In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set(color_codes=True)
import scipy.stats as stats
import warnings
warnings.filterwarnings("ignore")
import os
```

In [2]:
```
# Importing data
os.listdir(os.getcwd())
```

Out[2]:
```
['.ipynb_checkpoints',
 '2015_Street_Tree_Census_-_Tree_Data_20240605.csv',
 'aerofit_treadmill_data.csv',
 'BeautifulSoup and Requests.ipynb',
 'Cleaning Cricket Dataset.ipynb',
 'crime.csv',
 'crime.zip',
 'Customer Call List.xlsx',
 'Data Cleaing in Pandas.ipynb',
 'data_cleaning_challenge.csv',
 'data_cleaning_challenge.ipynb',
 'EDA of Crime Dataset.ipynb',
 'EDA of Crime Dataset.pdf',
 'EDA with Crime Dataset.ipynb',
 'layoffs.csv',
 'Loan Default Predictor',
 'Records for Test Matches.csv',
 'Records for Test Matches.xlsx',
 'Scraping Data from a Real Website + Pandas.ipynb',
 'SurveyMonkey Data Transformation and Analysis',
 'Treadmill Purchase Analysis.ipynb']
```

In [3]:
```
df = pd.read_csv('aerofit_treadmill_data.csv')
# Get overview of dataset
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]:
```
# Shape of dataframe
df.shape
```

Out[4]:
```
(180, 9)
```

In [5]:
```
# Identify name of all columns
df.columns
```

Out[5]:
```
Index(['Product', 'Age', 'Gender', 'Education', 'MaritalStatus', 'Usage',
       'Fitness', 'Income', 'Miles'],
      dtype='object')
```

In [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
```

In [7]:
```
# Convert columns with object data type
df['Product'] = df['Product'].astype('category')
df['Gender'] = df['Gender'].astype('category')
df['MaritalStatus'] = df['MaritalStatus'].astype('category')
```

In [8]:
```
df.dtypes
```

Out[8]:
```
Product          category
Age                 int64
Gender           category
Education           int64
MaritalStatus    category
Usage               int64
Fitness             int64
Income              int64
Miles               int64
dtype: object
```

In [9]:
```
df.skew()
```

Out[9]:
```
Age          0.982161
Education    0.622294
Usage        0.739494
Fitness      0.454800
Income       1.291785
Miles        1.724497
dtype: float64
```

Statistical Summary

In [10]:
```
df.describe(include='all')
```

Out[10]:

	Product	Age	Gender	Education	MaritalStatus	Usage	Fitness	Income	Miles
count	180	180.000000	180	180.000000	180	180.000000	180.000000	180.000000	180.000000
unique	3	NaN	2	NaN	2	NaN	NaN	NaN	NaN
top	KP281	NaN	Male	NaN	Partnered	NaN	NaN	NaN	NaN
freq	80	NaN	104	NaN	107	NaN	NaN	NaN	NaN
mean	NaN	28.788889	NaN	15.572222	NaN	3.455556	3.311111	53719.577778	103.194444
std	NaN	6.943498	NaN	1.617055	NaN	1.084797	0.958869	16506.684226	51.863605
min	NaN	18.000000	NaN	12.000000	NaN	2.000000	1.000000	29562.000000	21.000000
25%	NaN	24.000000	NaN	14.000000	NaN	3.000000	3.000000	44058.750000	66.000000
50%	NaN	26.000000	NaN	16.000000	NaN	3.000000	3.000000	50596.500000	94.000000
75%	NaN	33.000000	NaN	16.000000	NaN	4.000000	4.000000	58668.000000	114.750000
max	NaN	50.000000	NaN	21.000000	NaN	7.000000	5.000000	104581.000000	360.000000

Observations

- there are no missing values in the data
- there are 3 unique `products`
- `KP281` is the most frequent product
- min `age` is 18, max `age` is 50, and average `age` is 28.79

- most of the people have at most `16 years of education`
- majority of the data is from `male`

In [11]:
```
# Check for missing values
df.isnull().sum()
```

Out[11]:
```
Product          0
Age              0
Gender           0
Education        0
MaritalStatus    0
Usage            0
Fitness          0
Income           0
Miles            0
dtype: int64
```

In [12]:
```
# Check for duplicates in dataset
df.duplicated().sum()
```

Out[12]:
```
0
```

Non-Graphical Analysis

Value Counts

In [13]:
```
df['Product'].value_counts()
```

Out[13]:
```
KP281    80
KP481    60
KP781    40
Name: Product, dtype: int64
```

In [14]:
```
df['Gender'].value_counts()
```

Out[14]:
```
Male      104
Female     76
Name: Gender, dtype: int64
```

In [15]:
```
df['MaritalStatus'].value_counts()
```

Out[15]:
```
Partnered    107
Single        73
Name: MaritalStatus, dtype: int64
```

Unique Attributes

In [16]:
```
df.nunique()
```

Out[16]:
```
Product           3
Age              32
Gender            2
Education         8
MaritalStatus     2
Usage             6
Fitness           5
Income           62
Miles            37
dtype: int64
```

In [17]:
```
df['Product'].unique()
```

Out[17]:
```
['KP281', 'KP481', 'KP781']
Categories (3, object): ['KP281', 'KP481', 'KP781']
```

In [18]:
```
df['Age'].unique()
```

Out[18]:
```
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)
```

In [19]:
```
df['Education'].unique()
```

Out[19]:
```
array([14, 15, 12, 13, 16, 18, 20, 21], dtype=int64)
```

In [20]:
```
df['MaritalStatus'].unique()
```

Out[20]:
```
['Single', 'Partnered']
Categories (2, object): ['Partnered', 'Single']
```

In [21]:
```
df['Usage'].unique()
```

Out[21]:
```
array([3, 2, 4, 5, 6, 7], dtype=int64)
```

In [22]:
```
df['Fitness'].unique()
```

Out[22]:
```
array([4, 3, 2, 1, 5], dtype=int64)
```

In [23]:
```
df['Income'].unique()
```

Out[23]:
```
array([ 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], dtype=int64)
```

In [24]:
```
df['Miles'].unique()
```

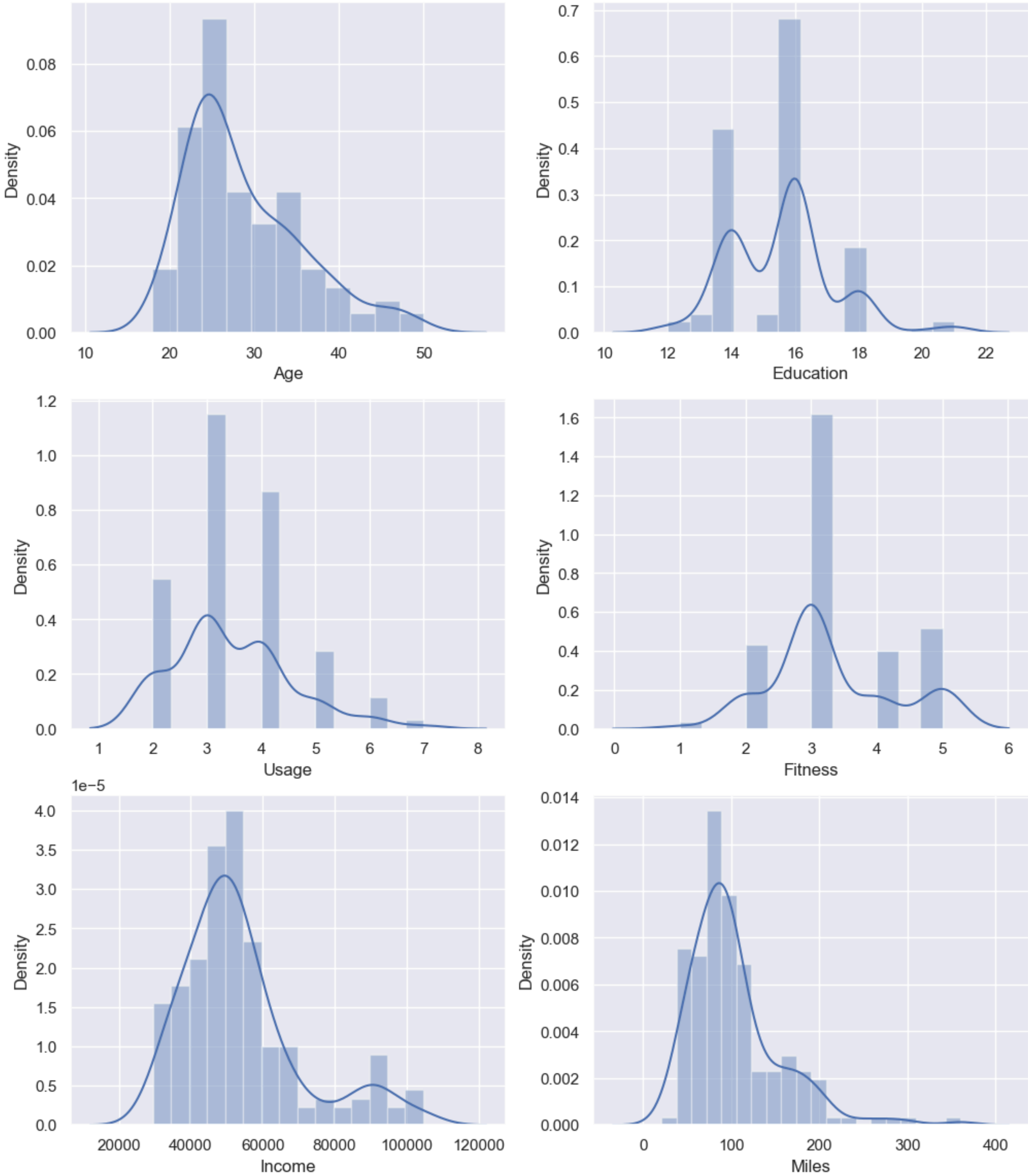
Out[24]:
```
array([112,  75,  66,  85,  47, 141, 103,  94, 113,  38, 188,  56, 132,
       169,  64,  53, 106,  95, 212,  42, 127,  74, 170,  21, 120, 200,
       140, 100,  80, 160, 180, 240, 150, 300, 280, 260, 360], dtype=int64)
```

Graphical Analysis

Univariate Analysis - Numerical Variables

Distance Plot

In [25]:
```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12,10))
fig.subplots_adjust(top=1.2)

sns.distplot(df['Age'], kde=True, ax=axis[0,0])
sns.distplot(df['Education'], kde=True, ax=axis[0,1])
sns.distplot(df['Usage'], kde=True, ax=axis[1,0])
sns.distplot(df['Fitness'], kde=True, ax=axis[1,1])
sns.distplot(df['Income'], kde=True, ax=axis[2,0])
sns.distplot(df['Miles'], kde=True, ax=axis[2,1])
plt.show()
```

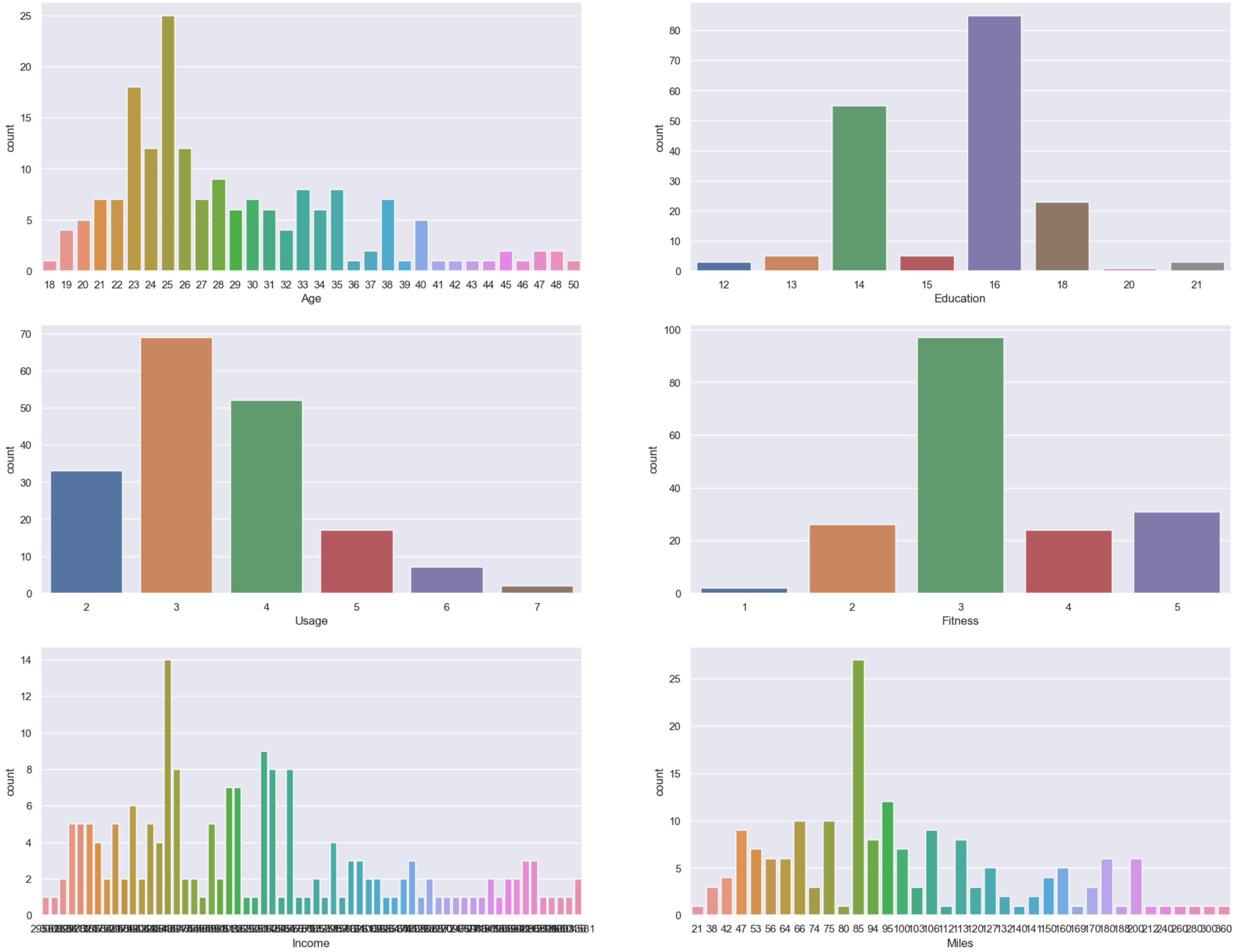


Observations

- `Income` and `Miles` are skewed to the right suggesting that they outliers
- most customers has `Fitness` level 3
- most customer has `Income` within the range of `$45,000 - $55,000`

Count Plot

In [26]:
```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(22,12))
fig.subplots_adjust(top=1.2)

sns.countplot(data=df, x='Age', ax=axis[0,0])
sns.countplot(data=df, x='Education', ax=axis[0,1])
sns.countplot(data=df, x='Usage', ax=axis[1,0])
sns.countplot(data=df, x='Fitness', ax=axis[1,1])
sns.countplot(data=df, x='Income', ax=axis[2,0])
sns.countplot(data=df, x='Miles', ax=axis[2,1])
plt.show()
```

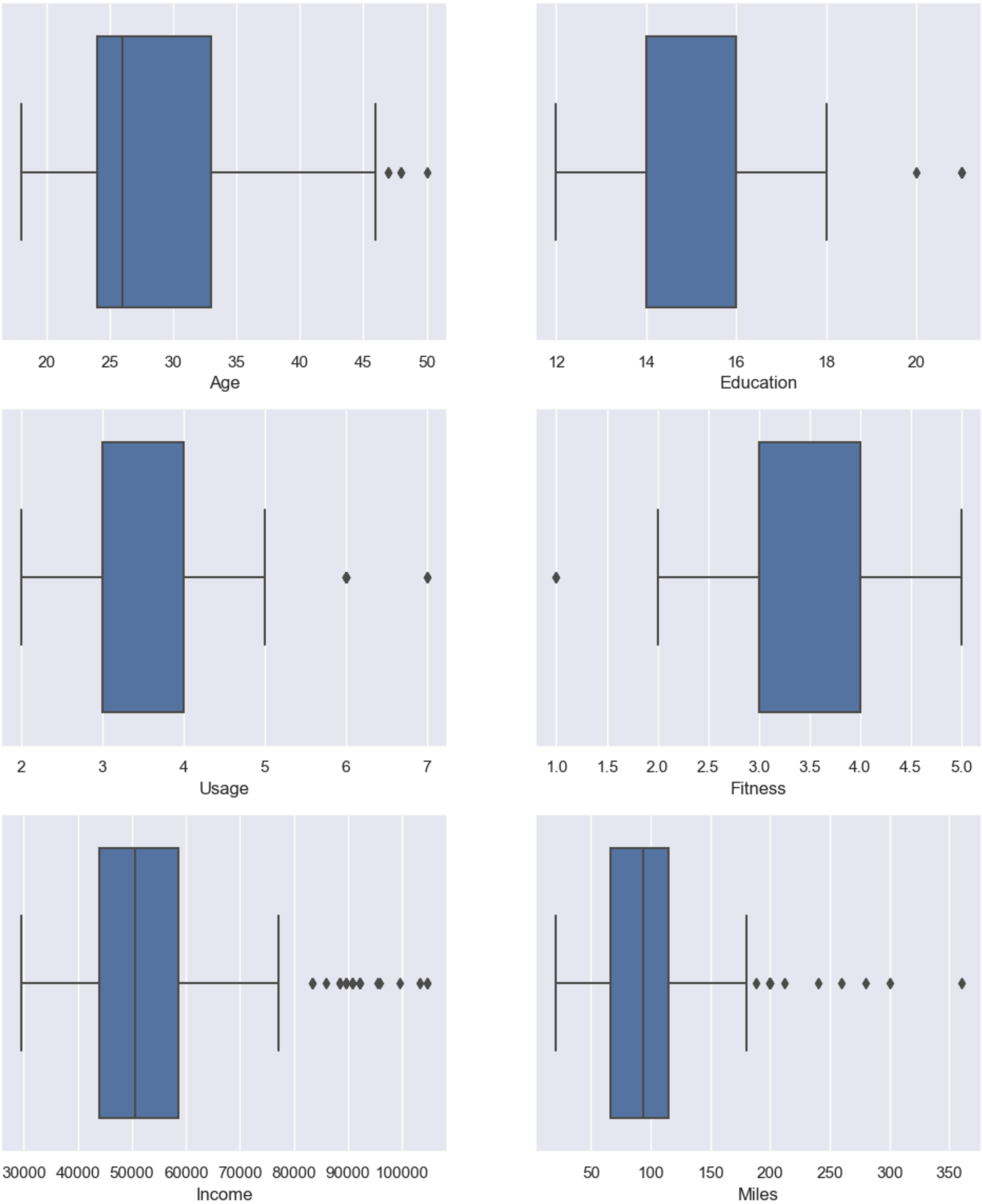


Observations

- people of `age 25` are more inclined to buy treadmills compared to older people

Box Plot

In [27]:
```
fig, axis = plt.subplots(nrows=3, ncols=2, figsize=(12,10))
fig.subplots_adjust(top=1.2)

sns.boxplot(data=df, x='Age', ax=axis[0,0])
sns.boxplot(data=df, x='Education', ax=axis[0,1])
sns.boxplot(data=df, x='Usage', ax=axis[1,0])
sns.boxplot(data=df, x='Fitness', ax=axis[1,1])
sns.boxplot(data=df, x='Income', ax=axis[2,0])
sns.boxplot(data=df, x='Miles', ax=axis[2,1])
plt.show()
```



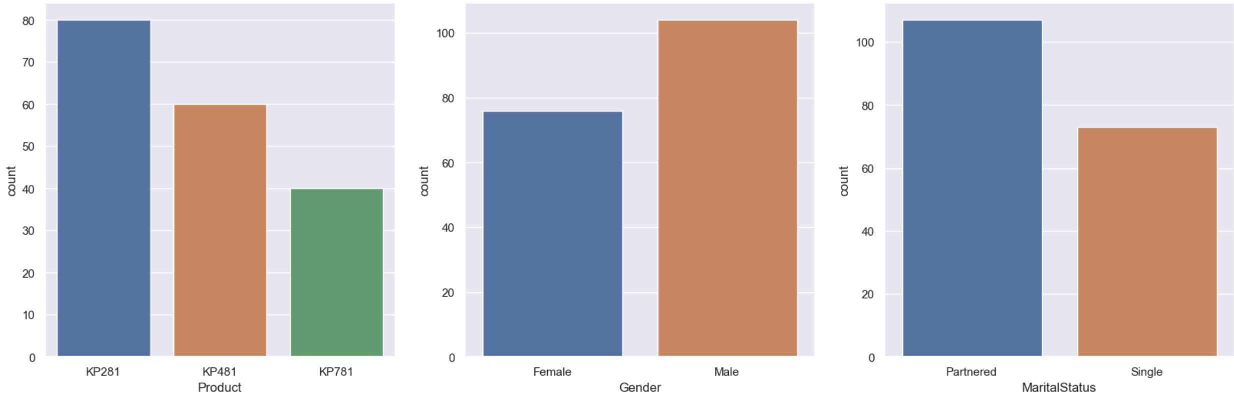
Observations

- `Age`, `Education`, `Usage`, and `Fitness` have very few outliers

Univariate Analysis - Categorical Variables

Count Plot

In [28]:
```
fig, axis = plt.subplots(nrows=1, ncols=3, figsize=(20,6))
sns.countplot(data=df, x='Product', ax=axis[0])
sns.countplot(data=df, x='Gender', ax=axis[1])
sns.countplot(data=df, x='MaritalStatus', ax=axis[2])

plt.show()
```



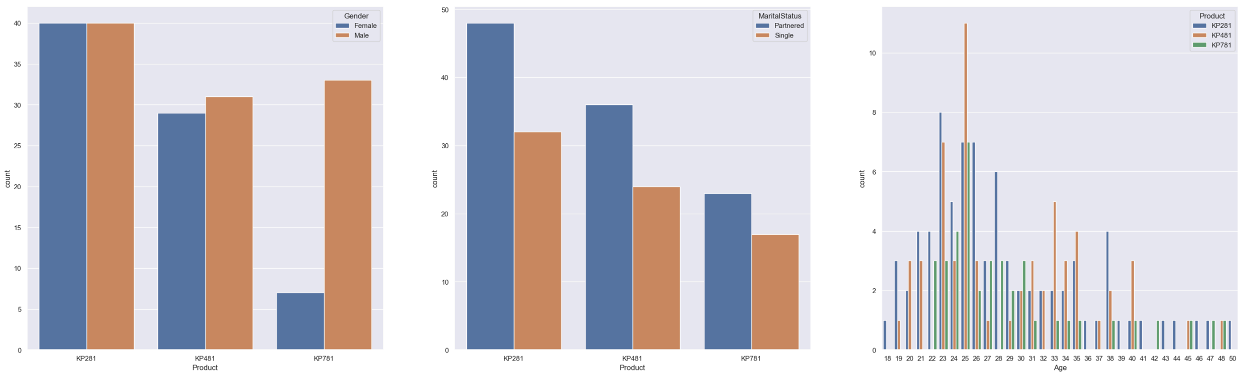
Observations

- most popular treadmill is the `KP281`
- most of the customers are `Male`
- most customers that purchase treadmills are `Partnered`

Bivariate Analysis

Checking if features have any effect on product being purchased.

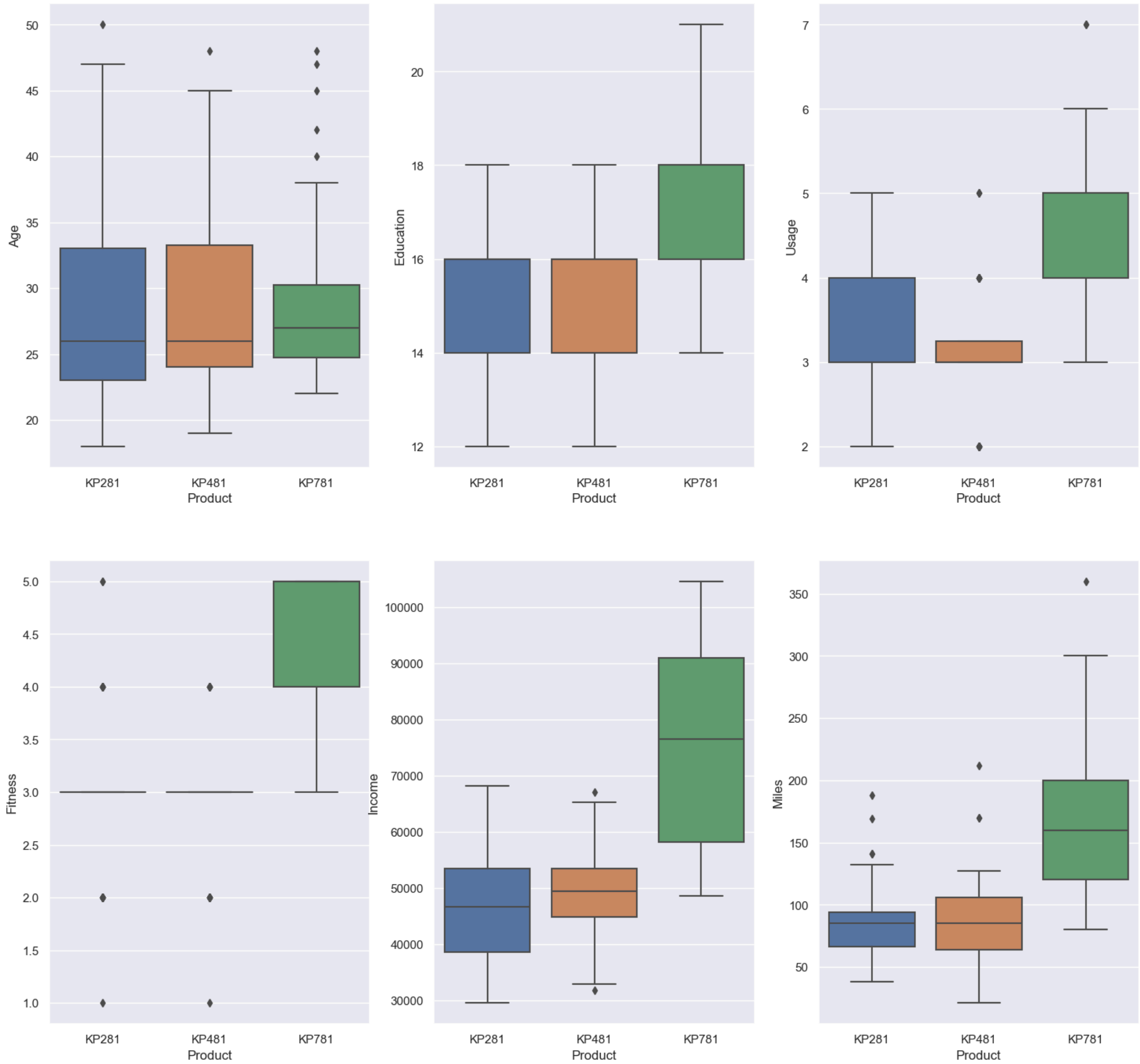
In [29]:
```
fig, axis = plt.subplots(nrows = 1, ncols = 3, figsize=(35,10))
sns.countplot(data = df, x = 'Product', hue = 'Gender', ax = axis[0])
sns.countplot(data = df, x = 'Product', hue = 'MaritalStatus', ax = axis[1])
sns.countplot(data = df, x = 'Age', hue = 'Product', ax = axis[2])

plt.show()
```



Observations

- Equal number of males and females have purchased the `KP281` which is the most desirable
- Most of the purchases were from `partnered` customers
- Customers of the `age 25` are more likely to purchase the `KP481`

In [30]:
```
attributes = ['Age', 'Education', 'Usage', 'Fitness', 'Income', 'Miles']
sns.set(color_codes = True)
fig,axis = plt.subplots(nrows = 2, ncols = 3, figsize = (18,12))
fig.subplots_adjust(top = 1.2)
count = 0
for i in range(2):
    for j in range(3):
        sns.boxplot(data = df, x = 'Product', y = attributes[count], ax = axis[i,j])
        count += 1
```



Observations

Product vs Age

- `KP281` and `KP481` share the same customer's median `Age`.
- Customers between age 25 - 30 are likely to purchase the `KP781`.

Product vs Education

- Customers that has over 16 years of education are more likely to purchase `KP781`.
- Customers with less than 16 years of education have equal chance of purchasing `KP281` or `KP481`.

Product vs Usage

- Customers who purchased `KP781` are likely to use it more than 4 times a week.

Product vs Fitness

- Customers with high fitness level (fitness > 3) have a higher chance of purchasing the `KP781`.

Product vs Income

- Customers with higher income (income > 60,000) are more likely to purchase the `KP781`.

Product vs Miles

- Customers that walk/run for more than 120 miles per week are likelier to buy the `KP781`.

Correlation Analysis

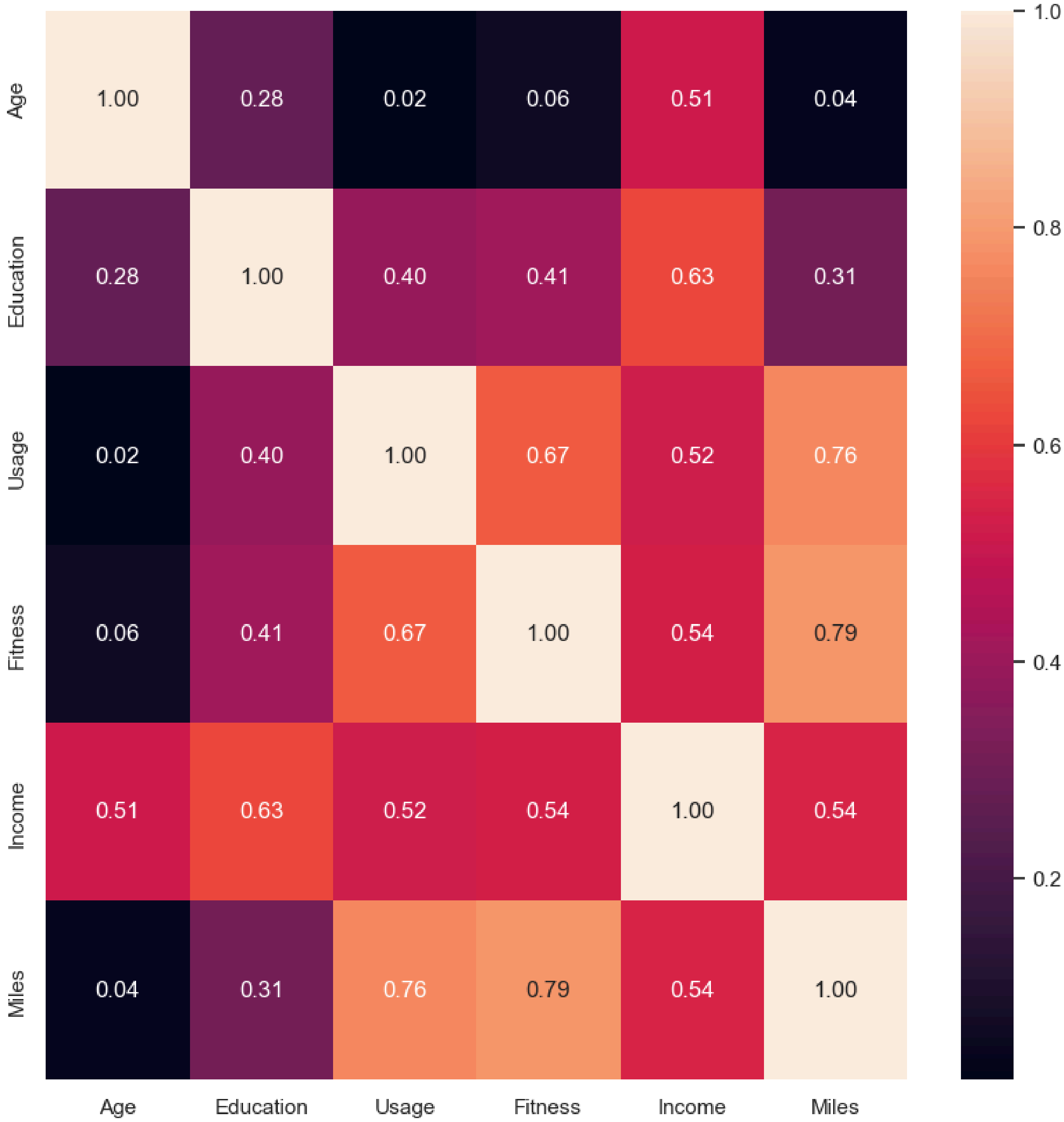
In [31]:
```
df.corr()
```

Out[31]:

	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

Heatmaps

In [34]:
```
fig, ax = plt.subplots(figsize=(10,10))
sns.set(color_codes=True)
sns.heatmap(df.corr(), ax=ax, annot=True, fmt='0.2f')
plt.show()
```



Observation

- (`Miles` & `Usage`) and (`Miles` & `Fitness`) attributes are highly correlated which means fit customers tend to use more treadmills.
- `Income` and `Education` shows a strong correlation. Customers with high income and very educated prefer the `KP781` treadmill.