Analysis of AMEO Data

Introduction

Dataset Description

The Aspiring Mind Employment Outcome 2015 (AMEO) dataset, released by Aspiring Minds, focuses on employment outcomes for engineering graduates. It includes dependent variables such as Salary, Job Titles, and Job Locations, along with standardized scores in cognitive skills, technical skills, and personality skills. With around 39 independent variables and 4000 data points, these variables encompass both continuous and categorical data. The dataset also includes demographic features and unique identifiers for each candidate.

Objective

The goal of this Exploratory Data Analysis (EDA) is to extensively investigate the provided dataset, with a particular emphasis on understanding the link between various variables and the target variable, Salary. The key aims of this analysis include: • Providing a detailed explanation of the dataset's features. • Find any observable patterns or trends in the data. • Investigating the relationships between the independent factors and the target variable (salary). • Identify any outliers or abnormalities in the dataset. • Offering practical insights and recommendations based on the analysis.

Importing Required Libraries

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import chi2_contingency
import warnings
warnings.filterwarnings("ignore")
```

The head, shape and description of the data.

In [2]:
```
df = pd.read_csv('data.xlsx - Sheet1.csv')
df
```

Out[2]:

	Unnamed: 0	ID	Salary	DOJ	DOL	Designation	JobCity	Gender	DOB	10percentage	...	Co
0	train	203097	420000.0	6/1/12 0:00	present	senior quality engineer	Bangalore	f	2/19/90 0:00	84.30	...	
1	train	579905	500000.0	9/1/13 0:00	present	assistant manager	Indore	m	10/4/89 0:00	85.40	...	
2	train	810601	325000.0	6/1/14 0:00	present	systems engineer	Chennai	f	8/3/92 0:00	85.00	...	
3	train	267447	1100000.0	7/1/11 0:00	present	senior software engineer	Gurgaon	m	12/5/89 0:00	85.60	...	
4	train	343523	200000.0	3/1/14 0:00	3/1/15 0:00	get	Manesar	m	2/27/91 0:00	78.00	...	
...	...	...	...	...	...	...	...	...	...	...	...	
3993	train	47916	280000.0	10/1/11 0:00	10/1/12 0:00	software engineer	New Delhi	m	4/15/87 0:00	52.09	...	
3994	train	752781	100000.0	7/1/13 0:00	7/1/13 0:00	technical writer	Hyderabad	f	8/27/92 0:00	90.00	...	
3995	train	355888	320000.0	7/1/13 0:00	present	associate software engineer	Bangalore	m	7/3/91 0:00	81.86	...	
3996	train	947111	200000.0	7/1/14 0:00	1/1/15 0:00	software developer	Asifabadbanglore	f	3/20/92 0:00	78.72	...	
3997	train	324966	400000.0	2/1/13 0:00	present	senior systems engineer	Chennai	f	2/26/91 0:00	70.60	...	

3998 rows × 39 columns

In [3]:
```
pd.set_option('display.max_columns', None)
df.head()
```

Out[3]:

	Unnamed: 0	ID	Salary	DOJ	DOL	Designation	JobCity	Gender	DOB	10percentage	10board	12g
0	train	203097	420000.0	6/1/12 0:00	present	senior quality engineer	Bangalore	f	2/19/90 0:00	84.3	board ofsecondary education,ap	
1	train	579905	500000.0	9/1/13 0:00	present	assistant manager	Indore	m	10/4/89 0:00	85.4	cbse	
2	train	810601	325000.0	6/1/14 0:00	present	systems engineer	Chennai	f	8/3/92 0:00	85.0	cbse	
3	train	267447	1100000.0	7/1/11 0:00	present	senior software engineer	Gurgaon	m	12/5/89 0:00	85.6	cbse	
4	train	343523	200000.0	3/1/14 0:00	3/1/15 0:00	get	Manesar	m	2/27/91 0:00	78.0	cbse	

In [4]:
```
df.shape
```

Out[4]: (3998, 39)

In [5]:
```
df.columns
```

Out[5]:
```
Index(['Unnamed: 0', 'ID', 'Salary', 'DOJ', 'DOL', 'Designation', 'JobCity',
       'Gender', 'DOB', '10percentage', '10board', '12graduation',
       '12percentage', '12board', 'CollegeID', 'CollegeTier', 'Degree',
       'Specialization', 'collegeGPA', 'CollegeCityID', 'CollegeCityTier',
       'CollegeState', 'GraduationYear', 'English', 'Logical', 'Quant',
       'Domain', 'ComputerProgramming', 'ElectronicsAndSemicon',
       'ComputerScience', 'MechanicalEngg', 'ElectricalEngg', 'TelecomEngg',
       'CivilEngg', 'conscientiousness', 'agreeableness', 'extraversion',
       'nueroticism', 'openess_to_experience'],
      dtype='object')
```

In [6]:
```
df.nunique()
```

Out[6]:
```
Unnamed: 0                  1
ID                       3998
Salary                    177
DOJ                        81
DOL                        67
Designation               419
JobCity                   339
Gender                      2
DOB                      1872
10percentage              851
10board                   275
12graduation               16
12percentage              801
12board                   340
CollegeID                1350
CollegeTier                 2
Degree                      4
Specialization             46
collegeGPA               1282
CollegeCityID            1350
CollegeCityTier             2
CollegeState               26
GraduationYear             11
English                   111
Logical                   107
Quant                     138
Domain                    243
ComputerProgramming        79
ElectronicsAndSemicon      29
ComputerScience            20
MechanicalEngg             42
ElectricalEngg             31
TelecomEngg                26
CivilEngg                  23
conscientiousness         141
agreeableness             149
extraversion              154
nueroticism               217
openess_to_experience     142
dtype: int64
```

```
ID: A unique ID to identify a candidate
Salary: Annual CTC offered to the candidate (in INR)
Gender: Candidate's gender
DOB: Date of birth of the candidate
10percentage: Overall marks obtained in grade 10 examinations
10board: The school board whose curriculum the candidate followed in grade 10
12graduation: Year of graduation - senior year high school
12percentage: Overall marks obtained in grade 12 examinations
12board: The school board whose curriculum the candidate followed
CollegeID: Unique ID identifying the university/college which the candidate attended for her/his undergraduate
CollegeTier: Each college has been annotated as 1 or 2. The annotations have been computed from the average AMCAT scores                      obtained by the students in the college/university. Colleges with an average score above a threshold are tagged as             1 and others as 2.
Degree: Degree obtained/pursued by the candidate
Specialization: Specialization pursued by the candidate
CollegeGPA: Aggregate GPA at graduation
CollegeCityID: A unique ID to identify the city in which the college is located in.
```

```
CollegeCityTier: The tier of the city in which the college is located in. This is annotated based on the population of the                          cities.
CollegeState: Name of the state in which the college is located
GraduationYear: Year of graduation (Bachelor's degree)
English: Scores in AMCAT English section
Logical: Score in AMCAT Logical ability section
Quant: Score in AMCAT's Quantitative ability section
Domain: Scores in AMCAT's domain module
ComputerProgramming: Score in AMCAT's Computer programming section
ElectronicsAndSemicon: Score in AMCAT's Electronics & Semiconductor Engineering section
ComputerScience: Score in AMCAT's Computer Science section
MechanicalEngg: Score in AMCAT's Mechanical Engineering section
ElectricalEngg: Score in AMCAT's Electrical Engineering section
TelecomEngg: Score in AMCAT's Telecommunication Engineering section
CivilEngg: Score in AMCAT's Civil Engineering section
conscientiousness: Scores in one of the sections of AMCAT's personality test
agreeableness: Scores in one of the sections of AMCAT's personality test
extraversion: Scores in one of the sections of AMCAT's personality test
nueroticism: Scores in one of the sections of AMCAT's personality test
openess_to_experience: Scores in one of the sections of AMCAT's personality test Note: To give you more context AMCAT is a job                          portal.
```

Data Description

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3998 entries, 0 to 3997
Data columns (total 39 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   Unnamed: 0             3998 non-null   object 
 1   ID                     3998 non-null   int64  
 2   Salary                 3998 non-null   float64
 3   DOJ                    3998 non-null   object 
 4   DOL                    3998 non-null   object 
 5   Designation            3998 non-null   object 
 6   JobCity                3998 non-null   object 
 7   Gender                 3998 non-null   object 
 8   DOB                    3998 non-null   object 
 9   10percentage           3998 non-null   float64
 10  10board                3998 non-null   object 
 11  12graduation           3998 non-null   int64  
 12  12percentage           3998 non-null   float64
 13  12board                3998 non-null   object 
 14  CollegeID              3998 non-null   int64  
 15  CollegeTier            3998 non-null   int64  
 16  Degree                 3998 non-null   object 
 17  Specialization         3998 non-null   object 
 18  collegeGPA             3998 non-null   float64
 19  CollegeCityID          3998 non-null   int64  
 20  CollegeCityTier        3998 non-null   int64  
 21  CollegeState           3998 non-null   object 
 22  GraduationYear         3998 non-null   int64  
 23  English                3998 non-null   int64  
 24  Logical                3998 non-null   int64  
 25  Quant                  3998 non-null   int64  
 26  Domain                 3998 non-null   float64
 27  ComputerProgramming    3998 non-null   int64  
 28  ElectronicsAndSemicon  3998 non-null   int64  
 29  ComputerScience        3998 non-null   int64  
 30  MechanicalEngg         3998 non-null   int64  
 31  ElectricalEngg         3998 non-null   int64  
 32  TelecomEngg            3998 non-null   int64  
 33  CivilEngg              3998 non-null   int64  
 34  conscientiousness      3998 non-null   float64
 35  agreeableness          3998 non-null   float64
 36  extraversion           3998 non-null   float64
 37  nueroticism            3998 non-null   float64
 38  openess_to_experience  3998 non-null   float64
dtypes: float64(10), int64(17), object(12)
memory usage: 1.2+ MB
```

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
Unnamed: 0               0
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
```

In [9]:
```
df.duplicated().any()
```

Out[9]:
```
False
```

In [10]:
```
df.describe().style.background_gradient(cmap='plasma')
```

Out[10]:

	ID	Salary	10percentage	12graduation	12percentage	CollegeID	CollegeTier	collegeGPA
count	3998.000000	3998.000000	3998.000000	3998.000000	3998.000000	3998.000000	3998.000000	3998.00000
mean	663794.540520	307699.849925	77.925443	2008.087544	74.466366	5156.851426	1.925713	71.48617
std	363218.245829	212737.499957	9.850162	1.653599	10.999933	4802.261482	0.262270	8.16733
min	11244.000000	35000.000000	43.000000	1995.000000	40.000000	2.000000	1.000000	6.45000
25%	334284.250000	180000.000000	71.680000	2007.000000	66.000000	494.000000	2.000000	66.40750
50%	639600.000000	300000.000000	79.150000	2008.000000	74.400000	3879.000000	2.000000	71.72000
75%	990480.000000	370000.000000	85.670000	2009.000000	82.600000	8818.000000	2.000000	76.32750
max	1298275.000000	4000000.000000	97.760000	2013.000000	98.700000	18409.000000	2.000000	99.93000

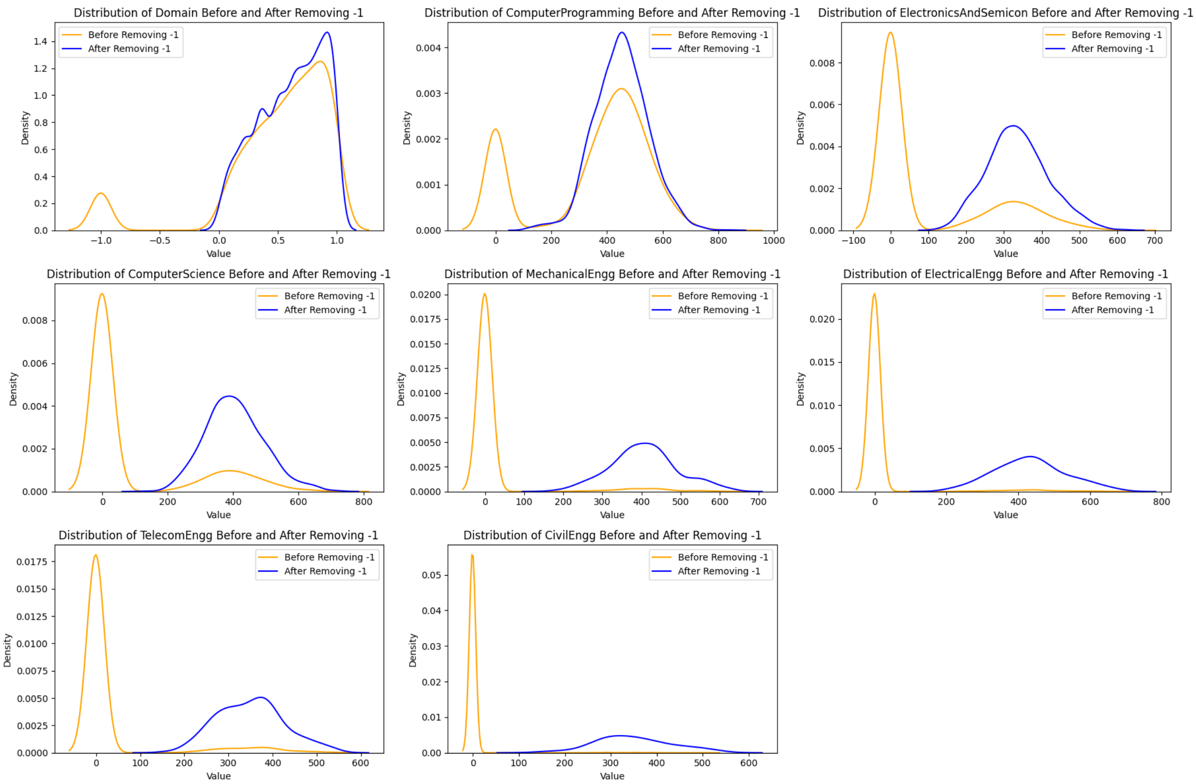
Data Preprocessing

In [11]:
```python
# creating list of categorical columns for one hot encoding
categorical_columns = [col for col in df.columns if df.dtypes[col] == 'object']

# creating list of numerical columns to standardized data
numerical_columns = [col for col in df.columns if (df.dtypes[col] != 'object')]

print('Numerical Features are : ',numerical_columns)
print('\n')
print('Categorical Features are : ',categorical_columns)
```

```
Numerical Features are :  ['ID', 'Salary', '10percentage', '12graduation', '12percentage', 'Colle
geID', 'CollegeTier', 'collegeGPA', 'CollegeCityID', 'CollegeCityTier', 'GraduationYear', 'Englis
h', 'Logical', 'Quant', 'Domain', 'ComputerProgramming', 'ElectronicsAndSemicon', 'ComputerScienc
e', 'MechanicalEngg', 'ElectricalEngg', 'TelecomEngg', 'CivilEngg', 'conscientiousness', 'agreeab
leness', 'extraversion', 'nueroticism', 'openess_to_experience']


Categorical Features are :  ['Unnamed: 0', 'DOJ', 'DOL', 'Designation', 'JobCity', 'Gender', 'DO
B', '10board', '12board', 'Degree', 'Specialization', 'CollegeState']
```

Assuming 'data' is your DataFrame and 'columns_to_check' are the columns with -1 values

In [12]:
```python

columns_to_check = ['Domain', 'ComputerProgramming', 'ElectronicsAndSemicon', 'ComputerScience', 'M

plt.figure(figsize=(18, 12))

for i, column_name in enumerate(columns_to_check, start=1):  # Use start=1 to start subplot numberi
    plt.subplot(3, 3, i)  # Assuming you want a 3x3 grid of subplots
    sns.kdeplot(df[column_name], color='orange', label='Before Removing -1')
    filtered_df = df[df[column_name] != -1]
    sns.kdeplot(filtered_df[column_name], color='blue', label='After Removing -1')
    plt.xlabel('Value')
    plt.ylabel('Density')
    plt.title('Distribution of ' + column_name + ' Before and After Removing -1')
    plt.legend()

plt.tight_layout()
plt.show()
```



After analyzing the plots above, we conclude that before and after removing the -1 values, the graphs show varying changes in density. Some columns exhibit an increase in density, while others show a decrease. This observation suggests that the removal of -1 values impacts the distribution of data differently across columns.

In [13]:
```
df1 = df.copy()
```

Datatype Conversion

Replace -1 with NaN for numerical & objective columns

In [14]:
```
df1.replace(-1, np.NaN,inplace=True)
```

In [15]:
```
# Replace -1 with NaN for object columns
obj_columns = df.select_dtypes(include='object').columns
df1[obj_columns] = df1[obj_columns].replace('-1', np.NaN)
```

In [16]:
```
### show the DOL column values counts
```

In [17]:
```
# show the DOL column values counts
df1['DOL'].value_counts()
```

Out[17]:
```
DOL
present         1875
4/1/15 0:00      573
3/1/15 0:00      124
5/1/15 0:00      112
1/1/15 0:00       99
                ... 
3/1/05 0:00        1
10/1/15 0:00       1
2/1/10 0:00        1
2/1/11 0:00        1
10/1/10 0:00       1
Name: count, Length: 67, dtype: int64
```

In [18]:
```
# Assuming 'data' is your DataFrame
df1['DOL'] = pd.to_datetime(df1['DOL'], errors='coerce')
```

In [19]:
```
# Assuming 'data' is your DataFrame
df1['DOB'] = pd.to_datetime(df1['DOB'])
df1['DOL'] = pd.to_datetime(df1['DOL'])
df1['DOJ'] = pd.to_datetime(df1['DOJ'])
```

In [20]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3998 entries, 0 to 3997
Data columns (total 39 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Unnamed: 0             3998 non-null   object
 1   ID                     3998 non-null   int64
 2   Salary                 3998 non-null   float64
 3   DOJ                    3998 non-null   datetime64[ns]
 4   DOL                    2123 non-null   datetime64[ns]
 5   Designation            3998 non-null   object
 6   JobCity                3537 non-null   object
 7   Gender                 3998 non-null   object
 8   DOB                    3998 non-null   datetime64[ns]
 9   10percentage           3998 non-null   float64
 10  10board                3998 non-null   object
 11  12graduation           3998 non-null   int64
 12  12percentage           3998 non-null   float64
 13  12board                3998 non-null   object
 14  CollegeID              3998 non-null   int64
 15  CollegeTier            3998 non-null   int64
 16  Degree                 3998 non-null   object
 17  Specialization         3998 non-null   object
 18  collegeGPA             3998 non-null   float64
 19  CollegeCityID          3998 non-null   int64
 20  CollegeCityTier        3998 non-null   int64
 21  CollegeState           3998 non-null   object
 22  GraduationYear         3998 non-null   int64
 23  English                3998 non-null   int64
 24  Logical                3998 non-null   int64
 25  Quant                  3998 non-null   int64
 26  Domain                 3752 non-null   float64
 27  ComputerProgramming    3130 non-null   float64
 28  ElectronicsAndSemicon  1144 non-null   float64
 29  ComputerScience        902 non-null    float64
 30  MechanicalEngg         235 non-null    float64
 31  ElectricalEngg         161 non-null    float64
 32  TelecomEngg            374 non-null    float64
 33  CivilEngg              42 non-null     float64
 34  conscientiousness      3998 non-null   float64
 35  agreeableness          3998 non-null   float64
 36  extraversion           3998 non-null   float64
 37  nueroticism            3998 non-null   float64
 38  openess_to_experience  3998 non-null   float64
dtypes: datetime64[ns](3), float64(17), int64(10), object(9)
memory usage: 1.2+ MB
```

In [21]:
```
df1.isnull().sum()/len(df1)*100
```

Out[21]:
```
Unnamed: 0                0.000000
ID                        0.000000
Salary                    0.000000
DOJ                       0.000000
DOL                      46.898449
Designation               0.000000
JobCity                  11.530765
Gender                    0.000000
DOB                       0.000000
10percentage              0.000000
10board                   0.000000
12graduation              0.000000
12percentage              0.000000
12board                   0.000000
CollegeID                 0.000000
CollegeTier               0.000000
Degree                    0.000000
Specialization            0.000000
collegeGPA                0.000000
CollegeCityID             0.000000
CollegeCityTier           0.000000
CollegeState              0.000000
GraduationYear            0.000000
English                   0.000000
Logical                   0.000000
Quant                     0.000000
Domain                    6.153077
ComputerProgramming      21.710855
ElectronicsAndSemicon    71.385693
ComputerScience          77.438719
MechanicalEngg           94.122061
ElectricalEngg           95.972986
TelecomEngg              90.645323
CivilEngg                98.949475
conscientiousness         0.000000
agreeableness             0.000000
extraversion              0.000000
nueroticism               0.000000
openess_to_experience     0.000000
dtype: float64
```

In the given columns, some columns have null values exceeding 70%, while the remaining columns have zero null values.

In [22]:
```
# drop the unused columns
df1 = df1.drop(['Unnamed: 0', 'ID', 'DOJ', 'DOL', 'DOB', 'CollegeID', 'Domain', 'ComputerProgrammir

df1.head(2)
```

Out[22]:

	Salary	Designation	JobCity	Gender	10percentage	10board	12graduation	12percentage	12board	College
0	420000.0	senior quality engineer	Bangalore	f	84.3	board ofsecondary education,ap	2007	95.8	board of intermediate education,ap	
1	500000.0	assistant manager	Indore	m	85.4	cbse	2007	85.0	cbse	

outlier

In [23]:
```python
df['Salary'].describe()
```

Out[23]:
```
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
Name: Salary, dtype: float64
```

In [24]:
```python
# Calculate the IQR
Q1 = df1['Salary'].quantile(0.25)
Q3 = df1['Salary'].quantile(0.75)
IQR = Q3 - Q1

# Define the outlier range
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Detect outliers
outliers = df1[(df1['Salary'] < lower_bound) | (df1['Salary'] > upper_bound)]
outliers.head()
```

Out[24]:

	Salary	Designation	JobCity	Gender	10percentage	10board	12graduation	12percentage	12board	College
3	1100000.0	senior software engineer	Gurgaon	m	85.60	cbse	2007	83.60	cbse	
76	800000.0	software engineer	Bangalore	m	93.44	karnataka state board	2008	90.00	karnataka state board	
92	1500000.0	application developer	Hyderabad	m	79.00	state board	2009	87.90	state board	
123	1200000.0	engineer trainee	Maharajganj	m	59.80	icse	2006	60.25	isc	
128	675000.0	senior software engineer	Noida	m	60.00	0	2004	59.00	0	

In [25]:
```python
# Remove outliers
df1 = df1[(df1['Salary'] >= lower_bound) & (df1['Salary'] <= upper_bound)]

df1
```

Out[25]:

	Salary	Designation	JobCity	Gender	10percentage	10board	12graduation	12percentage	12boarc
0	420000.0	senior quality engineer	Bangalore	f	84.30	board ofsecondary education,ap	2007	95.80	board o intermediate education,ap
1	500000.0	assistant manager	Indore	m	85.40	cbse	2007	85.00	cbse
2	325000.0	systems engineer	Chennai	f	85.00	cbse	2010	68.20	cbse
4	200000.0	get	Manesar	m	78.00	cbse	2008	76.80	cbse
5	300000.0	system engineer	Hyderabad	m	89.92	state board	2010	87.00	state boarc
...	...	...	...	...	...	...	...	...	..
3993	280000.0	software engineer	New Delhi	m	52.09	cbse	2006	55.50	cbse
3994	100000.0	technical writer	Hyderabad	f	90.00	state board	2009	93.00	state boarc
3995	320000.0	associate software engineer	Bangalore	m	81.86	bse,odisha	2008	65.50	chse,odisha
3996	200000.0	software developer	Asifabadbanglore	f	78.72	state board	2010	69.88	state boarc
3997	400000.0	senior systems engineer	Chennai	f	70.60	cbse	2008	68.00	cbse

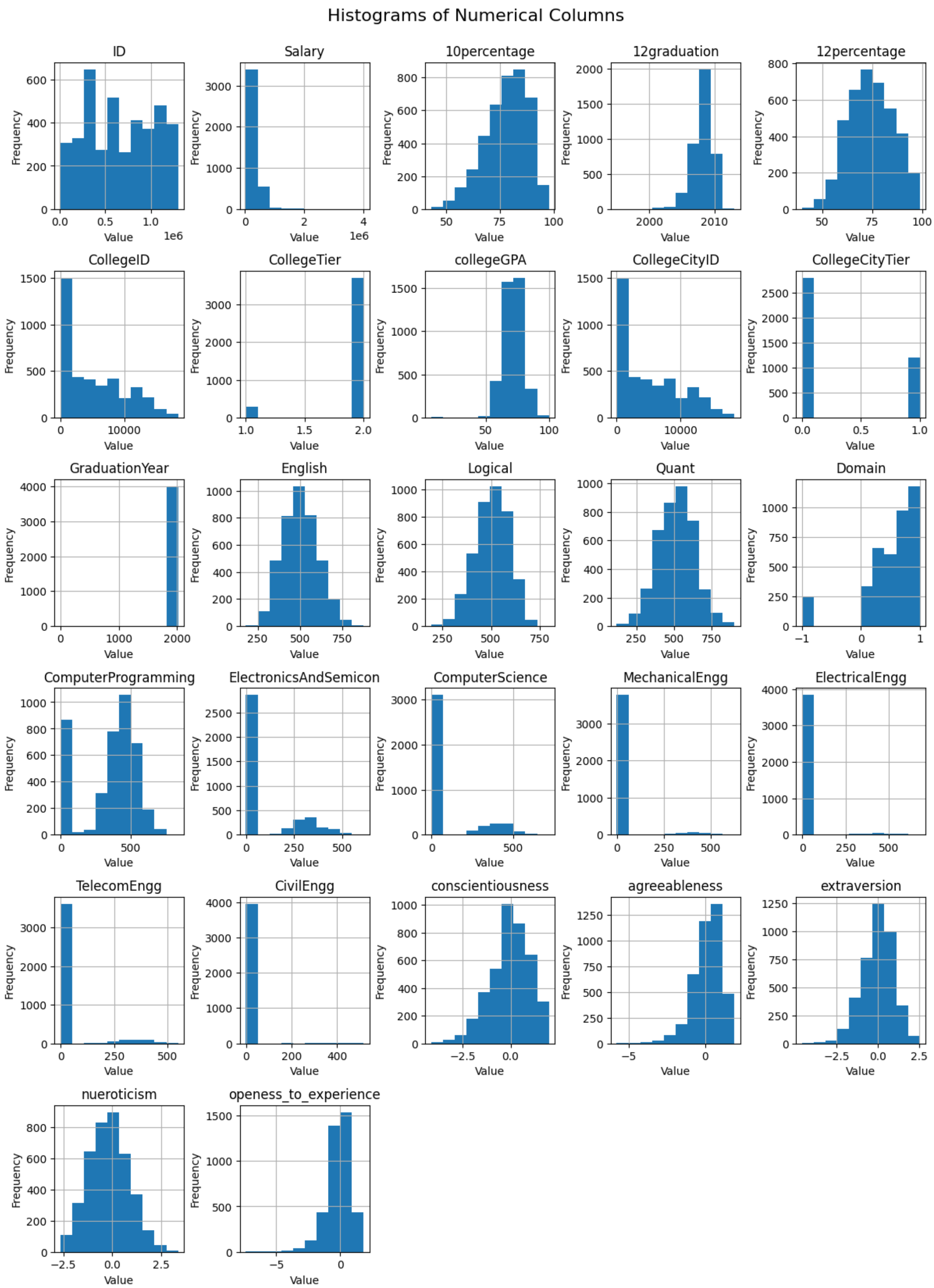
3889 rows × 25 columns

In [26]:
```python
df1['Salary'].describe()
```

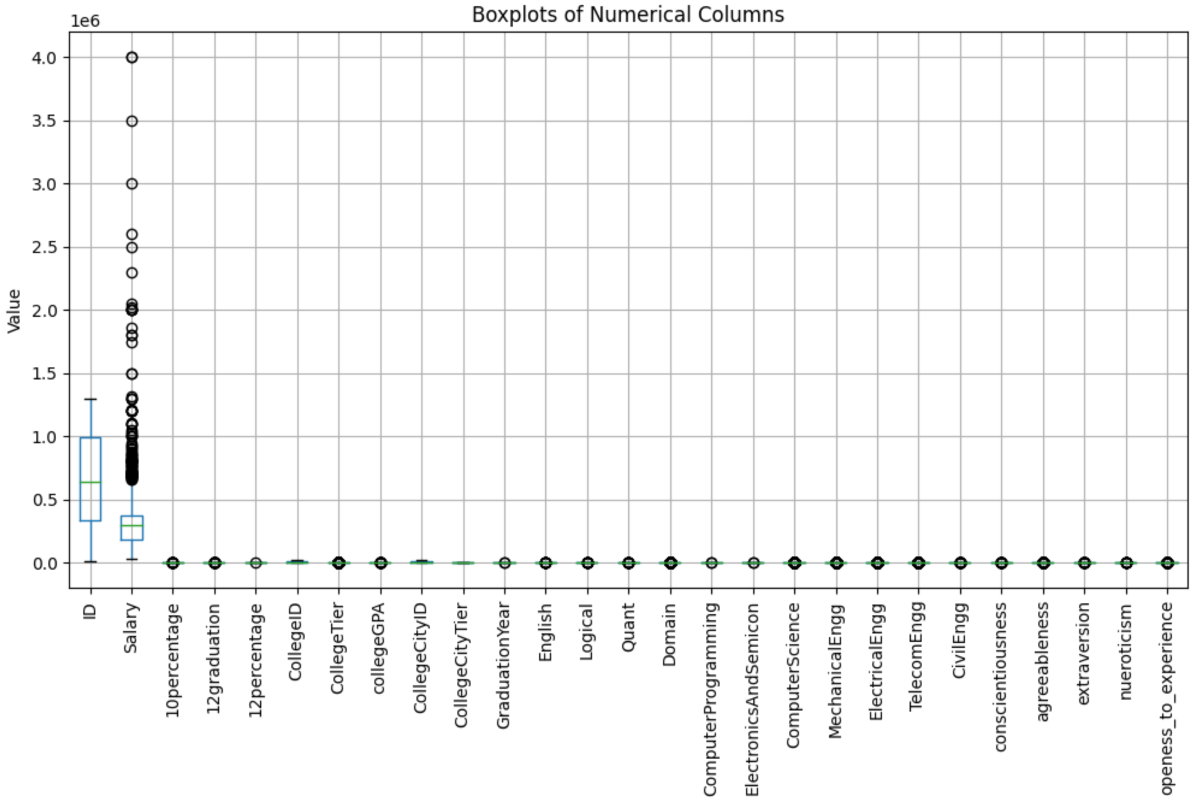
Out[26]:
```
count      3889.000000
mean     285447.158653
std      126514.542129
min       35000.000000
25%      180000.000000
50%      300000.000000
75%      360000.000000
max      655000.000000
Name: Salary, dtype: float64
```

Exploratory Data Analysis

In [27]:
```
# Histograms
df.hist(figsize=(12, 16))
plt.tight_layout()  # Adjust spacing between plots
plt.suptitle('Histograms of Numerical Columns', y=1.02, fontsize=16)  # Title for all histograms

# Labeling axes for each histogram
for ax in plt.gcf().get_axes():
    ax.set_xlabel('Value')
    ax.set_ylabel('Frequency')

plt.show()
```

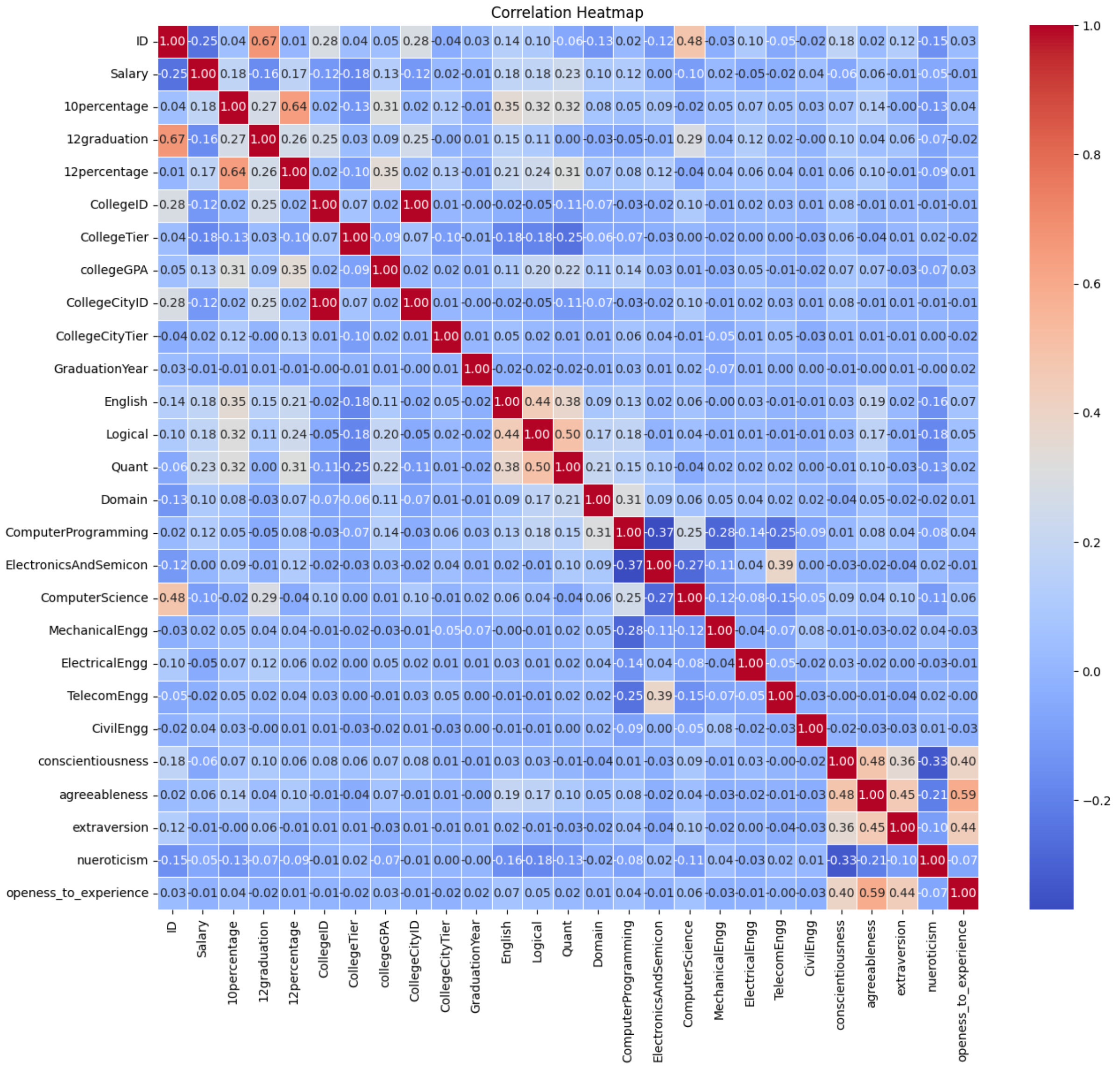


In [28]:
```
# Boxplots
plt.figure(figsize=(12, 6))
df.boxplot()
plt.title('Boxplots of Numerical Columns')
plt.ylabel('Value')
plt.xticks(rotation=90)  # Rotate x-axis labels for better readability
plt.show()
```



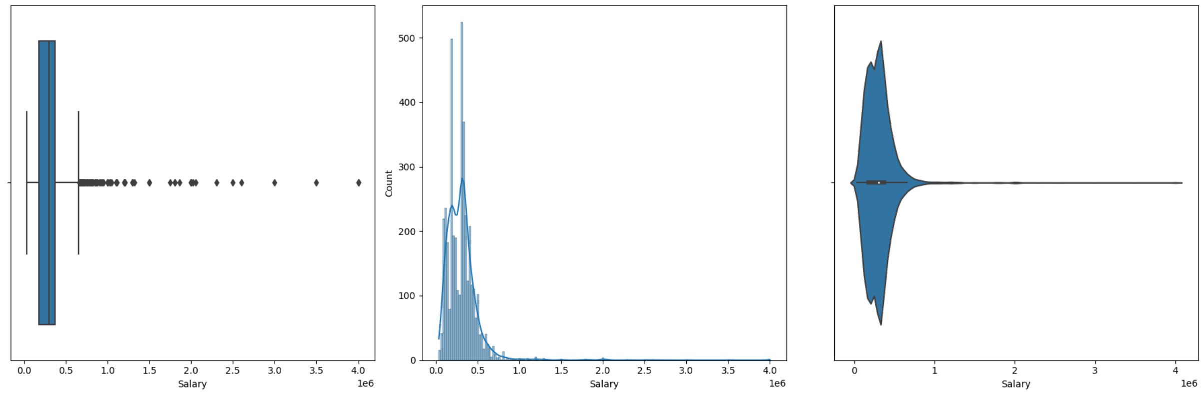
In the above plot numerical columns more ouliers in the Salary column

In [29]:
```python
temp = df.select_dtypes(include=['int64', 'float64'])

plt.figure(figsize=(15, 13))
sns.heatmap(temp.corr(), annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()
```

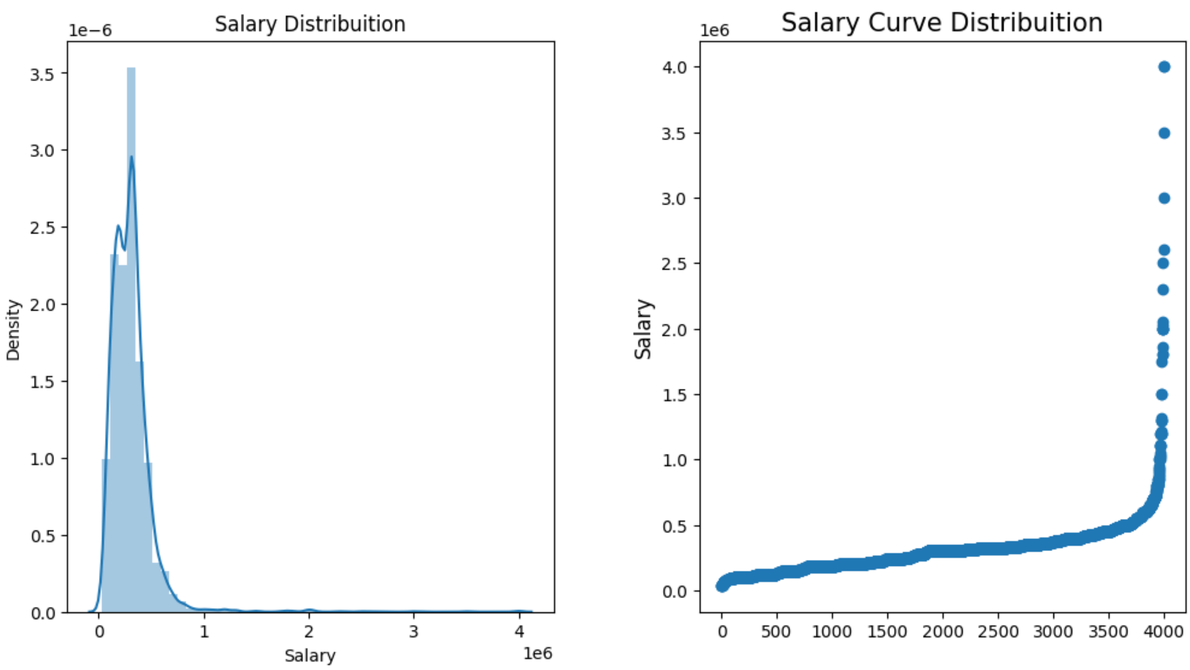


Univariate Analysis

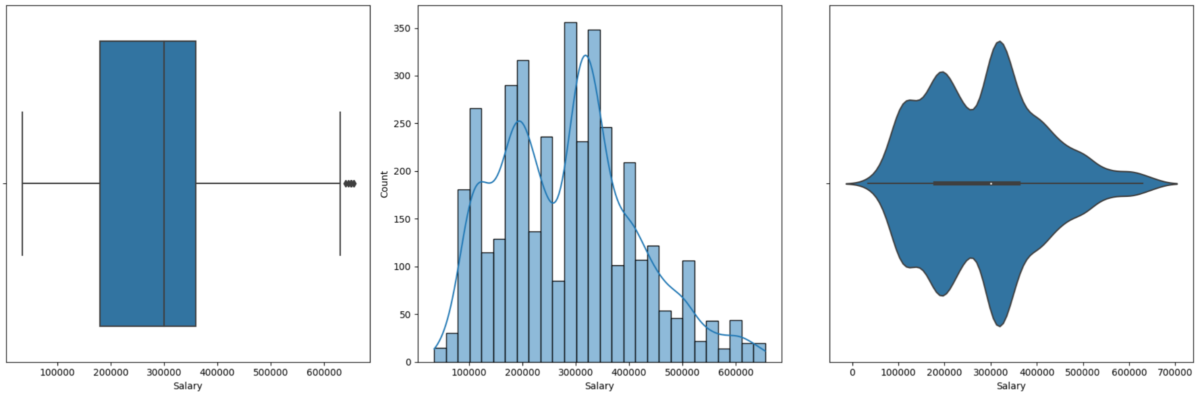
In [30]:
```python
plt.figure(figsize=(18, 6))

# Boxplot
plt.subplot(1, 3, 1)
sns.boxplot(x='Salary', data=df)

# Histogram with KDE
plt.subplot(1, 3, 2)
sns.histplot(df['Salary'], kde=True)

# Violin plot
plt.subplot(1, 3, 3)
sns.violinplot(x='Salary', data=df)

plt.tight_layout()
plt.show()
```



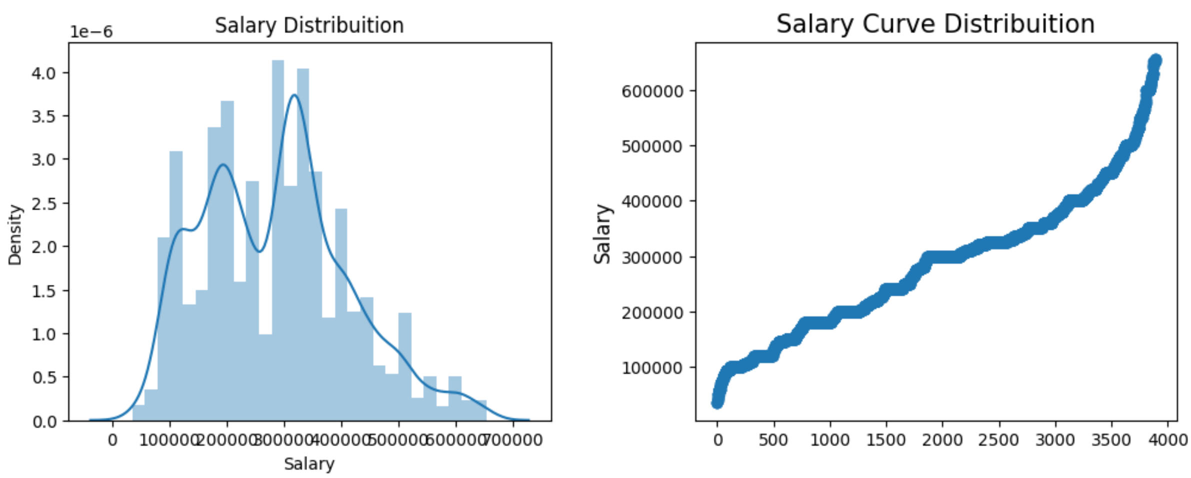
In [31]:
```python
plt.figure(figsize = (12, 6))

plt.subplot(121)
plt.title('Salary Distribuition')
sns.distplot(df['Salary'])

plt.subplot(122)
g1 = plt.scatter(range(df.shape[0]), np.sort(df.Salary.values))
g1= plt.title("Salary Curve Distribuition", fontsize=15)
g1 = plt.xlabel("")
g1 = plt.ylabel("Salary", fontsize=12)

plt.subplots_adjust(wspace = 0.3, hspace = 0.5,
                    top = 0.9)
plt.show()
```



In [32]:
```python
# Without Outliers
plt.figure(figsize=(18, 6))

# Boxplot
plt.subplot(1, 3, 1)
sns.boxplot(x='Salary', data=df1)

# Histogram with KDE
plt.subplot(1, 3, 2)
sns.histplot(df1['Salary'], kde=True)

# Violin plot
plt.subplot(1, 3, 3)
sns.violinplot(x='Salary', data=df1)
plt.tight_layout()
plt.show()
```

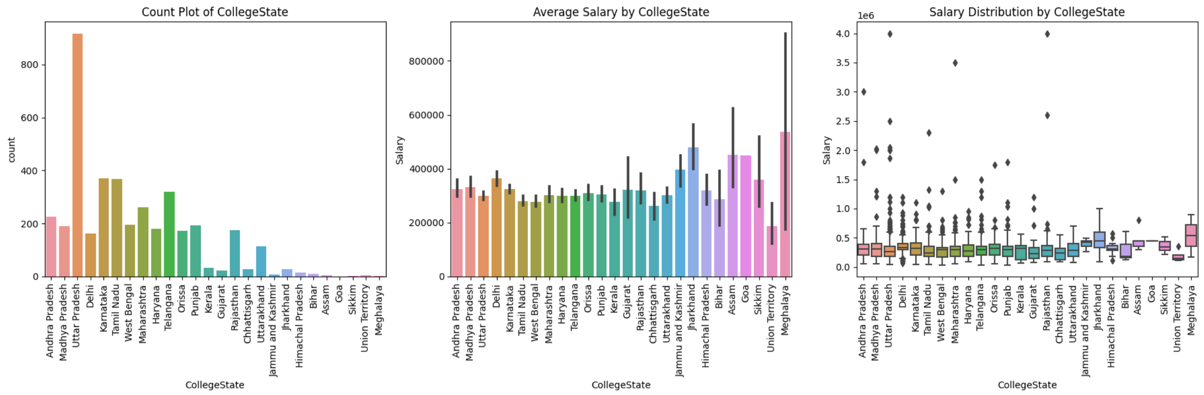


In [33]:
```python
# Without Outliers
plt.figure(figsize = (12, 4))

plt.subplot(121)
plt.title('Salary Distribuition')
sns.distplot(df1['Salary'])

plt.subplot(122)
g1 = plt.scatter(range(df1.shape[0]), np.sort(df1.Salary.values))
g1= plt.title("Salary Curve Distribuition", fontsize=15)
g1 = plt.xlabel("")
g1 = plt.ylabel("Salary", fontsize=12)

plt.subplots_adjust(wspace = 0.3, hspace = 0.5,
                    top = 0.9)
plt.show()
```

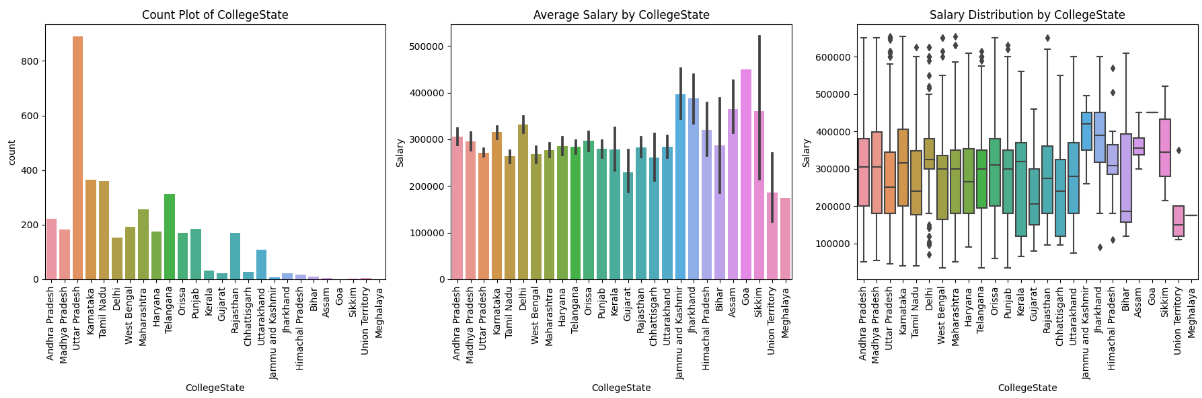


Most graduates have salaries under 6 lakhs, indicating a prevalent lower salary range among this group. The distribution of salaries appears to be positively skewed, as evidenced by a long tail on the right-hand side of the distribution compared to the left-hand side. This skewness suggests that while the majority of graduates earn lower salaries, there is a smaller number of graduates earning significantly higher salaries, leading to a rightward skew in the salary distribution

In [34]:
```
plt.figure(figsize=(18, 6))

# Countplot
plt.subplot(1, 3, 1)
sns.countplot(x='CollegeState', data=df)
plt.title('Count Plot of CollegeState')
plt.xticks(rotation=90)

# Barplot
plt.subplot(1, 3, 2)
sns.barplot(x='CollegeState', y='Salary', data=df)
plt.title('Average Salary by CollegeState')
plt.xticks(rotation=90)

# Boxplot
plt.subplot(1, 3, 3)
sns.boxplot(x='CollegeState', y='Salary', data=df)
plt.title('Salary Distribution by CollegeState')
plt.xticks(rotation=90)

plt.tight_layout()
plt.show()
```



In [35]:
```
# Without Outliers
plt.figure(figsize=(18, 6))

# Countplot
plt.subplot(1, 3, 1)
sns.countplot(x='CollegeState', data=df1)
plt.title('Count Plot of CollegeState')
plt.xticks(rotation=90)

# Barplot
plt.subplot(1, 3, 2)
sns.barplot(x='CollegeState', y='Salary', data=df1)
plt.title('Average Salary by CollegeState')
plt.xticks(rotation=90)

# Boxplot
plt.subplot(1, 3, 3)
sns.boxplot(x='CollegeState', y='Salary', data=df1)
plt.title('Salary Distribution by CollegeState')
plt.xticks(rotation=90)

plt.tight_layout()
plt.show()
```

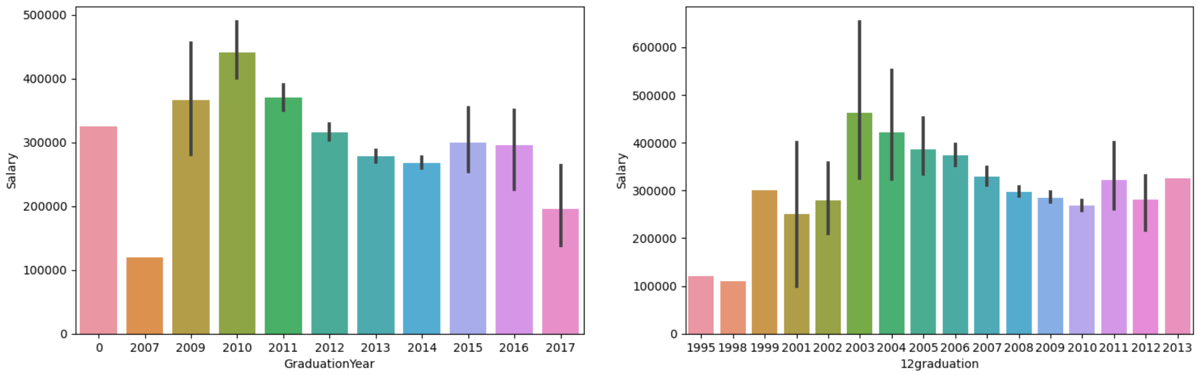


It is clearly visible from the plot that the most of the colleges located in Uttar pradesh

Bivariate Analysis

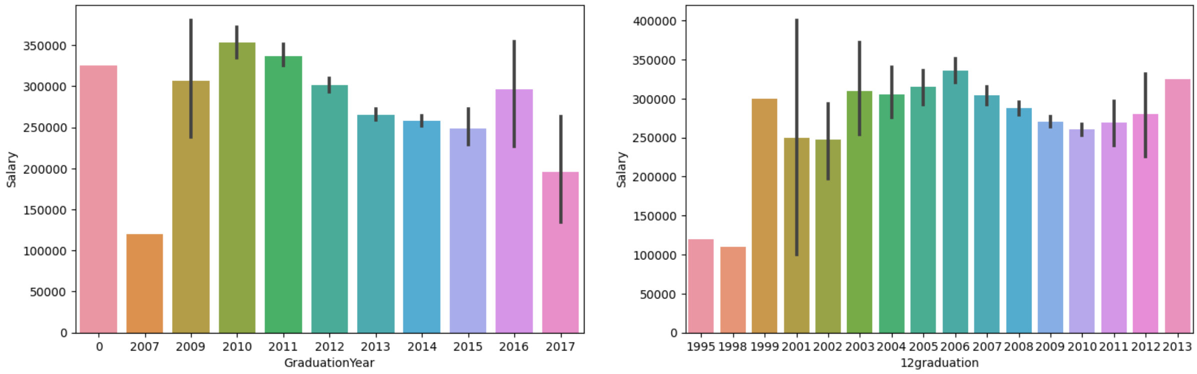
In [36]:
```
plt.figure(figsize = (17,5))
plt.subplot(1,2,1)
sns.barplot(data = df , x = 'GraduationYear',y = 'Salary')
plt.subplot(1,2,2)
sns.barplot(data = df , x = '12graduation',y = 'Salary')
```

Out[36]: <Axes: xlabel='12graduation', ylabel='Salary'>



In [37]:
```
# Without Outliers
plt.figure(figsize = (17,5))
plt.subplot(1,2,1)
sns.barplot(data = df1 , x = 'GraduationYear',y = 'Salary')
plt.subplot(1,2,2)
sns.barplot(data = df1 , x = '12graduation',y = 'Salary')
```

Out[37]: <Axes: xlabel='12graduation', ylabel='Salary'>

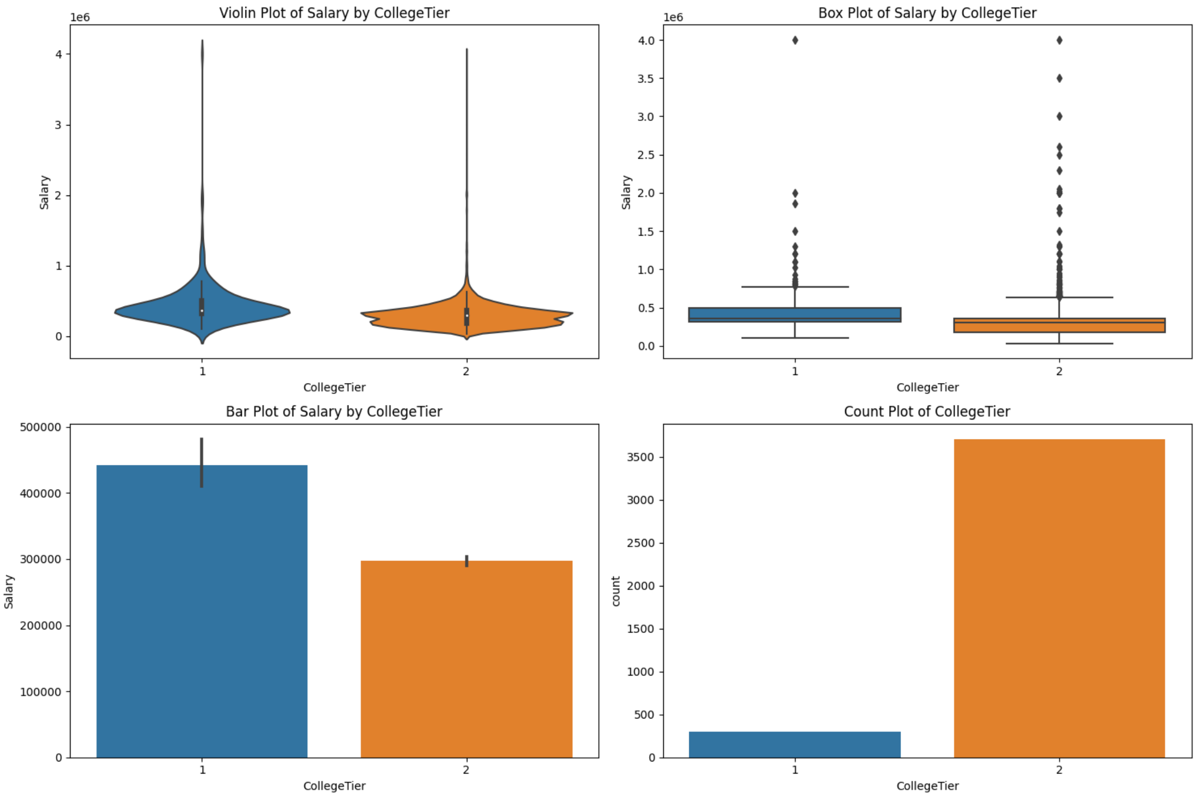


The data suggests that individuals who graduated in 2010 tend to have higher salaries.

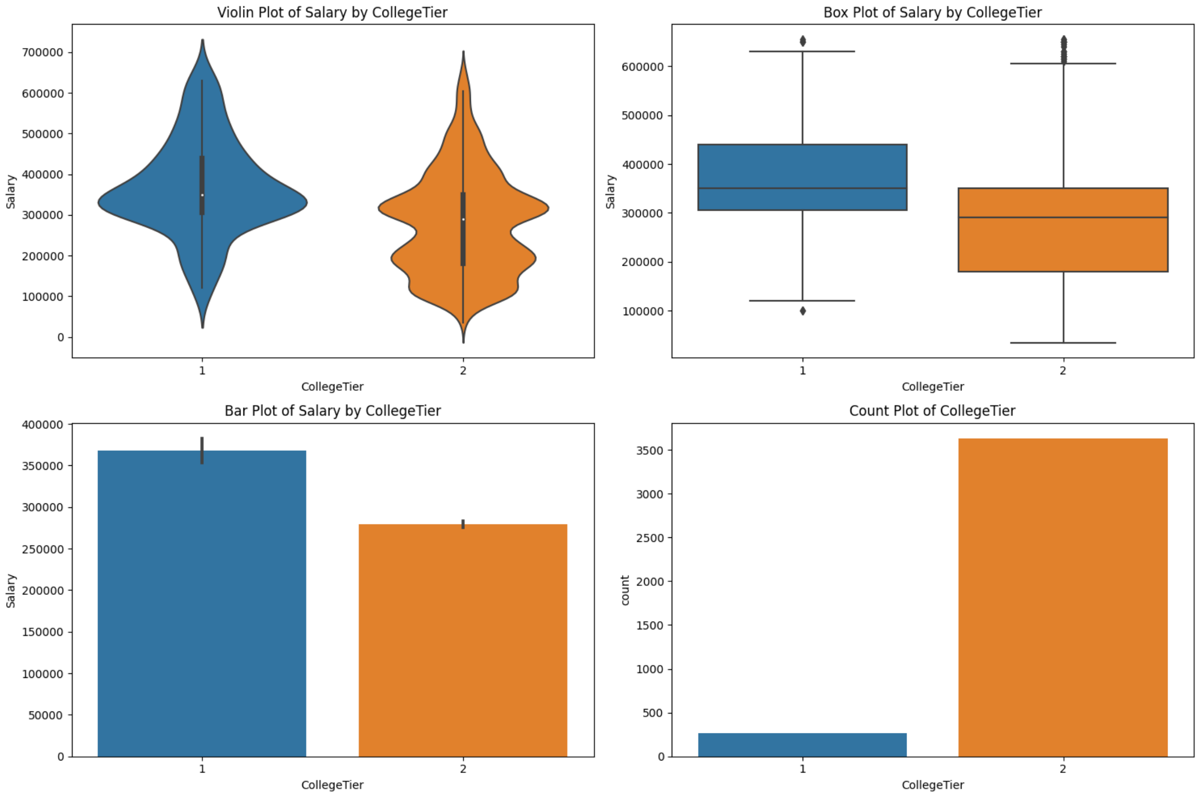
However, after removing outliers, the trend changes, and individuals who completed their 12th grade in 2003 have a higher chance of earning more. This changes to 2015 after removing outliers.

In [38]:
```python
print(df['CollegeTier'].value_counts())
fig, axs = plt.subplots(2, 2, figsize=(15, 10))

# Violin plot
sns.violinplot(x='CollegeTier', y='Salary', data=df, ax=axs[0, 0])
axs[0, 0].set_title('Violin Plot of Salary by CollegeTier')

# Box plot
sns.boxplot(x='CollegeTier', y='Salary', data=df, ax=axs[0, 1])
axs[0, 1].set_title('Box Plot of Salary by CollegeTier')

# Bar plot
sns.barplot(x='CollegeTier', y='Salary', data=df, ax=axs[1, 0])
axs[1, 0].set_title('Bar Plot of Salary by CollegeTier')

# Count plot
sns.countplot(x='CollegeTier', data=df, ax=axs[1, 1])
axs[1, 1].set_title('Count Plot of CollegeTier')

plt.tight_layout()
plt.show()
```

```
CollegeTier
2    3701
1     297
Name: count, dtype: int64
```

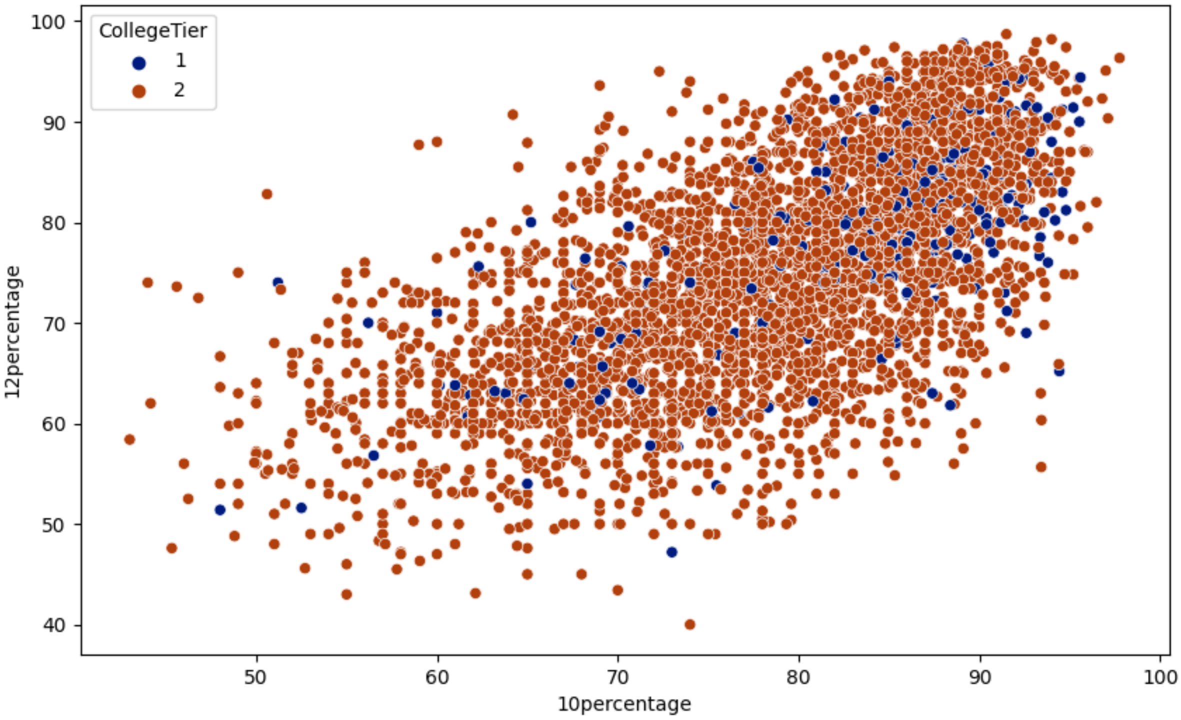


```
In [39]: # Without Outliers
fig, axs = plt.subplots(2, 2, figsize=(15, 10))

# Violin plot
sns.violinplot(x='CollegeTier', y='Salary', data=df1, ax=axs[0, 0])
axs[0, 0].set_title('Violin Plot of Salary by CollegeTier')

# Box plot
sns.boxplot(x='CollegeTier', y='Salary', data=df1, ax=axs[0, 1])
axs[0, 1].set_title('Box Plot of Salary by CollegeTier')

# Bar plot
sns.barplot(x='CollegeTier', y='Salary', data=df1, ax=axs[1, 0])
axs[1, 0].set_title('Bar Plot of Salary by CollegeTier')

# Count plot
sns.countplot(x='CollegeTier', data=df1, ax=axs[1, 1])
axs[1, 1].set_title('Count Plot of CollegeTier')

plt.tight_layout()
plt.show()
```



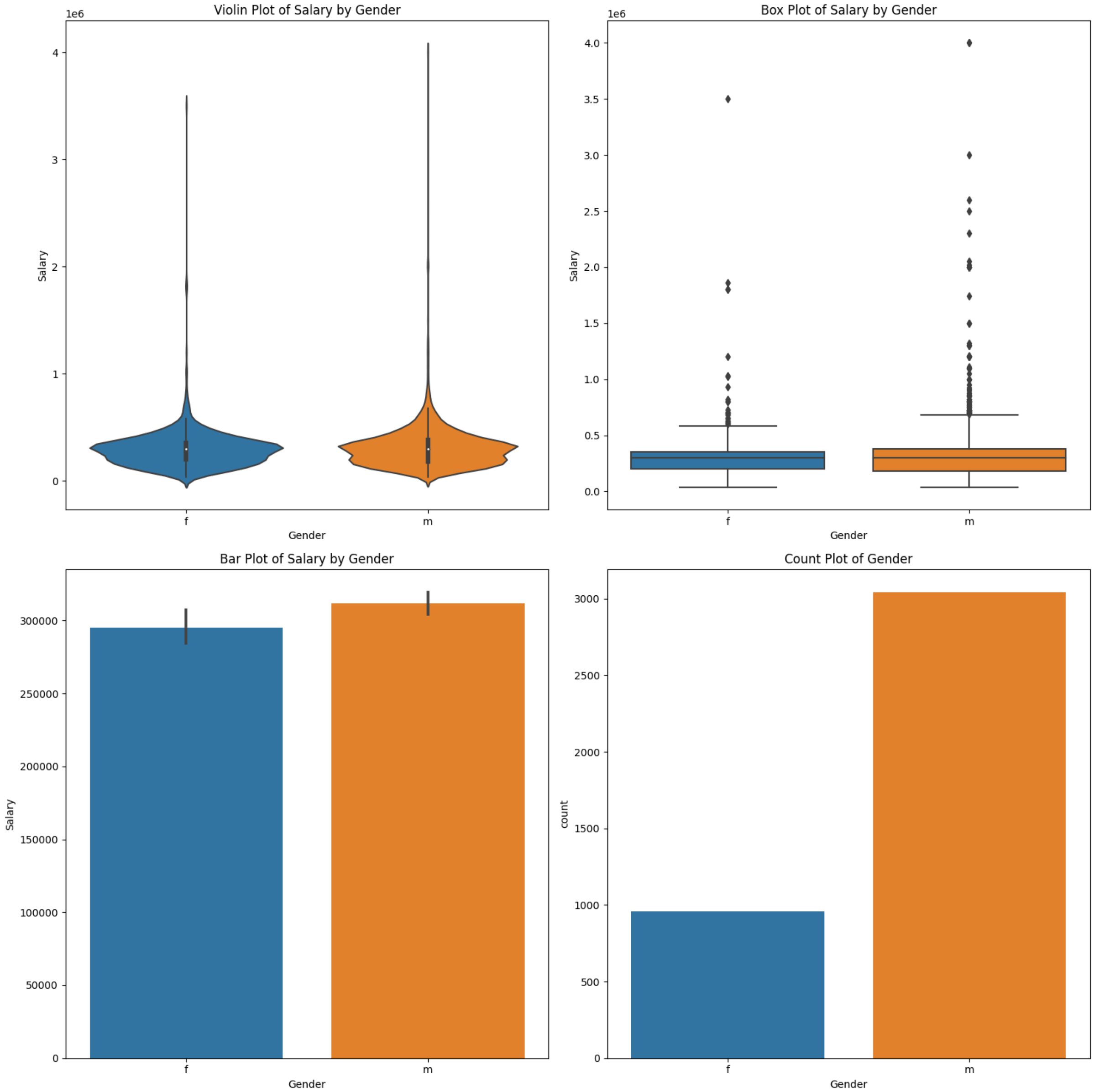
It is evident from the plot that the average salary for Tier 1 and Tier 2 appears to be higher. However, the number of Tier 2 individuals is three times higher than the number of Tier 1 individuals.

In [40]:
```
plt.figure(figsize=(10,6))
sns.scatterplot(x = '10percentage', y = '12percentage', hue = 'CollegeTier',palette='dark', data =
plt.show()
```

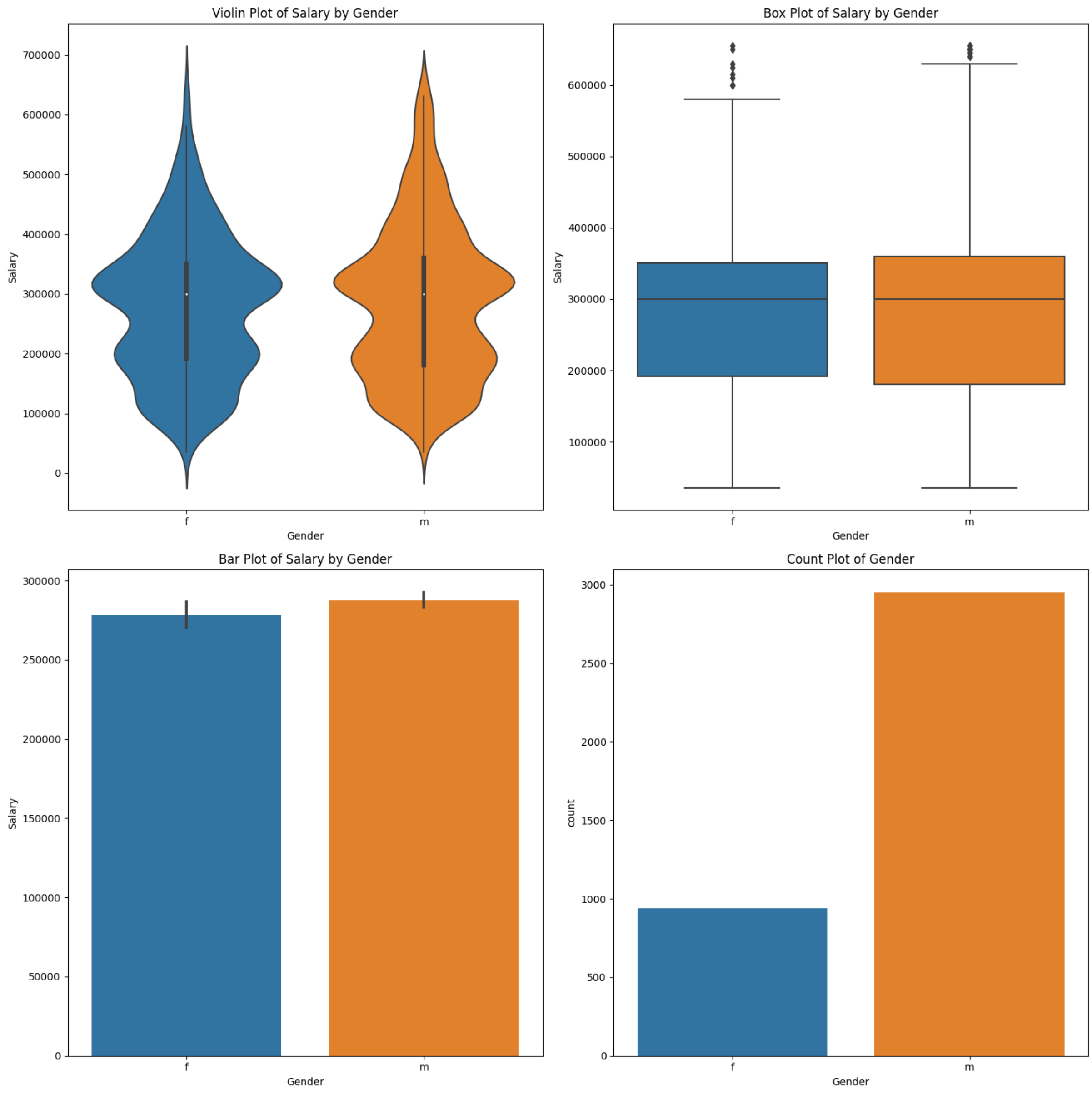


Based on the correlation plot and scatterplot, it is evident that the 10th and 12th grades are positively correlated. This indicates multicollinearity between the two variables. To address this issue, I have decided to keep only one of the grades in my analysis

In [41]:
```python
fig, axs = plt.subplots(2, 2, figsize=(15, 15))

# Violin plot
sns.violinplot(x='Gender', y='Salary', data=df, ax=axs[0, 0])
axs[0, 0].set_title('Violin Plot of Salary by Gender')

# Box plot
sns.boxplot(x='Gender', y='Salary', data=df, ax=axs[0, 1])
axs[0, 1].set_title('Box Plot of Salary by Gender')

# Bar plot
sns.barplot(x='Gender', y='Salary', data=df, ax=axs[1, 0])
axs[1, 0].set_title('Bar Plot of Salary by Gender')

# Count plot
sns.countplot(x='Gender', data=df, ax=axs[1, 1])
axs[1, 1].set_title('Count Plot of Gender')

plt.tight_layout()
plt.show()
```



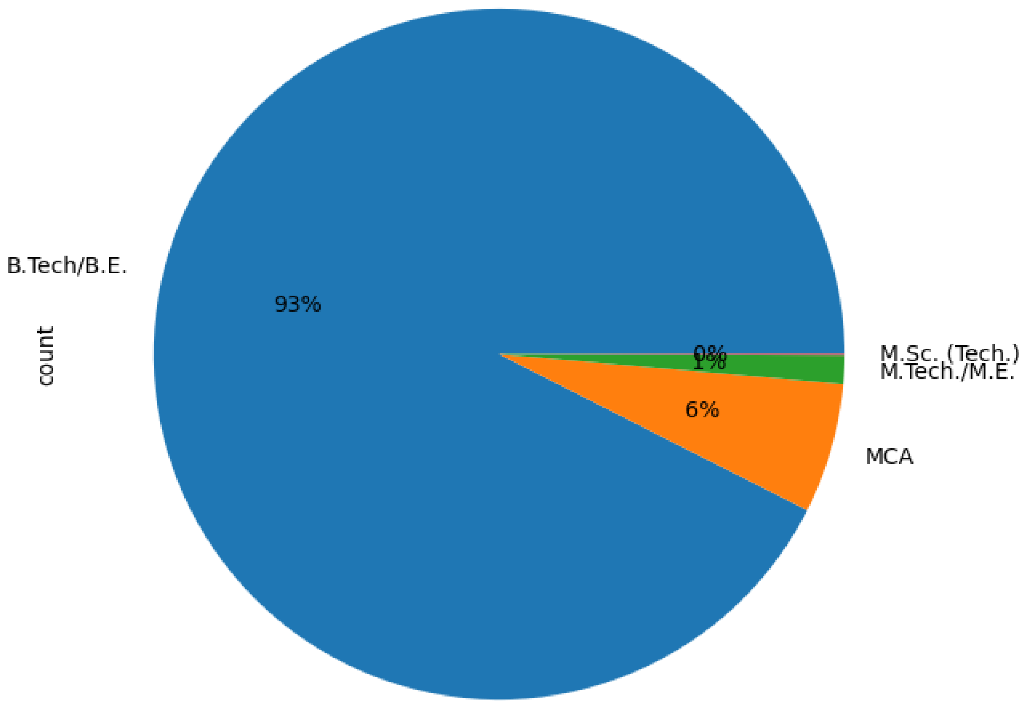
In [42]:
```python
# Without Outliers
fig, axs = plt.subplots(2, 2, figsize=(15, 15))

# Violin plot
sns.violinplot(x='Gender', y='Salary', data=df1, ax=axs[0, 0])
axs[0, 0].set_title('Violin Plot of Salary by Gender')

# Box plot
sns.boxplot(x='Gender', y='Salary', data=df1, ax=axs[0, 1])
axs[0, 1].set_title('Box Plot of Salary by Gender')

# Bar plot
sns.barplot(x='Gender', y='Salary', data=df1, ax=axs[1, 0])
axs[1, 0].set_title('Bar Plot of Salary by Gender')

# Count plot
sns.countplot(x='Gender', data=df1, ax=axs[1, 1])
axs[1, 1].set_title('Count Plot of Gender')

plt.tight_layout()
plt.show()
```



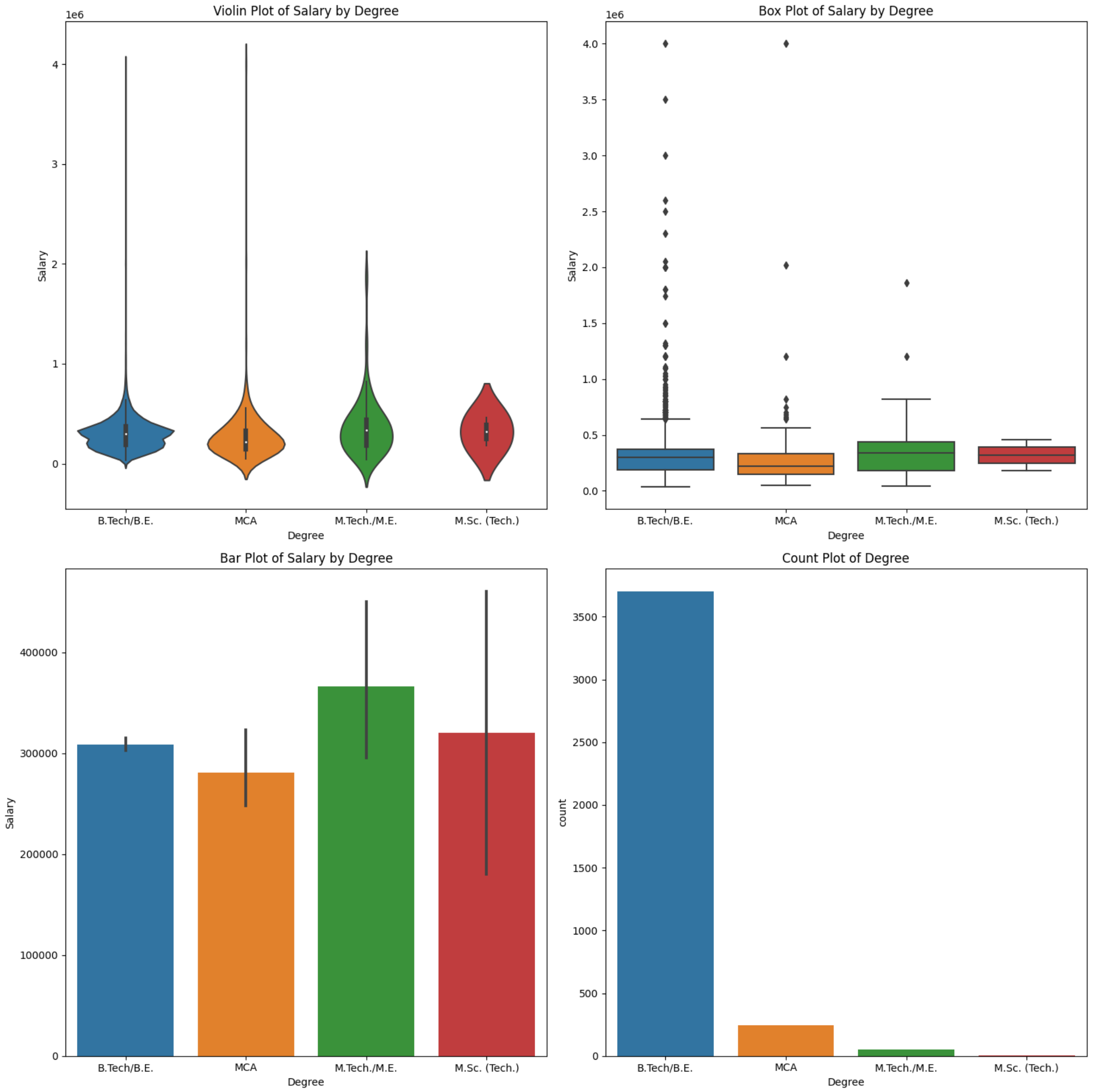
It is evident from the plot that the average salary for men and women appears to be almost the same. However, the number of males is three times higher than the number of females.

In [43]:
```
plt.figure(figsize = (7,7))
df['Degree'].value_counts().plot(kind = 'pie', autopct='%2.0f%%')

print(df['Degree'].value_counts())
```

```
Degree
B.Tech/B.E.      3700
MCA               243
M.Tech./M.E.       53
M.Sc. (Tech.)       2
Name: count, dtype: int64
```

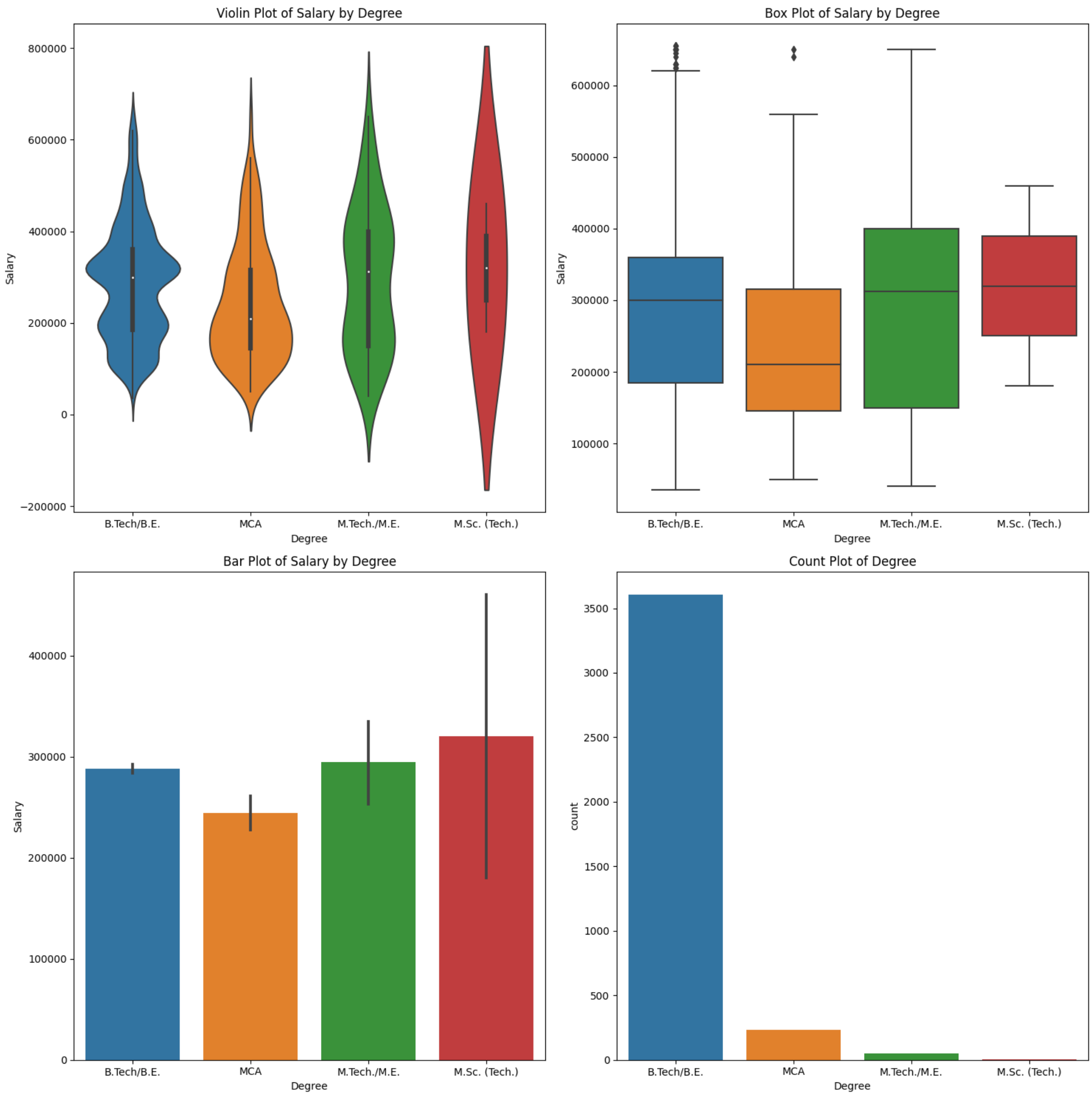


In [44]:
```
fig, axs = plt.subplots(2, 2, figsize=(15, 15))

# Violin plot
sns.violinplot(x='Degree', y='Salary', data=df, ax=axs[0, 0])
axs[0, 0].set_title('Violin Plot of Salary by Degree')

# Box plot
sns.boxplot(x='Degree', y='Salary', data=df, ax=axs[0, 1])
axs[0, 1].set_title('Box Plot of Salary by Degree')

# Bar plot
sns.barplot(x='Degree', y='Salary', data=df, ax=axs[1, 0])
axs[1, 0].set_title('Bar Plot of Salary by Degree')

# Count plot
sns.countplot(x='Degree', data=df, ax=axs[1, 1])
axs[1, 1].set_title('Count Plot of Degree')

plt.tight_layout()
plt.show()
```



In [45]:

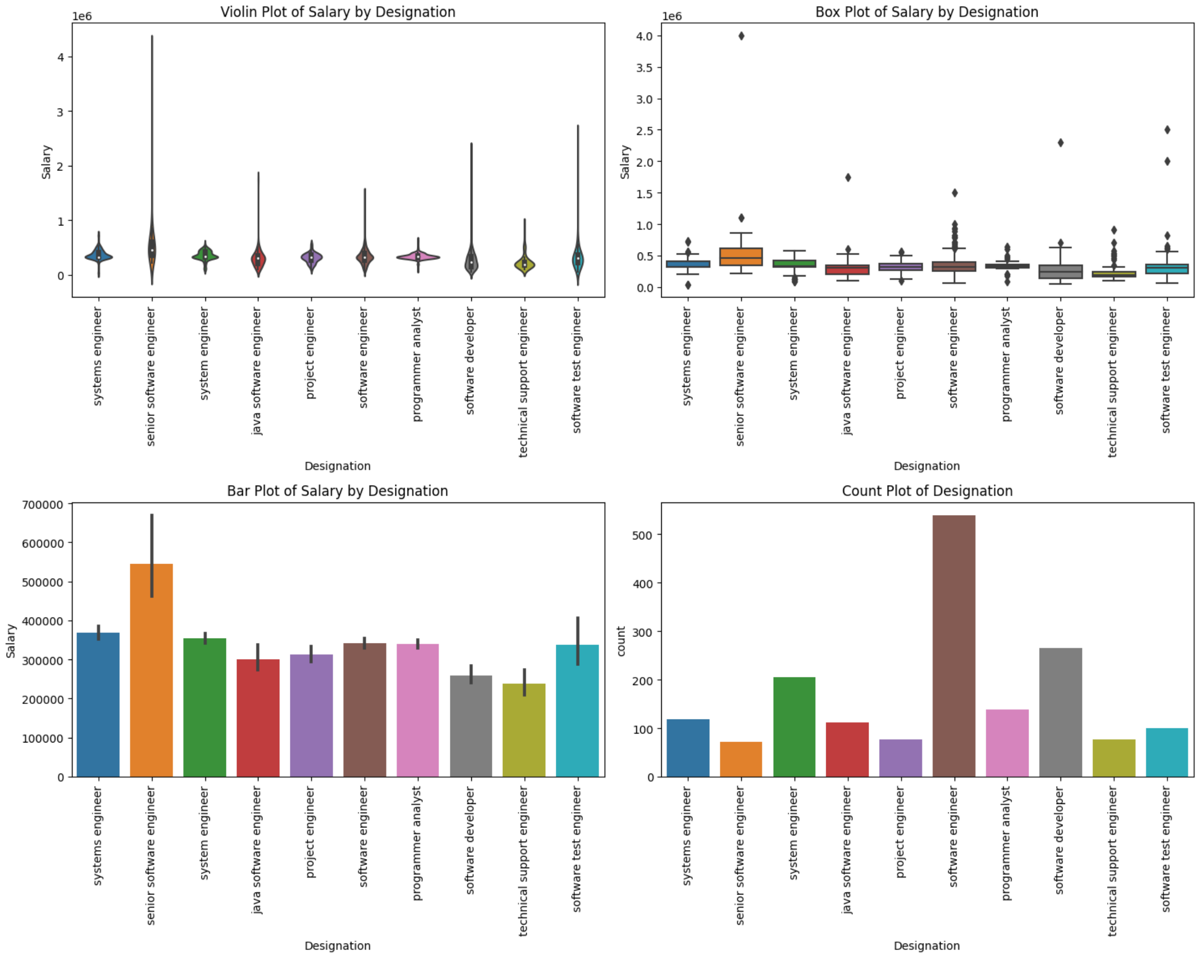
```
# Without Outliers
fig, axs = plt.subplots(2, 2, figsize=(15, 15))

# Violin plot
sns.violinplot(x='Degree', y='Salary', data=df1, ax=axs[0, 0])
axs[0, 0].set_title('Violin Plot of Salary by Degree')

# Box plot
sns.boxplot(x='Degree', y='Salary', data=df1, ax=axs[0, 1])
axs[0, 1].set_title('Box Plot of Salary by Degree')

# Bar plot
sns.barplot(x='Degree', y='Salary', data=df1, ax=axs[1, 0])
axs[1, 0].set_title('Bar Plot of Salary by Degree')

# Count plot
sns.countplot(x='Degree', data=df1, ax=axs[1, 1])
axs[1, 1].set_title('Count Plot of Degree')

plt.tight_layout()
plt.show()
```



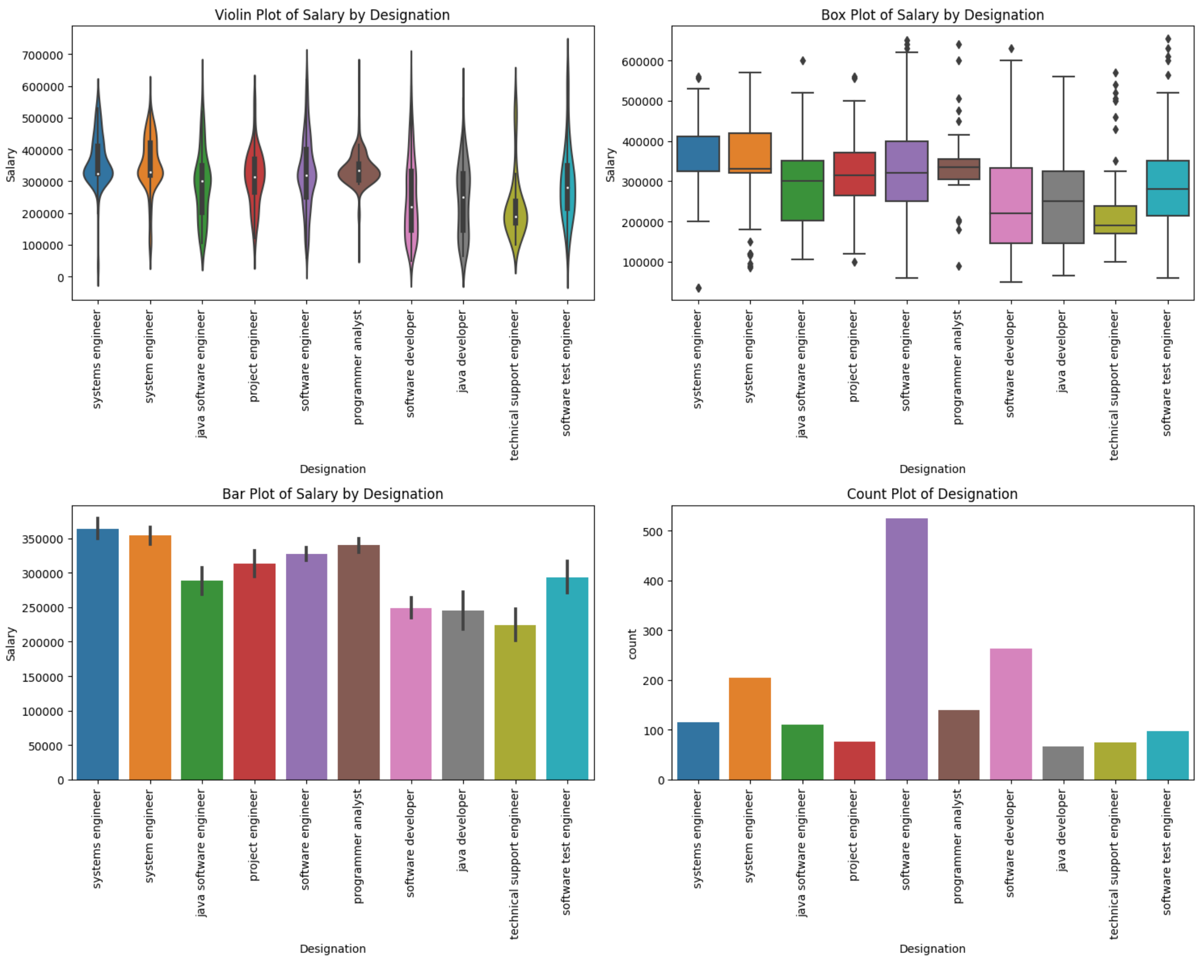
Average salary is highest for BE/B.tech graduates as compared to any other degree graduates.

According to the graph below, only 7 percent of BTech students are pursuing higher education, indicating that the majority of BTech students are not continuing their studies beyond their current degree.

In [46]:
```
top_10_designations = df['Designation'].value_counts().head(10).index
df_top_10 = df[df['Designation'].isin(top_10_designations)]

fig, axs = plt.subplots(2, 2, figsize=(15, 12))

# Violin plot
sns.violinplot(x='Designation', y='Salary', data=df_top_10, ax=axs[0, 0])
axs[0, 0].set_title('Violin Plot of Salary by Designation')
axs[0, 0].tick_params(axis='x', rotation=90)

# Box plot
sns.boxplot(x='Designation', y='Salary', data=df_top_10, ax=axs[0, 1])
axs[0, 1].set_title('Box Plot of Salary by Designation')
axs[0, 1].tick_params(axis='x', rotation=90)

# Bar plot
sns.barplot(x='Designation', y='Salary', data=df_top_10, ax=axs[1, 0])
axs[1, 0].set_title('Bar Plot of Salary by Designation')
axs[1, 0].tick_params(axis='x', rotation=90)

# Count plot
sns.countplot(x='Designation', data=df_top_10, ax=axs[1, 1])
axs[1, 1].set_title('Count Plot of Designation')
axs[1, 1].tick_params(axis='x', rotation=90)

plt.tight_layout()
plt.show()
```



In [47]:
```
# Without Outliers
top_10_designations = df1['Designation'].value_counts().head(10).index
df1_top_10 = df1[df1['Designation'].isin(top_10_designations)]

fig, axs = plt.subplots(2, 2, figsize=(15, 12))

# Violin plot
sns.violinplot(x='Designation', y='Salary', data=df1_top_10, ax=axs[0, 0])
axs[0, 0].set_title('Violin Plot of Salary by Designation')
axs[0, 0].tick_params(axis='x', rotation=90)

# Box plot
sns.boxplot(x='Designation', y='Salary', data=df1_top_10, ax=axs[0, 1])
axs[0, 1].set_title('Box Plot of Salary by Designation')
axs[0, 1].tick_params(axis='x', rotation=90)

# Bar plot
sns.barplot(x='Designation', y='Salary', data=df1_top_10, ax=axs[1, 0])
axs[1, 0].set_title('Bar Plot of Salary by Designation')
axs[1, 0].tick_params(axis='x', rotation=90)

# Count plot
sns.countplot(x='Designation', data=df1_top_10, ax=axs[1, 1])
axs[1, 1].set_title('Count Plot of Designation')
axs[1, 1].tick_params(axis='x', rotation=90)

plt.tight_layout()
plt.show()
```

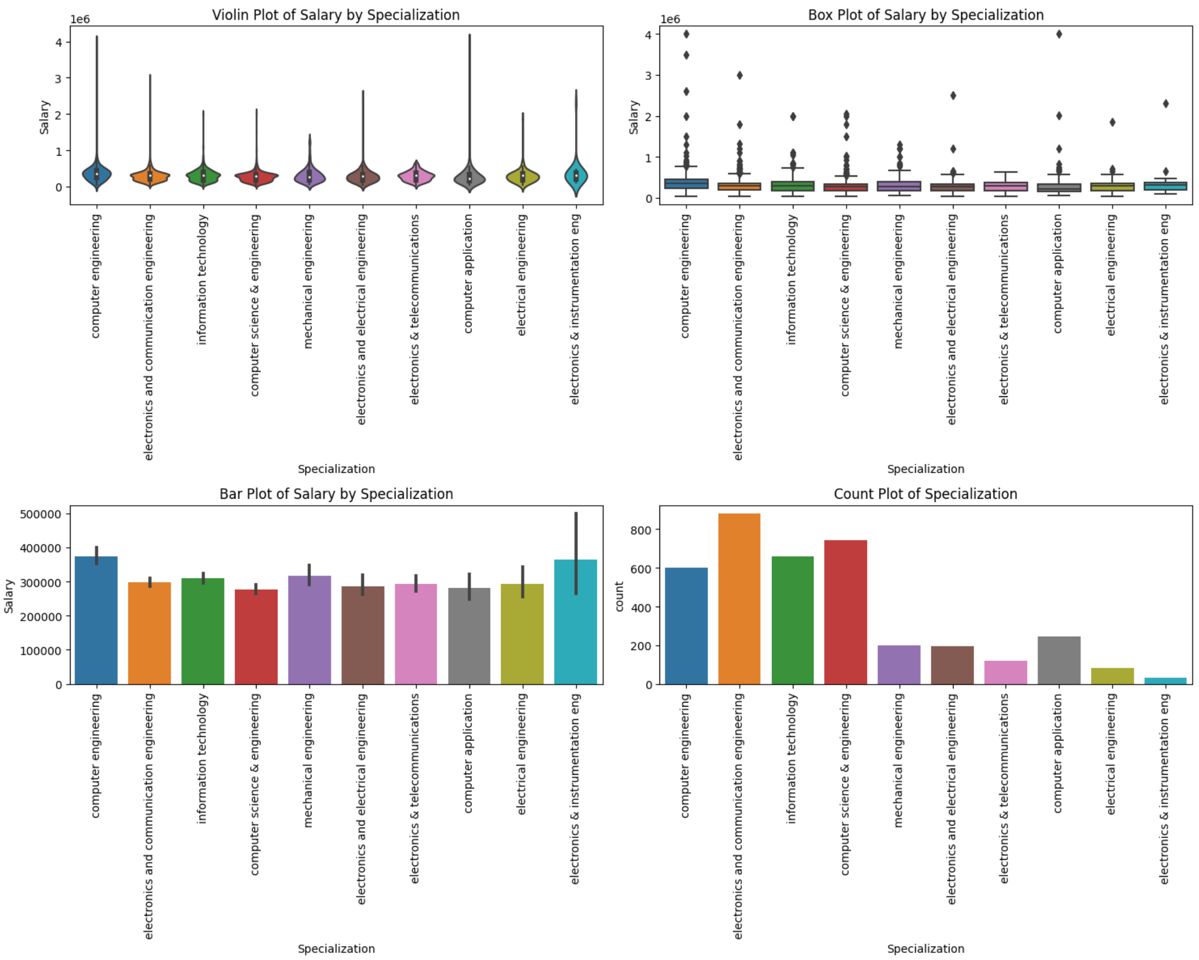


In the plot, senior software engineers earn more than other software employees.

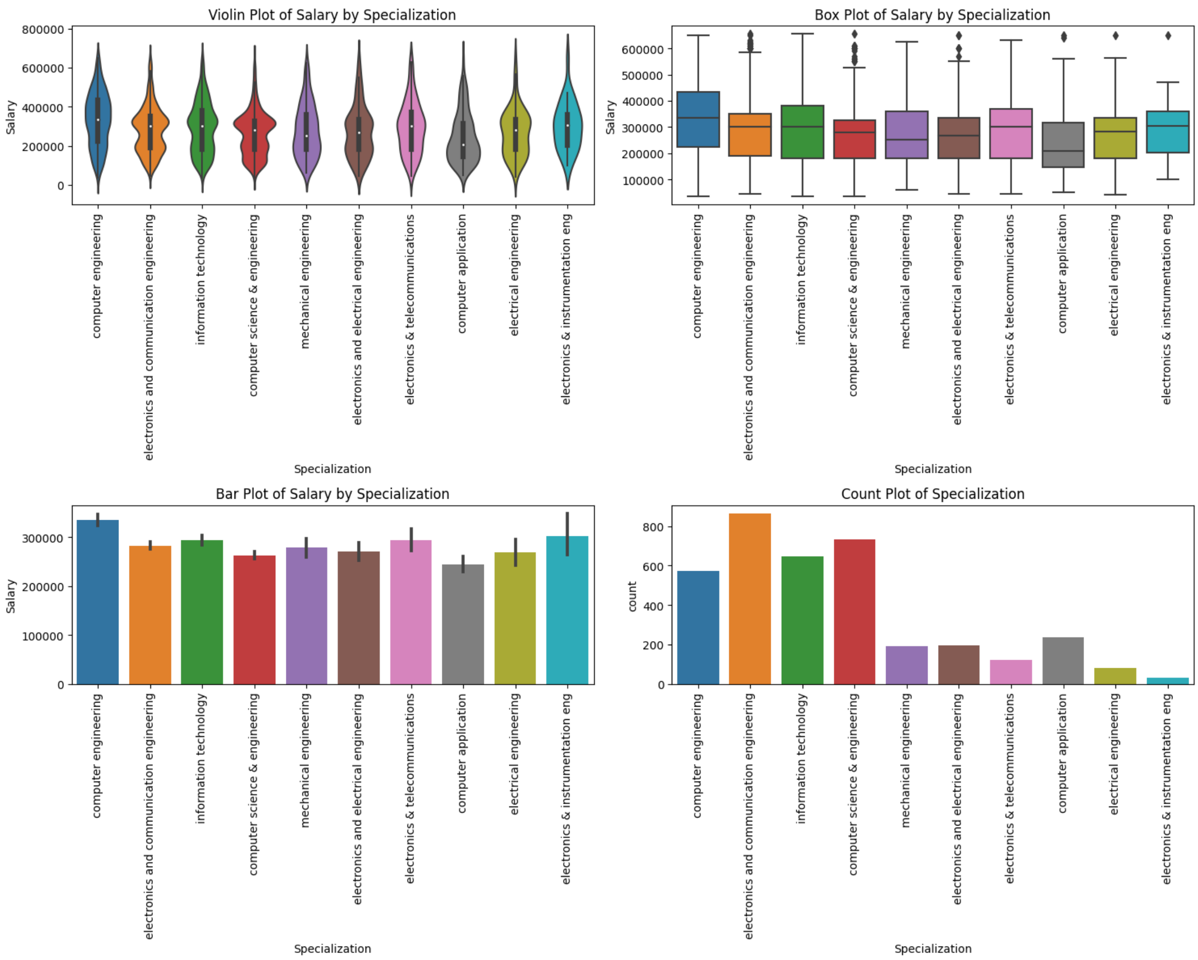
However, after removing outliers, the salaries are almost the same across different software employee roles.

In [48]:

```python
top_10_designations = df['Specialization'].value_counts().head(10).index
df_top_10 = df[df['Specialization'].isin(top_10_designations)]

fig, axs = plt.subplots(2, 2, figsize=(15, 12))

# Violin plot
sns.violinplot(x='Specialization', y='Salary', data=df_top_10, ax=axs[0, 0])
axs[0, 0].set_title('Violin Plot of Salary by Specialization')
axs[0, 0].tick_params(axis='x', rotation=90)

# Box plot
sns.boxplot(x='Specialization', y='Salary', data=df_top_10, ax=axs[0, 1])
axs[0, 1].set_title('Box Plot of Salary by Specialization')
axs[0, 1].tick_params(axis='x', rotation=90)

# Bar plot
sns.barplot(x='Specialization', y='Salary', data=df_top_10, ax=axs[1, 0])
axs[1, 0].set_title('Bar Plot of Salary by Specialization')
axs[1, 0].tick_params(axis='x', rotation=90)

# Count plot
sns.countplot(x='Specialization', data=df_top_10, ax=axs[1, 1])
axs[1, 1].set_title('Count Plot of Specialization')
axs[1, 1].tick_params(axis='x', rotation=90)

plt.tight_layout()
plt.show()
```

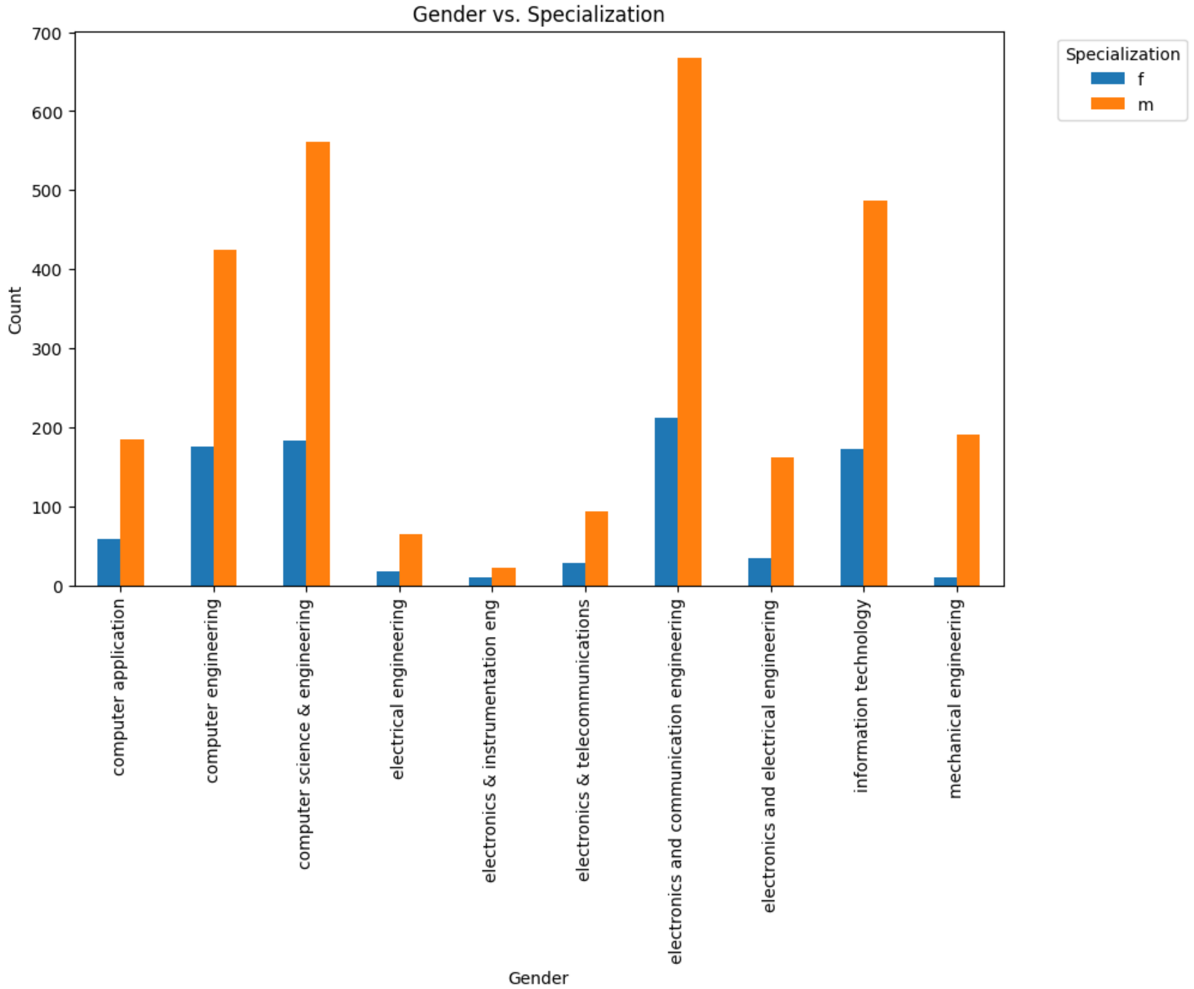


In [49]:
```python
# Without Outliers
top_10_designations = df1['Specialization'].value_counts().head(10).index
df1_top_10 = df1[df1['Specialization'].isin(top_10_designations)]

fig, axs = plt.subplots(2, 2, figsize=(15, 12))

# Violin plot
sns.violinplot(x='Specialization', y='Salary', data=df1_top_10, ax=axs[0, 0])
axs[0, 0].set_title('Violin Plot of Salary by Specialization')
axs[0, 0].tick_params(axis='x', rotation=90)

# Box plot
sns.boxplot(x='Specialization', y='Salary', data=df1_top_10, ax=axs[0, 1])
axs[0, 1].set_title('Box Plot of Salary by Specialization')
axs[0, 1].tick_params(axis='x', rotation=90)

# Bar plot
sns.barplot(x='Specialization', y='Salary', data=df1_top_10, ax=axs[1, 0])
axs[1, 0].set_title('Bar Plot of Salary by Specialization')
axs[1, 0].tick_params(axis='x', rotation=90)

# Count plot
sns.countplot(x='Specialization', data=df1_top_10, ax=axs[1, 1])
axs[1, 1].set_title('Count Plot of Specialization')
axs[1, 1].tick_params(axis='x', rotation=90)

plt.tight_layout()
plt.show()
```



It is clearly visible from the plot that the Average salary is below 5 Lakh but In the plot computer engineering students earn more than other department

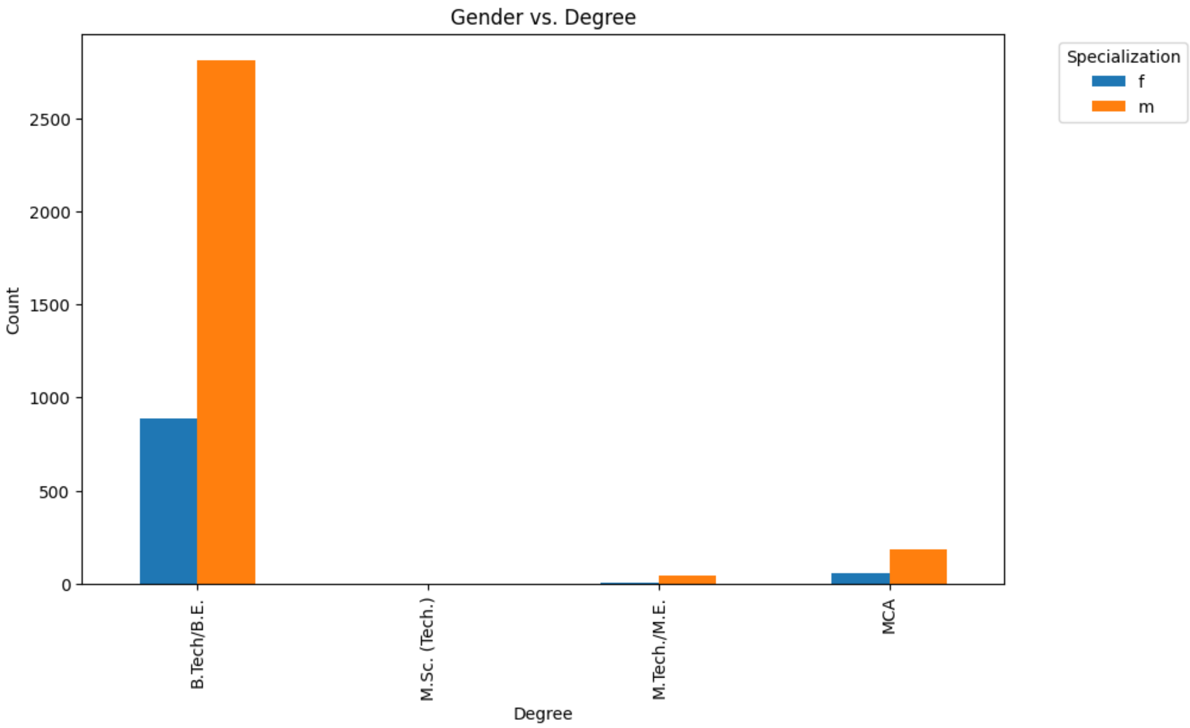
In [50]:
```
contingency_table = pd.crosstab(df_top_10['Specialization'], df['Gender'])

# Plotting
contingency_table.plot(kind='bar', figsize=(10, 6))
plt.xlabel('Gender')
plt.ylabel('Count')
plt.title('Gender vs. Specialization')
plt.legend(title='Specialization', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



There are almost males 2 times as of females in every specialization. Also, there are very less number of females who opted for mechanical and electronics.

```
In [51]: # Without Outliers
contingency_table = pd.crosstab(df['Degree'], df['Gender'])
print(df['Degree'].value_counts())
# Plotting
contingency_table.plot(kind='bar', figsize=(10, 6))
plt.xlabel('Degree')
plt.ylabel('Count')
plt.title('Gender vs. Degree')
plt.legend(title='Specialization', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```

```
Degree
B.Tech/B.E.      3700
MCA               243
M.Tech./M.E.       53
M.Sc. (Tech.)       2
Name: count, dtype: int64
```



- 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.” Test this claim with the data given to you

```
In [52]: filtered_data = df1[(df1['Specialization'] == 'computer science & engineering') &
    (df1['Designation'].isin(['programming analyst', 'software engineer', 'hardware engineer', 'ass

# Calculate the average salary
average_salary = filtered_data['Salary'].mean()
average_salary
```

```
Out[52]: 320543.47826086957
```

With an average salary of approximately 332,943.26 INR, the data suggests that fresh graduates in Computer Science Engineering working in the specified job roles (Programming Analyst, Software Engineer, Hardware Engineer, and Associate Engineer) earn higher than the claimed range of 2.5-3 lakhs as mentioned in the Times of India article

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

In [53]:
```
# Assuming 'data' is your DataFrame with 'Gender' and 'Specialization' columns
contingency_table = pd.crosstab(df['Gender'], df['Specialization'])

# Perform chi-squared test
chi2, p, dof, expected = chi2_contingency(contingency_table)

print("Chi-squared statistic:", chi2)
print("P-value:", p)
```

```
Chi-squared statistic: 104.46891913608455
P-value: 1.2453868176976918e-06
```

The small p-value suggests that the observed distribution of specializations is unlikely to have occurred by chance if there were no actual relationship between gender and specialization.

"Does the academic performance, specifically scoring above 70% in 12th grade and above 60% in BE/BTech, significantly impact job selection for fresher candidates in Computer Science Engineering, compared to candidates with an MTech, MCA, MSc, or ME degree scoring above 55%?"

In [54]:
```
# Filter the dataset based on the criteria
filtered_data = df[
    ((df['12percentage'] > 70) & (df['Degree'] == 'B.Tech/B.E.') & (df['collegeGPA'] > 60)) |
    ((df['Degree'].isin(['M.Tech./M.E.', 'MCA', 'M.Sc. (Tech.)'])) & (df['collegeGPA'] > 55))
]

# Check the proportion of selected candidates
selected_proportion = len(filtered_data) / len(df)

selected_proportion
```

Out[54]:
```
0.6548274137068534
```

The output indicates that approximately 65.48% of candidates meet the specified criteria for job selection based on academic performance and degree.

Conclusion

Senior Software Engineers earn the highest salaries but with more variability, while Software Developers and Technical Support Engineers earn below the average. Gender has a minor impact on average salary, with females earning less. Academic performance, based on 10th, 12th, and college GPA scores, does not show a clear correlation with pay