modelling_clustering_v2

August 12, 2025

0.0.1 Clustering

[2]:
```
# ensure scikit-learn's runs single-threaded to reduce memory load.
os.environ["OMP_NUM_THREADS"] = "1"   # OpenMP threads
os.environ["MKL_NUM_THREADS"] = "1"   # MKL's own thread pool
```

[ ]:
```
from dotenv import load_dotenv
import os
```

Load data

[ ]:
```
load_dotenv(".env")  # defaults to loading a `.env` file in the current␣
 ↪directory

host = os.getenv("MY_SQL_HOST")
user = os.getenv("MY_SQL_USER")
password = os.getenv("MY_SQL_PASSWORD")
database = os.getenv("MY_SQL_DATABASE")
```

[ ]:
```
import mysql.connector

def get_connection(host, user, password, database):
  mydb = mysql.connector.connect(
    host=host,
    user=user,
    password=password,
    database=database
  )
  return mydb
```

[ ]:
```
connection = get_connection(host=host, user=user, password=password,␣
 ↪database=database)
cursor = connection.cursor()
root_location = "E:\\applied data science␣
 ↪capstone\\anime-recommendation\\modelling\\clustering\\exploration"
```

[ ]:
```
query = """
SELECT
    user_id,
```

```
    anime_id,
    rating
FROM
    rating_v2
ORDER BY
    user_id;
"""
cursor.execute(query)
raw_data = cursor.fetchall()
```

[ ]:
```
import pandas as pd

df = pd.DataFrame(raw_data, columns=["user_id", "anime_id", "rating"])
df["rating"] = pd.to_numeric(df["rating"])
# save data to file
filename = "E:\\applied data science␣
 ↪capstone\\data\\etl\\extract\\transactions\\clustering_13_Jul.csv"
df.to_csv(filename, index=False)
```

[5]:
```
df = pd.read_csv(filename)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 47161882 entries, 0 to 47161881
Data columns (total 3 columns):
 #   Column    Dtype
---  ------    -----
 0   user_id   int64
 1   anime_id  int64
 2   rating    float64
dtypes: float64(1), int64(2)
memory usage: 1.1 GB
```

[12]:
```
df.isna().sum()
```

[12]:
```
user_id     0
anime_id    0
rating      0
dtype: int64
```

[7]:
```
from sklearn.model_selection import train_test_split
```

[ ]:
```
# split into train, test and validate
train_df, test_validate_df = train_test_split(df, test_size=0.25,␣
 ↪random_state=42)
test_df, validate_df = train_test_split(test_validate_df, test_size=0.2,␣
 ↪random_state=42)
```

[9]:
```python
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 35371411 entries, 27745566 to 21081788
Data columns (total 3 columns):
 #   Column    Dtype
---  ------    -----
 0   user_id   int64
 1   anime_id  int64
 2   rating    float64
dtypes: float64(1), int64(2)
memory usage: 1.1 GB
```

[10]:
```python
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 9432376 entries, 36901731 to 21750476
Data columns (total 3 columns):
 #   Column    Dtype
---  ------    -----
 0   user_id   int64
 1   anime_id  int64
 2   rating    float64
dtypes: float64(1), int64(2)
memory usage: 287.9 MB
```

[11]:
```python
validate_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2358095 entries, 39414737 to 31165642
Data columns (total 3 columns):
 #   Column    Dtype
---  ------    -----
 0   user_id   int64
 1   anime_id  int64
 2   rating    float64
dtypes: float64(1), int64(2)
memory usage: 72.0 MB
```

[13]:
```python
print(f"train percentage: {train_df.shape[0]/df.shape[0]}")
print(f"test percentage: {test_df.shape[0]/df.shape[0]}")
print(f"validate percentage: {validate_df.shape[0]/df.shape[0]}")
```

```
train percentage: 0.7499999893982178
test percentage: 0.19999999151857425
validate percentage: 0.05000001908320792
```

[14]:
```python
# save validate df for future user
```

```
filename = "E:\\applied data science␣
↪capstone\\data\\etl\\extract\\transactions\\validate_8_Aug.csv"
validate_df.to_csv(filename, index=False)
```

[24]:
```
anime_cat = train_df['anime_id'].astype('category') # create category
anime_codes = anime_cat.cat.codes # get code for categories
index_to_anime = dict(enumerate(anime_cat.cat.categories)) # create mapping for␣
↪index and anime
anime_to_index = {v: k for k, v in index_to_anime.items()} # reverse mapping␣
↪for index and anime
```

[25]:
```
user_cat = train_df['user_id'].astype('category') # create category
user_codes = user_cat.cat.codes # get code for categories
index_to_user = dict(enumerate(user_cat.cat.categories)) # create mapping for␣
↪index and user
user_to_index = {v: k for k, v in index_to_user.items()} # reverse mapping for␣
↪index and user
```

[ ]:
```
from scipy.sparse import coo_matrix
# build coo (non-zero values along with their coordinates), then convert to csr␣
↪(format for sparse matrix)
num_users  = user_codes.max() + 1
num_animes = anime_codes.max() + 1
data = train_df['rating'].values
user_item_sparse = coo_matrix((data, (user_codes, anime_codes)),␣
↪shape=(num_users, num_animes)).tocsr()
```

Training K = 2

[27]:
```
from sklearn.cluster import KMeans
```

[223]:
```
# evaluation metrics
inertia = []
silhoutte_scores = []
davies_bouldin_scores = []
precision_scores = []
recall_scores = []
```

[224]:
```
# create cluster
k = 2
kmeans = KMeans(n_clusters=k, random_state=42, max_iter=300)
cluster_labels = kmeans.fit_predict(user_item_sparse)

# inertia measures how internally coherent the k-means clusters are
# lower inertia means points are closer to the centroid
# higher inertia means points are further from the centroid
inertia.append(kmeans.inertia_)
```

Assessing K = 2

[225]:
```python
import numpy as np
```

[226]:
```python
# extract sample
random_generator = np.random.default_rng(42)
sample_indices = random_generator.choice(user_item_sparse.shape[0], size=3000,␣
↪replace=False)
sample_matrix = user_item_sparse[sample_indices]
sample_labels = cluster_labels[sample_indices]
sample_index_to_user = { k:v for k, v in index_to_user.items() if k in␣
↪sample_indices}
```

[227]:
```python
from sklearn.metrics import silhouette_score
from sklearn.metrics import davies_bouldin_score
```

Silhouette

[228]:
```python
# silhouette score is used to determine the effectiveness of the clusters
# close to -1 means points in cluster are closer to points in other clusters
# clost to 1 means the points are close to other points in the same cluster
sil_score = silhouette_score(sample_matrix, sample_labels, metric='cosine')
print(f"Silhouette Score: {sil_score:.3f}")
silhoutte_scores.append(sil_score)
```

```
Silhouette Score: -0.002
```

Davies-Bouldin Index

[229]:
```python
# davies-bouldin index is used to compare how well separated a cluster is to␣
↪its size
# lower score is better as it means the clusters are more compact and the␣
↪points are far apart from centroids
db_score = davies_bouldin_score(sample_matrix.toarray(), sample_labels)
print(f"Davies-Bouldin Index: {db_score:.3f}")
davies_bouldin_scores.append(db_score)
```

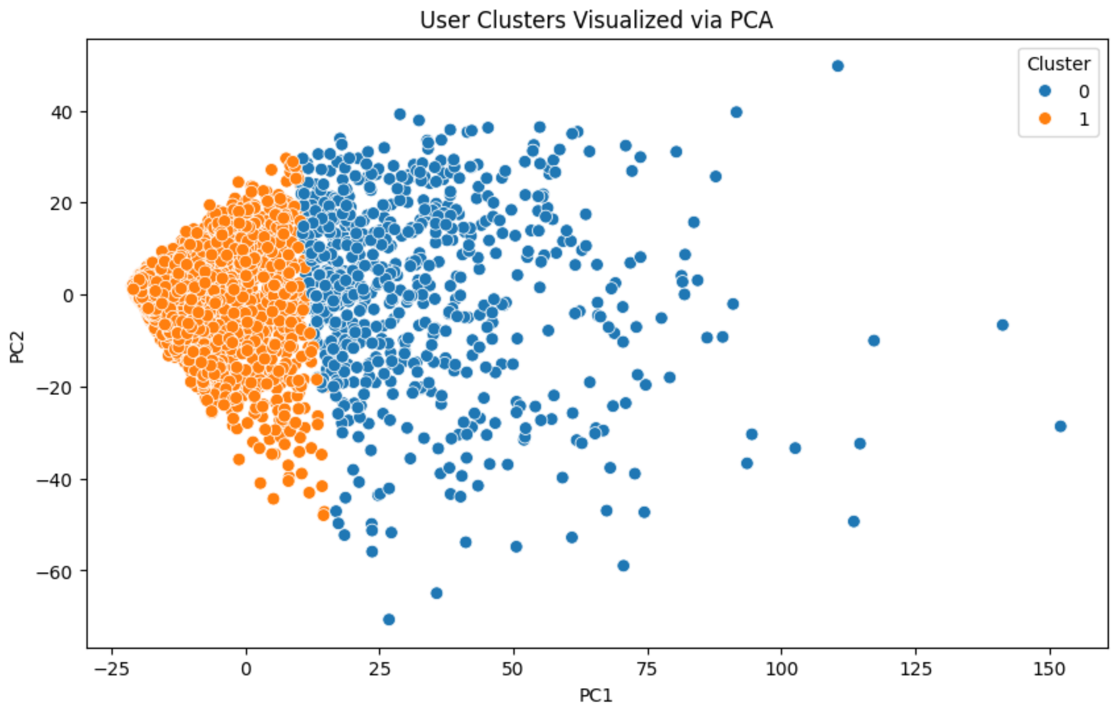
```
Davies-Bouldin Index: 3.621
```

Visualize clusters

[230]:
```python
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import seaborn as sns
plots_location = "E:\\applied data science␣
↪capstone\\anime-recommendation\\modelling\\clustering\\assessing"
```

[231]:
```python
# visualize inspect the clusters
pca = PCA(n_components=2)
user_2d = pca.fit_transform(sample_matrix.toarray())

df_plot = pd.DataFrame({
```

```
    'x': user_2d[:, 0],
    'y': user_2d[:, 1],
    'cluster': sample_labels
})

plt.figure(figsize=(10, 6))
sns.scatterplot(data=df_plot, x='x', y='y', hue='cluster', palette='tab10',␣
  ↪s=50)
plt.title("User Clusters Visualized via PCA")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.legend(title='Cluster')
plt.savefig(f"{plots_location}\\plots\\user_clusters_k_2.png")
plt.show()
```



Precision@2 and Recall@2

[232]:
```
# assign cluster to users
clusters_df = pd.DataFrame({
    'user_id' : [index_to_user[i] for i in range(len(cluster_labels))],
    'cluster': cluster_labels
})

clusters_train_df = train_df.merge(clusters_df, on="user_id")
```

[233]:
```
clusters_train_df.head()
```

[233]:

	user_id	anime_id	rating	cluster
0	287522	522	8.0	1
1	447249	2033	7.0	1
2	446384	31318	10.0	0
3	400930	3712	8.0	0
4	153921	37520	8.0	0

[234]:
```
# calulate mean rating for each anime across a cluster
cluster_mean_ratings_df = clusters_train_df.drop(columns=["user_id"]) \
    .groupby(["cluster", "anime_id"]).mean().reset_index()
```

[235]:
```
def precision_recall_at_k(user_id, k=5):
    # retrieve cluster for user
    cluster_id = clusters_train_df.loc[clusters_train_df["user_id"] == user_id,␣
 ↪'cluster'].values[0]
    cluster_profile = cluster_mean_ratings_df.
 ↪loc[cluster_mean_ratings_df["cluster"] == cluster_id] \
        .drop('cluster', errors='ignore')

    # sort by rating
    recommendations = cluster_profile.sort_values(by=["rating"],␣
 ↪ascending=False)

    # anime rated by user in test df and train df
    user_test_anime = test_df.loc[test_df["user_id"] == user_id, "anime_id"].
 ↪tolist()
    user_train_anime = train_df[train_df["user_id"] == user_id]

    # recommended top-k
    recommended = recommendations.loc[~recommendations["anime_id"] \
        .isin(user_train_anime["anime_id"].unique()), "anime_id"].tolist()
    recommended_k = recommended[:k]

    # no test data for user
    if len(user_test_anime) == 0:
        return None, None

    precision = len(set(recommended_k) & set(user_test_anime)) / k
    recall = len(set(recommended_k) & set(user_test_anime)) /␣
 ↪len(user_test_anime)
    return precision, recall
```

[236]:
```
precisions, recalls = [], []
for user_id in sample_index_to_user.values():
    p, r = precision_recall_at_k(user_id, k=5)
```

```
    if p is not None:
        precisions.append(p)
        recalls.append(r)

mean_precision = np.mean(precisions)
mean_recall = np.mean(recalls)

precision_scores.append(mean_precision)
recall_scores.append(mean_recall)

print(f"Precision@2: {mean_precision:.6f}")
print(f"Recall@2: {mean_recall:.6f}")
```

```
Precision@2: 0.017795
Recall@2: 0.001476
```

Training K = 3

[237]:
```
# create cluster
k = 3
kmeans = KMeans(n_clusters=k, random_state=42, max_iter=300)
cluster_labels = kmeans.fit_predict(user_item_sparse)

inertia.append(kmeans.inertia_)
```

Assessing K = 3

[238]:
```
sample_labels = cluster_labels[sample_indices]
```

Silhouette

[239]:
```
sil_score = silhouette_score(sample_matrix, sample_labels, metric='cosine')
print(f"Silhouette Score: {sil_score:.3f}")
silhoutte_scores.append(sil_score)
```

```
Silhouette Score: -0.023
```

Davies-Bouldin Index

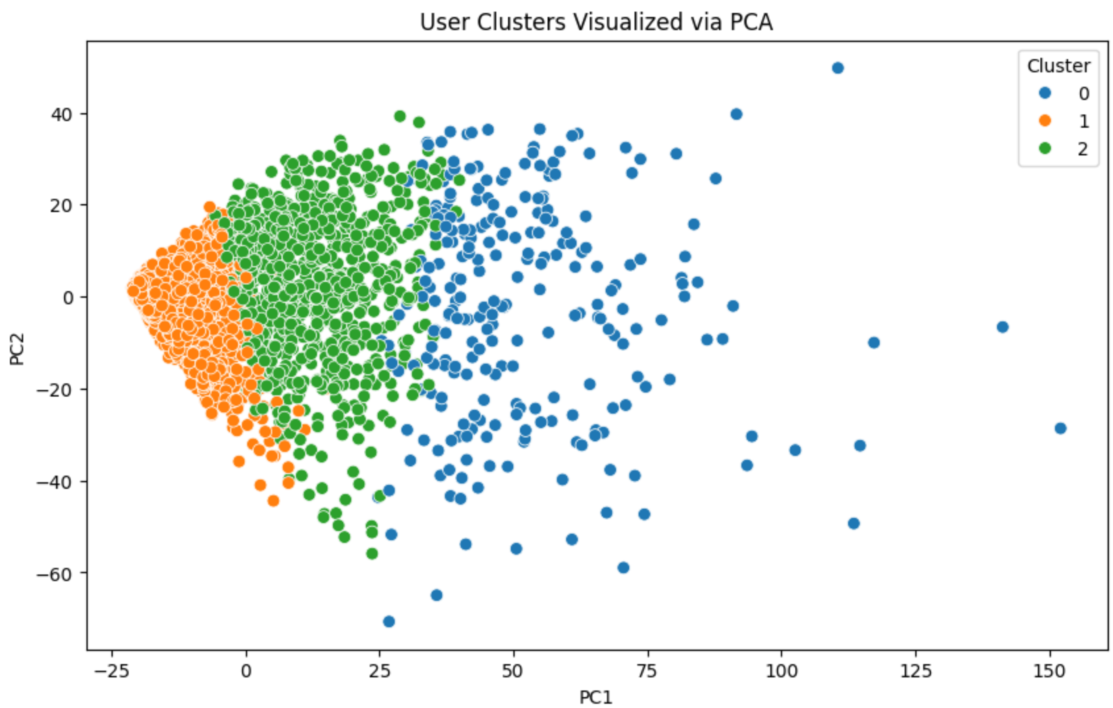
[240]:
```
db_score = davies_bouldin_score(sample_matrix.toarray(), sample_labels)
print(f"Davies-Bouldin Index: {db_score:.3f}")
davies_bouldin_scores.append(db_score)
```

```
Davies-Bouldin Index: 4.691
```

Visualize clusters

[241]:
```
# visualize inspect the clusters
pca = PCA(n_components=2)
user_2d = pca.fit_transform(sample_matrix.toarray())

df_plot = pd.DataFrame({
    'x': user_2d[:, 0],
```

```
    'y': user_2d[:, 1],
    'cluster': sample_labels
})

plt.figure(figsize=(10, 6))
sns.scatterplot(data=df_plot, x='x', y='y', hue='cluster', palette='tab10',␣
↪s=50)
plt.title("User Clusters Visualized via PCA")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.legend(title='Cluster')
plt.savefig(f"{plots_location}\\plots\\user_clusters_k_{k}.png")
plt.show()
```



Precision@3 and Recall@3

[242]:

```
# assign cluster to users
clusters_df = pd.DataFrame({
    'user_id' : [index_to_user[i] for i in range(len(cluster_labels))],
    'cluster': cluster_labels
})

clusters_train_df = train_df.merge(clusters_df, on="user_id")
```

[243]:

```
clusters_train_df.head()
```

[243]:

	user_id	anime_id	rating	cluster
0	287522	522	8.0	2
1	447249	2033	7.0	1
2	446384	31318	10.0	2
3	400930	3712	8.0	0
4	153921	37520	8.0	0

[244]:
```
# calulate mean rating for each anime across a cluster
cluster_mean_ratings_df = clusters_train_df.drop(columns=["user_id"]) \
    .groupby(["cluster", "anime_id"]).mean().reset_index()
```

[245]:
```
precisions, recalls = [], []
for user_id in sample_index_to_user.values():
    p, r = precision_recall_at_k(user_id, k=5)
    if p is not None:
        precisions.append(p)
        recalls.append(r)

mean_precision = np.mean(precisions)
mean_recall = np.mean(recalls)

precision_scores.append(mean_precision)
recall_scores.append(mean_recall)

print(f"Precision@3: {mean_precision:.6f}")
print(f"Recall@3: {mean_recall:.6f}")
```

```
Precision@3: 0.007657
Recall@3: 0.000430
```

Training K = 4

[246]:
```
# create cluster
k = 4
kmeans = KMeans(n_clusters=k, random_state=42, max_iter=300)
cluster_labels = kmeans.fit_predict(user_item_sparse)

inertia.append(kmeans.inertia_)
```

Assessing K = 4

[247]:
```
sample_labels = cluster_labels[sample_indices]
```

Silhouette

[248]:
```
sil_score = silhouette_score(sample_matrix, sample_labels, metric='cosine')
print(f"Silhouette Score: {sil_score:.6f}")
silhoutte_scores.append(sil_score)
```

```
Silhouette Score: -0.024993
```

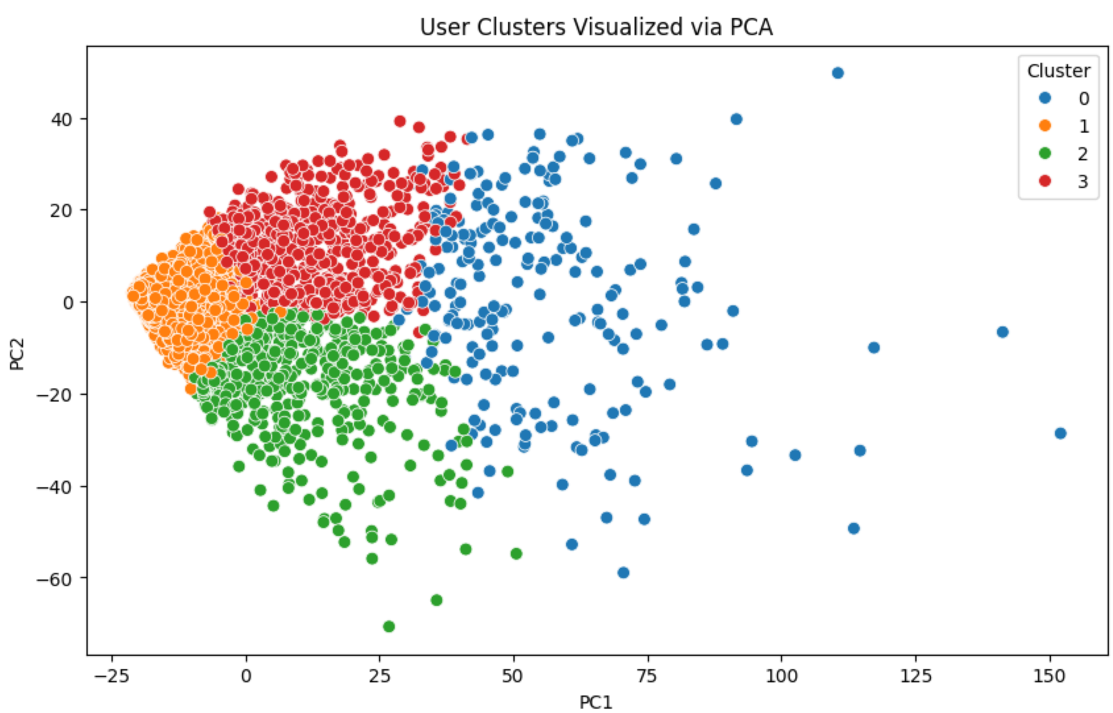
Davies-Bouldin Index

[249]:
```
db_score = davies_bouldin_score(sample_matrix.toarray(), sample_labels)
print(f"Davies-Bouldin Index: {db_score:.6f}")
davies_bouldin_scores.append(db_score)
```

```
Davies-Bouldin Index: 4.701756
```

Visualize clusters

[250]:
```
# visualize inspect the clusters
pca = PCA(n_components=2)
user_2d = pca.fit_transform(sample_matrix.toarray())

df_plot = pd.DataFrame({
    'x': user_2d[:, 0],
    'y': user_2d[:, 1],
    'cluster': sample_labels
})

plt.figure(figsize=(10, 6))
sns.scatterplot(data=df_plot, x='x', y='y', hue='cluster', palette='tab10',␣
 ↪s=50)
plt.title("User Clusters Visualized via PCA")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.legend(title='Cluster')
plt.savefig(f"{plots_location}\\plots\\user_clusters_k_{k}.png")
plt.show()
```



Precision@4 and Recall@4

[251]:
```
# assign cluster to users
clusters_df = pd.DataFrame({
    'user_id' : [index_to_user[i] for i in range(len(cluster_labels))],
    'cluster': cluster_labels
})

clusters_train_df = train_df.merge(clusters_df, on="user_id")
```

[252]:
```
clusters_train_df.head()
```

[252]:

	user_id	anime_id	rating	cluster
0	287522	522	8.0	2
1	447249	2033	7.0	1
2	446384	31318	10.0	3
3	400930	3712	8.0	0
4	153921	37520	8.0	0

[253]:
```
# calulate mean rating for each anime across a cluster
cluster_mean_ratings_df = clusters_train_df.drop(columns=["user_id"]) \
    .groupby(["cluster", "anime_id"]).mean().reset_index()
```

[254]:
```
precisions, recalls = [], []
for user_id in sample_index_to_user.values():
    p, r = precision_recall_at_k(user_id, k=5)
    if p is not None:
        precisions.append(p)
        recalls.append(r)

mean_precision = np.mean(precisions)
mean_recall = np.mean(recalls)

precision_scores.append(mean_precision)
recall_scores.append(mean_recall)

print(f"Precision@4: {mean_precision:.6f}")
print(f"Recall@4: {mean_recall:.6f}")
```

```
Precision@4: 0.006948
Recall@4: 0.000376
```

Training K = 5

[255]:
```
# create cluster
k = 5
kmeans = KMeans(n_clusters=k, random_state=42, max_iter=300)
```

```
cluster_labels = kmeans.fit_predict(user_item_sparse)

inertia.append(kmeans.inertia_)
```

Assessing K = 5

[256]:
```
sample_labels = cluster_labels[sample_indices]
```

Silhouette

[257]:
```
sil_score = silhouette_score(sample_matrix, sample_labels, metric='cosine')
print(f"Silhouette Score: {sil_score:.6f}")
silhoutte_scores.append(sil_score)
```

```
Silhouette Score: -0.029378
```

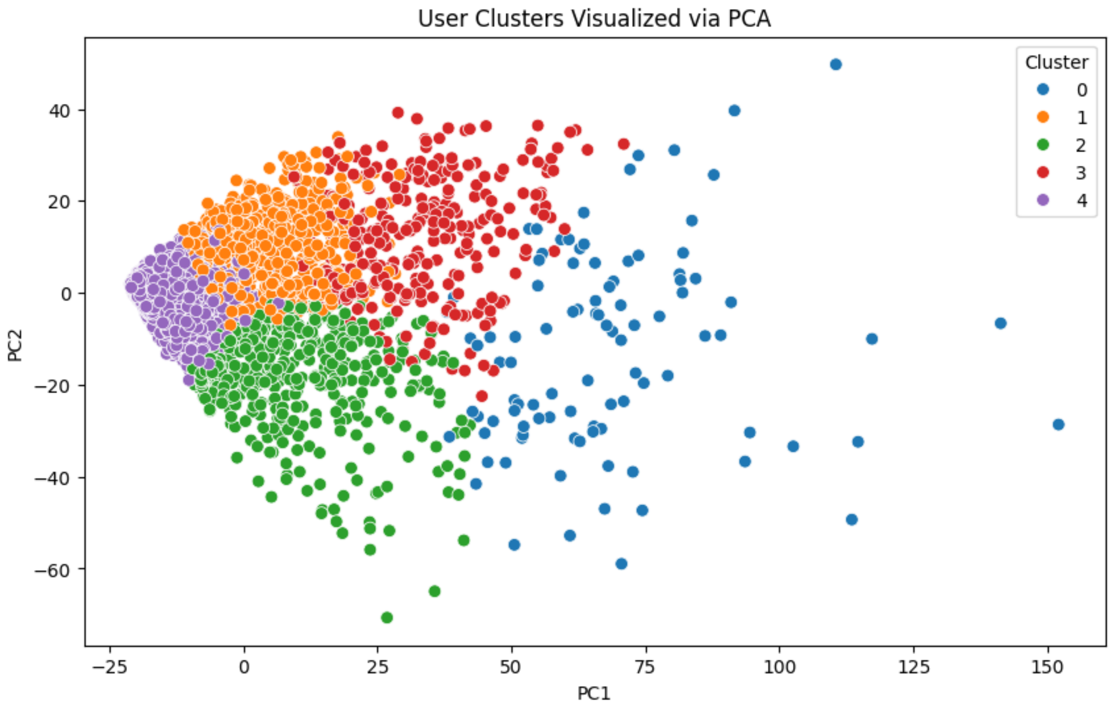
Davies-Bouldin Index

[258]:
```
db_score = davies_bouldin_score(sample_matrix.toarray(), sample_labels)
print(f"Davies-Bouldin Index: {db_score:.6f}")
davies_bouldin_scores.append(db_score)
```

```
Davies-Bouldin Index: 4.887560
```

Visualize clusters

[259]:
```
# visualize inspect the clusters
pca = PCA(n_components=2)
user_2d = pca.fit_transform(sample_matrix.toarray())

df_plot = pd.DataFrame({
    'x': user_2d[:, 0],
    'y': user_2d[:, 1],
    'cluster': sample_labels
})

plt.figure(figsize=(10, 6))
sns.scatterplot(data=df_plot, x='x', y='y', hue='cluster', palette='tab10',␣
 ↪s=50)
plt.title("User Clusters Visualized via PCA")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.legend(title='Cluster')
plt.savefig(f"{plots_location}\\plots\\user_clusters_k_{k}.png")
plt.show()
```



Precision@5 and Recall@5

[260]:
```
# assign cluster to users
clusters_df = pd.DataFrame({
    'user_id' : [index_to_user[i] for i in range(len(cluster_labels))],
    'cluster': cluster_labels
})

clusters_train_df = train_df.merge(clusters_df, on="user_id")
```

[261]:
```
clusters_train_df.head()
```

[261]:

	user_id	anime_id	rating	cluster
0	287522	522	8.0	2
1	447249	2033	7.0	4
2	446384	31318	10.0	3
3	400930	3712	8.0	0
4	153921	37520	8.0	3

[262]:
```
# calulate mean rating for each anime across a cluster
cluster_mean_ratings_df = clusters_train_df.drop(columns=["user_id"]) \
    .groupby(["cluster", "anime_id"]).mean().reset_index()
```

[263]:
```
precisions, recalls = [], []
for user_id in sample_index_to_user.values():
```

```
    p, r = precision_recall_at_k(user_id, k=5)
    if p is not None:
        precisions.append(p)
        recalls.append(r)

mean_precision = np.mean(precisions)
mean_recall = np.mean(recalls)

precision_scores.append(mean_precision)
recall_scores.append(mean_recall)

print(f"Precision@5: {mean_precision:.6f}")
print(f"Recall@5: {mean_recall:.6f}")
```

```
Precision@5: 0.003828
Recall@5: 0.000155
```

Training K = 6

[264]:
```
# create cluster
k = 6
kmeans = KMeans(n_clusters=k, random_state=42, max_iter=300)
cluster_labels = kmeans.fit_predict(user_item_sparse)

inertia.append(kmeans.inertia_)
```

Assessing K = 6

[265]:
```
sample_labels = cluster_labels[sample_indices]
```

Silhouette

[266]:
```
sil_score = silhouette_score(sample_matrix, sample_labels, metric='cosine')
print(f"Silhouette Score: {sil_score:.6f}")
silhoutte_scores.append(sil_score)
```

```
Silhouette Score: -0.031468
```

Davies-Bouldin Index

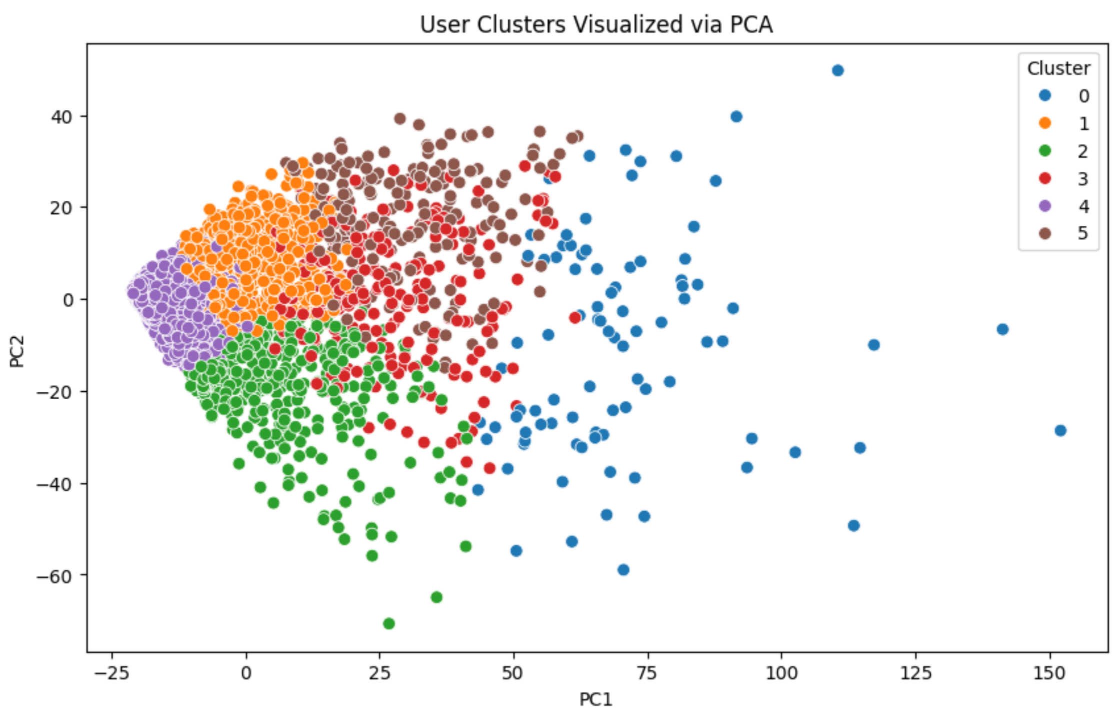
[267]:
```
db_score = davies_bouldin_score(sample_matrix.toarray(), sample_labels)
print(f"Davies-Bouldin Index: {db_score:.6f}")
davies_bouldin_scores.append(db_score)
```

```
Davies-Bouldin Index: 5.011471
```

Visualize clusters

[268]:
```
# visualize inspect the clusters
pca = PCA(n_components=2)
user_2d = pca.fit_transform(sample_matrix.toarray())

df_plot = pd.DataFrame({
```

```
    'x': user_2d[:, 0],
    'y': user_2d[:, 1],
    'cluster': sample_labels
})

plt.figure(figsize=(10, 6))
sns.scatterplot(data=df_plot, x='x', y='y', hue='cluster', palette='tab10',␣
 ↪s=50)
plt.title("User Clusters Visualized via PCA")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.legend(title='Cluster')
plt.savefig(f"{plots_location}\\plots\\user_clusters_k_{k}.png")
plt.show()
```



Precision@6 and Recall@6

[269]:
```
# assign cluster to users
clusters_df = pd.DataFrame({
    'user_id' : [index_to_user[i] for i in range(len(cluster_labels))],
    'cluster': cluster_labels
})

clusters_train_df = train_df.merge(clusters_df, on="user_id")
```

[270]:
```
clusters_train_df.head()
```

[270]:

	user_id	anime_id	rating	cluster
0	287522	522	8.0	2
1	447249	2033	7.0	4
2	446384	31318	10.0	5
3	400930	3712	8.0	0
4	153921	37520	8.0	5

[271]:
```
# calulate mean rating for each anime across a cluster
cluster_mean_ratings_df = clusters_train_df.drop(columns=["user_id"]) \
    .groupby(["cluster", "anime_id"]).mean().reset_index()
```

[272]:
```
precisions, recalls = [], []
for user_id in sample_index_to_user.values():
    p, r = precision_recall_at_k(user_id, k=5)
    if p is not None:
        precisions.append(p)
        recalls.append(r)

mean_precision = np.mean(precisions)
mean_recall = np.mean(recalls)

precision_scores.append(mean_precision)
recall_scores.append(mean_recall)

print(f"Precision@6: {mean_precision:.6f}")
print(f"Recall@6: {mean_recall:.6f}")
```

```
Precision@6: 0.001418
Recall@6: 0.000053
```

Training K = 7

[273]:
```
# create cluster
k = 7
kmeans = KMeans(n_clusters=k, random_state=42, max_iter=300)
cluster_labels = kmeans.fit_predict(user_item_sparse)

inertia.append(kmeans.inertia_)
```

Assessing K = 7

[274]:
```
sample_labels = cluster_labels[sample_indices]
```

Silhouette

[275]:
```
sil_score = silhouette_score(sample_matrix, sample_labels, metric='cosine')
print(f"Silhouette Score: {sil_score:.6f}")
silhoutte_scores.append(sil_score)
```

```
Silhouette Score: -0.032445
```

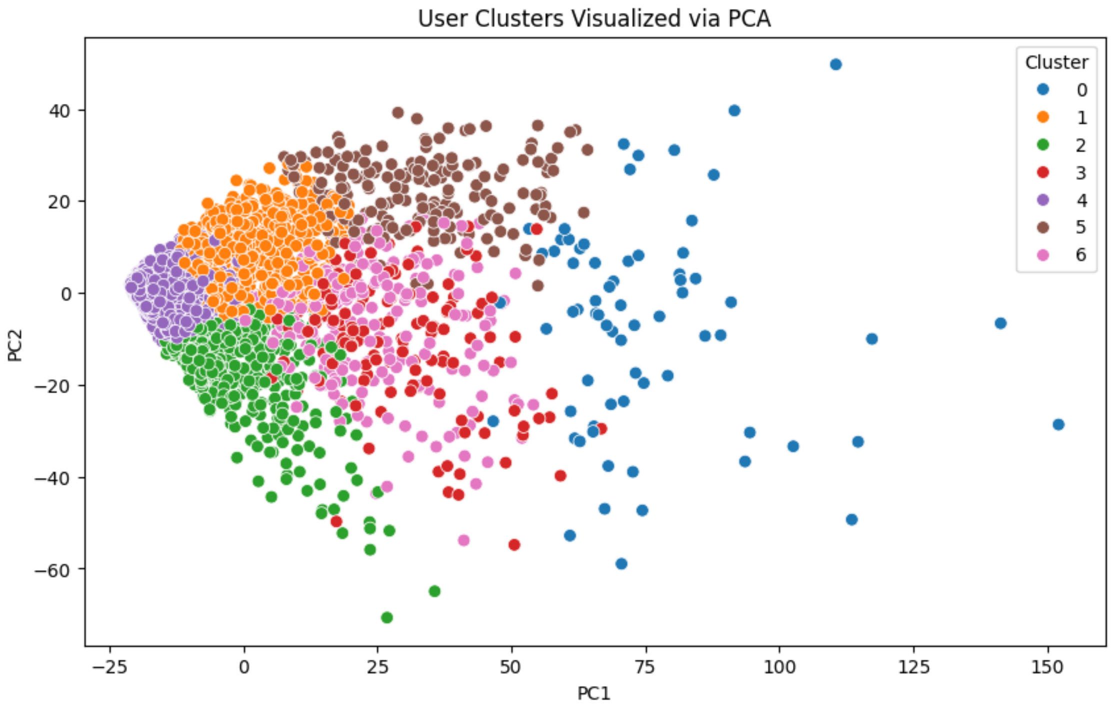
Davies-Bouldin Index

[276]:
```python
db_score = davies_bouldin_score(sample_matrix.toarray(), sample_labels)
print(f"Davies-Bouldin Index: {db_score:.6f}")
davies_bouldin_scores.append(db_score)
```

```
Davies-Bouldin Index: 4.883651
```

Visualize clusters

[277]:
```python
# visualize inspect the clusters
pca = PCA(n_components=2)
user_2d = pca.fit_transform(sample_matrix.toarray())

df_plot = pd.DataFrame({
    'x': user_2d[:, 0],
    'y': user_2d[:, 1],
    'cluster': sample_labels
})

plt.figure(figsize=(10, 6))
sns.scatterplot(data=df_plot, x='x', y='y', hue='cluster', palette='tab10',␣
 ↪s=50)
plt.title("User Clusters Visualized via PCA")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.legend(title='Cluster')
plt.savefig(f"{plots_location}\\plots\\user_clusters_k_{k}.png")
plt.show()
```



Precision@7 and Recall@7

[278]:
```
# assign cluster to users
clusters_df = pd.DataFrame({
    'user_id' : [index_to_user[i] for i in range(len(cluster_labels))],
    'cluster': cluster_labels
})

clusters_train_df = train_df.merge(clusters_df, on="user_id")
```

[279]:
```
clusters_train_df.head()
```

[279]:

	user_id	anime_id	rating	cluster
0	287522	522	8.0	2
1	447249	2033	7.0	4
2	446384	31318	10.0	5
3	400930	3712	8.0	0
4	153921	37520	8.0	5

[280]:
```
# calulate mean rating for each anime across a cluster
cluster_mean_ratings_df = clusters_train_df.drop(columns=["user_id"]) \
    .groupby(["cluster", "anime_id"]).mean().reset_index()
```

[281]:
```
precisions, recalls = [], []
for user_id in sample_index_to_user.values():
```

```
    p, r = precision_recall_at_k(user_id, k=5)
    if p is not None:
        precisions.append(p)
        recalls.append(r)

mean_precision = np.mean(precisions)
mean_recall = np.mean(recalls)

precision_scores.append(mean_precision)
recall_scores.append(mean_recall)

print(f"Precision@7: {mean_precision:.6f}")
print(f"Recall@7: {mean_recall:.6f}")
```

```
Precision@7: 0.001276
Recall@7: 0.000047
```

Training K = 8

[282]:
```
# create cluster
k = 8
kmeans = KMeans(n_clusters=k, random_state=42, max_iter=300)
cluster_labels = kmeans.fit_predict(user_item_sparse)

inertia.append(kmeans.inertia_)
```

Assessing K = 8

[283]:
```
sample_labels = cluster_labels[sample_indices]
```

Silhouette

[284]:
```
sil_score = silhouette_score(sample_matrix, sample_labels, metric='cosine')
print(f"Silhouette Score: {sil_score:.6f}")
silhoutte_scores.append(sil_score)
```

```
Silhouette Score: -0.032054
```

Davies-Bouldin Index

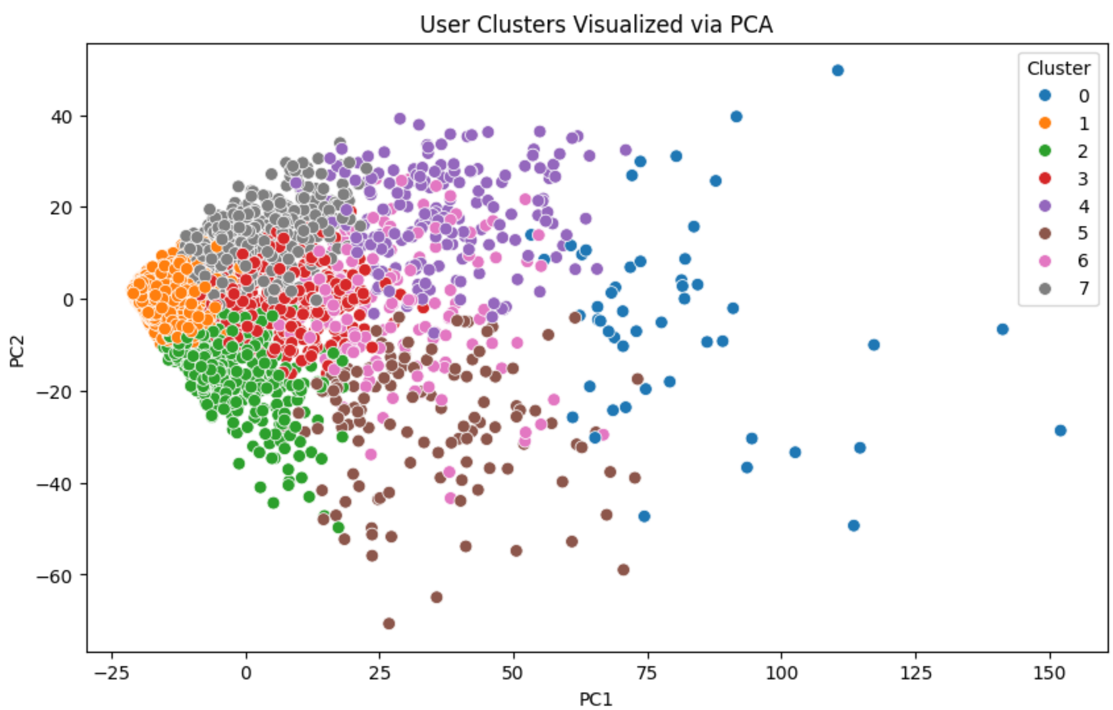
[285]:
```
db_score = davies_bouldin_score(sample_matrix.toarray(), sample_labels)
print(f"Davies-Bouldin Index: {db_score:.6f}")
davies_bouldin_scores.append(db_score)
```

```
Davies-Bouldin Index: 5.124099
```

Visualize clusters

[286]:
```
# visualize inspect the clusters
pca = PCA(n_components=2)
user_2d = pca.fit_transform(sample_matrix.toarray())

df_plot = pd.DataFrame({
```

```
    'x': user_2d[:, 0],
    'y': user_2d[:, 1],
    'cluster': sample_labels
})

plt.figure(figsize=(10, 6))
sns.scatterplot(data=df_plot, x='x', y='y', hue='cluster', palette='tab10',␣
 ↪s=50)
plt.title("User Clusters Visualized via PCA")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.legend(title='Cluster')
plt.savefig(f"{plots_location}\\plots\\user_clusters_k_{k}.png")
plt.show()
```



Precision@8 and Recall@8

[287]:
```
# assign cluster to users
clusters_df = pd.DataFrame({
    'user_id' : [index_to_user[i] for i in range(len(cluster_labels))],
    'cluster': cluster_labels
})

clusters_train_df = train_df.merge(clusters_df, on="user_id")
```

[288]:
```
clusters_train_df.head()
```

[288]:

	user_id	anime_id	rating	cluster
0	287522	522	8.0	2
1	447249	2033	7.0	1
2	446384	31318	10.0	4
3	400930	3712	8.0	0
4	153921	37520	8.0	4

[289]:
```
# calulate mean rating for each anime across a cluster
cluster_mean_ratings_df = clusters_train_df.drop(columns=["user_id"]) \
    .groupby(["cluster", "anime_id"]).mean().reset_index()
```

[290]:
```
precisions, recalls = [], []
for user_id in sample_index_to_user.values():
    p, r = precision_recall_at_k(user_id, k=5)
    if p is not None:
        precisions.append(p)
        recalls.append(r)

mean_precision = np.mean(precisions)
mean_recall = np.mean(recalls)

precision_scores.append(mean_precision)
recall_scores.append(mean_recall)

print(f"Precision@8: {mean_precision:.6f}")
print(f"Recall@8: {mean_recall:.6f}")
```

```
Precision@8: 0.001134
Recall@8: 0.000042
```

Training K = 9

[291]:
```
# create cluster
k = 9
kmeans = KMeans(n_clusters=k, random_state=42, max_iter=300)
cluster_labels = kmeans.fit_predict(user_item_sparse)

inertia.append(kmeans.inertia_)
```

Assessing K = 9

[292]:
```
sample_labels = cluster_labels[sample_indices]
```

Silhouette

[293]:
```
sil_score = silhouette_score(sample_matrix, sample_labels, metric='cosine')
print(f"Silhouette Score: {sil_score:.6f}")
silhoutte_scores.append(sil_score)
```

```
Silhouette Score: -0.034246
```

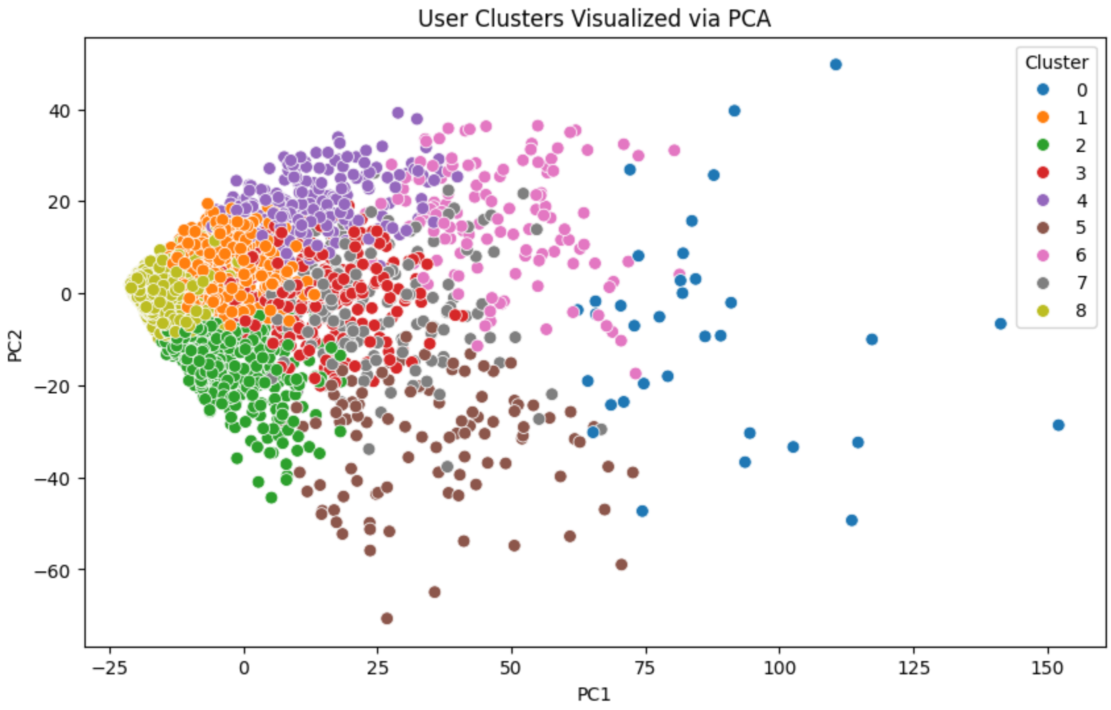
Davies-Bouldin Index

[294]:
```
db_score = davies_bouldin_score(sample_matrix.toarray(), sample_labels)
print(f"Davies-Bouldin Index: {db_score:.6f}")
davies_bouldin_scores.append(db_score)
```

```
Davies-Bouldin Index: 4.943429
```

Visualize clusters

[295]:
```
# visualize inspect the clusters
pca = PCA(n_components=2)
user_2d = pca.fit_transform(sample_matrix.toarray())

df_plot = pd.DataFrame({
    'x': user_2d[:, 0],
    'y': user_2d[:, 1],
    'cluster': sample_labels
})

plt.figure(figsize=(10, 6))
sns.scatterplot(data=df_plot, x='x', y='y', hue='cluster', palette='tab10',␣
 ↪s=50)
plt.title("User Clusters Visualized via PCA")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.legend(title='Cluster')
plt.savefig(f"{plots_location}\\plots\\user_clusters_k_{k}.png")
plt.show()
```



Precision@9 and Recall@9

[296]:
```
# assign cluster to users
clusters_df = pd.DataFrame({
    'user_id' : [index_to_user[i] for i in range(len(cluster_labels))],
    'cluster': cluster_labels
})

clusters_train_df = train_df.merge(clusters_df, on="user_id")
```

[297]:
```
clusters_train_df.head()
```

[297]:

	user_id	anime_id	rating	cluster
0	287522	522	8.0	2
1	447249	2033	7.0	8
2	446384	31318	10.0	4
3	400930	3712	8.0	0
4	153921	37520	8.0	6

[298]:
```
# calulate mean rating for each anime across a cluster
cluster_mean_ratings_df = clusters_train_df.drop(columns=["user_id"]) \
    .groupby(["cluster", "anime_id"]).mean().reset_index()
```

[299]:
```
precisions, recalls = [], []
for user_id in sample_index_to_user.values():
```

```
    p, r = precision_recall_at_k(user_id, k=5)
    if p is not None:
        precisions.append(p)
        recalls.append(r)

mean_precision = np.mean(precisions)
mean_recall = np.mean(recalls)

precision_scores.append(mean_precision)
recall_scores.append(mean_recall)

print(f"Precision@9: {mean_precision:.6f}")
print(f"Recall@9: {mean_recall:.6f}")
```

```
Precision@9: 0.000496
Recall@9: 0.000016
```

Training K = 10

[300]:
```
# create cluster
k = 10
kmeans = KMeans(n_clusters=k, random_state=42, max_iter=300)
cluster_labels = kmeans.fit_predict(user_item_sparse)

inertia.append(kmeans.inertia_)
```

Assessing K = 10

[301]:
```
sample_labels = cluster_labels[sample_indices]
```

Silhouette

[302]:
```
sil_score = silhouette_score(sample_matrix, sample_labels, metric='cosine')
print(f"Silhouette Score: {sil_score:.6f}")
silhoutte_scores.append(sil_score)
```

```
Silhouette Score: -0.033874
```

Davies-Bouldin Index

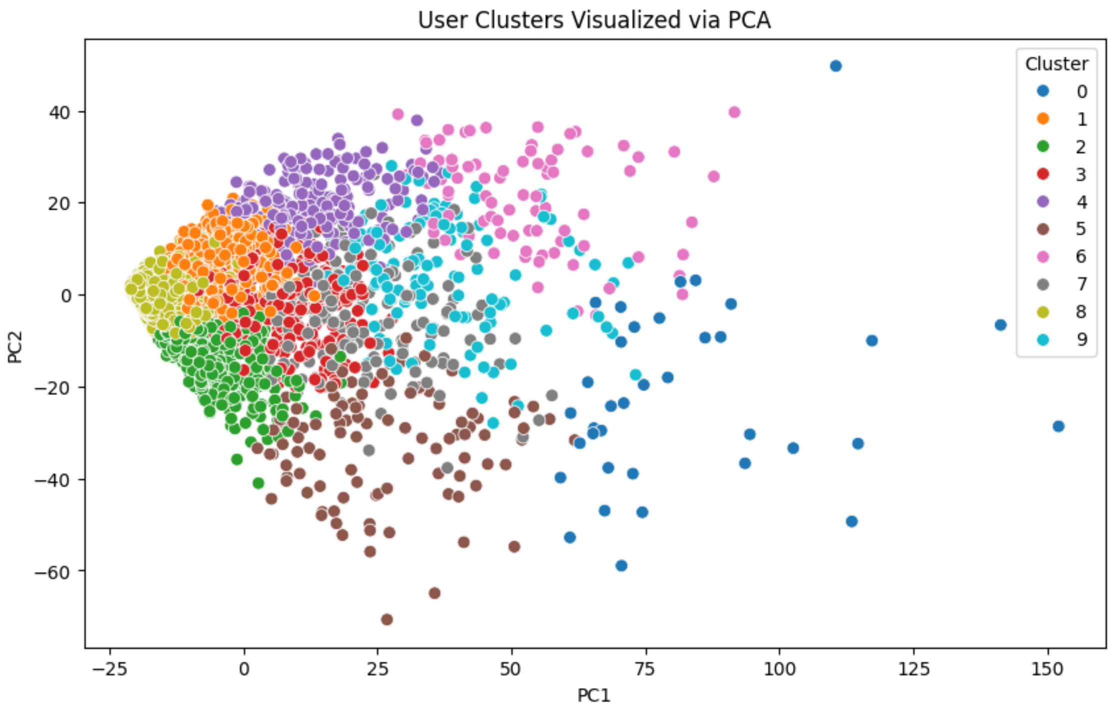
[303]:
```
db_score = davies_bouldin_score(sample_matrix.toarray(), sample_labels)
print(f"Davies-Bouldin Index: {db_score:.6f}")
davies_bouldin_scores.append(db_score)
```

```
Davies-Bouldin Index: 5.136440
```

Visualize clusters

[304]:
```
# visualize inspect the clusters
pca = PCA(n_components=2)
user_2d = pca.fit_transform(sample_matrix.toarray())

df_plot = pd.DataFrame({
```

```
    'x': user_2d[:, 0],
    'y': user_2d[:, 1],
    'cluster': sample_labels
})

plt.figure(figsize=(10, 6))
sns.scatterplot(data=df_plot, x='x', y='y', hue='cluster', palette='tab10',␣
 ↪s=50)
plt.title("User Clusters Visualized via PCA")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.legend(title='Cluster')
plt.savefig(f"{plots_location}\\plots\\user_clusters_k_{k}.png")
plt.show()
```



Precision@10 and Recall@10

[305]:
```
# assign cluster to users
clusters_df = pd.DataFrame({
    'user_id' : [index_to_user[i] for i in range(len(cluster_labels))],
    'cluster': cluster_labels
})

clusters_train_df = train_df.merge(clusters_df, on="user_id")
```

[306]:
```
clusters_train_df.head()
```

[306]:

	user_id	anime_id	rating	cluster
0	287522	522	8.0	2
1	447249	2033	7.0	2
2	446384	31318	10.0	6
3	400930	3712	8.0	0
4	153921	37520	8.0	6

[307]:
```
# calulate mean rating for each anime across a cluster
cluster_mean_ratings_df = clusters_train_df.drop(columns=["user_id"]) \
    .groupby(["cluster", "anime_id"]).mean().reset_index()
```

[308]:
```
precisions, recalls = [], []
for user_id in sample_index_to_user.values():
    p, r = precision_recall_at_k(user_id, k=5)
    if p is not None:
        precisions.append(p)
        recalls.append(r)

mean_precision = np.mean(precisions)
mean_recall = np.mean(recalls)

precision_scores.append(mean_precision)
recall_scores.append(mean_recall)

print(f"Precision@10: {mean_precision:.6f}")
print(f"Recall@10: {mean_recall:.6f}")
```

```
Precision@10: 0.000425
Recall@10: 0.000011
```

Training K = 11

[309]:
```
# create cluster
k = 11
kmeans = KMeans(n_clusters=k, random_state=42, max_iter=300)
cluster_labels = kmeans.fit_predict(user_item_sparse)

inertia.append(kmeans.inertia_)
```

Assessing K = 11

[310]:
```
sample_labels = cluster_labels[sample_indices]
```

Silhouette

[311]:
```
sil_score = silhouette_score(sample_matrix, sample_labels, metric='cosine')
print(f"Silhouette Score: {sil_score:.6f}")
silhoutte_scores.append(sil_score)
```

```
Silhouette Score: -0.033710
```

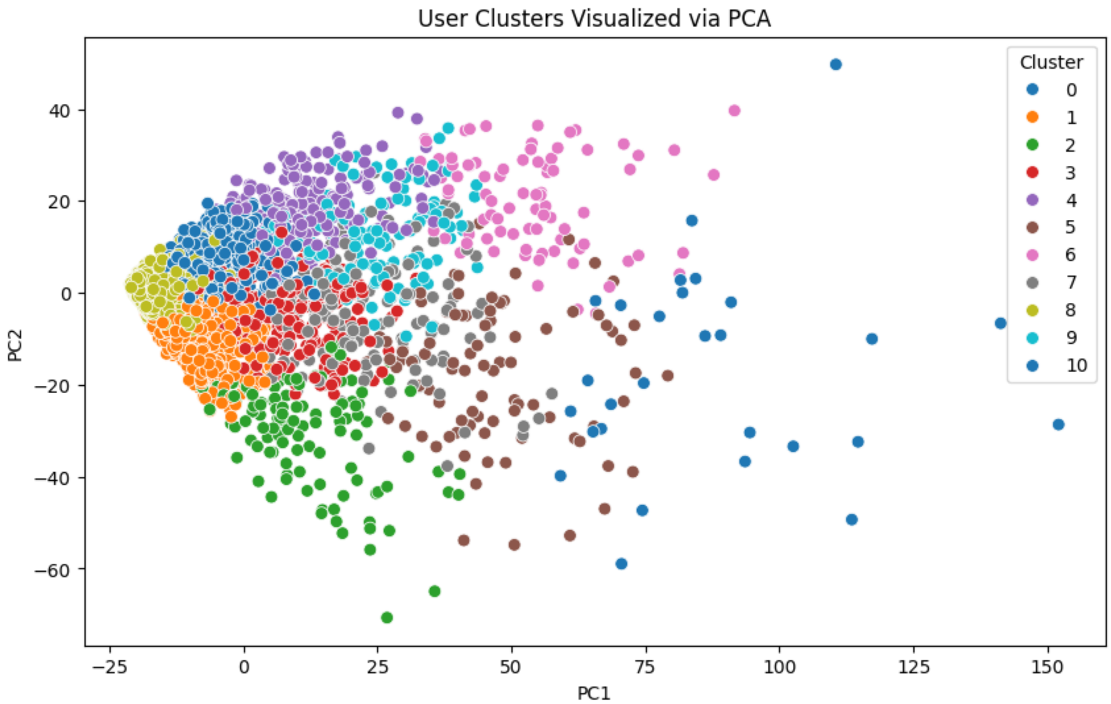
Davies-Bouldin Index

[312]:
```
db_score = davies_bouldin_score(sample_matrix.toarray(), sample_labels)
print(f"Davies-Bouldin Index: {db_score:.6f}")
davies_bouldin_scores.append(db_score)
```

```
Davies-Bouldin Index: 5.098260
```

Visualize clusters

[313]:
```
# visualize inspect the clusters
pca = PCA(n_components=2)
user_2d = pca.fit_transform(sample_matrix.toarray())

df_plot = pd.DataFrame({
    'x': user_2d[:, 0],
    'y': user_2d[:, 1],
    'cluster': sample_labels
})

plt.figure(figsize=(10, 6))
sns.scatterplot(data=df_plot, x='x', y='y', hue='cluster', palette='tab10',␣
 ↪s=50)
plt.title("User Clusters Visualized via PCA")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.legend(title='Cluster')
plt.savefig(f"{plots_location}\\plots\\user_clusters_k_{k}.png")
plt.show()
```



Precision@11 and Recall@11

[314]:
```
# assign cluster to users
clusters_df = pd.DataFrame({
    'user_id' : [index_to_user[i] for i in range(len(cluster_labels))],
    'cluster': cluster_labels
})

clusters_train_df = train_df.merge(clusters_df, on="user_id")
```

[315]:
```
clusters_train_df.head()
```

[315]:

	user_id	anime_id	rating	cluster
0	287522	522	8.0	2
1	447249	2033	7.0	1
2	446384	31318	10.0	6
3	400930	3712	8.0	0
4	153921	37520	8.0	6

[316]:
```
# calulate mean rating for each anime across a cluster
cluster_mean_ratings_df = clusters_train_df.drop(columns=["user_id"]) \
    .groupby(["cluster", "anime_id"]).mean().reset_index()
```

[317]:
```
precisions, recalls = [], []
for user_id in sample_index_to_user.values():
```

```
    p, r = precision_recall_at_k(user_id, k=5)
    if p is not None:
        precisions.append(p)
        recalls.append(r)

mean_precision = np.mean(precisions)
mean_recall = np.mean(recalls)

precision_scores.append(mean_precision)
recall_scores.append(mean_recall)

print(f"Precision@11: {mean_precision:.6f}")
print(f"Recall@11: {mean_recall:.6f}")
```

```
Precision@11: 0.000000
Recall@11: 0.000000
```

Training K = 12

[318]:
```
# create cluster
k = 12
kmeans = KMeans(n_clusters=k, random_state=42, max_iter=300)
cluster_labels = kmeans.fit_predict(user_item_sparse)

inertia.append(kmeans.inertia_)
```

Assessing K = 12

[319]:
```
sample_labels = cluster_labels[sample_indices]
```

Silhouette

[320]:
```
sil_score = silhouette_score(sample_matrix, sample_labels, metric='cosine')
print(f"Silhouette Score: {sil_score:.6f}")
silhoutte_scores.append(sil_score)
```

```
Silhouette Score: -0.034318
```

Davies-Bouldin Index

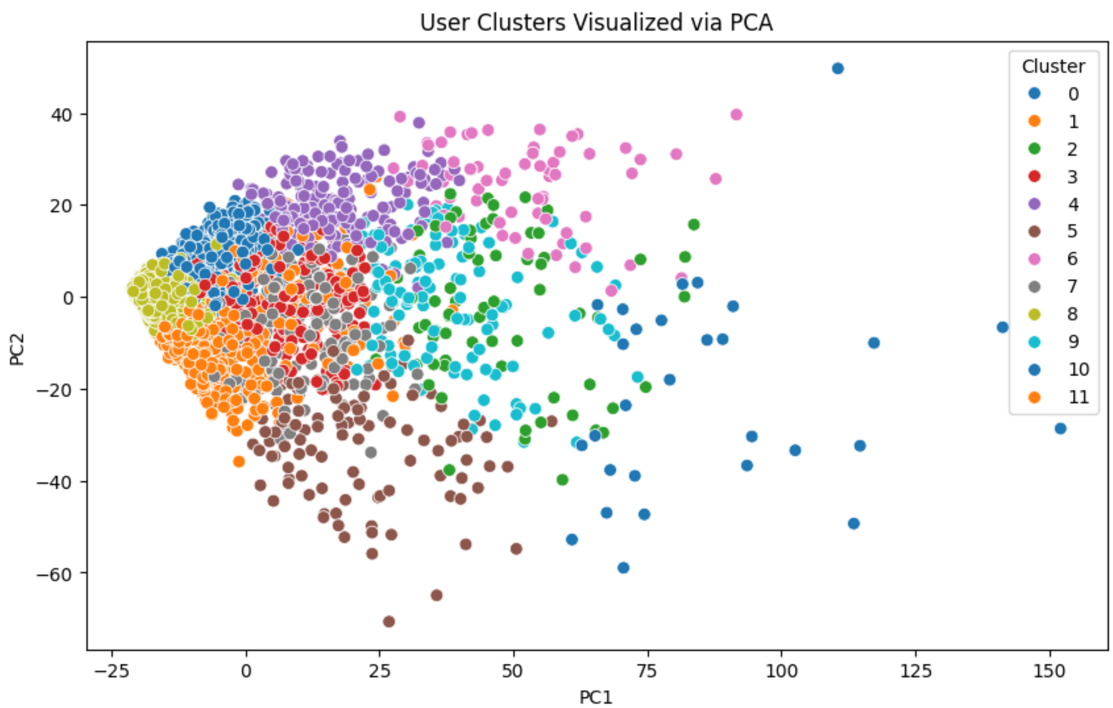
[321]:
```
db_score = davies_bouldin_score(sample_matrix.toarray(), sample_labels)
print(f"Davies-Bouldin Index: {db_score:.6f}")
davies_bouldin_scores.append(db_score)
```

```
Davies-Bouldin Index: 4.960168
```

Visualize clusters

[322]:
```
# visualize inspect the clusters
pca = PCA(n_components=2)
user_2d = pca.fit_transform(sample_matrix.toarray())

df_plot = pd.DataFrame({
```

```
    'x': user_2d[:, 0],
    'y': user_2d[:, 1],
    'cluster': sample_labels
})

plt.figure(figsize=(10, 6))
sns.scatterplot(data=df_plot, x='x', y='y', hue='cluster', palette='tab10',␣
 ↪s=50)
plt.title("User Clusters Visualized via PCA")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.legend(title='Cluster')
plt.savefig(f"{plots_location}\\plots\\user_clusters_k_{k}.png")
plt.show()
```



Precision@12 and Recall@12

[323]:
```
# assign cluster to users
clusters_df = pd.DataFrame({
    'user_id' : [index_to_user[i] for i in range(len(cluster_labels))],
    'cluster': cluster_labels
})

clusters_train_df = train_df.merge(clusters_df, on="user_id")
```

[324]:

```
clusters_train_df.head()
```

[324]:

	user_id	anime_id	rating	cluster
0	287522	522	8.0	7
1	447249	2033	7.0	11
2	446384	31318	10.0	6
3	400930	3712	8.0	0
4	153921	37520	8.0	6

[325]:

```
# calulate mean rating for each anime across a cluster
cluster_mean_ratings_df = clusters_train_df.drop(columns=["user_id"]) \
    .groupby(["cluster", "anime_id"]).mean().reset_index()
```

[326]:

```
precisions, recalls = [], []
for user_id in sample_index_to_user.values():
    p, r = precision_recall_at_k(user_id, k=5)
    if p is not None:
        precisions.append(p)
        recalls.append(r)

mean_precision = np.mean(precisions)
mean_recall = np.mean(recalls)

precision_scores.append(mean_precision)
recall_scores.append(mean_recall)

print(f"Precision@12: {mean_precision:.6f}")
print(f"Recall@12: {mean_recall:.6f}")
```

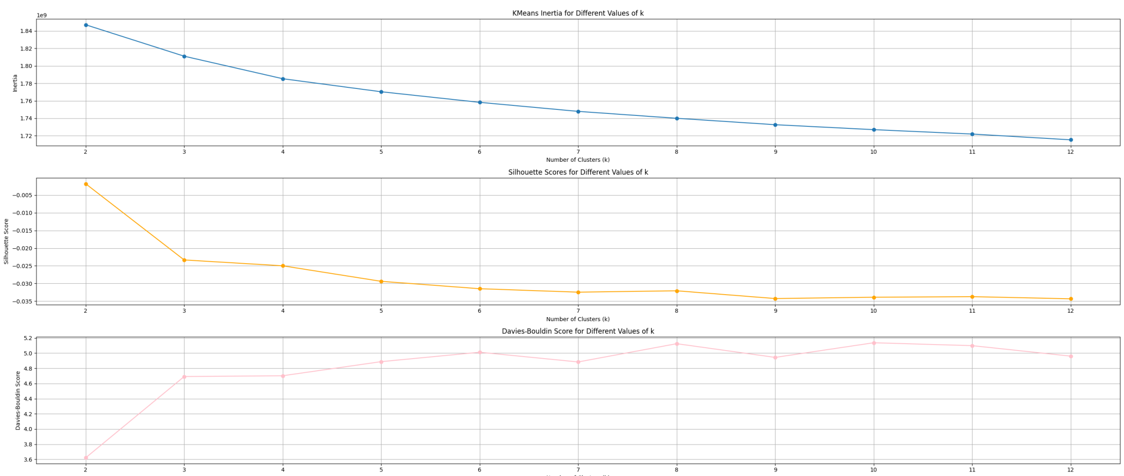
```
Precision@12: 0.001347
Recall@12: 0.000090
```

Assessing Inertia, Silhouette and Davies-Bouldin Scores

[ ]:

```
k_values = range(2, 13)

plt.figure(figsize=(28, 12))
plt.subplot(3, 1, 1)
plt.plot(k_values, inertia, marker='o')
plt.title('KMeans Inertia for Different Values of k')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
plt.xticks(k_values)
plt.grid(True)

plt.subplot(3, 1, 2)
plt.plot(k_values, silhoutte_scores, marker='o', color='orange')
plt.title('Silhouette Scores for Different Values of k')
```

```
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Silhouette Score')
plt.xticks(k_values)
plt.grid(True)

plt.subplot(3, 1, 3)
plt.plot(k_values, davies_bouldin_scores, marker='o', color='pink')
plt.title('Davies-Bouldin Score for Different Values of k')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Davies-Bouldin Score')
plt.xticks(k_values)
plt.grid(True)

plt.tight_layout()
plt.savefig(f"{plots_location}\\plots\\inertia_silhouette_davies_bouldin.png")
plt.show()
```



Comparing Precision@K and Recall@K

[328]:
```
recommendation_metrics_df = pd.DataFrame(columns=["K", "Precision", "Recall"])
recommendation_metrics_df["K"] = [i for i in range(2, 13)]
recommendation_metrics_df["Precision"] = precision_scores
recommendation_metrics_df["Recall"] = recall_scores
```

[330]:
```
recommendation_metrics_df
```

[330]:

	K	Precision	Recall
0	2	0.017795	0.001476
1	3	0.007657	0.000430
2	4	0.006948	0.000376
3	5	0.003828	0.000155

```
4    6  0.001418  0.000053
5    7  0.001276  0.000047
6    8  0.001134  0.000042
7    9  0.000496  0.000016
8   10  0.000425  0.000011
9   11  0.000000  0.000000
10  12  0.001347  0.000090
```

[332]:

```
recommendation_metrics_df.
 ↪to_csv(f"{plots_location}\\metrics\\precision_and_recall.csv", index=False)
```

k-means @ 4 is chosen for the model as it provides the best clusters based on visual inspection as well as the inertia, silhouette and davies-bouldin scores

[ ]:

```
import joblib
# create cluster
k = 4
kmeans = KMeans(n_clusters=k, random_state=42, max_iter=300)
cluster_labels = kmeans.fit_predict(user_item_sparse)

clusters_df = pd.DataFrame({
    'user_id' : [index_to_user[i] for i in range(len(cluster_labels))],
    'cluster': cluster_labels
})

clusters_train_df = train_df.merge(clusters_df, on="user_id")

model_bundle = {
    'kmeans': kmeans,
    'df': clusters_train_df,
    'id_to_user': index_to_user,
    'id_to_anime': index_to_anime
}

# Store to file
joblib.dump(model_bundle, "E:\\applied data science␣
 ↪capstone\\clusters\\user_clustering_model.joblib")
#
```