Recommender systems:
Hybrid proposal

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January 10, 2021

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1 Introduction

In this paper we will make a brief study of the systems of recommendations proposed so far and then implement a hybrid one. This model consists of a mixture of collaborative filtering and content-based recommendation systems. We have chosen this model because, as stated in the paper, this type of recommendation system seeks to solve the problems presented by each of the above-mentioned types. To prove this theory we will test the recommender system with the tastes of some real and fake users, and assess the quality of the results.

1.1 Search protocol

Due to the large number of articles proposing recommending systems, we needed to develop a search protocol that would allow us to get an idea of how the general picture of the area was. As the state of the art is not the main objective of the work, we did not carry out an exhaustive search in the field. Our method of searching consisted first of all in finding two articles that already presented a study of the area [12] and [7], and on the basis of these to choose the recommendation systems on which we would like to seek further information. In particular, we decided to look for more articles on content-based, collaborative filtering and hybrid systems. Thus, each team member selected one of these three models and looked for five articles on these recommendation systems, based on how interesting they were.

1.2 Types of recommendation systems

Taken from [12] and [7].

- **Content-based Filtering:** Which is based on the comparison between features of users and items. The main tasks related to CBF are the user profiling and the item representation. Its limitation lies in the existence of enough and normalized features to measure their similarity.
- **Collaborative Filtering:** Which captures information based on historic logs of users to infer their needs, but suffers from the cold-start problem as the main challenge.
- **Hybrid:** Which is a combination between the first two techniques, trying to overcome their individual limitations.
  - **Weighted:** Scores of several recommendations are combined to produce a single recommendation.
  - **Switching:** The system uses some criteria to switch between recommendation techniques.
  - **Mixed:** First a content-based method is used for textual description and then a collaborative method finds the preferences of the user. Recommendations from the two techniques suggest a final ranking.
  - **Feature combination:** Features from different recommendation data sources are used together in a single recommendation algorithm. It considers collaborative data without relying on it exclusively and have information about the inherent similarity of items that are otherwise opaque to a collaborative system.
  - **Feature augmentation:** A technique is used to rate an item and that information is then incorporated into the processing of the next recommendation technique.
  - **Cascade:** It involves the stage process where one recommendation technique is employed to produce a ranking of candidates and a second technique refines the recommendation from the candidate set.
  - **Meta-level:** Two recommendation techniques can be merged by using the model generated by one as the input for another.
- **Knowledge-Based:** Which relies on deep knowledge about the product domain to figure out the best items to recommend to a user. It can also use ontologies to contextualize information and leverage the match. It is considered a specialized CBR.
- **Group Recommendation Technique:** Design for the context in which more than one user is involved in the approval process.
- **Demographic Recommendation Technique:** The categorisation is based on the attributes. The profile of the user is created by representing the features of the users.

1.3 Issues in recommendation systems

Taken from [12].

- **Synonym:** It happens when same item is stored with more than one different names. At that time RS cannot easily identify that the term symbolize different items or the same items.
- **Shilling Attacks:** Some users provide false ratings to some items either to raise its fame or to decrease its values into the RS. This declines the quality and performance of the RS.
- **Privacy:** The RS needs personal data of the user for better recommendations, but this can lead to problems with privacy and security.
- **Scalability:** It happens when the number of elements and users grows extremely.
- **Grey Sheep Problem:** It occurs when a user neither agrees nor disagrees with a group of people. This problem arises when there are users with odd interests.
- **Cold Start Problem:** It arises when new products are added to the catalogue or new users enter the system. In these cases, we have to deal with how to rate the new product and what recommendations to make to the new user.
- **Diversity:** Most RS recommend items to the user based on their taste. However, sometimes people want to be surprised. This is why recommendations can be monotonous.
- **Data Sparsity:** Not all items are used/consumed by users and users do not rate all items. This action creates a sparse user item matrix which prevents the identification of useful neighbours and reduces the performance of the RS.

1.4 Selected papers

In the table 1.4, we can see all the papers that we have selected for further study. After all the research we have done, we have chosen the hybrid weighted model [17], since it says that it tries to solve the problems that collaborative filtering and content-based systems present on their own. We will check later on whether this assumption is true. In addition, this proposal incorporates a fuzzy expert system that we will explain in future sections.

2 Collaborative filtering

The collaborative filtering part of the recommender system creates a user-item matrix containing the ratings from users to movies in order to predict the most suitable movies for the user. There are two groups of collaborative filtering:

- Neighborhood-based (memory based) collaborative filtering
- Model-based collaborative filtering

In this work we opt for a model-based approach performing matrix decomposition, employing the single-value decomposition (SVD) method, with the aim of finding hidden factors in the data.

The first step of the collaborative filtering system is to read unique user IDs, unique movie IDs, and user movie ratings from the MovieLens dataset and to calculate the number of users and movies to create a matrix. Then, a user-item matrix is created containing users in rows and movies in columns. The values are ratings of individual movies. The next step consists of using the SVD algorithm to calculate matrix U, Σ, and V^T and a matrix containing the predicted movie rating, which predicts the movie ratings of the users [17]. The user-item matrix is factorized as follows:

$$A = U\Sigma V^T \tag{1}$$

Algorithm 1 shows the process for computing SVD. First the unavailable entries are masked and then replaced by the average rating for each item. Numpy´s svd method computes the decomposition and then we take only the k most significant features out of each component. We choose to keep k as an hyper parameter to allow the fine tuning of it according to the available data set in each case. Finally the extracted components are combined into the predictive matrix.

Paper	Type of RS	Citation
Collaborative filtering recommendation algorithm based on Bee Colony K-means clustering model	Collaborative Filtering	[13]
Differentially private user-based collaborative filtering recommendation based on K-means clustering	Collaborative Filtering	[4]
Applying artificial immune systems to collaborative filtering for movie recommendation	Collaborative Filtering	[3]
TagDC: A tag recommendation method for software information sites with a combination of deep learning and collaborative filtering	Collaborative Filtering	[9]
Improving neighbor-based collaborative filtering by using a hybrid similarity measurement	Collaborative Filtering	[18]
Discrete Collaborative Filtering	Collaborative Filtering	[20]
Social Collaborative Filtering by Trust	Collaborative Filtering	[19]
A new user similarity model to improve the accuracy of collaborative filtering	Collaborative Filtering	[11]
A novel Collaborative Filtering recommendation approach based on Soft Co-Clustering	Collaborative Filtering	[10]
Improving the performance of video Collaborative Filtering Recommender Systems using Optimization Algorithm	Collaborative Filtering	[16]
Recommender Systems Leveraging Multimedia Content	Content-based	[6]
VideoTopic: Content-Based Video Recommendation Using a Topic Model	Content-based	[21]
Content-based video recommendation system based on stylistic visual features	Content-based	[5]
A connotative space for supporting movie affective recommendation	Content-based	[2]
Content-Based Personalized Recommender System Using Entity Embeddings	Content-based	[15]
A hybrid recommender system for recommending relevant movies using an expert system	Hybrid	[17]
A novel hybrid approach towards movie recommender systems	Hybrid	[1]
Movie recommendation system using sentiment analysis from microblogging data	Hybrid	[8]
Social movie recommender system based on deep autoencoder network using Twitter data	Hybrid	[14]

Table 1: Consulted recommendation systems.

Algorithm 1: Single-Value Decomposition

Result: Predicted movie ratings

$masked \leftarrow masked\_array(utilMat, mask)$;

$utilMat \leftarrow masked.filled(item\_means)$;

$U, s, V \leftarrow np.linalg.svd(utilMat)$;

$U, s, V \leftarrow s[0:k, 0:k], U[:, 0:k], V[0:k, :]$;

$s\_root \leftarrow sqrtm(s)$;

$UsV \leftarrow (U * s\_root) * (s\_root * V)$;

For the selection of the hyper parameter k value, the system accuracy was evaluated, using the Root-mean-square deviation (RMSE), for several options. As shown in the Table. 2 the best accuracy was obtained for k=12.

The final step of the collaborative filtering system uses the user's liked and disliked genres to further refine the recommendations. Hence films of disliked genres are discarded from the output and films of liked genres gets a 0.3 boost in the predicted rating. Table. 3 shows an example of the collaborative filtering system output.

k-value	Accuracy
8	1.003 79
10	1.003 64
12	1.004 73
14	1.005 39
17	1.004 67
20	1.005 66

Table 2: Collaborative filtering system accuracy for several values of hyper parameter k.

Movie Id	Movie name	Score
736	Twister (1996)	0.775 92
158	Casper (1995)	0.683 00
648	Mission: Impossible (1996)	0.674 87
150	Apollo 13 (1995)	0.605 85
95	Broken Arrow (1996)	0.594 67
48	Pocahontas (1995)	0.493 27
434	Cliffhanger (1993)	0.473 81
364	Lion King, The (1994)	0.470 28
377	Speed (1994)	0.406 44
168	First Knight (1995)	0.374 23
350	Client, The (1994)	0.371 97
10	GoldenEye (1995)	0.355 62
455	Free Willy (1993)	0.343 27
733	Rock, The (1996)	0.311 14
590	Dances with Wolves (1990)	0.300 18
1552	Con Air (1997)	0.272 81
3082	World Is Not Enough, The (1999)	0.263 13
457	Fugitive, The (1993)	0.262 51
1721	Titanic (1997)	0.255 39
181	Mighty Morphin Power Rangers: The Movie (1995)	0.249 83

Table 3: Collaborative filtering system output example.

3 Content-based filtering

The content-based filtering part of the recommender system uses TF-IDF and cosine similarity on the movie synopses to know which movies are more related to the ones the user has seen.

3.1 Movie synopses processing

Movie synopses were extracted from IMBD API. The synopsis texts followed a normalization process that consisted of the following steps:

- The text was tokenized.
- All words were cast to lower case.
- Stop words were removed.
- All words were stemmed by using Snowball stemming.

The result of this process was a list of stemmed words for each movie.

3.2 Dictionary of frequencies

In order to facilitate TF-IDF calculation, dictionaries of frequencies were created. These dictionaries contain, for each movie, the total number of stemmed words of their synopses, along with the number of times each stemmed word appears in the text. These frequency dictionaries were calculated and stored *a priori* so as to improve the speed of the recommender system.

3.3 TF-IDF

TF-IDF (Term Frequency-Inverse Document Frequency) is a statistic that determines the importance of the words of a document in a collection of documents.
Term frequency in this work is calculated as follows:

$$TF(t,d) = \frac{Freq(t,d)}{T_d} \tag{2}$$

With Freq(t,d) as the number of times the term t appears in document d and T_d as the total number of terms in document d.
Inverse document frequency smooth is used as IDF:

$$IDF(t) = log(1 + \frac{D}{d_t}) \tag{3}$$

With D as the total number of documents and d_t as the number of documents that contain the term.
The final TF-IDF score is calculated as:

$$TF - IDF(t,d) = TF(t,d) * IDF(t) \tag{4}$$

The result of the process are vectors that contains the TF-IDF scores for the words of each movie synopsis.

3.4 Calculating the similarity

The similarity metric used in this work to know the degree of relation between movies is cosine similarity:

$$cosine\ similarity(u,v) = \frac{u \cdot v}{||u|| \times ||v||} \tag{5}$$

This cosine similarity is used with the TF-IDF vectors calculated in the previous step with some modifications: TF-IDF elements of both vectors were ordered to contain the TF-IDF score of the same word in the same position.
Since we are calculating which movies fit better with a specific user, the corpus used for calculating TF-IDF is all movies a user has seen plus the movie we want to compare.
With regard to the movies, two ways of calculating the similarity are contemplated in this work:

- **As part of the hybrid system:** It begins with the movies obtained from collaborative filtering, which from now on will be called $movies_{CF}$. For each $movie_{CF}$, it calculates its similarity with all user movies and gets the maximum similarity. Finally, $movies_{CF}$ are sorted according to the maximum similarity.
- **As an independent system:** The content-based system iterates the same way as it did when it was part of the hybrid system, but instead of using the result of collaborative filtering, it uses all movies not rated by the user.

Although the option of using the content-based filtering as an independent system was not present in the reference paper [17], we thought it would be interesting to compare its results with the rest of systems.

4 Fuzzy expert system

The fuzzy expert system integrates the results of collaborative and content-based filtering to obtain a score to order the recommended movies for a specific user.

4.1 Variables

The input variables the system uses, for a given movie and user, are the following:

- **INP1: Average rating:** Average of ratings of the movie in an interval [0, 5]
- **INP2: Total ratings:** Total number of ratings of the movie in an interval [0, 350]
- **INP3: Similarity:** Maximum similarity between the movie and the movies the user has rated, obtained from content-based filtering, in an interval [0, 1]

These variables were normalized and mapped to the membership functions seen in Figure 1,

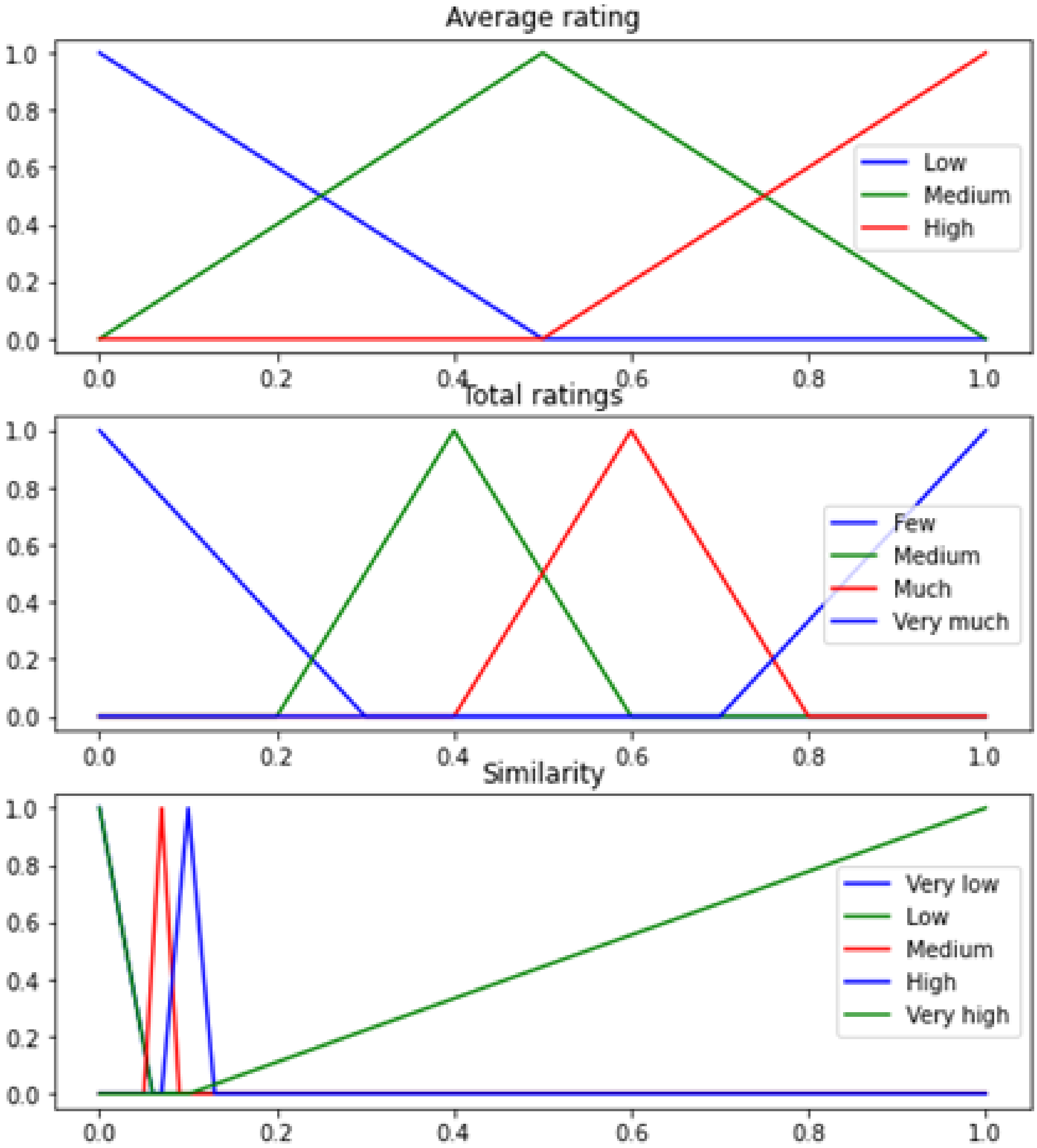

Figure 1: Normalized fuzzy membership functions

4.2 IF-THEN rules

The knowledge base of the fuzzy expert system contains a total of 144 IF-THEN rules. We can see them in the following tables: 4, 5 and 6.

4.3 Final value

The final value will be calculated by combining EXS IMPORTANCE, the value of a linguistic variable IMPORTANCE of the expert system, and the predicted value calculated so far.

if $PredictedEvaluation \leq 0$ **then**
 $FinalEvaluation = PredictedEvaluation * EXS\ IMPORTANCE$
if $PredictedEvaluation > 0$ **then**
 $FinalEvaluation = PredictedEvaluation * (1 + EXS\ IMPORTANCE)$

$PredictedEvaluation$ is only lower than 0 when the user makes few ratings or it concerns the calculation of $PredictedEvaluation$ in movies that do not correspond to the user's preferences. In such a case, $FinalEvaluation$ value is 0 or lower, because this movies should not appear in list of recommended movies. Otherwise, the value of $PredictedEvaluation$ is multiplied by value $1 + EXS\ IMPORTANCE$. The 1 was determined in [17], based on several experimental verifications.

Rule number	INP1	INP2	INP3	Importance
1	Low	Few	Low	Very low
2	Low	Few	Medium	Very low
3	Low	Few	High	Very low
4	Low	Few	Very high	Low
5	Low	Few	Low	Very low
6	Low	Few	Medium	Very low
7	Low	Few	High	Very low
8	Low	Few	Very high	Very low
9	Low	Few	Low	Very low
10	Low	Few	Medium	Very low
11	Low	Few	High	Very low
12	Low	Few	Very high	Very low
13	Low	Medium	Low	Very low
14	Low	Medium	Medium	Very low
15	Low	Medium	High	Very low
16	Low	Medium	Very high	Very low
17	Low	Medium	Low	Very low
18	Low	Medium	Medium	Very low
19	Low	Medium	High	Very low
20	Low	Medium	Very high	Very low
21	Low	Medium	Low	Very low
22	Low	Medium	Medium	Very low
23	Low	Medium	High	Very low
24	Low	Medium	Very high	Very low
25	Low	Much	Low	Very low
26	Low	Much	Medium	Very low
27	Low	Much	High	Very low
28	Low	Much	Very high	Very low
29	Low	Much	Low	Very low
30	Low	Much	Medium	Very low
31	Low	Much	High	Very low
32	Low	Much	Very high	Very low
33	Low	Much	Low	Very low
34	Low	Much	Medium	Very low
35	Low	Much	High	Very low
36	Low	Much	Very high	Very low
37	Low	Very much	Low	Very low
38	Low	Very much	Medium	Very low
39	Low	Very much	High	Very low
40	Low	Very much	Very high	Very low
41	Low	Very much	Low	Very low
42	Low	Very much	Medium	Very low
43	Low	Very much	High	Very low
44	Low	Very much	Very high	Very low
45	Low	Very much	Low	Very low
46	Low	Very much	Medium	Very low
47	Low	Very much	High	Very low
48	Low	Very much	Very high	Very low
49	Medium	Few	Low	Low
50	Medium	Few	Medium	Low
51	Medium	Few	High	Low
52	Medium	Few	Very high	Medium
53	Medium	Few	Low	Very low
54	Medium	Few	Medium	Very low
55	Medium	Few	High	Low
56	Medium	Few	Very high	Low
57	Medium	Few	Low	Very low

Table 4: IF-THEN rules of expert system (table 1)

Rule number	INP1	INP2	INP3	Importance
58	Medium	Few	Medium	Very low
59	Medium	Few	High	Very low
60	Medium	Few	Very high	Low
61	Medium	Medium	Low	Low
62	Medium	Medium	Medium	Medium
63	Medium	Medium	High	Medium
64	Medium	Medium	Very high	Medium
65	Medium	Medium	Low	Low
66	Medium	Medium	Medium	Low
67	Medium	Medium	High	Low
68	Medium	Medium	Very high	Medium
69	Medium	Medium	Low	Low
70	Medium	Medium	Medium	Low
71	Medium	Medium	High	Low
72	Medium	Medium	Very high	Low
73	Medium	Much	Low	Medium
74	Medium	Much	Medium	Medium
75	Medium	Much	High	Medium
76	Medium	Much	Very high	Medium
77	Medium	Much	Low	Low
78	Medium	Much	Medium	Low
79	Medium	Much	High	Medium
80	Medium	Much	Very high	Medium
81	Medium	Much	Low	Low
82	Medium	Much	Medium	Low
83	Medium	Much	High	Low
84	Medium	Much	Very high	Medium
85	Medium	Very much	Low	Medium
86	Medium	Very much	Medium	Medium
87	Medium	Very much	High	Medium
88	Medium	Very much	Very high	Medium
89	Medium	Very much	Low	Low
90	Medium	Very much	Medium	Medium
91	Medium	Very much	High	Medium
92	Medium	Very much	Very high	Medium
93	Medium	Very much	Low	Low
94	Medium	Very much	Medium	Low
95	Medium	Very much	High	Medium
96	Medium	Very much	Very high	Medium
97	High	Few	Low	Low
98	High	Few	Medium	Low
99	High	Few	High	Medium
100	High	Few	Very high	High
101	High	Few	Low	Low
102	High	Few	Medium	Low
103	High	Few	High	Medium
104	High	Few	Very high	Medium
105	High	Few	Low	Low
106	High	Few	Medium	Low
107	High	Few	High	Low
108	High	Few	Very high	Medium
109	High	Medium	Low	Medium
110	High	Medium	Medium	Medium
111	High	Medium	High	High
112	High	Medium	Very high	High
113	High	Medium	Low	Medium
114	High	Medium	Medium	Medium

Table 5: IF-THEN rules of expert system (table 2)

Rule number	INP1	INP2	INP3	Importance
115	High	Medium	High	Medium
116	High	Medium	Very high	High
117	High	Medium	Low	Medium
118	High	Medium	Medium	Medium
119	High	Medium	High	Medium
120	High	Medium	Very high	Medium
121	High	Much	Low	Medium
122	High	Much	Medium	High
123	High	Much	High	High
124	High	Much	Very high	Very high
125	High	Much	Low	Medium
126	High	Much	Medium	Medium
127	High	Much	High	High
128	High	Much	Very high	High
129	High	Much	Low	Medium
130	High	Much	Medium	Medium
131	High	Much	High	Medium
132	High	Much	Very high	High
133	High	Very much	Low	High
134	High	Very much	Medium	High
135	High	Very much	High	Very high
136	High	Very much	Very high	Very high
137	High	Very much	Low	High
138	High	Very much	Medium	High
139	High	Very much	High	High
140	High	Very much	Very high	Very high
141	High	Very much	Low	Medium
142	High	Very much	Medium	High
143	High	Very much	High	High
144	High	Very much	Very high	High

Table 6: IF-THEN rules of expert system (table 3)

5 Results

In this section we will analyse what negative aspects the collaborative system and the content-based system present separately. We will then see if the problems encountered in each of the models are overcome with the hybrid approach. To this end, each member of the team has rated a set of films and the programme has been run so that each of the three systems - content-based, collaborative filtering and hybrid - recommended a set of films.

First of all, we have included in the table 7 the genre preferences that each one has.

User ID		Genres
611	Likes	Thriller, Adventure, Action, Sci-Fi
611	Dislikes	Animation, Children
612	Likes	IMAX, Drama, Romance, Animation, Comedy
612	Dislikes	Adventure, Sci-Fi
613	Likes	{}
613	Dislikes	Adventure
614	Likes	(no genres listed), Children, Crime, Animation, Mystery, Romance
614	Dislikes	{}
615	Likes	Sci-Fi, Crime, Adventure, Thriller, Action
615	Dislikes	Children, Romance
616	Likes	Children, War, Romance, Comedy
616	Dislikes	Western, Thriller, Adventure, Action, IMAX, Sci-Fi

Table 7: Input genres for evaluation

5.1 611

This user is a fan of Marvel films. Let's see if the systems recommend more films from the franchise. And as result we got for example Iron Man as one of the recommendations, furthermore, its also recommended other sagas like Star Wars, X-Men, etc. Science Fiction related.

User ID	Movie ID	Movie name	Rating
611	122922	Doctor Strange (2016)	5.0
611	86332	Thor (2011)	4.0
611	122906	Black Panther (2017)	3.5
611	122926	Untitled Spider-Man Reboot (2017)	4.5
611	5349	Spider-Man (2002)	5.0
611	8636	Spider-Man 2 (2004)	4.5
611	44020	Ultimate Avengers (2006)	4.0
611	89745	Avengers, The (2012)	4.0
611	122912	Avengers: Infinity War - Part I (2018)	4.0
611	122892	Avengers: Age of Ultron (2015)	4.0

Table 8: Input movies for evaluation: User 611

User ID	Movie ID	Movie name	Rating
611	4993	Lord of the Rings: The Fellowship of the Ring, The (2001)	0.07225
611	5952	Lord of the Rings: The Two Towers, The (2002)	0.06723
611	1196	Star Wars: Episode V - The Empire Strikes Back (1980)	0.06433
611	5349	Spider-Man (2002)	0.06399
611	7153	Lord of the Rings: The Return of the King, The (2003)	0.06099
611	1198	Raiders of the Lost Ark (Indiana Jones and the Raiders of the Lost Ark) (1981)	0.05632
611	260	Star Wars: Episode IV - A New Hope (1977)	0.05137
611	1580	Men in Black (a.k.a. MIB) (1997)	0.05084
611	3793	X-Men (2000)	0.04709
611	72998	Avatar (2009)	0.04557
611	2571	Matrix, The (1999)	0.04554
611	6333	X2: X-Men United (2003)	0.04168
611	1210	Star Wars: Episode VI - Return of the Jedi (1983)	0.04139
611	6539	Pirates of the Caribbean: The Curse of the Black Pearl (2003)	0.04134
611	79132	Inception (2010)	0.04090
611	70286	District 9 (2009)	0.03833
611	1291	Indiana Jones and the Last Crusade (1989)	0.03785
611	780	Independence Day (a.k.a. ID4) (1996)	0.03783
611	59315	Iron Man (2008)	0.03746
611	2628	Star Wars: Episode I - The Phantom Menace (1999)	0.03650

Table 9: Collaborative Filtering: User 611

User ID	Movie ID	Movie name	Similarity
611	130518	The Amazing Screw-On Head (2006)	0.13316
611	7832	Thin Man Goes Home, The (1945)	0.13298
611	168456	Mercury Plains (2016)	0.13213
611	1305	Paris, Texas (1984)	0.13135
611	31422	Are We There Yet? (2005)	0.13102
611	5479	K-19: The Widowmaker (2002)	0.13099
611	6734	Memoirs of an Invisible Man (1992)	0.13009
611	8601	Zero de conduite (Zero for Conduct) (Zéro de conduite: Jeunes diables au collège) (1933)	0.12906
611	171759	The Beguiled (2017)	0.12840
611	128488	Wild Card (2015)	0.12840
611	31973	Germany Year Zero (Germania anno zero) (Deutschland im Jahre Null) (1948)	0.12660
611	138702	Feast (2014)	0.12654
611	3045	Peter's Friends (1992)	0.12639
611	5986	Fat City (1972)	0.12584
611	142056	Iron Man and Hulk: Heroes United (2013)	0.12571
611	80860	Life as We Know It (2010)	0.12523
611	952	Around the World in 80 Days (1956)	0.12400
611	88515	Blitz (2011)	0.12365
611	7333	Corbeau, Le (Raven, The) (1943)	0.12301
611	4594	Farewell to the King (1989)	0.12281

Table 10: Content Based: User 611

User ID	Movie ID	Movie name	CF rating	CB rating
611	5349	Spider-Man (2002)	0.06398	1.0
611	1580	Men in Black (a.k.a. MIB) (1997)	0.05084	0.10809
611	59315	Iron Man (2008)	0.03746	0.09120
611	79132	Inception (2010)	0.04090	0.07192
611	780	Independence Day (a.k.a. ID4) (1996)	0.03783	0.05958
611	72998	Avatar (2009)	0.04557	0.05557
611	1291	Indiana Jones and the Last Crusade (1989)	0.03785	0.05363
611	7153	Lord of the Rings: The Return of the King, The (2003)	0.06099	0.05149
611	5952	Lord of the Rings: The Two Towers, The (2002)	0.06722	0.05041
611	2571	Matrix, The (1999)	0.04554	0.04895
611	4993	Lord of the Rings: The Fellowship of the Ring, The (2001)	0.07224	0.04859
611	3793	X-Men (2000)	0.04708	0.04503
611	6539	Pirates of the Caribbean: The Curse of the Black Pearl (2003)	0.04134	0.04357
611	2628	Star Wars: Episode I - The Phantom Menace (1999)	0.03649	0.04181
611	1198	Raiders of the Lost Ark (Indiana Jones and the Raiders of the Lost Ark) (1981)	0.05632	0.04136
611	70286	District 9 (2009)	0.03832	0.03810
611	260	Star Wars: Episode IV - A New Hope (1977)	0.05137	0.03763
611	1196	Star Wars: Episode V - The Empire Strikes Back (1980)	0.06432	0.03415
611	6333	X2: X-Men United (2003)	0.04167	0.03036
611	1210	Star Wars: Episode VI - Return of the Jedi (1983)	0.04139	0.02866

Table 11: Collaborative Filtering + Content Based results: User 611

User ID	Movie ID	Movie name	Fuzzy score
611	5349	Spider-Man (2002)	0.09331
611	1580	Men in Black (a.k.a. MIB) (1997)	0.06806
611	59315	Iron Man (2008)	0.05008
611	79132	Inception (2010)	0.05026
611	780	Independence Day (a.k.a. ID4) (1996)	0.04621
611	72998	Avatar (2009)	0.05619
611	1291	Indiana Jones and the Last Crusade (1989)	0.04688
611	7153	Lord of the Rings: The Return of the King, The (2003)	0.07569
611	5952	Lord of the Rings: The Two Towers, The (2002)	0.08337
611	2571	Matrix, The (1999)	0.05641
611	4993	Lord of the Rings: The Fellowship of the Ring, The (2001)	0.08945
611	3793	X-Men (2000)	0.05813
611	6539	Pirates of the Caribbean: The Curse of the Black Pearl (2003)	0.05098
611	2628	Star Wars: Episode I - The Phantom Menace (1999)	0.04494
611	1198	Raiders of the Lost Ark (Indiana Jones and the Raiders of the Lost Ark) (1981)	0.06933
611	70286	District 9 (2009)	0.04706
611	260	Star Wars: Episode IV - A New Hope (1977)	0.06305
611	1196	Star Wars: Episode V - The Empire Strikes Back (1980)	0.07874
611	6333	X2: X-Men United (2003)	0.05087
611	1210	Star Wars: Episode VI - Return of the Jedi (1983)	0.05045

Table 12: Fuzzy expert system results: User 611

5.2 612

The user 612 corresponds to the tastes of a real user. They are keen on animation and fantasy movies, as well as comedies.

User ID	Movie ID	Movie name	Rating
612	1	Toy Story (1995)	3.0
612	2	Jumanji (1995)	4.0
612	184987	A Wrinkle in Time (2018)	1.0
612	173291	Valerian and the City of a Thousand Planets (2017)	3.0
612	171763	Baby Driver (2017)	4.0
612	152081	Zootopia (2016)	5.0
612	7147	Big Fish (2003)	5.0
612	162578	Kubo and the Two Strings (2016)	5.0
612	163134	Your Name. (2016)	4.5
612	5882	Treasure Planet (2002)	5.0

Table 13: Input movies for evaluation: User 612

User ID	Movie ID	Movie name	Rating
612	7147	Big Fish (2003)	0.01097
612	33794	Batman Begins (2005)	0.01077
612	344	Ace Ventura: Pet Detective (1994)	0.00957
612	51662	300 (2007)	0.00949
612	293	Léon: The Professional (a.k.a. The Professional) (Léon) (1994)	0.00882
612	69122	Hangover, The (2009)	0.00877
612	4223	Enemy at the Gates (2001)	0.00843
612	6373	Bruce Almighty (2003)	0.00835
612	1625	Game, The (1997)	0.00790
612	1645	The Devil's Advocate (1997)	0.00788
612	74458	Shutter Island (2010)	0.00778
612	6957	Bad Santa (2003)	0.00776
612	3081	Sleepy Hollow (1999)	0.00769
612	8874	Shaun of the Dead (2004)	0.00769
612	63082	Slumdog Millionaire (2008)	0.00764
612	19	Ace Ventura: When Nature Calls (1995)	0.00760
612	4344	Swordfish (2001)	0.00755
612	3510	Frequency (2000)	0.00747
612	784	Cable Guy, The (1996)	0.00734
612	4720	Others, The (2001)	0.00732

Table 14: Collaborative filtering: User 612

User ID	Movie ID	Movie name	Similarity
612	95717	Treasure Island (2012)	0.315 13
612	3114	Toy Story 2	0.288 36
612	246	Malcolm X (1992)	0.246 93
612	179401	Jumanji: Welcome to the Jungle (2017)	0.242 48
612	1991	Child's Play (1988)	0.239 66
612	8402	Book of Love (1990)	0.230 53
612	4080	Baby Boom (1987)	0.227 10
612	78499	Toy Story 3 (2010)	0.224 36
612	127202	Me and Earl and the Dying Girl (2015)	0.221 14
612	1993	Child's Play 3 (1991)	0.219 96
612	63992	Twilight (2008)	0.215 23
612	441	All-Star Superman (2011)	0.215 22
612	98122	Indie Game: The Movie (2012)	0.214 57
612	58492	Snow Angels (2007)	0.205 66
612	6405	Treasure Island (1950)	0.200 55
612	3360	Hoosiers (a.k.a. Best Shot) (1986)	0.196 73
612	121253	The Town that Dreaded Sundown (2014)	0.195 64
612	2555	Baby Geniuses (1999)	0.194 50
612	3916	Remember the Titans (2000)	0.194 22
612	58107	Step Up 2 the Streets (2008)	0.193 61

Table 15: Content Based results: User 612

User ID	Movie ID	Movie name	CF rating	CB rating
612	7147	Big Fish (2003)	0.01097	1.0
612	63082	Slumdog Millionaire (2008)	0.00764	0.12996
612	293	Léon: The Professional (a.k.a. The Professional) (Léon) (1994)	0.00882	0.09309
612	8874	Shaun of the Dead (2004)	0.00769	0.07298
612	6373	Bruce Almighty (2003)	0.00835	0.06280
612	3510	Frequency (2000)	0.00747	0.06022
612	1645	The Devil's Advocate (1997)	0.00788	0.05821
612	344	Ace Ventura: Pet Detective (1994)	0.00957	0.05594
612	6957	Bad Santa (2003)	0.00776	0.05150
612	3081	Sleepy Hollow (1999)	0.00769	0.05104
612	33794	Batman Begins (2005)	0.01077	0.04559
612	69122	Hangover, The (2009)	0.00877	0.04112
612	784	Cable Guy, The (1996)	0.00734	0.03784
612	4720	Others, The (2001)	0.00732	0.03415
612	4223	Enemy at the Gates (2001)	0.00843	0.03315
612	74458	Shutter Island (2010)	0.00778	0.03207
612	1625	Game, The (1997)	0.00790	0.03189
612	4344	Swordfish (2001)	0.00755	0.02481
612	19	Ace Ventura: When Nature Calls (1995)	0.00760	0.02245
612	51662	300 (2007)	0.00949	0.01283

Table 16: Collaborative Filtering + Content Based results: User 612

User ID	Movie ID	Movie name	Fuzzy score
612	7147	Big Fish (2003)	0.016 00
612	63082	Slumdog Millionaire (2008)	0.011 44
612	293	Léon: The Professional (a.k.a. The Professional) (Léon) (1994)	0.011 79
612	8874	Shaun of the Dead (2004)	0.009 53
612	6373	Bruce Almighty (2003)	0.010 14
612	3510	Frequency (2000)	0.009 11
612	1645	The Devil's Advocate (1997)	0.009 66
612	344	Ace Ventura: Pet Detective (1994)	0.011 79
612	6957	Bad Santa (2003)	0.009 63
612	3081	Sleepy Hollow (1999)	0.009 55
612	33794	Batman Begins (2005)	0.013 31
612	69122	Hangover, The (2009)	0.010 80
612	784	Cable Guy, The (1996)	0.009 01
612	4720	Others, The (2001)	0.008 96
612	4223	Enemy at the Gates (2001)	0.010 31
612	74458	Shutter Island (2010)	0.009 51
612	1625	Game, The (1997)	0.009 65
612	4344	Swordfish (2001)	0.009 18
612	19	Ace Ventura: When Nature Calls (1995)	0.009 23
612	51662	300 (2007)	0.011 49

Table 17: Fuzzy expert system results: User 612

The content-based results present Treasure Island movies, because they are related to Treasure Planet. It also presents Toy Story sequels, as the user likes Toy Story. Jumanji: Welcome to the Jungle is on the list because the user likes Jumanji.
The collaborative filtering results contains many Jim Carrey films (Ace Ventura, The Cable Guy, Bruce Almighty), and other comedies (The Hangover, Bad Santa, Shaun of the Dead), that match with the sense of humor of user 612.
This user also loves dramas. Slumdog Millionaire is one of their favourite movies and it is rated as the first unseen movie in the Collaborative Filtering + Content Based results, and the sixth movie in the Fuzzy expert system results.

5.3 613

The next user would be a fan of the Sharknado saga. This user was set up with the goal to see what if we choose all the films related to a saga, and as a result, we got recommendations with genres related, so the results are ok.

User ID	**Movie ID**	**Movie name**	**Rating**
613	136305	Sharknado 3: Oh Hell No! (2015)	5.0
613	161918	Sharknado 4: The 4th Awakens (2016)	5.0
613	103596	Sharknado (2013)	5.0

Table 18: Input movies for evaluation: User 613

User ID	**Movie ID**	**Movie name**	**Rating**
613	3527	Predator (1987)	0.01923
613	114180	Maze Runner, The (2014)	0.01757
613	96861	Taken 2 (2012)	0.01660
613	79185	Knight and Day (2010)	0.01655
613	356	Forrest Gump (1994)	0.01603
613	71530	Surrogates (2009)	0.01599
613	1982	Halloween (1978)	0.01578
613	32	Twelve Monkeys (a.k.a. 12 Monkeys) (1995)	0.01573
613	2571	Matrix, The (1999)	0.01505
613	4351	Point Break (1991)	0.01466
613	5673	Punch-Drunk Love (2002)	0.01401
613	104218	Grown Ups 2 (2013)	0.01389
613	91976	Grey, The (2012)	0.01375
613	2534	Avalanche (1978)	0.01324
613	111617	Blended (2014)	0.01323
613	103339	White House Down (2013)	0.01295
613	5507	xXx (2002)	0.01293
613	8984	Ocean's Twelve (2004)	0.01291
613	120635	Taken 3 (2015)	0.01273
613	4255	Freddy Got Fingered (2001)	0.01270

Table 19: Collaborative Filtering: User 613

User ID	Movie ID	Movie name	Similarity
613	724	Craft, The (1996)	0.07547
613	4215	Revenge of the Nerds II: Nerds in Paradise (1987)	0.07535
613	4104	Ernest Goes to Camp (1987)	0.07434
613	95309	Seeking a Friend for the End of the World (2012)	0.07428
613	58972	Toni Erdmann (2016)	0.07420
613	90439	Margin Call (2011)	0.07401
613	4626	Miracle Mile (1989)	0.07400
613	187541	Incredibles 2 (2018)	0.07386
613	6881	Pieces of April (2003)	0.07341
613	3577	Two Moon Junction (1988)	0.07324
613	110746	Hatchet III (2013)	0.07302
613	70301	Obsessed (2009)	0.07294
613	3897	Almost Famous (2000)	0.07285
613	147662	Return of the One-Armed Swordsman (1969)	0.07285
613	1389	Return of the One-Armed Swordsman (1969)	0.07264
613	71999	Aelita: The Queen of Mars (Aelita) (1924)	0.07223
613	5506	Blood Work (2002)	0.07192
613	2046	Flight of the Navigator (1986)	0.07123
613	5901	Empire (2002)	0.07120
613	144522	Sky High (2003)	0.06913

Table 20: Content Based: User 613

User ID	Movie ID	Movie name	CF rating	CB rating
613	1982	Halloween (1978)	0.01578	0.04130
613	4351	Point Break (1991)	0.01466	0.03738
613	104218	Grown Ups 2 (2013)	0.01389	0.03121
613	4255	Freddy Got Fingered (2001)	0.01270	0.03075
613	120635	Taken 3 (2015)	0.01273	0.02902
613	114180	Maze Runner, The (2014)	0.01757	0.02847
613	5673	Punch-Drunk Love (2002)	0.01401	0.02534
613	103339	White House Down (2013)	0.01295	0.02401
613	32	Twelve Monkeys (a.k.a. 12 Monkeys) (1995)	0.01573	0.02277
613	3527	Predator (1987)	0.01923	0.01932
613	71530	Surrogates (2009)	0.01599	0.01902
613	8984	Ocean's Twelve (2004)	0.01291	0.01529
613	111617	Blended (2014)	0.01323	0.01487
613	5507	xXx (2002)	0.01293	0.01466
613	356	Forrest Gump (1994)	0.01603	0.01391
613	2571	Matrix, The (1999)	0.01505	0.01145
613	96861	Taken 2 (2012)	0.01660	0.00766
613	79185	Knight and Day (2010)	0.01655	0
613	91976	Grey, The (2012)	0.01375	0
613	2534	Avalanche (1978)	0.01324	0

Table 21: Collaborative Filtering + Content Based results: User 613

User ID	Movie ID	Movie name	Fuzzy Score
613	1982	Halloween (1978)	0.01943
613	4351	Point Break (1991)	0.01799
613	104218	Grown Ups 2 (2013)	0.01696
613	4255	Freddy Got Fingered (2001)	0.01550
613	120635	Taken 3 (2015)	0.01553
613	114180	Maze Runner, The (2014)	0.02142
613	5673	Punch-Drunk Love (2002)	0.01704
613	103339	White House Down (2013)	0.01574
613	32	Twelve Monkeys (a.k.a. 12 Monkeys) (1995)	0.01911
613	3527	Predator (1987)	0.02333
613	71530	Surrogates (2009)	0.01940
613	8984	Ocean's Twelve (2004)	0.01564
613	111617	Blended (2014)	0.01602
613	5507	xXx (2002)	0.01566
613	356	Forrest Gump (1994)	0.01941
613	2571	Matrix, The (1999)	0.01821
613	96861	Taken 2 (2012)	0.02007
613	79185	Knight and Day (2010)	0.02000
613	91976	Grey, The (2012)	0.01661
613	2534	Avalanche (1978)	0.01600

Table 22: Fuzzy expert system results: User 613

5.4 614

This user is created in order to add noise to the recommender system, as there is no manga, comic genre in data, the recommender is not able to provide an exact result. But checking the results obtained, the films recommended suits quite well even though they are not manga films.

User ID	Movie ID	Movie name	Rating
614	53996	Transformers (2007)	2.5
614	122904	Deadpool (2016)	5.0
614	187593	Deadpool 2 (2018)	5.0
614	193583	No Game No Life: Zero (2017)	4.5
614	177285	Sword Art Online The Movie: Ordinal Scale (2017)	4.0
614	176601	Black Mirror	5.0
614	191005	Gintama (2017)	3.5
614	188301	Ant-Man and the Wasp (2018)	3.5
614	187031	Jurassic World: Fallen Kingdom (2018)	4.0
614	163134	Your Name. (2016)	4.5
614	5672	Pokemon 4 Ever (a.k.a. Pokemon 4: The Movie) (2002)	4.5
614	80083	Dragon Ball Z: Dead Zone (1989)	4.0
614	95163	Dragon Ball: Mystical Adventure (1988)	5.0
614	95182	Dragon Ball Z the Movie: The Tree of Might (1990)	5.0
614	6874	Kill Bill: Vol. 1 (2003)	4.5
614	27311	Batman Beyond: Return of the Joker (2000)	5.0
614	45499	X-Men: The Last Stand (2006)	4.0
614	44020	Ultimate Avengers (2006)	5.0
614	45722	Pirates of the Caribbean: Dead Man's Chest (2006)	4.0
614	45447	Da Vinci Code, The (2006)	4.5
614	54001	Harry Potter and the Order of the Phoenix (2007)	1.5

Table 23: Input movies for evaluation: User 614

User ID	Movie ID	Movie name	Rating
614	357	Four Weddings and a Funeral (1994)	0.02203
614	296	Pulp Fiction (1994)	0.02109
614	1625	Game, The (1997)	0.01915
614	1732	Big Lebowski, The (1998)	0.01858
614	2762	Sixth Sense, The (1999)	0.01856
614	1073	Willy Wonka and the Chocolate Factory (1971)	0.01785
614	2542	Lock, Stock and Two Smoking Barrels (1998)	0.01758
614	2804	Christmas Story, A (1983)	0.01695
614	4720	Others, The (2001)	0.01678
614	1221	Godfather: Part II, The (1974)	0.01601
614	318	Shawshank Redemption, The (1994)	0.01548
614	2232	Cube (1997)	0.01528
614	593	Silence of the Lambs, The (1991)	0.01505
614	608	Fargo (1996)	0.01493
614	4878	Donnie Darko (2001)	0.01476
614	1997	Exorcist, The (1973)	0.01465
614	4973	Amelie (Fabuleux destin d'Amélie Poulain, Le) (2001)	0.01457
614	3481	High Fidelity (2000)	0.01439
614	27773	Old Boy (2003)	0.01434
614	5110	Super Troopers (2001)	0.01387

Table 24: Collaborative Filtering: User 614

User ID	Movie ID	Movie name	Similarity
614	5027	Another 48 Hrs. (1990)	0.23084
614	2475	52 Pick-Up (1986)	0.22973
614	69844	Harry Potter and the Half-Blood Prince (2009)	0.22888
614	2184	Trouble with Harry, The (1955)	0.22813
614	127202	Me and Earl and the Dying Girl (2015)	0.22791
614	57669	In Bruges (2008)	0.22555
614	2579	Following (1998)	0.22502
614	3793	X-Men (2000)	0.22495
614	7013	Night of the Hunter, The (1955)	0.22470
614	58492	Snow Angels (2007)	0.22387
614	3360	Hoosiers (a.k.a. Best Shot) (1986)	0.22251
614	121253	The Town that Dreaded Sundown (2014)	0.22155
614	3213	Batman: Mask of the Phantasm (1993)	0.21894
614	79274	Batman: Under the Red Hood (2010)	0.21709
614	8402	The Crew (2016)	0.21490
614	2600	Miss Peregrine's Home for Peculiar Children (2016)	0.21485
614	26764	Captain America (1990)	0.21477
614	87520	Transformers: Dark of the Moon (2011)	0.21343
614	6159	All the Real Girls (2003)	0.21090
614	40815	Harry Potter and the Goblet of Fire (2005)	0.21012

Table 25: Content Based: User 614

User ID	Movie ID	Movie name	CF rating	CB rating
614	4973	Amelie (Fabuleux destin d'Amélie Poulain, Le) (2001)	0.01457	0.07700
614	2762	Sixth Sense, The (1999)	0.01856	0.07534
614	318	Shawshank Redemption, The (1994)	0.01548	0.07249
614	27773	Old Boy (2003)	0.01434	0.07215
614	2542	Lock, Stock and Two Smoking Barrels (1998)	0.01758	0.06911
614	608	Fargo (1996)	0.01493	0.06855
614	4720	Others, The (2001)	0.01678	0.06828
614	3481	High Fidelity (2000)	0.01439	0.06110
614	1221	Godfather: Part II, The (1974)	0.01601	0.05831
614	593	Silence of the Lambs, The (1991)	0.01505	0.05408
614	2232	Cube (1997)	0.01528	0.04697
614	2804	Christmas Story, A (1983)	0.01695	0.04678
614	296	Pulp Fiction (1994)	0.02109	0.04352
614	5110	Super Troopers (2001)	0.01387	0.04251
614	357	Four Weddings and a Funeral (1994)	0.02203	0.04144
614	1732	Big Lebowski, The (1998)	0.01858	0.03901
614	1073	Willy Wonka and the Chocolate Factory (1971)	0.01785	0.03725
614	1625	Game, The (1997)	0.01915	0.02909
614	4878	Donnie Darko (2001)	0.01476	0.02780
614	1997	Exorcist, The (1973)	0.01465	0.02708

Table 26: Collaborative Filtering + Content Based results: User 614

User ID	Movie ID	Movie name	Fuzzy Score
614	4973	Amelie (Fabuleux destin d'Amélie Poulain, Le) (2001)	0.01868
614	2762	Sixth Sense, The (1999)	0.02346
614	318	Shawshank Redemption, The (1994)	0.01912
614	27773	Old Boy (2003)	0.01766
614	2542	Lock, Stock and Two Smoking Barrels (1998)	0.02124
614	608	Fargo (1996)	0.01804
614	4720	Others, The (2001)	0.02028
614	3481	High Fidelity (2000)	0.01752
614	1221	Godfather: Part II, The (1974)	0.01961
614	593	Silence of the Lambs, The (1991)	0.01863
614	2232	Cube (1997)	0.01890
614	2804	Christmas Story, A (1983)	0.02096
614	296	Pulp Fiction (1994)	0.02601
614	5110	Super Troopers (2001)	0.01710
614	357	Four Weddings and a Funeral (1994)	0.02712
614	1732	Big Lebowski, The (1998)	0.02283
614	1073	Willy Wonka and the Chocolate Factory (1971)	0.02191
614	1625	Game, The (1997)	0.02335
614	4878	Donnie Darko (2001)	0.01798
614	1997	Exorcist, The (1973)	0.01784

Table 27: Fuzzy expert system results: User 614

5.5 615

The ID 615 corresponds to the personal tastes of a user. In particular, his preferences have a certain mix between the genres of drama, suspense and thriller; since he has given a high score to films such as Fight Club, Whiplash, Gone Girl, Kill Bill or No Country for Old Men. On the other hand, he also seems to be interested in the genre of superheroes and animation, since he has positively rated The Dark Knight, Avengers: Infinity War and Wall·e.

User ID	Movie ID	Movie name	Rating
615	112552	Whiplash (2014)	5.0
615	2959	Fight Club (1999)	5.0
615	58559	Dark Knight, The (2008)	5.0
615	112556	Gone Girl (2014)	4.5
615	6874	Kill Bill: Vol. 1 (2003)	5.0
615	176371	Blade Runner 2049 (2017)	0.5
615	125916	Fifty Shades of Grey (2015)	0.5
615	60069	WALL·E (2008)	5.0
615	122898	Justice League (2017)	2.0
615	174055	Dunkirk (2017)	2.5
615	89118	Skin I Live In, The (La piel que habito) (2011)	3.0
615	164909	La La Land (2016)	4.5
615	180297	The Disaster Artist (2017)	3.5
615	171763	Baby Driver (2017)	4.5
615	122912	Avengers: Infinity War - Part I (2018)	4.0
615	87306	Super 8 (2011)	3.0
615	55820	No Country for Old Men (2007)	4.0
615	1080	Monty Python's Life of Brian (1979)	4.0
615	1089	Reservoir Dogs (1992)	4.5
615	86882	Midnight in Paris (2011)	4.5
615	170957	Cars 3 (2017)	0.5

Table 28: Input movies for evaluation: User 615

User ID	Movie ID	Movie name	Rating
615	2571	Matrix, The (1999)	0.10868
615	2959	Fight Club (1999)	0.08909
615	296	Pulp Fiction (1994)	0.07216
615	79132	Inception (2010)	0.06878
615	7153	Lord of the Rings: The Return of the King, The (2003)	0.06351
615	858	Godfather, The (1972)	0.06313
615	1196	Star Wars: Episode V - The Empire Strikes Back (1980)	0.06246
615	593	Silence of the Lambs, The (1991)	0.06088
615	260	Star Wars: Episode IV - A New Hope (1977)	0.05912
615	4226	Memento (2000)	0.05788
615	6874	Kill Bill: Vol. 1 (2003)	0.04957
615	1210	Star Wars: Episode VI - Return of the Jedi (1983)	0.04828
615	50	Usual Suspects, The (1995)	0.04700
615	72998	Avatar (2009)	0.04677
615	33794	Batman Begins (2005)	0.04552
615	91529	Dark Knight Rises, The (2012)	0.04384
615	4993	Lord of the Rings: The Fellowship of the Ring, The (2001)	0.04264
615	2028	Saving Private Ryan (1998)	0.04244
615	47	Seven (a.k.a. Se7en) (1995)	0.04243
615	2762	Sixth Sense, The (1999)	0.04225

Table 29: Collaborative Filtering: User 615

User ID	Movie ID	Movie name	Similarity
615	8712	My Favorite Wife (1940)	0.20207
615	5026	Brotherhood of the Wolf (Pacte des loups, Le) (2001)	0.20077
615	79274	Batman: Under the Red Hood (2010)	0.19943
615	210	Wild Bill (1995)	0.19804
615	158388	Buck Rogers in the 25th Century (1979)	0.19629
615	110603	God's Not Dead (2014)	0.1948
615	5959	Narc (2002)	0.19272
615	6734	Memoirs of an Invisible Man (1992)	0.19095
615	99813	Batman: The Dark Knight Returns, Part 2 (2013)	0.19085
615	128488	Wild Card (2015)	0.18598
615	85736	BURN-E (2008)	0.18594
615	47382	Step Up (2006)	0.18484
615	8016	Getaway, The (1972)	0.1845
615	6890	Elephant (2003)	0.18409
615	134881	Love and Mercy (2014)	0.18335
615	96964	Tall Man, The (2012)	0.18207
615	44195	Thank You for Smoking (2006)	0.18069
615	848	Spitfire Grill, The (1996)	0.18043
615	68237	Moon (2009)	0.18015
615	93610	Space Battleship Yamato (2010)	0.17950

Table 30: Content Based: User 615

User ID	Movie ID	Movie name	CF rating	CB rating
615	2959	Fight Club (1999)	0.08909	0.99999
615	6874	Kill Bill: Vol. 1 (2003)	0.04957	0.99999
615	91529	Dark Knight Rises, The (2012)	0.04384	0.14979
615	33794	Batman Begins (2005)	0.04552	0.13707
615	79132	Inception (2010)	0.06878	0.07852
615	858	Godfather, The (1972)	0.06313	0.06495
615	7153	Lord of the Rings: The Return of the King, The (2003)	0.06351	0.06314
615	2028	Saving Private Ryan (1998)	0.04244	0.05957
615	2762	Sixth Sense, The (1999)	0.04225	0.05752
615	47	Seven (a.k.a. Se7en) (1995)	0.04243	0.05695
615	4226	Memento (2000)	0.05788	0.05512
615	1196	Star Wars: Episode V - The Empire Strikes Back (1980)	0.06246	0.05125
615	296	Pulp Fiction (1994)	0.07216	0.04990
615	50	Usual Suspects, The (1995)	0.04700	0.04968
615	260	Star Wars: Episode IV - A New Hope (1977)	0.05912	0.04868
615	593	Silence of the Lambs, The (1991)	0.06088	0.04844
615	72998	Avatar (2009)	0.04677	0.04601
615	4993	Lord of the Rings: The Fellowship of the Ring, The (2001)	0.04264	0.04590
615	1210	Star Wars: Episode VI - Return of the Jedi (1983)	0.04828	0.04340
615	2571	Matrix, The (1999)	0.10868	0.03587

Table 31: Collaborative Filtering + Content Based results: User 615

User ID	Movie ID	Movie name	Fuzzy Score
615	2959	Fight Club (1999)	0.12992
615	6874	Kill Bill: Vol. 1 (2003)	0.07229
615	91529	Dark Knight Rises, The (2012)	0.06560
615	33794	Batman Begins (2005)	0.06816
615	79132	Inception (2010)	0.08945
615	858	Godfather, The (1972)	0.07646
615	7153	Lord of the Rings: The Return of the King, The (2003)	0.07707
615	2028	Saving Private Ryan (1998)	0.05183
615	2762	Sixth Sense, The (1999)	0.05185
615	47	Seven (a.k.a. Se7en) (1995)	0.05215
615	4226	Memento (2000)	0.07144
615	1196	Star Wars: Episode V - The Empire Strikes Back (1980)	0.07750
615	296	Pulp Fiction (1994)	0.08945
615	50	Usual Suspects, The (1995)	0.05825
615	260	Star Wars: Episode IV - A New Hope (1977)	0.07321
615	593	Silence of the Lambs, The (1991)	0.07538
615	72998	Avatar (2009)	0.05780
615	4993	Lord of the Rings: The Fellowship of the Ring, The (2001)	0.05269
615	1210	Star Wars: Episode VI - Return of the Jedi (1983)	0.05954
615	2571	Matrix, The (1999)	0.13322

Table 32: Fuzzy expert system results: User 615

The system has been able to make good recommendations, as it has recommended quite a few thrillers and suspense films, such as Seven, The Godfather, Memento or The Silence of the Lambs. It has also merged the user's taste for superheroes and suspense, recommending Batman movies.

5.6 616

The ID 616 corresponds to the personal tastes of a user which prefers comedies, drama, suspense and adventure movies; he has given a high score to films such as Movie 43, The Great Gatsby, Princess Mononoke, Amores Perros, X-Men: Days of Future Past or Sin City.

User ID	Movie ID	Movie name	Rating
616	2116	Lord of the Rings, The (1978)	5.0
616	98809	Hobbit: An Unexpected Journey, The (2012)	5.0
616	99114	Django Unchained (2012)	4.0
616	99532	Miserables, Les (2000)	4.0
616	99813	Campfire Tales (1997)	2.0
616	101025	Jack the Giant Slayer (2013)	2.0
616	101076	G.I. Joe: Retaliation (2013)	2.0
616	33801	Godzilla: Final Wars (Gojira: Fainaru uôzu) (2004)	2.0
616	100083	Movie 43 (2013)	4.0
616	102407	Great Gatsby, The (2013)	5.0
616	3000	Mystery Science Theater 3000: The Movie (1996)	5.0
616	5618	Spirited Away (Sen to Chihiro no kamikakushi) (2001)	5.0
616	4235	Amores Perros (Love's a Bitch) (2000)	5.0
616	112183	Birdman: Or (The Unexpected Virtue of Ignorance) (2014)	5.0
616	1078	Bananas (1971)	5.0
616	1230	Annie Hall (1977)	5.0
616	103980	Blue Jasmine (2013)	4.0
616	80463	Social Network, The (2010)	3.0
616	106782	Wolf of Wall Street, The (2013)	5.0
616	109971	Ocho apellidos vascos (2014)	3.0
616	111362	X-Men: Days of Future Past (2014)	3.0
616	113573	Sin City: A Dame to Kill For (2014)	4.0

Table 33: Input movies for evaluation: User 616

User ID	Movie ID	Movie name	Rating
616	296	Pulp Fiction (1994)	0.05334
616	1732	Big Lebowski, The (1998)	0.03958
616	593	Silence of the Lambs, The (1991)	0.03809
616	50	Usual Suspects, The (1995)	0.03790
616	48385	Borat: Cultural Learnings of America for Make Benefit Glorious Nation of Kazakhstan (2006)	0.03731
616	924	2001: A Space Odyssey (1968)	0.03668
616	5618	Spirited Away (Sen to Chihiro no kamikakushi) (2001)	0.03585
616	1073	Willy Wonka and the Chocolate Factory (1971)	0.03308
616	4878	Donnie Darko (2001)	0.03177
616	1206	Clockwork Orange, A (1971)	0.03168
616	8874	Shaun of the Dead (2004)	0.03108
616	2710	Blair Witch Project, The (1999)	0.03102
616	32	Twelve Monkeys (a.k.a. 12 Monkeys) (1995)	0.03067
616	1270	Back to the Future (1985)	0.03057
616	46578	Little Miss Sunshine (2006)	0.03038
616	4226	Memento (2000)	0.03008
616	608	Fargo (1996)	0.02954
616	2012	Back to the Future Part III (1990)	0.02945
616	4979	Royal Tenenbaums, The (2001)	0.02828
616	5952	Lord of the Rings: The Two Towers, The (2002)	0.02806

Table 34: Collaborative Filtering: User 616

User ID	Movie ID	Movie name	Similarity
616	64497	Day the Earth Stood Still, The (2008)	0.17631
616	53466	Nancy Drew (2007)	0.172038
616	1690	Alien: Resurrection (1997)	0.16972
616	175431	Bobik Visiting Barbos (1977)	0.16684
616	4886	Monsters, Inc. (2001)	0.166837
616	67408	Monsters vs. Aliens (2009)	0.16621
616	6433	Man with the Movie Camera, The (Chelovek s kino-apparatom) (1929)	0.1661
616	5952	Lord of the Rings: The Two Towers, The (2002)	0.166042
616	70336	G.I. Joe: The Rise of Cobra (2009)	0.165613
616	5348	Hollywood Ending (2002)	0.16500
616	580	Princess Caraboo (1994)	0.164596
616	324	Sum of Us, The (1994)	0.161381
616	2665	Earth vs. the Flying Saucers (1956)	0.161093
616	1681	Mortal Kombat: Annihilation (1997)	0.161033
616	8577	Comandante (2003)	0.159726
616	2674	Loss of Sexual Innocence, The (1999)	0.159096
616	127172	A Story of Children and Film (2013)	0.158679
616	350	Client, The (1994)	0.15844
616	135567	Independence Day: Resurgence (2016)	0.158028
616	118696	The Hobbit: The Battle of the Five Armies (2014)	0.157200

Table 35: Content Based: User 616

User ID	Movie ID	Movie name	CF rating	CB rating
616	5618	Spirited Away (Sen to Chihiro no kamikakushi) (2001)	0.03585	0.99999
616	5952	Lord of the Rings: The Two Towers, The (2002)	0.02806	0.16604
616	2710	Blair Witch Project, The (1999)	0.03102	0.09495
616	2012	Back to the Future Part III (1990)	0.02945	0.08962
616	8874	Shaun of the Dead (2004)	0.03108	0.06828
616	1206	Clockwork Orange, A (1971)	0.03168	0.05880
616	608	Fargo (1996)	0.02954	0.05728
616	1073	Willy Wonka and the Chocolate Factory (1971)	0.03308	0.05262
616	4226	Memento (2000)	0.03008	0.05257
616	1270	Back to the Future (1985)	0.03057	0.04967
616	4979	Royal Tenenbaums, The (2001)	0.02828	0.04415
616	46578	Little Miss Sunshine (2006)	0.03038	0.04025
616	593	Silence of the Lambs, The (1991)	0.03809	0.03995
616	1732	Big Lebowski, The (1998)	0.03958	0.03920
616	50	Usual Suspects, The (1995)	0.03790	0.03555
616	48385	Borat: Cultural Learnings of America for Make Benefit Glorious Nation of Kazakhstan (2006)	0.03731	0.03482
616	4878	Donnie Darko (2001)	0.03177	0.03391
616	924	2001: A Space Odyssey (1968)	0.03668	0.03193
616	32	Twelve Monkeys (a.k.a. 12 Monkeys) (1995)	0.03067	0.03155
616	296	Pulp Fiction (1994)	0.05334	0.02570

Table 36: Collaborative Filtering + Content Based results: User 616

User ID	Movie ID	Movie name	Fuzzy Score
616	5618	Spirited Away (Sen to Chihiro no kamikakushi) (2001)	0.05229
616	5952	Lord of the Rings: The Two Towers, The (2002)	0.04196
616	2710	Blair Witch Project, The (1999)	0.04140
616	2012	Back to the Future Part III (1990)	0.03941
616	8874	Shaun of the Dead (2004)	0.03756
616	1206	Clockwork Orange, A (1971)	0.03876
616	608	Fargo (1996)	0.03628
616	1073	Willy Wonka and the Chocolate Factory (1971)	0.04108
616	4226	Memento (2000)	0.03736
616	1270	Back to the Future (1985)	0.03789
616	4979	Royal Tenenbaums, The (2001)	0.03490
616	46578	Little Miss Sunshine (2006)	0.03737
616	593	Silence of the Lambs, The (1991)	0.04684
616	1732	Big Lebowski, The (1998)	0.04865
616	50	Usual Suspects, The (1995)	0.04645
616	48385	Borat: Cultural Learnings of America for Make Benefit Glorious Nation of Kazakhstan (2006)	0.04570
616	4878	Donnie Darko (2001)	0.03889
616	924	2001: A Space Odyssey (1968)	0.04483
616	32	Twelve Monkeys (a.k.a. 12 Monkeys) (1995)	0.03746
616	296	Pulp Fiction (1994)	0.06490

Table 37: Fuzzy expert system results: User 616

The system has been able to make good recommendations, as it has recommended movies from the Lord of the Rings saga, suspense's from the Cohen brothers and some Quentin Tarantino films like Pulp Fiction.

5.7 About the content-based system

Problems:

- Cold Start Problem (with users): in order to obtain recommendations for a user, the system needs at least one rated movie, or they will not get any result. The system does not have any problem with new movies.
- Diversity: content-based recommendations are not diverse. If the ratings of an user do not change, they will always get the same recommendations. The only diversity seen in the results would be caused by the addition of new ratings or new movies to the catalogue.
- Scalability: the TF-IDF calculation has to be performed for each of the films in the database. Therefore, it would take too long if we expanded the films we are dealing with.

5.8 About the collaborative filtering system

Problems:

- Cold Start Problem (with users and movies): when we have few users, the system does not work well, as it does not know what to recommend to the few users who value movies.
- Grey Sheep Problem: if a person has strange tastes, different from those of most people who watch the movies they have rated, the system would fail to recommend films.
- Shilling Attacks: if false ratings are given to movies to increase their popularity, the system may mistakenly recommend them to other users.
- Scalability: although the collaborative filtering system is much more scalable than the content-based system, as the number of movies and users increase, so does the time the algorithm needs to get the recommendations.

5.9 About the hybrid system

We believe that combining the two systems solves problems such as grey sheep, since the recommendations are also based on the type of movies you like; diversity, because thanks to CF other users may have seen weird movies, and therefore be recommended by the system; and shilling attacks, since the algorithm does not depend only on user ratings. However, there are still two problems that have not been solved and that will challenge us for future work.

Problems:

- Cold Start Problem: as CF is the first algorithm of the system, the hybrid system has the same Cold Start Problem as CF alone. Nevertheless, the Cold Start Problem can be faced asking new users to rate some movies.
- Scalability: the hybrid system is much more scalable than the content-based system and a little less scalable than collaborative filtering. Nevertheless, the results show that this little decrease of scalability is worth it when compared to the quality of the final rankings of results.

6 Conclusions

One of the advantages of hybrid recommender systems is the ability to combine the outputs of content-based filters and collaborative filtering, reducing the impact of the cold-start problem. In the future of recommender systems an open field of study is the combination of hybrid systems and sentiment analysis on social networks data.

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