Recommender System:

Individual Assignment 2 

*Hans Alberto Franke,* [*h.a.franke@students.uu.nl*](mailto:h.a.franke@students.uu.nl)

Personalization for Public Media

Applied Data Science - Utrecht University - 2021

**Main Objective**

Build a recommender system, an interface taking in account users control

**Assignment 2: Algorithmic affordances and interfaces (40%)**

In this assignment you develop a recommender system based on a provided dataset. Besides

creating a prototype for a working recommender system you will also propose an interface that

provides control over the recommender system. Which implicit and explicit feedback mechanisms

provide the algorithm with the necessary data? For this assignment you will start by exploring the

dataset and develop audience metrics. From there, you use content-based and collaborative-based

filtering to give recommendations to the user. Parallel to this, you design an interface that translates

the audience metrics and provides the interface with the necessary data in order to support user

autonomy over values.

The assessment of the assignment will be based on:

● Short video presentation (20%) (of maximum 10 minutes) in which you demonstrate a mid-fidelity

prototype (interface) and briefly reflect on one or two central values and stakeholders affected by

certain design decisions. in which you elaborate and critically reflect on the connection between the

mid-fidelity prototype, metrics, the values addressed, and the stakeholders affected by the design

decisions. Please submit via SurfDrive, WeTransfer, Dropbox or other file sharing service via e-mail to

Erik Hekman.

● Technical report (20%): a maximum of 1,500 words where you describe and motivate the system you

have built and how it connects to the designed interface from a usability and technical perspective.

You should submit the code and screen designs of your recommender system as an appendix to the

document.

The assessment of the research report will be based on the following criteria:

● Level of research : able to connect design decisions to metrics, values, and the stakeholders

● Practical implementation of algorithmic affordances : level of technical sophistication, logic of design

choices, feasibility

● Level of reflection : academic discussion of the central values, motivation for technical choices made in the implementation of values, critical of own role in design process (potential blind spots)

# Introduction

* Define collaborative filters
* Define user based filters
* Why is important have both?
* Main goal of my recommend

Recommender systems have been researched extensively over the past decades. Whereas several algo- rithms have been developed and deployed in various application domains, recent research effort s are increasingly oriented towards the user experience of recommender systems. 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. In this paper, we present an interactive visualization framework that combines recommendation with visualization tech- niques to support human-recommender interaction. Then, we analyze existing interactive recommender systems along the dimensions of our framework, including our work. Based on our survey results, we present future research challenges and opportunities [1].

Many different stakeholders can use or affect a recommender system. These stakeholder have different values and desired outcomes. Which leads to the question of: How this can be connected and addressed in a single recommender system?

# Methodology

* Which patterns used and why

Recommender algorithms are often broadly categorized in three areas: *collaborative filtering* recognizes commonalities between users or between items on the basis of explicit (ratings, tags, etc.) or implicit (actions like reading, downloading.) relevance indica- tions ( Burke, 2010 ). A standard user-based collaborative filtering algorithm first identifies similar users based on their overlapping interactions or similar ratings of common items. It then makes rec- ommendations based on preferences of these similar users. A stan- dard item-based recommendation algorithm analyzes similarities between items and then uses these similar items to identify the set of items to be recommended. Collaborative filtering is the most widely implemented and most mature technology ( Burke, 2002 ). *Content-based filtering* matches descriptions of items to descrip- tions of users ( Pazzani & Billsus, 2007 ). They base their predictions on information about individual users and items, and ignore con- tributions from other users. This approach relates most closely to our work on metadata ( Ternier et al., 2009 ). *Hybrid recommender systems* combine recommendation techniques, to gain better per- formance with fewer drawbacks ( Burke, 2002 ).

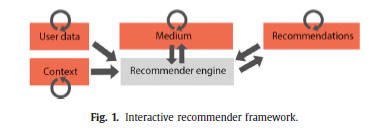
New approaches makes the user more relevant to provide inputs and context to a recommender, for example, providing feedback that is used to better predicting in the future. This is given, allowing user exert control over the algorithm, choosing your preferences or values for example. A teenager may be interested in more trand topics similar to his friend, but a adult on the other side may be interested in old very well rated movies of western genre.

EXPLAIN SOME USER VALUES!

Some well know values in literature are*, Transparency* deals with the “black-box”nature of current recommender systems by explaining the inner logic of the system to end users. Similar to transparency, *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. User control can occur at any step of the recommendation process, such as providing ratings, adjusting preference data, and revising or exploring recommendations.

A very difficult value to handle is *Diversity,* itrefers to providing recommendations with a relatively large coverage of the recommendation space ( Hu & Pu, 2011 ). 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. When a new item or a new user joins a recommender system, the system has no prior knowledge about it, i.e., no item- feature data, no ratings, no preference information. The inability ity 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 user.

There is many ways to asses these values, and the 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 [2]. These patterns can show many different possibilities to allow, measure and improve recommender system with very well designed interfaces.



**Figure1**. Adapted from [1]

These patterns summarize many common patterns described in literature, therefore is a nice source to understand what is the state of art and have nice ideas of interface design. In this work the interface was design based on 7 patterns proposed there: x1,x2,x4…..

The table bellow summarize all the approaches used in this work.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Pattern** | **Main Idea** | **How allow User Control** | **How do users understand the control?** | **How is used in My interface** |
| Peek Picker |  |  |  | Recommendations based on collaborative filter |
| Multiple Profiles |  |  |  | Change profile |
| Incognito |  |  |  | Button |
| Introduce Chance |  |  |  | Movies not based in any past experiences and random generator |
| Data Toggles |  |  |  | Allow user selection genres, actors, directors by list in interface |
| Social Context |  |  |  |  |
| Ordered List |  |  |  | List ranked by similarities and rating |
| Liking Items |  |  |  | Allow user rating movies (1-5) |

This work try to asses *Controllability* allowing user to explicitly and implicitly interact with recommender. Explicitly with the opportunity to choosing of parameters like preferred genre or actor during the navigation through the website or liking/disliking the recommendation presented, and implicitly by rating the movies after watching. This was the most relevant part of the work with many different patterns used to allow some form of control to user.

*Transparency* and *justify* were assessed but in an indirect way, with text showing to the user how the recommender was provided (f.e. based on movie you had watched or because of similar users watched), but not with high level detail (f.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, but as our system is static no approach to a new movies was assessed.

*Diversity,* was assessed allowing user receive random recommendations that he never watched, it can be a new genre or a new movie. In the login screen the user can chose if they value most his previous experiences compare to others and if he like most new content or liked content (f.e similar that what he has watched)

# Results

* Why my interface is fucker
* What kind of stakeholders I am addressing
* Limitations?
* Metrics:
  + Probability to predict correct?

# Conclusion

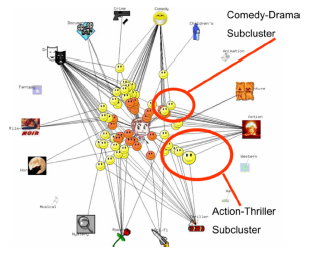
* My measures were ok?

# Bibliography

|  |  |
| --- | --- |
| [1] | D. P. ,. V. Chen He, "Interactive recommender systems: A survey of the state of the art and future research challenges and opportunities," 2016. |
| [2] | "https://aapatternlibrary.wordpress.com/". |

# Patterns used:

## Pattern 12: “Peer Picker”



**Main idea?** Recommendation systems can offer users to switch between their own recommendations and those of peers which are further away.

**Examples?** Still to be found in the wild.

**Input or output?** Input.

**How do users control the algorithm?** They can browse recommendations for similar users (in some respect, but different in others)

**How do users understand the control?**This is a form of direct control of the algorithm. It also gives insights into the ‘inner workings’ of an algorithm.

**Related patterns?**[Multiple Profiles](https://aapatternlibrary.wordpress.com/2021/02/18/multiple-profiles/)

**Academic research?**[Investigated by O’Donnovan et al. (2008)](https://sites.cs.ucsb.edu/~holl/pubs/ODonovan-2008-CHI.pdf)

## [Pattern 11: “Multiple Profiles”](https://aapatternlibrary.wordpress.com/2021/02/18/multiple-profiles/)

[](https://aapatternlibrary.wordpress.com/2021/02/18/multiple-profiles/)

**Main idea?** By allowing users to make multiple profiles they can tune the algoritms to specific behaviors, preferences or family members.

**Examples?** Netflix allows users to specify “Who’s watching”

**Input or output?** Input.

**How do users control the algorithm?** Users are offered a choice between recommenders trained on different datasets.

**How do users understand the control?**Users are in a position to compare different profiles so that they can find out what works for them

**Related patterns?**[Data Toggle](https://aapatternlibrary.wordpress.com/2021/02/17/pattern-6-enabling-inputs/), [Reset](https://aapatternlibrary.wordpress.com/2021/02/18/pattern-7-explanations/)

## [Pattern 10: “Incognito”](https://aapatternlibrary.wordpress.com/2021/02/18/pattern-10-incognito/)

[](https://aapatternlibrary.wordpress.com/2021/02/18/pattern-10-incognito/)

**Main idea?** User can be enabled to watch things without the algorithm learning from it with an incognito functionality

**Examples?** Browsing “incognito” in Google Chrome.

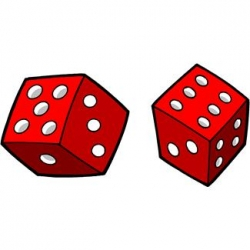
**Input or output?** Input

**How do users control the algorithm?** Users tell the algorithm to temporarily ignore what they are doing.

**How do users understand the control?**Users may have the expectation of not sharing any data with the algoritm which may be at odds with the specific implementation.

**Related patterns?**[Multiple profiles.](https://aapatternlibrary.wordpress.com/2021/02/18/multiple-profiles/)

## [Pattern 9: “Introduce Chance”](https://aapatternlibrary.wordpress.com/2021/02/18/pattern-9-introduce-chance/)

[](https://aapatternlibrary.wordpress.com/2021/02/18/pattern-9-introduce-chance/)

**Main idea?** Giving users the option to activate a chance effect into their recommendations leads to more diverse recommendations.

**Examples?**Google’s “I feel lucky” button is an early ancestor. The “[Spin the Reel](https://www.youtube.com/watch?v=4VsrS6HMX4M&feature=youtu.be)” concept also builds on this idea.

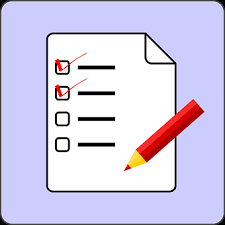
**Input or output?**  
Output.

**How do users control the algorithm?** By activating some random process they increase diversity of the output.

**How do users understand the control?**They understand chance plays a big role so they may expect recommendation surprises.

**Related patterns?**[Reset.](https://aapatternlibrary.wordpress.com/2021/02/18/pattern-7-explanations/)

## [Pattern 6: “Data Toggles”](https://aapatternlibrary.wordpress.com/2021/02/17/pattern-6-enabling-inputs/)

[](https://aapatternlibrary.wordpress.com/2021/02/17/pattern-6-enabling-inputs/)

**Main Idea?** Switches may enable the user to chose which data is used by the algoritm to arrive at a recommendation.

**Examples?** Still to be found in the wild. (example in [this](https://www.youtube.com/watch?v=XKeGvW_oDhE&feature=youtu.be) demo )

**Input or output?**Input

**How do users control the algorithm?** Users are allowed to enable or disable certain information from being used by the algorithm.

**How do users understand the control?**Users may manipulate this information to build a dynamic model of what information is vital to their recommendation.

**Related patterns?**[Decision paths](https://aapatternlibrary.wordpress.com/2021/02/18/pattern-13-descision-paths/)

## [Pattern 4: “Social Context”](https://aapatternlibrary.wordpress.com/2021/01/11/pattern-4-social-context/)

[](https://aapatternlibrary.wordpress.com/2021/01/11/pattern-4-social-context/)

**Main idea?** Social recommendation systems can be more transparent by indicating the social group their recommendations are based upon.

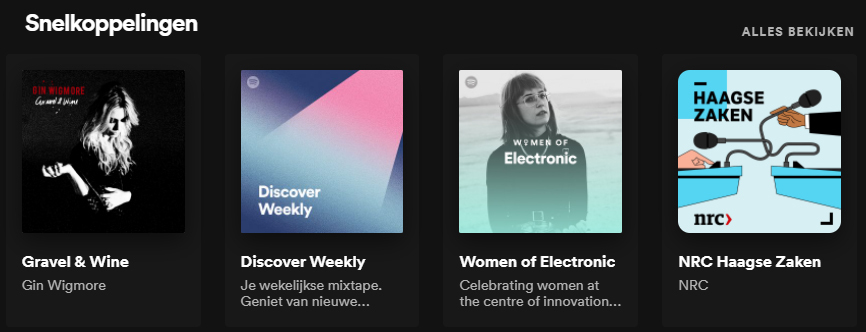
**Examples?** Many bookstores suggest items that others have looked at.

**Input or output?**Output.

**How do users control the algorithm?** The algorithm offers context to a selection made by the user.

**How do users understand the control?**Users are aware the suggestions are context sensitive.

## [Pattern 2: “Ordered List”](https://aapatternlibrary.wordpress.com/2021/01/05/pattern-2-ordered-list/)

[](https://aapatternlibrary.wordpress.com/2021/01/05/pattern-2-ordered-list/)

**Main idea?** By presenting top reccomendations in an ordered list, users can make a choice among multiple items that are recommended for them.

**Examples**? Spotify and Netflix present many of these.

**Input or output?**Both.

**How do users give input to the algorithm?** Users selections can be used as to tune the algorithm.

**How do users understand the control?**The user can choose among presented alternatives (and as such have the space to make a final decision, making the quality of the recommendation less critical). Users will mostly not be aware of the effects of a certain choice in training the algorithm.

**Related patterns?** Navigation-scapes

## [Pattern 1 “Liking Items”](https://aapatternlibrary.wordpress.com/2021/01/05/twitter-like/)

[](https://aapatternlibrary.wordpress.com/2021/01/05/twitter-like/)

**Main idea?**Users are given a lightweight control to express their opinion about an item, cumulatively resulting in feedback to the algorithm about user preferences.

**Examples**? Twitter Like (heart) or Facebook Like (thumbs-up)

**Input or output?**Input.

**How do users control the algorithm**? Likes support filtering of messages in timelines. Users do not see the immediate effect of this.

**How do users understand the control**? Likes are primarily seen as feedback to the author of a tweet (who often gets notified) or facebook post, secundary as a message to the broader audience (social group) and only thirtiary as an algoritmic control.

**Related patterns**? [Curated Lists](https://aapatternlibrary.wordpress.com/2021/01/09/pattern-3-users-curated-lists/)