Nantonac Collaborative Filtering
A Model-Based Approach

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Overview

Many prediction algorithms and user interfaces are developed for recommender systems

BUT

For collecting users' preference data, almost all systems use a **rating method** or a **scoring method**

↓

We proposed to use a **Ranking method**

Previous and New Contribution

Our previous contributions are…

- proposed to use a ranking method for collecting preference data
- developed a technique that enables to apply ranking data to existing recommendation algorithms designed for scores
- prediction accuracies are improved by using a ranking method in comparison with a scoring method

BUT

Superiority of a ranking method is tested only for memory-based algorithms

⬇

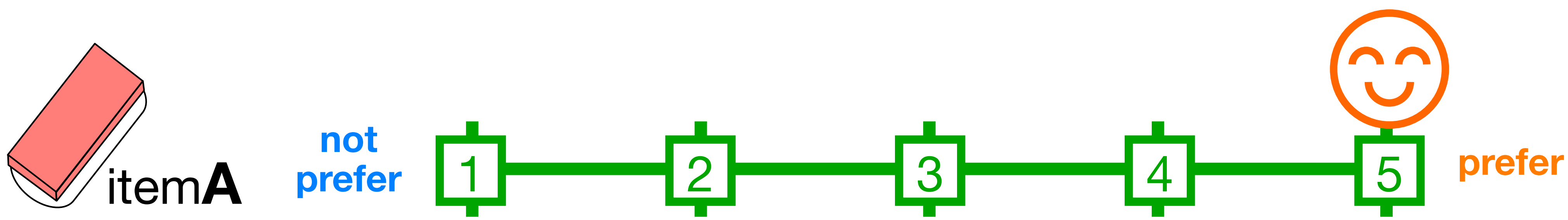
A ranking method is also **effective for model based algorithms: matrix decomposition and pLSA**

Rating / Scoring Methods

Scoring Method

Items are evaluated by using scales with scores, s.g., a five-points-scale

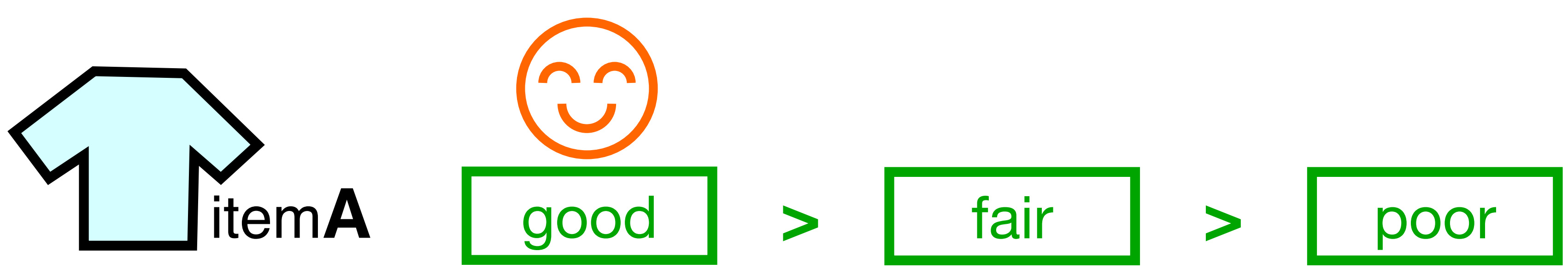
The user selects “5” in a five-point scale if she prefers the item A



Rating Method

Items are evaluated by using ordered ratings, s.g., {good, fair, poor}

The user selects “good” if she sets a high value the item A

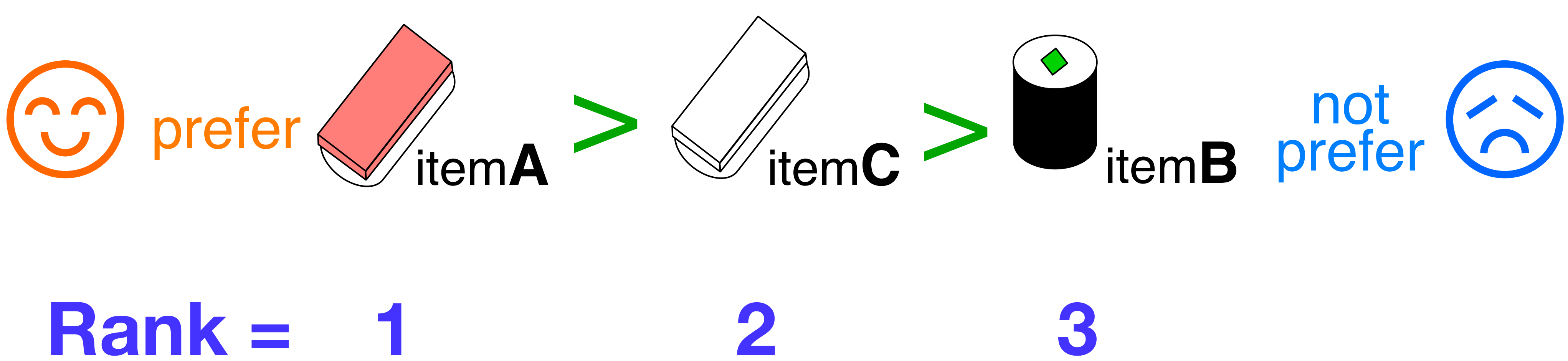


Ranking Method

Ranking Method

Objects are sorted according to the degree of preference

The user prefers the item A most, and the item B least

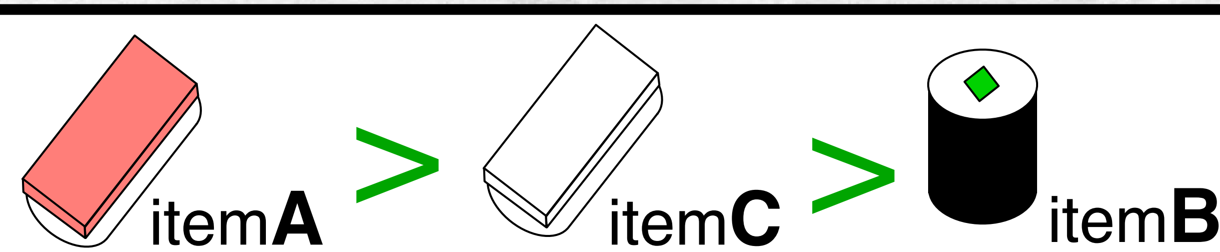


Ranks to Scores

We developed a simple technique to convert ranks in preferential orders to preferential scores based on order statistics theory

$$\text{expectation of ranks in a unobserved complete order} \propto \frac{\text{rank in a observed order}}{(\text{length of a observed order }) + 1}$$

Example:

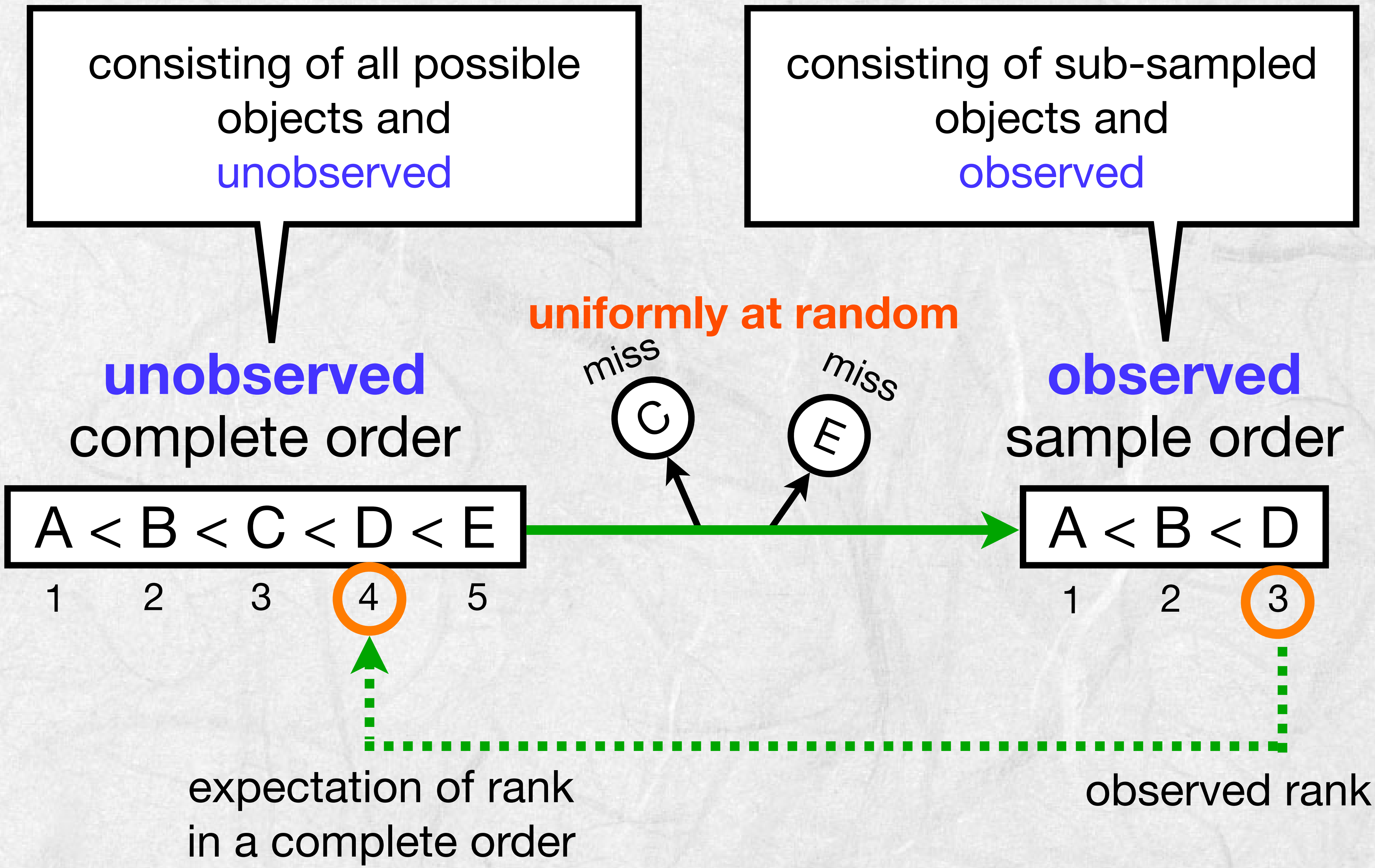


rank of item A is 1

length of observed order is **3**

Set the score **1/4 = 1 / (3 + 1)** to the item A

Assumption

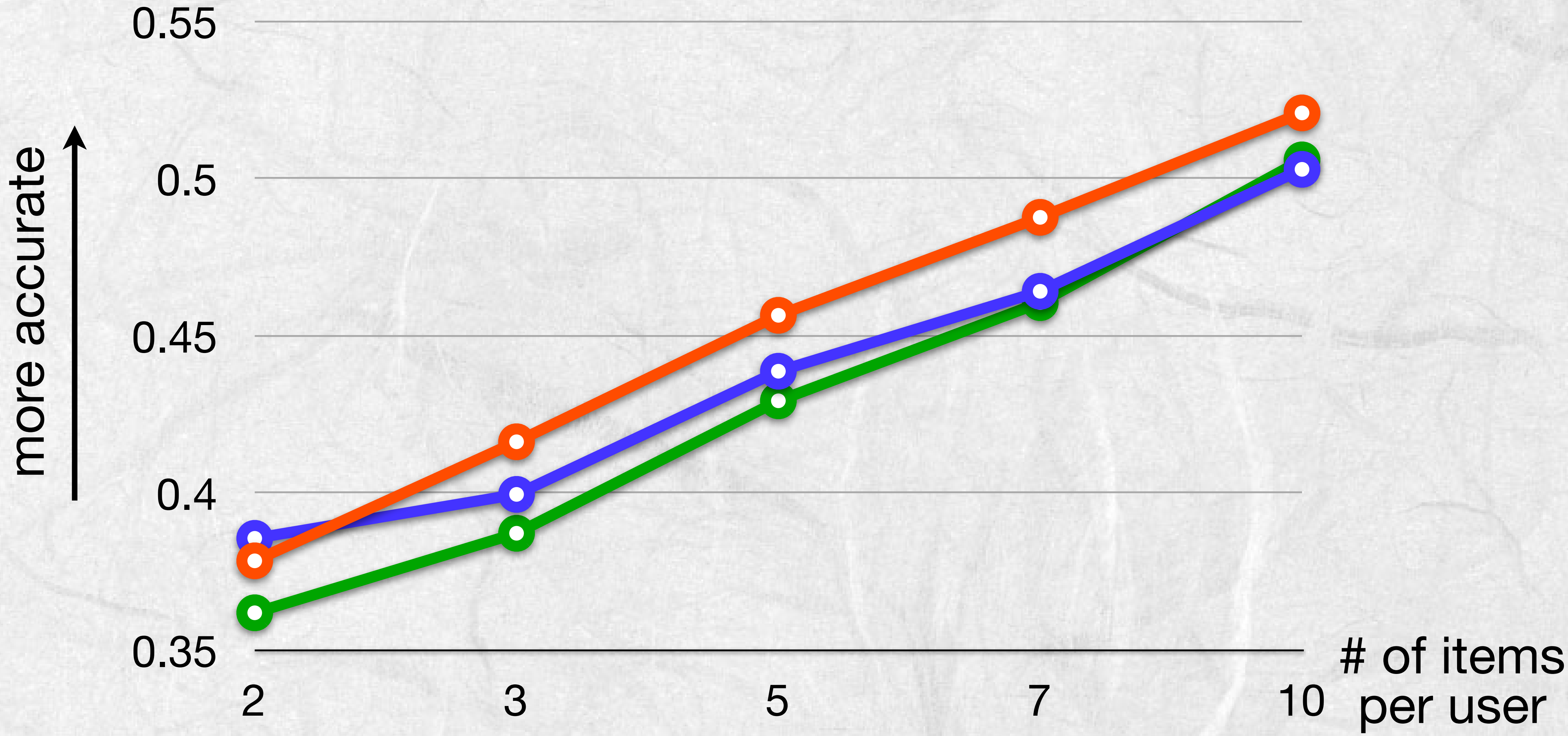

consisting of all possible objects and unobserved
consisting of sub-sampled objects and observed
uniformly at random
miss
miss
C
E
unobserved
complete order
observed
sample order
A < B < C < D < E
1 2 3 4 5
A < B < D
1 2 3
expectation of rank in a complete order
observed rank

Interface

WWW Interface for asking user preference by ranking method

1. show 10 items to the user
2. the user specify all the rank of each items
3. press “submit” button
4. if error (ex. the same ranks are assigned to the two items) is detected, the system request to re-input

Memory-Based Method



Grouplens like memory-based method

- ranking method + default voting
- scoring method + default voting + standardization (min-max range)
- scoring method + default voting + rank correlation

Matrix Decomposition Model

The user x's score to the item y is estimated by the following Eq.

overall bias — per item bias — user x's cross effect vector — information vector which items are rated

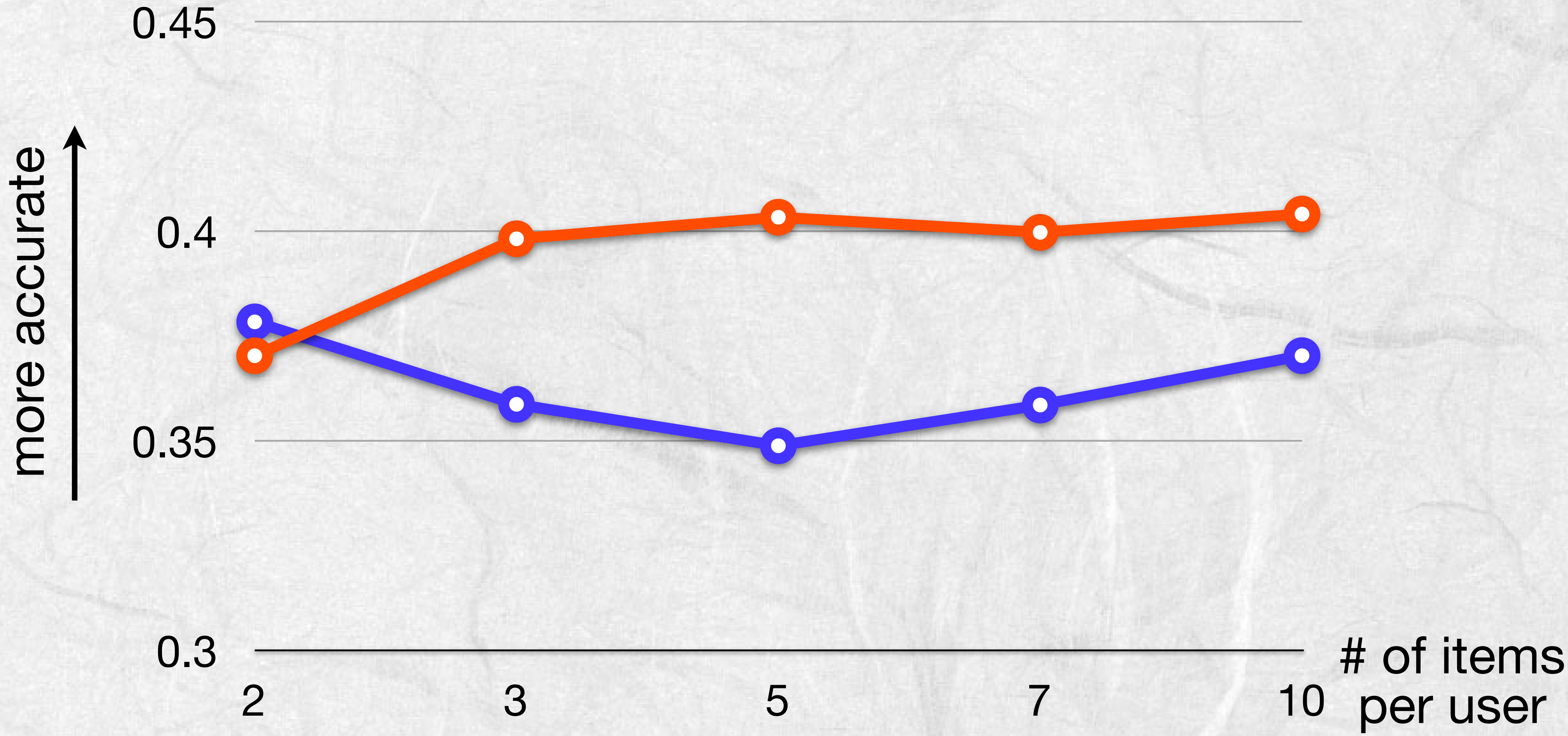
$$\hat{s}_{xy} = b + c_x + d_y + \mathbf{u}_y^\top \left[\mathbf{v}_x + \frac{1}{\sqrt{|\mathcal{Y}_x|}} \sum_{y' \in \mathcal{Y}_x} \mathbf{w}_{y'}) \right]$$

per user bias — item y's cross effect vector — a set of items rated by user x

Parameters are estimated by minimizing the loss function:

$$\mathrm{loss}(\mathcal{D}; \Theta) = \sum_{(x,y,s) \in \mathcal{D}} (s_{xy} - \hat{s}_{xy})^2 + \lambda[\mathrm{reg.term}]$$

Matrix Decomposition Model



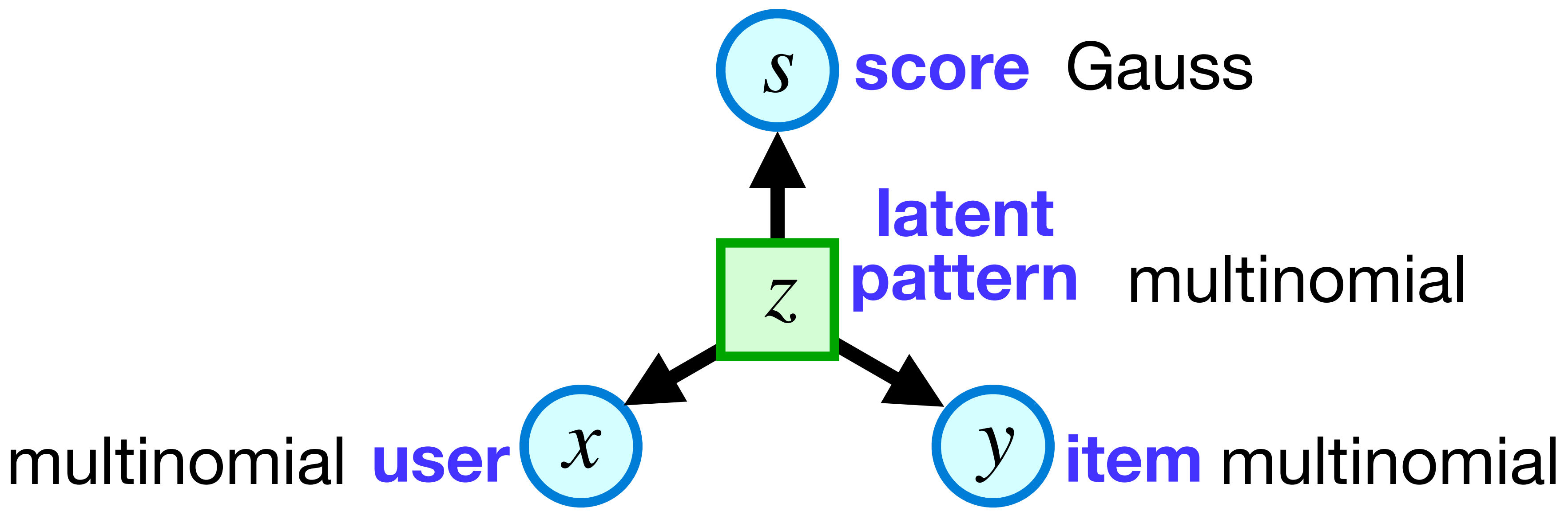
Memory-based method: Matrix decomposition

- ranking method + matrix decomposition
- scoring method + matrix decomposition

pLSA-like Model

Hoffman's pLSA model is modified so as to deal with real scores

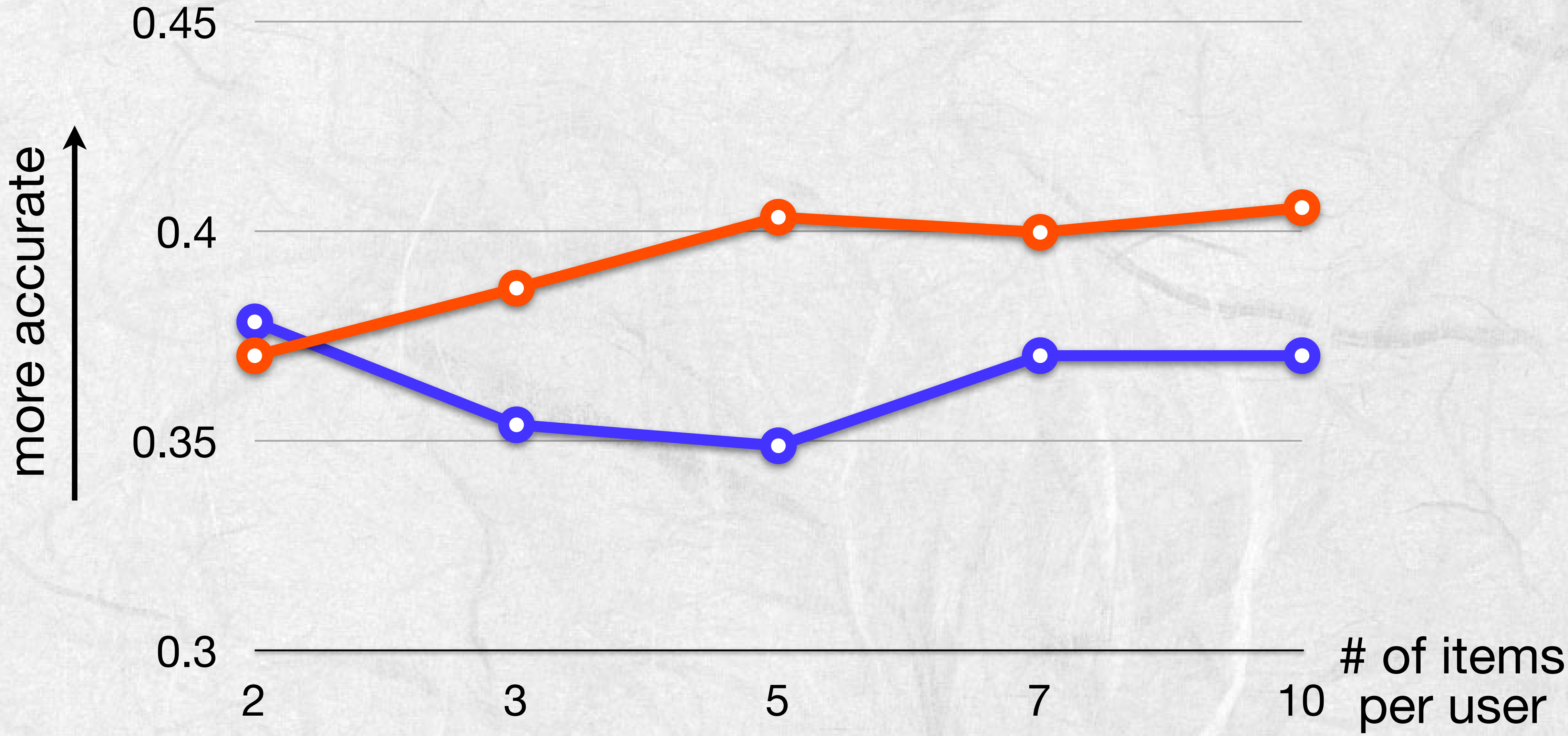
Graphical model of our pLSA-like model



Parameters are estimated by maximizing the likelihood functon

$$\mathcal{L}(\mathcal{D};\Theta) = \sum_{(x,y,s)\in\mathcal{D}} \log \sum_{z} \Pr[z]\Pr[x|z]\Pr[y|z]\mathcal{N}(s;\mu_z,\sigma_z^2)$$

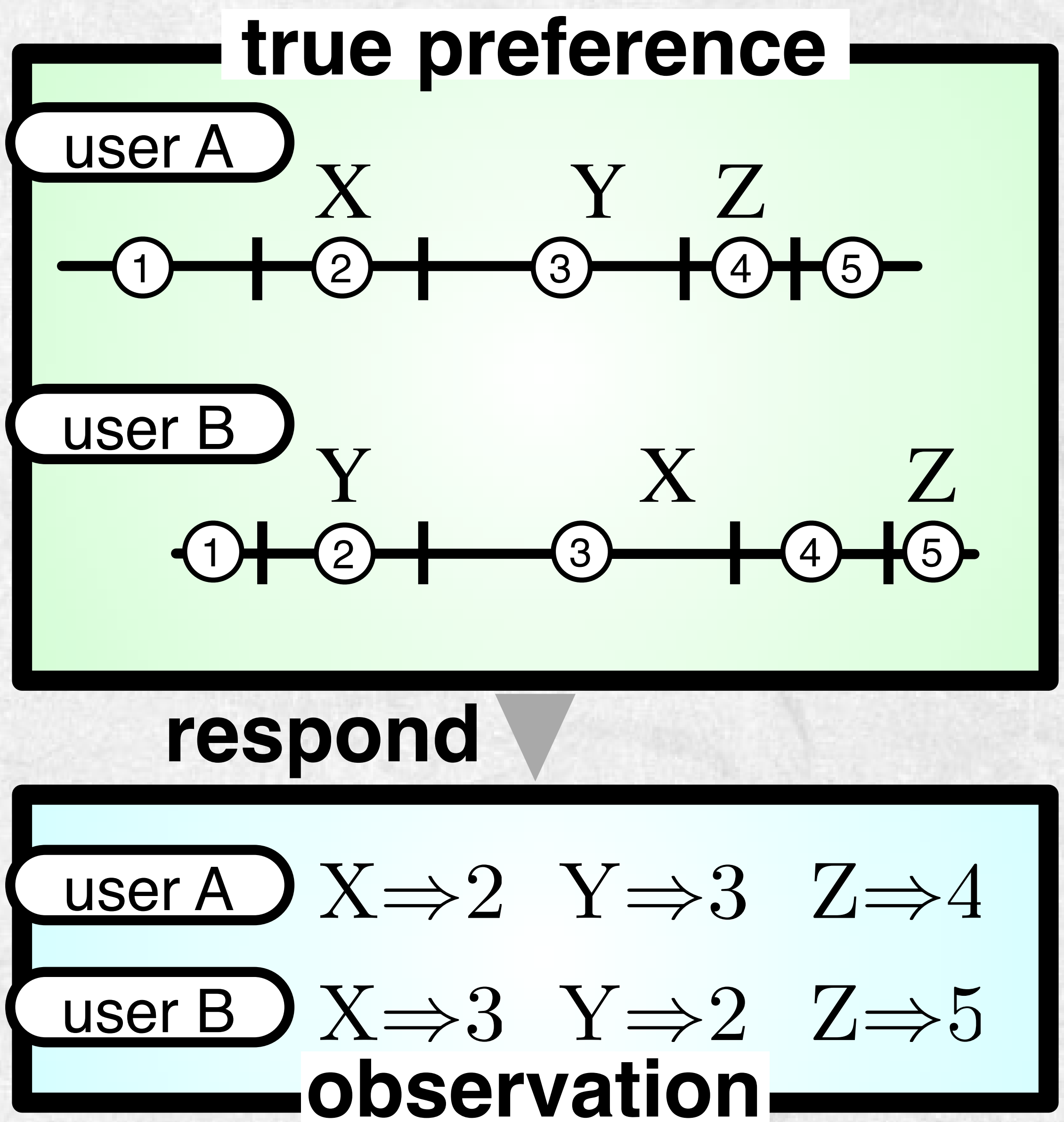
pLSA-like Model



Memory-based method: Matrix decomposition

- ranking method + pLSA-like model
- scoring method + pLSA-like model

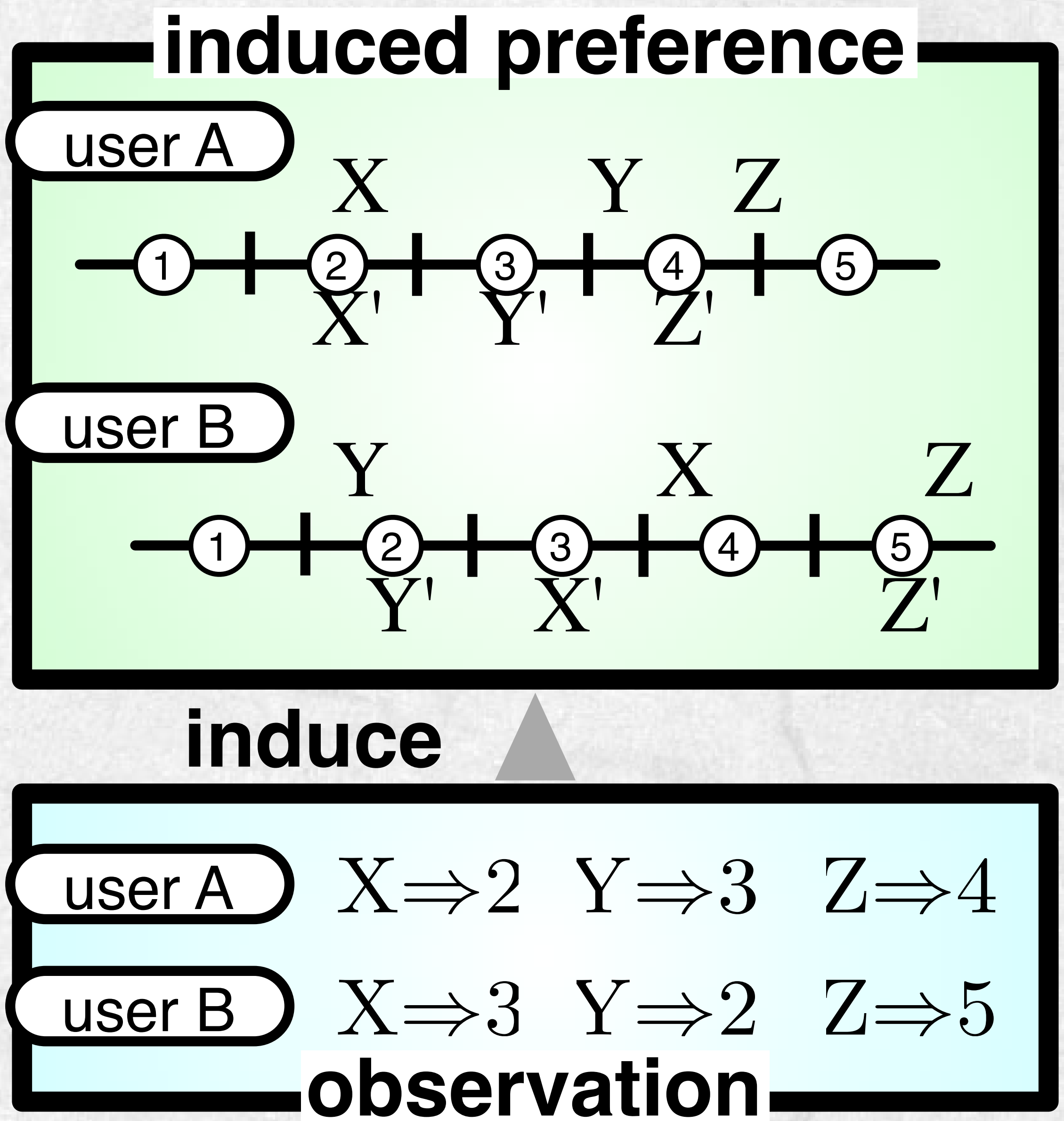
Why Ranking performed better?



- The degree of true preference cannot be observed directly
- Each user uses one's own mapping from the degree to rating score
- Ex: The degree of preference on X lies in interval 2 of user A

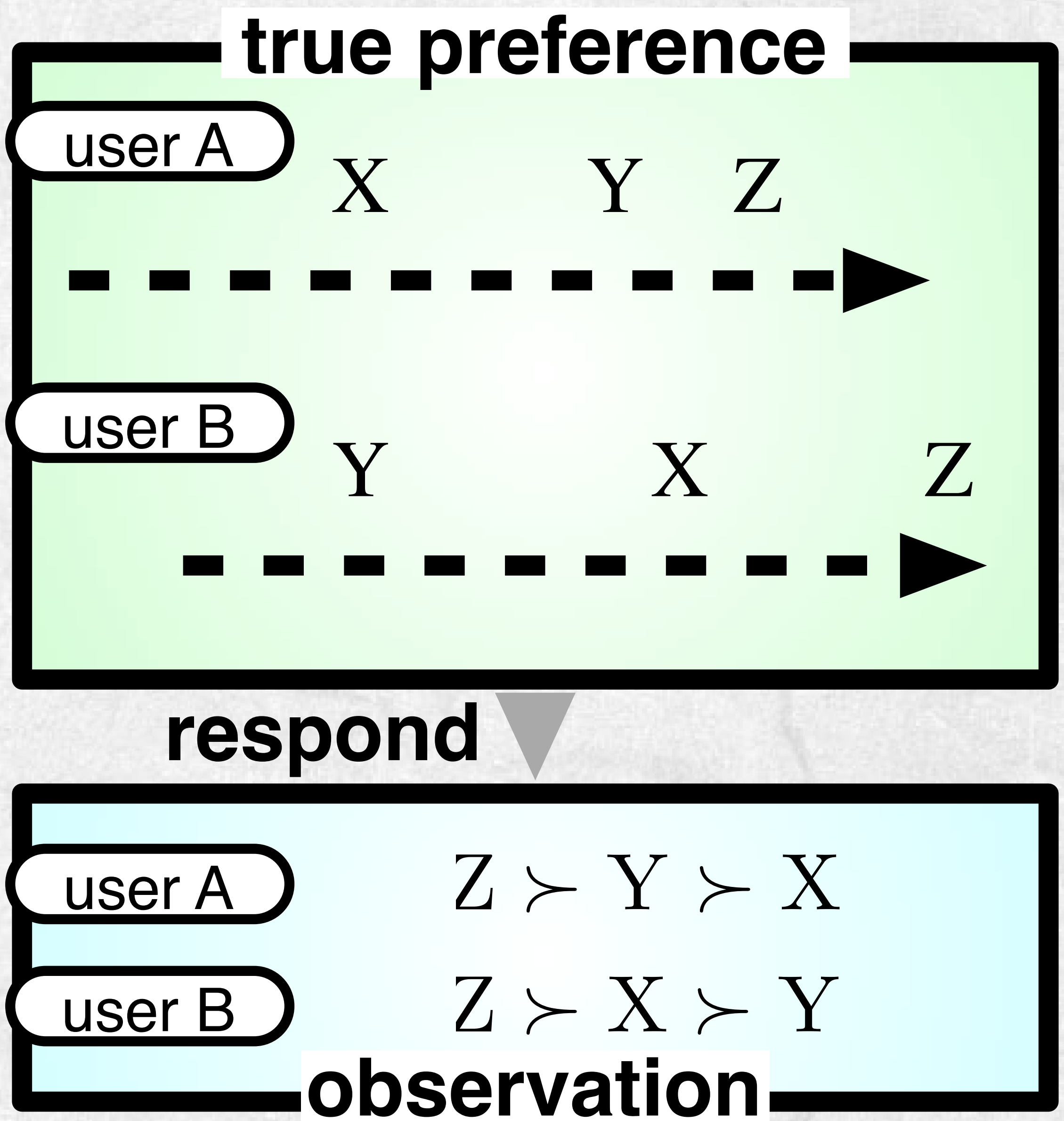
  ➡ User A replies rating score 2

Why Ranking performed better?



- We now want to induce the true degree of preference
- The true mapping to rating scores is unknown
- A common idealized mapping scale is of necessity used
- The induced degrees of preferences might not be true
- Ex: The true degrees of X, Y, and Z are changed to X’, Y’, and Z’, respectively

Why Ranking performed better?



- In a ranking method, the degrees of preferences are relatively specified
- We don’t need to use a unsafe groundless mapping between the degrees of preference and observed rating scores

Merits and Demerits of Ranking Methods

Merits

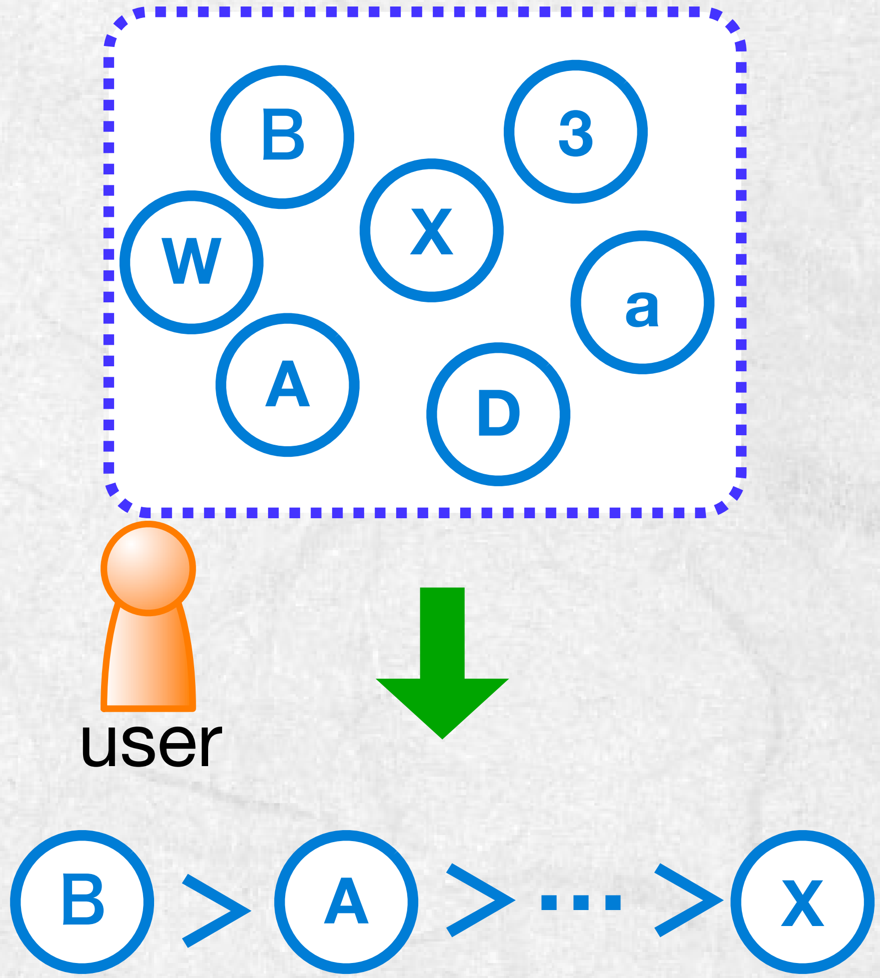
- **High consistency of preferences** between and with in users

Demerits

- **Less algorithms** for analysis are available
  ➡ Develop new algorithms
- **Difficult to rate many items** at the same time
  ➡ Subsets of items are sorted multiple times
- **Lack of absolute evaluation**

Ranking Many Objects

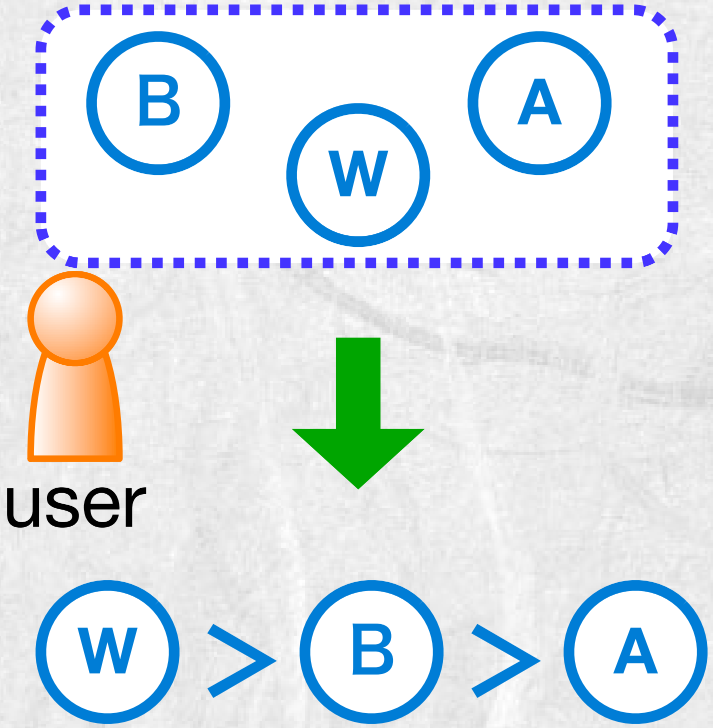
many objects



Sort all objects
AT THE SAME TIME

No!

sampling small sets of objects



sort these small sets of objects

Iterate sampling and Sorting

OK!

Relevance Feedback

[Joachims 02, Radlinski+ 05]

Leaning from relevance feedback is a typical absolute ranking task

Ranked List for the query Q

1: document A

2: document B

3: document C

4: document D

5: document E

selected by user

The user scans this list from the top, and selected the third document C.

The user checked the documents A and B, but these are not selected.

This user's behavior implies relevance feedbacks: C>A and C>B.

Object ranking methods can be used to update document's relevance based on these feedbacks

What's "Nantonac"

The word *nantonac* originates from a Japanese word, *nantonaku*, which means just somehow.

For example, in Japanese, if I say "I *nantonaku* understand something," I am saying that I cannot specifically explain why I understand it, but that I somehow do.

Order responses allow a more vague and intuitive expression of users' preferences, so we have named this method the *nantonac collaborative filtering*.

Our Related Publications

Our Related Publications

- T. Kamishima, "Nantonac Collaborative Filtering: Recommendation Based on Order Responses", Proc. of The 9th Int'l Conf. on Knowledge Discovery and Data Mining (KDD 2003)
- T. Kamishima and S. Akaho, "Nantonac Collaborative Filtering — Recommendation Based on Multiple Order Responses", Proc. of The Int'l Workshop on Data-Mining and Statistical Science (2006)

Our SUSHI data sets are available at

http://www.kamishima.net/sushi/