

# Multileave Gradient Descent for Fast Online Learning to Rank

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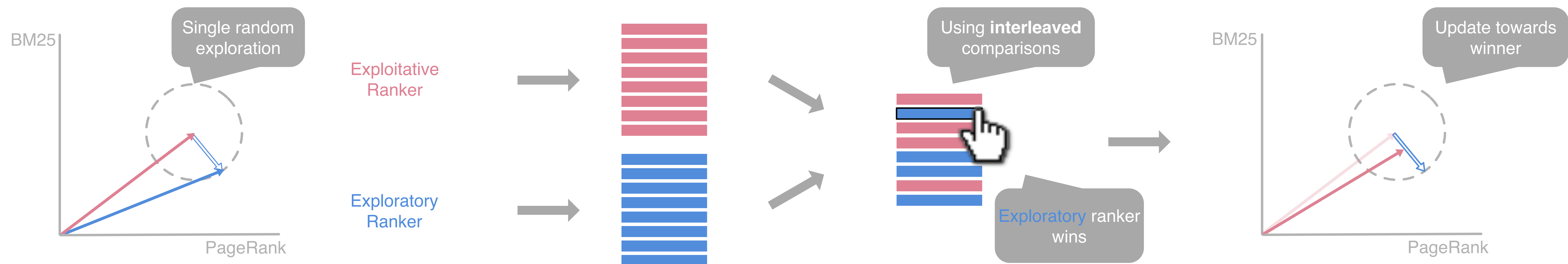
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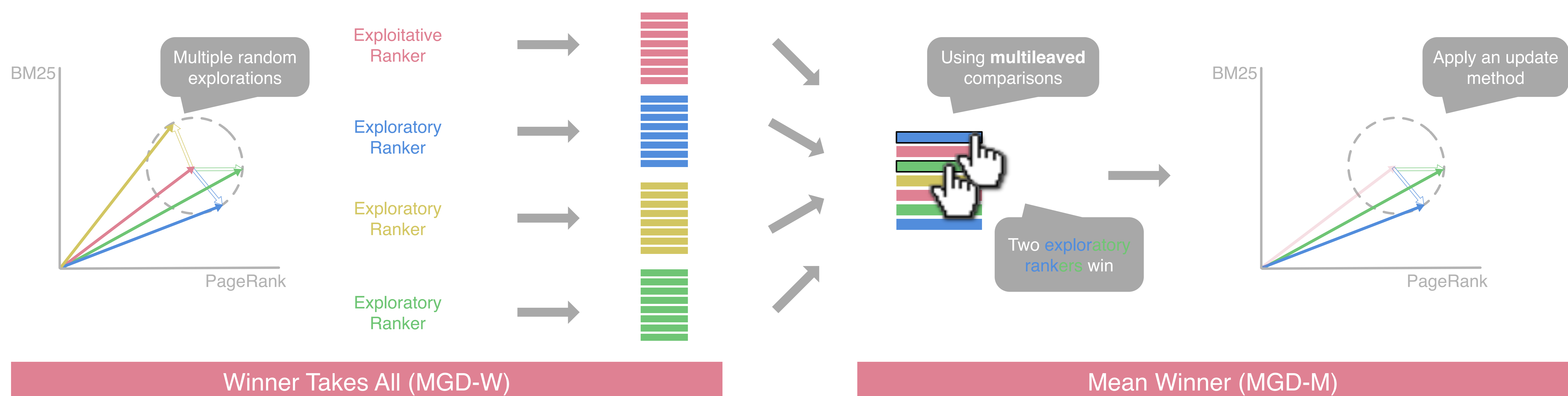
## Dueling Bandit Gradient Descent (DBGD)

- [1] T. Joachims. Optimizing search engines using clickthrough data. In KDD, 2002.  
[2] Y. Yue and T. Joachims. Interactively optimizing information retrieval systems as a dueling bandits problem. In ICML, 2009.



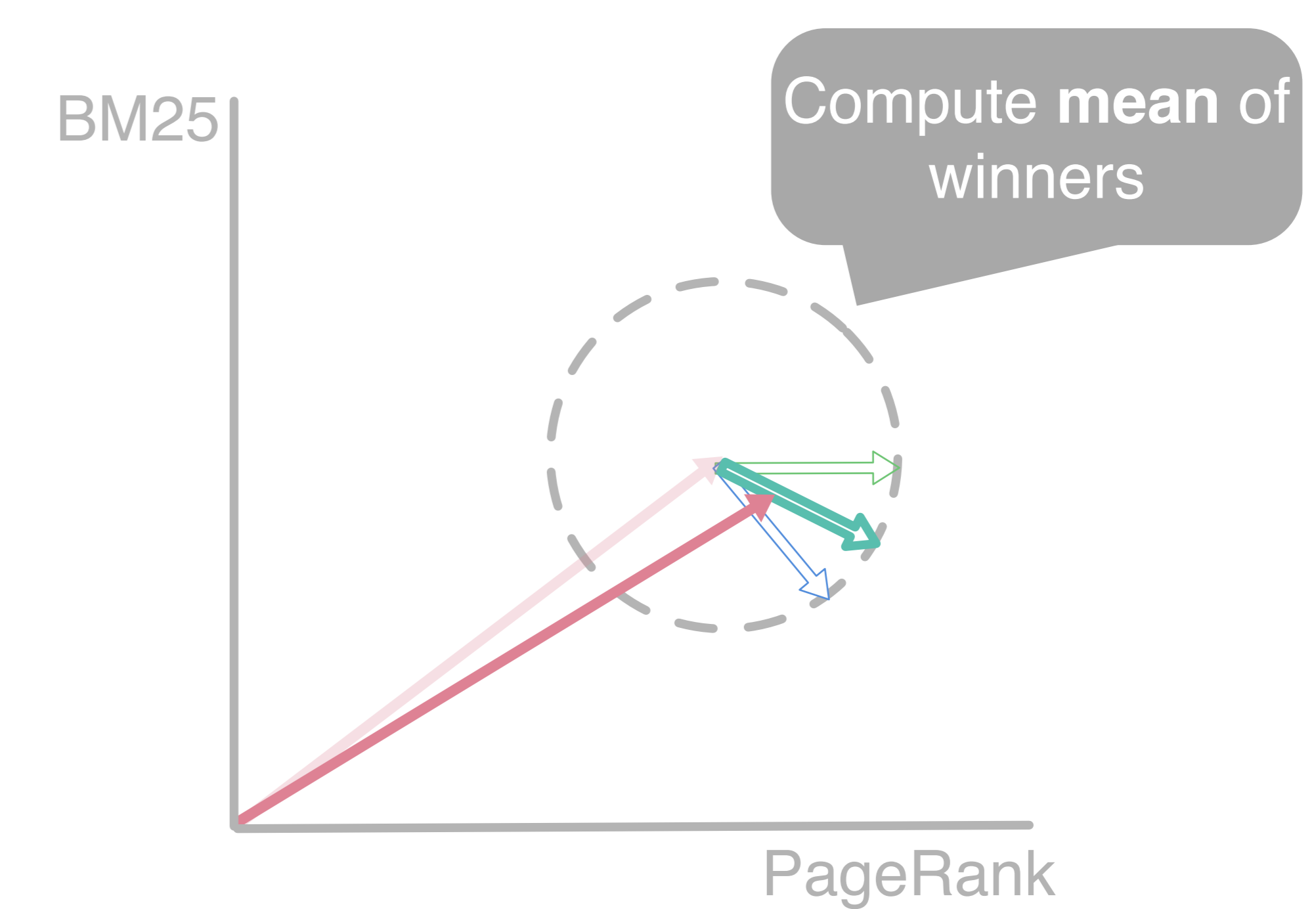
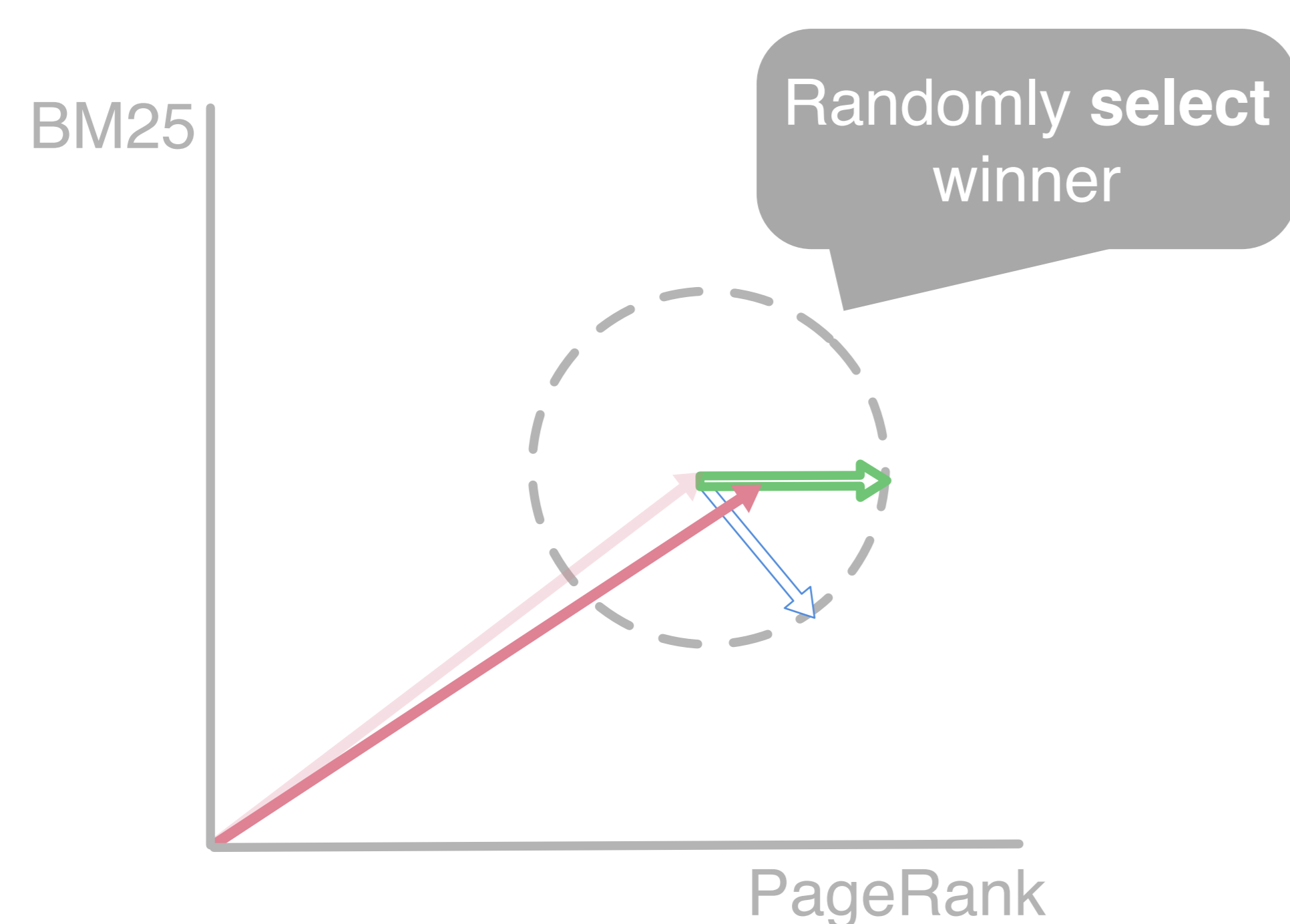
## Multileave Gradient Descent (MGD)

- [3] A. Schuth, F. Sietsma, S. Whiteson, D. Lefortier, and M. de Rijke. Multileaved comparisons for fast online evaluation. In CIKM, 2014.



Winner Takes All (MGD-W)

Mean Winner (MGD-M)

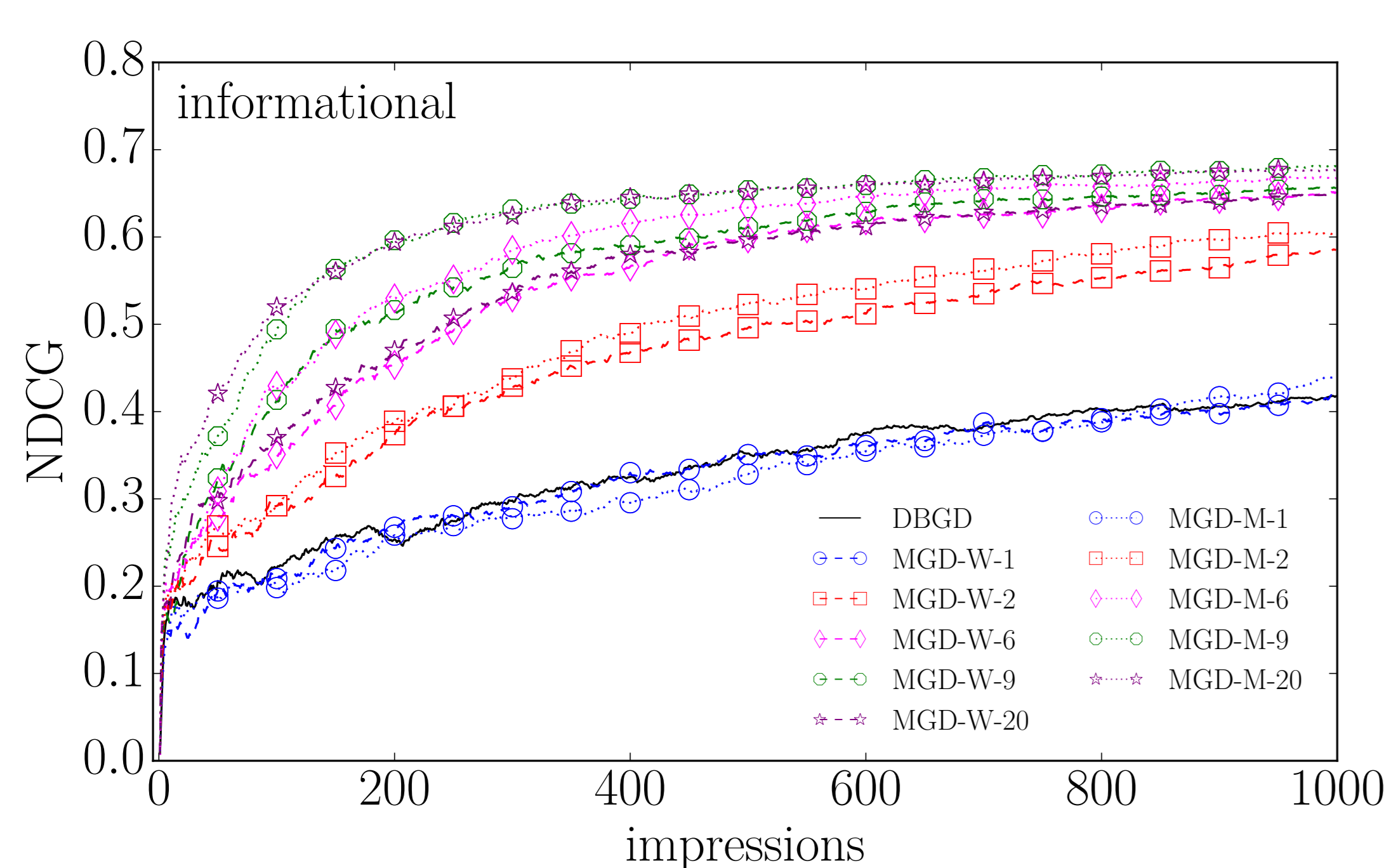


## Experimental Results

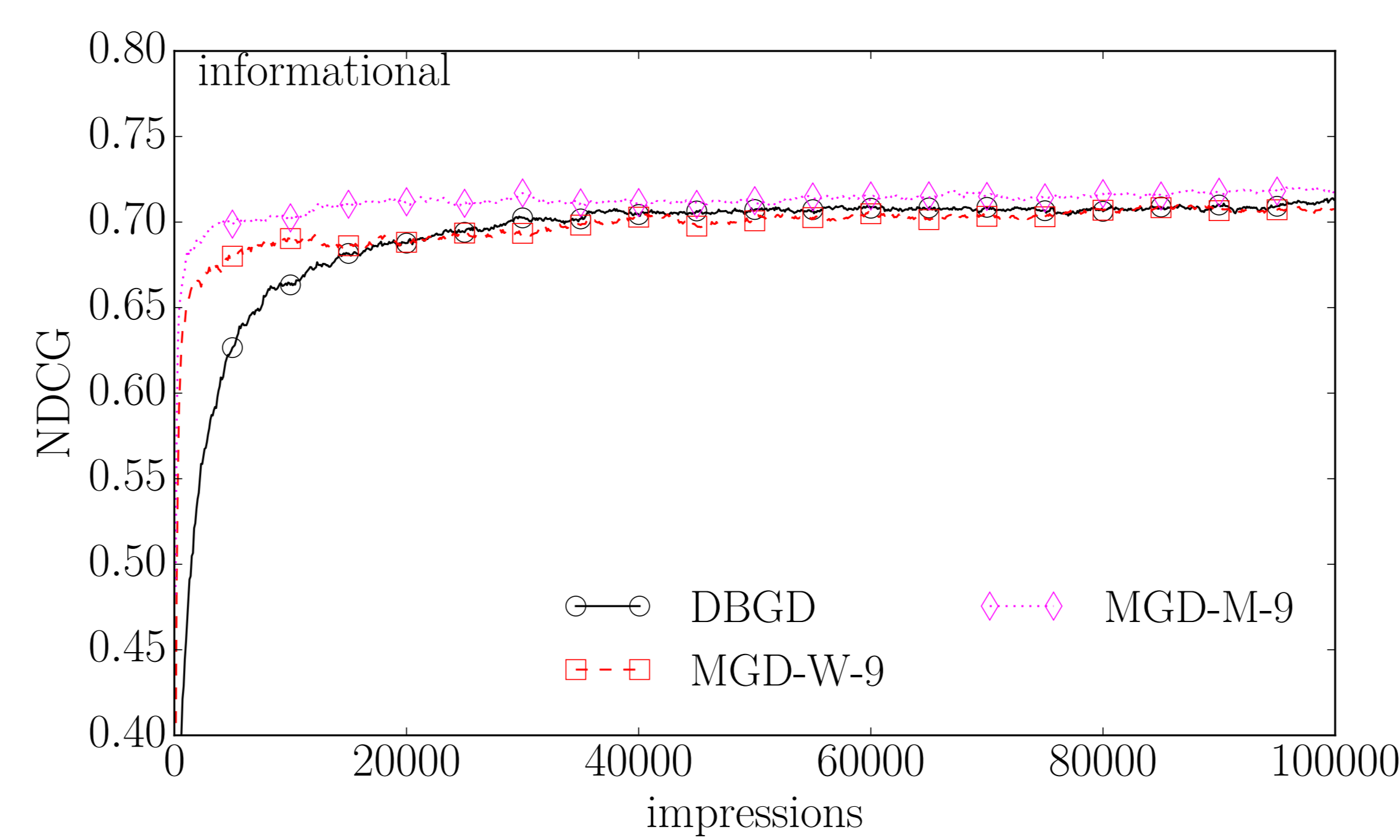
- [4] A. Schuth, K. Hofmann, S. Whiteson, and M. de Rijke. Lerot: An online learning to rank framework. In LivingLab Workshop at CIKM, 2013.



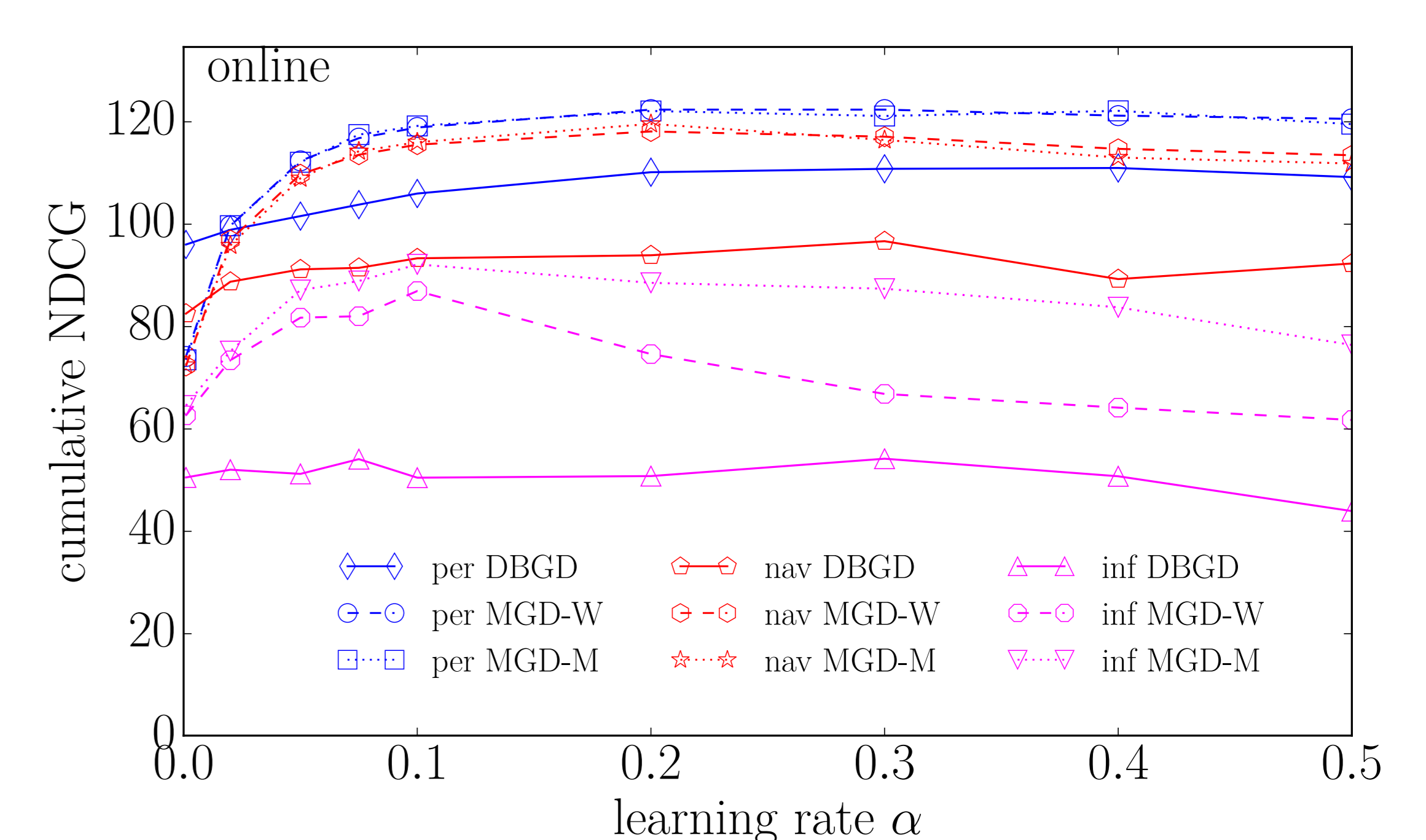
### Noisy Feedback



### Long Run



### Learning Rate



## Conclusions

- Experiments show dramatic improvements over the baseline
- In particular with noisy feedback, MGD learns much faster than DBGD

- MGD-M performs equal or outperforms MGD-W
- Orders of magnitude less interaction data is required
- Far fewer user are exposed to inferior rankers