Aerofit Business Project

Rohit Nargundkar

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

In [8]:
```
df=pd.read_csv(r"C:\Users\Administrator\Desktop\aerofit_treadmill.csv")
df
```

Out[8]:

	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	180

180 rows × 9 columns

1) Analysing Basic metrics

In [9]:
```
df.shape
# There are 180 rows and 9 columns
```

Out[9]: (180, 9)

In [10]:
```
df.info()
# There are no null values in the table
```

```
<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 [13]:
```
# Converting data types for different columns
df["Product"] = df["Product"].astype('category')
df["Gender"] = df["Gender"].astype('category')
df["MaritalStatus"]= df["MaritalStatus"].astype('category')
```

In [14]:
```
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    category
 1   Age            180 non-null    int64   
 2   Gender         180 non-null    category
 3   Education      180 non-null    int64   
 4   MaritalStatus  180 non-null    category
 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: category(3), int64(6)
memory usage: 9.5 KB
```

In [15]:
```
df.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

2) Non- Graphical Analysis : Value counts and unique attributes

In [16]:
```
df["Product"].value_counts()
# There are 3 products.
# Maximum number of sales are KP281
# Minimum number of sales are of KP781
```

Out[16]:
```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

In [17]:
```
df["Gender"].value_counts()
# There are more Men than Women
```

Out[17]:
```
Male      104
Female     76
Name: Gender, dtype: int64
```

In [20]:
```
df["MaritalStatus"].value_counts()
# There are more Couples than Single users.
```

Out[20]:
```
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64
```

In [22]:
```
df["Fitness"].value_counts()
# There are maximum 3 self rating and Least being 1
```

Out[22]:
```
3    97
5    31
2    26
4    24
1     2
Name: Fitness, dtype: int64
```

In [23]:
```
df["Usage"].value_counts()
```

Out[23]:
```
3    69
4    52
2    33
5    17
6     7
7     2
Name: Usage, dtype: int64
```

In [24]:
```
df["Usage"].nunique()
```

Out[24]: 6

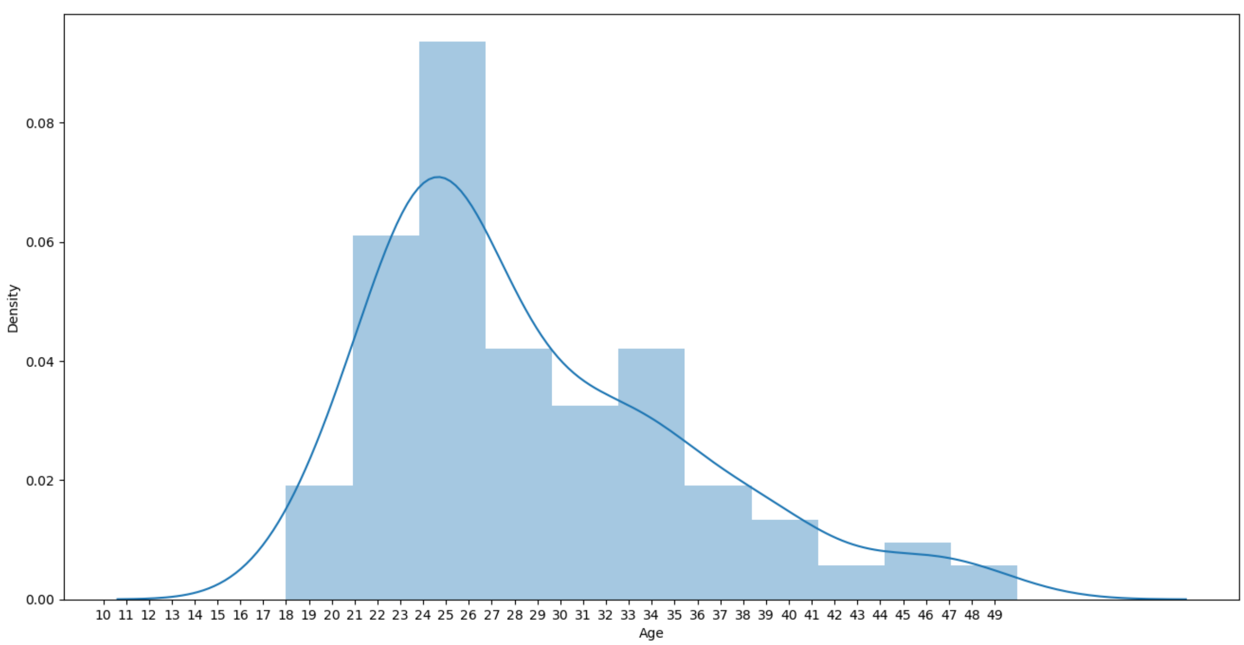
In [25]:
```
df["Education"].nunique()
```

Out[25]: 8

3) Visual Analysis : Univariate / Bivariate Plots

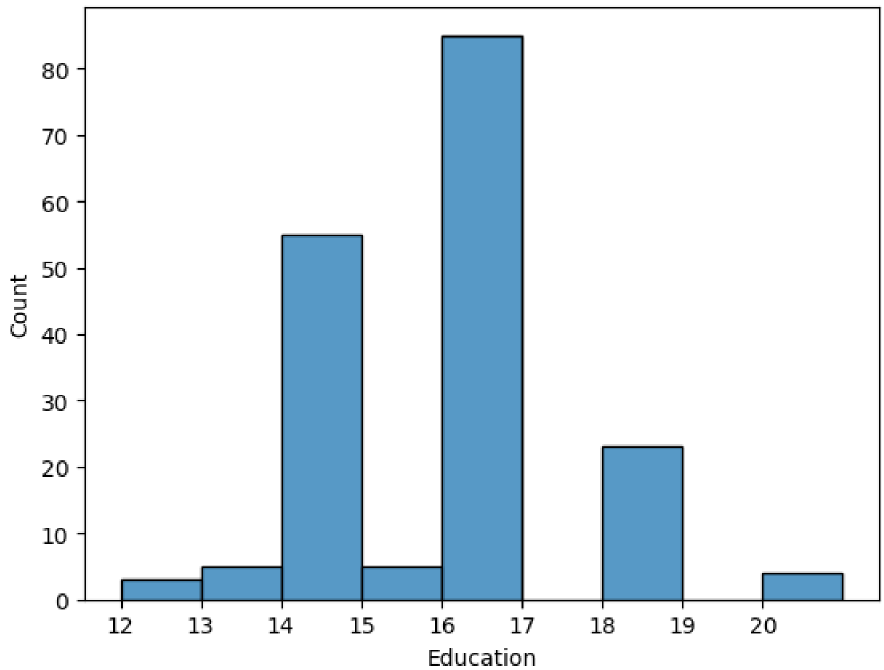
In [27]:
```
plt.figure(figsize=(16,8))
plt.xticks(list(range(10,50)))
sns.distplot(df["Age"])
# Most users are in the age group of  22 - 26
```

Out[27]: <Axes: xlabel='Age', ylabel='Density'>



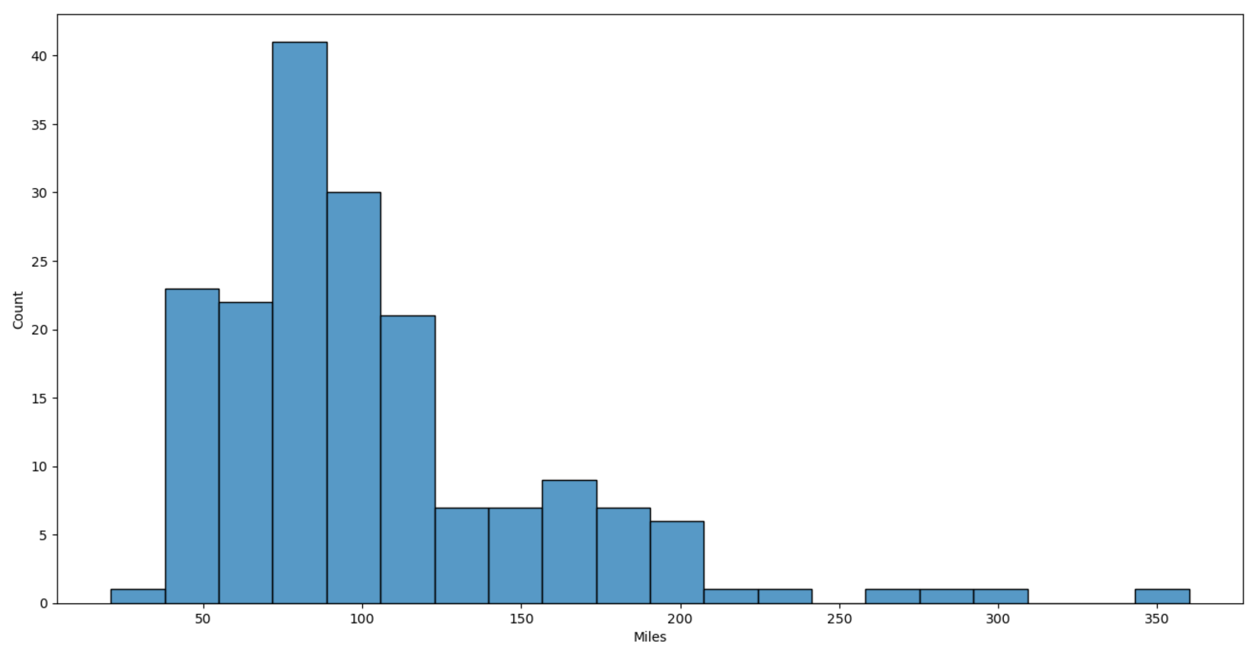
In [30]:
```
plt.xticks(list(range(min(df["Education"]),max(df["Education"]))))
sns.histplot(df,x=df["Education"],bins=9)
# Most users are educated for 14 to 16 years
```

Out[30]: <Axes: xlabel='Education', ylabel='Count'>



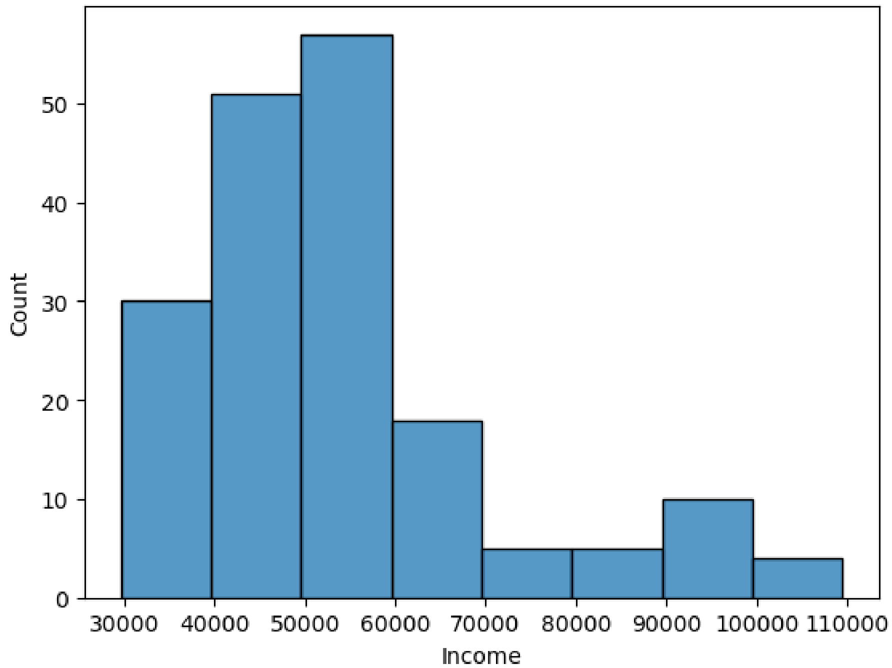
In [44]:
```
plt.figure(figsize=(16,8))
#plt.xticks(np.linspcae(20,360,18))
sns.histplot(df["Miles"])
# Majority of the people want to run 50- 100 miles. However there are outliers.
```

Out[44]: <Axes: xlabel='Miles', ylabel='Count'>



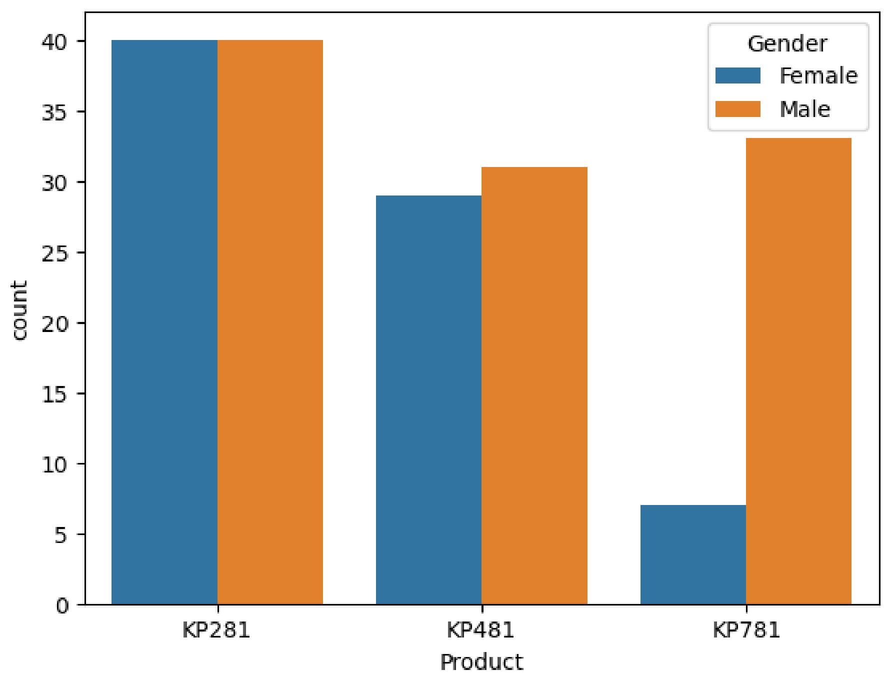
In [34]:
```python
sns.histplot(df["Income"],binwidth=10000)
# plt.xticks(np.linspace(25000,105000,9))
```

Out[34]: <Axes: xlabel='Income', ylabel='Count'>



In [36]:
```python
sns.countplot(df,x="Product", hue="Gender")
# KP781 is most purcahsed by Men.
```

Out[36]: <Axes: xlabel='Product', ylabel='count'>

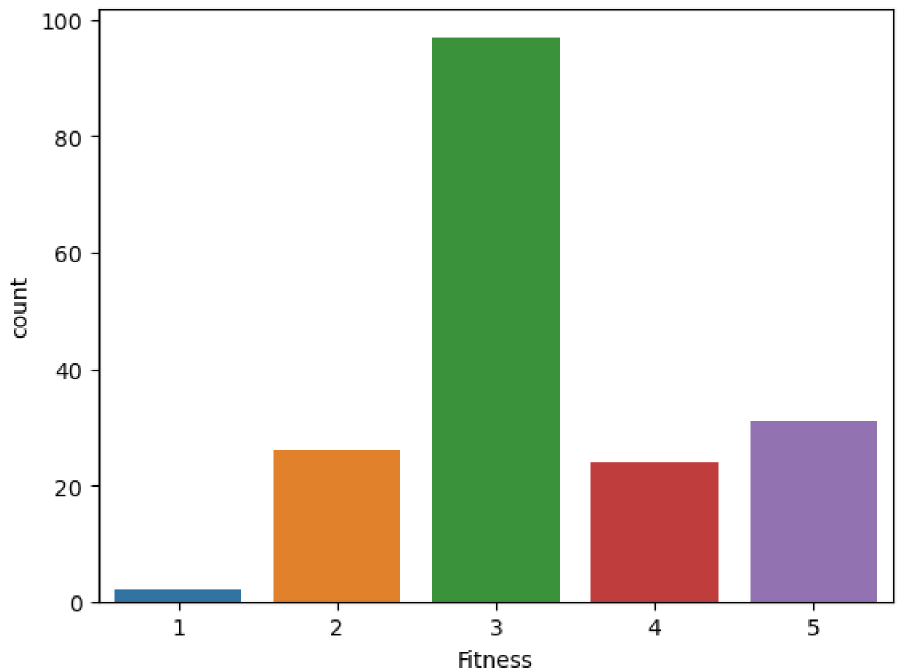


In [39]:
```python
df["Product"].value_counts()*100/np.sum(df["Product"].value_counts())
```

Out[39]:
```
KP281    44.444444
KP481    33.333333
KP781    22.222222
Name: Product, dtype: float64
```

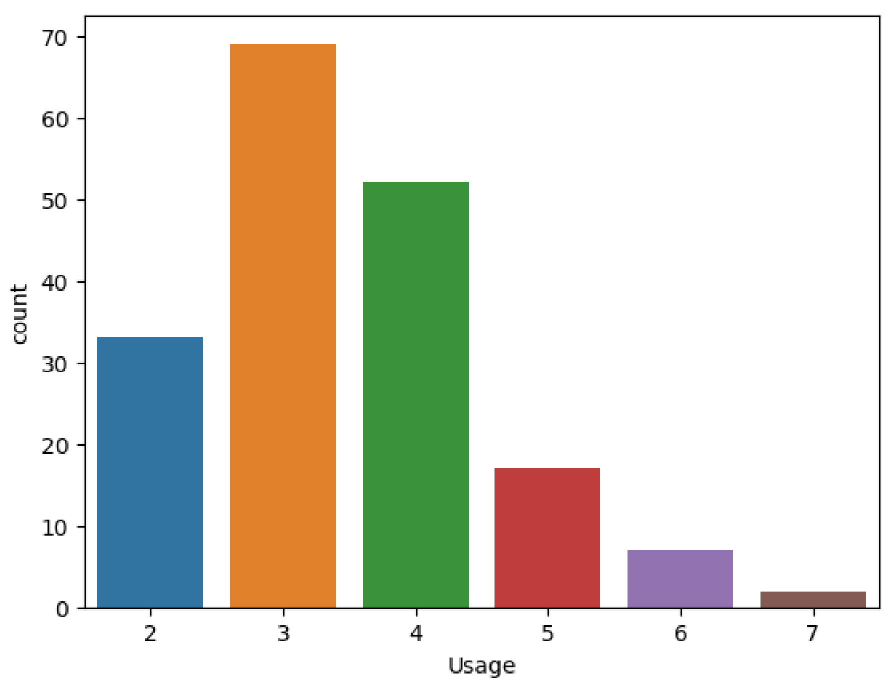
In [41]:
```python
sns.countplot(df,x="Fitness")
# Most people categorize themselves as average in fitness with a fitness rationg of 3.
```

Out[41]: <Axes: xlabel='Fitness', ylabel='count'>



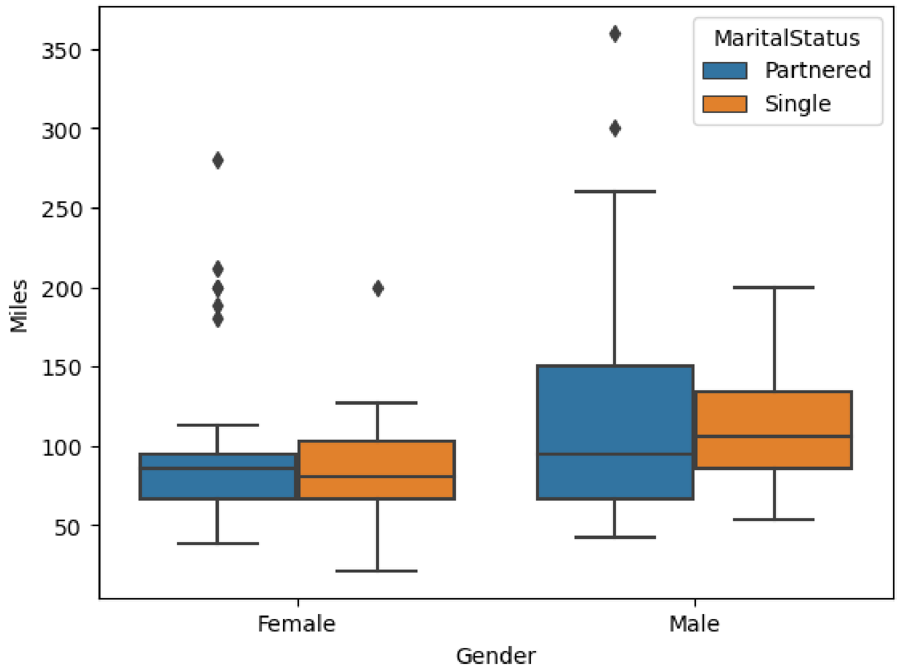
In [42]:
```python
sns.countplot(df,x="Usage")
```

Out[42]: <Axes: xlabel='Usage', ylabel='count'>



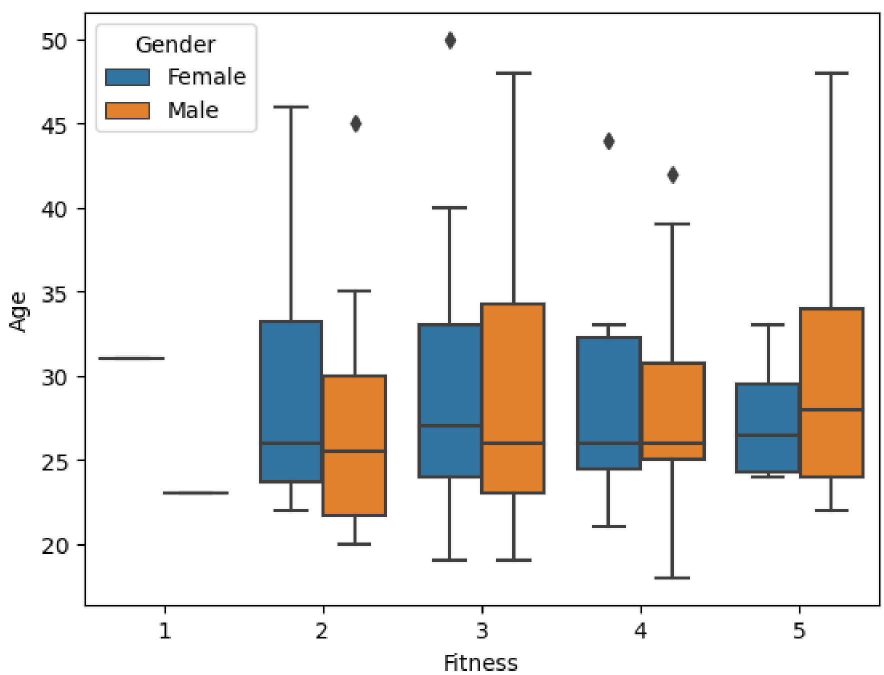
In [47]:
```
sns.boxplot(df,x="Gender",y="Miles", hue= "MaritalStatus")

# Men expect themselves to run more than women. Single men want tot run more than partnered men,
# Whereas partnered men and women have more outliers.
```

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



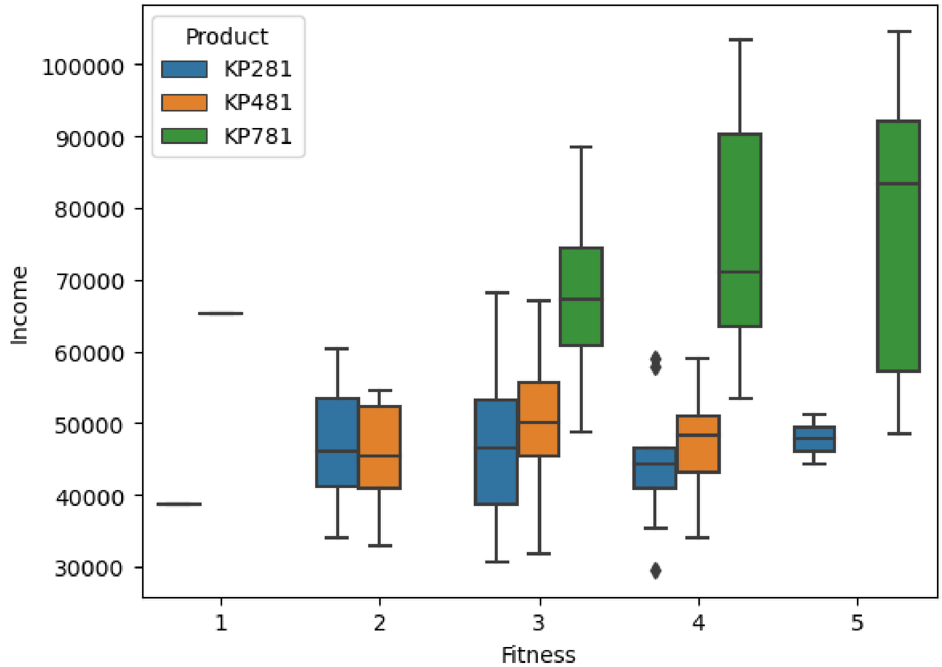
In [49]:
```
sns.boxplot(df,x="Fitness",y="Age",hue="Gender")
# Females are observed to be older when the fitness range is between 1-4.
```

Out[49]: `<Axes: xlabel='Fitness', ylabel='Age'>`



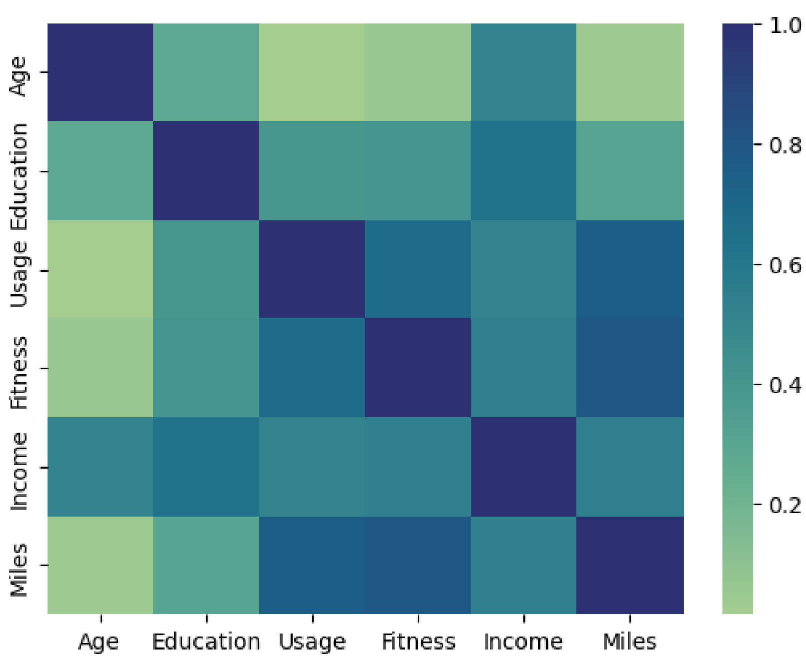
```
In [50]: sns.boxplot(df,x="Fitness",y= "Income",hue= "Product")
         # people with high income tend to buy the product 'KP781'
         # People with more fitness rating also tend to have high income
```

Out[50]: <Axes: xlabel='Fitness', ylabel='Income'>



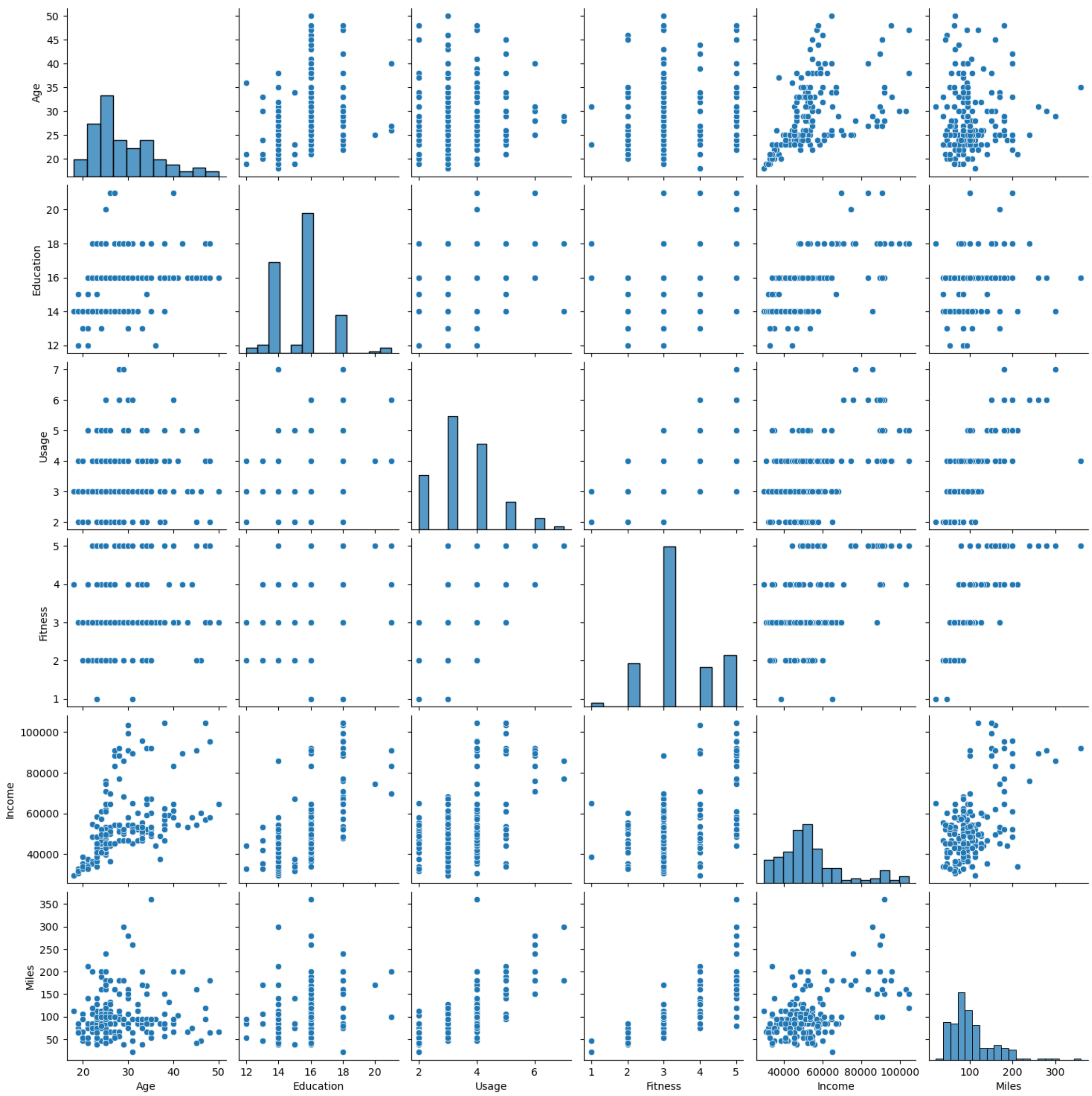

```
In [52]: sns.heatmap(df.loc[:,["Age","Education","Usage","Fitness","Income","Miles"]].corr(),cmap="crest")
         #1. Usage and miles have very high correlation
         #2. Usage and fitnes have very high correlation
         #3. Fitness and miles have high correlation
         #4. Age and Education have mild correlation between Income
         #5. Education has mild correlation between Miles, Usage, Fitness
         #6. Age has no correlation with fitness, usage.
```

Out[52]: <Axes: >



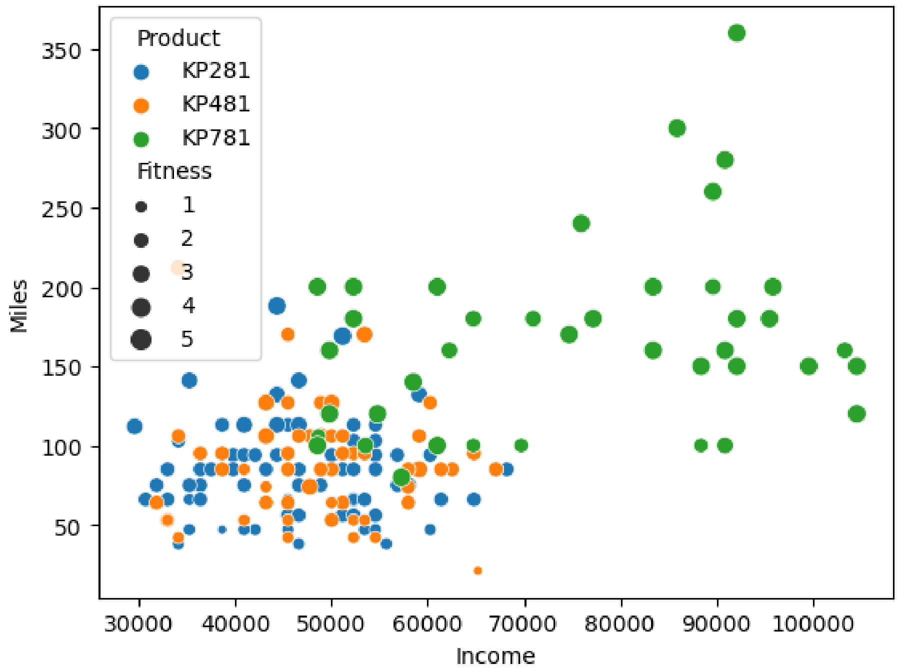
In [53]:
```
sns.pairplot(df)
#1. Usage and miles have very high correlation
#2. Usage and fitnes have very high correlation
#3. Fitness and miles have high correlation
#4. Age and Education have mild correlation between Income
#5. Education has mild correlation between Miles, Usage, Fitness
#6. Age has no correlation with fitness, usage.
```

Out[53]: <seaborn.axisgrid.PairGrid at 0x29def06d930>



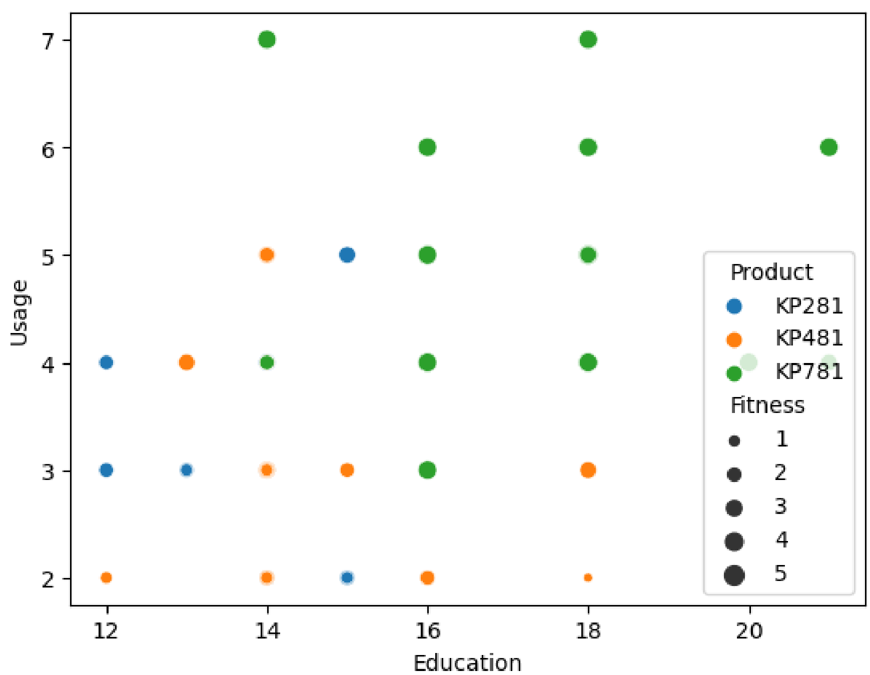
```
In [55]: sns.scatterplot(df,x="Income",y="Miles",hue="Product",size="Fitness")
         # People with high income are the ones to buy KP781
```

```
Out[55]: <Axes: xlabel='Income', ylabel='Miles'>
```




```
In [56]: sns.scatterplot(df,x="Education",y= "Usage",hue="Product", size ="Fitness")
         #People with less usage tend to buy KP481
         #People with more fitness and more usage tend to buy KP781
```

```
Out[56]: <Axes: xlabel='Education', ylabel='Usage'>
```



4) Missing values and Outlier Detection

In [57]:
```
df.describe()
```

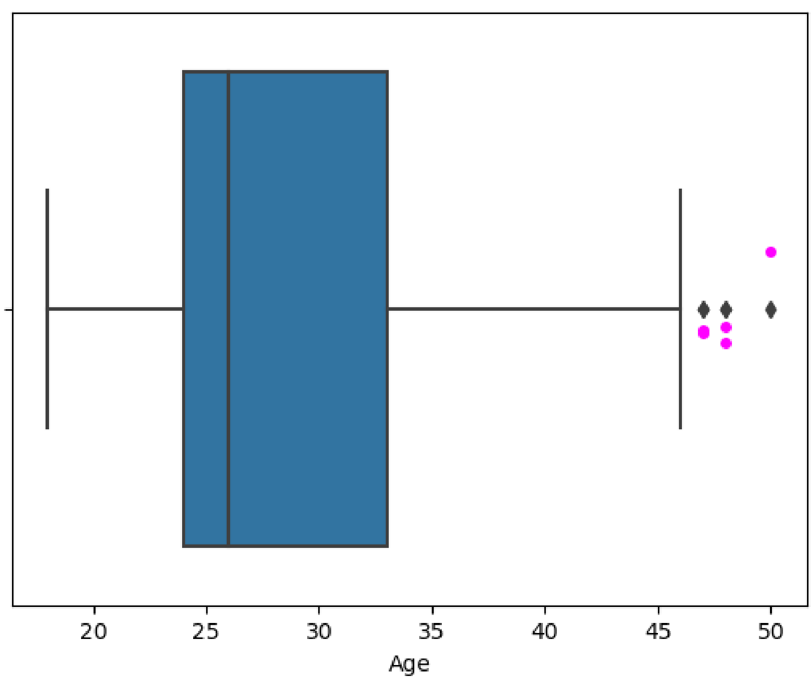
Out[57]:

	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

In [62]:
```
def outliers(arr):
    q1=np.percentile(arr,25)
    q2=np.percentile(arr,75)
    iqr=1.5*(q2-q1)
    low =max(q1-iqr,0)
    high = q2+ iqr
    outliers= arr[(arr>high)|(arr<low)]
    return outliers
```

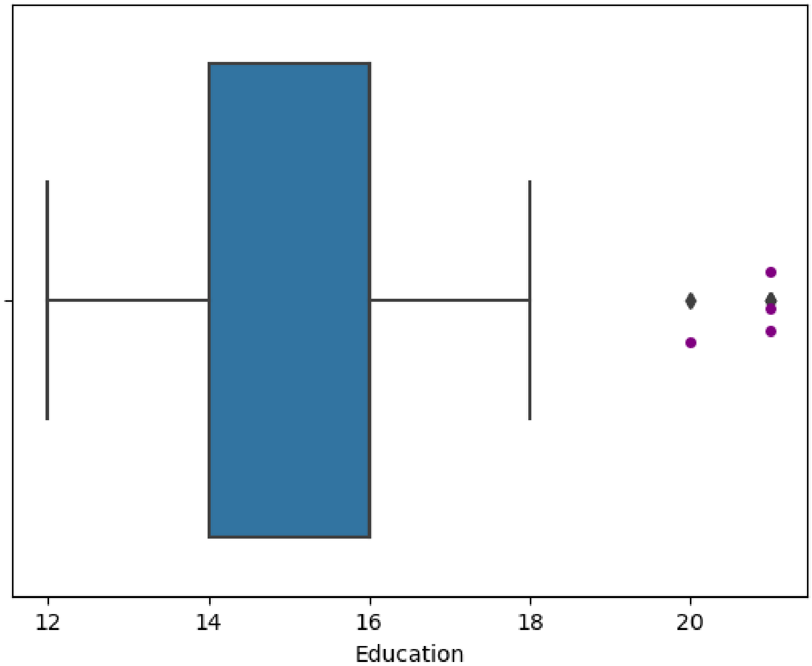
In [65]:
```
#Outliers in "Age" column
sns.boxplot(x=df["Age"])
sns.stripplot(x=outliers(df["Age"]),color="Magenta")
outliers(df["Age"])
```

Out[65]:
```
78     47
79     50
139    48
178    47
179    48
Name: Age, dtype: int64
```



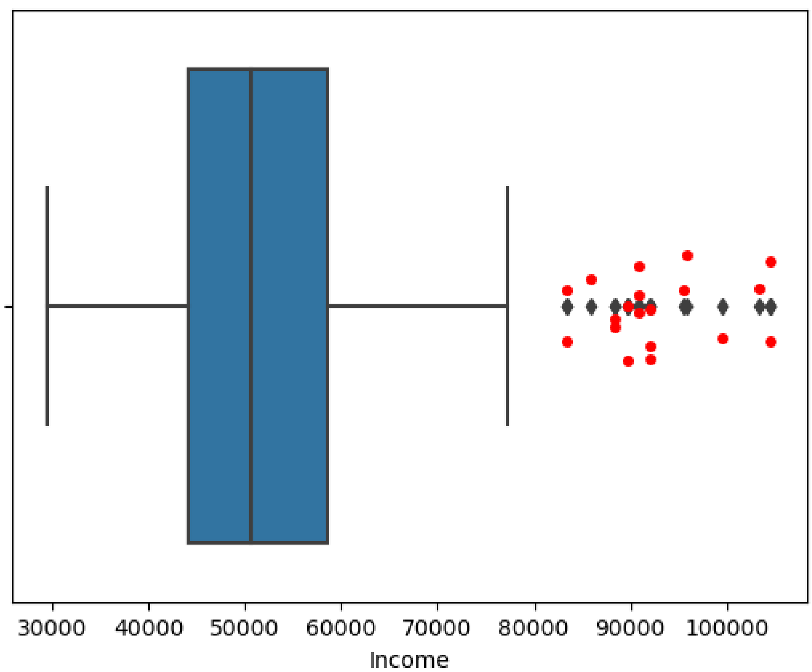
In [67]:
```python
#Outliers in "Education" column
sns.boxplot(x = df["Education"])
sns.stripplot(x = outliers(df["Education"]), color = "Purple")
outliers(df["Education"])
```

Out[67]:
```
156    20
157    21
161    21
175    21
Name: Education, dtype: int64
```



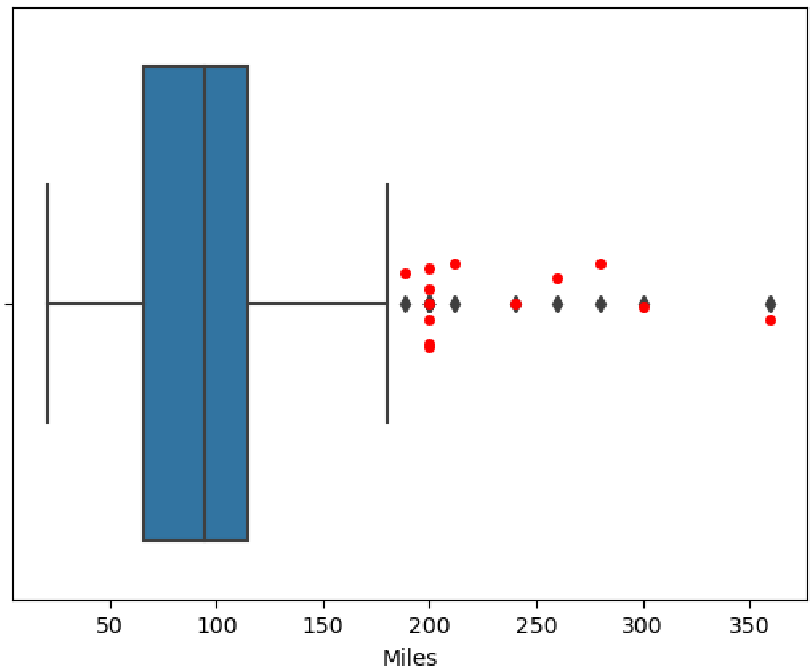
In [68]:
```python
#Outliers in "Income" column
sns.boxplot(x = df["Income"])
sns.stripplot(x = outliers(df["Income"]), color = "red")
outliers(df["Income"])
```

Out[68]:
```
159     83416
160     88396
161     90886
162     92131
164     88396
166     85906
167     90886
168    103336
169     99601
170     89641
171     95866
172     92131
173     92131
174    104581
175     83416
176     89641
177     90886
178    104581
179     95508
Name: Income, dtype: int64
```



In [69]:
```python
#Outliers in "Miles" column
sns.boxplot(x = df["Miles"])
sns.stripplot(x = outliers(df["Miles"]), color = "red")
outliers(df["Miles"])
```

Out[69]:
```
23     188
84     212
142    200
148    200
152    200
155    240
166    300
167    280
170    260
171    200
173    360
175    200
176    200
Name: Miles, dtype: int64
```



In [70]:
```python
# Categorzing numeric data of age
def func1(age):
    if age>np.median(df["Age"]):
        return"old"
    else:
        return"young"
df["age"]=df["Age"].apply(func1)
```

In [71]:
```python
#Categorzing numeric data of Education
def func2(education):
    if education > np.median(df["Education"]):
        return "high edu"
    else:
        return "low edu"

df["education"] = df["Education"].apply(func2)
```

In [72]:
```python
#Categorzing numeric data of usage
def func3(usage):
    if usage > np.median(df["Usage"]):
        return "regular"
    else:
        return "casual"

df["usage"] = df["Usage"].apply(func3)
```

In [73]:
```python
#Categorzing numeric data of Income
def func5(income):
    if income > np.median(df["Income"]):
        return "wealthy"
    else:
        return "middle class"

df["income"] = df["Income"].apply(func5)
```

In [74]:
```python
#Categorzing numeric data of Miles
def func6(miles):
    if miles > np.median(df["Miles"]):
        return "high"
    else:
        return "low"


df["miles"] = df["Miles"].apply(func6)
```

In [77]:
```python
# Making all the newly added columns into categorical data
df["age"] = df["age"].astype("category")
df["education"] = df["education"].astype("category")
df["usage"] = df["usage"].astype("category")
df["Fitness"] = df["Fitness"].astype("category")
df["income"] = df["income"].astype("category")
df["miles"] = df["miles"].astype("category")
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 14 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Product        180 non-null    category
 1   Age            180 non-null    int64
 2   Gender         180 non-null    category
 3   Education      180 non-null    int64
 4   MaritalStatus  180 non-null    category
 5   Usage          180 non-null    int64
 6   Fitness        180 non-null    category
 7   Income         180 non-null    int64
 8   Miles          180 non-null    int64
 9   age            180 non-null    category
 10  education      180 non-null    category
 11  usage          180 non-null    category
 12  income         180 non-null    category
 13  miles          180 non-null    category
dtypes: category(9), int64(5)
memory usage: 9.9 KB
```

In [78]:
```
df
```

Out[78]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles	age	education	usage	income	miles
0	KP281	18	Male	14	Single	3	4	29562	112	young	low edu	casual	middle class	high
1	KP281	19	Male	15	Single	2	3	31836	75	young	low edu	casual	middle class	low
2	KP281	19	Female	14	Partnered	4	3	30699	66	young	low edu	regular	middle class	low
3	KP281	19	Male	12	Single	3	3	32973	85	young	low edu	casual	middle class	low
4	KP281	20	Male	13	Partnered	4	2	35247	47	young	low edu	regular	middle class	low
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
175	KP781	40	Male	21	Single	6	5	83416	200	old	high edu	regular	wealthy	high
176	KP781	42	Male	18	Single	5	4	89641	200	old	high edu	regular	wealthy	high
177	KP781	45	Male	16	Single	5	5	90886	160	old	low edu	regular	wealthy	high
178	KP781	47	Male	18	Partnered	4	5	104581	120	old	high edu	regular	wealthy	high
179	KP781	48	Male	18	Partnered	4	5	95508	180	old	high edu	regular	wealthy	high

180 rows × 14 columns

Customer Profiling

In [79]:
```
pd.crosstab([df["Gender"],df["MaritalStatus"]],df["Product"], normalize = "index")
# A partnered Female tend to prefer KP281
# Single females prefer KP481
```

Out[79]:

	Product	KP281	KP481	KP781
Gender	**MaritalStatus**			
Female	**Partnered**	0.586957	0.326087	0.086957
	Single	0.433333	0.466667	0.100000
Male	**Partnered**	0.344262	0.344262	0.311475
	Single	0.441860	0.232558	0.325581

In [80]:
```
pd.crosstab([df["education"],df["Gender"],df["MaritalStatus"]],df["Product"], normalize = "index")
# Highly educated males and females tend to prefer KP781
# Less educated partnered female prefer KP281
# Less educated single males prefer KP281
```

Out[80]:

		Product	KP281	KP481	KP781
education	**Gender**	**MaritalStatus**			
high edu	**Female**	**Partnered**	0.000000	0.000000	1.000000
		Single	0.200000	0.400000	0.400000
	Male	**Partnered**	0.076923	0.000000	0.923077
		Single	0.000000	0.000000	1.000000
low edu	**Female**	**Partnered**	0.627907	0.348837	0.023256
		Single	0.480000	0.480000	0.040000
	Male	**Partnered**	0.416667	0.437500	0.145833
		Single	0.513514	0.270270	0.216216

In [81]:
```
pd.crosstab([df["education"],df["income"],df["MaritalStatus"]],df["Product"], normalize = "index")
# Highly educated and wealthy and partnered individuals prefer KP781
# Low education and middle class people prefer KP281
```

Out[81]:

education	income	MaritalStatus	KP281	KP481	KP781
high edu	middle class	Single	0.000000	0.500000	0.500000
	wealthy	Partnered	0.062500	0.000000	0.937500
		Single	0.111111	0.111111	0.777778
low edu	middle class	Partnered	0.608696	0.369565	0.021739
		Single	0.523810	0.404762	0.071429
	wealthy	Partnered	0.422222	0.422222	0.155556
		Single	0.450000	0.250000	0.300000

In [82]:
```
pd.crosstab([df["income"],df["Gender"],df["miles"]],df["Product"], normalize = "index")
# Middle class females who want to run more prefer KP481
# Middle class males and females who want to run less prefer KP281
# Wealthy individuals(both males and females) who want to run more prefer KP781
# Similarly middle class individuals(both males and females) who want to run less prefer KP281
```

Out[82]:

income	Gender	miles	KP281	KP481	KP781
middle class	Female	high	0.384615	0.615385	0.000000
		low	0.666667	0.333333	0.000000
	Male	high	0.350000	0.400000	0.250000
		low	0.666667	0.333333	0.000000
wealthy	Female	high	0.090909	0.272727	0.636364
		low	0.631579	0.368421	0.000000
	Male	high	0.121951	0.219512	0.658537
		low	0.631579	0.315789	0.052632

In [84]:

```
pd.crosstab([df["usage"],df["Fitness"],df["Gender"]],df["Product"], normalize = "index")
# Fit males who want to use less prefer KP481
# Fit females who want to use less prefer KP281
# Casual female users who are not fit prefer KP281
# Overall casual users whether fit or not prefer to use KP281 or KP481
# Fit individuals(males/females) who want to use regularly prefer KP781
# Regular users(males/females) who are not fit prefer KP281 and KP481
```

Out[84]:

		Product	KP281	KP481	KP781
usage	Fitness	Gender			
casual	1	Female	0.000000	1.000000	0.000000
		Male	1.000000	0.000000	0.000000
	2	Female	0.625000	0.375000	0.000000
		Male	0.375000	0.625000	0.000000
	3	Female	0.612903	0.387097	0.000000
		Male	0.529412	0.470588	0.000000
	4	Female	0.600000	0.400000	0.000000
		Male	0.400000	0.600000	0.000000
	5	Male	0.000000	0.000000	1.000000
regular	2	Male	0.500000	0.500000	0.000000
	3	Female	0.500000	0.428571	0.071429
		Male	0.555556	0.277778	0.166667
	4	Female	0.000000	0.666667	0.333333
		Male	0.363636	0.090909	0.545455
	5	Female	0.166667	0.000000	0.833333
		Male	0.041667	0.000000	0.958333

In [86]:
```
pd.crosstab([df["income"],df["Fitness"],df["Gender"]],df["Product"], normalize = "index")
# Middle income fit females prefer KP481
# Middle income unfit individuals prefer KP281
# Wealthy fit individuals prefer KP781
# Wealthy individuals who are not fit prefer either KP281 or KP481
```

Out[86]:

		Product	KP281	KP481	KP781
income	Fitness	Gender			
middle class	1	Male	1.000000	0.000000	0.000000
	2	Female	0.545455	0.454545	0.000000
		Male	0.400000	0.600000	0.000000
	3	Female	0.642857	0.357143	0.000000
		Male	0.555556	0.407407	0.037037
	4	Female	0.333333	0.666667	0.000000
		Male	0.714286	0.285714	0.000000
	5	Female	1.000000	0.000000	0.000000
		Male	0.000000	0.000000	1.000000
wealthy	1	Female	0.000000	1.000000	0.000000
	2	Female	0.800000	0.200000	0.000000
		Male	0.400000	0.600000	0.000000
	3	Female	0.470588	0.470588	0.058824
		Male	0.520000	0.400000	0.080000
	4	Female	0.500000	0.000000	0.500000
		Male	0.111111	0.222222	0.666667
	5	Female	0.000000	0.000000	1.000000
		Male	0.047619	0.000000	0.952381

In [88]:
```
pd.crosstab([df["income"],df["Fitness"],df["Gender"]],df["Product"], normalize = "columns")
# Here we see, out of the groups of people who purchased KP281, most of them come from middle class inc
# Among the people who purchased KP481, we see that most of them come from middle class, 'not fit' cate
# Among the people who purchased KP781, majority is from Wealthy and fit men.
```

Out[88]:

		Product	KP281	KP481	KP781
income	Fitness	Gender			
middle class	1	Male	0.0125	0.000000	0.000
	2	Female	0.0750	0.083333	0.000
		Male	0.0250	0.050000	0.000
	3	Female	0.2250	0.166667	0.000
		Male	0.1875	0.183333	0.025
	4	Female	0.0250	0.066667	0.000
		Male	0.0625	0.033333	0.000
	5	Female	0.0125	0.000000	0.000
		Male	0.0000	0.000000	0.100
	1	Female	0.0000	0.016667	0.000
		Female	0.0500	0.016667	0.000

Recommendations

1. We should try to sell the product KP481 to middle class females who want to run more.

2. We should market the product KP281 to Middle class males and females who want to run less.

3. We should recommend KP281 to partnered female and KP481 to single females.

4. We should market the product KP281 to wealthy individuals(both males and females) who want to run more.

5. For fit males who want to use less we should recommend KP481, whereas for fit females who want to use less we should recommend KP281.

6. Overall casual users whether fit or not should be recommended KP281 or KP481.

7. Fit individuals(males/females) who want to use regularly should be recommended KP781.

8. Regular users(males/females) who are not fit should be recommended KP281 and KP481.

9. Middle income unfit individuals should be recommended KP281.

10. KP781 is best suited for Wealthy and fit individuals.

11. Wealthy individuals who are not fit should be recommended KP481.

12. Middle income fit females should be recommended KP481.

In [ ]: