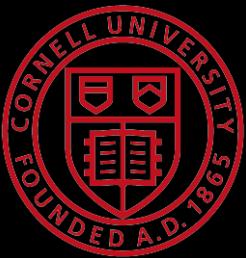


# Online Learning from User Interactions through Interventions

CS 7792 - Fall 2016

Thorsten Joachims

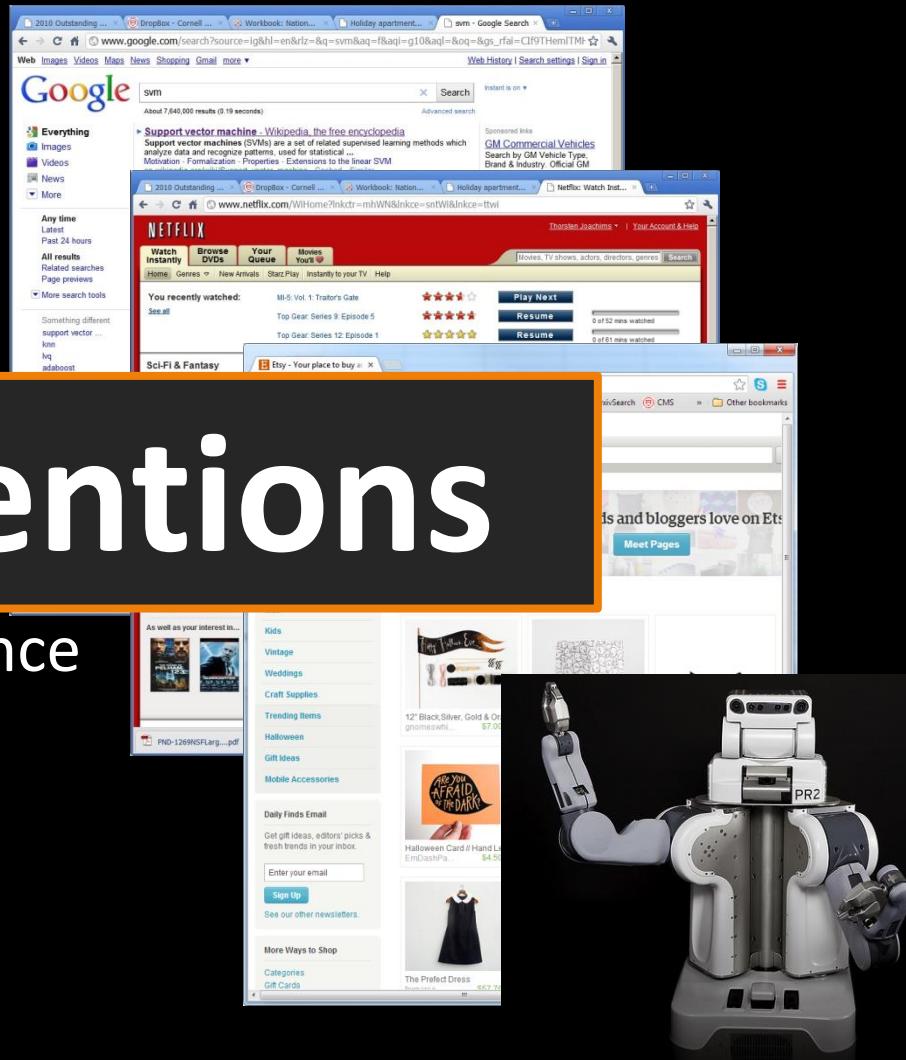
Department of Computer Science & Department of Information Science  
Cornell University



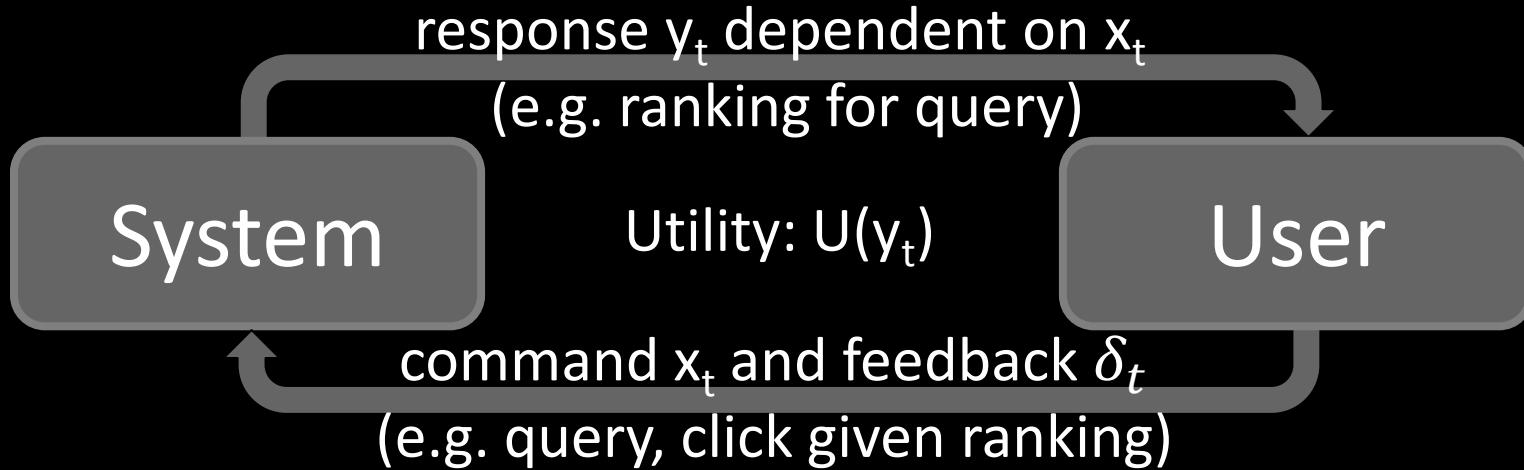
- Y. Yue, J. Broder, R. Kleinberg, T. Joachims. The K-armed Dueling Bandits Problem. In COLT, 2009.
- P. Shivaswamy, T. Joachims. Online Structured Prediction via Coactive Learning, ICML, 2012.

# Interactive Learning Systems

- Examples
  - Search engines
  - Entertainment media
  - E-commerce
  - Smart devices
- Learning interventions
  - Gathering and maintenance of knowledge
  - Measure and optimize performance
  - Personalization



# 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  $x=(\text{user}, \text{query})$

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/>
- ⋮

$U(tj, "SVM", y_1)$

1. School of Veterinary Medicine at UPenn  
<http://www.vet.upenn.edu/>
  2. Service Master Company  
<http://www.servicemaster.com/>
  3. Support Vector Machine  
<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/](http://ais.gmd.de/~thorsten/svm_light/)
- ⋮

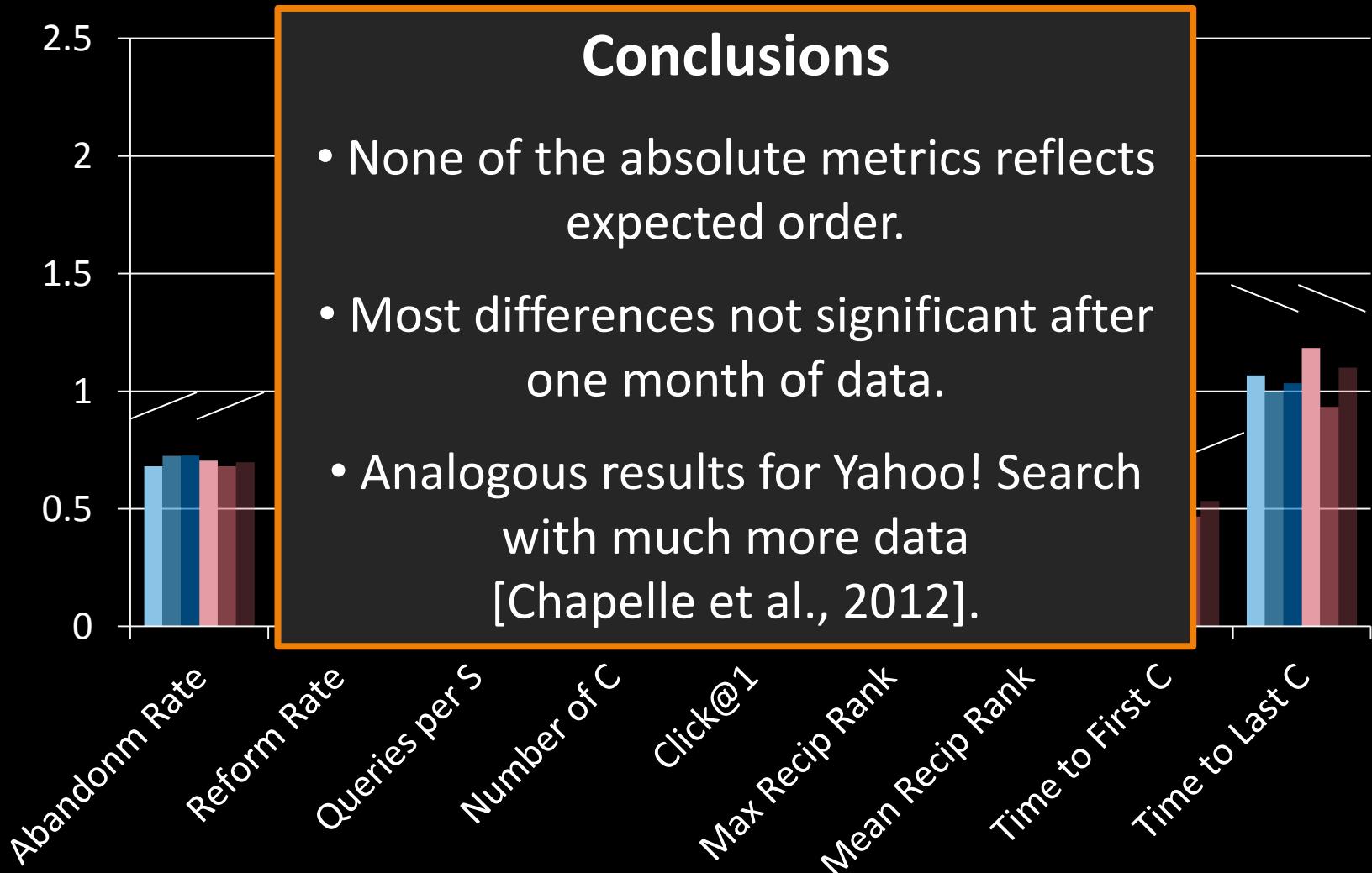
$U(tj, "SVM", y_2)$

# Measuring Utility

Name	Description	Aggregation	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



# 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

$$x=(u=tj, q=\text{"svm"})$$

$$f_1(x) \rightarrow y_1$$

$$f_2(x) \rightarrow y_2$$

1. Kernel Machines  
<http://svm.first.gmd.de/>
2. Support Vector Machine  
<http://jbolivar.freeservers.com/>
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/](http://ais.gmd.de/~thorsten/svm_light/)

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

## Model of User:

Better retrieval functions  
is more likely to get more  
clicks.

## Invariant:

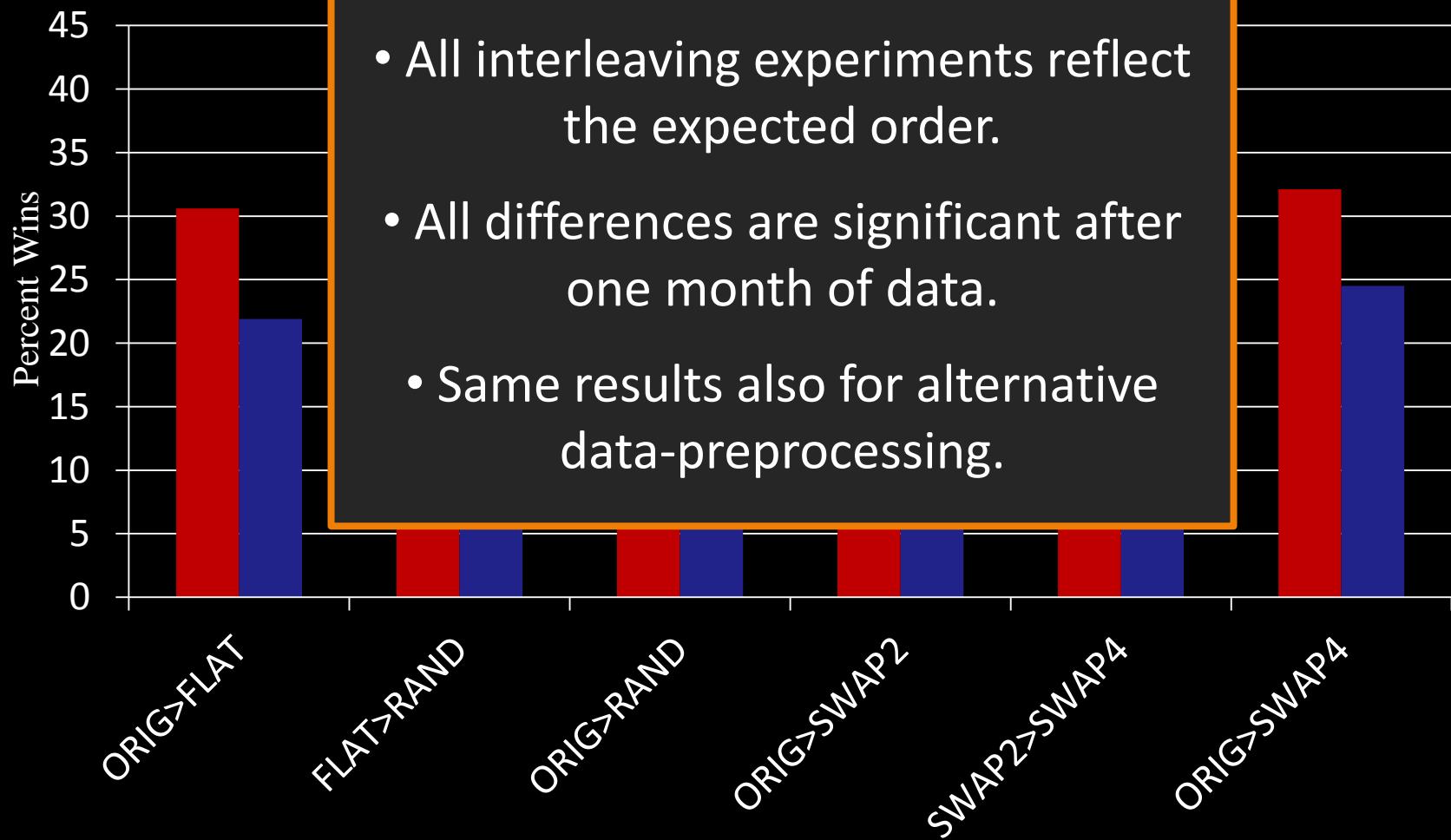
For all k, top k of  
balanced interleaving is  
union of top  $k_1$  of  $r_1$  and  
top  $k_2$  of  $r_2$  with  $k_1=k_2 \pm 1$ .

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

# 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.

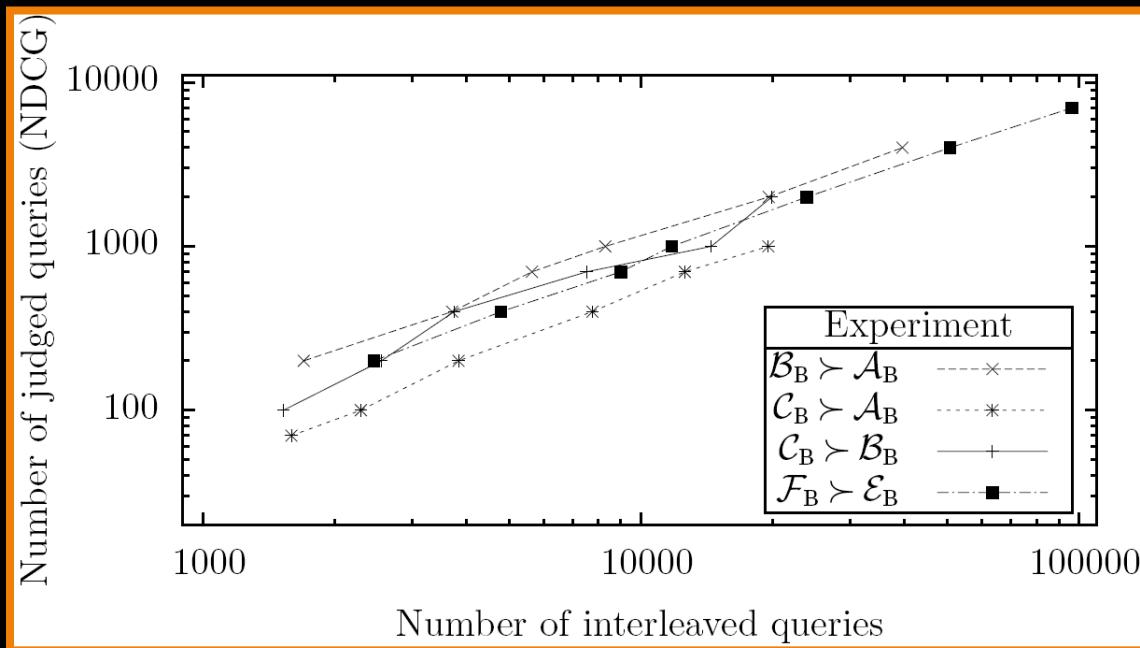


# Yahoo and Bing: Interleaving Results

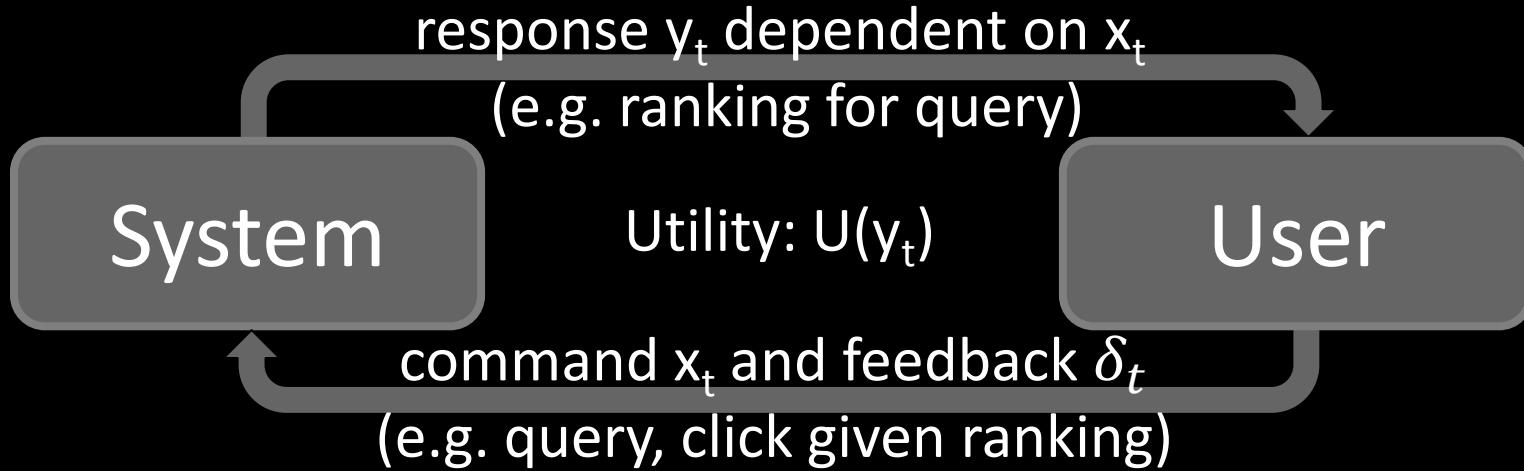
- Yahoo Web Search [Chapelle et al., 2012]
  - Four retrieval functions (i.e. 6 paired comparisons)
  - Balanced Interleaving
    - All paired comparisons consistent with ordering by NDCG.
- Bing Web Search [Radlinski & Craswell, 2010]
  - Five retrieval function pairs
  - Team-Game Interleaving
    - 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.



# 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

# 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  $f^*$

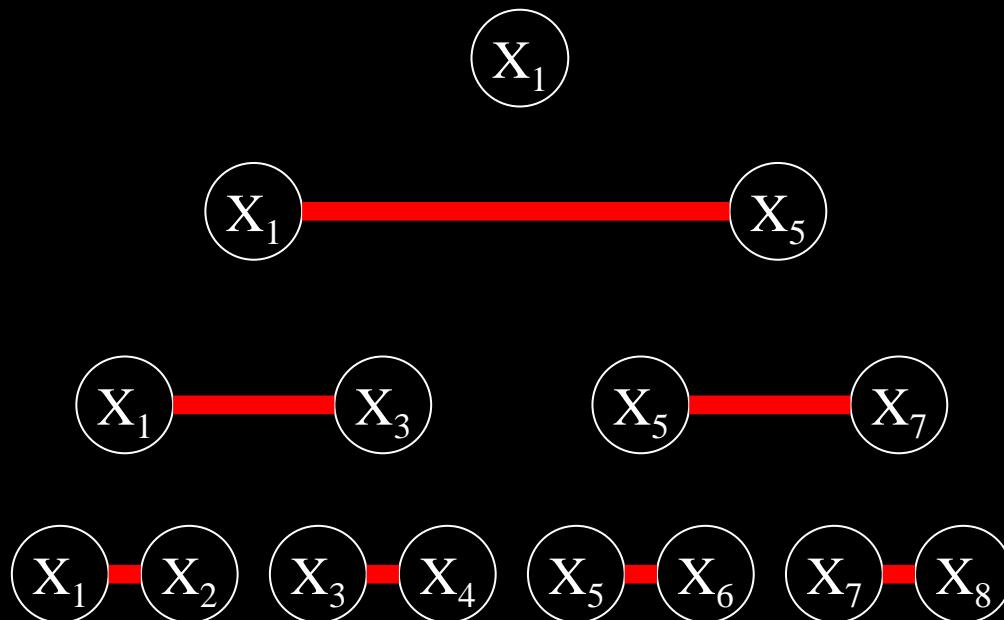
$$R(A) = \sum_{t=1}^T [P(f^* \succ f_t) - 0.5] + [P(f^* \succ f'_t) - 0.5]$$

→ 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={f1...fK})`

- 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  $T$ :  $\text{duel}(f', f')$

f <sub>1</sub>	f <sub>2</sub>	f'=f <sub>3</sub>	f <sub>4</sub>	f <sub>5</sub>
0/0	0/0		0/0	0/0
8/2	7/3		4/6	1/9
13/2	11/4	X	X	XX
f'=f <sub>1</sub>	f <sub>2</sub>		f <sub>4</sub>	
0/0	0/0	XX	XX	XX

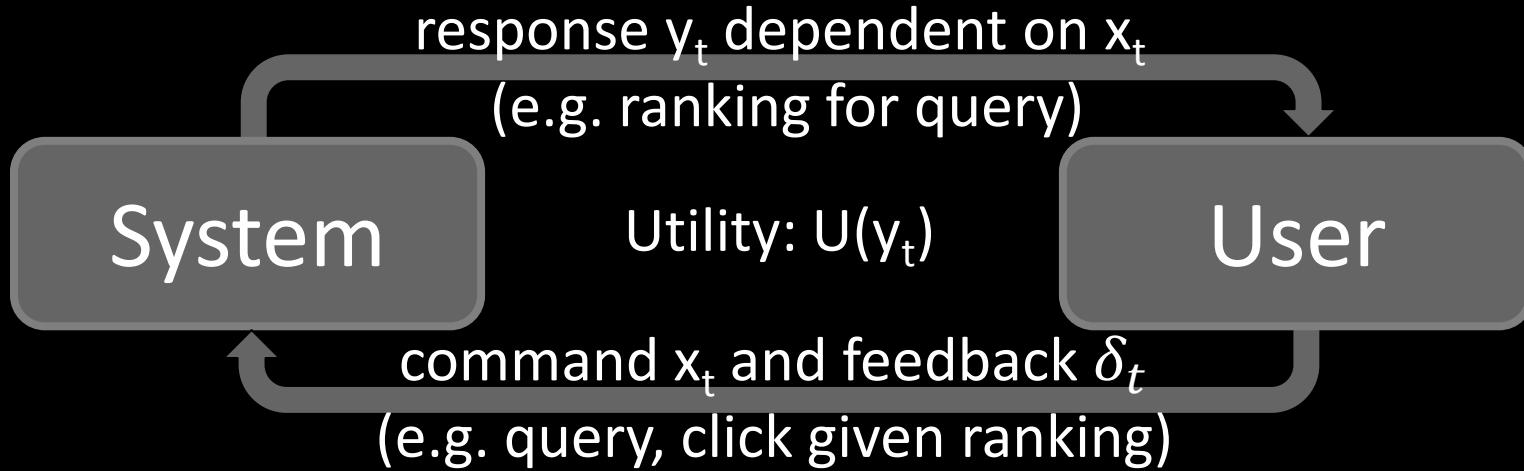
# Assumptions

- 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

- Stochastic Dominance:  $\frac{1}{T}E(R_T) \leq O\left(\frac{K \log T}{\varepsilon_{1,2}}\right)$
- Stochastic Triangle Inequality:  $t_i \succ t_j \succ t_k \rightarrow \varepsilon_{i,k} \leq \varepsilon_{i,j} + \varepsilon_{j,k}$   
 $\varepsilon_{1,2} = 0.01$  and  $\varepsilon_{2,3} = 0.01 \rightarrow \varepsilon_{1,3} \leq 0.02$
- $\varepsilon$ -Winner exists:  $\varepsilon = \max_i \{ P(f_1 \succ f_i) - 0.5 \} = \varepsilon_{1,2} > 0$

# 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

# Who does the exploring? Example 1

The image displays a dual-browser setup on a Mac OS X desktop. Both windows are titled "NETFLIX".

**Left Window (Background):**

- Header:** NETFLIX, Watch Instantly, Just for Kids.
- Recently Watched:** Miller Park Boys, AZIZ ANSARI Dangerously Delicious.
- Top Picks for Thorsten:** IN GOD WE RUST, DO FRIES AS YOU MOVE, LEWIS BLACK.

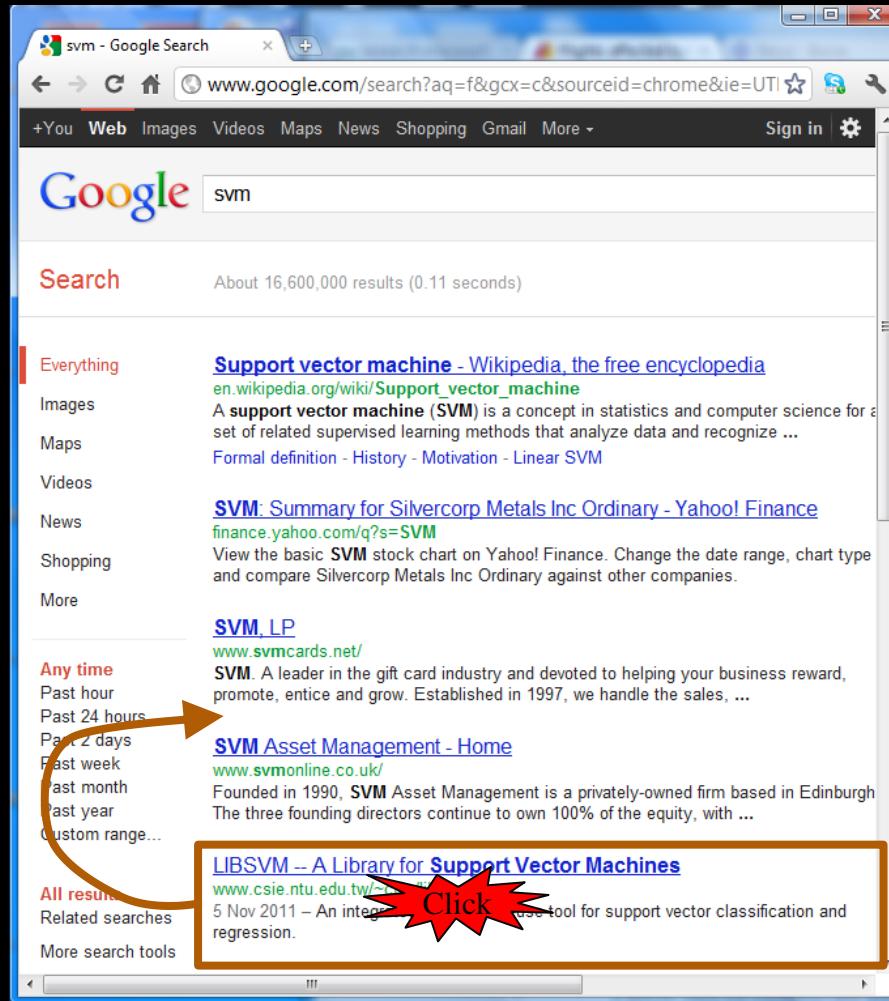
**Right Window (Foreground):**

- Header:** Watch Lie to Me Only!, NETFLIX, Watch Instantly, Just for Kids, Taste Profile, DVDs, DVD Queue.
- Search Bar:** Movies, TV shows, actors, directors, genres.
- User Profile:** Thorsten.
- Content:** Inappropriate button, page navigation (1-75), movie thumbnail for Lie to Me.
- Similar Content:** More Like Lie to Me section featuring NUMB3RS, BONES, FLASHPOINT, AWAKE, and CSI: NY.

At the bottom of both windows, there is a footer with copyright information and links to various Netflix services.

# Who does the exploring?

## Example 2



# Who does the exploring?

## Example 3

**svm - Google Search** [www.google.com/search?q=svm](http://www.google.com/search?q=svm)

Search About 16,600,000 results (0.11 seconds)

Everything Images Maps Videos News Shopping More

**Support vector machine - Wikipedia, the free encyclopedia** [en.wikipedia.org/wiki/Support\\_vector\\_machine](http://en.wikipedia.org/wiki/Support_vector_machine)  
A support vector machine (SVM) is a concept in statistics and computer science for solving classification problems. It is a set of related supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis.

**SVM: Summary for Silvercorp Metals Inc Ordinary - Yahoo! Finance** [finance.yahoo.com/q?s=SVM](http://finance.yahoo.com/q?s=SVM)  
View the basic SVM stock chart on Yahoo! Finance. Change the date and compare Silvercorp Metals Inc Ordinary against other companies.

**SVM, LP** [www.svmcards.net/](http://www.svmcards.net/)  
SVM. A leader in the gift card industry and devoted to helping your business promote, entice and grow. Established in 1997, we handle the sales, distribution and fulfillment.

**SVM Asset Management - Home** [www.svmonline.co.uk/](http://www.svmonline.co.uk/)  
Founded in 1990, SVM Asset Management is a privately-owned firm. The three founding directors continue to own 100% of the equity, with

**LIBSVM – A Library for Support Vector Machines** [www.csie.ntu.edu.tw/~cjlin/libsvm/](http://www.csie.ntu.edu.tw/~cjlin/libsvm/)  
5 Nov 2011 – An integrated and easy-to-use tool for support vector classification and regression.

**sv meppen - Google Search** [www.google.com/search?q=sv+meppen](http://www.google.com/search?q=sv+meppen)

Search About 939,000 results (0.09 seconds)

Everything Images Maps Videos News Shopping More Sign in | [Settings](#)

**SV Meppen 1912 e.V. - Offizielle Webseite** [www.svmeppen.de/](http://www.svmeppen.de/)  
Die offizielle Homepage des SV Meppen, ein ansprechender Fußballverein, der eine Live-Ticker und informiert über die Mannschaft.

**Willkommen auf www.svmeppen.de - SV Meppen 1912 e.V. ...** [1912.svmeppen.de/](http://1912.svmeppen.de/) - Translate this page  
SV Meppen e.V. 1912 - Offizielle Website - ... SV Meppen, meppen, emsländ, oberliga, oberliga nord, fussball, fußball, lingen, steve haensel, webcomtech.net, ...

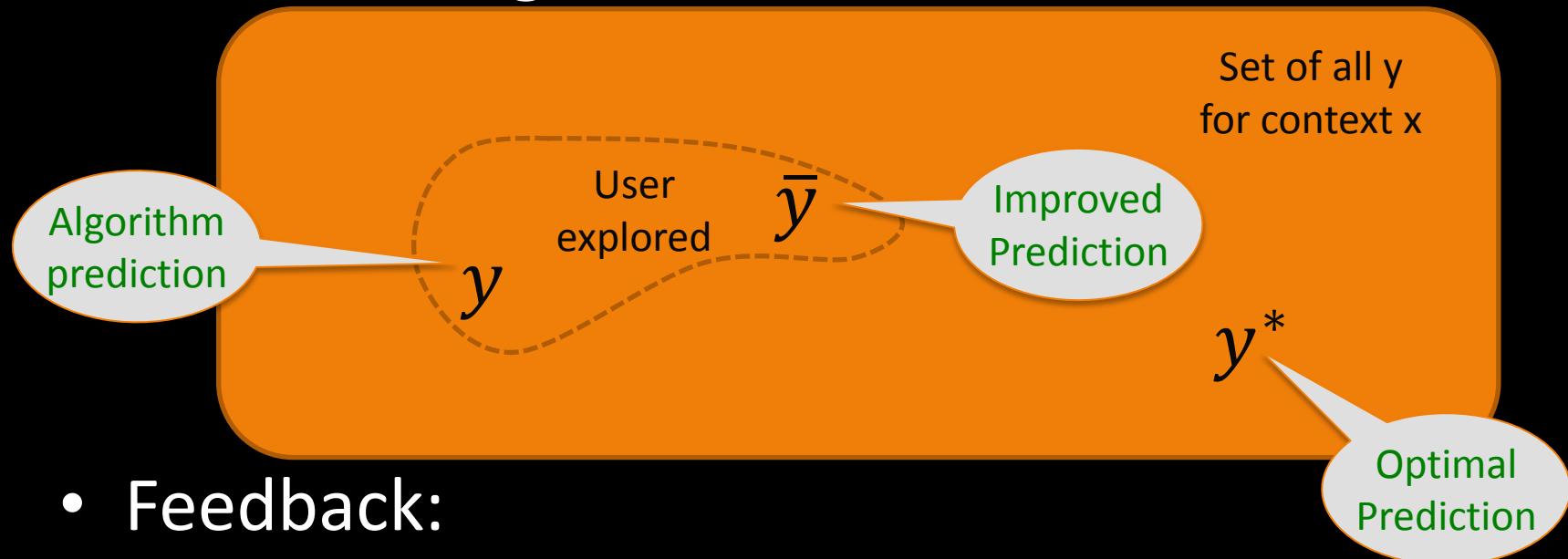
**SV Meppen - Wikipedia, the free encyclopedia** [en.wikipedia.org/wiki/SV\\_Meppen](http://en.wikipedia.org/wiki/SV_Meppen)  
SV Meppen is a German association football club playing in Meppen, Lower Saxony. The club was founded on 29 November 1912 as Amisia Meppen and ...  
History - Stadium - Records - Literature

**SV Meppen - Nachrichten, Liveticker, Bilder vom SV Meppen in der ...** [www.noz.de/sport/sv-meppen](http://www.noz.de/sport/sv-meppen) - Translate this page  
Berichte, Liveticker, Bilder und Audios vom SV Meppen, mehr zur Mannschaft sowie Analysen der Gegner in der Fußball-Regionalliga.

**SV Meppen - Fußballverein - transfermarkt.de** [www.transfermarkt.de/.../sv-meppen/...verein\\_24...](http://www.transfermarkt.de/.../sv-meppen/...verein_24...) - Translate this page  
Mit dieser Nachricht hatte Stephen Famewo (Foto) nicht gerechnet. Als umstrittener Stammspieler trug er dazu bei, dass der SV Meppen in die Regionalliga ...

# 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  $y_t^*$

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

# 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.



$\bar{y}_t$

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:  $U(y|x) = w^\top \phi(x,y)$
- Algorithm
  - FOR  $t = 1$  TO  $T$  DO
    - Observe  $x_t$
    - Present  $y_t = \operatorname{argmax}_y \{ w_t^\top \phi(x_t, y) \}$
    - 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  $y^*$

# Coactive Perceptron: Regret Bound

- Model  
 $U(\mathbf{y} | \mathbf{x}) = \mathbf{w}^\top \phi(\mathbf{x}, \mathbf{y})$ , where  $\mathbf{w}$  is unknown
- Feedback:  $\xi$ -Approximately  $\alpha$ -Informative

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

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

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

→ zero

model error

[Shivaswamy, Joachims, 2012]

# Preference Perceptron: Experiment

## Experiment:

- Automatically optimize Arxiv.org Fulltext Search

## Model

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

Analogous  
to DCG

## Feedback

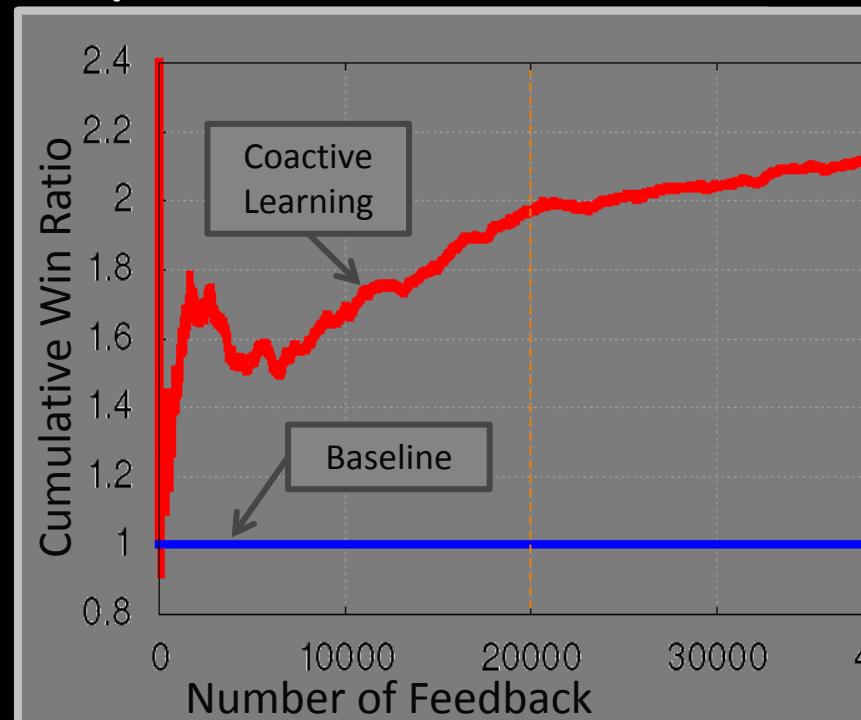
- Construct  $\bar{y}_t$  from  $y_t$  by moving clicked links one position higher.
- Perturbation [Raman et al., 2013]

## Baseline

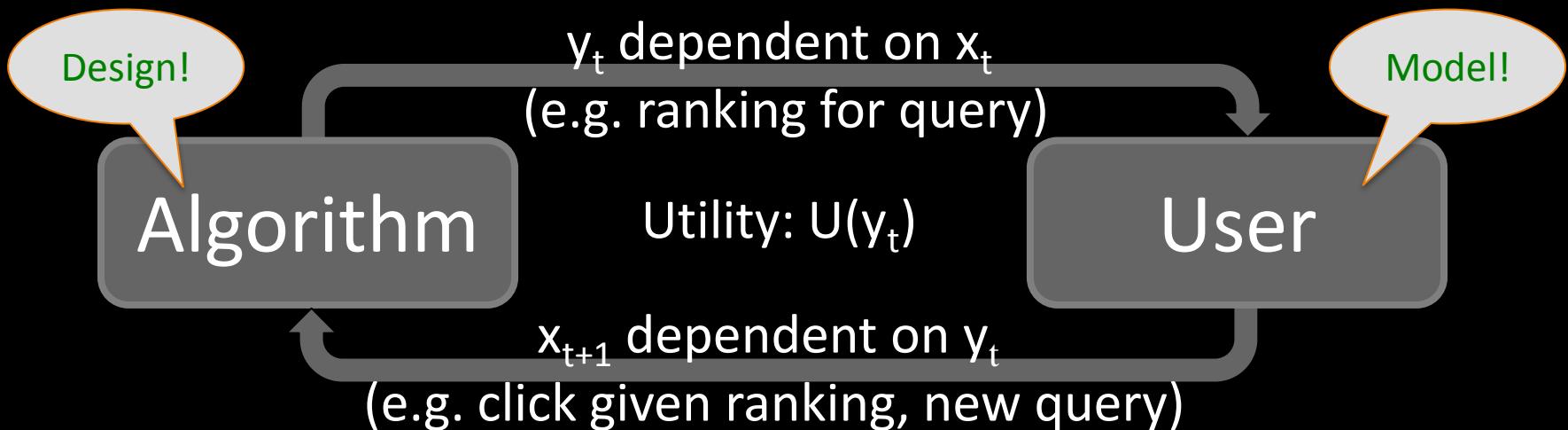
- Handtuned  $w_{base}$  for  $U_{base}(y|x)$

## Evaluation

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



# Interactive Learning System

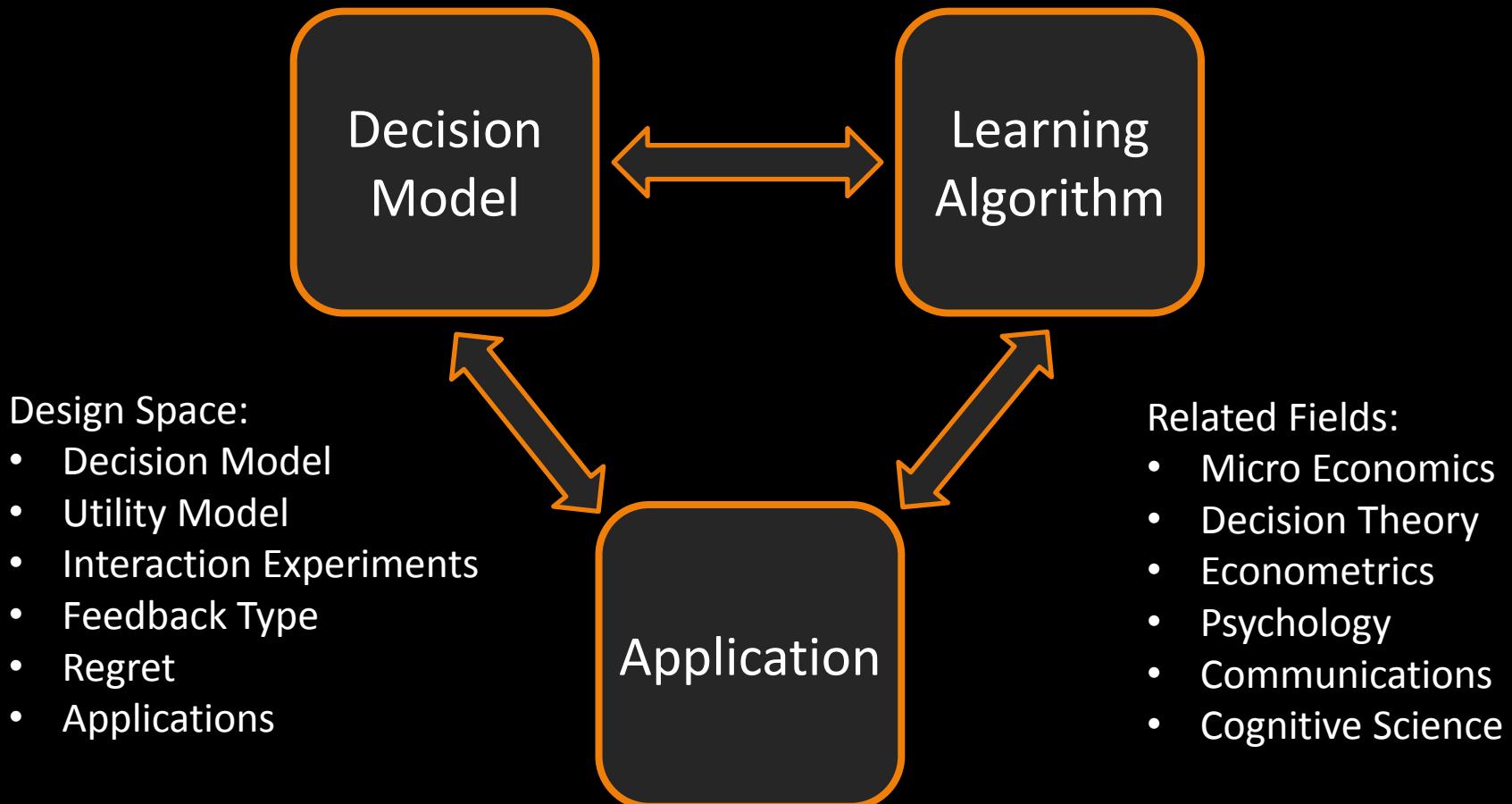


- Information Elicitation Interventions
- Decisions → Feedback → Learning Algorithm
  - Dueling Bandits
    - Model: Pairwise comparison test  $P( y_i \succ y_j \mid U(y_i) > U(y_j) )$
    - Algorithm: Interleaved Filter 2,  $O(|Y| \log(T))$  regret
  - Coactive Learning
    - Model: for given  $y$ , 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



Contact: [tj@cs.cornell.edu](mailto:tj@cs.cornell.edu)

Software + Papers: [www.joachims.org](http://www.joachims.org)