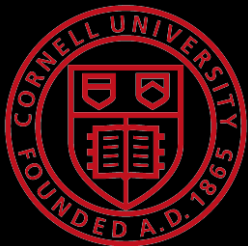


Counterfactual Model for Online Systems

CS 7792 - Fall 2016

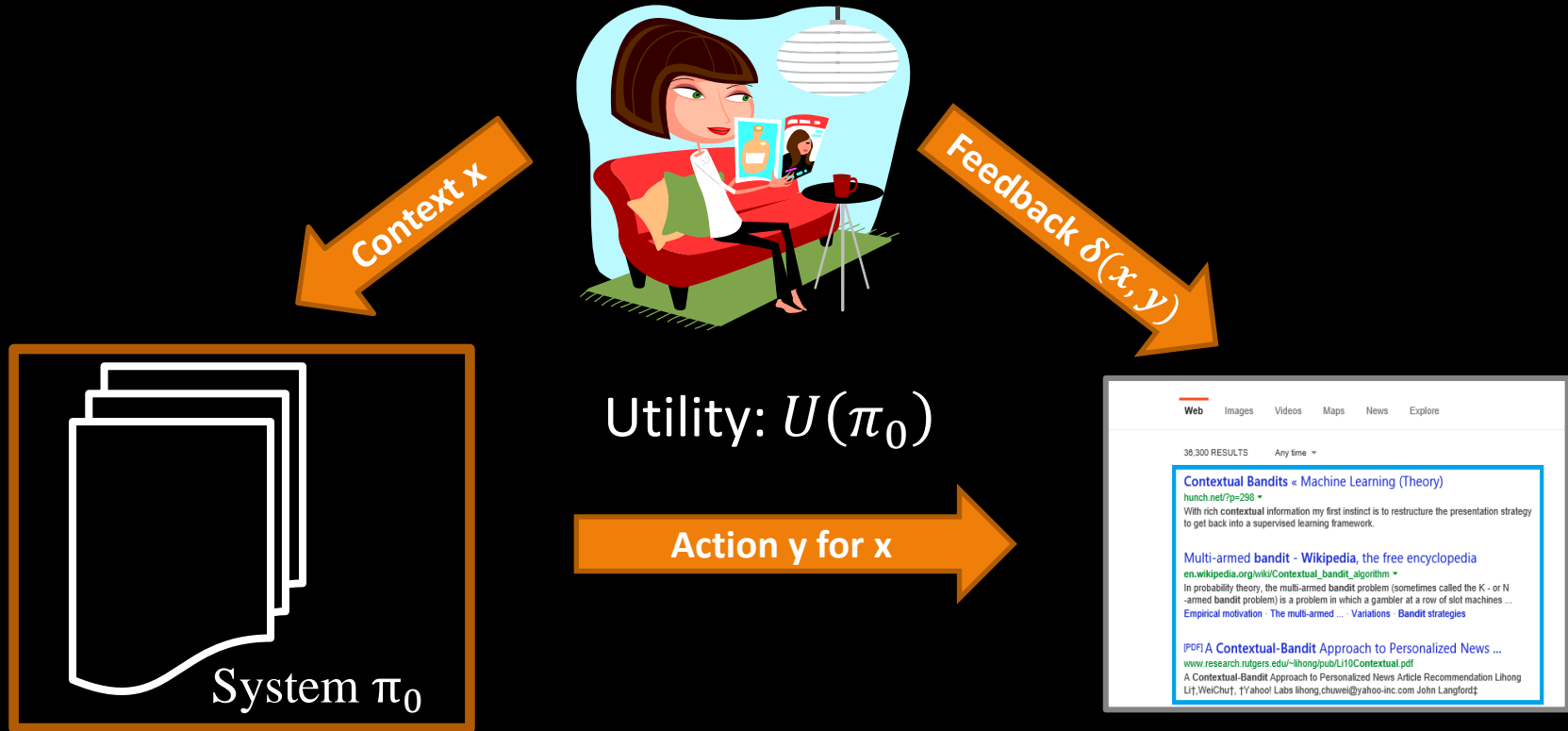
Thorsten Joachims

Department of Computer Science & Department of Information Science
Cornell University



Imbens, Rubin, Causal Inference for Statistical Social Science, 2015. Chapters 1,3,12.

Interactive System Schematic



News Recommender

- Context x :
 - User
- Action y :
 - Portfolio of newsarticles
- Feedback $\delta(x, y)$:
 - Reading time in minutes



The screenshot shows the New York Times website interface. The main headline is "Countries have borders. Stories don't." with a photo of a person walking on a dune. Below the main headline, there are several news articles:

- Amtrak Crash Illuminates Obstacles to Rail Safety** by Matt Flegenheimer, Patrick S. Onyiah, and Gabriel Rotondo. The article discusses the challenges of upgrading railroads in Washington.
- Mayor to Announce Plan to Revamp New York Public Housing** by Mireya Navarro. The article reports that Mayor Bill de Blasio will call for significant new financial help from the city.
- 170 Bikers Face Murder-Related Charges in Waco Melee** by Manny Fernandez, Serge F. Kovaleski, and Alan Blinder. The article describes a shootout among rival gangs in Texas.
- Critics Hear E.P.A.'s** (partially visible)
- Jon Hamm on the 'Mad Men' Series Finale** (partially visible)

On the right side, there is a sidebar titled "The Opinion Pages" with links to "In Egypt, Deplorable Death Sentences" and "Editorial Observer: Transgender Americans Defy Stereotypes". There is also a "Watching" section with a link to "Yingluck Shinawatra, the former prime has entered a plea of not guilty at the a rice subsidy scheme that lost billions".

Ad Placement

- Context x :
 - User and page
- Action y :
 - Ad that is placed
- Feedback $\delta(x, y)$:
 - Click / no-click

The screenshot shows a YouTube video player for the video "Frozen Let it Go - In Real Life" by the channel "Working with Lemons". The video is currently playing a scene with Elsa. An advertisement for "MID-YEAR MARVEL DEALS" is displayed on the right side of the page, featuring travel packages to Malaysia. Below the video, the channel's name, subscriber count (445,097), and video view count (25,728,122) are visible. The video description includes a link to the channel's merchandise store. The comments section shows a top comment from the channel itself, dated one month ago.

YouTube URL: <https://www.youtube.com/watch?v=hMeiDVv5t8I>

Video Title: Frozen Let it Go - In Real Life

Channel: Working with Lemons (445,097 subscribers)

Views: 25,728,122

Published: Mar 20, 2015

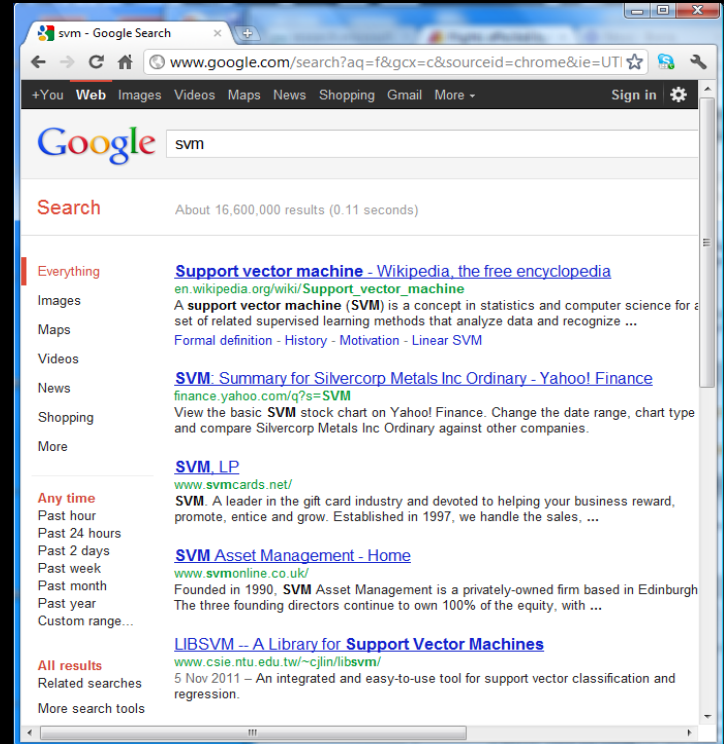
Description: Check out the Official Working with Lemons merchandise at: <http://shop.maker.tv/collections/work...> Thanks to all of our fans, cast and crew and especially Elsa played by Gamry Bagley. Please continue to share, like and subscribe!

Advertisement: MID-YEAR MARVEL DEALS. FROM HO CHI MINH CITY ECONOMY CLASS. KUALA LUMPUR MELBOURNE AMSTERDAM. 1,731,000 11,248,000 12,978,000. Book: 11 - 29 May 2016. Travel: 14 May - 31 Dec 2016. Terms & Conditions apply. See more deals.

Comments: 4,110. Top comment: Working with Lemons. Let it Go is here!!! Help us share the good news on Facebook and Twitter!

Search Engine

- Context x :
 - Query
- Action y :
 - Ranking
- Feedback $\delta(x, y)$:
 - win/loss against baseline in interleaving



Log Data from Interactive Systems

- Data

context

π_0 action

reward / loss

$$S = ((x_1, y_1, \delta_1), \dots, (x_n, y_n, \delta_n))$$

→ Partial Information (aka “Contextual Bandit”)
Feedback

- Properties

- Contexts x_i drawn i.i.d. from unknown $P(X)$
- Actions y_i selected by existing system $\pi_0: X \rightarrow Y$
- Feedback δ_i from unknown function $\delta: X \times Y \rightarrow \mathfrak{R}$

Goal

- Use interaction log data

$$S = ((x_1, y_1, \delta_1), \dots, (x_n, y_n, \delta_n))$$

for evaluation of system π :

- Estimate online measures of some system π offline.
- System π can be different from π_0 that generated log.

Evaluation: Outline

- Evaluating Online Metrics Offline
 - A/B Testing (on-policy)
 - Counterfactual estimation from logs (off-policy)
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Online Performance Metrics

Example metrics

- CTR
- Revenue
- Time-to-success
- Interleaving
- Etc.

→ Correct choice depends on application and is not the focus of this lecture.

This lecture:

Metric encoded as $\delta(x, y)$ [click/payoff/time for (x,y) pair]

System

- Definition [Deterministic Policy]:
Function

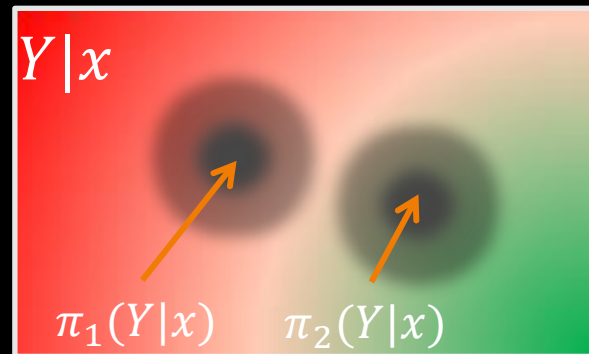
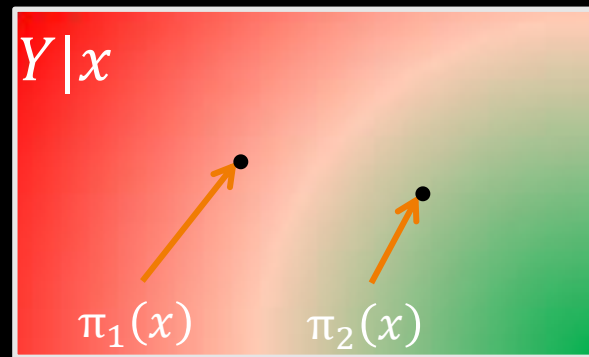
$$y = \pi(x)$$

that picks action y for context x .

- Definition [Stochastic Policy]:
Distribution

$$\pi(y|x)$$

that samples action y given context x

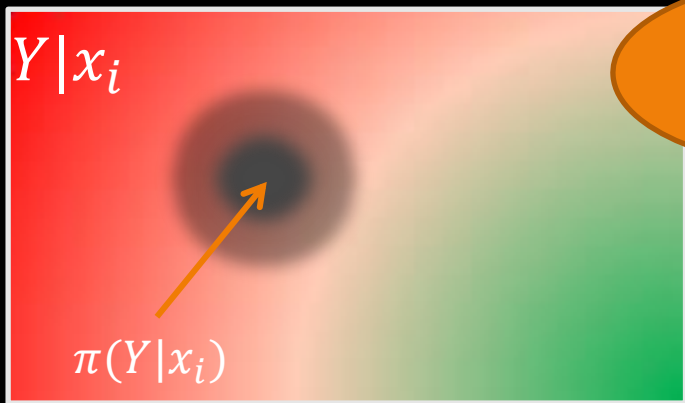


System Performance

Definition [Utility of Policy]:

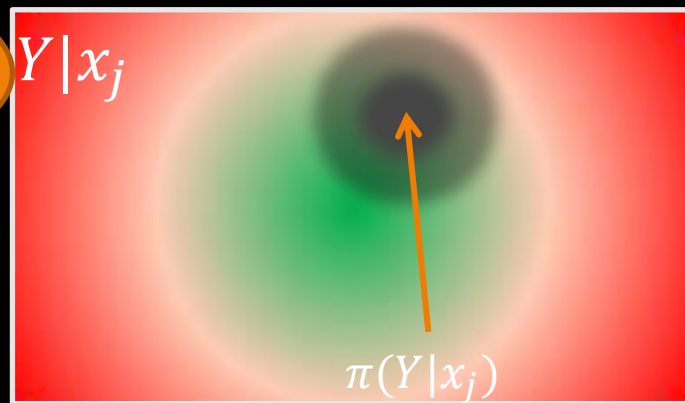
The expected reward / utility $U(\pi)$ of policy π is

$$U(\pi) = \int \int \delta(x, y) \pi(y|x) P(x) dx dy$$



e.g. reading
time of user x
for portfolio y

• • •



Online Evaluation: A/B Testing

Given $S = ((x_1, y_1, \delta_1), \dots, (x_n, y_n, \delta_n))$ collected under π_0 ,

$$\hat{U}(\pi_0) = \frac{1}{n} \sum_{i=1}^n \delta_i$$

→ A/B Testing

Deploy π_1 : Draw $x \sim P(X)$, predict $y \sim \pi_1(Y|x)$, get $\delta(x, y)$

Deploy π_2 : Draw $x \sim P(X)$, predict $y \sim \pi_2(Y|x)$, get $\delta(x, y)$

⋮

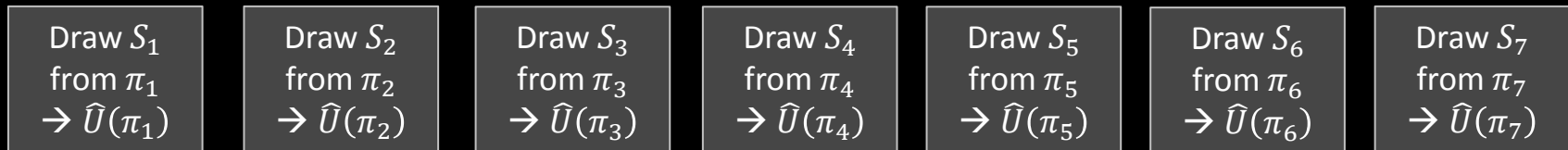
Deploy $\pi_{|H|}$: Draw $x \sim P(X)$, predict $y \sim \pi_{|H|}(Y|x)$, get $\delta(x, y)$

Pros and Cons of A/B Testing

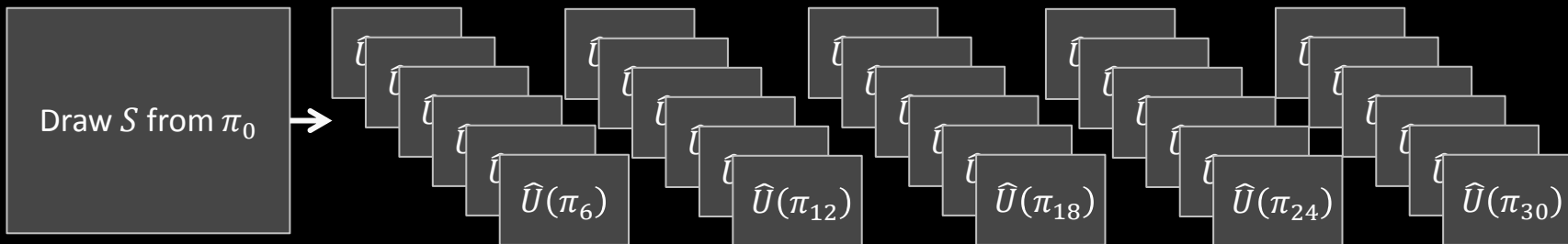
- Pro
 - User centric measure
 - No need for manual ratings
 - No user/expert mismatch
- Cons
 - Requires interactive experimental control
 - Risk of fielding a bad or buggy π_i
 - Number of A/B Tests limited
 - Long turnaround time

Evaluating Online Metrics Offline

- Online: On-policy A/B Test



- Offline: Off-policy Counterfactual Estimates



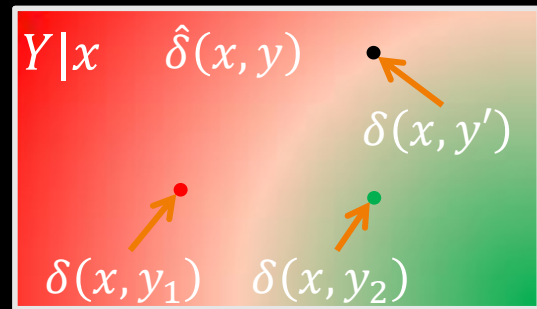
Evaluation: Outline

- Evaluating Online Metrics Offline
 - A/B Testing (on-policy)
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Approach 1: Reward Predictor

- Idea:

- Use $S = ((x_1, y_1, \delta_1), \dots, (x_n, y_n, \delta_n))$ from π_0 to estimate reward predictor $\hat{\delta}(x, y)$

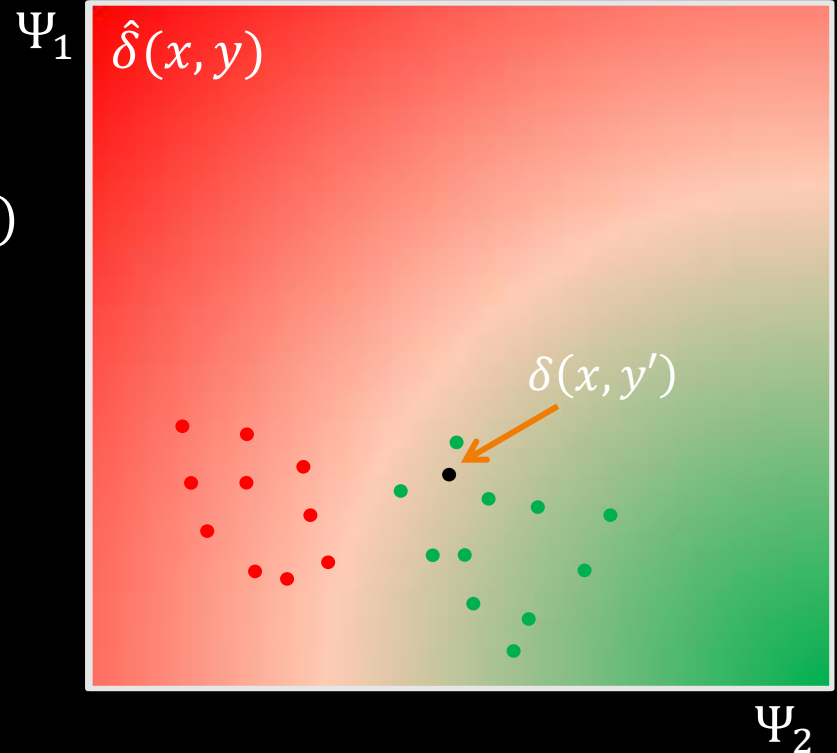


- Deterministic π : Simulated A/B Testing with predicted $\hat{\delta}(x, y)$
 - For actions $y'_i = \pi(x_i)$ from new policy π , generate predicted log $S' = ((x_1, y'_1, \hat{\delta}(x_1, y'_1)), \dots, (x_n, y'_n, \hat{\delta}(x_n, y'_n)))$
 - Estimate performance of π via $\hat{U}_{rp}(\pi) = \frac{1}{n} \sum_{i=1}^n \hat{\delta}(x_i, y'_i)$
- Stochastic π : $\hat{U}_{rp}(\pi) = \frac{1}{n} \sum_{i=1}^n \sum_y \hat{\delta}(x_i, y) \pi(y|x_i)$

Regression for Reward Prediction

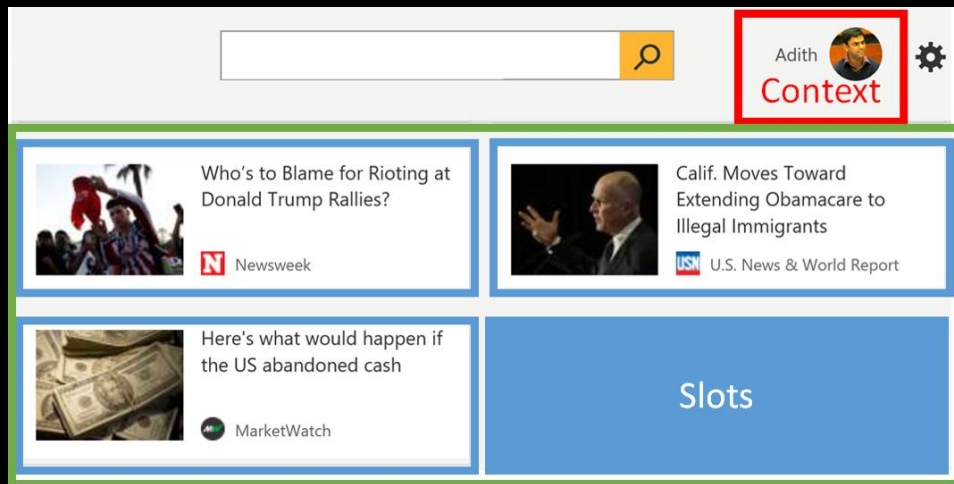
Learn $\hat{\delta}: x \times y \rightarrow \mathfrak{R}$

1. Represent via features $\Psi(x, y)$
2. Learn regression based on $\Psi(x, y)$ from S collected under π_0
3. Predict $\hat{\delta}(x, y')$ for $y' = \pi(x)$ of new policy π

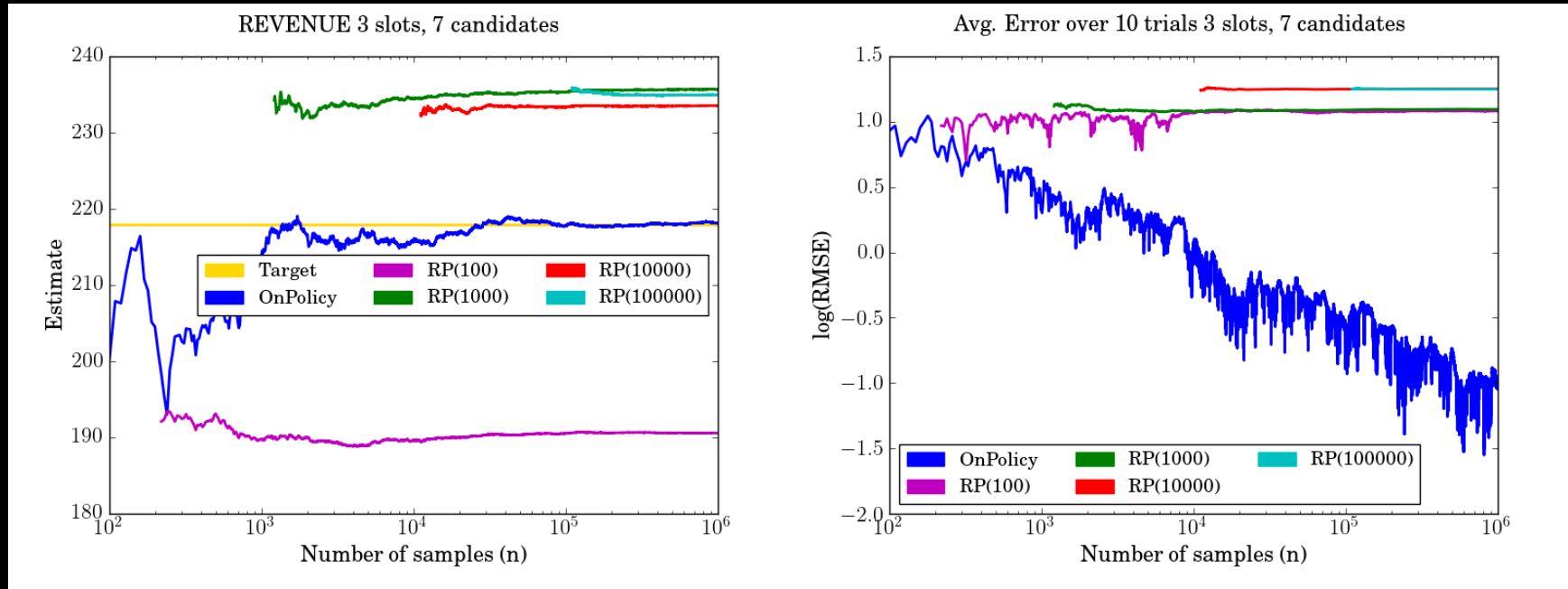


News Recommender: Exp Setup

- Context x : User profile
 - Pick from 7 candidates to place into 3 slots
- Action y : Ranking
 - Complicated hidden function
- Reward δ : “Revenue”
 - Logging policy π_0 : Non-uniform randomized logging system
 - Placket-Luce “explore around current production ranker”



News Recommender: Results



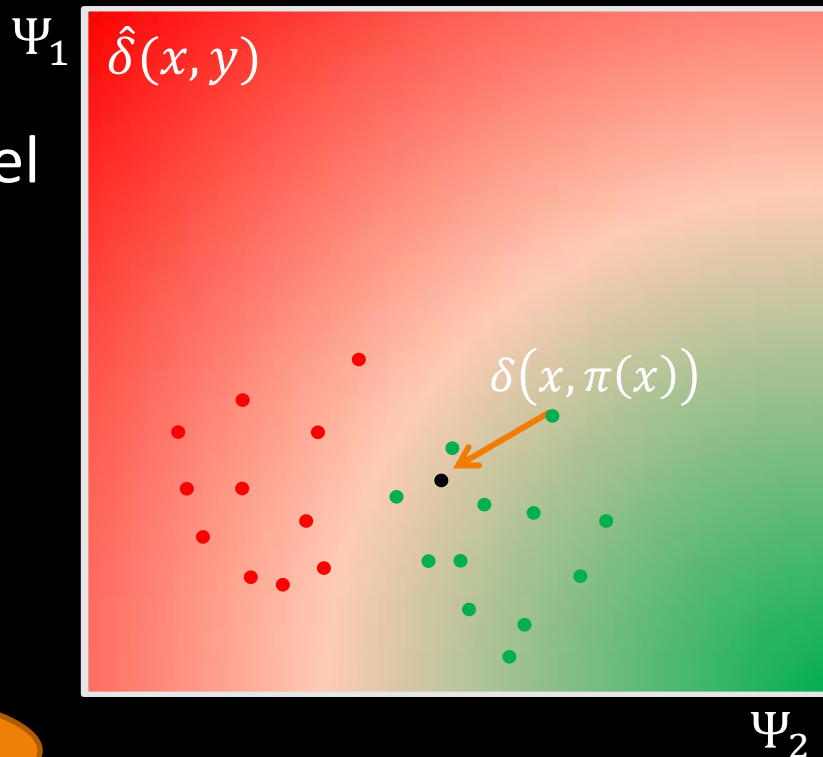
RP is inaccurate even with more training and logged data

Problems of Reward Predictor

- Modeling bias
 - choice of features and model
- Selection bias
 - π_0 's actions are over-represented

$$\rightarrow \hat{U}_{rp}(\pi) = \frac{1}{n} \sum_i \hat{\delta}(x_i, \pi(x_i))$$

Can be unreliable
and biased



Evaluation: Outline

- Evaluating Online Metrics Offline
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- • Approach 2: “Model the bias”
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Approach “Model the Bias”

- Idea:

Fix the mismatch between the distribution $\pi_0(Y|x)$ that generated the data and the distribution $\pi(Y|x)$ we aim to evaluate.

$$U(\pi) = \int \int \delta(x, y) \frac{\pi(y|x)}{\pi_0(y|x)} P(x) dx dy$$

Counterfactual Model

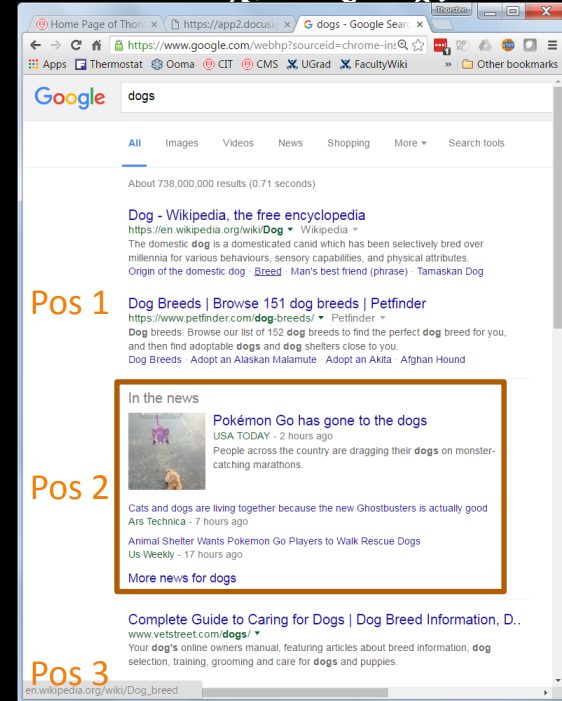
- Example: Treating Heart Attacks
 - Treatments: Y
 - Bypass / Stent / Drugs
 - Chosen treatment for patient x_i : y_i
 - Outcomes: δ_i
 - 5-year survival: 0 / 1
 - Which treatment is best?

	Bypass	Stent	Drugs
Patients $x_i \in \{1, \dots, n\}$	0	1	1
		0	1
	1		1
			1
	0	1	0
	1		

Counterfactual Model

Placing Vertical

- Example: ~~Treating Heart Attacks~~
 - Treatments: Y
 - ~~Bypass / Stent / Drugs~~ Pos 1 / Pos 2 / Pos 3
 - Chosen treatment for patient x_i : y_i
 - Outcomes: δ_i
 - ~~5-year survival: 0 / 1~~ Click / no Click on SERP
 - Which treatment is best?



Counterfactual Model

- Example: Treating Heart Attacks
 - Treatments: Y
 - Bypass / Stent / Drugs
 - Chosen treatment for patient x_i : y_i
 - Outcomes: δ_i
 - 5-year survival: 0 / 1
 - Which treatment is best?
 - Everybody Drugs
 - Everybody Stent
 - Everybody Bypass
- Drugs 3/4, Stent 2/3, Bypass 2/4 – really?

	Bypass	Stent	Drugs
Patients $x_i, i \in \{1, \dots, n\}$	0	1	1
		0	1
	1		1
			1
		1	0
	1		

Treatment Effects

- Average Treatment Effect of Treatment y

$$- U(y) = \frac{1}{n} \sum_i \delta(x_i, y)$$

- Example

$$- U(\textit{bypass}) = \frac{4}{11}$$

$$- U(\textit{stent}) = \frac{6}{11}$$

$$- U(\textit{drugs}) = \frac{3}{11}$$

	Bypass	Stent	Drugs
Factual Outcome	0	1	0
Counterfactual Outcomes	1	1	0
	0	0	1
	0	0	0
	0	1	1
	1	0	0
	1	0	1
	0	1	0
	0	1	0
	1	1	0
	1	1	0

Assignment Mechanism

- Probabilistic Treatment Assignment

- For patient i : $\pi_0(Y_i = y|x_i)$
- Selection Bias

- Inverse Propensity Score Estimator

- $$\hat{U}_{ips}(y) = \frac{1}{n} \sum_i \frac{\mathbb{I}\{y_i = y\}}{p_i} \delta(x_i, y_i)$$

- Propensity: $p_i = \pi_0(Y_i = y_i|x_i)$

- Unbiased: $E[\hat{U}(y)] = U(y)$,
if $\pi_0(Y_i = y|x_i) > 0$ for all i

- Example

- $$\hat{U}(drugs) = \frac{1}{11} \left(\frac{1}{0.8} + \frac{1}{0.7} + \frac{1}{0.8} + \frac{0}{0.1} \right)$$

$$= 0.36 < 0.75$$

	$\pi_0(Y_i = y x_i)$				Bypass	Stent	Drugs
Patients	0.3	0.6	0.1	0	1	0	
	0.5	0.4	0.1	1	1	0	
	0.1	0.1	0.8	0	0	1	
	0.6	0.3	0.1	0	0	0	
	0.2	0.5	0.7	0	1	1	
	0.7	0.2	0.1	1	0	0	
	0.1	0.1	0.8	1	0	1	
	0.1	0.8	0.1	0	1	0	
	0.3	0.3	0.4	0	1	0	
	0.3	0.6	0.1	1	1	0	
	0.4	0.4	0.2	1	1	0	

Experimental vs Observational

- Controlled Experiment
 - Assignment Mechanism under our control
 - Propensities $p_i = \pi_0(Y_i = y_i | x_i)$ are known by design
 - Requirement: $\forall y: \pi_0(Y_i = y | x_i) > 0$ (probabilistic)
- Observational Study
 - Assignment Mechanism not under our control
 - Propensities p_i need to be estimated
 - Estimate $\hat{\pi}_0(Y_i | z_i) = \pi_0(Y_i | x_i)$ based on features z_i
 - Requirement: $\hat{\pi}_0(Y_i | z_i) = \hat{\pi}_0(Y_i | \delta_i, z_i)$ (unconfounded)

Conditional Treatment Policies

- Policy (deterministic)
 - Context x_i describing patient
 - Pick treatment y_i based on x_i : $y_i = \pi(x_i)$
 - Example policy:
 - $\pi(A) = \text{drugs}, \pi(B) = \text{stent}, \pi(C) = \text{bypass}$

- Average Treatment Effect

- $$U(\pi) = \frac{1}{n} \sum_i \delta(x_i, \pi(x_i))$$

- IPS Estimator

- $$\hat{U}_{ips}(\pi) = \frac{1}{n} \sum_i \frac{\mathbb{I}\{y_i = \pi(x_i)\}}{p_i} \delta(x_i, y_i)$$

	Bypass	Stent	Drugs	x
	0	1	0	B
	1	1	0	C
	0	0	1	A
	0	0	0	B
	0	1	1	A
	1	0	0	B
	1	0	1	A
	0	1	0	C
	0	1	0	A
	1	1	0	C
	1	1	0	B

Patients

Stochastic Treatment Policies

- Policy (stochastic)
 - Context x_i describing patient
 - Pick treatment y based on x_i : $\pi(Y|x_i)$
- Note
 - Assignment Mechanism is a stochastic policy as well!
- Average Treatment Effect
 - $U(\pi) = \frac{1}{n} \sum_i \sum_y \delta(x_i, y) \pi(y|x_i)$
- IPS Estimator
 - $\hat{U}(\pi) = \frac{1}{n} \sum_i \frac{\pi(y_i|x_i)}{p_i} \delta(x_i, y_i)$

	Bypass	Stent	Drugs	x
	0	1	0	B
	1	1	0	C
	0	0	1	A
	0	0	0	B
	0	1	1	A
	1	0	0	B
	1	0	1	A
	0	1	0	C
	0	1	0	A
	1	1	0	C
	1	1	0	B

Counterfactual Model = Logs

Recorded in Log

Context x_i

Treatment y_i

Outcome δ_i

Propensities p_i

New Policy π

T-effect $U(\pi)$



Average quality of new policy.

Evaluation: Outline

- Evaluating Online Metrics Offline
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System Evaluation via Inverse Propensity Scoring

Definition [IPS Utility Estimator]:

Given $S = ((x_1, y_1, \delta_1), \dots, (x_n, y_n, \delta_n))$ collected under π_0 ,

$$\hat{U}_{ips}(\pi) = \frac{1}{n} \sum_{i=1}^n \delta_i \frac{\pi(y_i|x_i)}{\pi_0(y_i|x_i)}$$

Propensity
 p_i

→ Unbiased estimate of utility for any π , if propensity nonzero whenever $\pi(y_i|x_i) > 0$.

Note:

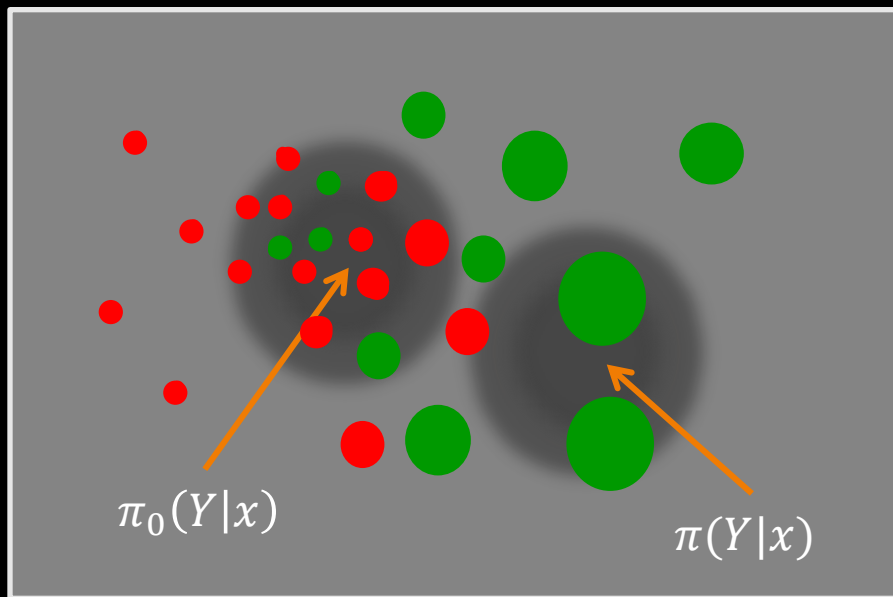
If $\pi = \pi_0$, then online A/B Test with $\hat{U}_{ips}(\pi_0) = \frac{1}{n} \sum_i \delta_i$

→ Off-policy vs. On-policy estimation.

Illustration of IPS

IPS Estimator:

$$\hat{U}_{IPS}(\pi) = \frac{1}{n} \sum_i \frac{\pi(y_i|x_i)}{\pi_0(y_i|x_i)} \delta_i$$

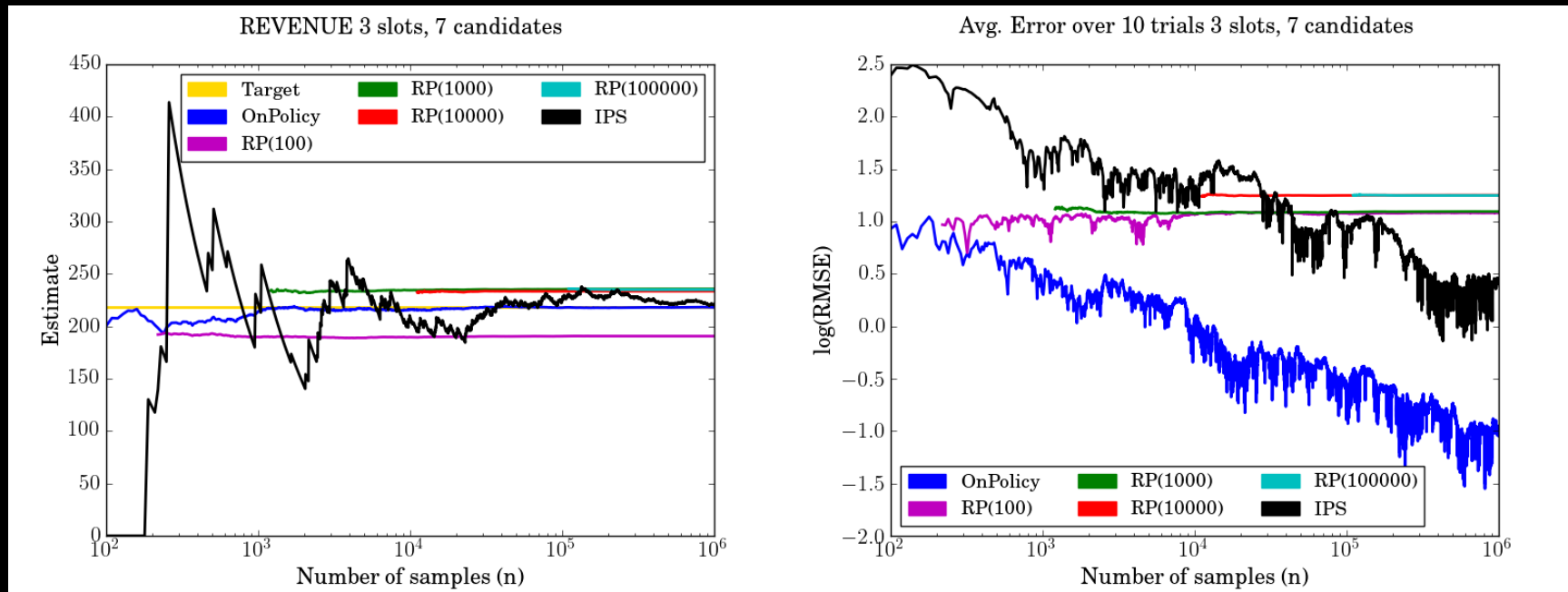


IPS Estimator is Unbiased

$$\begin{aligned} E[\widehat{U}(\pi)] &= \frac{1}{n} \sum_{x_1, y_1} \dots \sum_{x_n, y_n} \left[\sum_i \frac{\pi(y_i | x_i)}{\pi_0(y_i | x_i)} \delta(x_i, y_i) \right] \pi_0(y_1 | x_1) \dots \pi_0(y_n | x_n) P(x_1) \dots P(x_n) \\ &= \frac{1}{n} \sum_{x_1, y_1} \pi_0(y_1 | x_1) P(x_1) \dots \sum_{x_n, y_n} \pi_0(y_n | x_n) P(x_n) \left[\sum_i \frac{\pi(y_i | x_i)}{\pi_0(y_i | x_i)} \delta(x_i, y_i) \right] \\ &= \frac{1}{n} \sum_i \sum_{x_1, y_1} \pi_0(y_1 | x_1) P(x_1) \dots \sum_{x_n, y_n} \pi_0(y_n | x_n) P(x_n) \left[\frac{\pi(y_i | x_i)}{\pi_0(y_i | x_i)} \delta(x_i, y_i) \right] \\ &= \frac{1}{n} \sum_i \sum_{x_i, y_i} \pi_0(y_i | x_i) P(x_i) \left[\frac{\pi(y_i | x_i)}{\pi_0(y_i | x_i)} \delta(x_i, y_i) \right] \\ &= \frac{1}{n} \sum_i \sum_{x_i, y_i} \pi(y_i | x_i) P(x_i) \delta(x_i, y_i) = \frac{1}{n} \sum_i U(\pi) = U(\pi) \end{aligned}$$

Probabilistic
Assignment

News Recommender: Results



IPS eventually beats RP; variance decays as $O\left(\frac{1}{\sqrt{n}}\right)$

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