Aerofit Business Case - Descriptive Statistics

About Aerofit:

Aerofit is a leading brand in the field of fitness equipment. Aerofit provides a product range including machines such as treadmills, exercise bikes, gym equipment, and fitness accessories to cater to the needs of all categories of people.

Problem Statement:

The market research team at AeroFit wants to identify the characteristics of the target audience for each type of treadmill offered by the company, to provide a better recommendation of the treadmills to the new customers. The team decides to investigate whether there are differences across the product with respect to customer characteristics.

- Perform descriptive analytics to create a customer profile for each AeroFit treadmill product by developing appropriate tables and charts.
- For each AeroFit treadmill product, construct two-way contingency tables and compute all conditional and marginal probabilities along with their insights/impact on the business.

Column Profiling:

- Product Purchased: KP281, KP481, or KP781
- · Age: In years
- Gender: Male/Female
- · Education: In years
- · MaritalStatus: Single or partnered
- Usage: The average number of times the customer plans to use the treadmill each week.
- Income: Annual income (in \$)
- Fitness: Self-rated fitness on a 1-to-5 scale, where 1 is the poor shape and 5 is the excellent shape.
- Miles: The average number of miles the customer expects to walk/run each week

Importing Libraries and Dataset

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

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
```



#Finding the datatypes of the columns data.dtypes



0 Product object

int64 Age Gender object

Education int64

MaritalStatus object

int64 Usage

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):

200	0010000	J COTA	
#	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

0 Age

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
        Usage
                    6
        Fitness
                    5
        Income
         Miles
                   37
    dtype: int64
```

→ Analyzing value counts

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

count

Gender

Male 104

Female 76

dtype: int64
```

data['Product'].value_counts()

```
Product

KP281 80

KP481 60

KP781 40
```

dtype: int64

data['Education'].value_counts()

```
→
                count
     Education
        16
                   85
        14
                   55
        18
                   23
        15
                    5
        13
                    5
        12
        21
                    3
        20
    dtype: int64
```

data['MaritalStatus'].value_counts()

ααται	Maritaistatu	is].vaiue_cou
-		count
	MaritalStatu	s
	Partnered	107
	Single	73
	dtype: int64	

data['Usage'].value_counts()

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

dtype: int64

data['Fitness'].value_counts()

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

dtype: int64

data['Miles'].value_counts()

count

	count
Miles	
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()

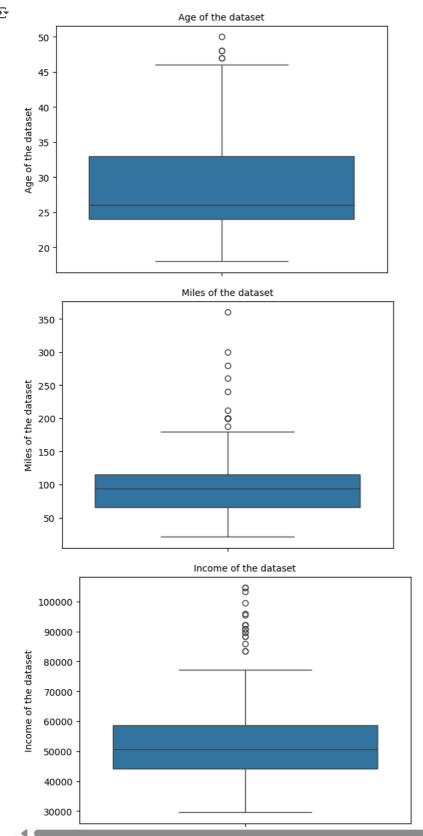
		_
•		۰
-	→	

	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()
```



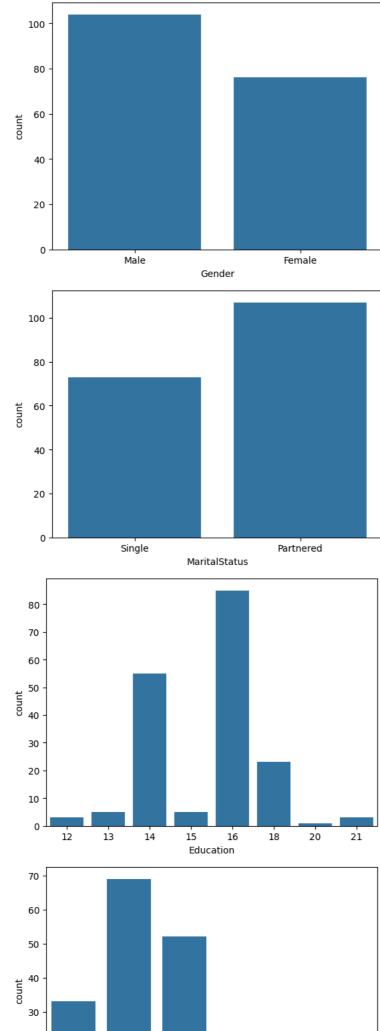


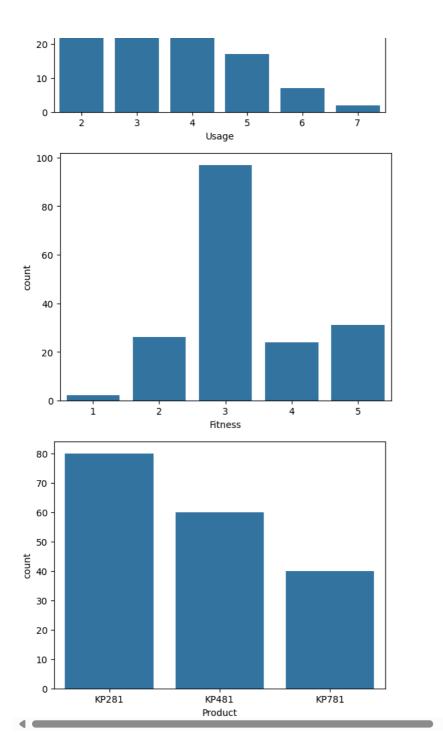
data.describe()

count 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.00000 180.000000 180.00000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 180.000000 16.000000 1.0084797 0.958869 16506.684226 51.863605 51.863605 180.000000 29562.000000 21.000000 21.000000 29562.000000 21.000000 40.00000 40.00000 40.00000 40.000000 58668.000000 114.750000		Age	Education	Usage	Fitness	Income	Miles
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 50596.500000 94.000000 75% 33.000000 16.000000 4.000000 4.000000 58668.000000 114.750000	count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000
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 4.000000 50596.500000 94.000000 75% 33.000000 16.000000 4.000000 58668.000000 114.750000	mean	28.788889	15.572222	3.455556	3.311111	53719.577778	103.194444
25% 24.000000 14.000000 3.000000 3.000000 44058.750000 66.000000 50% 26.000000 16.000000 3.000000 50596.500000 94.000000 75% 33.000000 16.000000 4.000000 58668.000000 114.750000	std	6.943498	1.617055	1.084797	0.958869	16506.684226	51.863605
50% 26.000000 16.000000 3.000000 50596.500000 94.000000 75% 33.000000 16.000000 4.000000 58668.000000 114.750000	min	18.000000	12.000000	2.000000	1.000000	29562.000000	21.000000
75% 33.000000 16.000000 4.000000 58668.000000 114.750000	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
max 50.000000 21.000000 7.000000 5.000000 104581.000000 360.000000	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

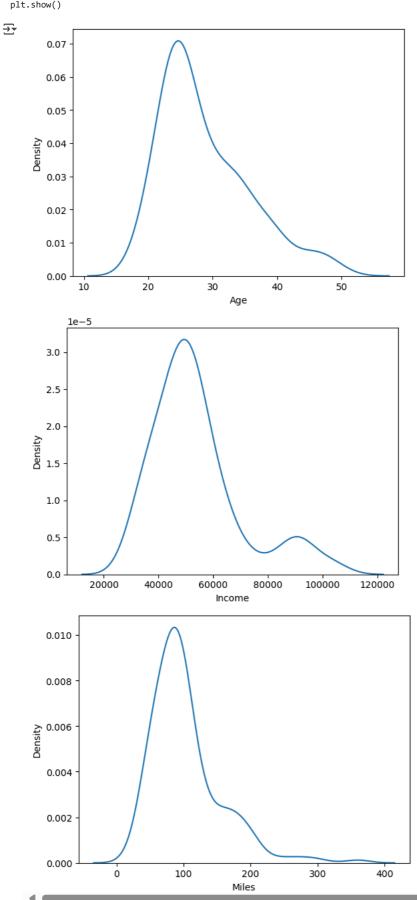
Univariate Analysis

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

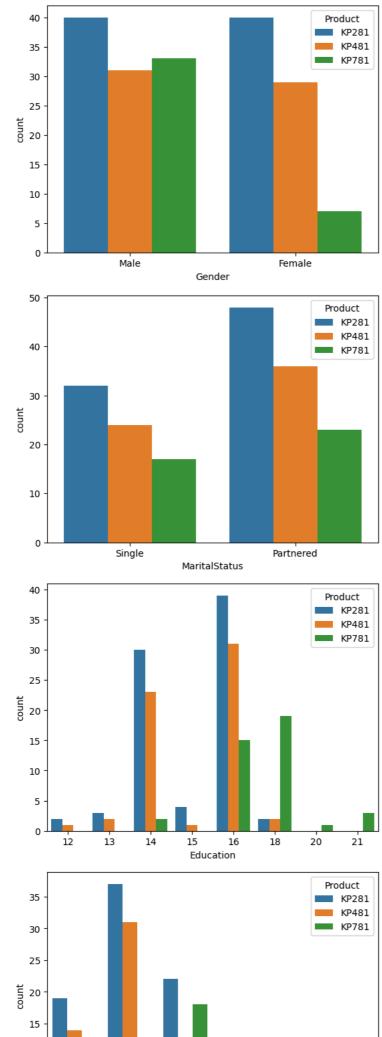


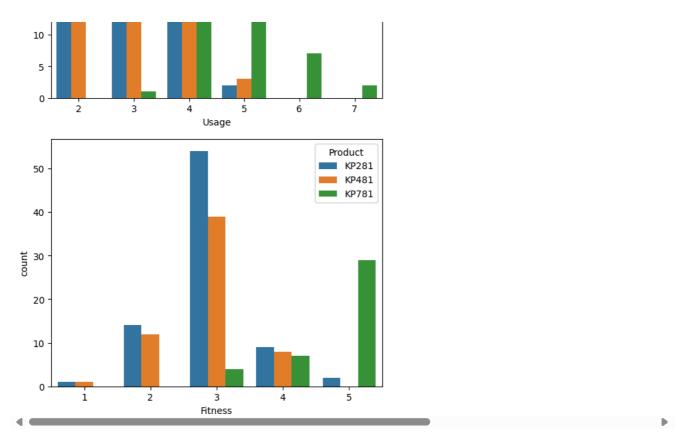


For Numerical variables
num_cols=['Age','Income','Miles']
for i in num_cols:
 sns.kdeplot(data[i])
 plt.show()

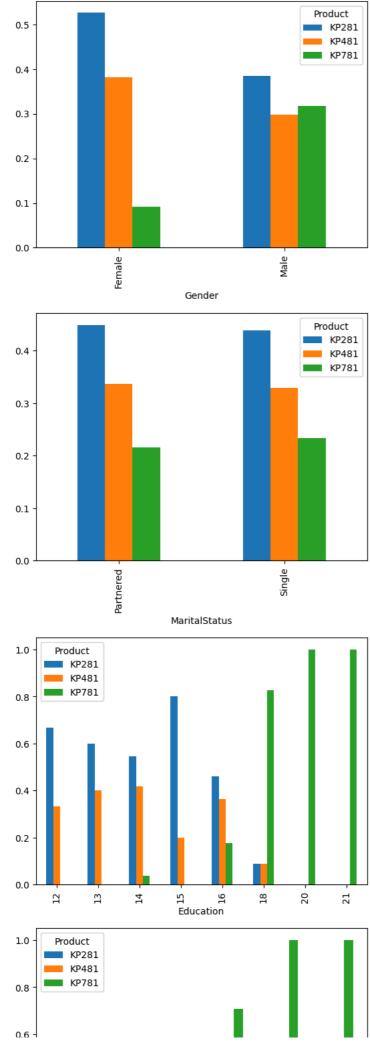


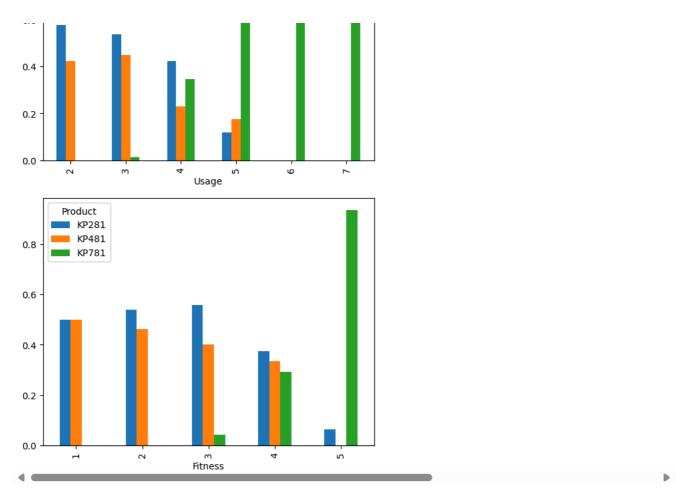
#Bivariate Analysis fo categorical using values
cat_cols=['Gender','MaritalStatus','Education','Usage','Fitness']
for i in cat_cols:
 sns.countplot(x=i,hue='Product',data=data)
 plt.show()



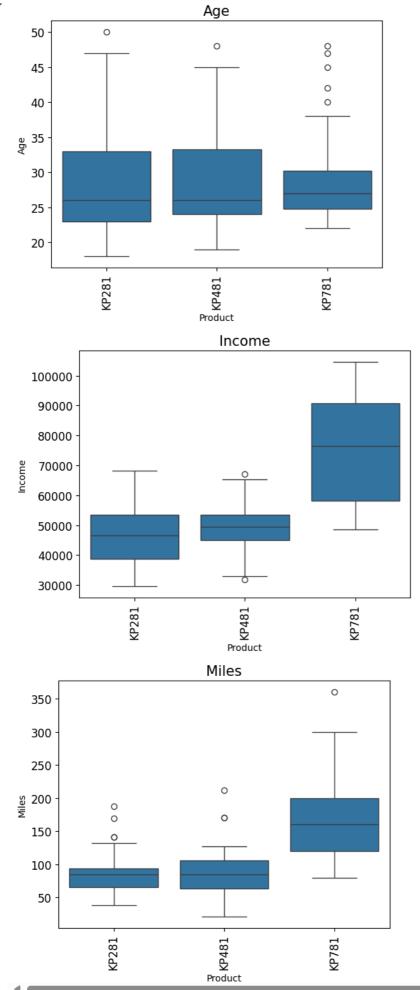


```
#Bivariate Analysis fo categorical using Propotions/Percentage
for i in cat_cols:
    i=pd.crosstab(data[i],data['Product'],normalize='index')
    i.plot(kind='bar')
    plt.show()
```





```
#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()
```

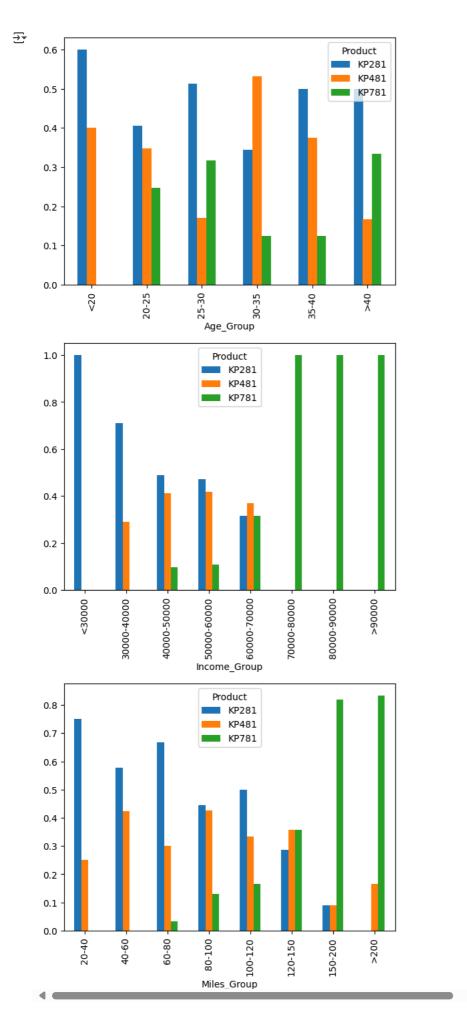


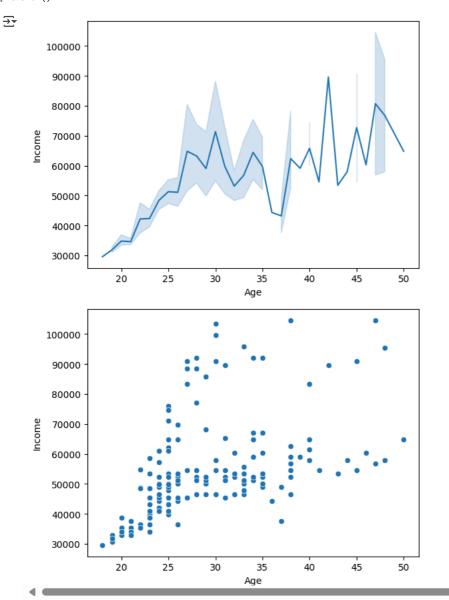
```
# Binning numerical columns to categorical
bins=[0,30000,40000,50000,60000,70000,80000,90000,120000]
labels=['<30000','30000-40000','40000-50000','50000-60000','60000-70000','70000-80000','80000-90000','>90000']
data['Income_Group']=pd.cut(data['Income'],bins=bins,labels=labels)
data.head()
bins=[0,20,25,30,35,40,51]
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	Income_Group	Age_Group	Miles_Group
	0	KP281	18	Male	14	Single	3	4	29562	112	<30000	<20	100-120
	1	KP281	19	Male	15	Single	2	3	31836	75	30000-40000	<20	60-80
	2	KP281	19	Female	14	Partnered	4	3	30699	66	30000-40000	<20	60-80
	3	KP281	19	Male	12	Single	3	3	32973	85	30000-40000	<20	80-100
	4	KP281	20	Male	13	Partnered	4	2	35247	47	30000-40000	<20	40-60
4	•												

#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()

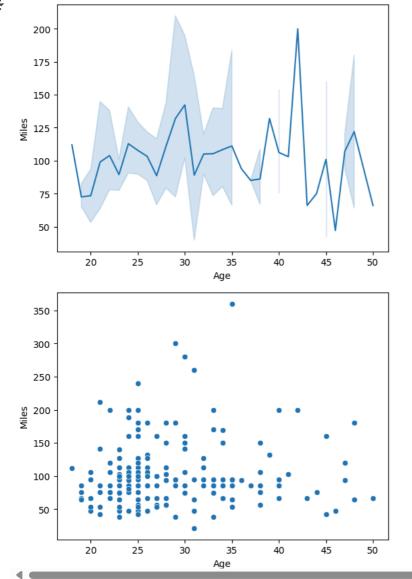
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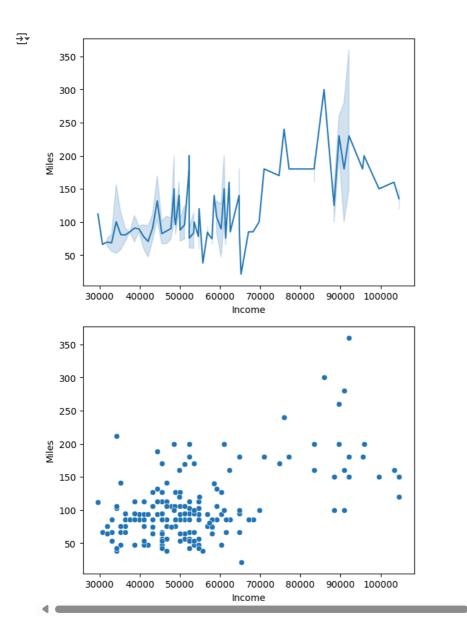
```
sns.lineplot(x='Age', y='Miles', data=data)
plt.show()
sns.scatterplot(x='Age', y='Miles', data=data)
plt.show()
```





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

 $\label{eq:sns.scatterplot} $$sns.scatterplot(x='Income', y='Miles', data=data)$ plt.show()$

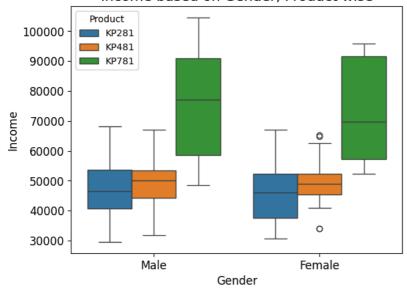


Multivariate

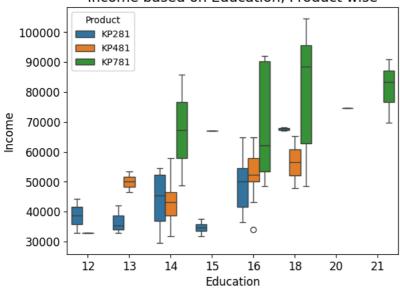
Multivariate analysis of Product on the basis of income.

```
data.columns
```

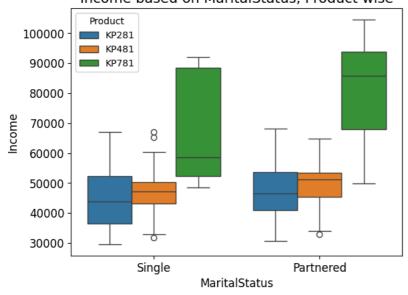
Income based on Gender, Product wise



Income based on Education, Product wise

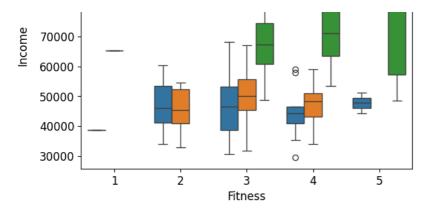


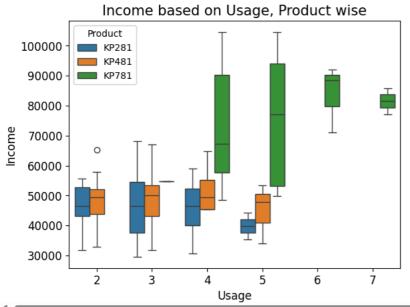
Income based on MaritalStatus, Product wise



Income based on Fitness, Product wise



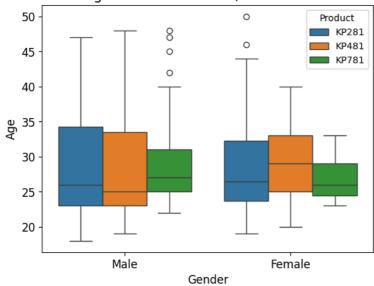




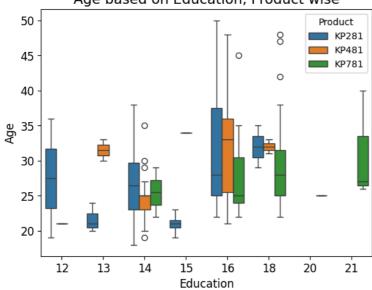
Multivariate analysis of Product on the basis of age:

```
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()
```

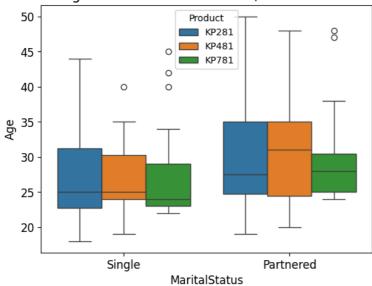
Age based on Gender, Product wise



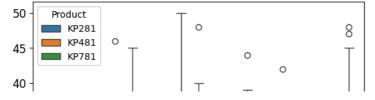
Age based on Education, Product wise

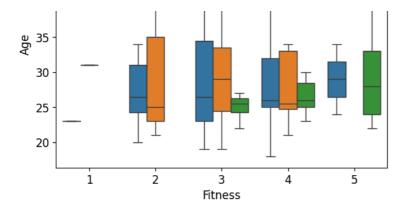


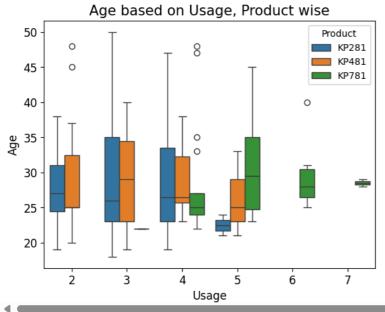
Age based on MaritalStatus, Product wise



Age based on Fitness, Product wise

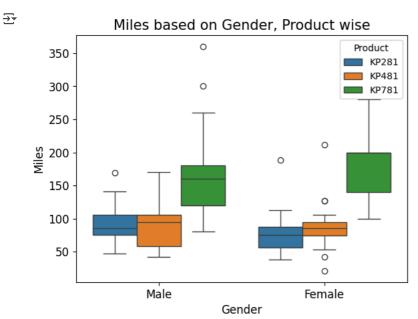






Multivariate analysis of Product on the basis of Miles:

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



Miles based on Education, Product wise