Milestone 1: Project Proposal and Data Selection/Preparation

Step 1: Preparing for Your Proposal

1. Which client/dataset did you select and why?

   I have chosen 'Client 3: SportsStats' with the Olympics Dataset for 120 years of data. The fact that I have chosen this client is that I spend a lot of my free time practicing sports, and I would like to get interesting insights from the dataset. in addition, the .csv files are not large and can be easily handled.

2. Describe the steps you took to import and clean the data.

   First, the data was downloaded and stored locally since the volume of files is not big, and does not require Databricks or several clusters to work with. I have used my own customized VSCode text editor for coding and querying since I am used to it. I have also used Excel to check the integrity of the data and both datasets appear to be OK.

   Second, I have used pandas from Python to read the .csv files, and the built-in to_sql() function to store the data in a MySQL dataset.

   Third, I checked the amount of NaN or NULL values to know how to deal with them, and remove them or not.

1. Perform an initial exploration of data and provide some screenshots or display some stats of the data you are looking at.

   This preliminary or initial EDA has been carried out with Pandas and Pandas SQL libraries to query the data. Other libraries like seaborn and numpy has been used to help the EDA.

   I have performed a quick EDA with simple queries. The athlete_events.csv contains 271116 entries. Some columns can be dropped, since are not relevant to this analysis, for example, the 'Team' column contains some character in the string that should be removed (e.g.: Poland-1). This is more tedious than just using the 'NOC' since it gives us the same information. Additionally, the 'Games' column is not going to be used, and we have this same information with columns 'Year' and 'Season'. Dropping these columns will not reduce the volume of data significantly like notice a speed-up in queries but would keep the data frame cleaner and simpler.

   An initial EDA with basic queries shows that there are 271116 entries or Event_ID, while there are entries that are fully completed (Sex, years, season...) and do not contain missing values, there are some others like Age, Height, and Weight, that show missing values.

1. Create an ERD or proposed ERD to show the relationships of the data you are exploring.

   The ERD shown below was intended for a small relational database, splitting them into two tables, the athletes and the event. Some modifications have been needed, for example, the column 'ID' had no unique values, so it could not be used as a primary key (PK), so a new *column "Event_ID" in the 'Event' table has been added as a PK, and as a FK in the 'Atheletes' Table.*

Image My_ERD

Step 2: Develop a Project Proposal

Description

The purpose of this project is to get some insight from the data to obtain several statistics based on athletes during different Olympic events in the last 120 years. The audience could be directed to sports enthusiasts and followers, or even coaches/trainers might find them useful. This data might be also relevant for Sports media and curiosity channels of communication.

Questions

- *How relevant is the athletes' age to affect the chance to obtain a medal in the event?*
- *What countries have more chances to get medals, those with more or fewer resources to invest in sports since early years?*
- *How is the Season-countries distribution? Are northern countries more likely to get medals in the Winter Seasons?*
- *Over the years, has the participation of men and women athletes reached equality? the participation of both are more equal in the last decades?*

Hypothesis

- *Countries at higher latitudes have better performance (medals) in Winter Sports.*
- *Female and Male participants tend to be equilibrated over the years.*
- *Developed countries have more medals on their records.*
- *It has to be an age of around 25 years, for the best winning medals.*

Approach

- *Distribution of age and Medals*
- *Distribution of medals and countries*
- *Distribution of men and women over the years*

In [57]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sqlite3 import connect

sns.set_theme(style='darkgrid')
```

Let's read the .csv files

In [58]:

```
regions = pd.read_csv('SportsStats/noc_regions.csv', sep=',')
events = pd.read_csv('SportsStats/athlete_events.csv', sep=',')
```

Let's take a look to the regions dataframe.

In [59]:

```
regions.head()
```

Out[59]:

	NOC	region	notes
0	AFG	Afghanistan	NaN
1	AHO	Curacao	Netherlands Antilles
2	ALB	Albania	NaN
3	ALG	Algeria	NaN
4	AND	Andorra	NaN

In [60]:

```python
regions.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 230 entries, 0 to 229
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   NOC     230 non-null    object
 1   region  227 non-null    object
 2   notes   21 non-null     object
dtypes: object(3)
memory usage: 5.5+ KB
```

Let's take a look to the events dataframe

In [61]:

```python
events.head()
```

Out[61]:

	ID	Name	Sex	Age	Height	Weight	Team	NOC	Games	Year	Season	
0	1	A Dijiang	M	24.0	180.0	80.0	China	CHN	1992 Summer	1992	Summer	Barcel
1	2	A Lamusi	M	23.0	170.0	60.0	China	CHN	2012 Summer	2012	Summer	Lon
2	3	Gunnar Nielsen Aaby	M	24.0	NaN	NaN	Denmark	DEN	1920 Summer	1920	Summer	Antwer
3	4	Edgar Lindenau Aabye	M	34.0	NaN	NaN	Denmark/Sweden	DEN	1900 Summer	1900	Summer	F
4	5	Christine Jacoba Aaftink	F	21.0	185.0	82.0	Netherlands	NED	1988 Winter	1988	Winter	Cal

In [62]:

```python
events.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 [63]:

```
events['Sport'].value_counts()
```

Out[63]:

```
Athletics        38624
Gymnastics       26707
Swimming         23195
Shooting         11448
Cycling          10859
                 ...
Racquets            12
Jeu De Paume        11
Roque                4
Basque Pelota        2
Aeronautics          1
Name: Sport, Length: 66, dtype: int64
```

Let's drop some columns and generate SQL tables, and add an 'Event_ID' column to them to work as a PK on the Event Table and as FK in the Athletes Table. (However, since the table is small, we will not need to make any join or especial manipulation.)

In [64]:

```
Athletes = events.drop(['Team','Games'], axis=1,inplace=False)
Athletes.insert(loc=1, column="Event_ID", value=range(1, 1 + len(Athletes)), allow_d
Event = events.drop(['ID', 'Name', 'Sex', 'Age', 'Height', 'Weight', 'Team', 'NOC',
Event.insert(loc=1, column="Event_ID", value=range(1, 1 + len(Event)), allow_duplica
```

In [65]:

```
# With this python library we need to create a connector to keep the SQL Tables
engine = connect(':memory:')
```

In [66]:

```
Athletes.to_sql('AthletesTable', con=engine)
Event.to_sql('EventTable', con=engine)
```

Out[66]:

```
271116
```

Let's find some quick statistics in the from the Tables making use of SQL. For example the ratio of male-female Athletes.

In [67]:

```
pd.read_sql('''
SELECT
    sex,
    COUNT(*)                              AS  count,
    COUNT(*)*100.0/SUM(COUNT(*)) OVER ( ) AS 'percentage (%)'
FROM
```

```
    AthletesTable
GROUP BY
    sex
''', con=engine)
```

Out[67]:

	Sex	count	percentage (%)
0	F	74522	27.487127
1	M	196594	72.512873

Or the average age, height and weight, per sport in the Games.

In [68]:

```
pd.read_sql('''
SELECT
    sport,
    AVG(age)    AS '<age>',
    AVG(height) AS '<height>',
    AVG(weight) AS '<weight>'
FROM
    AthletesTable
GROUP BY
    sport
''',con=engine)
```

Out[68]:

	Sport	<age>	<height>	<weight>
0	Aeronautics	26.000000	NaN	NaN
1	Alpine Skiing	23.205462	173.489052	72.068110
2	Alpinism	38.812500	NaN	NaN
3	Archery	27.935226	173.203085	70.011135
4	Art Competitions	45.901009	174.644068	75.290909
...	...	...	...	...
61	Tug-Of-War	29.309524	182.480000	95.615385
62	Volleyball	25.183800	186.994822	78.900214
63	Water Polo	25.659627	184.834648	84.566446
64	Weightlifting	25.502010	167.824801	78.726663
65	Wrestling	25.798289	172.358586	75.495570

66 rows × 4 columns

We can check also the percentage of NULL values in the Age, Height and Weight columns

In [69]:

```
pd.read_sql('''
SELECT
    COUNT(*) AS total_entries,
    (COUNT(*)-COUNT(age))*100/COUNT(*)          AS NULL_age,
    (COUNT(*)-COUNT(height))*100/COUNT(*)       AS NULL_height,
    (COUNT(*)-COUNT(weight))*100/COUNT(*)       AS NULL_weight
FROM
    AthletesTable
''', con=engine)
```

Out[69]:

	total_entries	NULL_age	NULL_height	NULL_weight
0	271116	3	22	23

Milestone 2: Descriptive Stats

1. Provide a summary of the different descriptive statistics you looked at and WHY.

To achieve the business objectives I would try to answer each of the hypotheses questions presented in the Milestone 1. Even if the hypotheses are not true, it does not matter, since it would help to get some insights from the data.

- *Countries at higher latitudes have better performance (medals) in Winter Sports.*

  As we can see the TOP-20 countries with more amount of medals are those with typically have long and hard strong winters, making sense that are most used to winter sports, or invest more money in this kind of sports.

- *Female and Male participants tend to be equilibrated over the years.*

  The plot shows larger male participation in the Olympic Games vs female participation up to approximately 1990. In the last 3 decades, the participation of both genres has followed the same trend, being slightly larger for men than women. However, it looks like this trend would converge for equality in the next years or soon decade.

- *Developed countries have more medals on their records.*

  The TOP-30 countries with more medals in their records are somehow related to a larger GDP, or at least they are not countries with the lowest GDP. It is noticeable, that even if there are countries whose GDPs are not maybe the best, these countries have a strong a solid culture on sports (e.g.: URSS ex-countries or east-Europe.)

- *It has to be an age of around 25 years, for the best winning medals.*

  It can be seen that for both genres, the average age for winning more medals in the Olympics is at the age of 25+/-5 years.

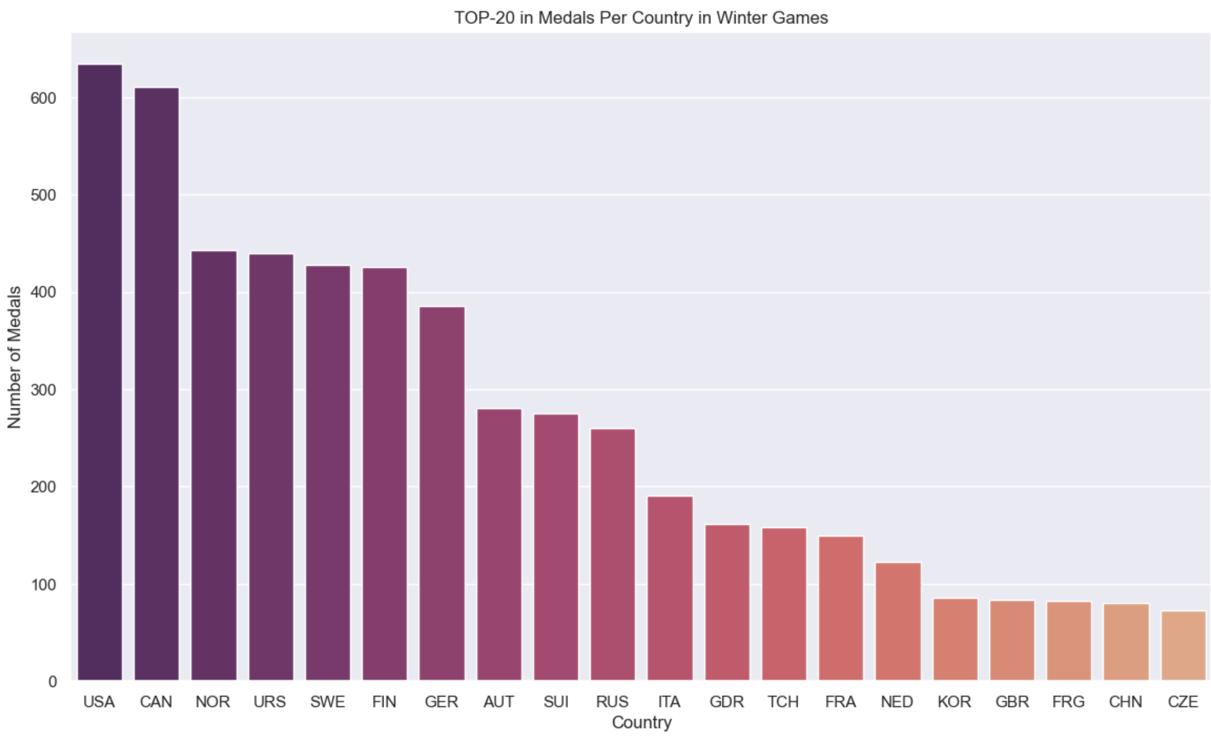
Let's find out the Top 20 Winter Games medallists.

In [70]:

```
medal_winter = pd.read_sql('''
SELECT
    NOC,
    medal_count
FROM (
    SELECT
        NOC,
        COUNT(*) AS total_count,
        SUM(CASE WHEN medal IS NOT NULL
                 THEN 1 ELSE 0
                 END) AS medal_count
    FROM
        AthletesTable
```

```
    WHERE
        season = 'Winter'
    GROUP BY
        NOC
    ) AS medals
WHERE NOC IS NOT NULL
ORDER BY medal_count DESC
LIMIT 20
''', con=engine)

plt.figure(figsize=[14,8])
sns.color_palette("rocket")
sns.barplot(x=medal_winter['NOC'], y = medal_winter['medal_count'], palette="flare_r
plt.xlabel('Country')
plt.ylabel('Number of Medals')
plt.title('TOP-20 in Medals Per Country in Winter Games')
plt.show()
```



Or maybe let's find out the optimal age for winning a medal for both men and women.

In [71]:

```
medal_age = pd.read_sql('''
SELECT
    age,
    sex,
    medal_count,
    CAST(medal_count AS float)*100 / 271116 AS ratio
FROM (
    SELECT
        age,
        sex,
        COUNT(*) AS total_count,
        SUM(CASE
            WHEN medal IS NOT NULL THEN 1 ELSE 0
            END) AS medal_count
    FROM
        AthletesTable
    GROUP BY
        age
    ) AS medals
WHERE age IS NOT NULL
```

```
''', con=engine)

medal_age
```

Out[71]:

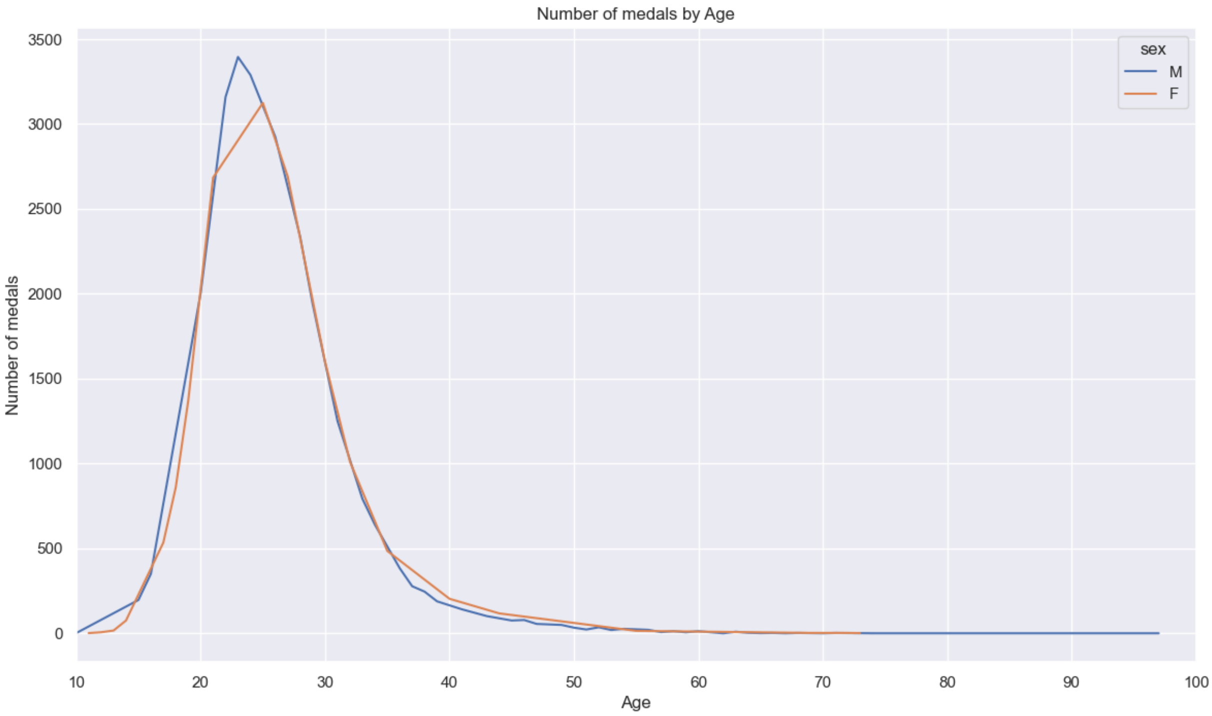
	age	sex	medal_count	ratio
0	10.0	M	1	0.000369
1	11.0	F	1	0.000369
2	12.0	F	6	0.002213
3	13.0	F	16	0.005902
4	14.0	F	75	0.027663
...	...	...	...	...
69	81.0	M	0	0.000000
70	84.0	M	0	0.000000
71	88.0	M	0	0.000000
72	96.0	M	0	0.000000
73	97.0	M	0	0.000000

74 rows × 4 columns

In [72]:

```
plt.figure(figsize=[14,8])

sns.lineplot(x=medal_age['age'], y=medal_age['medal_count'], hue=medal_age['sex'])
plt.xlabel('Age')
plt.ylabel('Number of medals')
plt.xlim(10,100)
plt.title('Number of medals by Age')
plt.show()
```

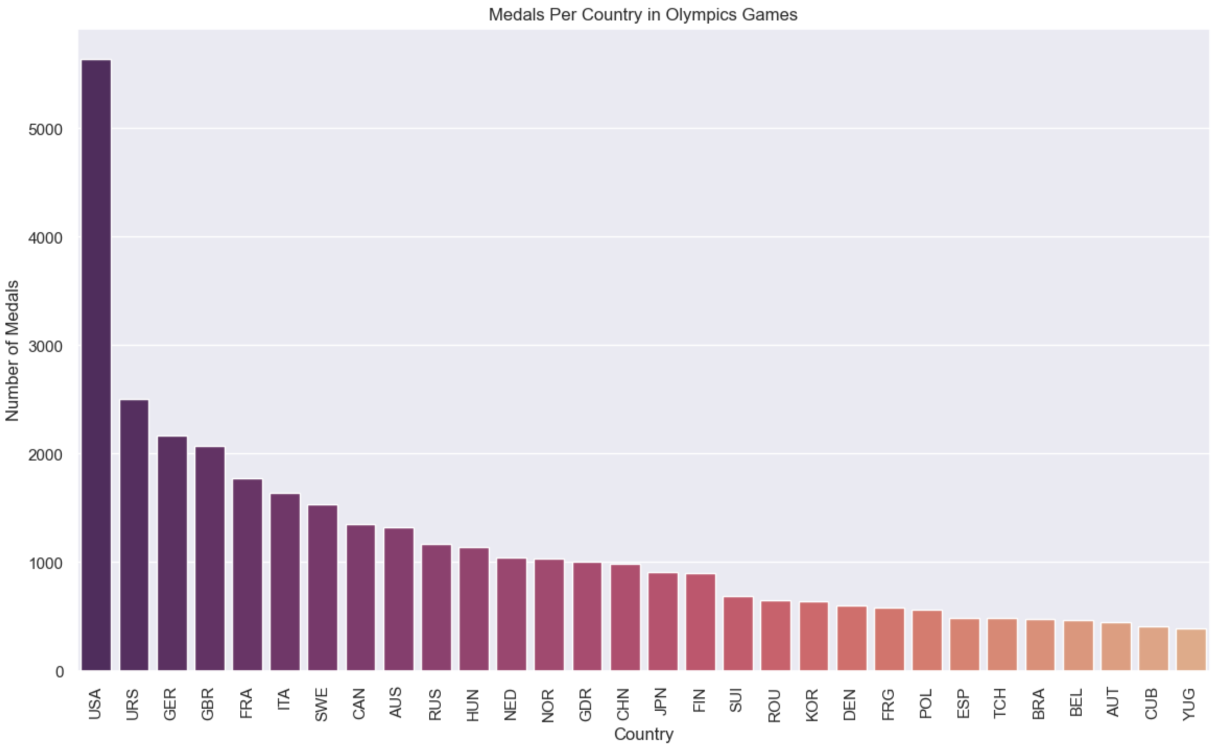


We can query the total number of medals won by country in the last 120 years.

In [73]:

```
medal_winter = pd.read_sql('''
SELECT
    NOC,
    medal_count
FROM (
    SELECT
        NOC,
        COUNT(*) AS total_count,
        SUM(CASE WHEN medal IS NOT NULL THEN 1 ELSE 0 END) AS medal_count
    FROM
        AthletesTable
    GROUP BY
        NOC
    ) AS medals
WHERE NOC IS NOT NULL
ORDER BY medal_count DESC
LIMIT 30
''', con=engine)

plt.figure(figsize=[14,8])
sns.barplot(x=medal_winter['NOC'], y = medal_winter['medal_count'], palette="flare_r
plt.xlabel('Country')
plt.xticks(rotation=90)
plt.ylabel('Number of Medals')
plt.title('Medals Per Country in Olympics Games')
plt.show()
```



We can check the participation of men and women in the Olympic Games.

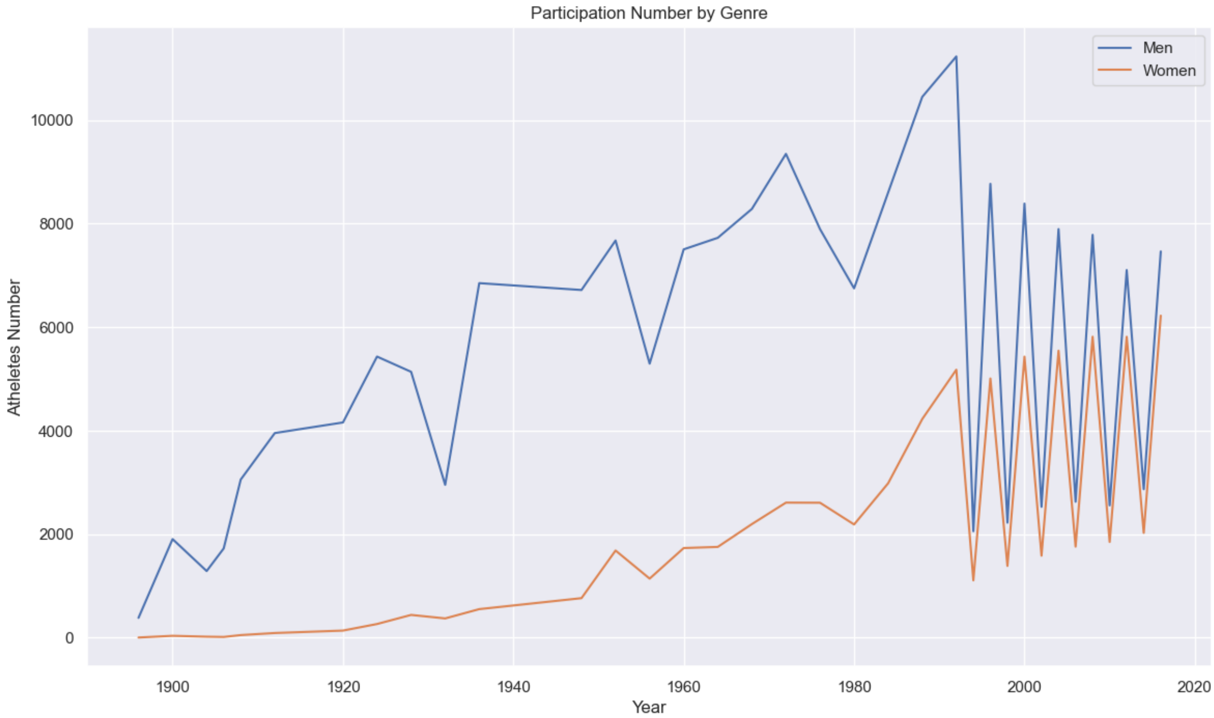
In [74]:

```
genre_count = pd.read_sql('''
SELECT
    Year,
    SUM(CASE WHEN sex = 'M' THEN 1 ELSE 0 END) AS male_count,
    SUM(CASE WHEN sex = 'F' THEN 1 ELSE 0 END) AS female_count
FROM
    AthletesTable
GROUP BY
```

```
    Year
''', con=engine)
```

In [75]:

```
plt.figure(figsize=[14,8])
sns.lineplot(x=genre_count['Year'], y=genre_count['male_count'], label='Men')
sns.lineplot(x=genre_count['Year'], y=genre_count['female_count'], label='Women')
plt.xlabel('Year')
plt.ylabel('Atheletes Number')
plt.title('Participation Number by Genre')
plt.show()
```



1. Submit 2-3 key points you may have discovered about the data, e.g. new relationships? Aha's! Did you come up with additional ideas for other things to review?

- *There is some drop in men's participation in the Olympics in some years, it could be interesting to find out why.*
- *Some countries do not exist anymore, or they have a new NOC, these medals should be added if the country has not changed geographically quite a lot.*
- *In the case of the URSS, the medallist country should be 'changed' to the actual country, but this could carry out some political issues.*

2. Did you prove or disprove any of your initial hypotheses? If so, which one and what do you plan to do next?

I prove that most of the hypotheses established in the beginning were right. However, it should be checked deeper into the data to get better insights. Until now, these results are barely shallow and should be understood as a general trend.

3. What additional questions are you seeking to answer?

- *Grouping Ex-URSS countries together.*
- *In the case of USA, race of the winners (e.g: how many Jamaicans run for USA, etc...)*
- *The distribution of age and Medal type (Gold, Silver, Bronze)*

- *The ratio between age and year by Medal type (e.g: if the average age of winning Silver is 30 years old, how has this evolved with the years)*
- *Dropping sports that have appeared in the Olympics just a few times (Roque, Basque Pelota, Areonautics)*

Milestone 3: Beyond Descriptive Stats

Dive Deeper

In this Milestone, I would look through correlations between features that initially were missed. For that, Pearson correlation can be useful as well as a heatmap between features.

It appears a Person's Correlation of 0.8 between Weight and Height, implying that these two features are quite related, as expected.

Go Broader

Let's examine which is the average BMI for each sport for the entries that we have enough data. We can see that the sports with the largest BMI are Weightlifting and Athletics, while Rhythmic Gymnastics has the lowest BMI, followed by Triathlon. Surprisingly, Curling is the 3rd sport with the largest BMI, above Ice Hockey or Rugby.

We can see also, that the evolution of the medals ratio has tended to be stabilized over the years, most probably a change in the regulations, or tech advances.

It exists a strong correlation of about 0.94 between the number of medals won in Summer and Winter Sports.

New Metric

- BMI: indicates a proper or suitable sport for an athlete
- Medal Ratio: Indicative of the distribution of medals

Let's find a quick correlation table of the Pearson coeeficient.

In [76]:
```
pears = Athletes.corr(method='pearson',numeric_only=True)
pears
```

Out[76]:

	ID	Event_ID	Age	Height	Weight	Year
ID	1.000000	0.999993	-0.003631	-0.011141	-0.009176	0.011885
Event_ID	0.999993	1.000000	-0.003648	-0.011172	-0.009198	0.011944
Age	-0.003631	-0.003648	1.000000	0.138246	0.212069	-0.115137
Height	-0.011141	-0.011172	0.138246	1.000000	0.796213	0.047578
Weight	-0.009176	-0.009198	0.212069	0.796213	1.000000	0.019095
Year	0.011885	0.011944	-0.115137	0.047578	0.019095	1.000000

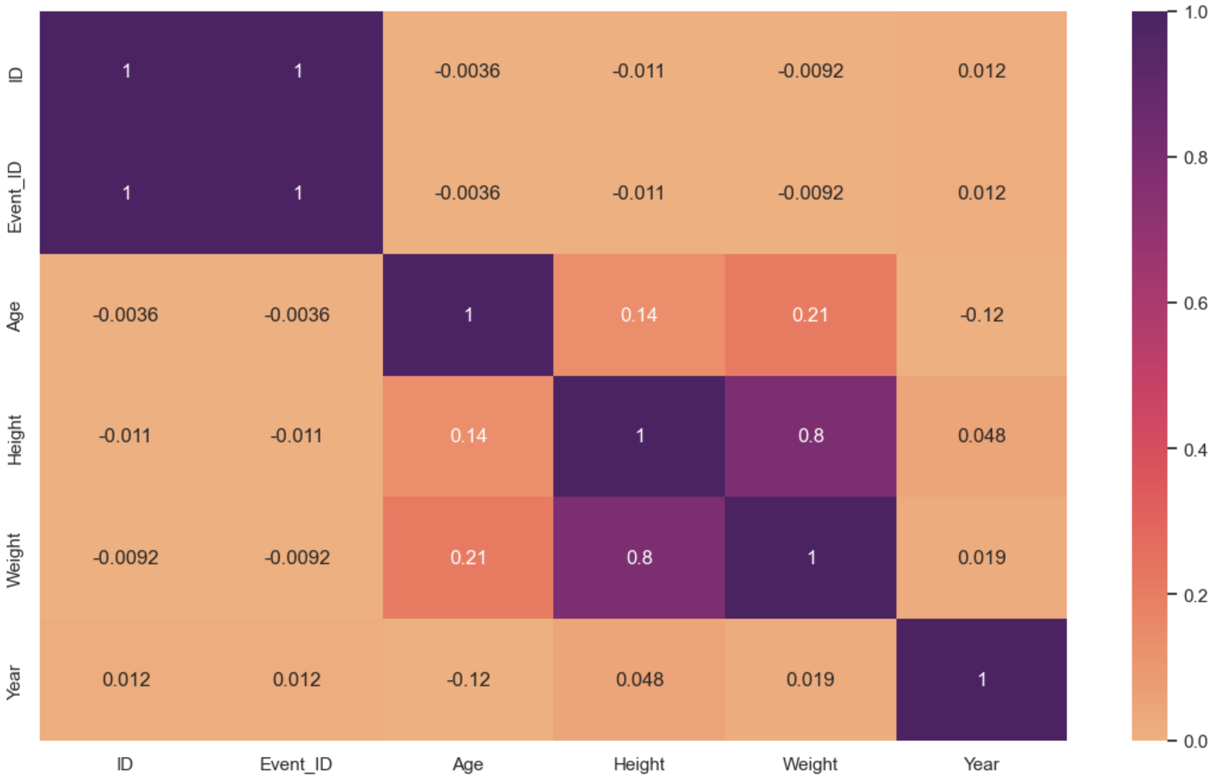
Transform it into a SQL Table

In [77]:
```
pears.to_sql('PearsonTable', con=engine, if_exists='replace')
```

Out[77]: 6

And vizualizate a heatmap for an easier intuition.

In [78]:
```
plt.figure(figsize=[14,8])
sns.heatmap(pears, vmin=0, vmax=1, cmap='flare', cbar=True, annot=True)
plt.show()
```



We can see a high correlation between the weight and height, that we can use for the BMI. So, lets make a BMI Table

In [79]:
```
BMI = pd.read_sql('''
SELECT
    Year,
    Age,
    Sex,
    Weight,
    Height,
    Season,
    Sport,
    (Weight)/(Height/100 * Height/100) AS BMI
FROM
    AthletesTable
WHERE
     (Height IS NOT NULL) AND (Weight IS NOT NULL)
GROUP BY
    Sport
ORDER BY
    BMI DESC
''', con=engine)

BMI
```

Out[79]:

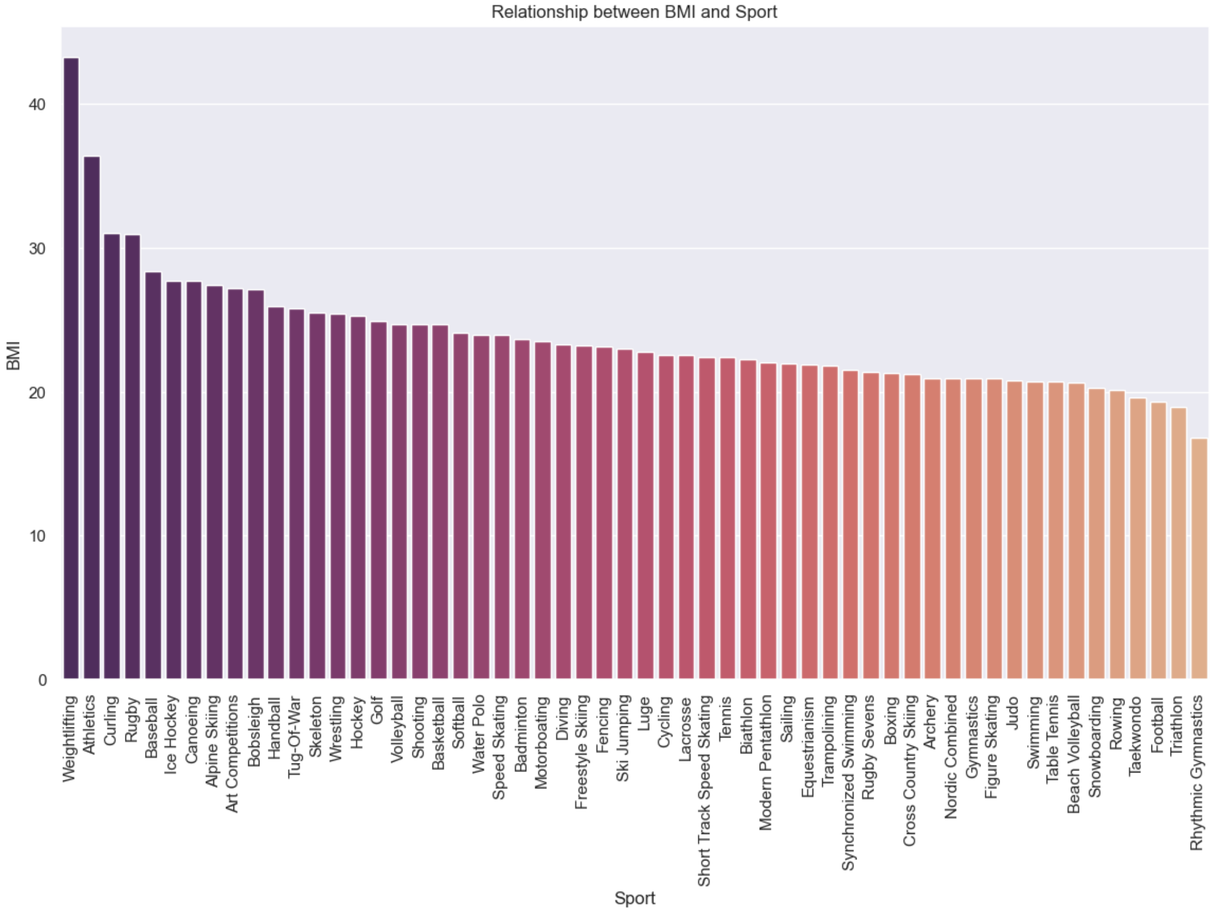
	Year	Age	Sex	Weight	Height	Season	Sport	BMI
0	2016	22.0	F	125.0	170.0	Summer	Weightlifting	43.252595
1	2000	31.0	M	130.0	189.0	Summer	Athletics	36.393158
2	2006	24.0	M	95.0	175.0	Winter	Curling	31.020408
3	1924	21.0	M	98.0	178.0	Summer	Rugby	30.930438
4	2000	21.0	M	91.0	179.0	Summer	Baseball	28.401111
5	2002	26.0	M	96.0	186.0	Winter	Ice Hockey	27.748873
6	1992	27.0	M	82.0	172.0	Summer	Canoeing	27.717685
7	1992	20.0	M	85.0	176.0	Winter	Alpine Skiing	27.440599
8	1932	44.0	M	91.0	183.0	Summer	Art Competitions	27.173102
9	1998	24.0	M	98.0	190.0	Winter	Bobsleigh	27.146814
10	2008	23.0	M	86.0	182.0	Summer	Handball	25.963048
11	1920	NaN	M	95.0	192.0	Summer	Tug-Of-War	25.770399
12	2002	24.0	M	78.0	175.0	Winter	Skeleton	25.469388
13	2000	22.0	M	89.0	187.0	Summer	Wrestling	25.451114
14	2000	25.0	M	80.0	178.0	Summer	Hockey	25.249337
15	2016	41.0	M	72.0	170.0	Summer	Golf	24.913495
16	2008	23.0	M	94.0	195.0	Summer	Volleyball	24.720579
17	1936	33.0	M	93.0	194.0	Summer	Shooting	24.710384
18	1992	24.0	M	80.0	180.0	Summer	Basketball	24.691358
19	2008	23.0	F	88.0	191.0	Summer	Softball	24.122146
20	1996	22.0	M	83.0	186.0	Summer	Water Polo	23.991213
21	1988	21.0	F	82.0	185.0	Winter	Speed Skating	23.959094
22	2000	31.0	M	70.0	172.0	Summer	Badminton	23.661439
23	1908	27.0	M	77.0	181.0	Summer	Motorboating	23.503556
24	2000	26.0	M	65.0	167.0	Summer	Diving	23.306680
25	1992	23.0	M	76.0	181.0	Winter	Freestyle Skiing	23.198315
26	2008	30.0	M	87.0	194.0	Summer	Fencing	23.116165
27	1932	19.0	M	56.0	156.0	Winter	Ski Jumping	23.011177
28	1984	17.0	F	65.0	169.0	Winter	Luge	22.758307
29	2004	21.0	F	60.0	163.0	Summer	Cycling	22.582709
30	1904	29.0	M	73.0	180.0	Summer	Lacrosse	22.530864
31	1992	24.0	M	64.0	169.0	Winter	Short Track Speed Skating	22.408179
32	2000	26.0	M	75.0	183.0	Summer	Tennis	22.395413
33	1994	32.0	F	65.0	171.0	Winter	Biathlon	22.229062
34	2004	22.0	M	60.0	165.0	Summer	Modern Pentathlon	22.038567
35	1996	30.0	F	55.5	159.0	Summer	Sailing	21.953246

	Year	Age	Sex	Weight	Height	Season	Sport	BMI
36	1992	34.0	M	75.0	185.0	Summer	Equestrianism	21.913806
37	2016	22.0	M	73.0	183.0	Summer	Trampolining	21.798202
38	2008	15.0	F	60.0	167.0	Summer	Synchronized Swimming	21.513859
39	2016	27.0	F	56.0	162.0	Summer	Rugby Sevens	21.338211
40	1988	24.0	M	66.0	176.0	Summer	Boxing	21.306818
41	1992	31.0	M	75.0	188.0	Winter	Cross Country Skiing	21.220009
42	2008	40.0	F	57.0	165.0	Summer	Archery	20.936639
43	1988	22.0	M	64.0	175.0	Winter	Nordic Combined	20.897959
44	1948	28.0	M	64.0	175.0	Summer	Gymnastics	20.897959
45	1964	15.0	M	64.0	175.0	Winter	Figure Skating	20.897959
46	2012	23.0	M	60.0	170.0	Summer	Judo	20.761246
47	1996	21.0	M	78.0	194.0	Summer	Swimming	20.724838
48	2000	19.0	F	53.0	160.0	Summer	Table Tennis	20.703125
49	2008	40.0	M	73.0	188.0	Summer	Beach Volleyball	20.654142
50	2006	18.0	M	68.0	183.0	Winter	Snowboarding	20.305175
51	1996	26.0	M	72.0	189.0	Summer	Rowing	20.156211
52	2000	24.0	M	58.0	172.0	Summer	Taekwondo	19.605192
53	1996	23.0	F	64.0	182.0	Summer	Football	19.321338
54	2016	26.0	F	51.0	164.0	Summer	Triathlon	18.961927
55	2004	19.0	F	48.0	169.0	Summer	Rhythmic Gymnastics	16.806134

And we can plot the relationship between BMI and the Sport in the Olympics

In [80]:

```
plt.figure(figsize=[14,8])
sns.barplot(x=BMI['Sport'], y=BMI['BMI'], palette="flare_r")
plt.xlabel('Sport')
plt.ylabel('BMI')
plt.title('Relationship between BMI and Sport')
plt.xticks(rotation=90)
plt.show()
```



We cna generate a SQL table where we can calculate the medal type ratio.

In [81]:

```
medal_ratio = pd.read_sql('''
SELECT
    sex,
    year,
    season,
    CAST(medal_count AS FLOAT) / total_count AS medal_ratio,
    CAST(gold_count AS FLOAT) / medal_count AS gold_ratio,
    CAST(silver_count AS FLOAT) / medal_count AS silver_ratio,
    CAST(bronze_count AS FLOAT) / medal_count AS bronze_ratio
FROM
(
    SELECT
        sex,
        year,
        season,
        COUNT(*) AS total_count,
        SUM(CASE WHEN Medal IS NOT NULL THEN 1 ELSE 0 END) AS medal_count,
        SUM(CASE WHEN Medal = 'Gold'    THEN 1 ELSE 0 END) AS Gold_count,
        SUM(CASE WHEN Medal = 'Silver'  THEN 1 ELSE 0 END) AS Silver_count,
        SUM(CASE WHEN Medal = 'Bronze'  THEN 1 ELSE 0 END) AS Bronze_count
        FROM
            AthletesTable
        GROUP BY
            year
    ) AS medalsTable
''', con=engine)

medal_ratio
```

Out[81]:

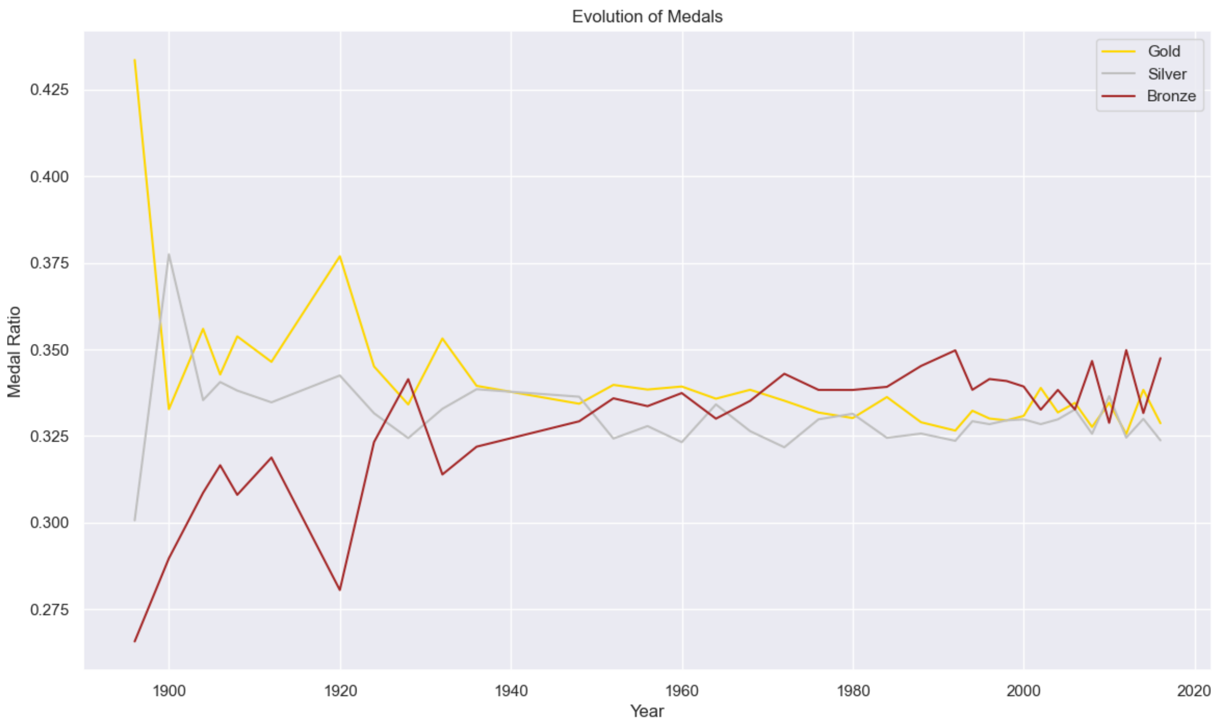
	sex	year	season	medal_ratio	gold_ratio	silver_ratio	bronze_ratio
0	M	1896	Summer	0.376316	0.433566	0.300699	0.265734

	sex	year	season	medal_ratio	gold_ratio	silver_ratio	bronze_ratio
1	M	1900	Summer	0.341983	0.332781	0.377483	0.289735
2	M	1904	Summer	0.373559	0.355967	0.335391	0.308642
3	M	1906	Summer	0.264282	0.342795	0.340611	0.316594
4	M	1908	Summer	0.267978	0.353791	0.338147	0.308063
5	M	1912	Summer	0.232921	0.346440	0.334750	0.318810
6	M	1920	Summer	0.304753	0.376911	0.342508	0.280581
7	M	1924	Summer	0.168979	0.345114	0.331601	0.323285
8	M	1928	Summer	0.147650	0.334143	0.324423	0.341434
9	F	1932	Summer	0.222523	0.353180	0.332882	0.313938
10	M	1936	Summer	0.138495	0.339512	0.338537	0.321951
11	M	1948	Summer	0.131952	0.334347	0.336373	0.329281
12	M	1952	Summer	0.110387	0.339787	0.324298	0.335915
13	M	1956	Winter	0.162108	0.338447	0.327900	0.333653
14	M	1960	Winter	0.114564	0.339319	0.323251	0.337429
15	M	1964	Winter	0.128165	0.335802	0.334156	0.330041
16	M	1968	Summer	0.119859	0.338376	0.326433	0.335191
17	M	1972	Summer	0.118237	0.335219	0.321782	0.342999
18	M	1976	Summer	0.145782	0.331809	0.329850	0.338341
19	M	1980	Winter	0.179255	0.330212	0.331461	0.338327
20	F	1984	Winter	0.146531	0.336278	0.324499	0.339223
21	F	1988	Winter	0.125715	0.328997	0.325745	0.345257
22	M	1992	Summer	0.123682	0.326601	0.323645	0.349754
23	F	1994	Winter	0.104747	0.332326	0.329305	0.338369
24	F	1996	Summer	0.133672	0.330076	0.328447	0.341477
25	M	1998	Winter	0.122053	0.329545	0.329545	0.340909
26	M	2000	Summer	0.144997	0.330838	0.329840	0.339321
27	M	2002	Winter	0.116330	0.338912	0.328452	0.332636
28	M	2004	Summer	0.148851	0.331834	0.329835	0.338331
29	M	2006	Winter	0.120037	0.334601	0.332700	0.332700
30	F	2008	Summer	0.150566	0.327637	0.325684	0.346680
31	M	2010	Winter	0.118128	0.334615	0.336538	0.328846
32	M	2012	Summer	0.150232	0.325605	0.324575	0.349820
33	M	2014	Winter	0.122061	0.338358	0.329983	0.331658
34	F	2016	Summer	0.147794	0.328720	0.323777	0.347504

And we can plot it over the years to check the evolution in the "medal regularization" for example.

In [82]:

```
plt.figure(figsize=[14,8])
sns.lineplot(data=medal_ratio, x='year', y = 'gold_ratio',   color='gold', label='Go
sns.lineplot(data=medal_ratio, x='year', y = 'silver_ratio', color='silver', label='
sns.lineplot(data=medal_ratio, x='year', y = 'bronze_ratio', color='brown', label='B
plt.xlabel('Year')
plt.ylabel('Medal Ratio')
plt.title('Evolution of Medals')
plt.show()
```



We can split it into Winter Sports

In [83]:

```
winter_ratio = pd.read_sql('''
SELECT
    sex,
    year,
    total_count,
    CAST(medal_count AS FLOAT) / total_count AS medal_ratio,
    CAST(gold_count AS FLOAT) / medal_count AS gold_ratio,
    CAST(silver_count AS FLOAT) / medal_count AS silver_ratio,
    CAST(bronze_count AS FLOAT) / medal_count AS bronze_ratio
FROM
(
    SELECT
        sex,
        year,
        COUNT(*) AS total_count,
        SUM(CASE WHEN Medal IS NOT NULL THEN 1 ELSE 0 END) AS medal_count,
        SUM(CASE WHEN Medal = 'Gold'    THEN 1 ELSE 0 END) AS Gold_count,
        SUM(CASE WHEN Medal = 'Silver'  THEN 1 ELSE 0 END) AS Silver_count,
        SUM(CASE WHEN Medal = 'Bronze'  THEN 1 ELSE 0 END) AS Bronze_count
        FROM
            AthletesTable
        WHERE
            Season = 'Winter'
        GROUP BY
            year
    ) AS medalsTable
''', con=engine)
```

```
winter_ratio
```

Out[83]:

	sex	year	total_count	medal_ratio	gold_ratio	silver_ratio	bronze_ratio
0	M	1924	460	0.282609	0.423077	0.292308	0.284615
1	M	1928	582	0.152921	0.337079	0.314607	0.348315
2	M	1932	352	0.261364	0.347826	0.347826	0.304348
3	M	1936	895	0.120670	0.333333	0.342593	0.324074
4	M	1948	1075	0.125581	0.303704	0.355556	0.340741
5	M	1952	1088	0.125000	0.330882	0.323529	0.345588
6	M	1956	1307	0.114767	0.340000	0.326667	0.333333
7	M	1960	1116	0.131720	0.340136	0.326531	0.333333
8	M	1964	1778	0.104612	0.327957	0.360215	0.311828
9	M	1968	1891	0.105235	0.331658	0.351759	0.316583
10	M	1972	1655	0.120242	0.351759	0.316583	0.331658
11	M	1976	1861	0.113380	0.331754	0.336493	0.331754
12	M	1980	1746	0.124857	0.330275	0.334862	0.334862
13	F	1984	2134	0.104030	0.333333	0.333333	0.333333
14	F	1988	2639	0.099659	0.330798	0.334601	0.334601
15	F	1992	3436	0.092549	0.327044	0.339623	0.333333
16	F	1994	3160	0.104747	0.332326	0.329305	0.338369
17	M	1998	3605	0.122053	0.329545	0.329545	0.340909
18	M	2002	4109	0.116330	0.338912	0.328452	0.332636
19	M	2006	4382	0.120037	0.334601	0.332700	0.332700
20	M	2010	4402	0.118128	0.334615	0.336538	0.328846
21	M	2014	4891	0.122061	0.338358	0.329983	0.331658

... and Summer Sports.

In [84]:

```
summer_ratio = pd.read_sql('''
SELECT
    sex,
    year,
    total_count,
    CAST(medal_count AS FLOAT) / total_count AS medal_ratio,
    CAST(gold_count AS FLOAT) / medal_count AS gold_ratio,
    CAST(silver_count AS FLOAT) / medal_count AS silver_ratio,
    CAST(bronze_count AS FLOAT) / medal_count AS bronze_ratio
FROM
(
    SELECT
        sex,
        year,
        COUNT(*) AS total_count,
        SUM(CASE WHEN Medal IS NOT NULL THEN 1 ELSE 0 END) AS medal_count,
        SUM(CASE WHEN Medal = 'Gold'     THEN 1 ELSE 0 END) AS Gold_count,
```

```
        SUM(CASE WHEN Medal = 'Silver'  THEN 1 ELSE 0 END) AS Silver_count,
        SUM(CASE WHEN Medal = 'Bronze'  THEN 1 ELSE 0 END) AS Bronze_count
        FROM
            AthletesTable
        WHERE
            season = 'Summer'
        AND
            year >= 1924
        GROUP BY
            year
    ) AS medalsTable
''', con=engine)

summer_ratio
```

Out[84]:

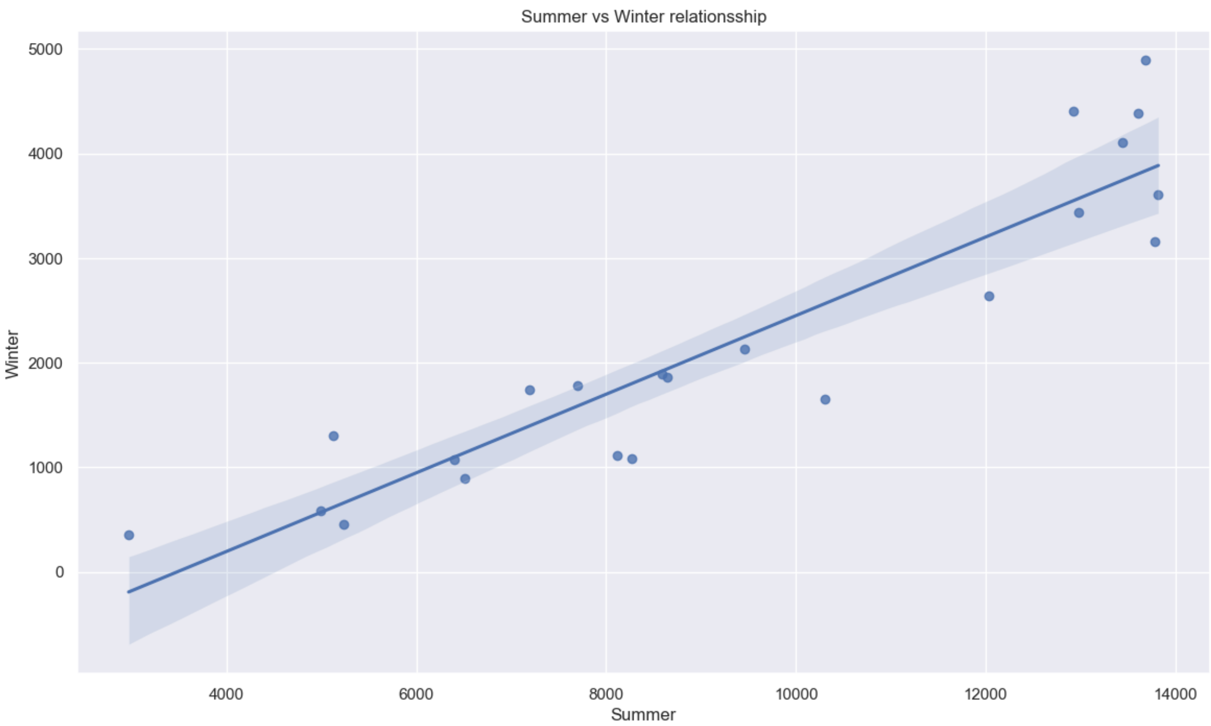
	sex	year	total_count	medal_ratio	gold_ratio	silver_ratio	bronze_ratio
0	M	1924	5233	0.158991	0.332933	0.337740	0.329327
1	M	1928	4992	0.147035	0.333787	0.325613	0.340599
2	F	1932	2969	0.217918	0.353941	0.330757	0.315301
3	M	1936	6506	0.140947	0.340240	0.338059	0.321701
4	M	1948	6405	0.133021	0.339202	0.333333	0.327465
5	M	1952	8270	0.108464	0.341137	0.324415	0.334448
6	M	1956	5127	0.174176	0.338186	0.328108	0.333707
7	M	1960	8119	0.112206	0.339188	0.322722	0.338090
8	M	1964	7702	0.133602	0.337221	0.329446	0.333333
9	M	1968	8588	0.123079	0.339640	0.321665	0.338694
10	M	1972	10304	0.117915	0.332510	0.322634	0.344856
11	M	1976	8641	0.152760	0.331818	0.328788	0.339394
12	M	1980	7191	0.192463	0.330202	0.330925	0.338873
13	M	1984	9454	0.156124	0.336721	0.323171	0.340108
14	F	1988	12037	0.131428	0.328698	0.324273	0.347029
15	M	1992	12977	0.131926	0.326519	0.320678	0.352804
16	F	1996	13780	0.133672	0.330076	0.328447	0.341477
17	M	2000	13821	0.144997	0.330838	0.329840	0.339321
18	M	2004	13443	0.148851	0.331834	0.329835	0.338331
19	F	2008	13602	0.150566	0.327637	0.325684	0.346680
20	M	2012	12920	0.150232	0.325605	0.324575	0.349820
21	F	2016	13688	0.147794	0.328720	0.323777	0.347504

And we can see if there is a correlation between those that are good at winning medals in Summer Sports are also in Winter Sports.

In [85]:

```
plt.figure(figsize=[14,8])
sns.regplot(x=summer_ratio['total_count'], y=winter_ratio['total_count'],fit_reg=Tru
plt.xlabel('Summer')
plt.ylabel('Winter')
```

```
plt.title('Summer vs Winter relationsship')
plt.show()
```



In [86]:
```
correlation_coeffs=np.corrcoef(x=summer_ratio['total_count'], y=winter_ratio['total_
correlation_coeffs
```

Out[86]:
```
array([[1.        , 0.92414254],
       [0.92414254, 1.        ]])
```