# TC1002s Activity 2: Descriptive statistics

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## An initial exploratory analysis of the Video-Games sales and ratings Dataset

Link to repository: https://github.com/DurandalAGB/TC1002sActivities/tree/main/Activity2

Link to original colab: https://colab.research.google.com/drive/1jW8gi-FbBbBaHSTDPqB-bOxrOgaRHMcq?usp=sharing

Before running any of the code blocks, please uplaod the Video_Games.csv file to the Files(Archivos) Section

```
#Step 1. we load our dataset to collab and  import the python libraries we need for our analysis
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
#We use Pandas to load our data
df = pd.read_csv("Video_Games.csv")

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16928 entries, 0 to 16927
Data columns (total 17 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   index            16928 non-null  int64
 1   Name             16926 non-null  object
 2   Platform         16928 non-null  object
 3   Year_of_Release  16655 non-null  float64
 4   Genre            16926 non-null  object
 5   Publisher        16873 non-null  object
 6   NA_Sales         16928 non-null  float64
 7   EU_Sales         16928 non-null  float64
 8   JP_Sales         16928 non-null  float64
 9   Other_Sales      16928 non-null  float64
 10  Global_Sales     16928 non-null  float64
 11  Critic_Score     8260 non-null   float64
 12  Critic_Count     8260 non-null   float64
```

```
 13  User_Score       10159 non-null  object
 14  User_Count       7718 non-null   float64
 15  Developer        10240 non-null  object
 16  Rating           10092 non-null  object
dtypes: float64(9), int64(1), object(7)
memory usage: 2.2+ MB
```

Using df.info(), we can examine the structure of our dataset.

It contains 16,928 entries and 17 columns, this should be enough information. There's variables like sales by region (NA_Sales, EU_Sales) Scores by type of person (User_Score and Critic_Score)

The data is mostly numerical (in float64), some columns are stored as string objects.

Also, some of the columns have missing values which we will need to clean before any future steps

df.head() and df.tail() will show us the first and last rows of our dataset respectively

```
df.head()
```

| | index | Name | Platform | Year_of_Release | Genre | Publisher | NA_Sales | EU_Sales | JP_Sales | Other_Sales | Global_Sales |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | Wii Sports | Wii | 2006.0 | Sports | Nintendo | 41.36 | 28.96 | 3.77 | 8.45 | 82.53 |
| **1** | 1 | Super Mario Bros. | NES | 1985.0 | Platform | Nintendo | 29.08 | 3.58 | 6.81 | 0.77 | 40.24 |
| **2** | 2 | Mario Kart Wii | Wii | 2008.0 | Racing | Nintendo | 15.68 | 12.76 | 3.79 | 3.29 | 35.52 |
| | | Wii | | | | | | | | | |

Próximos pasos: Generar código con df | Ver gráficos recomendados | New interactive sheet

```
df.tail()
```

| | index | Name | Platform | Year_of_Release | Genre | Publisher | NA_Sales | EU_Sales | JP_Sales | Other_Sales | Global_Sa |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **16923** | 16923 | Aliens: Colonial | PS3 | 2013.0 | Shooter | Sega | 0.20 | 0.29 | 0.00 | 0.11 | |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Marines | | | | | | | | |
| **16924** | 16924 | Backyard Wrestling: Don't Try This at Home | PS2 | 2003.0 | Fighting | Eidos Interactive | 0.30 | 0.23 | 0.00 | 0.08 |
| **16925** | 16925 | Yakuza: Dead Souls | PS3 | 2011.0 | Shooter | Sega | 0.09 | 0.06 | 0.42 | 0.03 |
| **16926** | 16926 | Fight Night Round 2 | XB | 2005.0 | Fighting | Electronic Arts | 0.42 | 0.16 | 0.00 | 0.02 |
| | | MonHun Nikki: | | | | | | | | |

Using df.dtypes, we examine the data types of each column in our dataset.

```
df.dtypes
```

| | 0 |
|---|---|
| **index** | int64 |
| **Name** | object |
| **Platform** | object |
| **Year_of_Release** | float64 |
| **Genre** | object |
| **Publisher** | object |
| **NA_Sales** | float64 |
| **EU_Sales** | float64 |
| **JP_Sales** | float64 |
| **Other_Sales** | float64 |
| **Global_Sales** | float64 |

| | |
|---|---|
| **Critic_Score** | float64 |
| **Critic_Count** | float64 |
| **User_Score** | object |
| **User_Count** | float64 |
| **Developer** | object |
| **Rating** | object |

**dtype:** object

```
df.columns
```

```
Index(['index', 'Name', 'Platform', 'Year_of_Release', 'Genre', 'Publisher',
       'NA_Sales', 'EU_Sales', 'JP_Sales', 'Other_Sales', 'Global_Sales',
       'Critic_Score', 'Critic_Count', 'User_Score', 'User_Count', 'Developer',
       'Rating'],
      dtype='object')
```

```
df.index
```

```
RangeIndex(start=0, stop=16928, step=1)
```

```
df.values
```

```
array([[0, 'Wii Sports', 'Wii', ..., 322.0, 'Nintendo', 'E'],
       [1, 'Super Mario Bros.', 'NES', ..., nan, nan, nan],
       [2, 'Mario Kart Wii', 'Wii', ..., 709.0, 'Nintendo', 'E'],
       ...,
       [16925, 'Yakuza: Dead Souls', 'PS3', ..., 69.0,
        'Ryu ga Gotoku Studios', 'M'],
       [16926, 'Fight Night Round 2', 'XB', ..., 27.0, 'EA Sports', 'T'],
       [16927, 'MonHun Nikki: Poka Poka Ailu Mura', 'PSP', ..., nan, nan,
        nan]], dtype=object)
```

We can examine individual rows with df.loc(), in this example we're looking at row 78, which represents the game Halo 2, . It was released in 2004 for the Xbox and developed by Bungie Software. It achieved:

Global Sales of 8,49 billion A Critical score of 95.0, placing it among the highest-rated games A user score of 8.2, indicating a good public reception And a user count of 1,218.

```
df.loc[78]
```

| | 78 |
|---|---|
| **index** | 78 |
| **Name** | Halo 2 |
| **Platform** | XB |
| **Year_of_Release** | 2004.0 |
| **Genre** | Shooter |
| **Publisher** | Microsoft Game Studios |
| **NA_Sales** | 6.82 |
| **EU_Sales** | 1.53 |
| **JP_Sales** | 0.05 |
| **Other_Sales** | 0.08 |
| **Global_Sales** | 8.49 |
| **Critic_Score** | 95.0 |
| **Critic_Count** | 91.0 |
| **User_Score** | 8.2 |
| **User_Count** | 1218.0 |
| **Developer** | Bungie Software |
| **Rating** | M |

**dtype:** object

```
#we can add filters inside of loc, too. This line only returns the games launched in 2015
display(df.loc[(df.Year_of_Release==2015)])
```

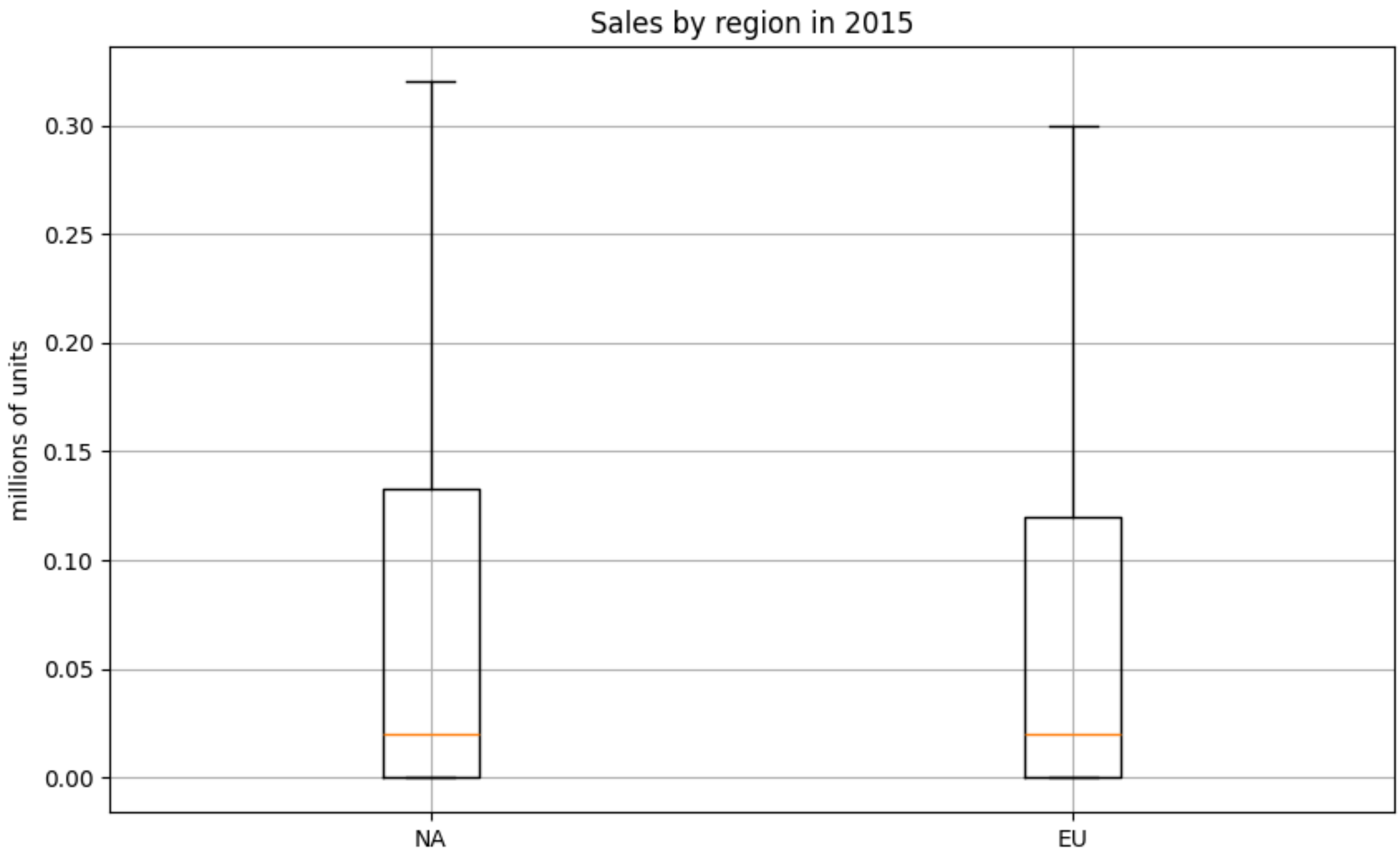
| index | Name | Platform | Year_of_Release | Genre | Publisher | NA_Sales | EU_Sales | JP_Sales | Other_Sales | Global |
|---|---|---|---|---|---|---|---|---|---|---|

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **31** | 31 | Call of Duty: Black Ops 3 | PS4 | 2015.0 | Shooter | Activision | 6.03 | 5.86 | 0.36 | 2.38 |
| **77** | 77 | FIFA 16 | PS4 | 2015.0 | Sports | Electronic Arts | 1.12 | 6.12 | 0.06 | 1.28 |
| **87** | 87 | Star Wars Battlefront (2015) | PS4 | 2015.0 | Shooter | Electronic Arts | 2.99 | 3.49 | 0.22 | 1.28 |
| **99** | 99 | Call of Duty: Black Ops 3 | XOne | 2015.0 | Shooter | Activision | 4.59 | 2.11 | 0.01 | 0.68 |
| **105** | 105 | Fallout 4 | PS4 | 2015.0 | Role-Playing | Bethesda Softworks | 2.53 | 3.27 | 0.24 | 1.13 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **16742** | 16742 | Hakuoki: Reimeiroku - Omouhase Kara | PSV | 2015.0 | Action | Idea Factory | 0.00 | 0.00 | 0.01 | 0.00 |
| **16763** | 16763 | Evolve | XOne | 2015.0 | Shooter | Take-Two Interactive | 0.37 | 0.20 | 0.00 | 0.06 |
| **16809** | 16809 | NHL 16 | PS4 | 2015.0 | Sports | Electronic Arts | 0.36 | 0.16 | 0.00 | 0.11 |
| **16825** | 16825 | LEGO Jurassic World | 3DS | 2015.0 | Action | Warner Bros. Interactive Entertainment | 0.31 | 0.23 | 0.03 | 0.05 |
| | | | | | | Namco | | | | |

```
import matplotlib.pyplot as plt

#we keep using games released on 2015
d = df[df["Year_of_Release"] == 2015]

#colums of regions to compare
columns_to_plot = ["NA_Sales", "EU_Sales"]

plt.figure(figsize=(10, 6))
```

```
plt.figure(figsize=(10, 6))
plt.boxplot([d[col].dropna() for col in columns_to_plot],
            labels=["NA", "EU"],
            showfliers=False)  #we take out massive sellers like CoD and FIFA to get better results

plt.title("Sales by region in 2015")
plt.ylabel("millions of units")
plt.grid(True)
plt.show()
```

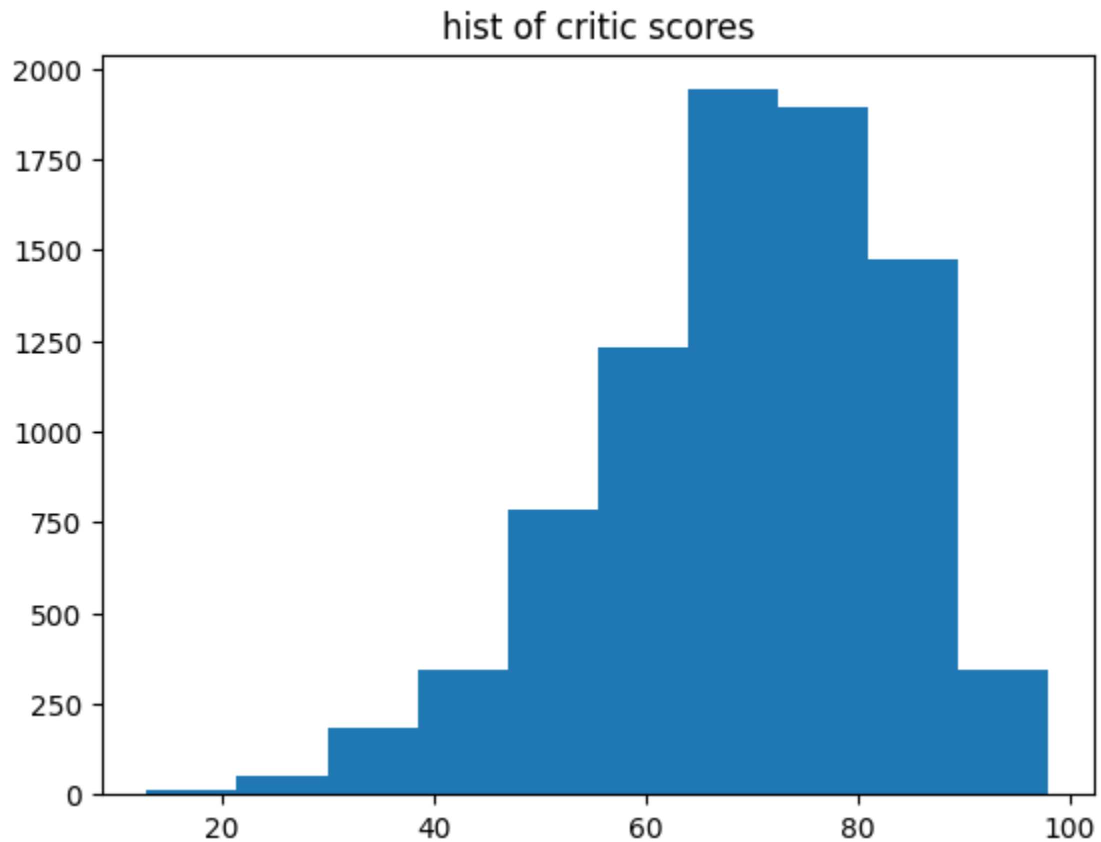
```
<ipython-input-8-8e5ef8bef1d3>:10: MatplotlibDeprecationWarning: The 'labels' parameter of boxplot() has been renamed
  plt.boxplot([d[col].dropna() for col in columns_to_plot],
```




This boxplot compares sales in the North American and Europe regions for 2015. It shows most games sold under 0.1 million units, a small number of games achieved higher sales.

North America shows slightly higher sales, but both regions follow a similar trend for this year.

```
plt.hist(df["Critic_Score"], bins=10)
plt.title("hist of critic scores")
plt.show()
```




This histogram displays video-game distributions based on their critic score, we can observe that:

most games received a critic score between 60 and 80.

There are very few low-scoring games (below 50).

```
df["User_Score"] = pd.to_numeric(df["User_Score"], errors='coerce')
```

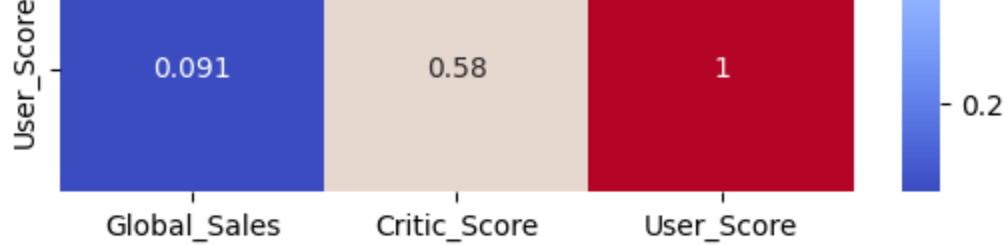
```
df_filtered = df[["Global_Sales", "Critic_Score", "User_Score"]].dropna()


correlaciones = df_filtered.corr()
print(correlaciones)
```

```
              Global_Sales  Critic_Score  User_Score
Global_Sales      1.000000      0.238471    0.091376
Critic_Score      0.238471      1.000000    0.580628
User_Score        0.091376      0.580628    1.000000
```

To explore possible relationships between sales and ratings, we created a correlation matrix using the corr() function.

Before doing it, we converted the User_Score column from string to numeric using pd.to_numeric(), setting incomplete values to NaN, and then used .dropna() to exclude these incomplete rows.

```
import seaborn as sns
import matplotlib.pyplot as plt

sns.heatmap(correlaciones, annot=True, cmap="coolwarm")
plt.title("corrrelation between sales and score")
plt.show()
```




To better visualize this correlation, we made a heatmap using seaborn, this shows the weak to moderate positive correlation between these values

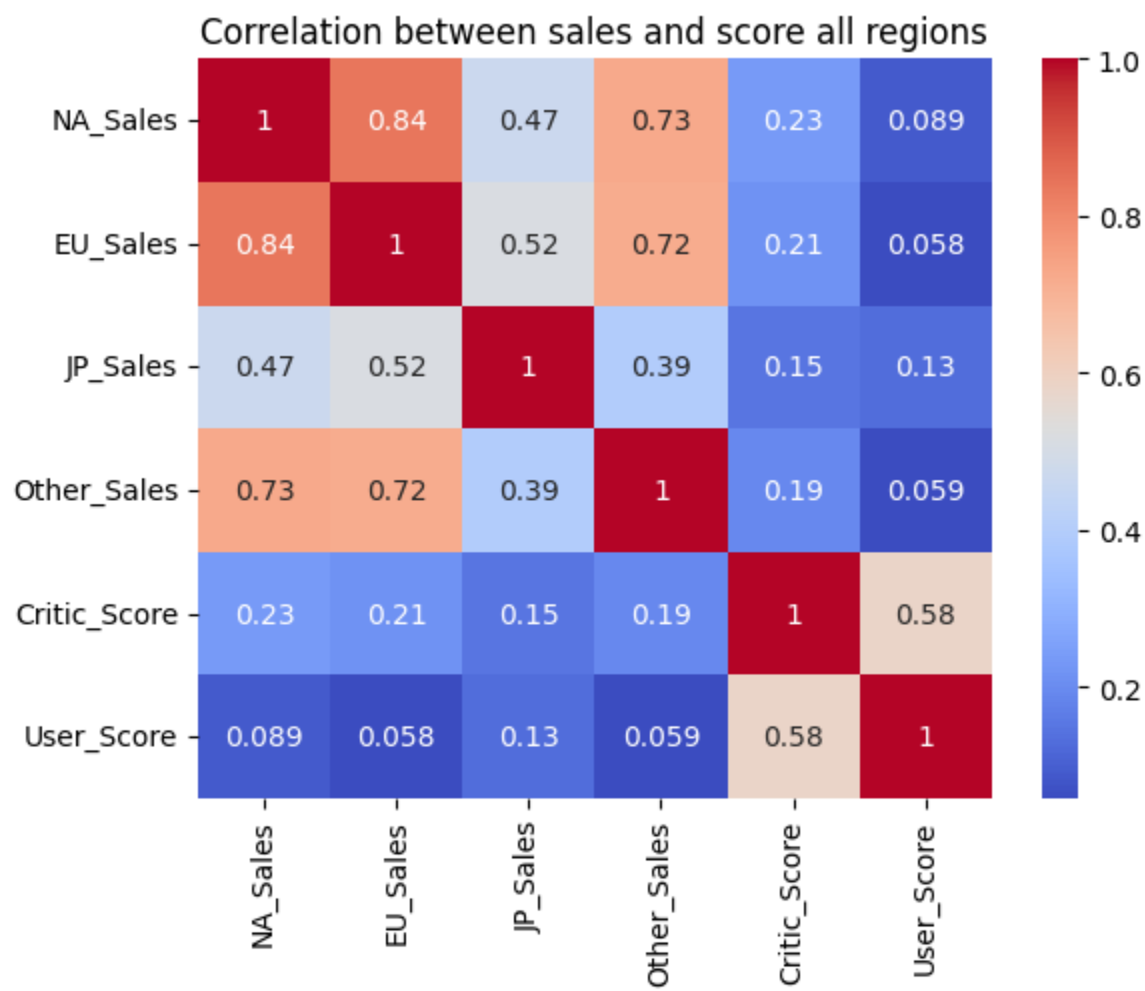
## To better understand the relationship between reviews and market performance, we extended our correlation analysis to include all regions

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

df["User_Score"] = pd.to_numeric(df["User_Score"], errors='coerce')

columns_to_include = ["NA_Sales", "EU_Sales", "JP_Sales", "Other_Sales", "Critic_Score", "User_Score"]
df_filtered = df[columns_to_include].dropna()

correlaciones1 = df_filtered.corr()
print(correlaciones1)
```

```
              NA_Sales  EU_Sales  JP_Sales  Other_Sales  Critic_Score  \
NA_Sales      1.000000  0.840603  0.469317     0.727629      0.234877
EU_Sales      0.840603  1.000000  0.517454     0.719458      0.213056
JP_Sales      0.469317  0.517454  1.000000     0.392828      0.148733
Other_Sales   0.727629  0.719458  0.392828     1.000000      0.191988
Critic_Score  0.234877  0.213056  0.148733     0.191988      1.000000
User_Score    0.089317  0.057828  0.130217     0.058857      0.580628

              User_Score
NA_Sales        0.089317
EU_Sales        0.057828
```

```
EU_Sales        0.057828
JP_Sales        0.130217
Other_Sales     0.058857
Critic_Score    0.580628
User_Score      1.000000
```

```
sns.heatmap(correlaciones1, annot=True, cmap="coolwarm")
plt.title("Correlation between sales and score all regions")
plt.show()
```




we can appreciate that critic reviews have a modest influence on sales, while user reviews don't have a lot of impact