Vaulin_Pr1_Olympics

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1 120 years of Olympic history: athletes and results

1.0.1 BI statisctics course Project 1

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The dataset is adapted by course instructor from kaggle.

[1]:
```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
from statsmodels.stats.multitest import multipletests
```

Also Jupyter Notebook like to sens us so many warnings such as FutureWarning and so on. Let's make our output more pretty:

[2]:
```
import warnings
warnings.filterwarnings('ignore')
```

1.0.2 Reading the data

We will define here special function which uploads all the files from some with a given extension to a combined pandas dataframe

[3]:
```
sep_readers = {
    ".csv": pd.read_csv,
    ".tsv": pd.read_table,
    ".hdf": pd.read_hdf,
    ".h5": pd.read_hdf,
    ".html": pd.read_html,
    ".htm": pd.read_html,
    ".xml": pd.read_xml,
    ".json": pd.read_json,
    ".xls": pd.read_excel,
    ".xlsx": pd.read_excel,
    ".xltx": pd.read_excel,
    ".ods": pd.read_excel
```

```
}


def read_one_table(folder, filename, extension):
    """
    Extra function to read one specific file with function suitable for a given␣
 ↪file extension
    """
    file = os.path.join(folder, filename)
    return sep_readers[extension](file)


def file_reader(folder: str = 'athlete_events', ext: str = '.csv') -> pd.
 ↪DataFrame:
    """
    This function uploads from disk a dataset divided into several files as a␣
 ↪single pandas data frame.

    Several input files should contain same columns! The number of rows doesn't␣
 ↪matter, the function provides
    row-wise concatenation of input files.

    Parameters:
        folder (str): name of a folder with input datasets to read
        ext (str): input files extension

    Output:
        Pandas Data.Frame combined from input files row-by-row
    """
    if not ext.startswith('.'):
        ext = f'.{ext}'
    files = [read_one_table(folder, f, ext.lower()) for f in os.listdir(folder)␣
 ↪if f.endswith(ext)]
    return pd.concat(files)
```

So let's load our data. We don't need any parameters here due to their default values definition

[4]:
```
df = file_reader(os.path.join('..', 'data', 'athlete_events'), '.csv')
```

Now let's proceed some initial EDA to check weather it everething alright with our data:

[5]:
```
df.head(3)
```

[5]:
```
   ID                Name Sex   Age  Height  Weight     Team  NOC  \
0   1           A Dijiang   M  24.0   180.0    80.0    China  CHN
1   2            A Lamusi   M  23.0   170.0    60.0    China  CHN
2   3 Gunnar Nielsen Aaby   M  24.0     NaN     NaN  Denmark  DEN
```

```
         Games    Year  Season       City       Sport  \
0  1992 Summer  1992.0  Summer  Barcelona  Basketball
1  2012 Summer  2012.0  Summer     London        Judo
2  1920 Summer  1920.0  Summer  Antwerpen    Football

                          Event Medal
0   Basketball Men's Basketball   NaN
1  Judo Men's Extra-Lightweight   NaN
2       Football Men's Football   NaN
```

Let's highlight here the numerical and categorical features.

Regarding the Year, this is neither a numerical nor a qualitative variable. Let's consider it a separate type - Time Series.

[6]:
```
num_features = ['Age', 'Height', 'Weight']
cat_features = ['Name', 'Sex', 'Team', 'NOC', 'Games', 'Season', 'City',␣
 ↪'Sport', 'Event', 'Medal']
```

[7]:
```
print(f'Here we have {len(df)} entries total in our dataframe\n')
print(f'Some summary about the data:\n')
print(df.info())
```

```
Here we have 271115 entries total in our dataframe

Some summary about the data:

<class 'pandas.core.frame.DataFrame'>
Int64Index: 271115 entries, 0 to 22390
Data columns (total 15 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   ID      271115 non-null  int64
 1   Name    271114 non-null  object
 2   Sex     271113 non-null  object
 3   Age     261639 non-null  float64
 4   Height  210943 non-null  float64
 5   Weight  208239 non-null  float64
 6   Team    271112 non-null  object
 7   NOC     271111 non-null  object
 8   Games   271110 non-null  object
 9   Year    271108 non-null  float64
 10  Season  271108 non-null  object
 11  City    271108 non-null  object
 12  Sport   271108 non-null  object
 13  Event   271107 non-null  object
 14  Medal   39782 non-null   object
dtypes: float64(4), int64(1), object(10)
```

```
memory usage: 33.1+ MB
None
```

This result also could be obtained with `df.isna().sum()` or `df.isnull().sum()` functions

According to the table all the columns expected to be numeric are actually numeric, so i don't see any numbers written as strings

1.0.3 Finding rubbish in data

We will deal with missing values later, here about the rabbish

[8]:
```python
for f in ['Sex', 'Season', 'Medal', 'Games', 'City', 'Sport']:
    print(f'Unique {f} values: {df[f].unique()}')
```

```
Unique Sex values: ['M' 'F' 'G' nan]
Unique Season values: ['Summer' 'Winter' nan]
Unique Medal values: [nan 'Gold' 'Bronze' 'Silver']
Unique Games values: ['1992 Summer' '2012 Summer' '1920 Summer' '1900 Summer'
'1988 Winter'
 '1992 Winter' '1994 Winter' '1932 Summer' '2002 Winter' '1952 Summer'
 '1980 Winter' '2000 Summer' '1996 Summer' '1912 Summer' '1924 Summer'
 '2014 Winter' '1948 Summer' '1998 Winter' '2006 Winter' '2008 Summer'
 '2016 Summer' '2004 Summer' '1960 Winter' '1964 Winter' '1984 Winter'
 '1984 Summer' '1968 Summer' '1972 Summer' '1988 Summer' '1936 Summer'
 '1952 Winter' '1956 Winter' '1956 Summer' '1960 Summer' '1928 Summer'
 '1976 Summer' '1980 Summer' '1964 Summer' '2010 Winter' '1968 Winter'
 '1906 Summer' '1972 Winter' '1976 Winter' '1924 Winter' '1904 Summer'
 '1928 Winter' '1908 Summer' '1948 Winter' '1932 Winter' '1936 Winter'
 '1896 Summer' '2000 Su' '2004 Summe' nan]
Unique City values: ['Barcelona' 'London' 'Antwerpen' 'Paris' 'Calgary'
'Albertville'
 'Lillehammer' 'Los Angeles' 'Salt Lake City' 'Helsinki' 'Lake Placid'
 'Sydney' 'Atlanta' 'Stockholm' 'Sochi' 'Nagano' 'Torino' 'Beijing'
 'Rio de Janeiro' 'Athina' 'Squaw Valley' 'Innsbruck' 'Sarajevo'
 'Mexico City' 'Munich' 'Seoul' 'Berlin' 'Oslo' "Cortina d'Ampezzo"
 'Melbourne' 'Roma' 'Amsterdam' 'Montreal' 'Moskva' 'Tokyo' 'Vancouver'
 'Grenoble' 'Sapporo' 'Chamonix' 'St. Louis' 'Sankt Moritz'
 'Garmisch-Partenkirchen' nan]
Unique Sport values: ['Basketball' 'Judo' 'Football' 'Tug-Of-War' 'Speed
Skating'
 'Cross Country Skiing' 'Athletics' 'Ice Hockey' 'Swimming' 'Badminton'
 'Sailing' 'Biathlon' 'Gymnastics' 'Art Competitions' 'Alpine Skiing'
 'Handball' 'Weightlifting' 'Wrestling' 'Luge' 'Water Polo' 'Hockey'
 'Rowing' 'Bobsleigh' 'Fencing' 'Equestrianism' 'Shooting' 'Boxing'
 'Taekwondo' 'Cycling' 'Diving' 'Canoeing' 'Tennis' 'Modern Pentathlon'
 'Figure Skating' 'Golf' 'Softball' 'Archery' 'Volleyball'
 'Synchronized Swimming' 'Table Tennis' 'Nordic Combined' 'Baseball'
```

```
'Rhythmic Gymnastics' 'Freestyle Skiing' 'Rugby Sevens' 'Trampolining'
'Beach Volleyball' 'Triathlon' 'Ski Jumping' 'Curling' 'Snowboarding'
'Rugby' 'Short Track Speed Skating' 'Skeleton' 'Lacrosse' 'Polo'
'Cricket' 'Racquets' 'Motorboating' 'Military Ski Patrol' 'Croquet'
'Jeu De Paume' nan 'Roque' 'Alpinism' 'Basque Pelota' 'Footba'
'Aeronautics']
```

I see some rubbish here:

- 'G' in Sex
- '2000 Su' and '2004 Summe' in Games
- 'Moskva' in City
- 'Footba' in Sport

For the Age:

[9]:
```
print(sorted(df.Age.dropna().unique()))
mav = df.Age.dropna().sort_values().value_counts().tail(1)
print(f'\nThe most Age value is {mav.index.values.astype(int)} and it appears␣
 ↪{mav.values} times')
```

```
[10.0, 11.0, 12.0, 13.0, 14.0, 15.0, 16.0, 17.0, 18.0, 19.0, 20.0, 21.0, 22.0,
23.0, 24.0, 25.0, 26.0, 27.0, 28.0, 29.0, 30.0, 31.0, 32.0, 33.0, 34.0, 35.0,
36.0, 37.0, 38.0, 39.0, 40.0, 41.0, 42.0, 43.0, 44.0, 45.0, 46.0, 47.0, 48.0,
49.0, 50.0, 51.0, 52.0, 53.0, 54.0, 55.0, 56.0, 57.0, 58.0, 59.0, 60.0, 61.0,
62.0, 63.0, 64.0, 65.0, 66.0, 67.0, 68.0, 69.0, 70.0, 71.0, 72.0, 73.0, 74.0,
75.0, 76.0, 77.0, 80.0, 81.0, 84.0, 88.0, 96.0, 97.0, 240.0]

The most Age value is [240] and it appears [1] times
```

This is an obvious outlier - the age is 240 years. The same outliers are observable for Height and Weight:

[10]:
```
mhv = df.Height.dropna().sort_values().value_counts().tail(1)
lwv = df.Weight.dropna().sort_values().value_counts().tail(1)
print(f'\nThe most Height value is {mhv.index.values.astype(int)} and it␣
 ↪appears {mhv.values} times')
print(f'\nThe least Weight value is {lwv.index.values.astype(int)} and it␣
 ↪appears {lwv.values} times')
```

```
The most Height value is [340] and it appears [1] times

The least Weight value is [7] and it appears [1] times
```

The NOC county 3-letter codes we will check with 'noc_regions.csv' from the kaggle. I will print Teams as well in order to understad what the country is behind the NOC code.

[11]:
```
noc_regions = pd.read_csv(os.path.join('..', 'data', 'noc_regions.csv'))
for region in df['NOC'].unique():
    if region not in noc_regions['NOC'].to_list():
```

```
        print(region)
        print(df[df['NOC'] == region].Team.unique())
```

```
SGP
['Singapore' 'June Climene' 'Rika II' 'Singapore-2' 'Singapore-1']
nan
[]
JP
['Japan']
```

By the way, such a method of finding strange values, which I show here, is the only possible one when working with a unique dataset. If this were a real task, i would have to sit and check every person and every team on the Internet. But we know that there is an ideal dataset on the Internet. We will not engage in stupidity, we will compare everything else with it, and at the same time we will double-check ourselves.

[12]:
```
true_df = pd.read_csv(os.path.join('..', 'data', 'athlete_events_ideal.csv'))
for feature in df.columns:
    print(feature, set(df[feature].unique()) - set(true_df[feature].unique()))
```

```
ID set()
Name {nan, 'Pietro Spec'}
Sex {nan, 'G'}
Age {nan, 240.0}
Height {nan, 340.0}
Weight {nan, 7.0}
Team {nan}
NOC {nan, 'JP'}
Games {nan, '2004 Summe', '2000 Su'}
Year {nan}
Season {nan}
City {nan}
Sport {nan, 'Footba'}
Event {nan, 'Gymnastics M'}
Medal set()
```

Most of theese mismatches we found on our own. Let's check what are the 'Pietro Spec' in Names and 'Gymnastics M' in Events

The Moskva is not a rubbish…

[13]:
```
df[df.Name == 'Pietro Spec']
```

[13]:
```
           ID         Name  Sex  Age  Height  Weight Team  NOC Games  Year  \
22409  113716  Pietro Spec  NaN  NaN     NaN     NaN  NaN  NaN   NaN   NaN

      Season City Sport Event Medal
22409    NaN  NaN   NaN   NaN   NaN
```

I see that we will say goodbye to Mr. Pietro Spe after clearing the missing values.

[14]:
```
df[df.Event == 'Gymnastics M']
```

[14]:
```
          ID                      Name Sex   Age  Height  Weight      Team  NOC  \
22601  57367  Velik Nikolov Kapsazov   M  25.0   167.0    67.0  Bulgaria  BUL

             Games    Year  Season  City       Sport          Event Medal
22601  1960 Summer  1960.0  Summer  Roma  Gymnastics  Gymnastics M   NaN
```

[15]:
```
print(true_df.query('ID == 57367 and City == "Roma"').Event)
print(df.query('ID == 57367 and City == "Roma"').Event)
```

```
113240    Gymnastics Men's Individual All-Around
113241          Gymnastics Men's Team All-Around
113242           Gymnastics Men's Floor Exercise
113243              Gymnastics Men's Horse Vault
113244            Gymnastics Men's Parallel Bars
113245           Gymnastics Men's Horizontal Bar
113246                    Gymnastics Men's Rings
113247          Gymnastics Men's Pommelled Horse
Name: Event, dtype: object
22599    Gymnastics Men's Individual All-Around
22600          Gymnastics Men's Team All-Around
22601                              Gymnastics M
0                  Gymnastics Men's Horse Vault
1                Gymnastics Men's Parallel Bars
2               Gymnastics Men's Horizontal Bar
3                        Gymnastics Men's Rings
4              Gymnastics Men's Pommelled Horse
Name: Event, dtype: object
```

Now we see 'Gymnastics Men's Floor Exercise' was lost

I also see some entry that was spoiled totally but presents in ideal df.

[16]:
```
one_id = int(true_df[true_df.Name == 'Thomas Hendrikus Maria "Thom" van Dijck'].
 ↪ID.values)
df[df.ID == one_id]
```

[16]:
```
           ID Name  Sex  Age  Height  Weight Team  NOC Games  Year Season  \
22463  124516  NaN  NaN  NaN     NaN     NaN  NaN  NaN   NaN   NaN    NaN

      City Sport Event Medal
22463  NaN   NaN   NaN   NaN
```

Let's fix all of this stuff

For sex 'G' obviously they are male:

[17]:
```
df[df.Sex == 'G']
```

[17]:
```
       ID               Name Sex   Age  Height  Weight            Team  NOC  \
42  79609          Pavel Mike   G  22.0   182.0    79.0  Czechoslovakia  TCH
74  79630  Anatoly Mikhaylin   G  37.0     NaN     NaN          Russia  RUS

          Games    Year  Season     City     Sport  \
42  1972 Summer  1972.0  Summer   Munich  Handball
74  1996 Summer  1996.0  Summer  Atlanta   Sailing

                                 Event   Medal
42             Handball Men's Handball  Silver
74  Sailing Mixed Two Person Keelboat     NaN
```

[18]:
```python
df.Sex.replace('G', 'M', inplace=True)
df.Sport.replace('Footba', 'Football', inplace=True)
df.Games.replace('2000 Su', '2000 Summer', inplace=True)
df.Games.replace('2004 Summe', '2004 Summer', inplace=True)
df.NOC.replace('JP', 'JPN', inplace=True)
df.Event.replace("Gymnastics M", "Gymnastics Men's Floor Exercise",␣
 ↪inplace=True)
```

[19]:
```python
df = df[df.Age != 240]
df = df[df.Height != 340]
df = df[df.Weight != 7]
```

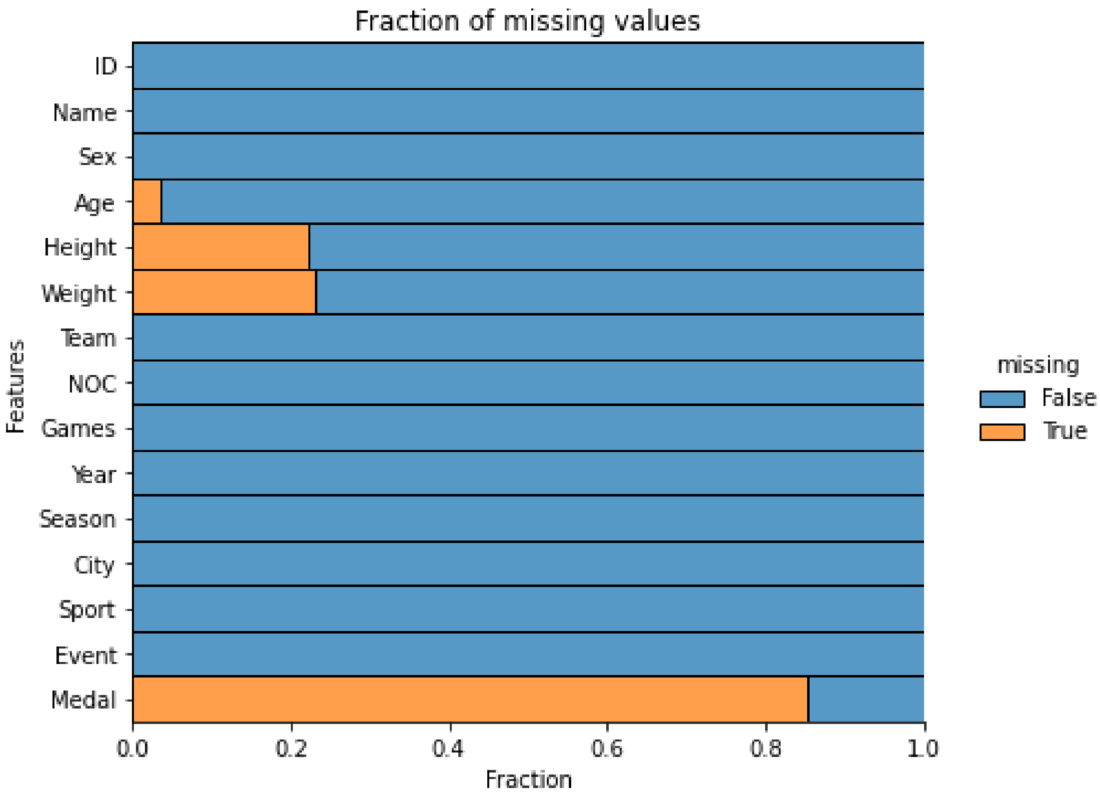
In any case, such a replacement would not be possible without an ideal dataset. In real life, you may have to restore corrupted values using the Internet or even drop them.

1.0.4 Dealing with missing values

We see there some missing values in some features. Let's make that numbers more illustratory:

[20]:
```python
plt.figure(figsize=(10, 6))
sns.displot(
    data=df.isna().melt(value_name="missing"),
    y="variable",
    hue="missing",
    multiple="fill",
    aspect=1.25
)
plt.xlabel("Fraction")
plt.ylabel("Features")
plt.title("Fraction of missing values")
plt.savefig("pictures/Missing_values_in_raw_dataset_count.png", dpi=100)
plt.show()
```

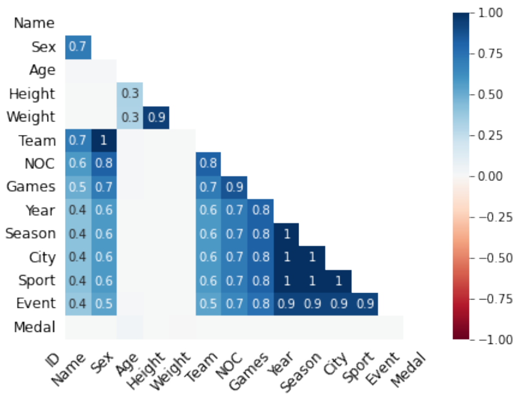
```
<Figure size 720x432 with 0 Axes>
```

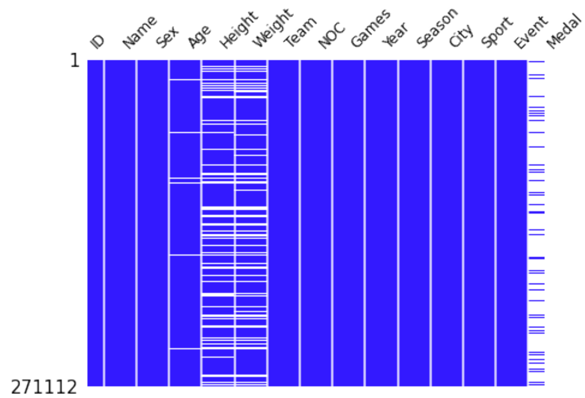


Here we see how many missing values are there. But how are they distributed? Let's check weather is there some correlation between value's missingnesses

[21]:
```
plt.figure()
fig, axes = plt.subplots(1, 2, sharex=True, figsize=(15, 5))
msno.heatmap(df, ax=axes[0], figsize=(8, 5), fontsize=12)
msno.matrix(df, ax=axes[1], sparkline=False, figsize=(6, 5), fontsize=12,␣
 ↪color=(0.2, 0.10, 1.0));
plt.savefig("pictures/Missing_values_in_raw_dataset_correlation.png", dpi=100)
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```





We have some features with 1 - 2 missing values, some with 7 - 8 and 4 features with much more missing values. Firstly, let's deal with first and seconds ones.

[22]:
```
df[df.Event.isna()]
```

[22]:
```
           ID                  Name  Sex   Age  Height  Weight      Team  \
22835   12005  Andrea Melissa Blackett    F  24.0   167.0    59.0  Barbados
22586   23433    Hadj Moussa Coulibaly    M  23.0     NaN     NaN      Mali
22557   34727         Carlotta Ferlito    F  17.0   160.0    50.0     Italy
22659   45919              Yuka Harada    F  28.0   170.0    60.0     Japan
22781   91137          Georgios Pantos    M   NaN     NaN     NaN  Athens-2
22409  113716              Pietro Spec  NaN   NaN     NaN     NaN       NaN
22463  124516                      NaN  NaN   NaN     NaN     NaN       NaN

       NOC        Games    Year  Season    City     Sport Event Medal
22835  BAR  2000 Summer     NaN     NaN     NaN       NaN   NaN   NaN
22586  MLI  2004 Summer     NaN     NaN     NaN       NaN   NaN   NaN
22557  NaN          NaN     NaN     NaN     NaN       NaN   NaN   NaN
22659  JPN          NaN     NaN     NaN     NaN       NaN   NaN   NaN
22781  GRE  1906 Summer  1906.0  Summer  Athina  Football   NaN   NaN
22409  NaN          NaN     NaN     NaN     NaN       NaN   NaN   NaN
22463  NaN          NaN     NaN     NaN     NaN       NaN   NaN   NaN
```

Here we see some obviously bad entries. There is no sence to try to fix it somehow, it is better just to drop that 8 rows on a 271115-length scale. Moreover, such features as Event, Sport, City and Season have strongest correlation in values lost so we will fix all of them at once. After that we will think about other missing values.

[23]:
```
df.dropna(axis=0, subset=["Event"], inplace = True)
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 271105 entries, 0 to 22390
```

```
Data columns (total 15 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   ID      271105 non-null  int64
 1   Name    271105 non-null  object
 2   Sex     271105 non-null  object
 3   Age     261632 non-null  float64
 4   Height  210938 non-null  float64
 5   Weight  208234 non-null  float64
 6   Team    271105 non-null  object
 7   NOC     271105 non-null  object
 8   Games   271105 non-null  object
 9   Year    271105 non-null  float64
 10  Season  271105 non-null  object
 11  City    271105 non-null  object
 12  Sport   271105 non-null  object
 13  Event   271105 non-null  object
 14  Medal   39782 non-null   object
dtypes: float64(4), int64(1), object(10)
memory usage: 33.1+ MB
None
```

Medal feature looks really intriguing with so many missing values!

[24]:
```
print(df.Medal.unique())
```

```
[nan 'Gold' 'Bronze' 'Silver']
```

O-o-o! For now it's clear. 'NaN' here means no medal. Thats easy to fix.

By the way, if we had machine learning here, we would immediately turn it into a numerical categorical feature from 0 to 3

[25]:
```
df.Medal.fillna("No medal", inplace = True)
print(df.Medal.unique())
```

```
['No medal' 'Gold' 'Bronze' 'Silver']
```

Let's take a clother look at Age, Height and Weight values:

For missing values in Age:

[26]:
```
print(f'The {round(len(df[df.Age.isna()])*100/len(df),1)}% of enties are␣
↪contain missing Age')
```

```
The 3.5% of enties are contain missing Age
```

Not great, not terrible, let's remove them.

[27]:
```
df.dropna(subset=["Age"], axis = 0, inplace = True)
```

With height and weight everything is a little more complicated. These variables are quite important, and the number of missing values in them is too large. Let's make two new dataframes using two different techniques, and then we'll see how it goes better. In one data frame we will completely remove all these missing values, and in the other, we will somehow replace them with.

[28]:
```
print(f'The {round(len(df[df.Height.isna()])*100/len(df),1)}% of enties are␣
↪contain missing Height')
```

```
The 19.7% of enties are contain missing Height
```

How to replace Height and Weight? Maybe we want to put here, for example, the average values. But this is impossible due to many other features in the dataset. Okay, you can say calculate the average for certain groups and substitute it depending on the group. Also incorrect - our data contains a time series. So, for time series, there are 3 main ways to fill in missing values: forward and backward filling and interpolation. In order to take into account all these moments, we will do, for example, backfilling with division into groups. As grouping variables, we will take age, gender, country and year - they should have the greatest influence on Height and Weight. Ideally, of course, we would break the age into separate intervals, but we have a lot of data and in this case we will not do feature generation and complicate things too much.

[29]:
```
print(f'Mean Height is {int(df.Height.mean())}')
print(f'Mean Weight is {int(df.Weight.mean())}')
df_gimp = df.copy()

df_drop = df.dropna(subset=['Height', 'Weight'])
df_gimp.Height = df.groupby(['Age', 'Sex'])['Height'].ffill().bfill()
df_gimp.Weight = df.groupby(['Age', 'Sex'])['Weight'].ffill().bfill()

print(f'df_gimp shape is {df_gimp.shape}')
print(f'df_drop shape is {df_drop.shape}')
```

```
Mean Height is 175
Mean Weight is 70
df_gimp shape is (261632, 15)
df_drop shape is (206158, 15)
```

Firts of all, let's try to work with imputed-one dataframe and the cleaned one will be reserved.

1.0.5 EDA

3. What is the age of most young sportsmens of both sexes at Olympics 1992?

[30]:
```
df_gimp[df_gimp.Year == 1992].groupby("Sex")["Age"].min()
```

[30]:
```
Sex
F    12.0
M    11.0
Name: Age, dtype: float64
```

4. What is the mean and standart deviation of the Height for both sexes

[31]:
```python
df_gimp.groupby("Sex")["Height"].describe()[["mean", "std"]]
# or
df_gimp.groupby("Sex").agg({'Height':["mean","std"]})
```

[31]:

	Height	
	mean	std
Sex		
F	167.942479	8.794632
M	179.066542	9.322936

5. What is the mean and standart deviation of the Height for woman in tennis at Olympics 2000?

[32]:
```python
df_gimp.query('Year == 2000 and Sex == "F" and Sport == "Tennis"').
↪agg({'Height': ["mean", "std"]})
```

[32]:

	Height
mean	171.801587
std	6.433686

6. In what sport did the heaviest sportsmen participated at Olympics 2006?

[33]:
```python
    max_weight = df_gimp.query('Year == 2006').Weight.max()
    df_gimp.query('Year == 2006')[df_gimp.query('Year == 2006').Weight ==␣
↪max_weight].Sport
```

[33]:
```
8102    Skeleton
Name: Sport, dtype: object
```

7. How many gold medals were won by women from 1980 to 2010?

[34]:
```python
df_gimp.query('1980 <= Year <= 2010 and Sex == "F" and Medal == "Gold"').
↪shape[0]
```

[34]: 2249

8. How many times has John Aalberg competed in the Olympics in different years?

[35]:
```python
JA_all = df_gimp.query('Name == "John Aalberg"').shape[0]
JA_games = df_gimp.query('Name == "John Aalberg"').Games.nunique()
JA_years = df_gimp.query('Name == "John Aalberg"').Year.nunique()
print(f'John Aalberg participated in {JA_all} competitions totally in␣
↪{JA_games} games in {JA_years} years')
```

```
John Aalberg participated in 8 competitions totally in 2 games in 2 years
```

9. Determine the least and most represented (by number of participants) age groups of athletes at the 2008 Olympics

[36]:
```python
df_gimp2008 = df_gimp.query('Year == 2008')
df_gimp2008["Age_group"] = pd.cut(x=df_gimp2008['Age'], bins=[15, 25, 35, 45,␣
↪55], right=False)
```

```
groups_count = df_gimp2008.groupby('Age_group').Name.count()
print(f'Our age groups are: \n{groups_count}')
print(f'The least group is {groups_count.nlargest(4).index[3]} and the most is␣
↪{groups_count.nlargest(4).index[0]}')
```

```
Our age groups are:
Age_group
[15, 25)    6294
[25, 35)    6367
[35, 45)     790
[45, 55)     116
Name: Name, dtype: int64
The least group is [45, 55) and the most is [25, 35)
```

10. How much has the number of sports changed in the 2002 Olympics compared to the 1994 Olympics?

[37]:
```
def n_sports(df, year):
    return df[df.Year == year].Sport.nunique()


print(f'There are {len(set(df[df.Year == 2002].Sport) - set(df[df.Year == 1994].
↪Sport))} sports changed')

# I suppose the sets difference is the most right way here becouse .nunique()␣
↪would not take into account cases when,
# for example, no new sports appeared but there were some changes
```

```
There are 3 sports changed
```

11. Output for the winter and summer Olympics separately the top 3 countries for each type of medals

[38]:
```
counts = df_gimp[['Medal', 'Season', 'NOC']].query('Medal != "No medal"').
↪groupby(['Season', "Medal"]).apply(
    lambda x: x.value_counts().head(3))
counts = counts.reset_index(level=[2, 3])[[0]].rename(columns={0: "Medals"})
counts
```

[38]:
```
                    Medals
Season Medal  NOC
Summer Bronze USA     1185
              GER      644
              URS      596
       Gold   USA     2461
              URS      832
              GBR      616
       Silver USA     1311
              GBR      674
```

```
                URS      635
Winter Bronze FIN      215
              SWE      177
              USA      161
       Gold   CAN      305
              URS      250
              USA      166
       Silver USA      308
              CAN      199
              NOR      165
```

12. Create a new variable Height__z__scores and store the values of the Height variable into it after it has been standardized

[39]:
```python
def standardize(values):
    return (values - values.mean()) / values.std()


df_gimp['Height_z_scores'] = standardize(df_gimp.Height)
```

13. Create a new variable Height__min__max__scaled and store the values of the Height variable into it after it has been min-max normalized Here I could define another one my own function, but since it is an additional task I also add some to solution (the thing I also wanted do in a previous task):

[40]:
```python
from sklearn.preprocessing import MinMaxScaler

min_max = MinMaxScaler()
min_max.fit(df_gimp[['Height']])
df_gimp['Height_min_max_scaled'] = min_max.transform(df_gimp[['Height']])
```

14. Compare the height, weight and age of men and women who competed in the Winter Olympics

[41]:
```python
from scipy import stats


def honest_t_test(x, y):
    for z in [x, y]:
        if stats.shapiro(z).pvalue < 0.05:
            raise Exception('The data is not normally distributed!')
    if stats.levene(x, y).pvalue < 0.05:
        raise Exception('Samples are not homoscedantic!')
    return stats.ttest_ind(x, y)
```

[42]:
```python
test_1 = stats.ttest_ind(df_gimp.query('Season == "Winter" and Sex == "M"').
 ↪Height,
                         df_gimp.query('Season == "Winter" and Sex == "F"').
 ↪Height)
```

```
test_2 = stats.ttest_ind(df_gimp.query('Season == "Winter" and Sex == "M"').
↪Weight,
                         df_gimp.query('Season == "Winter" and Sex == "F"').
↪Weight)
test_3 = stats.ttest_ind(df_gimp.query('Season == "Winter" and Sex == "M"').Age,
                         df_gimp.query('Season == "Winter" and Sex == "F"').Age)

tests = pd.DataFrame([['Height', test_1.pvalue], ['Weight', test_2.pvalue],␣
↪['Age', test_3.pvalue]],
                     columns=['Feature', 'p_value'])
tests['p_value_adj'] = [float(f'{x :.2g}') for x in multipletests(tests.p_value.
↪values, alpha=0.05, method='hs')[1]]
tests['p_value'] = [float(f'{x :.2g}') for x in tests['p_value']]
tests['Significant_differences'] = tests['p_value_adj'] < 0.05
tests = tests.set_index('Feature')
```

Here we tested 3 hypotises, conducted p-valiue adjustments, rounded results and labbeled whether are there significant differences between males and females . Now we can print it for publishind, for example, as a markdown table

[43]:
```
print(tests.to_markdown())
```

```
| Feature    |   p_value |   p_value_adj | Significant_differences   |
|:-----------|----------:|--------------:|:--------------------------|
| Height     | 0         |       0       | True                      |
| Weight     | 0         |       0       | True                      |
| Age        | 1.2e-223  |       1.2e-223 | True                      |
```

Do height, weight and age significantly differ for men and women who competed in the Winter Olympics?

Feature	p_value	p_value_adj	Significant_deffirinces
Height	0	0	True
Weight	0	0	True
Age	1.2e-223	1.2e-223	True

15. Are the Team and the Medal related? Lets build a contingency table‘

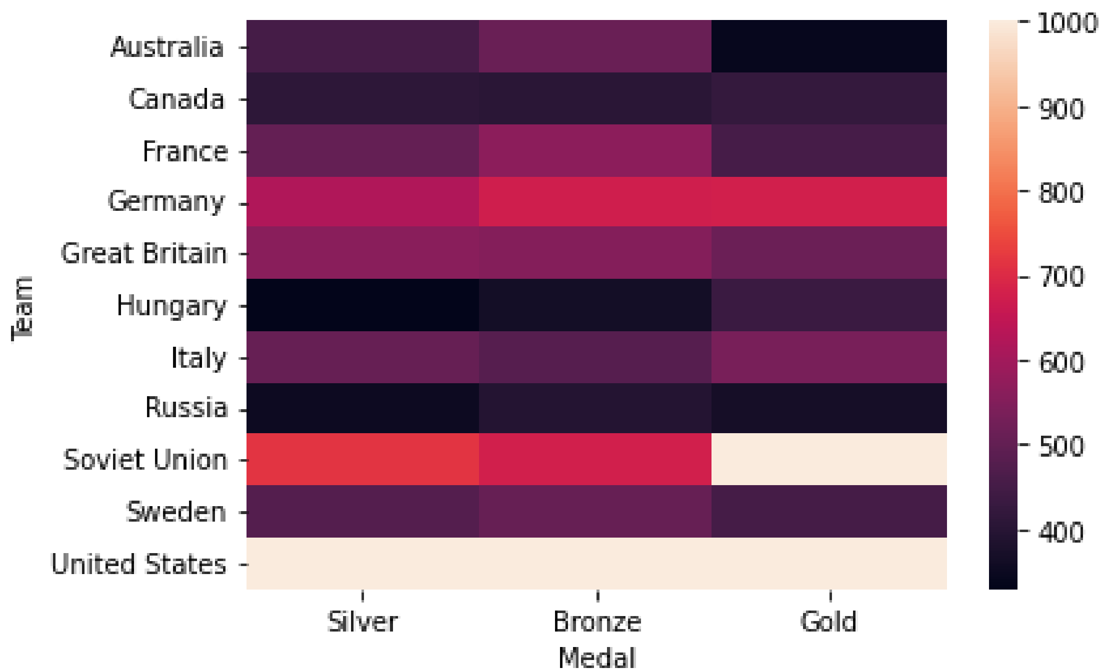
[44]:
```
ct = pd.crosstab(df_gimp.Team, df_gimp.Medal, margins=True)
ct.iloc[-5:]
```

[44]:
```
Medal     Bronze  Gold  No medal  Silver   All
Team
Zefyros        0     0         2       0     2
Zimbabwe       1    17       284       4   306
Zut            0     0         0       3     3
rn-2           0     0         5       0     5
```

```
All         13006   13224    222582    12820   261632
```

[45]:
```
sns.heatmap(ct.iloc[0:len(ct) - 2].query('Bronze + Silver + Gold > 1000')[['Silver', 'Bronze', 'Gold']], vmax=1000)
```

[45]:
```
<AxesSubplot: xlabel='Medal', ylabel='Team'>
```



Here we see some teams have more medals than the others, but we need somehow to prove it. Additionaly, of couse, we need take into account number of games a team played. Thus, lets normalize each team's values.

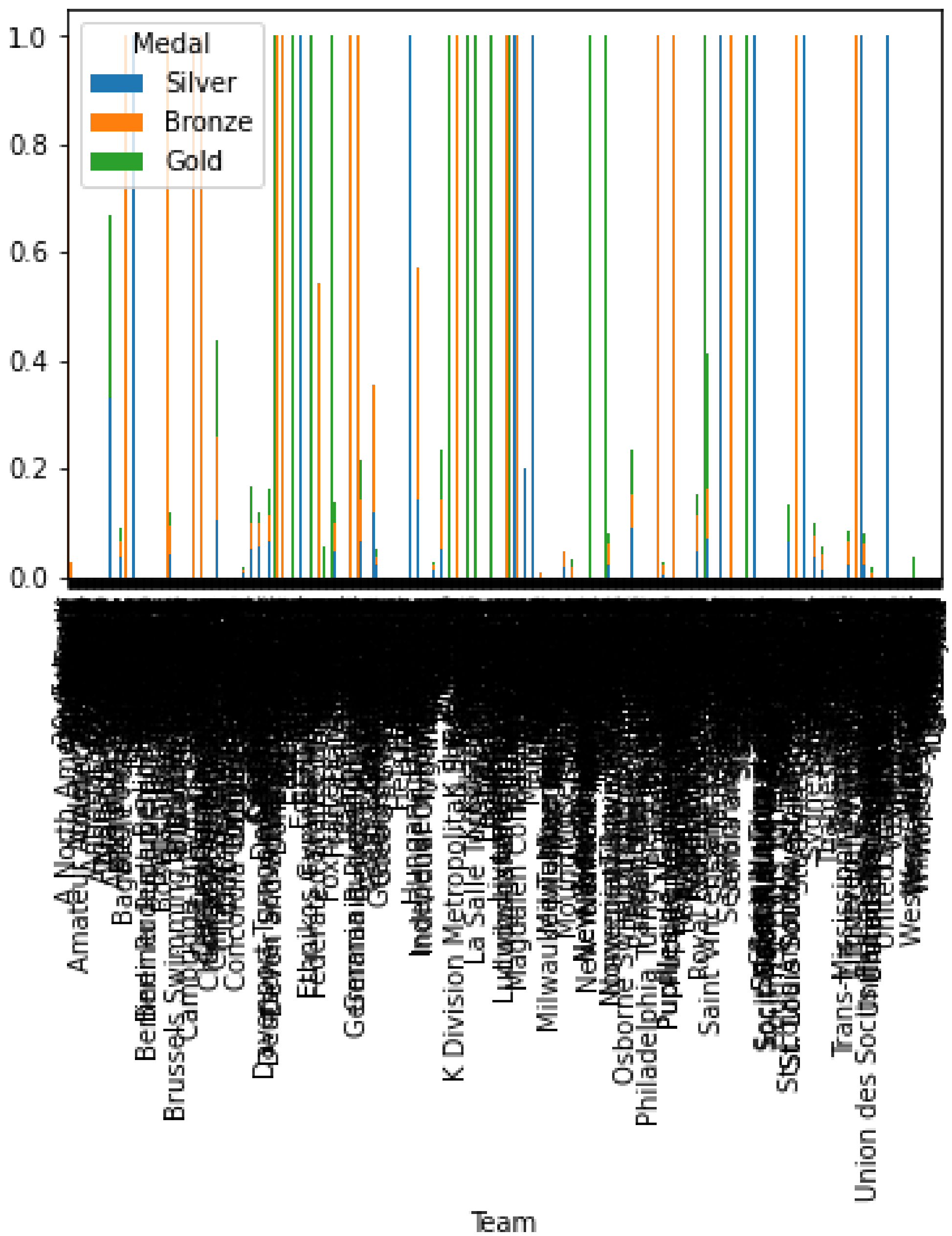
[46]:
```
ct_normalized = ct.apply(lambda x: x / ct.All, axis=0)
ct_normalized.iloc[-5:]
```

[46]:

Medal	Bronze	Gold	No medal	Silver	All
Team					
Zefyros	0.000000	0.000000	1.000000	0.000000	1.0
Zimbabwe	0.003268	0.055556	0.928105	0.013072	1.0
Zut	0.000000	0.000000	0.000000	1.000000	1.0
rn-2	0.000000	0.000000	1.000000	0.000000	1.0
All	0.049711	0.050544	0.850745	0.049000	1.0

[47]:
```
ct_normalized[['Silver','Bronze', 'Gold']].plot.bar(stacked=True)
```

[47]:
```
<AxesSubplot: xlabel='Team'>
```



Once again, we see medals not uniformely distributed. The teams are not clearly seen, yeah, this plot is not for publishing.

However, we need to do a statistical analysis of this. We use Pearson's chi-square test for cross tables. It could even be calculated manually, but I know a package that allows you to build contingency tables immediately with the calculation of these statistic. As before, we will normalize data by rows (only in this case, the normalization is not in fractions, but in percentages).

[48]:
```python
import researchpy as rp

ct_rp, ct_chi2_test = rp.crosstab(df_gimp.Team, df_gimp.Medal, prop='row',␣
 ↪test='chi-square')
ct_rp.head()
```

[48]:
```
                         Medal
Medal                   Bronze Gold No medal Silver    All
Team
30. Februar               0.00  0.0   100.00    0.0  100.0
A North American Team   100.00  0.0     0.00    0.0  100.0
Acipactli                 0.00  0.0   100.00    0.0  100.0
Acturus                   0.00  0.0   100.00    0.0  100.0
Afghanistan               2.56  0.0    97.44    0.0  100.0
```

[49]:
```python
ct_chi2_test
```

[49]:
```
                Chi-square test     results
0  Pearson Chi-square ( 3324.0) =   41021.6856
1                      p-value =       0.0000
2                   Cramer's V =       0.2286
```

[50]:
```python
if ct_chi2_test.results[1] < 0.05:
    dependence = 'some'
else:
    dependence = 'no'

print(
    f'The pearson chi-square statistics is {round(ct_chi2_test.results[0], 2)}␣
 ↪with p-value {ct_chi2_test.results[1]}')
print(f'That means there are {dependence} statistical dependence between Teams␣
 ↪and Medals')
```

```
The pearson chi-square statistics is 41021.69 with p-value 0.0
That means there are some statistical dependence between Teams and Medals
```

1.0.6 16. Additional hypotheses

Athletes height through the years

[51]:
```python
pearr = stats.pearsonr(df_gimp.Height, df_gimp.Year)

if pearr.pvalue < 0.05:
    dependence = 'some'
else:
    dependence = 'no'

if pearr.statistic < 0:
    changes = 'decrease'
```

```
else:
    changes = 'increase'

if abs(pearr.statistic) > 0.6:
    significance = 'significantly'
else:
    significance = 'slightly'

print(f'The pearson r coefficient is {round(pearr.statistic, 3)} with p-value␣
↪{pearr.pvalue:.2g}')
print(f'That means there are {dependence} statistical dependence between␣
↪athletes Height and Year')
print(f'Moeover, we can say that athletes Height {significance} {changes}␣
↪through the years')
```

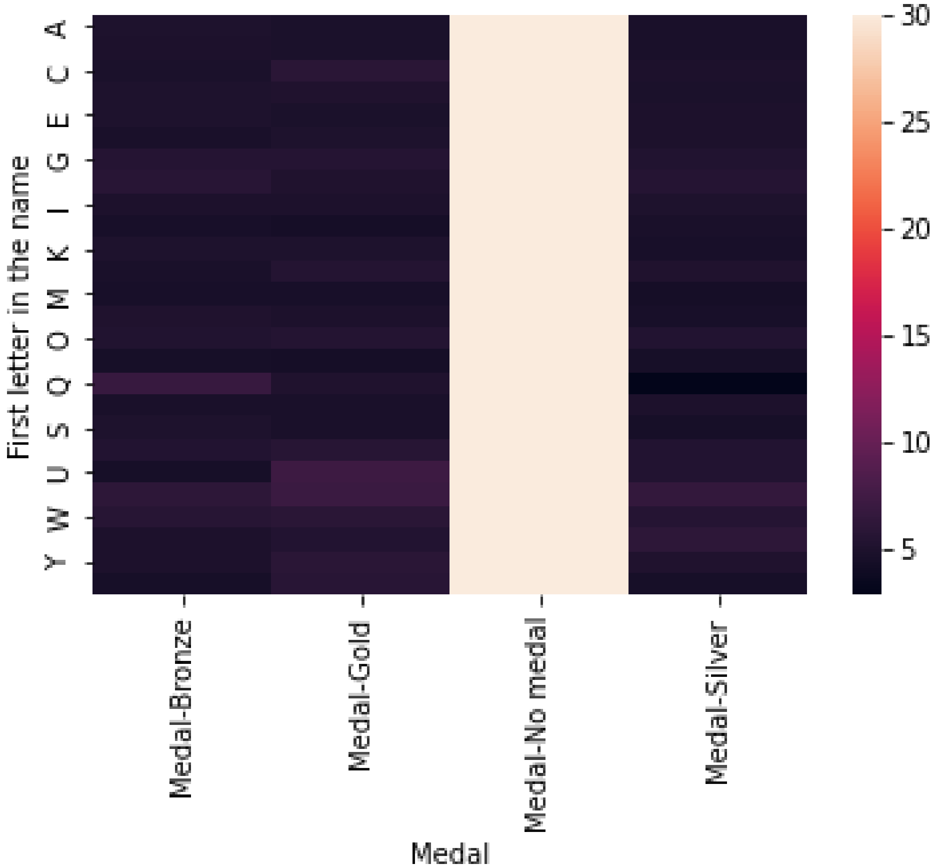
```
The pearson r coefficient is -0.061 with p-value 4.6e-212
That means there are some statistical dependence between athletes Height and
Year
Moeover, we can say that athletes Height slightly decrease through the years
```

Does the first letter in the name matter?

[52]:
```
df_gimp['First_letter'] = df_gimp.Name.apply(lambda x: x[0].upper())
ct_rp, ct_chi2_test = rp.crosstab(df_gimp.First_letter, df_gimp.Medal,␣
↪prop='row', test='chi-square')

if ct_chi2_test.results[1] < 0.05:
    dependence = 'some'
else:
    dependence = 'no'

print(
    f'The pearson chi-square statistics is {round(ct_chi2_test.results[0], 2)}␣
↪with p-value {ct_chi2_test.results[1]}')
print(f'That means there are {dependence} statistical dependence between first␣
↪letter in the name and medals')

sns.heatmap(ct_rp.iloc[1:len(ct_rp) - 1, 0:4], vmax=30);
plt.ylabel("First letter in the name")
plt.xlabel("Medal")
```

```
The pearson chi-square statistics is 390.01 with p-value 0.0
That means there are some statistical dependence between first letter in the
name and medals
```

[52]:
```
Text(0.5, 15.0, 'Medal')
```



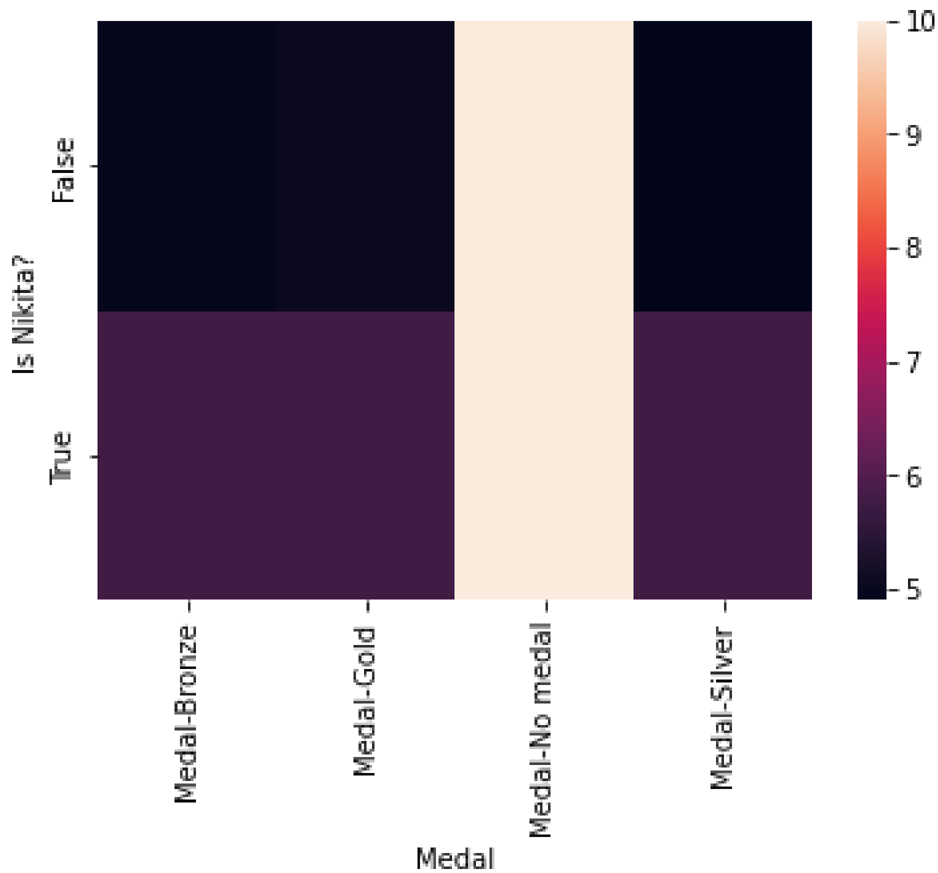
Let's take a closer look at what is that - to be a Nikita

[53]:
```
df_gimp['Is_Nikita'] = df_gimp.Name.str.contains('Nikita')

ct_rp, ct_chi2_test = rp.crosstab(df_gimp.Is_Nikita, df_gimp.Medal, prop='row',␣
 ↪test='chi-square')

if ct_chi2_test.results[1] < 0.05:
    dependence = 'some'
else:
    dependence = 'no'

print(
    f'The pearson chi-square statistics is {round(ct_chi2_test.results[0], 2)}␣
 ↪with p-value {ct_chi2_test.results[1]}')
print(f'That means there are {dependence} statistical dependence between␣
 ↪Nikitas and medals')

sns.heatmap(ct_rp.iloc[0:len(ct_rp) - 1, 0:4], vmax=10);
```

```
plt.xlabel("Medal")
plt.ylabel("Is Nikita?")
```

```
The pearson chi-square statistics is 0.23 with p-value 0.9719
That means there are no statistical dependence between Nikitas and medals
```

[53]: Text(33.0, 0.5, 'Is Nikita?')



As we can see, the p-value is quite large and there is not much statistical significance, but on the heatmap (despite the fact that the sizes of the groups are highly disproportional) with adjusted brightness, it can be seen that Nikita's medal strip is a little bit brighter. Noone can hide the truth!