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 \( x \).

\[ \Rightarrow \text{Learning-to-Rank} \]

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.

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

Fairness of Exposure

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

Position-Based Exposure Model

Definition:
- Exposure $e_j$ is the probability a users 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]

Fairness Constraints

$exposure = f(relevance)$

- 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 $\pi(y|x)$

$expo(|x|) = \sum P_{i,j} e_j$

$qual (\pi|x) = \sum \sum e_j P_{i,j} rel_i$

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

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

Group Exposure and Merit
\[ \text{expo}(G|P) = \sum_{i \in G} \text{expo}(i|x) \]

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.
\[ \pi^*(y|x) = \arg\max_{\pi} \left[ \text{qual}(\pi|x) \right] \]
\[ \text{s.t.} \quad \frac{\text{expo}(G_0|x)}{\text{rel}(G_0|x)} = \frac{\text{expo}(G_1|x)}{\text{rel}(G_1|x)} \]

→ Computationally hard!

Marginal Rank Distribution \( P \)

Computing the Best Fair Policy

• Optimal \( P^* \) is solution of linear program
\[ P^* = \arg\max_P \left[ r^T Pe \right] \]
\[ \text{s.t.} \quad 1^T P = 1 \]
\[ P1 = 1 \]
\[ 0 \leq P \leq 1 \]
\[ \text{rel}_2 g^T P e = \text{rel}_1 g_2^T P e \]

Quality

Fairness

Computing \( \pi^* \) from \( P^* \)

Birkhoff-von Neumann decomposition
\[ P^* = \theta_1 P_1 + \cdots + \theta_k P_k \]

where \( P_1 \ldots P_k \) are permutation matrices and \( \theta_1 \geq 0 \) with \( \sum \theta_i = 1 \).

→ 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
\[ P^* = \arg\max_P \left[ r^T P e \right] \]
\[ \text{s.t.} \quad 1^T P = 1 \]
\[ P1 = 1 \]
\[ 0 \leq P \leq 1 \]
\[ P \text{ is fair} \]
4. Compute ranking policy \( \pi^* \) from \( P^* \)
Example

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

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Conventional Ranking

Fair Ranking

Quality

Relative Unfairness

Estimating Merit from Interactions

Data
- Query distribution: \( x_j \sim P(X) \)
- Deployed ranker: \( y_j = \pi_0(x_j) \)
- Feedback: clicks, purchases, plays, reads

\( \rightarrow \) Feedback is biased!

Modeling Position Bias

- Assume:
  - Click implies observed and relevant: \( (\text{click}_i = 1) \leftrightarrow (\text{obs}_i = 1) \land (\text{rel}_i = 1) \)
- Problem:
  - No click can mean not relevant OR not observed
  \( (\text{click}_i = 0) \leftrightarrow (\text{obs}_i = 0) \lor (\text{rel}_i = 0) \)

\( \rightarrow \) Understand observation mechanism

Inverse Propensity Score Estimator

- Observation Propensities
  \( \rightarrow Q(\text{obs}_i = 1 \mid x, y) \)
  - Random variable \( \text{obs}_i \in \{0, 1\} \) indicates whether relevance label \( \text{rel}_i \) is observed.
  - Can use position-based exposure \( Q(\text{obs}_i = 1 \mid x, y) = e_i \)
- De-biased Regression via IPS weighting

\( \rightarrow \) In expectation independent of past rankings!

Counterfactual Policy Learning

- Policy Learning for Contextual Bandits and Ranking
  - Data is biased by past system actions
  - Propensity tagging 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], …
**Fairness of Exposure**

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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](http://www.joachims.org)

**Theme: Prediction and Action**

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

**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 → 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
  - * 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

Unsupervised Learning

- Clustering
  - None
- 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

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

→ CSE 6781 Theoretical Foundations of Machine Learning
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
  - 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