copy-of-scratchpad

April 11, 2023

[ ]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sns
```

[ ]:
```
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

[ ]:
```
data_path = "https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/
↪125/original/aerofit_treadmill.csv?1639992749"
df = pd.read_csv(data_path)
df
```

[ ]:

	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
..	…	…	…	…	…	…	…	…	…
175	KP781	40	Male	21	Single	6	5	83416	200
176	KP781	42	Male	18	Single	5	4	89641	200
177	KP781	45	Male	16	Single	5	5	90886	160
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	150

```
177    160
178    120
179    180

[180 rows x 9 columns]
```

[ ]:
```
print(f"Number of rows: {df.shape[0]}\nNumber of columns: {df.shape[1]}")
```

```
Number of rows: 180
Number of columns: 9
```

[ ]:
```
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
```

[ ]:
```
df.describe(include="all")
```

[ ]:
```
        Product         Age Gender   Education MaritalStatus       Usage  \
count       180  180.000000    180  180.000000           180  180.000000
unique        3         NaN      2         NaN             2         NaN
top       KP281         NaN   Male         NaN     Partnered         NaN
freq         80         NaN    104         NaN           107         NaN
mean        NaN   28.788889    NaN   15.572222           NaN    3.455556
std         NaN    6.943498    NaN    1.617055           NaN    1.084797
min         NaN   18.000000    NaN   12.000000           NaN    2.000000
25%         NaN   24.000000    NaN   14.000000           NaN    3.000000
50%         NaN   26.000000    NaN   16.000000           NaN    3.000000
75%         NaN   33.000000    NaN   16.000000           NaN    4.000000
max         NaN   50.000000    NaN   21.000000           NaN    7.000000

           Fitness         Income       Miles
count   180.000000     180.000000  180.000000
```

```
unique          NaN             NaN          NaN
top             NaN             NaN          NaN
freq            NaN             NaN          NaN
mean       3.311111    53719.577778   103.194444
std        0.958869    16506.684226    51.863605
min        1.000000    29562.000000    21.000000
25%        3.000000    44058.750000    66.000000
50%        3.000000    50596.500000    94.000000
75%        4.000000    58668.000000   114.750000
max        5.000000   104581.000000   360.000000
```

Observations:

```
There are no missing values in the data.
There are 3 unique products in the dataset.
KP281 is the most frequent product.
Minimum & Maximum age of the person is 18 & 50, mean is 28.79 and 75% of persons have age less
Most of the people are having 16 years of education i.e. 75% of persons are having education <=
Out of 180 data points, 104's gender is Male and rest are the female.
Standard deviation for Income & Miles is very high. These variables might have the outliers in
```

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

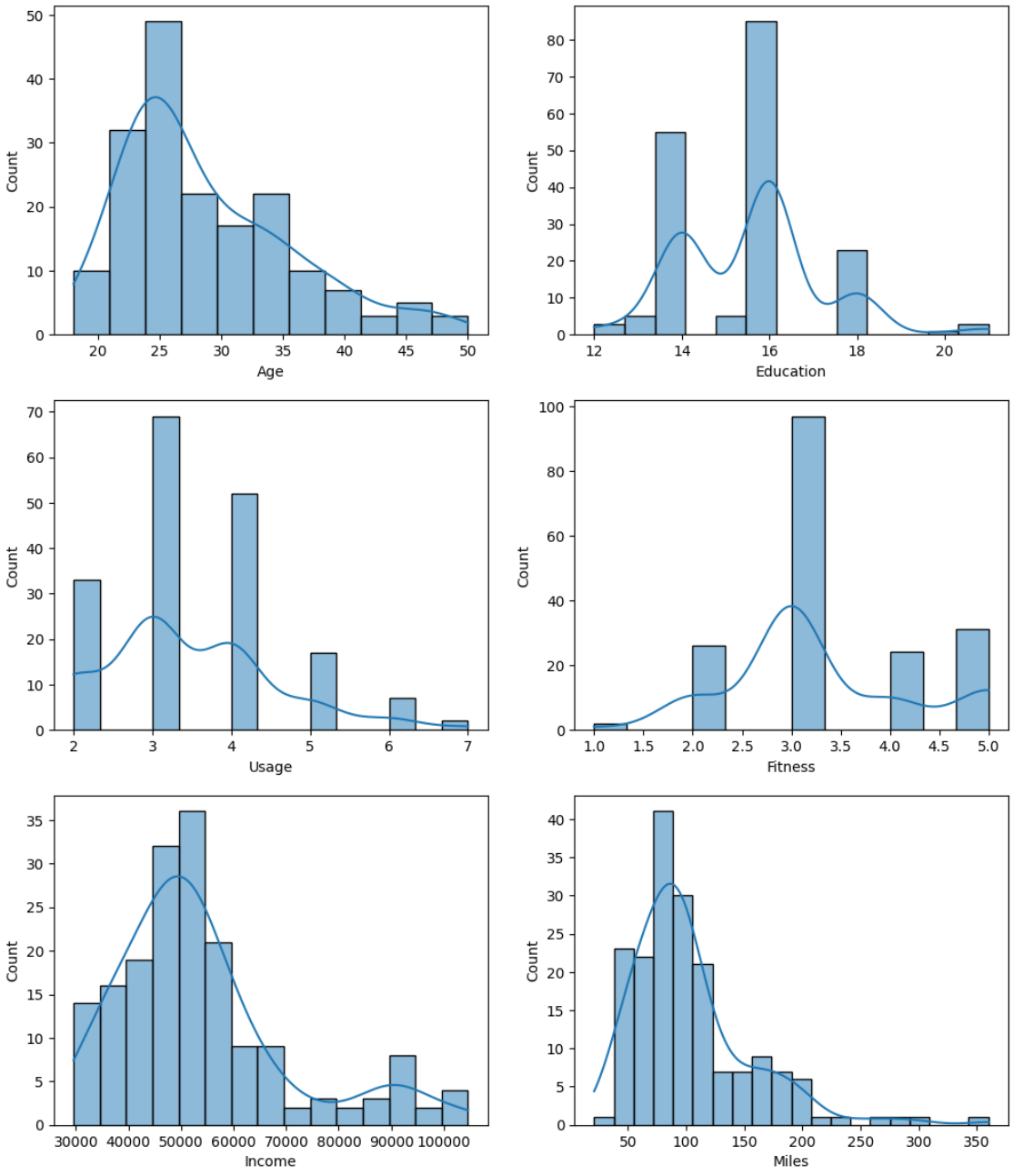
[ ]:
```
array(['KP281', 'KP481', 'KP781'], dtype=object)
```

There are 3 unique products available 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()
```

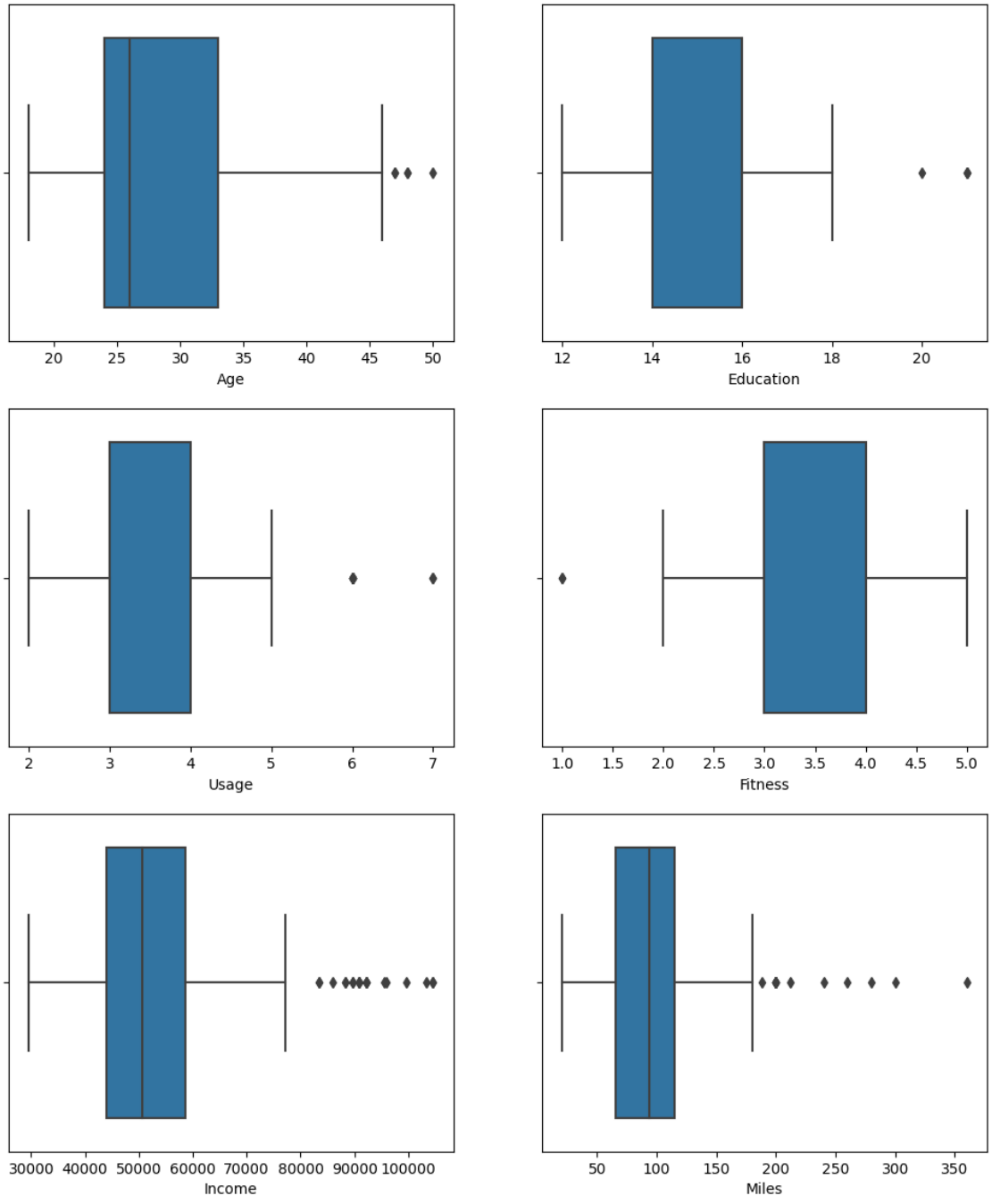


Outliers detection using BoxPlots

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

sns.boxplot(data=df, x="Age", orient='h', ax=axis[0,0])
sns.boxplot(data=df, x="Education", orient='h', ax=axis[0,1])
sns.boxplot(data=df, x="Usage", orient='h', ax=axis[1,0])
```

```
sns.boxplot(data=df, x="Fitness", orient='h', ax=axis[1,1])
sns.boxplot(data=df, x="Income", orient='h', ax=axis[2,0])
sns.boxplot(data=df, x="Miles", orient='h', ax=axis[2,1])
plt.show()
```



Obervation

Even from the boxplots it is quite clear that:

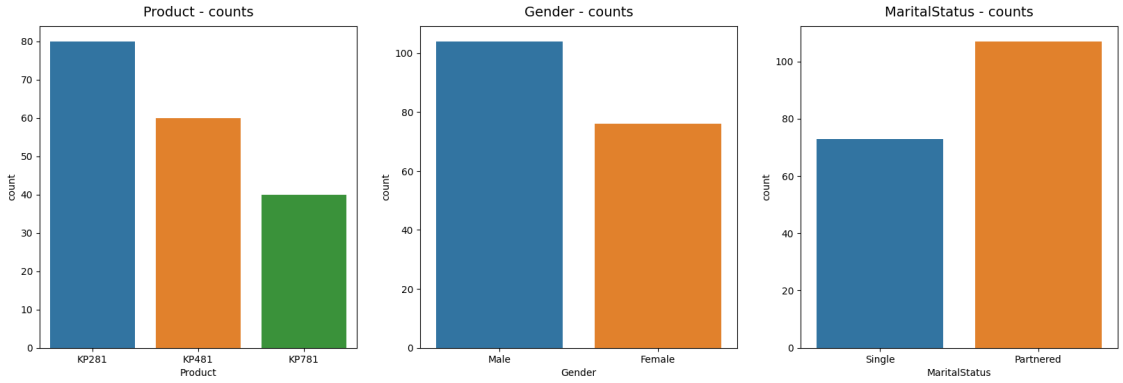
```
Age, Education and Usage are having very few outliers.
While Income and Miles are having more outliers.
```

Understanding the distribution of the data for the qualitative attributes:

```
Product
Gender
MaritalStatus
```

[ ]:
```
fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(20, 6))
sns.countplot(data=df, x='Product', ax=axs[0])
sns.countplot(data=df, x='Gender', ax=axs[1])
sns.countplot(data=df, x='MaritalStatus', ax=axs[2])

axs[0].set_title("Product - counts", pad=10, fontsize=14)
axs[1].set_title("Gender - counts", pad=10, fontsize=14)
axs[2].set_title("MaritalStatus - counts", pad=10, fontsize=14)
plt.show()
```



Obervations

```
KP281 is the most frequent product.
Thare are more Males in the data than Females.
More Partnered persons are there in the data.
```

To be precise - normalized count for each variable is shown below

[ ]:
```
df1 = df[['Product', 'Gender', 'MaritalStatus']].melt()
df1.groupby(['variable', 'value'])[['value']].count() / len(df)
```

[ ]:

		value
variable	value	
Gender	Female	0.422222
	Male	0.577778
MaritalStatus	Partnered	0.594444

```
                Single      0.405556
Product         KP281       0.444444
                KP481       0.333333
                KP781       0.222222
```

Obervations

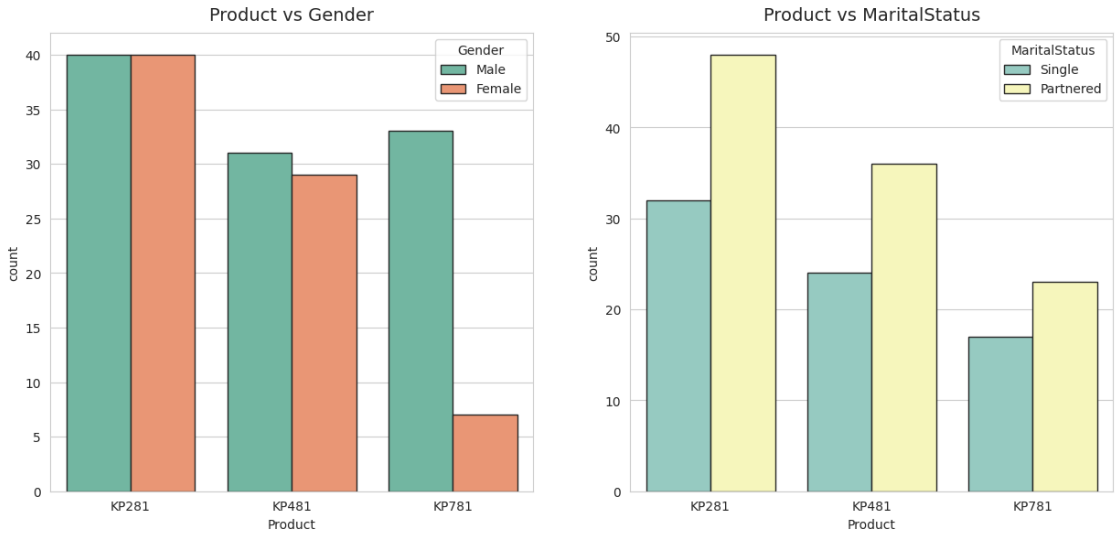
```
Product
    44.44% of the customers have purchased KP2821 product.
    33.33% of the customers have purchased KP481 product.
    22.22% of the customers have purchased KP781 product.

Gender
    57.78% of the customers are Male.

MaritalStatus
    59.44% of the customers are Partnered.
```

Bivariate Analysis Checking if features - Gender or MaritalStatus have any effect on the product purchased.¶

[ ]:
```
sns.set_style(style='whitegrid')
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(15, 6.5))
sns.countplot(data=df, x='Product', hue='Gender', edgecolor="0.15",␣
 ↪palette='Set2', ax=axs[0])
sns.countplot(data=df, x='Product', hue='MaritalStatus', edgecolor="0.15",␣
 ↪palette='Set3', ax=axs[1])
axs[0].set_title("Product vs Gender", pad=10, fontsize=14)
axs[1].set_title("Product vs MaritalStatus", pad=10, fontsize=14)
plt.show()
```



Obervations

Product vs Gender

Equal number of males and females have purchased KP281 product and Almost same for the proc
Most of the Male customers have purchased the KP781 product.

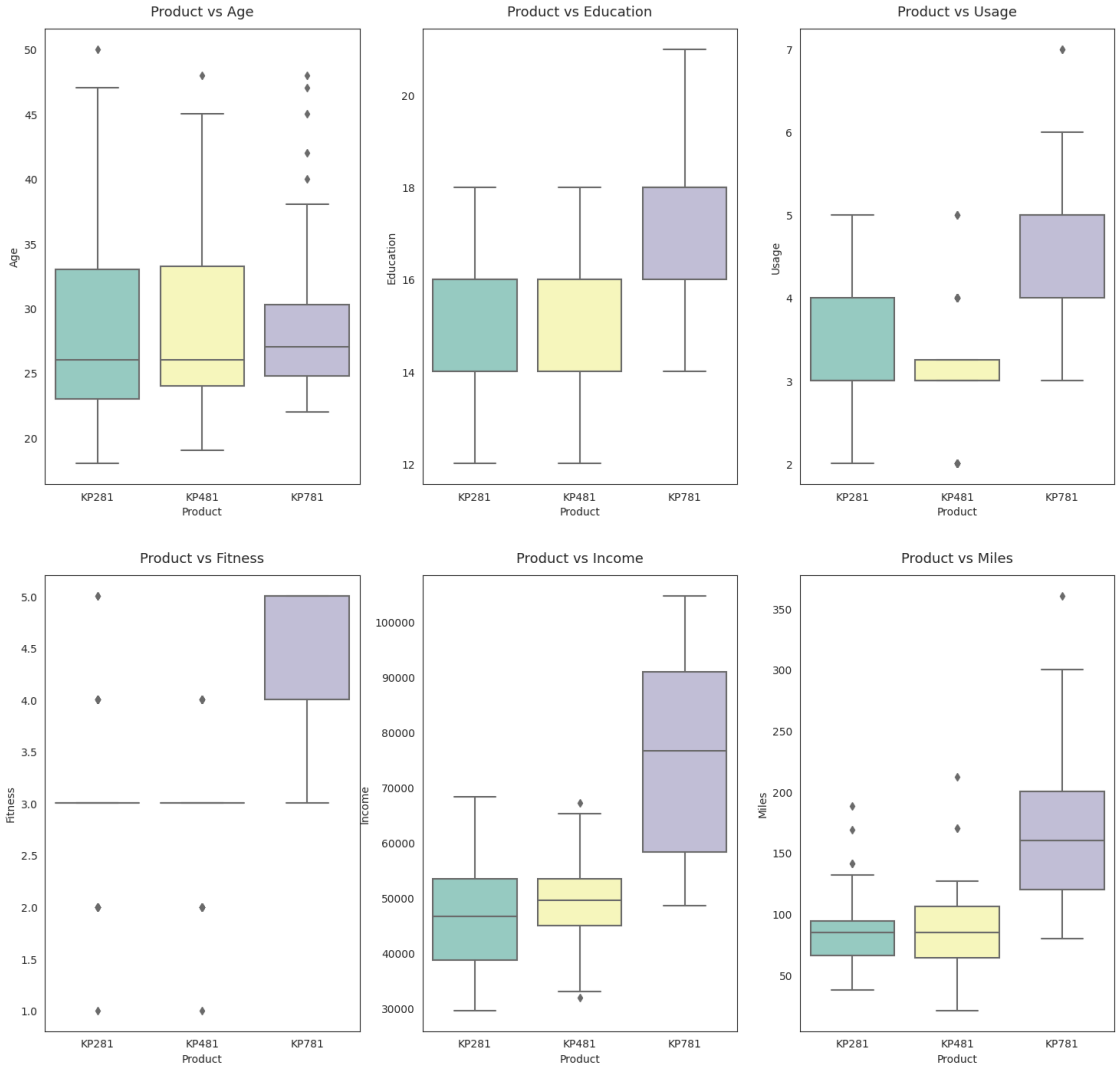
Product vs MaritalStatus

Customer who is Partnered, is more likely to purchase the product.

Checking if following features have any effect on the product purchased:

Age
Education
Usage
Fitness
Income
Miles

[ ]:
```
attrs = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
sns.set_style("white")
fig, axs = plt.subplots(nrows=2, ncols=3, figsize=(18, 12))
fig.subplots_adjust(top=1.2)
count = 0
for i in range(2):
    for j in range(3):
        sns.boxplot(data=df, x='Product', y=attrs[count], ax=axs[i,j],␣
 ↪palette='Set3')
        axs[i,j].set_title(f"Product vs {attrs[count]}", pad=12, fontsize=13)
        count += 1
```



Observations

Product vs Age

Customers purchasing products KP281 & KP481 are having same Age median value.
Customers whose age lies between 25-30, are more likely to buy KP781 product

Product vs Education

Customers whose Education is greater than 16, have more chances to purchase the KP781 produ
While the customers with Education less than 16 have equal chances of purchasing KP281 or K

Product vs Usage

Customers who are planning to use the treadmill greater than 4 times a week, are more likel
While the other customers are likely to purchasing KP281 or KP481.

Product vs Fitness

The more the customer is fit (fitness >= 3), higher the chances of the customer to purchase

Product vs Income

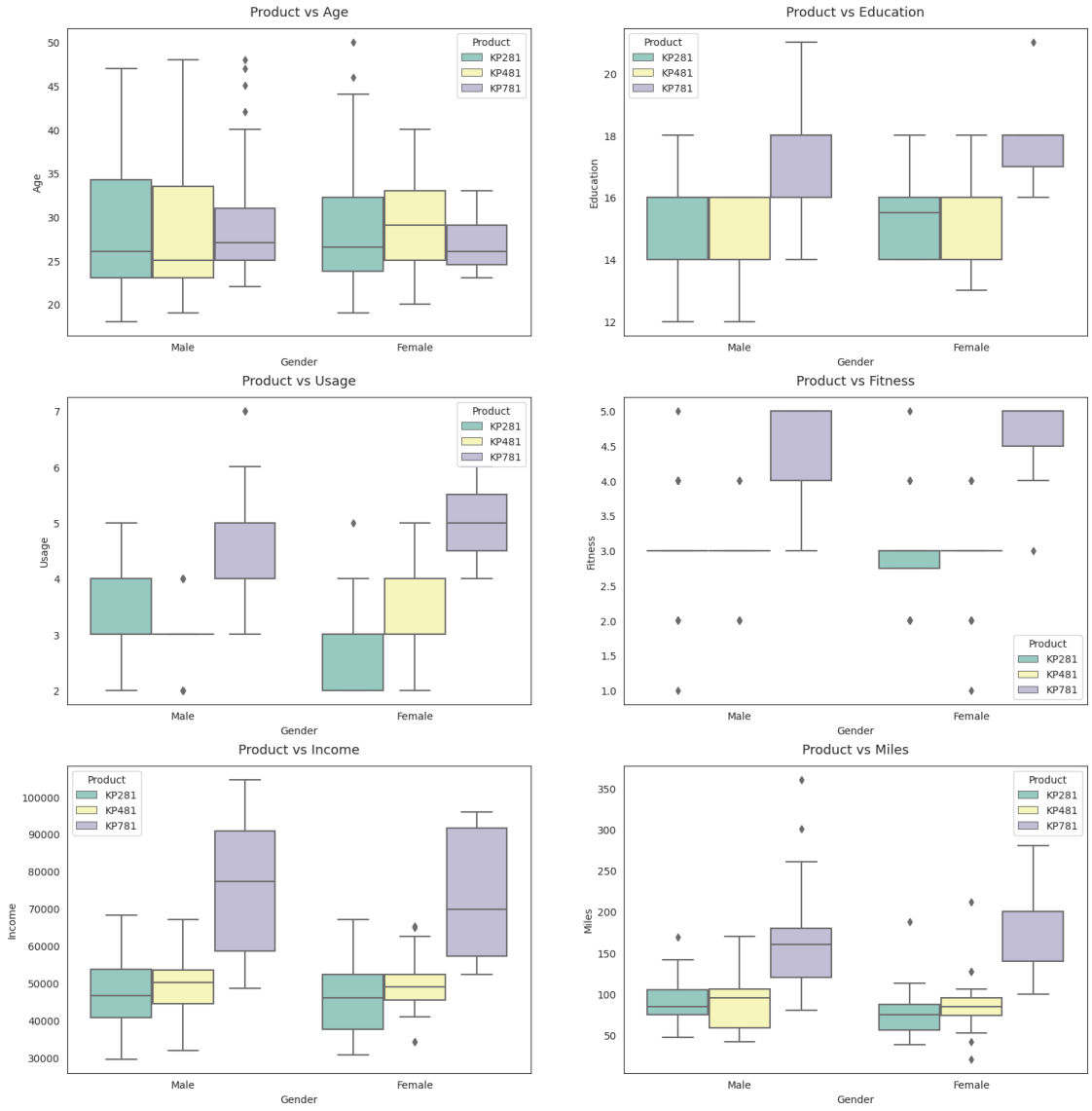
Higher the Income of the customer (Income >= 60000), higher the chances of the customer to

Product vs Miles

If the customer expects to walk/run greater than 120 Miles per week, it is more likely that

Multivariate Analysis

[ ]:
```
attrs = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
sns.set_style("white")
fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(18, 12))
fig.subplots_adjust(top=1.3)
count = 0
for i in range(3):
    for j in range(2):
        sns.boxplot(data=df, x='Gender', y=attrs[count], hue='Product',␣
 ↪ax=axs[i,j], palette='Set3')
        axs[i,j].set_title(f"Product vs {attrs[count]}", pad=12, fontsize=13)
        count += 1
```



Obervations

`Females planning to use treadmill 3-4 times a week, are more likely to buy KP481 product`

Computing Marginal & Conditional Probabilities Marginal Probability¶

[ ]:
```
df['Product'].value_counts(normalize=True)
```

[ ]:
```
KP281    0.444444
KP481    0.333333
KP781    0.222222
Name: Product, dtype: float64
```

Conditional Probabilities Probability of each product given gender¶

[ ]:
```
def p_prod_given_gender(gender, print_marginal=False):
    if gender is not "Female" and gender is not "Male":
        return "Invalid gender value."

    df1 = pd.crosstab(index=df['Gender'], columns=[df['Product']])
    p_781 = df1['KP781'][gender] / df1.loc[gender].sum()
    p_481 = df1['KP481'][gender] / df1.loc[gender].sum()
    p_281 = df1['KP281'][gender] / df1.loc[gender].sum()

    if print_marginal:
        print(f"P(Male): {df1.loc['Male'].sum()/len(df):.2f}")
        print(f"P(Female): {df1.loc['Female'].sum()/len(df):.2f}\n")

    print(f"P(KP781/{gender}): {p_781:.2f}")
    print(f"P(KP481/{gender}): {p_481:.2f}")
    print(f"P(KP281/{gender}): {p_281:.2f}\n")

p_prod_given_gender('Male', True)
p_prod_given_gender('Female')
```

```
P(Male): 0.58
P(Female): 0.42

P(KP781/Male): 0.32
P(KP481/Male): 0.30
P(KP281/Male): 0.38

P(KP781/Female): 0.09
P(KP481/Female): 0.38
P(KP281/Female): 0.53


<>:2: SyntaxWarning: "is not" with a literal. Did you mean "!="?
<>:2: SyntaxWarning: "is not" with a literal. Did you mean "!="?
<>:2: SyntaxWarning: "is not" with a literal. Did you mean "!="?
<>:2: SyntaxWarning: "is not" with a literal. Did you mean "!="?
<ipython-input-19-ddad40656196>:2: SyntaxWarning: "is not" with a literal. Did
you mean "!="?
  if gender is not "Female" and gender is not "Male":
<ipython-input-19-ddad40656196>:2: SyntaxWarning: "is not" with a literal. Did
you mean "!="?
  if gender is not "Female" and gender is not "Male":
```

Probability of each product given MaritalStatus¶

[ ]:
```
def p_prod_given_mstatus(status, print_marginal=False):
    if status is not "Single" and status is not "Partnered":
        return "Invalid marital status value."
```

```
    df1 = pd.crosstab(index=df['MaritalStatus'], columns=[df['Product']])
    p_781 = df1['KP781'][status] / df1.loc[status].sum()
    p_481 = df1['KP481'][status] / df1.loc[status].sum()
    p_281 = df1['KP281'][status] / df1.loc[status].sum()

    if print_marginal:
        print(f"P(Single): {df1.loc['Single'].sum()/len(df):.2f}")
        print(f"P(Partnered): {df1.loc['Partnered'].sum()/len(df):.2f}\n")

    print(f"P(KP781/{status}): {p_781:.2f}")
    print(f"P(KP481/{status}): {p_481:.2f}")
    print(f"P(KP281/{status}): {p_281:.2f}\n")

p_prod_given_mstatus('Single', True)
p_prod_given_mstatus('Partnered')
```

```
P(Single): 0.41
P(Partnered): 0.59

P(KP781/Single): 0.23
P(KP481/Single): 0.33
P(KP281/Single): 0.44

P(KP781/Partnered): 0.21
P(KP481/Partnered): 0.34
P(KP281/Partnered): 0.45


<>:2: SyntaxWarning: "is not" with a literal. Did you mean "!="?
<>:2: SyntaxWarning: "is not" with a literal. Did you mean "!="?
<>:2: SyntaxWarning: "is not" with a literal. Did you mean "!="?
<>:2: SyntaxWarning: "is not" with a literal. Did you mean "!="?
<ipython-input-20-eedeed19a247>:2: SyntaxWarning: "is not" with a literal. Did
you mean "!="?
  if status is not "Single" and status is not "Partnered":
<ipython-input-20-eedeed19a247>:2: SyntaxWarning: "is not" with a literal. Did
you mean "!="?
  if status is not "Single" and status is not "Partnered":
```

[ ]:
```
df
```

[ ]:

	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	

```
..       …  …      …         …             …     …       …      …
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
0      112
1       75
2       66
3       85
4       47
..     …
175    200
176    200
177    160
178    120
179    180

[180 rows x 9 columns]
```