Online Learning from User Interactions through Interventions

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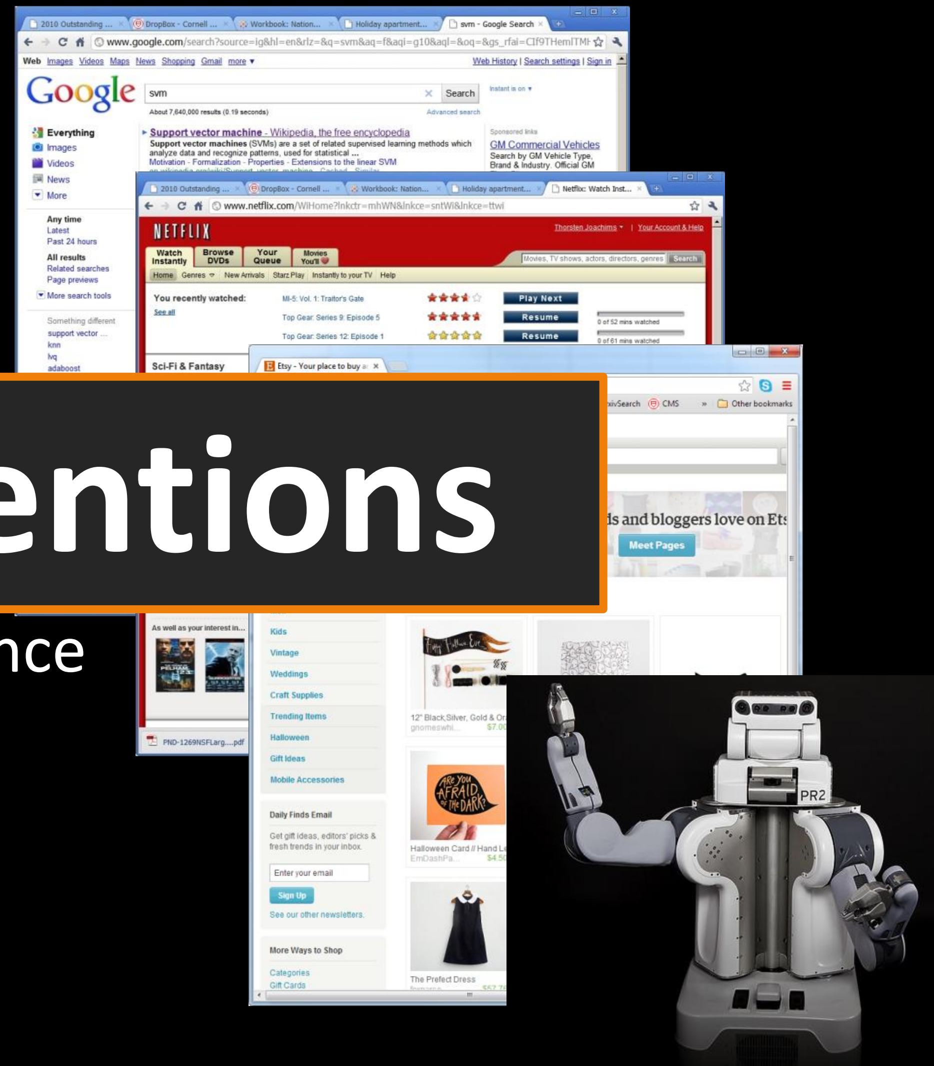
Y. Yue, J. Broder, R. Kleinberg, T. Joachims. The K-armed Dueling Bandits Problem. In COLT, 2009.

P. Shivaswamy, T. Joachims. Online Structured Prediction via Coactive Learning, ICML, 2012.

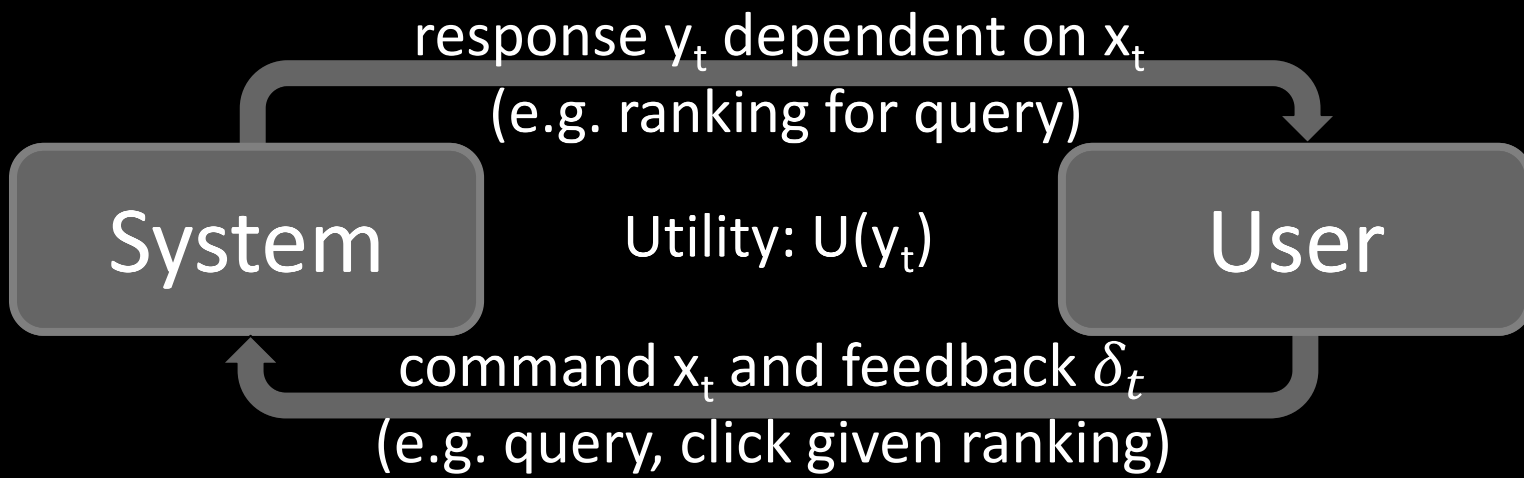
Interactive Learning Systems

- Examples
  - Search engines
  - Entertainment media
  - E-co
  - Sma
- Learni
  - Gathering and maintenance of knowledge
  - Measure and optimize performance
  - Personalization



Interventions

Interactive Learning System



- Information Elicitation from the User
  - Via generative behavioral model
  - Via information-elicitation interventions
- Online Learning with Interventions
  - Dueling Bandits: Algorithm-driven exploration
  - Coactive Learning: User-driven exploration

Decide between two Ranking Functions

Distribution P(x)
of x=(user, query)

⋮
(tj,"SVM")
⋮

Retrieval Function 1
$f_1(x) \rightarrow y_1$

Which one is better?

Retrieval Function 2
$f_2(x) \rightarrow y_2$

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/
4. An Introduction to Support Vector Machines
   http://www.support-vector.net/
5. Service Master Company
   http://www.servicemaster.com/

⋮

U(tj,"SVM",y_1)

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   http://www.servicemaster.com/
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   http://jbolivar.freeservers.com/
4. Archives of SUPPORT-VECTOR-MACHINES
   http://www.jiscmail.ac.uk/lists/SUPPORT...
5. SVM-Light Support Vector Machine
   http://ais.gmd.de/~thorsten/svm light/

⋮

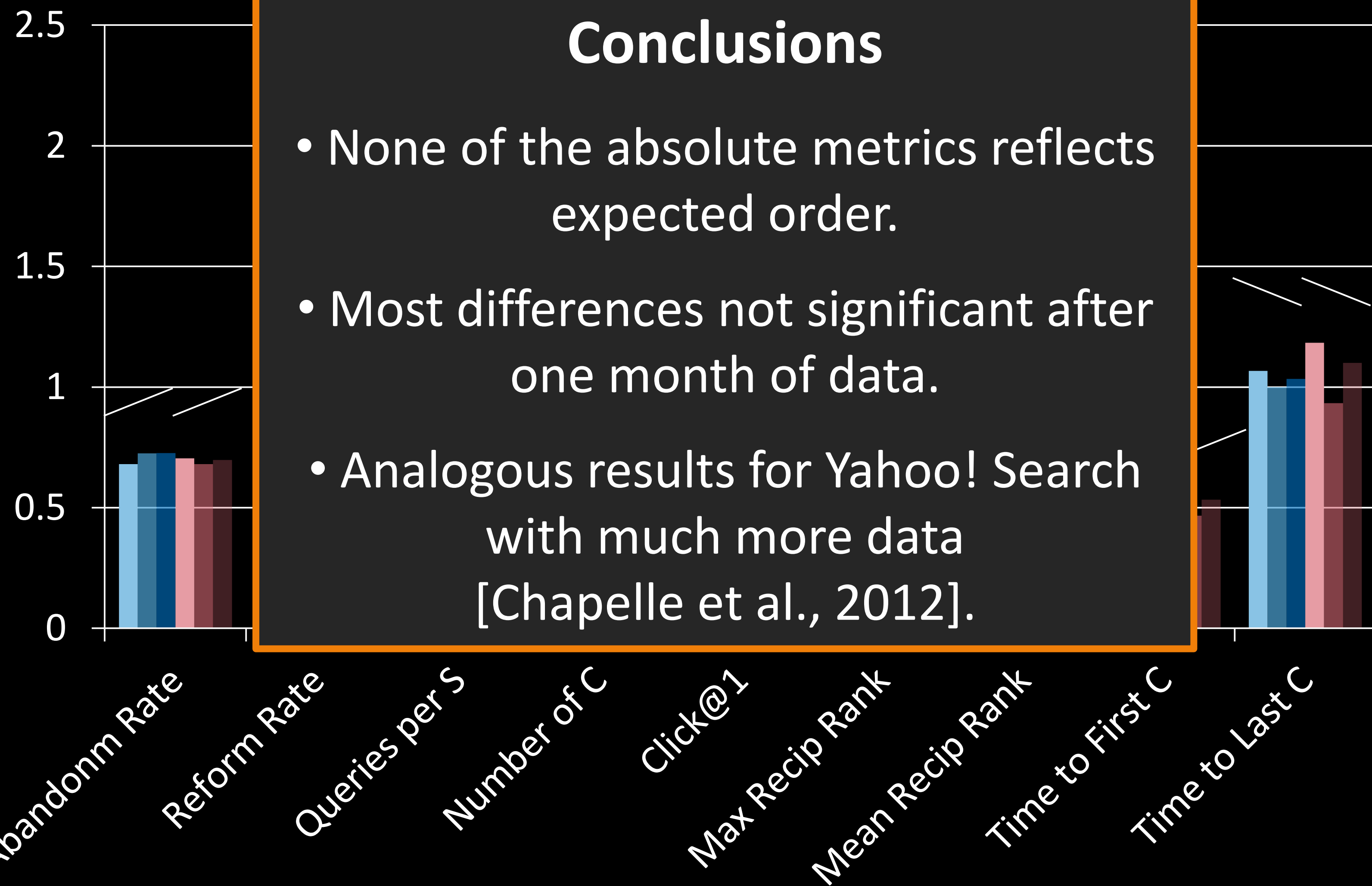
U(tj,"SVM",y_2)

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: Results



Conclusions

- None of the absolute metrics reflects expected order.
- Most differences not significant after one month of data.
- Analogous results for Yahoo! Search with much more data [Chapelle et al., 2012].

[Radlinski et al., 2008]

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

x=(u=tj, q="svm")

$f_1(x) \rightarrow y_1$

1. Kernel Machines
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3. An Introduction to Support Vector Machines
   http://www.support-vector.net/
4. Archives of SUPPORT-VECTOR-MACHINES ...
   http://www.jiscmail.ac.uk/lists/SUPPORT...
5. SVM-Light Support Vector Machine
   http://ais.gmd.de/~thorsten/svm light/

$f_2(x) \rightarrow y_2$

1. Kernel Machines
   http://svm.first.gmd.de/
2. SVM-Light Support Vector Machine
   http://ais.gmd.de/~thorsten/svm light/
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(y_1,y_2)

1. Kernel Machines — 1
   http://svm.first.gmd.de/
2. Support Vector Machine — 2
   http://jbolivar.freeservers.com/
3. SVM-Light Support Vector Machine — 2
   http://ais.gmd.de/~thorsten/svm light/
4. An Introduction to Support Vector Machines — 3
   http://www.support-vector.net/
5. Support Vector Machine and Kernel ... References — 3
   http://svm.research.bell-labs.com/SVMrefs.html
6. Archives of SUPPORT-VECTOR-MACHINES ... — 4
   http://www.jiscmail.ac.uk/lists/SUPPORT...
7. Lucent Technologies: SVM demo applet — 4
   http://svm.research.bell-labs.com/SVT/SVMsvt.html

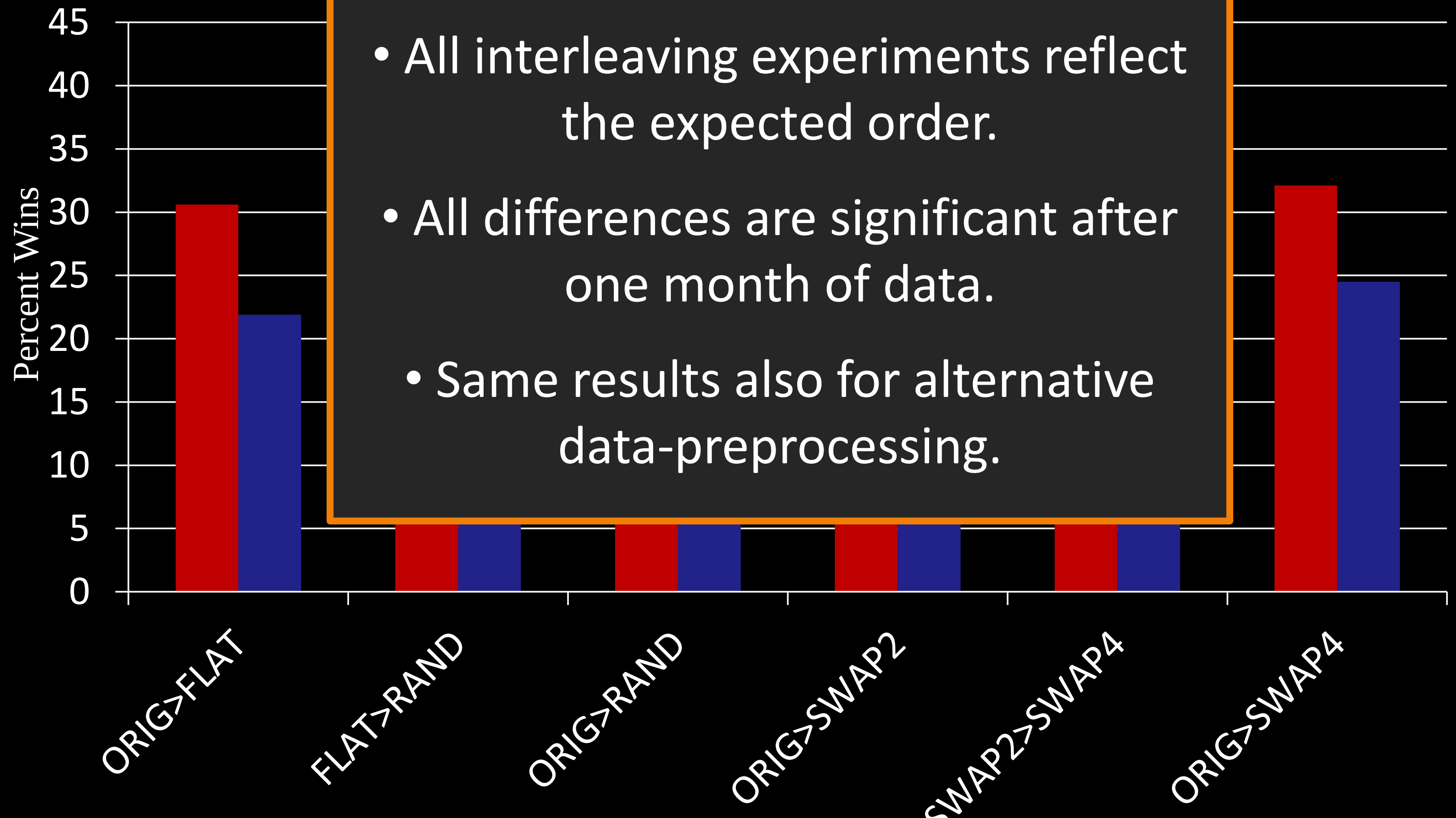
Model of User:
Better retrieval functions is more likely to get more clicks.

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: $(y_1 \succ y_2) \leftrightarrow$ clicks(topk(y_1)) > clicks(topk(y_2))
→ see also [Radlinski, Craswell, 2012] [Hofmann, 2012]

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

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

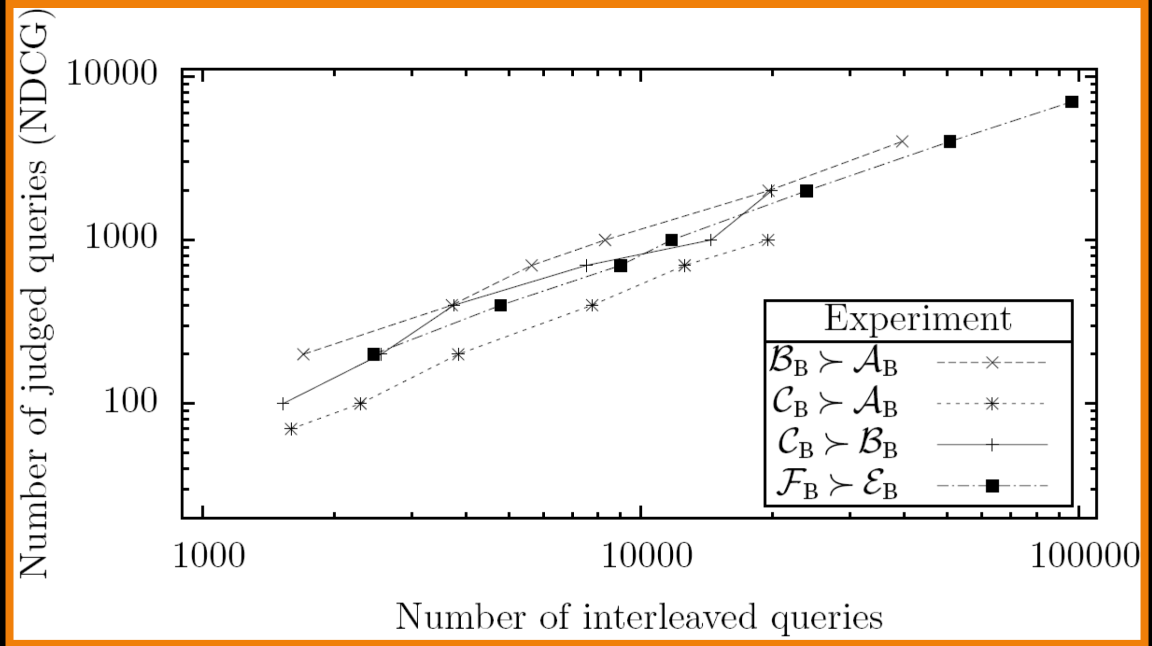
    → All paired comparisons consistent with ordering by NDCG.

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

    → Consistent with ordering by NDGC when NDCG significant.

Efficiency: Interleaving vs. Explicit

- Bing Web Search
  - 4 retrieval function pairs
  - ~12k manually judged queries
  - ~200k interleaved queries

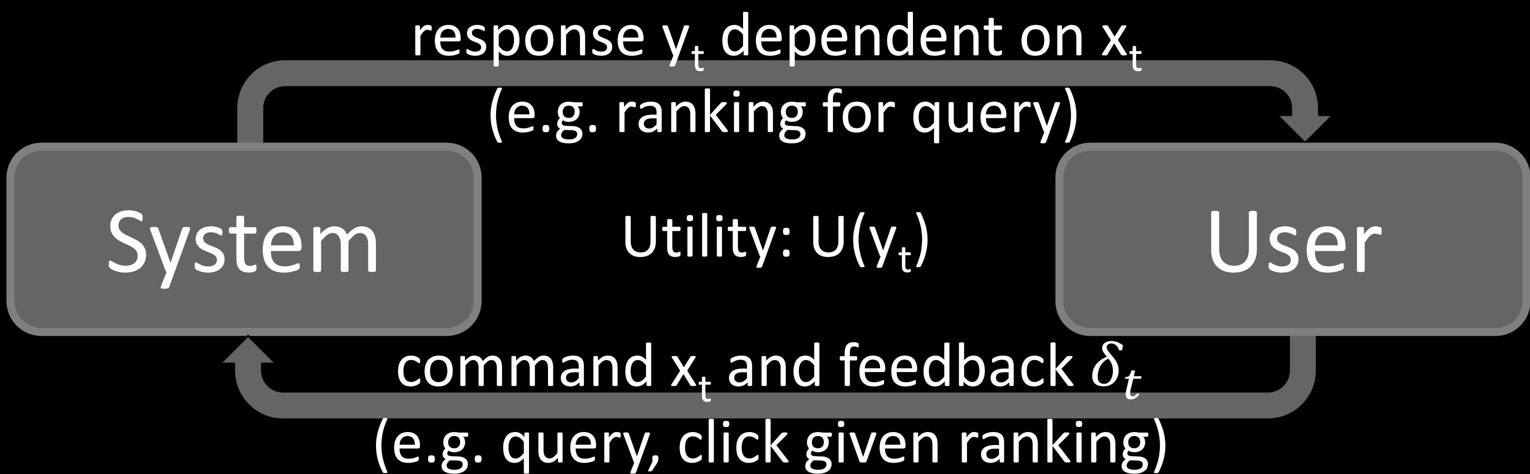


- Experiment
  - p = probability that NDCG is correct on subsample of size y
  - x = number of queries needed to reach same p-value with interleaving

➔ Ten interleaved queries are equivalent to one manually judged query.

[Radlinski & Craswell, 2010]

Interactive Learning System



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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^*

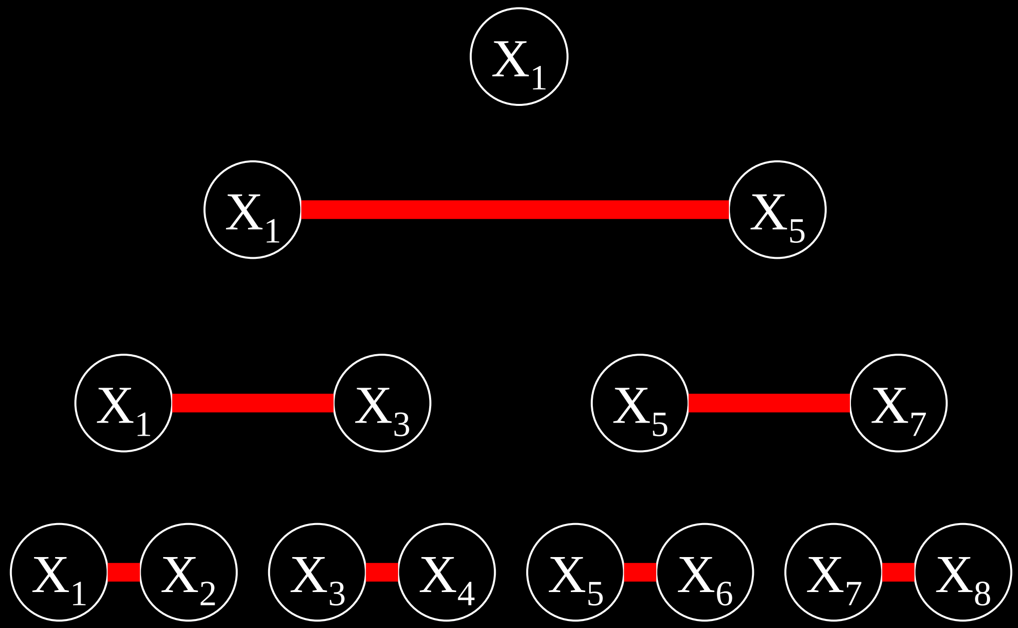
$$\mathrm{R(A)} = \sum_{t=1}^{T} [P(f^* \succ f_t) - 0.5] + [P(f^* \succ f_t') - 0.5]$$

→ 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,$W=\{f_1 \ldots f_K\}$)
    - Pick random f' from W
    - $\delta=1/(TK^2)$
    - WHILE $|W|>1$
      – FOR $b \in W$ 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 $1-\delta$]
      – IF there exists f'' with $P_{f''} > 0.5+c_t$ [BETTER WITH PROB $1-\delta$]
        » 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 $f_j \succ f_k \rightarrow f_i \succ f_k$

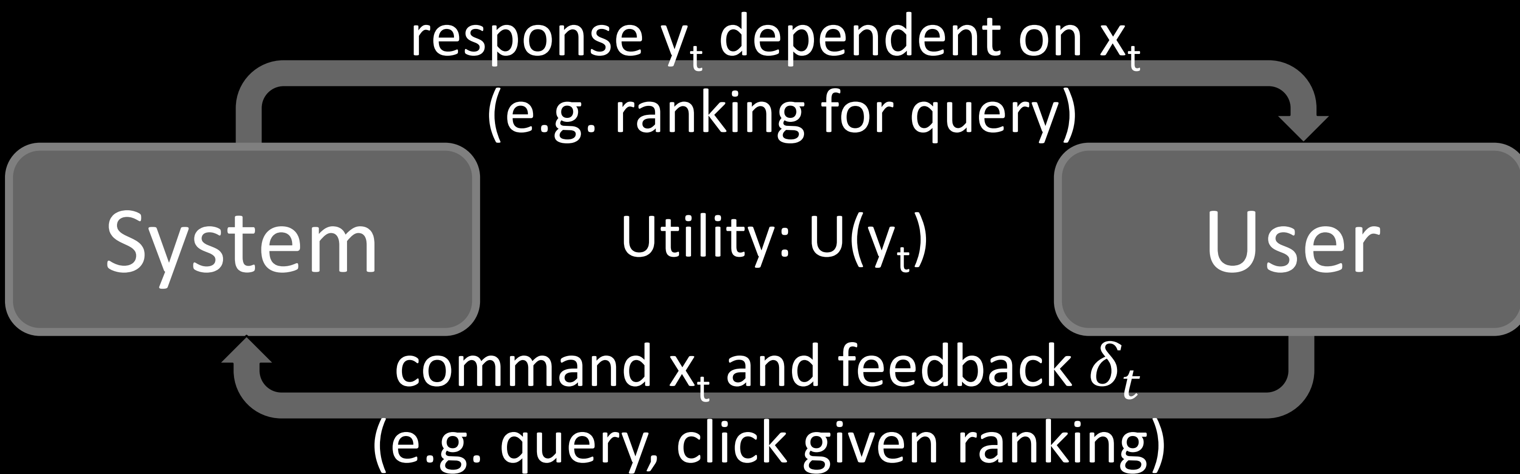
Theorem: IF2 incurs expected average regret bounded by

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

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

Interactive Learning System



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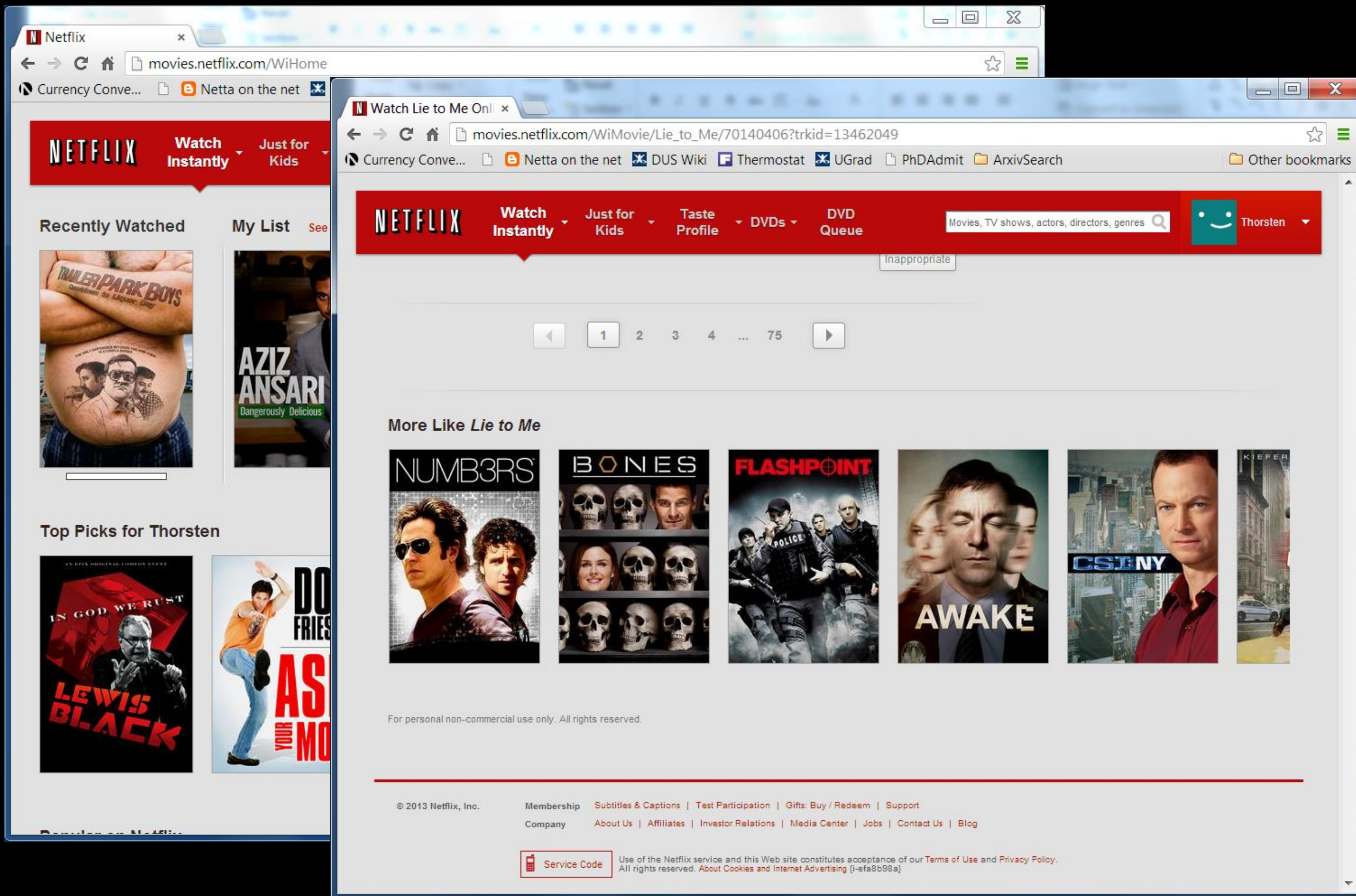
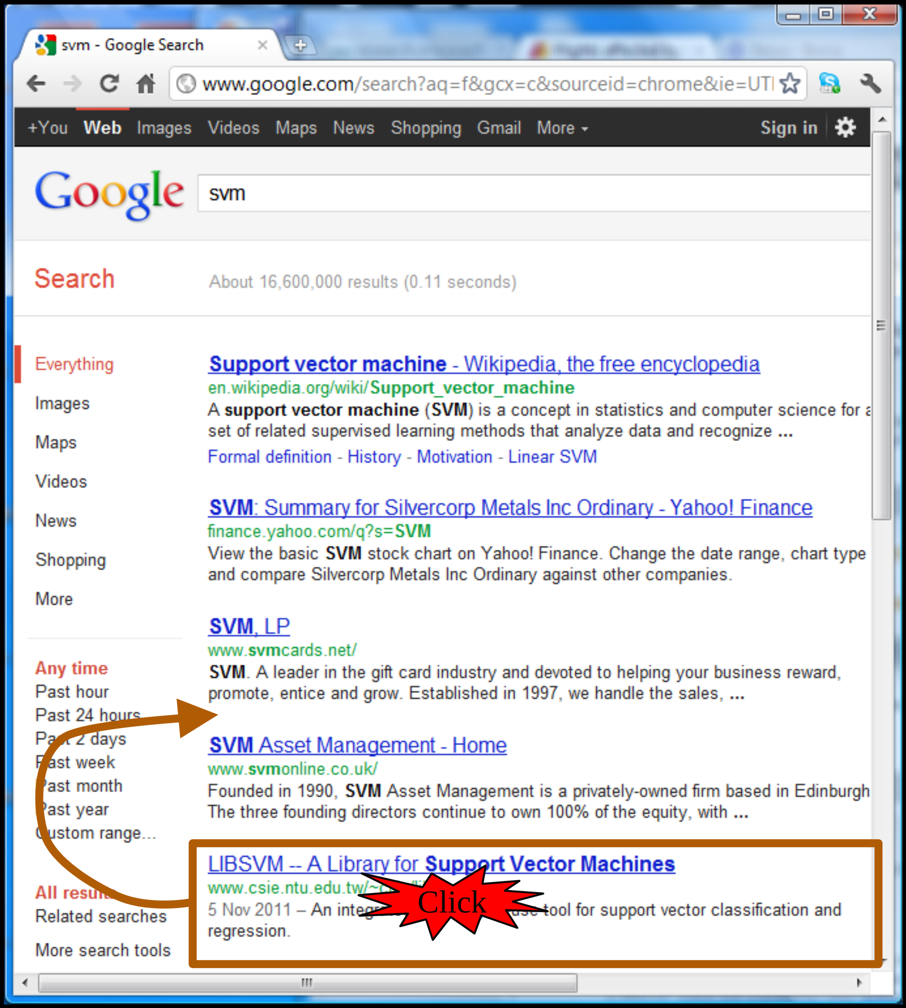
Who does the exploring?

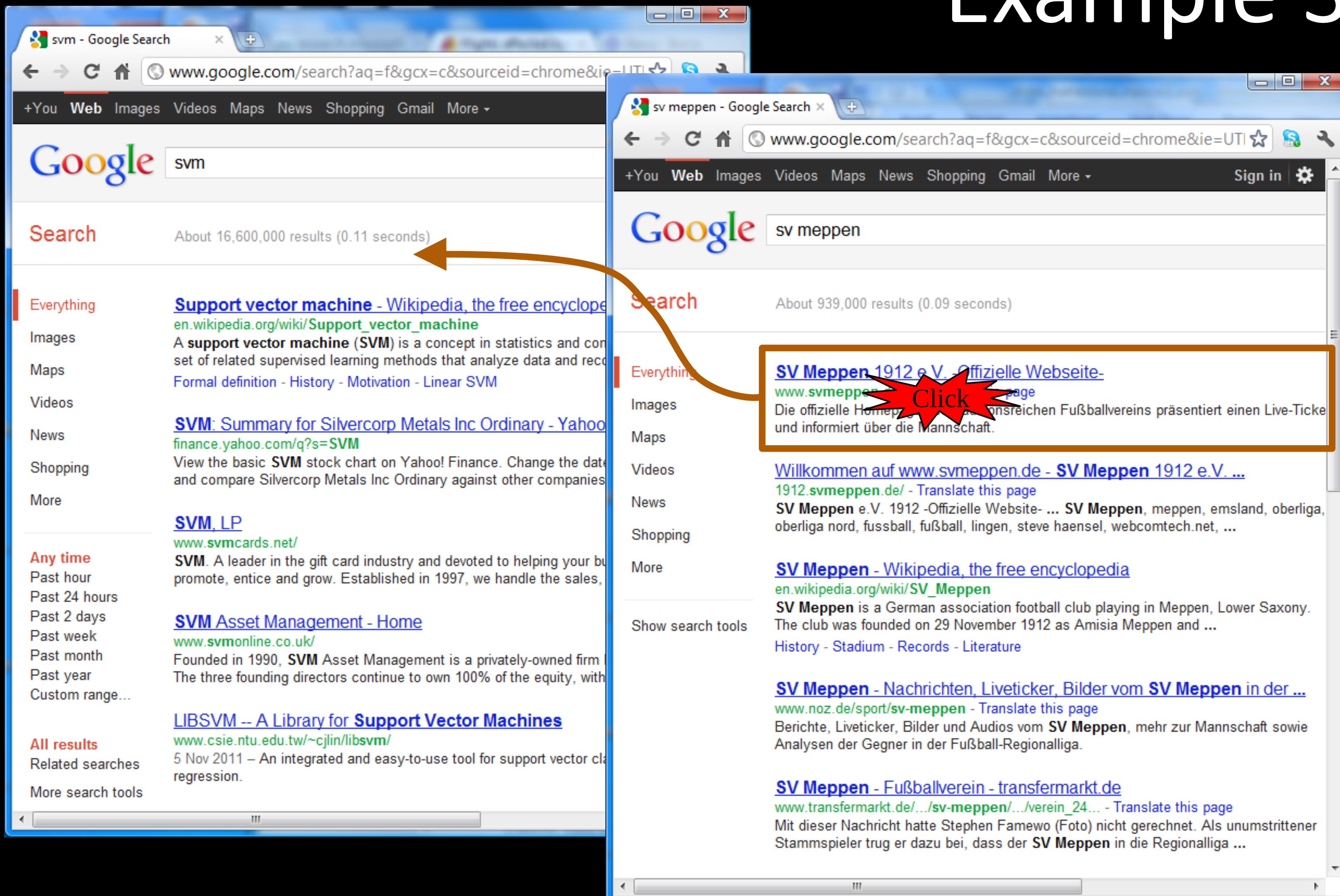
Example 1



Who does the exploring? Example 2

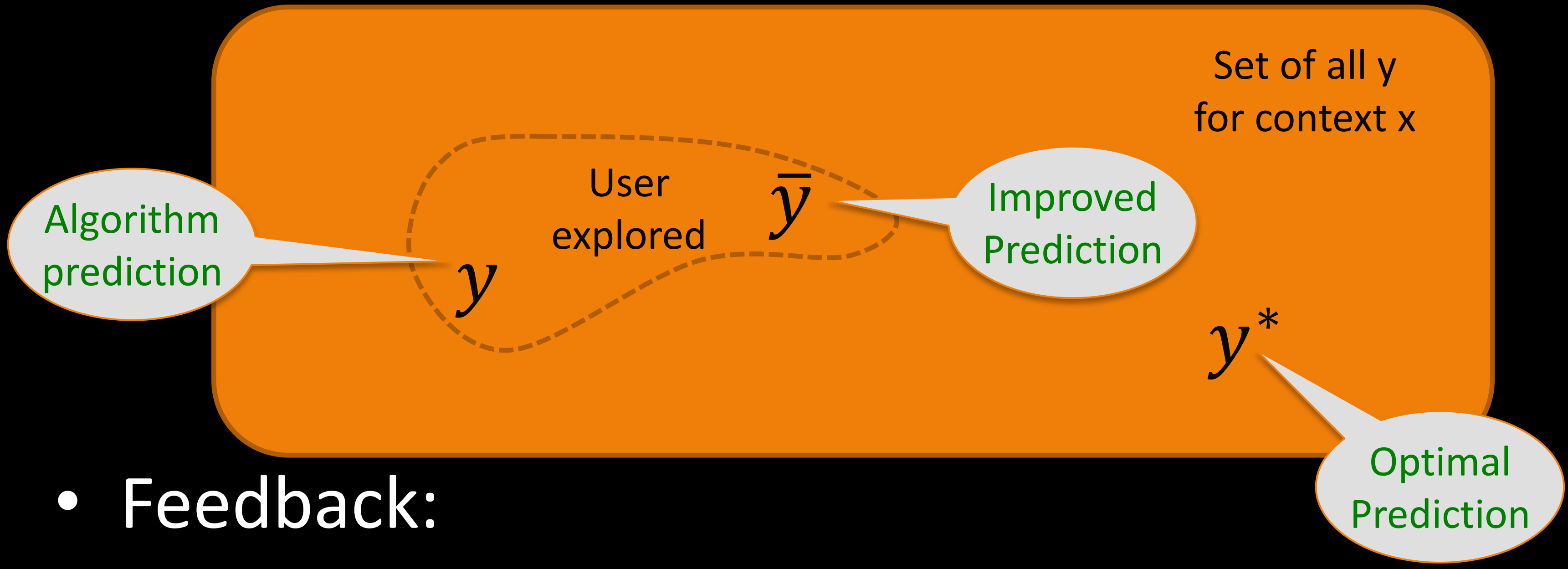


Who does the exploring?
Example 3



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^*

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

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.

$\prec$

$\bar{y}_t$

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.

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)

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

Never revealed:
- cardinal feedback
- optimal y^*

[Shivaswamy, Joachims, 2012]

Coactive Perceptron: Regret Bound

- Model

  $U(\mathbf{y}|\mathbf{x}) = \mathbf{w}^T \phi(\mathbf{x},\mathbf{y})$, where w is unknown

- Feedback: ξ-Approximately α-Informative

$$E[U(x_t, \bar{y}_t)] \geq U(x_t, y_t) + \alpha\big(U(x_t, y_t^*) - U(x_t, y_t)\big) - \xi_t$$

user feedback

system prediction

gap to optimal

model error

- Theorem

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

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

→ zero

model error

[Shivaswamy, Joachims, 2012]

Preference Perceptron: Experiment

Experiment:

- Automatically optimize Arxiv.org Fulltext Search

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

Analogous to DCG

Feedback

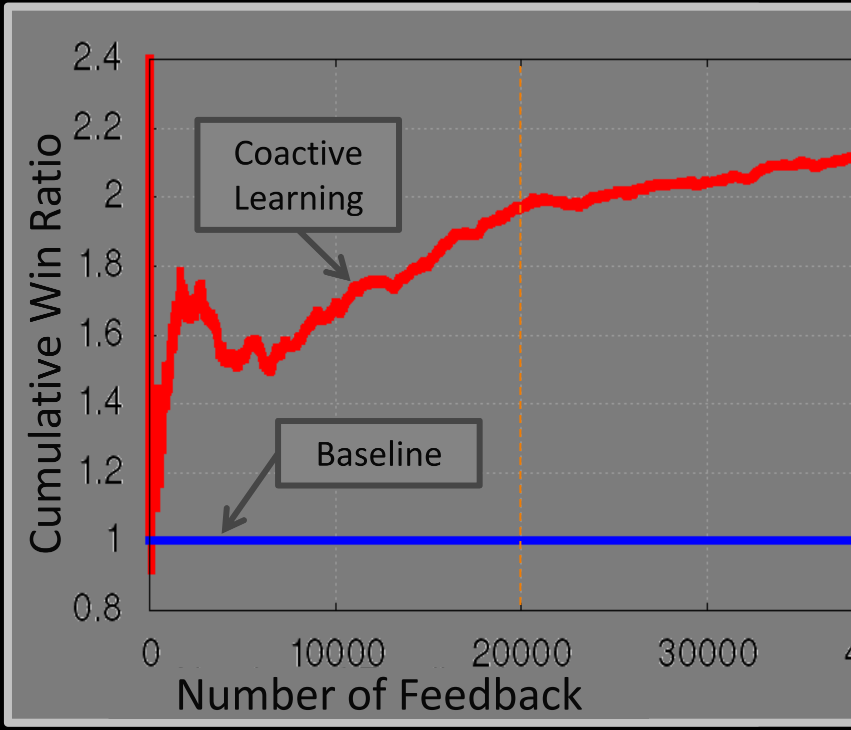
- Construct $\bar{y}_t$ from y_t by moving clicked links one position higher.
- Perturbation [Raman et al., 2013]

Baseline

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

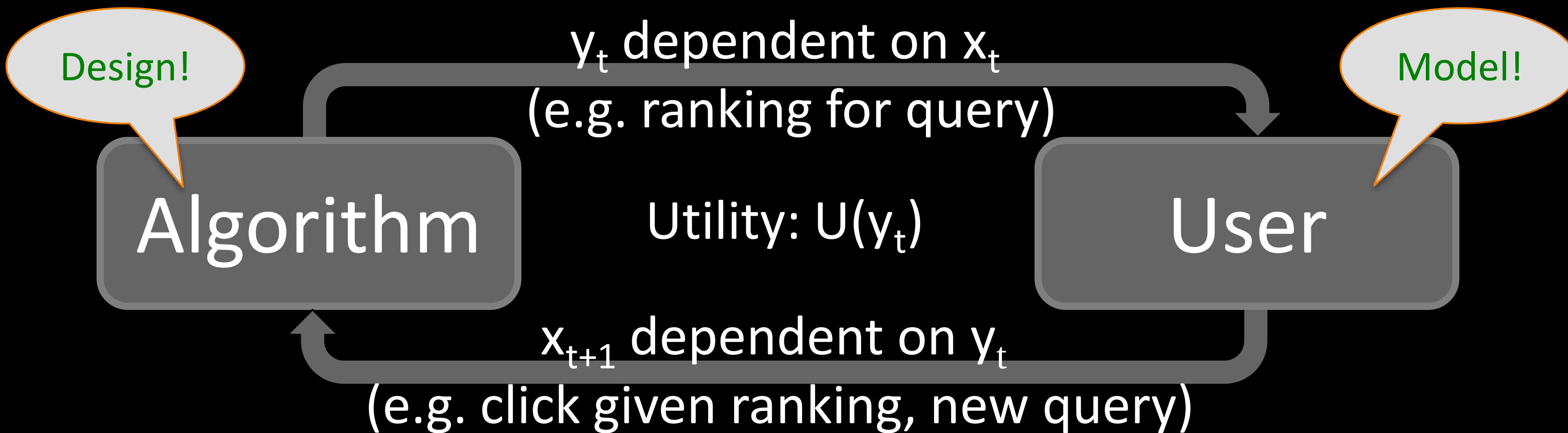
Evaluation

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



[Raman et al., 2013]

Interactive Learning System

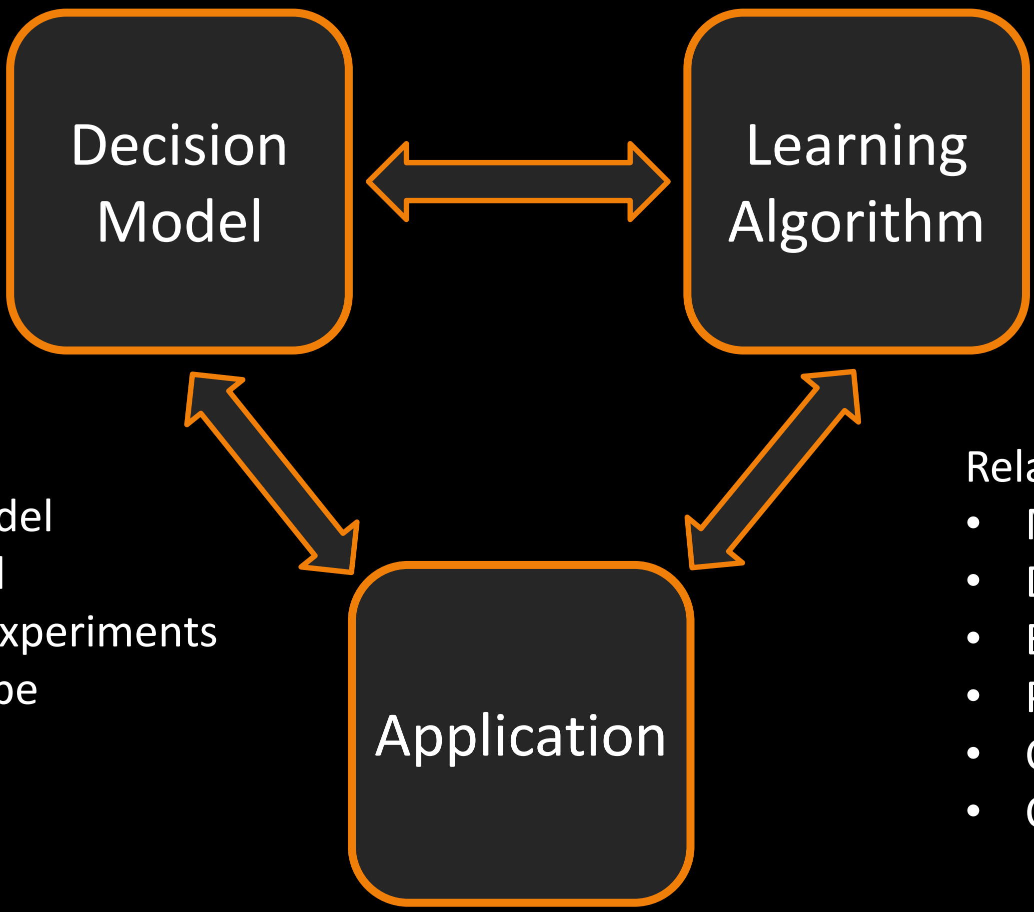


- Information Elicitation Interventions
- Decisions → Feedback → Learning Algorithm
  - Dueling Bandits
    - → Model: Pairwise comparison test $P(\, y_i \succ y_j \mid U(y_i) > U(y_j) \,)$
    - → Algorithm: Interleaved Filter 2, $O(|Y| \log(T))$ regret
  - Coactive Learning
    - → Model: for given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

Running
Interactive Learning Experiments

1) ~~Build your own system and provide service~~
   → ~~a lot of work~~
   → ~~too little data~~
2) ~~Convince others to run your experiments on commercial system~~
   → ~~good luck with that~~
3) Use large-scale historical log data from commercial system

Learning from Human Decisions



Design Space:
- Decision Model
- Utility Model
- Interaction Experiments
- Feedback Type
- Regret
- Applications

Related Fields:
- Micro Economics
- Decision Theory
- Econometrics
- Psychology
- Communications
- Cognitive Science

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