TC1002s - CS Tool - Mastering Analytics

Activity 3 - Patterns with K-means

Noel Sebastian Marquez Tovar - A01659730

Angel Guillermo Bosquez Baltazar - A01667100

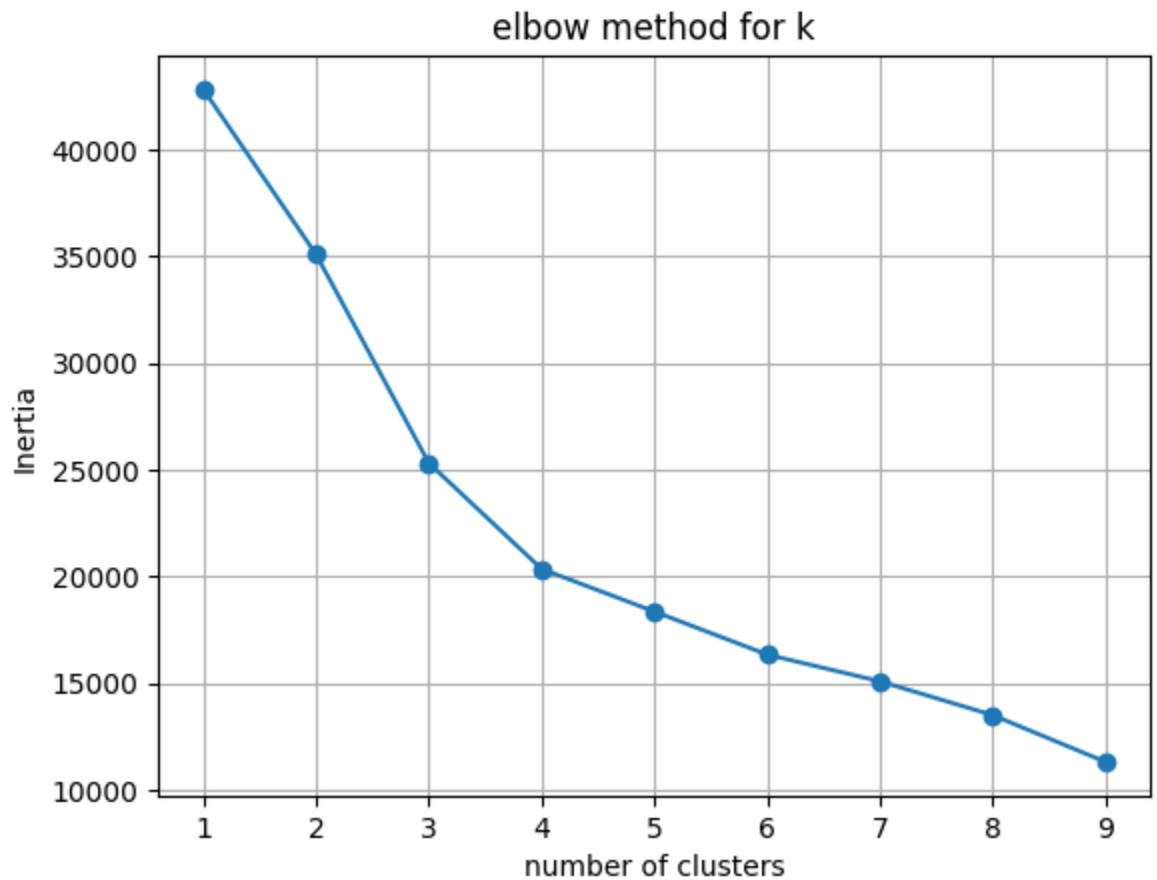
To use this file simply drag the Video_Games.csv incldued in Github to the Archivos(Files) Section

```
##Step 1: we load and prepare our dataset

import pandas as pd
import numpy as np
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import seaborn as sns

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

```
##Step 2: We select relevant variables for our analysis and clean them of empty values
variables = ["NA_Sales", "EU_Sales", "JP_Sales", "Other_Sales", "Critic_Score", "User_Score"]
df_cluster = df[variables].dropna()

## We also scale our data so they have the same influence when we calculate the distance in k-means
scaler = StandardScaler()
X_scaled = scaler.fit_transform(df_cluster)
```

```
#Step 3: We use the elbow method to determine our K value

#We added inertia to evaluate how well the K-means algorithm fits the data for different values of k

inertia = []
```

```
inertia = []
for k in range(1, 10):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    inertia.append(kmeans.inertia_)

plt.plot(range(1, 10), inertia, marker='o')
plt.title("elbow method for k")
plt.xlabel("number of clusters")
plt.ylabel("Inertia")
plt.grid(True)
plt.show()
```




```
# Step 4: From the graphic representation we decided to use 4 as our K-means value
k = 4
kmeans = KMeans(n_clusters=k, random_state=42)
kmeans.fit(X_scaled)
df_cluster["Cluster"] = kmeans.labels_
```

```python
#then we get the centroids and re-scale them to  their original size
centroids_scaled = kmeans.cluster_centers_
centroids = scaler.inverse_transform(centroids_scaled)
centroid_df = pd.DataFrame(centroids, columns=variables)
print("Centroides de cada cluster:")
print(centroid_df)
```

```
Centroides de cada cluster:
    NA_Sales  EU_Sales  JP_Sales  Other_Sales  Critic_Score  User_Score
0   0.174522  0.093377  0.013212     0.032496     54.457729    5.546773
1   0.321668  0.171577  0.045906     0.058763     75.964131    7.823006
2  11.971429  8.996429  3.371429     3.839286     82.714286    8.014286
3   2.700333  1.991000  0.582481     0.677481     85.314815    7.745185
```

```python
# Step 5: Add game names to df_cluster so we can inspect which titles belong to each cluster
df_cluster["Name"] = df.loc[df_cluster.index, "Name"]

# For each cluster label from 0 up to k-1…
for i in range(k):
    print(f"\nCluster {i} examples:")
    # 1) Filter df_cluster to only the rows assigned to cluster i
    # 2) Select the columns we care about (Name and key metrics)
    # 3) Use .head() to show just the first 5 entries for a quick sanity check
    examples = df_cluster[
        df_cluster["Cluster"] == i
    ][["Name", "Critic_Score", "User_Score", "NA_Sales"]].head()
    print(examples)
```

```
Cluster 0 examples:
                         Name  Critic_Score  User_Score  NA_Sales
294            Carnival Games          56.0         6.0      2.12
373  Assassin's Creed: Unity          72.0         4.1      2.27
418                 Wii Music          63.0         4.6      1.35
458               The Sims 4          70.0         3.9      1.00
493      Call of Duty: Ghosts          78.0         4.3      1.88

Cluster 1 examples:
                                     Name  Critic_Score  User_Score  \
238                       Madden NFL 2005          91.0         7.9
266                          Namco Museum          79.0         7.3
284                             Half-Life          96.0         9.1
```

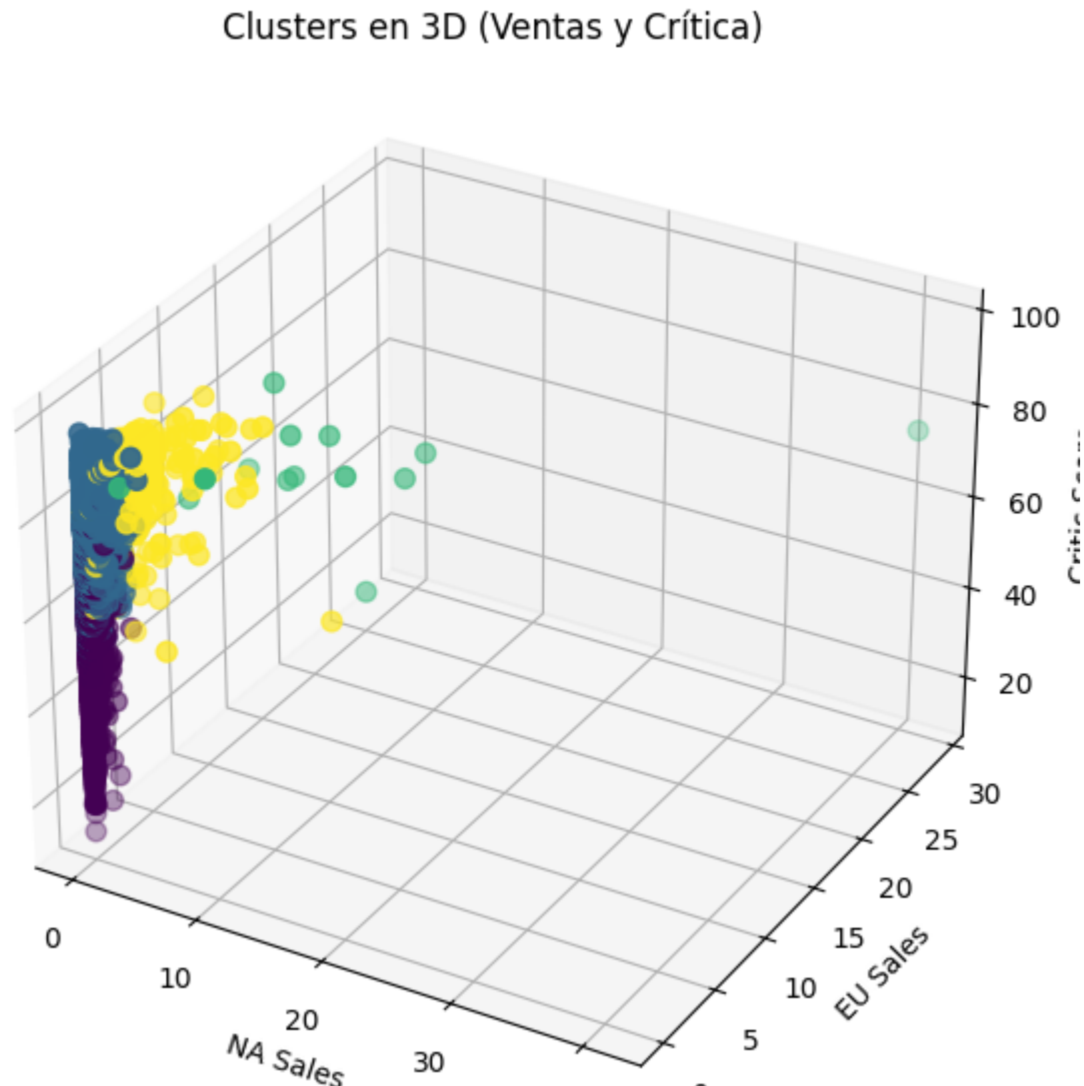
```
288       World of Warcraft: The Burning Crusade          91.0          7.9
329  LEGO Indiana Jones: The Original Adventures          77.0          7.5

     NA_Sales
238      4.18
266      3.00
284      4.03
288      2.57
329      2.40

Cluster 2 examples:
                  Name  Critic_Score  User_Score  NA_Sales
0           Wii Sports          76.0         8.0     41.36
2        Mario Kart Wii         82.0         8.3     15.68
3     Wii Sports Resort         80.0         8.0     15.61
6  New Super Mario Bros.        89.0         8.5     11.28
7             Wii Play          58.0         6.6     13.96

Cluster 3 examples:
                            Name  Critic_Score  User_Score  NA_Sales
14            Kinect Adventures!          61.0         6.3     15.00
23            Grand Theft Auto V          97.0         8.1      9.66
24     Grand Theft Auto: Vice City        95.0         8.7      8.41
28         Gran Turismo 3: A-Spec         95.0         8.4      6.85
29  Call of Duty: Modern Warfare 3        88.0         3.4      9.04
```

```
## Step 6 plot critic vs user scores colored by cluster to visualize the 2D grouping of games
sns.scatterplot(
    data=df_cluster,
    x="Critic_Score",
    y="User_Score",
    hue="Cluster",
    palette="tab10"
)


plt.title("Clusters for the games, based on the scores")
plt.xlabel("Critic Score")
plt.ylabel("User Score")
plt.grid(True)
plt.show()
```

Clusters for the games, based on the scores


```
##Step 7 visualasion of the clusters3D
# We create the figure and then we add the projection in 3D
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt

fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')

#  We define the axes and then we make the color points for each cluster
ax.scatter(
    df_cluster["NA_Sales"],
    df_cluster["EU_Sales"],
    df_cluster["Critic_Score"],
    c=df_cluster["Cluster"],
    cmap='viridis',
    s=50
)

# Put the name for the axes
```

```
ax.set_xlabel("NA Sales")
ax.set_ylabel("EU Sales")
ax.set_zlabel("Critic Score")

plt.title("Clusters en 3D (Ventas y Crítica)")
plt.show()



#in purple cluster 0
#in blue cluster 1
#in green, cluster 2
#in yellow cluster 3
```



Questions after analysis

Do you think these centers might be representative of the data? Why?

Yes, because the centroids and cluster reveal different patterns of videogame performance

How did you obtain the k value to use?

We used the elbow method, where we plotted different k-values, around 4 the decrease speed slowed significantly

Would the centers be more representative if you used a higher value? A lower value?

If we used a higher value it would probably increase the precision of the model but we'll lose some pattenr At lower values, it might create pattern that miss some details

How far apart are the centers? Are any very close to others?

The separation between mainstream and high scored games is well represented

Cluster 0 and 2 are closer together, reresenting games with moderate critic and user scores and low to medium sales numbers.

Clusters 2 and 3 represent games with higher review scores or sales numbers and are more spaced out between each other,

What would happen to the centers if we had many outliers in the box-and-whisker analysis?

Outliers would pull the centroids away from the core of the data, distorting the average positions, in this industry is not rare to hear about games with sales on the tens of millions

That's why scaling was very important, it balances the impact of these outliers

What can you say about the data based on the centers?

The data reveals the four categories we wanted to focus on

Cluster 0: low sales and average reviews. Niche or less sucessful games, usally directed to an specific audience

Cluster 1: better sales and higher reviews. But still in the moderate cateogry

Cluster 2: Very high sales and high reviews. Very popular games that are also perceived as being quality products.

Cluster 3: High review scores but medium sales. Possibly games that are well liked by the criticsbut not considered as best sellers