Aerofit - Descriptive Statistics & Probability

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1 Business Case: Aerofit - Descriptive Statistics & Probability

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

import math
from scipy.stats import norm, binom, geom, zscore, ttest_1samp, ttest_ind
sns.set_theme(style="darkgrid")
```

```
[ ]: aerofit = pd.read_csv("./aerofit_treadmill.csv")
    aerofit.head(5)
```

```
Product Age
                    Gender Education MaritalStatus Usage Fitness
[]:
                                                                     Income
                                                                            Miles
        KP281
    0
                18
                      Male
                                   14
                                             Single
                                                         3
                                                                      29562
                                                                               112
    1
        KP281
                19
                      Male
                                   15
                                             Single
                                                         2
                                                                  3
                                                                      31836
                                                                                75
                                          Partnered
                                                         4
    2
        KP281
                19 Female
                                   14
                                                                  3
                                                                      30699
                                                                                66
                                   12
                                             Single
                                                         3
    3
        KP281
                19
                      Male
                                                                      32973
                                                                                85
                                          Partnered
        KP281
                20
                      Male
                                   13
                                                                      35247
                                                                                47
```

1.1 Provided Inputs

```
[]: Product Price
0 KP281 1500
1 KP481 1750
2 KP781 2500
```

1.2 Exploring The Data Set

Education

dtype: int64

Fitness

Usage

0

0

0

```
[]: aerofit.shape
[]: (180, 9)
    aerofit.size
[]: 1620
[]: aerofit = aerofit[['Product', 'Gender', 'MaritalStatus', 'Age', 'Income', |
      []: 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
        Gender
                       180 non-null
                                       object
     2
        MaritalStatus 180 non-null
                                       object
     3
        Age
                       180 non-null
                                       int64
     4
        Income
                       180 non-null
                                       int64
     5
        Miles
                       180 non-null
                                       int64
     6
        Education
                       180 non-null
                                       int64
     7
                                       int64
        Fitness
                       180 non-null
        Usage
                       180 non-null
                                       int64
    dtypes: int64(6), object(3)
    memory usage: 12.8+ KB
    1.2.1 Missing value detection & fill with relevent data.
[]: aerofit.isnull().sum()
[]: Product
                     0
    Gender
                     0
    MaritalStatus
    Age
                     0
    Income
                     0
    Miles
                     0
```

1.2.2 Check for Outliers

```
[]: def check outlier(df, x):
         Q1 = df[x].quantile(0.25)
         Q3 = df[x].quantile(0.75)
         IQR = Q3 - Q1
         lower = Q1 - 1.5*IQR
         upper = Q3 + 1.5*IQR
         lower_outlier = df[x][df[x] < lower]</pre>
         upper_outlier = df[x][df[x] > upper]
         return {
             'lower': {
                 'list': lower outlier,
                 'length': len(lower_outlier)
             },
             'upper': {
                 'list': upper_outlier,
                 'length': len(upper_outlier)
             }}
[]: for i in aerofit[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].
      ⇔columns:
         # print(i)
         outlier = check_outlier(aerofit, i)
         print("{}: ({}, {})".format(i, outlier['lower']['length'],__
      →outlier['upper']['length']))
    Age : (0, 5)
    Income: (0, 19)
    Miles: (0, 13)
    Education: (0, 4)
    Fitness: (2, 0)
    Usage: (0, 9)
    1.2.3 Conversion of categorical attributes to 'category'.
[]: aerofit['Product'] = aerofit['Product'].astype('category')
     aerofit['Gender'] = aerofit['Gender'].astype('category')
     aerofit['MaritalStatus'] = aerofit['MaritalStatus'].astype('category')
     aerofit.info()
    <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 180 entries, 0 to 179
    Data columns (total 9 columns):
     #
         Column
                        Non-Null Count Dtype
                        _____
         Product
                        180 non-null
                                         category
         Gender
                       180 non-null
                                        category
```

```
MaritalStatus 180 non-null
 2
                                    category
 3
                  180 non-null
                                    int64
    Age
                   180 non-null
 4
    Income
                                    int64
 5
    Miles
                   180 non-null
                                    int64
    Education
                   180 non-null
                                    int64
    Fitness
                    180 non-null
                                    int64
8
    Usage
                    180 non-null
                                    int64
dtypes: category(3), int64(6)
memory usage: 9.5 KB
```

Insight * 'Product', 'Gender', 'MaritalStatus' are Converted as Type Category.

1.2.4 ****Consolidated Data****

```
[]: def aerofit_categorise(df):
         df["age\_group"] = pd.cut(x=df['Age'], bins=[0,15,20,25,30,35,40,45,50],
                         labels=["0-15", "15-20", "20-25", "25-30", "30-35", [
      →"35-40", "40-45", "45-50"])
         df['age_group'] = df['age_group'].astype('category')
         df["income group"] = pd.cut(x=df['Income'],
      ⇔bins=[0,25000,35000,45000,55000,65000,75000,85000,95000,105000],
                         labels=["0-25K", "25K-35K", "35K-45K", "45K-55K",
      55K-65K'', "65K-75K", "75K-85K", "85K-95K", "95K-105K"])
         df['income_group'] = df['income_group'].astype('category')
         df["miles_group"] = pd.cut(x=df['Miles'],__
      ⇒bins=[0,20,50,80,110,140,170,200,230,260,290,320,350,380],
                         labels=["0-20", "20-50", "50-80", "80-110", "110-140", [
      _{9}"140-170", "170-200", "200-230", "230-260", "260-290", "290-320", "320-350", _{\square}

¬"350-380"])
         df['miles_group'] = df['miles_group'].astype('category')
         df['education group'] = df['Education'].astype('category')
         df['fitness_group'] = df['Fitness'].astype('category')
         df['usage_group'] = df['Usage'].astype('category')
         return df
     aerofit = aerofit_categorise(aerofit)
     aerofit.info()
```

```
1
     Gender
                       180 non-null
                                        category
                       180 non-null
 2
     MaritalStatus
                                        category
 3
                       180 non-null
                                        int64
     Age
 4
     Income
                       180 non-null
                                        int64
 5
     Miles
                       180 non-null
                                        int64
 6
     Education
                       180 non-null
                                        int64
 7
     Fitness
                       180 non-null
                                        int64
                       180 non-null
 8
     Usage
                                        int64
 9
                       180 non-null
     age_group
                                        category
 10
                       180 non-null
     income_group
                                        category
     miles_group
                       180 non-null
 11
                                        category
 12
     education_group
                       180 non-null
                                        category
     fitness_group
 13
                       180 non-null
                                        category
 14 usage_group
                       180 non-null
                                        category
dtypes: category(9), int64(6)
```

memory usage: 12.7 KB

1.2.5 Statistical Summary

```
Descriptive Statistits
[]: aerofit[['Product', 'Gender', 'MaritalStatus']].describe()
[]:
            Product Gender MaritalStatus
     count
                180
                        180
                                       180
                          2
                                         2
     unique
                  3
     top
              KP281
                       Male
                                Partnered
     freq
                        104
                                       107
                 80
[]: aerofit[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].describe()
                                                      Education
[]:
                    Age
                                Income
                                              Miles
                                                                     Fitness
     count
            180.000000
                            180.000000
                                         180.000000
                                                     180.000000
                                                                  180.000000
             28.788889
                          53719.577778
                                         103.194444
                                                                    3.311111
     mean
                                                      15.572222
     std
              6.943498
                          16506.684226
                                          51.863605
                                                                    0.958869
                                                       1.617055
    min
             18.000000
                          29562.000000
                                          21.000000
                                                      12.000000
                                                                    1.000000
     25%
             24.000000
                          44058.750000
                                          66.000000
                                                      14.000000
                                                                    3.000000
     50%
             26.000000
                          50596.500000
                                          94.000000
                                                      16.000000
                                                                    3.000000
     75%
             33.000000
                          58668.000000
                                         114.750000
                                                      16.000000
                                                                    4.000000
                         104581.000000
                                         360.000000
                                                                    5.000000
     max
             50.000000
                                                      21.000000
                 Usage
            180.000000
     count
              3.455556
     mean
     std
              1.084797
    min
              2.000000
     25%
              3.000000
     50%
              3.000000
     75%
              4.000000
```

7.000000 max

```
[]: aerofit[['age_group', 'income_group', 'miles_group', 'education_group', |

¬'usage_group', 'fitness_group']].describe()

[]:
            age_group income_group miles_group
                                                 education_group usage_group \
                  180
                               180
     count
                                            180
                                                             180
                                                                           180
                    7
                                  8
                                                               8
                                                                             6
     unique
                                             11
     top
                20-25
                           45K-55K
                                         80-110
                                                               16
                                                                             3
                   69
                                77
                                             66
                                                              85
                                                                            69
     freq
             fitness_group
     count
                       180
```

top 3 freq 97

5

Unique Count

unique

```
[]: aerofit.nunique()
```

```
[]: Product
                          3
     Gender
                          2
     MaritalStatus
                          2
                         32
     Age
     Income
                         62
     Miles
                         37
     Education
                          8
     Fitness
                          5
     Usage
                          6
                          7
     age_group
     income_group
                          8
     miles_group
                         11
                          8
     education_group
                          5
     fitness_group
                          6
     usage_group
     dtype: int64
```

Mean

```
[]: aerofit[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].mean()
```

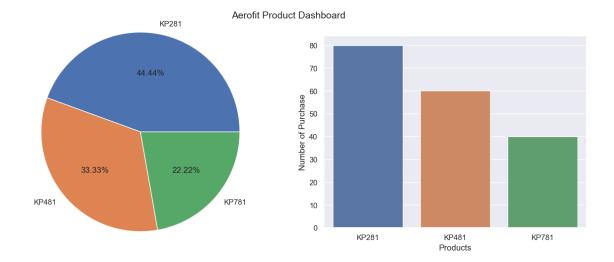
[]: Age 28.788889 Income 53719.577778 Miles 103.194444 Education 15.572222 Fitness 3.311111 Usage 3.455556

dtype: float64

```
Median
[]: aerofit[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].median()
[]: Age
                     26.0
     Income
                  50596.5
    Miles
                     94.0
    Education
                     16.0
    Fitness
                      3.0
    Usage
                      3.0
    dtype: float64
    \mathbf{Mode}
[]: for i in aerofit.columns:
       print(i,':',aerofit[i].mode()[0])
    Product: KP281
    Gender : Male
    MaritalStatus : Partnered
    Age : 25
    Income: 45480
    Miles: 85
    Education: 16
    Fitness: 3
    Usage: 3
    age_group : 20-25
    income_group : 45K-55K
    miles_group : 80-110
    education_group : 16
    fitness_group : 3
    usage_group : 3
    1.3 Uni Variate Analysis
    1.3.1 Product
[]: aerofit['Product'].unique()
[]: ['KP281', 'KP481', 'KP781']
     Categories (3, object): ['KP281', 'KP481', 'KP781']
[]: aerofit['Product'].value_counts()
[]: KP281
              80
    KP481
              60
    KP781
              40
    Name: Product, dtype: int64
```

Statitical Analysis

```
[]: aerofit['Product'].describe()
[]: count
                 180
    unique
                   3
              KP281
    top
     freq
                 80
    Name: Product, dtype: object
[]: aerofit['Product'].mode()[0]
[]: 'KP281'
    Find Probability
[]: aerofit['Product'].value_counts(normalize=True)*100
[]: KP281
             44.44444
             33.333333
    KP481
    KP781
             22.22222
    Name: Product, dtype: float64
    Plot the Graph
[]: plt.figure(figsize=(15,5)).suptitle("Aerofit Product Dashboard",fontsize=14)
     plt.subplot(1, 2, 1)
     plt.pie(aerofit['Product'].value_counts().values,labels = aerofit['Product'].
      ⇒value_counts().index,radius = 1.3,autopct = '%1.2f%%',) # type: ignore
     plt.subplot(1, 2, 2)
     sns.countplot(aerofit, x='Product')
     plt.xlabel('Products', fontsize=12)
     plt.ylabel('Number of Purchase', fontsize=12)
     plt.show()
```



Insight * There is only 3 type of Product. which are KP281, KP481 & KP781. * There are 80 KP281 which is equivalent to 44.44%. * There are 60 KP481 which is equivalent to 33.33%. * There are 40 KP781 which is equivalent to 22.22%.

1.3.2 Gender

```
[]: aerofit['Gender'].unique()
[]: ['Male', 'Female']
     Categories (2, object): ['Female', 'Male']
[]: aerofit['Gender'].value_counts()
[]: Male
               104
                76
    Female
     Name: Gender, dtype: int64
[]: aerofit['Gender'].value_counts(normalize=True)*100
[]: Male
               57.777778
     Female
               42.22222
    Name: Gender, dtype: float64
    Statitical Analysis
[]: aerofit['Gender'].describe()
[]: count
                180
                  2
    unique
     top
               Male
```

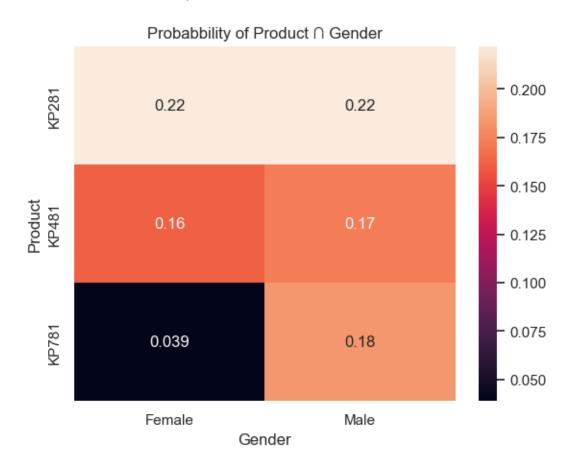
```
freq
                104
     Name: Gender, dtype: object
[]: aerofit['Gender'].mode()[0]
[]: 'Male'
[]: aerofit.groupby('Product')["Gender"].describe()
[]:
             count unique
                              top freq
     Product
     KP281
                80
                        2
                          Female
                                    40
    KP481
                60
                        2
                            Male
                                    31
    KP781
                40
                        2
                            Male
                                    33
    Find Probability
    Probability of a Product & Gender across all Combination "Product Gender"
[]: pd.crosstab(aerofit['Gender'], aerofit['Product'], normalize=True,
      ⇒margins=True)*100
[ ]: Product
                 KP281
                             KP481
                                        KP781
                                                      All
     Gender
             22.22222 16.111111
                                     3.888889
     Female
                                                42.22222
    Male
             22.22222
                        17.222222 18.333333
                                                57.777778
    All
             44.44444 33.333333
                                   22.22222
                                              100.000000
    Probability of Product's for given Gender "Product | Gender"
[]: pd.crosstab(aerofit['Gender'], aerofit['Product'], normalize='index',
      ⇒margins=True)*100
[]: Product
                 KP281
                            KP481
                                        KP781
    Gender
    Female
             52.631579 38.157895
                                     9.210526
    Male
             38.461538 29.807692
                                   31.730769
             44.44444 33.333333
     A11
                                   22.22222
    Probability of Gender for given Product "Gender | Product"
[]: pd.crosstab(aerofit['Gender'], aerofit['Product'], normalize='columns',
      →margins=True)*100
[]: Product KP281
                                             All
                         KP481 KP781
     Gender
     Female
               50.0
                    48.333333
                                 17.5 42.22222
    Male
               50.0 51.666667
                                 82.5 57.777778
```

Heat Map

```
[]: sns.heatmap(pd.crosstab(aerofit['Product'], aerofit['Gender'], onormalize='all'), annot=True)

plt.title('Probabbility of Product Gender', fontsize=12)
```

[]: Text(0.5, 1.0, 'Probabbility of Product Gender')

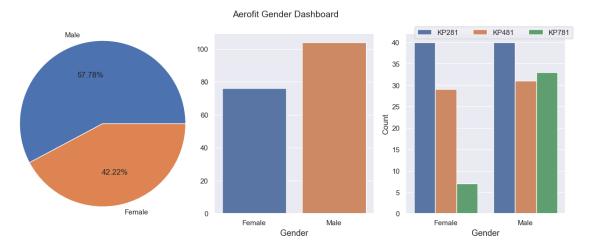


Descriptive Plot

```
plt.yticks(rotation= 0, fontsize=11)

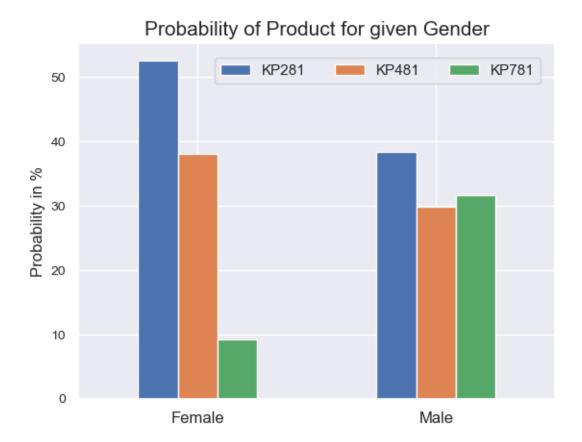
plt.subplot(1, 3, 3)
sns.countplot(aerofit, x='Gender', hue='Product')
plt.ylabel('Count', fontsize=12)
plt.xlabel('Gender', fontsize=13)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)
plt.legend(borderaxespad=-1, ncol=3)

plt.show()
```

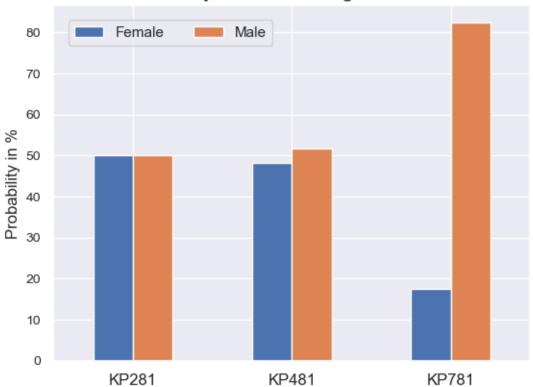


Probability Plot









Population Plot

```
pd.crosstab(aerofit['Gender'], aerofit['Product'], normalize="index").

plot(kind='pie', subplots=True, figsize=(12,4), labeldistance=None,
fontsize=10, legend=None, autopct = '%1.2f%%')

plt.legend(borderaxespad=-1, ncol=3)

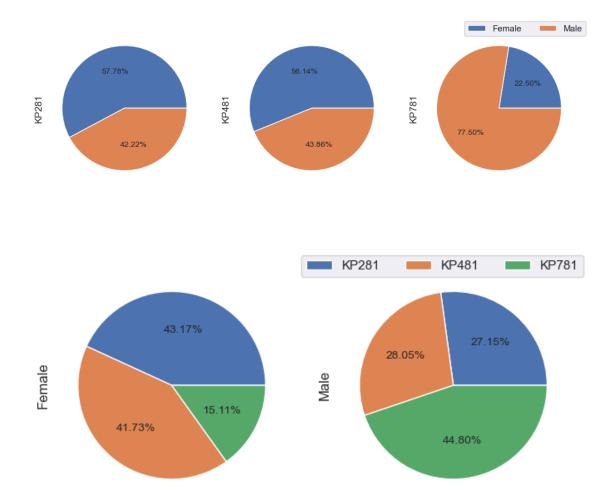
plt.show()

pd.crosstab(aerofit['Product'], aerofit['Gender'], normalize="index").

plot(kind='pie', subplots=True, figsize=(8,4), labeldistance=None,
fontsize=10, legend=None, autopct = '%1.2f%%')

plt.legend(borderaxespad=-1, ncol=3)

plt.show()
```



Insight * There are 104 Male which is equivalent to 57.78%. * There are 76 Female which is equivalent to 42.22%.

1.3.3 Marital Status

```
[]: aerofit['MaritalStatus'].unique()

[]: ['Single', 'Partnered']
    Categories (2, object): ['Partnered', 'Single']

[]: aerofit['MaritalStatus'].value_counts()

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

```
[]: aerofit['MaritalStatus'].value_counts(normalize=True)*100
[]: Partnered
                  59.444444
    Single
                  40.555556
     Name: MaritalStatus, dtype: float64
    Statitical Analysis
[]: aerofit['MaritalStatus'].describe()
[]: count
                     180
     unique
     top
               Partnered
     freq
                     107
     Name: MaritalStatus, dtype: object
[]: aerofit['MaritalStatus'].mode()[0]
[]: 'Partnered'
[]: aerofit.groupby('Product')["MaritalStatus"].describe()
[]:
             count unique
                                 top freq
    Product
    KP281
                        2 Partnered
                80
                                       48
    KP481
                60
                        2 Partnered
                                       36
    KP781
                40
                        2 Partnered
                                       23
    Find Probability
    Probability of a Product & Marital Status across all Combination "Product Marital
    Status"
[]: pd.crosstab(aerofit['MaritalStatus'], aerofit['Product'], normalize=True, ___
      ⇒margins=True)*100
[]: Product
                        KP281
                                   KP481
                                              KP781
                                                            A11
    MaritalStatus
     Partnered
                    26.666667
                               20.000000 12.777778
                                                      59.444444
                    17.777778 13.333333
                                           9.44444
     Single
                                                      40.555556
                    44.44444 33.33333 22.22222
     All
                                                     100.000000
    Probability of Product's for given Marital Status "Product | Marital Status"
[]: pd.crosstab(aerofit['MaritalStatus'], aerofit['Product'], normalize='index',
      ⇒margins=True)*100
[]: Product
                        KP281
                                   KP481
                                              KP781
    MaritalStatus
     Partnered
                    44.859813 33.644860 21.495327
```

Single 43.835616 32.876712 23.287671 All 44.44444 33.33333 22.222222

Probability of Marital Status for given Product "Marital Status | Product"

```
[]: pd.crosstab(aerofit['MaritalStatus'], aerofit['Product'], normalize='columns', ⊔

⇔margins=True)*100
```

[]:	Product	KP281	KP481	KP781	All
	MaritalStatus				
	Partnered	60.0	60.0	57.5	59.444444
	Single	40.0	40.0	42.5	40.555556

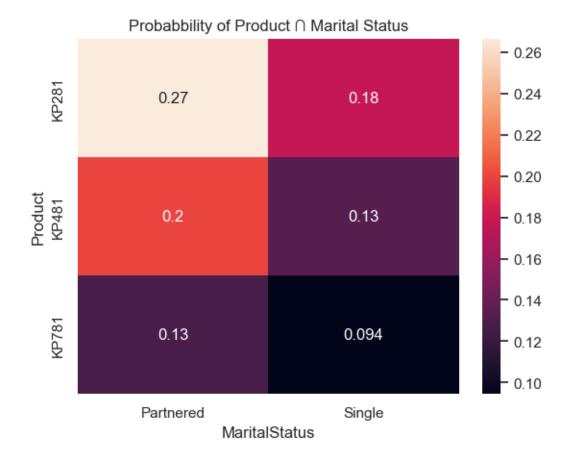
Plot the Graph

Heat Map

```
[]: sns.heatmap(pd.crosstab(aerofit['Product'], aerofit['MaritalStatus'], onormalize='all'),annot=True)

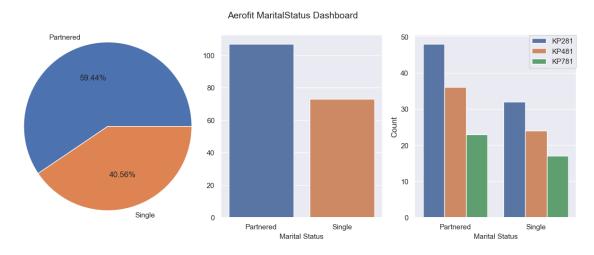
plt.title('Probabbility of Product Marital Status', fontsize=12)
```

[]: Text(0.5, 1.0, 'Probabbility of Product Marital Status')



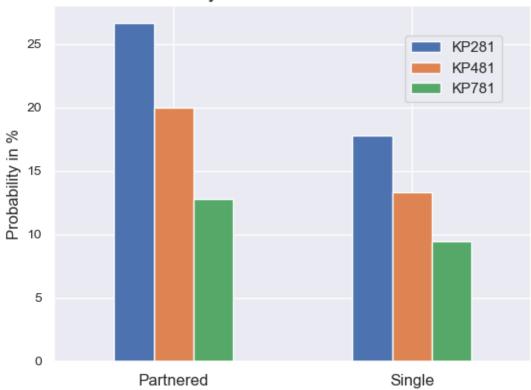
Descriptive Plot

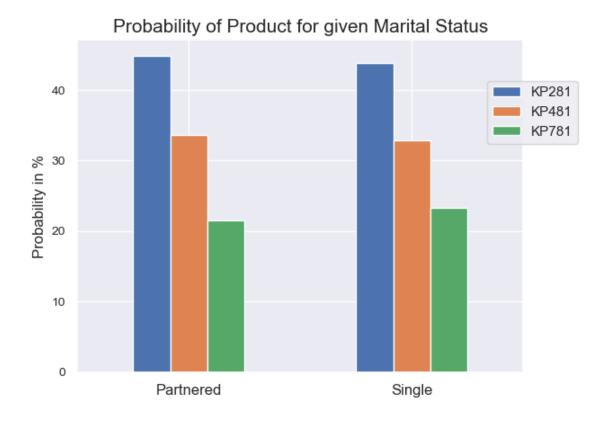
```
[]: plt.figure(figsize=(15,5)).suptitle("Aerofit MaritalStatus_
      →Dashboard",fontsize=14)
     plt.subplot(1, 3, 1)
     plt.pie(aerofit['MaritalStatus'].value_counts().values,labels =__
      ⊖aerofit['MaritalStatus'].value_counts().index,radius = 1.3,autopct = '%1.
      →2f%%',) # type: ignore
     plt.subplot(1, 3, 2)
     sns.countplot(aerofit, x='MaritalStatus')
     plt.ylabel('', fontsize=12)
     plt.xlabel('Marital Status', fontsize=11)
     plt.xticks(fontsize=11)
     plt.yticks(rotation= 0, fontsize=11)
     plt.subplot(1, 3, 3)
     sns.countplot(aerofit, x='MaritalStatus', hue='Product')
     plt.ylabel('Count', fontsize=12)
     plt.xlabel('Marital Status', fontsize=11)
     plt.xticks(fontsize=11)
     plt.yticks(rotation= 0, fontsize=11)
     plt.legend(borderaxespad=0, ncol=1)
     plt.show()
```

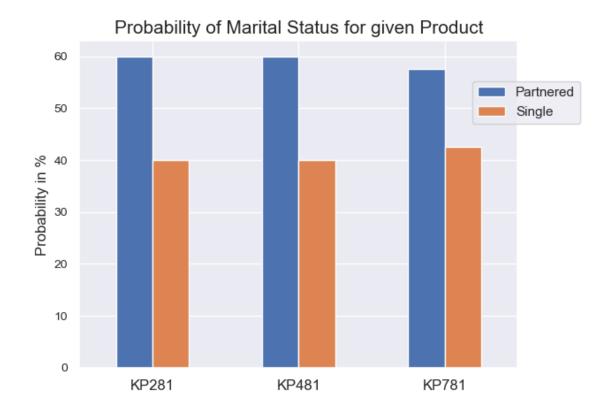


Probability Plot

Probability of Product & Marital Status







Population Plot

```
pd.crosstab(aerofit['MaritalStatus'], aerofit['Product'], normalize="index").

plot(kind='pie', subplots=True, figsize=(12,4), labeldistance=None,

fontsize=10, legend=None, autopct = '%1.2f%%')

plt.legend(borderaxespad=-1, ncol=3)

plt.show()

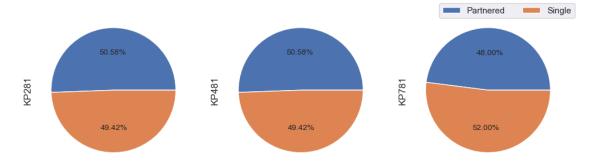
pd.crosstab(aerofit['Product'], aerofit['MaritalStatus'], normalize="index").

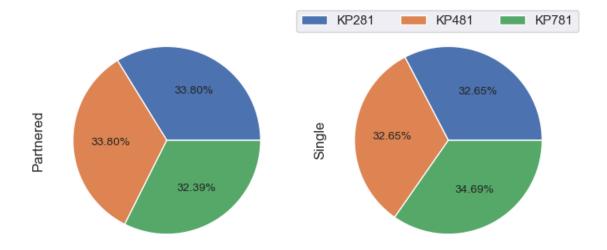
plot(kind='pie', subplots=True, figsize=(8,4), labeldistance=None,

fontsize=10, legend=None, autopct = '%1.2f%%')

plt.legend(borderaxespad=-1, ncol=3)

plt.show()
```





Insight * There are 107 Partnered which is equivalent to 59.44%. * There are 73 Single which is equivalent to 40.56%.

1.3.4 Age

```
Age value Count
[]: aerofit['Age'].unique()
[]: array([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, 50, 45, 48, 42],
           dtype=int64)
[]: aerofit['Age'].value_counts()[:5]
[]: 25
           25
     23
           18
     24
           12
     26
           12
     28
            9
    Name: Age, dtype: int64
[]: aerofit['Age'].value_counts(normalize=True)[:5]*100
[]: 25
           13.888889
           10.000000
     23
     24
            6.66667
```

```
26
            6.66667
     28
            5.000000
     Name: Age, dtype: float64
    Age Group Value Count
[]: aerofit['age_group'].unique()
[]: ['15-20', '20-25', '25-30', '30-35', '35-40', '40-45', '45-50']
     Categories (8, object): ['0-15' < '15-20' < '20-25' < '25-30' < '30-35' <
     '35-40' < '40-45' < '45-50']
[]: aerofit['age_group'].value_counts()[:5]
[]: 20-25
              69
     25-30
              41
     30-35
              32
     35-40
              16
     15-20
              10
     Name: age_group, dtype: int64
[]: aerofit['age_group'].value_counts(normalize=True)[:5]*100
[]: 20-25
              38.333333
     25-30
              22.777778
     30-35
              17.777778
               8.88889
     35-40
     15-20
               5.555556
    Name: age_group, dtype: float64
    Statitical Analysis
[]: aerofit['Age'].describe()
[]: count
              180.000000
               28.788889
    mean
     std
                6.943498
    min
               18.000000
     25%
               24.000000
     50%
               26.000000
     75%
               33.000000
               50.000000
    max
    Name: Age, dtype: float64
[]: aerofit['age_group'].describe()
[]: count
                 180
    unique
                   7
               20-25
     top
```

```
freq
                 69
    Name: age_group, dtype: object
[]: aerofit['Age'].mean()
[]: 28.788888888888888
[]: aerofit['Age'].median()
[]: 26.0
[]: aerofit['Age'].mode()[0]
[]: 25
[]: aerofit.groupby('Product')["Age"].describe()
[]:
             count
                     mean
                                std
                                      min
                                             25%
                                                   50%
                                                          75%
                                                                max
    Product
    KP281
              80.0 28.55 7.221452 18.0 23.00 26.0
                                                       33.00
                                                              50.0
              60.0 28.90 6.645248
                                     19.0 24.00 26.0
                                                        33.25
    KP481
                                                              48.0
    KP781
              40.0 29.10 6.971738 22.0 24.75 27.0 30.25
                                                               48.0
[]: aerofit.groupby('Product')["age_group"].describe()
[]:
            count unique
                            top freq
    Product
    KP281
                       7 20-25
               80
                                  28
    KP481
                       7 20-25
               60
                                  24
    KP781
               40
                       6 20-25
                                  17
    Check for Outliers
[]: check_outlier(aerofit, 'Age')['upper']
[]: {'list': 78
                    47
     79
            50
     139
            48
     178
            47
     179
            48
     Name: Age, dtype: int64,
     'length': 5}
[]: check_outlier(aerofit, 'Age')['lower']
[]: {'list': Series([], Name: Age, dtype: int64), 'length': 0}
```

Find Probability

Probability of a Product & Age Group across all Combination "Product Age Group"

```
[]: pd.crosstab(aerofit['age_group'], aerofit['Product'], normalize=True, use margins=True)*100
```

[]:	Product	KP281	KP481	KP781	All
	age_group				
	15-20	3.333333	2.22222	0.000000	5.555556
	20-25	15.555556	13.333333	9.444444	38.333333
	25-30	11.666667	3.888889	7.222222	22.777778
	30-35	6.111111	9.444444	2.22222	17.777778
	35-40	4.44444	3.333333	1.111111	8.888889
	40-45	1.666667	0.555556	1.111111	3.333333
	45-50	1.666667	0.555556	1.111111	3.333333
	All	44.44444	33.333333	22.22222	100.000000

Probability of Product's for given Age Group "Product | Age Group"

```
[]: pd.crosstab(aerofit['age_group'], aerofit['Product'], normalize='index', use margins=True)*100
```

[]:	Product	KP281	KP481	KP781
	age_group			
	15-20	60.000000	40.000000	0.000000
	20-25	40.579710	34.782609	24.637681
	25-30	51.219512	17.073171	31.707317
	30-35	34.375000	53.125000	12.500000
	35-40	50.000000	37.500000	12.500000
	40-45	50.000000	16.666667	33.333333
	45-50	50.000000	16.666667	33.333333
	All	44.44444	33.333333	22.22222

Probability of Age Group for given Product "Age Group | Product"

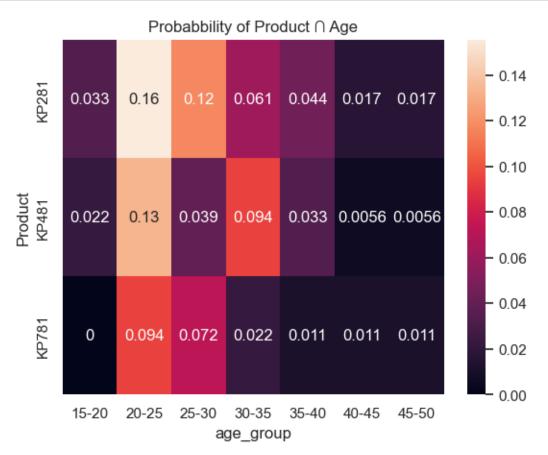
```
[]: pd.crosstab(aerofit['age_group'], aerofit['Product'], normalize='columns', ⊔

→margins=True)*100
```

[]:	Product	KP281	KP481	KP781	All
	age_group				
	15-20	7.50	6.666667	0.0	5.55556
	20-25	35.00	40.000000	42.5	38.333333
	25-30	26.25	11.666667	32.5	22.777778
	30-35	13.75	28.333333	10.0	17.777778
	35-40	10.00	10.000000	5.0	8.888889
	40-45	3.75	1.666667	5.0	3.333333
	45-50	3.75	1.666667	5.0	3.333333

Plot the Graph

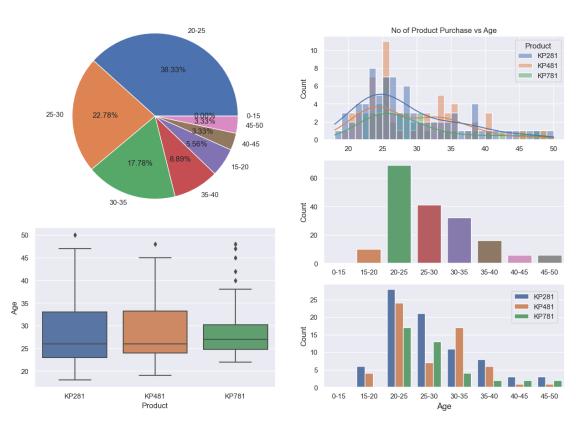
Heat Map



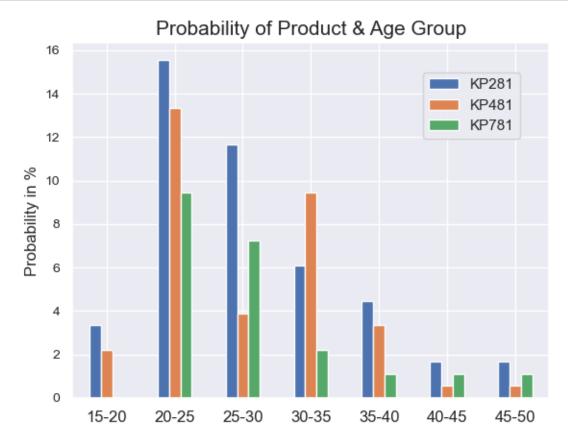
Descriptive Plot

```
plt.ylabel('Count', fontsize=12)
plt.xlabel('', fontsize=11)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)
plt.subplot(3, 2, 4)
sns.countplot(aerofit, x='age_group')
plt.ylabel('Count', fontsize=12)
plt.xlabel('', fontsize=11)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)
plt.subplot(3, 2, 6)
sns.countplot(aerofit, x='age_group', hue='Product')
plt.ylabel('Count', fontsize=12)
plt.xlabel('Age', fontsize=13)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)
plt.legend(borderaxespad=1, ncol=1)
plt.show()
```

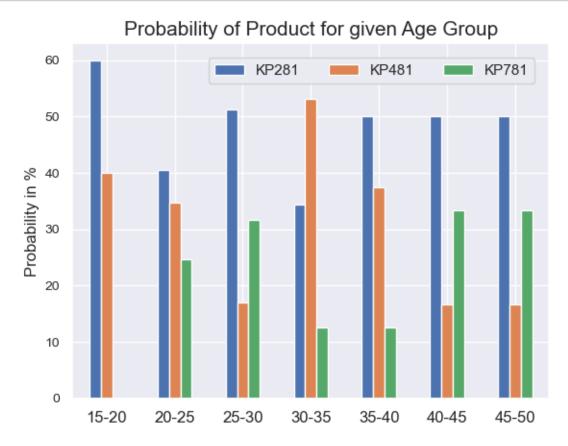
Aerofit Age Dashboard

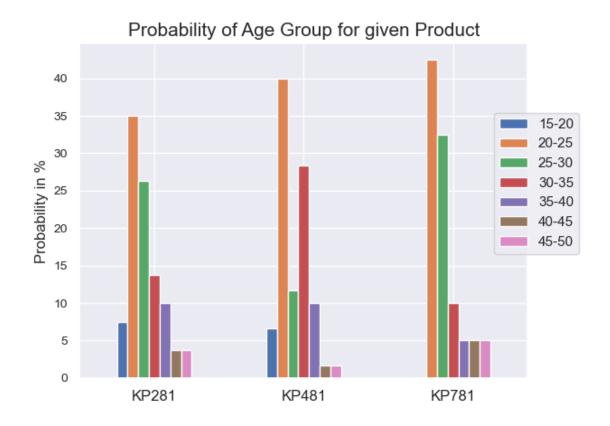


Probability Plot

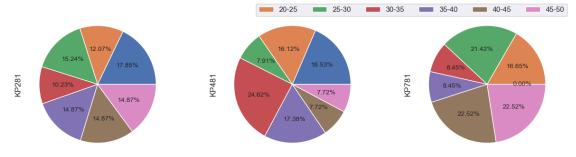


```
plt.legend(borderaxespad=1, ncol=3)
plt.show()
```





Population Plot



1.3.5 Income

Income value Count

```
[]: aerofit['Income'].unique()
[]: array([ 29562,
                    31836,
                            30699,
                                     32973, 35247,
                                                             36384.
                                                                     38658.
                                                     37521,
            40932,
                    34110,
                            39795,
                                     42069, 44343,
                                                     45480,
                                                             46617,
                                                                     48891,
            53439, 43206,
                                     51165, 50028,
                                                     54576, 68220,
                            52302,
                                                                     55713,
            60261, 67083,
                            56850,
                                     59124,
                                             61398,
                                                     57987,
                                                             64809,
                                                                     47754,
            65220, 62535,
                            48658,
                                     54781, 48556,
                                                     58516,
                                                             53536,
                                                                     61006,
            57271, 52291,
                                                            75946,
                            49801,
                                     62251,
                                             64741,
                                                     70966,
                                                                     74701,
            69721, 83416,
                            88396,
                                     90886, 92131,
                                                     77191,
                                                             52290,
                                                                     85906,
            103336, 99601,
                            89641,
                                     95866, 104581,
                                                     95508], dtype=int64)
[]: aerofit['Income'].value_counts()[:5]
[]: 45480
             14
     52302
               9
     46617
               8
     54576
               8
     53439
               8
     Name: Income, dtype: int64
[]: aerofit['Income'].value_counts(normalize=True)[:5]*100
[]: 45480
             7.777778
     52302
             5.000000
             4.44444
     46617
     54576
             4.44444
             4.44444
     53439
    Name: Income, dtype: float64
    Income Group Value Count
[]: aerofit['income_group'].unique()
[]: ['25K-35K', '35K-45K', '45K-55K', '65K-75K', '55K-65K', '75K-85K', '85K-95K',
     '95K-105K']
     Categories (9, object): ['0-25K' < '25K-35K' < '35K-45K' < '45K-55K' ...
     '65K-75K' < '75K-85K' < '85K-95K' < '95K-105K']
[]: aerofit['income_group'].value_counts()[:5]
[ ]: 45K-55K
               77
     35K-45K
               35
     55K-65K
               26
     25K-35K
                14
     85K-95K
                11
     Name: income_group, dtype: int64
[]: aerofit['income_group'].value_counts(normalize=True)[:5]*100
```

```
42.777778
[ ]: 45K-55K
    35K-45K
                19.44444
     55K-65K
                14.44444
     25K-35K
                 7.777778
     85K-95K
                 6.111111
     Name: income_group, dtype: float64
    Statitical Analysis
[]: aerofit['Income'].describe()
[]: count
                 180.000000
    mean
               53719.577778
     std
               16506.684226
               29562.000000
    min
    25%
               44058.750000
     50%
               50596.500000
    75%
               58668.000000
    max
              104581.000000
     Name: Income, dtype: float64
[]: aerofit['income_group'].describe()
[]: count
                   180
    unique
                     8
     top
               45K-55K
     freq
                    77
     Name: income_group, dtype: object
[]: aerofit['Income'].mean()
[]: 53719.5777777778
[]: aerofit['Income'].median()
[]: 50596.5
[]: aerofit['Income'].mode()[0]
[]: 45480
[]: aerofit.groupby('Product')["Income"].describe()
[]:
                                                                               75% \
              count
                                         std
                                                  min
                                                            25%
                                                                      50%
                          mean
     Product
     KP281
               80.0 46418.025
                                 9075.783190
                                              29562.0
                                                       38658.00
                                                                 46617.0
                                                                          53439.0
     KP481
               60.0 48973.650
                                 8653.989388
                                              31836.0
                                                       44911.50
                                                                 49459.5
                                                                          53439.0
    KP781
               40.0 75441.575
                               18505.836720
                                              48556.0
                                                       58204.75 76568.5
                                                                          90886.0
```

```
max
     Product
     KP281
               68220.0
     KP481
               67083.0
     KP781
              104581.0
[]: aerofit.groupby('Product')["income_group"].describe()
[]:
             count unique
                                top freq
     Product
     KP281
                80
                         5
                            45K-55K
                                       35
    KP481
                60
                         5
                            45K-55K
                                       33
    KP781
                40
                         6
                            85K-95K
                                       11
    Check for Outliers
[]: check_outlier(aerofit, 'Income')['upper']
[]: {'list': 159
                       83416
      160
              88396
              90886
      161
      162
              92131
      164
              88396
      166
              85906
      167
              90886
      168
             103336
      169
              99601
      170
              89641
      171
              95866
      172
              92131
      173
              92131
      174
             104581
      175
              83416
      176
              89641
      177
              90886
      178
             104581
      179
              95508
      Name: Income, dtype: int64,
      'length': 19}
[]: check_outlier(aerofit, 'Income')['lower']
[]: {'list': Series([], Name: Income, dtype: int64), 'length': 0}
```

Find Probability

Probability of a Product & Income Group across all Combination "Product Income Group"

```
[]: pd.crosstab(aerofit['income_group'], aerofit['Product'], normalize=True, __

margins=True)*100

[]: Product
                       KP281
                                   KP481
                                              KP781
                                                             All
     income_group
     25K-35K
                    4.44444
                                3.333333
                                           0.000000
                                                        7.777778
     35K-45K
                   14.44444
                                5.000000
                                           0.000000
                                                       19.44444
                   19.44444
                               18.333333
                                           5.000000
                                                       42.777778
     45K-55K
     55K-65K
                    5.000000
                                5.55556
                                           3.888889
                                                       14.44444
                                           1.666667
                                                        3.888889
     65K-75K
                    1.111111
                                1.111111
     75K-85K
                    0.000000
                                0.000000
                                           2.22222
                                                        2.22222
     85K-95K
                    0.000000
                                0.000000
                                           6.111111
                                                        6.111111
     95K-105K
                    0.000000
                                0.000000
                                           3.333333
                                                        3.333333
     All
                   44.44444
                               33.333333
                                          22.22222
                                                      100.000000
    Probability of Product's for given Income Group "Product | Income Group"
[]: pd.crosstab(aerofit['income_group'], aerofit['Product'], normalize='index', __

margins=True)*100

[]: Product
                       KP281
                                   KP481
                                               KP781
     income_group
     25K-35K
                   57.142857
                               42.857143
                                            0.000000
     35K-45K
                   74.285714
                               25.714286
                                            0.000000
     45K-55K
                   45.454545
                               42.857143
                                           11.688312
                   34.615385
                               38.461538
                                           26.923077
     55K-65K
     65K-75K
                   28.571429
                               28.571429
                                           42.857143
     75K-85K
                    0.000000
                                0.000000
                                          100.000000
                                0.000000
                                          100.000000
     85K-95K
                    0.000000
     95K-105K
                    0.000000
                                0.000000
                                          100.000000
     A11
                   44.44444
                               33.333333
                                           22.22222
    Probability of Income Group for given Product "Income Group | Product"
[]: pd.crosstab(aerofit['income_group'], aerofit['Product'], normalize='columns',__
      →margins=True)*100
[]: Product
                   KP281
                               KP481 KP781
                                                   A11
     income_group
     25K-35K
                   10.00
                           10.000000
                                        0.0
                                              7.777778
                   32.50
                           15.000000
                                        0.0
                                             19.44444
     35K-45K
     45K-55K
                   43.75
                           55.000000
                                       22.5
                                             42.777778
                   11.25
                                       17.5
     55K-65K
                           16.666667
                                             14.44444
```

Plot the Graph

2.50

0.00

0.00

0.00

3.333333

0.000000

0.000000

0.000000

65K-75K

75K-85K

85K-95K

95K-105K

3.888889

2.22222

6.111111

3.333333

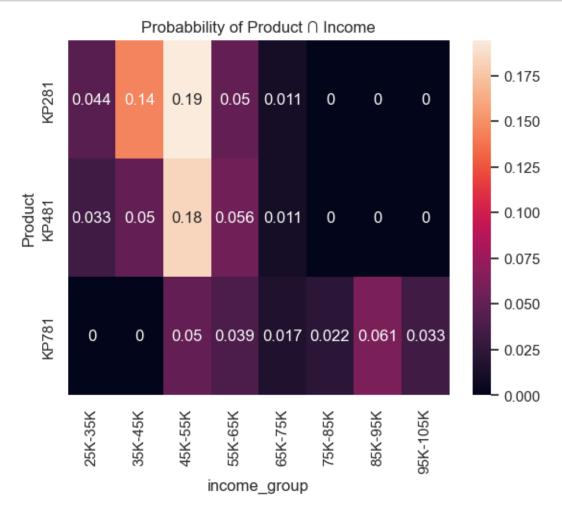
7.5

10.0

27.5

15.0

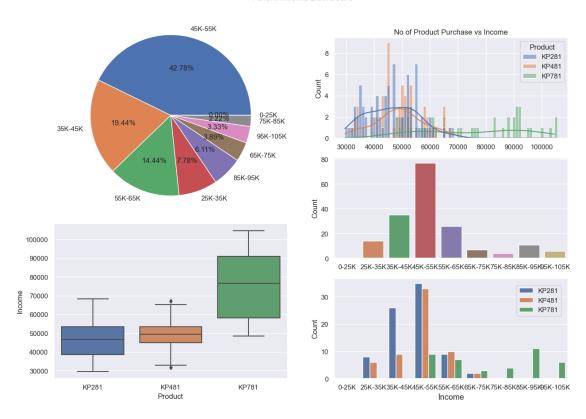
Heat Map

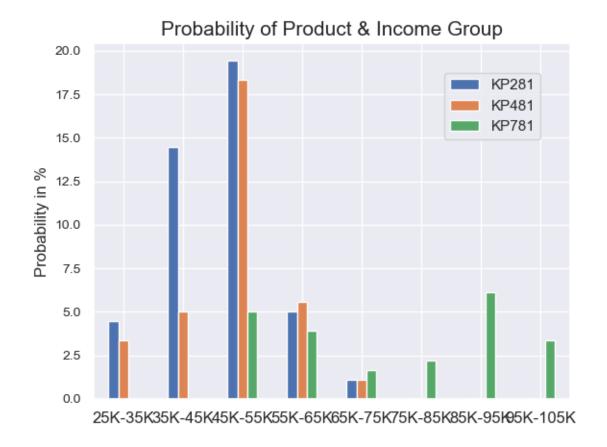


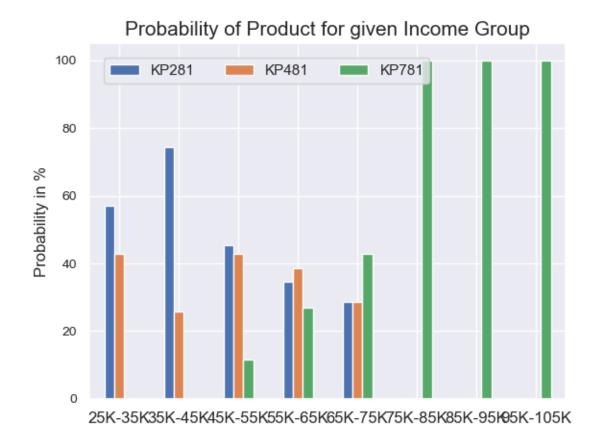
${\tt Descriptive}\ {\bf Plot}$

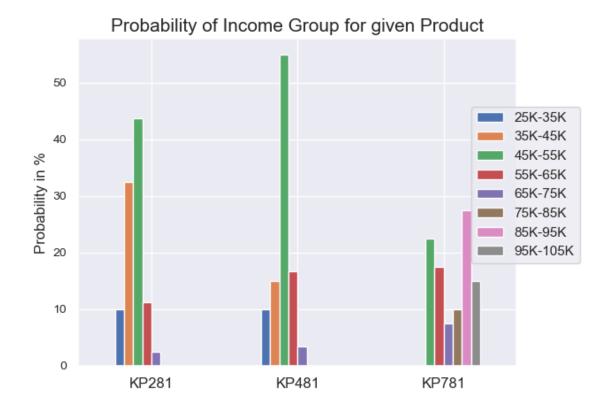
```
plt.subplot(3, 2, 2)
sns.histplot(aerofit, x='Income', binwidth=1000, kde=True, hue='Product')
plt.title('No of Product Purchase vs Income', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.xlabel('', fontsize=11)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)
plt.subplot(3, 2, 4)
sns.countplot(aerofit, x='income_group')
plt.ylabel('Count', fontsize=12)
plt.xlabel('', fontsize=11)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)
plt.subplot(3, 2, 6)
sns.countplot(aerofit, x='income_group', hue='Product')
plt.ylabel('Count', fontsize=12)
plt.xlabel('Income', fontsize=13)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)
plt.legend(borderaxespad=1, ncol=1)
plt.show()
```

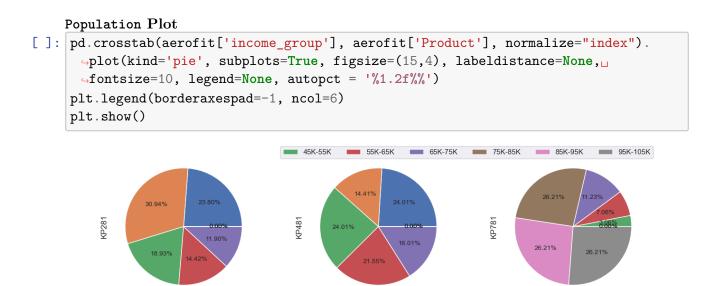
Aerofit Income Dashboard











1.3.6 MilesMiles value Count

```
[]: aerofit['Miles'].unique()
                      66, 85, 47, 141, 103, 94, 113, 38, 188, 56, 132,
[]: array([112, 75,
            169, 64,
                      53, 106, 95, 212, 42, 127, 74, 170, 21, 120, 200,
                      80, 160, 180, 240, 150, 300, 280, 260, 360], dtype=int64)
            140, 100,
[]: aerofit['Miles'].value_counts()[:5]
[]: 85
           27
    95
           12
     66
           10
     75
           10
     47
            9
     Name: Miles, dtype: int64
[]: aerofit['Miles'].value_counts(normalize=True)[:5]*100
[]: 85
          15.000000
     95
            6.66667
     66
            5.55556
     75
            5.55556
     47
            5.000000
     Name: Miles, dtype: float64
    Miles Group Value Count
[]: aerofit['miles_group'].unique()
[]: ['110-140', '50-80', '80-110', '20-50', '140-170', ..., '200-230', '230-260',
     '290-320', '260-290', '350-380']
    Length: 11
     Categories (13, object): ['0-20' < '20-50' < '50-80' < '80-110' ... '260-290' <
     '290-320' < '320-350' < '350-380']
[]: aerofit['miles_group'].value_counts()[:5]
[]: 80-110
                66
     50-80
                43
     110-140
                20
     20-50
               17
     140-170
               15
     Name: miles_group, dtype: int64
[]: aerofit['miles_group'].value_counts(normalize=True)[:5]*100
[]: 80-110
                36.666667
     50-80
               23.888889
               11.111111
     110-140
     20-50
                9.44444
```

```
Name: miles_group, dtype: float64
    Statitical Analysis
[]: aerofit['Miles'].describe()
              180.000000
[]: count
              103.194444
    mean
    std
               51.863605
    min
               21.000000
    25%
               66.000000
    50%
               94.000000
     75%
              114.750000
              360.000000
    max
    Name: Miles, dtype: float64
[]: aerofit['miles_group'].describe()
[]: count
                  180
     unique
                   11
               80-110
     top
     freq
                   66
     Name: miles_group, dtype: object
[]: aerofit['Miles'].mean()
[]: 103.1944444444444
[]: aerofit['Miles'].median()
[]: 94.0
[]: aerofit['Miles'].mode()[0]
[]: 85
[]: aerofit.groupby('Product')["Miles"].describe()
[]:
              count
                           mean
                                       std
                                             min
                                                    25%
                                                           50%
                                                                  75%
    Product
    KP281
               80.0
                     82.787500 28.874102
                                            38.0
                                                   66.0
                                                          85.0
                                                                 94.0
                                                                       188.0
               60.0
    KP481
                      87.933333 33.263135
                                            21.0
                                                   64.0
                                                          85.0
                                                               106.0
                                                                       212.0
    KP781
               40.0 166.900000 60.066544 80.0 120.0
                                                        160.0
                                                                200.0
                                                                       360.0
[]: aerofit.groupby('Product')["miles_group"].describe()
[]:
            count unique
                               top freq
    Product
```

140-170

8.333333

```
KP781
                40
                            170-200
                                      12
    Check for Outliers
[]: check_outlier(aerofit, 'Miles')['upper']
[]: {'list': 23
                     188
      84
             212
      142
             200
      148
             200
      152
             200
      155
             240
      166
             300
      167
             280
      170
             260
      171
             200
      173
             360
      175
             200
      176
             200
      Name: Miles, dtype: int64,
      'length': 13}
[]: check_outlier(aerofit, 'Miles')['lower']
[]: {'list': Series([], Name: Miles, dtype: int64), 'length': 0}
    Find Probability
    Probability of a Product & Miles Group across all Combination "Product Miles Group"
[]: pd.crosstab(aerofit['miles_group'], aerofit['Product'], normalize=True,__

margins=True)*100

[]: Product
                                  KP481
                                             KP781
                                                            All
                      KP281
     miles_group
     20-50
                   6.666667
                               2.777778
                                          0.000000
                                                       9.44444
     50-80
                  14.44444
                               8.88889
                                          0.555556
                                                      23.888889
     80-110
                  15.000000
                              17.222222
                                          4.44444
                                                      36.666667
                                          2.22222
     110-140
                   6.111111
                               2.777778
                                                      11.111111
     140-170
                   1.666667
                               1.111111
                                          5.55556
                                                       8.333333
     170-200
                   0.555556
                               0.000000
                                          6.66667
                                                       7.222222
                                          0.000000
     200-230
                   0.000000
                               0.555556
                                                       0.555556
     230-260
                   0.000000
                               0.000000
                                          1.111111
                                                       1.111111
     260-290
                   0.000000
                               0.000000
                                          0.555556
                                                       0.555556
     290-320
                   0.000000
                               0.000000
                                          0.555556
                                                       0.555556
     350-380
                   0.000000
                               0.000000
                                          0.555556
                                                       0.555556
                  44.44444
     All
                              33.333333
                                         22.22222 100.000000
```

KP281

KP481

80

60

80-110

80-110

6

27

31

Probability of Product's for given Miles Group "Product | Miles Group"

```
[]: pd.crosstab(aerofit['miles_group'], aerofit['Product'], normalize='index', ⊔

⇔margins=True)*100
```

[]:	Product	KP281	KP481	KP781
	miles_group			
	20-50	70.588235	29.411765	0.000000
	50-80	60.465116	37.209302	2.325581
	80-110	40.909091	46.969697	12.121212
	110-140	55.000000	25.000000	20.000000
	140-170	20.000000	13.333333	66.666667
	170-200	7.692308	0.000000	92.307692
	200-230	0.000000	100.000000	0.000000
	230-260	0.000000	0.000000	100.000000
	260-290	0.000000	0.000000	100.000000
	290-320	0.000000	0.000000	100.000000
	350-380	0.000000	0.000000	100.000000
	All	44.44444	33.333333	22.22222

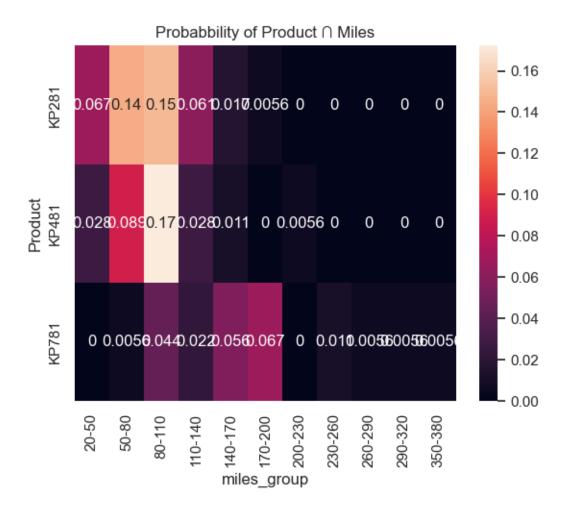
Probability of Miles Group for given Product "Miles Group | Product"

```
[]: pd.crosstab(aerofit['miles_group'], aerofit['Product'], normalize='columns', use margins=True)*100
```

[]:	Product	KP281	KP481	KP781	All
	miles_group				
	20-50	15.00	8.333333	0.0	9.44444
	50-80	32.50	26.666667	2.5	23.888889
	80-110	33.75	51.666667	20.0	36.666667
	110-140	13.75	8.333333	10.0	11.111111
	140-170	3.75	3.333333	25.0	8.333333
	170-200	1.25	0.000000	30.0	7.222222
	200-230	0.00	1.666667	0.0	0.555556
	230-260	0.00	0.000000	5.0	1.111111
	260-290	0.00	0.000000	2.5	0.555556
	290-320	0.00	0.000000	2.5	0.555556
	350-380	0.00	0.000000	2.5	0.555556

Plot the Graph

Heat Map



Descriptive Plot

```
plt.figure(figsize=(15,10)).suptitle("Aerofit Miles Dashboard",fontsize=14)

plt.subplot(2, 2, 1)
plt.pie(aerofit['miles_group'].value_counts().values,labels = aerofit['miles_group'].value_counts().index,radius = 1.3,autopct = '%1.

2f%") # type: ignore

plt.subplot(2, 2, 3)
sns.boxplot(aerofit, y="Miles", x='Product')

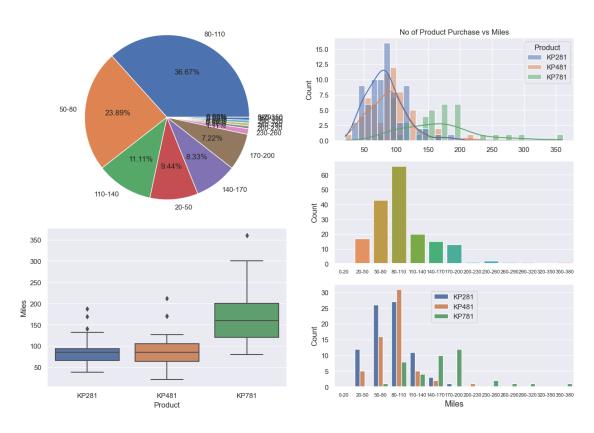
plt.subplot(3, 2, 2)
sns.histplot(aerofit, x='Miles', binwidth=10, kde=True, hue='Product')
plt.title('No of Product Purchase vs Miles', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.xlabel('', fontsize=11)
plt.xticks(fontsize=11)
```

```
plt.yticks(rotation= 0, fontsize=11)

plt.subplot(3, 2, 4)
sns.countplot(aerofit, x='miles_group')
plt.ylabel('Count', fontsize=12)
plt.xlabel('', fontsize=11)
plt.xticks(fontsize=8)
plt.yticks(rotation= 0, fontsize=11)

plt.subplot(3, 2, 6)
sns.countplot(aerofit, x='miles_group', hue='Product')
plt.ylabel('Count', fontsize=12)
plt.xlabel('Miles', fontsize=13)
plt.xticks(fontsize=8)
plt.yticks(rotation= 0, fontsize=11)
plt.legend(borderaxespad=1, ncol=1)
```

Aerofit Miles Dashboard



```
[]: (pd.crosstab(aerofit['miles_group'], aerofit['Product'], normalize=True)*100).

⇔plot(kind='bar')

plt.title('Probability of Product & Miles Group', fontsize=15)

plt.ylabel('Probability in %', fontsize=12)

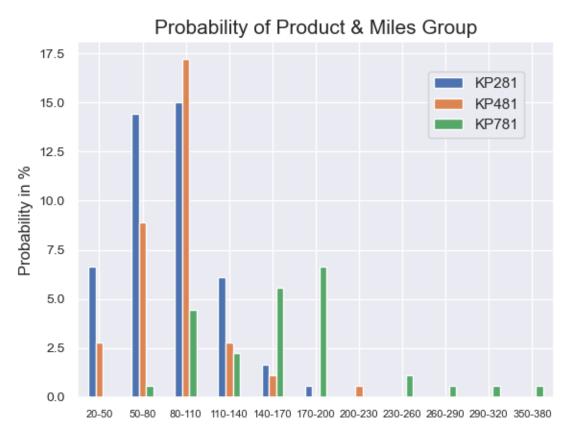
plt.xlabel('', fontsize=12)

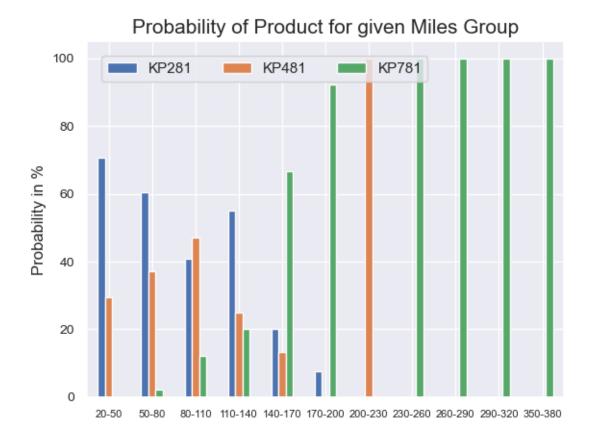
plt.xticks(rotation= 360, fontsize=8)

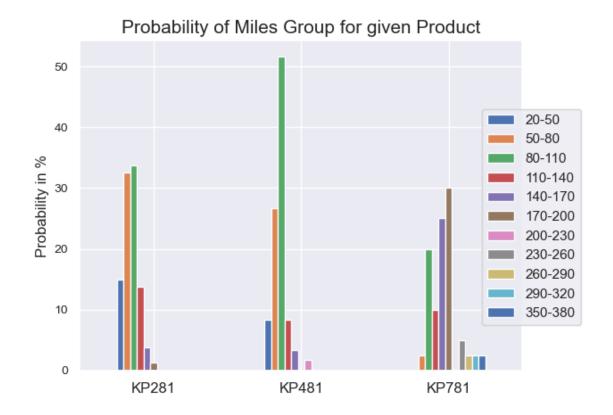
plt.yticks(rotation= 0, fontsize=10)

plt.legend(borderaxespad=2, ncol=1)

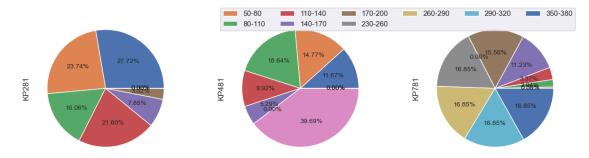
plt.show()
```







Population Plot



1.3.7 Education

```
[]: aerofit['Education'].unique()
[]: array([14, 15, 12, 13, 16, 18, 20, 21], dtype=int64)
[]: aerofit['Education'].value_counts()
[]: 16
           85
     14
           55
     18
           23
            5
     15
     13
            5
     12
            3
     21
            3
     20
            1
     Name: Education, dtype: int64
[]: aerofit['Education'].value_counts(normalize=True)*100
[]: 16
           47.22222
     14
           30.55556
     18
           12.777778
     15
            2.777778
     13
            2.777778
     12
            1.666667
     21
            1.666667
            0.555556
    Name: Education, dtype: float64
    Statitical Analysis
[]: aerofit['Education'].describe()
[]: count
              180.000000
    mean
               15.572222
     std
                1.617055
    min
               12.000000
     25%
               14.000000
     50%
               16.000000
    75%
               16.000000
               21.000000
    max
     Name: Education, dtype: float64
[]: aerofit['Education'].mean()
[]: 15.5722222222223
[]: aerofit['Education'].median()
```

```
[]: 16.0
[]: aerofit['Education'].mode()[0]
[]: 16
     aerofit.groupby('Product')["Education"].describe()
[]:
              count
                                      std
                                            min
                                                  25%
                                                        50%
                                                               75%
                          mean
                                                                     max
     Product
     KP281
               80.0
                     15.037500
                                1.216383
                                           12.0
                                                 14.0
                                                       16.0
                                                              16.0
                                                                    18.0
     KP481
               60.0
                     15.116667
                                 1.222552
                                           12.0
                                                 14.0
                                                       16.0
                                                              16.0
                                                                    18.0
     KP781
               40.0 17.325000
                                          14.0
                                                 16.0
                                1.639066
                                                       18.0
                                                             18.0 21.0
    Check for Outliers
[]: check_outlier(aerofit, 'Education')['upper']
[]: {'list': 156
                     20
      157
             21
      161
             21
      175
             21
      Name: Education, dtype: int64,
      'length': 4}
[]: check_outlier(aerofit, 'Education')['lower']
[]: {'list': Series([], Name: Education, dtype: int64), 'length': 0}
    Find Probability
    Probability of a Product & Education across all Combination "Product Education"
[]: pd.crosstab(aerofit['Education'], aerofit['Product'], normalize=True, ____
      →margins=True)*100
[]: Product
                    KP281
                               KP481
                                           KP781
                                                         All
     Education
     12
                 1.111111
                            0.555556
                                        0.000000
                                                    1.666667
     13
                 1.666667
                            1.111111
                                        0.000000
                                                    2.777778
     14
                16.666667
                           12.777778
                                        1.111111
                                                   30.555556
     15
                 2.22222
                            0.555556
                                        0.000000
                                                    2.777778
     16
                21.666667
                          17.222222
                                                   47.22222
                                        8.333333
     18
                 1.111111
                             1.111111
                                       10.555556
                                                   12.777778
     20
                 0.000000
                            0.000000
                                        0.555556
                                                    0.555556
     21
                 0.000000
                            0.000000
                                        1.666667
                                                    1.666667
                44.44444
     All
                           33.333333
                                       22.22222
                                                  100.000000
```

Probability of Product's for given Education "Product | Education"

```
[]: Product
                    KP281
                                KP481
                                            KP781
     Education
     12
                66.666667
                           33.333333
                                         0.000000
     13
                60.000000
                           40.000000
                                         0.000000
     14
                54.545455
                           41.818182
                                         3.636364
     15
                80.000000
                           20.000000
                                         0.000000
     16
                45.882353
                           36.470588
                                        17.647059
     18
                                        82.608696
                 8.695652
                            8.695652
     20
                 0.000000
                            0.000000
                                       100.000000
     21
                 0.000000
                            0.000000
                                       100.000000
     All
                44.44444
                           33.333333
                                        22.22222
```

Probability of Education for given Product "Education | Product"

```
[]: pd.crosstab(aerofit['Education'], aerofit['Product'], normalize='columns', 

⇔margins=True)*100
```

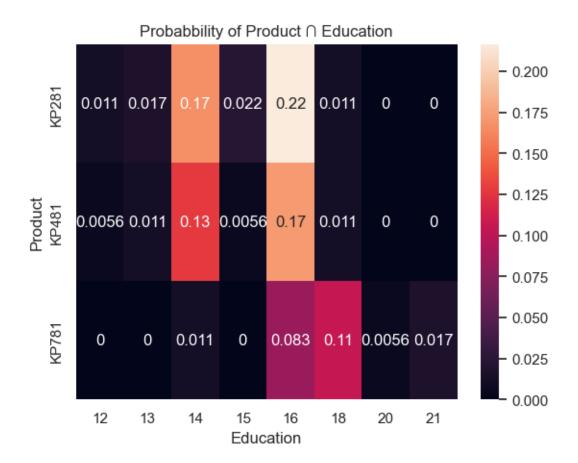
[]:	Product	KP281	KP481	KP781	All
	Education				
	12	2.50	1.666667	0.0	1.666667
	13	3.75	3.333333	0.0	2.777778
	14	37.50	38.333333	5.0	30.555556
	15	5.00	1.666667	0.0	2.777778
	16	48.75	51.666667	37.5	47.222222
	18	2.50	3.333333	47.5	12.777778
	20	0.00	0.000000	2.5	0.555556
	21	0.00	0.000000	7.5	1.666667

Plot the Graph

Heat Map

```
sns.heatmap(pd.crosstab(aerofit['Product'], aerofit['Education'], onermalize='all'), annot=True)
plt.title('Probabbility of Product Education', fontsize=12)
```

[]: Text(0.5, 1.0, 'Probabbility of Product Education')

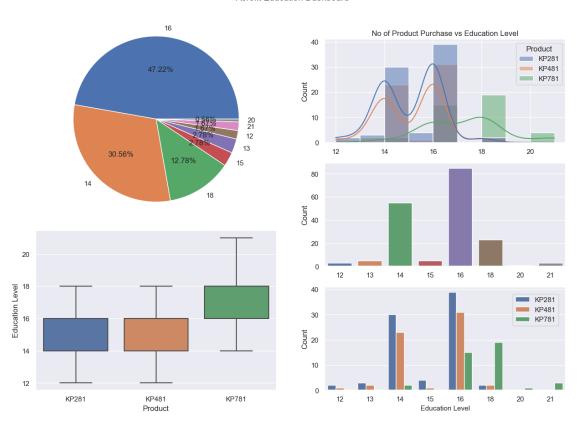


Descriptive Plot

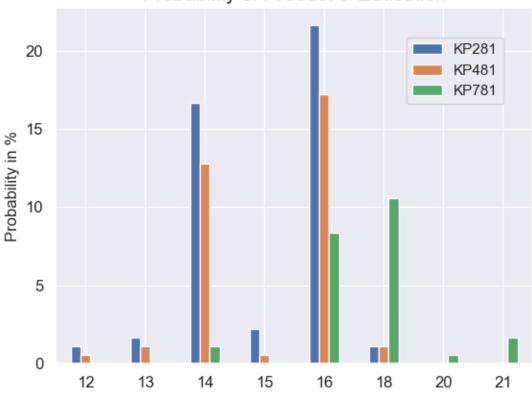
```
plt.subplot(3, 2, 4)
sns.countplot(aerofit, x='Education')
plt.ylabel('Count', fontsize=12)
plt.xlabel('', fontsize=11)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)

plt.subplot(3, 2, 6)
sns.countplot(aerofit, x='Education', hue='Product')
plt.ylabel('Count', fontsize=12)
plt.xlabel('Education Level', fontsize=11)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)
plt.yticks(rotation= 0, fontsize=11)
plt.legend(borderaxespad=1, ncol=1)
```

Aerofit Education Dashboard



Probability of Product & Education



```
[]: (pd.crosstab(aerofit['Education'], aerofit['Product'], normalize="index")*100).

⇔plot(kind='bar')

plt.title('Probability of Product for given Education', fontsize=15)

plt.ylabel('Probability in %', fontsize=12)

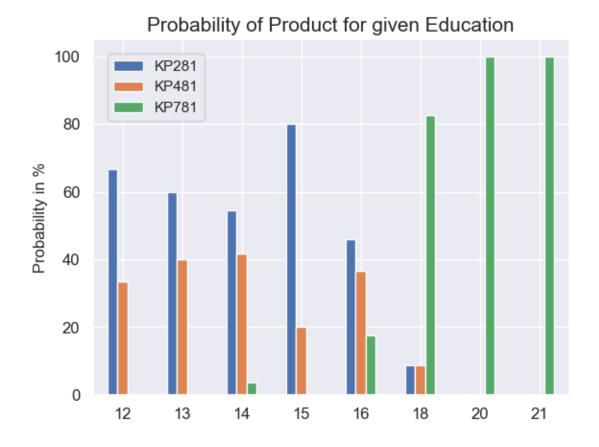
plt.xlabel('', fontsize=12)

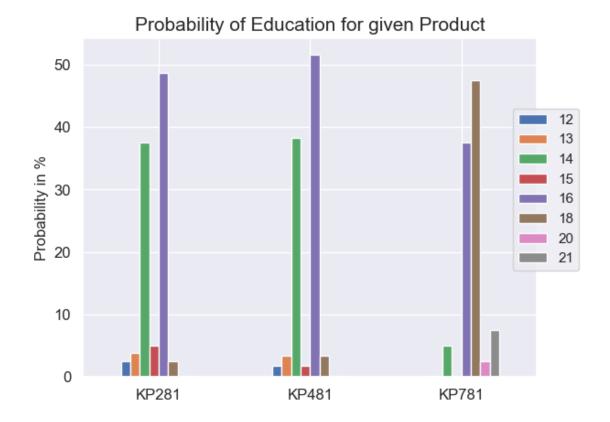
plt.xticks(rotation= 360, fontsize=12)

plt.yticks(rotation= 0, fontsize=12)

plt.legend(borderaxespad=1, ncol=1)

plt.show()
```





Population Plot

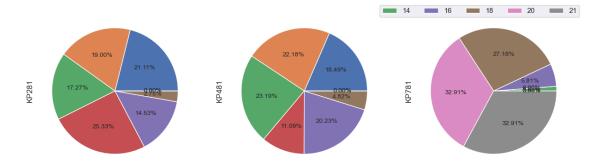
```
[]: pd.crosstab(aerofit['Education'], aerofit['Product'], normalize="index").

⇒plot(kind='pie', subplots=True, figsize=(15,5), labeldistance=None,

⇒fontsize=10, legend=None, autopct = '%1.2f%%')

plt.legend(borderaxespad=-1, ncol=5)

plt.show()
```



1.3.8 Fitness

```
[]: aerofit['Fitness'].unique()
[]: array([4, 3, 2, 1, 5], dtype=int64)
[]: aerofit['Fitness'].value_counts()
[]:3
         97
     5
          31
     2
          26
     4
          24
     Name: Fitness, dtype: int64
[]: aerofit['Fitness'].value_counts(normalize=True)*100
[]:3
          53.888889
          17.222222
     5
     2
          14.44444
     4
          13.333333
           1.111111
     1
    Name: Fitness, dtype: float64
    Statitical Analysis
[]: aerofit['Fitness'].describe()
[]: count
              180.000000
    mean
                3.311111
    std
                0.958869
    min
                1.000000
    25%
                3.000000
    50%
                3.000000
    75%
                4.000000
                5.000000
    Name: Fitness, dtype: float64
[]: aerofit['Fitness'].mean()
[]: 3.31111111111111
[]: aerofit['Fitness'].median()
[]: 3.0
[]: aerofit['Fitness'].mode()[0]
[]:3
```

```
[]: aerofit.groupby('Product')["Fitness"].describe()
[]:
                                           25% 50%
              count
                       mean
                                  std min
                                                     75%
    Product
    KP281
               80.0
                    2.9625
                             0.664540
                                       1.0
                                            3.0
                                                 3.0
                                                      3.0 5.0
                    2.9000
                             0.629770
                                            3.0
                                                 3.0
                                                      3.0 4.0
    KP481
               60.0
                                       1.0
    KP781
               40.0 4.6250
                             0.667467
                                       3.0
                                           4.0 5.0 5.0 5.0
    Check for Outliers
[]: check_outlier(aerofit, 'Fitness')['upper']
[]: {'list': Series([], Name: Fitness, dtype: int64), 'length': 0}
[]: check_outlier(aerofit, 'Fitness')['lower']
[]: {'list': 14
      117
     Name: Fitness, dtype: int64,
      'length': 2}
    Find Probability
    Probability of a Product & Fitness across all Combination "Product Fitness"
[]: pd.crosstab(aerofit['Fitness'], aerofit['Product'], normalize=True, ___
      →margins=True)*100
[ ]: Product
                  KP281
                             KP481
                                        KP781
                                                      All
    Fitness
     1
               0.555556
                          0.555556
                                     0.000000
                                                 1.111111
     2
               7.77778
                          6.66667
                                     0.000000
                                                14.44444
     3
              30.000000 21.666667
                                     2.22222
                                                53.888889
     4
               5.000000
                          4.44444
                                     3.888889
                                                13.333333
               1.111111
                          0.000000
                                    16.111111
                                                17.222222
     All
              44.44444
                        33.333333
                                    22.22222
                                               100.000000
    Probability of Product's for given Fitness "Product | Fitness"
[]: pd.crosstab(aerofit['Fitness'], aerofit['Product'], normalize='index',
      →margins=True)*100
[ ]: Product
                  KP281
                             KP481
                                        KP781
    Fitness
              50.000000 50.000000
     1
                                     0.000000
     2
              53.846154 46.153846
                                     0.00000
     3
              55.670103 40.206186
                                     4.123711
     4
              37.500000 33.333333
                                    29.166667
               6.451613
     5
                         0.000000
                                    93.548387
     All
              44.44444 33.333333
                                    22.22222
```

Probability of Fitness for given Product "Fitness | Product"

```
[]: pd.crosstab(aerofit['Fitness'], aerofit['Product'], normalize='columns', 

⇔margins=True)*100
```

[]:	Product	KP281	KP481	KP781	All
	Fitness				
	1	1.25	1.666667	0.0	1.111111
	2	17.50	20.000000	0.0	14.44444
	3	67.50	65.000000	10.0	53.888889
	4	11.25	13.333333	17.5	13.333333
	5	2.50	0.000000	72.5	17.222222

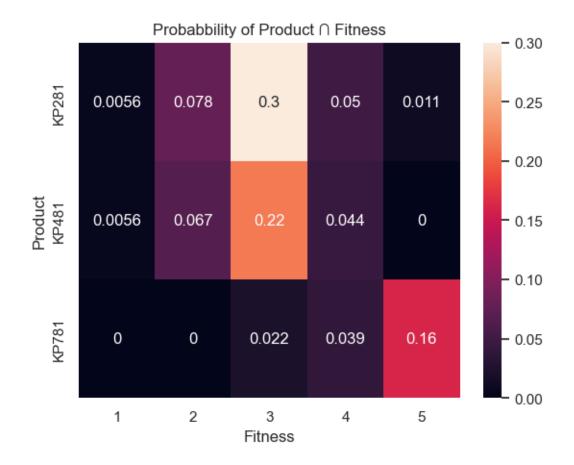
Plot the Graph

Heat Map

```
[]: sns.heatmap(pd.crosstab(aerofit['Product'], aerofit['Fitness'], onermalize='all'), annot=True)

plt.title('Probabbility of Product Fitness', fontsize=12)
```

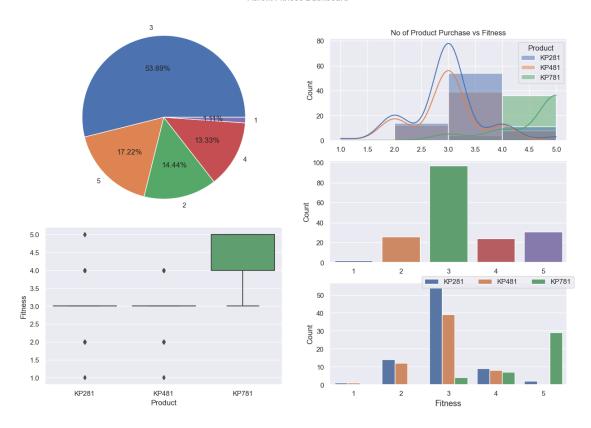
[]: Text(0.5, 1.0, 'Probabbility of Product Fitness')

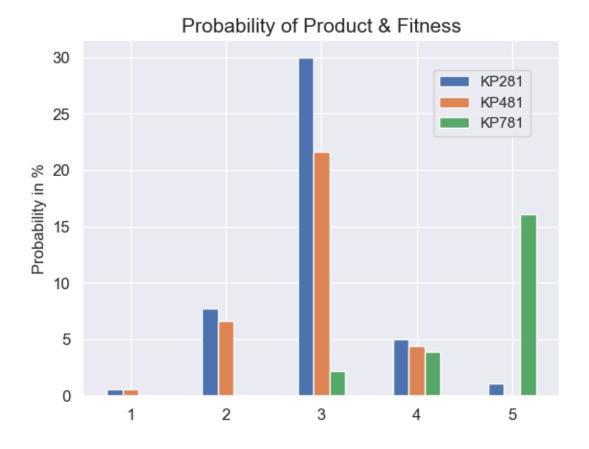


Descriptive Plot

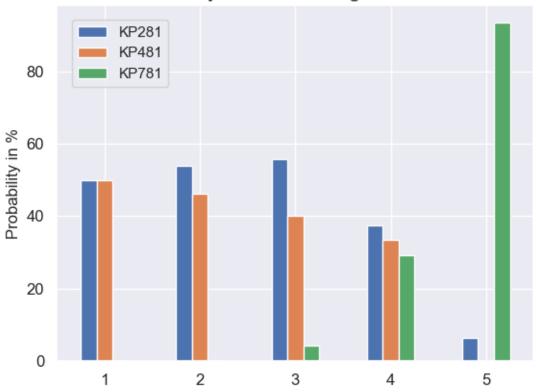
```
[]: plt.figure(figsize=(15,10)).suptitle("Aerofit Fitness Dashboard",fontsize=14)
     plt.subplot(2, 2, 1)
     plt.pie(aerofit['Fitness'].value_counts().values,labels = aerofit['Fitness'].
      ⇒value_counts().index,radius = 1.3,autopct = '%1.2f%%') # type: ignore
     plt.subplot(2, 2, 3)
     sns.boxplot(aerofit, y="Fitness", x='Product')
     plt.subplot(3, 2, 2)
     sns.histplot(aerofit, x='Fitness', binwidth=1, kde=True, hue="Product")
     plt.title('No of Product Purchase vs Fitness', fontsize=12)
     plt.ylabel('Count', fontsize=12)
     plt.xlabel('', fontsize=11)
     plt.xticks(fontsize=11)
     plt.yticks(rotation= 0, fontsize=11)
     plt.subplot(3, 2, 4)
     sns.countplot(aerofit, x='Fitness')
     plt.ylabel('Count', fontsize=12)
     plt.xlabel('', fontsize=11)
     plt.xticks(fontsize=11)
     plt.yticks(rotation= 0, fontsize=11)
     plt.subplot(3, 2, 6)
     sns.countplot(aerofit, x='Fitness', hue='Product')
     plt.ylabel('Count', fontsize=12)
     plt.xlabel('Fitness', fontsize=13)
     plt.xticks(fontsize=11)
     plt.yticks(rotation= 0, fontsize=11)
     plt.legend(borderaxespad=-1, ncol=3)
     plt.show()
```

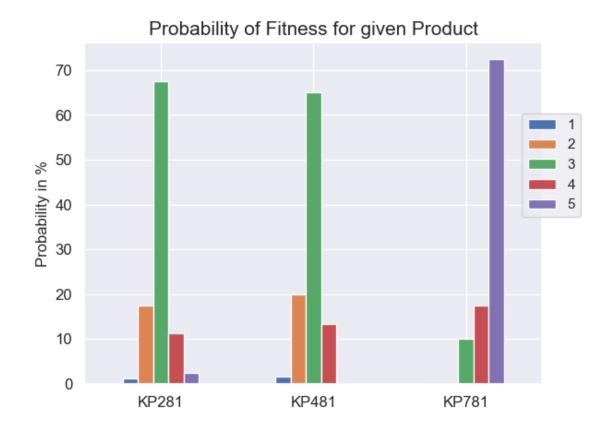
Aerofit Fitness Dashboard











${\tt Population} \ {\bf Plot}$

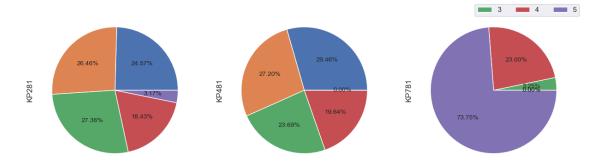
```
pd.crosstab(aerofit['Fitness'], aerofit['Product'], normalize="index").

plot(kind='pie', subplots=True, figsize=(15,5), labeldistance=None,

fontsize=10, legend=None, autopct = '%1.2f%%')

plt.legend(borderaxespad=-1, ncol=5)

plt.show()
```



```
1.3.9 Usage
```

```
[]: aerofit['Usage'].unique()
[]: array([3, 2, 4, 5, 6, 7], dtype=int64)
[]: aerofit['Usage'].value_counts()
[]:3
          69
     4
          52
     2
          33
     5
          17
     6
          7
           2
     Name: Usage, dtype: int64
[]: aerofit['Usage'].value_counts(normalize=True)*100
[]:3
          38.333333
     4
          28.888889
     2
          18.333333
     5
           9.444444
     6
           3.888889
           1.111111
     Name: Usage, dtype: float64
    Statitical Analysis
[]: aerofit['Usage'].describe()
[]: count
              180.000000
    mean
                3.455556
     std
                1.084797
    min
                2.000000
     25%
                3.000000
                3.000000
    50%
    75%
                4.000000
                7.000000
    max
     Name: Usage, dtype: float64
[]: aerofit['Usage'].mean()
[]: 3.4555555555555
[]: aerofit['Usage'].median()
[]: 3.0
[]: aerofit['Usage'].mode()[0]
```

```
[]:3
[]: aerofit.groupby('Product')["Usage"].describe()
[]:
                                    std min
                                              25% 50%
                                                         75%
              count
                         mean
                                                              max
    Product
    KP281
               80.0
                     3.087500
                               0.782624
                                         2.0
                                              3.0
                                                   3.0
                                                        4.00
                                                              5.0
    KP481
               60.0
                    3.066667
                               0.799717
                                         2.0
                                              3.0
                                                   3.0
                                                        3.25
                                                              5.0
                                         3.0 4.0 5.0 5.00 7.0
    KP781
               40.0 4.775000
                               0.946993
    Check for Outliers
[]: check_outlier(aerofit, 'Usage')['upper']
[]: {'list': 154
                     6
      155
             6
      162
             6
      163
             7
      164
             6
      166
             7
      167
             6
      170
             6
      175
             6
     Name: Usage, dtype: int64,
      'length': 9}
[]: check_outlier(aerofit, 'Usage')['lower']
[]: {'list': Series([], Name: Usage, dtype: int64), 'length': 0}
    Find Probability
    Probability of a Product & Usage across all Combination "Product Usage"
[]: pd.crosstab(aerofit['Usage'], aerofit['Product'], normalize=True,
      →margins=True)*100
[]: Product
                  KP281
                             KP481
                                        KP781
                                                      All
    Usage
     2
              10.555556
                          7.777778
                                     0.000000
                                                18.333333
     3
              20.555556
                         17.222222
                                     0.555556
                                                38.333333
     4
              12.222222
                          6.666667 10.000000
                                                28.888889
     5
               1.111111
                          1.666667
                                     6.66667
                                                 9.44444
     6
               0.000000
                          0.000000
                                                 3.888889
                                     3.888889
     7
               0.000000
                          0.000000
                                     1.111111
                                                 1.111111
     All
              44.44444
                         33.333333
                                    22.22222
                                               100.000000
```

Probability of Product's for given Usage "Product | Usage"

```
[]: pd.crosstab(aerofit['Usage'], aerofit['Product'], normalize='index', □ ←margins=True)*100
```

```
[]: Product
                  KP281
                             KP481
                                         KP781
    Usage
     2
              57.575758 42.424242
                                      0.000000
     3
              53.623188
                         44.927536
                                      1.449275
     4
              42.307692
                         23.076923
                                     34.615385
     5
              11.764706 17.647059
                                     70.588235
               0.000000
     6
                         0.000000
                                    100.000000
     7
               0.000000
                         0.000000
                                    100.000000
     All
              44.44444 33.333333
                                     22.22222
```

Probability of Usage for given Product "Fitness | Product"

```
[]: pd.crosstab(aerofit['Usage'], aerofit['Product'], normalize='columns', □ 

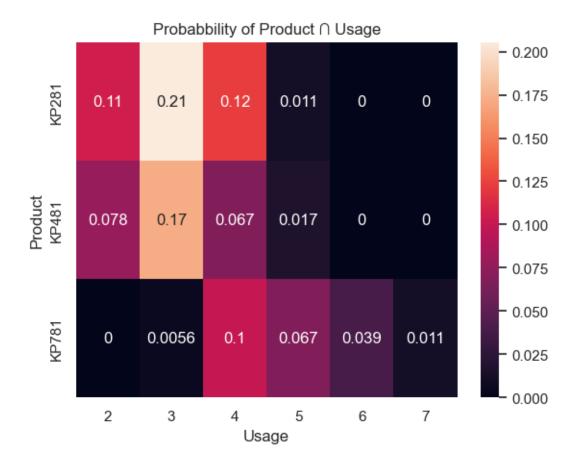
⇔margins=True)*100
```

[]:	Product	KP281	KP481	KP781	All
	Usage				
	2	23.75	23.333333	0.0	18.333333
	3	46.25	51.666667	2.5	38.333333
	4	27.50	20.000000	45.0	28.888889
	5	2.50	5.000000	30.0	9.44444
	6	0.00	0.000000	17.5	3.888889
	7	0.00	0.000000	5.0	1.111111

Plot the Graph

Heat Map

[]: Text(0.5, 1.0, 'Probabbility of Product Usage')

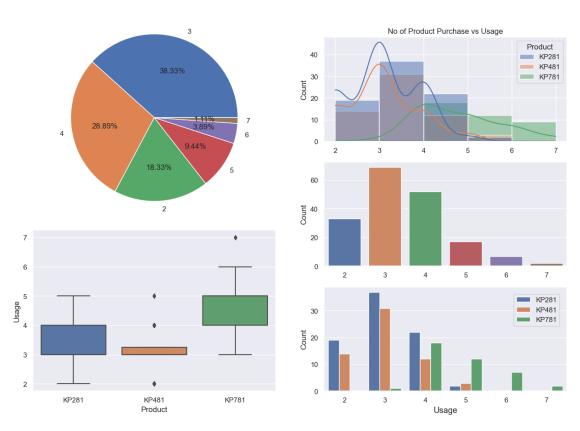


Descriptive Plot

```
sns.countplot(aerofit, x='Usage')
plt.ylabel('Count', fontsize=12)
plt.xlabel('', fontsize=11)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)

plt.subplot(3, 2, 6)
sns.countplot(aerofit, x='Usage', hue='Product')
plt.ylabel('Count', fontsize=12)
plt.xlabel('Usage', fontsize=13)
plt.xticks(fontsize=11)
plt.yticks(rotation= 0, fontsize=11)
plt.legend(borderaxespad=1, ncol=1)
```

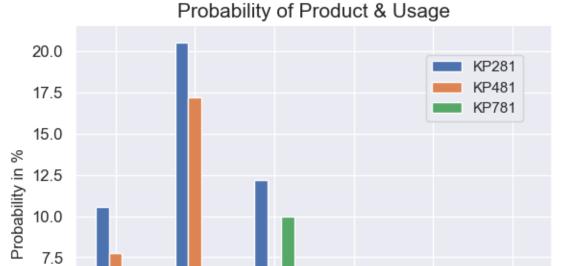
Aerofit Usage Dashboard



```
[]: (pd.crosstab(aerofit['Usage'], aerofit['Product'], normalize=True)*100).

→plot(kind='bar')
```

```
plt.title('Probability of Product & Usage', fontsize=15)
plt.ylabel('Probability in %', fontsize=12)
plt.xlabel('', fontsize=12)
plt.xticks(rotation= 360, fontsize=12)
plt.yticks(rotation= 0, fontsize=12)
plt.legend(borderaxespad=2, ncol=1)
plt.show()
```



7.5

5.0

2.5

0.0

2

3

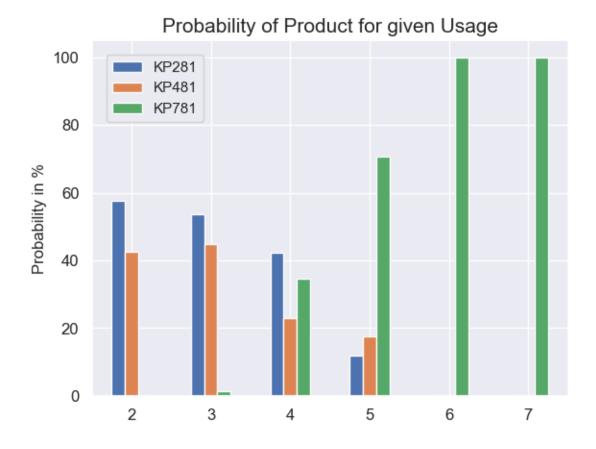
```
[]: (pd.crosstab(aerofit['Usage'], aerofit['Product'], normalize="index")*100).
     →plot(kind='bar')
     plt.title('Probability of Product for given Usage', fontsize=15)
     plt.ylabel('Probability in %', fontsize=12)
    plt.xlabel('', fontsize=12)
     plt.xticks(rotation= 360, fontsize=12)
     plt.yticks(rotation= 0, fontsize=12)
     plt.legend(borderaxespad=1, ncol=1)
     plt.show()
```

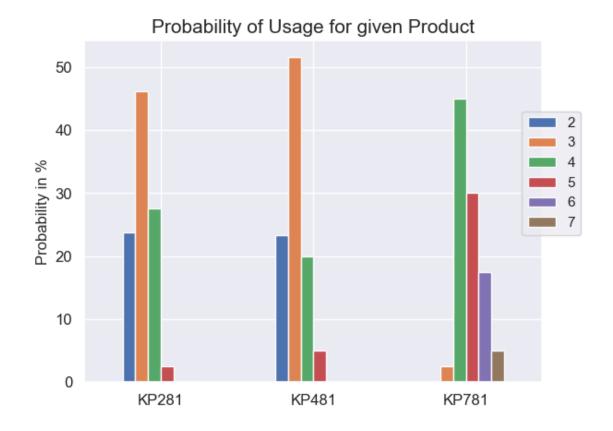
4

5

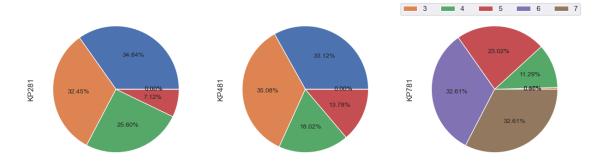
6

7





${\tt Population} \ {\bf Plot}$



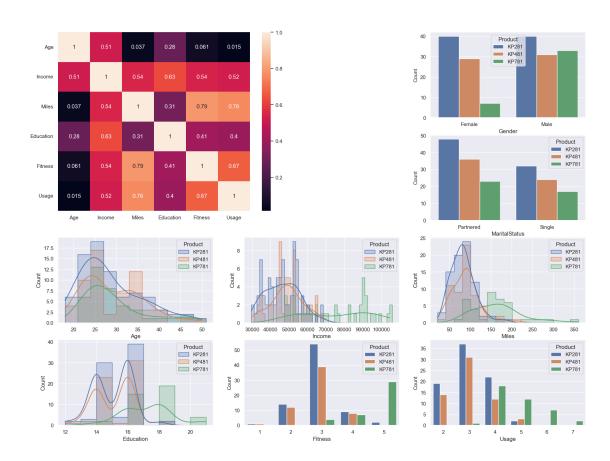
1.4 Customer Profile of Different Product

```
[]: KP281 = aerofit.copy().loc[aerofit['Product']=='KP281']
KP481 = aerofit.copy().loc[aerofit['Product']=='KP481']
KP781 = aerofit.copy().loc[aerofit['Product']=='KP781']
```

1.4.1 Cummulative Profile

```
[]: plt.figure(figsize=(20,15)).suptitle("Aerofit Customer Profile",fontsize=14)
     plt.subplot(2, 2, 1)
     sns.heatmap(aerofit[['Age', 'Income', 'Miles', 'Education', 'Fitness', __

¬'Usage']].corr(), annot=True)
     plt.yticks(rotation= 0, fontsize=11)
     plt.xticks(fontsize=11)
     plt.subplot(4, 3, 3)
     sns.countplot(aerofit, x='Gender', hue="Product")
     plt.ylabel("Count", fontsize=11)
     plt.subplot(4, 3, 6)
     sns.countplot(aerofit, x='MaritalStatus', hue="Product")
     plt.ylabel("Count", fontsize=11)
     plt.subplot(4, 3, 7)
     sns.histplot(aerofit, x="Age", binwidth=3, kde=True, hue="Product", __
      ⇔element="step")
     plt.subplot(4, 3, 8)
     sns.histplot(aerofit, x="Income", binwidth=1500, kde=True, hue="Product", u
      ⇔element="step")
     plt.subplot(4, 3, 9)
     sns.histplot(aerofit, x="Miles", binwidth=20, kde=True, hue="Product", __
      ⇔element="step")
     plt.subplot(4, 3, 10)
     sns.histplot(aerofit, x="Education", binwidth=1, kde=True, hue="Product", u
      ⇔element="step")
     plt.subplot(4, 3, 11)
     sns.countplot(aerofit, x='Fitness', hue="Product")
     plt.ylabel("Count", fontsize=11)
     plt.subplot(4, 3, 12)
     sns.countplot(aerofit, x='Usage', hue="Product")
     plt.ylabel("Count", fontsize=11)
     plt.show()
```



1.4.2 Profile of *KP281*

```
[]: KP281[['Gender', 'MaritalStatus', 'Fitness', 'Usage', 'Age']].

ovalue_counts(normalize=True)[:5]*100
```

[]:	Gender	MaritalStatus	Fitness	Usage	Age	
	Female	Partnered	2	2	25	2.5
	Male	Partnered	3	3	38	2.5
	Female	Single	3	4	24	2.5
		Partnered	3	2	28	2.5
	Male	Single	3	4	23	2.5
	dtype:	float64				

Statitical Analysis

```
[]: KP281[['Gender', 'MaritalStatus', 'age_group', 'income_group', 'miles_group', \
\( \text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\tin}\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\tet
```

```
Gender MaritalStatus age_group income_group miles_group \
                 80
     count
                               80
                                          80
                                                       80
                                                                    80
                  2
     unique
                                2
                                           7
                                                        5
                                                                     6
     top
             Female
                        Partnered
                                       20-25
                                                  45K-55K
                                                                80-110
     freq
                 40
                                48
                                                                    27
                                          28
                                                       35
             education group
                              fitness group
                                              usage group
     count
                          80
                                          80
                                                       80
                           6
                                           5
                                                        4
     unique
                                                        3
     top
                          16
                                           3
                          39
                                          54
                                                       37
     freq
[]: KP281[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].describe()
[]:
                            Income
                                          Miles Education
                                                             Fitness
                                                                           Usage
                  Age
            80.000000
                          80.00000
                                      80.000000
                                                 80.000000
                                                            80.00000
                                                                       80.00000
     count
            28.550000
                                      82.787500 15.037500
                                                                        3.087500
    mean
                       46418.02500
                                                             2.96250
     std
             7.221452
                        9075.78319
                                      28.874102
                                                  1.216383
                                                             0.66454
                                                                        0.782624
                                      38.000000 12.000000
    min
            18.000000
                       29562.00000
                                                             1.00000
                                                                        2.000000
     25%
            23.000000
                       38658.00000
                                      66.000000 14.000000
                                                             3.00000
                                                                        3.000000
     50%
            26.000000
                       46617.00000
                                      85.000000
                                                 16.000000
                                                             3.00000
                                                                        3.000000
     75%
            33.000000
                       53439.00000
                                      94.000000 16.000000
                                                             3.00000
                                                                        4.000000
            50.000000
                       68220.00000 188.000000 18.000000
                                                             5.00000
                                                                        5.000000
    max
[]: KP281[['Age', 'Income', 'Miles', 'Education', 'Usage', 'Fitness']].median()
[ ]: Age
                     26.0
     Income
                  46617.0
    Miles
                     85.0
    Education
                     16.0
    Usage
                      3.0
    Fitness
                      3.0
     dtype: float64
    Find Probability
[]: pd.crosstab([KP281.income_group], [KP281.age_group], normalize=True,
      ⇒margins=True)*100
[]: age_group
                   15-20
                          20-25
                                 25-30
                                         30-35 35-40
                                                       40-45
                                                              45-50
                                                                         All
     income_group
     25K-35K
                    6.25
                           3.75
                                  0.00
                                          0.00
                                                 0.00
                                                        0.00
                                                               0.00
                                                                       10.00
                    1.25
                          25.00
     35K-45K
                                  3.75
                                          0.00
                                                 2.50
                                                        0.00
                                                               0.00
                                                                       32.50
                    0.00
                                 21.25
                                                 3.75
                                                                       43.75
     45K-55K
                           6.25
                                         10.00
                                                        2.50
                                                               0.00
                                  0.00
                                                               3.75
                                                                       11.25
     55K-65K
                    0.00
                           0.00
                                          2.50
                                                 3.75
                                                        1.25
                    0.00
                           0.00
                                  1.25
                                                 0.00
                                                               0.00
                                                                        2.50
     65K-75K
                                          1.25
                                                        0.00
     All
                    7.50
                          35.00
                                 26.25 13.75
                                               10.00
                                                        3.75
                                                               3.75
                                                                     100.00
```

[]:

[]: pd.crosstab([KP281.Fitness, KP281.Gender, KP281.MaritalStatus], [KP281.

wmiles_group], normalize=True, margins=True)*100

[]:	miles_g	roup		20-50	50-80	80-110	110-140	140-170	170-200	\
			MaritalStatus							
	1	Male	Partnered	1.25	0.00	0.00	0.00	0.00	0.00	
	2	${\tt Female}$	Partnered	6.25	2.50	0.00	0.00	0.00	0.00	
			Single	2.50	1.25	0.00	0.00	0.00	0.00	
		Male	Partnered	5.00	0.00	0.00	0.00	0.00	0.00	
	3	${\tt Female}$	Partnered	0.00	12.50	8.75	1.25	0.00	0.00	
			Single	0.00	5.00	3.75	1.25	0.00	0.00	
		Male	Partnered	0.00	7.50	8.75	0.00	0.00	0.00	
			Single	0.00	2.50	12.50	3.75	0.00	0.00	
	4	${\tt Female}$	Partnered	0.00	0.00	0.00	1.25	0.00	0.00	
			Single	0.00	1.25	0.00	1.25	0.00	0.00	
		Male	Partnered	0.00	0.00	0.00	2.50	1.25	0.00	
			Single	0.00	0.00	0.00	2.50	1.25	0.00	
	5	Female	Partnered	0.00	0.00	0.00	0.00	0.00	1.25	
		Male	Single	0.00	0.00	0.00	0.00	1.25	0.00	
	All			15.00	32.50	33.75	13.75	3.75	1.25	
	miles_gr	roup		All						
	-0	-	MaritalStatus							
	1	Male	Partnered	1.25						
	2	Female	Partnered	8.75						
			Single	3.75						
		Male	Partnered	5.00						
	3	Female	Partnered	22.50						
			Single	10.00						
		Male	Partnered	16.25						
			Single	18.75						
	4	Female	Partnered	1.25						
			Single	2.50						
		Male	Partnered	3.75						
			Single	3.75						
	5	Female	Partnered	1.25						
		Male	Single	1.25						
	All		J	100.00						

[]: pd.crosstab([KP281.Fitness, KP281.Gender, KP281.MaritalStatus], [KP281. age_group], normalize=True, margins=True)*100

[]:	age_grou		15-20	20-25	25-30	30-35	35-40	40-45	45-50	\	
	Fitness	Gender	MaritalStatus								
	1	Male	Partnered	0.00	1.25	0.00	0.00	0.00	0.00	0.00	
	2	Female	Partnered	0.00	5.00	2.50	0.00	0.00	0.00	1.25	
			Single	0.00	0.00	0.00	3.75	0.00	0.00	0.00	

```
1.25
                                       1.25
                                                      1.25
                                                             0.00
                                                                     0.00
                                                                            0.00
        Male
               Partnered
                                               1.25
3
        Female Partnered
                                2.50
                                       5.00
                                               8.75
                                                      2.50
                                                             2.50
                                                                     0.00
                                                                            1.25
                                0.00
                                               1.25
                                                             0.00
                                                                     0.00
                                                                            0.00
               Single
                                       7.50
                                                      1.25
        Male
               Partnered
                                0.00
                                       3.75
                                               2.50
                                                      2.50
                                                             3.75
                                                                     2.50
                                                                            1.25
               Single
                                2.50
                                       7.50
                                               6.25
                                                      0.00
                                                             2.50
                                                                     0.00
                                                                            0.00
4
        Female Partnered
                                0.00
                                       0.00
                                               1.25
                                                      0.00
                                                             0.00
                                                                     0.00
                                                                            0.00
                                0.00
                                               0.00
                                                                            0.00
               Single
                                       0.00
                                                      1.25
                                                             0.00
                                                                     1.25
        Male
               Partnered
                                0.00
                                       0.00
                                               2.50
                                                      0.00
                                                             1.25
                                                                     0.00
                                                                            0.00
                                1.25
                                               0.00
                                                      0.00
                                                             0.00
                                                                     0.00
                                                                            0.00
               Single
                                       2.50
5
        Female Partnered
                                0.00
                                       1.25
                                               0.00
                                                      0.00
                                                             0.00
                                                                     0.00
                                                                            0.00
        Male
               Single
                                0.00
                                       0.00
                                               0.00
                                                      1.25
                                                             0.00
                                                                     0.00
                                                                            0.00
All
                                7.50 35.00
                                             26.25 13.75
                                                            10.00
                                                                     3.75
                                                                            3.75
age_group
                                  All
Fitness Gender MaritalStatus
        Male
               Partnered
                                 1.25
2
        Female Partnered
                                 8.75
               Single
                                 3.75
        Male
               Partnered
                                 5.00
3
        Female Partnered
                                22.50
               Single
                                10.00
        Male
               Partnered
                                16.25
               Single
                                18.75
4
        Female Partnered
                                 1.25
               Single
                                 2.50
               Partnered
        Male
                                 3.75
               Single
                                 3.75
5
        Female Partnered
                                 1.25
        Male
               Single
                                 1.25
All
                               100.00
```

[]: pd.crosstab([KP281.Fitness, KP281.Gender, KP281.MaritalStatus], [KP281.

income_group], normalize=True, margins=True)*100

[]:	income_g	group		25K-35K	35K-45K	45K-55K	55K-65K	65K-75K	\
	${\tt Fitness}$	${\tt Gender}$	MaritalStatus						
	1 Male		Partnered	0.00	1.25	0.00	0.00	0.00	
	2	${\tt Female}$	Partnered	1.25	2.50	3.75	1.25	0.00	
			Single	0.00	0.00	2.50	1.25	0.00	
		Male	Partnered	0.00	2.50	2.50	0.00	0.00	
	3	${\tt Female}$	Partnered	2.50	5.00	12.50	2.50	0.00	
			Single	1.25	6.25	1.25	0.00	1.25	
		Male	Partnered	0.00	2.50	8.75	3.75	1.25	
			Single	3.75	6.25	8.75	0.00	0.00	
	4	${\tt Female}$	Partnered	0.00	1.25	0.00	0.00	0.00	
			Single	0.00	0.00	1.25	1.25	0.00	
		Male	Partnered	0.00	1.25	1.25	1.25	0.00	

```
2.50
                                                      0.00
                                                               0.00
                                                                        0.00
                Single
                                  1.25
5
        Female Partnered
                                  0.00
                                            1.25
                                                      0.00
                                                               0.00
                                                                         0.00
        Male
                                  0.00
                                            0.00
                                                      1.25
                                                               0.00
                                                                         0.00
                Single
                                                    43.75
                                                              11.25
All
                                  10.00
                                           32.50
                                                                         2.50
                                  All
income_group
Fitness Gender MaritalStatus
1
        Male
               Partnered
                                  1.25
2
        Female Partnered
                                 8.75
                Single
                                 3.75
               Partnered
        Male
                                 5.00
3
        Female Partnered
                                22.50
                Single
                                 10.00
                                16.25
        Male
                Partnered
                Single
                                18.75
4
        Female Partnered
                                 1.25
                Single
                                 2.50
        Male
                Partnered
                                 3.75
                Single
                                  3.75
5
        Female Partnered
                                  1.25
        Male
                Single
                                  1.25
All
                               100.00
```

Check for Outliers

```
plt.figure(figsize=(15,10)).suptitle("KP281 Outliers",fontsize=14)

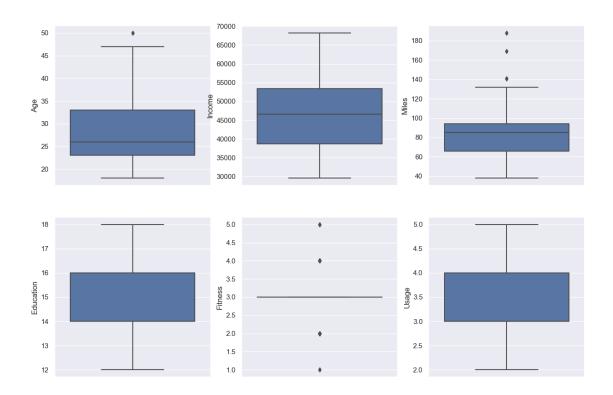
plt.subplot(2, 3, 1)
    sns.boxplot(KP281, y="Age")
    plt.subplot(2, 3, 2)
    sns.boxplot(KP281, y="Income")

plt.subplot(2, 3, 3)
    sns.boxplot(KP281, y="Miles")
    plt.subplot(2, 3, 4)
    sns.boxplot(KP281, y="Education")

plt.subplot(2, 3, 5)
    sns.boxplot(KP281, y='Fitness')
    plt.subplot(2, 3, 6)
    sns.boxplot(KP281, y='Usage')

plt.show()
```

KP281 Outliers



Plot the Graph

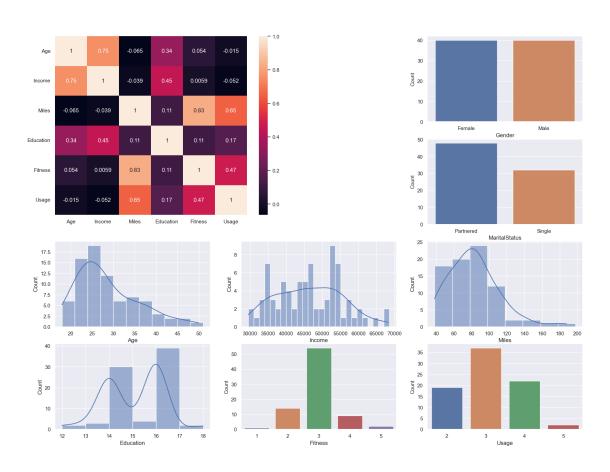
```
[]: plt.figure(figsize=(20,15)).suptitle("KP281 Customer Profile",fontsize=14)
     plt.subplot(2, 2, 1)
     sns.heatmap(KP281[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].
     ⇔corr(), annot=True)
     plt.yticks(rotation= 0, fontsize=11)
     plt.xticks(fontsize=11)
     plt.subplot(4, 3, 3)
     sns.countplot(KP281, x='Gender')
     plt.ylabel("Count", fontsize=11)
     plt.subplot(4, 3, 6)
     sns.countplot(KP281, x='MaritalStatus')
     plt.ylabel("Count", fontsize=11)
     plt.subplot(4, 3, 7)
     sns.histplot(KP281, x="Age", binwidth=3, kde=True)
     plt.subplot(4, 3, 8)
     sns.histplot(KP281, x="Income", binwidth=1500, kde=True)
     plt.subplot(4, 3, 9)
```

```
sns.histplot(KP281, x="Miles", binwidth=20, kde=True)

plt.subplot(4, 3, 10)
sns.histplot(KP281, x="Education", binwidth=1, kde=True)
plt.subplot(4, 3, 11)
sns.countplot(KP281, x='Fitness')
plt.ylabel("Count", fontsize=11)
plt.subplot(4, 3, 12)
sns.countplot(KP281, x='Usage')
plt.ylabel("Count", fontsize=11)

plt.show()
```

KP281 Customer Profile



Insight * There are highest number of customer have covered 70 miles.

1.4.3 Profile of *KP481*

```
[]: KP481[['Gender', 'MaritalStatus', 'Fitness', 'Usage', 'Age']].
      []: Gender
             MaritalStatus
                           Fitness
                                     Usage
                                            Age
     Male
                            3
                                     3
                                            23
             Partnered
                                                   5.000000
                                     2
                            2
                                            21
                                                   3.333333
     Female Partnered
                            2
                                     3
                                            23
                                                   1.666667
                                     2
     Male
             Partnered
                            2
                                            45
                                                   1.666667
                                     3
                                            35
                                                   1.666667
     dtype: float64
    Statitical Analysis
[]: KP481[['Gender', 'MaritalStatus', 'age_group', 'income_group', 'miles_group',

¬'education_group', 'fitness_group', 'usage_group' ]].describe()

[]:
            Gender MaritalStatus age_group income_group miles_group
                60
     count
                              60
                                        60
                                                     60
                                                                 60
     unique
                 2
                               2
                                         7
                                                      5
                                                                   6
                                     20-25
     top
                                                45K-55K
                                                              80-110
              Male
                       Partnered
     freq
                31
                                        24
                                                     33
                                                                 31
                              36
                                             usage_group
             education_group
                             fitness_group
     count
                          60
                                         60
                                                      60
                           6
                                          4
                                                       4
     unique
                                                       3
     top
                          16
                                          3
     freq
                          31
                                         39
                                                      31
[]: KP481[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].describe()
[]:
                             Income
                                          Miles
                                                 Education
                                                             Fitness
                                                                           Usage
                  Age
           60.000000
                          60.000000
                                      60.000000
                                                 60.000000
                                                            60.00000
                                                                       60.000000
     count
    mean
            28.900000
                       48973.650000
                                      87.933333
                                                 15.116667
                                                              2.90000
                                                                        3.066667
     std
             6.645248
                        8653.989388
                                      33.263135
                                                  1.222552
                                                             0.62977
                                                                        0.799717
            19.000000
                       31836.000000
                                      21.000000
                                                 12.000000
                                                             1.00000
                                                                        2.000000
    min
                                      64.000000
                                                             3.00000
     25%
            24.000000
                       44911.500000
                                                 14.000000
                                                                        3.000000
     50%
            26.000000
                       49459.500000
                                      85.000000
                                                 16.000000
                                                              3.00000
                                                                        3.000000
     75%
            33.250000
                       53439.000000
                                     106.000000
                                                 16.000000
                                                              3.00000
                                                                        3.250000
            48.000000
                       67083.000000
                                     212.000000
                                                 18.000000
                                                             4.00000
                                                                        5.000000
     max
[]: KP481[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].median()
[ ]: Age
                     26.0
     Income
                  49459.5
     Miles
                     85.0
    Education
                     16.0
    Fitness
                      3.0
```

Usage 3.0

dtype: float64

Find Probability

```
[]: pd.crosstab([KP481.income_group], [KP481.age_group], normalize=True, using=True)*100
```

```
[]: age_group
                      15-20
                                  20-25
                                             25-30
                                                        30-35
                                                                    35-40
                                                                              40-45 \
     income_group
     25K-35K
                              5.000000
                                          0.000000
                                                     0.000000
                                                                 0.000000
                                                                           0.000000
                   5.000000
                                                                           0.000000
     35K-45K
                   1.666667
                             13.333333
                                          0.000000
                                                     0.000000
                                                                 0.000000
     45K-55K
                   0.000000
                             21.666667
                                         10.000000
                                                    20.000000
                                                                 1.666667
                                                                           1.666667
     55K-65K
                   0.000000
                              0.000000
                                          1.666667
                                                     5.000000
                                                                 8.333333
                                                                           0.000000
     65K-75K
                   0.000000
                              0.000000
                                          0.000000
                                                     3.333333
                                                                 0.000000
                                                                           0.000000
                             40.000000
                                                    28.333333 10.000000
     All
                   6.666667
                                         11.666667
                                                                           1.666667
                      45-50
                                     All
     age_group
     income_group
                               10.000000
     25K-35K
                   0.000000
                   0.000000
                               15.000000
     35K-45K
     45K-55K
                   0.000000
                              55.000000
     55K-65K
                   1.666667
                               16.666667
     65K-75K
                   0.000000
                                3.333333
     All
                   1.666667
                             100.000000
```

pd.crosstab([KP481.Fitness, KP481.Gender, KP481.MaritalStatus], [KP481.

miles_group], normalize=True, margins=True)*100

[]:	miles_gr	roup		20-50	50-80	80-110	110-140	\
	Fitness	Gender	MaritalStatus					
	1	${\tt Female}$	Single	1.666667	0.000000	0.000000	0.000000	
	2 Female		Partnered	0.000000	3.333333	0.000000	0.000000	
			Single	1.666667	3.333333	1.666667	0.000000	
		Male	Partnered	5.000000	3.333333	0.000000	0.000000	
			Single	0.000000	1.666667	0.000000	0.000000	
	3	${\tt Female}$	Partnered	0.000000	1.666667	18.333333	0.000000	
			Single	0.000000	3.333333	6.666667	0.000000	
		Male	Partnered	0.000000	5.000000	13.333333	1.666667	
			Single	0.000000	3.333333	6.666667	3.333333	
	4 Female		Partnered	0.000000	0.000000	0.000000	0.000000	
			Single	0.000000	1.666667	0.000000	3.333333	
		Male	Partnered	0.000000	0.000000	3.333333	0.000000	
			Single	0.000000	0.000000	1.666667	0.000000	
	All			8.333333	26.666667	51.666667	8.333333	
	miles_g	roup		140-170	200-230	All		
	Fitness	Gender	MaritalStatus					

```
1
        Female Single
                                        0.000000
                              0.000000
                                                     1.666667
2
        Female Partnered
                              0.000000
                                        0.000000
                                                     3.333333
               Single
                              0.000000
                                        0.000000
                                                     6.66667
               Partnered
        Male
                                        0.000000
                              0.000000
                                                     8.333333
               Single
                              0.000000
                                        0.000000
                                                     1.666667
3
        Female Partnered
                              0.000000
                                        0.000000
                                                    20.000000
               Single
                              0.000000 0.000000
                                                    10.000000
        Male
               Partnered
                              1.666667
                                        0.000000
                                                    21.666667
               Single
                              0.000000
                                        0.000000
                                                    13.333333
4
        Female Partnered
                              0.000000
                                        1.666667
                                                     1.666667
               Single
                              0.000000
                                        0.000000
                                                     5.000000
        Male
               Partnered
                              1.666667
                                        0.000000
                                                     5.000000
               Single
                              0.000000
                                        0.000000
                                                     1.666667
All
                                                   100.000000
                              3.333333 1.666667
```

[]: pd.crosstab([KP481.Fitness, KP481.Gender, KP481.MaritalStatus], [KP481.age_group], normalize=True, margins=True)*100

[]:	age_grou	ıp		15-20	20-25	25-30	30-35	/
	Fitness	Gender	MaritalStatus					
	1	Female	Single	0.000000	0.000000	0.000000	1.666667	
	2	Female	Partnered	0.000000	1.666667	0.000000	1.666667	
			Single	0.000000	5.000000	0.000000	1.666667	
		Male	Partnered	0.000000	5.000000	0.000000	1.666667	
			Single	0.000000	0.000000	1.666667	0.000000	
	3	${\tt Female}$	Partnered	1.666667	3.333333	3.333333	6.666667	
			Single	0.000000	5.000000	3.333333	0.000000	
		Male	Partnered	0.000000	10.000000	0.000000	6.666667	
			Single	5.000000	3.333333	1.666667	3.333333	
	4	${\tt Female}$	Partnered	0.000000	1.666667	0.000000	0.000000	
			Single	0.000000	1.666667	1.666667	1.666667	
		Male	Partnered	0.000000	1.666667	0.000000	3.333333	
			Single	0.000000	1.666667	0.000000	0.000000	
	All			6.666667	40.000000	11.666667	28.333333	
	age_grou	ıp		35-40	40-45	45-50	All	
	Fitness	Gender	MaritalStatus					
	1	Female	Single	0.000000	0.000000	0.000000	1.666667	
	2	Female	Partnered	0.000000	0.000000	0.000000	3.333333	
			Single	0.000000	0.000000	0.000000	6.666667	
		Male	Partnered	0.000000	1.666667	0.000000	8.333333	
			Single	0.000000	0.000000	0.000000	1.666667	
	3	Female	Partnered	5.000000	0.000000	0.000000	20.000000	
			Single	1.666667	0.000000	0.000000	10.000000	
		Male	Partnered	3.333333	0.000000	1.666667	21.666667	
			Single	0.000000	0.000000	0.000000	13.333333	
	4	Female	Partnered	0.000000	0.000000	0.000000	1.666667	

```
Single
                     Partnered
             Male
                                     0.000000
                                                0.000000
                                                          0.000000
                                                                       5.000000
                     Single
                                     0.000000
                                                0.000000
                                                          0.000000
                                                                       1.666667
     All
                                    10.000000
                                                1.666667
                                                          1.666667
                                                                     100.000000
[]: pd.crosstab([KP481.Fitness, KP481.Gender, KP481.MaritalStatus], [KP481.
       ⇒income_group], normalize=True, margins=True)*100
[]: income_group
                                       25K-35K
                                                  35K-45K
                                                              45K-55K
                                                                         55K-65K \
     Fitness Gender MaritalStatus
     1
             Female Single
                                     0.000000
                                                 0.000000
                                                             0.000000
                                                                        0.000000
     2
             Female Partnered
                                                 1.666667
                                     0.000000
                                                             1.666667
                                                                        0.000000
                    Single
                                     0.000000
                                                 3.333333
                                                             3.333333
                                                                        0.000000
             Male
                    Partnered
                                     3.333333
                                                 0.000000
                                                            5.000000
                                                                        0.000000
                     Single
                                     0.000000
                                                 0.000000
                                                             1.666667
                                                                        0.000000
     3
             Female Partnered
                                     1.666667
                                                 0.000000
                                                           13.333333
                                                                        5.000000
                     Single
                                     0.000000
                                                 1.666667
                                                             5.000000
                                                                        3.333333
                     Partnered
             Male
                                     0.000000
                                                 3.333333
                                                           13.333333
                                                                        5.000000
                     Single
                                                             5.000000
                                     3.333333
                                                 1.666667
                                                                        1.666667
     4
             Female Partnered
                                     1.666667
                                                 0.000000
                                                             0.000000
                                                                        0.000000
                     Single
                                     0.000000
                                                 1.666667
                                                             3.333333
                                                                        0.000000
                    Partnered
             Male
                                     0.000000
                                                 1.666667
                                                             1.666667
                                                                        1.666667
                     Single
                                                                        0.000000
                                     0.000000
                                                 0.000000
                                                             1.666667
     All
                                    10.000000
                                                15.000000
                                                           55.000000
                                                                       16.666667
     income_group
                                     65K-75K
                                                      All
    Fitness Gender MaritalStatus
     1
             Female Single
                                    1.666667
                                                 1.666667
     2
             Female Partnered
                                                 3.333333
                                    0.000000
                    Single
                                    0.000000
                                                 6.66667
             Male
                    Partnered
                                    0.000000
                                                 8.333333
                     Single
                                    0.000000
                                                 1.666667
     3
             Female Partnered
                                    0.000000
                                                20.000000
                     Single
                                    0.000000
                                                10.000000
                     Partnered
             Male
                                    0.000000
                                                21.666667
                                                13.333333
                     Single
                                    1.666667
     4
             Female Partnered
                                    0.000000
                                                 1.666667
                     Single
                                    0.000000
                                                 5.000000
                     Partnered
             Male
                                    0.000000
                                                 5.000000
                     Single
                                    0.000000
                                                 1.666667
     All
                                               100.000000
                                    3.333333
    Check for Outliers
[]: plt.figure(figsize=(15,10)).suptitle("KP481 Outliers",fontsize=14)
     plt.subplot(2, 3, 1)
     sns.boxplot(KP481, y="Age")
```

0.000000

0.000000

0.000000

5.000000

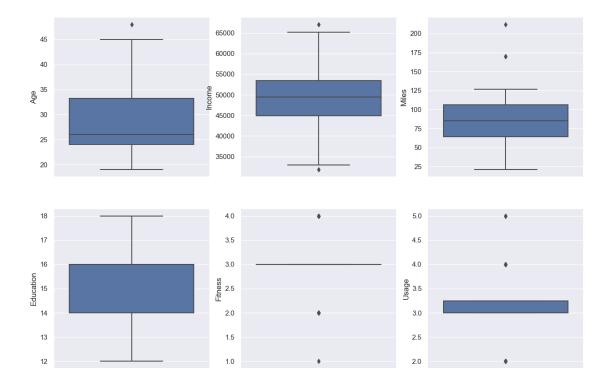
```
plt.subplot(2, 3, 2)
sns.boxplot(KP481, y="Income")

plt.subplot(2, 3, 3)
sns.boxplot(KP481, y="Miles")
plt.subplot(2, 3, 4)
sns.boxplot(KP481, y="Education")

plt.subplot(2, 3, 5)
sns.boxplot(KP481, y='Fitness')
plt.subplot(2, 3, 6)
sns.boxplot(KP481, y='Usage')

plt.show()
```

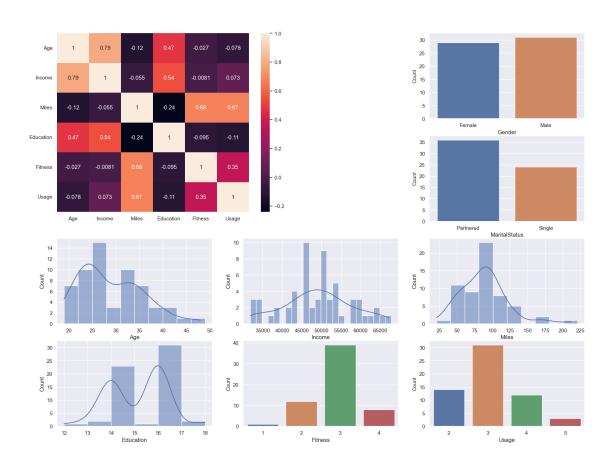
KP481 Outliers



Plot the Graph

```
plt.yticks(rotation= 0, fontsize=11)
plt.xticks(fontsize=11)
plt.subplot(4, 3, 3)
sns.countplot(KP481, x='Gender')
plt.ylabel("Count", fontsize=11)
plt.subplot(4, 3, 6)
sns.countplot(KP481, x='MaritalStatus')
plt.ylabel("Count", fontsize=11)
plt.subplot(4, 3, 7)
sns.histplot(KP481, x="Age", binwidth=3, kde=True)
plt.subplot(4, 3, 8)
sns.histplot(KP481, x="Income", binwidth=1500, kde=True)
plt.subplot(4, 3, 9)
sns.histplot(KP481, x="Miles", binwidth=20, kde=True)
plt.subplot(4, 3, 10)
sns.histplot(KP481, x="Education", binwidth=1, kde=True)
plt.subplot(4, 3, 11)
sns.countplot(KP481, x='Fitness')
plt.ylabel("Count", fontsize=11)
plt.subplot(4, 3, 12)
sns.countplot(KP481, x='Usage')
plt.ylabel("Count", fontsize=11)
plt.show()
```

KP481 Customer Profile



Insight * There are highest number of customer have covered 70 miles.

1.4.4 Profile of *KP781*

```
[]: KP781[['Gender', 'MaritalStatus', 'Fitness', 'Usage', 'Age']].

$\text{\text{\text{\text{ounts}(normalize=True)}[:5]*100}}$
```

[]:	Gender	MaritalStatus	Fitness	Usage	Age	
	Male	Partnered	5	4	25	5.0
		Single	5	4	23	5.0
	Female	Partnered	5	4	33	2.5
	Male	Single	5	3	22	2.5
		Partnered	5	6	31	2.5

dtype: float64

Statitical Analysis

```
[]: KP781[['Gender', 'MaritalStatus', 'age_group', 'income_group', 'miles_group',
      []:
           Gender MaritalStatus age_group income_group miles_group \
    count
               40
                             40
                                       40
                                                    40
                                                                40
                2
                              2
                                                                 9
    unique
                                        6
                                                     6
                                    20-25
    top
             Male
                      Partnered
                                               85K-95K
                                                           170-200
               33
    freq
                             23
                                       17
                                                    11
                                                                12
                             fitness_group
            education_group
                                            usage_group
    count
                         40
                                        40
                                                     40
                          5
    unique
                                         3
                                                      5
                         18
                                         5
                                                      4
    top
    freq
                         19
                                        29
                                                     18
[]: KP781[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].describe()
[]:
                 Age
                            Income
                                         Miles
                                                Education
                                                             Fitness
                                                                          Usage
           40.000000
                          40.00000
                                     40.000000
                                                40.000000
                                                           40.000000
                                                                      40.000000
    count
                       75441.57500 166.900000
    mean
           29.100000
                                                17.325000
                                                            4.625000
                                                                       4.775000
            6.971738
                       18505.83672
                                     60.066544
                                                 1.639066
                                                            0.667467
                                                                       0.946993
    std
    min
           22.000000
                       48556.00000
                                     80.000000
                                                14.000000
                                                            3.000000
                                                                       3.000000
    25%
           24.750000
                       58204.75000
                                    120.000000
                                                16.000000
                                                            4.000000
                                                                       4.000000
    50%
           27.000000
                       76568.50000
                                    160.000000
                                                18.000000
                                                            5.000000
                                                                       5.000000
    75%
           30.250000
                       90886.00000
                                    200.000000
                                                18.000000
                                                            5.000000
                                                                       5.000000
           48.000000
                      104581.00000
                                    360.000000
                                                21.000000
                                                            5.000000
                                                                       7.000000
    max
[]: KP781[['Age', 'Income', 'Miles', 'Education', 'Fitness', 'Usage']].median()
[]: Age
                    27.0
    Income
                 76568.5
    Miles
                   160.0
    Education
                    18.0
    Fitness
                     5.0
                     5.0
    Usage
    dtype: float64
    Find Probability
[]: pd.crosstab([KP781.income_group], [KP781.age_group], normalize=True,__
      →margins=True)*100
[]: age_group
                  20-25
                         25-30 30-35
                                       35-40
                                             40-45
                                                    45-50
                                                              All
    income_group
    45K-55K
                   20.0
                           2.5
                                  0.0
                                         0.0
                                                0.0
                                                       0.0
                                                             22.5
                   15.0
                           2.5
                                  0.0
                                         0.0
                                                0.0
                                                       0.0
                                                             17.5
    55K-65K
    65K-75K
                    5.0
                           2.5
                                  0.0
                                         0.0
                                                0.0
                                                       0.0
                                                              7.5
                    2.5
    75K-85K
                           5.0
                                  0.0
                                         2.5
                                                0.0
                                                       0.0
                                                             10.0
```

```
0.0
85K-95K
                     15.0
                             7.5
                                    0.0
                                          5.0
                                                 0.0
                                                       27.5
                     5.0
95K-105K
               0.0
                             2.5
                                    2.5
                                          0.0
                                                 5.0
                                                      15.0
              42.5
                     32.5
                                          5.0
                                                 5.0 100.0
All
                            10.0
                                    5.0
```

[]: pd.crosstab([KP781.Fitness, KP781.Gender, KP781.MaritalStatus], [KP781.willow] miles_group], normalize=True, margins=True)*100

[]:	miles_gr	roup		50-80	80-110	110-140	140-170	170-200 \
	Fitness	Gender	MaritalStatus					
	3	Female	Single	0.0	2.5	0.0	0.0	0.0
		Male	Partnered	0.0	2.5	0.0	0.0	0.0
			Single	0.0	5.0	0.0	0.0	0.0
	4	${\tt Female}$	Single	0.0	2.5	0.0	0.0	0.0
		Male	Partnered	0.0	2.5	0.0	5.0	5.0
			Single	0.0	0.0	0.0	0.0	2.5
	5	${\tt Female}$	Partnered	0.0	0.0	0.0	0.0	7.5
			Single	0.0	0.0	0.0	0.0	2.5
		Male	Partnered	2.5	0.0	5.0	10.0	5.0
			Single	0.0	5.0	5.0	10.0	7.5
	All			2.5	20.0	10.0	25.0	30.0
	miles_g	roup		230-260	260-29	90 290-32	20 350-38	O All
	${\tt Fitness}$	Gender	MaritalStatus					
	3	${\tt Female}$	Single	0.0	0.	.0 0	.0 0.	0 2.5
		Male	Partnered	0.0	0.	.0 0	.0 0.	0 2.5
			Single	0.0	0.	.0 0	.0 0.	0 5.0
	4	${\tt Female}$	Single	0.0	0.	.0 0	.0 0.	0 2.5
		Male	Partnered	0.0	0.	.0 0	.0 0.	0 12.5
			Single	0.0	0.	.0 0	.0 0.	0 2.5
	5	${\tt Female}$	Partnered	0.0	2.	.5 0	.0 0.	0 10.0
			Single	0.0	0.	.0 0	.0 0.	0 2.5
		Male	Partnered	5.0	0.	.0 2	.5 2.	5 32.5
			Single	0.0	0.	.0 0	.0 0.	0 27.5
	All			5.0	2.	.5 2	.5 2.	5 100.0

[]: pd.crosstab([KP781.Fitness, KP781.Gender, KP781.MaritalStatus], [KP781. age_group], normalize=True, margins=True)*100

[]:	age_grou	р		20-25	25-30	30-35	35-40	40-45	45-50	All
	Fitness	Gender	MaritalStatus							
	3	Female	Single	0.0	2.5	0.0	0.0	0.0	0.0	2.5
		Male	Partnered	2.5	0.0	0.0	0.0	0.0	0.0	2.5
			Single	2.5	2.5	0.0	0.0	0.0	0.0	5.0
	4	${\tt Female}$	Single	2.5	0.0	0.0	0.0	0.0	0.0	2.5
		Male	Partnered	5.0	7.5	0.0	0.0	0.0	0.0	12.5
			Single	0.0	0.0	0.0	0.0	2.5	0.0	2.5
	5	Female	Partnered	2.5	5.0	2.5	0.0	0.0	0.0	10.0

```
Single
                                      2.5
                                             0.0
                                                     0.0
                                                            0.0
                                                                   0.0
                                                                          0.0
                                                                                  2.5
                    Partnered
                                            10.0
                                                     5.0
                                                            2.5
                                                                   0.0
                                                                          5.0
                                                                                 32.5
             Male
                                     10.0
                    Single
                                     15.0
                                             5.0
                                                     2.5
                                                            2.5
                                                                   2.5
                                                                           0.0
                                                                                 27.5
                                            32.5
     All
                                     42.5
                                                    10.0
                                                            5.0
                                                                   5.0
                                                                          5.0 100.0
[]: pd.crosstab([KP781.Fitness, KP781.Gender, KP781.MaritalStatus], [KP781.
      ⇒income group], normalize=True, margins=True)*100
                                    45K-55K 55K-65K
                                                      65K-75K 75K-85K 85K-95K \
[]: income_group
     Fitness Gender MaritalStatus
             Female Single
                                        0.0
                                                 0.0
                                                           2.5
                                                                    0.0
                                                                              0.0
             Male
                    Partnered
                                        0.0
                                                  2.5
                                                           0.0
                                                                    0.0
                                                                              0.0
                    Single
                                        2.5
                                                 0.0
                                                           0.0
                                                                    0.0
                                                                              2.5
     4
             Female Single
                                        2.5
                                                 0.0
                                                           0.0
                                                                    0.0
                                                                              0.0
             Male
                    Partnered
                                        0.0
                                                 5.0
                                                           2.5
                                                                    0.0
                                                                              2.5
                                                                              2.5
                    Single
                                        0.0
                                                 0.0
                                                           0.0
                                                                    0.0
     5
             Female Partnered
                                        0.0
                                                 2.5
                                                           0.0
                                                                              5.0
                                                                    0.0
                    Single
                                        2.5
                                                 0.0
                                                           0.0
                                                                    0.0
                                                                              0.0
             Male
                    Partnered
                                        2.5
                                                 2.5
                                                           2.5
                                                                    7.5
                                                                              7.5
                                       12.5
                                                 5.0
                                                           0.0
                                                                    2.5
                                                                              7.5
                    Single
     All
                                                 17.5
                                                                             27.5
                                       22.5
                                                           7.5
                                                                   10.0
     income_group
                                    95K-105K
                                                All
     Fitness Gender MaritalStatus
             Female Single
                                         0.0
                                                2.5
     3
             Male
                    Partnered
                                         0.0
                                                 2.5
                    Single
                                         0.0
                                                5.0
     4
             Female Single
                                         0.0
                                                2.5
             Male
                    Partnered
                                         2.5
                                               12.5
                                                2.5
                    Single
                                         0.0
     5
             Female Partnered
                                               10.0
                                         2.5
                    Single
                                         0.0
                                                2.5
             Male
                    Partnered
                                        10.0
                                               32.5
                    Single
                                         0.0
                                               27.5
     All
                                        15.0 100.0
    Check for Outliers
[]: plt.figure(figsize=(15,10)).suptitle("KP781 Outliers",fontsize=14)
     plt.subplot(2, 3, 1)
     sns.boxplot(KP781, y="Age")
     plt.subplot(2, 3, 2)
     sns.boxplot(KP781, y="Income")
     plt.subplot(2, 3, 3)
```

sns.boxplot(KP781, y="Miles")

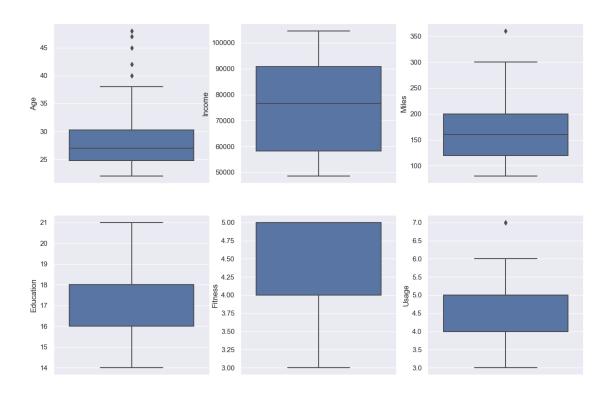
plt.subplot(2, 3, 4)

```
sns.boxplot(KP781, y="Education")

plt.subplot(2, 3, 5)
sns.boxplot(KP781, y='Fitness')
plt.subplot(2, 3, 6)
sns.boxplot(KP781, y='Usage')

plt.show()
```

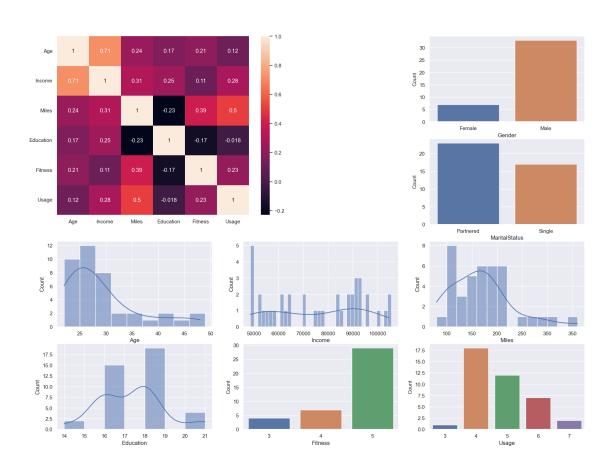
KP781 Outliers



Plot the Graph

```
plt.subplot(4, 3, 6)
sns.countplot(KP781, x='MaritalStatus')
plt.ylabel("Count", fontsize=11)
plt.subplot(4, 3, 7)
sns.histplot(KP781, x="Age", binwidth=3, kde=True)
plt.subplot(4, 3, 8)
sns.histplot(KP781, x="Income", binwidth=1500, kde=True)
plt.subplot(4, 3, 9)
sns.histplot(KP781, x="Miles", binwidth=20, kde=True)
plt.subplot(4, 3, 10)
sns.histplot(KP781, x="Education", binwidth=1, kde=True)
plt.subplot(4, 3, 11)
sns.countplot(KP781, x='Fitness')
plt.ylabel("Count", fontsize=11)
plt.subplot(4, 3, 12)
sns.countplot(KP781, x='Usage')
plt.ylabel("Count", fontsize=11)
plt.show()
```

KP781 Customer Profile



Insight * There are highest number of customer have covered 70 miles.

1.5 Questions

1.5.1 Q0. What is the probability of a male customer buying a KP781 treadmill?

```
[]: product_gender = pd.crosstab(aerofit['Gender'], aerofit['Product'],
      →normalize='index', margins=True)*100
     product_gender
[]: Product
                  KP281
                             KP481
                                        KP781
     Gender
     Female
              52.631579
                         38.157895
                                     9.210526
                         29.807692
                                    31.730769
    Male
              38.461538
     All
              44.44444
                         33.333333
                                    22.22222
[]: product_gender['KP781']['Male']
```

[]: 31.73076923076923

Insight * There is 31.73% chance a male customer will purchase KP781

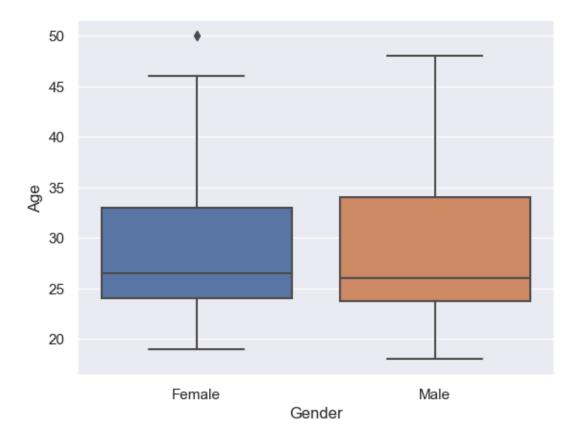
1.5.2 Q1. What is the total count of each product present in the dataset?

```
[]: Products = aerofit.groupby("Product")["Age"].describe().T
    Products[:1]
[]: Product KP281
                    KP481
                            KP781
     count
               80.0
                      60.0
                             40.0
[]: Products[:1]/1.8
[]: Product
                 KP281
                             KP481
                                        KP781
     count
              44.44444
                        33.333333
                                   22.22222
```

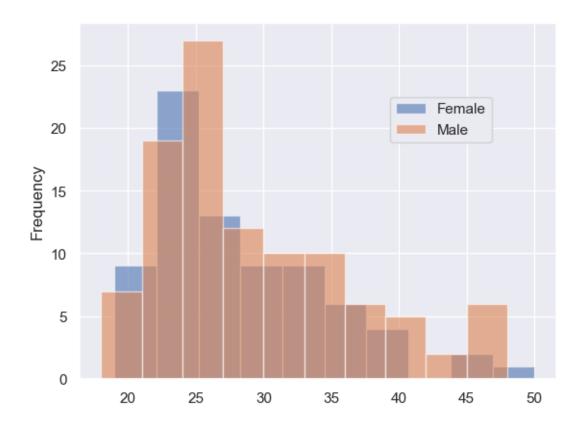
Insight * KP781 40 with 22.22% probability. * KP781 60 with 33.33% probability. * KP781 80 with 44.44% probability.

1.5.3 Q2. Describe the Age & Gender distribution of all the customers?

```
[]: aerofit.groupby("Gender")["Age"].describe()
[]:
             count
                                          min
                                                  25%
                                                        50%
                                                              75%
                         mean
                                    std
                                                                    max
     Gender
     Female
              76.0
                    28.565789
                               6.342104
                                          19.0
                                               24.00
                                                       26.5
                                                             33.0
                                                                   50.0
                    28.951923 7.377978
                                               23.75
    Male
             104.0
                                         18.0
                                                       26.0
                                                             34.0 48.0
[]: sns.boxplot(aerofit, x='Gender', y='Age')
     plt.show()
```



```
[]: aerofit.groupby('Gender').Age.plot(kind='hist', alpha=0.6)
plt.legend(bbox_to_anchor=(1.02, 1), loc='upper right', borderaxespad=5)
plt.show()
```



[]: 0.3567980420783239

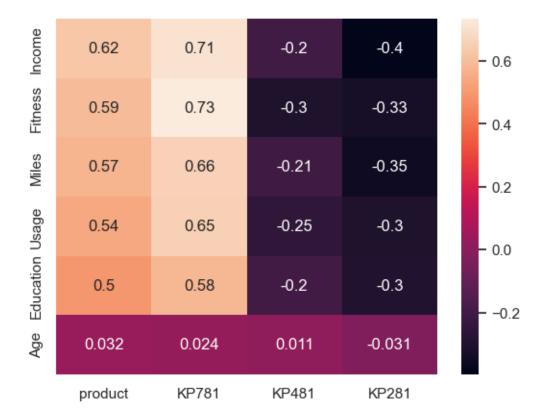
Insight * Their is a small difference between mean Age of Male & Female. * also, p-vale of T-Test of the 2 Group come out to be 35% (considering Male age is higher) * when following 95% Confidence Interval. So, we failed to prove that Male age are Higher then Female Age. amoung Customers.

1.5.4 Q3. Top 3 features having the highest coorelatios with the Product column. and Why?

```
[]: top_corr = aerofit.copy()
    def add product as column(x):
        return 1 if(x == 'KP281') else (2 if(x == 'KP481') else (3 if(x == 'KP781')_{\square}
      ⇔else 0))
    top_corr['product'] = top_corr.apply(lambda row:__
      →add_product_as_column(row['Product']),axis=1)
    def add_product_columns(x):
        x['KP281'] = np.where((x['Product'] == 'KP281'), 1, 0)
        x['KP481'] = np.where((x['Product'] == 'KP481'), 1, 0)
        x['KP781'] = np.where((x['Product'] == 'KP781'), 1, 0)
        return x
    top_corr = add_product_columns(top_corr)
[]: top3_correlations = top_corr[['Age', 'Income', 'Miles', 'Education', 'Fitness', __

¬'Usage', 'product', 'KP281', 'KP481', 'KP781']].corr()[['product', 'KP781', □]

      []: top3_correlations.sort_values('product', ascending=False, inplace=True)
[]: sns.heatmap(top3_correlations, annot=True)
    plt.show()
```



Insight * Product Have higher co-relation with Income, Fitness & Miles. * For KP781 we have observed same co-relation. * But, for KP481 Top 3 co-relation are Age, Education & Income. * But, for KP281 Top 3 co-relation are Age, Education & Usage.

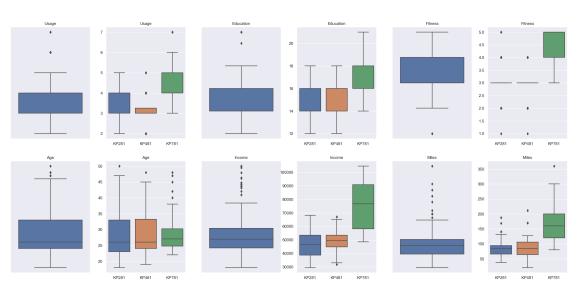
As, we know KP781 is the expansive & better one, mostly prefered by Athletes or Fitness enthusiast, whos also have higher Income. But, for KP481, KP281 people with good Education, who are health consious, want to have a Treadmill but can't efford a expansive one.

1.5.5 Q4. Were there any outliers present in the Data? If yes, suggest suitable method for their treatment?

```
[]: plt.figure(figsize=(24,12)).suptitle("Aerofit Outliers",fontsize=14)
     plt.subplots_adjust(right=1)
     plt.subplot(2, 6, 1)
     sns.boxplot(aerofit, y='Usage')
     plt.title('Usage', fontsize=11)
     plt.ylabel('', fontsize=12)
     plt.yticks([])
     plt.subplot(2, 6, 2)
     sns.boxplot(aerofit, y='Usage', x='Product')
     plt.title('Usage', fontsize=11)
     plt.xlabel('', fontsize=12)
     plt.ylabel('', fontsize=12)
     plt.subplot(2, 6, 3)
     sns.boxplot(aerofit, y="Education")
     plt.title('Education', fontsize=11)
     plt.ylabel('', fontsize=12)
     plt.yticks([])
     plt.subplot(2, 6, 4)
     sns.boxplot(aerofit, y="Education", x='Product')
     plt.title('Education', fontsize=11)
     plt.xlabel('', fontsize=12)
     plt.ylabel('', fontsize=12)
     plt.subplot(2, 6, 5)
     sns.boxplot(aerofit, y='Fitness')
     plt.title('Fitness', fontsize=11)
     plt.ylabel('', fontsize=12)
     plt.yticks([])
     plt.subplot(2, 6, 6)
```

```
sns.boxplot(aerofit, y='Fitness', x='Product')
plt.title('Fitness', fontsize=11)
plt.xlabel('', fontsize=12)
plt.ylabel('', fontsize=12)
plt.subplot(2, 6, 7)
sns.boxplot(aerofit, y="Age")
plt.title('Age', fontsize=11)
plt.ylabel('', fontsize=12)
plt.yticks([])
plt.subplot(2, 6, 8)
sns.boxplot(aerofit, y="Age", x='Product')
plt.title('Age', fontsize=11)
plt.xlabel('', fontsize=12)
plt.ylabel('', fontsize=12)
plt.subplot(2, 6, 9)
sns.boxplot(aerofit, y="Income")
plt.title('Income', fontsize=11)
plt.ylabel('', fontsize=12)
plt.yticks([])
plt.subplot(2, 6, 10)
sns.boxplot(aerofit, y="Income", x='Product')
plt.title('Income', fontsize=11)
plt.xlabel('', fontsize=12)
plt.ylabel('', fontsize=12)
plt.subplot(2, 6, 11)
sns.boxplot(aerofit, y="Miles")
plt.title('Miles', fontsize=11)
plt.ylabel('', fontsize=12)
plt.yticks([])
plt.subplot(2, 6, 12)
sns.boxplot(aerofit, y="Miles", x='Product')
plt.title('Miles', fontsize=11)
plt.xlabel('', fontsize=12)
plt.ylabel('', fontsize=12)
plt.show()
```

Aerofit Outliers



Using Z-Score

[]: aerofit[np.abs(zscore(aerofit['Age']))>2]

Г]:	aerolit[hp.abs(zscore(aerolit['Age']))/2]									
[]:		Product	Gender	MaritalStatus	Age	Income	Miles	Education	Fitness	\
	75	KP281	Male	Partnered	43	53439	66	16	3	
	76	KP281	Female	Single	44	57987	75	16	4	
	77	KP281	Female	Partnered	46	60261	47	16	2	
	78	KP281	Male	Partnered	47	56850	94	16	3	
	79	KP281	Female	Partnered	50	64809	66	16	3	
	138	KP481	Male	Partnered	45	54576	42	16	2	
	139	KP481	Male	Partnered	48	57987	64	16	3	
	177	KP781	Male	Single	45	90886	160	16	5	
	178	KP781	Male	Partnered	47	104581	120	18	5	
	179	KP781	Male	Partnered	48	95508	180	18	5	
		•	0 -0 1	income_group	miles		educatio	-0 -	-0 -	\
	75	3	40-45	5 45K-55K		50-80		16	3	
	76	3	40-45	5 55K-65K		50-80		16	4	
	77	3	45-50			20-50		16	2	
	78	4	45-50	55K-65K		80-110		16	3	
	79	3	45-50	55K-65K		50-80		16	3	
	138	2	40-45	45K-55K		20-50		16	2	
	139	2	45-50	55K-65K		50-80		16	3	
	177	5	40-45	85K-95K	1	40-170		16	5	
	178	4	45-50	95K-105K	1	10-140		18	5	
	179	4	45-50	95K-105K	1	70-200		18	5	

```
usage_group
     75
     76
                   3
     77
                   3
     78
                   4
     79
                   3
                   2
     138
                   2
     139
     177
                   5
     178
                   4
     179
                   4
    Using IQR (Inner Quartile Range)
[]: age_outlier = check_outlier(aerofit, 'Age')
     income_outlier = check_outlier(aerofit, 'Income')
     miles_outlier = check_outlier(aerofit, 'Miles')
     education_outlier = check_outlier(aerofit, 'Education')
     fitness_outlier = check_outlier(aerofit, 'Fitness')
     usage_outlier = check_outlier(aerofit, 'Usage')
[]: print("Age: \t\t => Lower outlier: {} => Upper outlier: {}".
      ⇔format(age_outlier['lower']['length'], age_outlier['upper']['length']))
     print("Income: \t => Lower outlier: {} => Upper outlier: {}" .
      oformat(income_outlier['lower']['length'], income_outlier['upper']['length']))
     print("Miles: \t\t => Lower outlier: {} => Upper outlier: {}" .
      oformat(miles_outlier['lower']['length'], miles_outlier['upper']['length']))
     print("Education: \t => Lower outlier: {} => Upper outlier: {}" .
      ⇔format(education_outlier['lower']['length'], __
      ⇔education_outlier['upper']['length']))
     print("Fitness: \t => Lower outlier: {} => Upper outlier: {}" .
      ⇔format(fitness_outlier['lower']['length'], ⊔

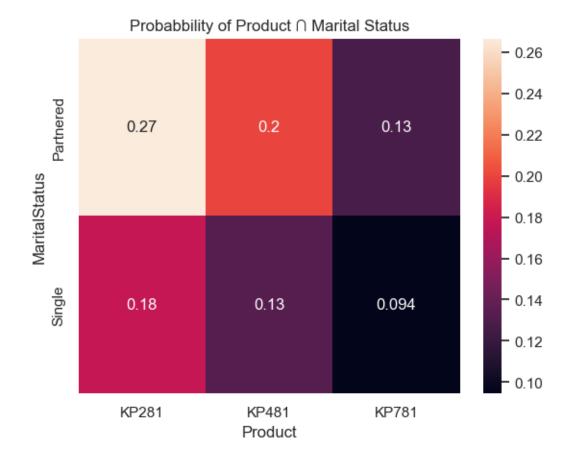
¬fitness_outlier['upper']['length']))
     print("Usage: \t\t => Lower outlier: {} => Upper outlier: {}" .
      oformat(usage_outlier['lower']['length'], usage_outlier['upper']['length']))
     # print("%d, %d" %(age outlier['lower']['length'],
      →age_outlier['upper']['length']))
                     => Lower outlier: 0 => Upper outlier: 5
    Age:
    Income:
                     => Lower outlier: 0 => Upper outlier: 19
                     => Lower outlier: 0 => Upper outlier: 13
    Miles:
                     => Lower outlier: 0 => Upper outlier: 4
    Education:
                     => Lower outlier: 2 => Upper outlier: 0
    Fitness:
                     => Lower outlier: 0 => Upper outlier: 9
    Usage:
```

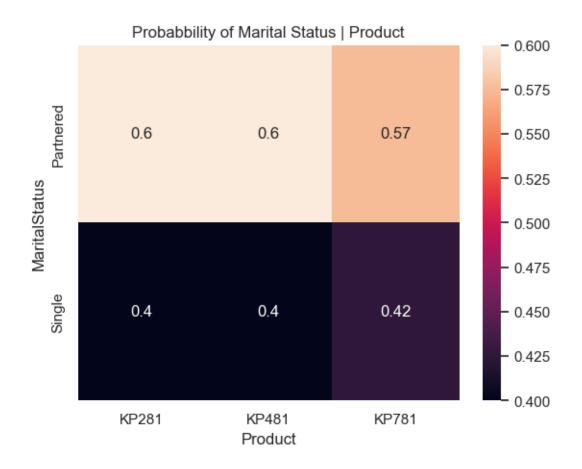
Insight * Yes, There is Outlier Present in DataSet for All of the Continuous Values, like

* Age: => Lower outlier: 0 => Upper outlier: 5 * Income: => Lower outlier: 0 => Upper outlier: 19 * Miles: => Lower outlier: 0 => Upper outlier: 13 * Education: => Lower outlier: 0 => Upper outlier: 2 => Upper outlier: 0 * Usage: => Lower outlier: 0 => Upper outlier: 9

When, we remove these outliers it might effect credebility of Product specific analysis. Because Some of the product dependent on the datas.

1.5.6 Q5. Marital Status Implies no significant information on the usages of different TreadMills? (T/F)

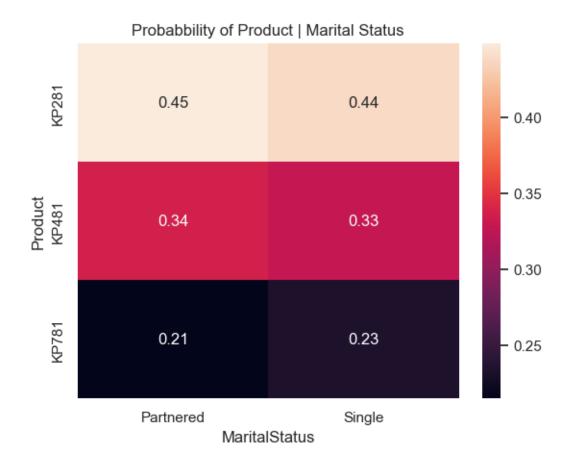




```
[]: sns.heatmap(pd.crosstab(aerofit['Product'], aerofit['MaritalStatus'], usince an armalize = 'columns'), annot = True)

plt.title('Probabbility of Product | Marital Status', fontsize = 12)

plt.show()
```



Insight * From Above Probability Heatmap, observed that for each product given marital status have nearly same probability.

Thus, Statement is True

1.5.7 Q6. The variance of Income in lower ages is smaller as compare to the variance in higher ages. In Statistics , this is known as



```
[ ]: low_income_age['Income'].var() < high_income_age['Income'].var()
[ ]: True
[ ]: low_income_age['Income'].std() < high_income_age['Income'].std()
[ ]: True</pre>
```

Insight * Here Variance & Standard Daviation in low Age Income Group is less then Higher Age Income Group. * Thus, It results a funnel shape & It's known as ${\tt Heteroscedasticity}$

1.5.8 Q7. What proportion of woman have brought the KP781 TreadMill? Provide reson of Answar.

```
[]: product_gender = pd.crosstab(aerofit['Gender'], aerofit['Product'], u

→normalize='index', margins=True)*100

product_gender
```

```
[]: Product
                 KP281
                             KP481
                                        KP781
     Gender
    Female
             52.631579
                        38.157895
                                     9.210526
    Male
             38.461538
                        29.807692
                                   31.730769
     All
             44.44444 33.333333
                                    22.22222
[]: product_gender['KP781']['Female']
```

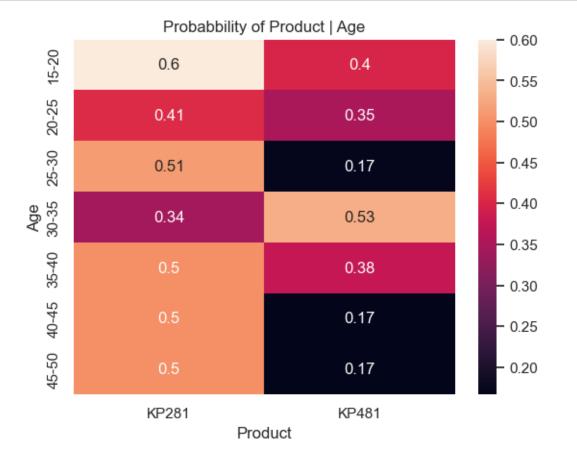
[]: 9.210526315789473

Insight * There is 9.21% chance a male customer will purchase KP781

1.5.9 Q8. Distinguish between Customer Profiles for KP281 and KP481 TreadMill.

Probability of Product's for given Age "Product | Age"

```
[]: sns.heatmap(pd.crosstab(aerofit['age_group'], aerofit['Product'], usinormalize='index')[['KP281', 'KP481']], annot=True)
plt.title('Probabbility of Product | Age', fontsize=12)
plt.ylabel('Age')
plt.show()
```



Probability of Product's for given Income "Product | Income"

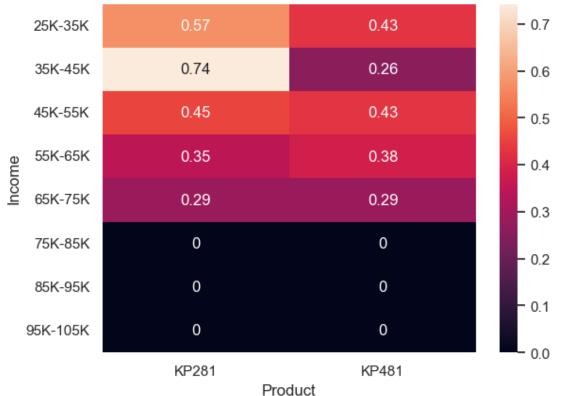
```
[]: sns.heatmap(pd.crosstab(aerofit['income_group'], aerofit['Product'], unormalize='index')[['KP281', 'KP481']], annot=True)

plt.title('Probabbility of Product | Income', fontsize=12)

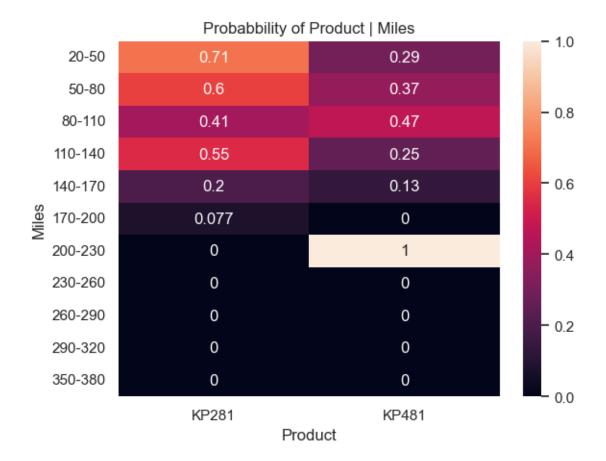
plt.ylabel('Income')

plt.show()
```





Probability of Product's for given Miles "Product | Miles"

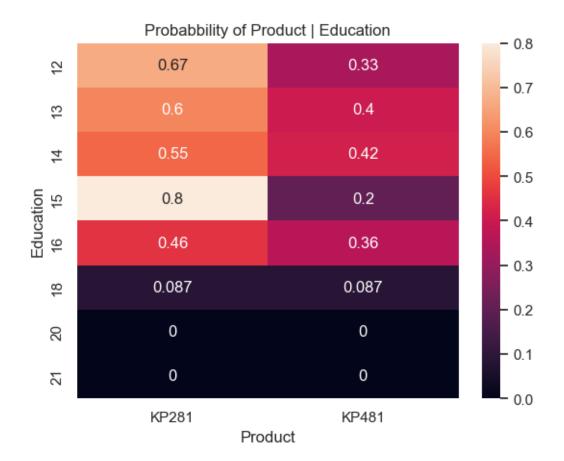


Probability of Product's for given Education "Product | Education"

```
[]: sns.heatmap(pd.crosstab(aerofit['Education'], aerofit['Product'], onormalize='index')[['KP281', 'KP481']], annot=True)

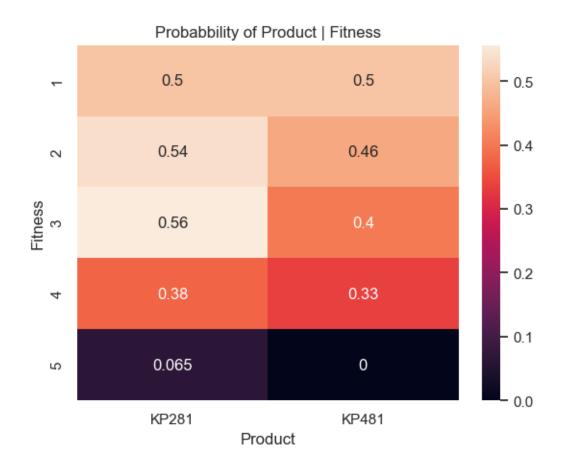
plt.title('Probabbility of Product | Education', fontsize=12)

plt.show()
```

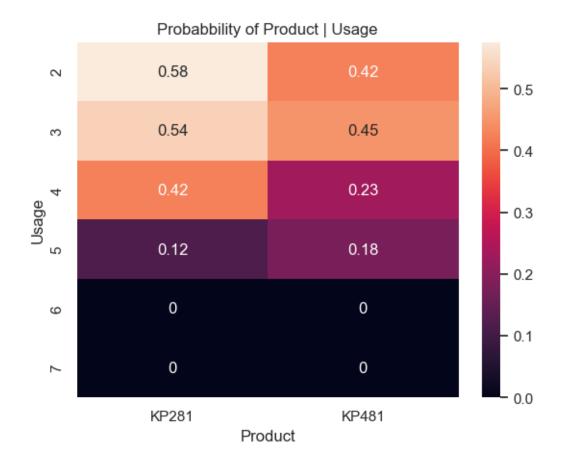


Probability of Product's for given Fitness "Product | Fitness"

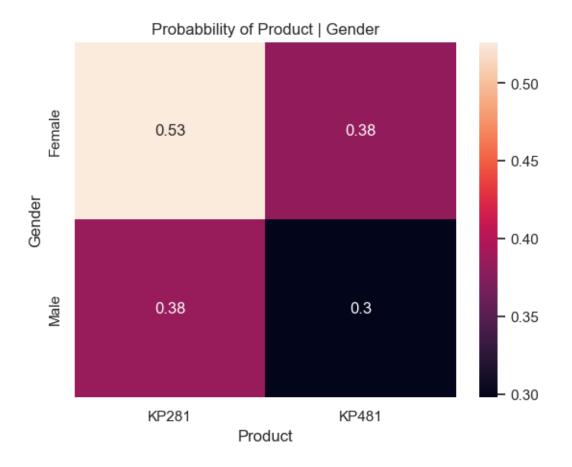
```
[]: sns.heatmap(pd.crosstab(aerofit['Fitness'], aerofit['Product'], onormalize='index')[['KP281', 'KP481']], annot=True)
plt.title('Probabbility of Product | Fitness', fontsize=12)
plt.show()
```



Probability of Product's for given Usage " $Product \mid Usage$ "



Probability of Product's for given Gender "Product | Gender"

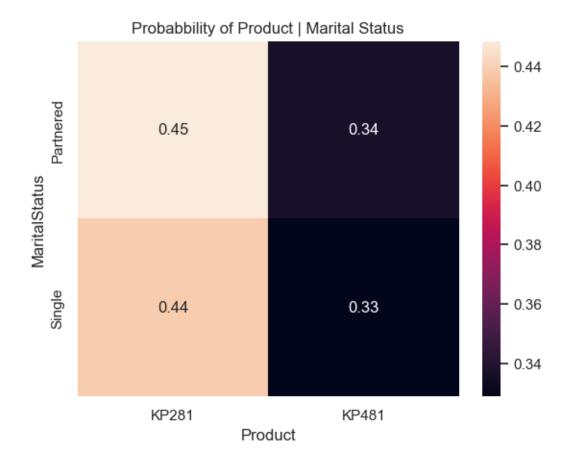


Probability of Product's for given MaritalStatus " $Product \mid Marital \; Status$ "

```
[]: sns.heatmap(pd.crosstab(aerofit['MaritalStatus'], aerofit['Product'], onormalize='index')[['KP281', 'KP481']], annot=True)

plt.title('Probabbility of Product | Marital Status', fontsize=12)

plt.show()
```



1.5.10 **Q9. The overall Probability of purchase for KP281, KP481 & KP781 TreadMill is $__$, $___$, **

```
[]: aerofit.groupby('Product')['Product'].count()/1.80
```

[]: Product

KP281 44.44444
KP481 33.333333
KP781 22.22222

Name: Product, dtype: float64

1.5.11 Q10. Give conditions when you will and when you 'll not recomended KP781 TreadMill to a Customer?

When to recomend KP781 * Male's * Age between 20-30. * Income with 90K. * Who inteded or alredy covered 150-200 Miles. * Have Education between 16-19. * Have Fitness of level5. * Have Usages level of 4-5.

When not to recomend KP781 * Females's * Age above 35. * Income below 75K. * Have Fitness level less than 3. * Have Usages level less than 4.

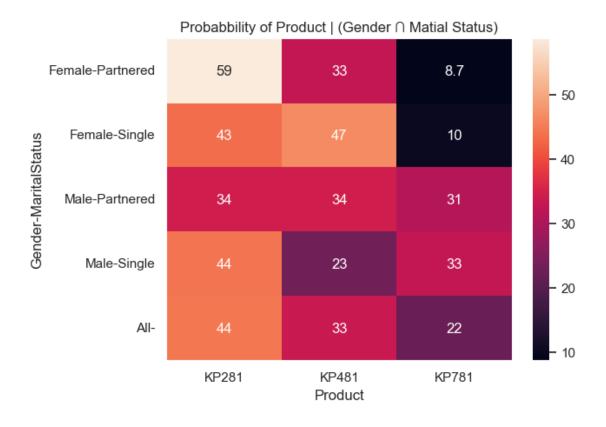
1.6 Multi Variate Analysis

Find Probability & Coorelation

Probability of Product's for given Gender & Marital Status " $Product \mid (Gender \; Matial \; Status)$ "

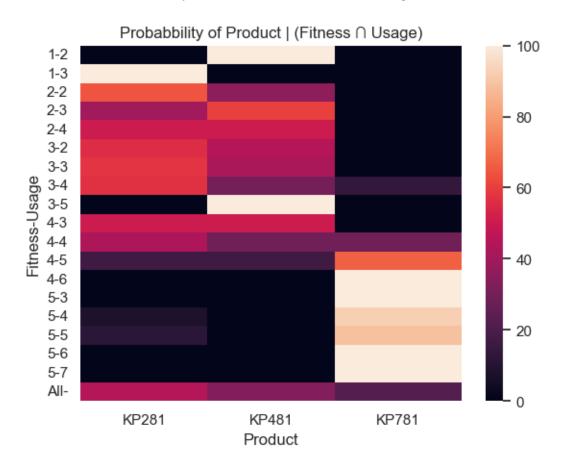
```
[]: sns.heatmap(p_pord_gend_marital, annot=True) plt.title('Probabbility of Product | (Gender Matial Status)', fontsize=12)
```

[]: Text(0.5, 1.0, 'Probabbility of Product | (Gender Matial Status)')



```
[]: sns.heatmap(p_pord_fit_usag) plt.title('Probabbility of Product | (Fitness Usage)', fontsize=12)
```

[]: Text(0.5, 1.0, 'Probabbility of Product | (Fitness Usage)')



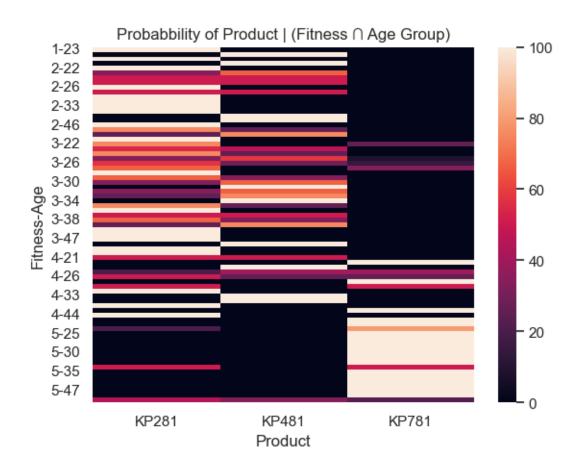
```
Probability of Product's for given Fitness & Age Group "Product | (Fitness Miles)"

[]: p_pord_fit_age_group= pd.crosstab([aerofit['Fitness'], aerofit['Age']], userofit['Product'], normalize='index', margins=True)*100

# p_pord_fit_age_group

[]: sns.heatmap(p_pord_fit_age_group)
plt.title('Probabbility of Product | (Fitness Age Group)', fontsize=12)
```

[]: Text(0.5, 1.0, 'Probabbility of Product | (Fitness Age Group)')



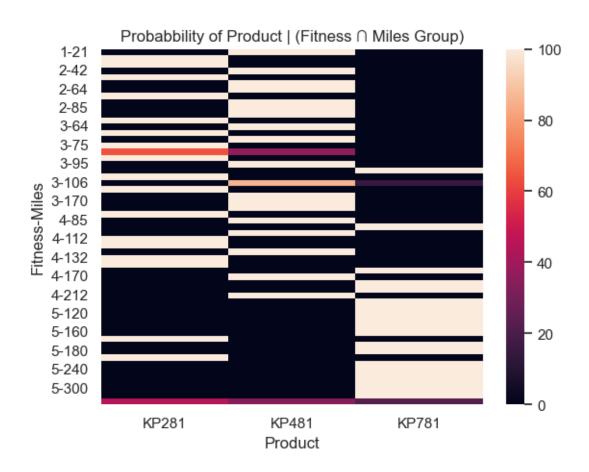
```
Probability of Product's for given Fitness & Mile Group "Product \mid (Fitness \quad Mile Group)"
```

```
p_pord_fit_mile_group= pd.crosstab([aerofit['Fitness'], aerofit['Miles']],__
aerofit['Product'], normalize='index', margins=True)*100

# p_pord_fit_mile_group
```

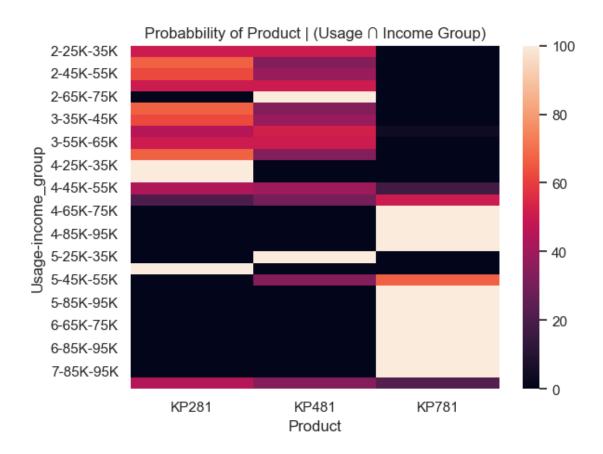
```
[]: sns.heatmap(p_pord_fit_mile_group) plt.title('Probabbility of Product | (Fitness Miles Group)', fontsize=12)
```

[]: Text(0.5, 1.0, 'Probabbility of Product | (Fitness Miles Group)')



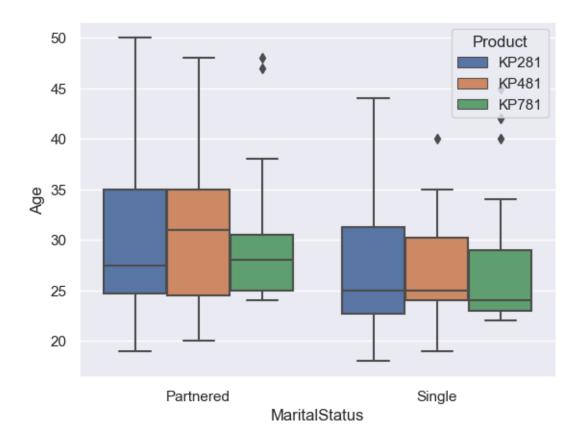
```
Probability of Product's for given Usage & Income Group "Product \mid (Fitness \quad Mile Group)"
```

[]: Text(0.5, 1.0, 'Probabbility of Product | (Usage Income Group)')



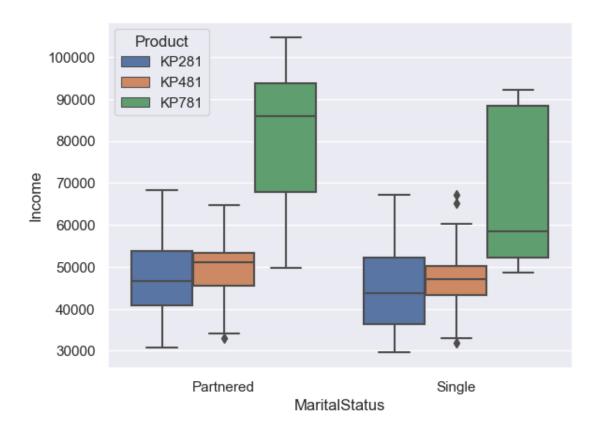
```
Find Correlation
[]: sns.boxplot(x="MaritalStatus", y="Age", hue="Product", data=aerofit)
```

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



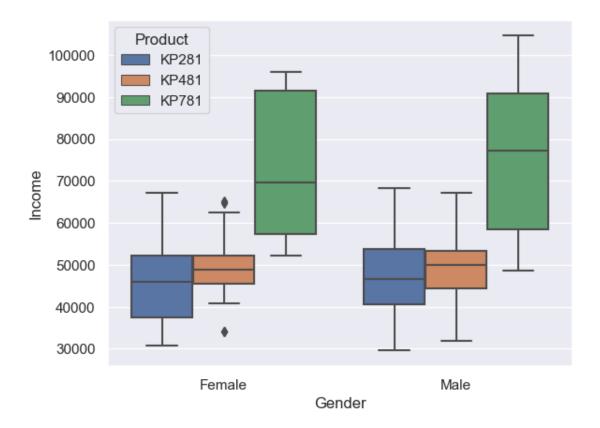
```
[]: sns.boxplot(x="MaritalStatus", y="Income", hue="Product", data=aerofit)
```

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



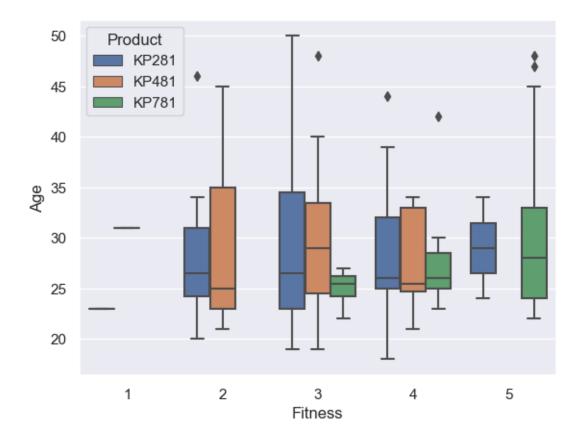
```
[]: sns.boxplot(x="Gender", y="Income", hue="Product", data=aerofit)
```

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



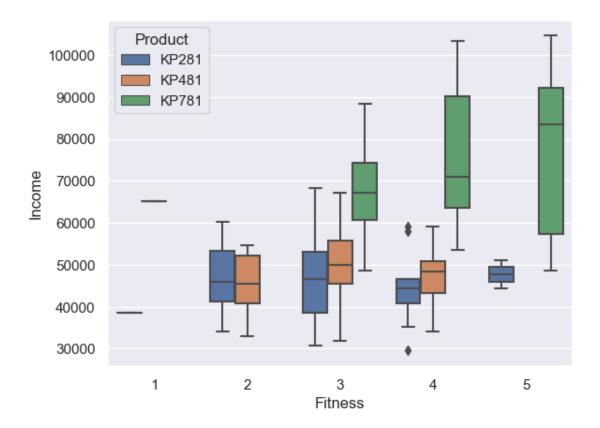
```
[]: sns.boxplot(x="Fitness", y="Age", hue="Product", data=aerofit)
```

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



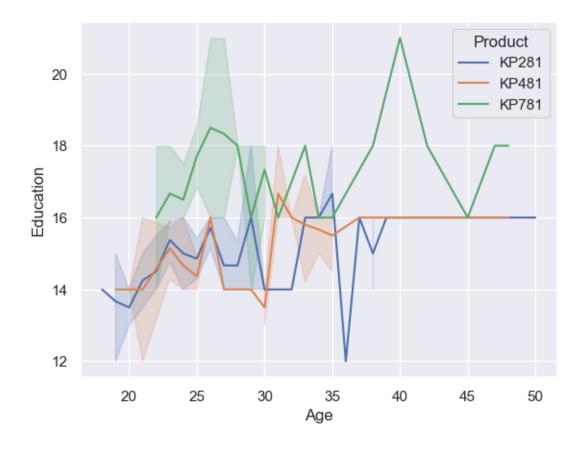
```
[]: sns.boxplot(x="Fitness", y="Income", hue="Product", data=aerofit)
```

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



```
[]: sns.lineplot(x="Age", y="Education", hue="Product", data=aerofit)
```

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



2 END