

Recommender System: Individual Assignment 2

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Main Objective

Build a recommender system and interface taking in account user's values like control, diversity, transparency and acceptance

1. Introduction

Whereas several algorithms have been developed and deployed in various application domains, recent research efforts are increasingly oriented towards the user experience of recommender systems [1]. This research goes beyond accuracy of recommendation algorithms and focuses on various human factors that affect acceptance of recommendations, such as user satisfaction, trust, transparency and sense of control.

Many different stakeholders can use or affect a recommender system. These stakeholder have different values and desired outcomes. Which leads to the question: How this can be connected and addressed in a single recommender system? How the interface can be used to answer for human values like **control**, **diversity**, **transparency** and **acceptance** and increase audience metrics like **usage** and **engagement**?

In this work, we present an interface that bridges the recommendation with visualization techniques to support human-recommender interaction.

2. Methodology

Some well know values in literature are, **Transparency** that deals with the “black-box” nature of current recommender systems by explaining the inner logic of the system to end users. **Justification** helps users understand why they get certain recommendations, but it may not relate to the inner logic of the recommendation techniques. **Controllability** strengthens user involvement by incorporating input and feedback from the end user into the recommendation process. It can occurs in any step, such as providing ratings, adjusting preference data, and revising or exploring recommendations.

Diversity, it refers to providing recommendations with a relatively large coverage of the recommendation space [2]. For instance, it is important to recommend items that the user would prefer,

but that are different from those which she has already purchased or experienced. The inability to make recommendation to new comers is called the **cold start** problem. Acquiring **contextual** information and incorporating it into recommendation processes in a flexible and fluid manner has gained increased interest over the past decades. The goal is to tailor recommendations to the current needs of the target user.

Algorithmic Affordance pattern library is a first attempt to give an overview over the possibilities for designers to give end-users more control over the outcomes of algorithms [3]. These patterns can show many different possibilities to allow, measure and improve recommender system with well-designed interfaces (see table1).

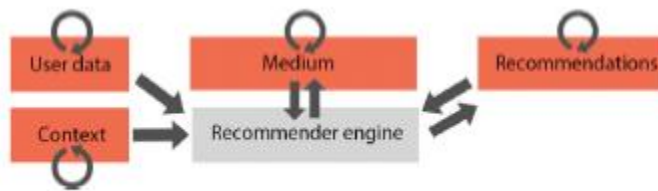


Fig. 1. Interactive recommender framework.

Figure1. Workflow of feedback from interaction of a user with recommender. Adapted from [4]

Pattern	Main Idea	How it is used in My interface
Peek Picker	Users can switch between their own recommendations and those of peers which are further away.	Recommendations based on collaborative filter (selecting friends / genres)
Multiple Profiles	User can select different profiles	Profile Change (So user can compare out what works for them)
Incognito	User can go "anonymous" not recording any statistics	Button Incognito on main page
Introduce Chance	Giving users the option to activate a chance effect into their recommendations leads to more diverse recommendations.	Movies based on never watched genres, tags, users and random generator. They understand chance plays a big role so they may expect recommendation surprises.
Data Toggles	Switches may enable the user to choose which data is used by the algorithm to arrive at a recommendation.	Allow user selection genres, actors, directors from a list in the interface. Users may manipulate this information to build a dynamic model of what information is vital to their recommendation.
Social Context	Social recommendation systems can be more transparent by indicating the social group their recommendations are based upon.	Show to user the friends, genres of which recommendation was based. Users are aware the suggestions are context sensitive.
Ordered List	By presenting top recommendations in an ordered list, users can make a choice among multiple items that are recommended for them.	Lists ranked by similarities and ratings, so the user can choose among presented alternatives
Liking Items	Users are given a lightweight control to express their opinion about an item, cumulatively resulting in feedback to the algorithm about user preferences.	Allow user rates movies (1-5), these ratings are using as input metrics to algorithm (explicit feedback)
Blacklist	Users can blacklist items, giving the algorithm an idea of their dislikes and preventing the algorithm from showing it again.	Users rates movies, so intuitively the algorithm will recommend less similar items. A user can filter a genre, so it will blacklist that genre from results.
Cold Star	Algorithms need basic information about users to be able to deliver their first recommendation.	User can define during register page settings like: favorite genres, news or rated movies.

Table1. Summary of patterns used in this work with connection on how they are implemented on the interface

3. Recommender System and User's Interface

3.1 How the interface allow users values to be assessed:

Users can and should provide feedback through interface. The interface was designed focusing on assessing the main values: **Controllability**, **Transparency**, **justify** and **Diversity**. It was designed following the patterns suggested in [3].

This work try to asses **Controllability** allowing user to explicitly and implicitly interact with recommender. The choices of genres, friends, tags, with search button, using anonymous mode are mechanisms to allow **control** in a **transparency** way, with users understand what is happening and with **acceptance** of the suggestions, once he participated in the recommendation through **explicit** (i.e rate, like/dislike, de-select of genre or movie) and **implicit** (i.e watching the movie, adding to his list or recommend to a friend.) feedback.

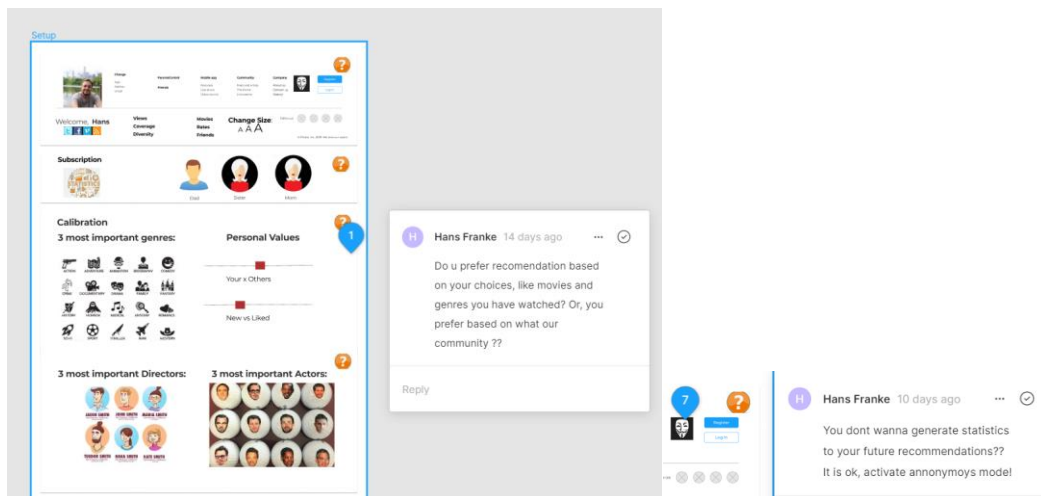


Figure2. Example on interface of user exerting control: he can select genres, directors and actors. Another form to exert control is rating a movie (explicitly), or for example simply watching a movie (implicitly). On right side, description to enter in **anonymous** mode.

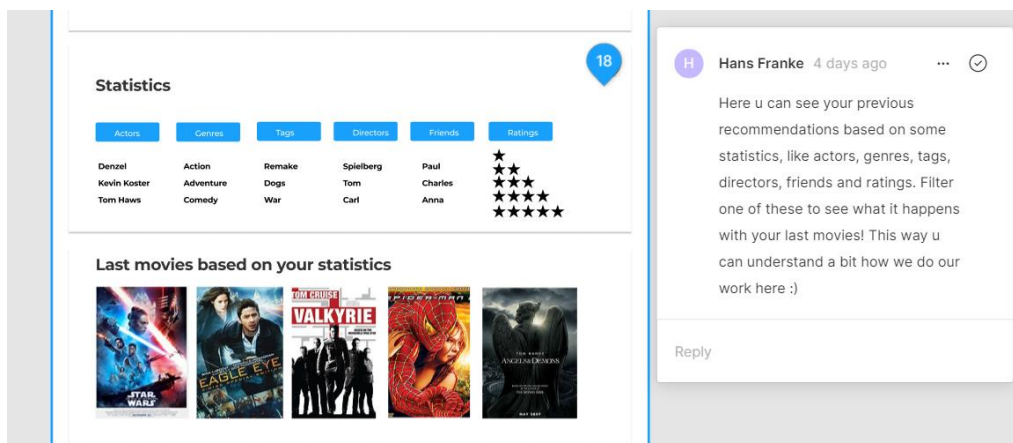


Figure3. User's statistics to improve acceptance through transparent explanations, showing the last movies recommended based on these statistics.

Transparency and **justify** (see figure 3, 4 and 5) were assessed but in an indirect way, with text showing to the user how the recommender was provided (i.e. based on movie you had watched or because of similar users watched), but not with high level detail (i.e what are the main similarities between users/movies). **Cold start** problem was answered in a login step with a user choosing 3 preferred genres (see figure2), but as our system is static no approach to a new movies was assessed.

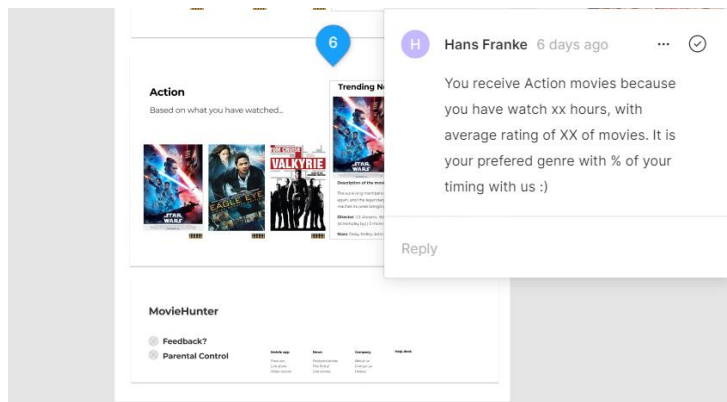


Figure4. Example of popup message to increase transparency and acceptance from the user.

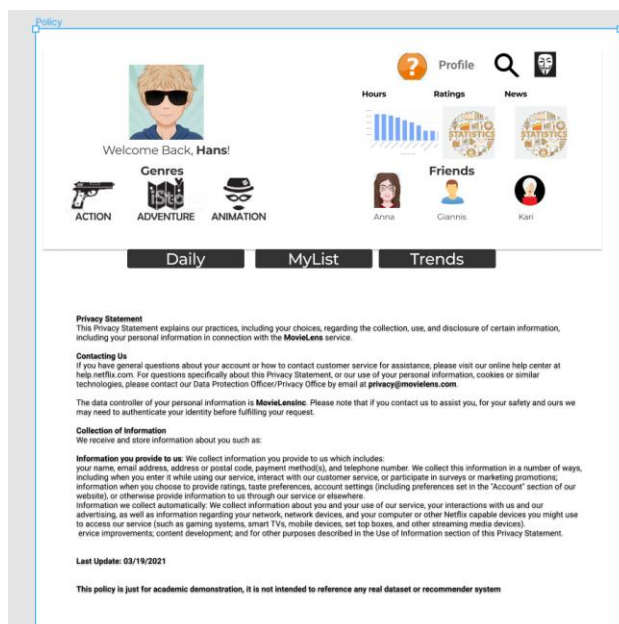


Figure5. Another example of transparency, on the policy page describe how the user data is collected.

Diversity, was assessed allowing user receive random recommendations that he never watched (see figure 6), it can be a new genre or a new movie unrelated to any similarity with movies or users. In the login screen the user can chose if they value most his previous experiences compare to others and if he likes most new content or liked content (i.e similar that what he has watched) (see figure2).

```
[29]: #show genres never watched!
genres

[29]: ['(no genres listed)', 'Sci-Fi', 'Film-Noir', 'Western', 'Horror', 'Fantasy']

[30]: #show list of movies of that genres!
movies_list.head()

[30]:
```

	index	movieid	title	genres	userid	rating	timestamp	tag
0	102973	913	Maltese Falcon, The (1941)	Film-Noir	16	4.0	1377477016	statue
1	108049	930	Notorious (1946)	Film-Noir	4	5.0	964538571	assassination
2	108310	968	Night of the Living Dead (1968)	Horror	64	3.5	1161536420	zombies
3	119586	1212	Third Man, The (1949)	Film-Noir	18	4.5	1455059742	ferris wheel
4	119784	1214	Alien (1979)	Horror	1	4.0	964981855	aliens

```

[31]: #predict scores for that movies and sort_by that
predictions2 = []
for i in range(0,len(movies_list)):
    movie_id = movies_list.loc[i]["movieid"]
    pred = svd.predict(user, movie_id).est #chase only the value of prediction!
    predictions2.append(pred)

#create a new column with the predictions
movies_list['pred'] = predictions2
movie_list = movies_list[['movieid', "title", "genres", "tag", "pred"]]

#order and return only 5 values!
movie_list.sort_values("pred", ascending=False)[0:5]

[31]:
```

	movieid	title	genres	tag	pred
5	1258	Shining, The (1980)	Horror	atmospheric	4.008160
0	913	Maltese Falcon, The (1941)	Film-Noir	statue	4.006685
1	930	Notorious (1946)	Film-Noir	assassination	3.994357
3	1212	Third Man, The (1949)	Film-Noir	ferris wheel	3.953664
47	109487	Interstellar (2014)	Sci-Fi	black hole	3.928913

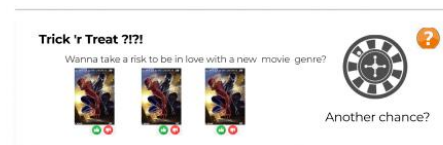


Figure6. Example of implementation of diversity, based on genres never watched by a user, and a print of the interface part of “Lucky wheel”. The prediction score was based on SVD(Single Value Decomposition).

The goal of the recommender is increase audience metrics. Crafting content that connects with its preferred audience requires understanding audience objectives and how these objectives match enterprise goals. Starting by aligning with your audience personas, use trend data to trace the lifecycle of a customer and their content needs.

3.2 Metrics

On the other side of the interface there is a company that need some metrics to measure the success of the recommender, not only based on users perspective but in business as well. For example, **users metrics**: diversity, engagement and satisfaction.

So to address **users values** the metrics would be, % of filters selection (i.e genres, tags, friends) this will measure how much **control** a user has over the recommender. **Diversity**, can be measure with how many %random chances the user is trying in the lucky wheel. **Engagement**, can measure by how many suggestion to friends a user made, or how many days/week a user join the website. **Satisfaction** can be measure by how many positive or negative feedbacks a user made, or number of friends invited.

Business metrics can be views hours, % of correct prediction (accuracy), coverage (how many genres a user has watched or % long tail movies), number of subscriptions. These metrics is not only for make more money, but they are important to measure if the user has his own metrics/values fulfilled, like a user that is increasing his average number of views probably has his values addressed.

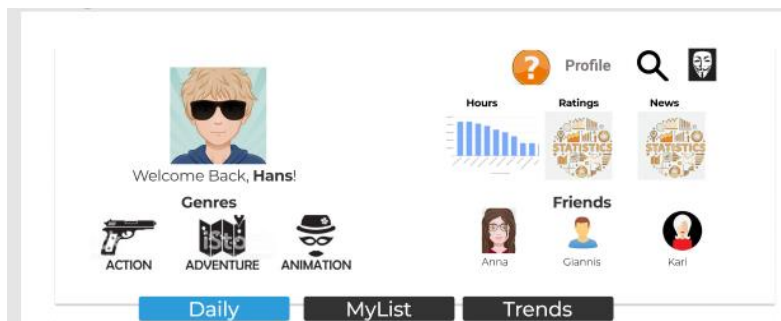


Figure7. On the main interface there is a quick overview of views (measured in hours) to show in a transparent way to the user his engagement to the website.

3.3 Explanation of algorithms:

3.3.a. Simpler Recommender

One simple way to recommend a movie is based on ratings. One can use weighted ratings based on rates and number of votes (i.e. score). It can be built on “best” movies, genres, tags, and many different filters. Who never go to google and typed: “best movies of all time?”, and the return is a list from **imdb** showing their famous TOP250 [<https://www.imdb.com/chart/top/>].

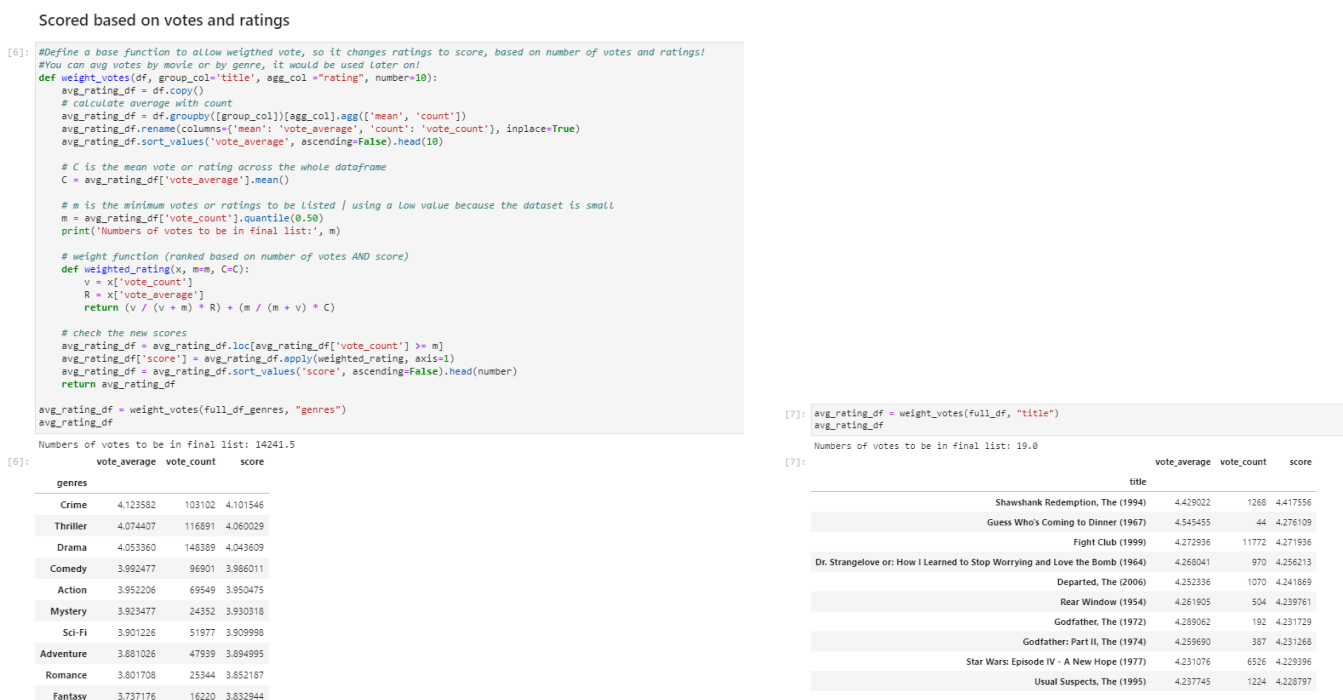


Figure7. Example of simple recommender based on weighted voting/rating, of genres and movies.

3.3.b. Content Based Recommender

The recommender we built in the previous section suffers some severe limitations. For one, it gives the same recommendation to everyone, regardless of the user's personal taste. If a person who loves

romantic movies (and hates action) were to look at our Top 10 Chart, he wouldn't probably like most of the movies. If he were to go one step further and look at our charts by genre, he wouldn't still be getting the best recommendations.

To personalize our recommendations more, an engine that computes similarity between movies based on certain metrics (i.e tags, genres, users views) and suggests movies that are most similar to a particular movie that a user liked. Since we will be using movie metadata (or content) to build this engine, this also known as **Content Based Filtering**. The user can provide input to this part choosing in the interface his preferences.

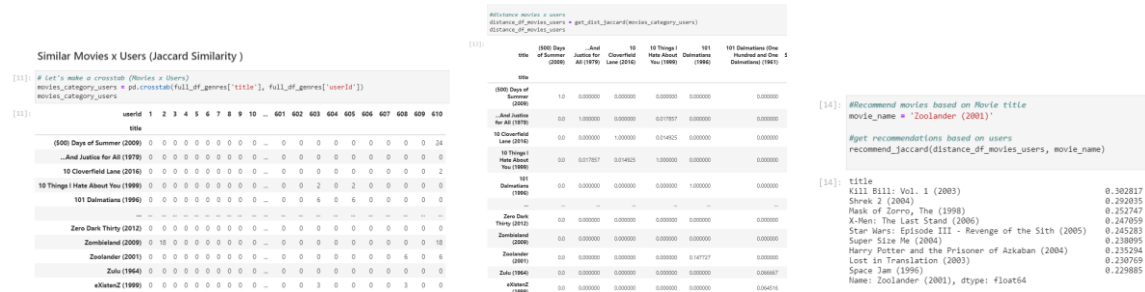


Figure8. Example of similarities using jaccard distances, on the left is similatiries from movies to users (which user watch that movies), center is distance from movie to movie based on users rates, and right part is recommend a movies based on “Zoolander”, order by the similarities.

3.3.c. Collaborative Filtering

Content based engine do not close all the gap, for it is only capable of suggesting movies which are *close* to a certain movie. That is, it is not capable of capturing **tastes** (i.e users preferences) and providing recommendations across genres. Also, the engine that we built is not really personal in that it doesn't capture the personal tastes and biases of a user. Anyone querying our engine for recommendations based on a movie will receive the same recommendations for that movie, regardless of who he is. Therefore, a technique called **Collaborative Filtering** is based on the idea that users similar to me can be used to predict how much one will like a particular product or service those users have used/experienced but one have not. Another, advantage of collaborative filtering is that it generates models that help users discover new interests.

In this work was used the **Surprise** library that used extremely powerful algorithms like **Singular Value Decomposition (SVD)** to minimize RMSE (Root Mean Square Error) and give great recommendations. The algorithm was improved with *gridSearch* (selection of the best parameters and errors metrics).

Single Value Decomposition

It works purely on the basis of an assigned movie ID and tries to predict ratings based on how the other users have predicted the movie.

```
from surprise import Reader, Dataset, SVD
from surprise.model_selection import cross_validate, GridSearchCV
reader = Reader()
ratings_df.head()

#Evaluate the best error metric
data = Dataset.load_from_df(ratings_df[['userId', 'movieId', 'rating']], reader)
svd = SVD()
cv = cross_validate(svd, data, measures=['RMSE', 'MAE'], cv=10, verbose=True)
cv
```

Evaluating RMSE, MAE of algorithm SVD on 10 split(s).

	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	Fold 6	Fold 7	Fold 8	Fold 9	Fold 10	Mean	Std
RMSE (testset)	0.8750	0.8670	0.8763	0.8837	0.8592	0.8705	0.8474	0.8750	0.8746	0.8709	0.8700	0.0097
MAE (testset)	0.6608	0.6693	0.6763	0.6777	0.6604	0.6684	0.6530	0.6680	0.6687	0.6674	0.6679	0.0067
Fit time	4.20	4.12	4.10	4.06	4.06	4.09	4.07	4.12	4.12	4.06	4.09	0.04
Test time	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.00

```
[23]: #Test our algorithm
svd.predict(474, 2)

[23]: Prediction(uid=474, iid=2, r_ui=None, est=3.5741258613710842, details={'was_impossible': False})
```

Figure9. Example of SVD: left is the training process and evaluating the error metrics (87% accuracy within RMSE), right is the prediction of user 474 rates movieId 2 with 3.57.

3.3.d. Hybrid Recommendation

Merging the 3 previous approaches in one single RS is the best scenario to take in account different criteria to fully satisfy a user. For example, we can start by assessing similarities based on others users (collaborative filter), then search the movies within the 10 most similar users (content based), filtering for the 3 target_user preferred genre (content based as well), ranking the movies by others users score (basic filter, weighted ratings). The final list of movies is the input for the SVD to predict based on that list which movies will have the most chance to assess the target user preferences(see figure10).

Within these techniques we are assessing the users values (user can change parameters of the algorithm explained on the interface and Methodology chapter), and assessing the metrics of the recommender like: user engagement, increasing views, and one of the most important: user satisfaction because we are increasing the chance to predict correctly. For example, one can filter which friend he/she want to compare, select genres that want to include, the level of similarities (own x others), and provide feedback in each iteration (i.e accept or refuse the recommendations).

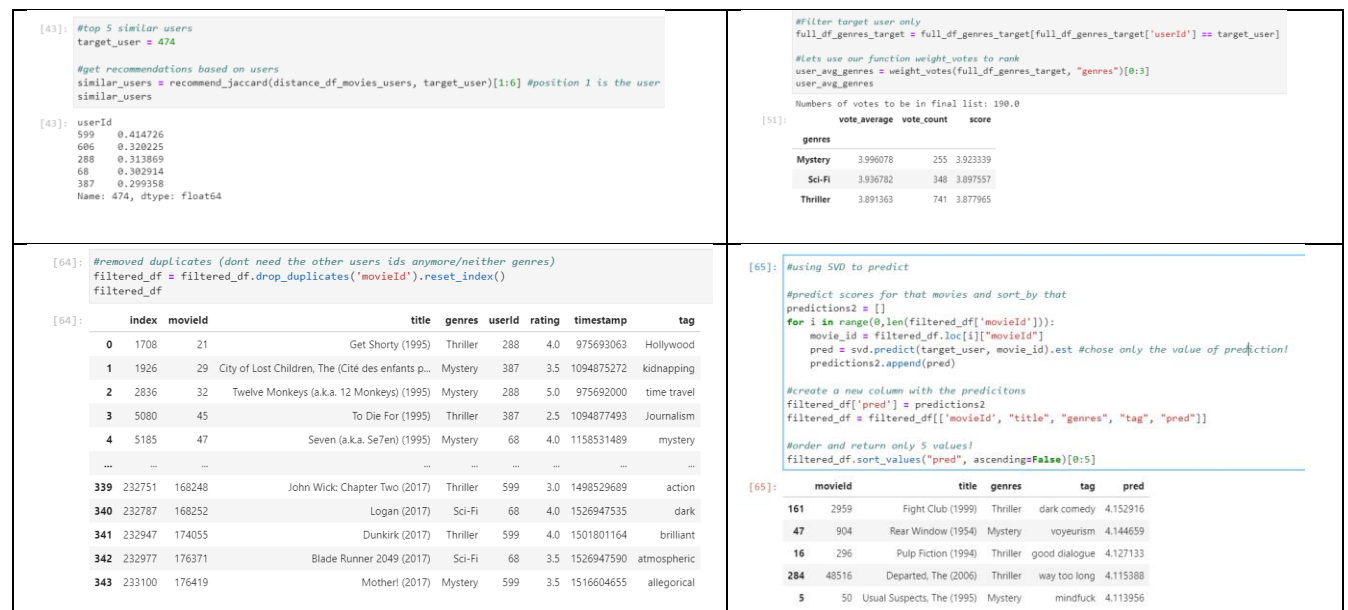


Figure10. Example of hybrid recommender: First, select similar users based on distances to movies (jaccard), then filter user top 3 genres (content based, based on voting score), after filter this df within similar users and preferred genres and finally use SVD to predict all movies and sort the list based on prediction scores.

4. Conclusion

In this work, was designed an interface using library patterns to asses **values**, allowing user **control** over the recommender. The interface is crucial, for it is the connection point from end-user to the recommender, through her that you are explaining to your users how you are building the recommendations (transparency and acceptance) and take his own **preferences** into account for future recommendations (predict power).

This strategy makes the user more relevant providing inputs and context to a recommender, for example, providing feedback that will be used to better predicting in the future. This is given, allowing user exert control over the algorithm, choosing his preferences (genres, actors, tags). A teenager may be interested in more trend topics similar to his friend, but an adult on the other side may be interested in old well rated movies of western genre. Using the interface the user can select parameters and visually notice how it changes his recommendations.

The work assessed metrics of **users** and **business**, trying to taking in account inevitable tensions like: more views or more diversity? Metrics sometimes contrary to each other, but the tension was minimized through transparency improving user acceptance and in a natural way increasing views because the algorithm would make better predictions, once it used users inputs and control.

5. Bibliography

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6. Appendix:

a. Code

The is provided in a jupyter notebook named: Media_RecommenderBackend_HansFranke.ipynb

Open in Github:

https://github.com/hansfranke1985/Public-Media/blob/main/Assigment_2/Media_RecommenderBackend_HansFranke.ipynb

Or you can open the html generated:

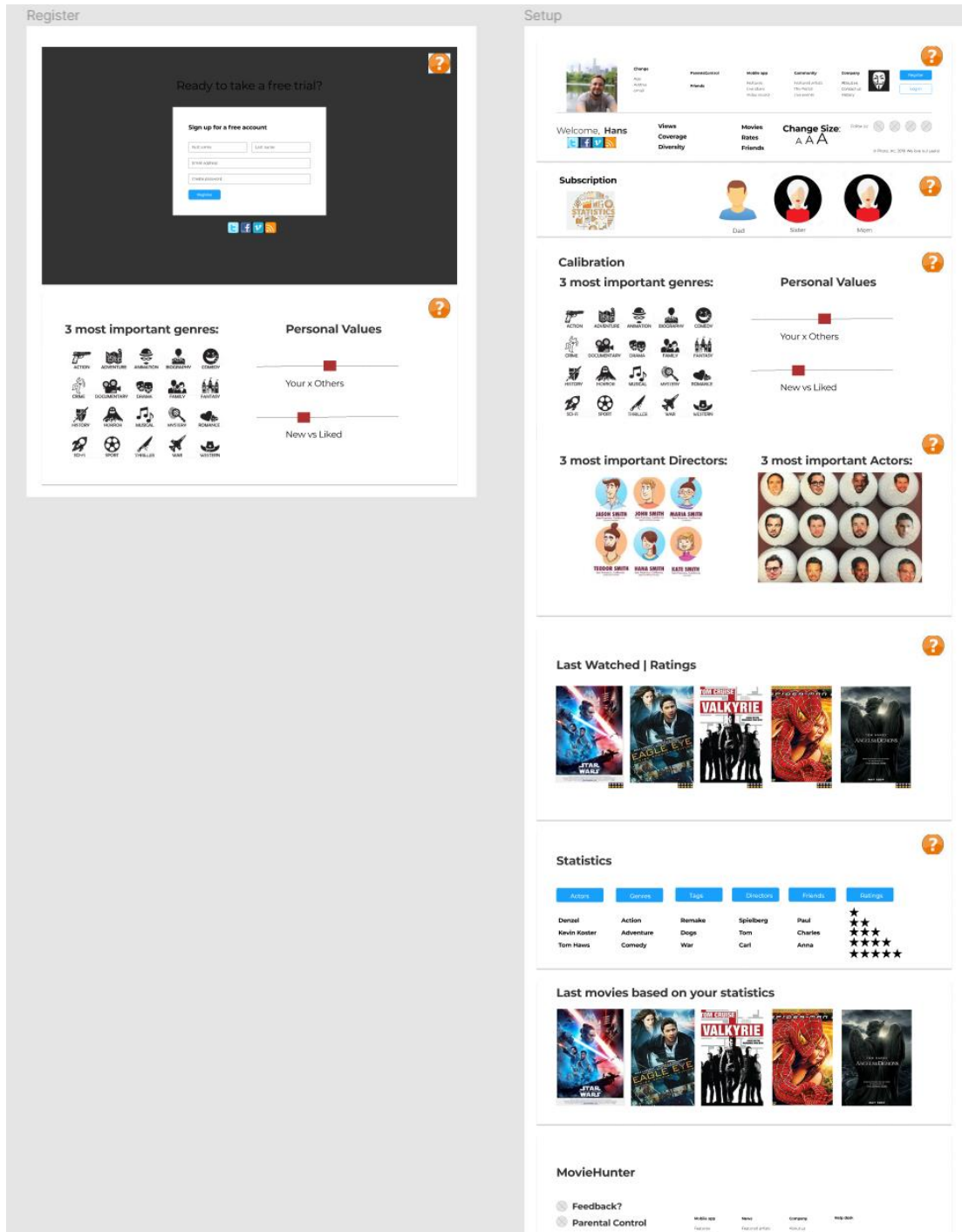


Media_Recommende
rBackend_HansFranke.

b. Interface


The interface is public available at: <https://www.figma.com/file/ItyHCF6CAdeDkbazTYkyAI/Media?node-id=23%3A83>

Sign and Setup pages:



Main Page and MainPage/MyList:

MainPage



Welcome Back, Hans!

Profile

Hours

Settings

News

Genres

Friends

Cart

ADVENTURE

ANIMATION




Daily

MyList

Trends

Cause you watched "Star Wars"

Movies that have same ratings, genres or tags, views.



Description of the movie




A former Roman Gladiator used to teach, a young man is used to the world of the Roman Empire and is used to the world of the Roman Empire.

Director: Ridley Scott

Gladiator is a 2000 American epic historical drama film directed by Ridley Scott. It stars Russell Crowe as Maximus, a Roman soldier who is betrayed by his fellow soldiers and is forced to fight in the arena.

Trick 'r Treat ?!?




Wanna take a risk to be in love with a new genre movie ?





Another chance?

What others users like you are watching?

The users that watch similar genres, friends, Tags and rated



Trending Now:



Description of the movie




The movie is a 2000 American epic historical drama film directed by Ridley Scott. It stars Russell Crowe as Maximus, a Roman soldier who is betrayed by his fellow soldiers and is forced to fight in the arena.

Director: Ridley Scott



Gladiator is a 2000 American epic historical drama film directed by Ridley Scott. It stars Russell Crowe as Maximus, a Roman soldier who is betrayed by his fellow soldiers and is forced to fight in the arena.

Terror

Based on what you have watched...



Trending Now:



Description of the movie




The movie is a 2000 American epic historical drama film directed by Ridley Scott. It stars Russell Crowe as Maximus, a Roman soldier who is betrayed by his fellow soldiers and is forced to fight in the arena.

Director: Ridley Scott



Gladiator is a 2000 American epic historical drama film directed by Ridley Scott. It stars Russell Crowe as Maximus, a Roman soldier who is betrayed by his fellow soldiers and is forced to fight in the arena.

Action

Based on what you have watched...



Trending Now:



Description of the movie

The movie is a 2000 American epic historical drama film directed by Ridley Scott. It stars Russell Crowe as Maximus, a Roman soldier who is betrayed by his fellow soldiers and is forced to fight in the arena.

Director: Ridley Scott

Gladiator is a 2000 American epic historical drama film directed by Ridley Scott. It stars Russell Crowe as Maximus, a Roman soldier who is betrayed by his fellow soldiers and is forced to fight in the arena.

MovieHunter

Feedback?


Parental Control

MovieHunter

Feedback?

Parental Control

MainPage_MyList



Welcome Back, Hans!

Profile

Hours

Settings

News

Genres

Friends

Cart

ADVENTURE

ANIMATION




Daily

MyList

Trends

Your List

Trailer



Description of the movie




A former Roman Gladiator used to teach, a young man is used to the world of the Roman Empire and is used to the world of the Roman Empire.

Director: Ridley Scott

Gladiator is a 2000 American epic historical drama film directed by Ridley Scott. It stars Russell Crowe as Maximus, a Roman soldier who is betrayed by his fellow soldiers and is forced to fight in the arena.

Trick 'r Treat ?!?




Wanna take a risk to be in love with a new movie genre?





Another chance?

Friends Suggestions:

Based on what your friends watched or suggest to you



Trailer



Description of the movie

A former Roman Gladiator used to teach, a young man is used to the world of the Roman Empire and is used to the world of the Roman Empire.

Director: Ridley Scott

Gladiator is a 2000 American epic historical drama film directed by Ridley Scott. It stars Russell Crowe as Maximus, a Roman soldier who is betrayed by his fellow soldiers and is forced to fight in the arena.

MovieHunter

Feedback?

Parental Control


MovieHunter

Feedback?


Parental Control


Search Page:


Search






Welcome Back, **Hans!**


**ACTION**


**ADVENTURE**


**ANIMATION**

**Profile**





Hours


Ratings

News

Friends

**Anna**



**Giannis**



**Kari**



Star wars Skywalker

Similar Movies you may like:



These are movies similar that you search... maybe u **add to your list** to watch it later?







Your Movie:




Description of the movie


The surviving members of the resistance face the First Order once again, and the legendary conflict between the Jedi and the Sith reaches its peak bringing the Skywalker saga to its end.

Director: J.J. Abrams **Writers:** Chris Terrio (screenplay by), J.J. Abrams (screenplay by) | 5 more credits »

Stars: Daisy Ridley, John Boyega, Oscar Isaac | See full cast & crew »

MovieHunter

**Feedback?**

**Parental Control**

Mobile app

Features
Live share
Video record

News

Featured artists
The Portal
Live events


Company

About us
Contact us
History


Help desk



Policy Page:

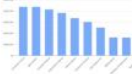
Policy





Welcome Back, **Hans!**

**Profile**





Hours


Ratings

News


Genres


**ACTION**


**ADVENTURE**

**ANIMATION**

Friends

**Anna**

**Giannis**

**Kari**

Daily**MyList****Trends**

Privacy Statement
This Privacy Statement explains our practices, including your choices, regarding the collection, use, and disclosure of certain information, including your personal information in connection with the **MovieLens** service.

Contacting Us
If you have general questions about your account or how to contact customer service for assistance, please visit our online help center at help.netflix.com. For questions specifically about this Privacy Statement, or our use of your personal information, cookies or similar technologies, please contact our Data Protection Officer/Privacy Office by email at privacy@movielens.com.

The data controller of your personal information is **MovieLensInc.** Please note that if you contact us to assist you, for your safety and ours we may need to authenticate your identity before fulfilling your request.

Collection of Information
We receive and store information about you such as:

Information you provide to us: We collect information you provide to us which includes: your name, email address, address or postal code, payment method(s), and telephone number. We collect this information in a number of ways, including when you enter it while using our service, interact with our customer service, or participate in surveys or marketing promotions; information when you choose to provide ratings, taste preferences, account settings (including preferences set in the "Account" section of our website), or otherwise provide information to us through our service or elsewhere.


Information we collect automatically: We collect information about you and your use of our service, your interactions with us and our advertising, as well as information regarding your network, network devices, and your computer or other Netflix capable devices you might use to access our service (such as gaming systems, smart TVs, mobile devices, set top boxes, and other streaming media devices).


service improvements; content development; and for other purposes described in the Use of Information section of this Privacy Statement.

Last Update: 03/19/2021

This policy is just for academic demonstration, it is not intended to reference any real dataset or recommender system

MovieHunter

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