Counterfactual Risk Minimization
Learning from logged bandit feedback

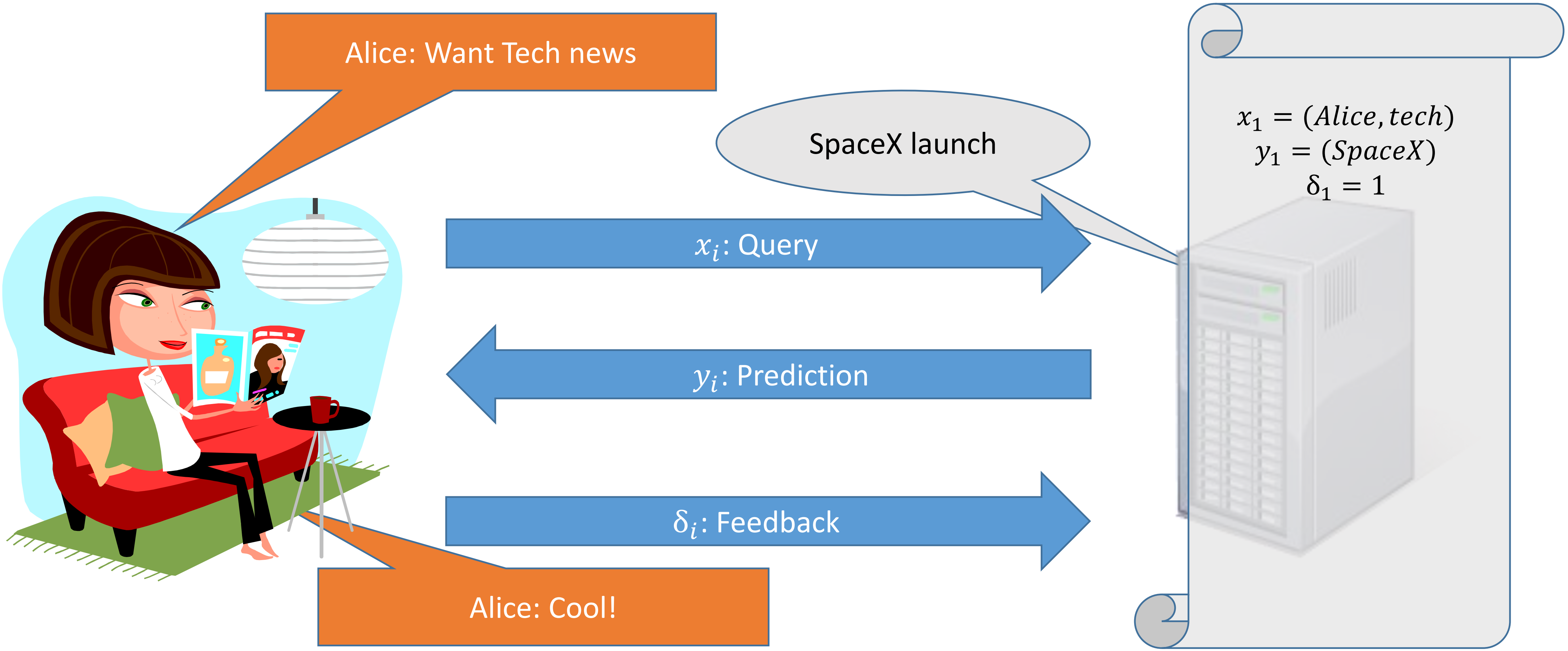
Adith Swaminathan, Thorsten Joachims

Software: http://www.cs.cornell.edu/~adith/poem/

Learning frameworks

x / y	**Online**	**Batch**
Full Information	Perceptron, …	SVM, …
Bandit Feedback	LinUCB, …	?

Logged bandit feedback is everywhere!



Goal

- Risk of $h: \mathbb{X} \mapsto \mathbb{Y}$

$$R(h) = \mathbb{E}_x[\delta(x, h(x))]$$

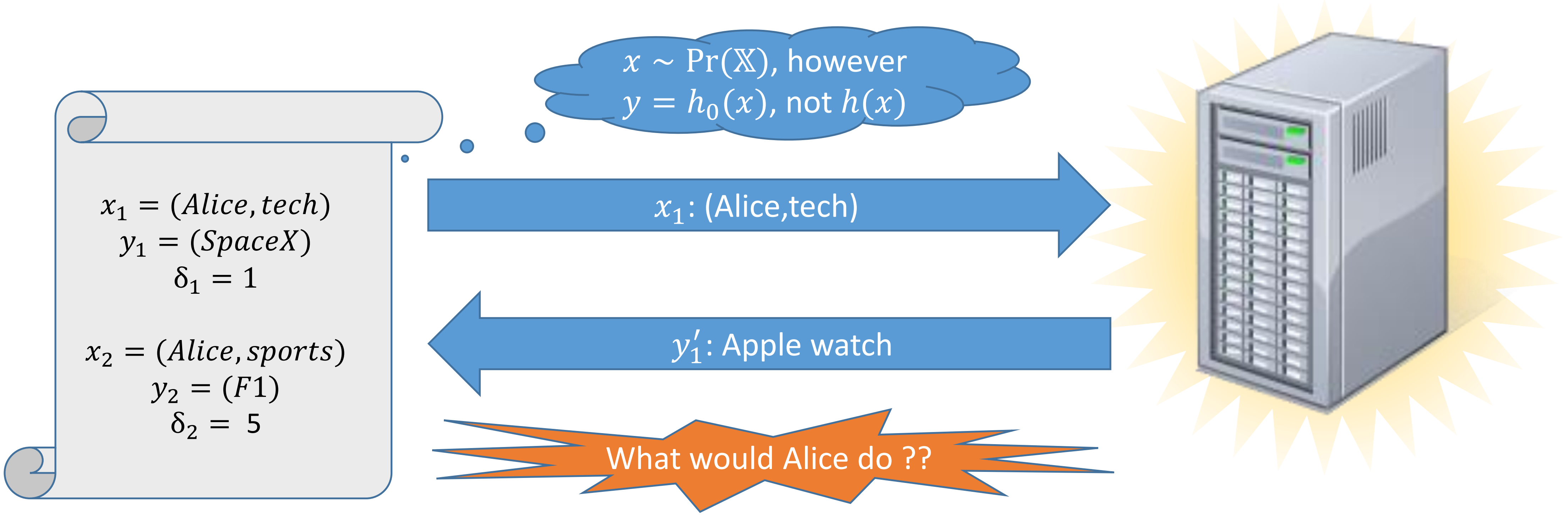
- Find $h^* \in \boldsymbol{\mathcal{H}}$ with minimum risk

- Can we find h^* using $\mathcal{D} =$ collected from h_0?

$$x_1 = (Alice, tech)$$
$$y_1 = (SpaceX)$$
$$\delta_1 = 1$$

$$x_2 = (Alice, sports)$$
$$y_2 = (F1)$$
$$\delta_2 = 5$$

Learning by replaying logs?

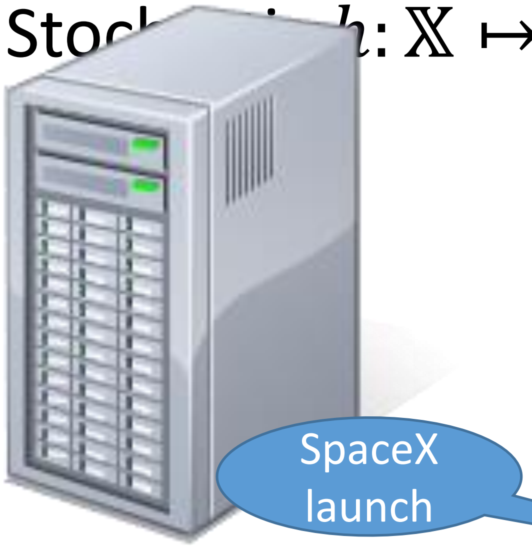


- Training/evaluation from logged data is counter-factual [Bottou et al]

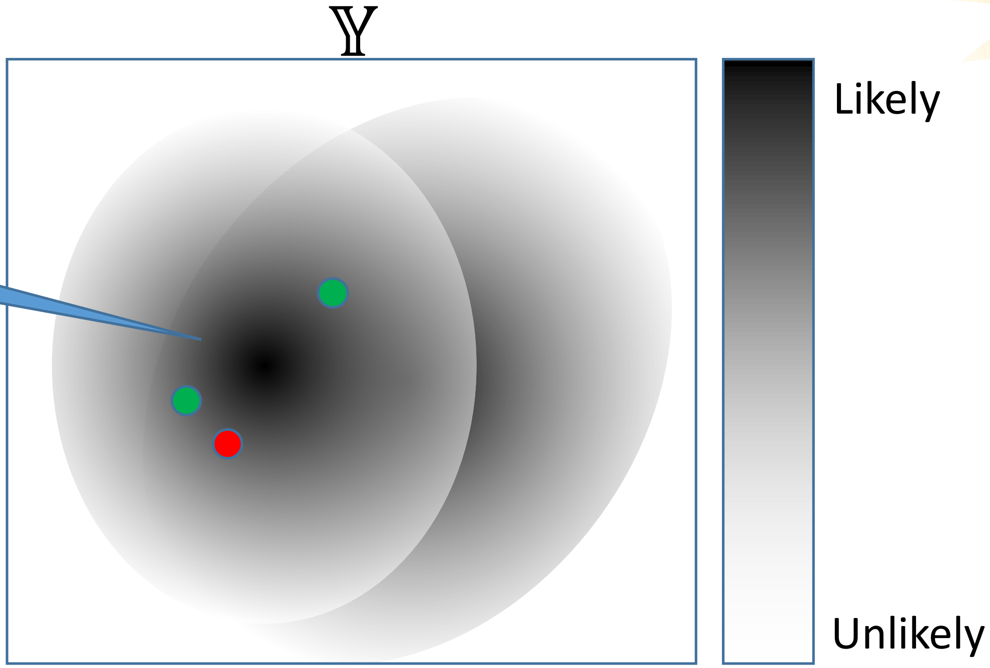
Stochastic policies to the rescue!

- Stoc[illegible] $h: \mathbb{X} \mapsto \Delta(\mathbb{Y}), y \sim h(x)$

$$R(h) = \mathbb{E}_x \mathbb{E}_{y \sim h(x)}[\delta(x, y)]$$



h_0



h

Counterfactual risk estimators

Basic Importance Sampling [Owen]

$$\mathbb{E}_x\left[\ \mathbb{E}_{y\sim h}\left[\ \delta(x,y)\ \right]\ \right] = \mathbb{E}_x\left[\ \mathbb{E}_{y\sim h_o}\left[\ \delta(x,y)\,\frac{h(y|x)}{h_0(y|x)}\right]\ \right]$$

Perf of new system

Samples from old system

Importance weight

- $\mathcal{D} = \{\ (x_1, y_1, \delta_1, p_1), (x_2, y_2, \delta_2, p_2), \dots, (x_n, y_n, \delta_n, p_n)\ \}$
- $p_i = h_0(y_i|x_i)$ … *propensity* [Rosenbaum et al]

$$\widehat{R_{\mathcal{D}}}(h) = \frac{1}{n}\sum_{i=1}^{n} \delta_i \frac{h(y_i|x_i)}{p_i}$$

Story so far

Logged bandit data → Fix h $vs.$ h_0 mismatch → Control variance → Tractable bound

Importance sampling causes non-uniform variance!

$x_1 = (Alice, sports)$
$y_1 = (F1)$
$\delta_1 = 5$
$p_1 = 0.9$

Want: Error bound that captures variance of importance sampling

$= (Sta$
$\delta_3 = 2$
$p_3 = 0.9$

$x_4 = (Alice, tech)$
$y_4 = (Tesla)$
$\delta_4 = 1$
$p_4 = 0.9$

h_1

$\widehat{R_{\mathcal{D}}}(h_1) = 1$

h_2

$\widehat{R_{\mathcal{D}}}(h_2) = 1.33$

Counterfactual Risk Minimization

- W.h.p. in $\mathcal{D} \sim h_0$

$$\forall h \in \boldsymbol{\mathcal{H}}, \qquad R(h) \leq \widehat{R_{\mathcal{D}}}(h) + O\left(\sqrt{\widehat{Var_{\mathcal{D}}}(h)/n}\right) + O(\boldsymbol{\mathcal{N}}_{\infty}(\boldsymbol{\mathcal{H}})/n)$$

*conditions apply. Refer [Maurer et al]

Empirical risk

Variance regularization

Capacity control

Learning objective

$$h^{CRM} = \operatorname*{argmin}_{h \in \boldsymbol{\mathcal{H}}} \widehat{R_{\mathcal{D}}}(h) + \lambda \sqrt{\frac{\widehat{Var_{\mathcal{D}}}(h)}{n}}$$

POEM: CRM algorithm for structured prediction

- CRFs: $h_w \in \mathcal{H}_{lin}$; $h_w(y|x) = \dfrac{\exp(w\phi(x,y))}{\mathbb{Z}(x;w)}$

- **P**olicy **O**ptimizer for **E**xponential **M**odels :

$$w^* = \underset{w}{\operatorname{argmin}} \left[\frac{1}{n} \sum_{i=1}^{n} \delta_i \frac{h_w(y_i|x_i)}{p_i} + \lambda \sqrt{\frac{\widehat{Var}(\boldsymbol{h}_w)}{n}} + \mu \|w\| \right]$$

Good: Gradient descent, search over infinitely many w

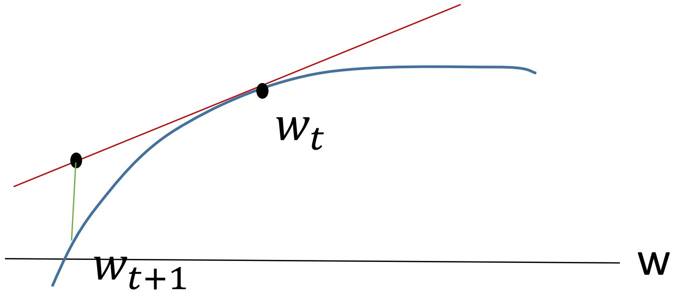
Bad: Not convex in w

Ugly: Resists stochastic optimization

Stochastically optimize $\sqrt{\widehat{Var}(\boldsymbol{h}_w)}$?

- Taylor-approximate!

$$\sqrt{\widehat{Var}(\boldsymbol{h}_w)} \leq A_{w_t} \sum_{i=1}^{n} h_w^i + B_{w_t} \sum_{i=1}^{n} \{h_w^i\}^2 + C_{w_t}$$



- During epoch: Adagrad with $\nabla h_w^i + \lambda\sqrt{n}(A_{w_t} \nabla h_w^i + 2B_{w_t} h_w^i \nabla h_w^i)\}$
- After epoch: $w_{t+1} \leftarrow w$, compute $A_{w_{t+1}}, B_{w_{t+1}}$

Experiment

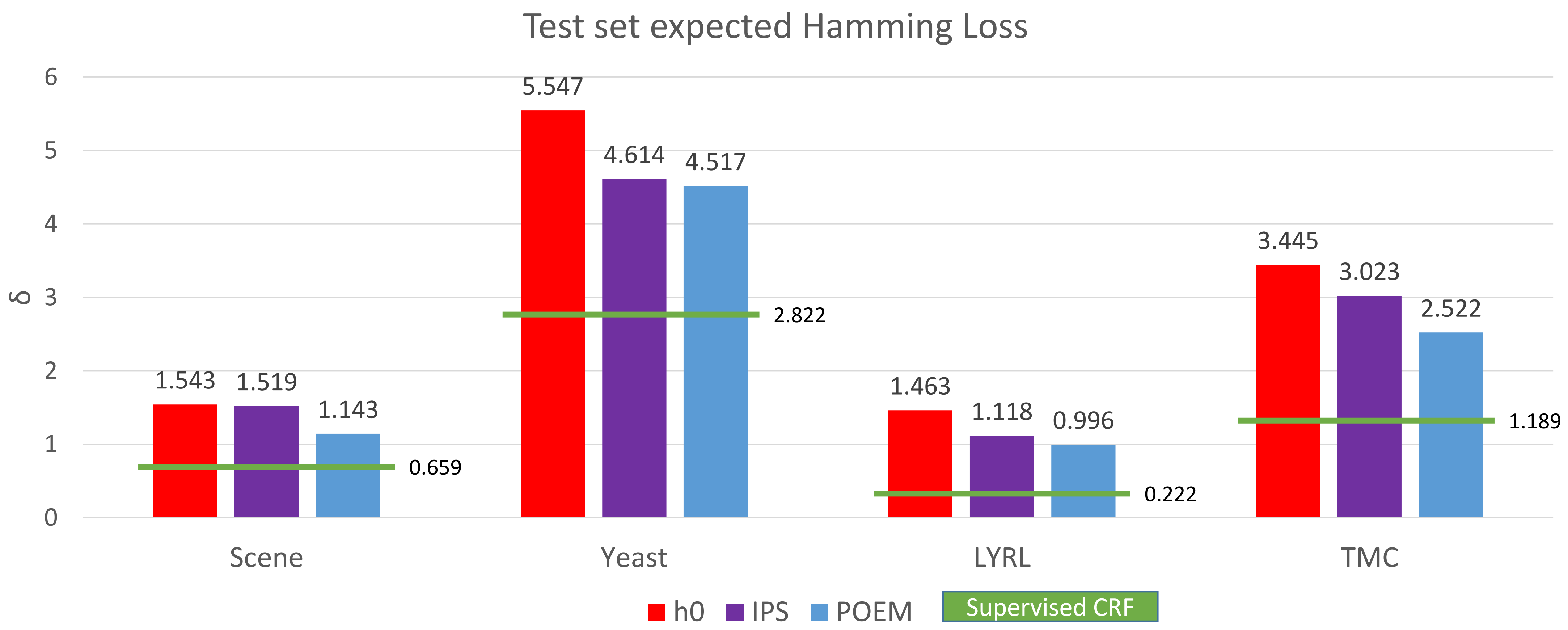
- Supervised → Bandit **MultiLabel** [Agarwal et al]
- $\delta(x, y) = \text{Hamming}(y^*(x), y)$ (smaller is better)
- LibSVM Datasets
  - Scene (few features, labels and data)
  - Yeast (many labels)
  - LYRL (many features and data)
  - TMC (many features, labels and data)

- Validate hyper-params (λ,μ) using $\hat{R}_{\mathcal{D}_{val}}(h)$
- Supervised test set expected Hamming loss

Approaches

- Baselines
  - h_0: Supervised CRF trained on 5% of training data
- Proposed
  - IPS (No variance penalty) (extends [Bottou et al])
  - POEM
- Skylines
  - Supervised CRF (independent logit regression)

(1) Does variance regularization help?

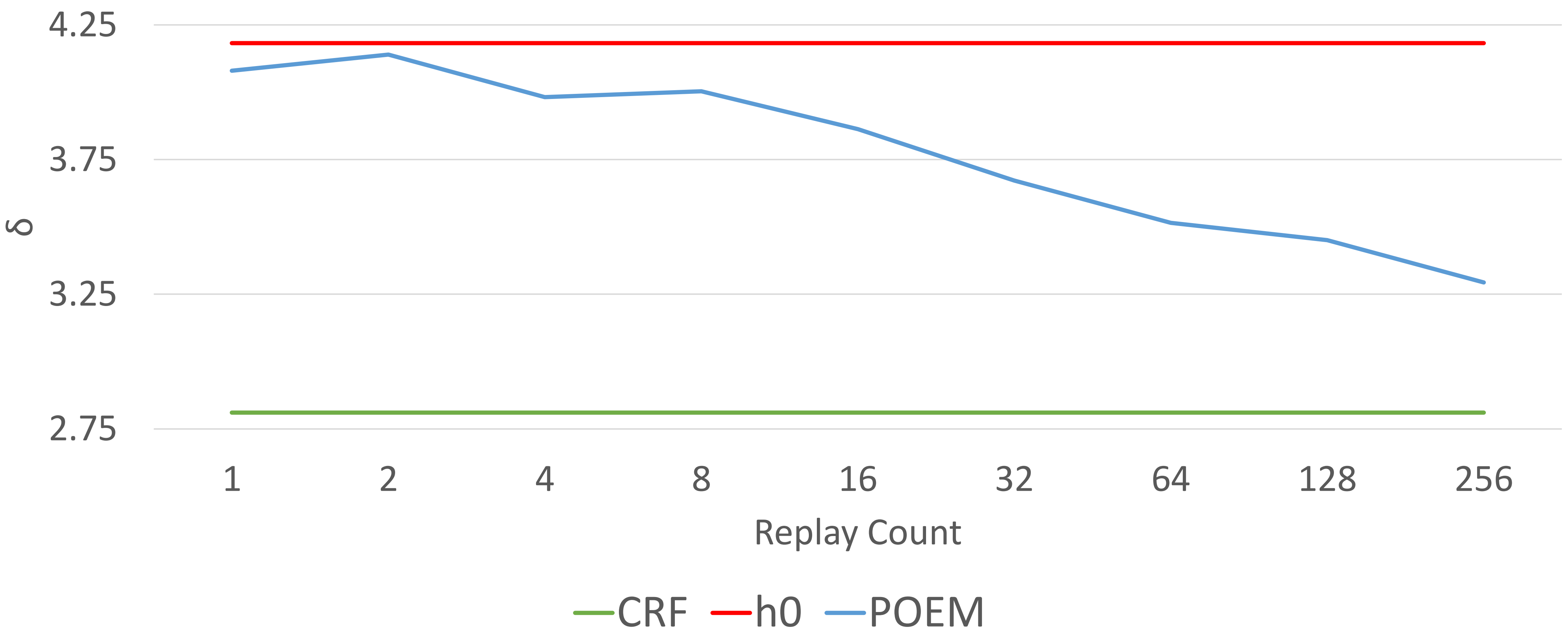


(2) Is it efficient?

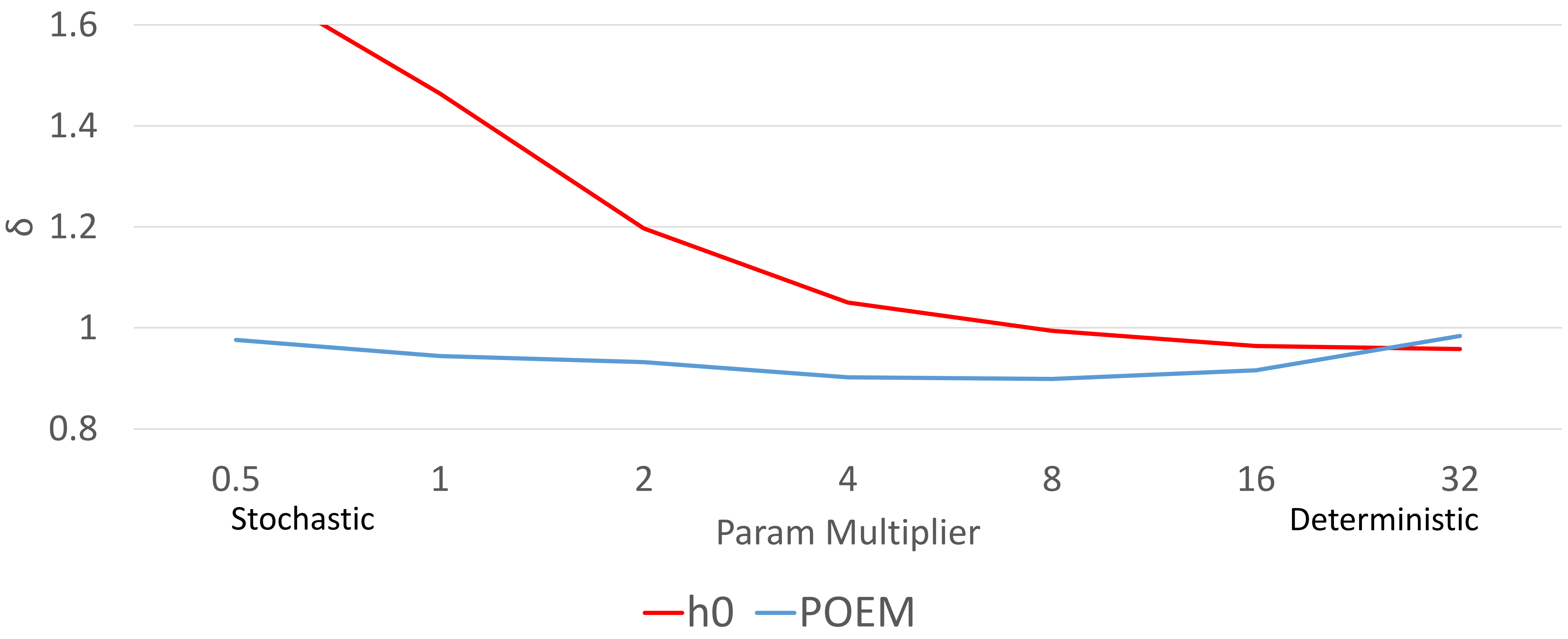
Avg Time (s)	Scene	Yeast	LYRL	TMC
POEM(B)	75.20	94.16	561.12	949.95
POEM(S)	4.71	5.02	120.09	276.13
CRF	4.86	3.28	62.93	99.18

- POEM recovers same performance at fraction of L-BFGS cost
- Scales as supervised CRF, learns from bandit feedback

(3) Does generalization improve as $n \to \infty$?



(4) Does stochasticity of h_0 affect learning?



Conclusion

- CRM principle to learn from logged bandit feedback
  - Variance regularization
- POEM for structured output prediction
  - Scales as supervised CRF, learns from bandit feedback

- Contact: adith@cs.cornell.edu
- POEM available at http://www.cs.cornell.edu/~adith/poem/

- Long paper: Counterfactual risk minimization – Learning from logged bandit feedback, http://jmlr.org/proceedings/papers/v37/swaminathan15.html

- Thanks!

References

1. Art B. Owen. 2013. *Monte Carlo theory, methods and examples*.
2. Paul R. Rosenbaum and Donald B. Rubin. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika 70.* 41-55.
3. Léon Bottou, Jonas Peters, Joaquin Quiñonero-Candela, Denis X. Charles, D. Max Chickering, Elon Portugaly, Dipankar Ray, Patrice Simard, and Ed Snelson. 2013. Counterfactual reasoning and learning systems: the example of computational advertising. *J. Mach. Learn. Res.* 14, 1, 3207-3260.
4. Alekh Agarwal, Daniel Hsu, Satyen Kale, John Langford, Lihong Li and Robert Schapire. 2014. Taming the Monster: A Fast and Simple Algorithm for Contextual Bandits. Proceedings of the 31st International Conference on Machine Learning. 1638-1646.
5. Andreas Maurer and Massimiliano Pontil. 2009. Empirical bernstein bounds and sample-variance penalization. Proceedings of the 22nd Conference on Learning Theory.
6. Adith Swaminathan and Thorsten Joachims. 2015. Counterfactual risk minimization: Learning from logged bandit feedback. Proceedings of the 32nd International Conference on Machine Learning.