When Recurrent Neural Networks meet the Neighborhood for Session-Based Recommendation

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Joint work with Dietmar Jannach

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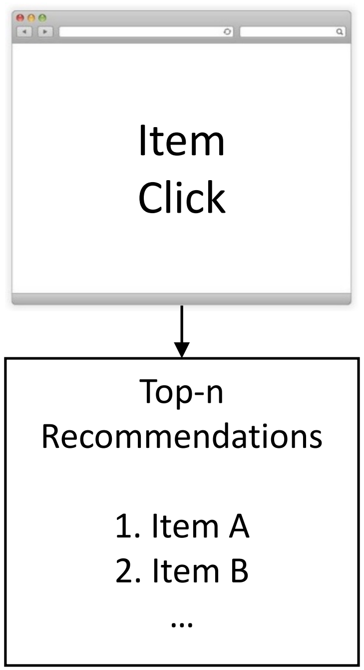
Session-Based Recommendation

- Continuously adopt to the most recent implicit feedback
  - For example: Item clicks in a user‘s shopping session



- Signals can be extracted from past sessions
- Special restriction: No user histories

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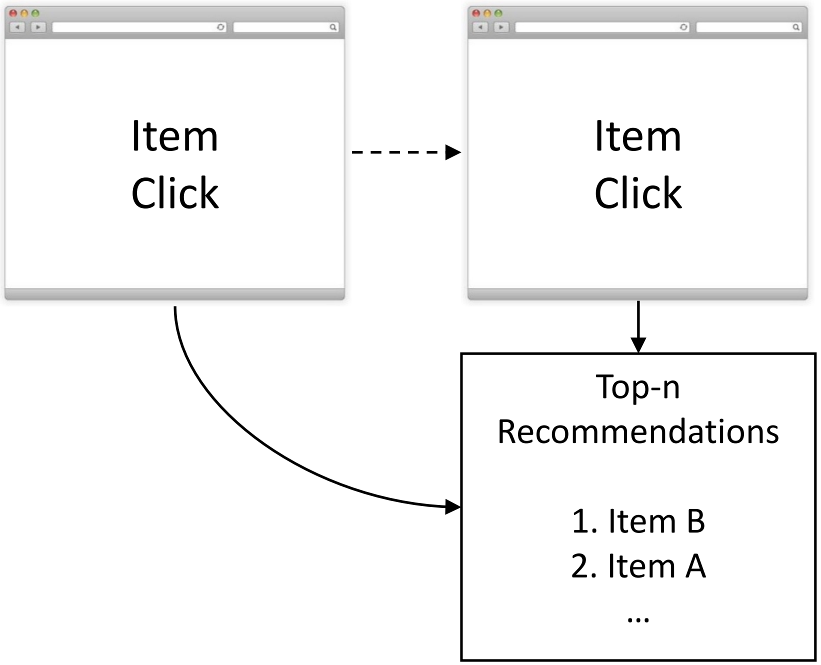

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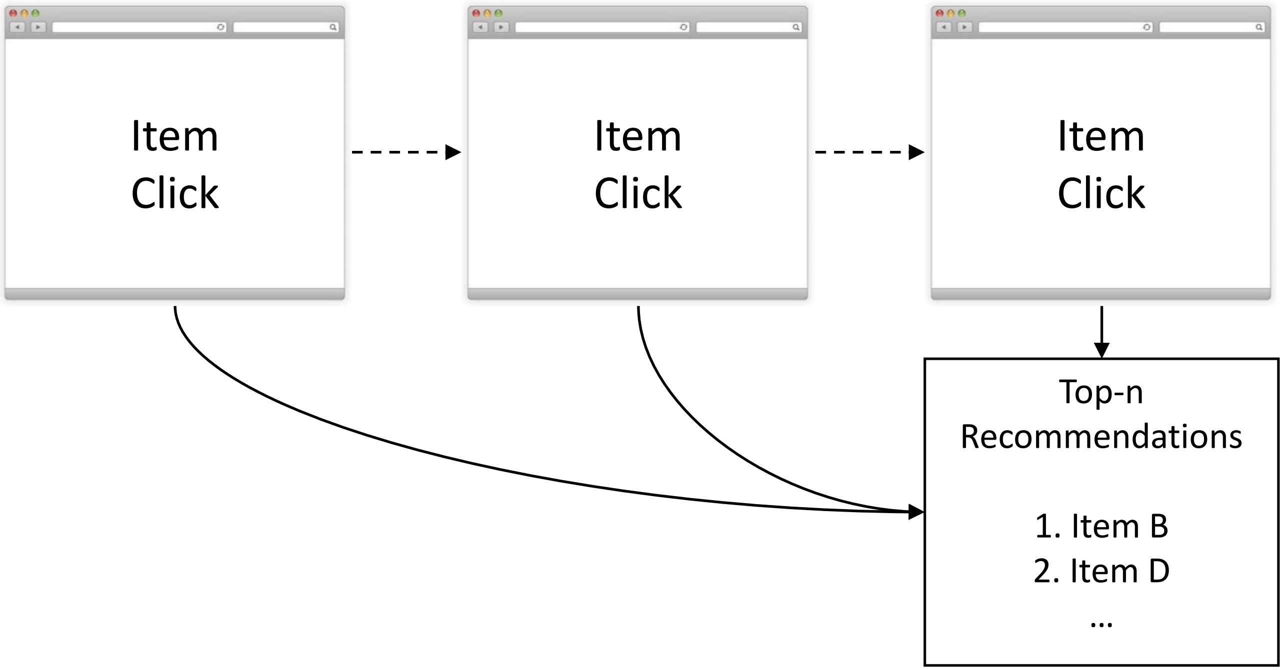

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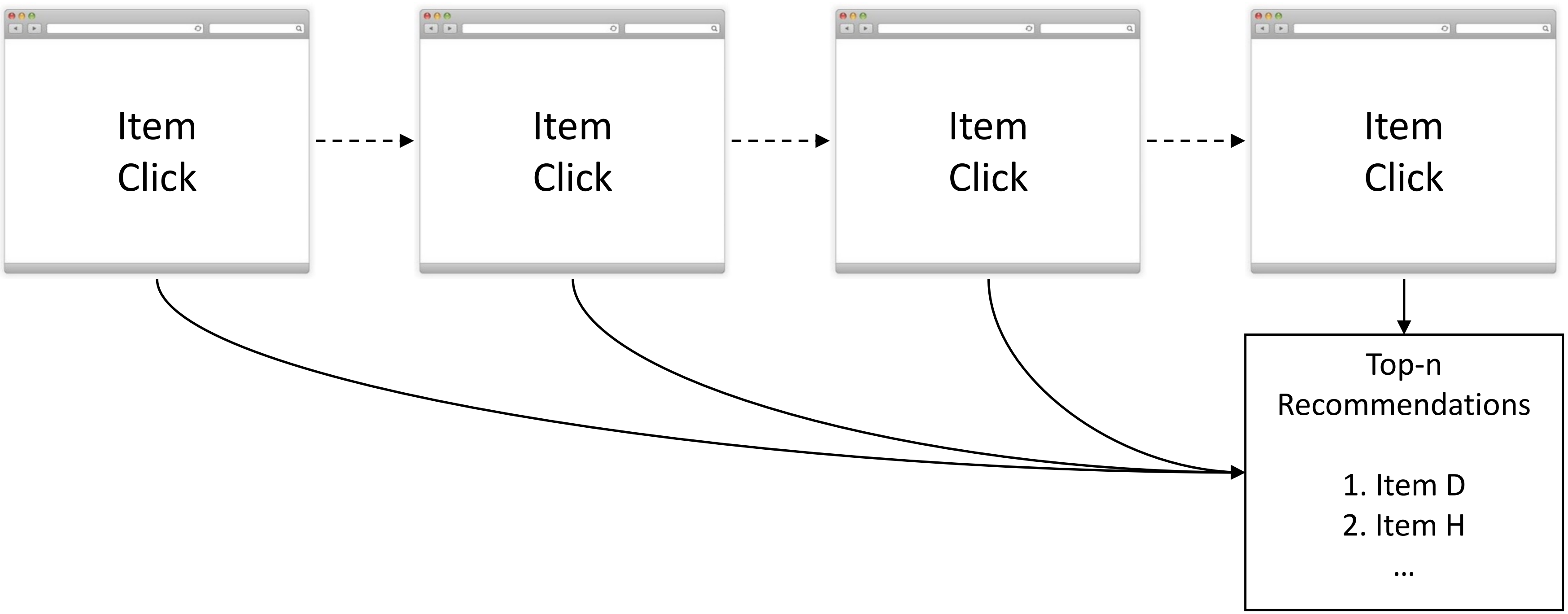

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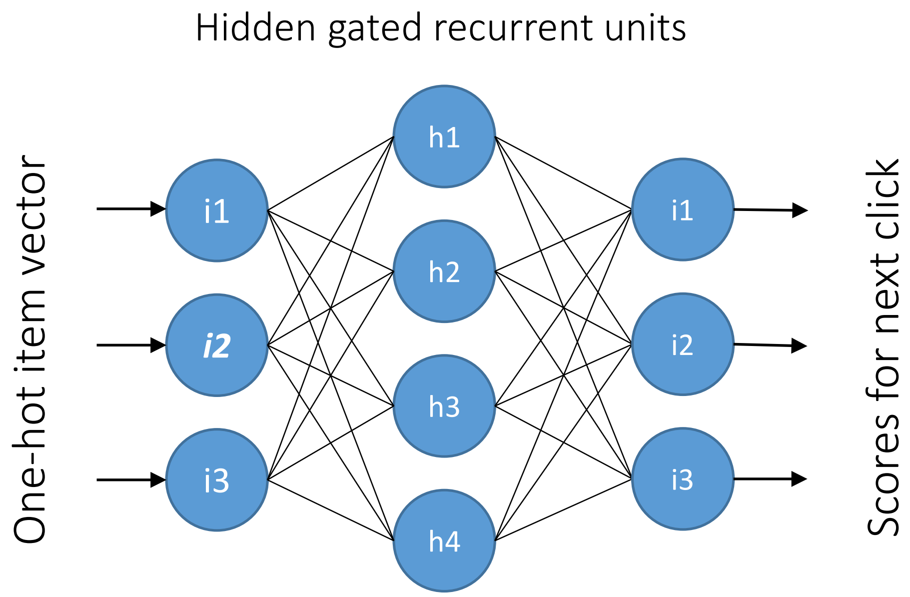
GRU4REC

- Recent approach to the problem by Hidasi et al.
- Using recurrent neural networks to model sequences in sessions



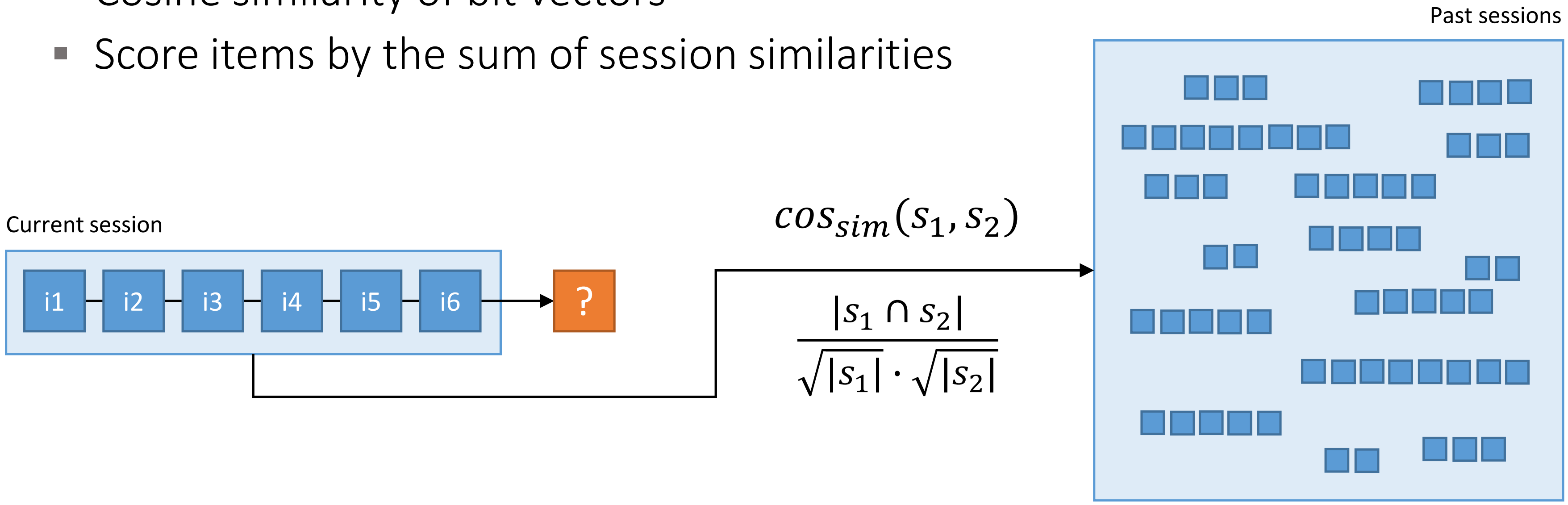
- SGD with pairwise ranking loss functions (BPR, TOP1)
- Significantly outperformed an Item-KNN approach

General Motivation

- True advantage of applying new and complex machine learning approaches to recommendation problems not easy to judge
  - Baselines might not be strong enough
  - Dependent on domain, dataset and evaluation method
  - Potential biases
  - Scalability
- Our goal
  - Provide a better understanding for session-based recommendation
  - Propose a simple neighborhood-based baseline for the scenario
  - Comparison with GRU4REC for multiple datasets

Session-Based KNN (S-KNN)

- Given the current session
  - Find *k* most similar past sessions
  - Cosine similarity of bit vectors
  - Score items by the sum of session similarities



- Getting the similarities for all sessions is slow
  - Only sessions with one item from the current session at minimum
  - Only the *n* most recent sessions

Datasets for Evaluation

E-Commerce

IJCAI-15 Competition (Tmall)
- 650k sessions over 1 year
- 300k items

RecSys Challenge 15 (RSC15)
- 8M sessions over 6 month
- 37k items

Music

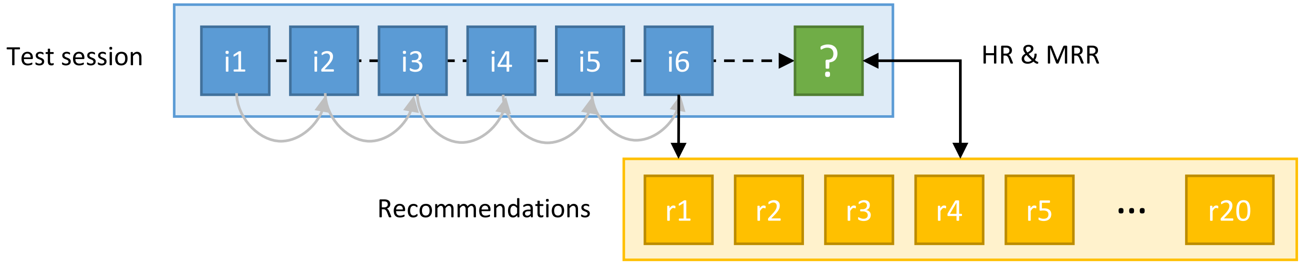
last.fm listening logs
- 120k sessions in 1 month
- 200k items

8tracks.com playlists
- 82k sessions
- 54k items

artofthemix.org playlists
- 82k sessions
- 54k items

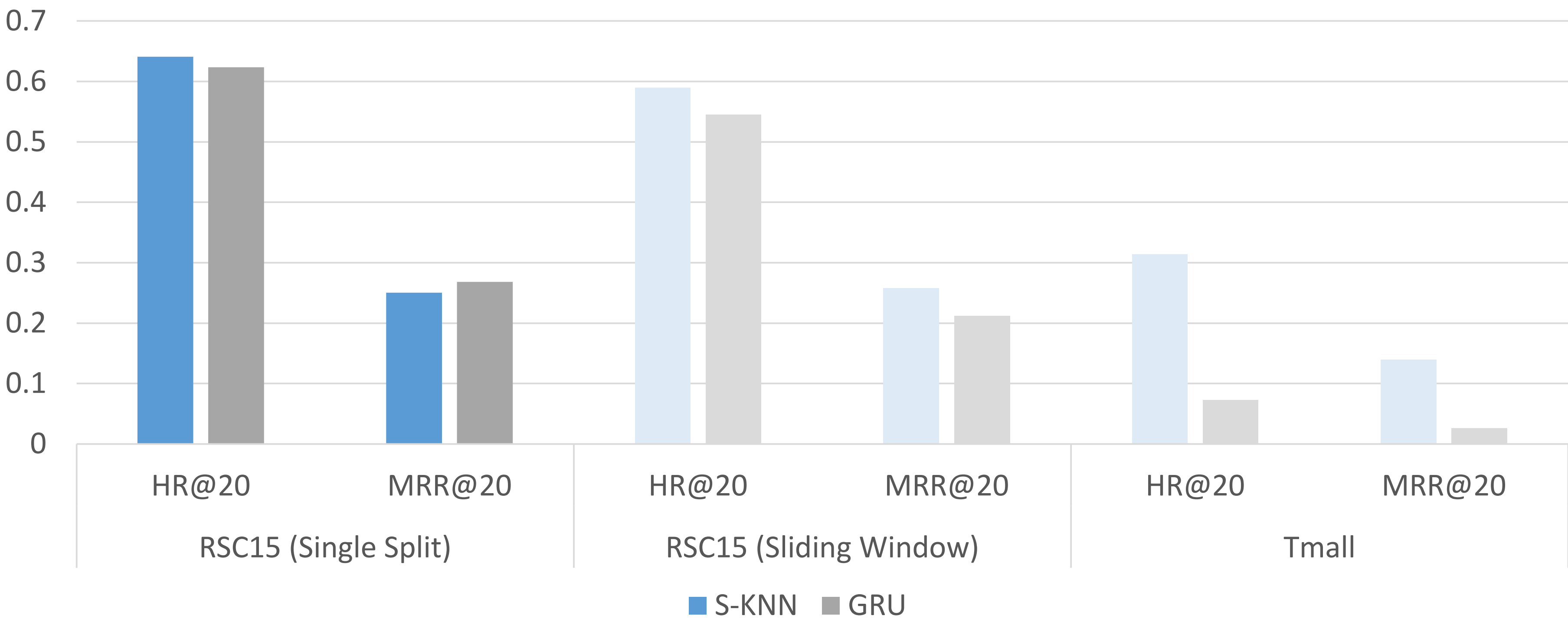
Protocol

- Evaluation protocol
  - Sliding window
  - Time-based splitting
  - Recommend for second to last click per session in the test set
  - Measure Hit rate and MRR at list length 20



- Additionally measure…
  - Popularity and catalog coverage
  - Runtimes and memory consumption
- Optimized parameters for each data set (validation set)

Results – E-Commerce



- Mixed results for a single split on RSC15
- S-KNN significantly better in a sliding window evaluation
- Bigger difference for Tmall
  - Maybe less sequential patterns in the data

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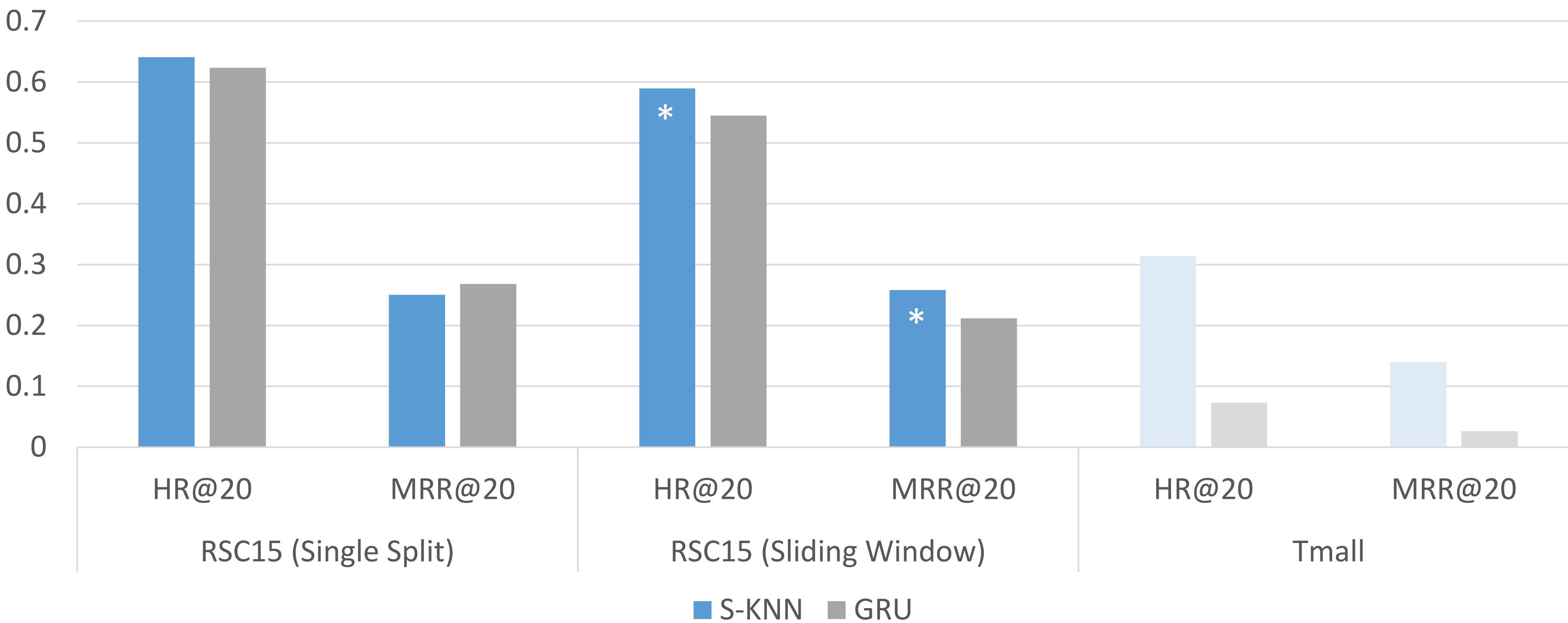

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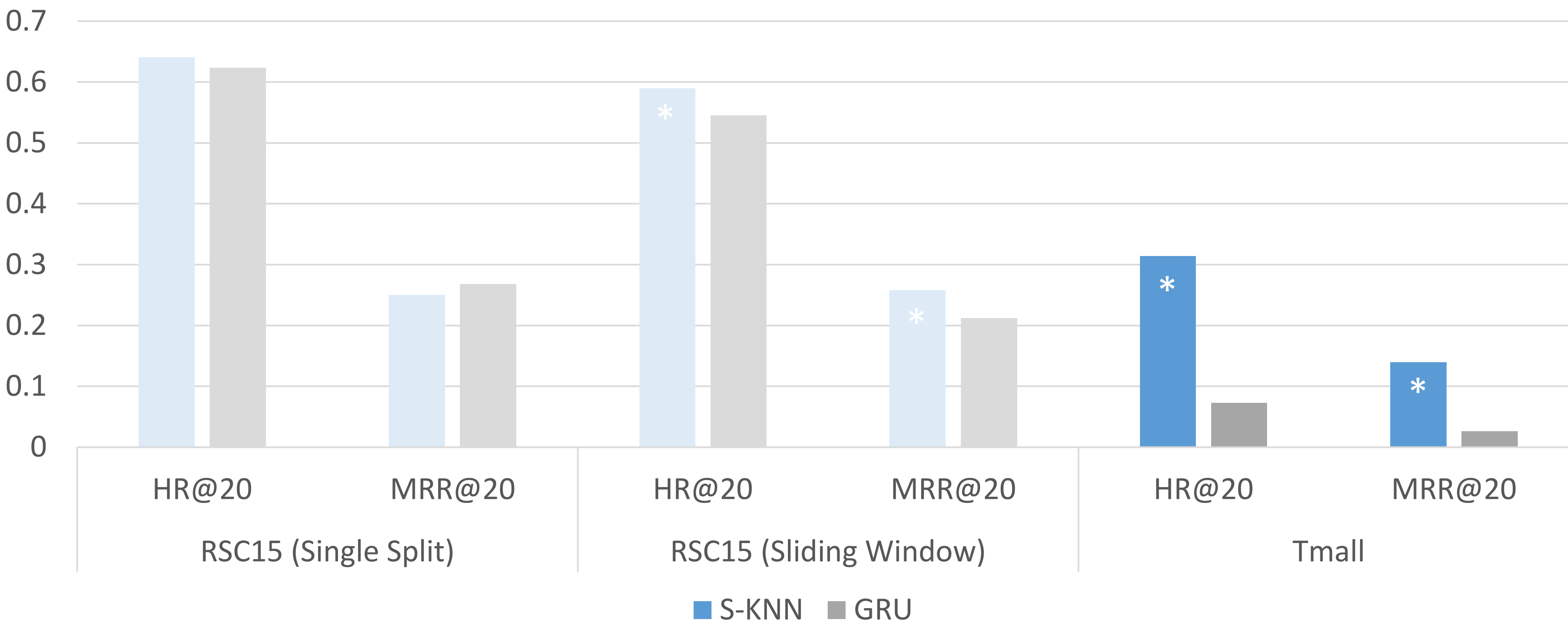

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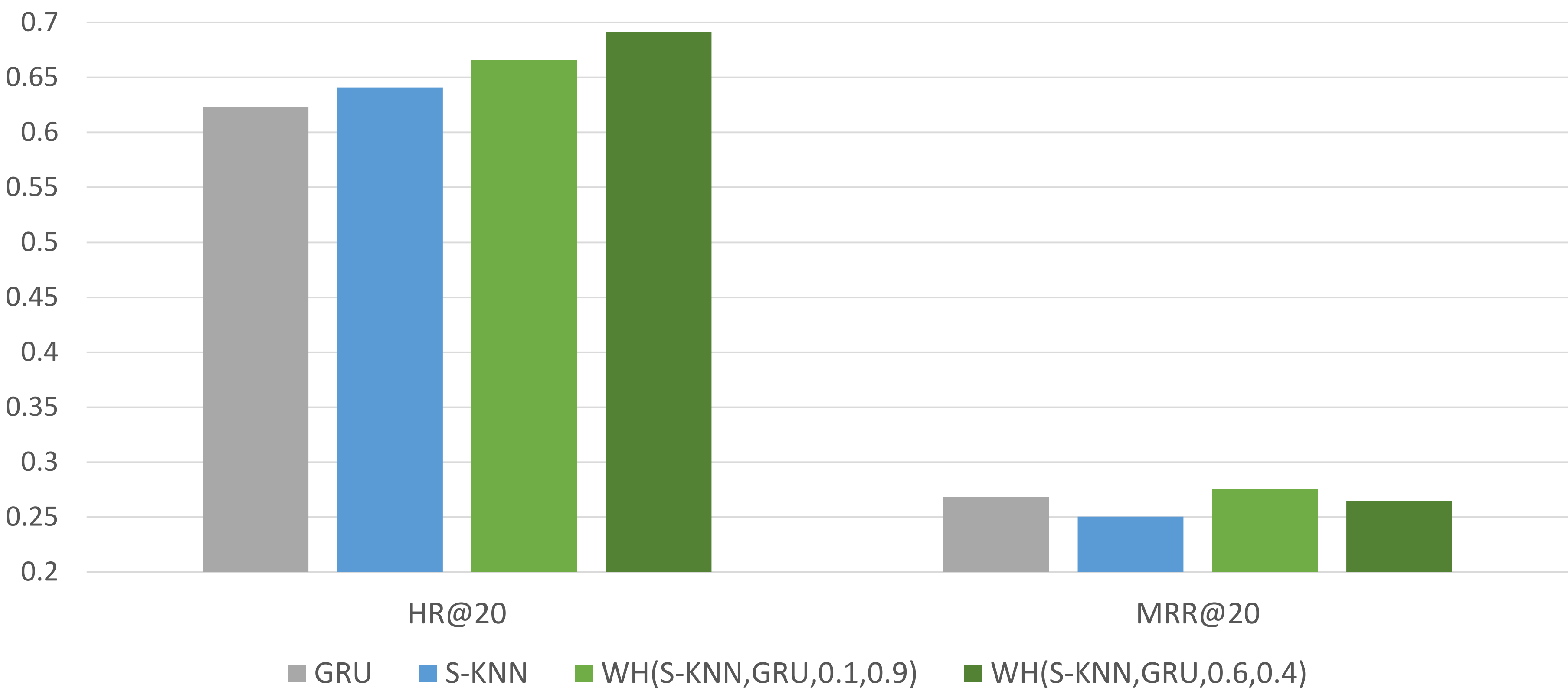
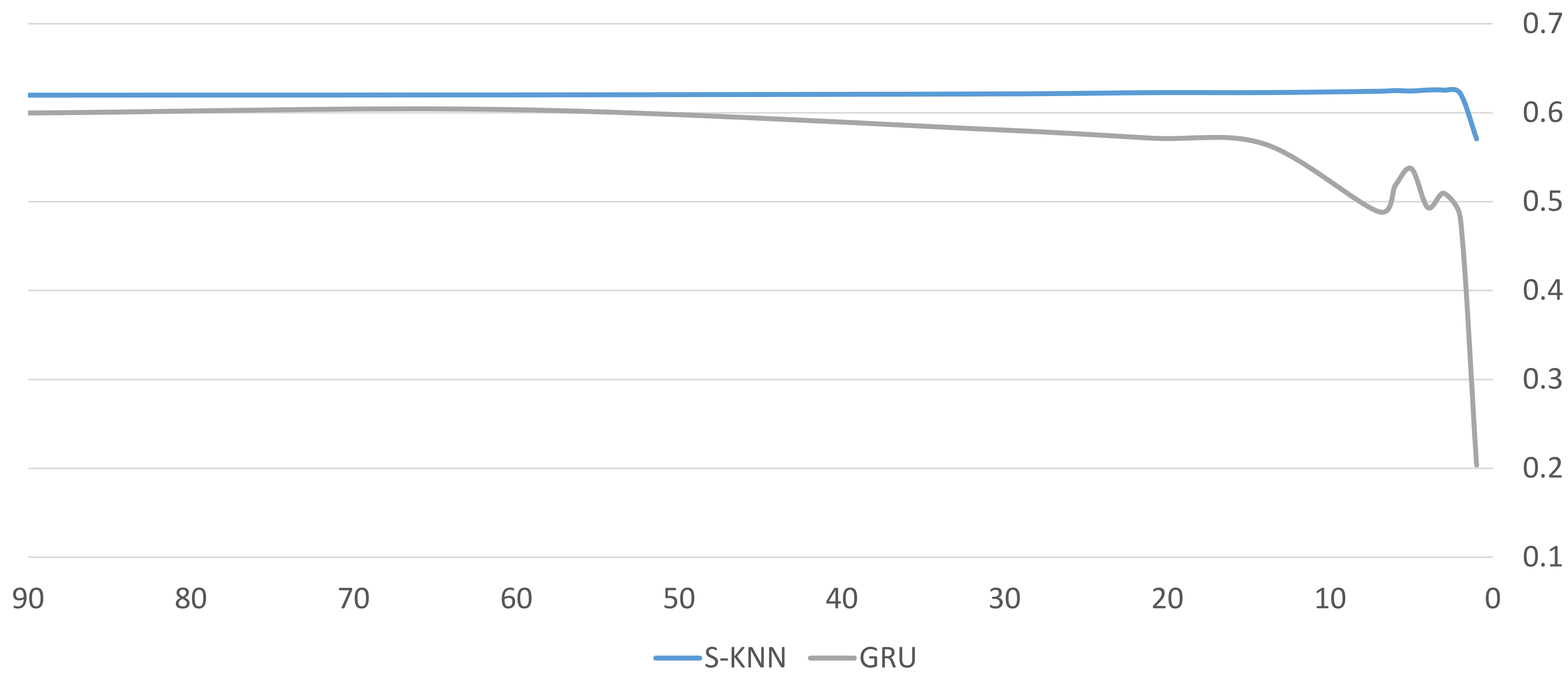
Combining Signals (RSC15)



- Using the approaches in a **weighted hybrid** (WH)
  - Combining the signals improves both HR@20 and MRR@20
  - Different optimal weights for the best HR and MRR

Effects of Data Sparsity (RSC15)



- Training the models with **data from** the **last *n* days**
  - Both approaches quite stable regarding the HR@20
  - Focusing the last few days is sufficient for S-KNN

Additional Measurements

- Runtimes and memory consumption
  - Desktop PC with an Intel i7-4790k on RSC15

	S-KNN	GRU	GRU(GPU)
Training	90s	23h	8h
Recommendation	26ms	12ms	12ms
Memory used	6GB	600MB	600MB

- Popularity bias
  - S-KNN recommends more popular items (0.036 vs. 0.028)
- Catalog coverage
  - GRU4REC has a slightly higher coverage (47% vs. 41%)
- Mixed results for music datasets
  - S-KNN performs better for *8tracks.com* and *artofthemix.org*
  - Advantages for GRU on *last.fm*

Conclusions & Future Work

- S-KNN shows competitive results
  - Potentially relevant sequential information missed by S-KNN
- Combinations of both approaches show promising results
- Further improvements for RNN-based approaches to be expected
- Meanwhile progress was made
  - GRU4REC
    - **0.636** HR@20 / **0.268** MRR@20
  - Simple heuristic with sequential patterns (see RecTemp `17)
    - **0.690** HR@20 / **0.307** MRR@20
  - New extensions to S-KNN
    - **0.709** HR@20 / **0.304** MRR@20
  - GRU4REC v2 already improved the performance
    - **0.711** HR@20 / **0.310** MRR@20
- Future: Extensive comparison of available methods
  - Which method works best for which data, and why?

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- Questions?