aerofit-case-study

March 20, 2024

[2]:
```
import pandas as pd
import numpy as np
from scipy.stats import binom
import matplotlib.pyplot as plt
import seaborn as sns
```

0.1 What does 'good' look like?

1. Import the dataset and do usual data analysis steps like checking the structure & characteristics of the dataset.

- The data type of all columns in the "customers" table.

  Hint: We want you to display the data type of each column present in the dataset.

- You can find the number of rows and columns given in the dataset

  Hint: We want you to find the shape of the dataset.

- Check for the missing values and find the number of missing values in each column

[3]:
```
!wget https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/
↪original/aerofit_treadmill.csv?1639992749 -O "Aerofit.csv"
```

```
--2024-03-20 13:03:48--  https://d2beiqkhq929f0.cloudfront.net/public_assets/ass
ets/000/001/125/original/aerofit_treadmill.csv?1639992749
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)…
108.157.172.183, 108.157.172.10, 108.157.172.176, …
Connecting to d2beiqkhq929f0.cloudfront.net
(d2beiqkhq929f0.cloudfront.net)|108.157.172.183|:443… connected.
HTTP request sent, awaiting response… 200 OK
Length: 7279 (7.1K) [text/plain]
Saving to: 'Aerofit.csv'

Aerofit.csv         100%[===================>]   7.11K  --.-KB/s    in 0s

2024-03-20 13:03:48 (4.25 GB/s) - 'Aerofit.csv' saved [7279/7279]
```

[4]:
```
df=pd.read_csv('Aerofit.csv')
```

[5]:
```
df.head()
```

[5]:

	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

[6]:
```
#Data Types of all columns in the Customers table
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    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
```

[7]:
```
#Describing the data, basic statistical analysis of all numeric columns
df.describe()
```

[7]:

	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	
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	

```
25%     66.000000
50%     94.000000
75%    114.750000
max    360.000000
```

###Insights: 1. The age range of customers is from 18 to 50 years , with a mean age of around 29 years. 2. Customer education levels vary between 12 and 21 years , with an average education duration of 16 years . 3. Customers use the aerofit products approximately 2 to 7 times per week , with an average usage frequency of 3 times per week . 4. On average, customers have rated their fitness at 3 on a 5-point scale, reflecting a moderate level of fitness . 5. The annual income of customers is in the range of 29,000 to 100,000 , with an average income of approximately 54,000 . 6. Customers' weekly running goals range from 21 to 360 miles , with an average target of 103 miles per week.

[8]:
```
#Number of rows and columns given in the dataset
df.shape
##180 rows, 9 columns
```

[8]:
```
(180, 9)
```

[9]:
```
#Finding the number of missing values in each column
df.isnull().sum()
#No missing values in any column in the dataset
```

[9]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

There are no missing values in the dataset.

[11]:
```
df.duplicated().value_counts()
```

[11]:
```
False    180
dtype: int64
```

There are no duplicates in the dataset

[12]:
```
df.nunique()
```

[12]:
```
Product     3
Age        32
```

```
Gender            2
Education         8
MaritalStatus     2
Usage             6
Fitness           5
Income           62
Miles            37
dtype: int64
```

[14]:
```
# checking the unique values for columns
for i in df.columns:
 print('Unique Values in',i,'column are :-')
 print(df[i].unique())
 print('-'*80)
```

```
Unique Values in Product column are :-
['KP281' 'KP481' 'KP781']
--------------------------------------------------------------------------------
Unique Values in Age column are :-
[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]
--------------------------------------------------------------------------------
Unique Values in Gender column are :-
['Male' 'Female']
--------------------------------------------------------------------------------
Unique Values in Education column are :-
[14 15 12 13 16 18 20 21]
--------------------------------------------------------------------------------
Unique Values in MaritalStatus column are :-
['Single' 'Partnered']
--------------------------------------------------------------------------------
Unique Values in Usage column are :-
[3 2 4 5 6 7]
--------------------------------------------------------------------------------
Unique Values in Fitness column are :-
[4 3 2 1 5]
--------------------------------------------------------------------------------
Unique Values in Income column are :-
[ 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]
--------------------------------------------------------------------------------
Unique Values in Miles column are :-
```

```
[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]
--------------------------------------------------------------------------------
```

[ ]:
```
df['Product'].value_counts()
```

[ ]:
```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

[ ]:
```
df['Gender'].value_counts()
```

[ ]:
```
Male      104
Female     76
Name: Gender, dtype: int64
```

[ ]:
```
df['Education'].value_counts()
```

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

###Observations:

1. There are no missing values in the data.
2. There are 3 unique products of Aerofit - 'KP281', 'KP481', 'KP781', top most being the product KP281 with 80 purchases.
3. There are a total of 180 rows and 9 columns in the dataset.
4. The Age range of people who have purchased and used the Aerofit products is 18 to 50, 28.79 being the mean value. Only 25% of the people are above 33 years of age.
5. Most of the people using the Aerofit products have atleast 16 years of Education completed.
6. Out of 180 purchase/usage records, 104 users are Male, 76 are female users.

0.2 2. Detect Outliers

- Find the outliers for every continuous variable in the dataset

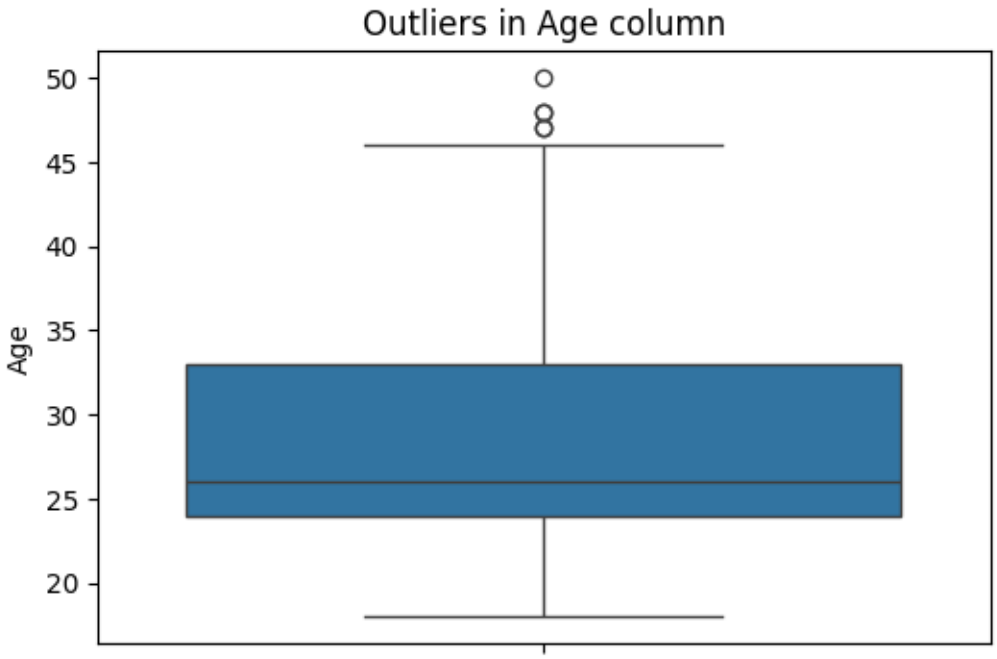
  Hint: We want you to use boxplots to find the outliers in the given dataset

- Remove/clip the data between the 5 percentile and 95 percentile

  Hint: We want You to use np.clip() for clipping the data

[ ]:
```
#AGE OUTLIERS
plt.figure(figsize=(6,4))
sns.boxplot(data=df,y='Age')
plt.title('Outliers in Age column')
```

[ ]:
```
Text(0.5, 1.0, 'Outliers in Age column')
```



[ ]:
```
iqr=df['Age'].quantile(0.75)-df['Age'].quantile(0.25)
ll=df['Age'].quantile(0.25) - (1.5*iqr) #lower limit -> 10.5
ul=df['Age'].quantile(0.75) + (1.5*iqr) #upper limit -> 46.5
ll
```

[ ]:
```
10.5
```

[ ]:
```
df[(df['Age']>46.5)|(df['Age']<10.5)] #outliers in Age column
```

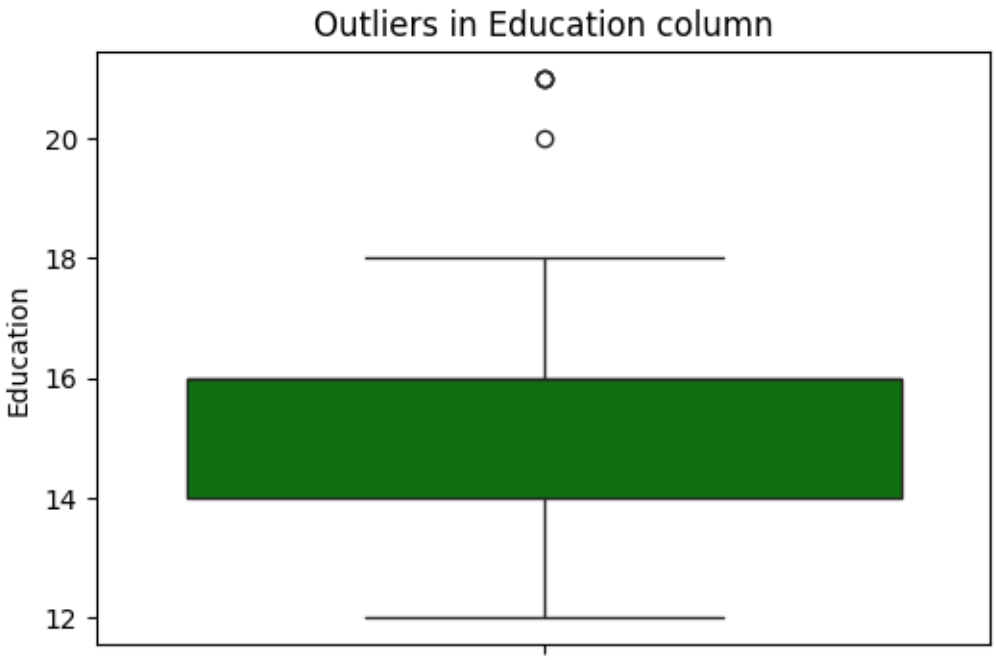
[ ]:
```
     Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
78     KP281   47    Male         16     Partnered      4        3   56850
79     KP281   50  Female         16     Partnered      3        3   64809
139    KP481   48    Male         16     Partnered      2        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
```

[ ]:
```
#EDUCATION (in years) OUTLIERS
plt.figure(figsize=(6,4))
sns.boxplot(data=df,y='Education',color='green')
plt.title('Outliers in Education column')
```

[ ]:
```
Text(0.5, 1.0, 'Outliers in Education column')
```



[ ]:
```
df['Education'].quantile(0.5)
```

[ ]:
```
16.0
```

[ ]:
```
iqr_education = df['Education'].quantile(0.75)-df['Education'].quantile(0.25)
ul_education=df['Education'].quantile(0.75) + (1.5*iqr_education)
ll_education=df['Education'].quantile(0.25) - (1.5*iqr_education)
ll_education
```

[ ]:
```
11.0
```

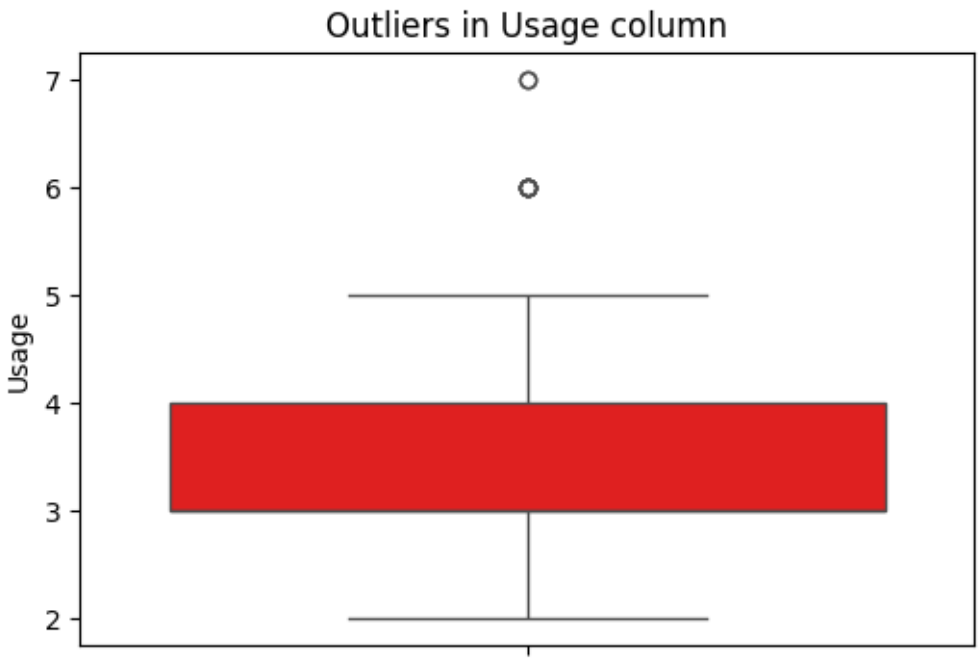
[ ]:
```
df[(df['Education']>19)|(df['Education']<11)] #outliers in Education column
```

[ ]:
```
     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
```

[ ]:
```
#USAGE OUTLIERS
plt.figure(figsize=(6,4))
sns.boxplot(data=df,y='Usage',color='red')
plt.title('Outliers in Usage column')
```

[ ]:
```
Text(0.5, 1.0, 'Outliers in Usage column')
```



[ ]:
```
df['Usage'].quantile(0.5)
```

[ ]:
```
3.0
```

[ ]:
```
iqr_Usage = df['Usage'].quantile(0.75)-df['Usage'].quantile(0.25)
ul_Usage=df['Usage'].quantile(0.75) + (1.5*iqr_Usage)
```

```
ll_Usage=df['Usage'].quantile(0.25) - (1.5*iqr_Usage)
ll_Usage
```

[ ]:
```
1.5
```

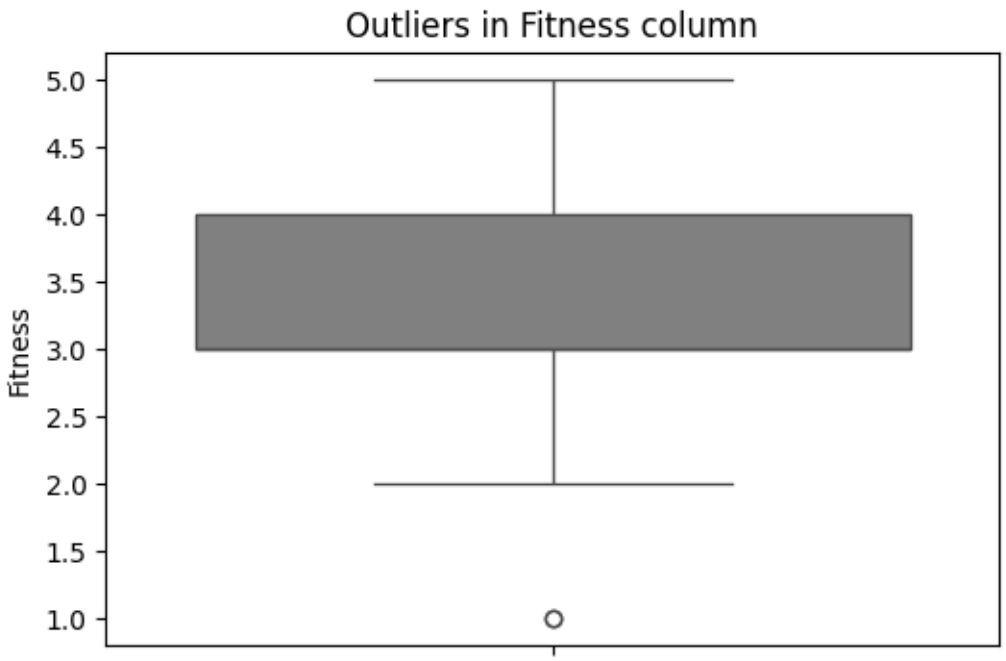
[ ]:
```
df[(df['Usage']>5.5)|(df['Usage']<1.5)] #outliers in Usage column
```

[ ]:
```
    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
```

[ ]:
```
#FITNESS OUTLIERS
plt.figure(figsize=(6,4))
sns.boxplot(data=df,y='Fitness',color='gray')
plt.title('Outliers in Fitness column')
```

[ ]:
```
Text(0.5, 1.0, 'Outliers in Fitness column')
```



[ ]:
```
df['Fitness'].quantile(0.5)
```

[ ]: 3.0

[ ]:
```
iqr_Fitness = df['Fitness'].quantile(0.75)-df['Fitness'].quantile(0.25)
ul_Fitness=df['Fitness'].quantile(0.75) + (1.5*iqr_Fitness)
ll_Fitness=df['Fitness'].quantile(0.25) - (1.5*iqr_Fitness)
ul_Fitness
```

[ ]: 5.5

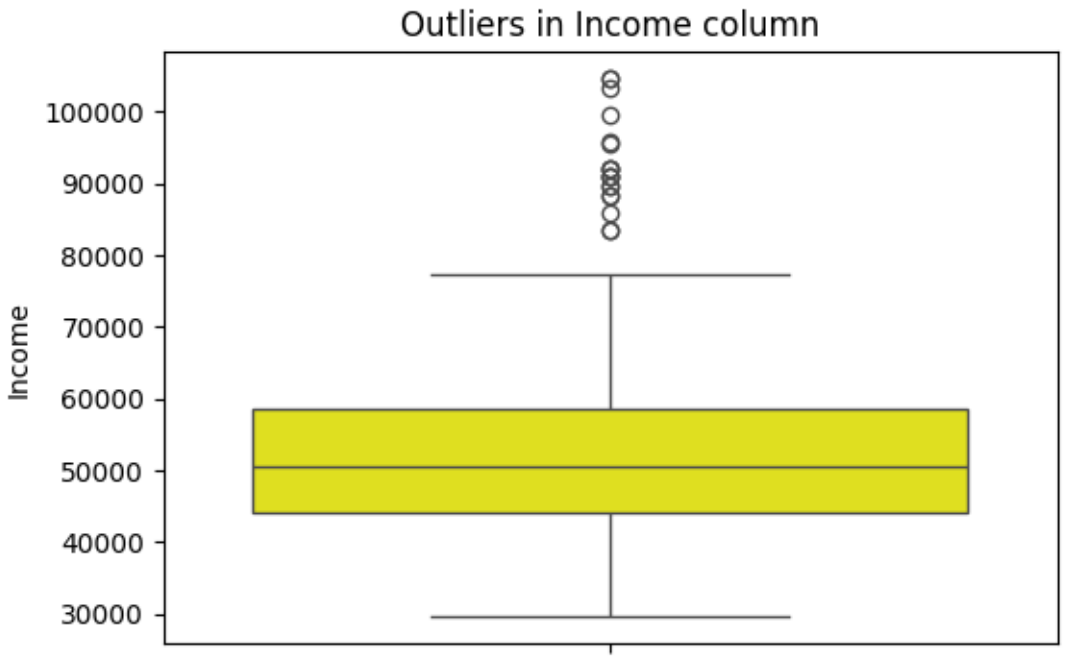
[ ]:
```
df[(df['Fitness']>5.5)|(df['Fitness']<1.5)] #outliers in Fitness column
```

[ ]:
```
     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
```

[ ]:
```
#INCOME OUTLIERS
plt.figure(figsize=(6,4))
sns.boxplot(data=df,y='Income',color='yellow')
plt.title('Outliers in Income column')
```

[ ]: Text(0.5, 1.0, 'Outliers in Income column')



[ ]:
```
df['Income'].quantile(0.5)
```

[ ]: 50596.5

[ ]:
```
iqr_Income = df['Income'].quantile(0.75)-df['Income'].quantile(0.25)
ul_Income=df['Income'].quantile(0.75) + (1.5*iqr_Income) #80581.875
ll_Income=df['Income'].quantile(0.25) - (1.5*iqr_Income) #22144.875
```

[ ]:
```
df[(df['Income']>80581.875)|(df['Income']<22144.875)] #outliers in Income column
```

[ ]:

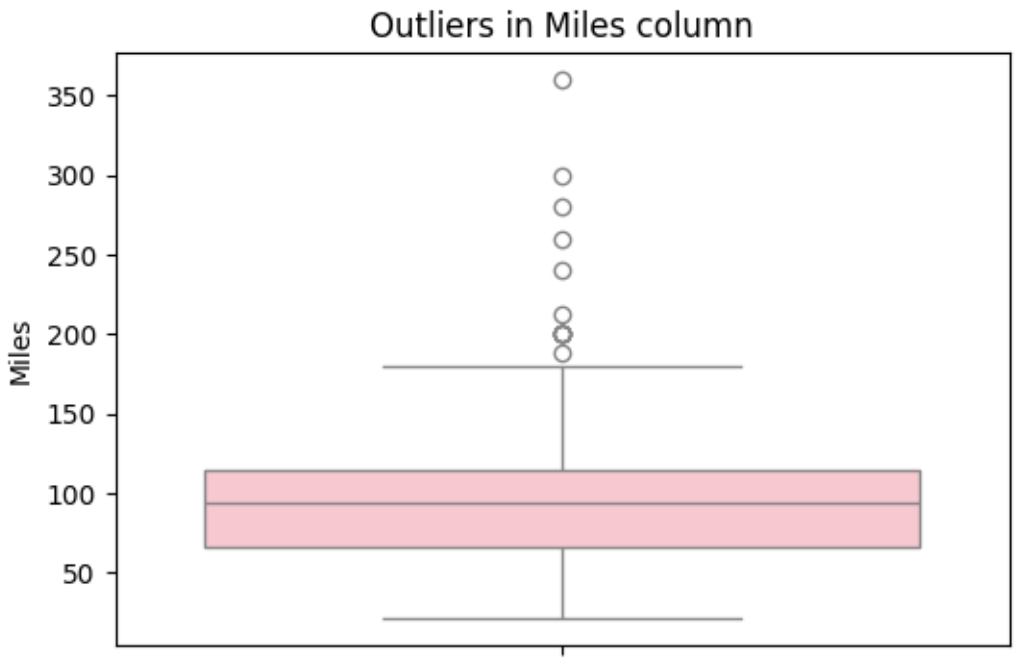
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	\
159	KP781	27	Male	16	Partnered	4	5	83416	
160	KP781	27	Male	18	Single	4	3	88396	
161	KP781	27	Male	21	Partnered	4	4	90886	
162	KP781	28	Female	18	Partnered	6	5	92131	
164	KP781	28	Male	18	Single	6	5	88396	
166	KP781	29	Male	14	Partnered	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
```

[ ]:
```
#MILES OUTLIERS
plt.figure(figsize=(6,4))
sns.boxplot(data=df,y='Miles',color='pink')
plt.title('Outliers in Miles column')
```

[ ]:
```
Text(0.5, 1.0, 'Outliers in Miles column')
```



[ ]:
```
df['Miles'].quantile(0.5)
```

[ ]: 94.0

[ ]:
```
iqr_Miles = df['Miles'].quantile(0.75)-df['Miles'].quantile(0.25)
ul_Miles=df['Miles'].quantile(0.75) + (1.5*iqr_Miles) #187.875
ll_Miles=df['Miles'].quantile(0.25) - (1.5*iqr_Miles) #-7.125 - Does not make␣
↪sense practically
```

[ ]:
```
df[(df['Miles']>187.875)] #outliers in Miles column
```

[ ]:

	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
```

###Observations: - Age, Education, Usage, Fitness data columns have very less (<10) outliers - Miles and Income data columns have plenty of outliers in the given dataset.

##Clipping data using np.clip()

[ ]:
```
#Age:

df['Age'] = np.clip(df['Age'],df['Age'].quantile(0.05),np.round(df['Age'].
 ↪quantile(0.95),2)) #5 percentile=20, 95 percentile = 43.049
df.head()
```

[ ]:
```
  Product   Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
0   KP281  20.0    Male         14        Single      3        4   29562
1   KP281  20.0    Male         15        Single      2        3   31836
2   KP281  20.0  Female         14     Partnered      4        3   30699
3   KP281  20.0    Male         12        Single      3        3   32973
4   KP281  20.0    Male         13     Partnered      4        2   35247

   Miles
0    112
1     75
2     66
3     85
4     47
```

[ ]:
```
#Education:

df['Education'] = np.clip(df['Education'],df['Education'].quantile(0.
 ↪05),df['Education'].quantile(0.95)) #5 percentile=14, 95 percentile = 18
df.head()
```

[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	\
0	KP281	20.0	Male	14	Single	3	4	29562	
1	KP281	20.0	Male	15	Single	2	3	31836	
2	KP281	20.0	Female	14	Partnered	4	3	30699	
3	KP281	20.0	Male	14	Single	3	3	32973	
4	KP281	20.0	Male	14	Partnered	4	2	35247	

	Miles
0	112
1	75
2	66
3	85
4	47

[ ]:
```
#Usage:

df['Usage'] = np.clip(df['Usage'],df['Usage'].quantile(0.05),np.
 ↪round(df['Usage'].quantile(0.95),2)) #5 percentile=2, 95 percentile = 5.05
df.head()
```

[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	\
0	KP281	20.0	Male	14	Single	3.0	4	29562	
1	KP281	20.0	Male	15	Single	2.0	3	31836	
2	KP281	20.0	Female	14	Partnered	4.0	3	30699	
3	KP281	20.0	Male	14	Single	3.0	3	32973	
4	KP281	20.0	Male	14	Partnered	4.0	2	35247	

	Miles
0	112
1	75
2	66
3	85
4	47

[ ]:
```
#Fitness:

df['Fitness'] = np.clip(df['Fitness'],df['Fitness'].quantile(0.
 ↪05),df['Fitness'].quantile(0.95)) #5 percentile=2, 95 percentile = 5
df.head()
```

[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	\
0	KP281	20.0	Male	14	Single	3.0	4	29562	
1	KP281	20.0	Male	15	Single	2.0	3	31836	
2	KP281	20.0	Female	14	Partnered	4.0	3	30699	
3	KP281	20.0	Male	14	Single	3.0	3	32973	
4	KP281	20.0	Male	14	Partnered	4.0	2	35247	

```
   Miles
0    112
1     75
2     66
3     85
4     47
```

[ ]:
```
#Income:

df['Income'] = np.clip(df['Income'],df['Income'].quantile(0.05),np.
 ↪round(df['Income'].quantile(0.95),2)) #5 percentile=34053.15, 95 percentile␣
 ↪= 90948.25
df.head()
```

[ ]:
```
  Product   Age  Gender  Education MaritalStatus  Usage  Fitness    Income  \
0   KP281  20.0    Male         14        Single    3.0        4  34053.15
1   KP281  20.0    Male         15        Single    2.0        3  34053.15
2   KP281  20.0  Female         14     Partnered    4.0        3  34053.15
3   KP281  20.0    Male         14        Single    3.0        3  34053.15
4   KP281  20.0    Male         14     Partnered    4.0        2  35247.00

   Miles
0    112
1     75
2     66
3     85
4     47
```

[ ]:
```
#Miles:

df['Miles'] = np.clip(df['Miles'],df['Miles'].quantile(0.05),df['Miles'].
 ↪quantile(0.95)) #5 percentile=47, 95 percentile = 200
df.head()
```

[ ]:
```
  Product   Age  Gender  Education MaritalStatus  Usage  Fitness    Income  \
0   KP281  20.0    Male         14        Single    3.0        4  34053.15
1   KP281  20.0    Male         15        Single    2.0        3  34053.15
2   KP281  20.0  Female         14     Partnered    4.0        3  34053.15
3   KP281  20.0    Male         14        Single    3.0        3  34053.15
4   KP281  20.0    Male         14     Partnered    4.0        2  35247.00

   Miles
0    112
1     75
2     66
3     85
4     47
```

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

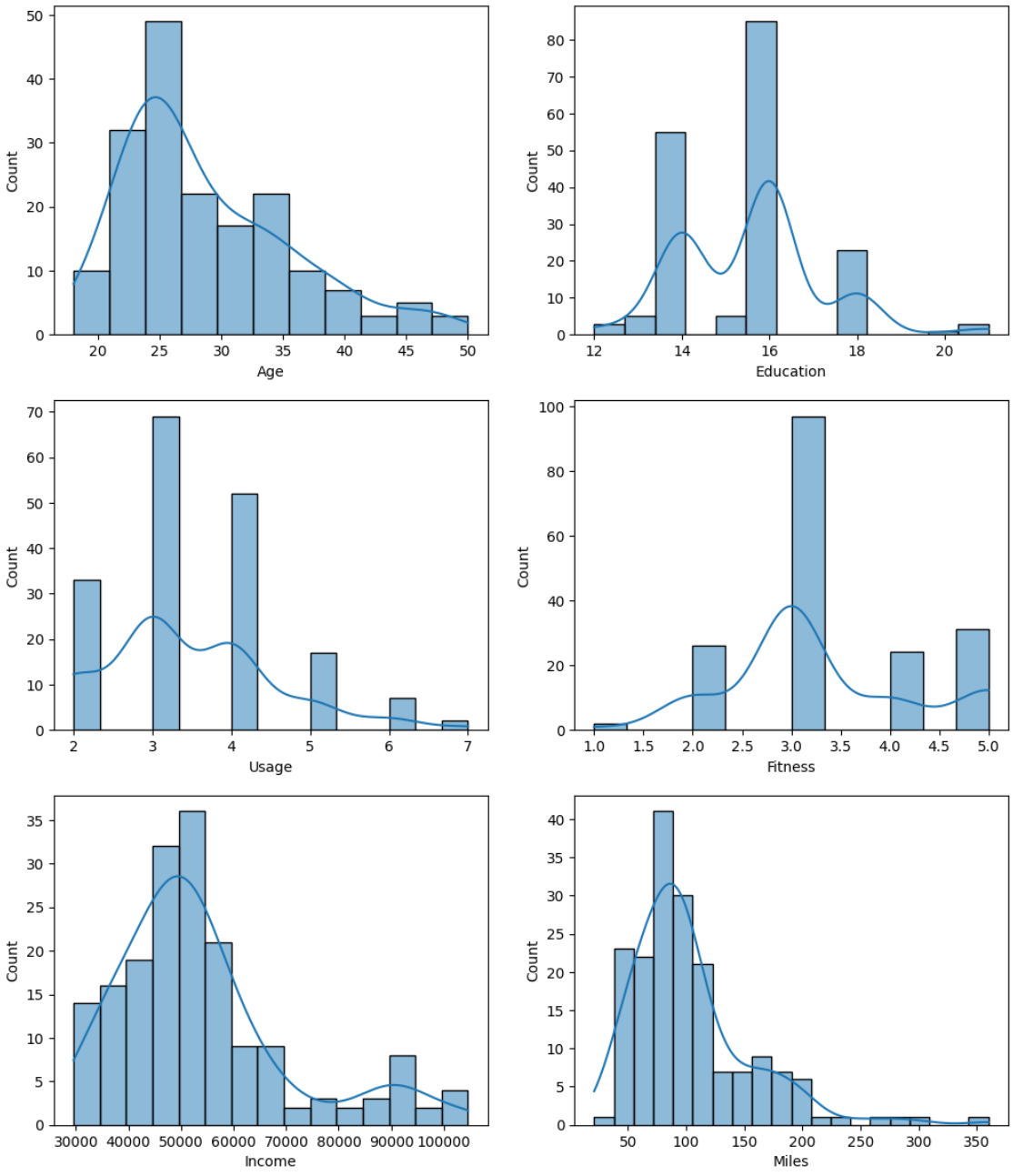
[ ]:
```
(180, 9)
```

####There are 180 records/ rows and 9 columns in the dataset.

###Univariate Analysis Understanding the distribution of the data for the quantitative attributes: Age, Education, Usage, Fitness, Income, Miles

[ ]:
```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12, 10))
fig.subplots_adjust(top=1.2)

sns.histplot(data=df, x="Age", kde=True, ax=axis[0,0])
sns.histplot(data=df, x="Education", kde=True, ax=axis[0,1])
sns.histplot(data=df, x="Usage", kde=True, ax=axis[1,0])
sns.histplot(data=df, x="Fitness", kde=True, ax=axis[1,1])
sns.histplot(data=df, x="Income", kde=True, ax=axis[2,0])
sns.histplot(data=df, x="Miles", kde=True, ax=axis[2,1])
plt.show()
```



0.3 3. Check if features like marital status, Gender, and age have any effect on the product purchased

- Find if there is any relationship between the categorical variables and the output variable in the data.

  Hint: We want you to use the count plot to find the relationship between categorical variables and output variables.

- Find if there is any relationship between the continuous variables and the output variable in the data.

  Hint: We want you to use a scatter plot to find the relationship between continuous variables and output variables.

Creating New Column and Categorizing values in Age,Education,Income and Miles to different classes for better visualization

Categorizing the values in age column in 4 different buckets: 1. Young Adult: from 18 - 25 2. Adults: from 26 - 35 3. Middle Aged Adults: 36-45 4. Elder :46 and above

Categorizing the values in education column in 3 different buckets: 1. Primary Education: upto 12 2. Secondary Education: 13 to 15 3. Higher Education: 16 and above

Categorizing the values in Income column in 4 different buckets: 1. Low Income - Upto 40,000 2. Moderate Income - 40,000 to 60,000 3. High Income - 60,000 to 80,000 4. Very High Income - Above 80,000

Categorizing the values in miles column in 4 different buckets: 1. Light Activity - Upto 50 miles 2. Moderate Activity - 51 to 100 miles 3. Active Lifestyle - 101 to 200 miles 4. Fitness Enthusiast - Above 200 miles

[16]:
```
#age bins
bin_range1 = [17,25,35,45,float('inf')]
bin_labels1 = ['Young Adults', 'Adults', 'Middle Aged Adults', 'Elder']
df['age_group'] = pd.cut(df['Age'],bins = bin_range1,labels = bin_labels1)

#education bins
bin_range2 = [0,12,15,float('inf')]
bin_labels2 = ['Primary Education', 'Secondary Education', 'Higher Education']
df['edu_group'] = pd.cut(df['Education'],bins = bin_range2,labels = bin_labels2)

#income bins
bin_range3 = [0,40000,60000,80000,float('inf')]
bin_labels3 = ['Low Income','Moderate Income','High Income','Very High Income']
df['income_group'] = pd.cut(df['Income'],bins = bin_range3,labels = bin_labels3)

#miles bins
bin_range4 = [0,50,100,200,float('inf')]
bin_labels4 = ['Light Activity', 'Moderate Activity', 'Active Lifestyle',␣
 ↪'Fitness Enthusiast ']
df['miles_group'] = pd.cut(df['Miles'],bins = bin_range4,labels = bin_labels4)
```

[17]:
```
df.head()
```

[17]:

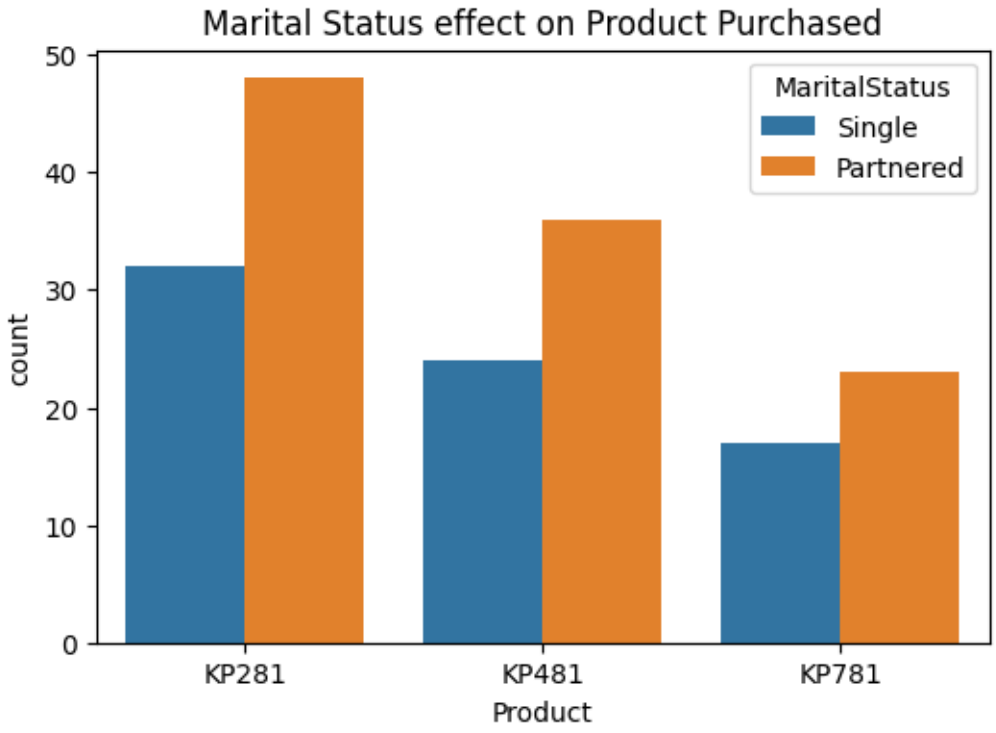
	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	\
0	KP281	18	Male	14	Single	3	4	29562	
1	KP281	19	Male	15	Single	2	3	31836	
2	KP281	19	Female	14	Partnered	4	3	30699	

```
3   KP281   19    Male          12         Single       3         3   32973
4   KP281   20    Male          13      Partnered       4         2   35247

   Miles     age_group            edu_group income_group        miles_group
0    112  Young Adults  Secondary Education   Low Income   Active Lifestyle
1     75  Young Adults  Secondary Education   Low Income  Moderate Activity
2     66  Young Adults  Secondary Education   Low Income  Moderate Activity
3     85  Young Adults    Primary Education   Low Income  Moderate Activity
4     47  Young Adults  Secondary Education   Low Income     Light Activity
```

[ ]:
```
#Marital Status effect on Product Purchased
plt.figure(figsize=(6,4))
sns.countplot(data=df,x='Product',hue='MaritalStatus')
plt.title('Marital Status effect on Product Purchased')
```

[ ]:
```
Text(0.5, 1.0, 'Marital Status effect on Product Purchased')
```



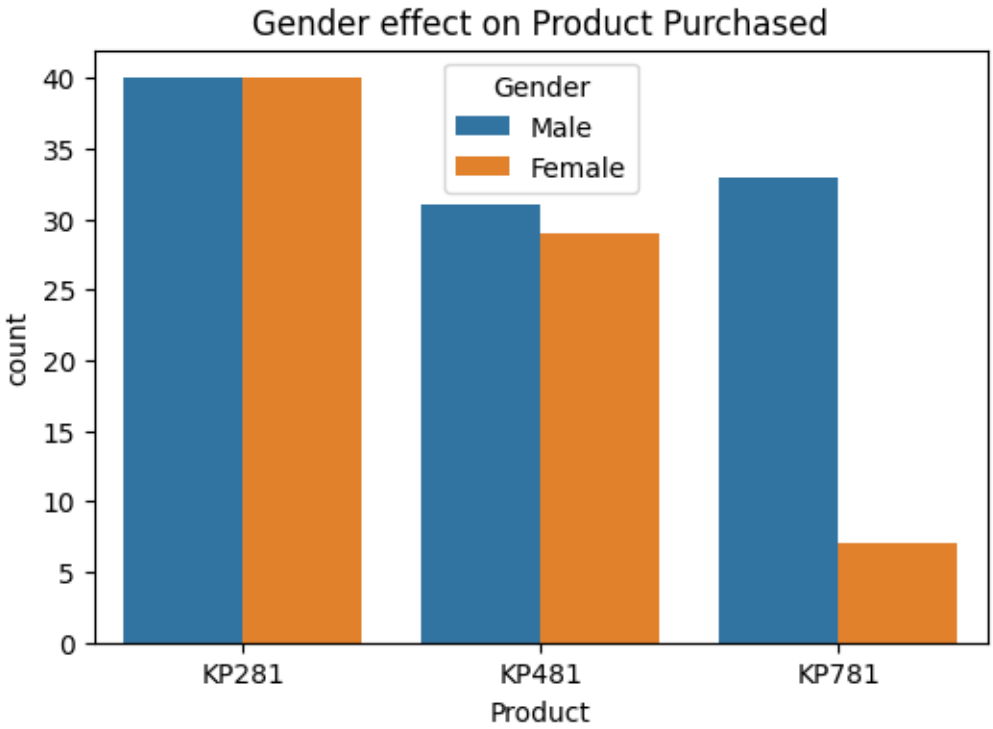
Insights:

– We can see that, for all 3 products, Partnered customers tend to buy the aerofit products more than single customers.

[ ]:
```
#Gender effect on Product Purchased
plt.figure(figsize=(6,4))
```

```
sns.countplot(data=df,x='Product',hue='Gender')
plt.title('Gender effect on Product Purchased')
```

[ ]: Text(0.5, 1.0, 'Gender effect on Product Purchased')

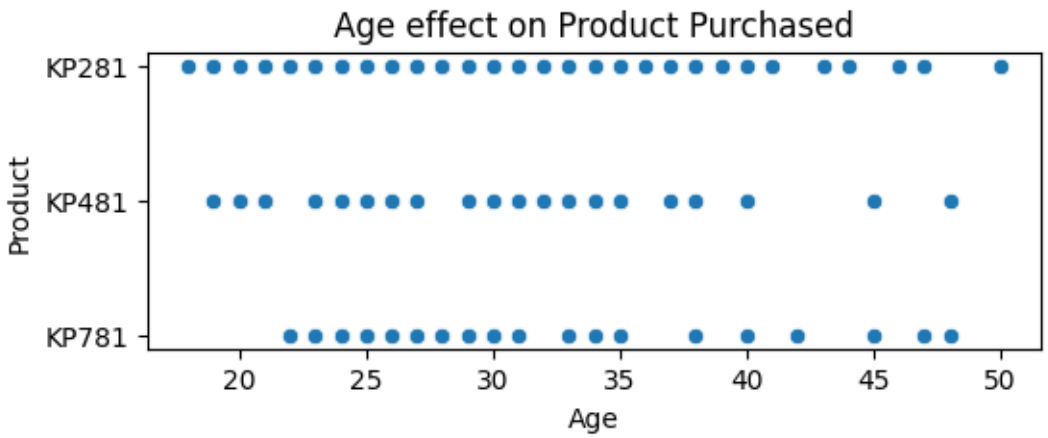


Insights:

– We see that KP281 has equal distribution based on gender, but KP781 is bought more by Male users than female.

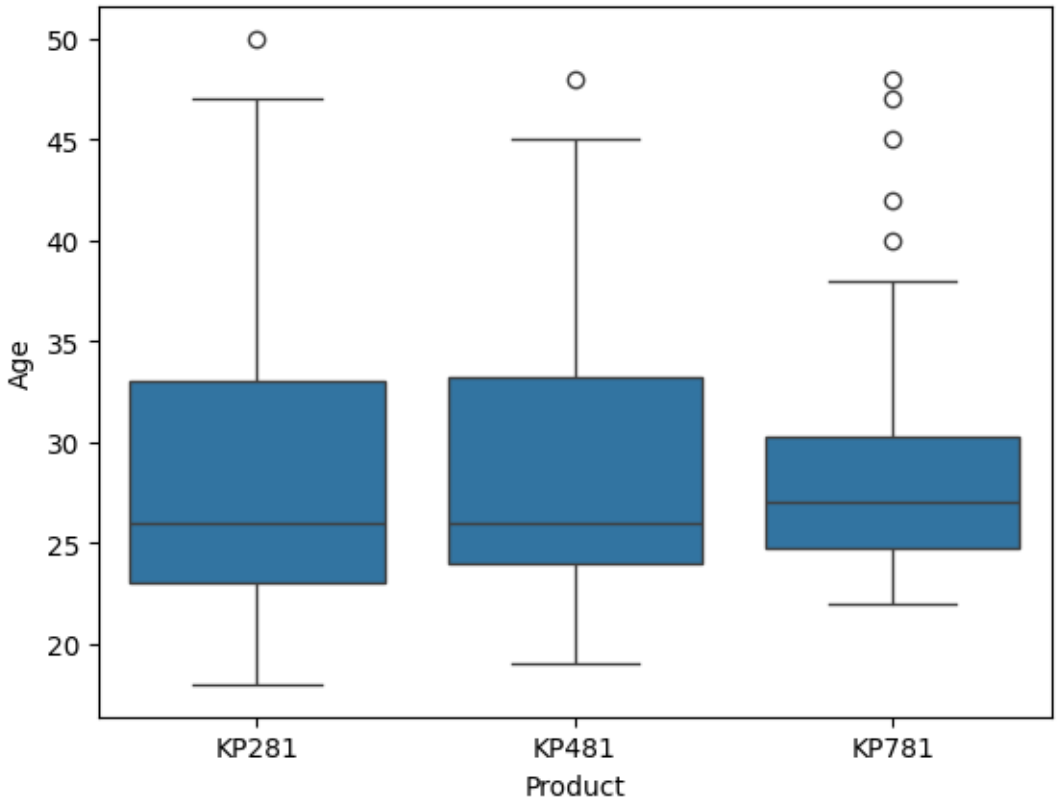
[39]:
```
#Age effect on Product Purchased
plt.figure(figsize=(6,2))
sns.scatterplot(data=df,x='Age',y='Product')
plt.title('Age effect on Product Purchased')
```

[39]: Text(0.5, 1.0, 'Age effect on Product Purchased')



[41]:
```
#PRODUCT vs AGE
sns.boxplot(data=df, x='Product', y='Age')
```

[41]:
```
<Axes: xlabel='Product', ylabel='Age'>
```



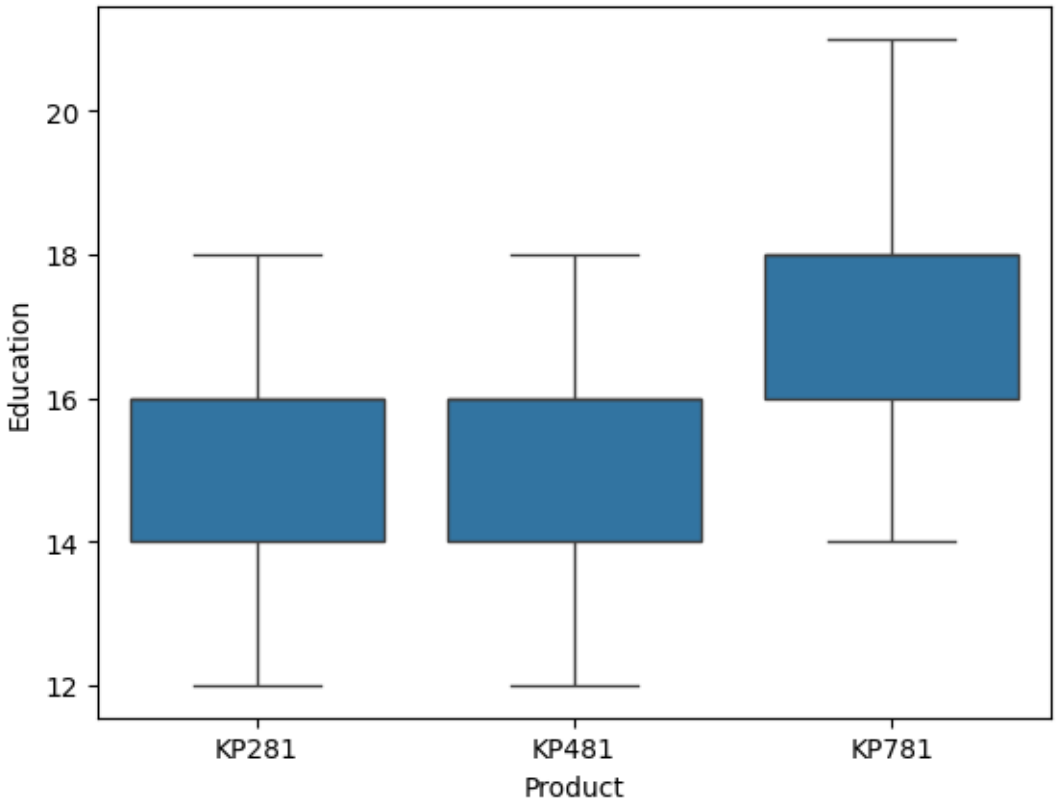
Insights:

– We see that the median age of customers purchasing KP281 and KP481 is almost the same.

– KP781 is mostly bought by people in the age group 25 to 30.

[42]:
```
#PRODUCT vs EDUCATION
sns.boxplot(data=df, x='Product', y='Education')
```

[42]:
```
<Axes: xlabel='Product', ylabel='Education'>
```

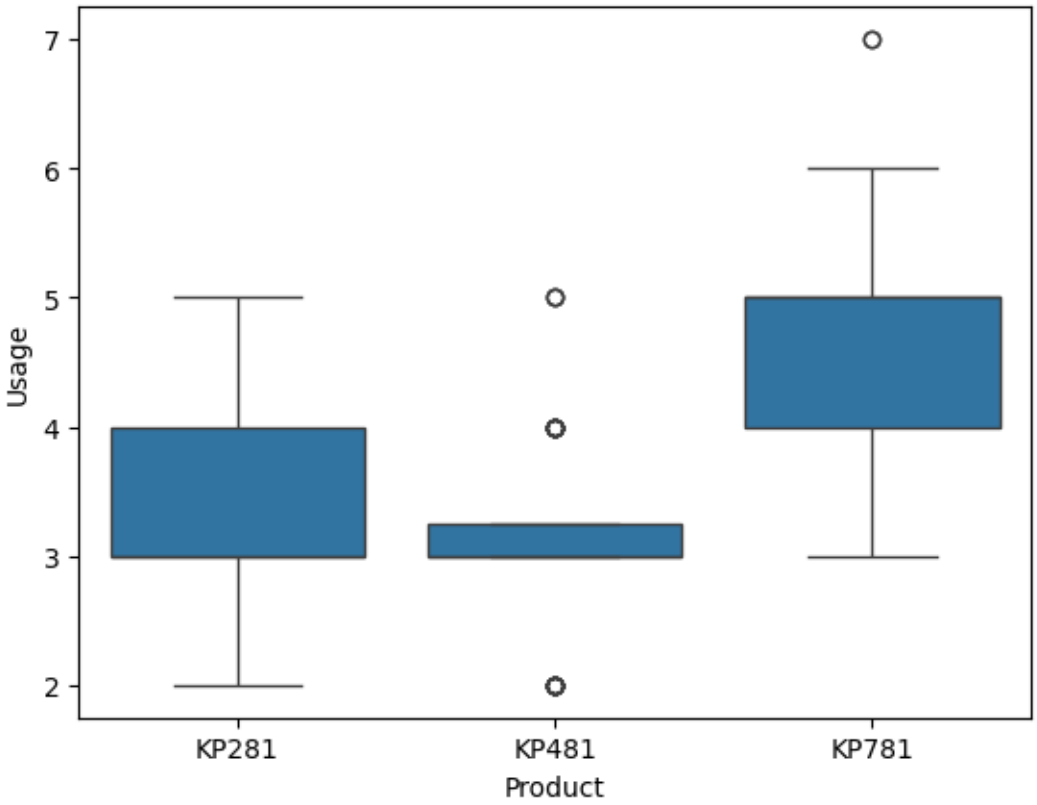


Insights:

– People who have completed 16 years of education tend to buy KP781. On the other hand, people who have less than 16 years of education have equal chances of buying KP281 and KP481.

[43]:
```
#PRODUCT vs USAGE
sns.boxplot(data=df, x='Product', y='Usage')
```

[43]:
```
<Axes: xlabel='Product', ylabel='Usage'>
```

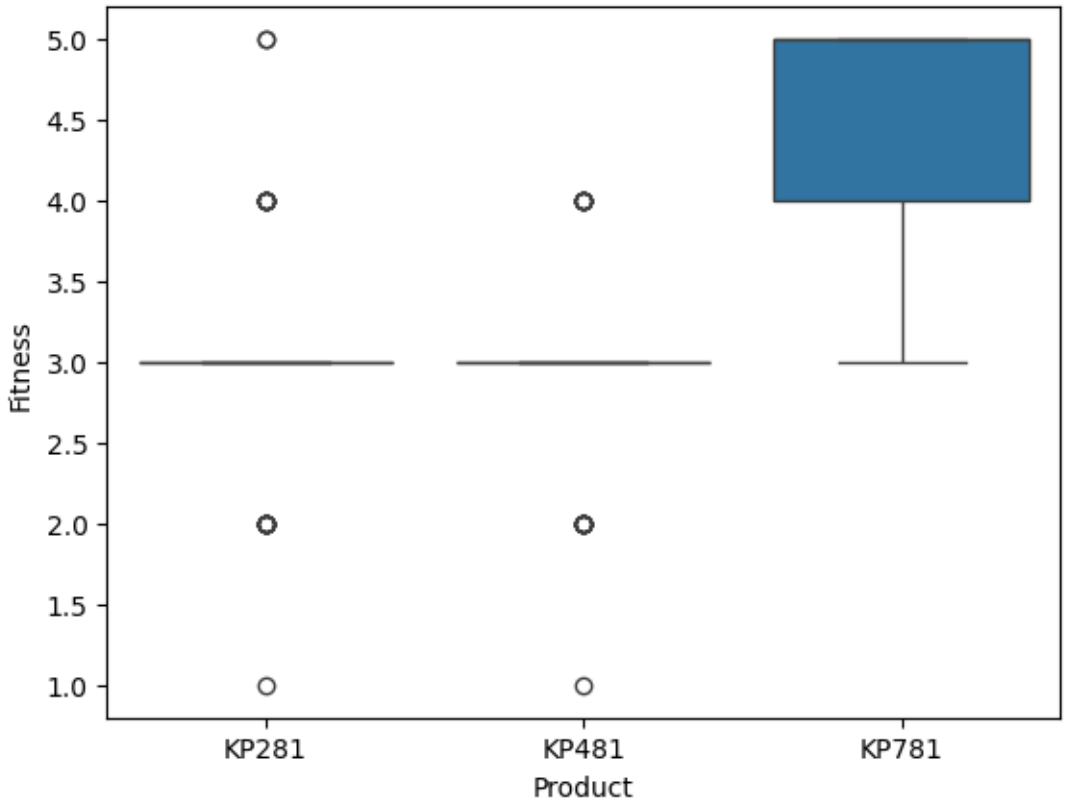


Insights:

–Customers who use treadmill atleast 4-5 times a week tend to buy KP781, rest fo the user base mostly buy KP281 and KP481.

[44]:
```
#PRODUCT vs FITNESS
sns.boxplot(data=df, x='Product', y='Fitness')
```

[44]:
```
<Axes: xlabel='Product', ylabel='Fitness'>
```



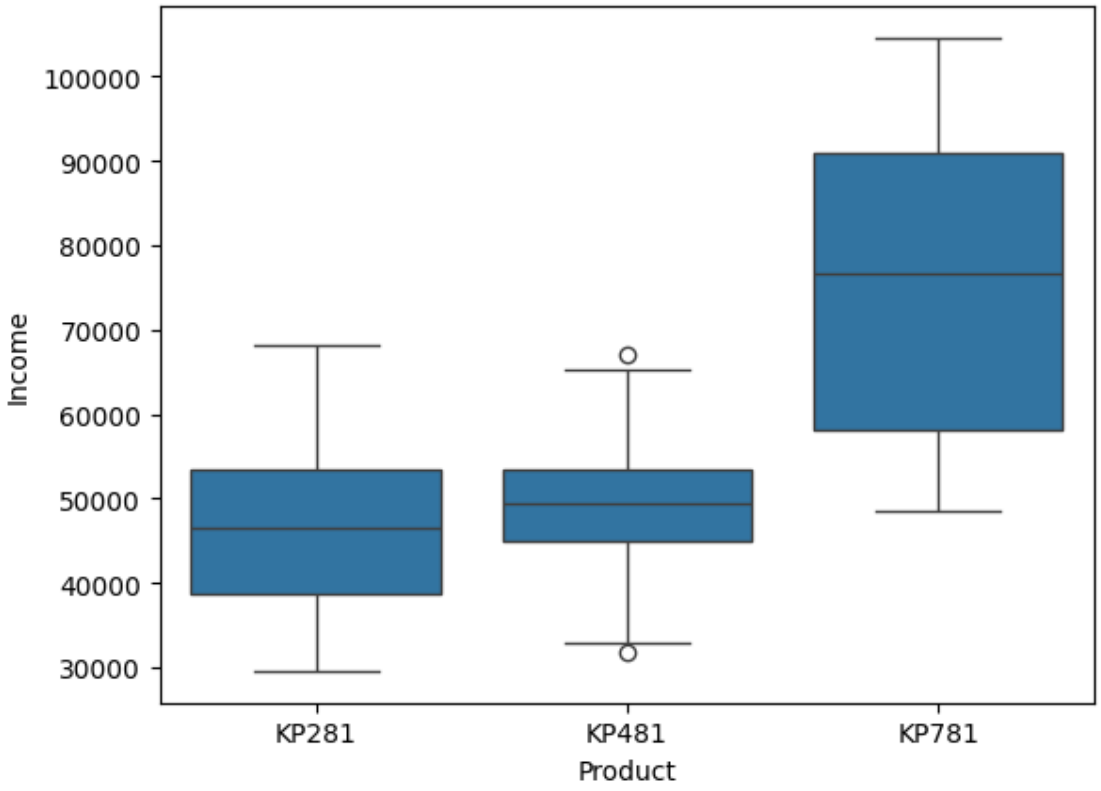
Insights:

– People who are in good shape, having better fitness of more than 4 on the scale of 1 to 5, use KP781.

– People using KP281 and KP481 mostly have moderate fitness value, i.e: 3

[45]:
```
#PRODUCT vs INCOME
sns.boxplot(data=df, x='Product', y='Income')
```

[45]:
```
<Axes: xlabel='Product', ylabel='Income'>
```

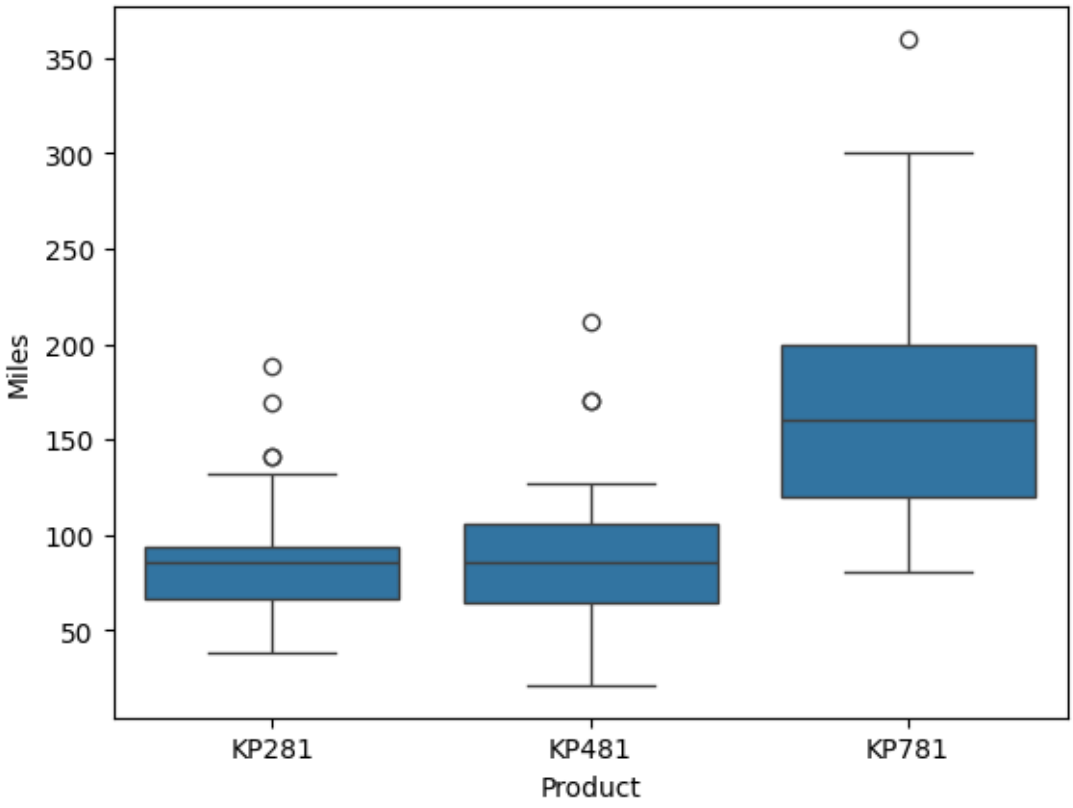


Insights:

–Since KP781 is on the costlier side, people having income greater than 60,000$ are able to buy it. The rest of the user base buys KP281 and KP481.

[47]:
```
#PRODUCT vs MILES
sns.boxplot(data=df, x='Product', y='Miles')
```

[47]:
```
<Axes: xlabel='Product', ylabel='Miles'>
```



Insights:

– People who buy KP781 are the people who usually tend to walk more than 120 miles per week. it shows that KP781 is very ideal for people who workout regularly and have interest in maintaining their fitness levels to a good shape.

0.4 4. Representing the Probability

- Find the marginal probability (what percent of customers have purchased KP281, KP481, or KP781)

  Hint: We want you to use the pandas crosstab to find the marginal probability of each product.

- Find the probability that the customer buys a product based on each column.

  Hint: Based on previous crosstab values you find the probability.

- Find the conditional probability that an event occurs given that another event has occurred. (Example: given that a customer is female, what is the probability she'll purchase a KP481)

  Hint: Based on previous crosstab values you find the probability.

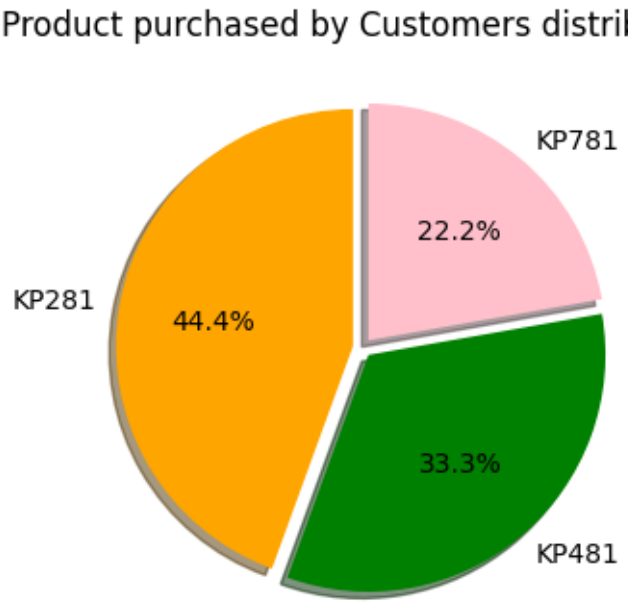
[ ]:
```
pd.crosstab(index=df['Product'],columns='Product',margins=True,normalize=True)
```

[ ]:
```
col_0      Product       All
Product
KP281     0.444444  0.444444
KP481     0.333333  0.333333
KP781     0.222222  0.222222
All       1.000000  1.000000
```

Analysis:

- 44.44% of customers have purchased Product KP281
- 33.33% of customers have purchased Product KP481
- 22.22% of customers have purchased Product KP781

[ ]:
```
#Product purchased by Customers distribution
plt.figure(figsize=(6,4))
plt.pie(df['Product'].value_counts(),explode=(0.04,0.04,0.04),␣
↪labels=df['Product'].value_counts().index,colors=['orange','green','pink'],
        autopct='%.1f%%',startangle=90,shadow=True)
plt.title('Product purchased by Customers distribution')
plt.show()
```



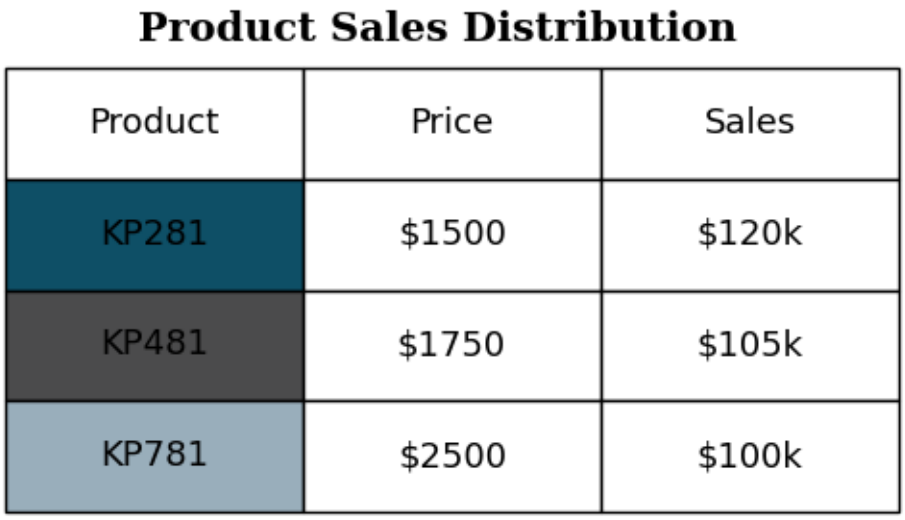
[28]:
```
fig = plt.figure(figsize = (6,3))
gs = fig.add_gridspec(1,1)

ax2 = fig.add_subplot(gs[0,0])
```

```
product_portfolio =␣
 ↪[['KP281','$1500','$120k'],['KP481','$1750','$105k'],['KP781','$2500','$100k']]
color_2d =␣
 ↪[['#0e4f66','#FFFFFF','#FFFFFF'],['#4b4b4c','#FFFFFF','#FFFFFF'],['#99AEBB','#FFFFFF','#FFF
table = ax2.table(cellText = product_portfolio, cellColours=color_2d,␣
 ↪cellLoc='center',colLabels =['Product','Price','Sales'],
 colLoc = 'center',bbox =[0, 0, 1, 1])
table.set_fontsize(13)

ax2.axis('off')

fig.suptitle('Product Sales Distribution',fontproperties = {'family':'serif',␣
 ↪'size':15,'weight':'bold'})
plt.show()
```



Insights:

1.KP281 has the highest number of units sold, i.e: 44% of total unit sales.

2.All three product variants have sales of minimum of 100k dollars.

[30]:
```
fig = plt.figure(figsize = (10,4))
gs = fig.add_gridspec(1,2)
 # creating pie chart for gender disribution and marital status
ax0 = fig.add_subplot(gs[0,0])
color_map = ["#3A7089", "#4b4b4c"]

ax0.pie(df['Gender'].value_counts().values,labels = df['Gender'].value_counts().
 ↪index,autopct = '%.1f%%',
```

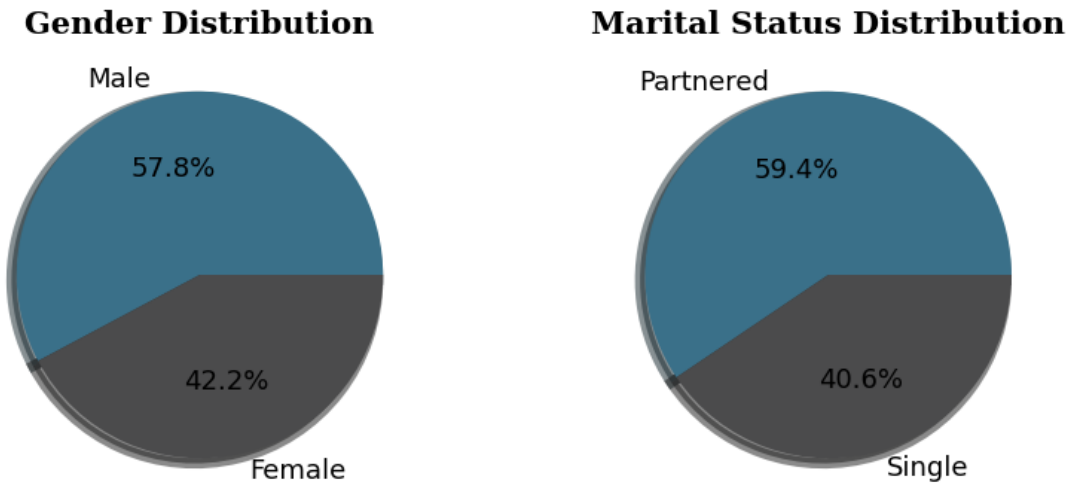
```
 shadow = True,colors = color_map,wedgeprops = {'linewidth':␣
 ↪5},textprops={'fontsize': 13, 'color': 'black'})

ax1 = fig.add_subplot(gs[0,1])

ax1.pie(df['MaritalStatus'].value_counts().values,labels = df['MaritalStatus'].
 ↪value_counts().index,autopct = '%.1f%%',
 shadow = True,colors = color_map,wedgeprops = {'linewidth':␣
 ↪5},textprops={'fontsize': 13, 'color': 'black'})

ax0.set_title('Gender Distribution',{'font':'serif', 'size':15,'weight':'bold'})
ax1.set_title('Marital Status Distribution',{'font':'serif', 'size':15,'weight':
 ↪'bold'})
```

[30]:
```
Text(0.5, 1.0, 'Marital Status Distribution')
```



[ ]:
```
pd.
 ↪crosstab(index=df['Product'],columns=df['Gender'],margins=True,normalize=True)
```

[ ]:
```
Gender     Female      Male       All
Product
KP281    0.222222  0.222222  0.444444
KP481    0.161111  0.172222  0.333333
KP781    0.038889  0.183333  0.222222
All      0.422222  0.577778  1.000000
```

There are 42% female and 58% of males users of Aerofit products.

[ ]:
```
#Conditional Probability given the gender of a person
pd.crosstab(index=df['Product'],columns=df['Gender'],normalize='columns')
```

[ ]:
Gender	Female	Male
Product		
KP281	0.526316	0.384615
KP481	0.381579	0.298077
KP781	0.092105	0.317308

Insights- 1. Given that the customer is male, the probability of them buying the products is 38%,29%,31% for KP281,KP481,KP781 respectively. 2. Given that the customer is female, the probability of them buying the products is 52%,38%,9% for KP281,KP481,KP781 respectively. 3. Male users buy KP781 way more than Female users.

[ ]:
```
#Conditional Probability given that the person has purchased the product
pd.crosstab(index=df['Product'],columns=df['Gender'],normalize='index')
```

[ ]:
Gender	Female	Male
Product		
KP281	0.500000	0.500000
KP481	0.483333	0.516667
KP781	0.175000	0.825000

Insights-

1. Given that the customer has purchased KP281, the probability of customers being female and male is 50%,50% respectively.
2. Given that the customer has purchased KP481, the probability of customers being female and male is 48%,52% respectively.
3. Given that the customer has purchased KP781, the probability of customers being female and male is 17%,82% respectively.

[32]:
```
pd.
↪crosstab(index=df['Product'],columns=df['edu_group'],margins=True,normalize=True)
```

[32]:
edu_group	Primary Education	Secondary Education	Higher Education	All
Product				
KP281	0.011111	0.205556	0.227778	0.444444
KP481	0.005556	0.144444	0.183333	0.333333
KP781	0.000000	0.011111	0.211111	0.222222
All	0.016667	0.361111	0.622222	1.000000

[33]:
```
#Conditional Probability given the Education of a person
pd.crosstab(index=df['Product'],columns=df['edu_group'],normalize='columns')
```

[33]:
edu_group	Primary Education	Secondary Education	Higher Education
Product			
KP281	0.666667	0.569231	0.366071
KP481	0.333333	0.400000	0.294643
KP781	0.000000	0.030769	0.339286

Insights:

1. Given that the customer has completed Primary education, There is 66.6% chace that they might buy KP281, 33% chance that they buy KP481 and 0% chance that they buy KP781.
2. Given that the customer has completed Secondary education, There is 56.9% chace that they might buy KP281, 40% chance that they buy KP481 and 3% chance that they buy KP781.
3. Given that the customer has completed Higher education, There is 36.6% chace that they might buy KP281, 29% chance that they buy KP481 and 33% chance that they buy KP781.

[34]:
```
#Conditional Probability of person being educated till # no of years given that␣
↪the person has purchased the product
pd.crosstab(index=df['Product'],columns=df['edu_group'],normalize='index')
```

[34]:

edu_group	Primary Education	Secondary Education	Higher Education
Product			
KP281	0.025000	0.462500	0.5125
KP481	0.016667	0.433333	0.5500
KP781	0.000000	0.050000	0.9500

Insights:

1. Given that the customer has bought KP281, there is a 2%,46%,51% probability that they have completed Primary, secondary and higher education respectively.
2. Given that the customer has bought KP481, there is 1.6%,43%,55% probability that they have completed Primary, secondary and higher education respectively.
3. Given that the customer has bought KP781, there is 0%,5%,95% probability that they have completed Primary, secondary and higher education respectively.

[35]:
```
pd.
↪crosstab(index=df['Product'],columns=df['age_group'],margins=True,normalize=True)
```

[35]:

age_group	Young Adults	Adults	Middle Aged Adults	Elder	All
Product					
KP281	0.188889	0.177778	0.061111	0.016667	0.444444
KP481	0.155556	0.133333	0.038889	0.005556	0.333333
KP781	0.094444	0.094444	0.022222	0.011111	0.222222
All	0.438889	0.405556	0.122222	0.033333	1.000000

[36]:
```
#Conditional Probability given the Age of a person
pd.crosstab(index=df['Product'],columns=df['age_group'],normalize='columns')
```

[36]:

age_group	Young Adults	Adults	Middle Aged Adults	Elder
Product				
KP281	0.43038	0.438356	0.500000	0.500000
KP481	0.35443	0.328767	0.318182	0.166667
KP781	0.21519	0.232877	0.181818	0.333333

Insights: 1. Given that the customer belongs to the Young adult category (18 to 25 age group), The probability of buying KP281,KP481 and KP781 are 43%,35.5% and 21.5% respectively. 2. Given that the customer belongs to the Adults category (26 to 35 age group), The probability of buying KP281,KP481 and KP781 are 44%,33% and 23% respectively. 3. Given that the customer

belongs to the Middle aged adult category (36 to 45 age), The probability of buying KP281,KP481 and KP781 are 50%,32% and 18% respectively. 4. Given that the customer belongs to the Elder category (46 and above), The probability of buying KP281,KP481 and KP781 are 50%,16.6% and 33.4% respectively.

[37]:
```
#Conditional Probability of person's age given that the person has purchased␣
↪the product
pd.crosstab(index=df['Product'],columns=df['age_group'],normalize='index')
```

[37]:
```
age_group  Young Adults   Adults  Middle Aged Adults     Elder
Product
KP281          0.425000   0.400            0.137500  0.037500
KP481          0.466667   0.400            0.116667  0.016667
KP781          0.425000   0.425            0.100000  0.050000
```

Insights:

1. Given that the person has bought the products, there is more than 82% probable that they are of the age group 18 to 35 years.
2. Very less probability of customers being elder provided that they have bought the product.

[ ]:
```
pd.
↪crosstab(index=df['Product'],columns=df['MaritalStatus'],margins=True,normalize=True)
```

[ ]:
```
MaritalStatus  Partnered    Single       All
Product
KP281           0.266667  0.177778  0.444444
KP481           0.200000  0.133333  0.333333
KP781           0.127778  0.094444  0.222222
All             0.594444  0.405556  1.000000
```

[ ]:
```
#Conditional Probability given the MaritalStatus of a person
pd.crosstab(index=df['Product'],columns=df['MaritalStatus'],normalize='columns')
```

[ ]:
```
MaritalStatus  Partnered    Single
Product
KP281           0.448598  0.438356
KP481           0.336449  0.328767
KP781           0.214953  0.232877
```

[ ]:
```
#Conditional Probability given that the person has purchased the product
pd.crosstab(index=df['Product'],columns=df['MaritalStatus'],normalize='index')
```

[ ]:
```
MaritalStatus  Partnered  Single
Product
KP281              0.600   0.400
KP481              0.600   0.400
KP781              0.575   0.425
```

[49]:
```
pd.crosstab(index=df['Product'],columns=df['Usage'],margins=True,normalize=True)
```

[49]:

Usage	2	3	4	5	6	7	All
Product							
KP281	0.105556	0.205556	0.122222	0.011111	0.000000	0.000000	0.444444
KP481	0.077778	0.172222	0.066667	0.016667	0.000000	0.000000	0.333333
KP781	0.000000	0.005556	0.100000	0.066667	0.038889	0.011111	0.222222
All	0.183333	0.383333	0.288889	0.094444	0.038889	0.011111	1.000000

[ ]:
```
#Conditional Probability given the Usage of a person
pd.crosstab(index=df['Product'],columns=df['Usage'],normalize='columns')
```

[ ]:

Usage	2.00	3.00	4.00	5.00	5.05
Product					
KP281	0.575758	0.536232	0.423077	0.117647	0.0
KP481	0.424242	0.449275	0.230769	0.176471	0.0
KP781	0.000000	0.014493	0.346154	0.705882	1.0

Insights:

1. Given that the user has less than 3 times of treadmill exercise per week, there is more than 98% chance that they buy KP281 and KP481.
2. If user has tendency to use treadmill more than 4 times per week, they mostly buy KP781 (around 70% chance)

[ ]:
```
#Conditional Probability given that the person has purchased the product
pd.crosstab(index=df['Product'],columns=df['Usage'],normalize='index')
```

[ ]:

Usage	2.00	3.00	4.00	5.00	5.05
Product					
KP281	0.237500	0.462500	0.275	0.025	0.000
KP481	0.233333	0.516667	0.200	0.050	0.000
KP781	0.000000	0.025000	0.450	0.300	0.225

[ ]:
```
pd.
↪crosstab(index=df['Product'],columns=df['Fitness'],margins=True,normalize=True)
```

[ ]:

Fitness	2	3	4	5	All
Product					
KP281	0.083333	0.300000	0.050000	0.011111	0.444444
KP481	0.072222	0.216667	0.044444	0.000000	0.333333
KP781	0.000000	0.022222	0.038889	0.161111	0.222222
All	0.155556	0.538889	0.133333	0.172222	1.000000

Observation: Majority of the users using Aerofit products have fitness of 3 on the scale of 1 to 5

[ ]:
```
#Conditional Probability given the Fitness of a person
pd.crosstab(index=df['Product'],columns=df['Fitness'],normalize='columns')
```

[ ]:
```
Fitness         2         3         4         5
Product
KP281    0.535714  0.556701  0.375000  0.064516
KP481    0.464286  0.402062  0.333333  0.000000
KP781    0.000000  0.041237  0.291667  0.935484
```

[ ]:
```
#Conditional Probability given that the person has purchased the product
pd.crosstab(index=df['Product'],columns=df['Fitness'],normalize='index')
```

[ ]:
```
Fitness         2      3         4      5
Product
KP281    0.187500  0.675  0.112500  0.025
KP481    0.216667  0.650  0.133333  0.000
KP781    0.000000  0.100  0.175000  0.725
```

[50]:
```
pd.
  ↪crosstab(index=df['Product'],columns=df['miles_group'],margins=True,normalize=True)
```

[50]:
```
miles_group  Light Activity  Moderate Activity  Active Lifestyle  \
Product
KP281              0.066667           0.277778          0.100000
KP481              0.027778           0.216667          0.083333
KP781              0.000000           0.044444          0.150000
All                0.094444           0.538889          0.333333

miles_group  Fitness Enthusiast       All
Product
KP281                  0.000000  0.444444
KP481                  0.005556  0.333333
KP781                  0.027778  0.222222
All                    0.033333  1.000000
```

[51]:
```
#Conditional Probability given the Miles walked
pd.crosstab(index=df['Product'],columns=df['miles_group'],normalize='columns')
```

[51]:
```
miles_group  Light Activity  Moderate Activity  Active Lifestyle  \
Product
KP281              0.705882           0.515464              0.30
KP481              0.294118           0.402062              0.25
KP781              0.000000           0.082474              0.45

miles_group  Fitness Enthusiast
Product
KP281                  0.000000
KP481                  0.166667
KP781                  0.833333
```

Observations: People who are Fitness Enthusiasts and Active Lifestyle usually go for KP781. Others

use KP281 and KP481.

[52]:
```
#Conditional Probability given that the person has purchased the product
pd.crosstab(index=df['Product'],columns=df['miles_group'],normalize='index')
```

[52]:
```
miles_group  Light Activity  Moderate Activity  Active Lifestyle  \
Product
KP281              0.150000              0.625             0.225
KP481              0.083333              0.650             0.250
KP781              0.000000              0.200             0.675

miles_group  Fitness Enthusiast
Product
KP281                  0.000000
KP481                  0.016667
KP781                  0.125000
```

[53]:
```
pd.
  ↪crosstab(index=df['Product'],columns=df['income_group'],margins=True,normalize=True)
```

[53]:
```
income_group  Low Income  Moderate Income  High Income  Very High Income  \
Product
KP281           0.127778         0.283333     0.033333          0.000000
KP481           0.050000         0.244444     0.038889          0.000000
KP781           0.000000         0.061111     0.055556          0.105556
All             0.177778         0.588889     0.127778          0.105556

income_group       All
Product
KP281         0.444444
KP481         0.333333
KP781         0.222222
All           1.000000
```

[54]:
```
#Conditional Probability given the income of user
pd.crosstab(index=df['Product'],columns=df['income_group'],normalize='columns')
```

[54]:
```
income_group  Low Income  Moderate Income  High Income  Very High Income
Product
KP281            0.71875         0.481132     0.260870               0.0
KP481            0.28125         0.415094     0.304348               0.0
KP781            0.00000         0.103774     0.434783               1.0
```

Observations: People with low income do not buy KP781, people with very high income only buy KP781.

[55]:
```
#Conditional Probability given that the person has purchased the product
pd.crosstab(index=df['Product'],columns=df['income_group'],normalize='index')
```

[55]:
income_group	Low Income	Moderate Income	High Income	Very High Income
Product				
KP281	0.2875	0.637500	0.075000	0.000
KP481	0.1500	0.733333	0.116667	0.000
KP781	0.0000	0.275000	0.250000	0.475

0.5 5. Check the correlation among different factors

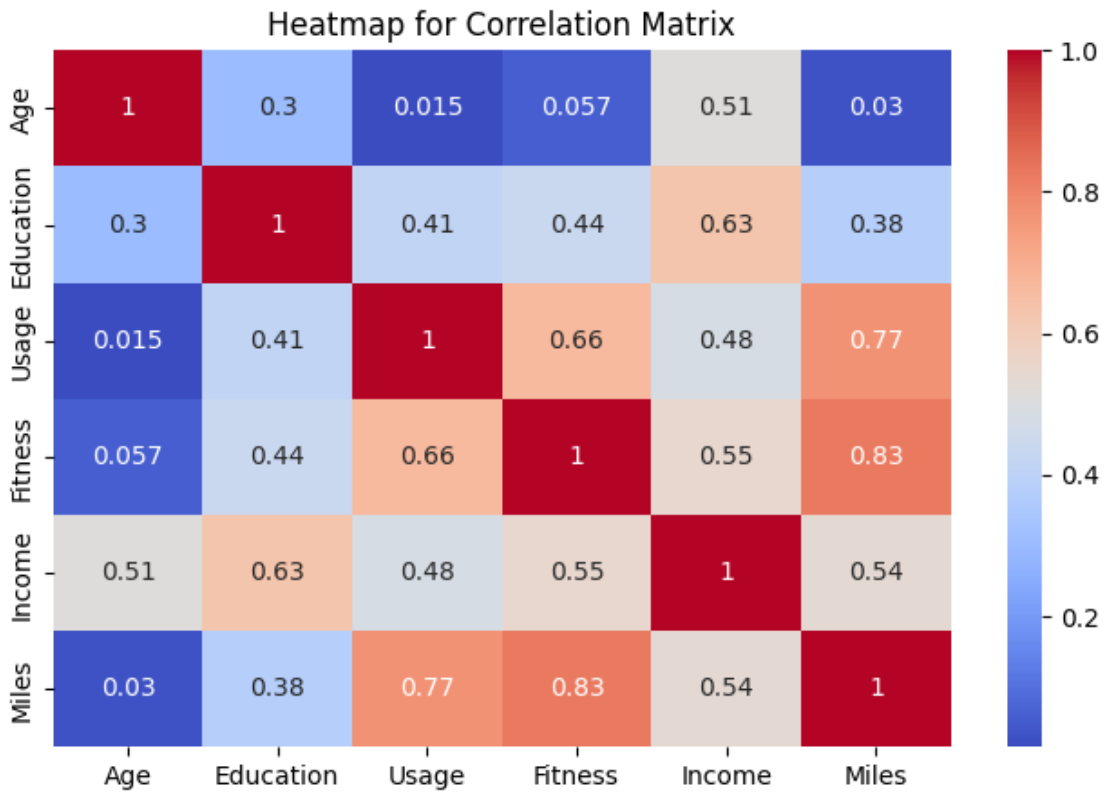
- Find the correlation between the given features in the table.

  Hint: We want you can use the heatmap and corr function to find the correlation between the variables

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

```
<ipython-input-70-64c351c5a7eb>:2: 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()
```

[ ]:
```
plt.figure(figsize=(8, 5))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Heatmap for Correlation Matrix')
plt.show()
```



Observations:

– Miles is highly correlated with Usage and Fitness

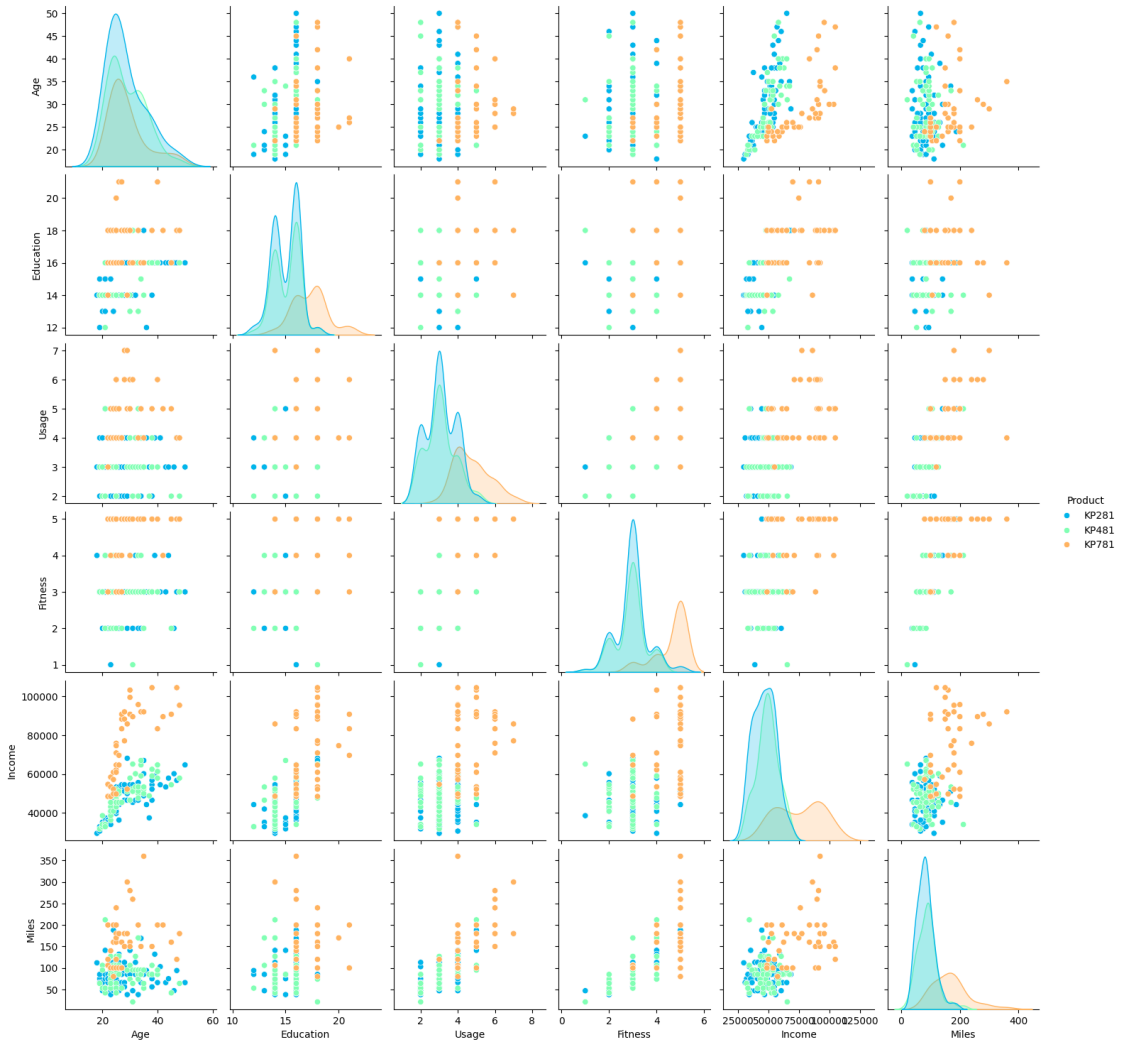
– Education and Income are positively correlated, so is the Age and Income.

–Fitness and Age are also positively correlated, which is correct in general.

0.5.1 Pairplots

[57]:
```
import copy
df_copy = copy.deepcopy(df)
```

[59]:
```
sns.pairplot(df_copy, hue ='Product', palette= 'rainbow')
plt.show()
```



##6. Customer profiling and recommendation

- Make customer profilings for each and every product.

  Hint: We want you to find at What age, gender, and income group buys product KP281

- Write a detailed recommendation from the analysis that you have done.

###Customer Profilings:

Based on above analysis –>

Probability of purchase of Product KP281 = 44%

Probability of purchase of Product KP481 = 33%

Probability of purchase of Product KP781 = 22%

1. Customer Profile for KP281:

- Gender - Both Male and Female - Equal distribution
- Age of customer mostly between 18 to 35 years with few between 35 to 50 years
- Education years of customer 13 years and above
- Annual Income of customer below USD 60,000
- Weekly Treadmill Usage - 2 to 4 times
- Fitness Scale - 2 to 4
- Weekly Running Miles - 50 to 100 miles

2. Customer Profile for KP481:

- Gender - Both Male and Female - Equal distribution
- Age of customer mostly between 18 to 35 years with few between 35 to 50 years
- Education years of customer 13 years and above
- Annual Income of customer between 40,000 and 80,000 USD.
- Weekly Treadmill Usage - 2 to 4 times
- Fitness Scale - 2 to 4
- Weekly Running Miles - 50 to 200 miles

3. Customer Profile for KP781:

- Gender - Mostly Male users
- Age of customer is majorly between 25 to 30 years.
- Education years of customer is mostly 16 years and above
- Annual Income of customer greater than 80,000 USD.
- Weekly Treadmill Usage - 4 to 7 times
- Fitness Scale - Greater than or equal to 4
- Weekly Running Miles - 120+ miles

##Recommendations:

- KP781 majorly caters to Male users, Aerofit needs to come up with a strategy that attracts Female users as well. Selective marketing strategy and advertising needs to be done to inspire and push more and more women to start using KP781. This might increase the very low 18% user base being female for KP781.
- KP281, which is the entry level runner treadmill needs to be more cost optimal. Since it is entry level and encourages users to start running for fitness, they can campaign around KP281 with lower costs, and then provide offers to upgrade to KP481 and KP781 gradually.
- Targeted marketing needed for KP781, since it is bringing in the major chunk of revenue and profits through its high price. Also, people with very high income will be able to afford it, so encouraging them to workout will be a better strategy for Aerofit.
- Tie up with gyms and fitness centers, customers of which will become a potential customers.
- Use Tools and technology to show and save the real-time fitness data and levels of the user through a digital application that can be installed in phones for ease of use and easy access that will ignite interest to workout in users. Announce rewards, gift cards for users that perform exceedingly well for the month or a quarter.