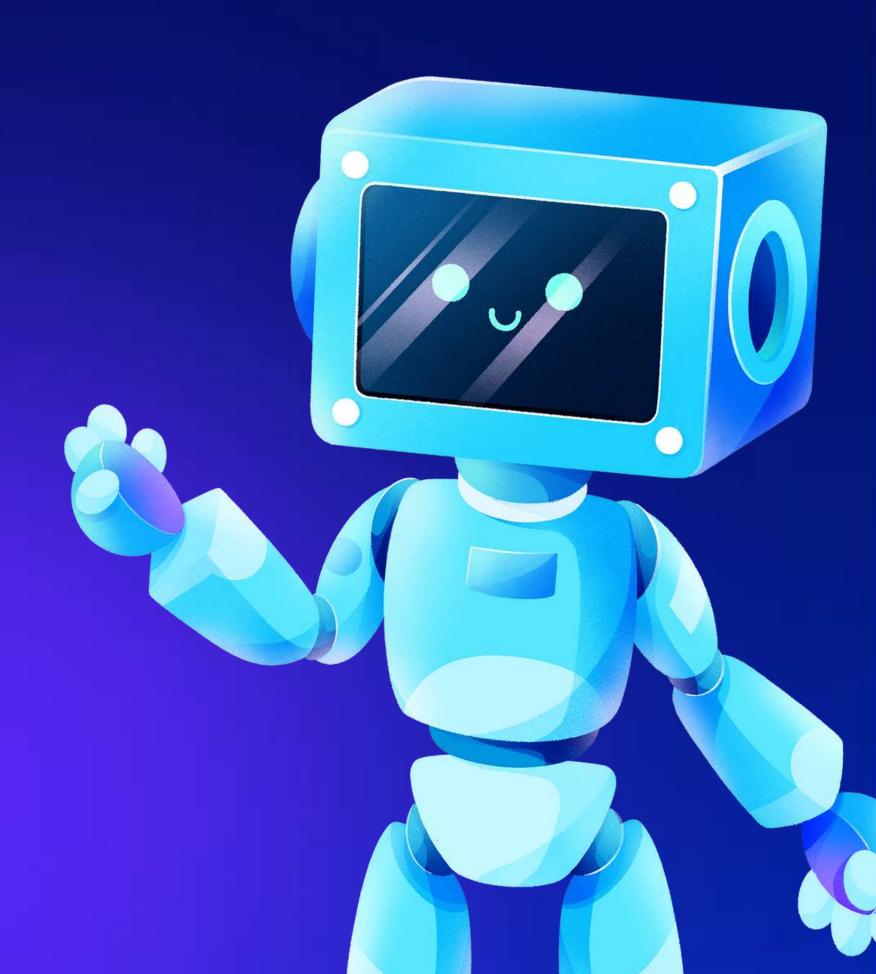


MOVIE RECOMMENDER SYSTEM

PROJECT

BY MOHAMED ALI





INTRODUCTION

WHAT IS A MOVIE RECOMMENDER SYSTEM?

A system designed to help users discover movies tailored to their preferences, based on previous interactions.

PURPOSE OF RECOMMENDER SYSTEMSE RECOMMENDER SYSTEM?

Enhance user experience by suggesting relevant content, making content discovery faster and more enjoyable.

CHALLENGES IN MOVIE RECOMMENDATIONS:

Addressing the vast amount of available content while tailoring suggestions to individual tastes and preferences.

SOLUTION:

Our system will use a data-driven model focusing on user ratings, applying advanced techniques for accurate predictions.



PROBLEM EXPLANATION

PROBLEM CONTEXT:

With thousands of movies available, users often struggle to find relevant options. An efficient recommendation system is essential for engagement.

ISSUES WITH TRADITIONAL SEARCH:

Traditional search functions rely heavily on user input, offering limited personalization.

OBJECTIVE OF THIS PROJECT:

To create a model that predicts user preferences and suggests movies they are likely to enjoy.

FOCUS ON USER RATINGS:

By leveraging historical user ratings, our model aims to uncover underlying patterns that correlate with user satisfaction.

TECHNIQUE USED TO SOLVE THE PROBLEM

RATING BASED ALGORITHM

CORE PRINCIPLE

Recommendations are based on past user ratings, predicting future preferences based on similar user or item behaviors.

HOW IT WORKS:

Identifies relationships between users with similar tastes and movies that receive similar ratings.

KEY STRENGTHS:

Directly reflects user satisfaction, offering a straightforward approach to discover preferred movies.

LIMITATIONS:

Pure rating-based filtering can suffer from data sparsity issues when there are few ratings, making it challenging to identify user patterns.

SINGULAR VALUE DECOMPOSITION (SVD)

WHAT IS SVD?

A mathematical technique that decomposes the user-item rating matrix into three smaller matrices, revealing latent factors.

SVD PROCESS FOR MOVIE RECOMMENDATIONS:

The user-item rating matrix is broken down, reducing dimensions to reveal hidden relationships between users and movies.

HANDLING SPARSITY WITH SVD:

By capturing underlying patterns, SVD compensates for sparse data, creating more accurate predictions even when data is limited.

WHY SVD IS EFFECTIVE FOR THIS SYSTEM:

It improves scalability and accuracy, addressing common challenges in rating-based filtering.

BENIFITS OF SVD



ENHANCED PERSONALIZATION

SVD identifies subtle correlations that aren't immediately visible, leading to a more tailored user experience.

SCALABILITY

Effective with extensive datasets, making it suitable for real-world applications where data grows continuously.

REDUCED NOISE

By filtering out irrelevant information, SVD helps the model focus on significant patterns, enhancing recommendation accuracy.

IMPROVED ACCURACY

Used by major streaming platforms to deliver recommendations at scale, proving its effectiveness and reliability.

EXPLORATORY DATA ANALYSIS

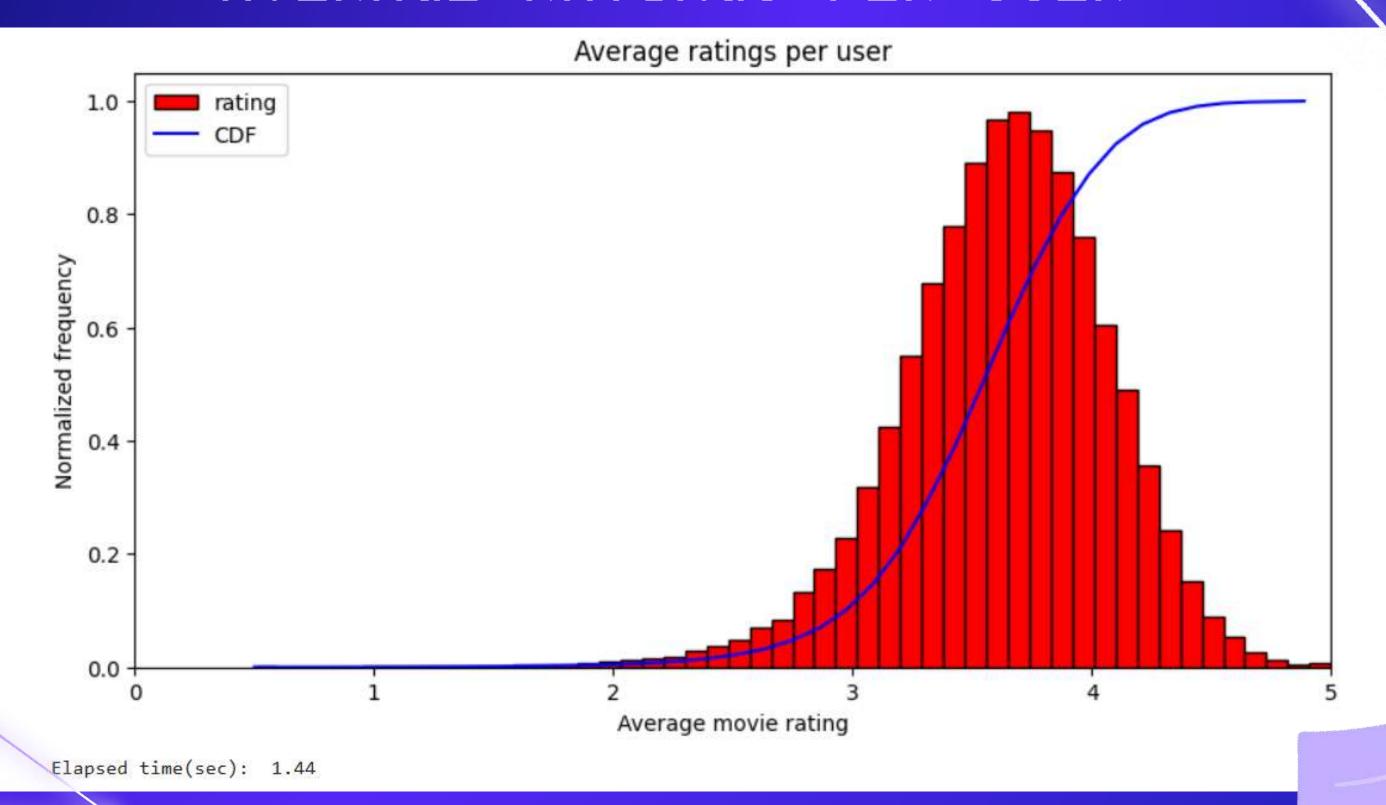
In [5]: print(movies.info()) <class 'pandas.core.frame.DataFrame'> RangeIndex: 27256 entries, 0 to 27255 Data columns (total 23 columns): Column Non-Null Count Dtype ----movieId 27256 non-null int64 title 27256 non-null object 27256 non-null float64 year (no genres listed) 27256 non-null bool Action 27256 non-null bool Adventure 27256 non-null bool Animation 27256 non-null bool Children 27256 non-null bool 27256 non-null bool Comedy Crime 27256 non-null bool 27256 non-null bool Documentary Drama 27256 non-null bool 11 27256 non-null bool 12 Fantasy Film-Noir 27256 non-null bool 14 Horror 27256 non-null bool IMAX 27256 non-null bool 15 Musical 27256 non-null bool 17 Mystery 27256 non-null bool Romance 27256 non-null bool Sci-Fi 27256 non-null bool 20 Thriller 27256 non-null bool 21 War 27256 non-null bool 27256 non-null bool 22 Western

dtypes: bool(20), float64(1), int64(1), object(1)

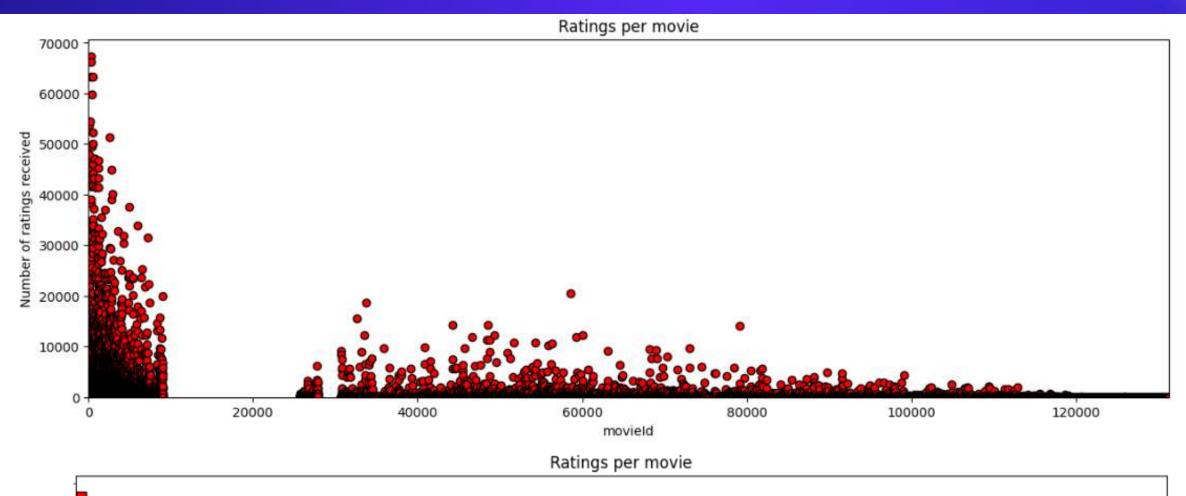
memory usage: 1.1+ MB

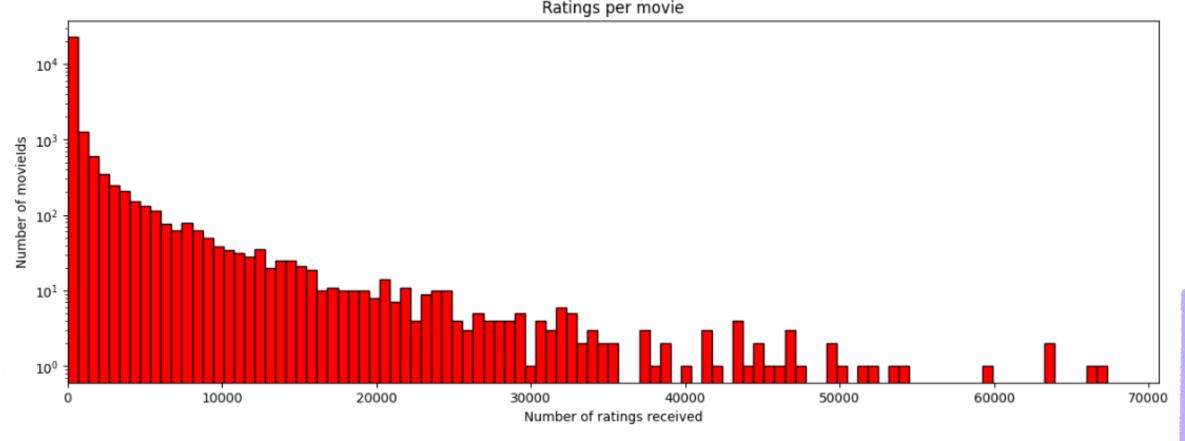
None

AVERAGE RATINGS PER USER

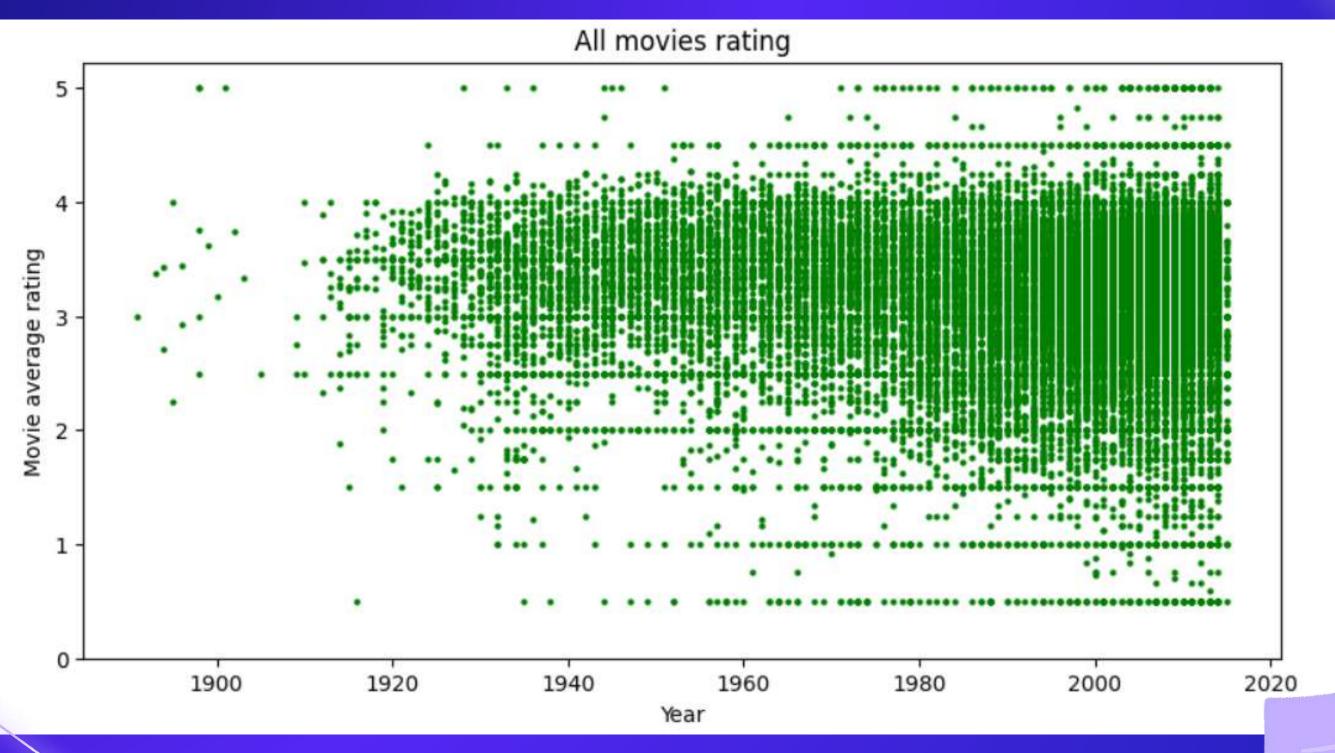


RATINGS PER MOVIE

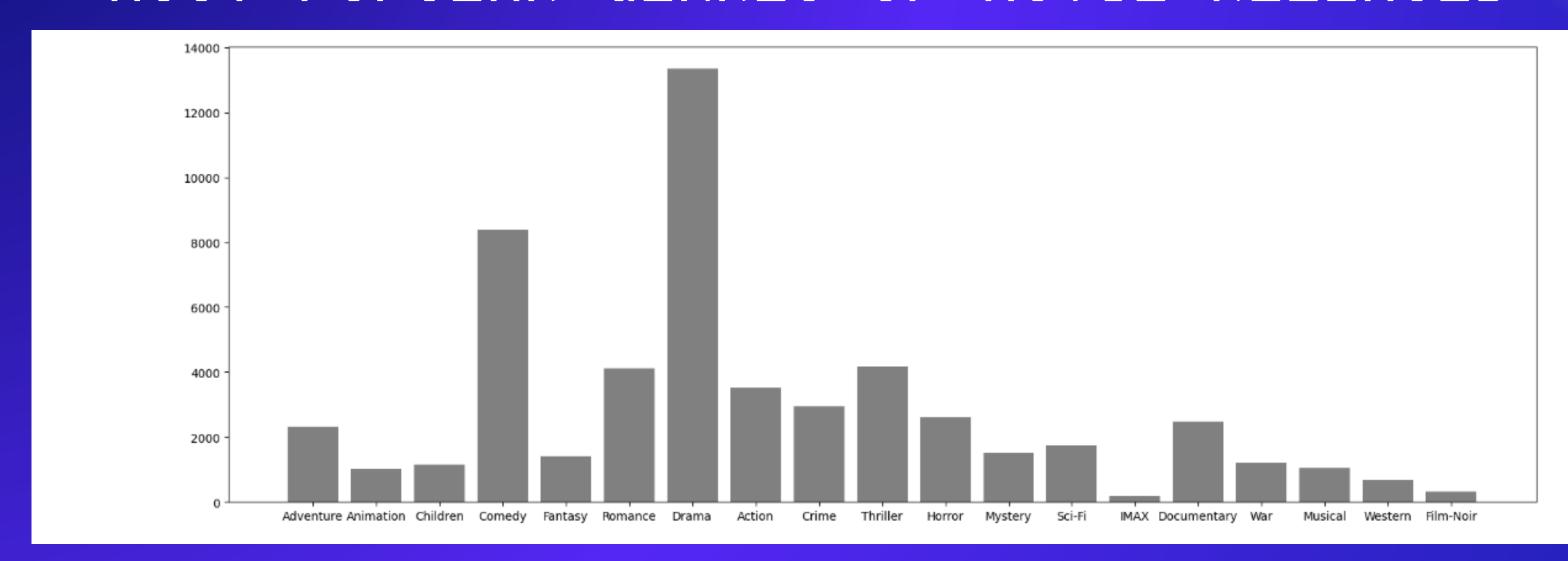




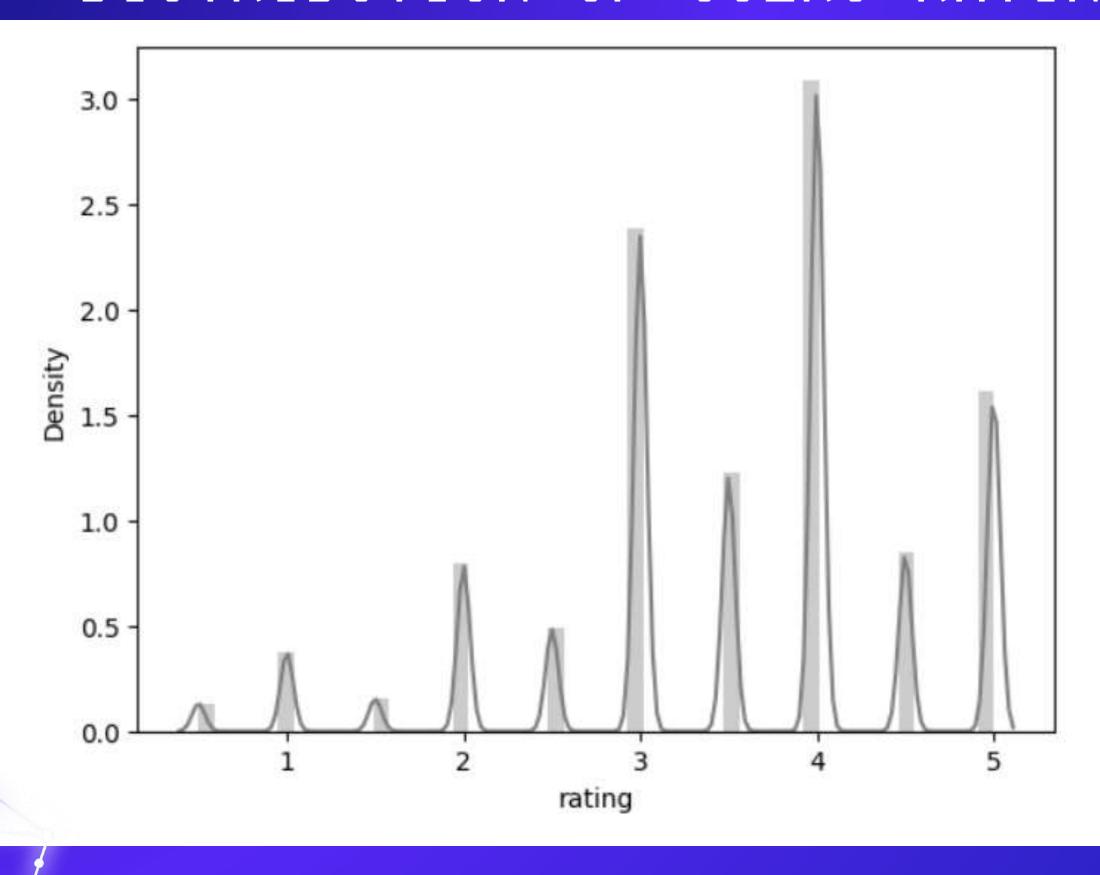
AVERAGE RATING FOR ALL INDIVIDUAL MOVIES



MOST POPULAR GENRES OF MOVIE RELEASED



DISTRIBUTION OF USERS RATING



INPUT FROM USER'S RATING

User 152 has already rated 154 movies.
Recommending top 20 movies not yet rated by User 152.
Top 20 movies that User 152 has rated:

					1	
0	152	2	3.0	2006-10-18	23:47:31	
1	152	16	4.5	2006-10-18	23:48:15	
2	152	19	2.5	2006-10-18	23:47:46	
3	152	39	5.0	2006-10-18	23:57:43	
4	152	47	4.0	2006-10-18	23:52:27	
5	152	50	4.0	2006-10-18	23:56:03	
6	152	72	2.0	2006-10-18	23:49:42	
7	152	104	3.0	2006-10-18	23:48:21	
8	152	141	3.5	2006-10-18	23:56:24	
9	152	150	3.5	2006-10-18	23:53:38	
10	152	153	4.0	2006-10-18	23:56:00	
11	152	185	2.5	2006-10-18	23:56:33	
12	152	231	5.0	2006-10-18	23:55:47	
13	152	235	3.5	2006-10-18	23:48:22	
14	152	260	3.5	2006-10-18	23:53:59	
15	152	296	4.0	2006-10-18	23:53:14	
16	152	337	4.0	2006-10-18	23:48:31	
17	152	339	2.0	2006-10-18	23:57:30	
18	152	344	3.5	2006-10-18	23:54:32	
19	152	356	2.0	2006-10-18	23:52:21	

year	genres	title	
1995	Adventure Children Fantasy	Jumanji	0
1995	Crime Drama	Casino	1
1995	Comedy	Ace Ventura: When Nature Calls	2
1995	Comedy Romance	Clueless	3
1995	Mystery Thriller	Seven (a.k.a. Se7en)	4
1995	Crime Mystery Thriller	Usual Suspects, The	5
1995	Comedy Drama	Kicking and Screaming	6
1996	Comedy	Happy Gilmore	7
1996	Comedy	Birdcage, The	8
1995	Adventure Drama IMAX	Apollo 13	9
1995	Action Adventure Comedy Crime	Batman Forever	10
1995	Action Crime Thriller	Net, The	11
1994	Adventure Comedy	Dumb & Dumber (Dumb and Dumber)	12
1994	Comedy Drama	Ed Wood	13
1977	Action Adventure Sci-Fi	Star Wars: Episode IV - A New Hope	14
1994	Comedy Crime Drama Thriller	Pulp Fiction	15
1993	Drama	What's Eating Gilbert Grape	16
1995	Comedy Romance	While You Were Sleeping	17
1994	Comedy	Ace Ventura: Pet Detective	18
1994	Comedy Drama Romance War	Forrest Gump	19

PREDICTION BY SVD MODEL

Top 20		hat User 152 may enjoy:		genres	year	Predicted_Rating
	movieId	title '	108	Action Drama War	1995	4.402149
108	110	Braveheart	315	Crime Drama	1994	4.373308
315	318	Shawshank Redemption, The	668	Drama Thriller	1993	4.324897
668	678	Some Folks Call It a Sling Blade	765	Comedy Crime Drama	1996	4.311534
765	778	Trainspotting	1231	Adventure Drama	1986	4.266745
1231	1259	Stand by Me	2239	Comedy Drama Romance War	1997	4.242765
2239	2324	Life Is Beautiful (La Vita è bella)	2244	Crime Drama	1998	4.240902
2244	2329	American History X	2920	Drama Thriller	1999	4.237502
2920	3006	Insider, The	3003	Drama	1987	4.237260
3003	3090	Matewan	5473	Drama Horror Thriller	1996	4.214426
5473	5570	Thesis (Tesis)	6873	Drama	1928	4.204239
6873	6985 7096	Passion of Joan of Arc, The (Passion de Jeanne Rivers and Tides	6984	Documentary	2001	4.204234
6984 7094	7206	Mon Oncle (My Uncle)	7094	Comedy	1958	4.195474
7356	7502	Band of Brothers	7356	Action Drama War	2001	4.192460
8937	26587	Decalogue, The (Dekalog)	8937	Crime Drama Romance	1989	4.186609
12204	55721	Elite Squad (Tropa de Elite)	12204	Action Crime Drama Thriller	2007	4.184683
12932	61240	Let the Right One In (Låt den rätte komma in)	12932	Drama Fantasy Horror Romance	2008	4.178458
15208	77658	Cosmos	15208	Documentary	1980	4.177516
17877	89759	Separation, A (Jodaeiye Nader az Simin)	17877	Drama	2011	4.176458
22679	108583	Fawlty Towers (1975-1979)	22679	Comedy	NaN	4.175005