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

Business Problem:

`Identify the characteristics of the target audience for each type of treadmill offered by the company, to provide a better recommendation of the treadmills to the new customers.`

- investigate whether there are differences across the product with respect to customer characteristics.

1. Descriptive analytics to create a customer profile for each AeroFit treadmill product.
2. For each AeroFit treadmill product, construct two-way contingency tables and compute all conditional and marginal probabilities along with their insights/impact on the business.

In [1]:
```
# About given Dataset :
```

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

In [ ]:
```

```

Product Portfolio:

The KP281 is an entry-level treadmill that sells for $1,500.

The KP481 is for mid-level runners that sell for $1,750.

The KP781 treadmill is having advanced features that sell for $2,500.

In [ ]:
```

```

In [ ]:
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```

In [ ]:
```

```

In [2]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib import figure
import warnings
warnings.filterwarnings('ignore')

sns.set(font_scale= 1)
```

In [3]:
```
df = pd.read_csv("aerofit_treadmill.txt")
```

In [4]:
```
df.shape
```

Out[4]: (180, 9)

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

Out[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

In [6]:
```
df.tail(5)
```

Out[6]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
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	180

In [7]:
```
# info about data/ columns and their datatypes:
```

In [8]:
```
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
```

In [ ]:
```

```

checking for Null Values in each columns

In [ ]:
```

```

In [9]:
```
df.isna().sum()
```

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

In [10]:
```
# No null values found in dataset.
```

In [ ]:

```

```

In [ ]:

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In [ ]:

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In [ ]:

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In [ ]:

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```

Pre-Processing Data for Analysis:

Fitness Category

In [11]:

```
# Converted fitness rating from Int to Object ! :

```

In [12]:

```
df["Fitness_category"] = df["Fitness"]
```

In [13]:

```
df["Fitness_category"].value_counts()
```

Out[13]:

```
3    97
5    31
2    26
4    24
1     2
Name: Fitness_category, dtype: int64
```

In [14]:

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

In [ ]:

```

```

In [15]:

```
# Product Portfolio:

# The KP281 is an entry-level treadmill that sells for $1,500.
# The KP481 is for mid-level runners that sell for $1,750.
# The KP781 treadmill is having advanced features that sell for $2,500.
```

Merging Price data with original DataSet

In [16]:

```
product_price = pd.DataFrame({
    "Product":["KP281","KP481","KP781"],
    "Product_price":[1500,1750,2500]

})
product_price
```

Out[16]:

	Product	Product_price
0	KP281	1500
1	KP481	1750
2	KP781	2500

In [17]:

```
data = df.merge(product_price,on="Product",how = "left")
```

Segmentising Age groups

In [18]:
```
data["Age_category"] = data["Age"]
```

In [19]:
```
data["Age_category"] = pd.cut(data["Age_category"], bins =[0,21,35,45,60], include_lowest=True, labels=["Teen
```

In [20]:
```
data["Age_category"] =data["Age_category"].astype("object")
```

Data Ready for Analysis :

In [21]:
```
data
```

Out[21]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	Fitness_category	Product_price	Age_category
0	KP281	18	Male	14	Single	3	4	29562	112	Good Shape	1500	Teen(0-21)
1	KP281	19	Male	15	Single	2	3	31836	75	Average Shape	1500	Teen(0-21)
2	KP281	19	Female	14	Partnered	4	3	30699	66	Average Shape	1500	Teen(0-21)
3	KP281	19	Male	12	Single	3	3	32973	85	Average Shape	1500	Teen(0-21)
4	KP281	20	Male	13	Partnered	4	2	35247	47	Bad Shape	1500	Teen(0-21)
...	...	...	...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200	Excellent Shape	2500	mid_age(36-45)
176	KP781	42	Male	18	Single	5	4	89641	200	Good Shape	2500	mid_age(36-45)
177	KP781	45	Male	16	Single	5	5	90886	160	Excellent Shape	2500	mid_age(36-45)
178	KP781	47	Male	18	Partnered	4	5	104581	120	Excellent Shape	2500	Towards_old-age(>46)
179	KP781	48	Male	18	Partnered	4	5	95508	180	Excellent Shape	2500	Towards_old-age(>46)

180 rows × 12 columns

In [ ]:
```

```

describing categorical features : :

In [22]:
```
data.describe(include="object").T
```

Out[22]:

	count	unique	top	freq
Product	180	3	KP281	80
Gender	180	2	Male	104
MaritalStatus	180	2	Partnered	107
Fitness_category	180	5	Average Shape	97
Age_category	180	4	Adult(22-35)	135

Describing numeric Data :

In [23]:
```
data.describe()
```

Out[23]:

	Age	Education	Usage	Fitness	Income	Miles	Product_price
count	180.000000	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	1805.555556
std	6.943498	1.617055	1.084797	0.958869	16506.684226	51.863605	387.978895
min	18.000000	12.000000	2.000000	1.000000	29562.000000	21.000000	1500.000000
25%	24.000000	14.000000	3.000000	3.000000	44058.750000	66.000000	1500.000000
50%	26.000000	16.000000	3.000000	3.000000	50596.500000	94.000000	1750.000000
75%	33.000000	16.000000	4.000000	4.000000	58668.000000	114.750000	1750.000000
max	50.000000	21.000000	7.000000	5.000000	104581.000000	360.000000	2500.000000

from above information ,

1. Median Age of Customer is 26 years.
2. Maximum users are Adults(22-35) years and are Male and Married.
3. Maximum Selling Product is KP281.
4. Maximum numbers of customers' fitness level is above average(>3 according to given data).
5. Median Miles run/walk per customer : 94 Miles

Additional information from data :

median income of the customers :50596.5 USD Median of average usage per customer : 3 days a week

Average Customer education is 15 to 16 years:

In [ ]:
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In [ ]:
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In [ ]:
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In [ ]:
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```

Correlation Between Features

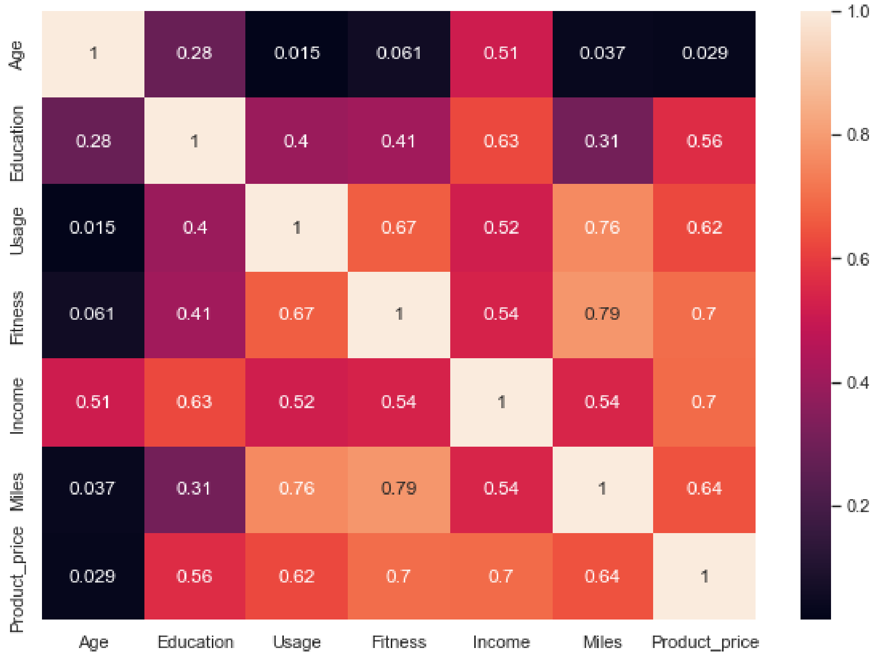
In [24]:
```
data.corr()
```

Out[24]:

	Age	Education	Usage	Fitness	Income	Miles	Product_price
Age	1.000000	0.280496	0.015064	0.061105	0.513414	0.036618	0.029263
Education	0.280496	1.000000	0.395155	0.410581	0.625827	0.307284	0.563463
Usage	0.015064	0.395155	1.000000	0.668606	0.519537	0.759130	0.623124
Fitness	0.061105	0.410581	0.668606	1.000000	0.535005	0.785702	0.696616
Income	0.513414	0.625827	0.519537	0.535005	1.000000	0.543473	0.695847
Miles	0.036618	0.307284	0.759130	0.785702	0.543473	1.000000	0.643923
Product_price	0.029263	0.563463	0.623124	0.696616	0.695847	0.643923	1.000000

In [25]:
```python
plt.figure(figsize=(10,7))
sns.heatmap(data.corr(),annot=True)
```

Out[25]: <AxesSubplot:>



features with higher correlation : >0.6

In [26]:
```python
# features with higher correlation : >0.65

data.corr().unstack()[(data.corr().unstack()>0.65) & (data.corr().unstack()!=1)]
```

Out[26]:
```
Usage          Fitness          0.668606
               Miles            0.759130
Fitness        Usage            0.668606
               Miles            0.785702
               Product_price    0.696616
Income         Product_price    0.695847
Miles          Usage            0.759130
               Fitness          0.785702
Product_price  Fitness          0.696616
               Income           0.695847
dtype: float64
```

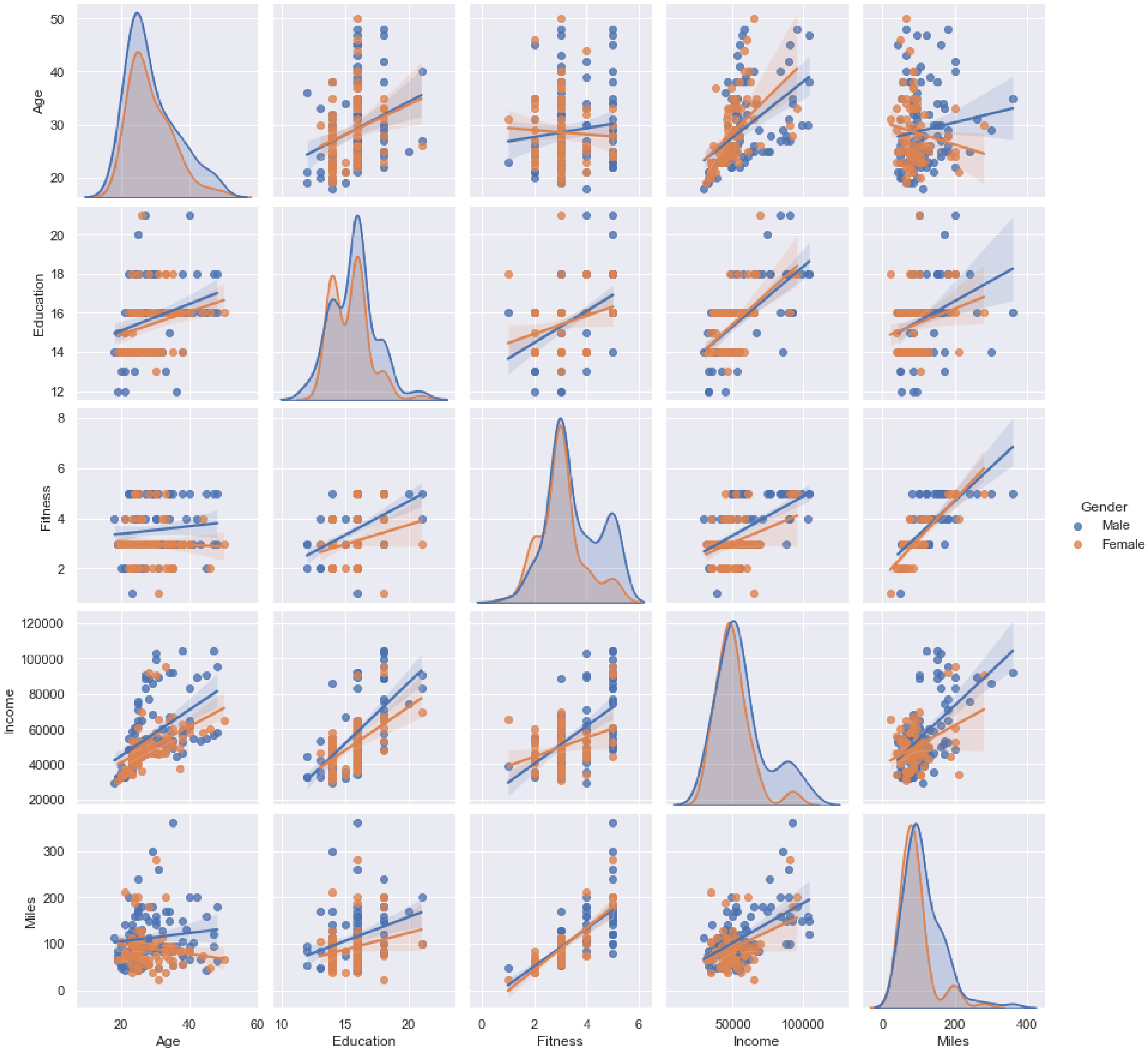
Important correlations :

1. Fitness & Miles : 0.785702
2. Product_price & Income : 0.695847

In [27]:
```python
d = data[["Age","Education","Fitness","Income","Miles","Gender"]]
```

In [28]:

```
x = sns.pairplot(d,
                 kind = "reg",
                 hue="Gender")
x.map_diag(sns.kdeplot)
plt.show()
```



In [ ]:

In [ ]:

In [ ]:

In [ ]:

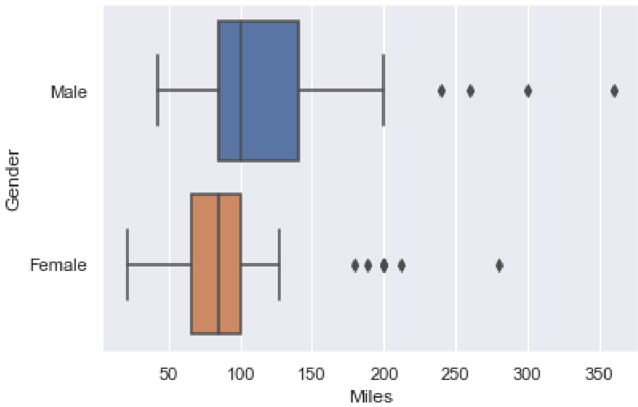
Distribution of all numerical features : and check for outliers :

In [ ]:

In [29]:
```
d = data[["Age","Education","Usage","Fitness","Income","Miles","Gender"]]

```

Distribution of Miles run by customer in given Data

In [30]:
```
sns.boxplot(x = "Miles",data = d,y="Gender")
plt.show()
```



In [31]:
```
IQR = np.percentile(data["Miles"],75)  -   np.percentile(data["Miles"],25)
Q3 = np.percentile(data["Miles"],75)
Q1 = np.percentile(data["Miles"],25)
UpperWhisker = Q3 + (1.5*(IQR))
UpperWhisker
```

Out[31]: 187.875

In [32]:
```
Q1
```

Out[32]: 66.0

In [33]:
```
Q3
```

Out[33]: 114.75

In [34]:
```
IQR
```

Out[34]: 48.75

In [35]:
```
outlier_data = data[data["Miles"]>UpperWhisker]
print("Outliers : ",len(outlier_data))
```

```
Outliers :  13
```

Insights from Customers who run more than 187.875 (outliers).

In [36]:
```
outlier_data["Product"].value_counts()
```

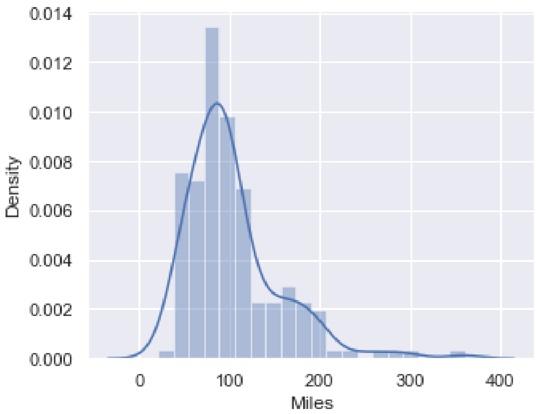
Out[36]:
```
KP781    11
KP281     1
KP481     1
Name: Product, dtype: int64
```

In [37]:
```

outlier_data["Fitness_category"].value_counts()
```

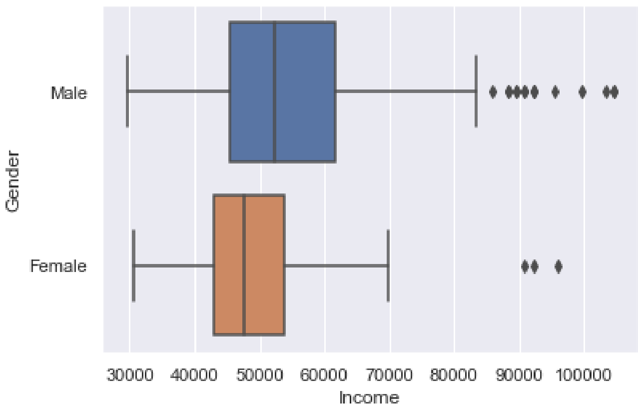
Out[37]:
```
Excellent Shape    11
Good Shape          2
Name: Fitness_category, dtype: int64
```

13 outlier in column "Miles". Customers who fall in outliers as per their miles run/walk , uses product KP781 and are in excellent shape.

In [38]:
```python
plt.figure(figsize=(5,4))
sns.distplot(data["Miles"])
plt.show()

```



In [39]:
```python
sns.boxplot(x = "Income",data = d,y="Gender")
plt.show()
```



In [40]:
```python
IQR = np.percentile(data["Income"],75)-np.percentile(data["Income"],25)
Q3 = np.percentile(data["Income"],75)
Q1 = np.percentile(data["Income"],25)
UpperWhisker = Q3 + (1.5*(IQR))
UpperWhisker
```

Out[40]:
```
80581.875
```

In [41]:
```python
(data["Income"] > UpperWhisker).value_counts()
```

Out[41]:
```
False    161
True      19
Name: Income, dtype: int64
```

 # 19 customers who's spending capacity is way more than most of the customers

In [ ]:
```python

```

In [ ]:
```python

```

In [ ]:
```python

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In [ ]:
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In [ ]:
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In [ ]:

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```

In [ ]:

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```

In [ ]:

```

```

General Sales Analysis :

In [42]:

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

```

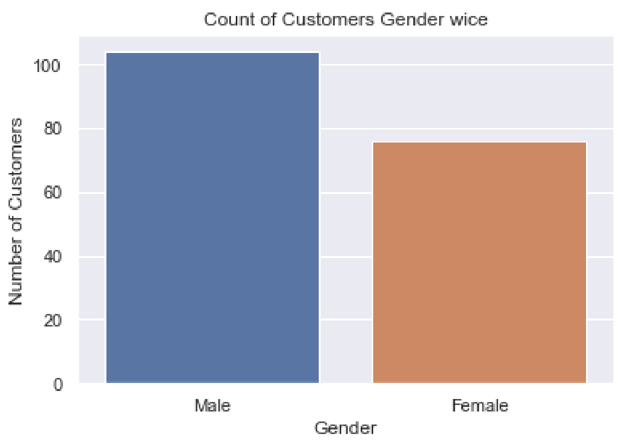
Out[42]:

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

In [43]:

```
sns.countplot(x = "Gender" , data = data)
plt.title("Count of Customers Gender wice")

plt.xlabel("Gender")
plt.ylabel("Number of Customers")
plt.show()
```



Quantity per Product Sold

In [44]:

```
data["Product"].value_counts(normalize=True)*100
```

Out[44]:

```
KP281    44.444444
KP481    33.333333
KP781    22.222222
Name: Product, dtype: float64
```

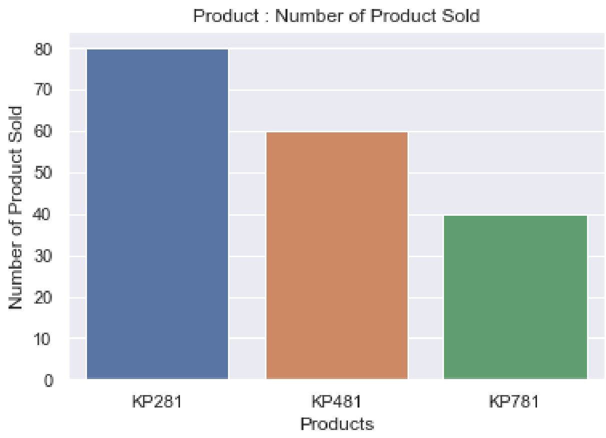
In [ ]:

```

```

In [45]:
```
sns.barplot(x = data["Product"].value_counts().index,
            y = data["Product"].value_counts())
plt.title("Product : Number of Product Sold")

plt.xlabel("Products")
plt.ylabel("Number of Product Sold")
plt.show()
```



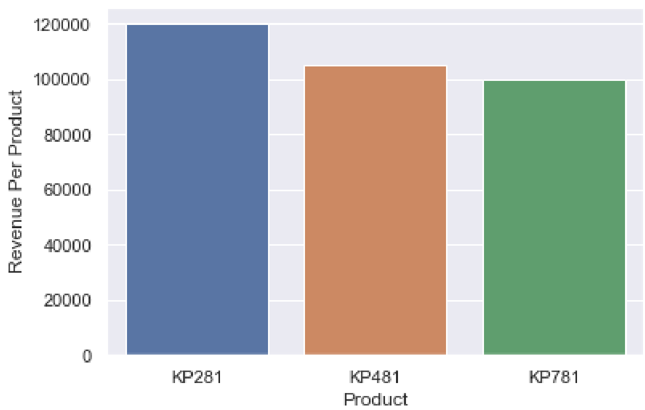
In [46]:
```
data.groupby("Product")["Product_price"].sum()
```

Out[46]:
```
Product
KP281    120000
KP481    105000
KP781    100000
Name: Product_price, dtype: int64
```

In [47]:
```
sns.barplot(x = data.groupby("Product")["Product_price"].sum().index,
            y = data.groupby("Product")["Product_price"].sum())

plt.ylabel("Revenue Per Product")
```

Out[47]:
```
Text(0, 0.5, 'Revenue Per Product')
```



Highest Selling Product is KP281 and other product's numbers are also significant.

As shown below Calulation , is the revenue generater per Product :

for KP281 is highest (120000 USD) and for KP481 and KP781 are around same as 100000 USD.

In [ ]:
```

```

In [ ]:
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```

In [ ]:
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```

In [ ]:
```

```

In [ ]:
```
1
```

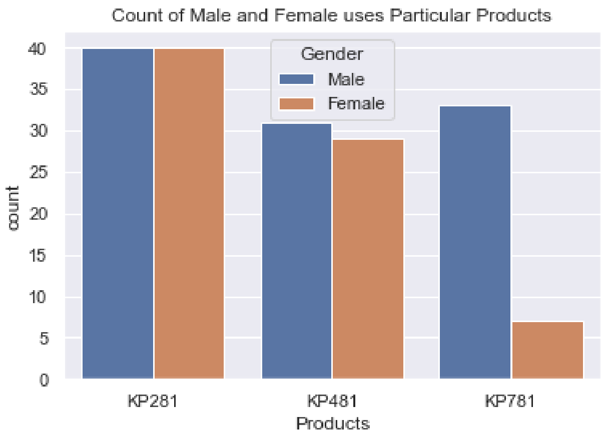
In [ ]:
```
1
```

In [ ]:
```
1
```

Two-Way Contingency Table :

Across gender

In [48]:
```
sns.countplot(x = "Product", data= data, hue = "Gender")
plt.xlabel("Products")
plt.title("Count of Male and Female uses Particular Products")
plt.show()
```



In [49]:
```
pd.crosstab([data["Product"]],df["Gender"],margins=True)
```

Out[49]:

Gender Product	Female	Male	All
KP281	40	40	80
KP481	29	31	60
KP781	7	33	40
All	76	104	180

In [50]:
```
((pd.crosstab(data["Product"],data["Gender"],margins=True))/180)*100
```

Out[50]:

Gender Product	Female	Male	All
KP281	22.222222	22.222222	44.444444
KP481	16.111111	17.222222	33.333333
KP781	3.888889	18.333333	22.222222
All	42.222222	57.777778	100.000000

```
1
```

Marginal Probability :

(from above tables)

Probability of Male Customer Purchasing any product is : 57.77 %

Probability of Female Customer Purchasing any product is : 42.22 %

Marginal Probability of any customer buying

product KP281 is : 44.44 % (cheapest / entry level product)

product KP481 is : 33.33 % (for intermediate users)

product KP781 is : 22.22 % (product for extensive use who run/walk more miles)

In [ ]:

```
 
```

Conditional Probabilities :

In [51]:

```
(pd.crosstab([data["Product"]],data["Gender"],margins=True,normalize="columns"))*100

```

Out[51]:

Gender	Female	Male	All
Product			
KP281	52.631579	38.461538	44.444444
KP481	38.157895	29.807692	33.333333
KP781	9.210526	31.730769	22.222222

Probability of users of KP281 given they male :

Probability of Selling Product

`KP281 | Female = 52 %`

`KP481 | Female = 38 %`

`KP781 | Female = 10 %`

`KP281 | male = 38 %`

`KP481 | male = 30 %`

`KP781 | male = 32 %`

Probability of Female customer buying KP281(52.63%) is more than male(38.46%).

KP281 is more recommended for female customers.

Probability of Male customer buying Product KP781(31.73%) is way more than female(9.21%).

Probability of Female customer buying Product KP481(38.15%) is significantly higher than male (29.80%.)

KP481 product is specifically recommended for Female customers who are intermediate user.

In [ ]:

```
 
```

In [ ]:

```
 
```

In [ ]:

```
 
```

In [ ]:

```
 
```

Across Marital Status

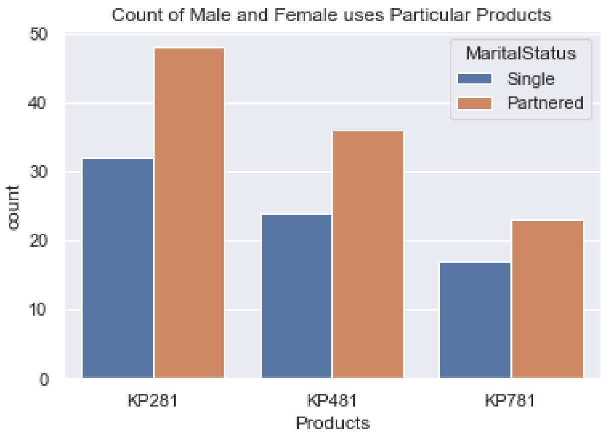
In [52]:

```
data["MaritalStatus"].value_counts(normalize=True)*100
```

Out[52]:

```
Partnered    59.444444
Single       40.555556
Name: MaritalStatus, dtype: float64
```

In [53]:
```
sns.countplot(x = "Product", data= data, hue = "MaritalStatus")
plt.xlabel("Products")
plt.title("Count of Male and Female uses Particular Products")
plt.show()
```



In [54]:
```
pd.crosstab([data["Product"]],df["MaritalStatus"],margins=True)
```

Out[54]:

MaritalStatus	Partnered	Single	All
Product			
KP281	48	32	80
KP481	36	24	60
KP781	23	17	40
All	107	73	180

In [55]:
```
(pd.crosstab([data["Product"]],df["MaritalStatus"],margins=True)/180)*100
```

Out[55]:

MaritalStatus	Partnered	Single	All
Product			
KP281	26.666667	17.777778	44.444444
KP481	20.000000	13.333333	33.333333
KP781	12.777778	9.444444	22.222222
All	59.444444	40.555556	100.000000

Marginal Probability for

- Married Customers : 59.44 %
- Single Customers : 40.555 %

In [56]:
```
pd.crosstab([data["Product"]],df["MaritalStatus"],margins=True,normalize="columns")*100
```

Out[56]:

MaritalStatus	Partnered	Single	All
Product			
KP281	44.859813	43.835616	44.444444
KP481	33.644860	32.876712	33.333333
KP781	21.495327	23.287671	22.222222

KP281 | Partnered = 44.85 %

KP481 | Partnered = 33.64 %

KP781 | Partnered = 21.49 %

KP281 | Single = 43.83 %

KP481 | Single = 32.87 %

KP781 | Single = 23.28 %

Probability of Married Person purchasing any product is 59.44 %

Probability of Single Person purchasing any product is 40.55 %

Probability of a Married person buying product KP281 and KP481 is slightly higher than the customers who are single.

Probability of a single person buying KP781 is higher than Married customers.

So , KP781 is also recommended for people who are single and exercises more.

In [ ]:

```
 
```

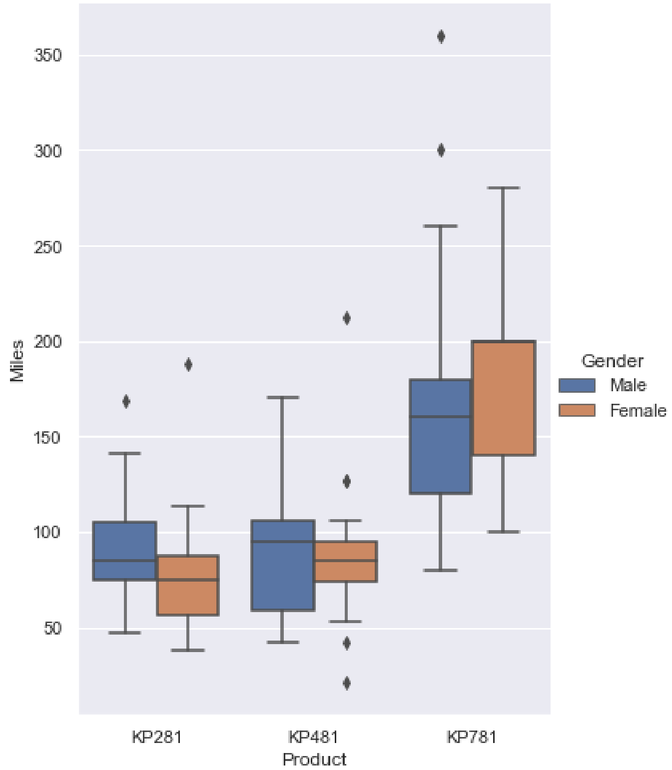
In [ ]:

```
 
```

Product - Gender - Mile

In [57]:

```
sns.catplot(x= "Product", y = "Miles",hue="Gender" ,kind = "box", data= data,height=7, aspect=8/11 )
plt.xticks(rotation = 0)
plt.show()
```



Since, the variation for Product KP481 for particularly Male is more , we can say KP481 is good for people who want to run/walk for 60 to 130 miles a week. It is more a genera purpose product for intermediate use.

In [ ]:

```
 
```

In [ ]:

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```

In [58]:
```
np.round(pd.crosstab([data["Product"]],df["Gender"],values=data["Miles"],aggfunc=np.mean,margins=True),2)
```

Out[58]:

Gender	Female	Male	All
Product			
KP281	76.20	89.38	82.79
KP481	87.34	88.48	87.93
KP781	180.00	164.12	166.90
All	90.01	112.83	103.19

Observations and Insights:

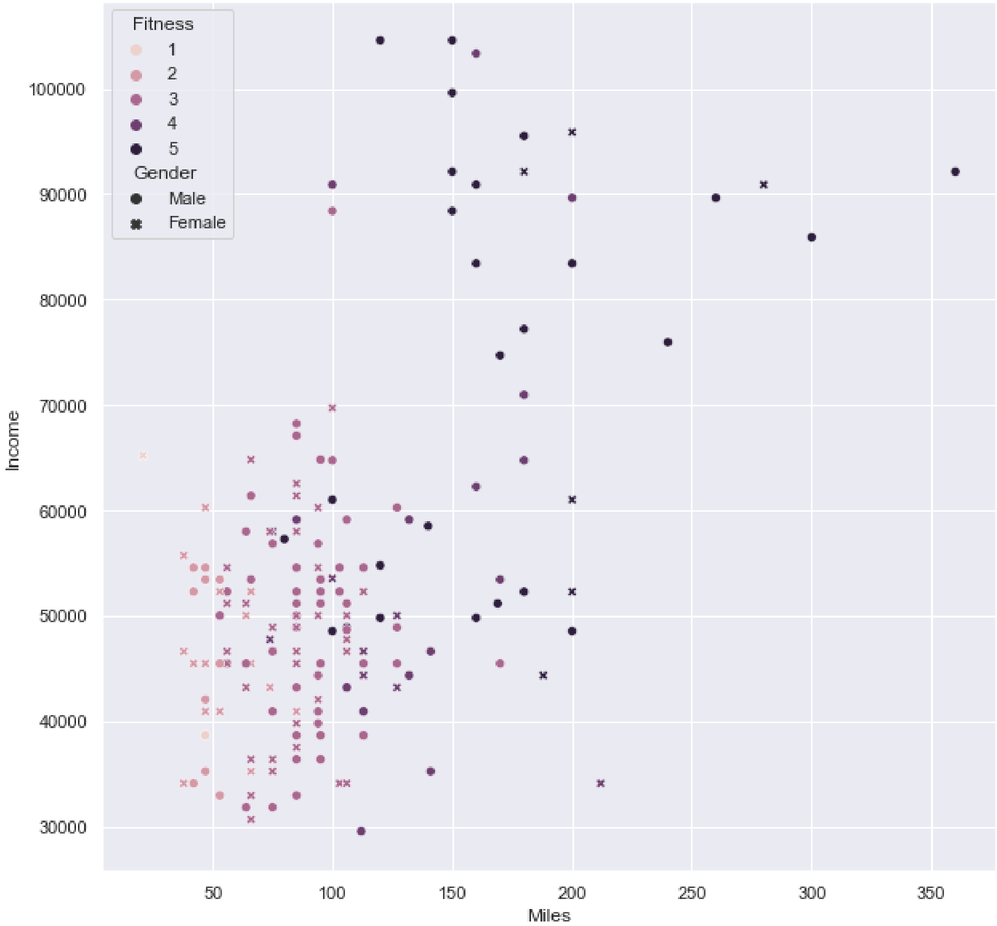
- From charts and Crosstab of average miles run by customer for particular product:
- Female Customers who are running average 180 miles (extensive exercise) , are using product KP781, which is higher than Male average using same product.
- KP781 can be recommended for Female customers who exercises extensively.
- Males customers who are running average of 90 miles (average exercise) , are using product KP281 .
- Males customers who are running average of 87 miles (average exercise) , are using product KP481 . and for female average running for same product is 88 miles.

Overall Picture over Few categorical and Numerical features :

In [59]:
```
plt.figure(figsize=(10,10))

sns.scatterplot(x = "Miles",y="Income",data = data, hue= "Fitness",style="Gender")
```

Out[59]: <AxesSubplot:xlabel='Miles', ylabel='Income'>



- Above scattered Plot shows the overall picture over customer's income, how much they exercise (run/walk miles) given their gender and their fitness level.
- Most of the customer's fitness level is around 3 to 4 . and it says people who run more miles are having good fitness level.
- Though there is a trend with income and miles. But there are very few customers who earn a lot and run more miles.

In [ ]:

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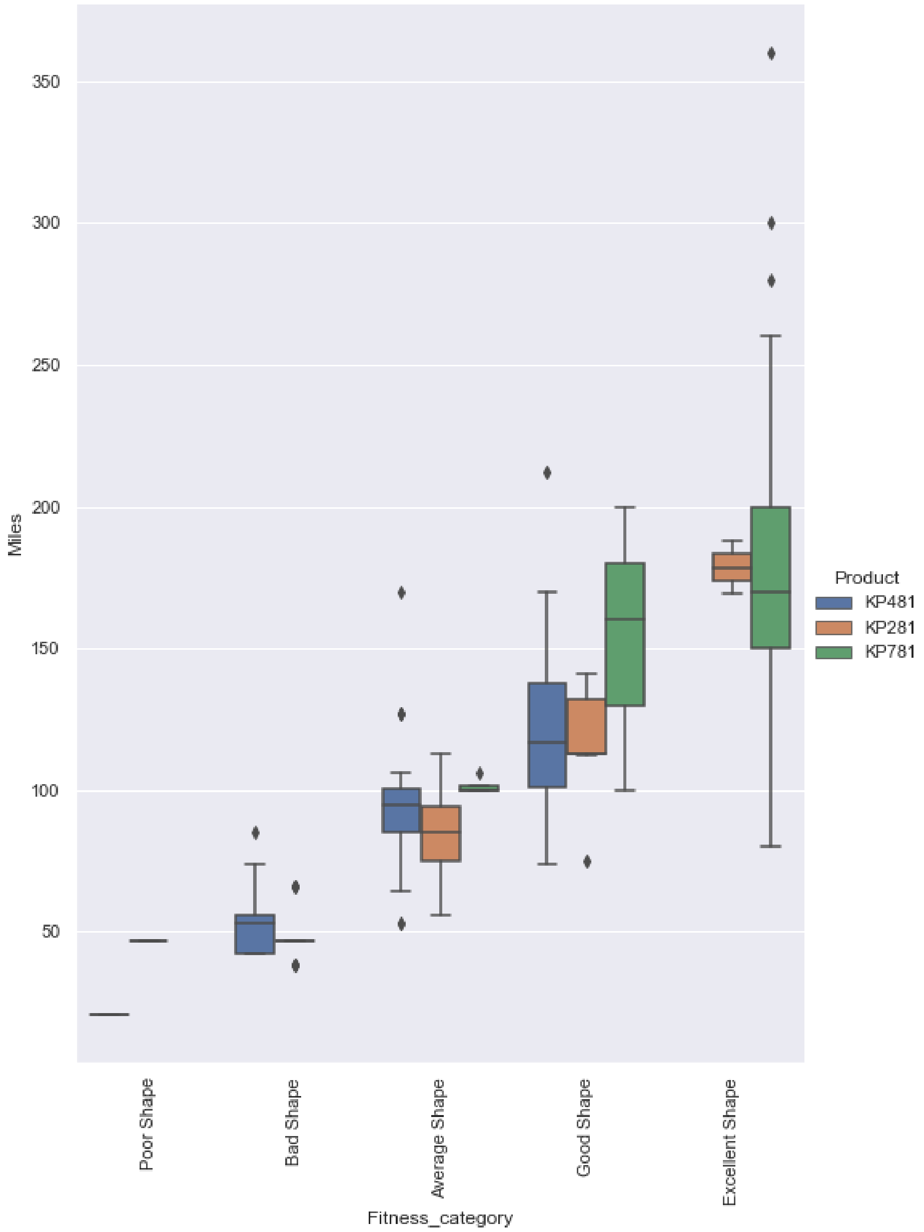
```

Product | Miles - Fitness

In [60]:

```

sns.catplot(x= "Fitness_category", y = "Miles" ,kind = "box",hue="Product", data= data.sort_values(by="Fitnes
plt.xticks(rotation = 90)
plt.show()
```



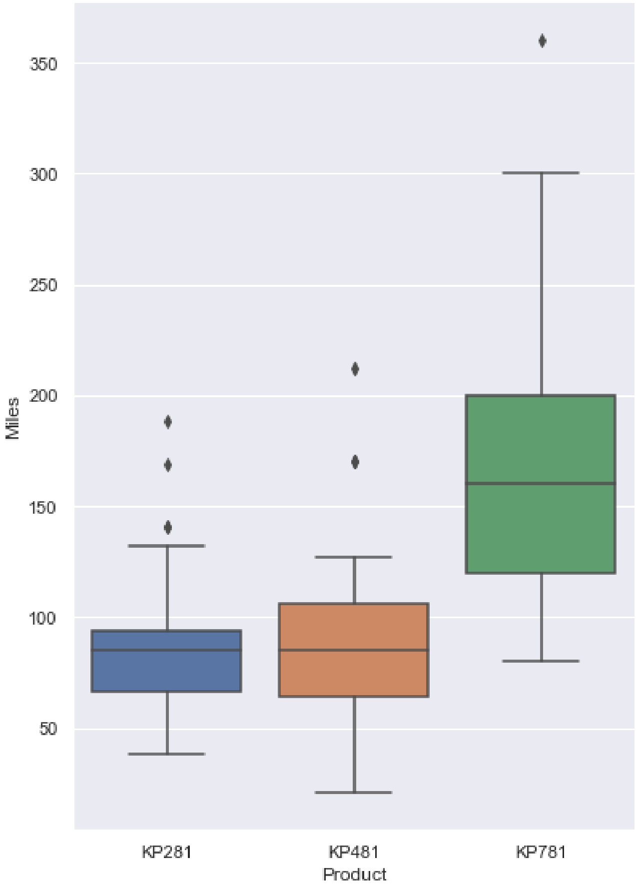
Product - Miles

People who run/walk more miles(>130) , are more likely to use KP781 product !

People who walk/run around 60 to 130 miles are more likely to use KP281 and KP481 products.

In [61]:

```
sns.catplot(x= "Product", y = "Miles" ,kind = "box", data= data,height=8, aspect=8/11)
plt.xticks(rotation = 0)
plt.show()
```



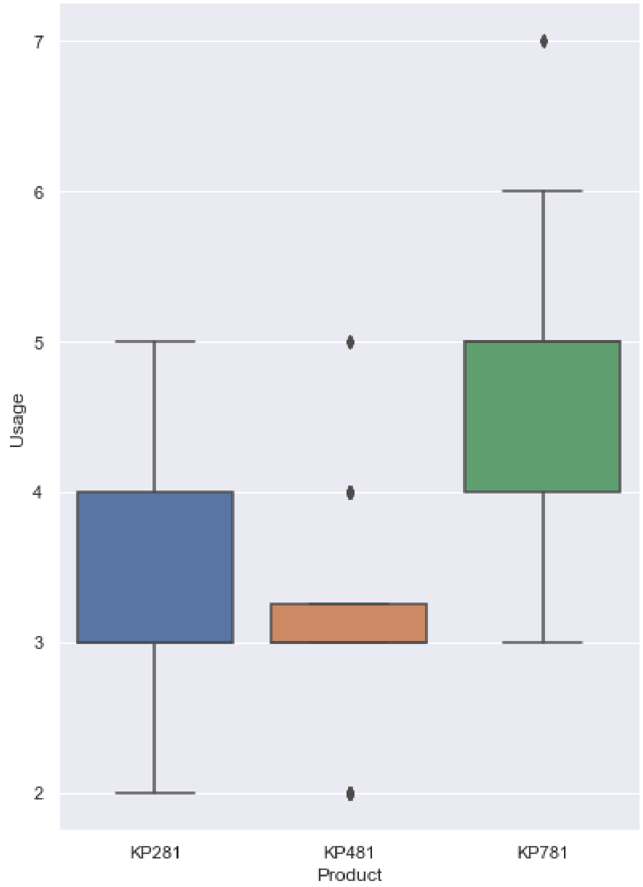
Customers who walk/run 70-90 miles, are using KP281

Customers who walk/run 70-130 or more miles are using KP481.

Customers who walk/run 120 to 200 or more miles uses KP781.

In [62]:

```
sns.catplot(x= "Product", y = "Usage" ,kind = "box", data= data,height=8, aspect=8/11)
plt.xticks(rotation = 0)
plt.show()
```



Customers who uses Treadmill 4 to 6 days a week , are more likely to use KP781 .

Customers who uses Treadmill 3 to 4 days a week , are more likely to use KP481 .

Customers who uses Treadmill 3 to 4 days a week , are more likely to use KP281 .

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Correlation Between Income and Product Price :

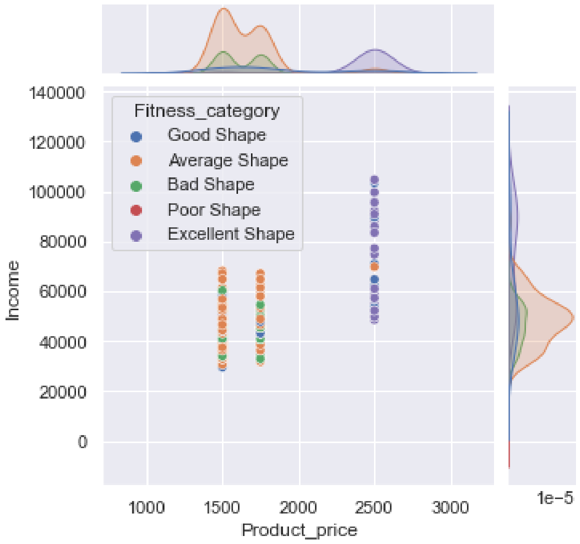
Observations and Insights:

from Plot,

- we can see a positive trend , that who are earning more are likely to buy the costlier product.
- people are in excellent and good shape, they are more likely spend mor amount and buy the costlier product which can be more reliable for extensive use.

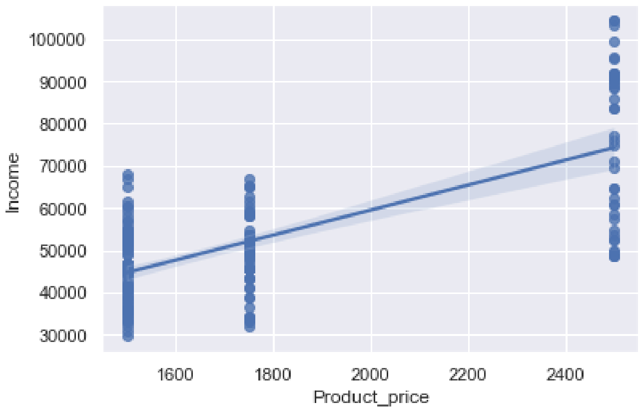
In [63]:
```
sns.jointplot(x = data["Product_price"],
              y= data["Income"],
             height=5, kind="scatter",hue=data["Fitness_category"])
```

Out[63]: <seaborn.axisgrid.JointGrid at 0x18fc5113b80>



In [64]:
```
sns.regplot(x = data["Product_price"],
            y= data["Income"],)
```

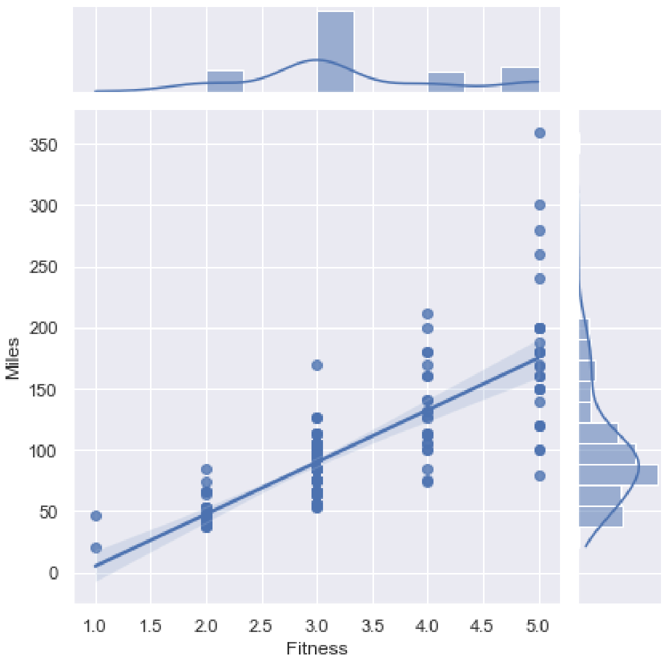
Out[64]: <AxesSubplot:xlabel='Product_price', ylabel='Income'>



Relashion of Miles and FitnessLevel

In [65]:
```
sns.jointplot(x = data["Fitness"],
              y= data["Miles"],
             height=6, kind="reg") # ['scatter', 'hist', 'hex', 'kde', 'reg', 'resid'],
```

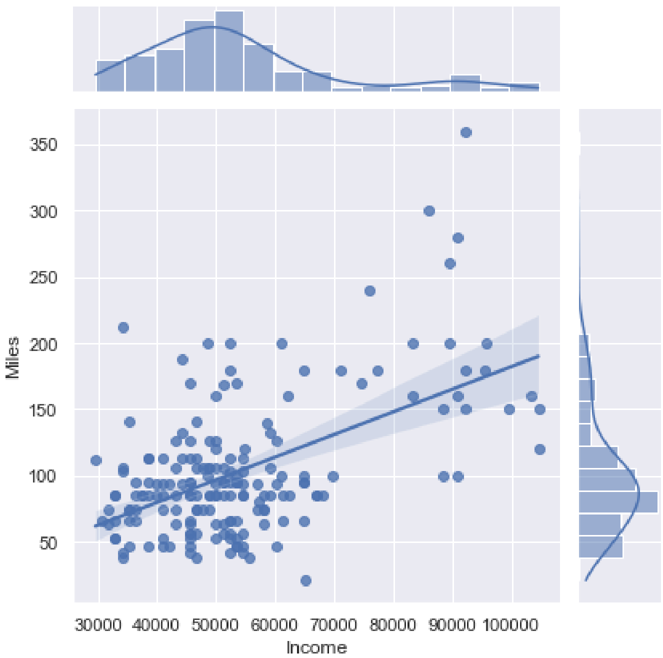
Out[65]: <seaborn.axisgrid.JointGrid at 0x18fc6896ee0>



Correlation between Income and miles :

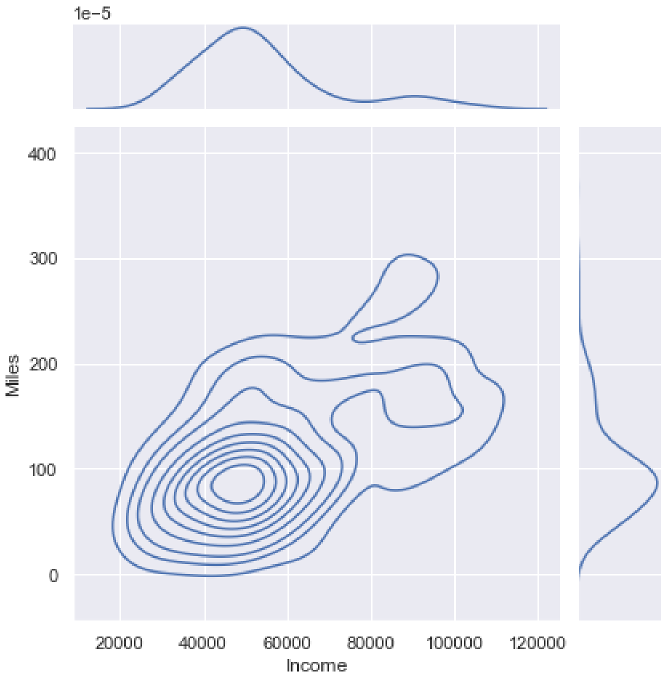
In [66]:
```python
sns.jointplot(x = data["Income"],
              y= data["Miles"],
             height=6, kind="reg") # ['scatter', 'hist', 'hex', 'kde', 'reg', 'resid'],
```

Out[66]: <seaborn.axisgrid.JointGrid at 0x18fc6c8b3a0>



In [67]:
```python
sns.jointplot(x = data["Income"],
              y= data["Miles"],
             height=6, kind="kde") # ['scatter', 'hist', 'hex', 'kde', 'reg', 'resid'],
```

Out[67]: <seaborn.axisgrid.JointGrid at 0x18fc6ffbeb0>



Observations and Insights:

- Majority customer base has earning from 25,000 to 75,000USD
- and prefer to exercises very less to 175 miles a week.

In [ ]:
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```

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In [ ]:
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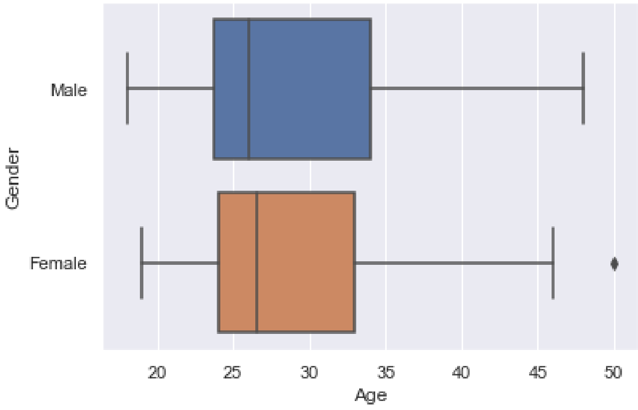
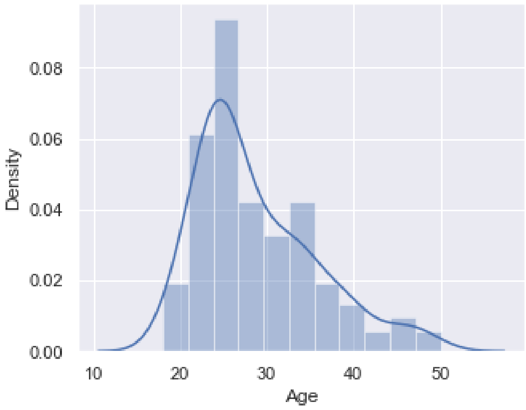
Customer Age

```
In [68]:
sns.boxplot(x = "Age",data = d,y="Gender")
plt.show()
```




```
In [69]:
plt.figure(figsize=(5,4))
sns.distplot(data["Age"])
plt.show()

```



Age category of customers per Product :

```
In [70]:
data.loc[data["Product"]=="KP281"]["Age_category"].value_counts()
```

```
Out[70]:
Adult(22-35)           56
mid_age(36-45)         11
Teen(0-21)             10
Towards_old-age(>46)    3
Name: Age_category, dtype: int64
```

```
In [71]:
data.loc[data["Product"]=="KP481"]["Age_category"].value_counts()
```

```
Out[71]:
Adult(22-35)           45
Teen(0-21)              7
mid_age(36-45)          7
Towards_old-age(>46)    1
Name: Age_category, dtype: int64
```

```
In [72]:
data.loc[data["Product"]=="KP781"]["Age_category"].value_counts()
```

```
Out[72]:
Adult(22-35)           34
mid_age(36-45)          4
Towards_old-age(>46)    2
Name: Age_category, dtype: int64
```

In [73]:
```
pd.crosstab(index=data["Product"],columns=data["Age_category"], margins=True)
```

Out[73]:

Age_category	Adult(22-35)	Teen(0-21)	Towards_old-age(>46)	mid_age(36-45)	All
Product					
KP281	56	10	3	11	80
KP481	45	7	1	7	60
KP781	34	0	2	4	40
All	135	17	6	22	180

In [74]:
```
np.round((pd.crosstab(index=data["Product"],columns=data["Age_category"],normalize="columns", margins=True))*
```

Out[74]:

Age_category	Adult(22-35)	Teen(0-21)	Towards_old-age(>46)	mid_age(36-45)	All
Product					
KP281	41.48	58.82	50.00	50.00	44.44
KP481	33.33	41.18	16.67	31.82	33.33
KP781	25.19	0.00	33.33	18.18	22.22

In [75]:
```
np.round((pd.crosstab(index=data["Product"],columns=data["Age_category"], margins=True)),2)
```

Out[75]:

Age_category	Adult(22-35)	Teen(0-21)	Towards_old-age(>46)	mid_age(36-45)	All
Product					
KP281	56	10	3	11	80
KP481	45	7	1	7	60
KP781	34	0	2	4	40
All	135	17	6	22	180

In [76]:
```
data.groupby("Age_category")["Product"].count()
```

Out[76]:
```
Age_category
Adult(22-35)            135
Teen(0-21)               17
Towards_old-age(>46)      6
mid_age(36-45)           22
Name: Product, dtype: int64
```

from above distribution ,

Most of the customer base is from Age category Adult (22-35) : 135 customer .

customers who are in Teen and mid_age category are 17 , 22 .

```
Probability of Teen Age Customer buying KP281 is 58.82 % , and KP481 is 41.18 %.

Probability of Adult buying KP281 is  41.48%  , KP481 is 33.33% and KP781 is 25.19%.

Probability of Customer age above 46 buying KP281 is 50%  , KP481 is 16.67% and KP781 is 33.33%.

Probability of Customer of mid age(36-45 years) buying KP281 is 50%  , KP481 is 31.82% and KP781 is 18.18%.
```

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```

Fitness category

In [77]:
```
pd.crosstab(columns=data["Fitness_category"],index=data["Product"],margins=True)
```

Out[77]:

Fitness_category	Average Shape	Bad Shape	Excellent Shape	Good Shape	Poor Shape	All
Product						
KP281	54	14	2	9	1	80
KP481	39	12	0	8	1	60
KP781	4	0	29	7	0	40
All	97	26	31	24	2	180

In [78]:
```
np.round(pd.crosstab(index=data["Product"],columns=data["Fitness_category"],normalize="columns")*100,2)
```

Out[78]:

Fitness_category	Average Shape	Bad Shape	Excellent Shape	Good Shape	Poor Shape
Product					
KP281	55.67	53.85	6.45	37.50	50.0
KP481	40.21	46.15	0.00	33.33	50.0
KP781	4.12	0.00	93.55	29.17	0.0

if the person is in excellent shape , the probabiliy that he is using KP781 is more than 90 %.

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Customer Profiling - Categorization of users.

KP281 :

- Most affordable and entry level and Maximum Selling Product.
- This model popular amongst both Male and Female customers
- Same number of Male and Female customers.
- Customers walk/run average 70 to 90 miles on this product.
- Customers use 3 to 4 times a week
- Fitness Level of this product users is Average Shape.
- More general purpose for all age group and fitness levels.

KP481 :

- Intermediate Price Range
- Fitness Level of this product users varies from Bad to Average Shape depending on their usage.
- Customers prefer KP481 model to use less frequent but to run more miles per week on this.
- Customer walk/run average 70 to 130 or more miles per week on his product.
- has higher probability of selling for female customers.
- Probability of Female customer buying KP481 is significantly higher than male.
    - KP481 product is specifically recommended for Female customers who are intermediate user.
- customers are from adult, teen and mid-age categories.

KP781 :

- least sold product.
- high price and preferred by customers who does exercises more extensively and run more miles.
- Customer walk/run average 120 to 200 or more miles per week on his product.
- Customers use 4 to 5 times a week at least.
- If person is in Excellent Shape , the probability that he is using KP781 is more than 90%.

- Female Customers who are running average 180 miles (extensive exercise) , are using product KP781, which is higher than Male average using same product.
- KP781 can be recommended for Female customers who exercises extensively.
- Probability of Male customer buying Product KP781(31.73%) is way more than female(9.21%).
- Probability of a single person buying KP781 is higher than Married customers. So , KP781 is also recommended for people who are single and exercises more.
- most of old people who are above 45 age and adult uses this product.

Recommendations :

- Recommend KP781 product to users who exercises/run more frequently and run more and more miles , and have high income. Since Kp781 is least selling product (22.2% share of all the products) , recommend this product some customers who exercise at intermediate to extensive level , if they are planning to go for KP481. Also the targeted Age Category is Adult and age above 45.
- Recommend KP481 product specifically for female customers who run/walk more miles , as data shows their probability is higher. Statistical Summery about fitness level and miles for KP481 is not good as KP281 which is cheaper product. Possibly because of price, customers prefer to purchase KP281. It is recommended to make some necessary changes to product K481 to increase customer experience.

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Some necessary exploration on Cross Tabs :

In [79]:

```
pd.crosstab(index=[data["Product"],data["Fitness_category"]],columns=data["Gender"])
```

Out[79]:

Product	Fitness_category	Female	Male
KP281	Average Shape	26	28
	Bad Shape	10	4
	Excellent Shape	1	1
	Good Shape	3	6
	Poor Shape	0	1
KP481	Average Shape	18	21
	Bad Shape	6	6
	Good Shape	4	4
	Poor Shape	1	0
KP781	Average Shape	1	3
	Excellent Shape	5	24
	Good Shape	1	6

In [80]:
```
pd.crosstab(index=[data["Product"],data["Fitness_category"]],columns=data["Gender"],normalize="index")*100
```

Out[80]:

	Gender	Female	Male
Product	Fitness_category		
KP281	Average Shape	48.148148	51.851852
	Bad Shape	71.428571	28.571429
	Excellent Shape	50.000000	50.000000
	Good Shape	33.333333	66.666667
	Poor Shape	0.000000	100.000000
KP481	Average Shape	46.153846	53.846154
	Bad Shape	50.000000	50.000000
	Good Shape	50.000000	50.000000
	Poor Shape	100.000000	0.000000
KP781	Average Shape	25.000000	75.000000
	Excellent Shape	17.241379	82.758621
	Good Shape	14.285714	85.714286

In [81]:
```
data[data["Miles"]>150]["Fitness_category"].value_counts()
```

Out[81]:
```
Excellent Shape    20
Good Shape          7
Average Shape       1
Name: Fitness_category, dtype: int64
```

In [82]:
```
data[data["Miles"]>np.percentile(data["Miles"],90)]["Fitness_category"].value_counts()
```

Out[82]:
```
Excellent Shape    11
Good Shape          2
Name: Fitness_category, dtype: int64
```

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In [83]:
```
pd.crosstab(index=[data["Product"],data["MaritalStatus"]],columns=data["Gender"],margins=True)
```

Out[83]:

	Gender	Female	Male	All
Product	MaritalStatus			
KP281	Partnered	27	21	48
	Single	13	19	32
KP481	Partnered	15	21	36
	Single	14	10	24
KP781	Partnered	4	19	23
	Single	3	14	17
All		76	104	180

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