In [1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.stats import norm
import seaborn as sns
```

Defining Problem Statement and Analysing basic metrics

we have to do customer profiling using bar, countplot etc and conditional and marginal probabilities along with their impact on the business(conditional and marginal probability are calculated using the pandas crosstab method)

In [2]:
```python
Aerofit_data = pd.read_csv('aerofit_treadmill.txt',sep=',')
```

In [3]:
```python
Aerofit_data.head()
```

Out[3]:

	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

From the below cell we can see that except Product, Gender and MaritalStatus(which are string datatype) are int data type in the future cells we will be converting categorical varibles such as Gender and MaritalStatus in to categories using replace method in pandas

from the below cell we see that their are no missing data in the dataset

In [4]:
```
Aerofit_data.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
```

from the shape of data it is clear that it contains the data of 180 individuals and 9 features are considered while preparing the data set

In [5]:
```
Aerofit_data.shape
```

Out[5]:
```
(180, 9)
```

form the below table it is clear that their are 3 unique products present

In [6]:
```
Aerofit_data['Product'].unique()
```

Out[6]:
```
array(['KP281', 'KP481', 'KP781'], dtype=object)
```

In [7]:
```
Aerofit_data['Age'].unique()
```

Out[7]:
```
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],
      dtype=int64)
```

In [8]:
```
Aerofit_data['Gender'].unique()
```

Out[8]:
```
array(['Male', 'Female'], dtype=object)
```

The columns present in the dataset are listed below

In [9]:
```
Aerofit_data.columns
```
Out[9]:
```
Index(['Product', 'Age', 'Gender', 'Education', 'MaritalStatus', 'Usage',
       'Fitness', 'Income', 'Miles'],
      dtype='object')
```

The education qualification varies from 14 years to 21 years

In [10]:
```
Aerofit_data['Education'].unique()
```
Out[10]:
```
array([14, 15, 12, 13, 16, 18, 20, 21], dtype=int64)
```
In [11]:
```
Aerofit_data['MaritalStatus'].unique()
```
Out[11]:
```
array(['Single', 'Partnered'], dtype=object)
```
In [12]:
```
Aerofit_data['Usage'].unique()
```
Out[12]:
```
array([3, 2, 4, 5, 6, 7], dtype=int64)
```
In [13]:
```
Aerofit_data['Fitness'].unique()
```
Out[13]:
```
array([4, 3, 2, 1, 5], dtype=int64)
```

Their are 107 partners and 73 unmarried people partisipated in the survey

In [14]:
```
Aerofit_data['MaritalStatus'].value_counts()
```
Out[14]:
```
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64
```

Stastical Analysis

Most number of people in the age group of 26(median) are buying the fitness products

most people use fitness machines 3 times a week

average fitness people are using the fitness products the most

Fitness products are most purchased by the Income group USD 50596.50

Most of the people run for 94 miles a week

In [15]:
```
Aerofit_data.describe()
```

Out[15]:

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

the product KP281 is most frequent one which appears 80 times

male are mostly using the fitness machines

partners are using the more than the unmarried people

In [16]:
```
Aerofit_data.describe(include='object')
```

Out[16]:

	Product	Gender	MaritalStatus
count	180	180	180
unique	3	2	2
top	KP281	Male	Partnered
freq	80	104	107

In [17]:
```
Aerofit_data['Gender'].unique()
```

Out[17]:
```
array(['Male', 'Female'], dtype=object)
```

converting both Gender and maritalStatus features to category using the dictionary inside replace method

In [18]:
```
replace_cat = {'Gender':{'Male':0,'Female':1},
               'MaritalStatus':{'Partnered':1,'Single':0}}
```

In [19]:
```
Aerofit_data = Aerofit_data.replace(replace_cat)
```

0 being Male and 1 being Female

In [20]:
```
Aerofit_data['Gender'].unique()
```

Out[20]:
```
array([0, 1], dtype=int64)
```

0 being single and 1 being married

In [21]:
```
Aerofit_data['MaritalStatus'].unique()
```

Out[21]:
```
array([0, 1], dtype=int64)
```

dataset after the categorical varible to category

In [22]:
```
Aerofit_data.head()
```

Out[22]:

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

In [23]:
```
Aerofit_data.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    int64 
 3   Education      180 non-null    int64 
 4   MaritalStatus  180 non-null    int64 
 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(8), object(1)
memory usage: 12.8+ KB
```

we can see that the dataset does not contain any missing values

In [24]:
```
Aerofit_data.isna().sum()
```

Out[24]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

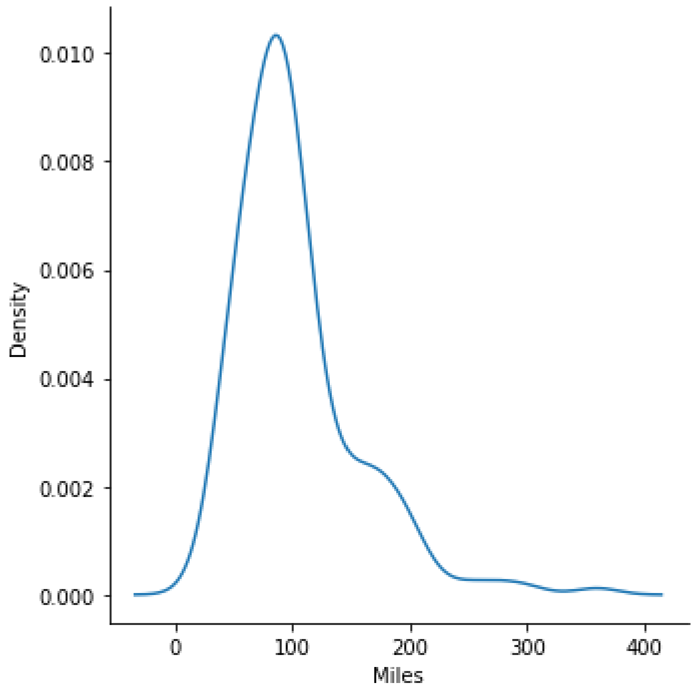
below is the distplot with and without kde

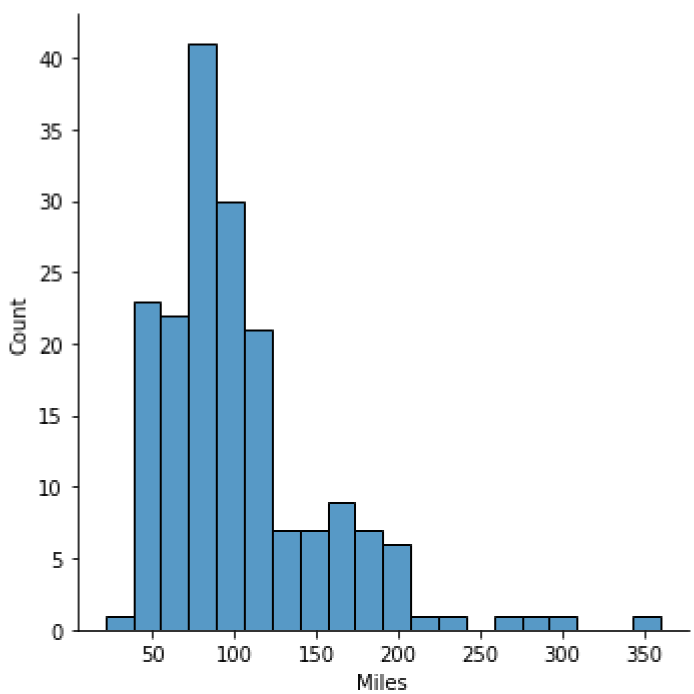
from the value_counts and kde and distplot it is clear that most number of people are using for 85 to 95 miles a week

In [39]:
```
Aerofit_data['Miles'].value_counts()[:5]
```

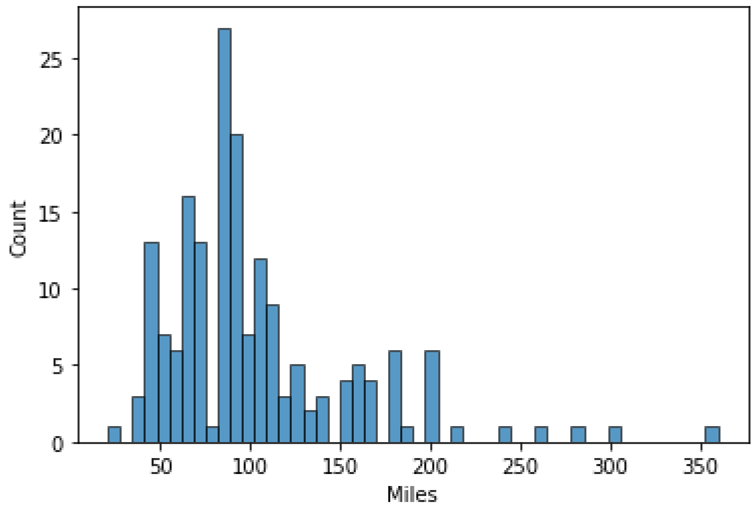
Out[39]:
```
85    27
95    12
66    10
75    10
47     9
Name: Miles, dtype: int64
```

In [25]:
```
ax = sns.displot(Aerofit_data['Miles'],kind='kde')
bx = sns.displot(Aerofit_data['Miles'])
plt.show()
```





In [26]:
```
ax = sns.histplot(Aerofit_data['Miles'],bins=50)
plt.show()
```



we can see that most of the prople are buying the inexpensive product KP281

In [27]:
```
Aerofit_data.groupby('Product')['Gender'].count()
```

Out[27]:
```
Product
KP281    80
KP481    60
KP781    40
Name: Gender, dtype: int64
```

Male are buying the fitnes product more than Female

In [43]:
```
Aerofit_data.groupby('Gender')['Product'].count()
```

Out[43]:
```
Gender
0    104
1     76
Name: Product, dtype: int64
```

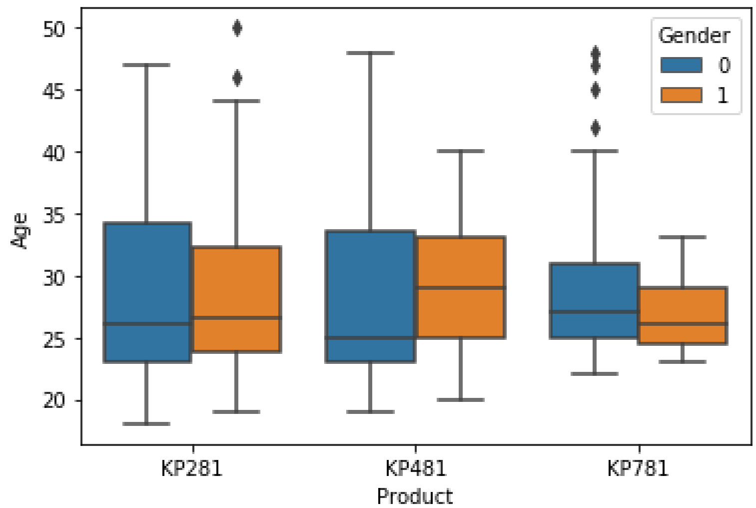
The product KP281 is bought by the Male age group of 26 the most and Female age group 27 the most

The producct KP481 is bought by Male age group of 25 the most and Female age group 29 the most

The product KP781 is bought by Male age group of 27 the emost and Female age group 26 the most

outliers are present in the female age group above 45 who brought the product KP281 and the male age group above 40 who brought the product KP781

In [28]:
```
ax = sns.boxplot(x=Aerofit_data['Product'],y=Aerofit_data['Age'],hue=Aerofit_data
plt.show()
```

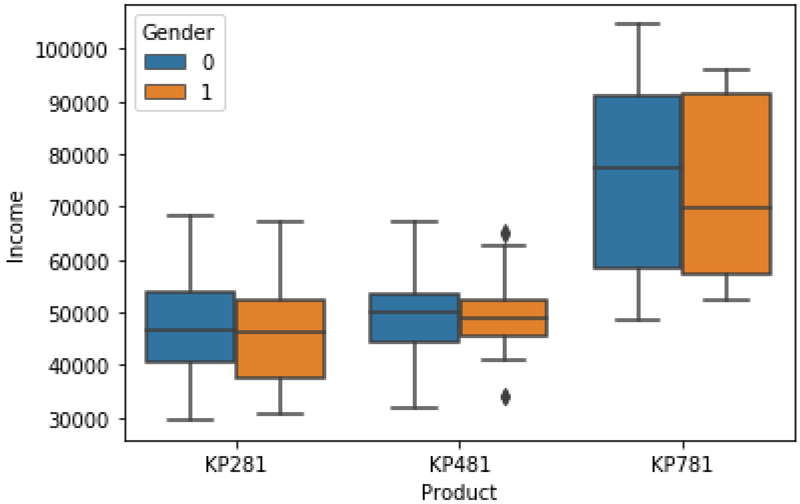


The most expensive product(KP781) is bought by high income group of both Male and Female

The less expensive product(KP281) is bought by low income group of both Male and Female

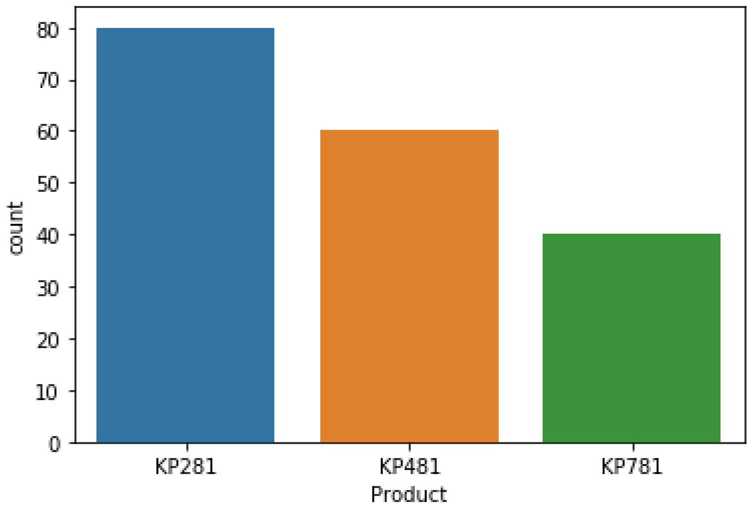
outliers are present in the female whoes income above USD 65000 and income below USD 35000

In [46]:
```
ax = sns.boxplot(x=Aerofit_data['Product'],y=Aerofit_data['Income'],hue=Aerofit_d
plt.show()
```



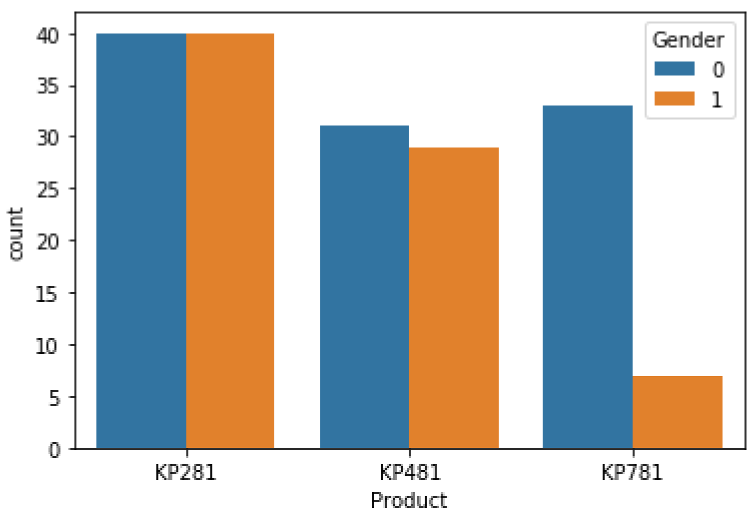
The least expensive product(KP281) is bought by most people and the most expensive product(KP781) is brought the least number oof people

In [29]:
```
ax = sns.countplot(x='Product',data=Aerofit_data)
plt.show()
```

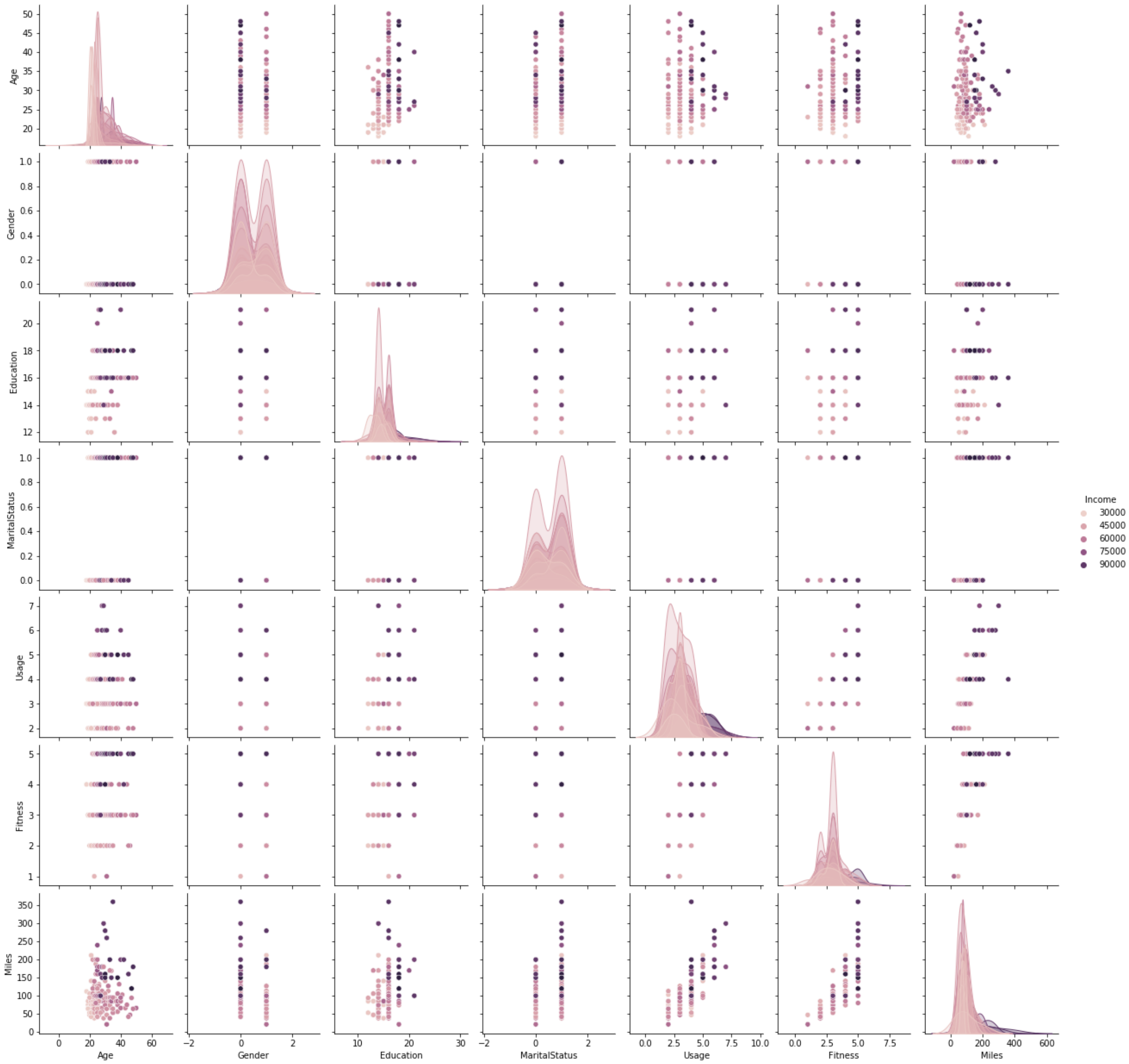


The most expensive product(KP781) is bought by the Male most

In [30]:
```
ax = sns.countplot(x='Product',hue='Gender',data=Aerofit_data)
plt.show()
```



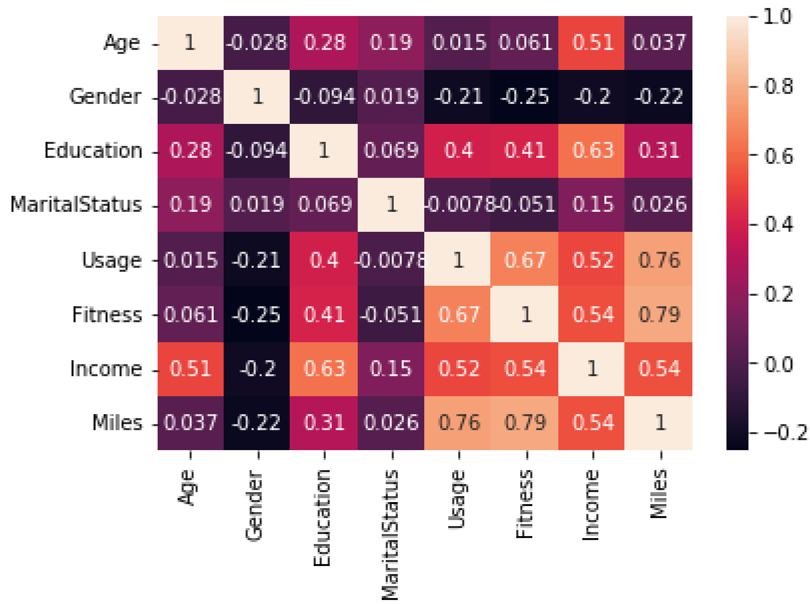
In [31]:
```
ax = sns.pairplot(Aerofit_data,hue='Income')
plt.show()
```



from the below we ca see the corelation of the features among themself

Miles and Fitness are most corelated followed by Miles and Usage

In [32]:
```
ax = sns.heatmap(Aerofit_data[['Age','Gender','Education','MaritalStatus','Usage'
plt.show()
```



The most expensive product(KP781) is bought by Male mostly

In [33]:
```
pd.crosstab(Aerofit_data['Product'],Aerofit_data['Gender'],margins=True,normalize
```

Out[33]:

Gender	0	1	All
Product			
KP281	0.222222	0.222222	0.444444
KP481	0.172222	0.161111	0.333333
KP781	0.183333	0.038889	0.222222
All	0.577778	0.422222	1.000000

calculative the marginal probability in order find the conditional probability

In [34]:
```
joint_probability = pd.crosstab(Aerofit_data['Product'],Aerofit_data['Gender'],nc
joint_probability
```

Out[34]:

Gender	0	1
Product		
KP281	0.222222	0.222222
KP481	0.172222	0.161111
KP781	0.183333	0.038889

In [35]:
```
product = joint_probability.sum(axis=1)
product
```

Out[35]:
```
Product
KP281    0.444444
KP481    0.333333
KP781    0.222222
dtype: float64
```

calculative the conditional probability using marginal probability and divide method

In [36]:
```
conditional_probability = joint_probability.divide(product,axis=0)
conditional_probability
```

Out[36]:

Gender	0	1
Product		
KP281	0.500000	0.500000
KP481	0.516667	0.483333
KP781	0.825000	0.175000

recomendation

most expensive product was brought by more income group

most expensive product was brought by the male more than the female

the least expensive product was brought by most people

most fitness products brought by the age group between 25 to 30

most people are using the fitness products 94 kms per week

most of the fitness users are average users using 3 times a week

married people are using the fitness products the most