Learning to Rank

CS6780 – Advanced Machine Learning
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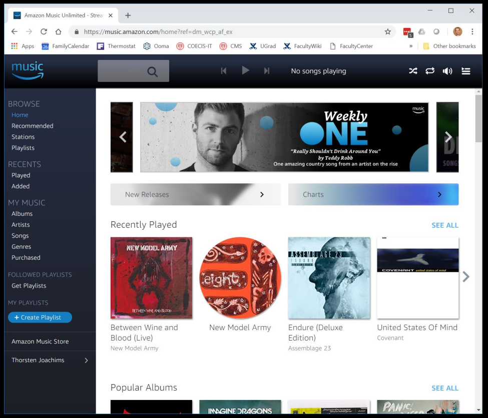
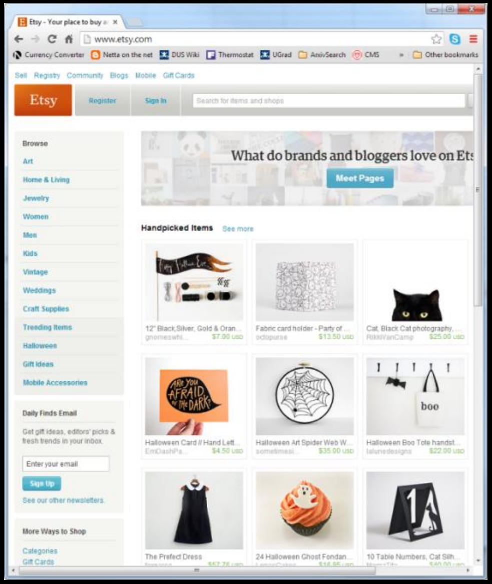
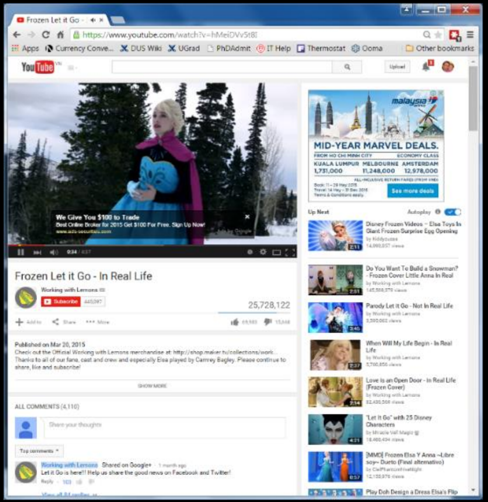
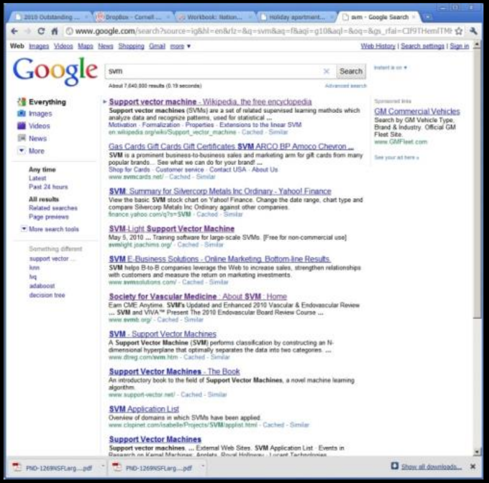
Learning To Rank





Goal: Learn policy $\pi(x)$ that produces a ranking y of candidates w.r.t. query x.



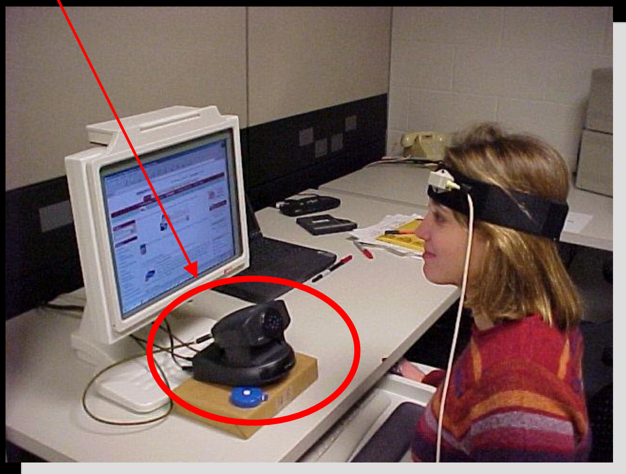


Evaluating Rankings

- What influences the quality of a ranking?
  - How relevant is document d at rank r?
    - Explicit feedback
      - User ratings
      - Expert ratings
    - Implicit feedback
      - Clicks, dwell time, mousing, scrolling, …
  - How likely is user going to view rank r?
    - Behavioral user model

Eye-Tracking

Eye tracking device



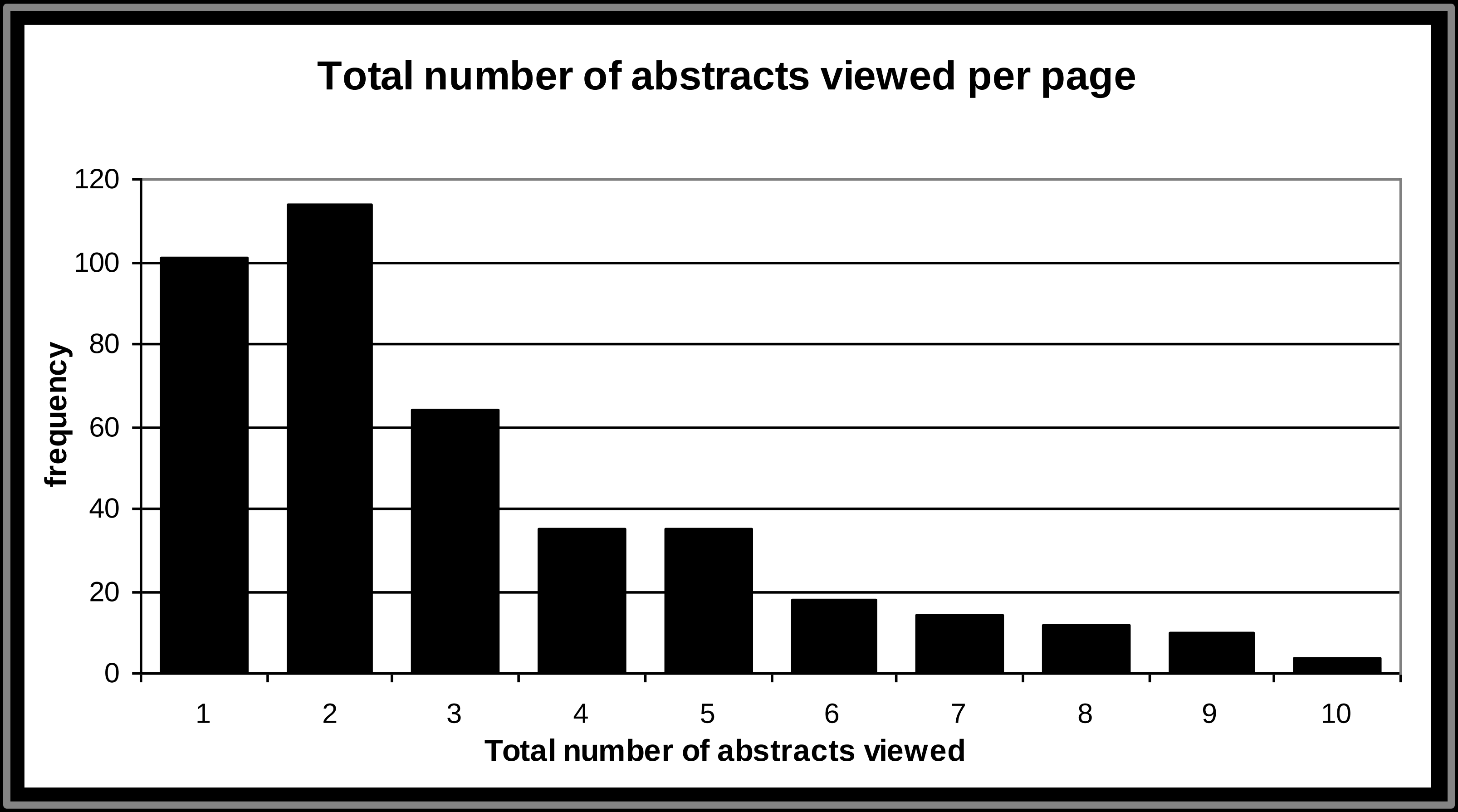
Record where and what people look at

- **Fixations**: ~200-300ms; information is acquired
- **Saccades**: extremely rapid movements between fixations
- **Pupil dilation**: size of pupil indicates interest, arousal

“Scanpath” output depicts pattern of movement throughout screen. Black markers represent fixations.

[Granka et al., 2007]

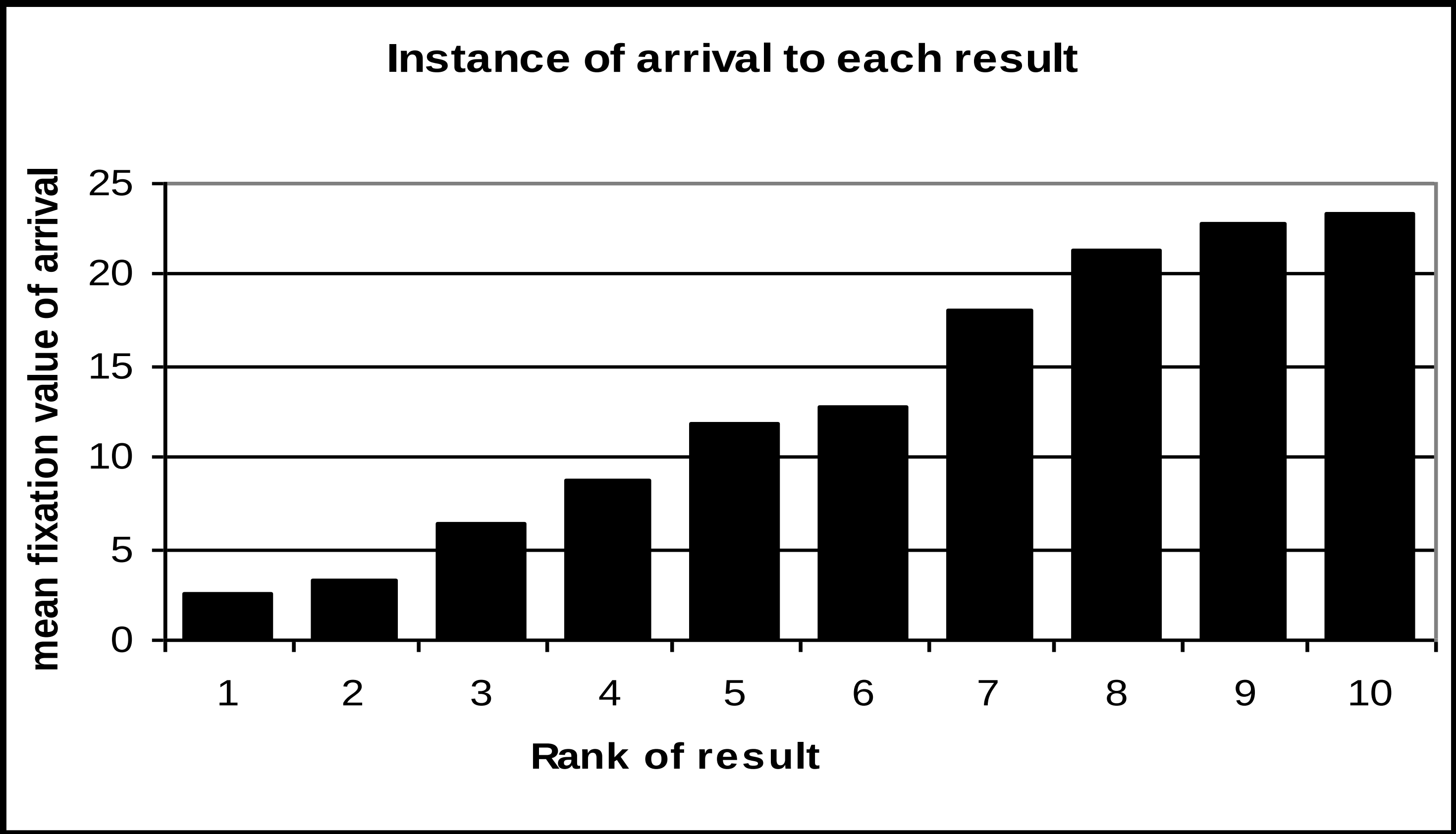
How Many Links do Users View?



Mean: 3.07 Median/Mode: 2.00

[Granka et al., 2007]

In Which Order are the Results Viewed?



=> Users tend to read the results in order

[Granka et al., 2007]

Do Users Look Below the Clicked Link?

Viewed Rank	Clicked Rank 1	2	3	4	5	6
1	90.6%	76.2%	73.9%	60.0%	54.5%	45.5%
2	56.8%	90.5%	82.6%	53.3%	63.6%	54.5%
3	30.2%	47.6%	95.7%	80.0%	81.8%	45.5%
4	17.3%	19.0%	47.8%	93.3%	63.6%	45.5%
5	8.6%	14.3%	21.7%	53.3%	100.0%	72.7%
6	4.3%	4.8%	8.7%	33.3%	18.2%	81.8%

=> Users typically do not look at links below before they click (except maybe the next link)

[Granka et al., 2007]

Ranking Evaluation Metrics

Given: vector of relevance labels r

- Precision@k
  - Percentage of relevant results in top k
- Rank of Relevant documents

$$\Delta(y|r) = \sum_i rank(i|y) \cdot r_i$$

- Discounted Cumulative Gain (DCG)

$$\Delta(y|r) = \sum_i \frac{r_i}{\log\left(1 + rank(i|y)\right)}$$

Learning to Rank Methods

- Joint feature map $\phi(x, d)$
  - Feature vector describing the match between query x and document d
- Pointwise LTR
  - Learn regression $\hat{r}: \phi(x, d) \to \Re$
  - Prediction via $y = \underset{D}{\operatorname{argsort}}\left\{\hat{r}\big(\phi(x, d)\big)\right\}$
- Listwise LTR
  - Learn ranking policy π
  - Risk $R(\pi) = \int \Delta(\pi(x)|r)\, P(x, r)$
  - Minimize Empirical Risk $\hat{R}(\pi) = \sum_{(x,r)} \Delta(\pi(x)|r)$

Ranking SVM

Query | Candidates | Relevances

- Data: $S = \left(x_j, D_j, r_j\right)^n$
- Policies: $y = \underset{D}{\operatorname{argsort}}\{w \cdot \phi(x, d)\}$
- Training QP:

Optimizes convex upper bound on rank of relevant documents!

$$w^* = \underset{w,\xi \geq 0}{\operatorname{argmin}} \frac{1}{2} w \cdot w + \frac{C}{n} \sum_j \sum_{(d,\bar{d})} \xi_j^{(d,\bar{d})}$$

$$\forall (d_1, \bar{d}_1) \in D_1 : w \cdot \left[\phi(x_1, d_1) - \phi(x_1, \bar{d}_1)\right] \geq 1 - \xi_1^{(d,\bar{d})}$$

$$\vdots$$

$$\forall (d_n, \bar{d}_n) \in D_n : w \cdot \left[\phi(x_1, d_n) - \phi(x_1, \bar{d}_n)\right] \geq 1 - \xi_1^{(d,\bar{d})}$$

- Loss Bound:

$$\forall w : rank(d, argsort(w \cdot \phi(x, d)) \leq \sum_i \xi^i + \#rel$$

[Herbrich at al., 1999] [Joachims et al., 2002] [Joachims et al., 2017]

Explicit vs. Implicit Feedback

Explicit feedback

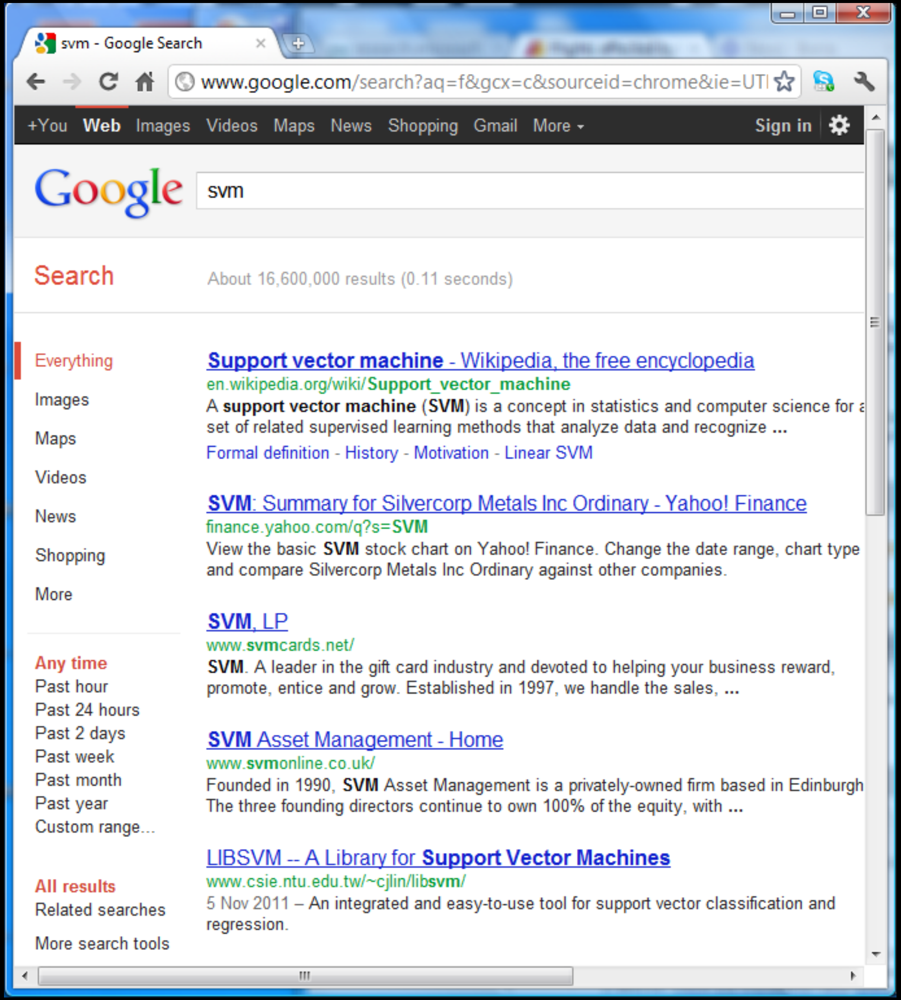
- Need to pay “experts”
- Slow to gather
- Potential expert-user mismatch
- Not personalized
- Complete feedback

Implicit feedback

- Free as by-product of system use
- Immediately available
- User provided, but spam-able
- Personalized
- Partial and biased by presentation

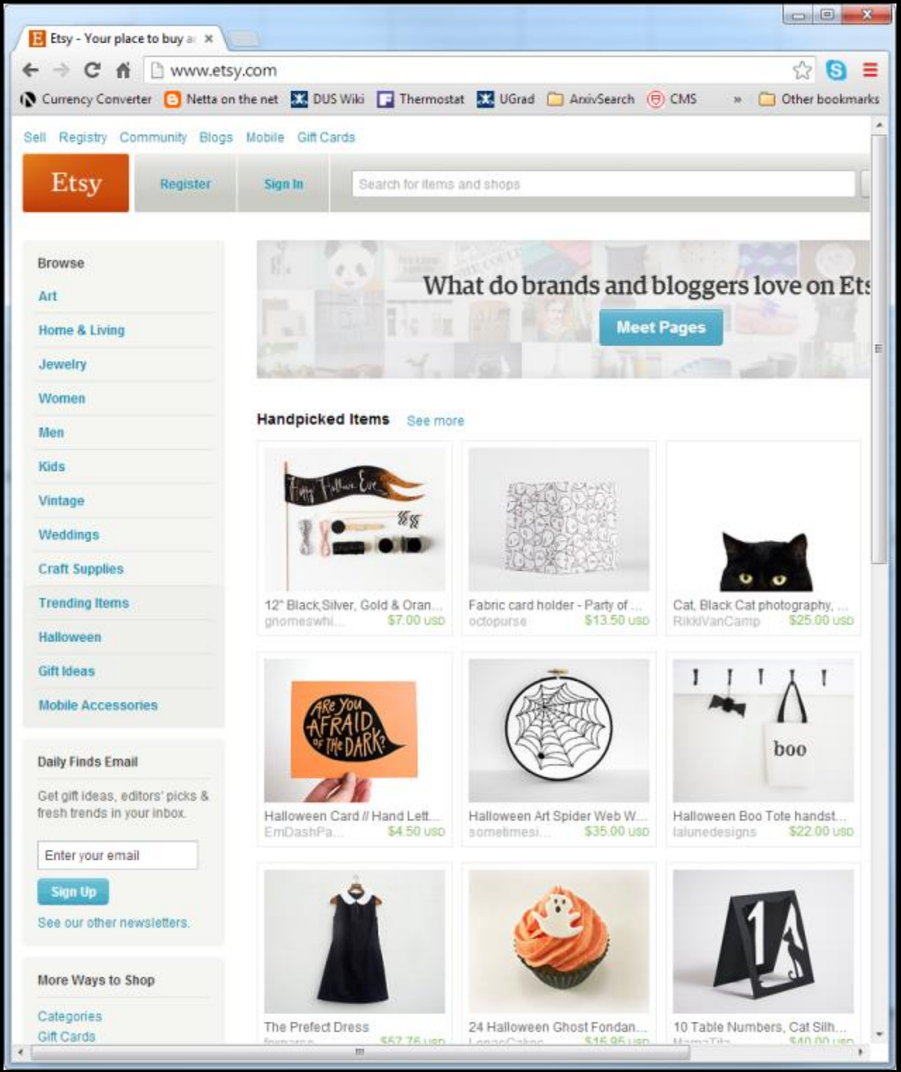
Interaction Logs: Search Engine

- Context x:
  - Query
- Action y:
  - Ranking
- Feedback $\delta(x, y)$:
  - Clicks on SERP



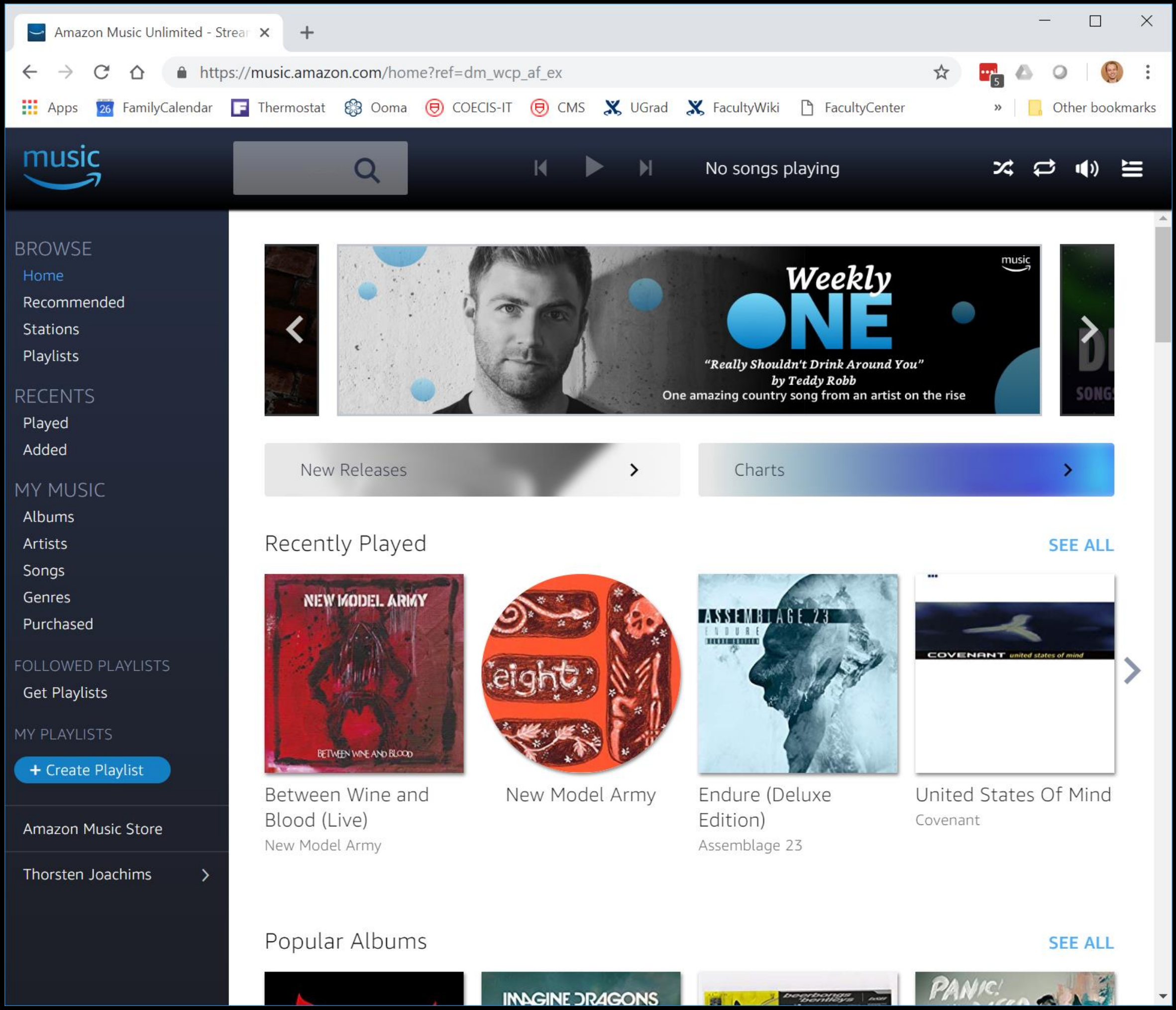
Interaction Logs: Online Retail

- Context x:
  - Category
- Action y:
  - Tile Layout
- Feedback $\delta(x, y)$:
  - Attributable purchases

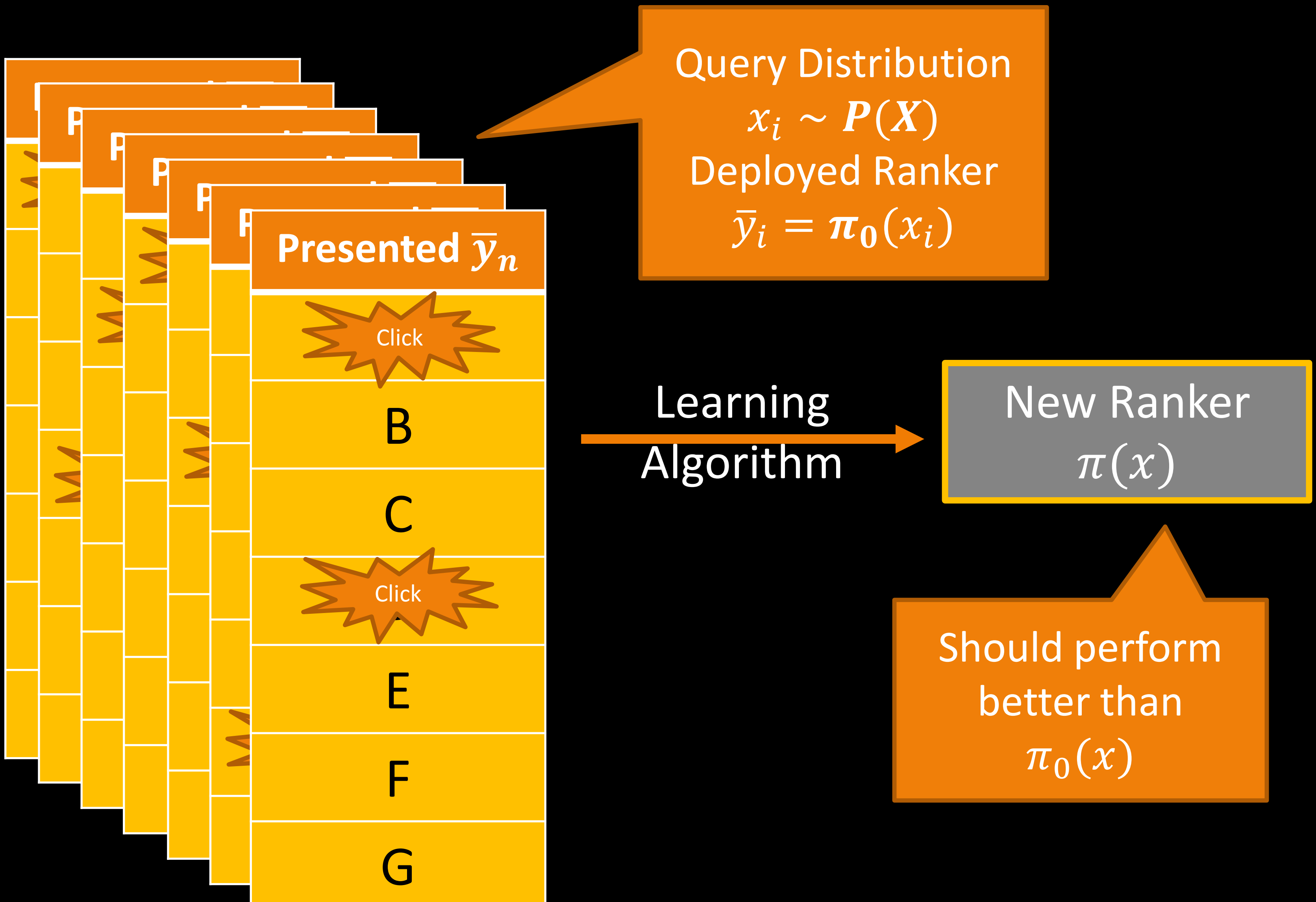


Interaction Logs: Streaming Media

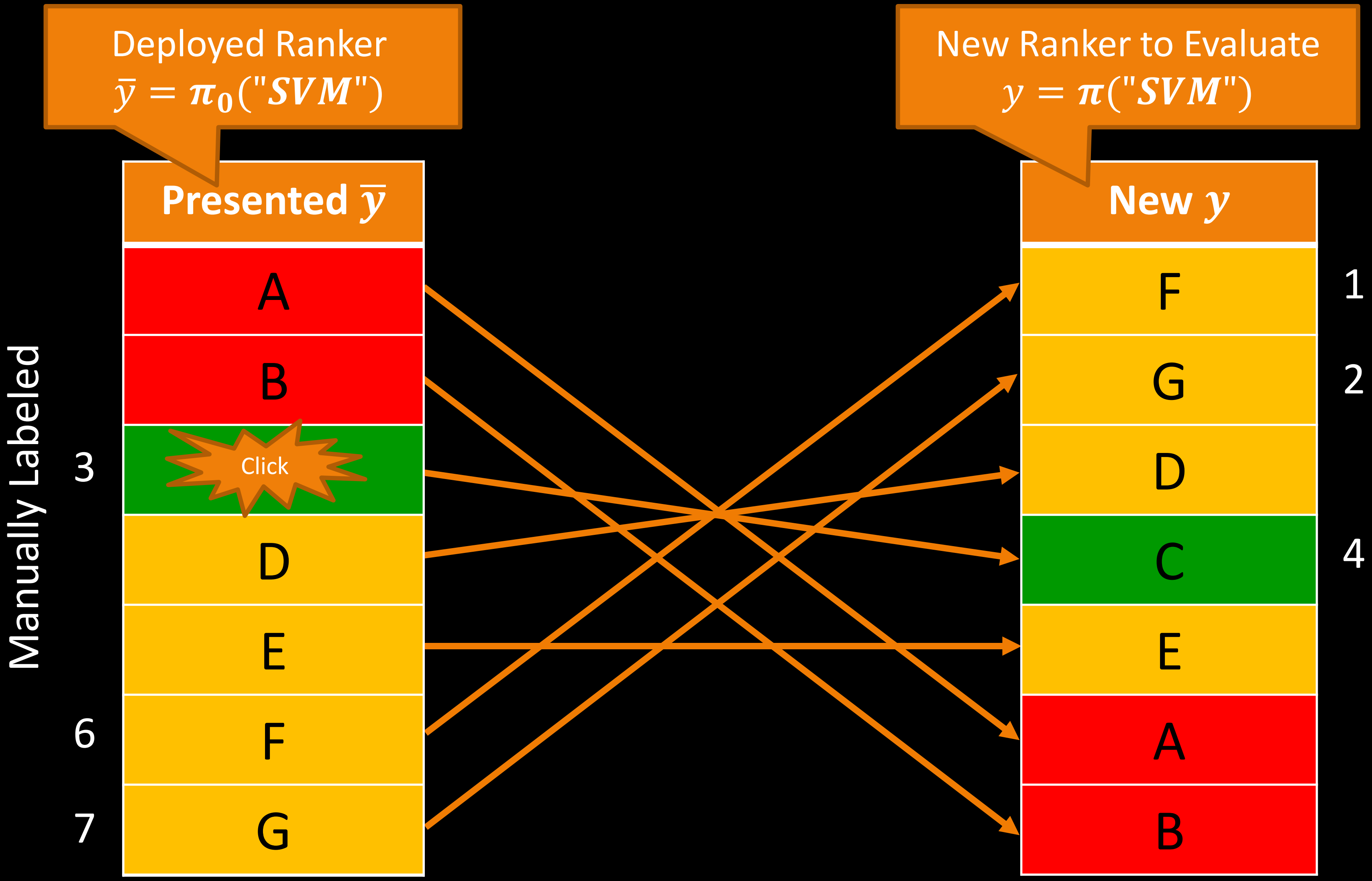
- Context x:
  - User
- Action y:
  - Tile layout
  - Scroll layout
- Feedback $\delta(x, y)$:
  - Plays



Learning-to-Rank from Clicks



Evaluating Rankings



Evaluation with Missing Judgments

- Loss: $\Delta(y|r)$
  - Relevance labels $r_i \in \{0,1\}$
  - This talk: rank of relevant documents

$$\Delta(y|r) = \sum_i rank(i|y) \cdot r_i$$

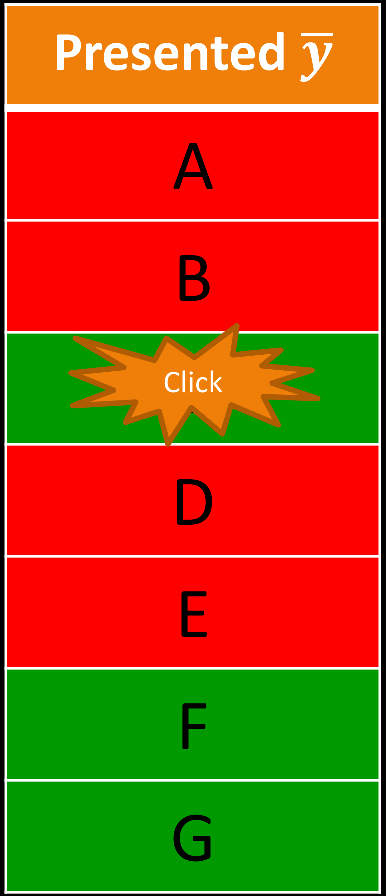
- Assume:
  - Click implies observed and relevant:

$$(c_i = 1) \leftrightarrow (o_i = 1) \wedge (r_i = 1)$$

- Problem:
  - No click can mean not relevant OR not observed

$$(c_i = 0) \leftrightarrow (o_i = 0) \vee (r_i = 0)$$

→ Understand observation mechanism



[Joachims et al., 2017]

Inverse Propensity Score Estimator

- Observation Propensities $Q(o_i = 1|x, \bar{y}, r)$
  - Random variable $o_i \in \{0,1\}$ indicates whether relevance label r_i for is observed
- Inverse Propensity Score (IPS) Estimator:

$$\hat{\Delta}(y|r,o) = \sum_{i:c_i=1} \frac{rank(i|y)}{Q(o_i = 1|\bar{y}, r)}$$

New Ranking

- Unbiasednes $\ldots_o\left[\hat{\Delta}(y \mid r,o)\right] = \Delta(y|r)$

Need to know the propensities only for relevant/clicked docs.

Presented $\bar{y}$	Q
A	1.0
B	0.8
C	0.5
D	0.2
E	0.2
F	0.2
G	0.1

[Horvitz & Thompson, 1952] [Rubin, 1983] [Zadrozny et al., 2003] [Langford, Li, 2009] [Joachims et al., 2017]

ERM for Partial-Information LTR

- Unbiased Empirical Risk:

$$\hat{R}_{IPS}(\pi) = \frac{1}{N} \sum_{(x,\bar{y},c)\in S} \sum_{i:c_i=1} \frac{rank(i|\pi(x))}{Q(o_i = 1|\bar{y}, r)}$$

Consistent Estimator of True Performance

- ERM Learning:

$$\hat{\pi} = \underset{S}{\operatorname{argmin}} \left[\hat{R}_{IPS}(\pi)\right]$$

Consistent ERM Learning

- Questions:
  - How do we optimize this empirical risk in a practical learning algorithm?
  - How do we define and estimate the propensity model $Q(o_i = 1|\bar{y}, r)$?

[Joachims et al., 2017]

Propensity-Weighted SVM Rank

- Data: $$S = \left(x_j, d_j, D_j, q_j\right)^n$$

Query

Clicked

Others

Propensity

- Training QP:

Optimizes convex upper bound on unbiased IPS risk estimate!

$$\boxed{\begin{gathered} w^* = \underset{w,\xi\geq 0}{\operatorname{argmin}} \frac{1}{2} w \cdot w + \frac{C}{n} \sum_j \frac{1}{q_j} \sum_i \xi_j^i \\ \forall \bar{d}^i \in D_1 \colon w \cdot \left[\phi(x_1, d_1) - \phi\left(x_1, \bar{d}^i\right)\right] \geq 1 - \xi_1^i \\ \vdots \\ \forall \bar{d}^i \in D_n \colon w \cdot \left[\phi(x_n, d_n) - \phi\left(x_n, \bar{d}^i\right)\right] \geq 1 - \xi_n^i \end{gathered}}$$

- Loss Bound:

$$\forall w \colon rank(d, sort(w \cdot \phi(x, d)) \leq \sum_i \xi^i + 1$$

[Herbrich at al., 1999] [Joachims et al., 2002] [Joachims et al., 2017]

Position-Based Propensity Model

- Model:

$$P\big(c_i = 1 | r_i, rank(i|\bar{y})\big) = q_{rank(i|\bar{y})} \cdot [r_i = 1]$$

- Assumptions
  - Examination only depends on rank
  - Click reveals relevance if rank is examined

Presented $\bar{y}$	Q
A	q_1
B	q_2
C	q_3
D	q_4
E	q_5
F	q_6
G	q_7

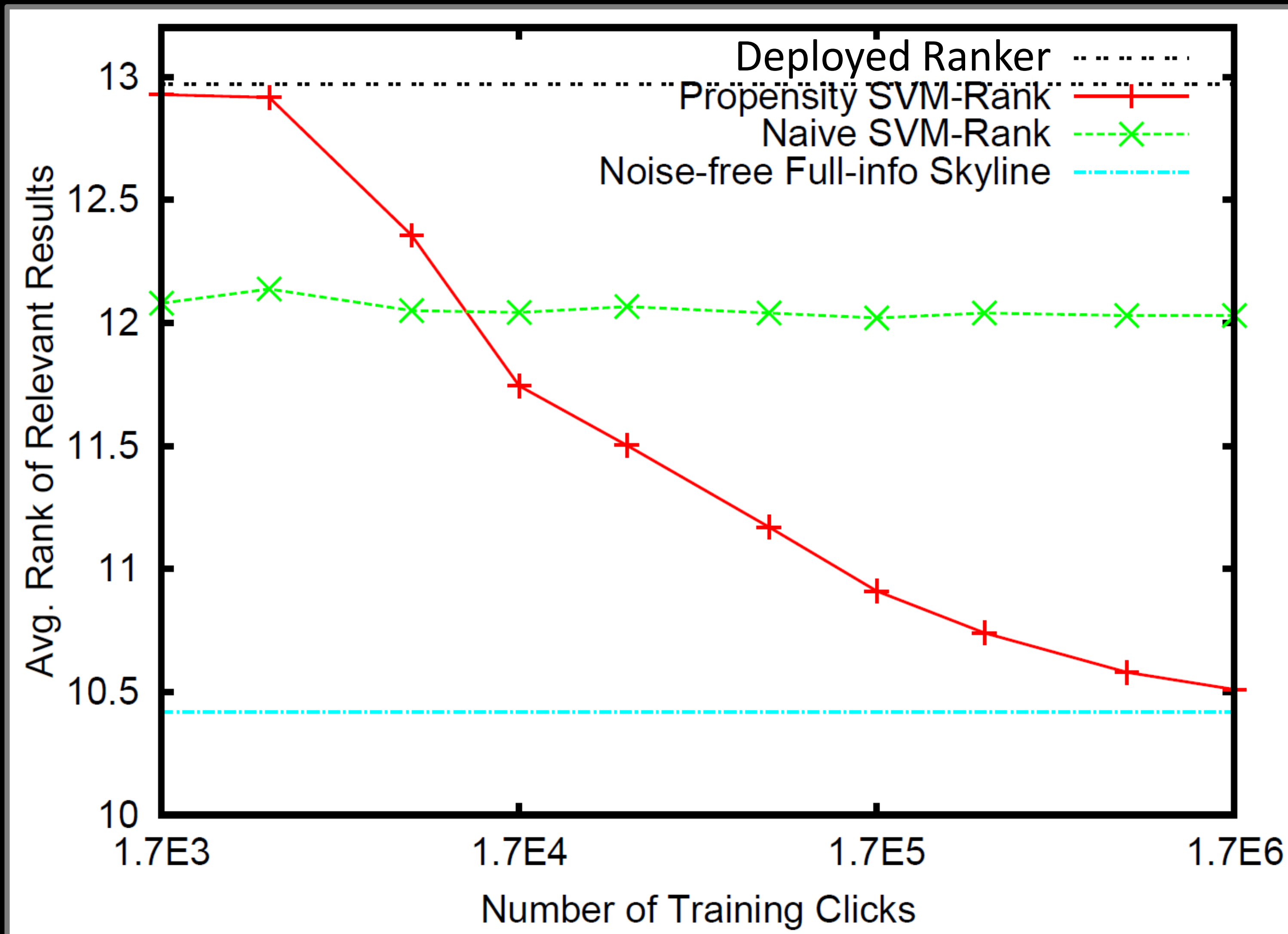
[Richardson et al., 2007] [Chuklin et al., 2015] [Wang et al., 2016]

Experiments

- Yahoo Web Search Dataset
  - Full-information dataset
  - Binarized relevance labels
- Generate synthetic click data based on
  - Position-based propensity model with $q_r = \left(\frac{1}{r}\right)^{\eta}$
  - Baseline "deployed" ranker to generate $\bar{y}$
  - 33% noisy clicks on irrelevant docs

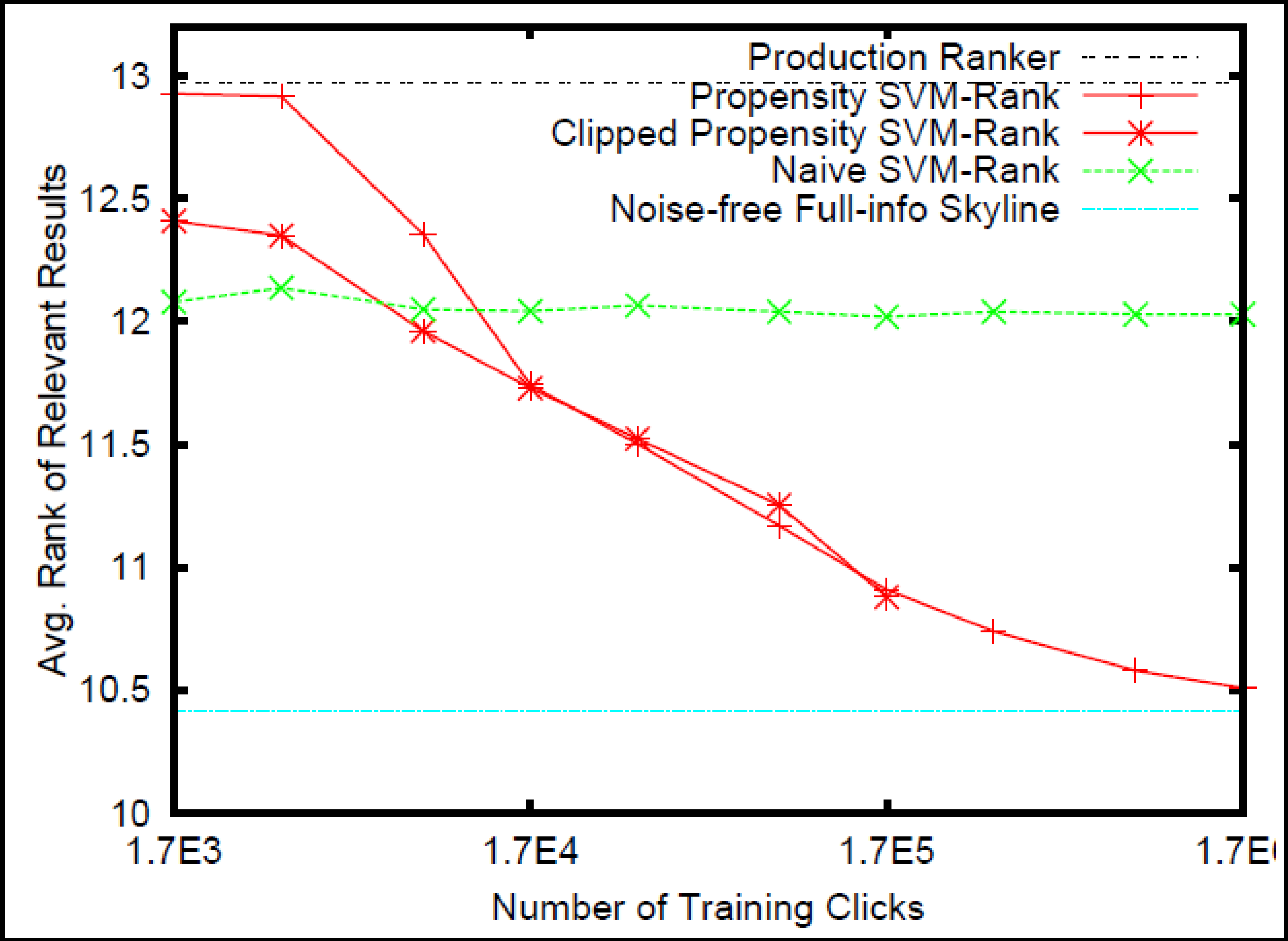
Presented $\bar{y}$	Q
A	q_1
B	q_2
Click	q_3
D	q_4
E	q_5
Click	q_6
G	q_7

Scaling with Training Set Size



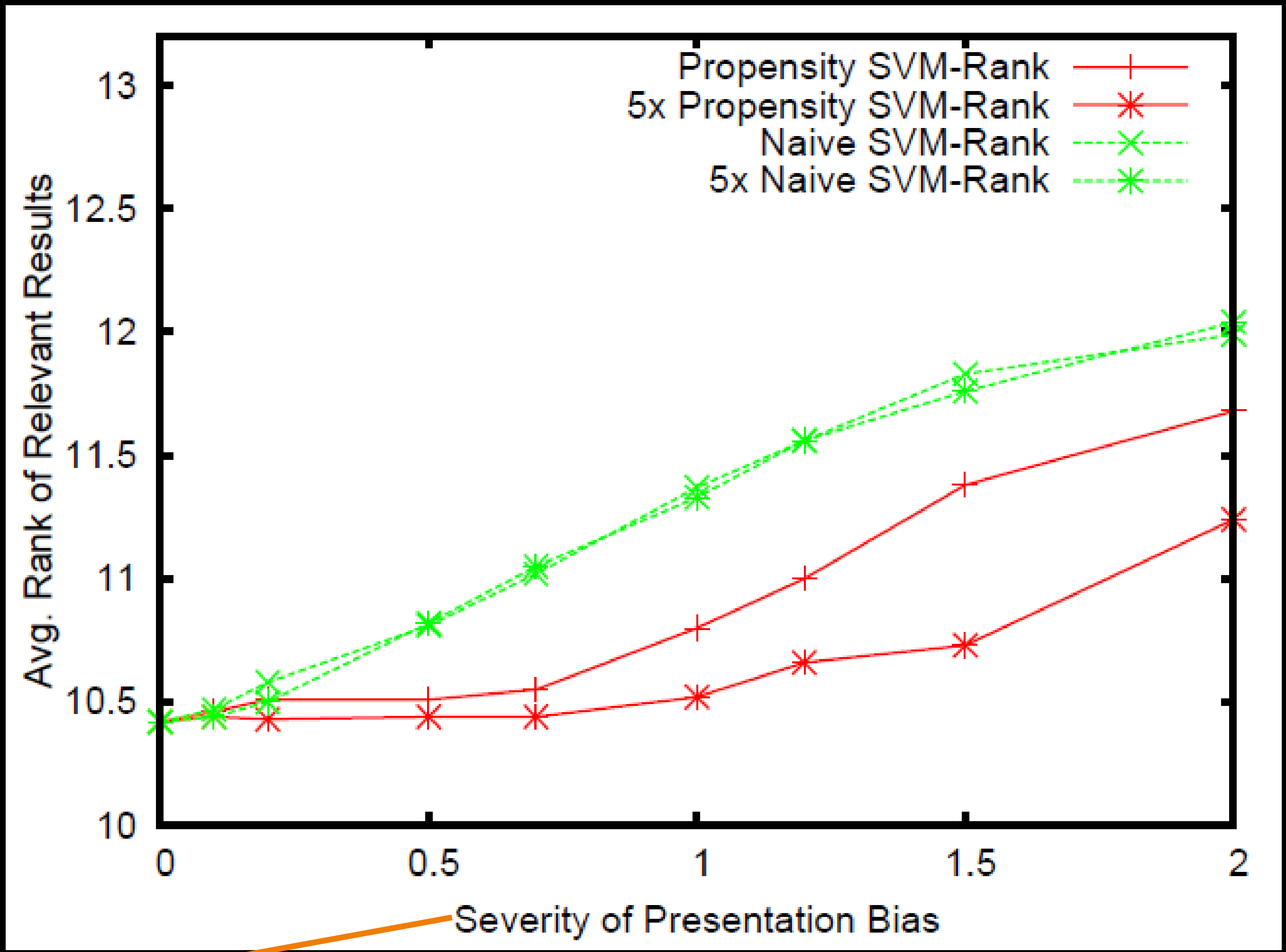
[Joachims et al., 2017]

Scaling with Training Set Size



[Joachims et al., 2017]

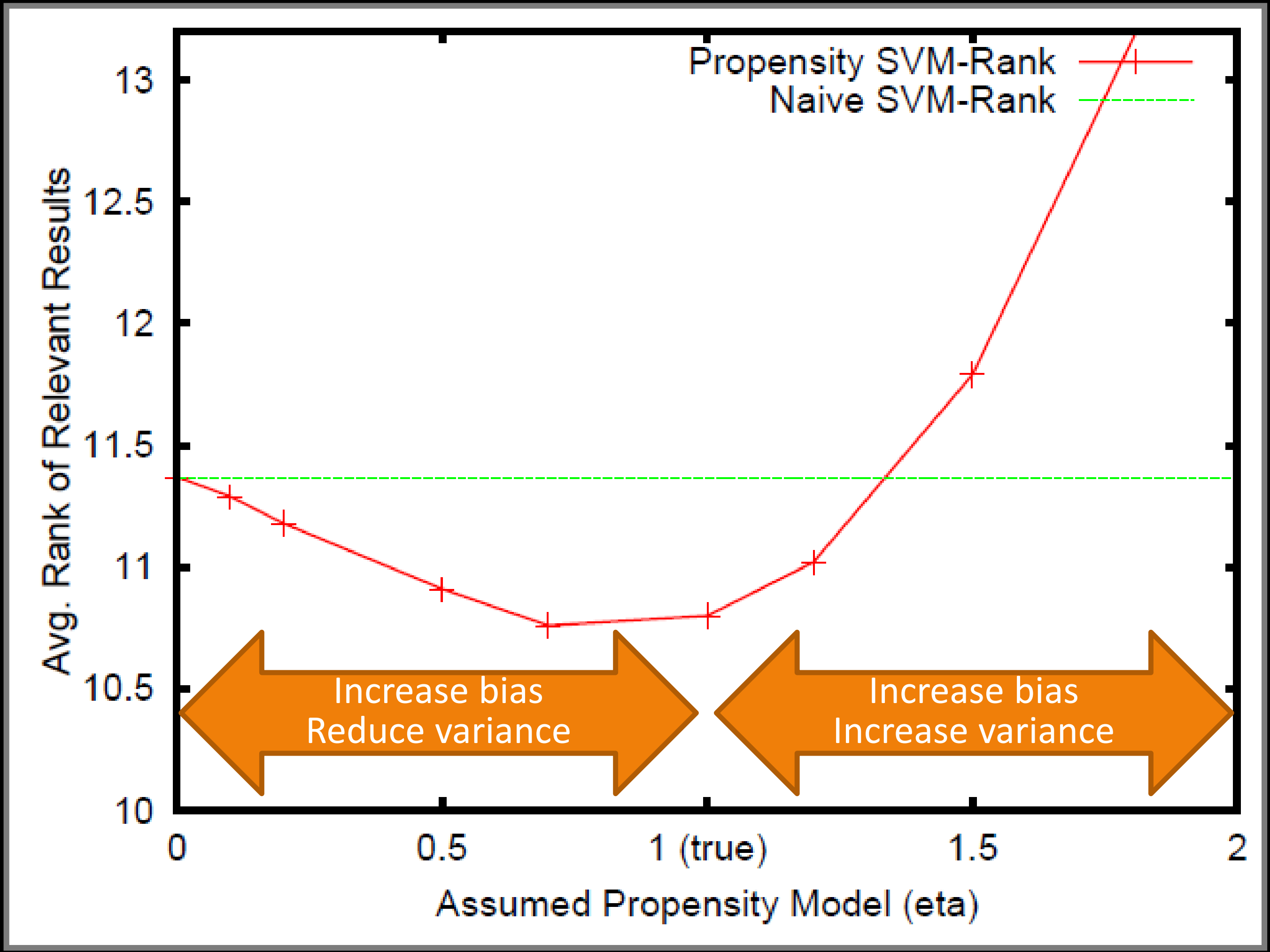
Severity of Presentation Bias



$$q_r = \left(\frac{1}{r}\right)^{\eta}$$

[Joachims et al., 2017]

Misspecified Propensities



$$q_r = \left(\frac{1}{r}\right)^{\eta}$$

[Joachims et al., 2017]

Position-Based Propensity Model

- Model:

$$P\big(c_i = 1 | r_i, rank(i|\bar{y})\big) = q_{rank(i|\bar{y})} \cdot [r_i = 1]$$

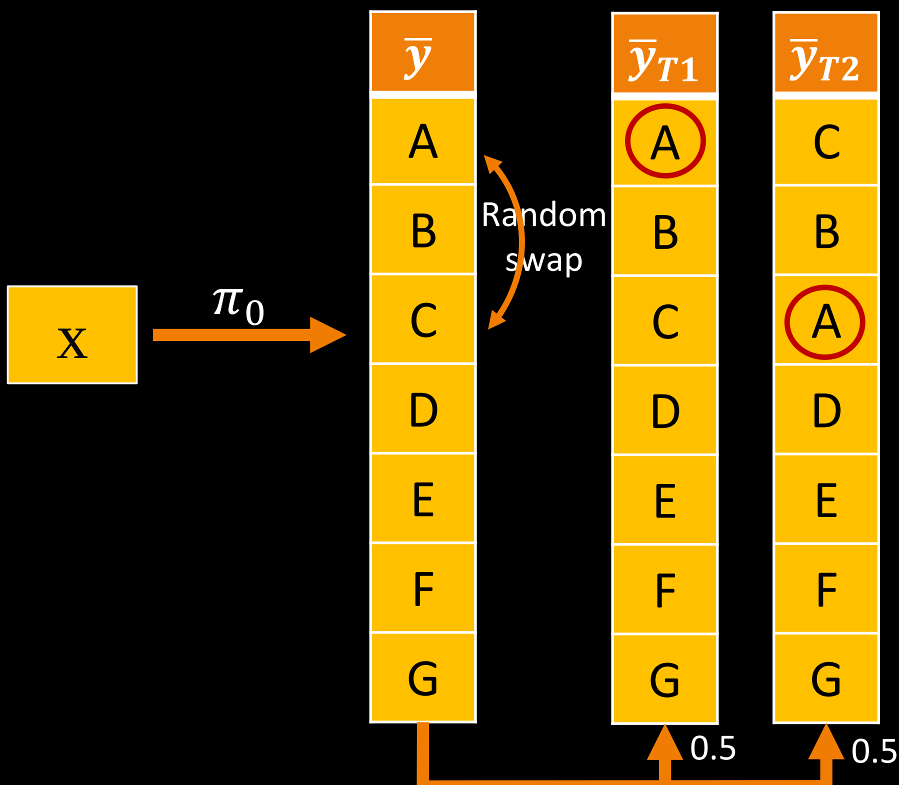
- Assumptions
  - Examination only depends on rank
  - Click reveals relevance if rank is examined

Presented $\bar{y}$	q
A	q_1
B	q_2
C	q_3
D	q_4
E	q_5
F	q_6
G	q_7

[Richardson et al., 2007] [Chuklin et al., 2015] [Wang et al., 2016] [Joachims et al., 2017]

Estimating the Propensities

- Idea: Randomization to control for relevance
  → Swap Interventions



$$\mathrm{E}(c_1|T1) = q_1 \cdot E(r_1 = 1|rank(d|\bar{y}) = 1)$$

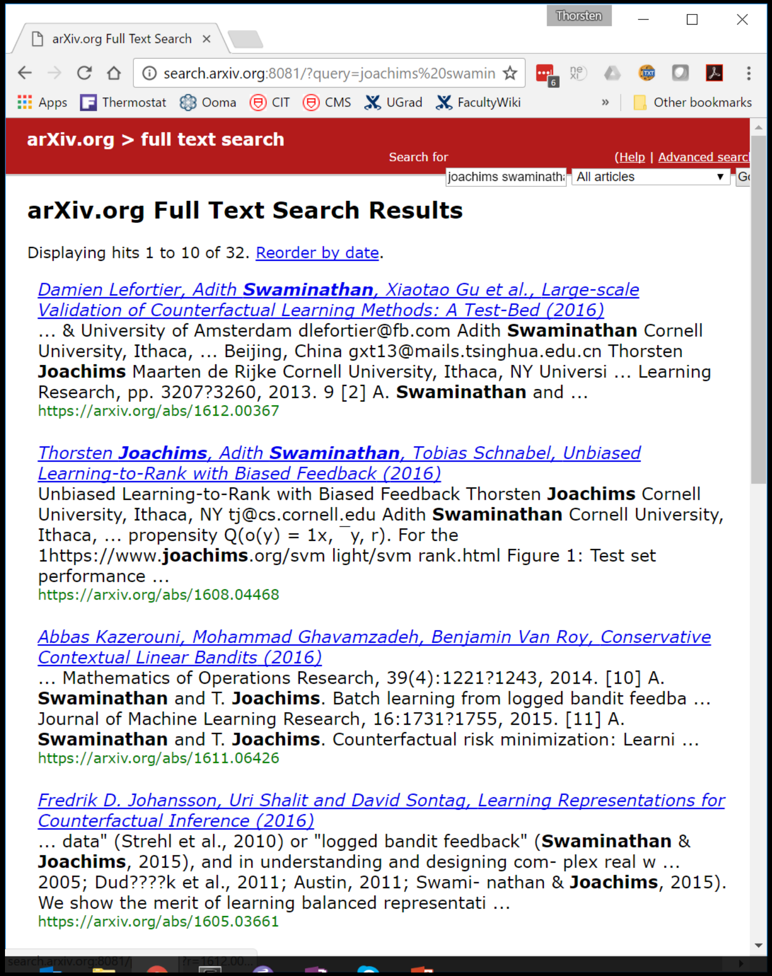
$$\mathrm{E}(c_3|T2) = q_3 \cdot E(r_1 = 1|rank(d|\bar{y}) = 1)$$

$$\rightarrow \frac{q_1}{q_k} = \frac{\mathrm{E}(c_1|T1)}{\mathrm{E}(c_k|T2)}$$

[Wang et al., 2016; Joachims et al., 2017]

Real-World Experiment

- Arxiv Full-Text Search
  - Run Swap(1,r) experiment to estimate q_r
  - Collect training clicks using production ranker
  - Train naïve / propensity SVM-Rank (1000 features)
  - A/B tests via interleaving



Interleaving Experiment	Propensity SVM-Rank wins	loses	ties
against Prod	87	48	83
against Naive SVM-Rank	95	60	102

Conclusions

- Learning to Rank
  - from expert ratings
    - Pointwise: estimate relevance
    - Listwise: ERM to optimize ranking metric
  - from user interactions
    - Deal with missing relevance labels
    - Use IPS to get unbiased ERM objective
- Other Aspects
  - Fairness constraints on ranking policy