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Information Retrieval

Online Learning to Rank

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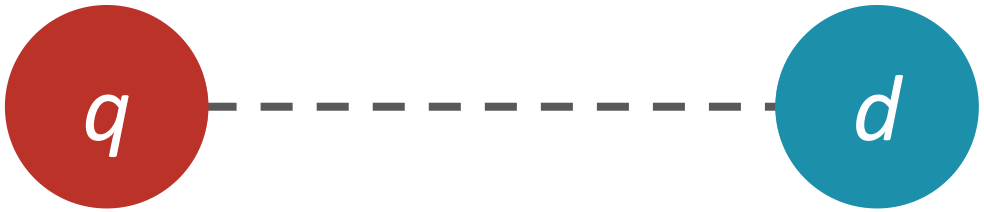
The ranking problem

$$f(q,d)$$

Learning to rank



$$f(\mathbf{x})$$

Learning to rank

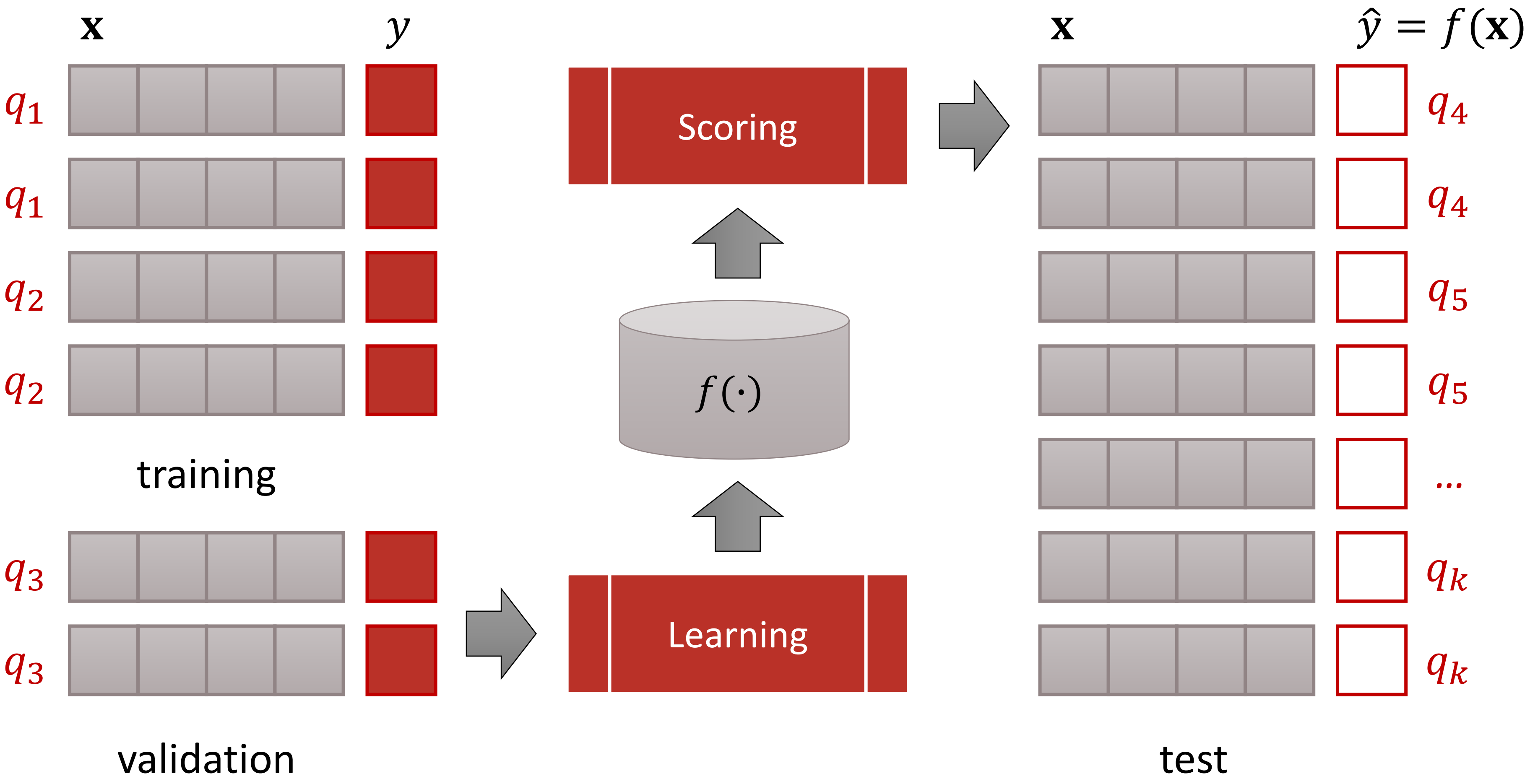
Feature-based representation

- Individual models as ranking ”features”

Discriminative learning

- Effective models learned from data
- Aka machine-learned ranking

Discriminative learning framework



Drawbacks

Scalability

- Relevance labels are costly
- More so if expert labels are needed

Realism

- Hired judges aren’t real users
- Real users’ preferences are contextualized

Credit: NIST

Contextualized preferences

Context has a significant influence on search behavior

- Addressing all possible settings individually, through supervised learning, is not feasible

Can’t sacrifice users while learning ranking models

- Need to look for scalable methods that can learn effective rankings without expensive tuning

Online learning to rank

Learn directly from natural interactions with users

- Typically implicit feedback (e.g., clicks)

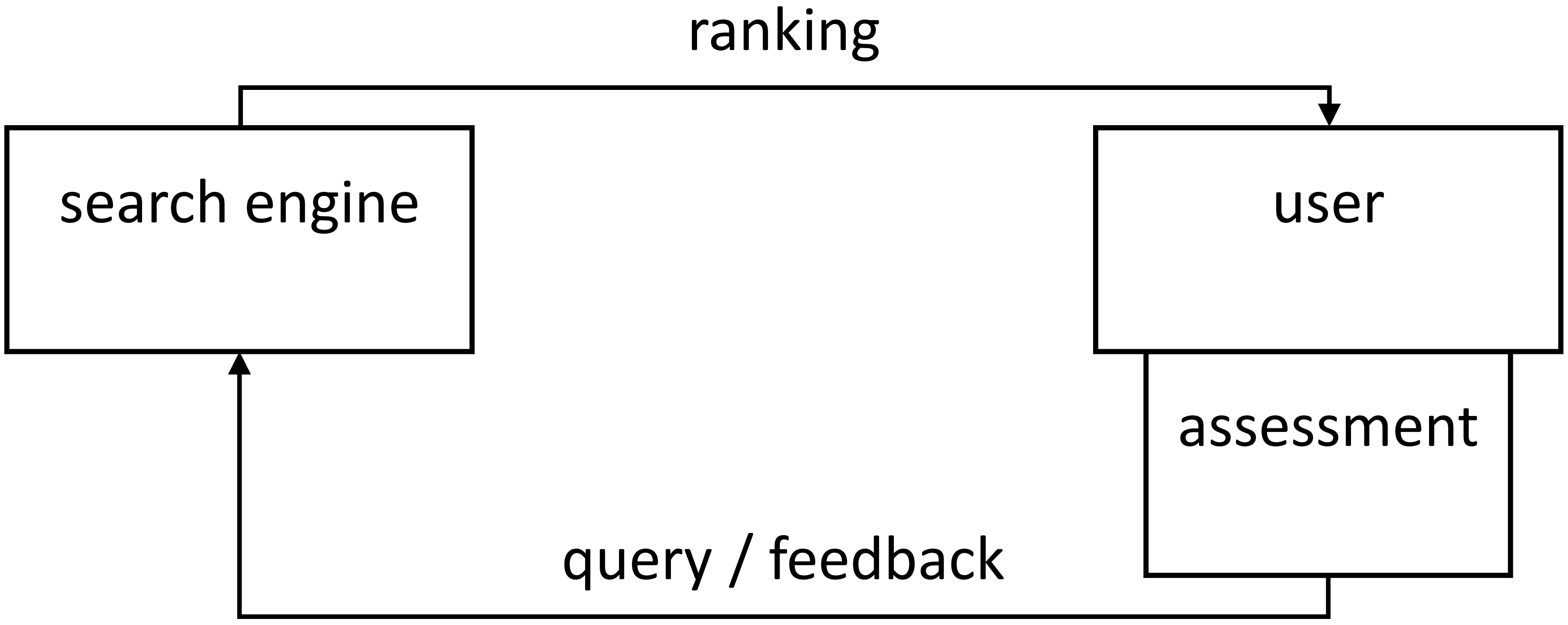
Update learned models incrementally

- Sequential as opposed to batch learning

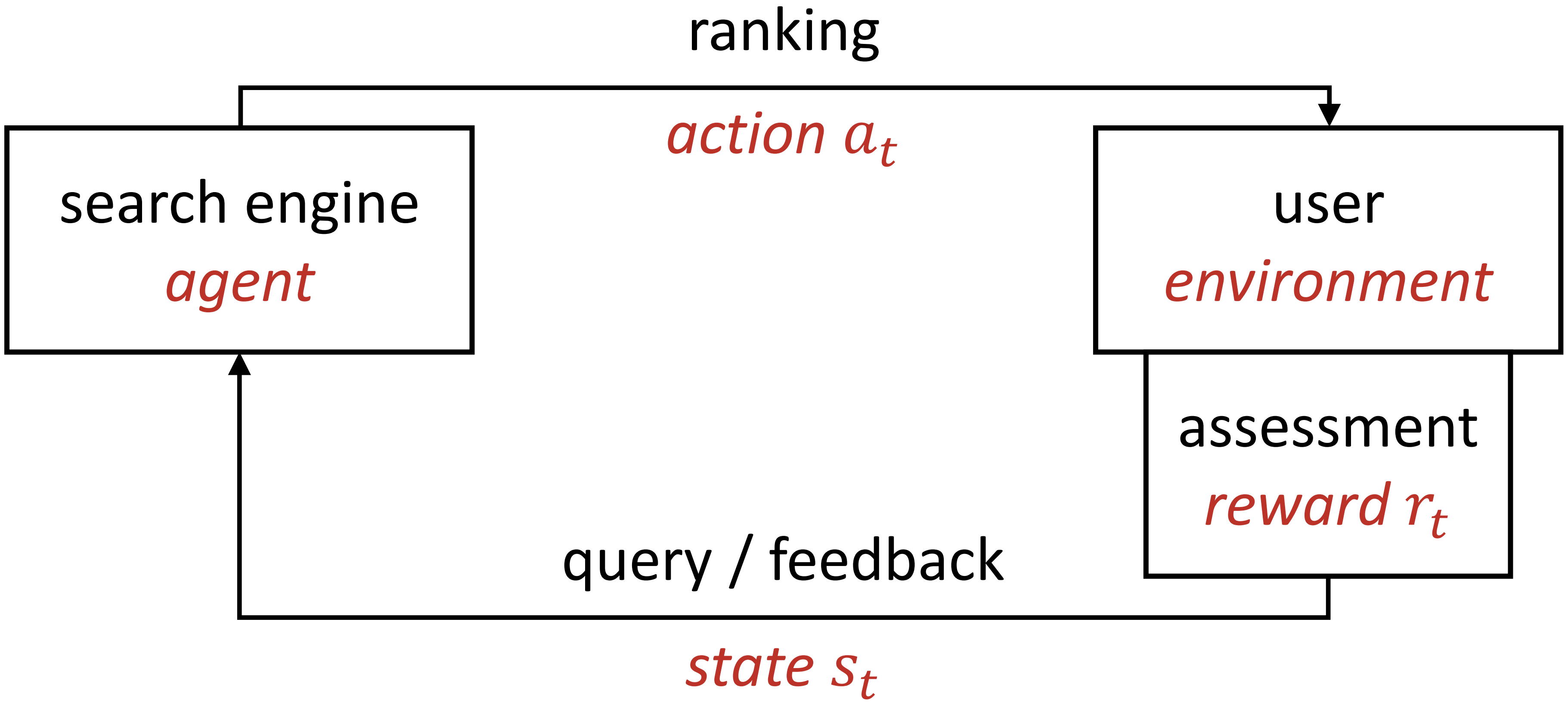
Continuously adapt as interactions progress

- From ”random” to fine-tuned rankings

Online learning to rank



Reinforcement learning



Reinforcement learning

At each discrete time step t

- Agent observes state s_t
- Agent selects action a_t
- Environment provides reward r_t
- Environment moves to a new state s_{t+1}

Goal is to maximize cumulated reward as $t \to \infty$

Credit: Google DeepMind

Exploration-exploitation trade-off

Exploration

- Reward is only provided for the selected action
- We want to uncover other rewarding actions

Exploitation

- Pure exploration risks selecting unrewarding actions
- We want to maximize total reward in the long run

Reinforcement learning for ranking

Online learning to rank as a bandit problem

- State (s_t) does not depend on past actions

Multi-armed bandits (MAB)

- State is not provided

Credit: Wikipedia

Reinforcement learning for ranking

Online learning to rank as a bandit problem

- State (s_t) does not depend on past actions

Multi-armed bandits (MAB)

- State is not provided

Contextual bandits

- State (context vector) is provided

Multi-armed bandits

No state (e.g., query or user profile) is provided

- Fits well with non-personalized recommendation

Example: homepage news recommendation

- New user arrives, recommender returns a news story (a_t) to show, observes whether user clicks (r_t)
- Goal: maximize clicks in a given period

Example: ϵ-greedy

Simple strategy

- Explore with probability $\epsilon \in [0,1]$
- Exploit with probability $1 - \epsilon$

Often works well in practice

- With hyperparameter ϵ suitably tuned

Example: UCB

True reward distribution of an action is unknown

- We can only observe samples r of it
- Each observed sample increases our confidence

Idea: explore actions with large confidence bounds

- Try the action a_x that maximizes $\bar{r}_x + \sqrt{(2\ln n)/n_x}$ for an average reward $\bar{r}_x$ after n_x observations

Contextual bandits

State (context) does not depend on past actions

- Fits well with independent user searches

Example: (stateless) web search

- User submits a query (s_t), search engine displays a ranking (a_t), observes if/where the user clicks (r_t)
- Goal: maximize ranking quality in a given period

Contextual bandits

k-armed contextual bandits

- Find the best among k ranking models
  (e.g., $k - 1$ candidate models vs. current best model)

Continuous-armed contextual bandits

- Find the best among infinite ranking models
  (i.e., feature-based ranking models)

How to infer ranking quality implicitly?

Problem

Rewards aren’t directly measurable

Absolute metrics

Document-level

- Click rate, click models

Ranking-level

- Reciprocal rank, CTR@k, time-to-click, abandonment

Session-level

- Queries per session, session length, time to first click

Relative metrics

Absolute document-level metrics are biased

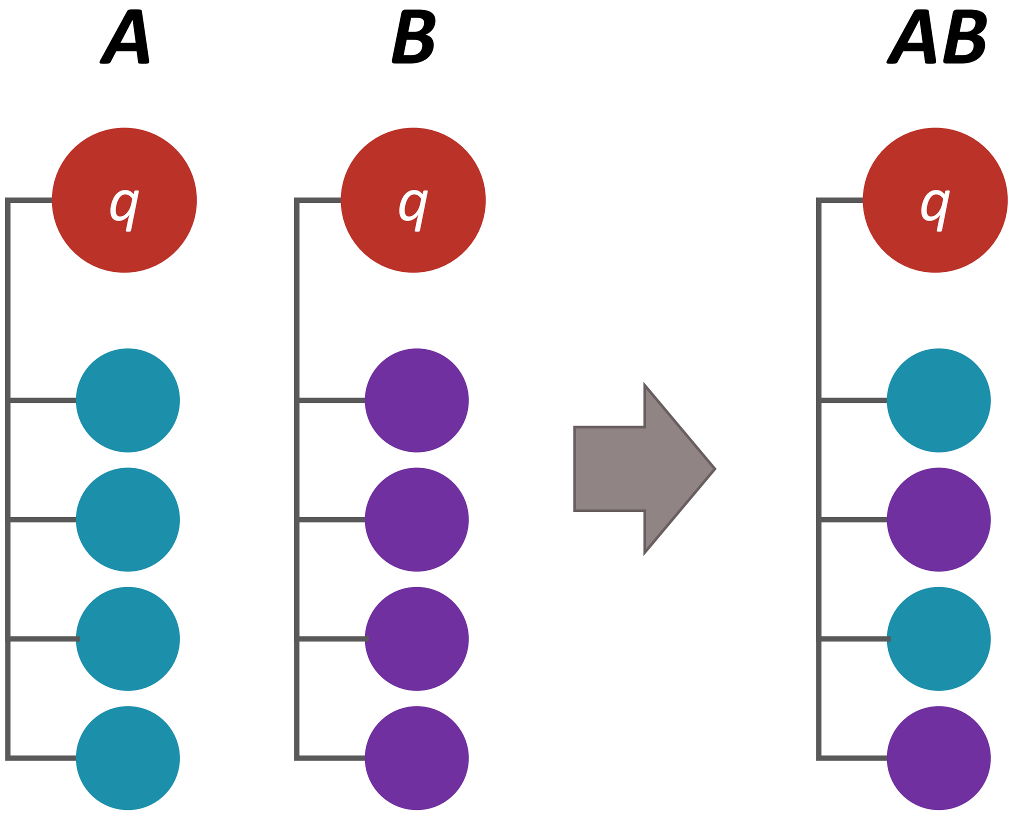
- Position bias: top ranked document favored
- Presentation bias: highlighted documents favored

Relative document-level metrics are less affected

- Click-skip, fair pairs

Better: relative ranking-level metrics!

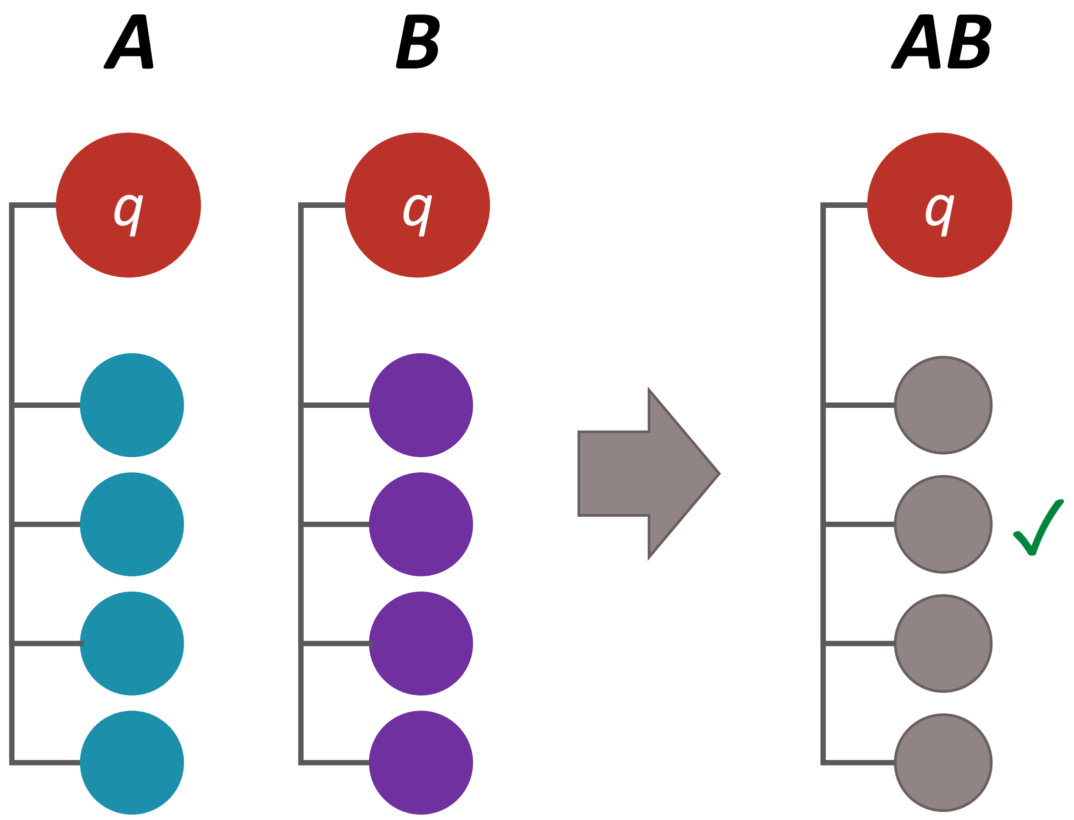
Interleaved comparisons
[Joachims, KDD 2002]



Blend results from both conditions into a single ranking

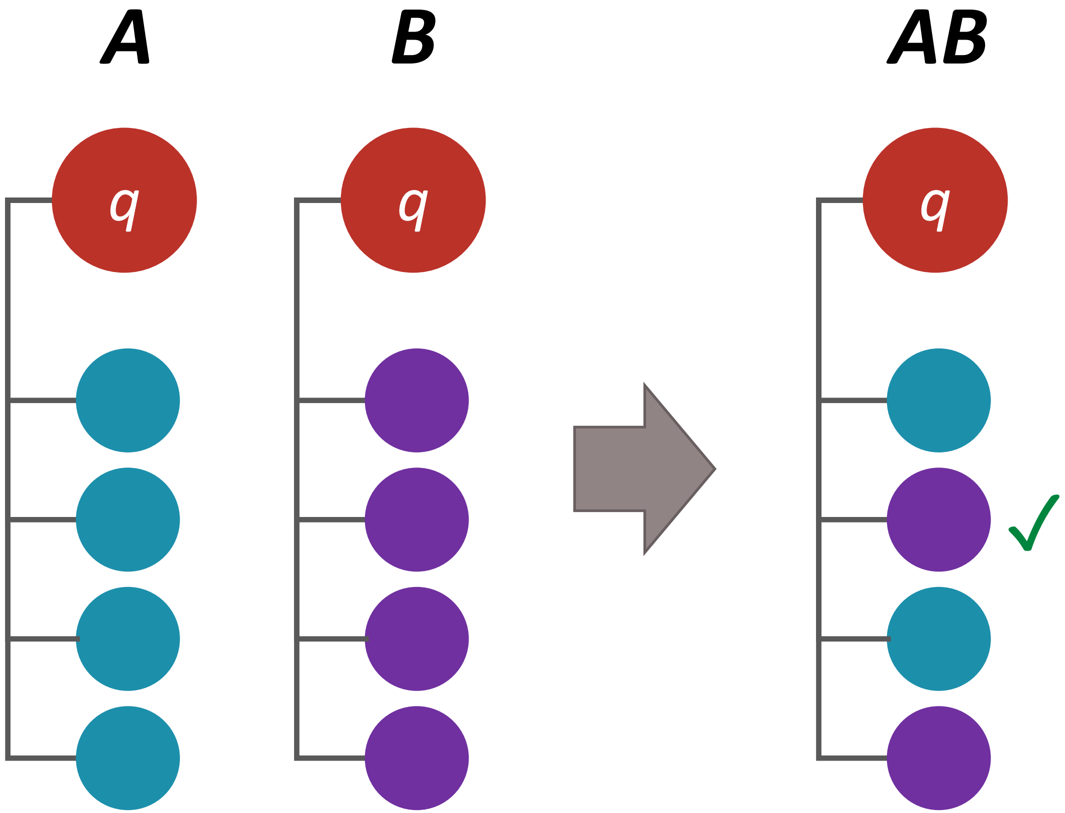
Interleaved comparisons

[Joachims, KDD 2002]



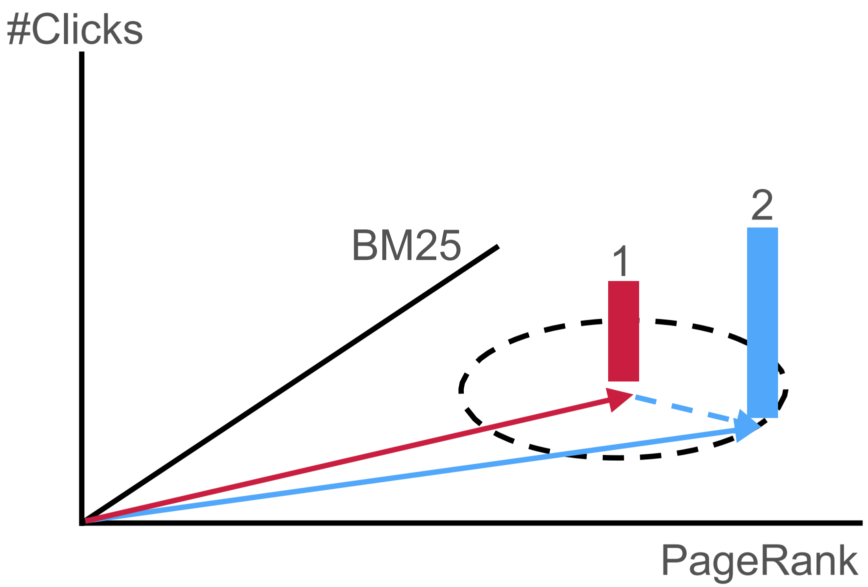
Hide provenance from the user and collect feedback

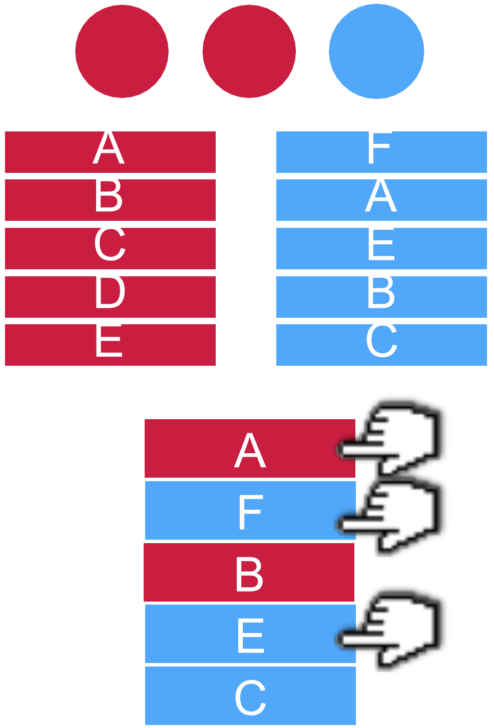
Interleaved comparisons
[Joachims, KDD 2002]



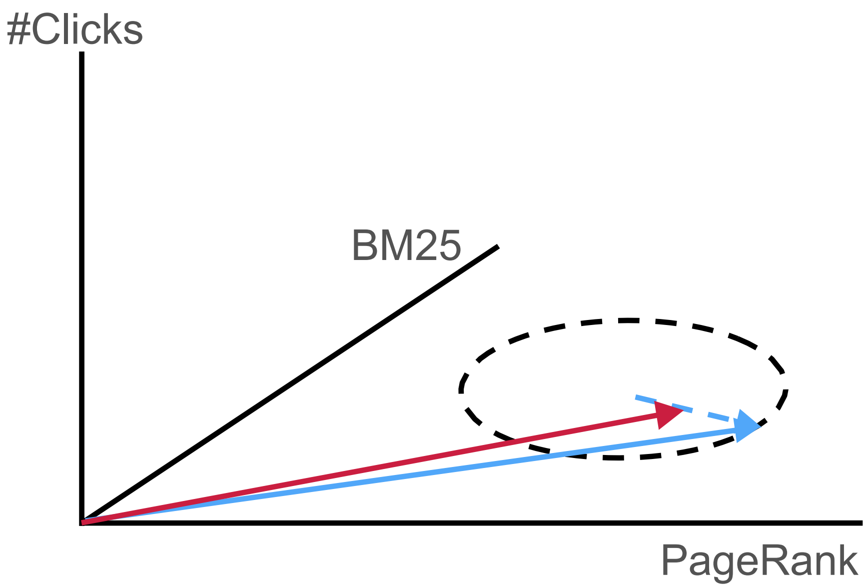
Assign credit:
e.g., B wins over A

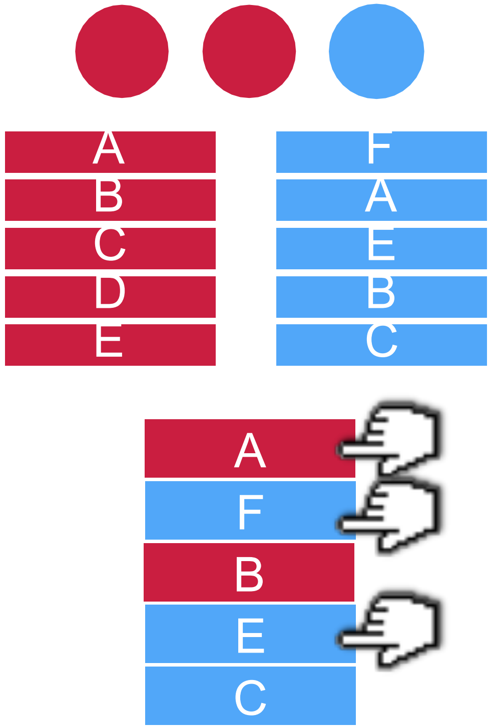
Dueling bandit gradient descent (DBGD)
[Yue et al., ICML 2009]





Dueling bandit gradient descent (DBGD)
[Yue et al., ICML 2009]





Dueling bandit gradient descent (DBGD)

[Yue et al., ICML 2009]

Algorithm 2 Dueling Bandit Gradient Descent (DBGD).

Require: $\alpha, \delta, \mathbf{w}_0^0$

for $t \leftarrow 1..\infty$ **do**

- $q_t \leftarrow receive\_query(t)$ — *// obtain a query from a user*
- $\mathbf{l}_0 \leftarrow generate\_list(\mathbf{w}_t^0, q_t)$ — *// ranking of current best*
- $\mathbf{u}_t^1 \leftarrow sample\_unit\_vector()$
- $\mathbf{w}_t^1 \leftarrow \mathbf{w}_t^0 + \delta \mathbf{u}_t^1$ — *// create a candidate ranker*
- $\mathbf{l}_1 \leftarrow generate\_list(\mathbf{w}_\mathbf{t}^\mathbf{1}, q_t)$ — *// exploratory ranking*
- $\mathbf{m}_t, \mathbf{t}_t \leftarrow TDI\_interleave(\mathbf{l})$ — *// interleaving and teams*
- $\mathbf{c}_t \leftarrow receive\_clicks(\mathbf{m}_t)$ — *// show interleaving to the user*
- $\mathbf{b}_t \leftarrow TDI\_infer(\mathbf{t}_t, \mathbf{c}_t)$ — *// set of winning candidates*
- **if** $\mathbf{w}_t^0 \in \mathbf{b}_t$ **then**
  - $\mathbf{w}_{t+1}^0 \leftarrow \mathbf{w}_t^0$ — *// if current best wins or ties, no update*
- **else**
  - $\mathbf{w}_{t+1}^0 \leftarrow \mathbf{w}_t^0 + \alpha \mathbf{u}_t^1$ — *// update α step towards candidate*

Dueling bandit gradient descent (DBGD)
[Yue et al., ICML 2009]

DBGD explores one direction at a time

- Exploring multiple directions could improve efficiency

Interleaving requires pairwise comparisons

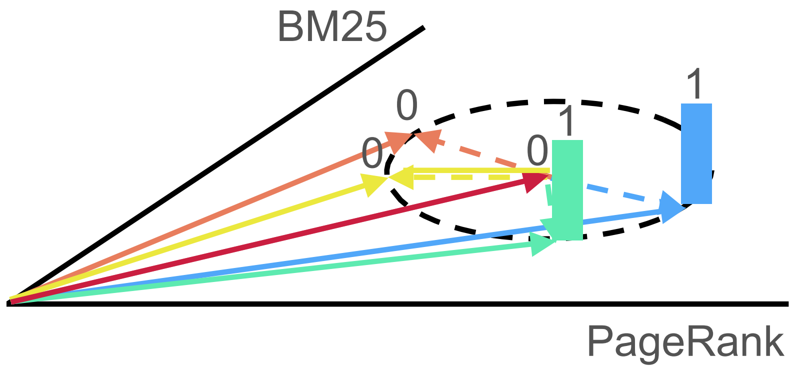
- Quadratic on the number of candidate models

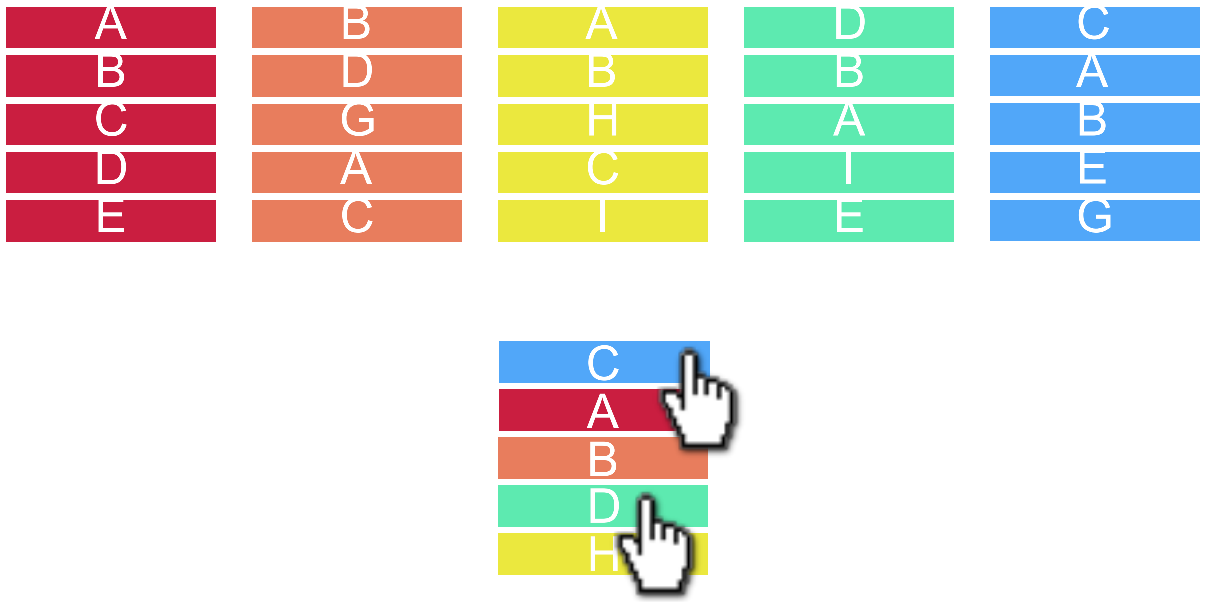
Multileaving to the rescue

- Credit clicks independently, declare winner(s)

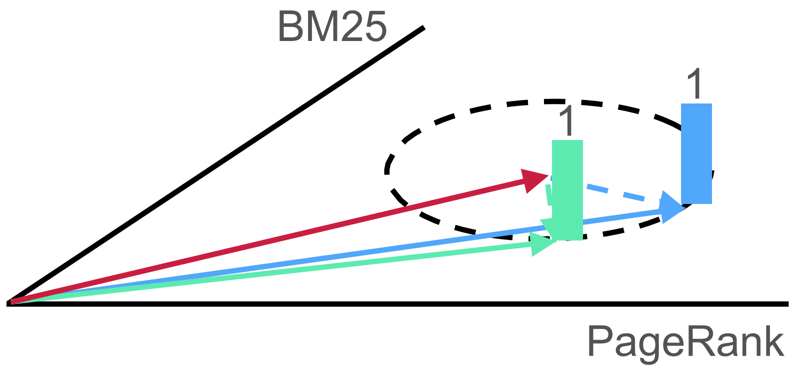
Multileave gradient descent (MGD)

[Schuth et al., WSDM 2016]





Multileave gradient descent (MGD)
[Schuth et al., WSDM 2016]



Winner takes all (MGD-W)

Randomly choose one of the winning models

Mean winner (MGD-M)

Use the average of the winning models

Multileave gradient descent (MGD)

[Schuth et al., WSDM 2016]

Algorithm 10 Multileave Gradient Descent (MGD).

Require: $n, \alpha, \delta, \mathbf{w}_0^0, update(\mathbf{w}, \alpha, \{\mathbf{b}\}, \{\mathbf{u}\})$

for $t \leftarrow 1..\infty$ **do**
  $q_t \leftarrow receive\_query(t)$ — *// obtain a query from a user*
  $\mathbf{l}_0 \leftarrow generate\_list(\mathbf{w}_t^0, q_t)$ — *// ranking of current best*
  for $i \leftarrow 1...n$ **do**
    $\mathbf{u}_t^i \leftarrow sample\_unit\_vector()$
    $\mathbf{w}_t^i \leftarrow \mathbf{w}_t^0 + \delta \mathbf{u}_t^i$ — *// create a candidate ranker*
    $\mathbf{l}_t^i \leftarrow generate\_list(\mathbf{w}_t^i, q_t)$ — *// exploratory ranking*
  $\mathbf{m}_t, \mathbf{t}_t \leftarrow TDM\_multileave(\mathbf{l}_t)$ — *// multileaving and teams*
  $\mathbf{c}_t \leftarrow receive\_clicks(\mathbf{m}_t)$ — *// show multileaving to the user*
  $\mathbf{b}_t \leftarrow TDM\_infer(\mathbf{t}_t, \mathbf{c}_t)$ — *// set of winning candidates*
  if $\mathbf{w}_t^0 \in \mathbf{b}_t$ **then**
    $\mathbf{w}_{t+1}^0 \leftarrow \mathbf{w}_t^0$ — *// if current best among winners, no update*
  else
    $\mathbf{w}_{t+1}^0 \leftarrow update(\mathbf{w}_t^0, \alpha, \mathbf{b}_t, \mathbf{u}_t)$ — *// Algorithm 11 or 12*

Summary

Online learning helps improve implicit metrics

- Explicit metrics still important – don’t fire assessors!

Research on MAB mostly focused on absolute feedback

- Relative feedback methods improve sensitivity

Inter- and multileaving further improves

- Orders of magnitude faster convergence

Open directions

Choosing among infinitely many models

- Probabilistic multileave gradient descent

Online learning of non-linear models

- e.g., regression trees, neural networks

Online learning from offline data

- Counterfactual learning to rank

References

Fast and reliable online learning to rank for information retrieval

Hofmann, PhD thesis 2013

Search engines that learn from their users

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Online learning to rank for information retrieval
Grotov and de Rijke, SIGIR 2016

Interactively optimizing information retrieval systems as a dueling bandits problem
Yue and Joachims, ICML 2009

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Coming next...

Seminars

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