aerofit

March 18, 2024

Dataset The company collected the data on individuals who purchased a treadmill from the AeroFit stores during the prior three months. The dataset has the following features:

Dataset link:- https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/125/original/aerofit_treadmi

```
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 $)
Fitness:    Self-rated fitness on a 1-to-5 scale, where 1 is the poor shape and 5 is the excell
Miles:  The average number of miles the customer expects to walk/run each week
```

0.0.1 price of products- Portfolio

"' Product Portfolio:

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

[4]:
```
%load_ext autoreload
%autoreload 2
```

[84]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import math
from scipy.stats import norm, binom, poisson, expon
```

[2]:
```
aerofit_weblink = 'https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/
↪000/001/125/original/aerofit_treadmill.csv?1639992749'
```

[7]:
```
df = pd.read_csv(aerofit_weblink)
df
```

[7]:
```
     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
..       …    …     …          …           …      …        …       …
175    KP781   40    Male         21        Single      6        5   83416
176    KP781   42    Male         18        Single      5        4   89641
177    KP781   45    Male         16        Single      5        5   90886
178    KP781   47    Male         18     Partnered      4        5  104581
179    KP781   48    Male         18     Partnered      4        5   95508

     Miles
0      112
1       75
2       66
3       85
4       47
..     …
175    200
176    200
177    160
178    120
179    180

[180 rows x 9 columns]
```

[8]:
```python
df.shape
```

[8]:
```
(180, 9)
```

[38]:
```python
df.dtypes
```

[38]:
```
Product          object
Age               int64
Gender           object
Education         int64
MaritalStatus    object
Usage             int64
Fitness           int64
Income            int64
Miles             int64
dtype: object
```

[40]:
```python
(df.dtypes.index, df.dtypes.values)
```

[40]: (Index(['Product', 'Age', 'Gender', 'Education', 'MaritalStatus', 'Usage',
        'Fitness', 'Income', 'Miles'],
       dtype='object'),
 array([dtype('O'), dtype('int64'), dtype('O'), dtype('int64'), dtype('O'),
        dtype('int64'), dtype('int64'), dtype('int64'), dtype('int64')],
       dtype=object))

just segregating numerical and categorical variables

[53]:
```
categorical_variable = list()
numerical_variable = list()
for i in range(len(df.dtypes.index)):
    if df.dtypes.values[i] == df.dtypes.values[0]:
        categorical_variable.append(df.dtypes.index[i])
    else:
        numerical_variable.append(df.dtypes.index[i])
```

[54]:
```
(categorical_variable, numerical_variable)
```

[54]: (['Product', 'Gender', 'MaritalStatus'],
 ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles'])

[66]:
```
pd.DataFrame({i : [df[i].unique()] for i in categorical_variable})
```

[66]:

	Product	Gender	MaritalStatus
0	[KP281, KP481, KP781]	[Male, Female]	[Single, Partnered]

[55]:
```
df.describe()
```

[55]:

	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
```

0.1 Couple observations -

The range of age is from 18 - 50

The median income or the higher # of people have income ~ 58000, which is a little away from mean ~ 53000- therefore, there might be outliers weighing the data to that side

the usgae of treadmill is around ~ 4 times

Value counts for each categorical variable

[67]:
```python
categorical_variable
```

[67]:
```
['Product', 'Gender', 'MaritalStatus']
```

[79]:
```python
for i in categorical_variable:
    print(df[i].value_counts().reset_index(), "\n")
```

```
   index  Product
0  KP281       80
1  KP481       60
2  KP781       40

    index  Gender
0    Male     104
1  Female      76

       index  MaritalStatus
0  Partnered            107
1     Single             73
```

0.2 observations

```
1. product "KP281" is the most used product
2. There are more male members than female
3. more couples than singles
```

[80]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
```

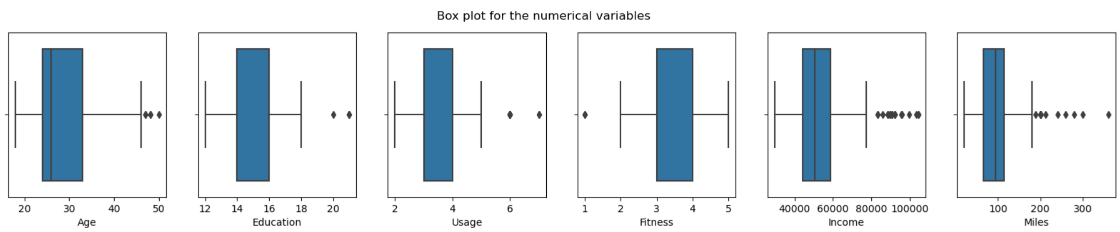
```
 0   Product        180 non-null    object
 1   Age            180 non-null    int64
 2   Gender         180 non-null    object
 3   Education      180 non-null    int64
 4   MaritalStatus  180 non-null    object
 5   Usage          180 non-null    int64
 6   Fitness        180 non-null    int64
 7   Income         180 non-null    int64
 8   Miles          180 non-null    int64
dtypes: int64(6), object(3)
memory usage: 12.8+ KB
```

0.3 Let's do some outlier detection

[81]:
```
numerical_variable
```

[81]: ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']

[94]:
```
fig, axes = plt.subplots(1, len(numerical_variable), figsize = (20, 3))
plt.suptitle('Box plot for the numerical variables')



i = 0
for col in numerical_variable:
    sns.boxplot(data = df, x = col, ax = axes[i])
    i = i + 1
```



[113]:
```
## function to calculate the ouliers

def calculate_outlier(data):
    q1 = np.percentile(data, 25)
    q3 = np.percentile(data, 75)

    iqr = q3 - q1

    lower_bound  = q1 - 1.5* iqr
    upper_bound = q3 + 1.5 * iqr
```

```
    outlier = [value for value in data if value < lower_bound or value >␣
↪upper_bound]

    return outlier
```

[114]:
```
outlier_dic  = {col : [calculate_outlier(df[col])] for col in␣
↪numerical_variable}

outlier_df = pd.DataFrame(outlier_dic)
```

[115]:
```
outlier_df
```

[115]:
```
                       Age          Education                        Usage  \
0  [47, 50, 48, 47, 48]  [20, 21, 21, 21]  [6, 6, 6, 7, 6, 7, 6, 6, 6]

  Fitness                                             Income  \
0  [1, 1]  [83416, 88396, 90886, 92131, 88396, 85906, 908…

                                               Miles
0  [188, 212, 200, 200, 200, 240, 300, 280, 260, …
```

[116]:
```
numerical_variable
```

[116]:
```
['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
```

[117]:
```
outlier_dic = dict()
for col in numerical_variable:
    outlier_dic.update({col : [len(calculate_outlier(df[col]))]})


pd.DataFrame(outlier_dic)
```

[117]:

	Age	Education	Usage	Fitness	Income	Miles
0	5	4	9	2	19	13

the above data frame shows the number of outliers in each numerical variable

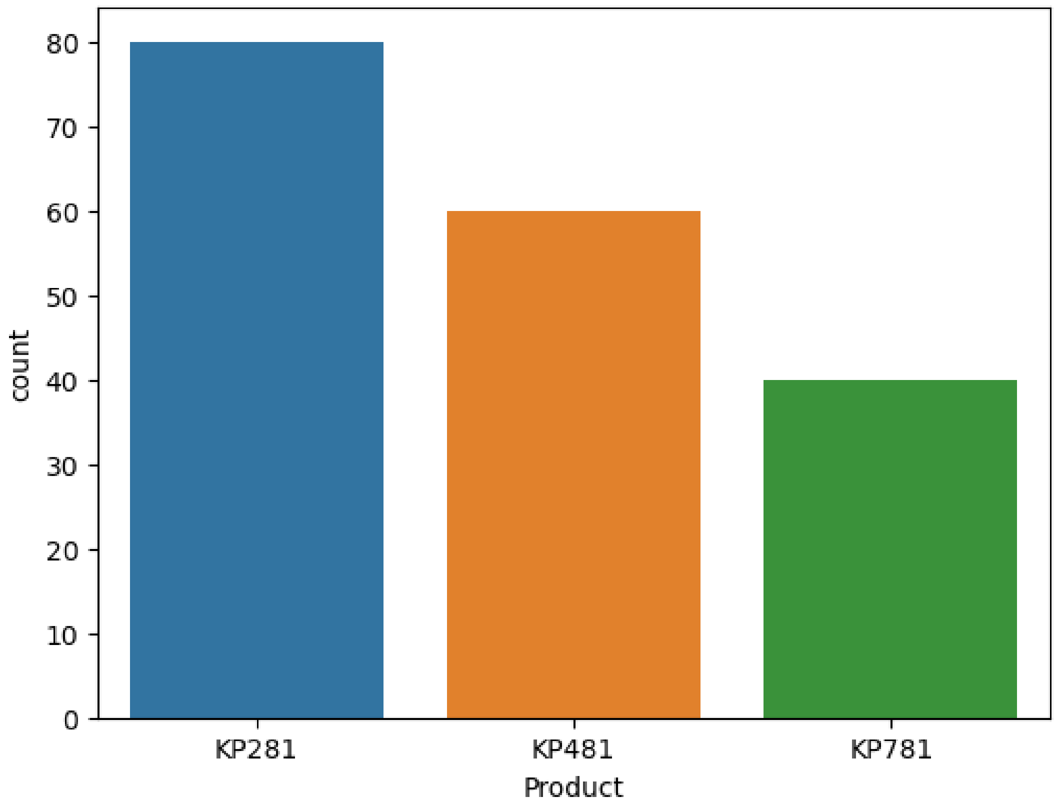
```
1. For all attributes, there are no missing values
2. For Age,Education, Usage there are very less outliers,
   For Income, Miles there are more outliers

3. the fitness seems to be a categrorical variable with more than 2 categories
```

0.4 Visual Analysis

Univariate

[118]:
```
sns.countplot(data = df, x = 'Product')
```

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



[148]:
```
df_product_count = df.groupby(['Product'])[['Product']].count()
df_product_count.rename({'Product': 'count'}, axis = 1, inplace = True)
df_product_count['price'] = pd.Series([1500, 1750, 2500]).values
df_product_count['% of units sold'] = (df_product_count['count'] /␣
↪df_product_count['count'].sum())* 100
df_product_count['Sales in $'] = df_product_count['count'] * df_product_count␣
↪['price']
df_product_count
```

[148]:

	count	price	% of units sold	Sales in $
Product				
KP281	80	1500	44.444444	120000
KP481	60	1750	33.333333	105000
KP781	40	2500	22.222222	100000

0.5 Insight

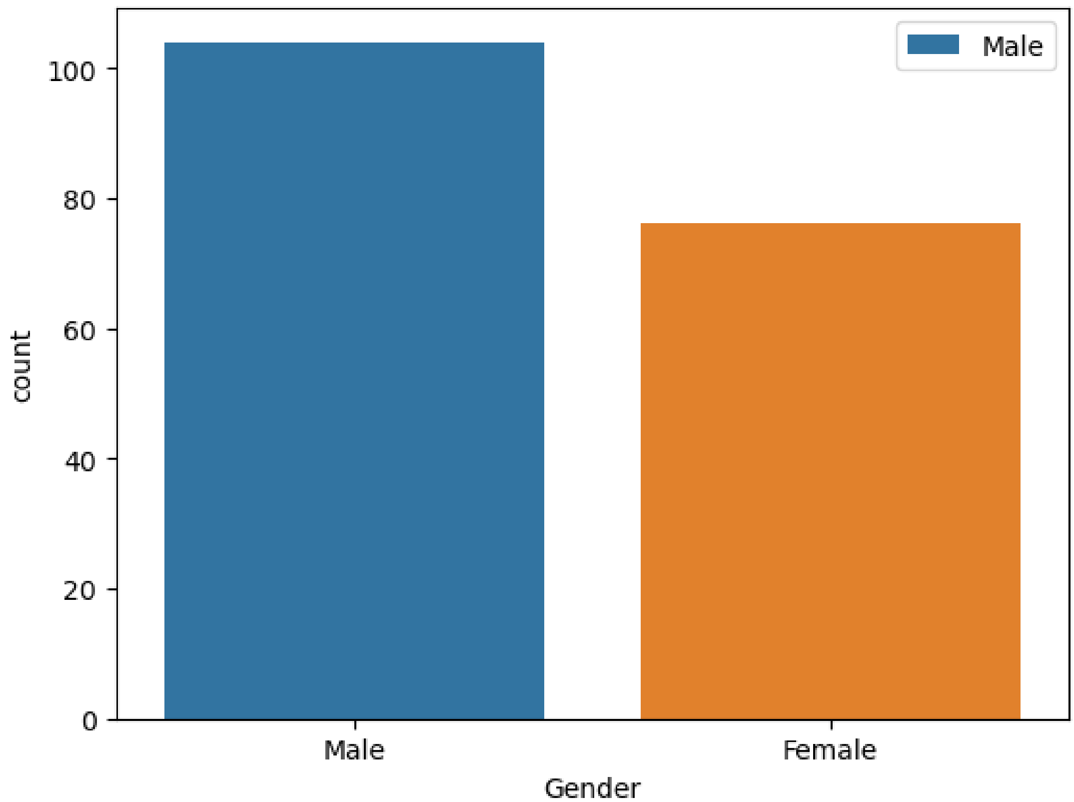
even though the count for KP281 is higher, the sale is more or less similar for all the produc

[149]:
```
df
```

[149]:
```
     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
..       …   …     …         …           …     …       …      …
175    KP781   40    Male         21        Single      6        5   83416
176    KP781   42    Male         18        Single      5        4   89641
177    KP781   45    Male         16        Single      5        5   90886
178    KP781   47    Male         18     Partnered      4        5  104581
179    KP781   48    Male         18     Partnered      4        5   95508

     Miles
0      112
1       75
2       66
3       85
4       47
..     …
175    200
176    200
177    160
178    120
179    180

[180 rows x 9 columns]
```

[152]:
```
sns.countplot(data = df, x = 'Gender')
```

[152]: <matplotlib.legend.Legend at 0x7f10b2bf9480>



[155]:
```
gender_df = df.groupby(['Gender'])[['Gender']].count()
gender_df.index.name = "gender"
gender_df.rename({"Gender": "Count"}, axis = 1, inplace = True)
gender_df['% of total'] = (gender_df['Count'] / gender_df['Count'].sum()) * 100
gender_df
```

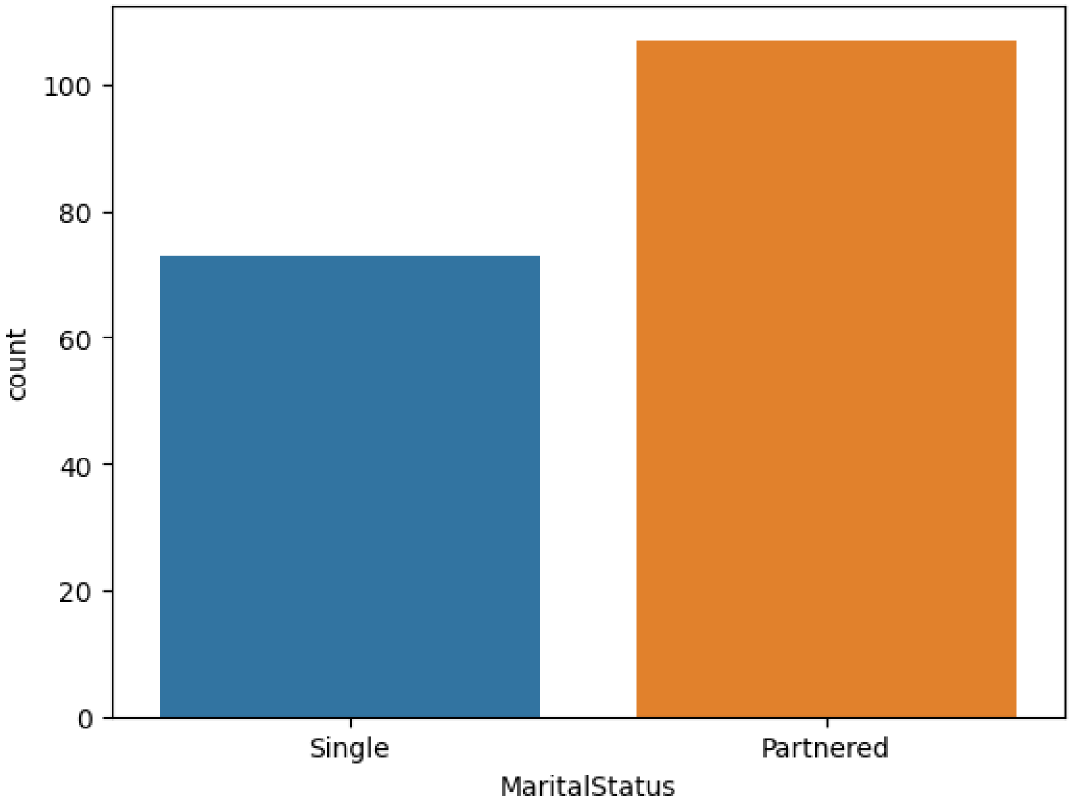
[155]:

	Count	% of total
gender		
Female	76	42.222222
Male	104	57.777778

the male participation (57%) is more than female

[156]:
```
sns.countplot(data = df, x = 'MaritalStatus')
```

[156]: <Axes: xlabel='MaritalStatus', ylabel='count'>



there are more partnered people than singles

[161]:
```
fit_df = df.groupby(['Fitness'])[['Fitness']].count()
fit_df.index.name = "fitness"
fit_df.rename({"Fitness": "count"}, axis = 1 , inplace = True)

fit_df['% of total'] = (fit_df['count'] / fit_df['count'].sum()) * 100
fit_df
```

[161]:

fitness	count	% of total
1	2	1.111111
2	26	14.444444
3	97	53.888889
4	24	13.333333
5	31	17.222222

0.5.1 around 53 % people, majority, treat them in 3 level fitness

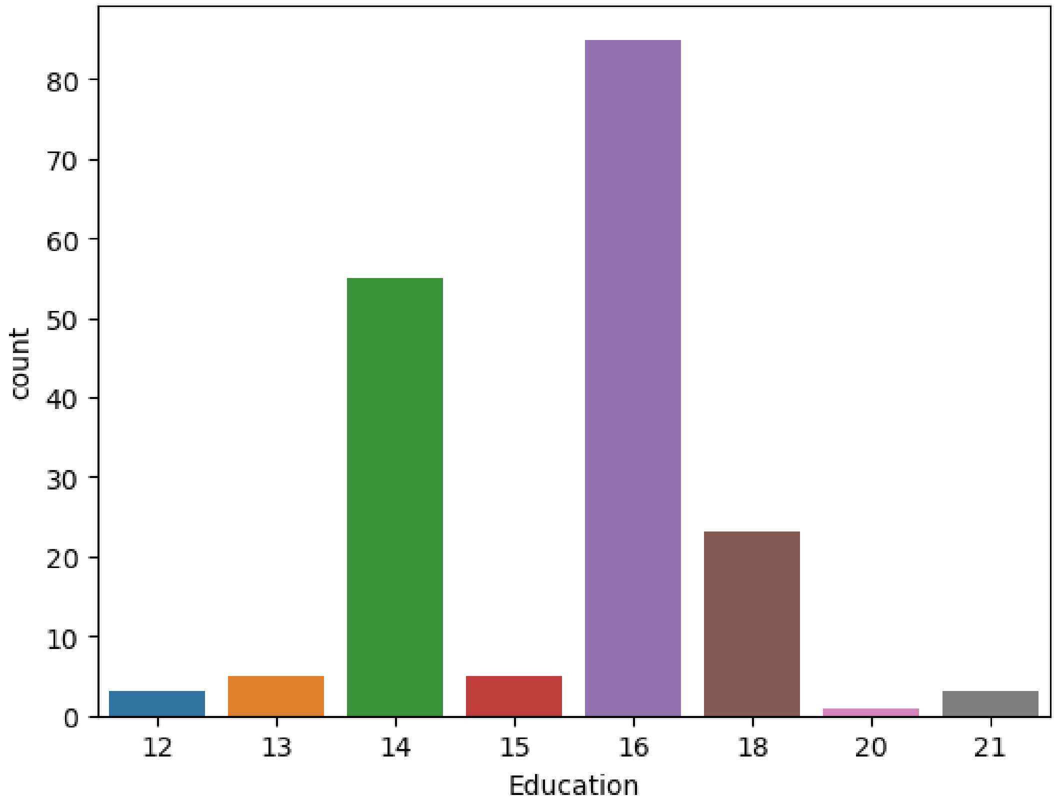
Lets look at the education of people now - might need binning here

[175]:
```
df['Education'].unique()
```

[175]: array([14, 15, 12, 13, 16, 18, 20, 21])

[176]:
```
sns.countplot(data = df, x = 'Education')
```

[176]: <Axes: xlabel='Education', ylabel='count'>

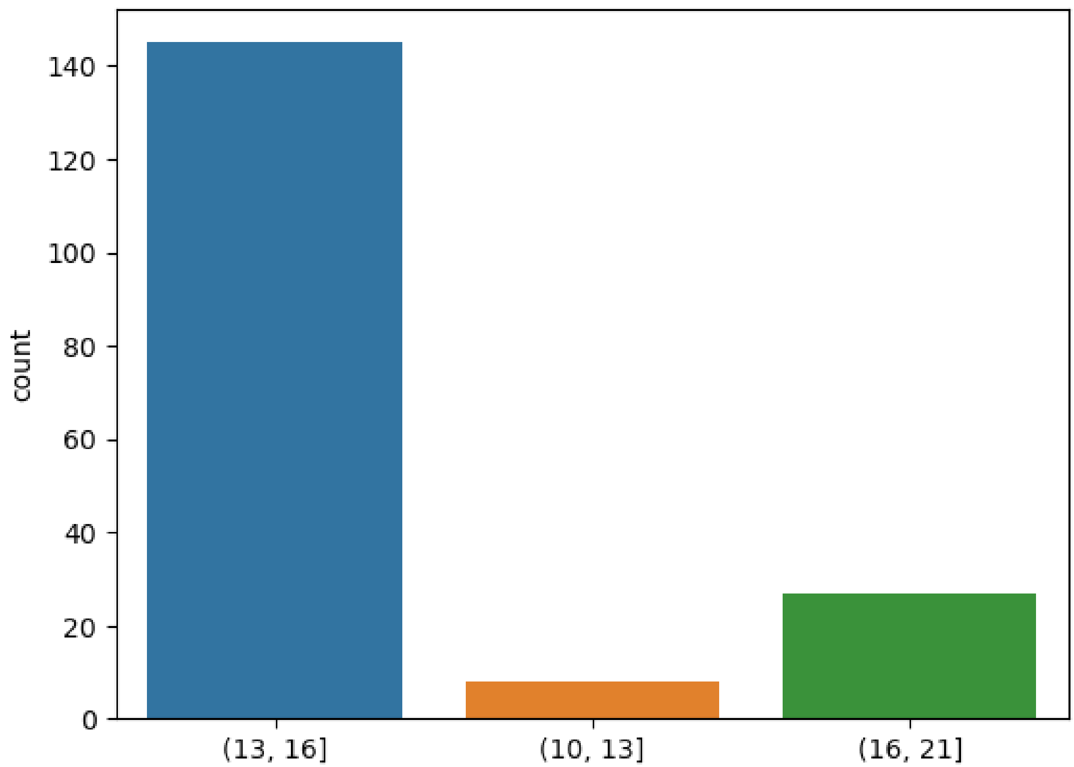


[194]:
```
count_series = pd.cut(df['Education'], [10, 13, 16, 21]).astype('str')
count_series
```

[194]:
```
0      (13, 16]
1      (13, 16]
2      (13, 16]
3      (10, 13]
4      (10, 13]
         …
175    (16, 21]
176    (16, 21]
177    (13, 16]
178    (16, 21]
179    (16, 21]
Name: Education, Length: 180, dtype: object
```

[196]:
```
sns.countplot(data = count_series, x = count_serr.values)
```

[196]: <Axes: ylabel='count'>



[204]:
```
df['Education']
```

[204]:
```
0      14
1      15
2      14
3      12
4      13
       ..
175    21
176    18
177    16
178    18
179    18
Name: Education, Length: 180, dtype: int64
```

[222]:
```
col = 'Education'
bin_series = pd.cut(df[col], [10,13,16,19,21]).astype('str')
print(bin_series, "\n")
```

```python
df_temp = pd.DataFrame({ col : bin_series})
print(df_temp, "\n")
df_temp = df_temp.groupby([col])[[col]].count()
df_temp.rename({col : "count"}, axis = 1, inplace = True)
print(df_temp, "\n")
```

```
0      (13, 16]
1      (13, 16]
2      (13, 16]
3      (10, 13]
4      (10, 13]
         …
175    (19, 21]
176    (16, 19]
177    (13, 16]
178    (16, 19]
179    (16, 19]
Name: Education, Length: 180, dtype: object

    Education
0    (13, 16]
1    (13, 16]
2    (13, 16]
3    (10, 13]
4    (10, 13]
..        …
175  (19, 21]
176  (16, 19]
177  (13, 16]
178  (16, 19]
179  (16, 19]

[180 rows x 1 columns]

           count
Education
(10, 13]       8
(13, 16]     145
(16, 19]      23
(19, 21]       4
```

0.6 creating a method to bin any numerical variable and find out the leading range

[225]:
```
def bin_col(df : pd.DataFrame, col: str, lims: list)-> pd.DataFrame:
    bin_series = pd.cut(df[col], lims).astype('str')
    df_temp = pd.DataFrame({col : bin_series, "count": df[col]})
    df_temp = df_temp.groupby([col])[[col]].count()
    df_temp.rename({col : "count"}, axis = 1, inplace = True)
    df_temp['% total'] = (df_temp["count"] / df_temp["count"].sum()) * 100

    return df_temp
```

[226]:
```
bin_col(df, 'Education', [10, 13, 16, 19, 21])
```

[226]:

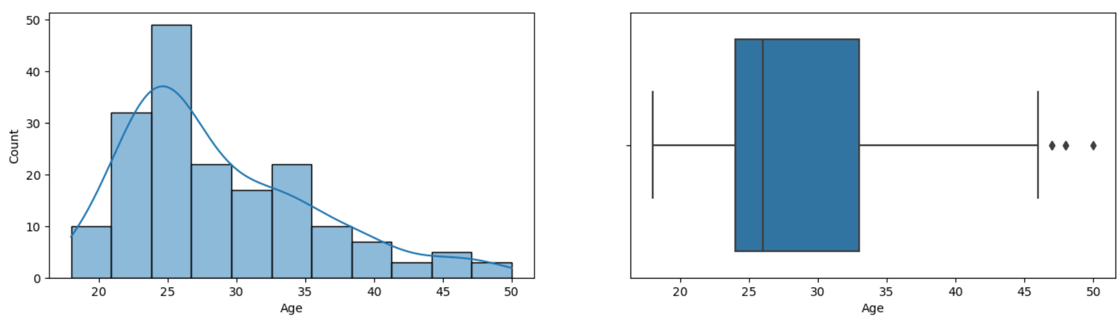
Education	count	% total
(10, 13]	8	4.444444
(13, 16]	145	80.555556
(16, 19]	23	12.777778
(19, 21]	4	2.222222

most of the customer have 14-16 years(both included) of education

now, lets look at histogram/distribution and box plot together to find out skewness in the data and the outliers

[239]:
```
def distnbox(df: pd.DataFrame, col: 'str'):
    fig, axes = plt.subplots(1, 2, figsize = (16, 4))
    sns.histplot(data = df, x = col, ax = axes[0], kde = True)
    sns.boxplot(data = df, x = col, ax = axes[1])
```

[240]:
```
distnbox(df, 'Age')
```



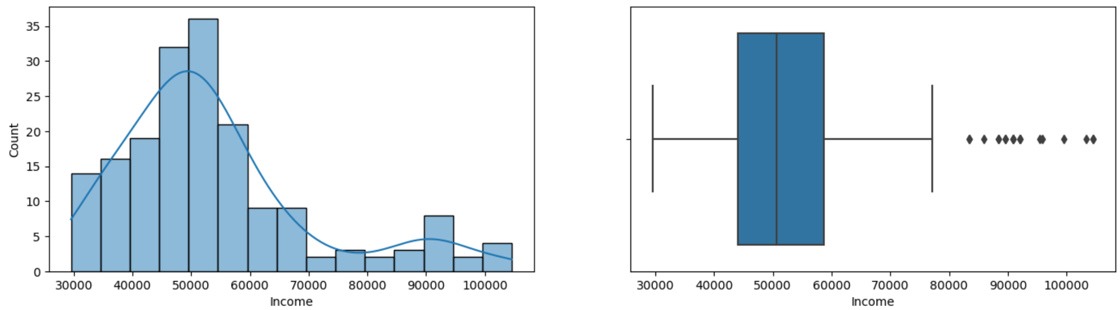
[241]:
```
bin_col(df, "Age", [10,  15, 25, 30, 35, 40, 45, 50])
```

[241]:

	count	% total
Age		
(15, 25]	79	43.888889
(25, 30]	41	22.777778
(30, 35]	32	17.777778
(35, 40]	16	8.888889
(40, 45]	6	3.333333
(45, 50]	6	3.333333

43% of people are located in the range of 16-25 yesrs old

[242]:
```
distnbox(df, 'Income')
```



[244]:
```
bin_col(df, "Income", [df['Income'].min(), 40000 , 60000, df['Income'].max() ])
```

[244]:

	count	% total
Income		
(29562, 40000]	31	17.222222
(40000, 60000]	106	58.888889
(60000, 104581]	42	23.333333
nan	1	0.555556

0.6.1 Comments:

1. 58% of of customers have income around $40000 to $60000
2. Only 17% are below this range and 23% are above $60000

lets do some correlation plots

[245]:
```
numerical_variable
```

[245]: ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']

[252]:
```
df[numerical_variable]
```

[252]:

```
      Age  Education  Usage  Fitness  Income  Miles
0      18         14      3        4   29562    112
1      19         15      2        3   31836     75
2      19         14      4        3   30699     66
3      19         12      3        3   32973     85
4      20         13      4        2   35247     47
..    …          …    …      …     …    …
175    40         21      6        5   83416    200
176    42         18      5        4   89641    200
177    45         16      5        5   90886    160
178    47         18      4        5  104581    120
179    48         18      4        5   95508    180

[180 rows x 6 columns]
```

[253]:

```python
df[numerical_variable].corr()
```

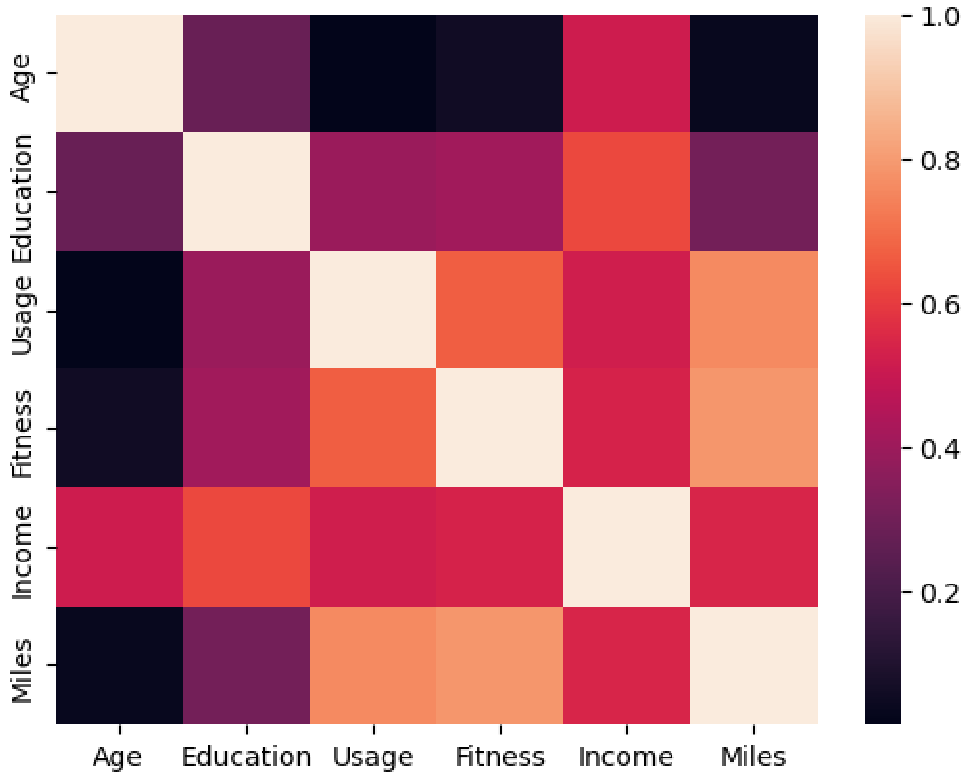
[253]:

	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

[254]:

```python
sns.heatmap(data = df[numerical_variable].corr())
```

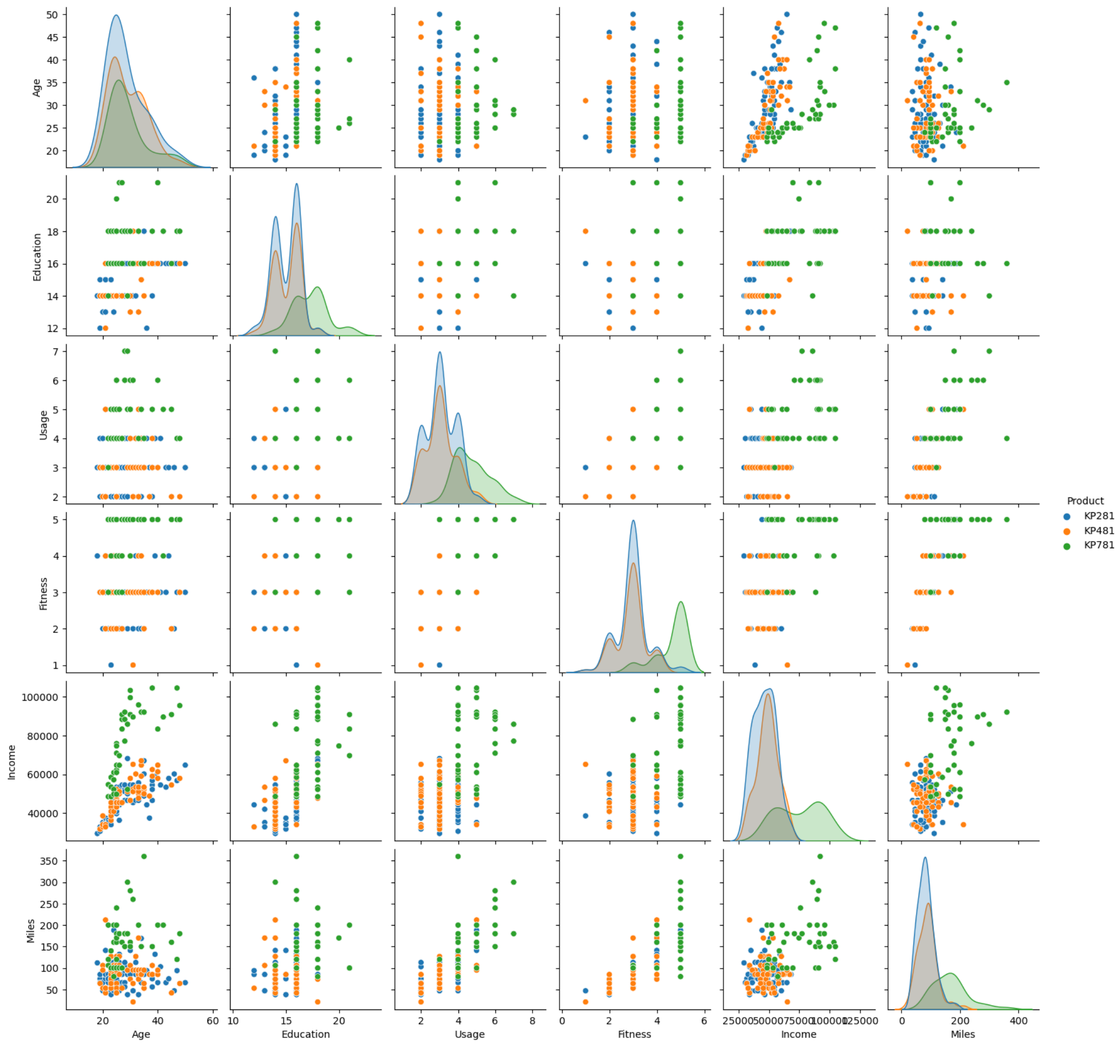
[254]: <Axes: >



Usage, miles planned to cover, and fitness are highly dependent on the age

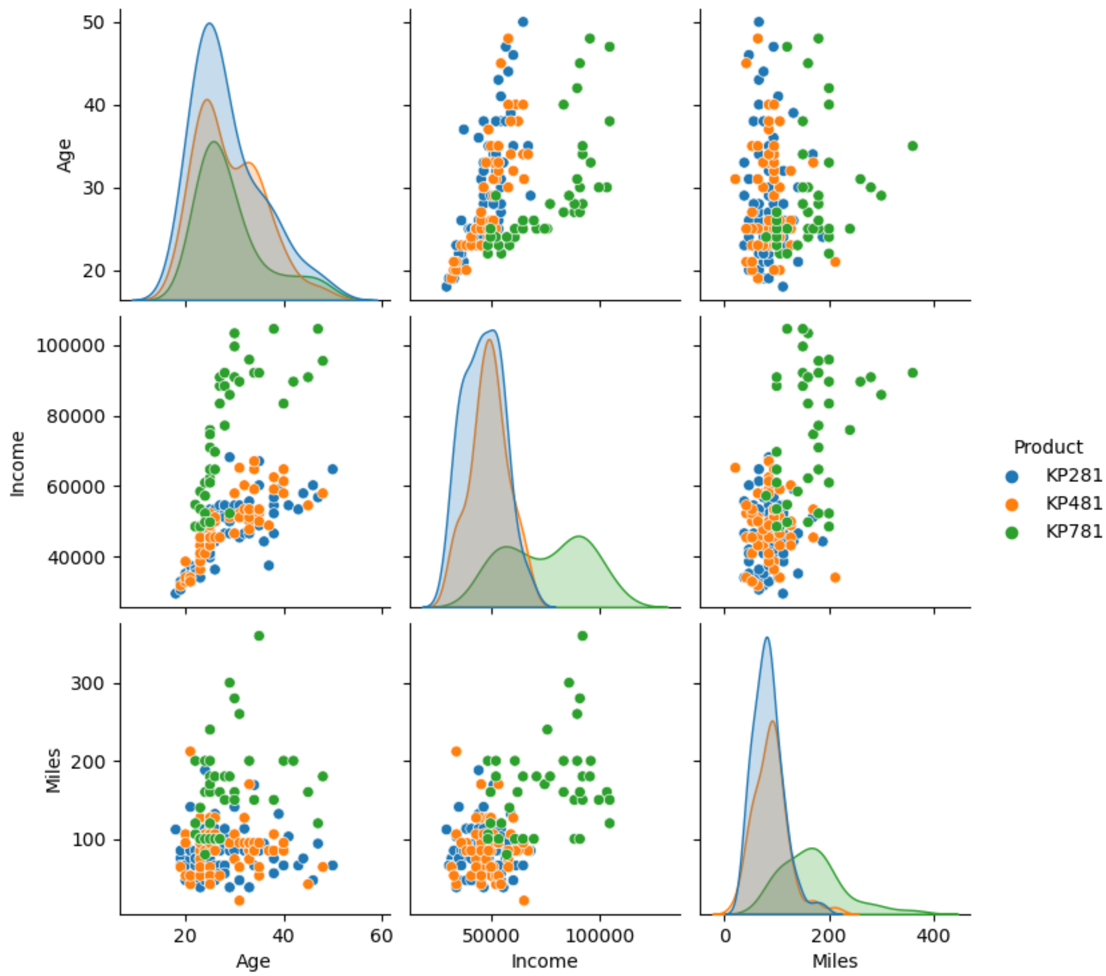
[255]:
```
sns.pairplot(data = df, hue = 'Product')
```

[255]: <seaborn.axisgrid.PairGrid at 0x7f10b1f52290>



[257]:
```
sns.pairplot(data = df[['Age', 'Income', 'Miles', 'Product']], hue = 'Product')
```

[257]: <seaborn.axisgrid.PairGrid at 0x7f10b113ccd0>



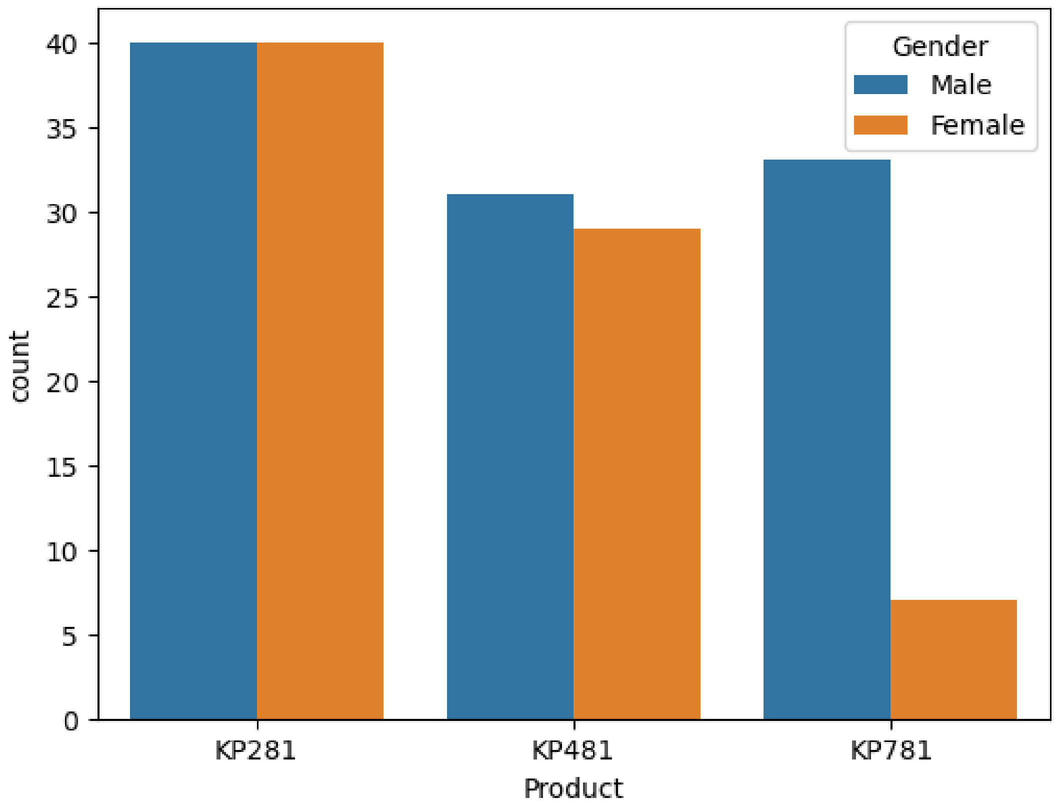
income has correlation with miles and age

0.7 Bivariate analysis

0.7.1 Product vs Gender

[258]:
```
sns.countplot(df, hue = 'Gender', x = 'Product')
```

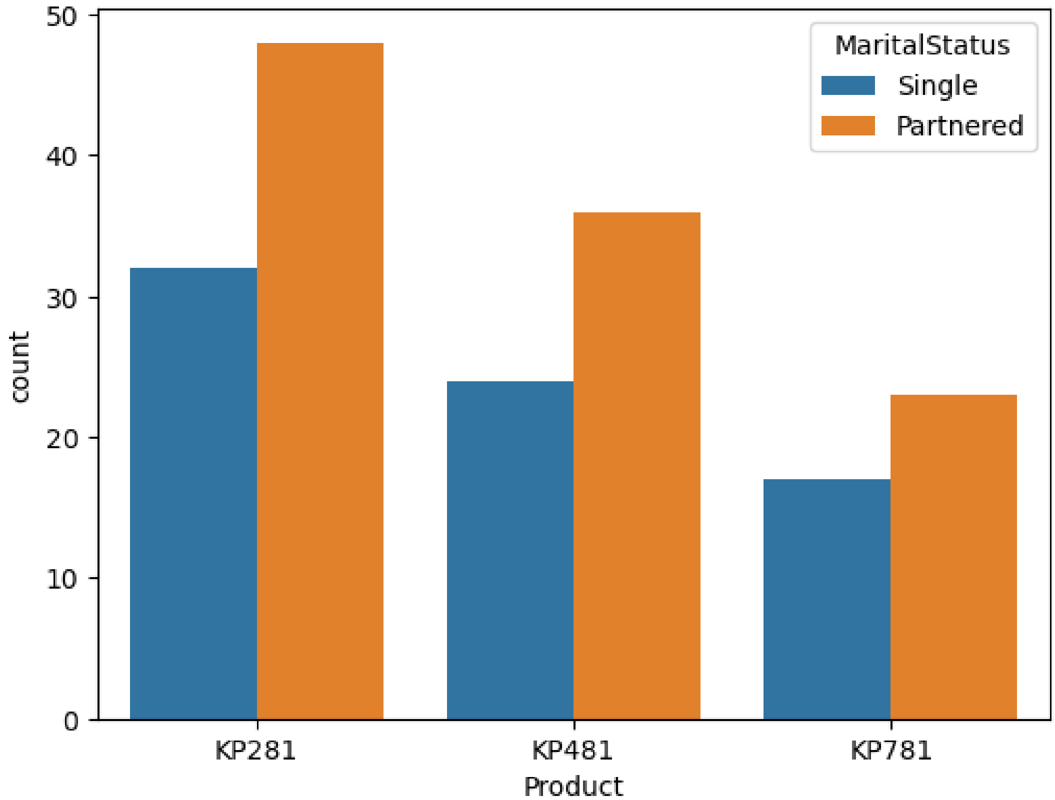
[258]: <Axes: xlabel='Product', ylabel='count'>



Product “KP781” is bought by Male customers more than Female customers Product “KP481” and “KP281” is bought by both Male and Female customers

[259]:
```
sns.countplot(df, x = 'Product', hue = 'MaritalStatus')
```

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

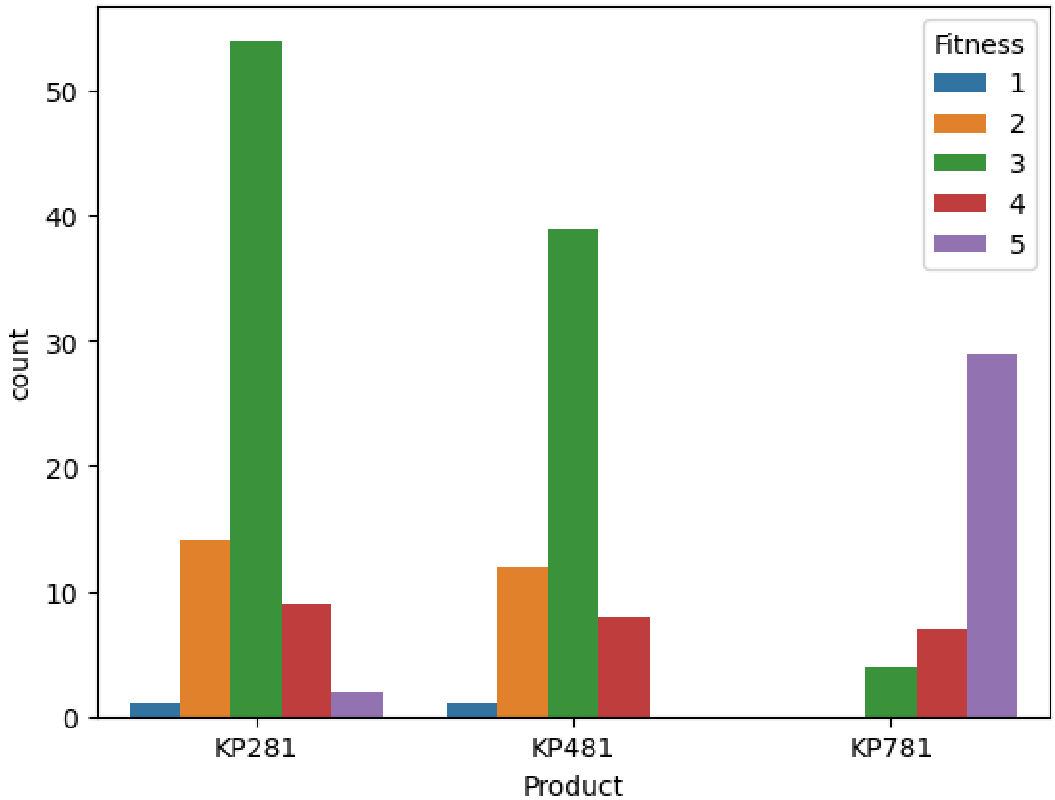


more of the partnered guys than singles for all the products

0.7.2 product vs fitness

[260]:
```
sns.countplot(df, x = 'Product', hue = 'Fitness')
```

[260]:
```
<Axes: xlabel='Product', ylabel='count'>
```

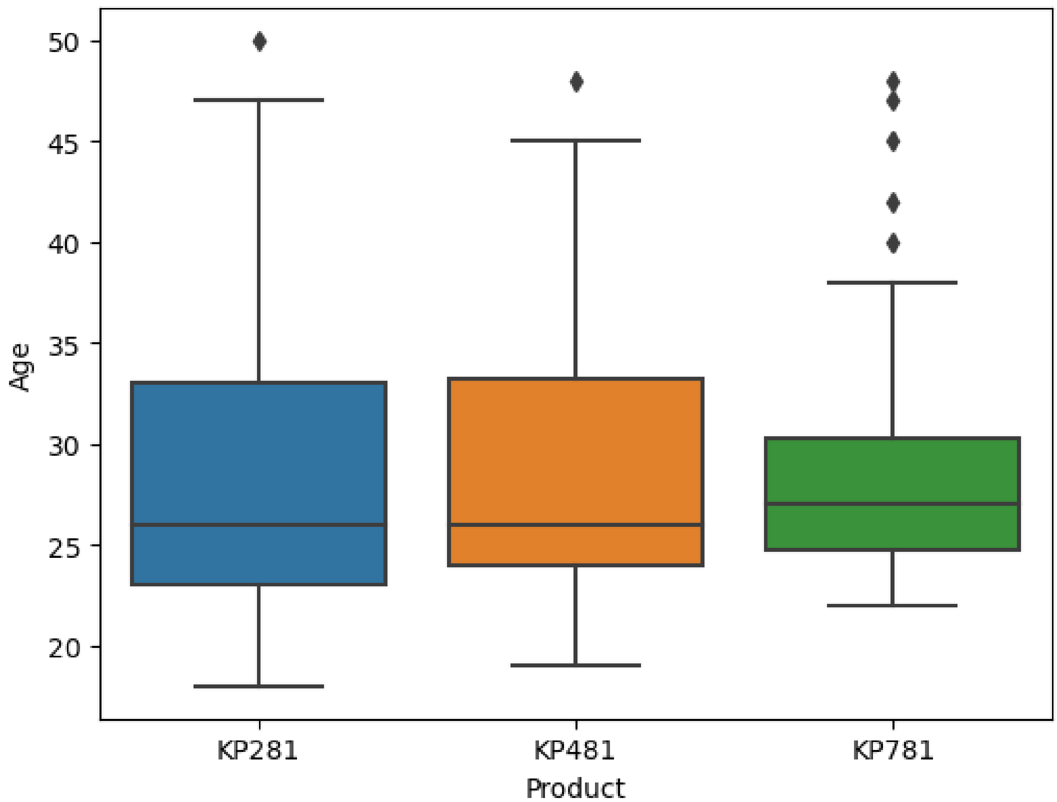


highly fit people use KP781

product vs age

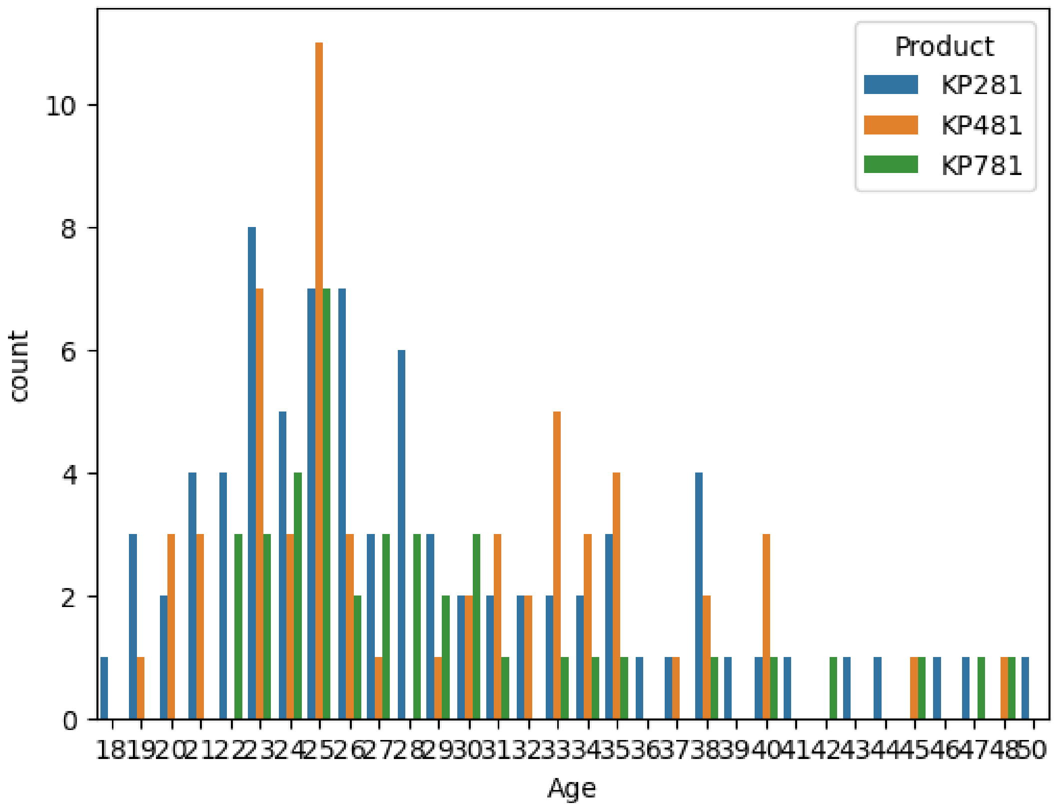
[261]:
```
sns.boxplot(data = df, y = 'Age' , x = 'Product')
```

[261]: <Axes: xlabel='Product', ylabel='Age'>



[262]:
```
sns.countplot(data = df, x = "Age", hue = "Product")
```

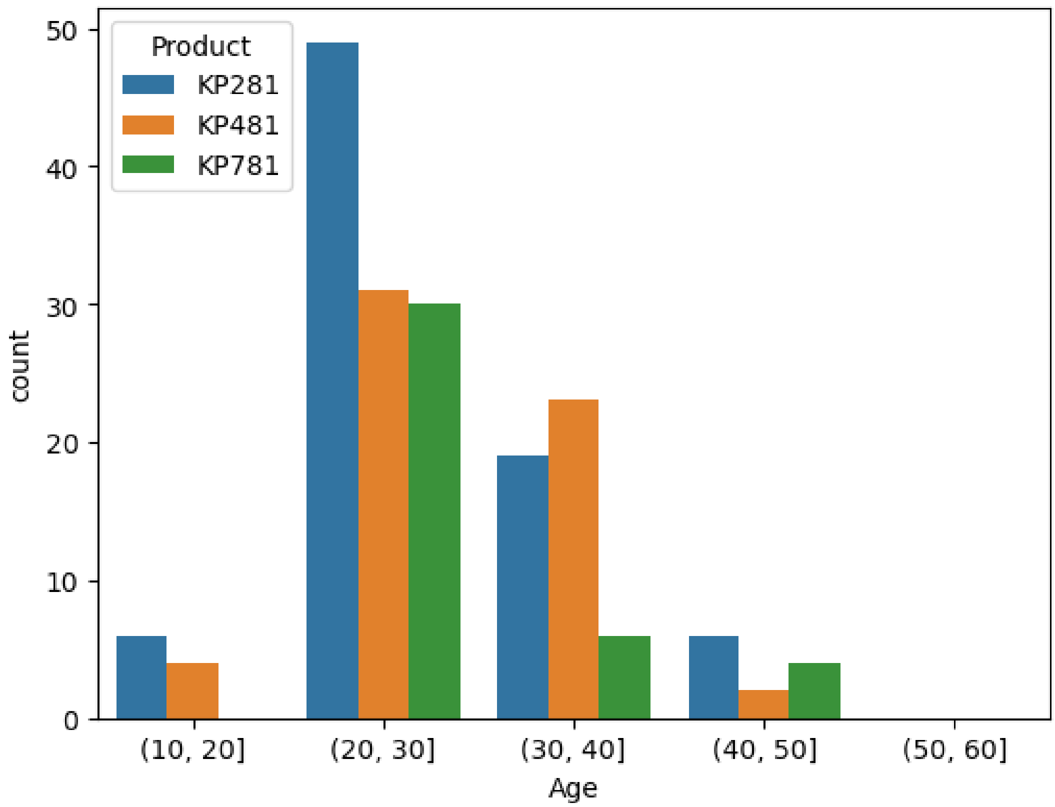
[262]: <Axes: xlabel='Age', ylabel='count'>



Doesn't make senes, therefore, lets bin Age

[263]:
```
sns.countplot(data = df, x = pd.cut(df['Age'], [10,20,30,40,50,60]), hue = 'Product')
```

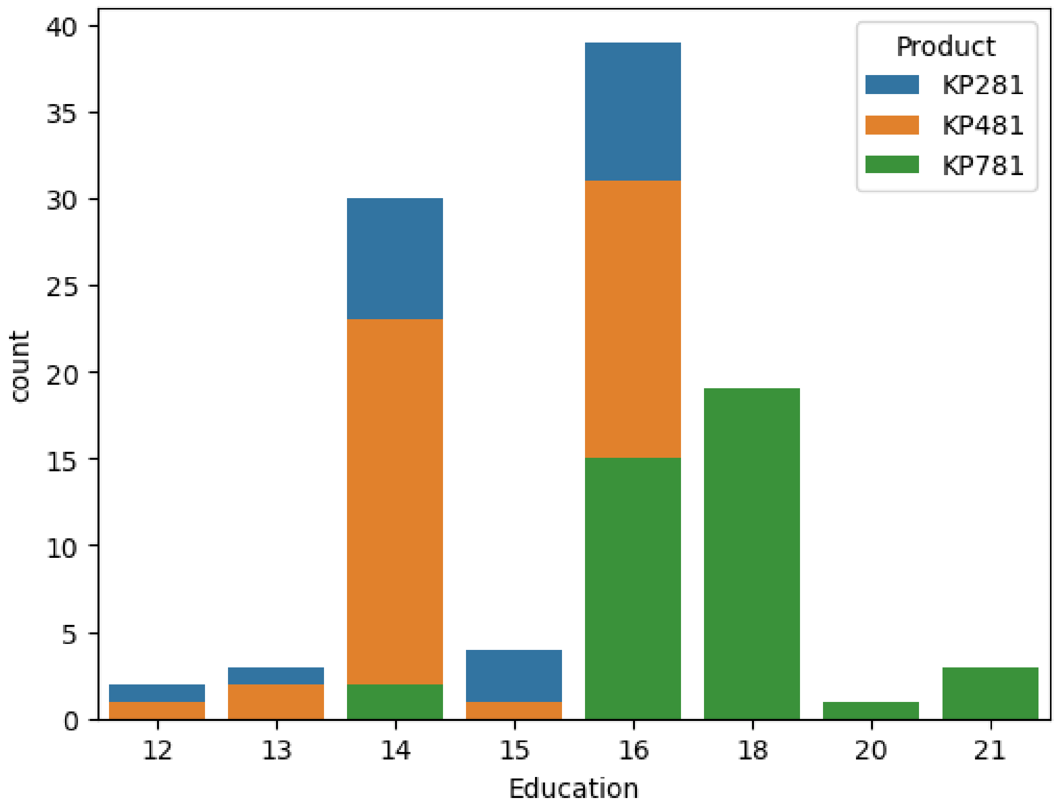
[263]: `<Axes: xlabel='Age', ylabel='count'>`



1. Almost all products attract age groups 25-30
2. 25-30 customers has bought KP281 more than others

[265]:
```
sns.countplot(data = df, x = 'Education', dodge = False, hue = 'Product')
```

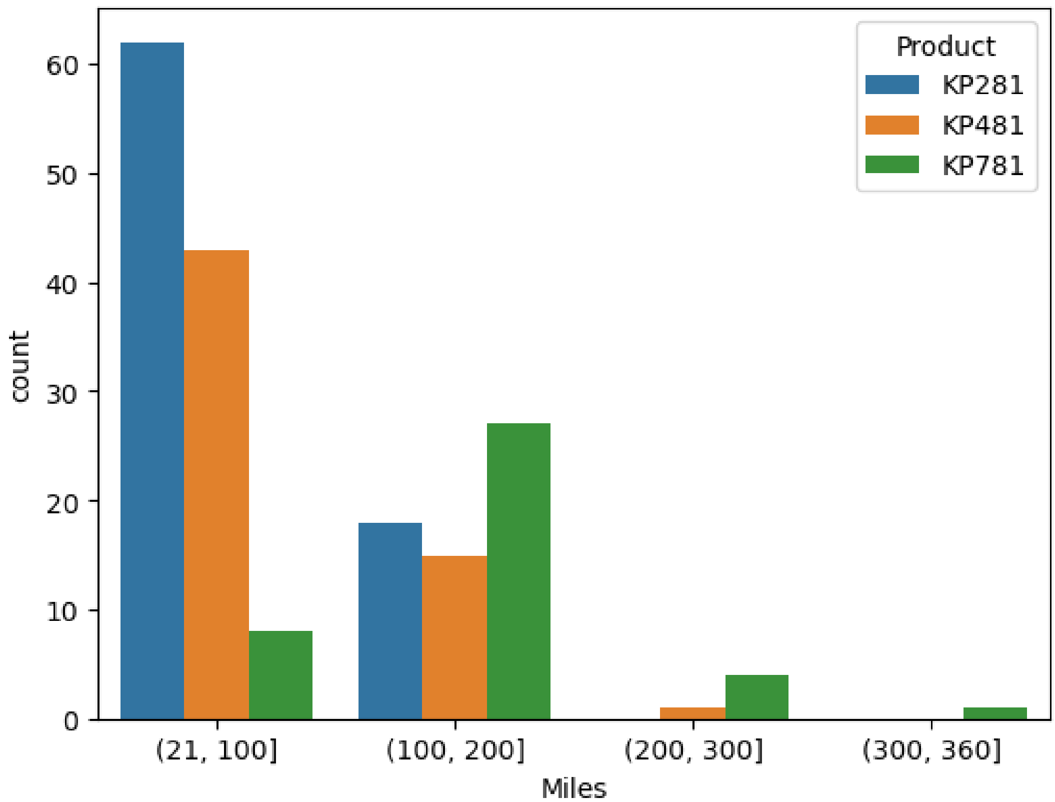
[265]: <Axes: xlabel='Education', ylabel='count'>




```
KP481, KP281 is bought by customers with 14-16 yrs of Education
KP781 is mostly bought by customers with 16-21 yrs
```

[267]:
```
sns.countplot(data = df, x = pd.cut(df['Miles'], [df['Miles'].min(),100, 200,␣
 ↪300 ,df['Miles'].max()]), hue = 'Product')
```

[267]:
```
<Axes: xlabel='Miles', ylabel='count'>
```



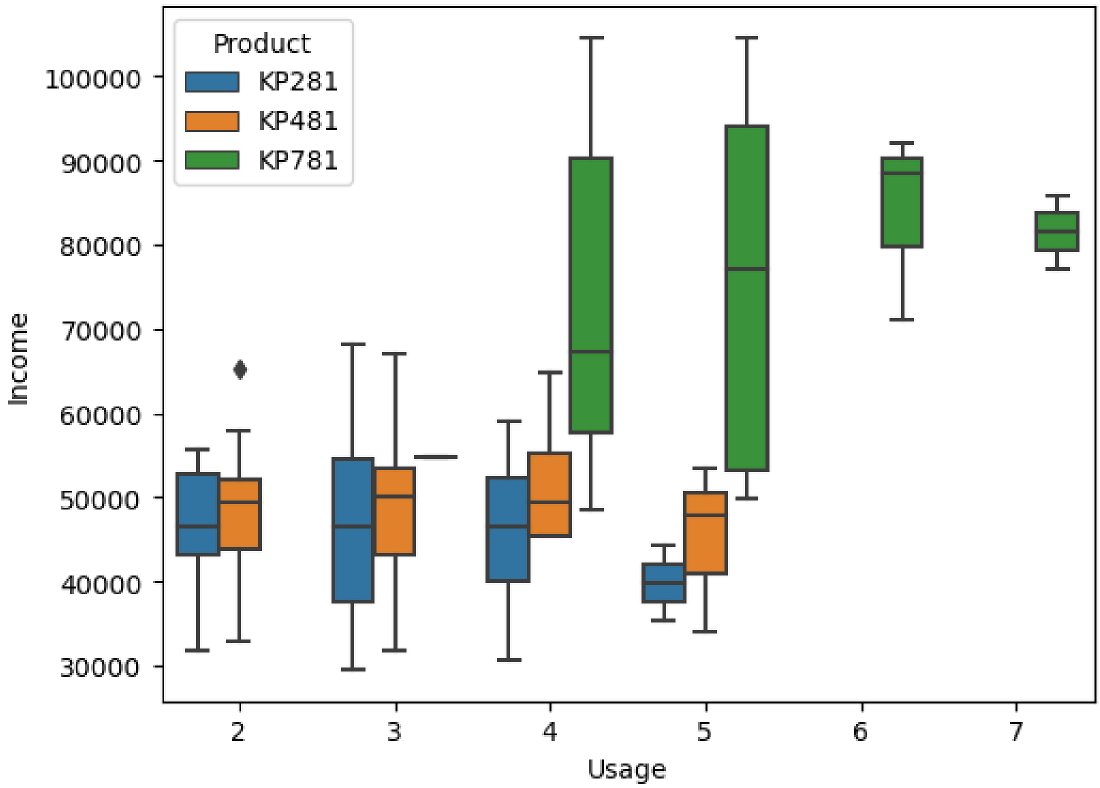

```
KP781 is bought mostly by customers with high "Miles" (Expected Walking distance)
KP 481, KP 281 are bought mostly by customers with Moderate/Low "Miles" value
```

summary

1. On the overall, Partnered customers buy more products.
2. Product "KP781" is bought by Male customers more than Female customers Otherwise There is not much correlation between Product Type and Gender
3. KP281, KP481 are bought by customer who are moderately fit or less fit. Where as KP781 is bought by customer who are very fit.
4. High usage: KP781 Moderate usage: KP481, KP281
5. Almost all products attract age groups 25-30
6. KP781 is bought mostly by customers with high income KP481, KP281 are bought mostly by customers with Moderate/Low income
7. KP781 is bought mostly by customers with high "Miles" (Expected Walking distance) KP 481, KP 281 are bought mostly by customers with Moderate/Low "Miles" value

[268]:
```
sns.boxplot(x = df['Usage'], y = df['Income'], hue = df['Product'])
```

[268]: <Axes: xlabel='Usage', ylabel='Income'>



Example Customer Profile for "KP481":

Fitness : 2-4 on scale of 5 Usage : 2-4 times a week Age : 20-40 Education : 14-16 Income : Moderate, Range: [40000 to 60000] Miles : 50-100

(Although Product "KP481" is bought by both Male and Female customers, Gender: Male is taken as example) (Although Product "KP481" is bought by both Partnered and Single customers, MaritalStatus: Partnered is taken as example)

Example Customer Profile for "KP781":

Gender : Male Fitness : 4-5 on scale of 5 (Very fit) Usage : 4-6 (High Usage) Age : 20-30 Education : 16-21 (High) Income : High, Range: [60000 to 90000] Miles : 100-200 (High)

0.8 Probabilty

0.8.1 Marginal Probabilites

[284]:
```
df_MP = df.groupby(['Product'])[['Product']].count()
df_MP
```

[284]:
```
         Product
Product
KP281         80
KP481         60
KP781         40
```

[285]:
```python
df_MP = df_MP / 180
df_MP
```

[285]:
```
          Product
Product
KP281    0.444444
KP481    0.333333
KP781    0.222222
```

[286]:
```python
df_MP[' '] = 'Probability that the customer buys ' + df_MP.index + ' ='
df_MP[[" ", "Product"]].reset_index(drop = True, inplace = True)
```

[287]:
```python
df_MP
```

[287]:
```
          Product
Product
KP281    0.444444  Probability that the customer buys KP281 =
KP481    0.333333  Probability that the customer buys KP481 =
KP781    0.222222  Probability that the customer buys KP781 =
```

the probbaility of buying lower end model KP281 is higher than other products

0.8.2 Conditional Probabilities

[288]:
```python
df_cross_PG = pd.crosstab(df['Product'], df['Gender'], margins = True)
df_cross_PG
```

[288]:
```
Gender   Female  Male  All
Product
KP281        40    40   80
KP481        29    31   60
KP781         7    33   40
All          76   104  180
```

[290]:
```python
pd.crosstab(df['Product'], df['Gender'], margins = True)
```

[290]:
```
Gender   Female  Male  All
Product
KP281        40    40   80
KP481        29    31   60
KP781         7    33   40
```

```
All          76   104  180
```

[291]:
```python
pd.crosstab(df['Product'], df['MaritalStatus'], margins=True)
```

[291]:
```
MaritalStatus  Partnered  Single  All
Product
KP281                 48      32   80
KP481                 36      24   60
KP781                 23      17   40
All                  107      73  180
```

[292]:
```python
pd.crosstab(df['Product'], df['Fitness'], margins=True)
```

[292]:
```
Fitness  1   2   3   4   5  All
Product
KP281    1  14  54   9   2   80
KP481    1  12  39   8   0   60
KP781    0   0   4   7  29   40
All      2  26  97  24  31  180
```

Given that 72% of customers with low income buy KP281, And it has high sales in the 20-30 yrs Age groups. This product targets the lower income groups. To help target this segment better, we can implement flexible payment plans so that customers can pay in installments.

1. Sales for all 3 products is less in the higher age bracket [40+] compared to the lower age brackets [20-30] KP481, being a mid-level-runner models can be improved by adding features like heart-rate monitors, personalised workout modes etc. to attract such age groups and position this product better.

2. Adding such differerentiators is important also because the customer demographics of KP281 and KP481 overlapp to a significant extent.

1. Only 17% of customers who buy KP781 are female, we can improve this metric by encourage female customers to buy this product, via special promotions/discounts targeting corresponding segment.

2. KP781 is not bought by customers with self-rated-fitness rating 1-3
it is recommended to emphasize the benifits and features of KP781 on how it can help the segment of customers who are not in excellent shape in it's advertising campaigns.

[ ]: