Personalized Transaction Kernels for Recommendation using MCTS

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Kassel, 25.09.2019

Outline

- Introduction and motivation
- Personalized transaction kernels
- Informed sampling strategies
- Empirical study
- Summary and Conclusions

Recommender Systems

- A user views the following item:

Goal: recommend an item(s) that is relevant to the user

Task: capture/understand the interests of users

Traditional Approaches

Collaborative filtering (Resnick et al., 1994): based on collecting information from many users

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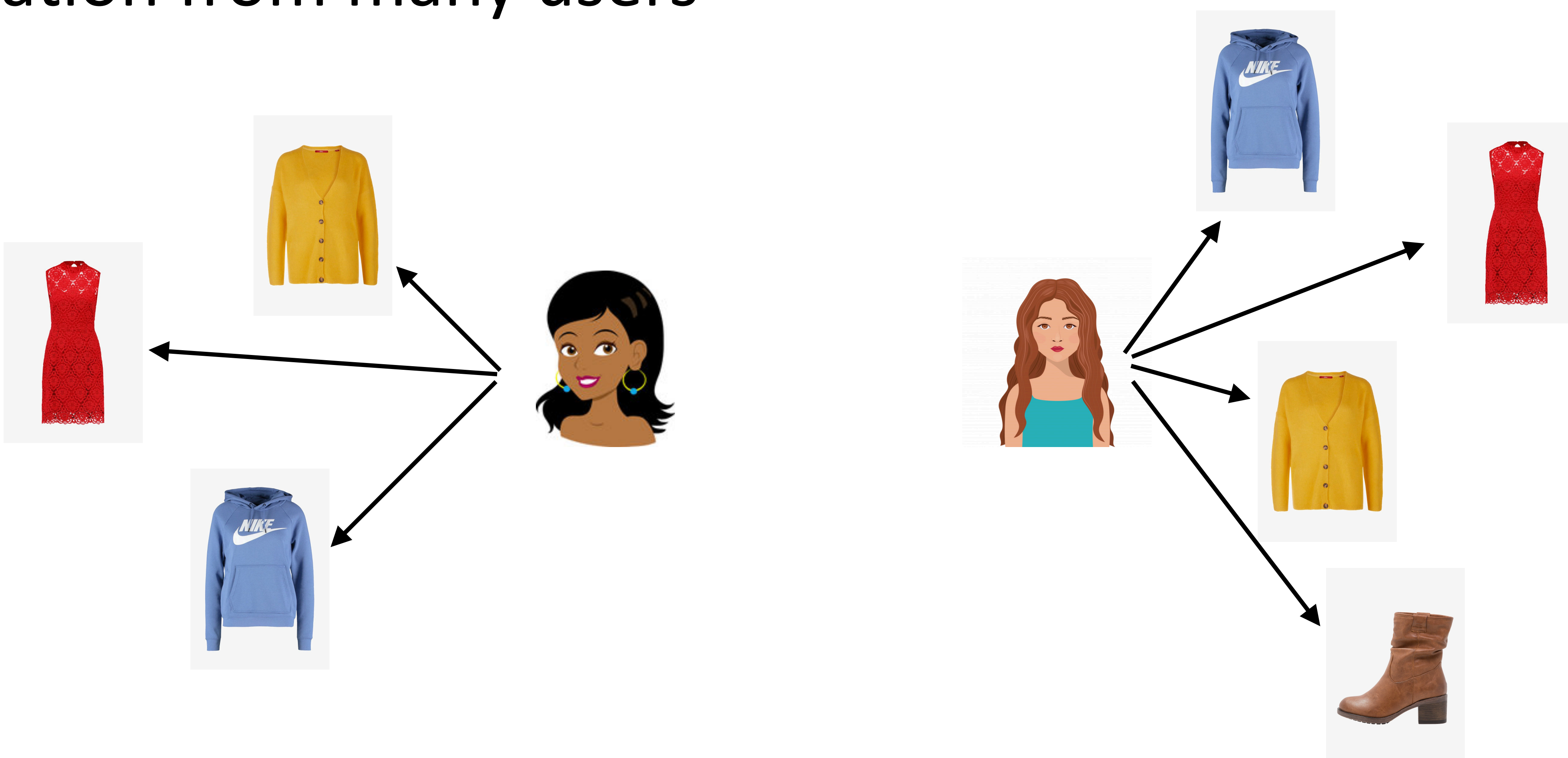

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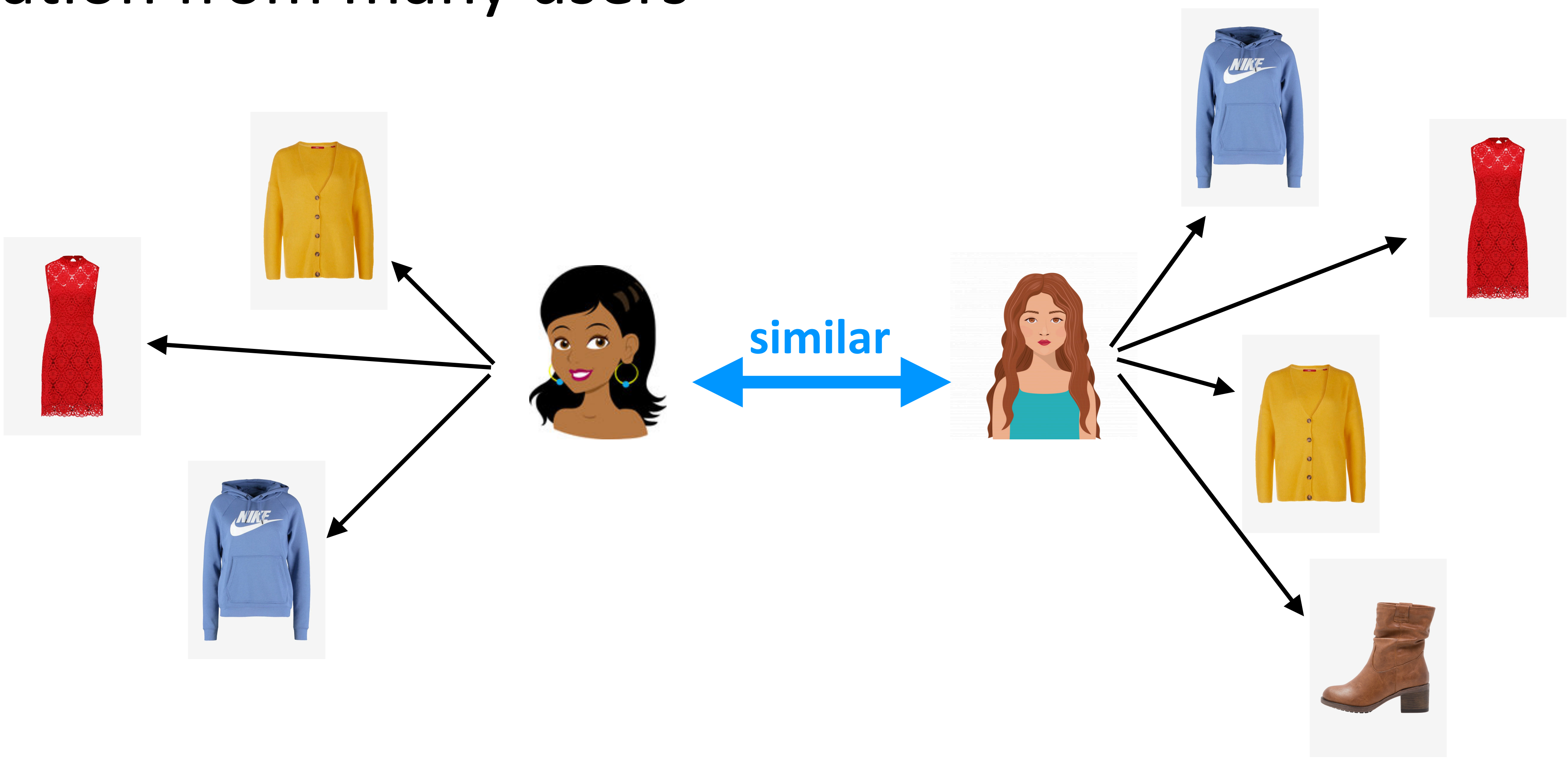

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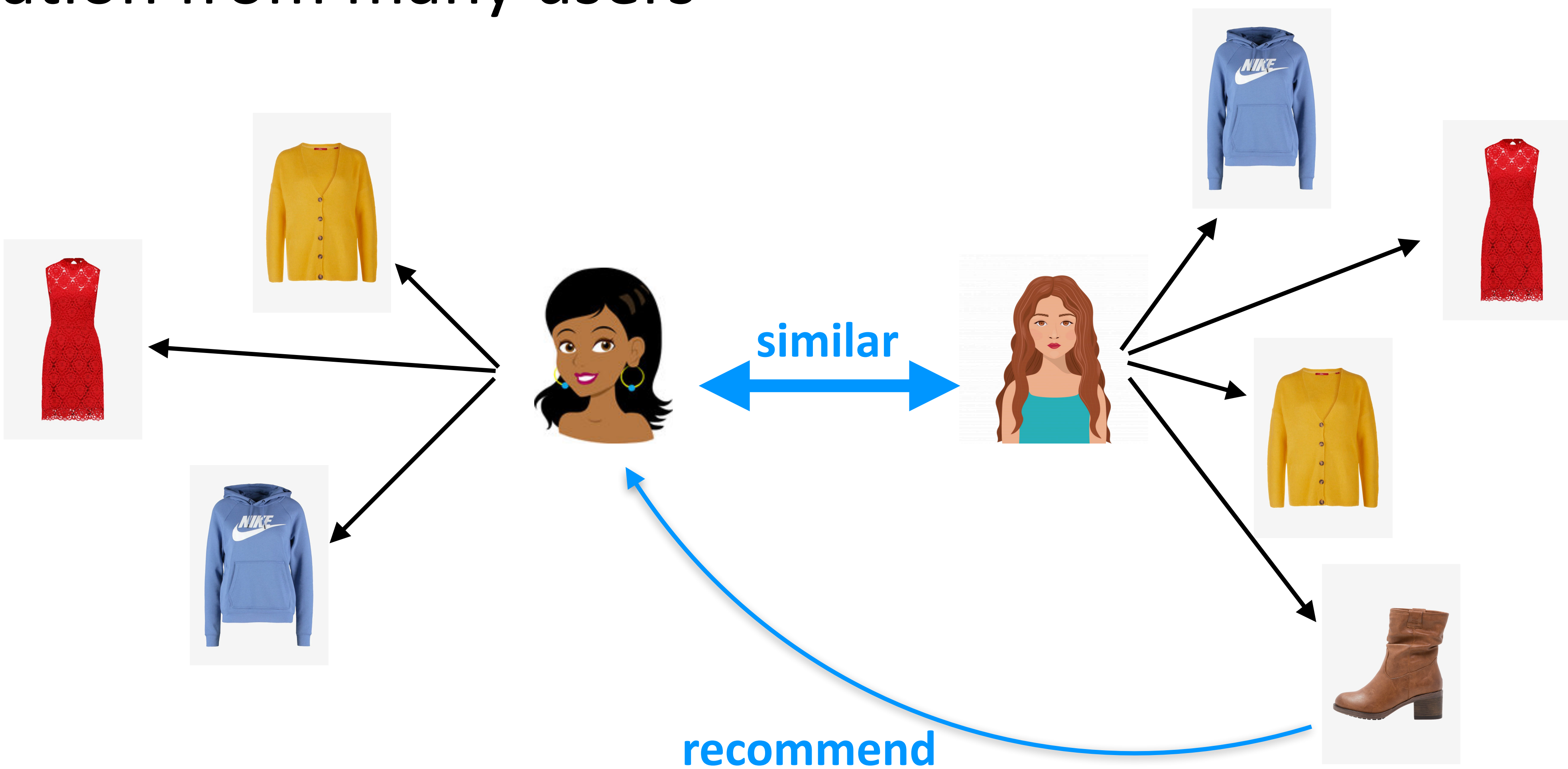

Shortcomings

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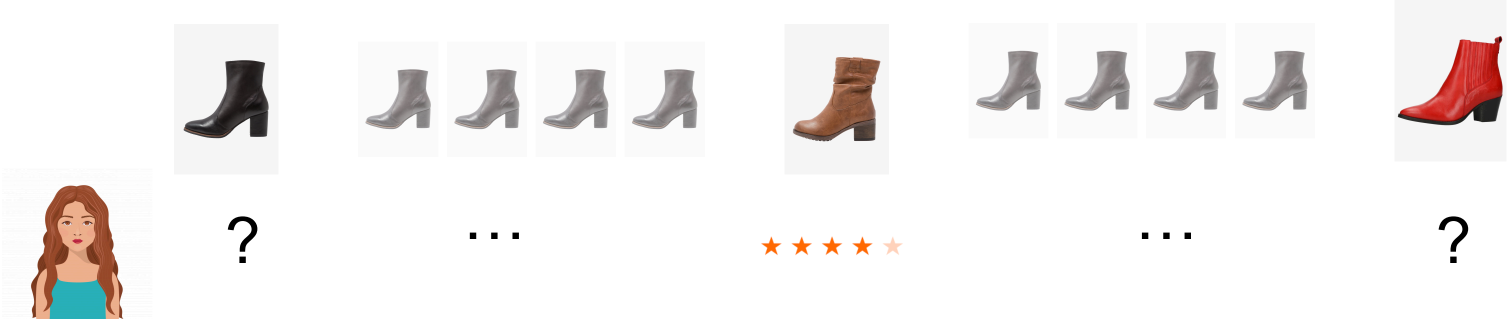

Shortcomings

- Operates with explicit feedback
- Computationally expensive for large-scale problems
- Does not cope with data sparsity
- Fails in cold-start problem

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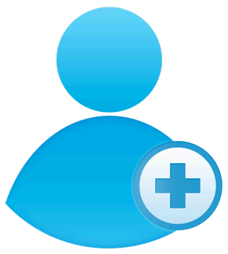

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Filling the Gap

- Explicit feedback → **preference-based feedback**
- Computational complexity:
  - Users (personalization) → **efficient multi-task learning**
  - Items (online recommendation) → **informed search**
- Data sparsity → **contextual model**
- Cold-start problem → **contextual model**

Qualitative Feedback

A user views the following item:

Qualitative Feedback

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recommended items:

Qualitative Feedback

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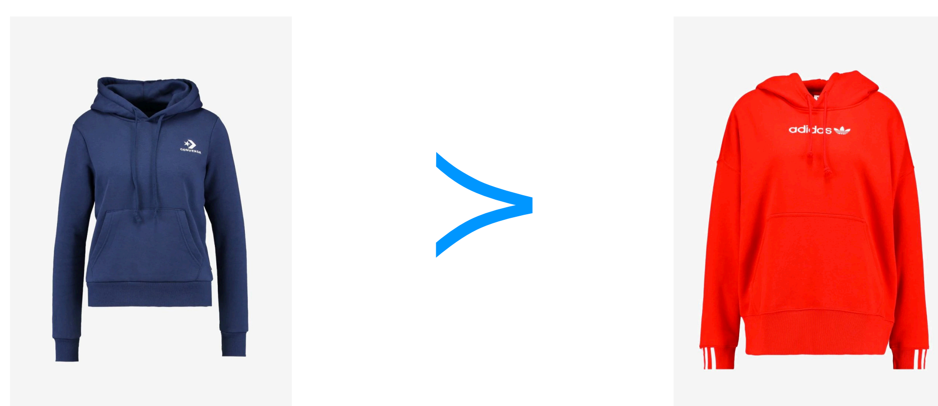

Main Contributions

- An **efficient** preference model is proposed for recommendation with qualitative feedback

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contextual model: tensor product

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online recommendation: bandit-based search tree

personalized transaction kernel

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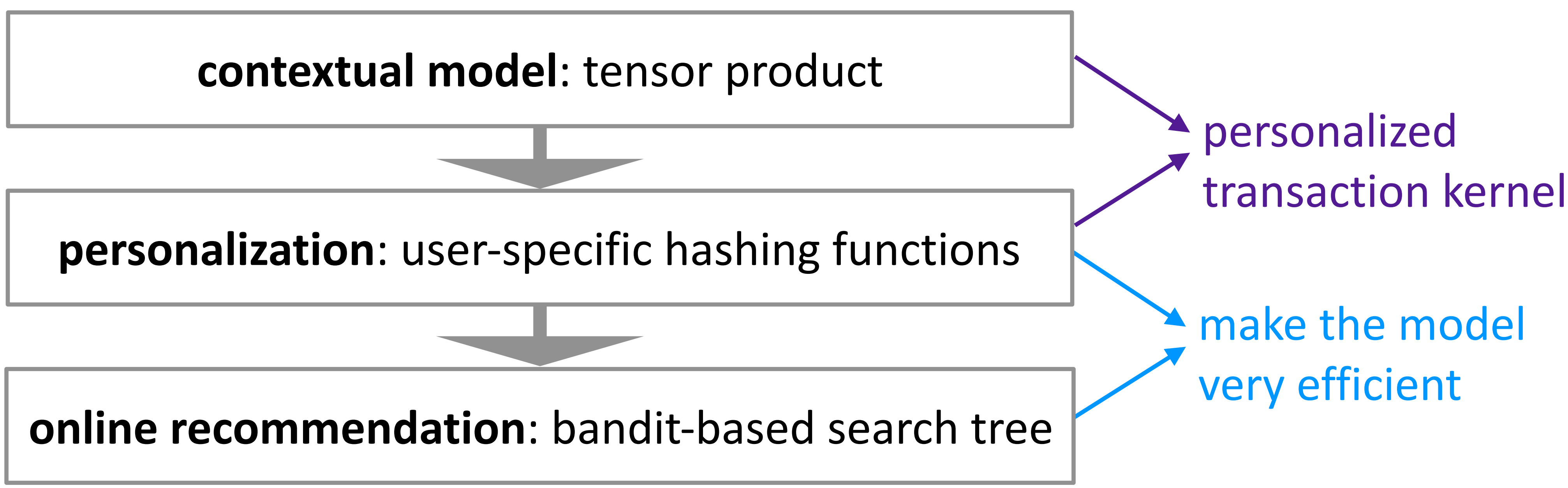

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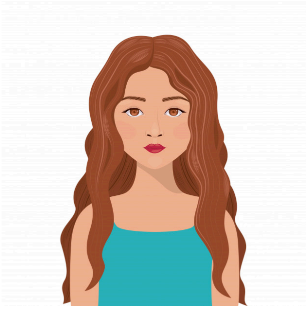
The Preference Model

The Preference Model

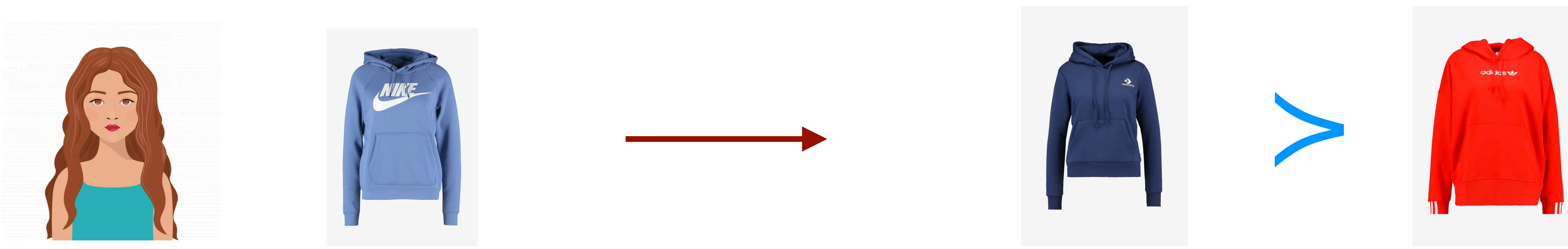
user



context

The Preference Model

user | context | pairwise preference



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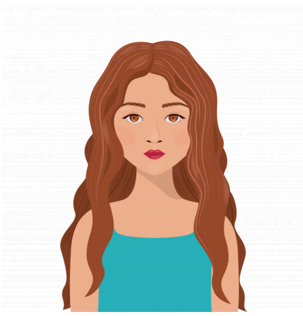

u

context

$\mathbf{s}_t$

pairwise preference

 $\succ$ 

$\mathbf{x}_i \succ \mathbf{x}_j$

$$\boxed{f(\mathbf{x}_i | u, \mathbf{s}_t) \succ f(\mathbf{x}_j | u, \mathbf{s}_t)}$$

The Preference Model

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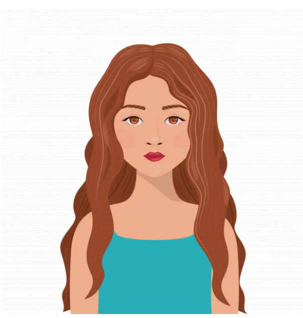

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using standard SVM method:
(Joachims, 2002)

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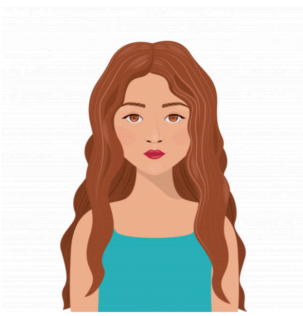

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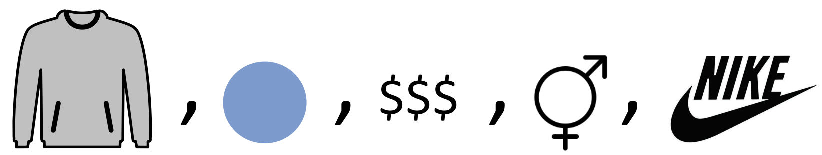
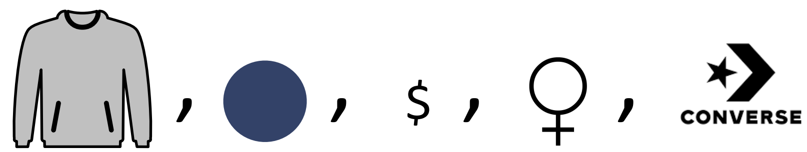
kernel function

Tensor Kernels

- context: 

- item: 

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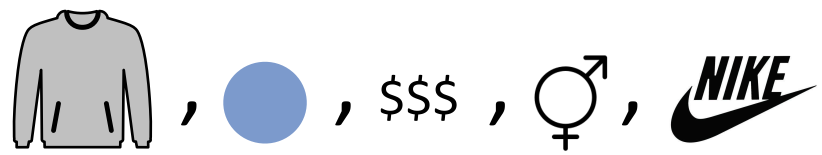
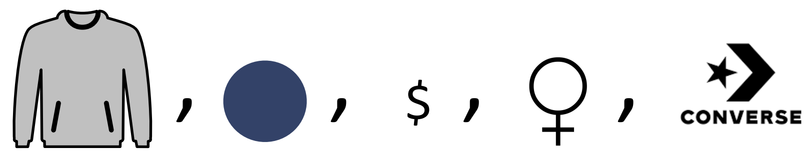
- context: 

- item: 

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Tensor Kernels

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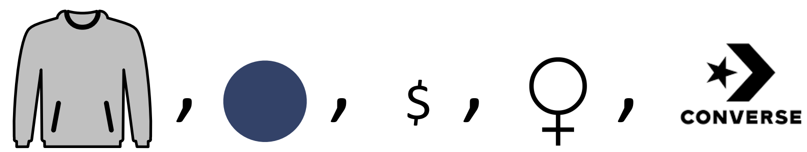
- item: 

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$$\left\langle \{\mathbf{x}^1 \otimes \ldots \otimes \mathbf{x}^m\}, \{\mathbf{z}^1 \otimes \ldots \otimes \mathbf{z}^m\} \right\rangle = \prod_{k=1}^{m} \langle \mathbf{x}^k, \mathbf{z}^k \rangle$$

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- Using different hashing functions for users:
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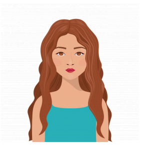 $\otimes$ context $\otimes$ item

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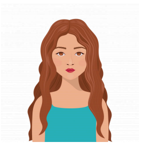 $\otimes$ context $\otimes$ item

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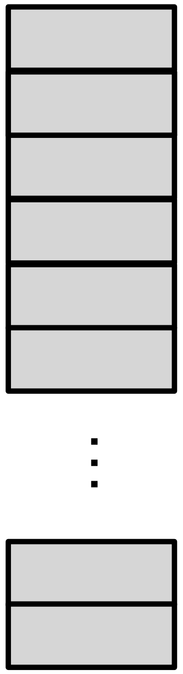

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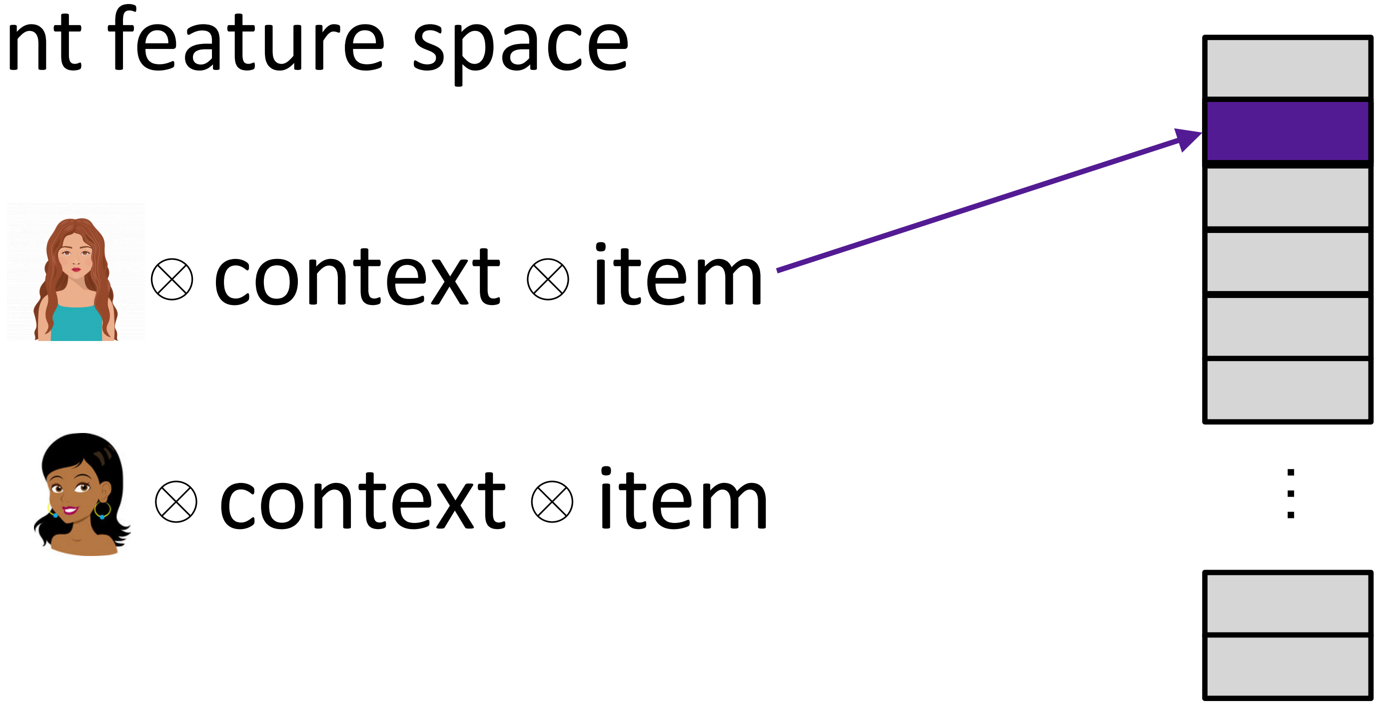

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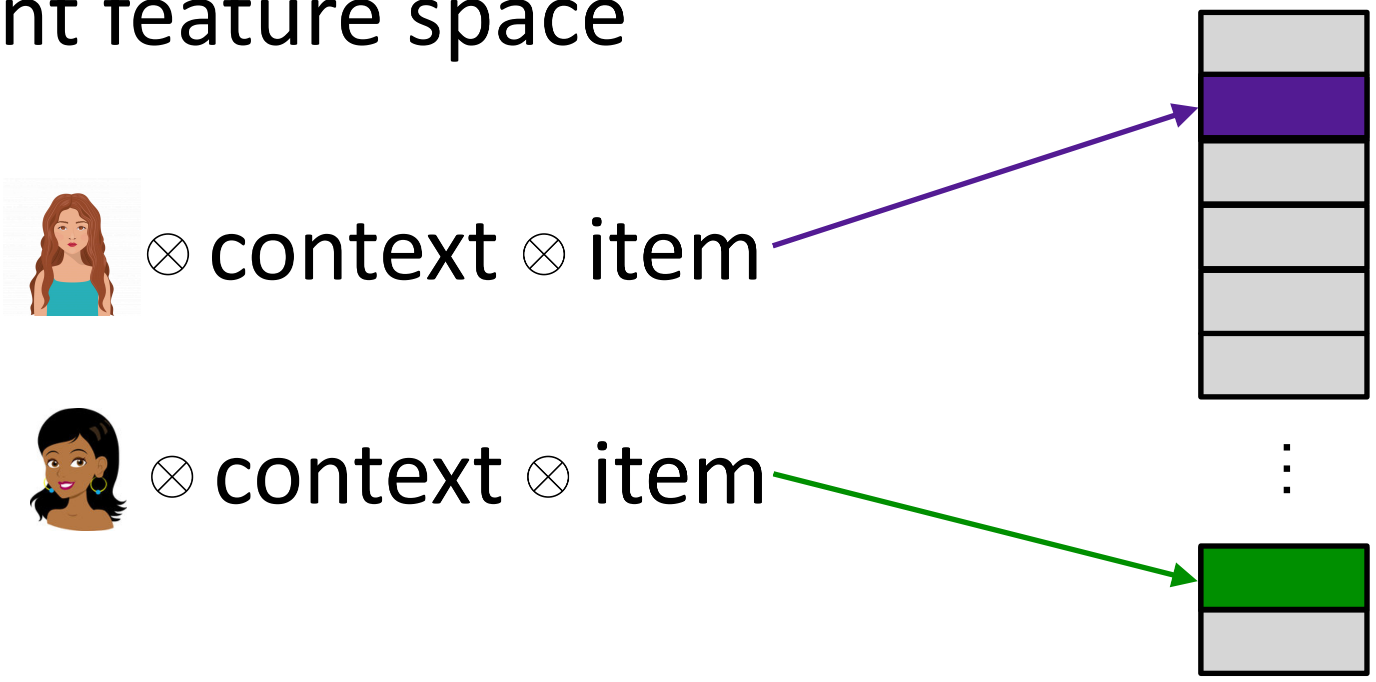

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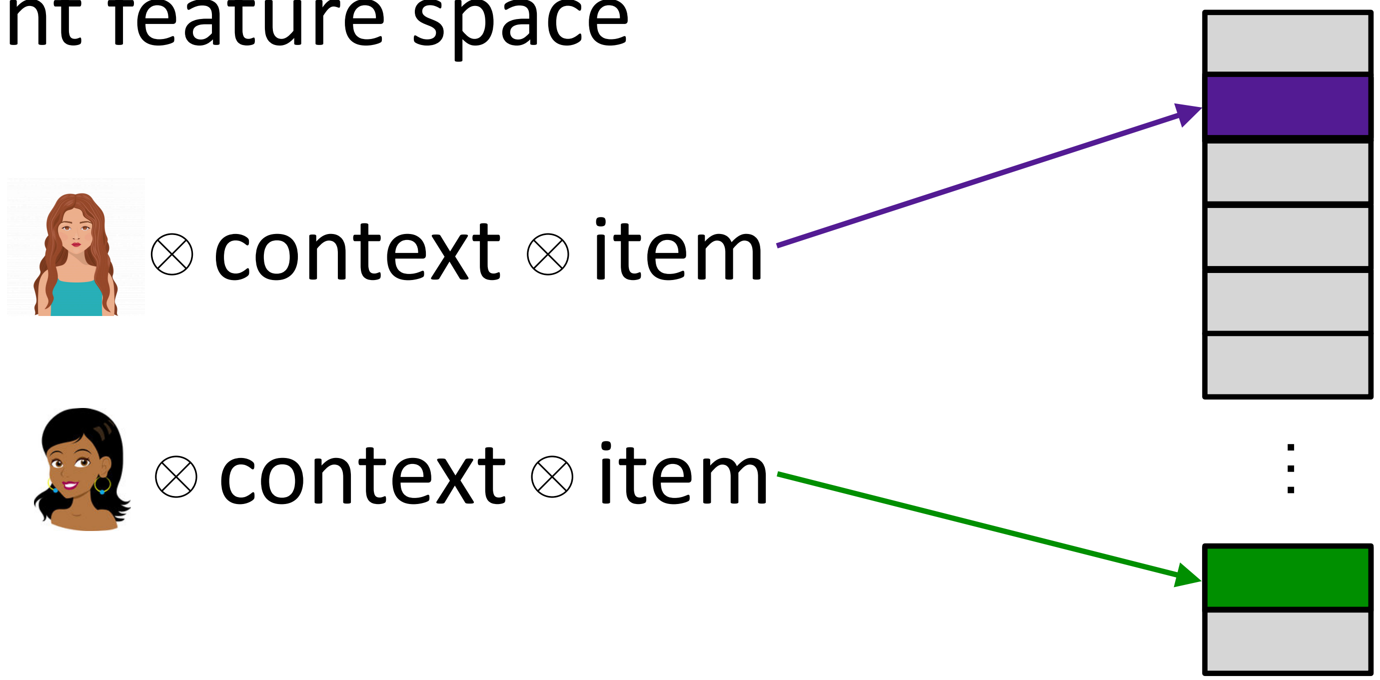

The interaction between random subspaces is negligible with high probability

(Weinberger, 2009)

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$$k(\mathbf{x}_i \succ \mathbf{x}_i', \mathbf{x}_j \succ \mathbf{x}_j') =$$

$$k^{pc}(\mathbf{x}_i, \mathbf{x}_j) - k^{pc}(\mathbf{x}_i, \mathbf{x}_j') - k^{pc}(\mathbf{x}_i', \mathbf{x}_j) + k^{pc}(\mathbf{x}_i', \mathbf{x}_j')$$

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Online Recommendation

- How to find the *best* product to recommend?
- Given the preference model:
  - enumerate over all available items
  - compute their utility for a given user and context
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too costly

Informed Sampling

- Smarten the search to approximate the (near-) optimal product
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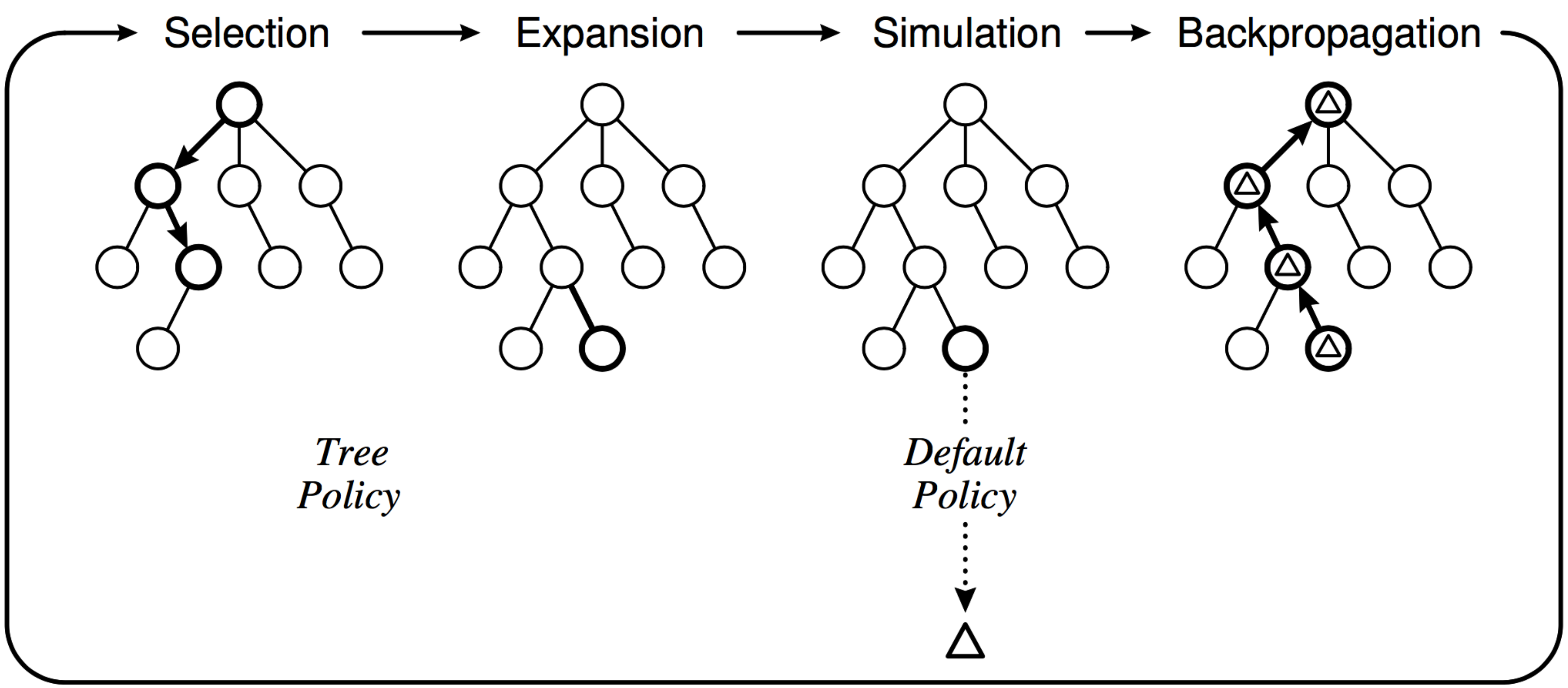

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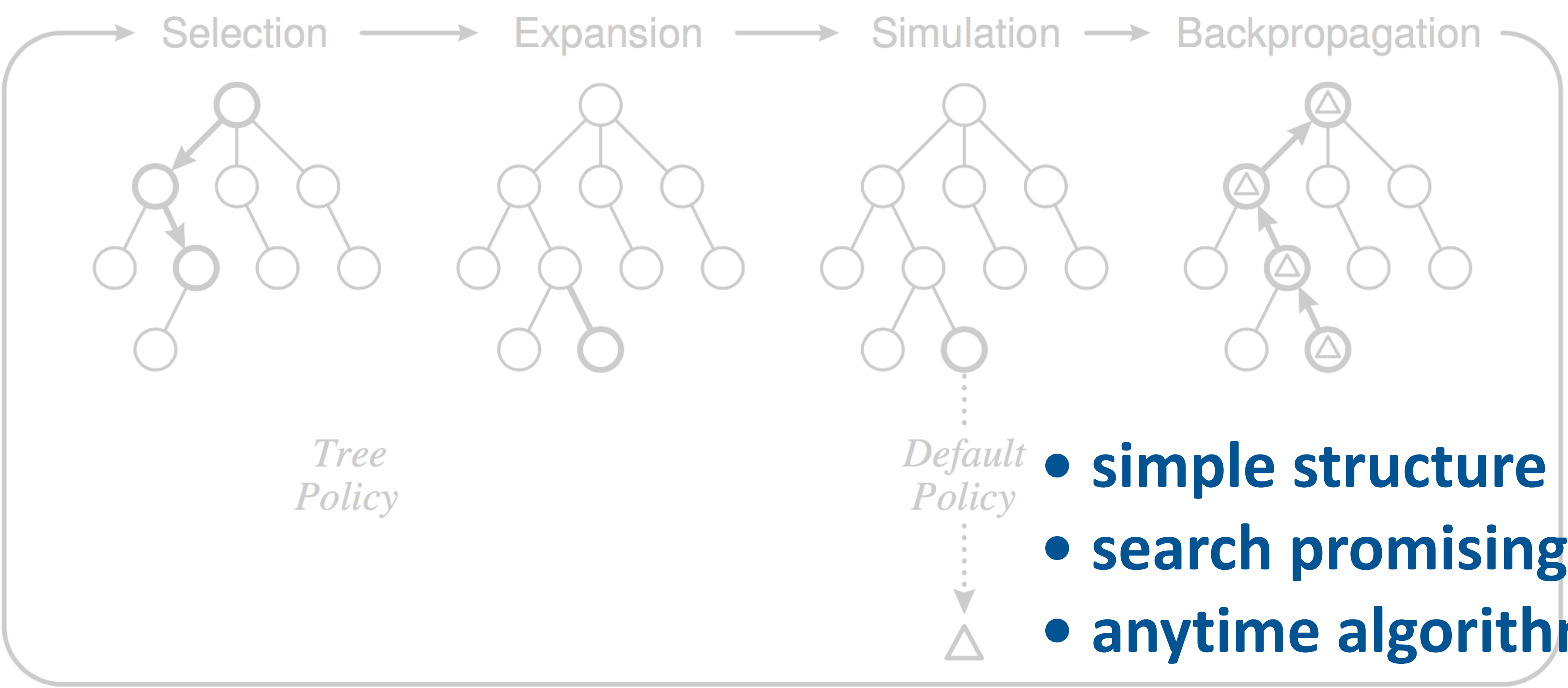
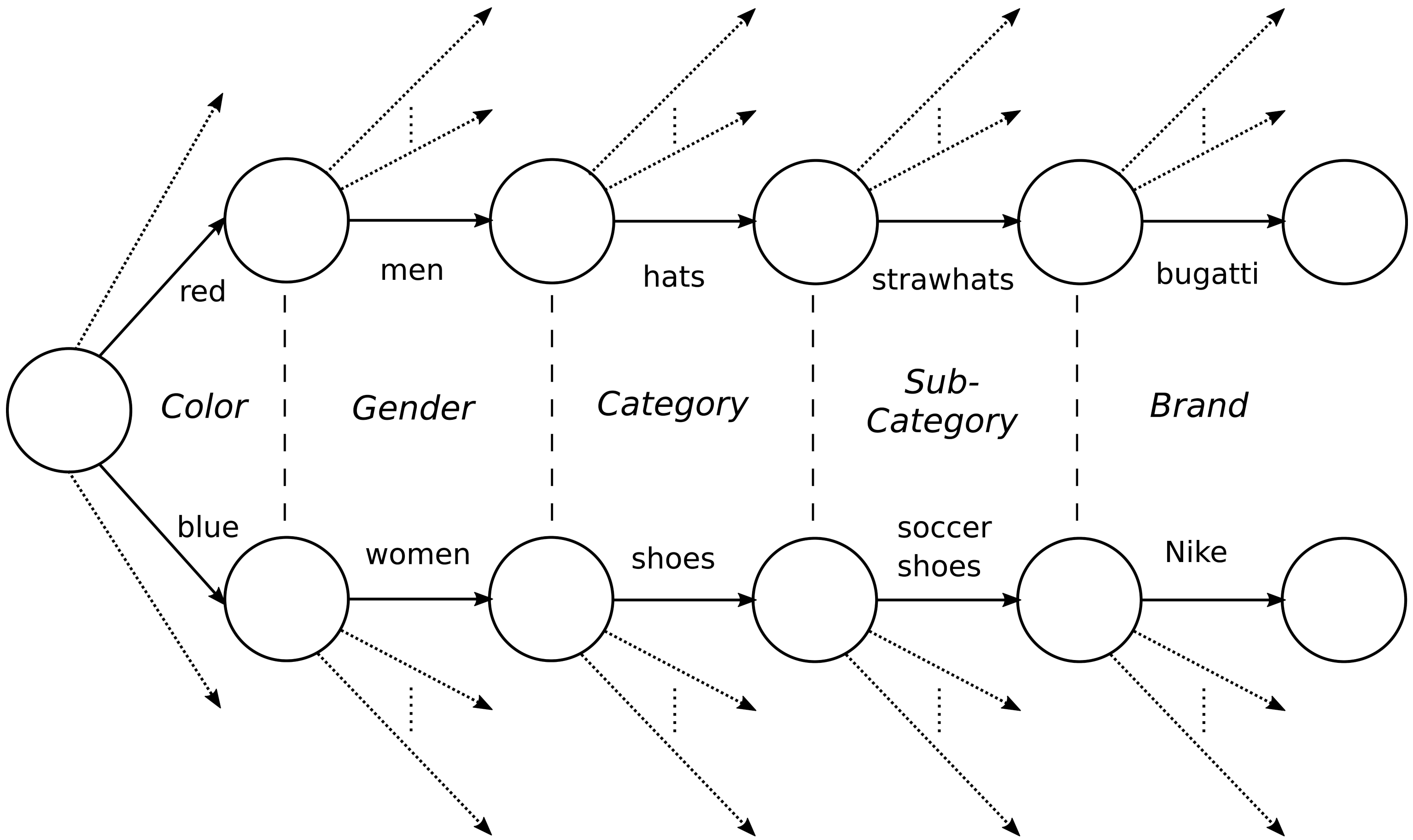


- **simple structure**
- **search promising branches**
- **anytime algorithm**
- **historically successful**

MCTS in Feature Space

- Leaf nodes specify a complete item with all categorical features



each layer selects an attribute

MCTS Modifications

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- Avoid redundant evaluation of the same product
  - Remove leaf nodes that have been tested form the tree

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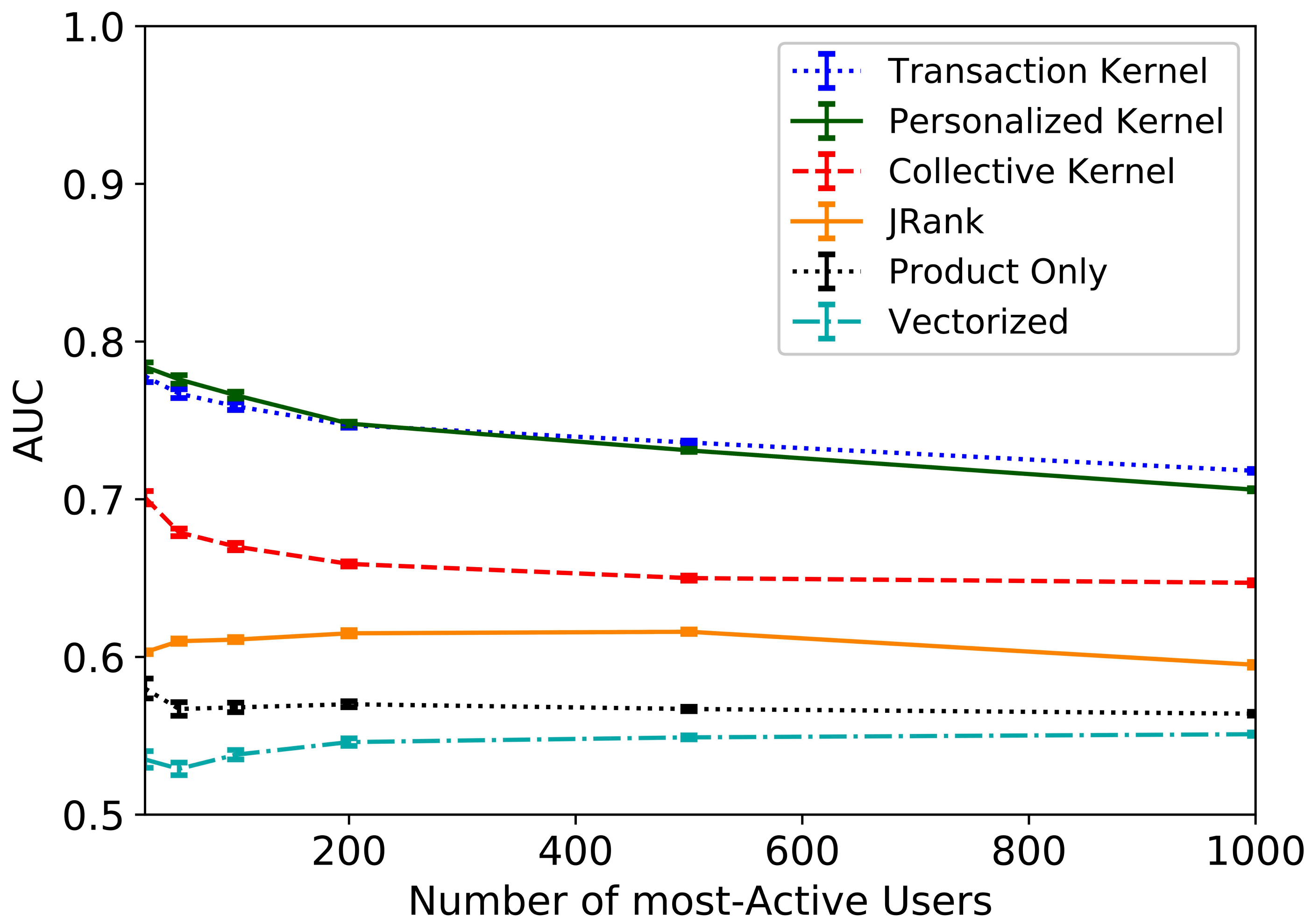
Empirical Study

- Pairwise preference data from Zalando (www.zalando.com)
- About 680k users and 16k products
- More than 3.5 million total transactions
- **Attributes:** category, sub-category, color, gender, brand
- **Baseline:** JRank(Basilico, Hofmann, 2004)(preference model), random subset exhaustion and greedy stochastic search (search)
- **Evaluation measure:** AUC (preference model), utility (search)

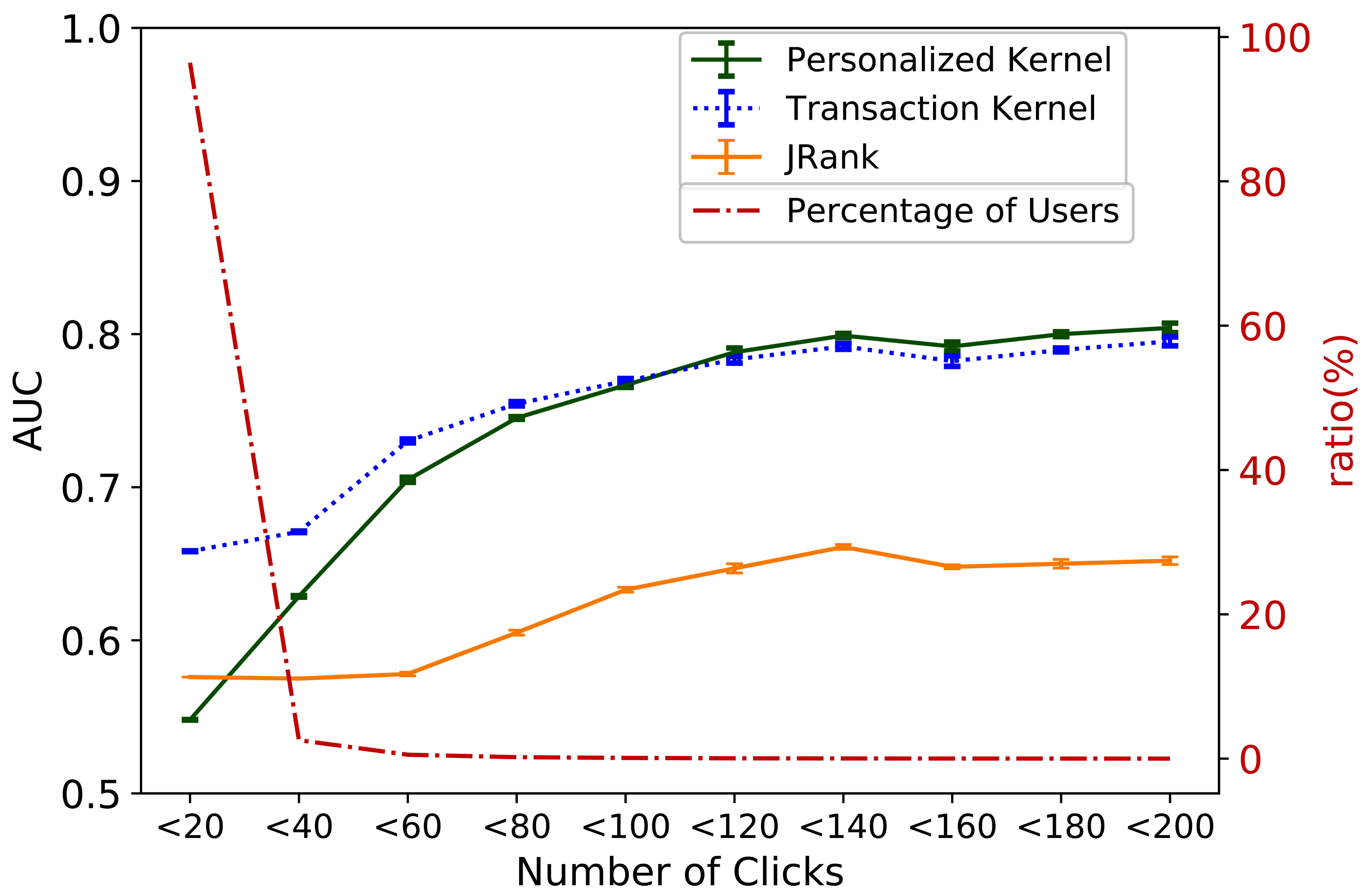
Results—Preference Model

Overall performance for 10-fold cross validation



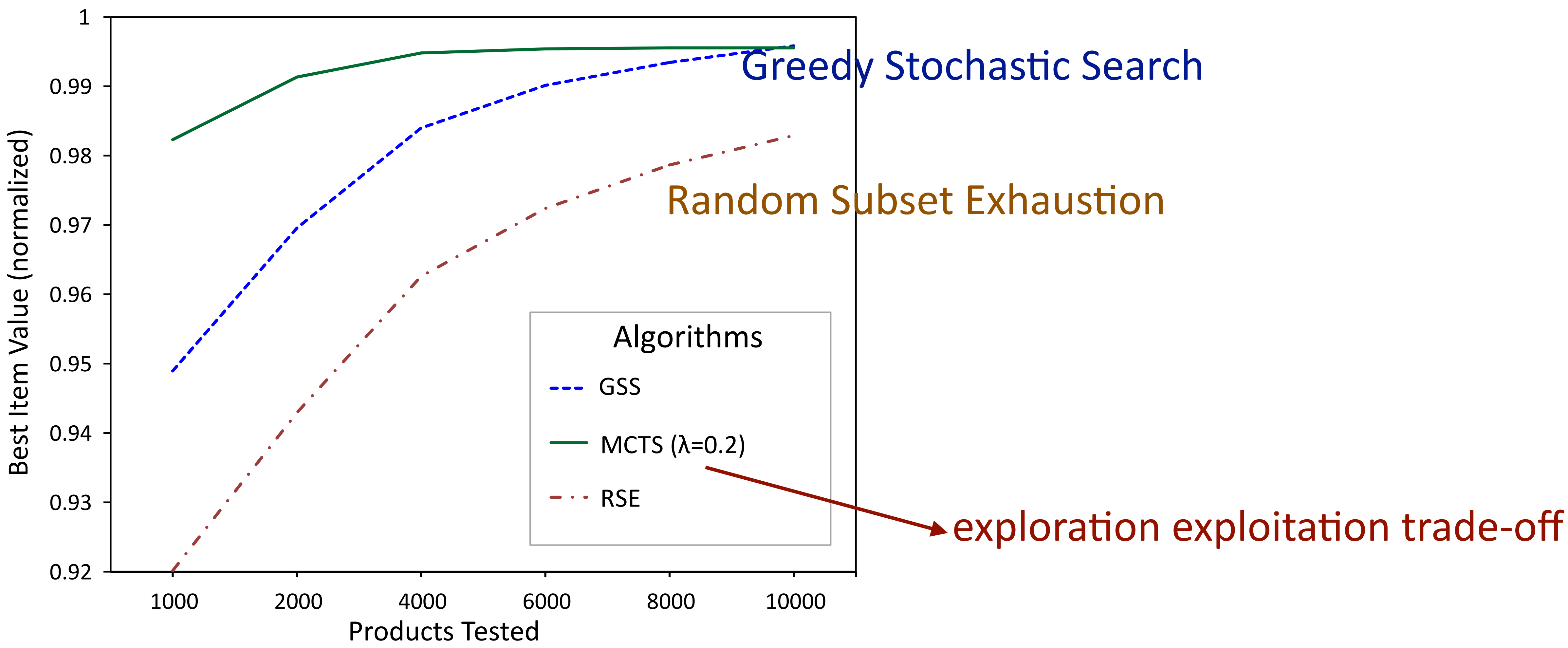
- highly accurate performance of personalized & combined model

Results—Preference Model



- more data per user: more robust personalization
  - but for most users, **collective kernel** has an important role

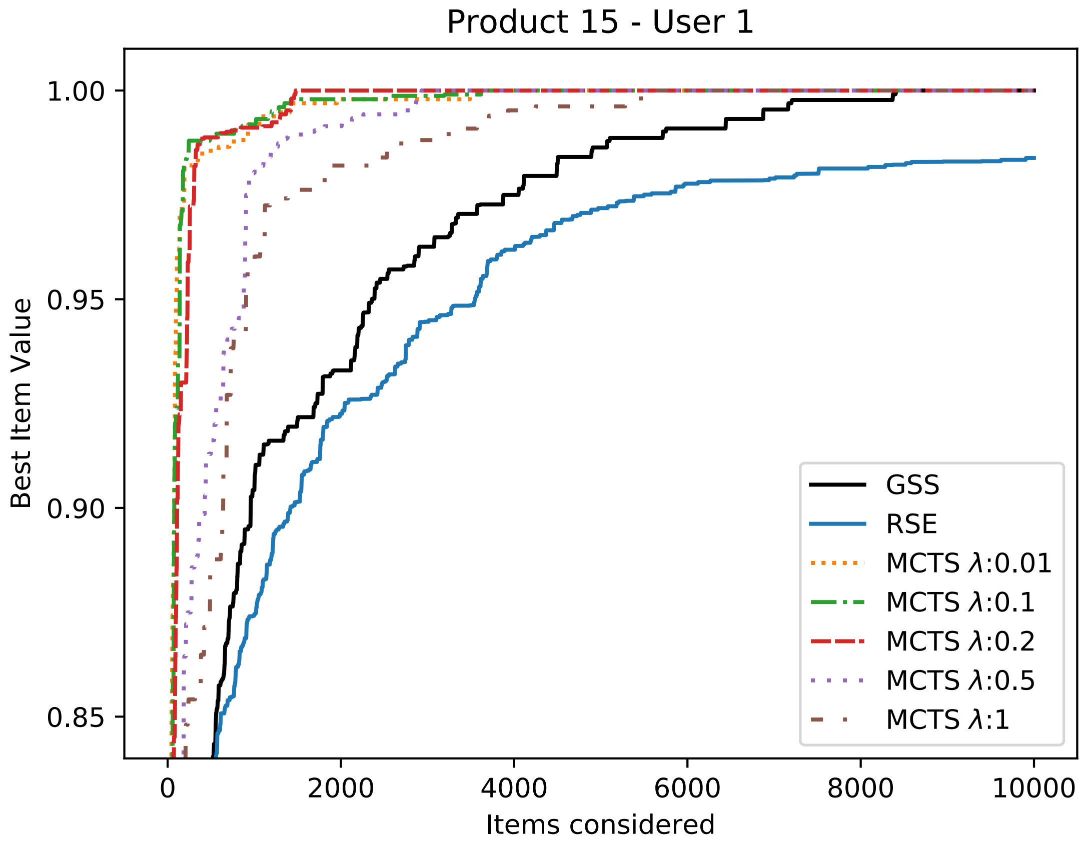
Results—Informed Sampling

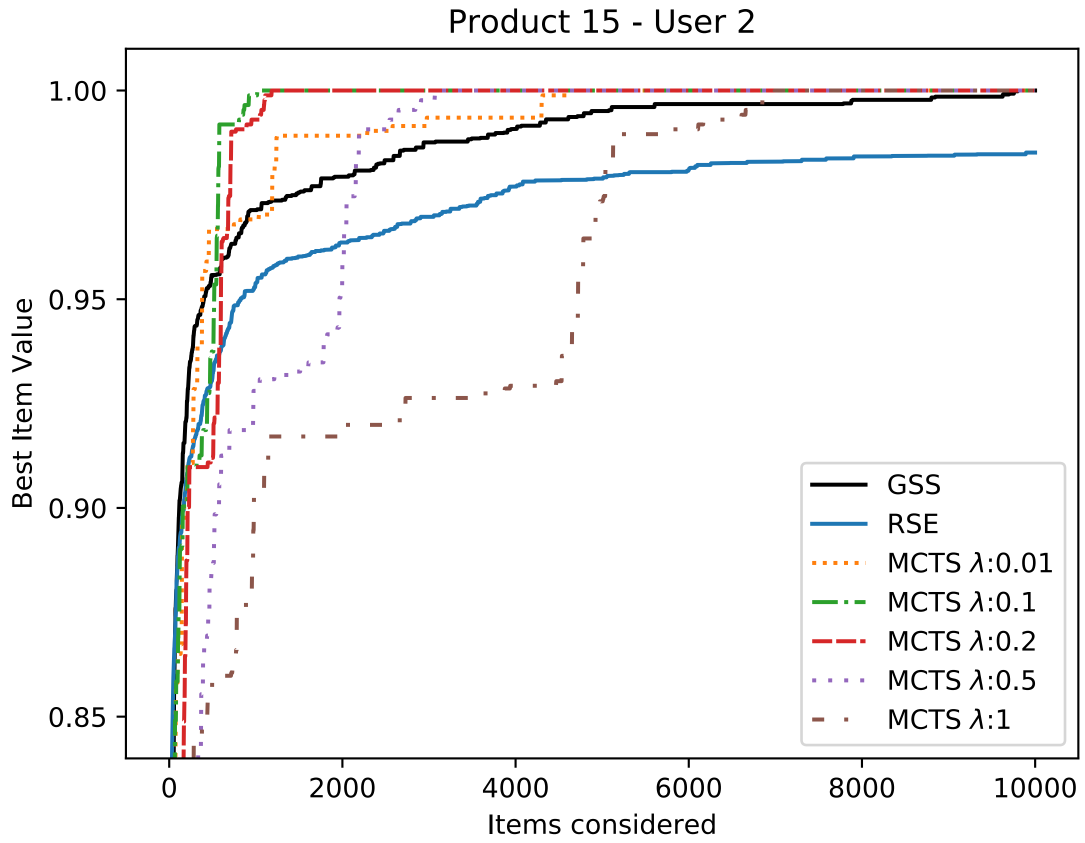


- MCTS outperforms the baselines in much smaller search spaces

Results—Informed Sampling

Example tests for a given product, four different users

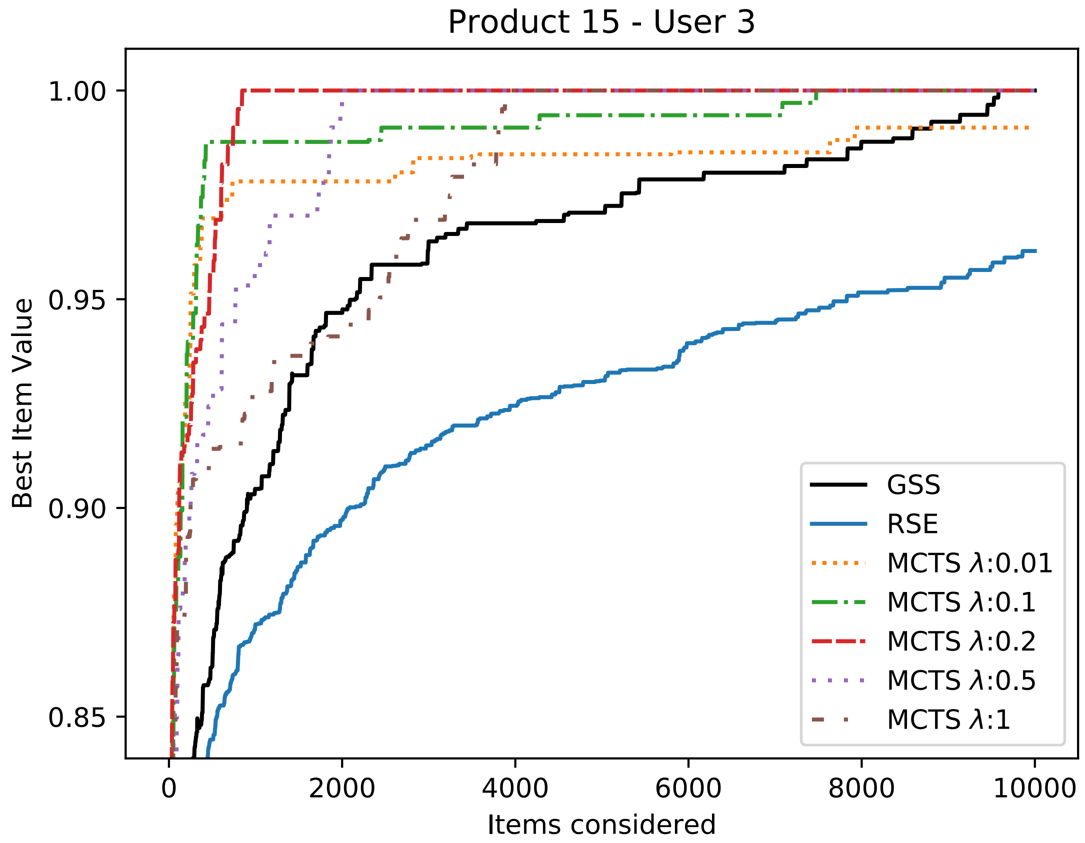


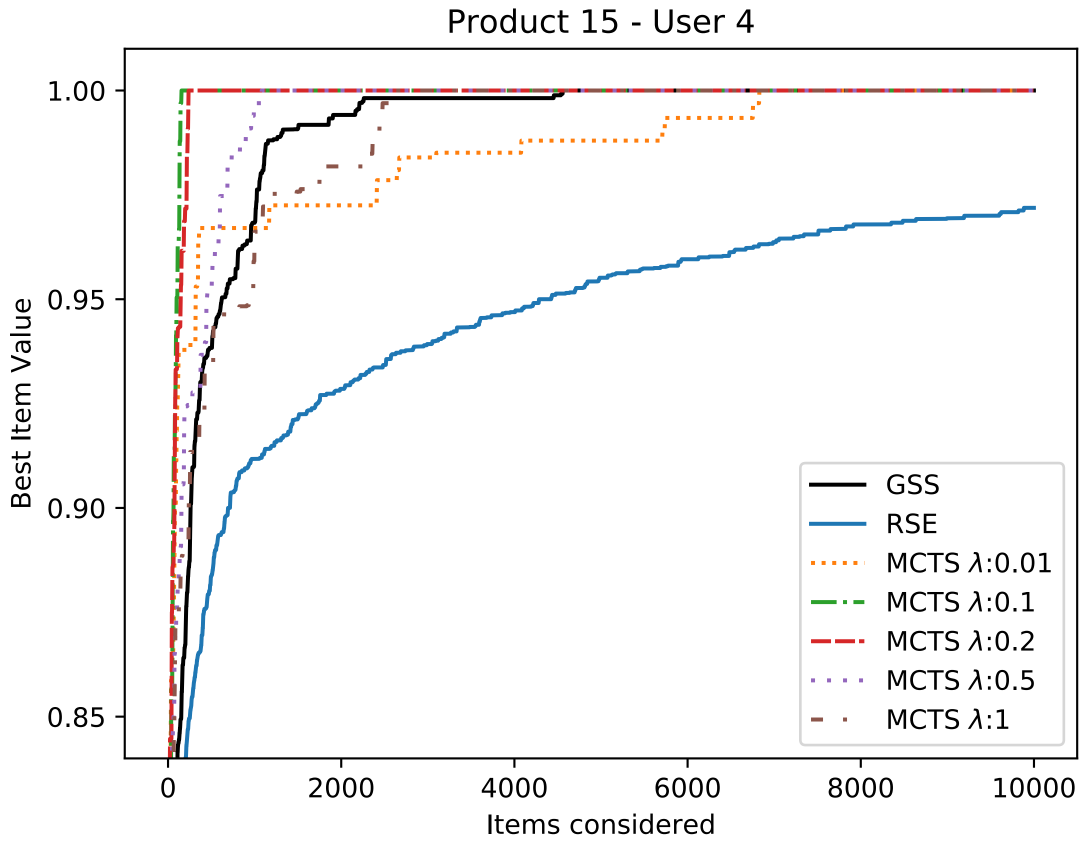


- the choice of λ is important in the performance

Results—Informed Sampling

User 4 is a new user without training data





- MCTS finds the optimal product with a lower number of samples

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- Preference-based learning to model personalized interests of users in contextual settings
- Transaction kernels combine **tensor products** with **hashing functions** to capture individual as well as collective user preferences
- A variant of MCTS method efficiently retrieves near-optimal items for online recommendation
- The model shows effective and efficient performance in real-world scenarios

Thanks for Your Attention!

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- References

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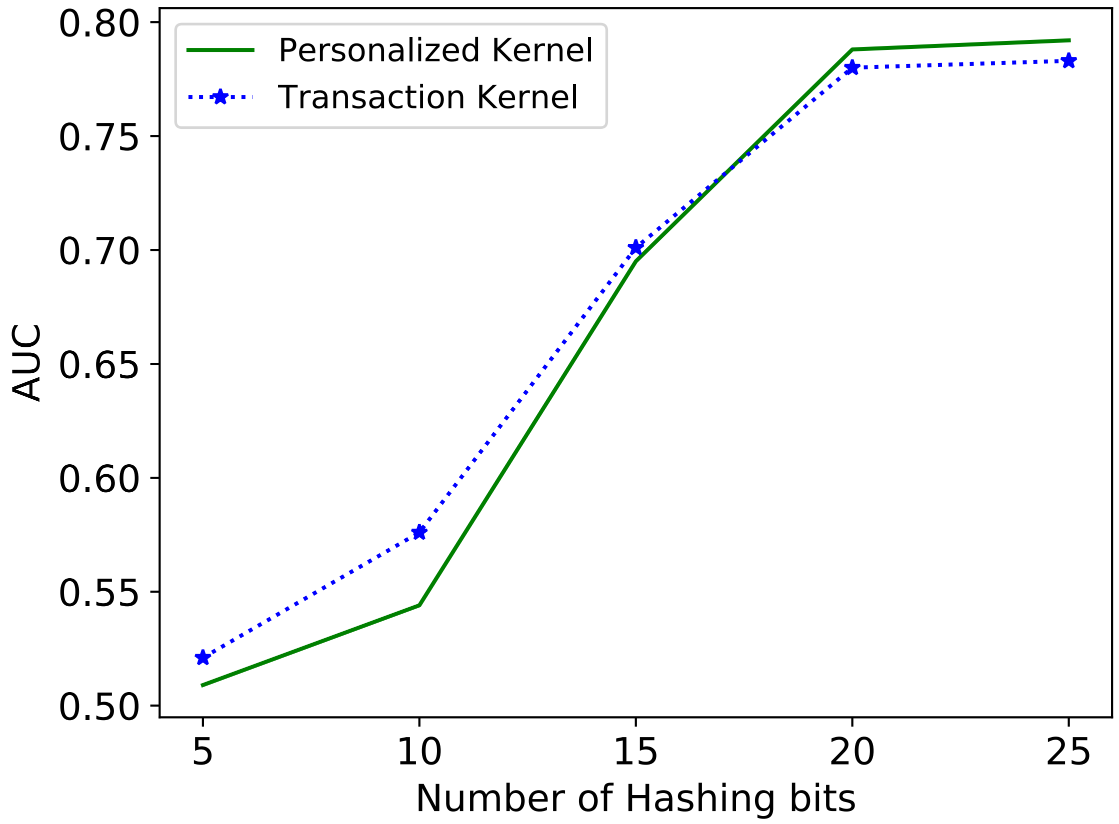
Results—Preference Model

The effect of the size of hashing function



- The more bits are used, the better the personalization model