Beyond Adaptive Testing: Adaptive Item Recommendation with Process Data

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Outline

1. Need for stronger adaptability

2. Recommender systems

3. An application of adaptive item recommendation

From "Selection" to "Recommendation"

- In conventional computerized adaptive testing,
  - Select and administer the best item from the item bank
  - Update the examinee's provisional ability estimate
  - Select the best item based on the updated ability
- "Limited adaptability" because CAT relies only on:
  - Item-level statistics (e.g., difficulty)
  - The examinee's ability to answer the administered items
- Intelligently matching the best items to examinees
  - Individualized item recommendations based on item and examinee attributes

On the Road to Stronger Adaptability

“Adaptive” Variables

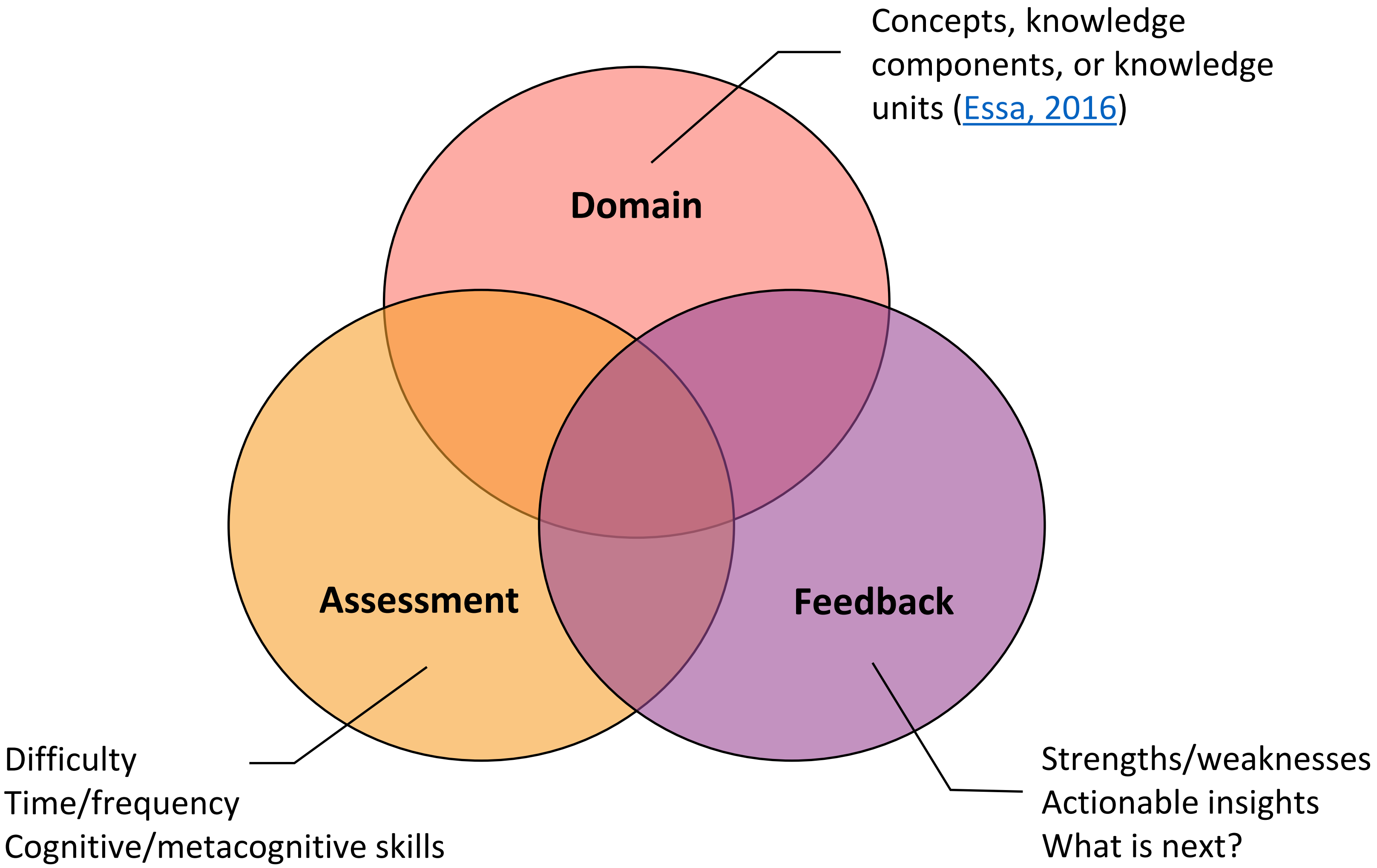
Cognitive learning styles

Preferences and interests

Learning progression

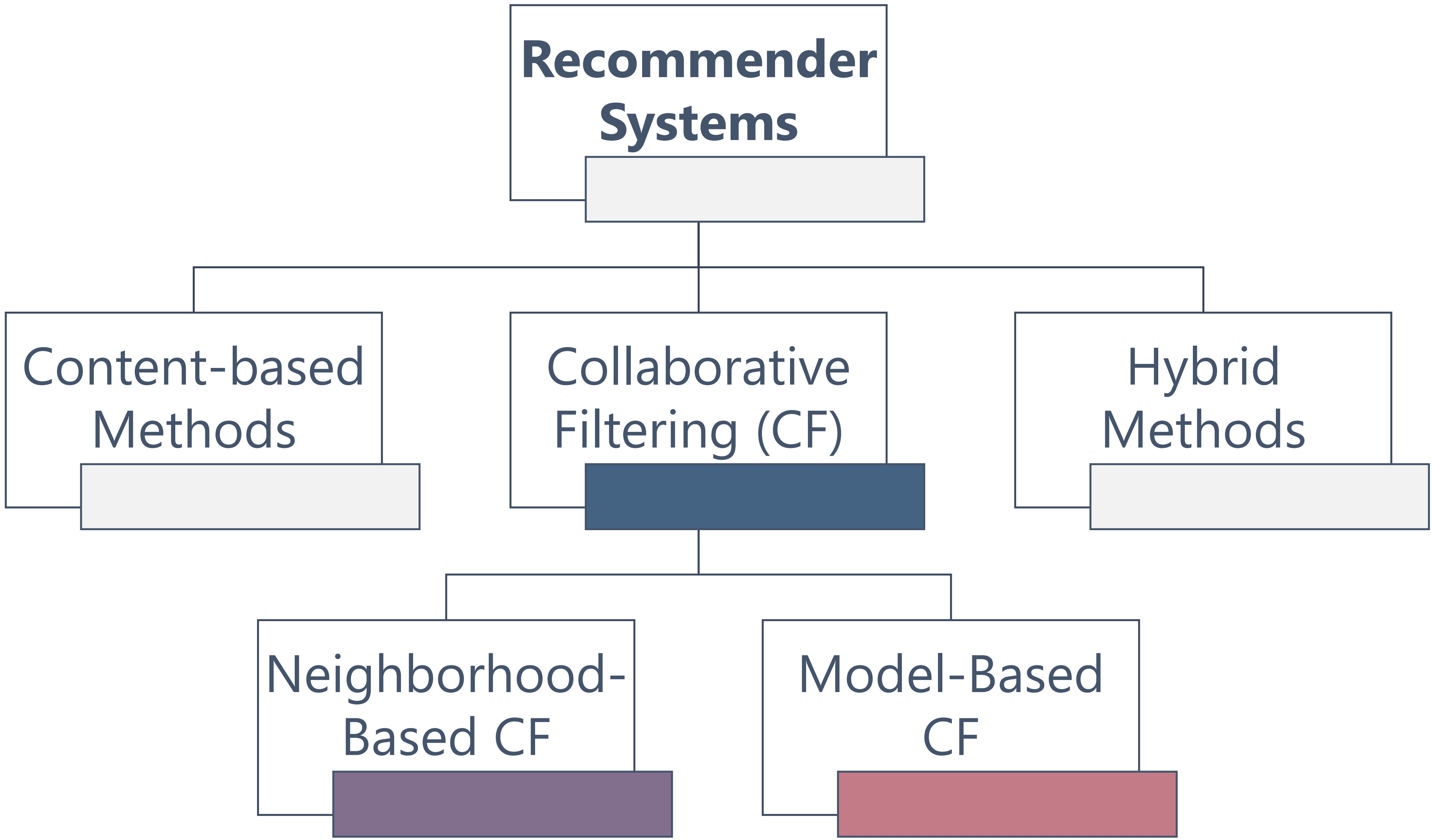
Demographic variables

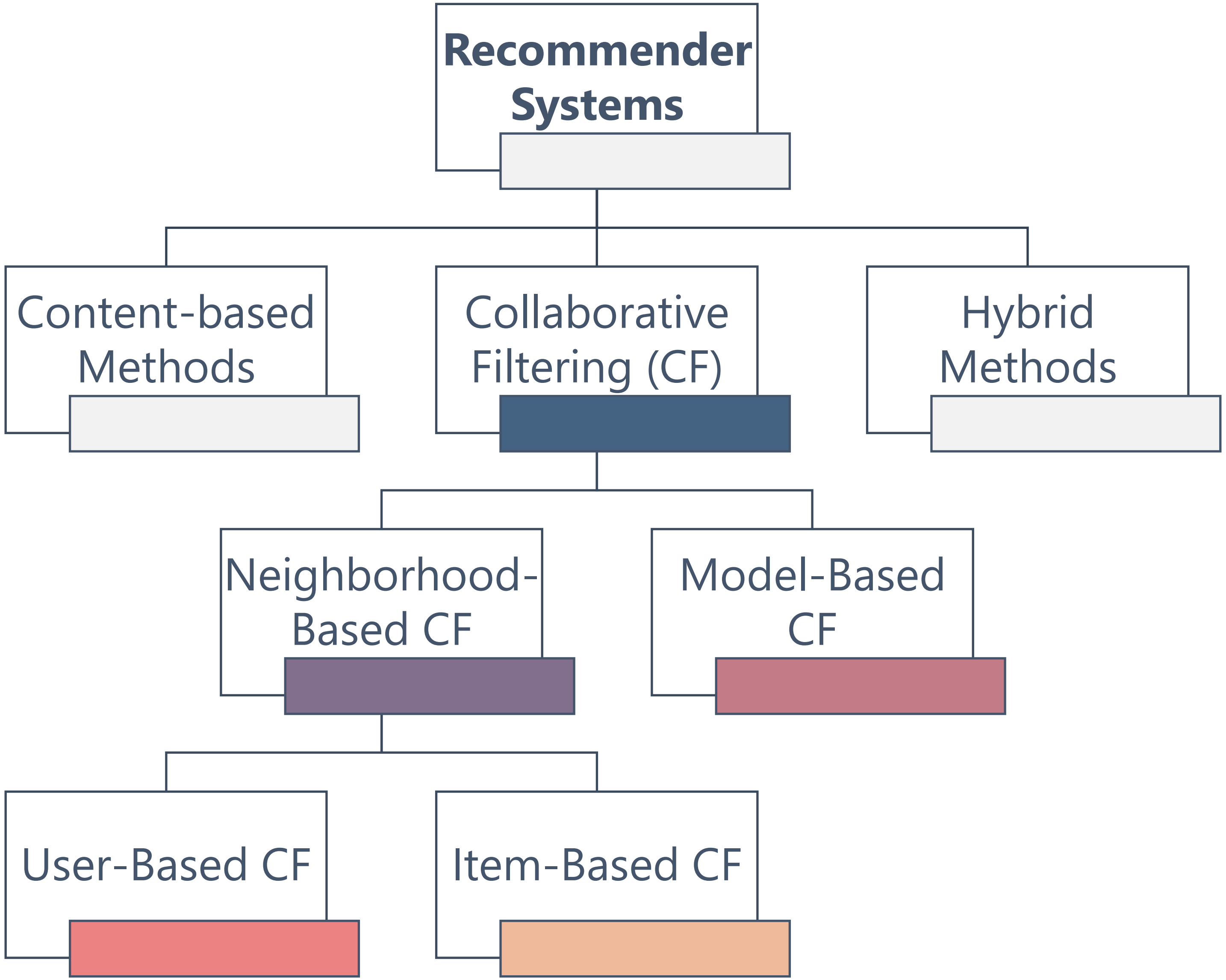
(Triantafillou et al., 2007)



Recommender systems

"… personalized information agents that provide recommendations: suggestions for items likely to be of use to a user" (Burke, 2007)


Recommender Systems
Content-based Methods
Collaborative Filtering (CF)
Hybrid Methods
Neighborhood-Based CF
Model-Based CF



Recommender Systems
Content-based Methods
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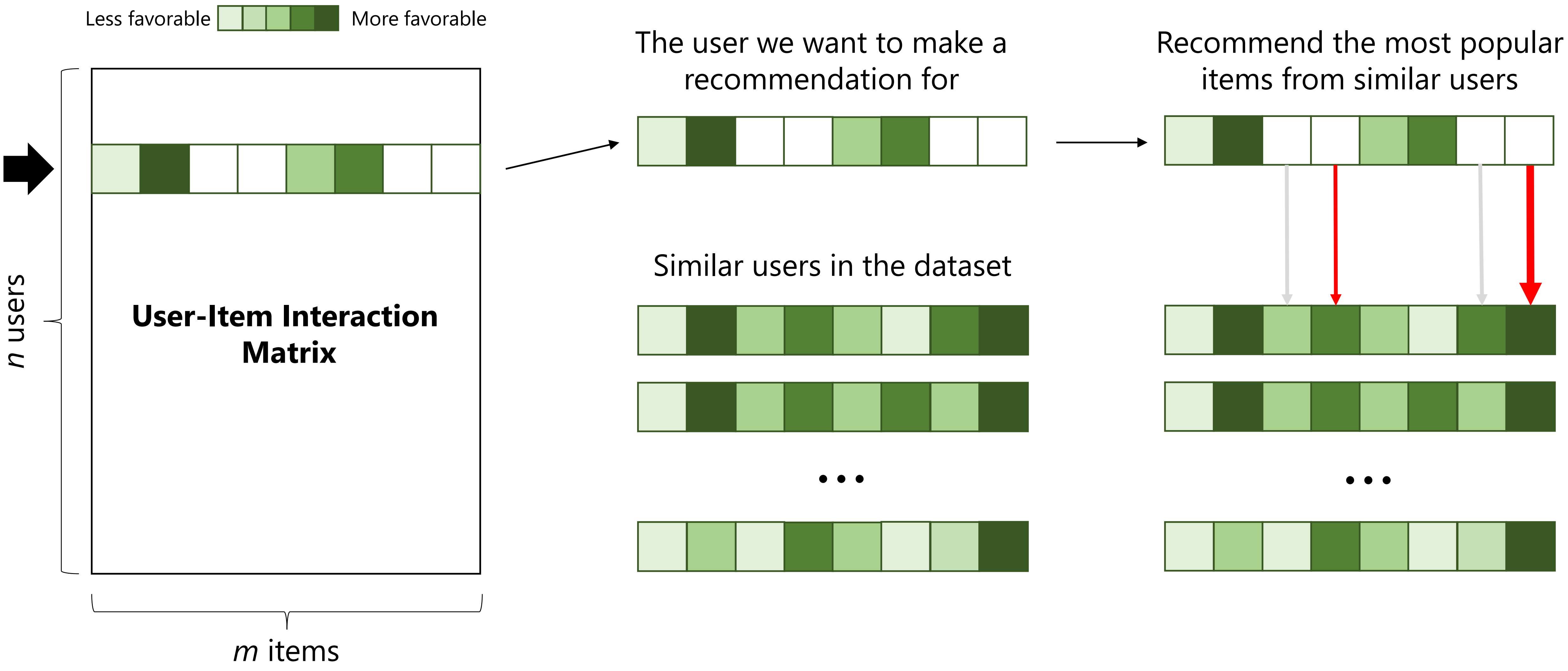
Hybrid Methods
Neighborhood-Based CF
Model-Based CF
User-Based CF
Item-Based CF

User-Based Collaborative Filtering



User-Based Collaborative Filtering

- **user** u_i, $i = 1, \ldots, n$
- **item** p_j, $j = 1, \ldots, m$
- **rating** r_{ij}

Step 1

$$sim(u_i, u_k) = \cos(u_i, u_k) = \frac{\sum_{j=1}^{m} r_{ij} r_{kj}}{\sqrt{\sum_{j=1}^{m} r_{ij}^2 \sum_{j=1}^{m} r_{kj}^2}}, \text{or}$$

$$sim(u_i, u_k) = cor(u_i, u_k) = \frac{\sum_{j=1} (r_{ij} - \overline{r_i})(r_{kj} - \overline{r_k})}{\sqrt{\sum_{j=1} (r_{ij} - \overline{r_i})^2 \sum_{j=1} (r_{kj} - \overline{r_k})^2}},$$

Step 2

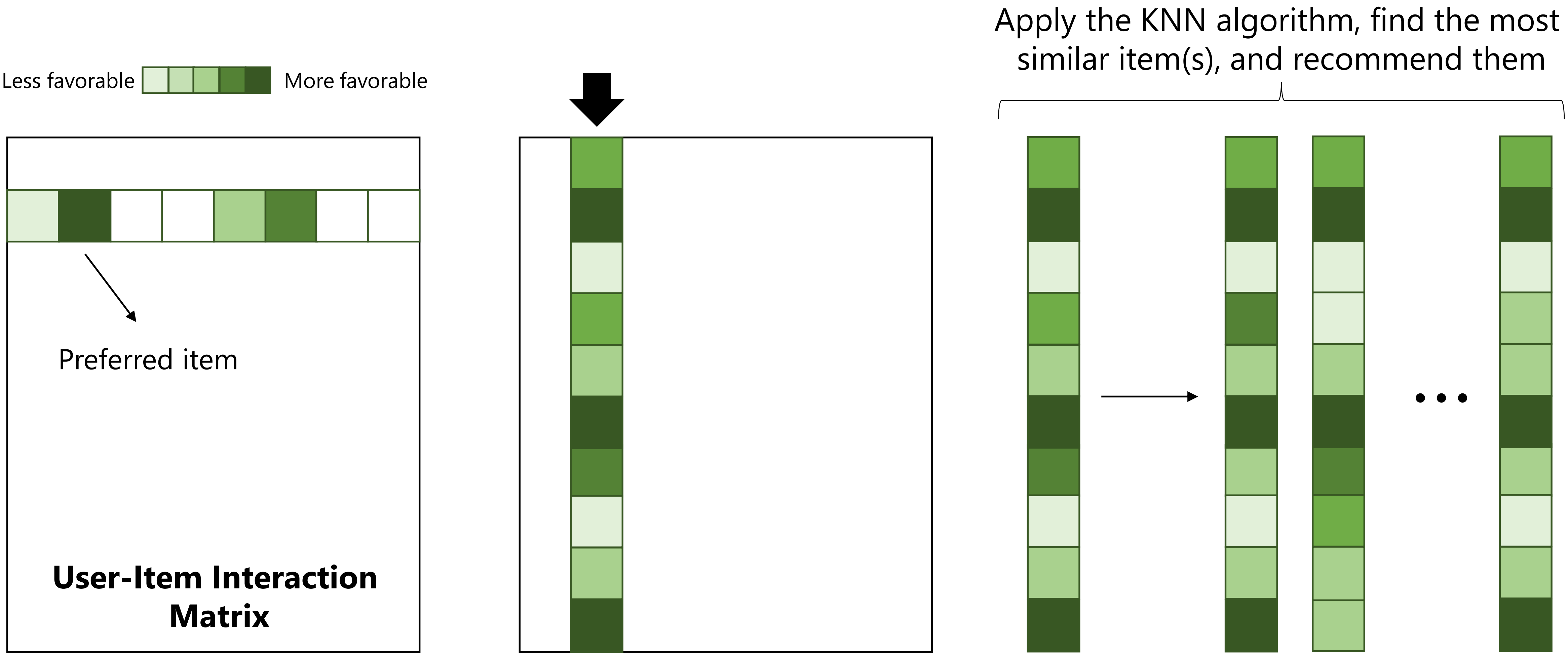
Perform *k*-nearest neighbors (KNN) to select the best neighbors of the target user (alternatively, use a similarity threshold)

Step 3

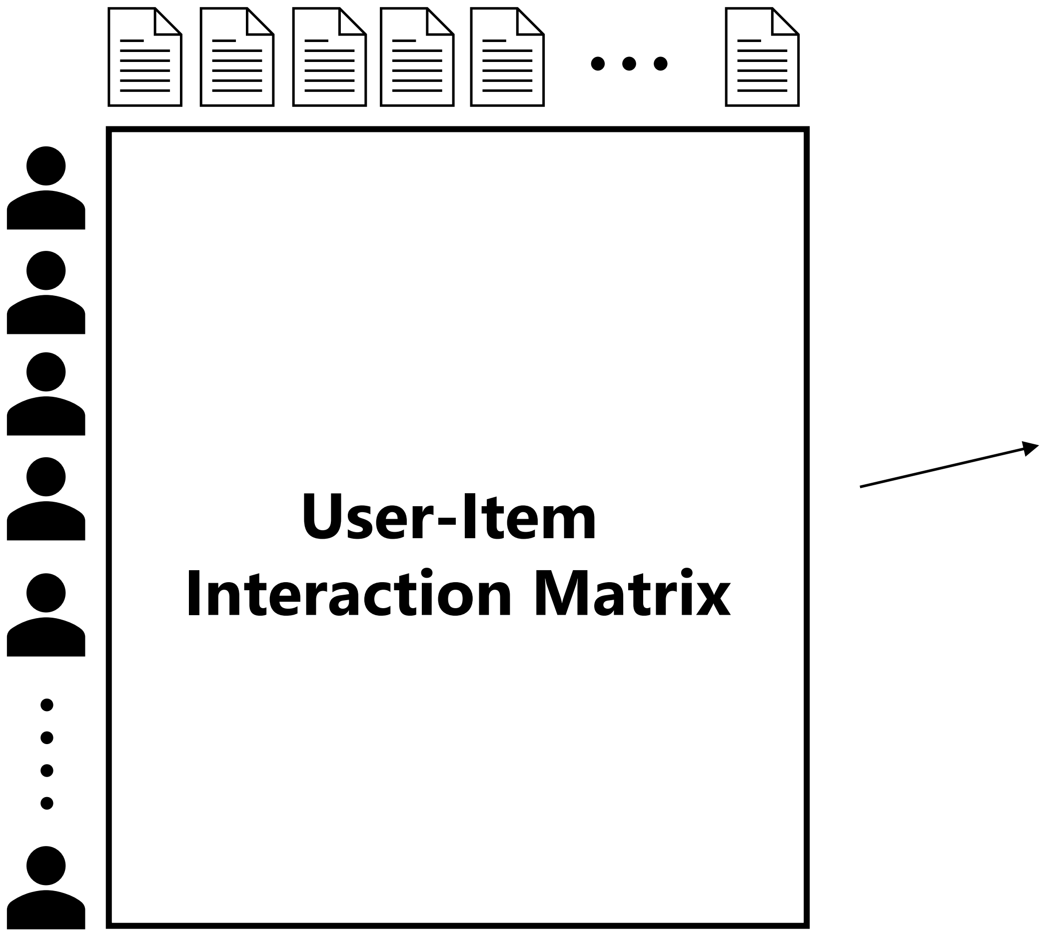
Predict an unknown rating for the target user based on the best neighbors identified in Step 2 (i.e., weighted average of ratings from the best neighbors).

$$\hat{r}_{ij} = \frac{\sum_k sim(u_i, u_k) r_{kj}}{\# \, of \, ratings} \quad \text{or} \quad \hat{r}_{ij} = \overline{r_i} + \frac{\sum_k sim(u_i, u_k)(r_{kj} - \overline{r_k})}{\# \, of \, ratings}$$

Item-Based Collaborative Filtering



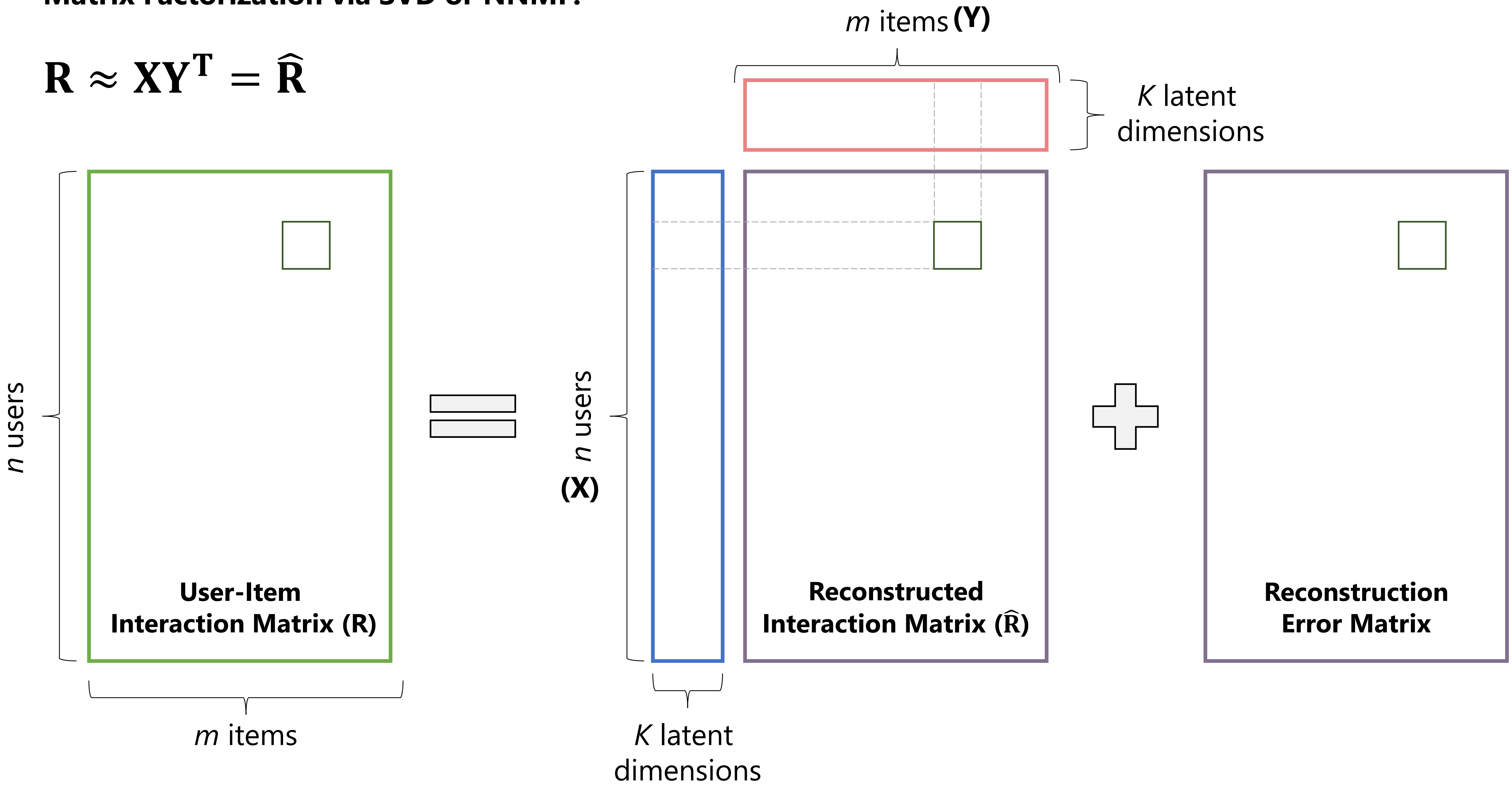
Model-Based Collaborative Filtering

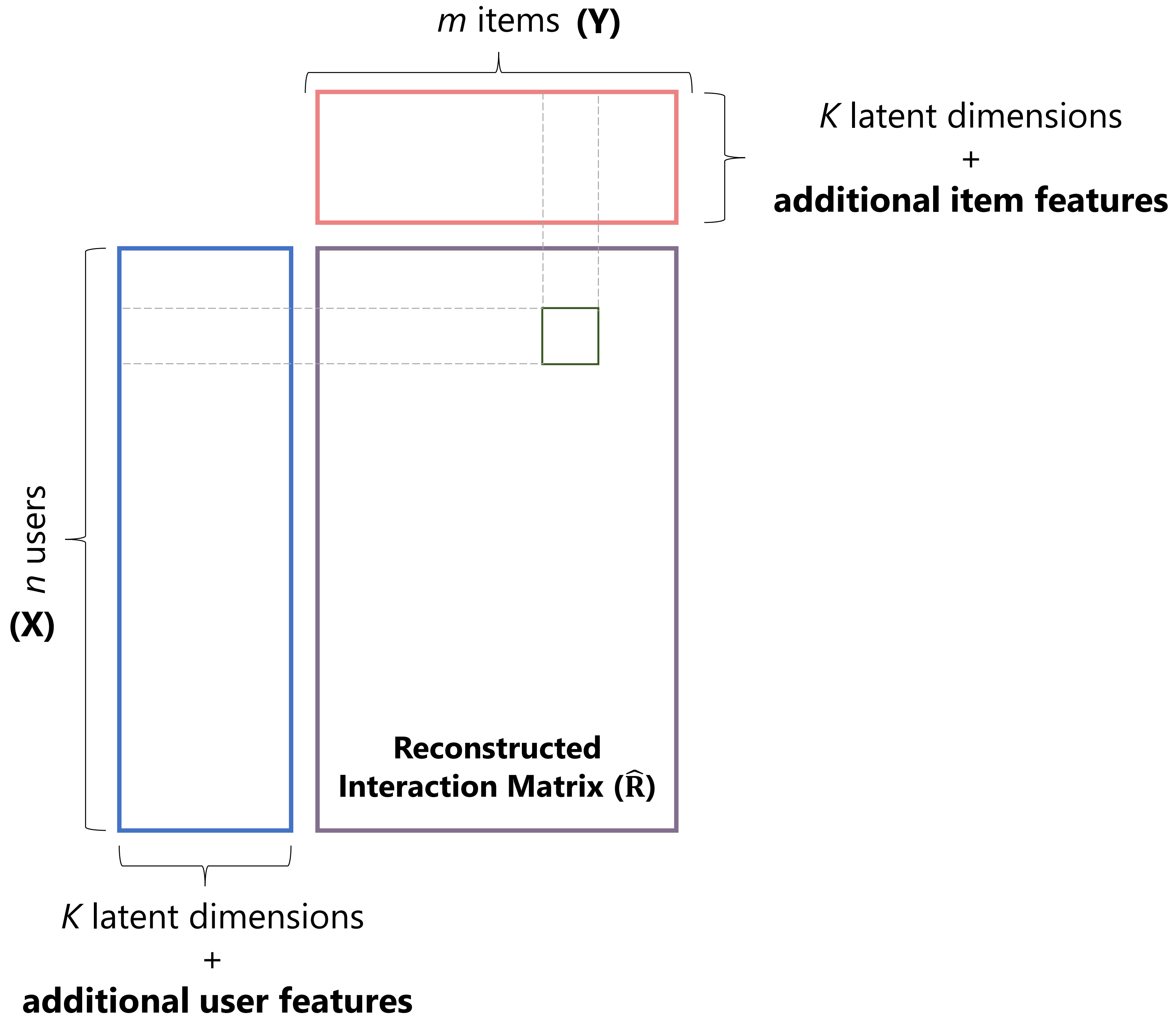


An underlying **generative** model that explains the user-item interactions.

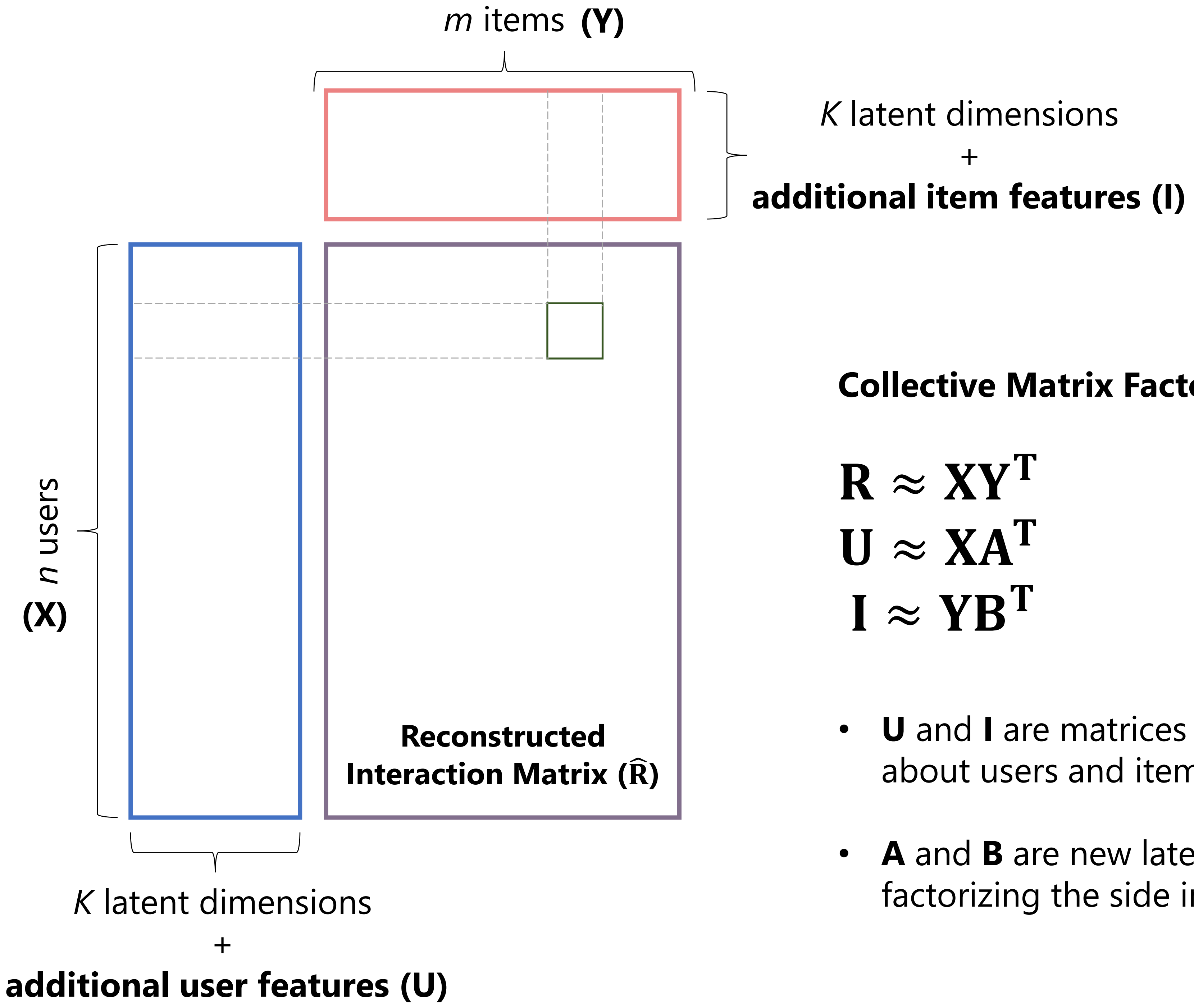
Matrix Factorization via SVD or NNMF:

$$\mathbf{R} \approx \mathbf{X}\mathbf{Y}^{\mathrm{T}} = \hat{\mathbf{R}}$$





m items **(Y)**
K latent dimensions
+
additional item features
n users **(X)**
Reconstructed
Interaction Matrix ($\hat{R}$)
K latent dimensions
+
additional user features

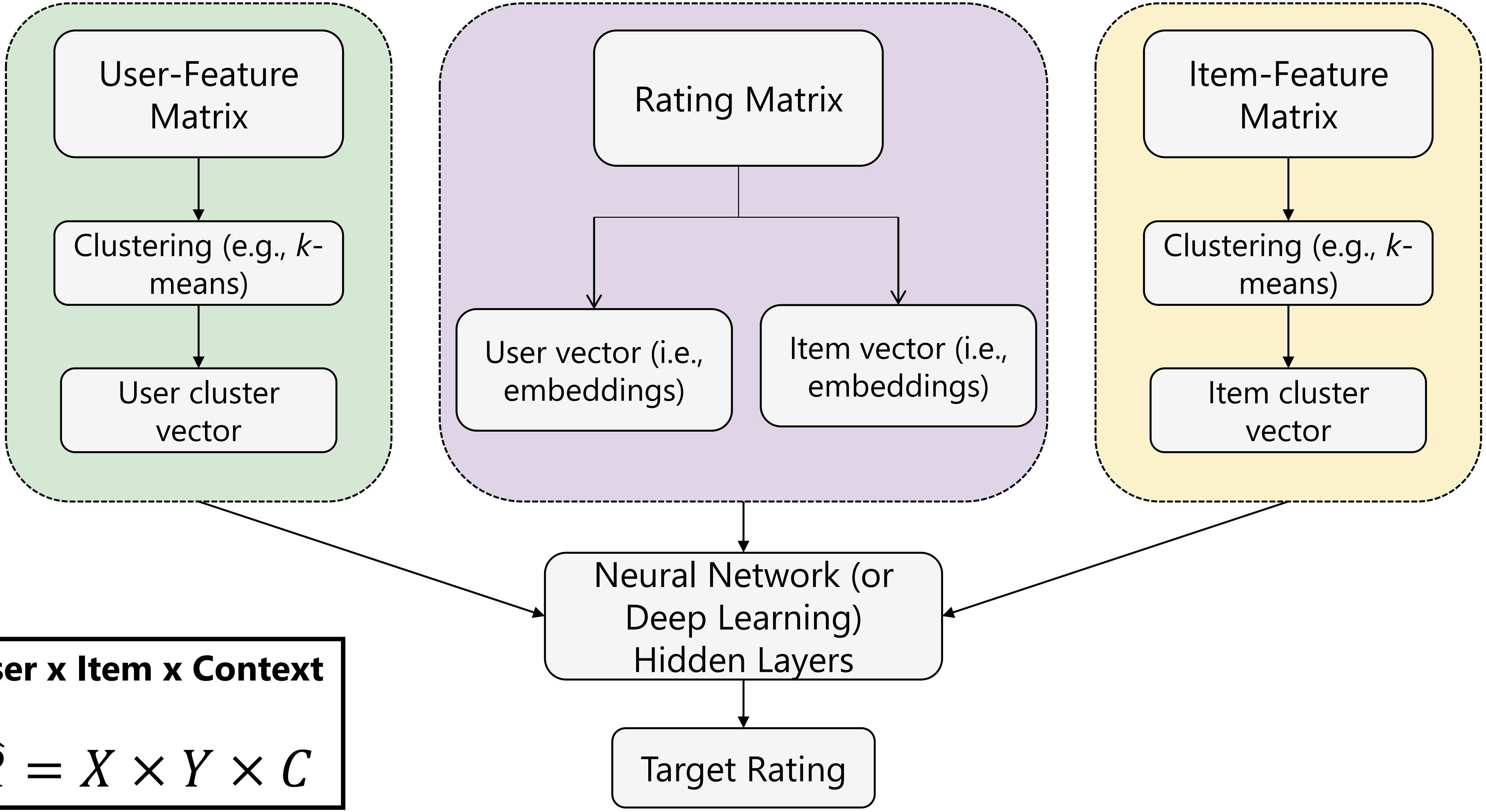


Collective Matrix Factorization:

$$\mathbf{R} \approx \mathbf{X}\mathbf{Y}^{\mathrm{T}}$$
$$\mathbf{U} \approx \mathbf{X}\mathbf{A}^{\mathrm{T}}$$
$$\mathbf{I} \approx \mathbf{Y}\mathbf{B}^{\mathrm{T}}$$

- **U** and **I** are matrices representing side information about users and items, respectively.
- **A** and **B** are new latent factor matrices used for factorizing the side information matrices

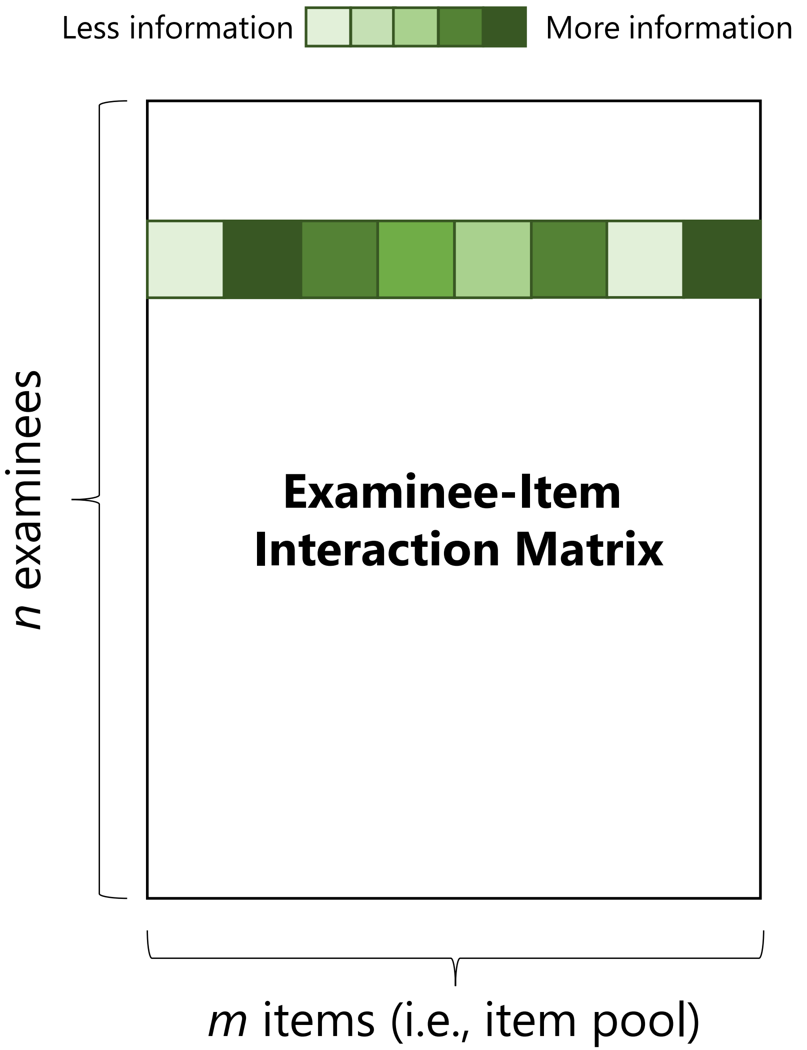
Hybrid Recommender Systems



User x Item x Context

$$\hat{R} = X \times Y \times C$$

Adaptive Item (or Task) Recommendation



Item selection with collaborative filtering in on-the-fly multistage adaptive testing (Xiao, & Bulut, 2022)

Stage 1 → **Stage 2** → **Stage 3**

Pre-assembled module → Top-N recommendation → Top-N recommendation

On-the-fly module assembly using:

- User-based CF (UBCF)
- Item-based CF (IBCF)
- Maximum Fisher information (MFI)

Results:

- Measurement accuracy: UBCF > MFI
- Item bank utilization: IBCF > MFI

Enhancing Accuracy and Adaptability

- **Adaptive variables** are necessary to enhance the performance of adaptive item recommendation.
  - Cold-start problem

- Thanks to the rise of digital assessments, it is now easier to collect process data (e.g., response time, action sequences, and time-stamped events).
  - Distinguishing response processes and behavioral patterns (e.g., He et al., 2021; Ulitzsch et al., 2021)
  - Improving scoring/ability estimation (e.g., Zhang et al., 2023)

- Examinee background characteristics also matter.
  - Background characteristics are correlated with digital problem solving (e.g., Zhang et al., 2021)

This Study

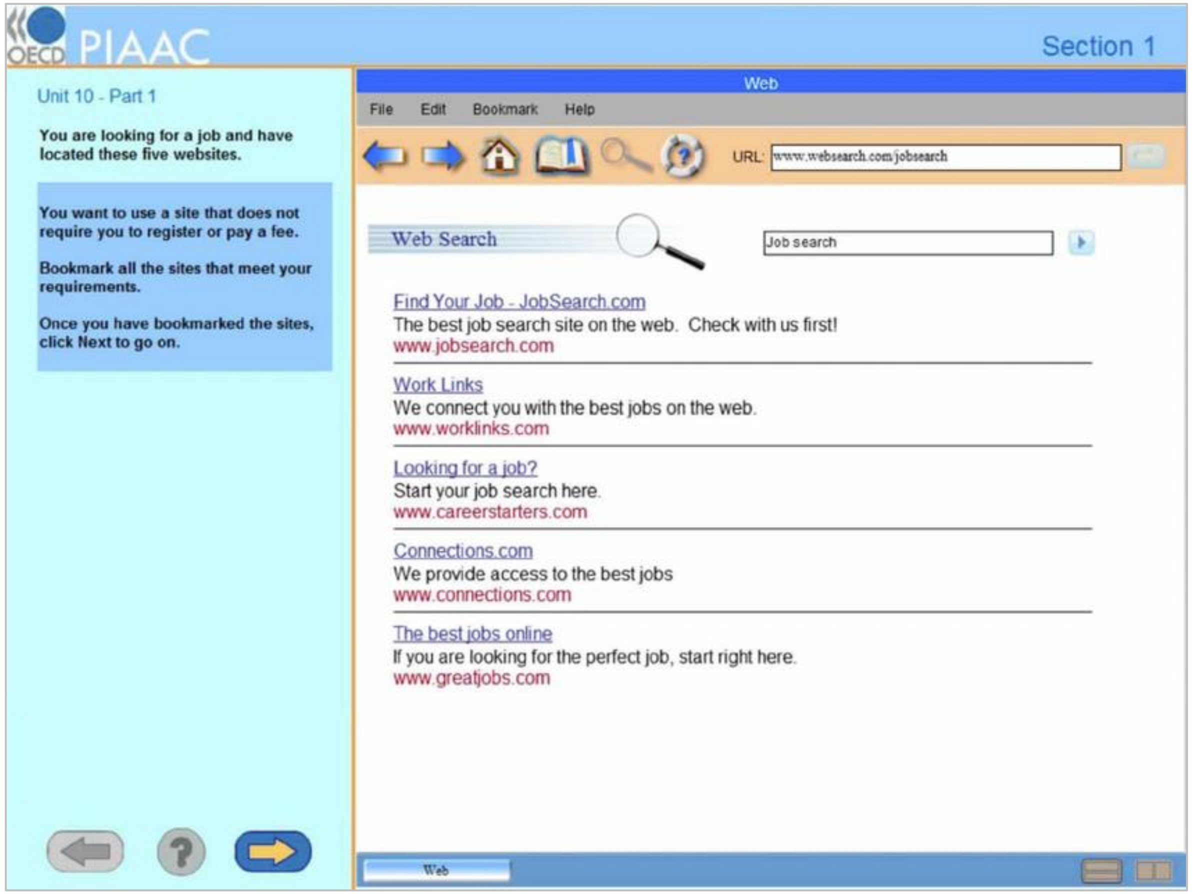
The goal of this study is to improve the quality of item recommendation by incorporating **adaptive variables** into the scoring process:

- Process data (generated on the fly *during* test administration)
- Background characteristics (available *before* test administration)

Simulation Design

Programme for the International Assessment of Adult Competencies (PIAAC)

- Problem-solving in technology-rich environments (PSTRE) tasks in PIAAC 2012
- 14 interactive tasks measuring higher-order skills (e.g., evaluating information and using it to solve a problem)



Simulation Design

- Design conditions:
  - 2000 examinees (training data = 1000, test data = 1000)
    - Theta was generated from a normal distribution, $N(0,1)$.
  - 60 hypothetical problem-solving tasks with up to 26 possible actions (each denoted with an English letter)
    - Actions were generated from a Markov model where the transition probabilities depended on theta.
  - Dichotomous response data
    - Responses were generated for each task based on top 10 n-grams that were most correlated with theta.
    - The 2PL IRT model was used for item calibration.
  - Examinee background variables
    - One binary and two continuous variables were generated (correlated with theta; $r = .25 - .35$).

An Example of Generated Sequence Data

- Examinee 1 (14 steps):
  - A-R-O-O-L-W-R-J-Q-R-Q-U-Z
- Examinee 3 (8 steps):
  - A-O-E-R-J-V-L-Z
- Examinee 5 (22 steps):
  - A-J-R-D-F-T-B-K-N-P-B-Y-G-N-H-P-J-H-X-X-M-Z
- On average, 25-26 actions per item (min = 2, max = 190)

Feature Extraction from Process Data (1)

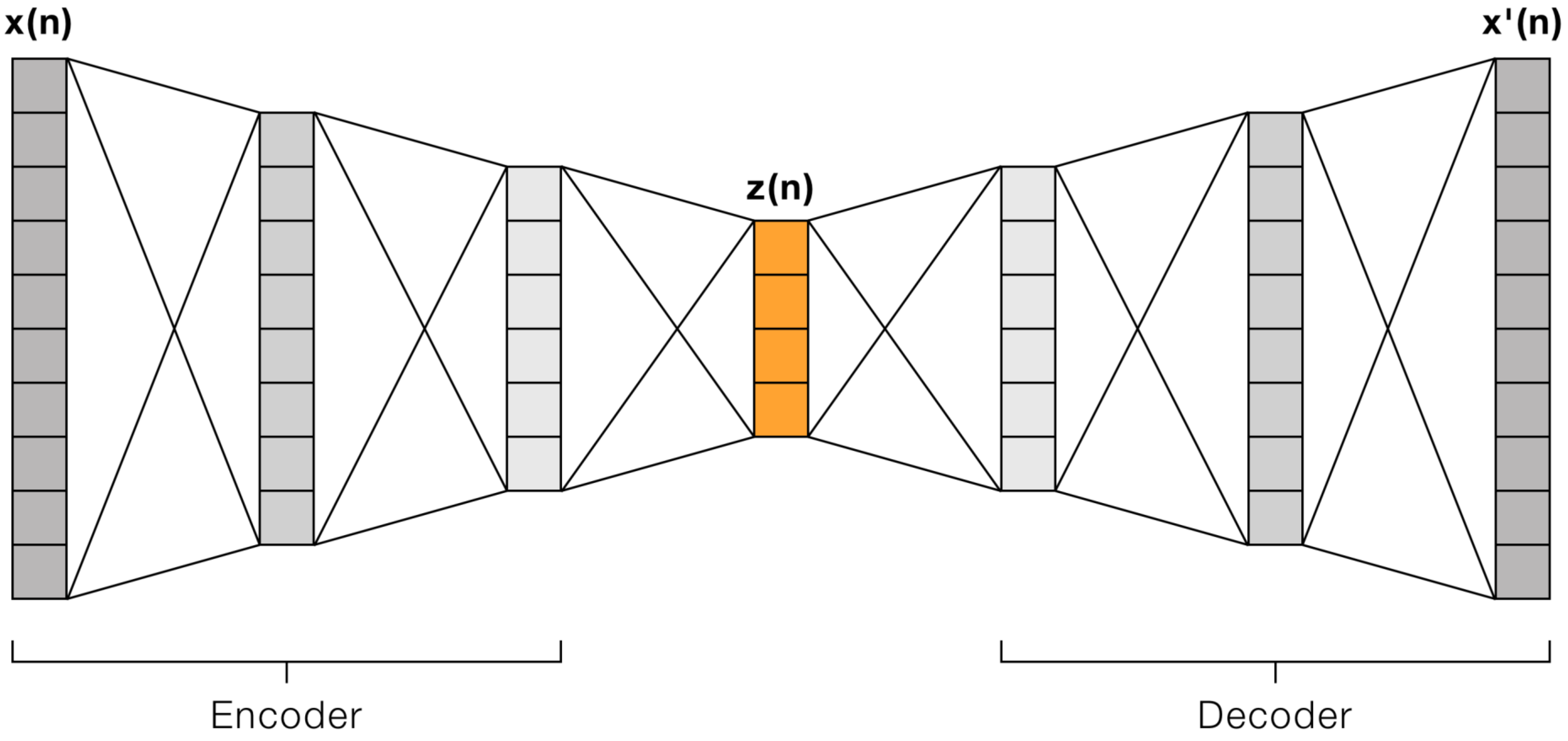
- Multidimensional scaling (MDS; Tang et al., 2020) was used to extract the latent features from the process data of each task.

- MDS maps action sequences into the *K*-dimensional Euclidean space based on **dis**similarity between the action sequences.
  - Ordering-based Sequence Similarity (OSS; Gomez-Alonso & Valls, 2008)
  - Assume two response processes: $a_i = (a_{i1}, \dots, a_{in_i})$ and $a_j = (a_{j1}, \dots, a_{jn_j})$ with different lengths (n_i and n_j) → $d_{ij} = d(a_i, a_j)$

$$d(a_i, a_j) = \frac{\boldsymbol{f(a_i, a_j)} + \boldsymbol{g(a_i, a_j)}}{n_i + n_j}$$

Common actions Uncommon actions

Alternative: Sequence-to-Sequence Autoencoders



Tang, X., Wang, Z., Liu, J., & Ying, Z. (2020). An exploratory analysis of the latent structure of process data via action sequence autoencoders. *British Journal of Mathematical and Statistical Psychology, 74*(1), 1-33.

Feature Extraction from Process Data (2)

1. For each item, find the distance matrix $\mathbf{D} = (d_{ij})_{n \times n}$ based on the pairwise dissimilarities.

2. Obtain K raw features by applying MDS to each **D** matrix (by minimizing the squared distance between d_{ij} and Euclidean distance between in persons i and j in the K-dimensional Euclidean space).
   - $K = 20$ raw features (i.e., problem-solving processes) were extracted for each hypothetical task.

3. Transform K raw features to K principal features via principal component analysis (for increased interpretability).
   - $K = 20$ principal features were extracted for each hypothetical task.

Process-Based Scoring (Zhang et al., 2023)

Goal: To *refine* the latent trait estimates with the additional information from the problem-solving process

1. For each item ($j = 1, \ldots, J$), estimate the ability based on the final response (Y_j) to item *j* only ($\hat{\theta}_{Y_j}$).

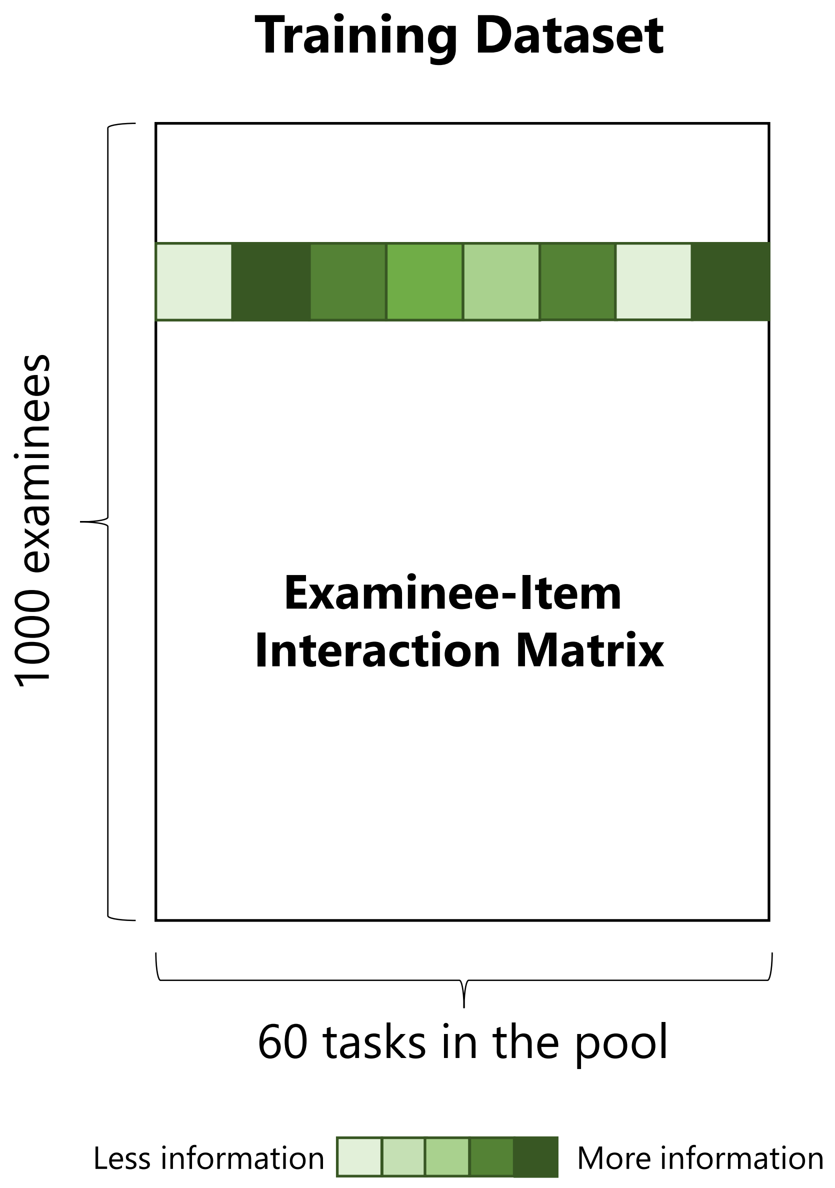
2. Also, estimate $\hat{\theta}_Y$ based on final responses to all items administered so far.

3. For each item, regress $\hat{\theta}_{Y_j}$ on all process features and examinee background variables $(\mathbf{X_{-j}})$, except for those on item *j* (via L2 regularization; ridge regression). The outcome is denoted as $T_{\mathbf{X_{-j}}}$.

4. Regress $\hat{\theta}_Y$ on $T_{\mathbf{X_{-j}}}$ and Y_j to obtain $\hat{\theta}_{\mathbf{X}_{-j}}$ (via ordinary least squares).

5. Compute the final process-incorporated ability by finding the average across all (*J*) items:

$$\hat{\theta}_X = \frac{1}{J}\sum_{j=1}^{J}\hat{\theta}_{\mathbf{X}_{-j}}$$

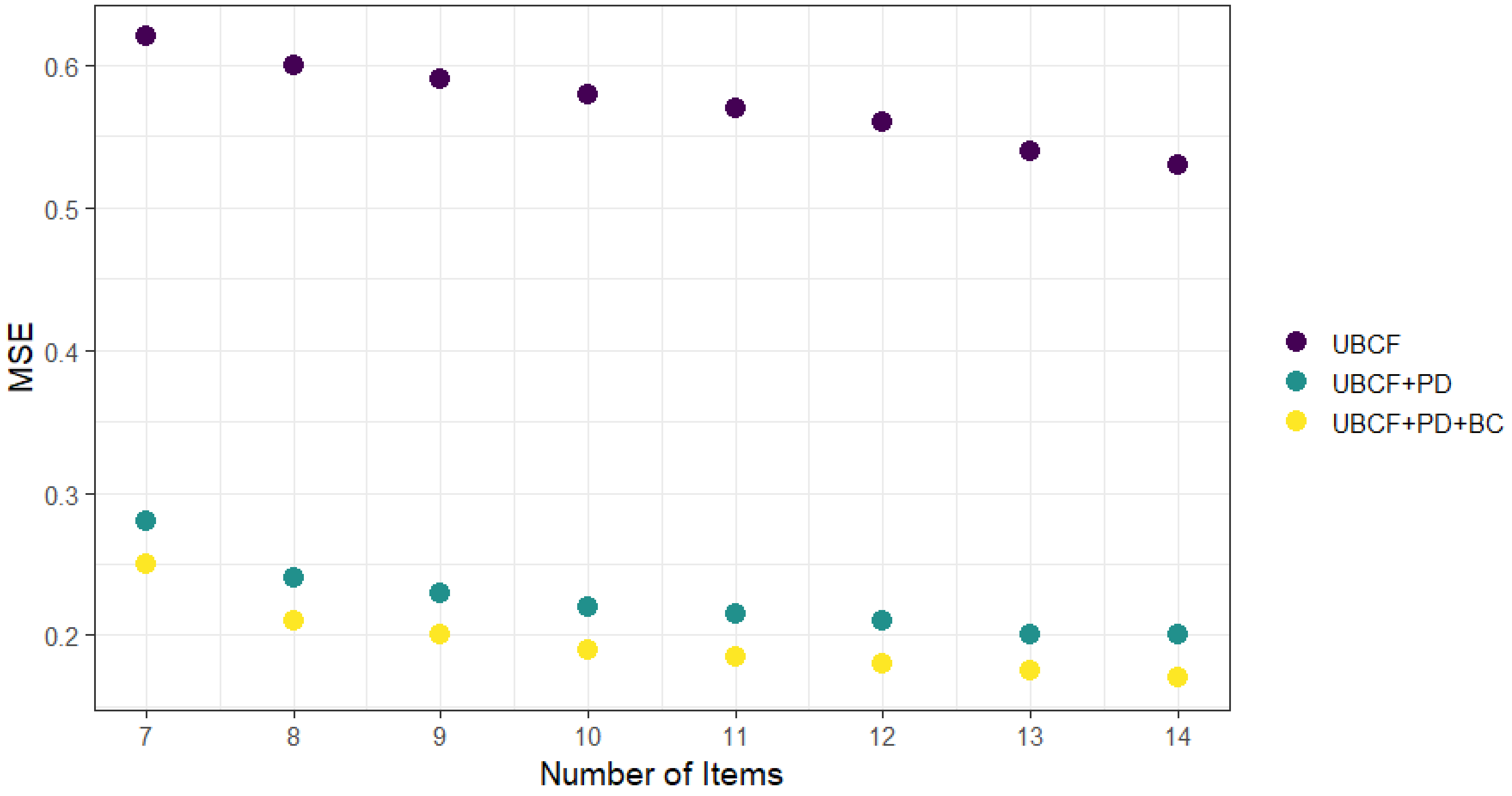


- The training dataset consisted of the Fisher information values calculated across 60 tasks and 1000 examinees.

- Adaptive item recommendation with:
  - User-based CF (UBCF) based on response-based scoring
  - UBCF based on process-based scoring

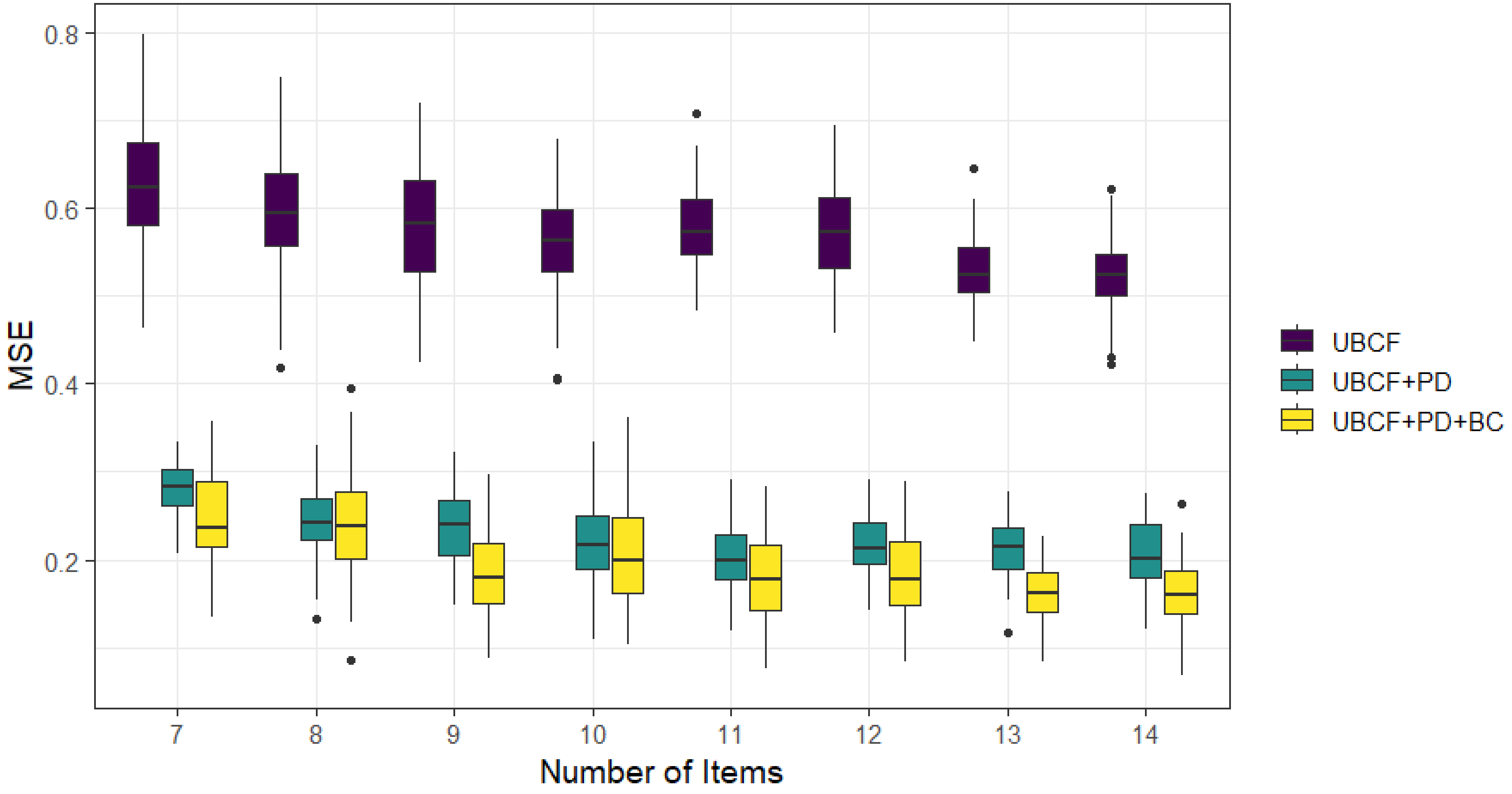
- **Procedure:**
  1. Administer a randomly selected task to the examinee
  2. Estimate ability using the item response (with or without process data and background variables)
  3. Identify top 5 items from the training data and recommend one of them (randomly) to the examinee
  4. Repeat Steps #2 and #3 until the maximum test length (from 7 to 14 tasks) is reached (50 iterations).

Results – Mean Squared Error (MSE)



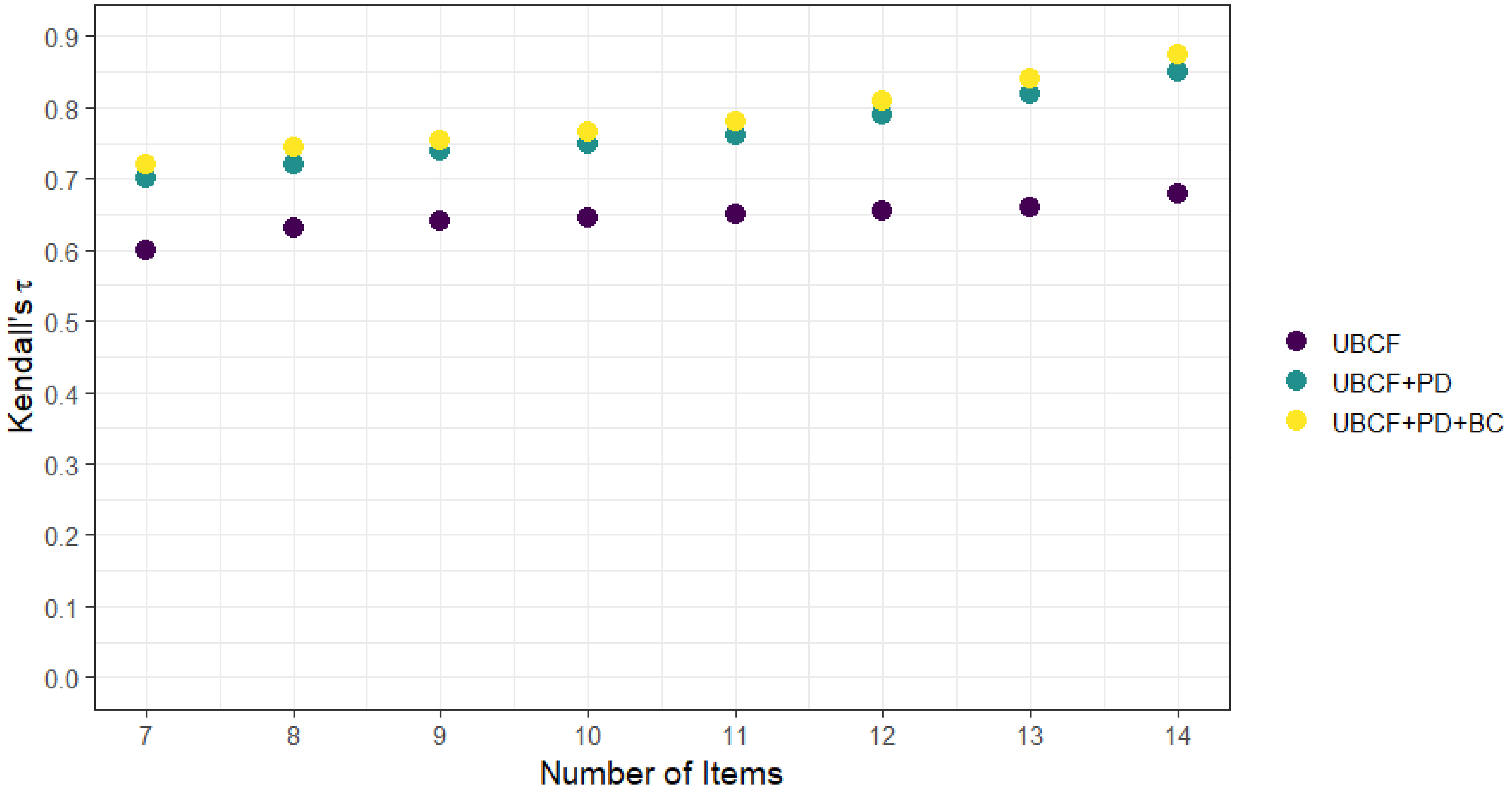
Note: PD: Process Data BC: Background Characteristics

Results – MSE Distribution



Note: PD: Process Data BC: Background Characteristics

Results – Kendall's τ



Note: PD: Process Data BC: Background Characteristics

Results – Item Bank Utilization

- All three methods yielded acceptable item bank utilization rates
  - More than 80% of the tasks in the pool were used.

- The item bank utilization rate was slightly higher for UBCF without process data or background characteristics.
  - This finding was mainly due to recommending similar items repeatedly to examinees who have similar ability as well as problem-solving sequences and background characteristics.

- With item exposure control, the item bank utilization could improve at the expense of measurement accuracy.

Concluding Remarks

- With the rise of digital assessments at all levels of education, it is now possible to obtain auxiliary information on examinees' response processes.

- Interactive tasks yield action sequences that include valuable information beyond dichotomous or polytomous item scores.

- Recommender systems can incorporate adaptive variables (e.g., process data and examinee background characteristics) to enhance the item recommendation process.

- Recommender systems with process data can also be applied to other settings, such as adaptive learning systems and personalized scheduling for adaptive tests (Bulut, Shin, & Cormier, 2022; Shin & Bulut, 2022; Bulut, Cormier, & Shin, 2020).

Future Research

- This study focused on “enhancing” ability estimation based on background variables and action sequences extracted from problem-solving tasks.

- Incorporating “item-related” process variables into the recommender system
  - Hand-crafted or data-driven item features
    - E.g., Problem-solving complexity/intensity of each task/item

- Process data can be directly utilized in making item recommendations:
  - Recurrent and convolutional neural models are particularly suitable for the sequential nature of process or log data (Tang & Wang, 2018).

  - If multimodal data (e.g., images, text, sound, etc.) about users/items are available, deep neural networks (DNNs) can be a better option for taking advantage of joint (end-to-end) representation learning (Zheng, Noroozi, & Yu, 2017)

Thank You!

For questions/comments:

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