AMCAT_Exploratory_Data_Analysis

Description :

The Aspiring Mind Employment Outcome 2015 (AMEO) dataset, released by Aspiring Minds, focuses on engineering students. It includes employment outcomes (Salary, Job Titles, Job Locations) and standardized scores in cognitive, technical, and personality skills. The dataset also features demographic information, with around 39 independent variables (both continuous and categorical) and 4000 data points. Each candidate has a unique identifier.

```
# Importing packages...
import numpy as np
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt

import warnings
warnings.simplefilter("ignore")

# importing dataset
path='/content/drive/MyDrive/Colab Notebooks/Project-1/data.xlsx -
Sheet1.csv'
amcat_data=pd.read_csv(path)
amcat_data.head()
```

{"type":"dataframe","variable_name":"amcat_data"}

```
#Removing unwanted columns
amcat_data.drop(columns=["Unnamed: 0"], inplace=True)

# Getting Discriptive Statistics
amcat_data.describe()
```

{"type":"dataframe"}

```
# Checking How many Records...
amcat_data.shape
```

```
(3998, 38)
```

```
# Checking columns in a dataset.
amcat_data.columns
```

```
Index(['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')

# Count of datatypes
amcat_data.dtypes.value_counts()

int64      17
object     11
float64    10
Name: count, dtype: int64

# Information about dataset.
amcat_data.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   float64
 2   DOJ                    3998 non-null   object
 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   object
 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: float64(10), int64(17), object(11)
memory usage: 1.2+ MB
```

```
# Finding Issues
# An issue founded that DOJ,DOB aren't in respective datatype,
# Also replacing present in DOL with current datetime....

col_lst = ['DOJ', 'DOL', 'DOB']
for col in col_lst:
    amcat_data[col] = amcat_data[col].replace('present',
pd.Timestamp.now())
    amcat_data[col] = pd.to_datetime(amcat_data[col], errors='coerce')

amcat_data.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   float64
 2   DOJ                        3998 non-null   datetime64[ns]
 3   DOL                        3998 non-null   datetime64[ns]
 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](3), float64(10), int64(17), object(8)
memory usage: 1.2+ MB
```

```
# Identifying null values
amcat_data.isnull().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
```

```
# Identifying duplicated values count
amcat_data.duplicated().sum()
```

```
0
```

```
# Identifying unique values count in each column
amcat_data.nunique().sort_values(ascending=False)
```

```
ID                         3998
DOB                        1872
CollegeID                  1350
CollegeCityID              1350
collegeGPA                 1282
10percentage                851
12percentage                801
Designation                 419
12board                     340
JobCity                     339
10board                     275
Domain                      243
nueroticism                 217
Salary                      177
extraversion                154
agreeableness               149
openess_to_experience       142
conscientiousness           141
Quant                       138
English                     111
Logical                     107
DOJ                          81
ComputerProgramming          79
DOL                          67
```

```
Specialization             46
MechanicalEngg             42
ElectricalEngg             31
ElectronicsAndSemicon      29
TelecomEngg                26
CollegeState               26
CivilEngg                  23
ComputerScience            20
12graduation               16
GraduationYear             11
Degree                      4
Gender                      2
CollegeTier                 2
CollegeCityTier             2
dtype: int64
```

```
# Segreation of datatype columns

amcat_int=amcat_data.select_dtypes(["int64"])
amcat_float=amcat_data.select_dtypes(["float64"])
amcat_object=amcat_data.select_dtypes(["object"])

amcat_int.columns.to_list()
```

```
['ID',
 '12graduation',
 'CollegeID',
 'CollegeTier',
 'CollegeCityID',
 'CollegeCityTier',
 'GraduationYear',
 'English',
 'Logical',
 'Quant',
 'ComputerProgramming',
 'ElectronicsAndSemicon',
 'ComputerScience',
 'MechanicalEngg',
 'ElectricalEngg',
 'TelecomEngg',
 'CivilEngg']
```

```
amcat_float.columns.to_list()
```

```
['Salary',
 '10percentage',
 '12percentage',
 'collegeGPA',
 'Domain',
 'conscientiousness',
```

```
 'agreeableness',
 'extraversion',
 'nueroticism',
 'openess_to_experience']
```

```
amcat_object.columns.to_list()
```

```
['Designation',
 'JobCity',
 'Gender',
 '10board',
 '12board',
 'Degree',
 'Specialization',
 'CollegeState']
```

```
# Now Let us start with Univariate Analysis
```

Univariate Analysis

Definition:

Univariate analysis is the simplest form of data analysis, focusing on a single variable

A) Univarate Categorical Analysis :

```
# Defining a function for univariate analysis
def Univariate_Categorical_Analysis(disc_data):
    for col in disc_data:
        print("*"*10,col,"*"*10)
        print(disc_data[col].agg(["count","unique","nunique"]),"\n")

#Just calling few columns
Univariate_Categorical_Analysis(amcat_object[["Designation","Gender","
Specialization"]])
```

```
********** Designation **********
count                                                   3998
unique     [senior quality engineer, assistant manager, s...
nunique                                                  419
Name: Designation, dtype: object

********** Gender **********
count         3998
unique      [f, m]
nunique          2
Name: Gender, dtype: object
```

```
********** Specialization **********
count                                                           3998
unique     [computer engineering, electronics and communi...
nunique                                                           46
Name: Specialization, dtype: object
```

B) Univariate Numerical Analysis :

```
def Univariate_Numerical_Analysis(disc_data):
    for col in disc_data:
        print("*"*10,col,"*"*10)

print(disc_data[col].agg(["min","max","mean","median","std","skew","ku
rtosis"]),"\n")

# calling integer columns
Univariate_Numerical_Analysis(amcat_int[['ComputerProgramming','Electr
onicsAndSemicon','ComputerScience']])
```

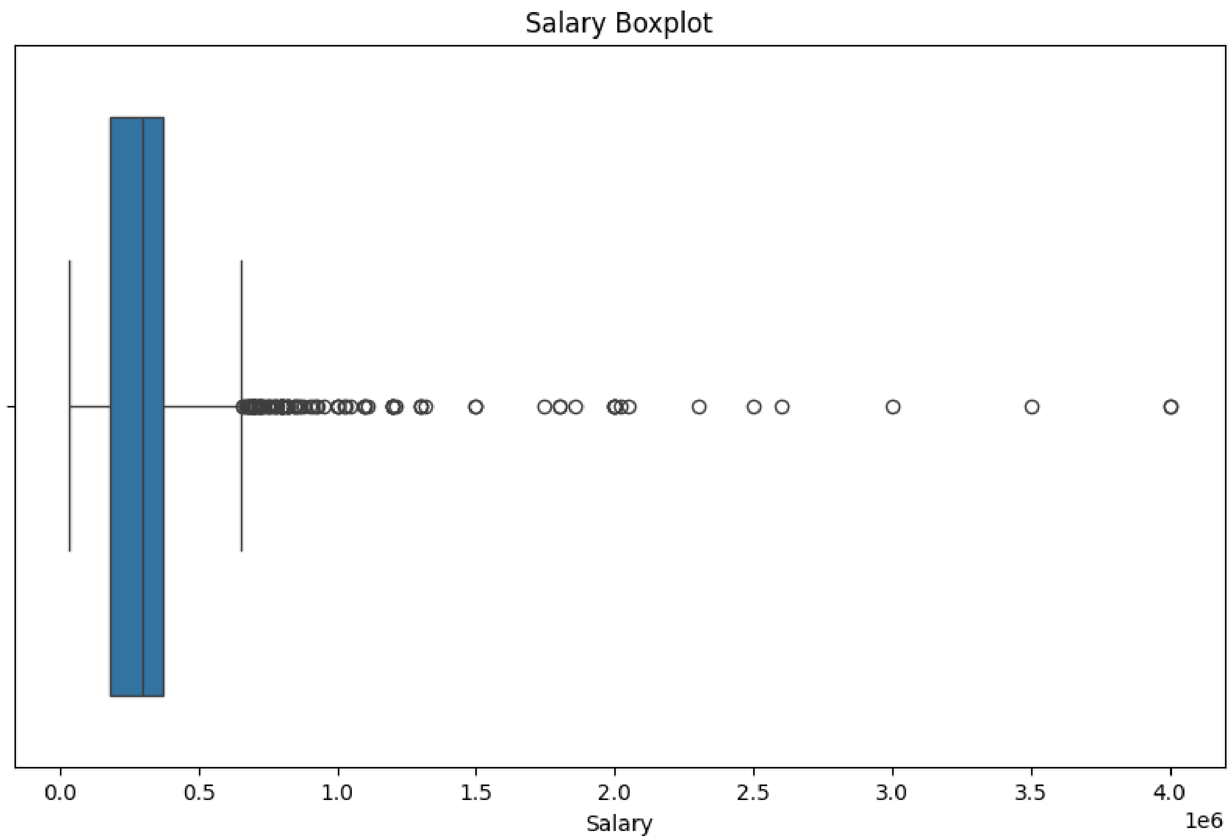
```
********** ComputerProgramming **********
min          -1.000000
max         840.000000
mean        353.102801
median      415.000000
std         205.355519
skew         -0.778106
kurtosis     -0.666352
Name: ComputerProgramming, dtype: float64

********** ElectronicsAndSemicon **********
min          -1.000000
max         612.000000
mean         95.328414
median       -1.000000
std         158.241218
skew          1.195975
kurtosis     -0.210374
Name: ElectronicsAndSemicon, dtype: float64

********** ComputerScience **********
min          -1.000000
max         715.000000
mean         90.742371
median       -1.000000
std         175.273083
skew          1.529521
kurtosis      0.692641
```

```
Name: ComputerScience, dtype: float64


# calling Float columns
Univariate_Numerical_Analysis(amcat_float.iloc[:, [3, 5,7]])

********** collegeGPA **********
min          6.450000
max         99.930000
mean        71.486171
median      71.720000
std          8.167338
skew        -1.249209
kurtosis    10.234244
Name: collegeGPA, dtype: float64

********** conscientiousness **********
min         -4.126700
max          1.995300
mean        -0.037831
median       0.046400
std          1.028666
skew        -0.527003
kurtosis     0.122596
Name: conscientiousness, dtype: float64

********** extraversion **********
min         -4.600900
max          2.535400
mean         0.002763
median       0.091400
std          0.951471
skew        -0.523267
kurtosis     0.643969
Name: extraversion, dtype: float64


# Get statistics ,plots regarding Salary .Interpret how it distributed
in data.

Univariate_Numerical_Analysis(amcat_float.loc[:, ["Salary"]])

********** Salary **********
min         3.500000e+04
max         4.000000e+06
mean        3.076998e+05
median      3.000000e+05
std         2.127375e+05
skew        6.451081e+00
kurtosis    8.093000e+01
```

```
Name: Salary, dtype: float64
```

```
# Histogram
plt.figure(figsize=(8, 5))
sb.histplot(amcat_data.Salary, kde=True)
plt.title('Salary Distribution')
plt.xlabel('Salary')
plt.ylabel('Frequency')
plt.show()
```

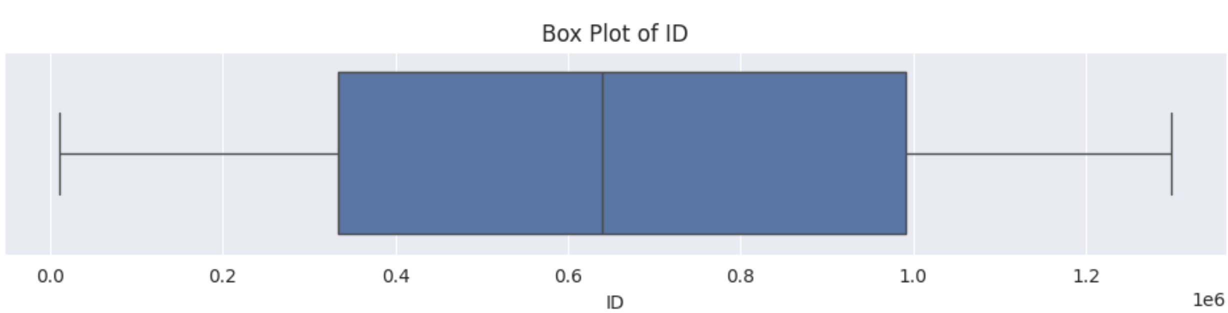

```
# Outliers in Salary
plt.figure(figsize=(10, 6))
sb.boxplot(x=amcat_data.Salary)
plt.title('Salary Boxplot')
plt.xlabel('Salary')
plt.show()
```

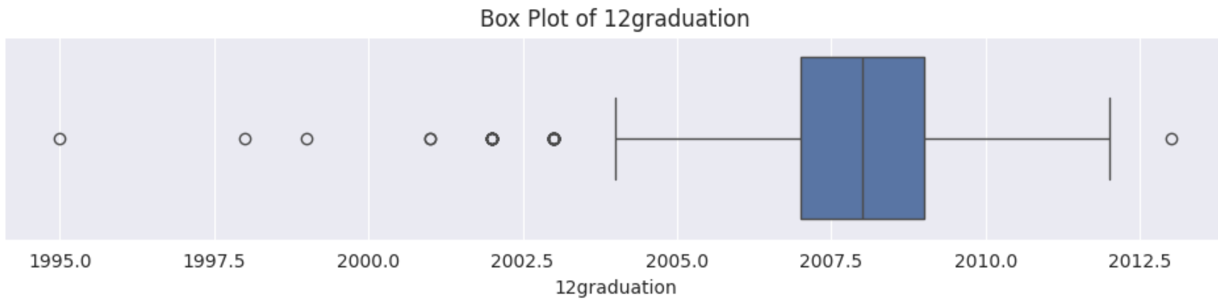


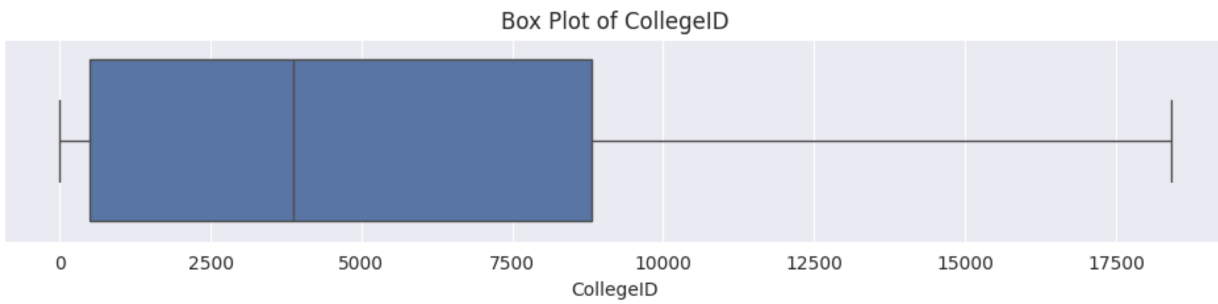
Insights:

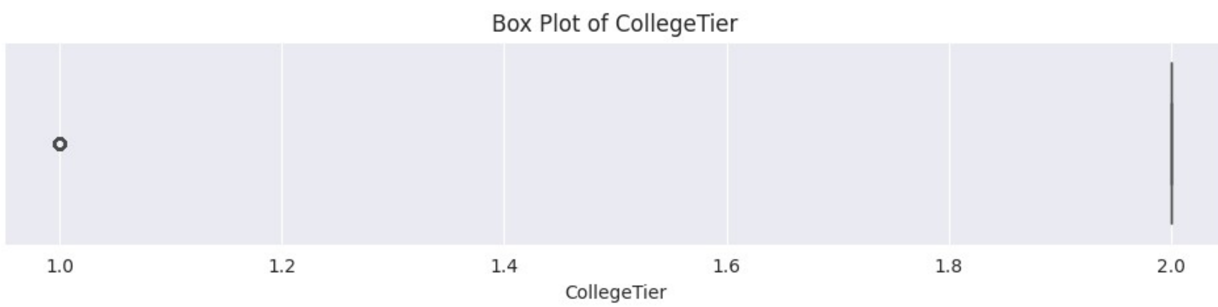
The targeted salary attribute having outliers that are skewed right.It indicates that most of the candidates candidates having higher salaries than the average.

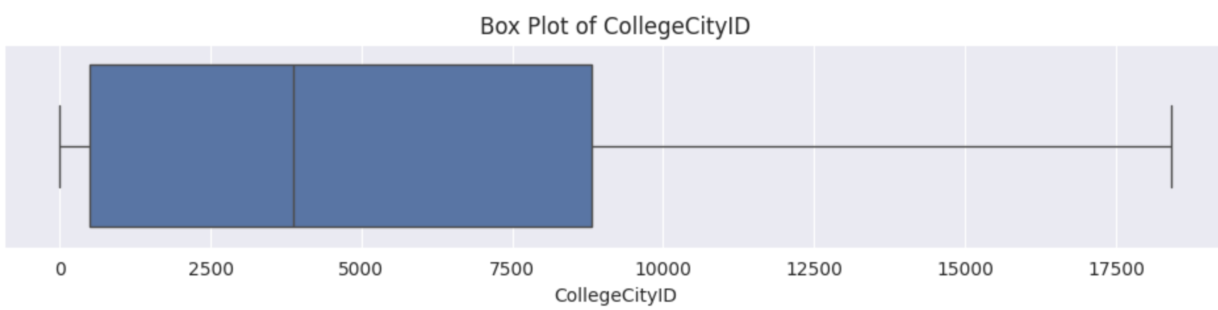
```
# Outliers detection in numeric columns

int_col=amcat_int.columns.to_list()
sb.set({"figure.figsize":(12,2)})
for i in range(len(int_col)):
    sb.boxplot(amcat_data[int_col[i]],orient="h")
    plt.title(f'Box Plot of {int_col[i]}')
    plt.show()
```

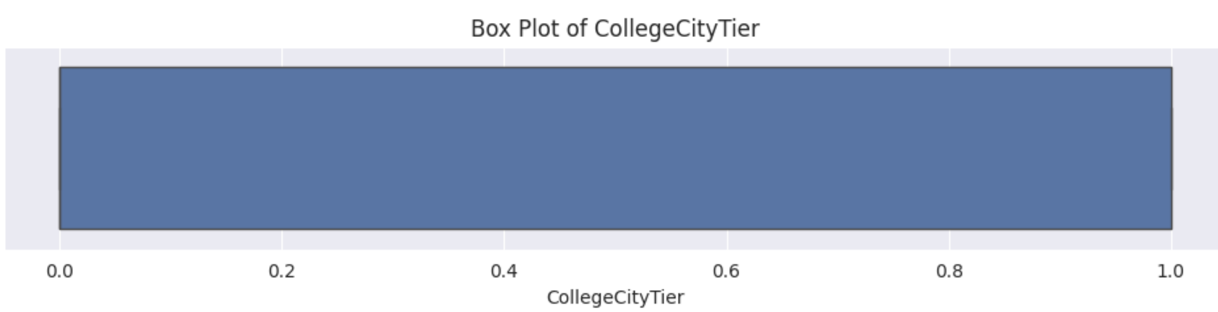


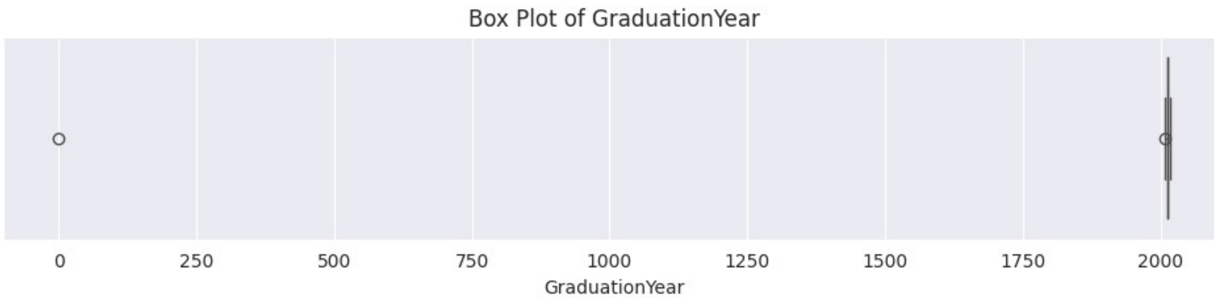

Box Plot of 12graduation
1995.0
1997.5
2000.0
2002.5
2005.0
2007.5
2010.0
2012.5
12graduation

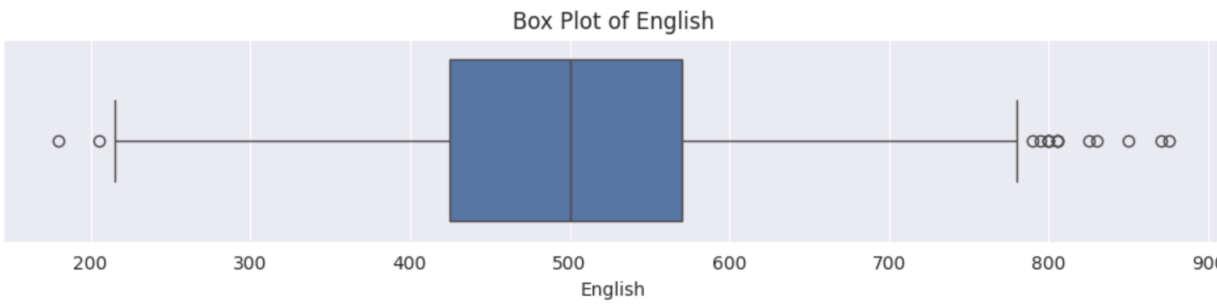

Box Plot of CollegeID
0
2500
5000
7500
10000
12500
15000
17500
CollegeID

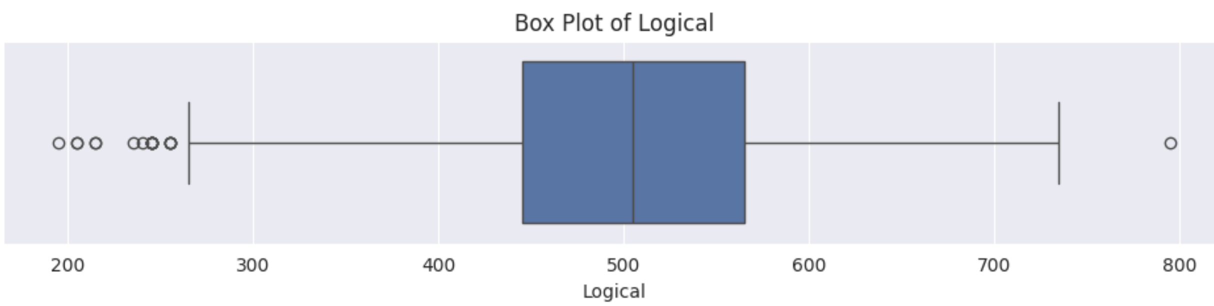

Box Plot of CollegeTier
1.0
1.2
1.4
1.6
1.8
2.0
CollegeTier

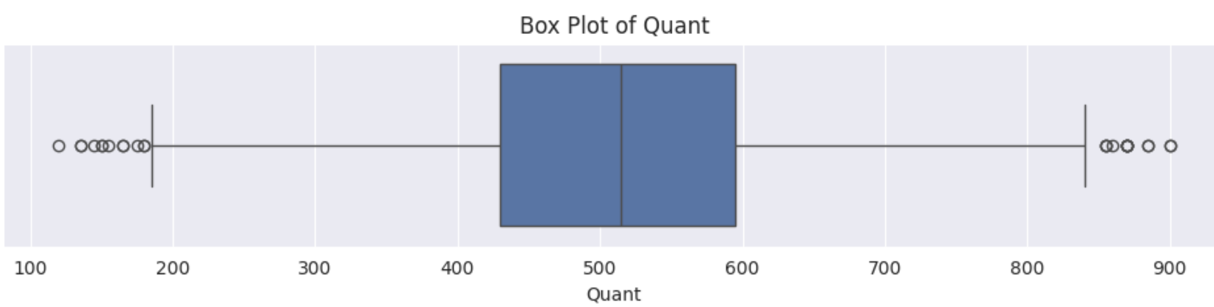

Box Plot of CollegeCityID
0
2500
5000
7500
10000
12500
15000
17500
CollegeCityID

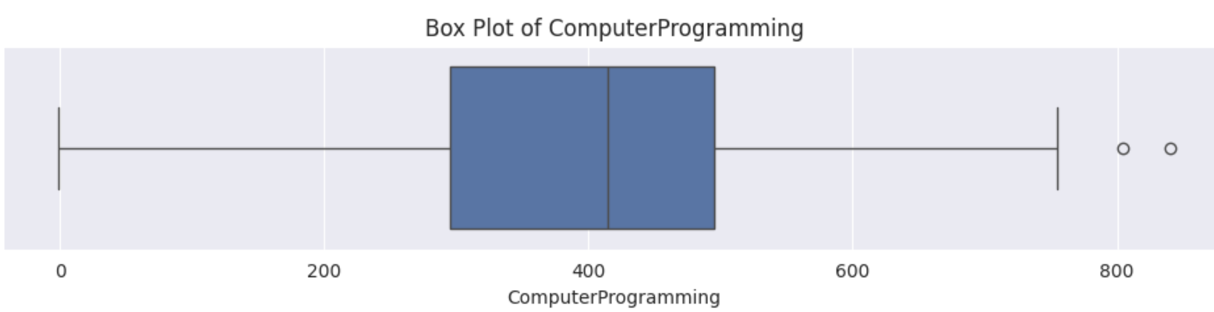

Box Plot of CollegeCityTier
0.0
0.2
0.4
0.6
0.8
1.0
CollegeCityTier

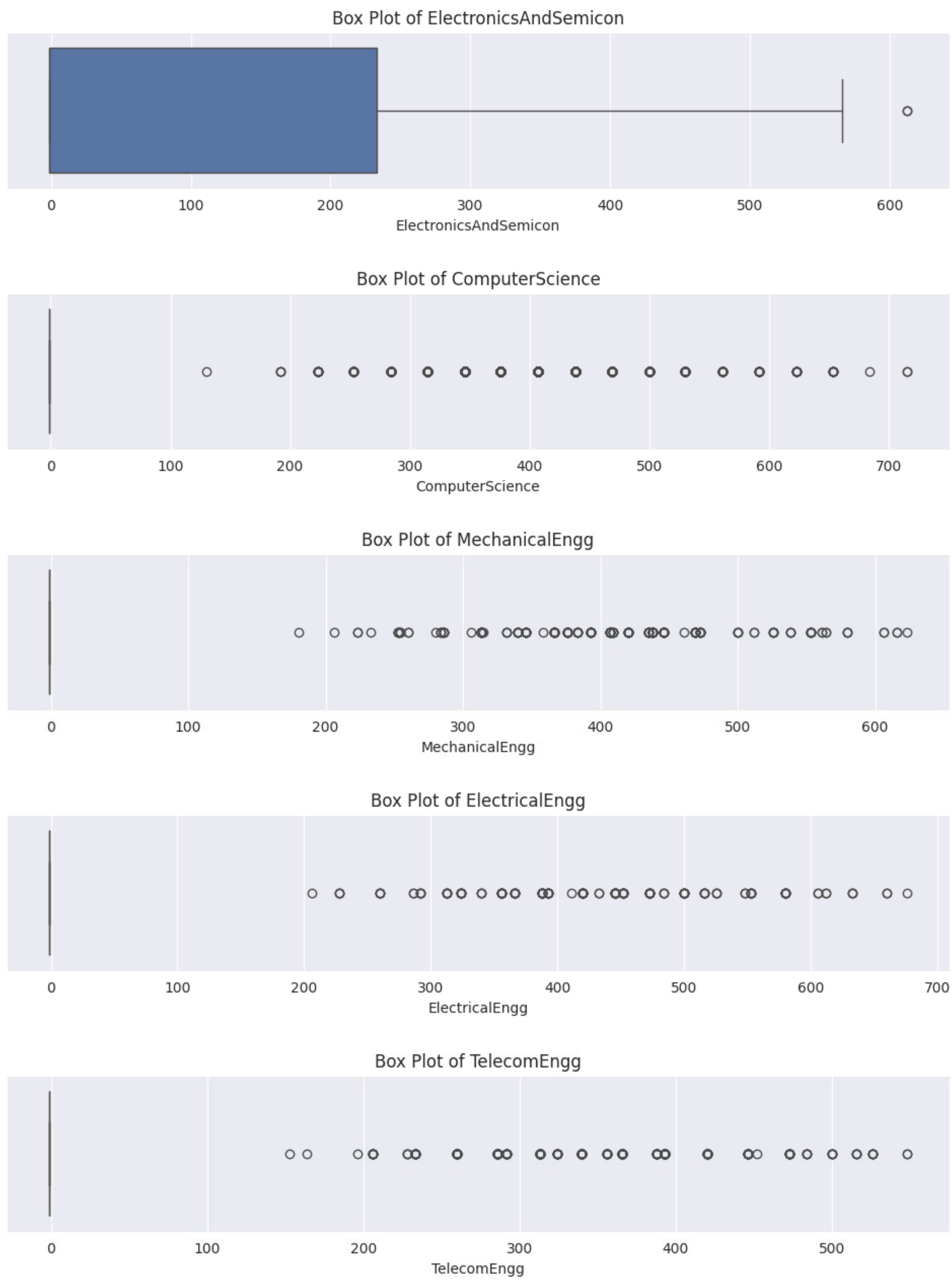

Box Plot of GraduationYear
0
250
500
750
1000
1250
1500
1750
2000
GraduationYear

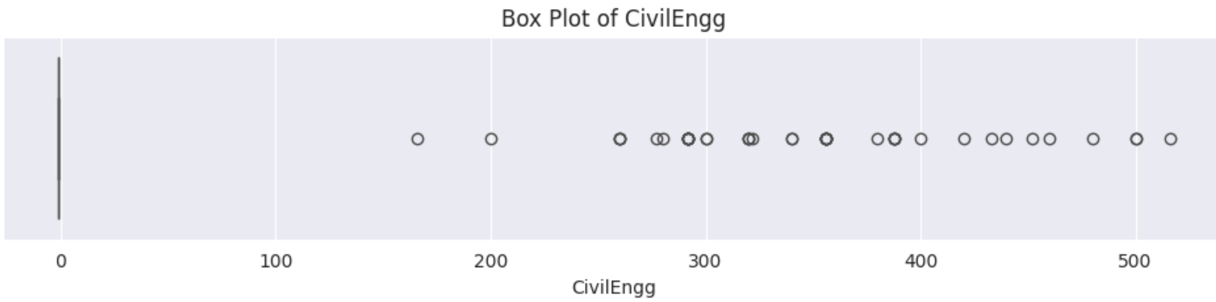

Box Plot of English
200
300
400
500
600
700
800
900
English


Box Plot of Logical
200
300
400
500
600
700
800
Logical


Box Plot of Quant
100
200
300
400
500
600
700
800
900
Quant


Box Plot of ComputerProgramming
0
200
400
600
800
ComputerProgramming

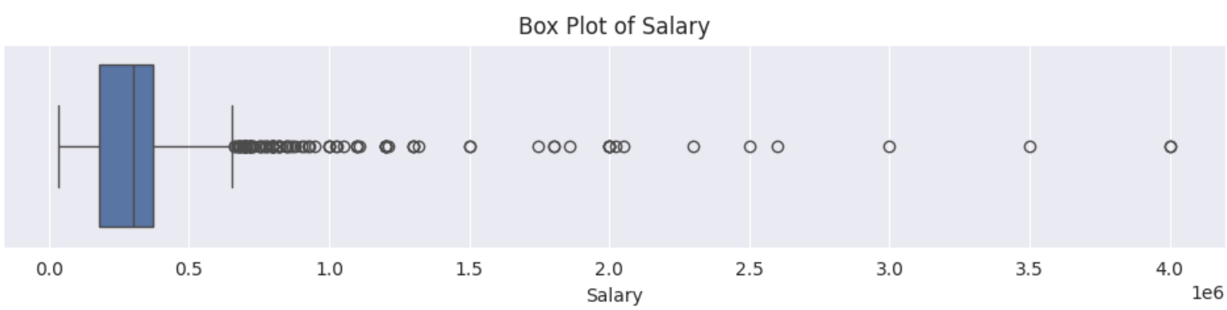

Box Plot of ElectronicsAndSemicon
0
100
200
300
400
500
600
ElectronicsAndSemicon
Box Plot of ComputerScience
0
100
200
300
400
500
600
700
ComputerScience
Box Plot of MechanicalEngg
0
100
200
300
400
500
600
MechanicalEngg
Box Plot of ElectricalEngg
0
100
200
300
400
500
600
700
ElectricalEngg
Box Plot of TelecomEngg
0
100
200
300
400
500
TelecomEngg

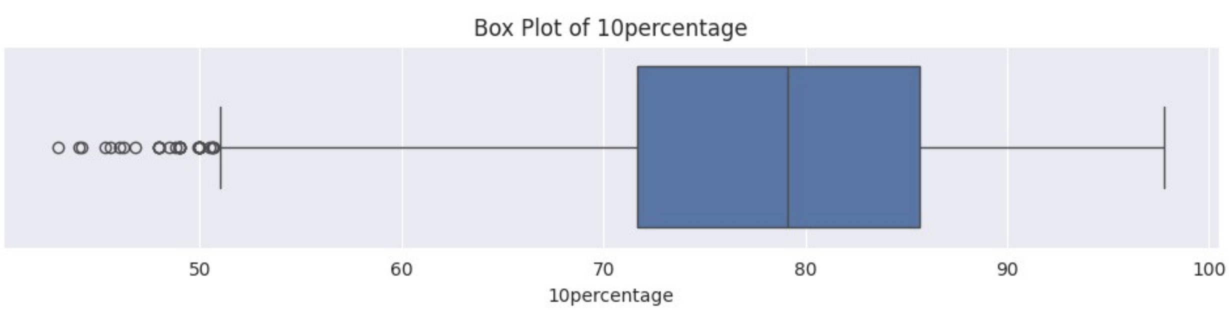


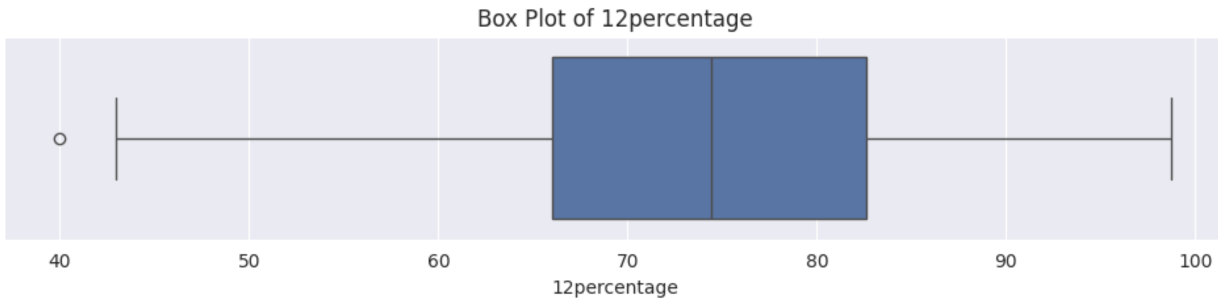
Insights:

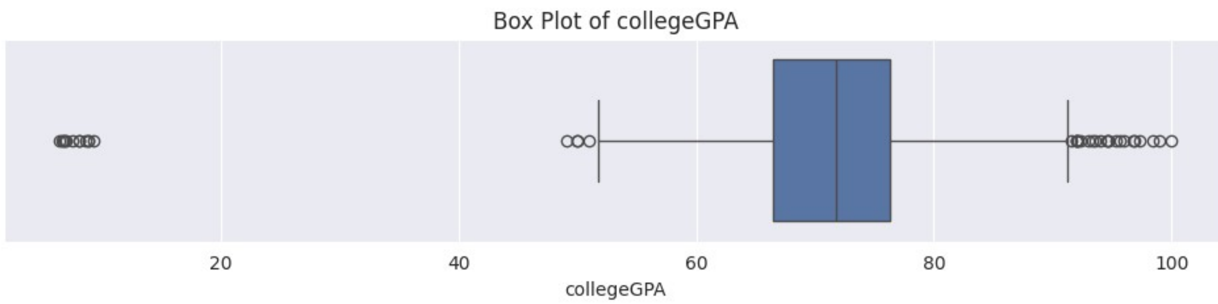
As compared to other boxplots,We can see from the boxplots such as ComputerScience,MechinicalEng,CiviEng,ElectricalEng,TelecomEng are having outliers that are skewed right.It indicates that while all listed engineering scores are a few higher scores pulling the mean to the right.

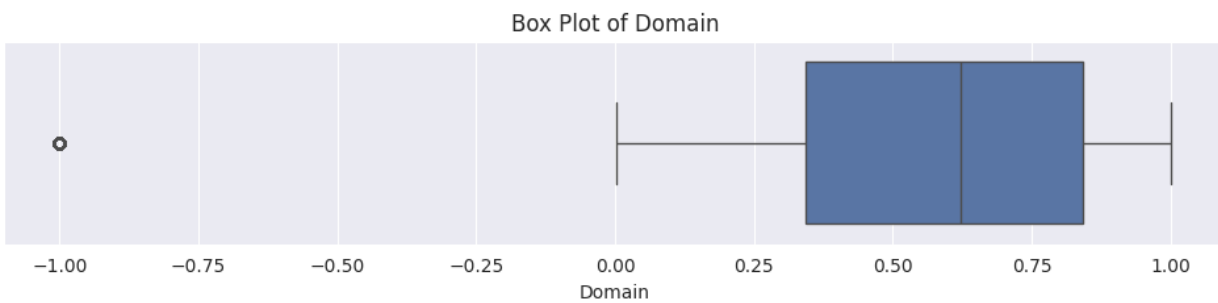
```
# Outlliers detection in numeric columns
float_col=amcat_float.columns.to_list()
sb.set({"figure.figsize":(12,2)})
for i in range(len(float_col)):
    sb.boxplot(amcat_data[float_col[i]],orient="h")
    plt.title(f'Box Plot of {float_col[i]}')
    plt.show()
```

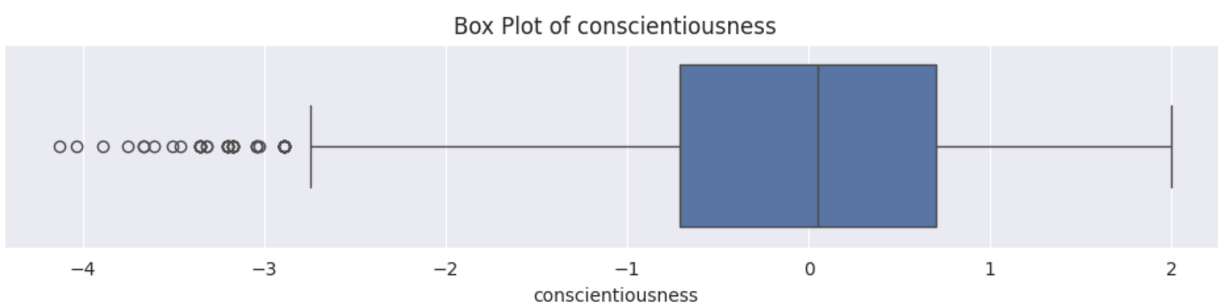


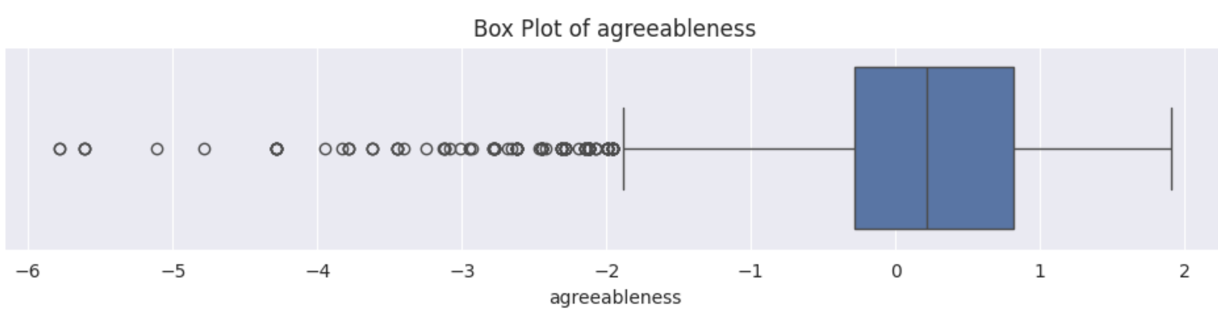


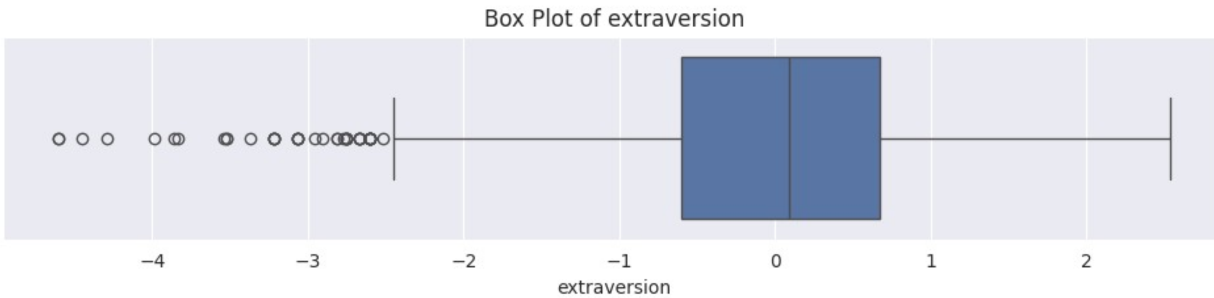

Box Plot of 12percentage
40
50
60
70
80
90
100
12percentage

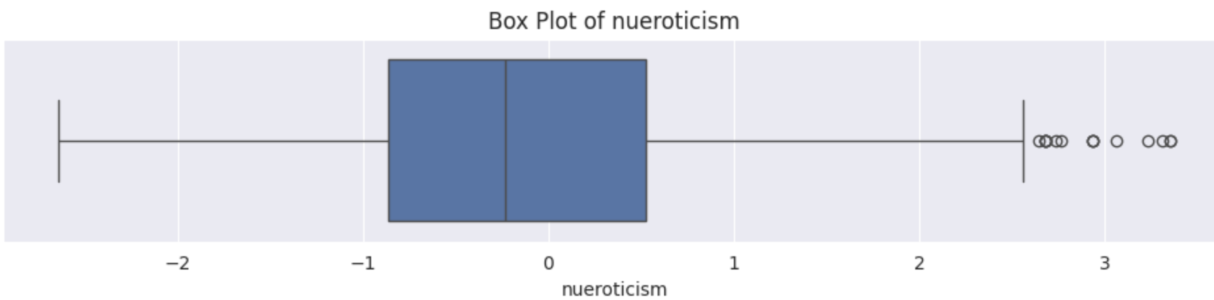

Box Plot of collegeGPA
20
40
60
80
100
collegeGPA

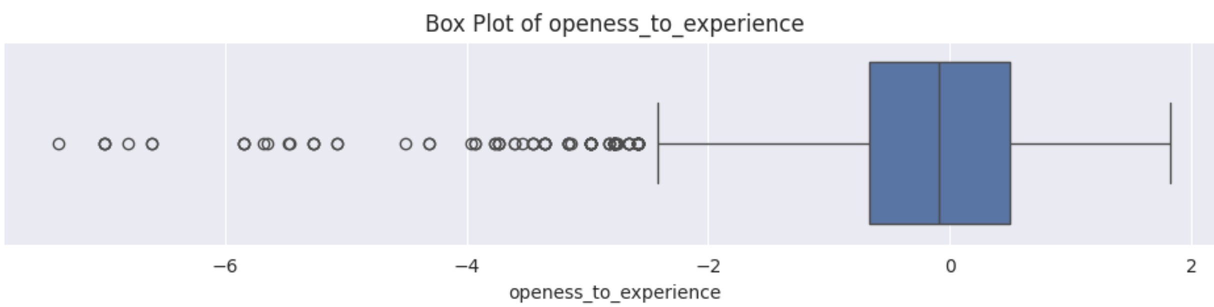

Box Plot of Domain
−1.00
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00
Domain


Box Plot of conscientiousness
−4
−3
−2
−1
0
1
2
conscientiousness


Box Plot of agreeableness
−6
−5
−4
−3
−2
−1
0
1
2
agreeableness







Insights:

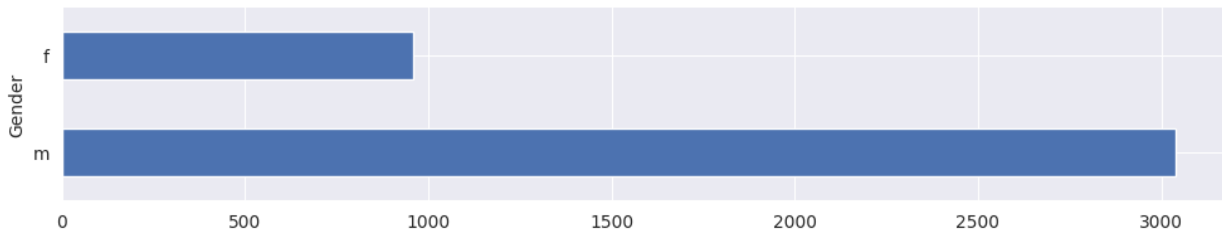
It is to be noted that the standardized scores of conscientiousness,agreeableness,extraversion, are having outliers that are skewed left as most of the students scored less.Whereas the salary pulling the mean to the right as few are earning more than the average.

```
# Vizualizing Salary Field
# What percentage of the dataset is male and female?
gender=amcat_data["Gender"].value_counts()
Male=gender["m"]/(gender["m"]+gender["f"])
Female=1-Male

print(f"Male : {round(Male,2)*100}%")
print(f"Female : {round(Female,2)*100}%")
```

```
Male : 76.0%
Female : 24.0%
```

```
# Plotting out male and female.

gender.plot(kind="barh")
```

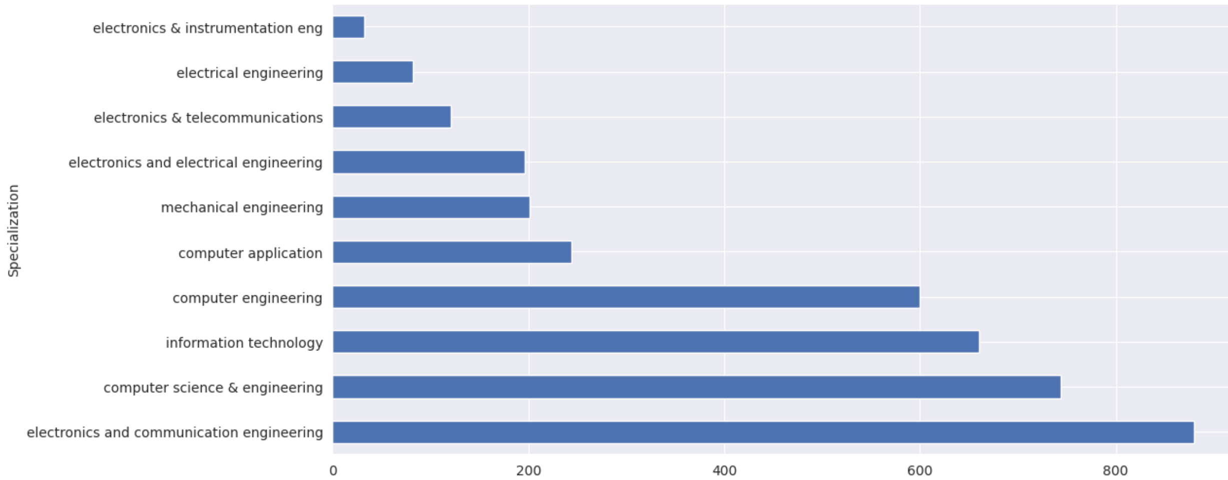
```
<Axes: ylabel='Gender'>
```



Insights:

It is to be noted that nearly 76% of male and Female of 24% had appeared for the AMCAT exam.

```
#What are the top 10 most common specializations among candidates?
spl=amcat_data["Specialization"].value_counts()[:10]
spl

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

# Plot the specializations
plt.figure(figsize=(12,6))
spl.plot(kind="barh")

<Axes: ylabel='Specialization'>
```



Insights:

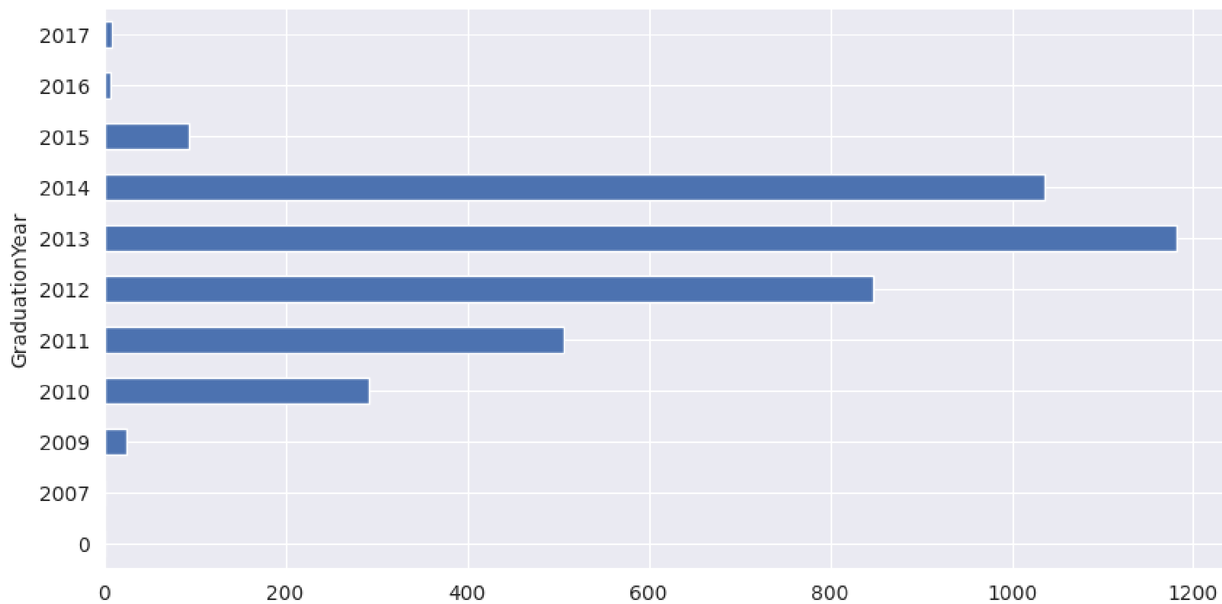
From the above plot it is observed that on top 10 Specializations, Electronics and Communication Engineering got topped in first with 800 candidates for this Specialization and the least admited course was Electronics and Instrumental engineering holds 32 cadidates.

```
#How many candidates graduated in each year?
grad=amcat_data.groupby("GraduationYear").size()
grad
```

```
GraduationYear
0          1
2007       1
2009      24
2010     292
2011     507
2012     847
2013    1181
2014    1036
2015      94
2016       7
2017       8
dtype: int64
```

```
# Plot the GraduationYear

plt.figure(figsize=(10,5))
grad.plot(kind="barh")
```

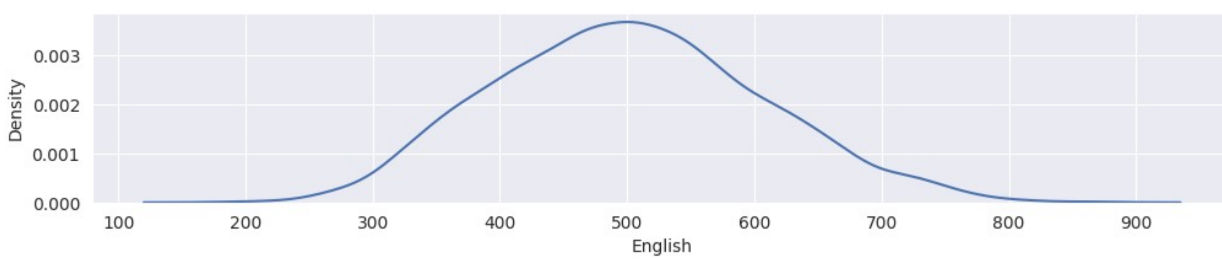
```
<Axes: ylabel='GraduationYear'>
```



Insights:

Above plot represents that the year 2013 had the maximum number of graduated candidates nearly 1181.

```
#How do the English scores vary across the dataset?
sb.kdeplot(data=amcat_data,x="English")

<Axes: xlabel='English', ylabel='Density'>
```



Insights:

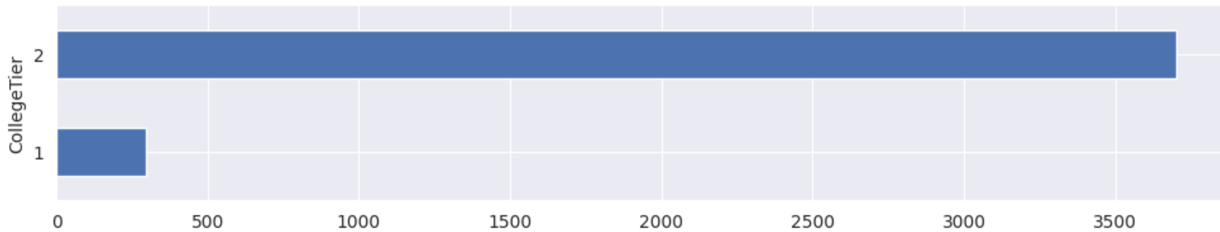
The possible scores for the English section are ranged from 100 to 900 ,in which the most peaked point at 500 is the most common scored marks.And the curve is skewed right as it notes that few are scored higher than the average.

```
#How many students are from each college tier ?

tier=amcat_data.groupby("CollegeTier").size()
tier

CollegeTier
1      297
```

```
2    3701
dtype: int64
```

```
# Plot the CollegeTier

tier.plot(x="CollegeTier",kind="barh")
```

```
<Axes: ylabel='CollegeTier'>
```



Insights:

Nearly 3,700 students appeared for the exam from Tier2 Colleges.

```
#What are the statistics of 12th board percentages?

Univariate_Numerical_Analysis(amcat_data[["12percentage"]])
```

```
********** 12percentage **********
min          40.000000
max          98.700000
mean         74.466366
median       74.400000
std          10.999933
skew         -0.032607
kurtosis     -0.630737
Name: 12percentage, dtype: float64
```

```
#How do agreeableness scores vary across different job cities?
agree_by_city = amcat_data.groupby('JobCity')
['agreeableness'].mean().sort_values(ascending=False)[:15]
print(agree_by_city)
```

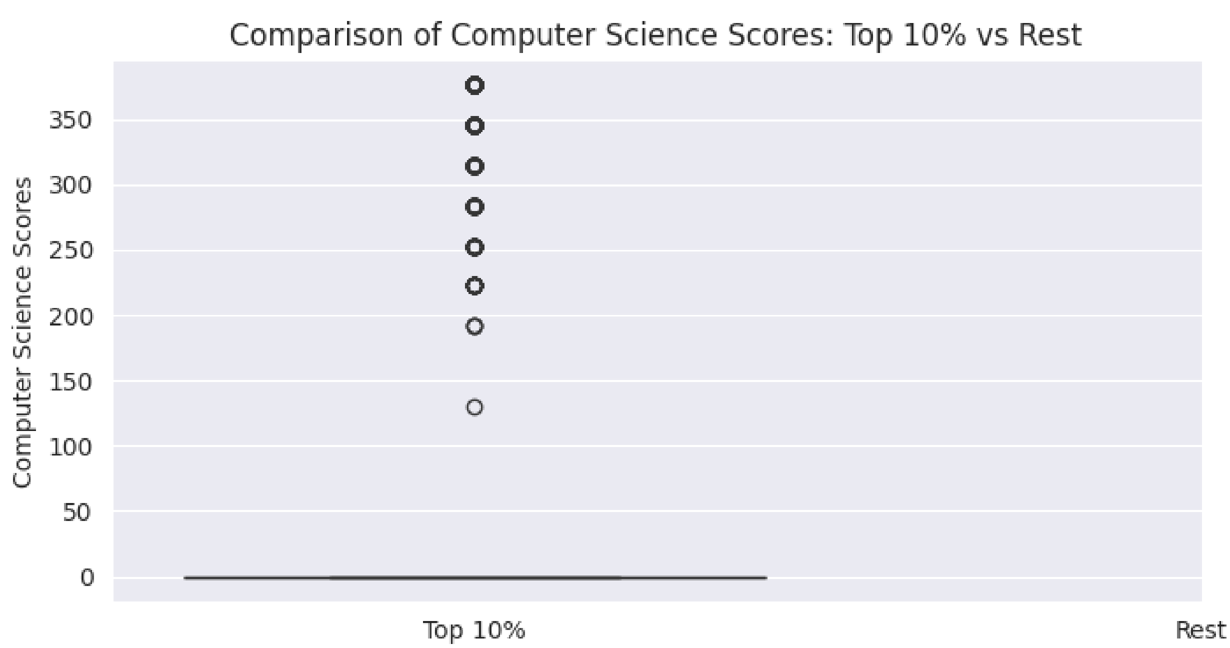
```
JobCity
 Pune                    1.9048
Kalmar, Sweden           1.7488
LONDON                   1.7109
Gorakhpur                1.5928
Trichur                  1.5928
Banagalore               1.5444
Jamnagar                 1.5444
Chennai, Bangalore       1.4368
sampla                   1.3779
```

```
VIZAG                      1.3779
Ganjam                     1.3198
Calicut                    1.2808
BAngalore                  1.2114
kakinada                   1.2114
Bhagalpur                  1.2114
Name: agreeableness, dtype: float64
```

```
#How do the top 10% of candidates in Computer Science scores compare
to the rest?
top_10_cent=amcat_data["ComputerScience"].quantile(.90)

top_10=amcat_data[amcat_data.ComputerScience>=top_10_cent]
rest=amcat_data[amcat_data.ComputerScience<top_10_cent]

print("Top_10_cent :",top_10_cent)
```

```
Top_10_cent : 407.0
```

```
# Visualize the comparison using box plots
plt.figure(figsize=(8, 4))
sb.boxplot(data=[top_10['ComputerScience'], rest['ComputerScience']],
palette='viridis')
plt.xticks([0, 1], ['Top 10%', 'Rest'])
plt.title('Comparison of Computer Science Scores: Top 10% vs Rest')
plt.ylabel('Computer Science Scores')
plt.show()
```



Insights:

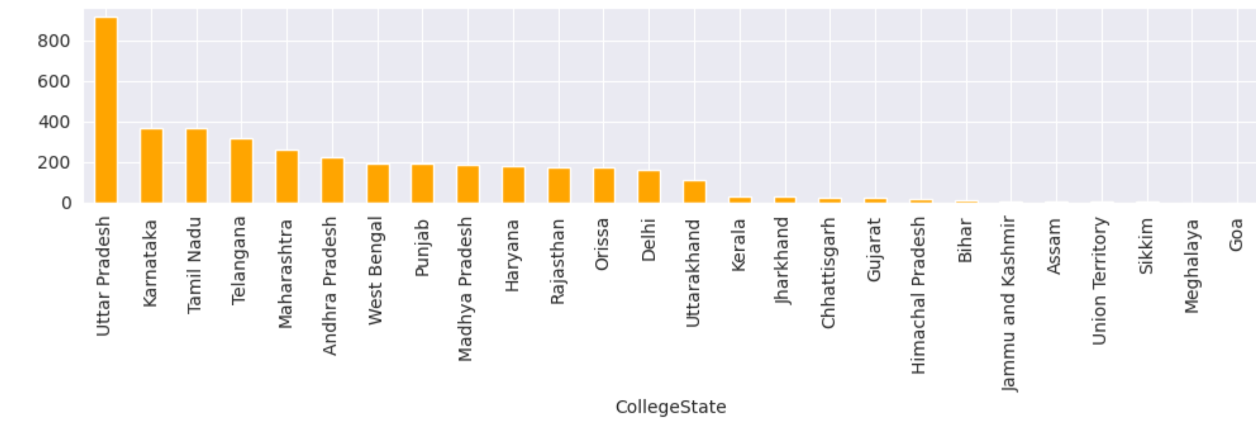
This comparison highlights that the top 10% of candidates not only score higher but also have more consistent performance in Computer Science,because of higher median scores with less variability. Unlike more variability and a lower median score of the rest scores

```
# How many college students from each state
each_state=amcat_data.groupby("CollegeState").size().sort_values(ascen
ding=False)
each_state
```

```
CollegeState
Uttar Pradesh        915
Karnataka            370
Tamil Nadu           367
Telangana            319
Maharashtra          262
Andhra Pradesh       225
West Bengal          196
Punjab               193
Madhya Pradesh       189
Haryana              180
Rajasthan            174
Orissa               172
Delhi                162
Uttarakhand          113
Kerala                33
Jharkhand             28
Chhattisgarh          27
Gujarat               24
Himachal Pradesh      16
Bihar                 10
Jammu and Kashmir      7
Assam                  5
Union Territory        5
Sikkim                 3
Meghalaya              2
Goa                    1
dtype: int64
```

```
# plot first 10 records from each_state.
each_state.plot(kind="bar",color="orange")
```

```
<Axes: xlabel='CollegeState'>
```



Insights:

From the top 10 records,this barplot highlights that students from Uttar Pradesh about 915 are in higher than other states taken AMCAT Exam.

```
# Get the student details from Andhra pradesh who took biotechnology
bioTech_ap=amcat_data[(amcat_data["CollegeState"]=="Andhra Pradesh") &
(amcat_data["Specialization"]=="biotechnology")]
bioTech_ap.T
```

{"summary":"{\n \"name\": \"bioTech_ap\",\n \"rows\": 38,\n \"fields\": [\n   {\n   \"column\": 555,\n   \"properties\": {\n   \"dtype\": \"string\",\n   \"num_unique_values\": 32,\n   \"samples\": [\n   2.1234,\n   \"B.Tech/B.E.\",\n   -1.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe"}

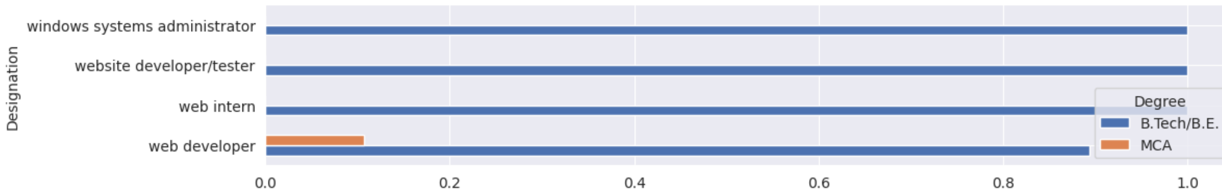
Bivariate Analysis

Definition:

Bivariate analysis is a statistical method used to examine the relationship between two variables.It helps in understanding the association, correlation, or causality between two variables.

A) Categorical vs Categorical Analysis

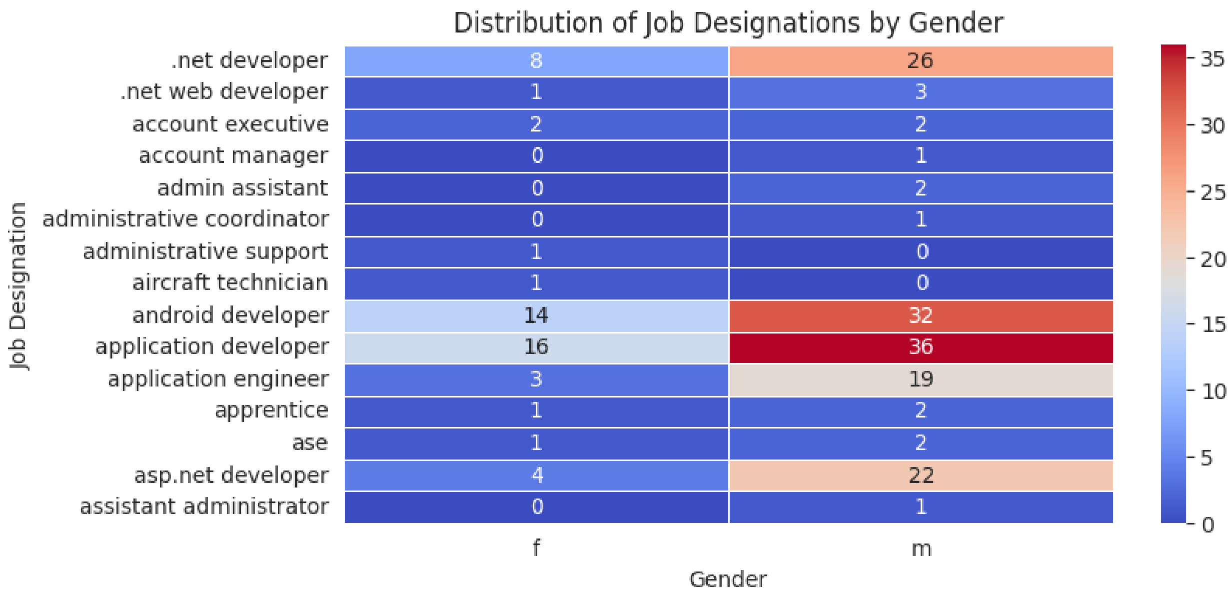
```
tab =
pd.crosstab(amcat_data["Designation"].sort_values(ascending=False)
[:50], amcat_data['Degree'], normalize='index')
tab.plot(kind='barh')

<Axes: ylabel='Designation'>
```




```
# Are certain job designations more common among male or female
candidates? Get first 15 designations.
desig_gender = pd.crosstab(amcat_data['Designation'],
amcat_data['Gender'])[:15]

desig_gender
```

{"summary":"{\n \"name\": \"desig_gender\",\n \"rows\": 15,\n
\"fields\": [\n   {\n   \"column\": \"Designation\",\n
\"properties\": {\n   \"dtype\": \"string\",\n
\"num_unique_values\": 15,\n   \"samples\": [\n
\"application developer\",\n   \"apprentice\",\n
\".net developer\"\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"f\",\n   \"properties\": {\n   \"dtype\": \"number\",\n
\"std\": 5,\n   \"min\": 0,\n   \"max\": 16,\n
\"num_unique_values\": 8,\n   \"samples\": [\n   1,\n
16,\n   8\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"m\",\n   \"properties\": {\n   \"dtype\": \"number\",\n
\"std\": 13,\n   \"min\": 0,\n   \"max\": 36,\n
\"num_unique_values\": 9,\n   \"samples\": [\n   19,\n
3,\n   32\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   }\n]\
n}","type":"dataframe","variable_name":"desig_gender"}

```
plt.figure(figsize=(8, 4))
sb.heatmap(desig_gender, annot=True, cmap='coolwarm', linewidths=.5)
plt.title('Distribution of Job Designations by Gender')
plt.xlabel('Gender')
plt.ylabel('Job Designation')
plt.show()
```



Insights:

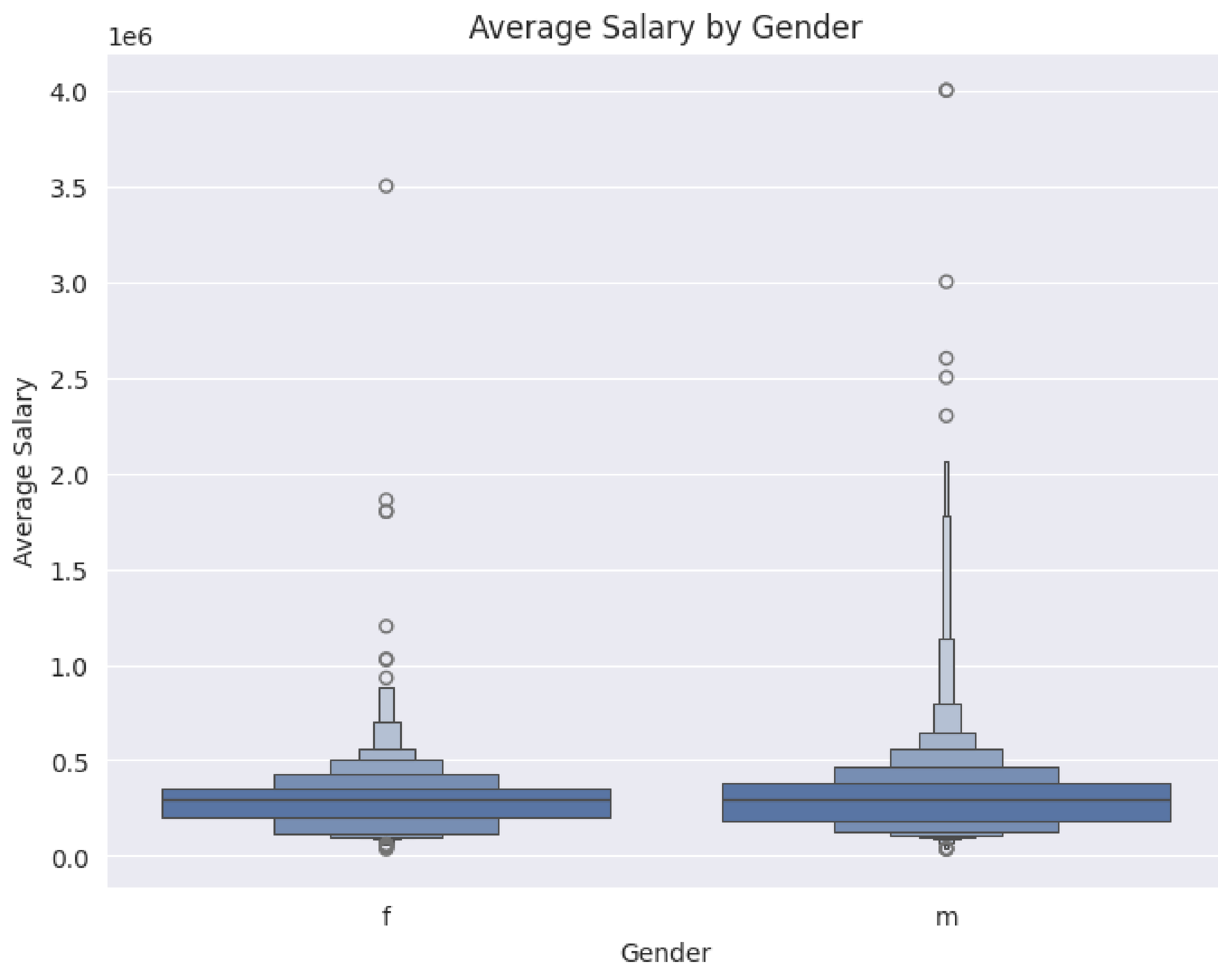
It's noted form the first 15 designations,that maximum number of males are associated with job designation as application developer with 36 counts and females with 16 counts.And females are the one with maximum distributions of "0" designation count.

B) Numerical vs Categorical Analysis :

```
#Do male and female candidates have different average salaries?
salary_by_gender = amcat_data.groupby('Gender')['Salary'].mean()
salary_by_gender
```

```
Gender
f    294937.304075
m    311716.211772
Name: Salary, dtype: float64
```

```
plt.figure(figsize=(8, 6))
sb.boxplot(x="Gender",y="Salary",data=amcat_data)
plt.title('Average Salary by Gender')
plt.xlabel('Gender')
plt.ylabel('Average Salary')
plt.xticks(rotation=0)
plt.show()
```



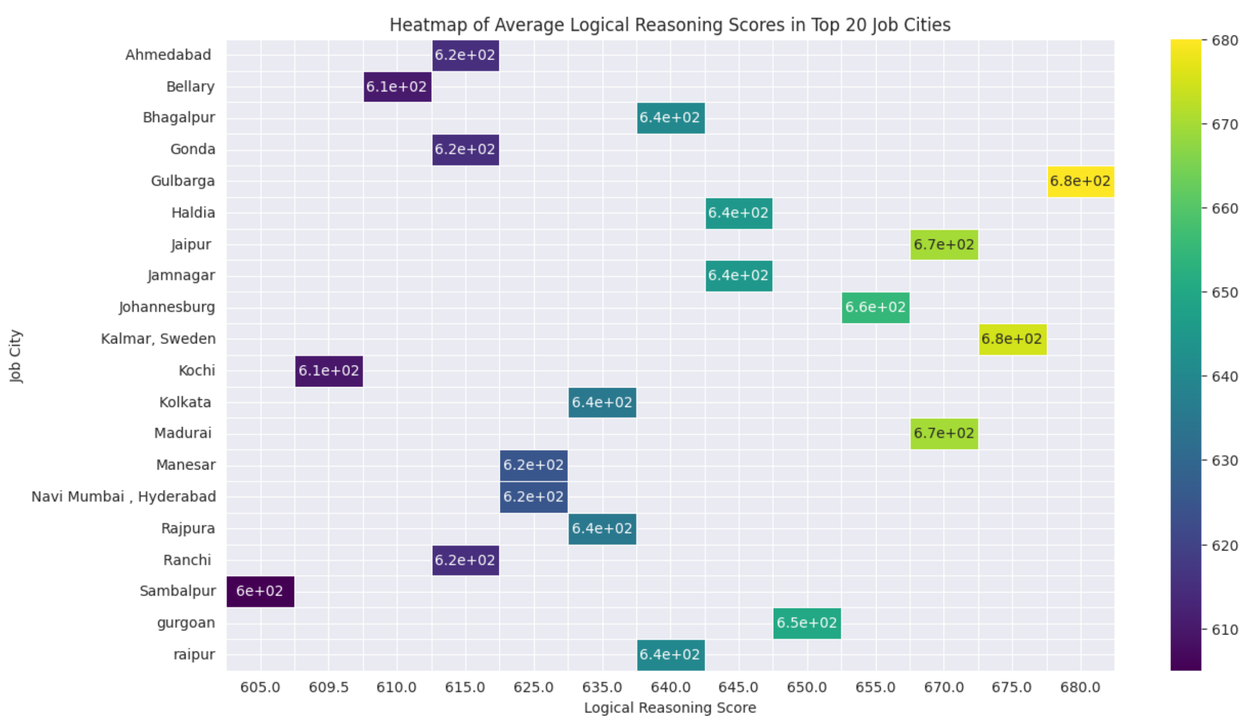
Insights:

We can see that males are tend to earn a higher distributed salaries compared to the females though the average salary tend to approximately same.

```
#How do logical reasoning scores vary across different job cities?Get top 20

job_logical=amcat_data.groupby("JobCity")
["Logical"].mean().sort_values(ascending=False)[:20]
job_logical

JobCity
Gulbarga                     680.0
Kalmar, Sweden               675.0
Madurai                      670.0
Jaipur                       670.0
Johannesburg                 655.0
gurgoan                      650.0
Haldia                       645.0
```

```
Jamnagar                      645.0
Bhagalpur                     640.0
raipur                        640.0
Rajpura                       635.0
Kolkata                       635.0
Manesar                       625.0
Navi Mumbai , Hyderabad       625.0
Ahmedabad                     615.0
Ranchi                        615.0
Gonda                         615.0
Bellary                       610.0
Kochi                         609.5
Sambalpur                     605.0
Name: Logical, dtype: float64
```

```python
heatmap = job_logical.reset_index().pivot(index='JobCity',
columns='Logical', values='Logical')

# Plot the data
plt.figure(figsize=(14, 8))
sb.heatmap(heatmap, annot=True, cmap='viridis', linewidths=.5)
plt.title('Heatmap of Average Logical Reasoning Scores in Top 20 Job
Cities')
plt.xlabel('Logical Reasoning Score')
plt.ylabel('Job City')
plt.show()
```



Insights:

For the top 20 jobcities,Gulbarga city had the higher logical reasoning score of 680 and lower score was found in Sambalpur city respectively.

```
#How does specialization affect the salary of candidates?
sal_special=amcat_data.groupby("Specialization")
["Salary"].mean().sort_values()
sal_special
```

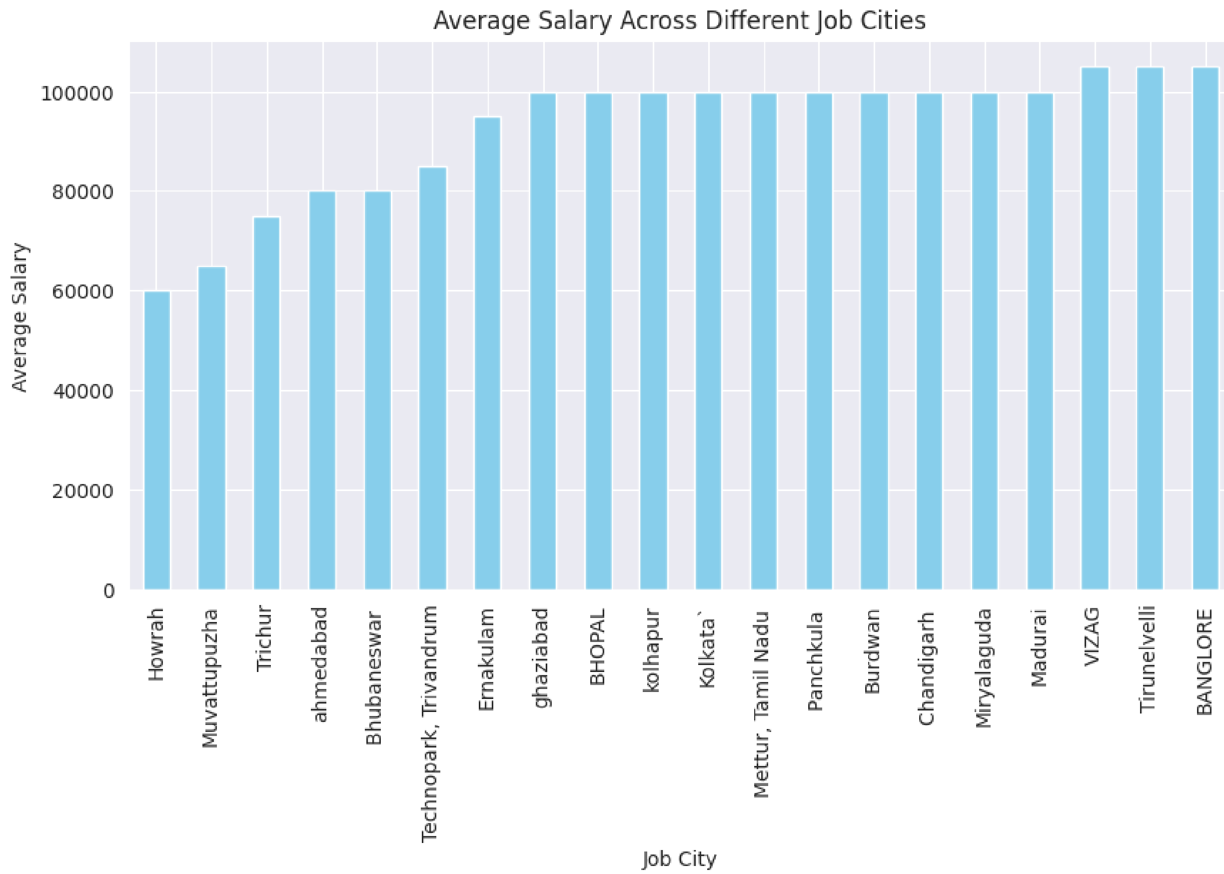
```
Specialization
electronics                                    40000.000000
mechanical & production engineering           100000.000000
power systems and automation                  100000.000000
computer and communication engineering        120000.000000
aeronautical engineering                      148333.333333
embedded systems technology                   200000.000000
electrical and power engineering              210000.000000
electronics and computer engineering          220000.000000
automobile/automotive engineering             222000.000000
instrumentation engineering                   240000.000000
computer science and technology               245833.333333
mechatronics                                  253750.000000
biotechnology                                 254333.333333
other                                         266538.461538
information science engineering               276296.296296
computer science & engineering                277439.516129
electronics engineering                       279473.684211
computer application                          280389.344262
electronics and electrical engineering        286913.265306
biomedical engineering                        290000.000000
computer science                              290000.000000
electronics & telecommunications              293553.719008
electrical engineering                        293780.487805
electronics and communication engineering     296812.500000
control and instrumentation engineering       305000.000000
information technology                        308492.424242
mechanical and automation                     309000.000000
mechanical engineering                        317457.711443
industrial & management engineering           320000.000000
electronics and instrumentation engineering   327407.407407
ceramic engineering                           335000.000000
metallurgical engineering                     337500.000000
telecommunication engineering                 342500.000000
applied electronics and instrumentation       348333.333333
internal combustion engine                    360000.000000
electronics & instrumentation eng             364531.250000
industrial engineering                        370000.000000
chemical engineering                          370000.000000
computer engineering                          374100.000000
civil engineering                             381206.896552
industrial & production engineering           384500.000000
```

```
information & communication technology        387500.000000
instrumentation and control engineering       394000.000000
information science                           460000.000000
computer networking                           565000.000000
polymer technology                            700000.000000
Name: Salary, dtype: float64
```

```
#What is the distribution of salaries across different job cities?
sal_special=amcat_data.groupby("JobCity")
["Salary"].mean().sort_values()[:20]
sal_special
```

```
JobCity
Howrah                        60000.0
Muvattupuzha                  65000.0
Trichur                       75000.0
ahmedabad                     80000.0
Bhubaneswar                   80000.0
Technopark, Trivandrum        85000.0
Ernakulam                     95000.0
ghaziabad                    100000.0
BHOPAL                       100000.0
kolhapur                     100000.0
Kolkata`                     100000.0
Mettur, Tamil Nadu           100000.0
Panchkula                    100000.0
Burdwan                      100000.0
Chandigarh                   100000.0
Miryalaguda                  100000.0
Madurai                      100000.0
VIZAG                        105000.0
Tirunelvelli                 105000.0
BANGLORE                     105000.0
Name: Salary, dtype: float64
```

```
#Plot distribution of salaries
plt.figure(figsize=(10, 5))
sal_special.plot(kind='bar', color='skyblue')
plt.title('Average Salary Across Different Job Cities')
plt.xlabel('Job City')
plt.ylabel('Average Salary')
plt.xticks(rotation=90)
plt.show()
```



Insights:

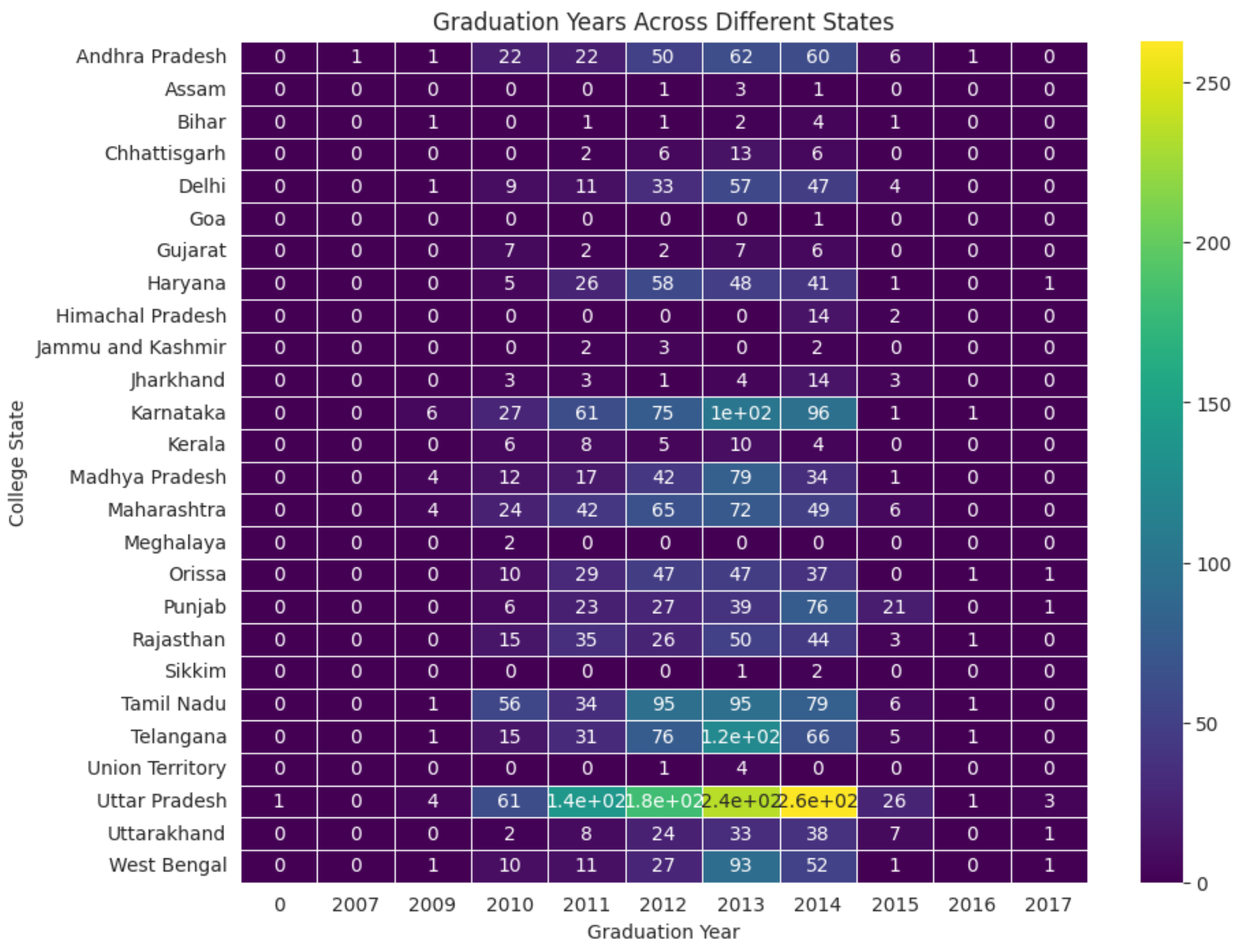
Out of top 20 jobcities,cities like VIZAG,Tirunelvelli,BANGLORE holds the same average salary package of 1,05,000.In which Howrah is the one with lowest average salary package.

```
#How does the distribution of graduation years vary across different
states?
state_gradyear = amcat_data.groupby(['CollegeState',
'GraduationYear']).size().unstack(fill_value=0)
state_gradyear
```

{"summary":"{\n \"name\": \"state_gradyear\",\n \"rows\": 26,\n
\"fields\": [\n   {\n   \"column\": \"CollegeState\",\n
\"properties\": {\n   \"dtype\": \"string\",\n
\"num_unique_values\": 26,\n   \"samples\": [\n
\"Himachal Pradesh\",\n   \"Orissa\",\n   \"Andhra
Pradesh\"\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\": 0,\n
\"properties\": {\n   \"dtype\": \"number\",\n   \"std\":
0,\n   \"min\": 0,\n   \"max\": 1,\n
\"num_unique_values\": 2,\n   \"samples\": [\n   1,\n
0\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":

```
2007,\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 0,\n        \"min\": 0,\n        \"max\": 1,\n
\"num_unique_values\": 2,\n        \"samples\": [\n          0,\n
1\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
2009,\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 1,\n        \"min\": 0,\n        \"max\": 6,\n
\"num_unique_values\": 4,\n        \"samples\": [\n          0,\n
4\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
2010,\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 16,\n        \"min\": 0,\n        \"max\": 61,\n
\"num_unique_values\": 15,\n        \"samples\": [\n          24,\n
10\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
2011,\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 29,\n        \"min\": 0,\n        \"max\": 139,\n
\"num_unique_values\": 17,\n        \"samples\": [\n          22,\n
0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
2012,\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 41,\n        \"min\": 0,\n        \"max\": 182,\n
\"num_unique_values\": 19,\n        \"samples\": [\n          50,\n
2\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
2013,\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 54,\n        \"min\": 0,\n        \"max\": 235,\n
\"num_unique_values\": 22,\n        \"samples\": [\n          62,\n
47\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
2014,\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 53,\n        \"min\": 0,\n        \"max\": 263,\n
\"num_unique_values\": 20,\n        \"samples\": [\n          60,\n
263\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
2015,\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 6,\n        \"min\": 0,\n        \"max\": 26,\n
\"num_unique_values\": 10,\n        \"samples\": [\n          26,\n
0\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
2016,\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 0,\n        \"min\": 0,\n        \"max\": 1,\n
\"num_unique_values\": 2,\n        \"samples\": [\n          0,\n
1\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
2017,\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 0,\n        \"min\": 0,\n        \"max\": 3,\n
\"num_unique_values\": 3,\n        \"samples\": [\n          0,\n
1\n        ],\n        \"semantic_type\": \"\",\n
```

```
\"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe","variable_name":"state_gradyear"}

# Visualize heatmap
plt.figure(figsize=(10, 8))
sb.heatmap(state_gradyear, annot=True, cmap='viridis', linewidths=.5)
plt.title('Graduation Years Across Different States')
plt.xlabel('Graduation Year')
plt.ylabel('College State')
plt.show()
```



Insights:

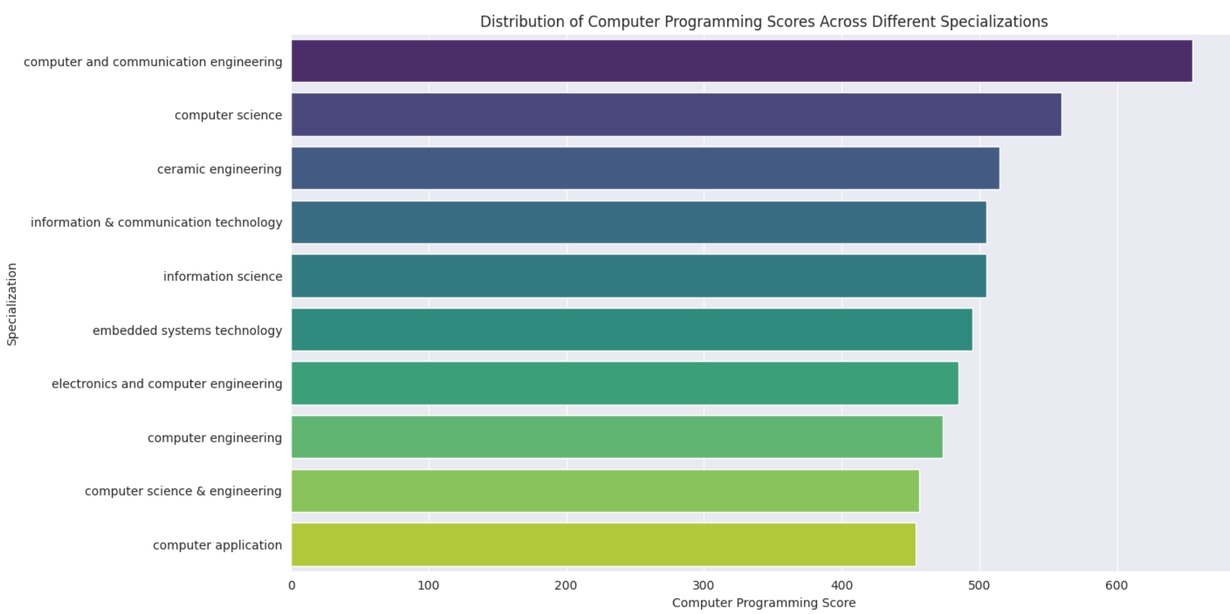
Concerned heatmap shows that 263 candidates form Uttar Pradesh got graduated in 2014 and 234 candidates in 2013,which correlates with the facilites avaliable in the cities to topped among all.

```
# How do computer programming scores vary across different
specializations?
special_scores = amcat_data.groupby('Specialization')
['ComputerProgramming'].mean().reset_index()
```

```
special_scores
=special_scores.sort_values(ascending=False,by="ComputerProgramming")
special_scores[:25]
```

{"summary":"{\n \"name\": \"special_scores[:25]\",\n \"rows\": 25,\n \"fields\": [\n   {\n   \"column\": \"Specialization\",\n   \"properties\": {\n   \"dtype\": \"string\",\n   \"num_unique_values\": 25,\n   \"samples\": [\n   \"computer science & engineering\",\n   \"power systems and automation\",\n   \"computer and communication engineering\"\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"ComputerProgramming\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 103.49962796270253,\n   \"min\": 239.53068181818182,\n   \"max\": 655.0,\n   \"num_unique_values\": 24,\n   \"samples\": [\n   453.87704918032784,\n   380.6666666666667,\n   655.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe"}

```
plt.figure(figsize=(14, 8))
sb.barplot(x='ComputerProgramming', y='Specialization',
data=special_scores[:10], palette='viridis')
plt.title('Distribution of Computer Programming Scores Across
Different Specializations')
plt.xlabel('Computer Programming Score')
plt.ylabel('Specialization')
plt.show()
```



Insights:

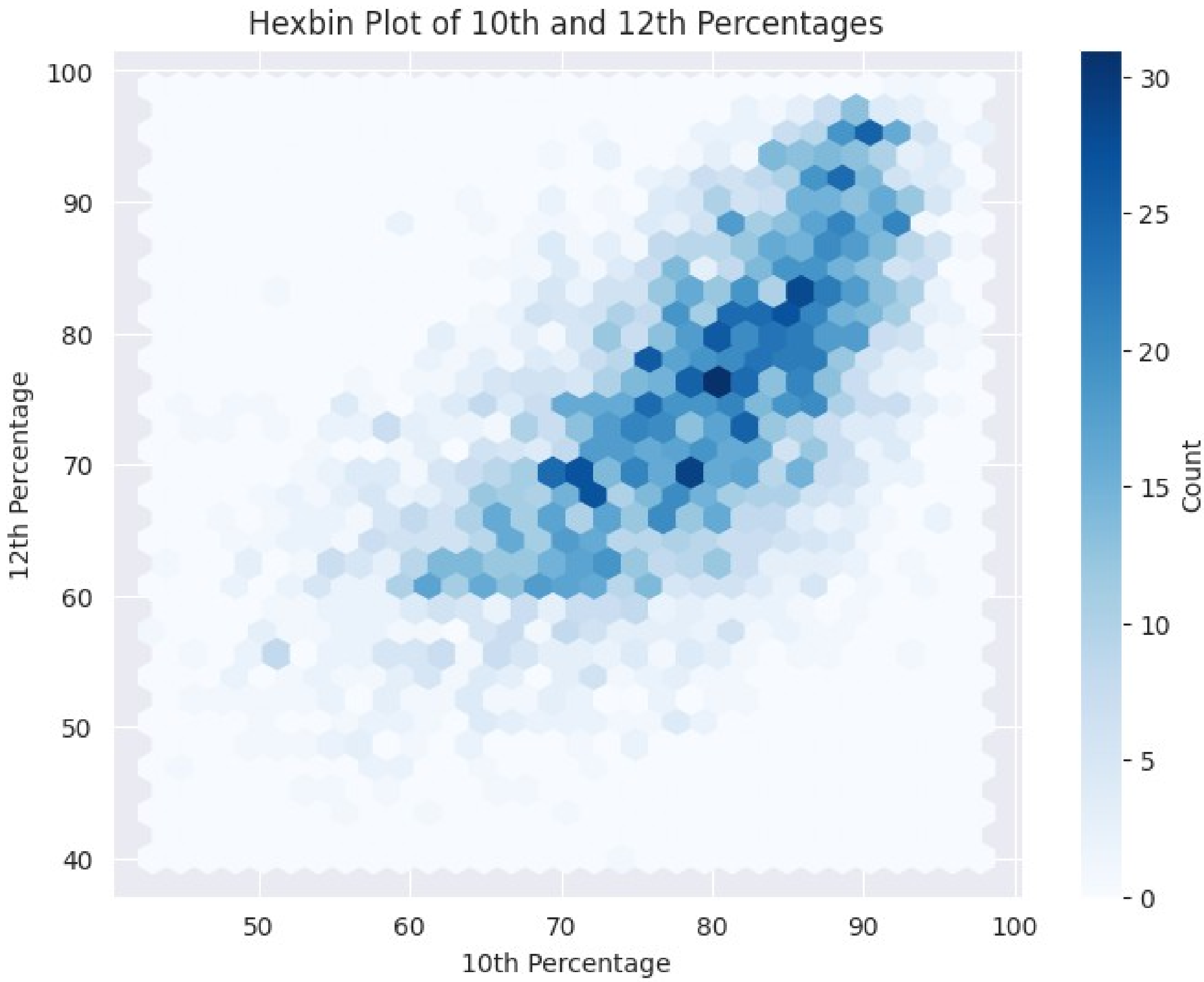
This barghaph of top 10 records indicates that computer and communication engineering specialization topped among the all with a score of computer programming is 655, in which computer applications scores less around 470.

C) Numerical vs Numerical Analysis :

```
#Is there a correlation between 10th and 12th percentages?
correlation =
amcat_data['10percentage'].corr(amcat_data['12percentage'])
print(f'Pearson correlation coefficient : {correlation}')
```

```
Pearson correlation coefficient : 0.6433777960234051
```

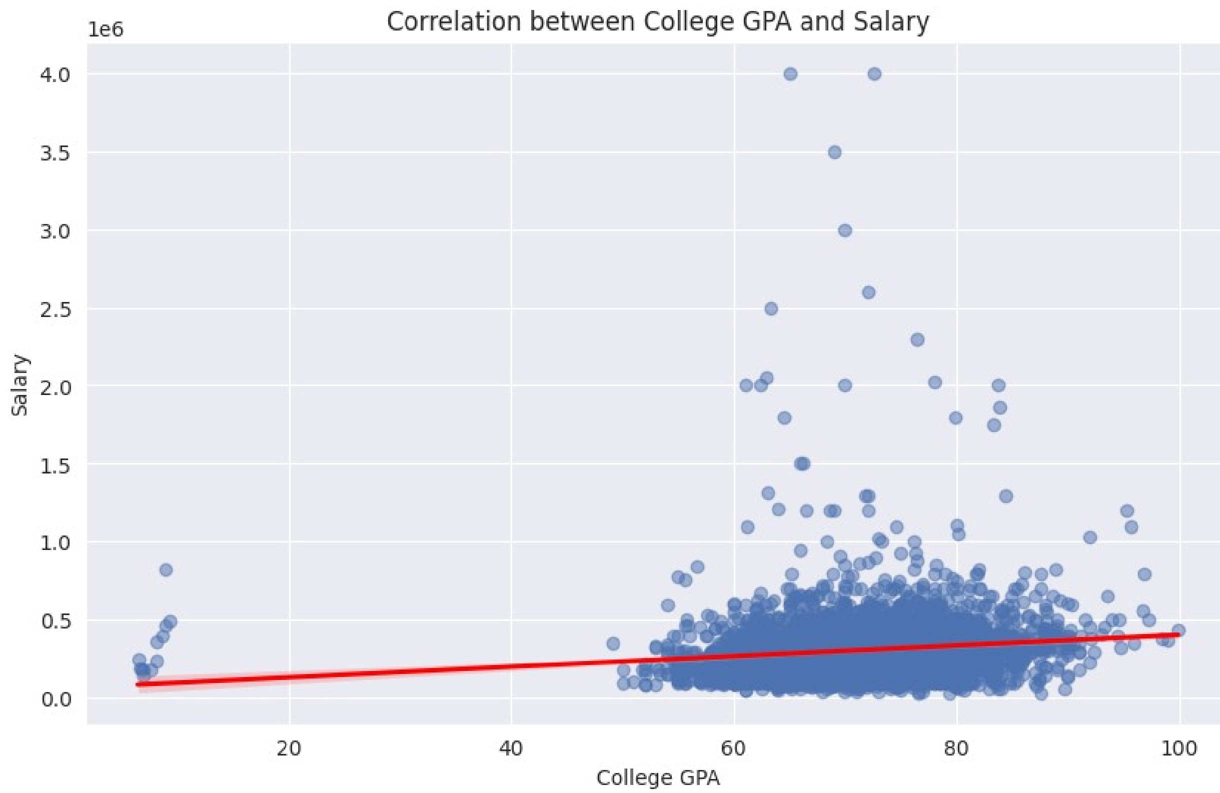
```
plt.figure(figsize=(8, 6))
plt.hexbin(amcat_data['10percentage'], amcat_data['12percentage'],
gridsize=30, cmap='Blues')
plt.colorbar(label='Count')
plt.title('Hexbin Plot of 10th and 12th Percentages')
plt.xlabel('10th Percentage')
plt.ylabel('12th Percentage')
plt.show()
```



Insights:

We can see the strong positive correlation between the 10th and 12th percentages with pearson value of correlation 0.64 .If the student who scores better in 10th will definitely score in 12th grade too.

```
#How does college GPA affect salary?
cgpa=amcat_data.collegeGPA.corr(amcat_data.Salary)
print(f'Pearson correlation between college GPA and salary: {cgpa}')

Pearson correlation between college GPA and salary:
0.13010251907112566

plt.figure(figsize=(10, 6))
sb.regplot(x='collegeGPA', y='Salary', data=amcat_data,
scatter_kws={'alpha':0.5}, line_kws={'color':'red'})
plt.title('Correlation between College GPA and Salary')
plt.xlabel('College GPA')
plt.ylabel('Salary')
plt.show()
```



Insights:

Though we see a weak positive correlation value of 0.13 ,Sometimes the cgpa will work as the it is high.Also ,in some cases external factors deals with salary such as Logical Reasoning ,Quant ,more...Finally, there is no relation b/w the variates in this analysis.

```
amcat_int.columns

Index(['ID', '12graduation', 'CollegeID', 'CollegeTier',
'CollegeCityID',
       'CollegeCityTier', 'GraduationYear', 'English', 'Logical',
'Quant',
       'ComputerProgramming', 'ElectronicsAndSemicon',
'ComputerScience',
       'MechanicalEngg', 'ElectricalEngg', 'TelecomEngg',
'CivilEngg'],
      dtype='object')

# Calculate the Pearson correlation coefficient and visualize using a
scatter plot for GraduationYear vs Salary.
grad_sal=amcat_data.openess_to_experience.corr(amcat_data.Salary)
grad_sal

-0.011312268472631561
```

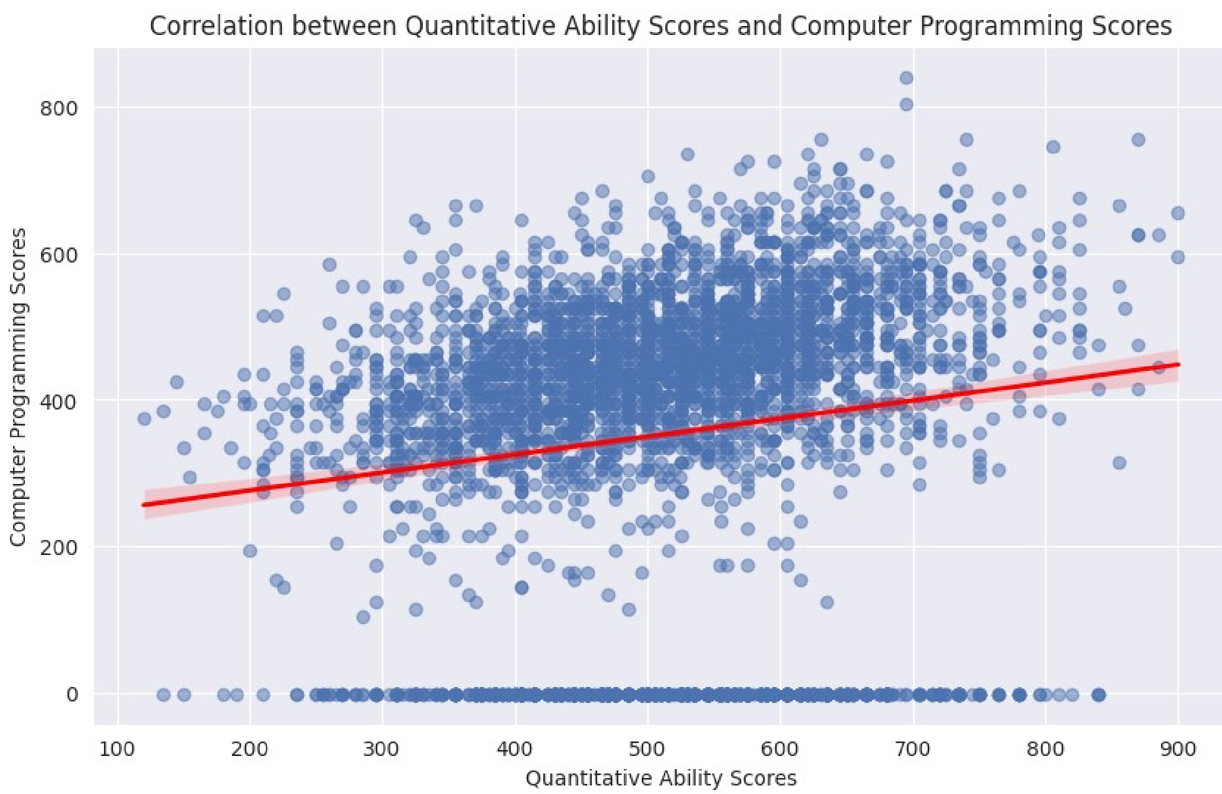
```
# Visualize
plt.figure(figsize=(10, 6))
sb.regplot(x='openess_to_experience', y='Salary', data=amcat_data,
scatter_kws={'alpha':0.5}, line_kws={'color':'red'})
plt.title('Correlation between Experience and Salary')
plt.xlabel('Graduation Year')
plt.ylabel('Salary')
plt.show()
```

Insights:

Though we see a weak positive correlation value of 0.104 ,There are only few chances if experience is more the salary is more only in growth areas which depends on skillset and external factors.

```
#How do quantitative ability scores correlate with computer
programming scores?
quant_scores =
amcat_data['Quant'].corr(amcat_data['ComputerProgramming'])
print(f'Pearson correlation coefficient : {correlation}')

# Visualize the correlation using a scatter plot with a regression
line
plt.figure(figsize=(10, 6))
sb.regplot(x='Quant', y='ComputerProgramming', data=amcat_data,
```

```
scatter_kws={'alpha':0.5}, line_kws={'color':'red'})
plt.title('Correlation between Quantitative Ability Scores and
Computer Programming Scores')
plt.xlabel('Quantitative Ability Scores')
plt.ylabel('Computer Programming Scores')
plt.show()

Pearson correlation coefficient : 0.6433777960234051
```

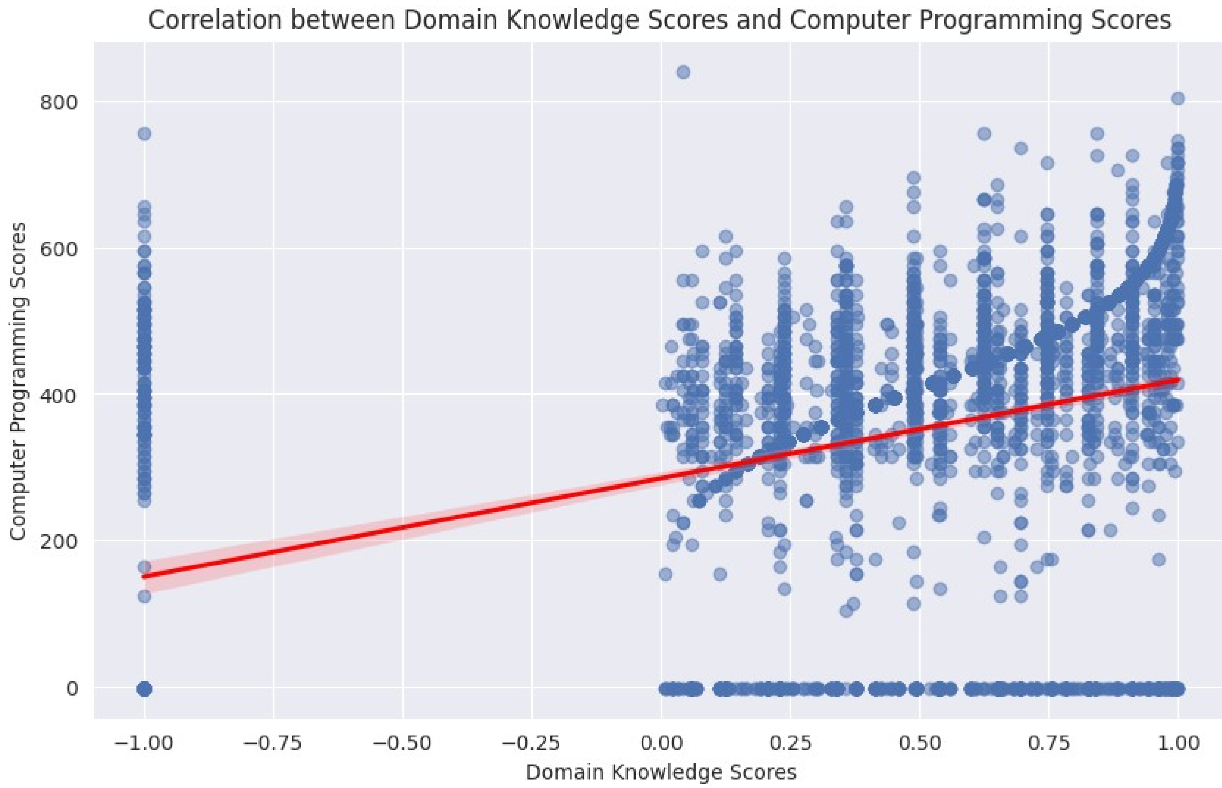


Insights:

A strong positive correlation value of 0.64 can be seen that there is linear relationship between programming scores and quantitative scores.And this type of candidates have good effect on salary & skillset.

```
#How do domain knowledge scores correlate with computer programming
scores?

correlation =
amcat_data['Domain'].corr(amcat_data['ComputerProgramming'])
print(f'Pearson correlation coefficient : {correlation}')

plt.figure(figsize=(10, 6))
sb.regplot(x='Domain', y='ComputerProgramming', data=amcat_data,
scatter_kws={'alpha':0.5}, line_kws={'color':'red'})
```

```
plt.title('Correlation between Domain Knowledge Scores and Computer
Programming Scores')
plt.xlabel('Domain Knowledge Scores')
plt.ylabel('Computer Programming Scores')
plt.show()

Pearson correlation coefficient : 0.30616038332724843
```



Insights:

Though we see a weak positive correlation value of 0.306 ,There are only few chances that the domain knoweledge can be appiled inorder to score in programming in case study scenerios,higher the domain knowledge the chances are high in programming scoring .

Research Questions

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.

```
from scipy import stats

# Concern roles
concern_role = ['programmer analyst', 'software engineer', 'hardware
engineer', 'associate engineer']
concern_data=amcat_data[amcat_data['Designation'].isin(concern_role)]
salary_data = concern_data["Salary"]

# one-sample t-test
mean_salary = 2.75 * (10**5)
t_stat, p_value = stats.ttest_1samp(salary_data,mean_salary)

# Print results
print(f"Mean Salary: {mean_salary}")
print(f"Concern_role Mean Salary: {salary_data.mean()}")
print(f"T-statistic: {t_stat:.4f}")
print(f"P-value: {p_value:.4f}")

alpha = 0.05
if p_value < alpha:
    print("\nReject the null hypothesis: The average salary is
significantly different from the claimed mean.")
else:
    print("\nFail to reject the null hypothesis: The average salary is
not significantly different from the claimed mean.")

Mean Salary: 275000.0
Concern_role Mean Salary: 339790.4624277457
T-statistic: 12.9330
P-value: 0.0000

Reject the null hypothesis: The average salary is significantly
different from the claimed mean.
```

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

```
import pandas as pd
from scipy import stats as st

# contingency table
conti_tab = pd.crosstab(index=amcat_data["Specialization"],
columns=amcat_data["Gender"])

# Chi-square test
chi2_stat, p_value, dof, exp_freq = st.chi2_contingency(conti_tab)

alpha = 0.05

# Print results
```

```
if p_value < alpha:
    print("\nReject the null hypothesis: There is a significant 
difference between gender and specialization.")
else:
    print("\nFail to reject the null hypothesis: There is no 
significant difference between gender and specialization.")
```

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

```
# Is there a correlation between English proficiency scores and 
logical reasoning scores?import pandas as pd

from scipy.stats import pearsonr

english_scores = amcat_data['English']
logical_scores = amcat_data['Logical']

correlation, p_value = pearsonr(english_scores, logical_scores)

# Print the results
print(f"Pearson correlation coefficient: {correlation:.4f}")
print(f"P-value: {p_value:.4f}")

alpha = 0.05
if p_value < alpha:
    print("There is a significant correlation between English 
proficiency scores and logical reasoning scores.")
else:
    print("There is no significant correlation between English 
proficiency scores and logical reasoning scores.")
```

```
Pearson correlation coefficient: 0.4444
P-value: 0.0000
There is a significant correlation between English proficiency scores 
and logical reasoning scores.
```

Conclusion

Through this entire Exploratory Data Analysis, the drawn insights deals with the salary field which gives the hypothetical ideas about the how the particular parameters contributes the job opportunities that may be the specialization,exam scores,skills and more in the path. Few key points are...

1. Salary Distribution:

The salary attribute shows right-skewed outliers, indicating that a few candidates earn significantly more than the average salary.

2. Engineering Scores:

Fields like Computer Science, Mechanical Engineering, Civil Engineering, Electrical Engineering, and Telecom Engineering have right-skewed outliers, suggesting higher scores pulling the mean to the right.

3. Personality Scores:

Standardized scores for conscientiousness, agreeableness, and extraversion are left-skewed, indicating most students scored lower in these traits.

4. Gender Distribution:

Approximately 76% of AMCAT exam takers are male, while 24% are female.

5. Specializations:

Electronics and Communication Engineering has the highest number of candidates (800), while Electronics and Instrumentation Engineering has the least (32).

6. State-wise Participation:

Uttar Pradesh has the highest number of candidates (915) taking the AMCAT exam, compared to other states.

7. Hypothesis Analysis:

We Reject the null hypothesis as " There is a significant difference between gender and specialization".It means that there is a statistically significant difference between gender and specialization. This implies that gender and specialization are not independent, and there is some form of association between them,since the p-value is less than at 0.05 significance level.

---END---