Recommender Systems

Simulation

""" User: ---------- age (numeric) gender (F,M) country (String) platform (String)

Game:

```
year_released:(numeric)
rating:(float)
category:(Action,Adventure,Sport,Strategy,Simulation)
min_required_age:(numeric)
price:(float)
platform:(Windows,MacOS,Linux)
has_offer:bool
min_system_req:(p,pp,ppp,pppp)"""

import random
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, confusion_matrix, classification_report
import csv
from fastapi import FastAPI
from pydantic import BaseModel
from typing import List
import joblib
import catboost
from catboost import CatBoostClassifier, CatBoostRegressor
import shap
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
from sklearn.mixture import GaussianMixture, BayesianGaussianMixture
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
import pycountry
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.cluster import KMeans
from sklearn.datasets import make_blobs
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, mean_absolute_error
from sklearn.model_selection import train_test_split
```

```python
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score
from dataclasses import dataclass
import os, warnings
import seaborn as sns
import numpy as np
import sklearn
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split
import shap
import plotly.graph_objects as go
import plotly.figure_factory as ff
from plotly.subplots import make_subplots
from plotly.offline import plot, iplot, init_notebook_mode
from scipy.cluster import hierarchy
from sklearn.cluster import AgglomerativeClustering, DBSCAN
from helper_functions import *
```

I chose to to a simulation for Steam video games

```python
games = generate_games(games_num = 1000)

# games[40]

games_check= pd.DataFrame(games)
```

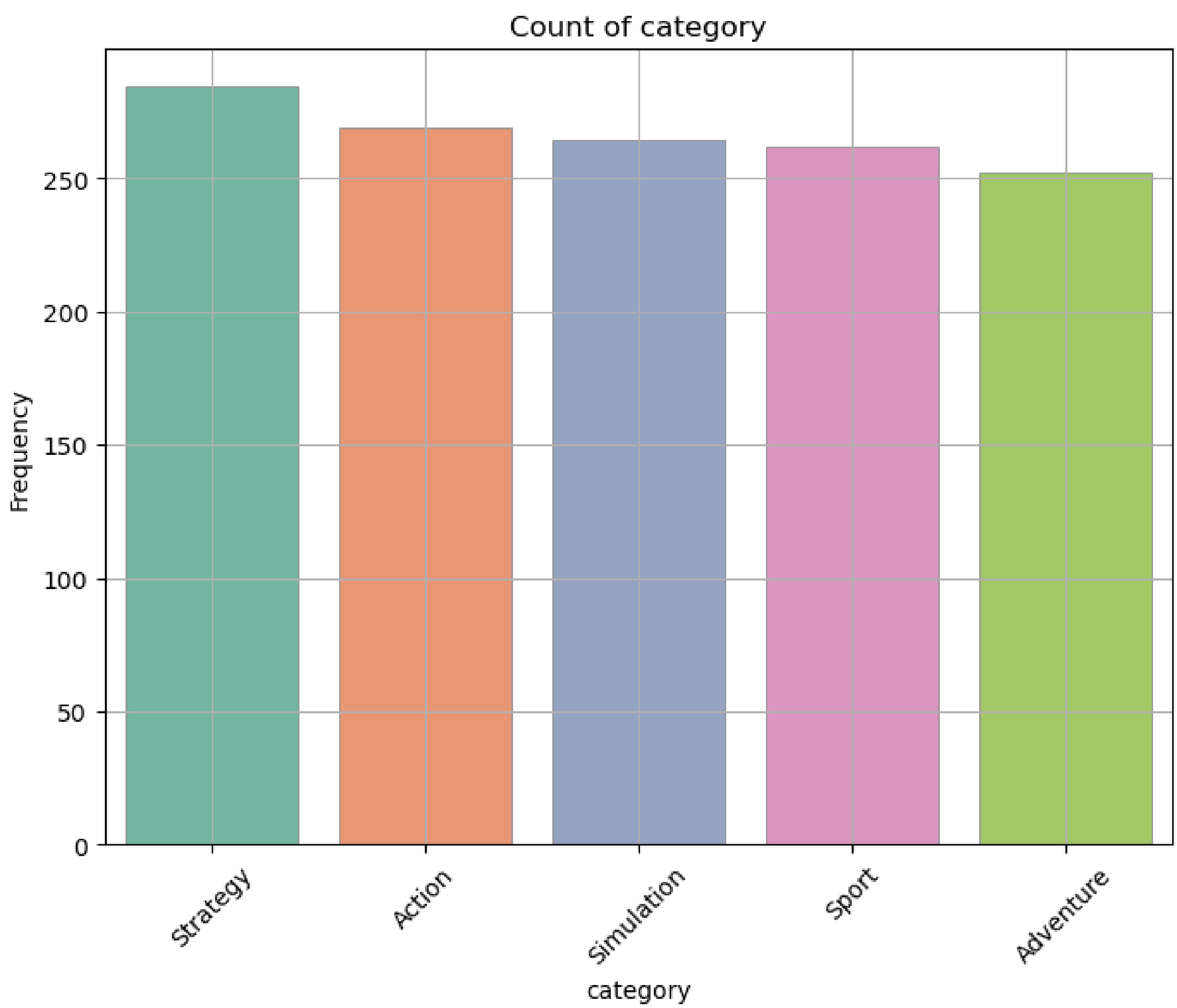
Below is a preview of the data created for the games dataset.

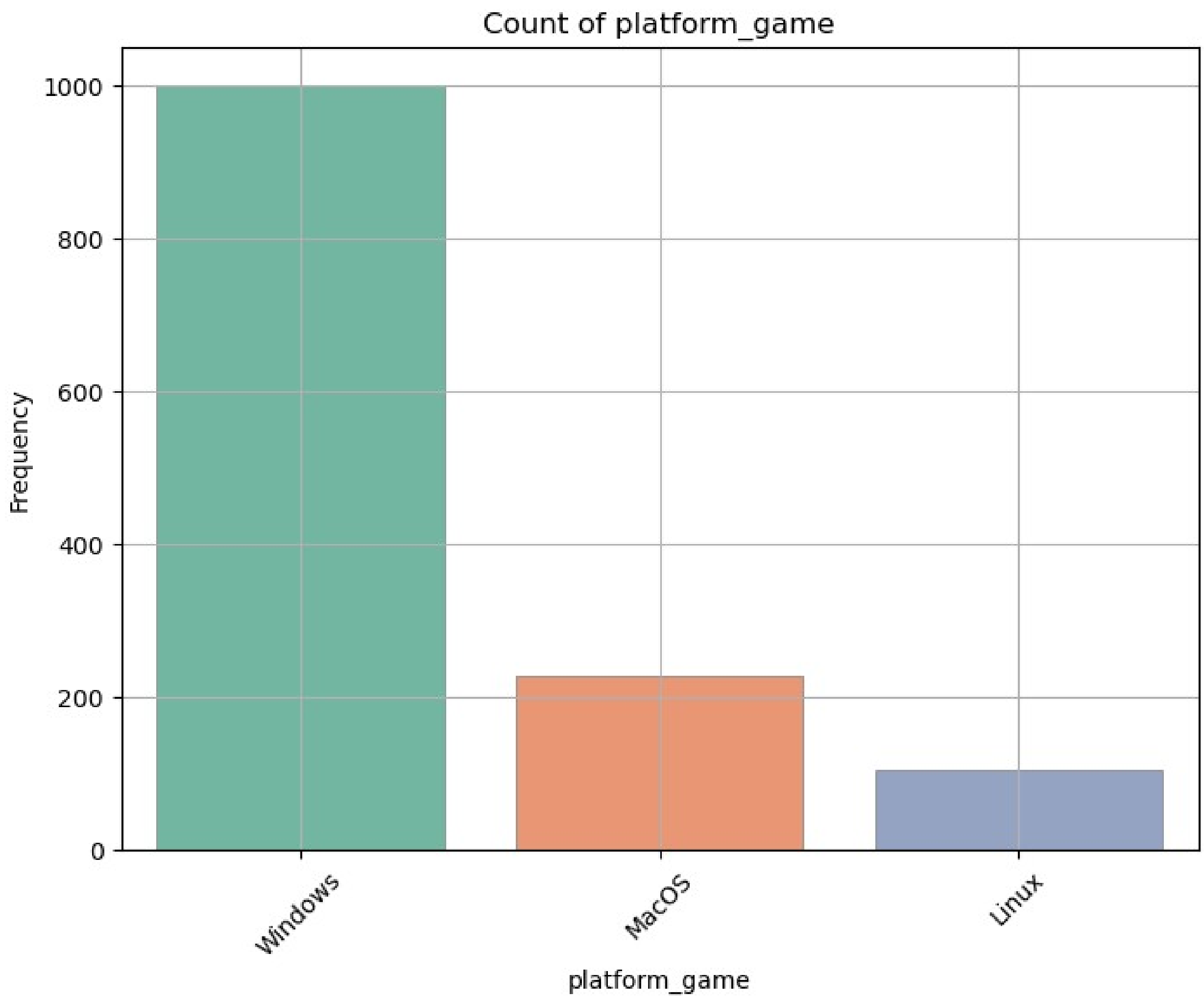
I tried to be as much closer to reality as closer, searching some real world data.

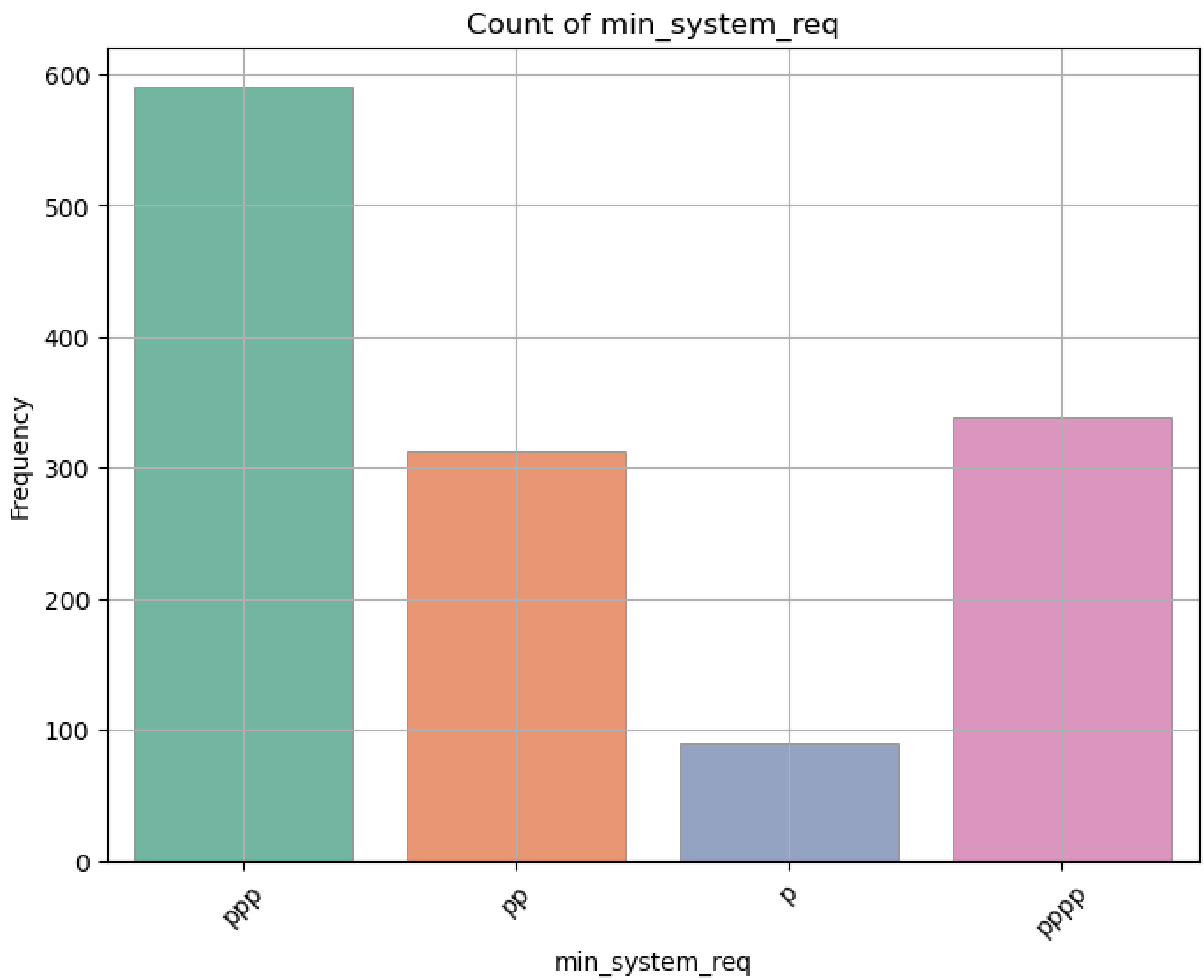
The creation of the data made by the use of custom functions that you can find in helper_functions.py file

```python
games_exploded = games_check.explode('platform_game')
categorical_columns = ['category', 'platform_game', 'min_system_req',
'min_required_age']
numeric_columns = ['year_released', 'rating', 'price']


for col in categorical_columns:
    plt.figure(figsize=(8, 6))
    sns.countplot(x=col, data=games_exploded, palette='Set2',
linewidth=0.5, edgecolor='gray')  # Set palette to 'Greys'
    plt.title(f'Count of {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')
    plt.xticks(rotation=45)
```

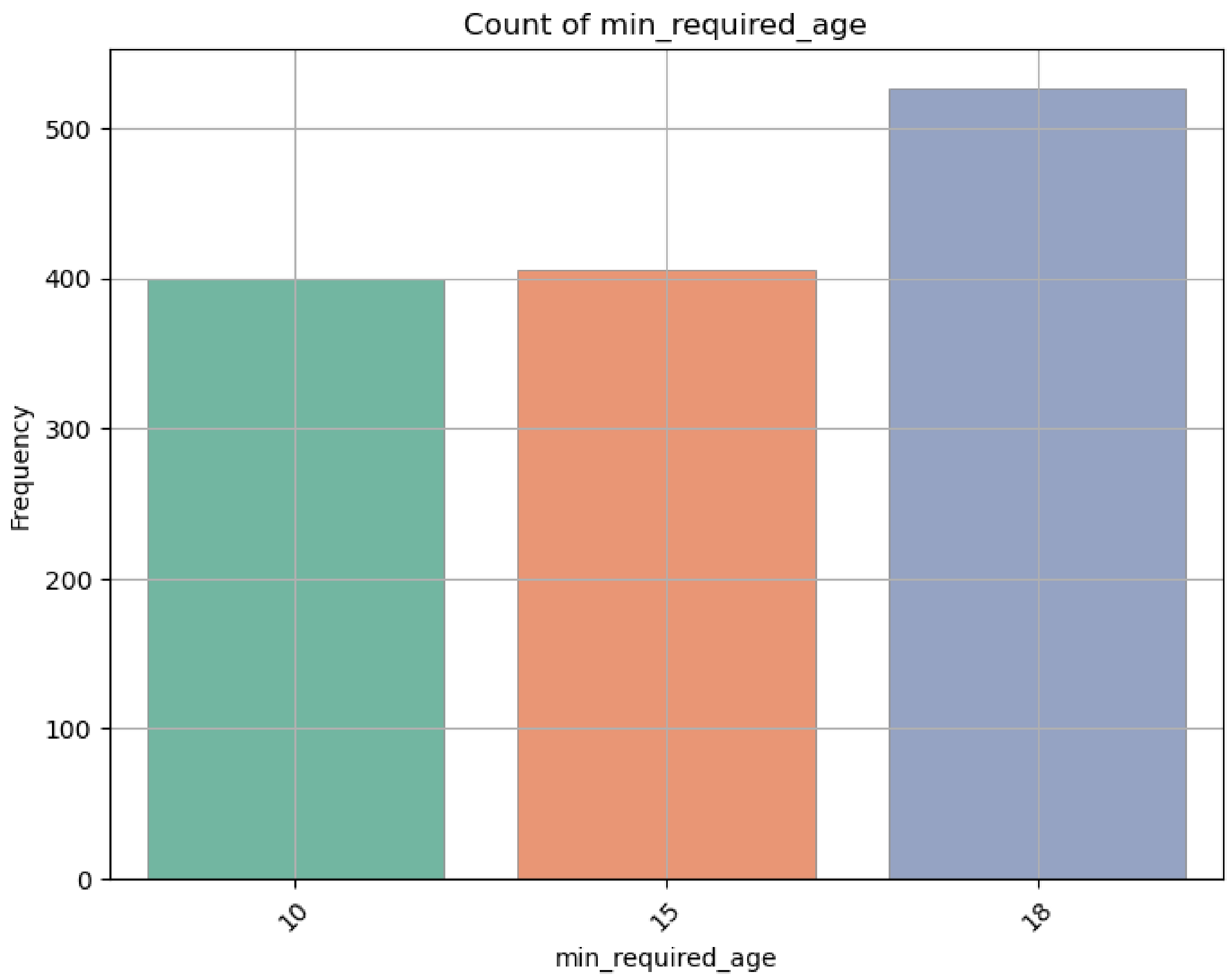
```
    plt.grid(True)
    plt.show()


for col in numeric_columns:
    plt.figure(figsize=(8, 6))
    sns.histplot(games_check[col], color='gray', bins=25)
    plt.title(f'Histogram of {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')
    plt.grid(True)
    plt.show()
```

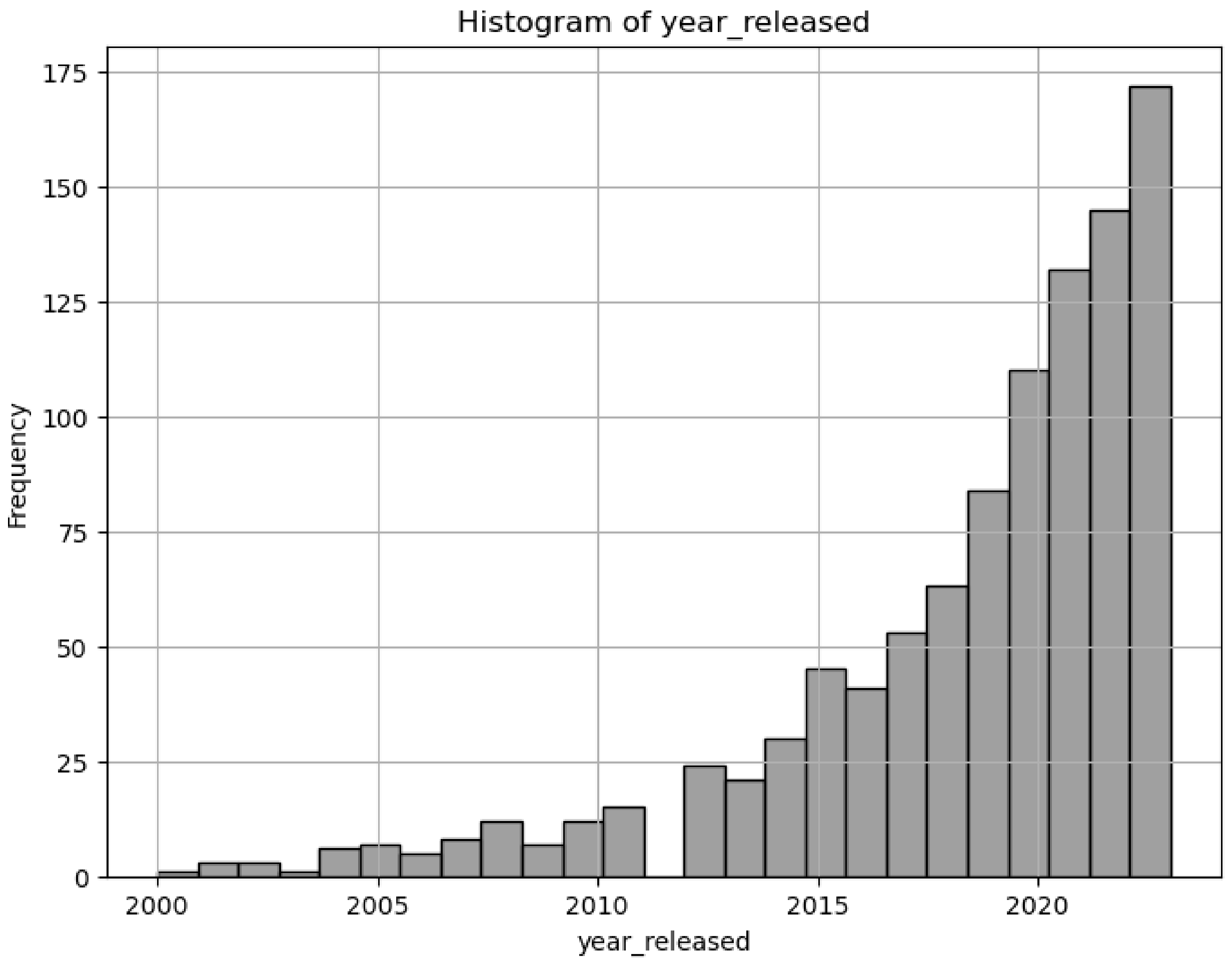



Count of platform_game
Frequency
1000
800
600
400
200
0
Windows
MacOS
Linux
platform_game

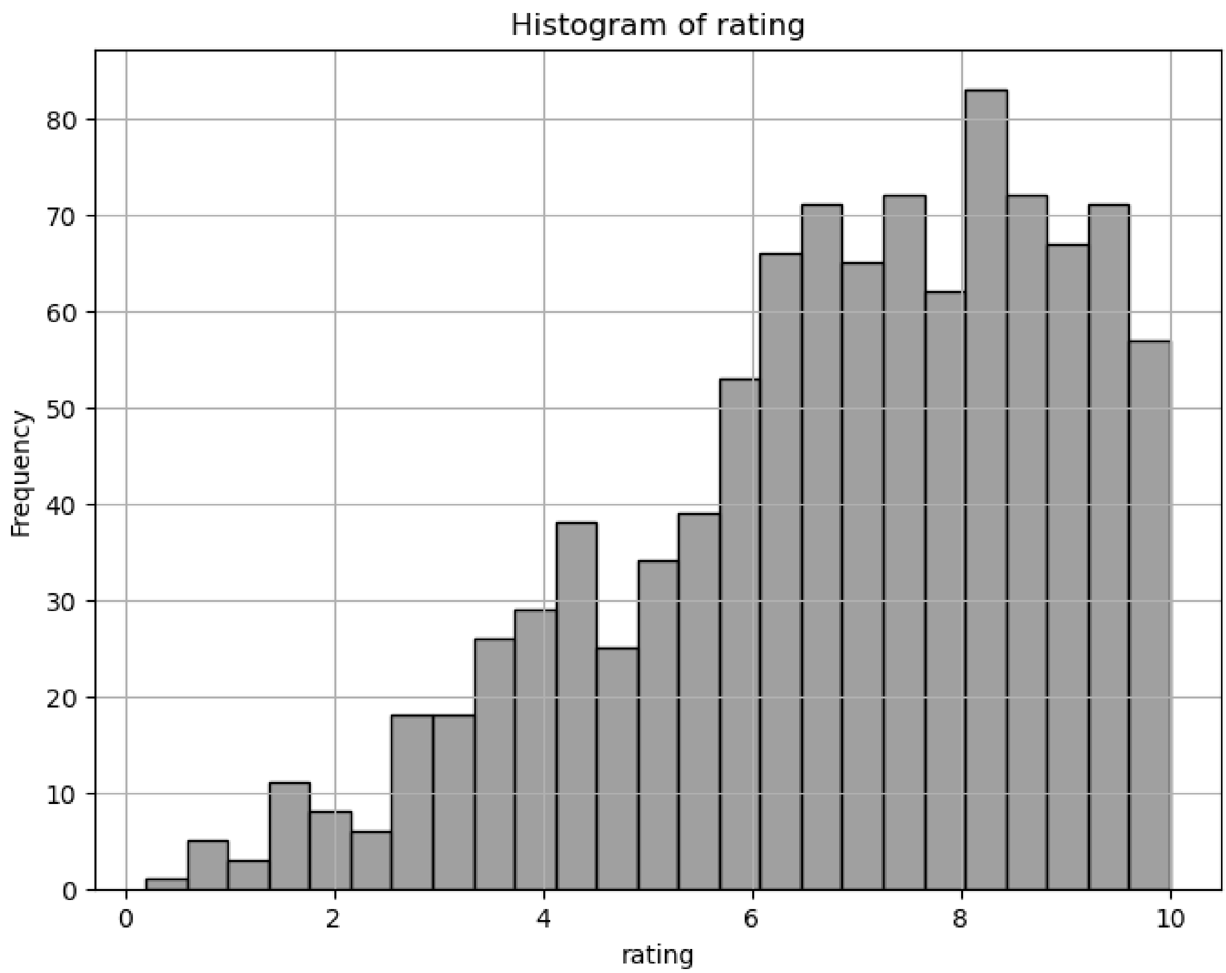


Count of min_system_req
Frequency
600
500
400
300
200
100
0
ppp
pp
p
pppp
min_system_req

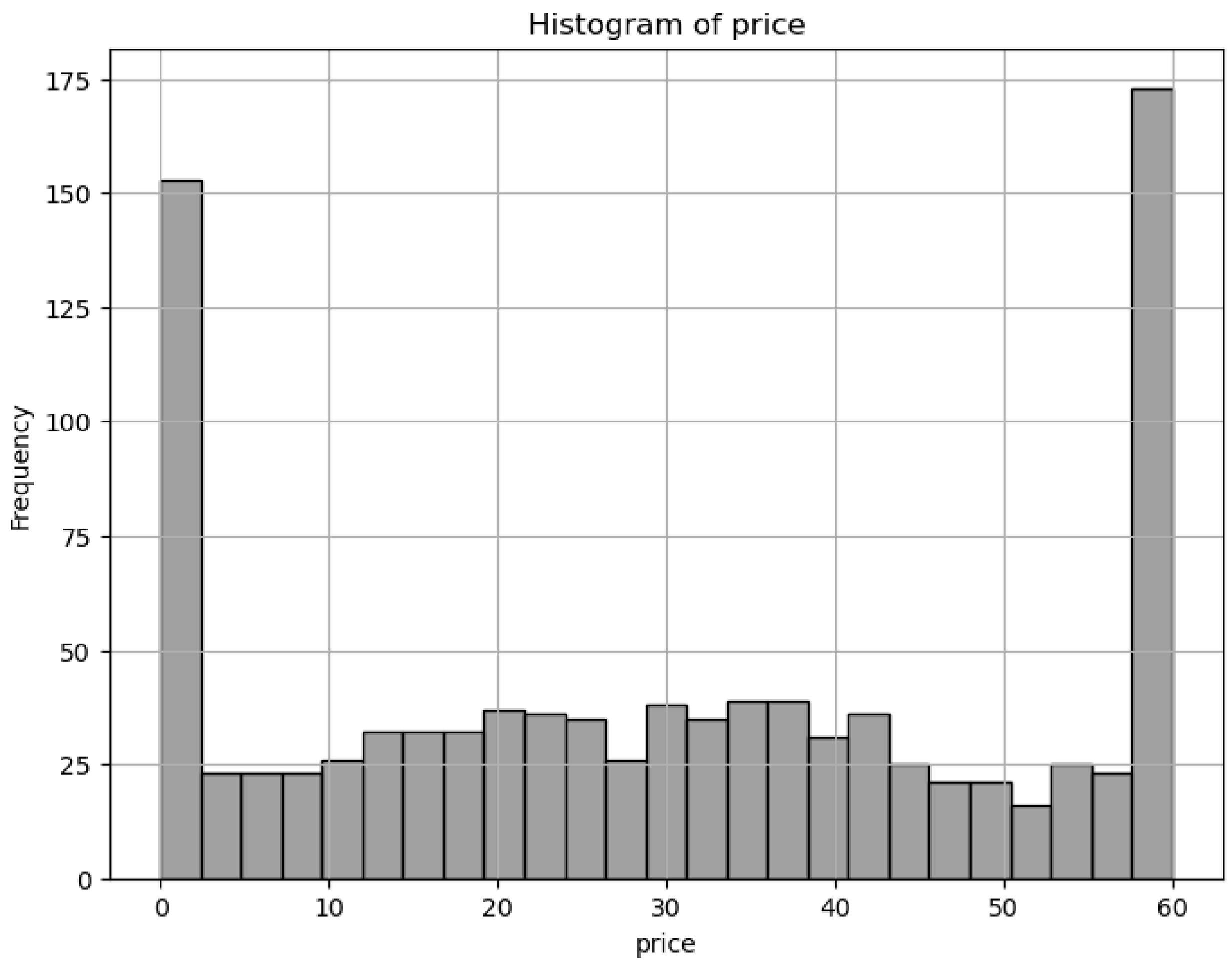

Count of min_required_age
Frequency
0
100
200
300
400
500
10
15
18
min_required_age



Histogram of year_released
Frequency
year_released
0
25
50
75
100
125
150
175
2000
2005
2010
2015
2020



Histogram of rating
Frequency
rating
0
10
20
30
40
50
60
70
80
0
2
4
6
8
10



Now lets create the users data

I created 4 segments, with my personal view of what type of games exist

You can see below the assumptions i made so i will create the users based on those characteristics

SEGMENT 1: Poor Gamer

- Age: Gaussian distro with a mean of 16
- price < 30
- min_system_req <= (p,pp)
- HAS_OFFER: 90% influence
- 90% consistent

SEGMENT 2: Epic Gamer - graphics lover

- Age: Gaussian distro with a mean of 35

- rating >9 if minimum system requirements (ppp)
- rating >8 if minimum system requirements (pppp)
- platform must be Windows
- 95% yes if its Adventure
- prefers the latest releases (beta distribution)
- 85% consistent

SEGMENT 3: Action - Shooting Gamer

- category : Action
- HAS_OFFER: 70% influence
- price as cheap as possible
- gender 95% Male

SEGMENT 4: Casual - Free time pass Gamer

- Age: Gaussian distro with a mean of 50, ok
- price = 0
- min_system_req (p,pp)
- rating > 7
- category (strategy,Simulation)

```
users_segment1=generate_users_segment1(user_num=25000,seed = 42)
generate_ratings_segment1(users_segment1,games)
```

```
ones 0.038978637513102314
```

```
users_segment2=generate_users_segment2(user_num=25000,seed = 42)
generate_ratings_segment2(users_segment2,games)
```

```
ones 0.1157639841342621
```

```
users_segment3=generate_users_segment3(user_num=25000,seed = 42)
generate_ratings_segment3(users_segment3,games)
```

```
ones 0.025326602592434206
```

```
users_segment4=generate_users_segment4(user_num=25000,seed = 4)
generate_ratings_segment4(users_segment4,games)
```

```
ones 0.01951580646736035
```

```
file_paths = ['segment1.csv', 'segment2.csv','segment3.csv',
'segment4.csv']
dfs = [pd.read_csv(file_path) for file_path in file_paths]
combined_df = pd.concat(dfs, ignore_index=True)
df = combined_df.sample(frac=1).reset_index(drop=True)
print(df.shape)
```

```
(50032432, 16)
```

After tries and testing of managing the dataset so i can cluster it, I understood that this wasnt possible.

The Tabular data with each row represeting a pair of user - game rating couldnt work.

So I decided to group by the data by user and do the clustering on the new generated dataset.

==

So i can make it clear for the categorical variables i created for each unique value 2 columns.

1: counting the games votes like

2: counting the games votes dislike

==

For the numerical variables i created 4 columns

1: average for the games votes like

2: std for the games votes like

3: average for the games votes dislike

4: std for the games votes dislike

```
df

               uid gender  age                  country platform_user  \
0           7155c2      M   28                  Mayotte       Windows
1          19341c1      F   15                  Türkiye       Windows
2            762c3      M   31                    China       Windows
3           3796c4      F   48                   Latvia       Windows
```

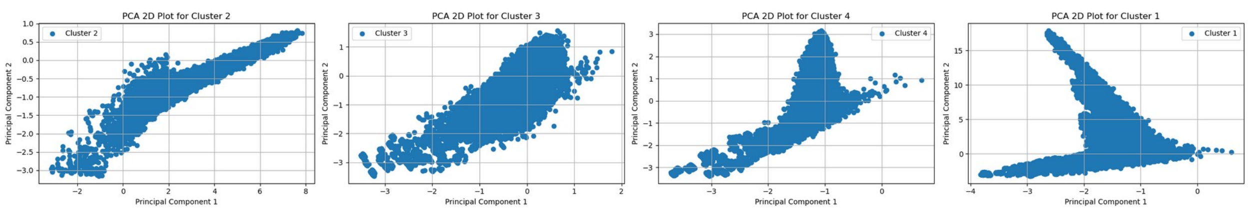
```
4           6410c3      M   30                        Maldives       Windows
...            ...    ...  ...                             ...           ...
50032427  13544c4       F   53                           Samoa       Windows
50032428  19240c1       F   18                           Malta         Linux
50032429  13222c1       F   11  Taiwan, Province of China          MacOS
50032430  21676c4       M   52         Trinidad and Tobago         Linux
50032431   9041c2       M   39                          Brazil       Windows

          cluster  year_released    category  min_required_age  price  \
0               2           2009   Adventure                15    0.0
1               1           2023      Action                15    4.1
2               3           2023   Adventure                10    0.0
3               4           2003  Simulation                18   14.1
4               3           2019       Sport                10   18.5
...           ...            ...         ...               ...    ...
50032427        4           2023  Simulation                10   60.0
50032428        1           2007    Strategy                18    0.0
50032429        1           2021   Adventure                15   32.6
50032430        4           2018   Adventure                10   29.9
50032431        2           2018    Strategy                18   60.0

                 platform_game  has_offer min_system_req  rating
result  \
0                  ['Windows']       True           pppp     5.6
0
1        ['Windows', 'MacOS']       True              p     0.2
-1
2                  ['Windows']      False           pppp     8.1
0
3                  ['Windows']       True             pp     9.5
0
```

```
4          ['Windows', 'MacOS']      False              pp     7.0
0
...                         ...        ...             ...      ...       .
..
50032427            ['Windows']      False             ppp     9.1
0
50032428  ['Windows', 'MacOS']       True            pppp     5.3
0
50032429            ['Windows']      False             ppp     7.5
0
50032430            ['Windows']      False            pppp     6.2
0
50032431            ['Windows']      False              pp     8.5
0

          gameid
0             70
1            632
2            336
3            487
4            779
...          ...
50032427     808
50032428     791
50032429      27
50032430     339
50032431     801

[50032432 rows x 16 columns]

df_with_gameid = df.copy()
df = df.drop(columns=['gameid'])

result_df_enc,result_df_enc_norm,result_df =
feature_engineering_result_1(df)# keeps only the data from the likes
```

Here is just a plot for an overview of our data using PCA for dimentionality reduction

```
clusters = result_df_enc['cluster']
data = result_df_enc.drop(columns=['cluster'])

scaler = StandardScaler()
scaled_data = scaler.fit_transform(data)

pca = PCA(n_components=2)
pca_result = pca.fit_transform(scaled_data)

pca_df = pd.DataFrame(data=pca_result, columns=['PC1', 'PC2'])
pca_df['cluster'] = clusters
```

```
unique_clusters = pca_df['cluster'].unique()
num_clusters = len(unique_clusters)
fig, axs = plt.subplots(1, num_clusters, figsize=(6*num_clusters, 4))

for i, cluster in enumerate(unique_clusters):
    cluster_data = pca_df[pca_df['cluster'] == cluster]
    axs[i].scatter(cluster_data['PC1'], cluster_data['PC2'],
label=f'Cluster {cluster}')
    axs[i].set_xlabel('Principal Component 1')
    axs[i].set_ylabel('Principal Component 2')
    axs[i].set_title(f'PCA 2D Plot for Cluster {cluster}')
    axs[i].legend()
    axs[i].grid(True)

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



By staring the process with the new dataset I used all the data from both likes and dislikes

But the results were not promising

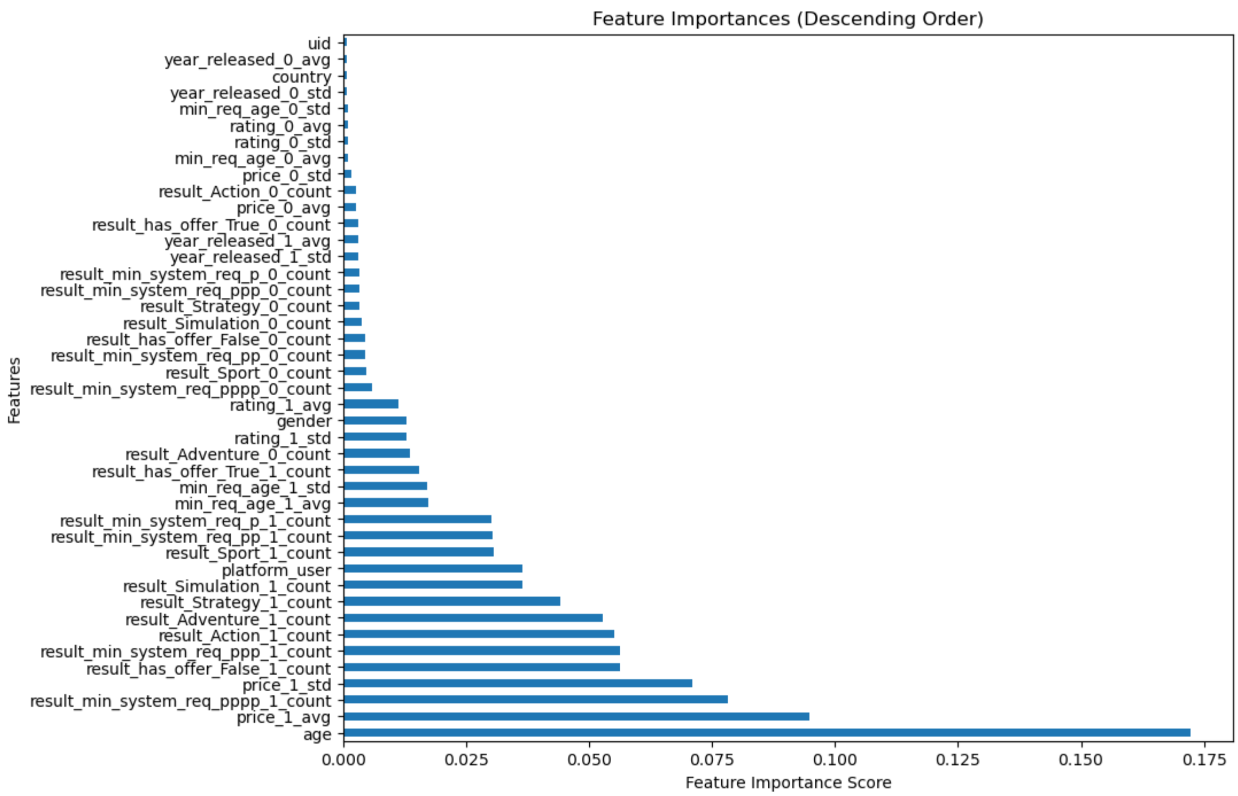
My result was the the data had too much noise with all the 0s not letting the algorythms to find any possible pattern, since the % of the like are pretty low

I first understood that from the plot below which even when i had all the data the most important features were the columns with the likes

You can see that on the below plot were the feature importance is calculated on the whole dataset

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.ensemble import ExtraTreesClassifier

result_df_enc_all,result_df_enc_norm_all,result_df_all =
feature_engineering(df)#keeps all data
```

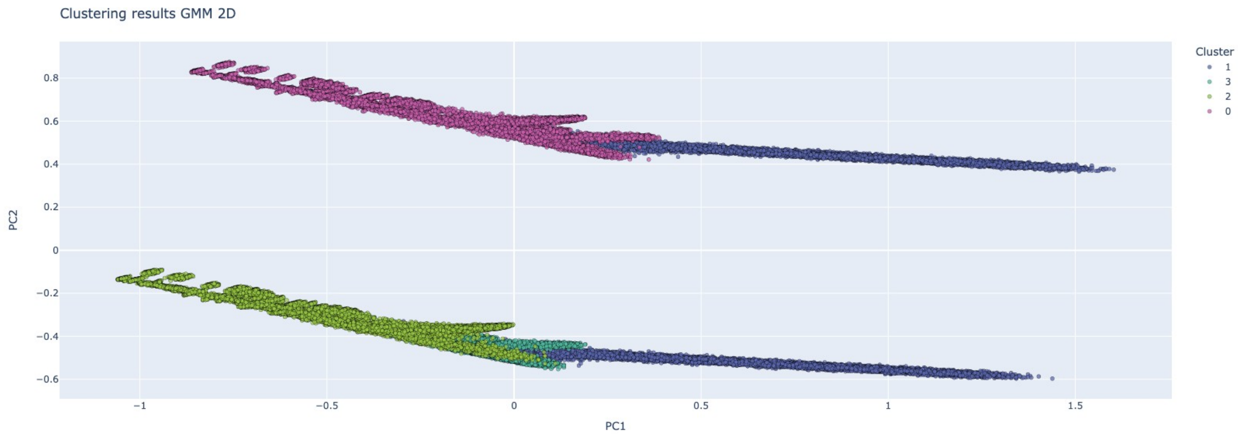
```
X = result_df_enc_norm_all
y = result_df_enc_all['cluster']

model = ExtraTreesClassifier()

model.fit(X, y)
feat_importances = pd.Series(model.feature_importances_,
index=X.columns)
feat_importances = feat_importances.sort_values(ascending=False)

plt.figure(figsize=(10, 8))
feat_importances.plot(kind='barh')
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title('Feature Importances (Descending Order)')
plt.show()
```

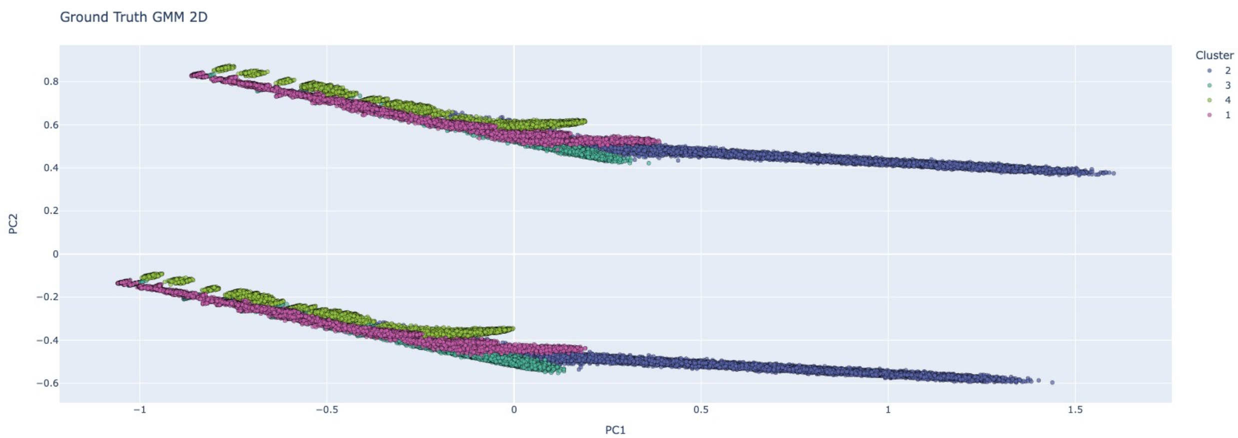


After I filtered the dataset I used plenty of clustering algorythms (Kmeans, Algomerative, DBSCAN) and dimentionality reduction methods (PCA,UMAP) for ploting

I decided that the best combination was the GMM for clustering and PCA for DR

```
#Clustering results
gmm = GaussianMixture(n_components=4, random_state=42)
gmm.fit(result_df_enc_norm)

clusters = gmm.predict(result_df_enc_norm)

pca = PCA(n_components=2)
pca_result = pca.fit_transform(result_df_enc_norm)

plot_gmm = pd.DataFrame(pca_result, columns=['PC1', 'PC2'])
plot_gmm['Cluster'] = clusters.astype(str)

fig = px.scatter(plot_gmm, x='PC1', y='PC2', color='Cluster',

color_discrete_sequence=px.colors.qualitative.Vivid[1:])
fig.update_traces(marker=dict(size=5, opacity=0.75,
line=dict(width=0.5, color='DarkSlateGrey')))
fig.update_layout(title="Clustering results GMM 2D",
                  width=800, height=600,
                  legend_title='Cluster')
fig.show()

#Ground Truth
# gmm = GaussianMixture(n_components=4, random_state=42)
# gmm.fit(result_df_enc_norm)
clusters_gt = result_df_enc['cluster']

pca = PCA(n_components=2)
pca_result = pca.fit_transform(result_df_enc_norm)

plot_gmm = pd.DataFrame(pca_result, columns=['PC1', 'PC2'])
plot_gmm['Cluster_gt'] = clusters_gt.astype(str)

fig = px.scatter(plot_gmm, x='PC1', y='PC2', color='Cluster_gt',

color_discrete_sequence=px.colors.qualitative.Vivid[1:])
fig.update_traces(marker=dict(size=5, opacity=0.75,
line=dict(width=0.5, color='DarkSlateGrey')))
fig.update_layout(title="Ground Truth GMM 2D",
                  width=800, height=600,
                  legend_title='Cluster')
fig.show()
```

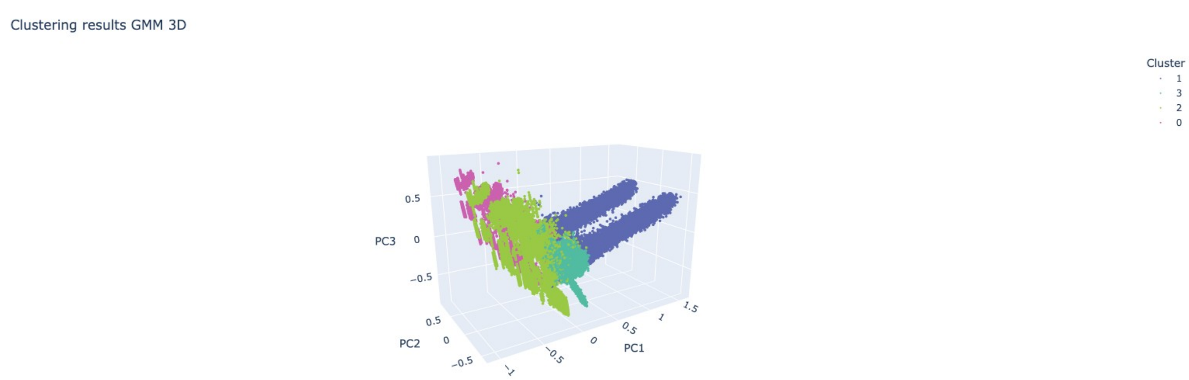


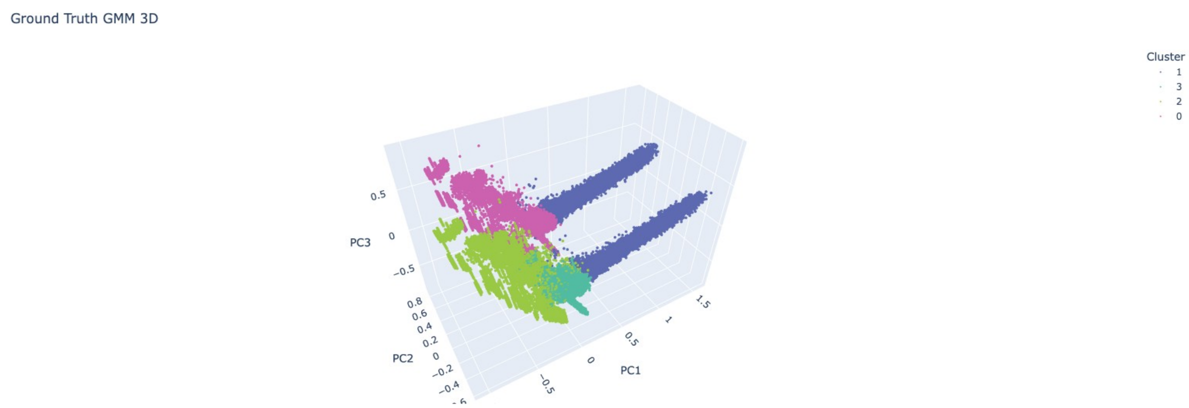


As we can see the 2 dimentions are not so helpfull so lets try the 3D plots

```
gmm = GaussianMixture(n_components=4, random_state=42)
gmm.fit(result_df_enc_norm)

clusters = gmm.predict(result_df_enc_norm)
pca = PCA(n_components=3)
pca_result = pca.fit_transform(result_df_enc_norm)

plot_gmm = pd.DataFrame(pca_result, columns=['PC1', 'PC2', 'PC3'])
plot_gmm['Cluster'] = clusters.astype(str)

# Plot clusters using PCA results
fig = px.scatter_3d(plot_gmm, x='PC1', y='PC2', z='PC3',
color='Cluster',

color_discrete_sequence=px.colors.qualitative.Vivid[1:])
fig.update_traces(marker=dict(size=2))
fig.update_layout(title="Clustering results GMM 3D",
                  width=800, height=600,
```

```
                  legend_title='Cluster')
fig.show()



# gmm = GaussianMixture(n_components=4, random_state=42)
# gmm.fit(result_df_enc_norm)

clusters_gt = result_df_enc['cluster']

pca = PCA(n_components=3)
pca_result = pca.fit_transform(result_df_enc_norm)

plot_gmm = pd.DataFrame(pca_result, columns=['PC1', 'PC2', 'PC3'])
plot_gmm['clusters_gt'] = clusters.astype(str)

fig = px.scatter_3d(plot_gmm, x='PC1', y='PC2', z='PC3',
color='clusters_gt',

color_discrete_sequence=px.colors.qualitative.Vivid[1:])
fig.update_traces(marker=dict(size=2))
fig.update_layout(title="Ground Truth GMM 3D",
                  width=800, height=600,
                  legend_title='Cluster')
fig.show()
```





As we can see the cluster are much easier to been recognised in 3D

Now lets create a confusion matrix so we can have the total overview

```
cluster_counts =
result_df_enc.groupby('cluster').size().reset_index(name='count')
print("===================")
cluster_counts
```

```
===================
```

	cluster	count
0	1	23664
1	2	24779
2	3	23204
3	4	22780

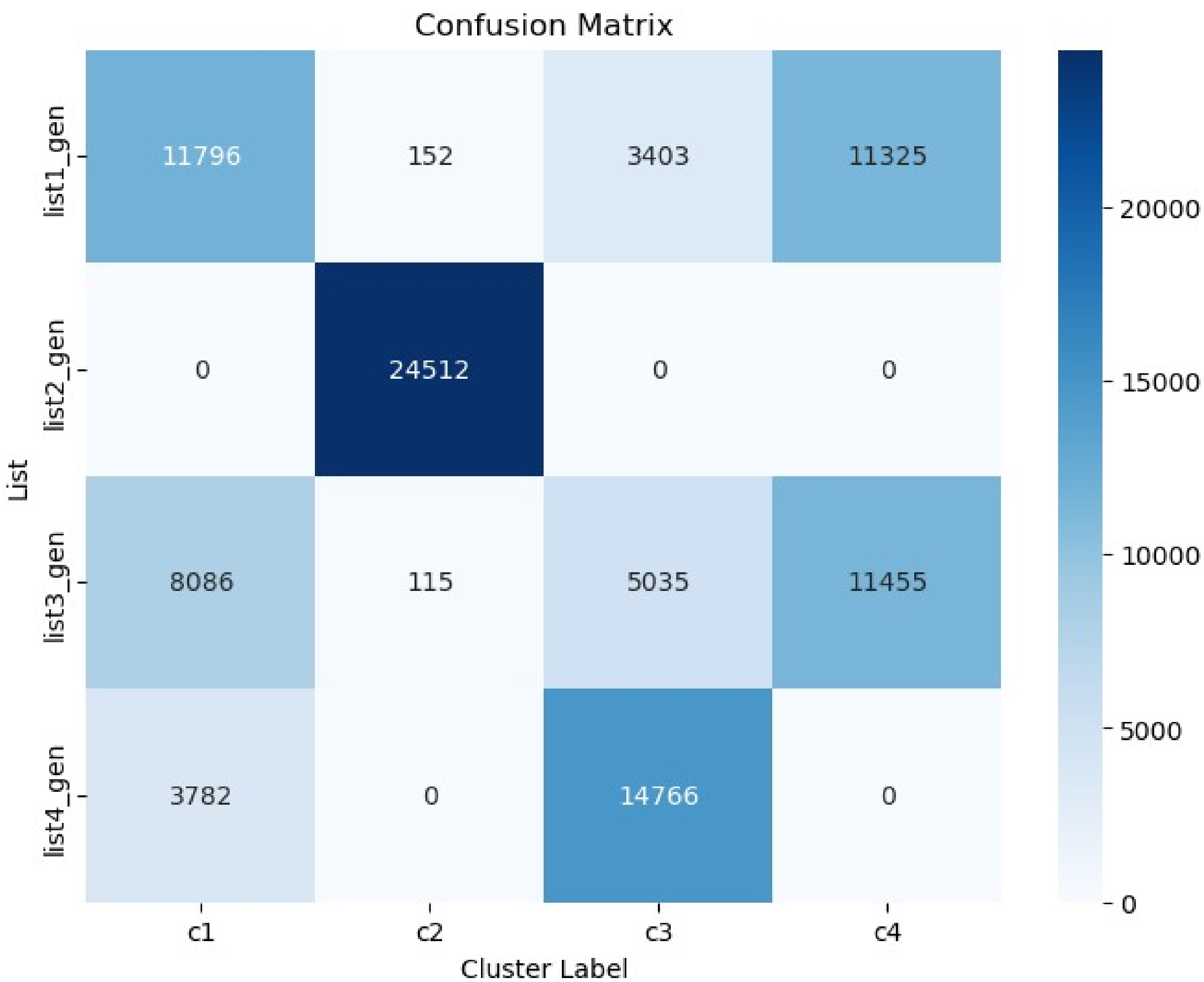
Not all the 100,000 users are being in the clusters, because as we can see below there are 5313 users with only dislikes, that is normal not been able to get clustered

```
# Group by 'uid' and filter groups where all 'result' values are 0
uids_with_only_zero = df.groupby('uid').filter(lambda x:
all(x['result'] == 0))['uid'].nunique()

print("Count of UIDs with only dislikes:", uids_with_only_zero)

uids_with_ones = df.groupby('uid').filter(lambda x: any(x['result'] ==
1) or (any(x['result'] == 0) and any(x['result'] == 1)))
['uid'].nunique()

print("Count of UIDs with likes and dislikes or only likes",
uids_with_ones)
```

```
Count of UIDs with only dislikes: 5313
Count of UIDs with likes and dislikes or only likes 94427
```

```
confusion_matrix(result_df,clusters)
```

```
Counts for list1_gen:
c1: 11796
c2: 152
c3: 3403
c4: 11325
Counts for list2_gen:
c1: 0
c2: 24512
c3: 0
c4: 0
Counts for list3_gen:
c1: 8086
c2: 115
c3: 5035
c4: 11455
Counts for list4_gen:
c1: 3782
c2: 0
c3: 14766
c4: 0
```



From the matrix we can see that there is cluster that is really easy to identify, 1 with a majority , and the rest 2 been difficult to identify (the smaller ones, that why the generated plots were actually pretty clear to identify

Now I would like to implement something extra

Lets say we create a FastAPI so that it can make some predictions, by given specific characteristics

```
df_with_gameid.head()

       uid gender  age  country platform_user  cluster  year_released
\
0   7155c2      M   28  Mayotte       Windows        2           2009

1  19341c1      F   15  Türkiye       Windows        1           2023
```

```
2    762c3       M   31      China       Windows        3           2023

3   3796c4       F   48     Latvia       Windows        4           2003

4   6410c3       M   30   Maldives       Windows        3           2019


     category  min_required_age  price          platform_game
has_offer  \
0   Adventure                15    0.0            ['Windows']
True
1      Action                15    4.1  ['Windows', 'MacOS']
True
2   Adventure                10    0.0            ['Windows']
False
3  Simulation                18   14.1            ['Windows']
True
4       Sport                10   18.5  ['Windows', 'MacOS']
False

  min_system_req  rating  result  gameid
0           pppp     5.6       0      70
1              p     0.2      -1     632
2           pppp     8.1       0     336
3             pp     9.5       0     487
4             pp     7.0       0     779

df_2 = df_with_gameid.loc[:, ['gender', 'age', 'platform_user',
'gameid','result']]

from sklearn.preprocessing import LabelEncoder

encoder = LabelEncoder()
df_2['gender'] = encoder.fit_transform(df_2['gender'])
df_2['platform_user'] = encoder.fit_transform(df_2['platform_user'])

scaler = MinMaxScaler()
df_2 = pd.DataFrame(scaler.fit_transform(df_2), columns=df_2.columns)

X = df_2.drop('result', axis=1)
y = df_2['result']

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

logreg_classifier = LogisticRegression(max_iter=100, random_state=42)

logreg_classifier.fit(X_train, y_train)

y_pred = logreg_classifier.predict(X_test)
```

```
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')

----------------------------------------------------------------------
-----
KeyError                                  Traceback (most recent call
last)
File
~/anaconda3/lib/python3.11/site-packages/pandas/core/indexes/base.py:3
653, in Index.get_loc(self, key)
   3652 try:
-> 3653     return self._engine.get_loc(casted_key)
   3654 except KeyError as err:

File
~/anaconda3/lib/python3.11/site-packages/pandas/_libs/index.pyx:147,
in pandas._libs.index.IndexEngine.get_loc()

File
~/anaconda3/lib/python3.11/site-packages/pandas/_libs/index.pyx:176,
in pandas._libs.index.IndexEngine.get_loc()

File pandas/_libs/hashtable_class_helper.pxi:7080, in
pandas._libs.hashtable.PyObjectHashTable.get_item()

File pandas/_libs/hashtable_class_helper.pxi:7088, in
pandas._libs.hashtable.PyObjectHashTable.get_item()

KeyError: 'cluster'

The above exception was the direct cause of the following exception:

KeyError                                  Traceback (most recent call
last)
Cell In[43], line 25
     23 recall = recall_score(y_test, y_pred, average='weighted')
     24 f1 = f1_score(y_test, y_pred, average='weighted')
---> 25 conf_matrix = confusion_matrix(y_test, y_pred)
     26 class_report = classification_report(y_test, y_pred)

File
~/Desktop/master/recommender_systems/assignment2/working_notebooks/
helper_functions.py:263, in confusion_matrix(result_df, clusters)
    260 result_df['cluster_gen'] = clusters
    262 cluster_lists = {}
--> 263 for cluster_id in result_df['cluster'].unique():
    264     cluster_data = result_df[result_df['cluster'] ==
cluster_id]
```

```
    265     uids = cluster_data['uid'].tolist()

File
~/anaconda3/lib/python3.11/site-packages/pandas/core/series.py:1007,
in Series.__getitem__(self, key)
   1004     return self._values[key]
   1006 elif key_is_scalar:
-> 1007     return self._get_value(key)
   1009 if is_hashable(key):
   1010     # Otherwise index.get_value will raise InvalidIndexError
   1011     try:
   1012         # For labels that don't resolve as scalars like tuples
and frozensets

File
~/anaconda3/lib/python3.11/site-packages/pandas/core/series.py:1116,
in Series._get_value(self, label, takeable)
   1113     return self._values[label]
   1115 # Similar to Index.get_value, but we do not fall back to
positional
-> 1116 loc = self.index.get_loc(label)
   1118 if is_integer(loc):
   1119     return self._values[loc]

File
~/anaconda3/lib/python3.11/site-packages/pandas/core/indexes/base.py:3
655, in Index.get_loc(self, key)
   3653     return self._engine.get_loc(casted_key)
   3654 except KeyError as err:
-> 3655     raise KeyError(key) from err
   3656 except TypeError:
   3657     # If we have a listlike key, _check_indexing_error will
raise
   3658     #  InvalidIndexError. Otherwise we fall through and re-
raise
   3659     #  the TypeError.
   3660     self._check_indexing_error(key)

KeyError: 'cluster'
```

```
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
```

```
Accuracy: 0.9502172940413554
Precision: 0.9029129058952755
Recall: 0.9502172940413554
F1 Score: 0.9259613363639148
```

So now by giving the information about the user and the game id, the model can predict if the user will like or not the game

```
joblib.dump(logreg_classifier, 'log_reg_like_dislike.joblib')#save the model
```

```
['log_reg_like_dislike.joblib']
```

```
import requests

# Define the URL of your FastAPI endpoint
url = "http://0.0.0.0:8002/like_dislike/" # Assuming "web" is the service name in your docker-compose.yaml

# Define the user features as a dictionary
user_features = {
    "gender": 1,
    "age": 30,
    "platform_user": 2,
    "gameid": 70
}

# Send a POST request to the endpoint with the user features
response = requests.post(url, json=user_features)

# Check if the request was successful
if response.status_code == 200:
    # Print the response JSON data
    print(response.json())
else:
    # Print an error message if the request failed
    print("Error:", response.status_code, response.text)
```

```
{'cluster_generated': 0}
```