Business Case: Aerofit

Importing Libraries

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


sns.set_style('darkgrid')
sns.set_palette('Set3')
# plt.rcParams['figure.figsize'] = (12, 8)
plt.rcParams['figure.facecolor'] = 'none'
```

Loading Dataset

In [ ]:
```
path="./Data/erofit_treadmill.csv"
aerofit = pd.read_csv(path)
```

Data Exploration

In [ ]:
```
# First 10 values

aerofit.head(10)
```

Out[ ]:

	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
5	KP281	20	Female	14	Partnered	3	3	32973	66
6	KP281	21	Female	14	Partnered	3	3	35247	75
7	KP281	21	Male	13	Single	3	3	32973	85
8	KP281	21	Male	15	Single	5	4	35247	141
9	KP281	21	Female	15	Partnered	2	3	37521	85

In [ ]:
```
# Last 10 values
```

```
aerofit.tail(10)
```

Out[ ]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
170	KP781	31	Male	16	Partnered	6	5	89641	260
171	KP781	33	Female	18	Partnered	4	5	95866	200
172	KP781	34	Male	16	Single	5	5	92131	150
173	KP781	35	Male	16	Partnered	4	5	92131	360
174	KP781	38	Male	18	Partnered	5	5	104581	150
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 [ ]:
```
# Shape of the dataset

aerofit.shape
```

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

In [ ]:
```
# Type of data in dataframe

aerofit.dtypes
```

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

In [ ]:
```
# Datasets information

aerofit.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
```

Observation:

- There are **180 rows and 9 columns** in dataset and all are **non-null values.**
- Product,Gender and Martial status are object datatype .
- While Age, Education,Usage,Fitness,Income,Miles are integer datatype.

Statistical Summary & Unique values

In [ ]:
```
# Count of unique features for each features

aerofit.nunique()
```

Out[ ]:
```
Product          3
Age             32
Gender           2
Education        8
MaritalStatus    2
Usage            6
Fitness          5
Income          62
Miles           37
dtype: int64
```

In [ ]:
```
# All unique value for each features

def findUniqueValue(df,features):
    n = len(features)
    for feature in range(n):
        print(f"{features[feature]}:{df[features[feature]].sort_values().unique()}")
        print('-'*50)

feature_name = aerofit.columns.to_list()
findUniqueValue(aerofit,feature_name)
```

```
Product:['KP281' 'KP481' 'KP781']
--------------------------------------------------
Age:[18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41
 42 43 44 45 46 47 48 50]
--------------------------------------------------
Gender:['Female' 'Male']
--------------------------------------------------
Education:[12 13 14 15 16 18 20 21]
--------------------------------------------------
MaritalStatus:['Partnered' 'Single']
--------------------------------------------------
Usage:[2 3 4 5 6 7]
--------------------------------------------------
Fitness:[1 2 3 4 5]
--------------------------------------------------
Income:[ 29562  30699  31836  32973  34110  35247  36384  37521  38658  39795
  40932  42069  43206  44343  45480  46617  47754  48556  48658  48891
  49801  50028  51165  52290  52291  52302  53439  53536  54576  54781
  55713  56850  57271  57987  58516  59124  60261  61006  61398  62251
  62535  64741  64809  65220  67083  68220  69721  70966  74701  75946
  77191  83416  85906  88396  89641  90886  92131  95508  95866  99601
 103336 104581]
--------------------------------------------------
Miles:[ 21  38  42  47  53  56  64  66  74  75  80  85  94  95 100 103 106 112
 113 120 127 132 140 141 150 160 169 170 180 188 200 212 240 260 280 300
 360]
--------------------------------------------------
```

In [ ]:
```
# Statistical Summary

aerofit.describe()
```

Out[ ]:

	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

- Customer Age lie between 18 to 50., with an average of 29 years and median of 26 years.
- Customer education lie between 12 -21 years, with average and median of 16 years and maximum of 21 years.
- Expected Treadmill usage is atleast 2 times a week , maximum is 7 times a week and on Average 3 times a week.
- Fitness rate is range betwwen 1-5. 1 is low and 5 is high. Average fitness rate is 3 and median is 3.

- Maximum income of treadmill user is 100K ,minimum income is 29K, Average income approx. 54K ,while median is is approx. 51K.
- Customer expects to runs on an average of 103.19 miles per week, median 94 miles per week.

Data Preprocessing

In [ ]:
```
# changing it to  object dtype to category  to save memory : Product,Gender and Martic

aerofit['Product'] = aerofit['Product'].astype('category')
aerofit['Gender'] = aerofit['Gender'].astype('category')
aerofit['MaritalStatus'] = aerofit['MaritalStatus'].astype('category')

aerofit.dtypes
```

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

In [ ]:
```
# Missing value ?

aerofit.isna().sum()
```

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

Observation:

- No Missing value found.

Outlier Dection

In [ ]:
```
aerofit.describe()
```

Out[ ]:

	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

Observation:

- Scaling variable with mean in 3 stage:

In [ ]:
```
# Three different variable groups

aerofit_low = aerofit[['Usage', 'Fitness']] # Low
aerofit_medium = aerofit[['Age', 'Education']]  # Medium
aerofit_high = aerofit[['Miles']]  # High
aerofit_extreme = aerofit[['Income']]  # Extreme
```

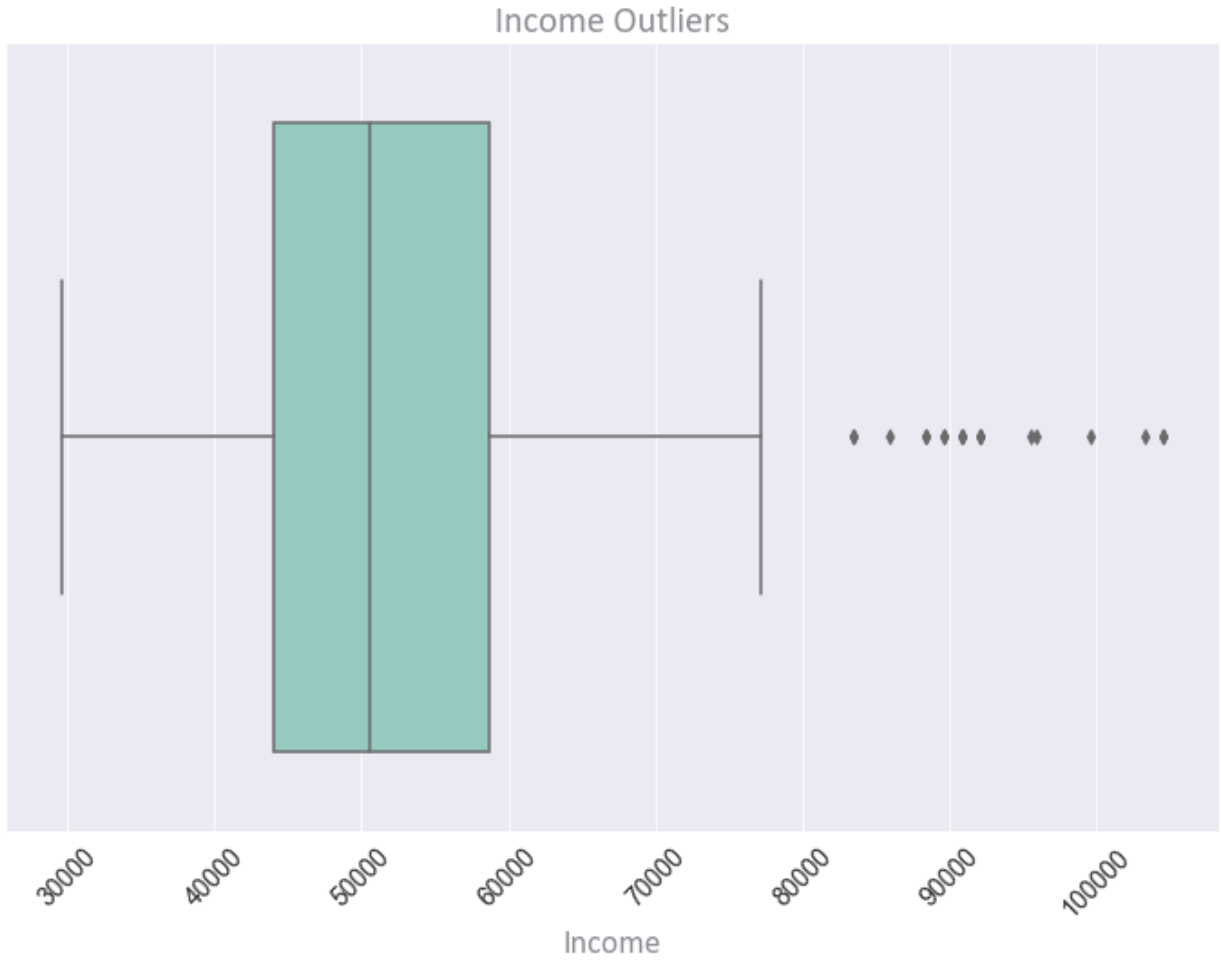
In [ ]:
```
#Tukey's method
def tukeys_method(df, variable):
    #Takes two parameters: dataframe & variable of interest as string
    q1 = df[variable].quantile(0.25)
    q3 = df[variable].quantile(0.75)
    iqr = q3-q1
    inner_fence = 1.5*iqr
    outer_fence = 3*iqr

    #inner fence lower and upper end
    inner_fence_le = q1-inner_fence
    inner_fence_ue = q3+inner_fence

    #outer fence lower and upper end
    outer_fence_le = q1-outer_fence
    outer_fence_ue = q3+outer_fence

    outliers_prob = []
    outliers_poss = []
    for index, x in enumerate(df[variable]):
        if x <= outer_fence_le or x >= outer_fence_ue:
            outliers_prob.append(index)
    for index, x in enumerate(df[variable]):
        if x <= inner_fence_le or x >= inner_fence_ue:
            outliers_poss.append(index)
    return outliers_prob, outliers_poss
```

In [ ]:
```
def detect_outlier(df,title):
    plt.figure(figsize=(12,8))
    sns.boxplot(data=df, orient="h", palette="Set3")
```

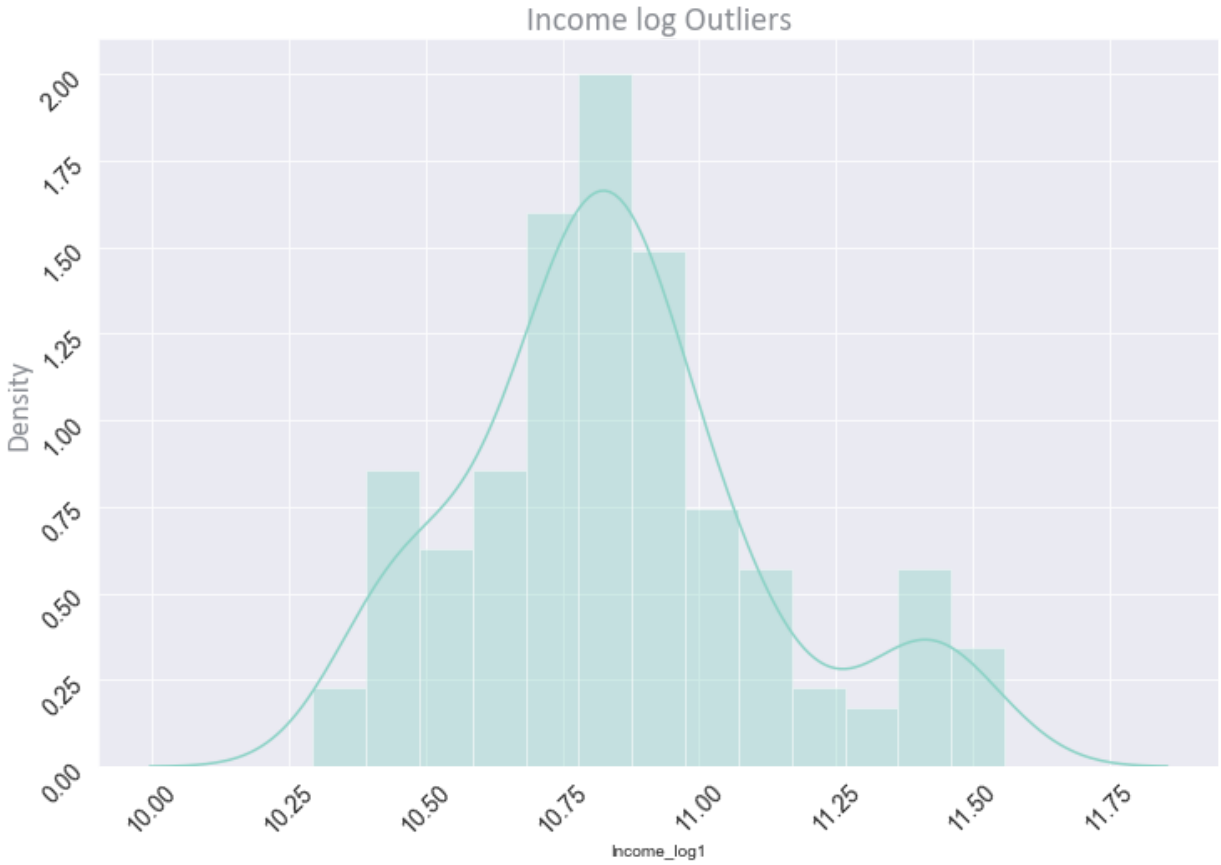
```
    plt.title(f'{title} Outliers',fontsize=20,color='#8a8d93',family="Calibri")
    plt.xticks(rotation=45,size=14)
    plt.yticks(rotation=45,size=14)
    plt.xlabel('Data Points',fontsize=18,color='#8a8d93',family="Calibri")
    plt.ylabel('Feature',fontsize=18,color='#8a8d93',family="Calibri")
    plt.show()
    print('-'*50)
    columns_lst = df.columns.to_list()
    for i in columns_lst:
        # Lets take a closer look to Each Features
        plt.figure(figsize=(12,8))
        sns.boxplot(data=aerofit,x=i)
        plt.title(f'{i} Outliers',fontsize=20,color='#8a8d93',family="Calibri")
        plt.xticks(rotation=45,size=14)
        plt.yticks(rotation=45,size=14)
        plt.xlabel('Data Points',fontsize=18,color='#8a8d93',family="Calibri")
        plt.xlabel(f'{i}')
        plt.show()
        probable_outliers_tm, possible_outliers_tm = tukeys_method(df, i)
        print(f"probable outliers: {probable_outliers_tm}")
        print(f"possible outliers: {possible_outliers_tm}")

        print('-'*50)

        #Transform 'CRIM' to log
        log_features = np.log(df[i])
        df[f'{i}_log'] = df[i]+1
        log_features = np.log(df[f'{i}_log'])
        df[f'{i}_log1'] = log_features

        #Plot
        plt.figure(figsize=(12,8))
        sns.distplot(df[f'{i}_log1'])
        plt.title(f'{i} log Outliers',fontsize=20,color='#8a8d93',family="Calibri")
        plt.xticks(rotation=45,size=14)
        plt.yticks(rotation=45,size=14)
        # plt.xlabel('Data Points',fontsize=18,color='#8a8d93',family="Calibri")
        plt.ylabel('Density',fontsize=18,color='#8a8d93',family="Calibri")
        plt.plot()

        #Calculate probable and possible outliers using log-iq method
        probable_outliers_logiq, possible_outliers_logiq = tukeys_method(df, f'{i}_log
        print(f"probable outliers logiq: {probable_outliers_logiq}")
        print(f"possible outliers logiq: {possible_outliers_logiq}")
```

In [ ]:
```
detect_outlier(aerofit_extreme,'aerofit Extreme')
```


aerofit Extreme Outliers
Feature
Income
30000
40000
50000
60000
70000
80000
90000
100000
Data Points

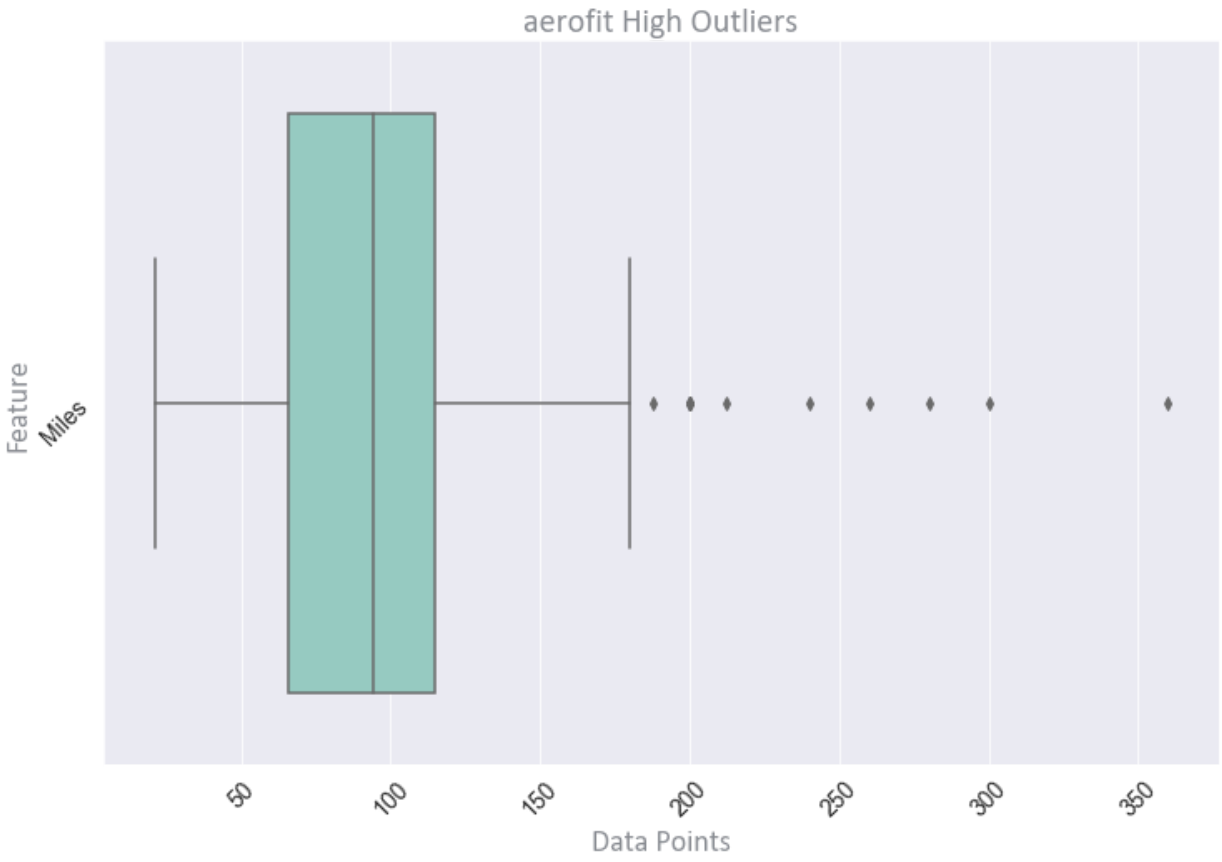

Income Outliers
30000
40000
50000
60000
70000
80000
90000
100000
Income

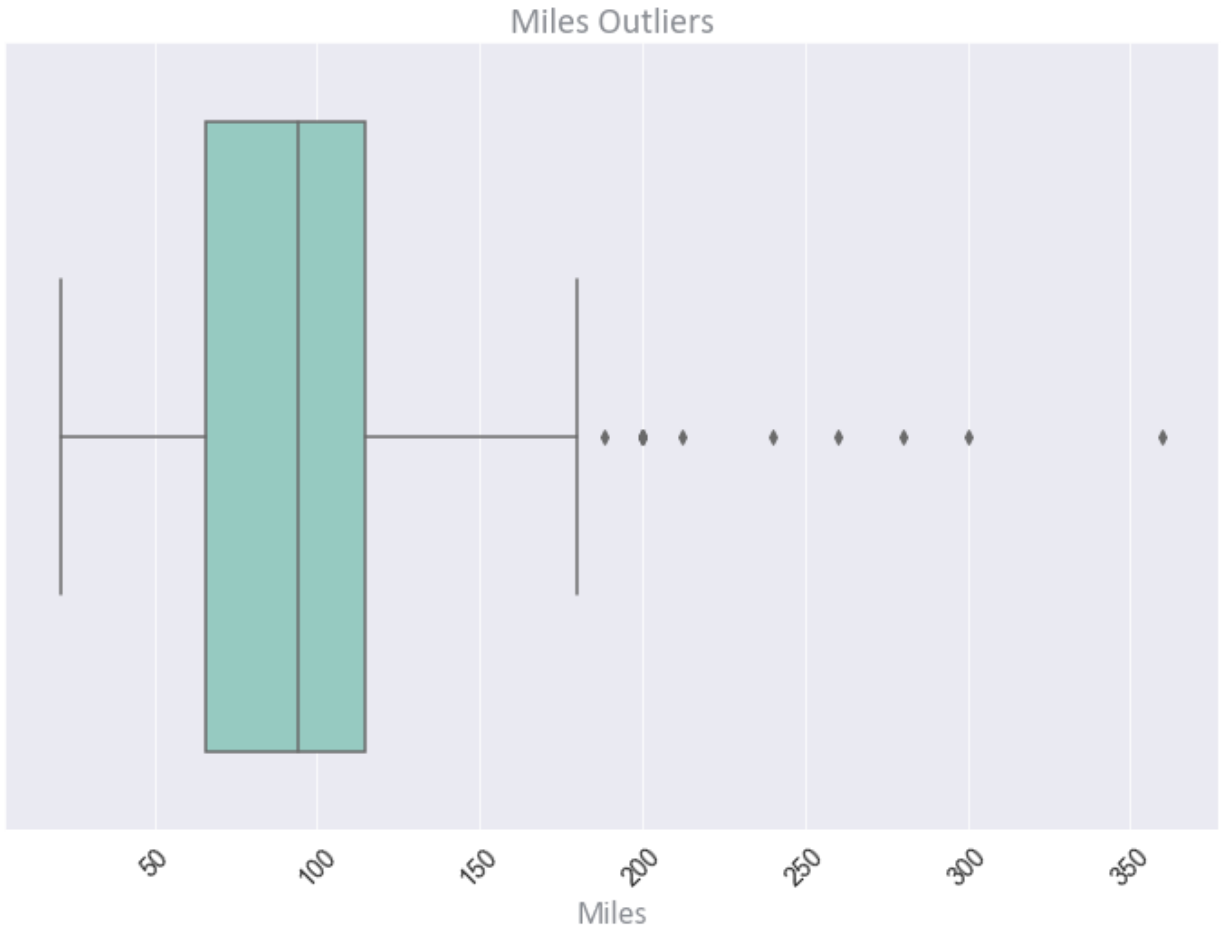
```
probable outliers: [168, 174, 178]
possible outliers: [159, 160, 161, 162, 164, 166, 167, 168, 169, 170, 171, 172, 173,
174, 175, 176, 177, 178, 179]
--------------------------------------------------
probable outliers logiq: []
possible outliers logiq: [161, 162, 167, 168, 169, 171, 172, 173, 174, 177, 178, 179]
```



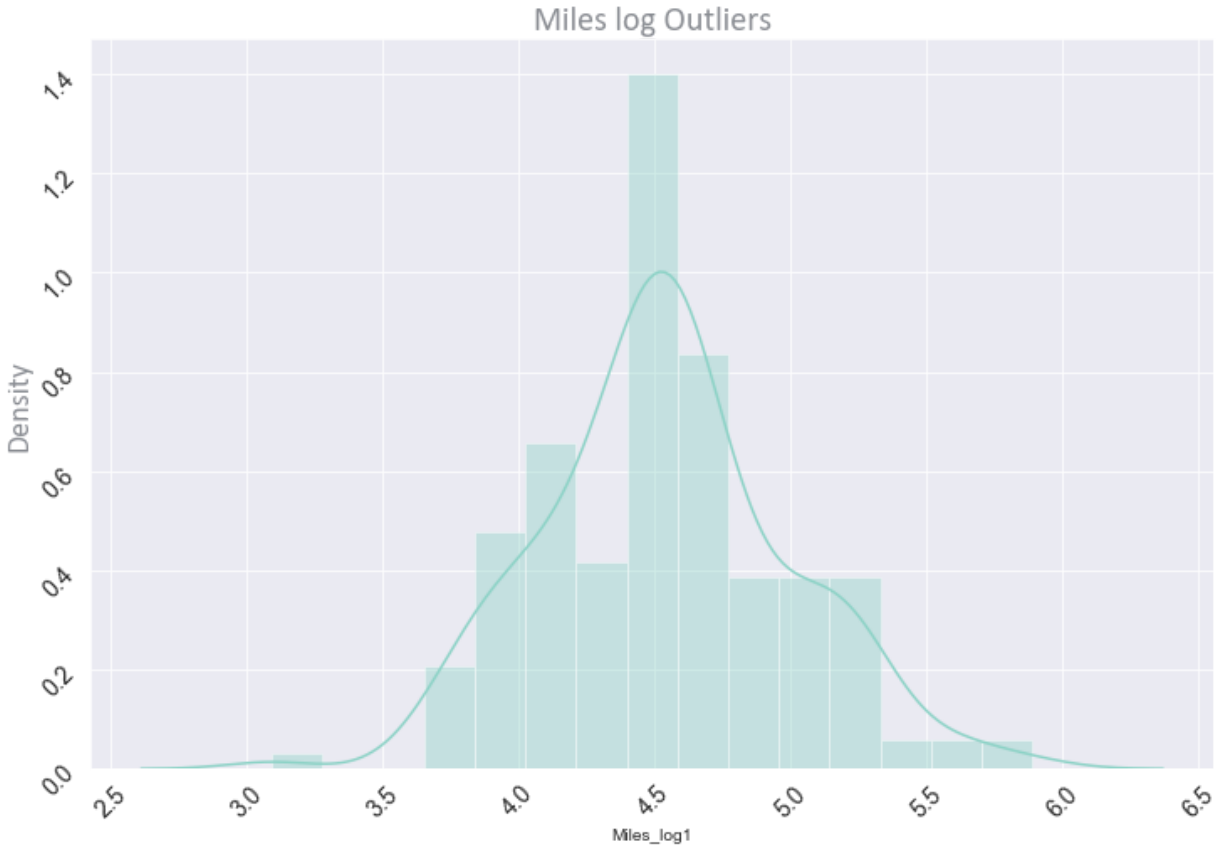
- *Observation:*
  - Income have most outliers.
  - Income have outliers exits after $80K.

In [ ]:
```
detect_outlier(aerofit_high,'aerofit High')
```


aerofit High Outliers
Feature
Miles
50
100
150
200
250
300
350
Data Points

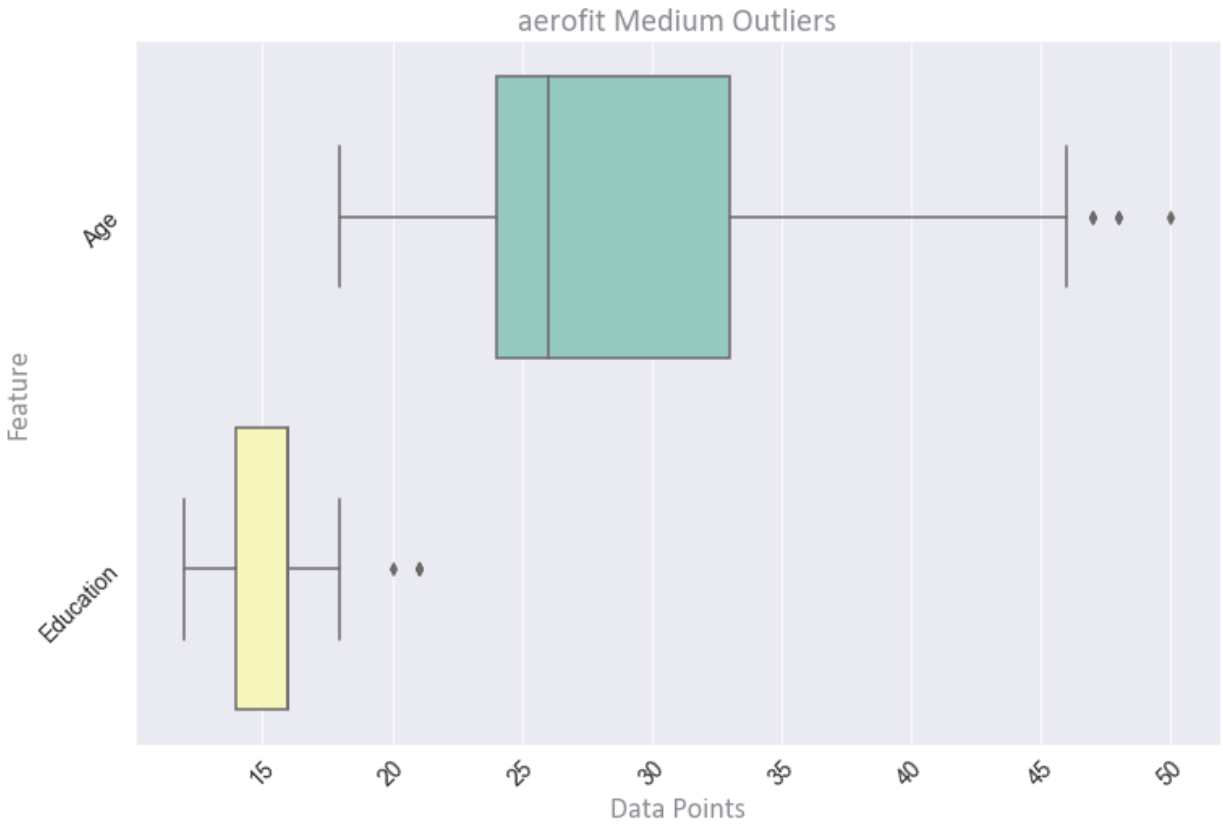

Miles Outliers
50
100
150
200
250
300
350
Miles

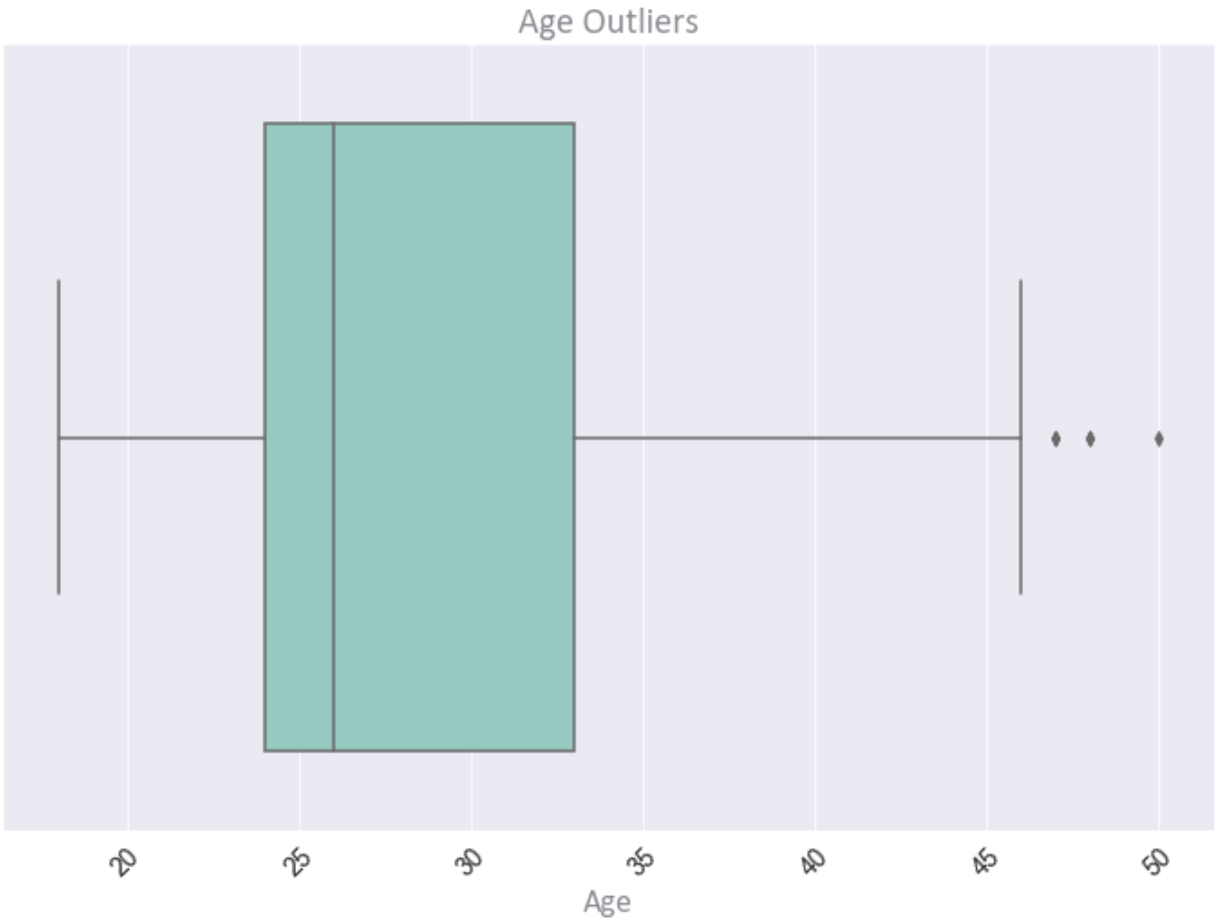
```
probable outliers: [166, 167, 173]
possible outliers: [23, 84, 142, 148, 152, 155, 166, 167, 170, 171, 173, 175, 176]
-------------------------------------------------
probable outliers logiq: []
possible outliers logiq: [117, 166, 167, 173]
```



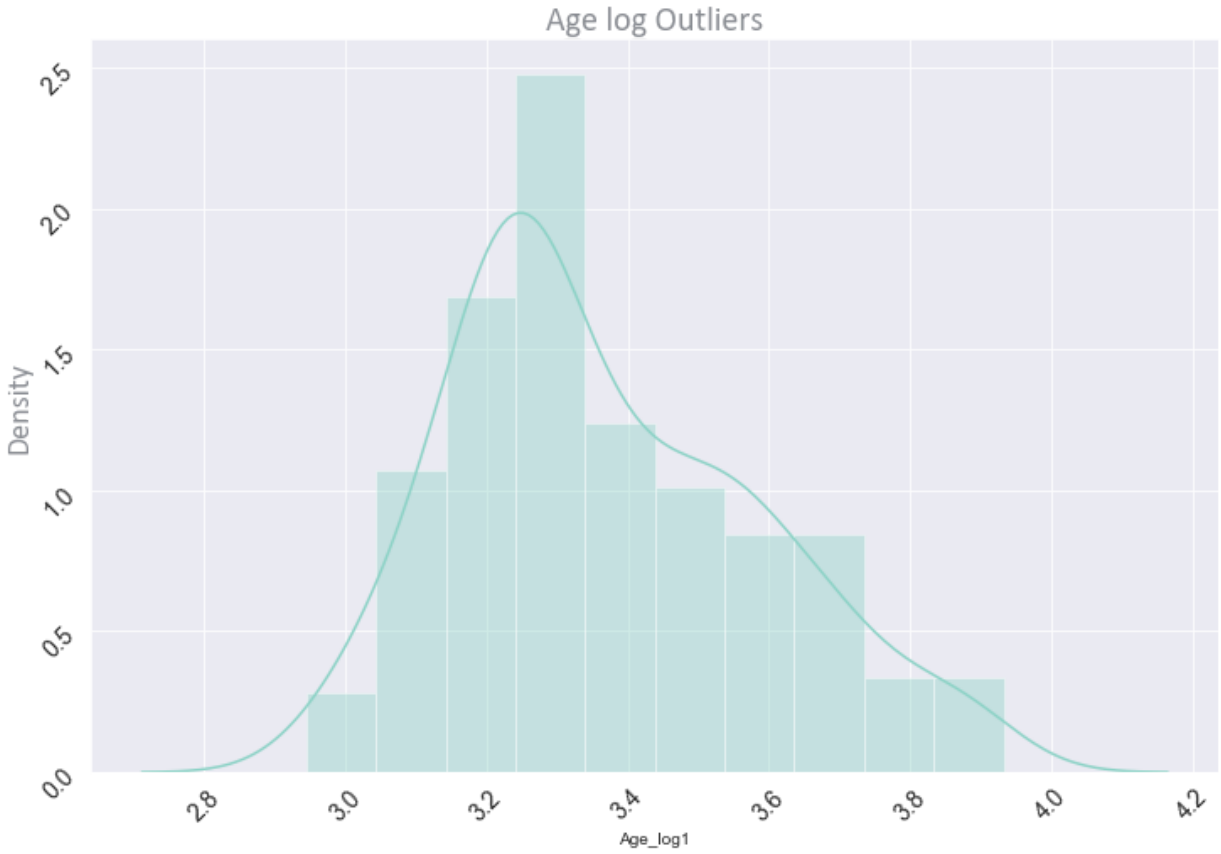
- *Observation:*
  - Miles have also outliers but less outliers than Income.
  - Miles have outliers exits after 185 Miles / week.

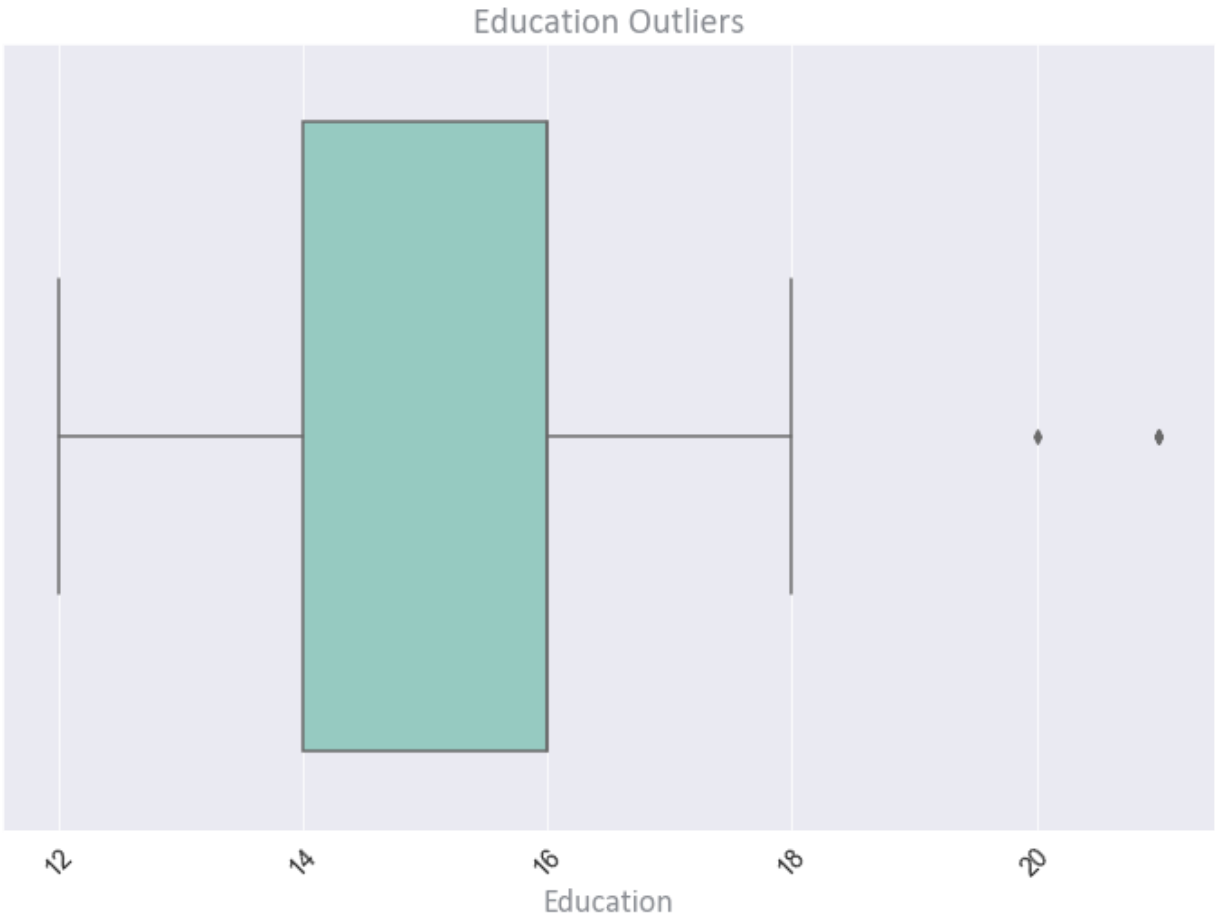
In [ ]:
```
detect_outlier(aerofit_medium,'aerofit Medium')
```


aerofit Medium Outliers
Age
Education
Feature
15
20
25
30
35
40
45
50
Data Points

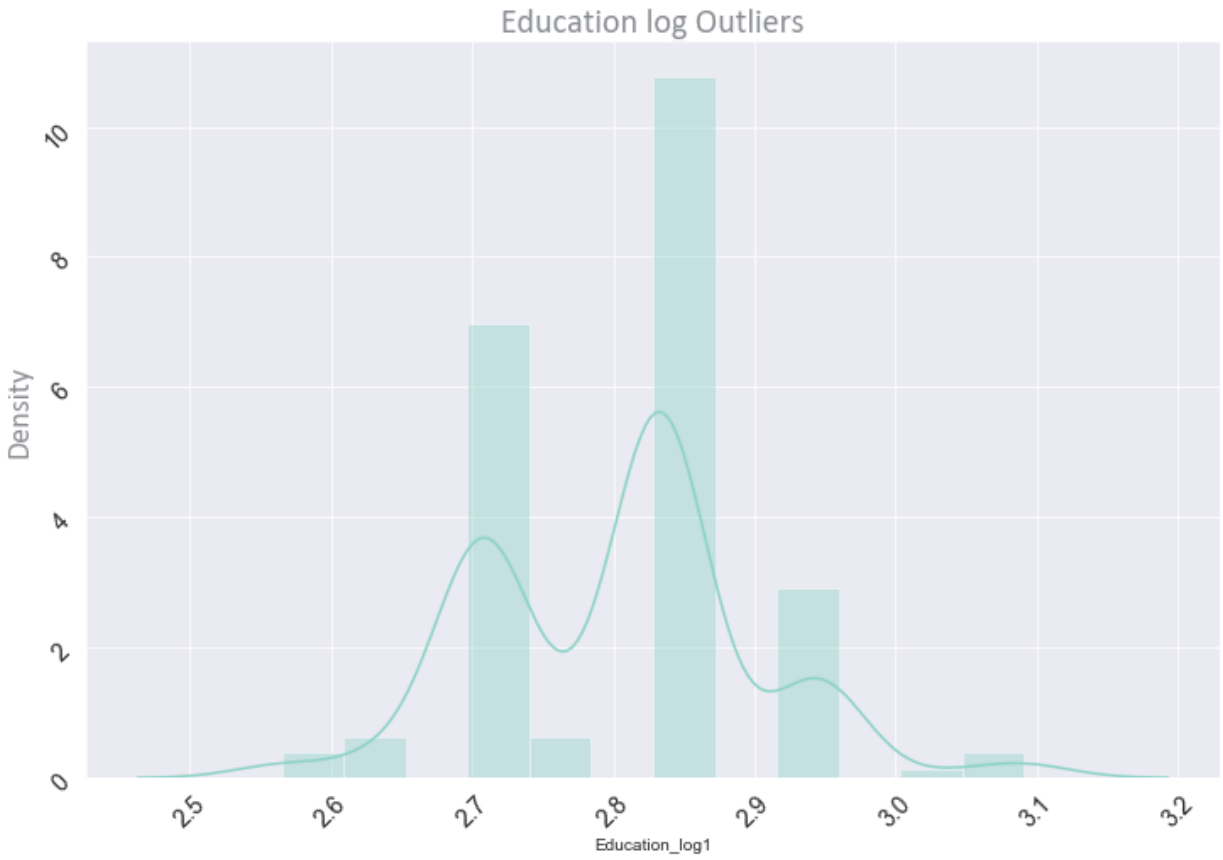

Age Outliers
20
25
30
35
40
45
50
Age

```
probable outliers: []
possible outliers: [78, 79, 139, 178, 179]
-------------------------------------------------
probable outliers logiq: []
possible outliers logiq: []
```



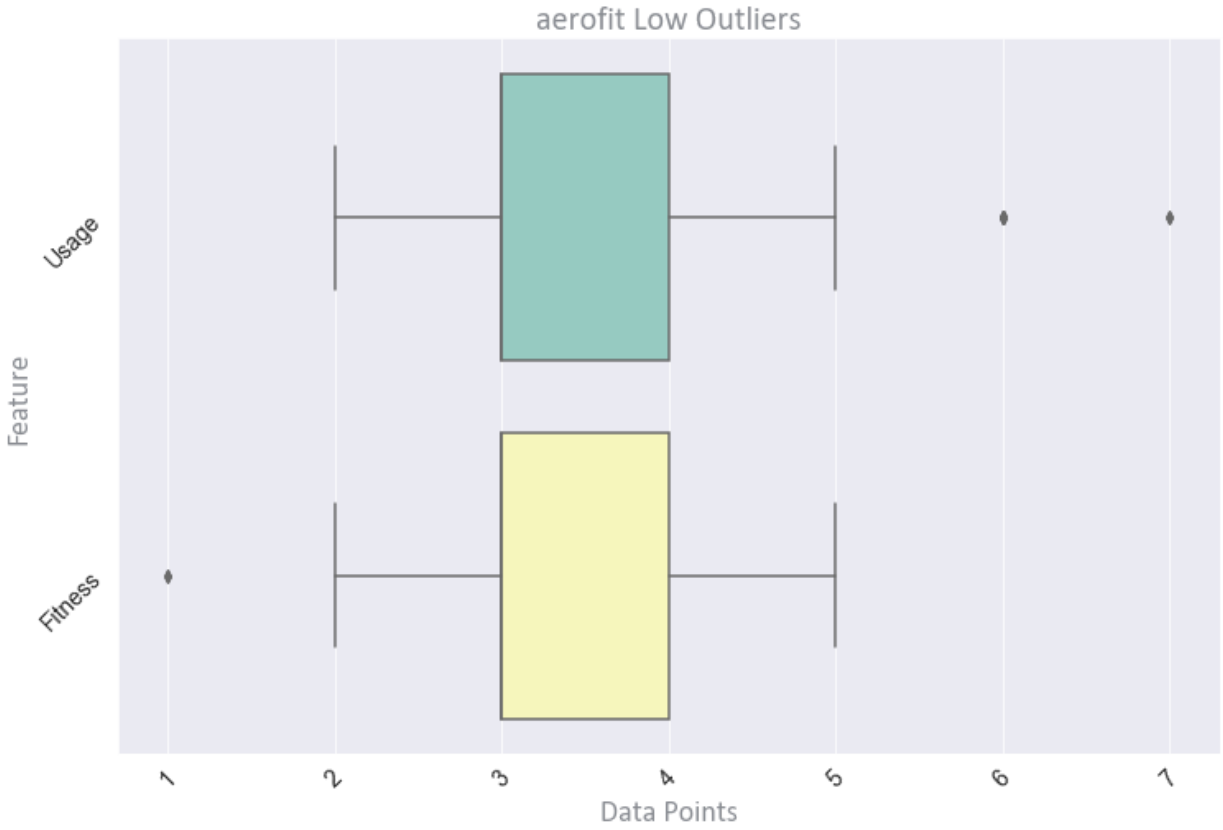


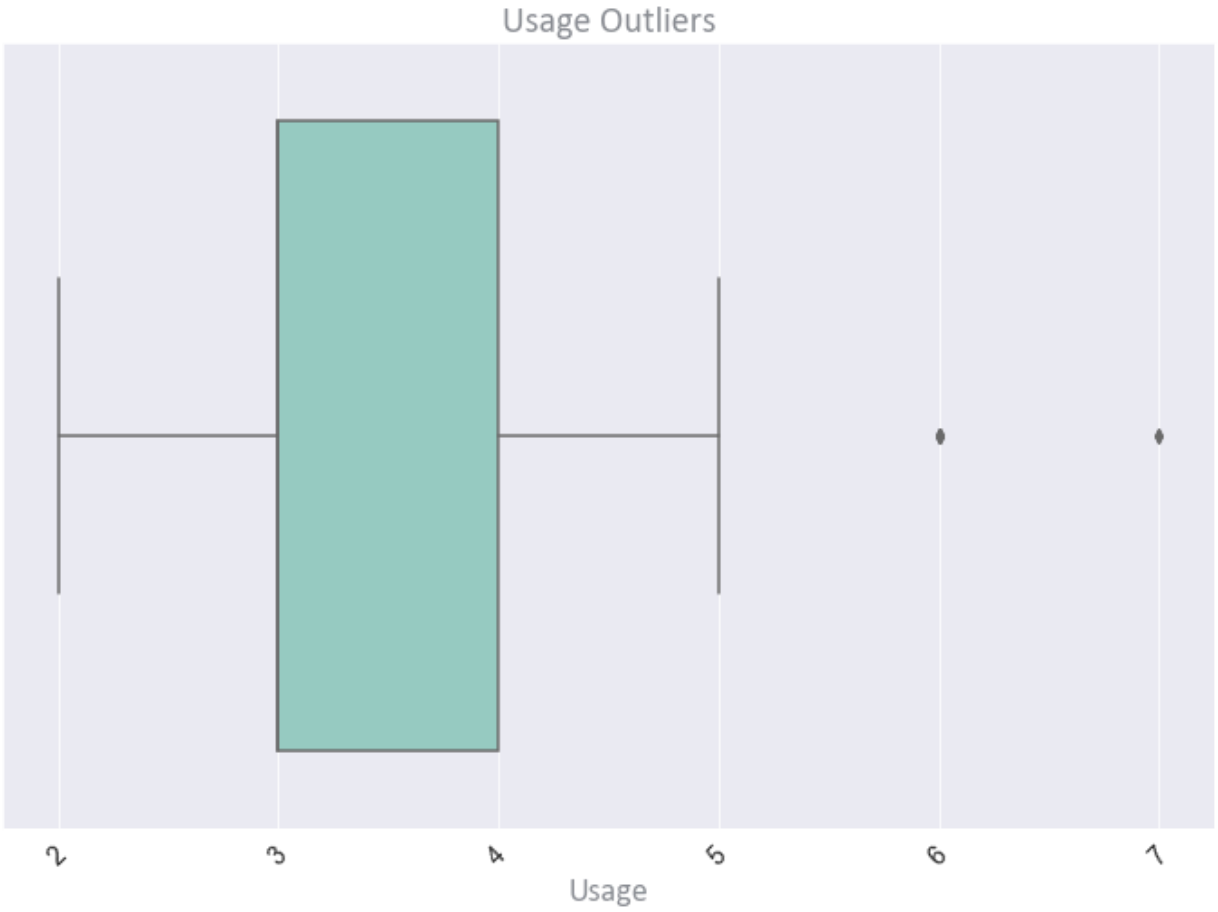

```
probable outliers: []
possible outliers: [156, 157, 161, 175]
-------------------------------------------------
probable outliers logiq: []
possible outliers logiq: [156, 157, 161, 175]
```



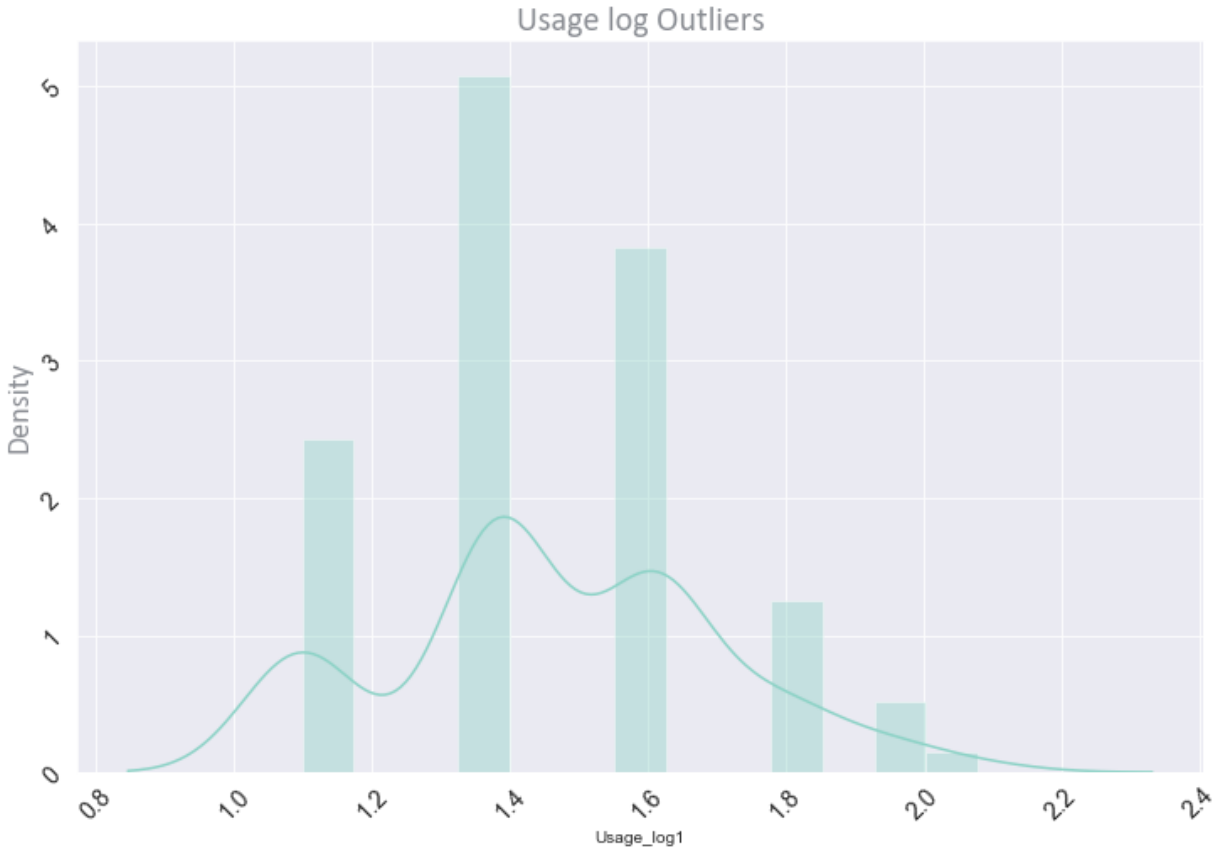
- *Observation:*
  - Age and Education have medium outliers as less than Miles.
  - Age have outliers exits after 47 years,
  - Education have outliers exits after 20 years.

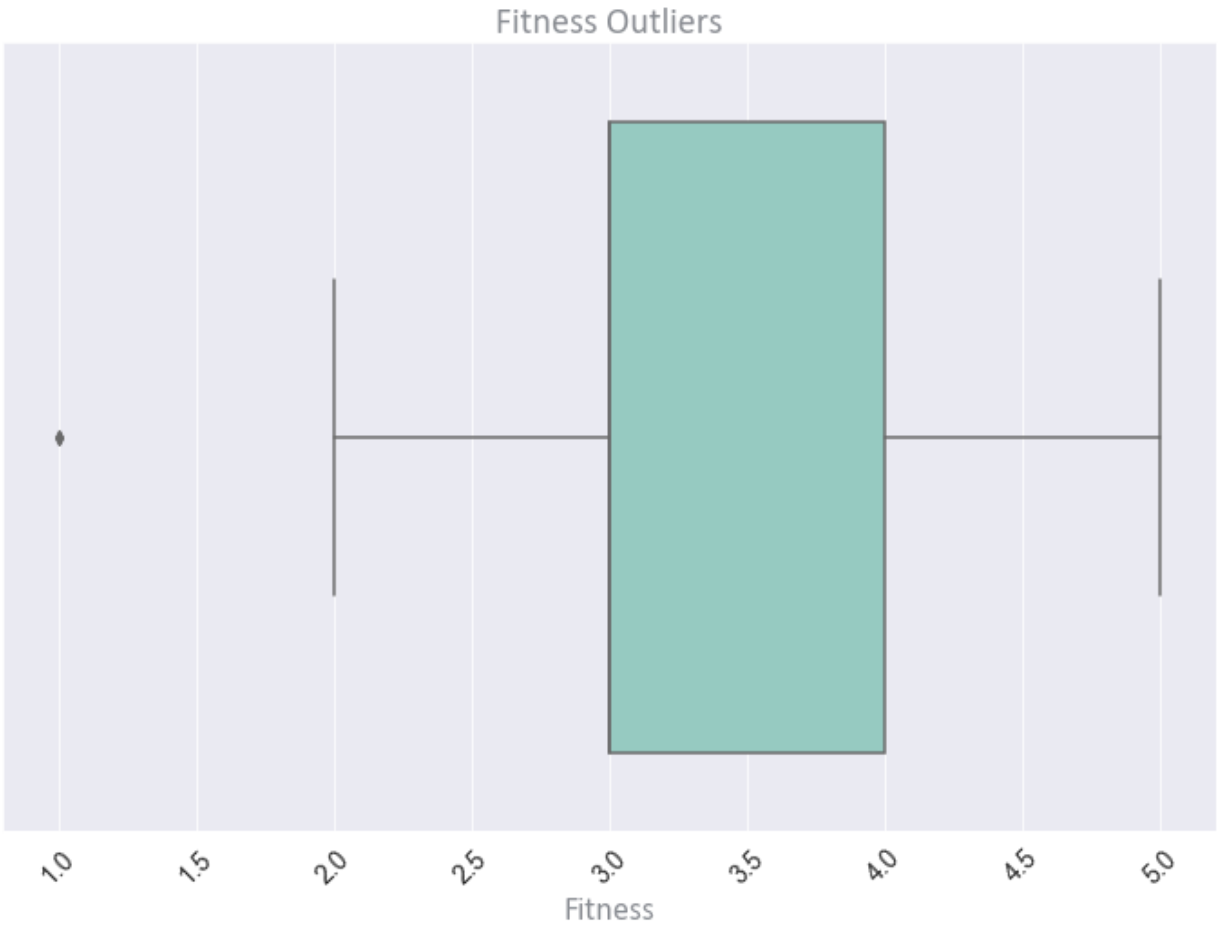
In [ ]:
```
detect_outlier(aerofit_low,'aerofit Low')
```


aerofit Low Outliers
Usage
Fitness
Feature
1
2
3
4
5
6
7
Data Points

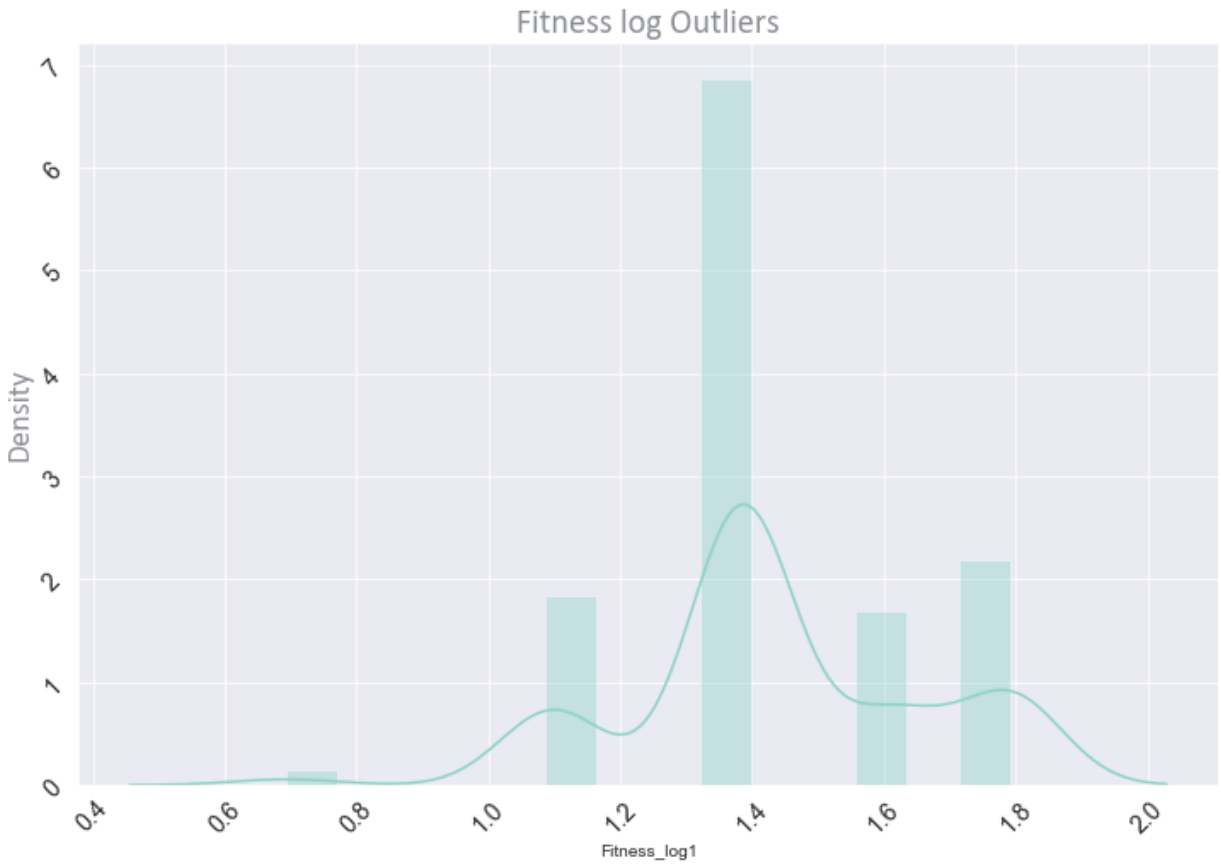

Usage Outliers
2
3
4
5
6
7
Usage

```
probable outliers: [163, 166]
possible outliers: [154, 155, 162, 163, 164, 166, 167, 170, 175]
-------------------------------------------------
probable outliers logiq: []
possible outliers logiq: [154, 155, 162, 163, 164, 166, 167, 170, 175]
```






```
probable outliers: []
possible outliers: [14, 117]
--------------------------------------------------
probable outliers logiq: [14, 117]
possible outliers logiq: [14, 117]
```



- *Observation:*
  - Usage and Fitness have low outliers as less than Age & Education.
  - Usage have outliers exits at 6-7 days in a week.
  - Fitness have outliers exits 1 rate fitness.

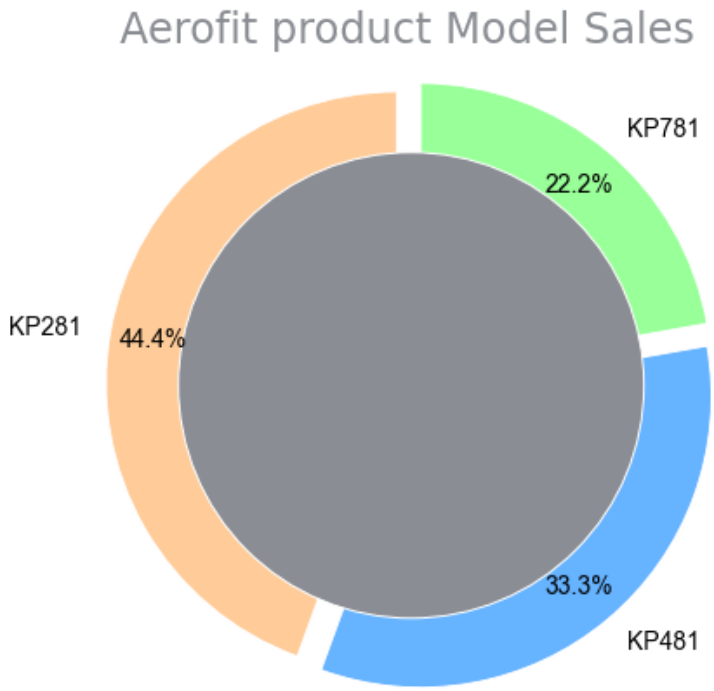
EDA

Univariate Analysis : Non-Visual & Visual

In [ ]:
```
# Sales percentage aerofit product Model ?

def donut_perc(df,feature,title):
    index = df[feature].value_counts().index
    data = df[feature].value_counts()
    print(data)

    plt.figure(figsize=(4,2))
    fig1, ax1 = plt.subplots(figsize=(10,6))
    explode = (0.05,0.05,0.05)
    colors = ['#ffcc99','#66b3ff','#99ff99']
    ax1.pie(data,autopct='%1.1f%%',explode=explode,labels=index,colors=colors,pctdista
    plt.title(title,fontsize=24,color='#8a8d93',family="'Bebas Neue', cursive")
    # plt.xticks(rotation=45,size=12)
    # plt.yticks(rotation=45,size=12)
    # plt.labels(index,fontsize=16,color='#8a8d93',family="'Bebas Neue', cursive")
```

```
    #draw circle
    centre_circle = plt.Circle((0,0),0.8,fc='#8a8d93')
    fig = plt.gcf()
    fig.gca().add_artist(centre_circle)

    ax1.axis('equal')
    plt.tight_layout()
    plt.show()

donut_perc(aerofit,'Product','Aerofit product Model Sales')
```

```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
<Figure size 288x144 with 0 Axes>
```



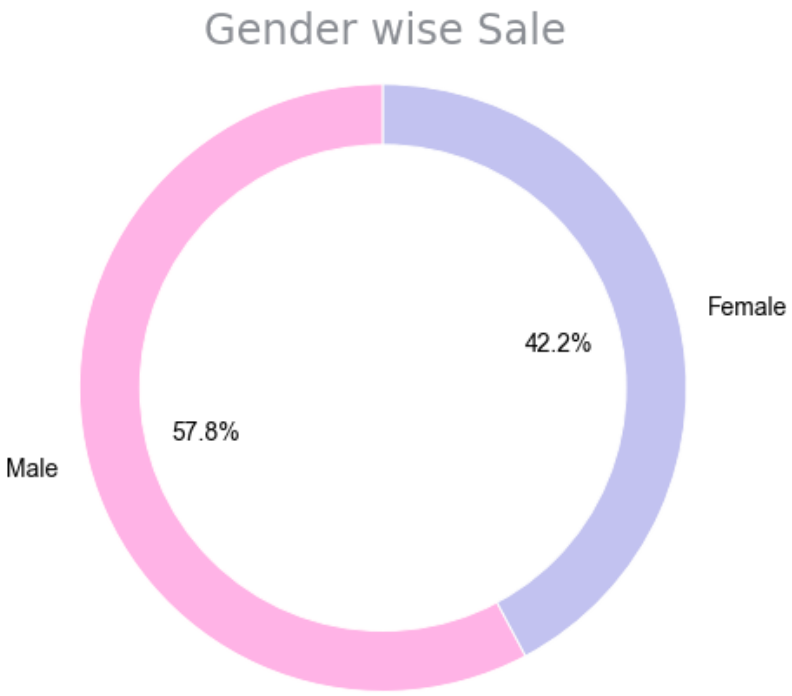
Observation:

- 44.4% customers brought KP281.
- 33.3% customers brought KP481.
- 22.2% customers brought KP781.
- Most sold Model is KP281 with sale of 44.4%.

In [ ]:
```
# Gender Wise Sale

def donut_perc(df,feature,title):
    index = df[feature].value_counts().index
    data = df[feature].value_counts()
    print(data)

    plt.figure(figsize=(4,2))
    fig1, ax1 = plt.subplots(figsize=(10,6))
    colors = ['#ffb3e6','#c2c2f0']
    ax1.pie(data,autopct='%1.1f%%',labels=index,colors=colors,startangle=90,textprops=
```

```
    plt.title(title,fontsize=24,color='#8a8d93',family="'Bebas Neue', cursive")


    #draw circle
    centre_circle = plt.Circle((0,0),0.8,fc='white')
    fig = plt.gcf()
    fig.gca().add_artist(centre_circle)

    ax1.axis('equal')
    plt.tight_layout()
    plt.show()
donut_perc(aerofit,'Gender','Gender wise Sale')
```

```
Male      104
Female     76
Name: Gender, dtype: int64
<Figure size 288x144 with 0 Axes>
```



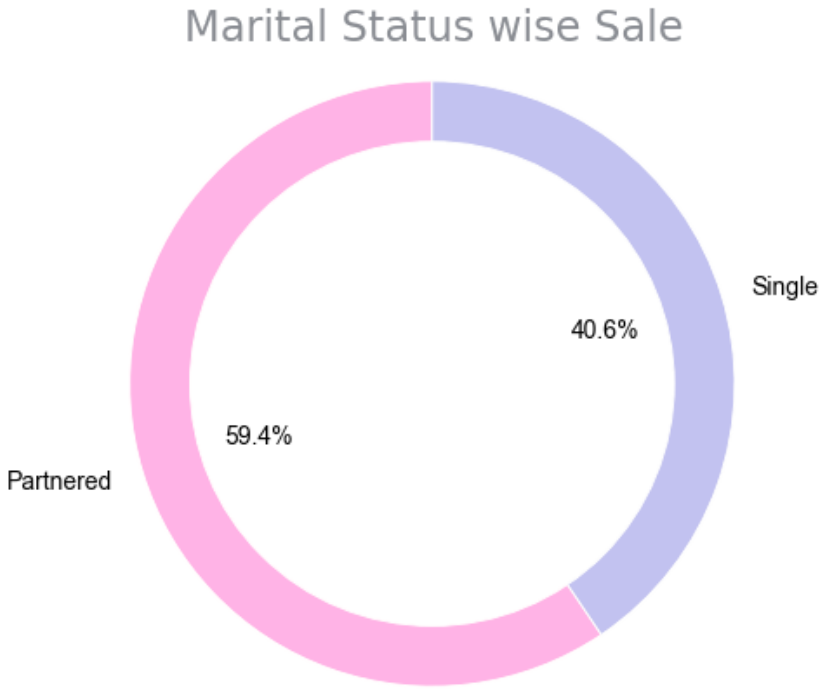
Observation:

- 104 Male customer buying traedmills while only 76 Female customer buying treadmils
- 57.8% of product was bought by male and 42.2% of product bought by Female.

In [ ]:
```
# MaritalStatus Wise Sale


def donut_perc(df,feature,title):
    index = df[feature].value_counts().index
    data = df[feature].value_counts()
    print(data)

    plt.figure(figsize=(4,2))
    fig1, ax1 = plt.subplots(figsize=(10,6))
    colors = ['#ffb3e6','#c2c2f0']
    ax1.pie(data,autopct='%1.1f%%',labels=index,colors=colors,startangle=90,textprops=
    plt.title(title,fontsize=24,color='#8a8d93',family="'Bebas Neue', cursive")
```

```
    #draw circle
    centre_circle = plt.Circle((0,0),0.8,fc='white')
    fig = plt.gcf()
    fig.gca().add_artist(centre_circle)

    ax1.axis('equal')
    plt.tight_layout()
    plt.show()
donut_perc(aerofit,'MaritalStatus','Marital Status wise Sale')
```

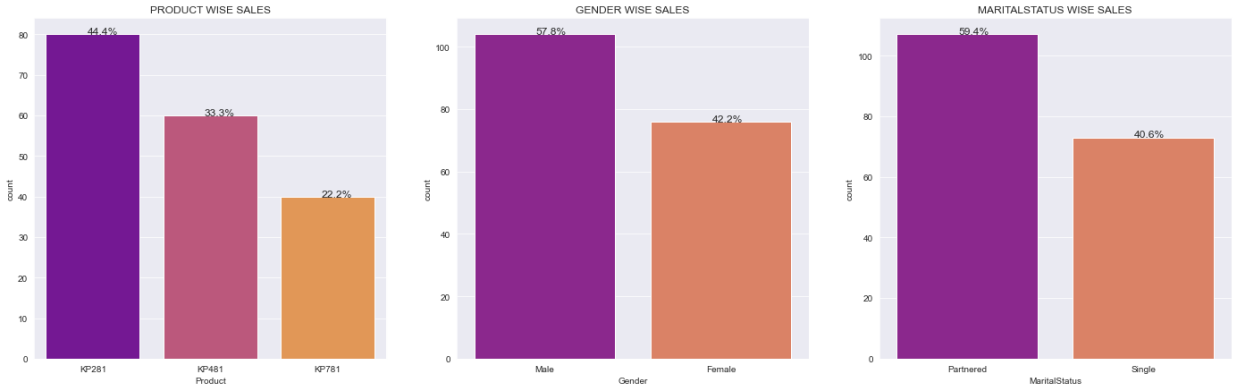
```
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64
<Figure size 288x144 with 0 Axes>
```



- Out of 180 product, 107 product was bought by Customer who is married.
- Out of 180 product, 73 product was bought by Customer who is Not married.
- 59.4% Sale comes from maried Customer whereas 40.6% sale comes from non-married customer.

In [ ]:
```
# Function to create barplots that indicate percentage for each category.
def bar_perc(plot, feature):
    '''
    plot
    feature: 1-d categorical feature array
    '''
    total = len(feature) # length of the column
    for p in plot.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total) # percentage of each
        x = p.get_x() + p.get_width() / 2 - 0.05 # width of the plot
        y = p.get_y() + p.get_height()           # hieght of the plot
        plot.annotate(percentage, (x, y), size = 12) # annotate the percentage
```

```
fig1, axes1 =plt.subplots(1,3,figsize=(24, 7))
list_col=['Product','Gender','MaritalStatus']
j=0
for i in range(len(list_col)):
    order = aerofit[list_col[i]].value_counts(ascending=False).index # to display bar
    axis = sns.countplot(x=list_col[i], data=aerofit, order=order, ax=axes1[i], palett
    bar_perc(axes1[i],aerofit[list_col[i]])
```



In [ ]:
```
aerofit[aerofit['Product']=='KP281'].describe().T
```

Out[ ]:

	count	mean	std	min	25%	50%	75%	max
Age	80.0	28.5500	7.221452	18.0	23.0	26.0	33.0	50.0
Education	80.0	15.0375	1.216383	12.0	14.0	16.0	16.0	18.0
Usage	80.0	3.0875	0.782624	2.0	3.0	3.0	4.0	5.0
Fitness	80.0	2.9625	0.664540	1.0	3.0	3.0	3.0	5.0
Income	80.0	46418.0250	9075.783190	29562.0	38658.0	46617.0	53439.0	68220.0
Miles	80.0	82.7875	28.874102	38.0	66.0	85.0	94.0	188.0

Observation:

- 80 customers bought KP281 model.
- Average age of customer who purchases KP281 is 28.5 , Median is 26 . Data is right skewed.Customer range is between 23-33.
- Average Education is 15 and median is 16.
- Expected usage is 3 day a week.
- Self rated fitness is 3 that is average fitness level.
- Average income and median is around $46K.
- Expected Miles to run is on an Average 82.78 miles per week and median is 85 miles per week.

In [ ]:
```
aerofit[aerofit['Product']=='KP481'].describe().T
```

Out[ ]:

	count	mean	std	min	25%	50%	75%	max
Age	60.0	28.900000	6.645248	19.0	24.0	26.0	33.25	48.0
Education	60.0	15.116667	1.222552	12.0	14.0	16.0	16.00	18.0
Usage	60.0	3.066667	0.799717	2.0	3.0	3.0	3.25	5.0
Fitness	60.0	2.900000	0.629770	1.0	3.0	3.0	3.00	4.0
Income	60.0	48973.650000	8653.989388	31836.0	44911.5	49459.5	53439.00	67083.0
Miles	60.0	87.933333	33.263135	21.0	64.0	85.0	106.00	212.0

Observation:

- 60 customers bought KP481 model.
- Average age of customer who purchases KP481 is 28.9 , Median is 26 . Data is right skewed.Customer range is between 24-33.
- Average Education is 15 and median is 16.
- Expected usage is 3 day a week.
- Self rated fitness is 3 that is average fitness level
- Average income and median is around $49K.
- Expected Miles to run is on an Average 87.93 miles per week and median is 85 miles per week.

In [ ]:
```
aerofit[aerofit['Product']=='KP781'].describe().T
```

Out[ ]:

	count	mean	std	min	25%	50%	75%	max
Age	40.0	29.100	6.971738	22.0	24.75	27.0	30.25	48.0
Education	40.0	17.325	1.639066	14.0	16.00	18.0	18.00	21.0
Usage	40.0	4.775	0.946993	3.0	4.00	5.0	5.00	7.0
Fitness	40.0	4.625	0.667467	3.0	4.00	5.0	5.00	5.0
Income	40.0	75441.575	18505.836720	48556.0	58204.75	76568.5	90886.00	104581.0
Miles	40.0	166.900	60.066544	80.0	120.00	160.0	200.00	360.0

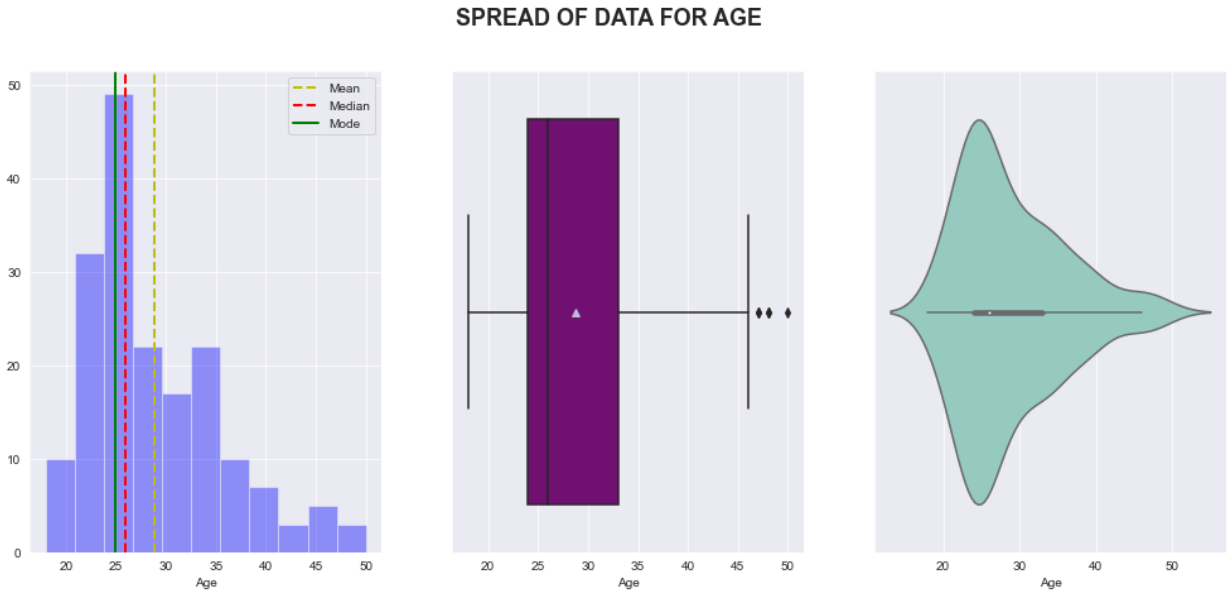
Observation:

- 40 customers bought KP781 model.
- Average age of customer who purchases KP781 is 29 , Median is 27. Customer range is between 24-30.
- Average Education is 17 and median is 18.
- Expected usage is 4-5 day a week.
- Self rated fitness is 4-5 that is Good fitness level.
- Average income and median is around $75K.
- Expected Miles to run is on an Average 167 miles per week and median is 160 miles per week.

In [ ]:
```
def data_distribution(data):
   data_name = data.name.upper()
   data_mean = data.mean()
   data_median = data.median()
   data_mode =  data.mode()[0]
   return data_name,data_mean,data_median,data_mode


def dist_box_violin(data):
 # function plots a combined graph for univariate analysis of continous variable
 #to check spread, central tendency , dispersion and outliers
   data_name,data_mean,data_median,data_mode = data_distribution(data)

   fig, axes =plt.subplots(1,3,figsize=(17, 7))
   fig.suptitle(f"SPREAD OF DATA FOR {data_name}", fontsize=18, fontweight='bold')
   sns.distplot(data,kde=False,color='Blue',ax=axes[0])
   axes[0].axvline(data_mean, color='y', linestyle='--',linewidth=2)
   axes[0].axvline(data_median, color='r', linestyle='dashed', linewidth=2)
   axes[0].axvline(data_mode,color='g',linestyle='solid',linewidth=2)
   axes[0].legend({'Mean':data_mean,'Median':data_median,'Mode':data_mode})

   sns.boxplot(x=data,showmeans=True, orient='h',color="purple",ax=axes[1])

   sns.violinplot(data,ax=axes[2],showmeans=True)
```

In [ ]:
```
# Customer Age distribution
import math
def age_distribution(data):
    data_name,data_mean,data_median,data_mode = data_distribution(data)
    data_mean =  math.ceil(data_mean)
    data_median = math.ceil(data_median)
    data_mode = (math.ceil(data_mode))
    print(f"Average {data_name}: {data_mean}")
    print(f"Median {data_name}: {data_median}")
    print(f"Mode {data_name}: {data_mode}")
    print('-'*50)
    print(data.describe().T)
    dist_box_violin(data)

age_distribution(aerofit['Age'])
```

```
Average AGE: 29
Median AGE: 26
Mode AGE: 25
--------------------------------------------------
count    180.000000
mean      28.788889
std        6.943498
min       18.000000
25%       24.000000
50%       26.000000
75%       33.000000
max       50.000000
Name: Age, dtype: float64
```

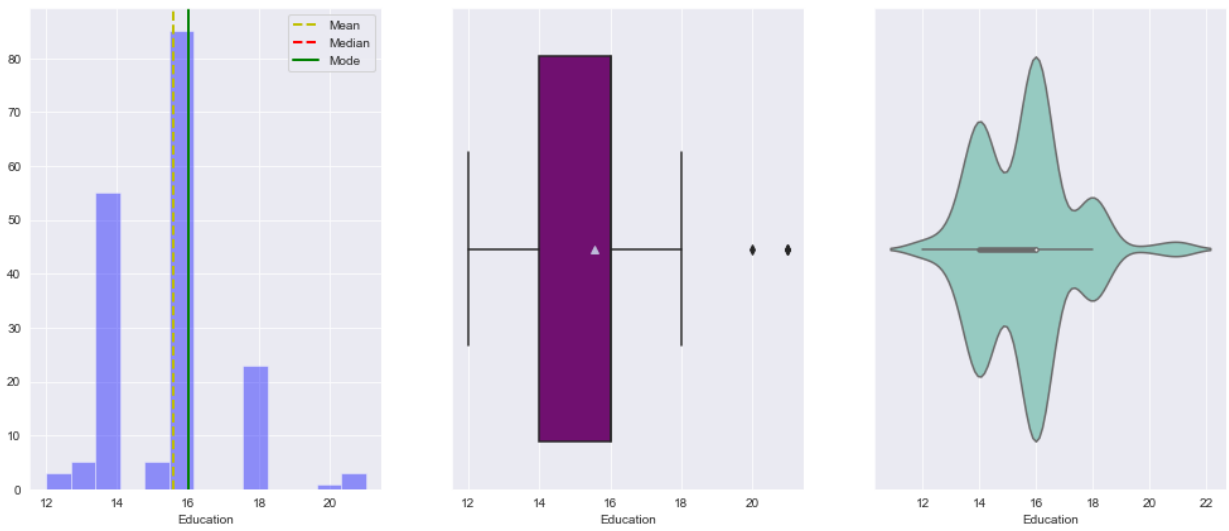


Observation:

- Age is Skewed to Right / Positive Skew as mean is usually to the right of the median.
- Most of the customer buying Aerofit product is of young age at an average age of 29.
- Aerofit have very few customer below 20 years and after 40 years.
- Most of the customer are between 24 - 33.

In [ ]:
```
# Customer Education distribution

import math
def education_distribution(data):
    data_name,data_mean,data_median,data_mode = data_distribution(data)
    data_mean =  math.ceil(data_mean)
    data_median = math.ceil(data_median)
    data_mode = (math.ceil(data_mode))
    print(f"Average {data_name}: {data_mean}")
    print(f"Median {data_name}: {data_median}")
    print(f"Mode {data_name}: {data_mode}")
    print('-'*50)
    print(data.describe().T)
    dist_box_violin(data)

education_distribution(aerofit['Education'])
```

```
Average EDUCATION: 16
Median EDUCATION: 16
Mode EDUCATION: 16
--------------------------------------------------
count    180.000000
mean      15.572222
std        1.617055
min       12.000000
25%       14.000000
50%       16.000000
75%       16.000000
max       21.000000
Name: Education, dtype: float64
```



Observation:

- Education is Normally Skew as mean same as median.
- Most of the customer buying Aerofit product have 16 year of education (assuming them to be college graduates or bachelors).
- Most of the customer have education between 14 -16 years of education.

In [ ]:
```
# Customer Income distribution
import math
def income_distribution(data):
    data_name,data_mean,data_median,data_mode = data_distribution(data)
    data_mean =  "${:,.2f}".format(math.ceil(data_mean))
    data_median ="${:,.2f}".format(math.ceil(data_median))
    data_mode =  "${:,.2f}".format(math.ceil(data_mode))
    print(f"Average {data_name}: {data_mean}")
    print(f"Median {data_name}: {data_median}")
    print(f"Mode {data_name}: {data_mode}")
    print('-'*50)
    print(data.describe())
    dist_box_violin(data)

income_distribution(aerofit['Income'])
```

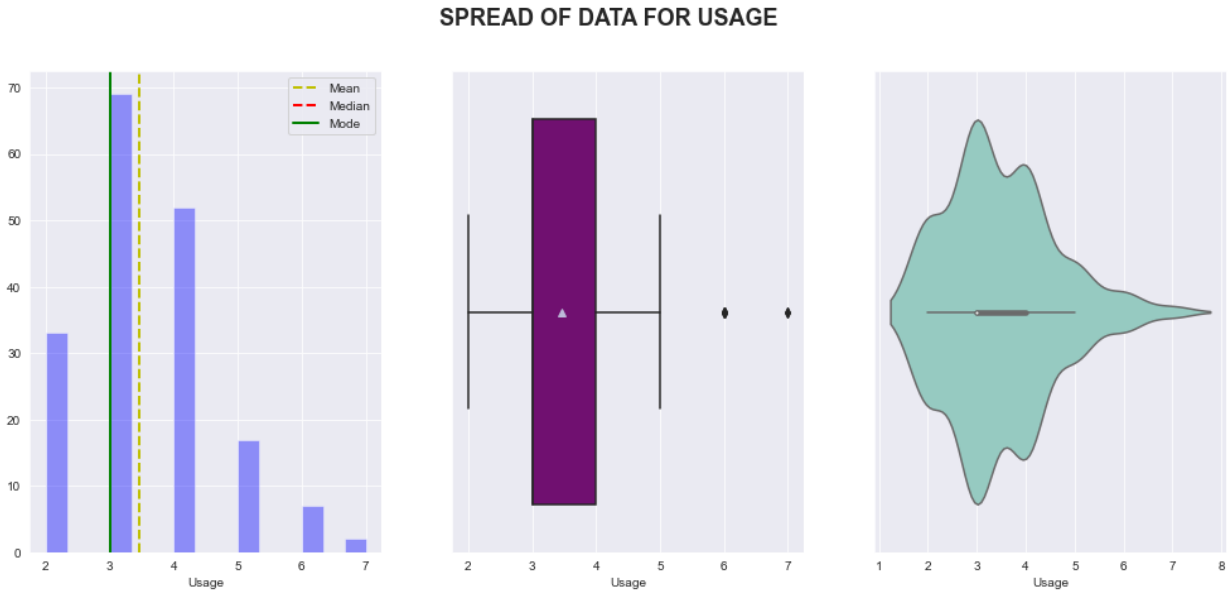
```
Average INCOME: $53,720.00
Median INCOME: $50,597.00
Mode INCOME: $45,480.00
--------------------------------------------------
count       180.000000
mean      53719.577778
std       16506.684226
min       29562.000000
25%       44058.750000
50%       50596.500000
75%       58668.000000
max      104581.000000
Name: Income, dtype: float64
```

Observation:

- Income is Skewed to Right / Positive Skew as mean is usually to the right of the median.
- Most of the customer buying Aerofit product is of income of $53,720.00.
- Most of the customer have income between $44K-59K$.
- As most of the customer is of younger age so most customer income is lower than 70K.

In [ ]:
```
# Customer Usage product per week distribution
import math
def usage_distribution(data):
    data_name,data_mean,data_median,data_mode = data_distribution(data)
    data_mean =  math.ceil(data_mean)
    data_median = math.ceil(data_median)
    data_mode = (math.ceil(data_mode))
    print(f"Average {data_name}: {data_mean} times/week")
    print(f"Median {data_name}: {data_median} times/week")
    print(f"Mode {data_name}: {data_mode} times/week")
    print('-'*50)
    print(data.describe())
    dist_box_violin(data)

usage_distribution(aerofit['Usage'])
```

```
Average USAGE: 4 times/week
Median USAGE: 3 times/week
Mode USAGE: 3 times/week
--------------------------------------------------
count    180.000000
mean       3.455556
std        1.084797
min        2.000000
25%        3.000000
50%        3.000000
75%        4.000000
max        7.000000
Name: Usage, dtype: float64
```

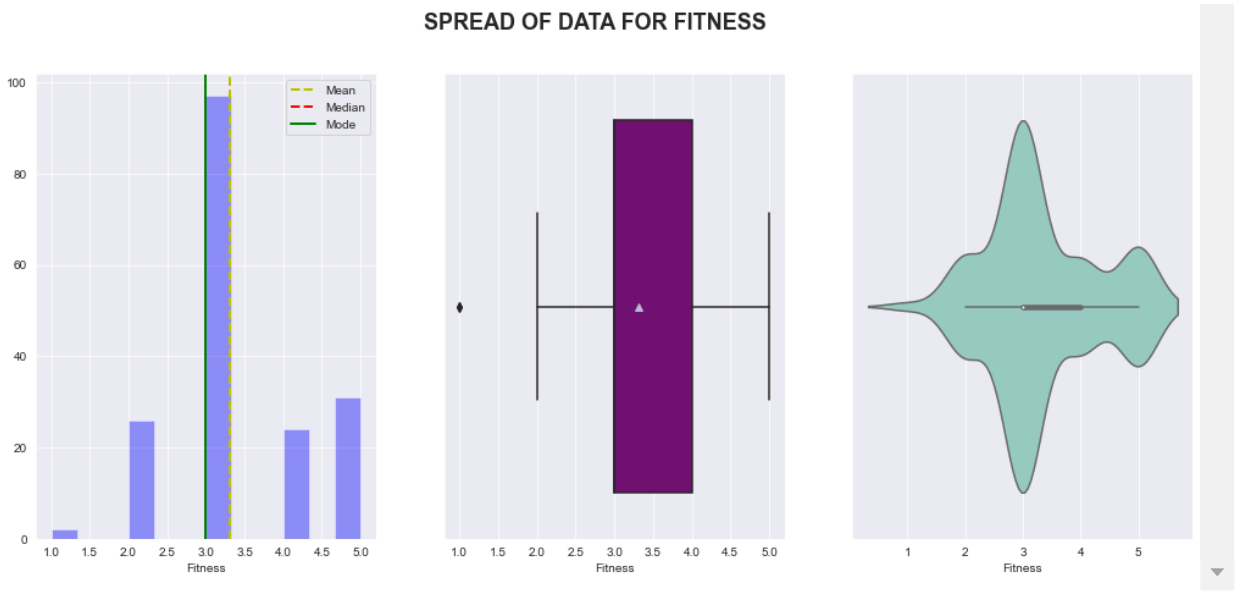


Observation:

- Usage is Skewed to Right / Positive Skew as mean is usually to the right of the median.
- Average customer use product 3-4 times per week.

In [ ]:
```
# Customer Fitness rate distribution

import math
def fitness_distribution(data):
    data_name,data_mean,data_median,data_mode = data_distribution(data)
    data_mean =  math.ceil(data_mean)
    data_median = math.ceil(data_median)
    data_mode = (math.ceil(data_mode))
    print(f"Average {data_name} Rate: {data_mean}")
    print(f"Median {data_name} Rate: {data_median}")
    print(f"Mode {data_name} Rate: {data_mode}")
    print('-'*50)
    print(data.describe())
    dist_box_violin(data)

fitness_distribution(aerofit['Fitness'])
```

```
Average FITNESS Rate: 4
Median FITNESS Rate: 3
Mode FITNESS Rate: 3
--------------------------------------------------
count    180.000000
mean       3.311111
std        0.958869
min        1.000000
25%        3.000000
50%        3.000000
75%        4.000000
max        5.000000
Name: Fitness, dtype: float64
```

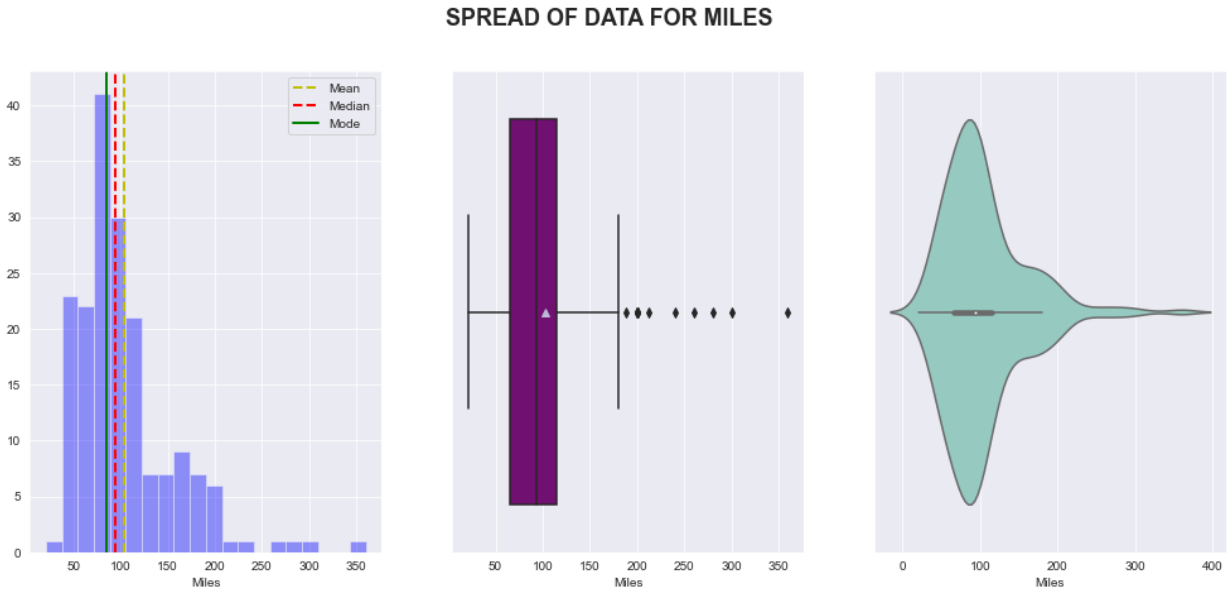


Observation:

- Fitness rate is between 1-5.
- Fitne ratess is Skewed to Right / Positive Skew as mean is usually to the right of the median.
- Most of the customers have self-rated their fitness as 3-4(average).

In [ ]:
```
# Customer Covers Miles per week distribution

import math
def miles_distribution(data):
    data_name,data_mean,data_median,data_mode = data_distribution(data)
    data_mean =  math.ceil(data_mean)
    data_median = math.ceil(data_median)
    data_mode = (math.ceil(data_mode))
    print(f"Average {data_name}: {data_mean}/week")
    print(f"Median {data_name}: {data_median}/week")
    print(f"Mode {data_name}: {data_mode}/week")
    print('-'*50)
    print(data.describe())
    dist_box_violin(data)

miles_distribution(aerofit['Miles'])
```

```
Average MILES: 104/week
Median MILES: 94/week
Mode MILES: 85/week
--------------------------------------------------
count    180.000000
mean     103.194444
std       51.863605
min       21.000000
25%       66.000000
50%       94.000000
75%      114.750000
max      360.000000
Name: Miles, dtype: float64
```



Observation:

- Miles is Skewed to Right / Positive Skew as mean is usually to the right of the median.
- Customers expect to run on an average 104 miles per week.
- Mostly Customer run between 66 miles per week - 115 miles per week.

Bivariate Analysis : Non-Visual & Visual

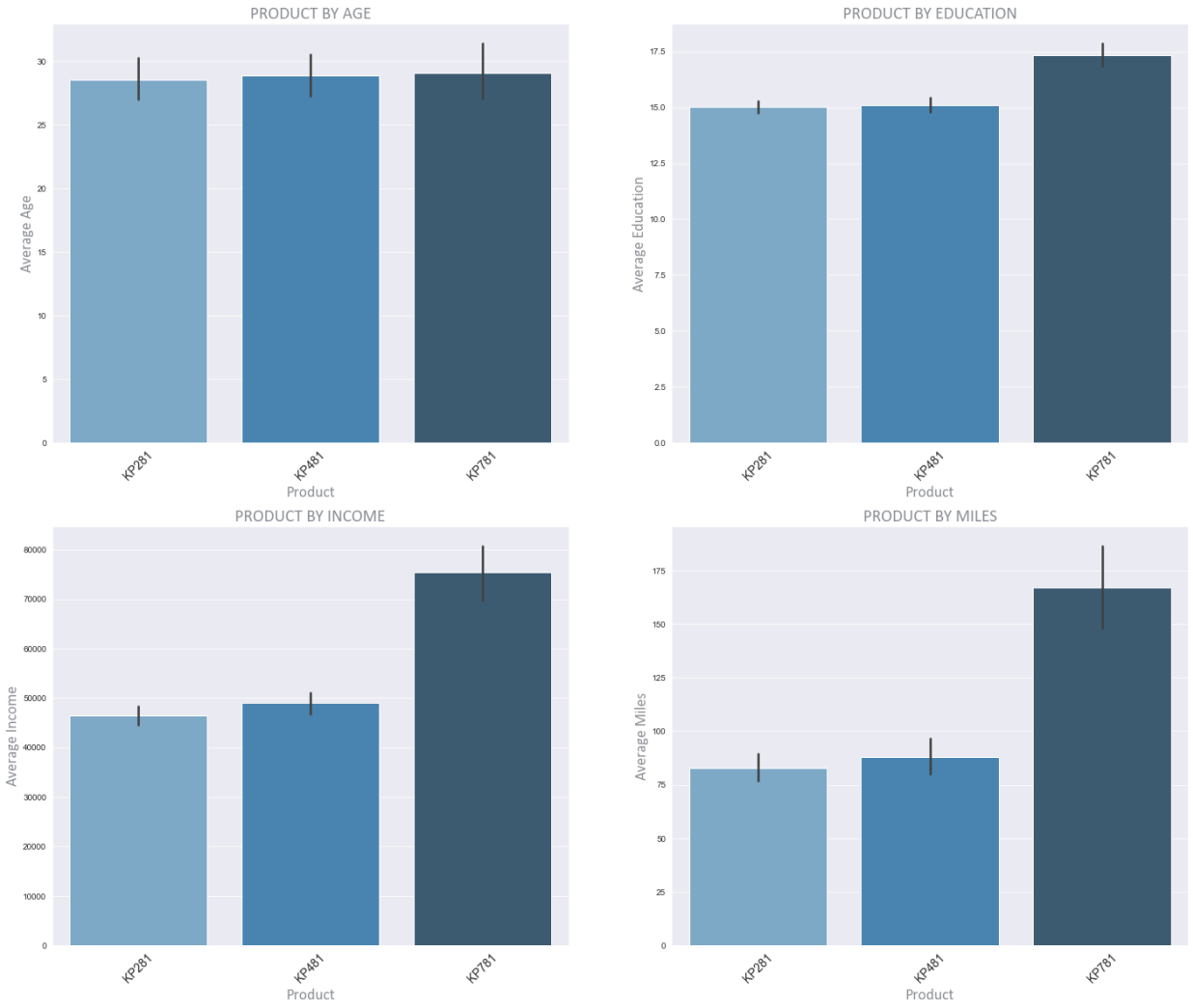
In [ ]:
```
# Average Age, Education, Income, Miles w.r.t different model

aerofit.groupby('Product')[['Age','Education','Income','Miles']].mean()
```

Out[ ]:

Product	Age	Education	Income	Miles
KP281	28.55	15.037500	46418.025	82.787500
KP481	28.90	15.116667	48973.650	87.933333
KP781	29.10	17.325000	75441.575	166.900000

In [ ]:
```
fig1, axes =plt.subplots(2,2,figsize=(24, 20))
list1_col=['Age','Education','Income','Miles']
x_tick = aerofit['Product'].unique().tolist()
#instead of writing  boxplot 6 times using for loop

for i in range(len(list1_col)):
    row=i//2
    col=i%2
    ax=axes[row,col]
    sns.barplot(aerofit['Product'],aerofit[list1_col[i]],ax=ax, palette="Blues_d")
    ax.set_title(f'PRODUCT BY {list1_col[i].upper()}', fontdict={'fontsize': 20, 'colo
    ax.set_xticklabels(x_tick,rotation=45,size=14)
    # ax.set_yticklabels(rotation=45,size=14)
    ax.set_xlabel('Product',fontsize=18,color='#8a8d93',family="Calibri")
    ax.set_ylabel(f'Average {list1_col[i]}',fontsize=18,color='#8a8d93',family="Calibr
```

```
plt.show()
```



Observation:

- //TODO

In [ ]:
```
pd.crosstab(aerofit['Product'],aerofit['Gender'] )

# pd.pivot_table(aerofit,'Gender','Product',aggfunc='count')
# aerofit.groupby(['Product','Gender']).size().unstack()
```

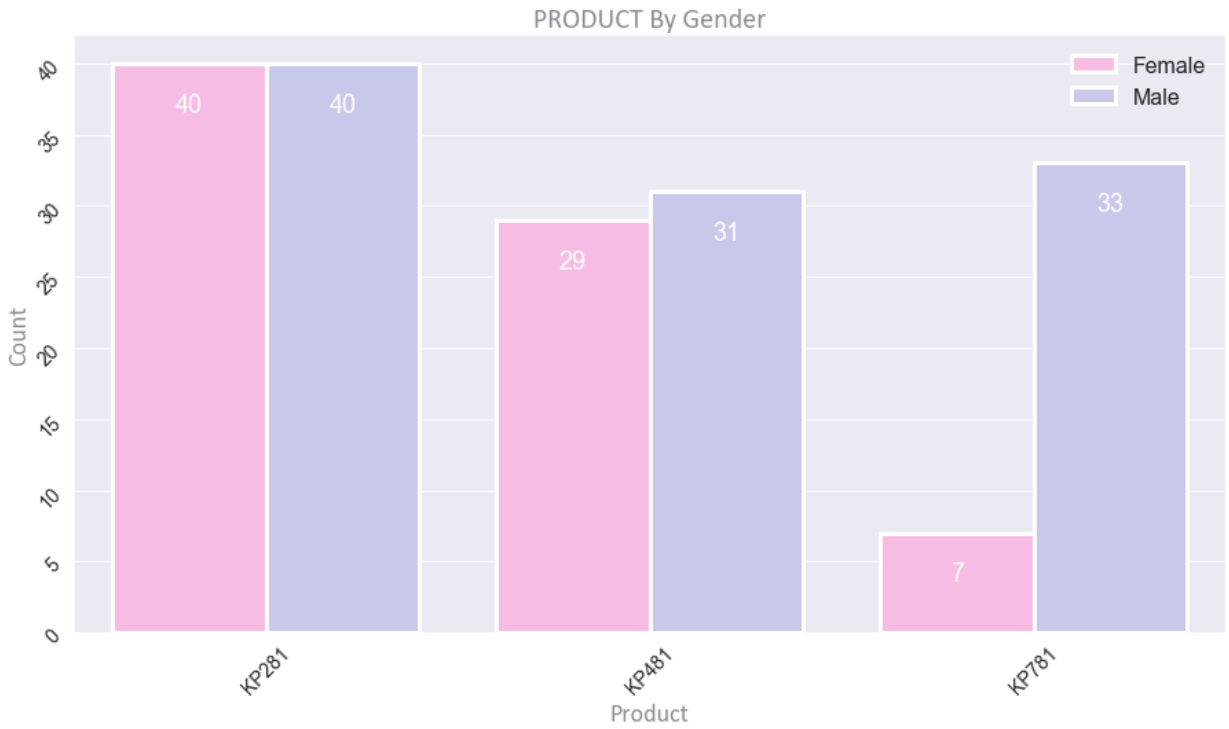
Out[ ]:

Gender	Female	Male
Product		
KP281	40	40
KP481	29	31
KP781	7	33

In [ ]:
```
def barPlot(aerofit,x_feature,hue_feature):
    plt.figure(figsize=(15,8))
    colors = ['#ffb3e6','#c2c2f0']
```

```
    ax = sns.countplot(data=aerofit,x=x_feature,hue=hue_feature,color=colors,palette=c
    plt.title("PRODUCT By Gender",fontsize=20,color='#8a8d93',family="Calibri")
    plt.xticks(rotation=45,size=14)
    plt.yticks(rotation=45,size=14)
    plt.xlabel('Product',fontsize=18,color='#8a8d93',family="Calibri")
    plt.ylabel('Count',fontsize=18,color='#8a8d93',family="Calibri")
    plt.legend(fontsize=16,frameon=False)
    for p in ax.patches:
      ax.annotate(f'\n{p.get_height()}', (p.get_x()+0.2, p.get_height()), ha='center',
    plt.show()
```

In [ ]:
```
barPlot(aerofit,'Product','Gender')
```



Observation:

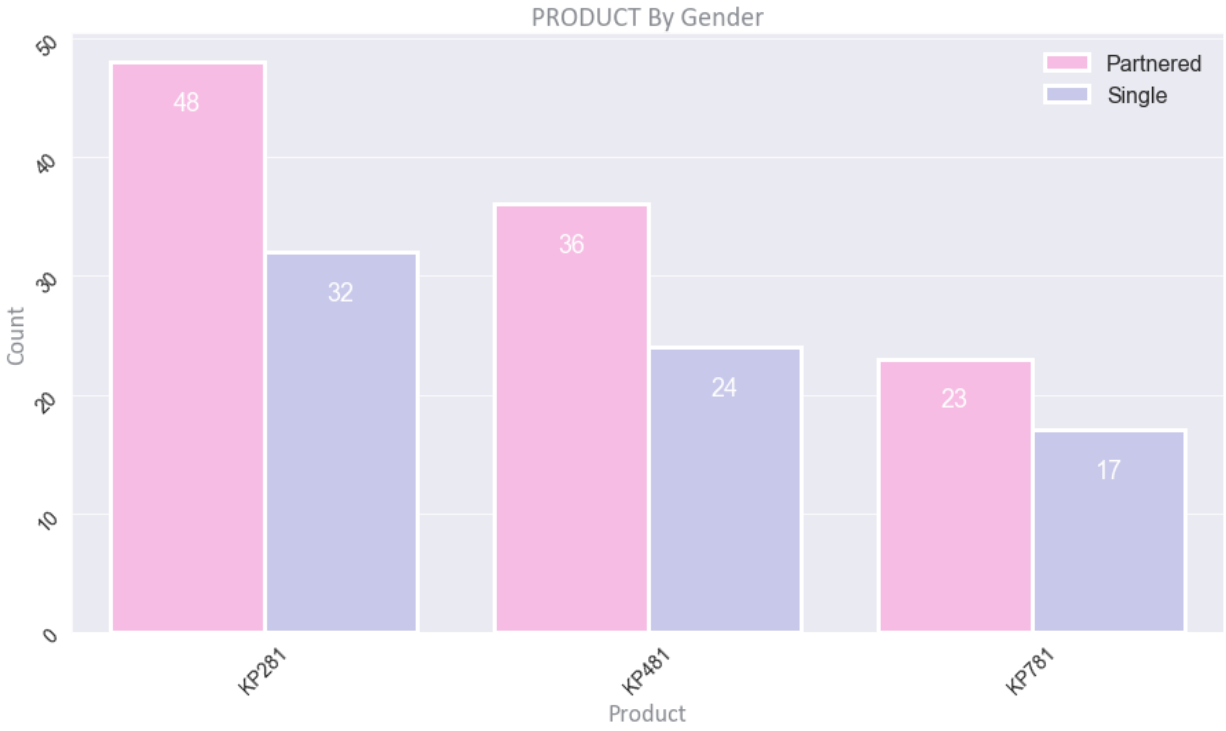
- KP281 Product is equally used by male or female customer.
- KP481 Product is bought more by Male as compare to female.
- KP781 Product is bought more by male as compare to female.

In [ ]:
```
pd.crosstab(aerofit['Product'],aerofit['MaritalStatus'] )
```

Out[ ]:

MaritalStatus	Partnered	Single
Product		
KP281	48	32
KP481	36	24
KP781	23	17

In [ ]:
```
barPlot(aerofit,'Product','MaritalStatus')
```



Observation:

- Ratio of KP281 product is used by Partnered or single customer of ratio 48:32.
- Ratio of KP481 product is used by Partnered or single customer of ratio 36:24.
- Ratio of KP781 product is used by Partnered or single customer of ratio 23:17.

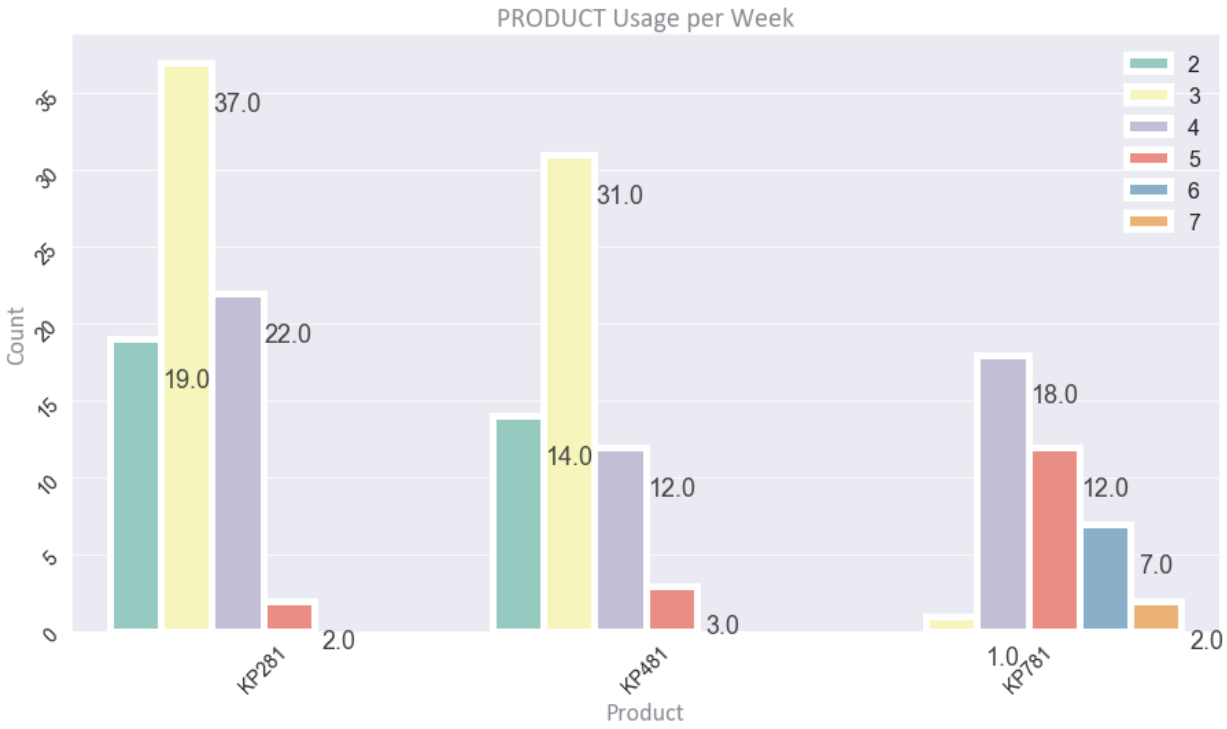
In [ ]:
```
pd.crosstab(aerofit['Product'],aerofit['Usage'] )
```

Out[ ]:

Product	Usage 2	3	4	5	6	7
KP281	19	37	22	2	0	0
KP481	14	31	12	3	0	0
KP781	0	1	18	12	7	2

In [ ]:
```
def barPlot(aerofit,x_feature,hue_feature):
    plt.figure(figsize=(15,8))
    colors = ['#ffb3e6','#c2c2f0']
    ax = sns.countplot(data=aerofit,x=x_feature,hue=hue_feature,color=colors,palette='
    )
    plt.title("PRODUCT Usage per Week",fontsize=20,color='#8a8d93',family="Calibri")
    plt.xticks(rotation=45,size=14)
    plt.yticks(rotation=45,size=14)
    plt.xlabel('Product',fontsize=18,color='#8a8d93',family="Calibri")
    plt.ylabel('Count',fontsize=18,color='#8a8d93',family="Calibri")
    plt.legend(fontsize=16,frameon=False)
    # ax.set_facecolor('#454545')
    for p in ax.patches:
      ax.annotate(f'\n{p.get_height()}', (p.get_x()+0.2, p.get_height()), ha='center',
    plt.show()
```

In [ ]:
```
barPlot(aerofit,'Product','Usage')
```



Observation:

- KP281 mostly usage 3 times a week.
- KP481 mostly usage 3 times a week.
- KP781 mostly usage 4 times a week.

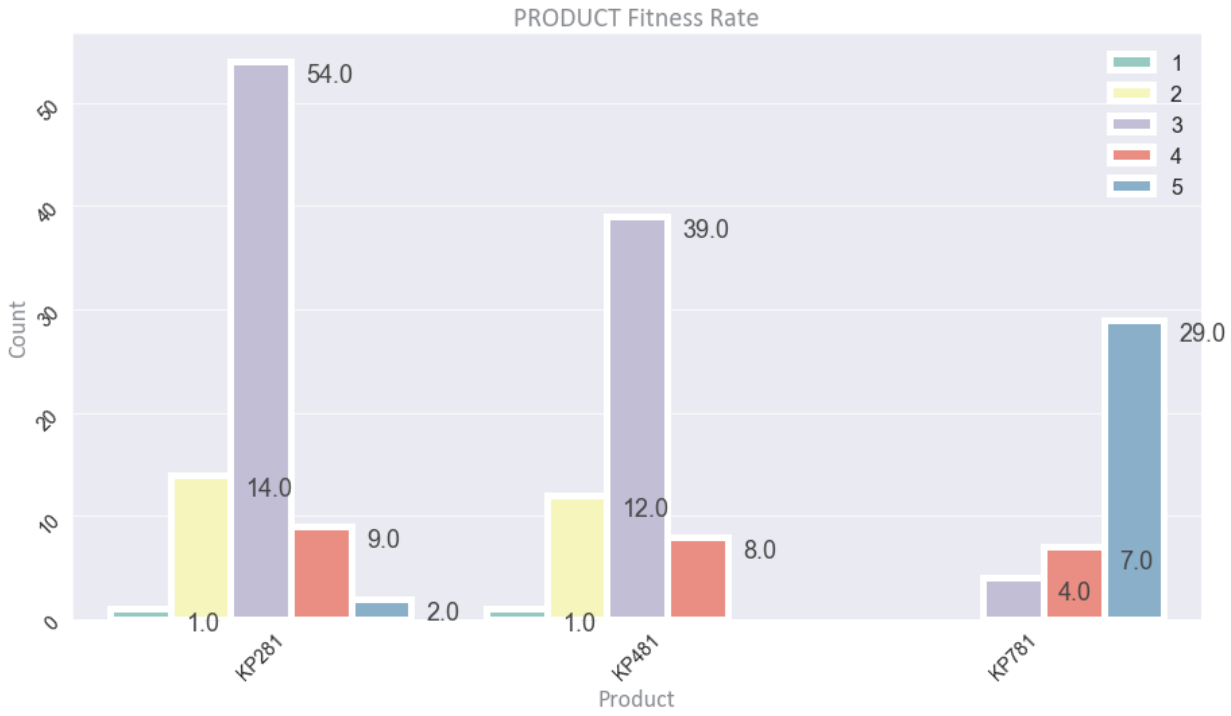
In [ ]:
```
pd.crosstab(aerofit['Product'],aerofit['Fitness'] )
```

Out[ ]:

Fitness	1	2	3	4	5
Product					
KP281	1	14	54	9	2
KP481	1	12	39	8	0
KP781	0	0	4	7	29

In [ ]:
```
def barPlot(aerofit,x_feature,hue_feature):
    plt.figure(figsize=(15,8))
    colors = ['#ffb3e6','#c2c2f0']
    ax = sns.countplot(data=aerofit,x=x_feature,hue=hue_feature,color=colors,palette='
    )
    plt.title("PRODUCT Fitness Rate",fontsize=20,color='#8a8d93',family="Calibri")
    plt.xticks(rotation=45,size=14)
    plt.yticks(rotation=45,size=14)
    plt.xlabel('Product',fontsize=18,color='#8a8d93',family="Calibri")
    plt.ylabel('Count',fontsize=18,color='#8a8d93',family="Calibri")
    plt.legend(fontsize=16,frameon=False)
    # ax.set_facecolor('#454545')
    for p in ax.patches:
      ax.annotate(f'\n{p.get_height()}', (p.get_x()+0.2, p.get_height()), ha='left', v
    plt.show()
```

In [ ]:
```
barPlot(aerofit,'Product','Fitness')
```



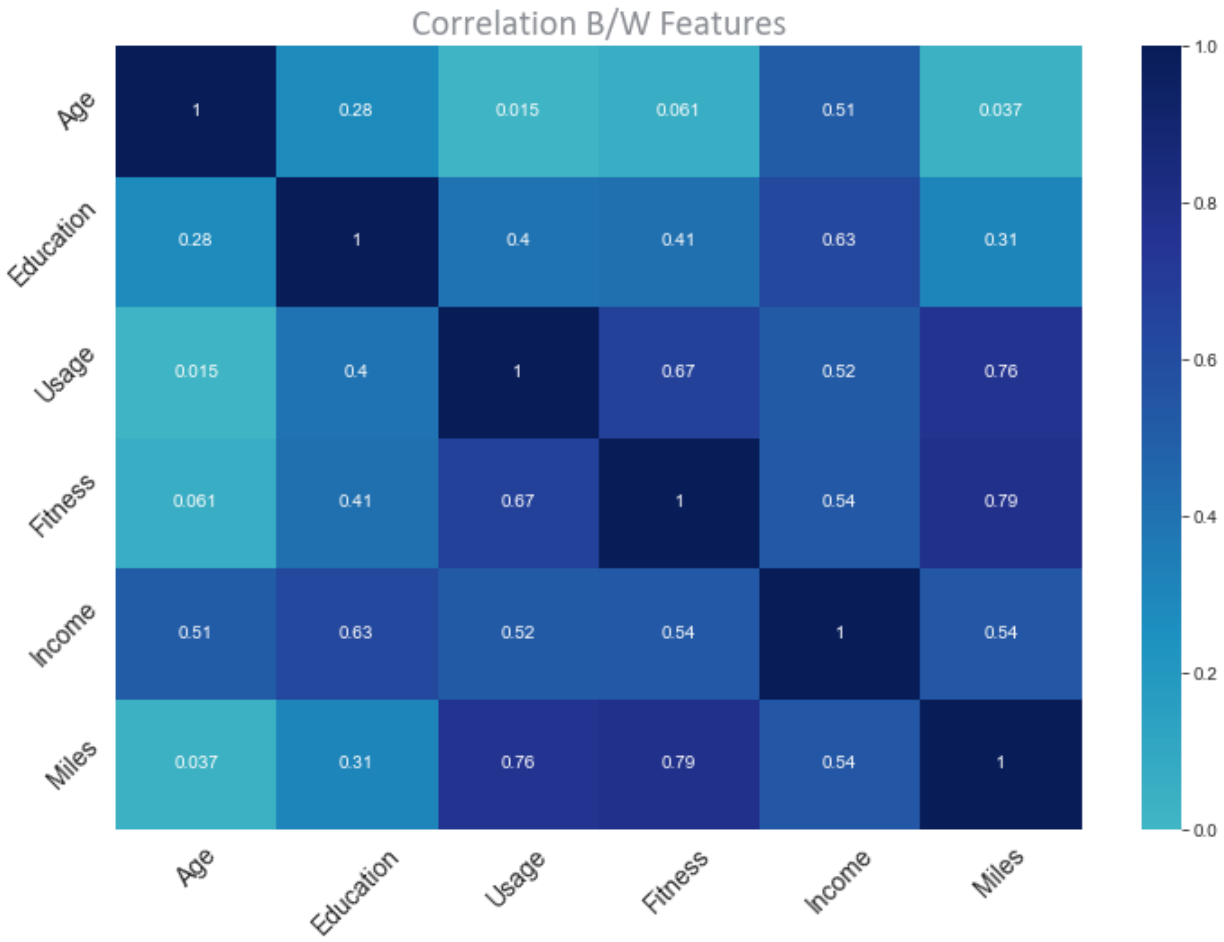
Observation:

- KP781 Product customer prefer to fit at 5 Fitness rate.
- KP481 Product customer prefer to fit at 3 Fitness rate.
- KP281 Product customer prefer to fit at 3 Fitness rate.

Multivariate Analysis : Non-Visual & Visual

Coorelation

In [ ]:
```
plt.figure(figsize=(12,8))
aerofit_corr = aerofit.corr()
sns.heatmap(aerofit_corr,annot=True,vmin=0, vmax=1,center=0,cmap="YlGnBu")
plt.title("Correlation B/W Features",fontsize=20,color='#8a8d93',family="Calibri")
plt.xticks(rotation=45,size=14)
plt.yticks(rotation=45,size=14)

plt.show()
```



In [ ]:
```
corr_pairs = aerofit_corr.unstack() # give pairs of correlation
print( corr_pairs[abs(corr_pairs)>0.5]) # Gives us correlated data
```

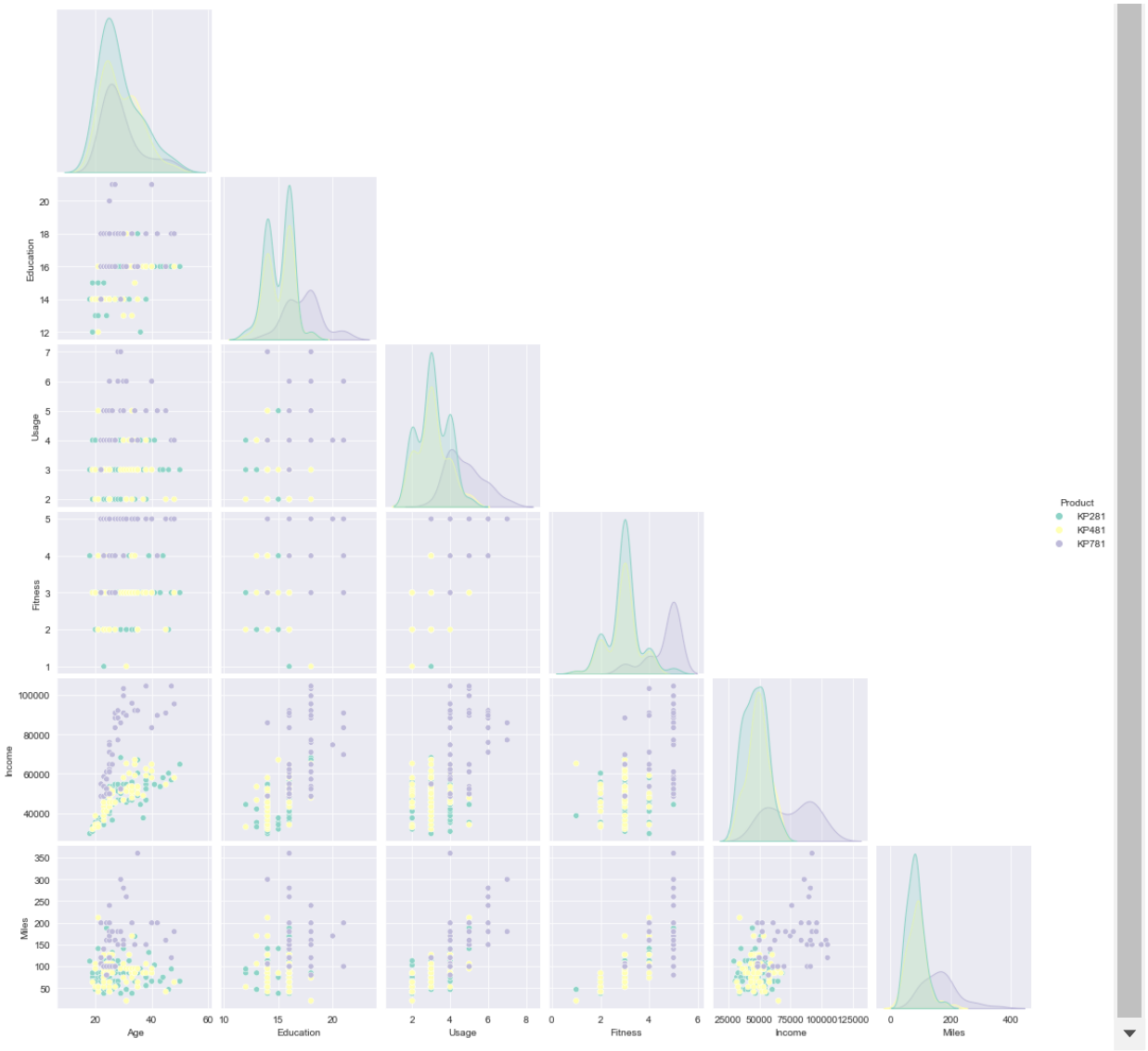
```
Age        Age          1.000000
           Income       0.513414
Education  Education    1.000000
           Income       0.625827
Usage      Usage        1.000000
           Fitness      0.668606
           Income       0.519537
           Miles        0.759130
Fitness    Usage        0.668606
           Fitness      1.000000
           Income       0.535005
           Miles        0.785702
Income     Age          0.513414
           Education    0.625827
           Usage        0.519537
           Fitness      0.535005
           Income       1.000000
           Miles        0.543473
Miles      Usage        0.759130
           Fitness      0.785702
           Income       0.543473
           Miles        1.000000
dtype: float64
```

In [ ]:
```
plt.figure(figsize=(12,8))
sns.pairplot(aerofit,corner=True)
plt.show()
```

```
<Figure size 864x576 with 0 Axes>
```

In [ ]:
```
plt.figure(figsize=(12,8))
g = sns.pairplot(aerofit,corner=True,hue='Product')
plt.xticks(rotation=45,size=14)
plt.yticks(rotation=45,size=14)
plt.show()
```

```
<Figure size 864x576 with 0 Axes>
```



- Observation
  - Age is correlate with Income with 0.5.
  - Education is correlated with Income with 0.63.
  - Usage is correlated with Fitness,Income,Miles at 0.67,0.52,0.76.
  - Fitness is correlated with Usage,income, Miles at 0.67,0.53,0.79.

Multivariate Analysis

In [ ]:
```
pd.pivot_table(aerofit,index=["Product","Gender"],columns=["MaritalStatus"],aggfunc=le
```

Out[ ]:

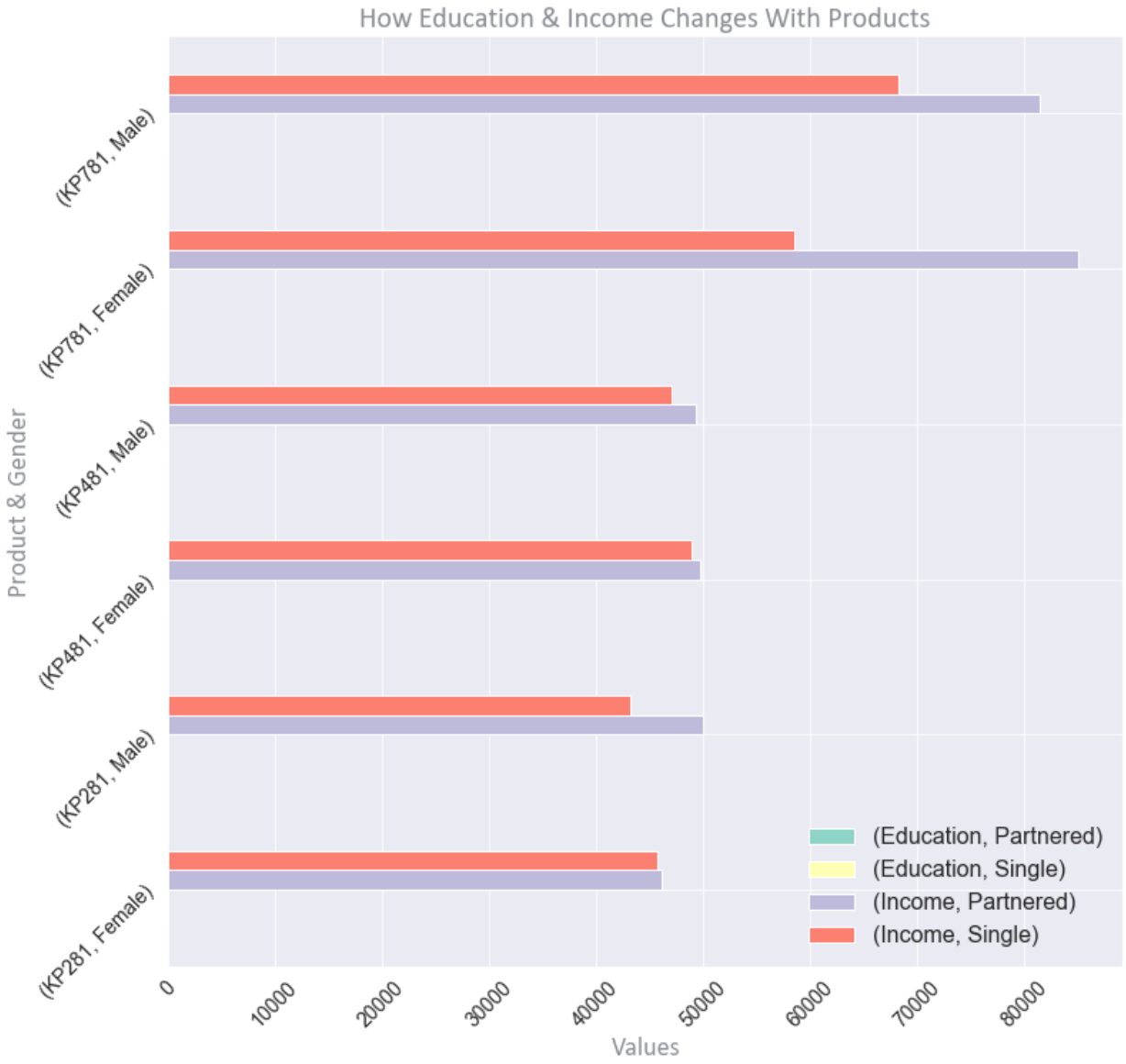
		Age		Education		Fitness		Income		P
	MaritalStatus	Partnered	Single	Partnered	Single	Partnered	Single	Partnered	Single	
Product	Gender									
KP281	Female	27	13	27	13	27	13	27	13	
	Male	21	19	21	19	21	19	21	19	
KP481	Female	15	14	15	14	15	14	15	14	
	Male	21	10	21	10	21	10	21	10	
KP781	Female	4	3	4	3	4	3	4	3	
	Male	19	14	19	14	19	14	19	14	

In [ ]:
```
a = pd.pivot_table(aerofit,['Income','Education'],index=["Product","Gender"],columns=[
a
```

Out[ ]:

		Education		Income	
	MaritalStatus	Partnered	Single	Partnered	Single
Product	Gender				
KP281	Female	14.888889	15.538462	46153.777778	45742.384615
	Male	15.428571	14.473684	50028.000000	43265.842105
KP481	Female	15.200000	15.214286	49724.800000	48920.357143
	Male	15.285714	14.500000	49378.285714	47071.800000
KP781	Female	17.500000	18.333333	84972.250000	58516.000000
	Male	17.421053	16.928571	81431.368421	68216.428571

In [ ]:
```
a.plot(kind='barh',figsize=(12, 12))
plt.title("How Education & Income Changes With Products",fontsize=20,color='#8a8d93',f
plt.xticks(rotation=45,size=14)
plt.yticks(rotation=45,size=14)
plt.xlabel('Values',fontsize=18,color='#8a8d93',family="Calibri")
plt.ylabel('Product & Gender',fontsize=18,color='#8a8d93',family="Calibri")
plt.legend(fontsize=16,frameon=False)
plt.show()
```



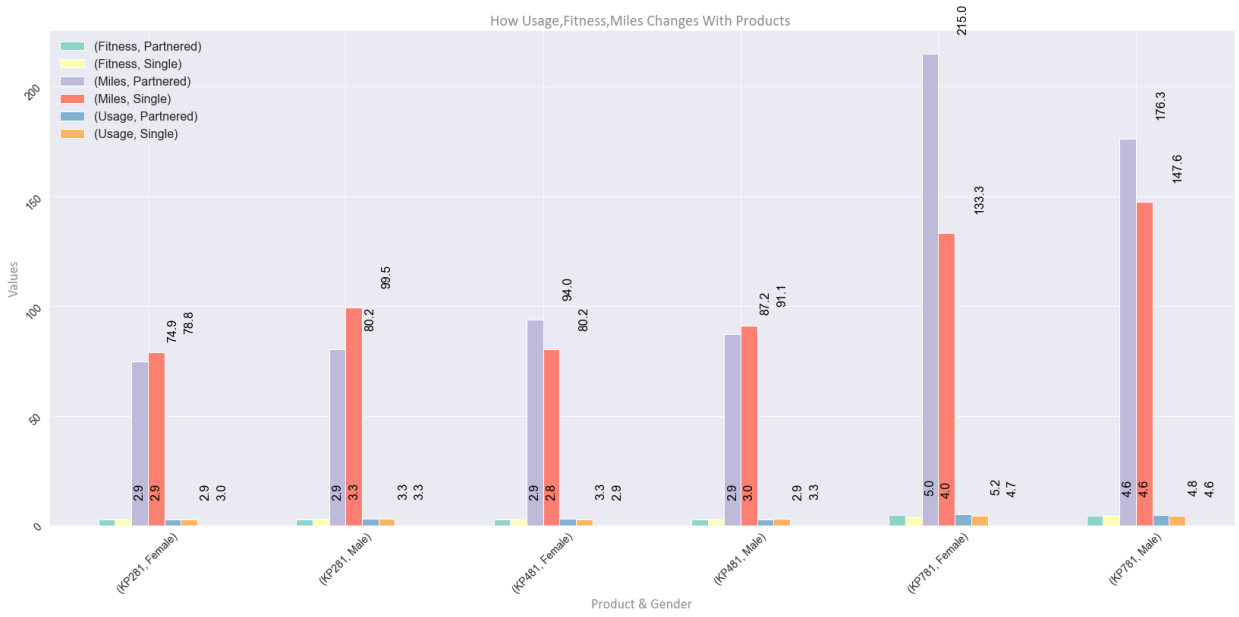
- Observation
  - KP781 Product Male& Female Customer have high Education and High Income.
  - KP481 Product Male Customer have same Education & Income as KP281 product Male Customer.
  - KP281 Product Female Customer have higher Education & Income as KP281 product Female Customer.

In [ ]:
```
 b= pd.pivot_table(aerofit,['Usage','Fitness','Miles'],index=["Product","Gender"],colu
b
```

Out[ ]:

		Fitness		Miles		Usage	
	MaritalStatus	Partnered	Single	Partnered	Single	Partnered	Single
Product	Gender						
KP281	Female	2.851852	2.923077	74.925926	78.846154	2.851852	3.000000
	Male	2.857143	3.263158	80.190476	99.526316	3.285714	3.263158
KP481	Female	2.933333	2.785714	94.000000	80.214286	3.333333	2.928571
	Male	2.904762	3.000000	87.238095	91.100000	2.857143	3.300000
KP781	Female	5.000000	4.000000	215.000000	133.333333	5.250000	4.666667
	Male	4.631579	4.642857	176.315789	147.571429	4.842105	4.571429

In [ ]:
```
ax = b.plot(kind='bar',figsize=(28, 12))
plt.title("How Usage,Fitness,Miles Changes With Products ",fontsize=20,color='#8a8d93'
plt.xticks(rotation=45,size=14)
plt.yticks(rotation=45,size=14)
plt.xlabel('Product & Gender',fontsize=18,color='#8a8d93',family="Calibri")
plt.ylabel('Values',fontsize=18,color='#8a8d93',family="Calibri")
plt.legend(fontsize=16,frameon=False)
for p in ax.patches:

    ax.annotate(f'\n{round(p.get_height(),1)}', (p.get_x()+0.2, p.get_height()), ha='r
plt.show()
```

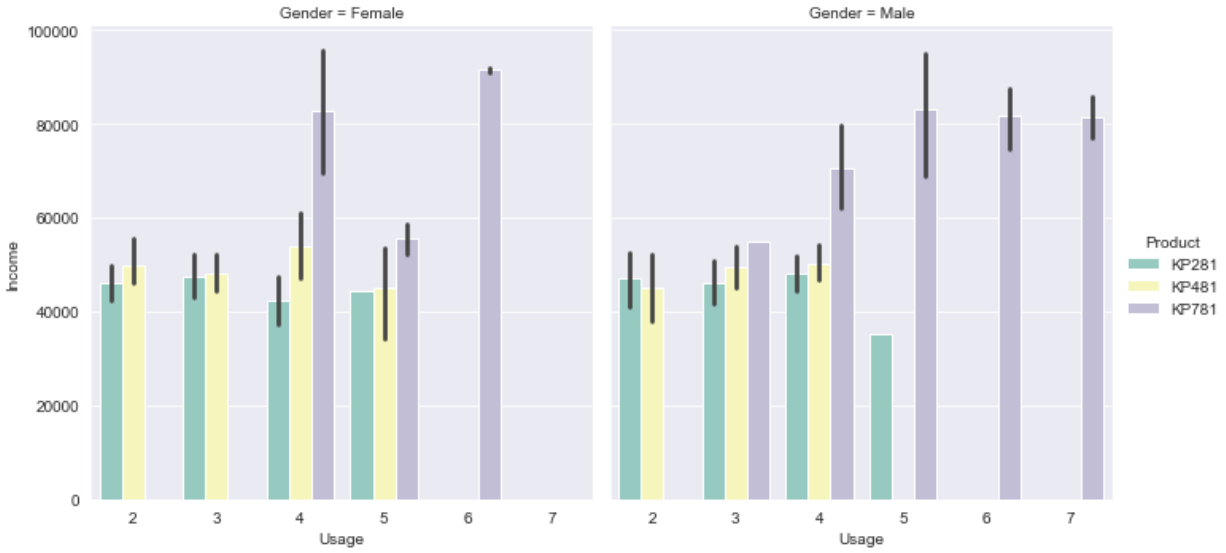


- Observation
  - Male & Female Customer with a fitness rate of 3 and Usage 3-4 times per week Prefer KP281,KP481 Model.
  - Male & Female Customer with a fitness rate of 4-5 ans Usage 5-6 times per week Prefer KP781 Model.

In [ ]:
```
plt.figure(figsize=(22,17))
```

```
sns.catplot(x="Usage", y="Income",
                col='Gender',hue='Product',
                data=aerofit, kind="bar"
               )
```

Out[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x23ceb60a7d0>

<Figure size 1584x1224 with 0 Axes>
```



- Observation
  - Male customer with higher income ,bought KP781 Model and expect to use treadmill 4-6 /week
  - Customer who bought KP281 and KP781 are in same income range and expect to use treadmill 3-4 /week.

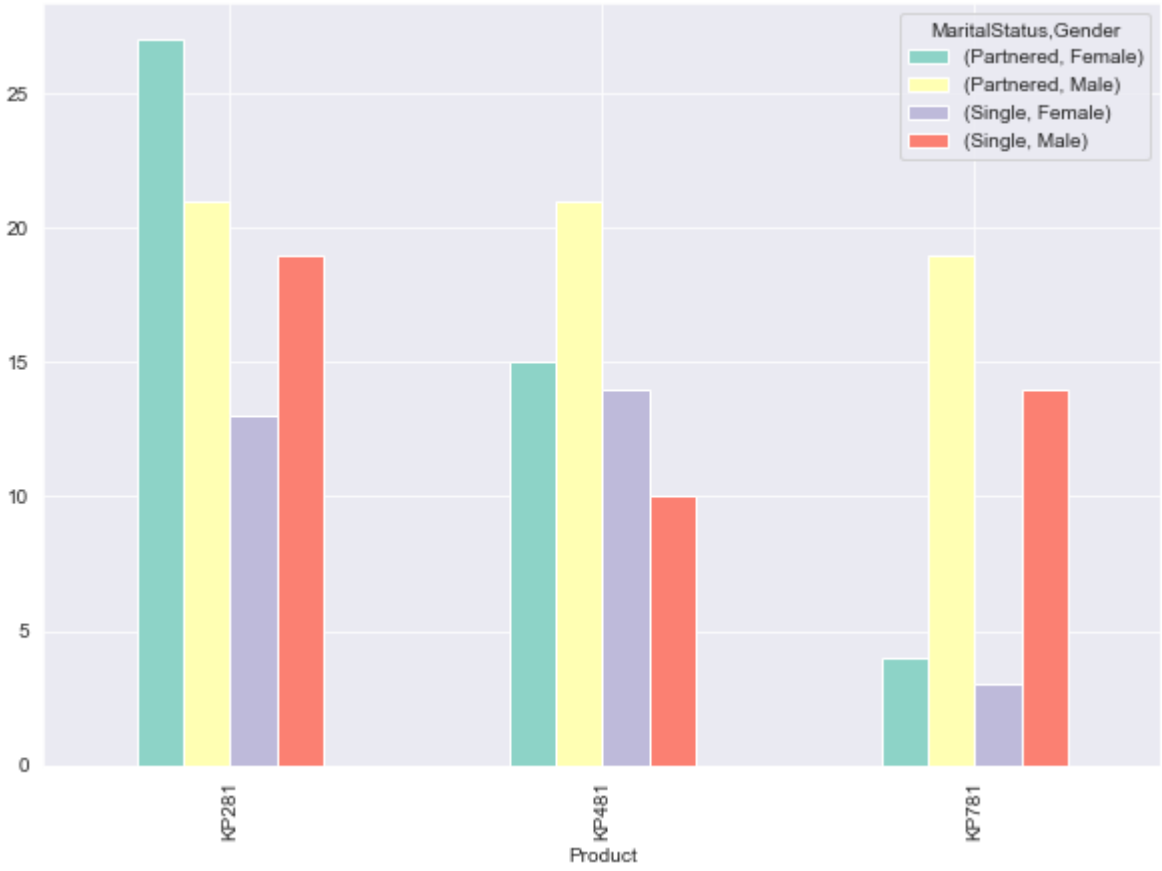
In [ ]:
```
pd.crosstab(index=[aerofit["Product"],aerofit['Gender']], columns=aerofit["MaritalStat
```

Out[ ]:

	MaritalStatus	Partnered	Single
Product	**Gender**		
KP281	**Female**	27	13
	Male	21	19
KP481	**Female**	15	14
	Male	21	10
KP781	**Female**	4	3
	Male	19	14

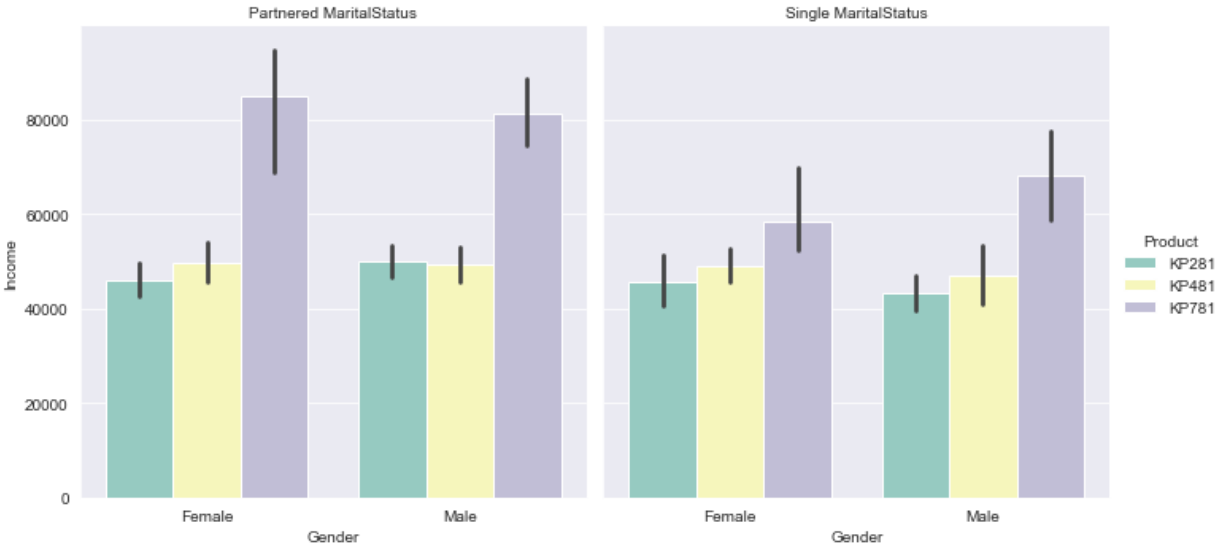
In [ ]:
```
c = pd.crosstab(index=[aerofit["Product"]], columns=[aerofit["MaritalStatus"],aerofit[
c.plot(kind='bar',figsize=(10,7))
```

Out[ ]:
```
<AxesSubplot:xlabel='Product'>
```



In [ ]:
```
plt.figure(figsize=(28,20))
g = sns.catplot(x="Gender", y="Income",
                col='MaritalStatus',hue='Product',
                data=aerofit, kind="bar"
               )
(g.set_axis_labels("Gender", "Income")
  .set_xticklabels(["Female", "Male"])
  .set_titles("{col_name} {col_var}")
)
plt.show()
```

```
<Figure size 2016x1440 with 0 Axes>
```



In [ ]:
```
pd.crosstab(index=aerofit['Product'],columns=[aerofit['Gender'],aerofit['Fitness']])
```

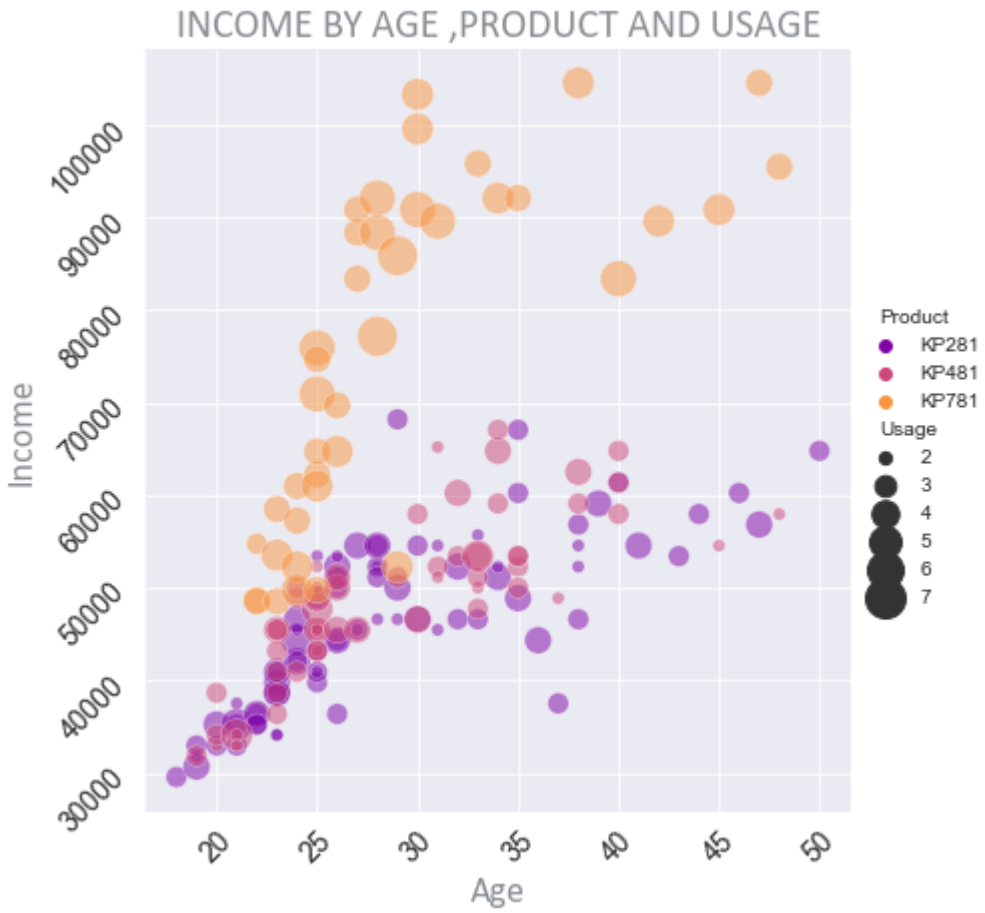
Out[ ]:

Gender	Female					Male				
Fitness	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
Product										
KP281	0	10	26	3	1	1	4	28	6	1
KP481	1	6	18	4	0	0	6	21	4	0
KP781	0	0	1	1	5	0	0	3	6	24

- *Observation:*
  - Single Female customers bought KP281 model more than Single male customers.
  - Partnered Male customers bought KP781 model more than Single Male customers.
  - There are more single males buying Treadmill than single Females.
  - Single Male customers bought KP781 Model compared to Single Female.
  - Sale are equally for KP281,KP481 model betwwen Male and female.
  - The majority of our buyers are man.

In [ ]:
```
#scatter plot between income, age ,product and usage
plt.figure(figsize=(16,12))
sns.relplot(x="Age", y="Income", hue="Product", size="Usage",

            sizes=(40, 400), alpha=.5, palette="plasma",
            height=6, data=aerofit)
plt.title("INCOME BY AGE ,PRODUCT AND USAGE",fontsize=20,color='#8a8d93',family="Calib
plt.xticks(rotation=45,size=14)
plt.yticks(rotation=45,size=14)
plt.xlabel('Age',fontsize=18,color='#8a8d93',family="Calibri")
plt.ylabel('Income',fontsize=18,color='#8a8d93',family="Calibri")
# plt.legend(fontsize=14,frameon=False)
plt.show()
```

```
<Figure size 1152x864 with 0 Axes>
```



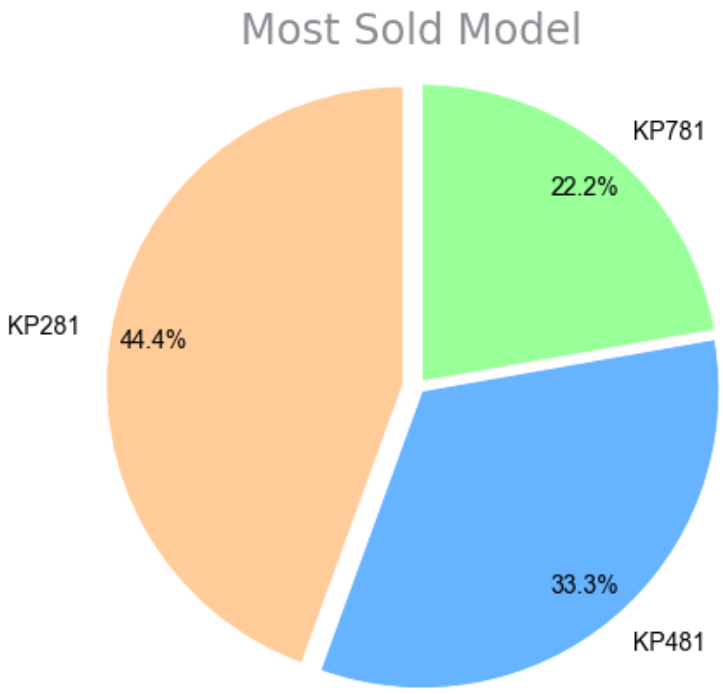
- *Observation:*
    - Products KP281 and KP481 are bought by people with lower than 70K as income and age is concentrated more in range of 23-35.
    - Product KP781 is mainly bought by people with higher than 70K income and age falls in range of 23-30.
    - Majority of people who buys the KP781 expect that they will run more than consumers of the other two products, on average.

Asking Questions

In [ ]:
```
# Which model is most sold?

def donut_perc(df,feature,title):
    index = df[feature].value_counts().index
    data = df[feature].value_counts()
    print(data)

    plt.figure(figsize=(4,2))
    fig1, ax1 = plt.subplots(figsize=(10,6))
    explode = (0.05,0.02,0.02)
    colors = ['#ffcc99','#66b3ff','#99ff99']
    ax1.pie(data,autopct='%1.1f%%',explode=explode,labels=index,colors=colors,pctdista
    plt.title(title,fontsize=24,color='#8a8d93',family="'Bebas Neue', cursive")
    ax1.axis('equal')
```

```
    plt.tight_layout()
    plt.show()

donut_perc(aerofit,'Product','Most Sold Model')
```

```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
<Figure size 288x144 with 0 Axes>
```



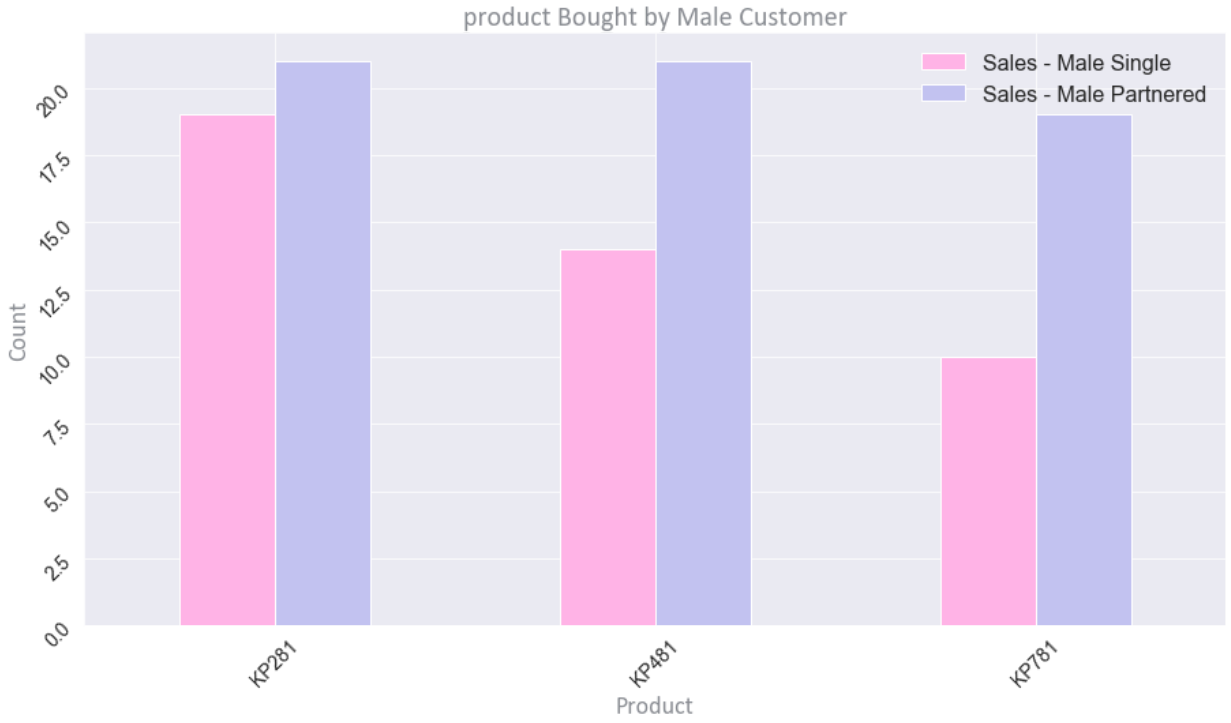
In [ ]:
```
# Which product is preffered by male Partned Customers and male Single Customer

a = aerofit[(aerofit['Gender']== 'Male') & (aerofit['MaritalStatus']== 'Single')]['Pro
b = aerofit[(aerofit['Gender']== 'Male') & (aerofit['MaritalStatus']== 'Partnered')]['
index = aerofit['Product'].unique().tolist()
frame = {'Sales - Male Single':a,'Sales - Male Partnered':b}
ans = pd.DataFrame(frame,index=index)
ans
```

Out[ ]:

	Sales - Male Single	Sales - Male Partnered
KP281	19	21
KP481	14	21
KP781	10	19

In [ ]:
```
colors = ['#ffb3e6','#c2c2f0']
ans.plot(kind='bar',color=colors,figsize=(15,8))
plt.title("product Bought by Male Customer",fontsize=20,color='#8a8d93',family="Calibr
plt.xticks(rotation=45,size=14)
plt.yticks(rotation=45,size=14)
plt.xlabel('Product',fontsize=18,color='#8a8d93',family="Calibri")
plt.ylabel('Count',fontsize=18,color='#8a8d93',family="Calibri")
plt.legend(fontsize=16,frameon=False)
```

```
for p in ax.patches:
      ax.annotate(f'\n{p.get_height()}', (p.get_x()+0.2, p.get_height()), ha='center',
```

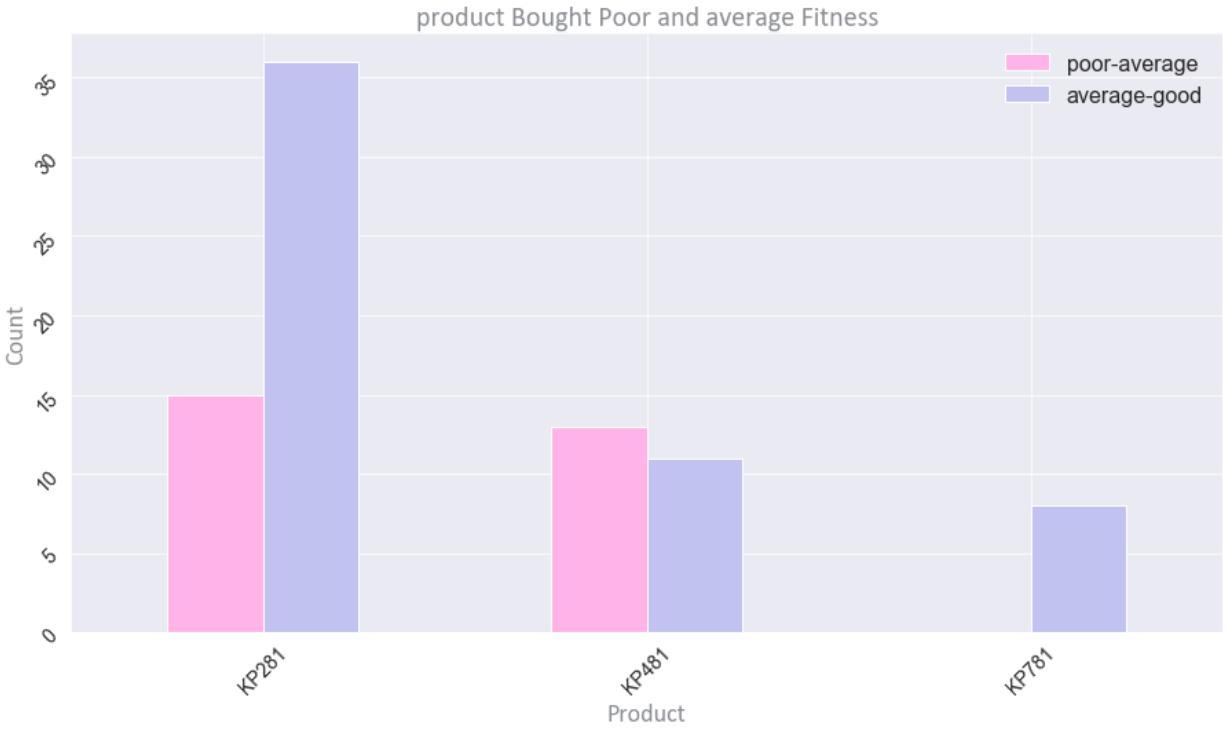


In [ ]:
```
# . Which product is preferred by customers having poor to average fitness
    #  and average to good fitness?

a = aerofit[aerofit['Fitness']<aerofit['Fitness'].median()]['Product'].value_counts().
b = aerofit[aerofit['Fitness']>aerofit['Fitness'].median()]['Product'].value_counts().
index = aerofit['Product'].unique().tolist()
frame = {'poor-average':a,'average-good':b}
ans = pd.DataFrame(frame,index=index)
ans
```

Out[ ]:

	poor-average	average-good
KP281	15	36
KP481	13	11
KP781	0	8

In [ ]:
```
colors = ['#ffb3e6','#c2c2f0']
ans.plot(kind='bar',color=colors,figsize=(15,8))
plt.title("product Bought Poor and average Fitness",fontsize=20,color='#8a8d93',family
plt.xticks(rotation=45,size=14)
plt.yticks(rotation=45,size=14)
plt.xlabel('Product',fontsize=18,color='#8a8d93',family="Calibri")
plt.ylabel('Count',fontsize=18,color='#8a8d93',family="Calibri")
plt.legend(fontsize=16,frameon=False)
for p in ax.patches:
      ax.annotate(f'\n{p.get_height()}', (p.get_x()+0.2, p.get_height()), ha='center',
```

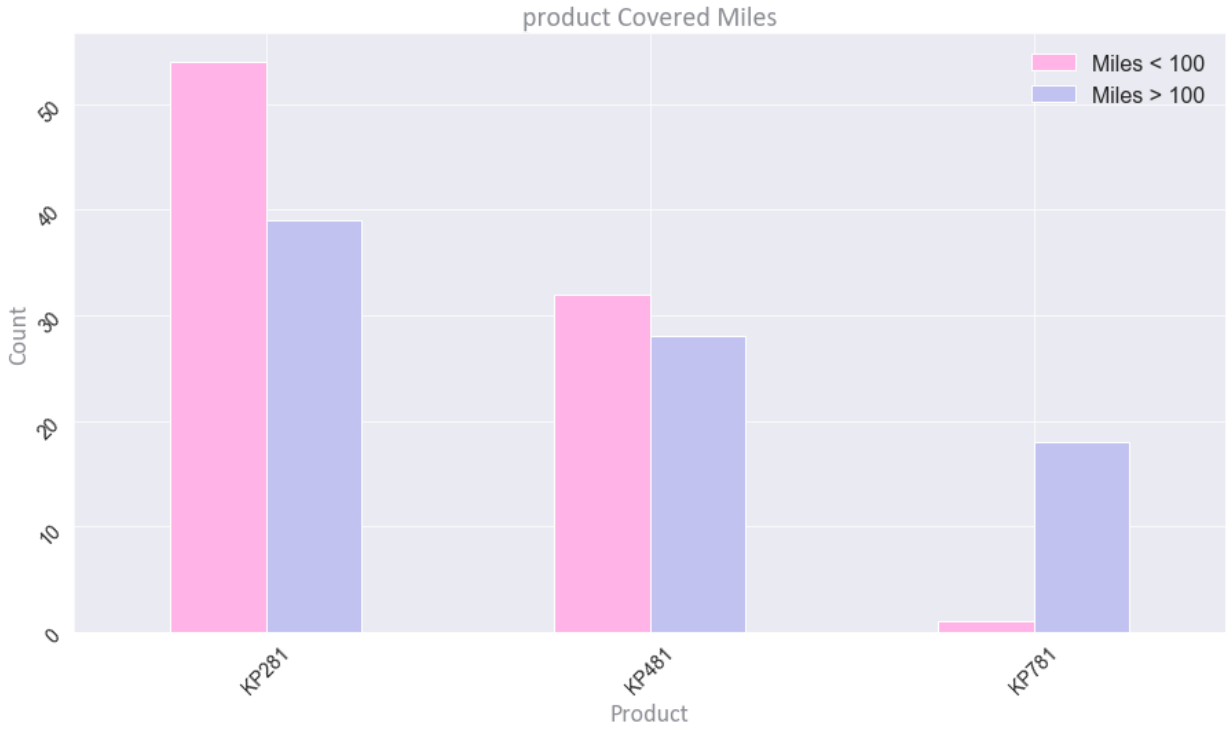


In [ ]:
```
#  Which product is preferred by customers expected to use for less than 100 miles?

a = aerofit[aerofit['Miles']<aerofit['Miles'].median()]['Product'].value_counts().to_l
b = aerofit[aerofit['Miles']>aerofit['Miles'].median()]['Product'].value_counts().to_l
index = aerofit['Product'].unique().tolist()
frame = {'Miles < 100':a,'Miles > 100':b}
ans = pd.DataFrame(frame,index=index)
ans
```

Out[ ]:

	Miles < 100	Miles > 100
KP281	54	39
KP481	32	28
KP781	1	18

In [ ]:
```
colors = ['#ffb3e6','#c2c2f0']
ans.plot(kind='bar',color=colors,figsize=(15,8))
plt.title("product Covered Miles",fontsize=20,color='#8a8d93',family="Calibri")
plt.xticks(rotation=45,size=14)
plt.yticks(rotation=45,size=14)
plt.xlabel('Product',fontsize=18,color='#8a8d93',family="Calibri")
plt.ylabel('Count',fontsize=18,color='#8a8d93',family="Calibri")
plt.legend(fontsize=16,frameon=False)
for p in ax.patches:
      ax.annotate(f'\n{p.get_height()}', (p.get_x()+0.2, p.get_height()), ha='center',
```

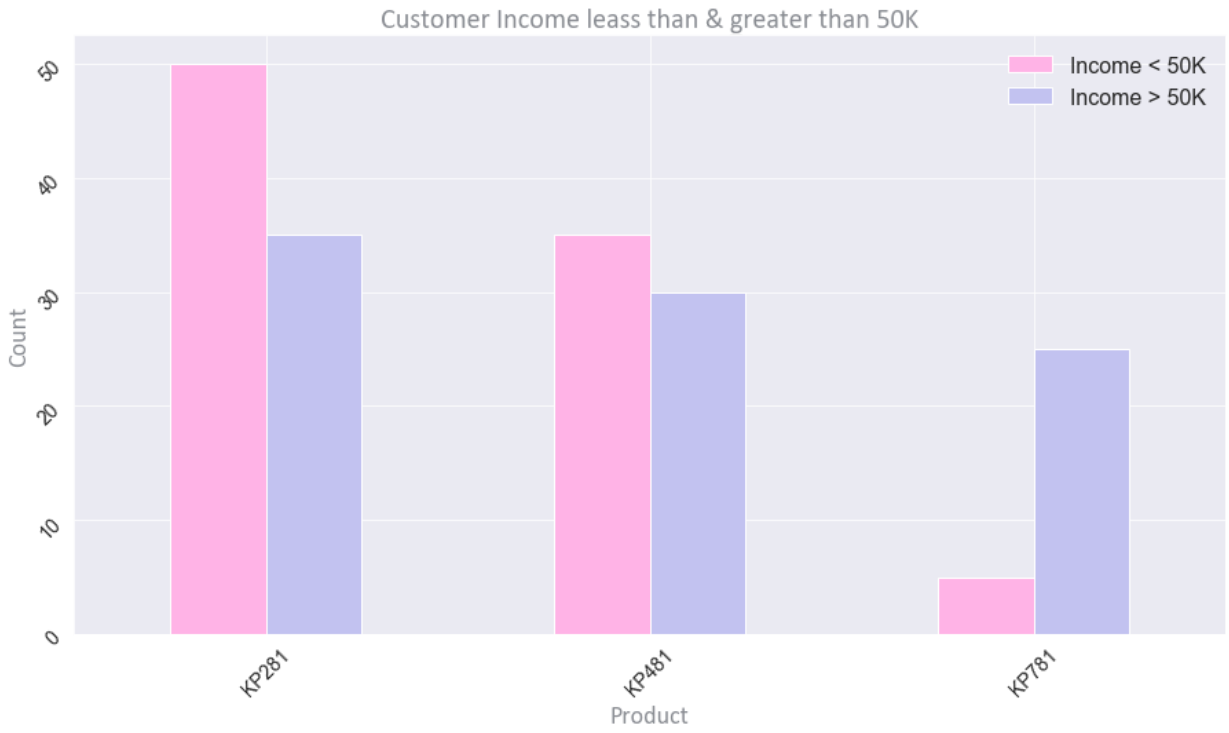


In [ ]:
```
# Customers having annual income less than and greater than 50K.


a = aerofit[aerofit['Income']<aerofit['Income'].median()]['Product'].value_counts().to
b = aerofit[aerofit['Income']>aerofit['Income'].median()]['Product'].value_counts().to
index = aerofit['Product'].unique().tolist()
frame = {'Income < 50K':a,'Income > 50K':b}
ans = pd.DataFrame(frame,index=index)
ans
```

Out[ ]:

	Income < 50K	Income > 50K
KP281	50	35
KP481	35	30
KP781	5	25

In [ ]:
```
colors = ['#ffb3e6','#c2c2f0']
ans.plot(kind='bar',color=colors,figsize=(15,8))
plt.title("Customer Income leass than & greater than 50K",fontsize=20,color='#8a8d93',
plt.xticks(rotation=45,size=14)
plt.yticks(rotation=45,size=14)
plt.xlabel('Product',fontsize=18,color='#8a8d93',family="Calibri")
plt.ylabel('Count',fontsize=18,color='#8a8d93',family="Calibri")
plt.legend(fontsize=16,frameon=False)
for p in ax.patches:
      ax.annotate(f'\n{p.get_height()}', (p.get_x()+0.2, p.get_height()), ha='center',
```

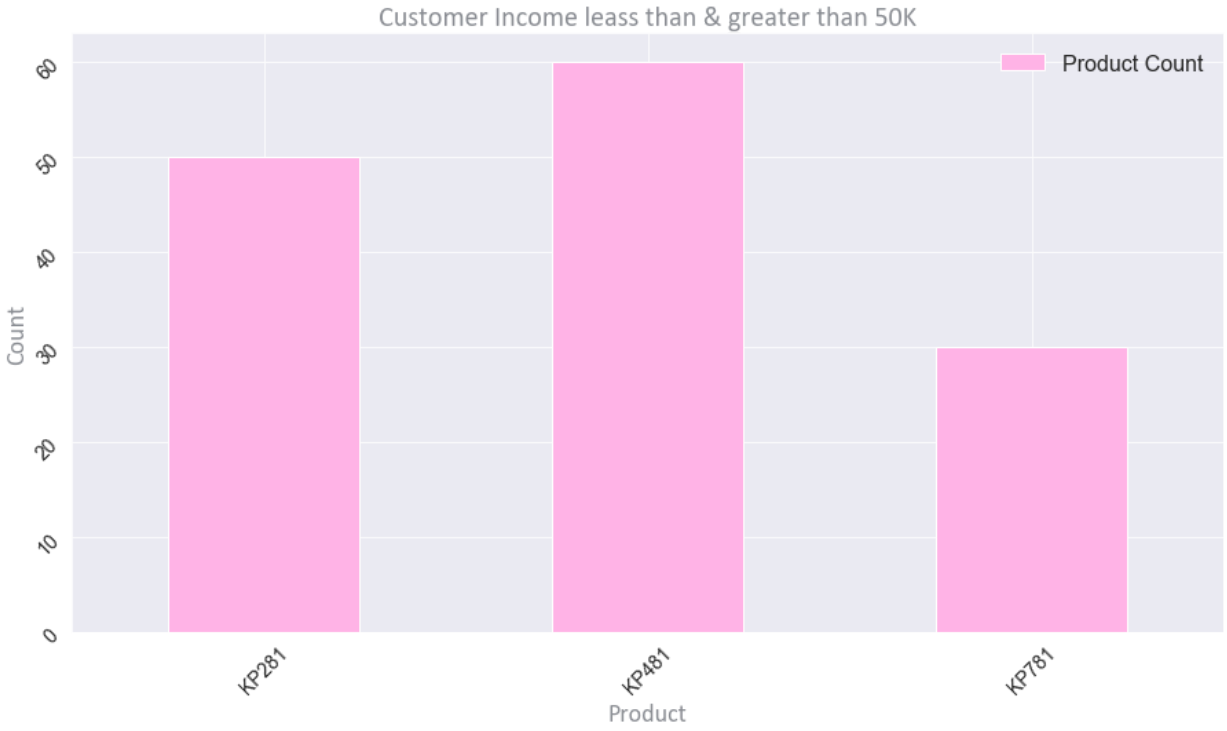


In [ ]:
```
# How is the love for a product for customers aiming average workout(80-150) compared

a = aerofit[(aerofit['Miles']<150) &(aerofit['Miles']>80)]['Product'].value_counts()*1
index = aerofit['Product'].unique().tolist()
frame = {'Product Count':a}
ans = pd.DataFrame(frame,index=index)
ans
```

Out[ ]:

	Product Count
KP281	50.0
KP481	60.0
KP781	30.0

In [ ]:
```
colors = ['#ffb3e6','#c2c2f0']
ans.plot(kind='bar',color=colors,figsize=(15,8))
plt.title("Customer Income leass than & greater than 50K",fontsize=20,color='#8a8d93',
plt.xticks(rotation=45,size=14)
plt.yticks(rotation=45,size=14)
plt.xlabel('Product',fontsize=18,color='#8a8d93',family="Calibri")
plt.ylabel('Count',fontsize=18,color='#8a8d93',family="Calibri")
plt.legend(fontsize=16,frameon=False)
for p in ax.patches:
      ax.annotate(f'\n{p.get_height()}', (p.get_x()+0.2, p.get_height()), ha='center',
```



- *Observation:*
  - The 60% customers who bought TM498 are aiming medium workout(80 - 150 miles per week), where as it is 50% for TM195 and 30% for TM798.

In [ ]:
```
# How values of income, usage, miles etc of females who bought KP781 are different fro

print("All female variable mean values")
print(aerofit[aerofit['Gender'] == 'Female'].mean())
print('-'*50)
print("Female who bought KP781 - variable mean values")
print(aerofit[(aerofit['Product'] == 'KP781') & (aerofit['Gender'] == 'Female')].mean(
```

```
All female variable mean values
Age             28.565789
Education       15.394737
Usage            3.184211
Fitness          3.026316
Income       49828.907895
Miles           90.013158
dtype: float64
--------------------------------------------------
Female who bought KP781 - variable mean values
Age             27.000000
Education       17.857143
Usage            5.000000
Fitness          4.571429
Income       73633.857143
Miles          180.000000
dtype: float64
```

- *Observation:*
  - It can be seen that females who bought KP781 have higher income, expected to run/walk more miles and are more fit.

Recommendations

1. Customers having very good fitness, expecting to use more number of times per week and those who expect to workout for more miles are interested in buying product KP718.
2. Even though products KP418 and KP218 have a similar customer base, the significant majority of people who bought KP418 are mid-income and those who expect to do medium workout.
3. Female customer of KP218 and KP418 are same, instaed of building both model, Aerofit can build only 1 model also.
4. Most sale is covered by male Customer and partened Customer.
5. Income lower than 50K are most prefer KP218 and KP418 Model.
6. Customer having higher income more than $55K , have must good fitness rate and miles travelled mostly prefer KP718 Model.

Customer Profile for Treadmill Products

KP218

1. Gender - Male or Female
2. Age - 18 to 33
3. Marital Status - Single or Partnered
4. Education - 12 to 16 years
5. Income - $29Kto$53K
6. Usage - 2 to 4 times per week
7. Miles - 38 to 94 miles per week
8. Fitness - 1 to 3

KP418

1. Gender - Male or Female
2. Age - 19 to 33
3. Marital Status - Single or Partnered
4. Education - 12 to 16 years
5. Income - $31Kto$53K
6. Usage - 2 to 3 times per week
7. Miles - 21 to 106 miles per week
8. Fitness - 1 to 3

KP718

1. Gender - Male or Female
2. Age - 24 to 30
3. Marital Status - Single or Partnered
4. Education - 14 to 18 years
5. Income - $48Kto$90K
6. Usage - 3 to 5 times per week
7. Miles - 80 to 200 miles per week
8. Fitness - 3 to 5