

# JonJacobsonDSC630Week10Exercise10.2

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## 1 Recommendation Systems

We will build four recommendation systems and then combine them to help compensate for weaknesses in each.

1. Popularity Ranking (Combining Ratings and Number of Ratings)
2. Nearest Neighbors Based Recommender
3. Correlation-Based Recommender
4. Genre-Based TFIDF Recommender

```
[276]: import pandas as pd

ratings = pd.read_csv("ratings.csv")
movies = pd.read_csv("movies.csv")

print("ratings.csv\n", ratings.head())
print()
print("movies.csv\n", movies.head())
```

```
ratings.csv
    userId   movieId   rating   timestamp
0       1         1     4.0  964982703
1       1         3     4.0  964981247
2       1         6     4.0  964982224
3       1        47     5.0  964983815
4       1        50     5.0  964982931

movies.csv
      movieId          title \
0           1    Toy Story (1995)
1           2        Jumanji (1995)
2           3  Grumpier Old Men (1995)
3           4    Waiting to Exhale (1995)
4           5  Father of the Bride Part II (1995)

      genres
0  Adventure|Animation|Children|Comedy|Fantasy
1  Adventure|Children|Fantasy
2  Comedy|Romance
```

3	Comedy   Drama   Romance
4	Comedy

### 1.0.1 Popularity Ranking (Combining Ratings and Number of Ratings)

```
[288]: # Add some features to our movies, including a custom metric for rating.

import math

movie_freq = ratings[['userId', 'movieId']].groupby(
    'movieId').count().reset_index()
movie_freq.columns = ['movieId', 'n_ratings']

mean_rating = ratings.groupby('movieId')[['rating']].mean()
mean_rating = mean_rating.rename(columns={'rating': 'mean_rating'})
combined = pd.merge(movie_freq, mean_rating, on='movieId')
combined = pd.merge(combined, movies, on='movieId')

# We use a custom metric that combines mean rating with the number of ratings.
# This attempts to quantify the increased chance that someone would like to see
# a movie that many others have seen.
combined['log_ratings'] = combined['n_ratings'].apply(
    lambda x: math.log(
        max(x-5, 0.1) # Don't count the first five ratings
        ,100) # Only count ratings at a slow logarithmic rate
    -0.85) # Adjust so that movies with 50 ratings are not affected.

combined['adj_rating'] = combined['mean_rating']+combined['log_ratings']
combined = combined[[
    'movieId',
    'mean_rating',
    'n_ratings',
    'log_ratings',
    'adj_rating'
]]
adj_movies = movies.merge(combined, on='movieId')
adj_movies.sort_values(by='adj_rating', ascending=False).head()
```

```
[288]:      movieId                                title \
277       318          Shawshank Redemption, The (1994)
2224      2959          Fight Club (1999)
257       296          Pulp Fiction (1994)
224       260  Star Wars: Episode IV - A New Hope (1977)
659       858          Godfather, The (1972)
314       356          Forrest Gump (1994)
1938      2571          Matrix, The (1999)
461       527  Schindler's List (1993)
```

46	50	Usual Suspects, The (1995)
510	593	Silence of the Lambs, The (1991)
897	1196	Star Wars: Episode V - The Empire Strikes Back...
899	1198	Raiders of the Lost Ark (Indiana Jones and the...
6693	58559	Dark Knight, The (2008)
921	1221	Godfather: Part II, The (1974)
898	1197	Princess Bride, The (1987)
913	1213	Goodfellas (1990)
910	1210	Star Wars: Episode VI - Return of the Jedi (1983)
1502	2028	Saving Private Ryan (1998)
1733	2329	American History X (1998)
6298	48516	Departed, The (2006)
895	1193	One Flew Over the Cuckoo's Nest (1975)
827	1089	Reservoir Dogs (1992)
602	750	Dr. Strangelove or: How I Learned to Stop Worr...
3633	4993	Lord of the Rings: The Fellowship of the Ring,...
4791	7153	Lord of the Rings: The Return of the King, The...
520	608	Fargo (1996)
694	912	Casablanca (1942)
908	1208	Apocalypse Now (1979)
862	1136	Monty Python and the Holy Grail (1975)
3136	4226	Memento (2000)
97	110	Braveheart (1995)
3617	4973	Amelie (Fabuleux destin d'Amélie Poulain, Le) ...
686	904	Rear Window (1954)
4900	7361	Eternal Sunshine of the Spotless Mind (2004)
2144	2858	American Beauty (1999)
2370	3147	Green Mile, The (1999)
4131	5952	Lord of the Rings: The Two Towers, The (2002)
968	1270	Back to the Future (1985)
1283	1704	Good Will Hunting (1997)
507	589	Terminator 2: Judgment Day (1991)
474	541	Blade Runner (1982)
7355	79132	Inception (2010)
974	1276	Cool Hand Luke (1967)
2992	4011	Snatch (2000)
398	457	Fugitive, The (1993)
43	47	Seven (a.k.a. Se7en) (1995)
3979	5618	Spirited Away (Sen to Chihiro no kamikakushi) ...
989	1291	Indiana Jones and the Last Crusade (1989)
925	1225	Amadeus (1984)
1729	2324	Life Is Beautiful (La Vita è bella) (1997)
98	111	Taxi Driver (1976)
905	1204	Lawrence of Arabia (1962)
31	32	Twelve Monkeys (a.k.a. 12 Monkeys) (1995)
6993	68157	Inglourious Basterds (2009)
922	1222	Full Metal Jacket (1987)

956	1258		Shining, The (1980)		
0	1		Toy Story (1995)		
950	1252		Chinatown (1974)		
254	293	Léon: The Professional (a.k.a. The Professional...)			
4170	6016		City of God (Cidade de Deus) (2002)		
			genres	mean_rating	n_ratings \
277			Crime Drama	4.429022	317
2224			Action Crime Drama Thriller	4.272936	218
257			Comedy Crime Drama Thriller	4.197068	307
224			Action Adventure Sci-Fi	4.231076	251
659			Crime Drama	4.289062	192
314			Comedy Drama Romance War	4.164134	329
1938			Action Sci-Fi Thriller	4.192446	278
461			Drama War	4.225000	220
46			Crime Mystery Thriller	4.237745	204
510			Crime Horror Thriller	4.161290	279
897			Action Adventure Sci-Fi	4.215640	211
899			Action Adventure	4.207500	200
6693			Action Crime Drama IMAX	4.238255	149
921			Crime Drama	4.259690	129
898		Action Adventure Comedy Fantasy Romance		4.232394	142
913			Crime Drama	4.250000	126
910			Action Adventure Sci-Fi	4.137755	196
1502			Action Drama War	4.146277	188
1733			Crime Drama	4.217054	129
6298			Crime Drama Thriller	4.252336	107
895			Drama	4.203008	133
827			Crime Mystery Thriller	4.202290	131
602			Comedy War	4.268041	97
3633			Adventure Fantasy	4.106061	198
4791		Action Adventure Drama Fantasy		4.118919	185
520			Comedy Crime Drama Thriller	4.116022	181
694			Drama Romance	4.240000	100
908			Action Drama War	4.219626	107
862			Adventure Comedy Fantasy	4.161765	136
3136			Mystery Thriller	4.122642	159
97			Action Drama War	4.031646	237
3617			Comedy Romance	4.183333	120
686			Mystery Thriller	4.261905	84
4900			Drama Romance Sci-Fi	4.160305	131
2144			Drama Romance	4.056373	204
2370			Crime Drama	4.148649	111
4131			Adventure Fantasy	4.021277	188
968			Adventure Comedy Sci-Fi	4.038012	171
1283			Drama Romance	4.078014	141
507			Action Sci-Fi	3.970982	224

474	Action Sci-Fi Thriller	4.100806	124
7355	Action Crime Drama Mystery Sci-Fi Thriller IMAX	4.066434	143
974	Drama	4.271930	57
2992	Comedy Crime Thriller	4.155914	93
398	Thriller	3.992105	190
43	Mystery Thriller	3.975369	203
3979	Adventure Animation Fantasy	4.155172	87
989	Action Adventure	4.046429	140
925	Drama	4.184211	76
1729	Comedy Drama Romance War	4.147727	88
98	Crime Drama Thriller	4.105769	104
905	Adventure Drama War	4.300000	45
31	Mystery Sci-Fi Thriller	3.983051	177
6993	Action Drama War	4.136364	88
922	Drama War	4.098039	102
956	Horror	4.082569	109
0	Adventure Animation Children Comedy Fantasy	3.920930	215
950	Crime Film-Noir Mystery Thriller	4.211864	59
254	Action Crime Drama Thriller	4.018797	133
4170	Action Adventure Crime Drama Thriller	4.146667	75

	log_ratings	adj_rating
277	0.397077	4.826099
2224	0.314190	4.587126
257	0.390003	4.587072
224	0.345468	4.576543
659	0.285921	4.574983
314	0.405273	4.569406
1938	0.368081	4.560527
461	0.316219	4.541219
46	0.299427	4.537172
510	0.368875	4.530166
897	0.306934	4.522573
899	0.295017	4.502517
6693	0.229181	4.467436
921	0.196711	4.456401
898	0.218360	4.450755
913	0.191393	4.441393
910	0.290517	4.428272
1502	0.281226	4.427502
1733	0.196711	4.413765
6298	0.154300	4.406637
895	0.203605	4.406613
827	0.200185	4.402475
602	0.131894	4.399935
3633	0.292779	4.398839
4791	0.277636	4.396555

520	0.272756	4.388778
694	0.138862	4.378862
908	0.154300	4.373926
862	0.208636	4.370400
3136	0.243760	4.366402
97	0.332744	4.364390
3617	0.180349	4.363682
686	0.098814	4.360718
4900	0.200185	4.360491
2144	0.299427	4.355799
2370	0.162653	4.311302
4131	0.281226	4.302502
968	0.260054	4.298066
1283	0.216769	4.294784
507	0.320222	4.291204
474	0.187773	4.288580
7355	0.219940	4.286373
974	0.008002	4.279931
2992	0.122241	4.278155
398	0.283586	4.275691
43	0.298333	4.273702
3979	0.106907	4.262079
989	0.215167	4.261595
925	0.075629	4.259840
1729	0.109539	4.257266
98	0.147818	4.253587
905	-0.048970	4.251030
31	0.267764	4.250815
6993	0.109539	4.245903
922	0.143386	4.241425
956	0.158517	4.241085
0	0.311110	4.232040
950	0.016197	4.228061
254	0.203605	4.222402
4170	0.072549	4.219216

[304]: # Build a base class for our recommenders.

```
class Recommender:
    def __init__(self,movies):
        self.movies = movies
        self.movie_dict = dict(zip(movies['movieId'], movies.
        ↪to_dict('records')))

    def movie_string(self,movie_id):
        movie = self.movie_dict[movie_id]
        return "  {:50s} {:5d} {:.2f} {:.3d}\n      {}".format(
```

```

        movie['title'][0:50],
        movie_id,
        movie['mean_rating'],
        movie['n_ratings'],
        movie['genres'],
    )

def recommend_similar_movies(self, movie_id, k=10):
    similar_ids = self.find_similar_movies(movie_id, k)

    class_name = self.__class__.__name__
    movie_string = self.movie_string(movie_id)
    print(f"{class_name}: Since you watched... \n{movie_string}\n... you\u202a
    might also like:")

    for i in similar_ids[0:k]:
        movie = self.movie_dict[i]
        if movie is None:
            continue
        print(self.movie_string(i))

def test_run(self, k=10):

    # Toy Story (1995)
    self.recommend_similar_movies(1)
    print()

    # Star Wars: Episode VI - Return of the Jedi (1983)
    self.recommend_similar_movies(1210)
    print()

    # Monty Python's Life of Brian (1979)
    self.recommend_similar_movies(1080)

```

### 1.0.2 Nearest Neighbors Based Recommender

```
[305]: # This KNN Recommender class was built from this walk-through:
# https://www.geeksforgeeks.org/recommendation-system-in-python/

import numpy as np

from scipy.sparse import csr_matrix
from sklearn.neighbors import NearestNeighbors

class KnnRecommender(Recommender):
    def __init__(self, ratings, movies):
        super().__init__(movies)
```

```

N = len(ratings['userId'].unique())
M = len(ratings['movieId'].unique())

    self.user_mapper = dict(zip(np.unique(ratings["userId"]), np.
                                list(range(N))))
    self.movie_mapper = dict(zip(np.unique(ratings["movieId"]), np.
                                list(range(M))))

    self.user_inv_mapper = dict(zip(list(range(N)), np.
                                    unique(ratings["userId"])))
    self.movie_inv_mapper = dict(zip(list(range(M)), np.
                                    unique(ratings["movieId"])))

user_index = [self.user_mapper[i] for i in ratings['userId']]
movie_index = [self.movie_mapper[i] for i in ratings['movieId']]

    self.X = csr_matrix((ratings["rating"], (movie_index, user_index)), np.
                        shape=(M, N))

def find_similar_movies(self, movie_id, k, metric='cosine', np.
show_distance=False):
    neighbour_ids = []

    if movie_id not in self.movie_mapper:
        print(f"Movie ID {movie_id} not found in movie_mapper!")
        return []

    movie_ind = self.movie_mapper[movie_id]
    movie_vec = self.X[movie_ind]
    k += 1
    kNN = NearestNeighbors(n_neighbors=k, algorithm="brute", metric=metric)
    kNN.fit(self.X)
    movie_vec = movie_vec.reshape(1, -1)
    neighbour = kNN.kneighbors(movie_vec, return_distance=show_distance)

    for i in range(0, k):
        n = neighbour.item(i)
        neighbour_ids.append(self.movie_inv_mapper[n])

    neighbour_ids.pop(0)
    return neighbour_ids

```

[306]: knn\_rec = KnnRecommender(ratings,adj\_movies)  
knn\_rec.test\_run()

KnnRecommender: Since you watched...

Toy Story (1995)

1 3.92 215

Adventure Animation Children Comedy Fantasy				
... you might also like:				
Toy Story 2 (1999)	3114	3.86	97	
Adventure Animation Children Comedy Fantasy				
Jurassic Park (1993)	480	3.75	238	
Action Adventure Sci-Fi Thriller				
Independence Day (a.k.a. ID4) (1996)	780	3.45	202	
Action Adventure Sci-Fi Thriller				
Star Wars: Episode IV - A New Hope (1977)	260	4.23	251	
Action Adventure Sci-Fi				
Forrest Gump (1994)	356	4.16	329	
Comedy Drama Romance War				
Lion King, The (1994)	364	3.94	172	
Adventure Animation Children Drama Musical IMAX				
Star Wars: Episode VI - Return of the Jedi (1983)	1210	4.14	196	
Action Adventure Sci-Fi				
Mission: Impossible (1996)	648	3.54	162	
Action Adventure Mystery Thriller				
Groundhog Day (1993)	1265	3.94	143	
Comedy Fantasy Romance				
Back to the Future (1985)	1270	4.04	171	
Adventure Comedy Sci-Fi				

KnnRecommender: Since you watched...

Star Wars: Episode VI - Return of the Jedi (1983)	1210	4.14	196	
Action Adventure Sci-Fi				
... you might also like:				
Star Wars: Episode V - The Empire Strikes Back (1980)	1196	4.22	211	
Action Adventure Sci-Fi				
Star Wars: Episode IV - A New Hope (1977)	260	4.23	251	
Action Adventure Sci-Fi				
Indiana Jones and the Last Crusade (1989)	1291	4.05	140	
Action Adventure				
Back to the Future (1985)	1270	4.04	171	
Adventure Comedy Sci-Fi				
Matrix, The (1999)	2571	4.19	278	
Action Sci-Fi Thriller				
Raiders of the Lost Ark (Indiana Jones and the Raids)	1198	4.21	200	
Action Adventure				
Terminator, The (1984)	1240	3.90	131	
Action Sci-Fi Thriller				
Star Wars: Episode I - The Phantom Menace (1999)	2628	3.11	140	
Action Adventure Sci-Fi				
Saving Private Ryan (1998)	2028	4.15	188	
Action Drama War				
Indiana Jones and the Temple of Doom (1984)	2115	3.64	108	
Action Adventure Fantasy				

```

KnnRecommender: Since you watched...
    Monty Python's Life of Brian (1979)           1080 3.93  89
        Comedy
... you might also like:
    Monty Python and the Holy Grail (1975)       1136 4.16 136
        Adventure|Comedy|Fantasy
    Monty Python's The Meaning of Life (1983)      6807 3.95  40
        Comedy
    Blues Brothers, The (1980)                   1220 3.81  84
        Action|Comedy|Musical
    Being John Malkovich (1999)                  2997 3.95  99
        Comedy|Drama|Fantasy
    Clockwork Orange, A (1971)                  1206 4.00 120
        Crime|Drama|Sci-Fi|Thriller
    Apocalypse Now (1979)                      1208 4.22 107
        Action|Drama|War
    Ferris Bueller's Day Off (1986)            2918 3.84 109
        Comedy
    Trainspotting (1996)                       778 4.04 102
        Comedy|Crime|Drama
    Fargo (1996)                            608 4.12 181
        Comedy|Crime|Drama|Thriller
    Blade Runner (1982)                      541 4.10 124
        Action|Sci-Fi|Thriller

```

### 1.0.3 Correlation-Based Recommender

```
[307]: # This "corrwith" class built from the walk-through here:
# https://analyticsindiamag.com/deep-tech/
#↳ how-to-build-your-first-recommender-system-using-python-movielens-dataset/

import warnings

class CorrRecommender(Recommender):
    def __init__(self,ratings,movies):
        super().__init__(movies)

        self.data = ratings.merge(movies,on='movieId', how='left')
        self.movie_user = self.data.
    ↳pivot_table(index='userId',columns='title',values='rating')

        avg_ratings = pd.DataFrame(self.data.groupby('title')['rating'].mean())
        avg_ratings['Total Ratings'] = pd.DataFrame(self.data.
    ↳groupby('title')['rating'].count())
        self.avg_ratings = avg_ratings

    def find_similar_movies(self,movie_id,k):
```

```

movie_title = self.movie_dict[movie_id]['title']

movie_slice = self.movie_user[movie_title]

with warnings.catch_warnings():
    warnings.simplefilter('ignore')
    correlations = self.movie_user.corrwith(movie_slice)

recommendation = pd.DataFrame(correlations,columns=['Correlation'])
recommendation.dropna(inplace=True)
recommendation = recommendation.merge(self.movies,on='title')

recc = recommendation[recommendation['n_ratings']>100] .
sort_values('Correlation',ascending=False).reset_index()
similar_ids = list(recc['movieId'])
similar_ids.pop(0)
return similar_ids[0:k]

```

[308]: corr\_rec = CorrRecommender(ratings,adj\_movies)  
corr\_rec.test\_run()

CorrRecommender: Since you watched...

Toy Story (1995)	1	3.92	215
Adventure Animation Children Comedy Fantasy			
... you might also like:			
Incredibles, The (2004)	8961	3.84	125
Action Adventure Animation Children Comedy			
Finding Nemo (2003)	6377	3.96	141
Adventure Animation Children Comedy			
Aladdin (1992)	588	3.79	183
Adventure Animation Children Comedy Musical			
Monsters, Inc. (2001)	4886	3.87	132
Adventure Animation Children Comedy Fantasy			
Mrs. Doubtfire (1993)	500	3.39	144
Comedy Drama			
Amelie (Fabuleux destin d'Amélie Poulain, Le) (2001)	4973	4.18	120
Comedy Romance			
American Pie (1999)	2706	3.38	103
Comedy Romance			
Die Hard: With a Vengeance (1995)	165	3.56	144
Action Crime Thriller			
E.T. the Extra-Terrestrial (1982)	1097	3.77	122
Children Drama Sci-Fi			
Home Alone (1990)	586	3.00	116
Children Comedy			

CorrRecommender: Since you watched...

Star Wars: Episode VI - Return of the Jedi (1983)	1210	4.14	196
---	------	------	-----

Action|Adventure|Sci-Fi

... you might also like:

Star Wars: Episode IV - A New Hope (1977)	260	4.23	251
Action Adventure Sci-Fi			
Star Wars: Episode V - The Empire Strikes Back (1977)	1196	4.22	211
Action Adventure Sci-Fi			
Good Will Hunting (1997)	1704	4.08	141
Drama Romance			
Firm, The (1993)	454	3.53	101
Drama Thriller			
Indiana Jones and the Temple of Doom (1984)	2115	3.64	108
Action Adventure Fantasy			
WALL·E (2008)	60069	4.06	104
Adventure Animation Children Romance Sci-Fi			
Lord of the Rings: The Return of the King, The (2003)	7153	4.12	185
Action Adventure Drama Fantasy			
Star Wars: Episode I - The Phantom Menace (1999)	2628	3.11	140
Action Adventure Sci-Fi			
Indiana Jones and the Last Crusade (1989)	1291	4.05	140
Action Adventure			
Schindler's List (1993)	527	4.22	220
Drama War			

CorrRecommender: Since you watched...

Monty Python's Life of Brian (1979)	1080	3.93	89
Comedy			
... you might also like:			
Ghostbusters (a.k.a. Ghost Busters) (1984)	2716	3.77	120
Action Comedy Sci-Fi			
Clockwork Orange, A (1971)	1206	4.00	120
Crime Drama Sci-Fi Thriller			
Back to the Future (1985)	1270	4.04	171
Adventure Comedy Sci-Fi			
Princess Bride, The (1987)	1197	4.23	142
Action Adventure Comedy Fantasy Romance			
Big Lebowski, The (1998)	1732	3.92	106
Comedy Crime			
Die Hard: With a Vengeance (1995)	165	3.56	144
Action Crime Thriller			
Star Wars: Episode IV - A New Hope (1977)	260	4.23	251
Action Adventure Sci-Fi			
Lord of the Rings: The Return of the King, The (2003)	7153	4.12	185
Action Adventure Drama Fantasy			
Outbreak (1995)	292	3.43	101
Action Drama Sci-Fi Thriller			
Departed, The (2006)	48516	4.25	107
Crime Drama Thriller			

#### 1.0.4 Genre-Based TFIDF Recommender

```
[309]: # The "Genre" class built from the walk-through here:  
# https://github.com/khanhnaml1994/movielens/blob/master/  
# Content_Based_and_Collaborative_Filtering_Models.ipynb  
from sklearn.feature_extraction.text import TfidfVectorizer  
from sklearn.metrics.pairwise import linear_kernel  
  
class GenreRecommender(Recommender):  
    def __init__(self, ratings, movies):  
        super().__init__(movies)  
  
        # Break up the big genre string into a string array  
        movies = movies[['title', 'genres', 'movieId']].copy()  
        movies['genres'] = movies['genres'].apply(lambda x: x.split(' | '))  
  
        # Convert genres to string value  
        movies['genres'] = movies['genres'].fillna("").astype('str')  
  
        tf = TfidfVectorizer(analyzer='word', ngram_range=(1, 2), min_df=0, □  
        ↵stop_words='english')  
        tfidf_matrix = tf.fit_transform(movies['genres'])  
  
        self.g_cosine = linear_kernel(tfidf_matrix, tfidf_matrix)  
  
        # Build a 1-dimensional array with movie ids  
        self.g_movie_ids = movies['movieId']  
        self.g_movie_idx = pd.Series(movies.index, index=movies['movieId'])  
  
        # Function that get movie recommendations based on the cosine similarity  
        ↵score of movie genres  
    def find_similar_movies(self, movie_id, k):  
        idx = self.g_movie_idx[movie_id]  
        sim_scores = list(enumerate(self.g_cosine[idx]))  
        sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)  
        sim_scores = sim_scores[1:k]  
        movie_indices = [i[0] for i in sim_scores]  
        return self.g_movie_ids.iloc[movie_indices]
```

```
[310]: genre_rec = GenreRecommender(ratings, adj_movies)  
genre_rec.test_run()
```

GenreRecommender: Since you watched...

Toy Story (1995)	1	3.92	215
Adventure Animation Children Comedy Fantasy			
... you might also like:			
Antz (1998)	2294	3.24	45
Adventure Animation Children Comedy Fantasy			

Toy Story 2 (1999)		3114	3.86	97
Adventure Animation Children Comedy Fantasy				
Adventures of Rocky and Bullwinkle, The (2000)		3754	2.22	9
Adventure Animation Children Comedy Fantasy				
Emperor's New Groove, The (2000)		4016	3.72	37
Adventure Animation Children Comedy Fantasy				
Monsters, Inc. (2001)		4886	3.87	132
Adventure Animation Children Comedy Fantasy				
Wild, The (2006)		45074	2.50	1
Adventure Animation Children Comedy Fantasy				
Shrek the Third (2007)		53121	3.02	21
Adventure Animation Children Comedy Fantasy				
Tale of Despereaux, The (2008)		65577	3.00	1
Adventure Animation Children Comedy Fantasy				
Asterix and the Vikings (Astérix et les Vikings) (	91355	5.00	1	
Adventure Animation Children Comedy Fantasy				

GenreRecommender: Since you watched...

Star Wars: Episode VI - Return of the Jedi (1983)		1210	4.14	196
Action Adventure Sci-Fi				

... you might also like:

Star Wars: Episode IV - A New Hope (1977)		260	4.23	251
Action Adventure Sci-Fi				
Stargate (1994)		316	3.38	140
Action Adventure Sci-Fi				
Demolition Man (1993)		442	3.09	81
Action Adventure Sci-Fi				
Star Wars: Episode V - The Empire Strikes Back (19	1196	4.22	211	
Action Adventure Sci-Fi				
Star Wars: Episode VI - Return of the Jedi (1983)		1210	4.14	196
Action Adventure Sci-Fi				
Star Trek III: The Search for Spock (1984)		1375	3.26	42
Action Adventure Sci-Fi				
Lost in Space (1998)		1831	2.45	29
Action Adventure Sci-Fi				
Rocketeer, The (1991)		2094	3.26	39
Action Adventure Sci-Fi				
Tron (1982)		2105	3.34	50
Action Adventure Sci-Fi				

GenreRecommender: Since you watched...

Monty Python's Life of Brian (1979)		1080	3.93	89
Comedy				

... you might also like:

Four Rooms (1995)		18	3.70	20
Comedy				
Ace Ventura: When Nature Calls (1995)		19	2.73	88
Comedy				

Bio-Dome (1996)		65	2.53	31
Comedy				
Friday (1995)		69	3.77	20
Comedy				
Black Sheep (1996)		88	3.16	16
Comedy				
Mr. Wrong (1996)		102	2.40	5
Comedy				
Happy Gilmore (1996)		104	3.44	99
Comedy				
Steal Big, Steal Little (1995)		119	3.00	2
Comedy				
Flirting With Disaster (1996)		125	3.58	12
Comedy				

### 1.0.5 Combined Recommendation System

```
[311]: class CombinedRecommender(Recommender):
    def __init__(self,ratings,movies):
        super().__init__(movies)
        self.movies = movies

    def make_index_hash(self,input_list):
        index_hash={}
        for index, element in enumerate(input_list):
            index_hash[element]=index
        return index_hash

    def find_similar_movies(self,movie_id,k):
        k_list = knnr.find_similar_movies(movie_id,1000)
        c_list = corrr.find_similar_movies(movie_id,1000)
        g_list = grec.find_similar_movies(movie_id,1000)
        r_list = self.movies.sort_values(by='adj_rating',u
        ↪ascending=False)[['movieId']]

        k_hash = self.make_index_hash(k_list)
        c_hash = self.make_index_hash(c_list)
        g_hash = self.make_index_hash(g_list)
        r_hash = self.make_index_hash(r_list)

        k_default = len(k_list)
        c_default = len(c_list)
        g_default = len(g_list)
        r_default = len(r_list)

        scores={}
        for index, row in self.movies.iterrows():


```

```

movie_id = row['movieId']

# Closest neighbor (based on ratings)
k_score = k_hash.get(movie_id,k_default)

# Best correlation (based on ratings)
c_score = c_hash.get(movie_id,c_default)

# Similar genre
g_score = g_hash.get(movie_id,g_default)

# Highly rated movies, regardless of similarity
r_score = r_hash.get(movie_id,r_default)

scores[movie_id]=k_score+c_score+g_score+r_score

results = sorted(scores, key=scores.get)
return results

```

[312]: combined = CombinedRecommender(ratings,adj\_movies)  
combined.test\_run()

CombinedRecommender: Since you watched...

Toy Story (1995)	1	3.92	215
Adventure Animation Children Comedy Fantasy			
... you might also like:			
Monsters, Inc. (2001)	4886	3.87	132
Adventure Animation Children Comedy Fantasy			
Shrek (2001)	4306	3.87	170
Adventure Animation Children Comedy Fantasy Romance			
Finding Nemo (2003)	6377	3.96	141
Adventure Animation Children Comedy			
Toy Story 2 (1999)	3114	3.86	97
Adventure Animation Children Comedy Fantasy			
Incredibles, The (2004)	8961	3.84	125
Action Adventure Animation Children Comedy			
Bug's Life, A (1998)	2355	3.52	92
Adventure Animation Children Comedy			
Antz (1998)	2294	3.24	45
Adventure Animation Children Comedy Fantasy			
Ice Age (2002)	5218	3.69	85
Adventure Animation Children Comedy			
Aladdin (1992)	588	3.79	183
Adventure Animation Children Comedy Musical			
Toy Story 3 (2010)	78499	4.11	55
Adventure Animation Children Comedy Fantasy IMAX			

CombinedRecommender: Since you watched...

Star Wars: Episode VI - Return of the Jedi (1983)	1210	4.14	196
Action Adventure Sci-Fi			
... you might also like:			
Star Wars: Episode IV - A New Hope (1977)	260	4.23	251
Action Adventure Sci-Fi			
Star Wars: Episode V - The Empire Strikes Back (1977)	1196	4.22	211
Action Adventure Sci-Fi			
Star Wars: Episode I - The Phantom Menace (1999)	2628	3.11	140
Action Adventure Sci-Fi			
X-Men (2000)	3793	3.70	133
Action Adventure Sci-Fi			
Jurassic Park (1993)	480	3.75	238
Action Adventure Sci-Fi Thriller			
Spider-Man (2002)	5349	3.54	122
Action Adventure Sci-Fi Thriller			
Star Wars: Episode III - Revenge of the Sith (2005)	33493	3.43	78
Action Adventure Sci-Fi			
Superman (1978)	2640	3.61	61
Action Adventure Sci-Fi			
Independence Day (a.k.a. ID4) (1996)	780	3.45	202
Action Adventure Sci-Fi Thriller			
Stargate (1994)	316	3.38	140
Action Adventure Sci-Fi			

CombinedRecommender: Since you watched...

Monty Python's Life of Brian (1979)	1080	3.93	89
Comedy			
... you might also like:			
Clerks (1994)	223	3.86	104
Comedy			
Raising Arizona (1987)	1394	3.99	58
Comedy			
This Is Spinal Tap (1984)	1288	4.02	66
Comedy			
Ferris Bueller's Day Off (1986)	2918	3.84	109
Comedy			
Dazed and Confused (1993)	441	3.93	42
Comedy			
Monty Python's And Now for Something Completely Di	2788	4.05	28
Comedy			
Hudsucker Proxy, The (1994)	471	3.55	40
Comedy			
Airplane! (1980)	2791	3.86	87
Comedy			
Bullets Over Broadway (1994)	348	3.58	30
Comedy			
Election (1999)	2599	3.66	56

Comedy

[ ]: