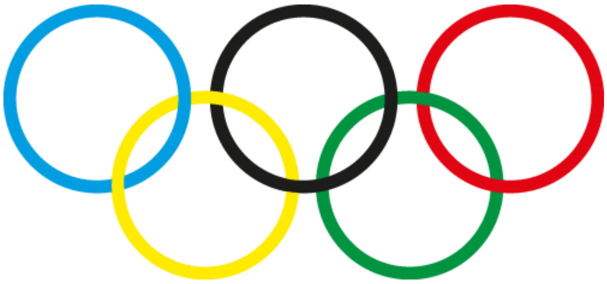
# Olympics Games EDA Project



## Context:

- The data includes 120 years (1896 to 2016) of Olympic games with information about athletes and medal results.
- This dataset provides an opportunity to ask questions about how the Olympics have evolved over time, including questions about the participation and performance according to genders, different nations, and different sports and events.
- Check out the original source if you are interested in using this data for other purposes (https://www.kaggle.com/heesoo37/120-years-of-olympic-history-athletes-and-results)

## Dataset Description:

Each row corresponds to an individual athlete competing in an individual Olympic event.

The columns are:

- **ID**: Unique number for each athlete
- **Name**: Athlete's name
- **Sex**: M or F
- **Age**: Integer
- **Height**: In centimeters
- **Weight**: In kilograms
- **Team**: Team name
- **NOC**: National Olympic Committee 3-letter code
- **Games**: Year and season
- **Year**: Integer
- **Season**: Summer or Winter
- **City**: Host city
- **Sport**: Sport
- **Event**: Event
- **Medal**: Gold, Silver, Bronze, or NA

## Objective:

- Examine/clean the dataset
- Explore distributions of single numerical and categorical features via statistics and plots
- Explore relationships of multiple features via statistics and plots

### Importing the libraries `Pandas` and `Seaborn`

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
```

### Importing the dataset

In [2]:
```
olympics = pd.read_csv('athlete_events.csv')
```

### Getting Basic Information about the Dataset

In [3]:
```
olympics.head()
```

Out[3]:

| | ID | Name | Sex | Age | Height | Weight | Team | NOC | Games | Year | Season | City | Sport | Event | Medal |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | A Dijiang | M | 24.0 | 180.0 | 80.0 | China | CHN | 1992 Summer | 1992 | Summer | Barcelona | Basketball | Basketball Men's Basketball | NaN |
| **1** | 2 | A Lamusi | M | 23.0 | 170.0 | 60.0 | China | CHN | 2012 Summer | 2012 | Summer | London | Judo | Judo Men's Extra-Lightweight | NaN |
| **2** | 3 | Gunnar Nielsen Aaby | M | 24.0 | NaN | NaN | Denmark | DEN | 1920 Summer | 1920 | Summer | Antwerpen | Football | Football Men's Football | NaN |
| **3** | 4 | Edgar Lindenau Aabye | M | 34.0 | NaN | NaN | Denmark/Sweden | DEN | 1900 Summer | 1900 | Summer | Paris | Tug-Of-War | Tug-Of-War Men's Tug-Of-War | Gold |
| **4** | 5 | Christine Jacoba Aaftink | F | 21.0 | 185.0 | 82.0 | Netherlands | NED | 1988 Winter | 1988 | Winter | Calgary | Speed Skating | Speed Skating Women's 500 metres | NaN |

In [4]:
```
olympics.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 271116 entries, 0 to 271115
Data columns (total 15 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   ID      271116 non-null  int64  
 1   Name    271116 non-null  object 
 2   Sex     271116 non-null  object 
 3   Age     261642 non-null  float64
 4   Height  210945 non-null  float64
 5   Weight  208241 non-null  float64
 6   Team    271116 non-null  object 
 7   NOC     271116 non-null  object 
 8   Games   271116 non-null  object 
 9   Year    271116 non-null  int64  
 10  Season  271116 non-null  object 
 11  City    271116 non-null  object 
 12  Sport   271116 non-null  object 
 13  Event   271116 non-null  object 
 14  Medal   39783 non-null   object 
dtypes: float64(3), int64(2), object(10)
memory usage: 31.0+ MB
```

In [5]:

```
olympics.describe()
```

Out[5]:

| | ID | Age | Height | Weight | Year |
|---|---|---|---|---|---|
| **count** | 271116.000000 | 261642.000000 | 210945.000000 | 208241.000000 | 271116.000000 |
| **mean** | 68248.954396 | 25.556898 | 175.338970 | 70.702393 | 1978.378480 |
| **std** | 39022.286345 | 6.393561 | 10.518462 | 14.348020 | 29.877632 |
| **min** | 1.000000 | 10.000000 | 127.000000 | 25.000000 | 1896.000000 |
| **25%** | 34643.000000 | 21.000000 | 168.000000 | 60.000000 | 1960.000000 |
| **50%** | 68205.000000 | 24.000000 | 175.000000 | 70.000000 | 1988.000000 |
| **75%** | 102097.250000 | 28.000000 | 183.000000 | 79.000000 | 2002.000000 |
| **max** | 135571.000000 | 97.000000 | 226.000000 | 214.000000 | 2016.000000 |

## Imputing the missing values in the dataset

### Using `IterativeImputer` in `sklearn` to impute based on columns `Year`, `Age`, `Height`, `Weight`

Importing libraries

In [6]:

```
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
```

Building a list of columns that will be used for imputation, which are `Year`, `Age`, `Height`, `Weight`

In [7]:

```
impute_cols = olympics[['Year', 'Age', 'Height', 'Weight']].columns
impute_cols
```

Out[7]:

```
Index(['Year', 'Age', 'Height', 'Weight'], dtype='object')
```

Creating an `IterativeImputer` object

In [8]:

```
iter_imp = IterativeImputer(min_value=olympics[impute_cols].min(), max_value=olympics[impute_cols].max())
```

Applying the imputer to fit and transform the columns

In [9]:

```
imputed_cols = iter_imp.fit_transform(olympics[impute_cols])
```

Assigning the imputed array back to the original DataFrame's columns

In [10]:

```
olympics[impute_cols] = imputed_cols
```

Checking the columns for missing values

In [11]:

```
olympics.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 271116 entries, 0 to 271115
Data columns (total 15 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   ID      271116 non-null  int64  
 1   Name    271116 non-null  object 
 2   Sex     271116 non-null  object 
 3   Age     271116 non-null  float64
 4   Height  271116 non-null  float64
 5   Weight  271116 non-null  float64
 6   Team    271116 non-null  object 
 7   NOC     271116 non-null  object 
 8   Games   271116 non-null  object 
 9   Year    271116 non-null  float64
 10  Season  271116 non-null  object 
 11  City    271116 non-null  object 
 12  Sport   271116 non-null  object 
 13  Event   271116 non-null  object 
 14  Medal   39783 non-null   object 
dtypes: float64(4), int64(1), object(10)
memory usage: 31.0+ MB
```

### Filling the missing values in the column `Medal` with string of 'NA'

In [12]:

```
olympics['Medal'] = olympics['Medal'].fillna('NA')
```

Double checking that all columns are imputed

In [13]:
```
olympics.info()
```

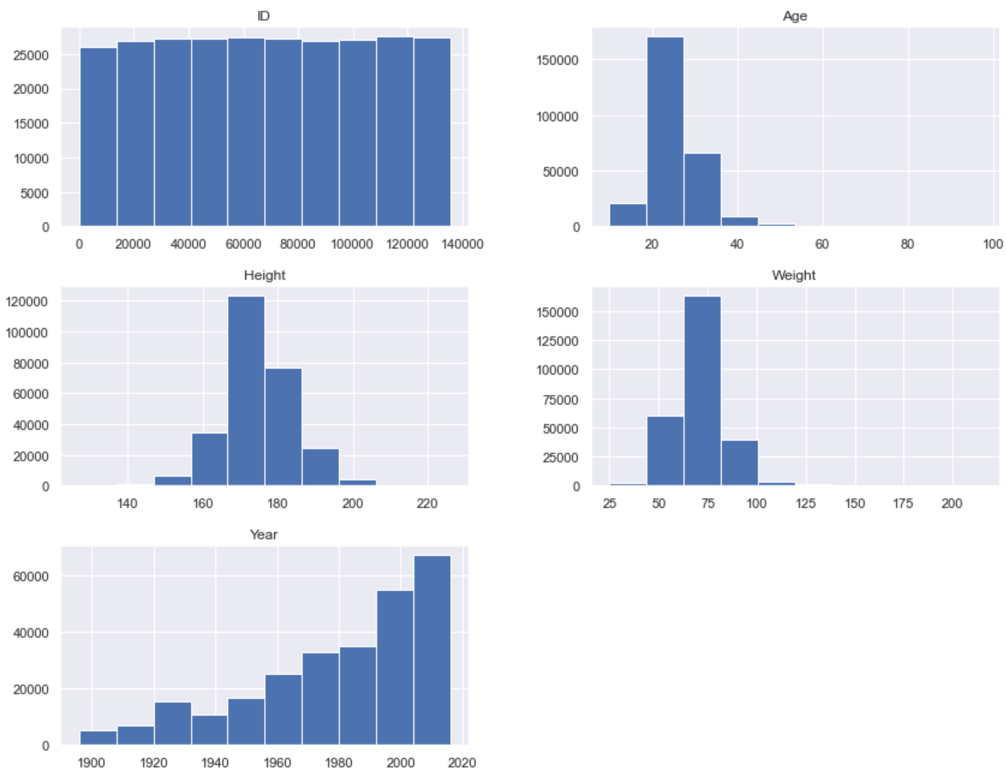
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 271116 entries, 0 to 271115
Data columns (total 15 columns):
 #   Column  Non-Null Count   Dtype  
---  ------  --------------   -----  
 0   ID      271116 non-null  int64  
 1   Name    271116 non-null  object 
 2   Sex     271116 non-null  object 
 3   Age     271116 non-null  float64
 4   Height  271116 non-null  float64
 5   Weight  271116 non-null  float64
 6   Team    271116 non-null  object 
 7   NOC     271116 non-null  object 
 8   Games   271116 non-null  object 
 9   Year    271116 non-null  float64
 10  Season  271116 non-null  object 
 11  City    271116 non-null  object 
 12  Sport   271116 non-null  object 
 13  Event   271116 non-null  object 
 14  Medal   271116 non-null  object 
dtypes: float64(4), int64(1), object(10)
memory usage: 31.0+ MB
```

In [14]:
```
olympics.isnull().sum()
```

Out[14]:
```
ID        0
Name      0
Sex       0
Age       0
Height    0
Weight    0
Team      0
NOC       0
Games     0
Year      0
Season    0
City      0
Sport     0
Event     0
Medal     0
dtype: int64
```

## 1. Ploting the histograms of the numerical columns using `Pandas`

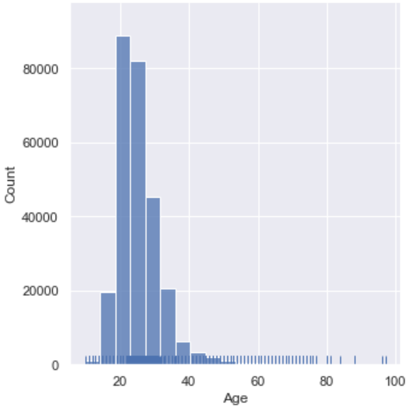
In [15]:
```
olympics.hist(figsize=(14,11))
plt.show()
```




## 2. Ploting the histogram with a rug plot of the column `Age` using `Seaborn`

In [16]:
```
sns.displot(data=olympics, x='Age', bins=20, rug=True)
```

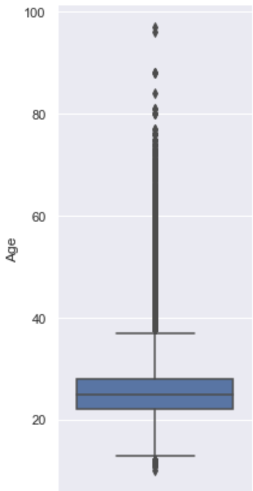
Out[16]:
```
<seaborn.axisgrid.FacetGrid at 0x2156f3afe48>
```




### 3. Ploting the boxplot of the column `Age` using `Seaborn`

In [17]:
```
sns.catplot(data=olympics, y='Age', kind='box', height=6, aspect=0.5)
```

Out[17]: <seaborn.axisgrid.FacetGrid at 0x2157a1dc208>




### 4. Calculate the first quartile, third quartile, and IQR of the column `Age`

In [18]:
```
Q1 = olympics['Age'].quantile(0.25)
Q3 = olympics['Age'].quantile(0.75)
IQR = Q3 - Q1
```

In [19]:
```
print(Q1)
print(Q3)
print(IQR)
```

```
22.0
28.0
6.0
```

### 5. Print out the lower and upper thresholds for outliers based on IQR for the column `Age`

In [20]:
```
print(f'Low age outlier threshold: {Q1 - 1.5*IQR}')
print(f'High age outlier threshold: {Q3 + 1.5*IQR}')
```

```
Low age outlier threshold: 13.0
High age outlier threshold: 37.0
```

### Q1. What are the `Sport` for the athletes of really young age

In [21]:
```
olympics[olympics['Age'] < (Q1 - 1.5*IQR)]['Sport'].value_counts()
```

Out[21]:
```
Swimming         25
Figure Skating   15
Gymnastics        5
Rowing            5
Athletics         2
Diving            1
Name: Sport, dtype: int64
```

### Q2. What are the `Sport` for the athletes of older age

In [22]:
```
olympics[olympics['Age'] < (Q1 + 1.5*IQR)]['Sport'].value_counts()
```

Out[22]:
```
Athletics      34307
Gymnastics     25039
Swimming       22923
Cycling         9661
Rowing          9471
```

```
                ...
Racquets           8
Jeu De Paume       5
Basque Pelota      2
Roque              1
Aeronautics        1
Name: Sport, Length: 66, dtype: int64
```

## Q3. Check for the number of unique values in each column

In [23]:
```
olympics.nunique()
```

Out[23]:
```
ID        135571
Name      134732
Sex            2
Age          785
Height      2475
Weight      3565
Team        1184
NOC          230
Games         51
Year          35
Season         2
City          42
Sport         66
Event        765
Medal          4
dtype: int64
```

## Q4. Use the `describe` method to check the non-numerical columns

In [24]:
```
olympics.describe(include=['object'])
```

Out[24]:

| | Name | Sex | Team | NOC | Games | Season | City | Sport | Event | Medal |
|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 271116 | 271116 | 271116 | 271116 | 271116 | 271116 | 271116 | 271116 | 271116 | 271116 |
| **unique** | 134732 | 2 | 1184 | 230 | 51 | 2 | 42 | 66 | 765 | 4 |
| **top** | Robert Tait McKenzie | M | United States | USA | 2000 Summer | Summer | London | Athletics | Football Men's Football | NA |
| **freq** | 58 | 196594 | 17847 | 18853 | 13821 | 222552 | 22426 | 38624 | 5733 | 231333 |

## Q5. Check the first record within the dataset for each Olympic `Sport`

In [25]:
```
olympics = olympics.sort_values('Year')
```

In [26]:
```
olympics
```

Out[26]:

| | ID | Name | Sex | Age | Height | Weight | Team | NOC | Games | Year | Season | City | Sport | Event | Medal |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **214333** | 107607 | Fritz Richard Gustav Schuft | M | 19.0 | 172.176206 | 67.355351 | Germany | GER | 1896 Summer | 1896.0 | Summer | Athina | Gymnastics | Gymnastics Men's Pommelled Horse | NA |
| **244717** | 122526 | Pierre Alexandre Tuffri | M | 19.0 | 172.176206 | 67.355351 | France | FRA | 1896 Summer | 1896.0 | Summer | Athina | Athletics | Athletics Men's Triple Jump | Silver |
| **244716** | 122526 | Pierre Alexandre Tuffri | M | 19.0 | 172.176206 | 67.355351 | France | FRA | 1896 Summer | 1896.0 | Summer | Athina | Athletics | Athletics Men's Long Jump | NA |
| **23912** | 12563 | Conrad Helmut Fritz Bcker | M | 25.0 | 173.609502 | 70.511914 | Germany | GER | 1896 Summer | 1896.0 | Summer | Athina | Gymnastics | Gymnastics Men's Horse Vault | NA |
| **23913** | 12563 | Conrad Helmut Fritz Bcker | M | 25.0 | 173.609502 | 70.511914 | Germany | GER | 1896 Summer | 1896.0 | Summer | Athina | Gymnastics | Gymnastics Men's Parallel Bars | NA |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **142355** | 71419 | Luis Fernando Lpez Erazo | M | 37.0 | 166.000000 | 60.000000 | Colombia | COL | 2016 Summer | 2016.0 | Summer | Rio de Janeiro | Athletics | Athletics Men's 20 kilometres Walk | NA |
| **47729** | 24610 | Enrico D'Aniello | M | 20.0 | 152.000000 | 53.000000 | Italy | ITA | 2016 Summer | 2016.0 | Summer | Rio de Janeiro | Rowing | Rowing Men's Coxed Eights | NA |
| **47728** | 24609 | Sabrina D'Angelo | F | 23.0 | 173.000000 | 71.000000 | Canada | CAN | 2016 Summer | 2016.0 | Summer | Rio de Janeiro | Football | Football Women's Football | Bronze |
| **47746** | 24621 | Andrea Mitchell D'Arrigo | M | 21.0 | 194.000000 | 85.000000 | Italy | ITA | 2016 Summer | 2016.0 | Summer | Rio de Janeiro | Swimming | Swimming Men's 200 metres Freestyle | NA |
| **236646** | 118650 | Blair Tarrant | M | 26.0 | 185.000000 | 83.000000 | New Zealand | NZL | 2016 Summer | 2016.0 | Summer | Rio de Janeiro | Hockey | Hockey Men's Hockey | NA |

271116 rows × 15 columns

In [27]:
```
olympics.groupby('Sport').first()
```

Out[27]:

| | ID | Name | Sex | Age | Height | Weight | Team | NOC | Games | Year | Season | City | Event | Medal |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Sport** | | | | | | | | | | | | | | |
| **Aeronautics** | 107506 | Hermann Schreiber | M | 26.000000 | 174.589865 | 71.098729 | Switzerland | SUI | 1936 Summer | 1936.0 | Summer | Berlin | Aeronautics Mixed Aeronautics | Gold |
| **Alpine Skiing** | 32818 | Reat Erce | M | 17.000000 | 172.439922 | 66.363886 | Turkey | TUR | 1936 Winter | 1936.0 | Winter | Garmisch-Partenkirchen | Alpine Skiing Men's Combined | NA |
| **Alpinism** | 74134 | George Herbert Leigh Mallory | M | 37.000000 | 176.995129 | 76.867544 | Great Britain | GBR | 1924 Winter | 1924.0 | Winter | Chamonix | Alpinism Mixed Alpinism | Gold |
| **Archery** | 67722 | Lecomte | M | 27.618563 | 174.310796 | 71.897322 | France | FRA | 1900 Summer | 1900.0 | Summer | Paris | Archery Men's Au Cordon Dore, 50 metres | NA |

| Sport | ID | Name | Sex | Age | Height | Weight | Team | NOC | Games | Year | Season | City | Event | Medal |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Art Competitions | 48741 | Konrad Hippenmeier | M | 31.000000 | 175.339389 | 73.692765 | Switzerland | SUI | 1912 Summer | 1912.0 | Summer | Stockholm | Art Competitions Mixed Architecture | NA |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| Tug-Of-War | 86368 | August Nilsson | M | 27.000000 | 174.161415 | 71.570173 | Denmark/Sweden | SWE | 1900 Summer | 1900.0 | Summer | Paris | Tug-Of-War Men's Tug-Of-War | Gold |
| Volleyball | 14306 | Georgi Spasov Boyadzhiev | M | 21.000000 | 177.000000 | 76.000000 | Bulgaria | BUL | 1964 Summer | 1964.0 | Summer | Tokyo | Volleyball Men's Volleyball | NA |
| Water Polo | 74733 | Auguste Jean Baptiste Louis Joseph Marc | M | 19.000000 | 172.250355 | 67.361423 | Pupilles de Neptune de Lille #2-1 | FRA | 1900 Summer | 1900.0 | Summer | Paris | Water Polo Men's Water Polo | Bronze |
| Weightlifting | 54456 | Alexander Viggo Jensen | M | 21.000000 | 172.653972 | 68.407539 | Denmark | DEN | 1896 Summer | 1896.0 | Summer | Athina | Weightlifting Men's Unlimited, One Hand | Silver |
| Wrestling | 122329 | Georgios Tsitas | M | 27.721559 | 174.261331 | 71.945520 | Greece | GRE | 1896 Summer | 1896.0 | Summer | Athina | Wrestling Men's Unlimited Class, Greco-Roman | Silver |

66 rows × 14 columns

## Q6. What are the average `Age`, `Height`, `Weight` of female versus male Olympic athletes

In [28]:
```
olympics.groupby('Sex')[['Age', 'Height', 'Weight']].mean()
```

Out[28]:

| Sex | Age | Height | Weight |
|---|---|---|---|
| F | 23.748234 | 168.476034 | 60.960650 |
| M | 26.302496 | 177.859161 | 74.740574 |

## Q7. What are the minimum, average, maximum `Age`, `Height`, `Weight` of athletes in different `Year`

In [29]:
```
olympics.groupby('Year')[['Age', 'Height', 'Weight']].agg(['min', 'mean', 'max'])
```

Out[29]:

| | Age | | | Height | | | Weight | | |
|---|---|---|---|---|---|---|---|---|---|
| Year | min | mean | max | min | mean | max | min | mean | max |
| 1896.0 | 10.0 | 25.364356 | 40.0 | 154.0 | 173.569607 | 188.000000 | 45.000000 | 70.982411 | 106.0 |
| 1900.0 | 13.0 | 28.454101 | 71.0 | 153.0 | 174.664627 | 191.000000 | 51.000000 | 72.502816 | 102.0 |
| 1904.0 | 14.0 | 26.867754 | 71.0 | 155.0 | 174.435046 | 195.000000 | 43.000000 | 71.715326 | 115.0 |
| 1906.0 | 13.0 | 27.272610 | 54.0 | 165.0 | 174.946975 | 196.000000 | 52.000000 | 72.309427 | 114.0 |
| 1908.0 | 14.0 | 27.061116 | 61.0 | 157.0 | 175.059627 | 201.000000 | 51.000000 | 72.484058 | 115.0 |
| 1912.0 | 13.0 | 27.528582 | 67.0 | 157.0 | 175.149494 | 200.000000 | 49.000000 | 72.354296 | 125.0 |
| 1920.0 | 13.0 | 28.861062 | 72.0 | 142.0 | 175.220153 | 218.770915 | 33.074491 | 72.791440 | 146.0 |
| 1924.0 | 11.0 | 28.101622 | 81.0 | 142.0 | 174.980222 | 218.578230 | 34.356723 | 72.217506 | 146.0 |
| 1928.0 | 11.0 | 28.728275 | 97.0 | 147.0 | 175.282553 | 211.000000 | 41.000000 | 72.568654 | 125.0 |
| 1932.0 | 11.0 | 32.002855 | 96.0 | 147.0 | 175.826347 | 200.000000 | 40.090648 | 73.867313 | 110.0 |
| 1936.0 | 11.0 | 27.506104 | 74.0 | 147.0 | 175.155241 | 205.000000 | 37.000000 | 71.960859 | 138.0 |
| 1948.0 | 12.0 | 28.407495 | 84.0 | 140.0 | 175.567741 | 213.000000 | 47.000000 | 72.408041 | 125.0 |
| 1952.0 | 12.0 | 26.165217 | 65.0 | 150.0 | 174.812820 | 213.000000 | 42.000000 | 71.097510 | 145.0 |
| 1956.0 | 12.0 | 25.949715 | 67.0 | 137.0 | 174.607226 | 218.000000 | 28.000000 | 71.041599 | 141.0 |
| 1960.0 | 11.0 | 25.187182 | 65.0 | 137.0 | 173.316035 | 218.000000 | 36.000000 | 69.480564 | 141.0 |
| 1964.0 | 12.0 | 24.948374 | 60.0 | 137.0 | 173.546073 | 218.000000 | 38.000000 | 69.759825 | 163.0 |
| 1968.0 | 11.0 | 24.263374 | 68.0 | 127.0 | 173.959439 | 216.000000 | 34.000000 | 69.609517 | 163.0 |
| 1972.0 | 12.0 | 24.318900 | 69.0 | 130.0 | 174.562405 | 223.000000 | 38.000000 | 70.003339 | 182.0 |
| 1976.0 | 12.0 | 23.850452 | 70.0 | 136.0 | 174.865117 | 220.000000 | 30.000000 | 70.000335 | 163.0 |
| 1980.0 | 13.0 | 23.734613 | 70.0 | 131.0 | 175.508742 | 220.000000 | 25.000000 | 70.624903 | 190.0 |
| 1984.0 | 12.0 | 23.925675 | 60.0 | 132.0 | 175.524970 | 218.000000 | 31.000000 | 70.257754 | 150.0 |
| 1988.0 | 11.0 | 24.085104 | 70.0 | 127.0 | 175.698459 | 223.000000 | 32.000000 | 70.443543 | 161.0 |
| 1992.0 | 11.0 | 24.319680 | 62.0 | 136.0 | 175.959574 | 226.000000 | 30.000000 | 70.862030 | 176.5 |
| 1994.0 | 13.0 | 24.422594 | 46.0 | 148.0 | 175.158296 | 200.000000 | 40.000000 | 70.972262 | 113.0 |
| 1996.0 | 12.0 | 24.915179 | 63.0 | 136.0 | 175.836214 | 223.000000 | 30.000000 | 70.818289 | 176.5 |
| 1998.0 | 14.0 | 25.163160 | 50.0 | 142.0 | 174.589636 | 200.000000 | 32.000000 | 70.898616 | 123.0 |
| 2000.0 | 13.0 | 25.422476 | 63.0 | 136.0 | 176.085713 | 226.000000 | 28.000000 | 71.106805 | 180.0 |
| 2002.0 | 15.0 | 25.916281 | 48.0 | 149.0 | 174.709888 | 201.000000 | 42.000000 | 71.164405 | 123.0 |
| 2004.0 | 13.0 | 25.639515 | 57.0 | 139.0 | 175.971393 | 226.000000 | 30.000000 | 71.284135 | 198.0 |
| 2006.0 | 14.0 | 25.959151 | 52.0 | 147.0 | 174.628393 | 206.000000 | 38.000000 | 70.512440 | 127.0 |

| | Age | | | Height | | | Weight | | |
|---|---|---|---|---|---|---|---|---|---|
| | min | mean | max | min | mean | max | min | mean | max |
| Year | | | | | | | | | |
| **2008.0** | 12.0 | 25.733541 | 67.0 | 137.0 | 176.209780 | 226.000000 | 28.000000 | 71.375322 | 214.0 |
| **2010.0** | 15.0 | 26.124262 | 51.0 | 149.0 | 174.918873 | 206.000000 | 38.000000 | 70.733917 | 116.0 |
| **2012.0** | 13.0 | 25.961378 | 71.0 | 140.0 | 176.247158 | 221.000000 | 30.071474 | 71.173434 | 214.0 |
| **2014.0** | 15.0 | 25.987324 | 55.0 | 146.0 | 174.818773 | 206.000000 | 38.066881 | 70.572661 | 116.0 |
| **2016.0** | 13.0 | 26.207919 | 62.0 | 133.0 | 176.024469 | 218.000000 | 30.000000 | 70.966084 | 170.0 |

### Q8. What are the minimum, average, median, maximum `Age` of athletes for different `Season` and `Sex` combinations

In [30]:
```
olympics.groupby(['Season', 'Sex'])['Age'].agg(['min', 'median', 'mean', 'max'])
```

Out[30]:

| | | min | median | mean | max |
|---|---|---|---|---|---|
| Season | Sex | | | | |
| **Summer** | **F** | 11.0 | 23.0 | 23.680377 | 74.0 |
| | **M** | 10.0 | 25.0 | 26.464649 | 97.0 |
| **Winter** | **F** | 11.0 | 24.0 | 24.015736 | 48.0 |
| | **M** | 12.0 | 25.0 | 25.512635 | 58.0 |

### Q9. What are the average `Age` of athletes, and numbers of unique `Team`, `Sport`, `Event`, for different `Season` and `Sex` combinations

In [31]:
```
olympics.groupby(['Season', 'Sex'])[['Age', 'Team', 'Sport', 'Event']].agg({'Age':'mean', 'Team':'nunique', 'Sport':'nunique', 'Event':'nunique'})
```

Out[31]:

| | | Age | Team | Sport | Event |
|---|---|---|---|---|---|
| Season | Sex | | | | |
| **Summer** | **F** | 23.680377 | 352 | 40 | 214 |
| | **M** | 26.464649 | 1118 | 49 | 491 |
| **Winter** | **F** | 24.015736 | 144 | 14 | 57 |
| | **M** | 25.512635 | 214 | 17 | 67 |

### Q10. What are the average `Age`, `Height`, `Weight` of athletes, for different `Medal`, `Season`, `Sex` combinations

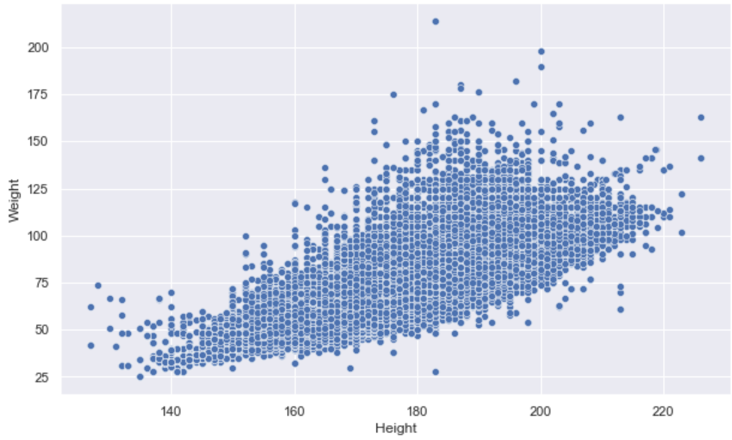
In [32]:
```
olympics.groupby(['Medal', 'Season', 'Sex'])[['Age', 'Height', 'Weight']].mean()
```

Out[32]:

| | | | Age | Height | Weight |
|---|---|---|---|---|---|
| Medal | Season | Sex | | | |
| **Bronze** | **Summer** | **F** | 24.637527 | 171.110734 | 63.903325 |
| | | **M** | 26.382673 | 179.283138 | 76.834194 |
| | **Winter** | **F** | 25.115578 | 167.339043 | 61.132946 |
| | | **M** | 26.387043 | 178.831087 | 77.296962 |
| **Gold** | **Summer** | **F** | 24.215093 | 171.594933 | 64.252235 |
| | | **M** | 26.501307 | 179.803255 | 77.426878 |
| | **Winter** | **F** | 25.202636 | 167.563734 | 62.006768 |
| | | **M** | 26.606436 | 179.569202 | 78.047604 |
| **NA** | **Summer** | **F** | 23.547521 | 168.283937 | 60.468257 |
| | | **M** | 26.454123 | 177.557129 | 74.215742 |
| | **Winter** | **F** | 23.855915 | 167.281733 | 60.539905 |
| | | **M** | 25.386328 | 177.741840 | 74.861337 |
| **Silver** | **Summer** | **F** | 24.296089 | 171.310947 | 63.903671 |
| | | **M** | 26.690500 | 179.391244 | 77.017761 |
| | **Winter** | **F** | 25.240527 | 167.916040 | 61.921625 |
| | | **M** | 26.430566 | 179.030573 | 77.429293 |

### Q11. Plot the scatterplot of `Height` and `Weight`

In [33]:
```
plt.figure(figsize=(10,6))
sns.scatterplot(data=olympics, x='Height', y='Weight')
plt.show()
```




### Q12. Plot the scatterplot of `Height` and `Weight`, using different colors and styles of dots for different `Sex`

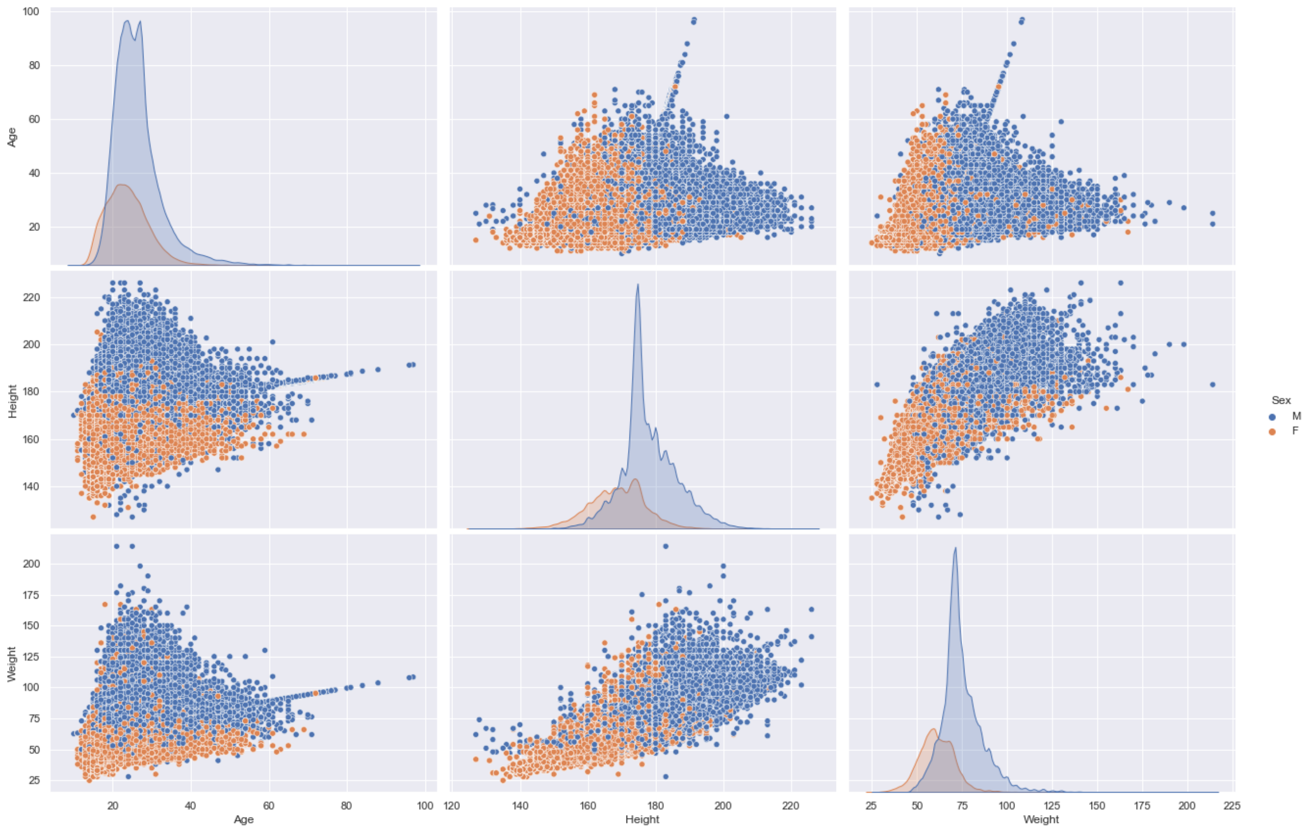
In [34]:
```
plt.figure(figsize=(10,6))
sns.scatterplot(data=olympics, x='Height', y='Weight', hue='Sex')
plt.show()
```


### Q13. Plot the pairwise relationships of `Age`, `Height`, `Weight`

In [35]:
```
sns.pairplot(data=olympics[['Age', 'Height', 'Weight']], height=4, aspect=1.5)
plt.show()
```


### Q14. Plot the pairwise relationships of `Age`, `Height`, `Weight`, with different colors for `Sex`

In [36]:
```
sns.pairplot(data=olympics[['Age', 'Height', 'Weight', 'Sex']], hue='Sex', height=4, aspect=1.5)
plt.show()
```




### Q15. Print out the correlation matrix of `Age`, `Height`, `Weight`

In [37]:
```
olympics[['Age', 'Height', 'Weight']].corr()
```

Out[37]:

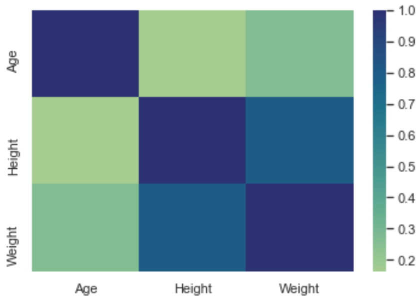
| | Age | Height | Weight |
|---|---|---|---|
| **Age** | 1.000000 | 0.161797 | 0.264409 |
| **Height** | 0.161797 | 1.000000 | 0.799258 |

| | Age | Height | Weight |
|---|---|---|---|
| **Weight** | 0.264409 | 0.799258 | 1.000000 |

### Q16. Use heatmap to demonstrate the correlation matrix of `Age`, `Height`, `Weight`, use a colormap (`cmap`) of 'crest'

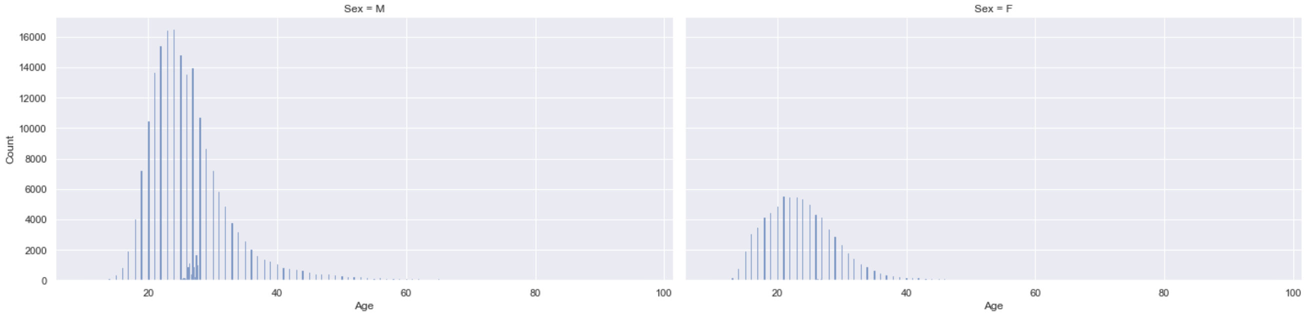
In [38]:
```
sns.heatmap(data=olympics[['Age', 'Height', 'Weight']].corr(), cmap='crest')
```

Out[38]: <AxesSubplot:>



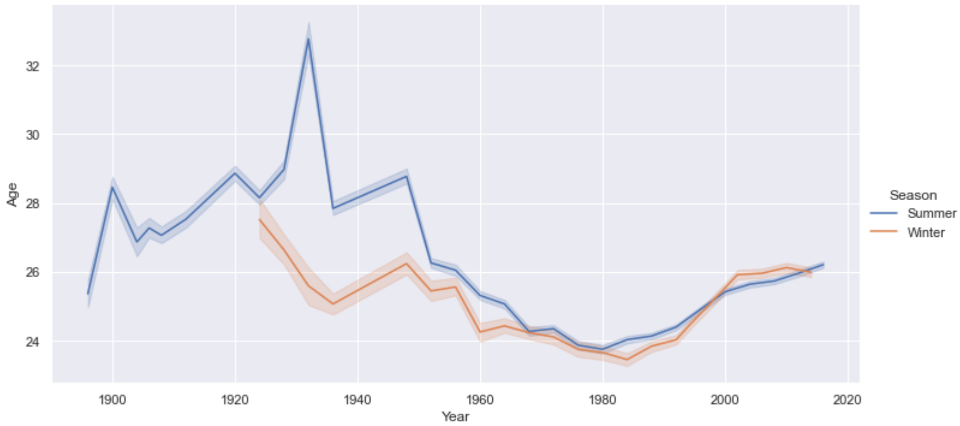

### Q17. Plot the histograms of `Age`, on separate plots for different `Sex`

In [39]:
```
sns.displot(data=olympics, x='Age', col='Sex', aspect=2)
plt.show()
```



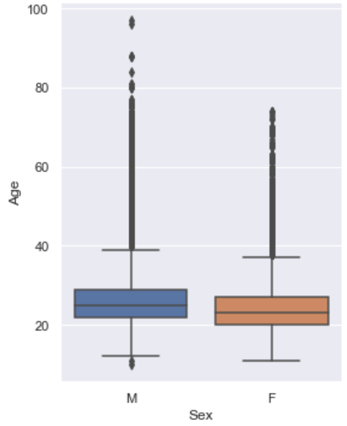

### Q18. Look at the changes of average `Age` across `Year` by line charts, with separate lines for different `Season` using different colors

In [40]:
```
sns.relplot(data=olympics, x='Year', y='Age', kind='line', hue='Season', aspect=2)
plt.show()
```



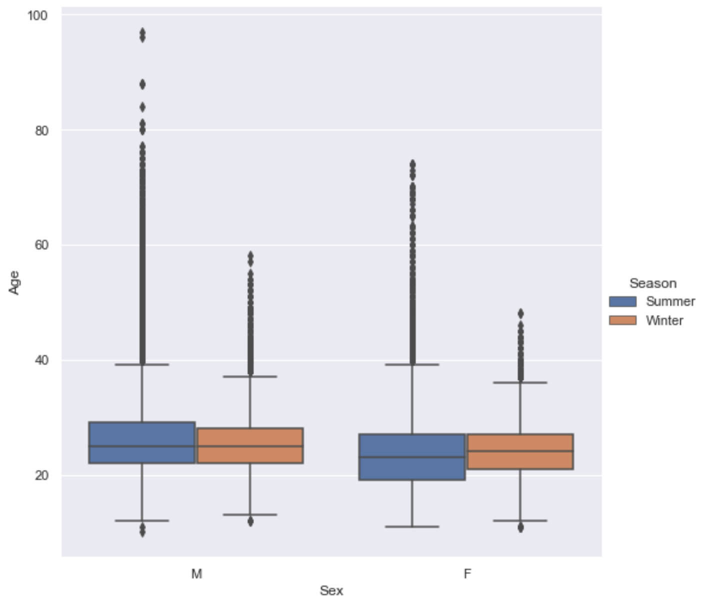

### Q19. Look at the distributions of `Age` for different `Sex` using boxplots

In [41]:
```
sns.catplot(data=olympics, y='Age', kind='box', x='Sex', height=5, aspect=0.8)
plt.show()
```




### Q20. Look at the distributions of `Age` for different `Sex` using boxplots, with different colors of plots for different `Season`

In [42]:
```
sns.catplot(data=olympics, y='Age', kind='box', x='Sex', hue='Season', height=7, aspect=1)
plt.show()
```




### Q21. Use count plots to look at the changes of number of athlete-events across `Year`, for different `Sex` by colors, and different `Season` on separate plots

In [43]:
```
sns.catplot(data=olympics, x='Year', kind='count', hue='Sex', col='Season', col_wrap=1, aspect=4)
plt.show()
```