Importing Libraries

In [1]:

```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
import scipy.stats as stats
```

Importing excel data to data frame

In [2]:

```
df=pd.read_excel("C:/Users/akash/Desktop/Scaler/aerofit.xlsx")
```

In [3]:

```
df.head()
```

Out[3]:

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

In [4]:

```
df.info()
```

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

In [5]:

```
df.describe(include=['object','int64'])
```

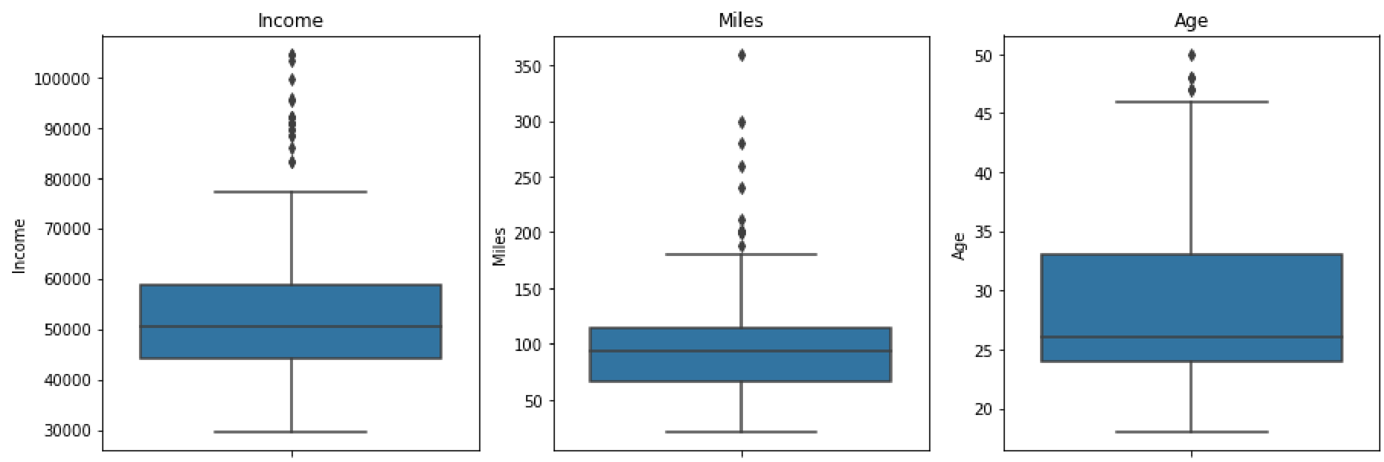
Out[5]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Mile
count	180	180.000000	180	180.000000	180	180.000000	180.000000	180.000000	180.00000
unique	3	NaN	2	NaN	2	NaN	NaN	NaN	Na
top	KP281	NaN	Male	NaN	Partnered	NaN	NaN	NaN	Na
freq	80	NaN	104	NaN	107	NaN	NaN	NaN	Na
mean	NaN	28.788889	NaN	15.572222	NaN	3.455556	3.311111	53719.577778	103.19444
std	NaN	6.943498	NaN	1.617055	NaN	1.084797	0.958869	16506.684226	51.86360
min	NaN	18.000000	NaN	12.000000	NaN	2.000000	1.000000	29562.000000	21.00000
25%	NaN	24.000000	NaN	14.000000	NaN	3.000000	3.000000	44058.750000	66.00000

50%	NaN	26.000000	NaN	16.000000	NaN	3.000000	3.000000	50596.500000	94.00000
75%	NaN	33.000000	NaN	16.000000	NaN	4.000000	4.000000	58668.000000	114.75000
max	NaN	50.000000	NaN	21.000000	NaN	7.000000	5.000000	104581.000000	360.00000

As we see Age,Income and Miles std >2 and there is a significant difference between mean and median.

In [6]:
```
l=['Income','Miles','Age']
fig, axs = plt.subplots(ncols=3,nrows=1,figsize=(15, 5))
axs=axs.flatten()
index=0
for i in l:
    sns.boxplot(y=i,data=df,ax=axs[index]).set(title=i)
    index+=1
```



Most of the outliers are seems to be lies in upper bound (1.5IQR+Q3)

Lets see how many outliers we have in each

In [7]:
```
Upper_bound_I = (1.5*stats.iqr(df['Income']))+np.quantile(df['Income'],0.75)
Upper_bound_A = (1.5*stats.iqr(df['Age']))+np.quantile(df['Age'],0.75)
Upper_bound_M = (1.5*stats.iqr(df['Miles']))+np.quantile(df['Miles'],0.75)
print('No of Outliers for Income - %s' %len(df.loc[df['Income']>Upper_bound_I]))
print('No of Outliers for Miles - %s' %len(df.loc[df['Miles']>Upper_bound_M]))
print('No of Outliers for Age - %s' %len(df.loc[df['Age']>Upper_bound_A]))
```

```
No of Outliers for Income - 19
No of Outliers for Miles - 13
No of Outliers for Age - 5
```

(19+13+5)=37 this is 20 percent of dataset so its not advicable to remove it.

How much percent of sales for each product (Marginal Probability)

In [8]:
```
df['Product'].value_counts()
```

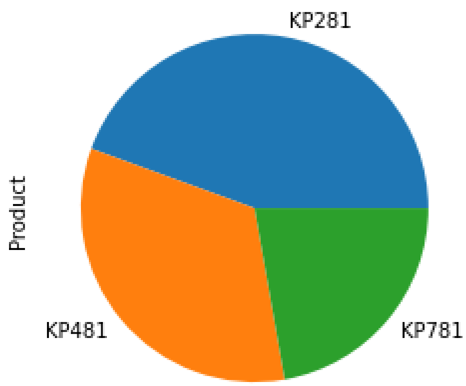
Out[8]:
```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

In [9]:
```
df['Product'].value_counts()*(100/180)
```

Out[9]:
```
KP281    44.444444
KP481    33.333333
```

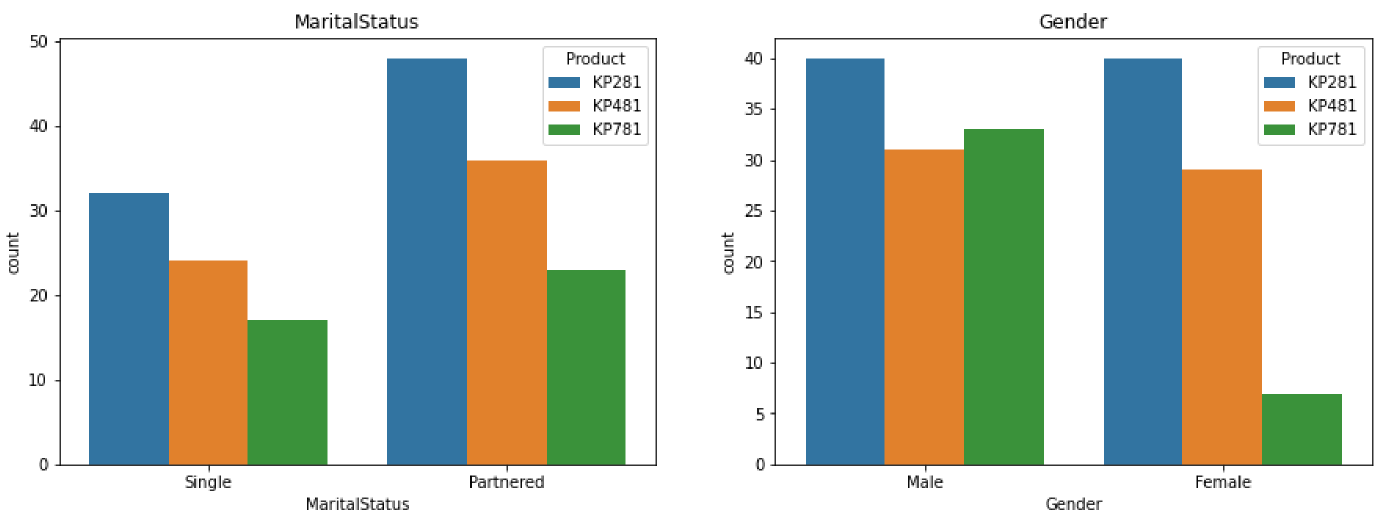
```
KP781    22.222222
Name: Product, dtype: float64
```

In [10]:
```
df['Product'].value_counts().plot(kind='pie')
plt.show()
```



How featurs like MaritalStatus and Gender affect the purchase (Conditional Probability)

In [11]:
```
l=['MaritalStatus','Gender']
fig, axs = plt.subplots(ncols=2,nrows=1,figsize=(15, 5))
axs=axs.flatten()
index=0
for i in l:
    sns.countplot(x=i,hue='Product',data=df,ax=axs[index]).set(title=i)
    index+=1
```



From above :

- we can clearly say partnered customers buy the most number of products in all 3 types of product.
- Male buys more number of advanced level product #### Above give us the pure count as we saw in describe we have more Male than Female so lets check the probability and see who have more probability to buy each product

In [12]:
```
no_of_females = len(df.loc[df['Gender'] == 'Female'])
no_of_males = len(df.loc[df['Gender'] == 'Male'])
no_of_single = len(df.loc[df['MaritalStatus'] == 'Single'])
no_of_partnered = len(df.loc[df['MaritalStatus'] == 'Partnered'])
df_g = pd.crosstab(df['Gender'],df['Product'])
df_m = pd.crosstab(df['MaritalStatus'],df['Product'])
```

In [13]:
```
df_m
```

Out[13]:

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

In [14]:
```
df_g.loc['Female'] = df_g.loc['Female']/no_of_females
df_g.loc['Male'] = df_g.loc['Male']/no_of_males
df_g
```

Out[14]:

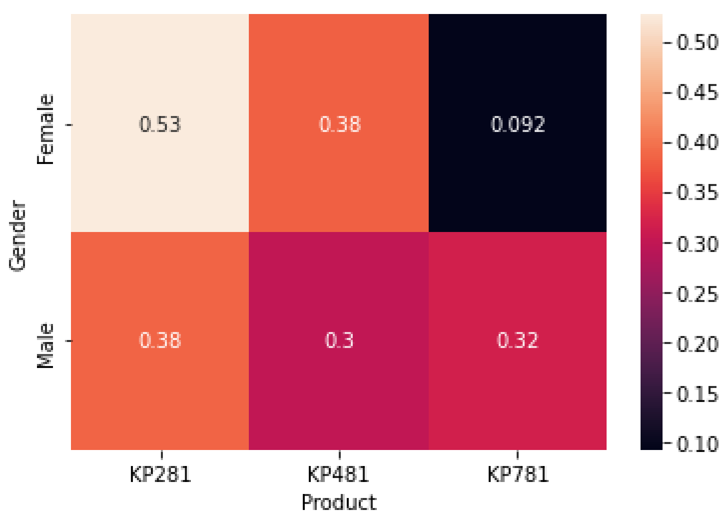
Gender \ Product	KP281	KP481	KP781
Female	0.526316	0.381579	0.092105
Male	0.384615	0.298077	0.317308

Above is conditional probabilities, for example 0.53 is probability of buying KP281 given customer is female.

Conclusions:

- Female prefer entry level
- Males prefer advanced level

In [15]:
```
sns.heatmap(df_g,annot=True)
plt.show()
```



In [16]:
```
df_m.loc['Single'] = df_m.loc['Single']/no_of_single
df_m.loc['Partnered'] = df_m.loc['Partnered']/no_of_partnered
df_m
```

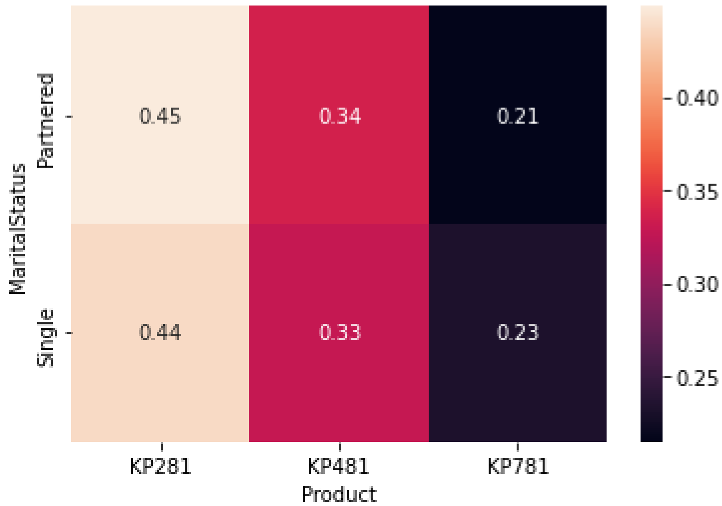
Out[16]:

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

Conclusions

- when we saw the graph it looked as partnered people buy more in all type of products but as we see the table Partnered and Single both have preety much the same probability in each product.

In [17]:
```
sns.heatmap(df_m,annot=True)
plt.show()
```



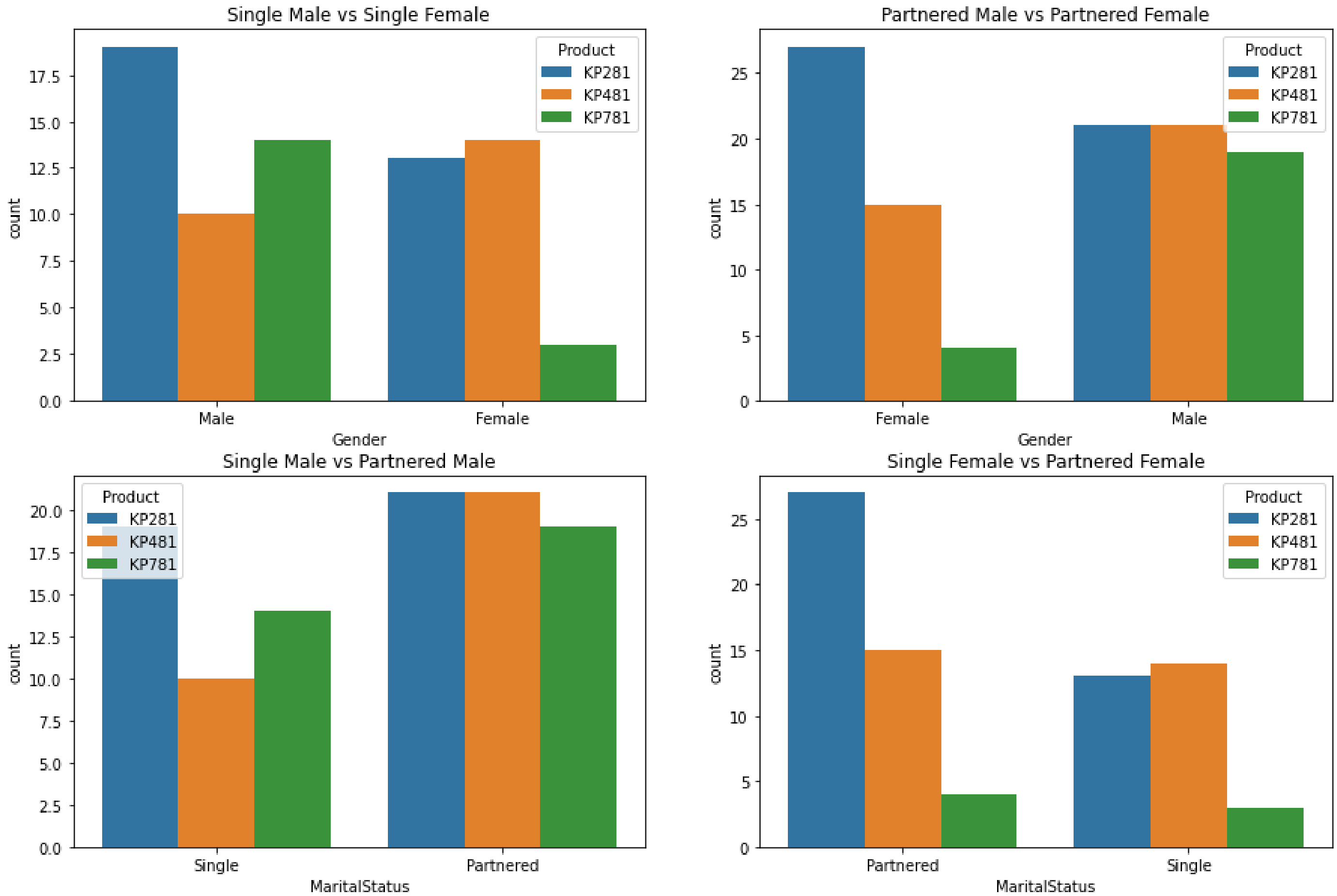
Lets compare

- Single male vs Single female
- Patnered male vs Patnered female
- Single male vs Patnered male
- Single female vs Patnered female

  ##### First lets go with graph as we followed in for above comparison then will go into probability

In [18]:
```
l=['Gender','MaritalStatus']
k=['Single','Partnered','Male','Female']
fig, axs = plt.subplots(ncols=2,nrows=2,figsize=(15, 10))
axs=axs.flatten()
index=0

for i in l:
    for _ in range(0,2):
        if i == 'Gender':
            t = k[index]+' Male vs '+k[index]+' Female'
            d=df.loc[df['MaritalStatus'] == k[index]]
        else:
            t = 'Single '+k[index]+' vs Partnered '+k[index]
            d=df.loc[df['Gender'] == k[index]]
        sns.countplot(x=i,hue='Product',data=d,ax=axs[index]).set(title=t)
        index+=1
```



Conclusions

Single Male vs Single Female

- Single male out buy single female in all type of product except for mid level. #### Partnered Male vs Partenerd Female
- Partenered Female prefers entry level model.
- Patnered Male seems to buy equally. #### Single Male vs Patnered Male
- Patnered male out buy Single male in all type of product. #### Single Female vs Patnered Female
- Patnered Female out buy Single Female in all type of product.
- Single Female prefers mid level and entry level product with almost same level. ##### Best Buyers for each Product in terms of count.
- KP281 -- Partnered Female
- KP481 -- Patnered Male
- KP781 -- Patnered Male

Lets check Probaility for all different features

In [19]:
```
df_male = df.loc[df['Gender'] == 'Male']
df_female = df.loc[df['Gender'] == 'Female']
no_of_singleMales = len(df_male.loc[df_male['MaritalStatus'] == 'Single'])
no_of_partneredMales = len(df_male.loc[df_male['MaritalStatus'] == 'Partnered'])
no_of_singleFemales = len(df_female.loc[df_female['MaritalStatus'] == 'Single'])
no_of_partneredFemales = len(df_female.loc[df_female['MaritalStatus'] == 'Partnered'])
df_givenMale = pd.crosstab(df_male['MaritalStatus'],df_male['Product'])
df_givenFemale = pd.crosstab(df_female['MaritalStatus'],df_female['Product'])
```

In [20]:
```
df_givenMale.loc['Partnered'] = df_givenMale.loc['Partnered']/no_of_partneredMales
df_givenMale.loc['Single'] = df_givenMale.loc['Single']/no_of_singleMales
```

```
df_givenMale['Given']=['Partnered Male','Single Male']
df_givenMale
```

Out[20]:

Product	KP281	KP481	KP781	Given
MaritalStatus				
Partnered	0.344262	0.344262	0.311475	Partnered Male
Single	0.441860	0.232558	0.325581	Single Male

In [21]:

```
df_givenFemale.loc['Partnered'] = df_givenFemale.loc['Partnered']/no_of_partneredFemales
df_givenFemale.loc['Single'] = df_givenFemale.loc['Single']/no_of_singleFemales
df_givenFemale['Given']=['Partnered Female','Single Female']
df_givenFemale
```

Out[21]:

Product	KP281	KP481	KP781	Given
MaritalStatus				
Partnered	0.586957	0.326087	0.086957	Partnered Female
Single	0.433333	0.466667	0.100000	Single Female

In [22]:

```
df_prob=df_givenMale.append(df_givenFemale)
df_prob.set_index('Given',inplace=True)
df_prob
```

Out[22]:

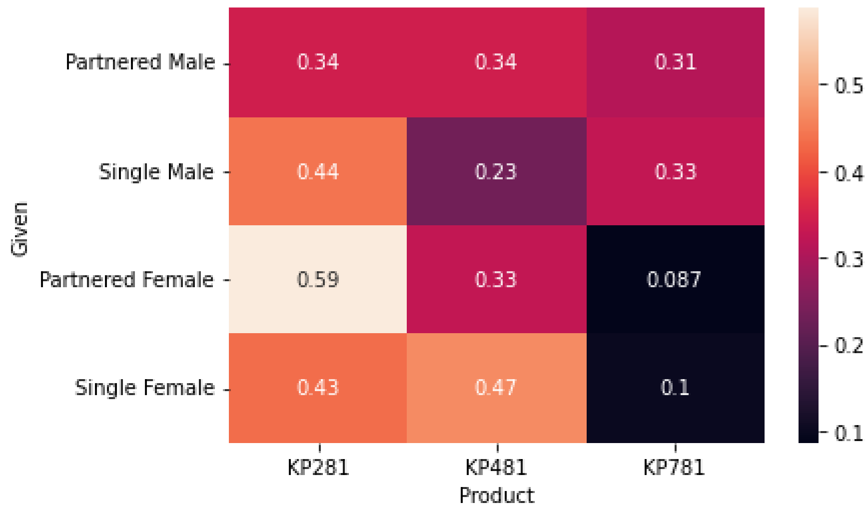
Product	KP281	KP481	KP781
Given			
Partnered Male	0.344262	0.344262	0.311475
Single Male	0.441860	0.232558	0.325581
Partnered Female	0.586957	0.326087	0.086957
Single Female	0.433333	0.466667	0.100000

Conclusions

- Partnered Female have more probability to buy KP281
- Single Female have more probability to buy KP481
- Single Male have more probability to buy KP781 , Also Partnered Male have almost same probability. As per counts we thought Partnered buy out Single male in all type of product which is proved wrong here with probability.

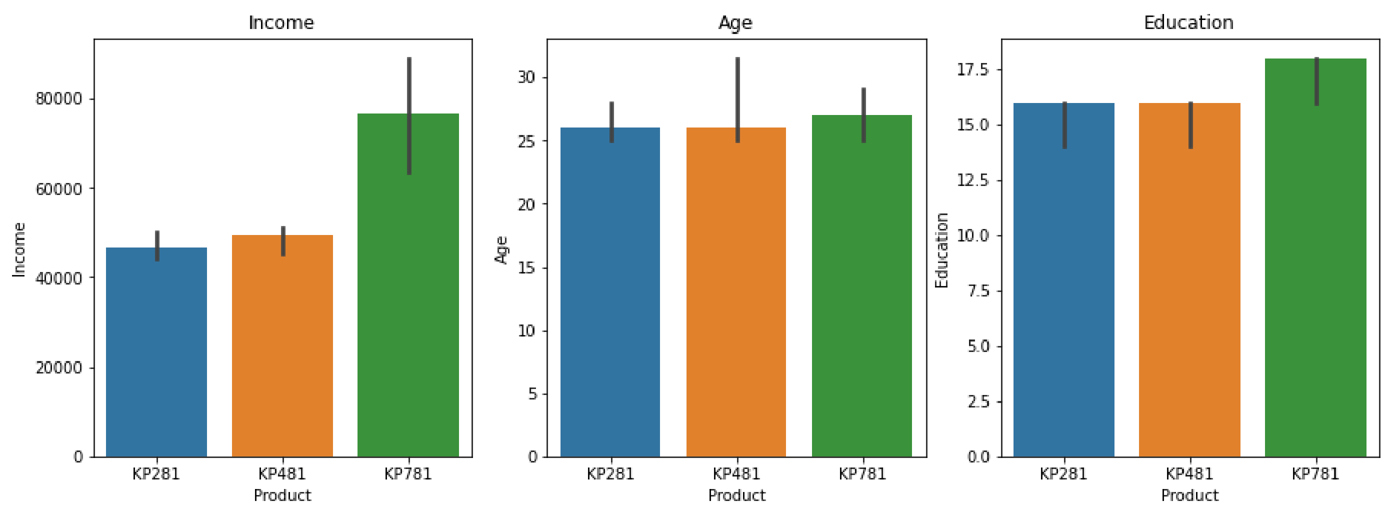
In [23]:

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



Lets compare Income, Age , Education vs product, Plot with median instead of mean as we had some outliers.

In [24]:
```
l=['Income','Age','Education']
fig, axs = plt.subplots(ncols=3,nrows=1,figsize=(15, 5))
axs=axs.flatten()
index=0
for i in l:
    sns.barplot(x='Product',y=i,data=df,ax=axs[index],estimator=np.median).set(title=i)
    index+=1
```



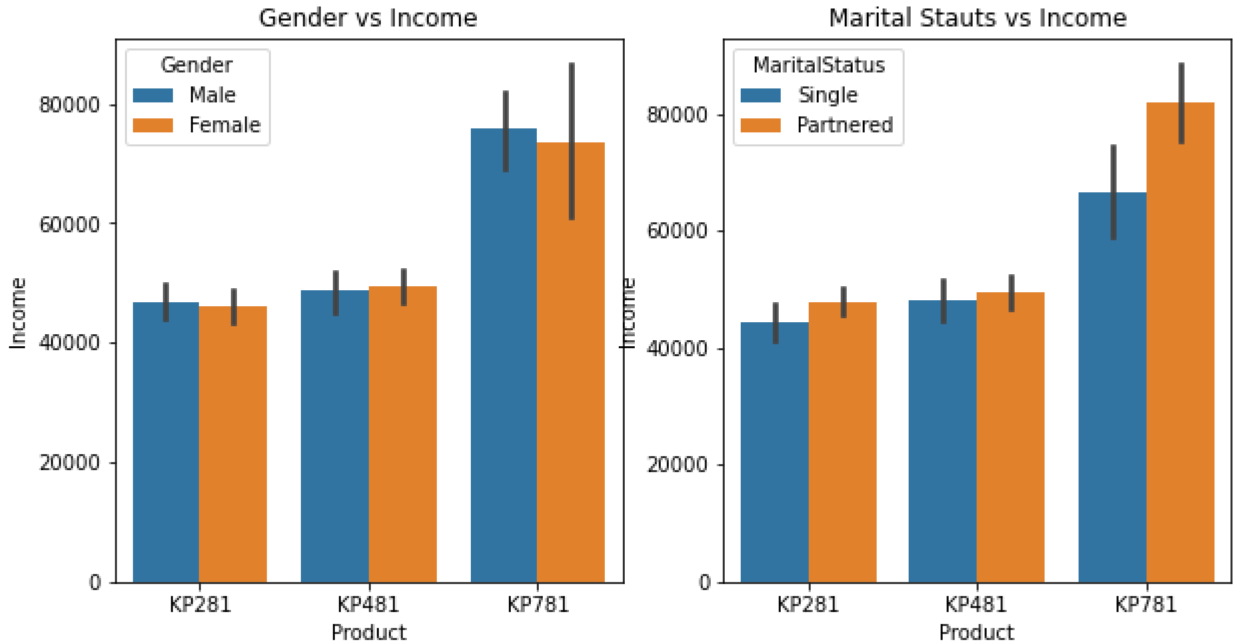
Income only seems to cause some significant changes , age seems to be almost equal and and education years poeple with more than 16 years prefer KP781 model

- People with more income buys advanced model makes sense.

Lets compare group of people with income and product.

- Group of people by single / partnered and male /Female

In [25]:
```
fig,axs=plt.subplots(nrows=1,ncols=2,figsize=(10,5))
sns.barplot(x='Product',y='Income',hue='Gender',data=df,ax=axs[0]).set(title='Gender vs
sns.barplot(x='Product',y='Income',hue='MaritalStatus',data=df,ax=axs[1]).set(title='Mar
plt.show()
```



- As we see in both it matches to above peeple with more income buys advanced model.

Lets do probability and check.

In [26]:

```
df_1 = df.loc[df['Income'] >= np.median(df['Income'])]
df_2 = df.loc[df['Income'] <= np.median(df['Income'])]
df_Income1=pd.crosstab(df_1['Gender'],df_1['Product'])
df_Income2=pd.crosstab(df_2['Gender'],df_2['Product'])
```

In [27]:

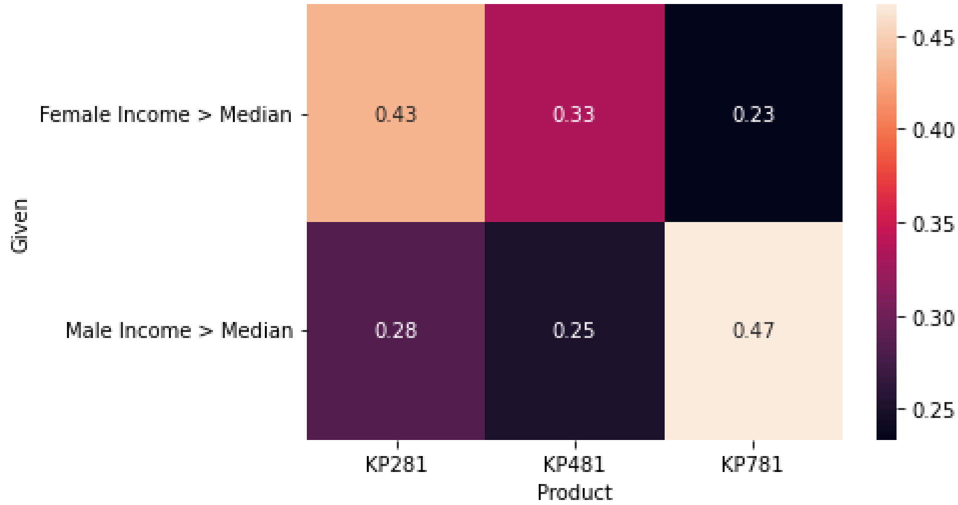
```
df_Income1.loc['Female'] = df_Income1.loc['Female']/sum(df_Income1.loc['Female'])
df_Income1.loc['Male'] = df_Income1.loc['Male']/sum(df_Income1.loc['Male'])
df_Income1['Given']=['Female Income > Median','Male Income > Median']
df_Income1.set_index('Given',inplace=True)
df_Income1
```

Out[27]:

Product	KP281	KP481	KP781
Given			
Female Income > Median	0.433333	0.333333	0.233333
Male Income > Median	0.283333	0.250000	0.466667

In [28]:

```
sns.heatmap(df_Income1,annot=True)
plt.show()
```



From above

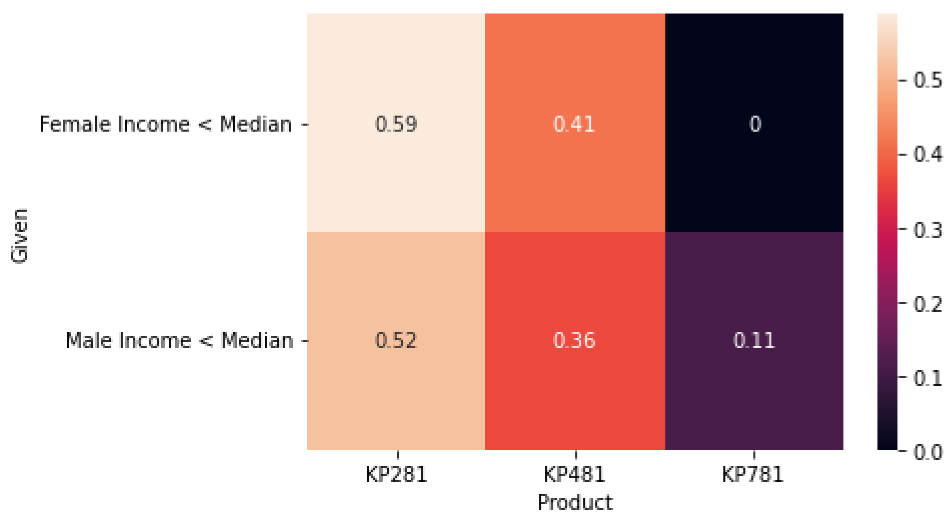
- we can say that Female with income greater than median also prefers entry model
- Male with more income prefers advanced model

In [29]:
```
df_Income2.loc['Female'] = df_Income2.loc['Female']/sum(df_Income2.loc['Female'])
df_Income2.loc['Male'] = df_Income2.loc['Male']/sum(df_Income2.loc['Male'])
df_Income2['Given']=['Female Income < Median','Male Income < Median']
df_Income2.set_index('Given',inplace=True)
df_Income2
```

Out[29]:

Product	KP281	KP481	KP781
Given			
Female Income < Median	0.586957	0.413043	0.000000
Male Income < Median	0.522727	0.363636	0.113636

In [30]:
```
sns.heatmap(df_Income2,annot=True)
plt.show()
```



From above

- Irrespective of male or female people with income lesser than median prefer entry level model.

Lets comapre partnered female vs single female with income greater than median

- Why we are taking this ? -- As we saw other categories seems to be perform as expected who have more income buys advanced model but here with more income goes for entry level product so lets compare and check how different female groups reacts.

In [31]:
```
df_M = df_1.loc[df_1['Gender'] == 'Female']
df_M = pd.crosstab(df_M['MaritalStatus'],df_M['Product'])
df_M.loc['Single'] = df_M.loc['Single']/sum(df_M.loc['Single'])
df_M.loc['Partnered'] = df_M.loc['Partnered']/sum(df_M.loc['Partnered'])
df_M['Given']=['Partnered Female Income > Median','Single Female Income > Median']
df_M.set_index('Given',inplace=True)
df_M
```

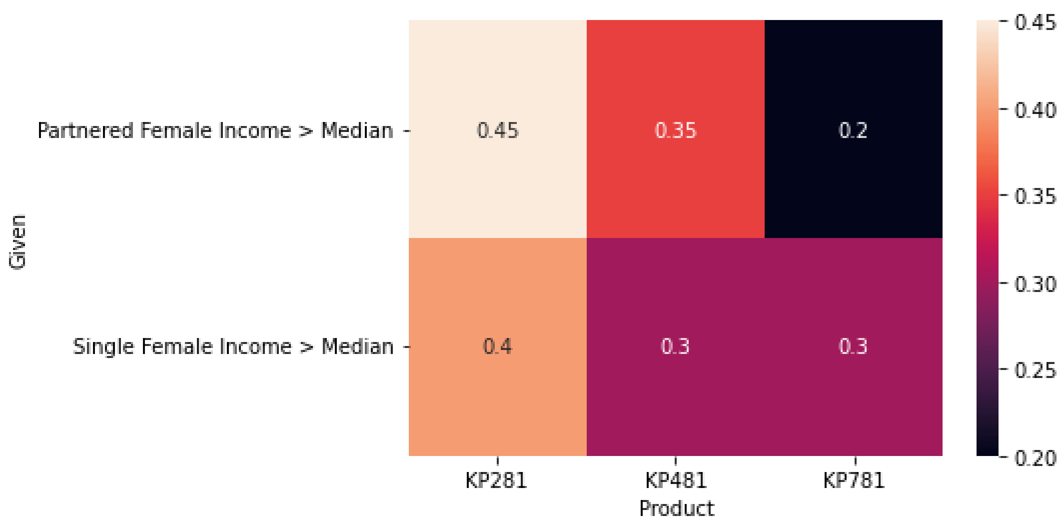
Out[31]:

Product	KP281	KP481	KP781
Given			
Partnered Female Income > Median	0.45	0.35	0.2
Single Female Income > Median	0.40	0.30	0.3

Conclusions

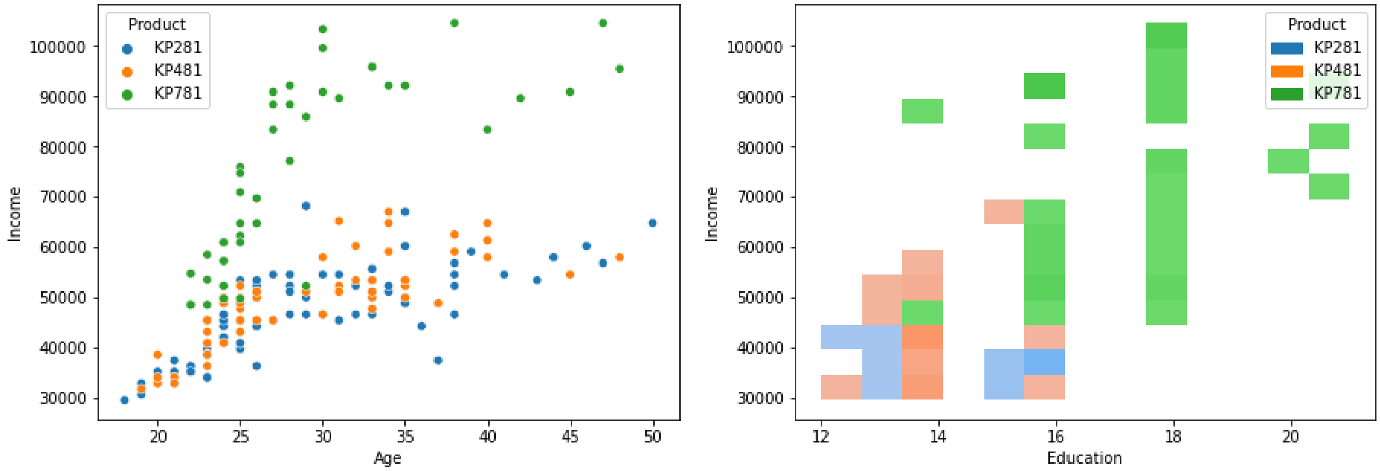
- As per above nothing has changed both single and partnered women prefers entry level model.

In [32]:
```
sns.heatmap(df_M,annot=True)
plt.show()
```



Lets compare Age vs Income and Education vs Income for different product

In [33]:
```
fig,axs=plt.subplots(nrows=1,ncols=2,figsize=(15,5))
sns.scatterplot(x='Age',y='Income',hue='Product',data=df,ax=axs[0])
sns.histplot(x='Education',y='Income',hue='Product',data=df,ax=axs[1])
plt.show()
```

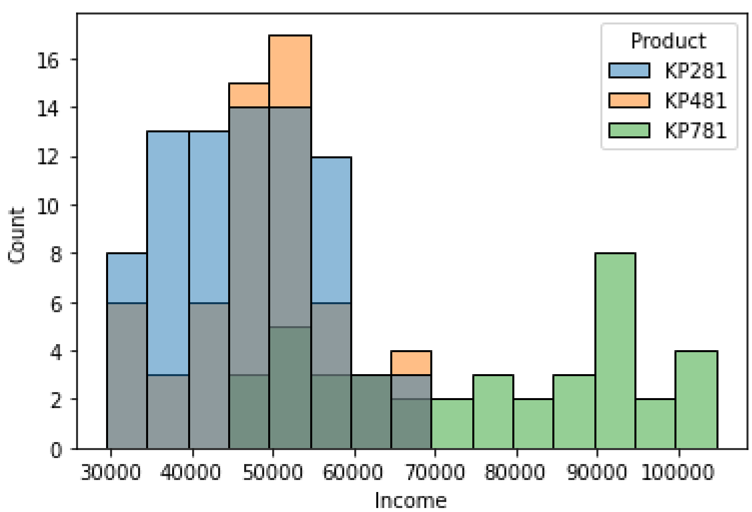


- Poeple with more Income buys advanced model irrespecctive of their age groups.
- People who have education more than 16 years always prefer advanced model irrespective of their income.

Lets check from where if income is greater than this number people will purely wants advanced level.

- As per below we see if income is greater than 70,000 people purely wants advanced level.

In [34]:
```
sns.histplot(x='Income',hue='Product',data=df)
plt.show()
```

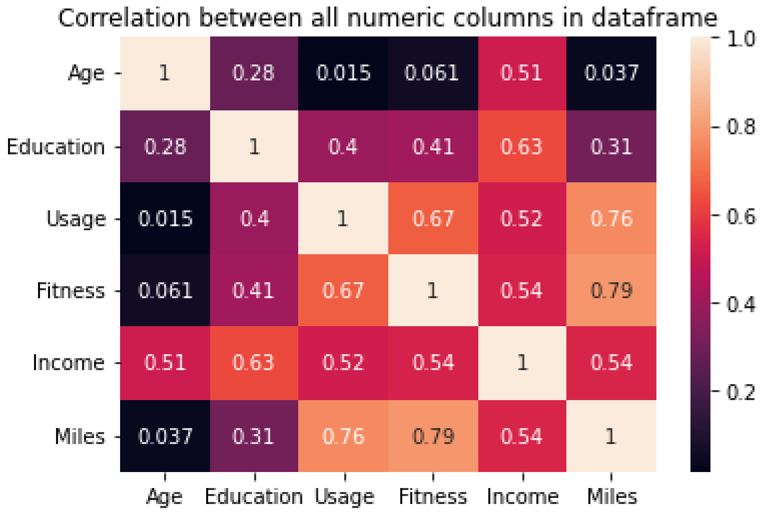


Correlation

Below have more correaltion and also it makes sense poeple who are fit would have used more and ran more miles.

- Fitness and Miles
- Fitness and usuage
- Usage and Miles

In [35]:
```
sns.heatmap(df.corr(),annot=True).set(title= 'Correlation between all numeric columns in
plt.show()
```



- As per below graph we can say if customers wants to be in atleast level 4 fitness , he or she expected to run more than 125 Miles.

In [36]:

```
sns.barplot(x='Fitness',y='Miles',data=df)
```

Out[36]:

```
<AxesSubplot:xlabel='Fitness', ylabel='Miles'>
```