aerofit-1

October 30, 2023

QUESTION 1:

Problem Statement for Aerofit Dataset: Given the attributes related to Aerofit product usage, such as product type, age, gender, education, marital status, frequency of usage, fitness level, income, and expected miles run, we can dive deep into :

"How can Aerofit better understand its customer base to tailor its marketing, sales, and product strategies, maximizing user satisfaction and profitability?"

This problem statement guides the analytical process towards understanding various factors(age, gender,maritalstatus….etc) and patterns that play a role in a customer's decision to purchase or use Aerofit products.

Analyzing Basic Metrics:

1. Shape of Data: Understanding the size (rows and columns) of your dataset gives you an idea of the volume of data we are dealing with. It helps in determining if we have sufficient data for meaningful analyses or if there are too many features (potential for dimensionality reduction).

2. Data Types of Attributes: Before diving into any analysis, understanding the data type of each attribute is crucial. It helps in deciding the kind of operations and statistical methods that can be applied to each attribute.

3. Conversion of Categorical Attributes: In many datasets, categorical attributes (like 'Gender' or 'MaritalStatus') may be represented as strings or integers. For efficient processing and accurate analysis, converting them to a 'category' data type in programming languages like Python can be beneficial. This also helps in reducing memory consumption.

4. Statistical Summary: This is a preliminary step to get a "feel" for the data:

Central Tendency: Understand the average and median of the data. Dispersion: See the spread of the data through measures like standard deviation. Frequency: For categorical data, understanding how often each category appears is essential. Range: Knowing the minimum and maximum values helps in understanding the bounds of numeric data.

5. Checking for Missing Values: Before diving deep into analysis, it's crucial to identify if there are any missing values in the dataset. If there are, decisions need to be made about how to handle them, e.g., imputation or removal.

6. Identifying Potential Outliers: Outliers can distort the results of the analysis. Using methods like visual box-plots or IQR (Interquartile Range) can help in spotting and handling outliers.

In conclusion, the combination of a well-defined problem statement and a preliminary analysis using basic metrics sets the stage for more sophisticated analyses and data modeling. It ensures that further steps are taken with a clear direction and understanding of the dataset at hand.

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

[ ]:
```
import numpy as np
```

[ ]:
```
df = pd.read_csv("/content/resource/aerofit_treadmill.txt")
```

SHAPE OF THE DATA

[ ]:
```
df.shape
```

[ ]:
```
(180, 9)
```

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

[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	18	Male	14	Single	3	4	29562	112
1	KP281	19	Male	15	Single	2	3	31836	75
2	KP281	19	Female	14	Partnered	4	3	30699	66
3	KP281	19	Male	12	Single	3	3	32973	85
4	KP281	20	Male	13	Partnered	4	2	35247	47

DATA TYPE OF THE DATA

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Product        180 non-null    category
 1   Age            180 non-null    int64
 2   Gender         180 non-null    category
 3   Education      180 non-null    int64
 4   MaritalStatus  180 non-null    category
 5   Usage          180 non-null    int64
 6   Fitness        180 non-null    int64
 7   Income         180 non-null    int64
 8   Miles          180 non-null    int64
dtypes: category(3), int64(6)
memory usage: 9.5 KB
```

STATISTICAL SUMMARY OF THE DATA

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

```
[ ]:               Age   Education       Usage     Fitness         Income  \
count  180.000000  180.000000  180.000000  180.000000     180.000000
mean    28.788889   15.572222    3.455556    3.311111   53719.577778
std      6.943498    1.617055    1.084797    0.958869   16506.684226
min     18.000000   12.000000    2.000000    1.000000   29562.000000
25%     24.000000   14.000000    3.000000    3.000000   44058.750000
50%     26.000000   16.000000    3.000000    3.000000   50596.500000
75%     33.000000   16.000000    4.000000    4.000000   58668.000000
max     50.000000   21.000000    7.000000    5.000000  104581.000000

            Miles
count  180.000000
mean   103.194444
std     51.863605
min     21.000000
25%     66.000000
50%     94.000000
75%    114.750000
max    360.000000
```

CONVERTING INTO CATEGORICAL ATTRIBUTE

```
[ ]: df['Product'] = df['Product'].astype('category')
```

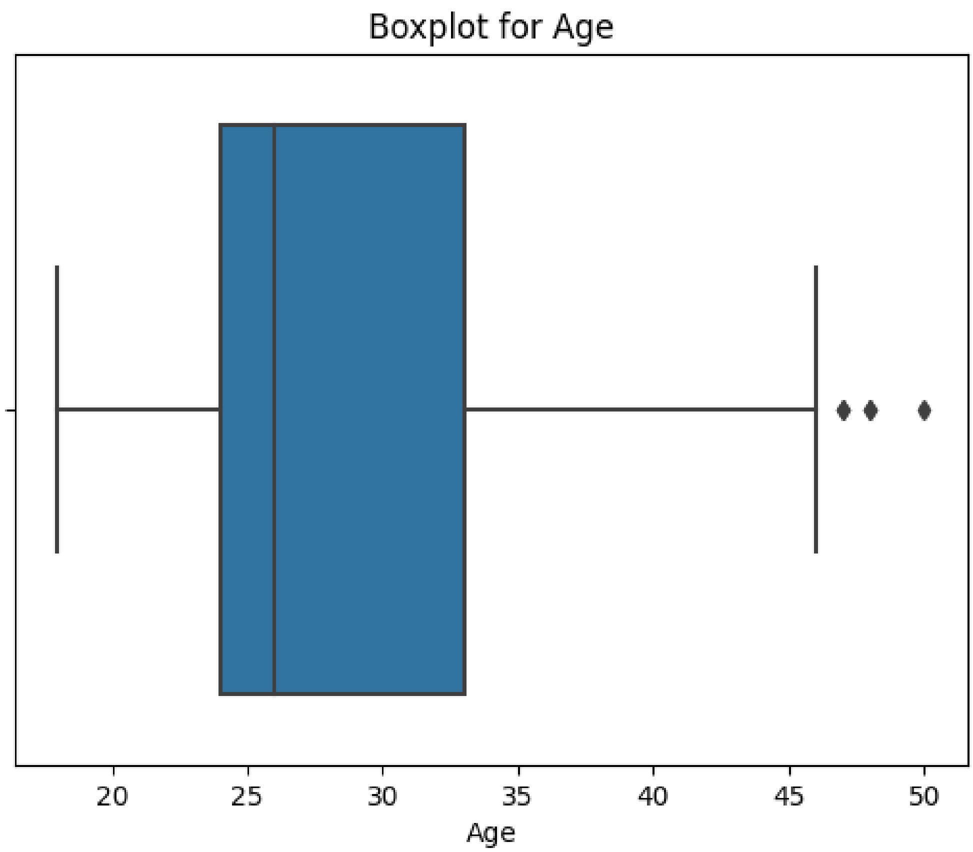
```
[ ]: df['Gender'] = df['Gender'].astype('category')

     df['MaritalStatus'] = df['MaritalStatus'].astype('category')
```

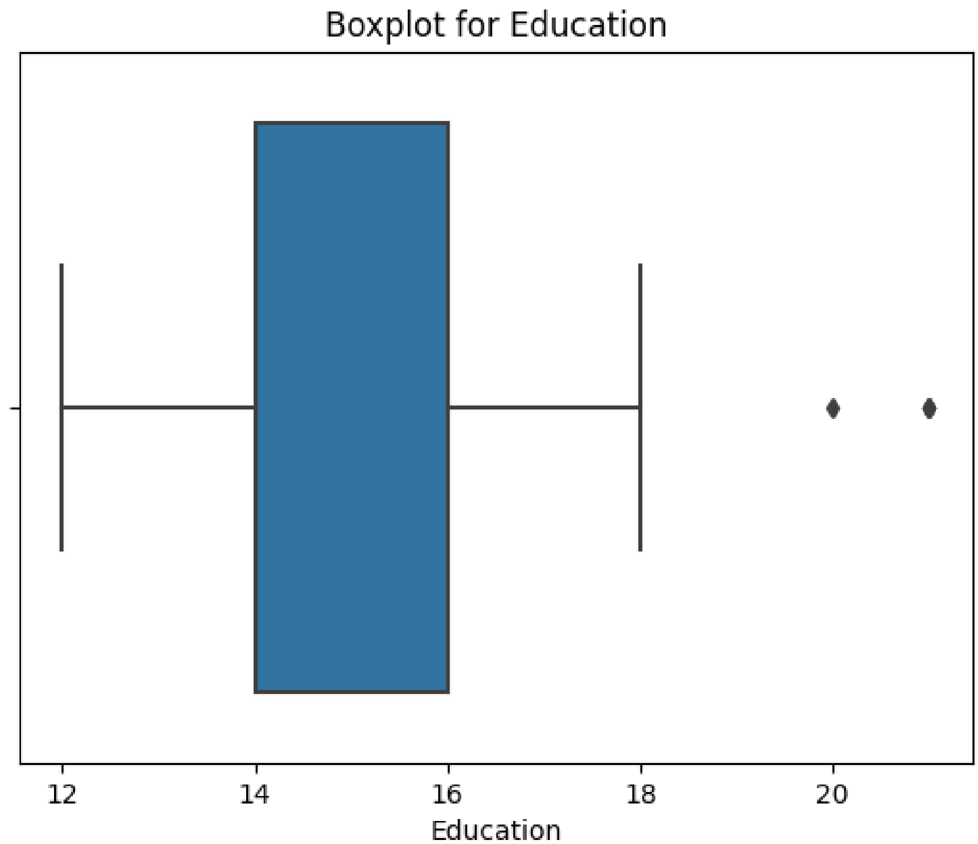
```
[ ]: df.info()
```

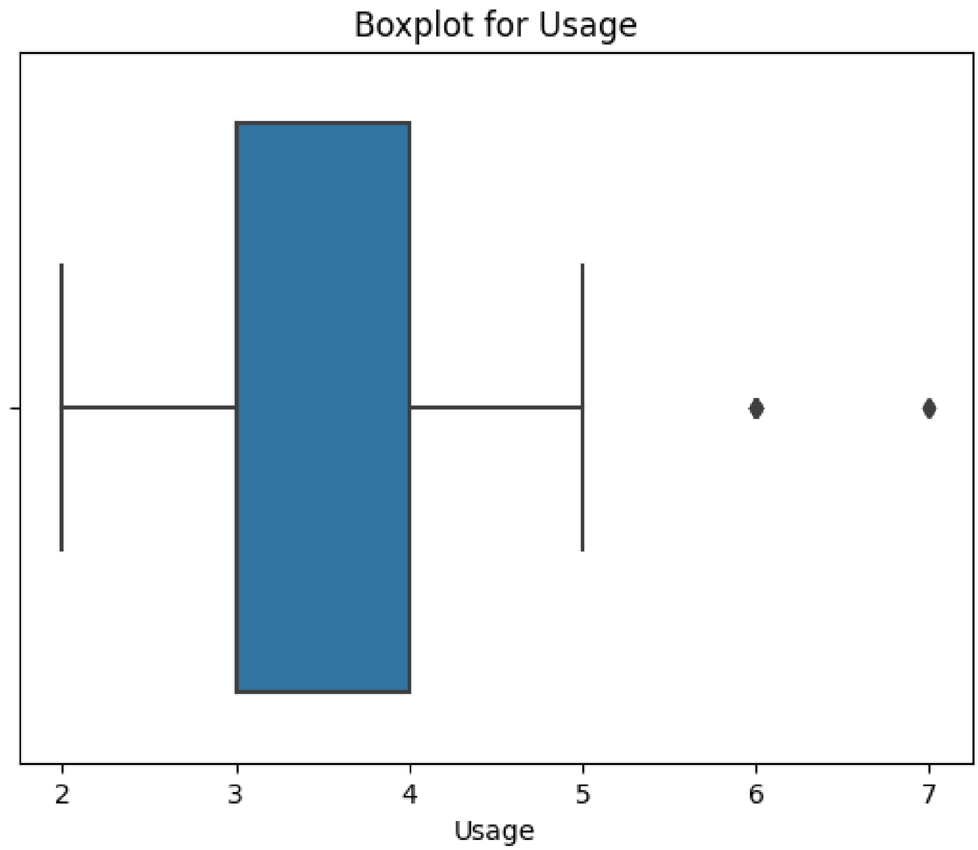
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Product        180 non-null    category
 1   Age            180 non-null    int64
 2   Gender         180 non-null    category
 3   Education      180 non-null    int64
 4   MaritalStatus  180 non-null    category
 5   Usage          180 non-null    int64
 6   Fitness        180 non-null    int64
 7   Income         180 non-null    int64
 8   Miles          180 non-null    int64
dtypes: category(3), int64(6)
memory usage: 9.5 KB
```

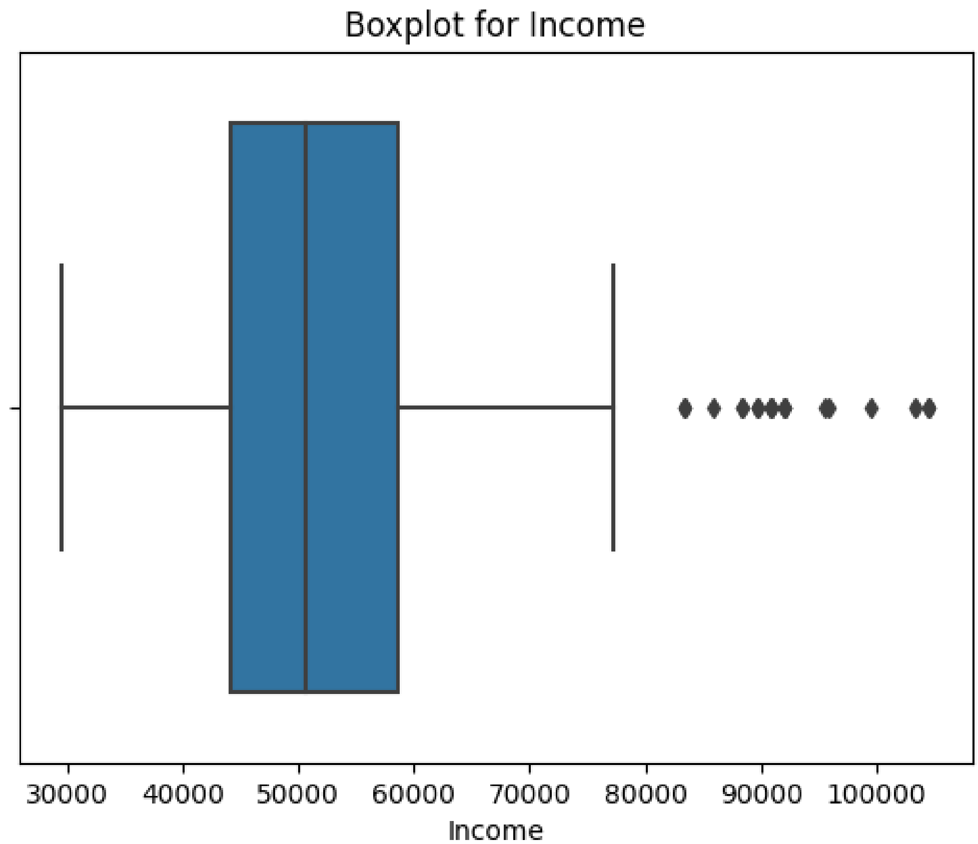
DETECTING OUTLIERS

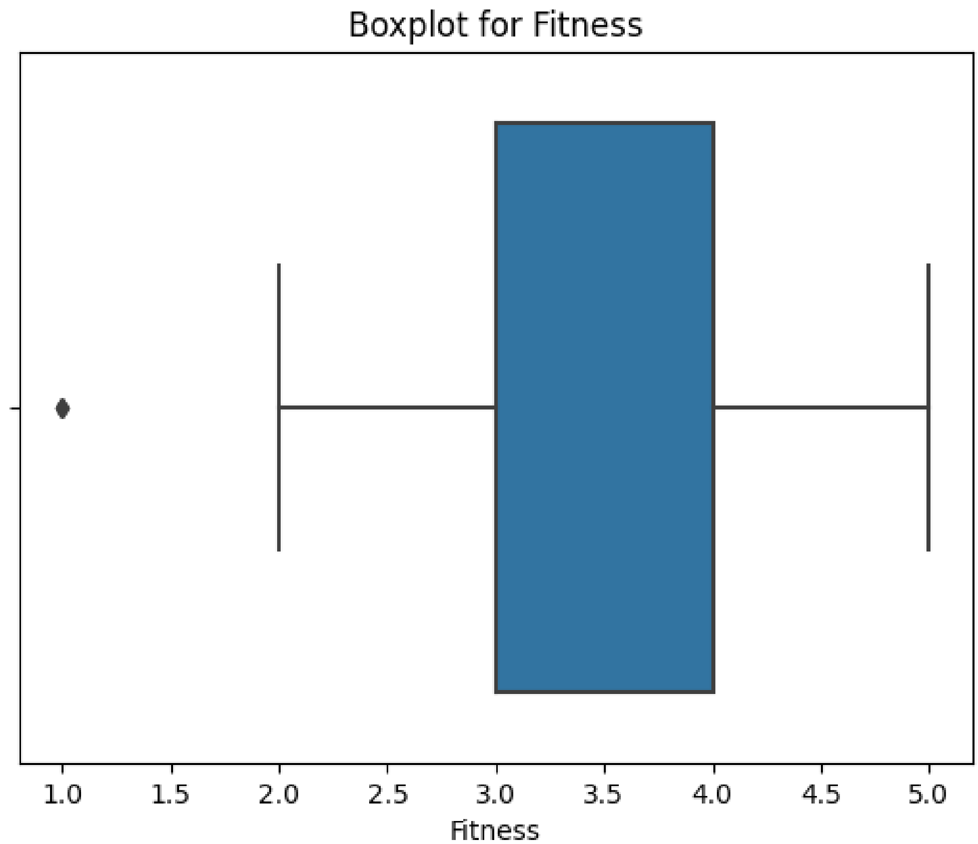
[ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt

numerical_features = ['Age', 'Education', 'Usage', 'Income', 'Fitness', 'Miles']
for feature in numerical_features:
    sns.boxplot(x=df[feature])
    plt.title(f'Boxplot for {feature}')
    plt.show()
```

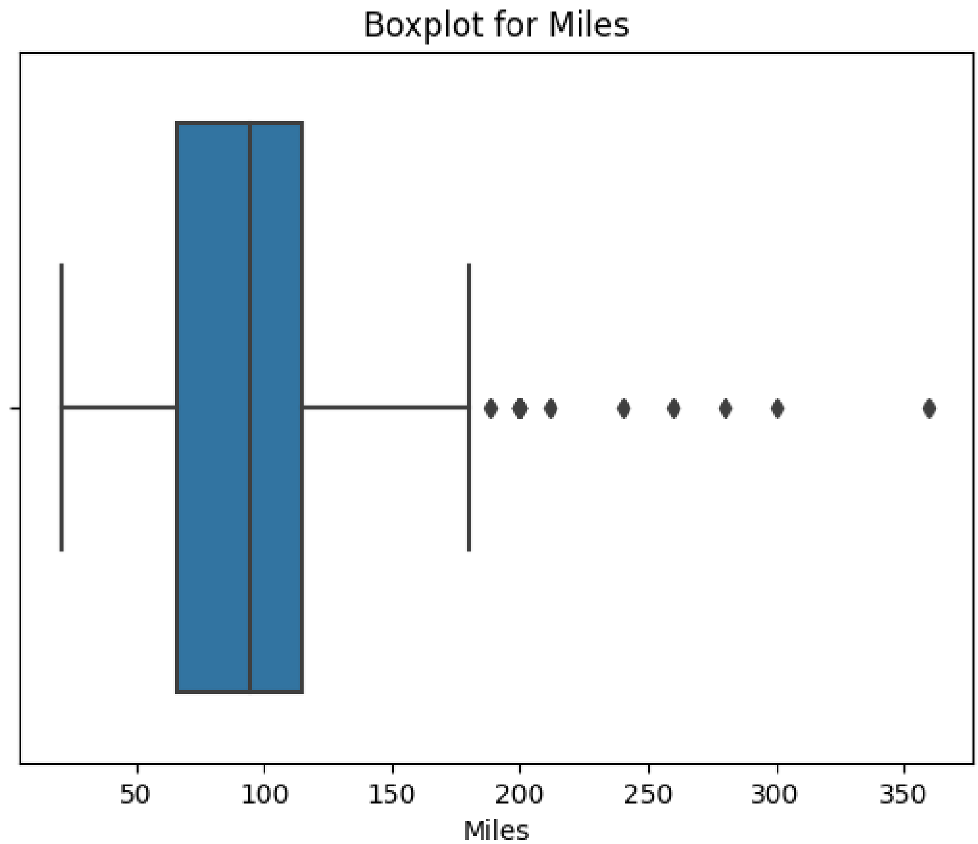



Boxplot for Education
12
14
16
18
20
Education


Boxplot for Usage
2
3
4
5
6
7
Usage


Boxplot for Income
30000
40000
50000
60000
70000
80000
90000
100000
Income

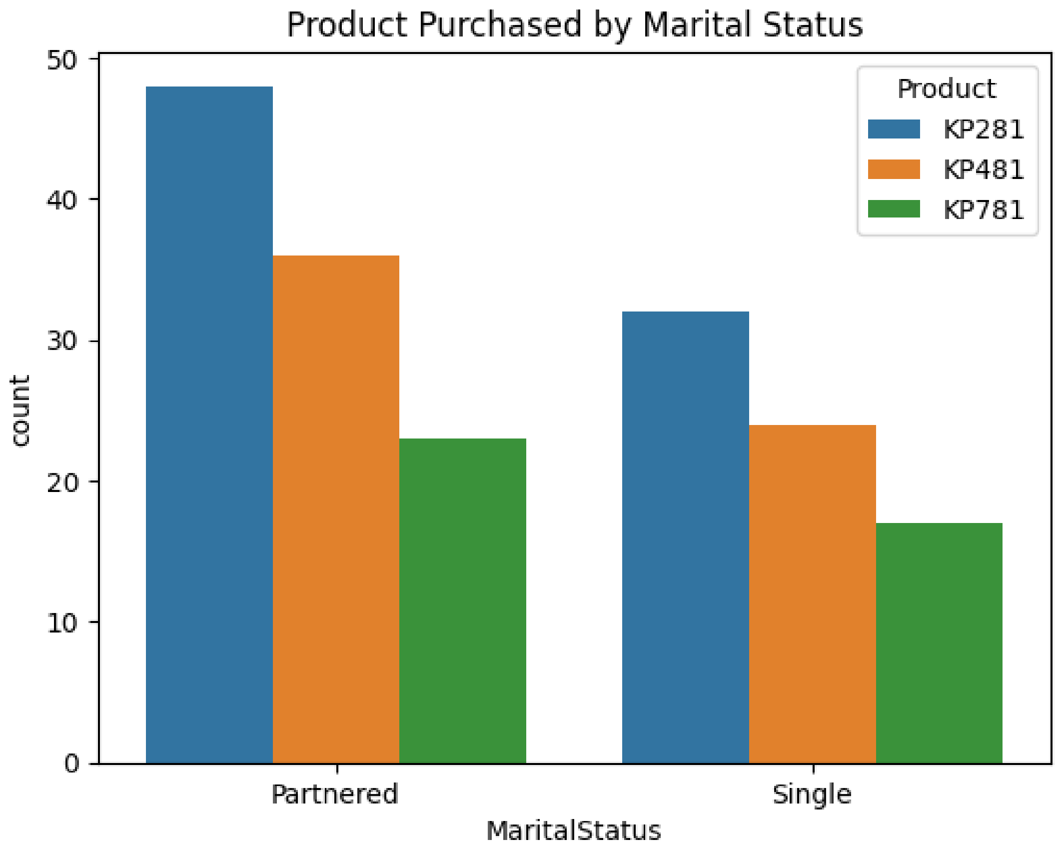

Boxplot for Fitness
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Fitness

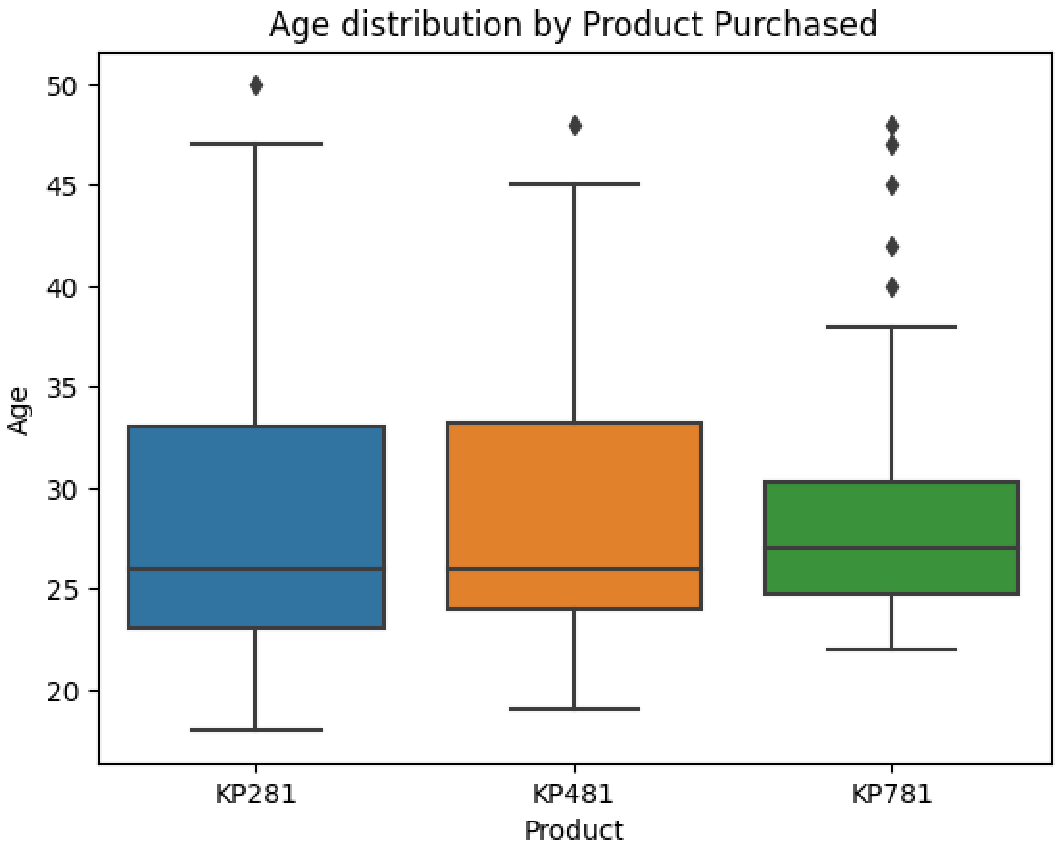


[ ]:

AFFECTS OF FEATURES ON PRODUCT PURCHASE

[ ]:
```
sns.countplot(x='MaritalStatus', hue='Product', data=df)
plt.title('Product Purchased by Marital Status')
plt.show()

sns.boxplot(x='Product', y='Age', data=df)
plt.title('Age distribution by Product Purchased')
plt.show()
```


Product Purchased by Marital Status
Product
KP281
KP481
KP781
count
0
10
20
30
40
50
Partnered
Single
MaritalStatus



MARGINAL PROBABILITY

```
[ ]: # Calculating the marginal probabilities
product_counts = df['Product'].value_counts()
print(product_counts)
total_entries = len(df)
marginal_probabilities = product_counts / total_entries

# Displaying the marginal probabilities
print(marginal_probabilities)
```

```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
KP281    0.444444
KP481    0.333333
KP781    0.222222
Name: Product, dtype: float64
```

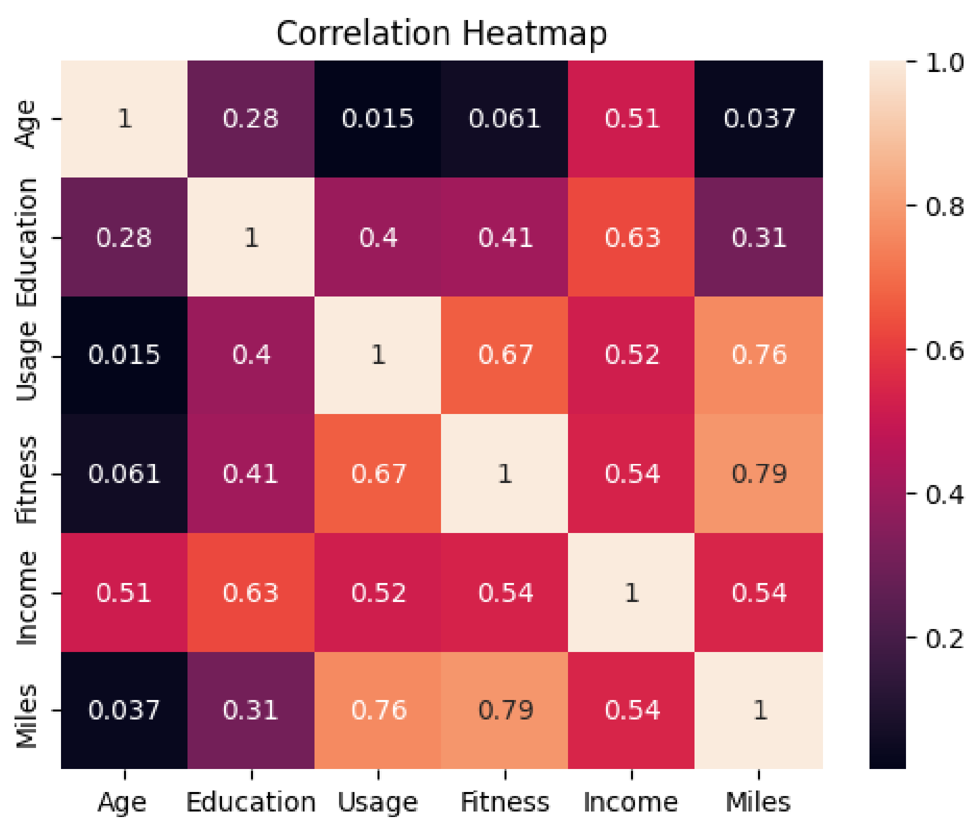
[ ]:
```
product_table = pd.crosstab(index=df['Product'], columns='count',␣
↪normalize=True) * 100
product_table
```

[ ]:
```
col_0        count
Product
KP281    44.444444
KP481    33.333333
KP781    22.222222
```

CHECKING CORRELATION BETWEEN DIFFERENT FACTORS

[ ]:
```
correlation_matrix = df.corr()
sns.heatmap(correlation_matrix, annot=True)
plt.title('Correlation Heatmap')
plt.show()
```

```
<ipython-input-19-eb799ab7fd5e>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  correlation_matrix = df.corr()
```



We can observe higher correlations among:

1. Fitness and miles
2. Usage and miles
3. Usage and Fitness
4. Education and Income

PAIRPLOT

[ ]:
```
sns.pairplot(df)
plt.show()
```

[ ]:

CUSTOMER PROFILING based on the product

[ ]:
```
kp281_df = df[df['Product'] == 'KP281']
kp281_df.describe()
```

[ ]:

	Age	Education	Usage	Fitness	Income	Miles
count	80.000000	80.000000	80.000000	80.00000	80.00000	80.000000
mean	28.550000	15.037500	3.087500	2.96250	46418.02500	82.787500
std	7.221452	1.216383	0.782624	0.66454	9075.78319	28.874102
min	18.000000	12.000000	2.000000	1.00000	29562.00000	38.000000
25%	23.000000	14.000000	3.000000	3.00000	38658.00000	66.000000
50%	26.000000	16.000000	3.000000	3.00000	46617.00000	85.000000
75%	33.000000	16.000000	4.000000	3.00000	53439.00000	94.000000
max	50.000000	18.000000	5.000000	5.00000	68220.00000	188.000000

[ ]:
```
kp481_df = df[df['Product'] == 'KP481']
kp481_df.describe()
```

[ ]:

	Age	Education	Usage	Fitness	Income	Miles
count	60.000000	60.000000	60.000000	60.00000	60.000000	60.000000
mean	28.900000	15.116667	3.066667	2.90000	48973.650000	87.933333
std	6.645248	1.222552	0.799717	0.62977	8653.989388	33.263135
min	19.000000	12.000000	2.000000	1.00000	31836.000000	21.000000
25%	24.000000	14.000000	3.000000	3.00000	44911.500000	64.000000
50%	26.000000	16.000000	3.000000	3.00000	49459.500000	85.000000
75%	33.250000	16.000000	3.250000	3.00000	53439.000000	106.000000
max	48.000000	18.000000	5.000000	4.00000	67083.000000	212.000000

[ ]:
```
kp781_df = df[df['Product'] == 'KP781']
kp781_df.describe()
```

[ ]:

	Age	Education	Usage	Fitness	Income	Miles
count	40.000000	40.000000	40.000000	40.000000	40.00000	40.000000
mean	29.100000	17.325000	4.775000	4.625000	75441.57500	166.900000
std	6.971738	1.639066	0.946993	0.667467	18505.83672	60.066544
min	22.000000	14.000000	3.000000	3.000000	48556.00000	80.000000
25%	24.750000	16.000000	4.000000	4.000000	58204.75000	120.000000
50%	27.000000	18.000000	5.000000	5.000000	76568.50000	160.000000
75%	30.250000	18.000000	5.000000	5.000000	90886.00000	200.000000
max	48.000000	21.000000	7.000000	5.000000	104581.00000	360.000000

CHECKING FOR ANY MISSING VALUES OR NAN COUNTS

[ ]:
```
nan_counts = df.applymap(lambda x :   x == 'nan').sum()
nan_counts
```

[ ]:
```
Product          0
Age              0
```

```
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

#Question 2. Non-Graphical Analysis: Value counts and unique attributes (10 Points)

[ ]:
```python
# Analysis function
def analyze_column(column_name):
    unique_values = df[column_name].unique()
    value_counts = df[column_name].value_counts()
    print(f"{column_name}:\nUnique Values: {unique_values}\nValue Count:
 ↪\n{value_counts}\n")

# Analyze each column
columns_to_analyze = ['Product', 'Age', 'Gender', 'Education', 'MaritalStatus',
 ↪'Usage', 'Fitness', 'Income', 'Miles']

for column in columns_to_analyze:
    analyze_column(column)
```

```
Product:
Unique Values: ['KP281', 'KP481', 'KP781']
Categories (3, object): ['KP281', 'KP481', 'KP781']
Value Count:
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64

Age:
Unique Values: [18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38
39 40 41
 43 44 46 47 50 45 48 42]
Value Count:
25    25
23    18
24    12
26    12
28     9
35     8
33     8
30     7
```

```
38     7
21     7
22     7
27     7
31     6
34     6
29     6
20     5
40     5
32     4
19     4
48     2
37     2
45     2
47     2
46     1
50     1
18     1
44     1
43     1
41     1
39     1
36     1
42     1
Name: Age, dtype: int64

Gender:
Unique Values: ['Male', 'Female']
Categories (2, object): ['Female', 'Male']
Value Count:
Male      104
Female     76
Name: Gender, dtype: int64

Education:
Unique Values: [14 15 12 13 16 18 20 21]
Value Count:
16    85
14    55
18    23
15     5
13     5
12     3
21     3
20     1
Name: Education, dtype: int64

MaritalStatus:
```

```
Unique Values: ['Single', 'Partnered']
Categories (2, object): ['Partnered', 'Single']
Value Count:
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64

Usage:
Unique Values: [3 2 4 5 6 7]
Value Count:
3    69
4    52
2    33
5    17
6     7
7     2
Name: Usage, dtype: int64

Fitness:
Unique Values: [4 3 2 1 5]
Value Count:
3    97
5    31
2    26
4    24
1     2
Name: Fitness, dtype: int64

Income:
Unique Values: [ 29562  31836  30699  32973  35247  37521  36384  38658  40932
34110
  39795  42069  44343  45480  46617  48891  53439  43206  52302  51165
  50028  54576  68220  55713  60261  67083  56850  59124  61398  57987
  64809  47754  65220  62535  48658  54781  48556  58516  53536  61006
  57271  52291  49801  62251  64741  70966  75946  74701  69721  83416
  88396  90886  92131  77191  52290  85906 103336  99601  89641  95866
 104581  95508]
Value Count:
45480    14
52302     9
46617     8
54576     8
53439     8
         ..
65220     1
55713     1
68220     1
30699     1
```

```
95508     1
Name: Income, Length: 62, dtype: int64

Miles:
Unique Values: [112  75  66  85  47 141 103  94 113  38 188  56 132 169  64  53
106  95
 212  42 127  74 170  21 120 200 140 100  80 160 180 240 150 300 280 260
 360]
Value Count:
85     27
95     12
66     10
75     10
47      9
106     9
94      8
113     8
53      7
100     7
180     6
200     6
56      6
64      6
127     5
160     5
42      4
150     4
38      3
74      3
170     3
120     3
103     3
132     2
141     2
280     1
260     1
300     1
240     1
112     1
212     1
80      1
140     1
21      1
169     1
188     1
360     1
Name: Miles, dtype: int64
```

Based on the provided snippet of the Aerofit dataset, here's a non-graphical analysis:

Product: 1. *Unique Values:* ['KP281' 'KP481' 'KP781'] 2. *Value Count*:

```
KP281    80
KP481    60
KP781    40
```

There are just 3 products with KP281 being the most popular.

Age:

1. *Unique Values*: age ranges from 18 to 50.
2.

```
Value Count:
25    25
23    18
24    12
26    12
28     9
```

The products are most popular among 25-28 age group

Gender: 1. Unique Values: ['Male' 'Female'] 2.

```
Value Count:
Male      104
Female     76
```

The number of male users are approx 50% higher with respect to female users.

Education:

```
Unique Values: [14 15 12 13 16 18 20 21]
Value Count:
16    85
14    55
18    23
15     5
13     5
12     3
21     3
20     1
```

The products are most popular among users with 16-18 years of education.

MaritalStatus:

```
Unique Values: ['Single', 'Partnered']

Value Count:
Partnered    107
Single        73
```

The product is more popular among partnered users.

Usage:

```
Unique Values: [3 2 4 5 6 7]
Value Count:
3    69
4    52
2    33
5    17
6     7
7     2
```

Most popular among moderate usage.

Fitness:

```
Unique Values: [4 3 2 1 5]
Value Count:
3    97
5    31
2    26
4    24
1     2
```

Most popular among moderate fitness level

Income:

```
Unique Values: [ 29562..104581]
Value Count:
45480    14
52302     9
46617     8
54576     8
53439     8
         ...
95508     1
```

Most popular among mid income group

Miles:

```
Unique Values: [112  75  66  85  47 141 103  94 113  38 188  56 132 169  64  53 106  95
 212  42 127  74 170  21 120 200 140 100  80 160 180 240 150 300 280 260
 360]
Value Count:
85     27
95     12
66     10
75     10
47      9
106     9
94      8
113     8
53      7
100     7
180     6
200     6
.....
21      1
```

Most popular miles count lies between 75 to 113 miles.

1 Question 3. Visual Analysis - Univariate & Bivariate (30 Points)

1. For continuous variable(s): Distplot, countplot, histogram for univariate analysis (10 Points)
2. For categorical variable(s): Boxplot (10 Points)
3. For correlation: Heatmaps, Pairplots(10 Points)

1.0.1 3.1 Univariate Analysis

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

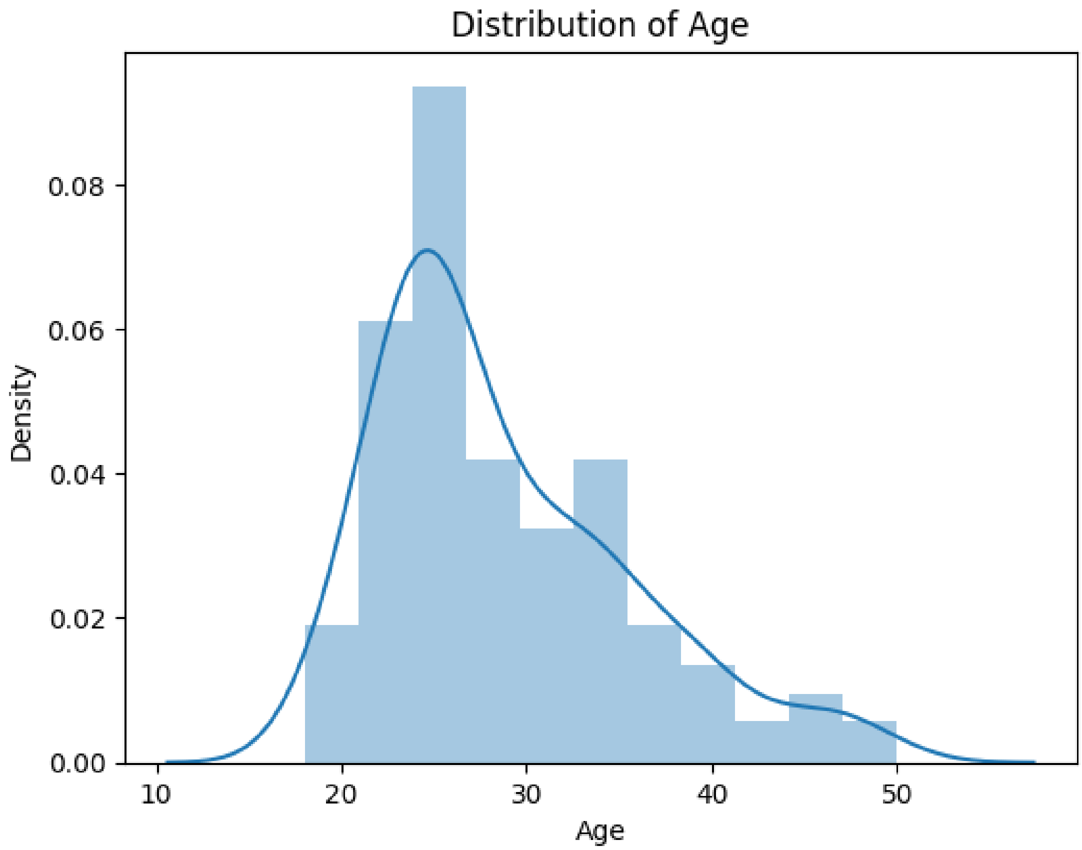
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Product        180 non-null    category
 1   Age            180 non-null    int64
 2   Gender         180 non-null    category
 3   Education      180 non-null    int64
 4   MaritalStatus  180 non-null    category
 5   Usage          180 non-null    int64
 6   Fitness        180 non-null    int64
 7   Income         180 non-null    int64
 8   Miles          180 non-null    int64
dtypes: category(3), int64(6)
```

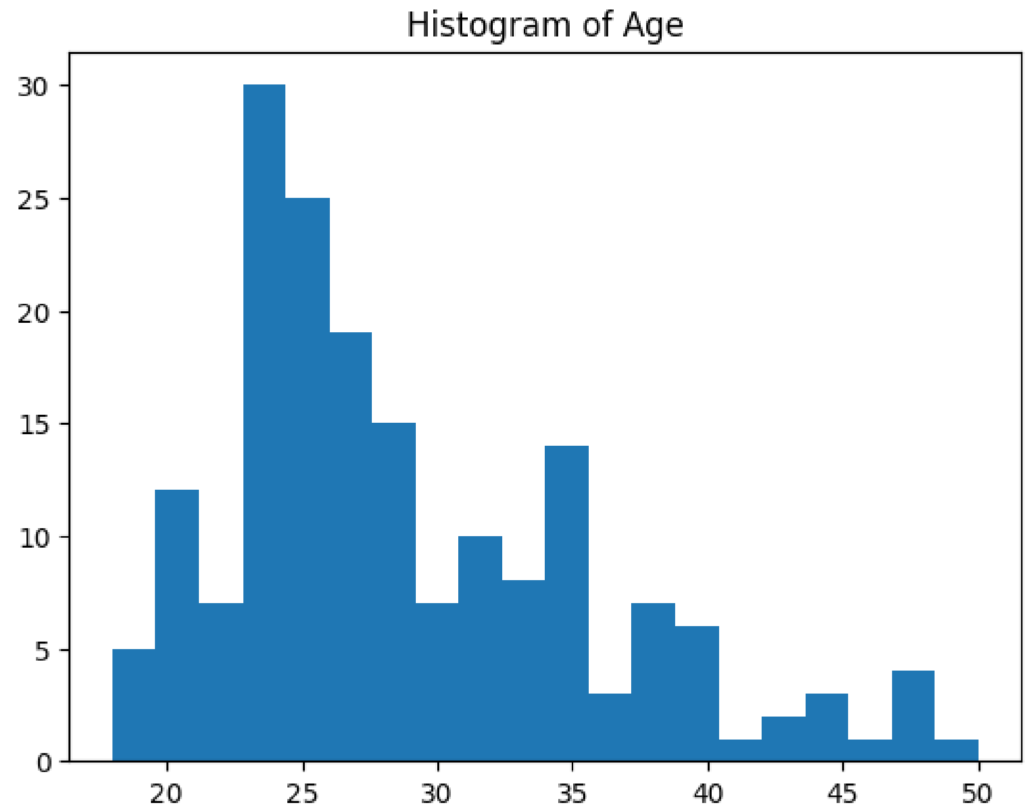
```
memory usage: 9.5 KB
```

3.1.1 Univariate Analysis for continuous variable and Category variable

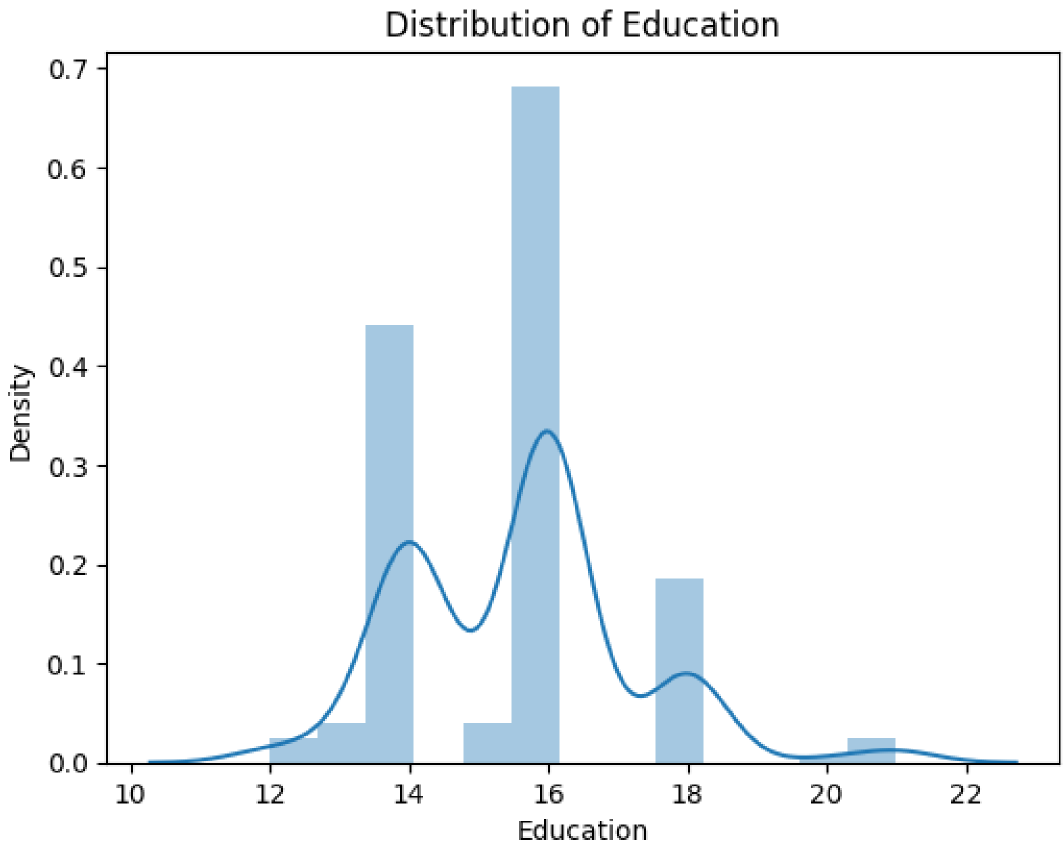
[ ]:
```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Continuous variables: Age, Education, Usage, Fitness, Income, Miles
category_vars = ['Product','Gender', 'MaritalStatus']
continuous_vars = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']

for var in continuous_vars:
    sns.distplot(df[var], kde=True)
    plt.title(f'Distribution of {var}')
    plt.show()

    plt.hist(df[var], bins=20)
    plt.title(f'Histogram of {var}')
    plt.show()



for var in category_vars:
    sns.histplot(df[var], kde=True)
    plt.title(f'Distribution of {var}')
    plt.show()

    plt.hist(df[var], bins=20)
    plt.title(f'Histogram of {var}')
    plt.show()
```

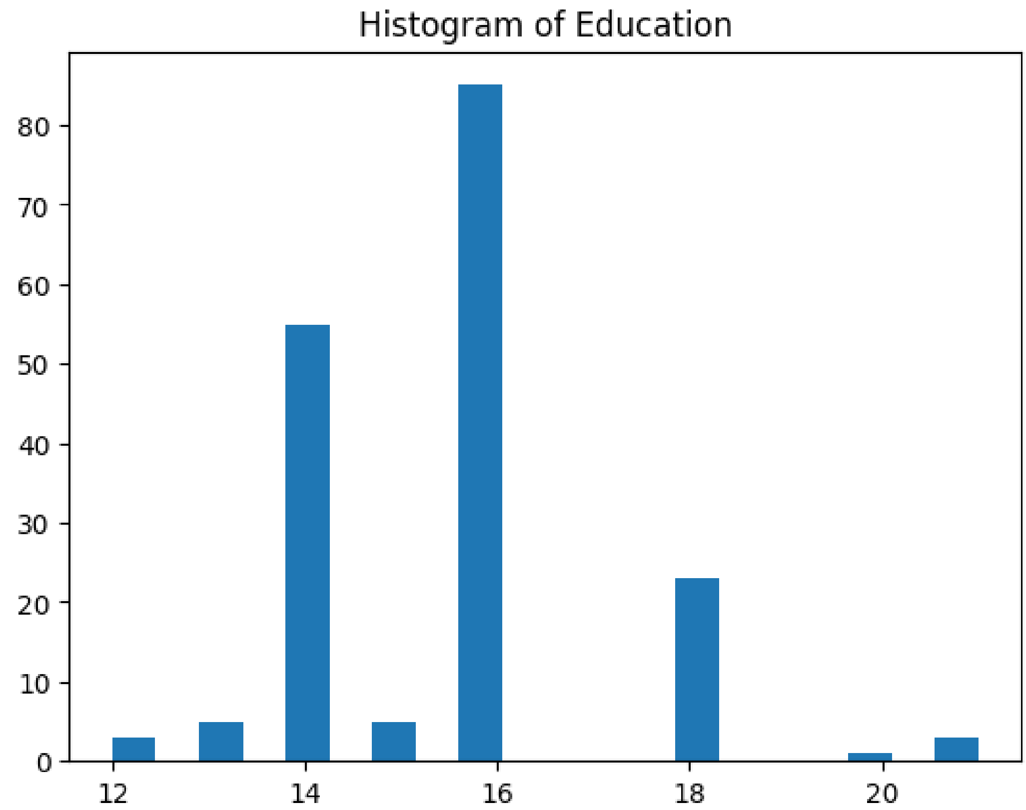
```
<ipython-input-27-3d469af8080d>:10: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df[var], kde=True)
```


Distribution of Age
Density
Age
0.00
0.02
0.04
0.06
0.08
10
20
30
40
50

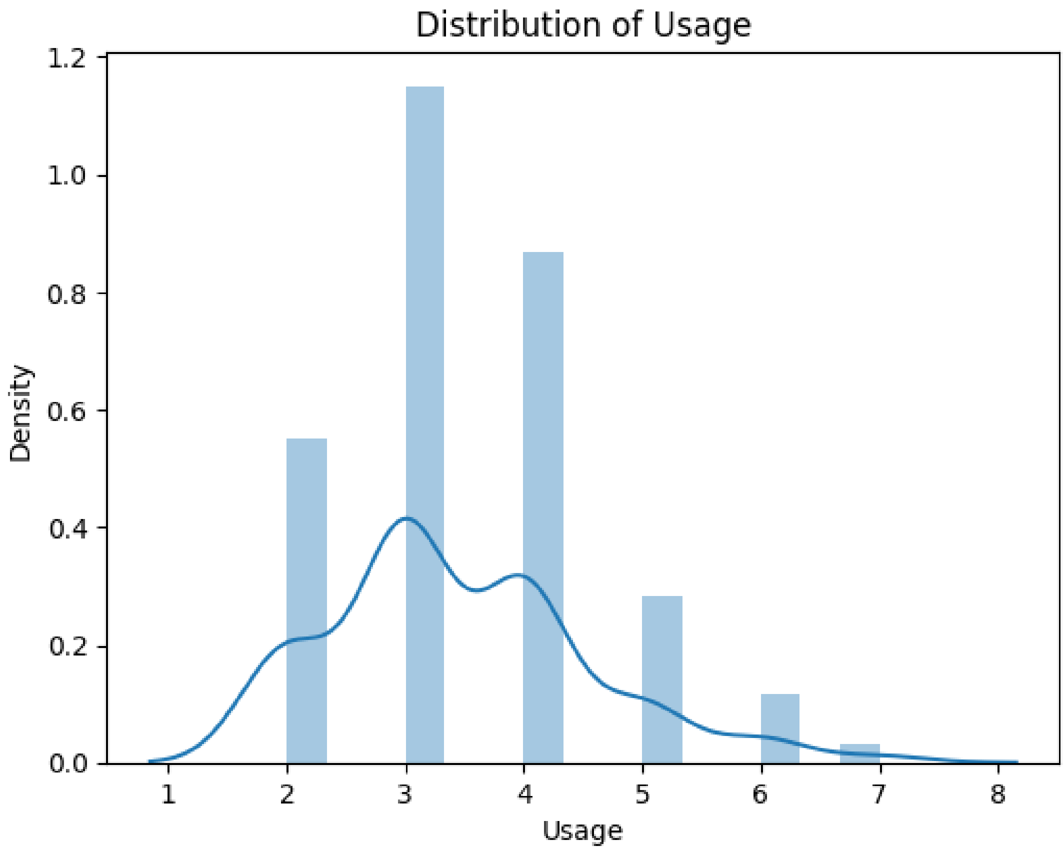


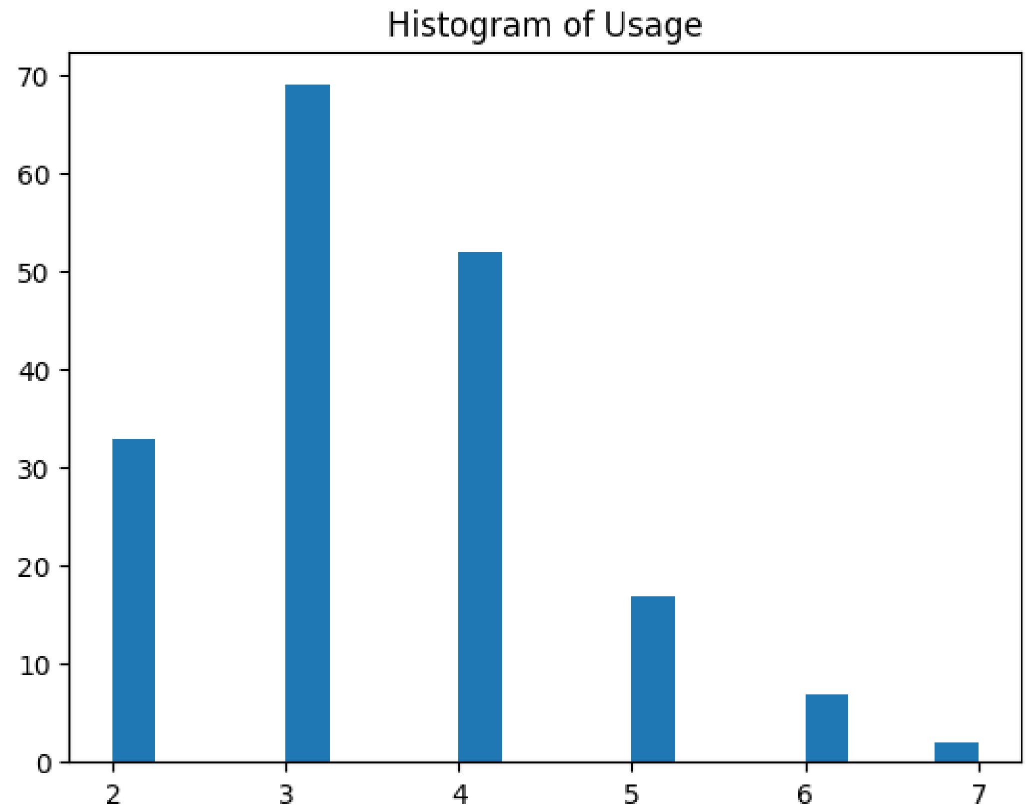

```
<ipython-input-27-3d469af8080d>:10: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df[var], kde=True)
```


Distribution of Education
Density
Education
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
10
12
14
16
18
20
22




```
<ipython-input-27-3d469af8080d>:10: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df[var], kde=True)
```


Distribution of Usage
Density
Usage
1.2
1.0
0.8
0.6
0.4
0.2
0.0
1
2
3
4
5
6
7
8




```
<ipython-input-27-3d469af8080d>:10: UserWarning:

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https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df[var], kde=True)
```
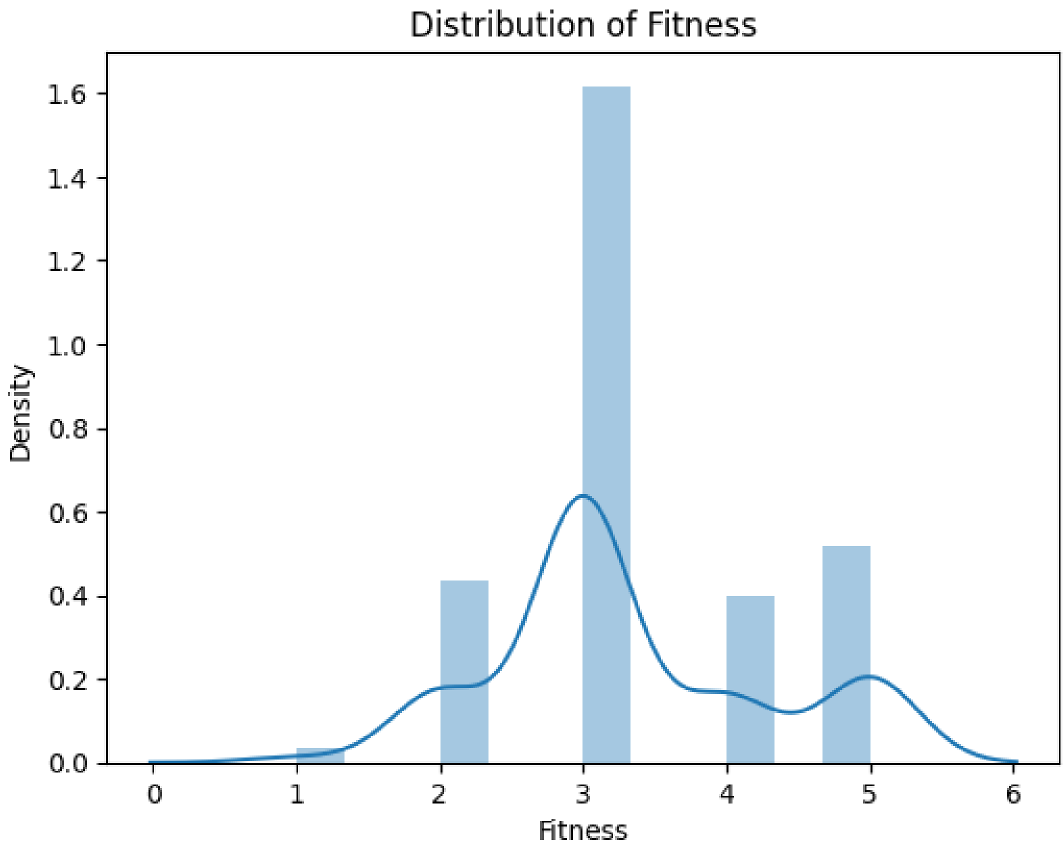
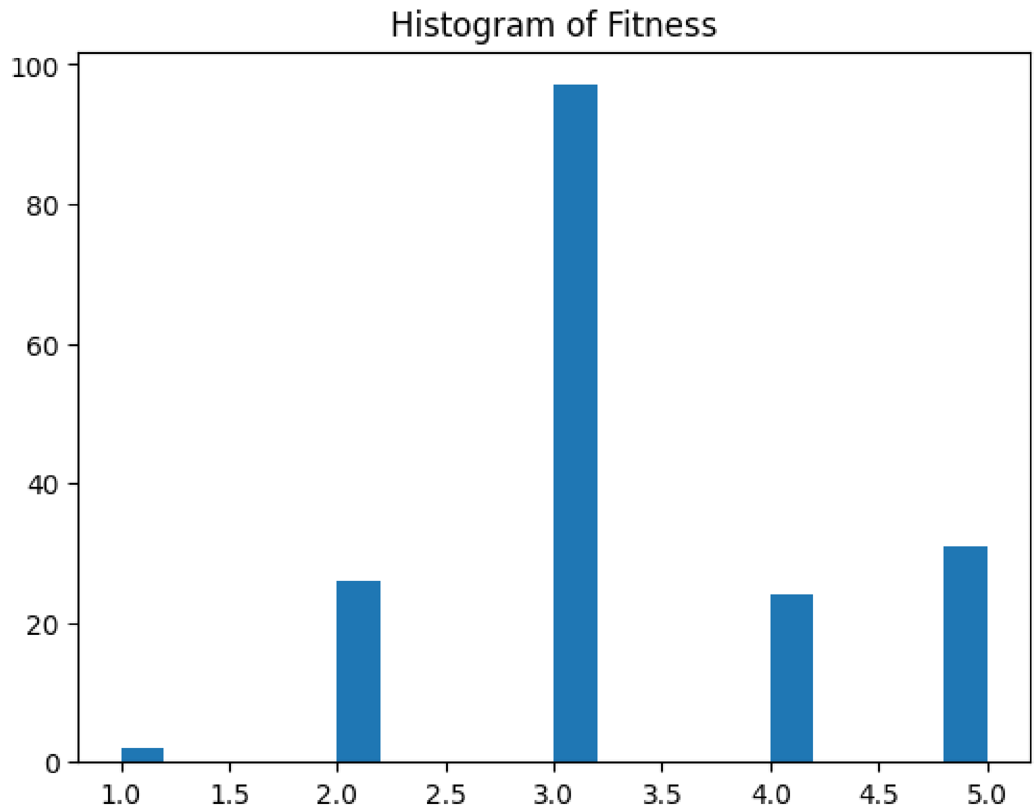


Distribution of Fitness
Density
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
0
1
2
3
4
5
6
Fitness




```
<ipython-input-27-3d469af8080d>:10: UserWarning:

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For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df[var], kde=True)
```
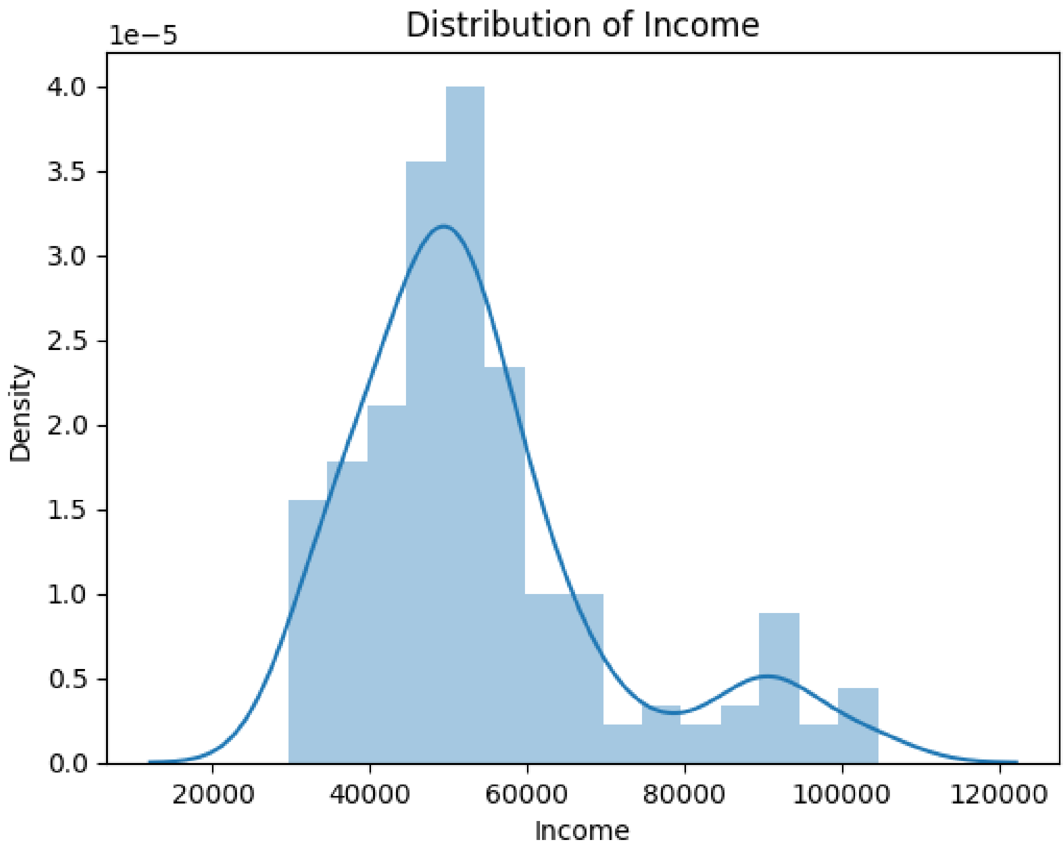
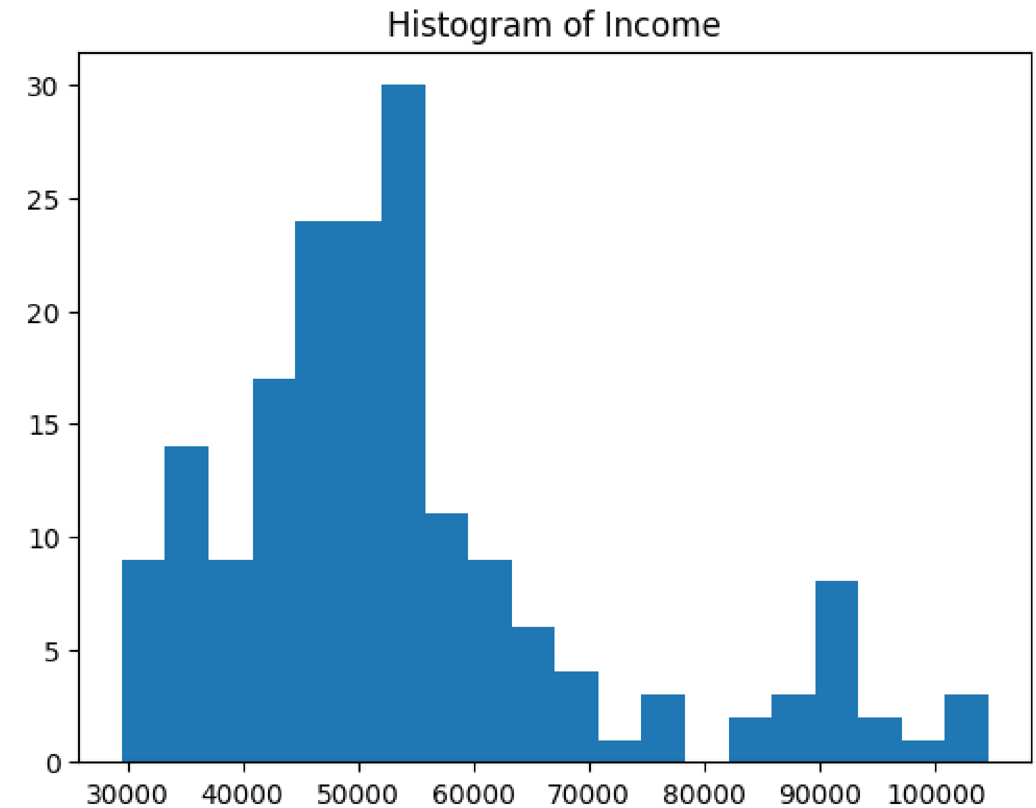


Distribution of Income
1e−5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Density
20000
40000
60000
80000
100000
120000
Income




```
<ipython-input-27-3d469af8080d>:10: UserWarning:

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https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df[var], kde=True)
```
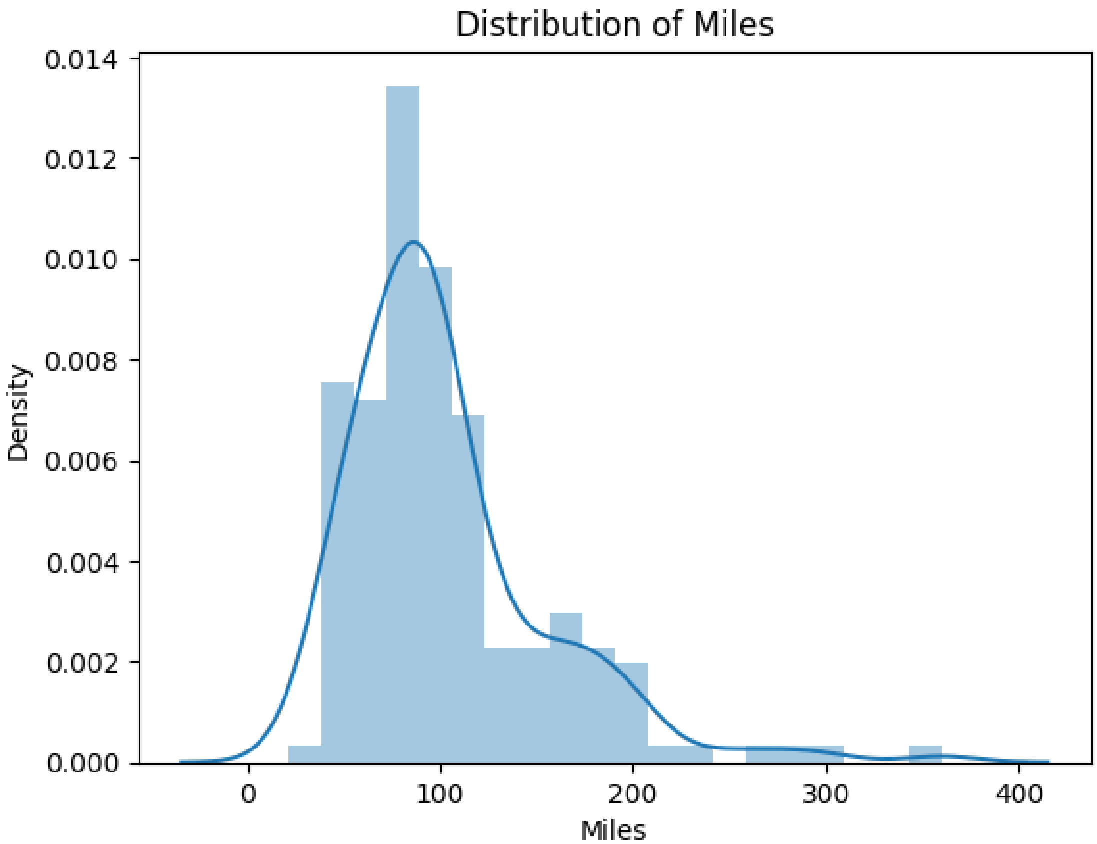
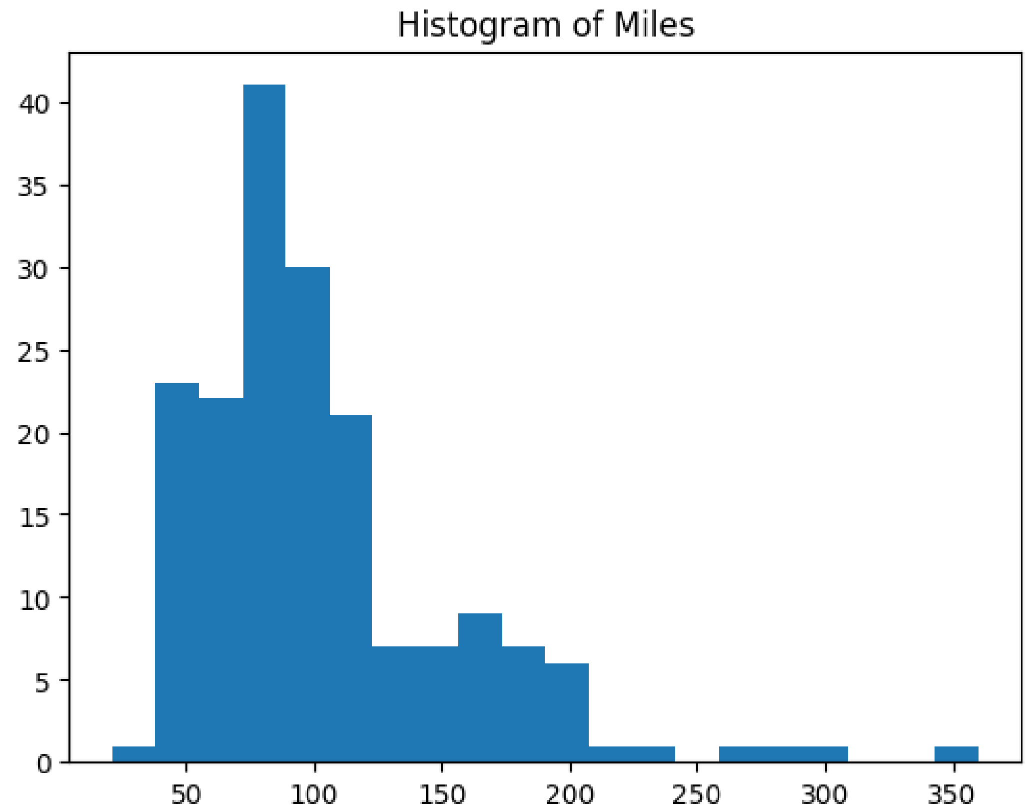
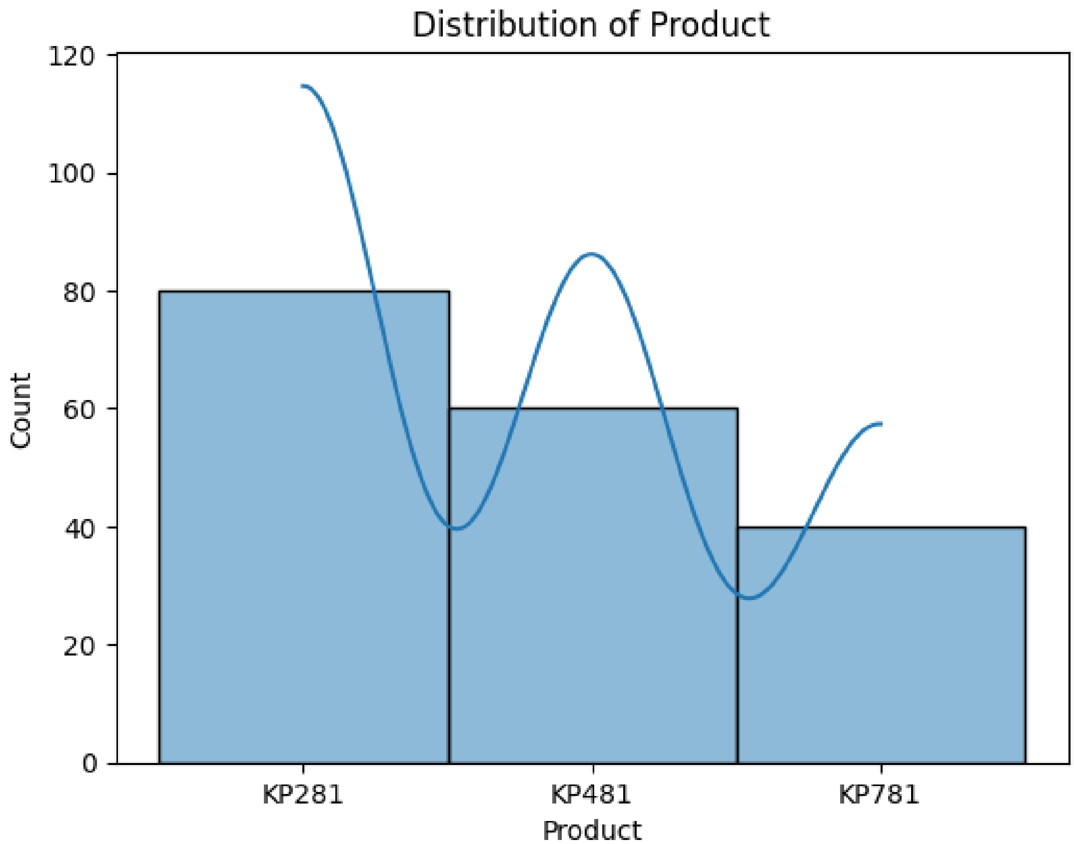
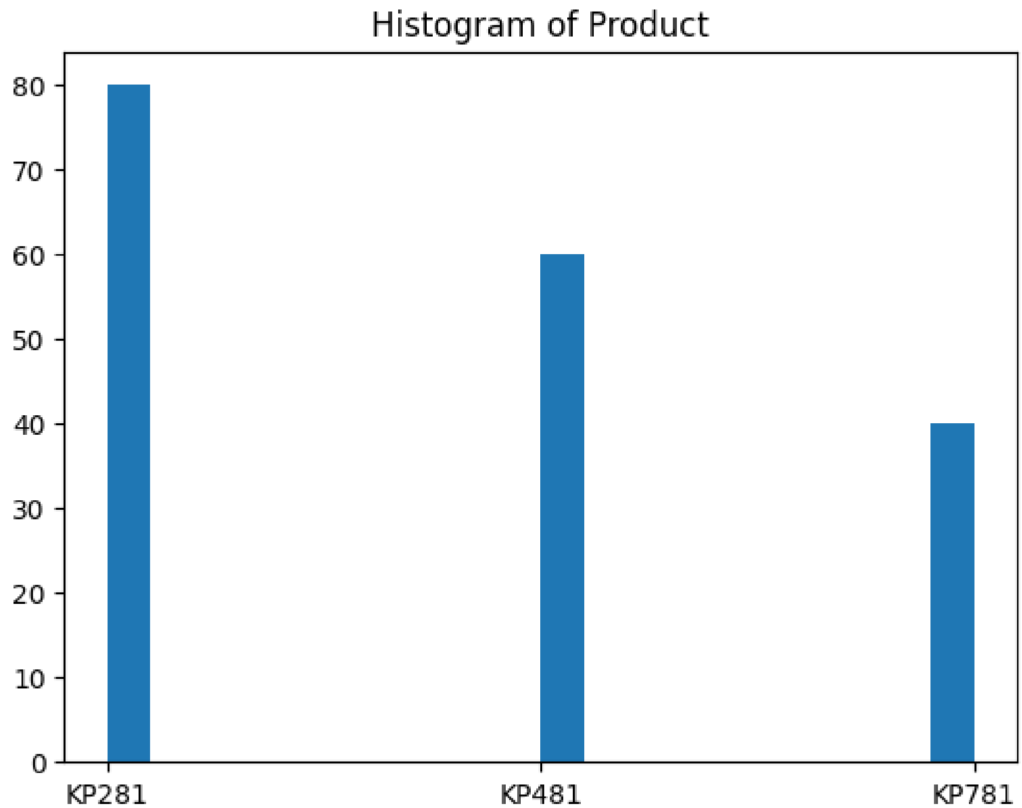
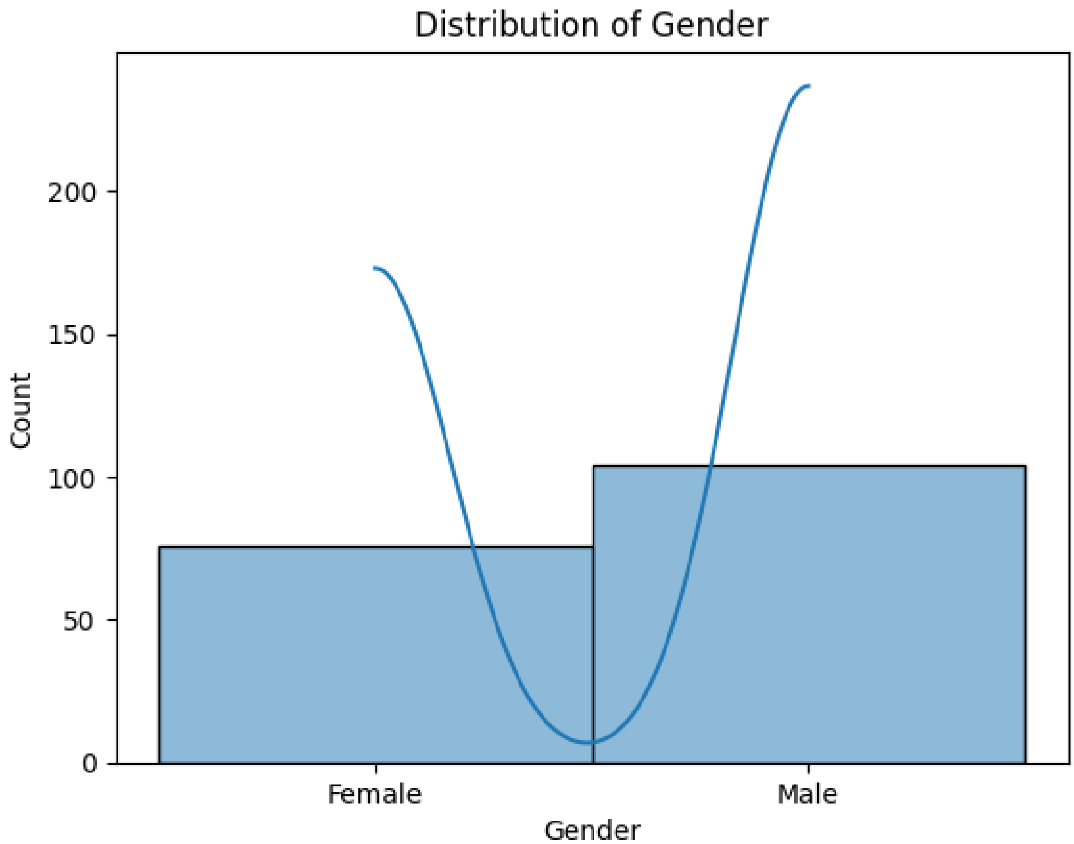


Distribution of Miles
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
Density
0
100
200
300
400
Miles

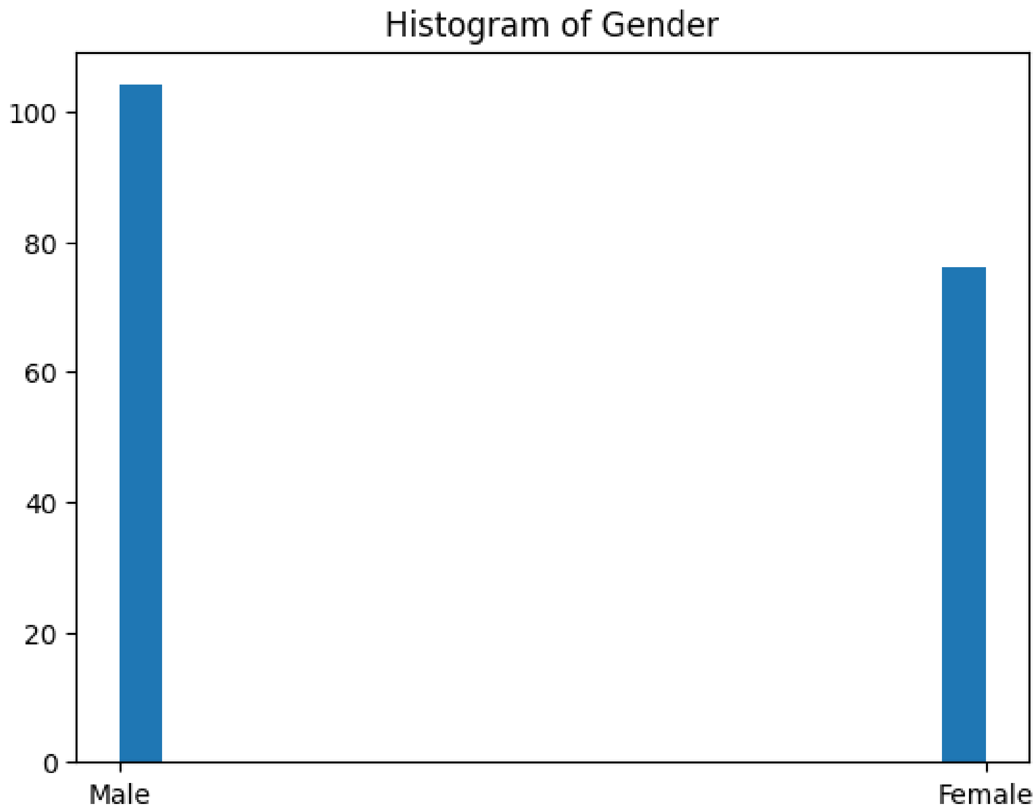

Histogram of Miles
40
35
30
25
20
15
10
5
0
50
100
150
200
250
300
350

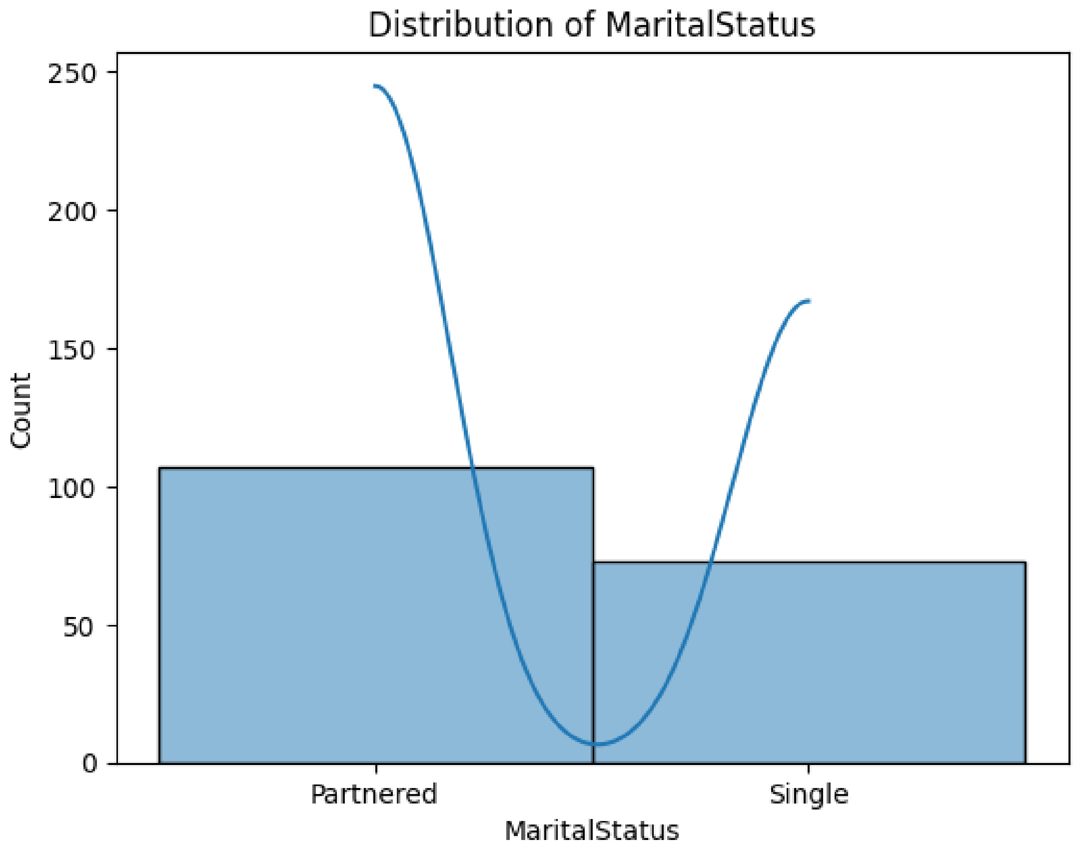


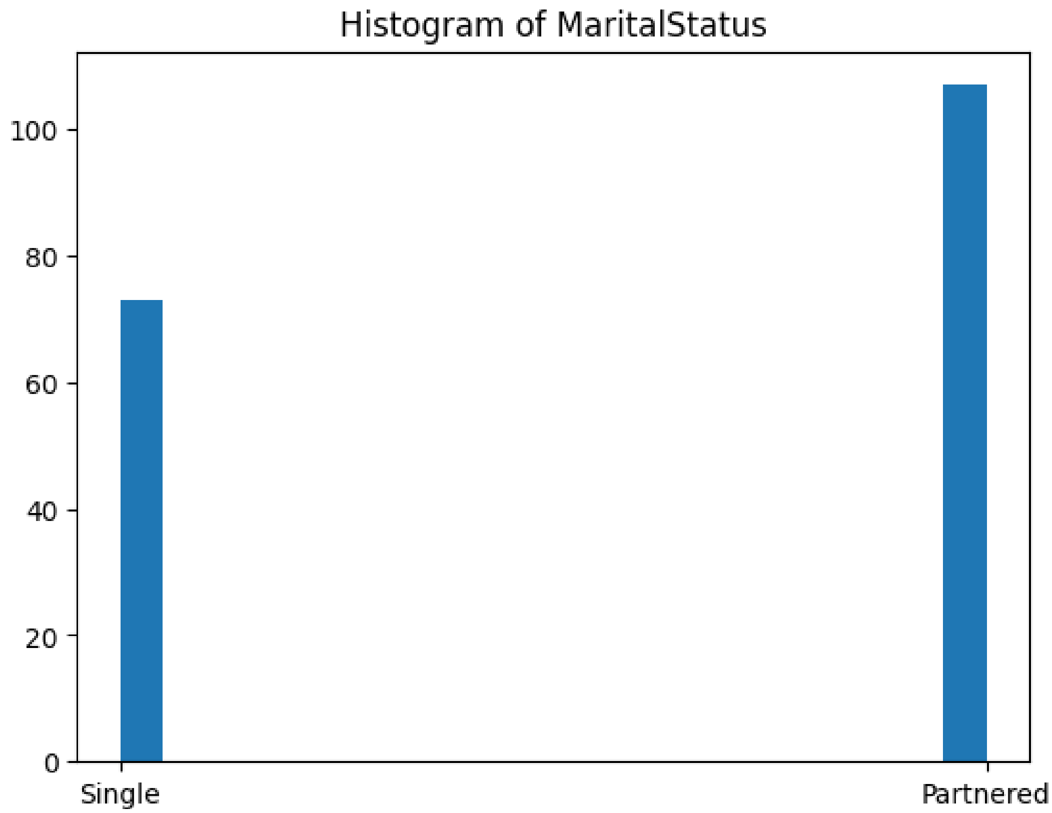
Distribution of Product
120
100
80
60
40
20
0
Count
KP281
KP481
KP781
Product


Histogram of Product
80
70
60
50
40
30
20
10
0
KP281
KP481
KP781


Distribution of Gender
Count
200
150
100
50
0
Female
Male
Gender


Histogram of Gender
100
80
60
40
20
0
Male
Female

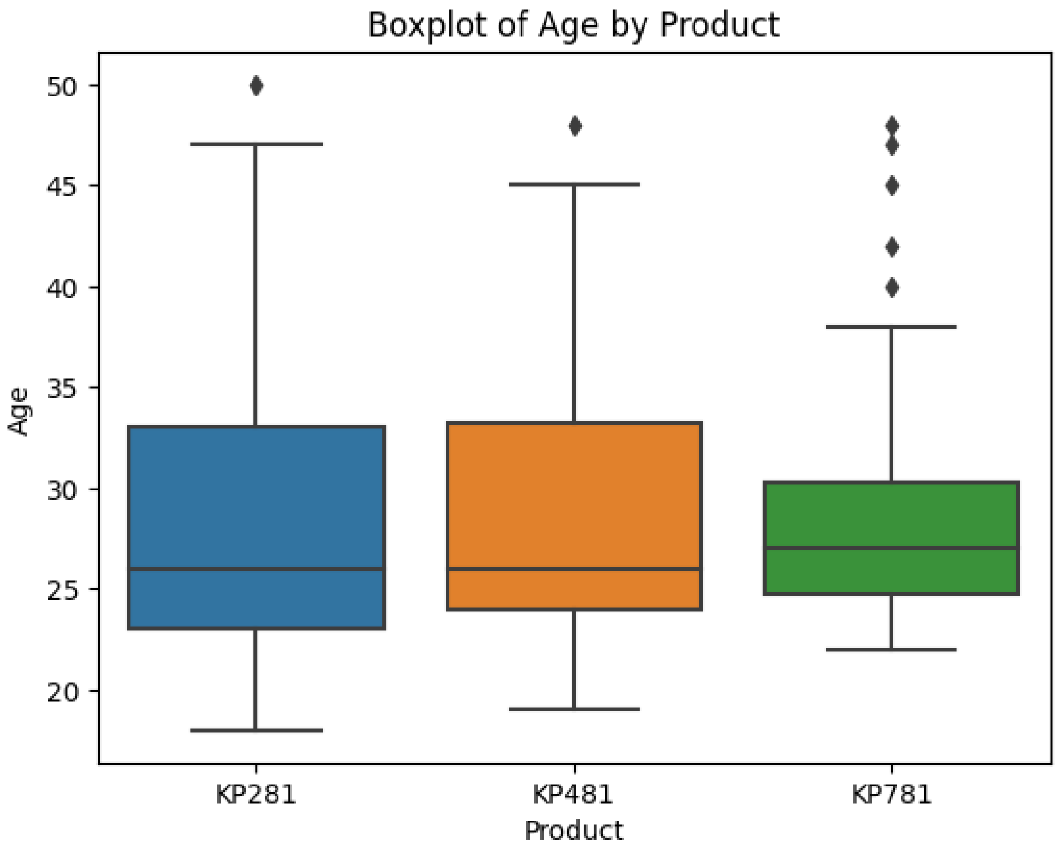

Distribution of MaritalStatus
250
200
150
100
50
0
Count
Partnered
Single
MaritalStatus

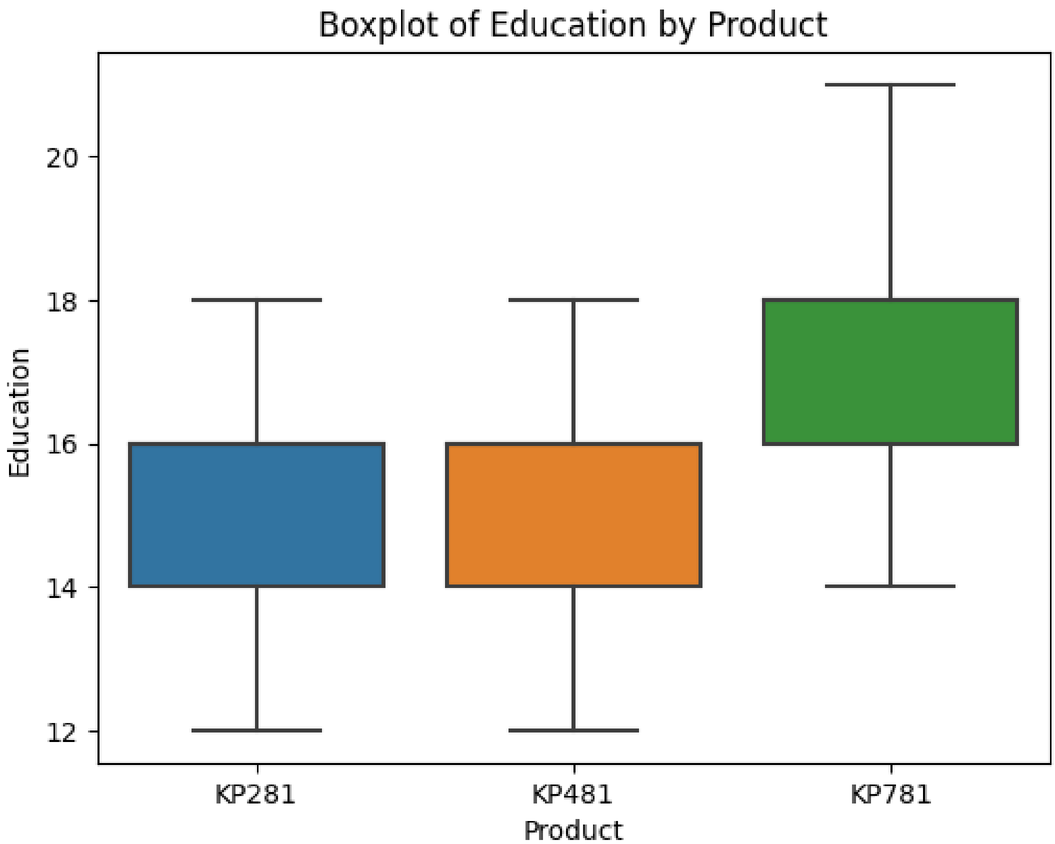


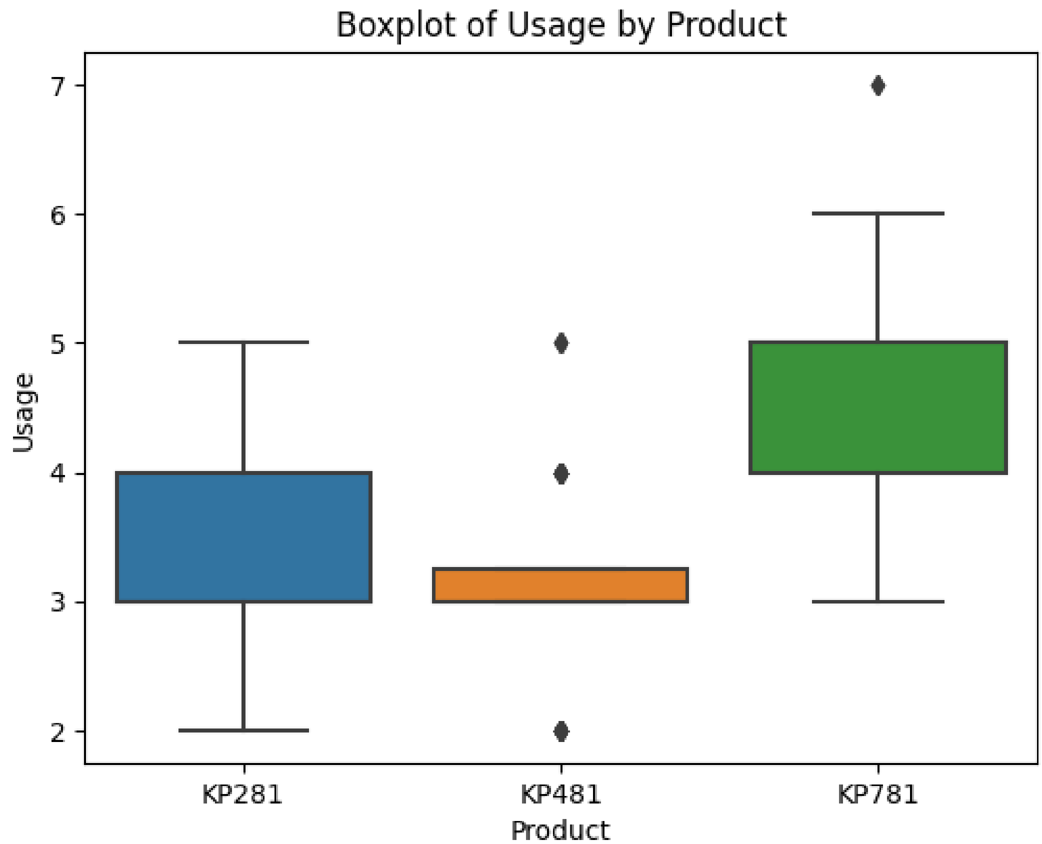
1.0.2 3.2 Bivariate Analysis

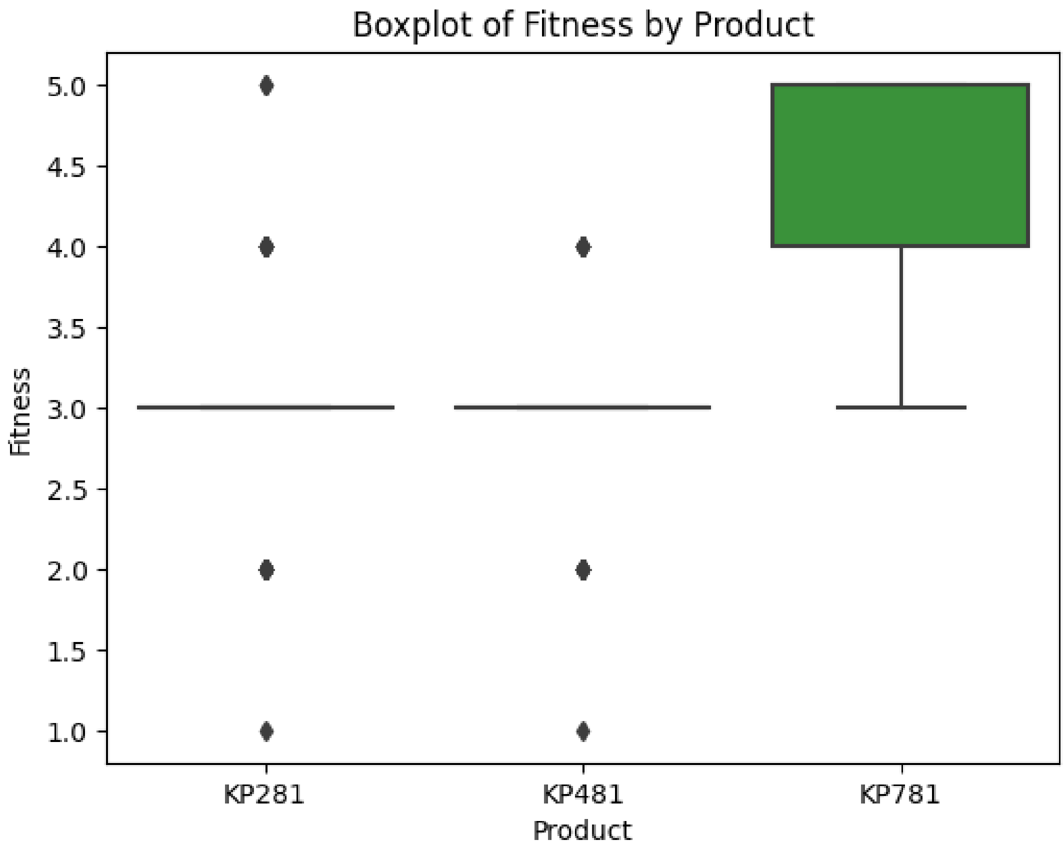
3.2.1 Bivariate analysis for continuous var Vs categorical data

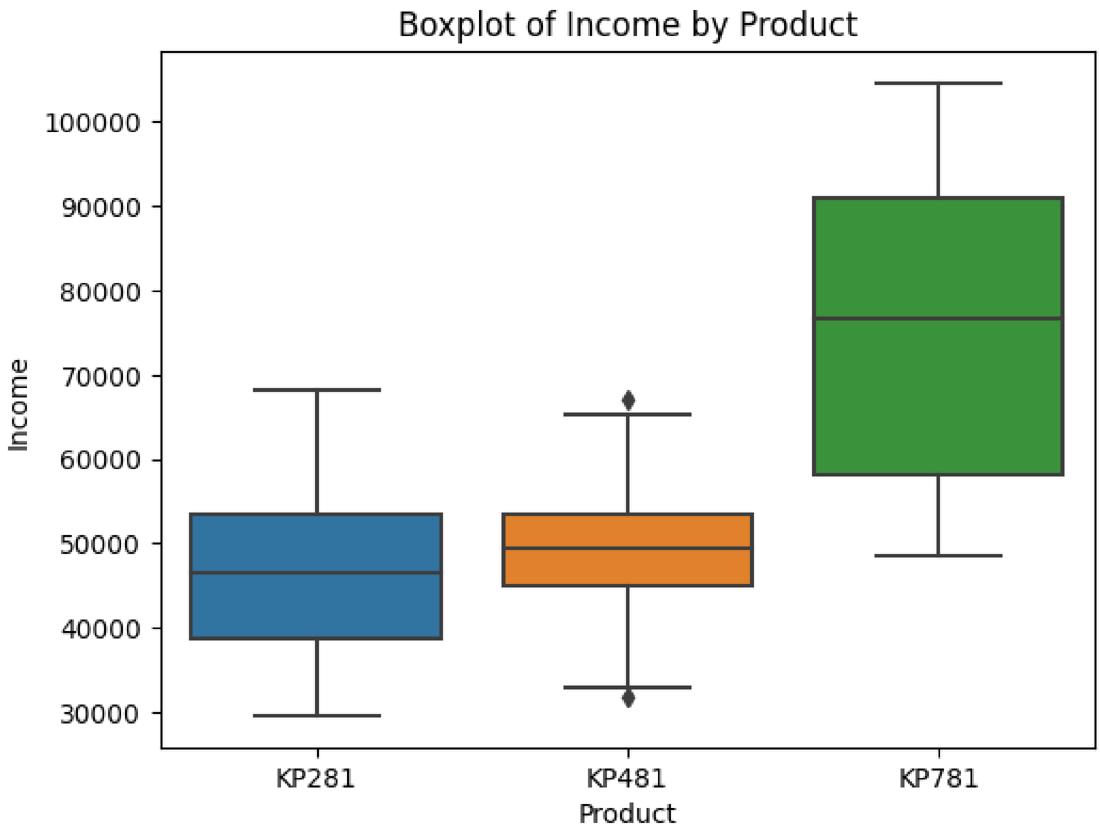
[ ]:
```
# Categorical variables: Product, Gender, MaritalStatus
categorical_vars = ['Product', 'Gender', 'MaritalStatus']

for cat_var in categorical_vars:
    for cont_var in continuous_vars:
        sns.boxplot(x=cat_var, y=cont_var, data=df)
        plt.title(f'Boxplot of {cont_var} by {cat_var}')
        plt.show()
```

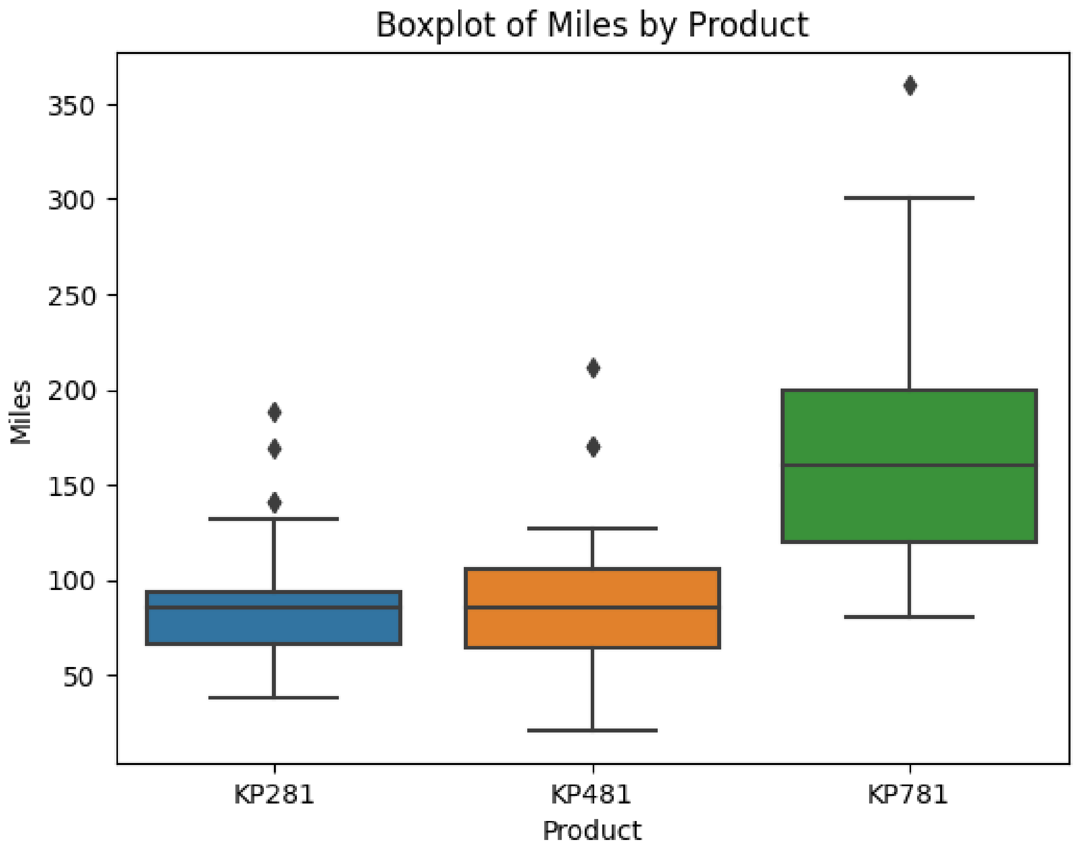

Boxplot of Age by Product
50
45
40
35
30
25
20
Age
KP281
KP481
KP781
Product

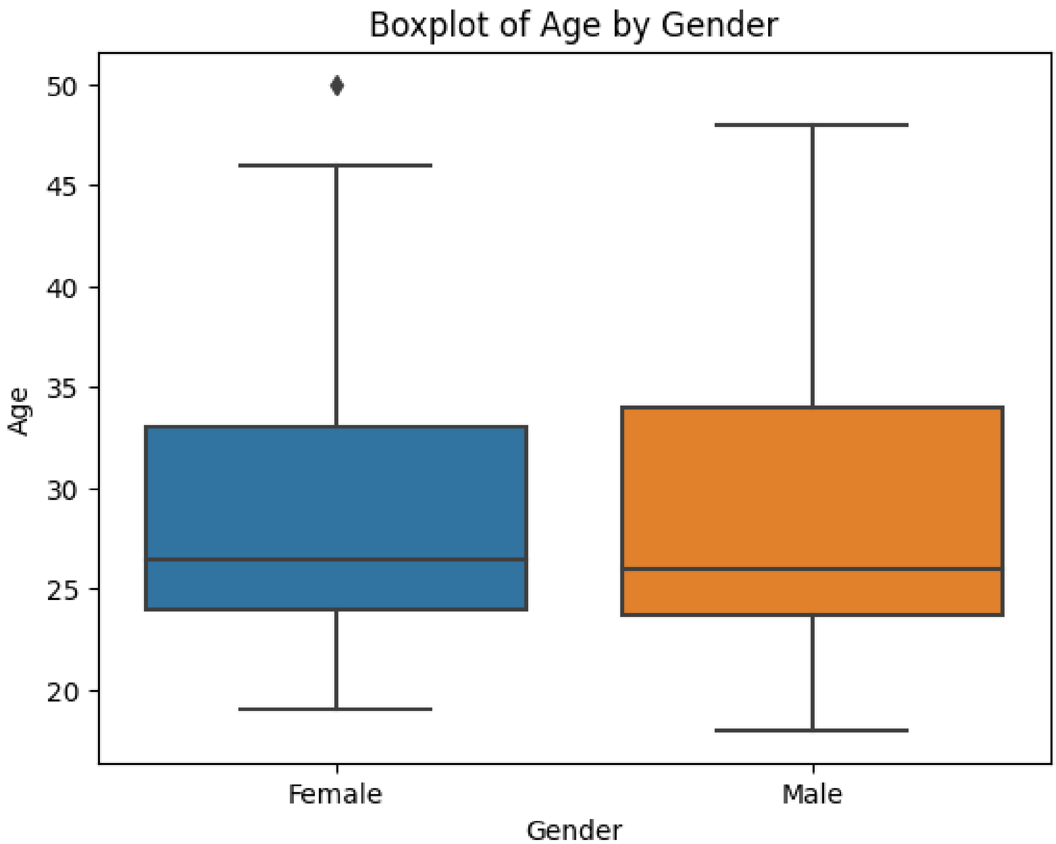

Boxplot of Education by Product
20
18
16
14
12
Education
KP281
KP481
KP781
Product

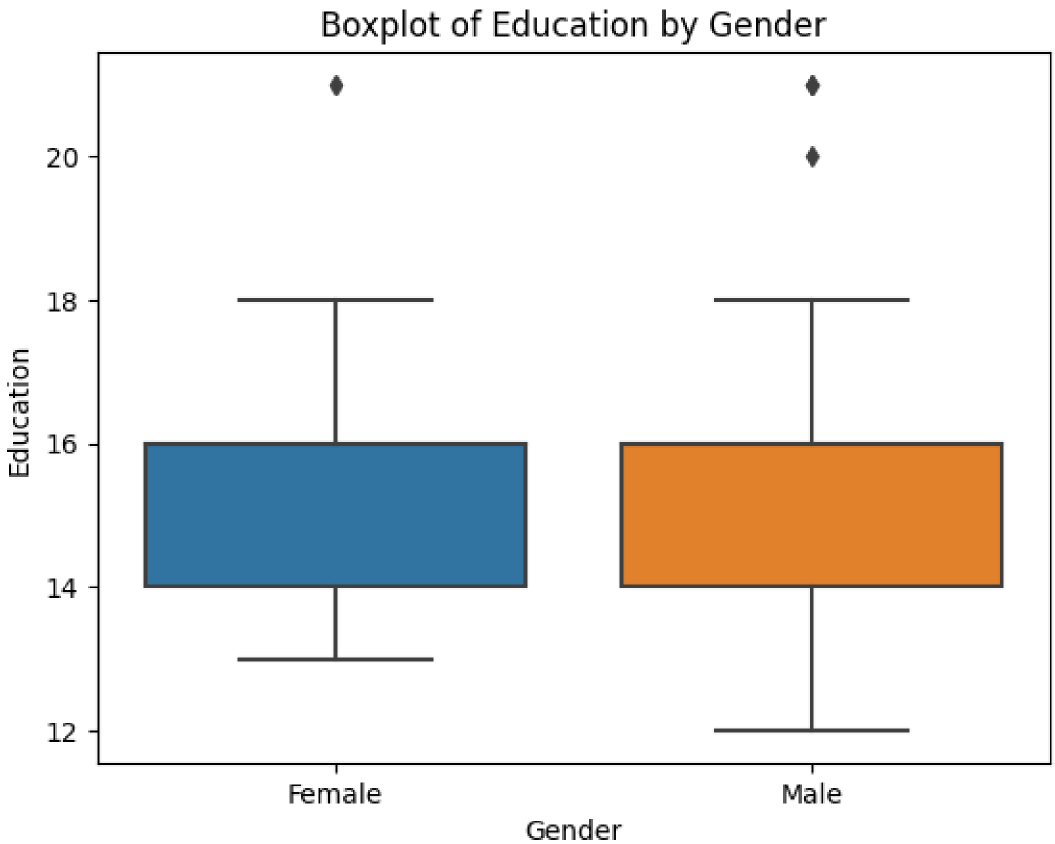

Boxplot of Usage by Product
Usage
7
6
5
4
3
2
KP281
KP481
KP781
Product

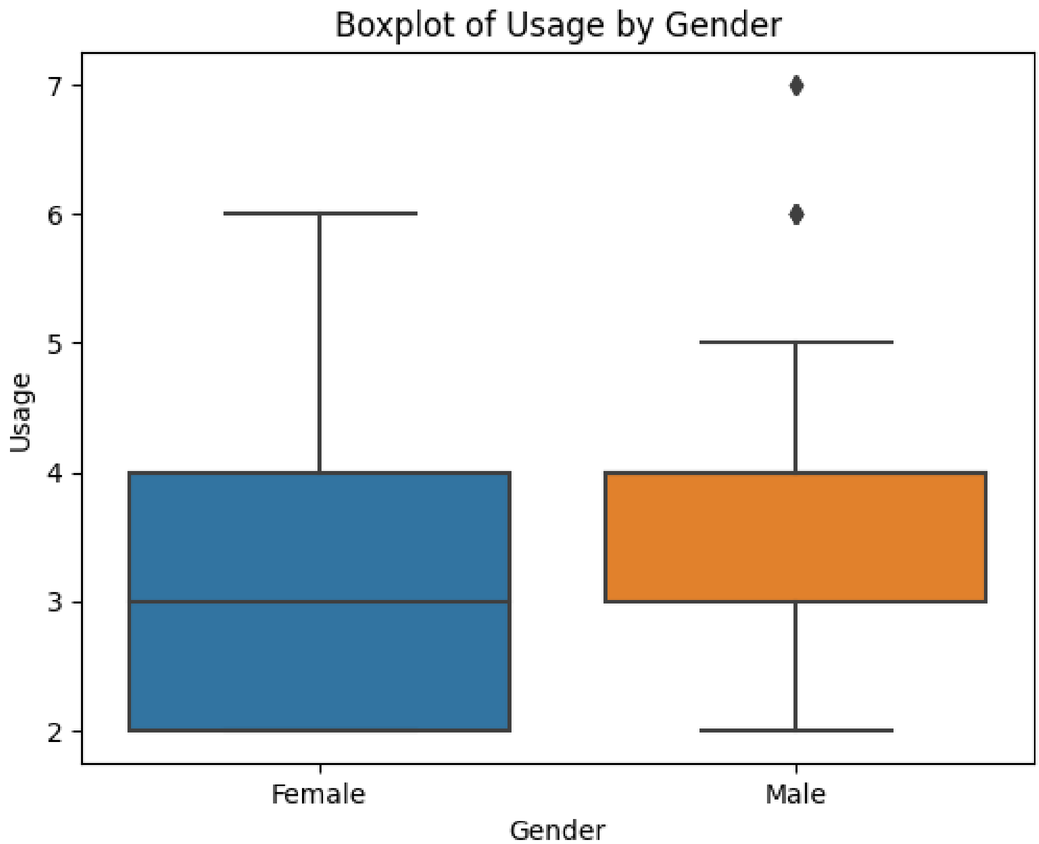

Boxplot of Fitness by Product
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
Fitness
KP281
KP481
KP781
Product

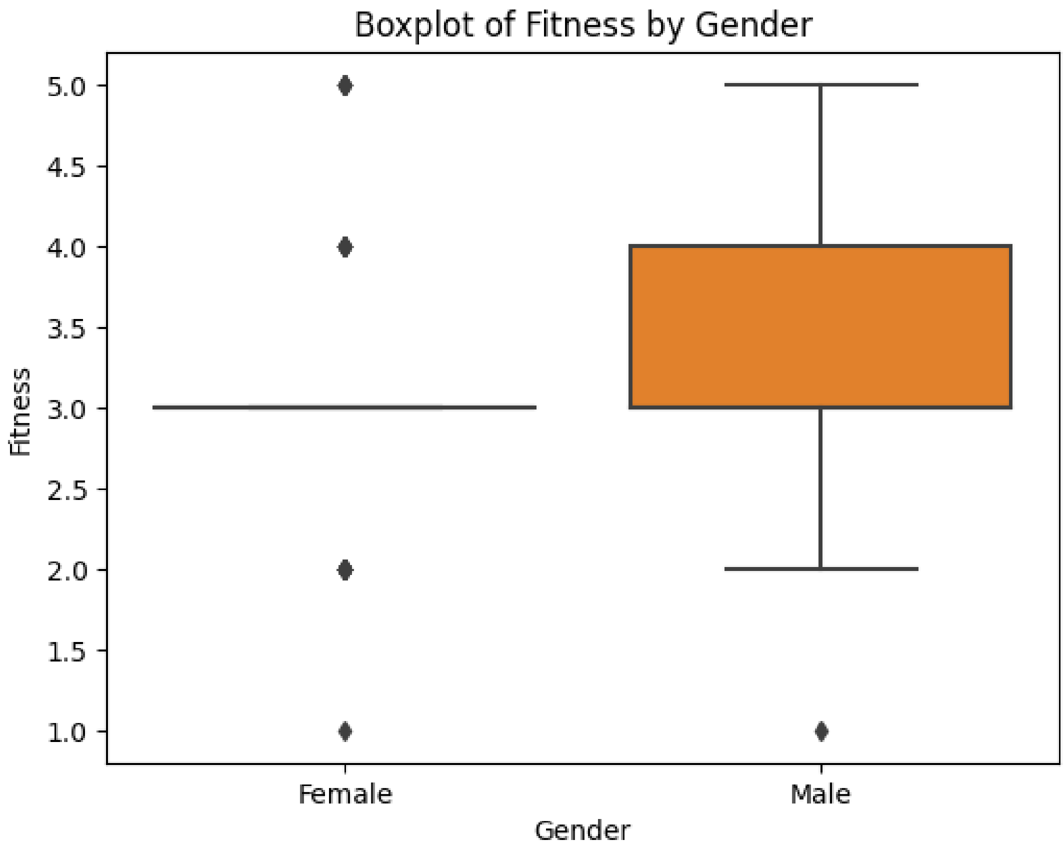

Boxplot of Income by Product
100000
90000
80000
70000
60000
50000
40000
30000
Income
KP281
KP481
KP781
Product

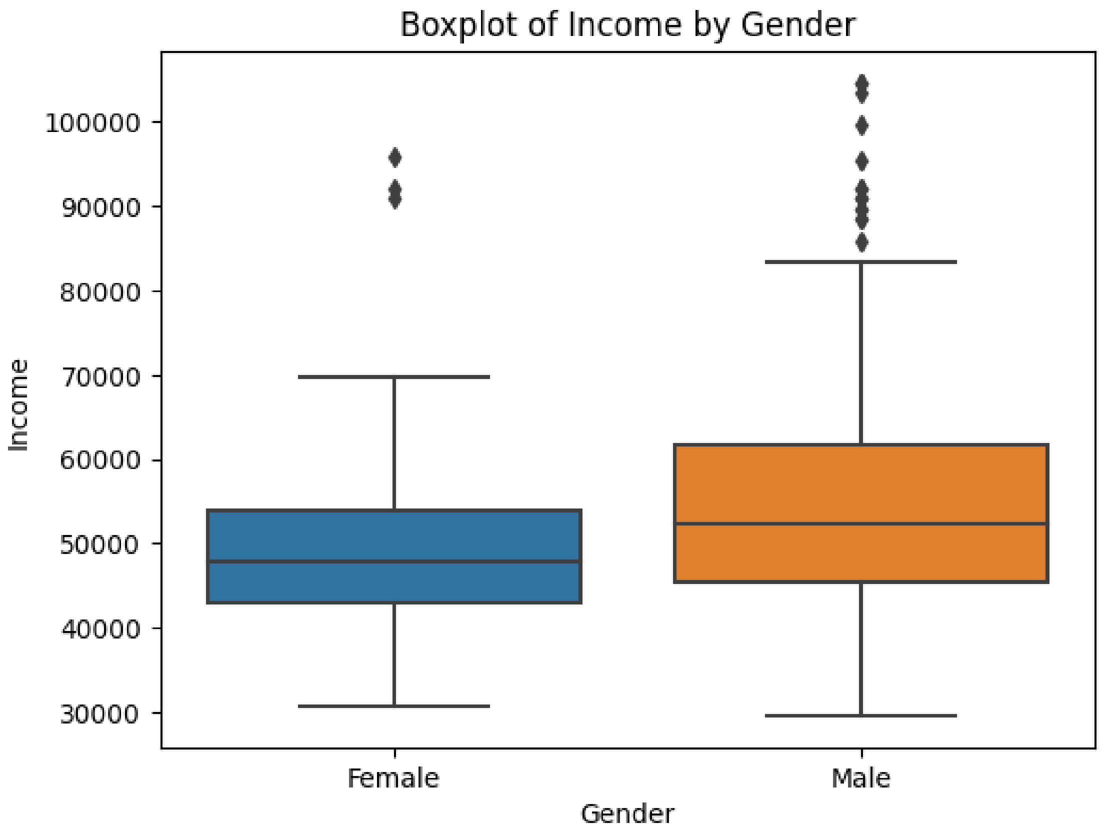

Boxplot of Miles by Product
Miles
350
300
250
200
150
100
50
KP281
KP481
KP781
Product

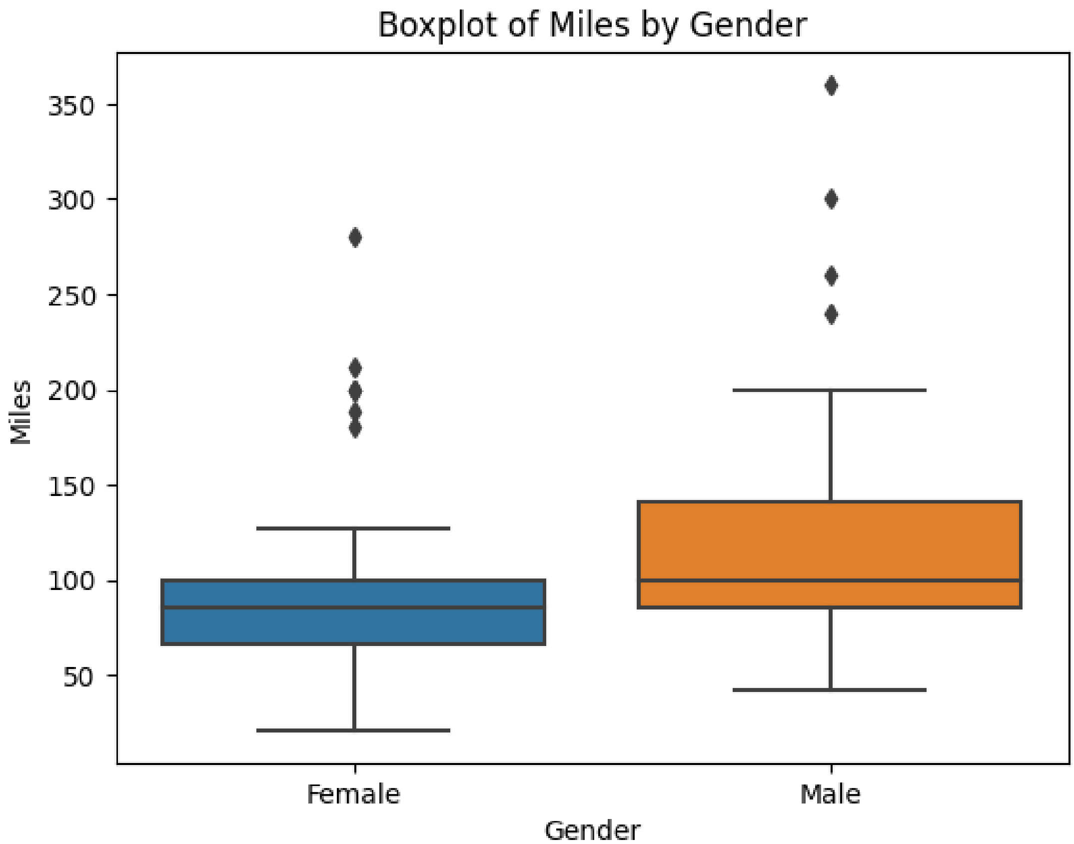

Boxplot of Age by Gender
Age
50
45
40
35
30
25
20
Female
Male
Gender

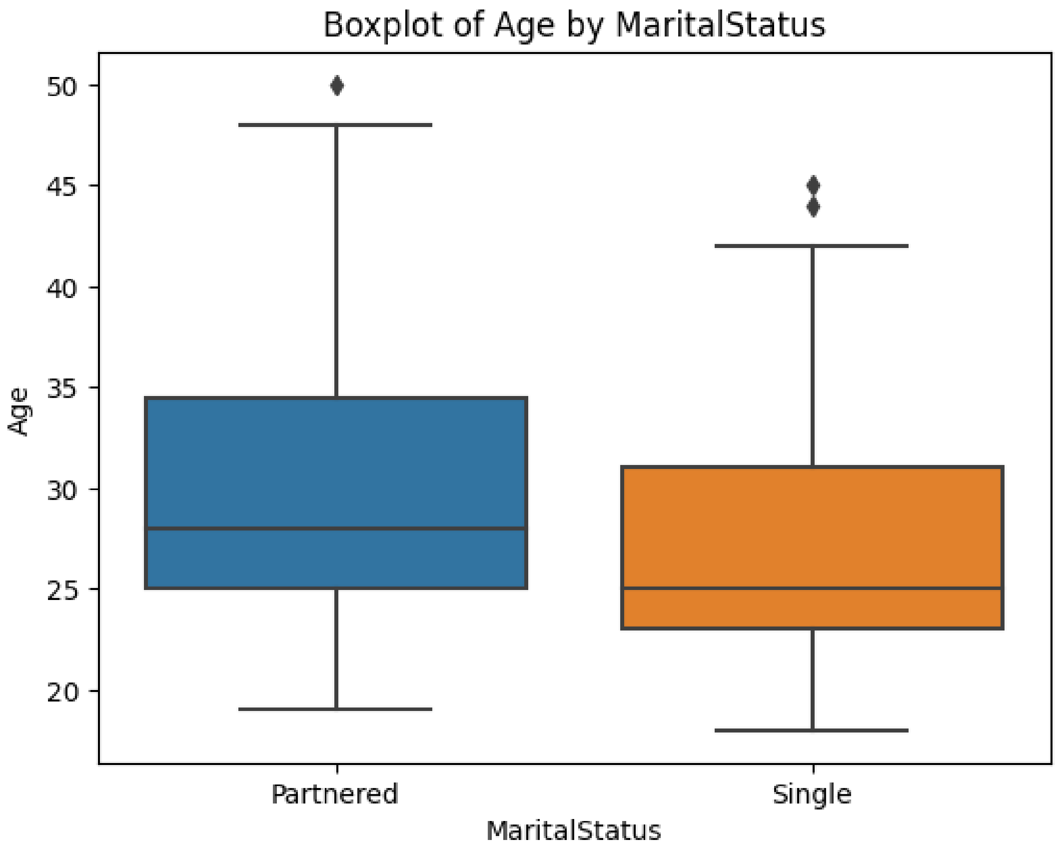

Boxplot of Education by Gender
Education
20
18
16
14
12
Female
Male
Gender

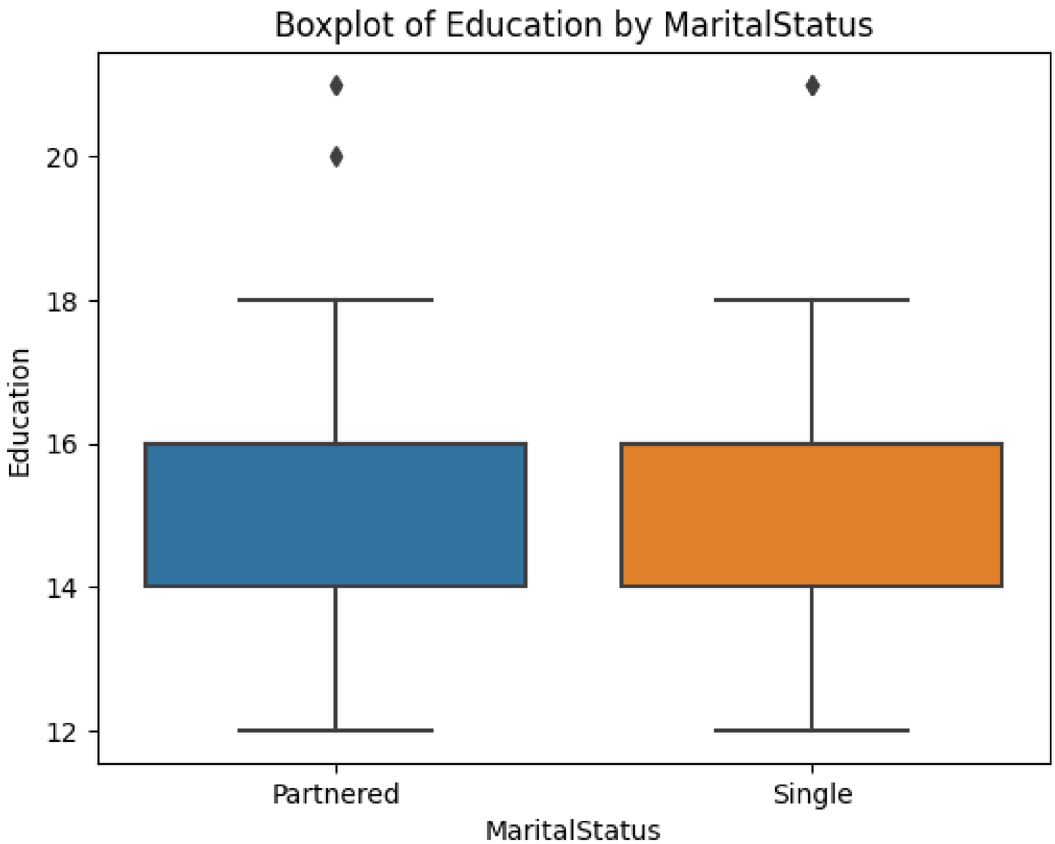

Boxplot of Usage by Gender
Usage
7
6
5
4
3
2
Female
Male
Gender

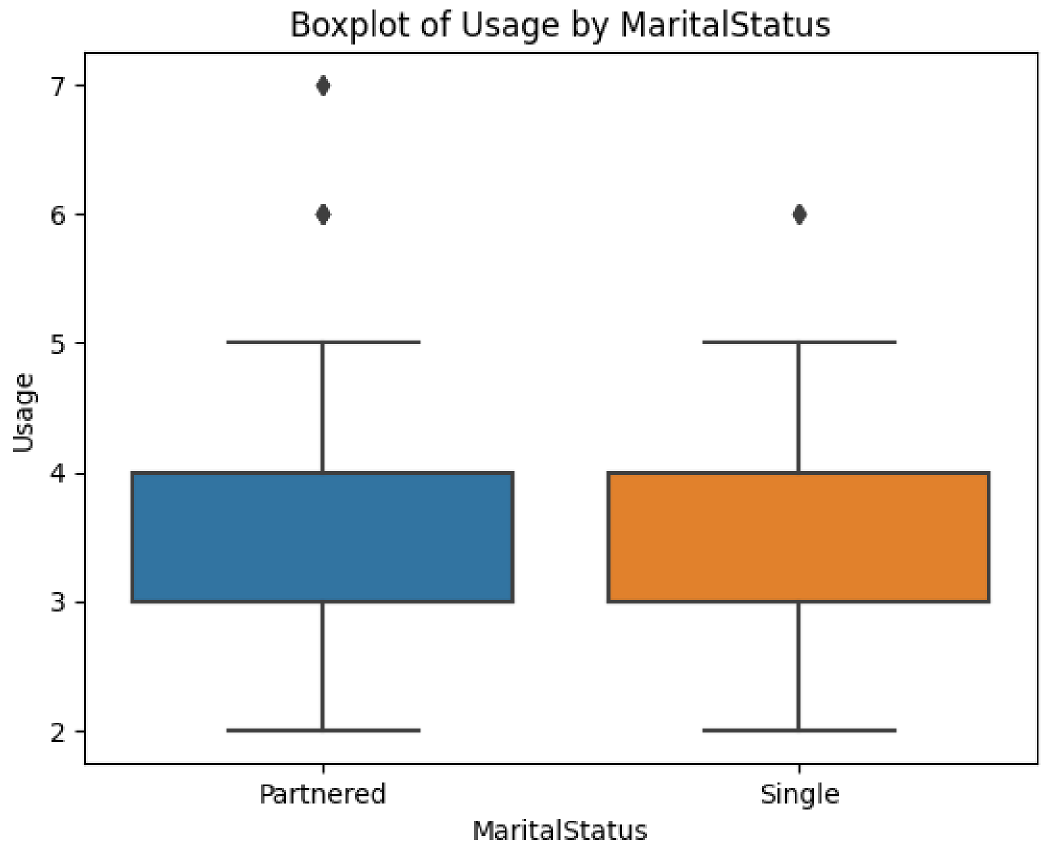

Boxplot of Fitness by Gender
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
Fitness
Female
Male
Gender

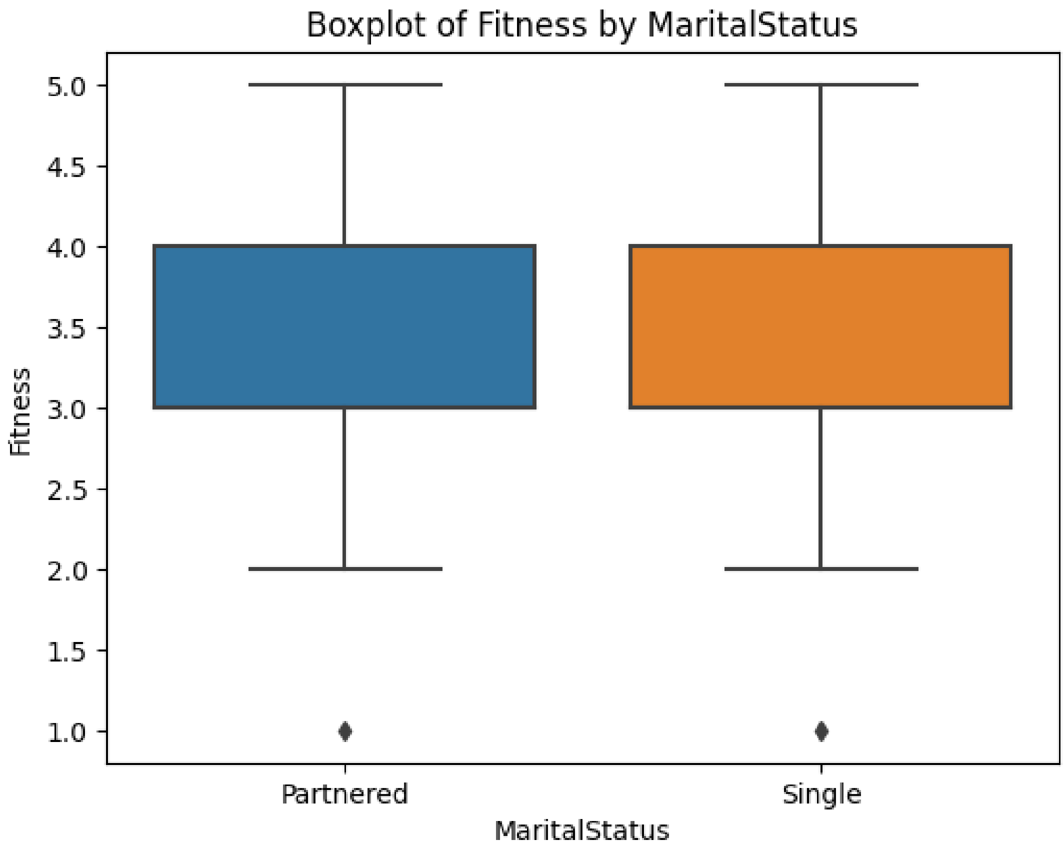

Boxplot of Income by Gender
100000
90000
80000
70000
60000
50000
40000
30000
Income
Female
Male
Gender

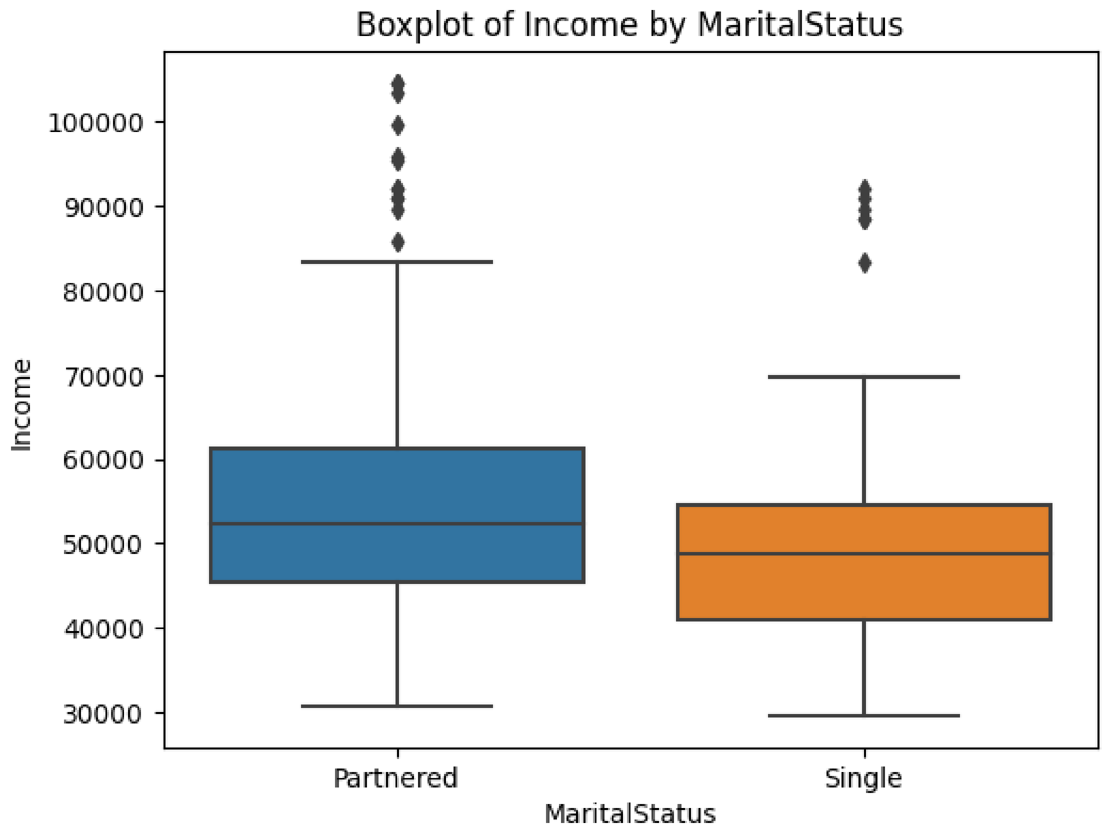

Boxplot of Miles by Gender
350
300
250
200
150
100
50
Miles
Female
Male
Gender

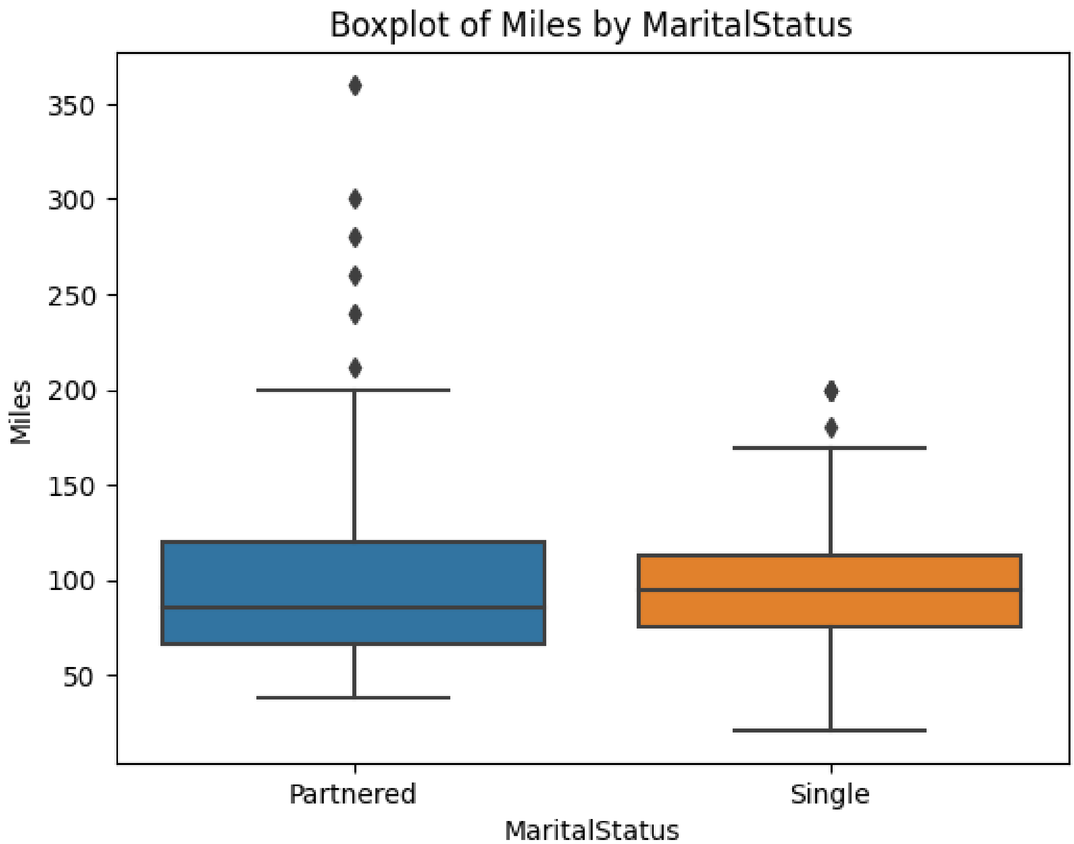

Boxplot of Age by MaritalStatus
50
45
40
35
30
25
20
Age
Partnered
Single
MaritalStatus


Boxplot of Education by MaritalStatus
20
18
16
14
12
Education
Partnered
Single
MaritalStatus


Boxplot of Usage by MaritalStatus
Usage
7
6
5
4
3
2
Partnered
Single
MaritalStatus


Boxplot of Fitness by MaritalStatus
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
Fitness
Partnered
Single
MaritalStatus


Boxplot of Income by MaritalStatus
100000
90000
80000
70000
60000
50000
40000
30000
Income
Partnered
Single
MaritalStatus

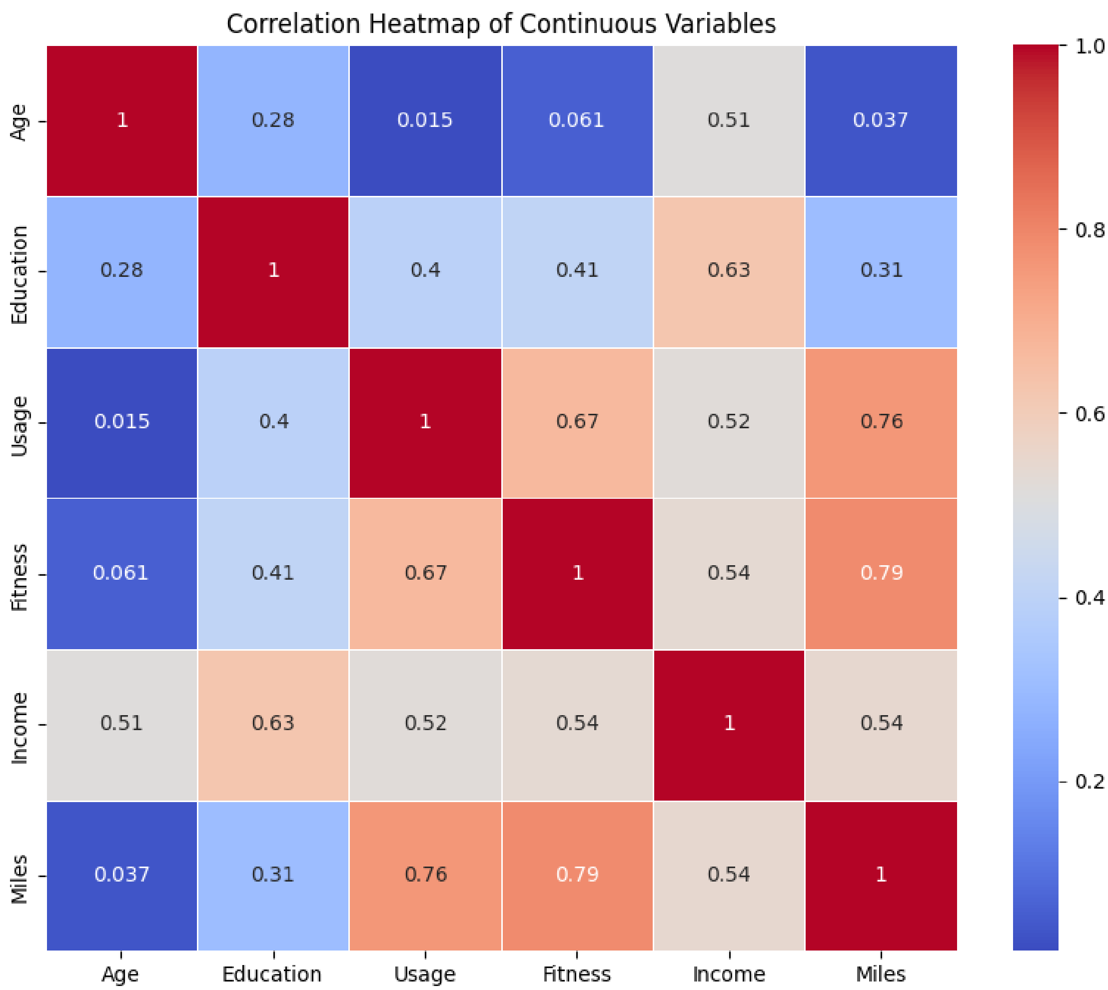


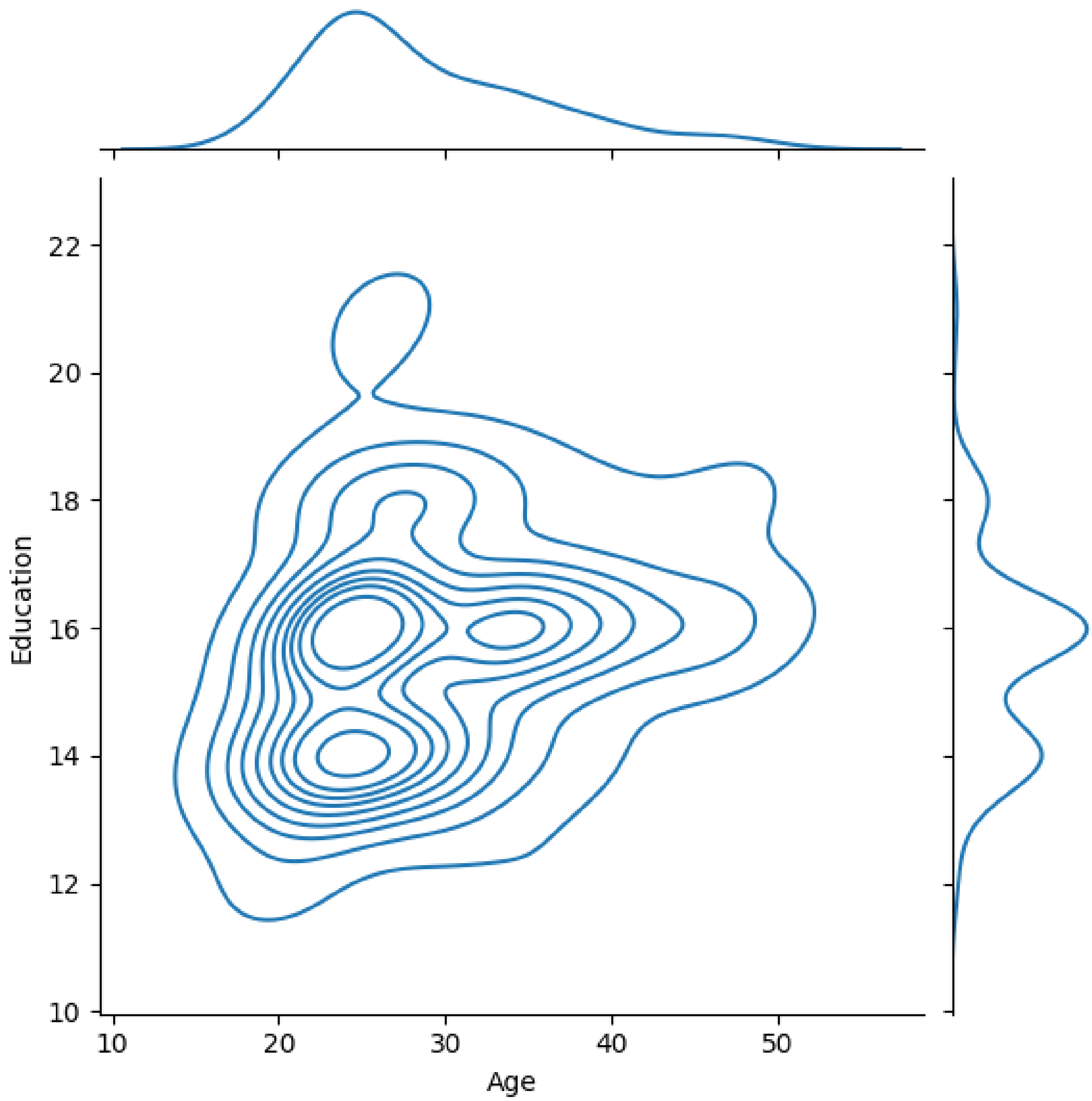
[ ]:

Bivariate analysis for Continous Variable vs continuous variable

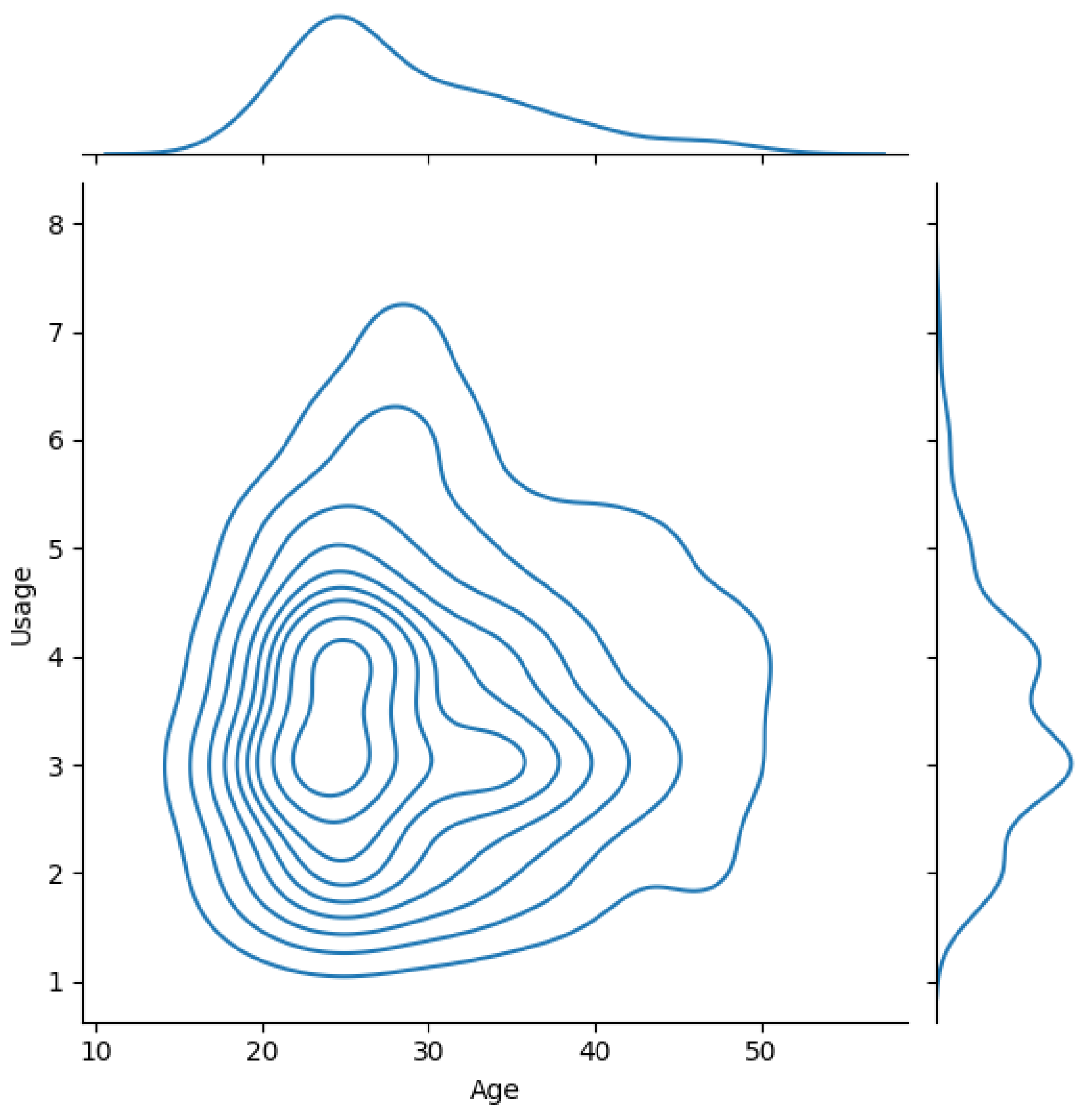
[ ]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Assuming you've already loaded your dataset into a DataFrame named 'df'
# df = pd.read_csv('path_to_aerofit_dataset.csv')

continuous_vars = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']

# Pairwise scatter plots for all continuous variables
sns.pairplot(df[continuous_vars])
plt.suptitle('Pairwise Scatter Plots of Continuous Variables', y=1.02)
plt.show()

# Correlation heatmap
correlation_matrix = df[continuous_vars].corr()
```

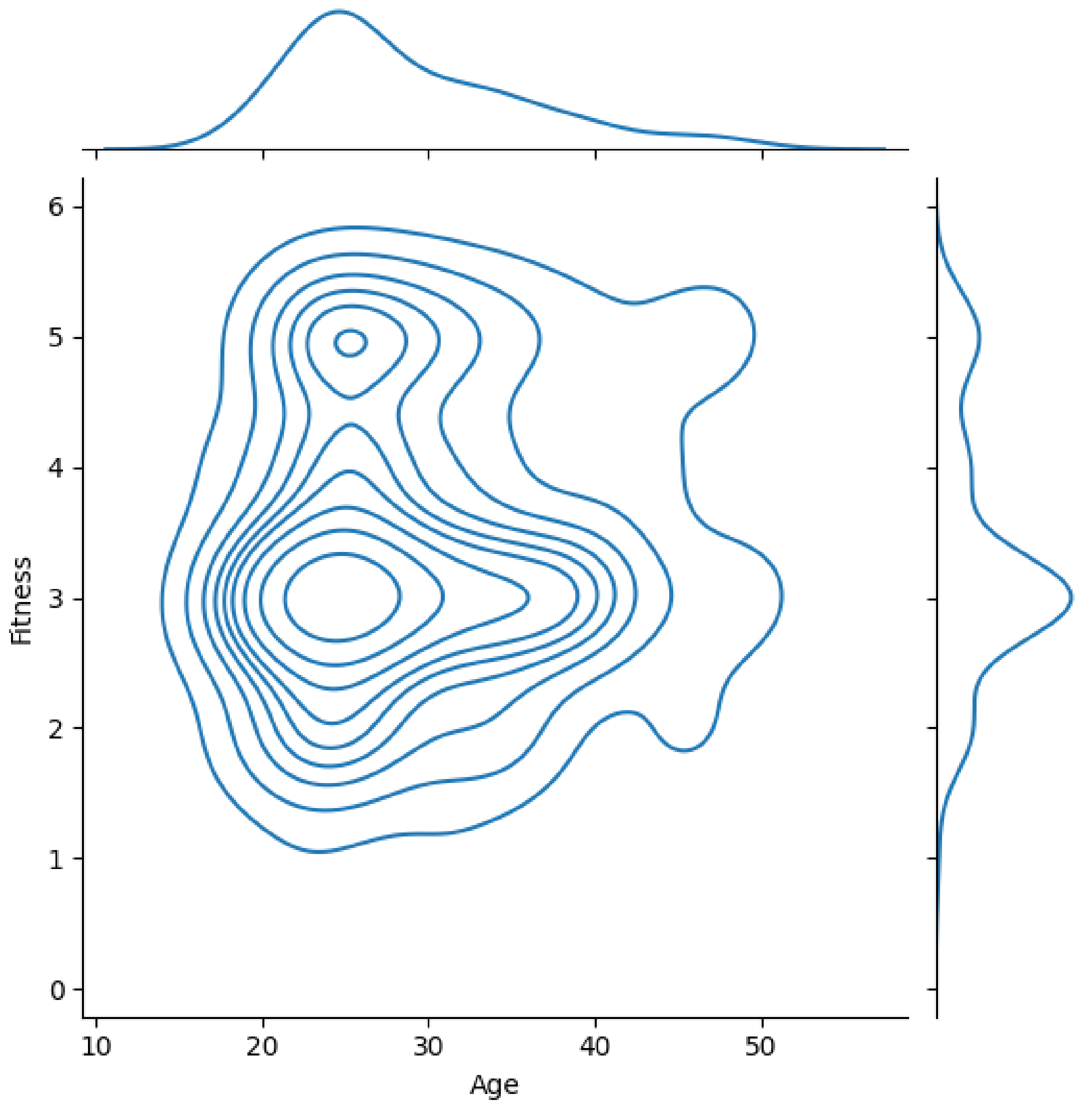
```python
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Heatmap of Continuous Variables')
plt.show()

# Optionally, if you want to look at joint distributions with KDE for specific pairs
for i in range(len(continuous_vars)):
    for j in range(i+1, len(continuous_vars)):
        sns.jointplot(x=continuous_vars[i], y=continuous_vars[j], data=df, kind='kde')
        plt.show()
```

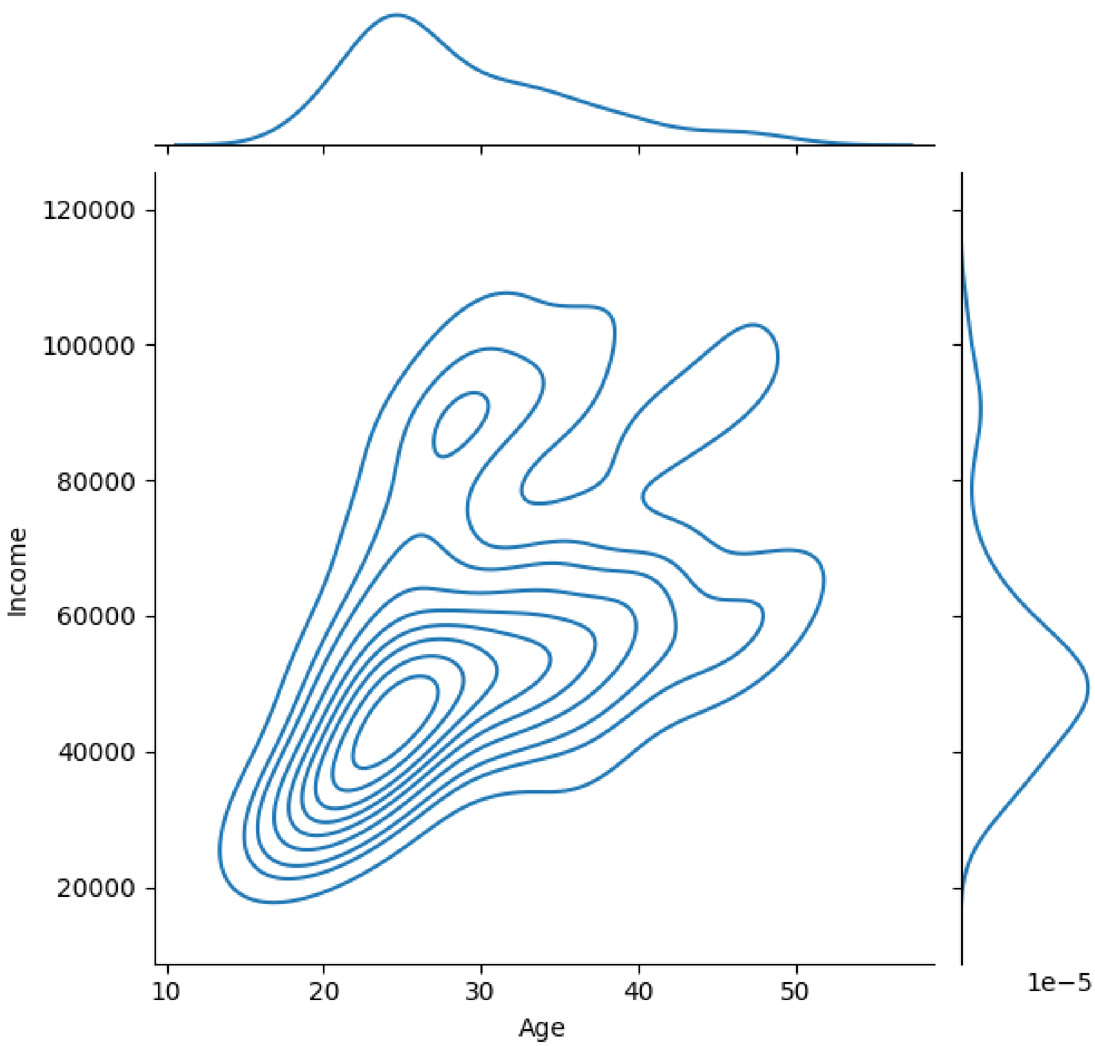

Correlation Heatmap of Continuous Variables
Age
Education
Usage
Fitness
Income
Miles
1
0.28
0.015
0.061
0.51
0.037
0.28
1
0.4
0.41
0.63
0.31
0.015
0.4
1
0.67
0.52
0.76
0.061
0.41
0.67
1
0.54
0.79
0.51
0.63
0.52
0.54
1
0.54
0.037
0.31
0.76
0.79
0.54
1
1.0
0.8
0.6
0.4
0.2

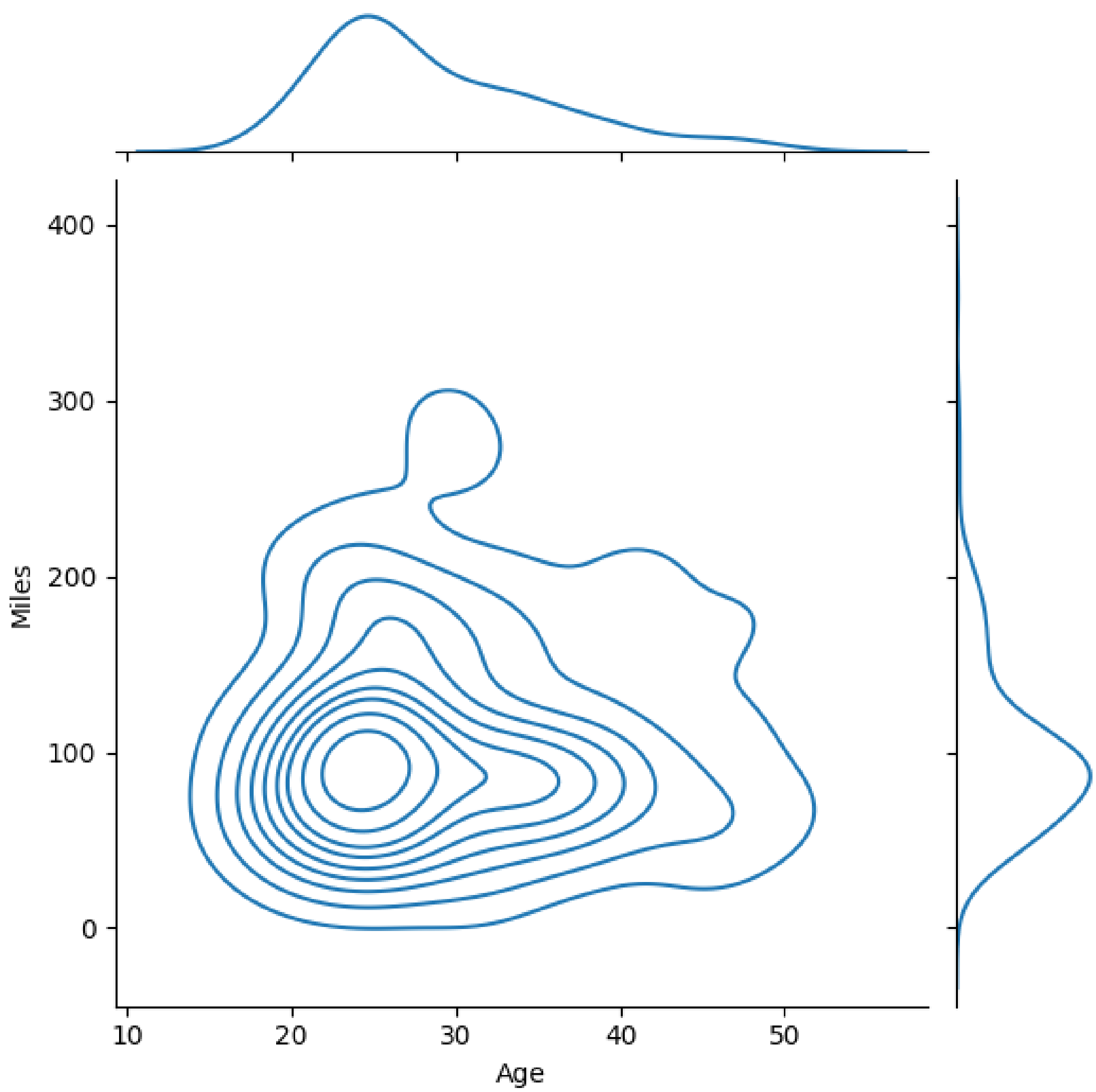


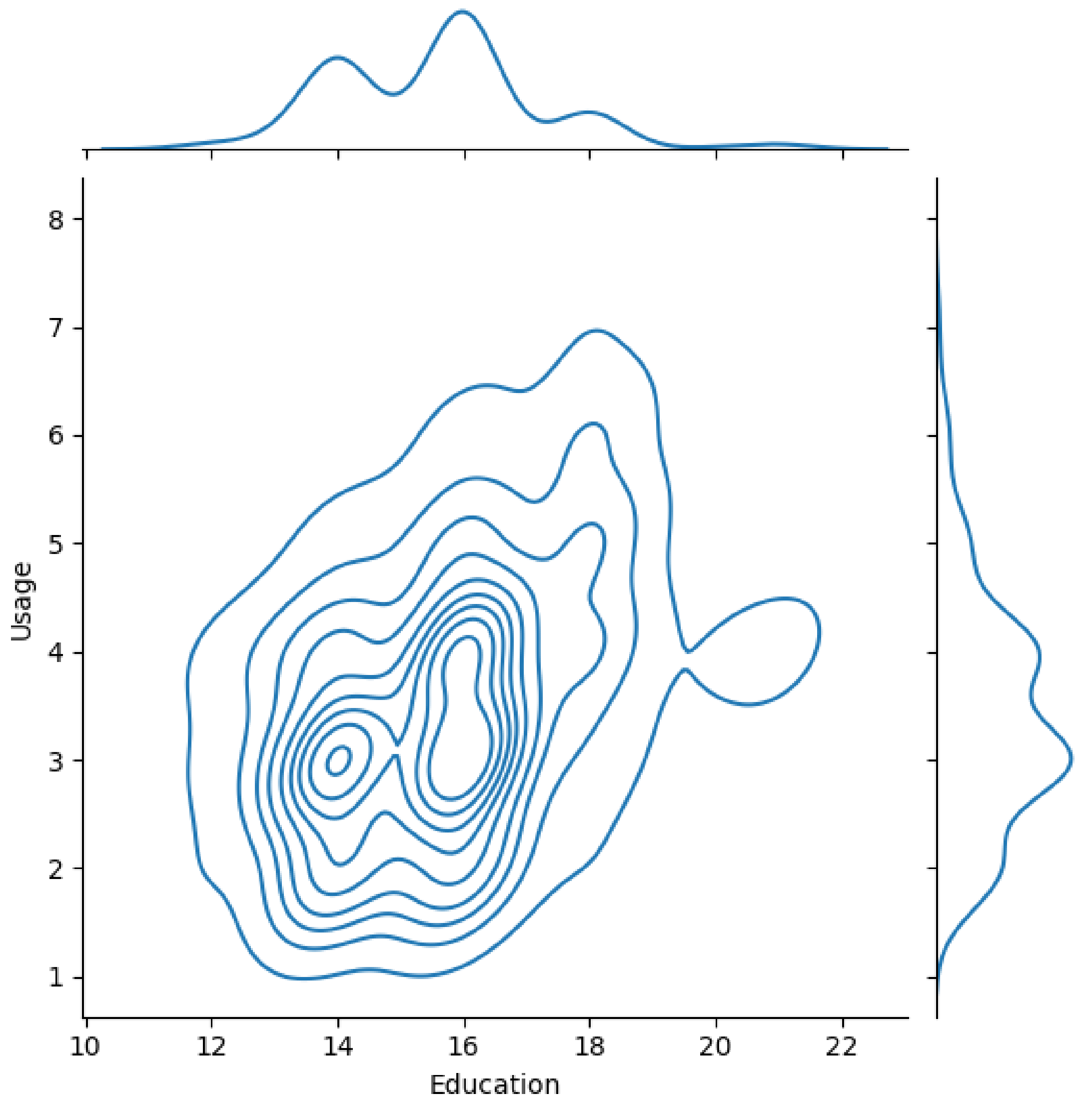
22
20
18
16
14
12
10
Education
10
20
30
40
50
Age


8
7
6
5
4
3
2
1
Usage
10
20
30
40
50
Age

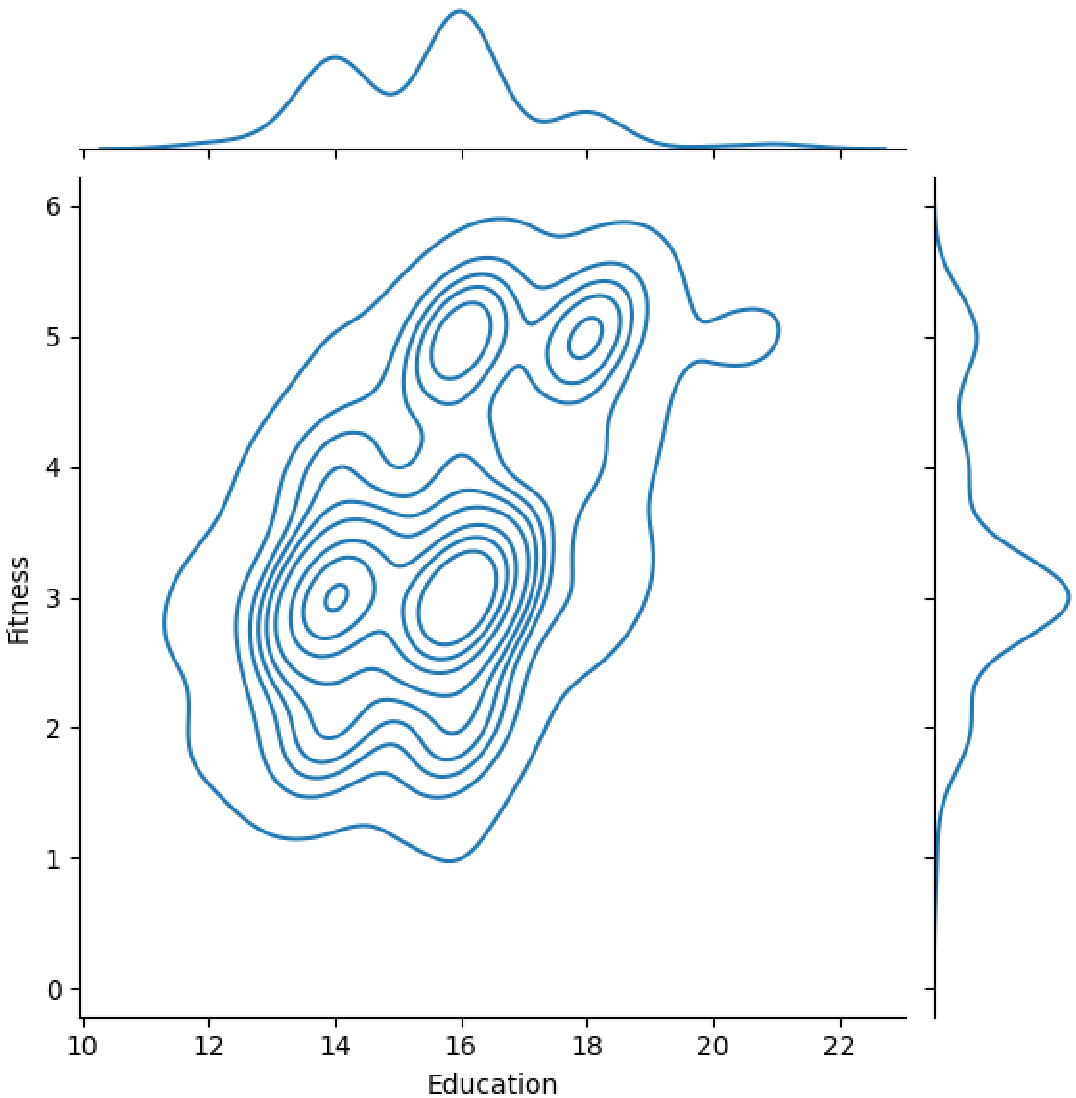

6
5
4
3
2
1
0
Fitness
10
20
30
40
50
Age


120000
100000
80000
60000
40000
20000
Income
10
20
30
40
50
Age
1e−5

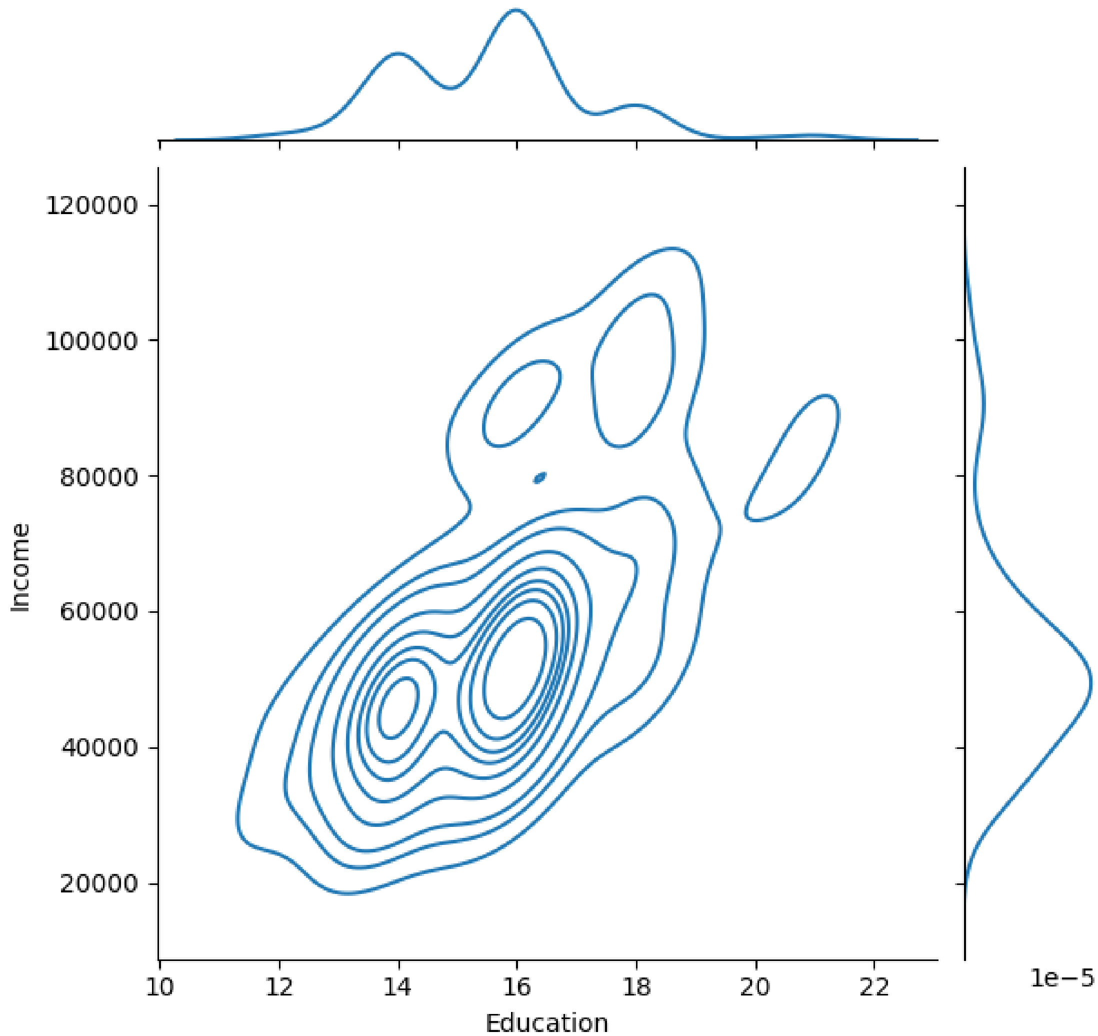

400
300
200
100
0
Miles
10
20
30
40
50
Age

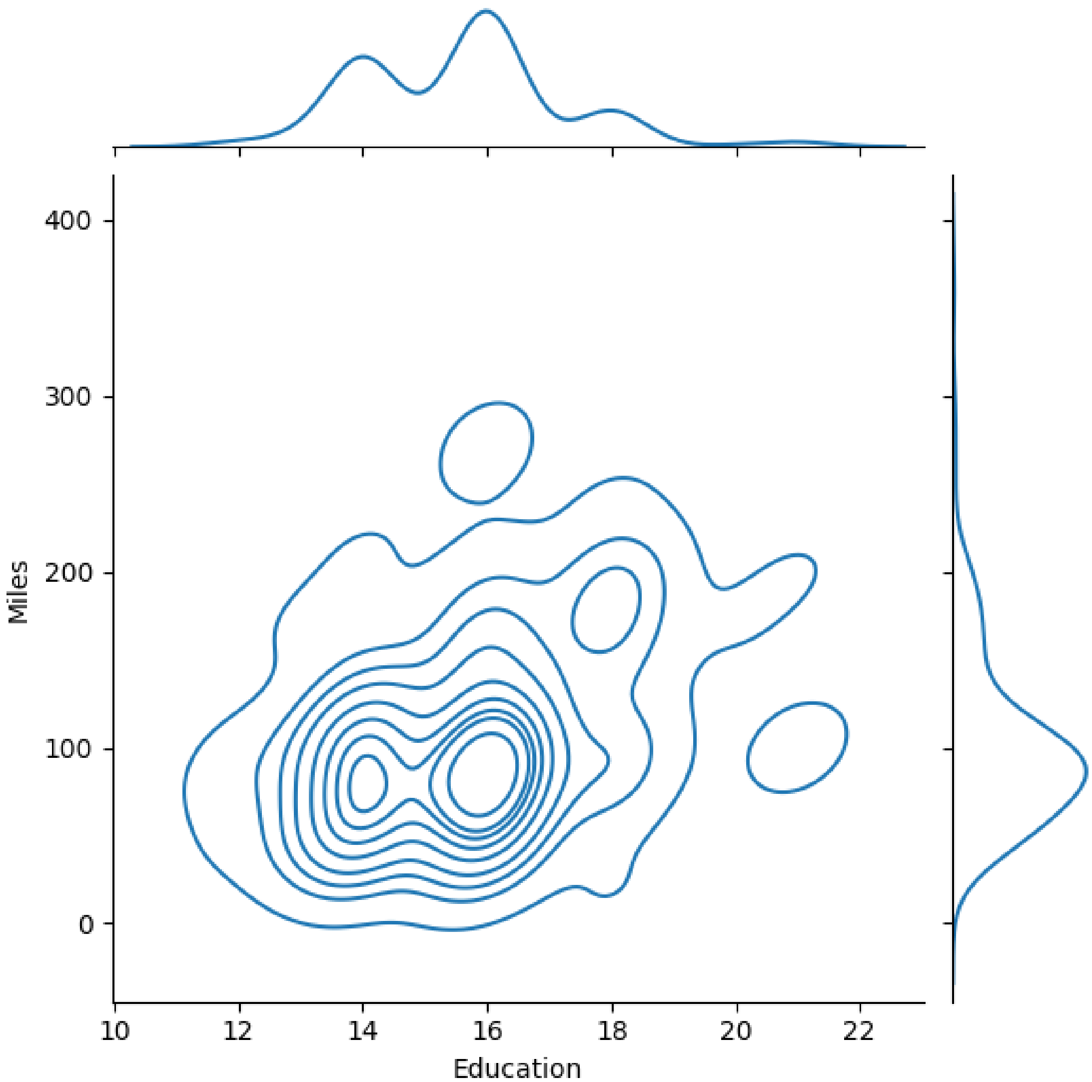


8
7
6
5
4
3
2
1
Usage
10
12
14
16
18
20
22
Education

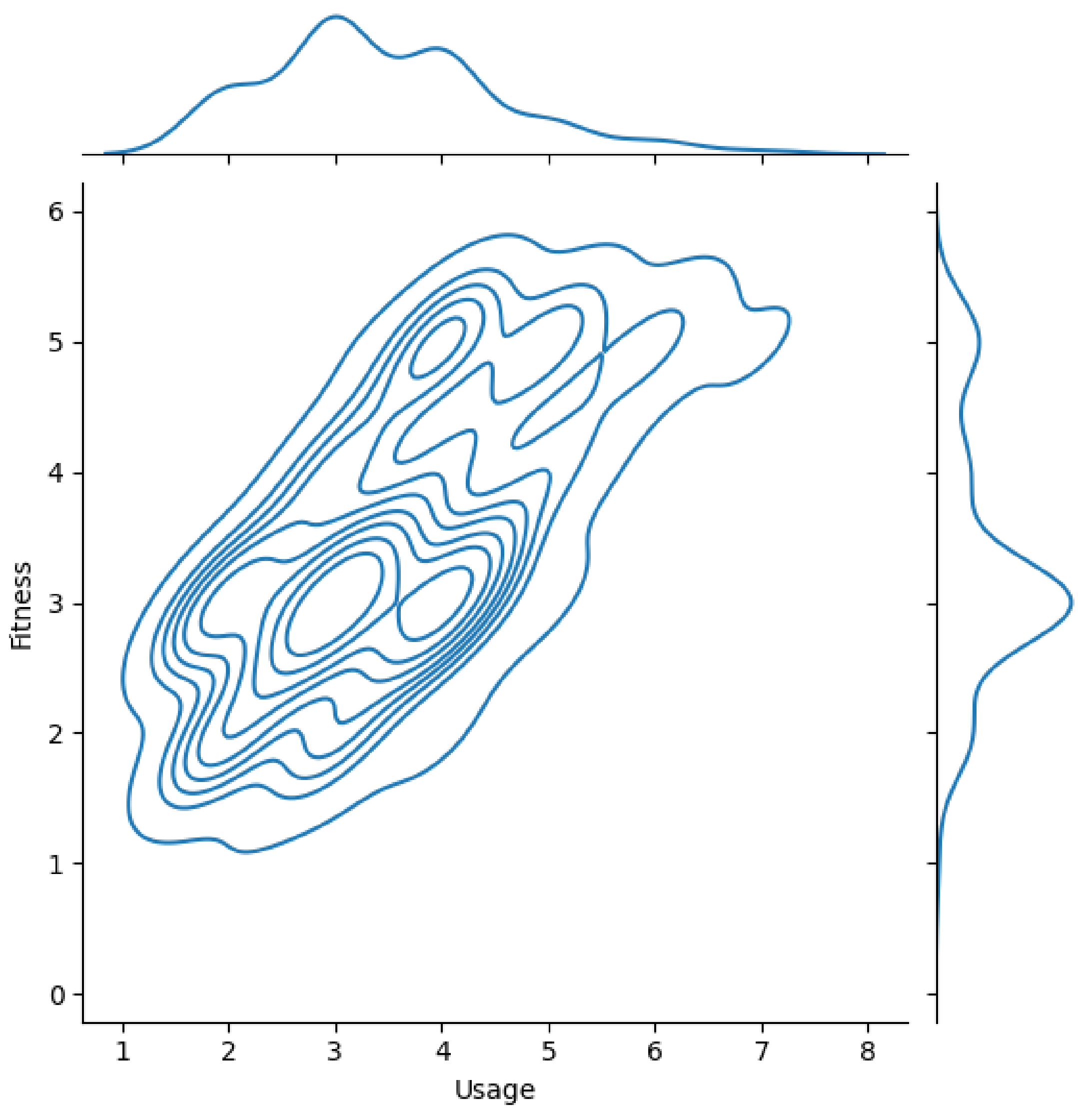


6
5
4
3
2
1
0
Fitness
10
12
14
16
18
20
22
Education

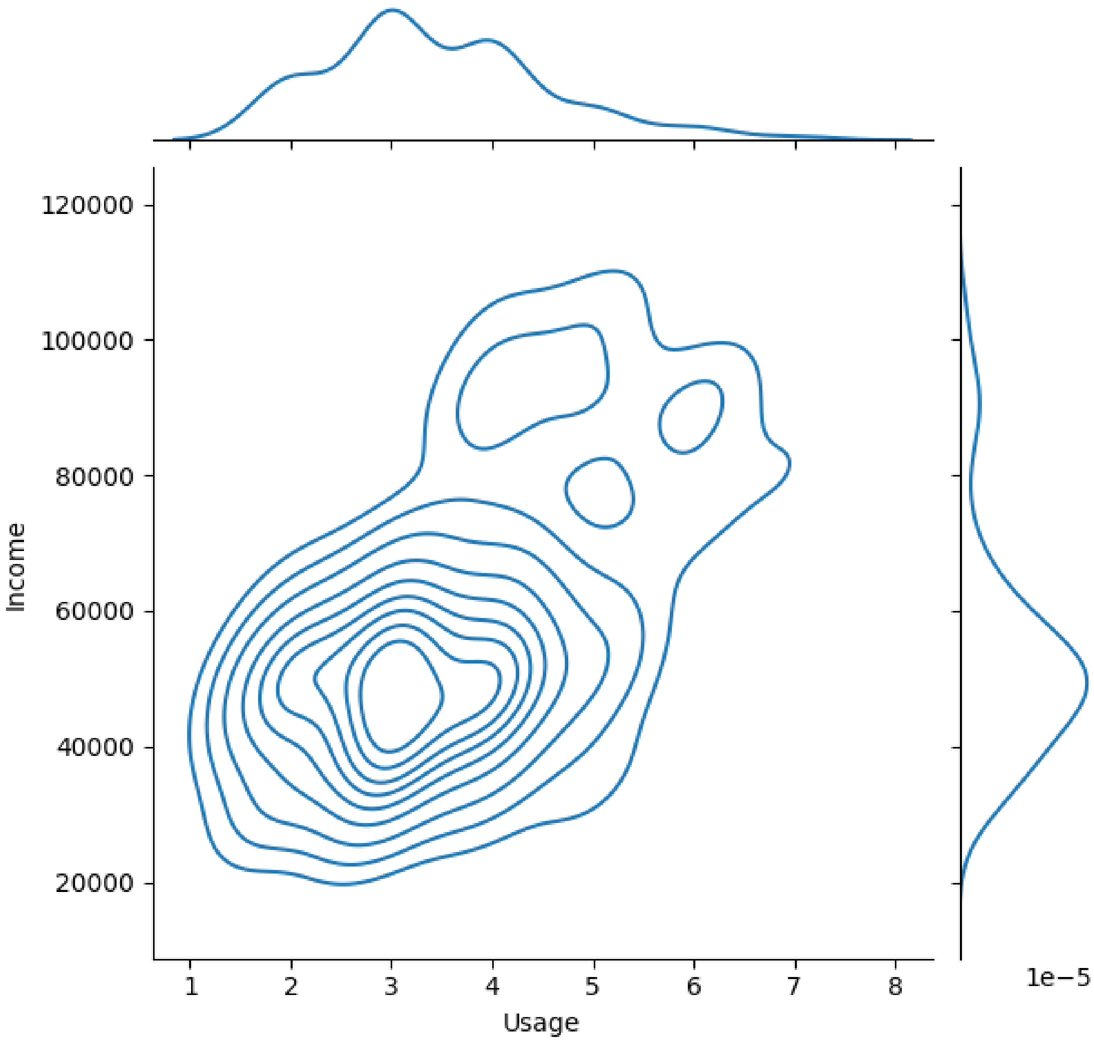

Income
120000
100000
80000
60000
40000
20000
10
12
14
16
18
20
22
Education
1e−5



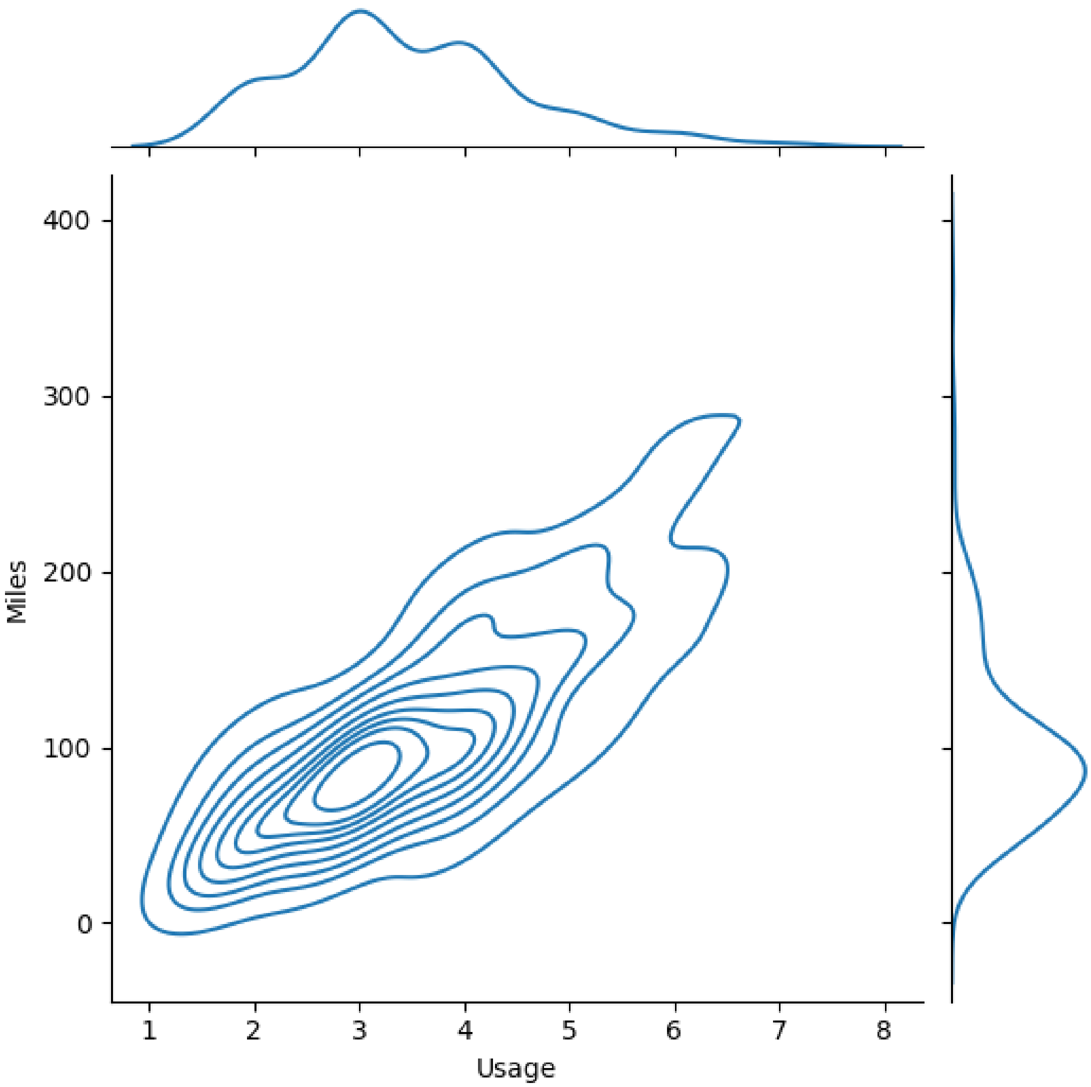
400
300
200
100
0
Miles
10
12
14
16
18
20
22
Education

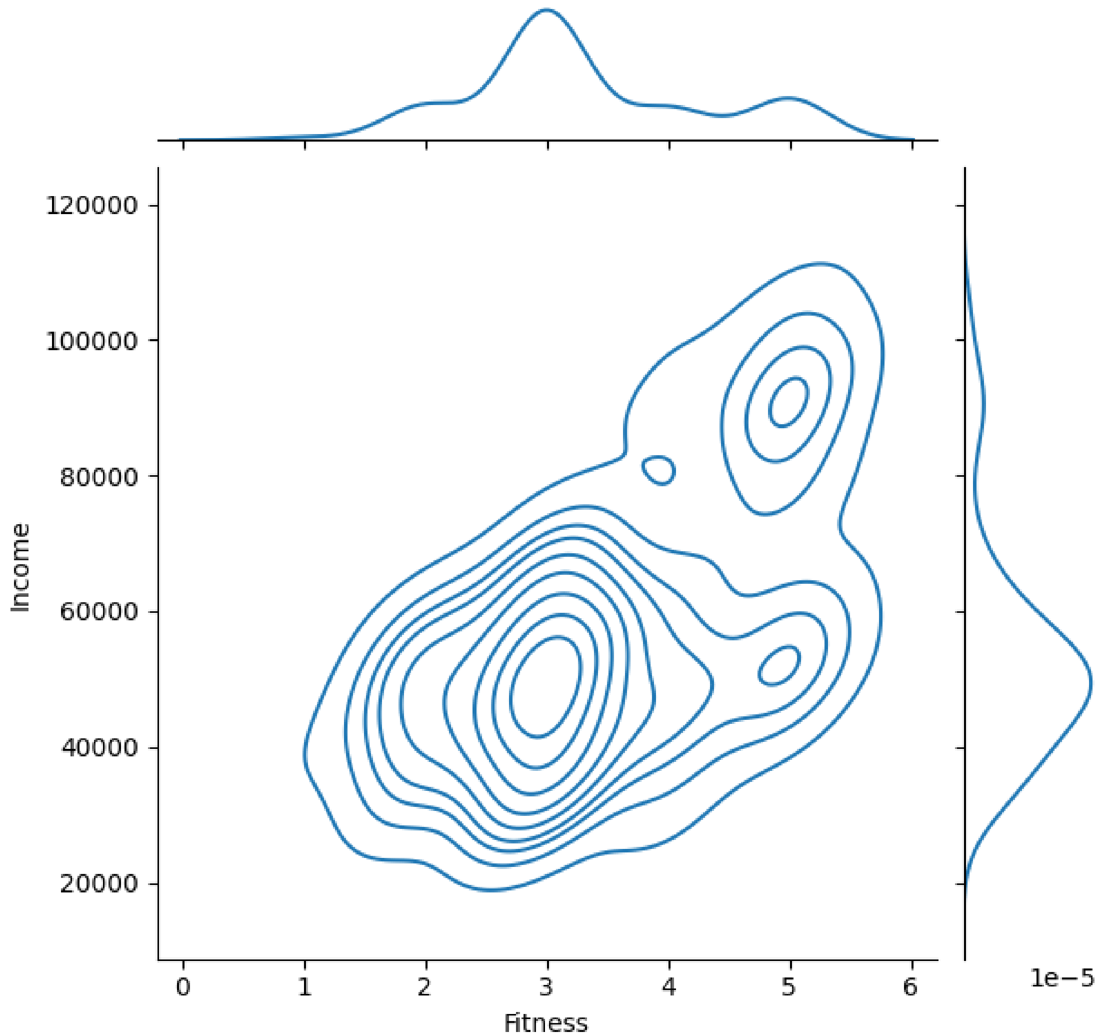


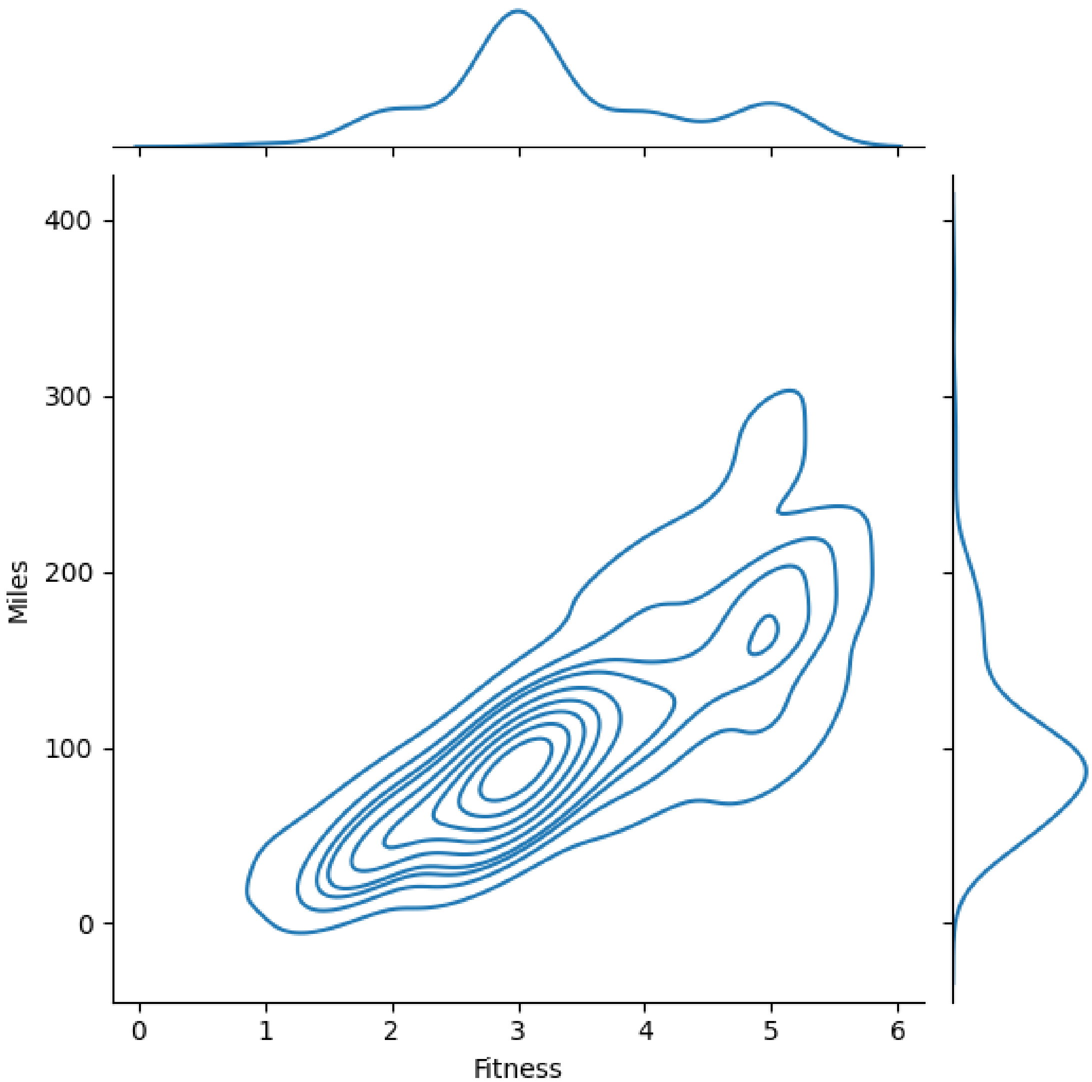
Fitness
Usage
0
1
2
3
4
5
6
1
2
3
4
5
6
7
8

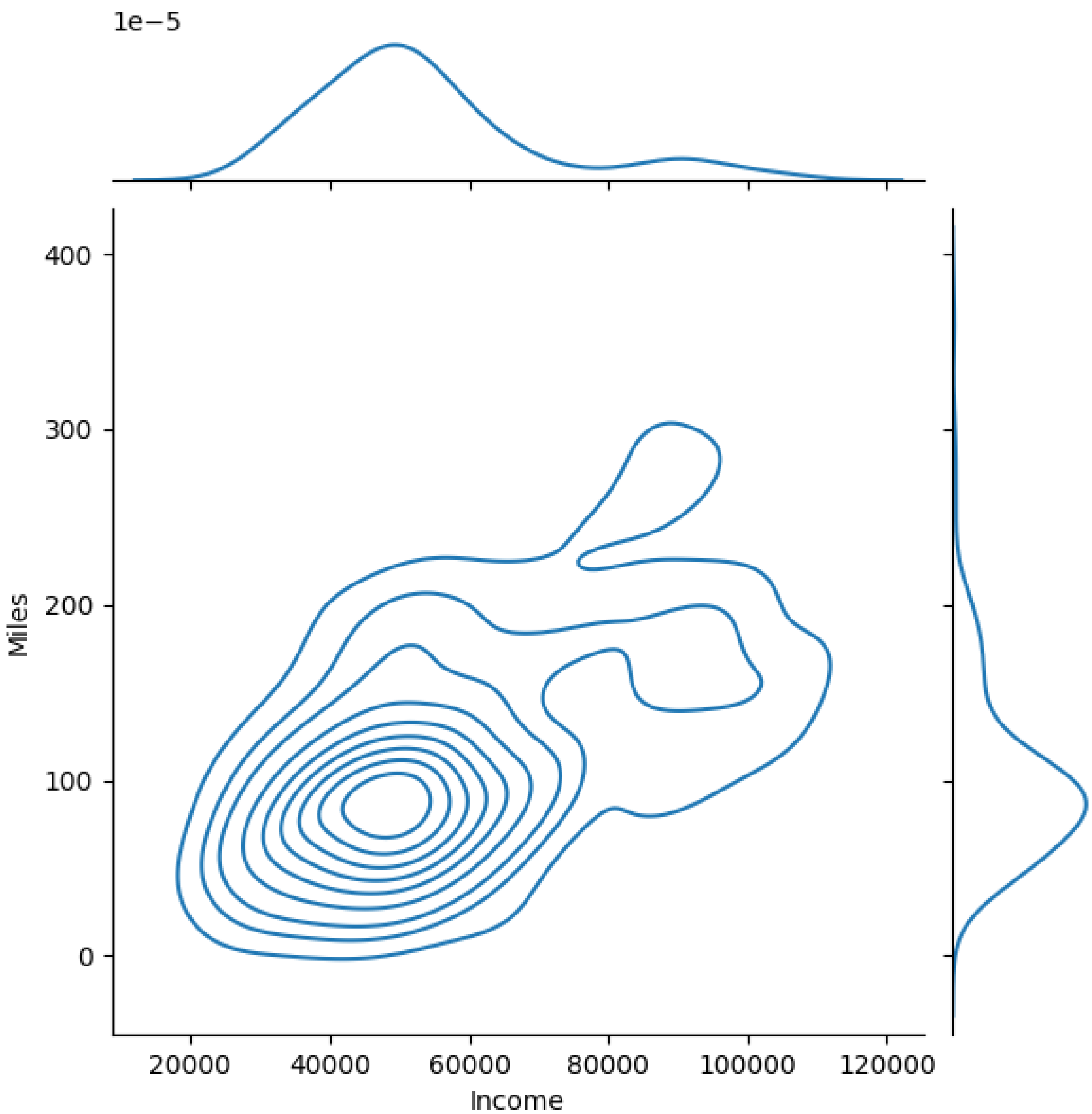


120000
100000
80000
60000
40000
20000
Income
1
2
3
4
5
6
7
8
Usage
1e−5


400
300
200
100
0
Miles
1
2
3
4
5
6
7
8
Usage


120000
100000
80000
60000
40000
20000
Income
0
1
2
3
4
5
6
Fitness
1e−5


400
300
200
100
0
Miles
0
1
2
3
4
5
6
Fitness



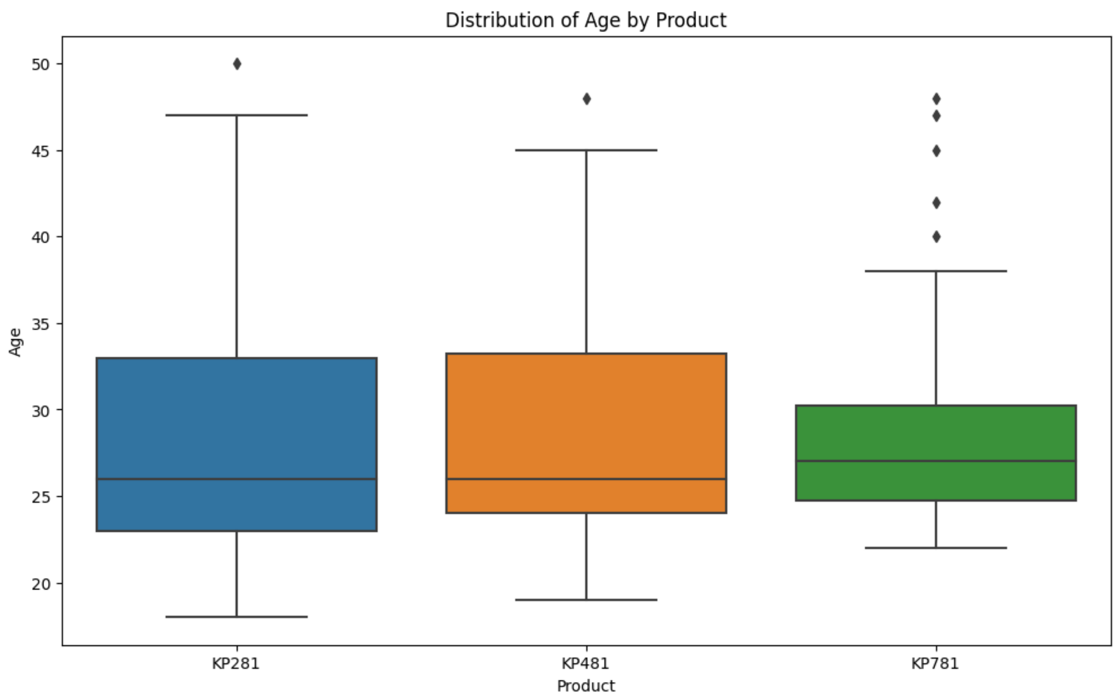
[ ]:

```

```

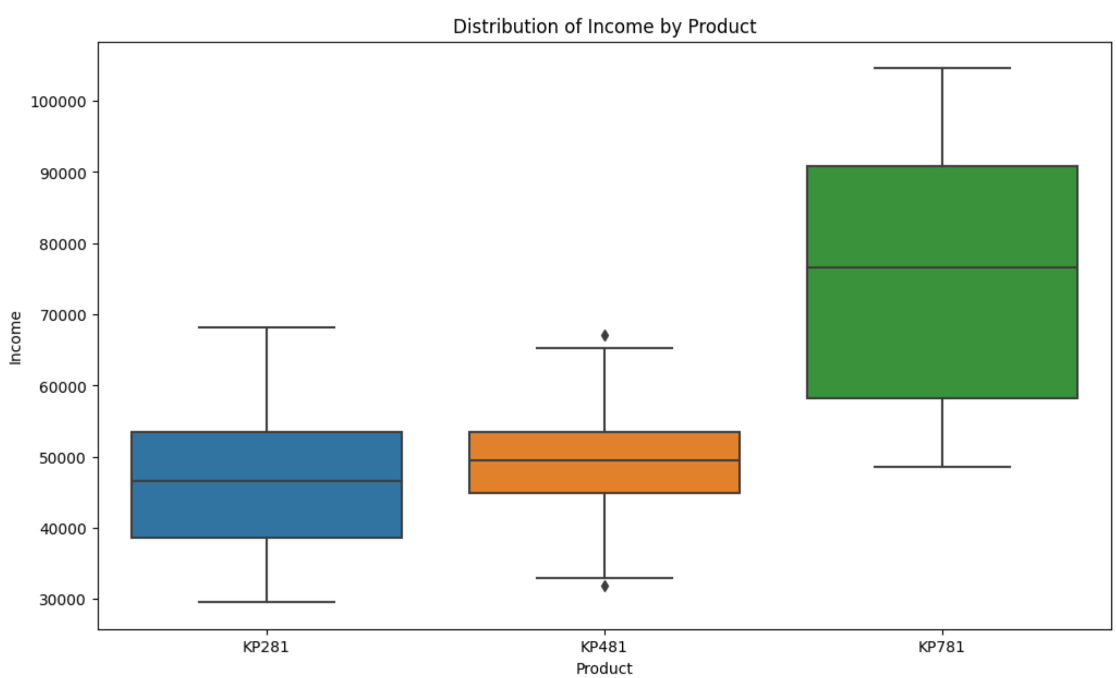
Looking Separately into few cases: 1. Age Vs Product 2. Income Vs Product 3. Gender Vs product

[ ]:

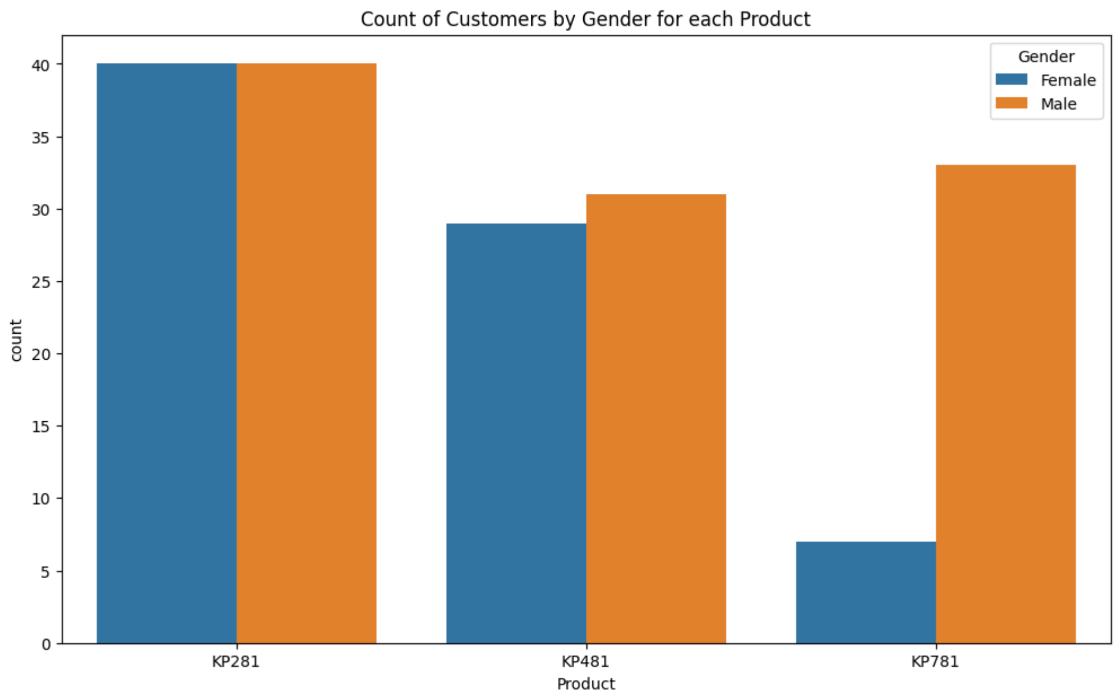
```
plt.figure(figsize=(12,7))
sns.boxplot(x=df['Product'], y=df['Age'])
plt.title('Distribution of Age by Product')
plt.show()
```



[ ]:
```
plt.figure(figsize=(12,7))
sns.boxplot(x=df['Product'], y=df['Income'])
plt.title('Distribution of Income by Product')
plt.show()
```

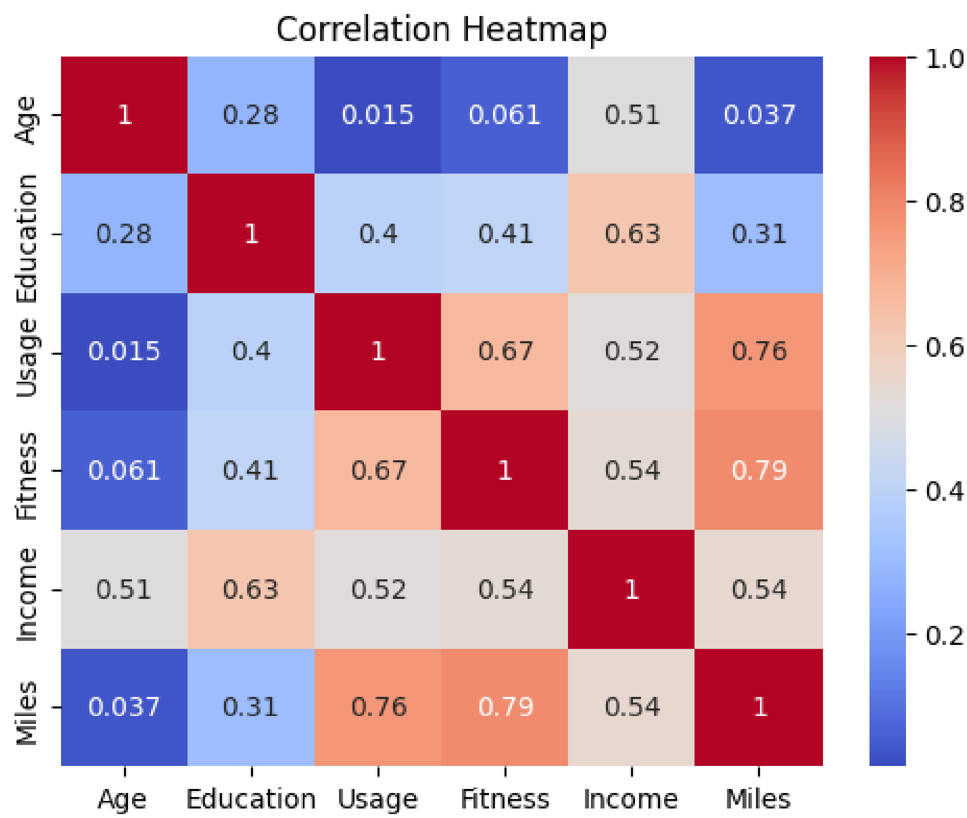


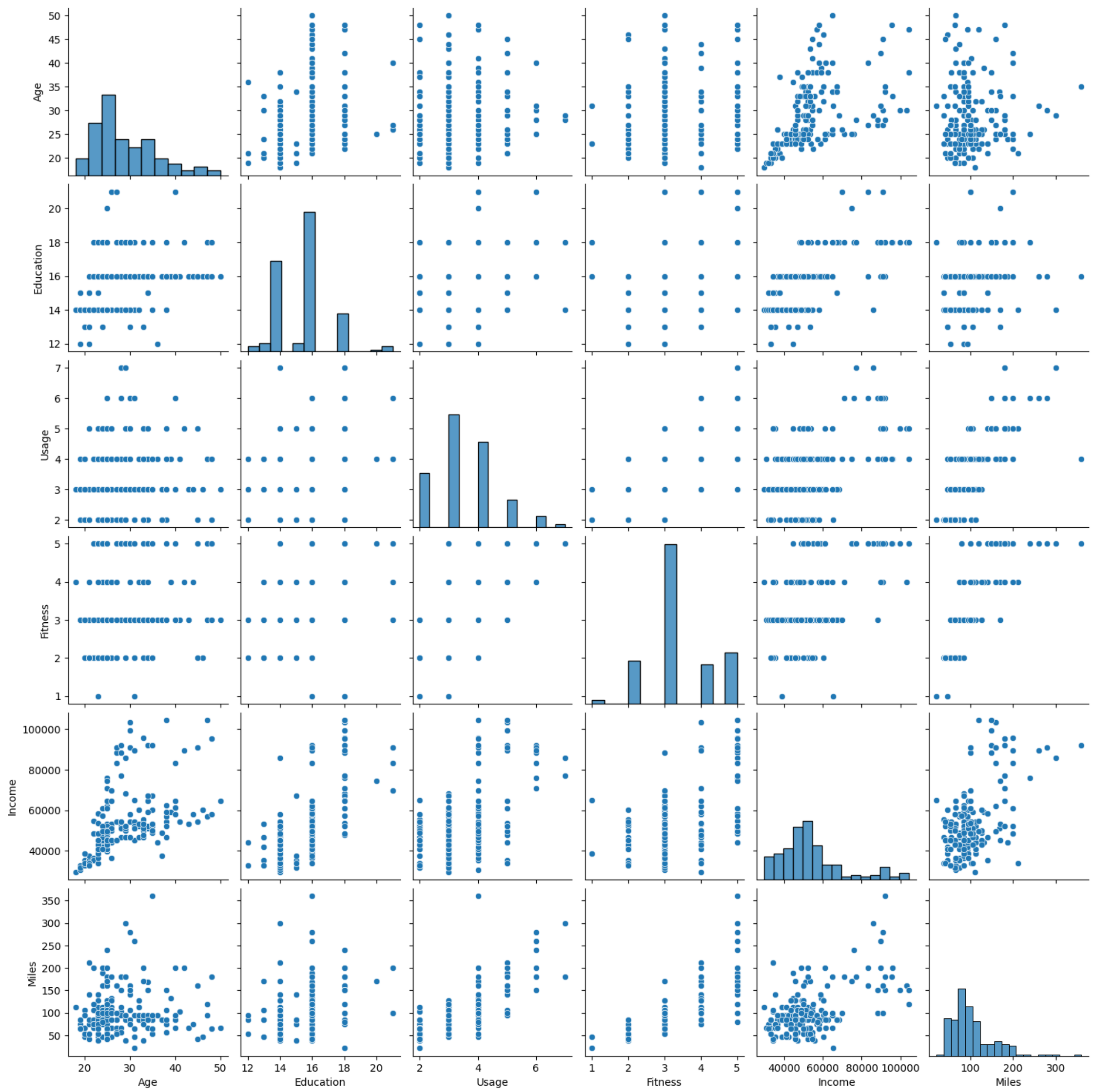
[ ]:
```python
plt.figure(figsize=(12,7))
sns.countplot(x=df['Product'], hue=df['Gender'])
plt.title('Count of Customers by Gender for each Product')
plt.show()
```



1.0.3 3.3 Correlation Analysis

[ ]:
```python
# Heatmap for correlation
correlation_matrix = df[continuous_vars].corr()
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm")
plt.title('Correlation Heatmap')
plt.show()

# Pairplot for correlation
sns.pairplot(df[continuous_vars])
plt.show()
```


Correlation Heatmap
Age
Education
Usage
Fitness
Income
Miles
1 0.28 0.015 0.061 0.51 0.037
0.28 1 0.4 0.41 0.63 0.31
0.015 0.4 1 0.67 0.52 0.76
0.061 0.41 0.67 1 0.54 0.79
0.51 0.63 0.52 0.54 1 0.54
0.037 0.31 0.76 0.79 0.54 1
Age
Education
Usage
Fitness
Income
Miles
1.0
0.8
0.6
0.4
0.2



[ ]:

[ ]:

1.1 Question 4. Missing Value & Outlier Detection (10 Points)

1.2 4.1 Missing Value

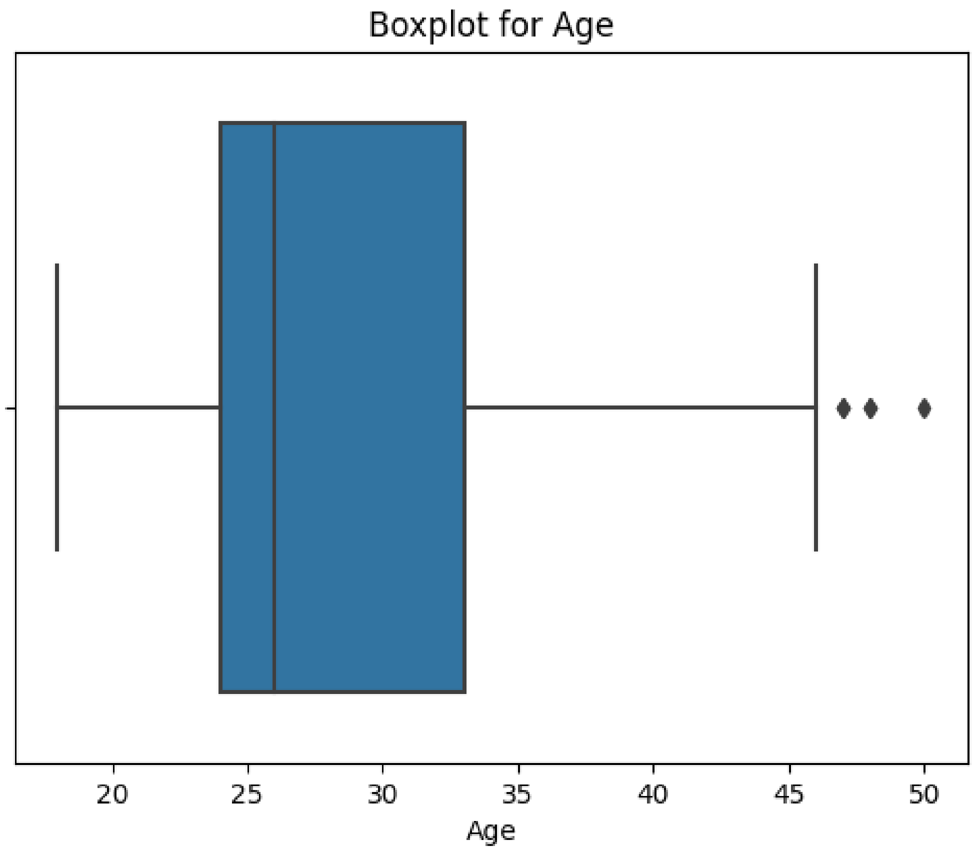
[ ]:
```
# Checking for missing values
missing_values = df.isnull().sum()
print("Missing values for each column:\n")
missing_values
```

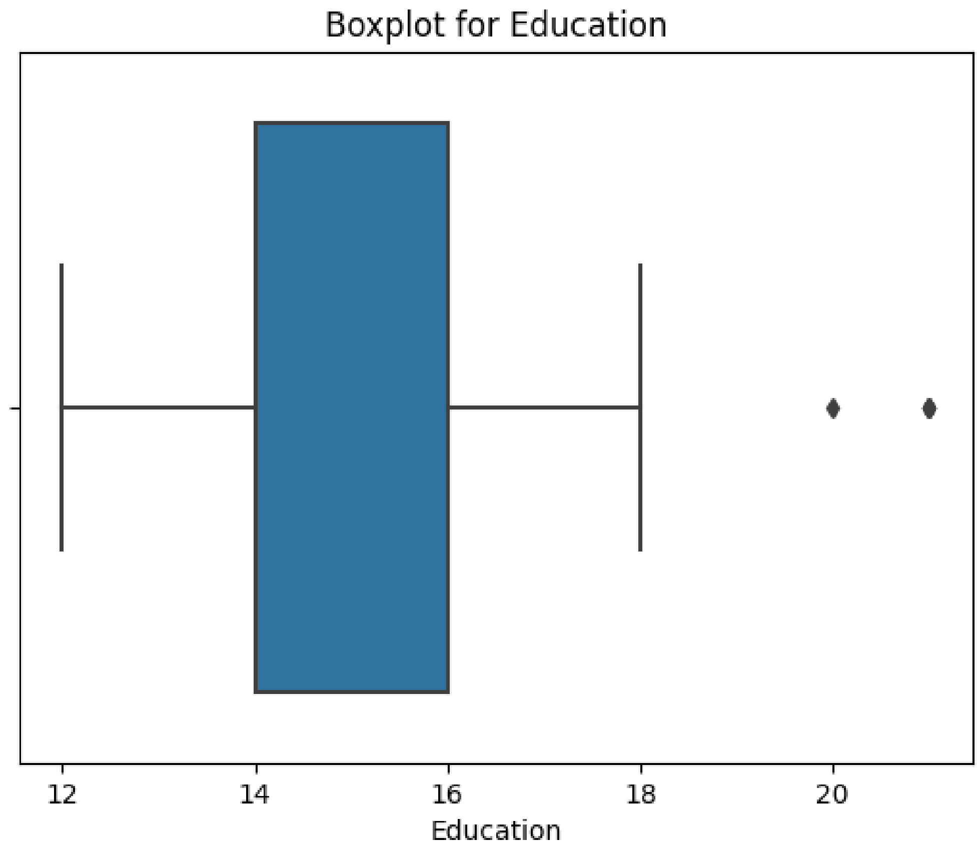
```
Missing values for each column:
```

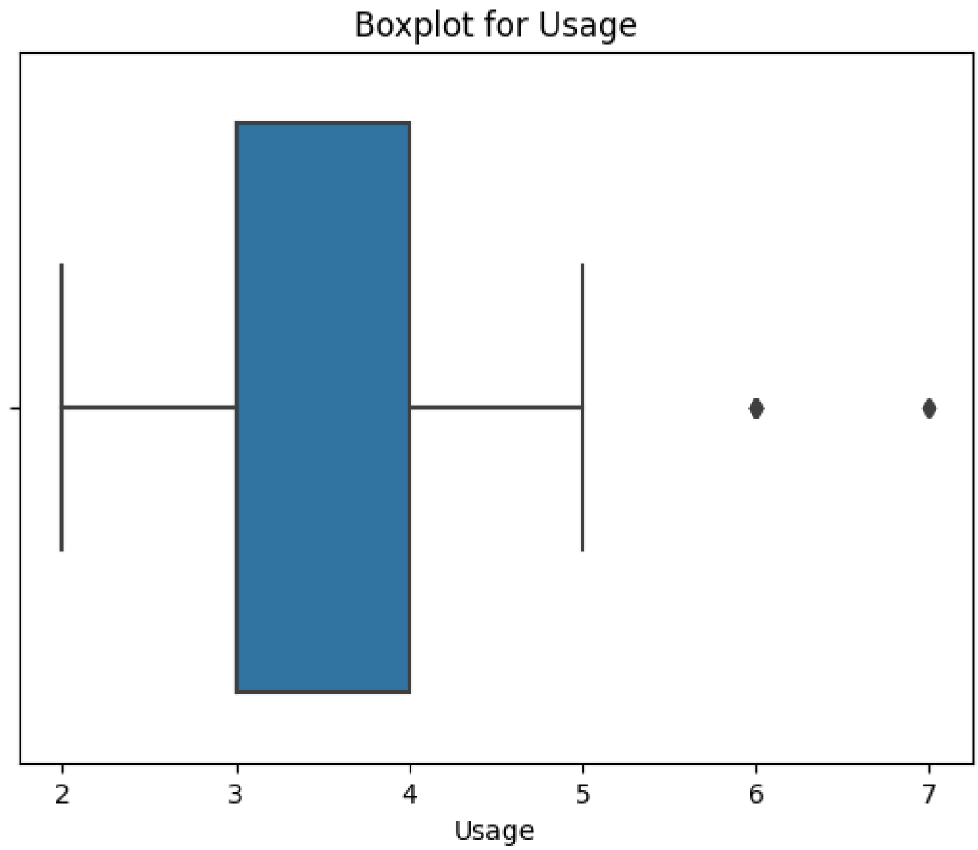
```
[ ]: Product          0
     Age              0
     Gender           0
     Education        0
     MaritalStatus    0
     Usage            0
     Fitness          0
     Income           0
     Miles            0
     dtype: int64
```

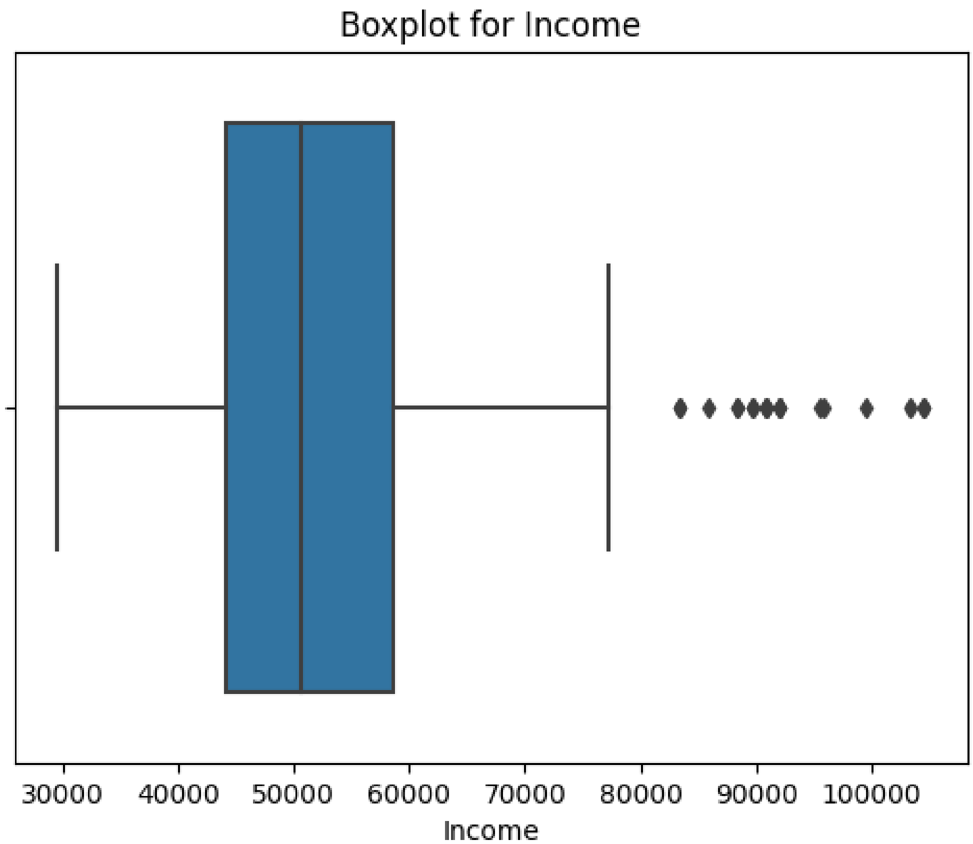
1.3 4.2 Outlier Detection

```
[ ]: import seaborn as sns
     import matplotlib.pyplot as plt

     numerical_features = ['Age', 'Education', 'Usage', 'Income', 'Fitness', 'Miles']
     for feature in numerical_features:
         sns.boxplot(x=df[feature])
         plt.title(f'Boxplot for {feature}')
         plt.show()
```

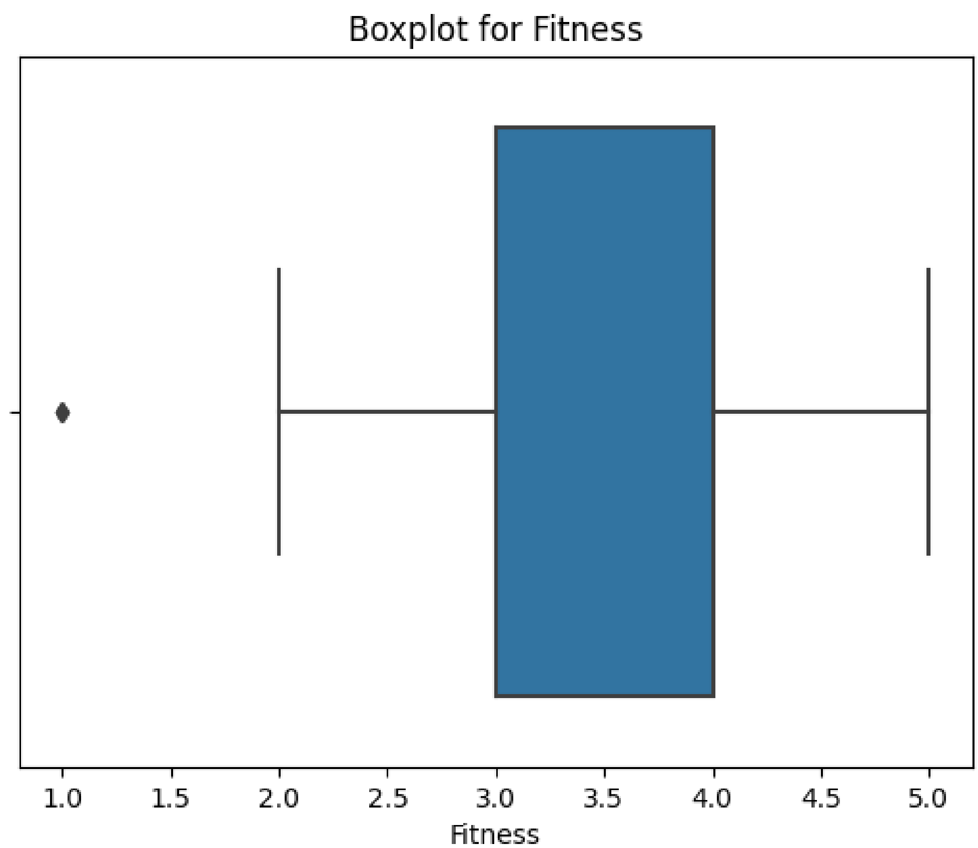

Boxplot for Age
20
25
30
35
40
45
50
Age

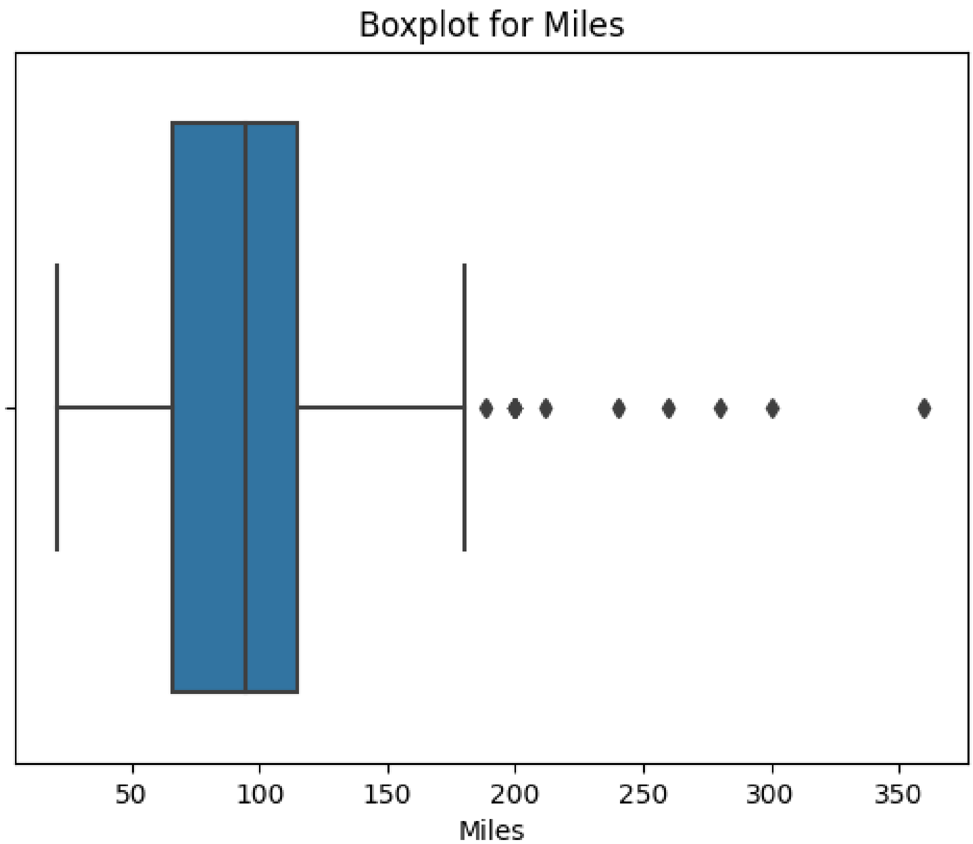

Boxplot for Education
12
14
16
18
20
Education


Boxplot for Usage
2
3
4
5
6
7
Usage



Boxplot for Income
30000
40000
50000
60000
70000
80000
90000
100000
Income


Boxplot for Fitness
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Fitness



[ ]:
```
def detect_outliers(df, column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    outliers = df[(df[column] < lower_bound) | (df[column] > upper_bound)]
    return outliers
```

[ ]:
```
detect_outliers(df, 'Age')
```

[ ]:
```
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
78    KP281   47    Male         16     Partnered      4        3   56850
79    KP281   50  Female         16     Partnered      3        3   64809
139   KP481   48    Male         16     Partnered      2        3   57987
178   KP781   47    Male         18     Partnered      4        5  104581
179   KP781   48    Male         18     Partnered      4        5   95508

     Miles
```

```
78      94
79      66
139     64
178    120
179    180
```

[ ]:
```
detect_outliers(df, 'Education')
```

[ ]:
```
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
156   KP781   25    Male         20     Partnered      4        5   74701
157   KP781   26  Female         21        Single      4        3   69721
161   KP781   27    Male         21     Partnered      4        4   90886
175   KP781   40    Male         21        Single      6        5   83416

     Miles
156    170
157    100
161    100
175    200
```

[ ]:
```
detect_outliers(df, 'Usage')
```

[ ]:
```
    Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
154   KP781   25    Male         18     Partnered      6        4   70966
155   KP781   25    Male         18     Partnered      6        5   75946
162   KP781   28  Female         18     Partnered      6        5   92131
163   KP781   28    Male         18     Partnered      7        5   77191
164   KP781   28    Male         18        Single      6        5   88396
166   KP781   29    Male         14     Partnered      7        5   85906
167   KP781   30  Female         16     Partnered      6        5   90886
170   KP781   31    Male         16     Partnered      6        5   89641
175   KP781   40    Male         21        Single      6        5   83416

     Miles
154    180
155    240
162    180
163    180
164    150
166    300
167    280
170    260
175    200
```

[ ]:
```
detect_outliers(df, 'Fitness')
```

[ ]:
```
     Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
14     KP281   23    Male         16     Partnered      3        1   38658
117    KP481   31  Female         18        Single      2        1   65220

     Miles
14      47
117     21
```

[ ]:
```
detect_outliers(df, 'Income')
```

[ ]:
```
     Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
159    KP781   27    Male         16     Partnered      4        5   83416
160    KP781   27    Male         18        Single      4        3   88396
161    KP781   27    Male         21     Partnered      4        4   90886
162    KP781   28  Female         18     Partnered      6        5   92131
164    KP781   28    Male         18        Single      6        5   88396
166    KP781   29    Male         14     Partnered      7        5   85906
167    KP781   30  Female         16     Partnered      6        5   90886
168    KP781   30    Male         18     Partnered      5        4  103336
169    KP781   30    Male         18     Partnered      5        5   99601
170    KP781   31    Male         16     Partnered      6        5   89641
171    KP781   33  Female         18     Partnered      4        5   95866
172    KP781   34    Male         16        Single      5        5   92131
173    KP781   35    Male         16     Partnered      4        5   92131
174    KP781   38    Male         18     Partnered      5        5  104581
175    KP781   40    Male         21        Single      6        5   83416
176    KP781   42    Male         18        Single      5        4   89641
177    KP781   45    Male         16        Single      5        5   90886
178    KP781   47    Male         18     Partnered      4        5  104581
179    KP781   48    Male         18     Partnered      4        5   95508

     Miles
159    160
160    100
161    100
162    180
164    150
166    300
167    280
168    160
169    150
170    260
171    200
172    150
173    360
174    150
175    200
```

```
176     200
177     160
178     120
179     180
```

[ ]:
```
detect_outliers(df, 'Miles')
```

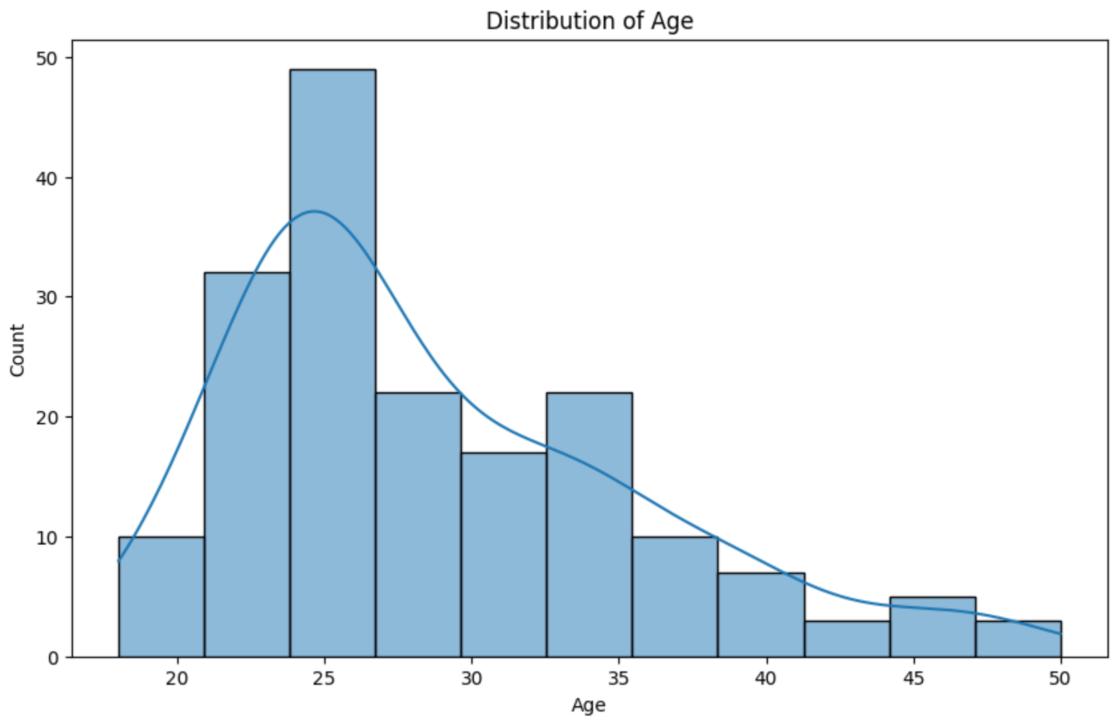
[ ]:
```
     Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
23     KP281   24  Female         16     Partnered      5        5   44343
84     KP481   21  Female         14     Partnered      5        4   34110
142    KP781   22    Male         18        Single      4        5   48556
148    KP781   24  Female         16        Single      5        5   52291
152    KP781   25  Female         18     Partnered      5        5   61006
155    KP781   25    Male         18     Partnered      6        5   75946
166    KP781   29    Male         14     Partnered      7        5   85906
167    KP781   30  Female         16     Partnered      6        5   90886
170    KP781   31    Male         16     Partnered      6        5   89641
171    KP781   33  Female         18     Partnered      4        5   95866
173    KP781   35    Male         16     Partnered      4        5   92131
175    KP781   40    Male         21        Single      6        5   83416
176    KP781   42    Male         18        Single      5        4   89641

     Miles
23     188
84     212
142    200
148    200
152    200
155    240
166    300
167    280
170    260
171    200
173    360
175    200
176    200
```

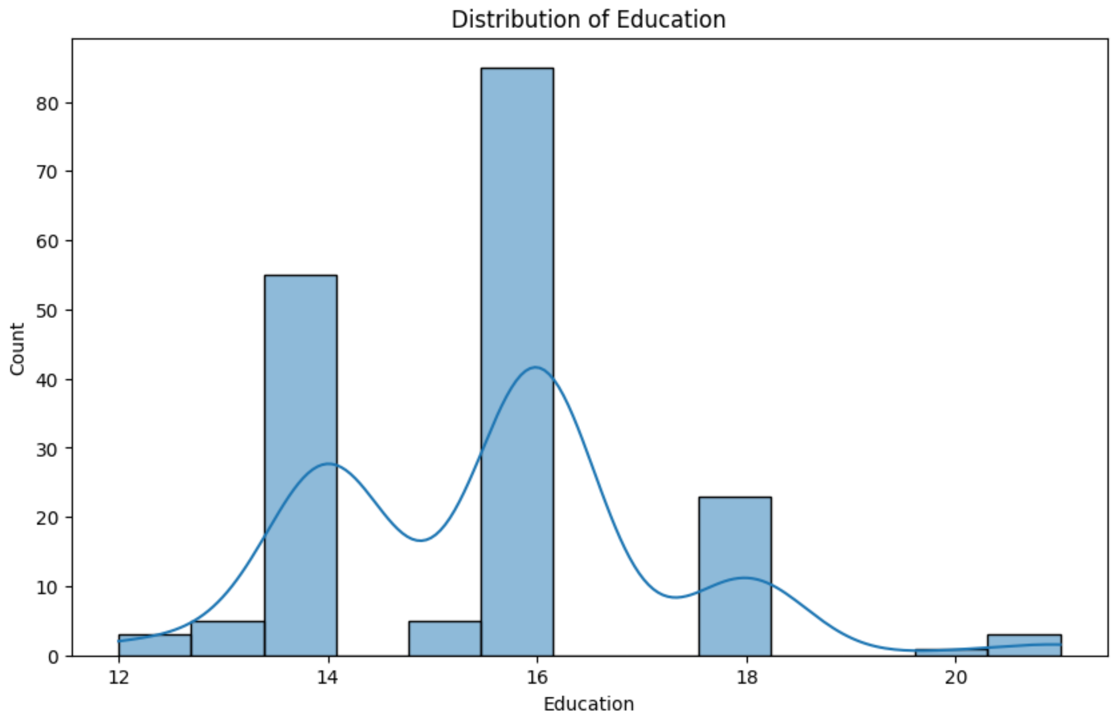
#Question 5. Business Insights based on Non-Graphical and Visual Analysis (10 Points) 1. Comments on the range of attributes 2. Comments on the distribution of the variables and relationship between them 3. Comments for each univariate and bivariate plot

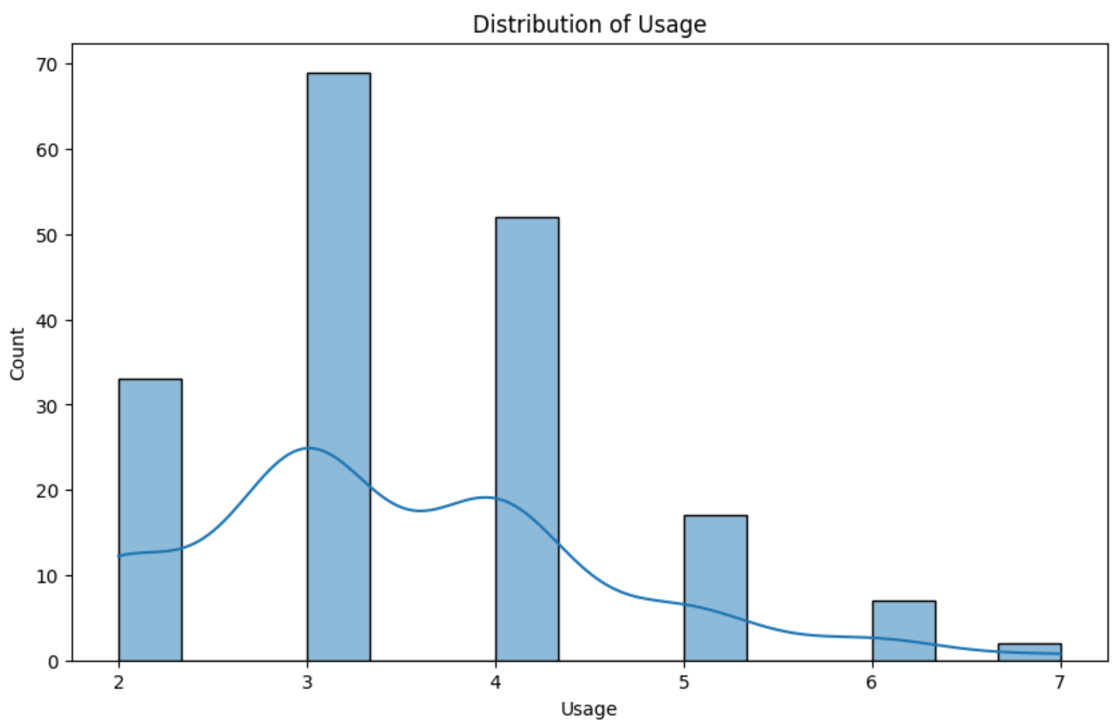
[ ]:
```
range_of_attributes = {}
for column in df.select_dtypes(include=['int64', 'float64']).columns:
    range_of_attributes[column] = (df[column].min(), df[column].max())

range_of_attributes
```

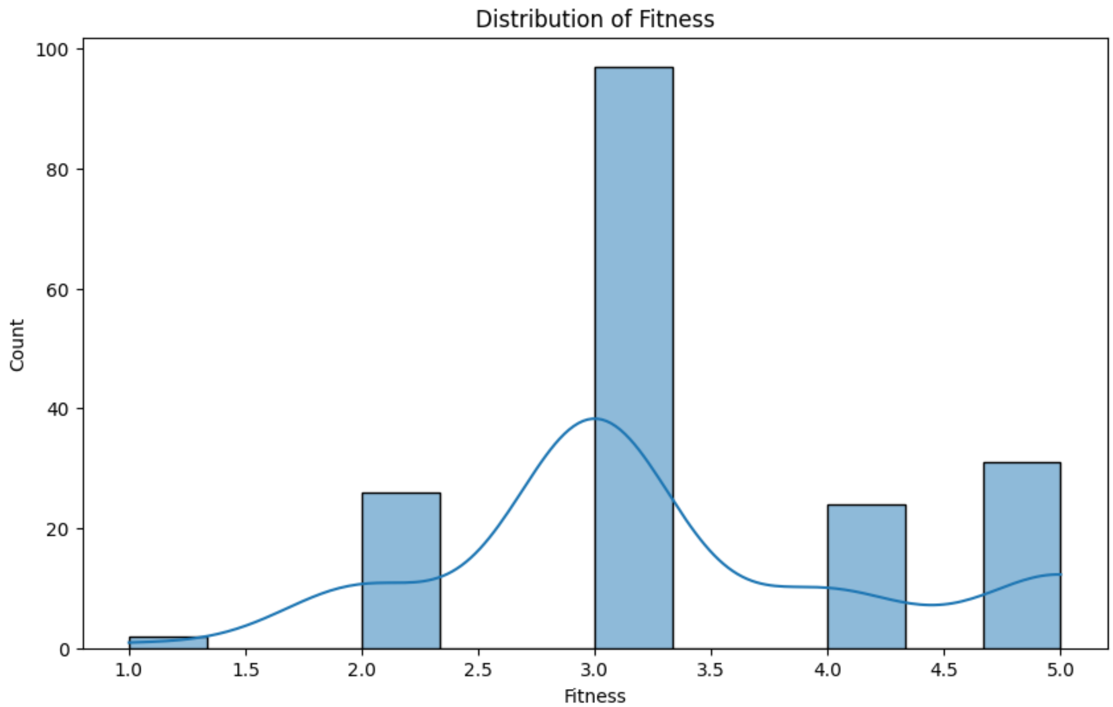
[ ]:
```
{'Age': (18, 50),
 'Education': (12, 21),
 'Usage': (2, 7),
 'Fitness': (1, 5),
 'Income': (29562, 104581),
 'Miles': (21, 360)}
```

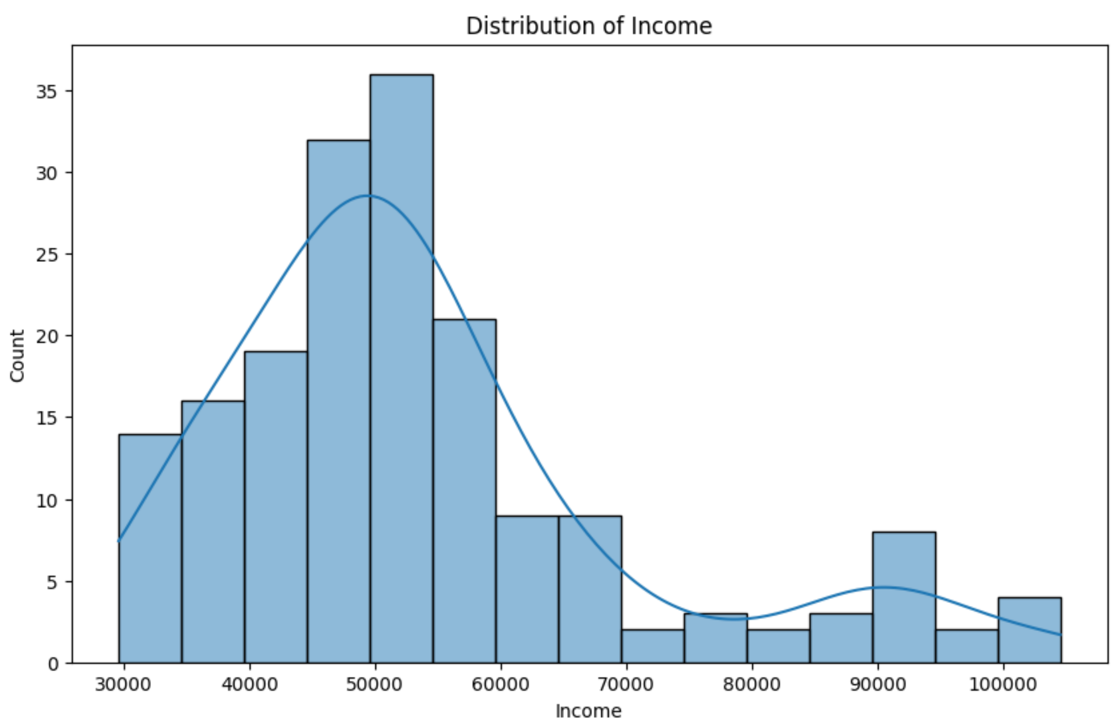
[ ]:
```python
# Distribution plots
for col in ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']:
    plt.figure(figsize=(10, 6))
    sns.histplot(df[col], kde=True)
    plt.title(f'Distribution of {col}')
    plt.show()
```

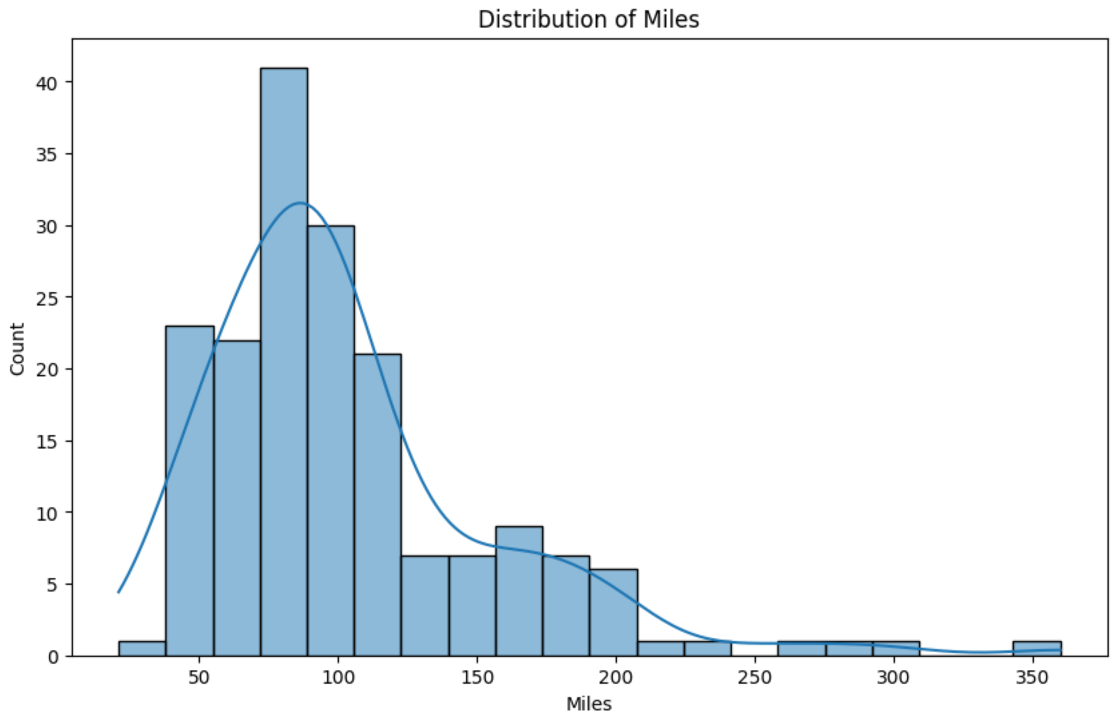



Distribution of Education
Count
Education
0
10
20
30
40
50
60
70
80
12
14
16
18
20

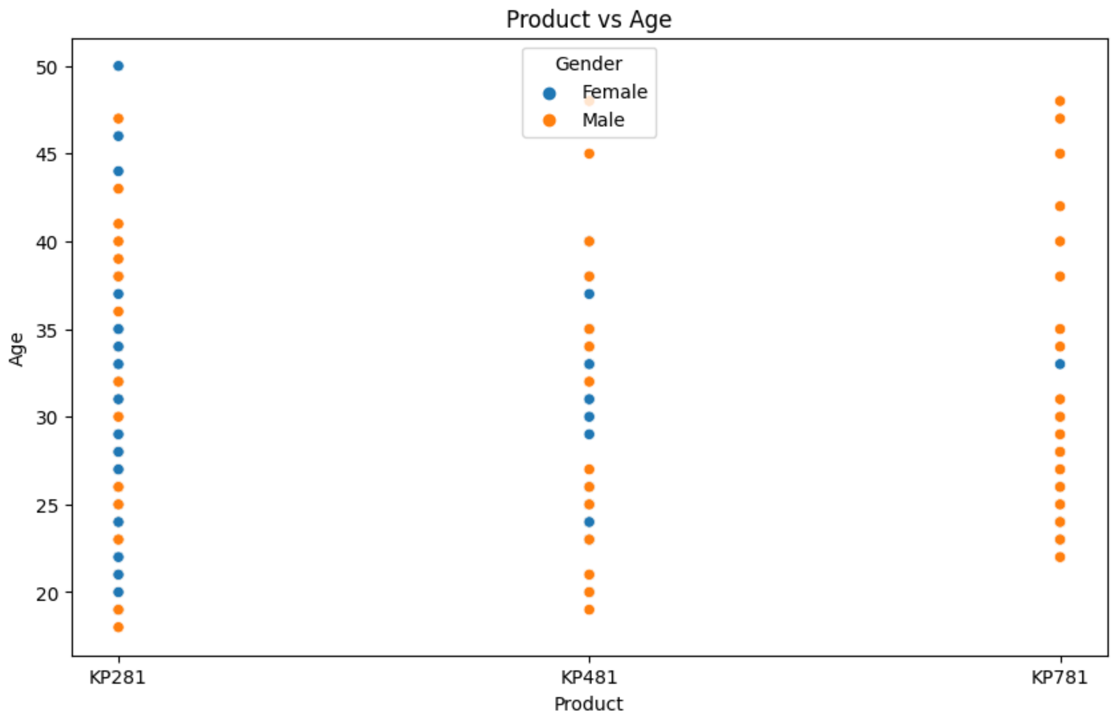

Distribution of Usage
Count
Usage
0
10
20
30
40
50
60
70
2
3
4
5
6
7

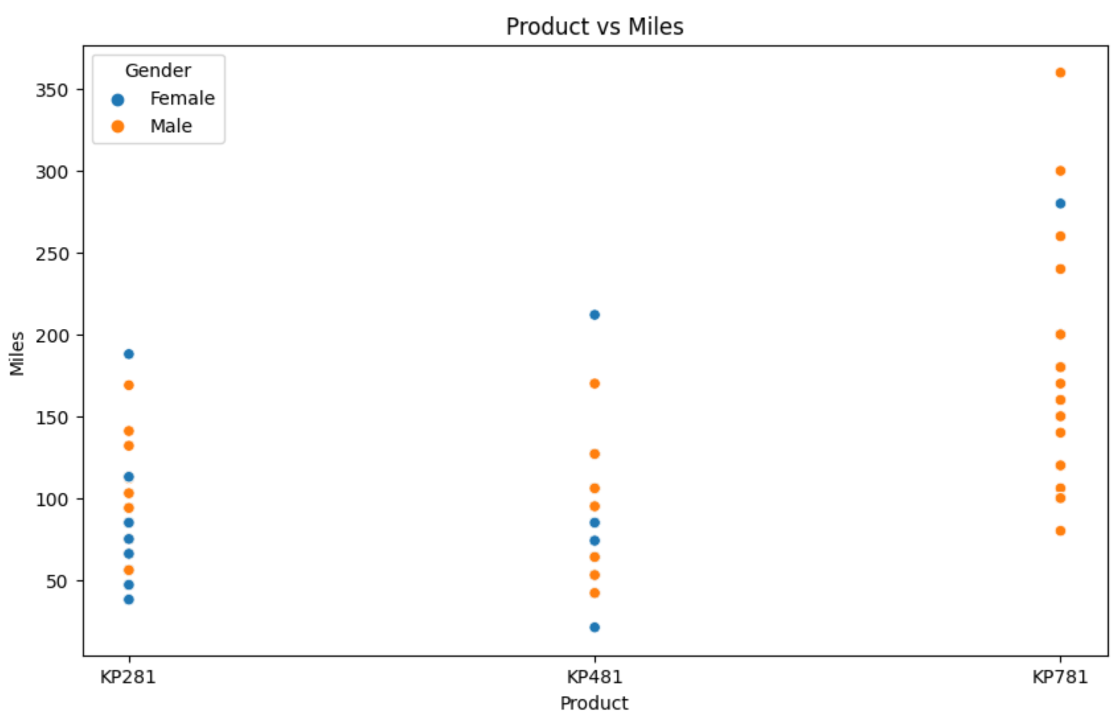

Distribution of Fitness
Count
Fitness
0
20
40
60
80
100
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0

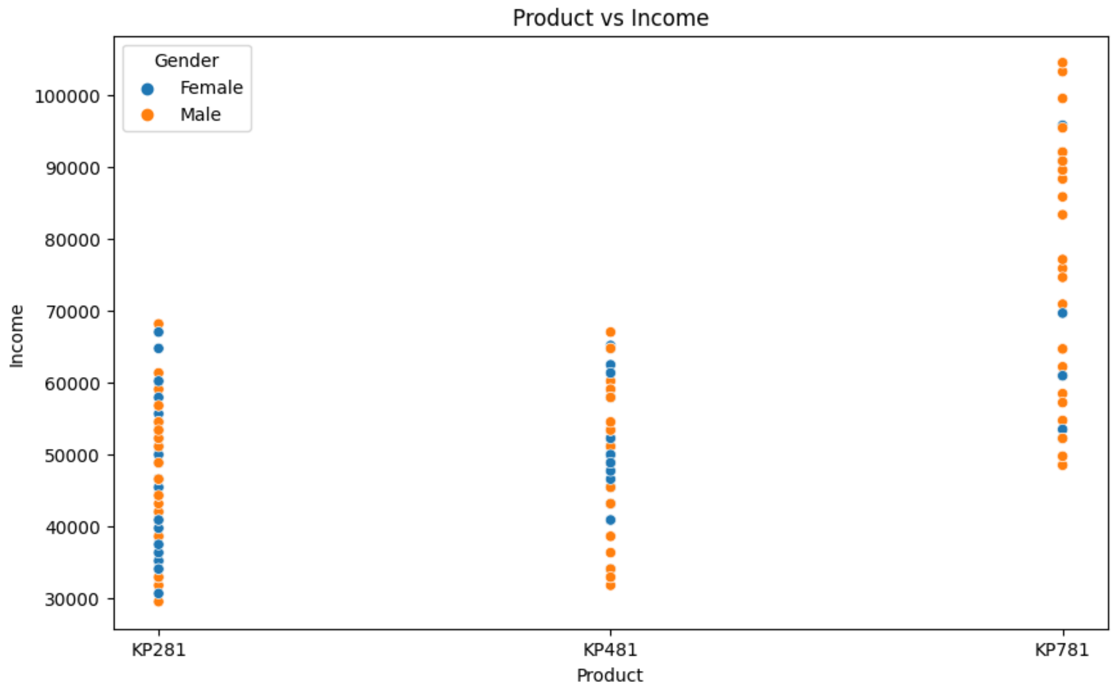

Distribution of Income
Count
Income
0
5
10
15
20
25
30
35
30000
40000
50000
60000
70000
80000
90000
100000




```
[ ]: # Bivariate plots
bivariate_cols = [( 'Product','Age'), ('Product','Miles'),('Product','Income')]
for col1, col2 in bivariate_cols:
    plt.figure(figsize=(10, 6))
    sns.scatterplot(data=df, x=col1, y=col2, hue='Gender')
    plt.title(f'{col1} vs {col2}')
    plt.show()
```

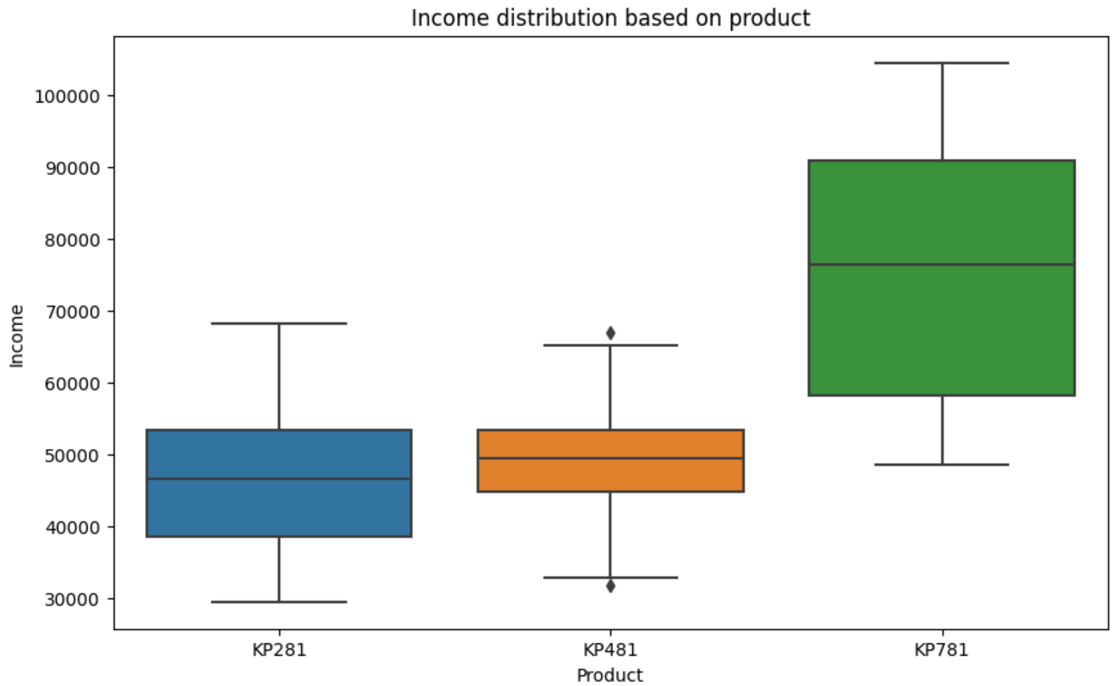

Product vs Age
Gender
Female
Male
50
45
40
35
30
25
20
Age
KP281
KP481
KP781
Product


Product vs Miles
Gender
Female
Male
350
300
250
200
150
100
50
Miles
KP281
KP481
KP781
Product



[ ]:

```
# Boxplot to check income distribution based on gender
plt.figure(figsize=(10, 6))
sns.boxplot(data=df, y='Income', x='Product')
plt.title('Income distribution based on product')
plt.show()
```




```
[ ]:
```

1.4 Question 6. Recommendations (10 Points) - Actionable items for business. No technical jargon. No complications. Simple action items that everyone can understand

Demographics Analysis:

1. Most users of product KP281 are in their early 20s to mid-30s. The data includes both male and female users, with both genders being well-represented.
2. Most users are either in a partnered relationship or single.
3. The education level of most users is around 14-16 years, suggesting that most users have some college education or have completed their bachelor's degree.
4. Usage and Fitness: The 'Usage' and 'Fitness' columns show that many users have a moderate to high usage and fitness level, indicating that the product KP281 might be popular among those who are fairly active or are looking to improve their fitness.
5. Income Analysis: The income of users varies, but many users seem to fall within the mid-income range. This might suggest that product KP281 is affordable and appeals to a wide range of consumers.
6. Miles Analysis: The 'Miles' column indicates how much each user expects to run/walk using the product. Many users anticipate moderate to high usage in terms of miles, which again points to the product being popular among active individuals.

7. Product Variation: While the majority of the data provided is for product KP281, there are entries for product KP481 as well.

Recommendations for Marketing and Sales/ Business actionable items:

1. Target Young Adults: A significant portion of the users are between ages 18-25. Aerofit should consider marketing campaigns targeting this age group.
2. Focus on Partnered Demographic: Many customers within this dataset are partnered. Design promotional offers or dual membership discounts to attract more partnered individuals.
3. Gender-specific Campaigns: The dataset contains both male and female customers. Aerofit can design gender-specific workout programs or promotions.
4. Higher Education Outreach: Most of the customers have 14-16 years of education. Partner with colleges or institutions for special student offers or campus promotions.
5. Promote Moderate Usage: Most customers fall into the '3' usage category. Offer classes or programs that fit this frequency to retain and attract this customer base.
6. Address Diverse Fitness Levels: While the dataset showcases a range of fitness levels, there's a notable presence in the mid-range (3-4). Ensure there are diverse offerings catering to various fitness levels.
7. Upsell Opportunities: For those with higher incomes, consider upselling premium services or advanced classes.
8. Incentivize Mile Goals: As 'Miles' seem to be a tracked metric, consider creating challenges or rewards for customers who hit certain mile markers.

Further Analysis:

1. To refine marketing and sales strategies, it might be helpful to get more detailed data on user preferences, reasons for purchasing the product, geographic location, and other factors.
2. Customer feedback and reviews can provide insights into the product's strengths and areas of improvement.
3. Periodically surveying the user base can help in understanding changing trends and adjusting product features and marketing strategies accordingly.

[ ]:
```

```