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 and interface taking in account user’s values like control, transparency and acceptance

**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

* Why is important to allow user control: based on values, like privacy, control, transparency?
* Main goal of my recommender

Recommender systems have been researched extensively over the past decades. Whereas several algorithms 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 techniques 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? How the interface can be used to answer for human values like **control**, **transparency** and **acceptance** and increase audience metrics like usage and engagement?

# Methodology

* Which patterns used and why
* Define collaborative filters
* Define user based filters
* Why is important have both?

The core job of analytics is to help companies gain insight into their customers. Then, the companies can optimize their marketing and deliver a better product. (Without analytics, companies are in the dark about their customers.) Analytics gives businesses the quantitative data they need to make better, more informed decisions and improve their services.

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 indications ( 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 recommendations based on preferences of these similar users. A standard 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 descriptions 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 performance with fewer drawbacks ( Burke, 2002 ).

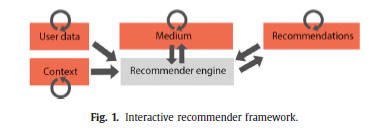
New approaches makes the user more relevant to provide inputs and context to a recommender, for example, providing feedback that is used to better predicting in the future. This is given, allowing user exert control over the algorithm, choosing your preferences or values for example. A teenager may be 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 XXXX patterns, the table below summarize all the approaches used in this work as well as reference from the authors [2].

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Pattern | Main Idea | How allow User Control | How do users understand the control? | How is used in My interface |
| Peek Picker | Users can switch between their own recommendations and those of peers which are further away. | They can browse recommendations for similar users (in some respect, but different in others) | This is a form of direct control of the algorithm. It also gives insights into the ‘inner workings’ of an algorithm. | Recommendations based on collaborative filter |
| Multiple Profiles | User can select different profiles | Users are offered a choice between recommenders trained on different datasets. | Users are in a position to compare different profiles so that they can find out what works for them | Profile Change |
| Incognito | User can go “anonymous” not recording any statistics | Users tell the algorithm to temporarily ignore what they are doing. | Users may have the expectation of not sharing any data with the algoritm which may be at odds with the specific implementation. | Button Incognito on main page |
| Introduce Chance | Giving users the option to activate a chance effect into their recommendations leads to more diverse recommendations. | By activating some random process they increase diversity of the output. | They understand chance plays a big role so they may expect recommendation surprises. | Movies based on never watched genres, tags, users and random generator |
| Data Toggles | Switches may enable the user to chose which data is used by the algoritm to arrive at a recommendation. | Users are allowed to enable or disable certain information from being used by the algorithm. | Users may manipulate this information to build a dynamic model of what information is vital to their recommendation. | Allow user selection genres, actors, directors by list in the interface |
| Social Context | Social recommendation systems can be more transparent by indicating the social group their recommendations are based upon. | The algorithm offers context to a selection made by the user. | Users are aware the suggestions are context sensitive. | Show to user the friends, genres of which recommendation was based |
| Ordered List | By presenting top reccomendations in an ordered list, users can make a choice among multiple items that are recommended for them. | Users selections can be used as to tune the algorithm. | 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. | Lists ranked by similarities and ratings |
| 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. | Likes support filtering of messages in timelines. Users do not see the immediate effect of this. | 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 (see Eslami et al. 2016). | Allow user rates movies (1-5) |
| Blacklist | Users can blacklist items, giving the algorithm an idea of their dislikes and preventing the algorithm from showing it again. | Blacklisting an item gives the recommender feedback about your dislikes. It also directly prevents the algorithm from delivering particular output. | Users may not have accurate ideas about the scope of the feedback they give through a blacklist action (e.g. single item or a whole categorie of content) | 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 | Algoritms need basic information about users to be able to deliver their first recommendation. | Users can consciously decide which information they want to feed the algorithm (constrained by the questionnaire) | Users are aware the lanswers are used as an input abeit not so much on how the alogritm uses the input. | User can define during register page settings like: favorite genres, news or rated movies. |

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

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.

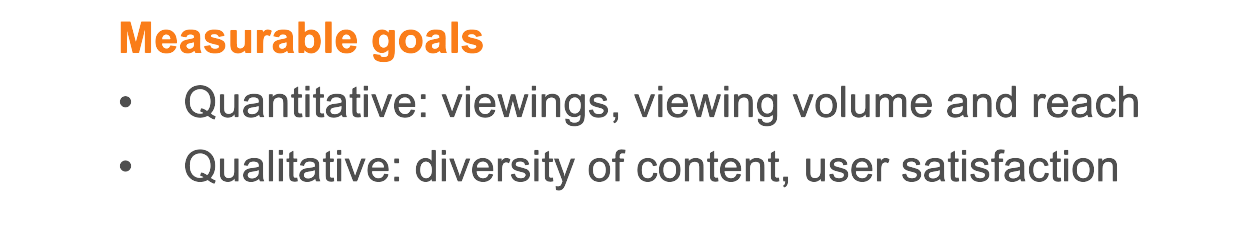
*Transparency* and *justify* were assessed but in an indirect way, with text showing to the user how the recommender was provided (f.e. based on movie you had watched or because of similar users watched), but not with high level detail (f.e what are the main similarities between users/movies). *Cold 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.

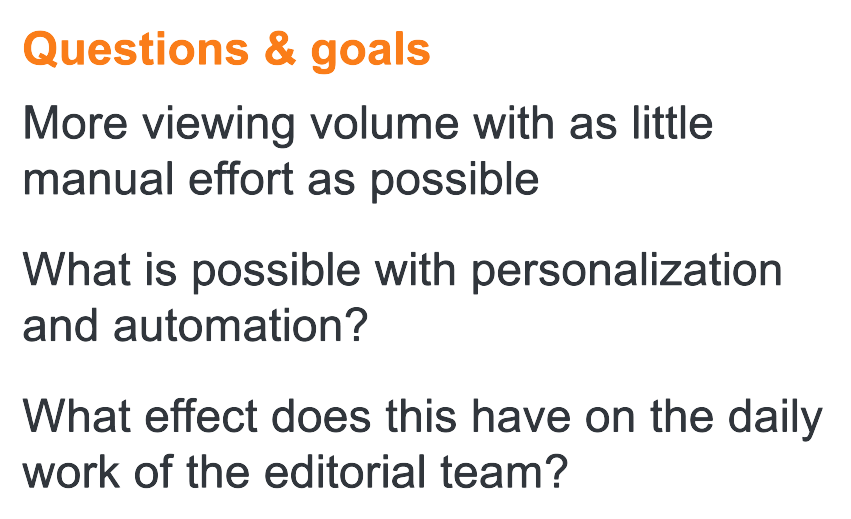
*Diversity,* was assessed allowing user receive random recommendations that he never watched, it can be a new genre or a new movie. In the login screen the user can chose if they value most his previous experiences compare to others and if he like most new content or liked content (f.e similar that what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

On the other side, a recommender must increase audience metrics. Crafting content that connects with its preferred audience requires understanding audience objectives – and how these objectives match enterprise goals. While often process can be as simple as soliciting direct feedback or taking requests, sometimes this ends up being more esoteric. Audiences may not *know* the kind of content that will have the most impact and fulfill a direct need – primarily because they may have never encountered content like it before. You can’t identify something that has yet to be named. To attempt to identify a need – naming the nameless, so to speak – start by mapping the journey your audience is taking involving your enterprise. Starting by aligning with your audience personas, use trend data to trace the lifecycle of a customer and their content needs.

# Recommender System and User’s Interface

* What kind of stakeholders I am addressing: Personas | how I will adapt to taking in account change of preferences over time
* Limitations? What I may improve in the future? Here or in conclusion?
* Clusters: trending, u may be interested in, …. Similar users like you
* Metrics:
  + Diversity
  + Engagement
  + Views
  + User Satisfaction
  + Probability to predict correct?





* How I implement:
  + Simple algorithms: Weighted ratings
  + Content Based Recommender
  + Collaborative
  + Hibrid: The best choice!

**How the interface allow personas/users values be assessed / Control:**

Users can and should provide feedback through interface control. The interface was design focusing on assessing the main values: *Controllability, Transparency*, *justify and Diversity.* This was design following the patterns suggested in [2]. Chose of genres, friends, tags, by search button, with anonymous mode are mechanisms to allow control in a transparency way, with users understand what is happening and with acceptance of the suggestions, because he participated in the recommendation.

Next sections are to describe what kind of techniques were used to model the recommender system.

**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. **Business metrics**: number or hours of views, probability to prediction correct, coverage, number of subscriptions.

**Explanation of algorithms:**

## Simpler Recommender

One simple way to recommend a movie is based on ratings. One can user weighted ratings based on rates and number of votes (i.e. score). It can be build on “best” movies, genres, tags, and many different filters. Who never go to google and type: “best movies of all time?”, and the return is a list from imbd showing their famous TOP250 [INSERT REFERENCE].

## 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 15 Chart, s/he wouldn't probably like most of the movies. If s/he were to go one step further and look at our charts by genre, s/he wouldn't still be getting the best recommendations.

For instance, consider a person who loves Dilwale Dulhania Le Jayenge, My Name is Khan and Kabhi Khushi Kabhi Gham. One inference we can obtain is that the person loves the actor Shahrukh Khan and the director Karan Johar. Even if s/he were to access the romance chart, s/he wouldn't find these as the top 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.**

## Collaborative Filtering

Our content based engine suffers from some severe limitations. It is only capable of suggesting movies which are close to a certain movie. That is, it is not capable of capturing tastes 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 s/he is.

Therefore, in this section, we will use a technique called **Collaborative Filtering** to make recommendations to Movie Watchers. Collaborative Filtering is based on the idea that users similar to me can be used to predict how much I will like a particular product or service those users have used/experienced but I have not.

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

## Hybrid Recommendation

Merging the 3 previous approachs in one single recommendation is the best scenario to take in account many different criteria’s to fully satisfy a user. For example, we can start by assessing similarities based on others users (collaborative filter), then search the movies with the 10 most similar users (content based), filtering for the 3 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 asses the target user preferences.

Using this techniques we are assessing the users values (user can change parameters of the algorithm explain 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.

# Conclusion

* My measures were ok?
* Which tensions I take care:
* Which tensions should focus on next working

In this work, It was built 4 different recommendation engines based on different ideas and algorithms. They are as follows:

1. **Simple Recommender:** This system used overall TMDB Vote Count and Vote Averages to build Top Movies Charts, in general and for a specific genre. The IMDB Weighted Rating System was used to calculate ratings on which the sorting was finally performed.
2. **Content Based Recommender:** We built two content based engines; one that took movie overview and taglines as input and the other which took metadata such as cast, crew, genre and keywords to come up with predictions. We also deviced a simple filter to give greater preference to movies with more votes and higher ratings.
3. **Collaborative Filtering:** We used the powerful Surprise Library to build a collaborative filter based on single value decomposition. The RMSE obtained was less than 1 and the engine gave estimated ratings for a given user and movie.
4. **Hybrid Engine:** We brought together ideas from content and collaborative filterting to build an engine that gave movie suggestions to a particular user based on the estimated ratings that it had internally calculated for that user.

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 minimize with transparency improving user acceptance and in a natural way watching more movies because simply the algorithm make better predictions, once it used users inputs and control.

# 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/". |
| [3] | Z. Fayyaz, M. Ebrahimian, D. Nawara, A. Ibrahim and R. Kashef, "Recommendation Systems: Algorithms, Challenges, Metrics, and Business Opportunities," 2020. |
| [4] | T. Asikis, J. Klinglmayr, D. Helbing and E. Pournaras, "How value-sensitive desing can empower sustainable consumption," no. https://doi.org/10.1098/rsos.201418, 2021. |
| [5] | H. Cramer, J. G. Gathright, A. Springer and S. Reddy, "Assessing and addressing algorithmic bias in practice," *https://doi.org/10.1145/3278156,* 2018. |
| [6] | J. Davis and L. Nathan, Value Sensitive Design: Applications, Adaptations, and Critiques, 2015. |
| [7] | R. Dobbe , S. Dean, T. Gilbert and N. Kohli, "A Broader View on Bias in Automated Decision-Making: Reflecting on Epistemology and Dynamics," no. https://doi.org/10.14763/2020.4.1534, 2018. |
| [8] | B. Friedman, Human Values and the Design of Computer Technology, Cambridge University Press, 1997. |
| [9] | S. Kheirandish, M. Funk, S. Wensveen, M. Verkerk and M. Rauterberg, "HuValue: a tool to support design students in considering human values in their design," *International Journal of Technology and Design Education,* no. https://doi.org/10.1007/s10798-019-09527-3, p. 30:101, 2020. |
| [10] | J. Simon, P.-H. Wong and G. Rieder, "Algorithmic bias and the Value Sensitive Design approach," 2020. |
| [11] | StakeholderMap, "https://www.stakeholdermap.com/retail-stakeholders.html". |

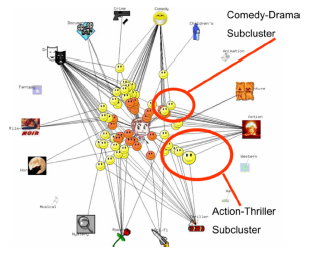
# Appendix:

## Code

## Interface

# Patterns

## 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.

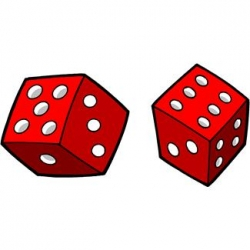
**Input or output?** Input

**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.

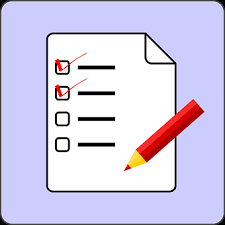
**Input or output?**  
Output.

**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.

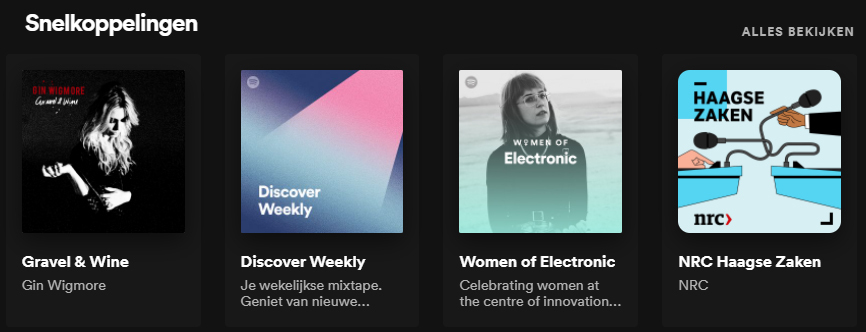
**Examples?** Many bookstores suggest items that others have looked at.

**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/)