Learning with Humans in the Loop

CS4780/5780 – Machine Learning
Fall 2014

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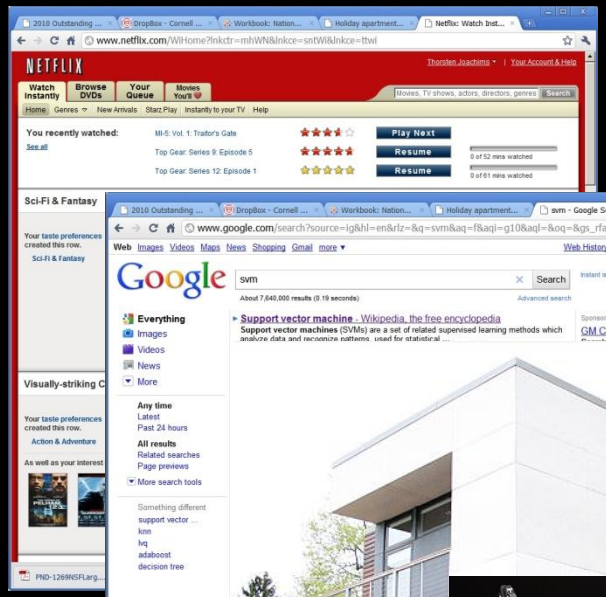
Cornell University

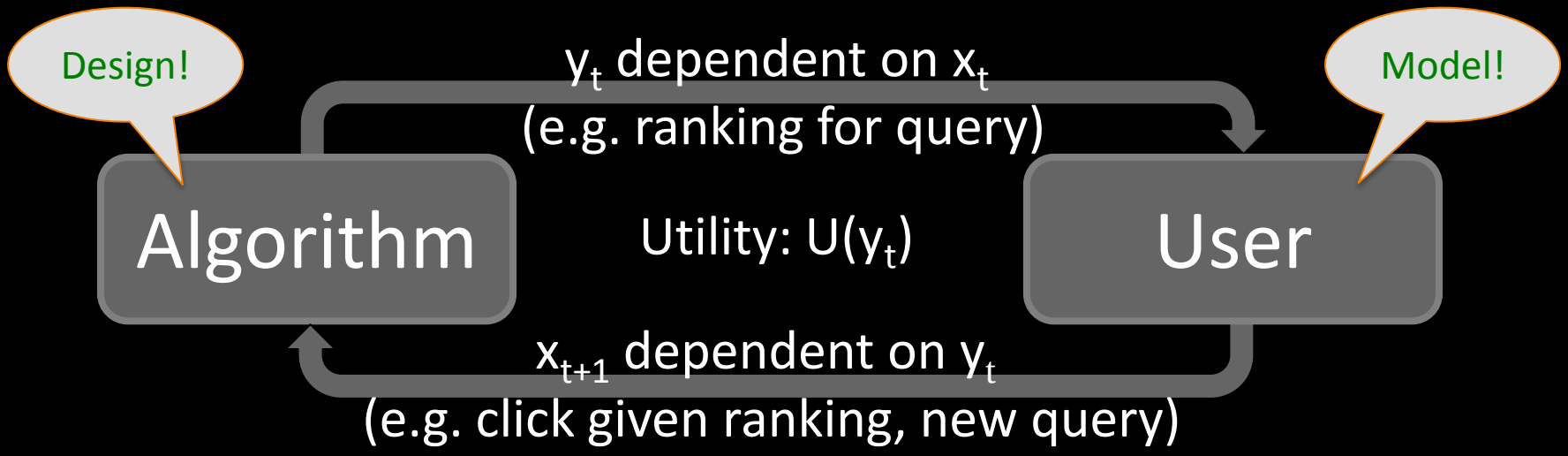
Optional Reading:
- Yisong Yue, J. Broder, R. Kleinberg, T. Joachims, *The K-armed Dueling Bandits Problem*, Conference on Learning Theory (COLT), 2009.
- P. Shivaswamy, T. Joachims, *Online Structured Prediction via Coactive Learning*, International Conference on Machine Learning (ICML), 2012.

User-Facing Machine Learning

- Examples
  - Search Engines
  - Netflix
  - Smart Home
  - Robot Assistant
- Learning
  - Gathering and maintenance of knowledge
  - Measure and optimize performance
  - Personalization



Interactive Learning System



- Observed Data ≠ Training Data
  - Observed data is user's decisions
  - Even explicit feedback reflects user's decision process
- Decisions → Feedback → Learning Algorithm

Decide between two Ranking Functions

Distribution P(u,q)
of users u, queries q

(tj,"SVM")

Retrieval Function 1
$f_1(u,q) \rightarrow r_1$

Which one is better?

Retrieval Function 2
$f_2(u,q) \rightarrow r_2$

1. Kernel Machines
   http://svm.first.gmd.de/
2. SVM-Light Support Vector Machine
   http://svmlight.joachims.org/
3. School of Veterinary Medicine at UPenn
   http://www.vet.upenn.edu/
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$U(tj,"SVM",r_1)$

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$U(tj,"SVM",r_2)$

Measuring Utility

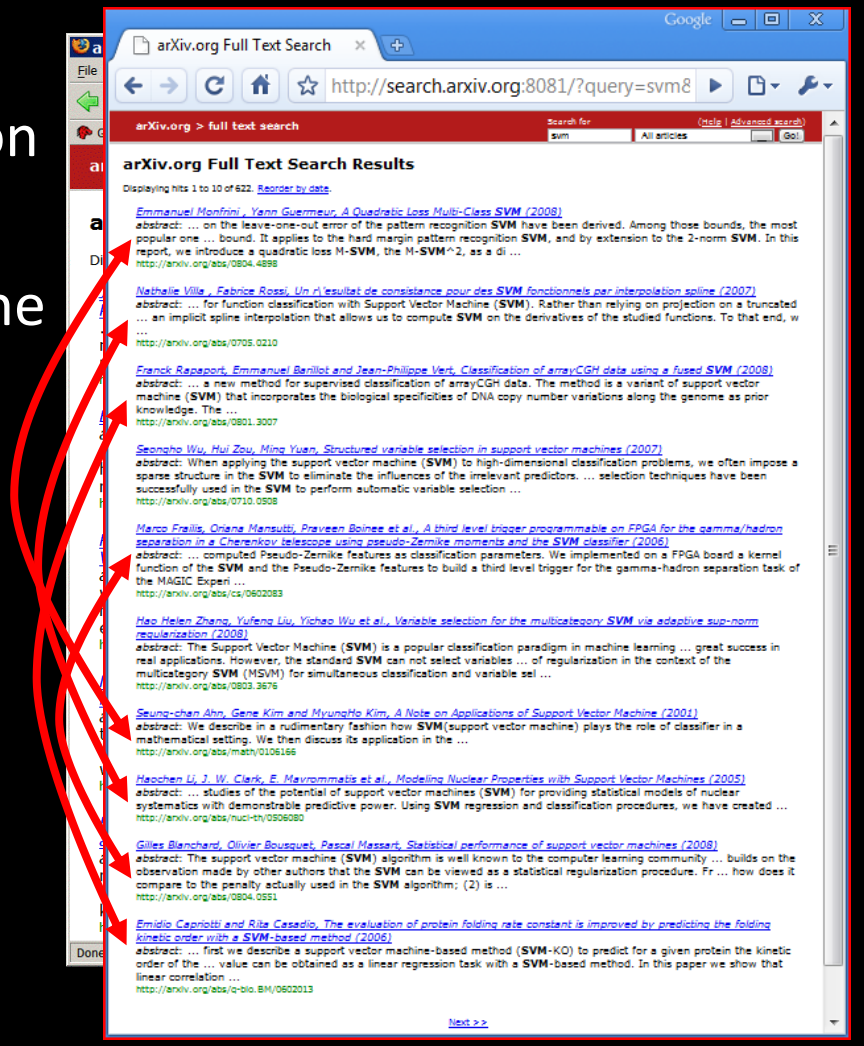
Name	Description	Aggre-gation	Hypothesized Change with Decreased Quality
Abandonment Rate	% of queries with no click	N/A	Increase
Reformulation Rate	% of queries that are followed by reformulation	N/A	Increase
Queries per Session	Session = no interruption of more than 30 minutes	Mean	Increase
Clicks per Query	Number of clicks	Mean	Decrease
Click@1	% of queries with clicks at position 1	N/A	Decrease
Max Reciprocal Rank*	1/rank for highest click	Mean	Decrease
Mean Reciprocal Rank*	Mean of 1/rank for all clicks	Mean	Decrease
Time to First Click*	Seconds before first click	Median	Increase
Time to Last Click*	Seconds before final click	Median	Decrease

(*) only queries with at least one click count

ArXiv.org: User Study

User Study in ArXiv.org

- Natural user and query population
- User in natural context, not lab
- Live and operational search engine
- Ground truth by construction
  - ORIG ≻ SWAP2 ≻ SWAP4
    - ORIG: Hand-tuned fielded
    - SWAP2: ORIG with 2 pairs swapped
    - SWAP4: ORIG with 4 pairs swapped
  - ORIG ≻ FLAT ≻ RAND
    - ORIG: Hand-tuned fielded
    - FLAT: No field weights
    - RAND : Top 10 of FLAT shuffled

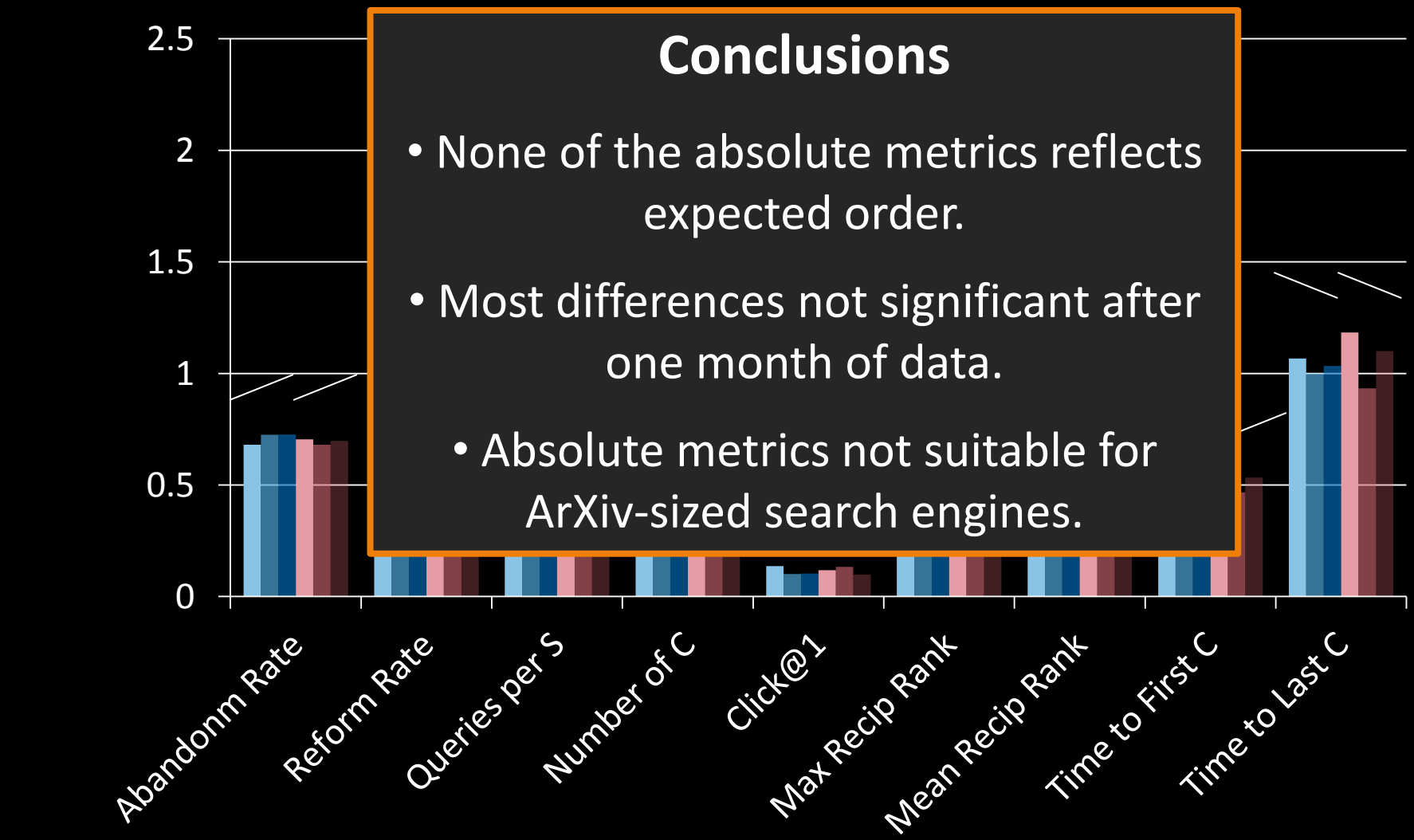


[Radlinski et al., 2008]

ArXiv.org: Experiment Setup

- Experiment Setup
  - Phase I: 36 days
    - Users randomly receive ranking from Orig, Flat, Rand
  - Phase II: 30 days
    - Users randomly receive ranking from Orig, Swap2, Swap4
  - User are permanently assigned to one experimental condition based on IP address and browser.
- Basic Statistics
  - ~700 queries per day / ~300 distinct users per day
- Quality Control and Data Cleaning
  - Test run for 32 days
  - Heuristics to identify bots and spammers
  - All evaluation code was written twice and cross-validated

Arxiv.org: Results



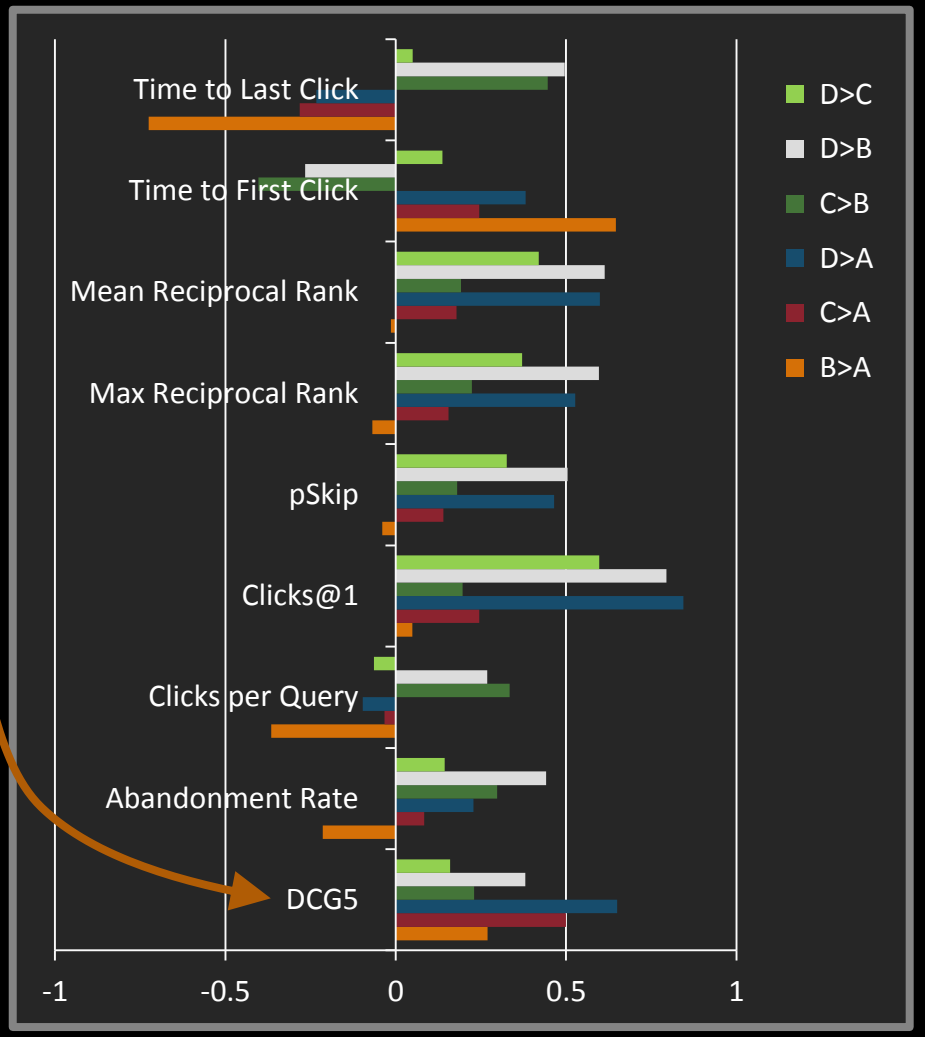
Conclusions

- None of the absolute metrics reflects expected order.
- Most differences not significant after one month of data.
- Absolute metrics not suitable for ArXiv-sized search engines.

[Radlinski et al., 2008]

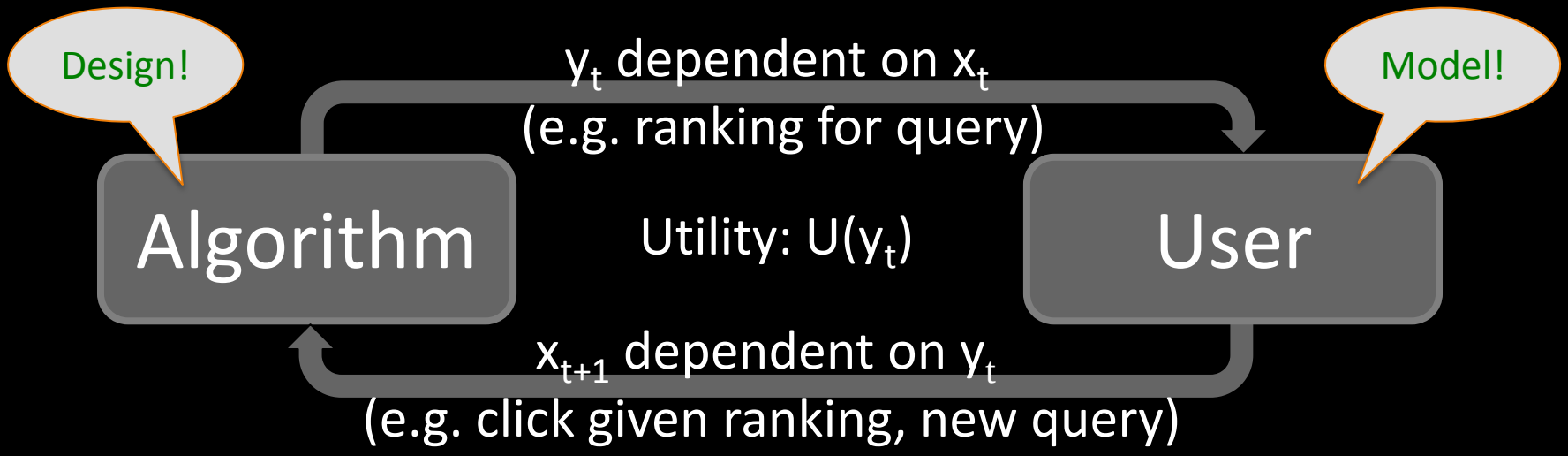
Yahoo! Search: Results

- Retrieval Functions
  - 4 variants of production retrieval function
- Data
  - 10M – 70M queries for each retrieval function
  - Expert relevance judgments
- Results
  - Still not always significant even after more than 10M queries per function
  - Only Click@1 consistent with DCG@5.



[Chapelle et al., 2012]

Interactive Learning System



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  - Model the users decision process to extract feedback
  - Design learning algorithm for this type of feedback

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⋮
(tj,"SVM")
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⋮

$U(tj,"SVM",r_2)$

A Model of how Users Click in Search

- Model of clicking:
  - Users explore ranking to position k
  - Users click on most relevant (looking) links in top k
  - Users stop clicking when time budget up or other action more promising (e.g. reformulation)
  - Empirically supported by [Granka et al., 2004]

Balanced Interleaving

(u=tj, q="svm")

$f_1(u,q) \rightarrow r_1$

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$f_2(u,q) \rightarrow r_2$

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3. Support Vector Machine and Kernel ... References
   *http://svm.*research.bell-labs.com/SVMrefs.html
4. Lucent Technologies: SVM demo applet
   *http://svm.*research.bell-labs.com/SVT/SVMsvt.html
5. Royal Holloway Support Vector Machine
   http://svm.dcs.rhbnc.ac.uk

Interleaving(r_1,r_2)

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6.	Archives of SUPPORT-VECTOR-MACHINES ... *http://www.jiscmail.ac.uk/lists/SUPPORT...*	4
7.	Lucent Technologies: SVM demo applet *http://svm.*research.bell-labs.com/SVT/SVMsvt.html	4

Model of User:
Better retrieval functions is more likely to get more clicks.

Invariant:
For all k, top k of balanced interleaving is union of top k_1 of r_1 and top k_2 of r_2 with $k_1=k_2 \pm 1$.

Interpretation: $(r_1 \succ r_2) \leftrightarrow$ clicks(topk(r_1)) > clicks(topk(r_2))

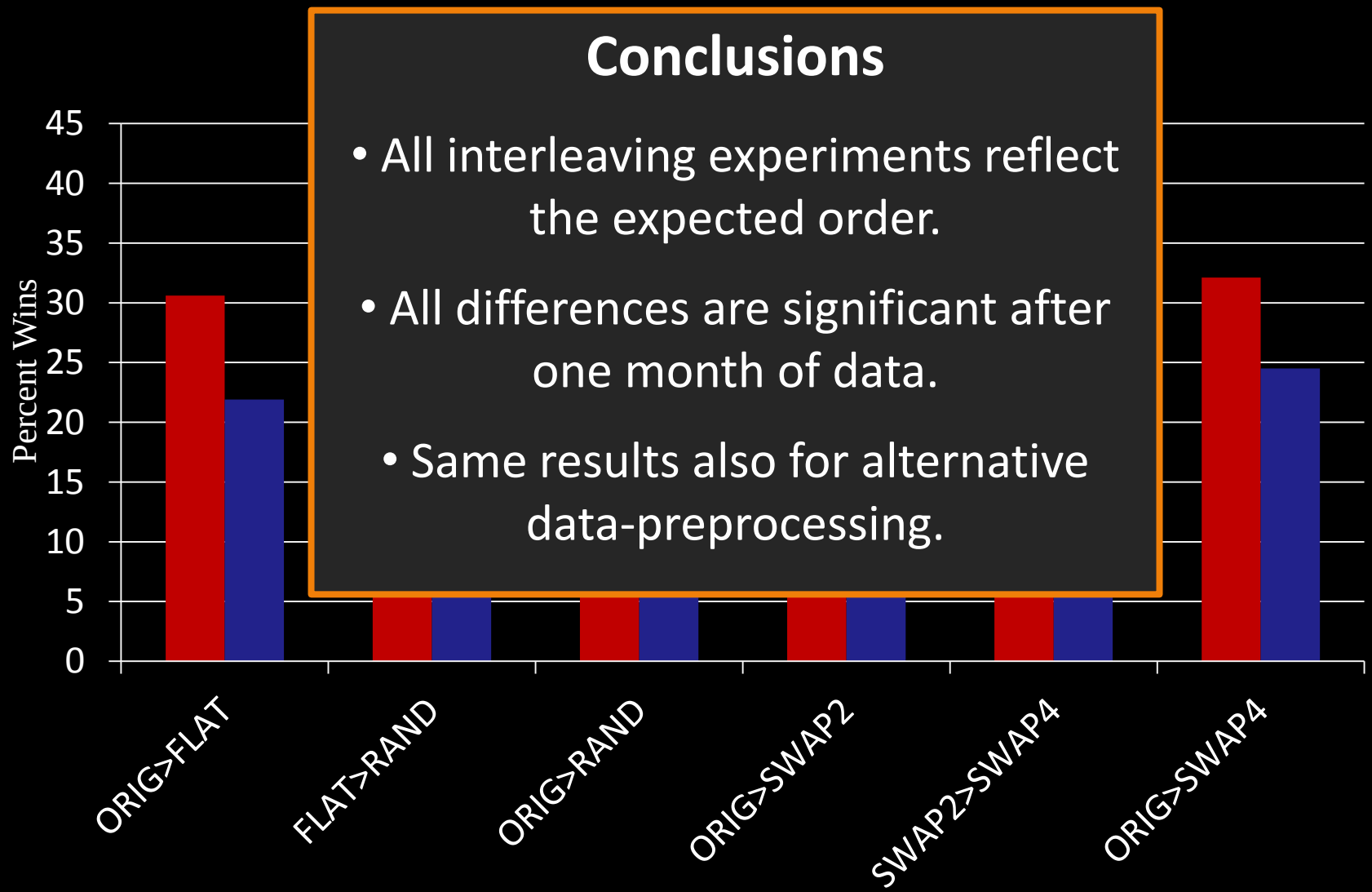
→ see also [Radlinski, Craswell, 2012] [Hofmann, 2012]

[Joachims, 2001] [Radlinski et al., 2008]

Arxiv.org: Interleaving Experiment

- Experiment Setup
  - Phase I: 36 days
    - Balanced Interleaving of (Orig,Flat) (Flat,Rand) (Orig,Rand)
  - Phase II: 30 days
    - Balanced Interleaving of (Orig,Swap2) (Swap2,Swap4) (Orig,Swap4)
- Quality Control and Data Cleaning
  - Same as for absolute metrics

Arxiv.org: Interleaving Results



Conclusions

- All interleaving experiments reflect the expected order.
- All differences are significant after one month of data.
- Same results also for alternative data-preprocessing.

Yahoo and Bing: Interleaving Results

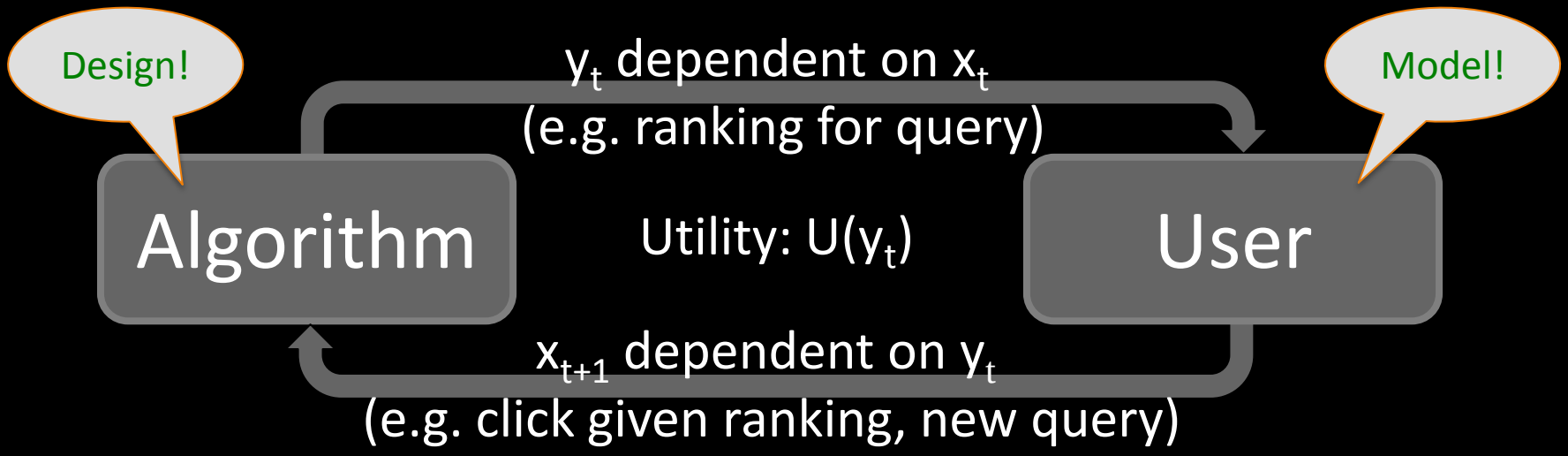
- Yahoo Web Search [Chapelle et al., 2012]
  - Four retrieval functions (i.e. 6 paired comparisons)
  - Balanced Interleaving

    → All paired comparisons consistent with ordering by NDCG.

- Bing Web Search [Radlinski & Craswell, 2010]
  - Five retrieval function pairs
  - Team-Game Interleaving

    → Consistent with ordering by NDGC when NDCG significant.

Interactive Learning System



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  - Design learning algorithm for this type of feedback

Learning on Operational System

- Example: 4 retrieval functions: A > B >> C > D
  - 10 possible pairs for interactive experiment
    - (A,B) → low cost to user
    - (A,C) → medium cost to user
    - (C,D) → high cost to user
    - (A,A) → zero cost to user
    - …
- Minimizing Regret
  - Don't present "bad" pairs more often than necessary
  - Trade off (long term) informativeness and (short term) cost
  - Definition: Probability of (f_t, f_t') losing against the best f^*

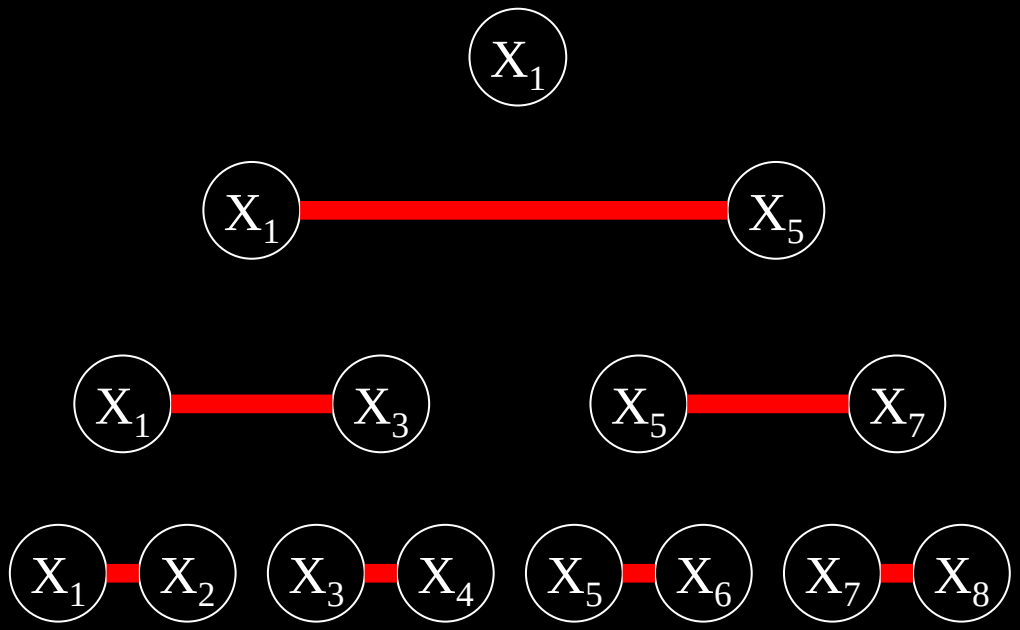
$$\mathrm{R(A)} = \sum_{t=1}^{T} [P(f^* \succ f_t) - 0.5] + [P(f^* \succ f_t') - 0.5]$$

→ Dueling Bandits Problem

[Yue, Broder, Kleinberg, Joachims, 2010]

First Thought: Tournament

- Noisy Sorting/Max Algorithms:
  - [Feige et al.]: Triangle Tournament Heap $O(n/\varepsilon^2 \log(1/\delta))$ with prob $1-\delta$
  - [Adler et al., Karp & Kleinberg]: optimal under weaker assumptions



Algorithm: Interleaved Filter 2

- Algorithm

  InterleavedFilter1(T,W={f_1…f_K})
  - Pick random f' from W
  - $\delta=1/(TK^2)$
  - WHILE |W|>1
    - FOR b ∈ W DO
      - » duel(f',f)
      - » update P_f
    - t=t+1
    - $c_t=(\log(1/\delta)/t)^{0.5}$
    - Remove all f from W with $P_f < 0.5-c_t$ [WORSE WITH PROB 1-δ]
    - IF there exists f'' with $P_{f''} > 0.5+c_t$ [BETTER WITH PROB 1-δ]
      - » Remove f' from W
      - » Remove all f from W that are empirically inferior to f'
      - » f'=f''; t=0
  - UNTIL T: duel(f',f')

f_1	f_2	$f'=f_3$	f_4	f_5
0/0	0/0		0/0	0/0

f_1	f_2	$f'=f_3$	f_4	f_5
8/2	7/3		4/6	1/9

f_1	f_2	$f'=f_3$	f_4	
13/2	11/4		~~7/8~~	XX

$f'=f_1$	f_2		f_4	
0/0	0/0	XX	XX	XX

Related Algorithms: [Hofmann, Whiteson, Rijke, 2011] [Yue, Joachims, 2009] [Yue, Joachims, 2011]

[Yue et al., 2009]

Assumptions

- Preference Relation: $f_i \succ f_j \Leftrightarrow P(f_i \succ f_j) = 0.5+\varepsilon_{i,j} > 0.5$
- Weak Stochastic Transitivity: $f_i \succ f_j$ and $f_j \succ f_k \rightarrow f_i \succ f_k$
- S

Theorem: IF2 incurs expected average regret bounded by

$$\frac{1}{T}E(R_T) \leq O\left(\frac{K}{\epsilon_{1,2}}\frac{\log T}{T}\right)$$

- Stochastic Triangle Inequality: $f_i \succ f_j \succ f_k \rightarrow \varepsilon_{i,k} \leq \varepsilon_{i,j}+\varepsilon_{j,k}$

  $\varepsilon_{1,2} = 0.01$ and $\varepsilon_{2,3} = 0.01 \rightarrow \varepsilon_{1,3} \leq 0.02$

- ε-Winner exists: $\varepsilon = \max_i\{ P(f_1 \succ f_i)-0.5 \} = \varepsilon_{1,2} > 0$

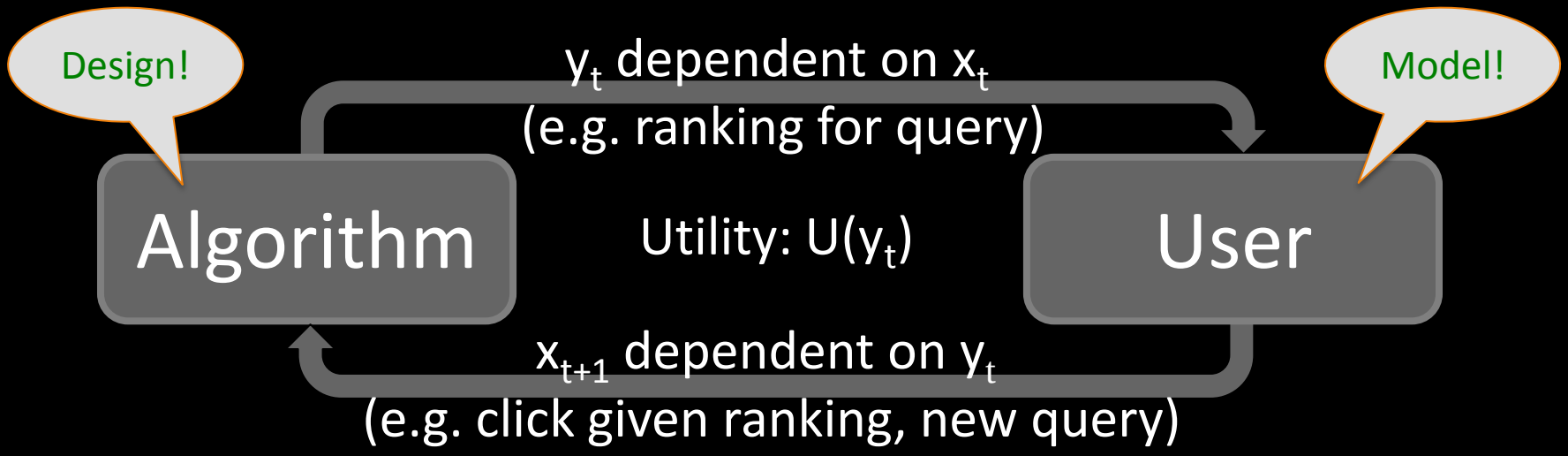
Lower Bound

- **Theorem:** Any algorithm for the dueling bandits problem has regret

$$R_T \leq \Omega\left(\frac{K}{\epsilon_{1,2}} \log T\right)$$

- Proof: [Karp, Kleinberg, 2007] [Kleinberg et al., 2007]
- Intuition:
  - Magically guess the best bandit, just verify guess
  - Worst case: $\forall f_i \succ f_j$: $P(f_i \succ f_j)=0.5+\varepsilon$
  - Need $O(1/\varepsilon^2 \log T)$ duels to get 1-1/T confidence.

Interactive Learning System



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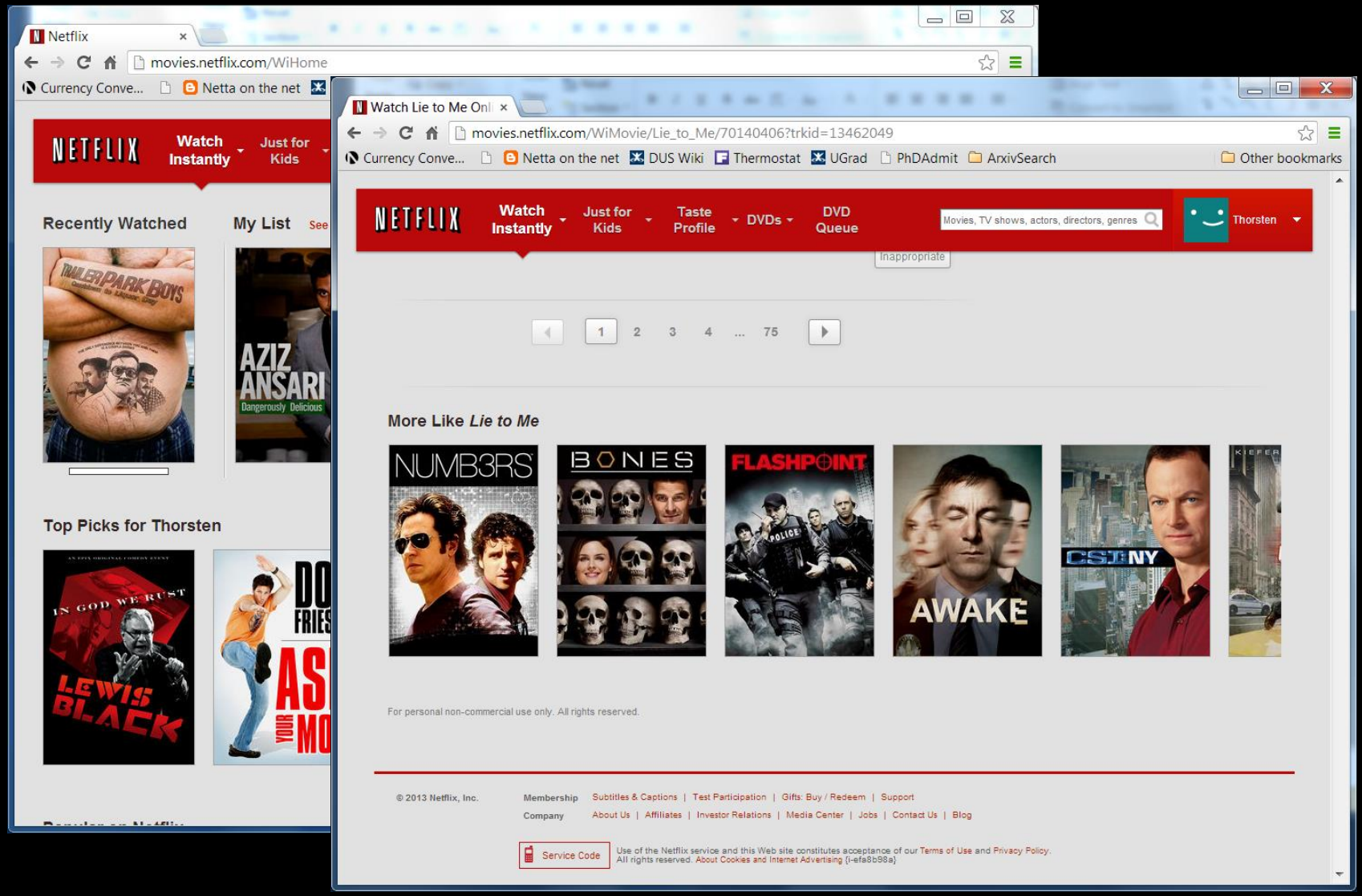
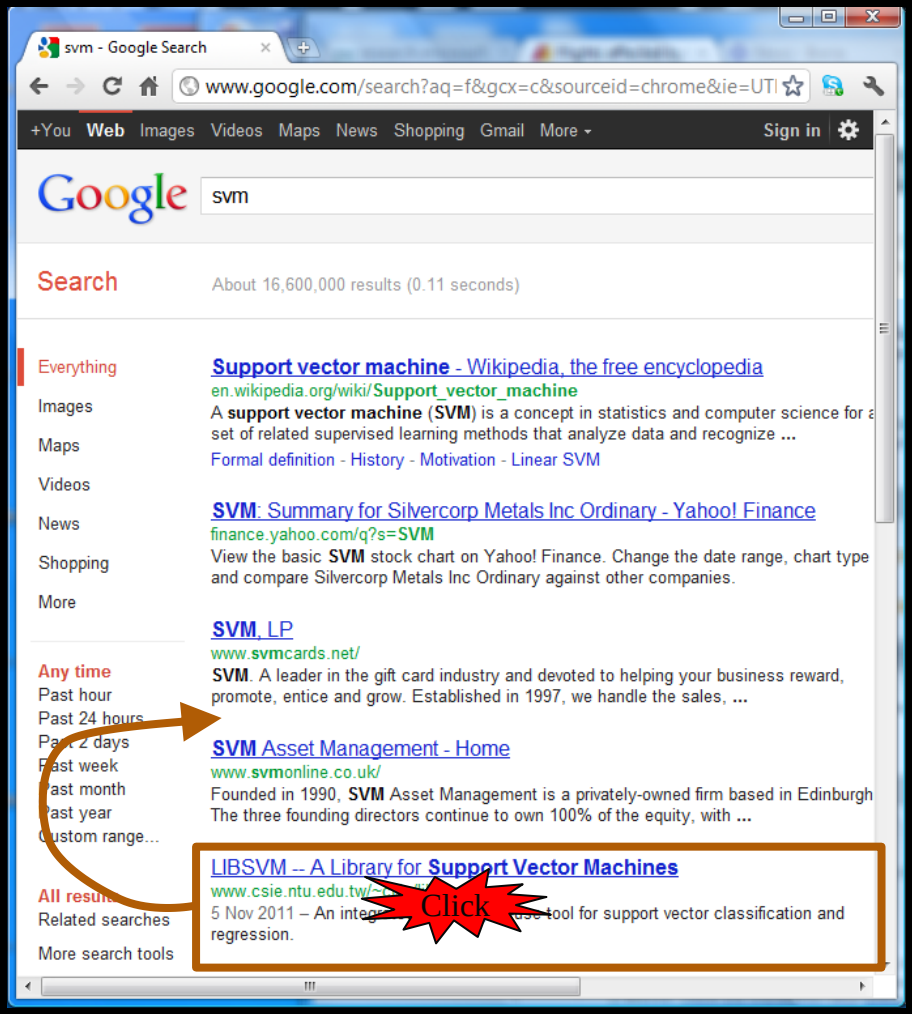
  - Model the users decision process to extract feedback ✓
    → Pairwise comparison test $P(y_i \succ y_j \mid U(y_i)>U(y_j))$
  - Design learning algorithm for this type of feedback ✓
    → Dueling Bandits problem and algorithms (e.g. IF2)

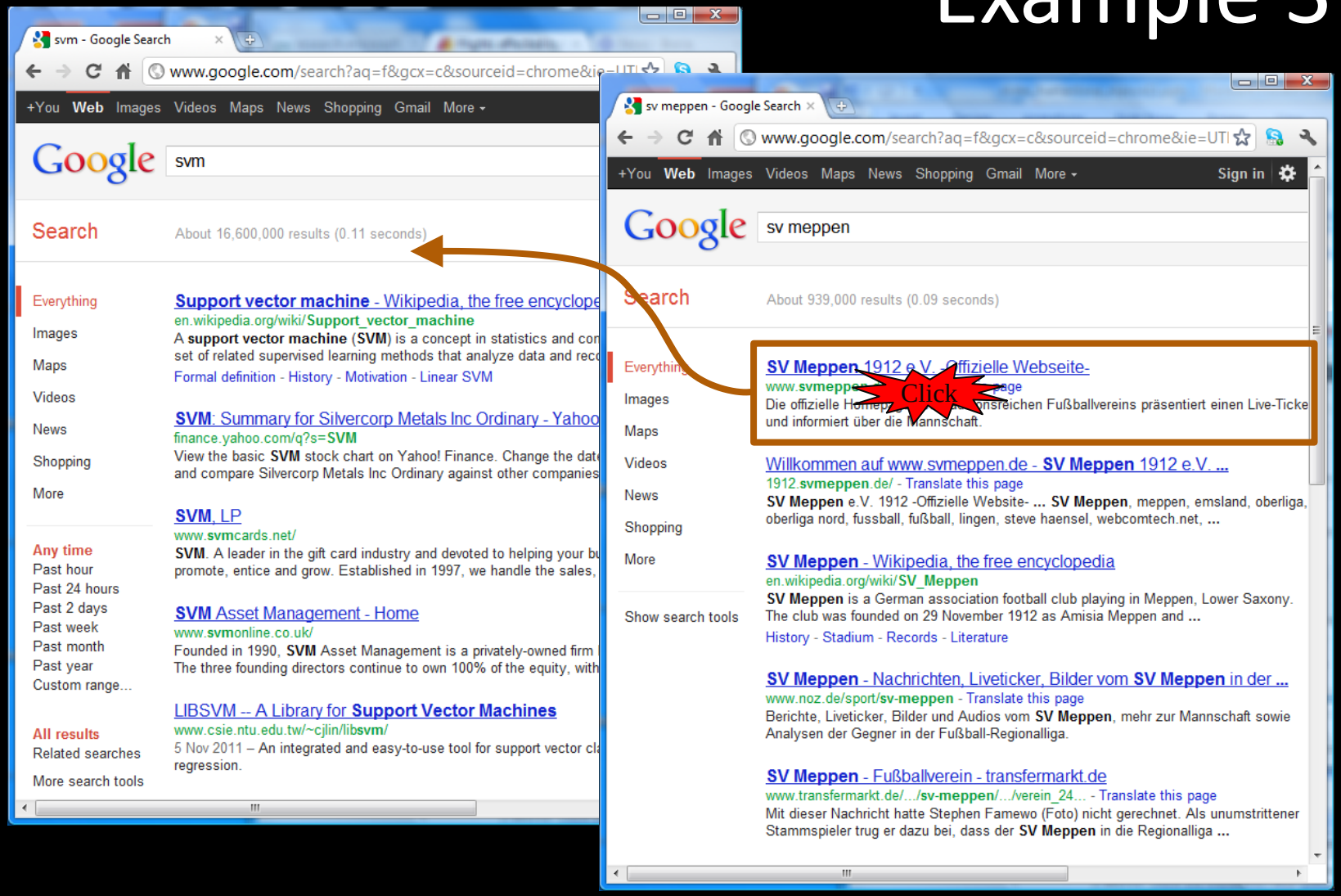
Who does the exploring? Example 1



Who does the exploring? Example 2

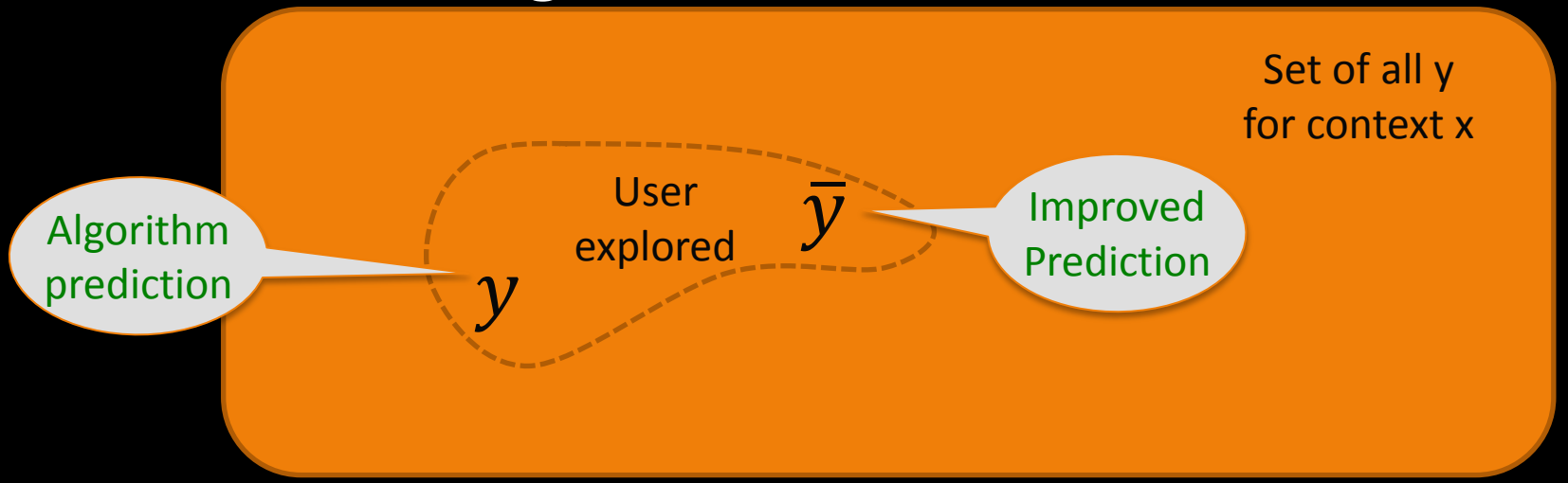


Who does the exploring? Example 3



Coactive Feedback Model

- Interaction: given x



- Feedback:
  - Improved prediction $\bar{y}_t$

$$U(\bar{y}_t | x_t) > U(y_t | x_t)$$

  - Supervised learning: optimal prediction y_t^*

$$y_t^* = \text{argmax}_y \, U(y | x_t)$$

Machine Translation

x_t

We propose Coactive Learning as a model of interaction between a learning system and a human user, where both have the common goal of providing results of maximum utility to the user.

y_t

Wir schlagen vor, koaktive Learning als ein Modell der Wechselwirkung zwischen einem Lernsystem und menschlichen Benutzer, wobei sowohl die gemeinsame Ziel, die Ergebnisse der maximalen Nutzen für den Benutzer.

$\prec$

Wir schlagen ~~vor,~~ koaktive Learning als ein Modell ~~der Wechselwirkung~~ des Dialogs zwischen einem Lernsystem und menschlichen Benutzer, wobei ~~sowohl die~~ beide das gemeinsame Ziel haben, die Ergebnisse der maximalen Nutzen für den Benutzer zu liefern.

$\bar{y}_t$

Coactive Learning Model

- Unknown Utility Function: U(y|x)
  - Boundedly rational user
- Algorithm/User Interaction:
  - LOOP FOREVER
    - Observe context x (e.g. query)
    - Learning algorithm presents y (e.g. ranking)
    - User returns $\bar{y}$ with $U(\bar{y}|x) > U(y|x)$
    - Regret = Regret + [$U(y^*|x) - U(y|x)$]

Never revealed:
- cardinal feedback
- optimal y^*

Loss for prediction $\hat{y}$

Optimal prediction $y^* = \text{argmax}_y \{ U(x,y) \}$

- Relationship to other online learning models
  - Expert setting: receive U(y|x) for all y
  - Bandit setting: receive U(y|x) only for selected y
  - Dueling bandits: for selected y and $\bar{y}$, receive $U(\bar{y}|x) > U(y|x)$
  - Coactive setting: for selected y, receive $\bar{y}$ with $U(\bar{y}|x) > U(y|x)$

Coactive Preference Perceptron

- Model
  - Linear model of user utility: $U(y|x) = w^T \phi(x,y)$
- Algorithm
  - FOR t = 1 TO T DO
    - Observe x_t
    - Present $y_t = \text{argmax}_y \{ w_t^T \phi(x_t,y) \}$
    - Obtain feedback $\bar{y}_t$ from user
    - Update $w_{t+1} = w_t + \phi(x_t,\bar{y}_t) - \phi(x_t,y_t)$
- This may look similar to a multi-class Perceptron, but
  - Feedback $\bar{y}_t$ is different (not get the correct class label)
  - Regret is different (misclassifications vs. utility difference)

$$\mathrm{R(A)} = \frac{1}{T}\sum_{t=1}^{T}[U(y_t^*|x) - U(y_t|x)]$$

Never revealed:
- cardinal feedback
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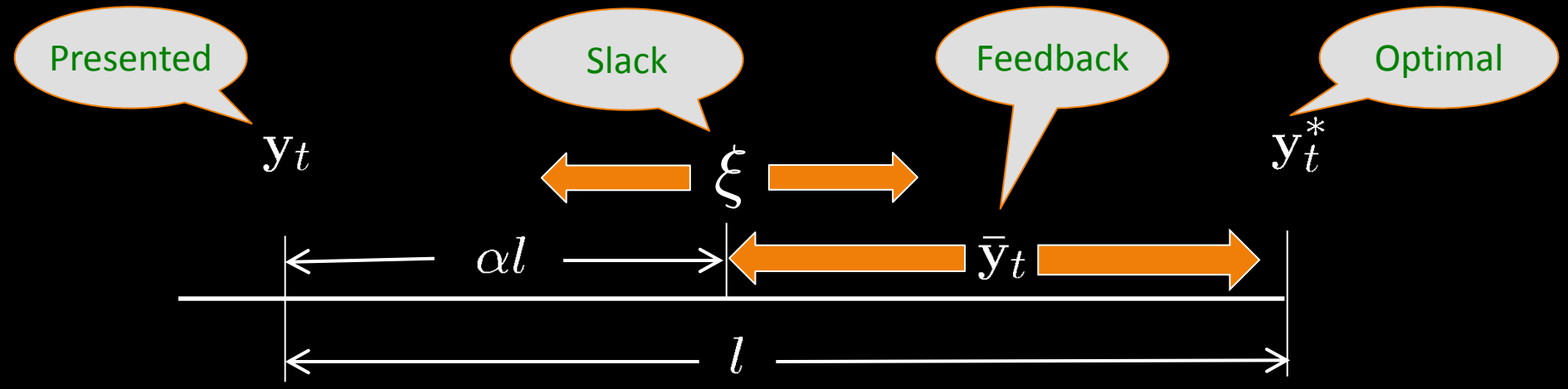
[Shivaswamy, Joachims, 2012]

α-Informative Feedback



Feedback ≥ Presented + α (Best – Presented)

- Definition: Strict α-Informative Feedback

$$U(\mathbf{x}_t, \bar{\mathbf{y}}_t) \geq U(\mathbf{x}_t, \mathbf{y}_t) + \alpha(U(\mathbf{x}_t, \mathbf{y}_t^*) - U(\mathbf{x}_t, \mathbf{y}_t))$$

- Definition: α-Informative Feedback

Slacks both pos/neg

$$U(\mathbf{x}_t, \bar{\mathbf{y}}_t) = U(\mathbf{x}_t, \mathbf{y}_t) + \alpha(U(\mathbf{x}_t, \mathbf{y}_t^*) - U(\mathbf{x}_t, \mathbf{y}_t)) - \xi_t$$

[Shivaswamy, Joachims, 2012]

Preference Perceptron: Regret Bound

- Assumption
  - $U(\mathbf{y}|\mathbf{x}) = \mathbf{w}^T \phi(\mathbf{x},\mathbf{y})$, but w is unknown
- Theorem

  For user feedback $\bar{\mathbf{y}}$ that is α-informative, the average regret of the Preference Perceptron is bounded by

$$\frac{1}{T}\sum_{t=1}^{T}\left[U(\mathbf{y}_t^*|\mathbf{x}) - U(\mathbf{y}_t|\mathbf{x})\right] \leq \frac{1}{\alpha T}\sum_{t=1}^{T}\xi_t + \frac{2R\|w\|}{\alpha\sqrt{T}}$$

  noise → zero
- Other Algorithms and Results
  - Feedback that is α-informative only in expectation
  - General convex loss functions of $U(\mathbf{y}^*|\mathbf{x})$-$U(\hat{\mathbf{y}}|\mathbf{x})$
  - Regret that scales log(T)/T instead of $T^{-0.5}$ for strongly convex

[Shivaswamy, Joachims, 2012]

Preference Perceptron: Experiment

Experiment:

- Automatically optimize Arxiv.org Fulltext Search

Analogous to DCG

Model

- Utility of ranking y for query x: $U_t(y|x) = \sum_i \gamma_i \, w_t^T \, \phi(x,y^{(i)})$ [~1000 features]

  →Computing argmax ranking: sort by $w_t^T \, \phi(x,y^{(i)})$

Feedback

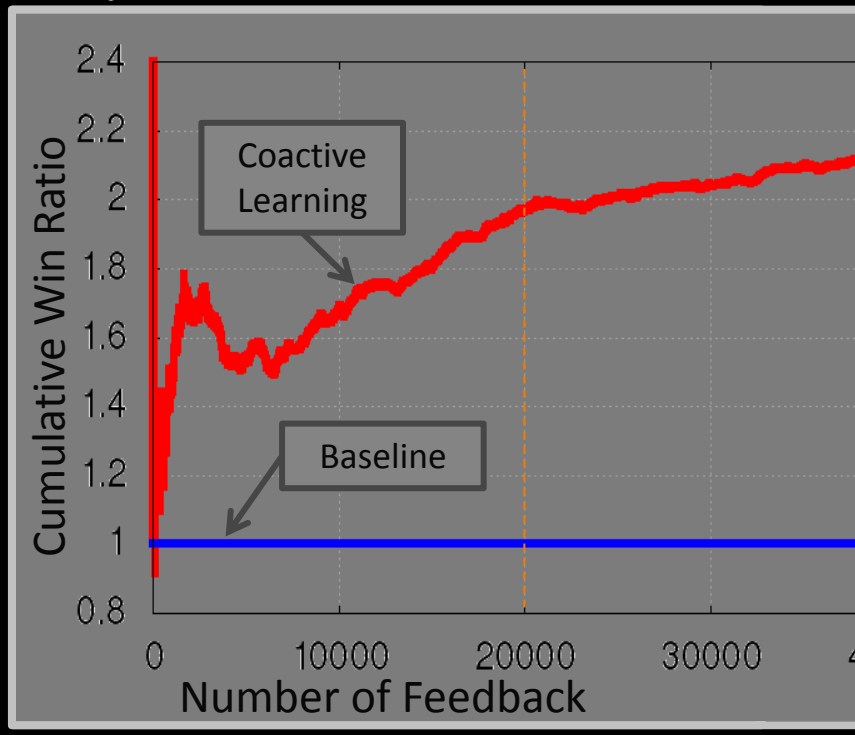
- Construct $\bar{y}_t$ from y_t by moving clicked links one position higher.
- Perturbation [Raman et al., 2013]

Baseline

- Handtuned w_{base} for $U_{base}(y|x)$

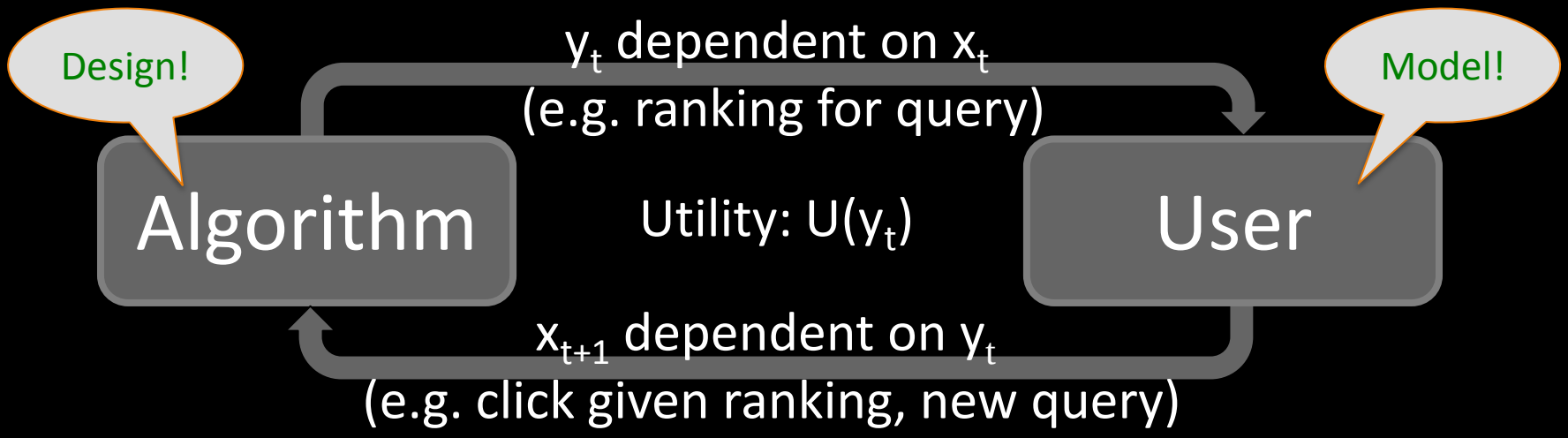
Evaluation

- Interleaving of ranking from $U_t(y|x)$ and $U_{base}(y|x)$



[Raman et al., 2013]

Summary and Conclusions



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  - Dueling Bandits
    - → Model: Pairwise comparison test $P(y_i \succ y_j \mid U(y_i)>U(y_j))$
    - → Algorithm: Interleaved Filter 2, $O(|Y|\log(T))$ regret
  - Coactive Learning
    - → Model: for given y, user provides $\bar{y}$ with $U(\bar{y}|x) > U(y|x)$
    - → Algorithm: Preference Perceptron, $O(\|w\| T^{0.5})$ regret