File Edit View Run Kernel Tabs Settings Help

Final_Sub.ipynb | case_info.ipynb | Netflix_case_stdy.ipynb

Markdown | Python 3

Import Library

[18]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

plt.rcParams['figure.figsize'] = [12, 8]
plt.rcParams['figure.dpi'] = 100
```

[3]:
```
df = pd.read_csv('aerofit_treadmill.csv')
```

[7]:
```
df.shape
```

[7]:
```
(180, 9)
```

[4]:
```
df.head()
```

[4]:

	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

[5]:
```
df.describe()
```

[5]:

	Age	Education	Usage	Fitness	Income	Miles
count	180.000000	180.000000	180.000000	180.000000	180.000000	180.000000
mean	28.788889	15.572222	3.455556	3.311111	53719.577778	103.194444
std	6.943498	1.617055	1.084797	0.958869	16506.684226	51.863605
min	18.000000	12.000000	2.000000	1.000000	29562.000000	21.000000
25%	24.000000	14.000000	3.000000	3.000000	44058.750000	66.000000
50%	26.000000	16.000000	3.000000	3.000000	50596.500000	94.000000
75%	33.000000	16.000000	4.000000	4.000000	58668.000000	114.750000
max	50.000000	21.000000	7.000000	5.000000	104581.000000	360.000000

[6]:
```
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
```

Columns which include categorical values

[13]:
```
df.describe(include='object').T
print(df.describe(include='object').T.index.tolist())
```

```
['Product', 'Gender', 'MaritalStatus']
```

[15]:
```
df['Product'].value_counts(normalize=True)*100
```

[15]:
```
KP281    44.444444
KP481    33.333333
KP781    22.222222
Name: Product, dtype: float64
```

- The majority of customers prefer KP281, making it a strong performer in the market.
- KP781, while less popular, still captures a notable portion of the market.

[16]:
```
df['Gender'].value_counts(normalize=True)*100
```

[16]:
```
Male      57.777778
Female    42.222222
Name: Gender, dtype: float64
```

The dataset is slightly skewed towards males, suggesting that there are more male observations compared to females.

[17]:
```
df['MaritalStatus'].value_counts(normalize=True)*100
```

[17]:
```
Partnered    59.444444
Single       40.555556
Name: MaritalStatus, dtype: float64
```

The dataset is skewed towards partnered individuals, suggesting that there are more observations of partnered individuals compared to singles.

Null value analysis

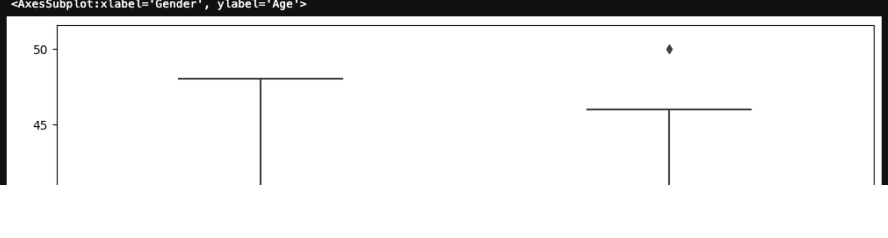
[9]:
```
df.isnull().sum()/len(df)*100
```

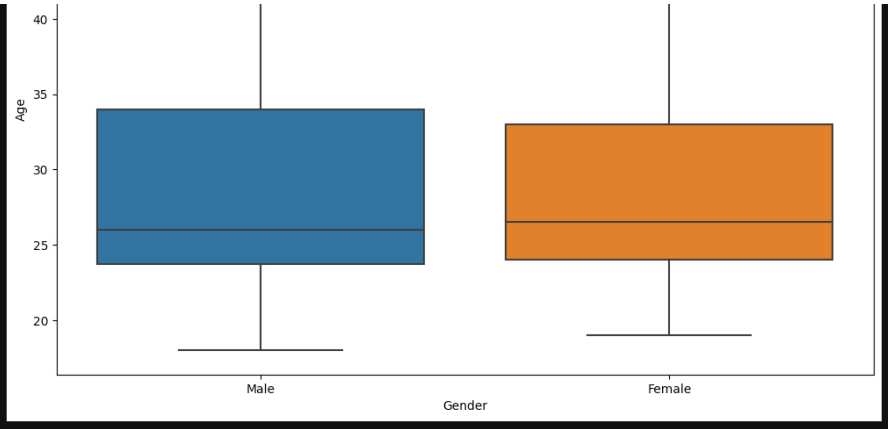
[9]:
```
Product          0.0
Age              0.0
Gender           0.0
Education        0.0
MaritalStatus    0.0
Usage            0.0
Fitness          0.0
Income           0.0
Miles            0.0
dtype: float64
```

This is good news as missing data can impact the accuracy and reliability of your analysis. A dataset without missing values allows for a more comprehensive and accurate exploration of the data.

[31]:
```
sns.boxplot(data=df, y='Age', x='Gender')
```

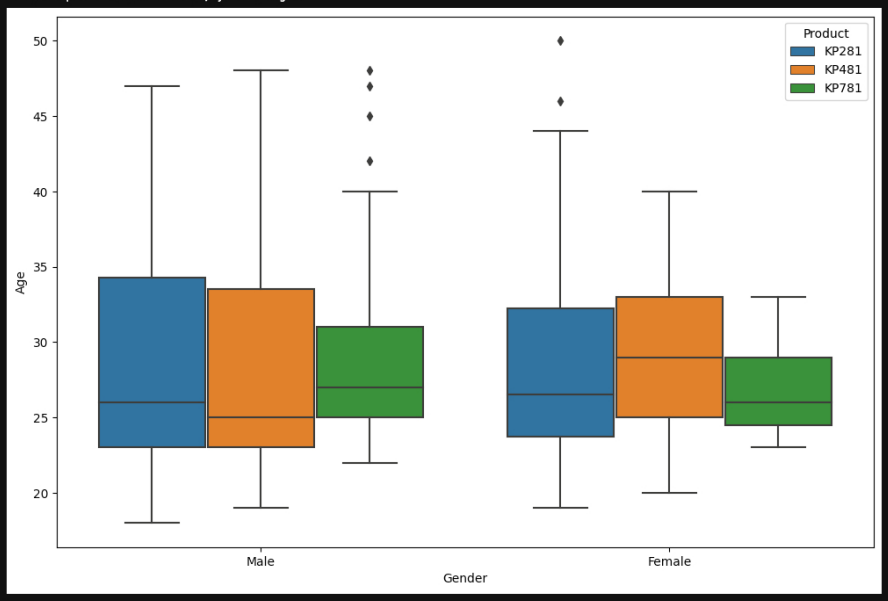
[31]:
```
<AxesSubplot:xlabel='Gender', ylabel='Age'>
```





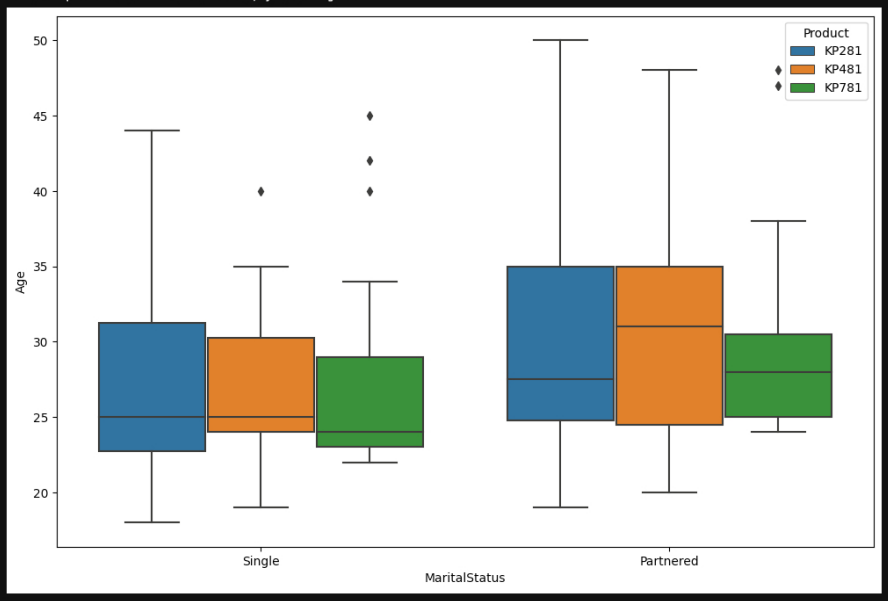
[27]:
```
sns.boxplot(data=df, y='Age', x='Gender', hue = 'Product')
```

[27]: <AxesSubplot:xlabel='Gender', ylabel='Age'>



[29]:
```
sns.boxplot(data=df, y='Age', x='MaritalStatus', hue = 'Product')
```

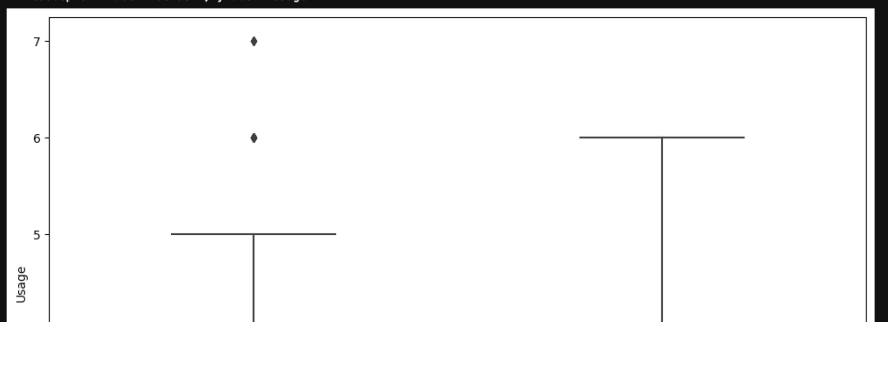
[29]: <AxesSubplot:xlabel='MaritalStatus', ylabel='Age'>

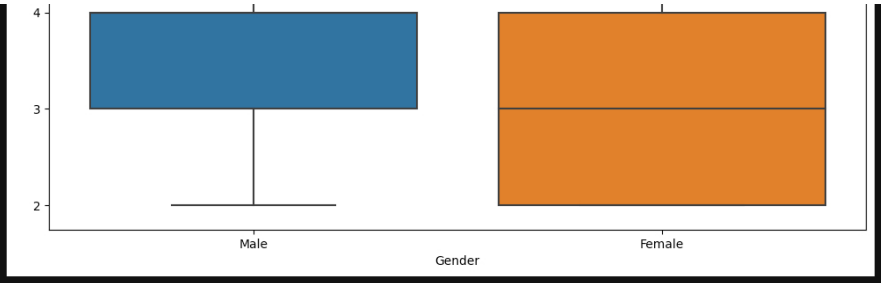


[ ]:
```
##
```

[32]:
```
sns.boxplot(data=df, y='Usage', x='Gender')
```

[32]: <AxesSubplot:xlabel='Gender', ylabel='Usage'>

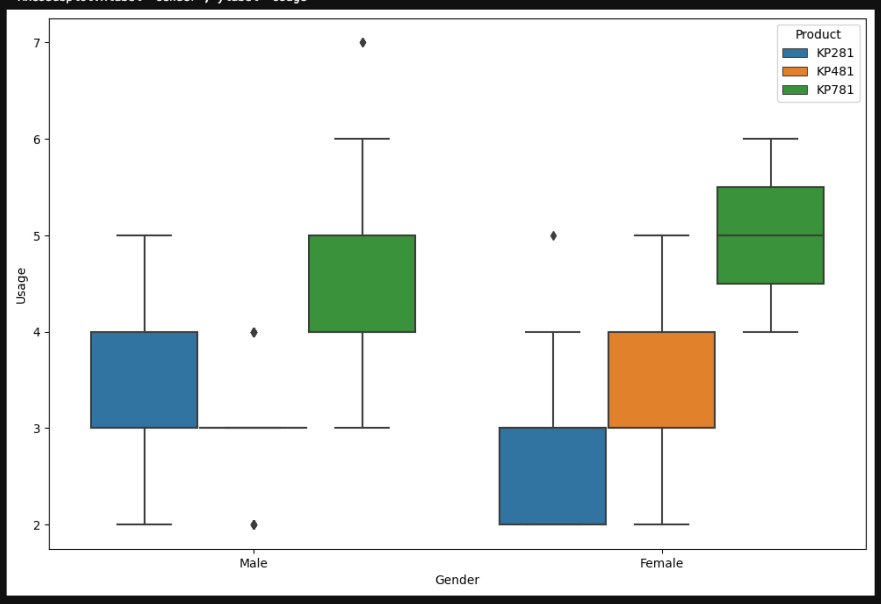




boxplot Gender vs Usage Shows that Female are using is higher as compared to Malem

[33]:
```
sns.boxplot(data=df, y='Usage', x='Gender', hue='Product')
```

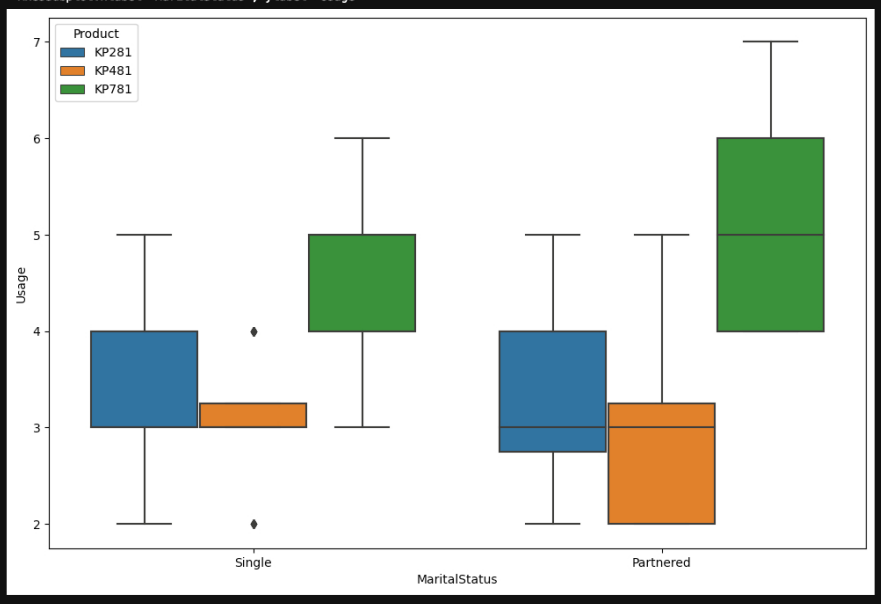
[33]: <AxesSubplot:xlabel='Gender', ylabel='Usage'>



boxplot Gender vs Usage Shows that Female are using is higher and most used product is KP781

[34]:
```
sns.boxplot(data=df, y='Usage', x='MaritalStatus', hue = 'Product')
```

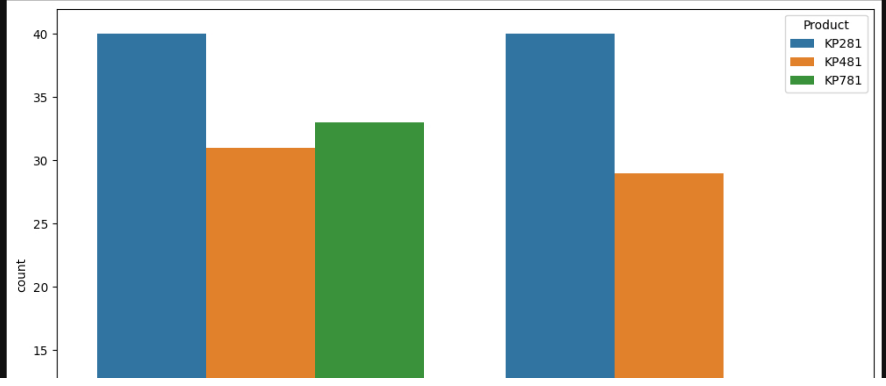
[34]: <AxesSubplot:xlabel='MaritalStatus', ylabel='Usage'>



boxplot MaritalStatus vs Usage Shows that partnered people are using is higher and most used product is KP781

[36]:
```
sns.countplot(data = df, x='Gender', hue='Product')
```

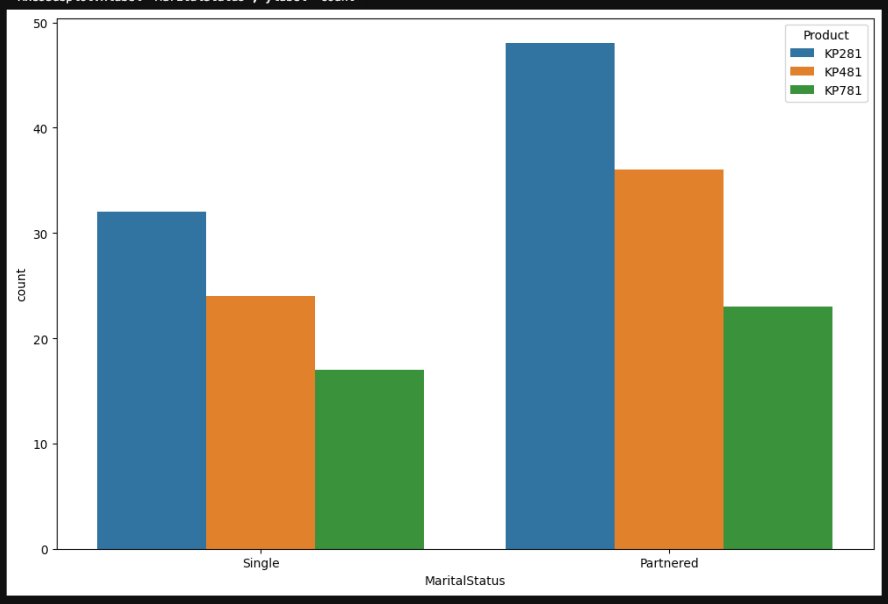
[36]: <AxesSubplot:xlabel='Gender', ylabel='count'>



countplot Male vs Female plot show that Male count is higher in all product compair to Female

[38]:
```
sns.countplot(data = df, x='MaritalStatus', hue='Product')
```

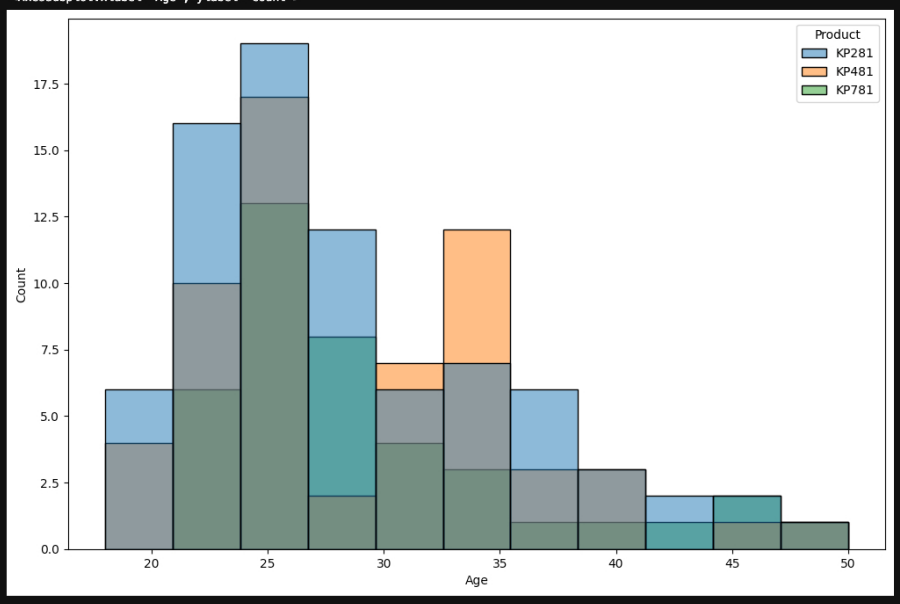
[38]: <AxesSubplot:xlabel='MaritalStatus', ylabel='count'>



countplot Single vs Partnered plot show that Partnered count is higher in all individual product compair to Single

[47]:
```
sns.histplot(data=df, x='Age', hue='Product')
```

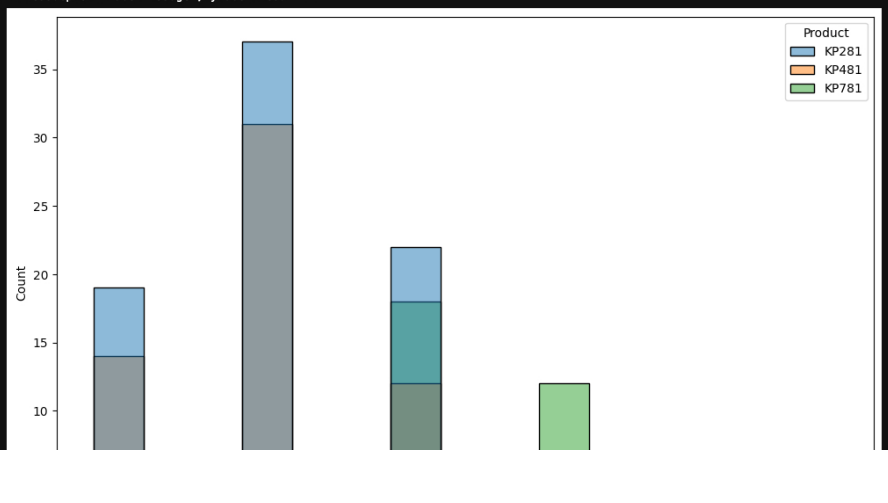
[47]: <AxesSubplot:xlabel='Age', ylabel='Count'>

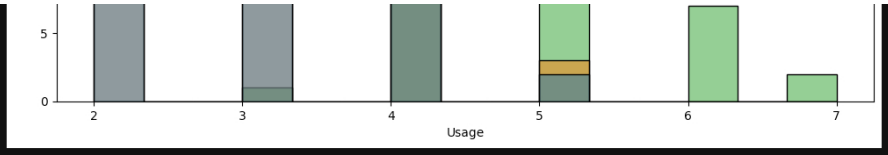


histplot count distribution along with age range and product

[132]:
```
sns.histplot(data=df, x='Usage', hue='Product')
```

[132]: <AxesSubplot:xlabel='Usage', ylabel='Count'>

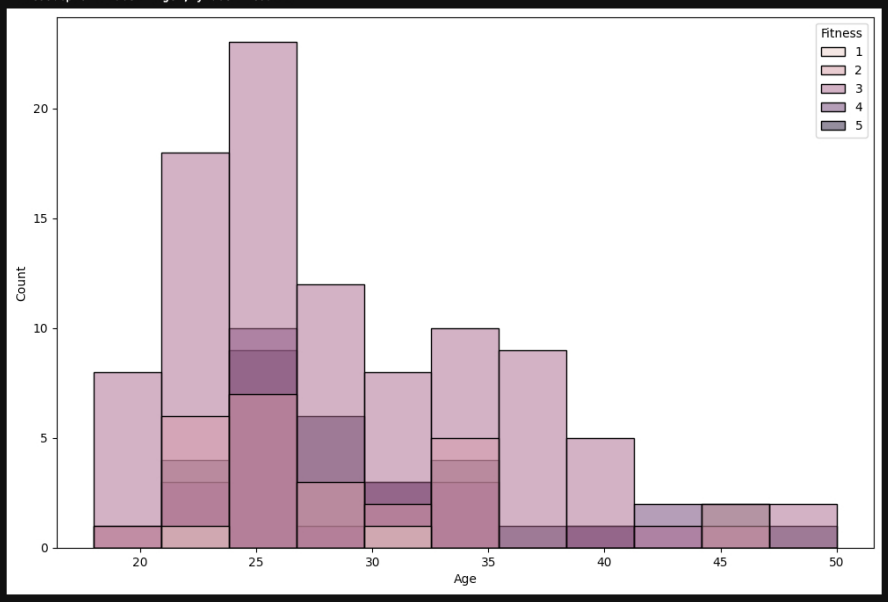




histplot count distribution along with Usage and product

```
[154]: sns.histplot(data=df, x='Age', hue='Fitness', color=sns.color_palette("bright", 5))
```

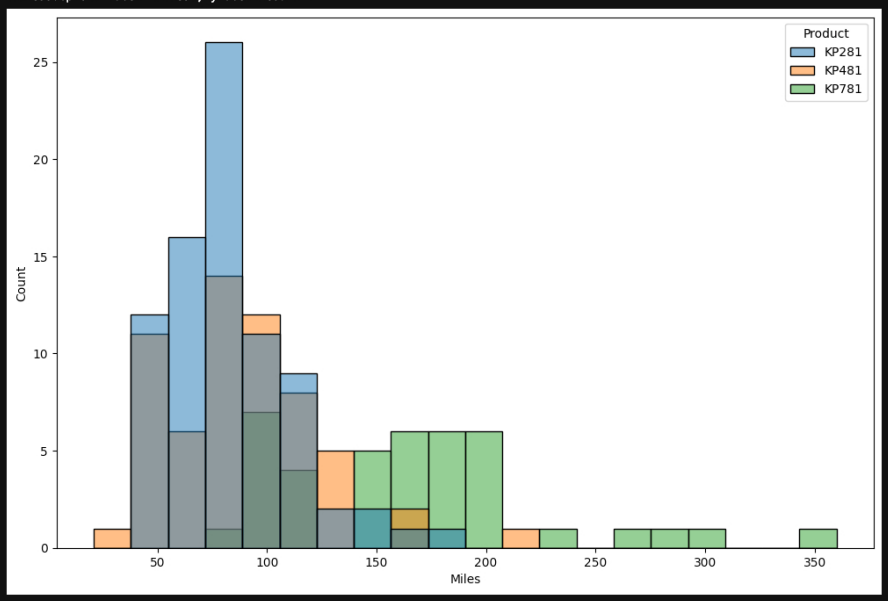
```
[154]: <AxesSubplot:xlabel='Age', ylabel='Count'>
```



histplot count distribution along with Age and Fitness gred?

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

```
[155]: <AxesSubplot:xlabel='Miles', ylabel='Count'>
```



histplot count distribution along with Miles and Product

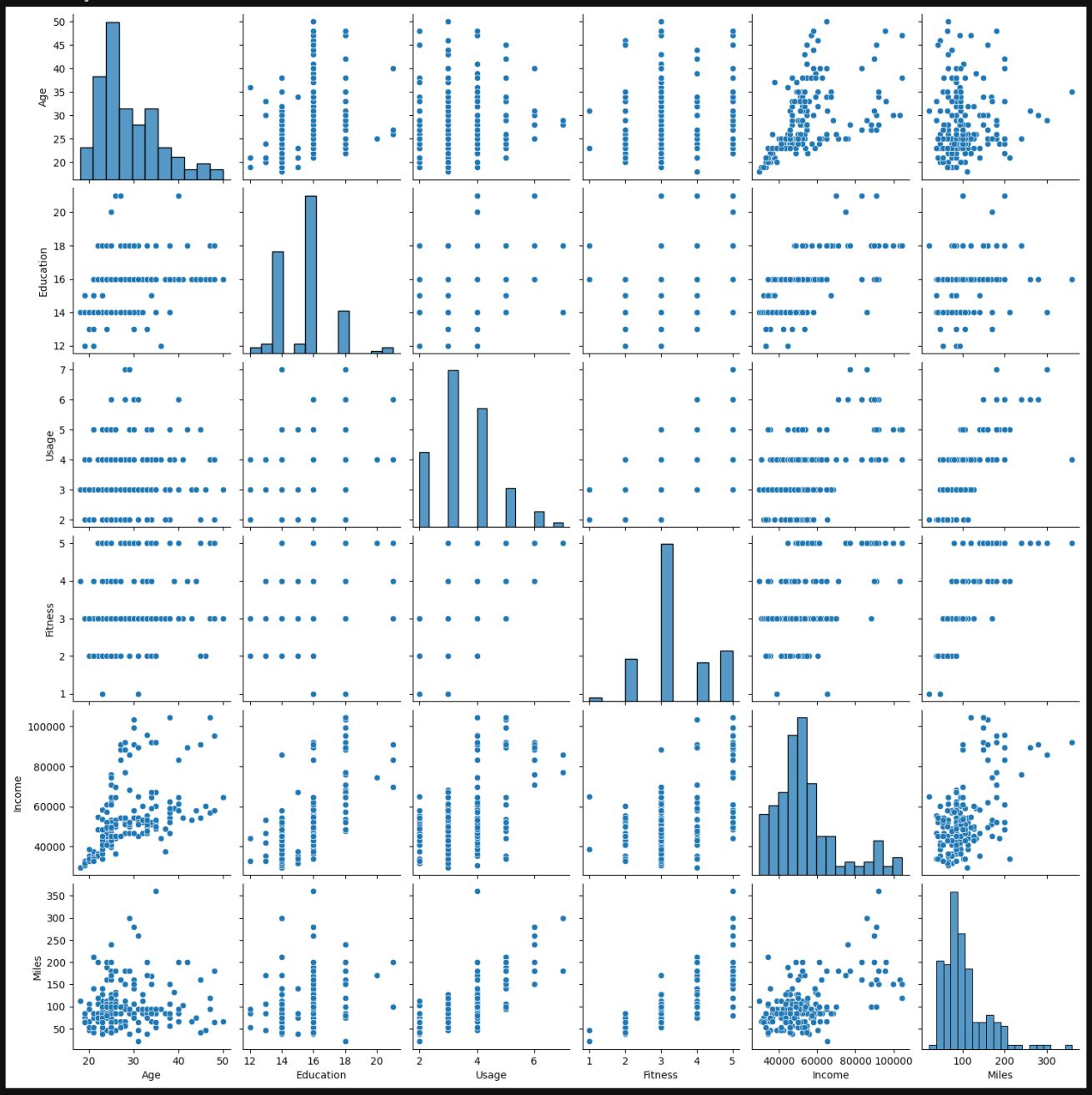
```
[50]: sns.heatmap(df.corr(), cmap="YlGnBu", annot=True)
```

```
[50]: <AxesSubplot:>
```

HeatMap of correlation with all of the other variables

[51]:
```
sns.pairplot(df)
```

[51]:
```
<seaborn.axisgrid.PairGrid at 0x7fa46d26e220>
```



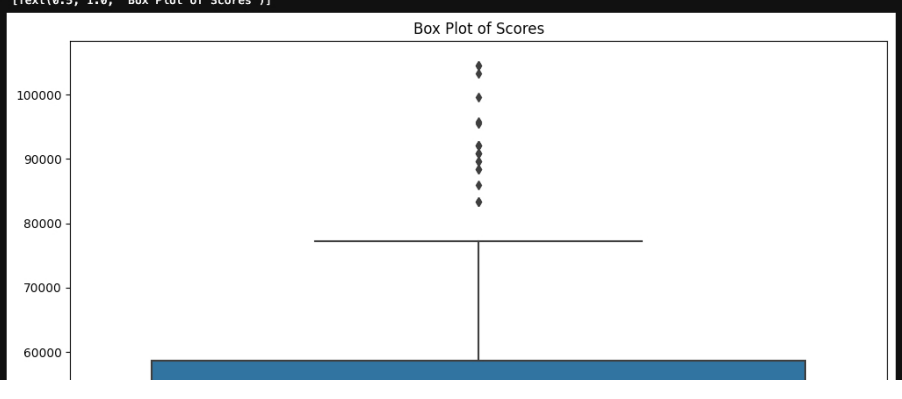
Outlier

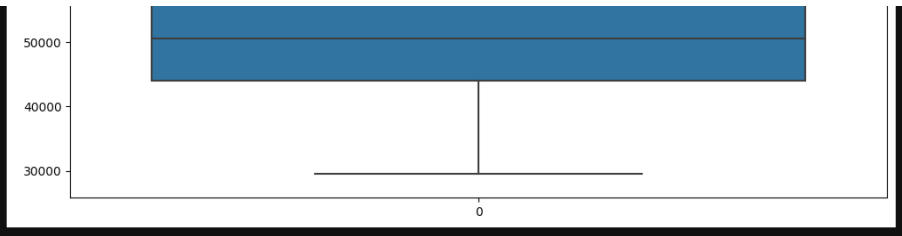
Detect Outliers Using the Interquartile Range (IQR)
In statistics, interquartile range or IQR is a quantity that measures the difference between the first and the third quartiles in a given dataset.

The first quartile is also called the one-fourth quartile, or the 25% quartile.
If q25 is the first quartile, it means 25% of the points in the dataset have values less than q25.
The third quartile is also called the three-fourth, or the 75% quartile.
If q75 is the three-fourth quartile, 75% of the points have values less than q75.
Using the above notations,
IQR = q75 - q25.

[54]:
```
sns.boxplot(data=df['Income']).set(title="Box Plot of Scores")
```

[54]:
```
[Text(0.5, 1.0, 'Box Plot of Scores')]
```





[90]:
```
# df.Income.describe?
```

[ ]:
```

```

[131]:
```
def outlier_using_IQR(df, columns='Income'):

    # q75 = df.Income.quantile(0.75)
    # q25 = df.Income.quantile(0.25)
    q25,q75 = np.percentile(a = df[columns], q=[25,75])

    IQR = q75-q25
    print(IQR)
    upper_limit = q75 + 1.5*IQR
    lower_limit = q25 - 1.5*IQR
    print(upper_limit, lower_limit)

    df_scores_filtered = df[(df[columns]>lower_limit) & (df[columns]<upper_limit)]
    return df_scores_filtered
```

[129]:
```
df.shape
```

[129]: (180, 9)

As a next step, filter the dataframe to retain records that lie in the permissible range.

Outlier for Income

[162]:
```
Income_outliers = outlier_using_IQR(df, columns='Income')
Income_outliers
```

```
14609.25
80581.875 22144.875
```

[162]:

	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
...	...	...	...	...	...	...	...	...	...
156	KP781	25	Male	20	Partnered	4	5	74701	170
157	KP781	26	Female	21	Single	4	3	69721	100
158	KP781	26	Male	16	Partnered	5	4	64741	180
163	KP781	28	Male	18	Partnered	7	5	77191	180
165	KP781	29	Male	18	Single	5	5	52290	180

161 rows × 9 columns

[164]:
```
print(f"As seen in the output, this method labels {len(df)-len(Income_outliers)} points as outliers, and the filtered dataframe is {len(Income_outliers)} records long.")
```

```
As seen in the output, this method labels 19 points as outliers, and the filtered dataframe is 161 records long.
```

Outlier for Age

[166]:
```
Age_outliers = outlier_using_IQR(df, columns='Age')
Age_outliers
```

```
9.0
46.5 10.5
```

[166]:

	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
...	...	...	...	...	...	...	...	...	...
173	KP781	35	Male	16	Partnered	4	5	92131	360
174	KP781	38	Male	18	Partnered	5	5	104581	150
175	KP781	40	Male	21	Single	6	5	83416	200
176	KP781	42	Male	18	Single	5	4	89641	200
177	KP781	45	Male	16	Single	5	5	90886	160

175 rows × 9 columns

[167]:
```
print(f"As seen in the output, this method labels {len(df)-len(Age_outliers)} points as outliers, and the filtered dataframe is {len(Age_outliers)} records long.")
```

```
As seen in the output, this method labels 5 points as outliers, and the filtered dataframe is 175 records long.
```

Outlier for Usage

[168]:
```
Usage_outliers = outlier_using_IQR(df, columns='Usage')
Usage_outliers
```

```
1.0
5.5 1.5
```

[168]:

	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
...	...	...	...	...	...	...	...	...	...
174	KP781	38	Male	18	Partnered	5	5	104581	150
176	KP781	42	Male	18	Single	5	4	89641	200
177	KP781	45	Male	16	Single	5	5	90886	160
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

171 rows × 9 columns

[169]:
```
print(f"As seen in the output, this method labels {len(df)-len(Usage_outliers)} points as outliers, and the filtered dataframe is {len(Usage_outliers)} records long.")
```

```
As seen in the output, this method labels 9 points as outliers, and the filtered dataframe is 171 records long.
```

Outlier for Miles

[170]:
```
Miles_outliers = outlier_using_IQR(df, columns='Miles')
Miles_outliers
```

```
48.75
187.875 -7.125
```

[170]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
0	KP281	18	Male	14	Single	3	4	29562	112
1	KP281	19	Male	15	Single	2	3	31836	75
2	KP281	19	Female	14	Partnered	4	3	30699	66
3	KP281	19	Male	12	Single	3	3	32973	85
4	KP281	20	Male	13	Partnered	4	2	35247	47
...	...	...	...	...	...	...	...	...	...
172	KP781	34	Male	16	Single	5	5	92131	150
174	KP781	38	Male	18	Partnered	5	5	104581	150
177	KP781	45	Male	16	Single	5	5	90886	160
178	KP781	47	Male	18	Partnered	4	5	104581	120
179	KP781	48	Male	18	Partnered	4	5	95508	180

167 rows × 9 columns

[171]:
```
print(f"As seen in the output, this method labels {len(df)-len(Miles_outliers)} points as outliers, and the filtered dataframe is {len(Miles_outliers)} records long.")
```

```
As seen in the output, this method labels 13 points as outliers, and the filtered dataframe is 167 records long.
```

[172]:
```
df.head()
```

[172]:

	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

Representing the marginal probability like - what percent of customers have purchased KP281, KP481, or KP781 in a table (can use pandas.crosstab here)

[174]:
```
pd.crosstab(df.Product, [df.MaritalStatus, df.Gender], rownames=['Product'], colnames=['MaritalStatus', 'Gender'])
```

[174]:

MaritalStatus	Partnered		Single	
Gender	Female	Male	Female	Male
Product				
KP281	27	21	13	19
KP481	15	21	14	10
KP781	4	19	3	14

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.

The table represents the count of individuals based on their MaritalStatus, Gender, and the specific Product (KP281, KP481, KP781) purchased. Let's derive some insights:

- Overall Purchase Distribution:
  KP281: The highest number of purchases is from partnered females, followed by single males. KP481: Partnerships seem to have a more balanced distribution, with a slightly higher count of purchases from single males.
  KP781: Again, partnered females lead in purchases, followed by single males.
- Marital Status Influence:
  For all products, partnered individuals, especially females, show a higher count of purchases compared to their single counterparts. This suggests that the marital status might play a role in the decision to purchase a treadmill, with partnered individuals being more likely to make a purchase.
- Gender Influence:
  Across all products, females, whether partnered or single, tend to have a higher count of purchases compared to males. This indicates that females are more likely to buy Aerofit treadmills than males.
- Product Preference:
  KP281 is the most popular product across all categories of MaritalStatus and Gender. KP781 is the least purchased, but partnered females show a higher preference for it compared to other groups. Single Males vs. Single Females:

Single males have a higher count of purchases for KP281 and KP781, suggesting that these products might cater more to this demographic. Partnered Males vs. Partnered Females:

Partnered females show a consistently higher count of purchases for all products, indicating a potential market preference among this group. Key Takeaways:

The marketing strategy for KP281 seems to be effective, as it attracts the highest number of purchases across all demographics. Partnered females are a notable customer segment, showing a strong preference for all products. There might be untapped potential among single males, especially for KP281 and KP781. These insights can guide marketing and sales strategies, helping to tailor promotions or advertising efforts based on the observed preferences and trends within different demographic groups.

[ ]:


Simple
0
0
Python 3 | Idle
Mode: Command
Ln 1, Col 1
Final_Sub.ipynb