#### Learning to Rank

#### CS6780 – Advanced Machine Learning Spring 2019

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#### Learning To Rank





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

query *x*.



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## **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 device





### **Eye-Tracking**

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.

#### How Many Links do Users View?



Mean: 3.07 Median/Mode: 2.00

# In Which Order are the Results Viewed?



=> Users tend to read the results in order

#### Do Users Look Below the Clicked Link?



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

#### **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)

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

#### 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  $\hat{r}: \phi(x, d) \rightarrow \Re$
  - Prediction via  $y = \underset{D}{\operatorname{argsort}} \{ \hat{r}(\phi(x, d)) \}$
- Listwise LTR
  - Learn ranking policy  $\pi$
  - $-\operatorname{Risk} R(\pi) = \int \Delta(\pi(x)|r) P(x,r)$

– Minimize Empirical Risk  $\hat{R}(\pi) = \sum_{(x,r)} \Delta(\pi(x)|r)$ 

# **Ranking SVM**

 $S = (x_j, D_j, r_j)$ Data: ightarrow

Query

Training QP:

Loss

 $\forall w$ 

ightarrow

Policies:  $y = \operatorname{argsort}\{w \cdot \phi(x, d)\}$ D

Candidates

Relevances

n

**Optimizes convex** upper bound on rank of relevant documents!

$$w^{*} = \underset{w,\xi \ge 0}{\operatorname{argmin}} \frac{1}{2} w \cdot w + \frac{c}{n} \sum_{j} \sum_{(d,\bar{d})} \xi_{j}^{(d,\bar{d})}$$

$$\forall (d_{1},\bar{d}_{1}) \in D_{1} : w \cdot [\phi(x_{1},d_{1}) - \phi(x_{1},\bar{d}_{1})] \ge 1 - \xi_{1}^{(d,\bar{d})}$$

$$\vdots$$

$$\forall (d_{n},\bar{d}_{n}) \in D_{n} : w \cdot [\phi(x_{1},d_{n}) - \phi(x_{1},\bar{d}_{n})] \ge 1 - \xi_{1}^{(d,\bar{d})}$$
Bound:
$$\operatorname{rank}(d \operatorname{argsort}(w \cdot \phi(x,d))) \le \sum_{j} \xi^{i} + \#rel$$

[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 spamable
- Personalized
- Partial and biased by presentation

#### Interaction Logs: Search Engine

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

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### Interaction Logs: Online Retail

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

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### 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:

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

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

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

 $\rightarrow$  Understand observation mechanism



#### **Inverse Propensity Score Estimator**

• Observation Propensities  $Q(o_i = 1 | x, \overline{y}, r)$ 

- Random variable  $o_i \in \{0,1\}$  indicates whether relevance label  $r_i$  for is observed

• Inverse Propensity Score (IPS) Estimator:

$$\widehat{\Delta}(y|r,o) = \sum_{i:c_i=1} \frac{rank(i|y)}{Q(o_i = 1|\overline{y},r)}$$
New Ranking
$$\int \left[\widehat{\Delta}(y|r,o)\right] = \Delta(y|r)$$
Need to know the propensities only for

relevant/clicked docs.

Presented $\overline{y}$	Q
А	1.0
В	0.8
С	0.5
D	0.2
E	0.2
F	0.2
G	0.1

### **ERM for Partial-Information LTR**

Unbiased Empirical Risk:

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

Consistent Estimator of True Performance

• ERM Learning:

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

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  $Q(o_i = 1|\bar{y}, r)$ ?

#### **Propensity-Weighted SVM Rank**

- Data:  $S = (x_{j}, d_{j}, D_{j}, q_{j})^{n}$ Query Clicked Others Propensity
  • Training QP:  $w^{*} = \underset{w,\xi \ge 0}{\operatorname{argmin}} \frac{1}{2} w \cdot w + \frac{C}{n} \sum_{j} \frac{1}{q_{j}} \sum_{i} \xi_{j}^{i}$   $\forall \overline{d}^{i} \in D_{1} : w \cdot [\phi(x_{1}, d_{1}) - \phi(x_{1}, \overline{d}^{i})] \ge 1 - \xi_{1}^{i}$   $\vdots$   $\forall \overline{d}^{i} \in D_{n} : w \cdot [\phi(x_{n}, d_{n}) - \phi(x_{n}, \overline{d}^{i})] \ge 1 - \xi_{n}^{i}$
- Loss Bound:

 $\forall w: rank(d, sort(w \cdot \phi(x, d)) \leq \sum_{i=1}^{n} \xi^{i} + 1$ 

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

#### **Position-Based Propensity Model**

• Model:

$$P(c_{i} = 1 | r_{i}, rank(i | \overline{y})) = q_{rank(i | \overline{y})} \cdot [r_{i} = 1]$$

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

Presented $\overline{y}$	Q
А	$q_1$
В	$q_2$
С	<i>q</i> <sub>3</sub>
D	$q_4$
E	$q_5$
F	$q_6$
G	$q_7$

### 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  $\overline{y}$
  - 33% noisy clicks on irrelevant docs

#### Scaling with Training Set Size



[Joachims et al., 2017]

#### Scaling with Training Set Size



#### Severity of Presentation Bias



 $q_r$ 

[Joachims et al., 2017]

### **Misspecified Propensities**



 $q_r$ 

[Joachims et al., 2017]

#### **Position-Based Propensity Model**

• Model:

$$P(c_{i} = 1 | r_{i}, rank(i | \overline{y})) = q_{rank(i | \overline{y})} \cdot [r_{i} = 1]$$

- Assumptions
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Presented $\overline{y}$	q
А	$q_1$
В	$q_2$
С	<i>q</i> <sub>3</sub>
D	$q_4$
E	$q_5$
F	$q_6$
G	$q_7$

#### Estimating the Propensities

Idea: Randomization to control for relevance
 → Swap Interventions



#### **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

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



#### arXiv.org Full Text Search Results

Displaying hits 1 to 10 of 32. Reorder by date.

Damien Lefortier, Adith **Swaminathan**, Xiaotao Gu et al., Large-scale Validation of Counterfactual Learning Methods: A Test-Bed (2016)

... & University of Amsterdam dlefortier@fb.com Adith **Swaminathan** Cornell University, Ithaca, ... Beijing, China gxt13@mails.tsinghua.edu.cn Thorsten **Joachims** Maarten de Rijke Cornell University, Ithaca, NY Universi ... Learning Research, pp. 3207;3260, 2013. 9 [2] A. **Swaminathan** and ... https://arxiv.org/abs/1612.00367

#### Thorsten **Joachims**, Adith **Swaminathan**, Tobias Schnabel, Unbiased Learning-to-Rank with Biased Feedback (2016)

Unbiased Learning-to-Rank with Biased Feedback Thorsten **Joachims** Cornell University, Ithaca, NY tj@cs.cornell.edu Adith **Swaminathan** Cornell University, Ithaca, ... propensity Q(o(y) = 1x,  $\neg$ y, r). For the 1https://www.**joachims**.org/svm light/svm rank.html Figure 1: Test set performance ... https://arxiv.org/abs/1608.04468

<u>Abbas Kazerouni, Mohammad Ghavamzadeh, Benjamin Van Roy, Conservative</u> <u>Contextual Linear Bandits (2016)</u>

... Mathematics of Operations Research, 39(4):1221?1243, 2014. [10] A. **Swaminathan** and T. **Joachims**. Batch learning from logged bandit feedba ... Journal of Machine Learning Research, 16:1731?1755, 2015. [11] A. **Swaminathan** and T. **Joachims**. Counterfactual risk minimization: Learni ... https://arxiv.org/abs/1611.06426

#### Fredrik D. Johansson, Uri Shalit and David Sontag, Learning Representations for Counterfactual Inference (2016)

... data" (Strehl et al., 2010) or "logged bandit feedback" (Swaminathan & Joachims, 2015), and in understanding and designing com- plex real w ... 2005; Dud????k et al., 2011; Austin, 2011; Swami- nathan & Joachims, 2015). We show the merit of learning balanced representati ... https://arxiv.org/abs/1605.03661

#### 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