

```
In [1]: 1 # Importing the libraries
        2 import numpy as np
        3 import pandas as pd
        4 import matplotlib.pyplot as plt
        5 import seaborn as sns
```

C:\Users\pcs\Anaconda3\lib\site-packages\pandas\compat_optional.py:138: UserWarning: Pandas requires version '2.7.0' or newer of 'numexpr' (version '2.6.8' currently installed).
warnings.warn(msg, UserWarning)

```
In [2]: 1 #Importing the dataset
        2 df=pd.read_csv(r'F:\Scaler\Aerofit Case Study\erofit_treadmill.txt')
```

```
In [3]: 1 df.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

```
In [4]: 1 df.tail()
```

Out[4]:

	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 [5]: 1 #Checking the shape of the data
        2 df.shape
```

Out[5]: (180, 9)

```
In [6]: 1 # Information about the dataset
```

In [7]: 1 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 [8]: 1 *# No null values are present in the dataset as all the columns have 180 Non-*

In [9]: 1 df.describe()

Out[9]:

	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 [10]: 1 df.describe(include=object)

Out[10]:

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

In [11]: 1 *# KP281 is the most popular product*

Checking the value count for each columns

```
In [12]: 1 df['Gender'].value_counts()
```

```
Out[12]: Male      104  
         Female    76  
         Name: Gender, dtype: int64
```

```
In [13]: 1 df['MaritalStatus'].value_counts()
```

```
Out[13]: Partnered  107  
         Single     73  
         Name: MaritalStatus, dtype: int64
```

```
In [14]: 1 df['Age'].value_counts(sort=True)  
         2 # Age group from 23 to 26 buys most of the products
```

```
Out[14]: 25      25  
         23      18  
         24      12  
         26      12  
         28       9  
         35       8  
         33       8  
         30       7  
         38       7  
         21       7  
         22       7  
         27       7  
         31       6  
         34       6  
         29       6  
         20       5  
         40       5  
         32       4  
         19       4  
         48       2  
         37       2  
         45       2  
         47       2  
         46       1  
         50       1  
         18       1  
         44       1  
         43       1  
         41       1  
         39       1  
         36       1  
         42       1  
         Name: Age, dtype: int64
```

```
In [15]: 1 df['Education'].value_counts()
          2 # Most of the people have 16 or 14 years of Education
```

```
Out[15]: 16    85
          14    55
          18    23
          15     5
          13     5
          12     3
          21     3
          20     1
          Name: Education, dtype: int64
```

```
In [16]: 1 df['Fitness'].value_counts()
          2 #Most of the customers have Fitness"3"
```

```
Out[16]: 3     97
          5     31
          2     26
          4     24
          1      2
          Name: Fitness, dtype: int64
```

```
In [17]: 1 df['Usage'].value_counts()
          2 # Most of the customers use treadmill 3 - 4 times a week
```

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

```
In [18]: 1 df.groupby('Product')['Gender'].value_counts()
```

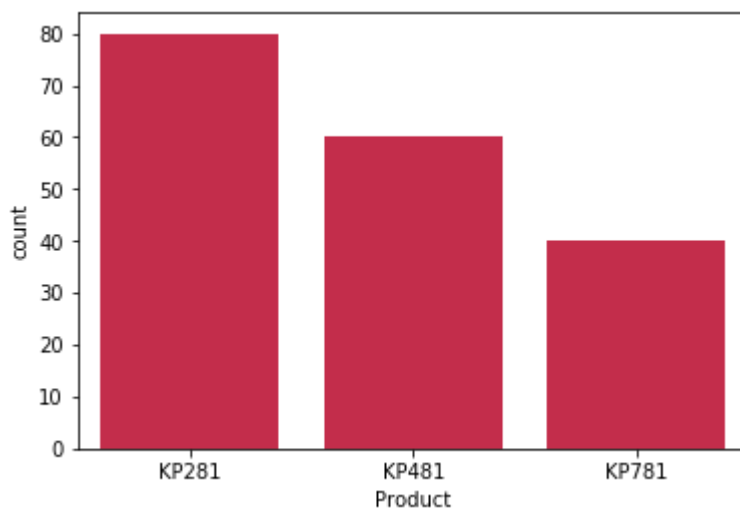
```
Out[18]: Product  Gender
          KP281    Female    40
              Male      40
          KP481    Male      31
              Female    29
          KP781    Male      33
              Female     7
          Name: Gender, dtype: int64
```

```
In [19]: 1 df.groupby(['Product', 'Gender'])['MaritalStatus'].value_counts()
```

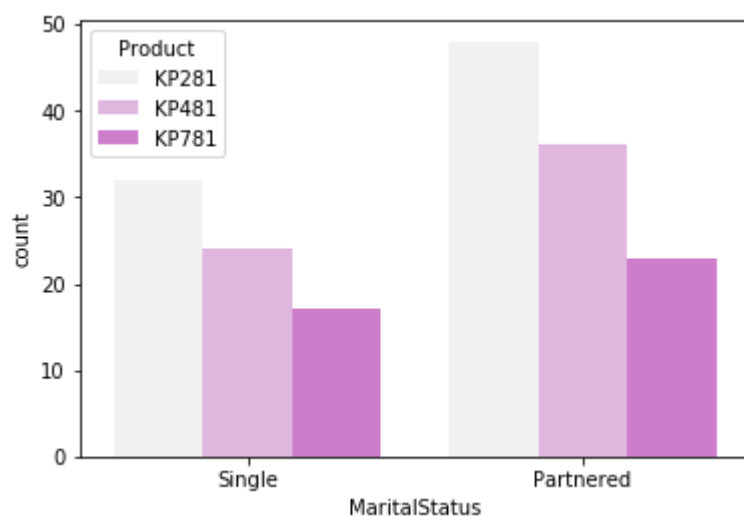
```
Out[19]: Product Gender MaritalStatus
KP281    Female Partnered      27
         Female Single       13
         Male   Partnered      21
         Male   Single       19
KP481    Female Partnered      15
         Female Single       14
         Male   Partnered      21
         Male   Single       10
KP781    Female Partnered       4
         Female Single       3
         Male   Partnered      19
         Male   Single       14
Name: MaritalStatus, dtype: int64
```

Visual Analysis

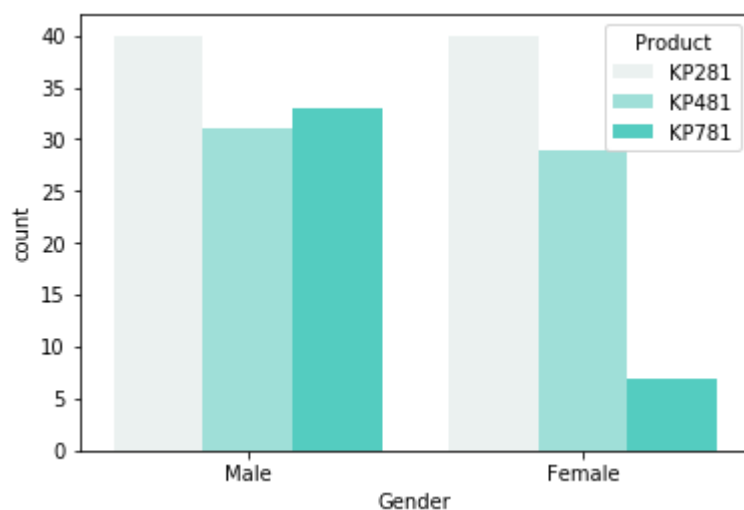
```
In [20]: 1 sns.countplot(x='Product', data=df, color='crimson')
        2 plt.show()
        3 # KP281 is the most popular product and KP781 is the least popular product
```



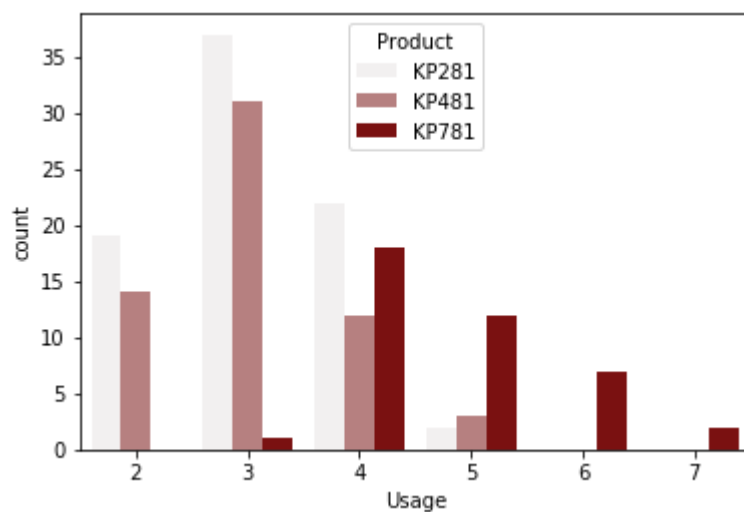
```
In [21]: 1 sns.countplot(x = 'MaritalStatus', data = df,color='orchid',hue='Product')
2         plt.show()
3
```



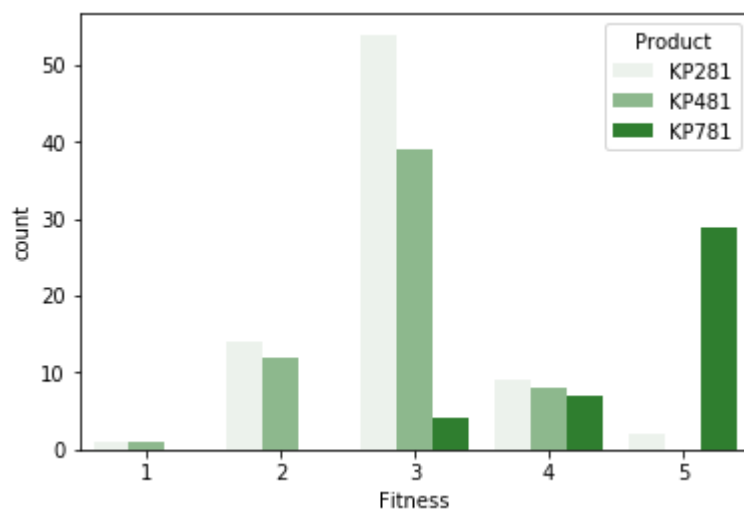
```
In [22]: 1 sns.countplot(x = 'Gender', data = df,hue='Product',color='turquoise')
2         plt.show()
```



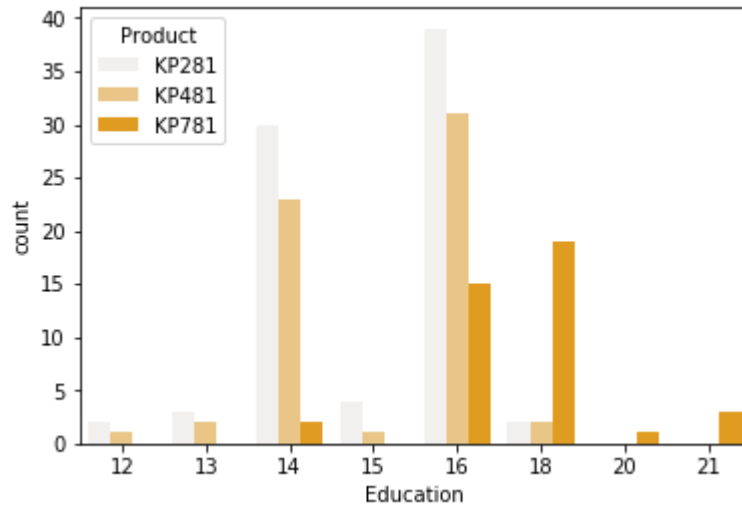
```
In [23]: 1 sns.countplot(x = 'Usage', data = df,hue='Product',color='darkred')  
2 plt.show()
```



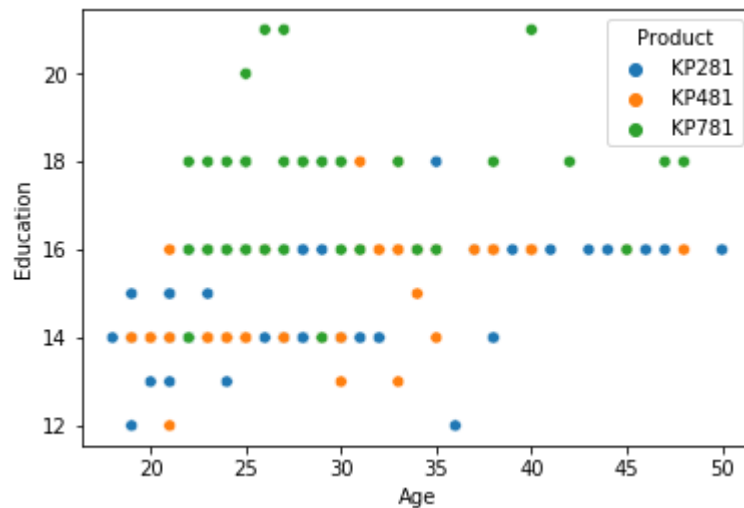
```
In [24]: 1 sns.countplot(x = 'Fitness', data = df,hue='Product',color='forestgreen')  
2 plt.show()
```



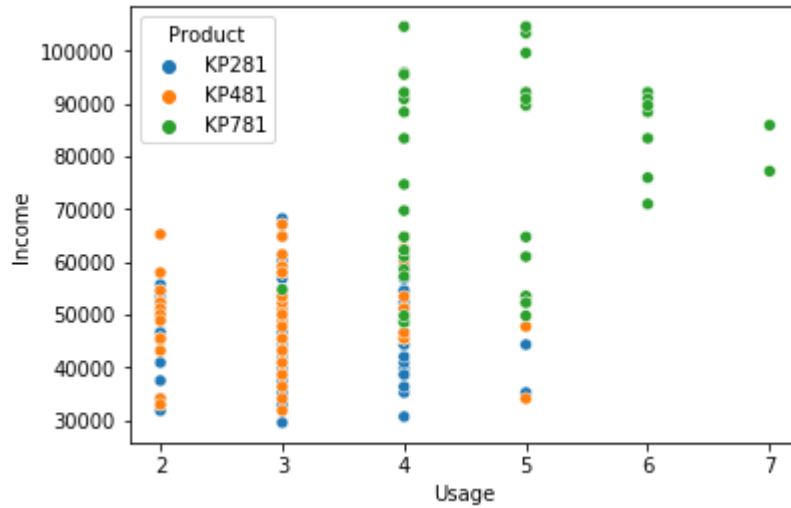
```
In [25]: 1 sns.countplot(x = 'Education', data = df,hue='Product',color='orange')  
2 plt.show()
```



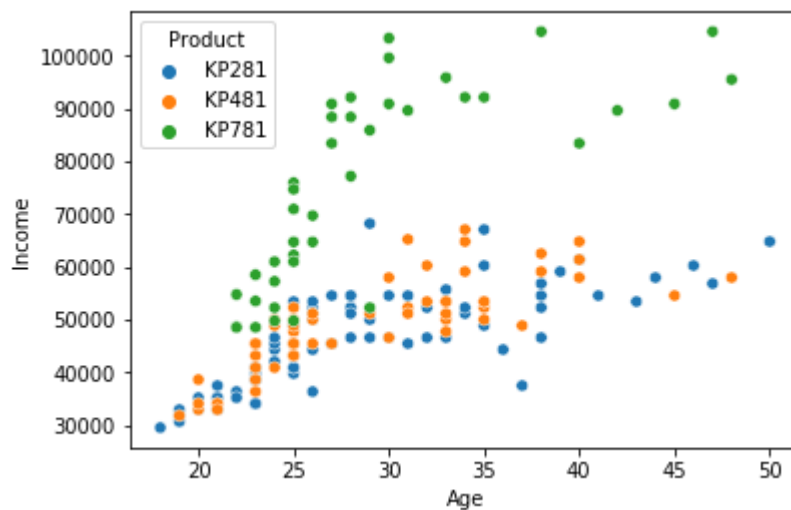
```
In [26]: 1 sns.scatterplot(x= df['Age'], y = df['Education'],hue='Product',data=df)  
2 plt.show()  
3 # Most of the person who has education of 18 or 18+ years opt for KP781
```



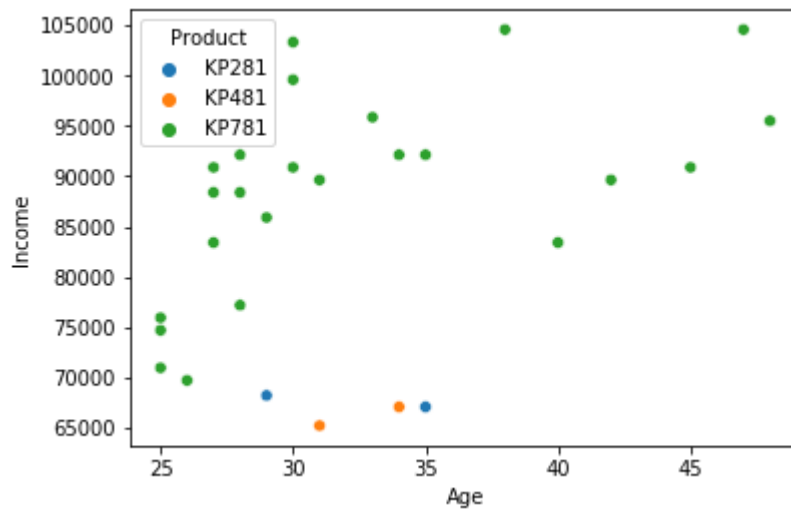

```
In [27]: 1 sns.scatterplot(x= df['Usage'], y = df['Income'] ,hue='Product',data=df)
2 plt.show()
```



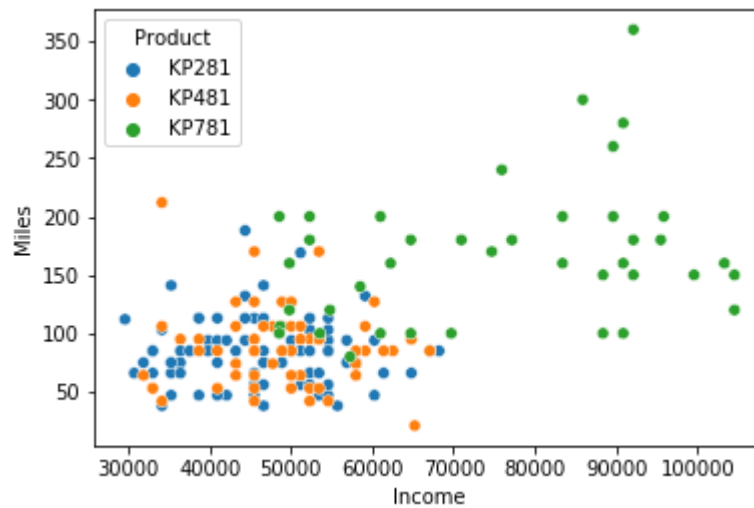
```
In [28]: 1 sns.scatterplot(x= df['Age'], y = df['Income'] ,hue='Product',data=df)
2 plt.show()
```



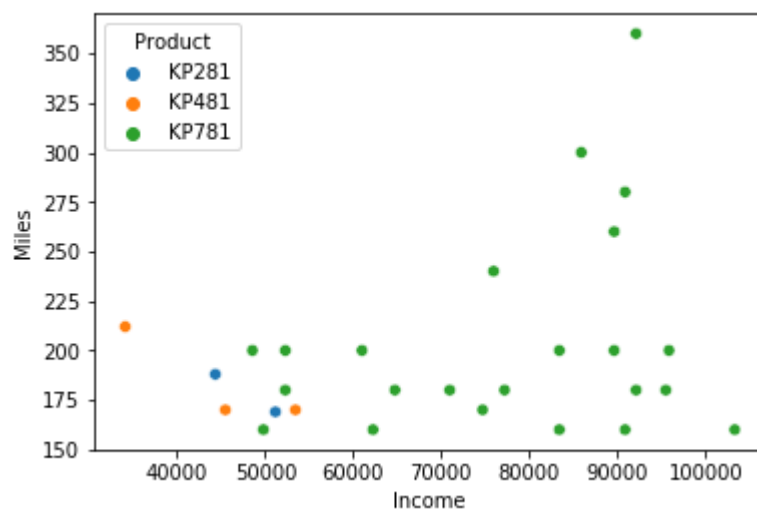
```
In [29]: 1 sns.scatterplot(x= 'Age', y = df.loc[df['Income']>65000]['Income'] ,hue='Pro
2 plt.show()
3 # Most of the customers who have Income more than 65000 opt for KP781
```



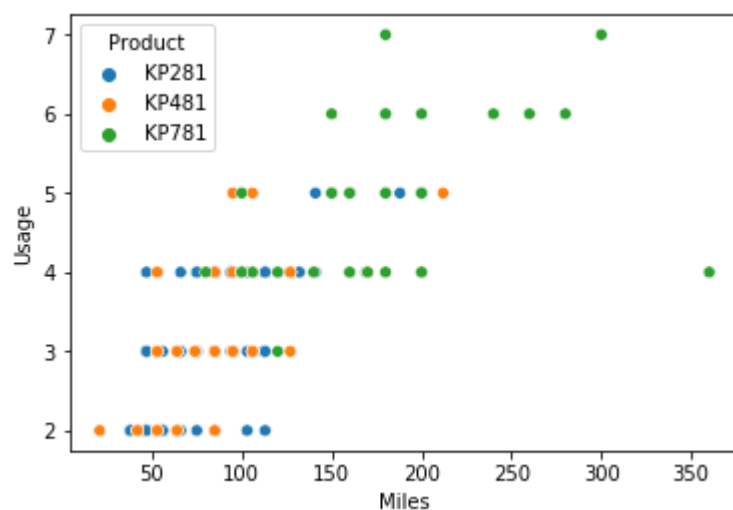
```
In [30]: 1 sns.scatterplot(x= df['Income'], y = df['Miles'] ,hue='Product',data=df)
2 plt.show()
```



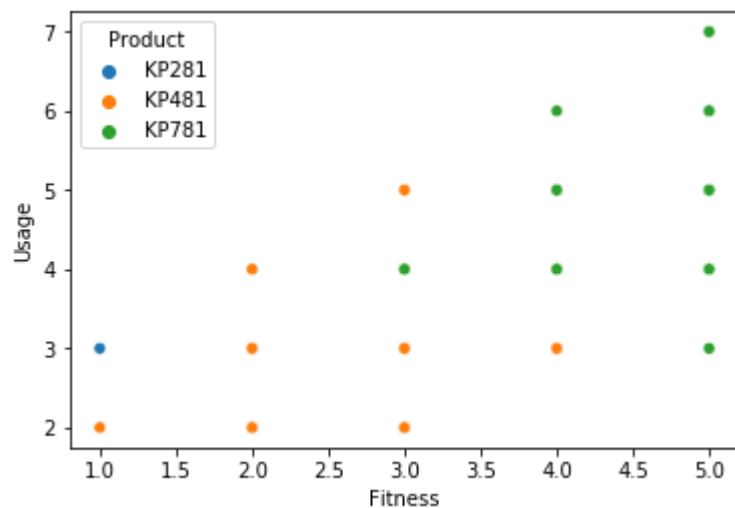
```
In [31]: 1 sns.scatterplot(x= df['Income'], y = df.loc[df['Miles']>150]['Miles'] ,hue='  
2 plt.show()
```



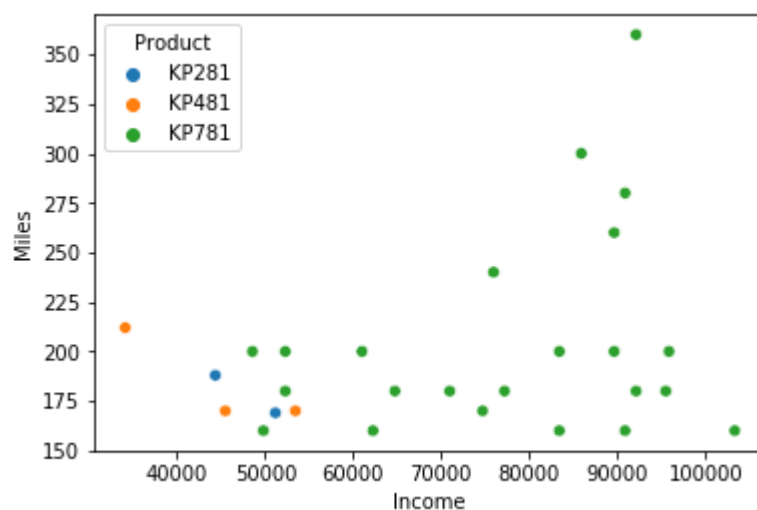
```
In [32]: 1 sns.scatterplot(x= df['Miles'], y = df['Usage'] ,hue='Product',data=df)  
2 plt.show()
```



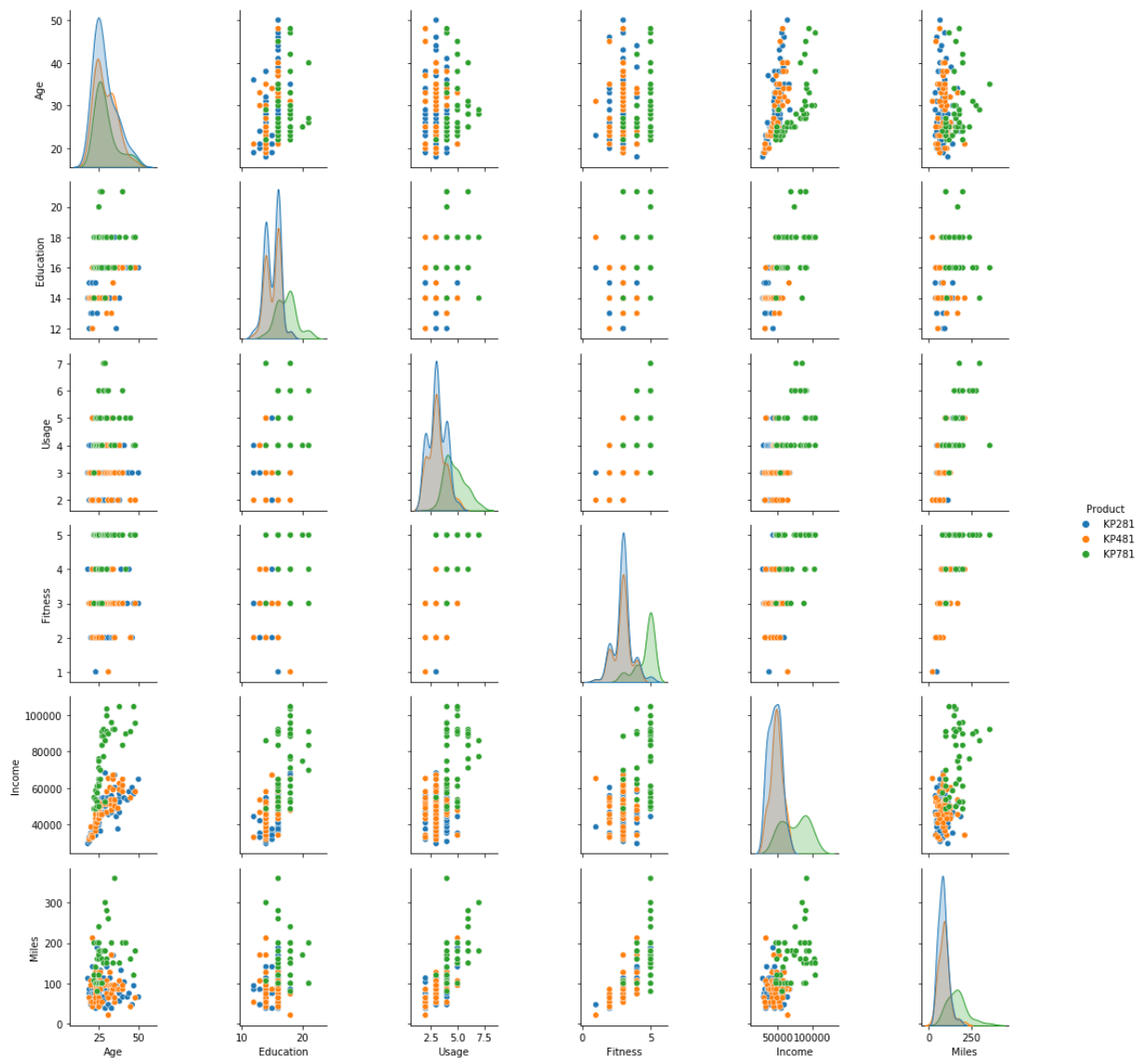
```
In [33]: 1 sns.scatterplot(x= df['Fitness'], y = df['Usage'] ,hue='Product',data=df,col
2          plt.show())
```



```
In [34]: 1 sns.scatterplot(x= df['Income'], y = df.loc[df['Miles']>150]['Miles'] ,hue='
2          plt.show())
```



```
In [35]: 1 sns.pairplot(data = df, hue= 'Product')
2 plt.show()
3 #Pair Plot
```



In [36]:

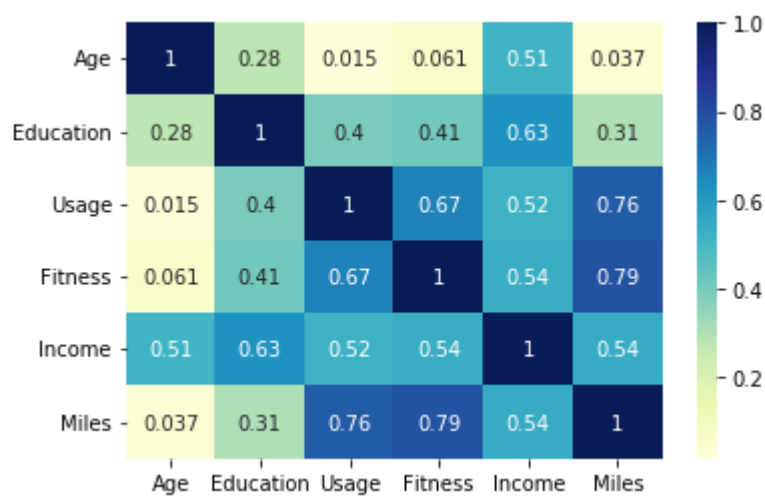
```
1 df.corr()
```

Out[36]:

	Age	Education	Usage	Fitness	Income	Miles
Age	1.000000	0.280496	0.015064	0.061105	0.513414	0.036618
Education	0.280496	1.000000	0.395155	0.410581	0.625827	0.307284
Usage	0.015064	0.395155	1.000000	0.668606	0.519537	0.759130
Fitness	0.061105	0.410581	0.668606	1.000000	0.535005	0.785702
Income	0.513414	0.625827	0.519537	0.535005	1.000000	0.543473
Miles	0.036618	0.307284	0.759130	0.785702	0.543473	1.000000

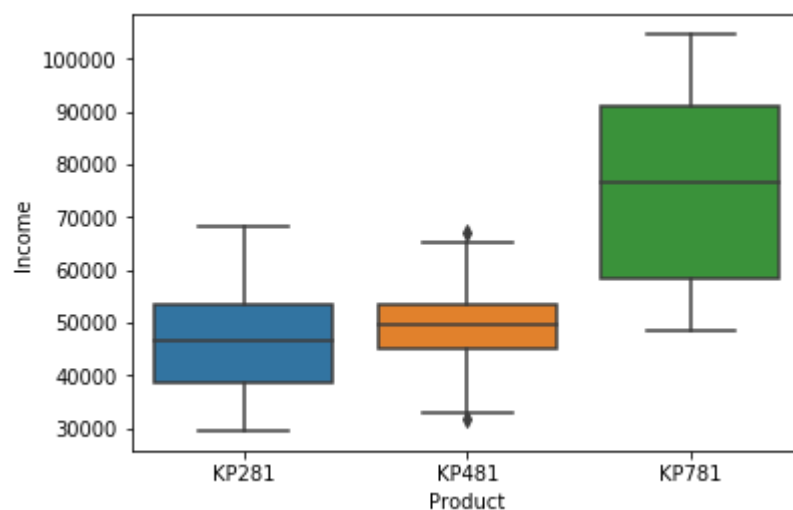
In [37]:

```
1 # Co-relation between different parameters
2 sns.heatmap(df.corr(), cmap= "YlGnBu", annot=True)
3 plt.show()
```

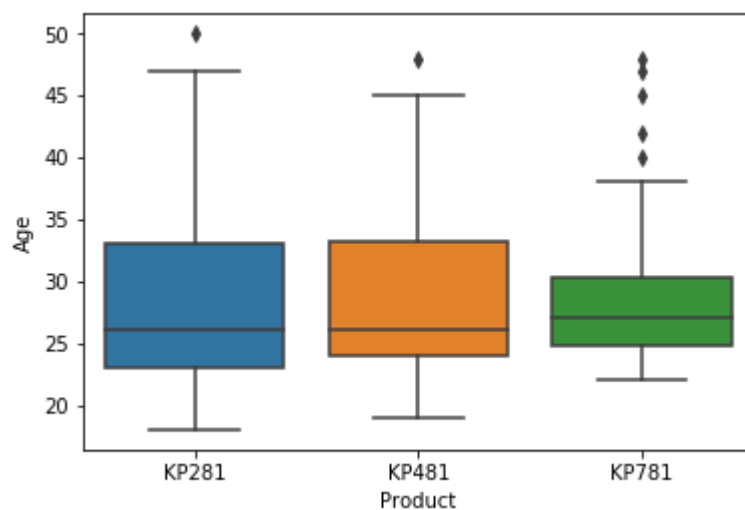


In [38]:

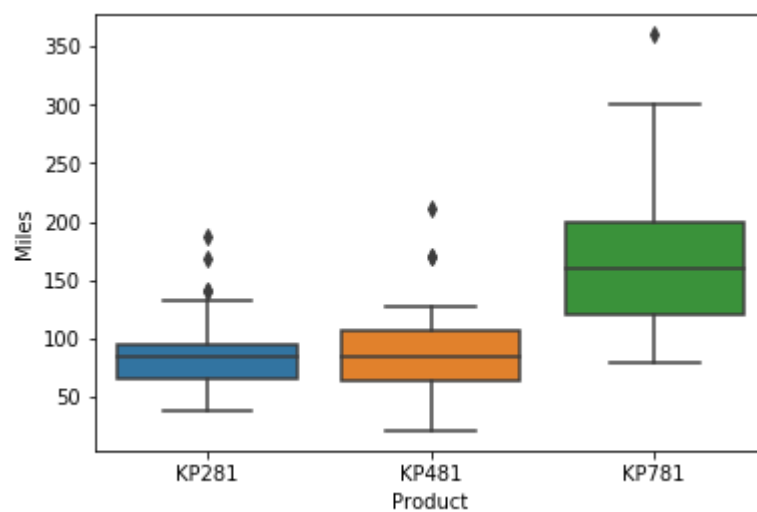
```
1 sns.boxplot(x = 'Product', y = 'Income', data = df)
2 plt.show()
```



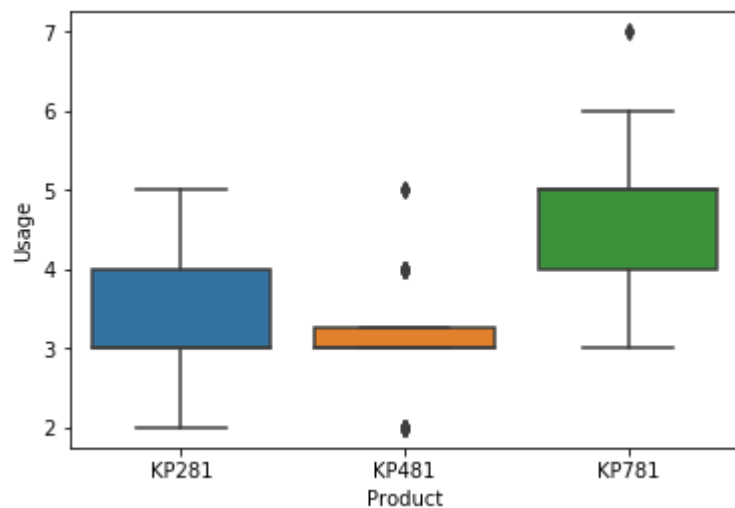
```
In [39]: 1 sns.boxplot(x = 'Product', y = 'Age', data = df)
2 plt.show()
3 # Most of the customers are b/w age 23 to 32
```



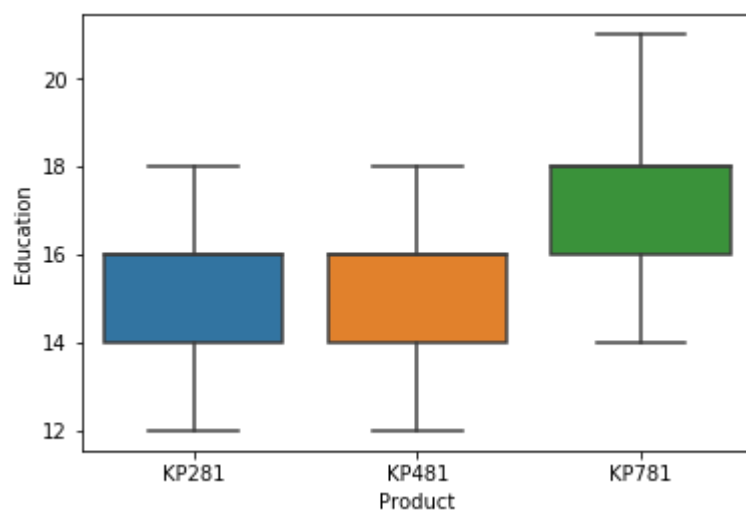
```
In [40]: 1 sns.boxplot(x = 'Product', y = 'Miles', data = df)
2 plt.show()
3 #Customers who run for more than 150 miles prefer KP781
```



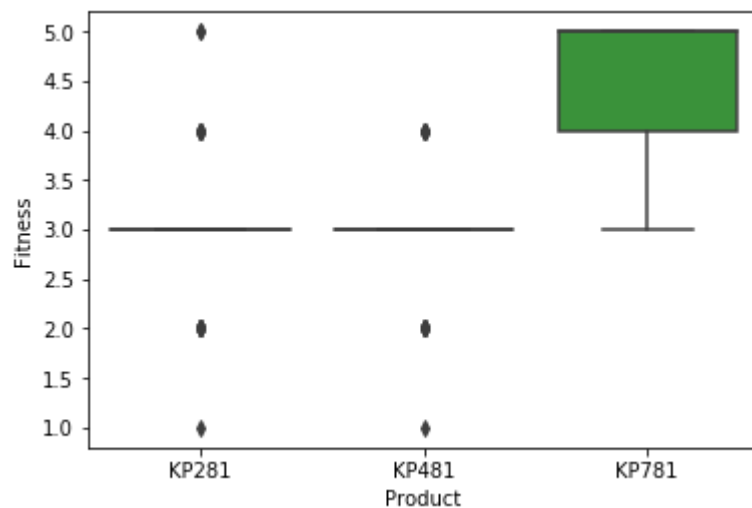
```
In [41]: 1 sns.boxplot(x = 'Product', y = 'Usage', data = df)
2         plt.show()
```



```
In [42]: 1 sns.boxplot(x = 'Product', y = 'Education', data = df)
2         plt.show()
3         # KP281 & KP481 has range b/w 14 to 16 but KP781 has range from 16-18
```




```
In [43]: 1 sns.boxplot(x = 'Product', y = 'Fitness', data = df)
          2 plt.show()
```



Probability Tables

```
In [44]: 1 pd.crosstab(df.Product, df.Gender, normalize='columns', margins=True, margins_na
```

Out[44]:

Gender	Female	Male	Total
Product			
KP281	0.526316	0.384615	0.444444
KP481	0.381579	0.298077	0.333333
KP781	0.092105	0.317308	0.222222

```
In [45]: 1 pd.crosstab(df.Product, df.MaritalStatus, normalize='columns')
```

Out[45]:

MaritalStatus	Partnered	Single
Product		
KP281	0.448598	0.438356
KP481	0.336449	0.328767
KP781	0.214953	0.232877

In [46]: 1 pd.crosstab(df.Product, df.Age,normalize=True)

Out[46]:

Age	18	19	20	21	22	23	24	25	26
Product									
KP281	0.005556	0.016667	0.011111	0.022222	0.022222	0.044444	0.027778	0.038889	0.038889
KP481	0.000000	0.005556	0.016667	0.016667	0.000000	0.038889	0.016667	0.061111	0.016667
KP781	0.000000	0.000000	0.000000	0.000000	0.016667	0.016667	0.022222	0.038889	0.011111

3 rows × 10 columns

In [47]: 1 pd.crosstab(df.Product, df.Usage,normalize=True)

Out[47]:

Usage	2	3	4	5	6	7
Product						
KP281	0.105556	0.205556	0.122222	0.011111	0.000000	0.000000
KP481	0.077778	0.172222	0.066667	0.016667	0.000000	0.000000
KP781	0.000000	0.005556	0.100000	0.066667	0.038889	0.011111

In [48]: 1 pd.crosstab(df.Product, df.Fitness,normalize=True)

Out[48]:

Fitness	1	2	3	4	5
Product					
KP281	0.005556	0.077778	0.300000	0.050000	0.011111
KP481	0.005556	0.066667	0.216667	0.044444	0.000000
KP781	0.000000	0.000000	0.022222	0.038889	0.161111

In [49]: 1 pd.crosstab(df.Product, df.Education,normalize=True)

Out[49]:

Education	12	13	14	15	16	18	20	21
Product								
KP281	0.011111	0.016667	0.166667	0.022222	0.216667	0.011111	0.000000	0.000000
KP481	0.005556	0.011111	0.127778	0.005556	0.172222	0.011111	0.000000	0.000000
KP781	0.000000	0.000000	0.011111	0.000000	0.083333	0.105556	0.005556	0.016667

```
In [50]: 1 pd.crosstab(df.Product,[df.Gender, df.MaritalStatus],normalize=True)
```

Out[50]:

Gender	Female		Male	
	Partnered	Single	Partnered	Single
Product				
KP281	0.150000	0.072222	0.116667	0.105556
KP481	0.083333	0.077778	0.116667	0.055556
KP781	0.022222	0.016667	0.105556	0.077778