Final Project Submission

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- Blog post URL:

Movie Recommendation Engine

Business Problem

We are a streaming service that wants to increase the value of it's service and grow it's user and movie base.

Goal: create a recommendation engine that will accurately predict movies that our users will rate highly.

Benefits:

1. Keeps our existing users coming back
    - Recommending movies they like and showing them movies they haven't seen will keep them interested
2. Helps identify movies to add to the service
    - New content will give users more movies to watch, keeping them on the service longer
3. Attracts new users
    - A well curated collection of movies will encourage streamers to use our service

The Data

The data used in the project is a rating data sets from the MovieLens web site (https://movielens.org (https://movielens.org)) collected by GroupLens Research. The particular dataet used is the ml-latest-small set.

This dataset describes 5-star rating and free-text tagging activity from MovieLens, a movie recommendation service. It contains:

- 100836 ratings
- 3683 tag applications
- 9742 movies
- 610 users

This is a small, development dataset collected between March 29, 1996 and September 24, 2018, and was generated on September 26, 2018.

Users were selected at random for inclusion. All selected users had rated at least 20 movies.

- Each user is represented by an id, and no other information is provided.

The data are contained in the files:

- data/links.csv
- data/movies.csv
- data/ratings.csv
- data/tags.csv.

Setup

Import relevant packages

In [1]:
```
import pandas as pd
import numpy as np
import scipy.stats as stats
import statsmodels.api as sm
import json

from surprise import Reader, Dataset
from surprise.model_selection import cross_validate, GridSearchCV
from surprise.prediction_algorithms import SVD, KNNWithMeans, KNNBasic
from surprise.model_selection import train_test_split
from surprise import accuracy

from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import f1_score, mean_squared_error, r2_score, rc

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

Load and Clean Data

Load the raw csv files

In [2]:
```
movies_df = pd.read_csv('data/movies.csv')
ratings_df = pd.read_csv('data/ratings.csv')
tags_df = pd.read_csv('data/tags.csv')
```

Movies DataFrame

In [3]:
```
movies_df.head()
```

Out[3]:

	movieId	title	genres
0	1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
1	2	Jumanji (1995)	Adventure|Children|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama|Romance
4	5	Father of the Bride Part II (1995)	Comedy

Ratings DataFrame

- drop the timestamp column

In [4]:
```
ratings = ratings_df.drop(columns=['timestamp'], axis=1)
ratings.head()
```

Out[4]:

	userId	movieId	rating
0	1	1	4.0
1	1	3	4.0
2	1	6	4.0
3	1	47	5.0
4	1	50	5.0

Tags DataFrame

- drop the timestamp column

In [5]:
```
tags = tags_df.drop(columns=['timestamp'], axis=1)
tags.head()
```

Out[5]:

	userId	movieId	tag
0	2	60756	funny
1	2	60756	Highly quotable
2	2	60756	will ferrell
3	2	89774	Boxing story
4	2	89774	MMA

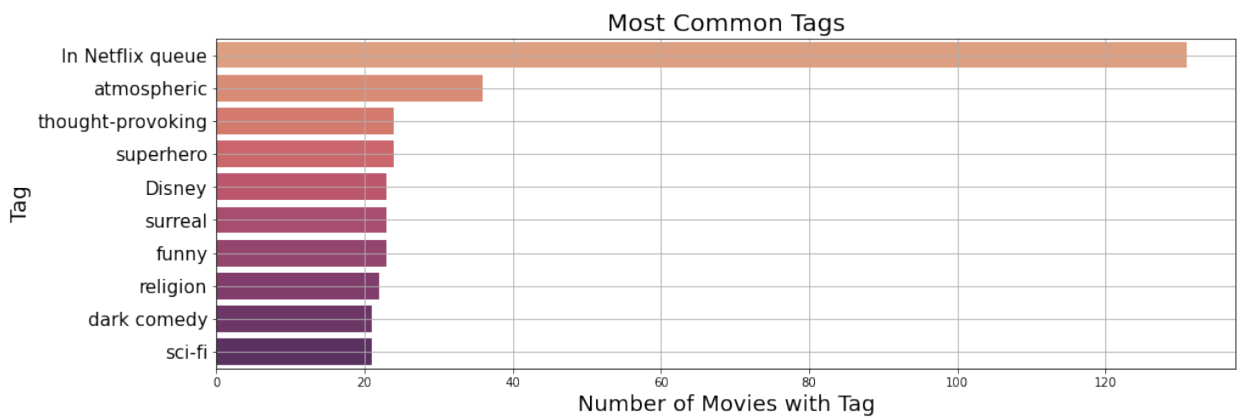
Total Dataset Visualizations

Visualizations to gain an comprehensive view of the data

Most common tags

- Look at the tags DataFrame to determine which tags occur the most often

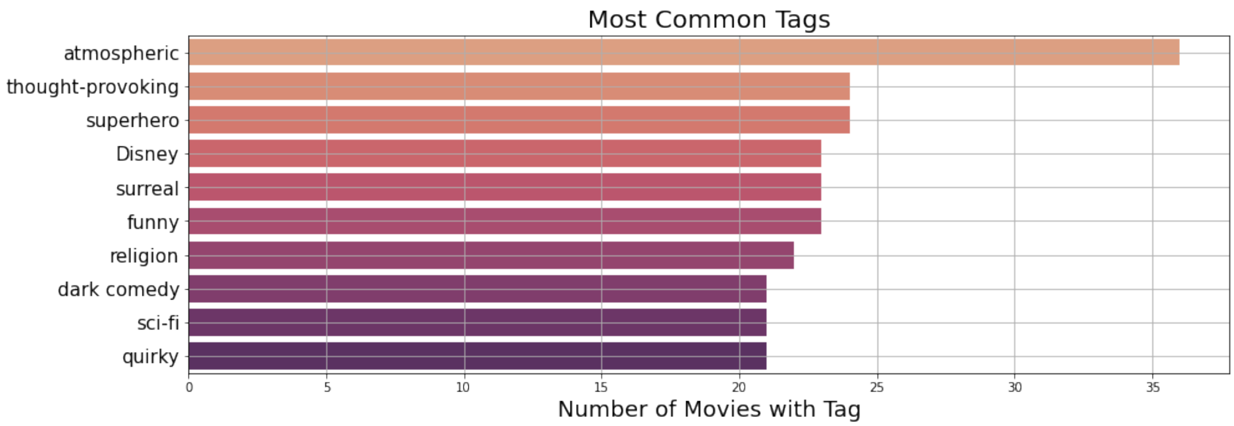
In [6]:
```
# group tags together and count their number of occurances. Sort by mo
tags_group = tags.drop(columns='userId', axis=1)
tags_group = tags_group.groupby('tag').count().sort_values(by='movieIc
tags_group = tags_group.rename(columns={'movieId': 'Count'})
top_tag_groups = tags_group[:10]

# plot the 10 most common tags
plt.figure(figsize=(15,5))
sns.barplot(data=top_tag_groups, x='Count', y=top_tag_groups.index, pa
plt.yticks(fontsize=15)
plt.xlabel('Number of Movies with Tag', fontsize=18)
plt.ylabel('Tag', fontsize=18)
plt.title('Most Common Tags', fontsize=20)
plt.grid()
```



Tags visualization with "In Netflix queue" removed

The "In Netflix queue" tag does not give much information about the movie itself, rather how it was positioned on their page. Removing this tag will bring the remaining tags into the same scale and keep tags related to the content of the movie.

In [7]:
```
# plot the 10 most common tags, removing the tag "In Netflix Queue"
top_tag_groups = tags_group[1:11]

plt.figure(figsize=(15,5))
sns.barplot(data=top_tag_groups, x='Count', y=top_tag_groups.index, pa
plt.yticks(fontsize=15)
plt.xlabel('Number of Movies with Tag', fontsize=18)
plt.ylabel('', fontsize=18)
plt.title('Most Common Tags', fontsize=20)
plt.grid()
```



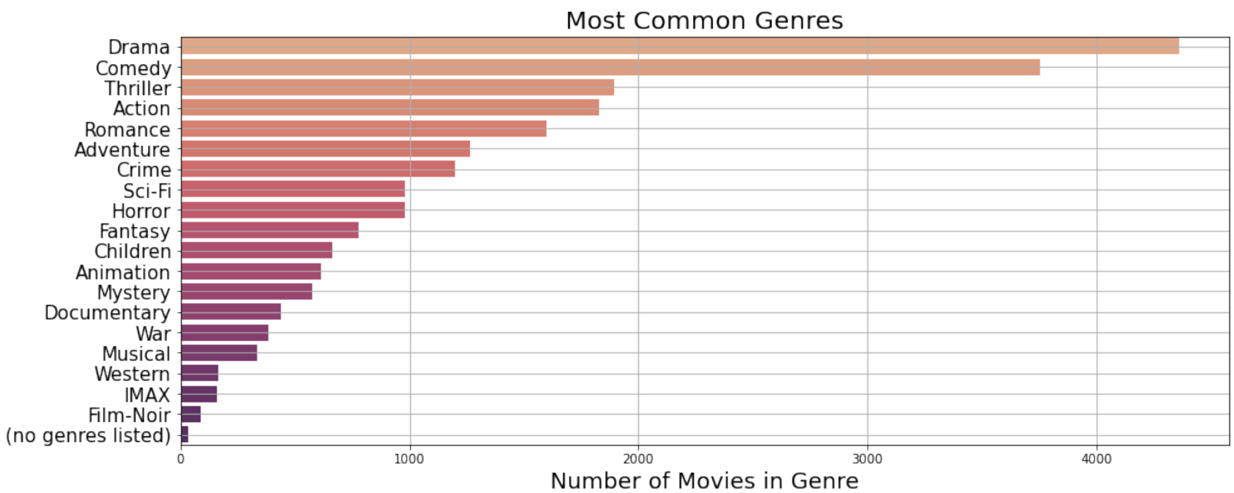
Interpretation:

The most common of tags represent a diverse set of descriptors that indicate that there is a wide range of movies that will appeal to many movie preferences.

Genre counts

- Determine how many movies belonging to each genre exist in the data set

In [8]:
```
# drop the titles from the dataframe
genres = movies_df.drop(columns=['title'], axis=1)

# convert genre tags to list
genres['genres'] = genres['genres'].map(lambda x: x.split('|'))
genres = genres.explode('genres')

# group the rows by genre and count the number of occurances, then sor
genres_group = genres.groupby('genres').count().sort_values(by='movieI
genres_group = genres_group.rename(columns={'movieId': 'Count'})
top_genres_group = genres_group[:20]

# plot the top genres
plt.figure(figsize=(15,6))
sns.barplot(data=top_genres_group, x='Count', y=top_genres_group.index
plt.yticks(fontsize=15)
plt.xlabel('Number of Movies in Genre', fontsize=18)
plt.ylabel('', fontsize=18)
plt.title('Most Common Genres', fontsize=20)
plt.grid()
```



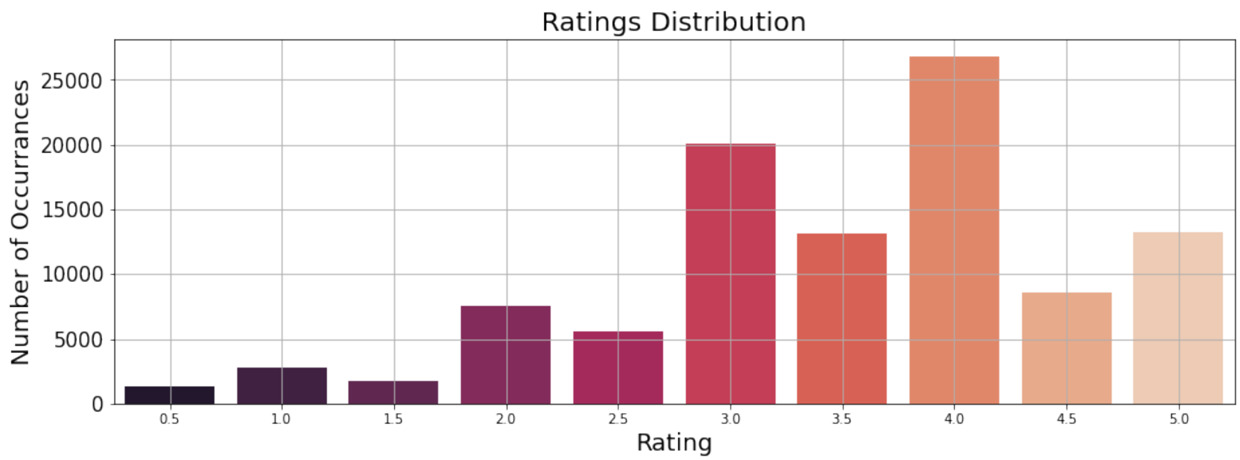
Interpretation:

The most common genres of movies are Drama and Comedy, meaning that those types of movies will be recommended most often. Musical, Western, IMAX, and Film-Noir are less common genres, so those will be rarer amongst the recommendations that we will see.

Histogram of Ratings

- view the distribution of ratings in the data set

In [9]:
```
# count the number of occurances for each rating
ratings_count = ratings.groupby("rating").count()
ratings_count.drop(columns=["userId"], axis=1)
ratings_count = ratings_count.rename(columns={'movieId': 'Count'})

# plot the ratings distribution
plt.figure(figsize=(15,5))
sns.barplot(data=ratings_count, x=ratings_count.index, y='Count', pale
plt.yticks(fontsize=15)
plt.xlabel('Rating', fontsize=18)
plt.ylabel('Number of Occurrances', fontsize=18)
plt.title('Ratings Distribution', fontsize=20)
plt.grid()
```



Interpretation:

The users in this dataset tend to be generous in their ratings, meaning more movies with high ratings will be available to recommend and will give us a diverse set of movies.

Create a Surprise Dataset from the Ratings DataFrame

The DataFrame will be converted to a surprise dataset in order to be compatible with the recommendation model functionality available with the Surprise package.

In [10]:
```
reader = Reader()
data = Dataset.load_from_df(ratings, reader)
```

In [11]:
```
dataset = data.build_full_trainset()
print(f"N users = {dataset.n_users}")
print(f"N items = {dataset.n_items}")
```

```
N users = 610
N items = 9724
```

Separate the data into test and train data

In [12]:
```
trainset, testset = train_test_split(data, test_size=0.2)
```

Create a function to train and test each KNN method

Define the parameter combinations for the KNN methods

In [13]:
```
sim_cos_item = {'params_name': 'cosine item',
                'params': {'name': 'cosine', 'user_based': False}
               }
sim_pearson_item = {'params_name': 'pearson item',
                    'params': {'name': 'pearson', 'user_based': False}
                   }
sim_cos_user = {'params_name': 'cosine user',
                'params': {'name': 'cosine', 'user_based': True}
                }
sim_pearson_user = {'params_name': 'pearson user',
                    'params': {'name': 'pearson', 'user_based': True}
                    }
```

Define a model to run a KNN method type model and return the error of the model

In [14]:
```
def run_KNN_model(method_type, params):
    """
    function to run k-Nearest Neightbor inspired methods to compare us

    args:
        - method_type: KNN method type to use: KNNBasi, KNNBaseline, o
        - params: paramters to use in model, including "name", and "us
    returns:
        - accuracy_rmse: root mean squared error for the model
        - accuracy_mae: mean aboslute error for the model
    """
    # select the KNN method to use
    if method_type == 'KNNBasic':
        model = KNNBasic(sim_options=params, verbose=False)
    elif method_type == 'KNNBaseline':
        model = KNNBaseline(sim_options=params, verbose=False)
    elif method_type == 'KNNWithMeans':
        model = KNNWithMeans(sim_options=params, verbose=False)
    else:
        return 'not a model'

    # fit the model and produce predicitons
    model.fit(trainset)
    predictions = model.test(testset)

    # calculate error scores
    accuracy_rmse = accuracy.rmse(predictions, verbose=False)
    accuracy_mae = accuracy.mae(predictions, verbose=False)

    return accuracy_rmse, accuracy_mae
```

Run several models to determine the most accurate final model

Several K-Nearest Neighbor methods will be run in order to determine the method that produces the lowest error.

- KNN Basic methods
- KNN Baseline methods
- KNN With Means methods
- Singular Value Decomposition
  - using a grid search to determine the optimal parameters

Train and Test KNN Methods

In [15]:
```
methods = ['KNNBasic', 'KNNBaseline', 'KNNWithMeans']
sim_params = [sim_pearson_user, sim_pearson_item, sim_cos_user, sim_co

# loop through method and paramter combinations to run and test 12 KNN
for method in methods:
    print(f'{method}')
    for sim_param in sim_params:
        rmse, mae = run_KNN_model(method, sim_param['params'])
        print(f'     {sim_param["params_name"]}: rmse = {round(rmse, 4
    print('')
```

```
KNNBasic
     pearson user: rmse = 0.9672, mae = 0.7464
     pearson item: rmse = 0.9644, mae = 0.7494
     cosine user: rmse = 0.966, mae = 0.7435
     cosine item: rmse = 0.9737, mae = 0.7601

KNNBaseline
     pearson user: rmse = 0.8688, mae = 0.6632
     pearson item: rmse = 0.8757, mae = 0.6742
     cosine user: rmse = 0.8697, mae = 0.6648
     cosine item: rmse = 0.8873, mae = 0.6849

KNNWithMeans
     pearson user: rmse = 0.8883, mae = 0.6763
     pearson item: rmse = 0.8981, mae = 0.6824
     cosine user: rmse = 0.8925, mae = 0.6824
     cosine item: rmse = 0.8978, mae = 0.6848
```

Train and Test SVD Methods

Grid Search

A grid search is performed in order to determine to SVD parameters that produce the the lowest error. All combinations of parameters are tested, with the cobmination resulting in the lowest error is returned.

Grid Search Parameter Selection:

The parameters for the grid search were chosen based on the parameters used in the Implementing Recommendation Systems lab completed in phase 4 of the Flatiron Data Science Program. The parameters are an expansion of the range of paramters used in that lab to perform a grid search to optimize the SVD model.

In [16]:
```
# define the paramters to use in the grid search
grid_search_params = {'n_factors': [30, 40, 50, 60, 70, 80, 90, 100, 1
                      'reg_all': [0.02, 0.04, 0.05, 0.06, 0.07, 0.1],
                      'n_epochs': [5, 10],
                      'lr_all': [0.005, 0.01]}

# perform the grid search to find the optimal SVD paramters and fit th
g_s_svd = GridSearchCV(SVD, param_grid=grid_search_params, n_jobs=-1)
g_s_svd.fit(data)

print(g_s_svd.best_score)
print(g_s_svd.best_params)
```

```
{'rmse': 0.8694547547564522, 'mae': 0.6678009354176557}
{'rmse': {'n_factors': 110, 'reg_all': 0.05, 'n_epochs': 10, 'lr_all'
: 0.01}, 'mae': {'n_factors': 110, 'reg_all': 0.05, 'n_epochs': 10, '
lr_all': 0.01}}
```

Define the Final Model

Metric: RMSE

RMSE was chosen as the metric to determine the final, based on the assumption that the error is normal (Gaussian)

Final Model: SVD model with the parameters;

```
- n_factors = 80
- reg_all = 0.05
- n_epochs = 10
- lr_all = 0.01
```

This model resulted in the lowest root mean squared error, of 0.8694

In [17]:
```
# define the best SVD parameters
svd_best_rmse = g_s_svd.best_params['rmse']

# define and fit the final model
final_model = SVD(n_factors=svd_best_rmse ['n_factors'], reg_all=svd_b
final_model.fit(dataset)
```

Out[17]:
```
<surprise.prediction_algorithms.matrix_factorization.SVD at 0x7fddf01
86f70>
```

Functions for filtering ratings and rankings based on key words

These functions will provide the opportunity to filter the movie recommendtions based on key genres and tags associated with a users top rated moves, or based on preferences indicated by the user upon profile creation.

Define several functions to filter a user's movie ratings and predictions based on the tags and genres of movies they've rated 4.0 and above

In [18]:
```
def get_user_ratings(ratings, userId):
    """
    function to obtain a DataFrame of ratings made by a specific user
    """
    user_ratings = ratings[ratings.userId == userId]
    return user_ratings
```

In [19]:
```
def look_up_tags(movieId):
    """
    Look up the tags associated with a given movie Id
    """
    tags_list = tags[tags['movieId']==movieId]['tag']
    tags_string = []
    for tag in tags_list:
        tags_string.append(tag)
    return list(np.unique(np.array(tags_string)))
```

In [20]:
```
def get_user_top_tags(user_ratings):
    """
    filter the tags submitted by a given user to only contain the tags
    """
    top_tags = []
    for movieId in user_ratings[user_ratings.rating >= 4.0].movieId:
        top_tags.extend(look_up_tags(movieId))
    return list(np.unique(np.array(top_tags)))
```

In [21]:
```
def filter_ratings_by_key_words(words):
    """
    filter the whole set of genres and tags to only contain genres or
    within the given list of key words
    """
    # check both tags and genres
    ids = []
    for word in words:
        ids.extend(genres[genres.genres == word].movieId)
        ids.extend(tags[tags.tag == word].movieId)

    ids = list(np.unique(np.array(ids)))

    filtered_ratings = ratings[ratings.movieId.isin(ids)]

    return filtered_ratings
```

Functions for generating recommendations for a given user

Thise set of functions performs all the necessary tasks for predicting a user's ranking for a specific movie, ranking the movies by predicted score, and returning a list of top recommendations.

In [22]:
```
def rank_movies(userId, ratings):
    """
    obtain a sorted (ranked) list of movies based on their predicted r
    """
    movies_list = []

    # loop through all movies and determine their predicted rating
    for movie_id in ratings.index.unique():
        user_prediction = final_model.predict(userId, movie_id)
        predicted_rating = user_prediction[3]
        movies_list.append((movie_id, predicted_rating))

    # sort the movies by predicted rating
    ranked_movies = sorted(movies_list, key=lambda x:x[1], reverse=Tru

    return ranked_movies
```

In [23]:
```
def look_up_movie(movieId):
    """
    look up the title of a movie given it's movieId
    """
    title = movies_df[movies_df['movieId']==movieId]['title']
    title_string = title[title.index[0]]
    return title_string
```

In [24]:
```
def get_recommended_titles(n_recs, ranked_movies):
    """
    get a list of a specified number of recommended titles for a user,
    """
    return [look_up_movie(id[0]) for id in ranked_movies[0:n_recs]]
```

In [25]:
```
def recommend_to_user(userId, n_recs, use_words=False):
    """
    Master prediction function:
        - call this function to generate a set of movie recommendation
        - option to filter the recommendations by key words

    Args:
        - userId: user Id to generate recommendations for
        - n_recs: the total number of recommendations to give the user
        - use_words: boolean to indicate whether to filter the movie r

    Retruns:
        - recommended_titles: list of movie titles to recommend to use
    """
    words = []
    filtered_ratings = ratings

    # use_words = True
    # determine the tags associated with the users top rated movies
    # filter the movie ratings to only contain movies associated with
    if use_words:
        user_ratings = get_user_ratings(ratings, user_id)
        words = get_user_top_tags(user_ratings)
        filtered_ratings = filter_ratings_by_key_words(words)

    # rank the movies by predicted rating and obtain the titles for th
    ranked_movies = rank_movies(userId, filtered_ratings)
    recommended_titles = get_recommended_titles(n_recs, ranked_movies)

    return recommended_titles
```

In [26]:
```
# test recommendation functions
user_id = 1
n_recs = 5

recommend_to_user(user_id, n_recs, use_words=True)
```

Out[26]:
```
['Shawshank Redemption, The (1994)',
 'Ghost in the Shell (Kôkaku kidôtai) (1995)',
 'Rear Window (1954)',
 'North by Northwest (1959)',
 'Casablanca (1942)']
```

Cold Start Problem

How do we recommend movies to a new user?

1. recommend the top 5 highest rated movies
2. recommend the top 5 movies with the highest number of ratings
3. prompt them to choose 3 key words to represent their movie taste upon profile creation
4. give them the option to rank movies they've alreay seen

Recommend the top 5 highest rated movies and most rated movies

To allow recommendations based on quality and popularity of movies based on the ratings provided by all users

In [27]:
```
def get_ratings_stats(ratings, sortby='rating'):
    """
    generate stats on the ratings dataset and sort the movies by those
        - average rating for each movie (quality)
        - total number of ratings per for movie (popularity)
    this allows us to determine what movies have the highest average r
    have been rated the most
    """
    # get average ratings and number of ratings for each movie id
    ratings_avg = ratings.groupby('movieId').mean()
    ratings_count = ratings.groupby('movieId').count()
    ratings_avg.head()

    # combine average and count into one stats dataframe
    ratings_stats = ratings_avg.drop(columns='userId')
    ratings_stats["n_ratings"] = ratings_count['userId']

    # drop all movies with less than 10 ratings
    ratings_stats = ratings_stats[ratings_stats['n_ratings'] > 50]

    # order the movies by highest rank and highest number of ratings
    if sortby == 'rating':
        ratings_stats_sorted = ratings_stats.sort_values(by='rating',
    else:
        ratings_stats_sorted = ratings_stats.sort_values(by='n_ratings

    return ratings_stats_sorted

# get the top 5 highest rated movies
ratings_stats_by_rating = get_ratings_stats(ratings)
# get the top 5 movies with the highest number of ratings
ratings_stats_by_count = get_ratings_stats(ratings, sortby='count')
```

In [28]:
```
def top_movies(n_movies, ratings):
    """
    get a list of a specified number of recommended titles for a user,
    """
    return [look_up_movie(movie_id) for movie_id in ratings[0:n_movies
```

Recommend the 5 most rated movies

In [29]:
```
top_movies(5, ratings_stats_by_count)
```

Out[29]:
```
['Forrest Gump (1994)',
 'Shawshank Redemption, The (1994)',
 'Pulp Fiction (1994)',
 'Silence of the Lambs, The (1991)',
 'Matrix, The (1999)']
```

Recommend the 5 highest rated movies

In [30]:
```
top_movies(5, ratings_stats_by_rating)
```

Out[30]:
```
['Shawshank Redemption, The (1994)',
 'Godfather, The (1972)',
 'Fight Club (1999)',
 'Cool Hand Luke (1967)',
 'Dr. Strangelove or: How I Learned to Stop Worrying and Love the Bom
b (1964)']
```

Recommend movies by new user's initial 3 words

Recommend movies to a user who has no ratings history yet, but has provided with intial key words indicating their movie preferences.

Once the words have been provided, the list of highest rated movies can be filtered to only contain movies associated with the key words they provided, based on genres and tags.

In [31]:
```
def recommend_by_start_words(start_words):

    # obtain ratings for movies that contain the given words, then cal
    filtered_ratings = filter_ratings_by_key_words(start_words)
    filtered_ratings_stats = get_ratings_stats(filtered_ratings)

    # recommend top movies containing the given words
    recs = top_movies(5, filtered_ratings_stats)

    return recs
```

Start words focussed on animation and children's movies

In [32]:
```
recommend_by_start_words(['Disney', 'Animation', 'Children'])
```

Out[32]:
```
['Spirited Away (Sen to Chihiro no kamikakushi) (2001)',
 'Toy Story 3 (2010)',
 'WALL·E (2008)',
 'Wallace & Gromit: The Wrong Trousers (1993)',
 "It's a Wonderful Life (1946)"]
```

Start words focussed on suspense and mystery

In [33]:
```
recommend_by_start_words(['suspense', 'psychology', 'Mystery'])
```

Out[33]:
```
['Fight Club (1999)',
 'Rear Window (1954)',
 'Departed, The (2006)',
 'Dark Knight, The (2008)',
 'Usual Suspects, The (1995)']
```

Create a profile for an individual user and make movie recommendations

Profile created in order to give an overview of the individual user and thier movie ratings and preferences prior to generating their movie recommendations.

- Pick a user and generate a user profile of common high rated genres and tags.
- Look at their highest rated movies
- Generate 5 movie recommendations

In [34]:
```
def user_top_movies(user_ratings, n):
    """
    Determine the top n highest rated movies by an individual user

    args:
        user_ratings: generated in function get_user_ratings
    """
    top_titles = []
    for movieId in user_ratings[:n].movieId:
        top_titles.append(look_up_movie(movieId))
    return top_titles
```

In [35]:
```
def look_up_genres(movieId):
    """
    function to look up the genres associated with a given movieId
    """
    genres_list = movies_df[movies_df['movieId']==movieId]['genres']
    genres_string = []
    for genre in genres_list:
        genres_string.append(genre.split('|'))
    return list(np.unique(np.array(genres_string)))
```

In [36]:
```
def user_top_movie_genres(user_ratings, n_movies):
    """
    determine the genres of the n highest rated movies for an individu
    """
    top_genres = []
    for movieId in user_ratings[:n_movies].movieId:
        top_genres.extend(look_up_genres(movieId))
    return list(np.unique(np.array(top_genres)))
```

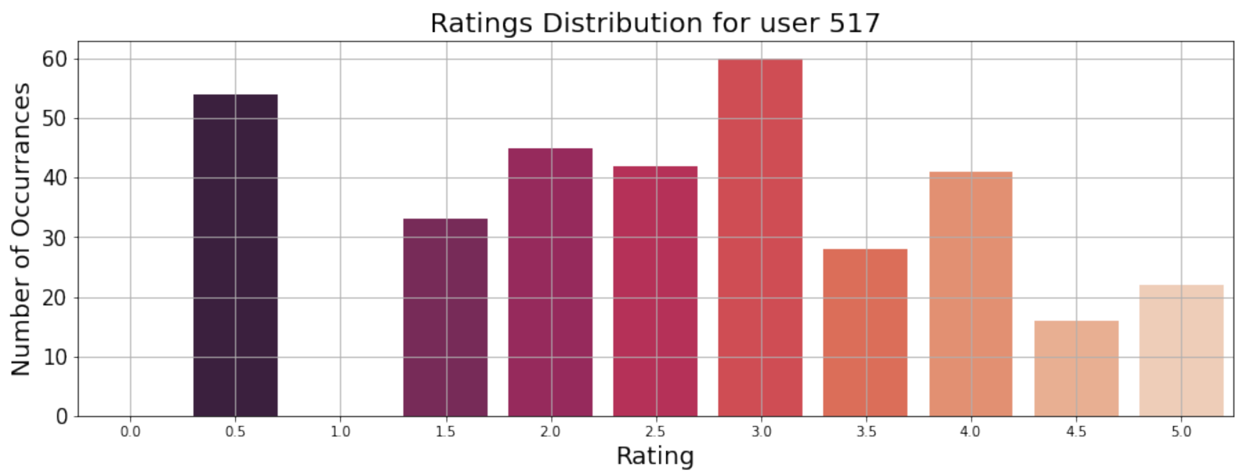
In [37]:
```
def user_ratings_distribution(user_ratings, userId):
    """
    generate a histogram showing the distribution of movie ratings for
    """
    # count the ratings for each rating value
    ratings_count = user_ratings.groupby("rating").count()
    ratings_count = ratings_count.drop(columns=["userId"], axis=1)
    ratings_count = ratings_count.rename(columns={'movieId': 'Count'})
    ratings_count.loc[1.0] = [0]

    # if any rating categories are missing, add them back in
    for rate in [0, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0]:
        if rate not in ratings_count.index:
            ratings_count.loc[rate] = [0]

    # plot the distribution of ratings
    plt.figure(figsize=(15,5))
    sns.barplot(data=ratings_count, x=ratings_count.index, y='Count',
    plt.yticks(fontsize=15)
    plt.xlabel('Rating', fontsize=18)
    plt.ylabel('Number of Occurrances', fontsize=18)
    plt.title(f'Ratings Distribution for user {userId}', fontsize=20)
    plt.grid()
```

In [38]:
```
def user_profile(userId, n):
    """
    function to create a profile for an individual user
    """

    # generate user basics: get their ratings and count the total numb
    user_ratings = get_user_ratings(ratings, userId)
    n_ratings = len(user_ratings)

    # filter their ratings to movies rated 4.0 and above
    filtered_user_ratings = user_ratings[user_ratings.rating > 3.5]

    print(f'n ratings = {n_ratings}')

    # get information on the movies they've rated highly, including ta
    top_movies = user_top_movies(user_ratings, n)
    top_tags = get_user_top_tags(filtered_user_ratings)
    top_genres = user_top_movie_genres(user_ratings, n)

    print(f'top {n} movies = {top_movies}')
    print(f'top genres = {top_genres}')

    # plot their rating distribution
    user_ratings_distribution(user_ratings, userId)
```

In [39]:
```
# test the user profile function then recommend movies for the given u
user_id = 517
n_movies = 10

user_profile(user_id, n_movies)
recommend_to_user(user_id, n_recs, use_words=True)
```

```
n ratings = 400
top 10 movies = ['Toy Story (1995)', 'Jumanji (1995)', 'GoldenEye (19
95)', 'Sense and Sensibility (1995)', 'Babe (1995)', 'Seven (a.k.a. S
e7en) (1995)', 'Muppet Treasure Island (1996)', 'Braveheart (1995)',
'Casper (1995)', 'Die Hard: With a Vengeance (1995)']
top genres = ['Action', 'Adventure', 'Animation', 'Children', 'Comedy
', 'Crime', 'Drama', 'Fantasy', 'Musical', 'Mystery', 'Romance', 'Thr
iller', 'War']
```

Out[39]:
```
['E.T. the Extra-Terrestrial (1982)',
 'Sound of Music, The (1965)',
 'Love Actually (2003)',
 "No Man's Land (2001)",
 'Across the Universe (2007)']
```



Create a New UserId

singular function to determine the next available user id to be given to a new user

In [40]:
```
def new_user_id():
    """
    function to determine the next available user id
    """
    return np.unique(np.array(ratings.userId)).max() + 1
```

Prompt User to Rate a Movie

Given a title name (based on what movie the user has just watched or selected to rate), create a new rating by the user for the movie

In [41]:
```
def rate_movie(movie_title, userId):
    """
    function to prompt a user to rate a movie, given the title
    """
    try:
        movie_id = int(movies_df[movies_df.title == movie_title].movie
    except TypeError:
        return {}

    print(movie_title)
    rating = input('How do you rate this movie on a scale of 1-5')
    rating = {'userId':userId, 'movieId': movie_id, 'rating': rating}

    return rating

def add_rating_to_df(rating):
    """
    add a single new rating to the ratings data frame and surprise dat
    """
    new_ratings_df = pd.DataFrame(rating)

    # update the index to continue the existing index in the ratings d
    new_ratings_df['new_index'] = [ratings.index.max()+1]
    new_ratings_df = new_ratings_df.set_index('new_index')

    updated_ratings_df = pd.concat([ratings, new_ratings_df], axis=0)
    updated_dataset = Dataset.load_from_df(new_ratings_df, reader)

    return updated_ratings_df, updated_dataset
```

In [42]:
```
new_user_id = new_user_id()
new_rating = rate_movie(movie_title='Spotlight (2015)', userId=new_use
ratings_df, data = add_rating_to_df([new_rating])

ratings_df.tail()
```

```
Spotlight (2015)
How do you rate this movie on a scale of 1-53
```

Out[42]:

	userId	movieId	rating
100832	610	168248	5
100833	610	168250	5
100834	610	168252	5
100835	610	170875	3
100836	611	142488	3

Look at top 10 recommendations for all users

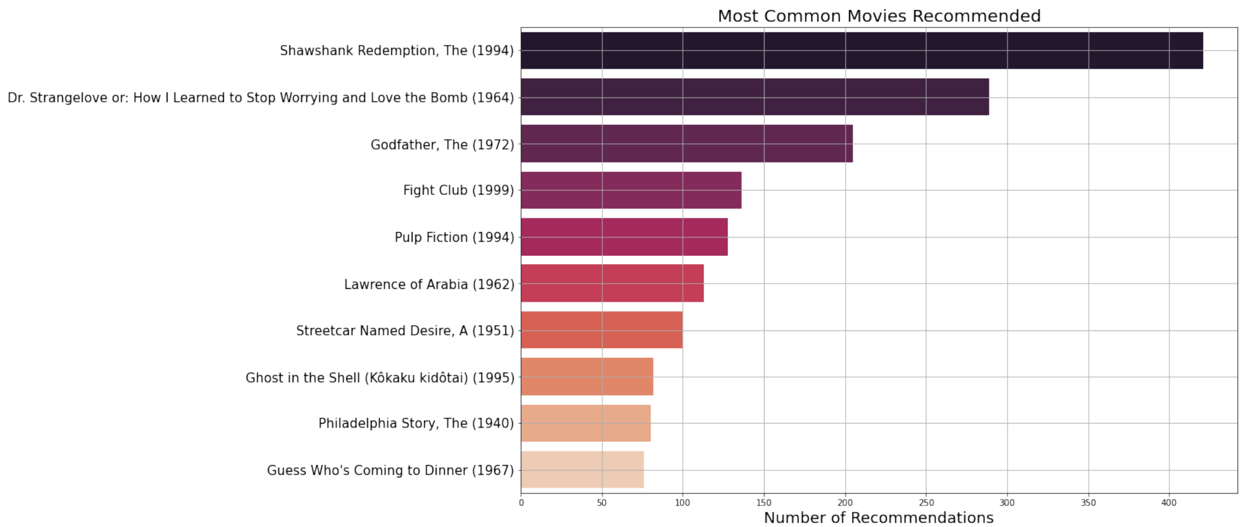
In order to get a feel for the tendencies of the recommendation model.

- determine the movies that are recommended most often to the given user profiles
- define a function to loop through all users and make recommendations for each

In [43]:
```
ef get_most_recommened_movies_for_all_users(n_recs, use_words=False):
    """
    function to loop through all userIds and generate 5 movie recommenda
    number of times each movie was recommended and return the top 10
    """
    userIds = list(np.unique(np.array(ratings.userId)))
    all_recs = []
    for Id in userIds:
        all_recs.extend(recommend_to_user(Id, n_recs, use_words=use_wor

    # get a list of unique movies
    unique_movies = list(np.unique(np.array(all_recs)))

    # count the number of times that movie was recommended and sort ther
    occurance_count = [all_recs.count(movie) for movie in unique_movies]
    movie_rec_count = pd.DataFrame({'movie': unique_movies, 'rec_count'

    # get the top 10 most recommened movies
    movie_rec_count = movie_rec_count[:10]

    # plot the top 10 most recommended movies

    plt.figure(figsize=(15,10))
    ax = sns.barplot(data=movie_rec_count, x='rec_count', y=movie_rec_co
    # ax.bar_label(ax.containers[0], fmt='%.1f')
    plt.yticks(fontsize=15)
    plt.xlabel('Number of Recommendations', fontsize=18)
    plt.ylabel('', fontsize=18)
    plt.title('Most Common Movies Recommended', fontsize=20)
    plt.grid()
    plt.show()

    return movie_rec_count
```

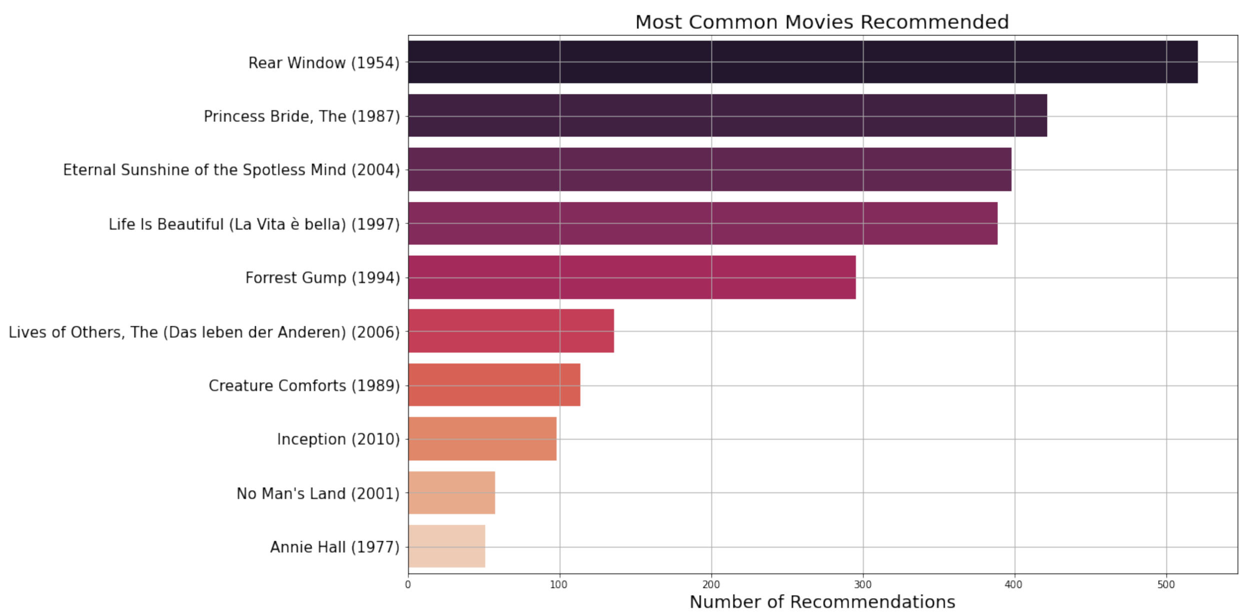
Look at the most common recommendations

In [44]:
```
top_movie_recs = get_most_recommened_movies_for_all_users(5, use_words
```



Look at the most common reccomendations when the top key words for each user are included

In [45]:
```
top_movie_recs_using_key_words = get_most_recommened_movies_for_all_us
```



Fin