Nantonac Collaborative Filtering: Recommendation Based on Order Responses

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Overview

Show and compare some methods of Collaborative Filtering (CF) based on preference orders

What's "Preference Orders" ?
Item sequence sorted according to users' preferences

ex. a sequence of *sushi* sorted according to my preference

"I prefer *Fatty Tuna* to *Squid* "
but "How much prefer" is unknown

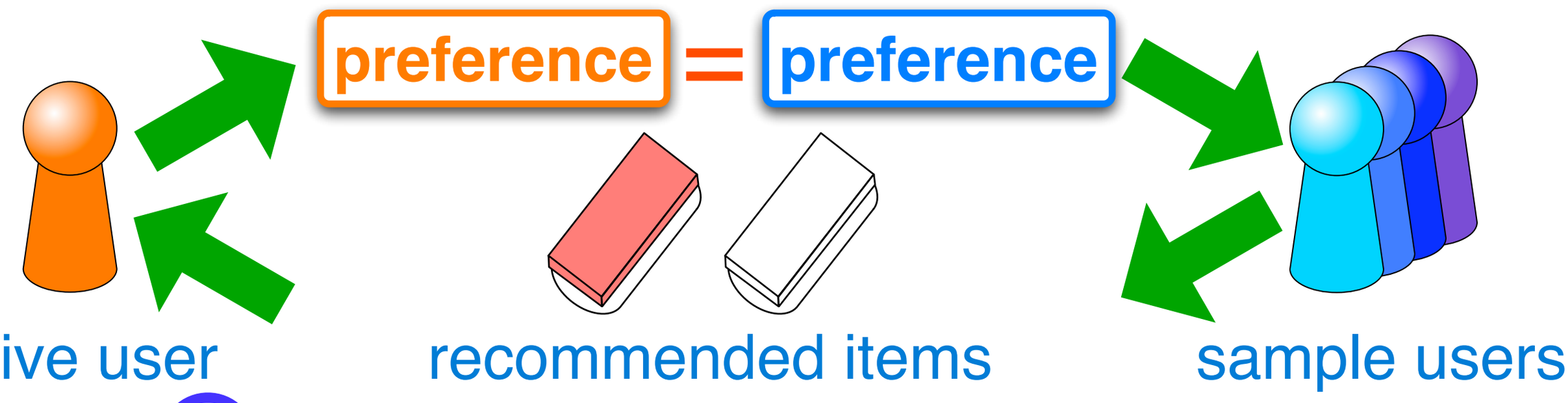
Orders improve prediction performance of CF

Collaborative Filtering

Method for recommending items preferred by users

1. The active user show his/her preference to the system

2. From DB, the system seeks sample users having similar preference



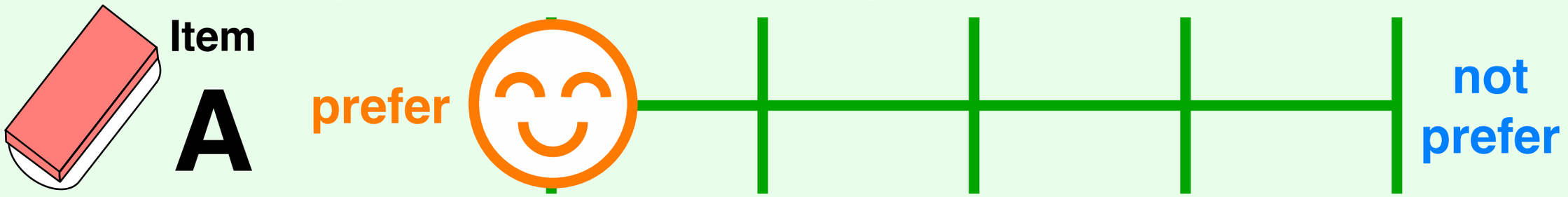
3. To the active user, the system recommends the items preferred by sample users

Measuring User Preferences

Traditional: Semantic Differential Method

measured by a scale, the extremes of which is symbolized by antonymous adjectives

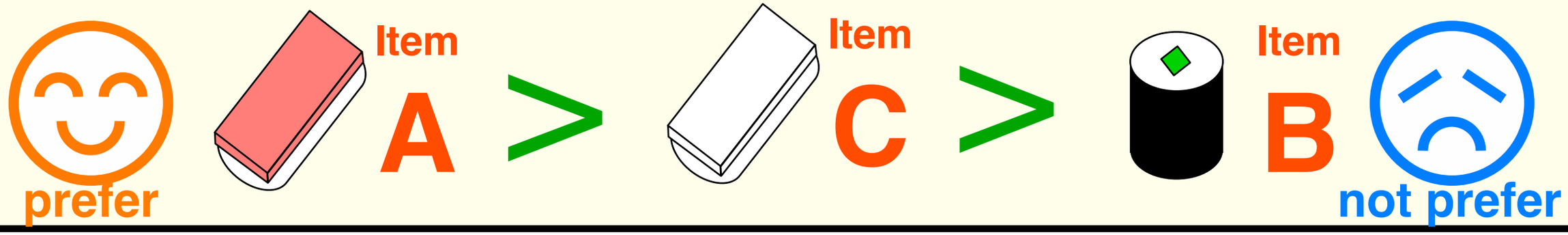
ex. If the user prefer “Item A”, choose “prefer” on the scale



Proposed: Ranking Method

Items are sorted according to the user’s preference

ex. The user prefer “item A” most, and dislike “item B” most.



Drawbacks of the SD Method (1)

1. SD method demands unrealistic assumption

- All users share an absolute values of scale extremes

  Even if both of the "user A" and "user B" pointed "most prefer" on the scale, the degree of preference in their mind are not equal

- The divisions of scales are equivalent

  Can users really divide their degree of preferences into equivalent intervals?

↕

Ranking method is free from such assumptions

- Specify relative preferences, no absolute degree of preferences
- Intervals of preferences are ignored

Drawbacks of the SD Method (2)

2. SD method disturbed by some psychological rator effects

ex. Central tendency effect: tendency to use only the near neutral portion of the rating scale

SD method is originally designed for measuring preferences of respondent group.
For this purpose, the above drawbacks is not so crucial.
However, the SD method is not suited for measuring personal preference as used in CF.

Grouplens' Method

Simple but effective CF method developed for GroupLens
User preferences are measured by SD method

① The active user rates some items

② Calculate weight of sample user X in the DB

$$\text{Weight}(\text{sample user X}) = \text{Correlation}(\text{active user ratings}, \text{sample user X ratings})$$

③ Calculate score of item A

$$\text{Score}(\text{item A}) = \sum_{\text{sample user DB}} \text{sample user X's rating of item A} \times \text{Weight}(\text{sample user X})$$

④ Sort Items according to Scores

Hi-scored items expected to be preferred by the active user

Filtering Based on Orders

1. Show some items to the active user
2. The active user sort items

   The active user sort shown items according to his/her preference

3. The system compare between the active user and the samples users
   - The system calculates similarities between the active user and each of sample user in DB
   - Or the system finds a group of sample users whose preference orders are similar to that of the active user
4. The system recommend items

   To the active user, the system recommends the items preferred by the sample users whose preference orders are similar

Memory-Based Method

Almost same as GroupLens' method

except for rating scores of items → Item ranks in preference order

Rank: ex. in the order, rank of item B is 3

item A	>	item C	>	item B
Rank 1		2		3

$$\text{Weight}(\text{sample user X}) = \text{Correlation}(\text{active user ranks}, \text{sample user X ranks})$$

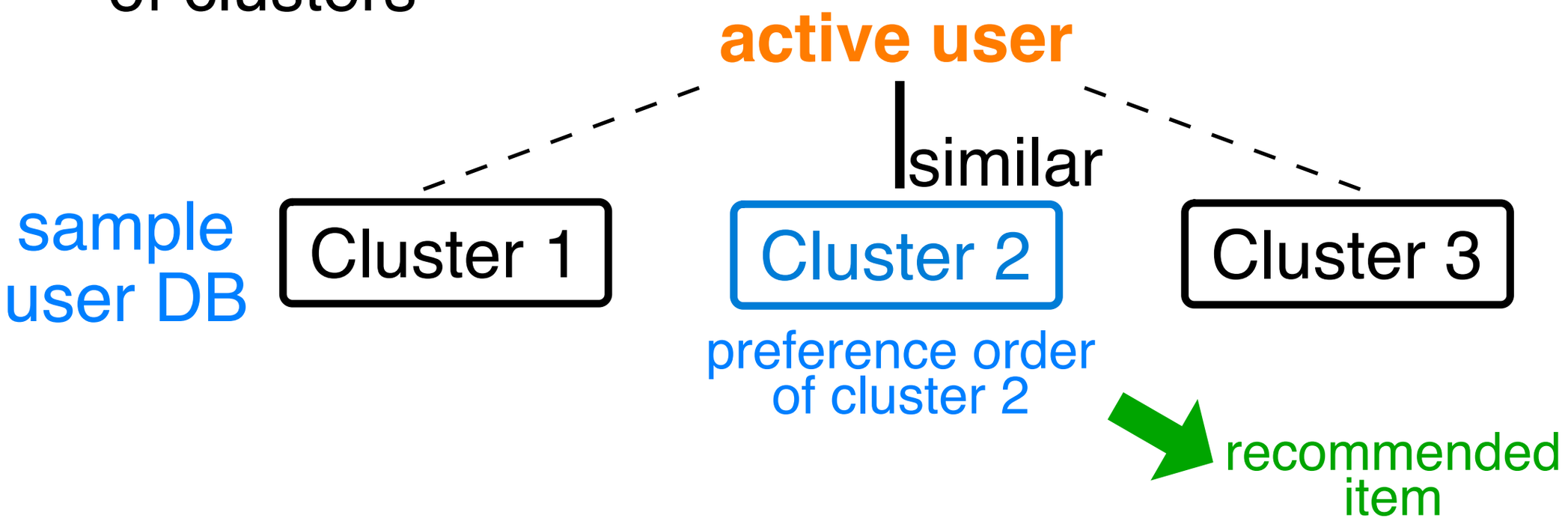
$$\text{Score}(\text{item A}) = \sum_{\text{sample user DB}} \text{sample user X's rank of item A} \times \text{Weight}(\text{sample user X})$$

Model-Based Method

Recommendation based on clustered sample users

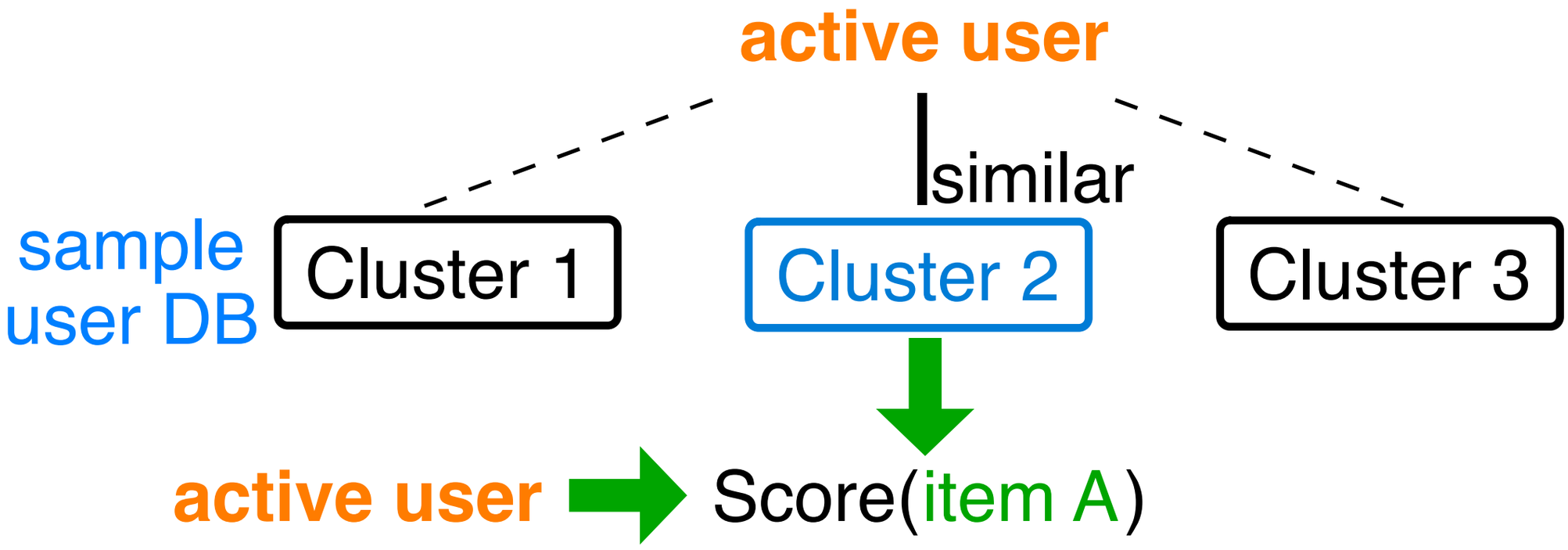
k-o'means: clustering method for orders

1. Sample users are clustered based on their preferences
2. Find the most similar cluster to the active user's preference order
3. Recommend items based on typical preference order of clusters



Hybrid Method

Hybrid of Memory-based and Model-based methods
Same as the Memory-based method except that the score calculation is limited in the nearest cluster



$$\text{Score}(\text{item A}) = \sum_{\text{most similar cluster}} \text{sample user X's rank of item A} \times \text{Weight}(\text{sample user X})$$

Experiment (Data)

Questionnaire survey of preference in sushi

- collected via commercial WWW survey service
- # of respondents = 1025, # of sushi = 100
- Test Data
  - 10 popular sushi, common for all respondents
  - preferences are measured by ranking method
- Training Data
  - 10 randomly selected sushi for each respondent
  - preferences are measured by both ranking and SD method
- Procedure
  - estimate the preference order based on preferences in sushi in training data
  - compare the order with the preference order of test data

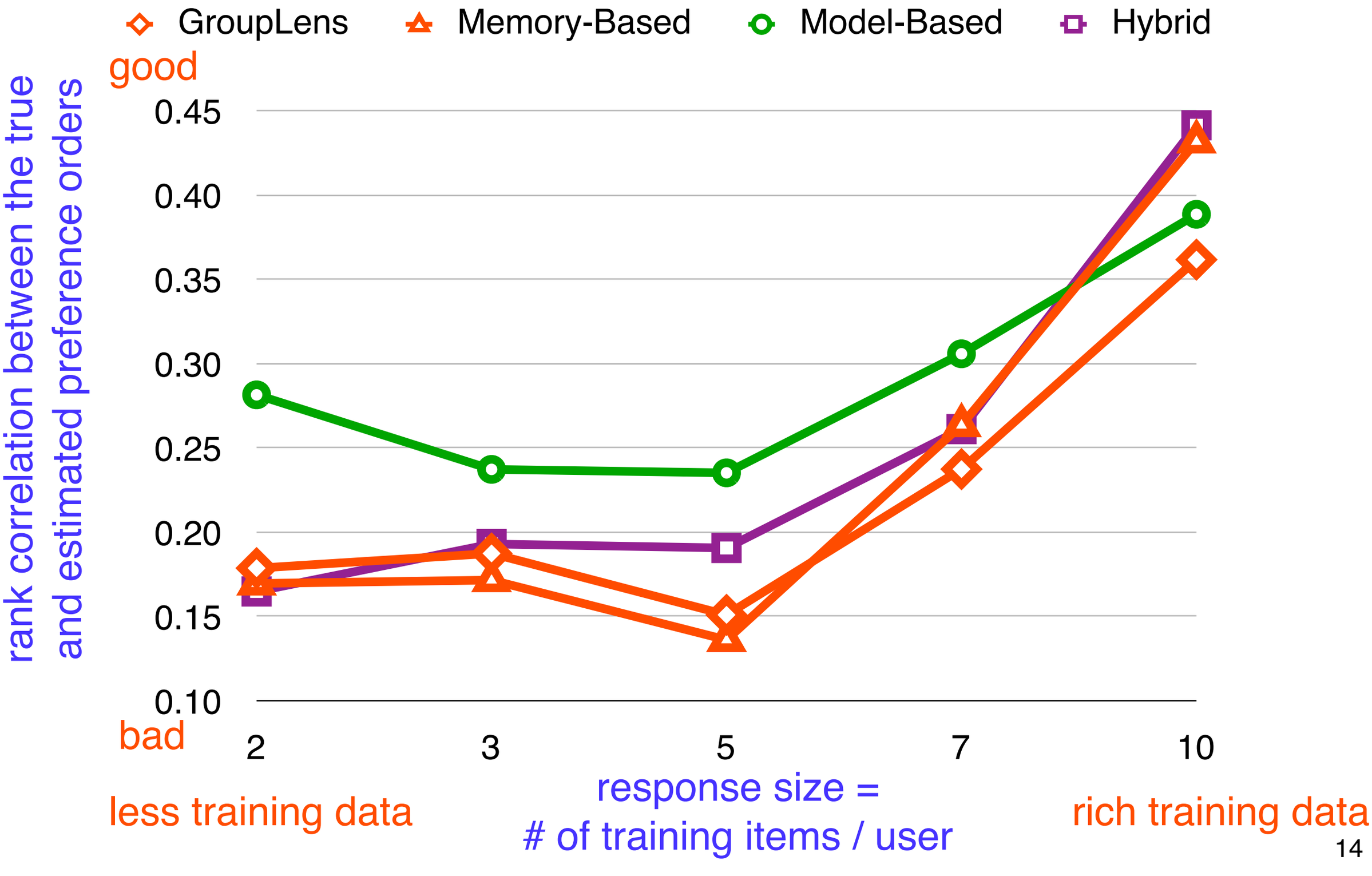
Experiment (interface)

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

name of sushi　　Specify Ranks

Experimental Results



Summary of Results

- If response size is small, model-based is better

  Since the model-based recommendation is based on preferences of groups, this method is superior if less personal information is supplied

- Hybrid and memory-based methods are tie

  By hybridization, online estimation time can be saved

- Grouplens method is inferior to our order-based method if response size ≥ 5

  We think Grouplens' estimation scheme itself is not bad, but this method was affected by the drawbacks of the SD method

Why Our Order-Based is better?

the ratios of each rating score selected by users

rating	1 not prefer	2	3 neutral	4	5 prefer
ratio of specified	0.082	0.095	0.226	0.224	0.372

Drawbacks of the SD method described before

- SD method demands unrealistic assumption
  - The distribution is highly skewed
  - → Scale extremes are not shared among respondents, and intervals of scale divisions are not equal
- SD method affected by some psychological effects
  - Users' ratings are concentrated at near the mean
  - → These preference data are biased by psychological effects