





Multileave Gradient Descent for Fast Online Learning to Rank

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Search engines are complex machines that base their ranking hundreds of signals



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Learn to combine these signals





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Learn to combine these signals

Offline: using labeled, static datasets



Search engines are complex machines that base their ranking hundreds of signals

Learn to combine these signals

- Offline: using labeled, static datasets
- Online: directly from users

Multileave Gradient Descent for Fast Online Learning to Rank



Dueling Bandit Gradient Descent (DBGD)



PageRank

[Yue et al., 2009; Hofmann et al., 2011;		
Radlinski et al., 2008]	Multileave Gradient Descent	3





[Yue et al., 2009; Hofmann et al., 2011;		
Radlinski et al., 2008]	Multileave Gradient Descent for Fast Online Learning to Rank	3



Dueling Bandit Gradient Descent (DBGD)

B



[Yue et al., 2009; Hofmann et al., 2011;		
Radlinski et al., 2008]	Multileave Gradient Descent for Fast Online Learning to Bank	3



Dueling Bandit Gradient Descent (DBGD)



[Yue et al., 2009; Hofmann et al., 2011;		
Radlinski et al., 2008]	Multileave Gradient Descent for Fast Online Learning to Rank	3

B





A
В
С
D

[Yue et al., 2009; Hofmann et al., 2011;		
Radlinski et al., 2008]	Multileave Gradient Descent for Fast Online Learning to Rank	3





[Yue et al., 2009; Hofmann et al., 2011;			
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A	F
В	A
С	E
D	В
E	С





A	F
В	A
С	E
D	В
E	С

[Yue et al., 2009; Hofmann et al., 2011;			
Radlinski et al., 2008]	Multileave Gradient Descent for Fast Online Learning to Rank	3	



Dueling Bandit Gradient Descent (DBGD)

Preferences through interleaved comparisons





[Yue et al., 2009; Hofmann et al., 2011;		
Radlinski et al., 2008]	Multileave Gradient Descent	3





[Yue et al., 2009; Hofmann et al., 2011;			
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A	F
В	A
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[Yue et al., 2009; Hofmann et al., 2011;		
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В

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В	
С	E
D	В
E	С

A
F

[Yue et al., 2009; Hofmann et al., 2011;		
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В

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[Yue et al., 2009; Hofmann et al., 2011;		
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Existing work







[Yue et al., 2009; Hofmann et al., 2011;			
Radlinski et al., 2008]	Multileave Gradient Descent	3	



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Existing work

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[Yue et al., 2009; Hofmann et al., 2011; Radlinski et al., 2008]

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Existing work

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DBGD updates after exploring only a single direction





DBGD updates after exploring only a single direction

Exploring multiple directions would lead to a better ranker with less updates





DBGD updates after exploring only a single direction

Exploring multiple directions would lead to a better ranker with less updates

But would be expensive when interleaving was used

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for Fast Online Learning to Rank



- DBGD updates after exploring only a single direction
- Exploring multiple directions would lead to a better ranker with less updates
- But would be expensive when interleaving was used
 - Requires pairwise comparisons between all pairs of directions



- DBGD updates after exploring only a single direction
- Exploring multiple directions would lead to a better ranker with less updates
- But would be expensive when interleaving was used
 - Requires pairwise comparisons between all pairs of directions

Multileaved comparisons can avoid this



Our work

Multileave Gradient Descent (MGD)



PageRank

[Yue et al., 2009; Hofmann et al., 2011;		
Radlinski et al., 2008; Schuth et al., 2014]	Multileave Gradient Descent for Fast Online Learning to Rank	5



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Multileave Gradient Descent (MGD)





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PageRank

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PageRank

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Radlinski et al., 2008; Schuth et al., 2014]Multileave Gradient Descent
for Fast Online Learning to Rank5



A	В	A	D	С
В	D	В	В	A
С	G		A	B
D	A			E
E	С		E	G

5

Our work



[Yue et al., 2009; Hofmann et al., 2011;	
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Multileave Gradient Descent (MGD)



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Multileave Gradient Descent (MGD)



PageRank

Multileave Gradient Descent	
or Fast Online Learning to Rank	

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Our work

Multileave Gradient Descent (MGD)



PageRank

Nultileave Gradient Descent	
or Fast Online Learning to Rank	

6



Our work

Multileave Gradient Descent (MGD)





Our work

Multileave Gradient Descent (MGD)





PageRank

Multileave Gradient Descent for Fast Online Learning to Rank



Our work

Multileave Gradient Descent (MGD)

Winner takes all (MGD-W)







PageRank





Our work

Multileave Gradient Descent (MGD)

Winner takes all (MGD-W)



Mean winner (MGD-M)







Our work

Multileave Gradient Descent (MGD)

Winner takes all (MGD-W)













Our work

Multileave Gradient Descent (MGD)

Winner takes all (MGD-W)







PageRank

Multileave Gradient Descent
for Fast Online Learning to Rank

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Our work

Multileave Gradient Descent (MGD)

Winner takes all (MGD-W)



Mean winner (MGD-M)









Our work

Multileave Gradient Descent (MGD)

Winner takes all (MGD-W)



Mean winner (MGD-M)







Our work

Multileave Gradient Descent (MGD)

Winner takes all (MGD-W)







Winner takes all (MGD-W)







Winner takes all (MGD-W)







Winner takes all (MGD-W)







Winner takes all (MGD-W)







Winner takes all (MGD-W)



Pick one of the winners
 Update with an alpha step



- Compute the mean of the winners
- Update with an alpha step

Multileave Gradient Descent for Fast Online Learning to Rank



Winner takes all (MGD-W)



Pick one of the winners
 Update with an alpha step



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Multileave Gradient Descent for Fast Online Learning to Rank



Experiments

Queries

Sampled from a L2R dataset





Experiments

Queries

Sampled from a L2R dataset

Clicks

Generated by a cascade click model





Experiments

Queries

Sampled from a L2R dataset

Clicks

Generated by a cascade click model

NDCG

Measured on held out data

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Conclusions

We introduce MGD, an extension of DBGD

- Multileaving instead of Interleaving
- Two update methods MGD-M and MGD-W
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 - Large improvements over baseline
 - Especially with noise in feedback

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Implications

- Orders of magnitude less interaction data required with MGD
- Search engines can adapt much faster







Thank you

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Dueling Bandit Gradient Descent (DBGD)	 T. Joachims. Optimizing search engines using clickthrough data. In KDD, 2002. Y. Yue and T. Joachims. Interactively optimizing information retrieval systems as a dueling bandits problem. In ICML, 2009.
EN25 Single random exploitative Restar PageRank Exploratory Ranker	Using interleaved comparisons BM25 Update towards winner Update towards winner Update towards winner PageRank
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.
EMS Multiple random regionators FageRank Exploratory PageRank Exploratory Rankar Exploratory	Horig multileved comparisons Horigon BM25 File
Winner Takes All (MGD-W)	Mean Winner (MGD-M)
BM25 Randomly select winar PageRank	BM25 Compute mean or winners PageRank
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 Ru by the state stat	un 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
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