Aerofit_BusinessCase

May 13, 2024

[ ]:
```
from google.colab import files
uploaded = files.upload()
```

```
&lt;IPython.core.display.HTML object&gt;
```

```
Saving aerofit_treadmill.csv to aerofit_treadmill.csv
```

[ ]:
```
import pandas as pd
import numpy as np
df = pd.read_csv('aerofit_treadmill.csv')
df.head()
```

[ ]:

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

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

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

Dataset contains 180 rows and 9 columns

[ ]:
```
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
```

Product, Gender and Marital Status are object(string) Age, Education, Usage, Fitness, Income and Miles are in int64(integer)

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

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

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

Descriptive Analysis

Total count of all columns is 180

Age: Mean age of the customer is 28 years, half of the customer's mean age is 26.

Education: Mean Education is 15 with maximum as 21 and minimum as 12.

Usage: Mean Usage per week is 3.4, with maximum as 7 and minimum as 2.

Fitness: Average rating is 3.3 on a scale of 1 to 5.

Miles: Average number of miles the customer walks is 103 with maximum distance travelled by most people is almost 115 and minimum is 21.

Income (in $): Most customer earns around 58K annually, with maximum of 104K and minimum almost 30K

[ ]:
```
#Non-Graphical Analysis: Value counts and unique attributes
```

[ ]:
```
# Total number of unique Product ids
df['Product'].nunique()
```

[ ]: 3

```
[ ]: # unique list of product ids
df['Product'].unique().tolist()
```

[ ]: ['KP281', 'KP481', 'KP781']

```
[ ]: # Total number of unique ages
total_uniq_age = df['Age'].nunique()
total_uniq_age
```

[ ]: 32

```
[ ]: # list of unique ages
df['Age'].unique()
```

```
[ ]: array([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])
```

```
[ ]: # Number of Male and Female customers
df['Gender'].value_counts()
```

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

```
[ ]: # list of unique Educations
df['Education'].unique().tolist()
```

[ ]: [14, 15, 12, 13, 16, 18, 20, 21]

```
[ ]: # Number of customer againts the rating scale 1 to 5
df['Fitness'].value_counts().sort_index()
```

```
[ ]: Fitness
1     2
2    26
3    97
4    24
5    31
Name: count, dtype: int64
```

```
[ ]: # Number of customers with 3 different product types
df['Product'].value_counts().sort_index()
```

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

[ ]:
```python
# Number of customers counts on Usage
df['Usage'].value_counts().sort_index()
```

[ ]:
```
Usage
2    33
3    69
4    52
5    17
6     7
7     2
Name: count, dtype: int64
```

[ ]:
```python
# Number of Single and Partnered customers
df['MaritalStatus'].value_counts()
```

[ ]:
```
MaritalStatus
Partnered    107
Single        73
Name: count, dtype: int64
```

- ☐ KP281, KP481, KP781 are the 3 different products
- ☐ Most commonly purchased treadmill product type is KP281
- ☐ There are 32 unique ages
- ☐ 104 Males and 76 Females are in the customers list
- ☐ 8 unique set of Educations (14, 15, 12, 13, 16, 18, 20, 21)
- ☐ Highest rated Fitness rating is 3
- ☐ Most customers usage treadmill atleast 3 days per week
- ☐ Majority of the customers who have purchased are Married/Partnered

conversion of categorical attributes to 'category'

[ ]:
```python
# Converting Int data type of fitness rating to object data type
df_cat = df
df_cat['Fitness_category'] = df.Fitness
df_cat.head()
```

[ ]:
```
  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  Fitness_category
0    112                 4
1     75                 3
2     66                 3
3     85                 3
4     47                 2
```

[ ]:
```
df_cat["Fitness_category"].replace({1:"Poor Shape",
                                    2:"Bad Shape",
                                    3:"Average Shape",
                                    4:"Good Shape",
                                    5:"Excellent Shape"},inplace=True)
df_cat.head()
```

[ ]:
```
  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 Fitness_category
0    112       Good Shape
1     75    Average Shape
2     66    Average Shape
3     85    Average Shape
4     47        Bad Shape
```

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

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

            Miles
count  180.000000
mean   103.194444
std     51.863605
min     21.000000
25%     66.000000
```

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

Missing Values

[ ]:
```
df.isna().sum()
```

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

[ ]:
```
df.duplicated().sum()
```

[ ]:
```
0
```

Outliers

Outliers for other categorical data are mentioned inline with the respective analysis

[ ]:
```
# Outlier calculation for Miles using Inter Quartile Range
q_75, q_25 = np.percentile(df['Miles'], [75 ,25])
miles_iqr = q_75 - q_25
print("Inter Quartile Range for Miles is", miles_iqr)
```

```
Inter Quartile Range for Miles is 48.75
```

Statistical Summary

[ ]:
```
# for unique list of products, listed in percentage
sr = df['Product'].value_counts(normalize=True)
stat = sr.map(lambda calc: round(100*calc,2))
stat
```

[ ]:
```
Product
KP281    44.44
KP481    33.33
KP781    22.22
```

```
Name: proportion, dtype: float64
```

44.44% of customers bought KP281 product type

33.33% of customers bought KP481 product type

22.22% of customers bought KP781 product **type**

[ ]:
```
# Customer Gender statistics (listed in %)
gender = df['Gender'].value_counts(normalize=True)
gender_res = gender.map(lambda calc: round(100*calc,2))
gender_res
```

[ ]:
```
Gender
Male      57.78
Female    42.22
Name: proportion, dtype: float64
```

57.78% of customers are Male and 42.22% customers are Female

[ ]:
```
# Customers Marital Status (listed in %)
marital_status = df['MaritalStatus'].value_counts(normalize=True)
marital_status_res = marital_status.map(lambda calc:round(100*calc,2))
marital_status_res
```

[ ]:
```
MaritalStatus
Partnered    59.44
Single       40.56
Name: proportion, dtype: float64
```

59.44% of customers are Married/Partnered

40.56% of customers are Single

[ ]:
```
# Usage: Number of days used per week (listed in %)
usage = df['Usage'].value_counts(normalize=True).map(lambda calc:
 ↪round(100*calc,2)).reset_index()
usage.rename(columns={'index':'DaysPerWeek'},inplace=True)
usage
```

[ ]:

	Usage	proportion
0	3	38.33
1	4	28.89
2	2	18.33
3	5	9.44
4	6	3.89
5	7	1.11

Around 39% of customers use 3 days per week

Less than 2% of customers use 7 days per week

[ ]:
```
# Customer rating of their fitness (listed in %)
rating = df['Fitness'].value_counts(normalize=True).map(lambda calc:
 ↪round(100*calc,2)).reset_index()
rating.rename(columns={'index':'Rating'},inplace=True)
rating
```

[ ]:

	Fitness	proportion
0	3	53.89
1	5	17.22
2	2	14.44
3	4	13.33
4	1	1.11

More than 53% of customers have rated themselves as average in fitness (rated 3)

14% of customers have rated their fitness less than average

Over 17% of customers have peak fitness ratings

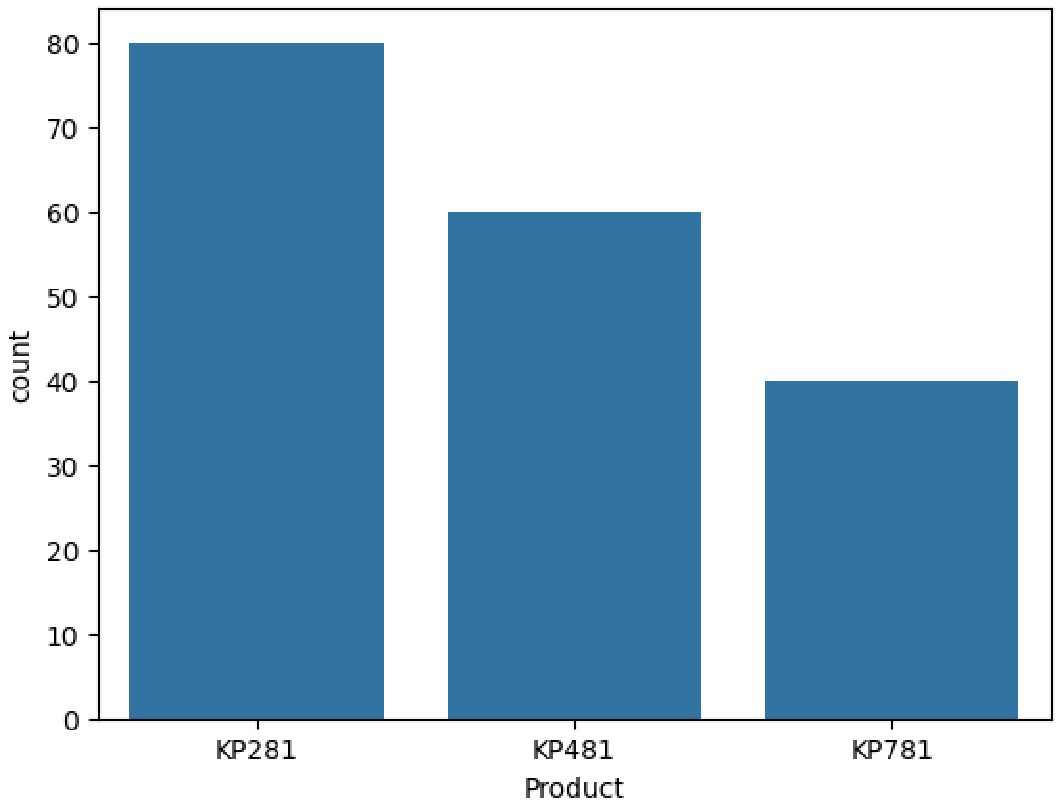
Visual Analysis - Univariate & Bivariate

Univariate Analysis

For Continous Variable(s):Distplot, countplot, histogram for univariate analysis

[ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

[ ]:
```
#product analysis
sns.countplot(data=df,x='Product')
plt.show()
```

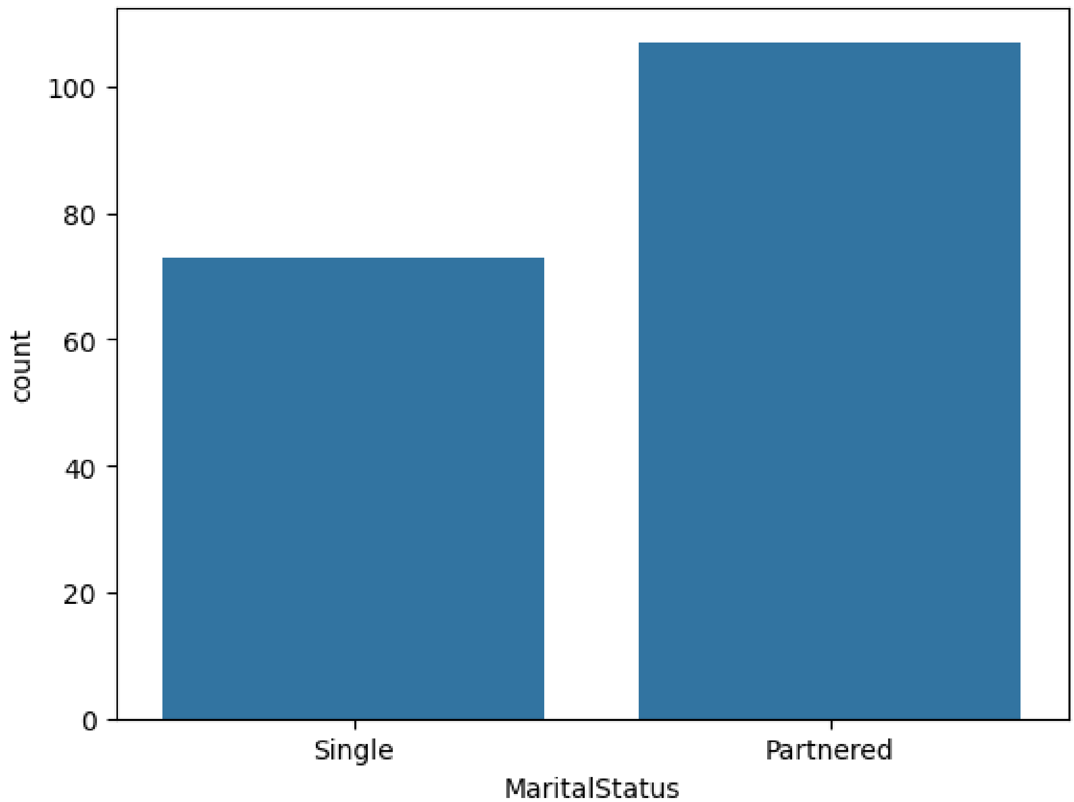


KP281 is the most commonly purchase product type

KP481 is the second most top product type purchased

KP781 is the least purchased product type

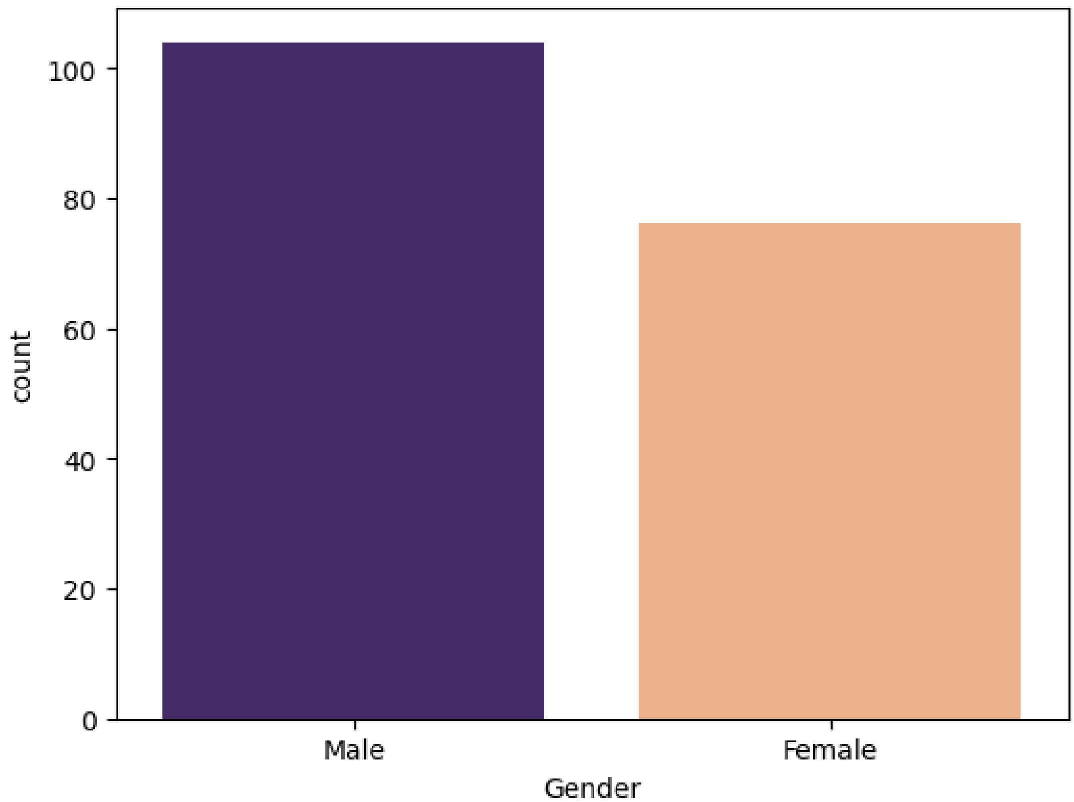
[ ]:
```
# Marital Status Analysis - Count plot
sns.countplot(data=df,x='MaritalStatus')
plt.show()
```



Most products purchased by couples/Married/Partnered customer category

[ ]:
```
# Gender Analysis - Count Plot
sns.countplot(data=df,x='Gender',palette=['#432371',"#FAAE7B"])
plt.show
```

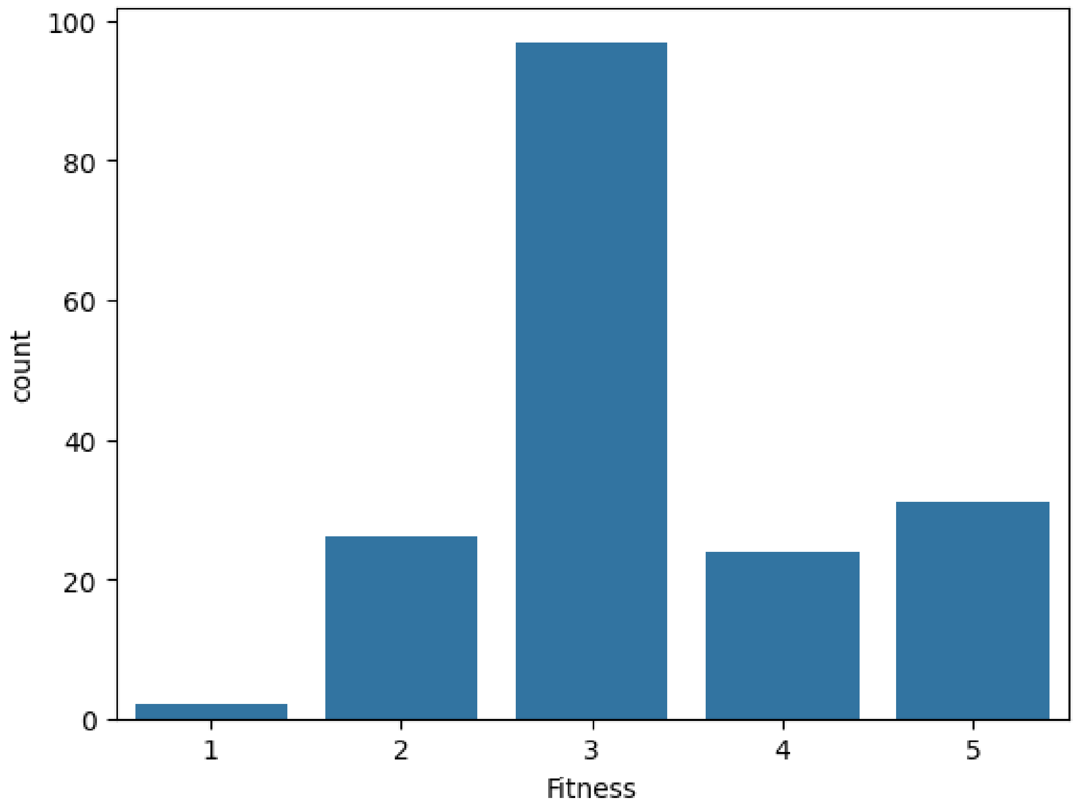
[ ]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



Most products purchased by Males, females are less interested in the product compared to Males

[ ]:
```
# Fitness rating analysis - count plot
sns.countplot(data=df,x='Fitness')
plt.show
```

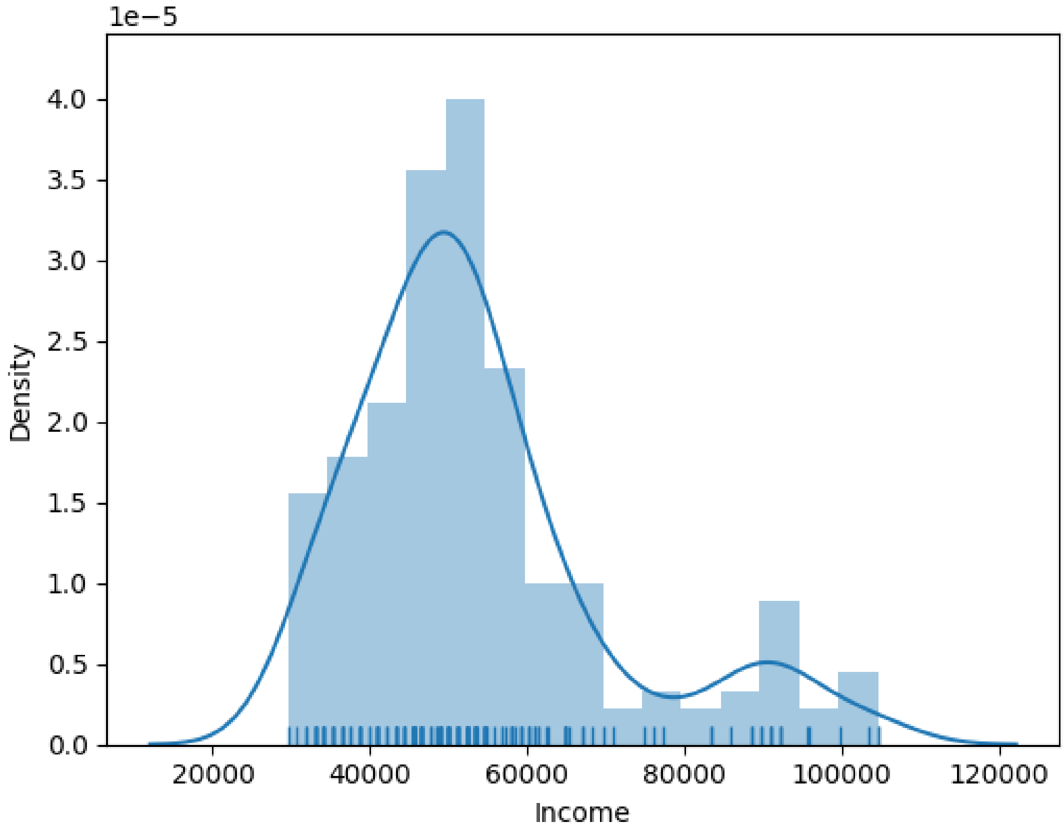
[ ]: `<function matplotlib.pyplot.show(close=None, block=None)>`



More than 90 customers have rated their physical fitness rating as Average

Excellent shape is the second highest rating provided by the customers

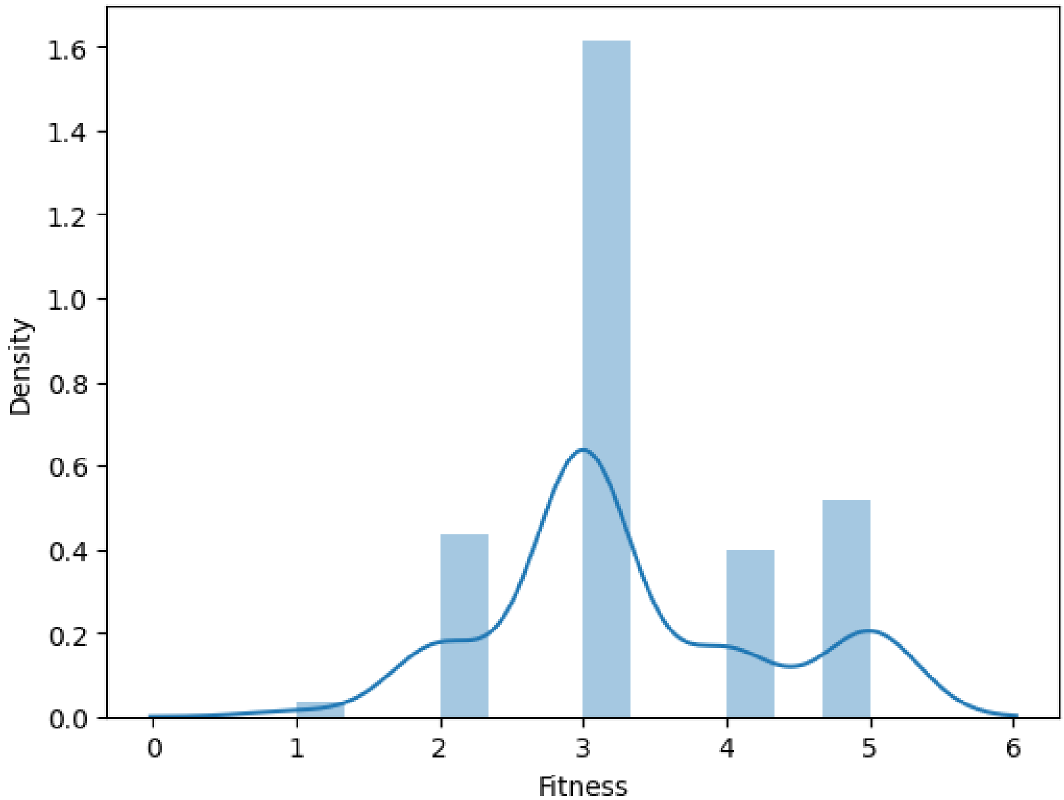
[ ]:
```
# Income Analysis - Distplot
sns.distplot(df.Income,rug=True)
plt.show()
```



Most of customers who have purchased the product have a average income between 40K to 60K

Average Income density is over 3.0

[ ]:
```
# Fitness Rating Analysis - Distplot
sns.distplot(df.Fitness)
plt.show()
```

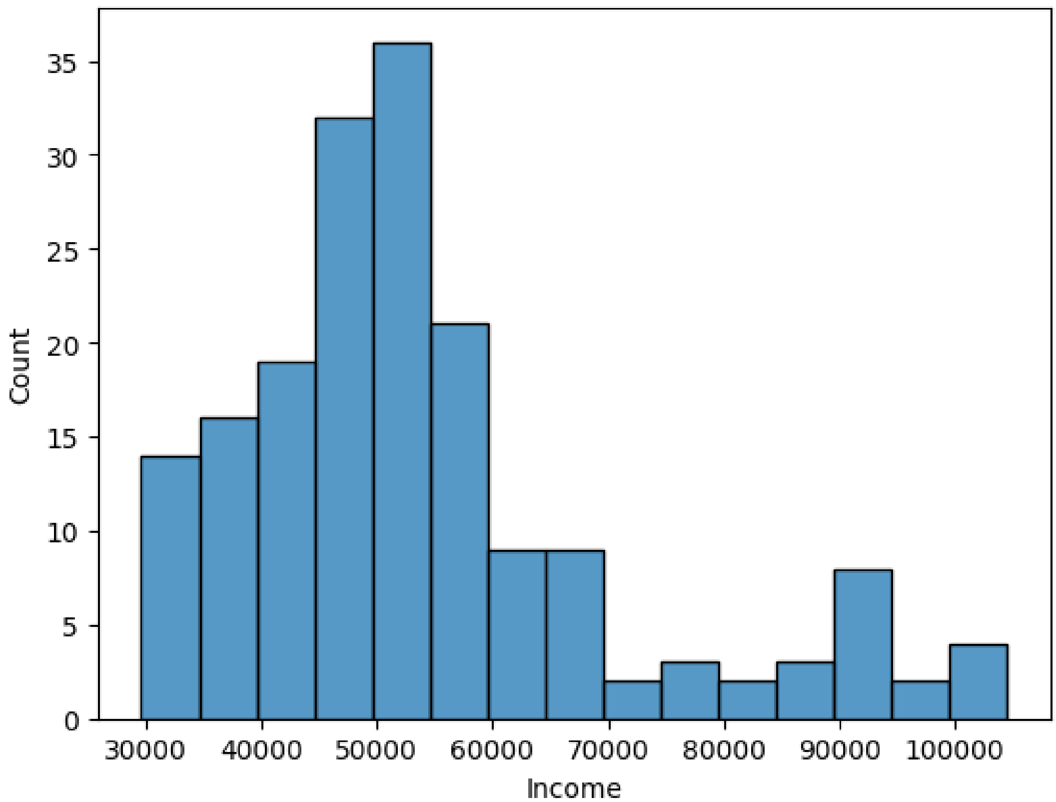


Over 1.5 density customer population have rated their physical fitness rating as Average

Second highest customer population density have rated Excellent shape as their fitness rating

[ ]:
```
# Income Analysis - Histogram
sns.histplot(data=df,x='Income')
```

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



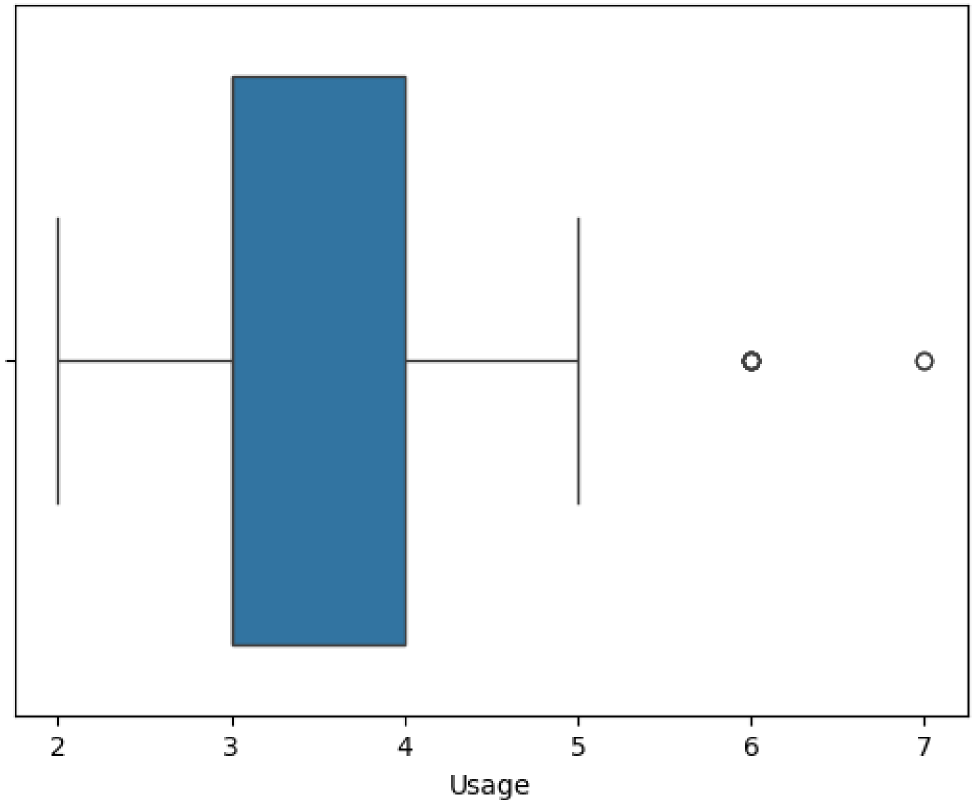
More than 35 customers earn 50-55K per year

More than 30 customers earn 45-50K per year

More than 20 customers earn 55-60K per year

For categorical variable(s): Boxplot

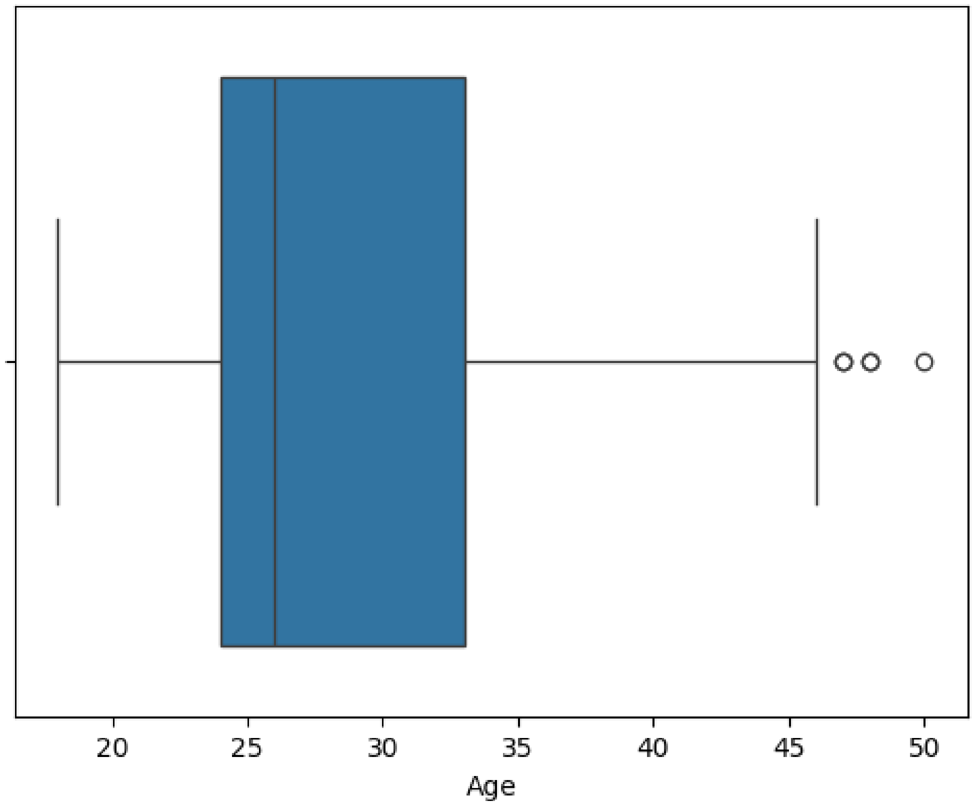
[ ]:
```
# Usage Analysis - Box plot
sns.boxplot(data=df,x='Usage')
plt.show()
```



3 to 4 days is the most preferred usage days for customers

6 and 7 days per week is roughly the usage days for few customers (Outliers)

[ ]:
```
# Age Analysis - Box plot
sns.boxplot(data=df,x='Age')
plt.show()
```



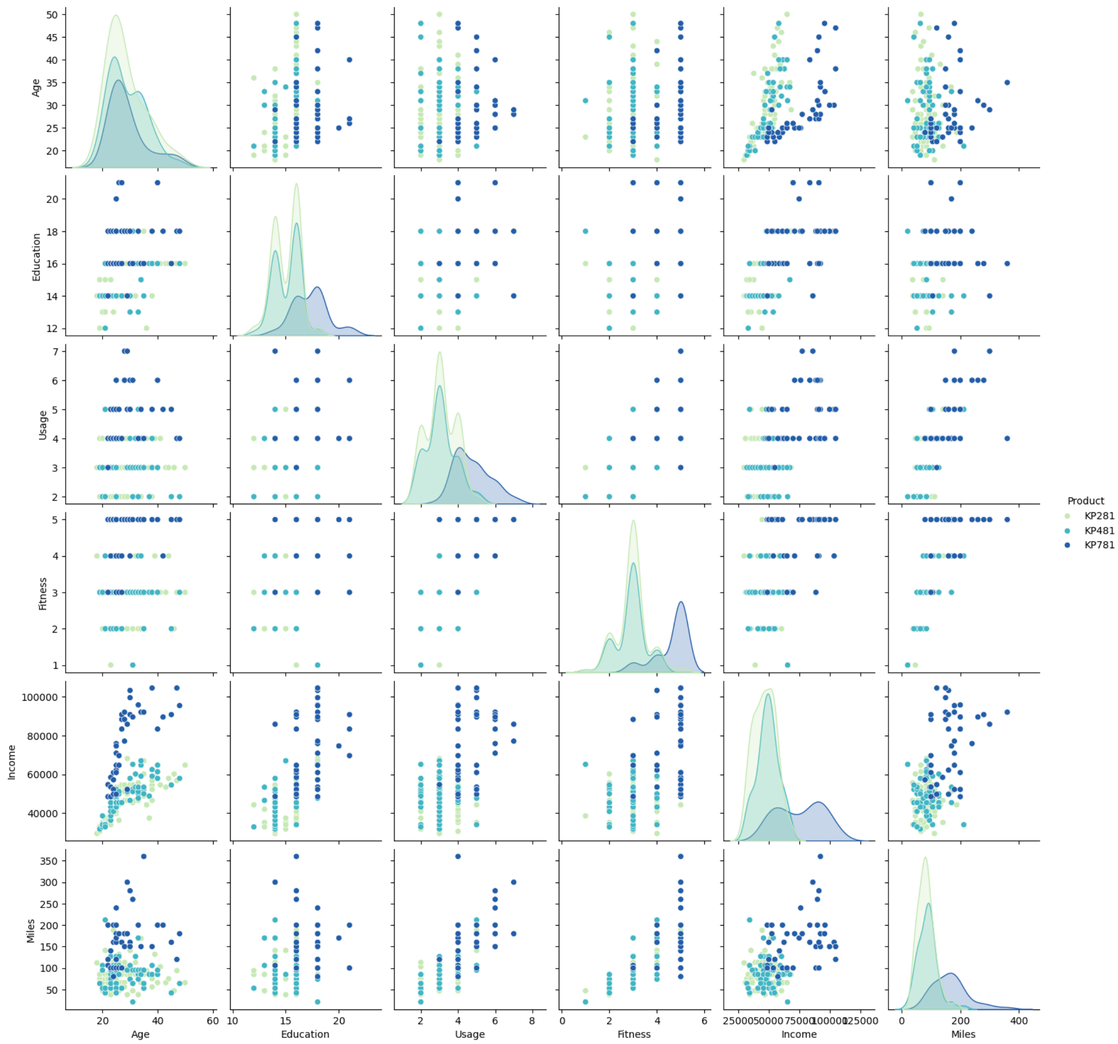
23 to 34 is the most common customer age group that has purchased the product

Above 45 years old customers are very few compared to the young age group given in the dataset

For correlation: Heatmaps, Pairplots

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

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



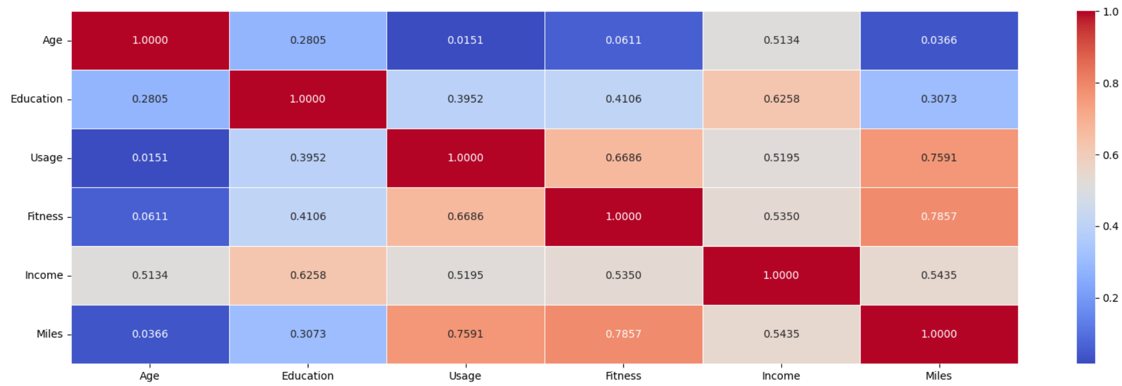
[ ]:
```
df_copy['Usage'] = df_copy['Usage'].astype('int')
df_copy['Fitness'] = df_copy['Fitness'].astype('int')

df_copy.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
```

[ ]:
```python
#Correlation HeatMap
plt.figure(figsize=(20,6))
ax = sns.heatmap(df.corr(numeric_only=True),annot=True,fmt='.4f',linewidths=.
 ↪5,cmap='coolwarm')
plt.yticks(rotation=0)
plt.show()
```



In the above heatmap linear relationship between data points is evaluated

Correlation between Age and Miles is 0.03

Correlation between Education and Income is 0.62

Correlation between Usage and Fitness is 0.66

Correlation between Fitness and Age is 0.06

Correlation between Income and Usage is 0.51

Correlation between Miles and Age is 0.03

Bivariate Analysis

[ ]:
```python
# Average usage of each product type by the customer
df.groupby('Product')['Usage'].mean()
```

[ ]:
```
Product
KP281    3.087500
KP481    3.066667
KP781    4.775000
```

```
Name: Usage, dtype: float64
```

Mean usage for product KP281 is 3.08

Mean usage for product KP481 is 3.06

Mean usage for product KP781 is 4.77

[ ]:
```
# Average Education of customer using each product
df.groupby('Product')['Education'].mean()
```

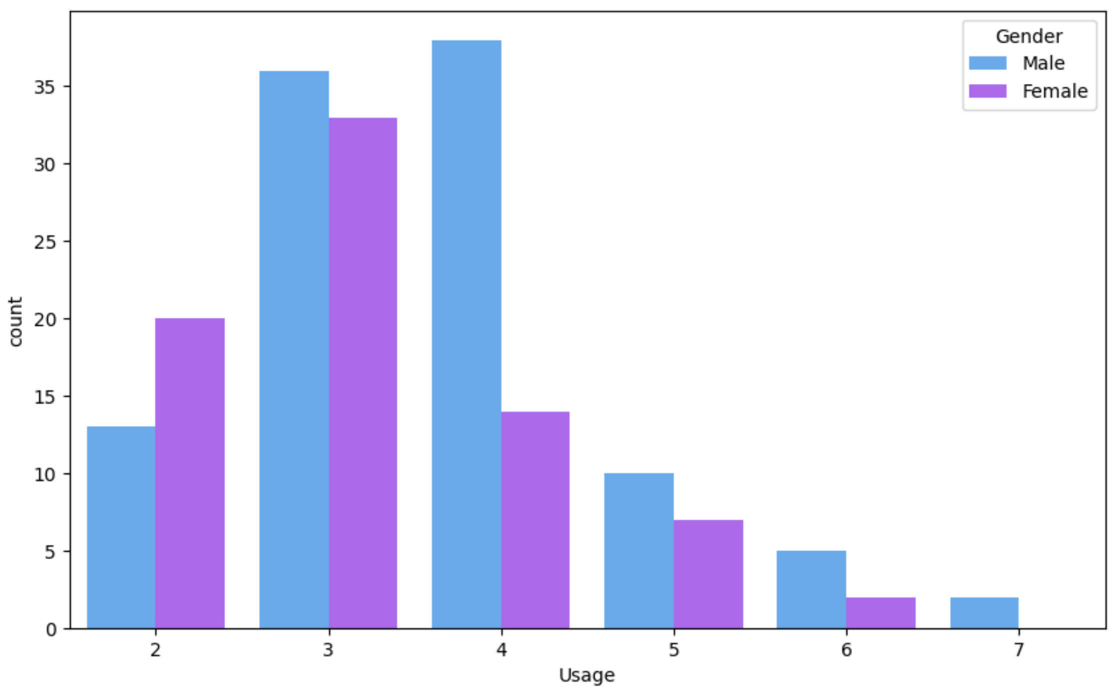
[ ]:
```
Product
KP281    15.037500
KP481    15.116667
KP781    17.325000
Name: Education, dtype: float64
```

Mean Education qualification of the customer who purchased product KP281 is 15.03

Mean Education qualification of the customer who purchased product KP481 is 15.11

Mean Education qualification of the customer who purchased product KP781 is 17.32

[ ]:
```
# Purchased product usage among Gender
plt.figure(figsize=(10,6))
sns.countplot(data=df,x='Usage',hue='Gender',palette='cool')
plt.show()
```

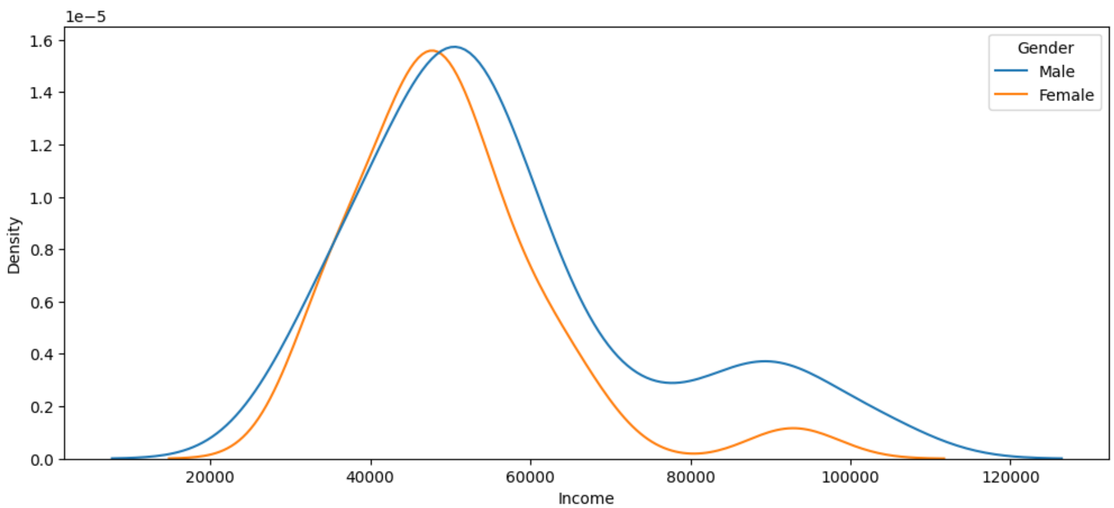


Among Male and Female genders, Male's usage is 4 days per week

Female customers mostly use 3 days per week

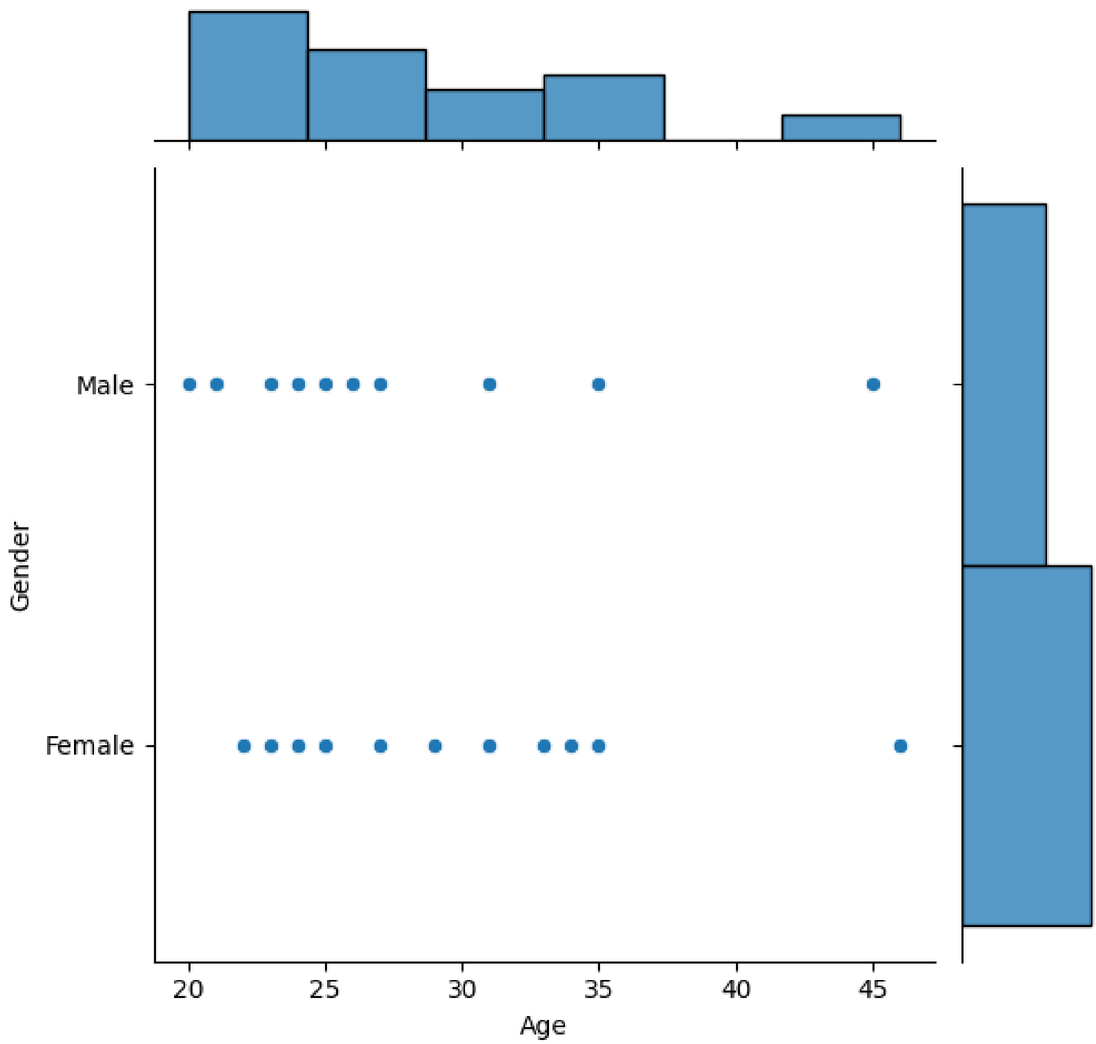
Only few Male customers use 7 days per week whereas female customer's maximum usage is only 6 days per week

[ ]:
```
# Product purchased Customers Income and their Gender
plt.figure(figsize=(12,5))
sns.kdeplot(data=df,x='Income',hue='Gender')
plt.show()
```



From the above diagram, we can conclude the spike from 40K to around 80K is the most common income per annum of the customers

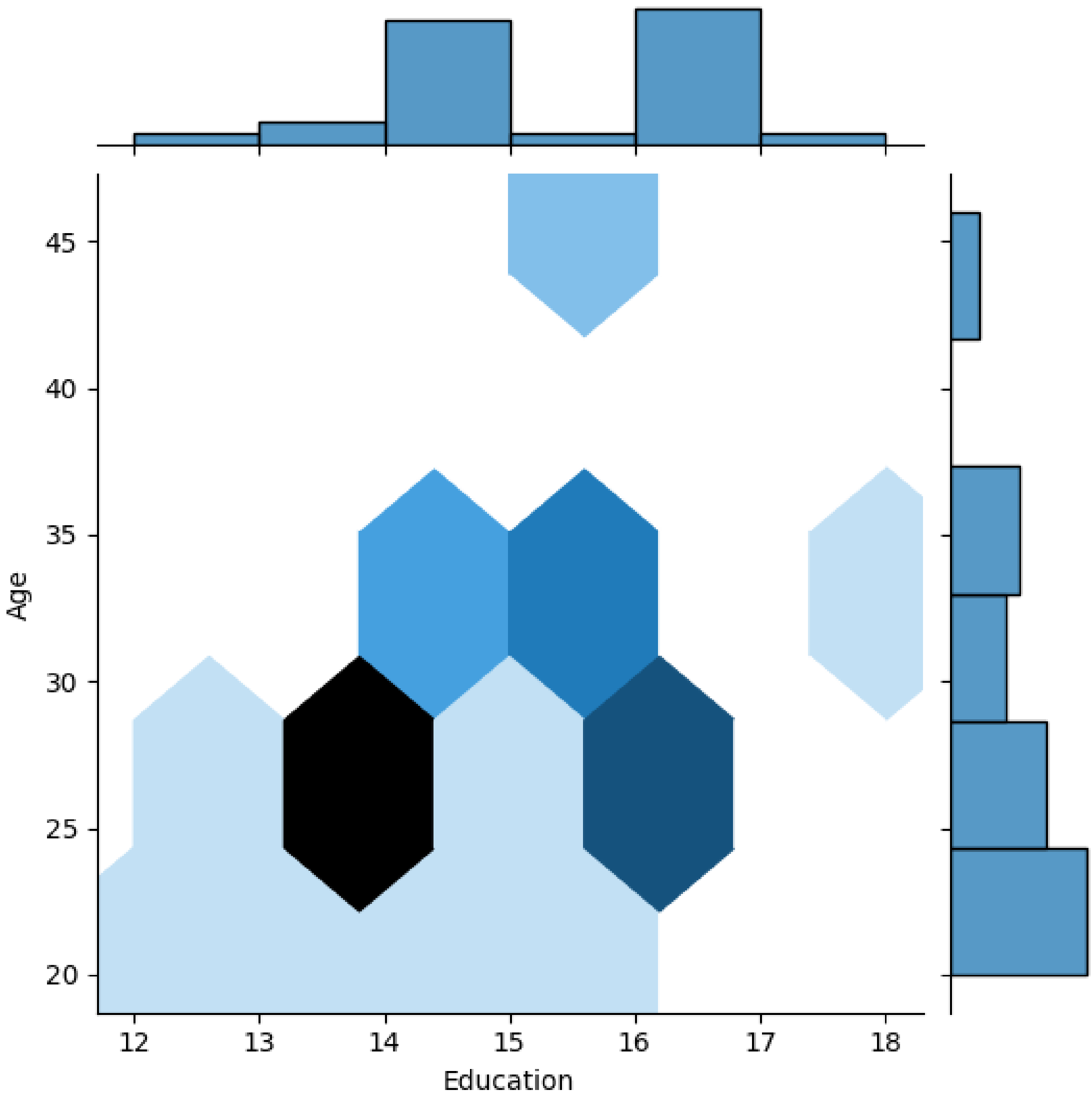
[ ]:
```
# Scatterplot for customers Gender and Age who rated less than 2 in Fitness␣
 ↪rating
sns.jointplot(x='Age',y='Gender',data=df[df.Fitness<3])
plt.show()
```



Above Joint plot describes the relationship between the customer age and their gender grouping.

Product is not familiar with older or middle age womens

[ ]:
```
# Hex Scatterplot for customers Education and Age who rated less than 2 in␣
↪Fitness rating
sns.jointplot(x='Education',y='Age',kind='hex',data=df[df.Fitness<3])
plt.show()
```



Majority of the age and education density falls on 25-30 age group and 13-14 education

Computing Probability - Marginal, Conditional Probability

Probability of product purchase w.r.t. gender

[ ]:
```
pd.crosstab(index =df['Product'],columns = df['Gender'],margins =␣
↪True,normalize = True ).round(2)
```

[ ]:

Gender	Female	Male	All
Product			
KP281	0.22	0.22	0.44
KP481	0.16	0.17	0.33
KP781	0.04	0.18	0.22

```
All         0.42  0.58  1.00
```

Insights

The Probability of a treadmill being purchased by a female is 42%.

The conditional probability of purchasing the treadmill model given that the customer is female is

For Treadmill model KP281 - 22%

For Treadmill model KP481 - 16%

For Treadmill model KP781 - 4%

The Probability of a treadmill being purchased by a male is 58%.

The conditional probability of purchasing the treadmill model given that the customer is male is -

For Treadmill model KP281 - 22%

For Treadmill model KP481 - 17%

For Treadmill model KP781 - 18%

[ ]:
```
#binning the age values into categories
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)

#binning the education values into categories
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)

#binning the income values into categories
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)

#binning the miles values into categories
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)
```

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

```
[ ]:   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
```

```python
[ ]: #Probability of product purchase w.r.t. Age
     pd.crosstab(index =df['Product'],columns = df['age_group'],margins =␣
      ↪True,normalize = True ).round(2)
```

```
[ ]: age_group  Young Adults  Adults  Middle Aged Adults  Elder   All
     Product
     KP281              0.19    0.18                0.06   0.02  0.44
     KP481              0.16    0.13                0.04   0.01  0.33
     KP781              0.09    0.09                0.02   0.01  0.22
     All                0.44    0.41                0.12   0.03  1.00
```

Insights The Probability of a treadmill being purchased by a Young Adult(18-25) is 44%.

The conditional probability of purchasing the treadmill model given that the customer is Young Adult is

For Treadmill model KP281 - 19%

For Treadmill model KP481 - 16%

For Treadmill model KP781 - 9%

The Probability of a treadmill being purchased by a Adult(26-35) is 41%.

The conditional probability of purchasing the treadmill model given that the customer is Adult is -

For Treadmill model KP281 - 18%

For Treadmill model KP481 - 13%

For Treadmill model KP781 - 9%

The Probability of a treadmill being purchased by a Middle Aged(36-45) is 12%.

The Probability of a treadmill being purchased by a Elder(Above 45) is only 3%.

Probability of product purchase w.r.t. Education level

[ ]:
```
pd.crosstab(index =df['Product'],columns = df['edu_group'],margins =␣
↪True,normalize = True ).round(2)
```

[ ]:

edu_group	Primary Education	Secondary Education	Higher Education	All
Product				
KP281	0.01	0.21	0.23	0.44
KP481	0.01	0.14	0.18	0.33
KP781	0.00	0.01	0.21	0.22
All	0.02	0.36	0.62	1.00

[ ]:
```
pd.crosstab(index =df['Product'],columns = df['income_group'],margins =␣
↪True,normalize = True ).round(2)
```

[ ]:

income_group	Low Income	Moderate Income	High Income	Very High Income	All
Product					
KP281	0.13	0.28	0.03	0.00	0.44
KP481	0.05	0.24	0.04	0.00	0.33
KP781	0.00	0.06	0.06	0.11	0.22
All	0.18	0.59	0.13	0.11	1.00

Insights

The Probability of a treadmill being purchased by a customer with Low Income(<40k) is 18%.

The conditional probability of purchasing the treadmill model given that the customer has Low Income is - For Treadmill model KP281 - 13%

For Treadmill model KP481 - 5%

For Treadmill model KP781 - 0%

The Probability of a treadmill being purchased by a customer with Moderate Income(40k - 60k) is 59%.

The conditional probability of purchasing the treadmill model given that the customer has Moderate Income is - For Treadmill model KP281 - 28%

For Treadmill model KP481 - 24%

For Treadmill model KP781 - 6%

The Probability of a treadmill being purchased by a customer with High Income(60k - 80k) is 13%

The conditional probability of purchasing the treadmill model given that the customer has High Income is -

For Treadmill model KP281 - 3%

For Treadmill model KP481 - 4%

For Treadmill model KP781 - 6%

The Probability of a treadmill being purchased by a customer with Very High Income(>80k) is 11%

The conditional probability of purchasing the treadmill model given that the customer has High Income is -

For Treadmill model KP281 - 0%

For Treadmill model KP481 - 0%

For Treadmill model KP781 - 11%

Probability of product purchase w.r.t. Marital Status

[ ]:
```
pd.crosstab(index =df['Product'],columns = df['MaritalStatus'],margins =
↪True,normalize = True ).round(2)
```

[ ]:

MaritalStatus	Partnered	Single	All
Product			
KP281	0.27	0.18	0.44
KP481	0.20	0.13	0.33
KP781	0.13	0.09	0.22
All	0.59	0.41	1.00

The Probability of a treadmill being purchased by a Married Customer is 59%.

Probability of product purchase w.r.t. weekly mileage

[ ]:
```
pd.crosstab(index =df['Product'],columns = df['miles_group'],margins =
↪True,normalize = True ).round(2)
```

[ ]:

miles_group	Light Activity	Moderate Activity	Active Lifestyle	\
Product				
KP281	0.07	0.28	0.10	
KP481	0.03	0.22	0.08	
KP781	0.00	0.04	0.15	
All	0.09	0.54	0.33	

miles_group	Fitness Enthusiast	All
Product		
KP281	0.00	0.44
KP481	0.01	0.33
KP781	0.03	0.22
All	0.03	1.00

The Probability of a treadmill being purchased by a customer with lifestyle of Light Activity(0 to 50 miles/week) is 9%.

The conditional probability of purchasing the treadmill model given that the customer has Light Activity Lifestyle is -

For Treadmill model KP281 - 7%

For Treadmill model KP481 - 3%

For Treadmill model KP781 - 0%

The Probability of a treadmill being purchased by a customer with lifestyle of Moderate Activity(51 to 100 miles/week) is 54%.

The conditional probability of purchasing the treadmill model given that the customer with lifestyle of Moderate Activity is - For Treadmill model KP281 - 28%

For Treadmill model KP481 - 22%

For Treadmill model KP781 - 4%

The Probability of a treadmill being purchased by a customer has Active Lifestyle(100 to 200 miles/week) is 33%.

The conditional probability of purchasing the treadmill model given that the customer has Active Lifestyle is - For Treadmill model KP281 - 10%

For Treadmill model KP481 - 8%

For Treadmill model KP781 - 15%

The Probability of a treadmill being purchased by a customer who is Fitness Enthusiast(>200 miles/week) is 3% only

Customer Profiling Based on above analysis

Probability of purchase of KP281 = 44%

Probability of purchase of KP481 = 33%

Probability of purchase of KP781 = 22%

Customer Profile for KP281 Treadmill:

Age of customer mainly between 18 to 35 years with few between 35 to 50 years Education level of customer 13 years and above Annual Income of customer below USD 60,000 Weekly Usage - 2 to 4 times Fitness Scale - 2 to 4 Weekly Running Mileage - 50 to 100 miles Customer Profile for KP481 Treadmill:

Age of customer mainly between 18 to 35 years with few between 35 to 50 years Education level of customer 13 years and above Annual Income of customer between USD 40,000 to USD 80,000 Weekly Usage - 2 to 4 times Fitness Scale - 2 to 4 Weekly Running Mileage - 50 to 200 miles Customer Profile for KP781 Treadmill:

Gender - Male Age of customer between 18 to 35 years Education level of customer 15 years and above Annual Income of customer USD 80,000 and above Weekly Usage - 4 to 7 times Fitness Scale - 3 to 5 Weekly Running Mileage - 100 miles and above

Recommendations

Marketing Campaigns for KP781

The KP784 model exhibits a significant sales disparity in terms of gender, with only 18% of total sales attributed to female customers. To enhance this metric, it is recommended to implement targeted strategies such as offering special promotions and trials exclusively designed for the female customers.

Affordable Pricing and Payment Plans

Given the target customer's age, education level, and income, it's important to offer the KP281 and KP481 Treadmill at an affordable price point. Additionally, consider providing flexible payment plans that allow customers to spread the cost over several months. This can make the treadmill more accessible to customers with varying budgets.

User-Friendly App Integration

Create a user-friendly app that syncs with the treadmill. This app could track users' weekly running mileage, provide real-time feedback on their progress, and offer personalized recommendations for workouts based on their fitness scale and goals.This can enhance the overall treadmill experience and keep users engaged.