Deconstructing the filter bubble

Poster text

Time limit: 10 minutes (keeping location change of listeners and possible questions in mind)

# Introduction

What do youtube and amazon have in common?

They both have giant product spaces. On youtube it is videos and on amazon actual products you can buy. And because of that, it is impossible for a user to be aware of every single items that is on the website. And even if you knew everything that was on it, it would be very hard to decide which item you would like the best. Often, you can only now for sure that you liked a youtube video after you’ve watched it. So, this is where recommender system come in play. They help you see the items you might actually like.

However, some people are worried that personalized recommender system might have unintended side effects, like filter bubbles. A filter bubble is when a user gets isolated from a diversity of viewpoints or content. For example if you have been looking for a new iPhone and have been reading about how good they are, and after that you don’t get articles about how good an android phone might be. The risk might be that you think: “iPhone good, android bad”. It is found however that even without recommendation, the user behaviour is consistent with the filter bubble effect and that they are less likely to fall into a filter bubble if recommendation is used.

Personalized recommendation might also lead to users becoming increasingly more homogenized, like when a whole group of users suddenly gets the same 10 year old video in their recommendations on youtube.

It is important to know how recommender systems influence user behaviour, not only for the consequences, but also for guiding their design. We have been studying a theoretical model that simulates the decision-making of users and how recommender systems influence this process.

# *Model*

This model has four central components:

## Large itemset

The first is that user consume items sequentially and have a large set of items to choose from. The users can only consume a small fraction of the total itemset in their lifetime.

## Spillover and risk-aversion

The second component is that users are uncertain about how much they will like different items before they have consumed them. The motivation behind this, is that recommender systems are typically deployed in contexts with experience goods, of which the true value can only be determined after consumption.

The third component is that when an item is consumed any uncertainty about the item is resolved. Its consumption also reveals information that changes the user his beliefs about how they value similar items. This is because of the learning spillover, the learned value says most about items that are closer. If the consumed item gave a high value, the user is likely to keep also consume items that are nearby. We can also be more confident that the estimated value of a closer item is more likely to be correct than a item that is further away.

## Recommendation = information

The last component is that recommendation provides the users with information. The realized values on which the personal recommendations are made are modelled as: a sum of a value that reflects the personal preference of the user (an idiosyncratic component) and a weighted common-value. The recommender can learn the common-value from previous users their data.

## Risk-aversion

The spillover effect is important, as not only the expected value influences which item an user chooses next, but also how much uncertainty there still is about an item. This is described by how risk-averse a user is. A more risk-averse user might go for an expected value that is significantly lower than another item’s expected value, if that means there is less uncertainty. (possible money example). However, this effect is reduced, since the recommendation also provides information, which makes it more likely for a user to explore more of the product space than without recommendation.