Fairness in Ranking & Wrap-Up

CS4780/5780 – Machine Learning
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Reading:
None
Ranking in Online Systems

Ranking function $\pi$ that ranks items for context $x$. → Learning-to-Rank
How do we train these systems?

Goal: Maximize utility of rankings to the users.

Probability Ranking Principle [Robertson, 1977]:

- Rank documents by probability of relevance \( y^* \)
- For virtually any measure \( \Delta \) of ranking quality

\[
y^* := \arg\max_y [\Delta(y|x)]
\]
Two-Sided Market

Online Retail

• Utility to Users:
  Customers find products they want

• Utility to Items:
  Sellers get revenue
Two-Sided Market

Music Streaming

• Utility to Users:
  Customers find music they enjoy

• Utility to Items:
  Artists get streaming revenue
Two-Sided Market

News

• Utility to Users:
  Readers find relevant articles

• Utility to Items:
  Writers get their voice out (and ad revenue)
What can go wrong?

Current Learning-to-Rank methods focus only on users, and are oblivious to impact on items.
Fairness of Exposure

Fair ranking policy $\pi$ allocates exposure to items based on merit.

**Endogenous Factors**
How to allocate exposure based on merit in order to
- Satisfy legal requirements
- Shape marketplace dynamics (e.g. Spotify, superstar economics)
- Spam, Polarization

**Exogenous Factors**
How to estimate merit without biases like
- Position bias
- Trust bias
- Uncertainty bias
- Historical actions
- Stereotypes
Are Conventional Methods Fair?

Probability Ranking Principle:
• Rank documents by probability of relevance $\rightarrow y^*$ [Robertson, 1977]
• For virtually any measure $\Delta$ of ranking quality
  
  $$y^* := \arg\max_y [\Delta(y|x)]$$

• Are rankings fair/desirable?

<table>
<thead>
<tr>
<th>Rank</th>
<th>Item</th>
<th>P(read)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Times 1</td>
<td>50.99</td>
</tr>
<tr>
<td>2</td>
<td>Times 2</td>
<td>50.98</td>
</tr>
<tr>
<td>3</td>
<td>Times 3</td>
<td>50.97</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>100</td>
<td>Post 1</td>
<td>49.99</td>
</tr>
<tr>
<td>101</td>
<td>Post 2</td>
<td>49.98</td>
</tr>
<tr>
<td>102</td>
<td>Post 3</td>
<td>49.97</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>
Position-Based Exposure Model

Definition:
Exposure $e_j$ is the probability a user observes the item at position $j$.

How to estimate?
• Eye tracking [Joachims et al. 2007]
• Intervention studies [Joachims et al. 2017]
• Intervention harvesting [Agarwal et al. 2019] [Fang et al. 2019]

<table>
<thead>
<tr>
<th>Rank</th>
<th>Exposure P(observe)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$e_1$</td>
</tr>
<tr>
<td>2</td>
<td>$e_2$</td>
</tr>
<tr>
<td>3</td>
<td>$e_3$</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>100</td>
<td>$e_{100}$</td>
</tr>
<tr>
<td>101</td>
<td>$e_{101}$</td>
</tr>
<tr>
<td>102</td>
<td>$e_{102}$</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>
Fairness Constraints

\[ \text{exposure} = f(\text{relevance}) \]

- **Disparate Exposure:**
  - Expected exposure proportional to the expected relevance of the group
- **Disparate Impact:**
  - Expected revenue (e.g. clicks) proportional to the expected relevance of the group
- **Group parity:**
  - Expected exposure equal for all groups
Probabilistic Ranking Policies $\pi(y|x)$

Exposure and Quality for $\pi(y|x)$

$\text{expo}(i|x) = \sum_j \mathbb{P}_{i,j} e_j$

$\text{qual}(\pi|x) = \sum_i \sum_j e_j \mathbb{P}_{i,j} \text{rel}_i$

$\mathbb{P}_{i,j} = \text{Prob that item } i \text{ is ranked at position } j$

$e_j = \text{exposure at position } j$
Disparate Exposure Constraint

Group Exposure and Merit

\[ \text{expo}(G|P) = \sum_{i \in G} \text{expo} (i|x) \quad \text{rel}(G|P) = \sum_{i \in G} \text{rel}(i|x) \]

Group Fairness Constraint

\[ \frac{\text{expo}(G_0|x)}{\text{rel}(G_0|x)} = \frac{\text{expo}(G_1|x)}{\text{rel}(G_1|x)} \]

→ Make exposure proportional to relevance
Computing the Best Fair Policy

Goal: Maximize ranking quality while fair to items.

\[ \pi^*(y|x) = \arg\max_{\pi} \ \text{argmax}_\pi \]

\[ \text{subject to} \]

\[ \frac{\exp(q_0|x)}{\text{rel}(q_0|x)} = \frac{\exp(q_1|x)}{\text{rel}(q_1|x)} \]

→ Computationally hard!
Marginal Rank Distribution $\mathbb{P}$

\[ \mathbb{P} \]

\[ \pi, \mathbb{P} \]

\[ \begin{array}{cccc}
  y_1 & y_2 & y_3 & y_4 \\
  A & B & A & B \\
  B & A & C & C \\
  C & D & B & A \\
  D & E & E & F \\
  E & F & F & E \\
  F & F & G & D \\
  G & G & G & D \\
\end{array} \]

\[ \begin{array}{cccc}
  1 & 2 & 3 & 4 \\
  0.72 & 0.23 & 0.05 & 0 \\
  0.28 & 0.52 & 0.20 & 0 \\
  ... & ... & ... & ... \\
\end{array} \]

\[ \mathbb{P}_{i,j} \]
Computing the Best Fair Policy

• Optimal $\mathbb{P}^*$ is solution of linear program

$$\mathbb{P}^* = \arg\max_{\mathbb{P}} \left[ \text{rel}^T \mathbb{P} \text{e} \right]$$

s.t.

$$1^T \mathbb{P} = 1$$
$$\mathbb{P} 1 = 1$$
$$0 \leq \mathbb{P} \leq 1$$

$$\text{rel}_2 g_1^T \mathbb{P} \text{e} = \text{rel}_1 g_2^T \mathbb{P} \text{e}$$

Quality

P is doubly stochastic

Fairness
Computing $\pi^*$ from $\mathbb{P}^*$

Birkhoff-von Neumann decomposition

$$\mathbb{P}^* = \theta_1 P_1 + \cdots + \theta_k P_k$$

where $P_1 \ldots P_k$ are permutation matrices and $\theta_i \geq 0$ with $\sum_i \theta_i = 1$.

$\rightarrow$ Ranking policy $\pi^*(y|x) = \begin{cases} 
\theta_i & \text{if } (y = P_i) \\
0 & \text{else}
\end{cases}$
Summary of Method

1. Estimate relevances $r$ for query $x$
2. Define (merit-based) fairness constraint
3. Solve linear program for marginal rank matrix
   
   \[
   \mathbb{P}^* = \arg\max_{\mathbb{P}} \left[ r^T \mathbb{P} q \right]
   \]
   \[
   s.t. \quad 1^T \mathbb{P} = 1
   \]
   \[
   \mathbb{P} 1 = 1
   \]
   \[
   0 \leq \mathbb{P} \leq 1
   \]
   \[
   \mathbb{P} \text{ is fair}
   \]

4. Compute ranking policy $\pi^*$ from $\mathbb{P}^*$
Example

- Six items, two groups
- Relevances: $\text{rel}(G_1) = \{82\%, 81\%, 80\%\}$, $\text{rel}(G_2) = \{79\%, 78\%, 77\%\}$

![Diagram showing conventional and fair ranking with DCG and DTR values]
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Estimating Merit from Interactions

Data
- Query distribution: $x_j \sim P(X)$
- Deployed ranker: $\tilde{y}_j = \pi_0(x_j)$
- Feedback: clicks, purchases, plays, reads

$\rightarrow$ Feedback is biased!
Modeling Position Bias

- **Assume:**
  - Click implies observed and relevant:
    \[ (\text{click}_i = 1) \iff (\text{obs}_i = 1) \land (\text{rel}_i = 1) \]

- **Problem:**
  - No click can mean not relevant OR not observed
    \[ (\text{click}_i = 0) \iff (\text{obs}_i = 0) \lor (\text{rel}_i = 0) \]

\[ \Rightarrow \text{Understand observation mechanism} \]
Inverse Propensity Score Estimator

- Observation Propensities
  - $Q(obs_i = 1|x, \bar{y})$
  - Random variable $obs_i \in \{0, 1\}$ indicates whether relevance label $rel_i$ is observed.
  - Can use position-based exposure
    
    $Q(obs_i = 1|x, \bar{y}) = e_i$

- De-biased Regression via IPS weighting

  $\rightarrow$ In expectation independent of past rankings!

<table>
<thead>
<tr>
<th>Presented $\bar{y}$</th>
<th>$Q$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1.0</td>
</tr>
<tr>
<td>B</td>
<td>0.8</td>
</tr>
<tr>
<td>C</td>
<td>0.5</td>
</tr>
<tr>
<td>D</td>
<td>0.2</td>
</tr>
<tr>
<td>E</td>
<td>0.2</td>
</tr>
<tr>
<td>F</td>
<td>0.2</td>
</tr>
</tbody>
</table>
Counterfactual Policy Learning

• Policy Learning for Contextual Bandits and Ranking
  – Data is biased by past system actions
    • Propensity logging and/or propensity estimation
  – Unbiased learning objective based on causal inference
    • Inverse Propensity Score (IPS) weighting estimators
  – Directly optimize effectiveness of policy

• Transforming how industry approaches these problems
  – YouTube recommendations [Chen et al. 2019], Spotify [McInerny et al. 2018], Google Drive [Agarwal et al. 2019], ...
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Summary and Conclusions

• Take care of the biases in the data
  – Improve quality, solid foundation for decisions

• Shape how system serves all constituencies
  – Fairness, incentives and market dynamics, legal

→ Long term health of the system

http://www.joachims.org
Theme: Prediction and Action

• Building intelligent systems vs. analyzing existing systems
  – Prediction
  – Intelligent action
  – Guarantees on prediction/action quality

→ CS4786 Machine Learning for Data Science
→ CS4850 Math Found for the Information Age
→ INFO 6150 Advanced Topic Models
Theme: Overfitting

• Fundamental trade-off in learning
  – Training error vs. prediction error
  – Model capacity
  – Statistical learning theory
  – Empirical risk minimization
Theme: Massive Overparameterization

• The success story of machine learning
  – Regularized linear models
  – Kernels
  – Deep networks
  → Number of parameters $\gg$ number of examples
Theme: Theoretical Underpinning

• Theory for understanding sake
  – Identify the mechanisms at play in ML
  – Understand model complexity
  – Understand common themes between algorithms
Design Approaches for ML

• Empirical Risk Minimization (ERM)
  – Fixed at training time: class of decision rules \( h: X \rightarrow Y \), loss, \( x \) and \( y \)
  – Strategy: minimize training loss

• Conditional Probability Models
  – Fixed at training time: class of models for \( P(Y|X) \), \( x \) and \( y \)
  – Strategy: max conditional likelihood or MAP (or Bayes)

• Generative Models
  – Fixed at training time: class models for \( P(Y,X) \)
  – Strategy: max likelihood or MAP (or Bayes)

• Not covered: Bayesian ML perspective \( \rightarrow \) ORIE 6741
Batch Learning for Classification

- **ERM**
  - Decision Trees
  - Perceptron
  - SVMs
  - Neural Networks
  - Boosting

- **Conditional Probability**
  - Logistic Regression
  - Conditional Random Fields
  - Ridge Regression

- **Generative**
  - Multinomial Naïve Bayes
  - Multivariate Naïve Bayes
  - Linear Discriminant

- **Other Methods**
  - Gaussian Processes
  - Deep Networks
  - Recurrent Networks
  - Parametric (Graphical) Models
  - Matrix factorization
  - Many, many more …
  - *-Regression
  - *-Multiclass
Structured Output Prediction

• ERM
  – Structural SVMs

• Conditional Probability
  – Conditional Random Fields

• Generative
  – Hidden Markov Model

• Other Methods
  – Maximum Margin Markov Networks
  – Markov Random Fields
  – Bayesian Networks
  – Statistical Relational Learning
  – Markov Logic Networks
  – Encoder/Decoder Networks

→ NLP classes
Online Learning

• Expert Setting
  – Halving Algorithm
  – Weighted Majority
  – Randomized WM

• Bandit Setting
  – None

• Other Methods
  – UCB
  – EXP3
  – Follow the Leader
  – Partial Monitoring
  – Contextual Bandits
  – Dueling Bandits
  – Coactive Learning

→ CS6781 Theoretical Foundations of Machine Learning
Unsupervised Learning

• Clustering
  – None

→ CS4786 Machine Learning for Data Science
→ CS4850 Math Found for the Information Age
→ INFO 6150 Advanced Topic Models

• Other Methods
  – Spectral Clustering
  – Multi-Dimensional Scaling
  – Latent Dirichlet Allocation
  – Semantic Embeddings
  – Deep Auto-Encoders

• Other Tasks
  – Outlier Detection
  – Novelty Detection
  – Dimensionality Reduction
  – Non-Linear Manifold Detection
ML in Computer Visions

• Covered
  – Feedforward Neural Networks

• Other
  – Convolutional Networks
  – More Deep Learning
  – Even more Deep Learning

→ CS6670 Computer Vision
→ CS4670 Intro Computer Vision
Learning to Act

- Covered
  - Off-policy policy learning
  - Contextual Bandits

- Other
  - Reinforcement learning
  - Markov Decision Processes
  - Model-based vs. model-free
  - On policy vs. off policy
  - Policy gradient

→ CS4700 Artificial Intelligence
ML and Causality

- Covered
  - Potential outcomes model

- Other
  - Observational setting
  - Instrumental variables
  - Continuous treatments
  - Longitudinal treatments
  - Causal discovery
  - Parameter inference
  - Causal networks
  - Structural equation models
ML and Fairness

• Covered
  – Privacy
  – Intelligibility
  – Fairness

• Other
  – Accountability
  – Transparency
  – Algorithms and guarantees

→ INFO4270: Ethics and Policy in DS
FINAL EXAM
SUNDAY 7:00PM, BARTON