UNIVERSITY OF CAMBRIDGE

UNIVERSITY OF CAMBRIDGE COMPUTER LABORATORY
RAINBOW RESEARCH GROUP

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Active Sampling for Pairwise Comparisons via Approximate Message Passing and Information Gain Maximization

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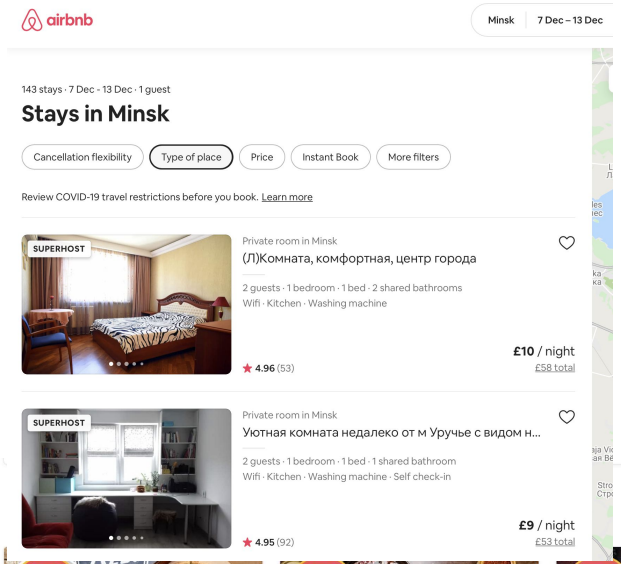
Problem overview - Inferring Scale

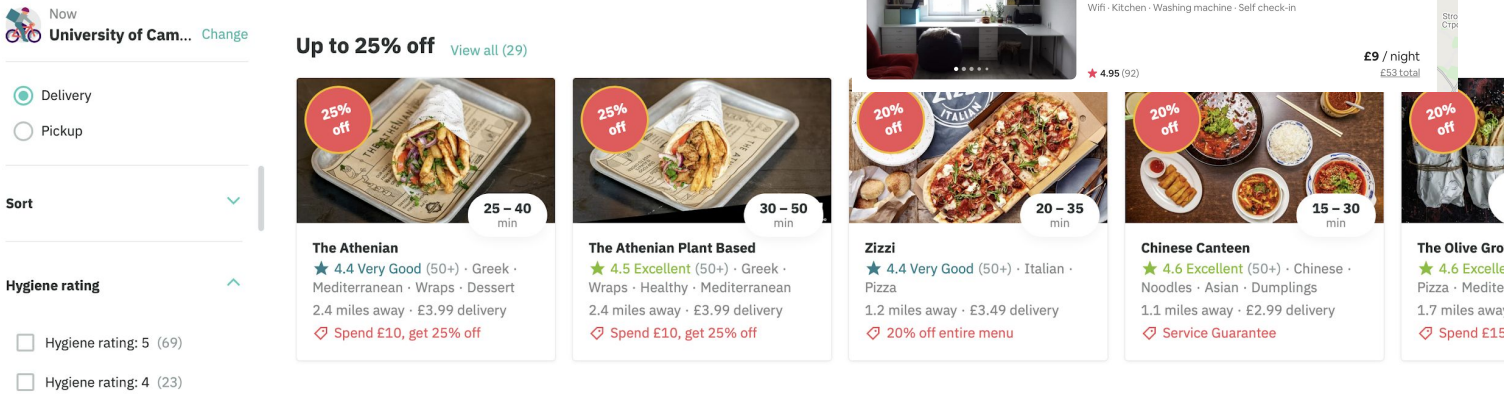
WCSC 2010 Kanazawa 2010

		1	2	3	4	5	6	7	8	9	
1	**Shredder**	*	½	1	½	1	1	1	1	1	7.0 / 8
2	**Rondo**	½	*	½	1	½	1	1	1	1	6.5 / 8
3	**Thinker**	0	½	*	½	1	½	1	1	1	5.5 / 8
4	**Pandix Breakthrough**	½	0	½	*	½		1	1	1	4.5 / 7
5	**Deep Junior**	0	½	0	½	*		1	1	1	4.0 / 7
6	**Jonny**	0	0	½			*		1	1	2.5 / 5
7	**Darmenios**	0	0	0	0	0		*	1	1	2.0 / 7
8	**Fridolin**	0	0	0	0	0	0	0	*	1	1.0 / 8
9	**Hector For Chess**	0	0	0	0	0	0	0	0	*	0.0 / 8

(33 Games)

Problem overview





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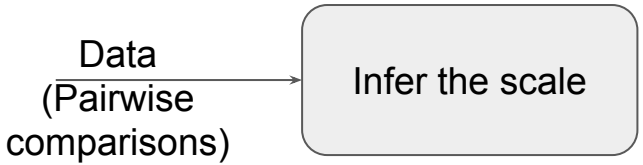
Algorithm

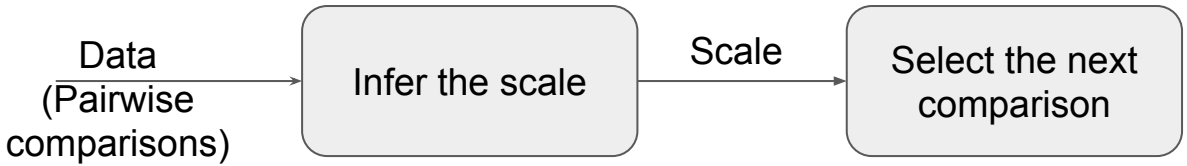
Data
(Pairwise
comparisons)

Algorithm



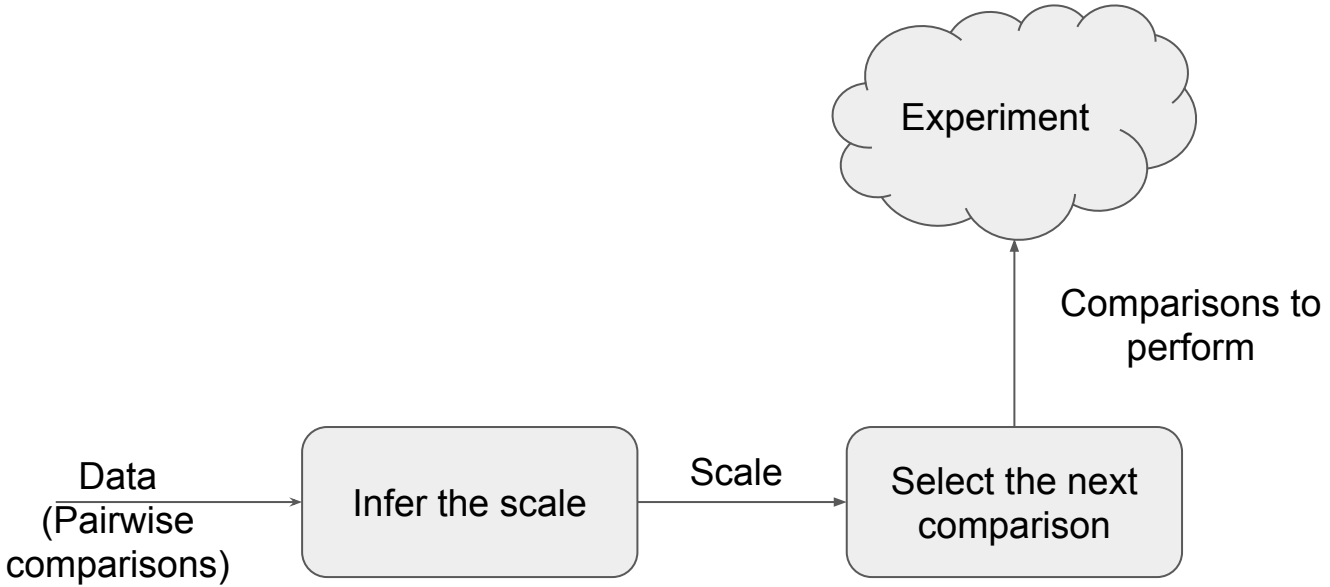
Most methods approximate, we do not

Algorithm

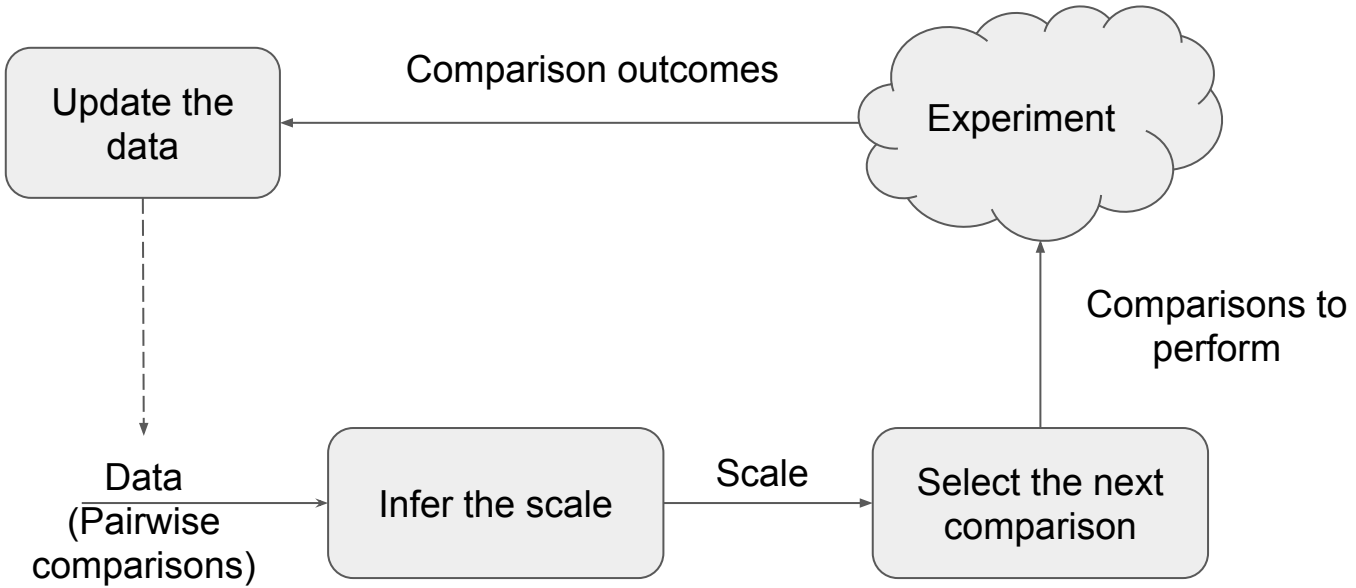


Most methods do not improve speed, we do

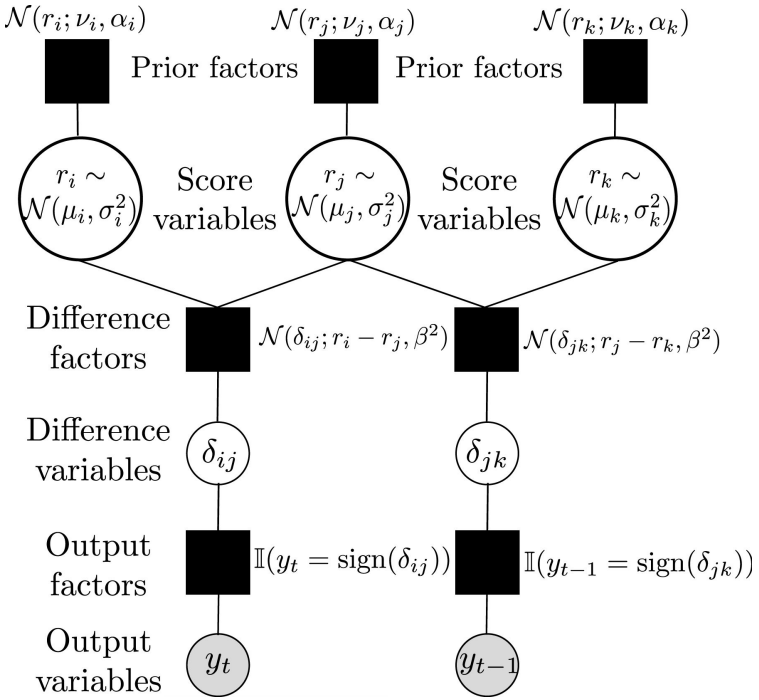
Algorithm


Experiment
Comparisons to perform
Data (Pairwise comparisons)
Infer the scale
Scale
Select the next comparison

Algorithm

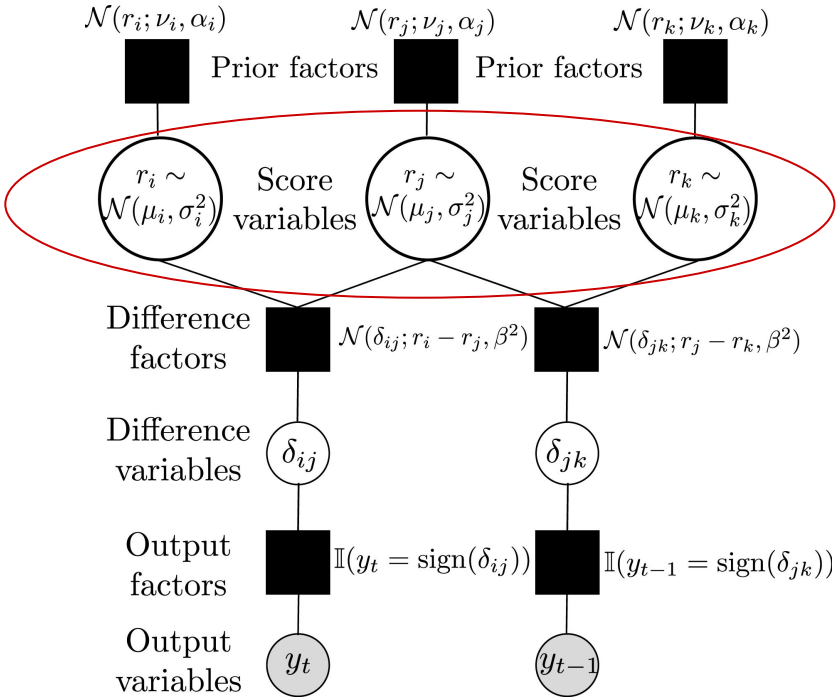

Update the data
Comparison outcomes
Experiment
Comparisons to perform
Data (Pairwise comparisons)
Infer the scale
Scale
Select the next comparison

Bayesian Score Inference (TrueSkill based [1])



T. Minka, R. Cleven, and Y. Zaykov, “Trueskill 2: An improved bayesian skill rating system,” Microsoft, Tech. Rep. MSR-TR-2018-8, March 2018.

Bayesian Score Inference (TrueSkill based)



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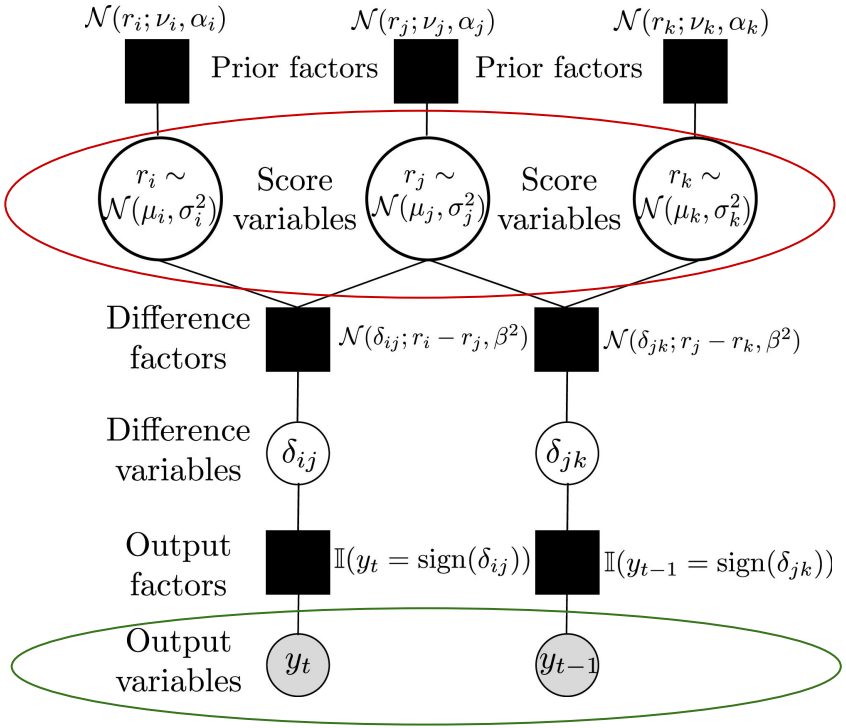
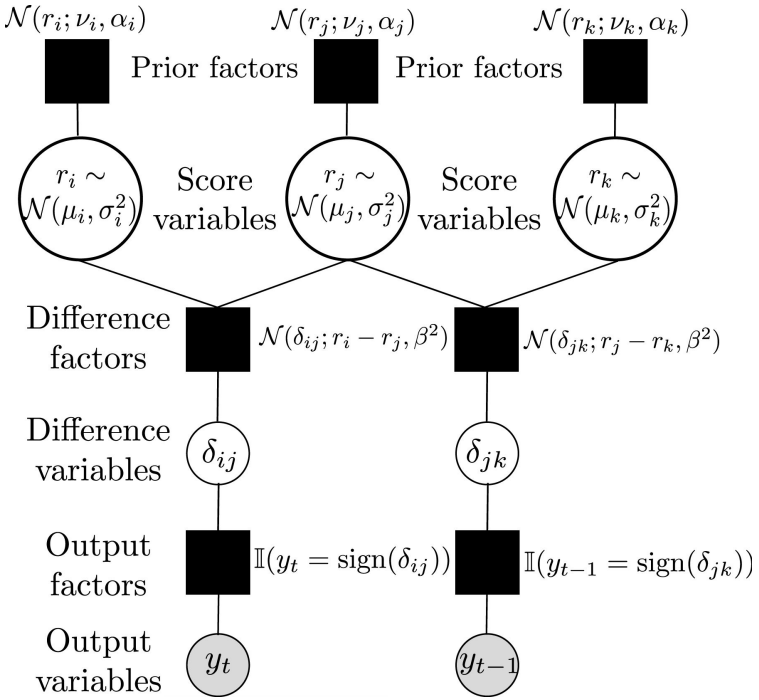


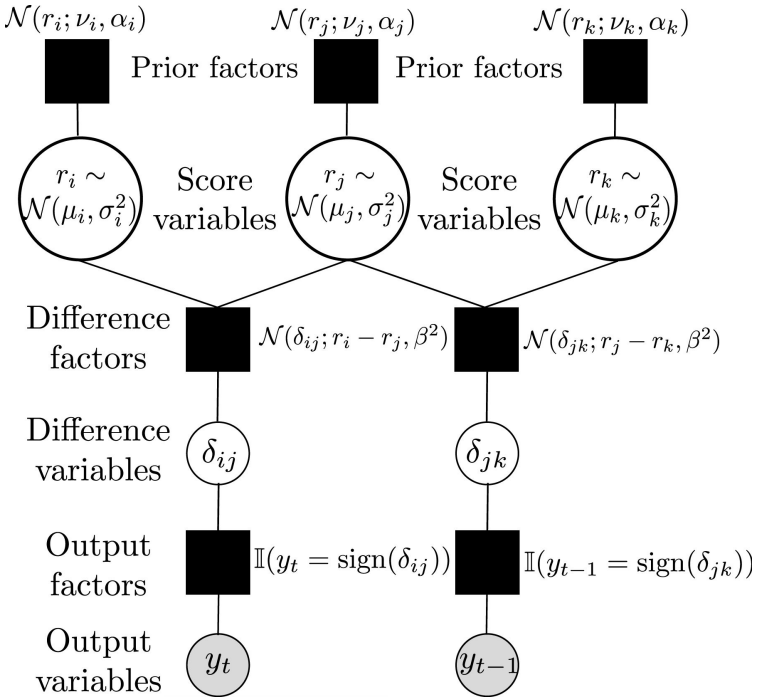
Bayesian Score Inference (TrueSkill based)

- Sum-product algorithm using expectation propagation via moment matching



Bayesian Score Inference (TrueSkill based)

- Sum-product algorithm using expectation propagation via moment matching
- k*O(n+t) complexity of inferring the scores (k - number of iterations)



Expected Information Gain (EIG)

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Collected data so far

0	1	2	3
3	0	3	1
4	1	0	3
0	2	1	0

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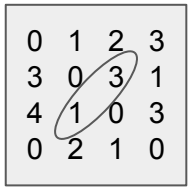
Collected data so far



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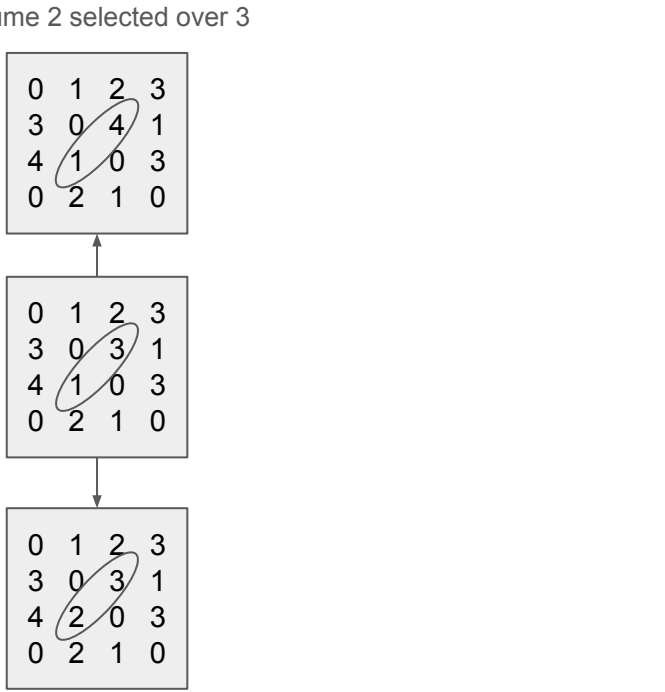

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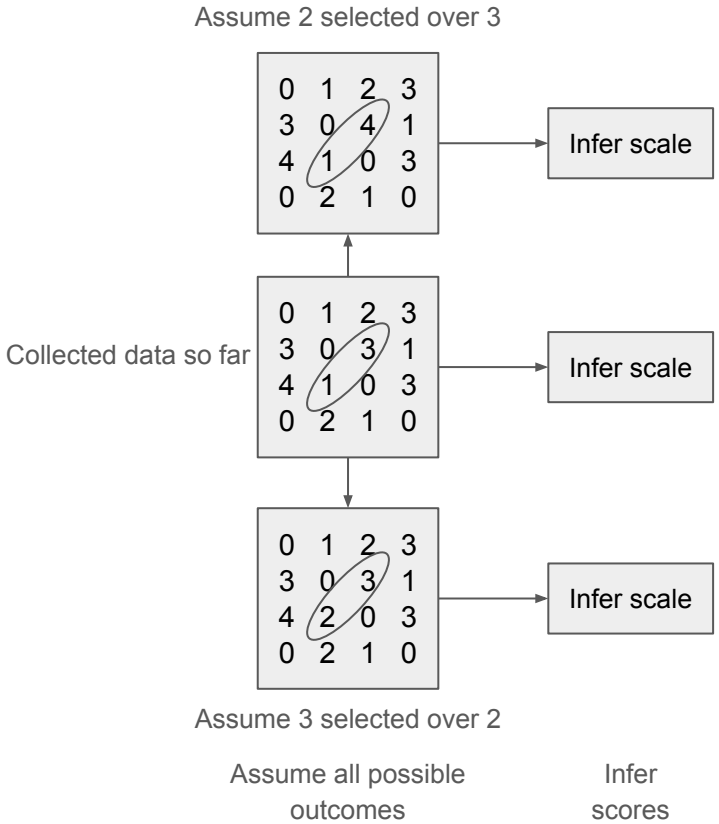

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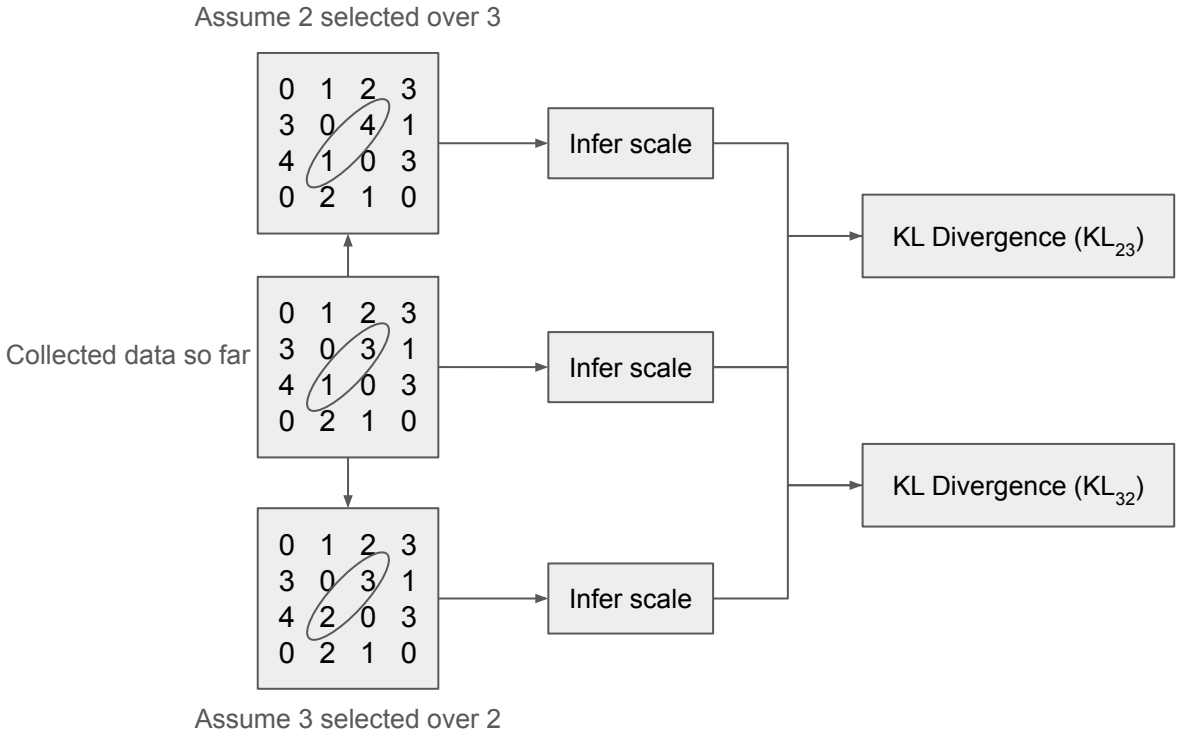

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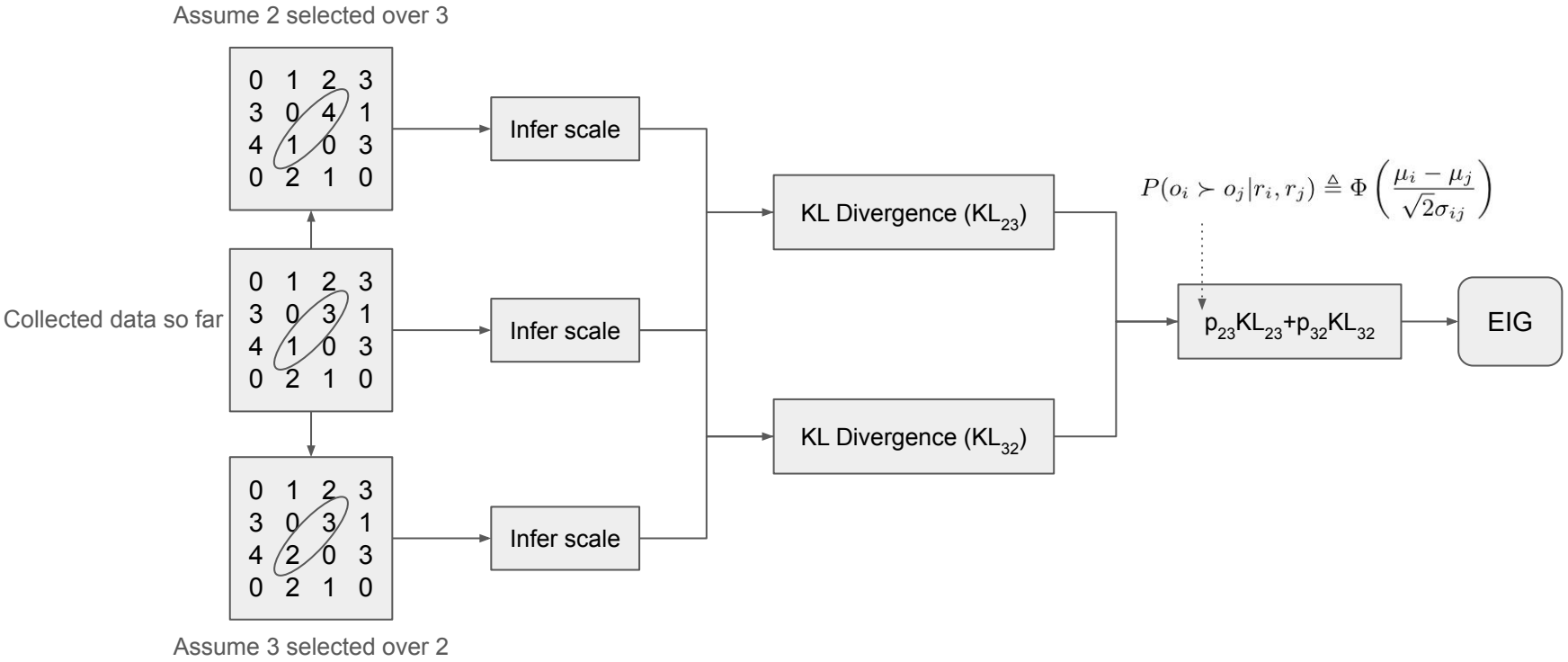

Efficiency considerations

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- We consider two strategies to improve the speed:
  - Selective EIG evaluations
  - Batch mode with Minimum Spanning Tree (MST)

Selective EIG evaluations

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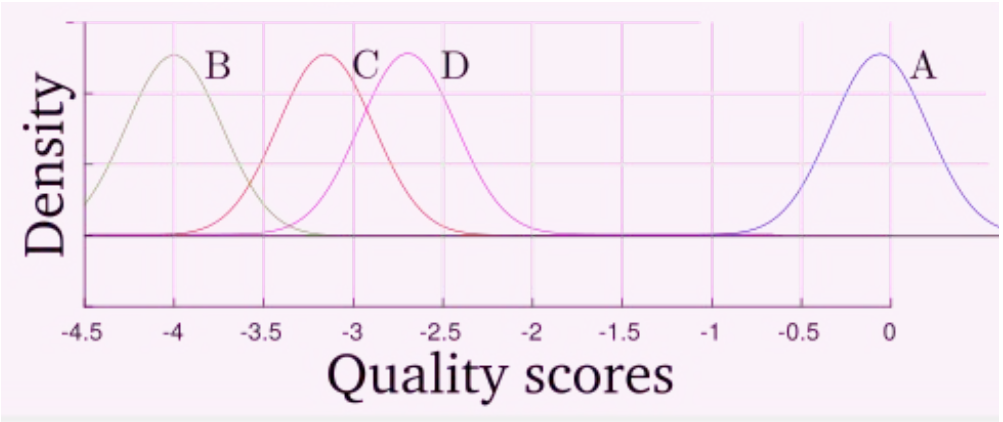
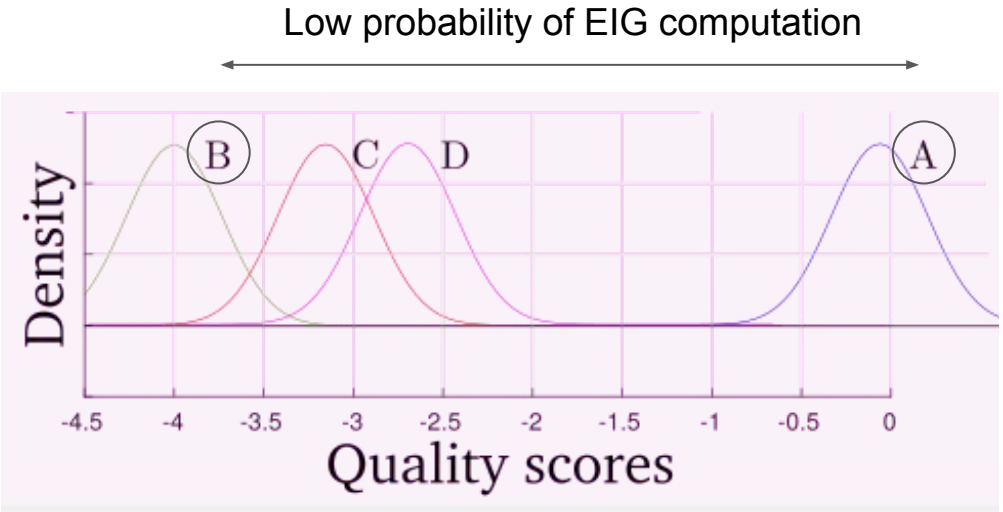


Selective EIG evaluations



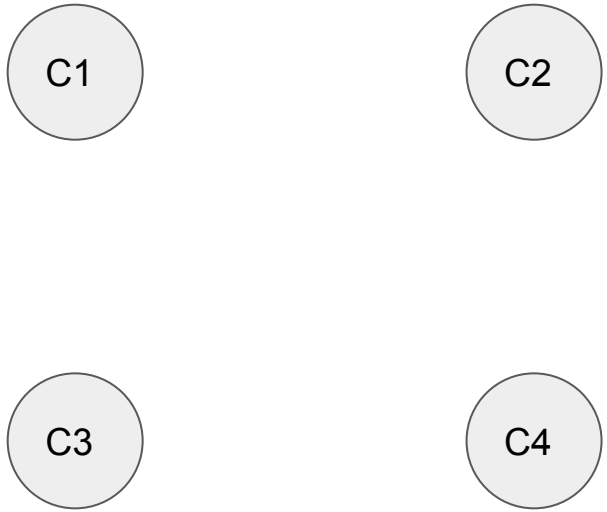
Selective EIG evaluations

High probability of EIG computation

Batch Mode

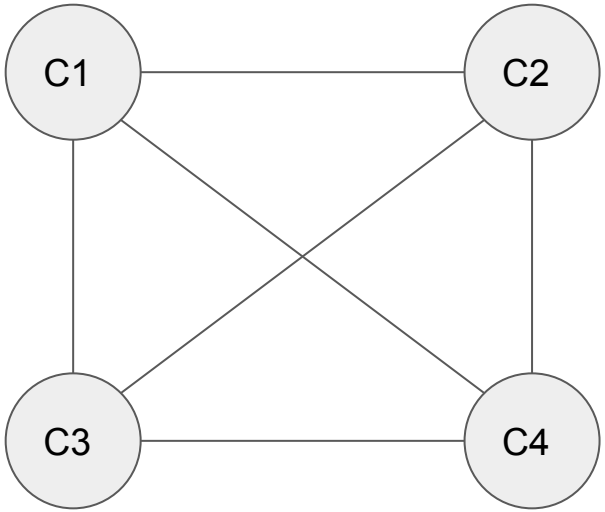
Batch Mode

- Vertices are conditions



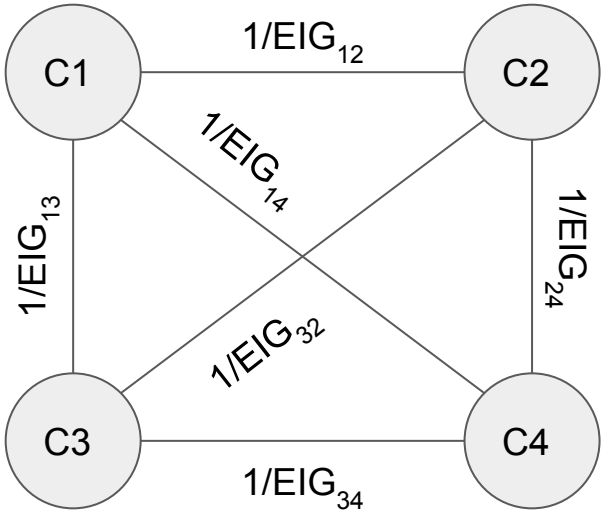
Batch Mode

- Vertices are conditions
- Edges are possible comparisons



Batch Mode

- Vertices are conditions
- Edges are possible comparisons
- Weights are inverse of the expected information gain for comparison



Batch Mode

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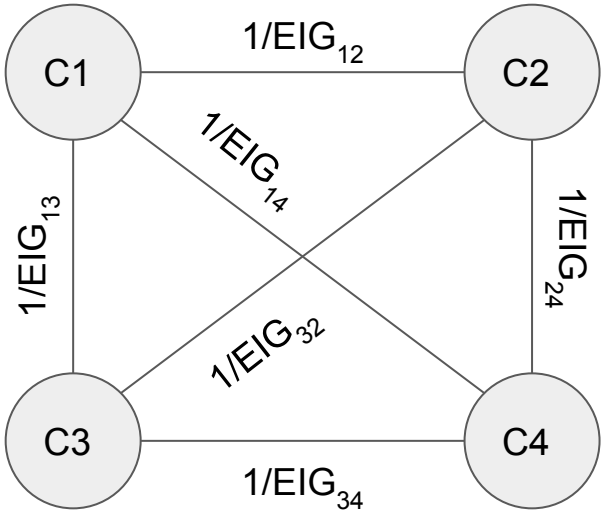
- Edges are possible comparisons
- Weights are inverse of the expected information gain for comparison
- Batch - comparisons forming edges in the minimum spanning tree (MST) [2]



[2] J. Li, R. Mantiuk, J. Wang, S. Ling, and P. Le Callet, “Hybrid-MST: A hybrid active sampling strategy for pairwise preference aggregation,” NIPS, 31st Conference on Neural Information Processing Systems, 2018.

Monte Carlo Simulation

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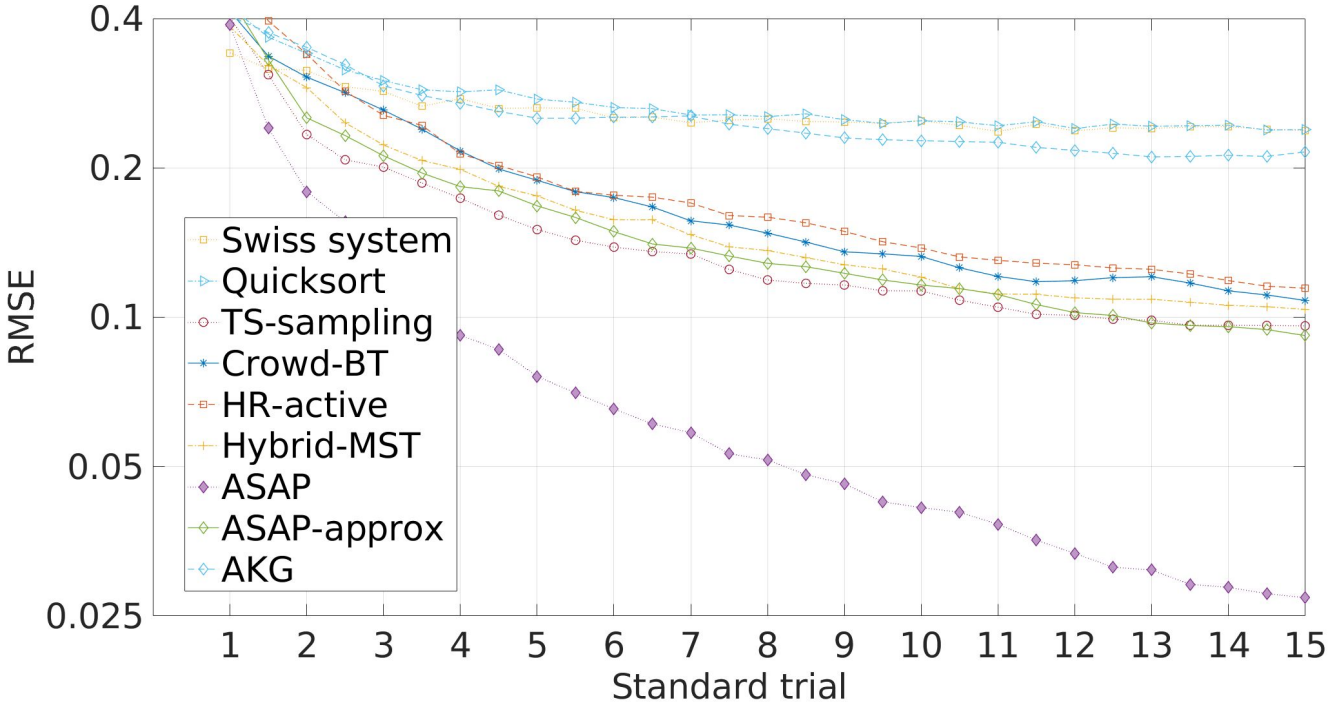

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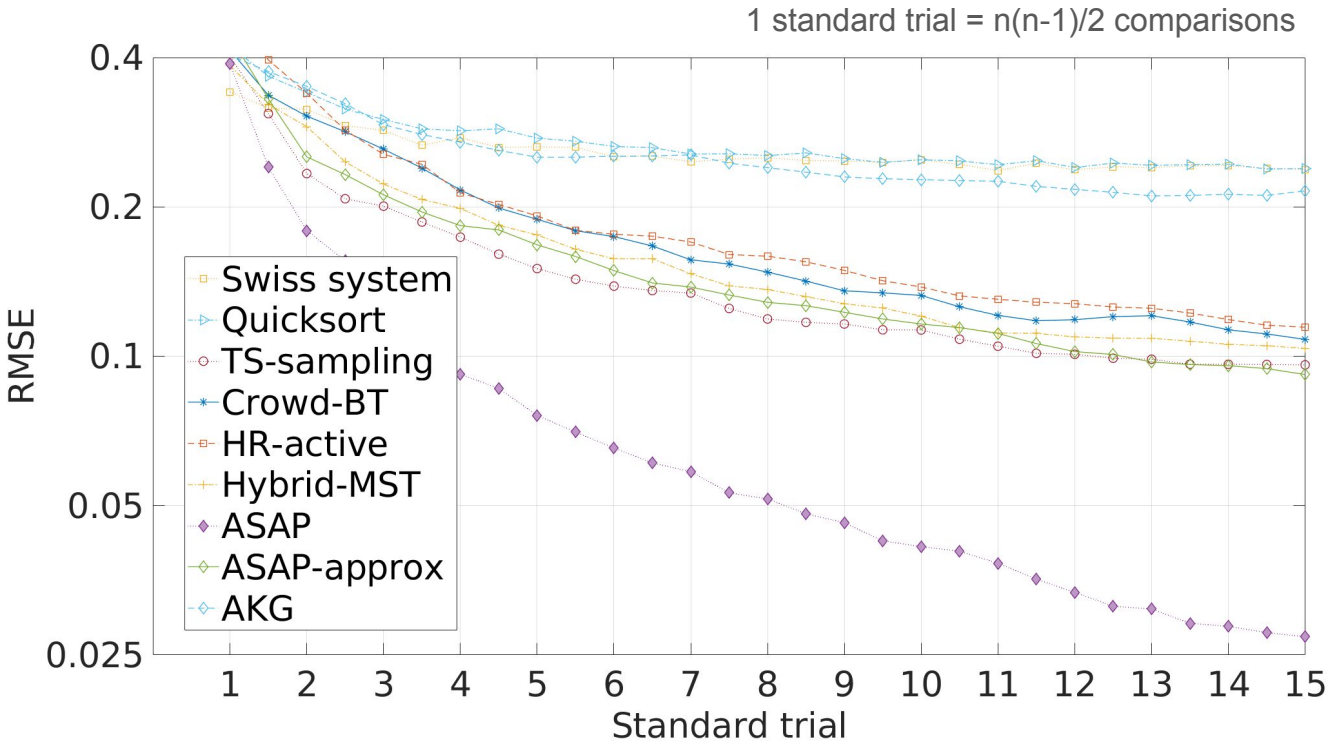

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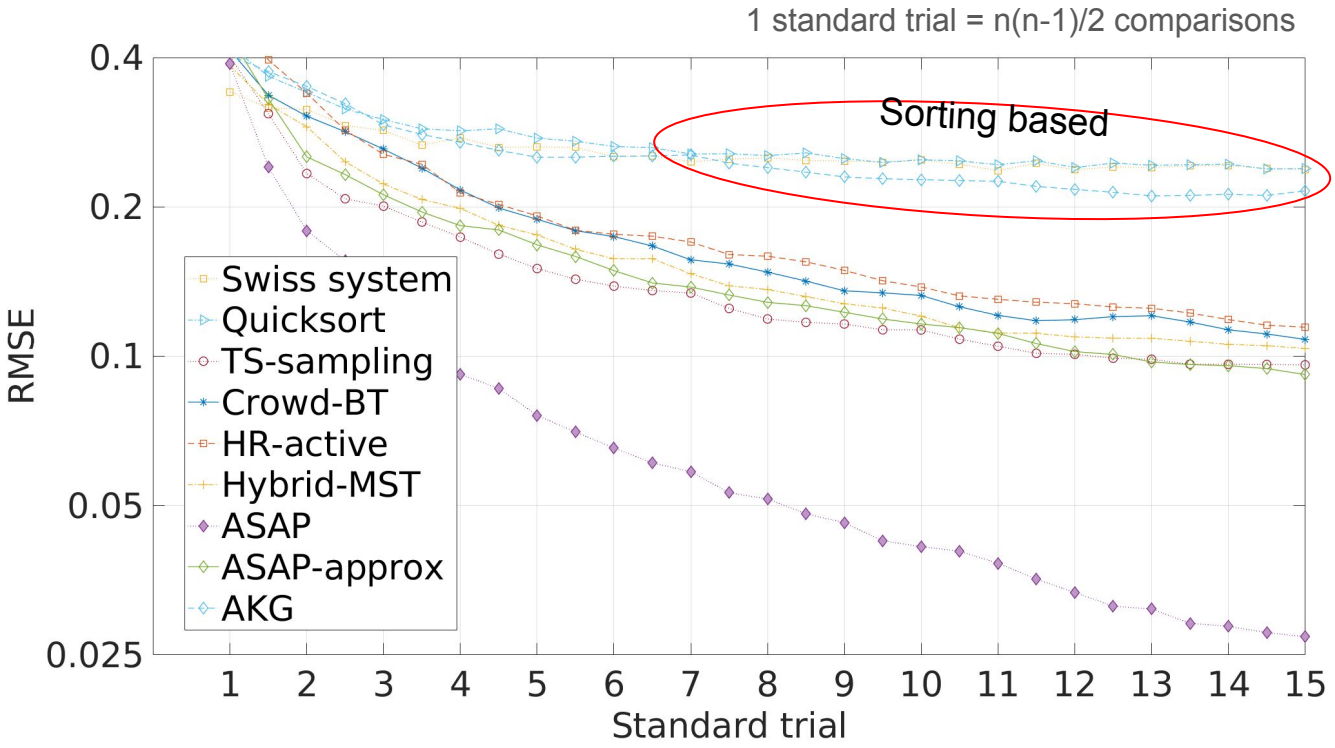

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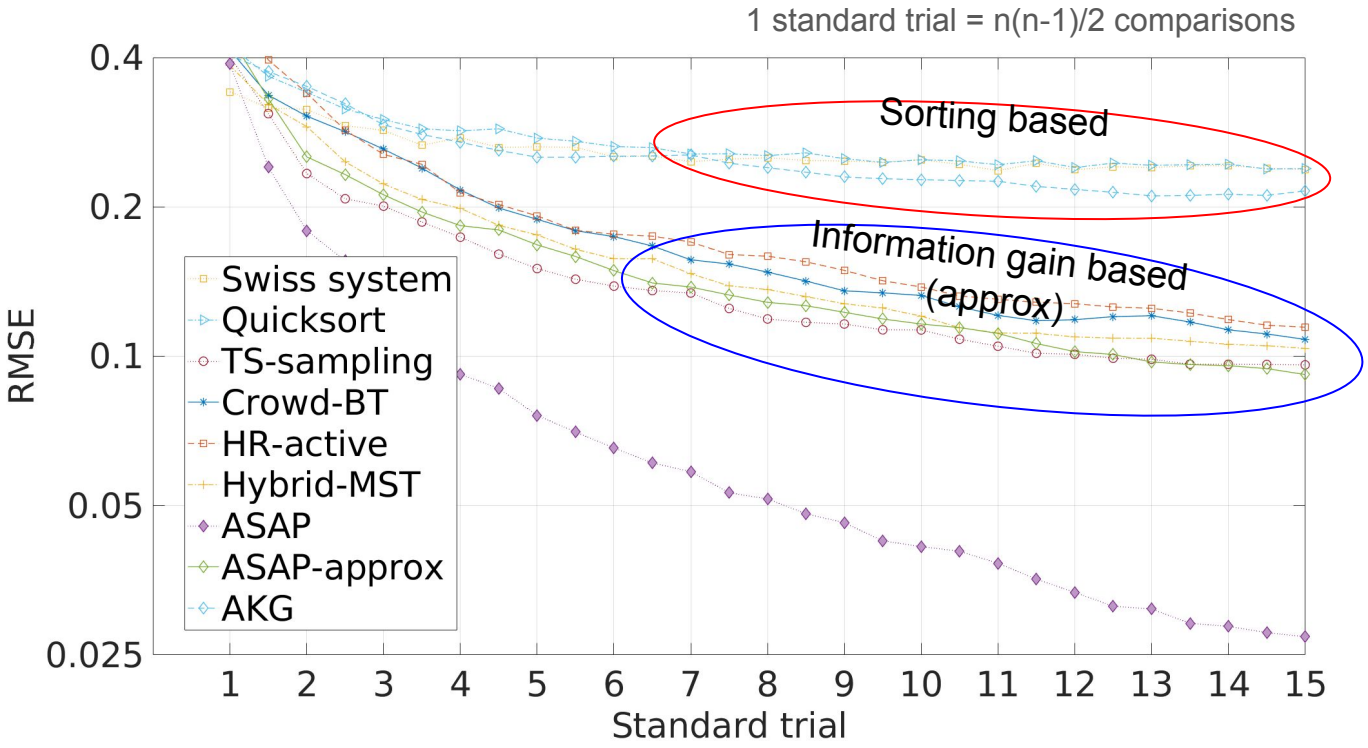

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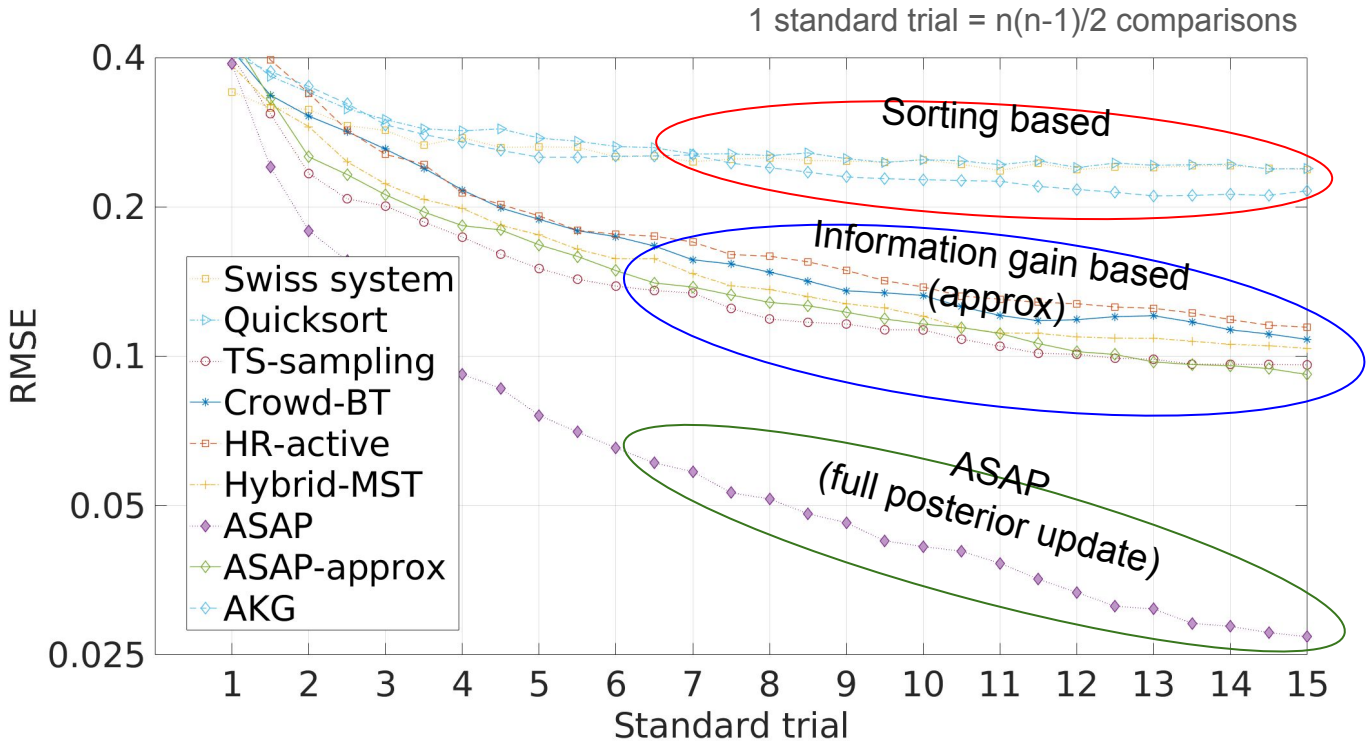
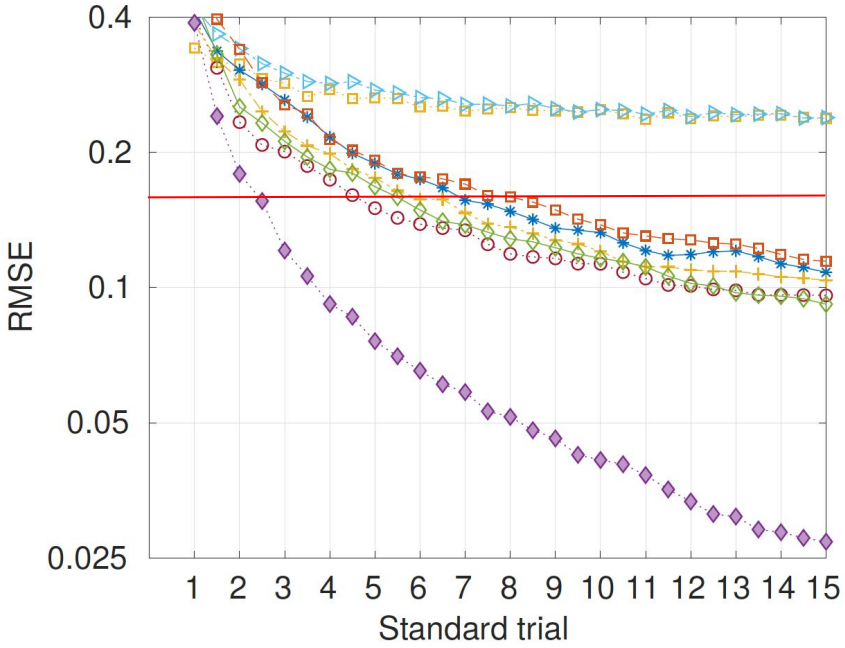


Experimental Effort

- Experimental Effort = time to achieve 0.15 RMSE



Experimental Effort

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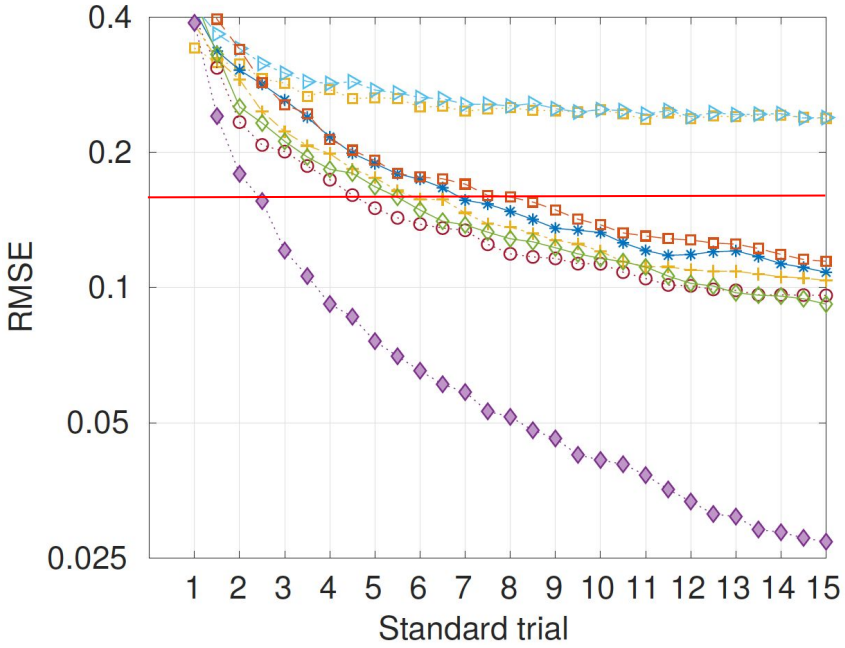
- Assume 5s decision time



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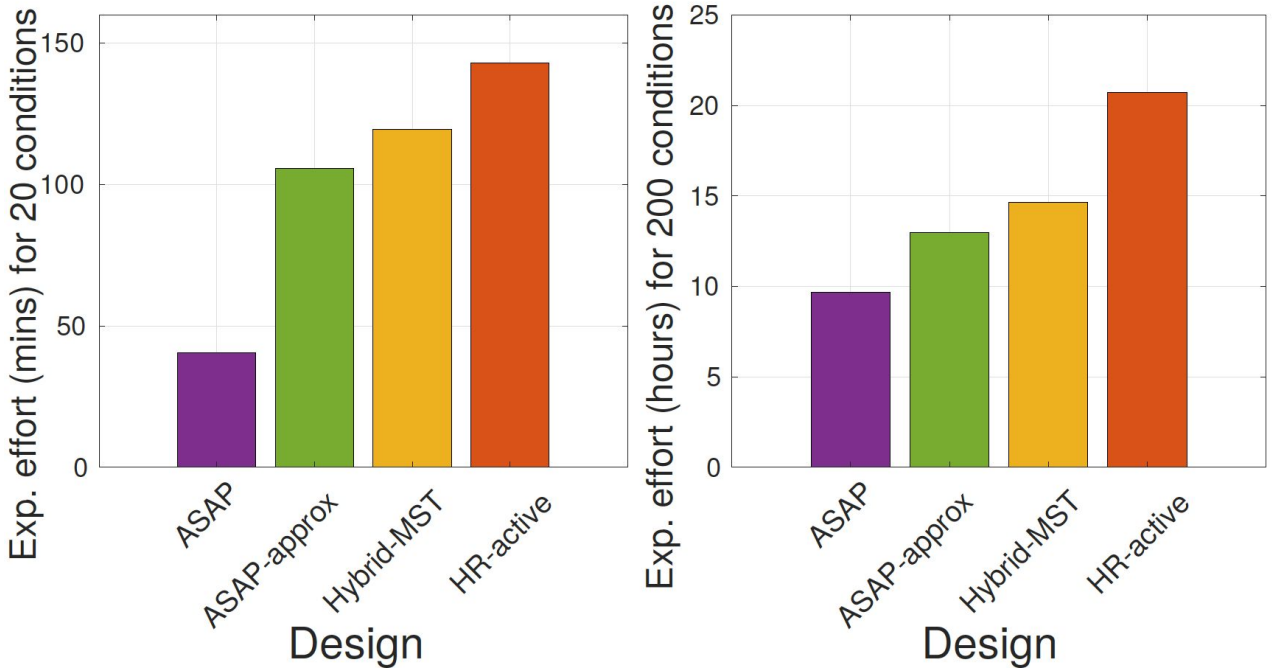

Summary

- **Current methods** are sub-optimal, relying on **partial update** of the posterior distribution;
- **ASAP** computes the **full posterior update**, crucial to achieving **highest accuracy**;
- **ASAP** computes EIG for most informative pairs, **reducing the computational cost** by up to 80%;
- **ASAP** selects **batches** using a minimum spanning tree method**.**

Code: https://github.com/gfxdisp/asap

Contact: am2442@cam.ac.uk