MovieLens Recommendation

With an overwhelming amount of information, it can be challenging for people to decide and watch a movie that they would enjoy. Recommendation systems are developed to help resolve this issue by providing movie recommendations.

The following notebooks encode various recommendation systems using information provided by the latest and smallest dataset from MovieLens. It was created in 1997 by GroupLens Research, and the specific dataset used for this project has about 100,000 ratings for 9,000 movies by 600 users. The selected content-based and collaborative filtering recommendation systems were chosen with respect to evaluating them appropriately across the same metric, the **mean average precision at k (MAP@k)**.

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In [4]:
```
#Import libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from scipy.stats import pearsonr
from sklearn.metrics.pairwise import cosine_similarity

import surprise
from surprise import Dataset, Reader, SVD, KNNWithMeans, KNNBasic
from sklearn.model_selection import train_test_split

import ml_metrics as metrics

get_ipython().run_line_magic('matplotlib', 'inline')
```

In [5]:
```
#Load functions

def load_file(df):
    """
```

```
    Reads csv file as a Pandas dataframe.

    Parameters
    ----------
    df: name of csv file

    Returns
    -------
    Dataframe of csv file

    ---
    """
    return pd.read_csv(df)



def surprise_algo(algo, trainset_surprise, testset_surprise, userIds):
    '''
    A list with lists of recommendations for each user; list requires to be stored else

    ---
    Parameters


    algo: Surprise package algorithm

    trainset_surprise: training data, setup from Surprise (not the same as Pandas dataf

    testset_surprise: testing data, setup from Surprise (not the same as Pandas datafra

    userIds: list of all the userIds; to recommend each user in userIds

    ---
    Returns

    A list with lists of recommendations

    ---

    '''

    #Fit SVD recommender
    algo.fit(trainset_surprise)
    algo_pred = algo.test(testset_surprise)

    #Dataframe of test set including predicted ratings
    algo_pred = pd.DataFrame(algo_pred).drop('details', axis=1)
    algo_pred.columns = ['userId','movieId','rating','pred_rating']
    algo_pred = algo_pred.sort_values(['userId','pred_rating'], ascending=[True,False])

    #Recommendations for all users in the test data
    algo_recs = []

    for userId in userIds:
        algo_recs_ = algo_pred.set_index('userId').loc[userId]['movieId'].tolist()
        algo_recs.append(algo_recs_)

    return algo_recs
```

Load Data

In [6]:

```
#Load data and define dataframes
movies = load_file("movies.csv")
ratings = load_file("ratings.csv")
```

Clean data

In [7]:

```
#movies preview
movies.head()

# Check nulls and duplicate rows**
print('Number of nulls in "movies" dataframe:\n' , movies.isnull().sum())
print('\nNumber of duplicate rows in "movies" dataframe :', movies.duplicated().sum())


#Check duplicate movie titles since titles tend to get repeated in movies
print('Number of duplicates: ', movies[['title']].duplicated().sum())
```

```
Number of nulls in "movies" dataframe:
 movieId    0
title      0
genres     0
dtype: int64

Number of duplicate rows in "movies" dataframe : 0
Number of duplicates:  5
```

Duplicate Investigation

In [8]:

```
#Dataframe of duplicates
duplicates = movies[movies['title'].duplicated()]
display(duplicates)

#Store movieIds and titles of duplicates
duplicate_id = list(duplicates['movieId'])
duplicate_title = list(duplicates['title'])

#Dataframe of movie titles with duplicates
duplicate_df = movies[movies['title'].isin(duplicate_title)]
duplicate_df

#Dataframe of original movies with duplicates
original_df = duplicate_df[~duplicate_df['movieId'].isin(duplicate_id)]
display(original_df)

#Original movieIds
original_id = list(original_df['movieId'])
```

	movieId	title	genres
5601	26958	Emma (1996)	Romance
6932	64997	War of the Worlds (2005)	Action|Sci-Fi

	movieId	title	genres
9106	144606	Confessions of a Dangerous Mind (2002)	Comedy|Crime|Drama|Romance|Thriller
9135	147002	Eros (2004)	Drama|Romance
9468	168358	Saturn 3 (1980)	Sci-Fi|Thriller

	movieId	title	genres
650	838	Emma (1996)	Comedy|Drama|Romance
2141	2851	Saturn 3 (1980)	Adventure|Sci-Fi|Thriller
4169	6003	Confessions of a Dangerous Mind (2002)	Comedy|Crime|Drama|Thriller
5854	32600	Eros (2004)	Drama
5931	34048	War of the Worlds (2005)	Action|Adventure|Sci-Fi|Thriller

Combine Genres

Use unique genre values to combine genres.

Merge combined genres to 'movies':

- Fill na with non-duplicates in new genre col
- Drop original 'genres' from "movies"

In [9]:

```
#Combine genres
merge_genres = duplicate_df.groupby(['title'])['genres'].apply('|'.join).reset_index()
merge_genres

#'movies' length
print('Movies length:', len(movies), '\n')

#Remove duplicate titles in movies
movies = movies[~movies['title'].duplicated()]

#Check if duplicates were removed from 'movies'
print('Movies length after removing duplicates:', len(movies), '\n')

#Merge combined genres to 'movies'
movies = pd.merge(movies, merge_genres, on='title', how='left')

#Check merging of combined genres
movies['genres_y'].notnull().sum()

#Fill NaNs with original genres - originals were not duplicates
movies['genres_y'] = movies['genres_y'].fillna(movies['genres_x'])

#Check number of filling non-duplicates
sum(movies['genres_y'] == movies['genres_x'])

#Drop original genres column, 'genres_x'
movies.drop('genres_x',axis=1, inplace=True)

#Rename new genres, which includes combined genres of duplicates
```

```
movies.rename(columns={'genres_y':'genres'}, inplace=True)

#Convert strings of genres into lists
movies['genres'] = movies['genres'].apply(lambda x: str(x).split('|'))

#Keep list of uniques from each list of genres
movies['genres'] = movies['genres'].apply(lambda x: list(set(x)))

#Explode 'genres'
#Create a row for each list element from a column containing lists
movies = movies.explode('genres')
# len(movies)

movies.head()
```

```
Movies length: 9742

Movies length after removing duplicates: 9737
```

Out[9]:

	movieId	title	genres
0	1	Toy Story (1995)	Animation
0	1	Toy Story (1995)	Comedy
0	1	Toy Story (1995)	Children
0	1	Toy Story (1995)	Adventure
0	1	Toy Story (1995)	Fantasy

Additional Cleanups

1. Create new column for year
2. Load ratings
3. Drop timestamp
4. Update movieIDs (replace duplicates with original)
5. Merge movieIDs and ratings

In [10]:

```
#Create 'year' column from extracting title
movies['year'] = movies['title'].str.extract('(\(\d\d\d\d\))',expand=False)
#Remove parentheses in 'year' column
movies['year'] = movies['year'].str.extract('(\d\d\d\d)',expand=False)
#Removing '(year)' in 'title' column
movies['title'] = movies['title'].str.replace('(\(\d\d\d\d\))', '')
#Apply the strip function to get rid of any ending whitespace characters that may have
movies['title'] = movies['title'].apply(lambda x: x.strip())

#Convert years from string to integers
movies['year'] = pd.to_numeric(movies['year'])
movies['year'] = movies['year'].astype('Int64')
print('Number of movie titles with missing year:', movies['year'].isnull().sum(), '\n')

print('Number of nulls in "ratings" dataframe: \n', ratings.isnull().sum())
print('\n Number of duplicates rows in "ratings" dataframe :', ratings.duplicated().sum

ratings.drop('timestamp', axis=1, inplace=True)
```

```
#Find movieIds that require updating
#movieIds reference duplicates
duplicate_ratings = ratings[ratings['movieId'].isin(duplicate_id)]
duplicate_ratings

#Update movieIds - replace duplicate movieIds with original movieIds
print('List of original movieIds: ', original_id)
print('List of duplicate movieIds: ', duplicate_id)

#Dataframe of correpsonding original and duplicate movieIds
update_id = pd.DataFrame([original_id, duplicate_id]).transpose()
update_id.columns = ['original_id','duplicate_id']
display(update_id)

#Merge
ratings = pd.merge(ratings, update_id, left_on='movieId', right_on='duplicate_id', how=

#Number of updated movieIds
ratings['original_id'].notnull().sum()

#Fill nulls with original movieIds (no updates needed for these)
ratings['original_id'] = ratings['original_id'].fillna(ratings['movieId'])

#Drop irrelevant columns
ratings.drop(['movieId','duplicate_id'], axis=1, inplace=True)

#Rename back to original 'movieId'
ratings.rename(columns={'original_id':'movieId'}, inplace=True)

#Convert movieIds to integers
ratings['movieId'] = ratings['movieId'].astype(int)

#Rearrange columns back to original order
ratings = ratings[['userId','movieId','rating']]

#Check for duplicates after updates
pd.merge(ratings, ratings[ratings.duplicated()], how='inner')

#Drop duplicates
ratings.drop_duplicates(inplace=True)

#Number of users
print('Number of users:', len(set(ratings['userId'])), '\n')

#Range - number of ratings
ratings.groupby('userId')['rating'].count().sort_values()

#Preview
ratings.head()

print('Number of movies in "ratings": ', len(set(ratings['movieId'])), '\n')
print('Number of movies in "movies": ', len(set(movies['movieId'])), '\n')

#Check what movies are missing between the two
movies_movielist = pd.Series(list(set(movies['movieId'])))
ratings_movielist = pd.Series(list(set(ratings['movieId'])))

#Movies in 'movies' and not in 'ratings'
movies_movielist[movies_movielist.isin(ratings_movielist)==False]
```

```
#Movies in 'ratings' and not in 'movies'
ratings_movielist[ratings_movielist.isin(movies_movielist)==False]

#Store list of missing movieIds
missing_movies = list(movies_movielist[movies_movielist.isin(ratings_movielist)==False]
```

```
Number of movie titles with missing year: 16

Number of nulls in "ratings" dataframe:
 userId       0
movieId      0
rating       0
timestamp    0
dtype: int64

 Number of duplicates rows in "ratings" dataframe : 0
List of original movieIds:  [838, 2851, 6003, 32600, 34048]
List of duplicate movieIds:  [26958, 64997, 144606, 147002, 168358]
```

	original_id	duplicate_id
0	838	26958
1	2851	64997
2	6003	144606
3	32600	147002
4	34048	168358

```
Number of users: 610

Number of movies in "ratings":  9719

Number of movies in "movies":  9737
```

Notes:

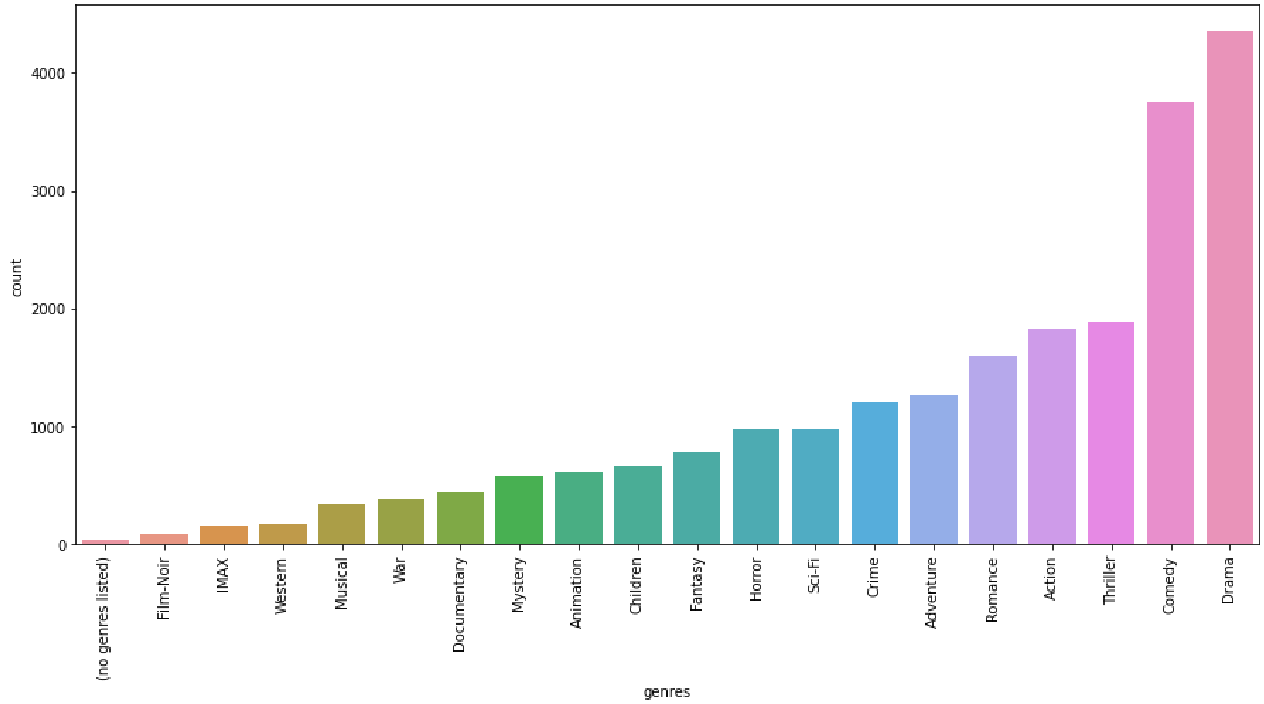
- More movies than users; implying that item-item collaborative filtering would provide better results than user-user collaborative filtering
- Each user rated at least 20 movies (at most 2,698 movies).
- Not all movies have been seen by any of the users

Exploratory Data Analysis (EDA)

Number of releases per genre

In [11]:

```
plt.figure(figsize=(15,7))
sns.countplot(data = movies, x = 'genres', order = movies['genres'].value_counts(ascend
plt.xticks(rotation=90)
plt.show()
```

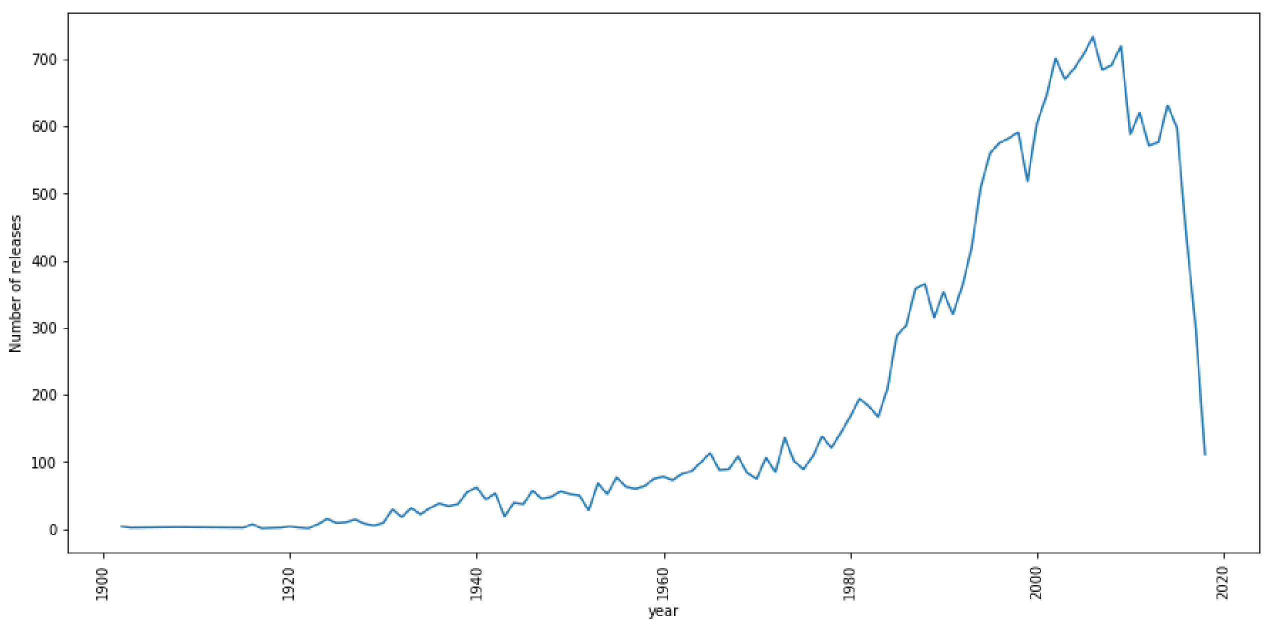


Drama and Comedy are the most common genres found.

Releases per year

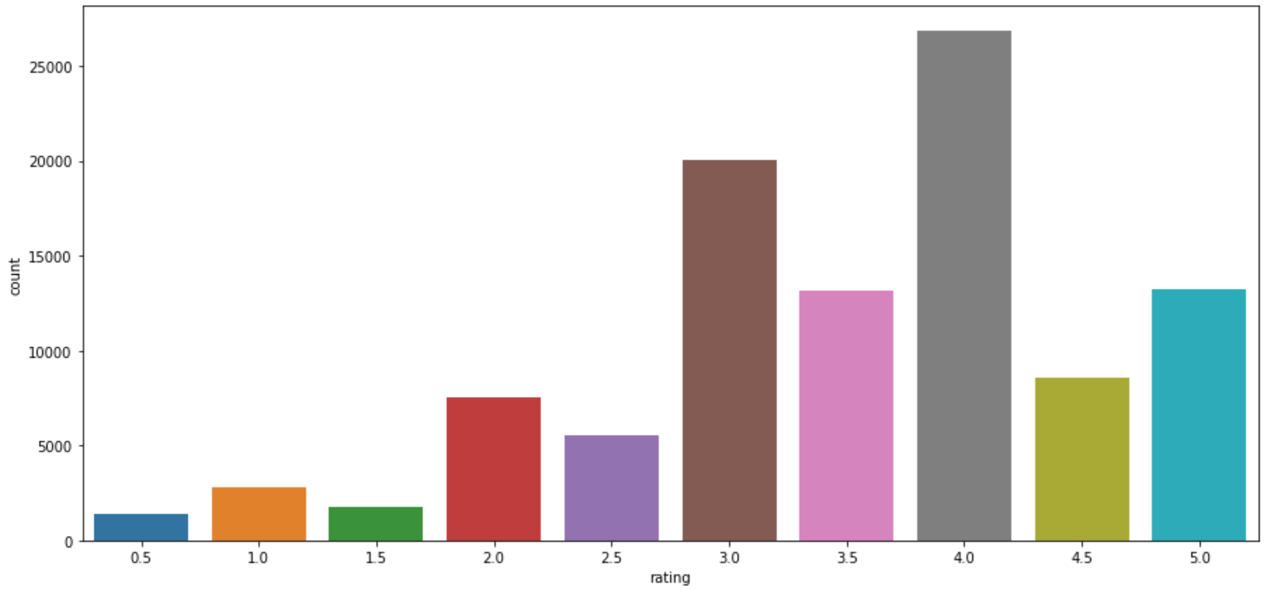
In [12]:

```
year_df = pd.DataFrame(movies.groupby(['year'])['title'].count().reset_index())

plt.figure(figsize=(15,7))
sns.lineplot(data=year_df, x='year', y='title')

years = range(1900,2021,20)
plt.xticks(rotation=90)
plt.xticks(years)
plt.ylabel('Number of releases')

plt.show()
```



Ratings

In [13]:
```
plt.figure(figsize=(15,7))
sns.countplot(data=ratings, x='rating')

plt.show()
```



In [14]:
```
pd.DataFrame(ratings['rating'].describe()).transpose()
```

Out[14]:

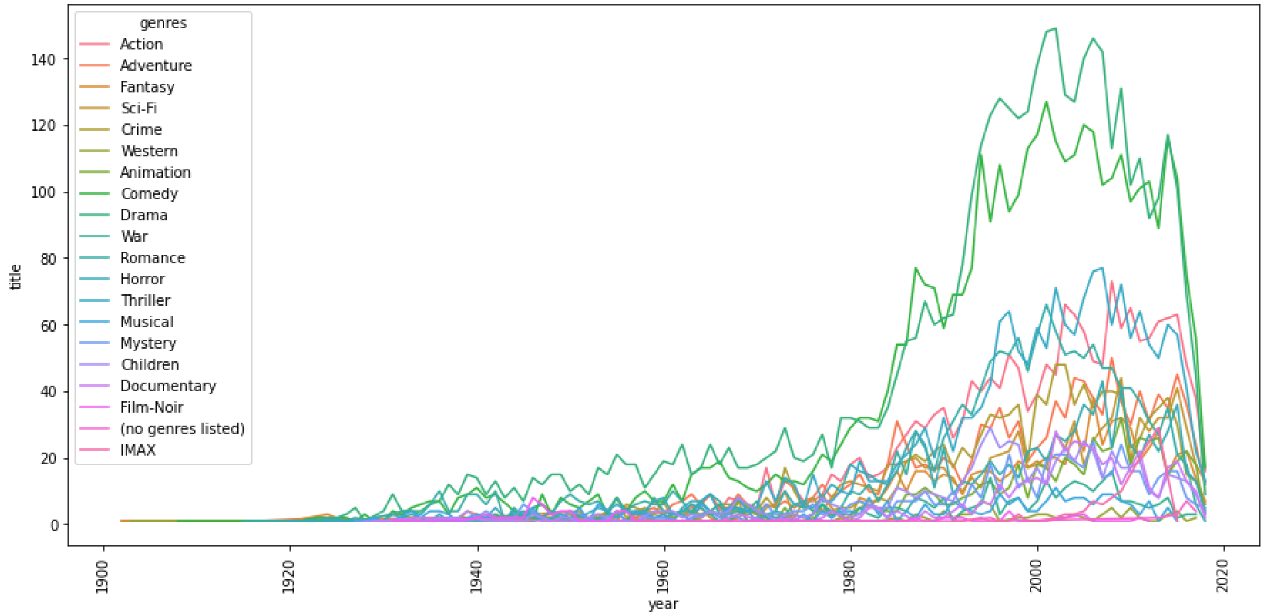
	count	mean	std	min	25%	50%	75%	max
rating	100834.0	3.501552	1.042538	0.5	3.0	3.5	4.0	5.0

Notes:

- Lowest rating is 0.5
- Most ratings 3 or 4 creating a bimodal distribution
- Ratings are also slightly skewed left
- Users perceive a 3 out of 5 as below average, 3.5 out of 5 as an average rating, and 4 out of 5 as an above-average rating.

Number of Releases per year per genre

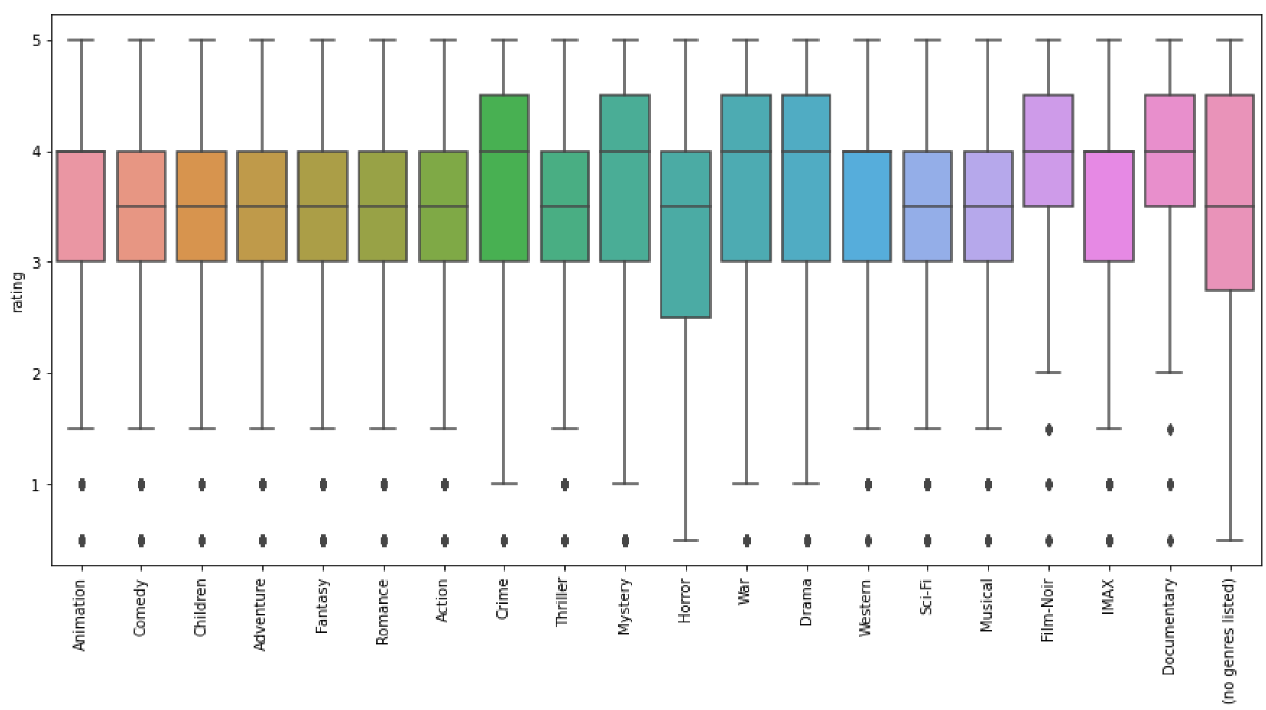
In [15]:
```
year_genres_df = pd.DataFrame(movies.groupby(['year','genres'])['title'].count().reset_
plt.figure(figsize=(15,7))
sns.lineplot(data=year_genres_df, x='year', y='title', hue='genres')

years = range(1900,2021,20)
plt.xticks(rotation=90)
plt.xticks(years)

plt.show()
```



Ratings per genre

In [16]:

```
ratings_df = ratings.merge(movies, how='left', on='movieId')

#Drop columns irrelevant for EDA
ratings_df.drop(['userId','movieId'], axis=1, inplace=True)


#Box plot of genres in ratings data
plt.figure(figsize=(15,7))
sns.boxplot(data = ratings_df, x = 'genres', y = 'rating')
plt.xticks(rotation=90)

plt.show()
```



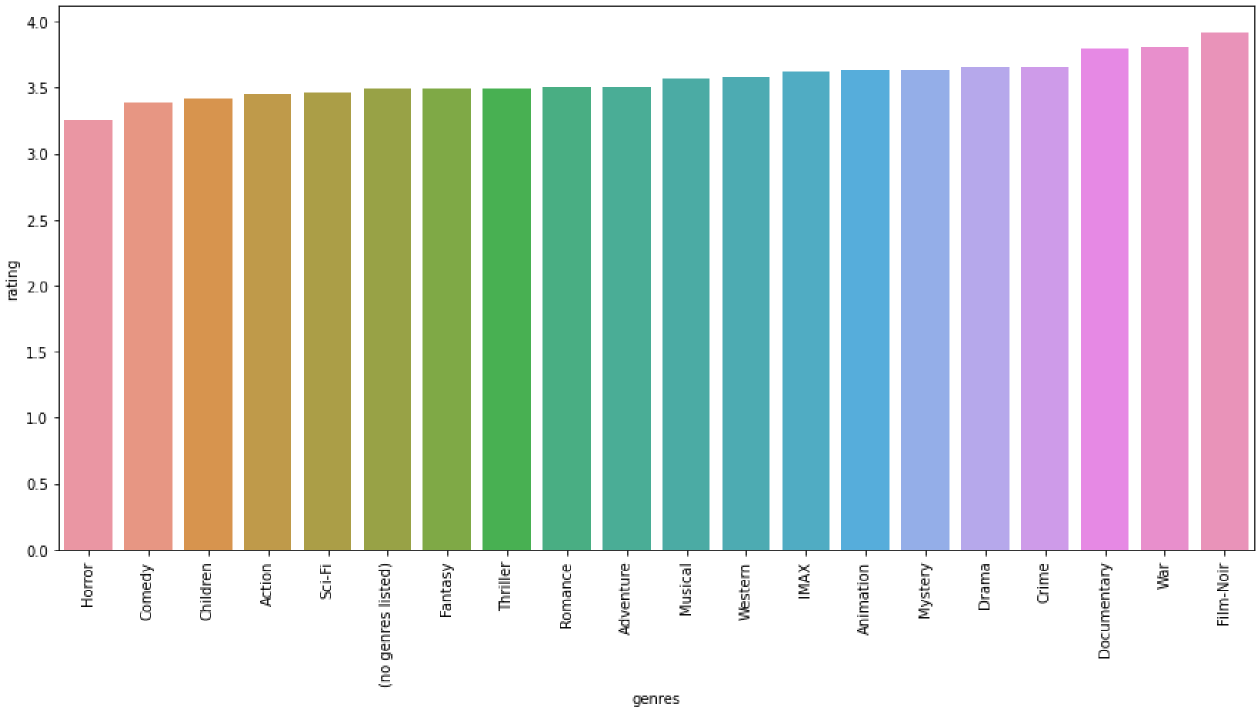
Notes

- The ratings distributions show higher median ratings for Drama, Mystery, Animation, Film-Noir and Documentary movies, while the Children genre show a more likely tendency of lower ratings.

Average Ratings

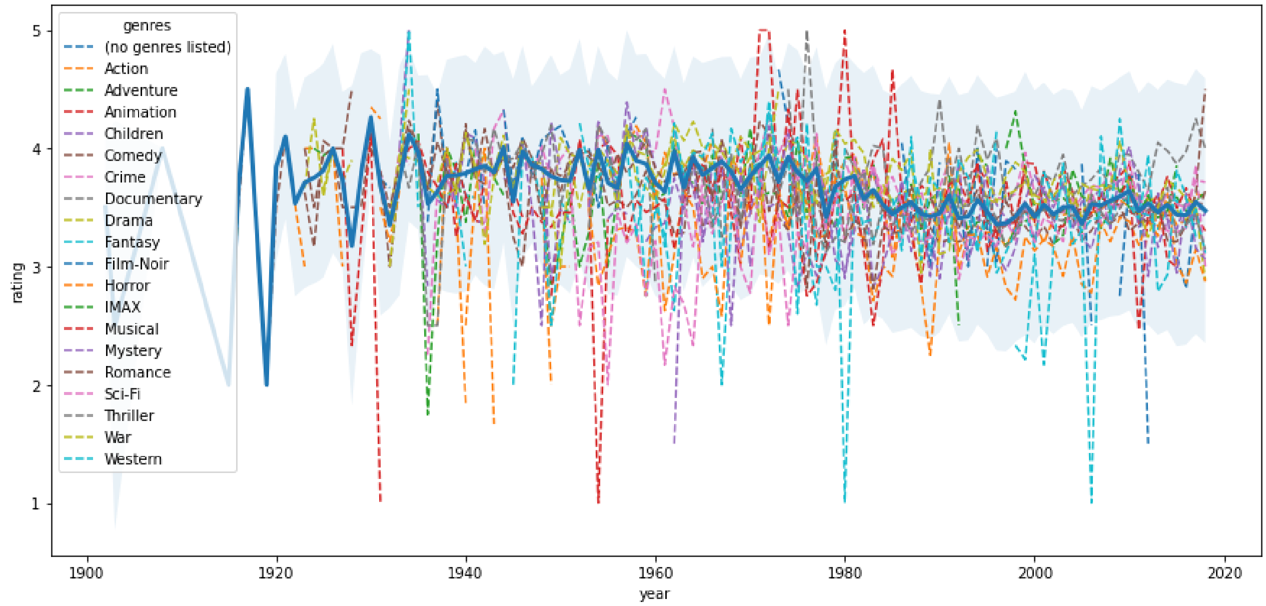
In [17]:

```
avg_ratings = ratings_df.groupby(['genres'])['rating'].mean().sort_values().reset_index

plt.figure(figsize=(15,7))
sns.barplot(data = avg_ratings, x='genres',y='rating')
plt.xticks(rotation=90)

plt.show()
```



In [18]:

```
year_mean = ratings_df.groupby(['year'])['rating'].mean()
year_std = ratings_df.groupby(['year'])['rating'].std()
year = list(year_mean.index.sort_values())

ratings_df.groupby(['genres','year'])['rating'].mean().unstack(0).plot(kind='line', fig

year_mean.plot(kind='line', linewidth=3)
plt.fill_between(year, year_mean - year_std, year_mean + year_std, alpha=0.1)
plt.ylabel('rating')

plt.show()
```



There seems to be a general decline in overall ratings over time.

Data Preparation

In [20]:

```
#Dataframe of one-hot-encoded genres
genres = pd.get_dummies(movies['genres'])

#Concat 'genres' and 'movies'
movies_ = pd.concat([movies, genres], axis=1)


#Drop 'genres' columns
movies_.drop('genres', axis=1, inplace=True)

#Combine one-hot-encoded genres for each movie, unique by movieId
genres_ = movies_.drop(['title','year'], axis=1).groupby(['movieId']).sum().reset_index
genres_ = genres_.set_index('movieId')

#Dataframe of unique movies
unique_movies = movies[['movieId','title','year']].drop_duplicates()

#Keep dataframe on unique movies by movieId and title only (exc. year)
unique_movies = unique_movies[['movieId', 'title']]

# * Train test split was used to evaluate the recommenders
# * Cross validation was not used due to the lengthy execution time (excluding model-ba

# A reader is still needed but only the rating_scale param is required
reader = Reader(rating_scale=(0.5, 5))

#Train-test split
trainset, testset = train_test_split(ratings, test_size=0.25, stratify=ratings['userId'

# A reader required to read rating scale between 0.5 and 5
reader = Reader(rating_scale=(0.5, 5))

# Train and Test Set for SVD
#Train set for surprise (SVD)
```

```
# The columns must correspond to user id, item id and ratings (in that order).
trainset_surprise = Dataset.load_from_df(trainset[['userId', 'movieId', 'rating']], rea
trainset_surprise = trainset_surprise.build_full_trainset()

#Test set for surprise (SVD)
testset_surprise = list(testset.to_records(index=False))
testset_surprise = [tuple(i)for i in testset_surprise]


#Dataframe containing relevant movies only, i.e. 'truths' are seen as ratings > 3.5 (ab
threshold = testset[testset['rating']>3.5]
threshold = threshold.sort_values(['userId','rating'], ascending=[True,False])

truths = []
userIds = list(set(ratings['userId']))

for userId in userIds:
    relevant_ = threshold[threshold['userId']==userId]['movieId'].tolist()
    truths.append(relevant_)
```

User-Movie (item) matrix

- One for the train set [0] and one for the test set [1]
- Not all movies were rated - movieIds of unseen movies in 'missing_movies'
- Incorporate unrated movies to user-item matrix

In [21]:

```
#Make copies and store train and test sets
datasets = [trainset, testset]

#Lists
userIds = list(set(ratings['userId']))
movieIds = list(set(movies['movieId']))

#Set up user-item matrices and store copies
ui_matrix_ = pd.DataFrame(np.nan, index=userIds, columns=movieIds)

train_ui_ = ui_matrix_.copy()
test_ui_ = ui_matrix_.copy()

ui_matrices = [train_ui_, test_ui_]

#Update user-item matrices
#0 = training set
#1 = test set

for i in 0,1:
    dataset_ui_ = pd.pivot_table(datasets[i], values='rating', index=['userId'], column
    ui_matrices[i].update(dataset_ui_)

#Preview of training set user-item matrix
train_ui = ui_matrices[0]
print('Preview training set UI Matrix:\n')
print(train_ui.head())
#Preview of test set user-item matrix
test_ui = ui_matrices[1]
print('Preview training set UI Matrix:\n')
print(test_ui.head())
```

```
#Check nulls
print('Number of not nulls in blank user-item matrix: ', ui_matrix_.notnull().sum().sum
print('Number of not nulls in training set user-item matrix: ', ui_matrices[0].notnull(
print('Number of not nulls in test set user-item matrix: ', ui_matrices[1].notnull().su
print('Number of ratings in total: ', len(ratings))
```

```
Preview training set UI Matrix:

   1      2      3      4      ...  32743  98279  65514  98296
1    NaN    NaN    4.0    NaN  ...    NaN    NaN    NaN    NaN
2    NaN    NaN    NaN    NaN  ...    NaN    NaN    NaN    NaN
3    NaN    NaN    NaN    NaN  ...    NaN    NaN    NaN    NaN
4    NaN    NaN    NaN    NaN  ...    NaN    NaN    NaN    NaN
5    4.0    NaN    NaN    NaN  ...    NaN    NaN    NaN    NaN

[5 rows x 9737 columns]
Preview training set UI Matrix:

   1      2      3      4      ...  32743  98279  65514  98296
1    4.0    NaN    NaN    NaN  ...    NaN    NaN    NaN    NaN
2    NaN    NaN    NaN    NaN  ...    NaN    NaN    NaN    NaN
3    NaN    NaN    NaN    NaN  ...    NaN    NaN    NaN    NaN
4    NaN    NaN    NaN    NaN  ...    NaN    NaN    NaN    NaN
5    NaN    NaN    NaN    NaN  ...    NaN    NaN    NaN    NaN

[5 rows x 9737 columns]
Number of not nulls in blank user-item matrix:  0
Number of not nulls in training set user-item matrix:  75625
Number of not nulls in test set user-item matrix:  25209
Number of ratings in total:  100834
```

Boolean Matrices

- Boolean identifier of training set and ratings to be predicted:

> 1 = rated, 0 = not rated (true ui) 1 = not rated, 0 = rated (pred ui)

In [24]:

```
pred_ui_bool = train_ui_.isnull().astype(float)
true_ui_bool = 1-pred_ui_bool
print(pred_ui_bool.head())
print(true_ui_bool.head())
```

```
   1      2      3      4      ...  32743  98279  65514  98296
1    1.0    1.0    0.0    1.0  ...    1.0    1.0    1.0    1.0
2    1.0    1.0    1.0    1.0  ...    1.0    1.0    1.0    1.0
3    1.0    1.0    1.0    1.0  ...    1.0    1.0    1.0    1.0
4    1.0    1.0    1.0    1.0  ...    1.0    1.0    1.0    1.0
5    0.0    1.0    1.0    1.0  ...    1.0    1.0    1.0    1.0

[5 rows x 9737 columns]
   1      2      3      4      ...  32743  98279  65514  98296
1    0.0    0.0    1.0    0.0  ...    0.0    0.0    0.0    0.0
2    0.0    0.0    0.0    0.0  ...    0.0    0.0    0.0    0.0
3    0.0    0.0    0.0    0.0  ...    0.0    0.0    0.0    0.0
4    0.0    0.0    0.0    0.0  ...    0.0    0.0    0.0    0.0
5    1.0    0.0    0.0    0.0  ...    0.0    0.0    0.0    0.0

[5 rows x 9737 columns]
```

User History

In [25]:

```
user_movies = []
user_ratings = []

for userId in userIds:
    user_ = pd.DataFrame(train_ui_.loc[userId][train_ui_.loc[userId].notnull()])
    user_ = user_.reset_index()
    user_.columns=['movieId', 'rating']
    movies_ = list(user_['movieId'])
    ratings_ = list(user_['rating'])

    user_movies.append(movies_)
    user_ratings.append(ratings_)

#Convert lists to dataframe
user_items = pd.DataFrame([userIds, user_movies, user_ratings, truths]).transpose()

#Name columns
user_items.columns=['userId','movieId','rating','actuals']
#Set index
user_items = user_items.set_index('userId')

user_items
```

Out[25]:

	movieId	rating	actuals
userId			
1	[3, 6, 47, 50, 70, 101, 110, 151, 157, 223, 23...	[4.0, 4.0, 5.0, 5.0, 3.0, 5.0, 4.0, 5.0, 5.0, ...	[216, 362, 3033, 1954, 457, 2571, 2692, 1224, ...
2	[333, 131724, 99114, 3578, 71535, 6874, 106782...	[4.0, 5.0, 3.5, 4.0, 3.0, 4.0, 5.0, 3.5, 4.0, ...	[122882, 60756, 68157, 1704, 80489, 79132]
3	[527, 647, 688, 849, 914, 1124, 1263, 1275, 13...	[0.5, 0.5, 0.5, 5.0, 0.5, 0.5, 0.5, 3.5, 0.5, ...	[7991, 70946, 5746, 6835]
4	[21, 45, 47, 106, 125, 126, 162, 171, 222, 232...	[3.0, 3.0, 2.0, 4.0, 5.0, 1.0, 5.0, 3.0, 1.0, ...	[1834, 3851, 1967, 2791, 912, 2692, 898, 2174,...
5	[1, 21, 34, 36, 50, 58, 110, 150, 232, 247, 25...	[4.0, 4.0, 4.0, 4.0, 4.0, 5.0, 4.0, 3.0, 4.0, ...	[290, 596, 590, 474, 261, 531]
...	...	...	...
606	[1, 7, 11, 15, 18, 29, 32, 36, 46, 47, 50, 58,...	[2.5, 2.5, 2.5, 3.5, 4.0, 4.5, 4.0, 3.5, 4.0, ...	[931, 296, 63082, 7579, 3310, 905, 232, 3083, ...
607	[11, 34, 86, 110, 112, 153, 165, 204, 208, 241...	[3.0, 3.0, 4.0, 5.0, 2.0, 3.0, 4.0, 3.0, 3.0, ...	[1917, 318, 1997, 736, 150, 2403, 2762, 2268, ...
608	[1, 2, 3, 10, 19, 21, 24, 31, 34, 44, 47, 48, ...	[2.5, 2.0, 2.0, 4.0, 2.0, 3.5, 2.0, 3.0, 3.5, ...	[2502, 2028, 4995, 6618, 8970, 16, 6373, 4776,...
609	[10, 110, 116, 137, 150, 161, 185, 208, 253, 2...	[4.0, 3.0, 3.0, 3.0, 3.0, 3.0, 3.0, 3.0, 4.0, ...	[457]
610	[1, 6, 16, 32, 47, 50, 70, 95, 110, 111, 112, ...	[5.0, 5.0, 4.5, 4.5, 5.0, 4.0, 4.0, 3.5, 4.5, ...	[100906, 5772, 1279, 78499, 778, 112290, 1258,...

610 rows × 3 columns

Modeling

1. Content-based filtering
2. Collaborative filtering

Content-based filtering

- Makes use of item attributes to make recommendation, using movie genre.

In [28]:

```
user_profiles = []

for index in user_items.index:
    user_movies = user_items['movieId'][index]
    user_rating = user_items['rating'][index]

    #Convert list to array
    user_rating = np.array(user_rating)
    #Convert dataframe to a numpy array
    user_genres = genres_.reset_index()[genres_.reset_index()['movieId'].isin(user_movi
    user_genres = user_genres.set_index('movieId')
    user_genres = user_genres.to_numpy()

    #Dot product of arrays to compute user profile
    user_profile = user_rating.dot(user_genres)

    #Convert user profile values between 0 and 1
    profile_sum = sum(user_profile)
    user_profile = [x/profile_sum for x in user_profile]

    #Append to 'user_profiles'
    user_profiles.append(user_profile)

#Convert to dataframe of user profiles
user_profiles = pd.DataFrame(user_profiles)

#Compute recommendation scores (between 0 and 1)*

#Create genres matrix (genres x movieIds)
genres_array = genres_.transpose().to_numpy()
#Dot product of user profiles and genres to compute recommendation scores
content_rec = pd.DataFrame(np.dot(user_profiles,genres_array))

content_rec.index = userIds
content_rec.index.name = 'userId'

content_rec.columns = movieIds
content_rec.columns.name = 'movieId'

#Unseen movies (predicted)
print('Predicted unseen movies:\n')
print(pred_ui_bool.head())

#Scores of unseen movies (recommendations only)
rec_scores_df = pred_ui_bool*content_rec
print('Scores of unseen movies:\n')
print(rec_scores_df.head())
```

```
#Store ordered recommendations
rec_ordered_scores = []

for userId in userIds:
    rec_ordered_scores_ = list(rec_scores_df.loc[userId].sort_values(ascending=False).i
    rec_ordered_scores.append(rec_ordered_scores_)

#Convert dataframe to lists for each user
rec_ordered = pd.DataFrame(rec_ordered_scores).values.tolist()

#Store recommendations to new column in user_items
user_items['content_based_rec']=rec_ordered

print(user_items.head())
```

```
Predicted unseen movies:

   1      2      3      4      ...  32743  98279  65514  98296
1    1.0    1.0    0.0    1.0  ...    1.0    1.0    1.0    1.0
2    1.0    1.0    1.0    1.0  ...    1.0    1.0    1.0    1.0
3    1.0    1.0    1.0    1.0  ...    1.0    1.0    1.0    1.0
4    1.0    1.0    1.0    1.0  ...    1.0    1.0    1.0    1.0
5    0.0    1.0    1.0    1.0  ...    1.0    1.0    1.0    1.0

[5 rows x 9737 columns]
Scores of unseen movies:

      1         2         3       ...     98279     65514     98296
1  0.418645  0.259387  0.000000  ...  0.098403  0.174363  0.112214
2  0.149758  0.048309  0.101449  ...  0.234300  0.149758  0.101449
3  0.232779  0.190024  0.047506  ...  0.064133  0.171021  0.038005
4  0.321060  0.106038  0.305596  ...  0.232695  0.063328  0.199558
5  0.000000  0.185083  0.196133  ...  0.204420  0.107735  0.118785

[5 rows x 9737 columns]
                                                  movieId  ...
content_based_rec
userId                                                     ...
1       [3, 6, 47, 50, 70, 101, 110, 151, 157, 223, 23...  ...  [180497, 26171, 178615,
4298, 128852, 74647, 5...
2       [333, 131724, 99114, 3578, 71535, 6874, 106782...  ...  [180497, 81784, 71530, 1
285, 4105, 5771, 122, ...
3       [527, 647, 688, 849, 914, 1124, 1263, 1275, 13...  ...  [178615, 44511, 171811,
128852, 172233, 7223, ...
4       [21, 45, 47, 106, 125, 126, 162, 171, 222, 232...  ...  [180497, 4105, 4298, 344
5, 1642, 5009, 73042, ...
5       [1, 21, 34, 36, 50, 58, 110, 150, 232, 247, 25...  ...  [4105, 1635, 180497, 122
932, 4298, 27370, 5009...

[5 rows x 4 columns]
```

- Movies with more genres tend to be the top recommendations since content-based filtering tend to resolve cold starts.

Collaborative-based filtering - Model-based

> - Utilizes the `Surprise` package to conduct SVD, KNNBasic, and KNNwithMeans algorithms to predcit unseen movie ratings.

In [29]:
```
#SVD, matrix factorisation
svd = SVD()

#KNN user-user collaborative filtering
knn_uu = KNNWithMeans(sim_options = {'name': 'pearson'}, user_based = True)

#KNN item-item collaborative filtering
knn_ii = KNNBasic(sim_options = {'name': 'cosine'}, user_based = False)

surprise_models = [svd, knn_uu, knn_ii]

#Recommendations from surprise
# Save recommendations
surprise_recs = []

for model in surprise_models:
    model_recs = surprise_algo(model, trainset_surprise, testset_surprise, userIds)
    surprise_recs.append(model_recs)

surprise_recs = pd.DataFrame(surprise_recs).transpose()
surprise_recs.index = userIds
surprise_recs.columns = ['SVD_recs', 'KNN_user_user_recs', 'KNN_item_item_recs']


user_items = pd.merge(user_items, surprise_recs, left_index=True, right_index=True)
user_items
```

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

Out[29]:

	movieId	rating	actuals	content_based_rec	SVD_recs	KNN_user_user_recs	KNN_item_item_recs
userId							
1	[3, 6, 47, 50, 70, 101, 110, 151, 157, 223, 23...	[4.0, 4.0, 5.0, 5.0, 3.0, 5.0, 4.0, 5.0, 5.0, ...	[216, 362, 3033, 1954, 457, 2571, 2692, 1224, ...	[180497, 26171, 178615, 4298, 128852, 74647, 5...	[1, 3147, 923, 2005, 593, 2997, 2571, 1408, 45...	[457, 3147, 1024, 2596, 2761, 1, 1090, 2571, 1...	[2571, 296, 1222, 1291, 3147, 2502, 1, 923, 45..
2	[333, 131724, 99114, 3578, 71535, 6874, 106782...	[4.0, 5.0, 3.5, 4.0, 3.0, 4.0, 5.0, 3.5, 4.0, ...	[122882, 60756, 68157, 1704, 80489, 79132]	[180497, 81784, 71530, 1285, 4105, 5771, 122, ...	[318, 1704, 79132, 68157, 80489, 122882, 60756]	[318, 79132, 1704, 122882, 68157, 80489, 60756]	[318, 68157, 79132, 80489, 1704, 122882, 60756]

	movieId	rating	actuals	content_based_rec	SVD_recs	KNN_user_user_recs	KNN_item_item_recs
userId							
3	[527, 647, 688, 849, 914, 1124, 1263, 1275, 13...	[0.5, 0.5, 0.5, 5.0, 0.5, 0.5, 0.5, 3.5, 0.5, ...	[7991, 70946, 5746, 6835]	[178615, 44511, 171811, 128852, 172233, 7223, ...	[1272, 720, 1093, 5746, 6835, 31, 6238, 7991, ...	[70946, 5746, 6835, 720, 1272, 7991, 6238, 201...	[1272, 720, 1093, 5746, 6835, 2018, 6238, 31, ..
4	[21, 45, 47, 106, 125, 126, 162, 171, 222, 232...	[3.0, 3.0, 2.0, 4.0, 5.0, 1.0, 5.0, 3.0, 1.0, ...	[1834, 3851, 1967, 2791, 912, 2692, 898, 2174,...	[180497, 4105, 4298, 3445, 1642, 5009, 73042, ...	[1136, 912, 1198, 1196, 1219, 2921, 648, 1073,...	[4144, 2921, 1136, 1719, 1198, 1834, 4741, 279...	[176, 2921, 1719, 912, 1198, 898, 1196, 1136, ..
5	[1, 21, 34, 36, 50, 58, 110, 150, 232, 247, 25...	[4.0, 4.0, 4.0, 4.0, 4.0, 5.0, 4.0, 3.0, 4.0, ...	[290, 596, 590, 474, 261, 531]	[4105, 1635, 180497, 122932, 4298, 27370, 5009...	[265, 590, 531, 290, 474, 261, 596, 39, 592, 3...	[265, 590, 531, 261, 474, 596, 290, 592, 344, ...	[590, 265, 261, 290, 474, 592, 596, 531, 39, 3..
...	...	...	...	...	...	...	..
606	[1, 7, 11, 15, 18, 29, 32, 36, 46, 47, 50, 58,...	[2.5, 2.5, 2.5, 3.5, 4.0, 4.5, 4.0, 3.5, 4.0, ...	[931, 296, 63082, 7579, 3310, 905, 232, 3083, ...	[4105, 4298, 180497, 6994, 5009, 1642, 3445, 8...	[2959, 4848, 858, 2329, 318, 296, 2318, 1136, ...	[30803, 6345, 7121, 26810, 5915, 943, 1701, 23...	[30803, 6345, 26810, 5915, 7121, 318, 1701, 85..
607	[11, 34, 86, 110, 112, 153, 165, 204, 208, 241...	[3.0, 3.0, 4.0, 5.0, 2.0, 3.0, 4.0, 3.0, 3.0, ...	[1917, 318, 1997, 736, 150, 2403, 2762, 2268, ...	[180497, 71530, 178615, 4298, 172233, 26171, 4...	[318, 2762, 3363, 1394, 1356, 593, 1207, 1079,...	[188, 318, 1079, 1997, 2268, 150, 1394, 2403, ...	[318, 2762, 589, 593, 1207, 150, 1079, 2791, 1..

userId	movieId	rating	actuals	content_based_rec	SVD_recs	KNN_user_user_recs	KNN_item_item_recs
608	[1, 2, 3, 10, 19, 21, 24, 31, 34, 44, 47, 48, ...	[2.5, 2.0, 2.0, 4.0, 2.0, 3.5, 2.0, 3.0, 3.5, ...	[2502, 2028, 4995, 6618, 8970, 16, 6373, 4776,...	[180497, 4105, 4298, 26171, 71530, 5670, 17861...	[2329, 2502, 3275, 4995, 1350, 32, 1215, 2194,...	[7773, 3275, 741, 50, 4733, 1136, 6104, 1208, ...	[5952, 1089, 50, 2329, 4993, 608, 3275, 4995, ..
609	[10, 110, 116, 137, 150, 161, 185, 208, 253, 2...	[4.0, 3.0, 3.0, 3.0, 3.0, 3.0, 3.0, 3.0, 4.0, ...	[457]	[180497, 8874, 422, 5016, 4298, 71530, 4105, 1...	[457, 1, 1059, 1056, 892, 613, 329, 292, 231]	[1, 892, 1059, 457, 329, 292, 1056, 231, 613]	[457, 1, 1059, 892, 292, 329, 231, 1056, 613]
610	[1, 6, 16, 32, 47, 50, 70, 95, 110, 111, 112, ...	[5.0, 5.0, 4.5, 4.5, 5.0, 4.0, 4.0, 3.5, 4.5, ...	[100906, 5772, 1279, 78499, 778, 112290, 1258,...	[180497, 71530, 26171, 172233, 4298, 178615, 8...	[6874, 48516, 78499, 1136, 1200, 4011, 8874, 1...	[89118, 7894, 136016, 27563, 5772, 1283, 80831...	[115122, 27563, 5772, 86142, 7894, 48516, 1214..

610 rows × 7 columns

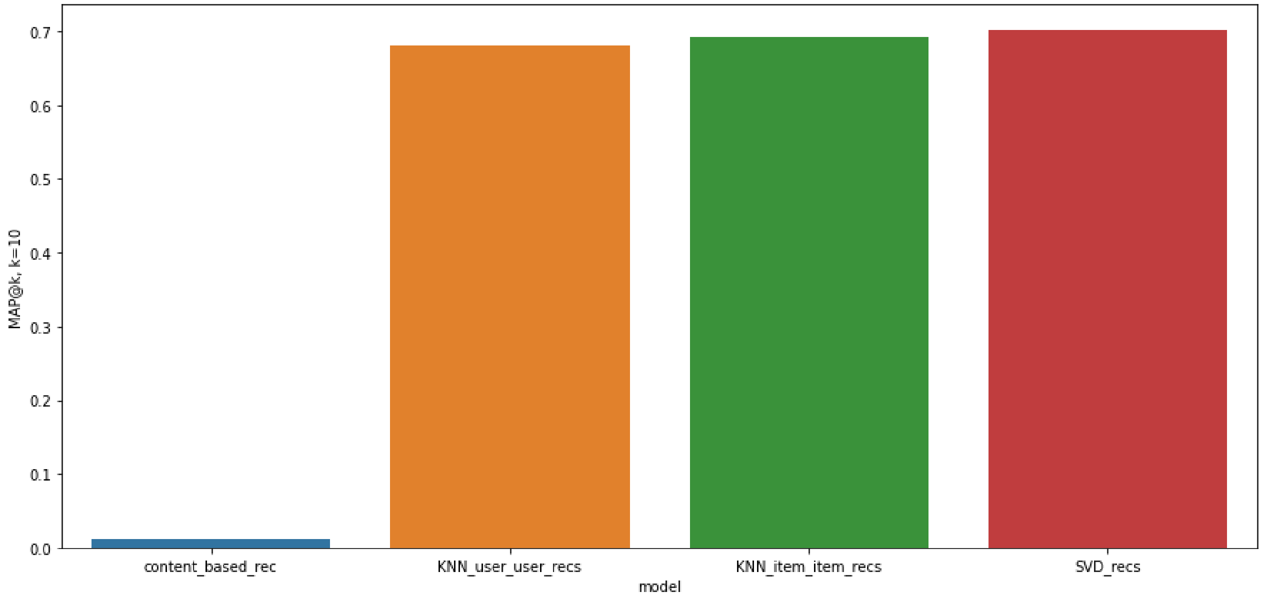
Evaluation

In [30]:

```
#Take column for user recommendations
rec_cols = user_items.columns[3:]

#Results for Mean Average Precision @ K (MAPk), where K = 10

#Print and store MAPk results
mapk = []

for rec in rec_cols:
    mapk_ = metrics.mapk(user_items['actuals'], user_items[rec], k=10)
    print(rec, ': ', mapk_)
    mapk.append(mapk_)

#Results dataframe
mapk = pd.DataFrame([rec_cols, mapk]).transpose()
mapk.columns = ['model', 'MAP@k, k=10']
mapk = mapk.sort_values('MAP@k, k=10')

#Plot results
```

```
plt.figure(figsize=(15,7))
sns.barplot(data = mapk, x='model', y= 'MAP@k, k=10')

plt.show()
```

```
content_based_rec :  0.012197567004944053
SVD_recs :  0.7012493200376689
KNN_user_user_recs :  0.680704846009442
KNN_item_item_recs :  0.6934258342833187
```



Results

- Content-based filtering based on movie genres did not produce a material MAP@k. There is a bias towards movies associated with more genres listed. This recommeder can be improved by adding more attributes. This can include movie cast names, directors, movie tags, etc.
- Model-based recommenders performed better in terms of MAP@k. This can be attributed to sparsity in the user-item matrix wherein only a selected number of user/item with significant levels of similarities was used during computation.

This is likely due to the algorithms selecting only a number of user/item similarities rather than applying all users/items during computation. Given the sparsity in the user-item matrix, it is likely most users/items show insignificant levels of similarities.

- The MAP@K, where K = 10, shows the SVD recommender performed the best on the test set, and marginally better than the other algorithms.