ANIME RECOMMENDER SYSTEM

Context

This data set which is taken from kaggle contains information on user preference data from 73,516 users on 12,294 anime. Each user is able to add anime to their completed list and give it a rating and this data set is a compilation of those ratings. The anime data and user ratings is provided by myanimelist.net API.

Content

Anime.csv

anime_id - myanimelist.net's unique id identifying an anime.

name - full name of anime.

genre - comma separated list of genres for this anime.

type - movie, TV, OVA, etc.

episodes - how many episodes in this show. (1 if movie).

rating - average rating out of 10 for this anime.

members - number of community members that are in this anime's "group".

Rating.csv

user_id - non identifiable randomly generated user id.

anime_id - the anime that this user has rated.

rating - rating out of 10 this user has assigned (-1 if the user watched it but didn't assign a rating).

Import libraries and load the dataset

In [151]:

```
import pandas as pd
import numpy as np
import math
import re
from scipy.sparse import csr_matrix
import matplotlib.pyplot as plt
import seaborn as sns
import surprise
from surprise import Reader, Dataset, SVD, evaluate
sns.set_style("ticks")
```

In [152]:

```
ratings = pd.read_csv('rating.csv')
ratings.head(10)
```

Out[152]:

	user_id	anime_id	rating
0	1	20	-1
1	1	24	-1
2	1	79	-1

	user_id	anime_id	rating
3	1	226	-1
4	1	241	-1
5	1	355	-1
6	1	356	-1
7	1	442	-1
8	1	487	-1
9	1	846	-1

In [167]:

```
# checking for any null values
print("No of Nan values in our dataframe : ", sum(ratings.isnull().any()))
```

```
No of Nan values in our dataframe :  0
```

In [170]:

```
print("Total data ")
print("-"*50)
print("\nTotal no of ratings :",ratings.shape[0])
print("Total No of Users   :", len(np.unique(ratings.user_id)))
print("Total No of Anime  :", len(np.unique(ratings.anime_id)))
```

```
Total data
--------------------------------------------------

Total no of ratings : 7813737
Total No of Users   : 73515
Total No of Anime  : 11200
```

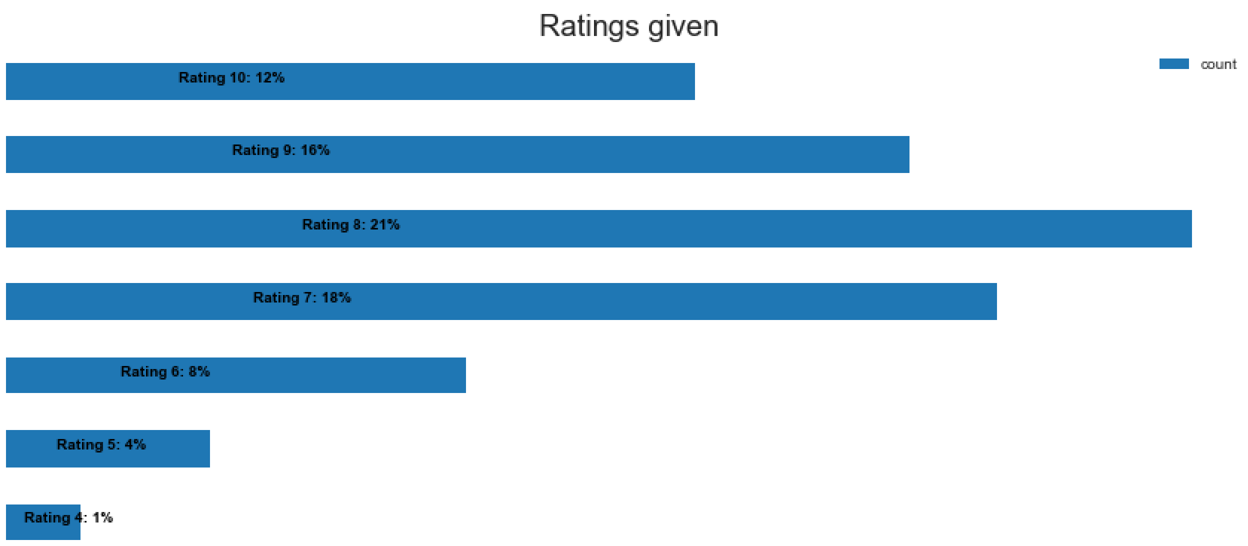
VISUALIZATION OF RATINGS

In [144]:

```
p = ratings.groupby('rating')['rating'].agg(['count'])
ax = p.plot(kind = 'barh', legend = True, figsize = (15,10))


plt.title('Ratings given',fontsize=20)
plt.axis('off')

for i in range(1,12):
    ax.text(p.iloc[i-1][0]/4, i-1, 'Rating {}: {:.0f}%'.format(i-1, p.iloc[i-1][0]*100 / p.sum()[0])
, color = 'black', weight = 'bold')
```



In [153]:

```
#converting ratings from 1-5
ratings['rating'] = (ratings['rating'])/2
ratings.head()
```

Out[153]:

	user_id	anime_id	rating
0	1	20	-0.5
1	1	24	-0.5
2	1	79	-0.5
3	1	226	-0.5
4	1	241	-0.5

In [173]:

```
ratings['rating'].describe()
```

Out[173]:

```
count    7.813737e+06
mean     3.072015e+00
std      1.863900e+00
min     -5.000000e-01
25%      3.000000e+00
50%      3.500000e+00
75%      4.500000e+00
max      5.000000e+00
Name: rating, dtype: float64
```

SLICING THE DATASET

In [2]:

```
#references: https://www.kaggle.com/laowingkin/netflix-movie-recommendation
```

In [154]:

```
f = ['count','mean']

anime_summary = ratings.groupby('anime_id')['rating'].agg(f)
anime_summary.index = anime_summary.index.map(int)
anime_min = round(anime_summary['count'].quantile(0.8),0)
drop_anime_list = anime_summary[anime_summary['count'] < anime_min].index

print('Minimum times of reviews for anime: {}'.format(anime_min))

df_cust_summary = ratings.groupby('user_id')['rating'].agg(f)
df_cust_summary.index = df_cust_summary.index.map(int)
cust_min = round(df_cust_summary['count'].quantile(0.8),0)
drop_cust_list = df_cust_summary[df_cust_summary['count'] < cust_min].index


print('Minimum times of reviews for a customer: {}'.format(cust_min))
```

```
print('Minimum times of reviews for a customer: {}'.format(cust_min))
```

```
Minimum times of reviews for anime: 634.0
Minimum times of reviews for a customer: 164.0
```

In [155]:

```
print('Original Shape: {}'.format(ratings.shape))
df = ratings[~ratings['anime_id'].isin(drop_anime_list)]
df = ratings[~ratings['user_id'].isin(drop_cust_list)]
print('After Trim Shape: {}'.format(df.shape))
print('-Data Examples-')
print(df.head())
```

```
Original Shape: (7813737, 3)
After Trim Shape: (4821593, 3)
-Data Examples-
     user_id  anime_id  rating
302        5         6     4.0
303        5        15     3.0
304        5        17     3.0
305        5        18     3.0
306        5        20     3.0
```

LOAD THE ANIME DATASET

In [183]:

```
anime_data = pd.read_csv('anime.csv')
```

In [159]:

```
anime_data.head()
```

Out[159]:

	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

In [161]:

```
anime_data.set_index('anime_id', inplace = True)
print (anime_data.head(10))
```

```
                                                 name  \
anime_id                                                
32281                                  Kimi no Na wa.   
5114                 Fullmetal Alchemist: Brotherhood   
28977                                        Gintama°   
9253                                      Steins;Gate   
9969                                    Gintama&#039;   
32935     Haikyuu!!: Karasuno Koukou VS Shiratorizawa Ga...   
11061                              Hunter x Hunter (2011)   
820                                  Ginga Eiyuu Densetsu   
15335     Gintama Movie: Kanketsu-hen - Yorozuya yo Eien...   
15417                            Gintama&#039;: Enchousen   

                                                genre   type episodes  \
```

```
                                                        genre   type episodes  \
anime_id
32281                   Drama, Romance, School, Supernatural  Movie        1
5114      Action, Adventure, Drama, Fantasy, Magic, Mili...     TV       64
28977     Action, Comedy, Historical, Parody, Samurai, S...     TV       51
9253                                       Sci-Fi, Thriller     TV       24
9969      Action, Comedy, Historical, Parody, Samurai, S...     TV       51
32935                  Comedy, Drama, School, Shounen, Sports     TV       10
11061                 Action, Adventure, Shounen, Super Power     TV      148
820                            Drama, Military, Sci-Fi, Space    OVA      110
15335     Action, Comedy, Historical, Parody, Samurai, S...  Movie        1
15417     Action, Comedy, Historical, Parody, Samurai, S...     TV       13

          rating  members
anime_id
32281       9.37   200630
5114        9.26   793665
28977       9.25   114262
9253        9.17   673572
9969        9.16   151266
32935       9.15    93351
11061       9.13   425855
820         9.11    80679
15335       9.10    72534
15417       9.11    81109
```

WHAT USER 226 HAS WATCHED AND LIKED BEFORE:

In [162]:

```python
n = 226
df_n = df[(df['user_id'] == n) & (df['rating'] >4)]
df_n = df_n.set_index('anime_id')
nm = anime_data['name']
df_n = df_n.join(nm)
print(df_n)
```

```
          user_id  rating                                      name
anime_id
180           226     4.5                                  Vandread
181           226     4.5                Vandread: The Second Stage
245           226     5.0                     Great Teacher Onizuka
269           226     5.0                                    Bleach
419           226     4.5                       Samurai Deeper Kyou
857           226     4.5                                  Air Gear
889           226     4.5                              Black Lagoon
1067          226     4.5              Kishin Houkou Demonbane (TV)
1127          226     4.5                     UFO Princess Valkyrie
1195          226     4.5                          Zero no Tsukaima
1250          226     5.0                            Erementar Gerad
1482          226     4.5                               D.Gray-man
1519          226     4.5           Black Lagoon: The Second Barrage
1575          226     5.0             Code Geass: Hangyaku no Lelouch
1604          226     4.5                   Katekyo Hitman Reborn!
1726          226     4.5                            Devil May Cry
1840          226     4.5      Zero no Tsukaima: Futatsuki no Kishi
2002          226     5.0                               Heroic Age
2904          226     5.0          Code Geass: Hangyaku no Lelouch R2
2993          226     4.5                        Rosario to Vampire
3299          226     5.0               H2O: Footprints in the Sand
3455          226     4.5                               To LOVE-Ru
3503          226     4.5                                   Kanokon
3594          226     4.5                           Tears to Tiara
3712          226     4.5   Zero no Tsukaima: Princesses no Rondo
4186          226     5.0                     Chrome Shelled Regios
4214          226     4.5                  Rosario to Vampire Capu2
4901          226     4.5    Black Lagoon: Roberta&#039;s Blood Trail
5041          226     5.0                                Guin Saga
5042          226     4.5                               Kiss x Sis
...           ...     ...                                       ...
26243         226     4.5                           Owari no Seraph
26443         226     5.0                                  Triage X
27631         226     4.5                                 God Eater
27775         226     4.5                          Plastic Memories
27899         226     5.0                            Tokyo Ghoul √A
```

```
27991          226     4.5                                  K: Return of Kings
28121          226     4.5   Dungeon ni Deai wo Motomeru no wa Machigatteir...
28249          226     4.5                                   Arslan Senki (TV)
28283          226     4.5                                      Sengoku Musou
28537          226     4.5                               Garo: Guren no Tsuki
28791          226     4.5                Gunslinger Stratos: The Animation
28927          226     4.5                 Owari no Seraph: Nagoya Kessen-hen
28999          226     4.5                                          Charlotte
29093          226     5.0              Grisaia no Meikyuu: Caprice no Mayu 0
29095          226     5.0                                  Grisaia no Rakuen
29101          226     4.5                        Grisaia no Kajitsu Specials
29786          226     4.5   Shimoneta to Iu Gainen ga Sonzai Shinai Taikut...
29803          226     4.5                                           Overlord
29854          226     4.5                                  Ushio to Tora (TV)
30123          226     5.0                           Akagami no Shirayuki-hime
30250          226     4.5                          Triage X: Recollection XOXO
30276          226     4.5                                       One Punch Man
30296          226     4.5                             Rakudai Kishi no Cavalry
30901          226     5.0                      Utawarerumono: Itsuwari no Kamen
30911          226     4.5                               Tales of Zestiria the X
31338          226     4.5                                             Hundred
31716          226     5.0                                             Rewrite
32094          226     4.5                   Reikenzan: Hoshikuzu-tachi no Utage
32313          226     4.5   Concrete Revolutio: Choujin Gensou - The Last ...
32370          226     4.5                                  D.Gray-man Hallow

[153 rows x 3 columns]
```

BUILD SVD MODEL USING TRAINSET

In [164]:

```
reader = Reader()
user_n = anime_data.copy()
user_n = user_n.reset_index()
user_n = user_n[~user_n['anime_id'].isin(drop_anime_list)]
svd = SVD()
# getting full dataset
data = Dataset.load_from_df(df[['user_id', 'anime_id', 'rating']], reader)

trainset = data.build_full_trainset()
model = svd.train(trainset)
```

```
C:\Users\Asus PC\Anaconda3\lib\site-packages\surprise\prediction_algorithms\algo_base.py:51:
UserWarning: train() is deprecated. Use fit() instead
  warnings.warn('train() is deprecated. Use fit() instead', UserWarning)
```

TOP 10 RECOMMENDATIONS FOR THE USER

In [165]:

```
user_n['Estimate_Score'] = df['anime_id'].apply(lambda x: svd.predict(n, x).est)

#user_n = user_n.drop('anime_id', axis = 1)

user_n = user_n.sort_values('Estimate_Score', ascending=False)
print(user_n.head(10))
```

```
       anime_id                                               name  \
2164       2847  Pokemon Diamond &amp; Pearl: Dialga vs. Palkia...
3617       1760                                           Golgo 13
4214      14093                        Pokemon Best Wishes! Season 2
4688      31144                                          Mottainai
11185      9311  Kateikyoushi no Oneesan 2 The Animation: H no ...
1103      32365  Boruto: Naruto the Movie - Naruto ga Hokage ni...
9418      16131             Machine Robo: Butchigiri Battle Hackers
3808      31980                        Okusama ga Seitokaichou! OVA
4208      32962                                       Occultic;Nine
749       22125           Kuroko no Basket: Mou Ikkai Yarimasen ka

                                                 genre     type episodes  \
```

```
2164     Action, Adventure, Comedy, Drama, Fantasy, Kids    Movie        1
3617          Action, Adventure, Drama, Military, Seinen    Movie        1
4214            Action, Adventure, Comedy, Fantasy, Kids       TV       24
4688                                       Slice of Life  Special        1
11185                                             Hentai      OVA        2
1103   Action, Comedy, Martial Arts, Shounen, Super P...  Special        1
9418                                Action, Mecha, Sci-Fi       TV       31
3808                     Comedy, Ecchi, Romance, Shounen      OVA        1
4208                                    Mystery, Sci-Fi       TV       12
749                      Comedy, School, Shounen, Sports  Special        1

       rating  members  Estimate_Score
2164     7.34    38238        4.623925
3617     6.93     6344        4.623925
4214     6.78    19603        4.623925
4688     6.66     2234        4.623925
11185    7.15     5091        4.623925
1103     7.68    16868        4.623925
9418     6.22      239        4.623925
3808     6.88    13602        4.623925
4208     6.78    82532        4.587527
749      7.86    20397        4.534112
```

USE TRAINSET AND TESTSET

In [174]:

```python
from surprise import SVD
from surprise import Dataset
from surprise import accuracy
from surprise.model_selection import train_test_split


# sample random trainset and testset
# test set is made of 25% of the ratings.
trainset, testset = train_test_split(data, test_size=.25)

# We'll use the famous SVD algorithm.

# Train the algorithm on the trainset, and predict ratings for the testset
svd.fit(trainset)
predictions = svd.test(testset)
```

EVALUATE RMSE AND MAE FOR SVD

In [176]:

```python
print(accuracy.rmse(predictions))
print(accuracy.mae(predictions))
```

```
RMSE: 1.0878
1.0877919712104502
MAE:  0.7794
0.7794174683652741
```

TOP-10 RECOMMENDATIONS FOR ALL USERS USING SVD

In [ ]:

```python
from collections import defaultdict

from surprise import SVD
from surprise import Dataset

def get_top_n(predictions, n=10):

    # First map the predictions to each user.
    top_n = defaultdict(list)
    for uid, iid, true_r, est, _ in predictions:
```

```
        top_n[uid].append((iid, est))

    # Then sort the predictions for each user and retrieve the k highest ones.
    for uid, user_ratings in top_n.items():
        user_ratings.sort(key=lambda x: x[1], reverse=True)
        top_n[uid] = user_ratings[:n]

    return top_n

top_n = get_top_n(predictions, n=10)

# Print the recommended items for each user
for uid, user_ratings in top_n.items():
    print(uid, [iid for (iid, _) in user_ratings])
```

CALCULATE PRECISION AND RECALL

In [1]:

```
#references: https://surprise.readthedocs.io/en/stable/FAQ.html
```

In [32]:

```
from collections import defaultdict
from surprise import Dataset
from surprise import SVD
from surprise.model_selection import KFold

kf = KFold(n_splits=5)

def precision_recall_at_k(predictions, k=10, threshold=3.5):
    #Return precision and recall at k metrics for each user.
    # First map the predictions to each user.
    user_est_true = defaultdict(list)
    for uid, _, true_r, est, _ in predictions:
        user_est_true[uid].append((est, true_r))

    precisions = dict()
    recalls = dict()
    for uid, user_ratings in user_est_true.items():

        # Sort user ratings by estimated value
        user_ratings.sort(key=lambda x: x[0], reverse=True)

        # Number of relevant items
        n_rel = sum((true_r >= threshold) for (_, true_r) in user_ratings)

        # Number of recommended items in top k
        n_rec_k = sum((est >= threshold) for (est, _) in user_ratings[:k])

        # Number of relevant and recommended items in top k
        n_rel_and_rec_k = sum(((true_r >= threshold) and (est >= threshold))
                              for (est, true_r) in user_ratings[:k])

        # Precision@K: Proportion of recommended items that are relevant
        precisions[uid] = n_rel_and_rec_k / n_rec_k if n_rec_k != 0 else 1

        # Recall@K: Proportion of relevant items that are recommended
        recalls[uid] = n_rel_and_rec_k / n_rel if n_rel != 0 else 1
    return precisions, recalls


for trainset, testset in kf.split(data):
    precisions, recalls = precision_recall_at_k(predictions, k=5, threshold=4)

    # Precision and recall can then be averaged over all users
print("Precision:", sum(prec for prec in precisions.values()) / len(precisions))
print("Recall:", sum(rec for rec in recalls.values()) / len(recalls))
```

```
Precision: 0.8991305230394231
Recall: 0.16636605881617858
```

k- NEAREST NEIGHBOR ITEM BASED

In [177]:

```
import io

from surprise import KNNBasic
from surprise import Dataset
from surprise import get_dataset_dir


sim_options = {'name': 'pearson', 'user_based': False}
knn = KNNBasic(sim_options=sim_options)
knn.fit(trainset)
predictions = knn.test(testset)
```

```
Computing the pearson similarity matrix...
Done computing similarity matrix.
```

In [178]:

```
print(accuracy.rmse(predictions))
print(accuracy.mae(predictions))
```

```
RMSE: 1.1845
1.1844714497331137
MAE:  0.8833
0.8832844551653122
```

TOP-10 RECOMMENDATIONS

In [185]:

```
from surprise import Dataset
from surprise import get_dataset_dir

neighbors = knn.get_neighbors(0, k=10)
print()
print('The 10 nearest neighbors of Kimi no Na Wa are:')


for i in neighbors:
    for j in anime_data['anime_id']:
        if j== i:
            print(anime_data['name'][j])
```

```
The 10 nearest neighbors of Kimi no Na Wa are:
Code Geass: Hangyaku no Lelouch
Shokugeki no Souma
Ookami to Koushinryou II
Major S3
Natsume Yuujinchou: Itsuka Yuki no Hi ni
NHK ni Youkoso!
Shelter
InuYasha: Kanketsu-hen
One Piece Film: Gold
```

In [194]:

```
for trainset, testset in kf.split(data):
    precisions, recalls = precision_recall_at_k(predictions, k=10, threshold=4)

    # Precision and recall can then be averaged over all users
print("Precision:", sum(prec for prec in precisions.values()) / len(precisions))
print("Recall:", sum(rec for rec in recalls.values()) / len(recalls))
```

```
Precision: 0.9527133899773845
Recall: 0.13032166885177313
```

k-NN BASELINE USING STOCHASTIC GRADIENT DESCENT

In [187]:

```
import io

from surprise import KNNBaseline
from surprise import Dataset
from surprise import get_dataset_dir


sim_options = {'name': 'pearson_baseline', 'user_based': False}
bsl_options = {'method': 'sgd',
               'learning_rate': .005,
               }
knn_b = KNNBaseline(bsl_options=bsl_options, sim_options=sim_options)
knn_b.fit(trainset)
predictions_b = knn_b.test(testset)
```

```
Estimating biases using sgd...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
```

In [188]:

```
print(accuracy.rmse(predictions_b))
print(accuracy.mae(predictions_b))
```

```
RMSE: 1.0803
1.0802914817857145
MAE:  0.7690
0.7690469968304519
```

TOP-10 RECOMMENDATIONS

In [190]:

```
neighbors_b = knn_b.get_neighbors(0, k=10)
print()
print('The 10 nearest neighbors of Kimi no Na Wa are:')


for i in neighbors_b:
    for j in anime_data['anime_id']:
        if j== i:
            print(anime_data['name'][j])
```

```
The 10 nearest neighbors of Kimi no Na Wa are:
JoJo no Kimyou na Bouken: Stardust Crusaders
Aoki Hagane no Arpeggio: Ars Nova DC
Kara no Kyoukai 5: Mujun Rasen
Bleach Movie 1: Memories of Nobody
Detective Conan OVA 01: Conan vs. Kid vs. Yaiba
Durarara!!x2 Shou: Watashi no Kokoro wa Nabe Moyou
Sword Art Online: Extra Edition
Huyao Xiao Hongniang: Yue Hong
Slam Dunk
```

In [195]:

```
for trainset, testset in kf.split(data):
    precisions, recalls = precision_recall_at_k(predictions_b, k=5, threshold=4)

    # Precision and recall can then be averaged over all users
print("Precision:", sum(prec for prec in precisions.values()) / len(precisions))
print("Recall:", sum(rec for rec in recalls.values()) / len(recalls))
```

```
Precision: 0.932154859372506
Recall: 0.153987420609633
```

```
Recall: 0.1559874206096557
```