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1 CHAPTER 1: DEFINITION OF THE PROBLEM STATEMENT AND ANALYZING BASIC METRICS

##**Introduction to Aerofit**

HISTORY: > `Aerofit` is a leading brand in the field of fitness equipment. Tag line of the Aerofit is `From Fit-less to Fitness`. Aerofit brand is owned by `Nityasach fitness Pvt Ltd` company. The parent company is `M/s Sachdev Sports Co` which was established as early as 1928 by late `Shri. Ram Ratan Sachdev.`

AEROFIT PRODUCTS: > Aerofit provides a product range including machines such as `treadmills`, exercise bikes, gym equipment and fitness accessories to cater to the needs of all categories of people.

##**Problem Definition**

> The market research team at Aerofit wants to identify the `characteristics of the target audience for each type of treadmill` offered by the company.
>
> So that company can provide `better recommendations of the treadmills` to the new customers.
>
> The team decides to investigate whether there are any differences across the product with respect to customer characteristics.
>
> Perform descriptive analytics `to create a customer profile` for each Aerofit treadmill product by developing appropriate tables and charts.
>
> For each Aerofit treadmill product, construct `two-way contingency tables` and compute all `conditinal and marginal probabilities` along with their insights/impact on the business.

##**Dataset**

> The company collected the data on individuals who `purchased a treadmill from the Aerofit stores` during the `prior three months`

###Importing the required Libraries

[167]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
from scipy.stats import binom
from scipy.stats import norm
from scipy.stats import poisson
from scipy.stats import expon
from scipy.stats import lognorm
import io
```

1.0.1 *Importing the dataset `Aerofit_treadmill.csv`*

[168]:
```
# from google.colab import files
# uploaded = files.upload()
```

[169]:
```
aerofit = pd.read_csv(io.BytesIO(uploaded['aerofit_treadmill.csv']))
```

[170]:
```
aerofit.head()
```

[170]:

	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

1.0.2 *Details regarding each column in dataset*

Details	Regarding information
Product Purchased:	KP281, KP481, KP781
Age:	In years
Gender:	Male/Female
Education:	In years
Marital Status:	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 and 5 is the excellent shape
Miles:	The average number of miles the customer expects to walk/run each week

1.0.3 *Treadmill Product Portfolio*

The KP281 is an entry-level treadmill that sells for $1500.

The KP481 is for mid-level runners that sell for $1750.

The KP781 is having advanced features that sell for $2500.

Analysing Basic metrics

Observations on shape of data, data types of all the attributes, conversion of categorical attributes to 'category' (If required), statistical summary

[171]:
```
#Length of data
len(aerofit)
```

[171]:
```
180
```

Number of rows in given dataset = 180

[172]:
```
# Checking datatypes
aerofit.dtypes
```

[172]:
```
Product          object
Age               int64
Gender           object
Education         int64
MaritalStatus    object
Usage             int64
Fitness           int64
Income            int64
Miles             int64
dtype: object
```

String or Text related columns are with `Object` datatype. Whereas All remaining number related columns are with `int64` datatype.

[173]:
```
#number of unique values in given dataset
for i in aerofit.columns:
    print(i,":",aerofit[i].nunique())
```

```
Product : 3
Age : 32
Gender : 2
Education : 8
MaritalStatus : 2
Usage : 6
Fitness : 5
Income : 62
Miles : 37
```

Product has only 3 unique categories: KP281, KP481, KP781

Gender has 2 categories: Male or Female

Marital Status has 2 categories: Single or Partnered

Range of Attributes

[174]:
```
# Minimum and Maximum values of Numerical columns such as -
# Age, Education years, Usage years, Income, Miles columns
L = ["Age","Education","Usage","Fitness","Income","Miles"]
for i in L:
    print("Maximum value of ",i,"is",aerofit[i].max())
    print("Minimum value of ",i,"is",aerofit[i].min())
```

```
Maximum value of  Age is 50
Minimum value of  Age is 18
Maximum value of  Education is 21
Minimum value of  Education is 12
Maximum value of  Usage is 7
Minimum value of  Usage is 2
Maximum value of  Fitness is 5
Minimum value of  Fitness is 1
Maximum value of  Income is 104581
Minimum value of  Income is 29562
Maximum value of  Miles is 360
Minimum value of  Miles is 21
```

Range of Age is 18 to 50 years

Range of Education life in years is 12 to 21 years

Range of Usage of treadmill is 2 to 7 years

Range of Fitness rating is 1 to 5

Range of Income is $29562 to $104581 per year

Range of Miles runned on treadmill is 21 to 360 miles

[175]:
```
#Statistical Summary
aerofit.describe(include="all")
```

[175]:

	Product	Age	Gender	Education	MaritalStatus	Usage	\
count	180	180.000000	180	180.000000	180	180.000000	
unique	3	NaN	2	NaN	2	NaN	
top	KP281	NaN	Male	NaN	Partnered	NaN	
freq	80	NaN	104	NaN	107	NaN	
mean	NaN	28.788889	NaN	15.572222	NaN	3.455556	
std	NaN	6.943498	NaN	1.617055	NaN	1.084797	
min	NaN	18.000000	NaN	12.000000	NaN	2.000000	
25%	NaN	24.000000	NaN	14.000000	NaN	3.000000	
50%	NaN	26.000000	NaN	16.000000	NaN	3.000000	
75%	NaN	33.000000	NaN	16.000000	NaN	4.000000	
max	NaN	50.000000	NaN	21.000000	NaN	7.000000	

	Fitness	Income	Miles
count	180.000000	180.000000	180.000000

```
unique         NaN            NaN         NaN
top            NaN            NaN         NaN
freq           NaN            NaN         NaN
mean      3.311111   53719.577778  103.194444
std       0.958869   16506.684226   51.863605
min       1.000000   29562.000000   21.000000
25%       3.000000   44058.750000   66.000000
50%       3.000000   50596.500000   94.000000
75%       4.000000   58668.000000  114.750000
max       5.000000  104581.000000  360.000000
```

Mean > age: 28.7888 years > Education life : 15.5722 years > Usage years: 3.4555 years > Fitness rating: 3.3111 > Income: $53719.5777 > Miles runned: 103.1944 miles

Standard Deviation > age: 6.9434 years > Education life : 1.6170 years > Usage years: 1.0847 years > Fitness rating: 0.9588 > Income: $16506.6842 > Miles runned: 51.8636 miles

Median or 50% percentile > age: 26 years > Education life : 16 years > Usage years: 3 years > Fitness rating: 3 > Income: $50596.5 > Miles runned: 94 miles

[176]:
```
#mode value of each column
print("Mode values of all columns (both categorical and numerical")
aerofit.mode()
```

```
Mode values of all columns (both categorical and numerical
```

[176]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	25	Male	16	Partnered	3	3	45480	85

2 CHAPTER 2: MISSING VALUE AND OUTLIER DETECTION

##**Missing value Detection**

[177]:
```
#checking null values in every column of our data
aerofit.isnull().sum()
```

[177]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

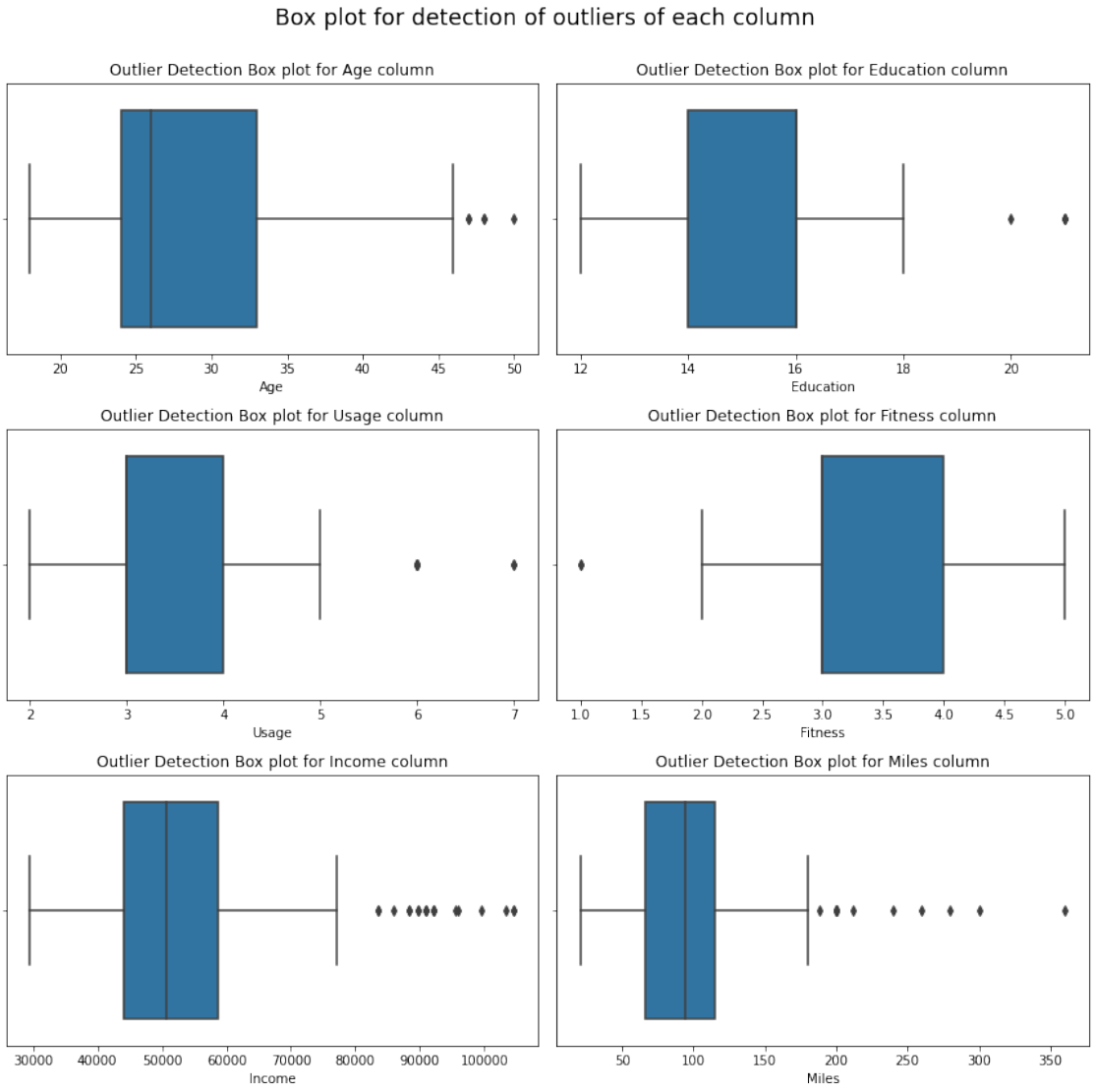
Interestingly, No null values in the given dataset

So no need to do any type of imputations or no need to handle null values

##**Outlier Detection**

###Boxplot for detection of outliers of each column

[178]:
```
fig = plt.figure(figsize = (12,12))
fig.suptitle("Box plot for detection of outliers of each column\n",fontsize =␣
 ↪"xx-large" )
iloc_positions_of_numerical_columns = [1,3,5,6,7,8]
k = 1
for i in iloc_positions_of_numerical_columns:
    plt.subplot(3,2,k)
    plt.title("Outlier Detection Box plot for {} column".format(aerofit.
 ↪columns[i]))
    plt.xlabel(aerofit.columns[i])
    sns.boxplot(data=aerofit, x = aerofit.iloc[:,i],orient="h")
    k = k+1
plt.tight_layout()
plt.show()
```



More number of outliers are observed in Income and Miles column

2.0.1 Finding Outliers using Statistical methods

[179]:
```
#create a function to find outliers using IQR
def find_outliers_IQR(df):
    q1=df.quantile(0.25)
    q3=df.quantile(0.75)
    IQR=q3-q1
    outliers = df[((df<(q1-1.5*IQR)) | (df>(q3+1.5*IQR)))]
    return outliers
iloc_positions_of_numerical_columns = [1,3,5,6,7,8]
for i in iloc_positions_of_numerical_columns:
```

```
    outliers = find_outliers_IQR(aerofit.iloc[:,i])
    print("Outliers of {}".format(aerofit.columns[i]))
    print("number of outliers of {}: ".format(aerofit.columns[i])+␣
↪str(len(outliers)))
    print("max outlier value of {}: ".format(aerofit.columns[i])+ str(outliers.
↪max()))
    print("min outlier value of {}: ".format(aerofit.columns[i])+ str(outliers.
↪min()),end="\n\n")
```

```
Outliers of Age
number of outliers of Age: 5
max outlier value of Age: 50
min outlier value of Age: 47

Outliers of Education
number of outliers of Education: 4
max outlier value of Education: 21
min outlier value of Education: 20

Outliers of Usage
number of outliers of Usage: 9
max outlier value of Usage: 7
min outlier value of Usage: 6

Outliers of Fitness
number of outliers of Fitness: 2
max outlier value of Fitness: 1
min outlier value of Fitness: 1

Outliers of Income
number of outliers of Income: 19
max outlier value of Income: 104581
min outlier value of Income: 83416

Outliers of Miles
number of outliers of Miles: 13
max outlier value of Miles: 360
min outlier value of Miles: 188
```

2.0.2 Bounding/Capping the outliers to upper or lower limits

[180]:
```
aerofit.describe()
```

[180]:

	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
```

[181]:
```
iloc_positions_of_numerical_columns = [1,3,5,6,7,8]
for i in iloc_positions_of_numerical_columns:
    # finding upper limit and lower limit by using 3 sigma on either side of␣
 ↪mean value
    upper_limit = aerofit.iloc[:,i].mean() + 3*aerofit.iloc[:,i].std()
    print("The upper bound limit of {} is ".format(aerofit.
 ↪columns[i]),upper_limit)
    lower_limit = aerofit.iloc[:,i].mean() - 3*aerofit.iloc[:,i].std()
    print("The lower bound limit of {} is ".format(aerofit.
 ↪columns[i]),lower_limit)
    aerofit.iloc[:,i] = np.where(aerofit.iloc[:,i] > upper_limit,
                                 upper_limit,
                                 np.where(aerofit.iloc[:,i] <␣
 ↪lower_limit,
                                          lower_limit,aerofit.iloc[:,i]))
print("\nDataset Outliers are Bounded")
```

```
The upper bound limit of Age is  49.61938329508827
The lower bound limit of Age is  7.958394482689503
The upper bound limit of Education is  20.423386915641892
The lower bound limit of Education is  10.721057528802552
The upper bound limit of Usage is  6.709946658744286
The lower bound limit of Usage is  0.2011644523668248
The upper bound limit of Fitness is  6.187716807969046
The lower bound limit of Fitness is  0.434505414253175
The upper bound limit of Income is  103239.63045649364
The lower bound limit of Income is  4199.525099061917
The upper bound limit of Miles is  258.7852584298724
The lower bound limit of Miles is  -52.396369540983486
```

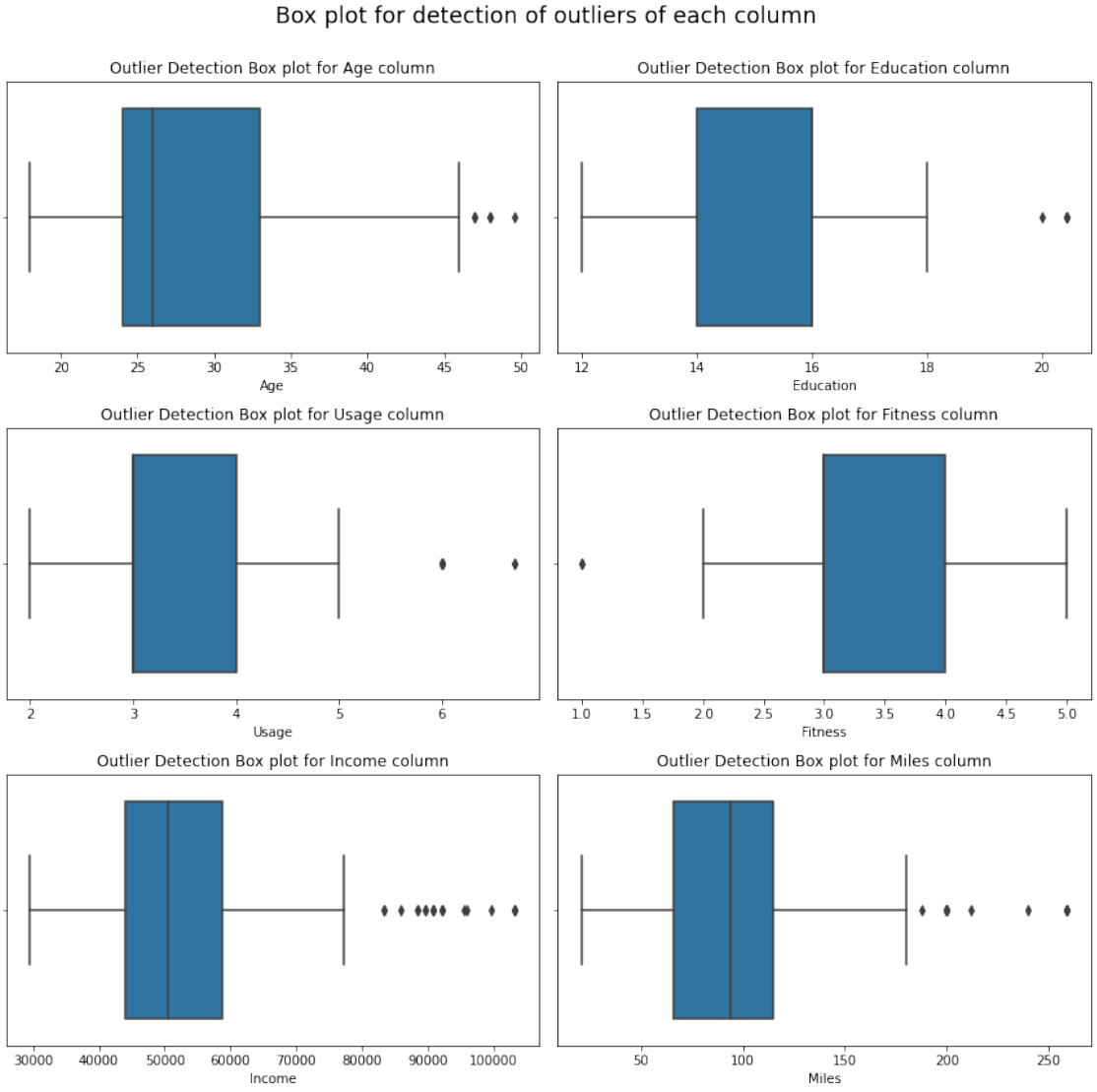
Dataset Outliers are Bounded

[182]:
```
aerofit.describe() # after Bounding the outliers
```

[182]:

	Age	Education	Usage	Fitness	Income	Miles
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000
mean	28.786774	15.562612	3.452333	3.311111	53704.138285	102.278561
std	6.937057	1.586014	1.074588	0.958869	16459.421538	48.302671
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	49.619383	20.423387	6.709947	5.000000	103239.630456	258.785258

[183]:
```
# Box plot after bounding
fig = plt.figure(figsize = (12,12))
fig.suptitle("Box plot for detection of outliers of each column\n",fontsize =␣
 ↪"xx-large" )
iloc_positions_of_numerical_columns = [1,3,5,6,7,8]
k = 1
for i in iloc_positions_of_numerical_columns:
    plt.subplot(3,2,k)
    plt.title("Outlier Detection Box plot for {} column".format(aerofit.
 ↪columns[i]))
    plt.xlabel(aerofit.columns[i])
    sns.boxplot(data=aerofit, x = aerofit.iloc[:,i],orient="h")
    k = k+1
plt.tight_layout()
plt.show()
```



By Bounding the outliers to upper limit or lower limit, There is `difference between statistical values of miles column`. Number of outliers in Miles are decreased

2.0.3 Important Observations:

1. There are `no NULL Values` in the dataset.
2. There are 3 Threadmills. `KP281 (Low range), KP481 (Mid range) and KP781 (High range)`
3. KP281 is mostly bought product. (`USERS CHOICE`)
4. There are 180 customers data records. Out of 180, `Male : Female = 104 : 76,Single: Partnered = 73 : 107`
5. `25% of customers have Age below 24 years and 75% of customers have Age below 33 years`. Range of Age is 18 to 50 years.
6. `25% of customers have Education life below 14 years and 75% of customers`

have Education life below 16 years. Range of Education life is 12 to 21 years.

7. Most of the customers are using the product about 3 to 4 years (according to 75 percentile and 25 percentile)
8. According to Box plot outliers and Statistical analysis using IQR, Number of outliers are more in the Income and Miles column.
9. After Bounding the outliers, The Mean income value modified from $53719 to $53704. The Max income value modified from $104581 to $103239.63
10. After Bounding the outliers, The Mean miles runned modified from 103.19 to 102.27. The Max miles runned modified from 360 to 258.78

3 CHAPTER 3: NON-GRAPHICAL ANALYSIS

3.1 Value counts

[184]:
```
# Checking the occurences of each of the column.
for i in aerofit.columns:
    print(i,aerofit[i].value_counts(),sep="\n")
    print("\n")
```

```
Product
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64


Age
25.000000    25
23.000000    18
24.000000    12
26.000000    12
28.000000     9
35.000000     8
33.000000     8
30.000000     7
38.000000     7
21.000000     7
22.000000     7
27.000000     7
31.000000     6
34.000000     6
29.000000     6
20.000000     5
40.000000     5
32.000000     4
19.000000     4
48.000000     2
37.000000     2
```

```
45.000000     2
47.000000     2
46.000000     1
49.619383     1
18.000000     1
44.000000     1
43.000000     1
41.000000     1
39.000000     1
36.000000     1
42.000000     1
Name: Age, dtype: int64


Gender
Male      104
Female     76
Name: Gender, dtype: int64


Education
16.000000    85
14.000000    55
18.000000    23
15.000000     5
13.000000     5
12.000000     3
20.423387     3
20.000000     1
Name: Education, dtype: int64


MaritalStatus
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64


Usage
3.000000    69
4.000000    52
2.000000    33
5.000000    17
6.000000     7
6.709947     2
Name: Usage, dtype: int64
```

```
Fitness
3.0    97
5.0    31
2.0    26
4.0    24
1.0     2
Name: Fitness, dtype: int64


Income
45480.0    14
52302.0     9
54576.0     8
53439.0     8
46617.0     8
           ..
65220.0     1
55713.0     1
68220.0     1
30699.0     1
95508.0     1
Name: Income, Length: 61, dtype: int64


Miles
85.000000     27
95.000000     12
75.000000     10
66.000000     10
47.000000      9
106.000000     9
94.000000      8
113.000000     8
100.000000     7
53.000000      7
180.000000     6
56.000000      6
200.000000     6
64.000000      6
127.000000     5
160.000000     5
150.000000     4
42.000000      4
258.785258     4
74.000000      3
170.000000     3
120.000000     3
38.000000      3
```

```
103.000000     3
132.000000     2
141.000000     2
212.000000     1
169.000000     1
21.000000      1
140.000000     1
188.000000     1
80.000000      1
240.000000     1
112.000000     1
Name: Miles, dtype: int64
```

3.2 Unique Attributes

[185]:
```
# Checking the unique attributes for all columns
for i in aerofit.columns:
    print(i,aerofit[i].unique(),sep="\n")
    print("\n")
```

```
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.
 43.        44.        46.        47.        49.6193833 45.
 48.        42.       ]


Gender
['Male' 'Female']


Education
[14.         15.         12.         13.         16.         18.
 20.         20.42338692]


MaritalStatus
['Single' 'Partnered']
```

```
Usage
[3.         2.         4.         5.         6.         6.70994666]


Fitness
[4. 3. 2. 1. 5.]


Income
[ 29562.          31836.          30699.          32973.
  35247.          37521.          36384.          38658.
  40932.          34110.          39795.          42069.
  44343.          45480.          46617.          48891.
  53439.          43206.          52302.          51165.
  50028.          54576.          68220.          55713.
  60261.          67083.          56850.          59124.
  61398.          57987.          64809.          47754.
  65220.          62535.          48658.          54781.
  48556.          58516.          53536.          61006.
  57271.          52291.          49801.          62251.
  64741.          70966.          75946.          74701.
  69721.          83416.          88396.          90886.
  92131.          77191.          52290.          85906.
 103239.63045649  99601.          89641.          95866.
  95508.        ]


Miles
[112.          75.          66.          85.          47.
 141.         103.          94.         113.          38.
 188.          56.         132.         169.          64.
  53.         106.          95.         212.          42.
 127.          74.         170.          21.         120.
 200.         140.         100.          80.         160.
 180.         240.         150.         258.78525843]
```

##Cross_tab - Marginal and Conditional Probabilities

[186]:
```
pd.crosstab(aerofit["MaritalStatus"],aerofit["Product"],margins=True)
```

[186]:
```
Product        KP281  KP481  KP781  All
MaritalStatus
Partnered         48     36     23  107
Single            32     24     17   73
All               80     60     40  180
```

MARGINAL PROBABILITIES

What is the probability that a customer is single? Ans: 73/180 = 0.4055

What is the probability that a customer is partnered? Ans: 107/180 = 0.5944

What is the probability that a customer buys KP281? Ans: 80/180 = 0.4444

What is the probability that a customer buys KP481? Ans: 60/180 = 0.3333

What is the probability that a customer buys KP781? Ans: 40/180 = 0.2222

CONDITIONAL PROBABILITIES

What is the probability that a customer buys KP281, given that he/she is single? Ans: 32/73 = 0.4383

What is the probability that a customer buys KP281, given that he/she is Partnered? Ans: 48/107 = 0.4485

What is the probability that a customer buys KP481, given that he/she is single? Ans: 24/73 = 0.3287

What is the probability that a customer buys KP481, given that he/she is Partnered? Ans: 36/107 = 0.3364

What is the probability that a customer buys KP781, given that he/she is single? Ans: 17/73 = 0.2328

What is the probability that a customer buys KP781, given that he/she is Partnered? Ans: 23/107 = 0.2149

[187]:
```
pd.crosstab(aerofit["Gender"],aerofit["Product"],margins=True)
```

[187]:

Product	KP281	KP481	KP781	All
Gender				
Female	40	29	7	76
Male	40	31	33	104
All	80	60	40	180

MARGINAL PROBABILITIES

What is the probability that a customer is Male? Ans: 104/180 = 0.5777

What is the probability that a customer is Female? Ans: 76/180 = 0.4222

CONDITIONAL PROBABILITIES

What is the probability that a customer buys KP281, given that he/she is Male? Ans: 40/104 = 0.3846

What is the probability that a customer buys KP281, given that he/she is Female? Ans: 40/76 = 0.5263

What is the probability that a customer buys KP481, given that he/she is Male? Ans: 31/104 = 0.29807

What is the probability that a customer buys KP481, given that he/she is Female? Ans: $29/76 = 0.3815$

What is the probability that a customer buys KP781, given that he/she is Male? Ans: $33/104 = 0.3173$

What is the probability that a customer buys KP781, given that he/she is Female? Ans: $7/76 = 0.0921$

[188]:
```
pd.
↪crosstab(aerofit["Product"],[aerofit["Gender"],aerofit["MaritalStatus"]],margins␣
↪= True)
```

[188]:

Gender	Female		Male		All
MaritalStatus	Partnered	Single	Partnered	Single	
Product					
KP281	27	13	21	19	80
KP481	15	14	21	10	60
KP781	4	3	19	14	40
All	46	30	61	43	180

CONDITIONAL PROBABILITIES on FEMALE PARTNERED AND SINGLE CUSTOMER

What is the probability that a customer buys KP281 given that she is a female and partnered? Ans: $27/46 = 0.5869$

What is the probability that a customer buys KP481 given that she is a female and partnered? Ans: $15/46 = 0.3260$

What is the probability that a customer buys KP781 given that she is a female and partnered? Ans: $4/46 = 0.0869$

What is the probability that a customer buys KP281 given that she is a female and single? Ans: $13/30 = 0.4333$

What is the probability that a customer buys KP481 given that she is a female and single? Ans: $14/30 = 0.4666$

What is the probability that a customer buys KP781 given that she is a female and single? Ans: $3/30 = 0.1$

CONDITIONAL PROBABILITIES MALE PARTNERED AND SINGLE CUSTOMER

What is the probability that a customer buys KP281 given that she is a male and partnered? Ans: $21/61 = 0.3442$

What is the probability that a customer buys KP481 given that she is a male and partnered? Ans: $21/61 = 0.3442$

What is the probability that a customer buys KP781 given that she is a male and partnered? Ans: $19/61 = 0.3114$

What is the probability that a customer buys KP281 given that she is a male and single? Ans: $19/43 = 0.4418$

What is the probability that a customer buys KP481 given that she is a male and single?
Ans: 10/43 = 0.2325

What is the probability that a customer buys KP781 given that she is a male and single?
Ans: 14/43 = 0.3255

BASED ON GENDER AND PRODUCT, CONDITIONAL PROBABILITIES

What is the probability of customer being a female , given that customer bought KP281?
Ans: 40/80 = 0.5

What is the probability of customer being a male , given that customer bought KP281?
Ans: 40/80 = 0.5

What is the probability of customer being a female , given that customer bought KP481?
Ans: 29/60 = 0.4833

What is the probability of customer being a male , given that customer bought KP481?
Ans: 31/60 = 0.5166

What is the probability of customer being a female , given that customer bought KP781?
Ans: 7/40 = 0.175

What is the probability of customer being a male , given that customer bought KP781?
Ans: 33/40 = 0.825

BASED ON MARITALSTATUS AND PRODUCT, CONDITIONAL PROBABILITIES

What is the probability of customer being a PARTNERED , given that customer bought KP281? Ans: 48/80 = 0.6

What is the probability of customer being a SINGLE , given that customer bought KP281? Ans: 32/80 = 0.4

What is the probability of customer being a PARTNERED , given that customer bought KP481? Ans: 36/60 = 0.6

What is the probability of customer being a SINGLE , given that customer bought KP481? Ans: 24/60 = 0.4

What is the probability of customer being a PARTNERED , given that customer bought KP781? Ans: 23/40 = 0.575

What is the probability of customer being a SINGLE , given that customer bought KP781? Ans: 17/40 = 0.425

3.3 Cross tab with Mean Aggregate function (Categorical vs Numerical columns)

[189]:
```
pd.crosstab(aerofit["Product"],aerofit["MaritalStatus"],values =␣
↪aerofit["Age"],aggfunc = "mean",margins = True)
```

[189]:

MaritalStatus	Partnered	Single	All
Product			
KP281	29.658737	26.875000	28.545242

```
KP481          30.222222  26.916667  28.900000
KP781          29.826087  28.117647  29.100000
All            29.884293  27.178082  28.786774
```

Average age of KP281 Single customers is 26.875

Average age of KP481 Partnered customer is 30.222

[190]:
```
pd.crosstab(aerofit["Product"],aerofit["Gender"],values =␣
↪aerofit["Age"],aggfunc = "mean",margins = True)
```

[190]:
```
Gender      Female       Male        All
Product
KP281    28.440485  28.650000  28.545242
KP481    29.103448  28.709677  28.900000
KP781    27.000000  29.545455  29.100000
All      28.560781  28.951923  28.786774
```

Average age of KP781 female customers is 27

Average age of KP781 male customer is 29.545

[191]:
```
pd.crosstab(aerofit["Product"],aerofit["MaritalStatus"],values =␣
↪aerofit["Education"],aggfunc = "mean",margins = True)
```

[191]:
```
MaritalStatus  Partnered     Single        All
Product
KP281          15.125000  14.906250  15.037500
KP481          15.250000  14.916667  15.116667
KP781          17.409712  17.108634  17.281754
All            15.658162  15.422559  15.562612
```

Average Education life of single customers who bought KP281 is 14.9 years

Average Education life of Partnered Customer who bought KP781 is 17.40 years

[192]:
```
pd.crosstab(aerofit["Product"],aerofit["Gender"],values =␣
↪aerofit["Education"],aggfunc = "mean",margins = True)
```

[192]:
```
Gender      Female       Male        All
Product
KP281    15.100000  14.975000  15.037500
KP481    15.206897  15.032258  15.116667
KP781    17.774770  17.177175  17.281754
All      15.387150  15.690834  15.562612
```

Average Education life of Female customers who bought KP781 is 17.77 years

Average Education life of male Customer who bought KP281 is 14.97 years

[193]:
```
pd.
↪crosstab(aerofit["Product"],[aerofit["Gender"],aerofit["MaritalStatus"]],values␣
↪= aerofit["Education"],aggfunc="mean",margins = True)
```

[193]:

Gender	Female		Male		All
MaritalStatus	Partnered	Single	Partnered	Single	
Product					
KP281	14.888889	15.538462	15.428571	14.473684	15.037500
KP481	15.200000	15.214286	15.285714	14.500000	15.116667
KP781	17.500000	18.141129	17.390705	16.887385	17.281754
All	15.217391	15.647446	15.990547	15.265660	15.562612

Average Education life of Male single customer of KP281 is 14.47 years

Average Education life of Female Single customer of KP781 is 18.141 years

[194]:
```
pd.crosstab(aerofit["Product"],aerofit["MaritalStatus"],values =␣
↪aerofit["Usage"],aggfunc = "mean",margins = True)
```

[194]:

MaritalStatus	Partnered	Single	All
Product			
KP281	3.041667	3.156250	3.087500
KP481	3.055556	3.083333	3.066667
KP781	4.887821	4.588235	4.760497
All	3.443177	3.465753	3.452333

Average Usage of Partnered customers who bought KP281 is 3.0416 per week

Average Usage of Partnered Customer who bought KP781 is 4.887 per week

[195]:
```
pd.crosstab(aerofit["Product"],aerofit["Gender"],values =␣
↪aerofit["Usage"],aggfunc = "mean",margins = True)
```

[195]:

Gender	Female	Male	All
Product			
KP281	2.900000	3.275000	3.087500
KP481	3.137931	3.000000	3.066667
KP781	5.000000	4.709694	4.760497
All	3.184211	3.648268	3.452333

Average Usage of Female customers who bought KP281 is 2.9 per week

Average Usage of male Customer who bought KP781 is 5 per week

[196]:
```
pd.
↪crosstab(aerofit["Product"],[aerofit["Gender"],aerofit["MaritalStatus"]],values␣
↪= aerofit["Usage"],aggfunc="mean",margins = True)
```

[196]:
Gender	Female		Male		All
MaritalStatus	Partnered	Single	Partnered	Single	
Product					
KP281	2.851852	3.000000	3.285714	3.263158	3.087500
KP481	3.333333	2.928571	2.857143	3.300000	3.066667
KP781	5.250000	4.666667	4.811573	4.571429	4.760497
All	3.217391	3.133333	3.613441	3.697674	3.452333

Average Usage of Female Partnered customer of KP281 product is 2.851852 per week

Average Usage of Female Partnered customer of KP781 product is 5.25 per week

[197]:
```
pd.crosstab(aerofit["Product"],aerofit["MaritalStatus"],values =␣
↪aerofit["Income"],aggfunc = "mean",margins = True)
```

[197]:
MaritalStatus	Partnered	Single	All
Product			
KP281	47848.750000	44271.937500	46418.025000
KP481	49522.666667	48150.125000	48973.650000
KP781	81926.343103	66504.588235	75372.097284
All	55737.027022	50724.424658	53704.138285

Average Income of Single customers who bought KP281 is $44271.937

Average Income of Partnered Customer who bought KP781 is $81926.343

[198]:
```
pd.crosstab(aerofit["Product"],aerofit["Gender"],values =␣
↪aerofit["Income"],aggfunc = "mean",margins = True)
```

[198]:
Gender	Female	Male	All
Product			
KP281	46020.075000	46815.975000	46418.025000
KP481	49336.448276	48634.258065	48973.650000
KP781	73633.857143	75740.814890	75372.097284
All	49828.907895	56536.037417	53704.138285

Average Income of Female customers who bought KP281 is $46020.075

Average Income of male Customer who bought KP781 is $73633.857

[199]:
```
pd.
↪crosstab(aerofit["Product"],[aerofit["Gender"],aerofit["MaritalStatus"]],values␣
↪= aerofit["Income"],aggfunc="mean",margins = True)
```

[199]:
Gender	Female		Male		\
MaritalStatus	Partnered	Single	Partnered	Single	
Product					
KP281	46153.777778	45742.384615	50028.000000	43265.842105	
KP481	49724.800000	48920.357143	49378.285714	47071.800000	
KP781	84972.250000	58516.000000	81285.099546	68216.428571	

```
All            50693.760870  48502.800000  59540.145760  52274.395349
```

```
Gender                  All
MaritalStatus
Product
KP281          46418.025000
KP481          48973.650000
KP781          75372.097284
All            53704.138285
```

Average Income of male Single customer of KP281 product is $43265.8421

Average Income of Female Partnered customer of KP781 is $84972.25

[200]:
```
pd.crosstab(aerofit["Product"],aerofit["MaritalStatus"],values =␣
↪aerofit["Fitness"],aggfunc = "mean",margins = True)
```

[200]:
```
MaritalStatus  Partnered    Single       All
Product
KP281           2.854167  3.125000  2.962500
KP481           2.916667  2.875000  2.900000
KP781           4.695652  4.529412  4.625000
All             3.271028  3.369863  3.311111
```

Average Fitness of Partnered customers who bought KP281 is 2.85

Average Fitness of Partnered Customer who bought KP781 is 4.69

[201]:
```
pd.crosstab(aerofit["Product"],aerofit["Gender"],values =␣
↪aerofit["Fitness"],aggfunc = "mean",margins = True)
```

[201]:
```
Gender     Female      Male       All
Product
KP281    2.875000  3.050000  2.962500
KP481    2.862069  2.935484  2.900000
KP781    4.571429  4.636364  4.625000
All      3.026316  3.519231  3.311111
```

Average Fitness of Female customers who bought KP781 is 4.57

Average Fitness of Female Customer who bought KP481 is 2.86

[202]:
```
pd.
↪crosstab(aerofit["Product"],[aerofit["Gender"],aerofit["MaritalStatus"]],values␣
↪= aerofit["Fitness"],aggfunc="mean",margins = True)
```

[202]:
```
Gender           Female                Male                 All
MaritalStatus Partnered    Single Partnered    Single
Product
KP281          2.851852  2.923077  2.857143  3.263158  2.962500
```

```
KP481          2.933333  2.785714  2.904762  3.000000  2.900000
KP781          5.000000  4.000000  4.631579  4.642857  4.625000
All            3.065217  2.966667  3.426230  3.651163  3.311111
```

Average Fitness of female Single customer of KP481 product 2.78

Average Fitness of Female Partnered customer of KP781 is 5

[203]:
```
pd.crosstab(aerofit["Product"],aerofit["MaritalStatus"],values =␣
↪aerofit["Miles"],aggfunc = "mean",margins = True)
```

[203]:
```
MaritalStatus   Partnered      Single         All
Product
KP281            77.229167   91.125000   82.787500
KP481            90.055556   84.750000   87.933333
KP781           175.875697  145.058824  162.778526
All             102.748982  101.589041  102.278561
```

Average Miles runned by Partnered customers who bought KP281 is 77.22 miles

Average Miles runned by Partnered Customer who bought KP781 is 175.875 miles

[204]:
```
pd.crosstab(aerofit["Product"],aerofit["Gender"],values =␣
↪aerofit["Miles"],aggfunc = "mean",margins = True)
```

[204]:
```
Gender       Female        Male         All
Product
KP281     76.200000   89.375000   82.787500
KP481     87.344828   88.483871   87.933333
KP781    176.969323  159.768357  162.778526
All       89.734017  111.445729  102.278561
```

Average Miles runned by Female customers who bought KP781 is 176.96 miles

Average Miles runned by Female Customer who bought KP281 is 76.2 miles

[205]:
```
pd.
↪crosstab(aerofit["Product"],[aerofit["Gender"],aerofit["MaritalStatus"]],values␣
↪= aerofit["Miles"],aggfunc="mean",margins = True)
```

[205]:
```
Gender             Female                    Male                       All
MaritalStatus   Partnered      Single   Partnered      Single
Product
KP281            74.925926   78.846154   80.190476   99.526316   82.787500
KP481            94.000000   80.214286   87.238095   91.100000   87.933333
KP781           209.696315  133.333333  168.755567  147.571429  162.778526
All              92.864897   84.933333  110.202554  113.209302  102.278561
```

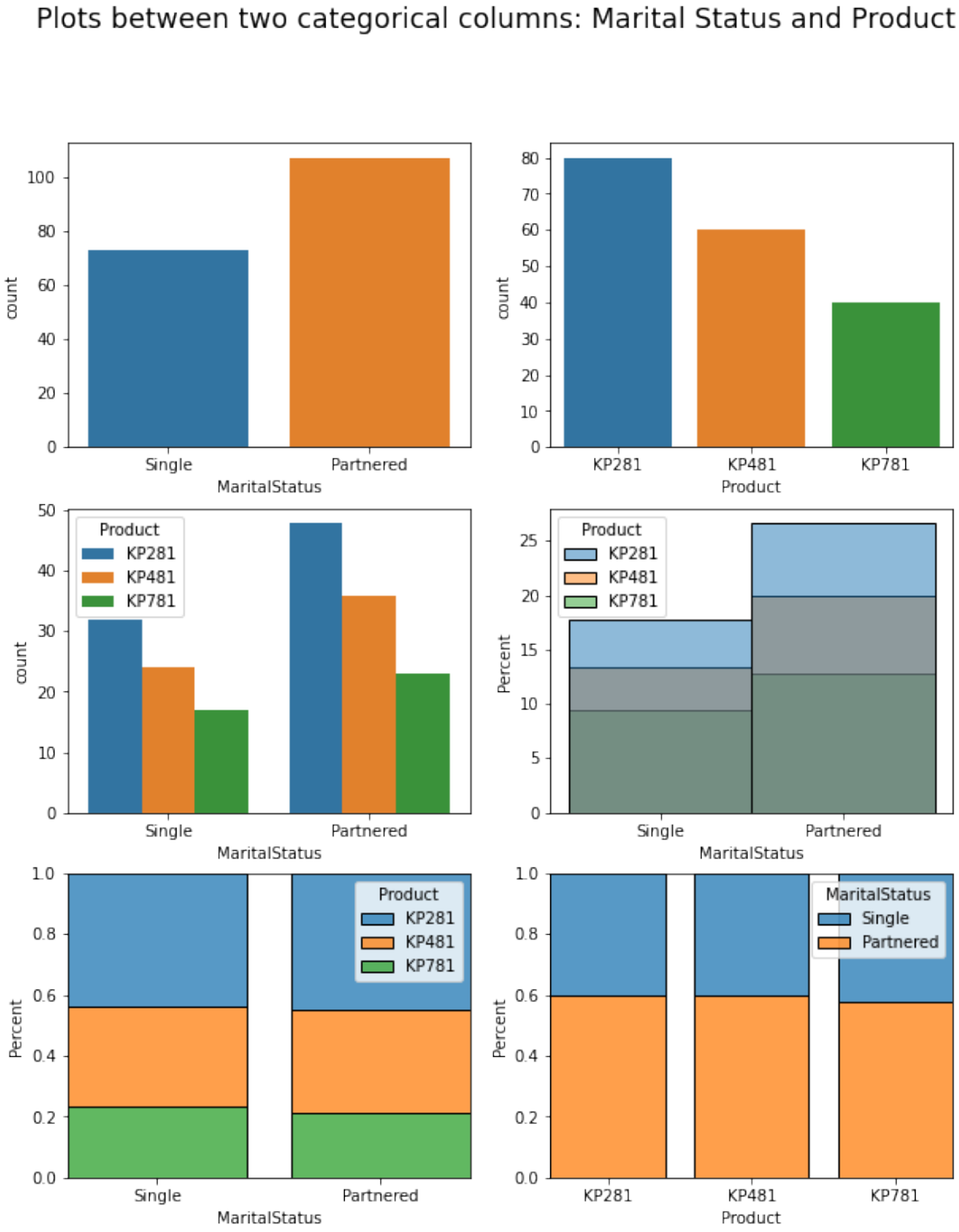
Average Miles runned by female Partnered customer of KP281 product 74.92

Average Miles runned by Female Partnered customer of KP781 is 209.69

4 CHAPTER 4: VISUAL ANALYSIS

##Univariate and Bivariate Plots between two categorical columns: Marital Status and Product

[206]:
```
plt.figure(figsize=(10,12))
plt.suptitle("Plots between two categorical columns: Marital Status and␣
 ↪Product",fontsize = "xx-large")
plt.subplot(3,2,1)
sns.countplot(data=aerofit,x="MaritalStatus")
plt.subplot(3,2,2)
sns.countplot(data=aerofit,x="Product")
plt.subplot(3,2,3)
sns.countplot(data=aerofit,x="MaritalStatus",hue="Product")
plt.subplot(3,2,4)
sns.histplot(data=aerofit,x="MaritalStatus",hue="Product",stat="percent")
plt.subplot(3,2,5)
sns.
 ↪histplot(data=aerofit,x="MaritalStatus",hue="Product",stat="percent",multiple="fill",shrink
 ↪8)
plt.subplot(3,2,6)
sns.
 ↪histplot(data=aerofit,x="Product",hue="MaritalStatus",stat="percent",multiple="fill",shrink
 ↪8)
plt.show()
```



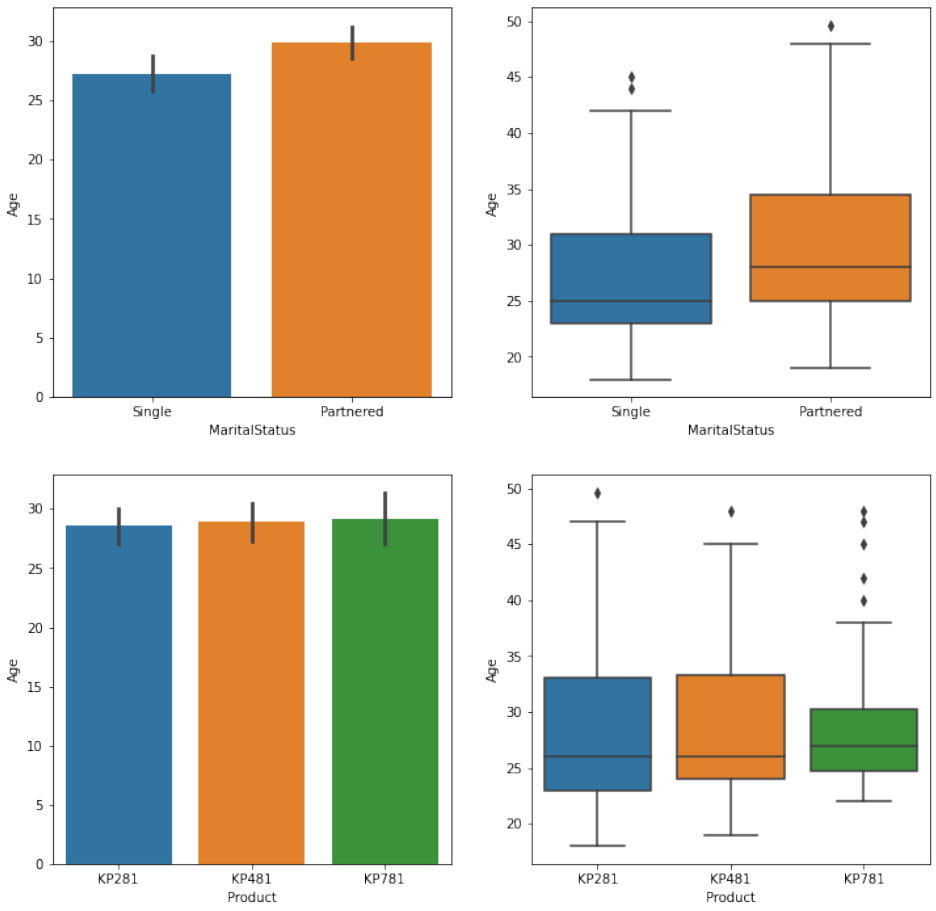
Observations from above graphs: > Number of partnered customers were greater than Number of Single customers

Descending order sequence of Number of customer of each product is KP 281 –> 481 –> 781 (Same trend is followed for Single and partnered customers individually also)

```
According to stacked hist plot, slightly more Percentage of single
customers were bought KP 781. Whereas Slightly more percentage of
partnered customers were bought KP 281.
```

##Bivariate Plots between categorical columns 'Product','MaritalStatus' and numerical column 'Age'

[207]:
```
plt.figure(figsize=(12,12))
plt.suptitle("Bivariate Plots between categorical columns␣
 ↪'Product','MaritalStatus' and numerical column 'Age'",fontsize = "xx-large")
plt.subplot(2,2,1)
sns.barplot(data=aerofit,x="MaritalStatus",y="Age")
plt.subplot(2,2,2)
sns.boxplot(data=aerofit,x="MaritalStatus",y="Age")
plt.subplot(2,2,3)
sns.barplot(data=aerofit,x="Product",y="Age")
plt.subplot(2,2,4)
sns.boxplot(data=aerofit,x="Product",y="Age")
plt.show()
```



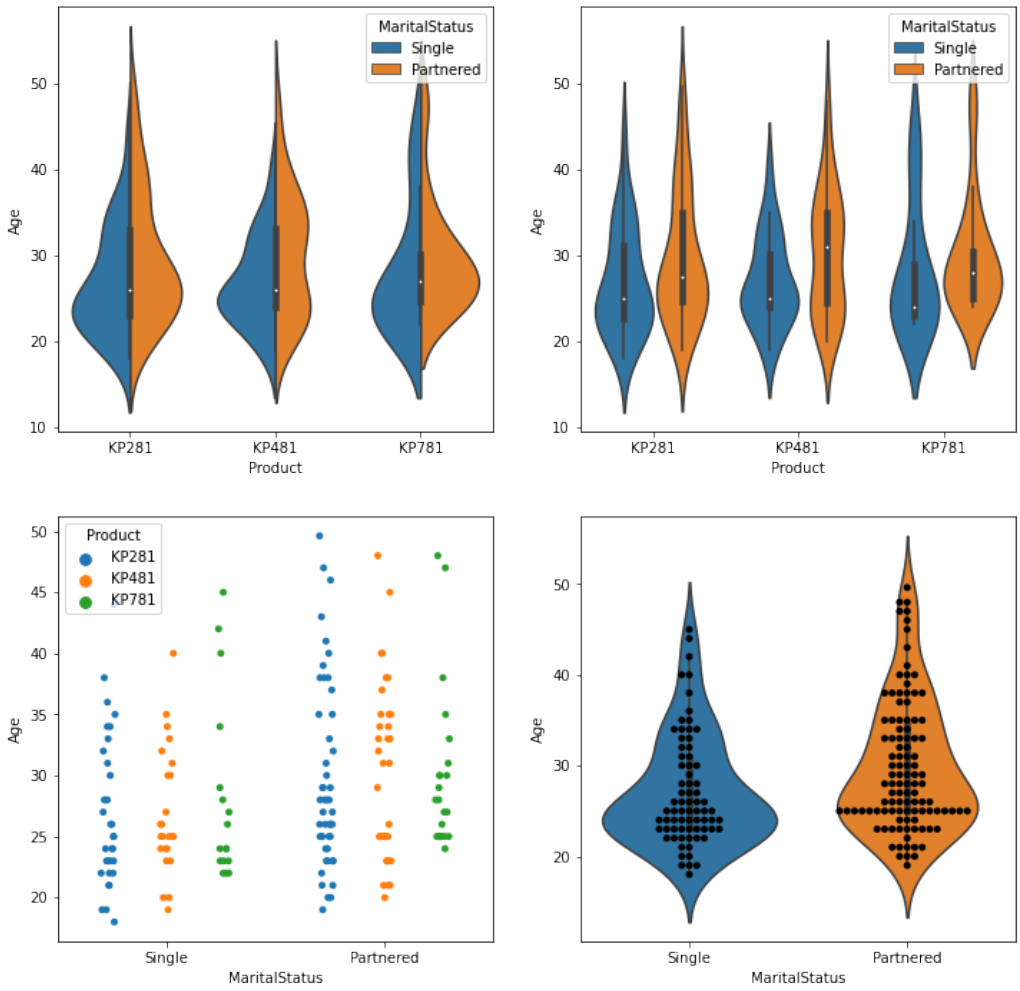
with respect to Age, KP281 product is dispersed over all types of ages. But KP 781 has more number of outliers. It is mostly prefered from Age range of 24 to 30 years.

All percentile values of partnered customers are having higher values than single customers.

##Trivariate Plots between categorical columns 'Product','Marital Status' and numerical column 'Age'

[208]:
```
plt.figure(figsize=(12,12))
plt.suptitle("Trivariate Plots between categorical columns 'Marital Status' and␣
 ↪numerical column 'Age'",fontsize = "xx-large")
plt.subplot(2,2,1)
sns.violinplot(data=aerofit,x="Product",y="Age",hue =␣
 ↪"MaritalStatus",split=True)
plt.subplot(2,2,2)
sns.violinplot(data=aerofit,x="Product",y="Age",hue =␣
 ↪"MaritalStatus",split=False)
plt.subplot(2,2,3)
sns.stripplot(data=aerofit,x="MaritalStatus",y="Age",hue = "Product",jitter =␣
 ↪True, dodge = True,)
plt.subplot(2,2,4)
sns.violinplot(data=aerofit,x="MaritalStatus",y="Age")
sns.swarmplot(data=aerofit,x="MaritalStatus",y="Age",color="black")
plt.show()
```

Trivariate Plots between categorical columns 'Marital Status' and numerical column 'Age'



4.1 Binning of Age column

[209]:
```
bins = list(range(18,51,4))
bins.insert(0,-np.inf)
bins.append(np.inf)
bins
```

[209]: [-inf, 18, 22, 26, 30, 34, 38, 42, 46, 50, inf]

[210]:
```
aerofit_bins = aerofit.copy(deep = True)
aerofit_bins["Age_bins"] = pd.cut(aerofit["Age"],bins)
```

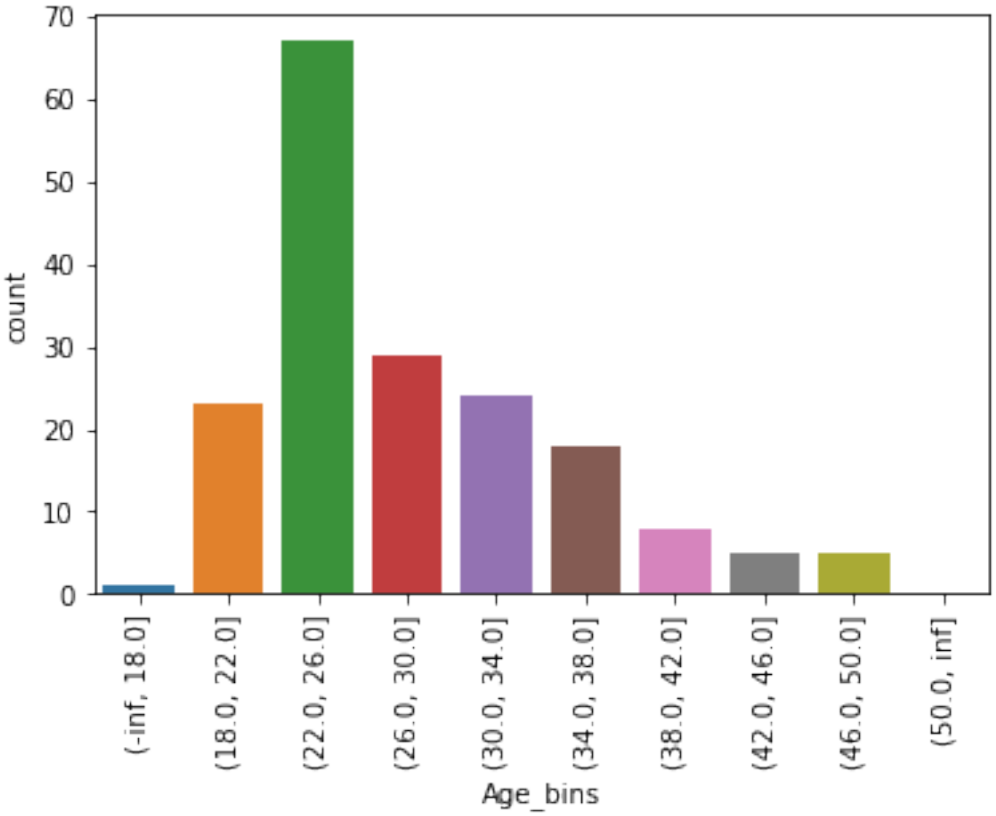
[211]:
```
aerofit_bins["Age_bins"].value_counts()
```

[211]:
```
(22.0, 26.0]    67
(26.0, 30.0]    29
(30.0, 34.0]    24
(18.0, 22.0]    23
(34.0, 38.0]    18
(38.0, 42.0]     8
(42.0, 46.0]     5
(46.0, 50.0]     5
(-inf, 18.0]     1
(50.0, inf]      0
Name: Age_bins, dtype: int64
```

[212]:
```
pd.crosstab(aerofit_bins["MaritalStatus"], aerofit_bins["Age_bins"],margins =␣
↪True)
```

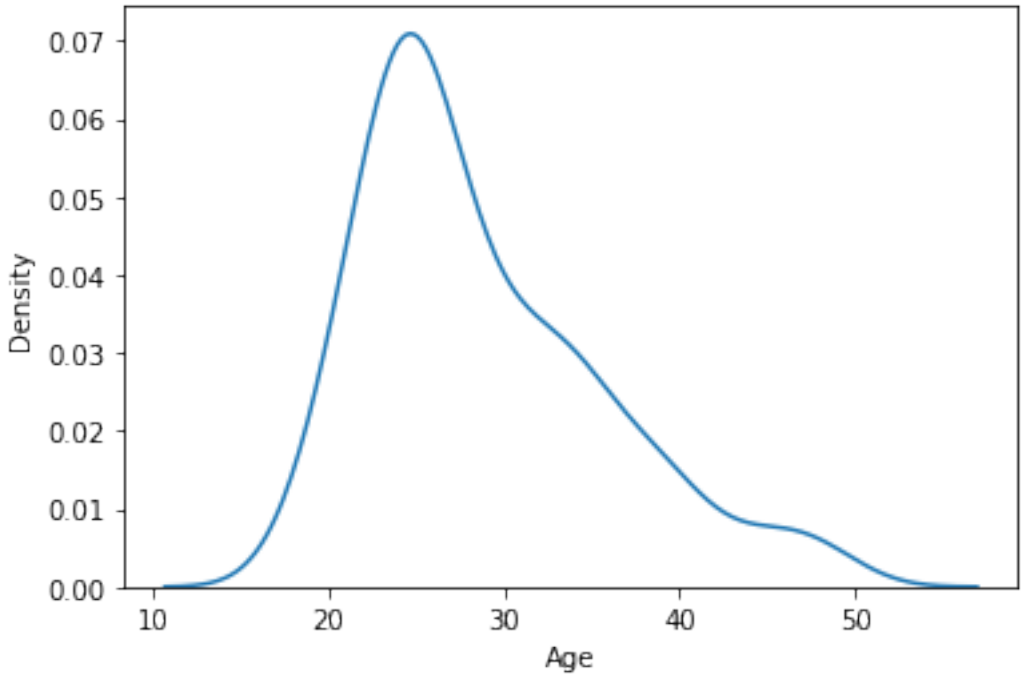
[212]:
```
Age_bins       (-inf, 18.0]  (18.0, 22.0]  (22.0, 26.0]  (26.0, 30.0]  \
MaritalStatus
Partnered                 0            10            37            19
Single                    1            13            30            10
All                       1            23            67            29

Age_bins       (30.0, 34.0]  (34.0, 38.0]  (38.0, 42.0]  (42.0, 46.0]  \
MaritalStatus
Partnered                14            14             5             3
Single                   10             4             3             2
All                      24            18             8             5

Age_bins       (46.0, 50.0]  All
MaritalStatus
Partnered                 5  107
Single                    0   73
All                       5  180
```

[213]:
```
sns.countplot(data=aerofit_bins,x="Age_bins")
plt.xticks(rotation=90)
plt.show()
```



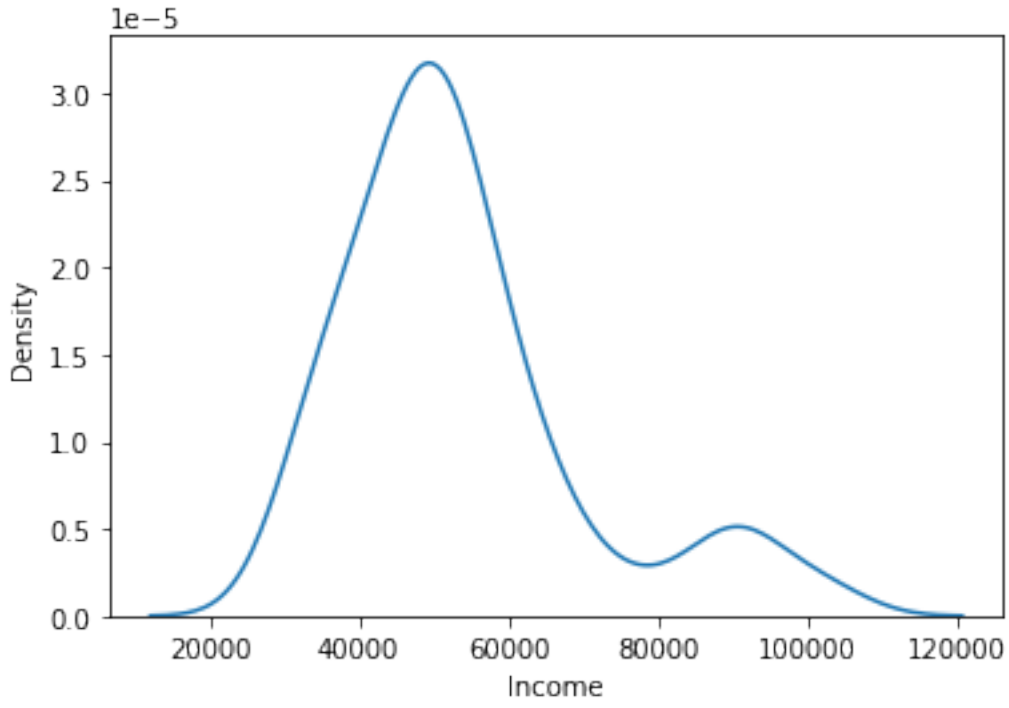
[214]:
```
sns.kdeplot(data = aerofit, x="Age",)
```

[214]: <AxesSubplot:xlabel='Age', ylabel='Density'>



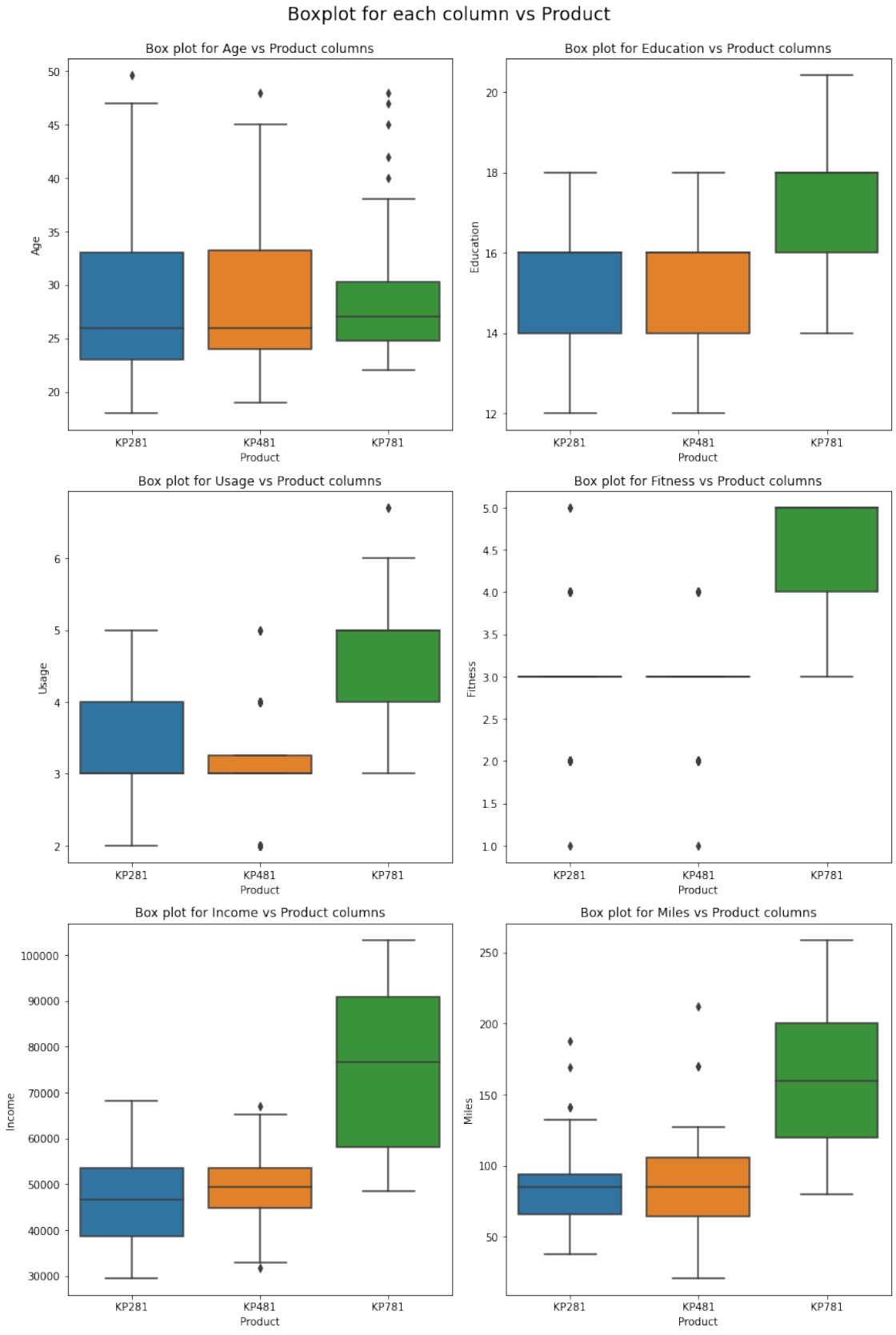
[215]:
```
sns.kdeplot(data = aerofit, x="Income",)
```

[215]: <AxesSubplot:xlabel='Income', ylabel='Density'>



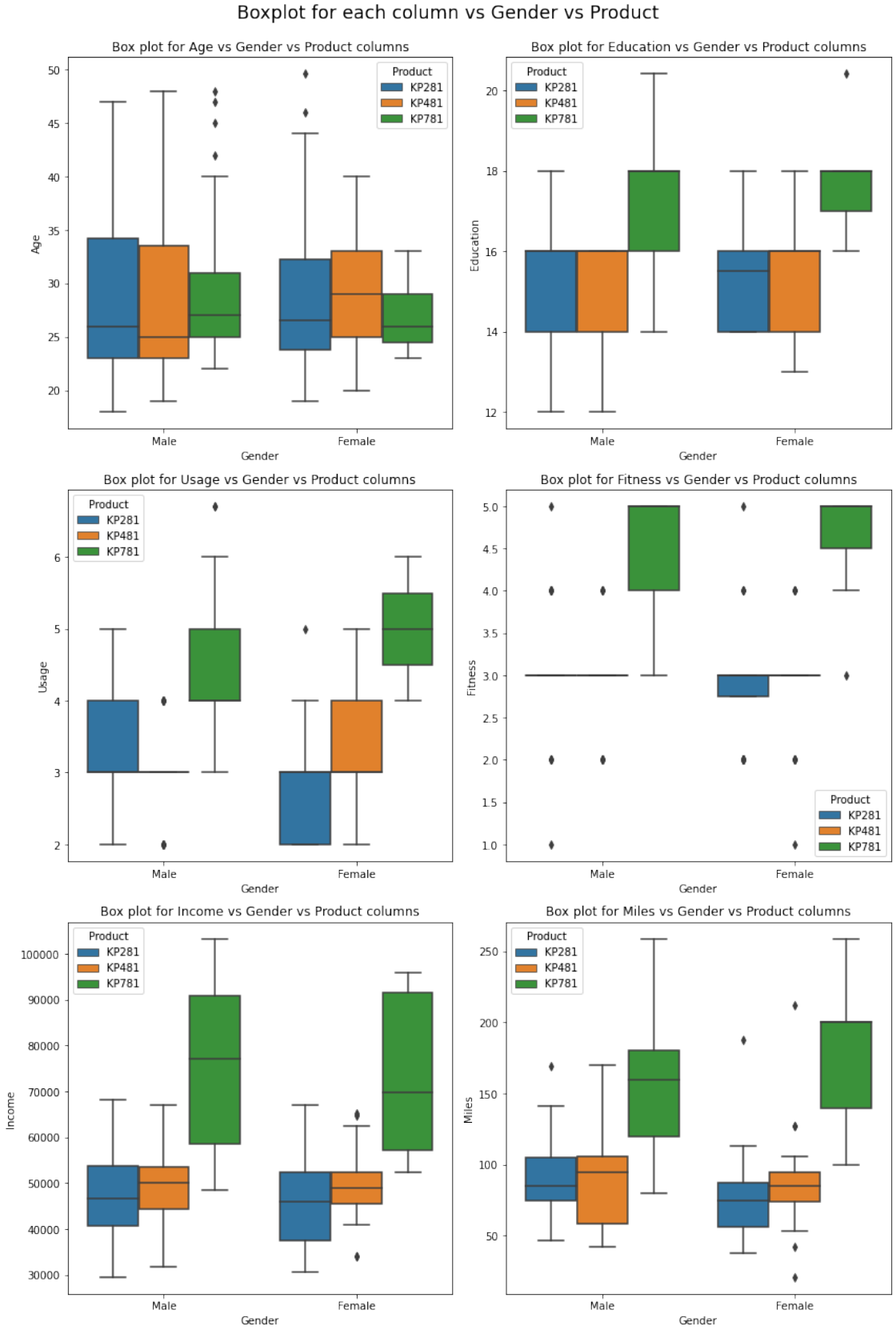
##Box plots with respect to products

[216]:
```
#create a Boxplots
fig = plt.figure(figsize = (12,18))
fig.suptitle("Boxplot for each column vs Product\n",fontsize = "xx-large" )
iloc_positions_of_numerical_columns = [1,3,5,6,7,8]
k = 1
for i in iloc_positions_of_numerical_columns:
    plt.subplot(3,2,k)
    plt.title("Box plot for {} vs Product columns".format(aerofit.columns[i]))
    plt.xlabel(aerofit.columns[i])
    sns.boxplot(data=aerofit, x="Product",y = aerofit.iloc[:,i])
    k = k+1
plt.tight_layout()
plt.show()
```

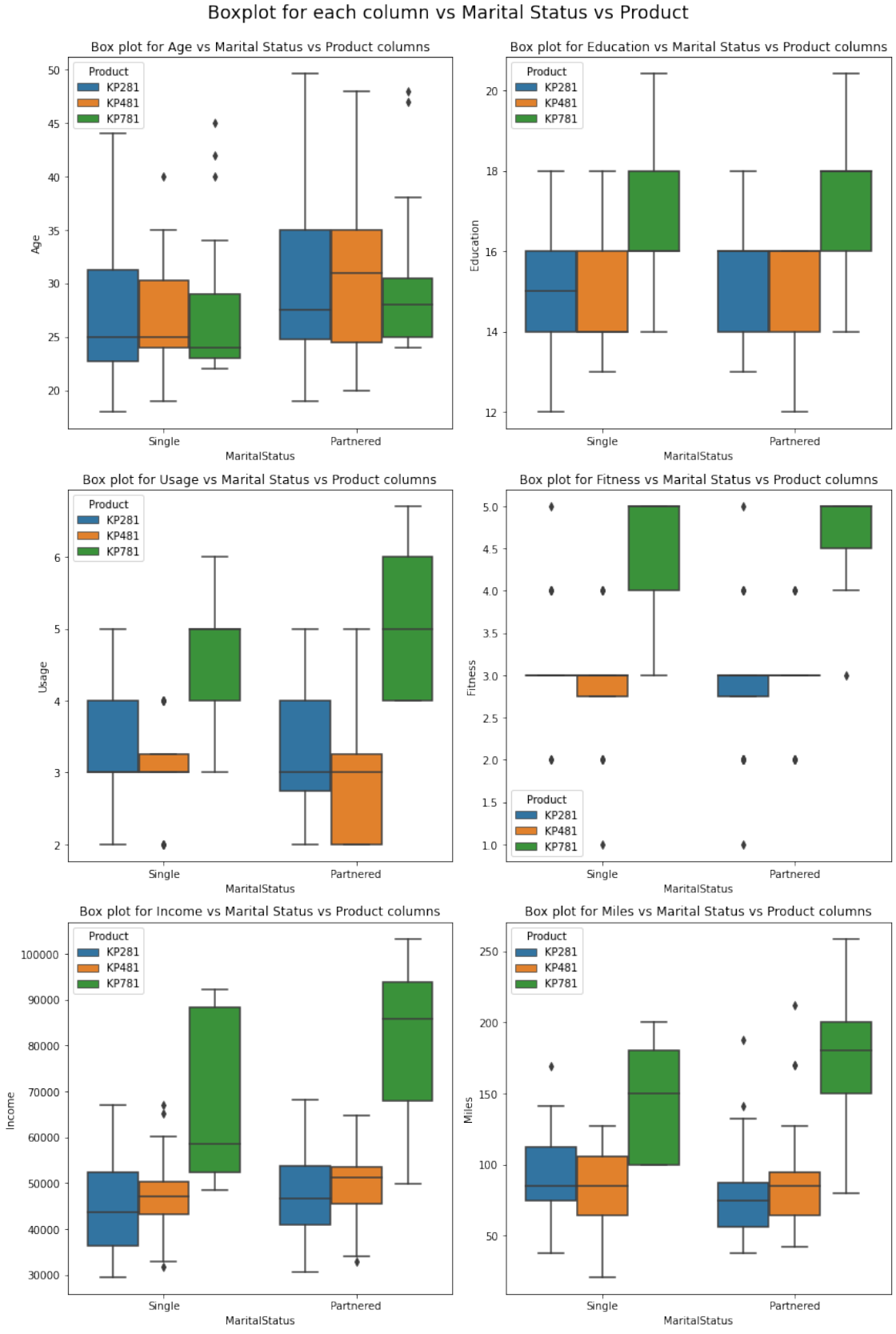

Boxplot for each column vs Product
Box plot for Age vs Product columns
Age
Product
KP281
KP481
KP781
Box plot for Education vs Product columns
Education
Box plot for Usage vs Product columns
Usage
Box plot for Fitness vs Product columns
Fitness
Box plot for Income vs Product columns
Income
Box plot for Miles vs Product columns
Miles

Multivariate Box plots with Product as legend

[217]:
```
#create a Boxplots
fig = plt.figure(figsize = (12,18))
fig.suptitle("Boxplot for each column vs Gender vs Product\n",fontsize =␣
 ↪"xx-large" )
iloc_positions_of_numerical_columns = [1,3,5,6,7,8]
k = 1
for i in iloc_positions_of_numerical_columns:
    plt.subplot(3,2,k)
    plt.title("Box plot for {} vs Gender vs Product columns".format(aerofit.
 ↪columns[i]))
    plt.xlabel(aerofit.columns[i])
    sns.boxplot(data=aerofit, x="Gender",y = aerofit.iloc[:,i],hue = "Product")
    k = k+1
plt.tight_layout()
plt.show()
```

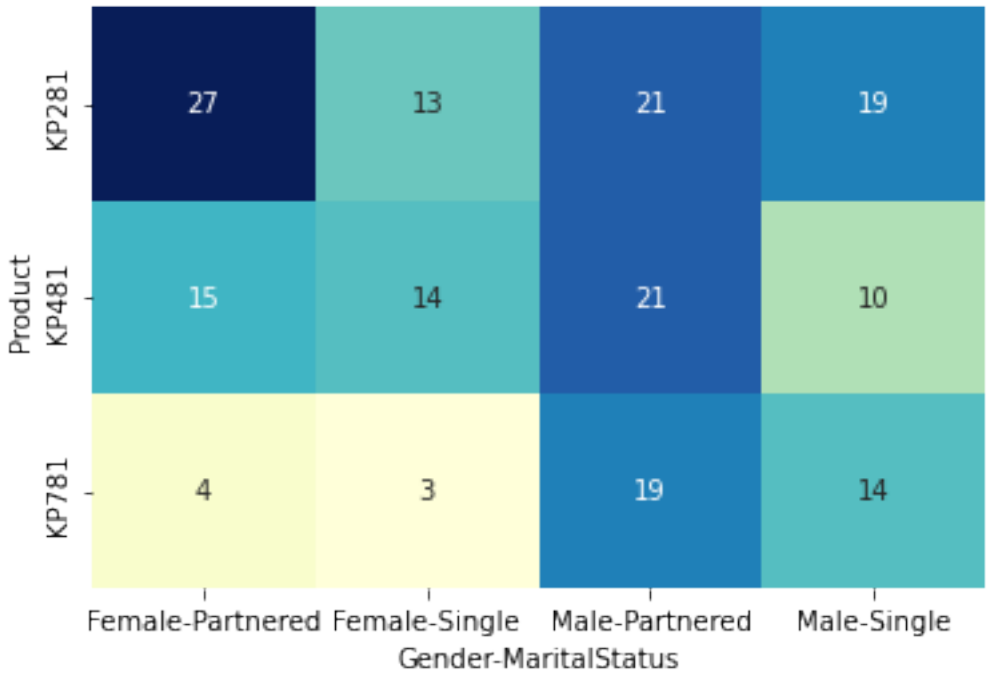

Boxplot for each column vs Gender vs Product
Box plot for Age vs Gender vs Product columns
Box plot for Education vs Gender vs Product columns
Box plot for Usage vs Gender vs Product columns
Box plot for Fitness vs Gender vs Product columns
Box plot for Income vs Gender vs Product columns
Box plot for Miles vs Gender vs Product columns
Product
KP281
KP481
KP781
Age
Education
Usage
Fitness
Income
Miles
Gender
Male
Female

[218]:
```
#create a Boxplots
fig = plt.figure(figsize = (12,18))
fig.suptitle("Boxplot for each column vs Marital Status vs Product\n",fontsize␣
 ↪= "xx-large" )
iloc_positions_of_numerical_columns = [1,3,5,6,7,8]
k = 1
for i in iloc_positions_of_numerical_columns:
    plt.subplot(3,2,k)
    plt.title("Box plot for {} vs Marital Status vs Product columns".
 ↪format(aerofit.columns[i]))
    plt.xlabel(aerofit.columns[i])
    sns.boxplot(data=aerofit, x="MaritalStatus",y = aerofit.iloc[:,i],hue =␣
 ↪"Product")
    k = k+1
plt.tight_layout()
plt.show()
```

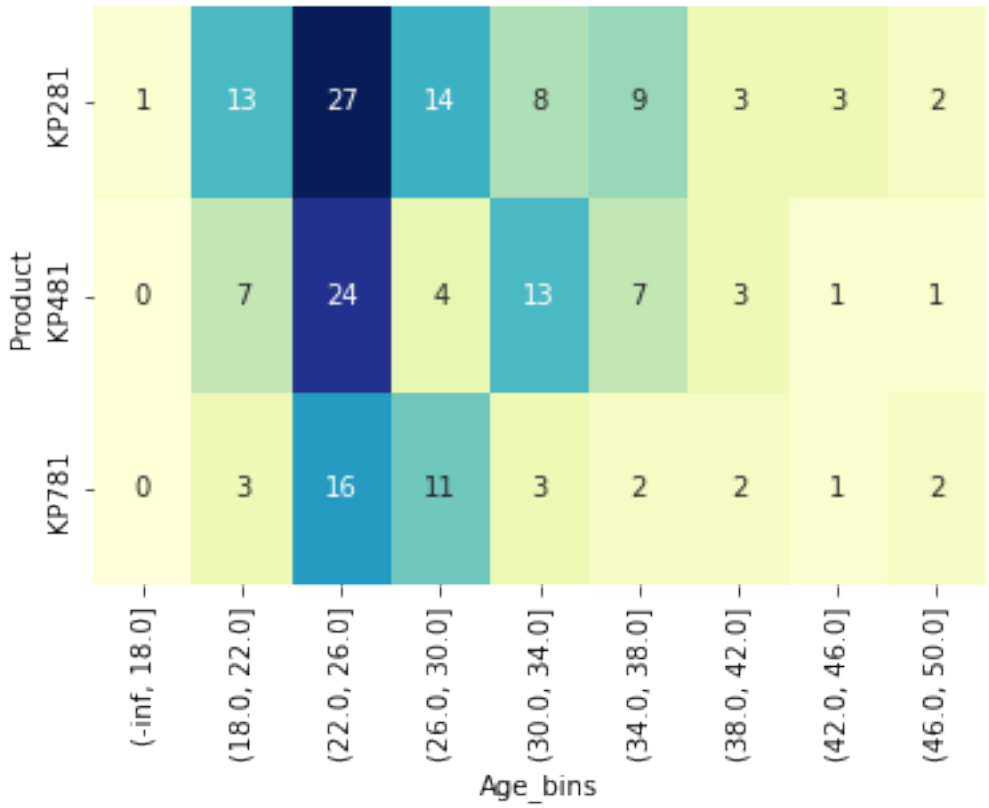

Boxplot for each column vs Marital Status vs Product
Box plot for Age vs Marital Status vs Product columns
Box plot for Education vs Marital Status vs Product columns
Box plot for Usage vs Marital Status vs Product columns
Box plot for Fitness vs Marital Status vs Product columns
Box plot for Income vs Marital Status vs Product columns
Box plot for Miles vs Marital Status vs Product columns
Product
KP281
KP481
KP781
Age
Education
Usage
Fitness
Income
Miles
MaritalStatus
Single
Partnered

4.2 Heatmaps

[219]:
```
sns.heatmap(pd.
  ↪crosstab([aerofit["Product"]],[aerofit["Gender"],aerofit["MaritalStatus"]]),cmap="YlGnBu",a
  ↪=True,cbar = False)
plt.show()
```



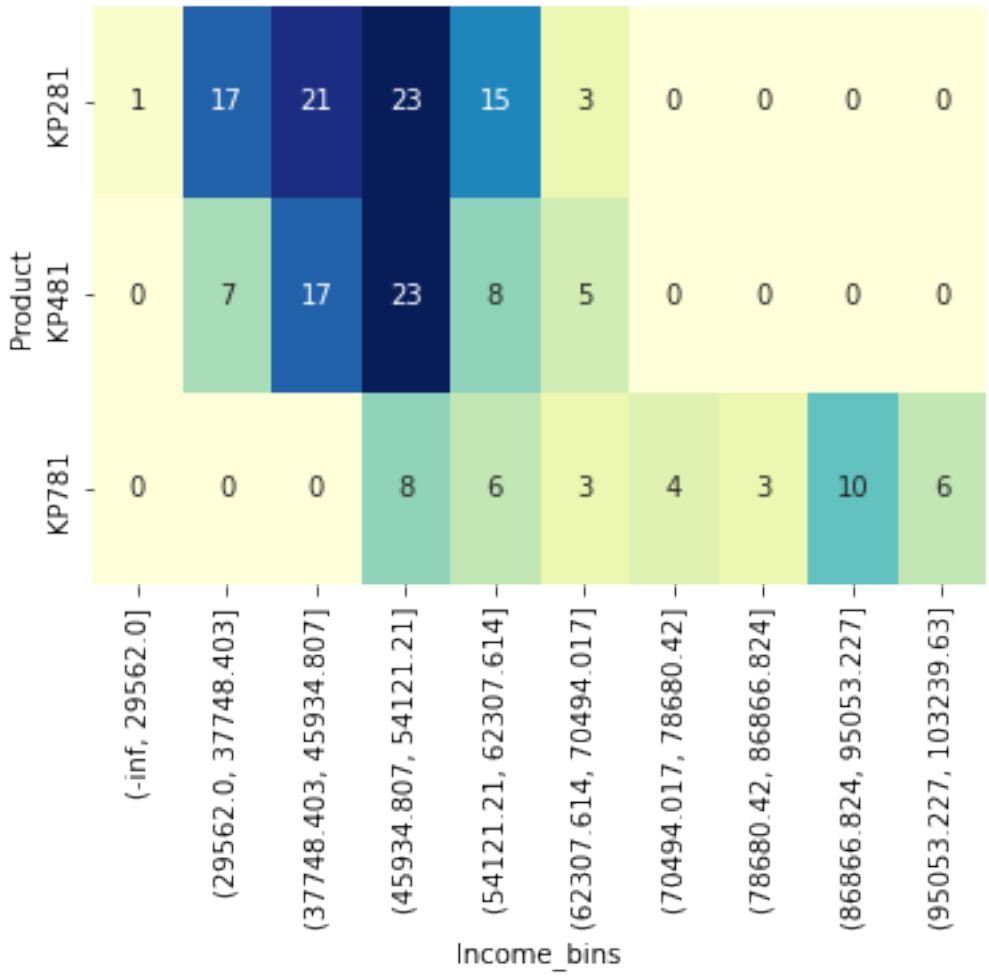
[220]:
```
sns.heatmap(pd.
  ↪crosstab([aerofit_bins["Product"]],aerofit_bins["Age_bins"]),cmap="YlGnBu",annot␣
  ↪=True,cbar = False)
plt.show()
```



Binning of Income

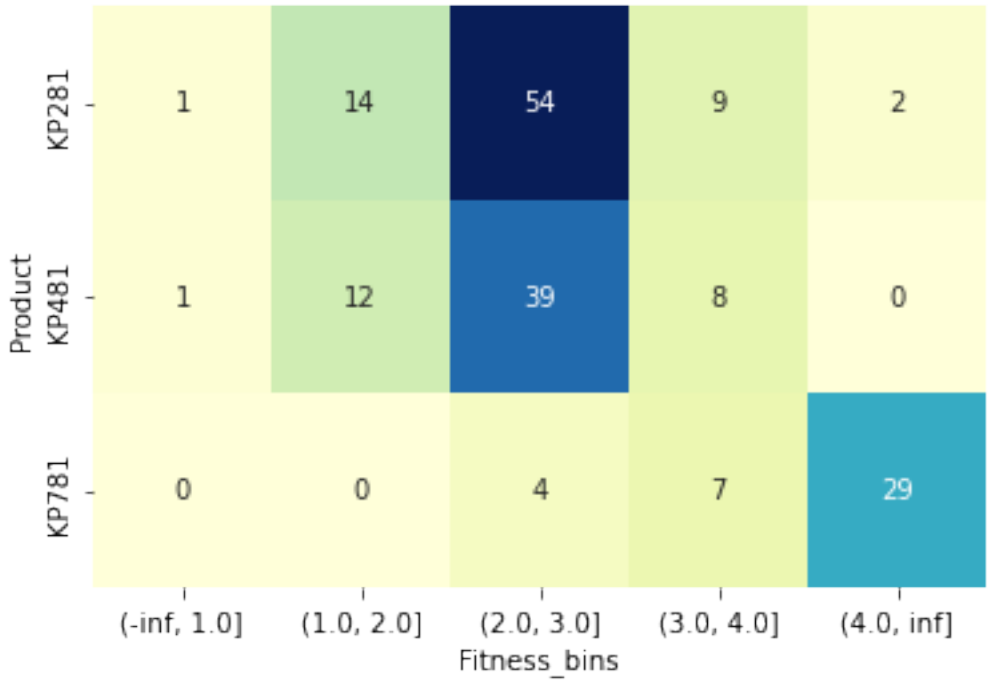
[221]:
```
bins = list(np.linspace(aerofit["Income"].min(),aerofit["Income"].max(),10))
bins.insert(0,-np.inf)
bins.append(np.inf)
print(bins)
aerofit_bins["Income_bins"] = pd.cut(aerofit["Income"],bins)
sns.heatmap(pd.
  ↪crosstab([aerofit_bins["Product"]],aerofit_bins["Income_bins"]),cmap="YlGnBu",annot␣
  ↪=True,cbar = False)
plt.show()
```

```
[-inf, 29562.0, 37748.40338405485, 45934.8067681097, 54121.210152164545,
62307.613536219396, 70494.01692027424, 78680.42030432909, 86866.82368838394,
95053.22707243879, 103239.63045649364, inf]
```



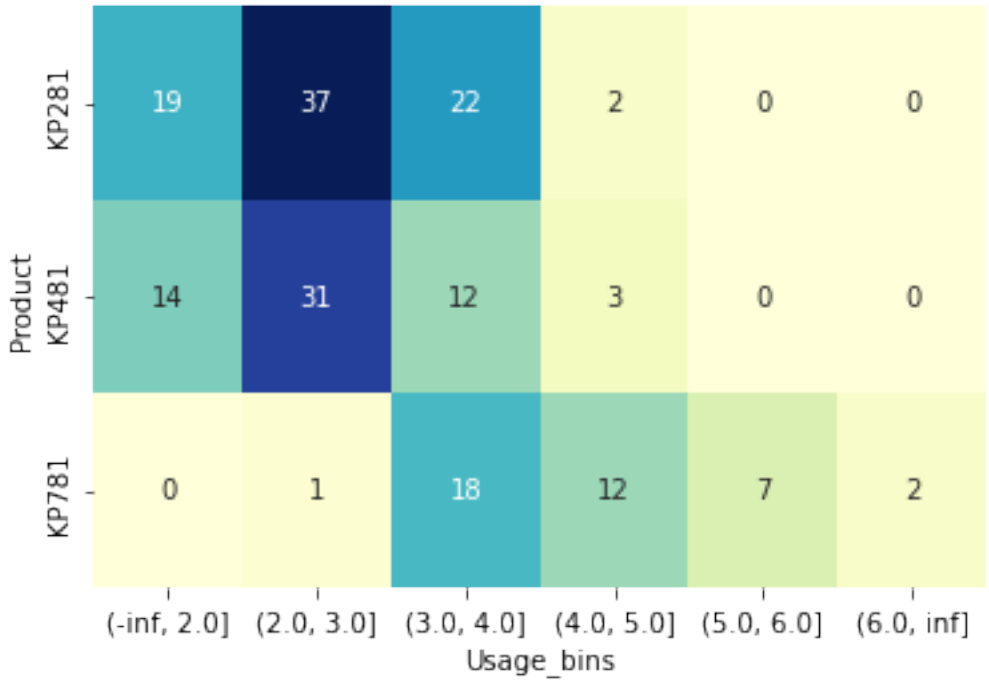
[222]:
```
bins = list(np.arange(aerofit["Fitness"].min(),aerofit["Fitness"].max(),1))
bins.insert(0,-np.inf)
bins.append(np.inf)
print(bins)
aerofit_bins["Fitness_bins"] = pd.cut(aerofit["Fitness"],bins)
sns.heatmap(pd.
  ↪crosstab([aerofit_bins["Product"]],aerofit_bins["Fitness_bins"]),cmap="YlGnBu",annot␣
  ↪=True,cbar = False)
plt.show()
```

```
[-inf, 1.0, 2.0, 3.0, 4.0, inf]
```



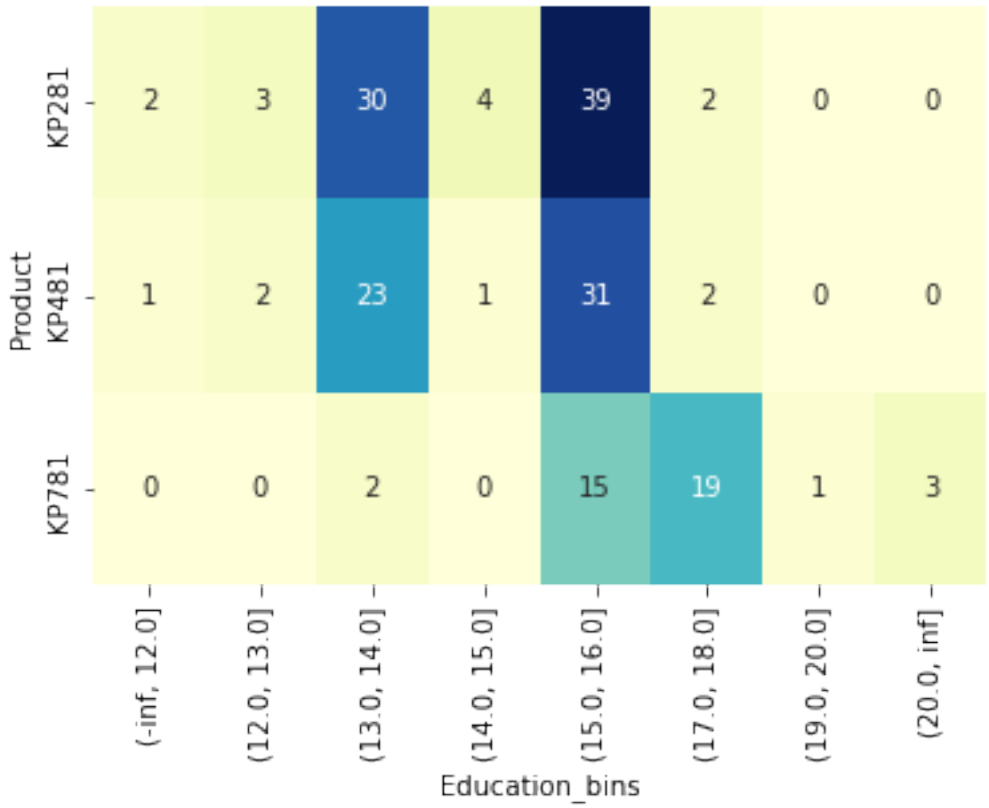
[223]:
```
bins = list(np.arange(aerofit["Usage"].min(),aerofit["Usage"].max(),1))
bins.insert(0,-np.inf)
bins.append(np.inf)
print(bins)
aerofit_bins["Usage_bins"] = pd.cut(aerofit["Usage"],bins)
sns.heatmap(pd.
  ↪crosstab([aerofit_bins["Product"]],aerofit_bins["Usage_bins"]),cmap="YlGnBu",annot␣
  ↪=True,cbar = False)
plt.show()
```

```
[-inf, 2.0, 3.0, 4.0, 5.0, 6.0, inf]
```



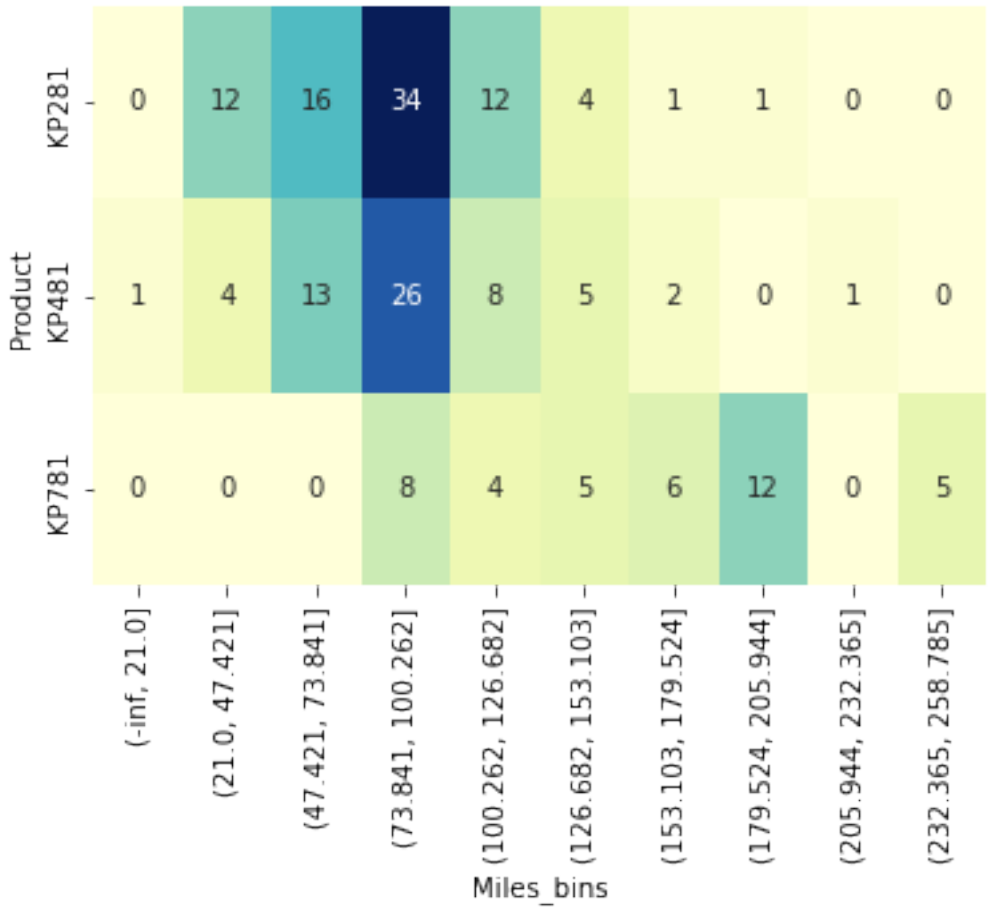
[224]:
```
bins = list(np.arange(aerofit["Education"].min(),aerofit["Education"].max(),1))
bins.insert(0,-np.inf)
bins.append(np.inf)
print(bins)
aerofit_bins["Education_bins"] = pd.cut(aerofit["Education"],bins)
sns.heatmap(pd.
  ↪crosstab([aerofit_bins["Product"]],aerofit_bins["Education_bins"]),cmap="YlGnBu",annot␣
  ↪=True,cbar = False)
plt.show()
```

```
[-inf, 12.0, 13.0, 14.0, 15.0, 16.0, 17.0, 18.0, 19.0, 20.0, inf]
```



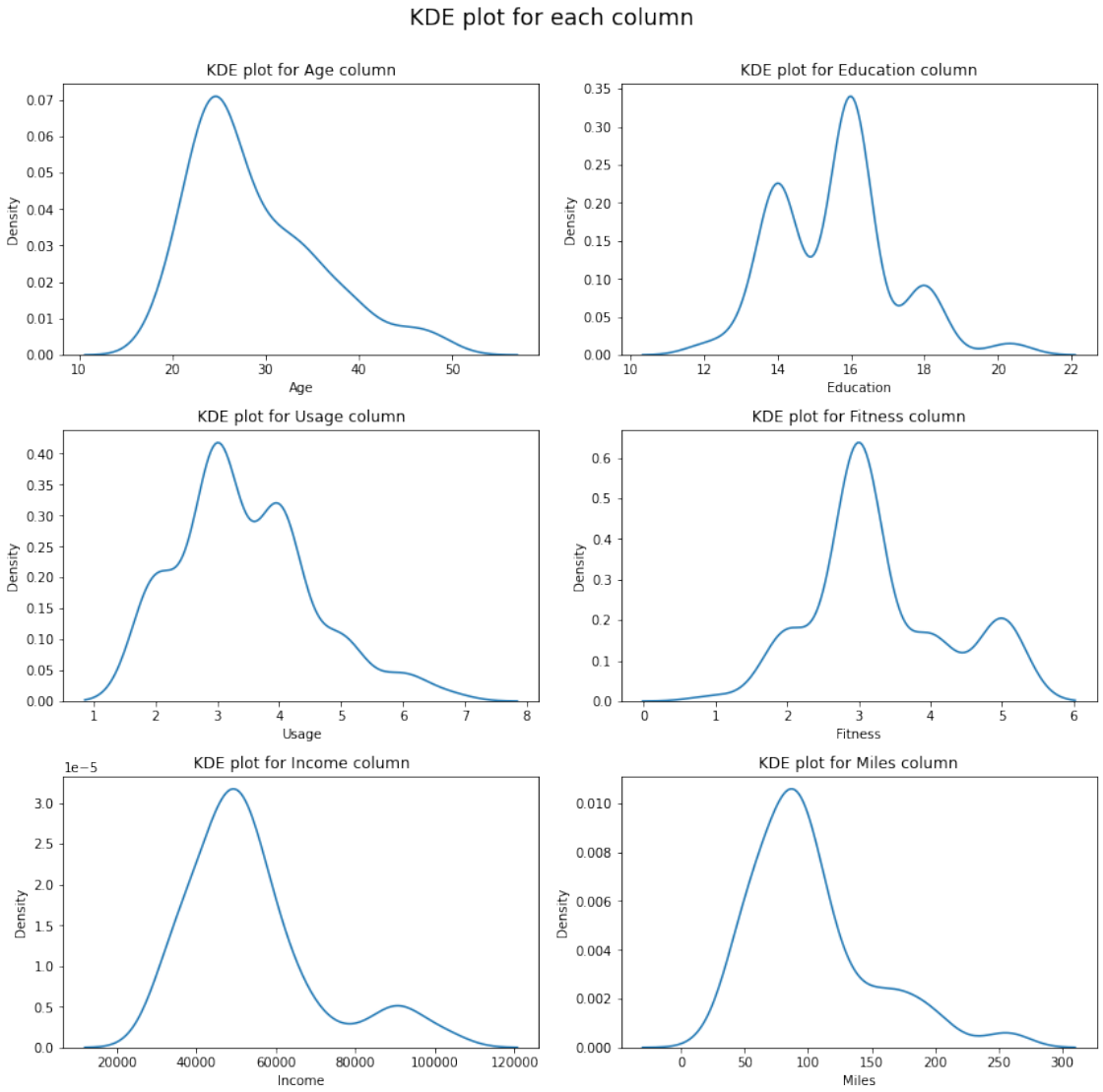
[225]:
```
bins = list(np.linspace(aerofit["Miles"].min(),aerofit["Miles"].max(),10))
bins.insert(0,-np.inf)
bins.append(np.inf)
print(bins)
aerofit_bins["Miles_bins"] = pd.cut(aerofit["Miles"],bins)
sns.heatmap(pd.
  ↪crosstab([aerofit_bins["Product"]],aerofit_bins["Miles_bins"]),cmap="YlGnBu",annot␣
  ↪=True,cbar = False)
plt.show()
```

```
[-inf, 21.0, 47.420584269985824, 73.84116853997165, 100.26175280995746,
126.68233707994328, 153.1029213499291, 179.5235056199149, 205.94408988990074,
232.36467415988656, 258.7852584298724, inf]
```



##KDE plots

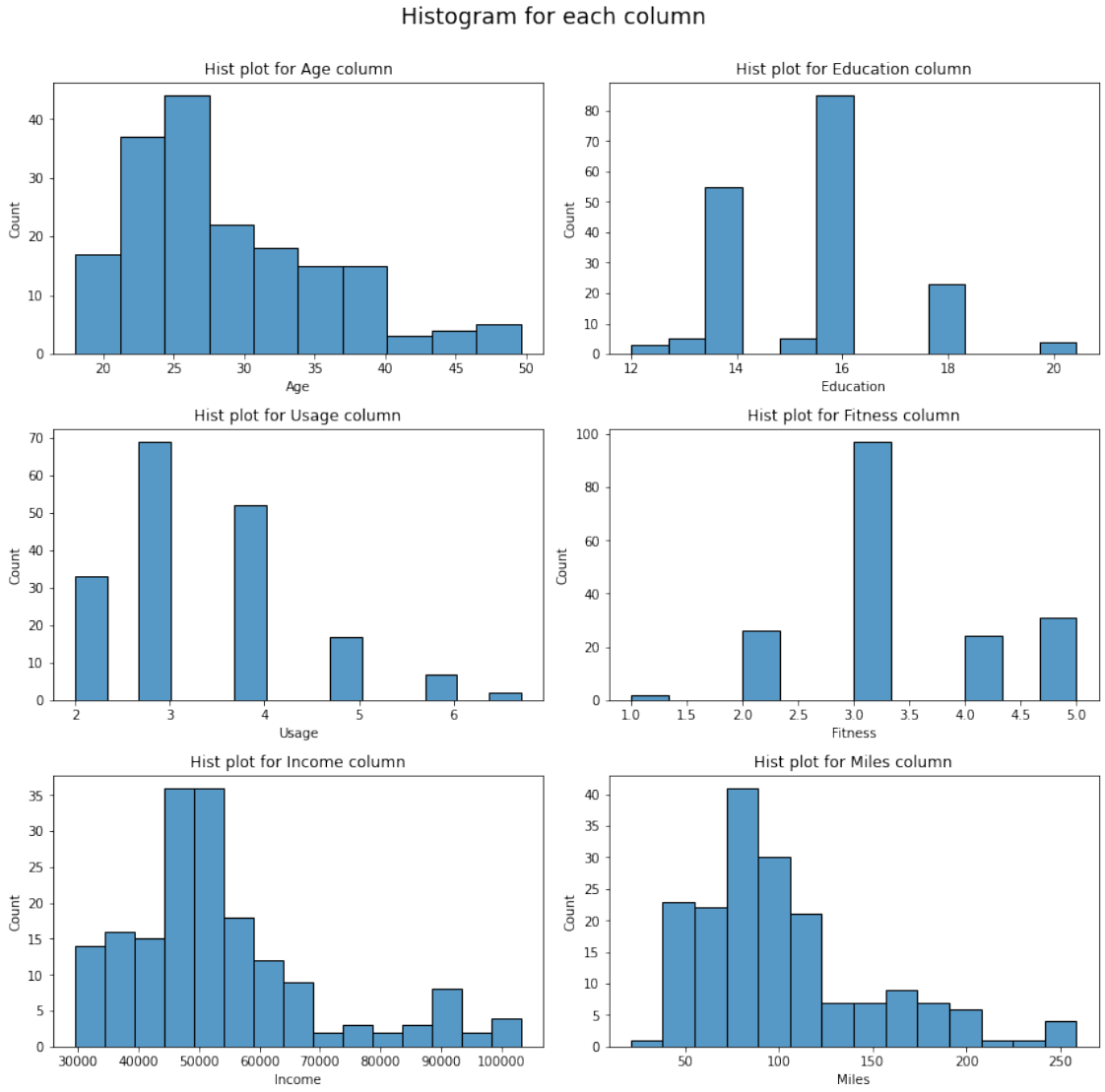
[226]:
```
#create a kde plot
fig = plt.figure(figsize = (12,12))
fig.suptitle("KDE plot for each column\n",fontsize = "xx-large" )
iloc_positions_of_numerical_columns = [1,3,5,6,7,8]
k = 1
for i in iloc_positions_of_numerical_columns:
    plt.subplot(3,2,k)
    plt.title("KDE plot for {} column".format(aerofit.columns[i]))
    plt.xlabel(aerofit.columns[i])
    sns.kdeplot(data=aerofit, x = aerofit.iloc[:,i])
    k = k+1
plt.tight_layout()
plt.show()
```



##Hist plots on all columns

[227]:
```
#create a histogram
fig = plt.figure(figsize = (12,12))
fig.suptitle("Histogram for each column\n",fontsize = "xx-large" )
iloc_positions_of_numerical_columns = [1,3,5,6,7,8]
k = 1
for i in iloc_positions_of_numerical_columns:
    plt.subplot(3,2,k)
    plt.title("Hist plot for {} column".format(aerofit.columns[i]))
    plt.xlabel(aerofit.columns[i])
    sns.histplot(data=aerofit, x = aerofit.iloc[:,i])
    k = k+1
```

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



No Numerical column has perfect normal distribution.

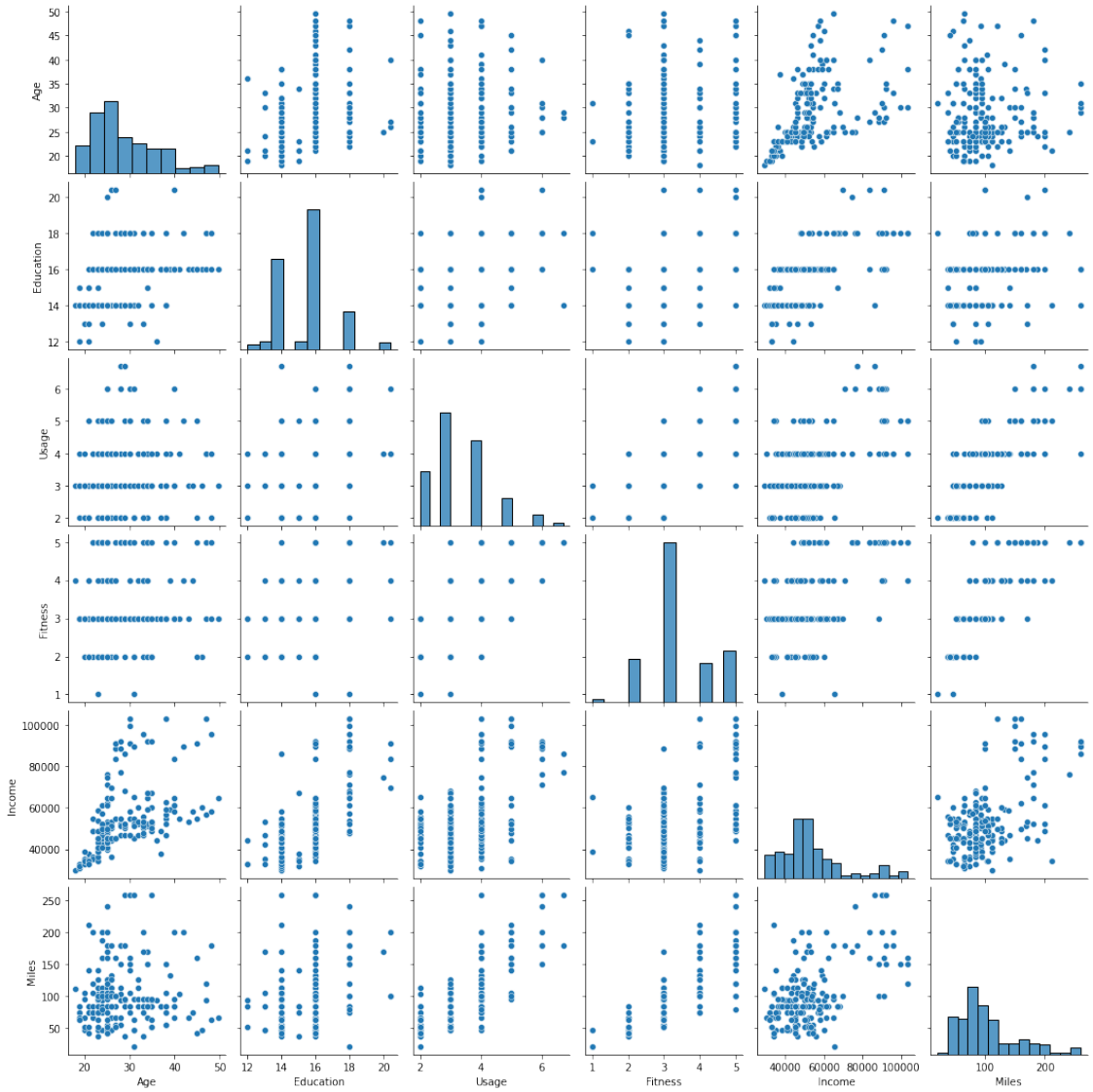
Fitness column has rating = 3 predominantly.

Histogram are indicating the MODE values of each column perfectly.

4.3 Pair plot

[228]:
```
plt.figure(figsize = (20,20))
sns.pairplot(data = aerofit)
plt.show()
```

```
<Figure size 1440x1440 with 0 Axes>
```



#CHAPTER 5: BUSINESS INSIGHTS BASED ON NON-GRAPHICAL AND VISUAL ANALYSIS

4.4 Product Profiling

Important Observations made on KP281 Product: 1. Unit cost = $1500 2. 44.44% chances that a customer buys this product 3. If customer is female, 52.63% of chances to buy this product. 4. Average age of KP281 Single customers is 26.875 years 5. Average Education life of KP281 Single customers is 14.9 years 6. Average Education life of KP281 Male customer = 14.97 years 7. Average usage of KP281 is aroung 2.8 to 3 per week. Particularly Female Partnered customers using in this range. (lesser compared to KP781) 8. Average income of KP281 is in the range of $43000 to $46000 9. Average Miles runned by customer of KP281 is in range of 74 to 78

Important Observations made on KP781 Product: 1. Unit cost = $2500 2. 22.22% chances that a customer buys this product 3. If customer is female, 9% of chances to buy this product. 4. Average age of KP781 customer in range of 27 to 30 years 5. Average Education life of KP781 Customers is around 17 to 18 years. 7. Average usage of KP781 is around 4 to 5.25 per week. 8. Average income of KP781 is in the range of $73000 to $85000 9. Average fitness of KP781 customers in range of 4 to 5 9. Average Miles runned by customer of KP781 is in range of 175 to 210 miles

4.5 Customer Profiling

Observations on Male customers: 1. 57% customers are male 2. 82.5% of KP781 customers are male

Observations on Female customers: 1. 42.2% customers are Female 2. Only 9% female buys KP781.

Observations on Single customers: 1. 40.5% customers are single 2. Average age of KP281 single customers is 26.875 3. Average Education of KP281 single customers is 14.9 years 4. Average income of KP281 single customer is $44271.937

Observations of Partnered Customers: 1. 59.44% customers are partnered 2. Average age of KP481 partnered customers is 30.22 3. Average education of KP781 Partnered is 17.40 years

##BUSINESS INSIGHTS

- Lesser income customers prefers KP281 and Higher income customers prefers KP781
- Higher Education customers prefers KP781
- KP781 customers are using more number of years
- KP781 customers fitness levels are more.
- Female customers are not prefering KP781
- Miles runned on KP781 higher than others
- KP781 customers uses more frequently
- Female who uses 3 to 4 times per week may buy KP481

#CHAPTER 6: RECOMMENDATIONS

- KP281 should be prefered to Less income, Low education, who uses less number of times per week, Less fitness customers
- KP781 should be prefered to higher income, high education, who uses more frequently, higher fitness customers
- Marketing on attracting Female customers onto KP781 is required
- Marketing on Higher Age person fitness is also required.
- KP281 is `USERS CHOICE`
- KP781 is `FITNESS FREAK CHOICE`