Recommendations as Treatments: Debiasing Learning and Evaluation

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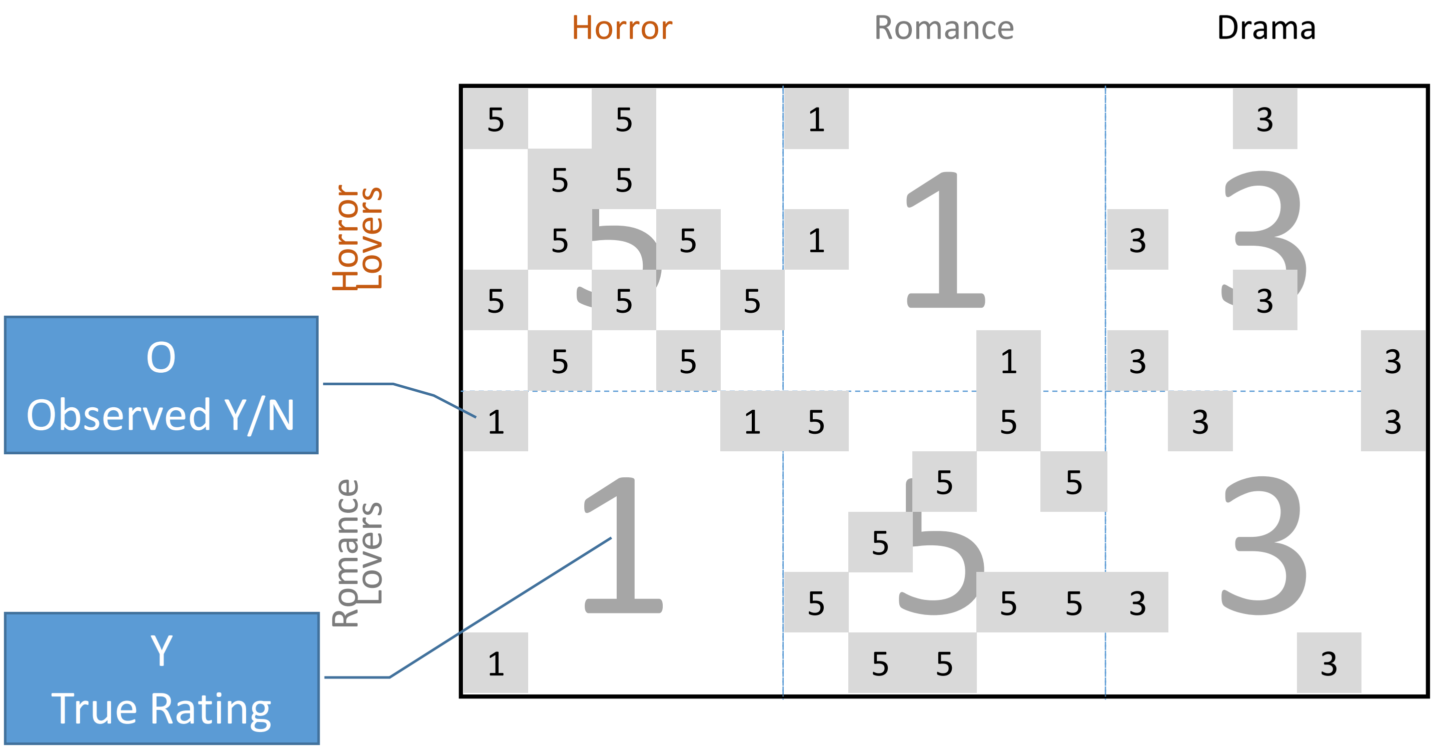
Movie recommendation

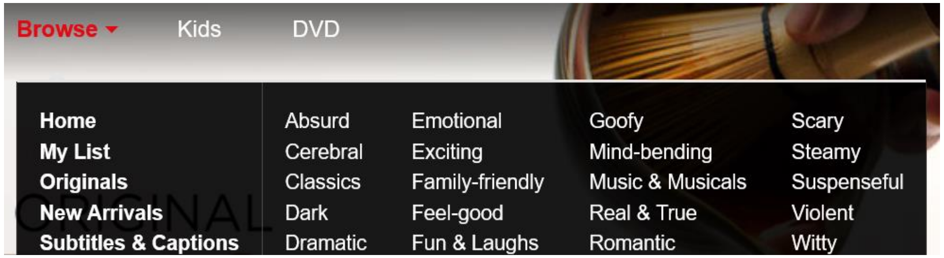


⇒ Data is Missing Not At Random (MNAR)

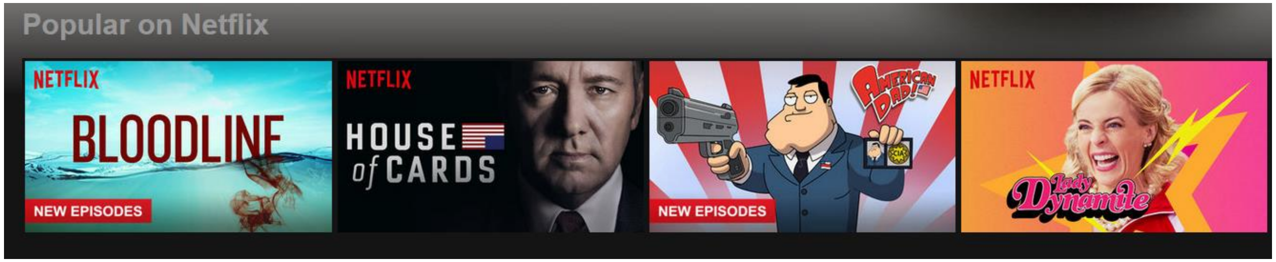
Example adapted from (Steck et al., 2010)

Selection Bias in Recommendation

- **Why is there selection bias?**
  - User-induced bias (e.g., browsing)



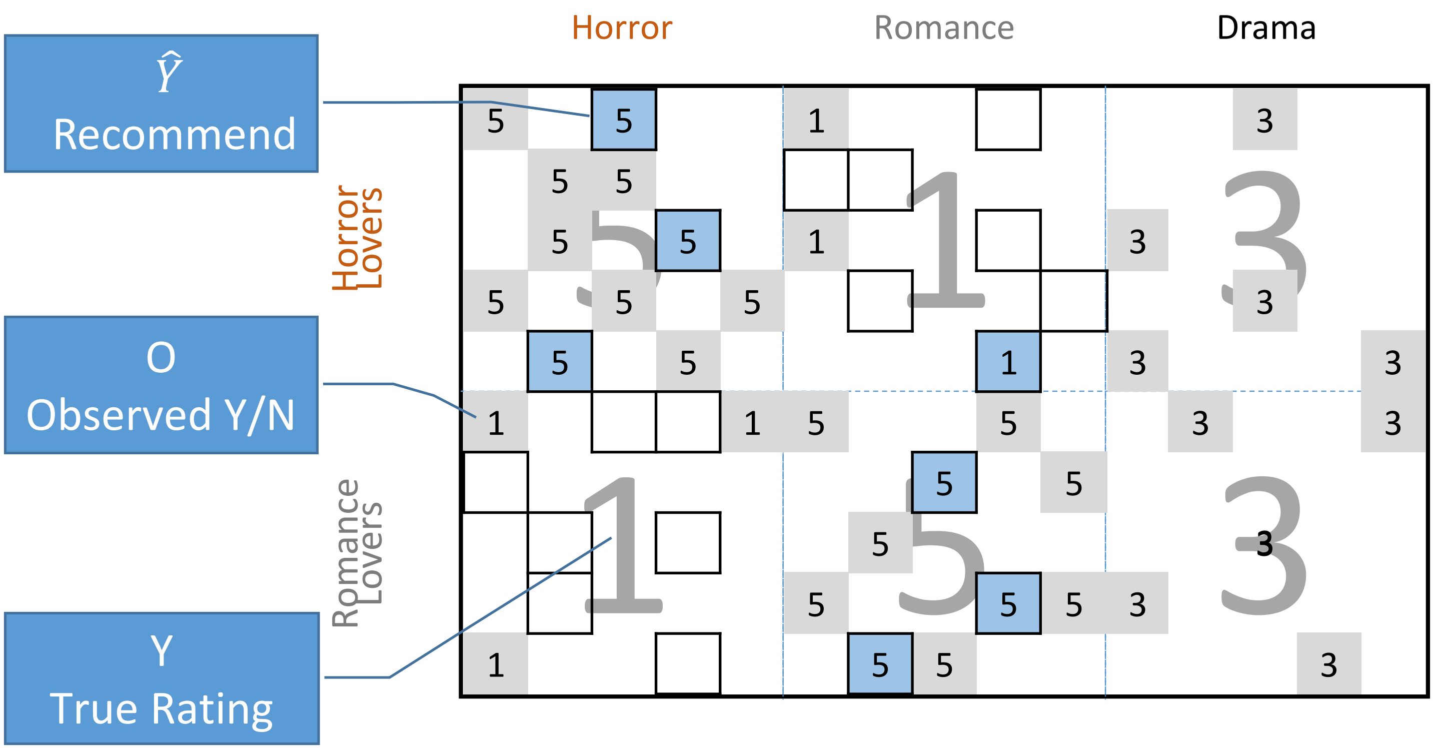
  - System-induced bias (e.g., advertising)



- **Question:** What happens if we ignore selection bias?

(Marlin et al., 2007; Steck, 2011; Hernándandez-Lobato et al., 2014)

Evaluating Recommendations under Selection Bias



⇒ Observed ratings are misleading due to selection bias

Evaluating Predicted Ratings under Selection Bias

$\hat{Y}_1$ Pred Ratings (worse)

	Horror					Romance					Drama				
Horror Lovers	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
Romance Lovers	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3

	Horror	Romance	Drama
Horror Lovers	5	1	3
Romance Lovers	1	5	3

$\hat{Y}_2$ Pred Ratings (better)

	Horror					Romance					Drama				
Horror Lovers	5	5	5	5	5	1	1	1	1	1	5	5	5	5	5
	5	5	5	5	5	1	1	1	1	1	5	5	5	5	5
	5	5	5	5	5	1	1	1	1	1	5	5	5	5	5
	5	5	5	5	5	1	1	1	1	1	5	5	5	5	5
	5	5	5	5	5	1	1	1	1	1	5	5	5	5	5
Romance Lovers	1	1	1	1	1	5	5	5	5	5	5	5	5	5	5
	1	1	1	1	1	5	5	5	5	5	5	5	5	5	5
	1	1	1	1	1	5	5	5	5	5	5	5	5	5	5
	1	1	1	1	1	5	5	5	5	5	5	5	5	5	5
	1	1	1	1	1	5	5	5	5	5	5	5	5	5	5

	Horror	Romance	Drama
Horror Lovers	5	1	3
Romance Lovers	1	5	3

Evaluating Predicted Ratings under Selection Bias

$\hat{Y}_1$
Pred Ratings (worse)

	Horror					Romance					Drama				
Horror Lovers	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
Romance Lovers	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3

$\hat{Y}_2$
Pred Ratings (better)

	Horror					Romance					Drama				
Horror Lovers	5	5	5	5	5	1	1	1	1	1	5	5	5	5	5
	5	5	5	5	5	1	1	1	1	1	5	5	5	5	5
	5	5	5	5	5	1	1	1	1	1	5	5	5	5	5
	5	5	5	5	5	1	1	1	1	1	5	5	5	5	5
	5	5	5	5	5	1	1	1	1	1	5	5	5	5	5
Romance Lovers	1	1	1	1	1	5	5	5	5	5	5	5	5	5	5
	1	1	1	1	1	5	5	5	5	5	5	5	5	5	5
	1	1	1	1	1	5	5	5	5	5	5	5	5	5	5
	1	1	1	1	1	5	5	5	5	5	5	5	5	5	5
	1	1	1	1	1	5	5	5	5	5	5	5	5	5	5

Evaluating Predicted Ratings under Selection Bias

$\hat{Y}_1$ Pred Ratings (worse)

	Horror					Romance					Drama				
Horror Lovers	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
Romance Lovers	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3
	5	5	5	5	5	5	5	5	5	5	3	3	3	3	3

$\hat{Y}_2$ Pred Ratings (better)

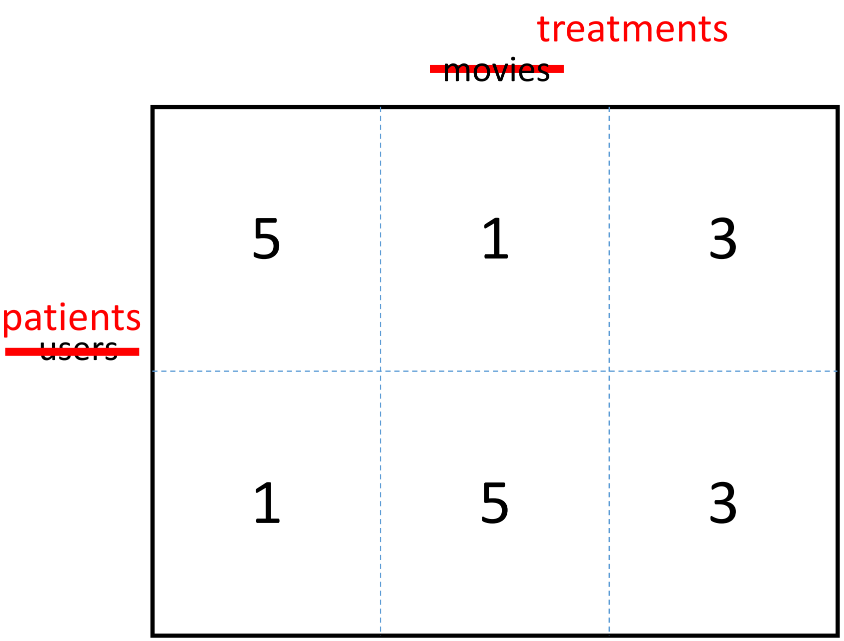
	Horror					Romance					Drama				
Horror Lovers	5	5	5	5	5	1	1	1	1	1	5	5	5	5	5
	5	5	5	5	5	1	1	1	1	1	5	5	5	5	5
	5	5	5	5	5	1	1	1	1	1	5	5	5	5	5
	5	5	5	5	5	1	1	1	1	1	5	5	5	5	5
	5	5	5	5	5	1	1	1	1	1	5	5	5	5	5
Romance Lovers	1	1	1	1	1	5	5	5	5	5	5	5	5	5	5
	1	1	1	1	1	5	5	5	5	5	5	5	5	5	5
	1	1	1	1	1	5	5	5	5	5	5	5	5	5	5
	1	1	1	1	1	5	5	5	5	5	5	5	5	5	5
	1	1	1	1	1	5	5	5	5	5	5	5	5	5	5

⇒ Observed losses are misleading due to selection bias

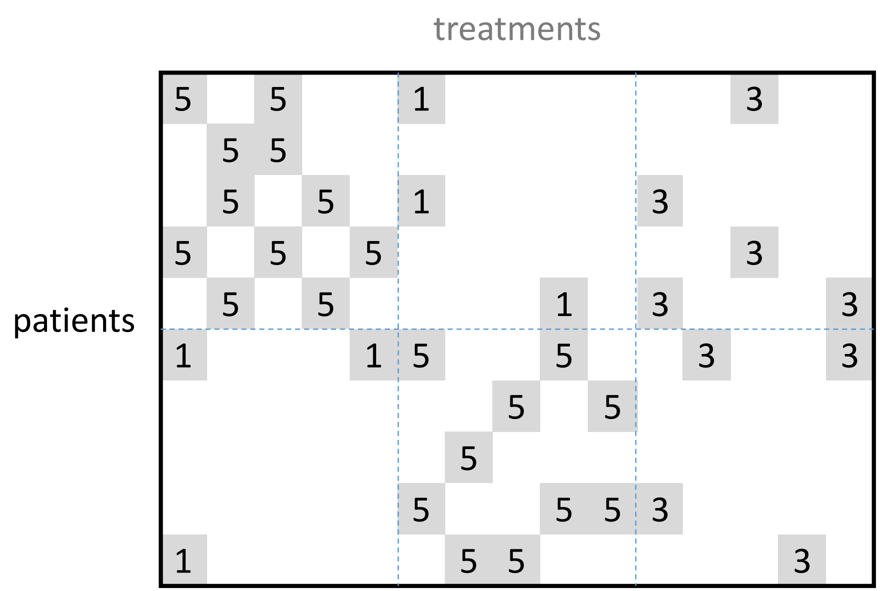
Recommendations as Treatments

- **Question:** How can we fix the effects of selection bias?
  - Connection to **potential outcomes framework**

Counterfactual Outcomes Y



Observed Outcomes $\tilde{Y}$



⇒ Understand **assignment mechanism** (Imbens & Ruben, 2015)

Debiasing Evaluation

- **Assignment mechansim** for recommendation:
  - $P_{u,i} = P(O_{u,i} = 1)$
- Use **Inverse-Propensity-Scoring Estimator (IPS)** to obtain unbiased estimate:

$$\hat{R}_{IPS}(\hat{Y}|P) = \frac{1}{U \cdot I} \sum_{(u,i):O_{ui}=1} \frac{1}{P_{u,i}} (Y_{u,i} - \hat{Y}_{u,i})^2$$

(Little & Rubin, 2002; Cortes et al., 2008; Bickel et al., 2009; Sugiyama & Kawanabe, 2012).

Propensities P

Horror	Romance	Drama
p	p/10	p/2
p/10	p	p/2

Propensity estimation

- Two settings:
  - **Experimental** – Propensities are under our control; known by design (e.g., ad placement)
  - **Observational** – Users self-select; need to estimate $P_{u,i}$
    - Estimate parameter of **binary** random variables:

$$P_{u,i} = P\left(O_{u,i} = 1 \mid X, \tilde{Y}\right)$$

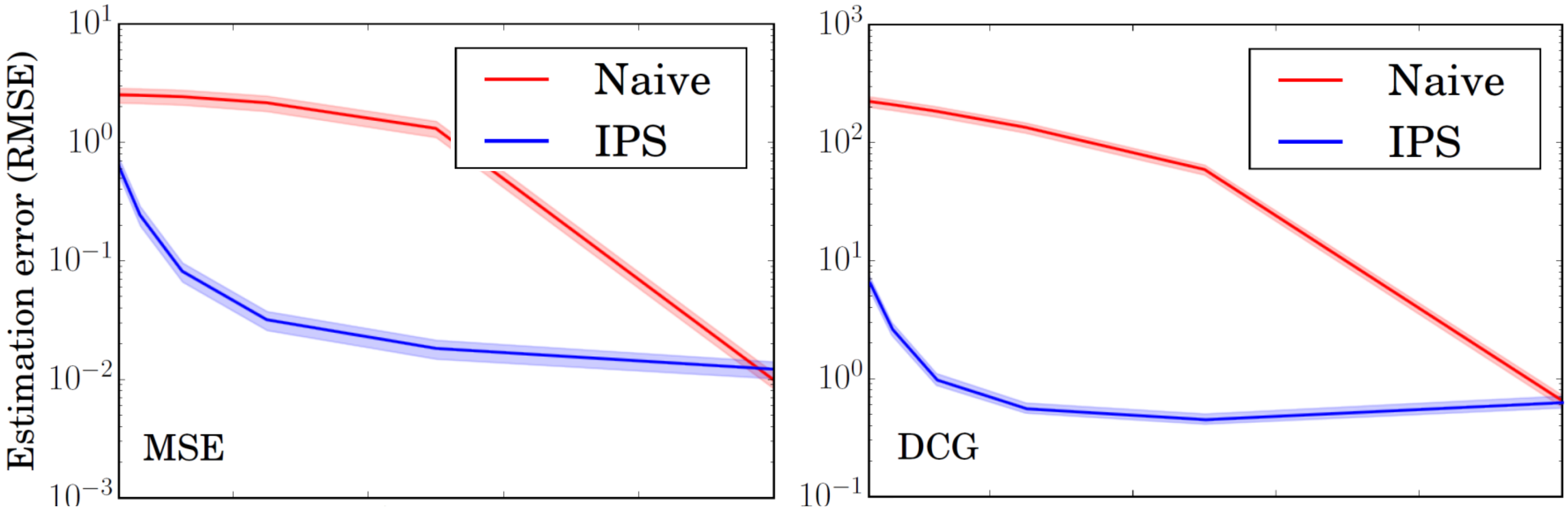
    - **Variety of models:** Logistic Regression, Naïve Bayes, etc.

Observations O

Horror					Romance					Drama				
1	0	1	0	0	1	0	0	0	0	0	0	1	0	0
0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	1	0	1	0	0	0	0	1	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	1	0	0
0	1	0	1	0	0	0	0	1	0	1	0	0	0	1
1	0	0	0	1	1	0	0	1	0	0	1	0	0	1
0	0	0	0	0	0	0	1	0	1	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	0	0	1	0	0
0	0	0	0	0	1	0	0	0	1	1	0	0	0	0
1	0	0	0	0	0	1	1	0	0	0	0	0	1	0

Debiasing Evaluation

- Robustness to selection bias:

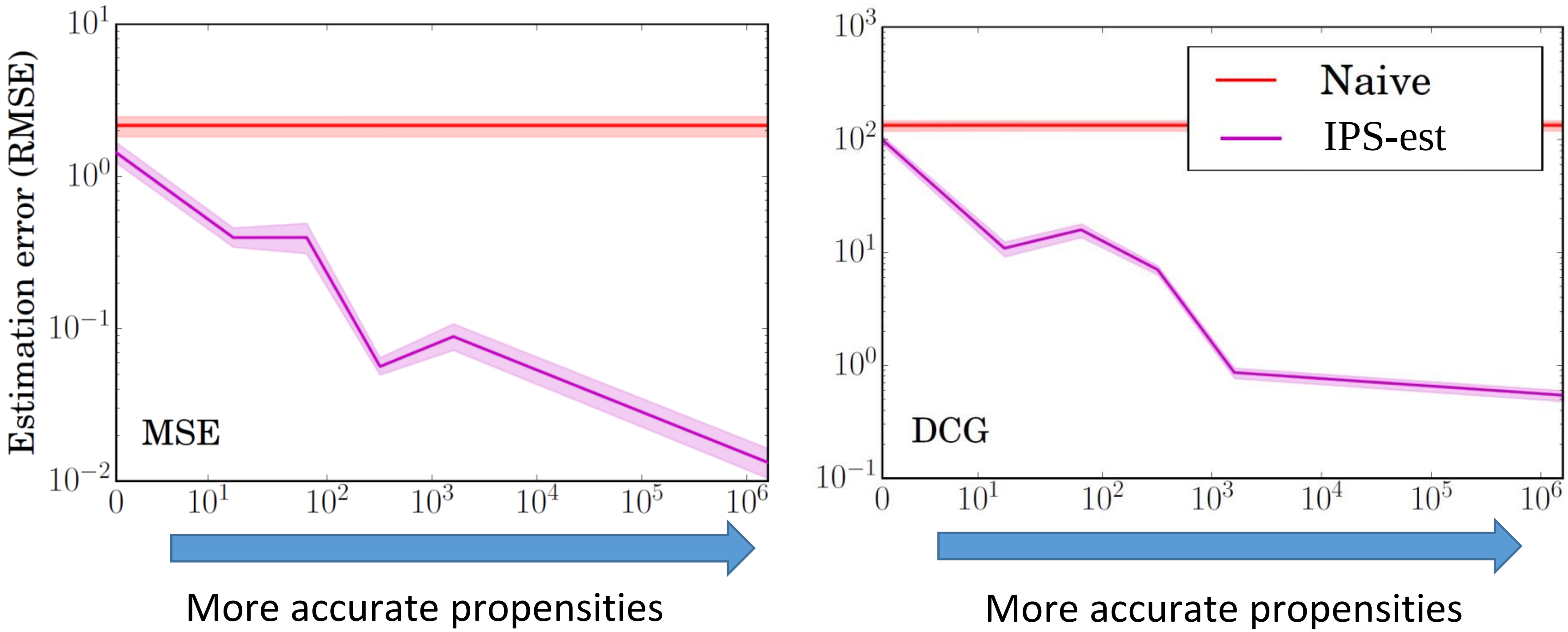


Severity of Selection Bias

Severity of Selection Bias

Debiasing Evaluation

- Robustness to inaccurate propensities:



Debiasing Learning

- **Empirical Risk Minimization** (ERM) successful in many settings (Cortes & Vapnik, 1995)
- Use **ERM** together with **Inverse-Propensity-Scoring Estimator (IPS)**

$$\hat{Y}^{ERM} = \underset{\hat{Y} \in \mathcal{H}}{\operatorname{argmin}} \left\{ \hat{R}_{IPS}\left(\hat{Y} \mid P\right) \right\}$$

- For **matrix factorization** with MSE loss:

$$\hat{Y}^{ERM} = \underset{V,W}{\operatorname{argmin}} \left\{ \sum_{O_{u,i}=1} \frac{1}{P_{u,i}} \left(Y_{u,i} - V_u W_i\right)^2 + \lambda \left(\|V\|_F^2 + \|W\|_F^2 \right) \right\}$$

propensity weight

Generalization Error

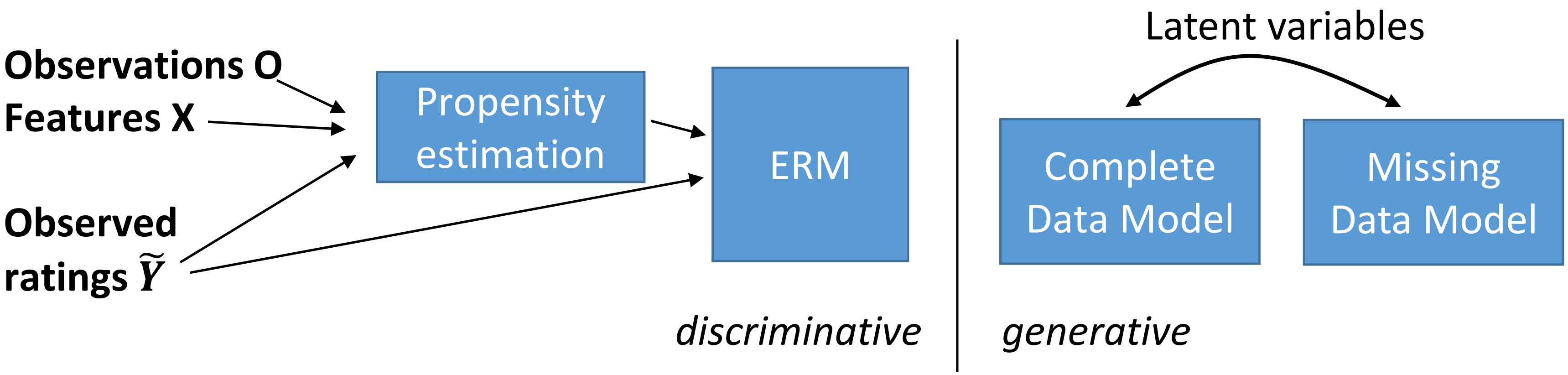
- **Theoretical** insights:
  - **Additional trade-off** between bias and variance
- With probability $1-\eta$, capacity $|\mathcal{H}|$, maximum loss Δ:

$$R\left(\hat{Y}^{ERM}\right) \leq \hat{R}_{IPS}\left(\hat{Y}^{ERM}|\hat{P}\right) + \frac{\Delta}{U \cdot I} \underbrace{\sum_{u,i} \left|1 - \frac{P_{u,i}}{\hat{P}_{u,i}}\right|}_{\text{Bias}}$$

$$+ \frac{\Delta}{U \cdot I} \sqrt{\frac{\log(2|\mathcal{H}|\eta)}{2}} \underbrace{\sqrt{\sum_{u,i} \frac{1}{\hat{P}_{u,i}^2}}}_{\text{Variance}}$$

Propensity-scored ERM

- Approach is **modular** and **discriminative**:
  1. Pick and estimate propensity model
  2. Use estimated propensities in ERM objective



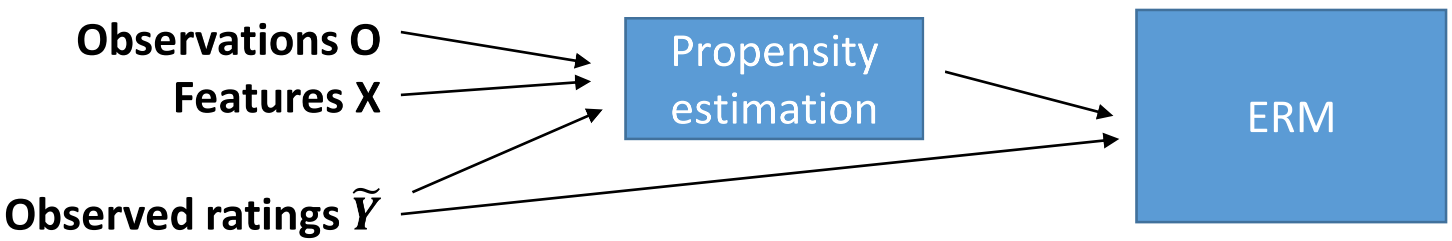
(Marlin et al., 2007; Steck, 2011; Hernándandez-Lobato et al., 2014)

Debiasing Learning

- Results on two **real-world datasets**:
  - COAT: Shopping dataset (300 users; newly collected)
  - YAHOO: Song rating dataset (15400 users; Marlin & Zemel, 2009)
- Report performance on **MAR test data**:
  - HL: Latest generative approach (Hernández-Lobato et al., 2014)

	YAHOO		COAT	
	MAE	MSE	MAE	MSE
MF-IPS	**0.810**	**0.989**	**0.860**	**1.093**
MF-Naive	1.154	1.891	0.920	1.202
HL MNAR	1.177	2.175	0.884	1.214
HL MAR	1.179	2.166	0.892	1.220

Conclusions



- **Discriminative propensity scoring**:
  - Modular
  - Directly optimizes target loss
  - No latent variables
  - Scalable
- **Data** and **code**:
  - http://www.cs.cornell.edu/~schnabts/mnar/