```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Problem defination: The market research team at AeroFit wants to identify the characteristics of the target audience for each type of treadmill offered by the company, to provide a better recommendation of the treadmills to the new customers. The team decides to investigate whether there are differences across the product with respect to customer characteristics.

Perform descriptive analytics to create a customer profile for each AeroFit treadmill product by developing appropriate tables and charts. For each AeroFit treadmill product, construct two-way contingency tables and compute all conditional and marginal probabilities along with their insights/impact on the business.

```python
data = pd.read_csv('/content/aerofit_treadmill.csv')

data.head(2)
```

```
  Product  Age Gender  Education MaritalStatus  Usage  Fitness  Income
Miles
0   KP281   18   Male         14        Single      3        4   29562
112
1   KP281   19   Male         15        Single      2        3   31836
75
```

```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Product        180 non-null    object
 1   Age            180 non-null    int64
 2   Gender         180 non-null    object
 3   Education      180 non-null    int64
 4   MaritalStatus  180 non-null    object
 5   Usage          180 non-null    int64
 6   Fitness        180 non-null    int64
 7   Income         180 non-null    int64
 8   Miles          180 non-null    int64
dtypes: int64(6), object(3)
memory usage: 12.8+ KB
```

No missing value

```python
data.isna().sum()/data.shape[0]
```

```
Product          0.0
Age              0.0
Gender           0.0
Education        0.0
MaritalStatus    0.0
Usage            0.0
Fitness          0.0
Income           0.0
Miles            0.0
dtype: float64
```

```
# row that are duplicate
# no duplicate found
print(f"Number of duplicate data {data.duplicated().sum()}")
data[data.duplicated()]
```

```
Number of duplicate data 0

Empty DataFrame
Columns: [Product, Age, Gender, Education, MaritalStatus, Usage,
Fitness, Income, Miles]
Index: []
```

Changing

1. Usage and Fitness to Category
2. Because Fitness is rating between 1-5 and Usage is count value for no of usage per week

```
data['Usage']=data['Usage'].astype('object')
data['Fitness']=data['Fitness'].astype('object')

data.describe()
```

	Age	Education	Income	Miles
count	180.000000	180.000000	180.000000	180.000000
mean	28.788889	15.572222	53719.577778	103.194444
std	6.943498	1.617055	16506.684226	51.863605
min	18.000000	12.000000	29562.000000	21.000000
25%	24.000000	14.000000	44058.750000	66.000000
50%	26.000000	16.000000	50596.500000	94.000000
75%	33.000000	16.000000	58668.000000	114.750000
max	50.000000	21.000000	104581.000000	360.000000

univariate analysis

Unique category and its distribution ratio

```
for col in data.columns:
  print("")
```

```
  print(f" Feature $ {col} $ \n unique categories:
{data[col].unique()} \n number of unique categories:
{data[col].nunique()} \n value counts:
{data[col].value_counts(normalize=True)} ")
  print("")
```

```
 Feature $ Product $
 unique categories: ['KP281' 'KP481' 'KP781']
 number of unique categories:  3
 value counts:  KP281    0.444444
KP481    0.333333
KP781    0.222222
Name: Product, dtype: float64


 Feature $ Age $
 unique categories: [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]
 number of unique categories:  32
 value counts:  25    0.138889
23    0.100000
24    0.066667
26    0.066667
28    0.050000
35    0.044444
33    0.044444
30    0.038889
38    0.038889
21    0.038889
22    0.038889
27    0.038889
31    0.033333
34    0.033333
29    0.033333
20    0.027778
40    0.027778
32    0.022222
19    0.022222
48    0.011111
37    0.011111
45    0.011111
47    0.011111
46    0.005556
50    0.005556
18    0.005556
44    0.005556
43    0.005556
41    0.005556
```

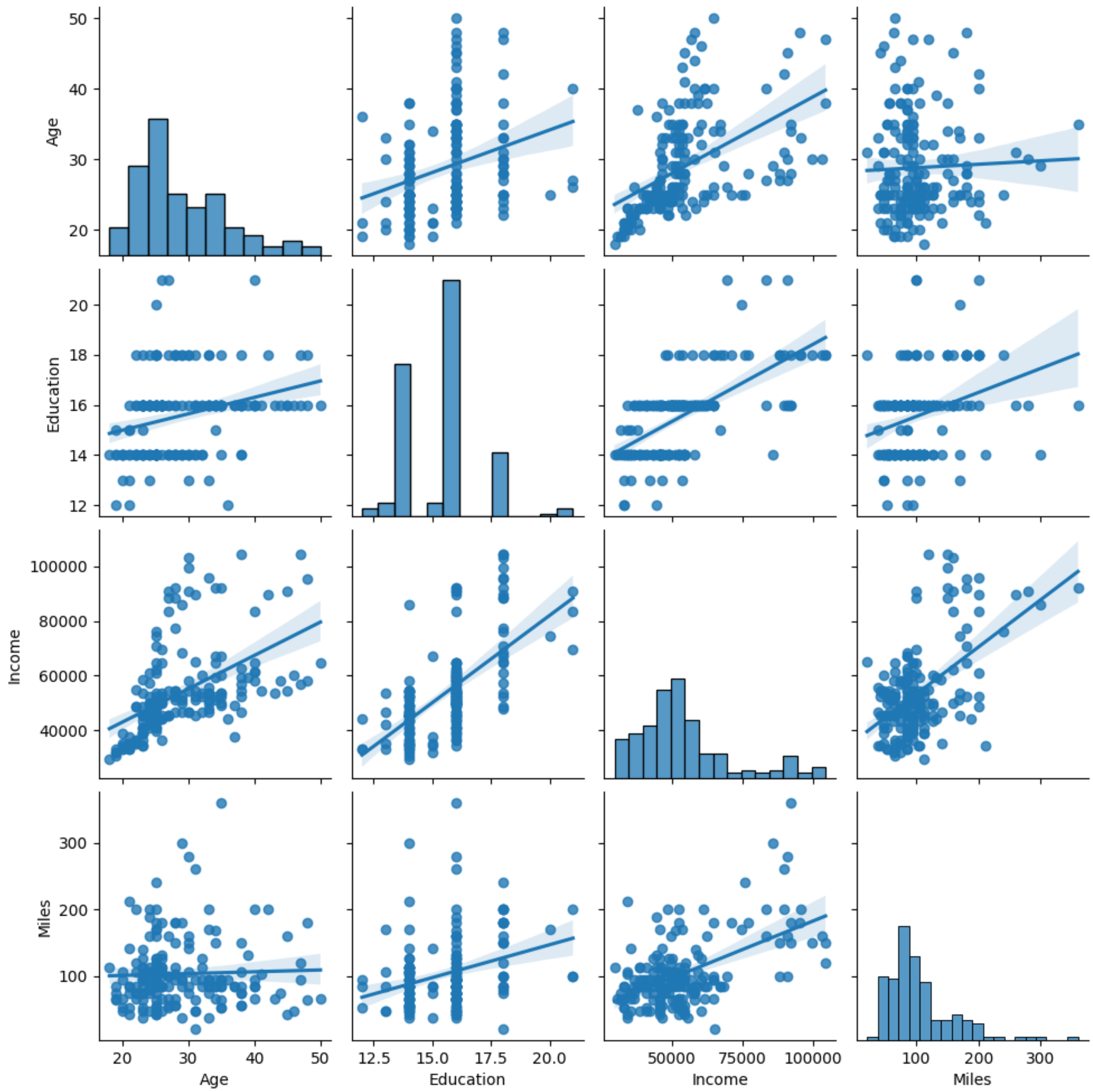
```
39    0.005556
36    0.005556
42    0.005556
Name: Age, dtype: float64


 Feature $ Gender $
 unique categories: ['Male' 'Female']
 number of unique categories:  2
 value counts:  Male      0.577778
Female    0.422222
Name: Gender, dtype: float64


 Feature $ Education $
 unique categories: [14 15 12 13 16 18 20 21]
 number of unique categories:  8
 value counts:  16    0.472222
14    0.305556
18    0.127778
15    0.027778
13    0.027778
12    0.016667
21    0.016667
20    0.005556
Name: Education, dtype: float64


 Feature $ MaritalStatus $
 unique categories: ['Single' 'Partnered']
 number of unique categories:  2
 value counts:  Partnered    0.594444
Single       0.405556
Name: MaritalStatus, dtype: float64


 Feature $ Usage $
 unique categories: [3 2 4 5 6 7]
 number of unique categories:  6
 value counts:  3    0.383333
4    0.288889
2    0.183333
5    0.094444
6    0.038889
7    0.011111
Name: Usage, dtype: float64


 Feature $ Fitness $
 unique categories: [4 3 2 1 5]
```

```
 number of unique categories:  5
 value counts:  3    0.538889
5    0.172222
2    0.144444
4    0.133333
1    0.011111
Name: Fitness, dtype: float64


 Feature $ Income $
 unique categories: [ 29562  31836  30699  32973  35247  37521  36384
38658  40932  34110
  39795  42069  44343  45480  46617  48891  53439  43206  52302  51165
  50028  54576  68220  55713  60261  67083  56850  59124  61398  57987
  64809  47754  65220  62535  48658  54781  48556  58516  53536  61006
  57271  52291  49801  62251  64741  70966  75946  74701  69721  83416
  88396  90886  92131  77191  52290  85906 103336  99601  89641  95866
 104581  95508]
 number of unique categories:  62
 value counts:  45480    0.077778
52302    0.050000
46617    0.044444
54576    0.044444
53439    0.044444
           ...
65220    0.005556
55713    0.005556
68220    0.005556
30699    0.005556
95508    0.005556
Name: Income, Length: 62, dtype: float64


 Feature $ Miles $
 unique categories: [112  75  66  85  47 141 103  94 113  38 188  56
132 169  64  53 106  95
 212  42 127  74 170  21 120 200 140 100  80 160 180 240 150 300 280
260
 360]
 number of unique categories:  37
 value counts:  85     0.150000
95     0.066667
66     0.055556
75     0.055556
47     0.050000
106    0.050000
94     0.044444
113    0.044444
53     0.038889
100    0.038889
```

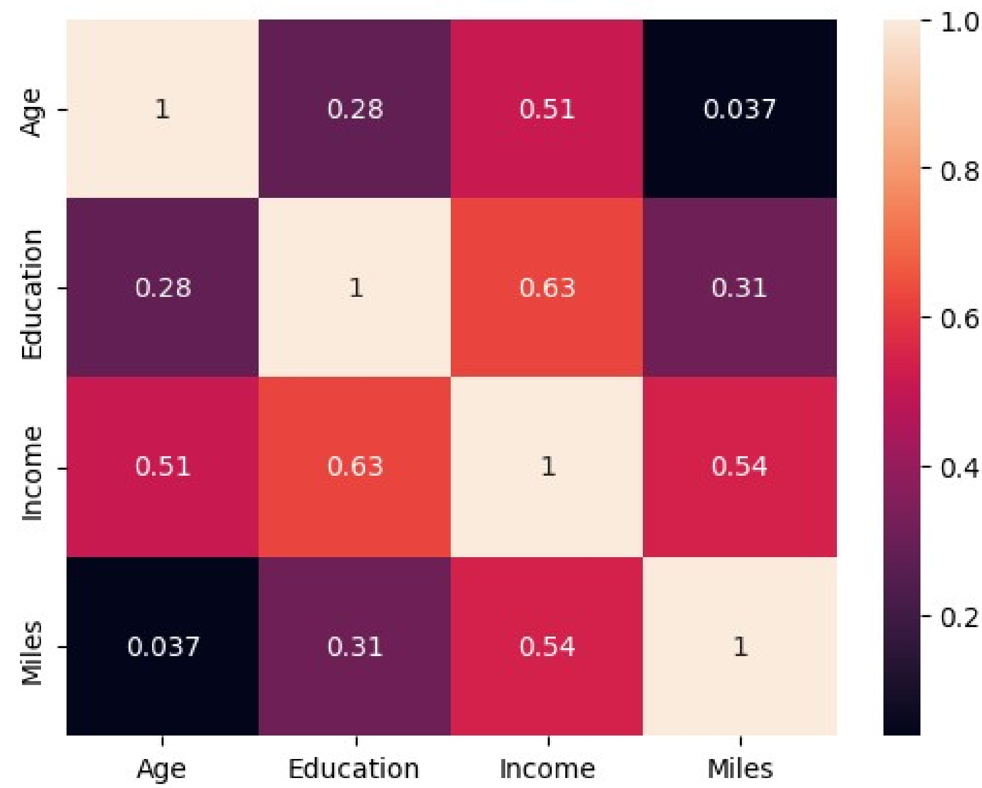
```
180    0.033333
200    0.033333
56     0.033333
64     0.033333
127    0.027778
160    0.027778
42     0.022222
150    0.022222
38     0.016667
74     0.016667
170    0.016667
120    0.016667
103    0.016667
132    0.011111
141    0.011111
280    0.005556
260    0.005556
300    0.005556
240    0.005556
112    0.005556
212    0.005556
80     0.005556
140    0.005556
21     0.005556
169    0.005556
188    0.005556
360    0.005556
Name: Miles, dtype: float64
```

```
numeric_feature =data.select_dtypes(include =np.number)
print(f"numeric feature name: {numeric_feature.columns}")
sns.pairplot(numeric_feature , kind ='reg')
plt.plot()
```

```
numeric feature name: Index(['Age', 'Education', 'Income', 'Miles'],
dtype='object')

[]
```



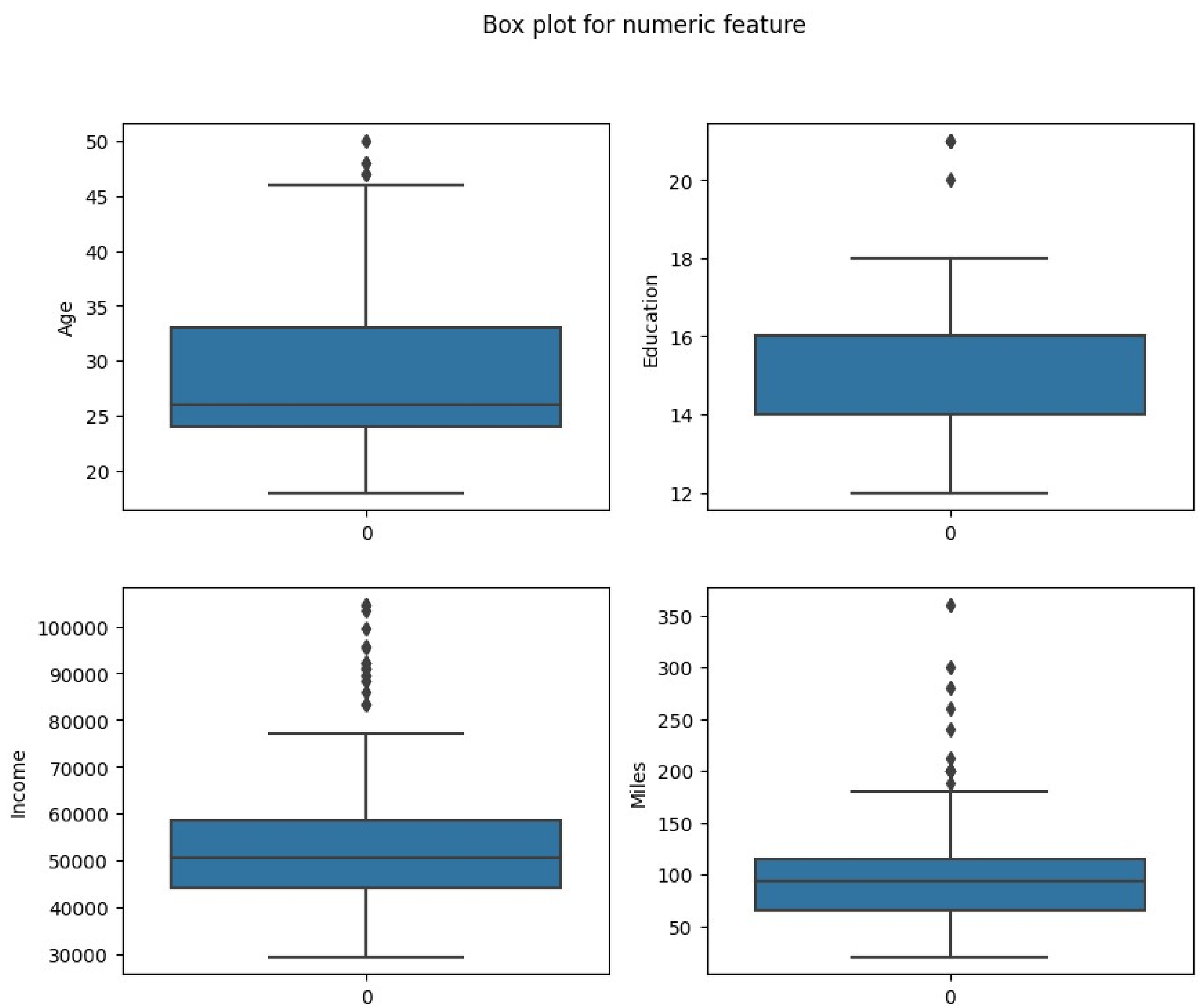

```
sns.heatmap(numeric_feature.corr(), annot=True)
plt.show()
```



1. 'Age' and positive correlation with Income as age increases Income increases.
2. 'Age' and very slightly positive correlation with Miles Mature customer tend to commit for higher number of miles per week
3. 'Age' and positive correlation with Education mature customer have passed exam more recently
4. 'Education' is very positevly correlated with Income -- more educated people tend to earn more
5. 'Education' is positevly correlated with Miles -- more educated people tend commit more miles per week

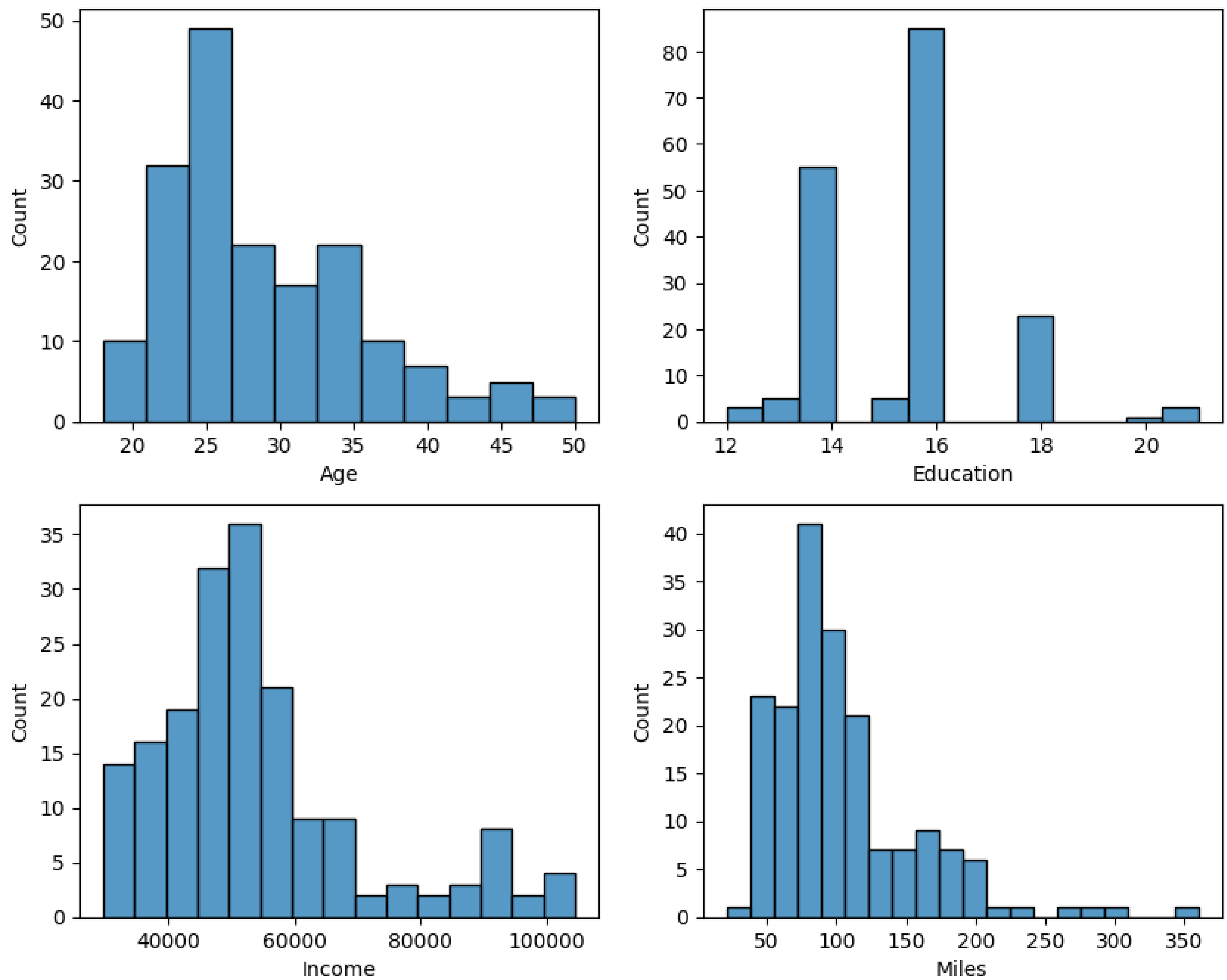
1. We can target KP781 older customer as they tend earn more so they can spend more
2. For younger customer we can target KP281 or KP481 as they tend to earn less.
3. We can target KP781 to customer who have higher Education year
4. We can target KP781 customer that have higher income as they tend earn more so they can spend more and KP281 or KP481 to those who earn less

```
fig , ax = plt.subplots( 2,2 , figsize = (10,8))
for i,axis   in enumerate(ax.ravel()):
  name =numeric_feature.iloc[:,i].name
  sns.boxplot(numeric_feature[name]   , ax = axis)
  axis.set_ylabel(name)
plt.suptitle(" Box plot for numeric feature")
plt.show()
```




```
fig , ax = plt.subplots( 2,2 , figsize = (10,8))
for i,axis   in enumerate(ax.ravel()):
  name =numeric_feature.iloc[:,i].name
  sns.histplot(numeric_feature[name]  , ax = axis)
  axis.set_xlabel(name)
plt.suptitle(" Box plot for numeric feature")
plt.show()
```

Box plot for numeric feature




```
print("Basic descriptive stats of numerical fetaures")
for col in numeric_feature.columns:
  print(f" $ {col} $:\n mean {round(numeric_feature[col].mean(),2)}\n
median: {round(numeric_feature[col].median(),2)}\n std:
{round(numeric_feature[col].std(),2)} \n range:
{numeric_feature[col].min() ,numeric_feature[col].max()}")
```

```
Basic descriptive stats of numerical fetaures
 $ Age $:
 mean 28.79
 median: 26.0
 std: 6.94
 range: (18, 50)
 $ Education $:
 mean 15.57
 median: 16.0
```

```
std: 1.62
range: (12, 21)
$ Income $:
mean 53719.58
median: 50596.5
std: 16506.68
range: (29562, 104581)
$ Miles $:
mean 103.19
median: 94.0
std: 51.86
range: (21, 360)
```

1. Age has outlier outlier very few people above 45 tend to buy product , bulk of the sales is between 22 -32 years of age
2. Most people have (Education) passed in year 2016 about (47%) , very few people have passed from 2020 onwards and those are taken as outliers
3. Most people who buy product has income between 40k to 60k , income above 80k is treated as outliers
4. Most people say they can will do 60 - 120 miles per week, Miles above 200 is treated as outliers, some people are very optimistic and some people are very pesimistic on number of miles they can do in a week, range varies from 21 miles to 360 miles

1. People who quote high miles number can have high probality to buy product as they look highly motivated
2. Age between 22-32 look good to to target them for sales
3. Age between 40k -60k look good to to target them for sales

Categorical features

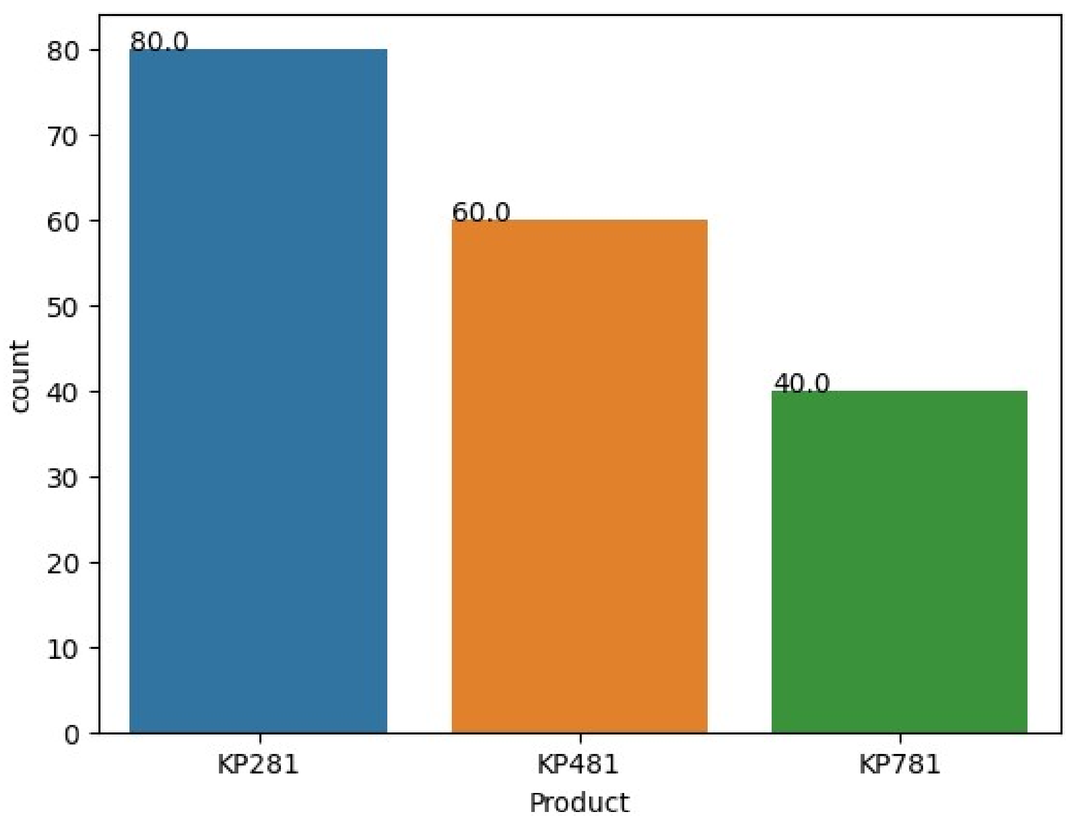
```
categorical_features =data.select_dtypes(include ='object')

data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 180 entries, 0 to 179
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Product        180 non-null    object
 1   Age            180 non-null    int64
 2   Gender         180 non-null    object
 3   Education      180 non-null    int64
 4   MaritalStatus  180 non-null    object
 5   Usage          180 non-null    object
 6   Fitness        180 non-null    object
 7   Income         180 non-null    int64
 8   Miles          180 non-null    int64
```

```
dtypes: int64(4), object(5)
memory usage: 12.8+ KB

categorical_features.columns

Index(['Product', 'Gender', 'MaritalStatus', 'Usage', 'Fitness'],
dtype='object')
```

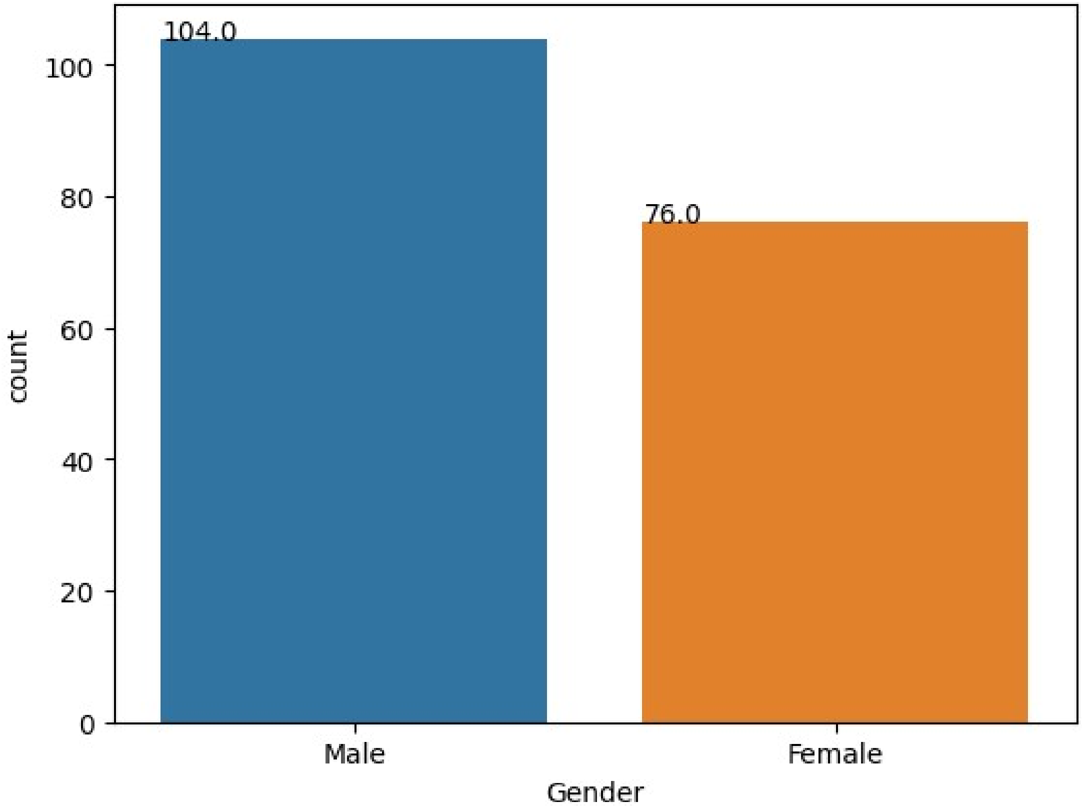
Categorical feature

Mode of catgory and its population ratio with count plot

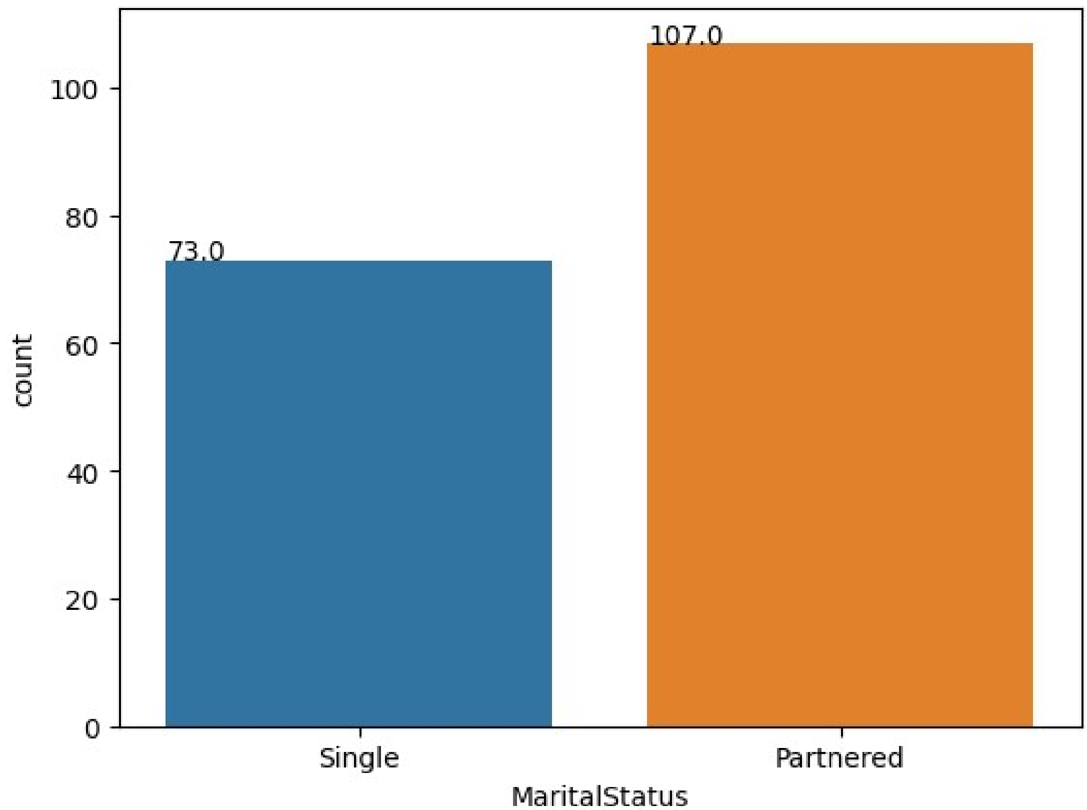
```
# count plot
for col  in categorical_features.columns:
  vc =categorical_features[col].value_counts(normalize =np.True_)
  mode , value =vc[vc==vc.max()].index[0]  ,
round(vc[vc==vc.max()].values[0],2)
  print(f"mode of category {col} -- {mode} -- {value}%")
  ax =sns.countplot(x= categorical_features[col])
  for p in ax.patches:
        ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x(),
p.get_height()))
  plt.show()

mode of category Product -- KP281 -- 0.44%
```



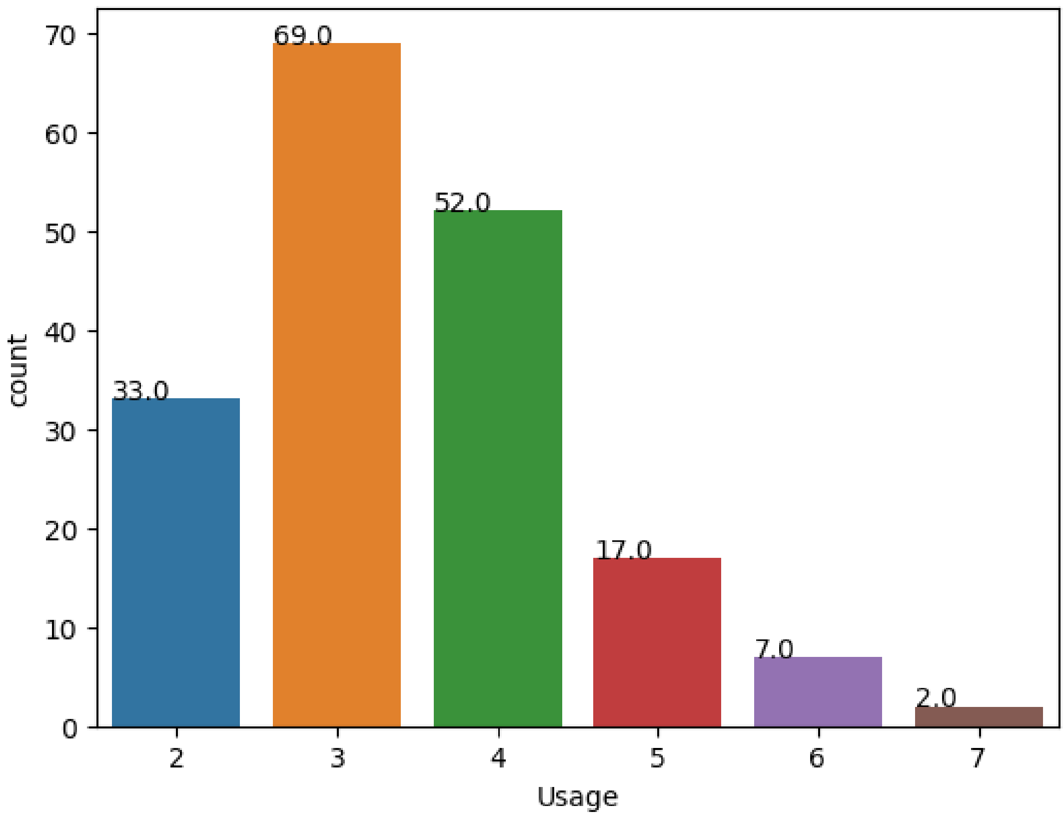
```
mode of category Gender -- Male -- 0.58%
```



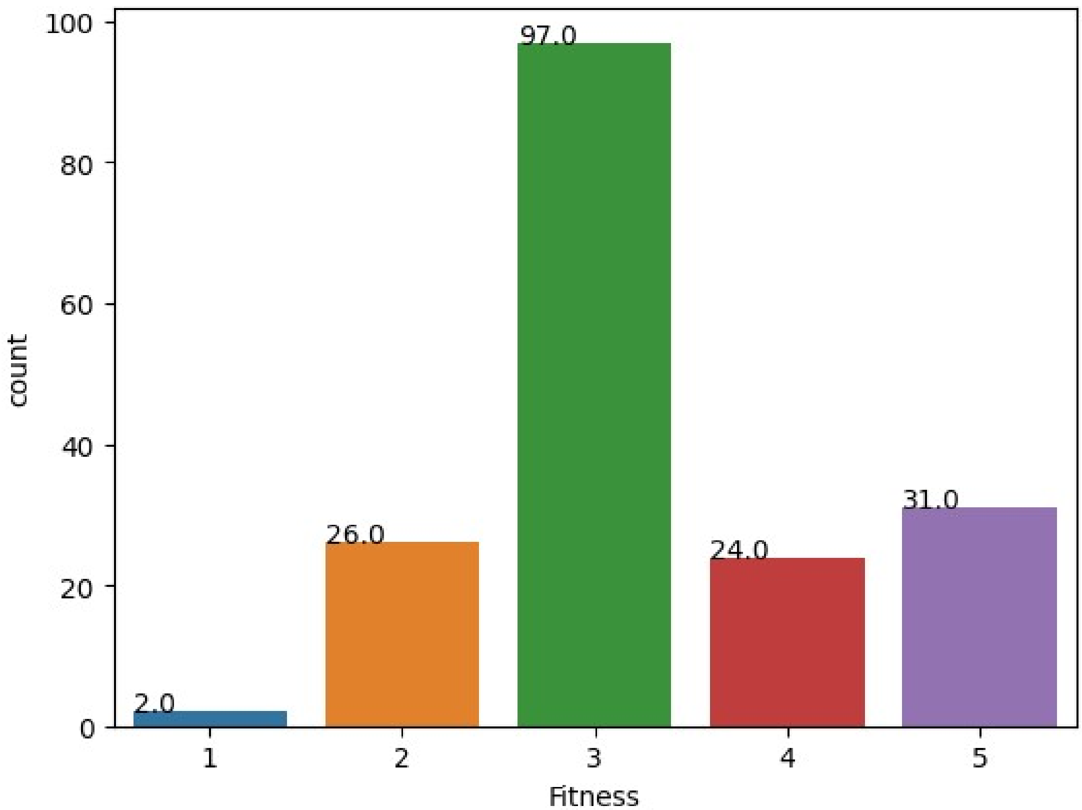

```
mode of category MaritalStatus -- Partnered -- 0.59%
```




```
mode of category Usage -- 3 -- 0.38%
```




```
mode of category Fitness -- 3 -- 0.54%
```



1. Most sold 'Product' is kp281 followed by kp481 and kp781 -- people tend to by cheaper product more
2. Most numerous 'Gender' is male about 59 % and female with 41 %
3. More patnered people tend to buy product about 59 %
4. Most people say they will use product 3 times a week about 38 %
5. Most people say there fitness is 3 on scale of 1-5

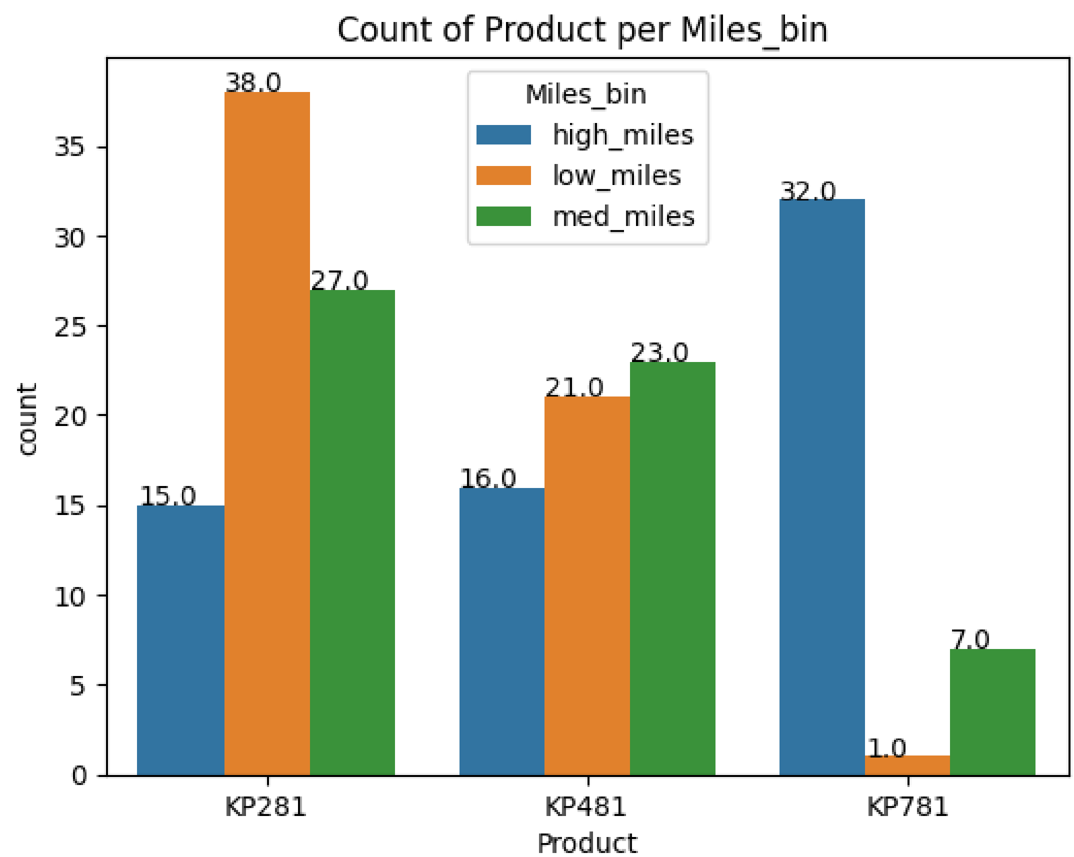
1. Male tend to buy product more than women but the differnce in only 18 % so we can target male and may be put some offer for female
2. Its comparatively easiler to sale product to patnered people
3. Its easier to sale product to people with fitness above 1

Bi and multivariate analysis

Binning numerical features

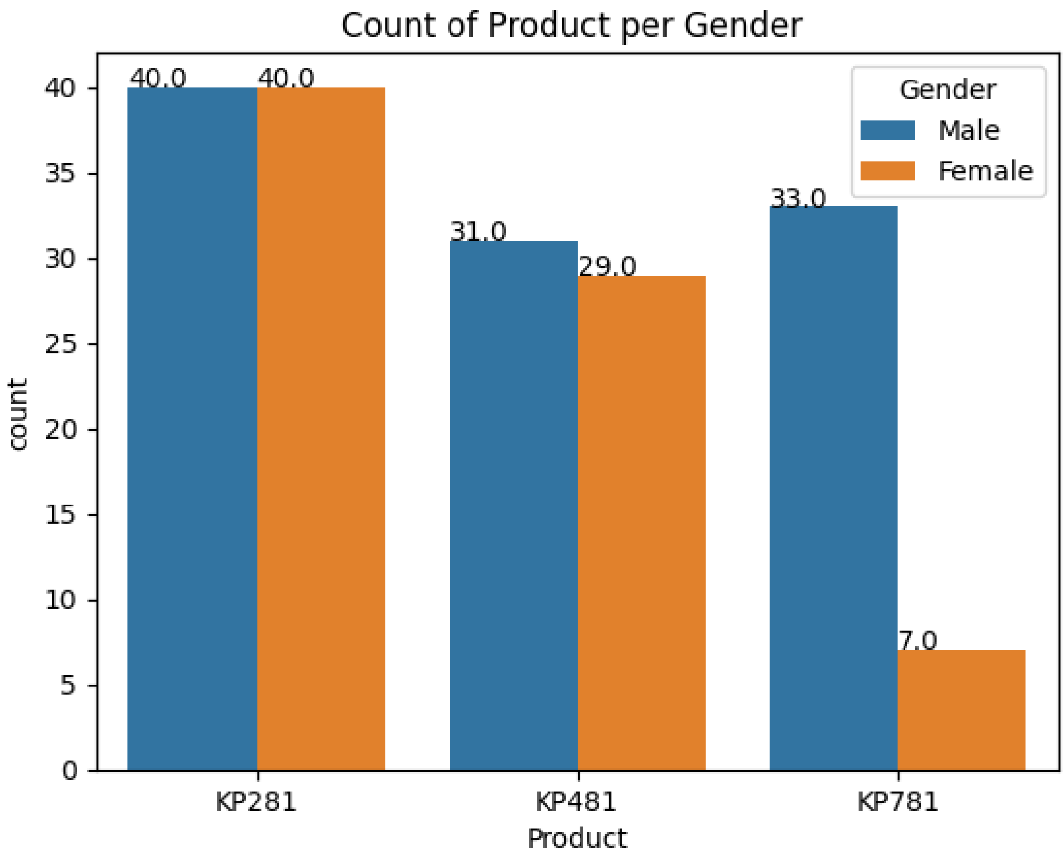
```
category ='Age_bin'
def age_bin(x):
  if x< 26:
    return 'low_age'
  elif x>= 26 and x <36:
    return 'med_age'
```

```
  elif x>= 36:
    return "high_age"
data[category]=data['Age'].apply(lambda x : age_bin(x) )

category ='Income_bin'
def age_bin(x):
  if x< 45480:
    return 'low_income'
  elif x>= 45480 and x <54576:
    return 'med_income'
  elif x>= 54576:
    return "high_income"
data[category]=data['Income'].apply(lambda x : age_bin(x) )

category ='Income_bin'
def age_bin(x):
  if x< 45480:
    return 'low_income'
  elif x>= 45480 and x <54576:
    return 'med_income'
  elif x>= 54576:
    return "high_income"
data[category]=data['Income'].apply(lambda x : age_bin(x) )

category ='Miles_bin'
def age_bin(x):
  if x< 80.35:
    return 'low_miles'
  elif x>= 80.35 and x <106.00:
    return 'med_miles'
  elif x>= 106.00:
    return "high_miles"
data[category]=data['Miles'].apply(lambda x : age_bin(x) )


ax=sns.countplot(data = data , x = 'Product' , hue ='Miles_bin')
for p in ax.patches:
      ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x(),
p.get_height()))

plt.title("Count of Product per Miles_bin ")
plt.show()
```



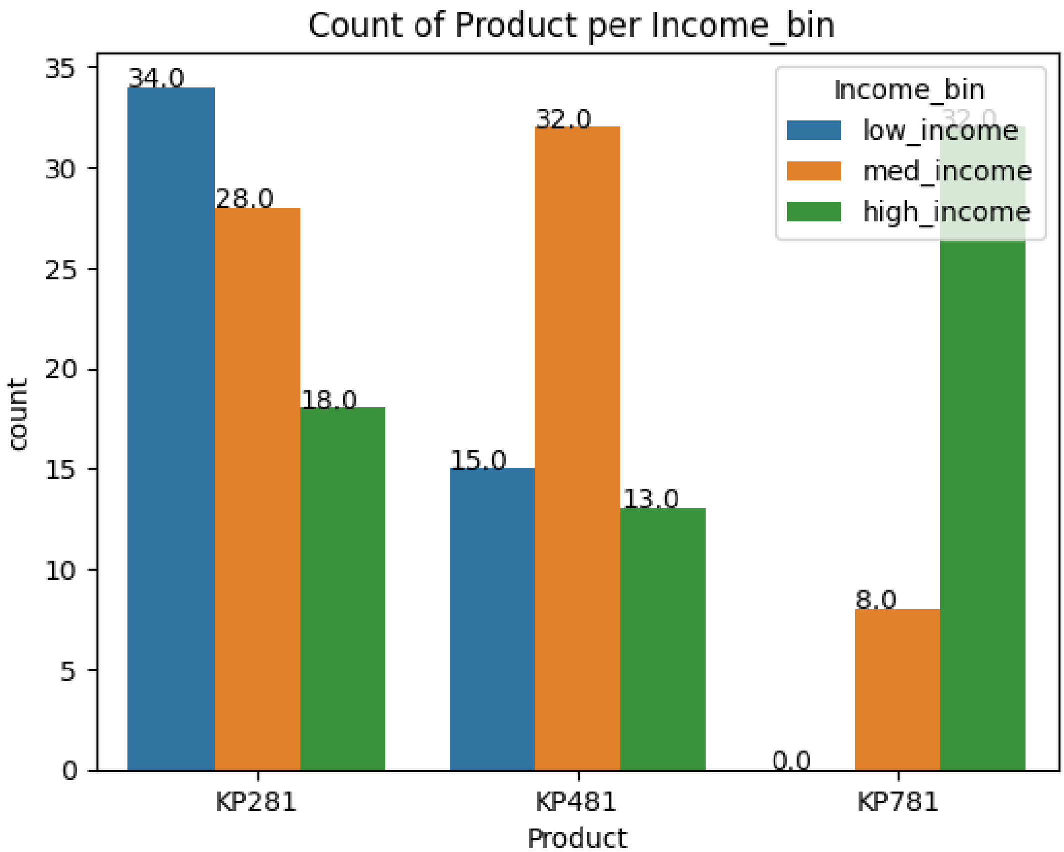
- kp281- low Miles bin people
- kp481 -- medium Miles bin people
- kp781 -- high Miles bin people
- As commited miles increse people tend to buy costly product

```
ax=sns.countplot(data = data , x = 'Product' , hue ='Gender')
for p in ax.patches:
      ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x(),
p.get_height()))

plt.title("Count of Product per Gender ")
plt.show()
```



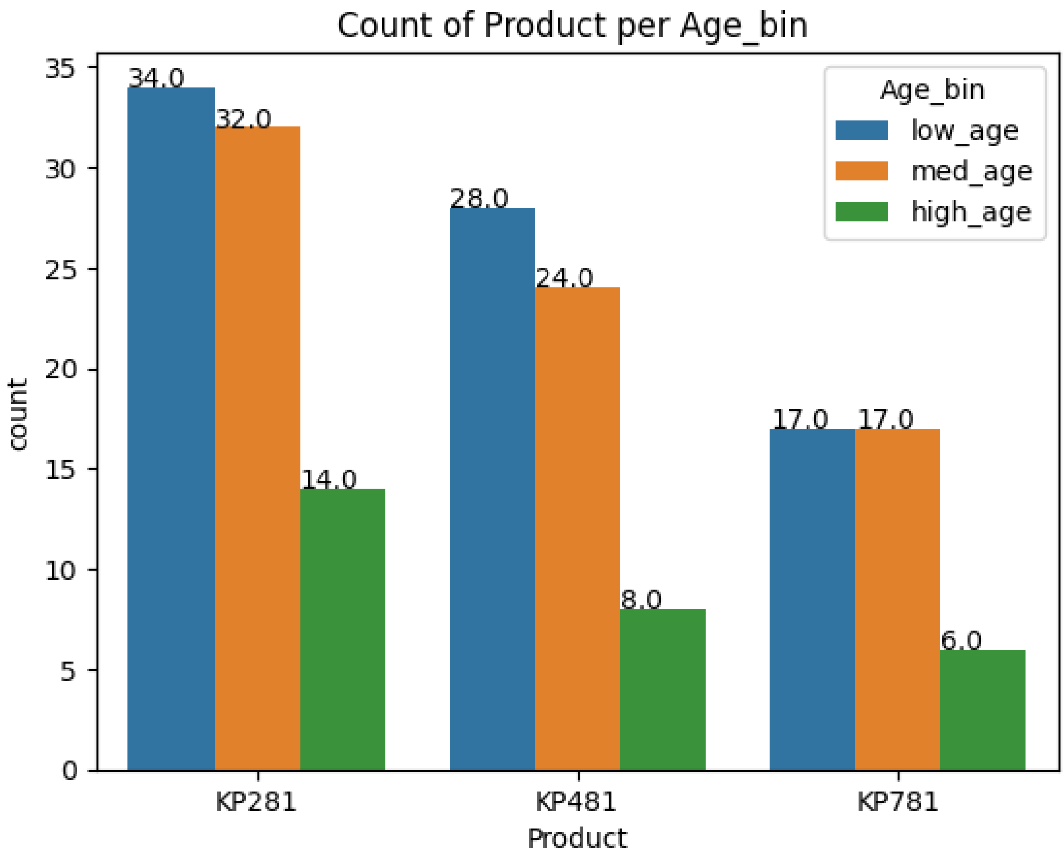
- kp281- both male and female buy same amount
- kp481 -- Male buy more
- kp781 -- Male buy more
- Costly product is mostly bought by male

```
ax=sns.countplot(data = data , x = 'Product' , hue ='Income_bin')
for p in ax.patches:
      ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x(),
p.get_height()))

plt.title("Count of Product per Income_bin ")
plt.show()
```



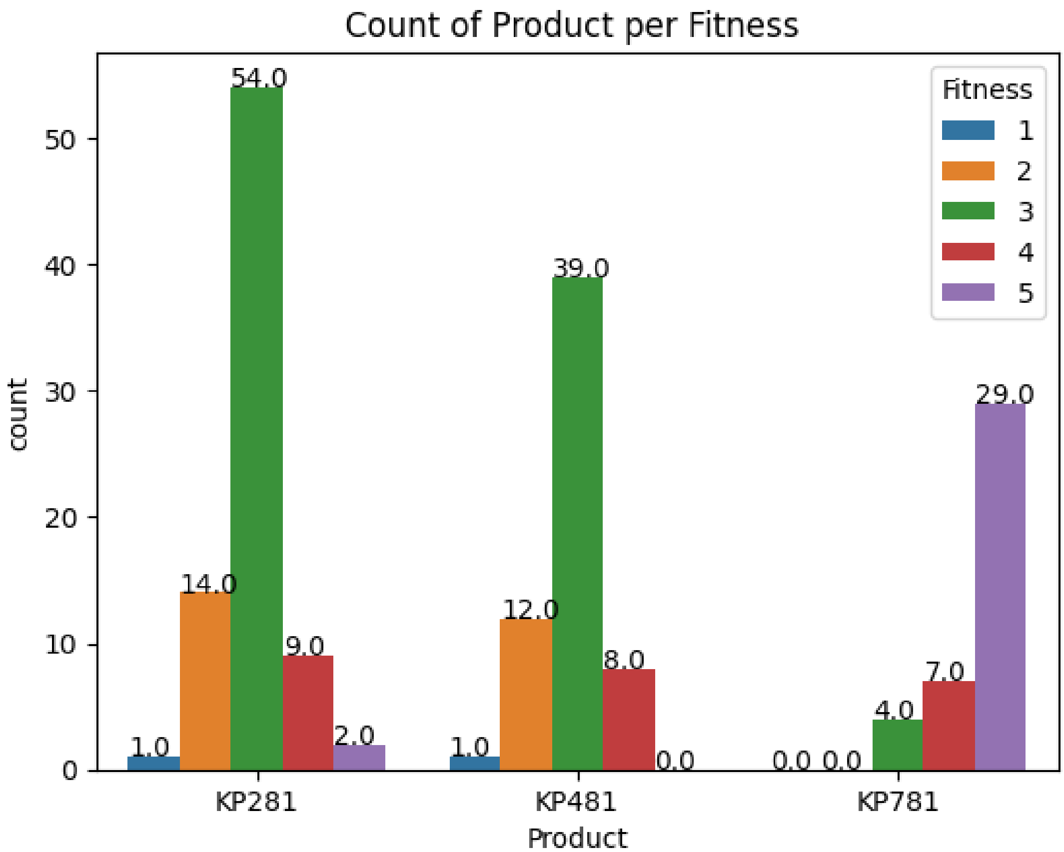
- kp281 -- Is bought more by low income people
- kp481 -- Is bought more by low income people
- kp781 -- Is bought more by low and medium income people

```
ax=sns.countplot(data = data , x = 'Product' , hue ='Age_bin')
for p in ax.patches:
      ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x(),
p.get_height()))

plt.title("Count of Product per Age_bin ")
plt.show()
```



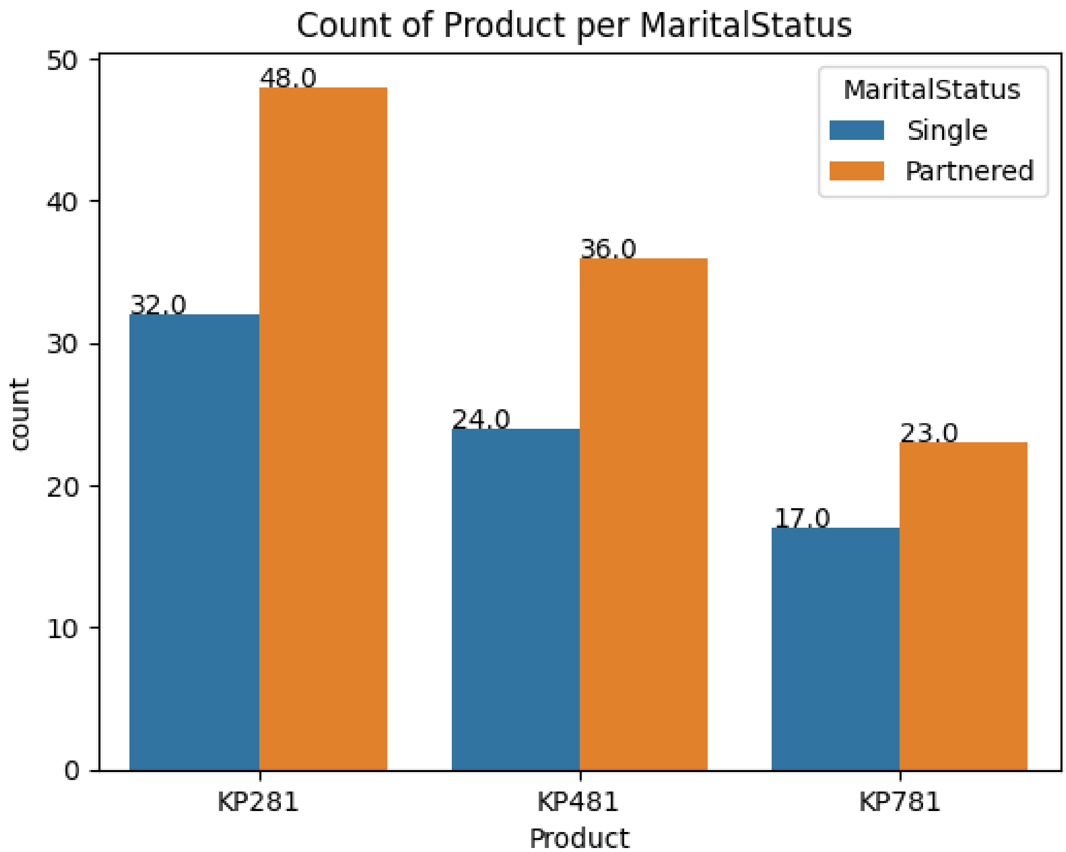
- kp281 -- Is bought more by low income people
- kp481 -- Is bought more by low income people
- kp781 -- Is bought more by low and medium income people

```
ax=sns.countplot(data = data , x = 'Product' , hue ='Fitness')
for p in ax.patches:
      ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x(),
p.get_height()))

plt.title("Count of Product per Fitness ")
plt.show()
```



- Kp281 and kp481 is mostly bought by people by with fitness level 3
- Kp781 is mostly bought by people by with fitness level 5
- Higher fitness level people buy costly product

```
ax=sns.countplot(data = data , x = 'Product' , hue ='MaritalStatus')
for p in ax.patches:
      ax.annotate('{:.1f}'.format(p.get_height()), (p.get_x(),
p.get_height()))

plt.title("Count of Product per MaritalStatus ")
plt.show()
```



- More partner people buy kp281
- More partner people buy kp481
- More partner people buy kp781 On an avg Patnered people buy product more easily

```
def write_conclusion(row ,category ='Education'   ):

  data_subset =row[1]
  keys =['KP281', 'KP481', 'KP781']
  values =data_subset[['KP281', 'KP481', 'KP781']]
  i_max =np.argmax(values)
  key=keys[i_max]
  value =values[np.argmax(values)]
  print(f"Highest probality to buy product type `{key}` with p(product
= {key}/{category}= {row[1][category]}) = {round(value*100,1)} % ")

category ='Gender'
tab=pd.crosstab(data['Gender'], data['Product'],normalize='index')
display(tab)
all_tab =tab.reset_index()
for  row  in all_tab.iterrows():
  write_conclusion(row ,category)

Product     KP281     KP481     KP781
Gender
```

```
Female    0.526316  0.381579  0.092105
Male      0.384615  0.298077  0.317308

Highest probality to buy product type `KP281` with p(product =
KP281/Gender= Female) = 52.6 %
Highest probality to buy product type `KP281` with p(product =
KP281/Gender= Male) = 38.5 %
```

```
category ='Education'
tab =pd.crosstab(data[category], data['Product'],normalize='index')
display(tab)
all_tab =tab.reset_index()
for  row  in all_tab.iterrows():
  write_conclusion(row ,category)
```

```
Product       KP281     KP481     KP781
Education
12         0.666667  0.333333  0.000000
13         0.600000  0.400000  0.000000
14         0.545455  0.418182  0.036364
15         0.800000  0.200000  0.000000
16         0.458824  0.364706  0.176471
18         0.086957  0.086957  0.826087
20         0.000000  0.000000  1.000000
21         0.000000  0.000000  1.000000

Highest probality to buy product type `KP281` with p(product =
KP281/Education= 12.0) = 66.7 %
Highest probality to buy product type `KP281` with p(product =
KP281/Education= 13.0) = 60.0 %
Highest probality to buy product type `KP281` with p(product =
KP281/Education= 14.0) = 54.5 %
Highest probality to buy product type `KP281` with p(product =
KP281/Education= 15.0) = 80.0 %
Highest probality to buy product type `KP281` with p(product =
KP281/Education= 16.0) = 45.9 %
Highest probality to buy product type `KP781` with p(product =
KP781/Education= 18.0) = 82.6 %
Highest probality to buy product type `KP781` with p(product =
KP781/Education= 20.0) = 100.0 %
Highest probality to buy product type `KP781` with p(product =
KP781/Education= 21.0) = 100.0 %
```

```
category ='MaritalStatus'
tab =pd.crosstab(data[category], data['Product'],normalize='index')
display(tab)
all_tab =tab.reset_index()
for  row  in all_tab.iterrows():
  write_conclusion(row ,category)
```

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

Highest probality to buy product type `KP281` with p(product =
KP281/MaritalStatus= Partnered) = 44.9 %
Highest probality to buy product type `KP281` with p(product =
KP281/MaritalStatus= Single) = 43.8 %
```

```
category ='Usage'
tab =pd.crosstab(data[category], data['Product'],normalize='index')
display(tab)
all_tab =tab.reset_index()
for  row  in all_tab.iterrows():
  write_conclusion(row ,category)
```

```
Product     KP281     KP481     KP781
Usage
2        0.575758  0.424242  0.000000
3        0.536232  0.449275  0.014493
4        0.423077  0.230769  0.346154
5        0.117647  0.176471  0.705882
6        0.000000  0.000000  1.000000
7        0.000000  0.000000  1.000000

Highest probality to buy product type `KP281` with p(product =
KP281/Usage= 2.0) = 57.6 %
Highest probality to buy product type `KP281` with p(product =
KP281/Usage= 3.0) = 53.6 %
Highest probality to buy product type `KP281` with p(product =
KP281/Usage= 4.0) = 42.3 %
Highest probality to buy product type `KP781` with p(product =
KP781/Usage= 5.0) = 70.6 %
Highest probality to buy product type `KP781` with p(product =
KP781/Usage= 6.0) = 100.0 %
Highest probality to buy product type `KP781` with p(product =
KP781/Usage= 7.0) = 100.0 %
```

```
category ='Fitness'
tab =pd.crosstab(data[category], data['Product'],normalize='index')
display(tab)
all_tab =tab.reset_index()
for  row  in all_tab.iterrows():
  write_conclusion(row ,category)
```

```
Product     KP281     KP481     KP781
Fitness
1        0.500000  0.500000  0.000000
2        0.538462  0.461538  0.000000
3        0.556701  0.402062  0.041237
```

```
4         0.375000  0.333333  0.291667
5         0.064516  0.000000  0.935484

Highest probality to buy product type `KP281` with p(product =
KP281/Fitness= 1.0) = 50.0 %
Highest probality to buy product type `KP281` with p(product =
KP281/Fitness= 2.0) = 53.8 %
Highest probality to buy product type `KP281` with p(product =
KP281/Fitness= 3.0) = 55.7 %
Highest probality to buy product type `KP281` with p(product =
KP281/Fitness= 4.0) = 37.5 %
Highest probality to buy product type `KP781` with p(product =
KP781/Fitness= 5.0) = 93.5 %

category ='Age_bin'
tab =pd.crosstab(data[category], data['Product'],normalize='index')
display(tab)
all_tab =tab.reset_index()
for  row  in all_tab.iterrows():
  write_conclusion(row ,category)

Product      KP281     KP481     KP781
Age_bin
high_age  0.500000  0.285714  0.214286
low_age   0.430380  0.354430  0.215190
med_age   0.438356  0.328767  0.232877

Highest probality to buy product type `KP281` with p(product =
KP281/Age_bin= high_age) = 50.0 %
Highest probality to buy product type `KP281` with p(product =
KP281/Age_bin= low_age) = 43.0 %
Highest probality to buy product type `KP281` with p(product =
KP281/Age_bin= med_age) = 43.8 %

category ='Income_bin'
tab =pd.crosstab(data[category], data['Product'],normalize='index')
display(tab)
all_tab =tab.reset_index()
for  row  in all_tab.iterrows():
  write_conclusion(row ,category)

Product         KP281     KP481     KP781
Income_bin
high_income  0.285714  0.206349  0.507937
low_income   0.693878  0.306122  0.000000
med_income   0.411765  0.470588  0.117647

Highest probality to buy product type `KP781` with p(product =
KP781/Income_bin= high_income) = 50.8 %
Highest probality to buy product type `KP281` with p(product =
KP281/Income_bin= low_income) = 69.4 %
```

```
Highest probality to buy product type `KP481` with p(product =
KP481/Income_bin= med_income) = 47.1 %

category ='Miles_bin'

tab =pd.crosstab(data[category], data['Product'],normalize='index')
display(tab)
all_tab =tab.reset_index()
for  row  in all_tab.iterrows():
  write_conclusion(row ,category)

Product         KP281     KP481     KP781
Miles_bin
high_miles   0.238095  0.253968  0.507937
low_miles    0.633333  0.350000  0.016667
med_miles    0.473684  0.403509  0.122807

Highest probality to buy product type `KP781` with p(product =
KP781/Miles_bin= high_miles) = 50.8 %
Highest probality to buy product type `KP281` with p(product =
KP281/Miles_bin= low_miles) = 63.3 %
Highest probality to buy product type `KP281` with p(product =
KP281/Miles_bin= med_miles) = 47.4 %
```

Recommendations

1. People who commit higher than 106 miles has 50+% probality of buying kp781
2. People with income lower than 45480 has 69+% probality of buying kp281
3. People with income higher than 54576 has 50+% probality of buying kp781
4. People with age lower than 26 has 50+% probality of buying kp281

5. People with high fitness level 5 has 93+% probality of buying kp781
6. People with high usage value 6 and 7 have 100% probality of buying kp781
7. Both Patnered and single people tend to buy kp281 with probality of 44% and 43%
8. if education year is 20 or 21 or 18 have 100% 100% and 82 % probality of buying kp781
9. if education year less than 18 probality of buying kp281 is higher
10. Both male and female has higher probality of buying kp281 with probality of 38.5% and 52.6%