Aerofit - Descriptive Statistics & Probability

```
[ ]: import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
     import seaborn as sns
     from scipy.stats import norm,poisson,geom,expon
```

Question:

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.

Product Portfolio:

The KP281 is an entry-level treadmill that sells for $1,500.

The KP481 is for mid-level runners that sell for $1,750.

The KP781 treadmill is having advanced features that sell for $2,500.

```
[ ]: data = pd.read_csv('aerofit_treadmill.csv')
```

Basic Analysis

```
[ ]: data.sample(5)
```

```
[ ]:     Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  \
     137   KP481   40    Male         16     Partnered      3        3   64809
     60    KP281   33  Female         16     Partnered      3        3   46617
     114   KP481   30  Female         13        Single      4        3   46617
     85    KP481   21    Male         16     Partnered      2        2   34110
     59    KP281   33  Female         16        Single      2        2   55713

          Miles
     137     95
     60      85
     114    106
     85      42
     59      38
```

```
[ ]: data.shape
```

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

```
[ ]: 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
```

```
[ ]: data['Product'].value_counts()
```

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

Checking for null values.

```
[ ]: data.isnull().sum()
```

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

Basic Probability and Statistics Analysis

[ ]:
```
data.describe()
```

[ ]:
```
              Age   Education       Usage     Fitness         Income  \
count  180.000000  180.000000  180.000000  180.000000     180.000000
mean    28.788889   15.572222    3.455556    3.311111   53719.577778
std      6.943498    1.617055    1.084797    0.958869   16506.684226
min     18.000000   12.000000    2.000000    1.000000   29562.000000
25%     24.000000   14.000000    3.000000    3.000000   44058.750000
50%     26.000000   16.000000    3.000000    3.000000   50596.500000
75%     33.000000   16.000000    4.000000    4.000000   58668.000000
max     50.000000   21.000000    7.000000    5.000000  104581.000000

            Miles
count  180.000000
mean   103.194444
std     51.863605
min     21.000000
25%     66.000000
50%     94.000000
75%    114.750000
max    360.000000
```

Total number of males and females

[ ]:
```
data['Gender'].value_counts()
```

[ ]:
```
Gender
Male      104
Female     76
Name: count, dtype: int64
```

Total number of parented and singles.

[ ]:
```
data['MaritalStatus'].value_counts()
```

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

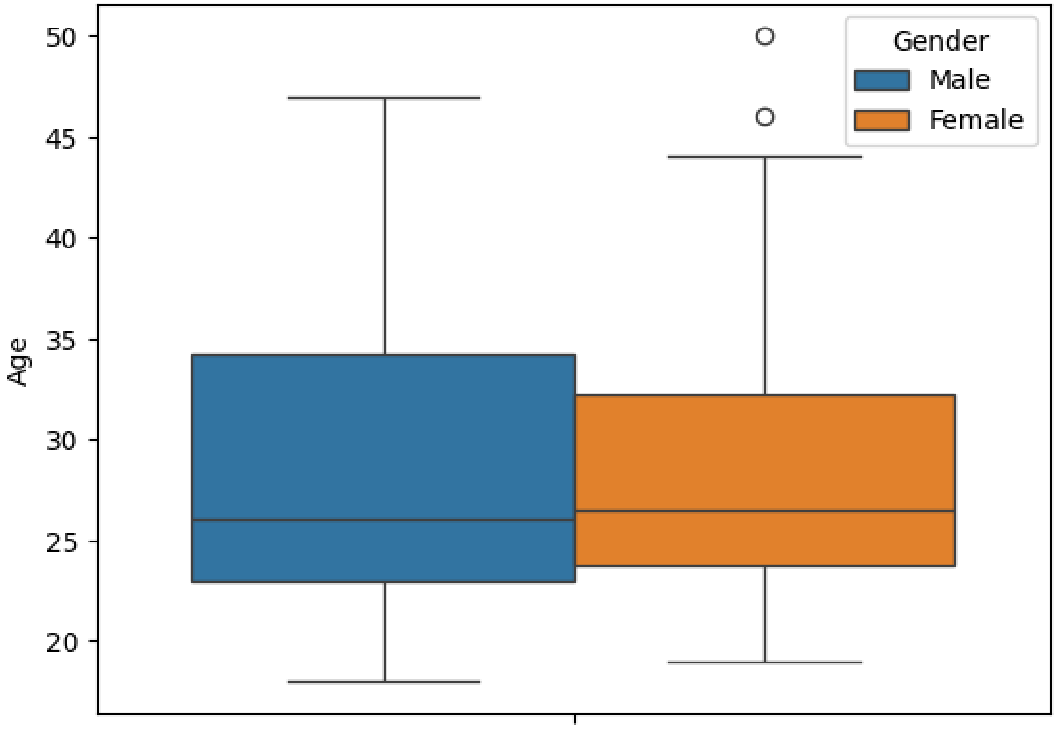
Filtering Data by Product Codes (KP281, KP481, KP781)

[ ]:
```
kp281 = data.loc[data['Product']=='KP281']
kp481 = data.loc[data['Product']=='KP481']
kp781 = data.loc[data['Product']=='KP781']
```

Checking for Outliers

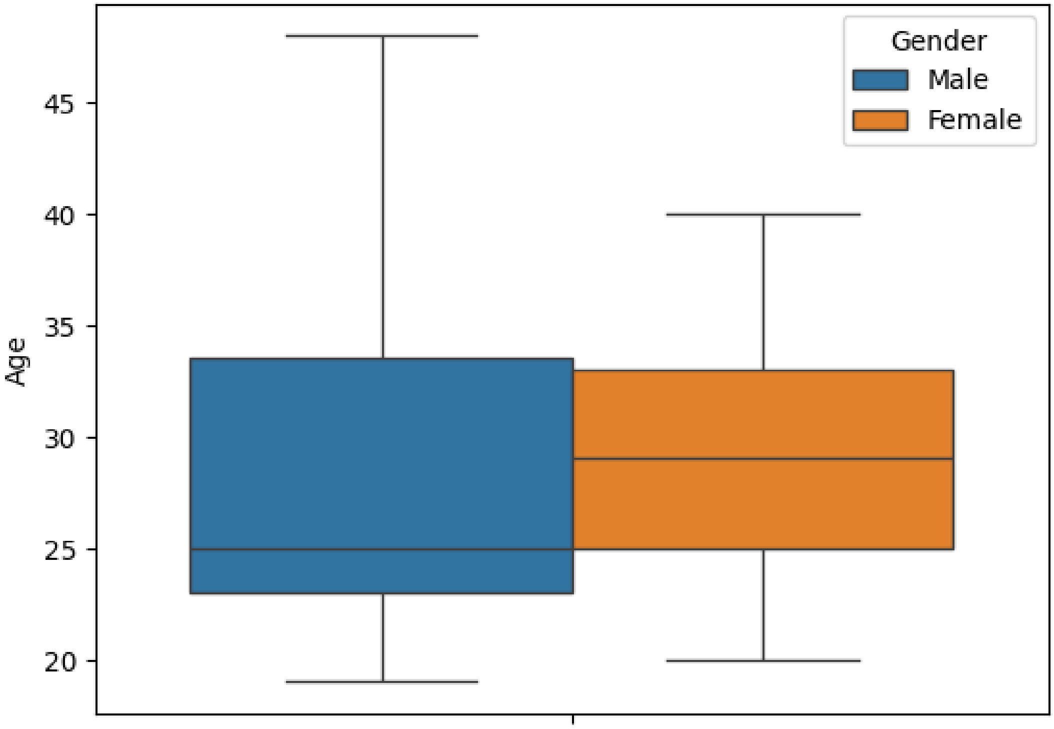
[ ]:
```
sns.boxplot(data=kp281,y='Age',hue = 'Gender')
```

```
[ ]: <Axes: ylabel='Age'>
```



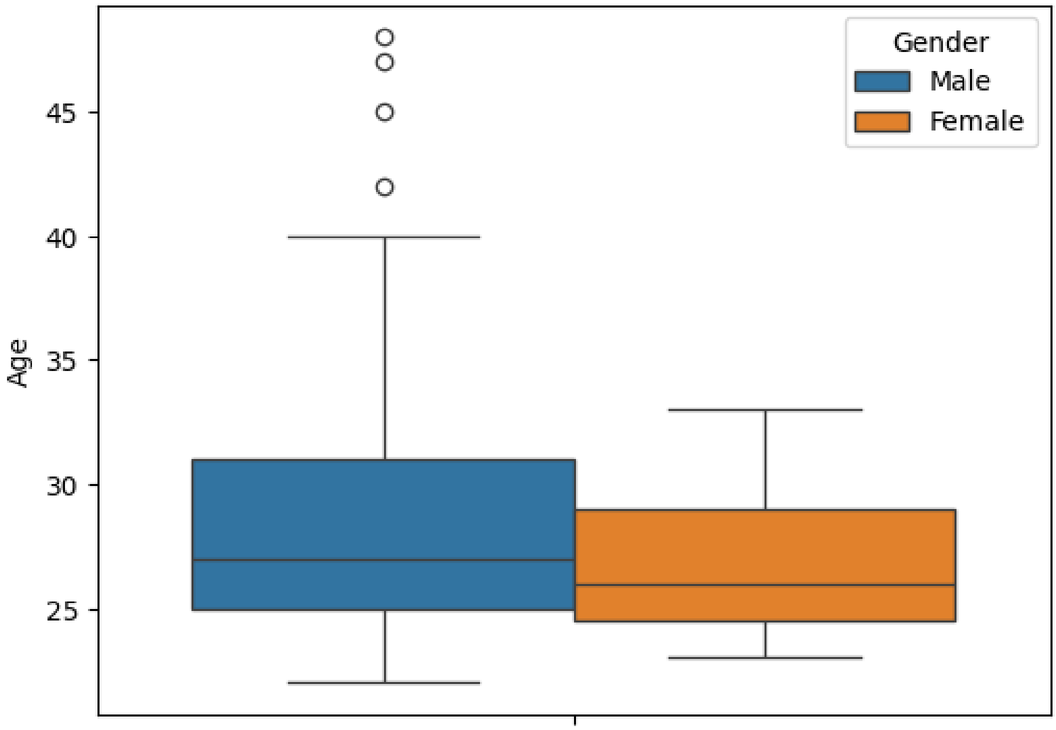
```
[ ]: sns.boxplot(data=kp481,y='Age',hue = 'Gender')
```

```
[ ]: <Axes: ylabel='Age'>
```



```
[ ]: sns.boxplot(data=kp781,y='Age',hue = 'Gender')
```

```
[ ]: <Axes: ylabel='Age'>
```



[ ]:

```
q1_281 = kp281['Age'].quantile(0.25)
q3_281 = kp281['Age'].quantile(0.75)
iqr_281 = q3_281 - q1_281
lower_281 = q1_281 - 1.5*iqr_281
upper_281 = q3_281 + 1.5*iqr_281
lower_281,upper_281
```

[ ]:

```
(8.0, 48.0)
```

[ ]:

```
q1_481 = kp481['Age'].quantile(0.25)
q3_481 = kp481['Age'].quantile(0.75)
iqr_481 = q3_481 - q1_481
lower_481 = q1_481 - 1.5*iqr_481
upper_481 = q3_481 + 1.5*iqr_481
lower_481,upper_481
```

[ ]:

```
(10.125, 47.125)
```

[ ]:

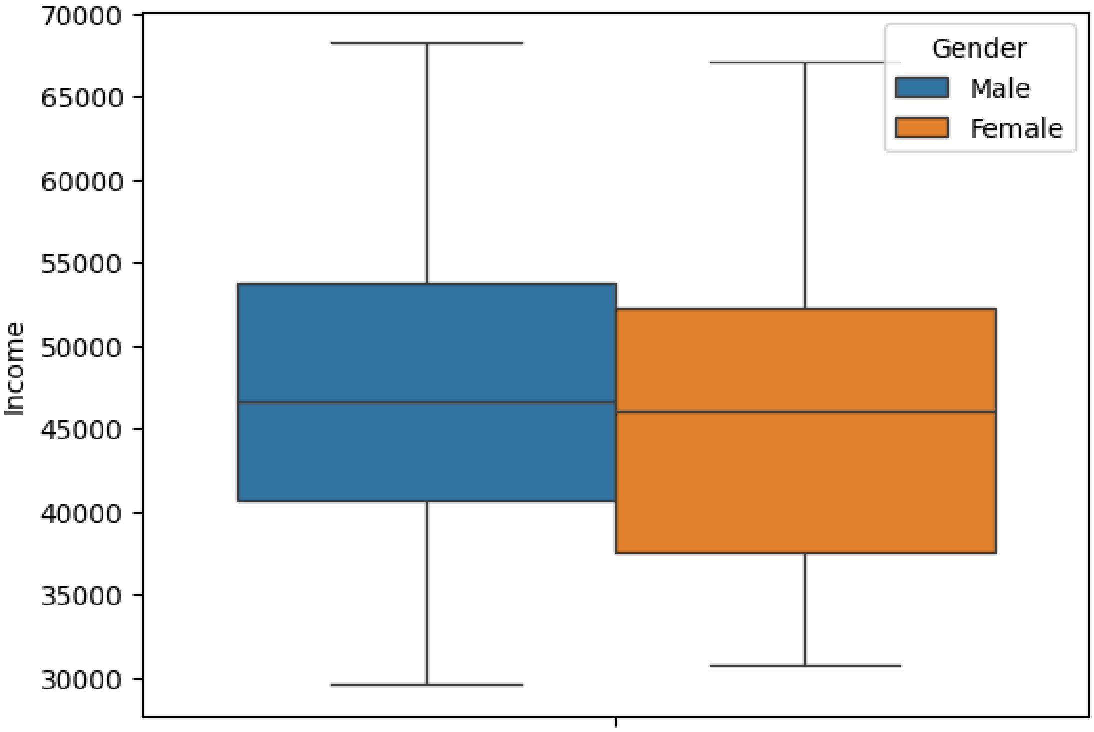
```
q1_781 = kp781['Age'].quantile(0.25)
q3_781 = kp781['Age'].quantile(0.75)
iqr_781 = q3_781 - q1_781
lower_781 = q1_781 - 1.5*iqr_781
upper_781 = q3_281 + 1.5*iqr_781
```

```
lower_781,upper_781
```

```
[ ]: (16.5, 41.25)
```

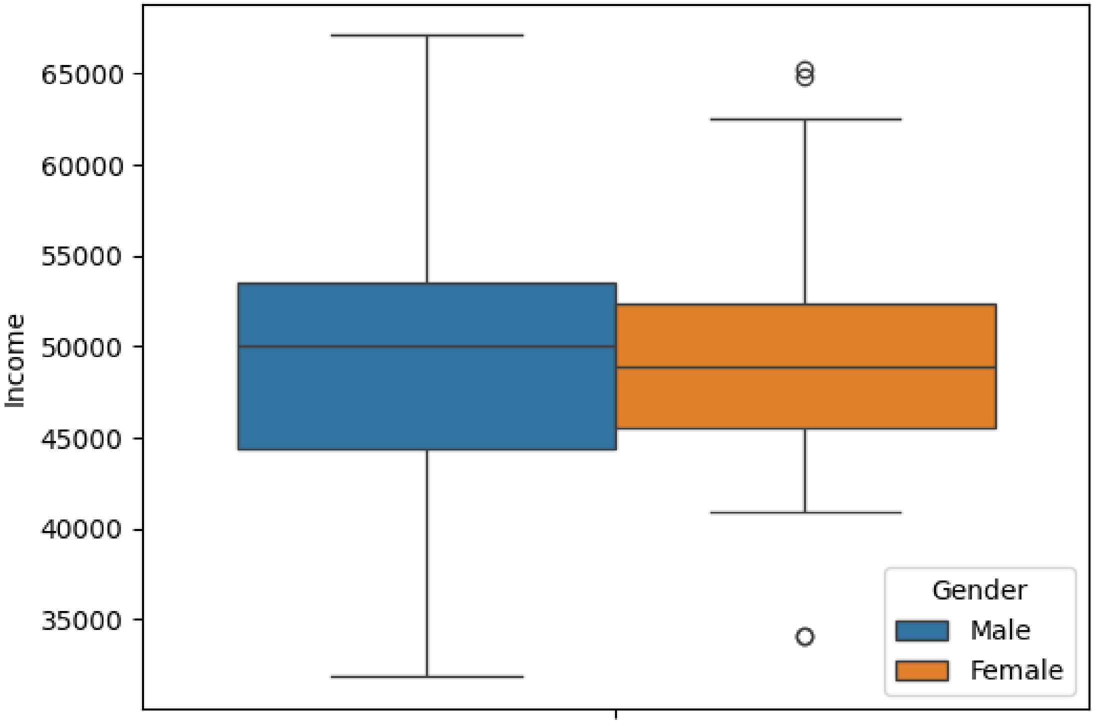
```
[ ]: sns.boxplot(data=kp281,y='Income',hue = 'Gender')
```

```
[ ]: <Axes: ylabel='Income'>
```



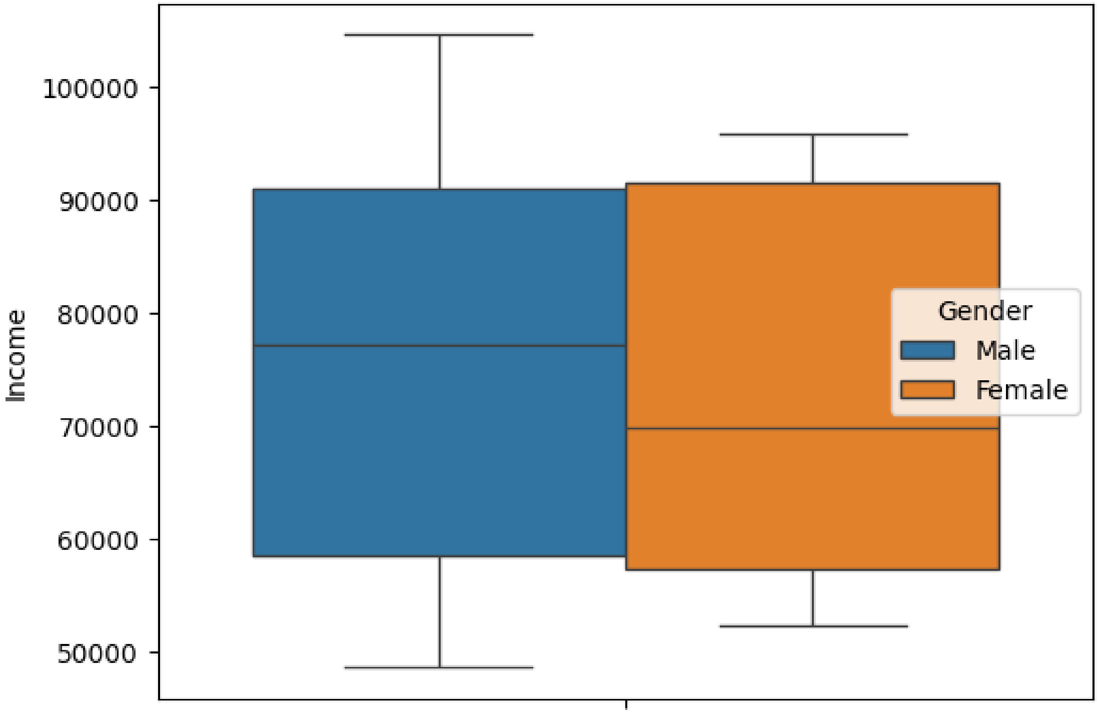
```
[ ]: sns.boxplot(data=kp481,y='Income',hue = 'Gender')
```

```
[ ]: <Axes: ylabel='Income'>
```



```
[ ]: sns.boxplot(data=kp781,y='Income',hue = 'Gender')
```

```
[ ]: <Axes: ylabel='Income'>
```



```
[ ]: q1_281_income = kp281['Income'].quantile(0.25)
     q3_281_income = kp281['Income'].quantile(0.75)
     iqr_281_income = q3_281_income - q1_281_income
     lower_281_income = q1_281_income - 1.5*iqr_281_income
     upper_281_income = q3_281_income + 1.5*iqr_281_income
     lower_281_income,upper_281_income
```

```
[ ]: (16486.5, 75610.5)
```

```
[ ]: q1_481_income = kp481['Income'].quantile(0.25)
     q3_481_income = kp481['Income'].quantile(0.75)
     iqr_481_income = q3_481_income - q1_481_income
     lower_481_income = q1_481_income - 1.5*iqr_481_income
     upper_481_income = q3_481_income + 1.5*iqr_481_income
     lower_481_income,upper_481_income
```

```
[ ]: (32120.25, 66230.25)
```

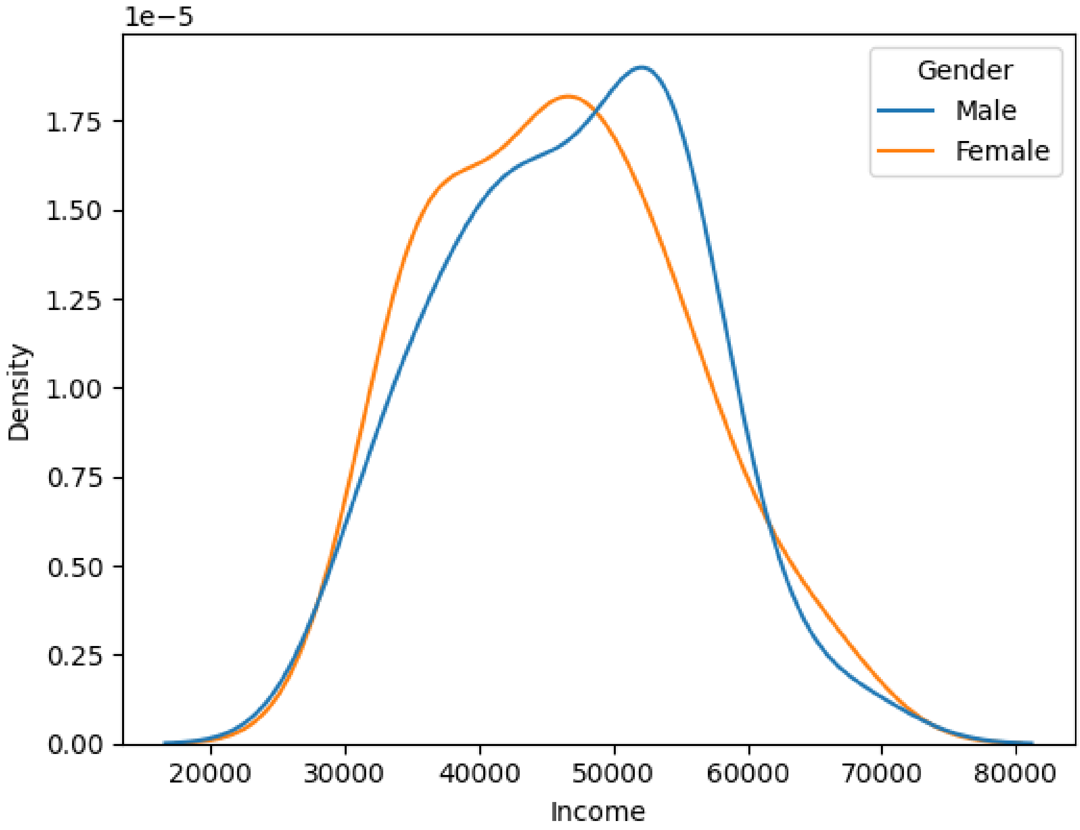
```
[ ]: q1_781_income = kp781['Income'].quantile(0.25)
     q3_781_income = kp781['Income'].quantile(0.75)
     iqr_781_income = q3_781_income - q1_781_income
     lower_781_income = q1_781_income - 1.5*iqr_781_income
     upper_781_income = q3_781_income + 1.5*iqr_781_income
```

```
lower_781_income,upper_781_income
```

```
[ ]: (9182.875, 139907.875)
```

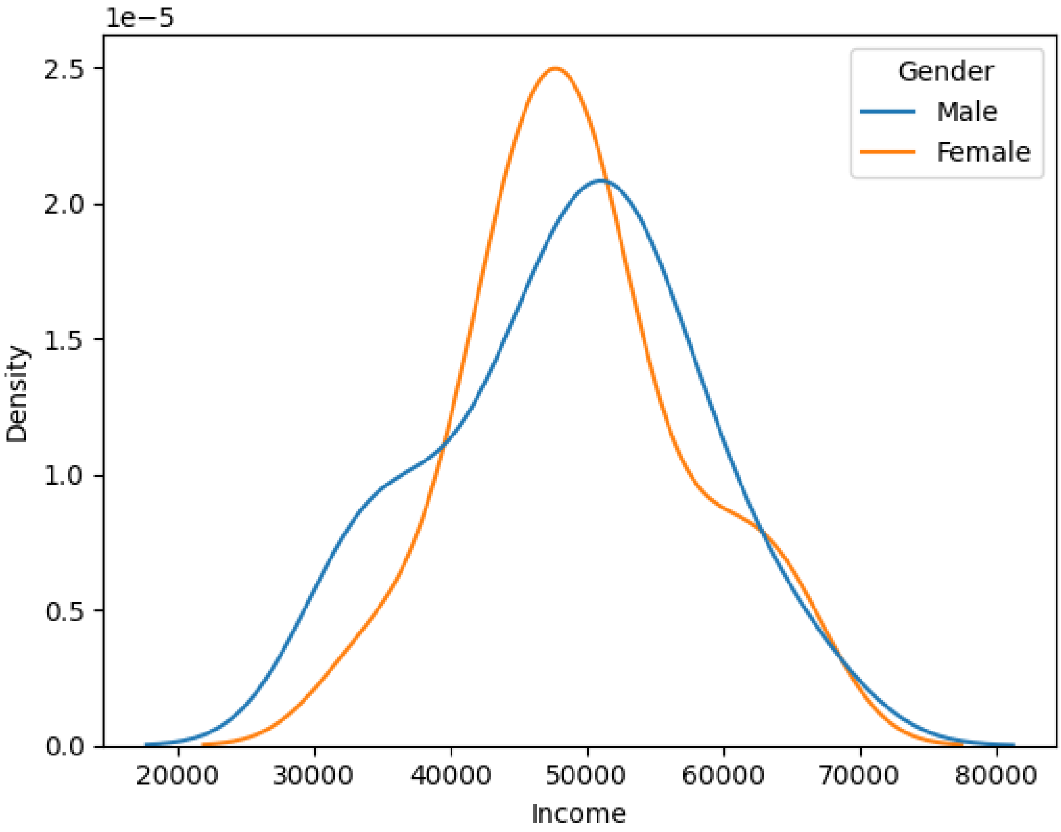
```
[ ]: sns.kdeplot(data=kp281,x='Income',hue='Gender')
```

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



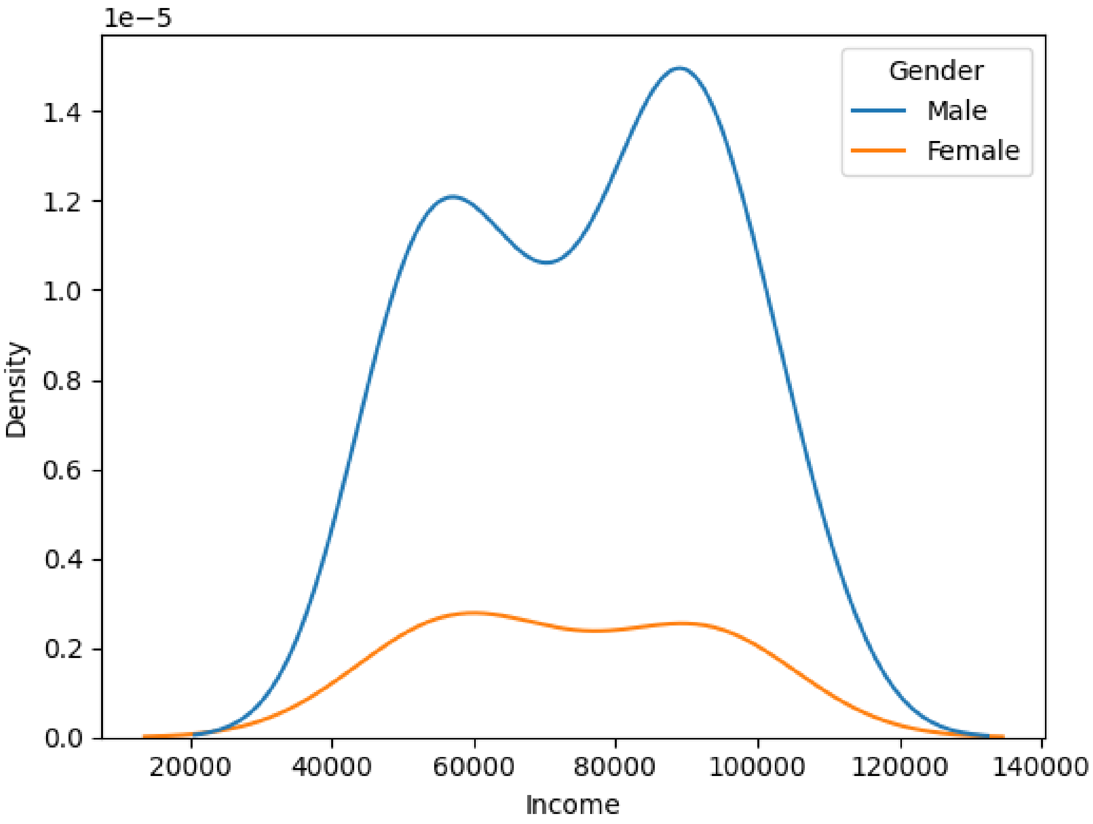
```
[ ]: sns.kdeplot(data=kp481,x='Income',hue='Gender')
```

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



[ ]:
```
sns.kdeplot(data=kp781,x='Income',hue='Gender')
```

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



Total Number of Males and Females in Each Product

```
[ ]: data.groupby('Product',as_index = False)['Gender'].value_counts()
```

```
[ ]:   Product  Gender  count
     0   KP281  Female     40
     1   KP281    Male     40
     2   KP481    Male     31
     3   KP481  Female     29
     4   KP781    Male     33
     5   KP781  Female      7
```

Total Number of Single and Parented in Each Product

```
[ ]: data.groupby('Product',as_index = False)['MaritalStatus'].value_counts()
```

```
[ ]:   Product MaritalStatus  count
     0   KP281     Partnered     48
     1   KP281        Single     32
     2   KP481     Partnered     36
     3   KP481        Single     24
```

```
4   KP781     Partnered     23
5   KP781        Single     17
```

```
[ ]: pd.crosstab(data['Product'], data['Gender'],normalize= True,margins = True)
```

```
[ ]: Gender     Female      Male       All
     Product
     KP281    0.222222  0.222222  0.444444
     KP481    0.161111  0.172222  0.333333
     KP781    0.038889  0.183333  0.222222
     All      0.422222  0.577778  1.000000
```

```
[ ]: pd.crosstab(data['Product'], data['MaritalStatus'],normalize= True,margins =␣
       ↪True)
```

```
[ ]: MaritalStatus  Partnered    Single       All
     Product
     KP281           0.266667  0.177778  0.444444
     KP481           0.200000  0.133333  0.333333
     KP781           0.127778  0.094444  0.222222
     All             0.594444  0.405556  1.000000
```

```
[ ]: data.head()
```

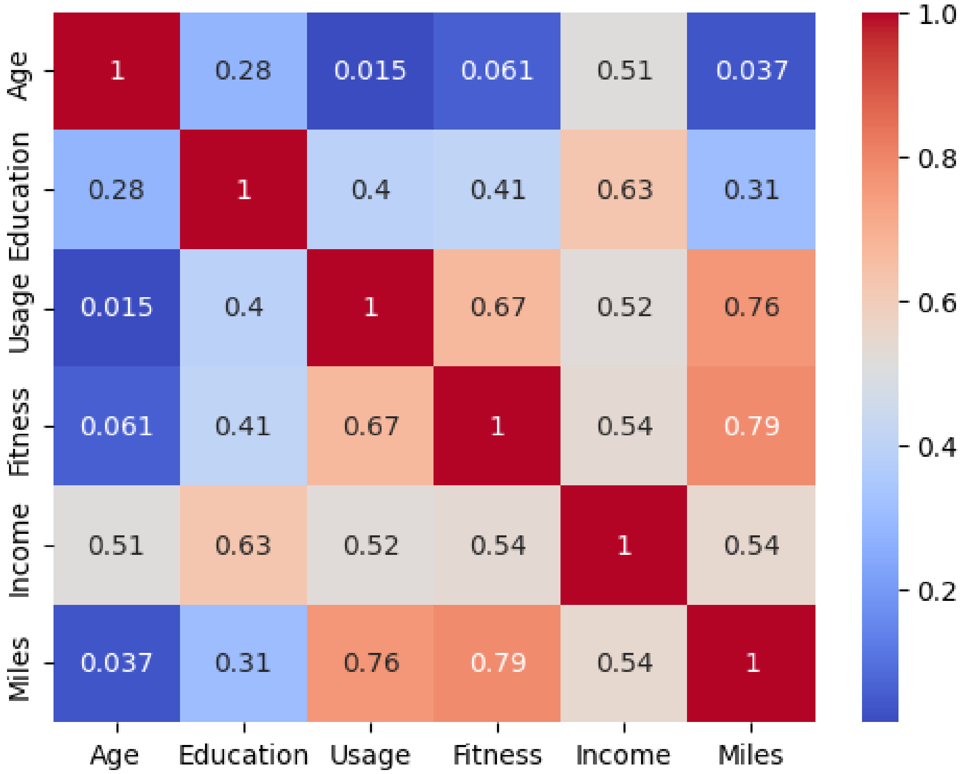
```
[ ]:   Product  Age  Gender  Education MaritalStatus  Usage  Fitness  Income  Miles
     0   KP281   18    Male         14        Single      3        4   29562    112
     1   KP281   19    Male         15        Single      2        3   31836     75
     2   KP281   19  Female         14     Partnered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

```
[ ]: data[['Age','Education','Usage','Fitness','Income','Miles']].corr()
```

```
[ ]:                 Age  Education     Usage   Fitness    Income     Miles
     Age        1.000000   0.280496  0.015064  0.061105  0.513414  0.036618
     Education  0.280496   1.000000  0.395155  0.410581  0.625827  0.307284
     Usage      0.015064   0.395155  1.000000  0.668606  0.519537  0.759130
     Fitness    0.061105   0.410581  0.668606  1.000000  0.535005  0.785702
     Income     0.513414   0.625827  0.519537  0.535005  1.000000  0.543473
     Miles      0.036618   0.307284  0.759130  0.785702  0.543473  1.000000
```

```
[ ]: sns.heatmap(data[['Age','Education','Usage','Fitness','Income','Miles']].
       ↪corr(),annot=True, cmap='coolwarm')
```

```
[ ]: <Axes: >
```



```
[ ]: kp281.groupby('Gender',as_index = False)['Fitness'].value_counts()
```

```
[ ]:    Gender  Fitness  count
     0  Female        3     26
     1  Female        2     10
     2  Female        4      3
     3  Female        5      1
     4    Male        3     28
     5    Male        4      6
     6    Male        2      4
     7    Male        1      1
     8    Male        5      1
```

```
[ ]: kp481.groupby('Gender',as_index = False)['Fitness'].value_counts()
```

```
[ ]:    Gender  Fitness  count
     0  Female        3     18
     1  Female        2      6
     2  Female        4      4
     3  Female        1      1
     4    Male        3     21
     5    Male        2      6
```

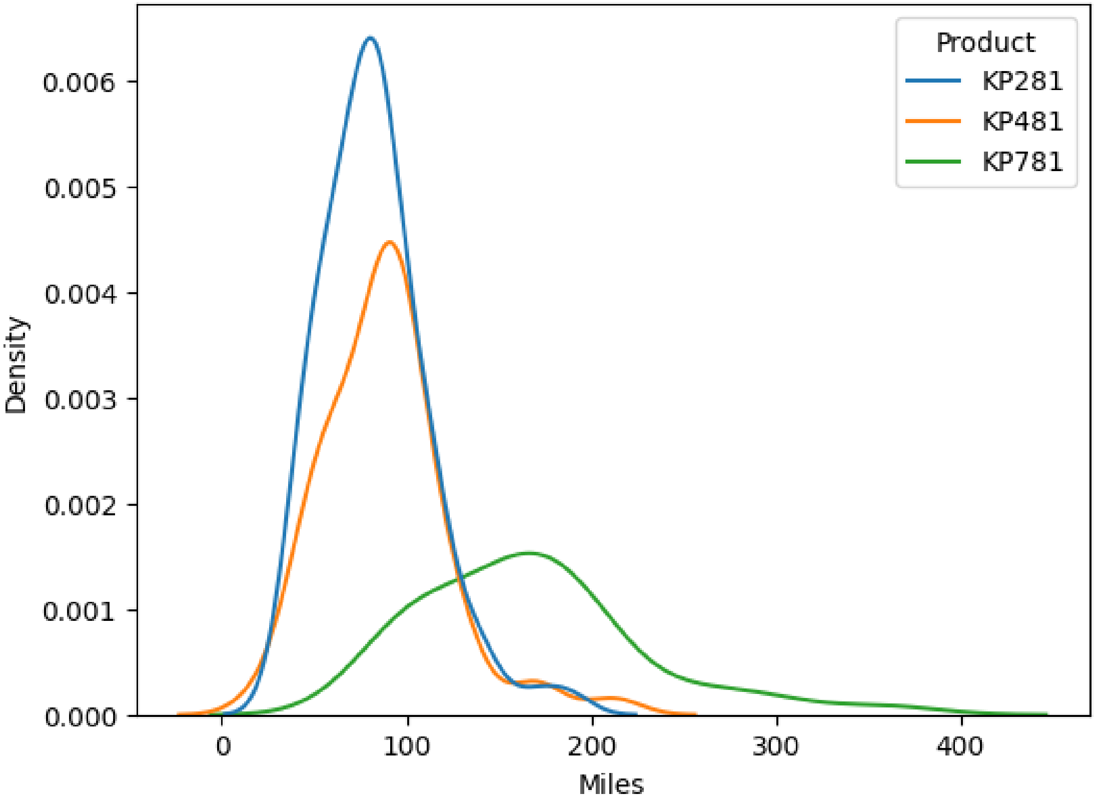
```
6     Male         4      4
```

```
[ ]: kp781.groupby('Gender',as_index = False)['Fitness'].value_counts()
```

```
[ ]:    Gender  Fitness  count
     0  Female        5      5
     1  Female        3      1
     2  Female        4      1
     3    Male        5     24
     4    Male        4      6
     5    Male        3      3
```

```
[ ]: sns.kdeplot(data,x = 'Miles', hue = 'Product')
```

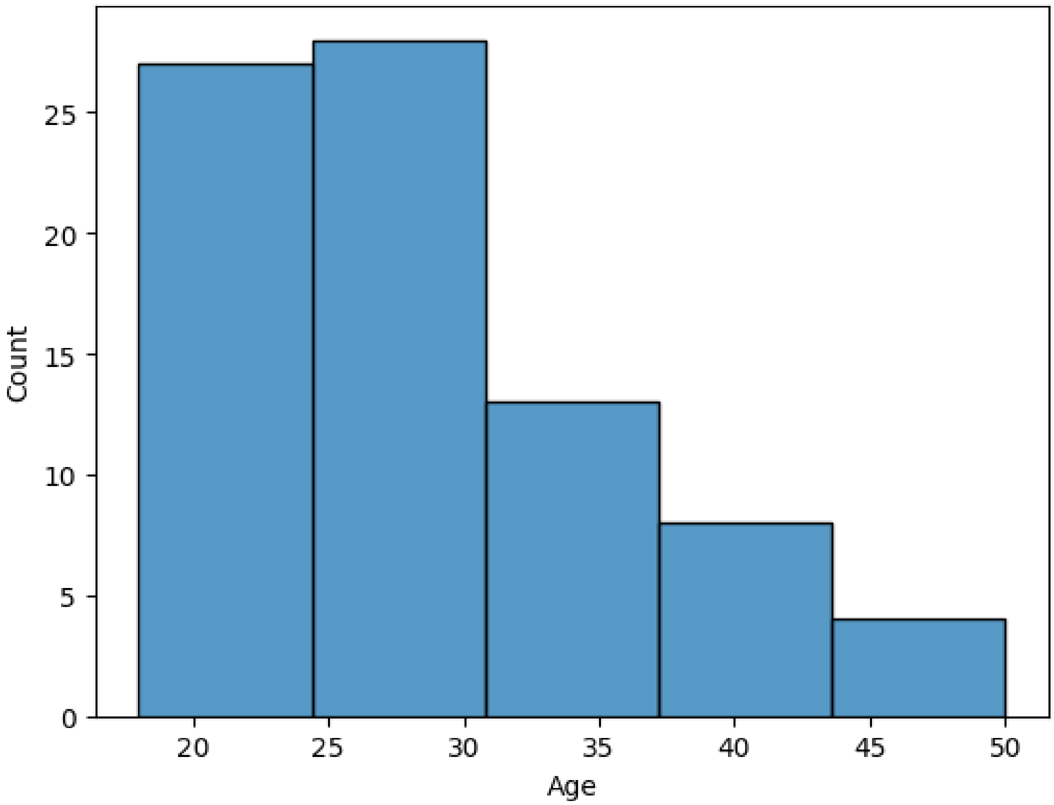
```
[ ]: <Axes: xlabel='Miles', ylabel='Density'>
```



Count of people across age intervals.

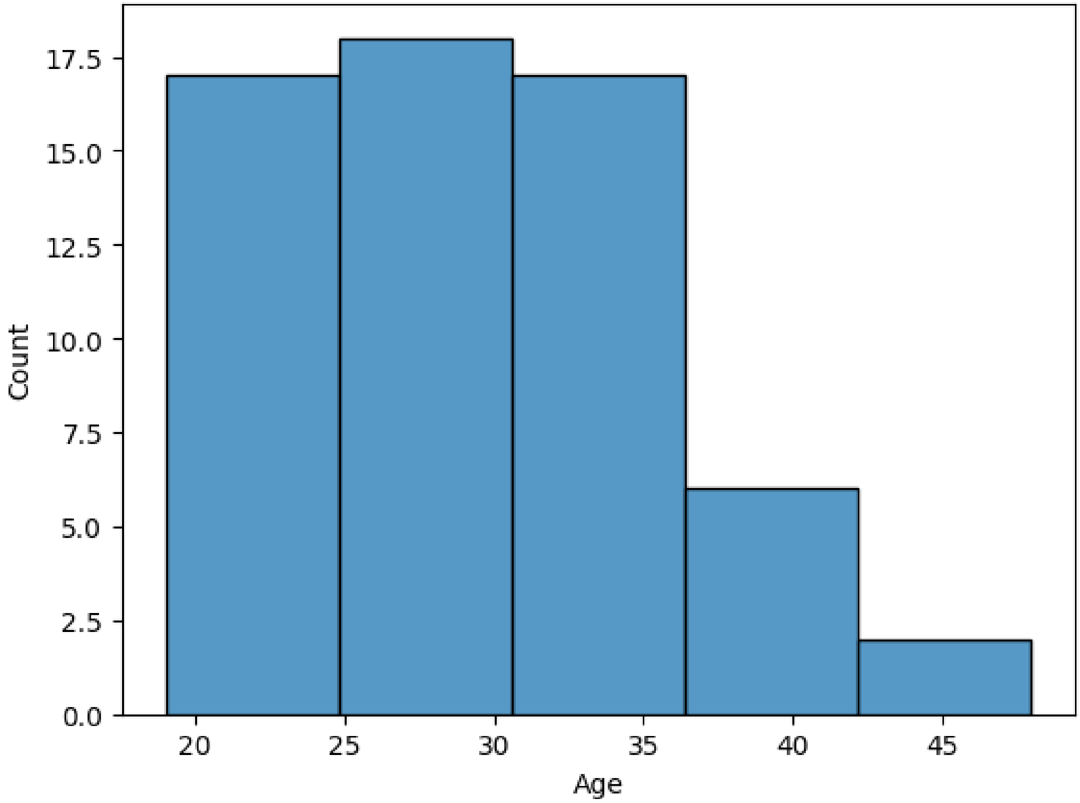
```
[ ]: sns.histplot(kp281['Age'],bins = 5)
```

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



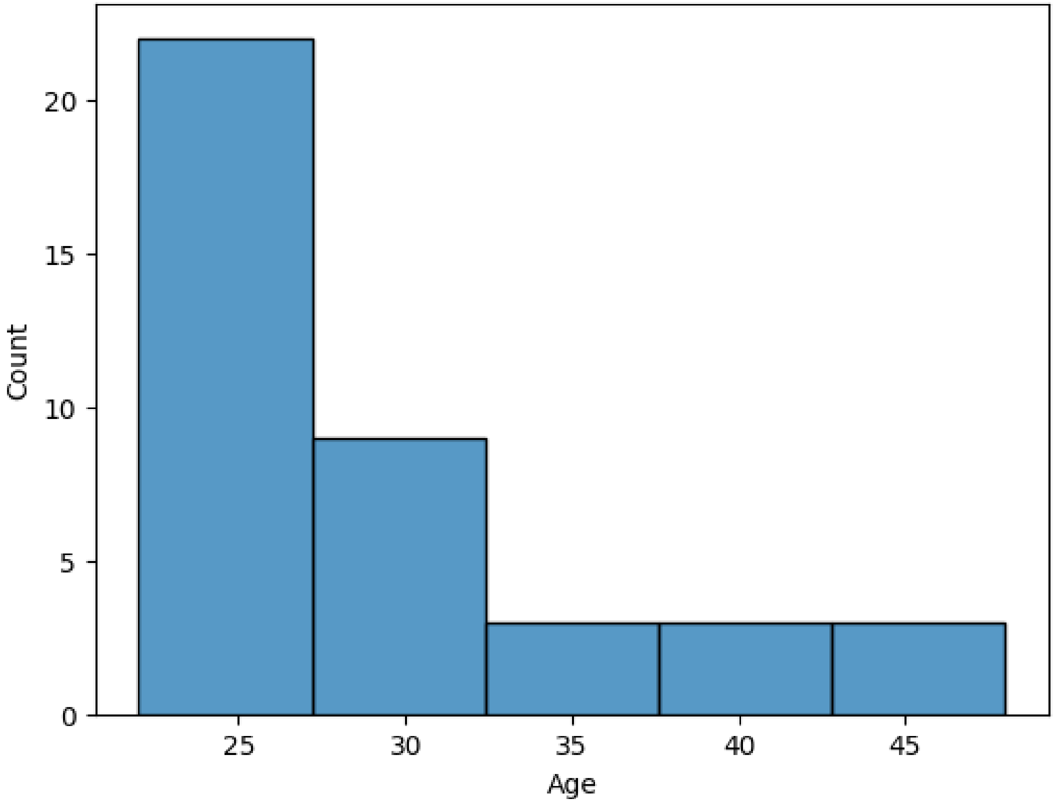
```
[ ]: sns.histplot(kp481['Age'],bins = 5)
```

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



[ ]:
```
sns.histplot(kp781['Age'],bins = 5)
```

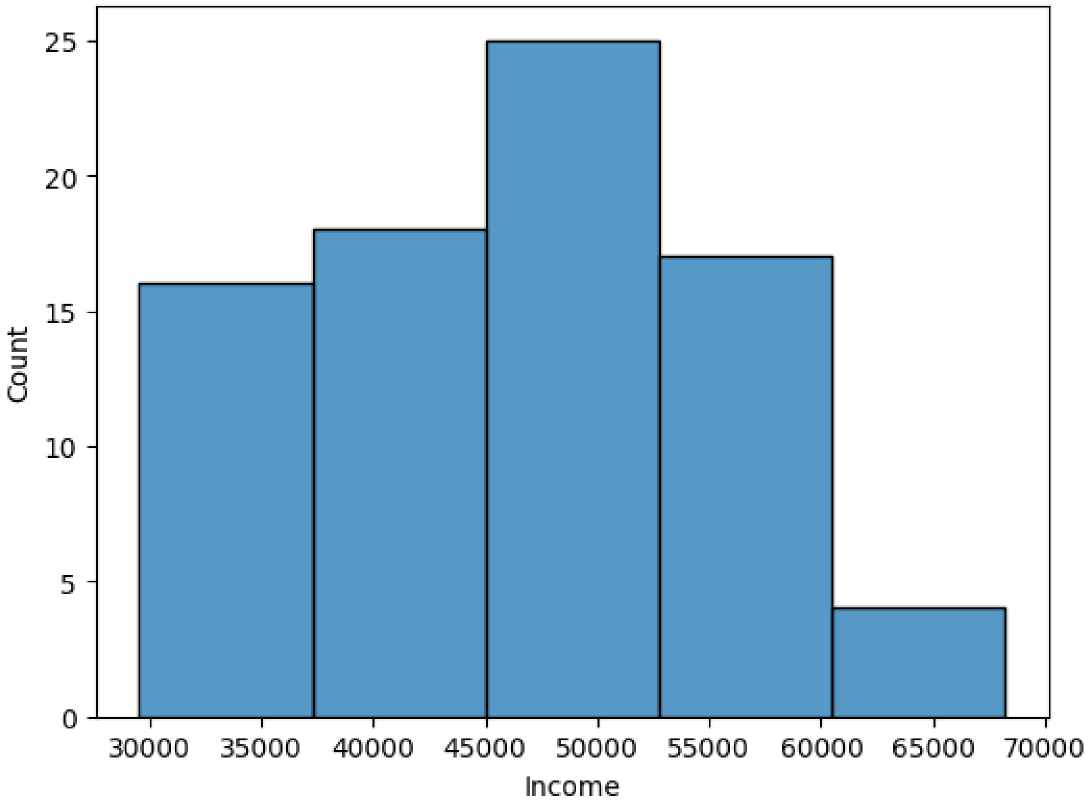
[ ]:
```
<Axes: xlabel='Age', ylabel='Count'>
```



Count of people across income intervals.

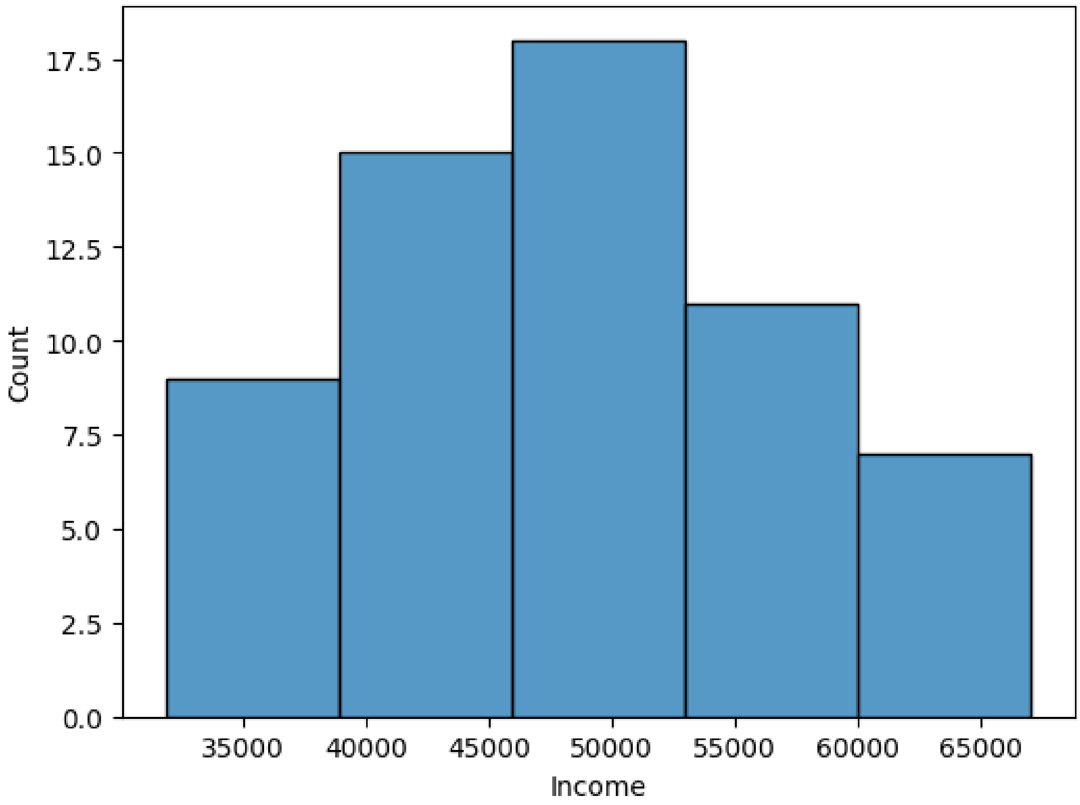
```
[ ]: sns.histplot(kp281['Income'],bins = 5)
```

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



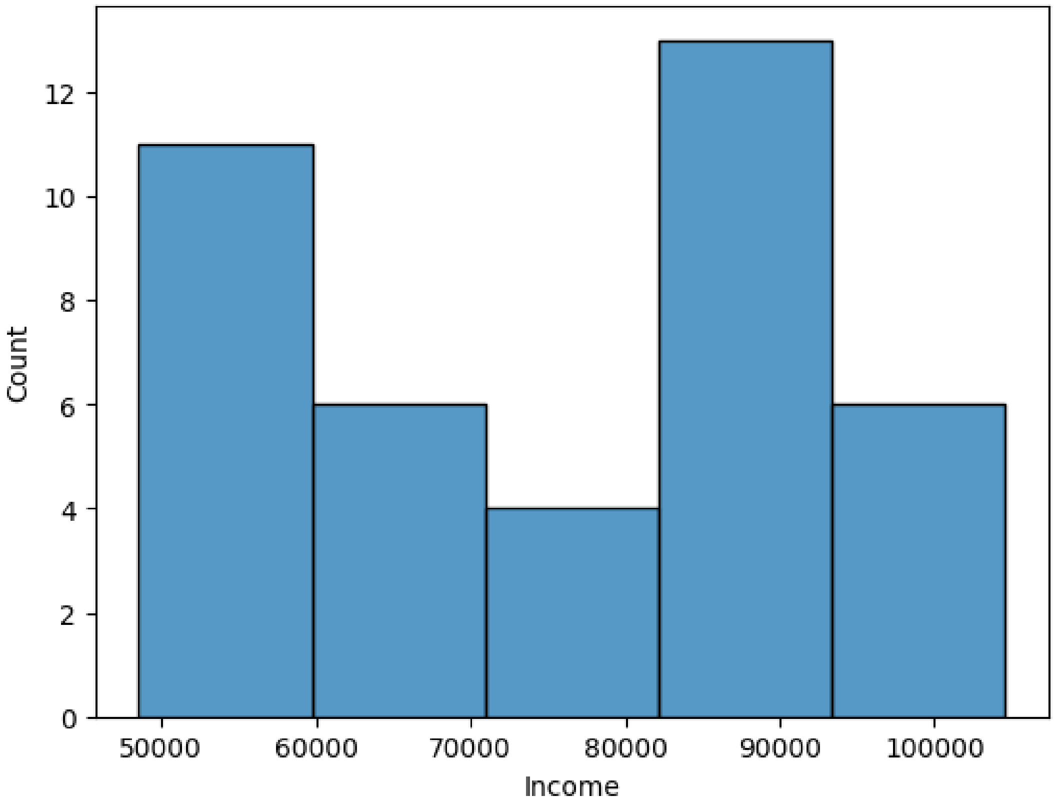
```
[ ]: sns.histplot(kp481['Income'],bins = 5)
```

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



```
[ ]: sns.histplot(kp781['Income'],bins = 5)
```

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



Count of people at each education level for each product.

```
[ ]: data.groupby('Product',as_index = False)['Education'].value_counts()
```

```
[ ]:    Product  Education  count
     0    KP281         16     39
     1    KP281         14     30
     2    KP281         15      4
     3    KP281         13      3
     4    KP281         12      2
     5    KP281         18      2
     6    KP481         16     31
     7    KP481         14     23
     8    KP481         13      2
     9    KP481         18      2
     10   KP481         12      1
     11   KP481         15      1
     12   KP781         18     19
     13   KP781         16     15
     14   KP781         21      3
     15   KP781         14      2
```

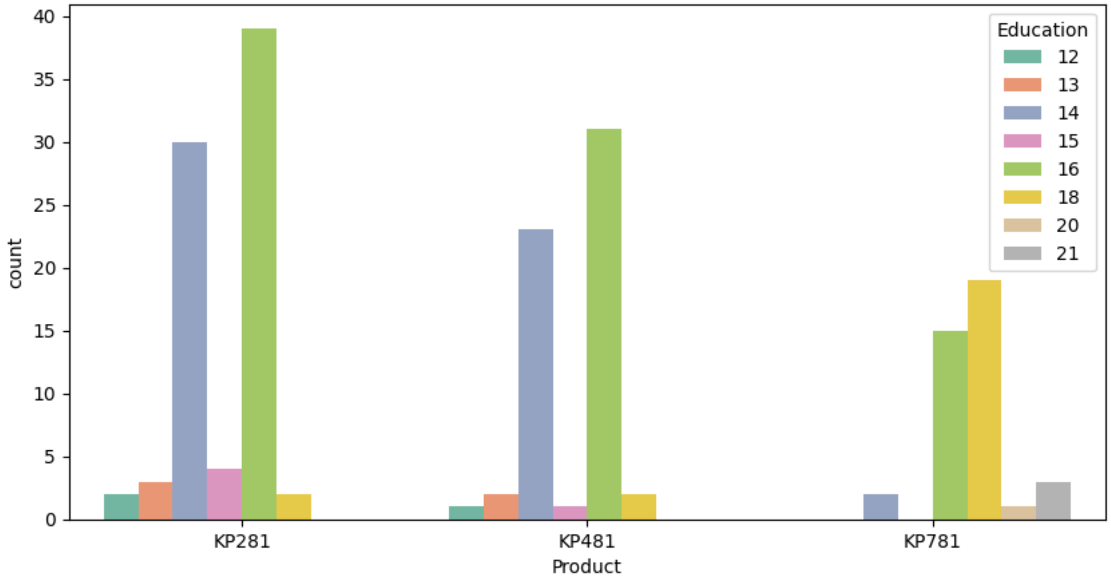
```
16    KP781          20       1
```

[ ]:

```
plt.figure(figsize=(10,5))
sns.countplot(data = data, x = 'Product', hue = 'Education',palette='Set2')
```

[ ]:

```
<Axes: xlabel='Product', ylabel='count'>
```



Product Recommendations Based on Customer Data

Total Customers: 180
- **KP281:** 80 customers (44%)
- **KP481:** 60 customers (33%)
- **KP781:** 40 customers (22%)

0.0.1 KP281 Insights

- **Age:**
  - 50% of buyers are aged between **8** and **48**.

  - Majority are between **20** and **30**.

- **Income:**
  - 50% fall within **16,400 – 75,000**.

  - Most buyers earn between **45,000** and **55,000**.

- **Gender:**

    - **40** males and **40** females.

- **Marital Status:**
    - **48** parented and **32** single.

- **Education:**
    - **39** buyers have **16** years of education.

    - **30** buyers have **14** years of education.

- **Fitness Level:**
    - **26** out of **40** females rated their fitness as **3**.

    - **28** out of **40** males rated their fitness as **3**.

Recommendation for KP281:
Suggest KP281 to customers who:
- Rate their fitness as **3**.
- Earn between **45,000 – 55,000**.
- Have **14** or **16** years of education.
- Are **parented**.
- Are aged between **20 – 30**.

0.0.2 KP481 Insights

- **Age:**
    - 50% of buyers are aged between **10** and **47**.

    - Most fall between **20 – 35**.

- **Income:**
    - 50% earn between **32,000 – 66,000**.

    - Majority earn between **45,000 – 55,000**.

- **Gender:**
    - **31** males and **29** females.

- **Marital Status:**
    - **36** parented and **24** single.

- **Education:**
    - **31** buyers have **16** years of education.

    - **29** buyers have **14** years of education.

- **Fitness Level:**

- **18** out of **29** females rated their fitness as **3**.

- **21** out of **31** males rated their fitness as **3**.

Recommendation for KP481:
Suggest KP481 to customers who:
- Rate their fitness as **3**.
- Earn between **45,000 – 55,000**.
- Have **14** or **16** years of education.
- Are **parented**.
- Are aged between **20 – 35**.

> **Note:** Both KP281 and KP481 appeal to similar profiles, but older customers tend to prefer **KP281**, while younger ones lean towards **KP481**.

0.0.3 KP781 Insights

- **Age:**
  - 50% of buyers are aged between **16 – 41**.
  - Most are between **22 – 27**.
- **Income:**
  - 50% earn between **9,000 – 130,000**.
  - Majority earn between **80,000 – 95,000**.
- **Gender:**
  - **33** males and **7** females.
- **Marital Status:**
  - **23** parented and **17** single.
- **Education:**
  - **19** buyers have **18** years of education.
  - **15** buyers have **16** years of education.
- **Fitness Level:**
  - **5** out of **7** females rated their fitness as **5**.
  - **24** out of **33** males rated their fitness as **5**.

Recommendation for KP781:
Suggest KP781 to customers who:
- Rate their fitness as **5**.
- Are aged between **22 – 27**.
- Earn between **80,000 – 95,000**.

- Have **18** years of education.