```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
data=pd.read_csv("https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/
```

```
data.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

Checking the structure & characteristics of the dataset

```
#finding the shape of the dataset
data.shape
```

```
(180, 9)
```

```
#Finding the datatypes of the columns
data.dtypes
```

	0
Product	object
Age	int64
Gender	object
Education	int64
MaritalStatus	object
Usage	int64
Fitness	int64
Income	int64
Miles	int64

dtype: object

```
#Getting the information regarding the count of non-null values
data.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    object
 1   Age            180 non-null    int64 
 2   Gender         180 non-null    object
 3   Education      180 non-null    int64 
 4   MaritalStatus  180 non-null    object
 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: int64(6), object(3)
memory usage: 12.8+ KB
```

```
#Checking the null values for each column
data.isna().sum()
```

	0
Product	0
Age	0
Gender	0
Education	0
MaritalStatus	0
Usage	0
Fitness	0
Income	0
Miles	0

dtype: int64

```
#Getting the count unique values in each column
data.nunique()
```

	0
Product	3
Age	32
Gender	2
Education	8
MaritalStatus	2
Usage	6
Fitness	5
Income	62
Miles	37

dtype: int64

Analyzing value counts

```
data['Gender'].value_counts()
```

Gender	count
Male	104
Female	76

dtype: int64

```
data['Product'].value_counts()
```

Product	count
KP281	80
KP481	60
KP781	40

dtype: int64

```
data['Education'].value_counts()
```

Education	count
16	85
14	55
18	23
15	5
13	5
12	3
21	3
20	1

dtype: int64

```
data['MaritalStatus'].value_counts()
```

MaritalStatus	count
Partnered	107
Single	73

dtype: int64

```
data['Usage'].value_counts()
```

Usage	count
3	69
4	52
2	33
5	17
6	7
7	2

dtype: int64

```
data['Fitness'].value_counts()
```

Fitness	count
3	97
5	31
2	26
4	24
1	2

dtype: int64

```
data['Miles'].value_counts()
```

Miles	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

dtype: int64

Outlier Detection

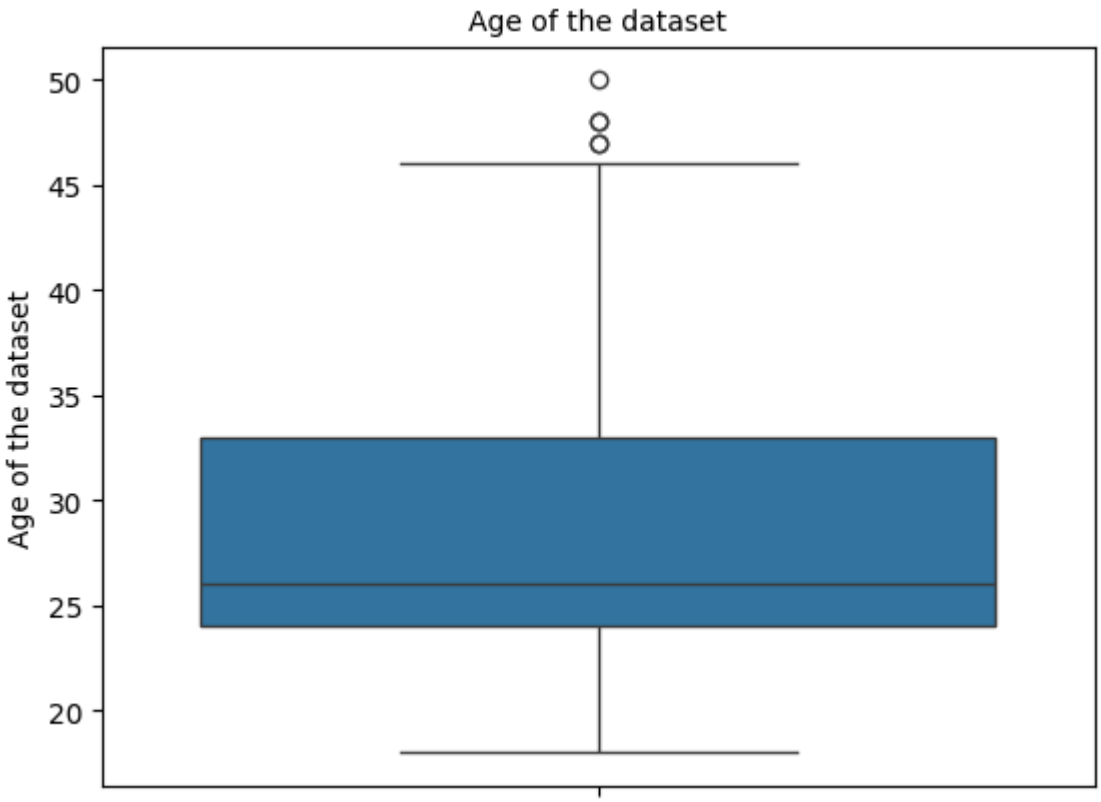
Outliers can be resolved using binning which is used in the following discussion

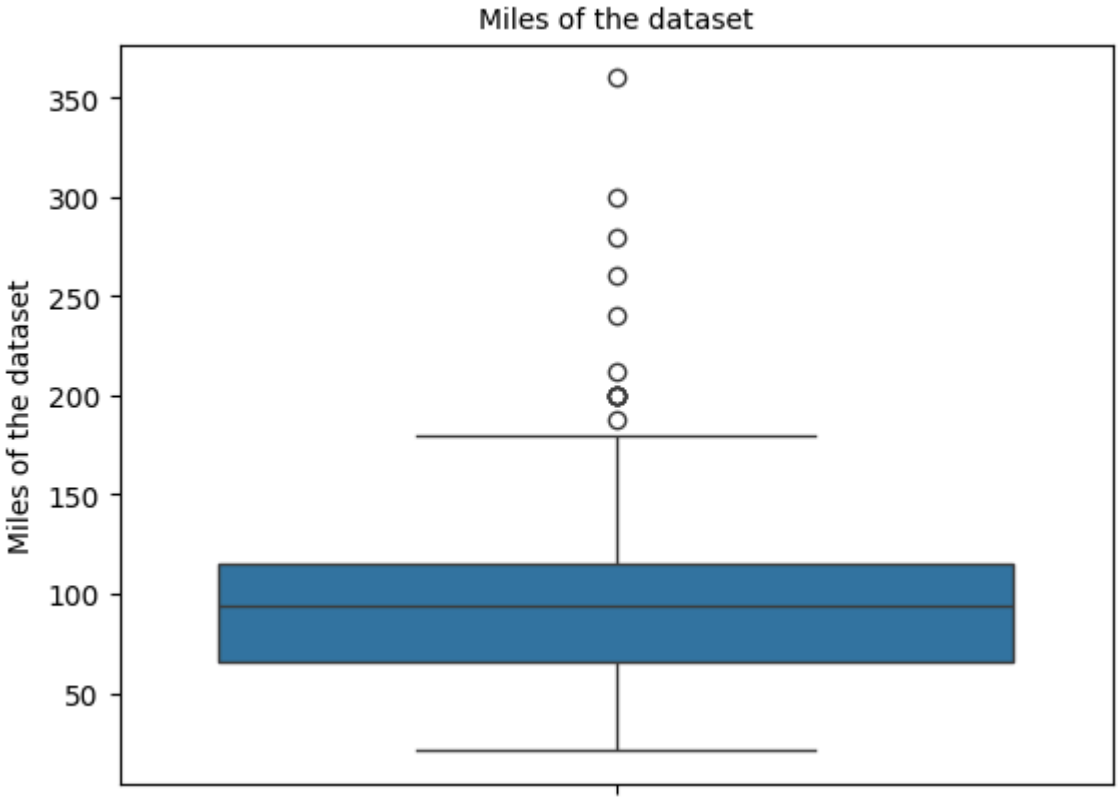
```
data.describe()
```

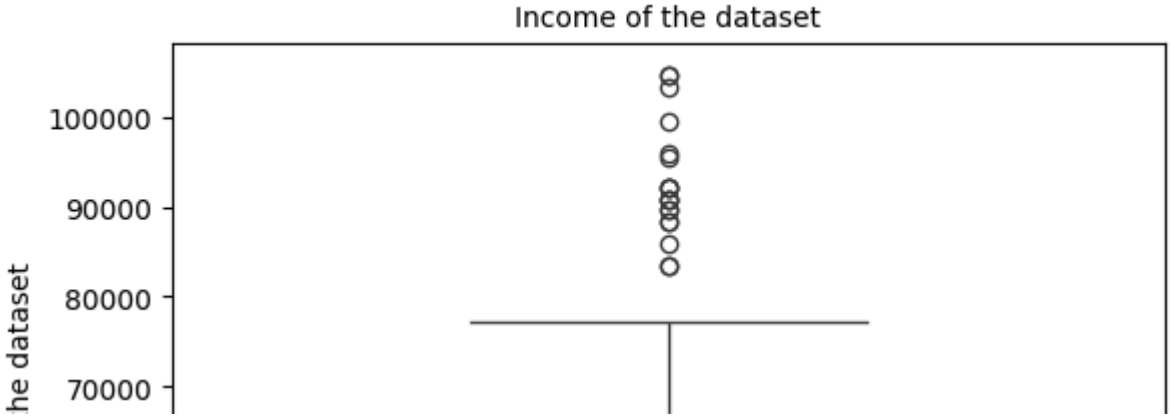
	Age	Education	Usage	Fitness	Income	Miles
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000
mean	28.788889	15.572222	3.455556	3.311111	53719.577778	103.194444
std	6.943498	1.617055	1.084797	0.958869	16506.684226	51.863605
min	18.000000	12.000000	2.000000	1.000000	29562.000000	21.000000
25%	24.000000	14.000000	3.000000	3.000000	44058.750000	66.000000
50%	26.000000	16.000000	3.000000	3.000000	50596.500000	94.000000
75%	33.000000	16.000000	4.000000	4.000000	58668.000000	114.750000
max	50.000000	21.000000	7.000000	5.000000	104581.000000	360.000000

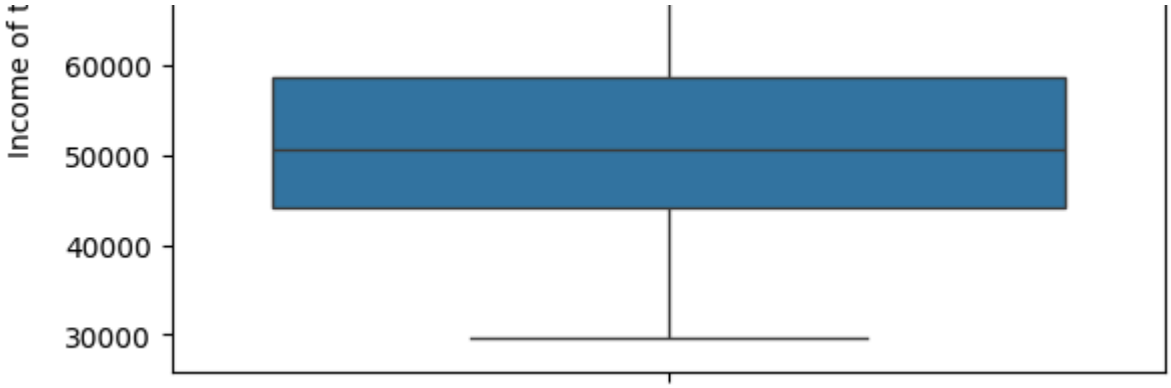
```
Num_cols=['Age','Miles','Income']
```

```
for i in Num_cols:
  sns.boxplot(y = data[i])
  plt.yticks(fontsize=10)
  plt.ylabel(f"{i} of the dataset", fontsize=10)
  plt.title(f"{i} of the dataset", fontsize=10)
  plt.show()
```


Age of the dataset
Age of the dataset
50
45
40
35
30
25
20


Miles of the dataset
Miles of the dataset
350
300
250
200
150
100
50


Income of the dataset
100000
90000
80000
70000

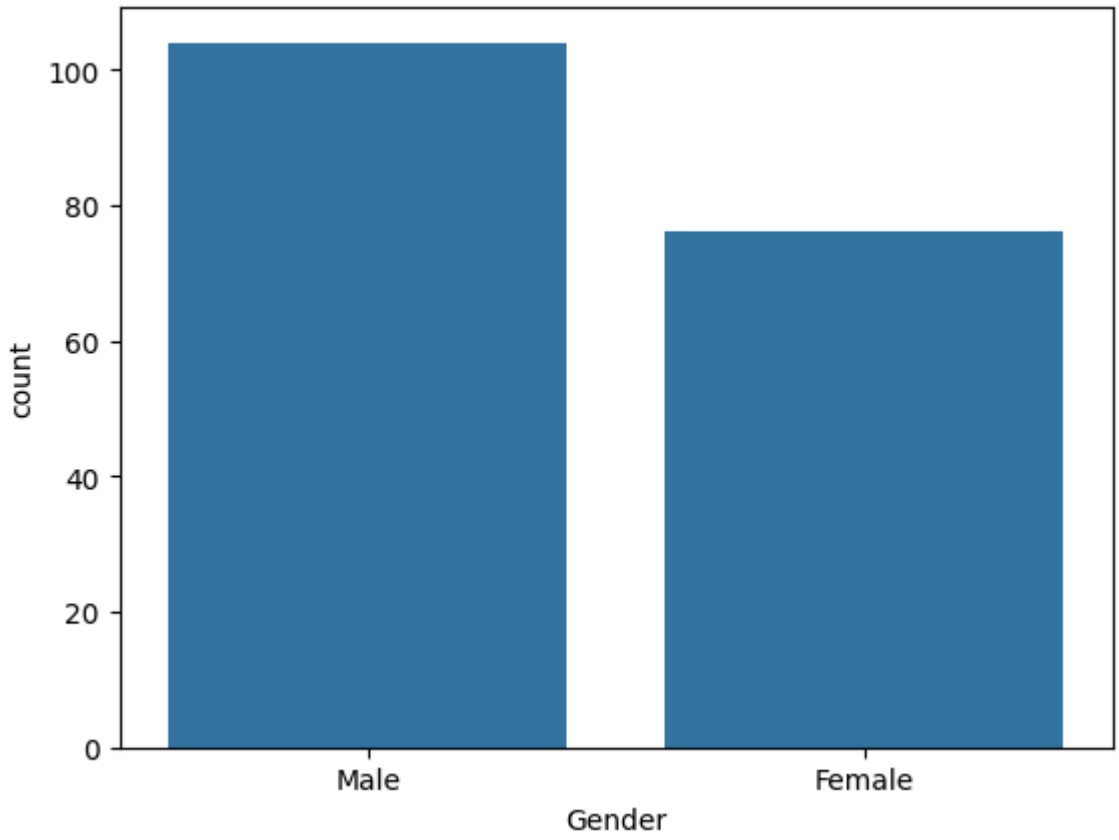


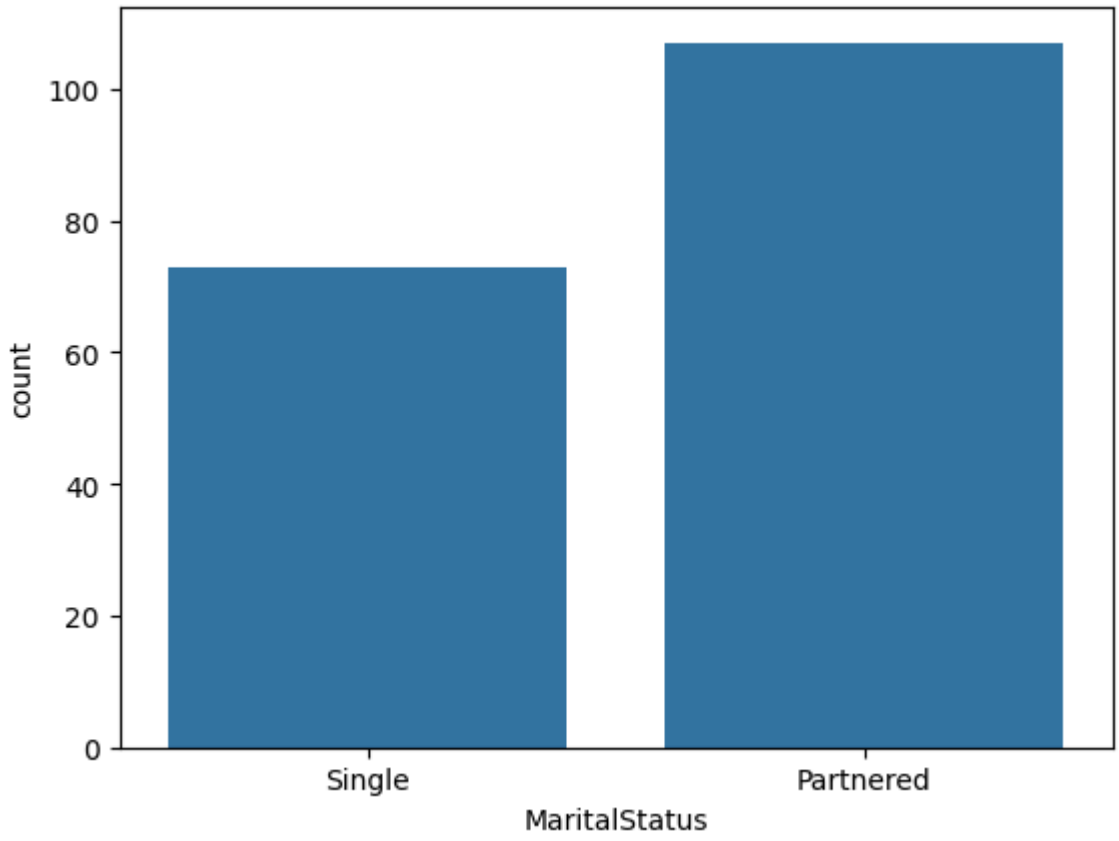

```
data.describe()
```

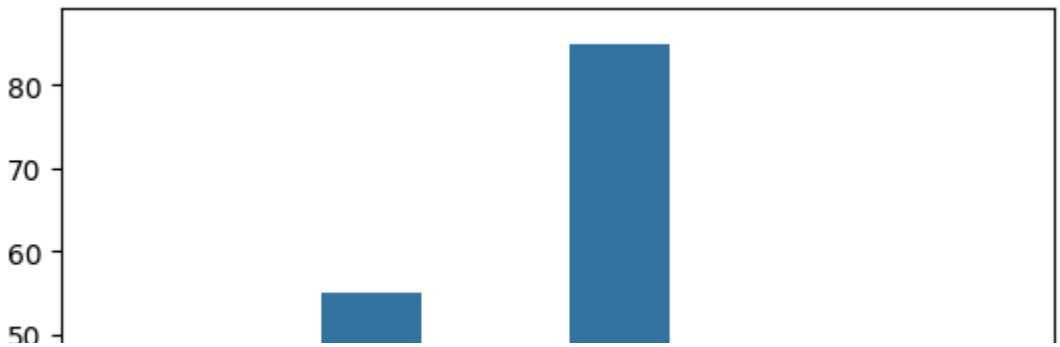
	Age	Education	Usage	Fitness	Income	Miles
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000
mean	28.788889	15.572222	3.455556	3.311111	53719.577778	103.194444
std	6.943498	1.617055	1.084797	0.958869	16506.684226	51.863605
min	18.000000	12.000000	2.000000	1.000000	29562.000000	21.000000
25%	24.000000	14.000000	3.000000	3.000000	44058.750000	66.000000
50%	26.000000	16.000000	3.000000	3.000000	50596.500000	94.000000
75%	33.000000	16.000000	4.000000	4.000000	58668.000000	114.750000
max	50.000000	21.000000	7.000000	5.000000	104581.000000	360.000000

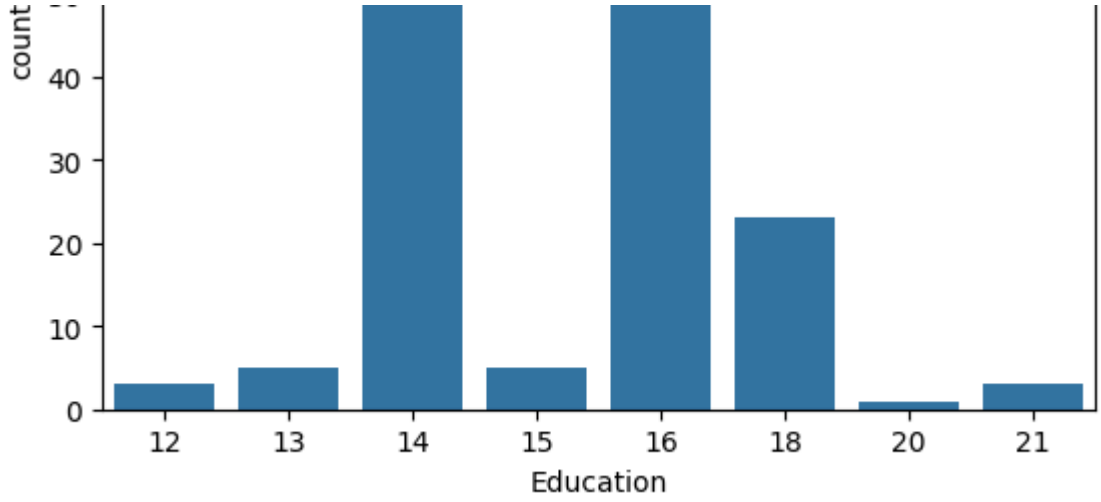
Univariate Analysis

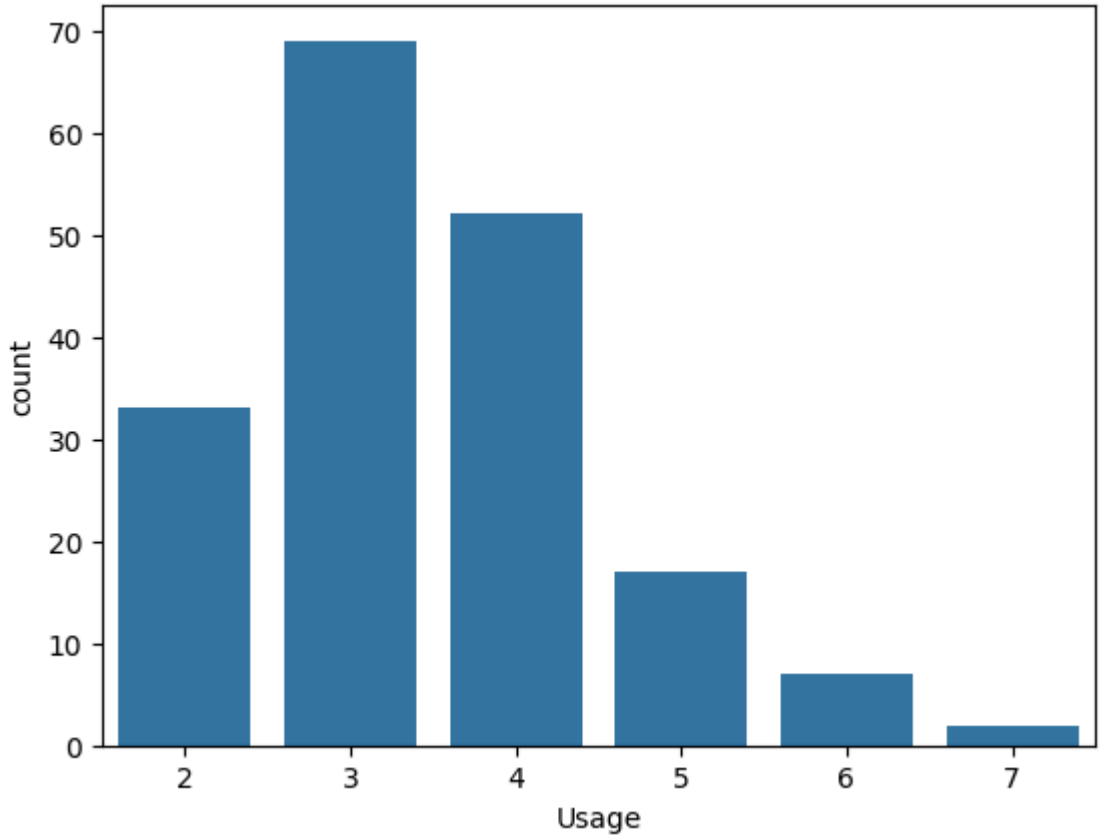
```
# For categorical variables
cat_cols=['Gender','MaritalStatus','Education','Usage','Fitness','Product']
for i in cat_cols:
  sns.countplot(x=i,data=data)
  plt.show()
```

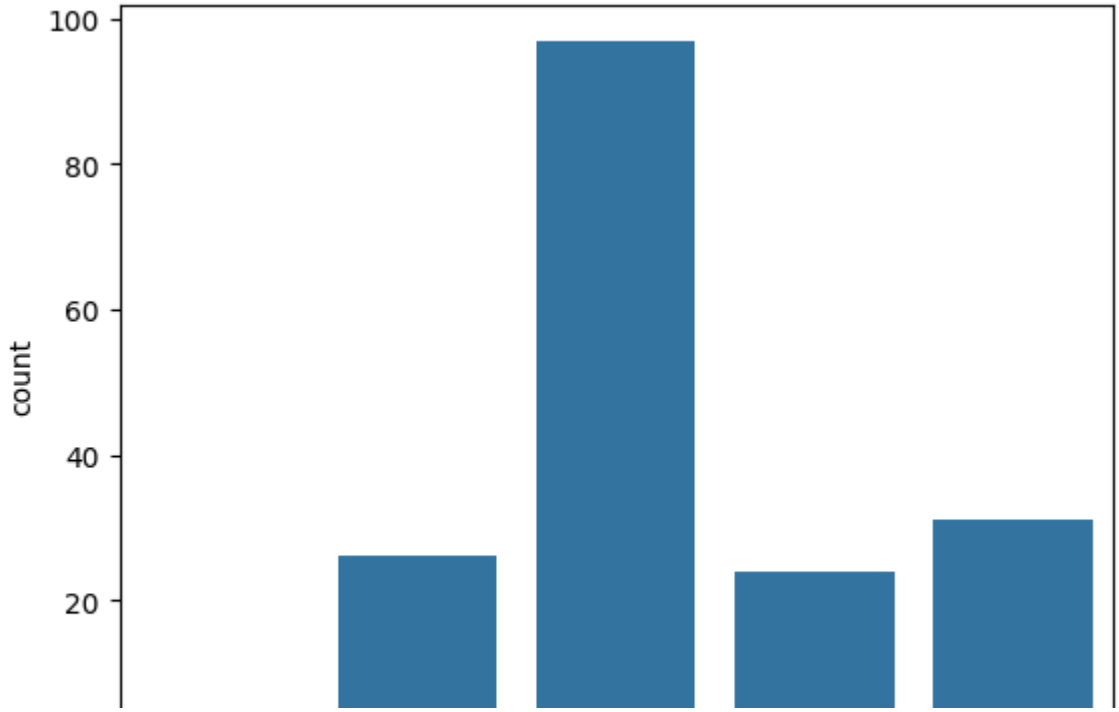

100
80
60
40
20
0
count
Male
Female
Gender

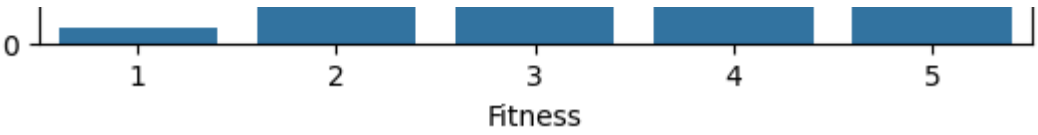

100
80
60
40
20
0
count
Single
Partnered
MaritalStatus

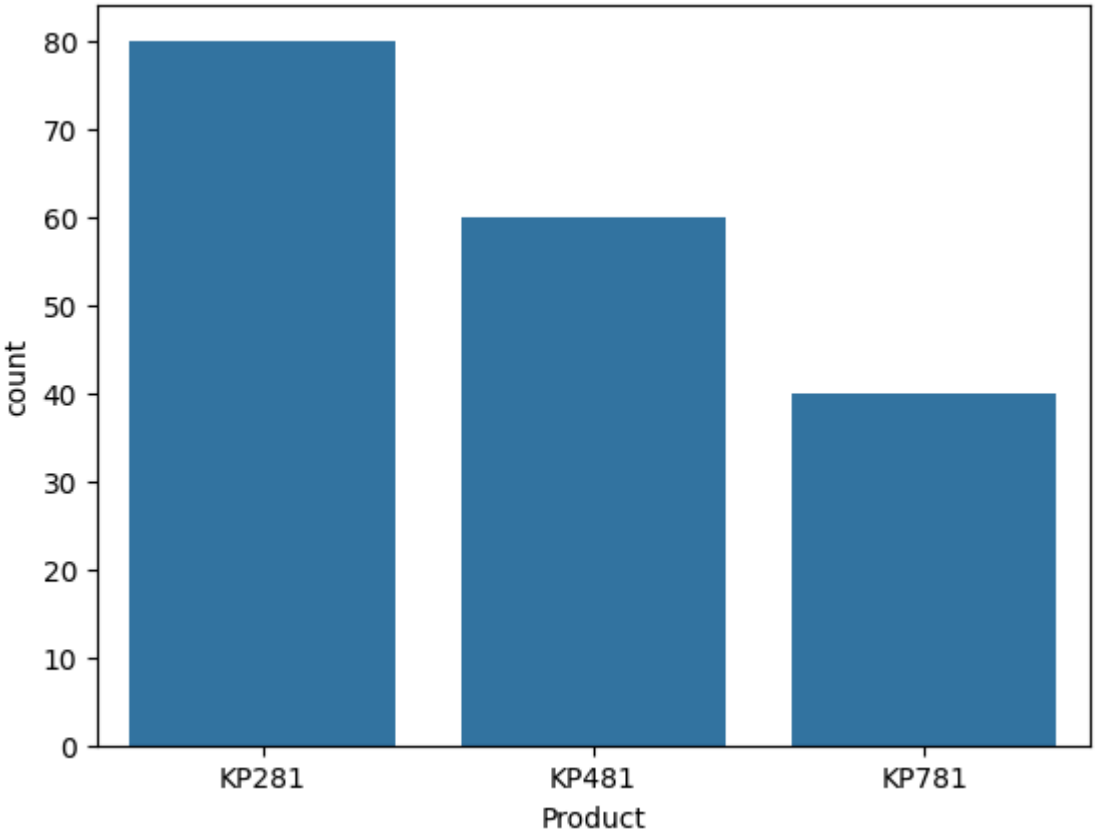

80
70
60
50


count
40
30
20
10
0
12
13
14
15
16
18
20
21
Education

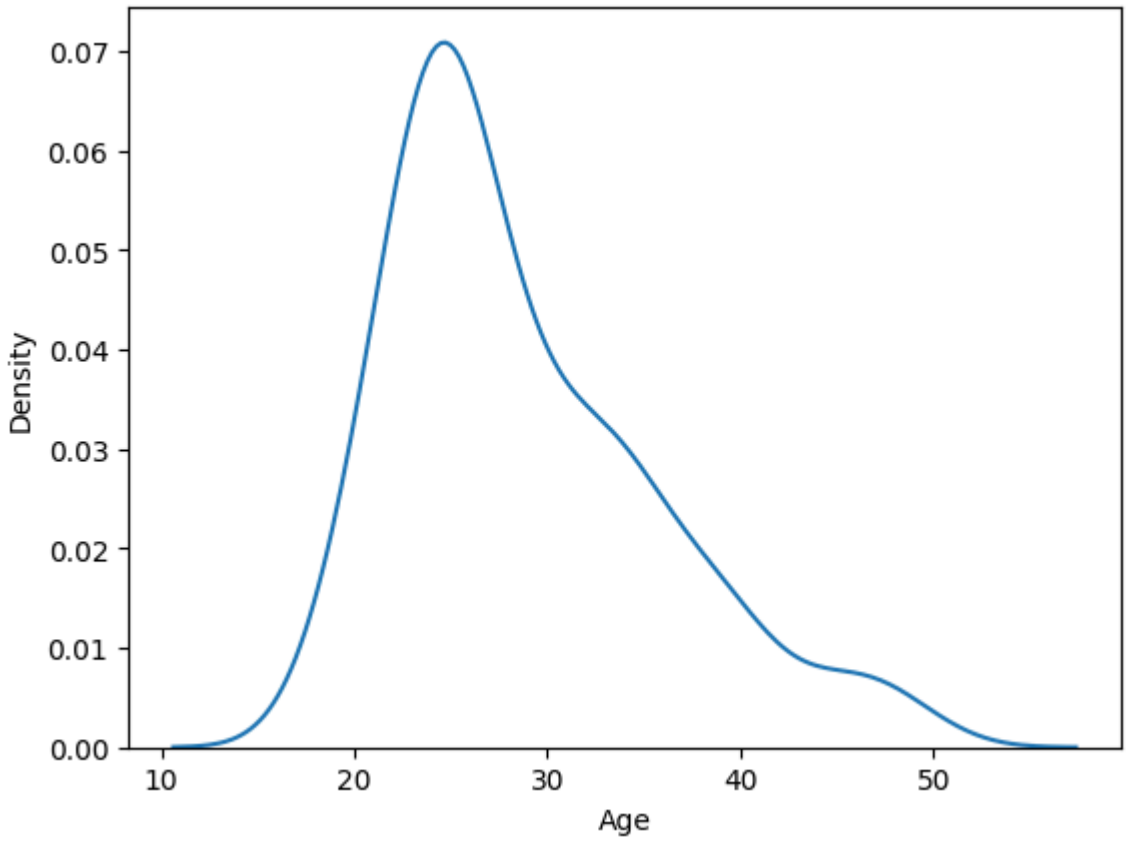

70
60
50
40
30
20
10
0
count
2
3
4
5
6
7
Usage

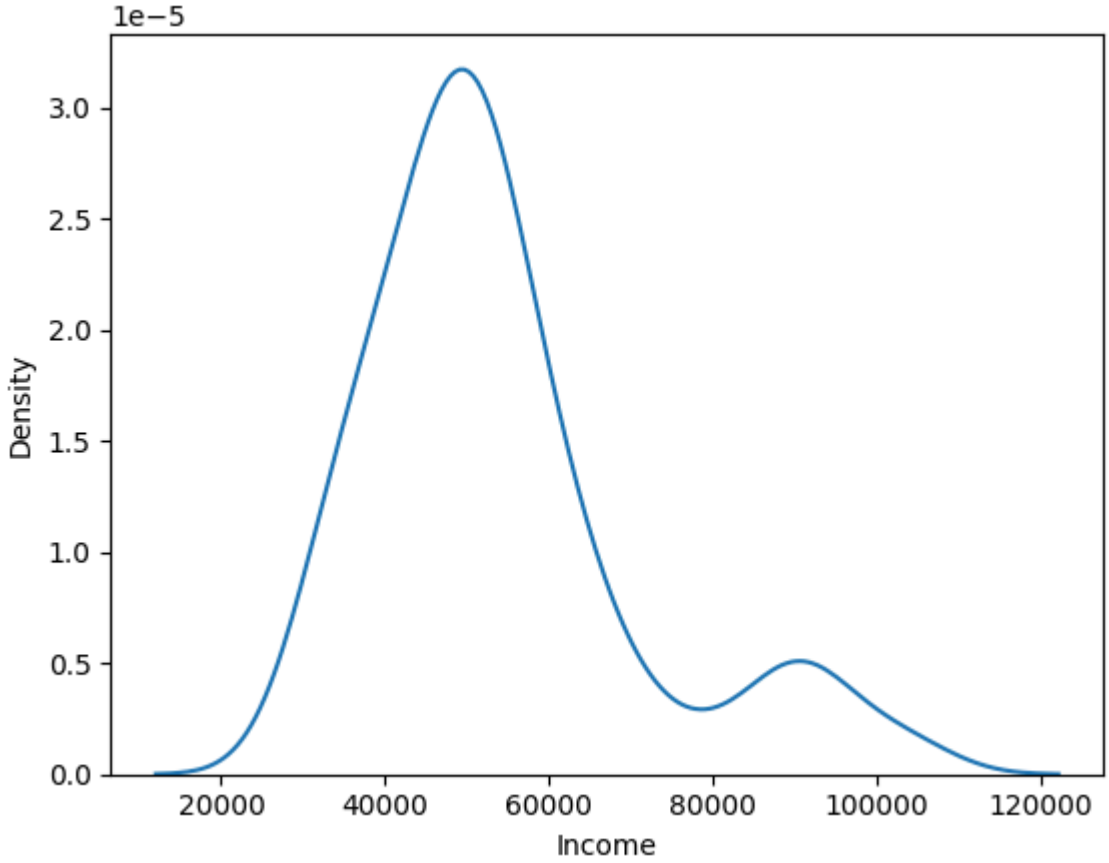

100
80
60
40
20
count

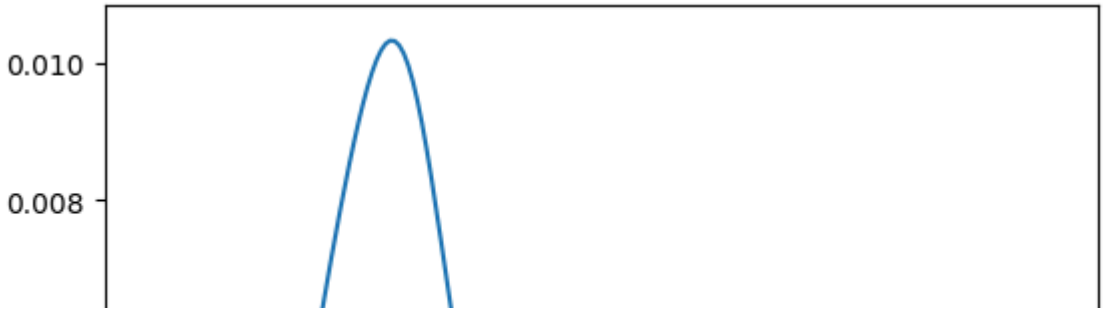

0
1
2
3
4
5
Fitness

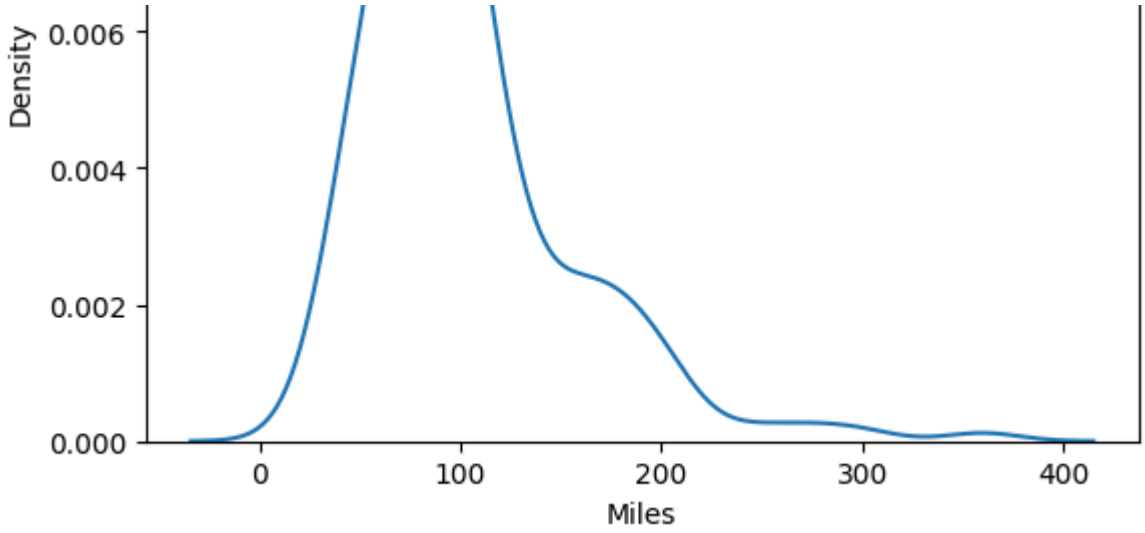

80
70
60
50
40
30
20
10
0
count
KP281
KP481
KP781
Product

```
# For Numerical variables
num_cols=['Age','Income','Miles']
for i in num_cols:
  sns.kdeplot(data[i])
  plt.show()
```


0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
Density
10
20
30
40
50
Age

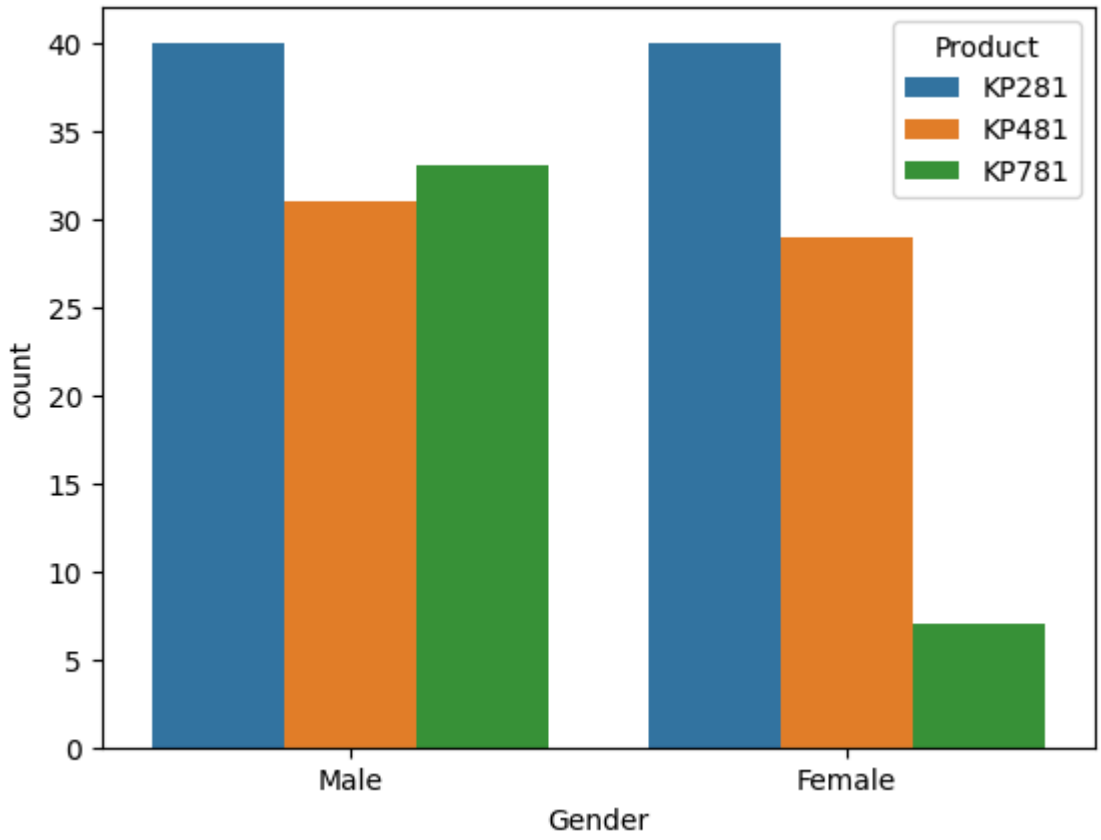

1e−5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Density
20000
40000
60000
80000
100000
120000
Income

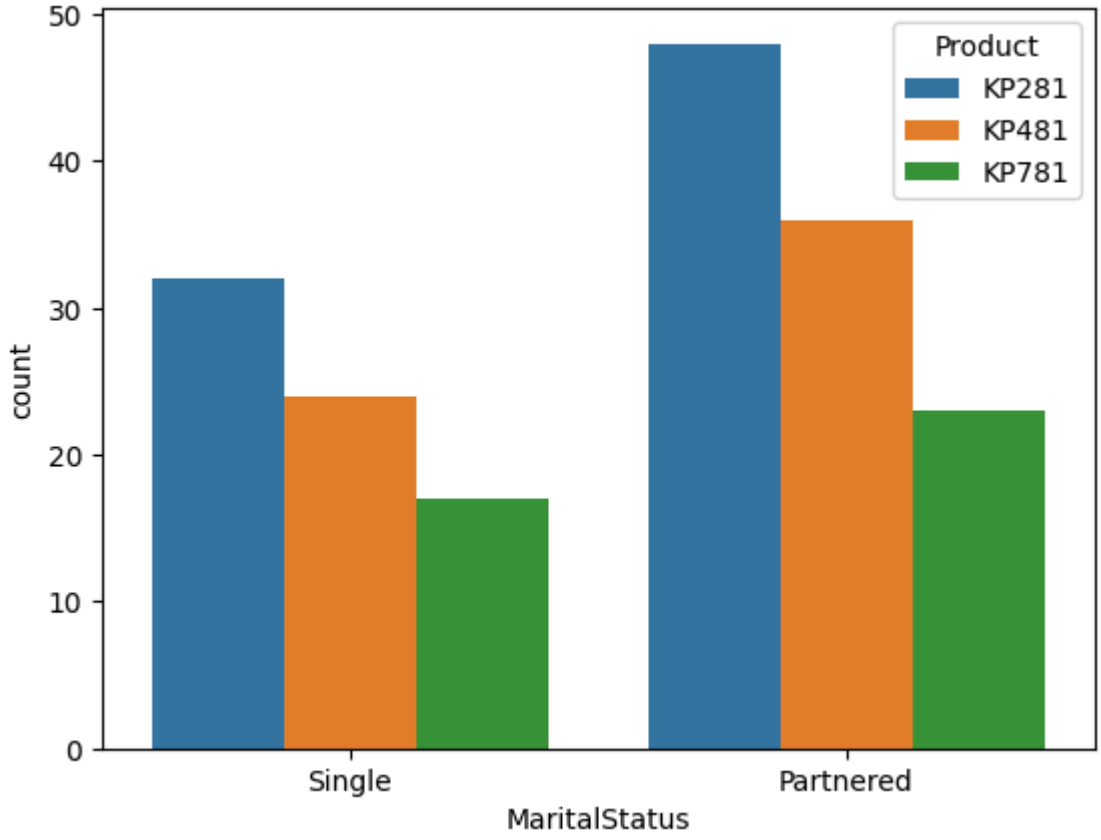

0.010
0.008

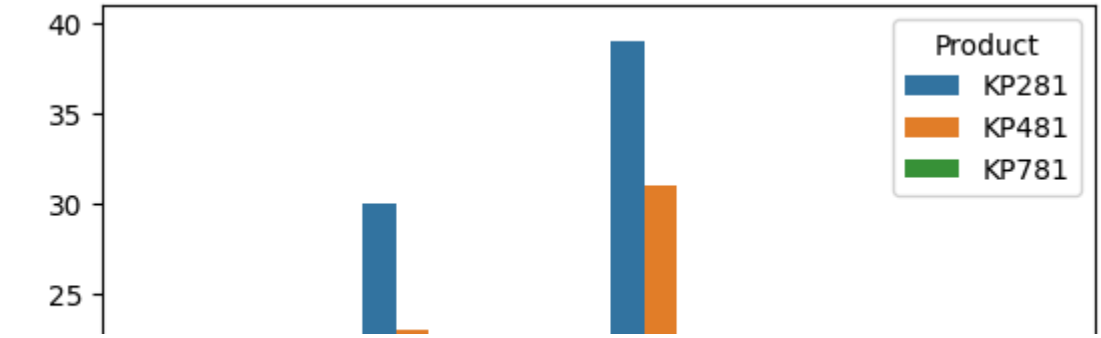


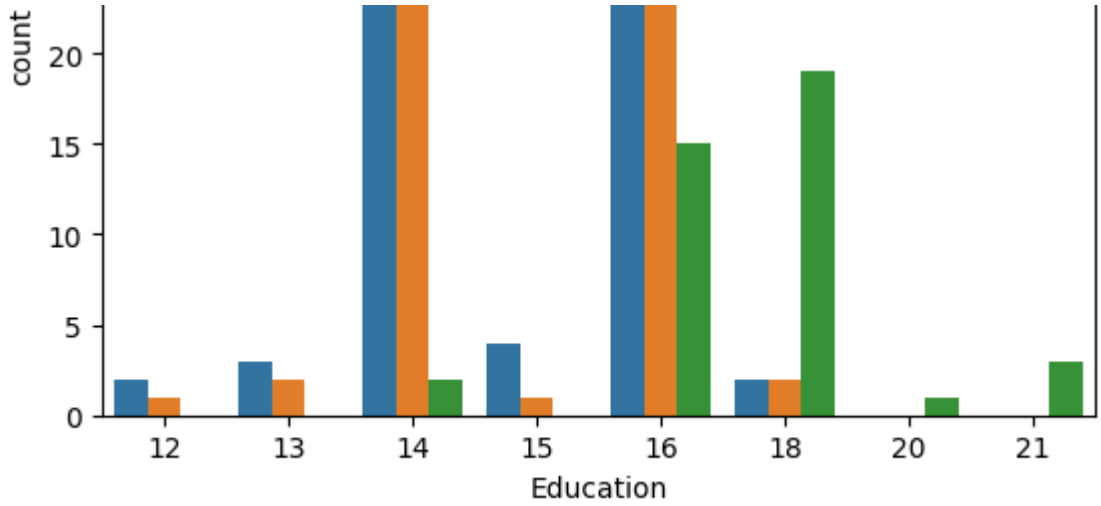
Bivariate Analysis

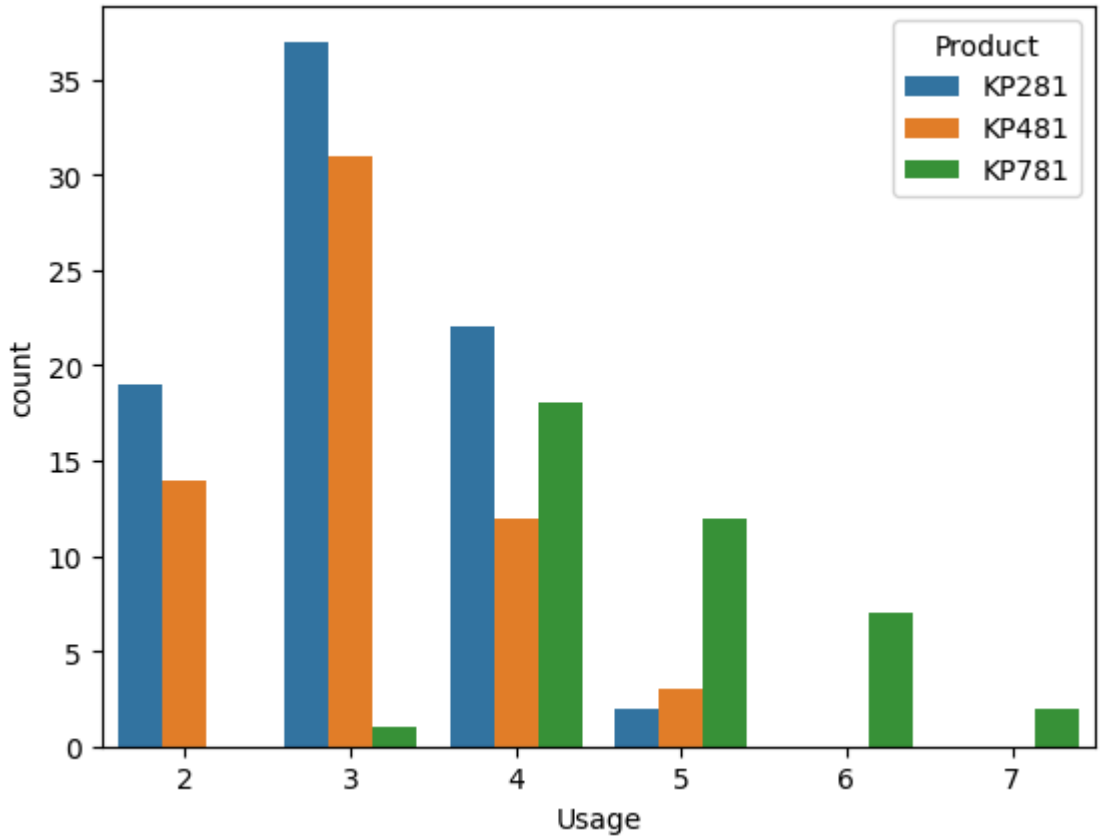
```
#Bivariate Analysis fo categorical using values
cat_cols=['Gender','MaritalStatus','Education','Usage','Fitness']
for i in cat_cols:
  sns.countplot(x=i,hue='Product',data=data)
  plt.show()
```

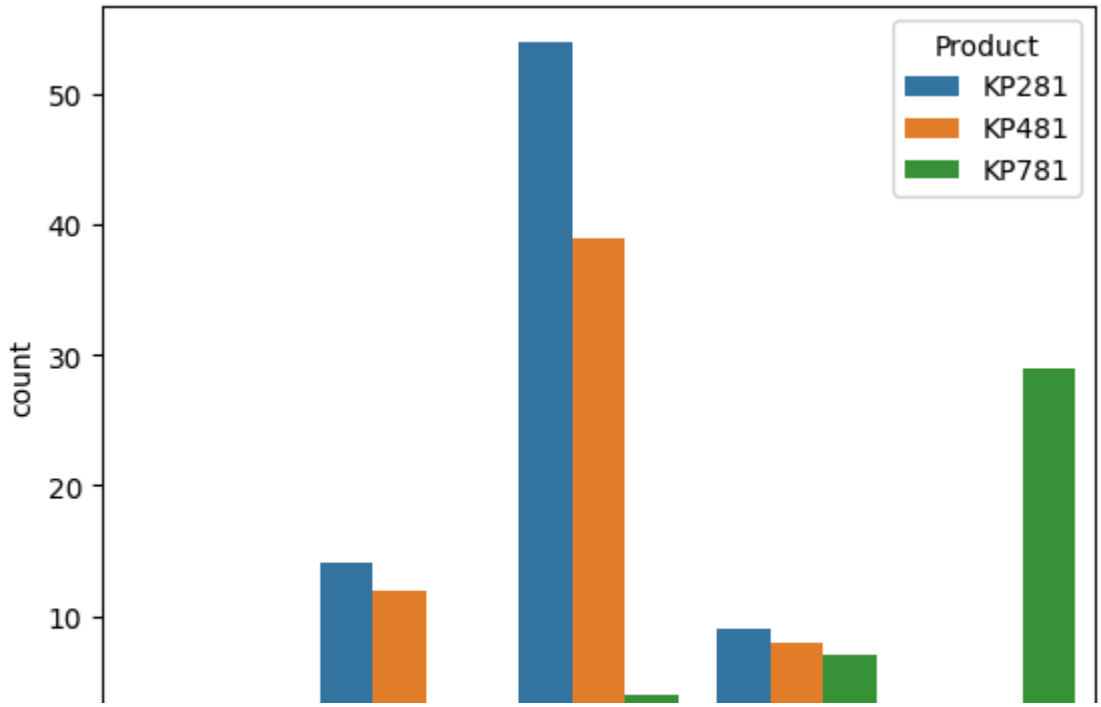

Product
KP281
KP481
KP781
count
Male
Female
Gender

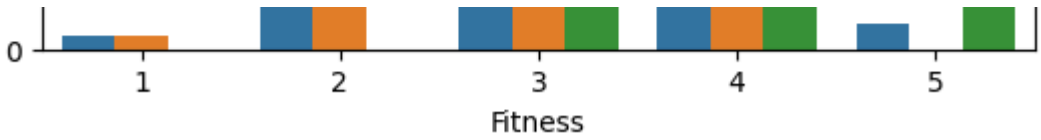

Product
KP281
KP481
KP781
count
Single
Partnered
MaritalStatus


Product
KP281
KP481
KP781

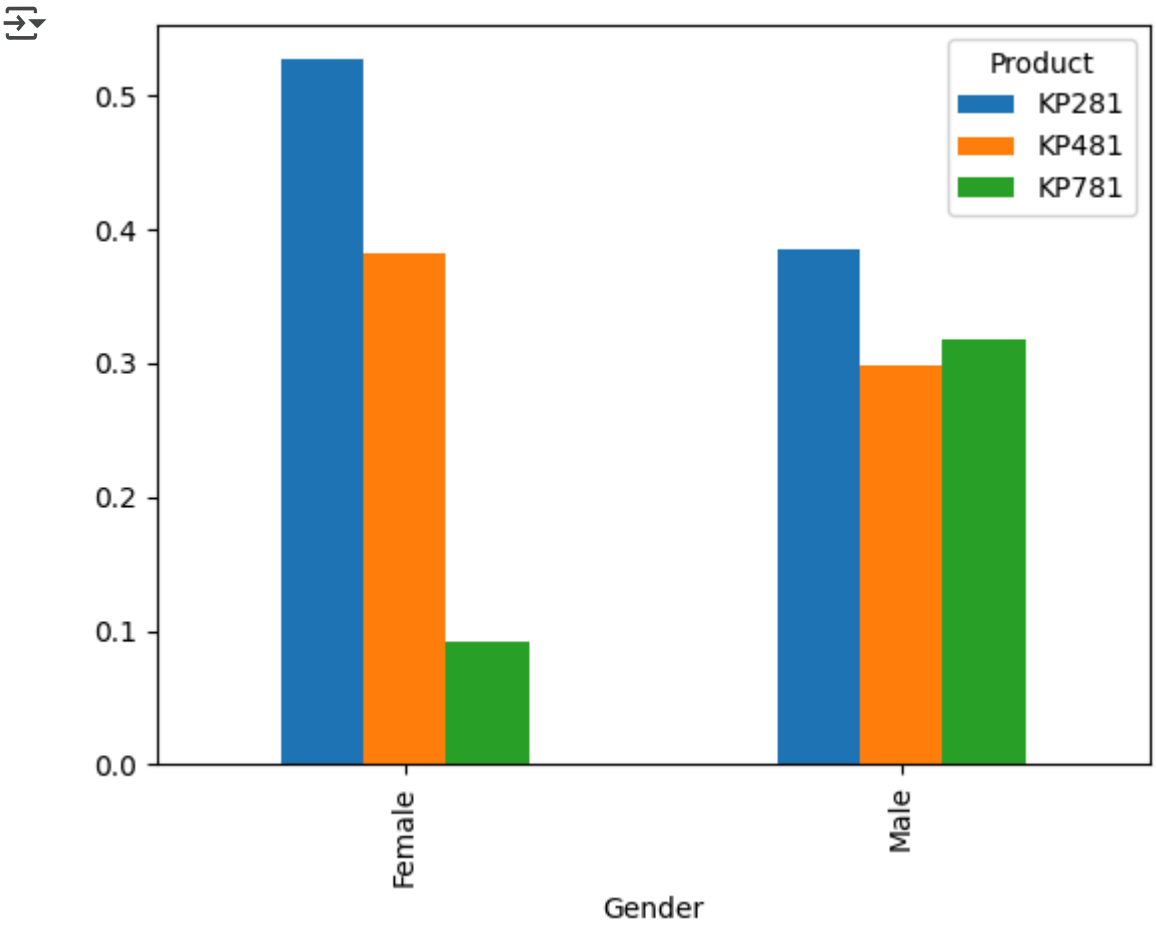

count
20
15
10
5
0
12
13
14
15
16
18
20
21
Education

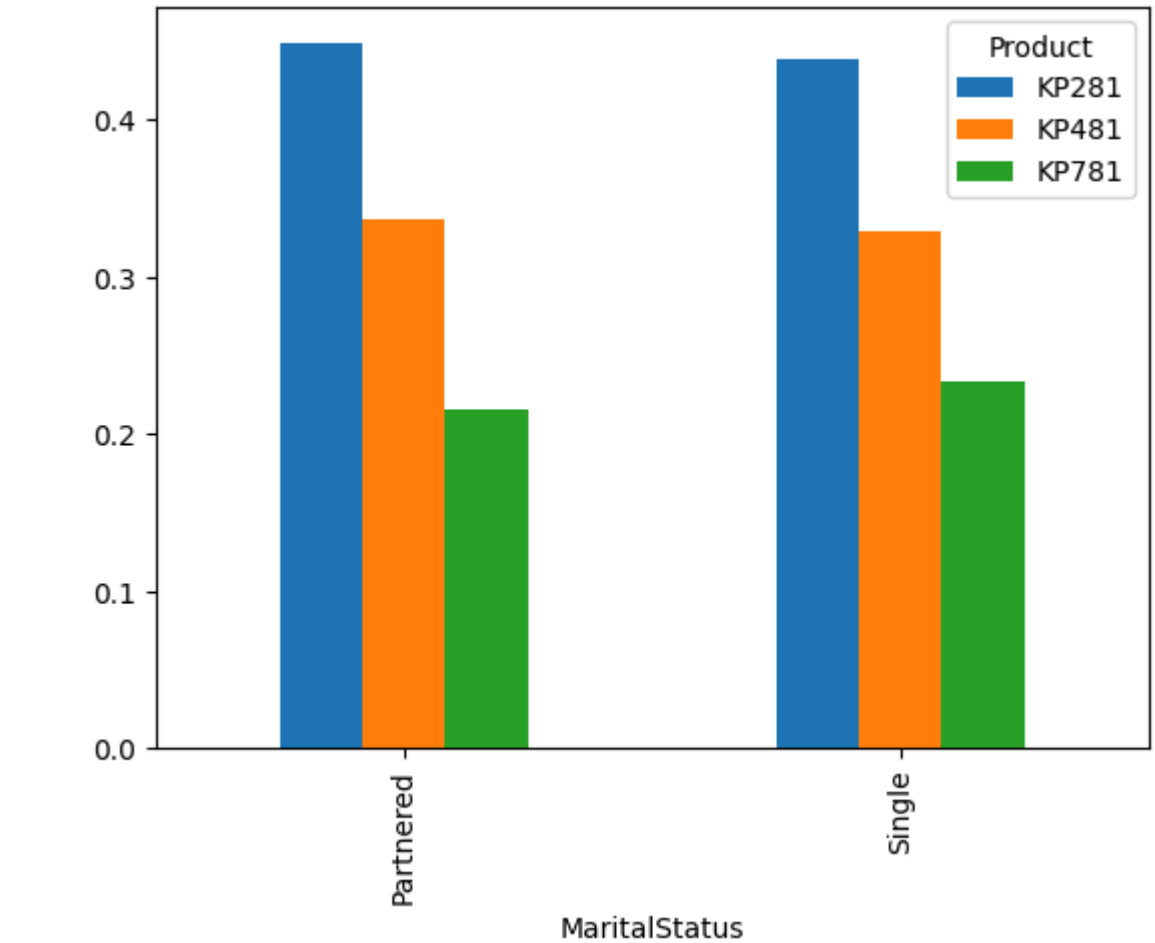

Product
KP281
KP481
KP781
count
35
30
25
20
15
10
5
0
2
3
4
5
6
7
Usage


Product
KP281
KP481
KP781
count
50
40
30
20
10

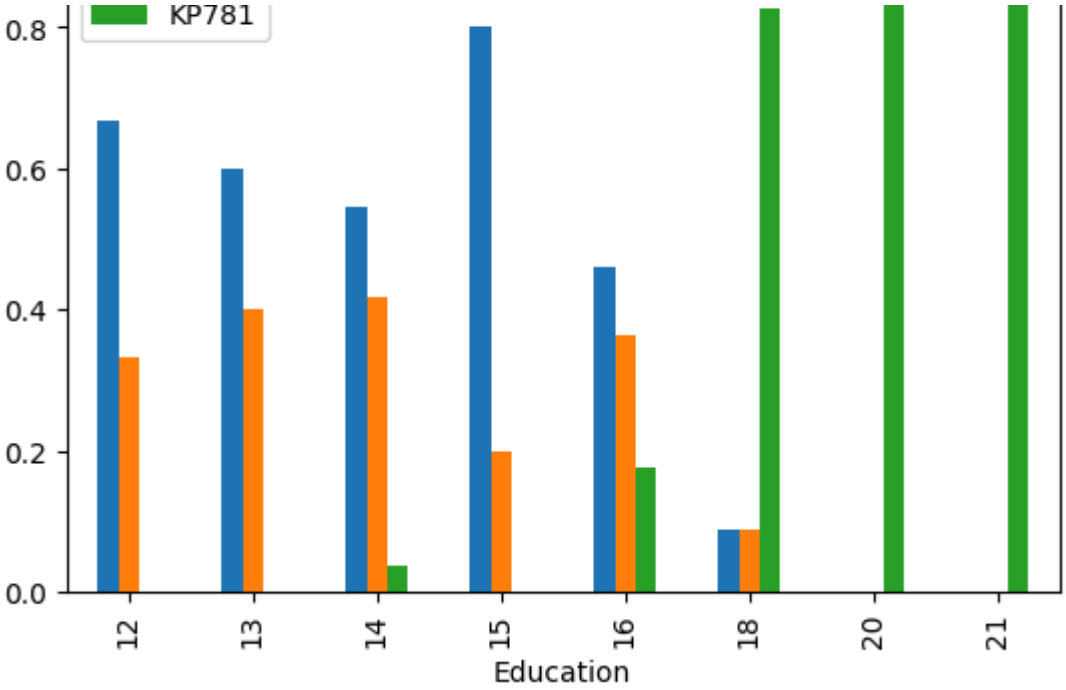

0
1
2
3
4
5
Fitness

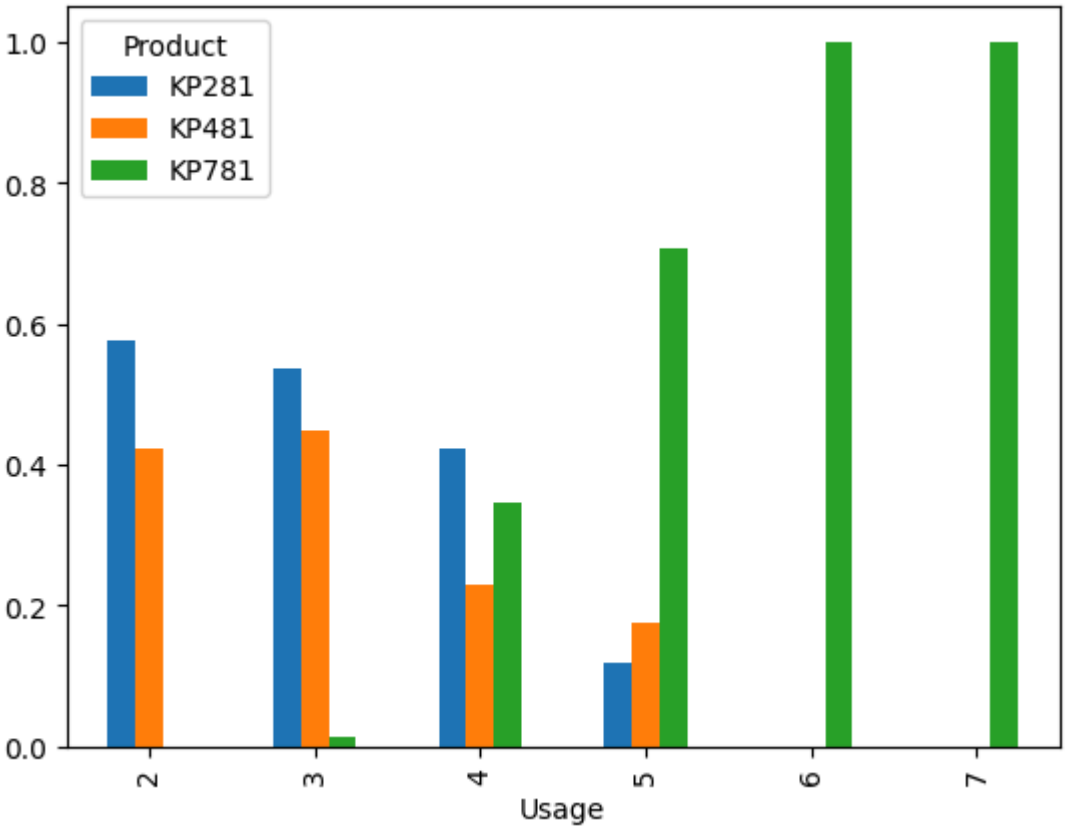
```
#Bivariate Analysis fo categorical using Propotions/Percentage
for i in cat_cols:
   i=pd.crosstab(data[i],data['Product'],normalize='index')
   i.plot(kind='bar')
   plt.show()
```

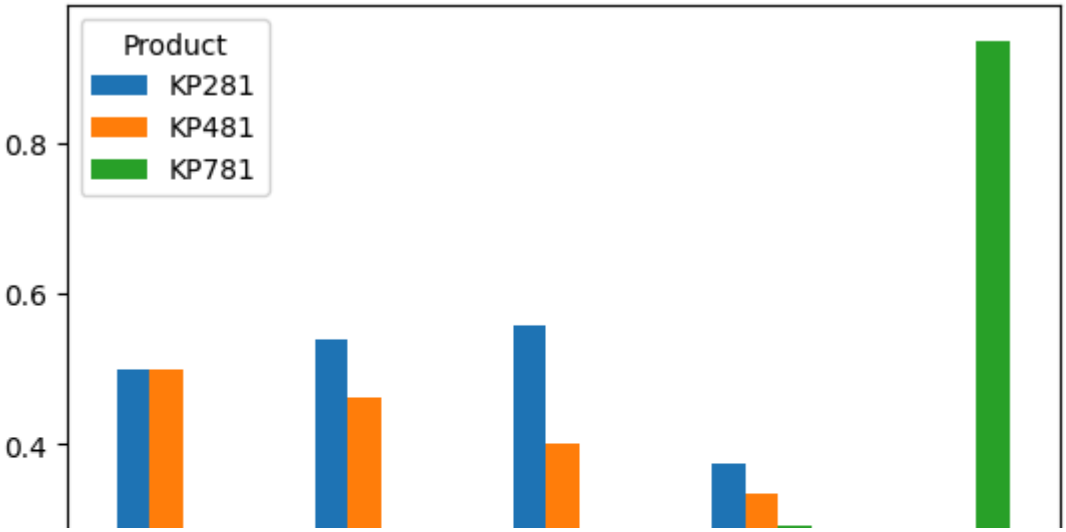

Product
KP281
KP481
KP781
0.5
0.4
0.3
0.2
0.1
0.0
Female
Male
Gender

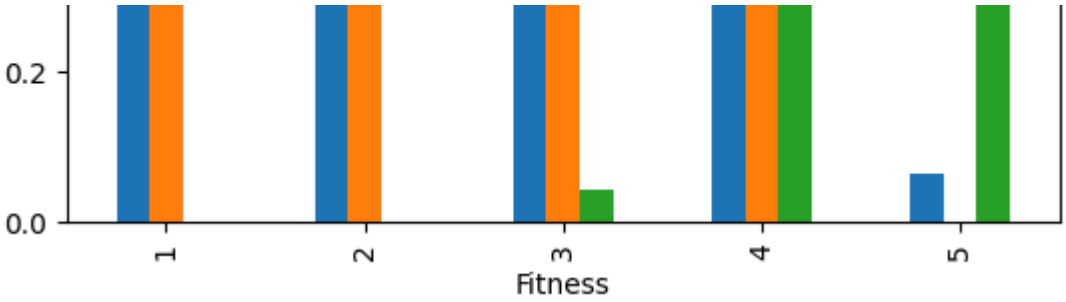

Product
KP281
KP481
KP781
0.4
0.3
0.2
0.1
0.0
Partnered
Single
MaritalStatus


Product
KP281
KP481
1.0

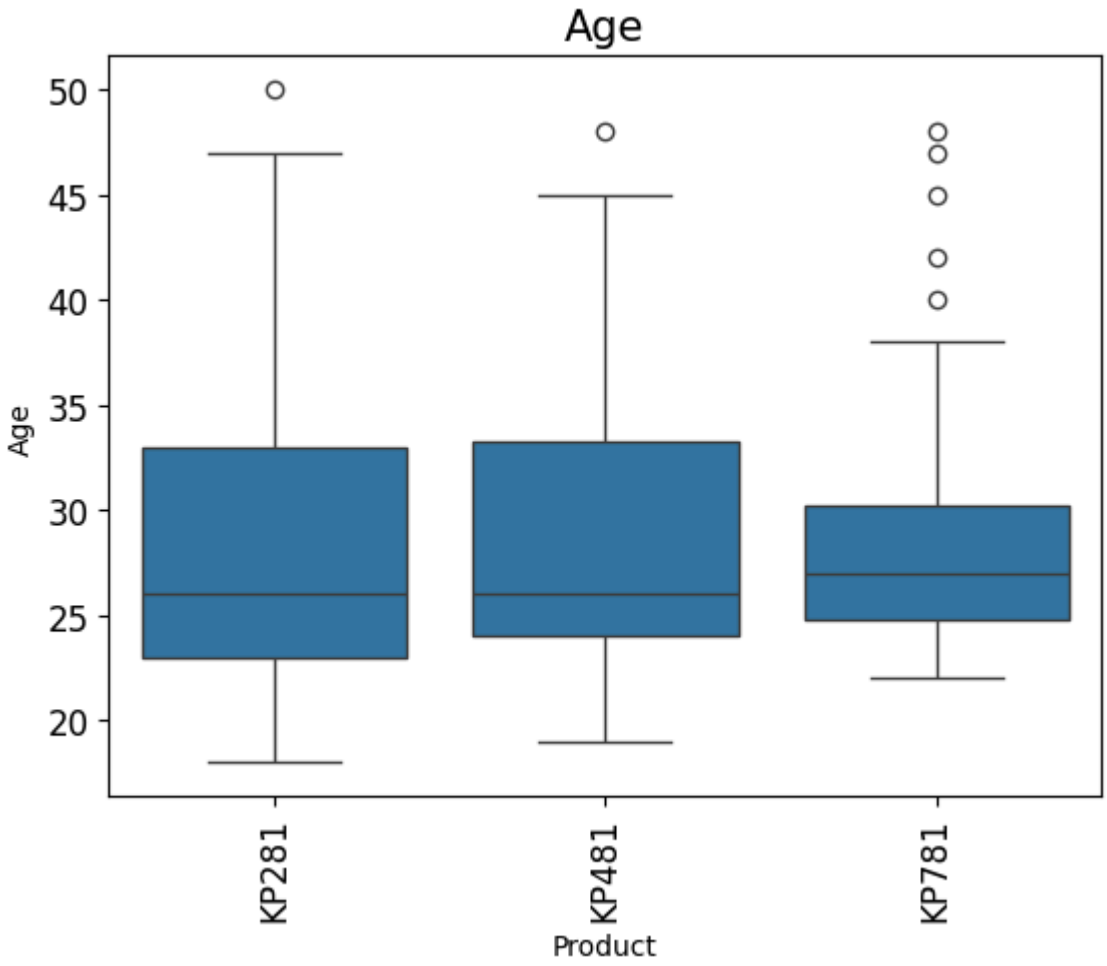

KP781
0.8
0.6
0.4
0.2
0.0
12
13
14
15
16
18
20
21
Education

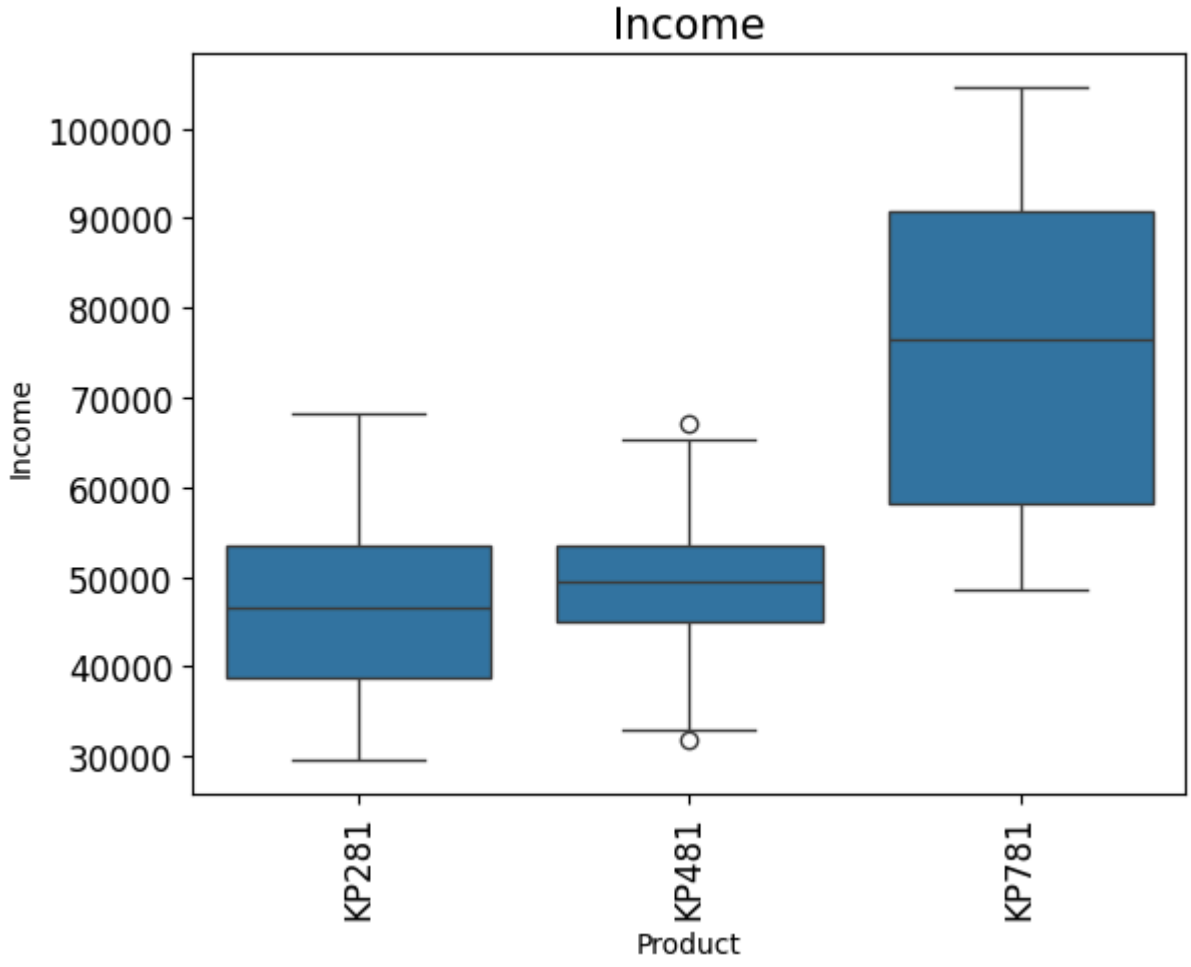

Product
KP281
KP481
KP781
1.0
0.8
0.6
0.4
0.2
0.0
2
3
4
5
6
7
Usage


Product
KP281
KP481
KP781
0.8
0.6
0.4

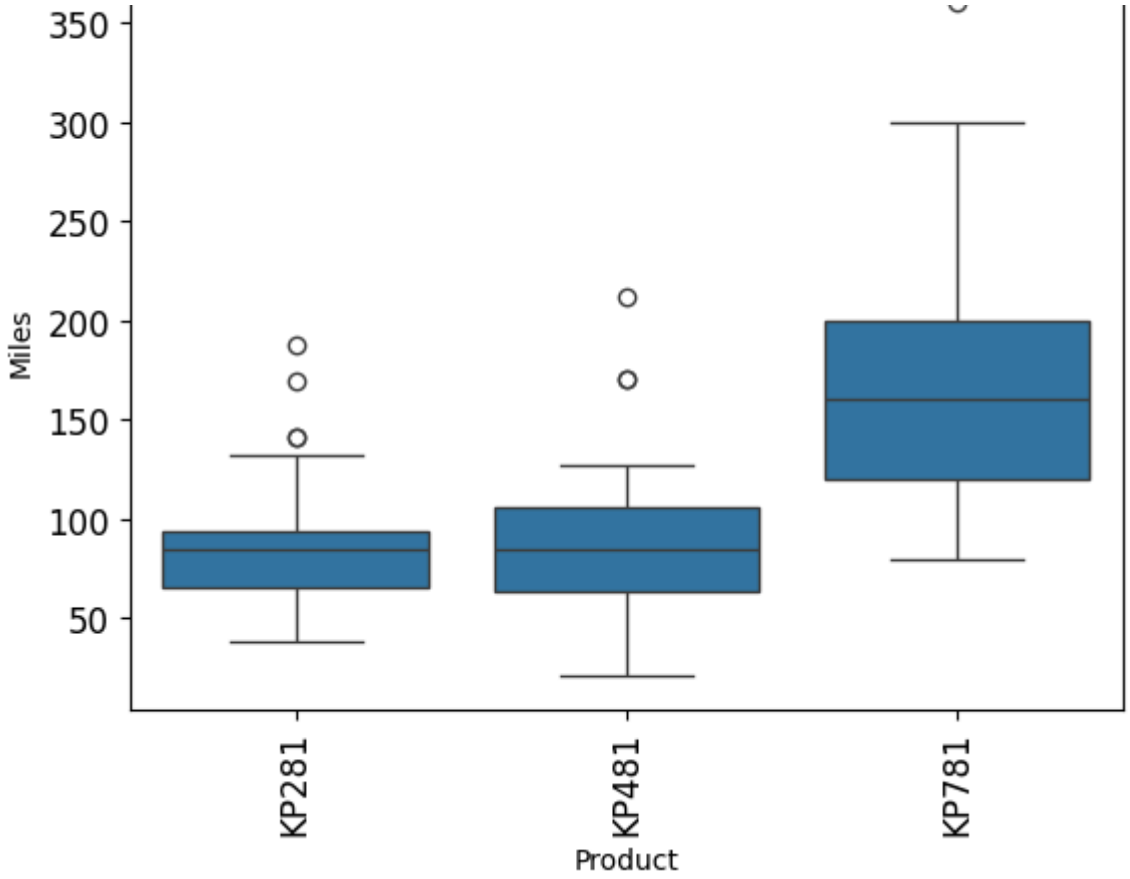

0.2
0.0
1
2
3
4
5
Fitness

```
#Bivariate Analysis fo Numerical variables using values
num_cols=['Age','Income','Miles']
for i in num_cols:
  sns.boxplot(x='Product', y=i, data=data)
  plt.xticks(rotation=90,fontsize=12)
  plt.yticks(fontsize=12)
  plt.title(i, fontsize=15)
  plt.show()
```


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


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

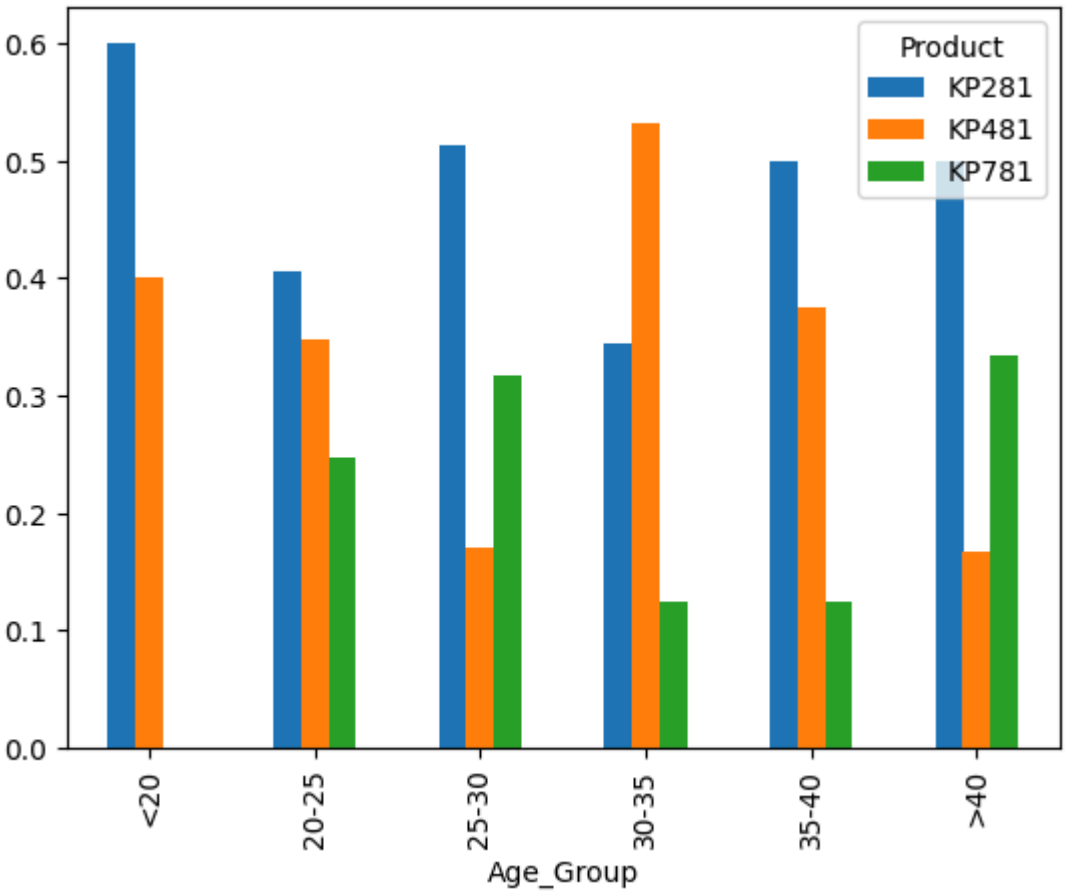

Miles

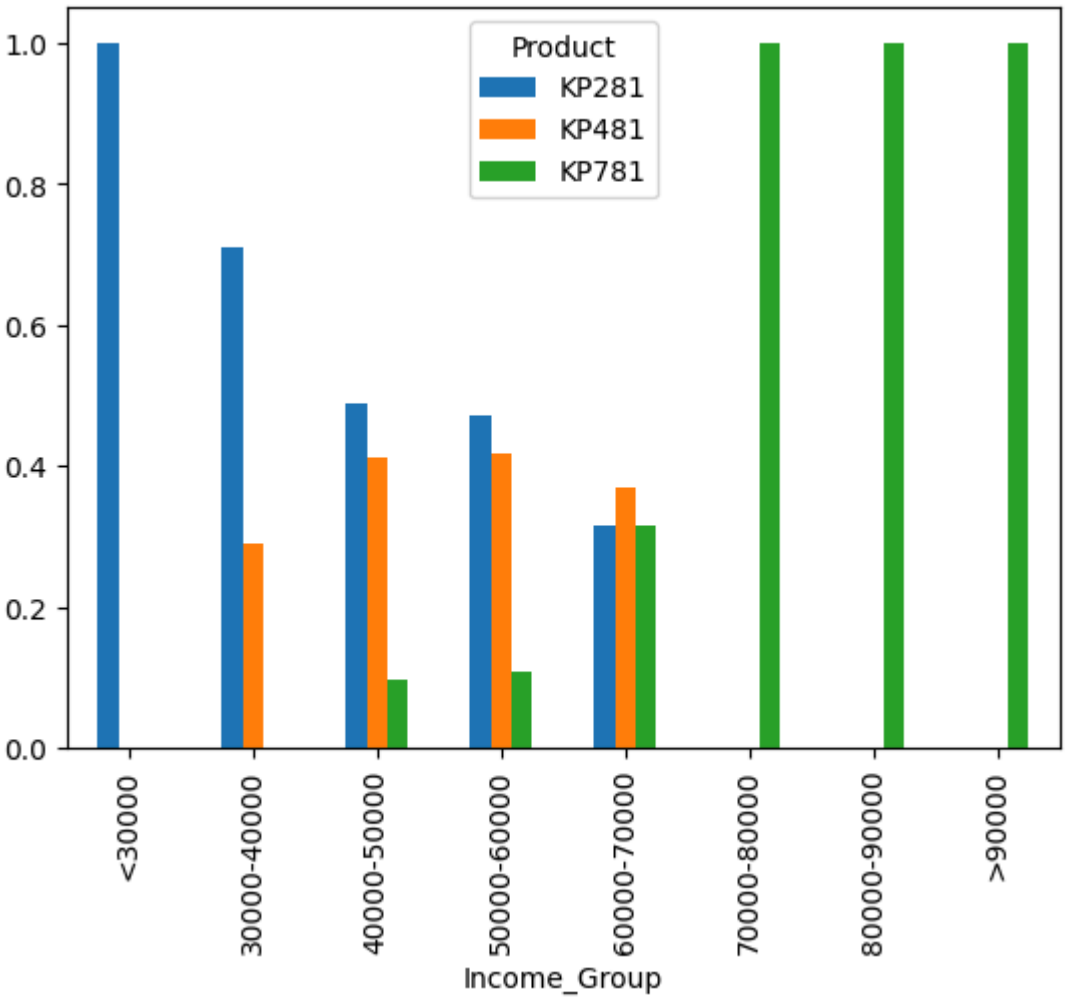



```
data_copy=data.copy()


# Binning numerical columns to categorical
bins=[0,30000,40000,50000,60000,70000,80000,90000,120000]
labels=['<30000','30000-40000','40000-50000','50000-60000','60000-70000','70000-80000','8
data['Income_Group']=pd.cut(data['Income'],bins=bins,labels=labels)
data.head()
bins=[0,20,25,30,35,40,51]
labels=['<20','20-25','25-30','30-35','35-40','>40']
data['Age_Group']=pd.cut(data['Age'],bins=bins,labels=labels)
data.head()
bins=[0,20,40,60,80,100,120,150,200,360]
labels=['<20','20-40','40-60','60-80','80-100','100-120','120-150','150-200','>200']
data['Miles_Group']=pd.cut(data['Miles'],bins=bins,labels=labels)
data.head()
```

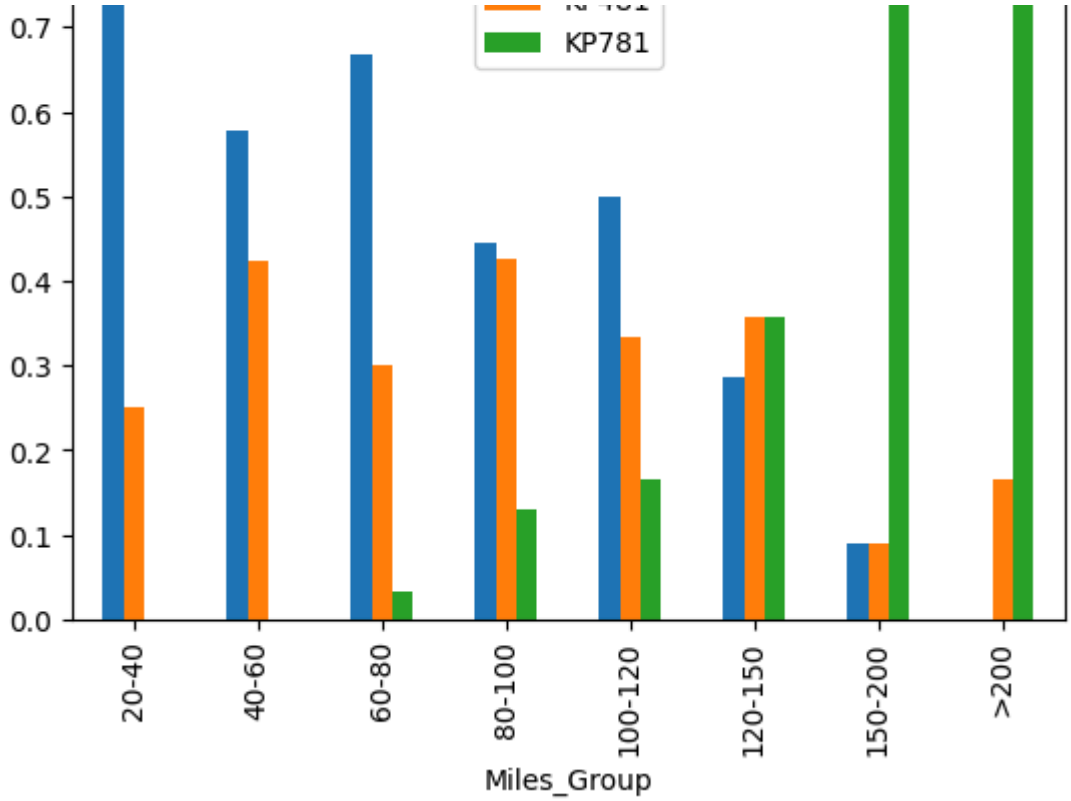
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Inco
0	KP281	18	Male	14	Single	3	4	29562	112	
1	KP281	19	Male	15	Single	2	3	31836	75	30
2	KP281	19	Female	14	Partnered	4	3	30699	66	30
3	KP281	19	Male	12	Single	3	3	32973	85	30
4	KP281	20	Male	13	Partnered	4	2	35247	47	30

```
#Bivariate Analysis fo Numerical variables using its propotion/percentage
num_cols=['Age_Group','Income_Group','Miles_Group']
for i in num_cols:
   i=pd.crosstab(data[i],data['Product'],normalize='index')
   i.plot(kind='bar')
   plt.show()
```

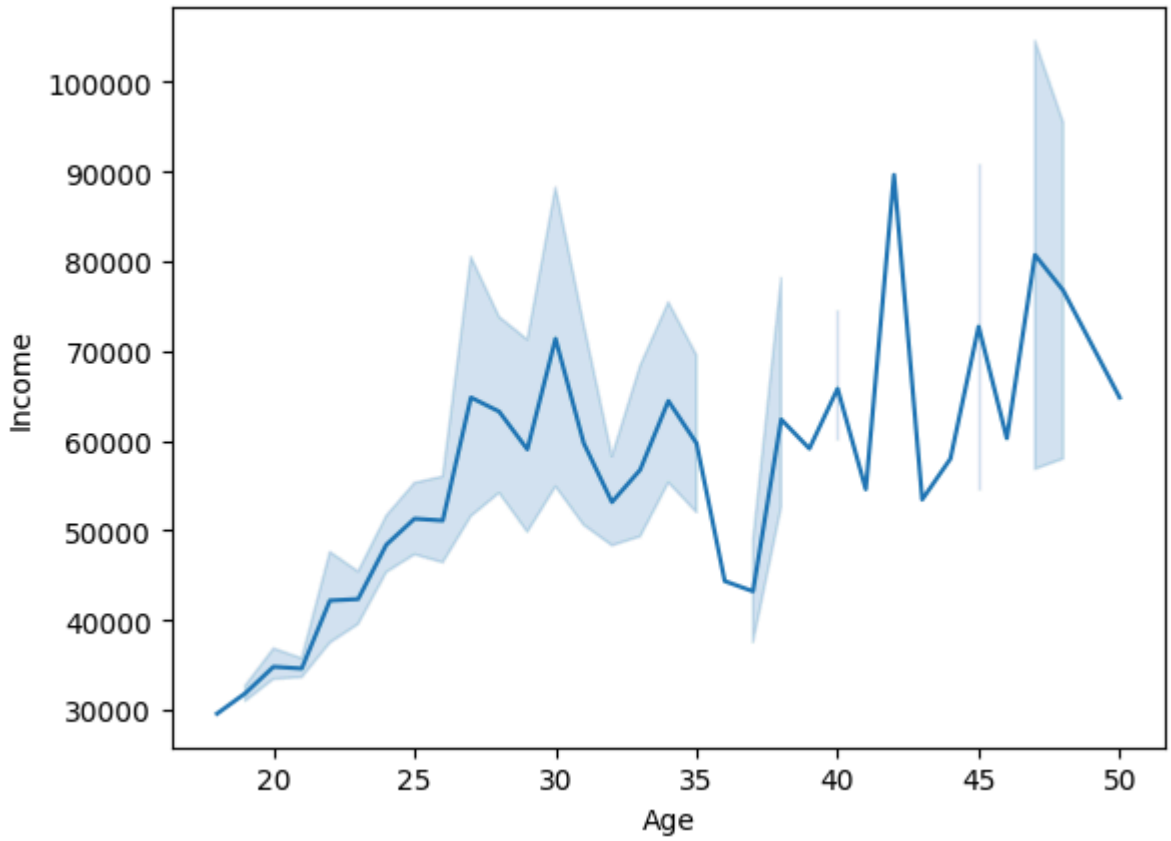

Product
KP281
KP481
KP781
0.6
0.5
0.4
0.3
0.2
0.1
0.0
<20
20-25
25-30
30-35
35-40
>40
Age_Group

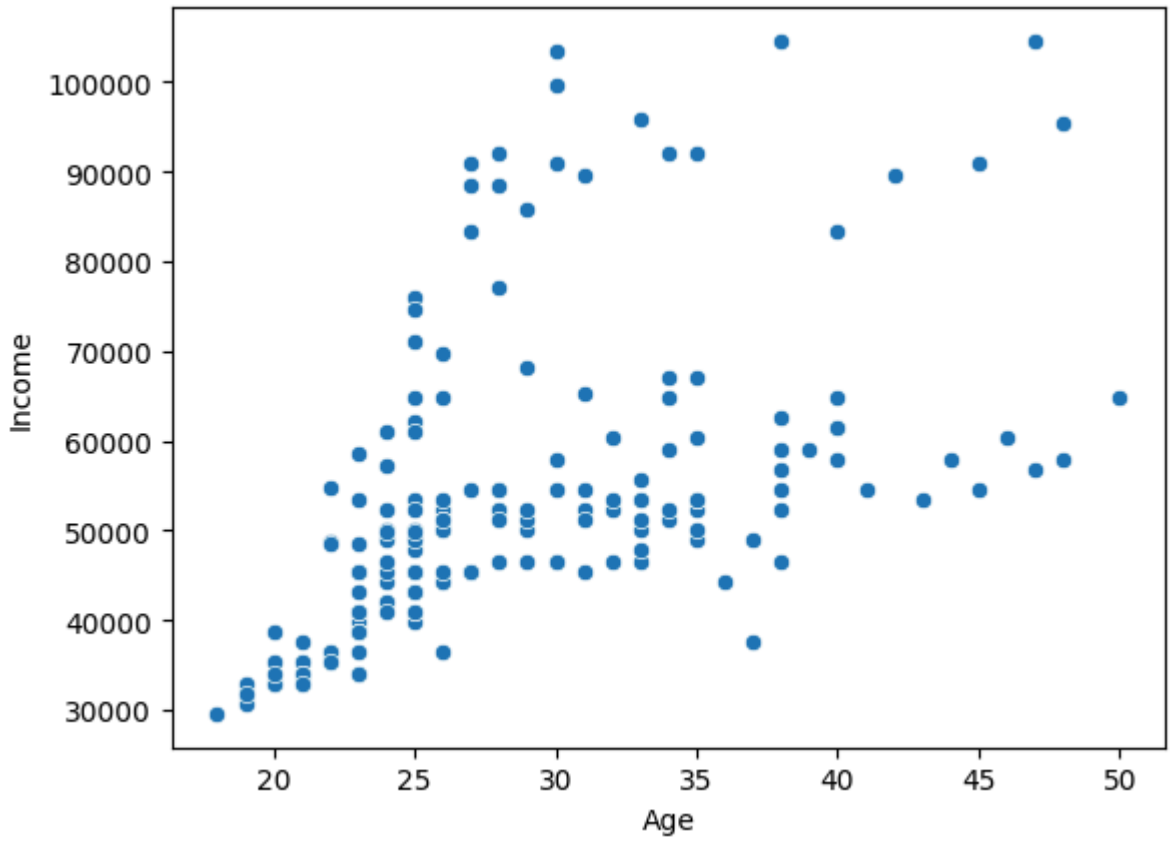

Product
KP281
KP481
KP781
1.0
0.8
0.6
0.4
0.2
0.0
<30000
30000-40000
40000-50000
50000-60000
60000-70000
70000-80000
80000-90000
>90000
Income_Group


Product
KP281
0.8

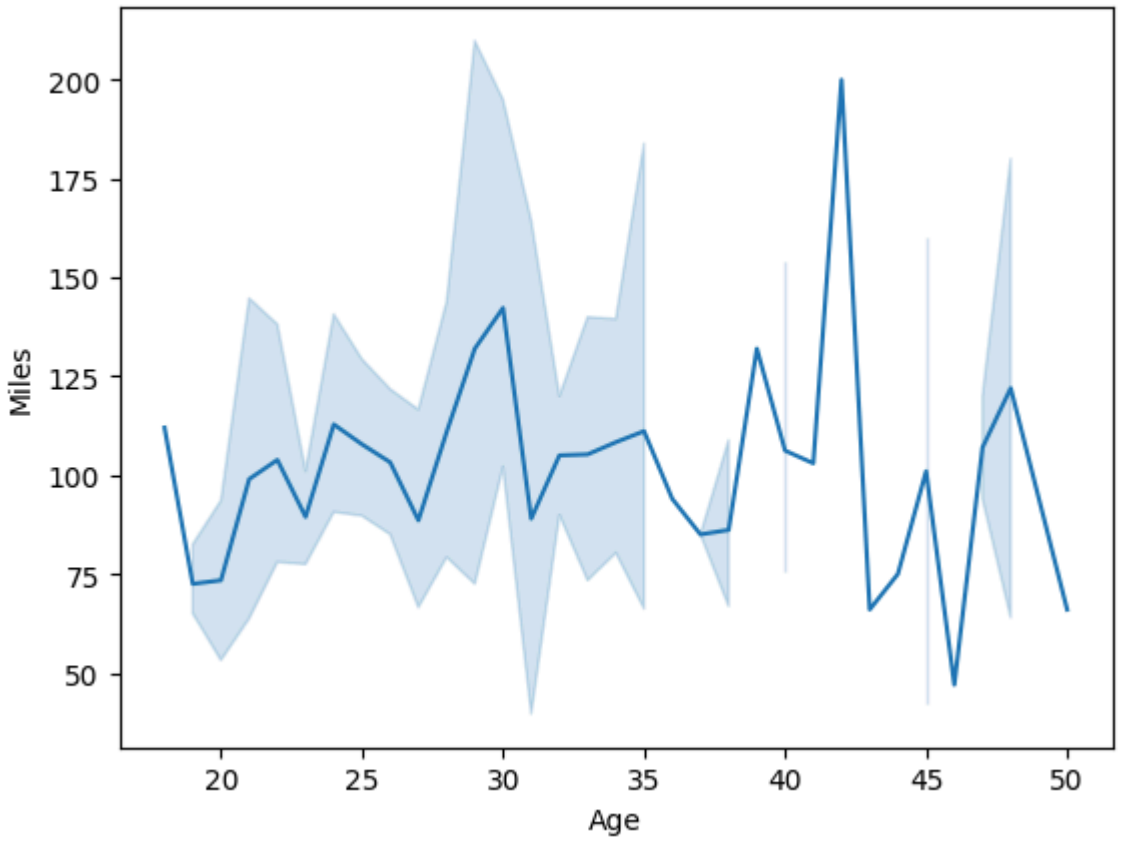


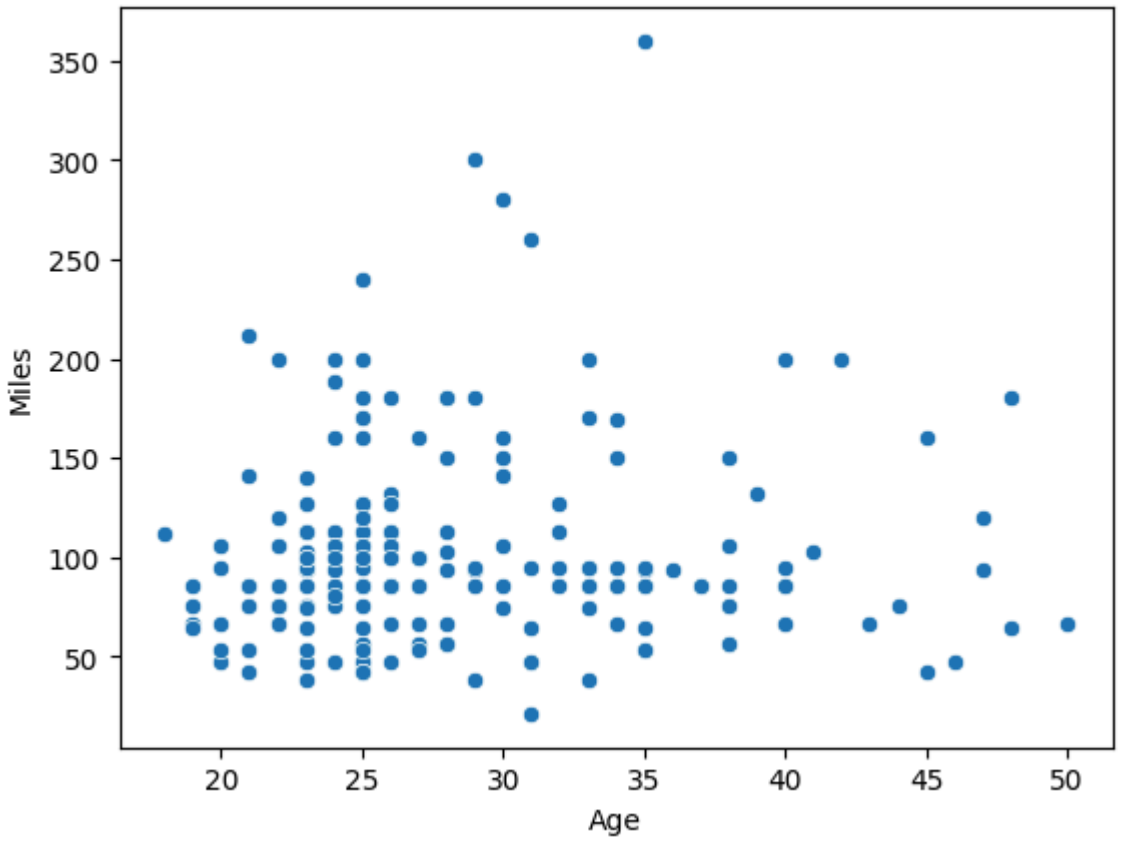

```
sns.lineplot(x='Age', y='Income', data=data)
plt.show()

sns.scatterplot(x='Age', y='Income', data=data)
plt.show()
```



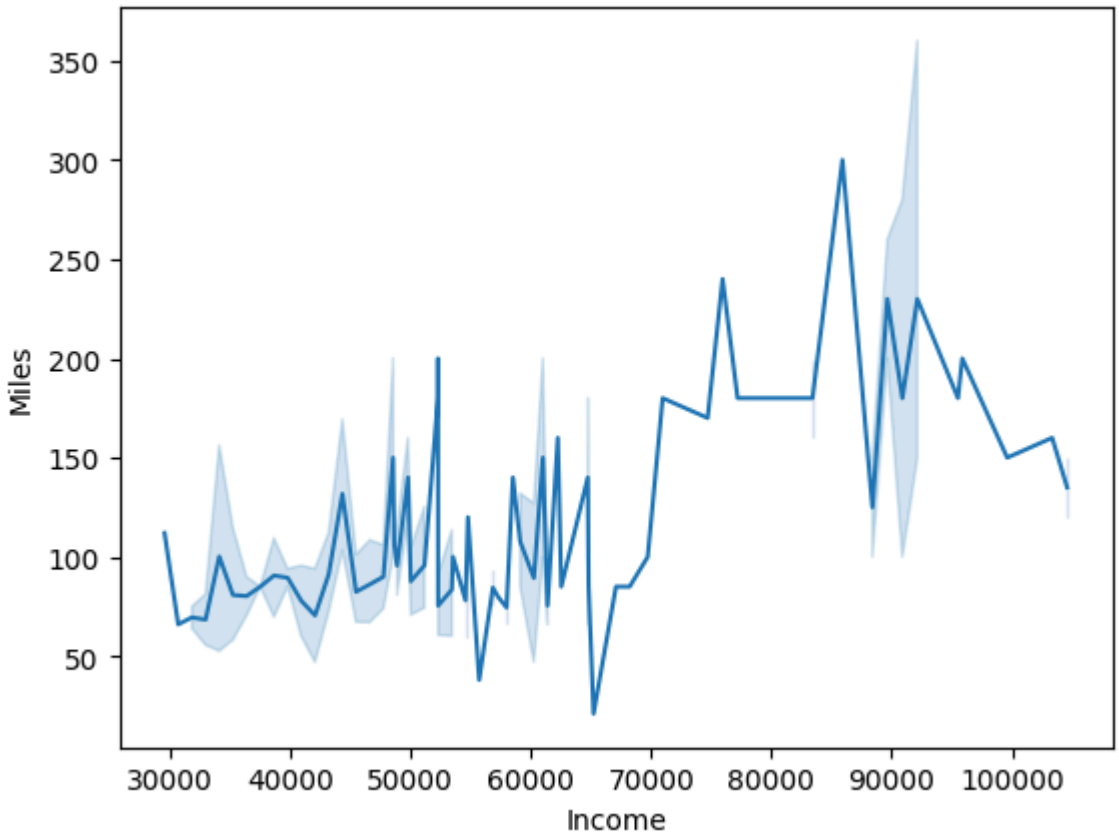


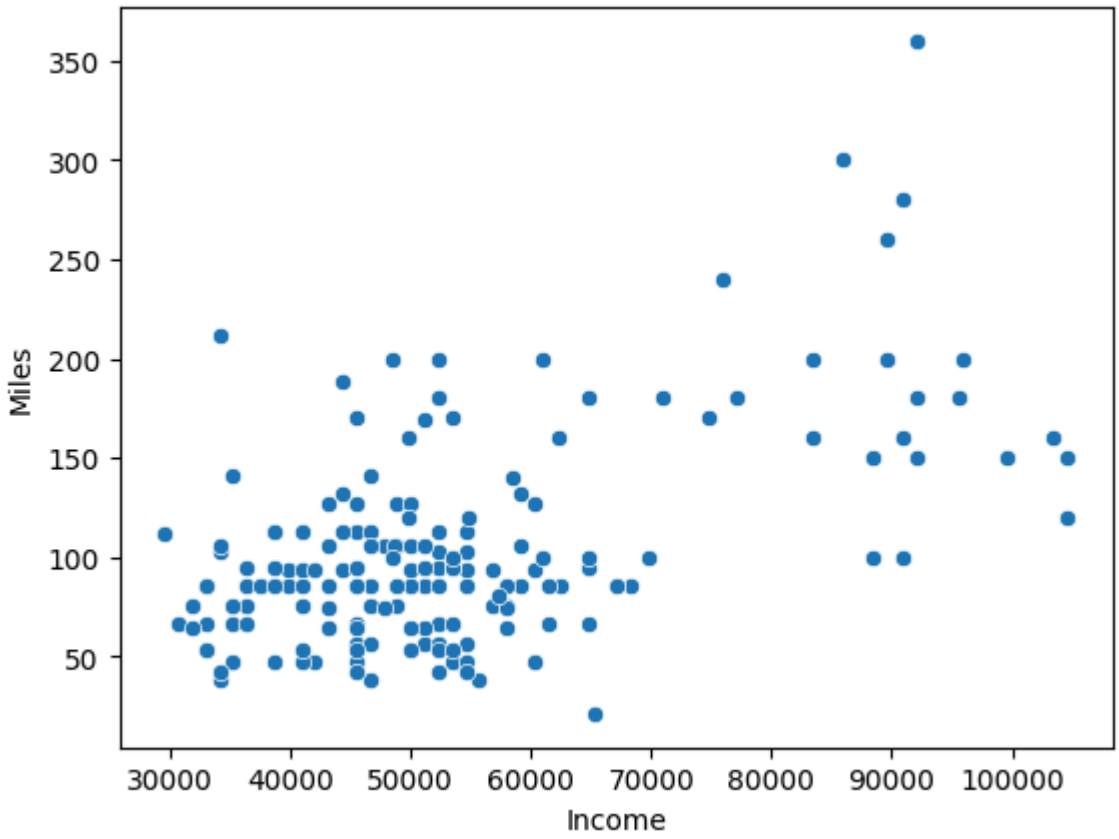

```
sns.lineplot(x='Age', y='Miles', data=data)
plt.show()

sns.scatterplot(x='Age', y='Miles', data=data)
plt.show()
```






```
sns.lineplot(x='Income', y='Miles', data=data)
plt.show()

sns.scatterplot(x='Income', y='Miles', data=data)
plt.show()
```





Multivariate

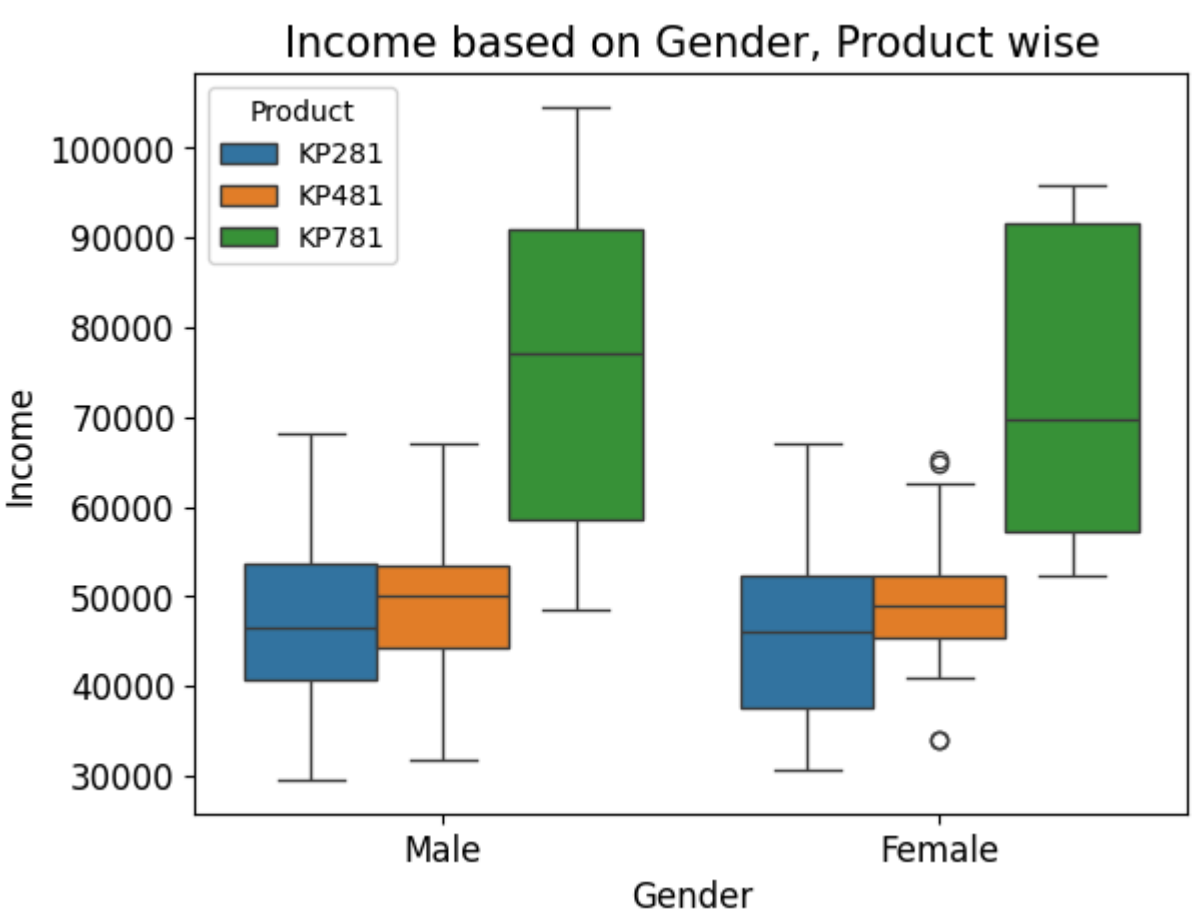
Multivariate analysis of Product on the basis of income.

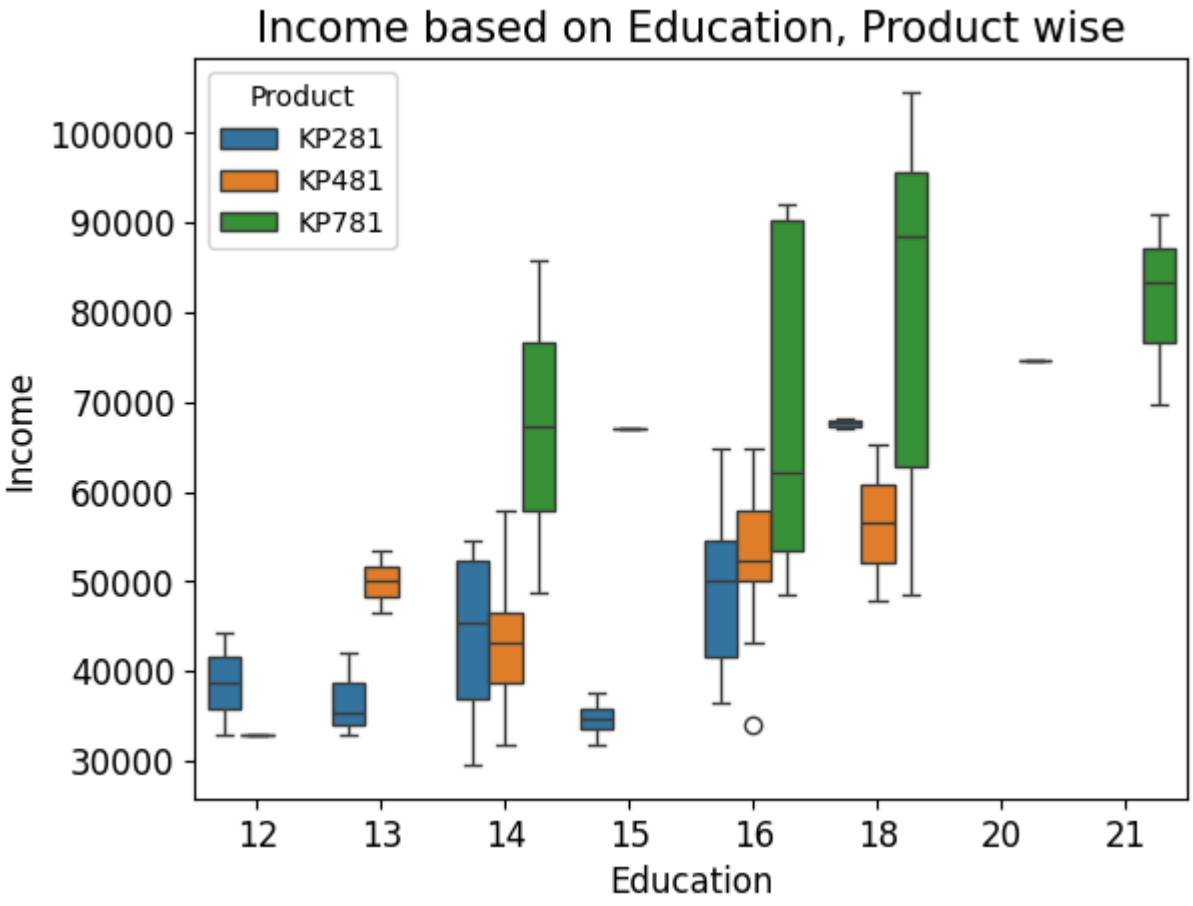
```
data.columns
```

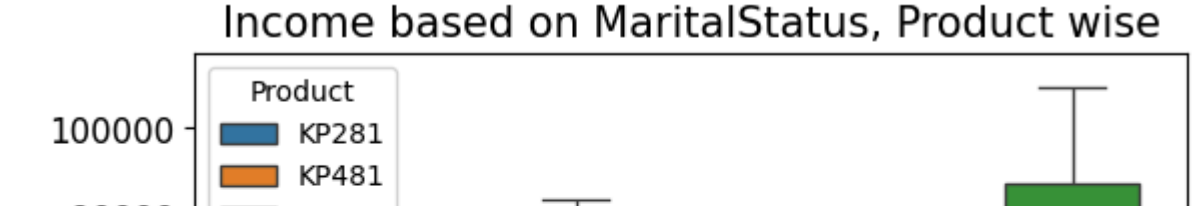
```
Index(['Product', 'Age', 'Gender', 'Education', 'MaritalStatus', 'Usage',
       'Fitness', 'Income', 'Miles', 'Income_Group', 'Age_Group',
       'Miles_Group'],
      dtype='object')
```

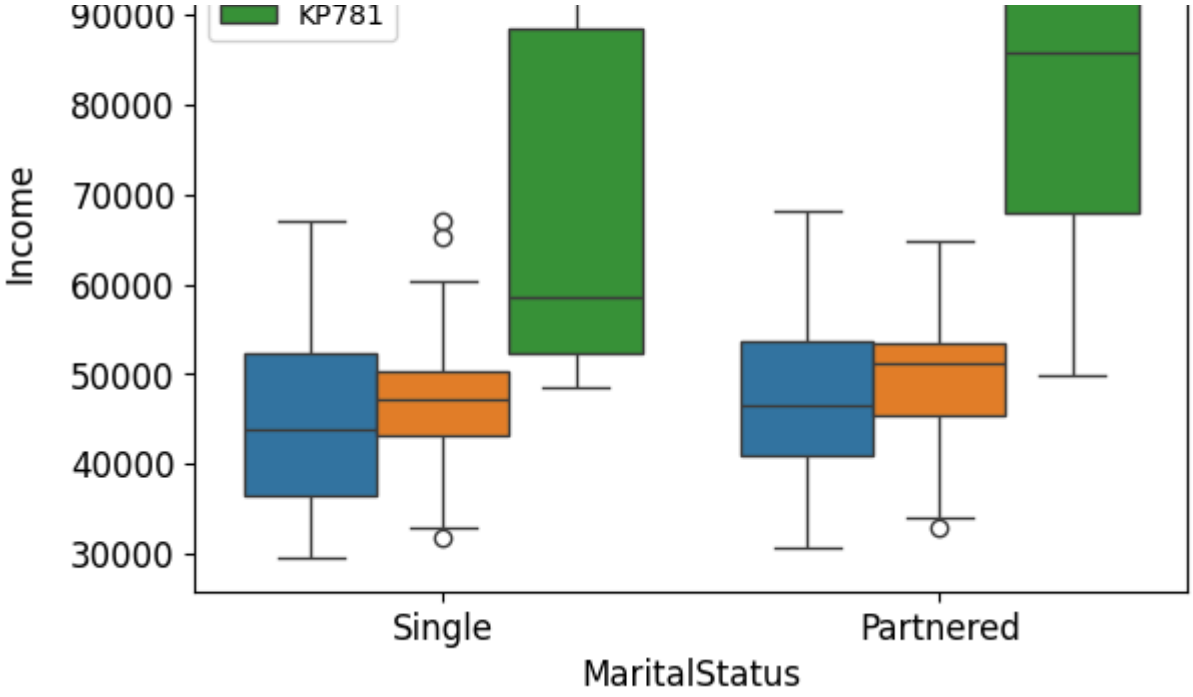
```
catcols=['Gender','Education','MaritalStatus','Fitness','Usage']
```

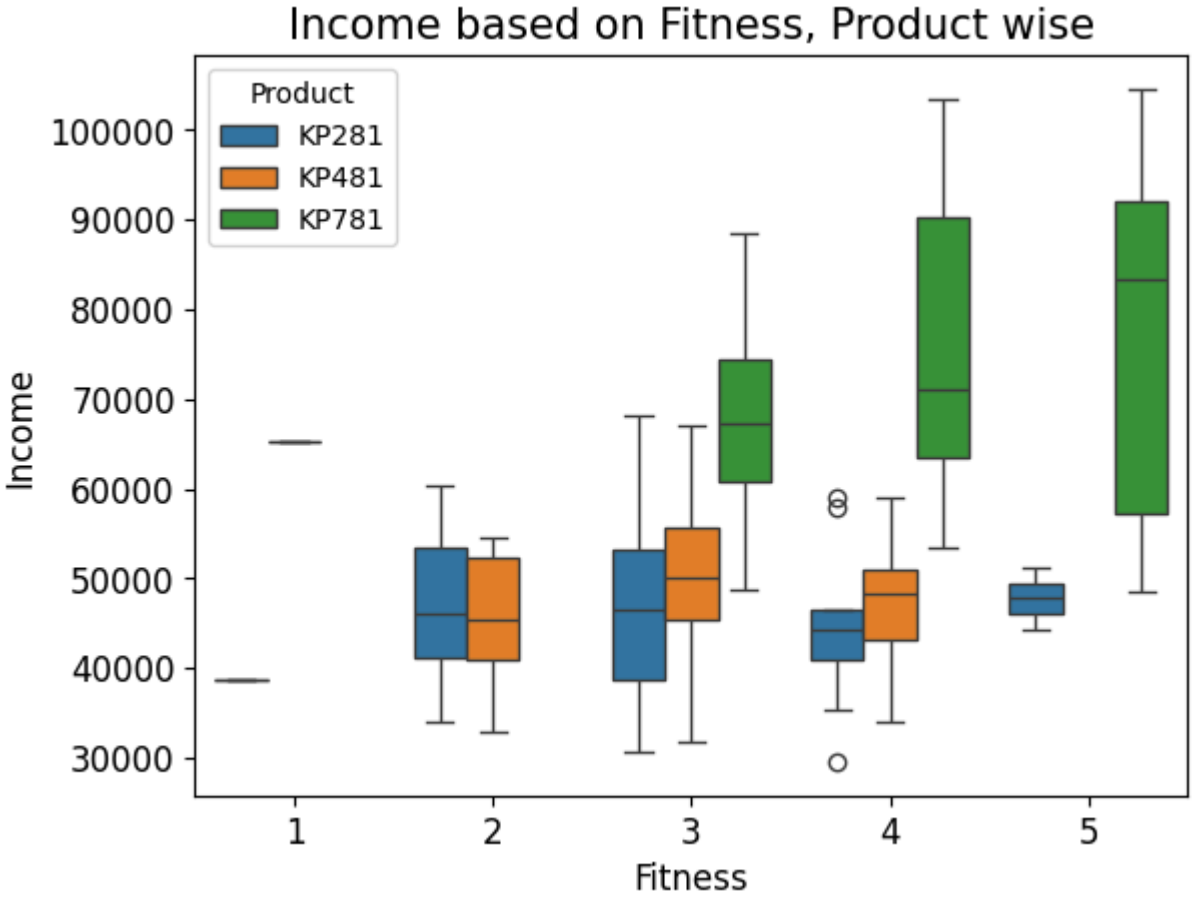
```
for i in catcols:
  sns.boxplot(x=i,y='Income',hue='Product',data=data)
  plt.xlabel(i, fontsize=12)
  plt.ylabel('Income', fontsize=12)
  plt.xticks(fontsize=12)
  plt.yticks(fontsize=12)
  plt.title(f'Income based on {i}, Product wise', fontsize=15)
  plt.show()
```

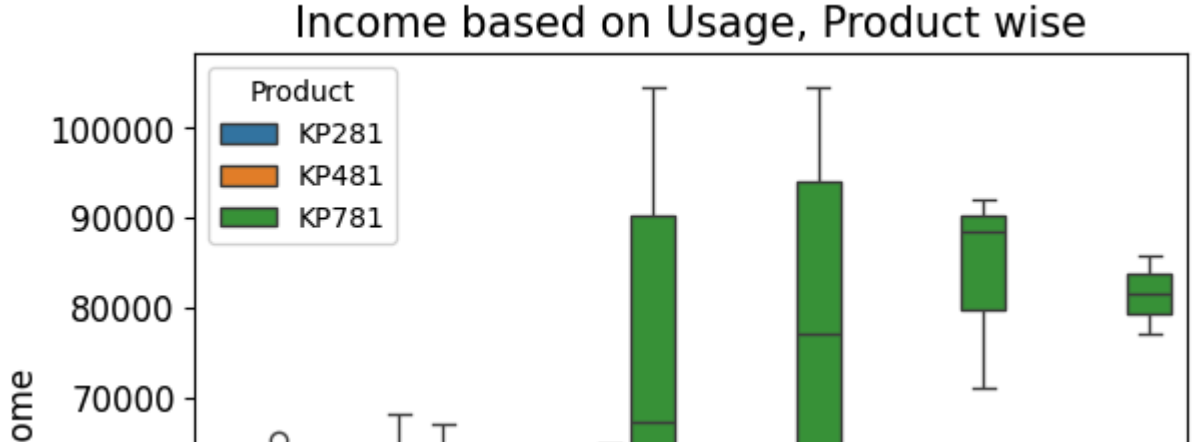

Income based on Gender, Product wise
Product
KP281
KP481
KP781
Income
100000
90000
80000
70000
60000
50000
40000
30000
Male
Female
Gender

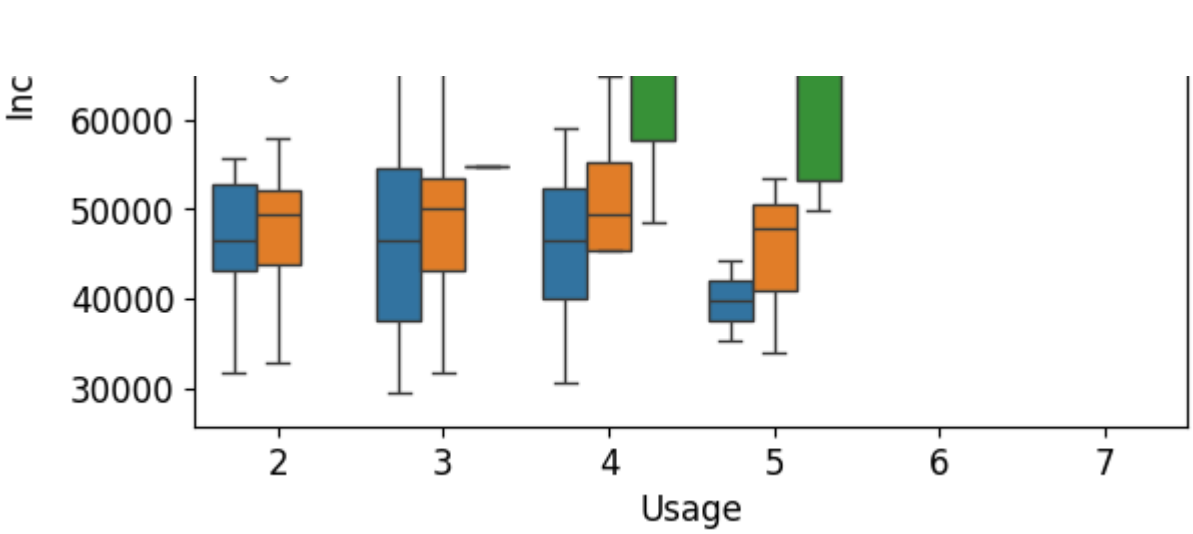

Income based on Education, Product wise
Product
KP281
KP481
KP781
Income
100000
90000
80000
70000
60000
50000
40000
30000
12
13
14
15
16
18
20
21
Education


Income based on MaritalStatus, Product wise
Product
KP281
KP481
100000


KP781
90000
80000
70000
60000
50000
40000
30000
Income
Single
Partnered
MaritalStatus

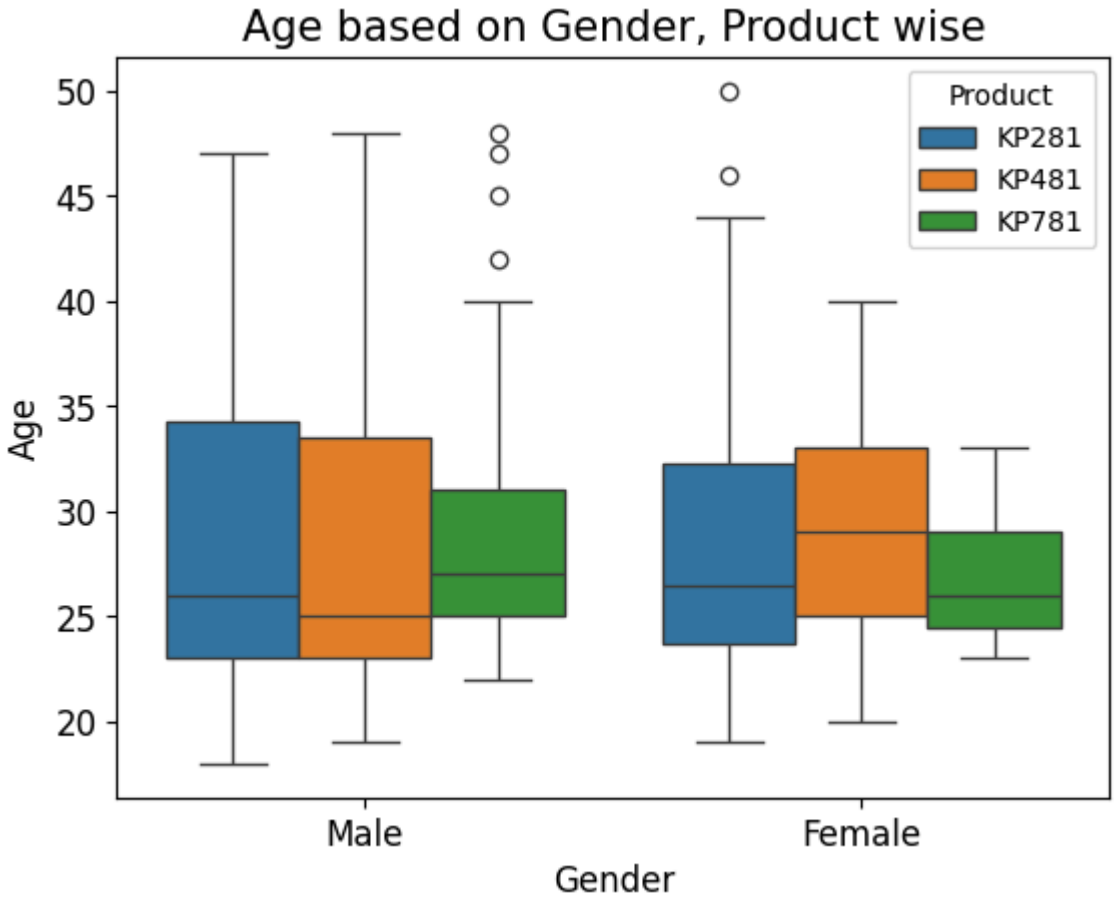

Income based on Fitness, Product wise
Product
KP281
KP481
KP781
100000
90000
80000
70000
60000
50000
40000
30000
Income
1
2
3
4
5
Fitness

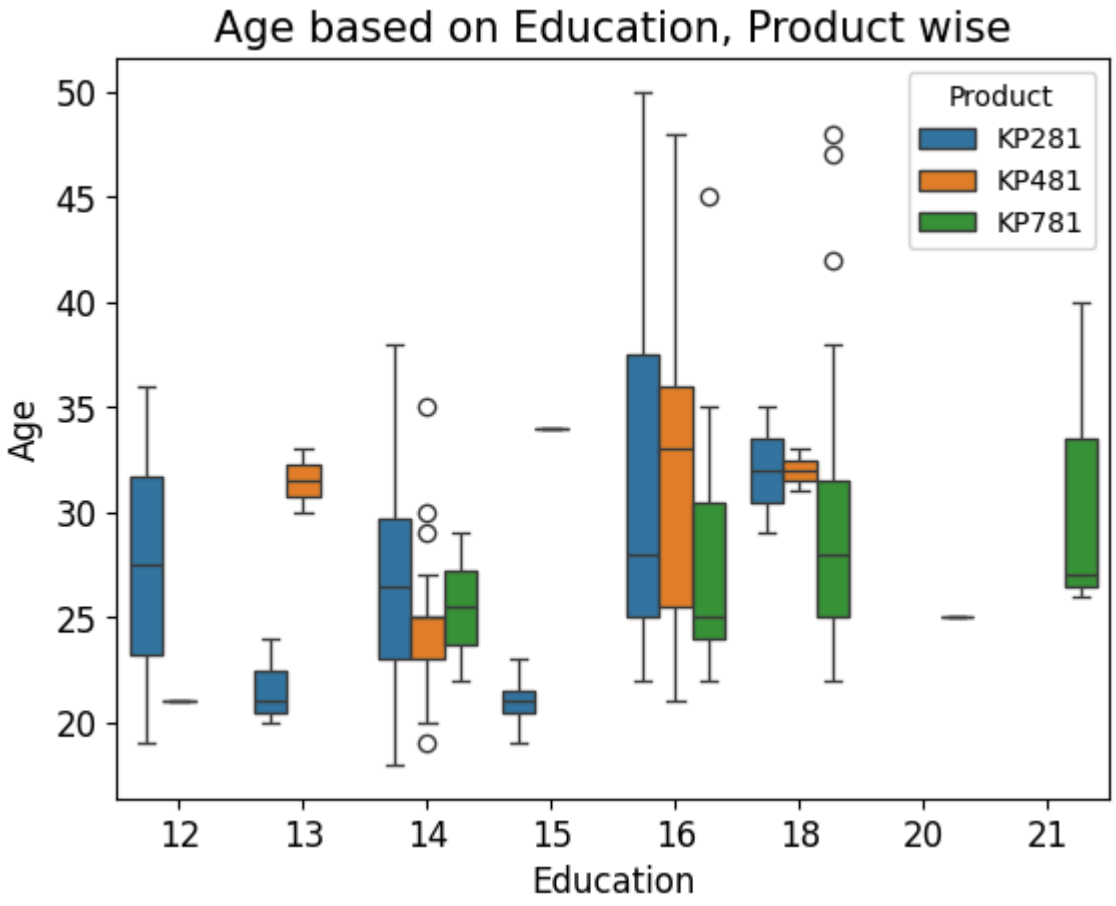

Income based on Usage, Product wise
Product
KP281
KP481
KP781
100000
90000
80000
70000

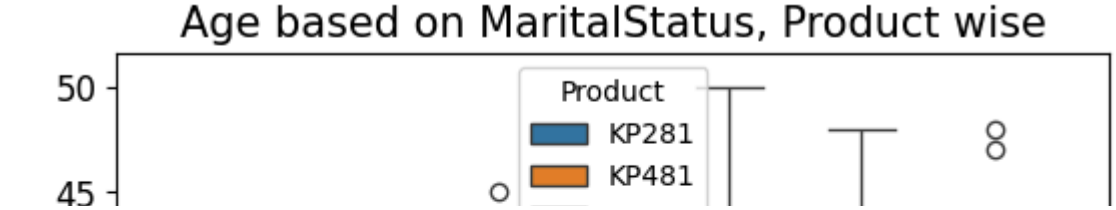

Inc
60000
50000
40000
30000
2
3
4
5
6
7
Usage

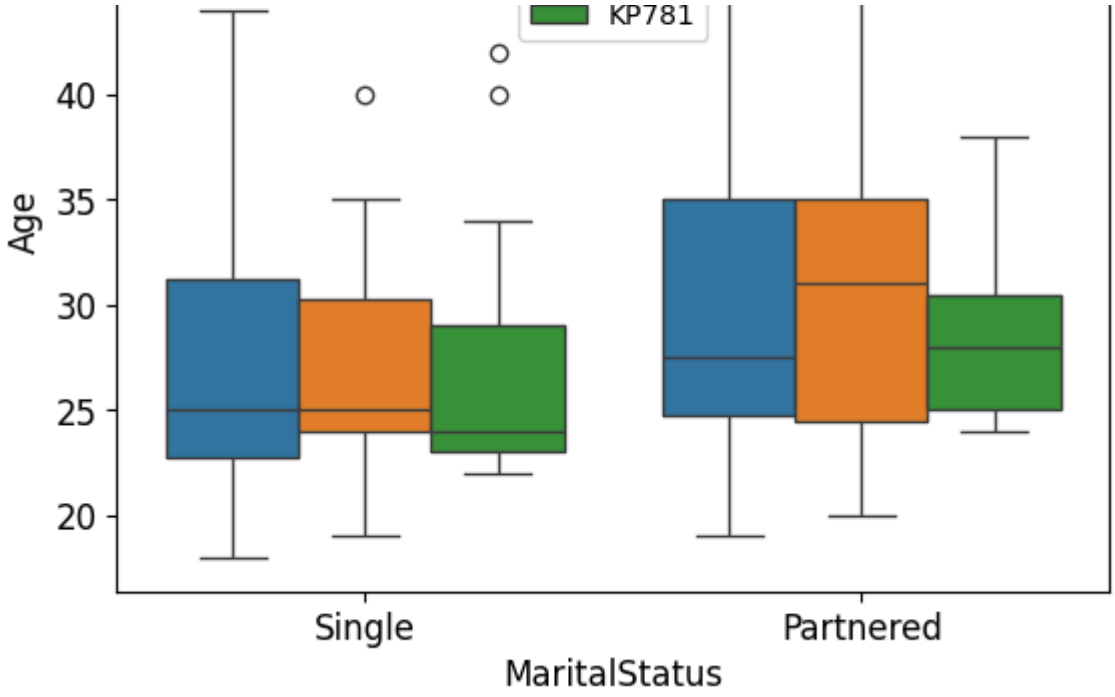
Multivariate analysis of Product on the basis of age:

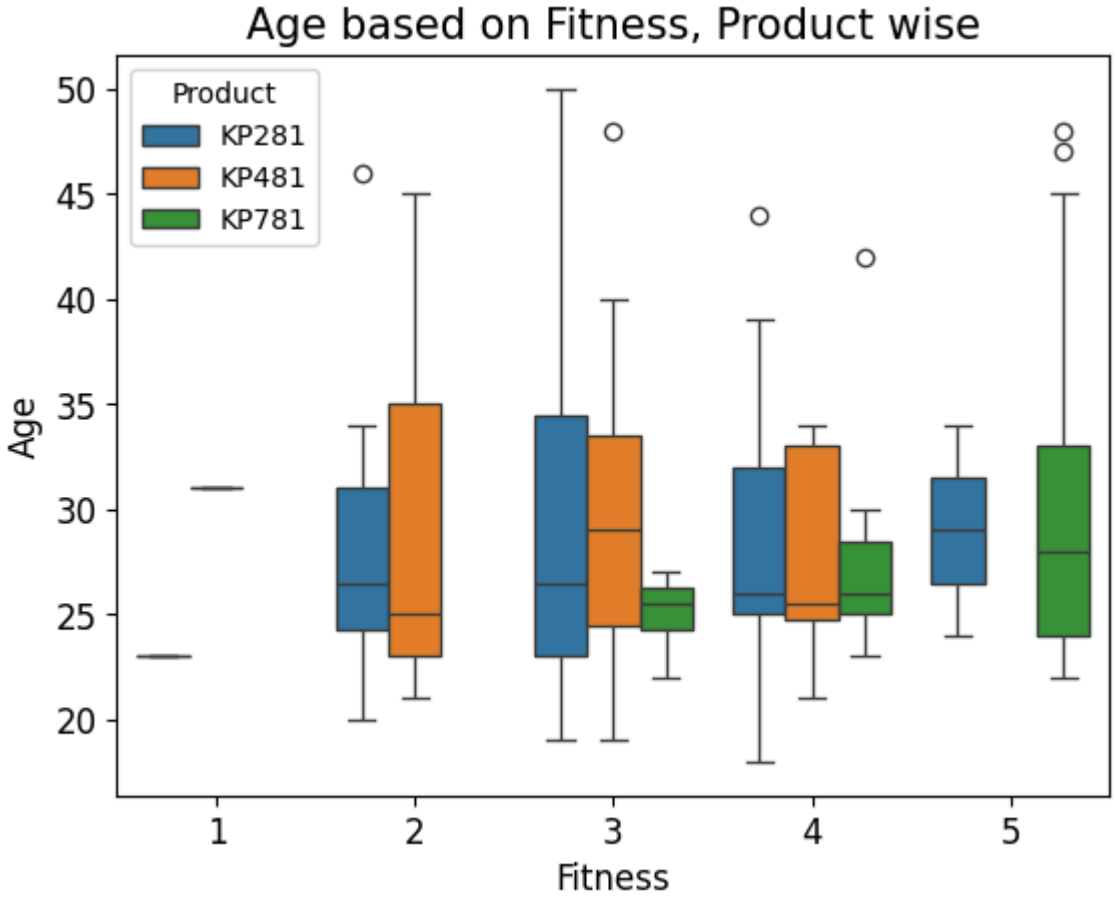
```
for i in catcols:
  sns.boxplot(x=i,y='Age',hue='Product',data=data)
  plt.xlabel(i, fontsize=12)
  plt.ylabel('Age', fontsize=12)
  plt.xticks(fontsize=12)
  plt.yticks(fontsize=12)
  plt.title(f'Age based on {i}, Product wise', fontsize=15)
  plt.show()
```

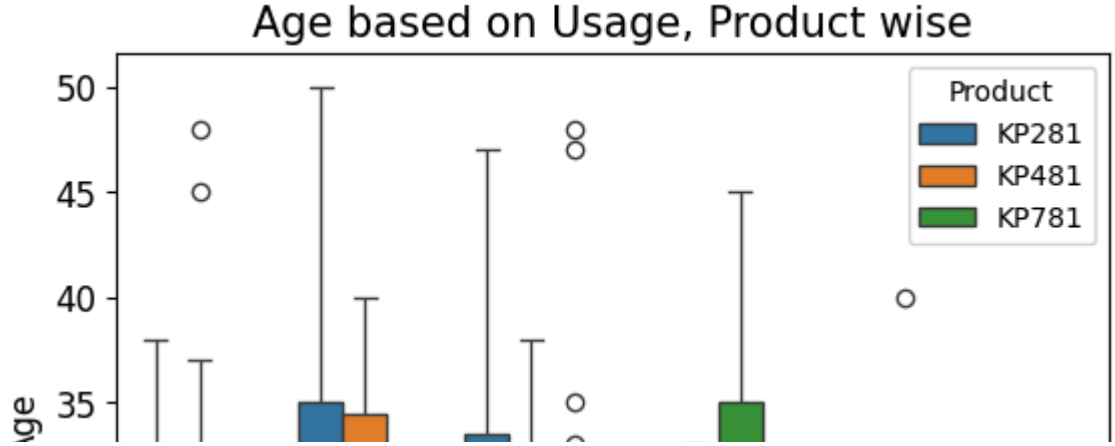

Age based on Gender, Product wise
Product
KP281
KP481
KP781
Age
50
45
40
35
30
25
20
Male
Female
Gender

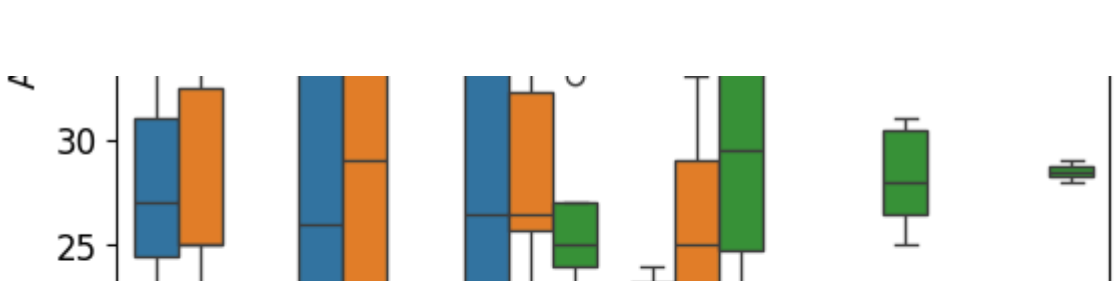

Age based on Education, Product wise
Product
KP281
KP481
KP781
Age
50
45
40
35
30
25
20
12
13
14
15
16
18
20
21
Education


Age based on MaritalStatus, Product wise
Product
KP281
KP481
50
45


KP781
40
35
30
25
20
Age
Single
Partnered
MaritalStatus


Age based on Fitness, Product wise
Product
KP281
KP481
KP781
50
45
40
35
30
25
20
Age
1
2
3
4
5
Fitness


Age based on Usage, Product wise
Product
KP281
KP481
KP781
50
45
40
35


30
25