s07_t01_hypothesis_testing

March 30, 2022

1 IT Academy - Data Science Itinerary

1.1 S07 T01: Hypothesis Testing

---

[1]:
```
# importing libraries
import pandas as pd
import kaggle
import scipy
from scipy import stats
import os
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotnine as p9
from sklearn import preprocessing
import pylab
from scipy.stats import norm
import statsmodels.api as sm
```

---

first, let's search for a dataset:

[2]:
```
!kaggle datasets list -s "Olympic"
```

```
ref                                                                 title
size  lastUpdated          downloadCount  voteCount  usabilityRating
------------------------------------------------------------------------
-------------------------------------------------  -----  -------------------
-------------  ---------  ---------------
datasets/heesoo37/120-years-of-olympic-history-athletes-and-results    120 years
```

```
of Olympic history: athletes and results    5MB  2018-06-15 06:10:41
96622       1701  0.8235294
datasets/stefanzivanov/olympic-games-2021-medals                        Olympic
Games 2021 Medals                             3KB  2021-10-16 20:07:59
2100         44  1.0
datasets/mysarahmadbhat/120-years-of-olympic-history                    120 Years
of Olympic History                           5MB  2021-08-09 02:26:36
2036         57  1.0
datasets/jayrav13/olympic-track-field-results                           Olympic
Track & Field Results                         80KB  2017-05-26 02:42:35
3536         53  0.7647059
datasets/the-guardian/olympic-games                                     Olympic
Sports and Medals, 1896-2014                483KB  2017-01-24 15:05:37
23398        210  0.7058824
datasets/piterfm/beijing-2022-olympics                                  Beijing
2022 Olympic Winter Games                   255KB  2022-02-20 12:07:42
1761         43  1.0
datasets/berkayalan/2021-olympics-medals-in-tokyo                       Tokyo
2020 Olympics Medals                          1KB  2021-08-09 19:36:13
2757         62  1.0
datasets/ramontanoeiro/winter-olympic-medals-1924-2018                  Winter
Olympic Medals 1924 - 2018                    3KB  2021-09-09 02:39:45
332         13  1.0
datasets/piterfm/olympic-games-medals-19862018                          Olympic
Games, 1986-2021                            14MB  2022-01-30 17:53:56
1076         19  1.0
datasets/ramontanoeiro/summer-olympic-medals-1986-2020                  Summer
Olympic Medals 1896 - 2020                   10KB  2021-09-09 02:34:15
1161         33  1.0
datasets/piterfm/tokyo-2020-olympics                                    Tokyo
2020 Olympic Summer Games                    670KB  2021-08-30 21:26:33
1660         25  1.0
datasets/mpwolke/cusersmarilonedriverea-de-trabalhomedalcsv             Olympic
Medal Rewards                               513B  2021-07-28 13:33:43
62         15  1.0
datasets/piterfm/olympic-results-biathlon                               Olympic
Results Biathlon                             5KB  2018-09-17 10:39:56
327          7  1.0
datasets/vaibhavchopra2/olympic-games-beijing-2022                      Olympic
Games Beijing 2022                          10KB  2022-02-22 05:21:57
621         19  0.7058824
datasets/alexkoshchii/olympicflags                                      Olympic
Flags                                       761KB  2021-09-21 15:53:25
20          4  0.875
datasets/rushikeshlavate/olympic-games-medal-datasetfrom-1896-to-2018  Olympic
Games medal Dataset(from 1896 to 2018)        4KB  2021-01-03 05:56:23
971         25  0.7647059
datasets/mathurinache/women-in-the-olympic-games                        Women in
```

```
the Olympic Games                                 113KB  2021-03-14 21:02:10
166          11  1.0
datasets/kukuroo3/beijing-olympic2022-athlete-profile                    Beijing
Olympic(2022) athlete Profile                     1MB  2022-02-01 13:48:54
98           13  0.5882353
datasets/jeronimojr/tokyo-2021-medal-table                               Tokyo
2020 Medal Table                                    1KB  2021-09-30 01:16:15
241          10  0.9411765
datasets/piterfm/olympic-games-hosts                                     Olympic
Games Hosts                                       3KB  2020-04-24 20:46:29
120           1  1.0
```

for this exercice we are going to use this dataset

let's use the following code to download the dataset from kagggle:

[4]:
```
PATH = "./data"

if not os.path.exists(PATH):
    os.makedirs(PATH)
if not os.listdir(PATH):
    !kaggle datasets download -d "heesoo37/
 ↪120-years-of-olympic-history-athletes-and-results" --unzip -p $PATH
```

```
Downloading 120-years-of-olympic-history-athletes-and-results.zip to ./data
100%|                    | 5.43M/5.43M [00:04<00:00, 1.44MB/s]
100%|                    | 5.43M/5.43M [00:04<00:00, 1.33MB/s]
```

[5]:
```
files = [os.path.join(PATH, f) for f in os.listdir(PATH)]

for f in files:
    print(f)
```

```
./data/noc_regions.csv
./data/athlete_events.csv
```

[6]:
```
df = pd.read_csv(files[1])
```

[7]:
```
display(df.head())
```

	ID	Name	Sex	Age	Height	Weight	Team	\
0	1	A Dijiang	M	24.0	180.0	80.0	China	
1	2	A Lamusi	M	23.0	170.0	60.0	China	
2	3	Gunnar Nielsen Aaby	M	24.0	NaN	NaN	Denmark	
3	4	Edgar Lindenau Aabye	M	34.0	NaN	NaN	Denmark/Sweden	
4	5	Christine Jacoba Aaftink	F	21.0	185.0	82.0	Netherlands	

```
   NOC        Games  Year  Season       City          Sport  \
0  CHN  1992 Summer  1992  Summer  Barcelona     Basketball
1  CHN  2012 Summer  2012  Summer     London           Judo
2  DEN  1920 Summer  1920  Summer  Antwerpen       Football
3  DEN  1900 Summer  1900  Summer      Paris     Tug-Of-War
4  NED  1988 Winter  1988  Winter    Calgary  Speed Skating

                             Event Medal
0       Basketball Men's Basketball   NaN
1      Judo Men's Extra-Lightweight   NaN
2           Football Men's Football   NaN
3       Tug-Of-War Men's Tug-Of-War  Gold
4  Speed Skating Women's 500 metres   NaN
```

[8]:
```
df.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
```

[9]:
```
#preaparing a sample from the dataset

df_sample = df.sample(frac=1/5, random_state=2021)

df_sample.shape
```

[9]:
```
(54223, 15)
```

____ #### Exercise 1

Grab a sports theme dataset you like and select an attribute from the dataset. Calculate the p-value and say if you reject the null hypothesis by taking a 5% alpha.

For this exercise we are going to consider the following situation:

First of all, we are going to check if the atribute to use complies with the assumption of normality. As we are going to work with the weight attribute:

- let's make some plots of the weight atribute (for both the population and the sample) to see if satisfy with the condition of normality.
- let's check whether the condition of normality is satisfied using some test
- *we will do the same with the sample that we have prepared before.*

Once the verification is done, we'll choose what statistical test to use in order to do the following:

- test the difference between the population and the sample weight

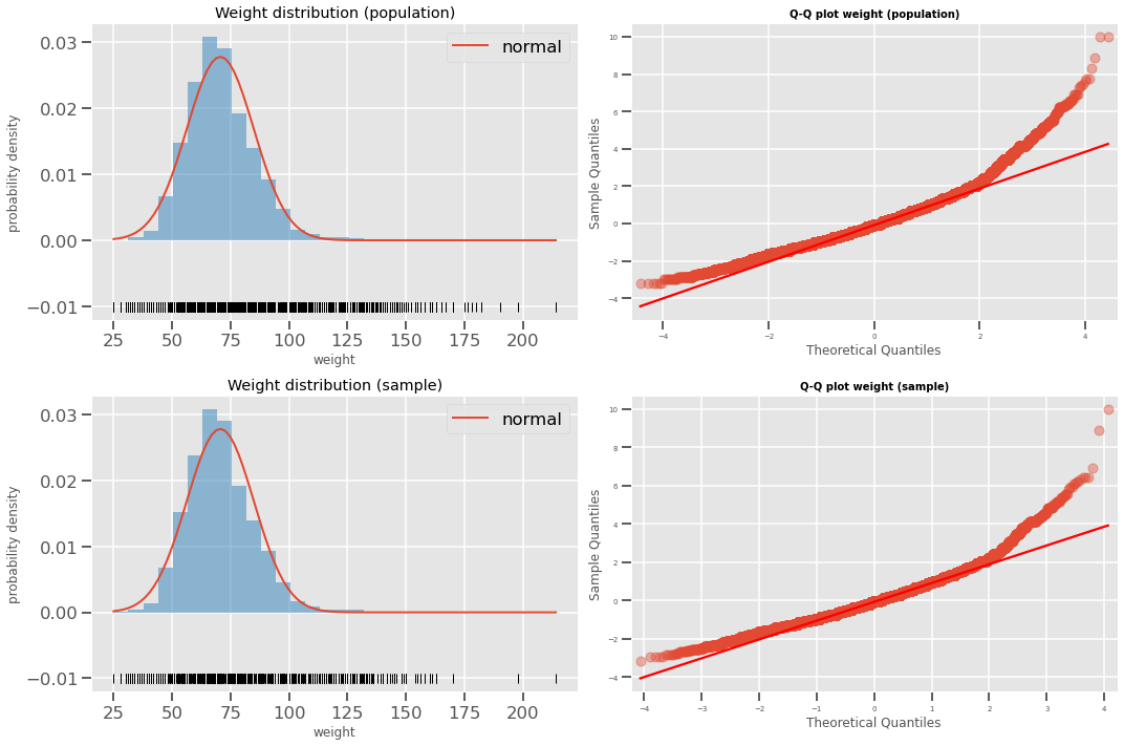
We want to see whether the mean weight of the athelets in this sample is significantly different from population mean

- Plotting the data:

[10]:
```
sns.set_context("talk")
plt.style.use('ggplot')

#POP
weight = df[df["Weight"].notnull()]["Weight"]


# values of mean (mu) and standar desviation (sigma) of the population
mu, sigma = stats.norm.fit(weight)

#  Theoretical values of the normal in the observed range
x_hat = np.linspace(min(weight), max(weight), num=100)
y_hat = stats.norm.pdf(x_hat, mu, sigma)
```

```
#SAMPLE

weight_sample = df_sample[df_sample["Weight"].notnull()]["Weight"]

# values of mean (mu) and standar desviation (sigma) of the population
mu_sample, sigma_sample = stats.norm.fit(weight_sample)
#  Theoretical values of the normal in the observed range
x_hat = np.linspace(min(weight_sample), max(weight_sample), num=100)
y_hat = stats.norm.pdf(x_hat, mu_sample, sigma_sample)




# plots

fig,axes = plt.subplots(2,2,figsize=(15,10))

axes[0,0].plot(x_hat, y_hat, linewidth=2, label='normal')
axes[0,0].hist(x=weight, density=True, bins=30, color="#3182bd", alpha=0.5)
axes[0,0].plot(weight, np.full_like(weight, -0.01), '|k', markeredgewidth=1)
axes[0,0].set_title('Weight distribution (population)')
axes[0,0].set_xlabel('weight')
axes[0,0].set_ylabel('probability density')
axes[0,0].legend()

axes[1,0].plot(x_hat, y_hat, linewidth=2, label='normal')
axes[1,0].hist(x=weight_sample, density=True, bins=30, color="#3182bd", alpha=0.
↪5)
axes[1,0].plot(weight_sample, np.full_like(weight_sample, -0.01), '|k',␣
↪markeredgewidth=1)
axes[1,0].set_title('Weight distribution (sample)')
axes[1,0].set_xlabel('weight')
axes[1,0].set_ylabel('probability density')
axes[1,0].legend()

sm.qqplot(weight,
    fit   = True,
    line  = 'q',
    alpha = 0.4,
    lw    = 2,
    ax    = axes[0,1]

)
axes[0,1].set_title('Q-Q plot weight (population)', fontsize = 10,
           fontweight = "bold")
axes[0,1].tick_params(labelsize = 7)
```

```
sm.qqplot(weight_sample,
    fit   = True,
    line  = 'q',

    alpha = 0.4,
    lw    = 2,
    ax    = axes[1,1]

)
axes[1,1].set_title('Q-Q plot weight (sample)', fontsize = 10,
         fontweight = "bold")
axes[1,1].tick_params(labelsize = 7)


plt.tight_layout()
plt.show()
```



In the plots of distribution seems that the weight (for the population and the sample) have a normal distribution. However, the Q-Q plot shows the opposite. in order to confirm the normality of the data let's use the D'Agostino's K-squared test to determine if our atribute weight have a normal

distribution

we use this test and not the Shapiro-Wilk test because the amount of data is greater than 5000. With N >5000, p-value may not be accurate

[11]:
```
#our N >5000

print(len(weight))
print(len(weight_sample))
```

208241
41746

[12]:
```
# D'Agostino's K-squared test Normality Test

stat, p = stats.normaltest(weight)
alpha= 0.05
print('stat=%.3f, p=%.3f' % (stat, p))


if p < alpha:  # null hypothesis: weight comes from a normal distribution

    print("The null hypothesis can be rejected")

else:

    print("The null hypothesis cannot be rejected")
```

stat=27009.310, p=0.000
The null hypothesis can be rejected

[13]:
```
# D'Agostino's K-squared  Normality Test

stat, p = stats.normaltest(weight_sample)
alpha= 0.05

print('stat=%.3f, p=%.3f' % (stat, p))


if p < alpha:  # null hypothesis: weight_sample comes from a normal distribution

    print("The null hypothesis can be rejected")

else:

    print("The null hypothesis cannot be rejected")
```

```
stat=5794.522, p=0.000
The null hypothesis can be rejected
```

Although the previous test confirms that the data does not have a normal distribution, we can also try with the Jarque-Bera test.

This tests whether the sample has the skewness and kurtosis matching with a normal distribution, i.e., skewness=0 and kurtosis =3

[14]:
```
# Jarque vera Normality Test
stat, p = stats.jarque_bera(weight)
alpha= 0.05

print('stat=%.3f, p=%.3f' % (stat, p))

if p < alpha:  # null hypothesis: weight comes from a normal distribution

    print("The null hypothesis can be rejected")

else:

    print("The null hypothesis cannot be rejected")
```

```
stat=57370.084, p=0.000
The null hypothesis can be rejected
```

[15]:
```
# Jarque vera Normality Test
stat, p = stats.jarque_bera(weight_sample)
alpha= 0.05

print('stat=%.3f, p=%.3f' % (stat, p))

if p < alpha:  # null hypothesis: weight_sample comes from a normal distribution

    print("The null hypothesis can be rejected")

else:

    print("The null hypothesis cannot be rejected")
```

```
stat=13334.426, p=0.000
The null hypothesis can be rejected
```

we can confirm that weight (both for the population and for the sample) does not have a normal distribution. For this reason, we will have to use non-parametric tests.

Now let's see if the difference between the sample and that of the population weight are statistically significant

[16]:
```
# weight population

print(df.Weight.describe())
```

```
count    208241.000000
mean         70.702393
std          14.348020
min          25.000000
25%          60.000000
50%          70.000000
75%          79.000000
max         214.000000
Name: Weight, dtype: float64
```

[17]:
```
# weight  sample

print(weight_sample.describe())
```

```
count    41746.000000
mean        70.587465
std         14.342593
min         25.000000
25%         60.000000
50%         70.000000
75%         79.000000
max        214.000000
Name: Weight, dtype: float64
```

we see that there is a difference (70.70 - 70.58) betwen the population and the sample weight

Having calculate the test it will allow us to verify the following:

- $H_0 : \mu_A = \mu_B$
- $H_1 : \mu_A \neq \mu_B$
- where: μ_A = weight_sample and μ_B = population weight

[18]:
```
# Perform the Wilcoxon rank-sum test
wilc = stats.ranksums(weight_sample, weight)
print(wilc)
```

```
RanksumsResult(statistic=-1.458469541390247, pvalue=0.14471116470087755)
```

[19]:
```
# Test significance
alpha = 0.05
if (wilc [1] < alpha):
    print("value of Sample  differs from given value")
else:
    print("No significant difference found")
```

```
No significant difference found
```

Conclusion: We cannot reject null hypothesis with the significance level of 5%. With a p-value greater than 0.05, the difference between the population and the sample weight is not statistically significant.

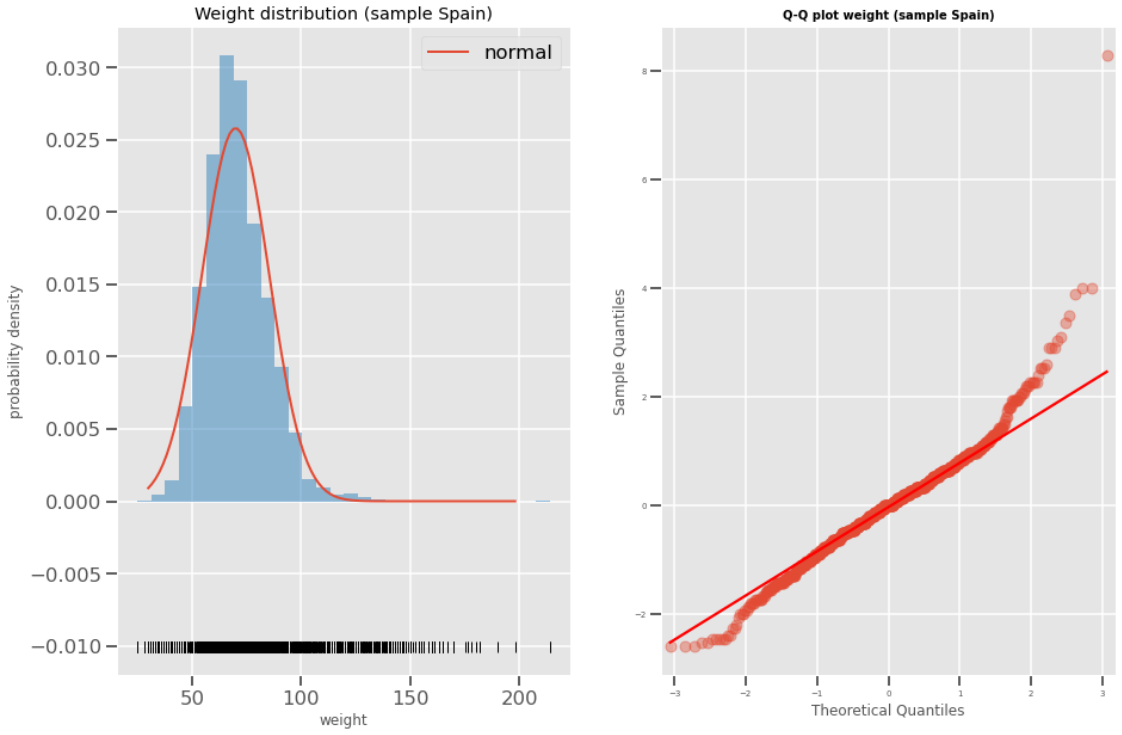
Let's repeat the exercise, but with a more restrictive sample. For the same sample, let's filtering and using only the values from Spain.

[20]:
```
df_sample_spain = df_sample[(df_sample["Team"] =="Spain") &␣
 ↪(df_sample["Weight"].notnull())]
```

let's make some plot to check if there are normality distribution in the new sample:

[21]:
```
#sample spain

weight_spain = df_sample_spain[df_sample_spain["Weight"].notnull()]["Weight"]

# values of mean (mu) and standar desviation (sigma) of the sample(spain)
mu_spain, sigma_spain = stats.norm.fit(weight_spain)

#  Theoretical values of the normal in the observed range
x_hat = np.linspace(min(weight_spain), max(weight_spain), num=100)
y_hat = stats.norm.pdf(x_hat, mu_spain, sigma_spain)

# plots
fig,axes = plt.subplots(1,2,figsize=(15,10))

axes[0].plot(x_hat, y_hat, linewidth=2, label='normal')
axes[0].hist(x=weight, density=True, bins=30, color="#3182bd", alpha=0.5)
axes[0].plot(weight, np.full_like(weight, -0.01), '|k', markeredgewidth=1)
```

```
axes[0].set_title('Weight distribution (sample Spain)')
axes[0].set_xlabel('weight')
axes[0].set_ylabel('probability density')
axes[0].legend()

sm.qqplot(weight_spain,
    fit   = True,
    line  = 'q',
    alpha = 0.4,
    lw    = 2,
    ax    = axes[1]

)
axes[1].set_title('Q-Q plot weight (sample Spain)', fontsize = 10,
    fontweight = "bold")
axes[1].tick_params(labelsize = 7)
```



the plots show that there is no normal distribution in this sample.

As len(weight_spain) < 5000 we can use the shapiro test to confirm it

[22]:
```
shapiro_test = stats.shapiro(weight_spain)
shapiro_test

alpha= 0.05

print('stat=%.3f, p=%.3f' % (stat, p))

if p < alpha:  # null hypothesis: weight_spain comes from a normal distribution

    print("The null hypothesis can be rejected")

else:

    print("The null hypothesis cannot be rejected")
```

```
stat=13334.426, p=0.000
The null hypothesis can be rejected
```

Since the assumption of normality is not satisfied, we will use a non-parametric test to see if the difference between the new sample and that of the population weight are statistically significant

[23]:
```
df_sample_spain.Weight.describe()
```

[23]:
```
count    894.000000
mean      69.978747
std       15.462507
min       30.000000
25%       61.000000
50%       70.000000
75%       78.000000
max      198.000000
Name: Weight, dtype: float64
```

As we can see that there is a bigger difference between the mean of the spanish athletes weight and the population mean (69.97 - 70.70).

Now, we are going to verify if the difference that we observe is statistically significant. For this, we consider the following:

- $H_0 : \mu_A = \mu_B$
- $H_1 : \mu_A \neq \mu_B$
- where: μ_A = weight_spain and μ_B = population weight

[24]:
```
# Perform the Wilcoxon rank-sum test
wilc = stats.ranksums(weight, weight_spain)
print(wilc)
```

```
RanksumsResult(statistic=0.6697401163895398, pvalue=0.5030234737295822)
```

[25]:
```
# Test significance
alpha = 0.05
if (wilc[1] < alpha):
    print("mean value of Sample  differs from given value")
else:
    print("No significant difference found")
```

```
No significant difference found
```

Conclusion: We can reject null hypothesis with the significance level of 5%

Let's try a different test. Suppose we want to see whether or not there is a bias on the ratio of male to female athletes significantly depart from 50-50. To test this we have to perform a Chi-square test

[26]:
```
sexratio = df["Sex"].value_counts()
sexratio
```

[26]:
```
M    196594
F     74522
Name: Sex, dtype: int64
```

[27]:
```
# Perform Chi-square test
chi= stats.chisquare(sexratio)
print(chi)
```

```
Power_divergenceResult(statistic=54963.82797031529, pvalue=0.0)
```

[28]:
```
# Test significance
alpha= 0.05
if chi[1] < alpha:
    print("Difference between sexes is statistically significant")
else:
    print("No significant difference between sexes found")
```

```
Difference between sexes is statistically significant
```

the Chi-square test shows that there are significantly more men than women

____ #### Exercise 2

Continue with the sports theme dataset you like and select two other attributes from the dataset. Calculate the p-values and say if they reject the null hypothesis by taking a 5% alpha.

____

for this exercise, we are focusing on just one event, the women's 100 meter running race. let's look at how the heights of competitors have changed over time. A Pearson correlation test allows us to determine whether a linear relationship exists between two variables (*year* and *height*)

- First, let's make some plots, to see how the runners' weights have changed over time.

[29]:
```
#filter our dataset
women_100 = df[(df["Event"] == "Athletics Women's 100 metres") & df["Height"].
 ↪notnull()]
women_100
```

[29]:

	ID	Name	Sex	Age	Height	\
26	8	Cornelia "Cor" Aalten (-Strannood)	F	18.0	168.0	
526	299	Dana Abdul Razak (Hussain-)	F	22.0	163.0	
527	299	Dana Abdul Razak (Hussain-)	F	26.0	163.0	
1081	609	Fartun Abukar Omar	F	18.0	170.0	
1096	613	Kariman Abuljadayel	F	22.0	180.0	
…	…	…	..	…	…	
269182	134695	Lyudmila Ilyinichna Zharkova-Maslakova	F	20.0	175.0	
269184	134695	Lyudmila Ilyinichna Zharkova-Maslakova	F	24.0	175.0	
269320	134764	Marina Serafimovna Zhirova (Titova-)	F	25.0	170.0	
270763	135410	Zaidatul Husniah Zulkifli	F	22.0	156.0	
271053	135547	Viktoriya Viktorovna Zyabkina	F	23.0	174.0	

	Weight	Team	NOC	Games	Year	Season	City	\
26	NaN	Netherlands	NED	1932 Summer	1932	Summer	Los Angeles	
526	56.0	Iraq	IRQ	2008 Summer	2008	Summer	Beijing	
527	56.0	Iraq	IRQ	2012 Summer	2012	Summer	London	
1081	58.0	Somalia	SOM	2004 Summer	2004	Summer	Athina	
1096	70.0	Saudi Arabia	KSA	2016 Summer	2016	Summer	Rio de Janeiro	
…	…	…	…	…	…	…	…	
269182	59.0	Soviet Union	URS	1972 Summer	1972	Summer	Munich	
269184	59.0	Soviet Union	URS	1976 Summer	1976	Summer	Montreal	
269320	58.0	Soviet Union	URS	1988 Summer	1988	Summer	Seoul	
270763	40.0	Malaysia	MAS	2016 Summer	2016	Summer	Rio de Janeiro	

```
271053    62.0    Kazakhstan  KAZ  2016 Summer  2016  Summer  Rio de Janeiro

            Sport                          Event Medal
26      Athletics  Athletics Women's 100 metres   NaN
526     Athletics  Athletics Women's 100 metres   NaN
527     Athletics  Athletics Women's 100 metres   NaN
1081    Athletics  Athletics Women's 100 metres   NaN
1096    Athletics  Athletics Women's 100 metres   NaN
…           …                              …   …
269182  Athletics  Athletics Women's 100 metres   NaN
269184  Athletics  Athletics Women's 100 metres   NaN
269320  Athletics  Athletics Women's 100 metres   NaN
270763  Athletics  Athletics Women's 100 metres   NaN
271053  Athletics  Athletics Women's 100 metres   NaN

[930 rows x 15 columns]
```

[30]:
```
#define our variables
w_height = women_100["Height"]
w_year =  women_100["Year"]
```

[31]:
```
sns.set_context("talk")

#plot
fig,axes = plt.subplots(1,1, figsize=(15,10))

#plot shows the regression line

sns.regplot(x=w_year, y=w_height,data=women_100,ax=axes,

            scatter_kws={'alpha':0.3})

axes.set_title("Scatter plot: relationship between \
metres height and year",fontsize=8)
axes.set_xlabel("years")
axes.set_ylabel("Height (in cm)")
axes.spines['top'].set_visible(False)
axes.spines['right'].set_visible(False)
```

From what the plot shows, it seems that there is no relationship between the variables.

Despite this, let's calculate Pearson's correlation coefficient and see whether or not there is correlation between the variables

[32]:
```
pearson = stats.pearsonr(w_height,w_year)
print(pearson)
```

```
(-0.018466713687361733, 0.5738097081189003)
```

[33]:
```
# Test if p-value is bigger or smaller than alpha
alpha = 0.05
if pearson[1] < alpha:
    print("Weights and year are significantly correlated")
else:
    print("No significant correlation found")
```

```
No significant correlation found
```

Let's repeat the exercise, but now let's see if there is a relationship between the weight and the height of the athletes:

[34]:
```
#filter our dataset
women_100 = df[(df["Event"] == "Athletics Women's 100 metres") & df["Height"].
↪notnull() & df["Weight"].notnull()]
women_100
```

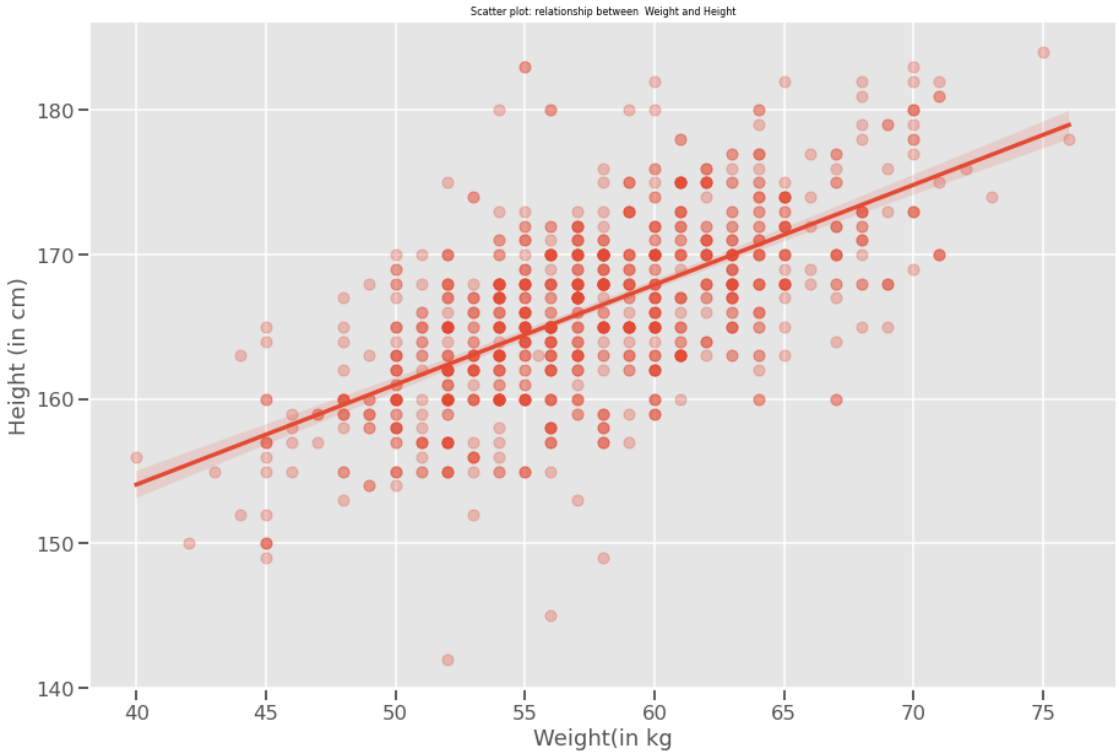
[34]:

	ID	Name	Sex	Age	Height	Weight	Team	NOC	Games	Year	Season	City	Sport	Event	Medal
526	299	Dana Abdul Razak (Hussain-)	F	22.0	163.0	56.0	Iraq	IRQ	2008 Summer	2008	Summer	Beijing	Athletics	Athletics Women's 100 metres	NaN
527	299	Dana Abdul Razak (Hussain-)	F	26.0	163.0	56.0	Iraq	IRQ	2012 Summer	2012	Summer	London	Athletics	Athletics Women's 100 metres	NaN
1081	609	Fartun Abukar Omar	F	18.0	170.0	58.0	Somalia	SOM	2004 Summer	2004	Summer	Athina	Athletics	Athletics Women's 100 metres	NaN
1096	613	Kariman Abuljadayel	F	22.0	180.0	70.0	Saudi Arabia	KSA	2016 Summer	2016	Summer	Rio de Janeiro	Athletics	Athletics Women's 100 metres	NaN
1159	644	Claudia Acerenza Marez	F	22.0	160.0	55.0	Uruguay	URU	1988 Summer	1988	Summer	Seoul	Athletics	Athletics Women's 100 metres	NaN
…	…	…	..	…	…	…	…	…	…	…	…	…	…	…	…
269182	134695	Lyudmila Ilyinichna Zharkova-Maslakova	F	20.0	175.0	59.0	Soviet Union	URS	1972 Summer	1972	Summer	Munich	Athletics	Athletics Women's 100 metres	NaN
269184	134695	Lyudmila Ilyinichna Zharkova-Maslakova	F	24.0	175.0	59.0	Soviet Union	URS	1976 Summer	1976	Summer	Montreal	Athletics	Athletics Women's 100 metres	NaN
269320	134764	Marina Serafimovna Zhirova (Titova-)	F	25.0	170.0	58.0	Soviet Union	URS	1988 Summer	1988	Summer	Seoul	Athletics	Athletics Women's 100 metres	NaN
270763	135410	Zaidatul Husniah Zulkifli	F	22.0	156.0	40.0	Malaysia	MAS	2016 Summer	2016	Summer	Rio de Janeiro	Athletics	Athletics Women's 100 metres	NaN
271053	135547	Viktoriya Viktorovna Zyabkina	F	23.0	174.0	62.0	Kazakhstan	KAZ	2016 Summer	2016	Summer	Rio de Janeiro	Athletics	Athletics Women's 100 metres	NaN

```
[921 rows x 15 columns]
```

[35]:
```
#define our variables
w_height = women_100["Height"]
w_weight = women_100["Weight"]
```

[36]:
```
sns.set_context("talk")

#plot
fig,axes = plt.subplots(1,1, figsize=(15,10))

#plot shows the regression line

sns.regplot(x=w_weight, y=w_height,data=women_100,ax=axes,

            scatter_kws={'alpha':0.3})

axes.set_title("Scatter plot: relationship between \
 Weight and Height",fontsize=8)
axes.set_xlabel("Weight(in kg")
axes.set_ylabel("Height (in cm)")
axes.spines['top'].set_visible(False)
axes.spines['right'].set_visible(False)
```



From what the plot shows, it seems that there is positive relationship between weight and height.

let's calculate Pearson's correlation coefficient and see whether or not there is correlation between the variables and if there are significantly correlated,

[37]:
```
pearson = stats.pearsonr(w_weight,w_height)
print(pearson)
```

```
(0.644174799814726, 4.284134810199894e-109)
```

[38]:
```
# Test if p-value is bigger or smaller than alpha
alpha = 0.05
if pearson[1] < alpha:
    print("Weights and height are significantly correlated")
else:
    print("No significant correlation found")
```

```
Weights and height are significantly correlated
```

____ #### Exercise 3

Continue with the sports theme dataset you like and select three attributes from the dataset. Calculate the p-value and say if you reject the null hypothesis by taking a 5% alpha.

____

For this exercise, we are going to check if the are presence of significant variantion in Weight of Olympic male athletes from teams of USA, France and China

- First, let's do a some plots to see how our variables are distributed.
- Then, let's performance a test to see whether any differences between these groups of values are significant.

the test will allow us to verify the following:

- H_0 : $\mu_A = \mu_B = \mu_C$ (There is no difference between weight of the groups)
- H_1 : there is a difference between the means and groups

Where
+ μ_A is weight from athletes of USA + μ_B is weight from athletes of China + μ_C is weight from athletes of France

[39]:
```
df_group= df[(df["NOC"] == "CHN") | (df["NOC"] == "FRA") | (df["NOC"]== "USA")]
df_group= df_group[df_group["Sex"]=="M"]
df_group= df_group[df_group["Event"].str.contains("Athletics")]
df_group= df_group[df_group["Weight"].notnull()]
```

[40]:
```
display(df_group.head())
display(df_group.info())
display(df_group.shape)
display(df_group.NOC.unique())
```

```
      ID                                 Name Sex   Age  Height  Weight  \
98    34  Jamale (Djamel-) Aarrass (Ahrass-)   M  30.0   187.0    76.0
145   52                        Patrick Abada   M  22.0   189.0    80.0
273  142                  David "Dave" Abbott   M  26.0   183.0    75.0
466  256          Abdihakim "Abdi" Abdirahman   M  23.0   178.0    61.0
467  256          Abdihakim "Abdi" Abdirahman   M  27.0   178.0    61.0

              Team  NOC        Games  Year  Season       City      Sport  \
98          France  FRA  2012 Summer  2012  Summer     London  Athletics
145         France  FRA  1976 Summer  1976  Summer   Montreal  Athletics
273  United States  USA  1928 Summer  1928  Summer  Amsterdam  Athletics
466  United States  USA  2000 Summer  2000  Summer     Sydney  Athletics
467  United States  USA  2004 Summer  2004  Summer     Athina  Athletics

                            Event Medal
98    Athletics Men's 1,500 metres   NaN
145     Athletics Men's Pole Vault   NaN
273   Athletics Men's 5,000 metres   NaN
466  Athletics Men's 10,000 metres   NaN
467  Athletics Men's 10,000 metres   NaN
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3122 entries, 98 to 271044
Data columns (total 15 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   ID      3122 non-null   int64
 1   Name    3122 non-null   object
 2   Sex     3122 non-null   object
 3   Age     3117 non-null   float64
 4   Height  3122 non-null   float64
 5   Weight  3122 non-null   float64
 6   Team    3122 non-null   object
 7   NOC     3122 non-null   object
 8   Games   3122 non-null   object
 9   Year    3122 non-null   int64
 10  Season  3122 non-null   object
 11  City    3122 non-null   object
```

```
 12  Sport   3122 non-null   object
 13  Event   3122 non-null   object
 14  Medal   867 non-null    object
dtypes: float64(3), int64(2), object(10)
memory usage: 390.2+ KB
```

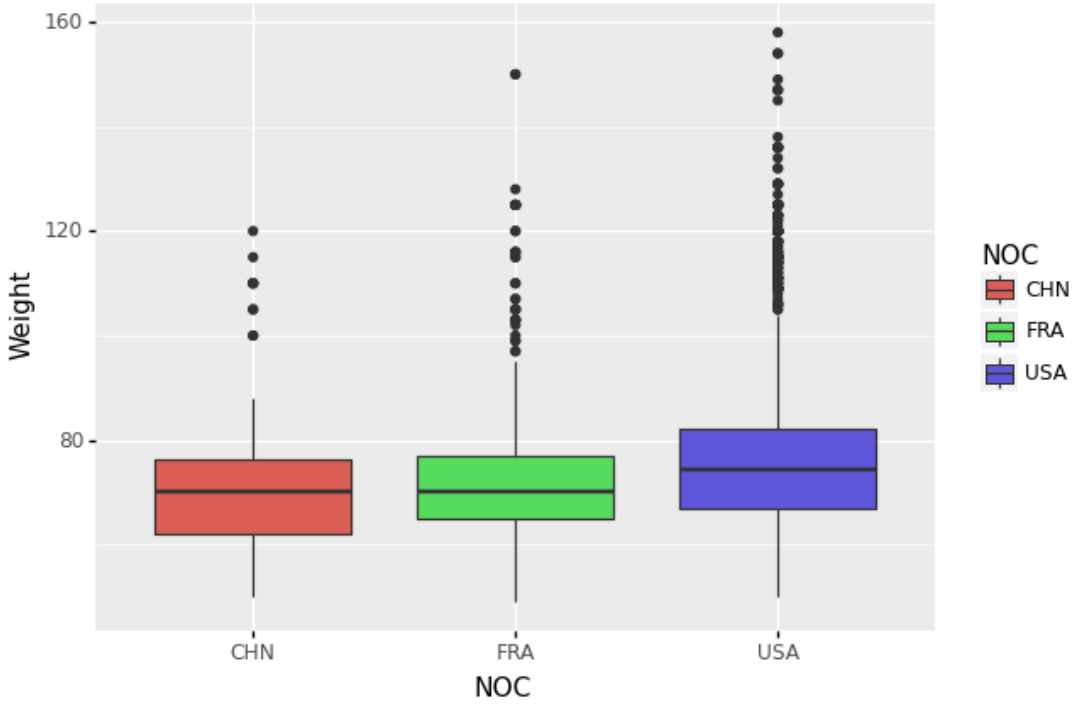
```
None
```

```
(3122, 15)
```

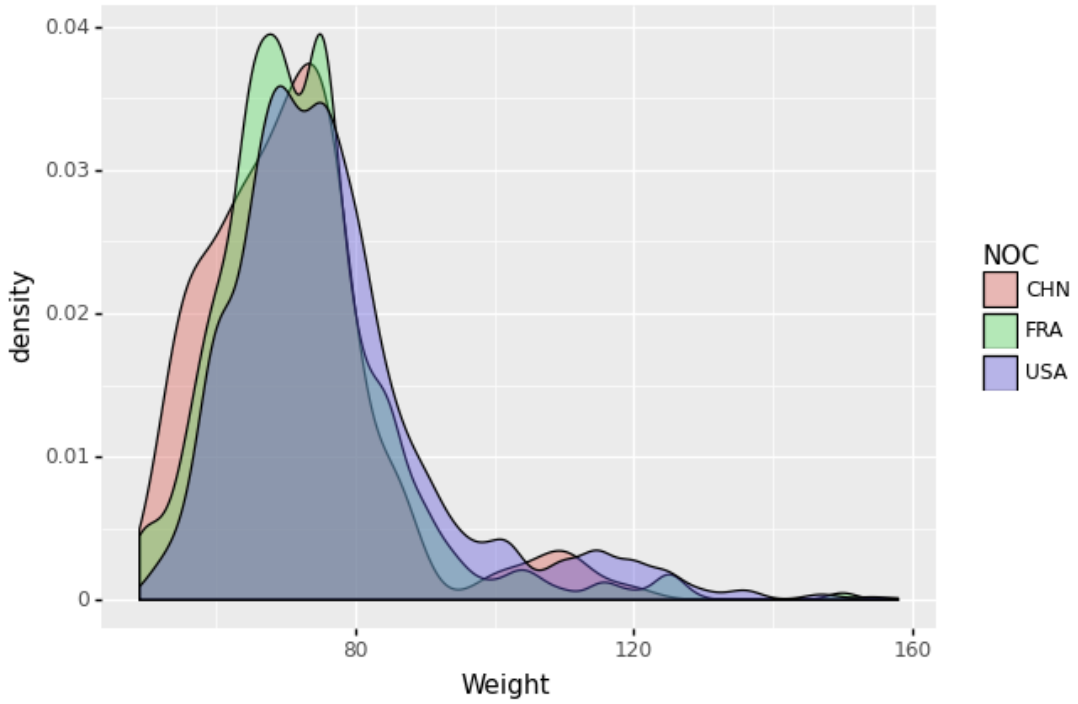
```
array(['FRA', 'USA', 'CHN'], dtype=object)
```

Let's make some plots:

[41]:
```
print(p9.ggplot(df_group)+ p9.aes(x='NOC',y='Weight', fill='NOC')+ p9.
↪geom_boxplot())
```



[42]:
```
print(p9.ggplot(df_group)+ p9.aes(x='Weight', fill='NOC') + p9.
↪geom_density(alpha=0.4))
```



In the plots above we see that possibly our variables do not have a normal distribution. Since the normality of the data distribution is an assumption we have to check let's do the verification

let's use the Shapiro-Wilk test to determine if our variables have a normal distribution

[43]:
```
# Create arrays
France_athletes = df_group[df_group.NOC == "FRA"].Weight
US_athletes = df_group[df_group.NOC == "USA"].Weight
China_athletes = df_group[df_group.NOC == "CHN"].Weight
```

[44]:
```
print(len(France_athletes))
print(len(US_athletes))
print(len(China_athletes))
```

```
806
2140
176
```

[45]:
```
# Shapiro-Wilk Normality Test

stat, p = stats.shapiro(France_athletes)
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
        print('Probably Gaussian')
else:
        print('Probably not Gaussian')
```

```
stat=0.890, p=0.000
Probably not Gaussian
```

[46]:
```
# Shapiro-Wilk Normality Test

stat, p = stats.shapiro(US_athletes)
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
        print('Probably Gaussian')
else:
        print('Probably not Gaussian')
```

```
stat=0.879, p=0.000
Probably not Gaussian
```

[47]:
```
# Shapiro-Wilk Normality Test


stat, p = stats.shapiro(China_athletes)
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
        print('Probably Gaussian')
else:
        print('Probably not Gaussian')
```

```
stat=0.899, p=0.000
Probably not Gaussian
```

we have determined that our variables do not comply the assumption of normality

how we already detectet data do not comply with the assumption of normality. For this reason, we will have to use non-parametric test.

[48]:
```
# Perform The Kruskal-Wallis -test
kustal = stats.kruskal(France_athletes,US_athletes,China_athletes)
print(kustal)
```

```
KruskalResult(statistic=71.08813416155202, pvalue=3.659382462661707e-16)
```

Having calculate the test it will allow us to verify the following:

- H_0 : The median is equal across all groups.
- H_1 : The median is not equal across all groups.

[49]:
```
# Test significance
alpha = 0.05
if (kustal[1] < alpha):
    print("we can reject the null hypothesis")
else:
    print("No significant difference found")
```

```
we can reject the null hypothesis
```

The p value obtained from Kruskal-Wallis -test analysis is significant ($p < 0.05$), and therefore, we conclude that there are significant differences significant differences exist between the weights of athletes for each country.

____ #### Conclusions

+ There are different methods to verify the normality of the data distribution. + The graphic approach (for the analysis of the normality of the data distribution) is useful but we cannot only rely on the plots, it is also necessary to use the statistical tests + Before performing a statistical test, it is important to know what assumptions this test requires.

***References*:**

- Scipy Stats ttest_1samp Hypothesis Testing
- Chi-Square Test, with Python
- Experimental Design in Python
- Análisis de normalidad con python
- Methods for Normality Test with Application in Python
- How to Perform a Kruskal-Wallis Test in Python