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Online Learning to Rank

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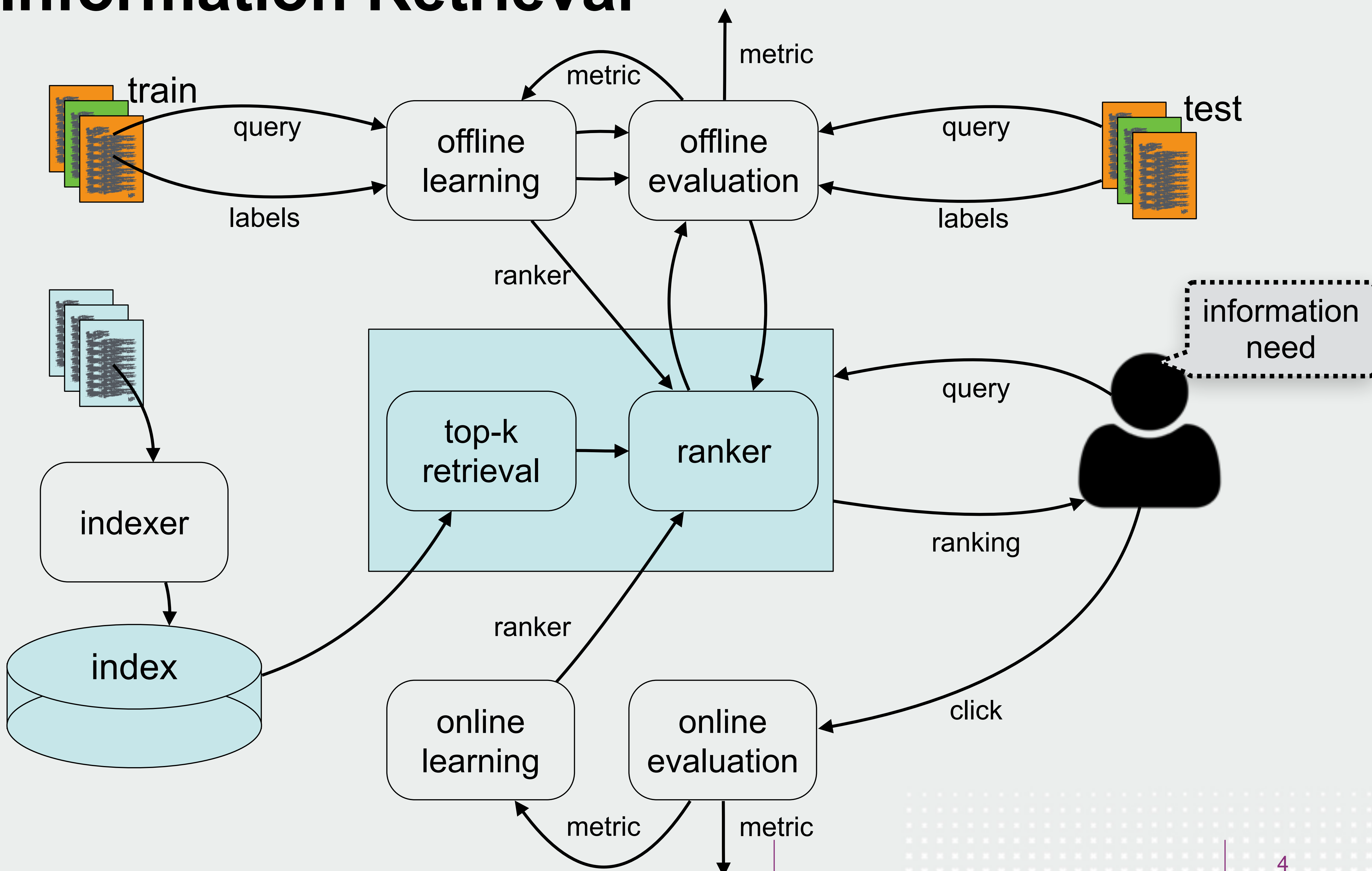
Outline

- Information Retrieval
- Offline
  - Evaluation
  - Learning to Rank
- Online
  - Evaluation
  - Learning to Rank
- Wrap up

Information Retrieval

- **Users** have an **information need**
  - users want to find the perfect job/candidate
- User come to a **search engine** because they hope (or know) the answer is in the **collection**
- Information need is translated into a **query**
  - queries are often **ambiguous,** information is not
- **Search engine**'s task is to **retrieve** documents **relevant** to information need
  - **rank** documents descending by relevance

Information Retrieval



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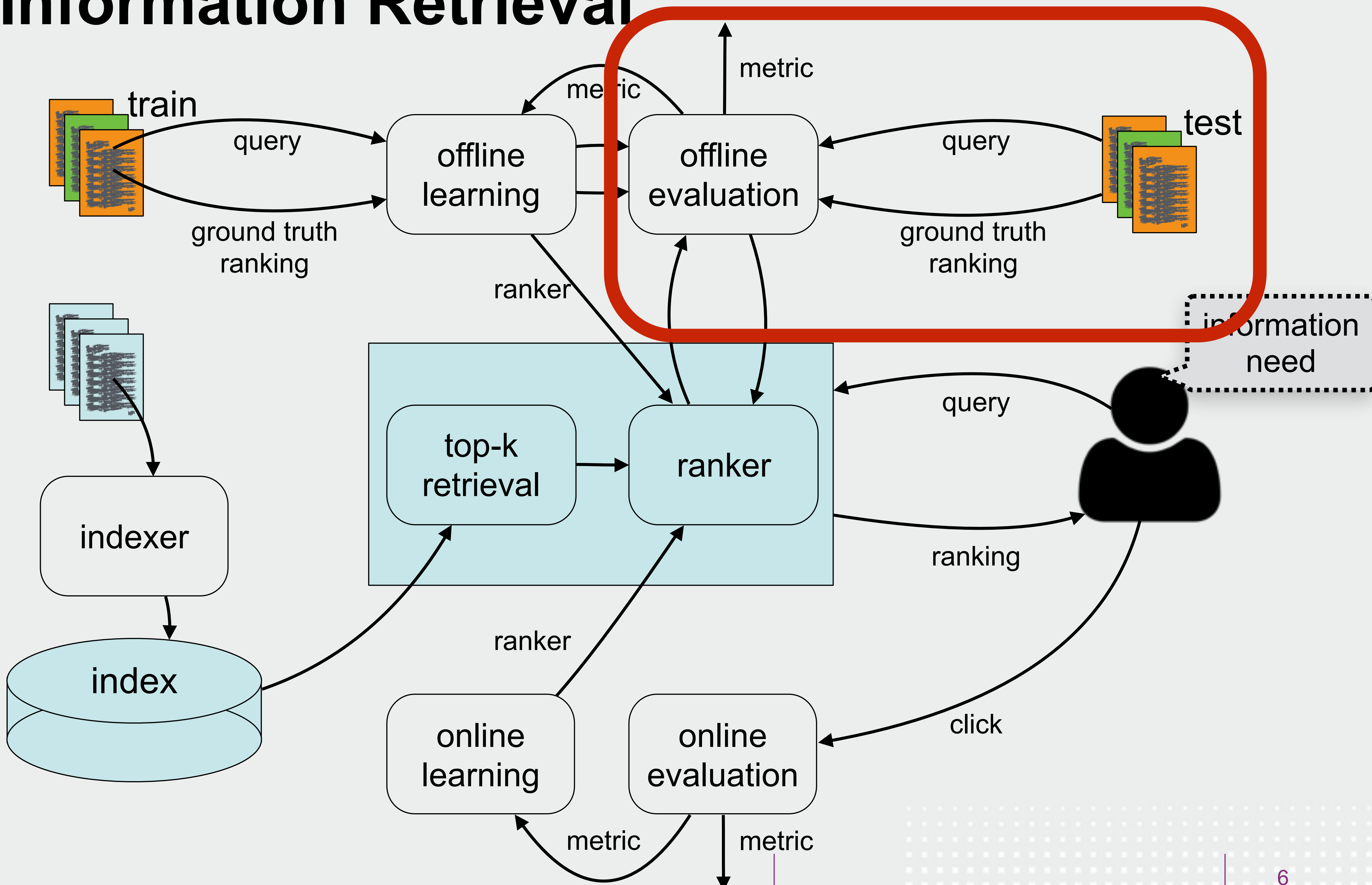
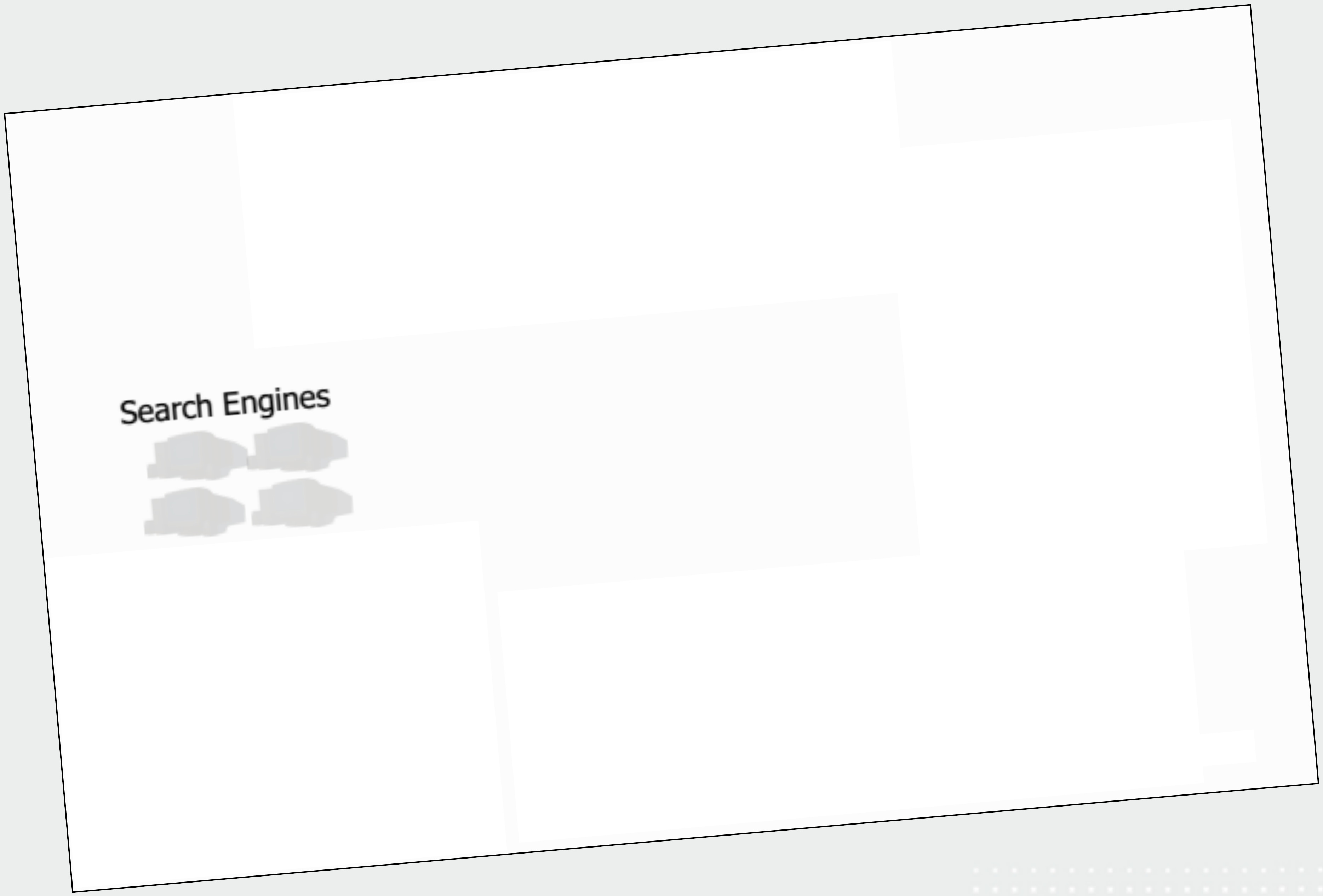


Offline Evaluation - Levels of evaluation

Level	Metrics
System	efficiency, throughput, tps, qps
Effectiveness	precision, recall, utility, gain
Task	task completion, time, success, satisfaction, understanding

Adapted from Ian Soboroff, NIST

Offline Evaluation - Effectiveness

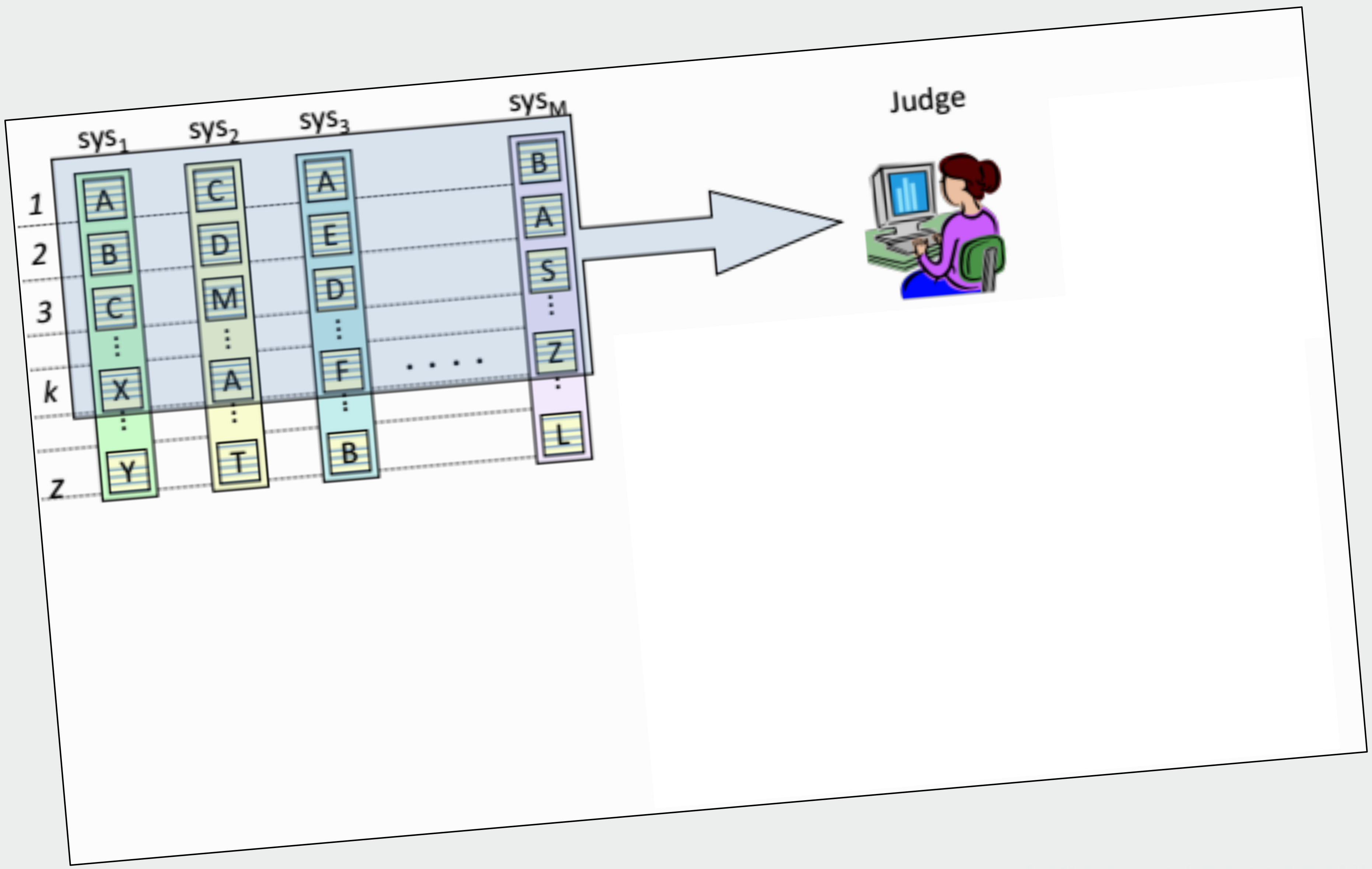


Adapted from Carterette, Kanoulas & Yilmaz

Offline Evaluation - Effectiveness Metrics

- Precision
  - How much of result list was relevant
- Recall
  - How much relevance was in result list
- nDCG
  - Take position of relevance in result list into account
- DCG, MAP, ERR, …

Offline Evaluation - Pooling



Adapted from Carterette, Kanoulas & Yilmaz

Offline Evaluation - Pooling

- Top-k from participating systems
- K has to be chosen
- Consequence:
  - A very different system can not be evaluated
- Annotated data
  - laborious
  - expensive
  - difficult
  - bias towards assessors instead of users

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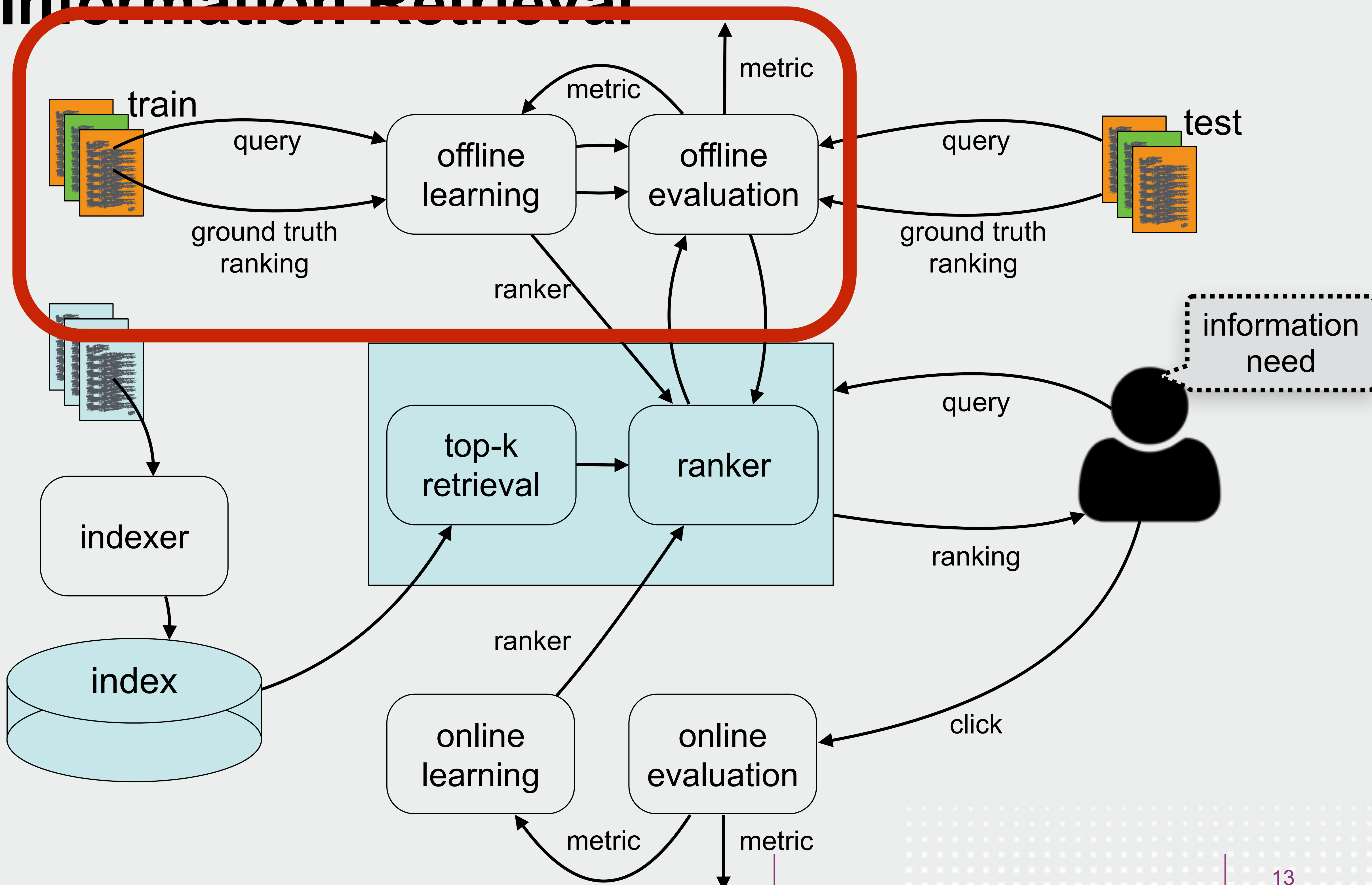


Offline Learning to Rank

Conventional Ranking Models

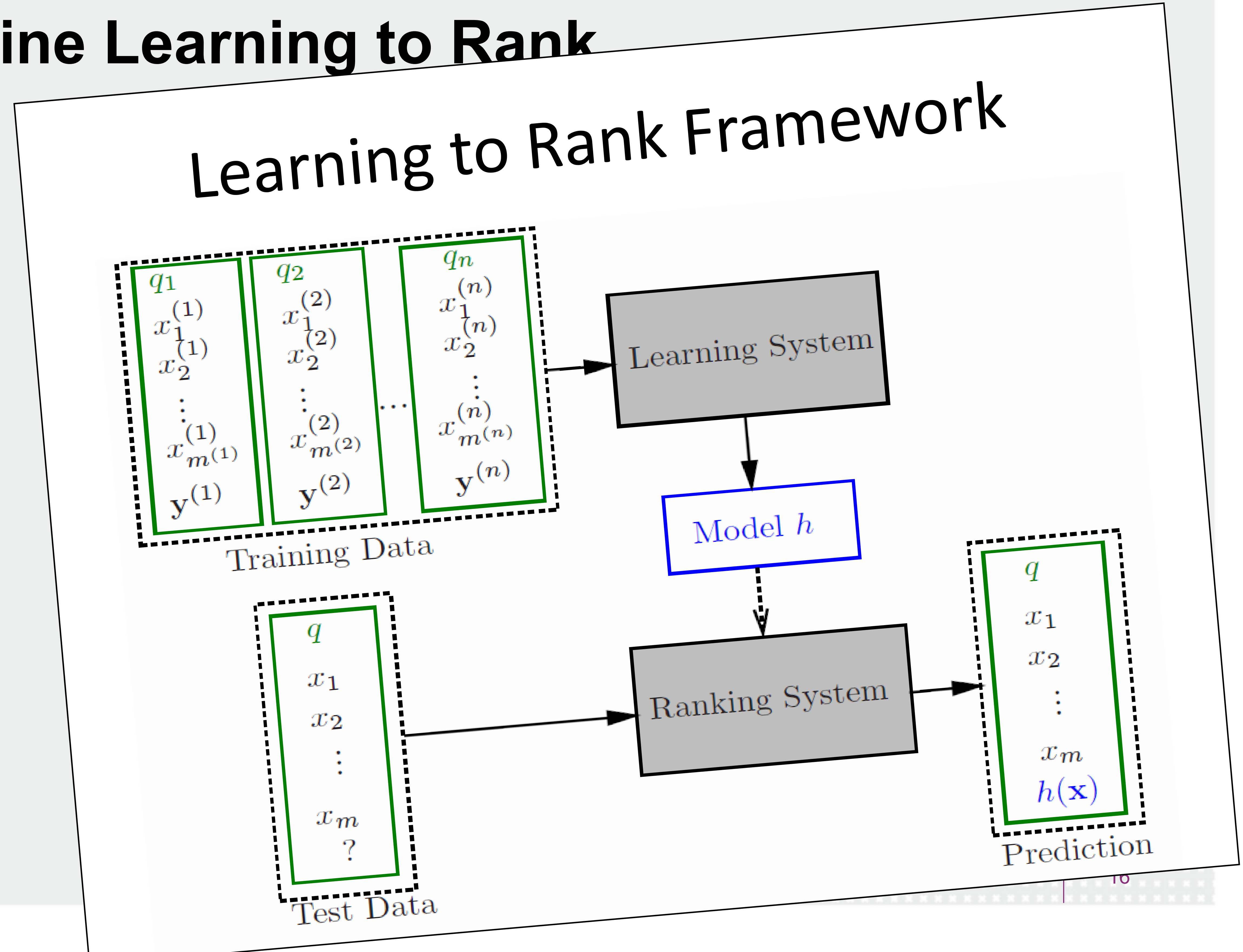
- Query-dependent
  - Boolean model, extended Boolean model, etc.
  - Vector space model, latent semantic indexing (LSI), etc.
  - BM25 model, statistical language model, etc.
  - Span based model, distance aggregation model, etc.
- Query-independent
  - PageRank, TrustRank, BrowseRank, Toolbar Clicks, etc.

Offline Learning to Rank

Feature Based

- Documents represented by feature vectors.
  - Features are extracted for each query-document pair.
  - Even if a feature is the output of an existing retrieval model, one assumes that the parameter in the model is fixed, and only learns the optimal way of combining these features.
- The capability of combining a large number of features is very promising.
  - It can easily incorporate any new progress on retrieval model, by including the output of the model as a feature.

Offline Learning to Rank



Offline Learning to Rank

Learning to Rank Algorithms

Least Square Retrieval Function (TOIS 1989)
Query refinement (WWW 2008)
Nested Ranker (SIGIR 2006)
SVM-MAP (SIGIR 2007)
ListNet (ICML 2007)
Pranking (NIPS 2002)
MPRank (ICML 2007)
LambdaRank (NIPS 2006)
Frank (SIGIR 2007)
Learning to retrieval info (SCC 1995)
MHR (SIGIR 2007)
RankBoost (JMLR 2003)
LDM (SIGIR 2005)
IRSVM (SIGIR 2006)
Large margin ranker (NIPS 2002)
Ranking SVM (ICANN 1999)
RankNet (ICML 2005)
SVM Structure (JMLR 2005)
Discriminative model for IR (SIGIR 2004)
Subset Ranking (COLT 2006)
OAP-BPM (ICML 2003)
QBRank (NIPS 2007)
GBRank (SIGIR 2007)
GPRank (LR4IR 2007)
McRank (NIPS 2007)
SoftRank (LR4IR 2007)
Constraint Ordinal Regression (ICML 2005)
ListMLE (ICML 2008)
AdaRank (SIGIR 2007)
CCA (SIGIR 2007)
RankCosine (IP&M 2007)
Supervised Rank Aggregation (WWW 2007)
Learning to order things (NIPS 1998)
Relational ranking (WWW 2008)
Round robin ranking (ECML 2003)

Offline Learning to Rank

Categorization of the Algorithms

Category	Algorithms
Pointwise Approach	**Regression**: Least Square Retrieval Function (TOIS 1989), Regression Tree for Ordinal Class Prediction (Fundamenta Informaticae, 2000), Subset Ranking using Regression (COLT 2006), … **Classification**: Discriminative model for IR (SIGIR 2004), McRank (NIPS 2007), … **Ordinal regression**: Pranking (NIPS 2002), OAP-BPM (EMCL 2003), Ranking with Large Margin Principles (NIPS 2002), Constraint Ordinal Regression (ICML 2005), …
Pairwise Approach	Learning to Retrieve Information (SCC 1995), Learning to Order Things (NIPS 1998), Ranking SVM (ICANN 1999), RankBoost (JMLR 2003), LDM (SIGIR 2005), RankNet (ICML 2005), Frank (SIGIR 2007), MHR(SIGIR 2007), GBRank (SIGIR 2007), QBRank (NIPS 2007), MPRank (ICML 2007), IRSVM (SIGIR 2006), LambdaRank (NIPS 2006),…
Listwise Approach	**Non-measure specific**: ListNet (ICML 2007), ListMLE (ICML 2008), BoltzRank (ICML 2009) … **Measure-specific**: AdaRank (SIGIR 2007), SVM-MAP (SIGIR 2007), SoftRank (LR4IR 2007), RankGP (LR4IR 2007), …

Offline Learning to Rank

The Pointwise Approach

- Reduce ranking to
  - Regression
    - Subset Ranking
  - Classification
    - Discriminative model for IR
    - MCRank
  - Ordinal regression
    - PRanking
    - Ranking with large margin principle

$$q \leftrightarrow \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{pmatrix}$$

$$\{(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m)\}$$

Offline Learning to Rank

The Pairwise Approach

- Reduce ranking to pairwise classification
  - RankNet and Frank
  - RankBoost
  - Ranking SVM
  - MHR
  - IR-SVM

$$q \leftrightarrow \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{pmatrix}$$

$$\Downarrow$$

$$\left\{ \begin{matrix} (x_1, x_2, +1), (x_2, x_1, -1), \ldots, \\ (x_2, x_m, +1), (x_m, x_2, -1) \end{matrix} \right\}$$

Offline Learning to Rank

Listwise Approach

- Measure-specific loss
  - Optimize the IR evaluation measures directly
- Non measure-specific loss
  - Optimize a loss function defined on all documents associated with a query, according to the unique properties of ranking

Issues with Offline Learning/Evaluation

- Annotated data
  - laborious
  - expensive
  - difficult
  - bias towards assessors instead of users
- Fixed optimal ranking
- Optimal for metric
- Niche deployment is problematic

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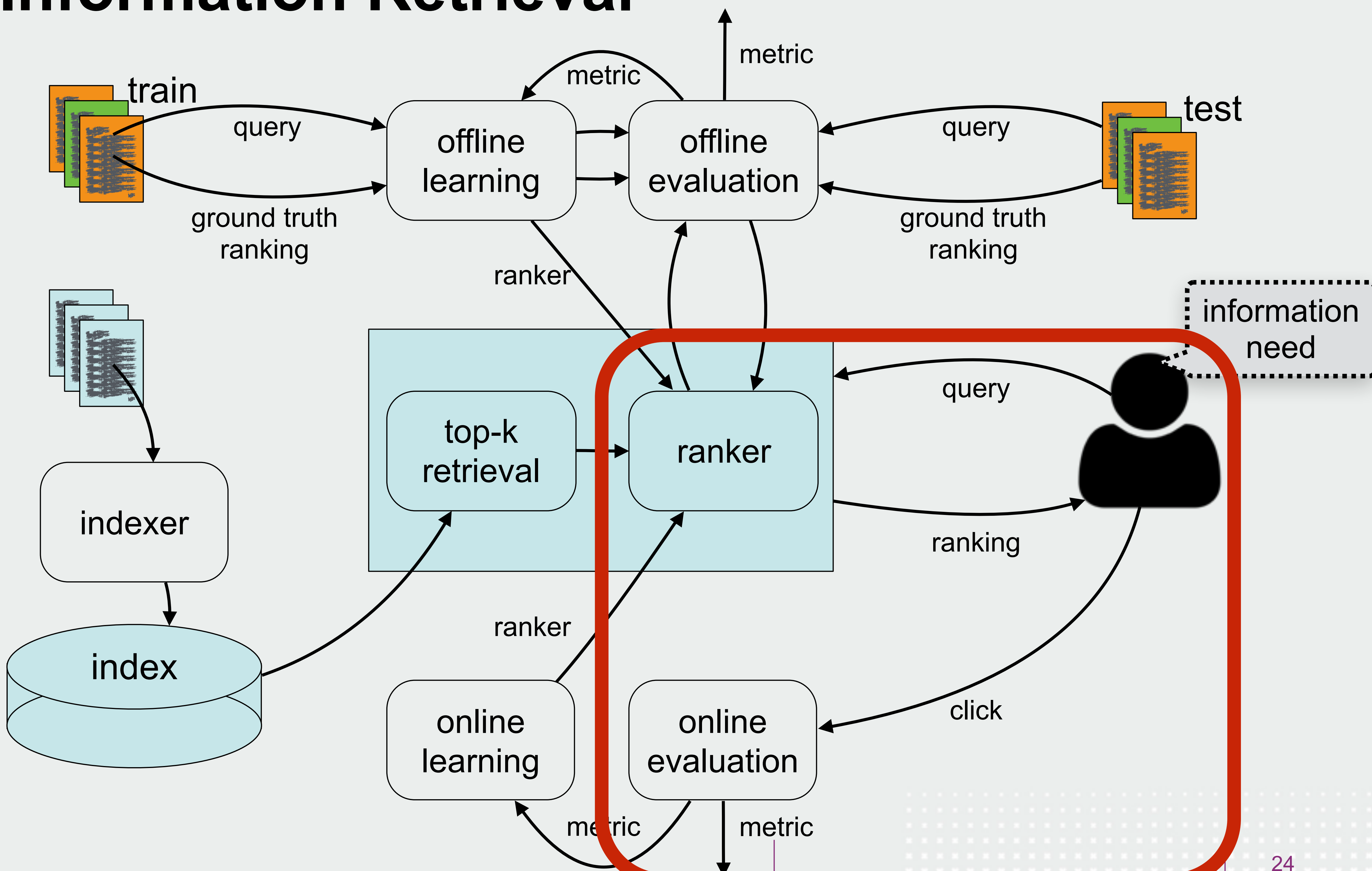
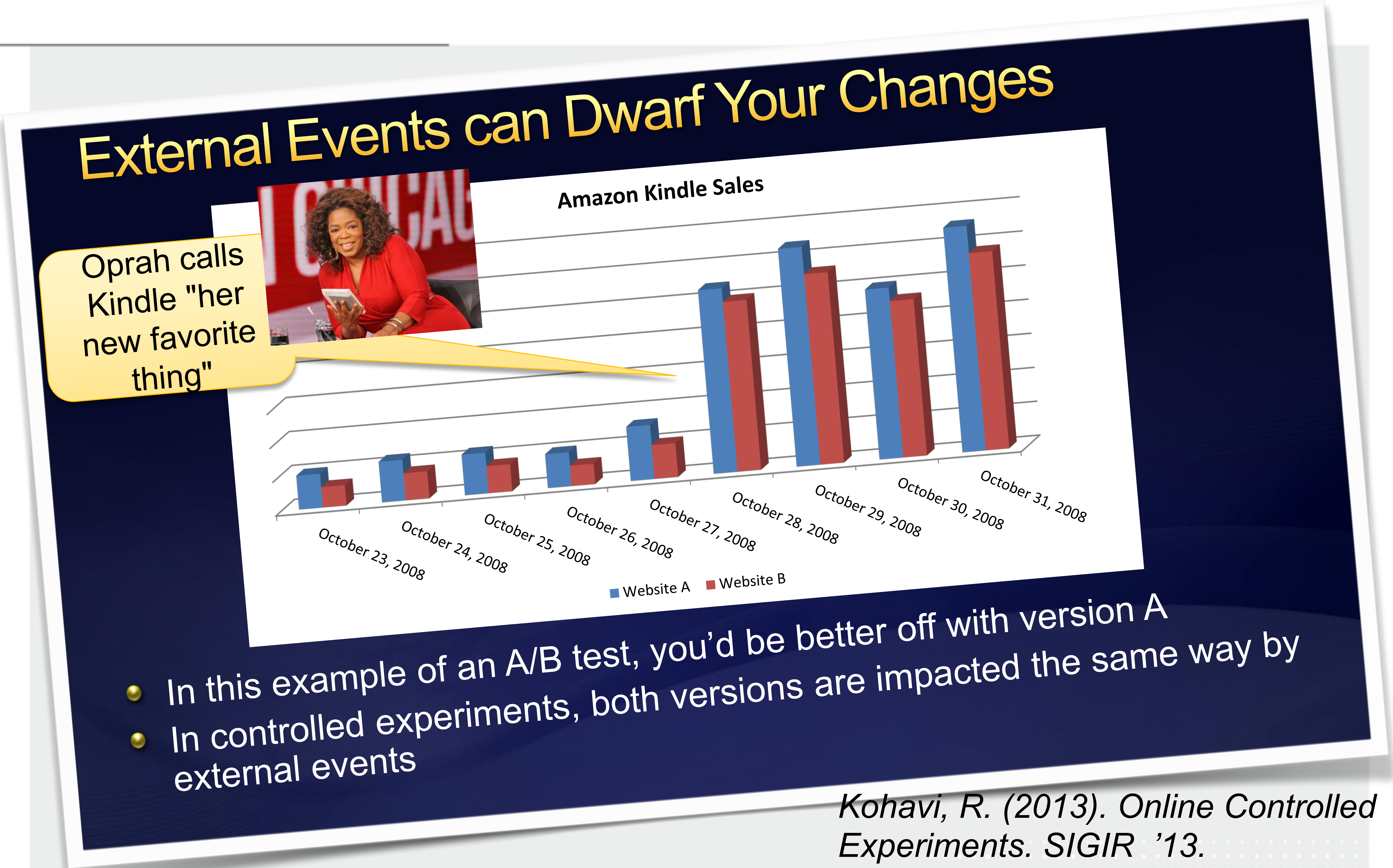
Information Retrieval



What about Observational Studies?

Why not compare with historical data?
Here's an example of Kindle Sales over time.
You changed the site, and there was an amazing spike

Kohavi, R. (2013). Online Controlled Experiments. SIGIR '13.



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Example: Rich Result Summarization

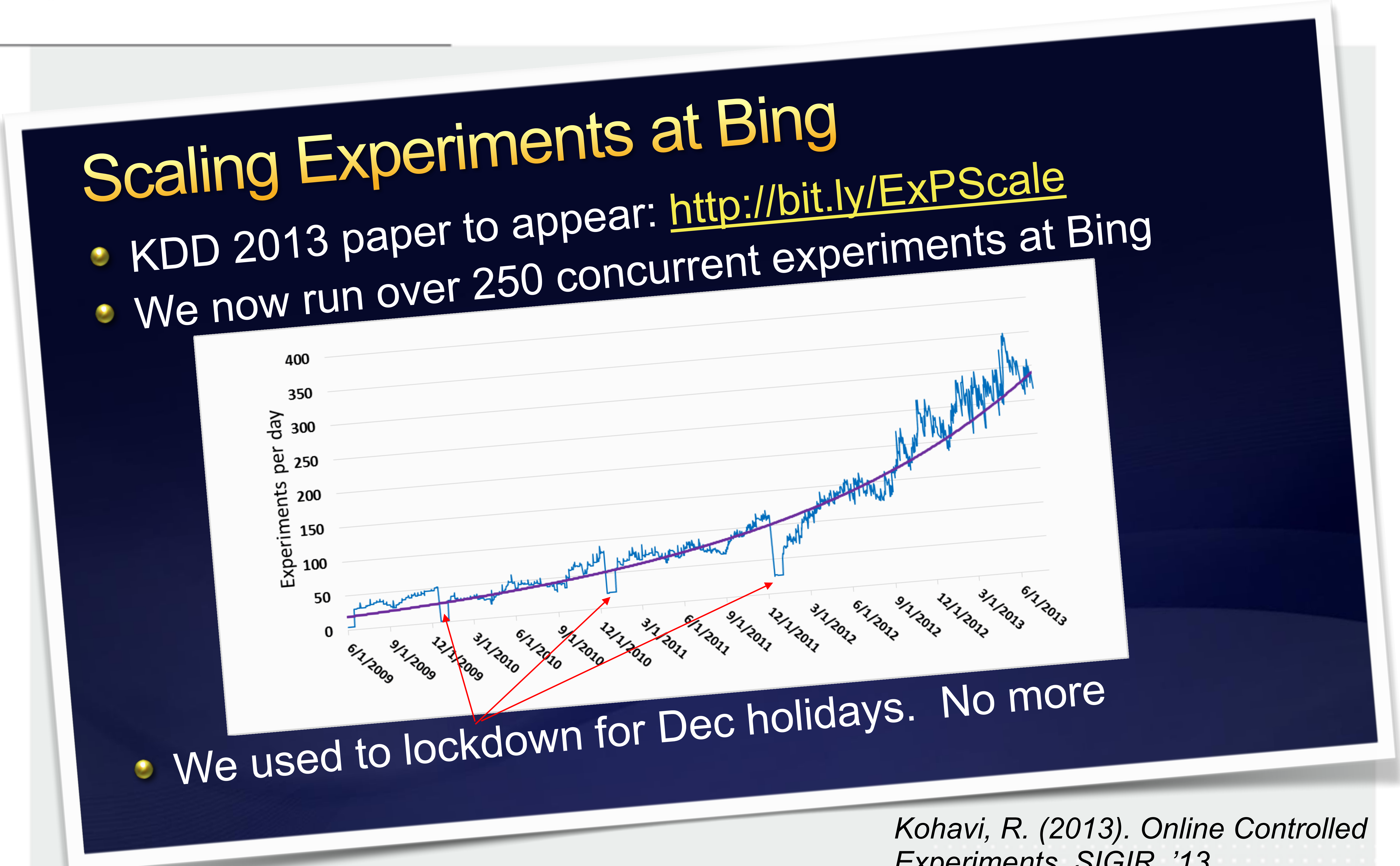
Idea: Users like to know how dishes look like for recipes.

Let's generate nicer captions by including an image.

Chicken Marsala | Chicken Recipes | Savory Sweet Life - Easy ...
savorysweetlife.com/2010/03/chicken-marsala
Mar 09, 2010 · This **chicken marsala recipe** is so quick and easy. Perfect for a weeknight, this **chicken** mushroom dinner can be prepared within 30 minutes.

22

Buscher, G. (2013). IR Evaluation: Perspectives From Within a Living Lab.



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Running Controlled Experiments at Scale (1)

Numbers below are approximate to give sense of scale

- In a visit, you're in about 15 experiments
  - There is no single Bing.
    There are 30B variants (5^15)
  - 90% of users are in experiments.
    10% are kept as holdout
- Sensitivity: we need to detect small effects
  - 0.1% change in the revenue/user metric > $1M/year
  - Not uncommon to see unintended revenue impact of +/-1% (>$10M)
  - Sessions/UU, a key component of our OEC, is hard to move, so we're looking for small effects
  - Important experiments run on 10-20% of users

UI	Ex	Ex p 2	Ex P 3	Exp 4	Exp 5
Ads	Ex P 1	Ex P 2	Ex P 3	ExP 4	Exp 5
Rele vance	…				
…					
Feature area					

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Online Evaluation

- Deployed search engines constantly evolve
- Which changes in the engine cause what?
  - Log versions
  - Log experiments
- Many things are beyond your control
  - So, control
- Understand every interaction with the engine
  - Which exact ranking did a user see
  - Follow users
  - Clean logs from noise (bots)

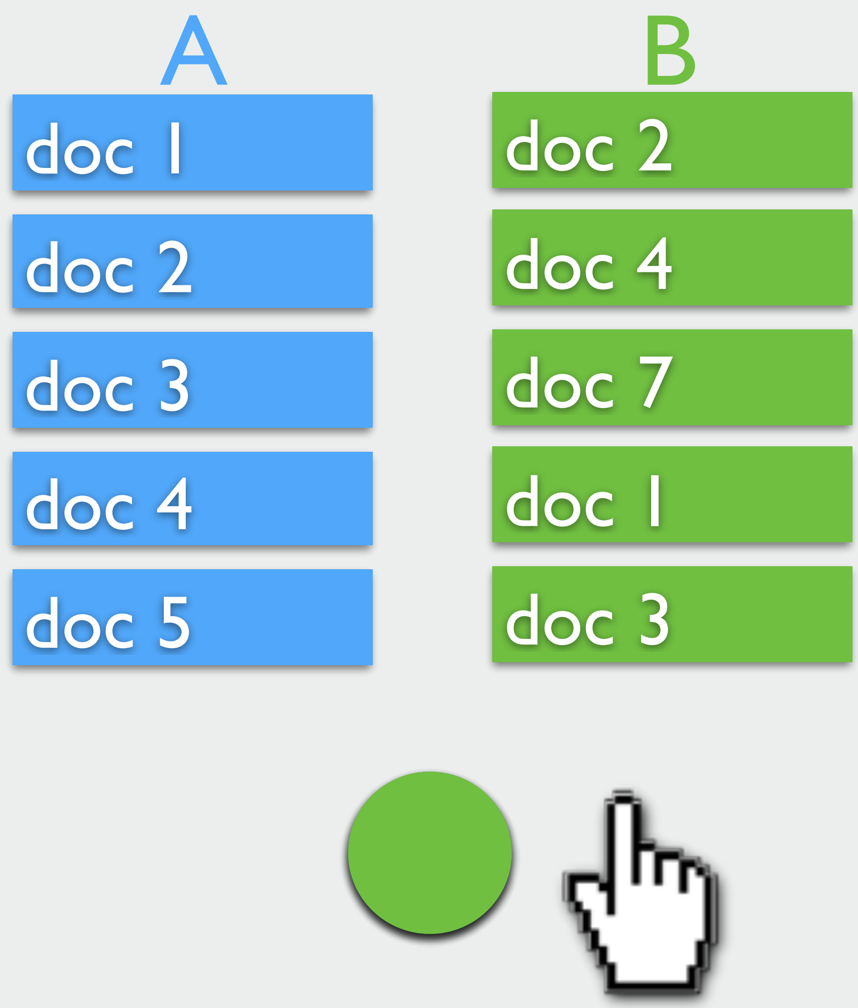
Online Evaluation

- Basic Idea:

  User can tell you what works and what not

- A/B testing
  - “Bucket” users, show A to one bucket, B to the other
  - Make sure users stay in the same bucket
- Interleaving
  - For ranking evaluation only
  - Avoid buckets, reduce variance

Interleaving



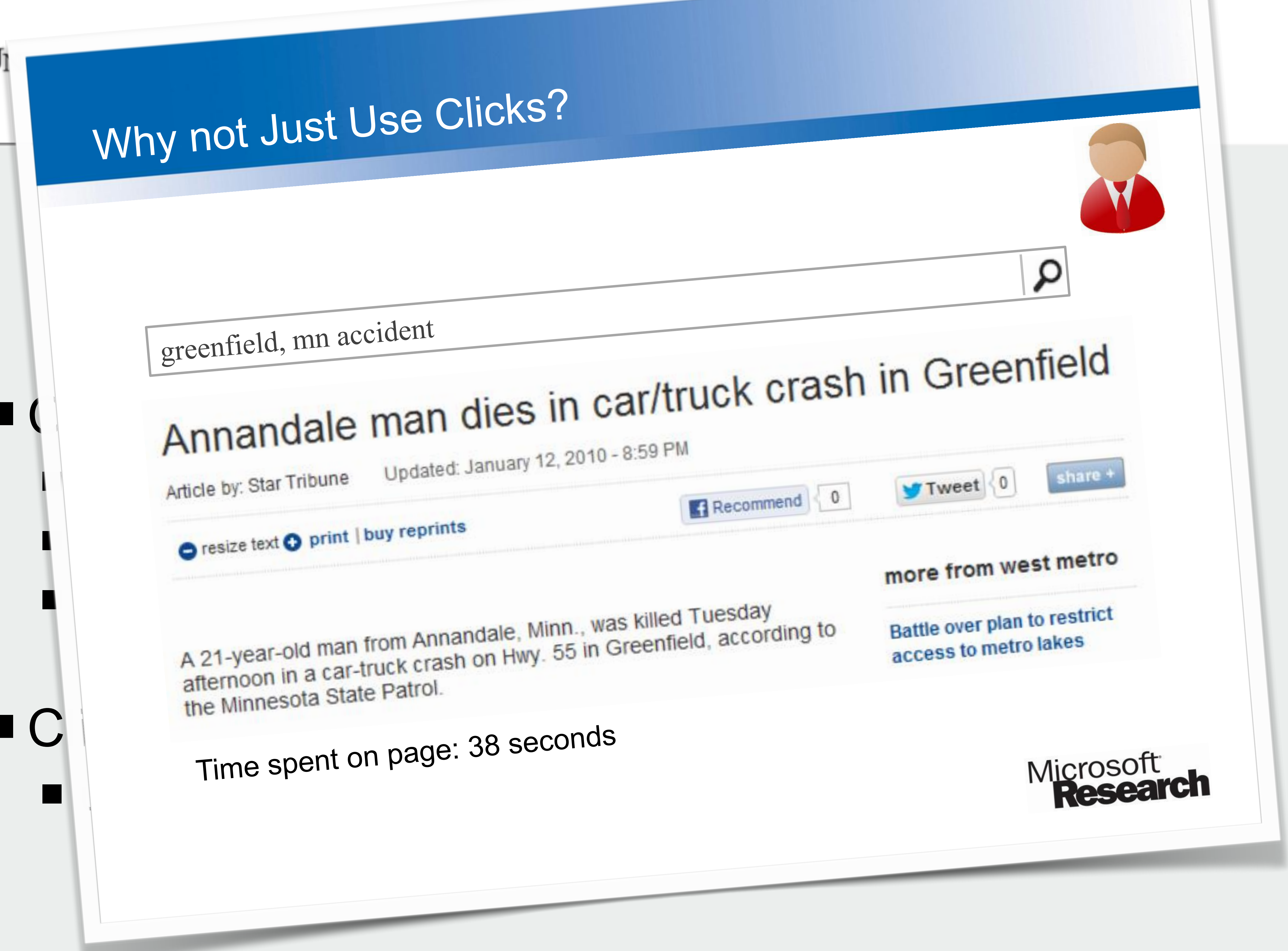
Inference:

B > A

F. Radlinski, M. Kurup, and T. Joachims. How does clickthrough data reflect retrieval quality? In CIKM '08. ACM Press, 2008

Online Evaluation - Clicks

- Clicks are biased
  - users won’t click on things you didn’t show them
  - user are likely to click on things that appear high
  - it matters how you present documents
    - snippets, images, colors, font size, grouped with other documents
- Clicks are noisy
  - they don’t always mean what you hope



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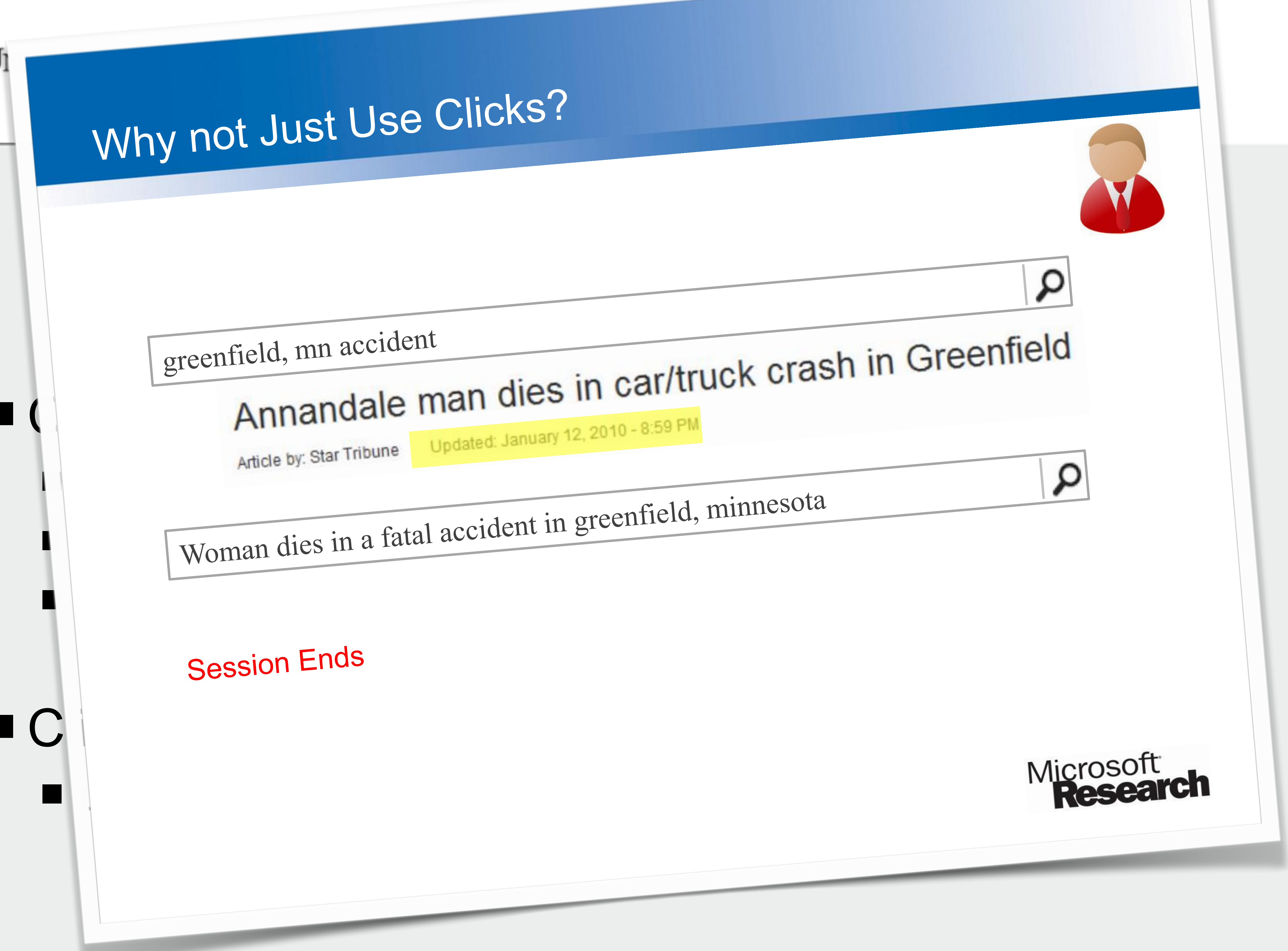

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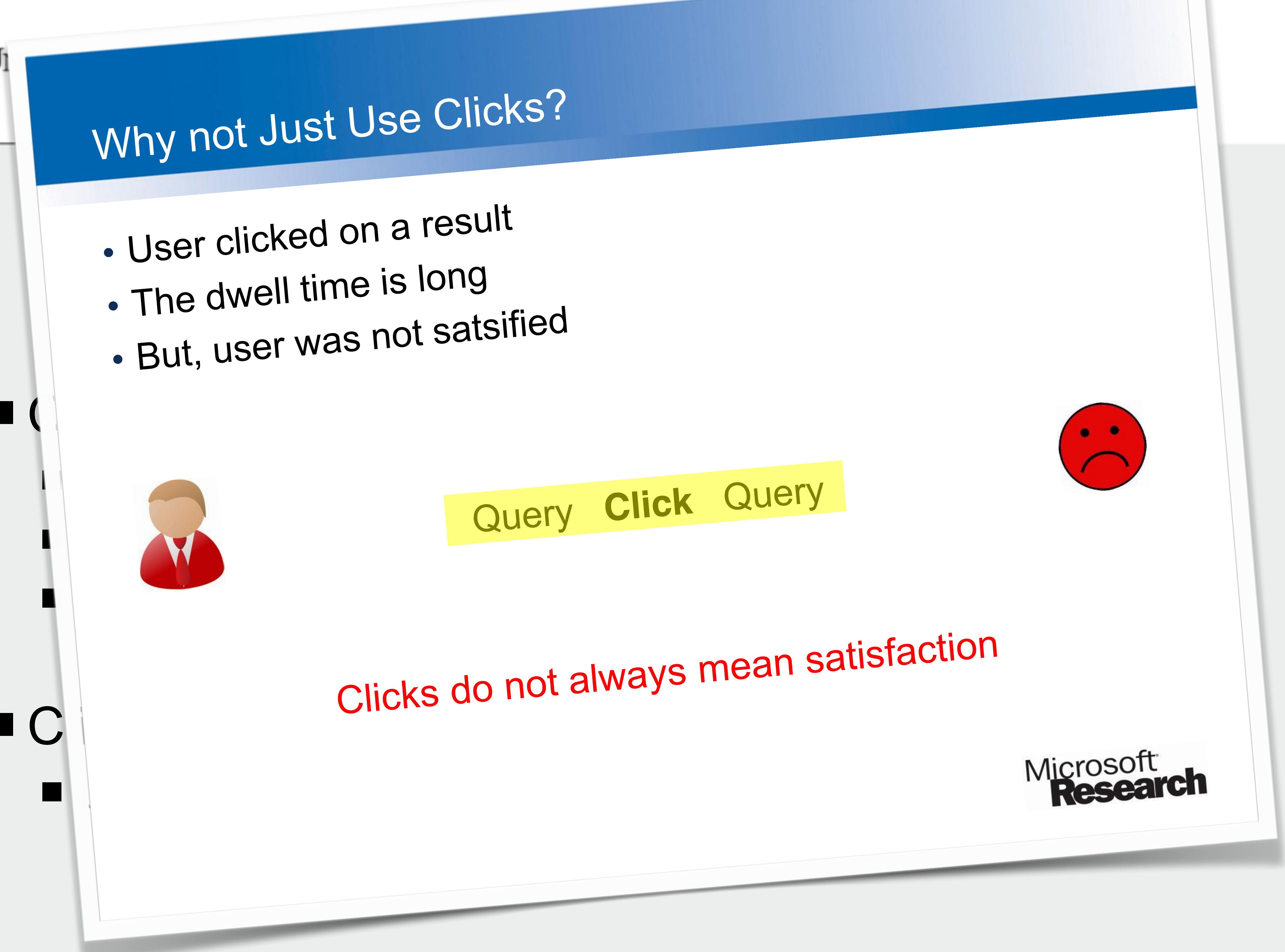

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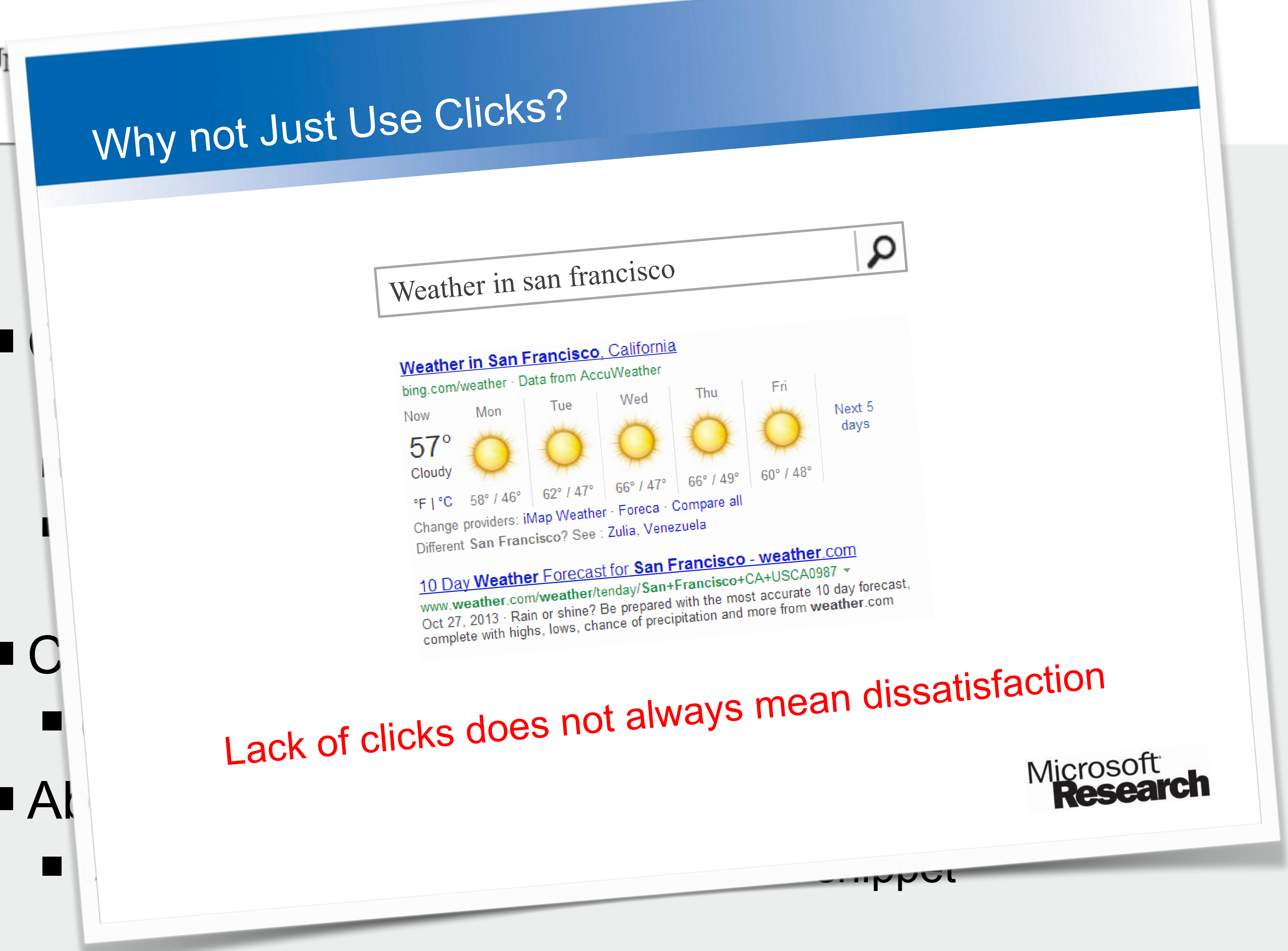
  - it matters how you present documents
    - snippets, images, colors, font size, grouped with other documents
- Clicks are noisy
  - they don't always mean what you hope
- Absence of clicks is not always negative
  - users might be satisfied due to info in snippet



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Online Evaluation - Clicks

- User interactions are strong ranking features
  - Raw clicks
  - Long clicks
  - Latest clicks
  - Visits
  - Mouseovers
  - …
- Potentially also from outside:
  - Twitter?
  - Inlinks?
  - Wikipedia edits?
  - …

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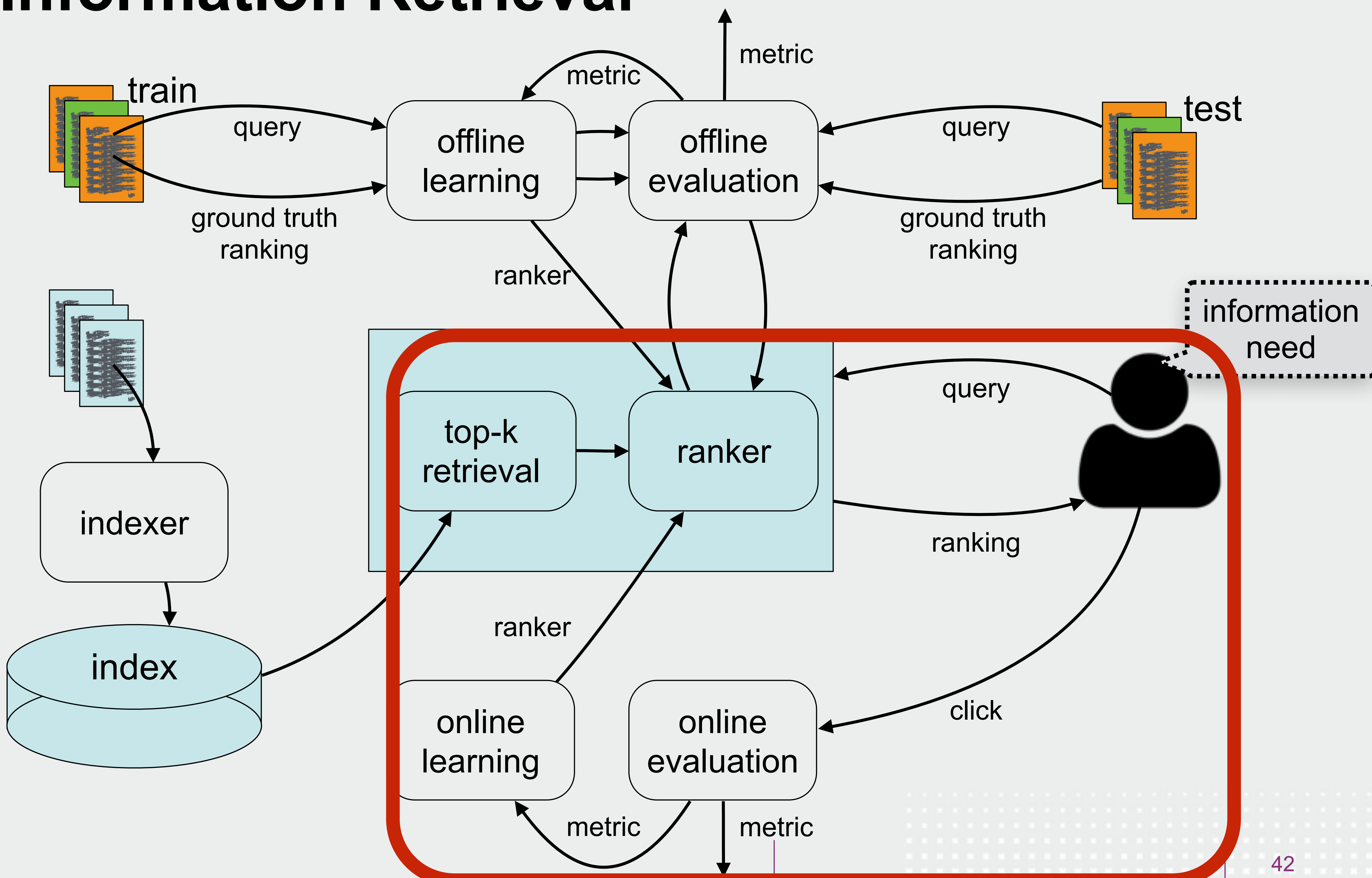
Information Retrieval



Online Learning to Rank

- Goal: learn weights **w**
  - note: we choose a linear model
- Two methods for learning **w**
  - Pairwise
    - Hofmann, K., Whiteson, S., & de Rijke, M. (2011). Balancing Exploration and Exploitation in Learning to Rank Online. In ECIR ’11.
  - Listwise
    - Yue, Y., & Joachims, T. (2009). Interactively optimizing information retrieval systems as a dueling bandits problem. In ICML ’09.

Pairwise Learning

- learn optimal weights

$$\hat{\mathbf{w}} = \arg\min_{\mathbf{w}} \left[\frac{1}{P} \sum_{i=0}^{P} L(\mathbf{w}, \mathbf{x}_i, y_i) + \frac{\lambda}{2} ||\mathbf{w}||_2^2 \right]$$

- where

$$x = (x_a - x_b)$$

$$L(\mathbf{w}, \mathbf{x}, y) = \max(0, 1 - y\mathbf{w}^T\mathbf{x})$$

- can be incremental

$$\mathbf{w}_t = \mathbf{w}_{t\text{-}1} + \eta y_i \,(\mathbf{x}_{a\_i} - \mathbf{x}_{b\_i}) - \eta\lambda\, \mathbf{w}_{t\text{-}1}$$

x_a		x_b	y
C	>	A	
0.1 0.5 0.4 0.4	-	0.9 0.3 0.2 0.2	+1
C	>	B	
0.1 0.5 0.4 0.4	-	0.001 0.9 0.9 0.9	+1
A	<	C	
0.9 0.3 0.2 0.2	-	0.1 0.5 0.4 0.4	-1
B	<	C	
0.001 0.9 0.9 0.9	-	0.1 0.5 0.4 0.4	-1

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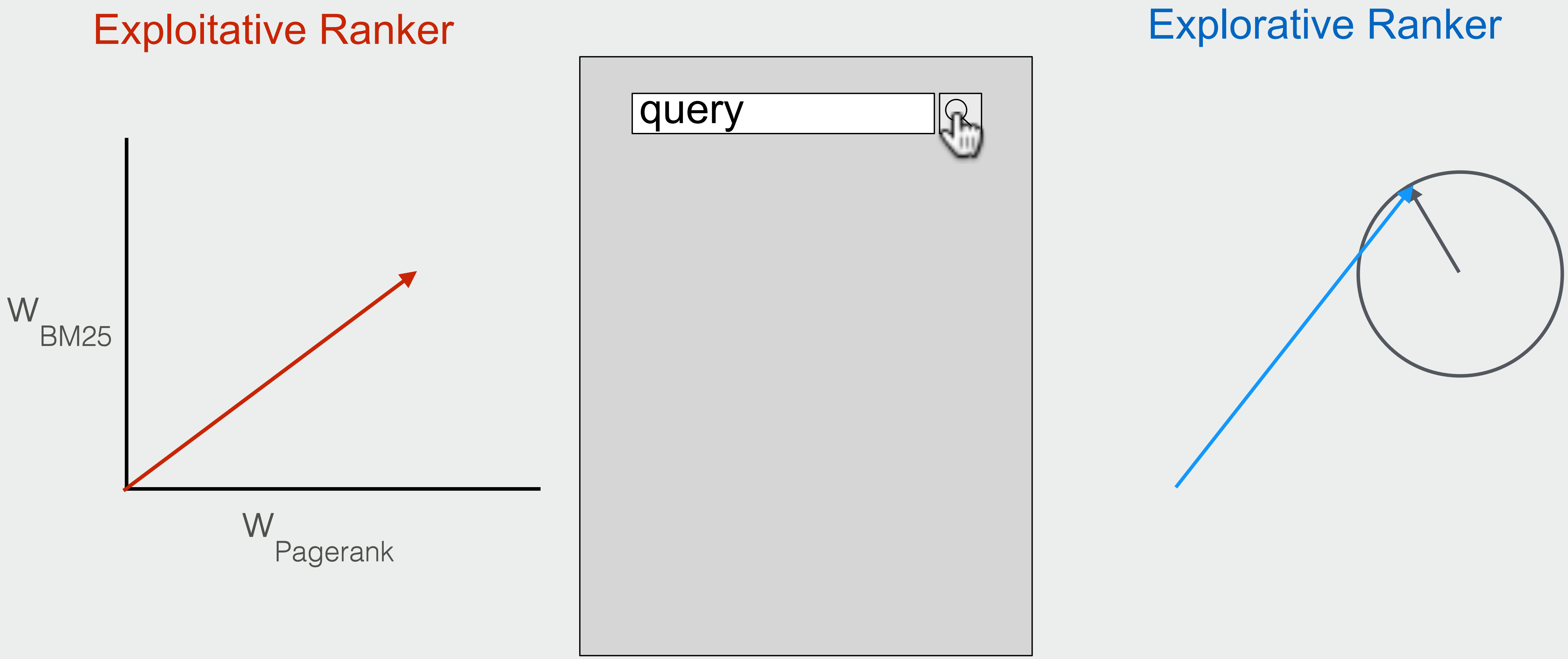
  - Listwise
    - Dueling Bandit Gradient Descent
    - Yue, Y., & Joachims, T. (2009). Interactively optimizing information retrieval systems as a dueling bandits problem. In ICML '09.

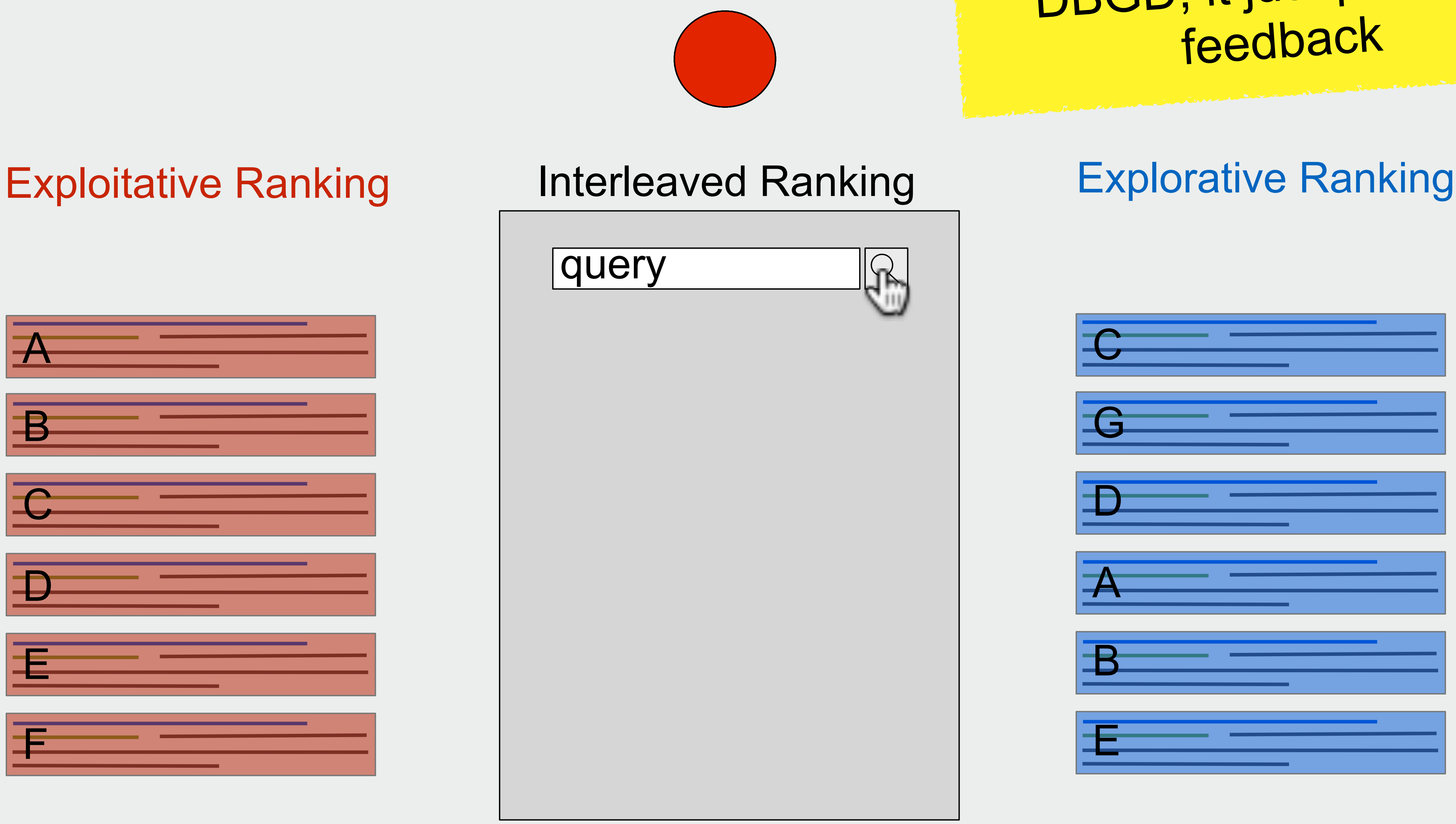
Dueling Bandit Gradient Descent



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

TeamDraft Interleave

note: the interleaving method is NOT part of DBGD, it just provides feedback



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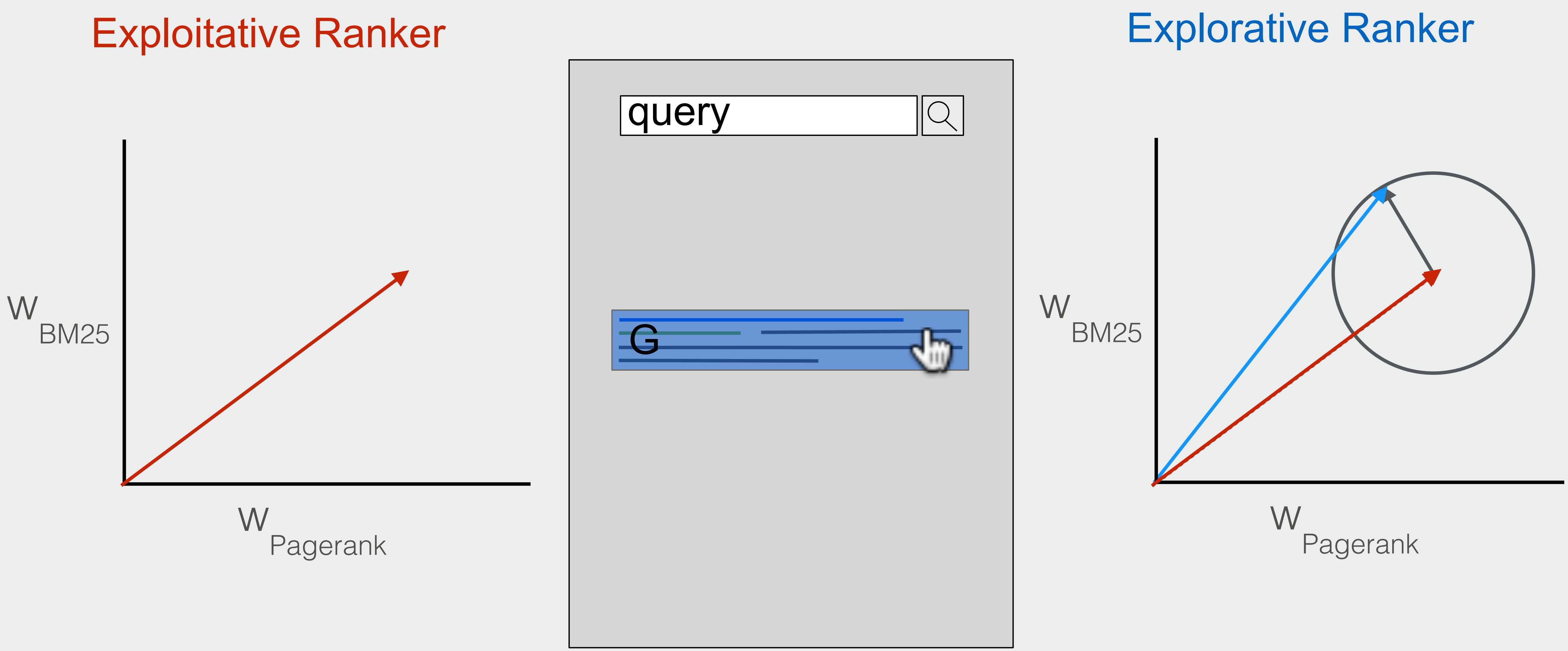
Dueling Bandit Gradient Descent



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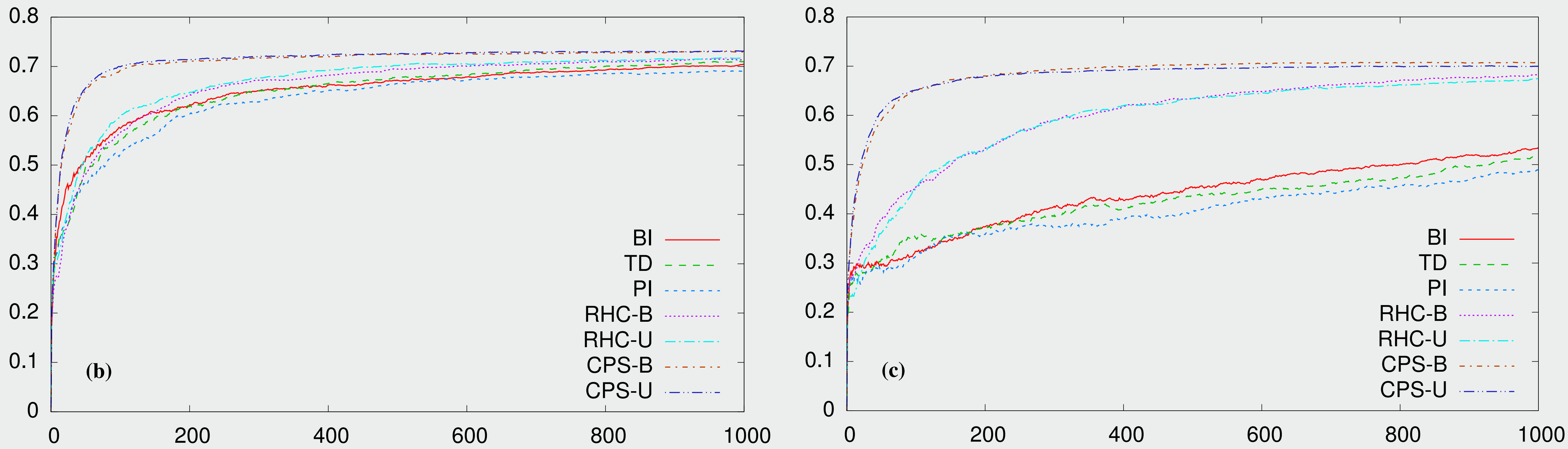
Dueling Bandit Gradient Descent



Offline performance in NDCG

- computed on held-out test queries after each learning step
- on the *TREC NP2003* data set
- for the *navigational (b)*, and *informational (c)* click models.

Hofmann, K., Schuth, A., Whiteson, S., & de Rijke, M. (2013). Reusing Historical Interaction Data for Faster Online Learning to Rank for IR. In WSDM '13.

Dueling Bandit Gradient Descent

- By nature explorative
  - Unlike pairwise learning, DBGD can not learn from pure exploitation
- Hill climbing
  - Is it a hill we're climbing?
- Annealing
  - implied
- Queries and clicks are used only once

Online Learning to Rank - Future

- (Re-)use historical interaction data
- Non linear models
- Non convex optimization landscapes

Issues with Online Evaluation/Learning

- You may hurt a user
- Performance metrics are not absolute
- Dependent on volume of user traffic
- Overhead of experimental framework
- Model limitations
  - incrementally updatable
- Learning limitations
  - hill climbing

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Wrap up

- Offline
  - Pros
    - Established method
    - Don't hurt users
    - Easy experiment
    - Absolute feedback
  - Cons
    - Metric dependent
    - Not adaptive
    - Biased toward assessors
    - Expensive
    - Assessments are hard
- Online
  - Pros
    - Real users
    - Natural byproduct
    - Cheap (not free)
    - Adaptive
    - Niche deployment
  - Cons
    - Not established (yet)
    - Necessarily hurts users
    - Does not scale
    - Choice of learning method/model
    - No absolute metric

Thanks

Lerot

bitbucket.org/ilps/lerot

anneschuth.nl

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References

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