Spotify ML Day, July 9th, 2018

Explore, Exploit, and Explain: Personalizing Explainable Recommendations with Bandits

James McInerney, Ben Lacker, Samantha Hansen, Karl Higley, Hugues Bouchard, Alois Gruson, Rishabh Mehrotra

Spotify

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Talk Outline

1. Pareto principle for content producers
2. a causal diagnosis of filter bubbles in recommendation
3. contextual bandits for recommendation
4. explained recommendations
5. introducing Bart (bandits for recommendations as treatments)
6. offline and online experiments on homepage data
7. conclusions & future work

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producer popularity

leads to leads to

exposure to new consumers

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- known as the Matthew effect or Pareto principle

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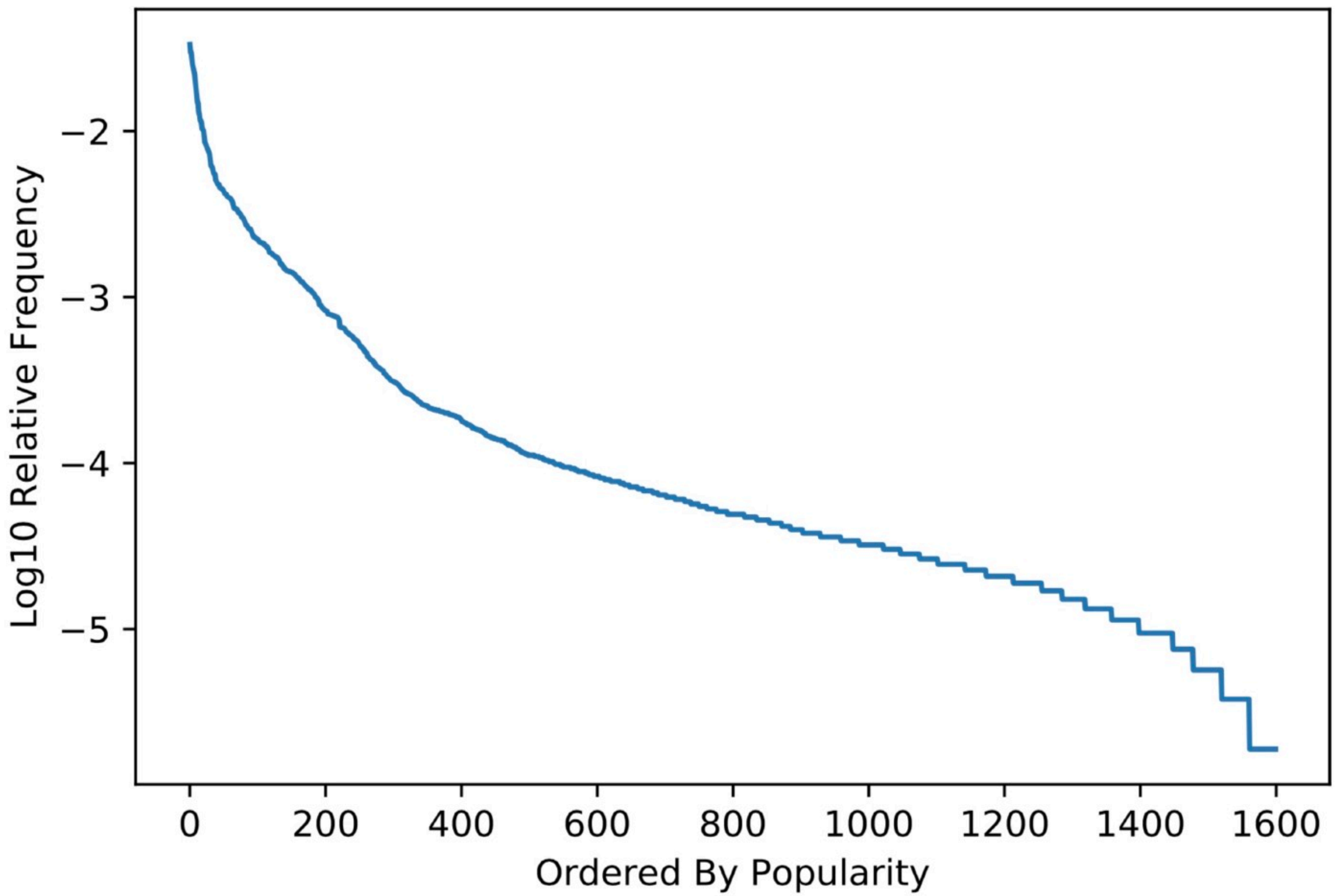

Collaborative filtering perpetuates the Pareto principle

e.g. matrix factorization

$$\mathbf{Y} = \mathbf{U}\mathbf{V}^\top$$

#users $\times$ #items

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- in general: collaborative filtering engines use implicit feedback data from users to learn a model of user preferences

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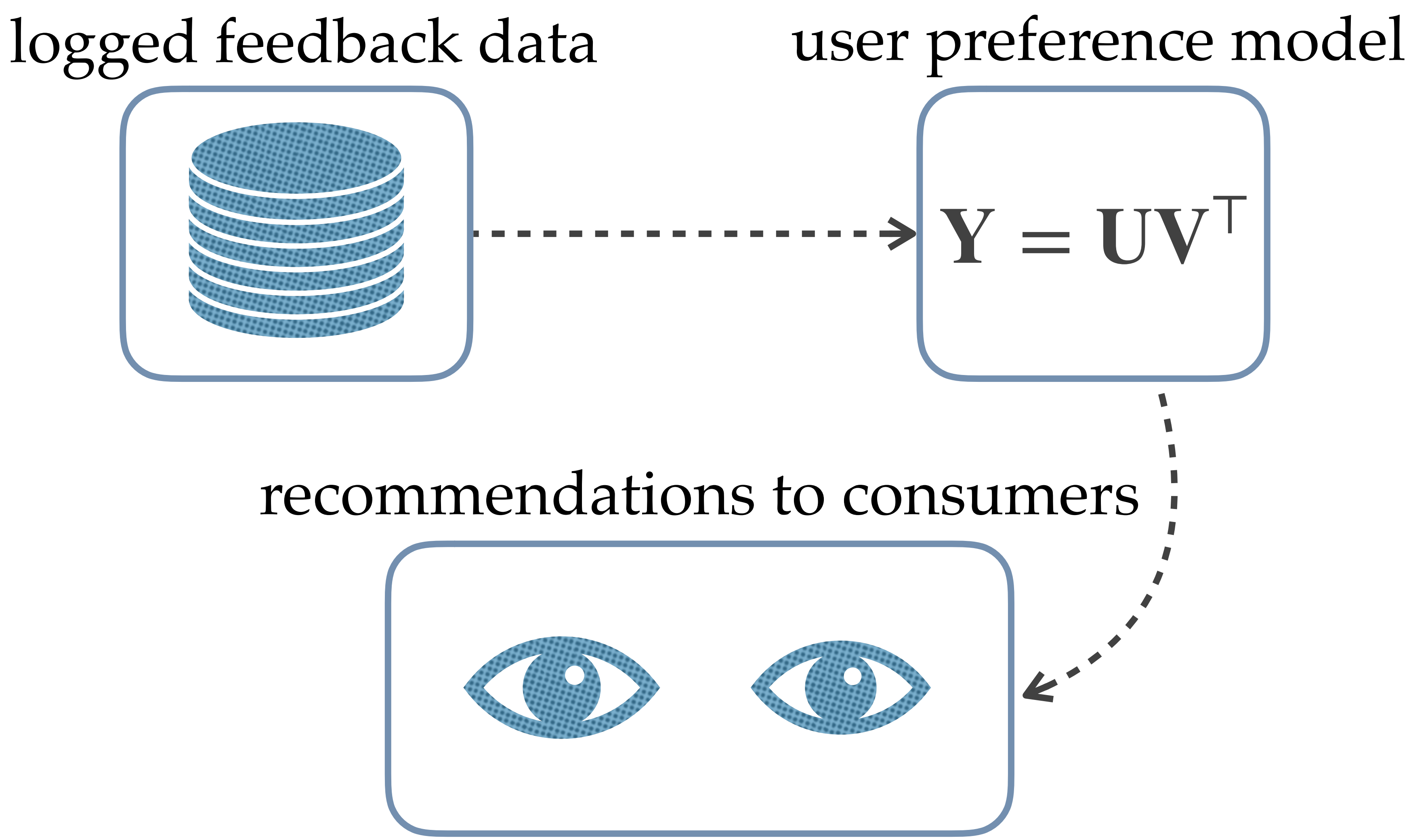

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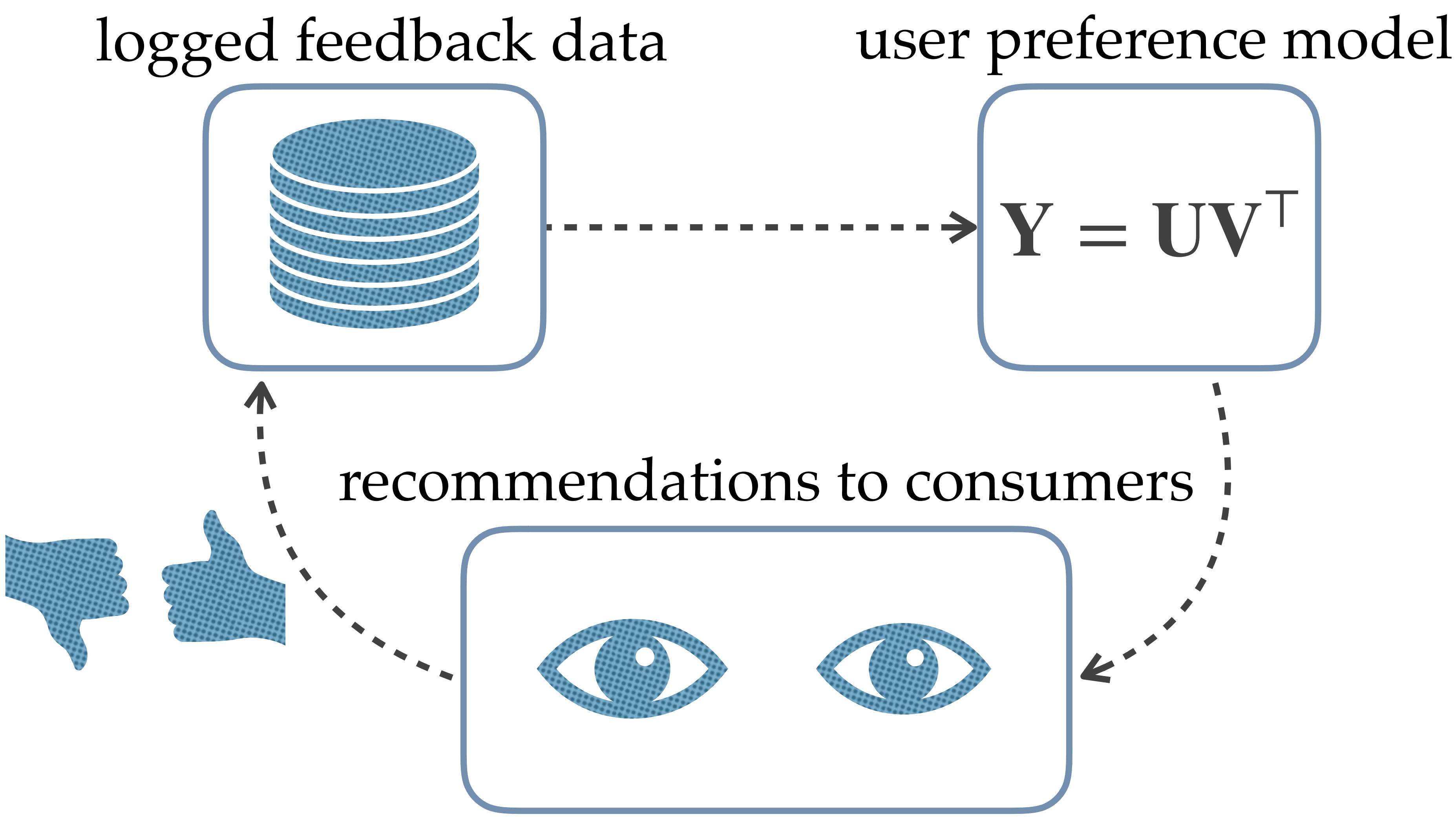

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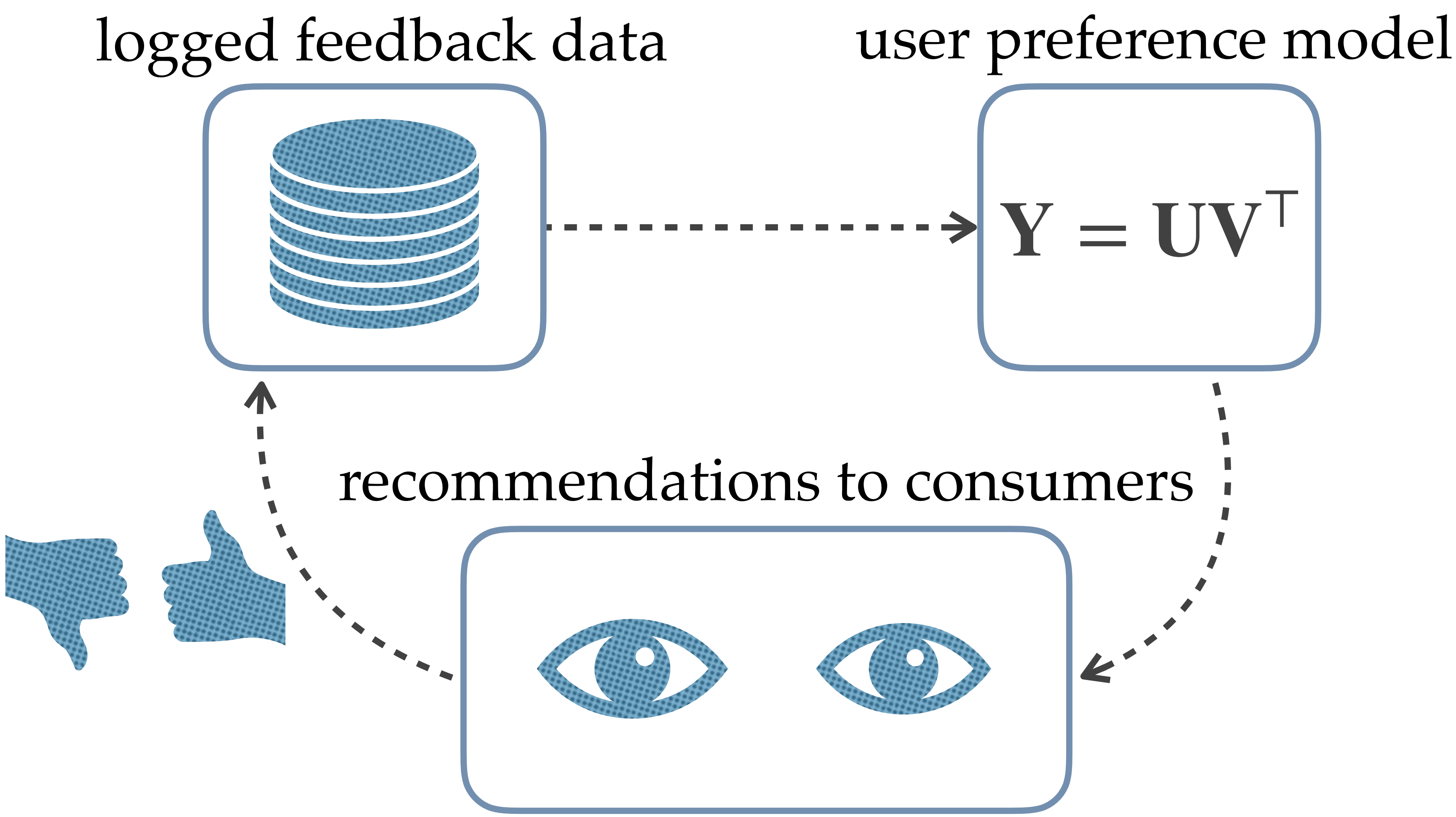

"How Algorithmic Confounding in Recommendation Systems Increases Homogeneity and Decreases Utility" (Chaney et al. 2017)

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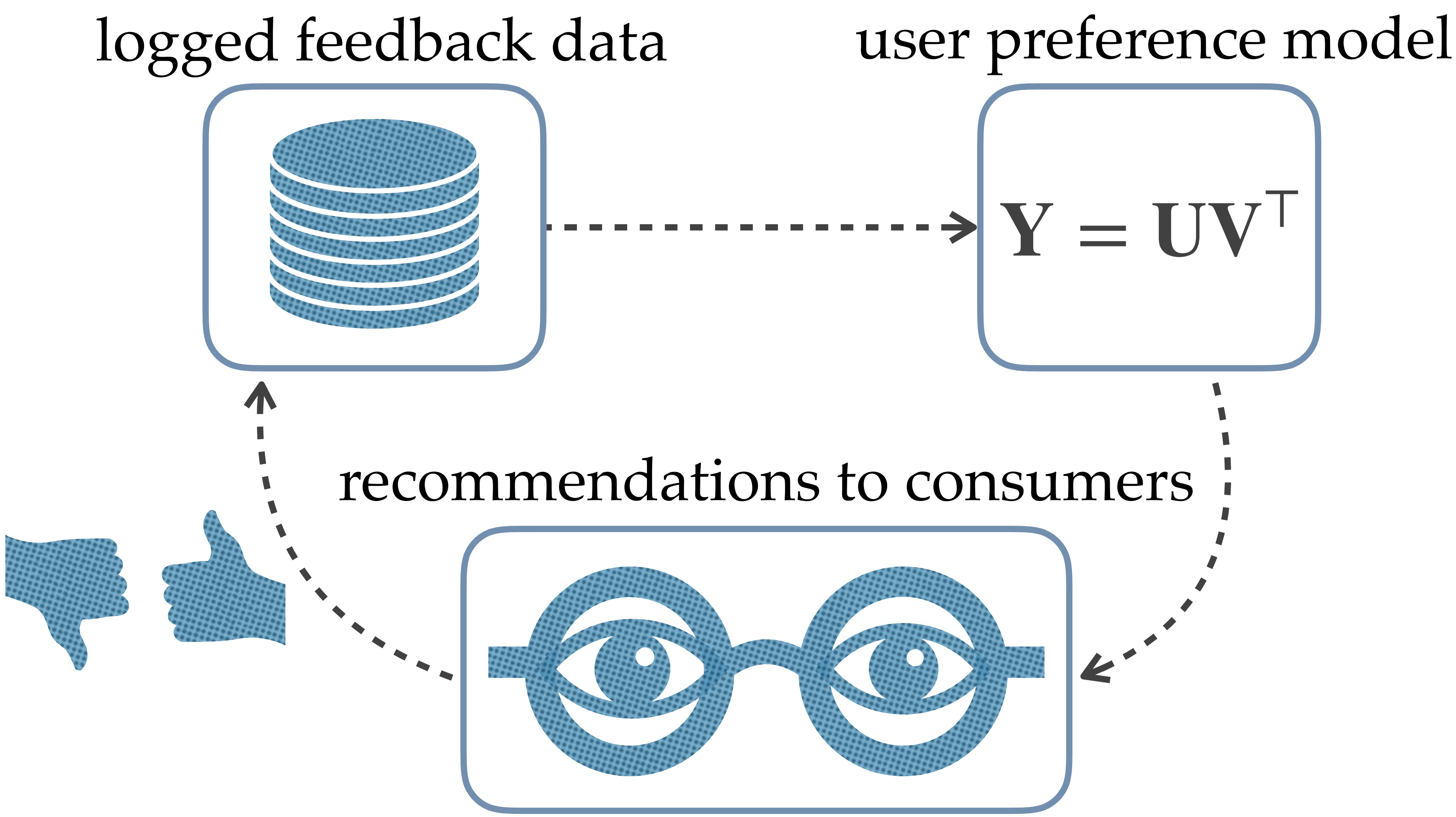

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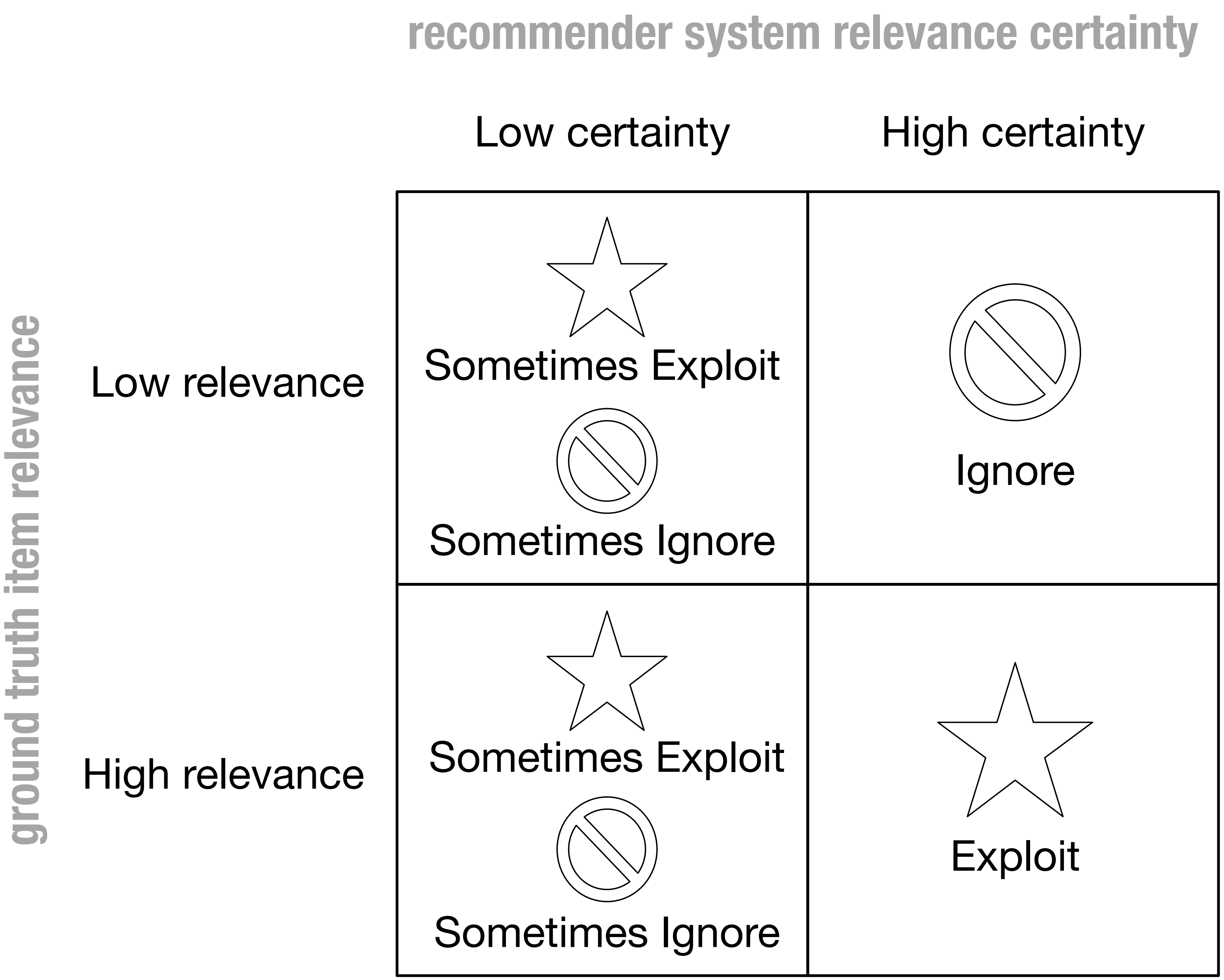

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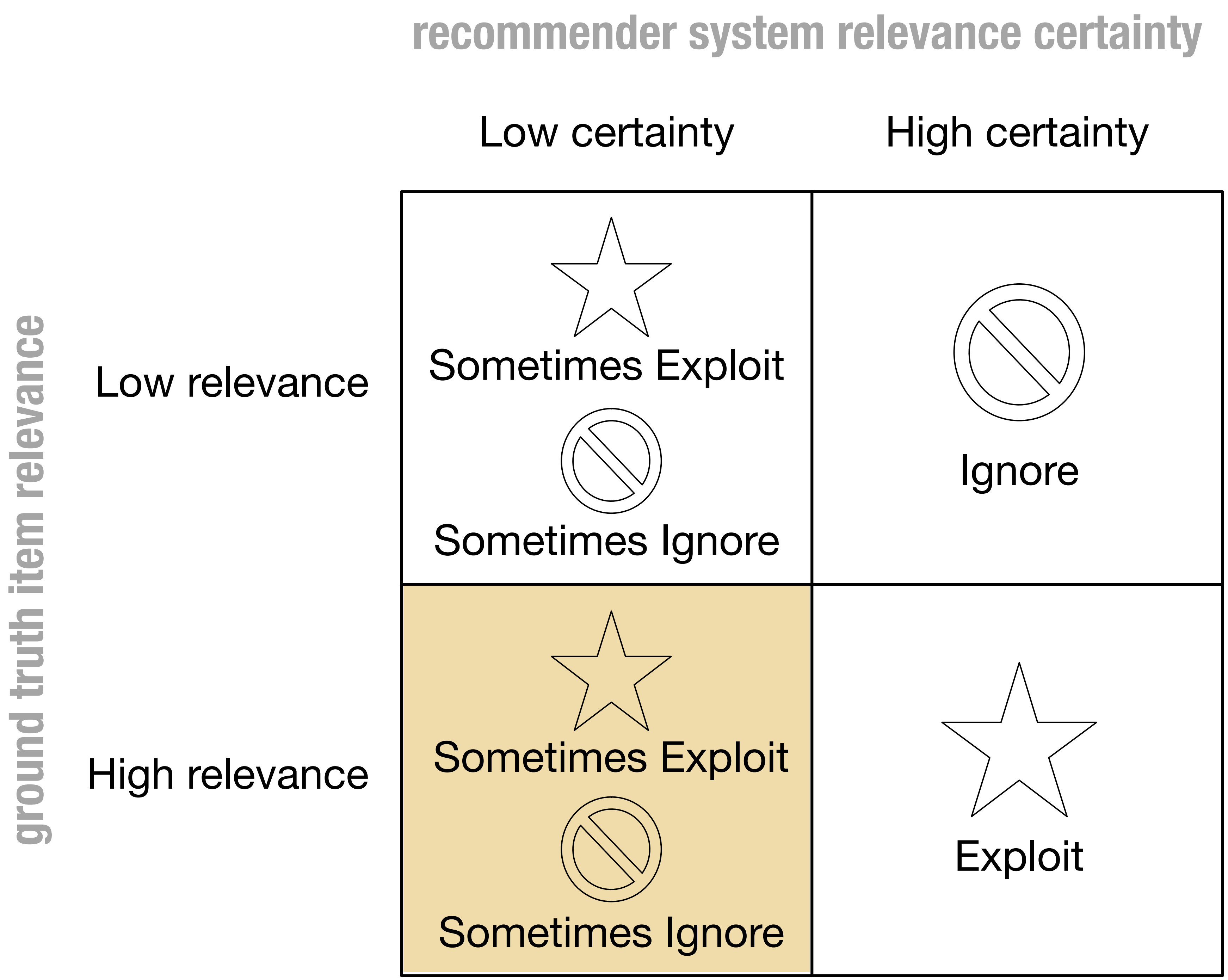

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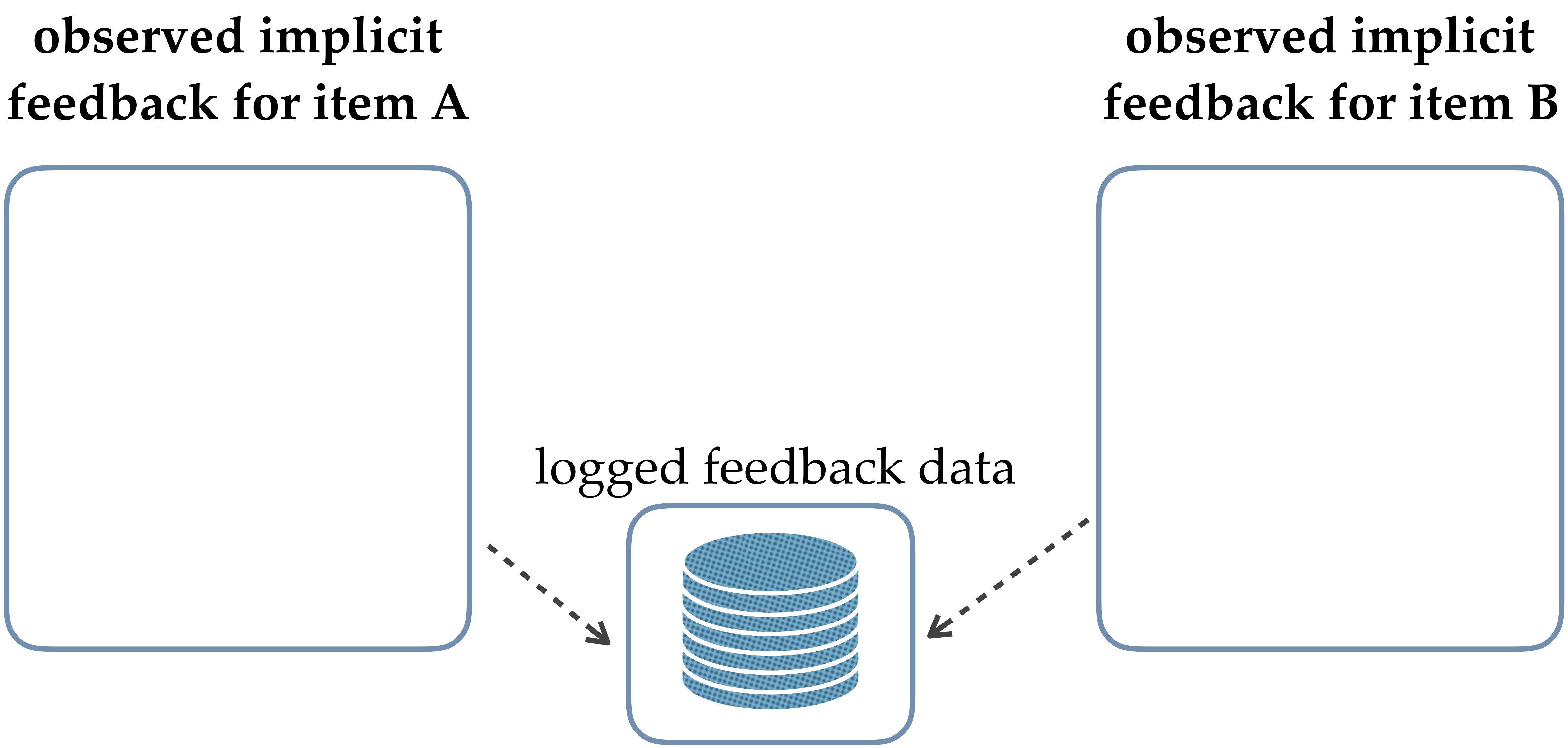

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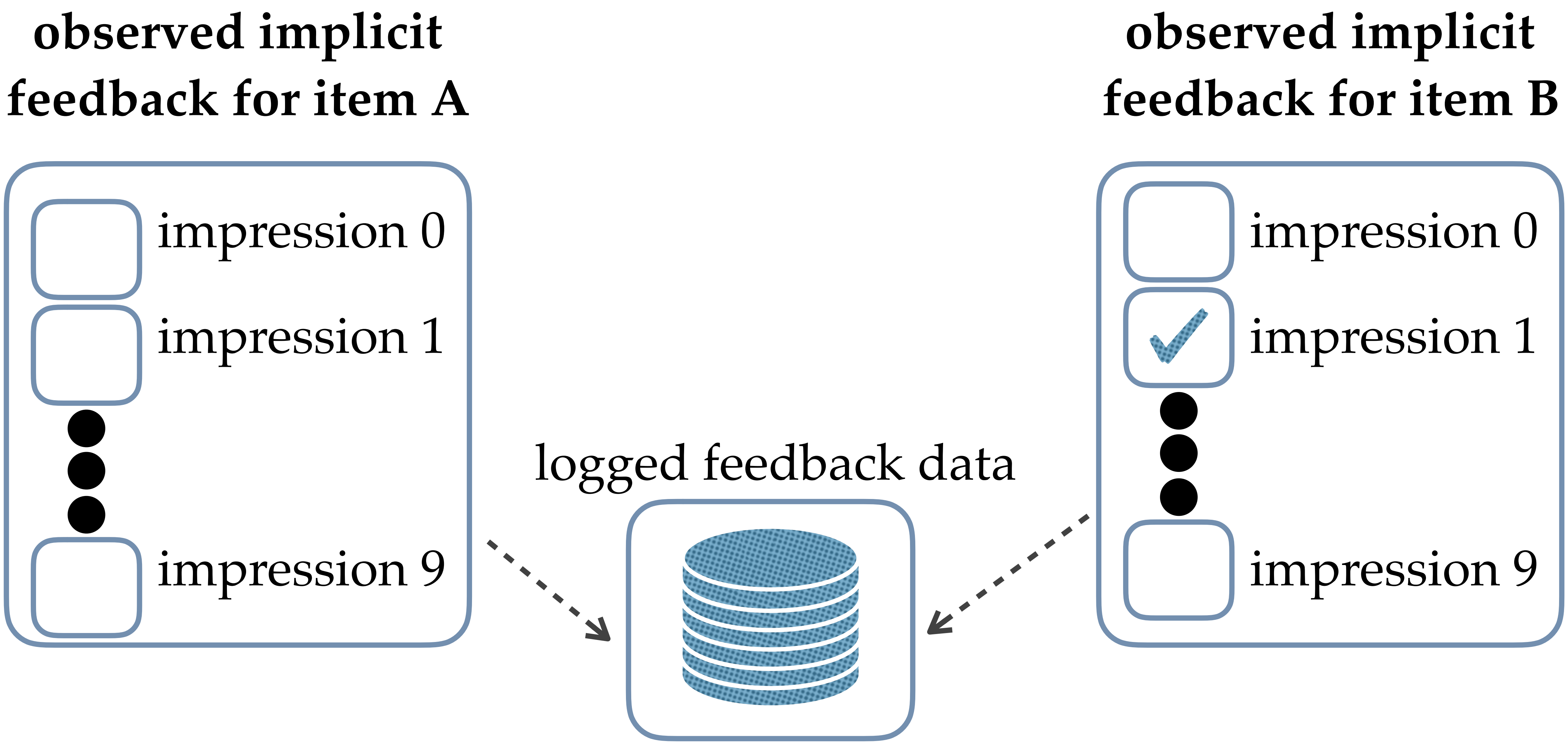

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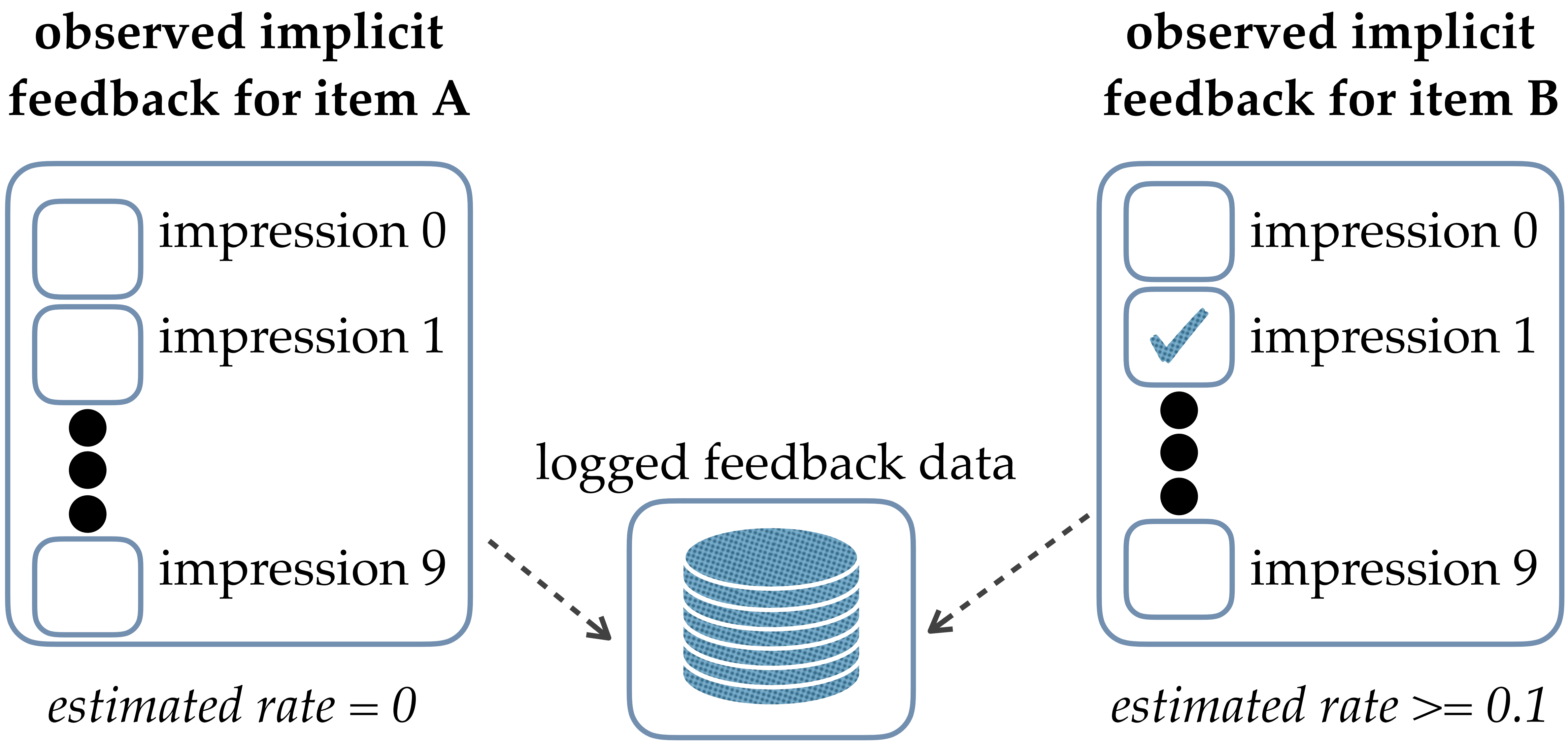

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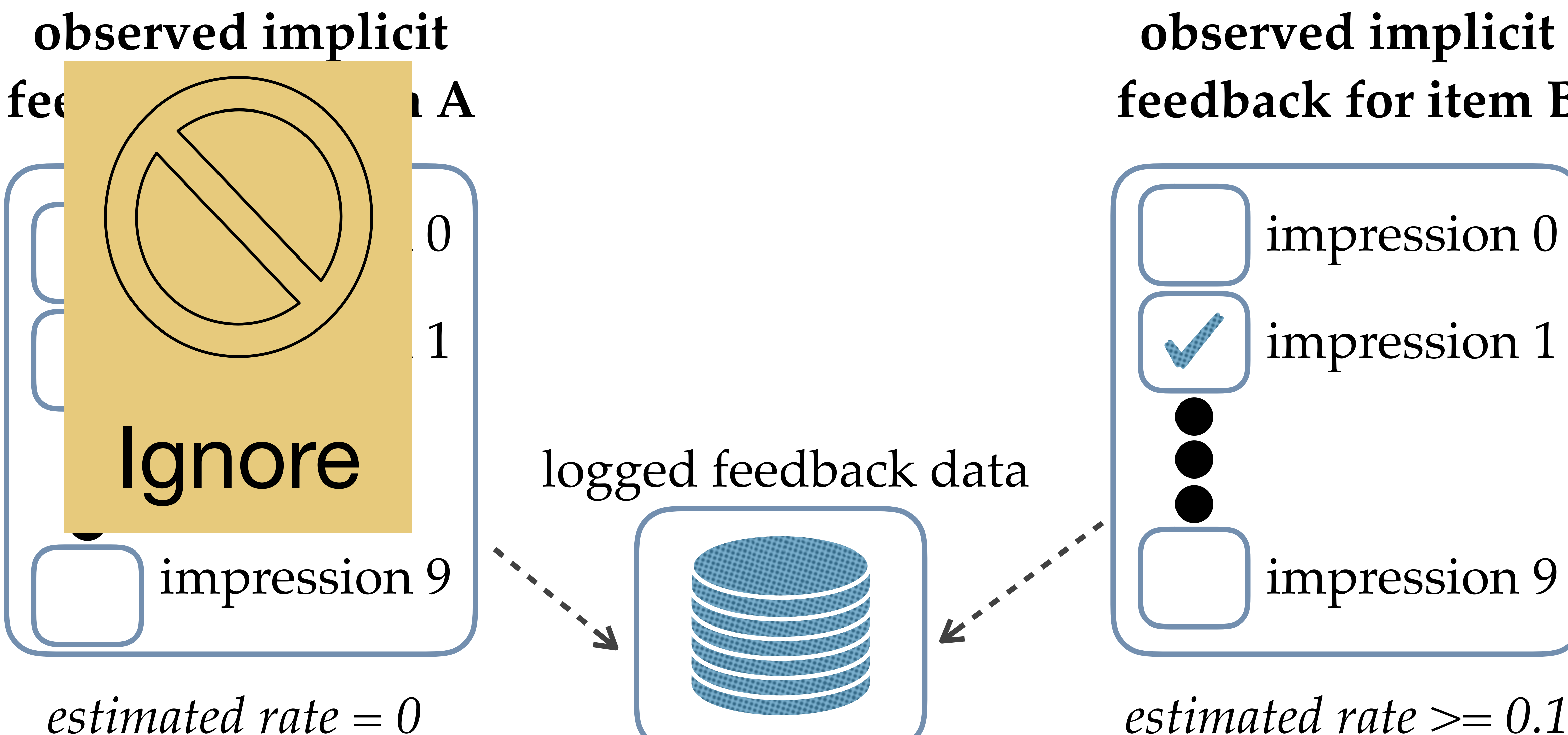

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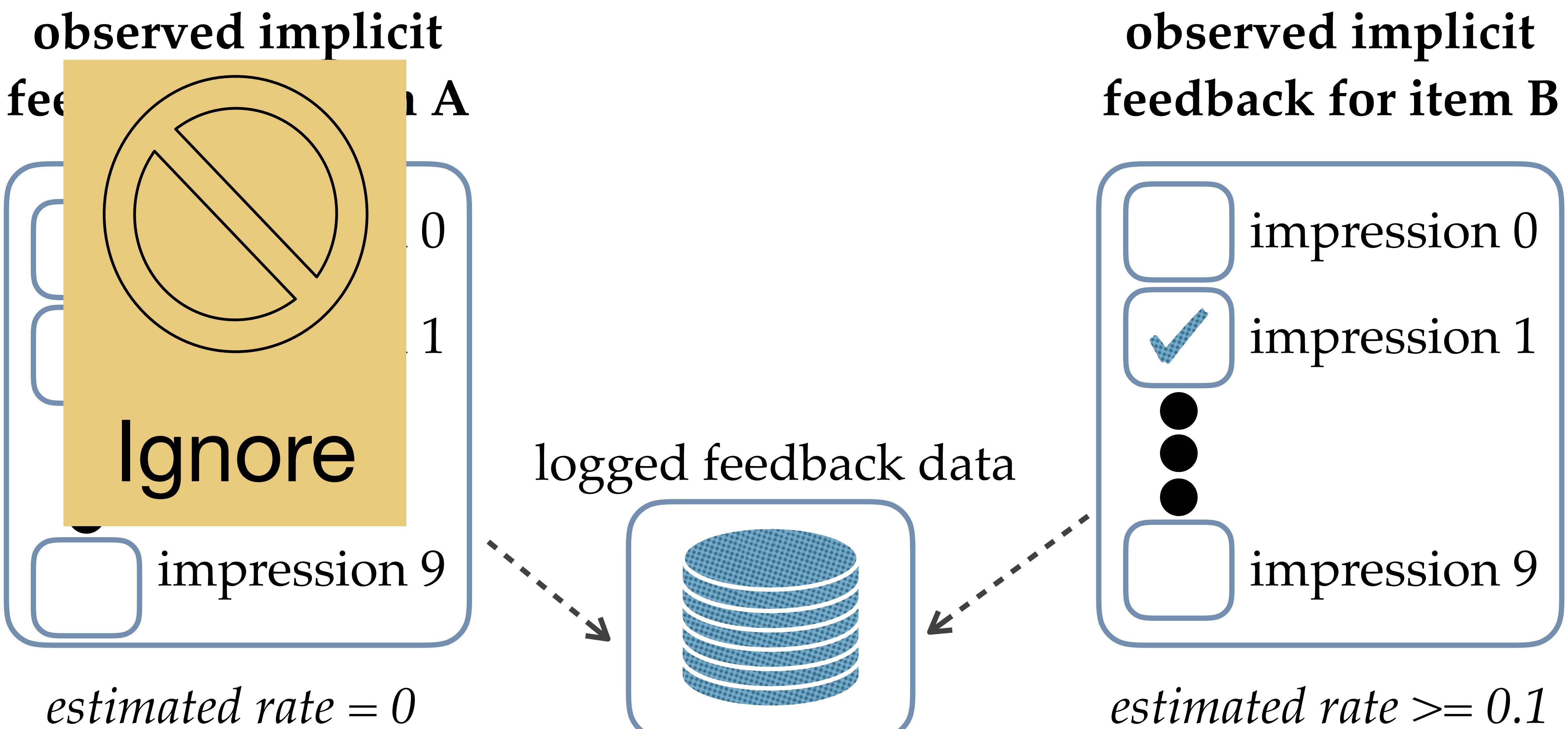
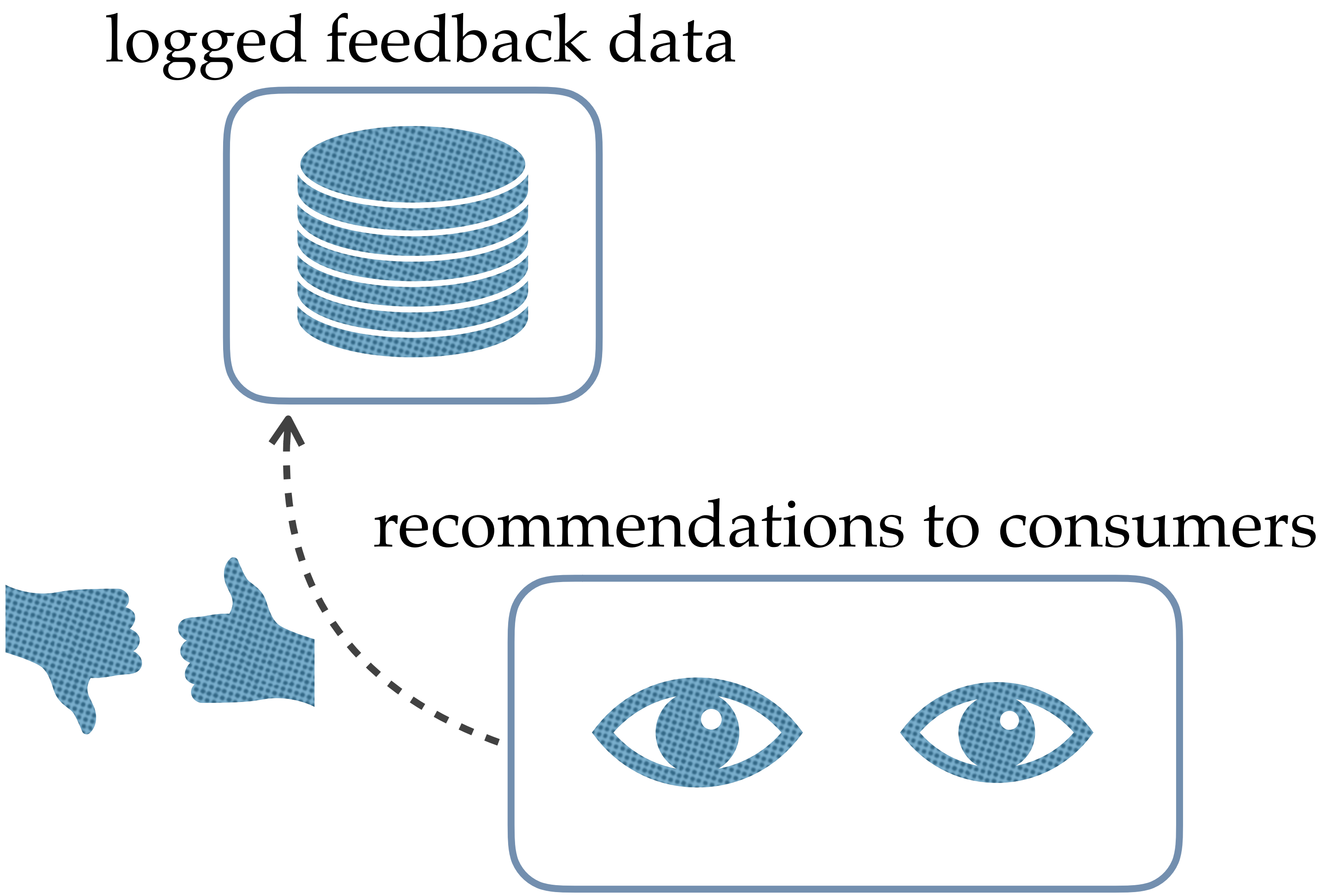


- for this example, this outcome happens 22.7% of the time.

Let's restart from the basic ideal of randomized controlled trials



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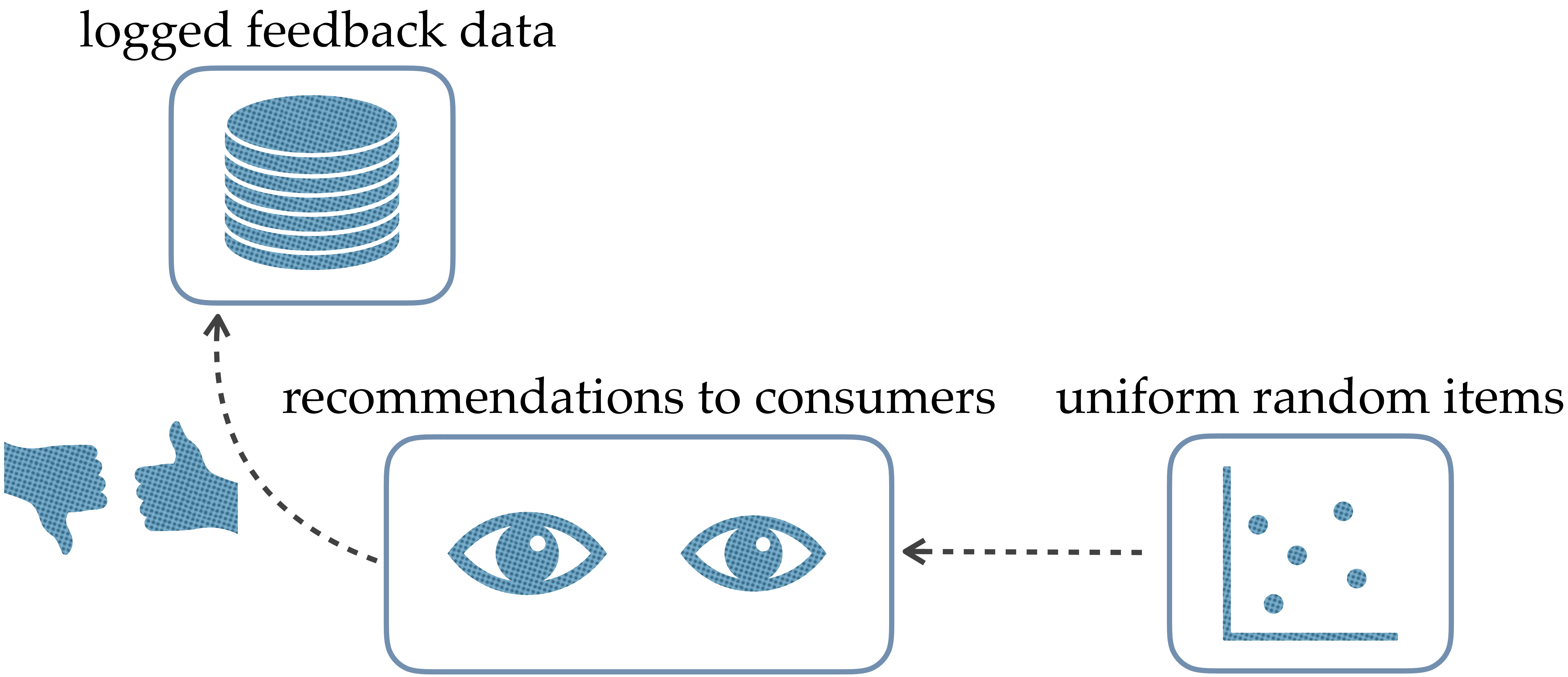

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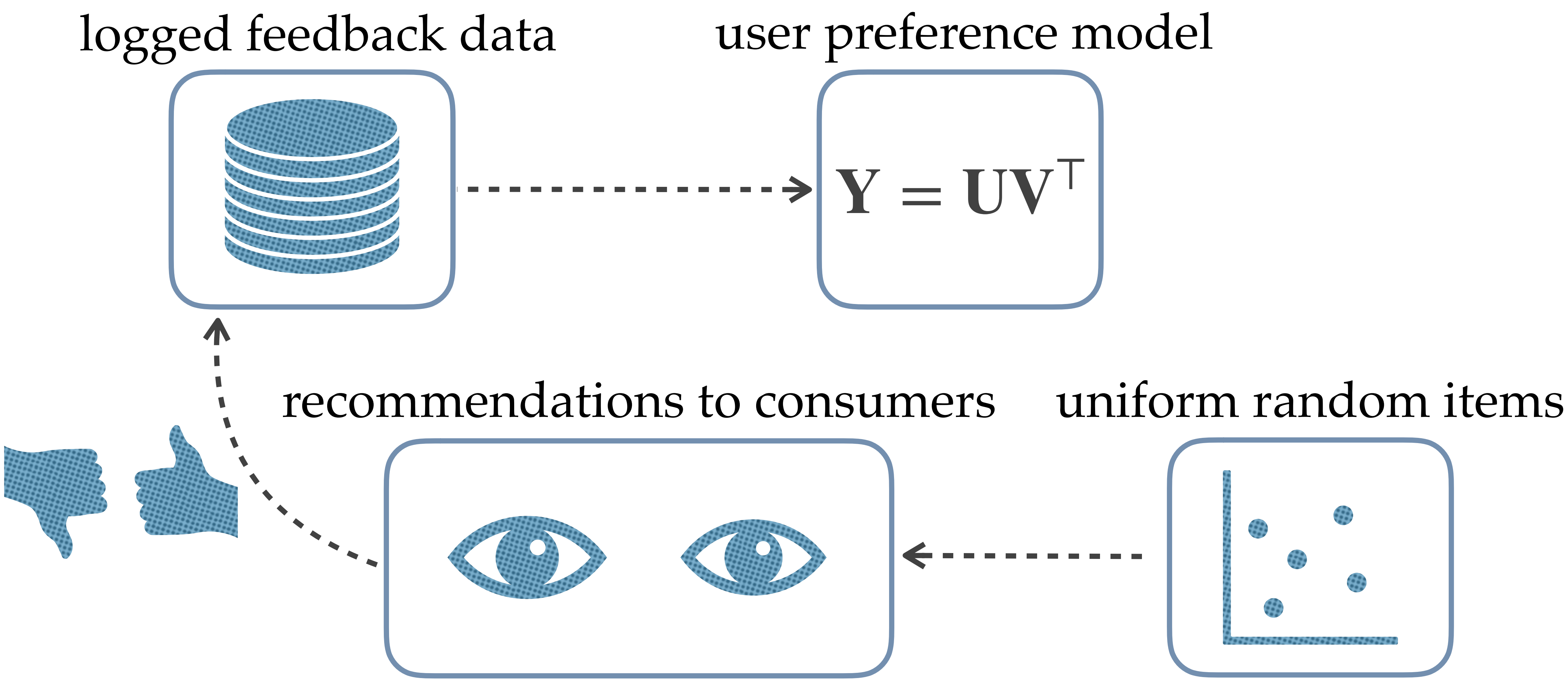

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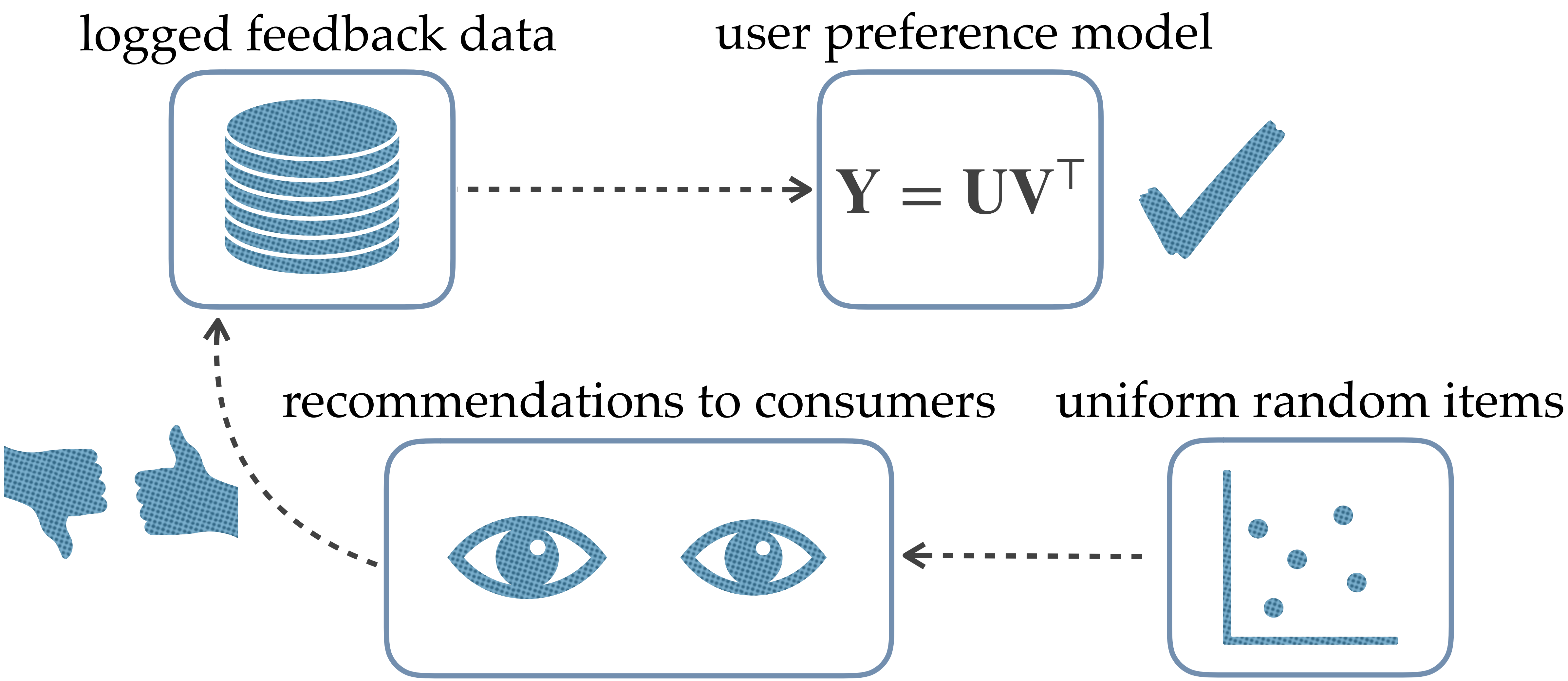

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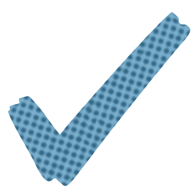

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set of all items

model parameters

context

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- aside: matrix factorization is a special case when the context is the user index vector.

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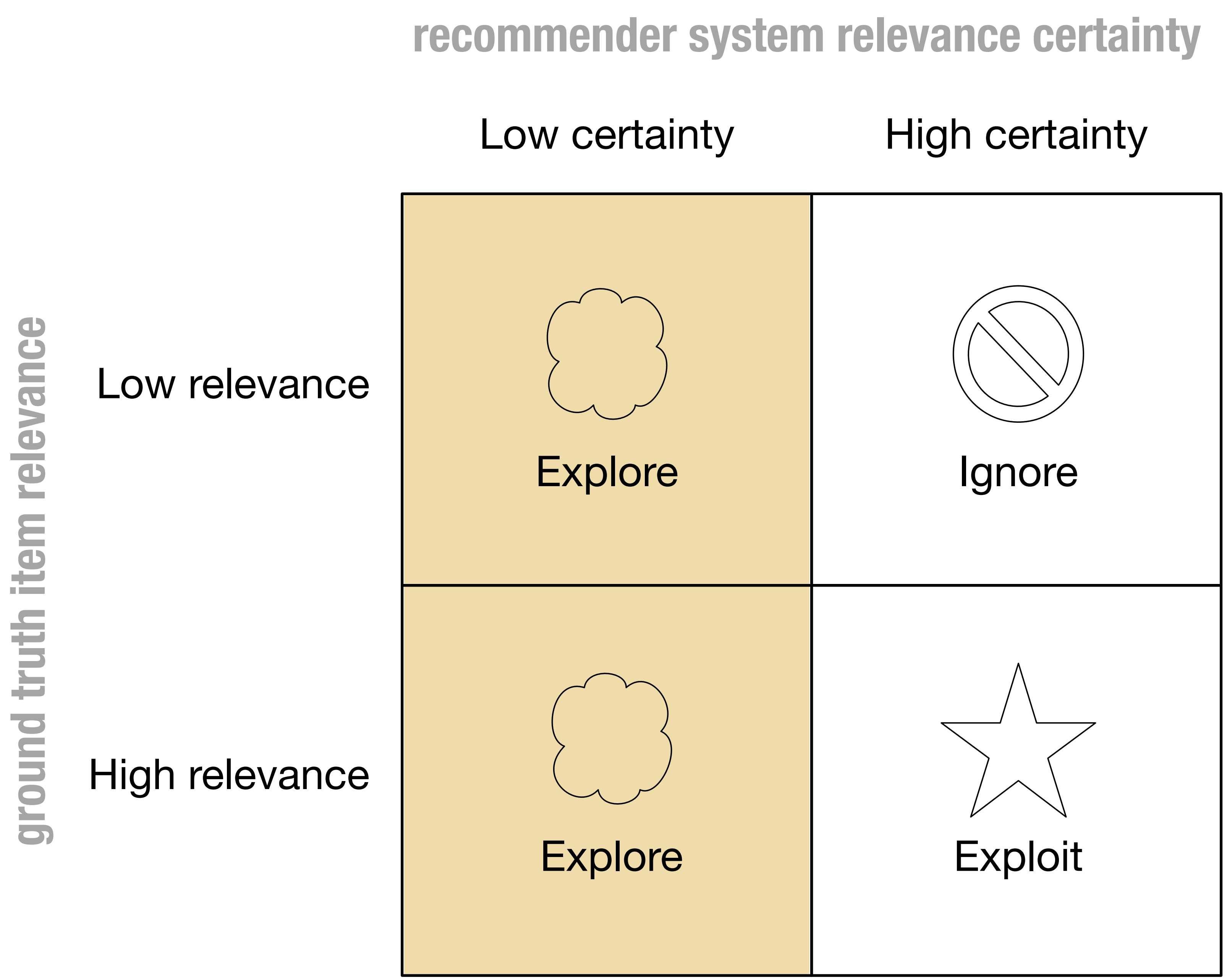

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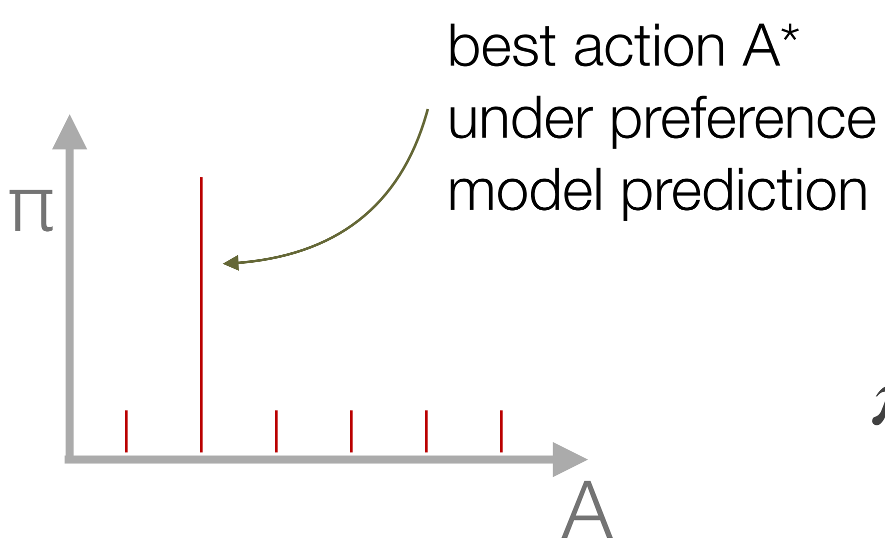

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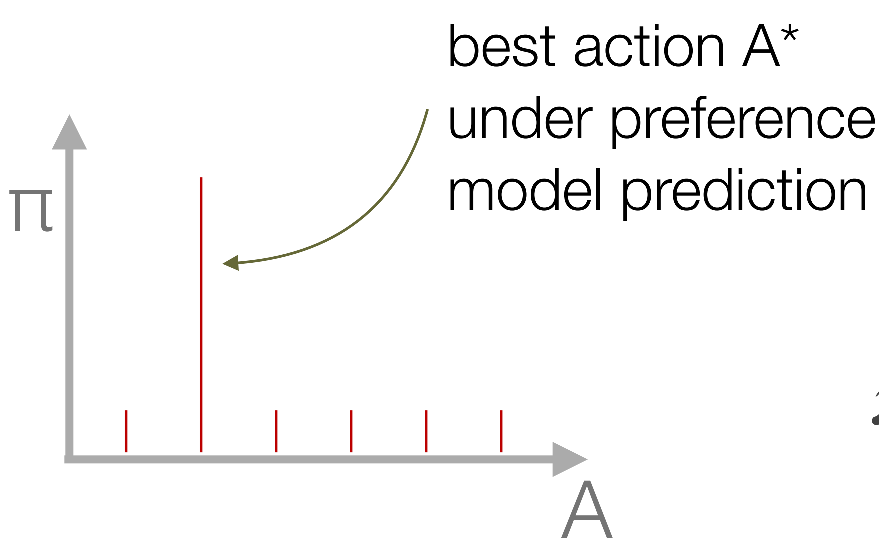

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exploration parameter (when fixed -> crude exploitation; can also decay over time)

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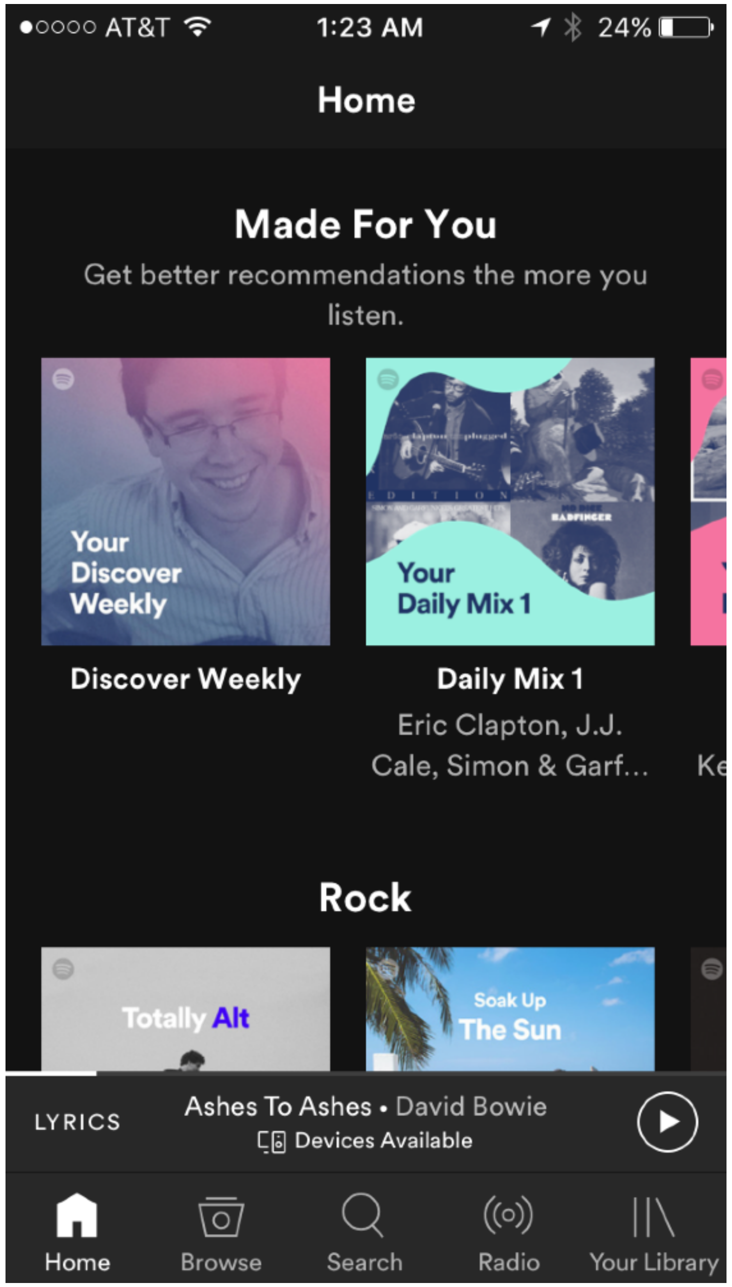

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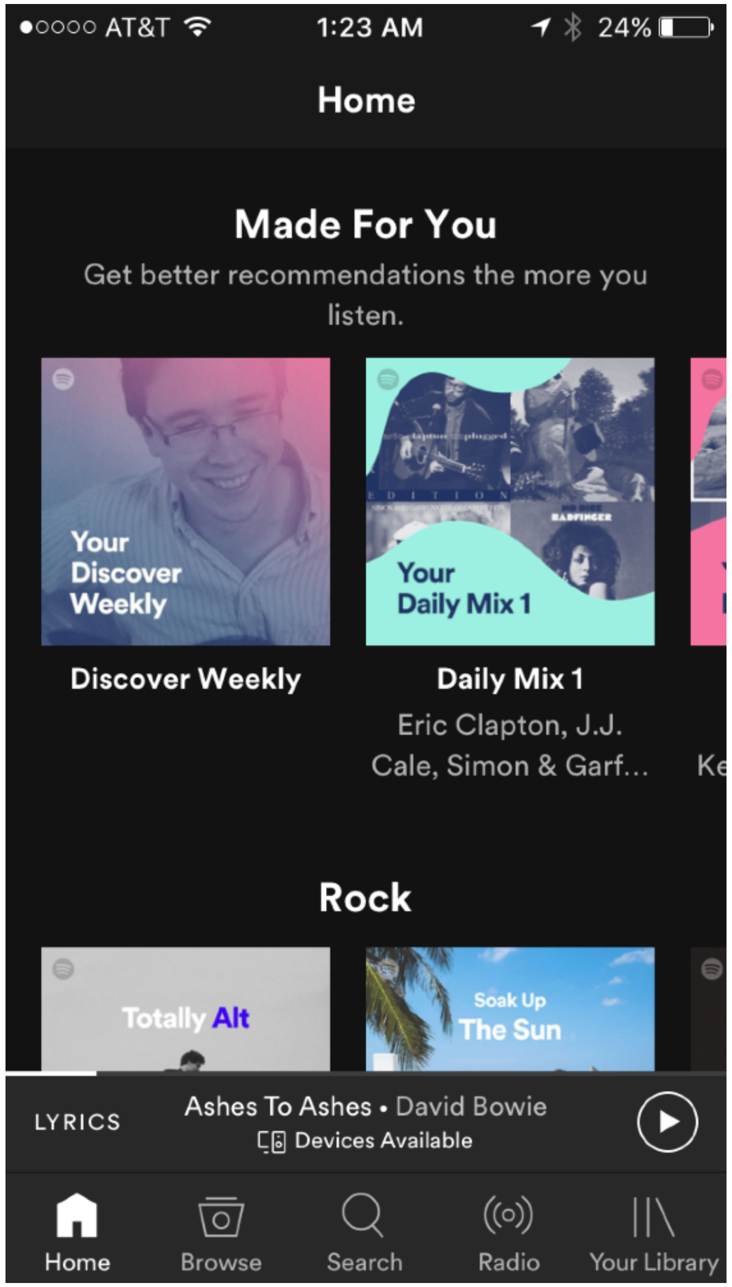

- e.g. home page of Spotify, YouTube, or Netflix
- items arranged into shelves, each shelf has a title or <u>explanation</u> for the associated recommendation
- naively, the bandit has to try every possible combination of item and explanation many times before being able to exploit the best combinations

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Assumptions of shelf browsing model

Horizontal scrolling

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User awareness

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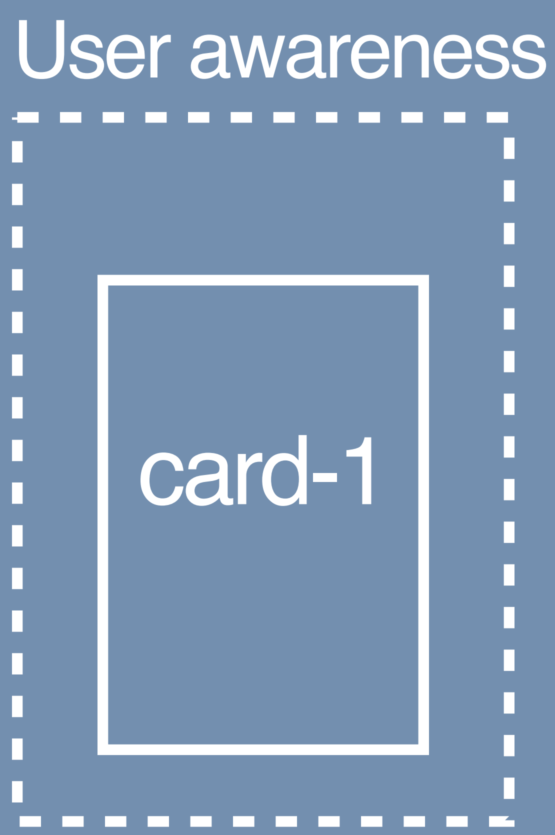

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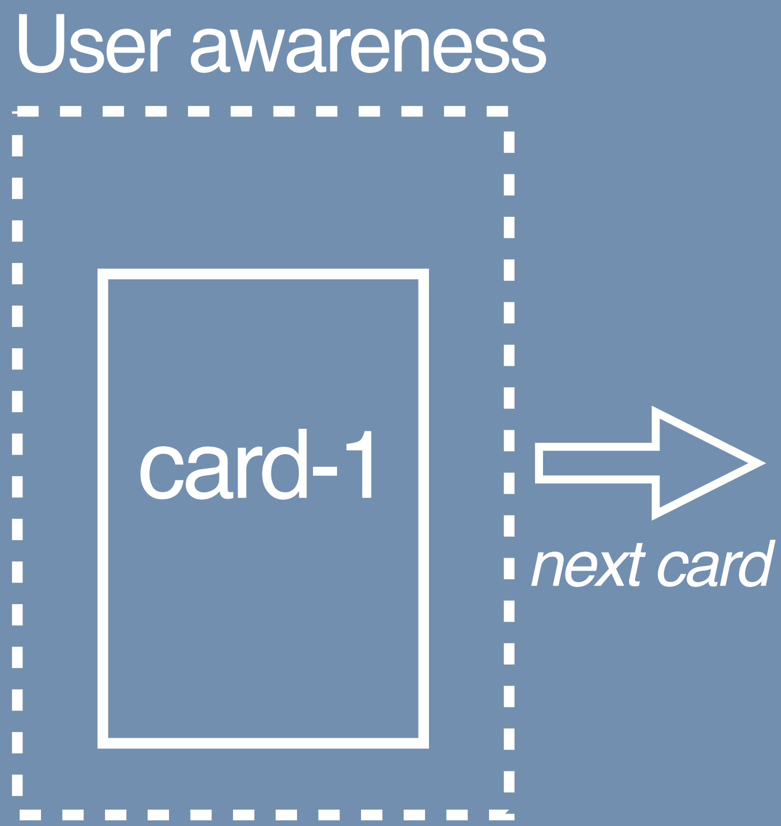

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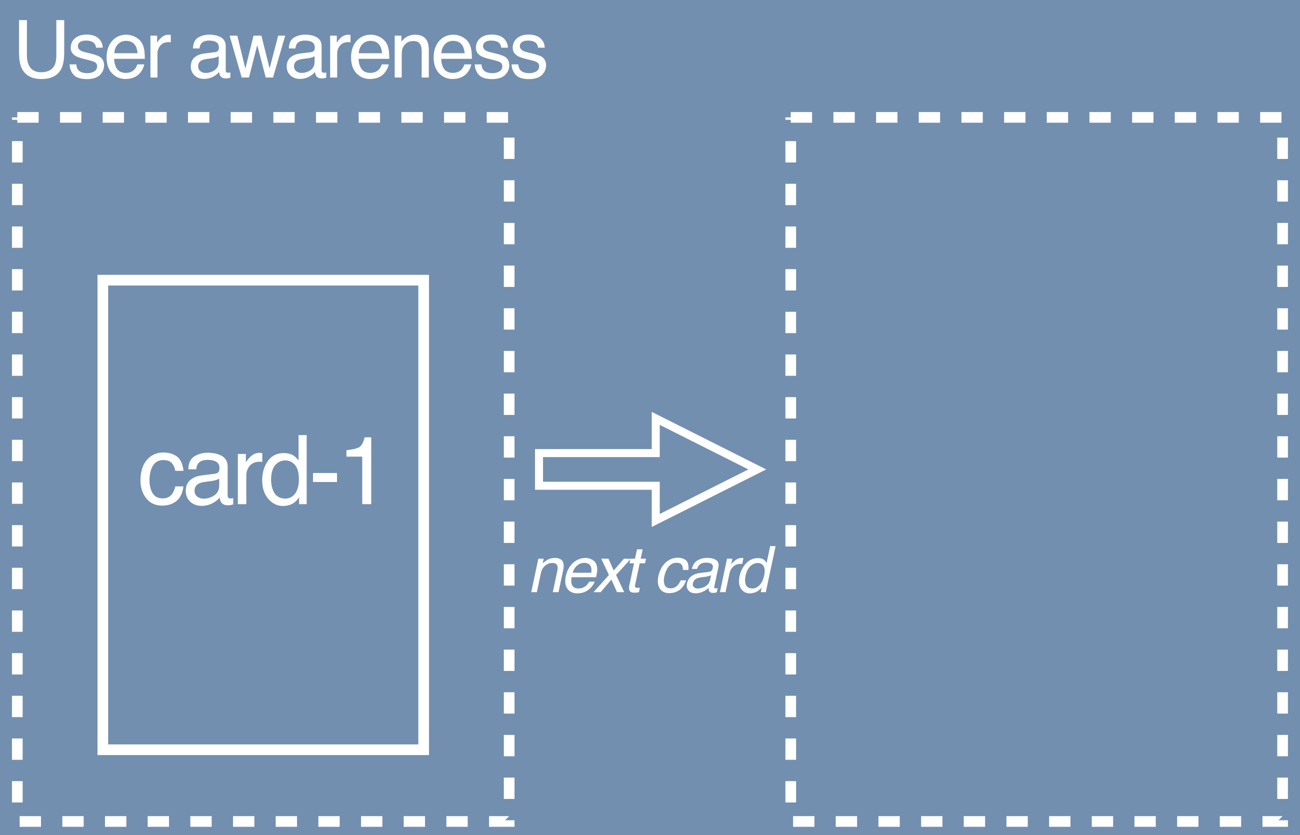

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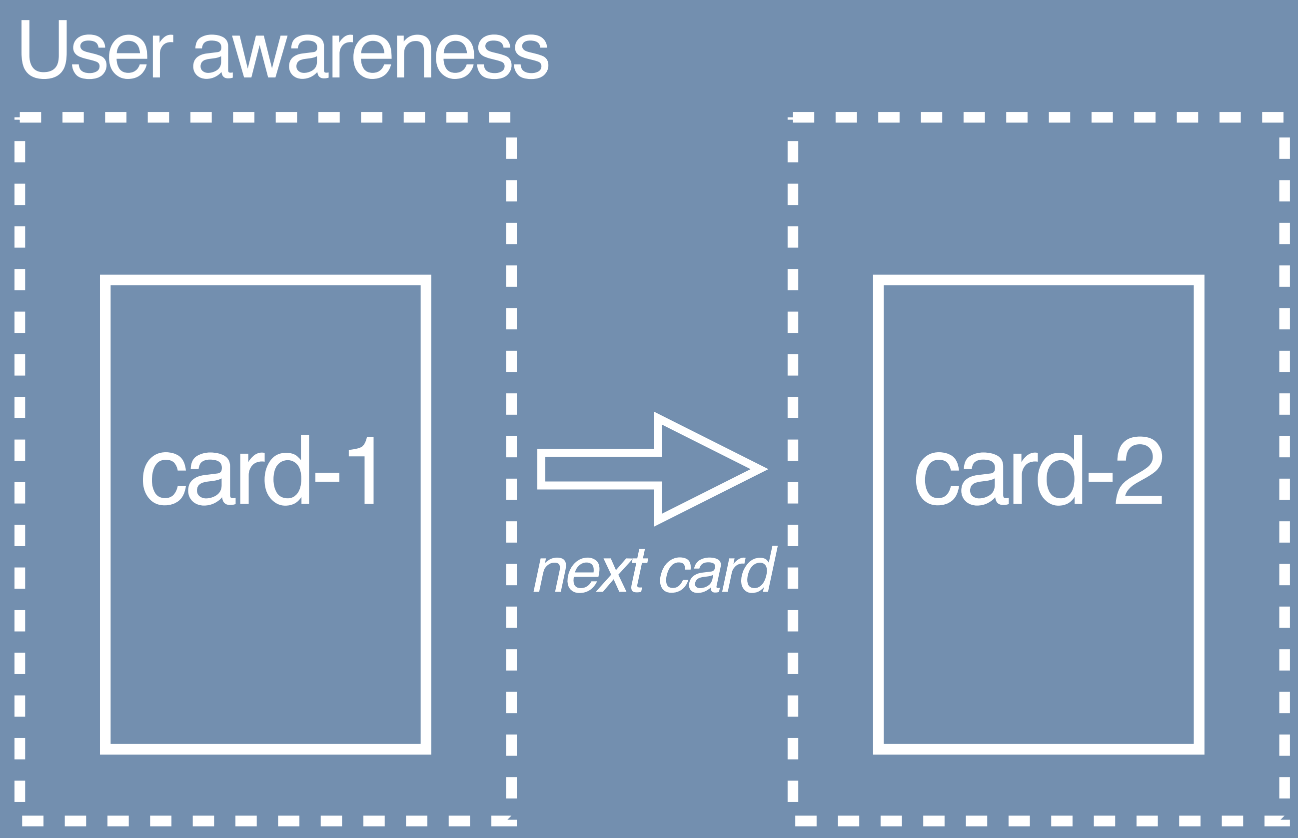

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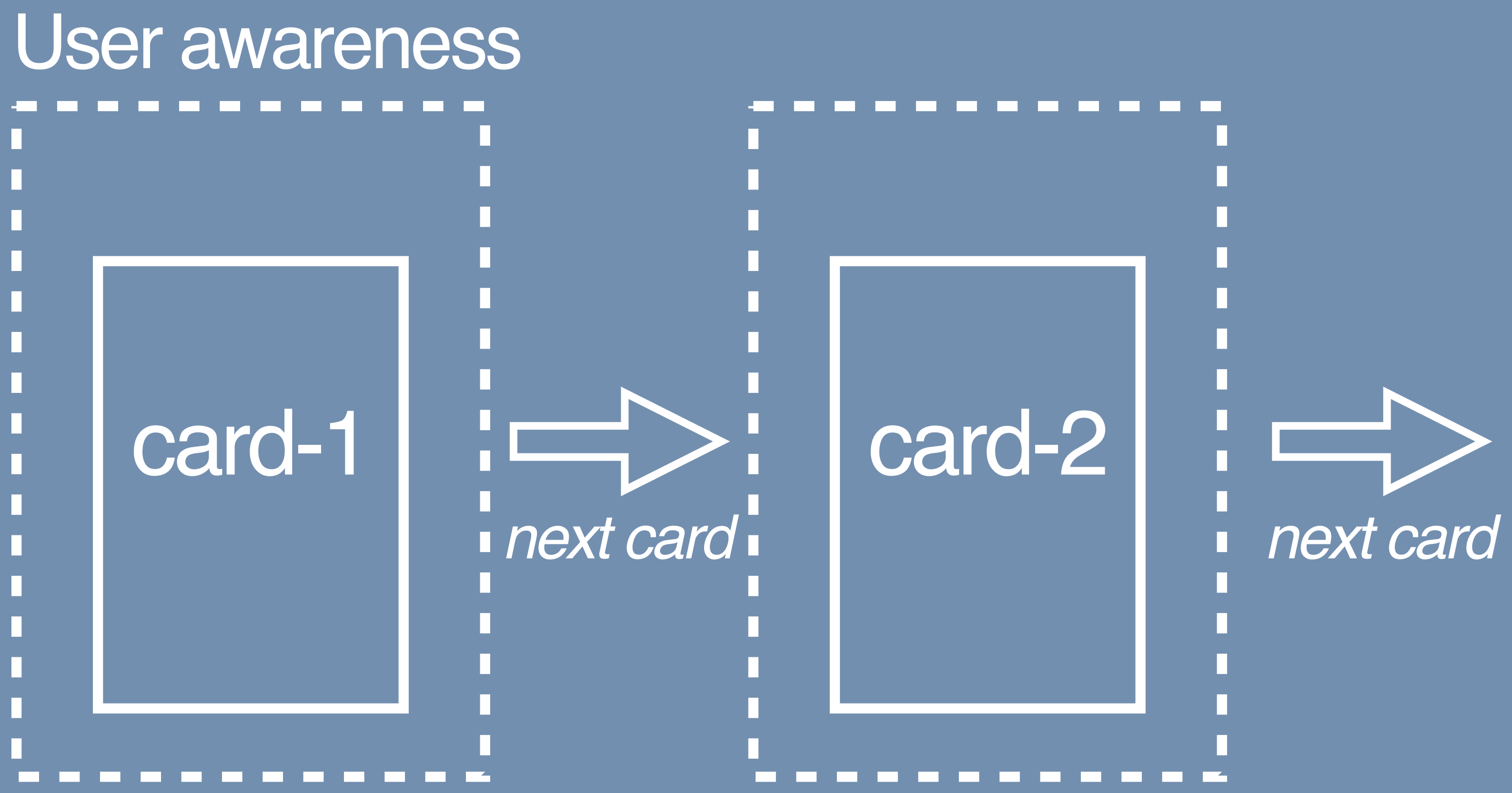

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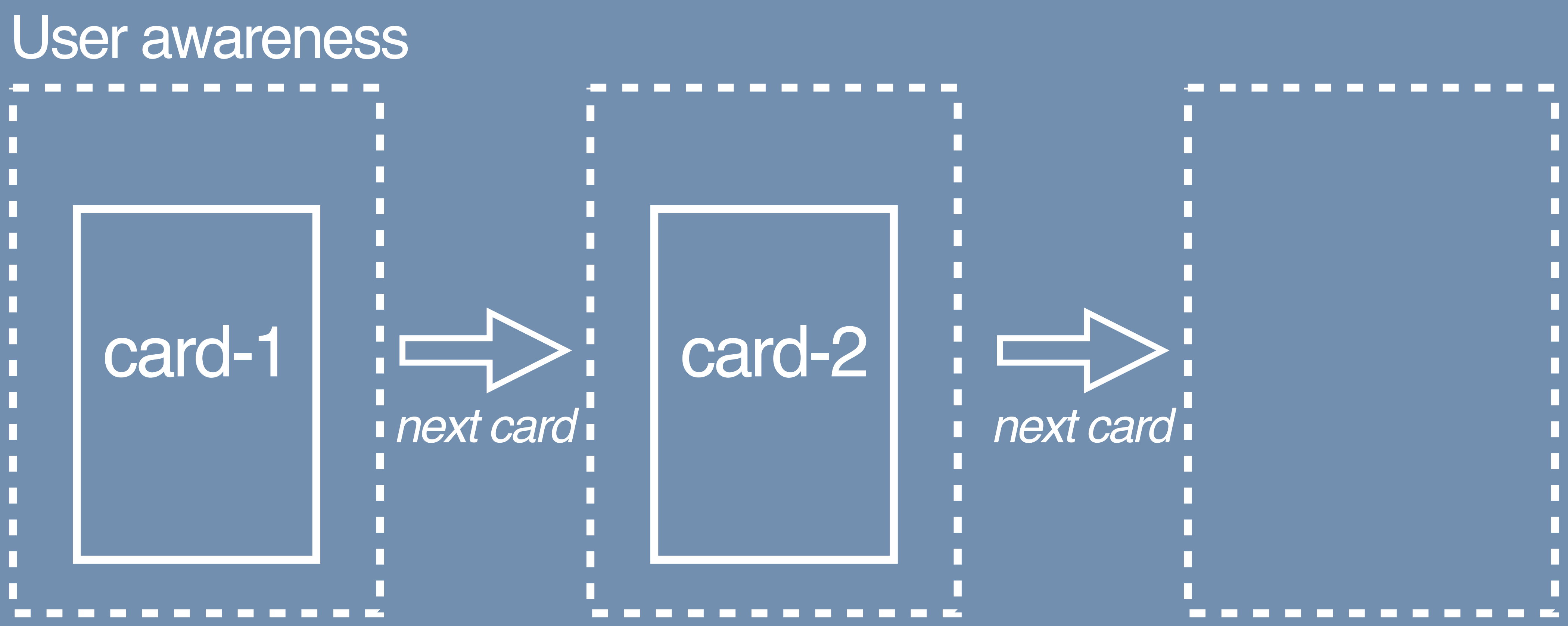

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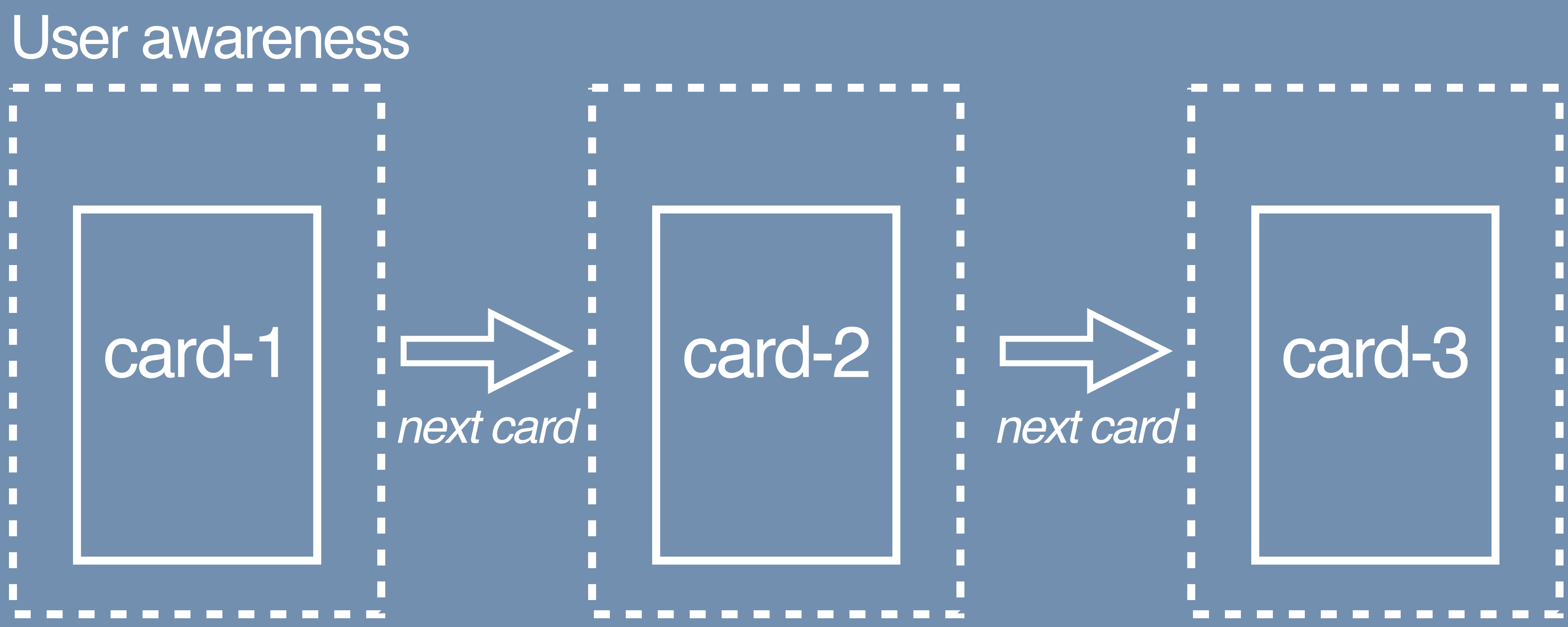

Animation of ranking procedure with bandit

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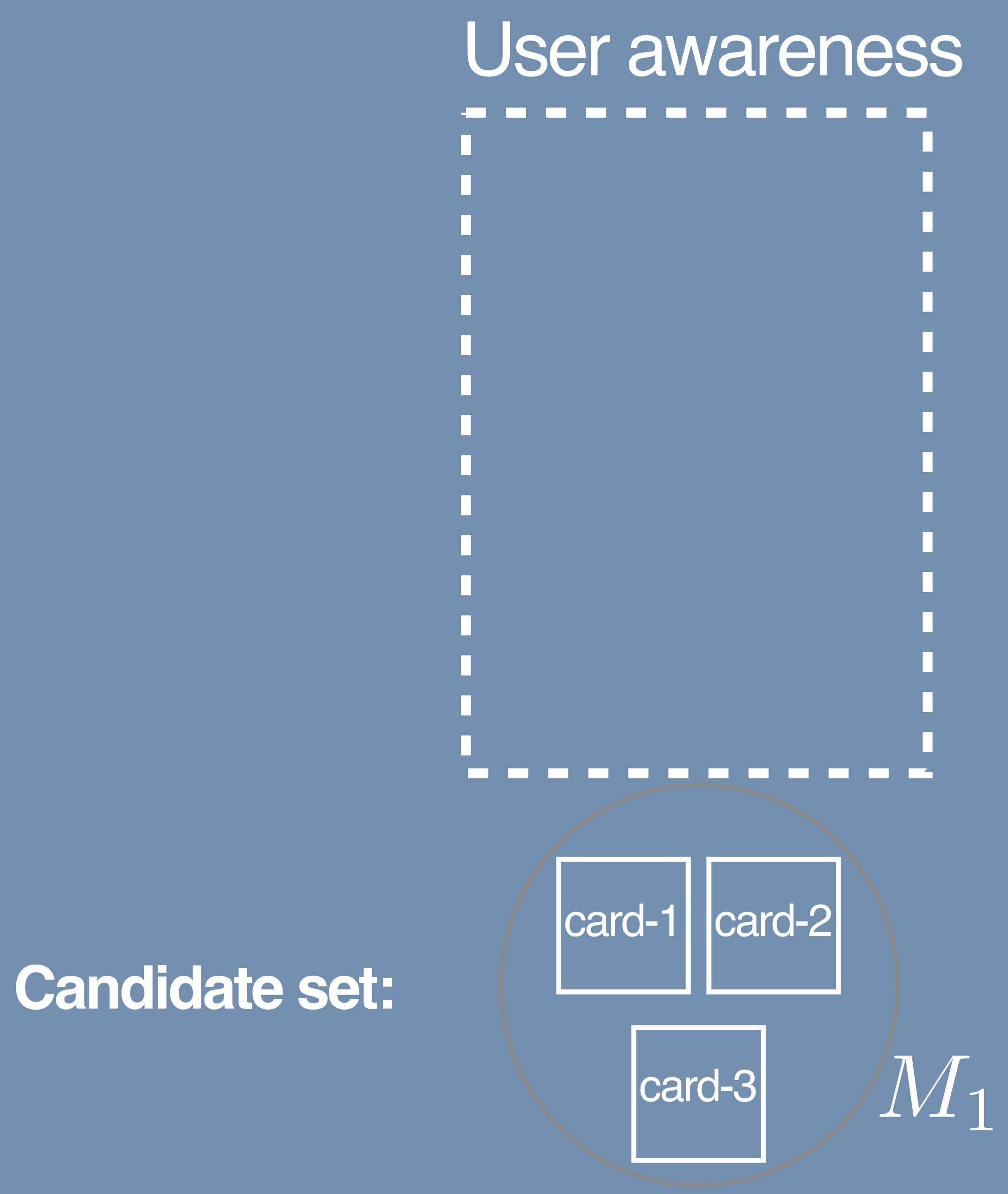

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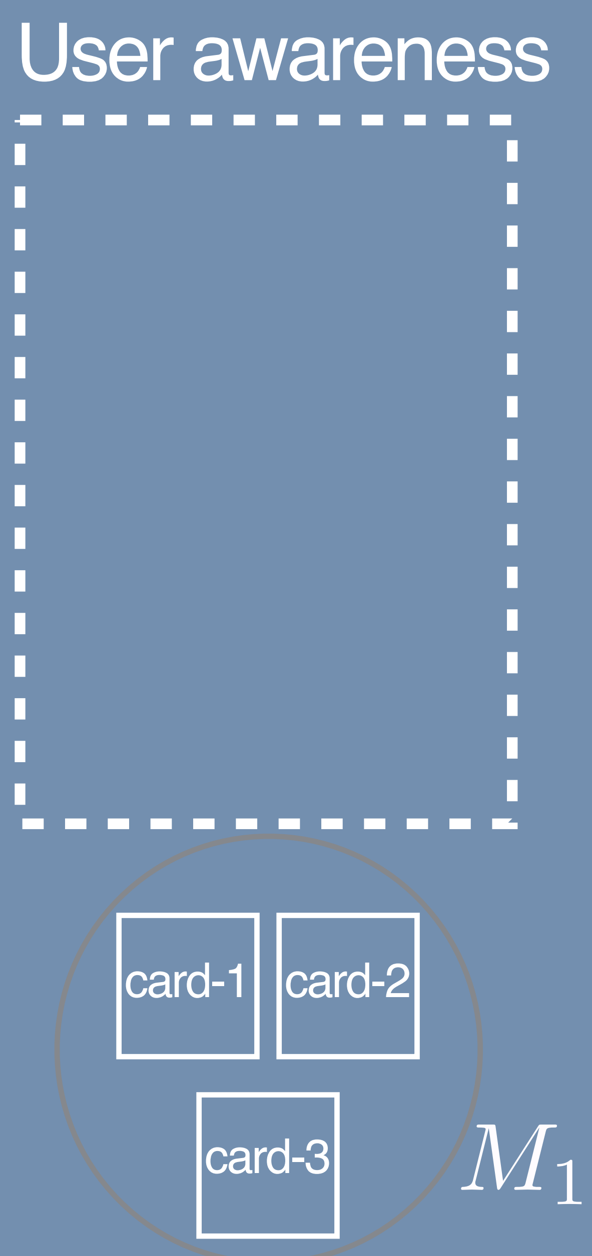

Candidate set:

Action select: $\mathrm{card}_1 \sim \pi_{s,r}(M_1)$

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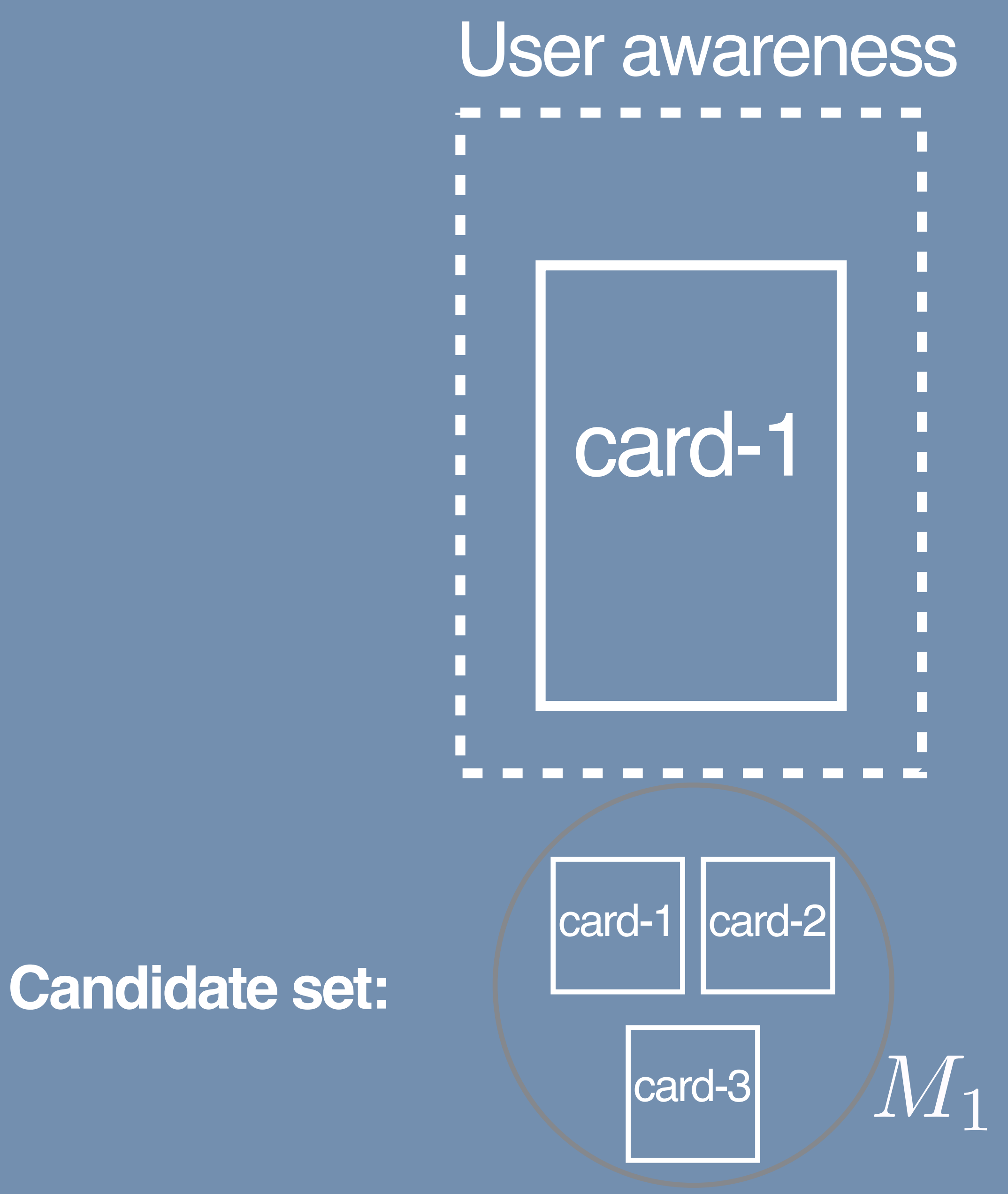

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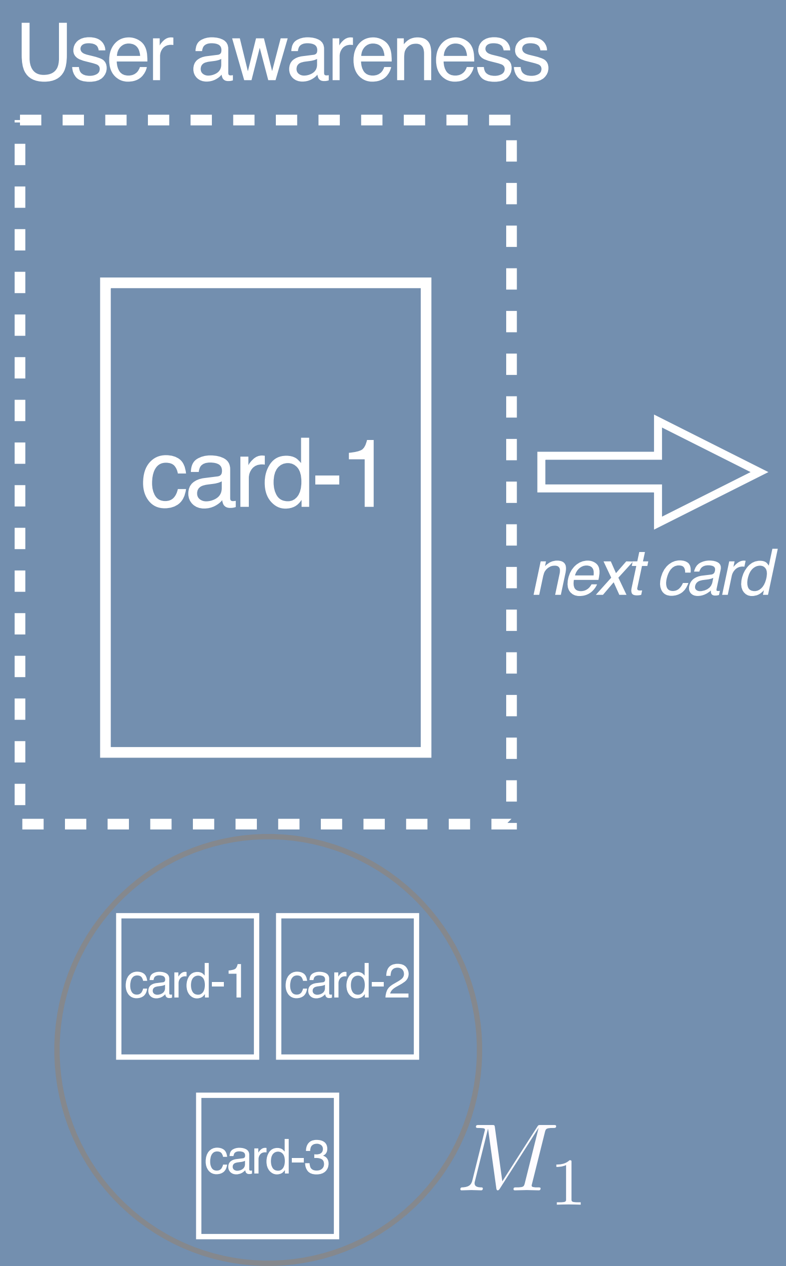

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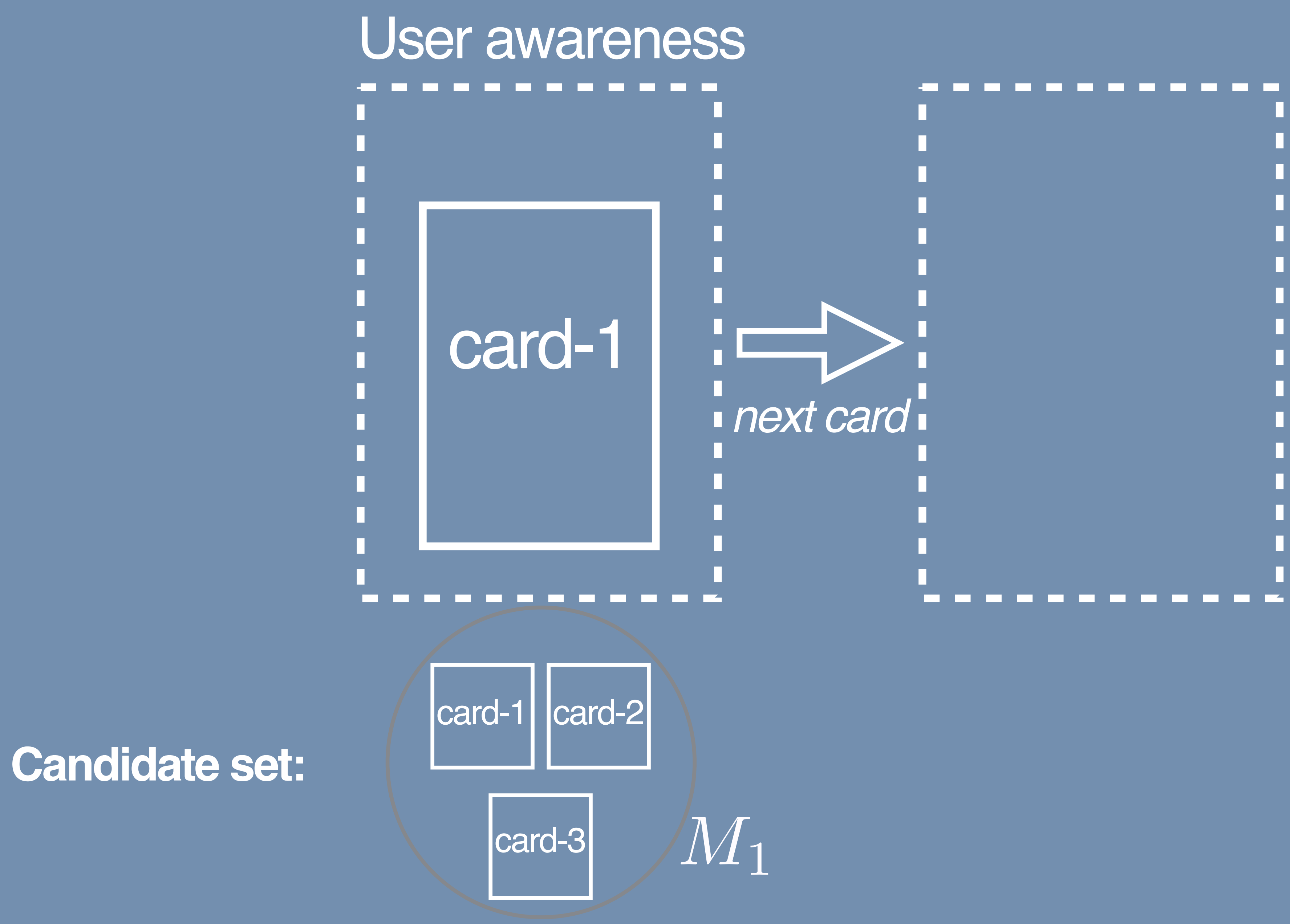

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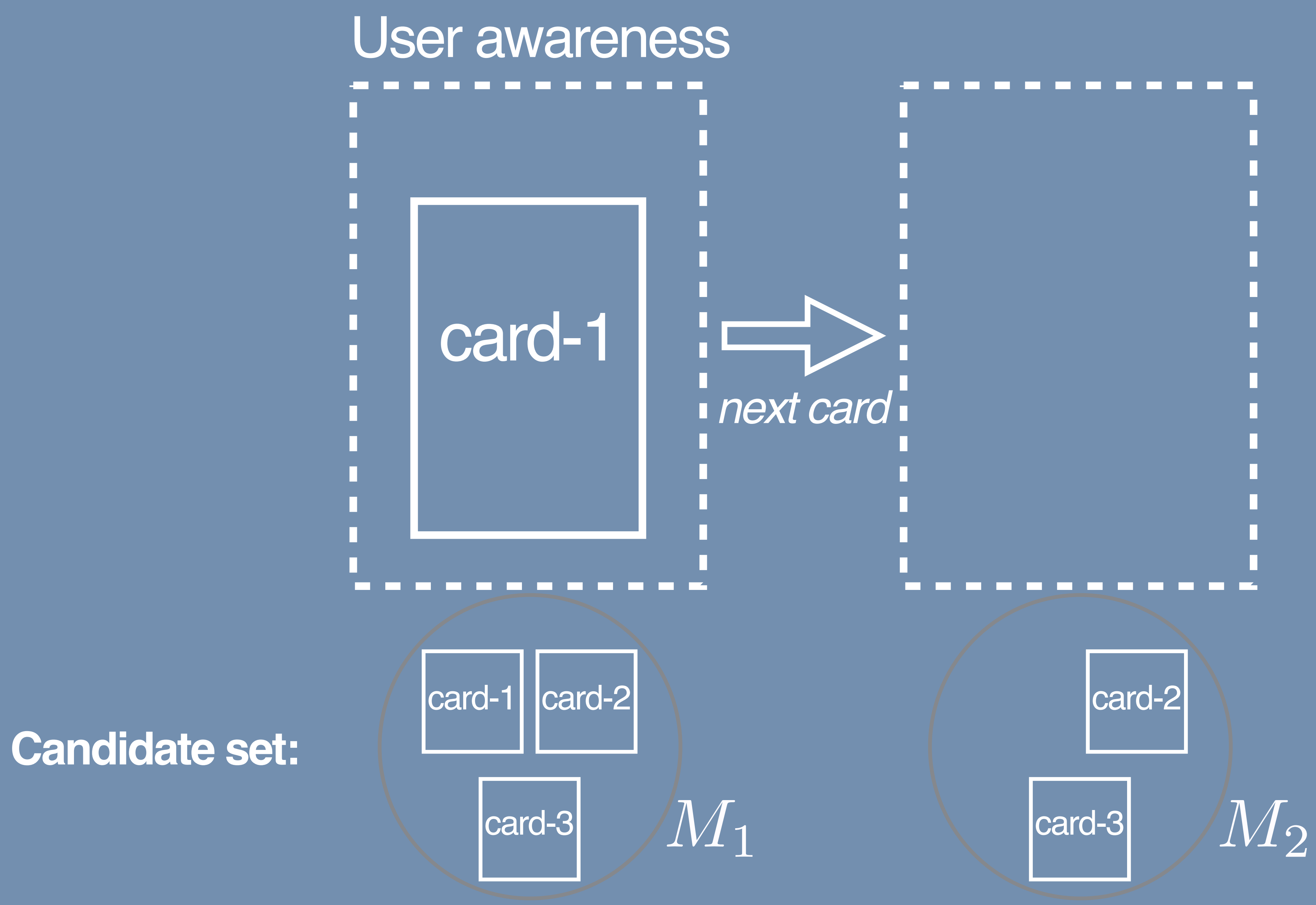

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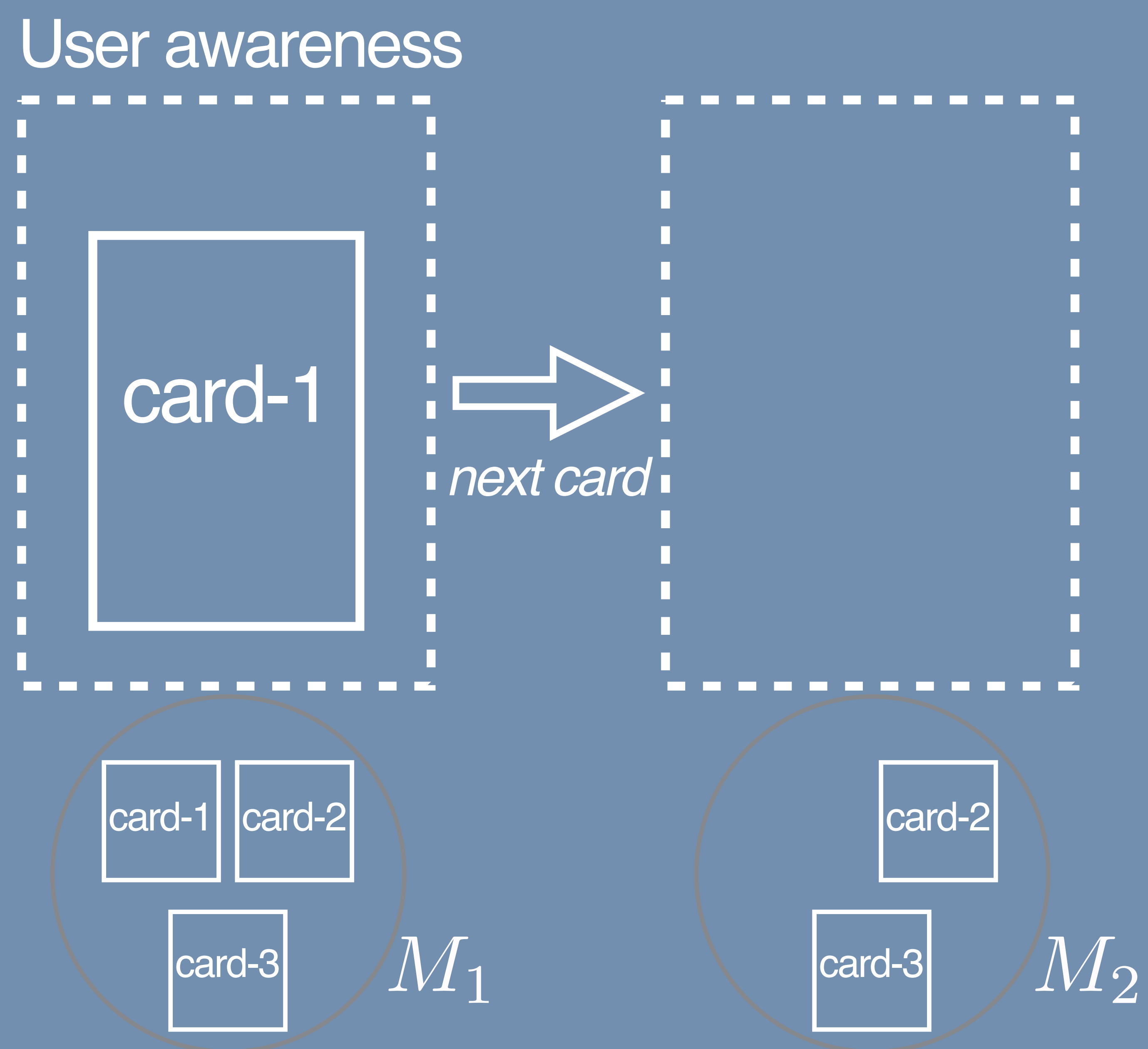

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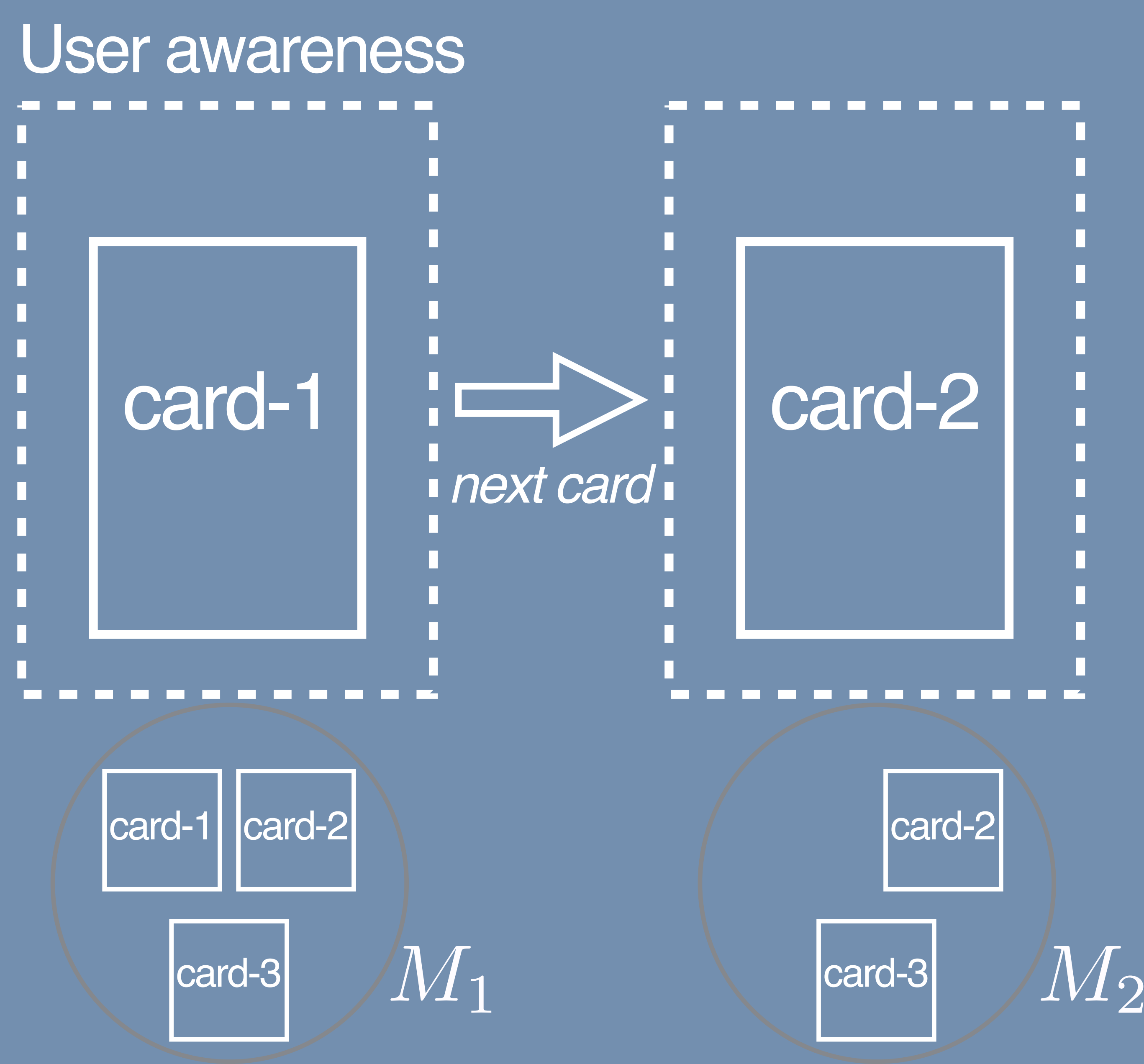

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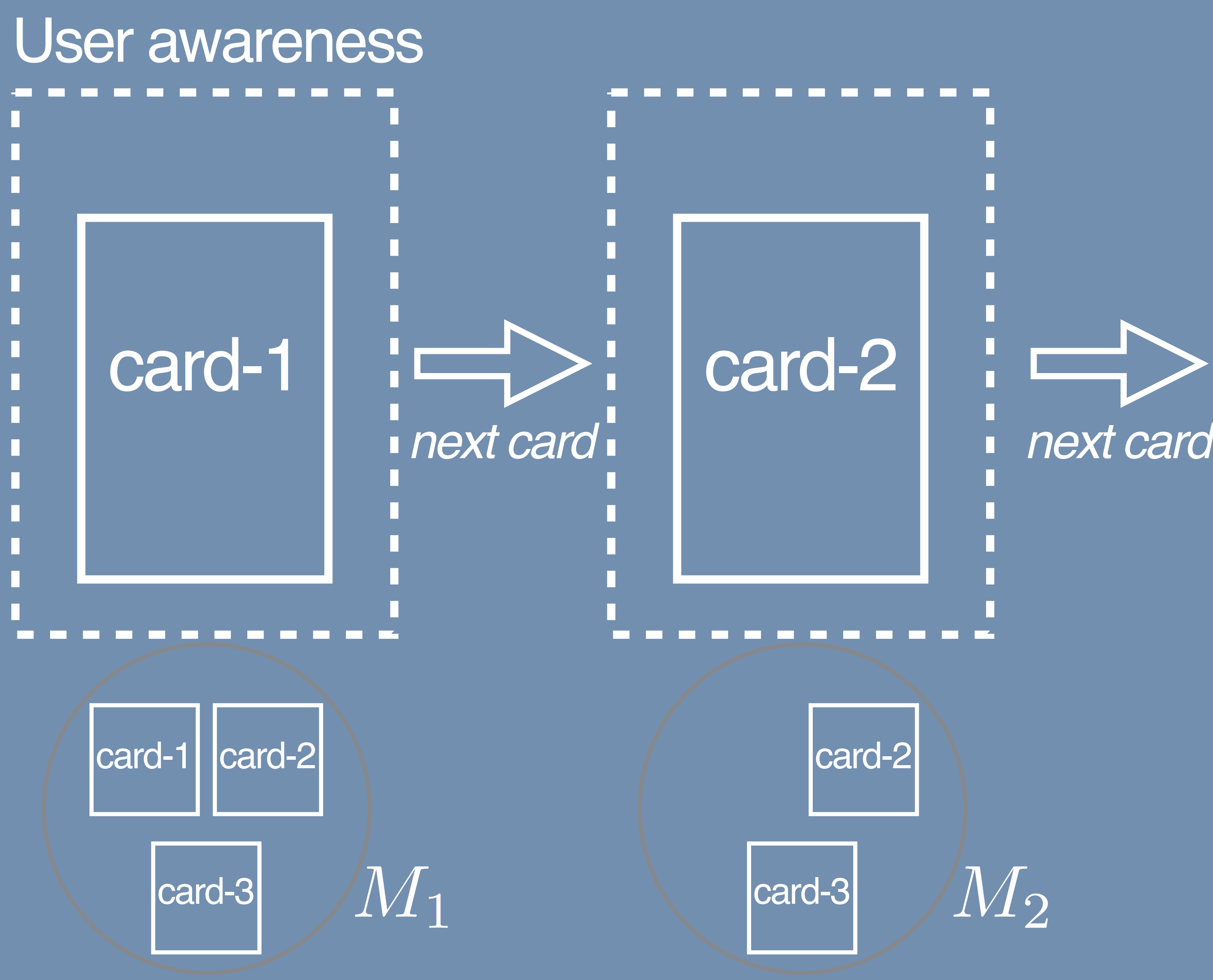

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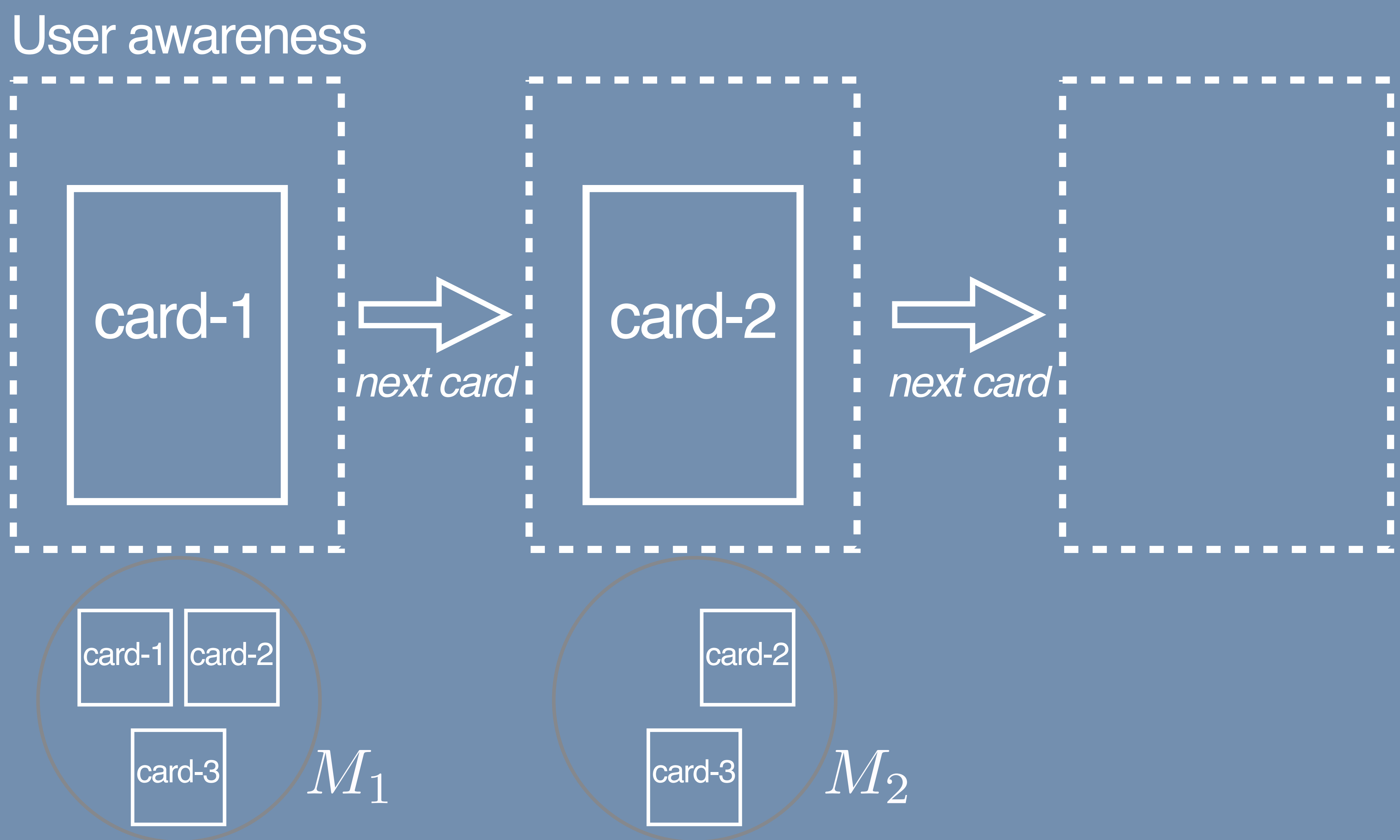

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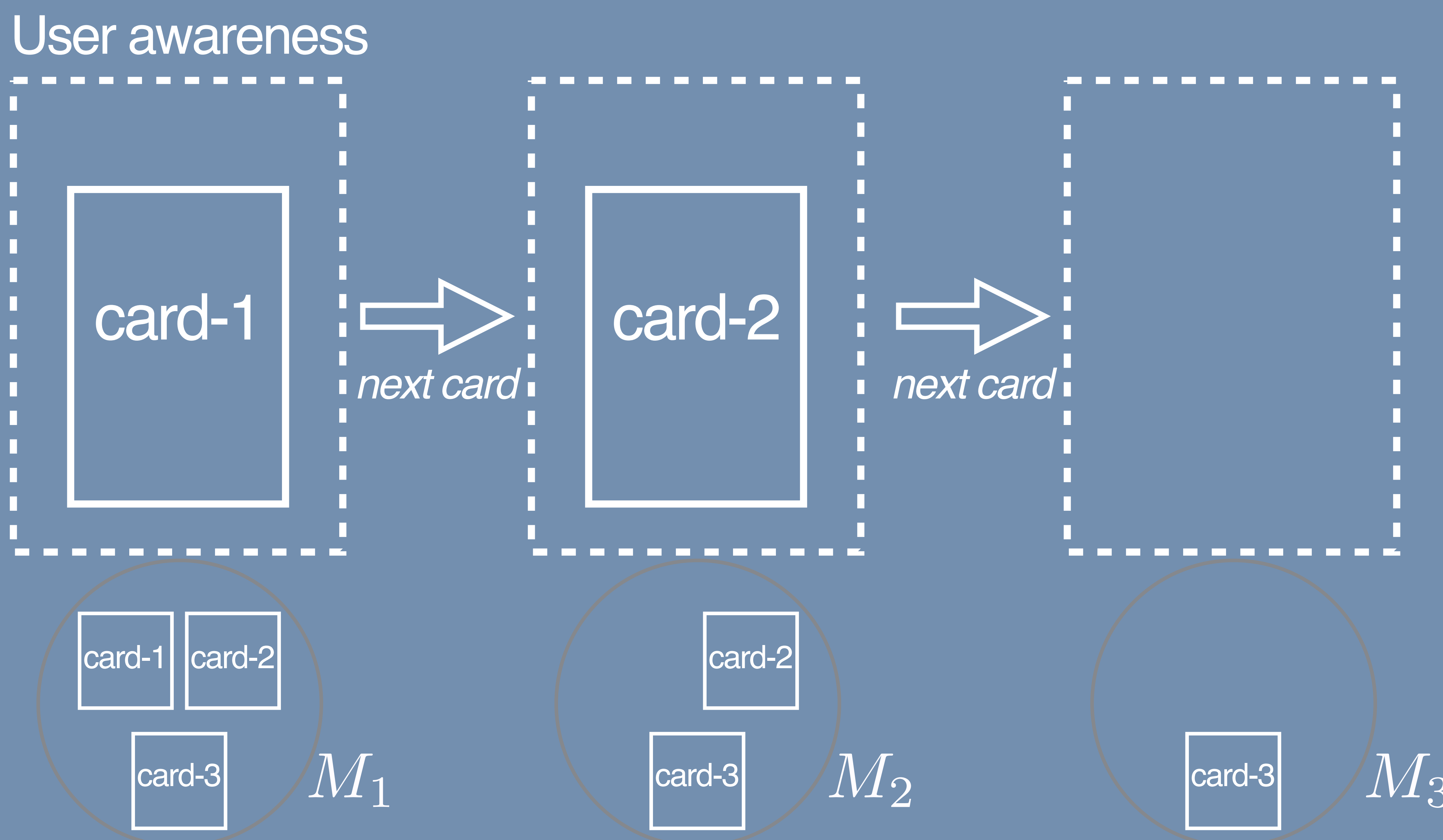

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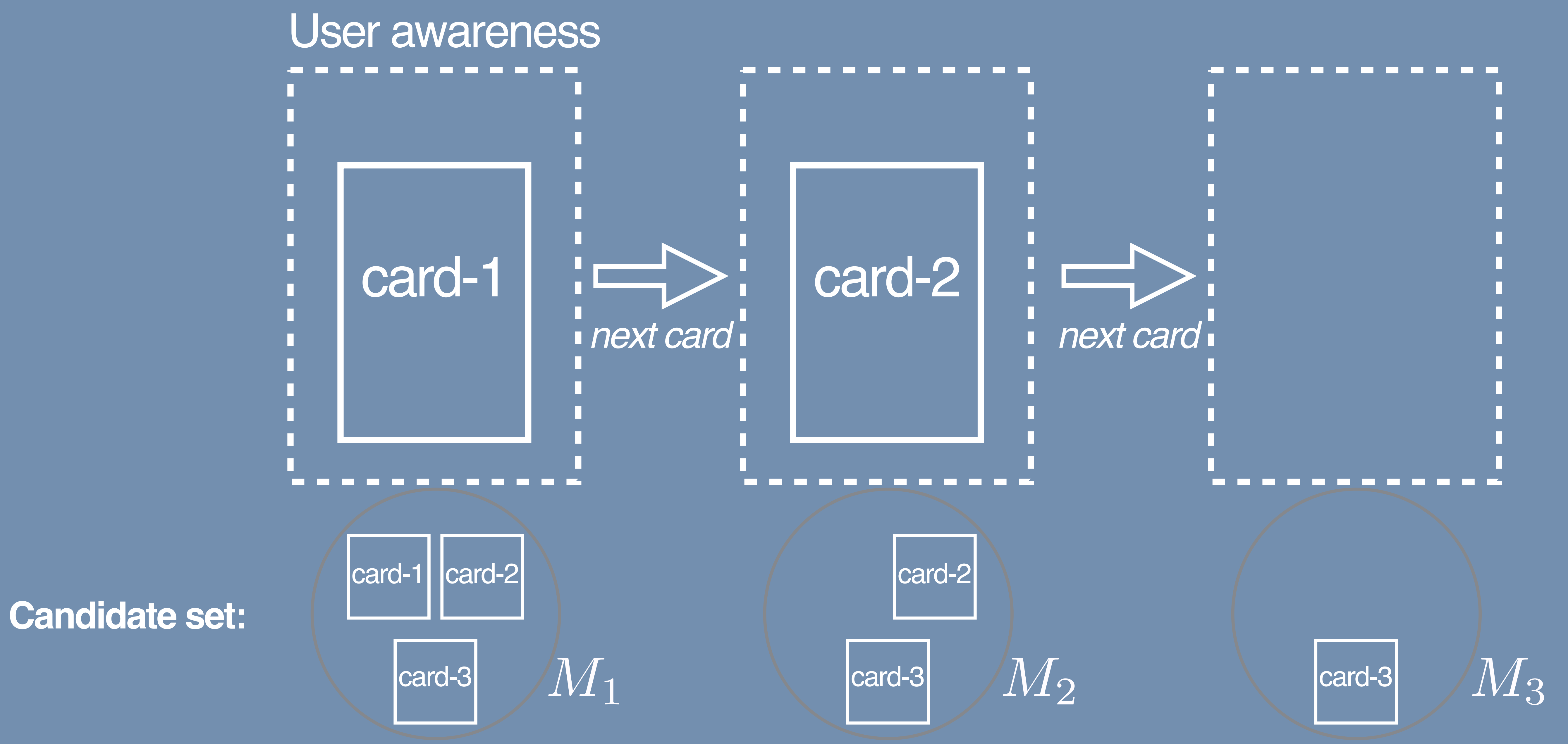

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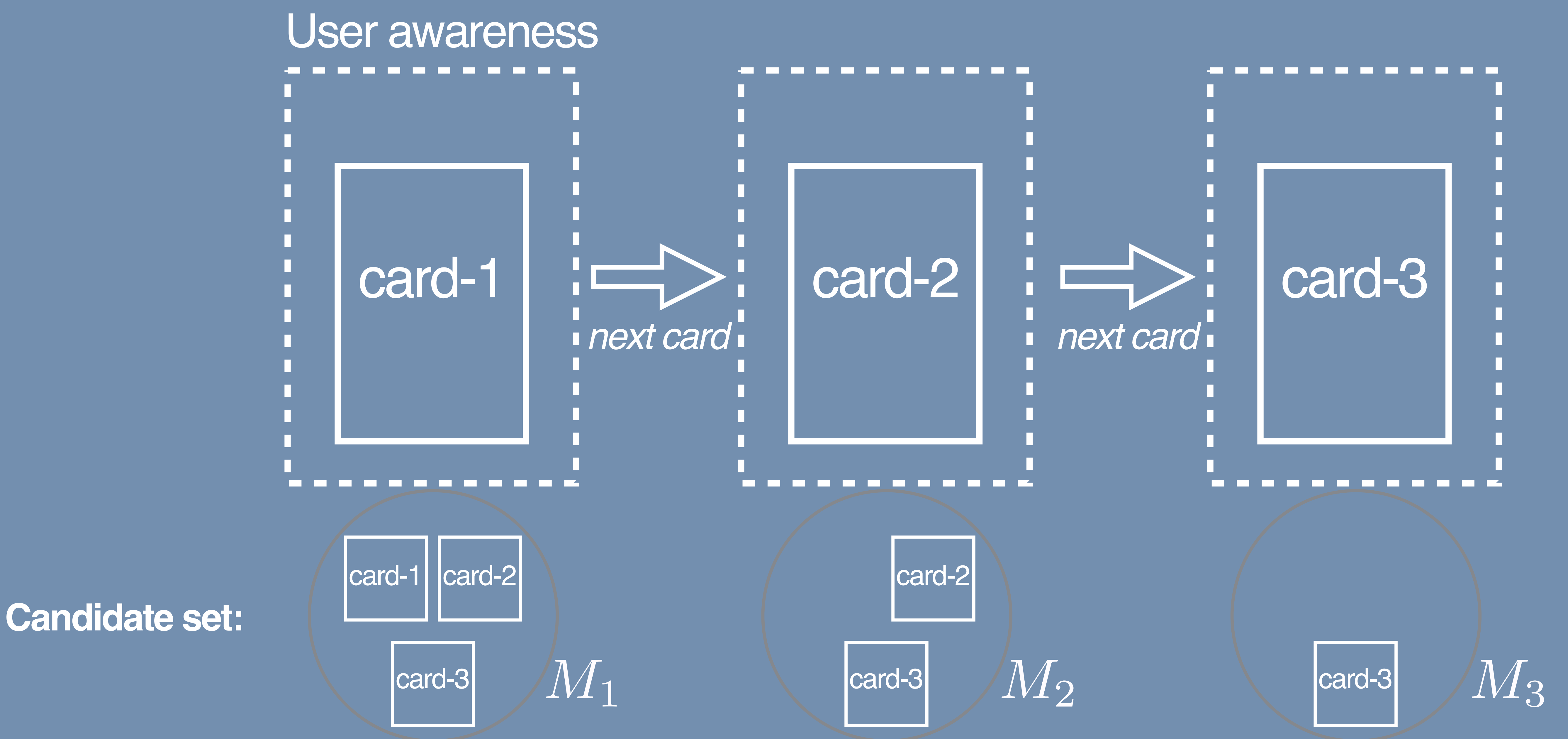

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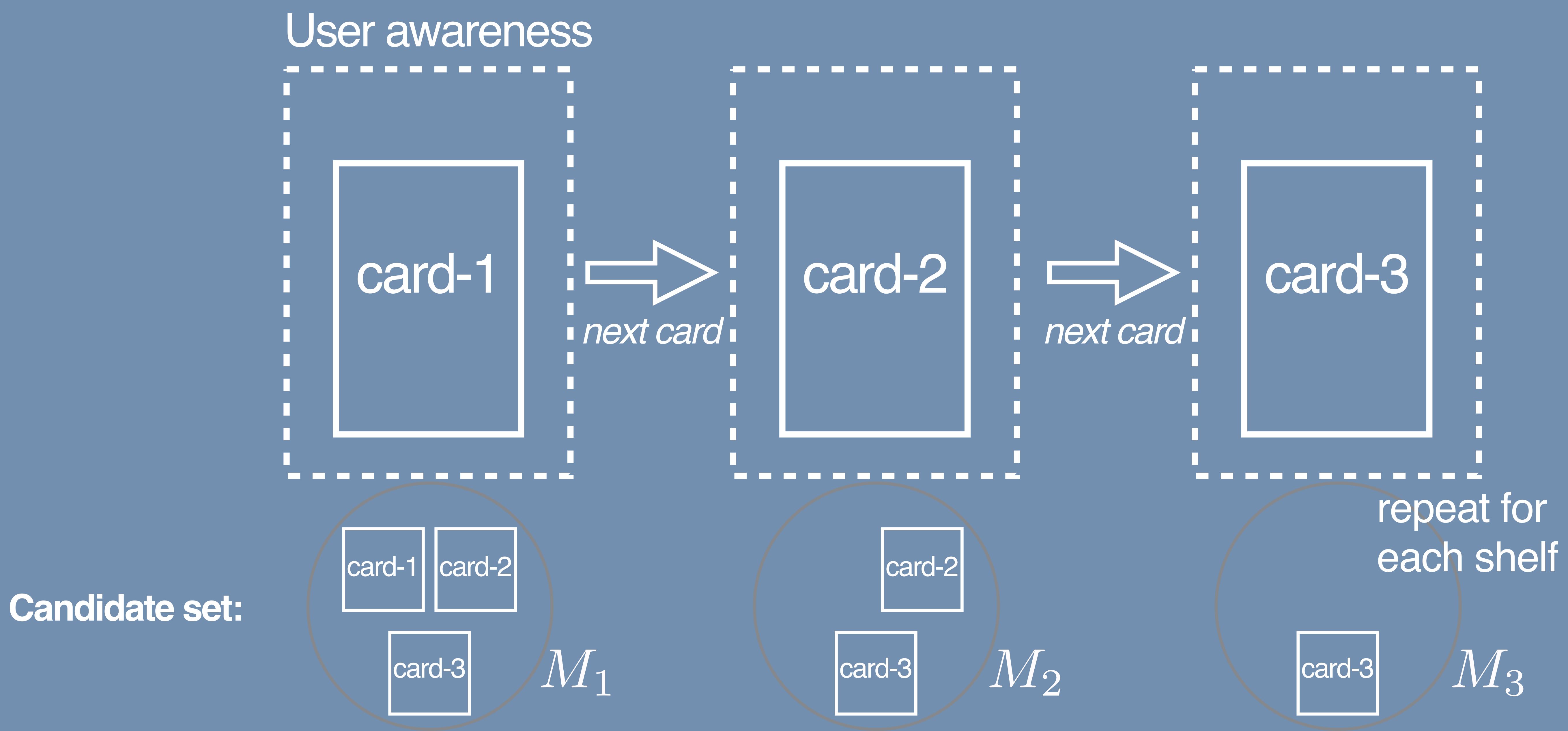
Horizontal scrolling



Action select: $\mathrm{card}_1 \sim \pi_{s,r}(M_1)$ $\mathrm{card}_2 \sim \pi_{s,r}(M_2)$ $\mathrm{card}_3 \sim \pi_{s,r}(M_3)$

Animation of ranking procedure with bandit

Vertical scrolling

User awareness

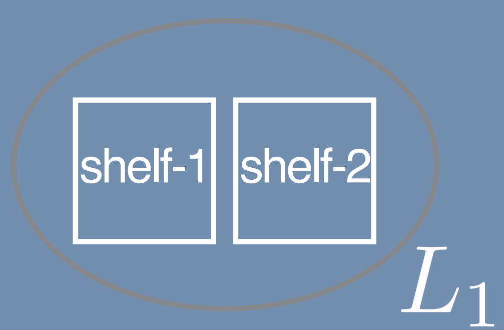
Animation of ranking procedure with bandit

Vertical scrolling

Animation of ranking procedure with bandit

Vertical scrolling

Candidate set



Action select

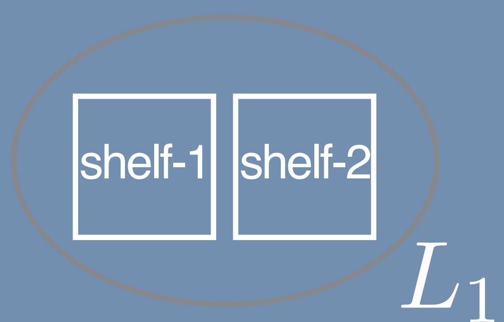
$$\text{shelf}_1 \sim \pi_{s,r'}(L_1)$$

User awareness

Animation of ranking procedure with bandit

Vertical scrolling

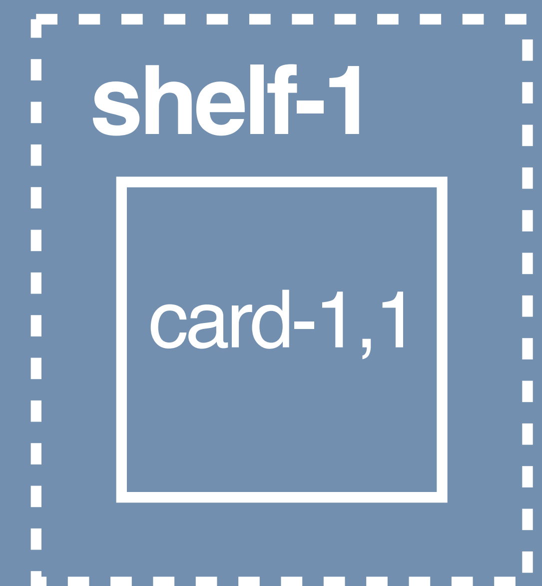
Candidate set



Action select

$$\text{shelf}_1 \sim \pi_{s,r'}(L_1)$$

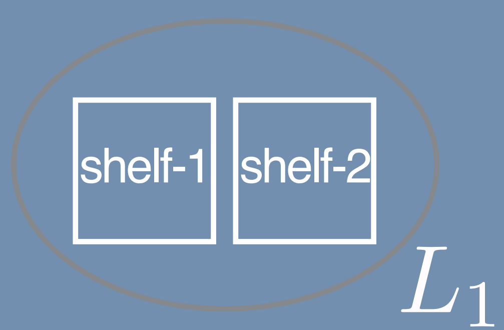
User awareness



Animation of ranking procedure with bandit

Vertical scrolling

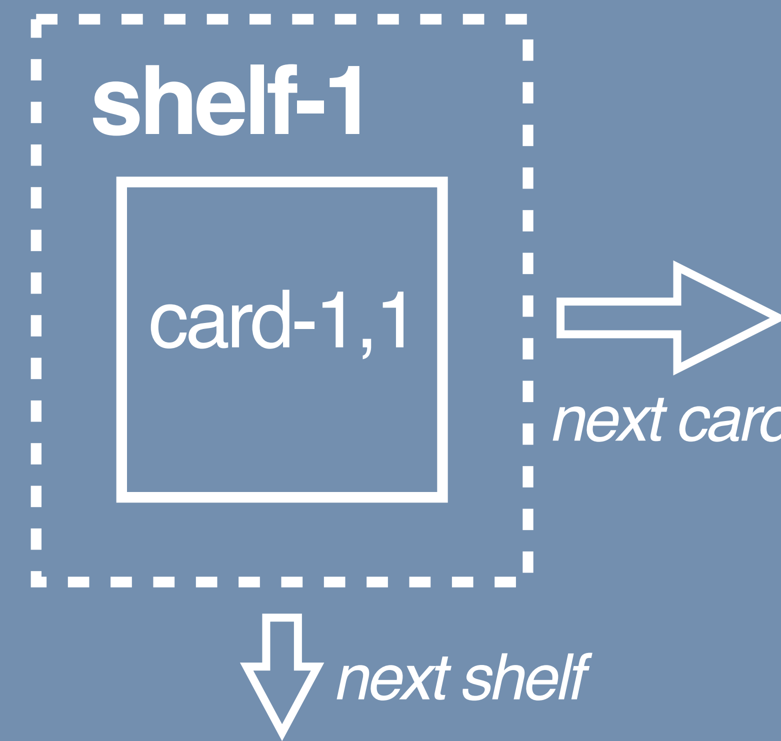
Candidate set



Action select

$$\mathrm{shelf}_1 \sim \pi_{s,r'}(L_1)$$

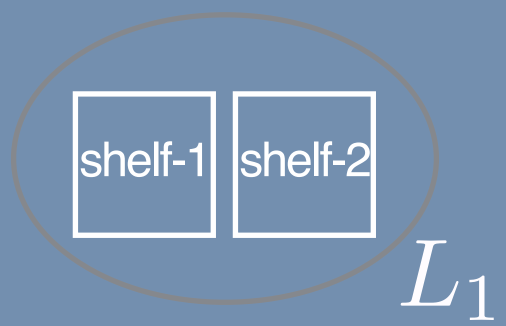
User awareness



Animation of ranking procedure with bandit

Vertical scrolling

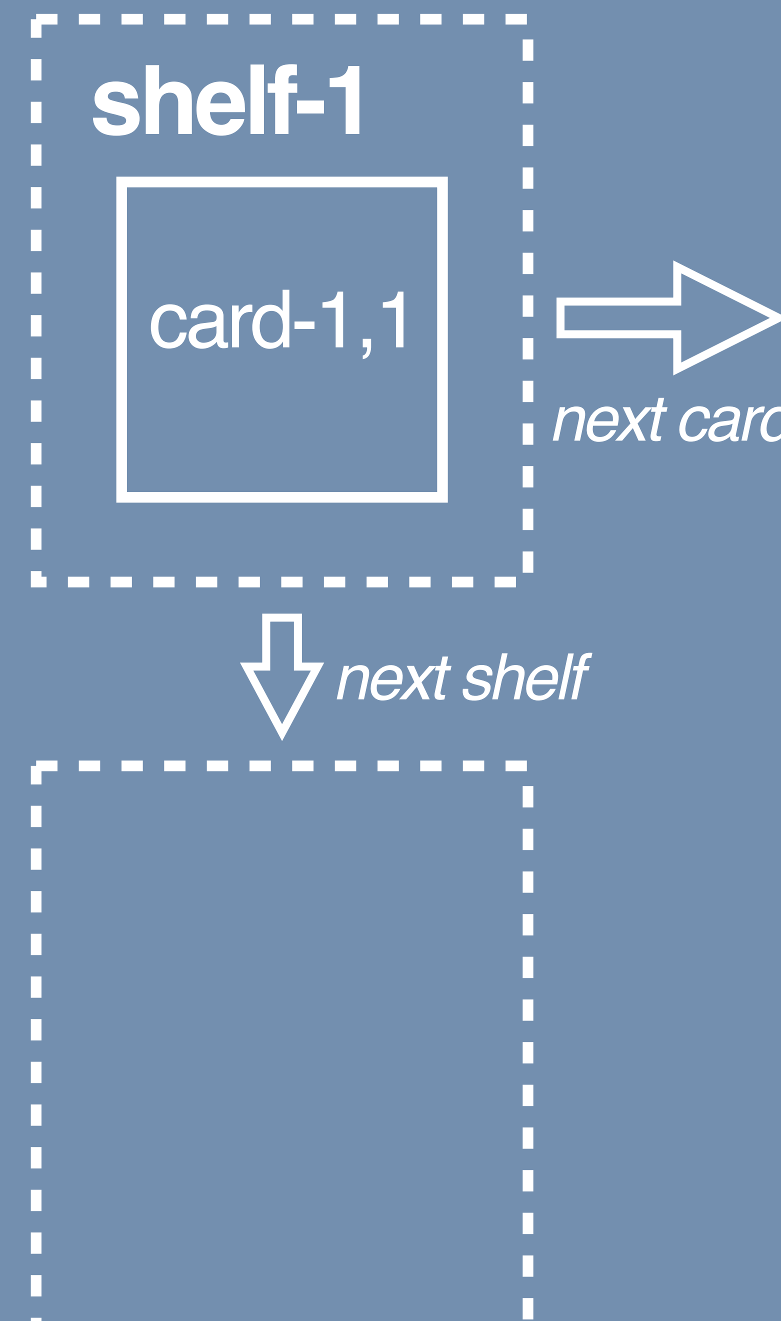
Candidate set



Action select

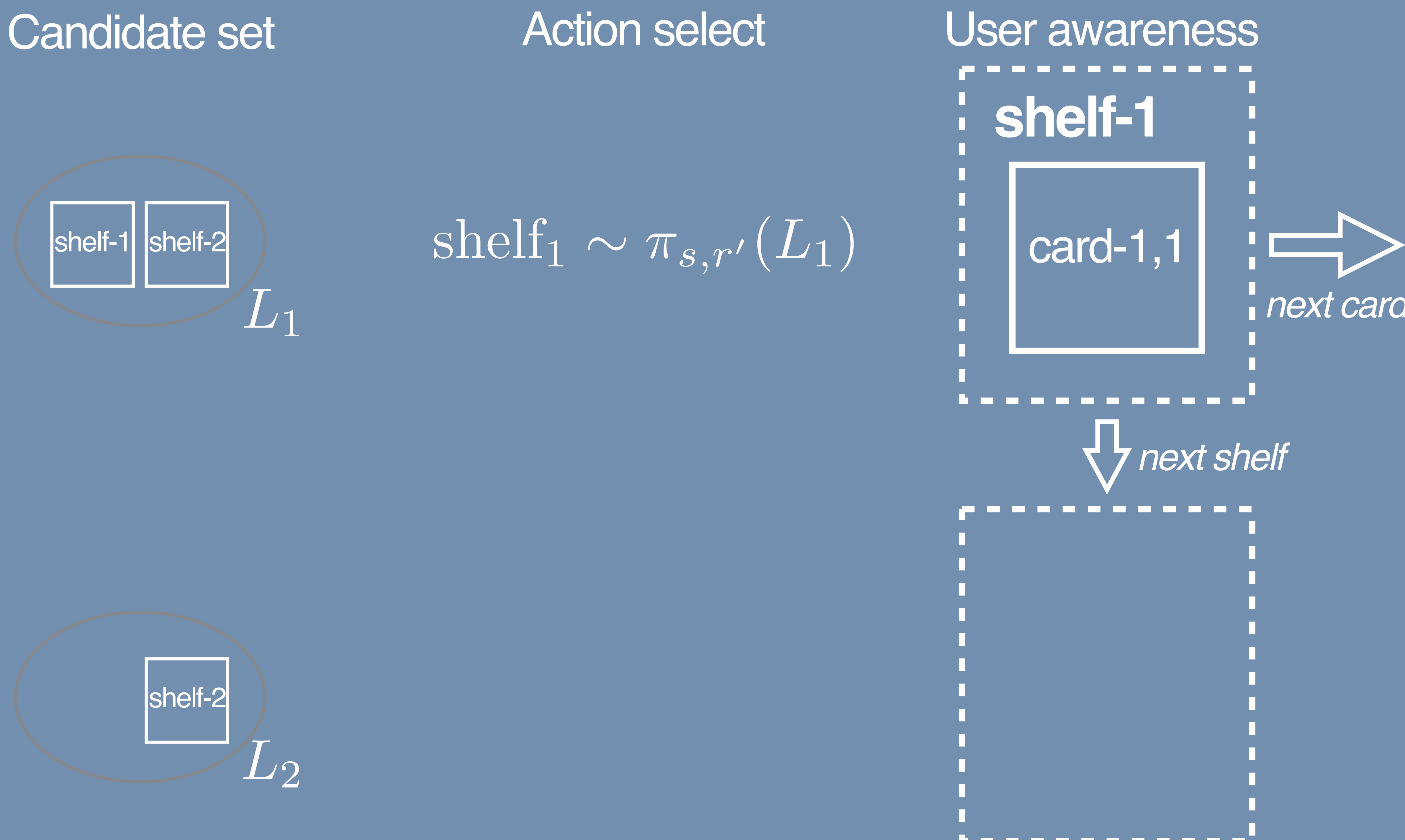
$$\text{shelf}_1 \sim \pi_{s,r'}(L_1)$$

User awareness



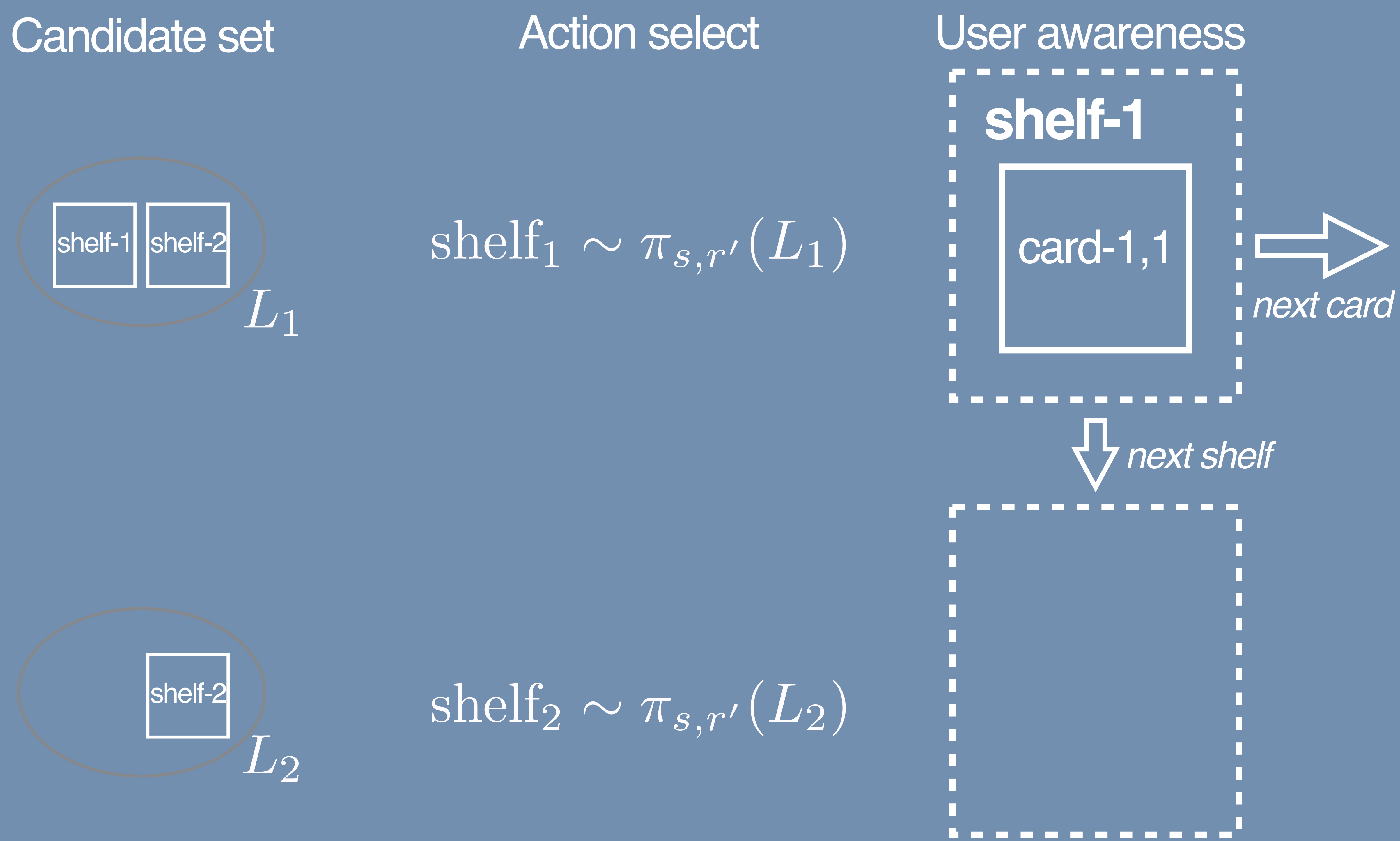
Animation of ranking procedure with bandit

Vertical scrolling



Animation of ranking procedure with bandit

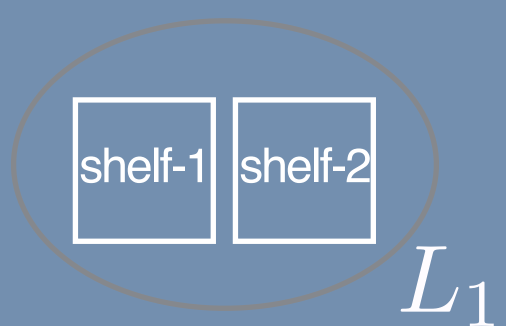
Vertical scrolling



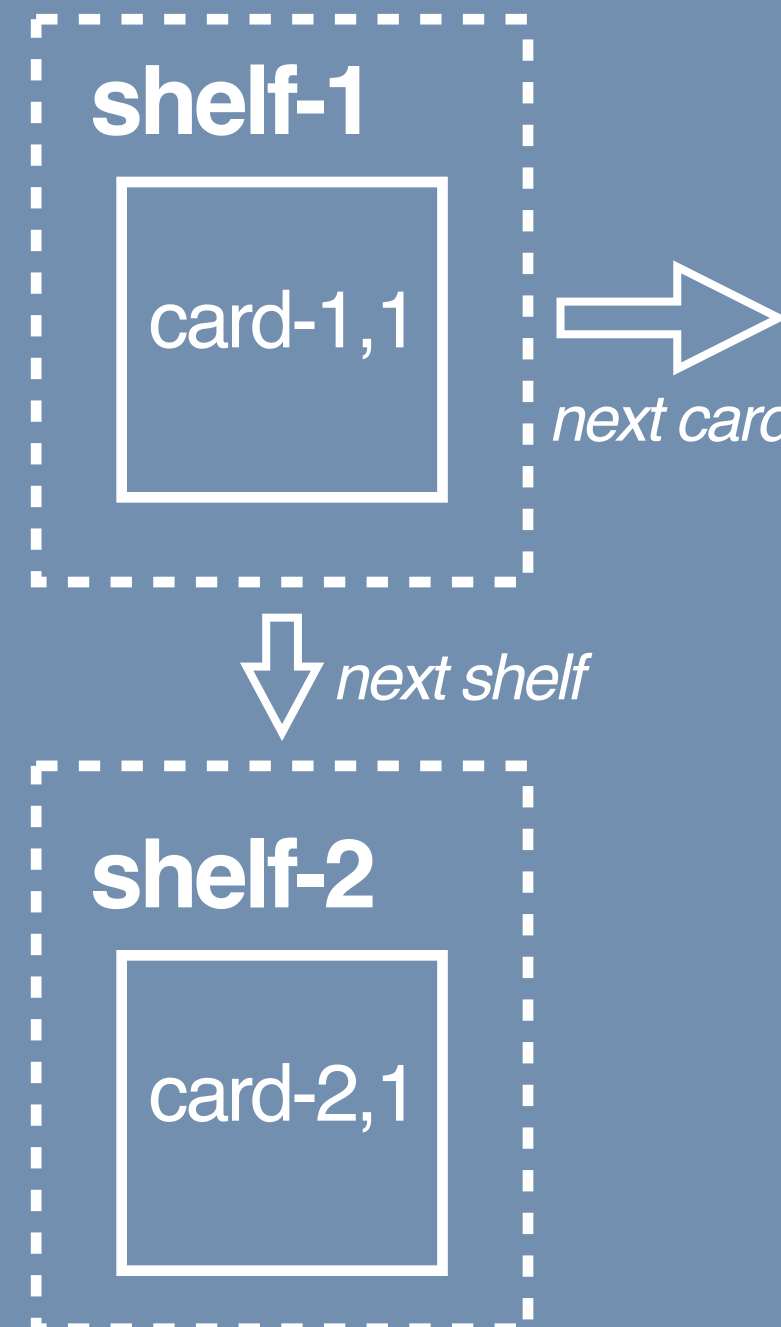
Animation of ranking procedure with bandit

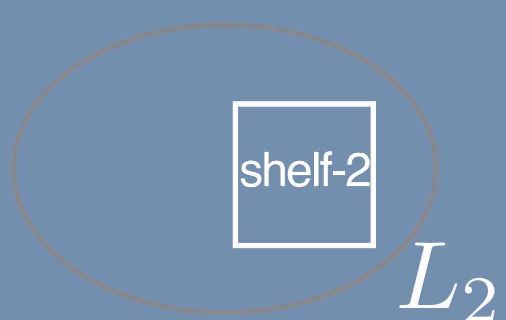
Vertical scrolling

Candidate set | Action select | User awareness



$$\text{shelf}_1 \sim \pi_{s,r'}(L_1)$$

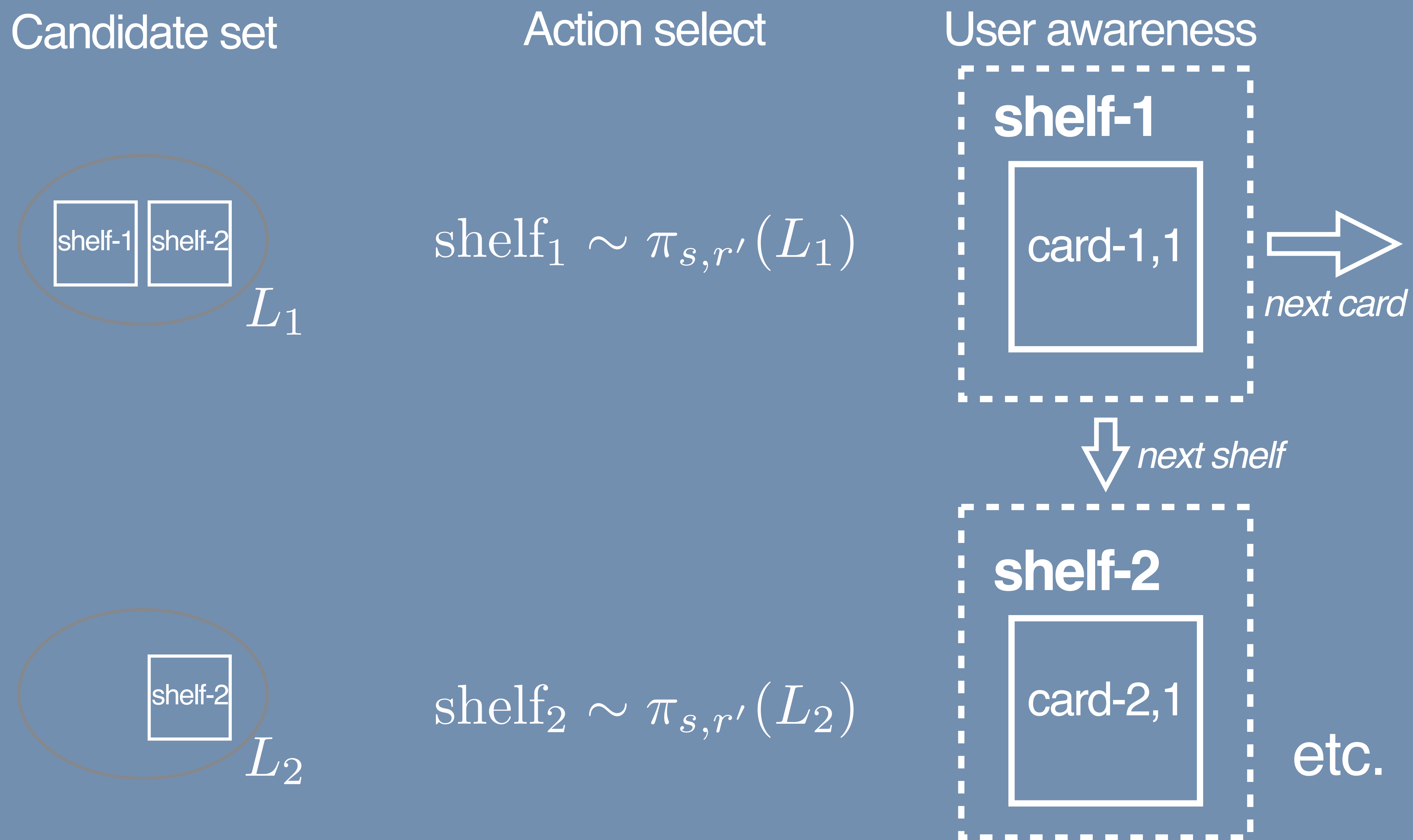




$$\text{shelf}_2 \sim \pi_{s,r'}(L_2)$$

Animation of ranking procedure with bandit

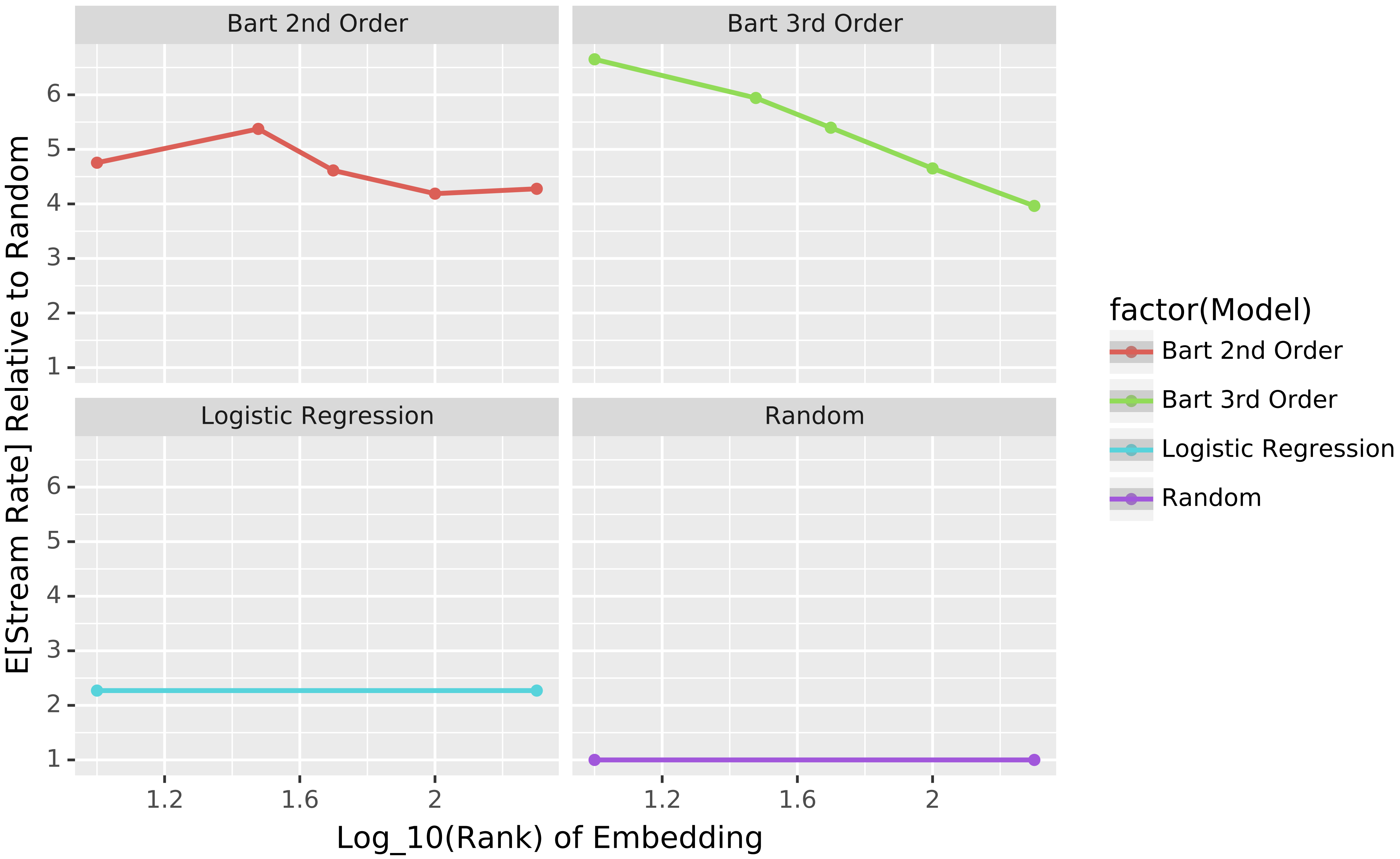
Vertical scrolling



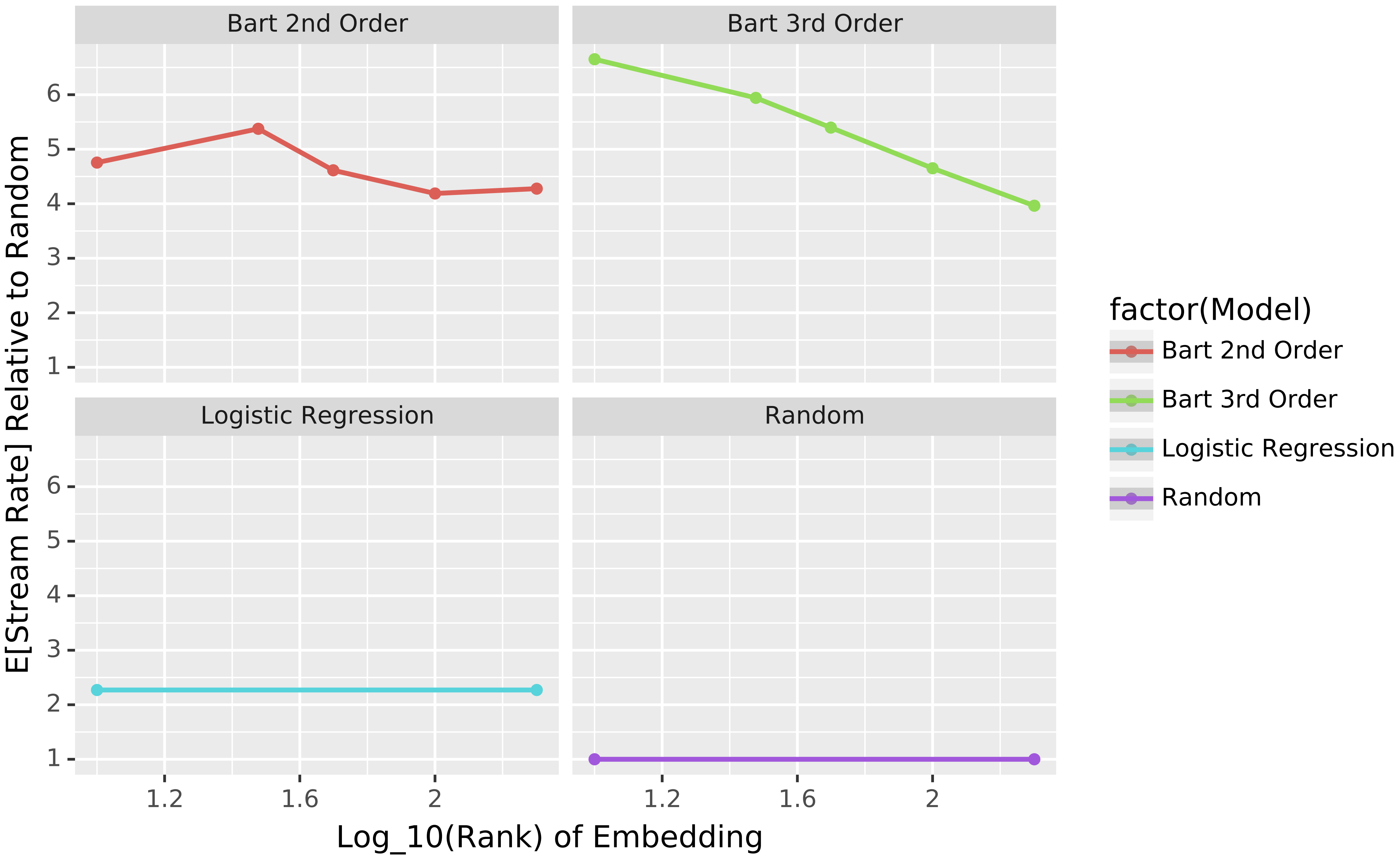
Experimental evaluation

- we collected randomized recommendation data
- offline experiments:
    - counterfactual estimation of A/B test performance using importance sampling reweighting
- online A/B test experiments

Offline experiments

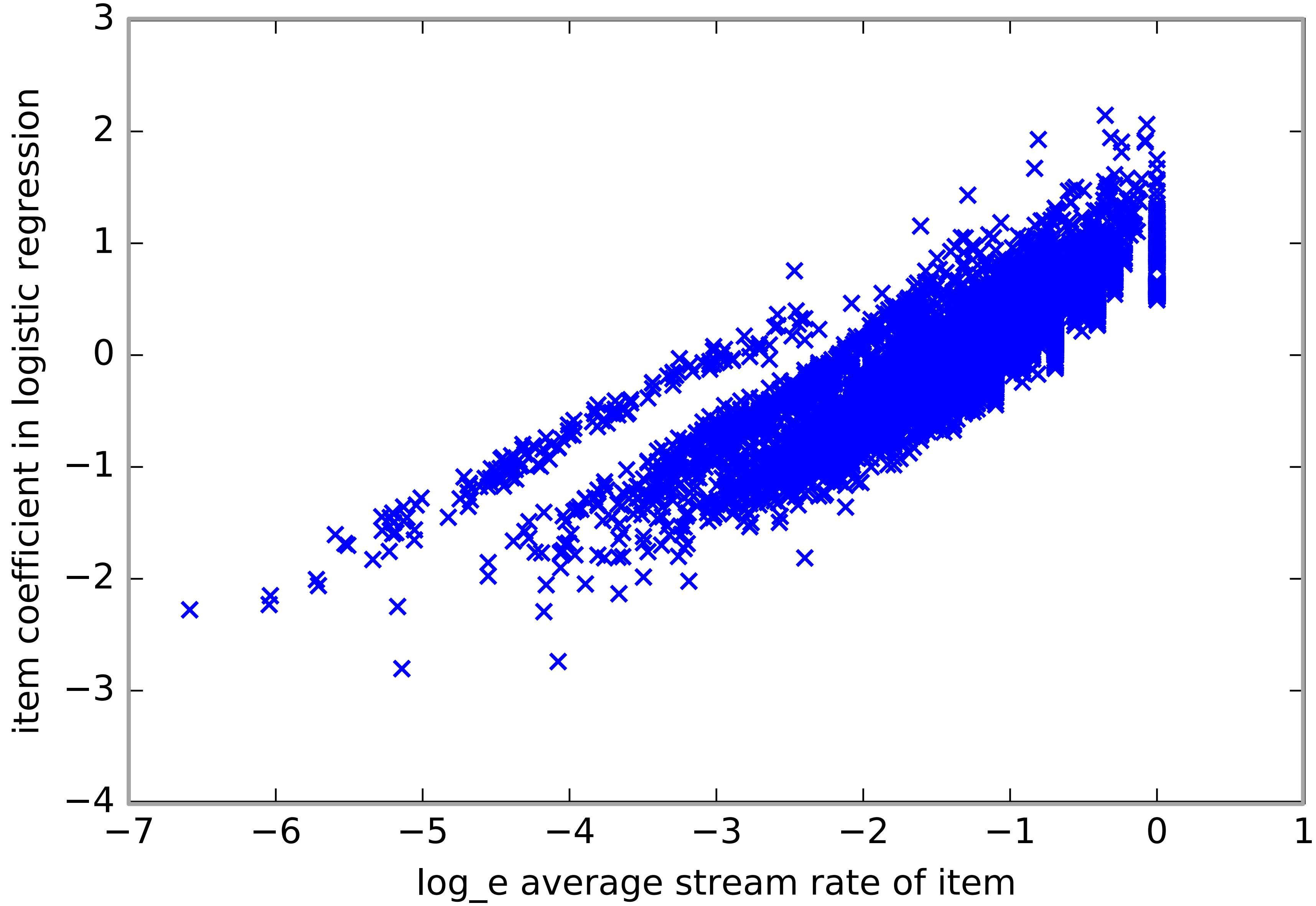


Offline experiments

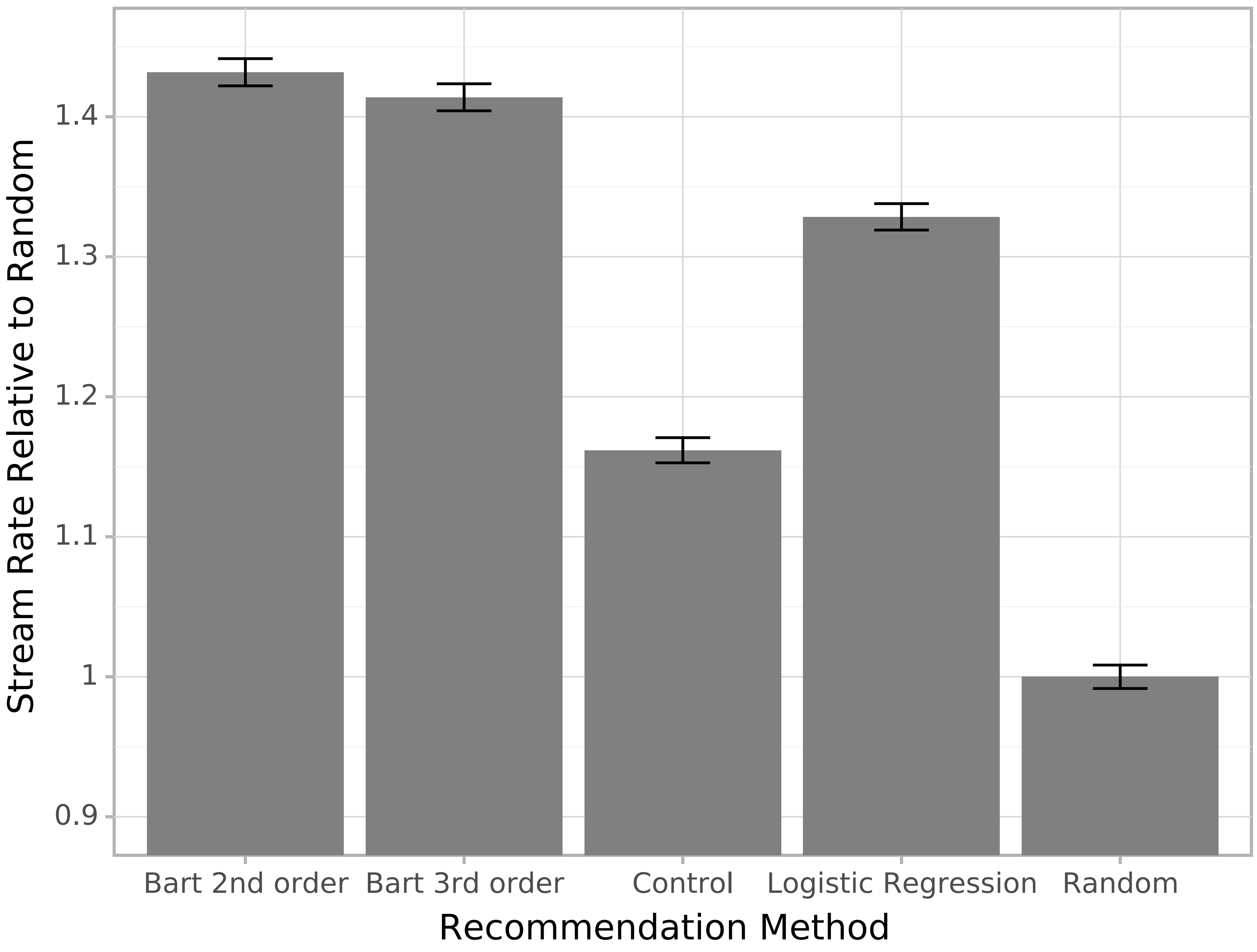


(similar conclusions as NDCG@10 for the metric)

Offline experiments



Online A/B test



Bart limitations and future work

- user preference model:
  - assumes independence of impression outcomes
  - attempts to estimate absolute reward, competitive pairwise model might improve predictions
  - maximizes our defined reward, does it approximate user satisfaction?
- ranking model not defined to promote diversity, slate recommendation could be incorporated
- exploration-exploitation over a <u>candidate set</u> not the full item set

Thank you, any questions?

email: jamesm@spotify.com