Import

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics.pairwise import cosine_similarity
```

Upload datasets

```
Start coding or generate with AI.
```

```
ratings = pd.read_csv('/content/rating.csv')
anime   = pd.read_csv('/content/anime.csv')
```

EDA part

Preview Ratings dataset

```
ratings.head()
```

	user_id	anime_id	rating
0	1	20	-1
1	1	24	-1
2	1	79	-1
3	1	226	-1
4	1	241	-1

Replacing "rating" column with "user_rating" because the anime dataset already has "rating column". Looking for merging them.

```
ratings['user_rating'] = ratings['rating']
ratings.drop('rating', axis=1, inplace = True)
ratings.head()
```

	user_id	anime_id	user_rating
0	1	20	-1
1	1	24	-1
2	1	79	-1
3	1	226	-1
4	1	241	-1

Preview Anime dataset

```
anime.head()
```

	anime_id	name	genre	type	episodes	rating	members
0	32281	Kimi no Na wa.	Drama, Romance, School, Supernatural	Movie	1	9.37	200630
1	5114	Fullmetal Alchemist: Brotherhood	Action, Adventure, Drama, Fantasy, Magic, Mili...	TV	64	9.26	793665
2	28977	Gintama°	Action, Comedy, Historical, Parody, Samurai, S...	TV	51	9.25	114262
3	9253	Steins;Gate	Sci-Fi, Thriller	TV	24	9.17	673572
4	9969	Gintama'	Action, Comedy, Historical, Parody, Samurai, S...	TV	51	9.16	151266

Next steps: Generate code with anime | View recommended plots | New interactive sheet

View the number of rows and columns in our dataset

```
print(f'Shape of ratings:{ratings.shape}\nShape of anime:{anime.shape}')
```

```
Shape of ratings:(871126, 3)
Shape of anime:(12294, 7)
```

View the number of unique values foreach column

```
anime.nunique()
```

	0
anime_id	12294
name	12292
genre	3264
type	6
episodes	187
rating	598
members	6706

"name" column analysis

```
anime['name'].isna().sum()
```

```
0
```

```
anime[anime.duplicated(['name'])]
```

	anime_id	name	genre	type	episodes	rating	members
10141	30059	Saru Kani Gassen	Drama	Movie	1	4.75	76
10194	33195	Shi Wan Ge Leng Xiaohua	Action, Adventure, Comedy, Fantasy, Parody	Movie	1	7.07	110

```
anime[(anime['name'] == 'Saru Kani Gassen')|(anime['name'] == 'Shi Wan Ge Leng Xiaohua')]
```

	anime_id	name	genre	type	episodes	rating	members
10140	22399	Saru Kani Gassen	Kids	OVA	1	5.23	62
10141	30059	Saru Kani Gassen	Drama	Movie	1	4.75	76
10193	33193	Shi Wan Ge Leng Xiaohua	Comedy, Parody	ONA	12	6.67	114
10194	33195	Shi Wan Ge Leng Xiaohua	Action, Adventure, Comedy, Fantasy, Parody	Movie	1	7.07	110

"genre column analysis"

```
anime['genre'].isna().sum()
```

```
62
```

```
anime['genre'].value_counts().sort_values(ascending=False).head(20)
```

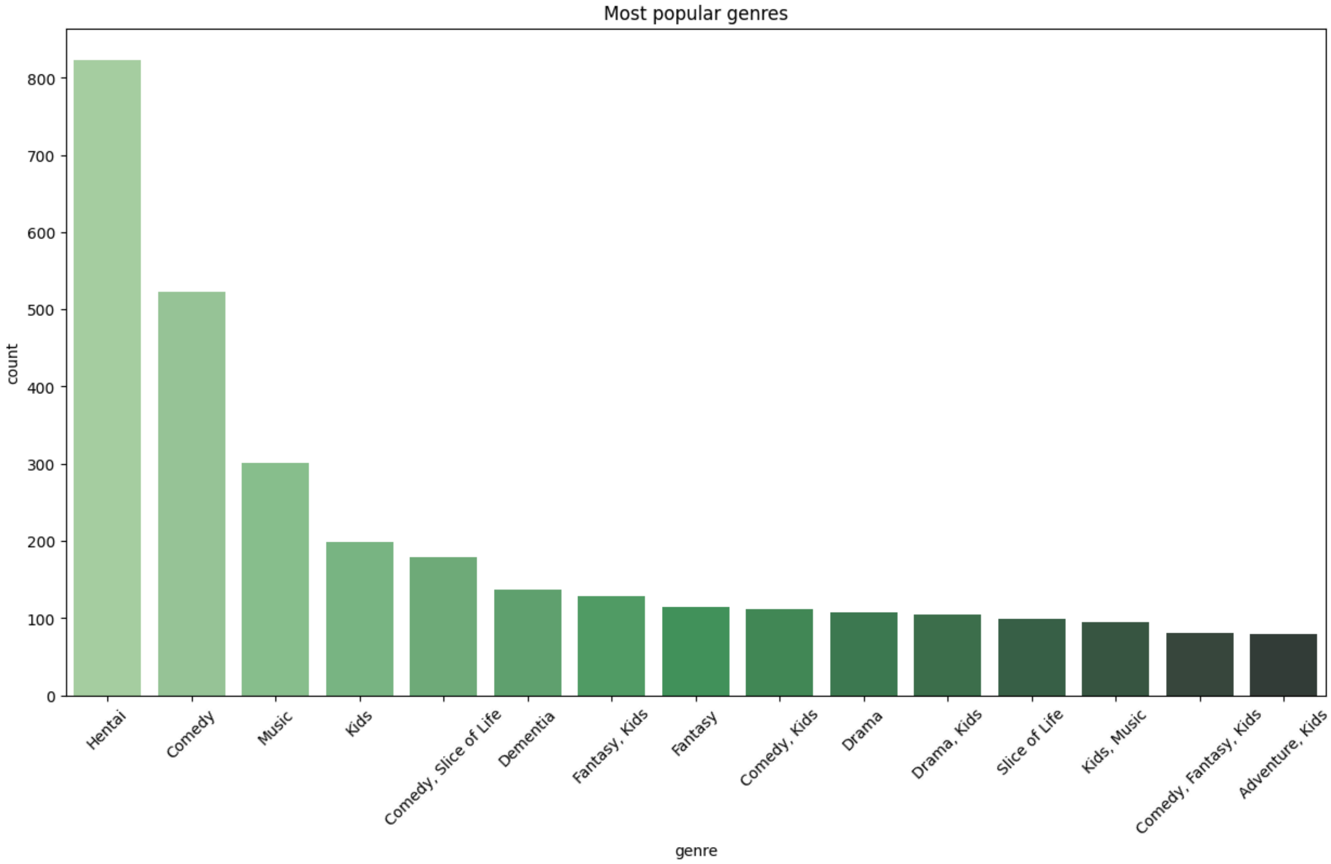
genre	count
Hentai	823
Comedy	523
Music	301
Kids	199
Comedy, Slice of Life	179
Dementia	137
Fantasy, Kids	128
Fantasy	114
Comedy, Kids	112
Drama	107
Drama, Kids	105
Slice of Life	99
Kids, Music	95
Comedy, Fantasy, Kids	81
Adventure, Kids	80
Adventure	79
Adventure, Fantasy	78
Action, Mecha, Sci-Fi	77
Comedy, Parody	74
Historical	68

```
plt.figure(figsize=(15, 8))
plt.title('Most popular genres')
sns.countplot(x='genre', data=anime, palette="Greens_d", order=anime['genre'].value_counts().iloc[:15].index)
plt.xticks(rotation=45)
plt.show()
```

```
<ipython-input-18-b41d47099672>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `le

  sns.countplot(x='genre', data=anime, palette="Greens_d", order=anime['genre'].value_counts().iloc[:15].index)
```



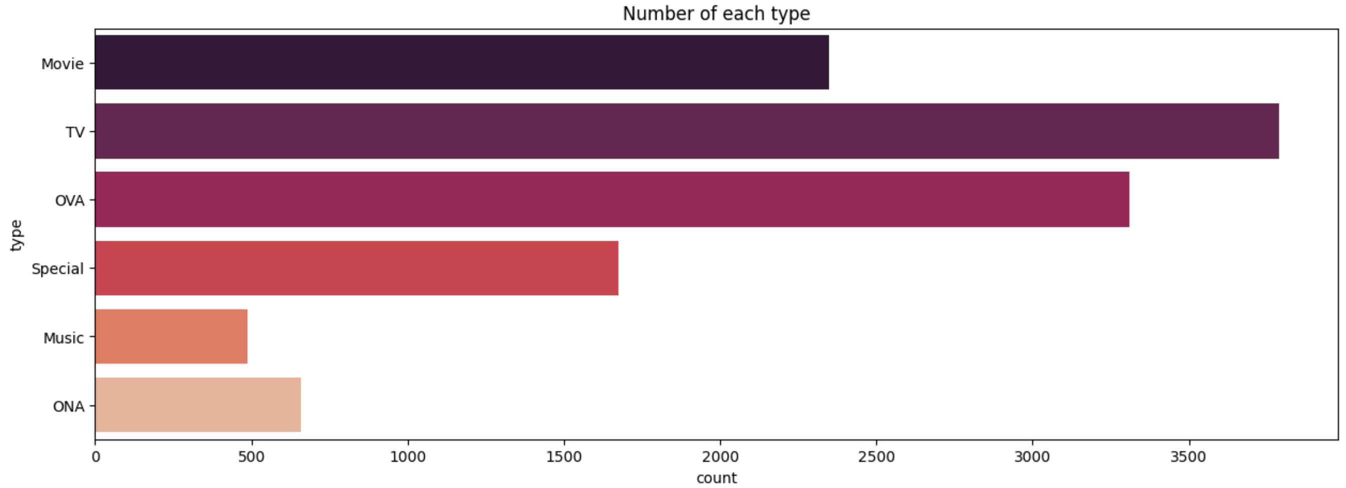
"type" column analysis

```
plt.figure(figsize=(15, 5))
plt.title('Number of each type')
sns.countplot(y='type', data=anime, palette='rocket')
plt.show()
```

```
<ipython-input-19-1cb267772b3f>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `le

  sns.countplot(y='type', data=anime, palette='rocket')
```



"rating" column analysis

```
anime.dropna(inplace=True)
```

```
anime['rating'].value_counts().sort_values(ascending=False).head(15)
```

rating	count
6.00	141
7.00	98
6.50	90
6.25	84
5.00	76
6.75	72
6.67	68
6.38	67
6.80	67
5.67	66
6.73	64
7.33	64
6.34	63
6.81	63
6.33	62

```
anime['rating'].isna().sum()
```

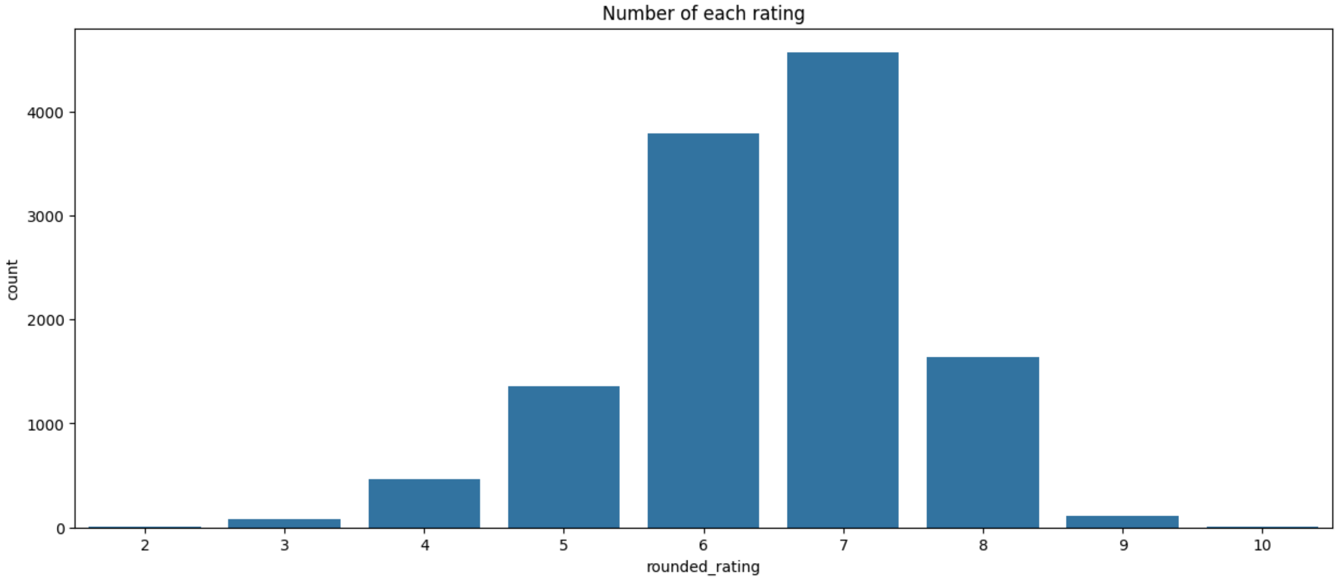
```
0
```

```
anime['rounded_rating'] = anime['rating'].apply(lambda x: round(x))
anime.head()
```

	anime_id	name	genre	type	episodes	rating	members	rounded_rating
0	32281	Kimi no Na wa.	Drama, Romance, School, Supernatural	Movie	1	9.37	200630	9
1	5114	Fullmetal Alchemist: Brotherhood	Action, Adventure, Drama, Fantasy, Magic, Mili...	TV	64	9.26	793665	9
2	28977	Gintama°	Action, Comedy, Historical, Parody, Samurai, S...	TV	51	9.25	114262	9
3	9253	Steins;Gate	Sci-Fi, Thriller	TV	24	9.17	673572	9

Next steps: Generate code with anime View recommended plots New interactive sheet

```
plt.figure(figsize=(15,6))
sns.countplot(data=anime, x='rounded_rating')
plt.title('Number of each rating')
plt.show()
```




```
ratings.head()
```

	user_id	anime_id	user_rating
0	1	20	-1
1	1	24	-1
2	1	79	-1
3	1	226	-1
4	1	241	-1

When the users didn't leave rating it was set to -1, so lets drop them

```
ratings['user_rating'] = ratings['user_rating'].apply(lambda x: np.nan if x == -1 else x)
ratings.dropna(inplace=True)
ratings.head()
```

	user_id	anime_id	user_rating
47	1	8074	10.0
81	1	11617	10.0
83	1	11757	10.0
101	1	15451	10.0
153	2	11771	10.0

Getting the average user rating to each anime

```
user_ratings = ratings.groupby(['anime_id'], as_index=False)['user_rating'].mean()
```

Merging datasets

```
anime_user_rating = pd.merge(anime, user_ratings, on='anime_id')
```

```
anime_user_rating.head(3)
```

	anime_id	name	genre	type	episodes	rating	members	rounded_rating	user_rating
0	32281	Kimi no Na wa.	Drama, Romance, School, Supernatural	Movie	1	9.37	200630	9	9.374302
1	5114	Fullmetal Alchemist: Brotherhood	Action, Adventure, Drama, Fantasy, Magic, Mili...	TV	64	9.26	793665	9	9.341739

Next steps: Generate code with anime_user_rating View recommended plots New interactive sheet

Recommendation engine

Choosing the columns that i think are important

```
columns = ['name','genre','type','rating','user_rating']
```

```
anime_user_rating[columns].isna().sum()
```

	0
name	0
genre	0
type	0
rating	0
user_rating	0

Create the column with all these important columns together

```
def get_important_features(data):
    important_features = []
    for i in range(0, data.shape[0]):
                important_features.append(data['name'][i]+' '+data['genre'][i]+' '+data['type'][i]+' '+str(data['rating'][i])+' '+st

    return important_features
```

```
anime_user_rating['important_features'] = get_important_features(anime_user_rating)
```

```
anime_user_rating.head(3)
```

	anime_id	name	genre	type	episodes	rating	members	rounded_rating	user_rating	important_features
0	32281	Kimi no Na wa.	Drama, Romance, School, Supernatural	Movie	1	9.37	200630	9	9.374302	Kimi no Na wa. Drama, Romance, School, Superna...
1	5114	Fullmetal Alchemist: Brotherhood	Action, Adventure, Drama, Fantasy, Magic, Mili...	TV	64	9.26	793665	9	9.341739	Fullmetal Alchemist: Brotherhood Action, Adven...

Next steps: Generate code with anime_user_rating View recommended plots New interactive sheet

```
cm = CountVectorizer().fit_transform(anime_user_rating['important_features'])
```

```
cs = cosine_similarity(cm)
print(cs)
```

```
[[1.         0.0836242  0.         ... 0.         0.         0.12309149]
 [0.0836242  1.         0.24019223 ... 0.         0.         0.        ]
 [0.         0.24019223 1.         ... 0.         0.         0.        ]
 ...
 [0.         0.         0.         ... 1.         0.36514837 0.33333333]
 [0.         0.         0.         ... 0.36514837 1.         0.36514837]
 [0.12309149 0.         0.         ... 0.33333333 0.36514837 1.        ]]
```

```
title = 'Fullmetal Alchemist: Brotherhood'
anime_id = anime_user_rating[anime_user_rating['name'] == title]['anime_id'].values[0]
```

```
print(anime_id)
```

```
5114
```

```
scores = list(enumerate(cs[anime_id]))
```

```
sorted_scores = sorted(scores, key = lambda x: x[1], reverse=True)
sorted_scores = sorted_scores[1:]
```

```
j = 0
print('The 5 most recommended anime to', title, 'are:\n')
for item in sorted_scores:
    # Filter the DataFrame based on anime_id
    filtered_df = anime_user_rating[anime_user_rating['anime_id'] == item[0]]

    # Check if the filtered DataFrame is empty
    if not filtered_df.empty:
        # If not empty, get the movie title
        movie_title = filtered_df['name'].values[0]
        print(j + 1, movie_title)
        j += 1
        if j > 4:
            break
    else:
        # If empty, skip this item and continue to the next
        continue
```

```
The 5 most recommended anime to Fullmetal Alchemist: Brotherhood are:

1 Kyoushirou to Towa no Sora
2 Mobile Suit Gundam Seed
3 Yokohama Kaidashi Kikou
4 Choujikuu Seiki Orguss 02
5 Ijoku
```

Deep Learning-Based Collaborative Filtering

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

ratings = pd.read_csv('/content/rating.csv')
anime   = pd.read_csv('/content/anime.csv')

ratings_filtered = ratings[ratings['rating'] > 0].copy()

# Encode 'user_id' and 'anime_id' for use in embedding layers
user_encoder = LabelEncoder()
anime_encoder = LabelEncoder()
ratings_filtered['user'] = user_encoder.fit_transform(ratings_filtered['user_id'])
ratings_filtered['anime'] = anime_encoder.fit_transform(ratings_filtered['anime_id'])

# Split the data into training and validation sets
train_data, val_data = train_test_split(ratings_filtered, test_size=0.2, random_state=42)

# Display the first few rows of the processed data for verification
train_data.head(), val_data.head()
```

```
(         user_id  anime_id  rating  user  anime
 921733      8308       181       7  7878    157
 233674      2403       813      10  2253    728
 813830      7507      9919       7  7109   5021
 455363      4687      1132      10  4400   1021
 1022430     9723       226       6  9201    201,
          user_id  anime_id  rating  user  anime
 428175      4409     23283       8  4138   6832
 863970      7880       420       6  7470    390
 1004712     9437       317      10  8929    290
```

```
141459      1431      2993        6  1344    2622
713205      6710     10620        8  6342    5251)
```

```
import tensorflow as tf
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Embedding, Input, Dense, Flatten, Concatenate

# Hyperparameters
embedding_dim = 50  # Dimension of the embedding space

# Input layers for user and anime IDs
user_input = Input(shape=(1,), name='user_input')
anime_input = Input(shape=(1,), name='anime_input')

# Embedding layers for users and anime
user_embedding = Embedding(input_dim=len(user_encoder.classes_), output_dim=embedding_dim, name='user_embedding')(user_input)
anime_embedding = Embedding(input_dim=len(anime_encoder.classes_), output_dim=embedding_dim, name='anime_embedding')(anime_input)

# Flatten embeddings
user_flat = Flatten()(user_embedding)
anime_flat = Flatten()(anime_embedding)

# Concatenate user and anime embeddings
concat = Concatenate()([user_flat, anime_flat])

# Dense layers to learn interactions
x = Dense(128, activation='relu')(concat)
x = Dense(64, activation='relu')(x)
x = Dense(32, activation='relu')(x)

# Output layer (predicting the rating)
output = Dense(1)(x)

# Define the model
model = Model(inputs=[user_input, anime_input], outputs=output)

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error', metrics=[tf.keras.metrics.RootMeanSquaredError()])

# Summary of the model
model.summary()
```

Model: "functional"

Layer (type)	Output Shape	Param #	Connected to
user_input (InputLayer)	(None, 1)	0	-
anime_input (InputLayer)	(None, 1)	0	-
user_embedding (Embedding)	(None, 1, 50)	463,250	user_input[0][0]
anime_embedding (Embedding)	(None, 1, 50)	396,250	anime_input[0][0]
flatten (Flatten)	(None, 50)	0	user_embedding[0][0]
flatten_1 (Flatten)	(None, 50)	0	anime_embedding[0][0]
concatenate (Concatenate)	(None, 100)	0	flatten[0][0], flatten_1[0][0]
dense (Dense)	(None, 128)	12,928	concatenate[0][0]
dense_1 (Dense)	(None, 64)	8,256	dense[0][0]
dense_2 (Dense)	(None, 32)	2,080	dense_1[0][0]
dense_3 (Dense)	(None, 1)	33	dense_2[0][0]

```
# Prepare inputs for training
train_user_ids = train_data['user'].values
train_anime_ids = train_data['anime'].values
train_ratings = train_data['rating'].values

val_user_ids = val_data['user'].values
val_anime_ids = val_data['anime'].values
val_ratings = val_data['rating'].values

# Train the model
```

```
history = model.fit(
    [train_user_ids, train_anime_ids], train_ratings,
    validation_data=([val_user_ids, val_anime_ids], val_ratings),
    epochs=10,  # You can adjust the number of epochs as needed
    batch_size=256,  # Adjust batch size depending on available resources
    verbose=1
)
```

```
n_squared_error: 1.1958

n_squared_error: 1.1923

n_squared_error: 1.1884

n_squared_error: 1.1957

n_squared_error: 1.2072

n_squared_error: 1.2165

n_squared_error: 1.2356

n_squared_error: 1.2426

n_squared_error: 1.2473

n_squared_error: 1.2591
 is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_
```

```
#save model
model.save('model.keras')
```

```
# Evaluate the model on the validation set
val_loss, val_rmse = model.evaluate([val_user_ids, val_anime_ids], val_ratings, verbose=1)
print(f"Validation RMSE: {val_rmse:.4f}")
```

```
5228/5228 ━━━━━━━━━━━━━━━━━━━━ 7s 1ms/step - loss: 1.5945 - root_mean_squared_error: 1.2626
Validation RMSE: 1.2590
```

Predict Ratings: For each user, we'll predict the ratings for all anime they haven't rated yet. Recommend Top Anime: Sort anime by predicted rating and select the top recommendations.

```
import numpy as np

# Function to get recommendations for a specific user
def get_recommendations(user_id, top_n=10):
    # Get internal user index
    user_idx = user_encoder.transform([user_id])[0]

    # Get all anime indices
    all_anime_indices = np.arange(len(anime_encoder.classes_))

    # Predict ratings for all anime for the specified user
    user_array = np.array([user_idx] * len(all_anime_indices))
    predicted_ratings = model.predict([user_array, all_anime_indices], verbose=0)

    # Sort anime by predicted rating
    top_anime_indices = np.argsort(predicted_ratings.flatten())[-top_n:][::-1]
    recommended_anime_ids = anime_encoder.inverse_transform(top_anime_indices)

    # Retrieve anime titles based on IDs
    recommendations = anime[anime['anime_id'].isin(recommended_anime_ids)][['anime_id', 'name']]

    return recommendations

# Example: Get top 10 recommendations for a specific user
user_id = 1  # Replace with an actual user_id from your dataset
top_recommendations = get_recommendations(user_id, top_n=10)
print(f"Top 10 recommendations for user {user_id}")
print(top_recommendations)
```

```
Top 10 recommendations for user 1
      anime_id                                name
264       4814                  Junjou Romantica 2
```

```
437      3092                                 Junjou Romantica
1054     6152  Final Fantasy VII: Advent Children - Venice Fi...
1288    22539                    One More Time, One More Chance
2015    10825  Ranma ½: Battle ga Ippai 29-nin no Korinai Yat...
2130     9241                 Super Robot Taisen OG: The Inspector
2866     7113                          30th Gundam Perfect Mission
2925    10819          Ranma ½: Tendou-ke no Oyobidenai Yatsura!
3274     4208                              Tetsujin 28-gou (1980)
7383    17843                              Inferno Cop: Fact Files
```

Identify Genres: Filter recommendations to ensure a variety of genres appear in the top recommendations. Select Top Anime per Genre: For each genre, select highly rated anime for the user.

```
# Function to get diverse recommendations by genre
def get_diverse_recommendations(user_id, top_n=10):
    user_idx = user_encoder.transform([user_id])[0]
    all_anime_indices = np.arange(len(anime_encoder.classes_))

    # Predict ratings for all anime for the specified user
    user_array = np.array([user_idx] * len(all_anime_indices))
    predicted_ratings = model.predict([user_array, all_anime_indices], verbose=0).flatten()

    # Merge predictions with anime information
    anime_predictions = pd.DataFrame({
        'anime_id': anime_encoder.inverse_transform(all_anime_indices),
        'predicted_rating': predicted_ratings
    })
    anime_predictions = anime_predictions.merge(anime[['anime_id', 'name', 'genre']], on='anime_id')

    # Initialize a dictionary to store diverse recommendations
    genre_groups = anime_predictions.groupby('genre')
    diverse_recommendations = []

    for genre, group in genre_groups:
        # Sort by predicted rating and take the top recommendation for each genre
        top_anime_per_genre = group.sort_values(by='predicted_rating', ascending=False).head(1)
        diverse_recommendations.append(top_anime_per_genre)

    # Concatenate results and get top N recommendations based on the predicted rating
    diverse_recommendations = pd.concat(diverse_recommendations).sort_values(by='predicted_rating', ascending=False).head(top_n)
    return diverse_recommendations[['anime_id', 'name', 'genre', 'predicted_rating']]

# Example: Get top 10 diverse recommendations for a user
user_id = 1  # Replace with an actual user_id
diverse_recommendations = get_diverse_recommendations(user_id, top_n=10)
print(f"Top 10 diverse recommendations for user {user_id}")
print(diverse_recommendations)
```

```
      anime_id                                             name  \
5330     10825  Ranma ½: Battle ga Ippai 29-nin no Korinai Yat...
4367      7113                          30th Gundam Perfect Mission
3339      4208                              Tetsujin 28-gou (1980)
3563      4814                                   Junjou Romantica 2
6243     17843                              Inferno Cop: Fact Files
4033      6152  Final Fantasy VII: Advent Children - Venice Fi...
6752     22539                    One More Time, One More Chance
4851      9241                 Super Robot Taisen OG: The Inspector
1135      1254                                          Saint Seiya
5972     15451                                  High School DxD New

                                                genre  predicted_rating
5330               Comedy, Martial Arts, Slice of Life         10.899734
4367                                     Mecha, Sci-Fi         10.863212
3339                                     Action, Mecha         10.813325
3563                Comedy, Drama, Romance, Shounen Ai         10.782046
6243                             Action, Comedy, Police         10.742402
4033                      Action, Drama, Fantasy, Sci-Fi         10.668103
6752              Drama, Music, Romance, Slice of Life         10.541017
4851                        Action, Mecha, Sci-Fi, Space         10.513913
1135               Adventure, Fantasy, Sci-Fi, Shounen         10.497052
5972  Action, Comedy, Demons, Ecchi, Harem, Romance,...         10.481244
```

Grouping by Genre: The code groups predictions by genre and then picks the top recommendation from each genre. Selecting Top N: After selecting top recommendations per genre, the function takes the top N to ensure diversity.

New Users: Recommend popular anime or trending genres based on overall ratings. New Anime: Recommend to users who have shown interest in similar genres.

```
# Function to recommend popular anime for a new user
def recommend_for_new_user(top_n=10):
    # Select top-rated anime from overall ratings
    popular_anime = ratings.groupby('anime_id').rating.mean().sort_values(ascending=False).head(top_n).index
    recommendations = anime[anime['anime_id'].isin(popular_anime)][['anime_id', 'name', 'genre']]
    return recommendations

# Example: Get recommendations for a new user
new_user_recommendations = recommend_for_new_user(top_n=10)
print("Recommendations for a new user:")
print(new_user_recommendations)
```

```
Recommendations for a new user:
      anime_id                                              name  \
3039      5895                           Tistou Midori no Oyayubi
3241     27653  Crayon Shin-chan Movie 23: Ora no Hikkoshi Mon...
4418      8542                                   Shin Ace wo Nerae!
4902      8140          Konchuu Monogatari Minashigo Hutch (1989)
6644     28959                                    Kizuna (Special)
6648     29323                           Oyaji no, Imo no Kamisama.
7098     28813                          Bamboo Blade: Fanfu-Fufe-Fo
9181     17985      Kero Kero Keroppi no Boku-tachi no Takaramono
9238      6012                                   Kinpatsu no Jeanie
9537      5994                       Midoriyama Koukou Koushien-hen

                                   genre
3039                   Historical, Magic
3241                Comedy, Kids, Shounen
4418  Drama, Romance, School, Shoujo, Sports
4902               Adventure, Comedy, Drama
6644          Drama, Romance, Slice of Life
6648                        Slice of Life
7098                       Comedy, Parody
9181                        Fantasy, Kids
9238                    Drama, Historical
9537                Comedy, School, Sports
```

```
# Function to find users interested in genres similar to a new anime
def recommend_new_anime(new_anime_id, top_n=10):
    # Get the genre of the new anime
    new_anime_genre = anime.loc[anime['anime_id'] == new_anime_id, 'genre'].values[0]

    # Find users who highly rated anime with similar genres
    similar_anime = anime[anime['genre'] == new_anime_genre]['anime_id']
    interested_users = ratings[ratings['anime_id'].isin(similar_anime) & (ratings['rating'] >= 4)]

    # Recommend this new anime to the top interested users
    top_users = interested_users['user_id'].value_counts().head(top_n).index
    recommended_users = user_encoder.inverse_transform(top_users)

    return recommended_users

# Example: Get users who might like a new anime
new_anime_id = 5114  # Replace with an actual anime_id
users_for_new_anime = recommend_new_anime(new_anime_id, top_n=10)
print(f"Users who might like {anime[anime['anime_id'] == new_anime_id]['name'].values[0]}:")
print(users_for_new_anime)
```

```
Users who might like Fullmetal Alchemist: Brotherhood:
[   5 6435 6390 6393 6406 6410 6411 6412 6413 6420]
```

Popular Anime for New Users: We select anime with the highest average ratings. Similar Genre Users for New Anime: We recommend a new anime to users who liked other anime in the same genre.

Identify Favorite Genres: For each user, calculate the genres they rate the highest. Recommend Anime from Favorite Genres: Prioritize anime in these genres that the user hasn’t rated yet.

```
# Function to identify favorite genres for a user
def get_favorite_genres(user_id, top_n=3):
    # Filter ratings for the specified user
    user_ratings = ratings[ratings['user_id'] == user_id]

    # Merge with anime data to get genres
    user_ratings = user_ratings.merge(anime[['anime_id', 'genre']], on='anime_id')
```