

Fairness in Ranking & Wrap-Up

CS4780/5780 – Machine Learning

Fall 2019

Nika Haghtalab & Thorsten Joachims

Cornell University

Reading:

None

Ranking in Online Systems

Ranking function π that ranks items for context x .
→ Learning-to-Rank

svm at DuckDuckGo

duckduckgo.com/?q=svm&it=h&bs=about

svm

Web Images Videos News Maps Meanings Stock Settings

All Regions Safe Search: Moderate Any Time

Support-vector machine

In machine learning, support-vector machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Wikipedia

Support-vector machine - Wikipedia

https://en.wikipedia.org/wiki/Support_vector_machine

In machine learning, support-vector machines (SVMs), also support-vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis.

SVM - Gas Gift Card & Promotion Management

<https://www.svmcards.com>

SVM is a leading provider of gift card marketing, management & customization services. Find over 250 brands promotional gift card solutions for gas, retail & services

Silvercorp Metals Inc. (SVM) - Yahoo Finance

<https://finance.yahoo.com/quote/SVM/>

Find the latest Silvercorp Metals Inc. (SVM) stock quote, history, news and other vital information to help you with your stock trading and investing.

Introduction to Support Vector Machine(SVM) | Dimensionless ...

<https://dimensionless.in/introduction-to-svm/>

A Support Vector Machine(SVM) is yet another supervised machine learning algorithm. It

metal table legs | Etsy

metal table legs

metal dining table legs metal coffee table legs metal hairpin table legs table legs

All categories Home & Living Craft Supplies & Tools Art & Collectibles Paper & Party Supplies

Special offers

Free shipping

On sale

Ready to ship in

1 business day

1-3 business days

Price (\$)

Any price

Under \$100

\$100 to \$500

\$500 to \$1,000

Over \$1,000

Custom

Low to High

Style

metal table legs (5,758 Results)

Ad

Heavy Duty Metal Table Legs... Modern/Industrial

★★★★★ (4,165)

\$15.74 \$22.48 (30% off)

FREE shipping

Ad

2 Pack U Shape Legs (1.5" W)... Classic/Custom/Rustic

★★★★★ (1,960)

\$16.20 \$18.00 (10% off)

FREE shipping

Ad

Heavy Duty Metal Table Legs... Modern/Industrial

★★★★★ (4,165)

\$15.74 \$22.48 (30% off)

FREE shipping

Ad

2 Pack - (2" Wide - 1/4" Thick)... Classic/Custom/Rustic

★★★★★ (1,960)

\$32.40 \$36.00 (10% off)

FREE shipping

Netflix

Netflix

TOAST LONDON

SPECIAL DOUBLE ISSUE

HAPPYISH

CRIMINAL MINDS SEASON 5

NETFLIX ORIGINALS

THE GREAT BRITISH BAKING SHOW

THE LAST KINGDOM

THE KAMIKAZE METHOD

HuffPost - Breaking News

HuffPost

TOP STORIES

Pelosi Announces House Will Vote On Impeachment Process After Weeks of GOP Protests

Katie Hill Speaks Out On Resignation: 'I'm Hurt, I'm Angry'

Court Strikes Down North Carolina Congressional Map

Democratic Former Sen. Kay Hagan Dies At 86

Trump Publicly Revels In Death And Spectacle: 'Boom Boom Boom!'

U.S. LANDS CHIEF WROTE ANTI-ENVIRONMENTAL SCREENS

Trump's Public Lands Chief Wrote For A Cult Extremist's Magazine

By Chris D'Angelo and Alexander C. Kaufman

UKRAINE CALL WITNESS NO-SHOWS IMPACT HEARING

Former White House Aide Won't Show For Scheduled Impeachment

Paalbear Who Snubbed Mitch McConnell At Elijah Cummings' Memorial Breaks Silence

Waiting for alicemeredmond.

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 $\rightarrow y^*$
- For virtually any measure Δ of ranking quality

$$y^* := \operatorname{argmax}_y [\Delta(y|x)]$$

Two-Sided Market

Online Retail

- Utility to Users:
Customers find products they want
- Utility to Items:
Sellers get revenue

The screenshot shows a web browser displaying the Etsy search results for 'metal table legs'. The browser's address bar shows the URL 'etsy.com/search?q=metal%20table%20legs'. The Etsy logo is visible in the top left, and a 'Sign in' button is in the top right. Below the search bar, there are filter tabs for 'metal dining table legs', 'metal coffee table legs', 'metal hairpin table legs', and 'table legs'. The search results are displayed in a grid format, showing four items. Each item includes a product image, a title, the seller's name, a star rating, the price, and a 'FREE shipping' badge. The first item is 'Heavy Duty Metal Table Legs...' by ModernUrbanMetals, priced at \$15.74 (30% off from \$22.48). The second item is '2 Pack U Shape Legs (1.5" Wi...' by CsonkasCustomRustics, priced at \$16.20 (10% off from \$18.00). The third item is 'Heavy Duty Metal Table Legs...' by ModernUrbanMetals, priced at \$15.74 (30% off from \$22.48). The fourth item is '2 Pack - (2" Wide - 1/4" Thick ...' by CsonkasCustomRustics, priced at \$32.40 (10% off from \$36.00). On the left side of the page, there are filters for 'All categories', 'Special offers', 'Ready to ship in', 'Price (\$)', and 'Style'.

Two-Sided Market

Music Streaming

- Utility to Users:
Customers find music they enjoy
- Utility to Items:
Artists get streaming revenue

Spotify - Home

open.spotify.com/browse/featured

Spotify

Home

Search

Your Library

PLAYLISTS

Create Playlist

Localify - Ithaca

Nena - Nena 40 - Das ...

Victor Davich - 8 Minu...

Hold Hope

Annie 2014

Ukulele beats

ukulele

Calming Christian

Spread the Gospel

Rhythm & Praise

Install App

Thorsten Joachims

Recently played

SEE ALL

Kid's Car Mix

Marmor, Stein & Eisen Bricht
Drafi Deutscher

KIDZ BOP 39 (Deluxe Edition)
Kidz Bop Kids

Your heavy rotation

SEE ALL

The music you've had on repeat this month.

Slaapliedjes

The Greatest Showman (Origin...
Various artists

Annie 2014

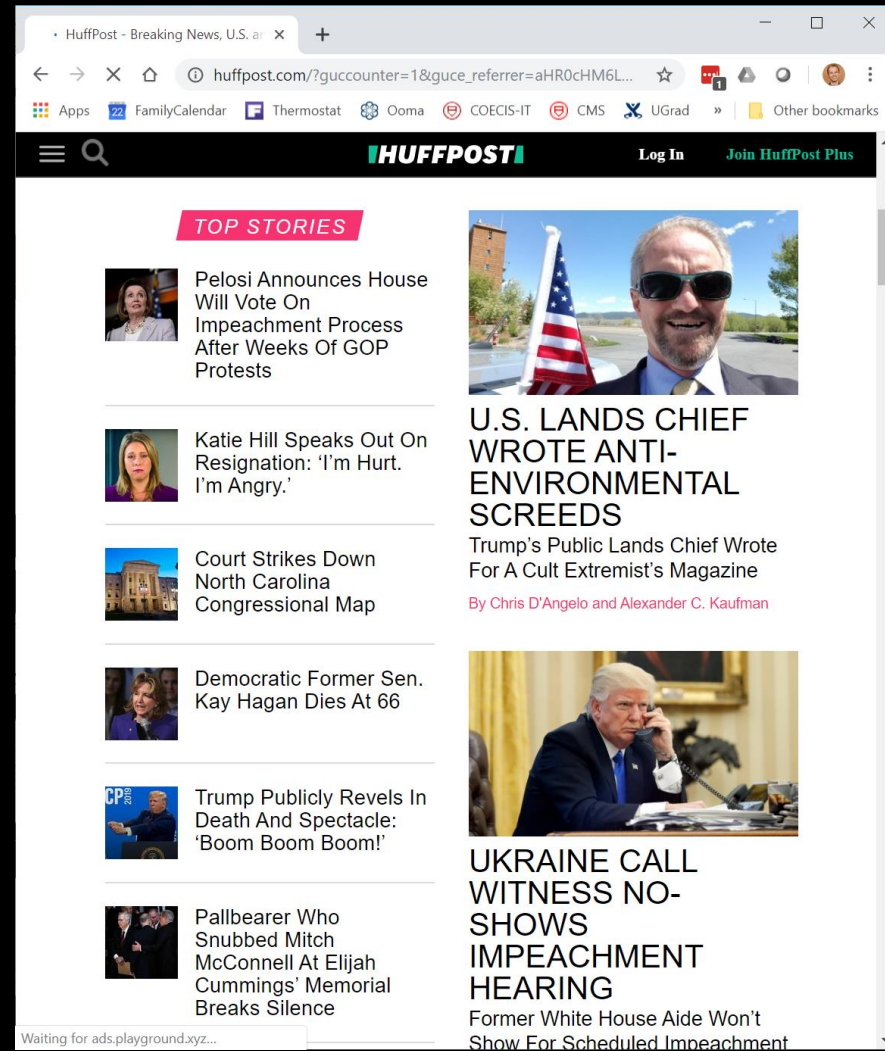
Come Th...
The Praise ...

0:00 3:37

Two-Sided Market

News

- Utility to Users:
Readers find relevant articles
- Utility to Items:
Writers get their voice out (and ad revenue)



The screenshot shows the HuffPost website interface. At the top, there's a navigation bar with the HuffPost logo, a search icon, and links for 'Log In' and 'Join HuffPost Plus'. Below the navigation bar is a 'TOP STORIES' section. On the left side, there's a vertical list of five news items, each with a small thumbnail image and a headline. On the right side, there's a larger featured article with a large image of a man in sunglasses and a headline. At the bottom of the page, there's a small text box that says 'Waiting for ads.playground.xyz...'.


HuffPost - Breaking News, U.S. a | x +


huffpost.com/?guccounter=1&guce_referrer=aHR0cHM6L... ☆


Apps FamilyCalendar Thermostat Ooma COECIS-IT CMS UGrad Other bookmarks


HUFFPOST Log In Join HuffPost Plus


TOP STORIES


 Pelosi Announces House Will Vote On Impeachment Process After Weeks Of GOP Protests


 Katie Hill Speaks Out On Resignation: 'I'm Hurt. I'm Angry.'


 Court Strikes Down North Carolina Congressional Map

 Democratic Former Sen. Kay Hagan Dies At 66

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Former White House Aide Won't Show For Scheduled Impeachment

Waiting for ads.playground.xyz...

What can go wrong?

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

Technology **BBC**

Google hit with record EU fine over Shopping service

By Leo Kelion
Technology desk editor

Wenn Maschinen kalt entscheiden

Algorithmen urteilen über Arbeitslose, Straftäter und Job-Bewerber. Eine Kommission der Bundesregierung will ihre Macht nun bändigen. Kann das gelingen?

Eine Analyse von **Ann-Kathrin Nezik** ZEIT ONLINE

23. Oktober 2019, 16:46 Uhr / Editiert am 24. Oktober 2019, 15:40 Uhr / DIE ZEIT Nr. 44/2019, 24. Oktober 2019 / [9 Kommentare](#)

Machine Bias



There's software used across the country to predict future criminals. And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica

May 23, 2016

BUSINESS NEWS OCTOBER 9, 2018 / 11:12 PM / A YEAR AGO



Amazon scraps secret AI recruiting tool that showed bias against women

Jeffrey Dastin

8 MIN READ



Fairness of Exposure

Fair ranking policy π 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 Δ of ranking quality

$$y^* := \operatorname{argmax}_y [\Delta(y|x)]$$

- Are rankings fair/desirable?

Top News Stories		
Rank	Item	P(read)
1	Times 1	50.99
2	Times 2	50.98
3	Times 3	50.97
...
100	Post 1	49.99
101	Post 2	49.98
102	Post 3	49.97
...

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]

Rank	Exposure P(observe)
1	e_1
2	e_2
3	e_3
...	...
100	e_{100}
101	e_{101}
102	e_{102}
...	...

Fairness Constraints

$$\textit{exposure} = f(\textit{relevance})$$

- 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 $\pi(y|x)$

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

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

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

e_j = exposure at position j

π

y_1	y_2	y_3	y_4
A	B	A	B
B	A	C	C
C	C	B	A
D	D	D	G
E	E	E	F
F	F	F	E
G	G	G	D

0.52 0.23 0.20 0.05

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.

$$\pi^*(y|x) = \underset{\pi}{\operatorname{argmax}} \quad [qual(\pi|x)]$$
$$s.t. \quad \frac{expo(G_0|x)}{rel(G_0|x)} = \frac{expo(G_1|x)}{rel(G_1|x)}$$

→ Computationally hard!

Marginal Rank Distribution \mathbb{P}

π

	y_1	y_2	y_3	y_4
A	A	B	A	B
B	B	A	C	C
C	C	D	B	A
D	D	C	D	G
E	E	E	E	F
F	F	F	F	E
G	G	G	G	D

0.52 0.23 0.20 0.05



\mathbb{P}

	1	2	3	4	5	6	7
A	0.72	0.23	0.05	0	0	0	0
B	0.28	0.52	0.20	0	0	0	0
C	...						
D				$\mathbb{P}_{i,j}$			
E							
F							
G							

Computing the Best Fair Policy

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

$$\mathbb{P}^* = \operatorname{argmax}_{\mathbb{P}}$$

s. t.

$$[rel^T \mathbb{P} e]$$

$$\mathbf{1}^T \mathbb{P} = \mathbf{1}$$

$$\mathbb{P} \mathbf{1} = \mathbf{1}$$

$$0 \leq \mathbb{P} \leq \mathbf{1}$$

$$rel_2 g_1^T \mathbb{P} e = rel_1 g_2^T \mathbb{P} e$$

Quality

P is doubly stochastic

Fairness

Computing π^* from \mathbb{P}^*

Birkhoff-von Neumann decomposition

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

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

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

Summary of Method

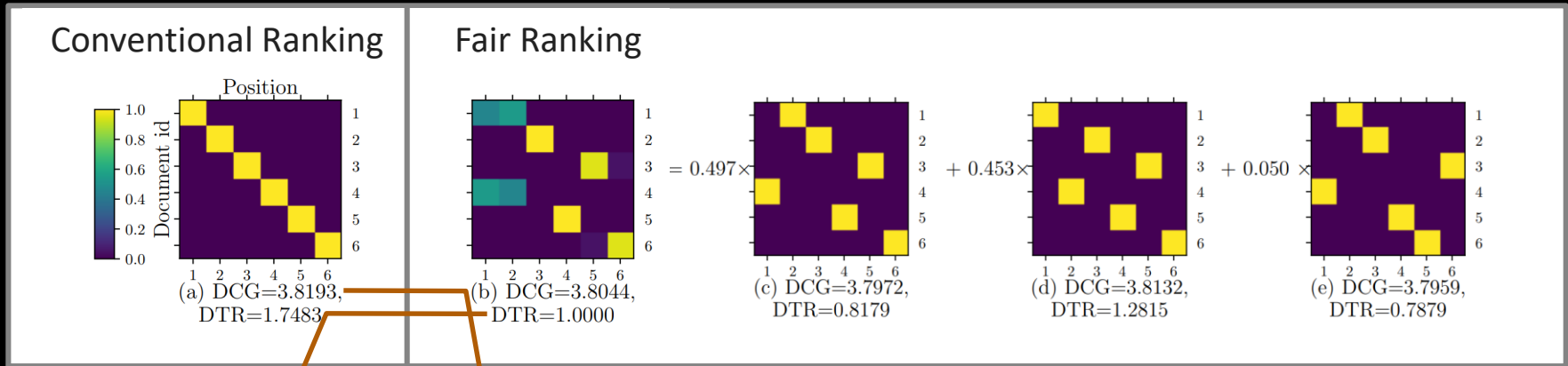
1. Estimate relevances r for query x
2. Define (merit-based) fairness constraint
3. Solve linear program for marginal rank matrix

$$\begin{aligned} \mathbb{P}^* = \operatorname{argmax}_{\mathbb{P}} \quad & [r^T \mathbb{P} q] \\ \text{s.t.} \quad & \mathbf{1}^T \mathbb{P} = \mathbf{1} \\ & \mathbb{P} \mathbf{1} = \mathbf{1} \\ & 0 \leq \mathbb{P} \leq 1 \\ & \mathbb{P} \text{ is fair} \end{aligned}$$

4. Compute ranking policy π^* from \mathbb{P}^*

Example

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



Relative
Unfairness

Quality

Fairness of Exposure

Fair ranking policy π allocates exposure to items based on merit.

Endogenous Factors

How to allocate exposure based on merit in order to

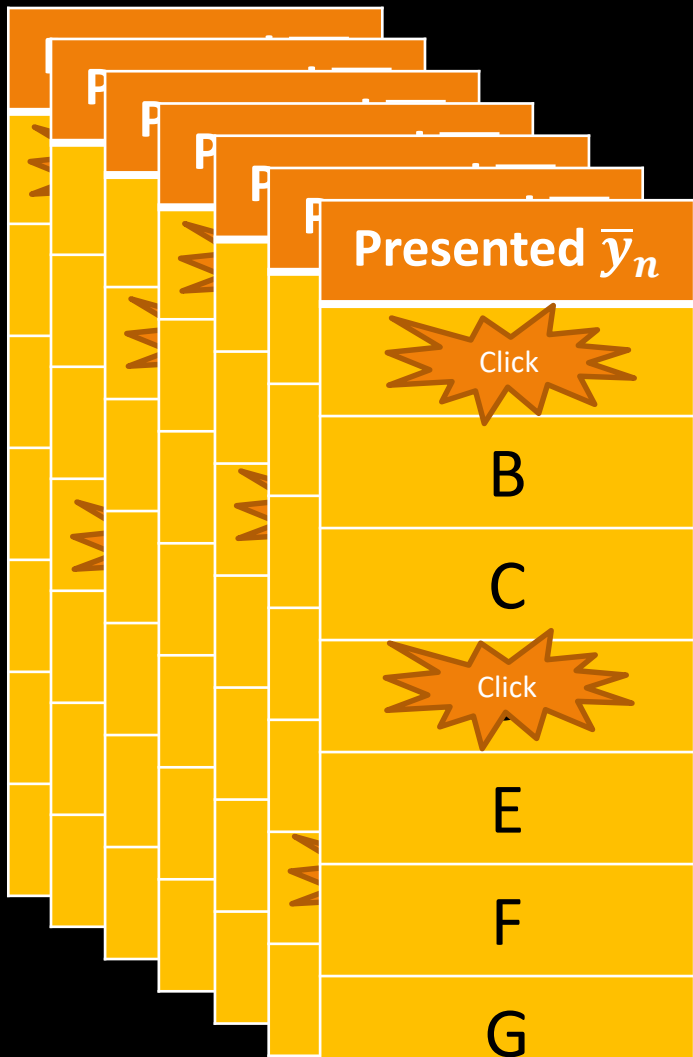
- Satisfy legal requirements
- Shape marketplace dynamics (e.g. Spotify, superstar economics)
- Spam, Polarization

Exogenous Factors ←

How to estimate merit without biases like

- Position bias
- Trust bias
- Uncertainty bias
- Historical actions
- Stereotypes

Estimating Merit from Interactions



Data

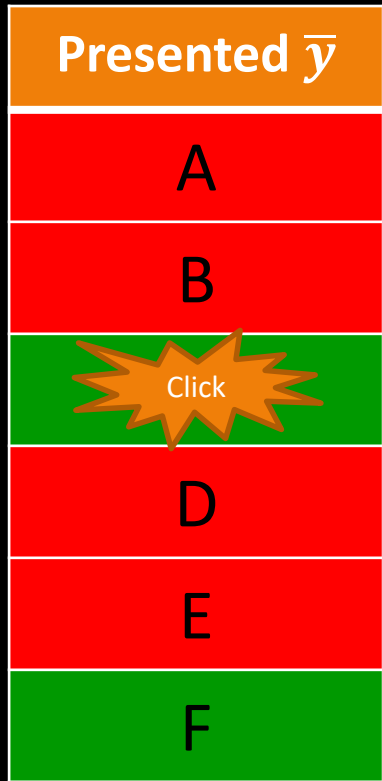
- Query distribution: $x_j \sim P(X)$
- Deployed ranker: $\bar{y}_j = \pi_0(x_j)$
- Feedback: clicks, purchases, plays, reads

→ Feedback is biased!

Modeling Position Bias

- Assume:
 - Click implies observed and relevant:
 $(click_i = 1) \leftrightarrow (obs_i = 1) \wedge (rel_i = 1)$
- Problem:
 - No click can mean not relevant OR not observed
 $(click_i = 0) \leftrightarrow (obs_i = 0) \vee (rel_i = 0)$

→ 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
 - In expectation independent of past rankings!

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

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
 - Policy-gradient methods like POEM [Swaminathan & Joachims 2015], BanditNet [Joachims et al. 2018], Propensity LTR [Joachims et al. 2017]
- 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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Endogenous Factors

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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>

WRAP-UP

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 → 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

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