Recommender Systems

CS6780 – Advanced Machine Learning
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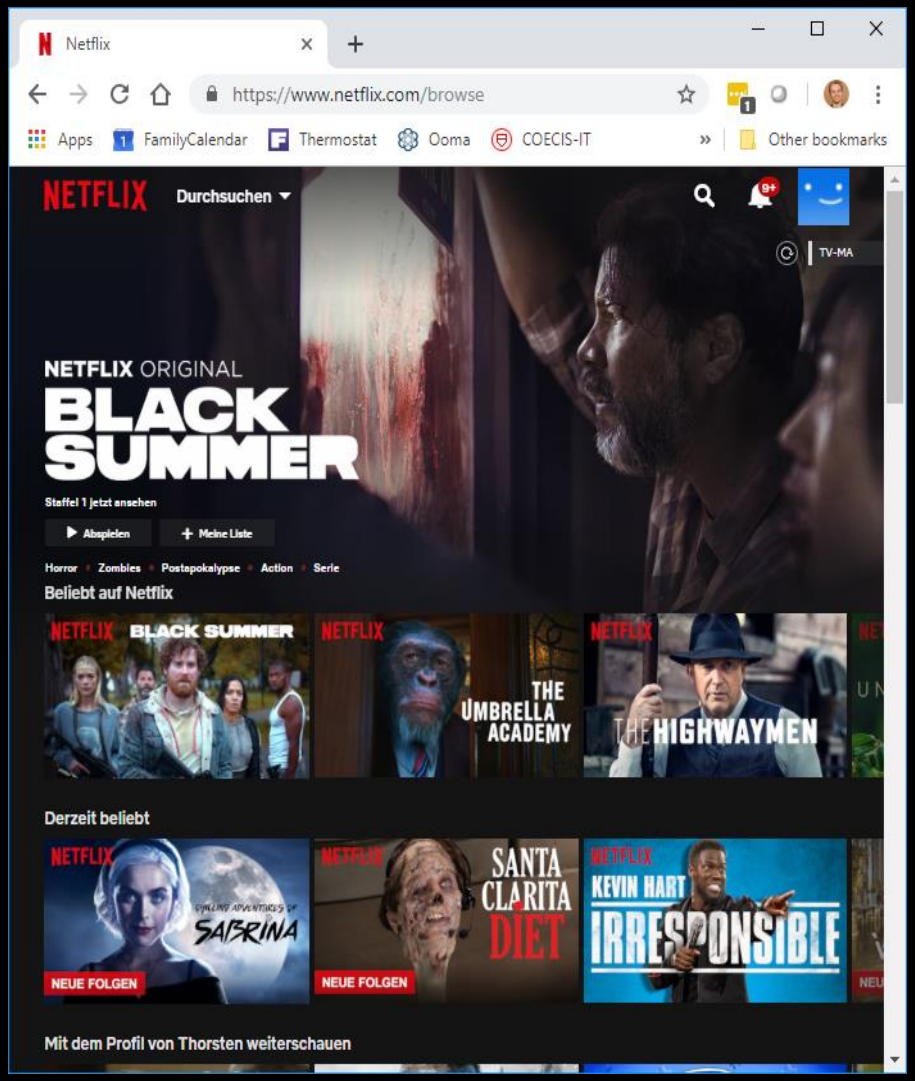
Reading:

Y. Koren, R. Bell, C. Volinsky, Matrix Factorization Techniques for Recommender Systems, IEEE Computer, 42:8, 2009. (link)

Movie Recommender

Recommendation

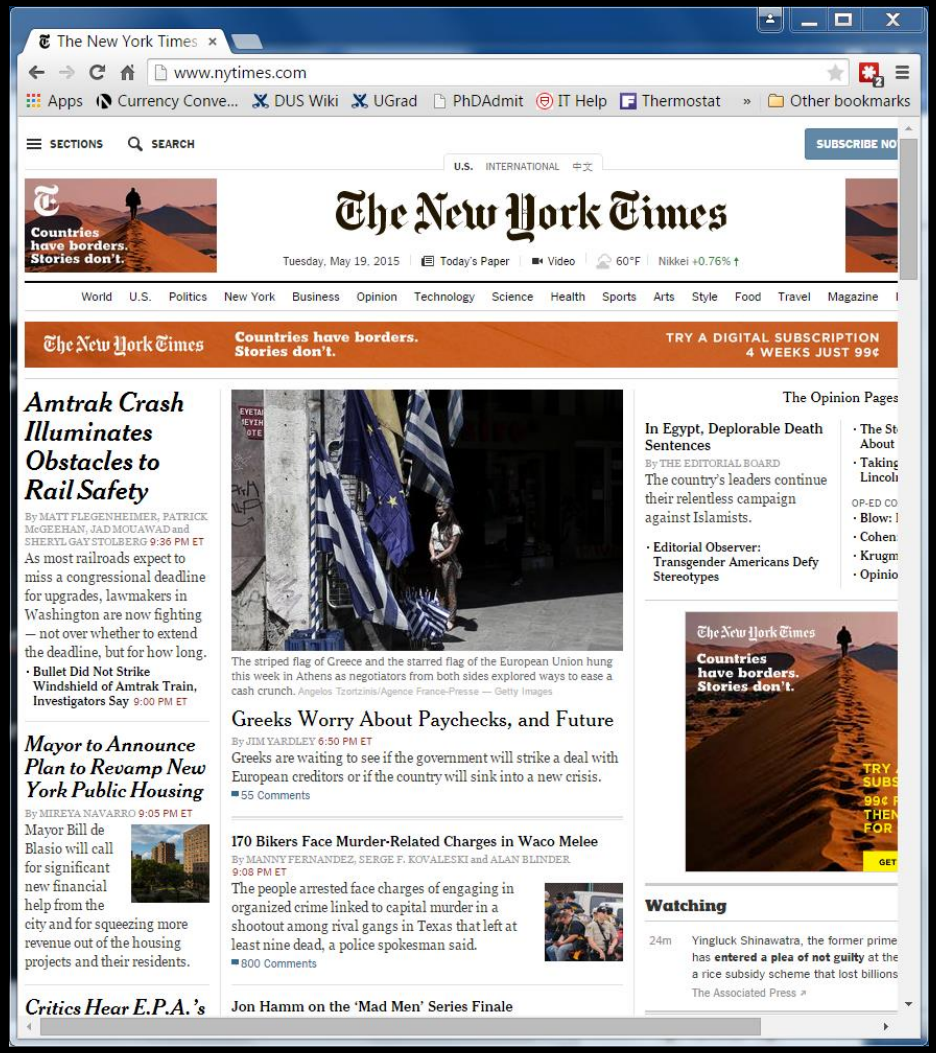
Movie to watch



News Recommender

Recommendation

Portfolio of newsarticles



Voice Assistant

Recommendation for "Alexa, play music"

- Playlist

Recommender Systems

Examples

- Netflix: Movies
- Amazon: Products
- Spotify: Music
- YouTube: Videos
- Xbox Live: Games/Players
- Facebook: News

Problem

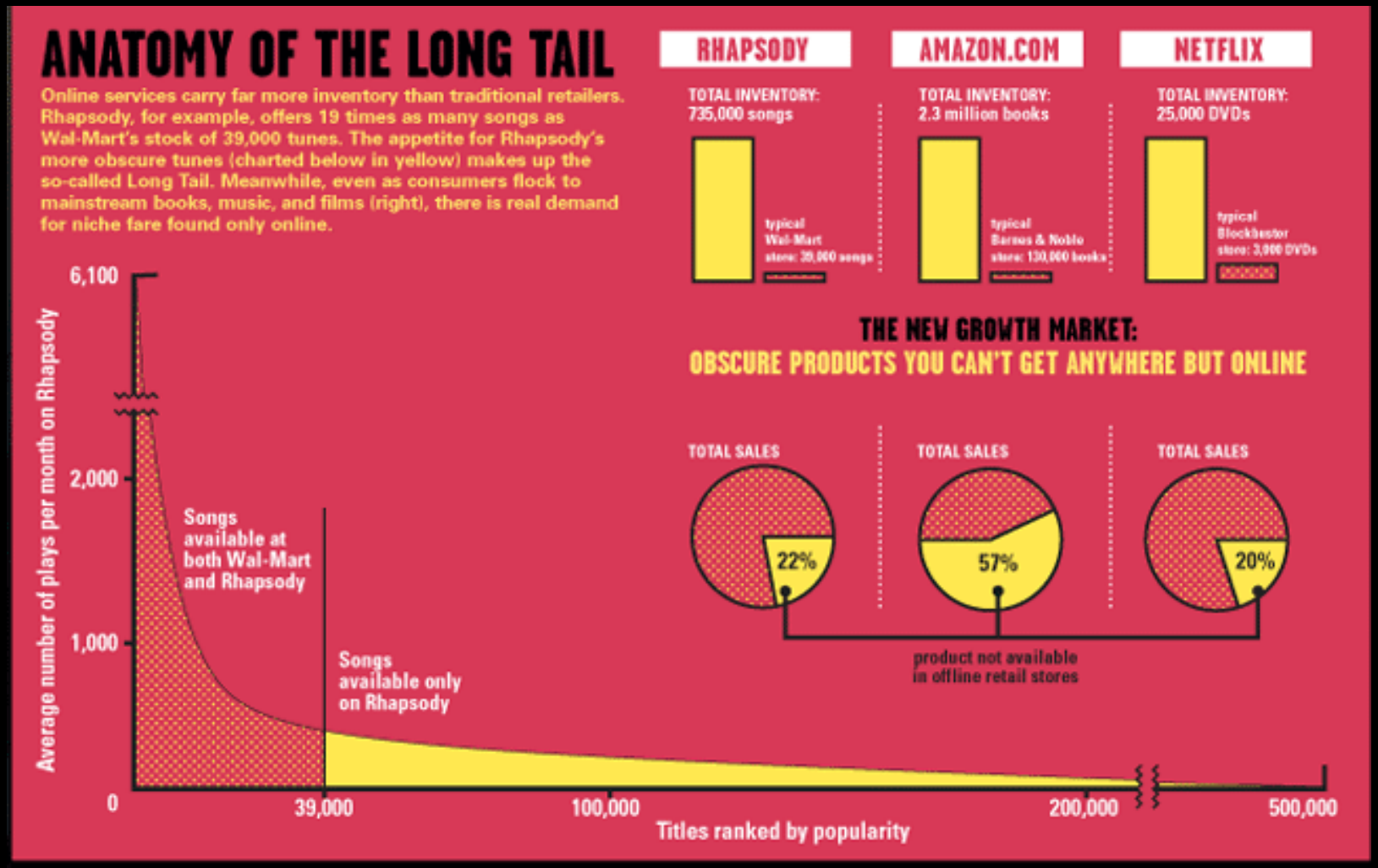
- There are far more “items” than an individual user could browse.

Goal

- Narrow down the choices to the items that are likely of interest to user.

The Long Tail

(Chris Anderson, 2004)



When do Recommender Systems work?

- Main Ideas
  - Past user preferences are predictive of future user preferences.
    - Example: If user u enjoyed action movies with Arnold Schwarzenegger in the past, recommend more action movies with Arnold Schwarzenegger.
  - There is a small number of user types.
    - Example: Users u_1 and u_2 both like the Red Hot Chilli Peppers. If u_1 also likes Linkin Park, then recommend Linkin Park to u_2.

Setup

- Set of users: U
- Set of items: V
- Ratings Y: $U \times V \rightarrow \Re$
  - Explicit Feedback
    - Star rating [1-5]
  - Implicit Feedback
    - Watched/skipped [0,1]
    - Visited web pages [1]

Observed Rating Matrix $\tilde{Y}$

Items

Users

$$\begin{bmatrix} & 4 & 5 & & & & & 2 & \\ 4 & & 3 & & & & & & \\ 3 & 4 & & & & & & & \\ & 4 & 4 & & & 2 & & & \\ & & & 5 & 3 & & & & \\ & & & 4 & & 4 & & & \\ & & & & & & 5 & 3 & \\ & & & & 2 & & & 3 & 3 \\ 1 & & & & & & 4 & & 4 \end{bmatrix}$$

Content-Based Recommendation

- Idea:

  Supervised learning for each row or column

  $$h_u: X_v \to Y$$
  $$h_v: X_u \to Y$$

- Challenge:

  Need to come up with features for users and/or items.

Observed Rating Matrix $\tilde{Y}$

Items V

Users U

$$\begin{bmatrix} & 4 & 5 & & & & & 2 & \\ 4 & & 3 & & & & & & \\ 3 & 4 & & & & & & & \\ & 4 & 4 & & & 2 & & & \\ & & & 5 & 3 & & & & \\ & & & 4 & & 4 & & & \\ & & & & & & 5 & 3 & \\ & & & & 2 & & & 3 & 3 \\ 1 & & & & & & 4 & & 4 \end{bmatrix}$$

Collaborative Recommendation

- Idea:

  Find users with similar ratings and fill in unobserved ratings.

  Find items with similar ratings and fill in unobserved ratings.

Observed Rating Matrix $\tilde{Y}$

Items V

Users U

$$\begin{bmatrix} & 4 & 5 & & & & & 2 & \\ 4 & & 3 & & & & & & \\ 5 & 4 & 4 & & & & & & \\ & 4 & 4 & & & 2 & & & \\ & & & 5 & 3 & & & & \\ & & & 4 & & 4 & & & \\ & & & & & & 5 & 3 & \\ & & & & 2 & & & 3 & 3 \\ 1 & & & & & & 4 & & 4 \end{bmatrix}$$

Matrix Completion Model

Observed Rating Matrix $\tilde{Y}$

$$
\begin{array}{cc}
 & \text{Items V} \\
\text{Users U} & \begin{bmatrix}
 & 4 & 5 & & & & & & 2 \\
4 & & 3 & & & & & & \\
5 & 4 & 4 & & & & & & \\
 & 4 & 4 & & & 2 & & & \\
 & & & 5 & 3 & & & & \\
 & & & 4 & & 4 & & & \\
 & & & & & & 5 & 3 & \\
 & & & & 2 & & & 3 & 3 \\
1 & & & & & & 4 & & 4
\end{bmatrix}
\end{array}
= \overset{k}{\begin{bmatrix} \\ \\ \\ \end{bmatrix}} \times \begin{bmatrix} \\ \\ \end{bmatrix} k
$$

- Low rank assumption: rank k
- For each user u_i and item v_j

$$Y_{ij} = u_i \, v_j$$

- Learn feature vectors u_i and v_j for each user/item

Matrix Completion Training

Observed Rating Matrix $\tilde{Y}$

Items V

$$
\text{Users U}\begin{bmatrix}
 & 4 & 5 & & & & & & 2 \\
4 & & 3 & & & & & & \\
5 & 4 & 4 & & & & & & \\
 & 4 & 4 & & & 2 & & & \\
 & & & 5 & 3 & & & & \\
 & & & 4 & & 4 & & & \\
 & & & & & & 5 & 3 & \\
 & & & & 2 & & & 3 & 3 \\
1 & & & & & & 4 & & 4
\end{bmatrix}
=
\begin{array}{c} k \\ \begin{bmatrix} \\ \\ \end{bmatrix} \end{array}
\times
\begin{array}{c} \begin{bmatrix} \end{bmatrix} \\ k \end{array}
$$

Given: Sample S of observed entries of $\tilde{R}$

Training: Solve for U and V with k rows/cols respectively

$$\min_{U,V} \sum_{(i,j)\in S} \left(\tilde{Y}_{ij} - u_i v_j\right)^2$$

Prediction: Fill in entries not in S with $Y_{ij} = u_i\, v_j$

Movie Recommendation

Horror | Romance | Comedy

True Rating Matrix Y^*

Movies

Horror lovers

Romance lovers

Comedy lovers

$$\begin{bmatrix} 5 & 4 & 5 & 1 & 3 & 1 & 1 & 1 & 3 \\ 4 & 4 & 3 & 2 & 1 & 2 & 2 & 2 & 2 \\ 3 & 4 & 4 & 2 & 2 & 1 & 1 & 3 & 1 \\ 3 & 4 & 4 & 2 & 2 & 2 & 2 & 1 & 2 \\ 1 & 2 & 1 & 5 & 3 & 5 & 3 & 2 & 3 \\ 1 & 1 & 3 & 4 & 4 & 4 & 2 & 1 & 1 \\ 1 & 2 & 2 & 1 & 1 & 1 & 5 & 3 & 5 \\ 2 & 2 & 1 & 2 & 2 & 2 & 4 & 3 & 3 \\ 1 & 1 & 1 & 3 & 1 & 1 & 4 & 3 & 4 \end{bmatrix}$$

Partially revealed →

← Predict $\hat{Y}$

Observed Rating Matrix $\tilde{Y}$

Movies

Users

$$\begin{bmatrix} & 4 & 5 & & & & & 2 & \\ 4 & & 3 & & & & & & \\ 3 & 4 & & & & & & & \\ & 4 & 4 & & & 2 & & & \\ & & & 5 & 3 & & & & \\ & & & 4 & & 4 & & & \\ & & & & & & 5 & 3 & \\ & & & & 2 & & & 3 & 3 \\ 1 & & & & & & 4 & & 4 \end{bmatrix}$$

→ Missing Not At Random (MNAR) Problem

MNAR and Evaluation

Predicted Rating Matrices $\hat{Y}_1$ and $\hat{Y}_2$

$\hat{Y}_1$

Movies

Users

$$\begin{bmatrix} 5 & 5 & 5 & 1 & 1 & 1 & 1 & 1 & 1 \\ 5 & 5 & 5 & 1 & 1 & 1 & 1 & 1 & 1 \\ 5 & 5 & 5 & 1 & 1 & 1 & 1 & 1 & 1 \\ 5 & 5 & 5 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 5 & 5 & 5 & 1 & 1 & 1 \\ 1 & 1 & 1 & 5 & 5 & 5 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 5 & 5 & 5 \\ 1 & 1 & 1 & 1 & 1 & 1 & 5 & 5 & 5 \\ 1 & 1 & 1 & 1 & 1 & 1 & 5 & 5 & 5 \end{bmatrix}$$

$\hat{Y}_2$

Movies

Users

$$\begin{bmatrix} 4 & 4 & 4 & 5 & 5 & 5 & 5 & 5 & 5 \\ 4 & 4 & 4 & 5 & 5 & 5 & 5 & 5 & 5 \\ 4 & 4 & 4 & 5 & 5 & 5 & 5 & 5 & 5 \\ 4 & 4 & 4 & 5 & 5 & 5 & 5 & 5 & 5 \\ 5 & 5 & 5 & 4 & 4 & 4 & 5 & 5 & 5 \\ 5 & 5 & 5 & 4 & 4 & 4 & 5 & 5 & 5 \\ 5 & 5 & 5 & 5 & 5 & 5 & 4 & 4 & 4 \\ 5 & 5 & 5 & 5 & 5 & 5 & 4 & 4 & 4 \\ 5 & 5 & 5 & 5 & 5 & 5 & 4 & 4 & 4 \end{bmatrix}$$

$$MAE(\hat{Y}_1, \tilde{Y}) = 24$$

$$MAE(\hat{Y}, \tilde{Y}) = \sum_{ij} |\hat{y}_{ij} - \tilde{y}_{ij}|$$

$$MAE(\hat{Y}_2, \tilde{Y}) = 22$$

Observed Rating Matrix $\tilde{Y}$

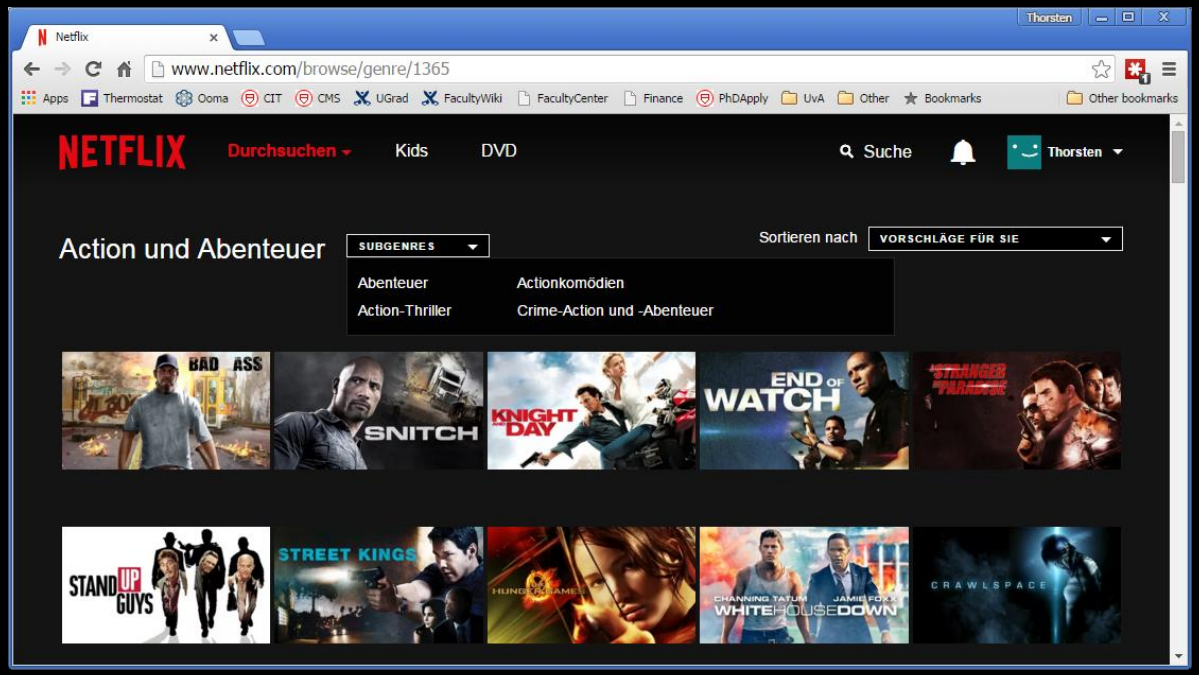
Movies

Users

$$\begin{bmatrix} & 4 & 5 & & & & & & 2 \\ 4 & & 3 & & & & & & \\ 3 & 4 & & & & & & & \\ & 4 & 4 & & & 2 & & & \\ & & & 5 & 3 & & & & \\ & & & 4 & & 4 & & & \\ & & & & & & 5 & 3 & \\ & & & & 2 & & & 3 & 3 \\ 1 & & & & & & 4 & & 4 \end{bmatrix}$$

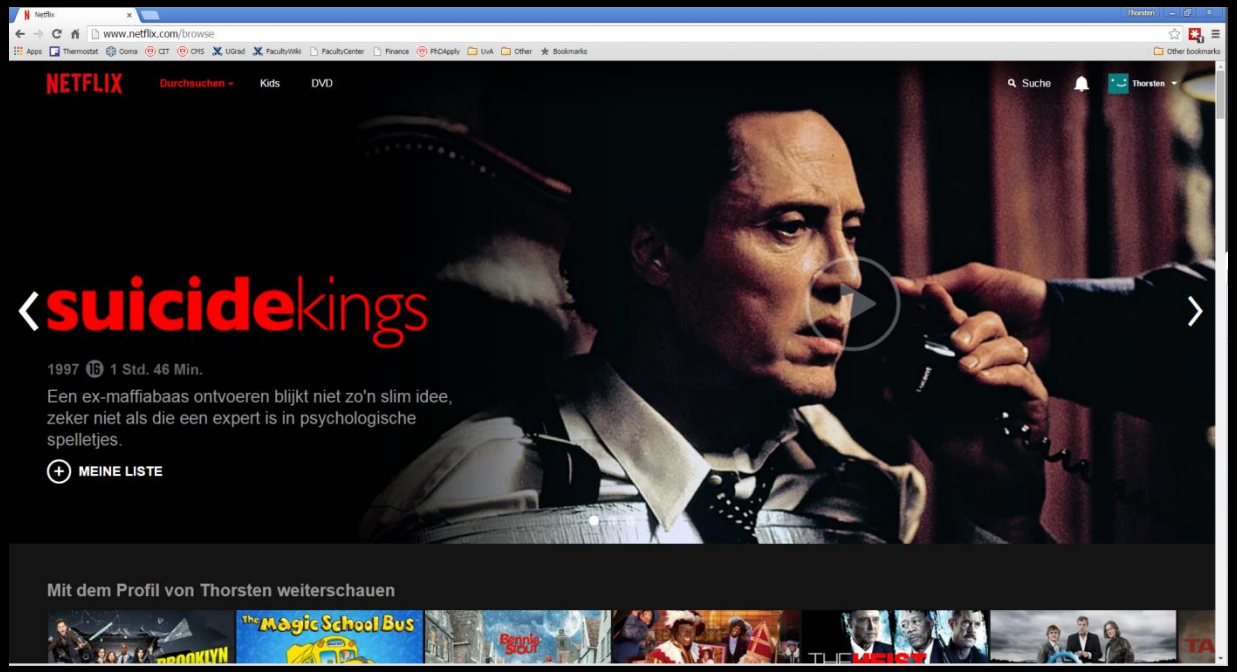
→ Severly biased performance estimates!

Why is the Data MNAR?



- User Induced MNAR

Why is the Data MNAR?



- System Induced MNAR