#Milestone 4: Presenting Your Findings (Storytelling)

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##Contents

##Audience

External audience, for my classmates.

##1. **Questions to Answer / Hypothesis / Approach**

###Questions to Answer

- How many Peruvians won a gold medal?
- Has Cristiano Ronaldo (CR7) won any medals?
- Which sporting event gathered the most athletes?
- In which year were the most gold medals awarded?
- In the 120 years of the Olympic Games, which country's team won the most medals?
- Are there more men or women who have won a gold medal?
- If the dataset only has events up to the year 2016, how do you predict which medal a new athlete will win?

###Initial Hyphothesis

- **How many Peruvians won a gold medal?** Of course there are Peruvians who won gold medals
- **Has Cristiano Ronaldo (CR7) won any medals?** I think that CR7 has won a gold medal
- **Which sporting event gathered the most athletes?** Without a doubt, football is the sporting event that gathers more athletes
- **In which year were the most gold medals awarded?** I believe that more gold medals were awarded between the years 2006 to 2010

- **In the 120 years of the Olympic Games, which country's team won the most medals?** From my perspective, Poland has more medals
- **Are there more men or women who have won a gold medal?** There are more male athletes, therefore, I think that men win more medals
- **If the dataset only has events up to the year 2016, how do you predict which medal a new athlete will win?** I have no idea what will happen, but we will find out using machine learning later.

###**Data Analysis Approach**

The working environment will be in google colab with the python programming language and sqlite will be used to analyze the data.

In the first instance, the files **athlet_events.csv** and **noc_regions.csv** that are related through the NOC column will be loaded. That is, the column exists in both files. Then it will be necessary to remove or replace the NA values for better analysis.

Finally, to answer the questions posed, statistical inference and graphic visualization will be used to determine if there is a relationship between the columns.

##2. **Discuss Technical Challenges**

- Google Colab with Python and SQLite was used for all analyzes.
- Various python software packages were used such as **pandas**, **sqlite3**, **numpy**, **matplotlib**, **sklearn**, etc.
- The sqlite3 package gave no results when it was used to calculate the SUM of the NA values. Therefore, another software called DB Browser for SQLite was used to perform the calculation

##3. **Detail: Entity Relationship Diagram (ERD)**

##4. **Initial Findings**

###**Creating a olympics database** Sqlite is a lightweight database that can be started as an empty text file. You can create the file with touch **olympics.db** or with this equivalent Python code:

```
from pathlib import Path import os

db_name='olympics.db' if os.path.exists(db_name):
  os.remove(db_name)

Path(db_name).touch()
```

###**Creating regions table**

```
import sqlite3
import pandas as pd

conn = sqlite3.connect('olympics.db')
cursor = conn.cursor()

cursor.execute('''create table regions(
NOC    varchar(45),  region
varchar(150),  notes text   ) ''')

pd.read_sql("pragma table_info('regions')",conn)
```

	cid	name	type	notnull	dflt_value	pk
0	0	NOC	varchar(45)	0	None	0
1	1	region	varchar(150)	0	None	0
2	2	notes	text	0	None	0

```
cursor.execute('''create table athletes(
  ID int,
  Name varchar(250),
  Sex char(1),
  Age float,
  Height  float,
 Weight float,
 Team    varchar(100),
 NOC    varchar(45),
Games   varchar(100),
Year  int,
Season  varchar(45),
City  varchar(100),
Sport varchar(100),
Event varchar(100),
Medal varchar(45),
 foreign key(NOC) references regions(NOC)
  ) ''')

pd.read_sql("pragma table_info('athletes')",conn)
```

	cid	name	type	notnull	dflt_value	pk
0	0	ID	int	0	None	0
1	1	Name	varchar(250)	0	None	0
2	2	Sex	char(1)	0	None	0
3	3	Age	float	0	None	0
4	4	Height	float	0	None	0
5	5	Weight	float	0	None	0
6	6	Team	varchar(100)	0	None	0
7	7	NOC	varchar(45)	0	None	0
8	8	Games	varchar(100)	0	None	0

```
9     9    Year           int        0       None   0
10   10  Season   varchar(45)        0       None   0
11   11    City  varchar(100)        0       None   0
12   12   Sport  varchar(100)        0       None   0
13   13   Event  varchar(100)        0       None   0
14   14   Medal   varchar(45)        0       None   0
```

###Import data

```
url =
'https://raw.githubusercontent.com/Emermv/sql-for-data-science/master/
athlete_events.csv' athlete_events = pd.read_csv(url)
athlete_events.info() athlete_events.head(5)

<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

   ID                      Name  ...                                Event
Medal
0   1                 A Dijiang  ...       Basketball Men's Basketball
NaN
1   2                  A Lamusi  ...      Judo Men's Extra-Lightweight
NaN
2   3       Gunnar Nielsen Aaby  ...           Football Men's Football
NaN
3   4       Edgar Lindenau Aabye  ...        Tug-Of-War Men's Tug-Of-
    WarGold
```

```
4   5  Christine Jacoba Aaftink  ...  Speed Skating Women's 500 metres
NaN

[5 rows x 15 columns]
regions_url = 'https://raw.githubusercontent.com/Emermv/sql-for-
datascience/master/noc_regions.csv' regions =
pd.read_csv(regions_url) regions.info() regions.head(5)

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

###Write the data to a sqlite table

```
regions.to_sql('regions', conn, if_exists='append', index = False)

athlete_events.to_sql('athletes', conn, if_exists='append', index =
False)
```

###Preview data

```
pd.read_sql("select * from regions limit 5",conn)
   NOC       region                  notes
0  AFG  Afghanistan                   None
1  AHO      Curacao  Netherlands Antilles
2  ALB      Albania                   None
3  ALG      Algeria                   None
4  AND      Andorra                   None
pd.read_sql("select * from athletes  limit 5",conn)

   ID                      Name  ...                                  Event
Medal
0   1                 A Dijiang  ...       Basketball Men's Basketball
```

```
None
1   2                A Lamusi  ...      Judo Men's Extra-LightweightNone
2   3      Gunnar Nielsen Aaby  ...          Football Men's FootballNone
3   4       Edgar Lindenau Aabye   ...         Tug-Of-War Men's Tug-Of-
    WarGold
4   5   Christine Jacoba Aaftink   ...   Speed Skating Women's 500
    metresNone

[5 rows x 15 columns]
```

###**Descriptive statistics** Descriptive statistical analyzes were carried out on some of the variables for a better understanding of the distributions. Some of the variables include:

- Age
- Height
- Weight

```
descriptive_statistical=pd.read_sql("""select
round(Age,0) as Age, round(Height,0) as
Height, round(Weight,0) as Weight from
athletes where Age is not null and Height is
not null and Weight is not null""",conn)
descriptive_statistical.describe()
```

	Age	Height	Weight
count	206165.000000	206165.000000	206165.000000
mean	25.055509	175.371950	70.690670
std	5.483096	10.546088	14.341004
min	11.000000	127.000000	25.000000
25%	21.000000	168.000000	60.000000
50%	24.000000	175.000000	70.000000
75%	28.000000	183.000000	79.000000
max	71.000000	226.000000	214.000000

###**Initial findings summary** I have rejected the following initial hypotheses: I thought that the country with the most medals was Poland. However, after carefully analyzing the data, I discovered that it was USA. I also thought that CR7 had won a gold medal, but it is not true.

The next thing I am planning to do is analyze my data extensively to validate my hypotheses. For this I will use descriptive statistics techniques such as: tables, graphs, measures of central tendency, dispersion, etc.

Additionally I will build a machine learning model to predict which medals will be won the most in future events of the olympic games

##5. **Deeper Analysis**

###**How many Peruvians won a gold medal?** Only one Peruvian has won a gold medal

```
pd.read_sql('''SELECT * FROM athletes where NOC='PER' and Medal='Gold'
''', conn)
       ID  ... Medal
0  125468  ...  Gold
[1 rows x 15 columns]
```

###Has Cristiano Ronaldo (CR7) won any medals? No, CR7 has not won a gold medal at the olympic games

```
pd.read_sql('''SELECT * FROM athletes where NOC='POR' and Name like
'%cristiano%' ''', conn)

      ID                                       Name  ...
Event  Medal
0   23835  Cristiano Ronaldo dos Santos Aveiro  ...  Football  Men's
Football   None

[1 rows x 15 columns]
```

###Which sporting event gathered the most athletes? Football has more athletes

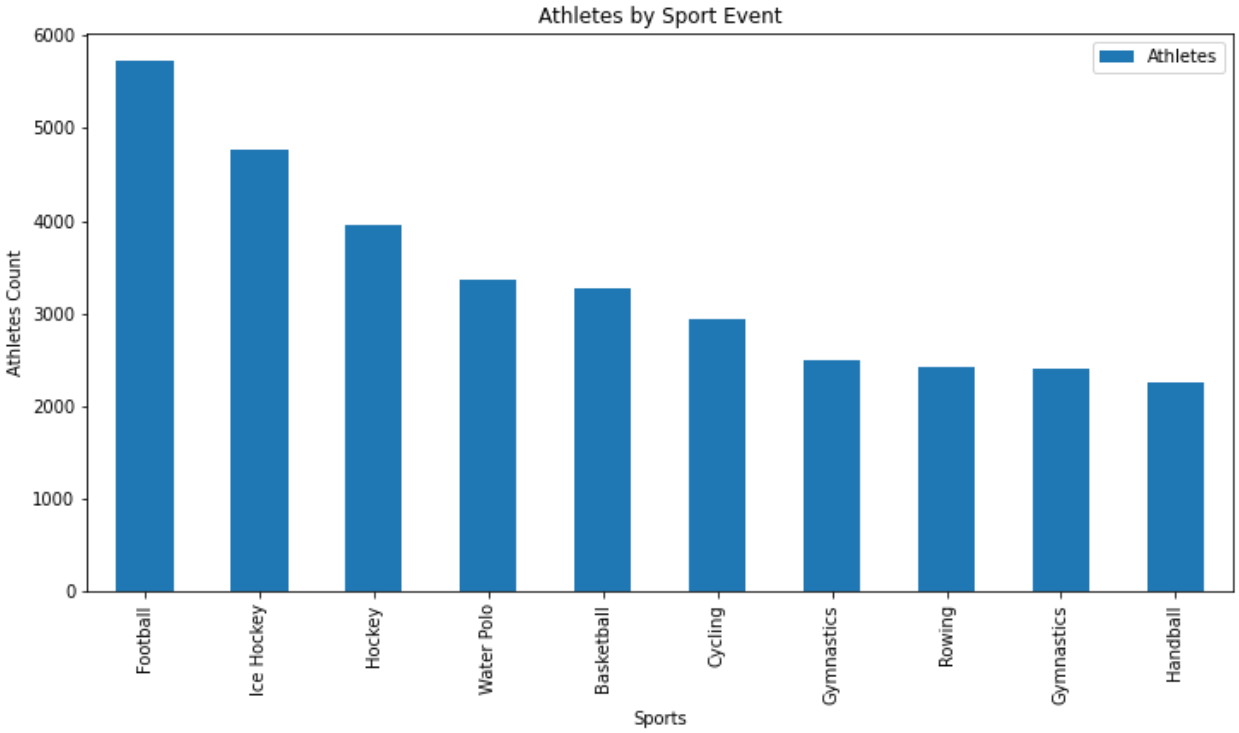
```
import matplotlib.pyplot as plt
athletes_by_event=pd.read_sql('''
              SELECT
                Sport,
Event,
                count(Id) as athletes_count
FROM athletes  group by Event
              order by athletes_count desc limit 10 ''', conn)

athletes_by_event_series={'Athletes':[]}
columns=[] for row in
athletes_by_event.iterrows():
sport=row[1]['Sport']
columns.append(sport)
  athletes_by_event_series['Athletes'].append(row[1]
['athletes_count'])

plotdata = pd.DataFrame(athletes_by_event_series,
index=columns
)
```

```
plt.rcParams["figure.figsize"] = (12,6)
plotdata.plot(kind="bar") plt.title("Athletes by Sport Event")
plt.xlabel("Sports") plt.ylabel("Athletes Count")

Text(0, 0.5, 'Athletes Count')
```



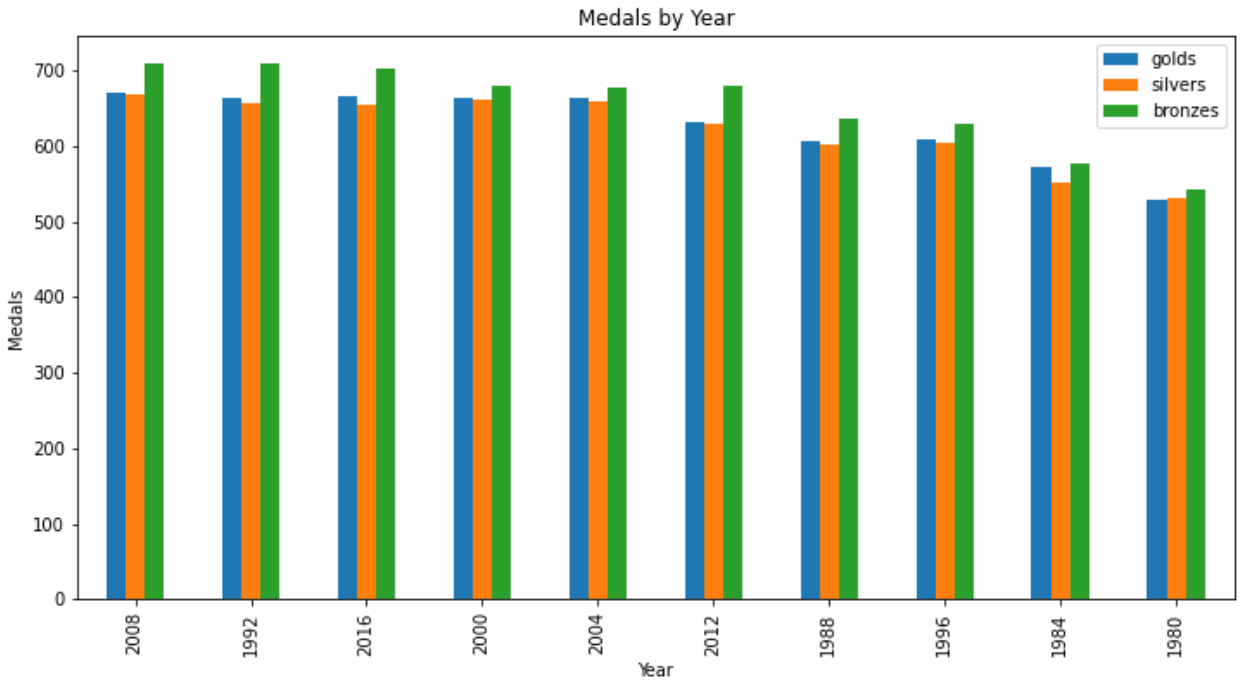
###**In which year were the most gold medals awarded?** In 2008, more gold medals were awarded

```
medals_by_year=pd.read_sql("""
select a.Year,
(select count(Id) from athletes where  Medal='Gold' and Year=a.Year)
as Gold_medals,
(select count(Id) from athletes where  Medal='Silver' and Year=a.Year)
as Silver_medals,
(select count(Id) from athletes where  Medal='Bronze' and Year=a.Year)
as Bronze_medals, count(Medal) as Medal_count from athletes as a where
a.Medal is not null group by a.Year order by Medal_count desc limit 10
""",conn)
```

```
series={'golds':[],'silvers':[],'bronzes':[]}
columns=[] for row in
medals_by_year.iterrows():
year=row[1]['Year']    columns.append(year)
  series['golds'].append(row[1]['Gold_medals'])
series['silvers'].append(row[1]['Silver_medals'])
series['bronzes'].append(row[1]['Bronze_medals'])

plotdata = pd.DataFrame(series,
index=columns
)
plt.rcParams["figure.figsize"] = (12,6)
plotdata.plot(kind="bar")
plt.title("Medals by Year")
plt.xlabel("Year")
plt.ylabel("Medals")
```

```
Text(0, 0.5, 'Medals')
```



###In the 120 years of the Olympic Games, which country's team won the most medals? USA has more medals

```
sql_update_query = """update regions set NOC='RUS' where NOC='URS'"""
cursor.execute(sql_update_query) conn.commit()

sql_update_query = """update athletes set NOC='RUS' where NOC='URS'"""
```

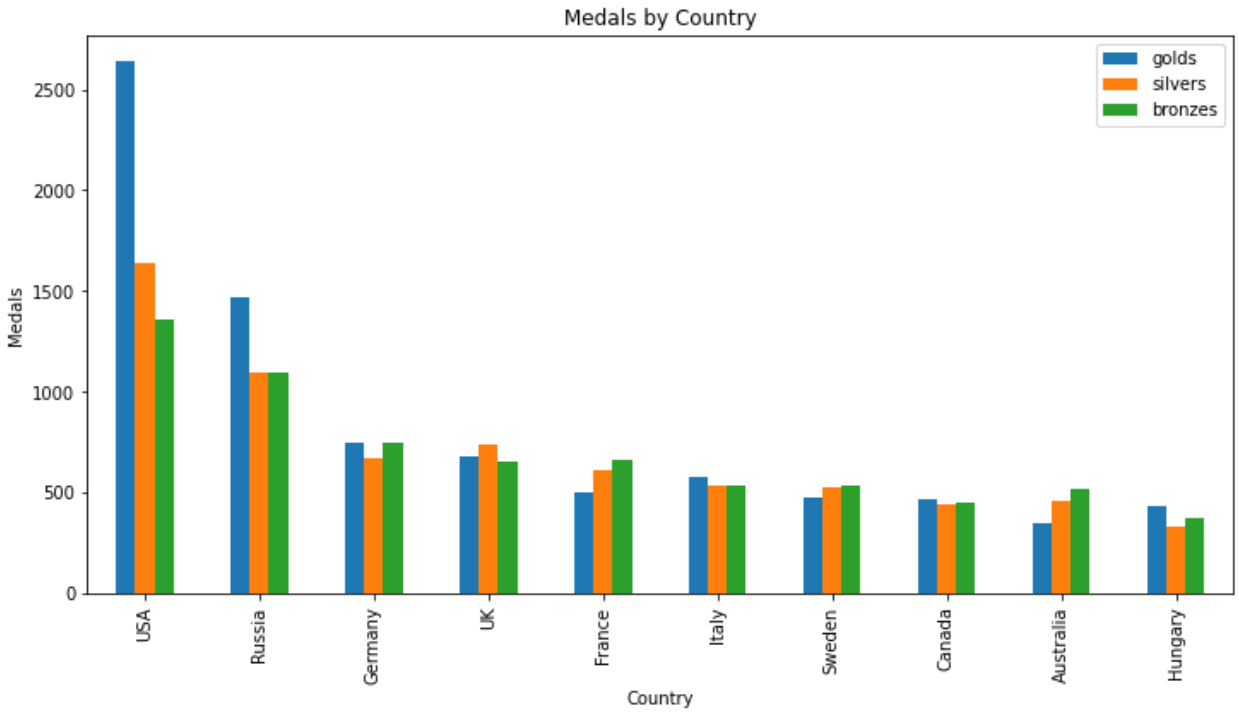
```
cursor.execute(sql_update_query)
conn.commit()

medals_by_country=pd.read_sql("""
select a.NOC,
r.region,
(select count(Id) from athletes where  Medal='Gold' and NOC=a.NOC) as
Gold_medals,
(select count(Id) from athletes where  Medal='Silver' and NOC=a.NOC)
as Silver_medals,
(select count(Id) from athletes where  Medal='Bronze' and NOC=a.NOC)
as Bronze_medals,
((select count(Id) from athletes where  Medal='Gold' and NOC=a.NOC)+
(select count(Id) from athletes where  Medal='Silver' and NOC=a.NOC)+
(select count(Id) from athletes where  Medal='Bronze' and
NOC=a.NOC))as Medals
from athletes as a
left join regions as r on r.NOC=a.NOC where
a.Medal in ('Gold','Silver','Bronze') group
by a.NOC order by Medals desc limit 10
""",conn)

series={'golds':[],'silvers':[],'bronzes':[]}
columns=[] for row in
medals_by_country.iterrows():
region=row[1]['region']
columns.append(region)
  series['golds'].append(row[1]['Gold_medals'])
series['silvers'].append(row[1]['Silver_medals'])
series['bronzes'].append(row[1]['Bronze_medals'])

plotdata = pd.DataFrame(series,
index=columns
)
plt.rcParams["figure.figsize"] = (12,6)
plotdata.plot(kind="bar")
plt.title("Medals by Country")
plt.xlabel("Country")
plt.ylabel("Medals")

Text(0, 0.5, 'Medals')
```



###**Are there more men or women who have won a gold medal?** Like I said, there are more men with gold medals

```
pd.read_sql("""
select
count(*) as medals,
'M' as gender from
athletes where
Medal='Gold' and
Sex='M' union
select
count(*) as medals,
'F' as gender from
athletes where
Medal='Gold' and
Sex='F' """,conn)
```

	medals	gender
0	3747	F
1	9625	M

###**If the dataset only has events up to the year 2016, how do you predict which medal a new athlete will win?**

To answer this question I will use Logistic Regression. I will create a model that can predict whether an athlete will win a gold, silver or bronze medal.

####**Logistic Regression** Logistic Regression is a Supervised Algorithm and is used for classification.

I will use these 4 columns:

- Age
- Height
- Weight
- Medal (Gold: 1, Silver: 2, Bronze: 3, None: 4)

A sample must be drawn from each type of medal so that the model can predict well

```
length=20000
golds=pd.read_sql("""
select
(case Sex when 'M' then 1 else 0 end) as Sex,
Year,
round(Age,0) as Age,
round(Height,0) as Height,
round(Weight,0) as Weight,
1     as Medal from
athletes where Age is
not null and Height is
not null and Weight is
not null and
Medal='Gold' ORDER BY
RANDOM() limit {}
""".format(length),conn)

silvers=pd.read_sql("""
select
(case Sex when 'M' then 1 else 0 end) as Sex,
Year,
round(Age,0) as Age,
round(Height,0) as Height,
round(Weight,0) as Weight,
2     as Medal from
athletes where Age is
not null and Height is
not null and Weight is
not null and
Medal='Silver' ORDER
BY RANDOM() limit {}
""".format(length),conn)

bronzes=pd.read_sql("""
select
(case Sex when 'M' then 1 else 0 end) as Sex,
```

```
Year,
round(Age,0) as Age,
round(Height,0) as Height,
round(Weight,0) as Weight,
3     as Medal from
athletes where Age is
not null and Height is
not null and Weight is
not null and
Medal='Bronze' ORDER
BY RANDOM() limit {}
""".format(length),conn)

no_medals=pd.read_sql("""
select
(case Sex when 'M' then 1 else 0 end) as Sex,
Year,
round(Age,0) as Age,
round(Height,0) as Height,
round(Weight,0) as Weight,
4     as Medal from
athletes where Age is
not null and Height is
not null and Weight is
not null and Medal is
null ORDER BY RANDOM()
limit 1000 """,conn)
data_train=pd.concat([golds,silvers,bronzes,no_medals])
#data_train[['Age', 'Height', 'Weight','Medal']] = data_train[['Age',
'Height', 'Weight','Medal']].astype(int)
#print(data_train.dtypes)
data_train.describe()
```

	Sex	Year	...	Weight	Medal
count	31181.000000	31181.000000	...	31181.000000	31181.000000
mean	0.657804	1988.079728	...	73.610660	2.063532
std	0.474452	22.605889	...	14.998293	0.880790
min	0.000000	1896.000000	...	28.000000	1.000000
25%	0.000000	1976.000000	...	63.000000	1.000000
50%	1.000000	1992.000000	...	73.000000	2.000000
75%	1.000000	2006.000000	...	83.000000	3.000000
max	1.000000	2016.000000	...	182.000000	4.000000

[8 rows x 6 columns]

Then we will analyze how many results we have of each type using the groupby function

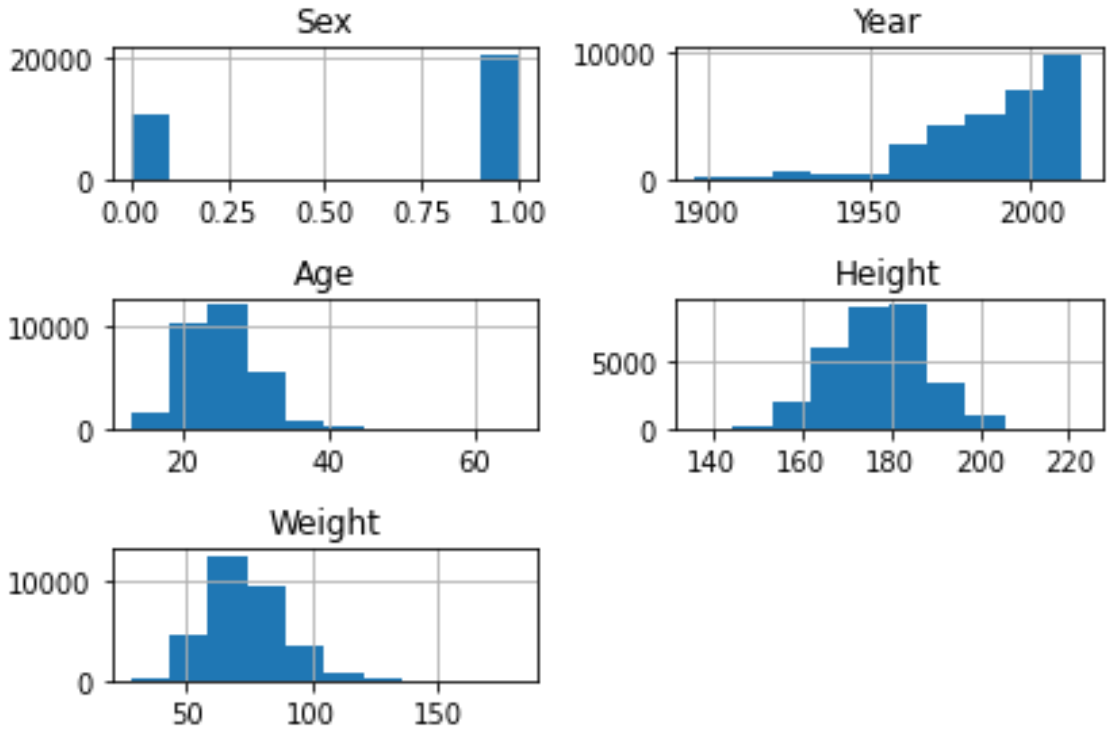
```
print(data_train.groupby('Medal').size())
```

```
Medal
1    10167
2     9866
3    10148
4     1000
dtype: int64
```

####**Data visualization** Before starting to process the data set, I made some visualizations that can often help to better understand the characteristics of the information we are working with and their correlation.

First I visualized in history format the four input Features with names "Age", "Height", "Wight" and "Medal". We can see graphically between which values their minimums and maximums are understood and in which intervals they concentrate the greatest density of records. .

```
data_train.drop(['Medal'],1).hist()
plt.tight_layout() plt.show()
```



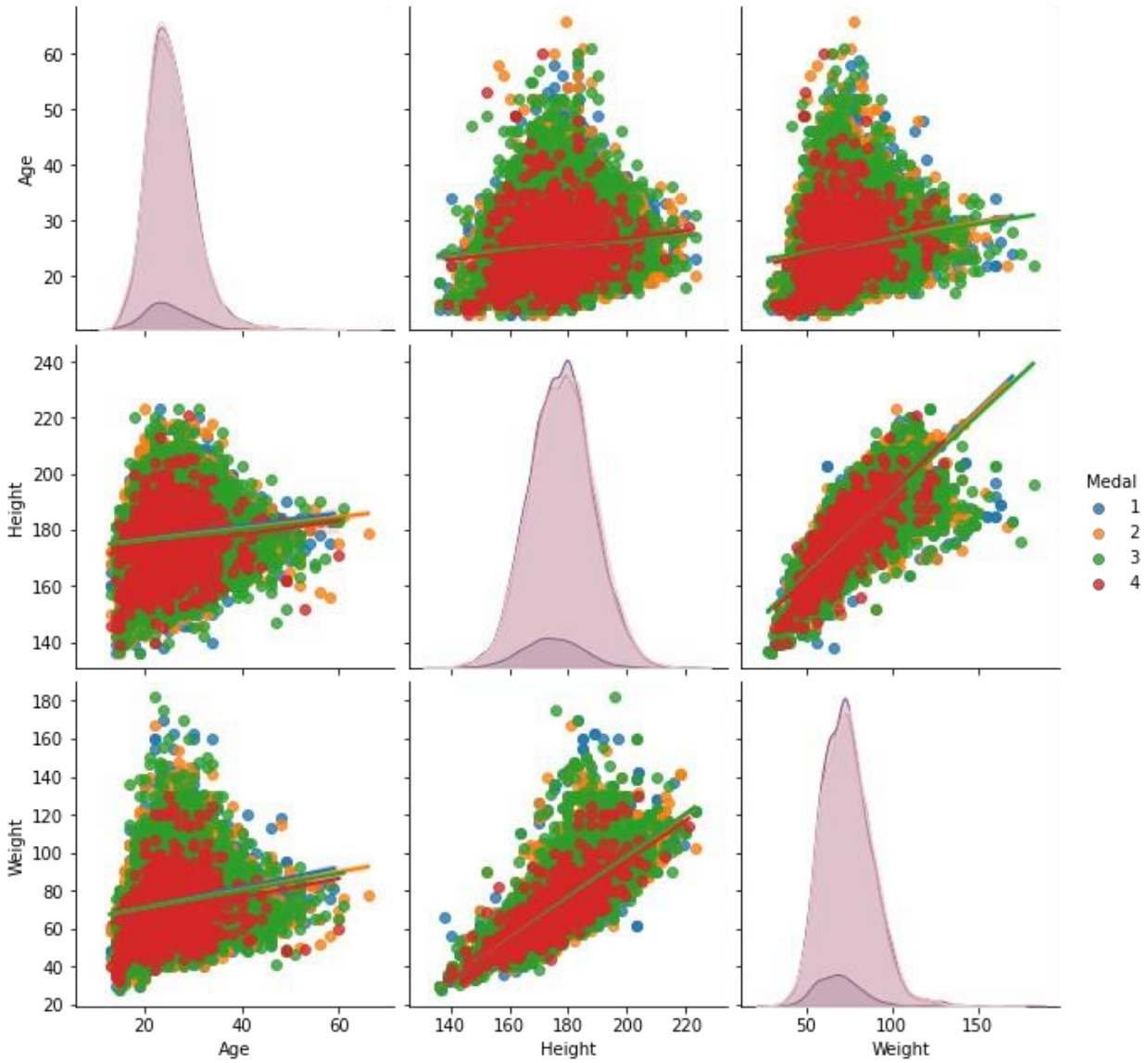
And we can also interrelate the inputs in pairs, to see how the outputs of medals by colors are linearly concentrated

```
#import numpy as np from sklearn
import linear_model
```

```
from sklearn import model_selection
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix from
sklearn.metrics import accuracy_score
#import matplotlib.pyplot as plt
import seaborn as sb %matplotlib
inline df=data_train
df.reset_index(inplace=True)
sb.pairplot(df.dropna(),
hue='Medal',size=3,vars=["Age","Height","Weight"],kind='reg')
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/axisgrid.py:2076:
UserWarning: The `size` parameter has been renamed to `height`; please
update your code.   warnings.warn(msg, UserWarning)
```

```
<seaborn.axisgrid.PairGrid at 0x7f5a8e2e5d90>
```



####**We create the Logistic Regression Model** Now we load the variables of the 4 input columns in X excluding the column "Medal" with the `drop()` method. Instead we add the column "Medal" in the variable y. We run X.shape to check the dimension of our matrix with input data of 4000 records by 3 columns.

```
X = np.array(data_train.drop(['Medal'],1)) y =
np.array(data_train['Medal'])
X.shape

(31181, 5)
```

And we create our model and make it fit (fit) to our set of inputs X and outputs 'y'

```
model =
```

```
linear_model.LogisticRegression(max_iter=1000*1000,penalty='none')
#model = linear_model.LogisticRegression() model.fit(X,y)
```

```
LogisticRegression(max_iter=1000000, penalty='none')
```

Once our model is compiled, we make it classify our entire set of X inputs using the "predict (X)" method and we review some of its outputs and see that it matches the actual outputs of the data.

```
predictions = model.predict(X) print(predictions[0:5])

[1 3 3 3 3]
```

And we confirm how good our model was using model.score () which returns the average precision of the predictions, in our case 34%.

```
model.score(X,y)

0.3370963086494981
```

####**Validation of our model** A good practice in Machine Learning is to subdivide our input data set into a training set and another to validate the model (which is not used during training and therefore the machine is unknown). This will avoid problems in which our algorithm can fail by "overgeneralizing" the knowledge.

To do this, we subdivide our input data randomly (mixed) using 80% of records for training and 20% for validation.

```
validation_size = 0.20
seed = 457
X_train, X_validation, Y_train, Y_validation =
model_selection.train_test_split(X,y, test_size=validation_size,
random_state=seed)
```

We recompile our Logistic Regression model but this time with only 80% of the input data and we calculate the new scoring that now gives us 34%.

```
name='Logistic Regression'
#kfold = model_selection.KFold(n_splits=3,
random_state=seed,shuffle=True)
kfold = model_selection.KFold(random_state=848, shuffle=True)
cv_results = model_selection.cross_val_score(model, X_train, Y_train,
cv=kfold, scoring='accuracy')
msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
print(msg)

Logistic Regression: 0.335031 (0.004490)
```

And now we make the predictions - actually classification - using our "cross validation set", that is, the subset that we had set aside. In this case we see that the hits were 34%.

```
predictions = model.predict(X_validation)
print(accuracy_score(Y_validation, predictions))

0.33702100368767035
```

####Classification (or prediction) of new values

```
data_test=pd.read_sql("""select
(case Sex when 'M' then 1 else 0 end) as Sex,
Year,
Age,
Height,
Weight,
(case Medal when 'Gold' then 1 when 'Silver' then 2  when 'Bronze'
then 3 else 4 end) as Medal from athletes where
 Age is not null and
Height is not null and
Weight is not null
limit 10112,1
""",conn)
#data_test.describe()
print(data_test)
model.predict(data_test.drop(['Medal'],1))
   Sex  Year   Age  Height  Weight  Medal
0    0  1992  27.0   157.0    51.0      3
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:439:
UserWarning: X has feature names, but LogisticRegression was fitted
without feature names
  f"X has feature names, but {self.__class__.__name__} was fitted
without" array([3])
```

####Experiment

```
new_data=pd.DataFrame({'Sex':[0],'Year':[2021],'Age':[28],'Height':
[190],'Weight':[50]})
print(new_data)
model.predict(new_data)
   Sex  Year  Age  Height  Weight
0    0  2021   28     190      50
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:439:
UserWarning: X has feature names, but LogisticRegression was fitted
without feature names
  f"X has feature names, but {self.__class__.__name__} was fitted
without" array([1])
```

##6. Hypotheses Results

- **How many Peruvians won a gold medal?** Only one Peruvian has won a gold medal
- **Has Cristiano Ronaldo (CR7) won any medals?** No, CR7 has not won a gold medal at the olympic games
- **Which sporting event gathered the most athletes?** Football has more athletes
- **In which year were the most gold medals awarded?** In 2008, more gold medals were awarded
- **In the 120 years of the Olympic Games, which country's team won the most medals?** USA has more medals
- **Are there more men or women who have won a gold medal?** Like I said, there are more men with gold medals
- **If the dataset only has events up to the year 2016, how do you predict which medal a new athlete will win?** A machine learning model has been created to predict new data from training with existing data. It is observed that the model is capable of predicting when new values are introduced

##7. Recommendations Positive, linear and strong correlation between height and weight. The Weight variable is a significant predictor of the Height variable. The observed studies lack experimental design principles. Therefore, the findings on the data cannot infer causality.
Observational studies can only infer correlation