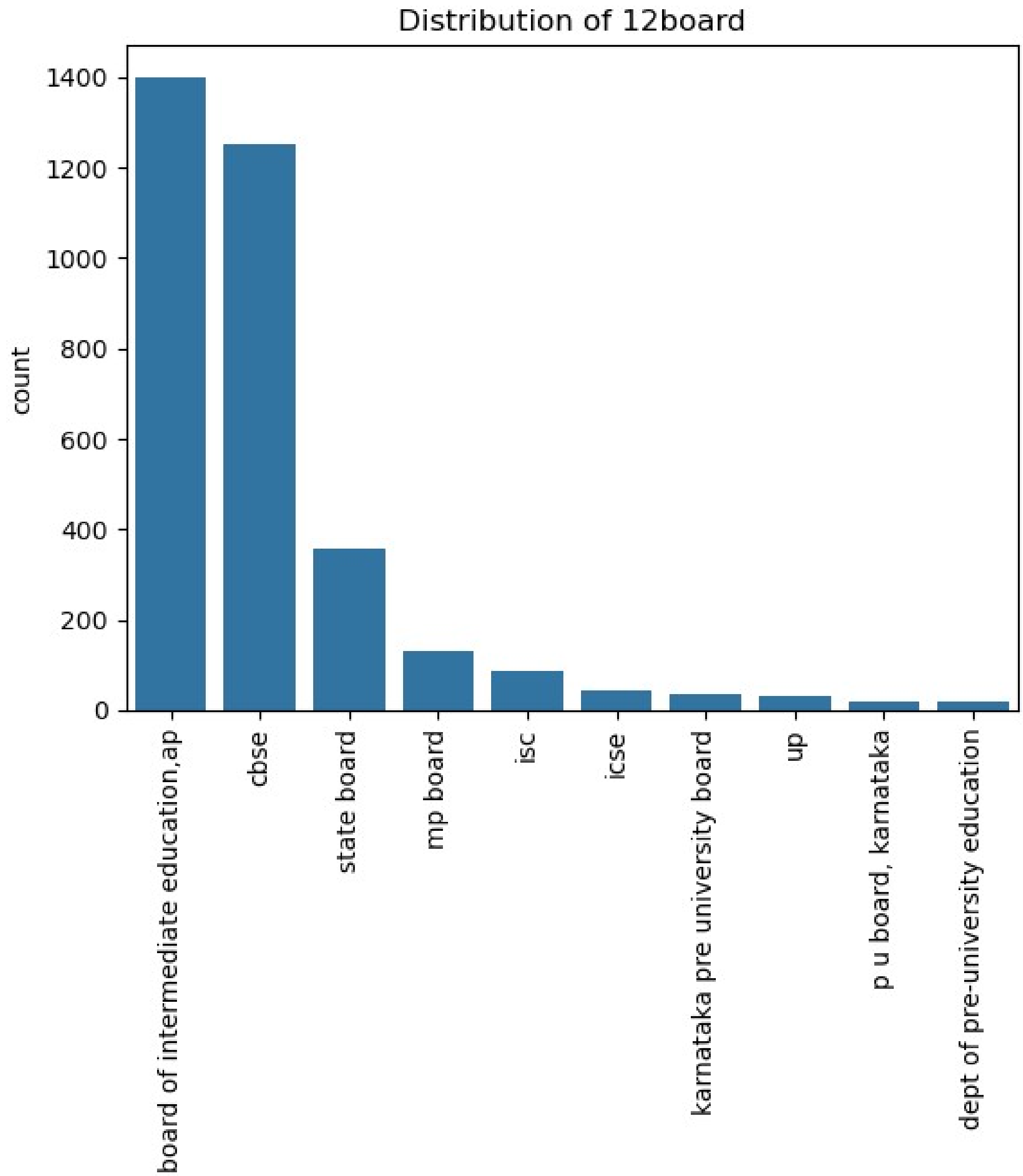


Distribution of Designation
count
0
100
200
300
400
500
senior quality engineer
assistant manager
systems engineer
senior software engineer
get
system engineer
java software engineer
mechanical engineer
electrical engineer
project engineer

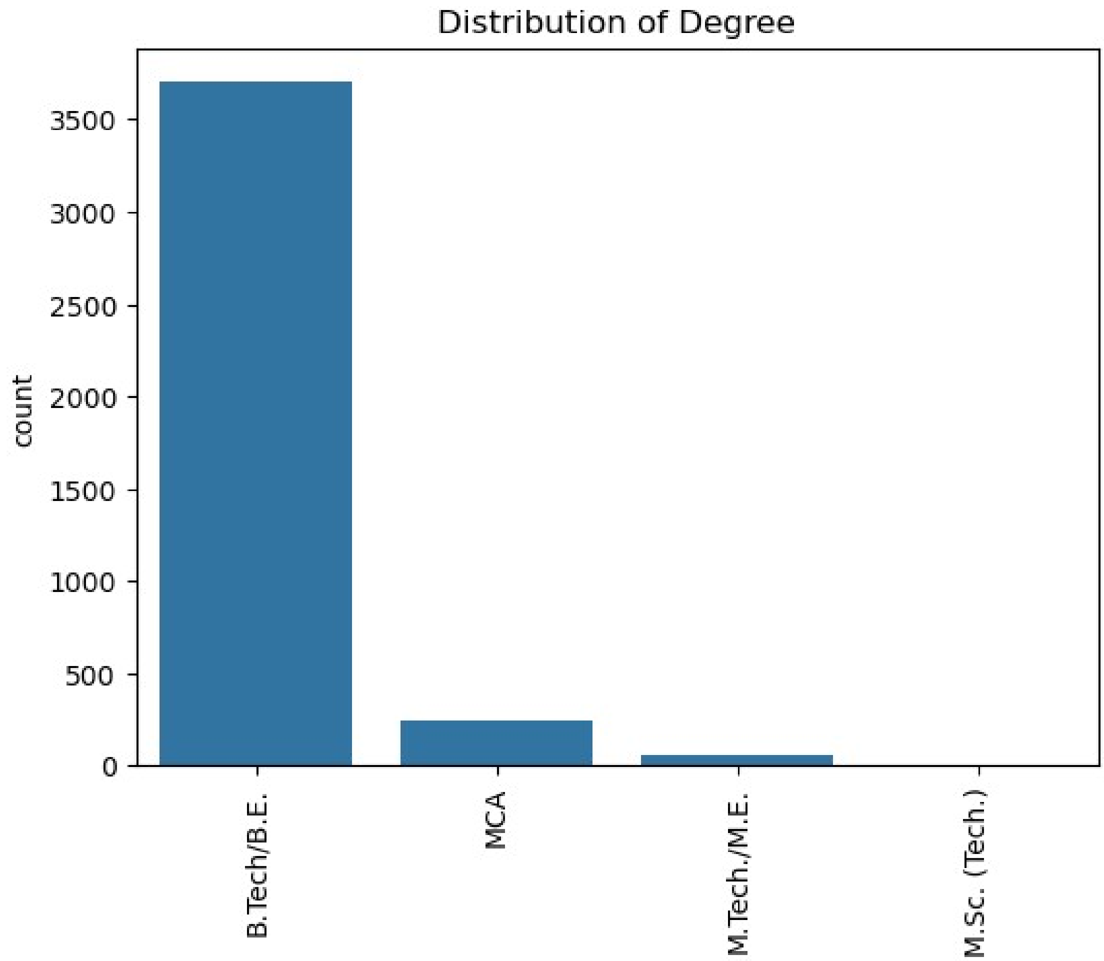

Distribution of JobCity
count
0
100
200
300
400
500
600
Bangalore
Indore
Chennai
Gurgaon
Manesar
Hyderabad
Banglore
Noida
Kolkata
Pune

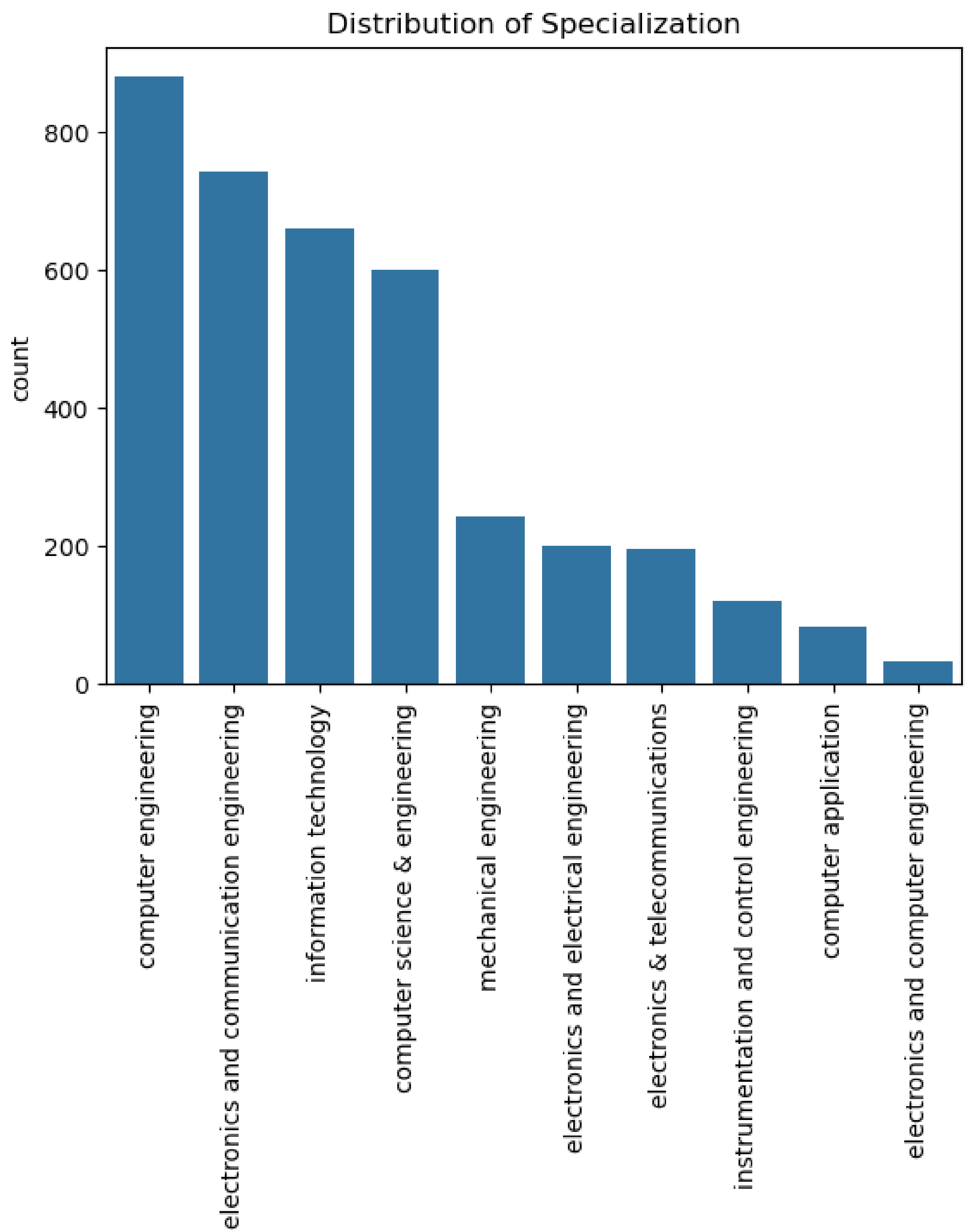

Distribution of Gender
count
3000
2500
2000
1500
1000
500
0
f
m


Distribution of 10board
count
0
200
400
600
800
1000
1200
1400
board ofsecondary education,ap
cbse
state board
mp board bhopal
icse
karnataka secondary school of examination
up
karnataka state education examination board
ssc
kerala state technical education

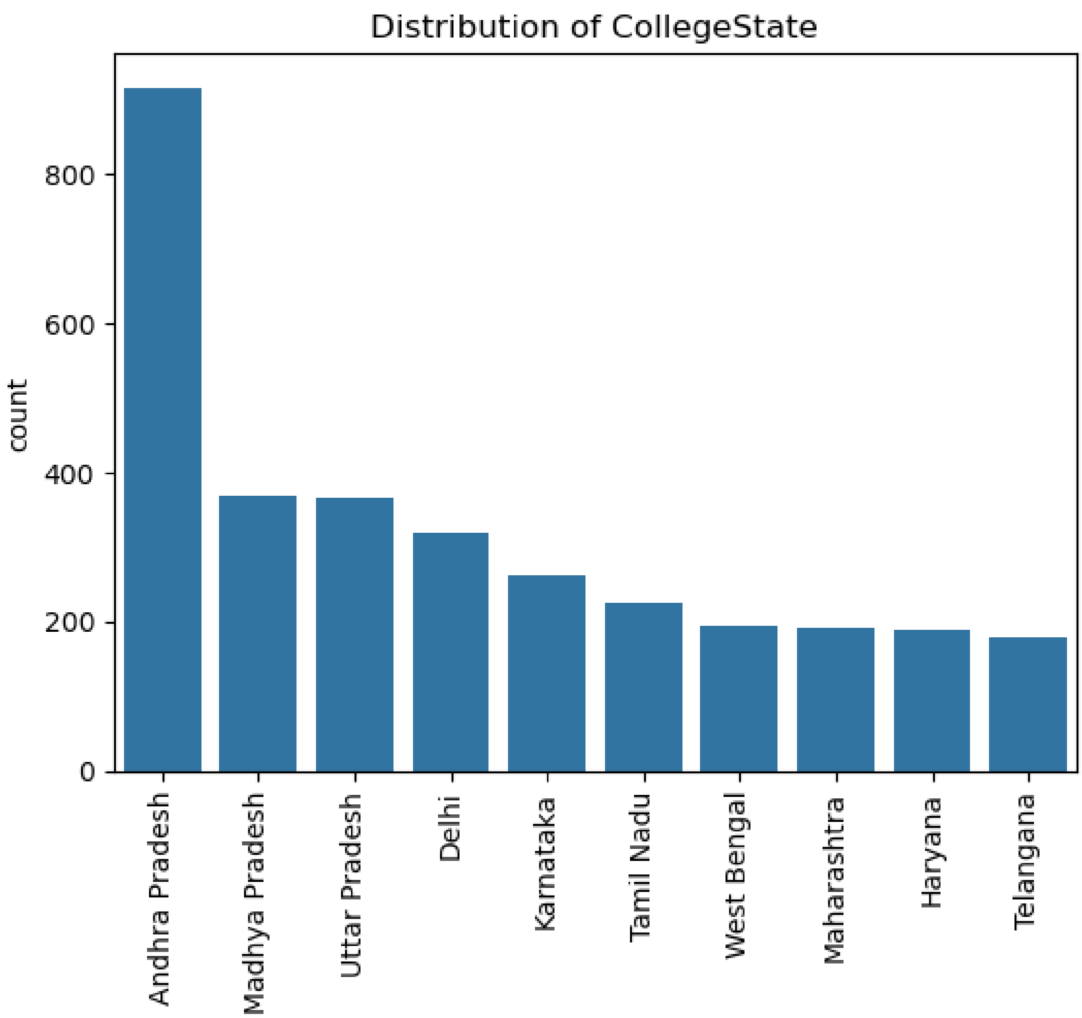


Distribution of 12board
count
1400
1200
1000
800
600
400
200
0
board of intermediate education,ap
cbse
state board
mp board
isc
icse
karnataka pre university board
up
p u board, karnataka
dept of pre-university education


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
0
200
400
600
800
computer engineering
electronics and communication engineering
information technology
computer science & engineering
mechanical engineering
electronics and electrical engineering
electronics & telecommunications
instrumentation and control engineering
computer application
electronics and computer engineering



Bivariate Analysis

- Analysing the data using two features.

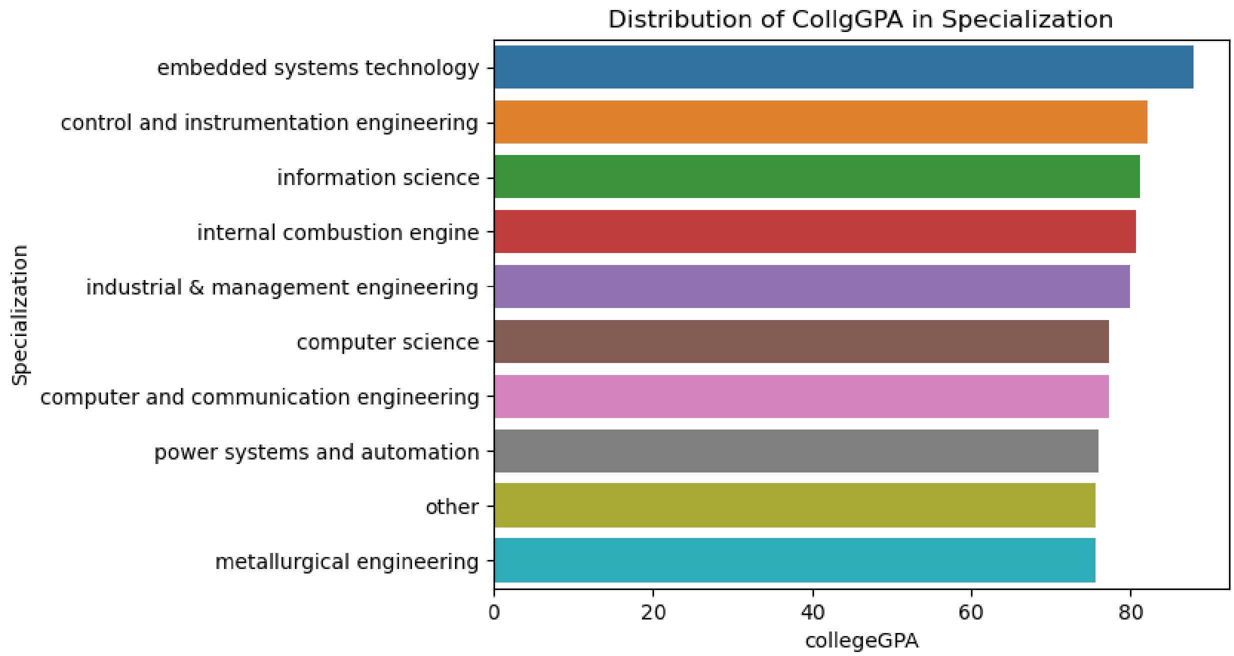
How does collegeGPA vary across different Specialization?

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

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

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

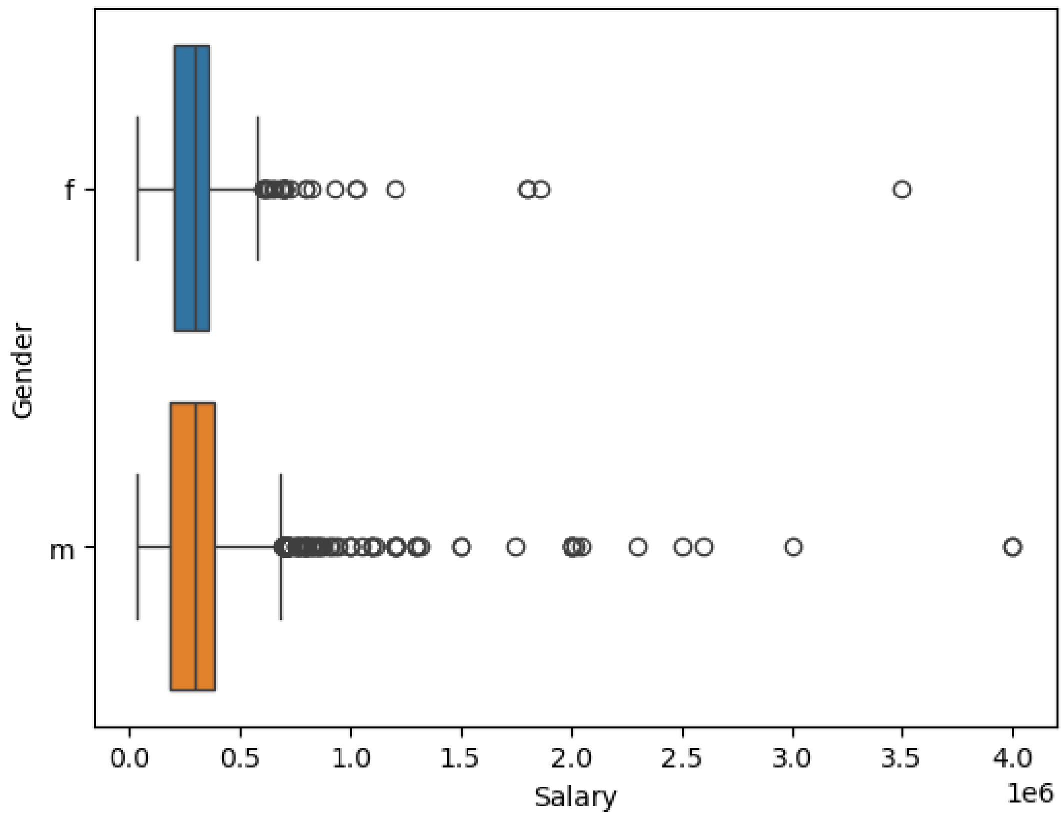


Insights

- 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?

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



Does the GraduationYear impact JobCity selection?

```
g2=pd.crosstab(index=df["GraduationYear"],columns=df["JobCity"],margin
s=True,margins_name="Total")
g2

JobCity          -1   Chennai   Delhi   Mumbai   Pune   ariyalur
bangalore  \
GraduationYear

0                 0         0       0        0      0          0
0
2007              0         0       0        0      0          0
0
2009              1         0       0        0      0          0
0
2010             16         0       0        1      0          1
1
2011             44         0       0        0      0          0
0
2012            115         1       0        0      1          0
0
2013            170         0       1        1      0          0
0
2014            108         0       0        0      0          0
```

```
0
2015                6         0       0        0      0          0
0
2016                0         0       0        0      0          0
0
2017                1         0       0        0      0          0
0
Total             461         1       1        2      1          1
1

JobCity           mumbai  A-64,sec-64,noida  AM  ...  shahibabad
singaruli  \
GraduationYear                                    ...

0                      0                  0   0  ...           0
0
2007                   0                  0   0  ...           0
0
2009                   0                  0   0  ...           0
1
2010                   0                  0   0  ...           0
0
2011                   0                  0   0  ...           0
0
2012                   0                  0   0  ...           0
0
2013                   1                  0   0  ...           1
0
2014                   0                  1   1  ...           0
0
2015                   0                  0   0  ...           0
0
2016                   0                  0   0  ...           0
0
2017                   0                  0   0  ...           0
0
Total                  1                  1   1  ...           1
1

JobCity           sonepat  thane  trivandrum  udaipur  vapi  vizag  \
GraduationYear
0                       0      0           0        0     0      0
2007                    0      0           0        0     0      0
2009                    0      0           0        0     0      0
2010                    1      0           0        0     0      0
2011                    0      1           0        1     0      0
2012                    0      0           0        1     0      0
2013                    0      0           1        0     0      0
2014                    0      0           1        0     1      1
2015                    0      0           0        0     0      0
```

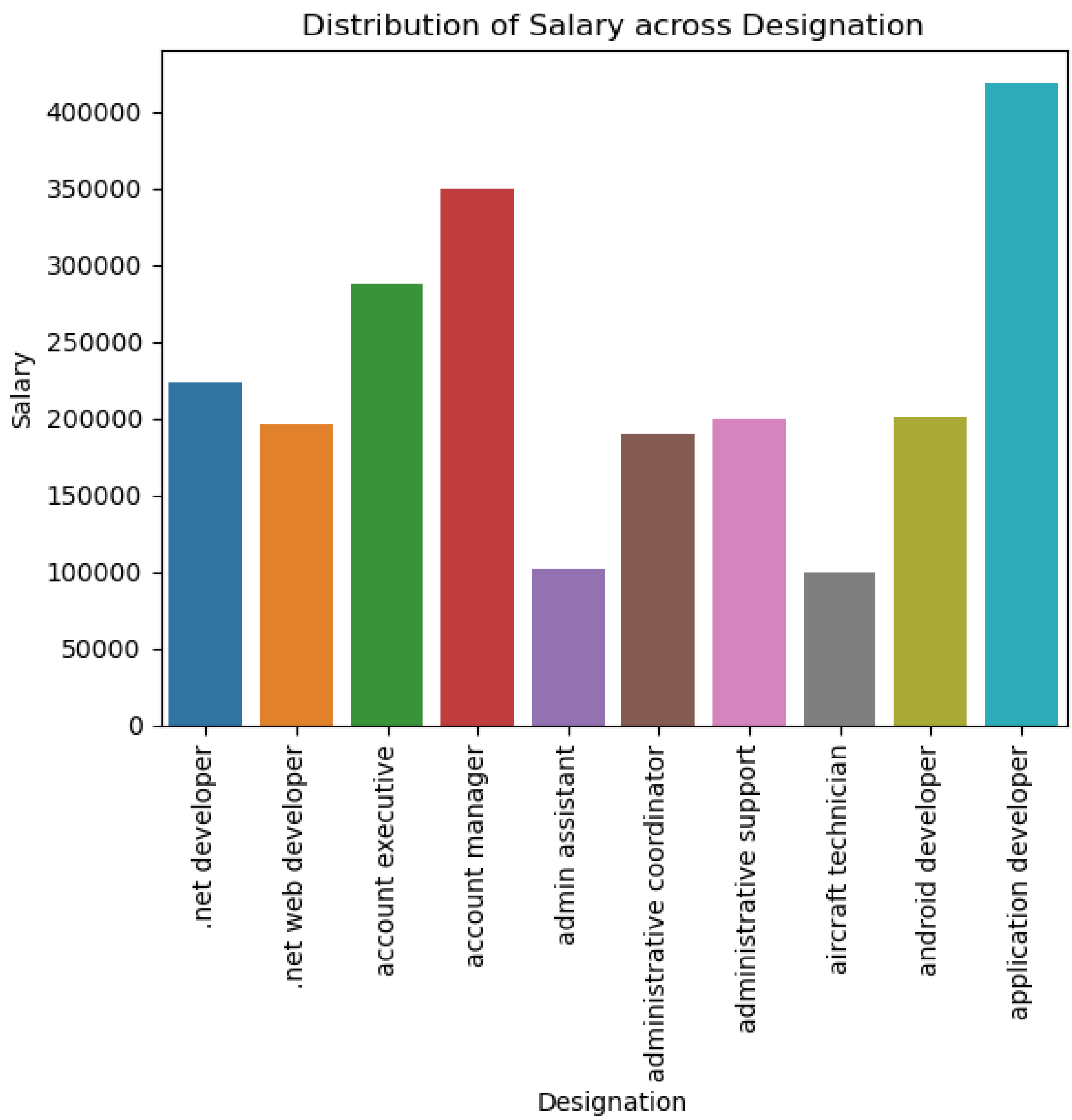
```
2016                      0      0           0        0     0      0
2017                      0      0           0        0     0      0
Total                     1      1           2        2     1      1

JobCity          vsakhapttnam  Total
GraduationYear
0                           0      1
2007                        0      1
2009                        0     24
2010                        1    292
2011                        0    507
2012                        0    847
2013                        0   1181
2014                        0   1036
2015                        0     94
2016                        0      7
2017                        0      8
Total                       1   3998

[12 rows x 340 columns]
```

Does Designation affect Salary?

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

```
                                        Salary
Designation
.net developer                   223382.352941
.net web developer               196250.000000
account executive                287500.000000
account manager                  350000.000000
admin assistant                  102500.000000
...                                        ...
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 x 1 columns]
```

```
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

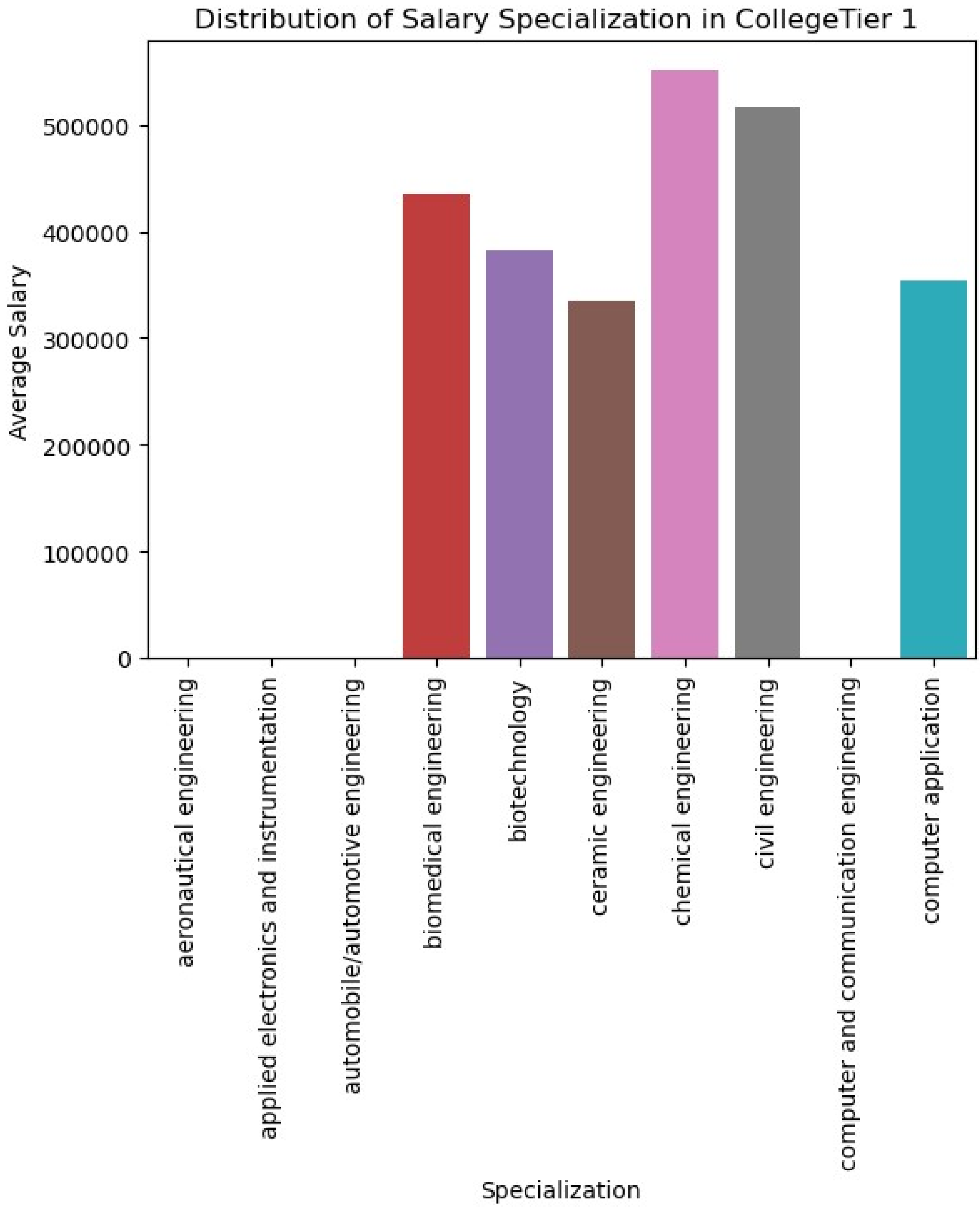
- Analysing the data using more then two features.

Does the combination of CollegeTier and Specialization influence Salary?

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

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

```
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()
```

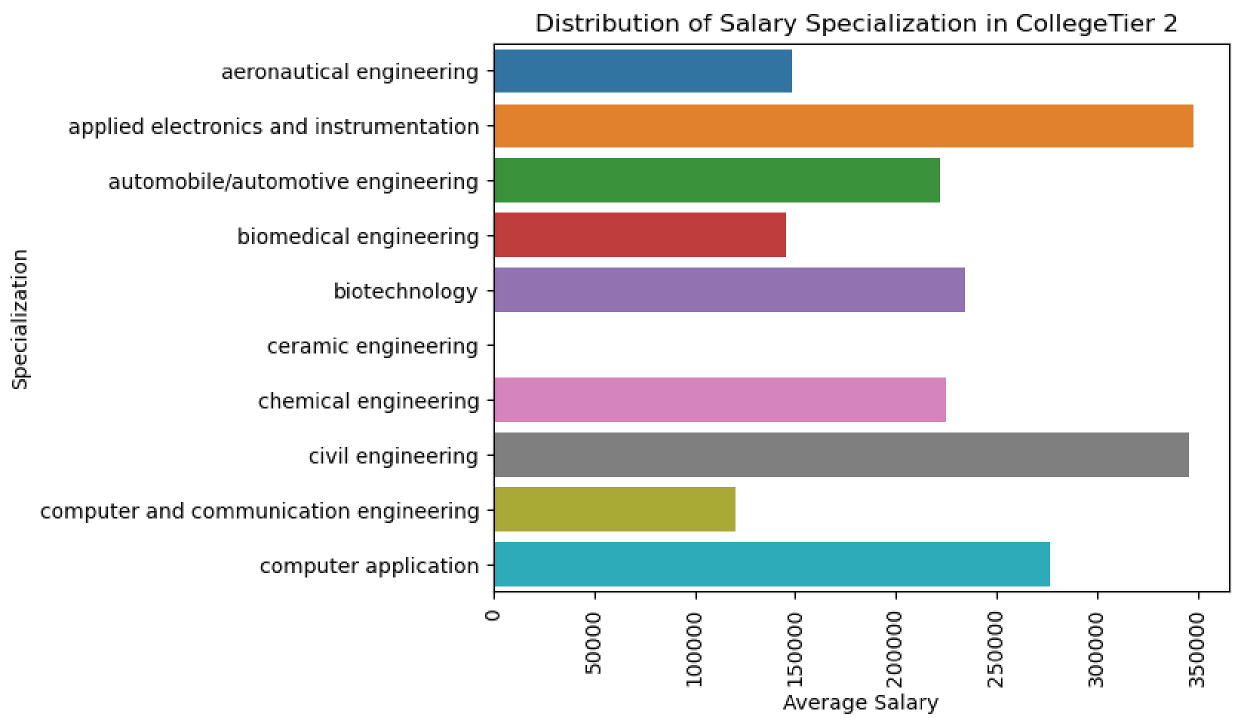


Insights

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

```
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()
```

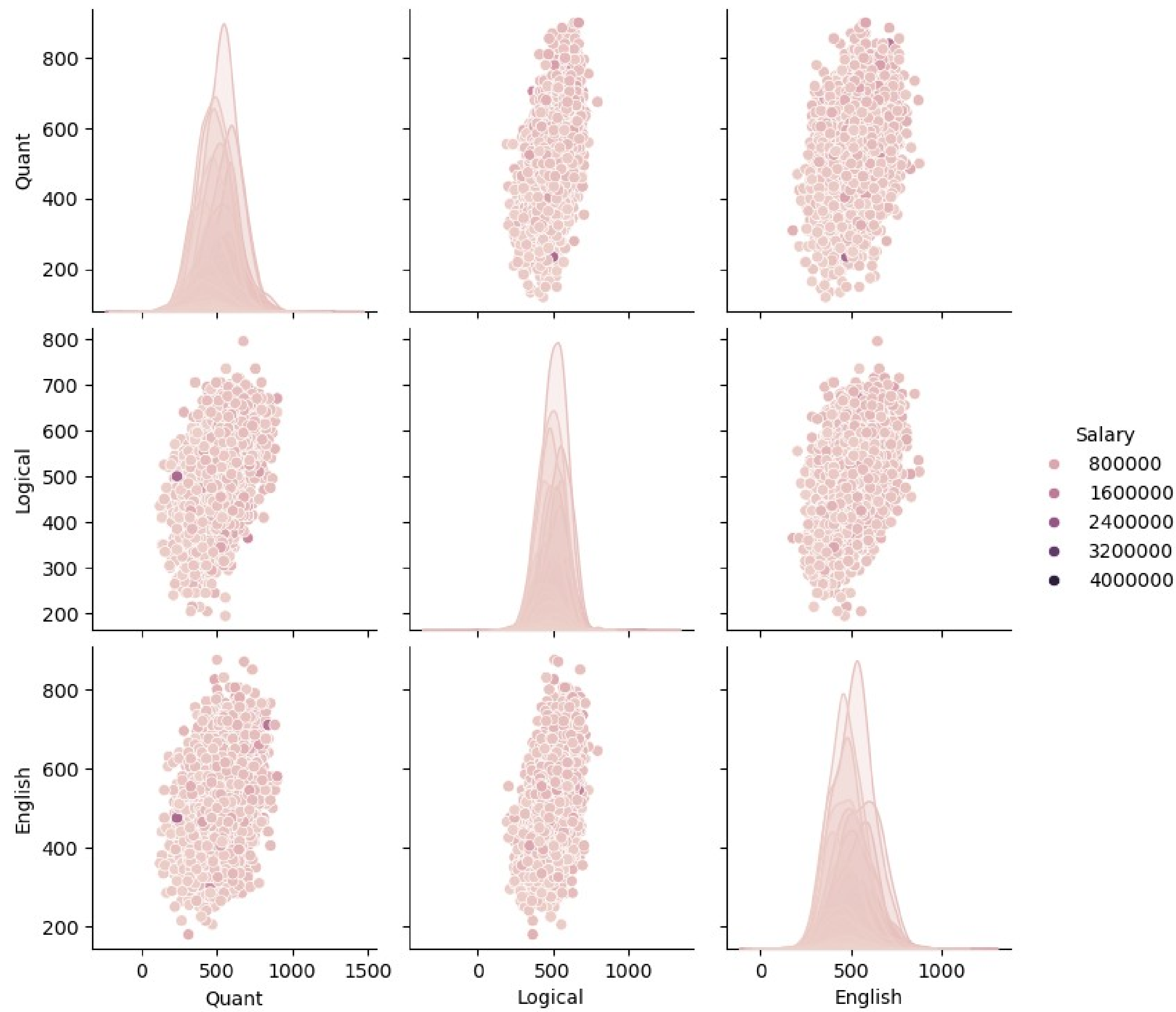


Insights

- 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?

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

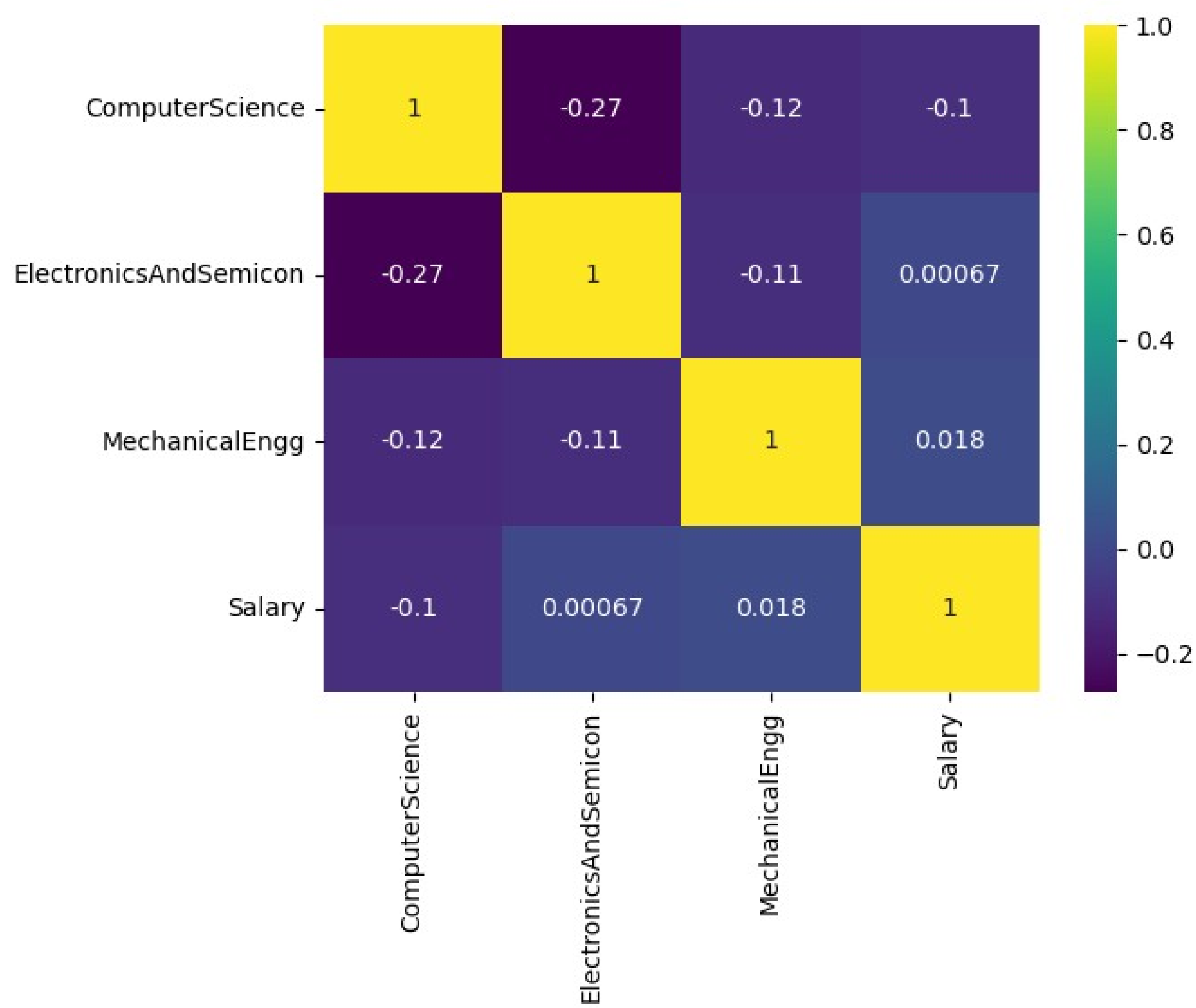


How do different Engineering specializations (e.g., ComputerScience, ElectronicsAndSemicon, MechanicalEngg) contribute to Salary?

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

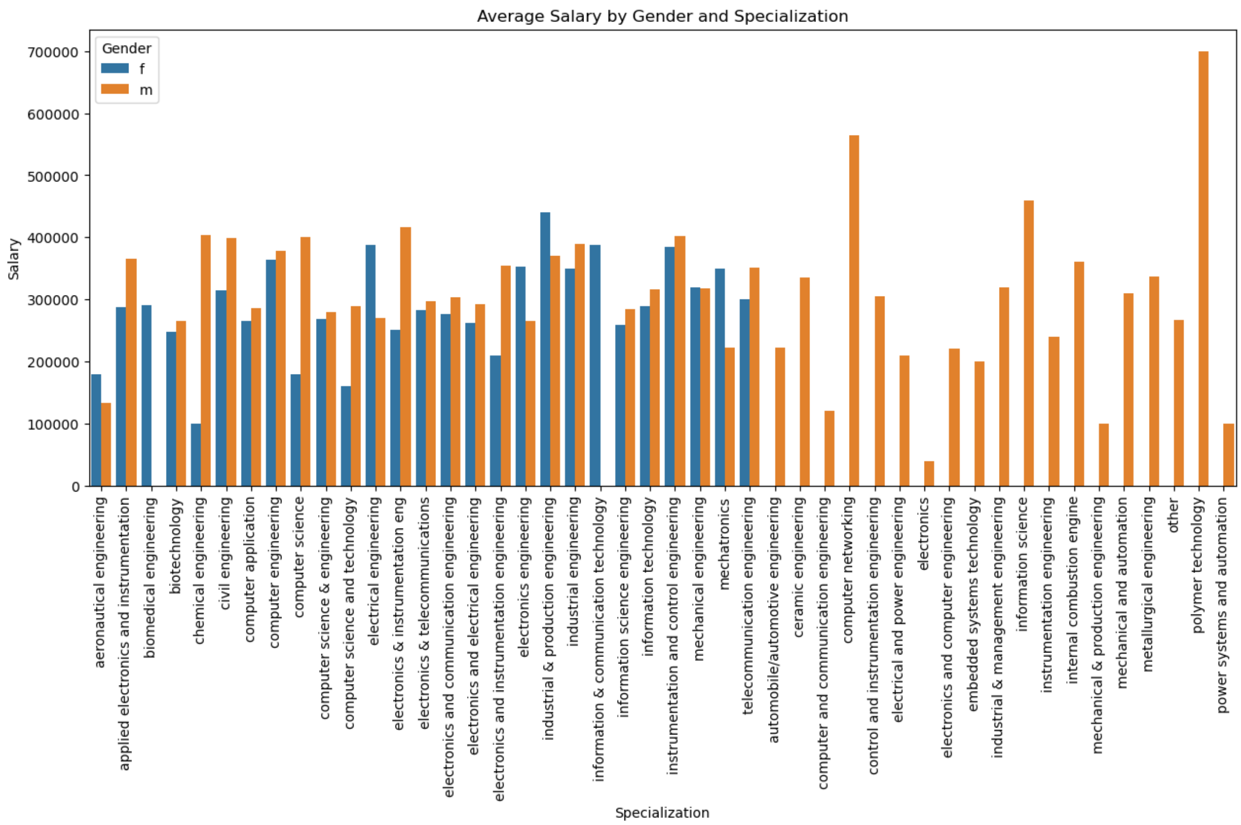
```
                       ComputerScience  ElectronicsAndSemicon
MechanicalEngg  \
ComputerScience               1.000000              -0.273707        -
0.124355
ElectronicsAndSemicon        -0.273707               1.000000        -
0.109434
MechanicalEngg               -0.124355              -0.109434
1.000000
Salary                       -0.100720               0.000665
```

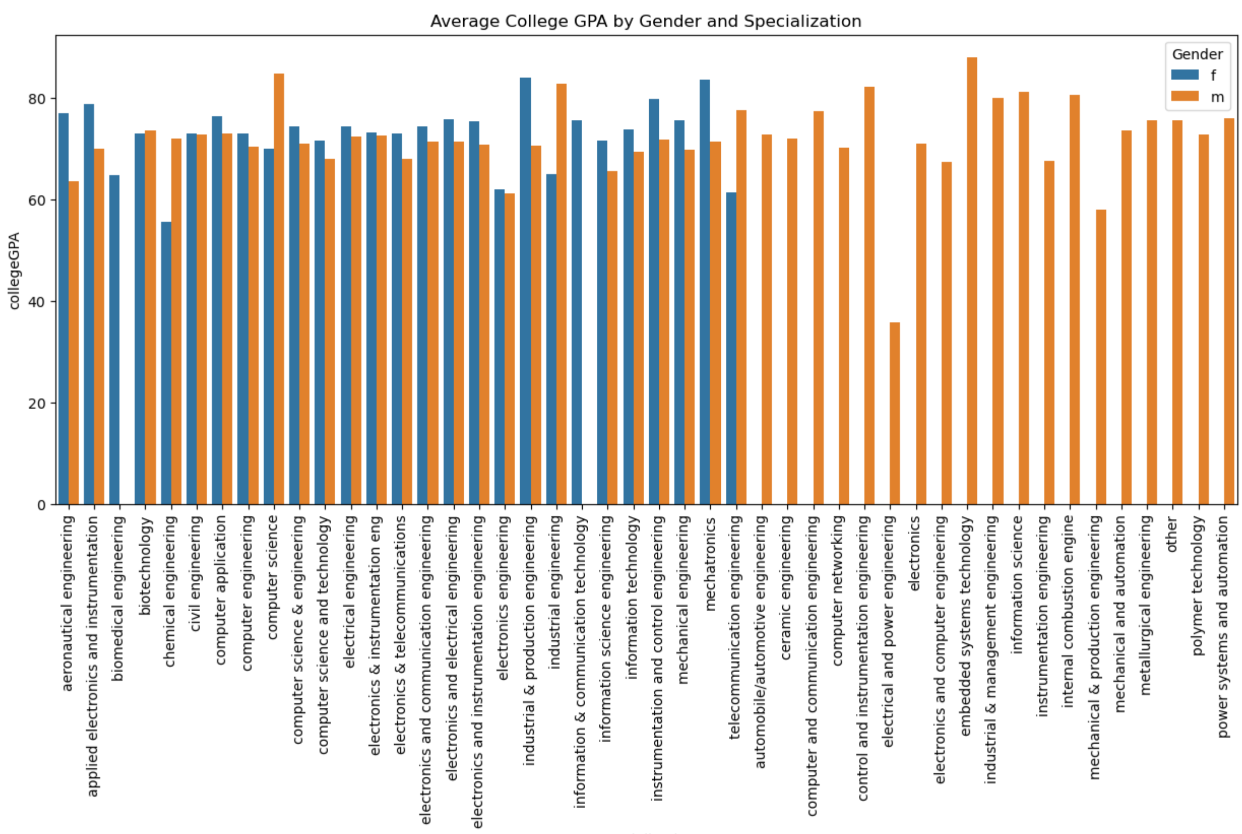
```
0.018475

                            Salary
ComputerScience          -0.100720
ElectronicsAndSemicon     0.000665
MechanicalEngg            0.018475
Salary                    1.000000

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



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

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

                                                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 x 2 columns]

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()
```


Average Salary by Gender and Specialization
Gender
f
m
Salary
Specialization


Average College GPA by Gender and Specialization
Gender
f
m
collegeGPA
Specialization

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."

```
from scipy import stats
relevant_roles = ['programmer Analyst', 'software engineer', 'hardware
engineer', 'associate 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 claimed mean.
```

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

```
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 gender 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 Specialization.
```

Conclusion

The analysis of the AMCAT dataset offers valuable insights into salary trends, specializations, and skill sets of recent graduates across various roles. Key findings include:

Salary Trends:

The statistical analysis confirms that the average salaries for roles such as Programming Analyst, Software Engineer, Hardware Engineer, and Associate Engineer align with the salary ranges reported in the Times of India article. There is no significant difference between the reported and actual salary data, indicating that the industry standards for these roles remain consistent.

Influence of Specialization:

Graduates specializing in Computer Science and IT-related fields tend to secure higher salaries, reaffirming the strong demand for these skills within the technology sector

Gender Representation:

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

Skill Assessment:

Technical skills such as programming, computer science, and related competencies demonstrate a strong positive correlation with salary, underscoring their significance in achieving higher compensation. Additionally, behavioral traits like conscientiousness, agreeableness, and openness to experience show a moderate correlation with job performance and salary, highlighting the valuable role of soft skills in career success

Educational Background:

Graduates from Tier 1 institutions tend to secure higher starting salaries compared to those from Tier 2 or Tier 3 colleges, highlighting the significant influence of institutional reputation on initial job placements and compensation packages.

https://www.linkedin.com/feed/update/urn:li:activity:7248547513320833024/