Safe Reinforcement Learning

Philip S. Thomas

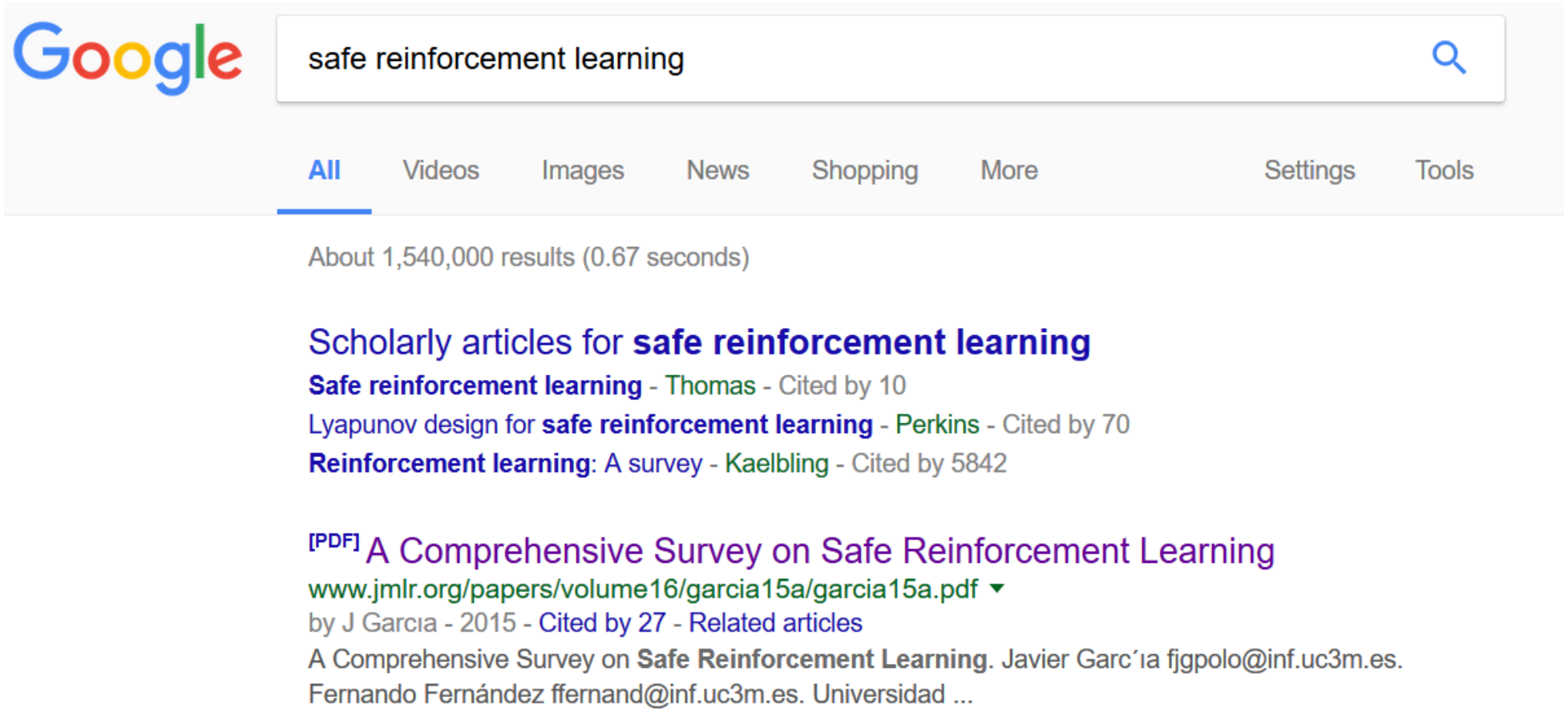
Stanford CS234: Reinforcement Learning, Guest Lecture

May 24, 2017

Lecture overview

- What makes a reinforcement learning algorithm *safe*?
- Notation
- Creating a safe reinforcement learning algorithm
  - Off-policy policy evaluation (OPE)
  - High-confidence off-policy policy evaluation (HCOPE)
  - Safe policy improvement (SPI)
- Empirical results
- Research directions

What does it mean for a reinforcement learning algorithm to be *safe*?



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A Comprehensive Survey on Safe Reinforcement Learning

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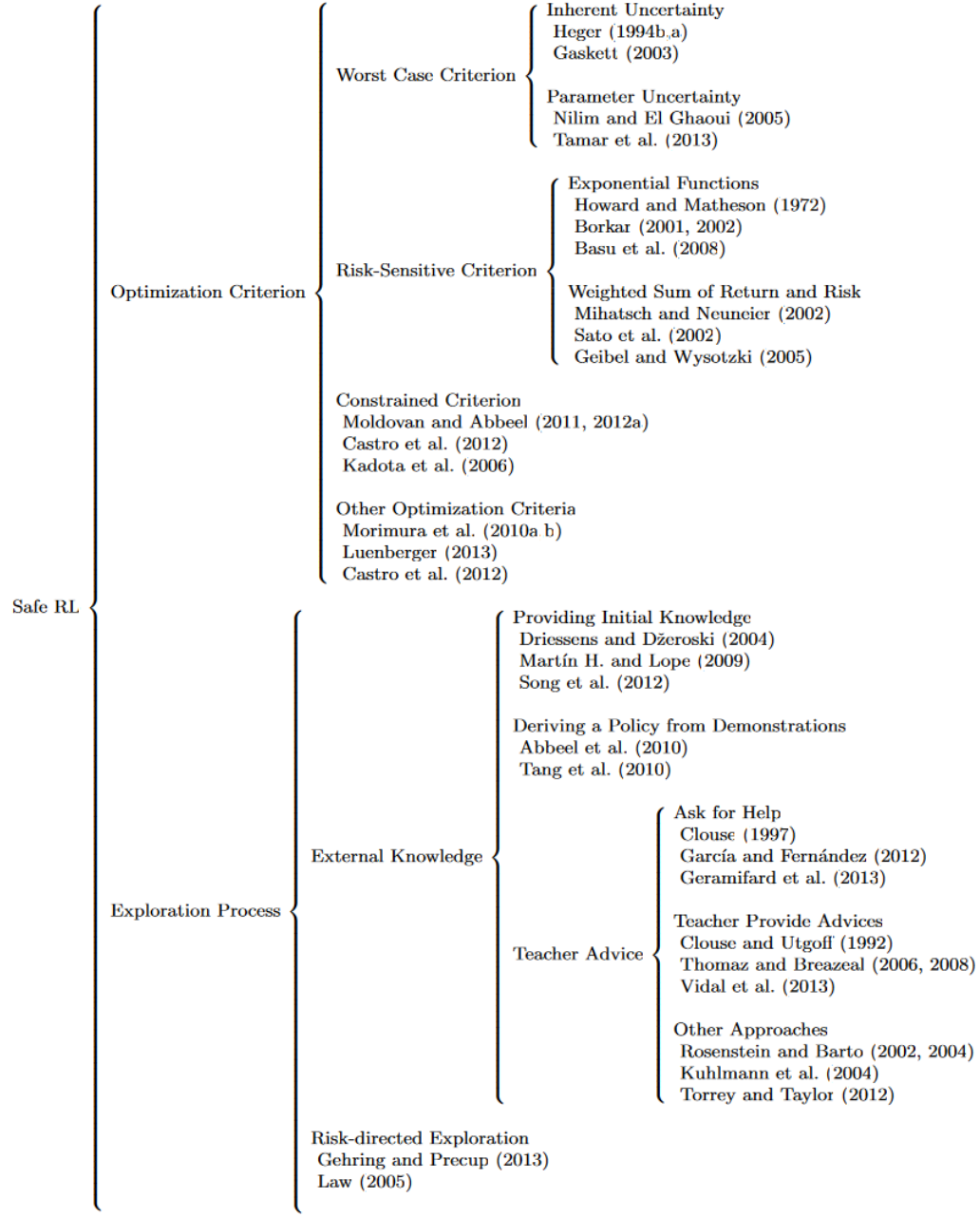
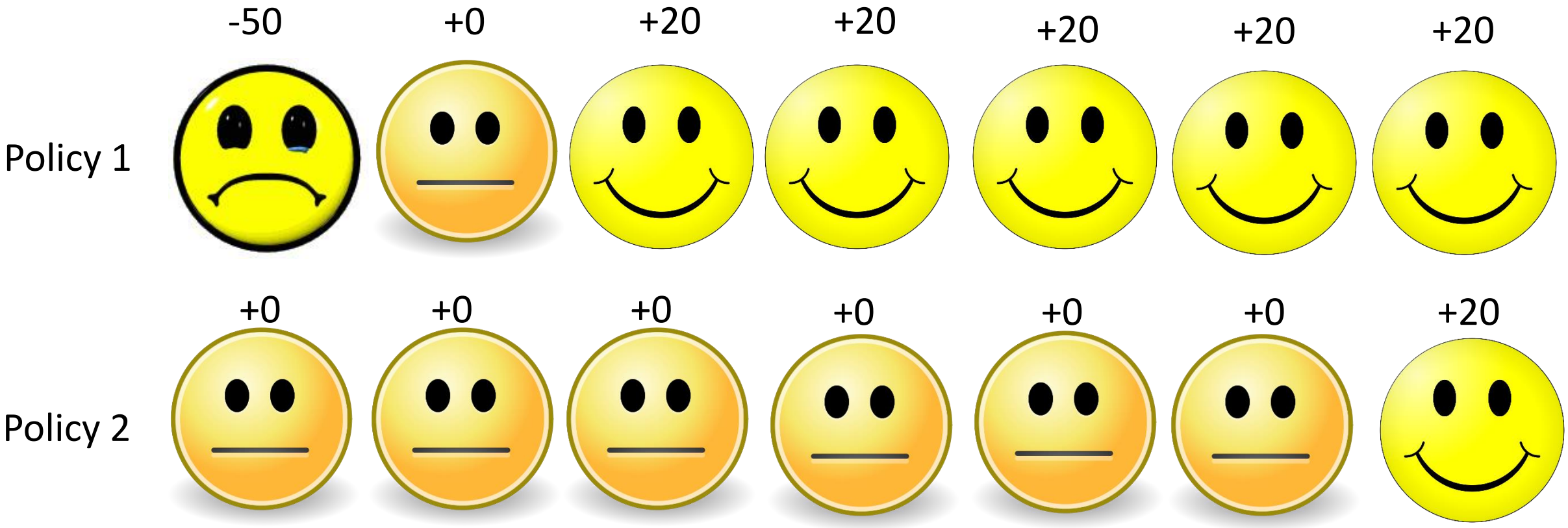


Table 1: Overview of the approaches for Safe Reinforcement Learning considered in this survey.

Changing the objective



Changing the objective

- Policy 1:
  - Reward = 0 with probability 0.999999
  - Reward = 10^9 with probability 1-0.999999
  - Expected reward approximately 1000
- Policy 2:
  - Reward = 999 with probability 0.5
  - Reward = 1000 with probability 0.5
  - Expected reward 999.5

Another notion of safety

Safe and efficient off-policy reinforcement learning

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Another notion of safety (Munos et. al)

We start from the recent work of Harutyunyan et al. (2016), who show that naive off-policy policy evaluation, without correcting for the "off-policyness" of a trajectory, still converges to the desired Q^π value function provided the behavior μ and target π policies are not too far apart (the maximum allowed distance depends on the λ parameter). Their $Q^\pi(\lambda)$ algorithm learns from trajectories generated by μ simply by summing discounted off-policy corrected rewards at each time step. Unfortunately, the assumption that μ and π are close is restrictive, as well as difficult to uphold in the control case, where the target policy is greedy with respect to the current Q-function. In that sense this algorithm is not *safe*: it does not handle the case of arbitrary "off-policyness".

Alternatively, the Tree-backup (TB(λ)) algorithm (Precup et al., 2000) tolerates arbitrary target/behavior discrepancies by scaling information (here called *traces*) from future temporal differences by the product of target policy probabilities. TB(λ) is not *efficient* in the "near on-policy" case (similar μ and π), though, as traces may be cut prematurely, blocking learning from full returns.

Another notion of safety

Reachability-Based Safe Learning with Gaussian Processes

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SAFE REINFORCEMENT LEARNING

A Dissertation Presented

by

PHILIP S. THOMAS

The Problem

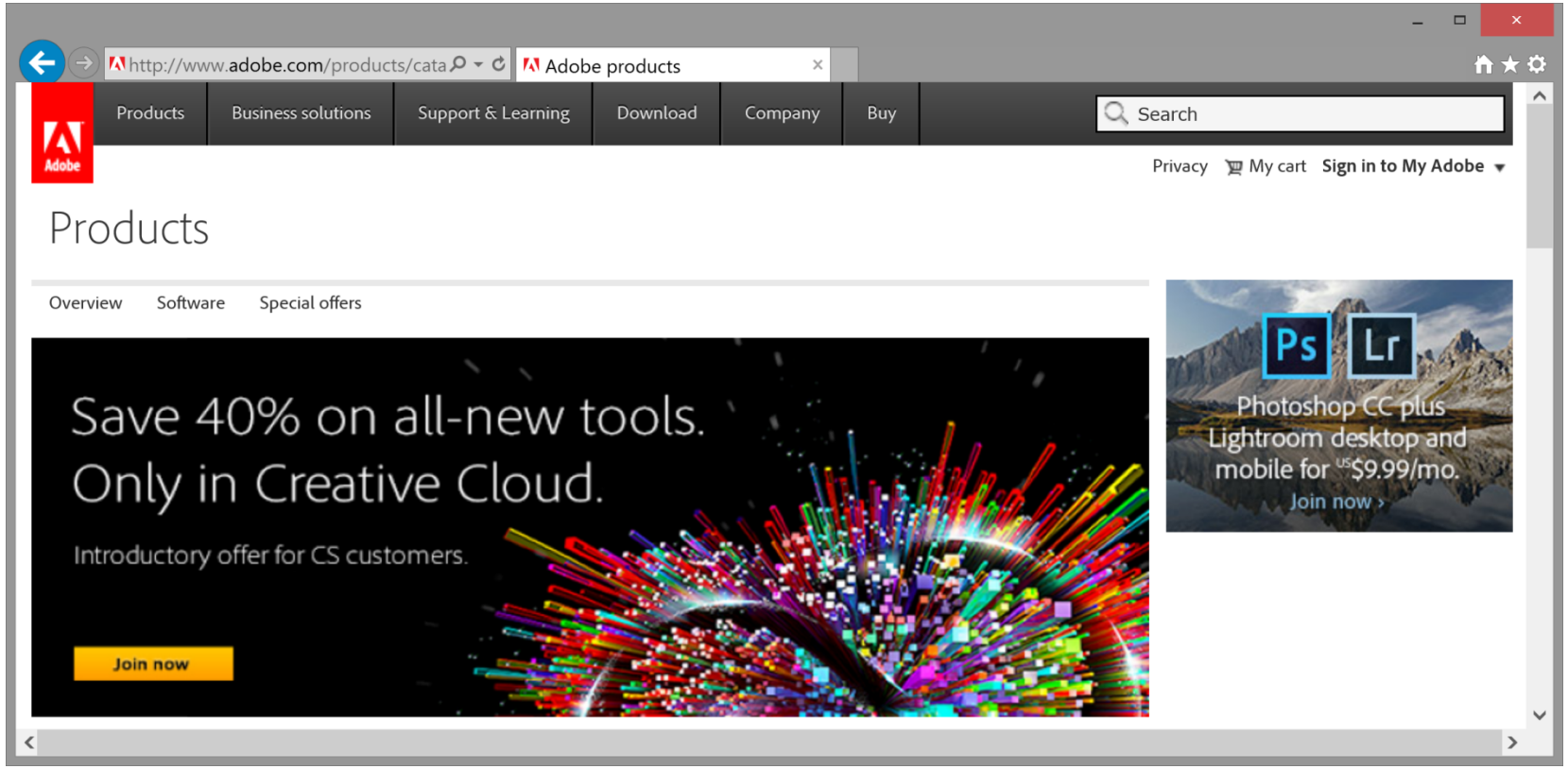
- If you apply an existing method, do you have confidence that it will work?

Reinforcement learning successes

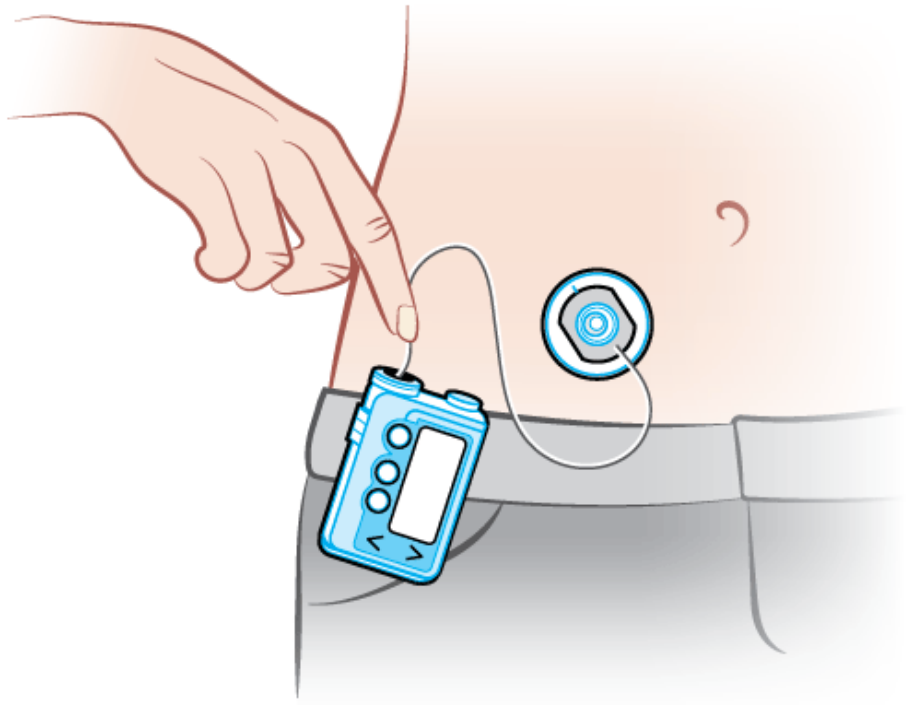
A property of many real applications

- Deploying “bad” policies can be **costly** or **dangerous**.

Deploying bad policies can be **costly**



Deploying bad policies can be **dangerous**



What property should a *safe* algorithm have?

- Guaranteed to work on the first try
  - "I guarantee that with probability at least $1 - \delta$, I will not change your policy to one that is worse than the current policy."
  - You get to choose δ
  - This guarantee is not contingent on the tuning of any hyperparameters

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Notation

- Policy, π

$$\pi(a|s) = \Pr(A_t = a|S_t = s)$$

- History:

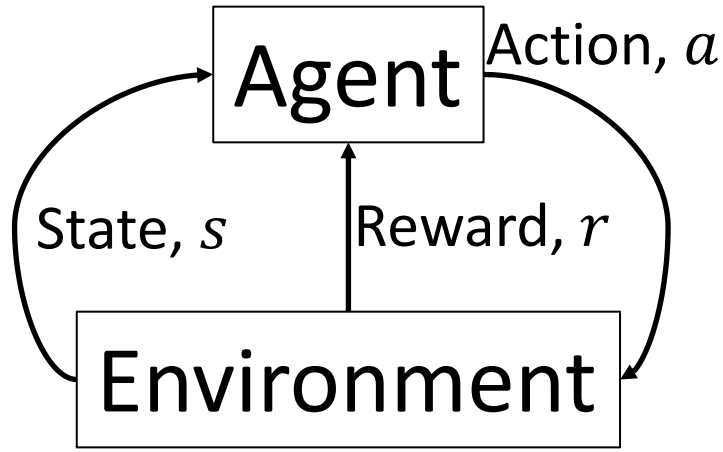
$$H = (s_1, a_1, r_1, s_2, a_2, r_2, \dots, s_L, a_L, r_L)$$

- Historical data:

$$D = \{H_1, H_2, \dots, H_n\}$$

- Historical data from *behavior policy*, π_{b}
- Objective:

$$J(\pi) = \mathbf{E}\left[\sum_{t=1}^{L} \gamma^t R_t \middle| \pi\right]$$



Safe reinforcement learning algorithm

- Reinforcement learning algorithm, a
- Historical data, D, which is a random variable
- Policy produced by the algorithm, $a(D)$, which is a random variable
- A safe reinforcement learning algorithm, a, satisfies:

$$\Pr\left(J\left(a(D)\right) \geq J(\pi_{\mathrm{b}})\right) \geq 1 - \delta$$

or, in general:

$$\Pr\left(J\left(a(D)\right) \geq J_{\min}\right) \geq 1 - \delta$$

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Creating a safe reinforcement learning algorithm

- Off-policy policy evaluation (OPE)
  - For any *evaluation policy*, π_{e}, Convert historical data, D, into n independent and unbiased estimates of $J(\pi_{\mathrm{e}})$
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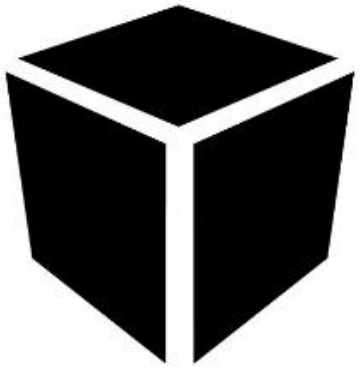
  - Use a concentration inequality to convert the n independent and unbiased estimates of $J(\pi_{\mathrm{e}})$ into a $1-\delta$ confidence lower bound on $J(\pi_{\mathrm{e}})$
- Safe policy improvement (SPI)
  - Use HCOPE method to create a safe reinforcement learning algorithm, a

Off-policy policy evaluation (OPE)

Historical Data, D
Proposed Policy, π_{e}

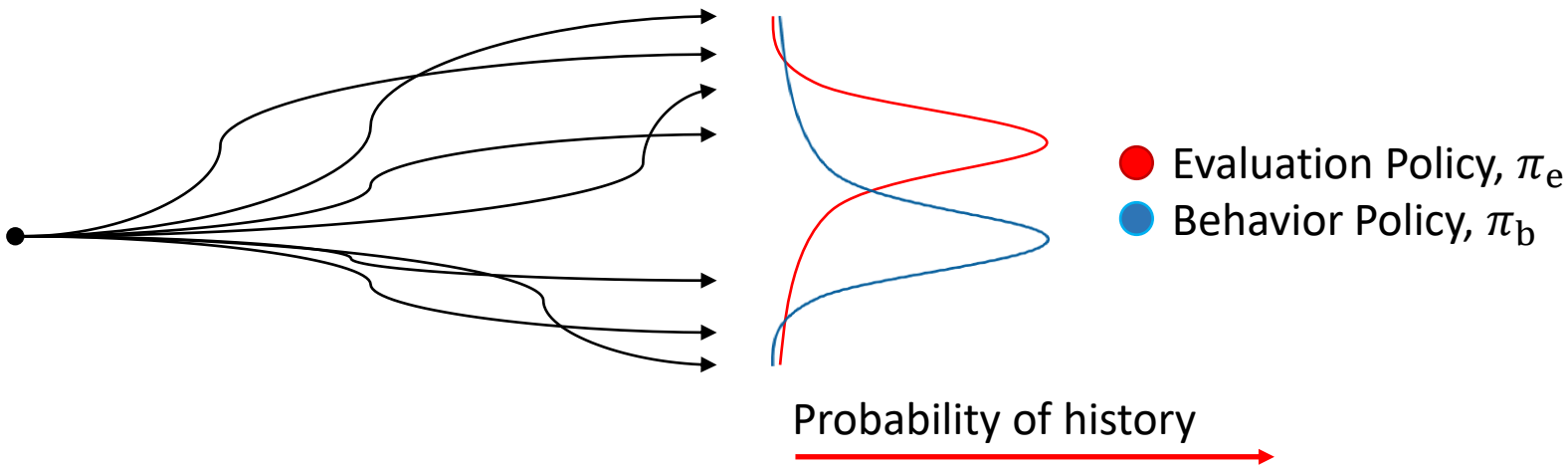


Estimate of $J(\pi_{\mathrm{e}})$

Importance Sampling (Intuition)

- Reminder:
  - History, $H = (s_1, a_1, r_1, s_2, a_2, r_2, \ldots, s_L, a_L, r_L)$
  - Objective, $J(\pi_e) = \mathbf{E}[\sum_{t=1}^{L} \gamma^t R_t \,|\pi_e]$

$$\hat{J}(\pi_e) = \frac{1}{n} \sum_{i=1}^{n} w_i \sum_{t=1}^{L} \gamma^t R_t^i$$



$$w_i = \frac{\Pr(H_i|\pi_e)}{\Pr(H_i|\pi_b)} = \prod_{t=1}^{L} \frac{\pi_e(a_t|s_t)}{\pi_b(a_t|s_t)}$$

Importance sampling (History)

- Kahn, H., Marhshall, A. W. (1953). Methods of reducing sample size in Monte Carlo computations. In *Journal of the Operations Research Society of America*, 1(5):263–278
  - Let $X = 0$ with probability $1 - 10^{-10}$ and $X = 10^{10}$ with probability 10^{-10}
  - $\mathbf{E}[X] = 1$
  - Monte Carlo estimate from $n \ll 10^{10}$ samples of X is almost always zero
  - Idea: Sample X from some other distribution and use importance sampling to "correct" the estimate
  - Can produce lower variance estimates.
- Josiah Hannah et. al, ICML 2017 (to appear).

Importance sampling (History, continued)

- Precup, D., Sutton, R. S., Singh, S. (2000). Eligibility traces for off-policy policy evaluation. In *Proceedings of the 17th International Conference on Machine Learning*, pp. 759–766. Morgan Kaufmann

Importance sampling (Proof)

- Estimate $\mathbf{E}_p[f(X)]$ given a sample of $X \sim q$
- Let $P = \text{supp}(p)$, $Q = \text{supp}(q)$, and $F = \text{supp}(f)$
- Importance sampling estimate: $\frac{p(X)}{q(X)} f(X)$

$$\mathbf{E}_q\left[\frac{p(X)}{q(X)} f(X)\right] = \sum_{x \in Q} q(X) \frac{p(X)}{q(X)} f(X)$$

$$= \sum_{x \in P} p(X)\, f(X) + \sum_{x \in \bar{P} \cap Q} p(X)\, f(X) - \sum_{x \in P \cap \bar{Q}} p(X) f(X)$$

$$= \sum_{x \in P} p(X)\, f(X) - \sum_{x \in P \cap \bar{Q}} p(X) f(X)$$

Importance sampling (Proof)

- Assume $P \subseteq Q$ (can relax assumption to $P \subseteq Q \cup \bar{F}$)

$$\mathbf{E}_q\left[\frac{p(X)}{q(X)} f(X)\right] = \sum_{x \in P} p(X)\, f(X) - \sum_{x \in P \cap \bar{Q}} p(X) f(X)$$

$$= \sum_{x \in P} p(X)\, f(X)$$

$$= \mathbf{E}_p[f(X)]$$

- Importance sampling is an unbiased estimator of $\mathbf{E}_p[f(X)]$

Importance sampling (proof)

- Assume $f(x) \geq 0$ for all x

$$\begin{aligned}\mathbf{E}_q\left[\frac{p(X)}{q(X)} f(X)\right] &= \sum_{x \in P} p(X)\, f(X) - \sum_{x \in P \cap \bar{Q}} p(X) f(X) \\ &\leq \sum_{x \in P} p(X)\, f(X) \\ &= \mathbf{E}_p[f(X)]\end{aligned}$$

- Importance sampling is a negative-bias estimator of $\mathbf{E}_p[f(X)]$

Importance sampling (reminder)

$$\mathrm{IS}(D) = \frac{1}{n}\sum_{i=1}^{n}\left(\prod_{t=1}^{L}\frac{\pi_{\mathrm{e}}(a_t|s_t)}{\pi_{\mathrm{b}}(a_t|s_t)}\right)\left(\sum_{t=1}^{L}\gamma^t R_t^i\right)$$

$$\mathbf{E}[\mathrm{IS}(D)] = J(\pi_{\mathrm{e}})$$

Creating a safe reinforcement learning algorithm

- Off-policy policy evaluation (OPE)
  - For any *evaluation policy*, π_e, Convert historical data, D, into n independent and unbiased estimates of $J(\pi_e)$
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  - Use a concentration inequality to convert the n independent and unbiased estimates of $J(\pi_e)$ into a $1-\delta$ confidence lower bound on $J(\pi_e)$
- Safe policy improvement (SPI)
  - Use HCOPE method to create a safe reinforcement learning algorithm, a

High confidence off-policy policy evaluation (HCOPE)

Historical Data, D

Proposed Policy, π_e

Probability, $1-\delta$

$1-\delta$ confidence lower bound on $J(\pi_e)$

Hoeffding's inequality

- Let $X_1, \ldots, X_n$ be n independent identically distributed random variables such that $X_\mathrm{i} \in [0, b]$
- Then with probability at least $1 - \delta$:

$$\mathbf{E}[X_i] \geq \overbrace{\frac{1}{n}\sum_{i=1}^{n} X_i}^{\frac{1}{n}\sum_{i=1}^{n}\left(w_i \sum_{t=1}^{L} \gamma^t R_t^i\right)} - b\sqrt{\frac{\ln\left(1/\delta\right)}{2n}}$$

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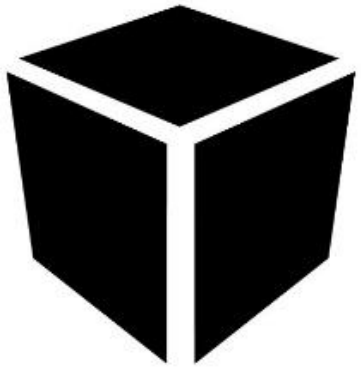
Safe policy improvement (SPI)

Historical Data, D

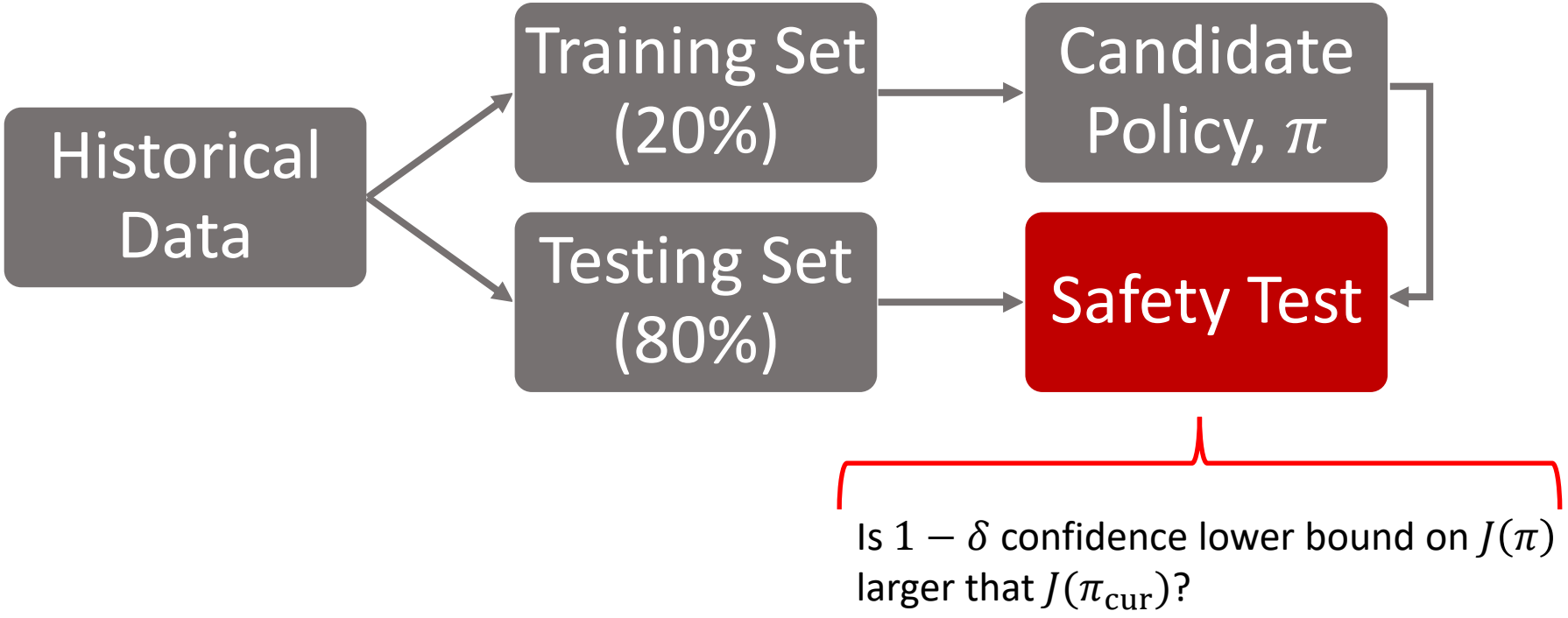
Probability, $1 - \delta$



New policy π, or

`No Solution Found`

Safe policy improvement (SPI)



Creating a safe reinforcement learning algorithm

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WON'T WORK

Off-policy policy evaluation (revisited)

- Importance sampling (IS):

$$\mathrm{IS}(D) = \frac{1}{n}\sum_{i=1}^{n}\left(\prod_{t=1}^{L}\frac{\pi_{\mathrm{e}}(a_t|s_t)}{\pi_{\mathrm{b}}(a_t|s_t)}\right)\left(\sum_{t=1}^{L}\gamma^t R_t^i\right)$$

- Per-decision importance sampling (PDIS)

$$\mathrm{PDIS}(D) = \sum_{t=1}^{L}\gamma^t\frac{1}{n}\sum_{i=1}^{n}\left(\prod_{\tau=1}^{t}\frac{\pi_{\mathrm{e}}(a_\tau|s_\tau)}{\pi_{\mathrm{b}}(a_\tau|s_\tau)}\right)R_t^i$$

Off-policy policy evaluation (revisited)

- Importance sampling (IS):

$$\mathrm{IS}(D) = \frac{1}{n}\sum_{i=1}^{n} w_i \left(\sum_{t=1}^{L} \gamma^t R_t^i \right)$$

- Weighted importance sampling (WIS)

$$\mathrm{WIS}(D) = \frac{1}{\sum_{i=1}^{n} w_i} \sum_{i=1}^{n} w_i \left(\sum_{t=1}^{L} \gamma^t R_t^i \right)$$

Off-policy policy evaluation (revisited)

- Weighted importance sampling (WIS)

$$\frac{1}{\sum_{i=1}^{n} w_i} \sum_{i=1}^{n} w_i \left(\sum_{t=1}^{L} \gamma^t R_t^i \right)$$

- **Not** unbiased. When $n = 1$, $\mathbf{E}[\mathrm{WIS}] = J(\pi_\mathrm{b})$
- Strongly consistent estimator of $J(\pi_\mathrm{e})$
  - i.e., $\Pr\left(\lim_{n \to \infty} \mathrm{WIS}(D) = \mathrm{J}(\pi_\mathrm{e}) \right) = 1$
  - If
    - Finite horizon
    - One behavior policy, or bounded rewards

Off-policy policy evaluation (revisited)

- Weighted per-decision importance sampling
  - Also called consistent weighted per-decision importance sampling
  - A fun exercise!

Control variates

- Given: X
- Estimate: $\mu = \mathbf{E}[X]$
- $\hat{\mu} = X$
- Unbiased: $\mathbf{E}[\hat{\mu}] = \mathbf{E}[X] = \mu$
- Variance: $\mathrm{Var}(\hat{\mu}) = \mathrm{Var}(X)$

Control variates

- Given: $X, Y, \mathbf{E}[Y]$
- Estimate: $\mu = \mathbf{E}[X]$
- $\hat{\mu} = X - Y + \mathbf{E}[\mathrm{Y}]$
- Unbiased:

$$\mathbf{E}[\hat{\mu}] = \mathbf{E}[X - Y + \mathbf{E}[Y]] = \mathbf{E}[X] - \mathbf{E}[Y] + \mathbf{E}[Y] = \mathbf{E}[X] = \mu$$

- Variance:

$$\mathrm{Var}(\hat{\mu}\,) = \mathrm{Var}(X - Y + \mathbf{E}[Y]) = \mathrm{Var}(X - Y) = \mathrm{Var}(X) + \mathrm{Var}(Y) - 2\mathrm{Cov}(X, Y)$$

- Lower variance if $2\mathrm{Cov}(X, Y) > \mathrm{Var}(Y)$
- We call Y a *control variate.*

Off-policy policy evaluation (revisited)

- Idea: add a control variate to importance sampling estimators
  - X is the importance sampling estimator
  - Y is a control variate build from an *approximate model* of the MDP
    - $\mathbf{E}[Y] = 0$ in this case
  - $\mathrm{PDIS}_{\mathrm{CV}}(D) = \mathrm{PDIS}(D) - \mathrm{CV}(D)$
- Called the *doubly robust* estimator (Jiang and Li, 2015)
  - Robust to 1) poor approximate model, and 2) error in estimates of π_{b}
    - If the model is poor, the estimates are still unbiased
    - If the sampling policy is unknown, but the model is good, MSE will still be low
  - $\mathrm{DR}(D) = \mathrm{PDIS}_{\mathrm{CV}}(D)$
- Non-recursive and weighted forms, as well as control variate view provided by Thomas and Brunskill (2016)

Off-policy policy evaluation (revisited)

$$\mathrm{DR}(\pi_e|\mathcal{D}) = \underbrace{\frac{1}{n}\sum_{i=1}^{n}\sum_{t=0}^{\infty}}\gamma^t w_t^i\left(R_t^i - \hat{q}^{\pi_\mathrm{e}}\left(S_t^i, A_t^i\right)\right) + \gamma^t \rho_{t-1}^i \hat{v}^{\pi_e}\left(S_t^i\right)$$

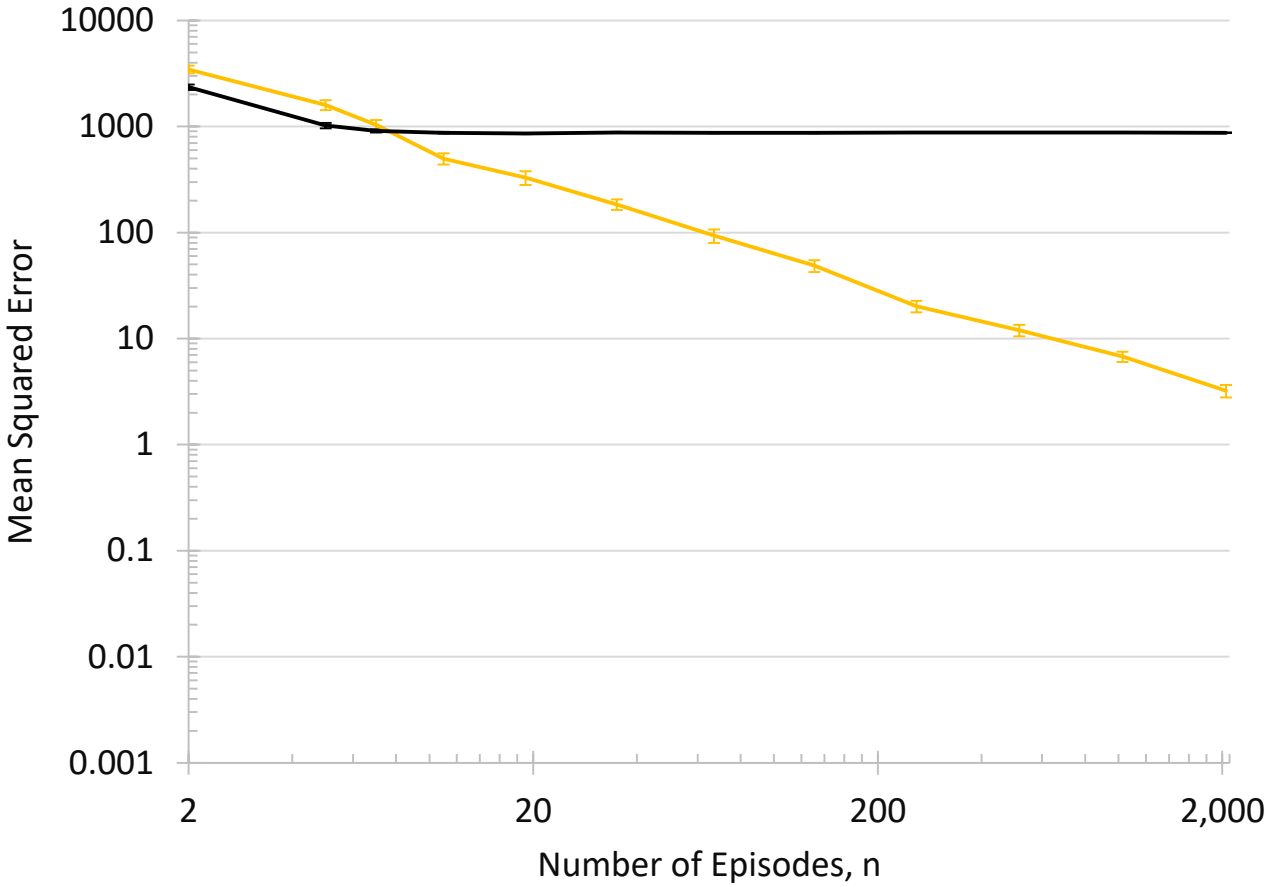
Per-decision importance sampling (PDIS)

$$w_t^i = \prod_{\tau=1}^{t}\frac{\pi_\mathrm{e}(a_\tau|s_\tau)}{\pi_\mathrm{b}(a_\tau|s_\tau)}$$

- Recall: we want the control variate, Y, to cancel with X:

$$R - q(S,A) + \gamma v(S')$$

Empirical Results (Gridworld)

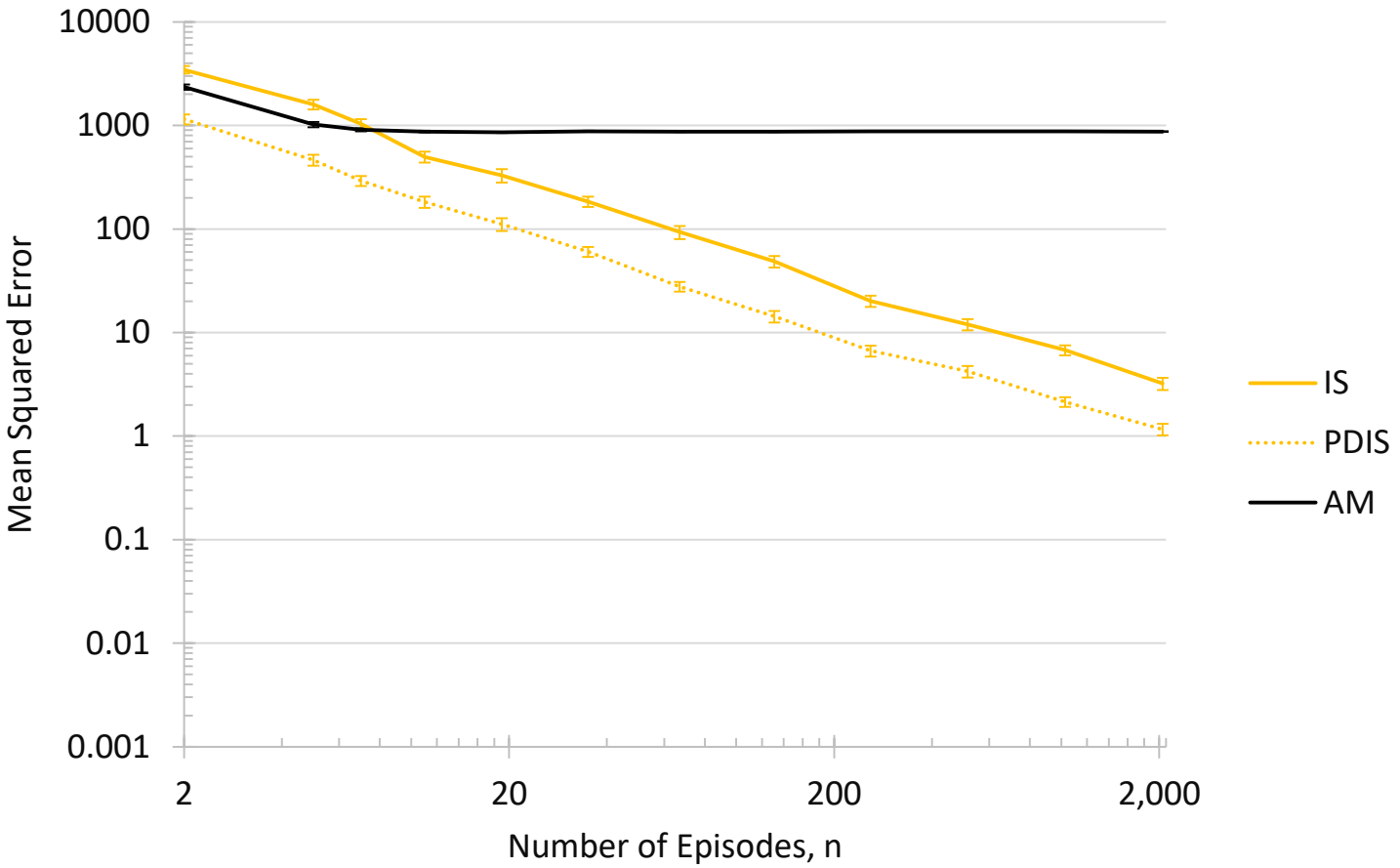


Approximate model

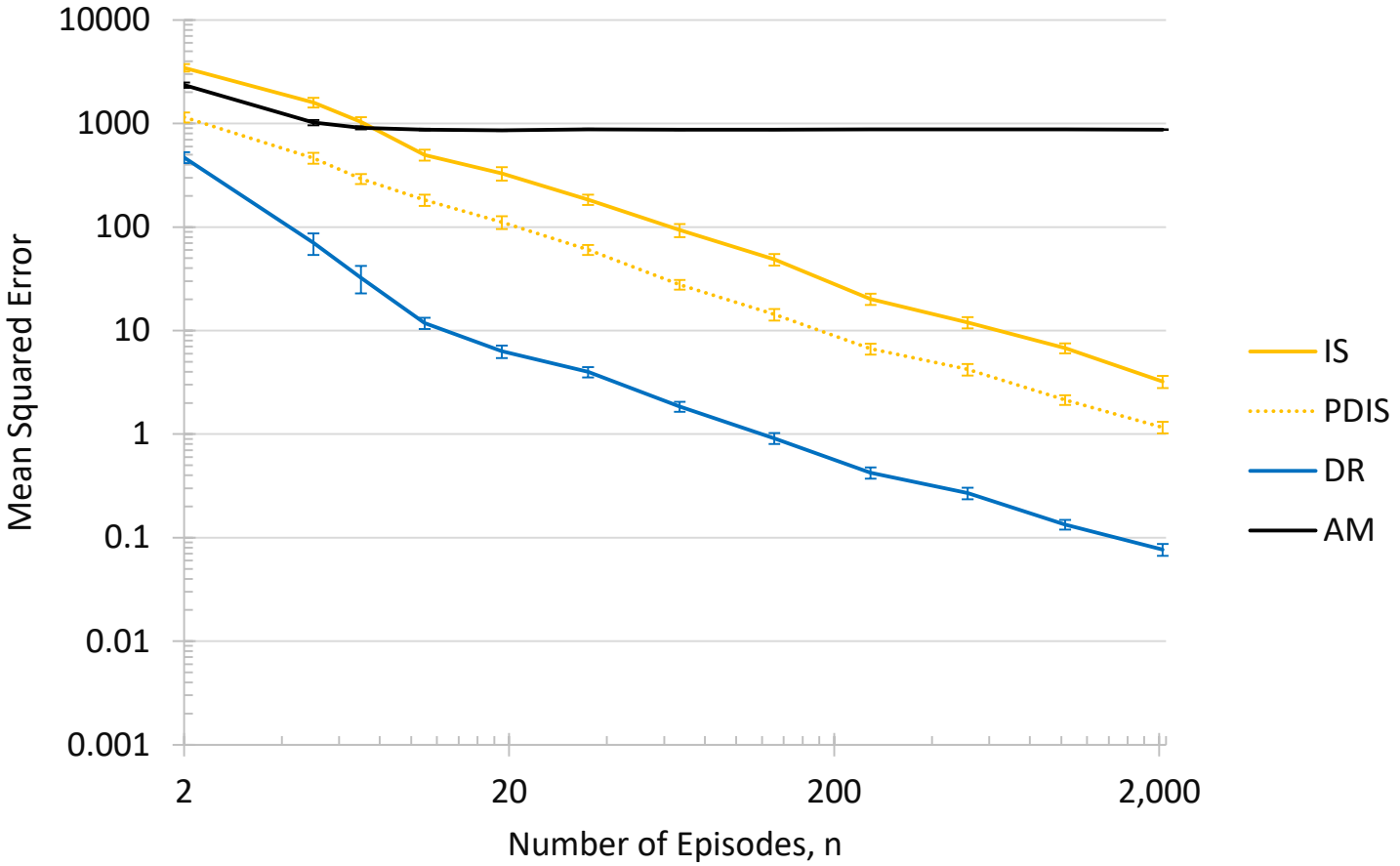
Direct method (Dudik, 2011)

Indirect method (Sutton and Barto, 1998)

Empirical Results (Gridworld)



Empirical Results (Gridworld)



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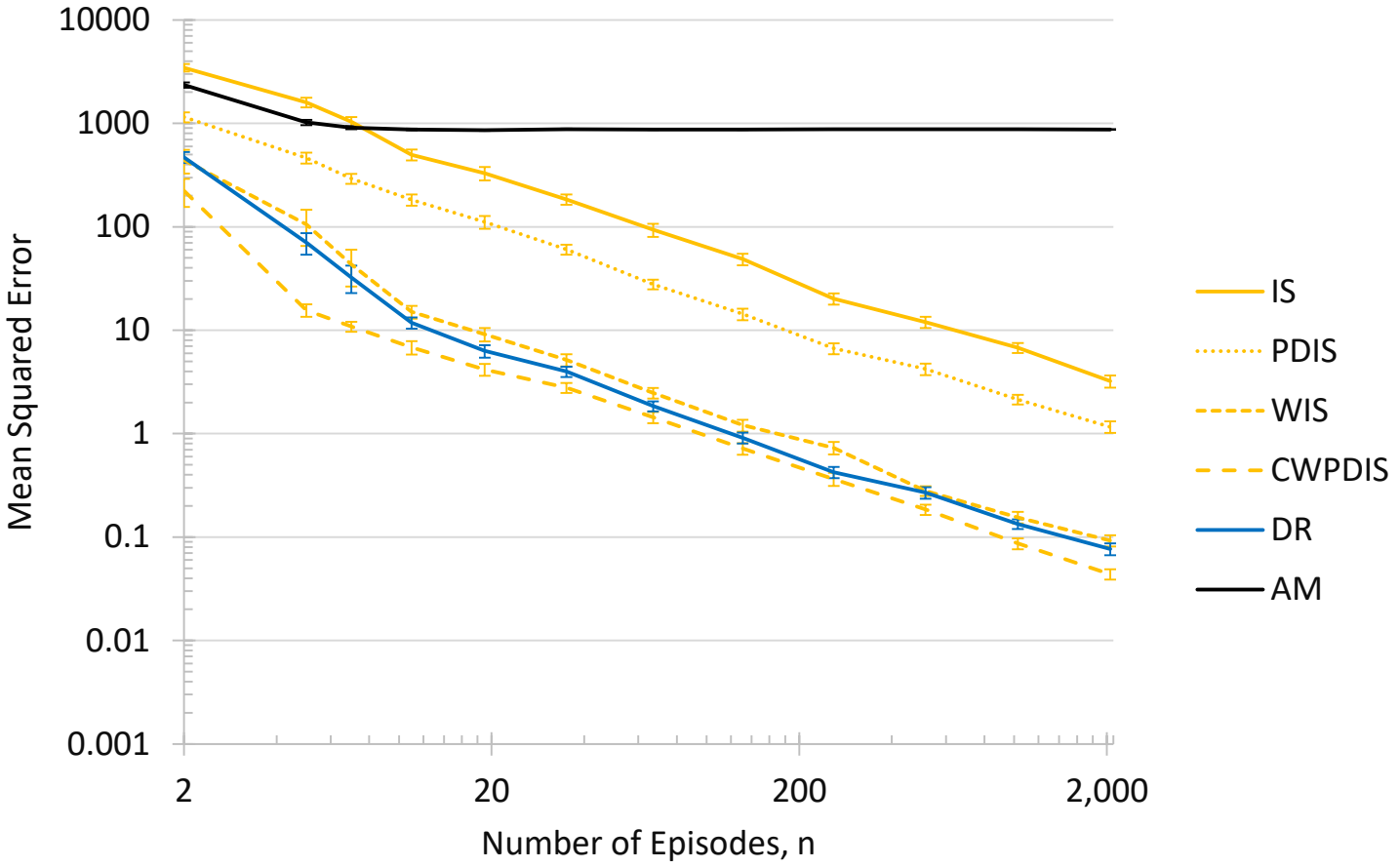
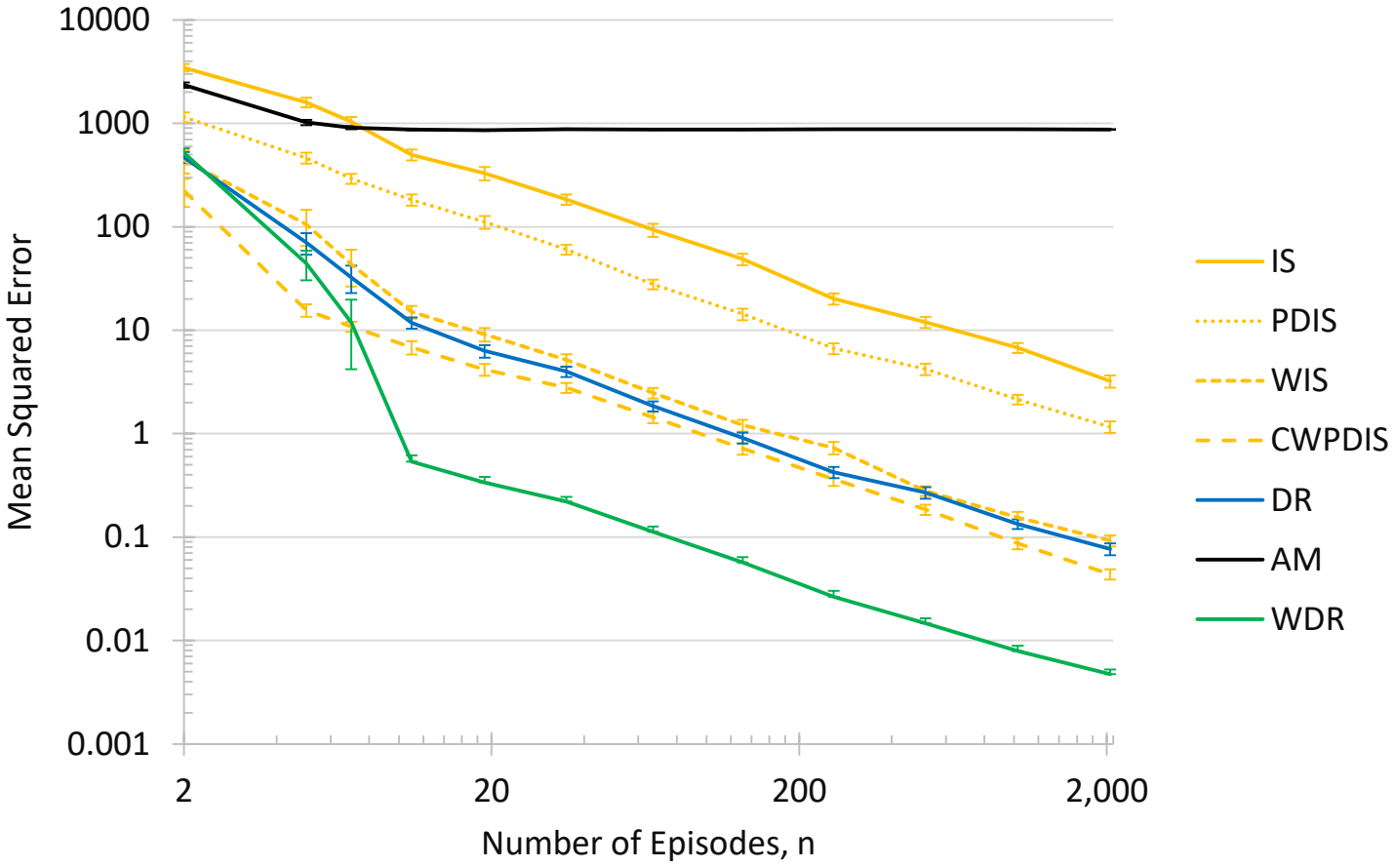


Empirical Results (Gridworld)

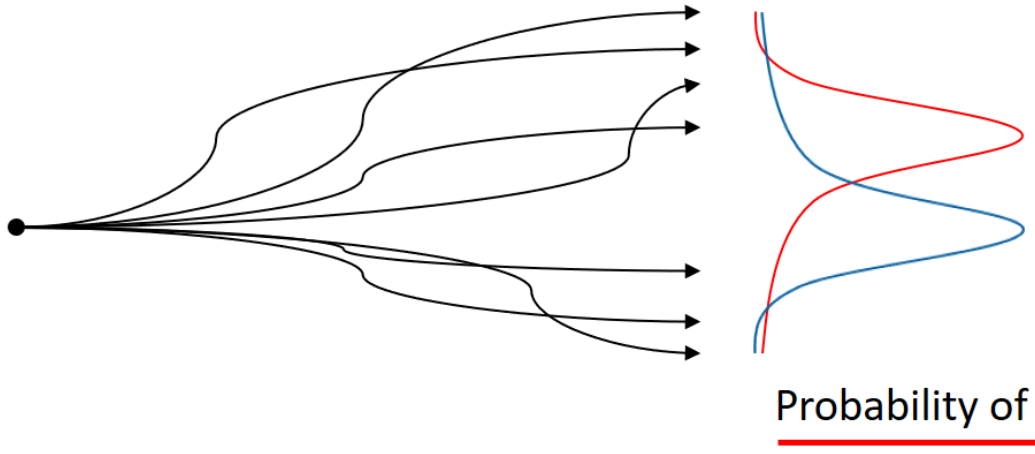


Off-policy policy evaluation (revisited)

- What if $\text{supp}(\pi_e) \subset \text{supp}(\pi_b)$?
- There is a state-action pair, (s, a), such that

$$\pi_e(a|s) = 0, \text{ but } \pi_b(a|s) \neq 0$$

- If we see a history where (s, a) occurs, what weight should we give it?

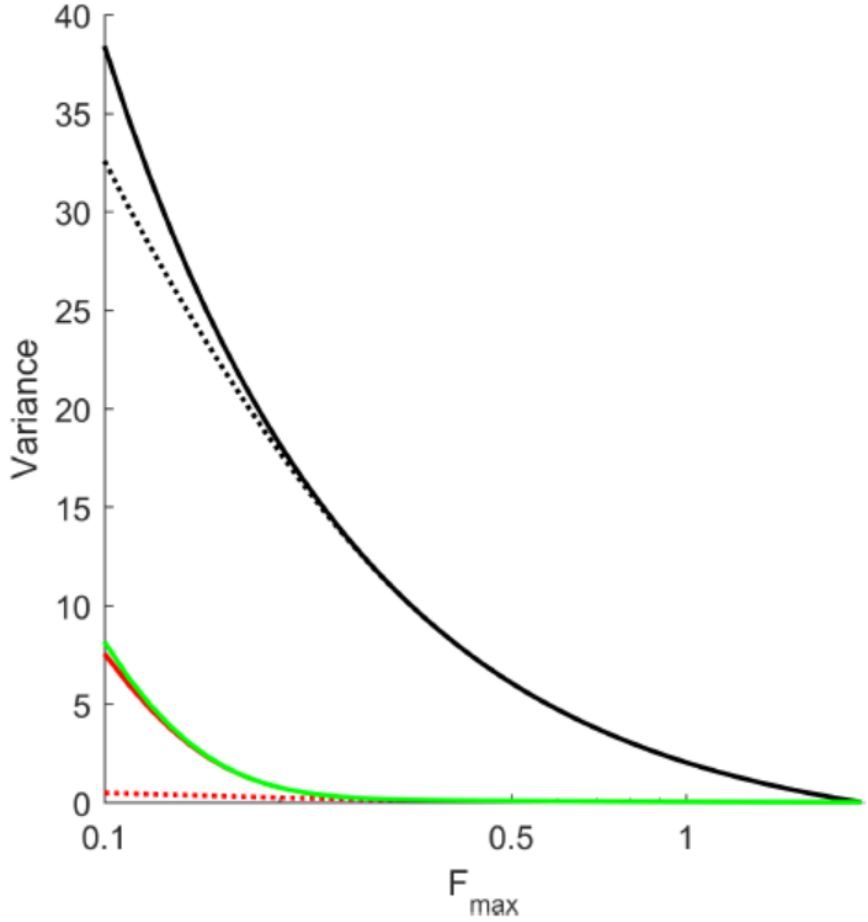


$$\text{IS}(D) = \frac{1}{n}\sum_{i=1}^{n}\left(\prod_{t=1}^{L}\frac{\pi_e(a_t|s_t)}{\pi_b(a_t|s_t)}\right)\left(\sum_{t=1}^{L}\gamma^t R_t^i\right)$$

Off-policy policy evaluation (revisited)

- What if there are zero samples ($n = 0$)?
  - The importance sampling estimate is undefined
- What if no samples are in $\text{supp}(\pi_e)$ (or $\text{supp}(p)$ in general)?
  - Importance sampling says: the estimate is zero
  - Alternate approach: undefined
- Importance sampling estimator is unbiased if $n > 0$
- Alternate approach will be unbiased given that at least one sample is in the support of p.
- Alternate approach detailed in Importance Sampling with Unequal Support (Thomas and Brunskill, AAAI 2017)

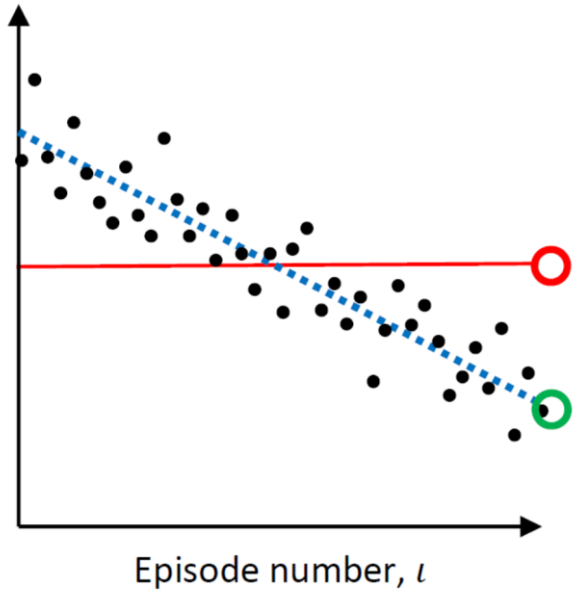
Off-policy policy evaluation (revisited)

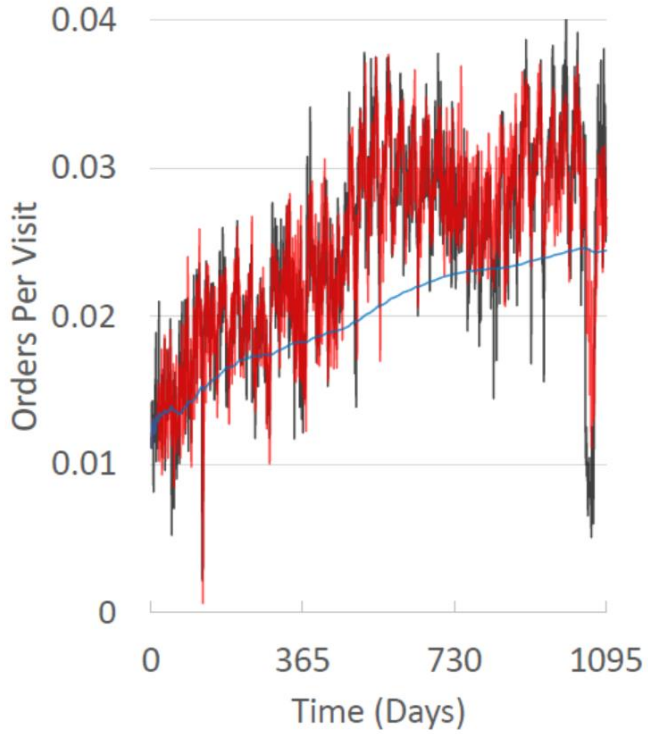


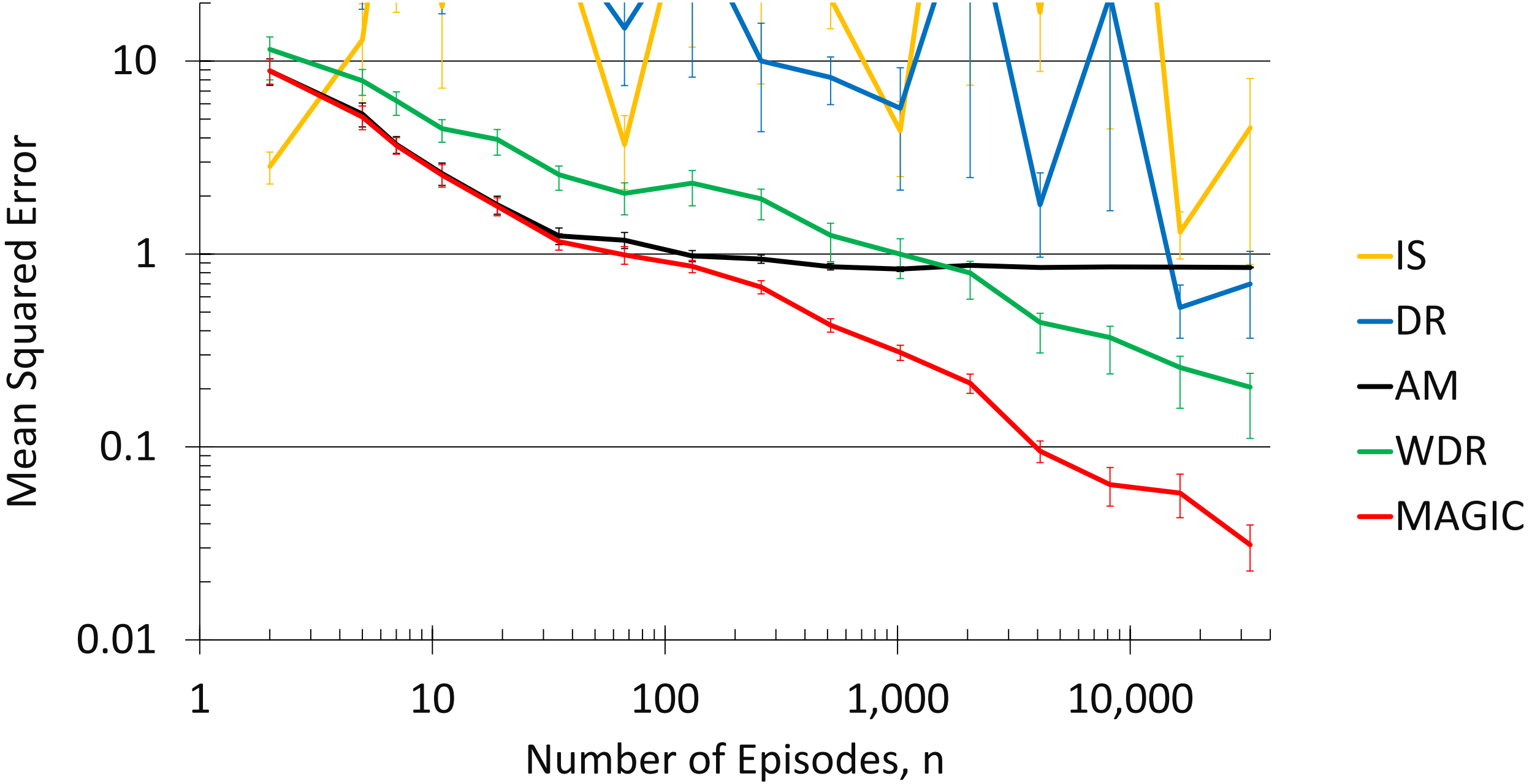
IS, IS (conditional), US, US (conditional) MSE(US)

Off-policy policy evaluation (revisited)

- Thomas et. al. Predictive Off-Policy Policy Evaluation for Nonstationary Decision Problems, with Applications to Digital Marketing (AAAI 2017)





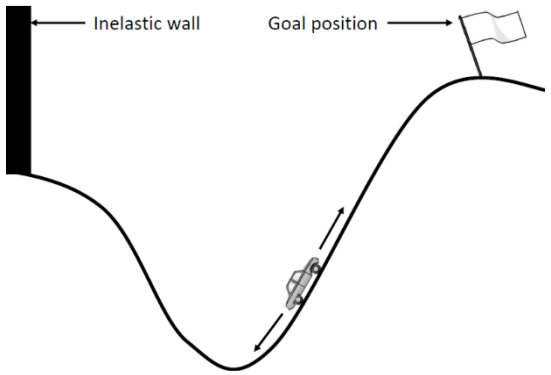

Mean Squared Error
10
1
0.1
0.01
1
10
100
1,000
10,000
Number of Episodes, n
IS
DR
AM
WDR
MAGIC

Creating a safe reinforcement learning algorithm

- Off-policy policy evaluation (OPE)
  - For any *evaluation policy*, π_e, Convert historical data, D, into n independent and unbiased estimates of $J(\pi_e)$
- High-confidence off-policy policy evaluation (HCOPE)
  - Use a concentration inequality to convert the n independent and unbiased estimates of $J(\pi_e)$ into a $1-\delta$ confidence lower bound on $J(\pi_e)$
- Safe policy improvement (SPI)
  - Use HCOPE method to create a safe reinforcement learning algorithm, a

High-confidence off-policy policy evaluation (revisited)

- Consider using IS + Hoeffding's inequality for HCOPE on mountain car



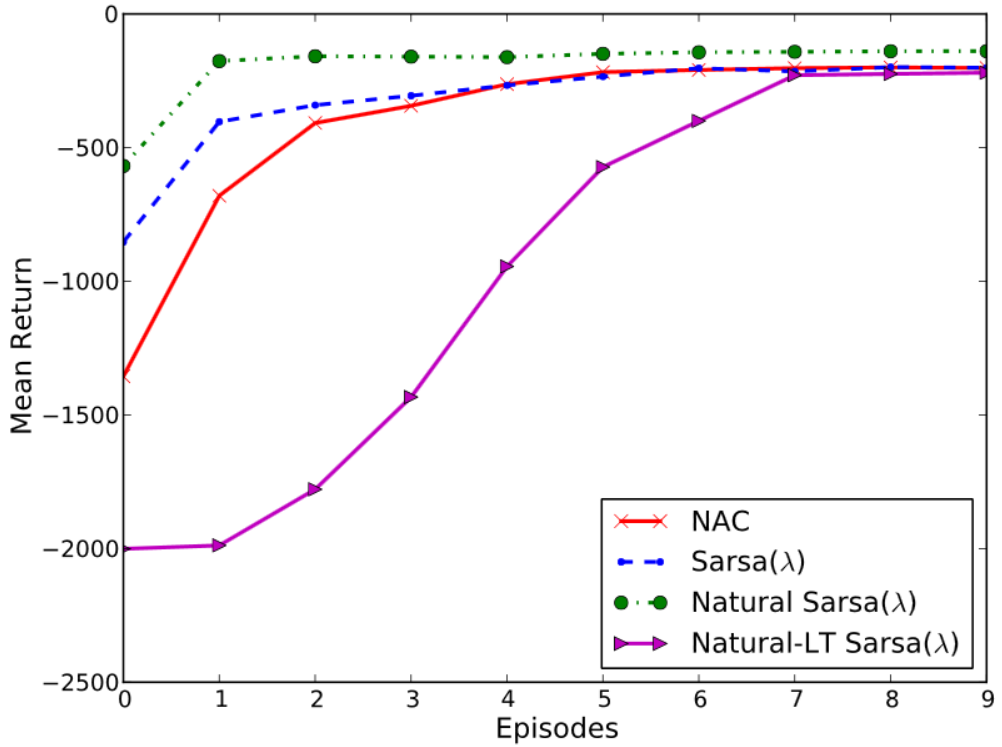


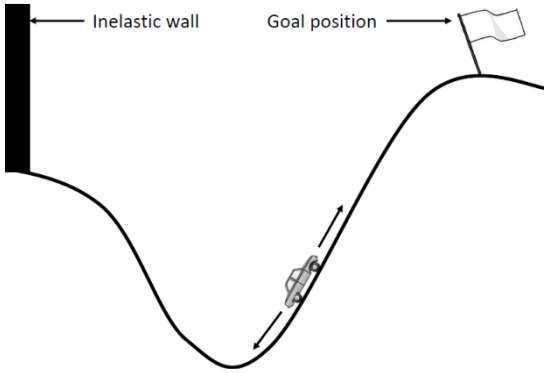
Figure 3: Mountain Car (Sarsa(λ))

Natural Temporal Difference Learning, Dabney and Thomas, 2014

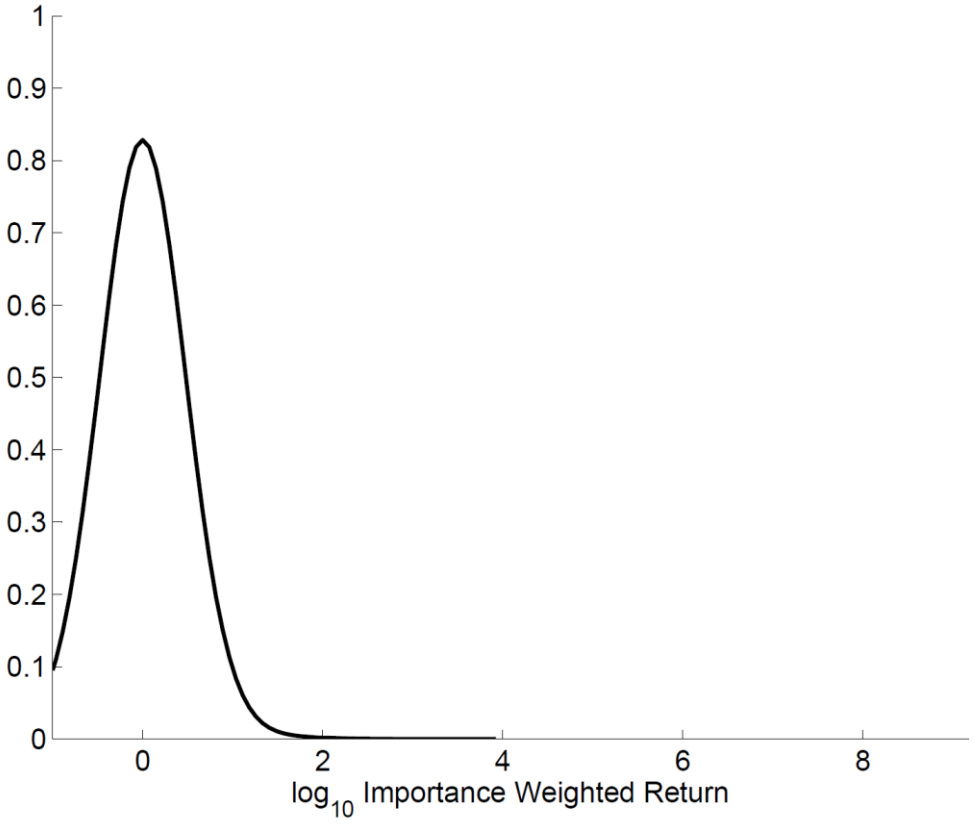
High-confidence off-policy policy evaluation (revisited)

- Using 100,000 trajectories
- Evaluation policy's true performance is $0.19 \in [0,1]$.
- We get a 95% confidence lower bound of:

$$-5{,}831{,}000$$



What went wrong?



$$w_i = \prod_{t=1}^{L} \frac{\pi_{\mathrm{e}}(a_t|s_t)}{\pi_{\mathrm{b}}(a_t|s_t)}$$

What went wrong?

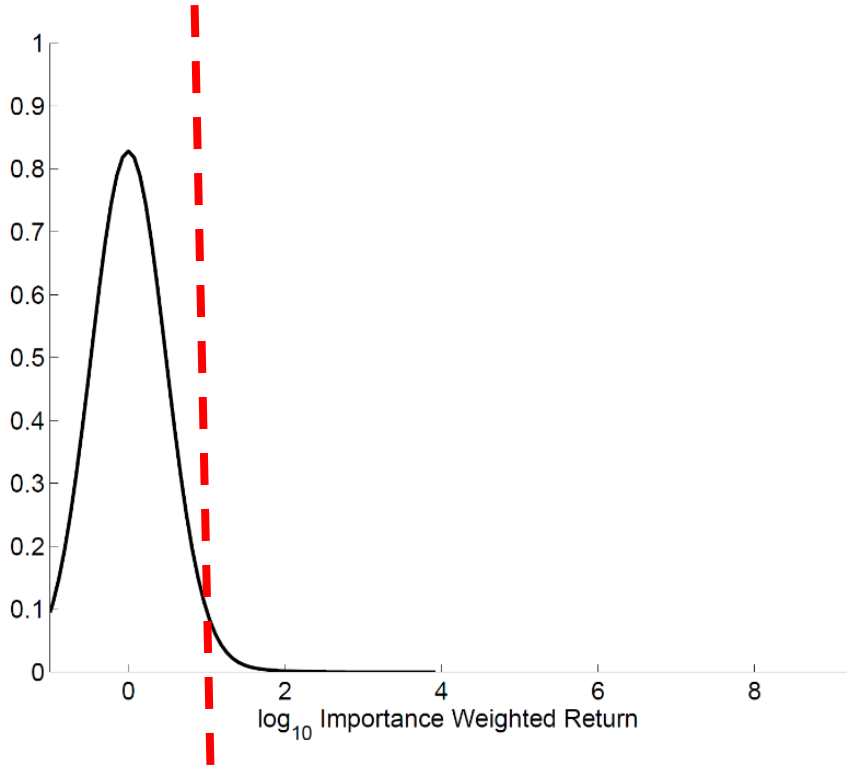
$$\mathbf{E}[X_i] \geq \frac{1}{n}\sum_{i=1}^{n} X_i - b\sqrt{\frac{\ln\left(1/\delta\right)}{2n}}$$

$$b \approx 10^{9.4}$$

Largest observed importance weighted return: 316.

High-confidence off-policy policy evaluation (revisited)

- Removing the upper tail only decreases the expected value.



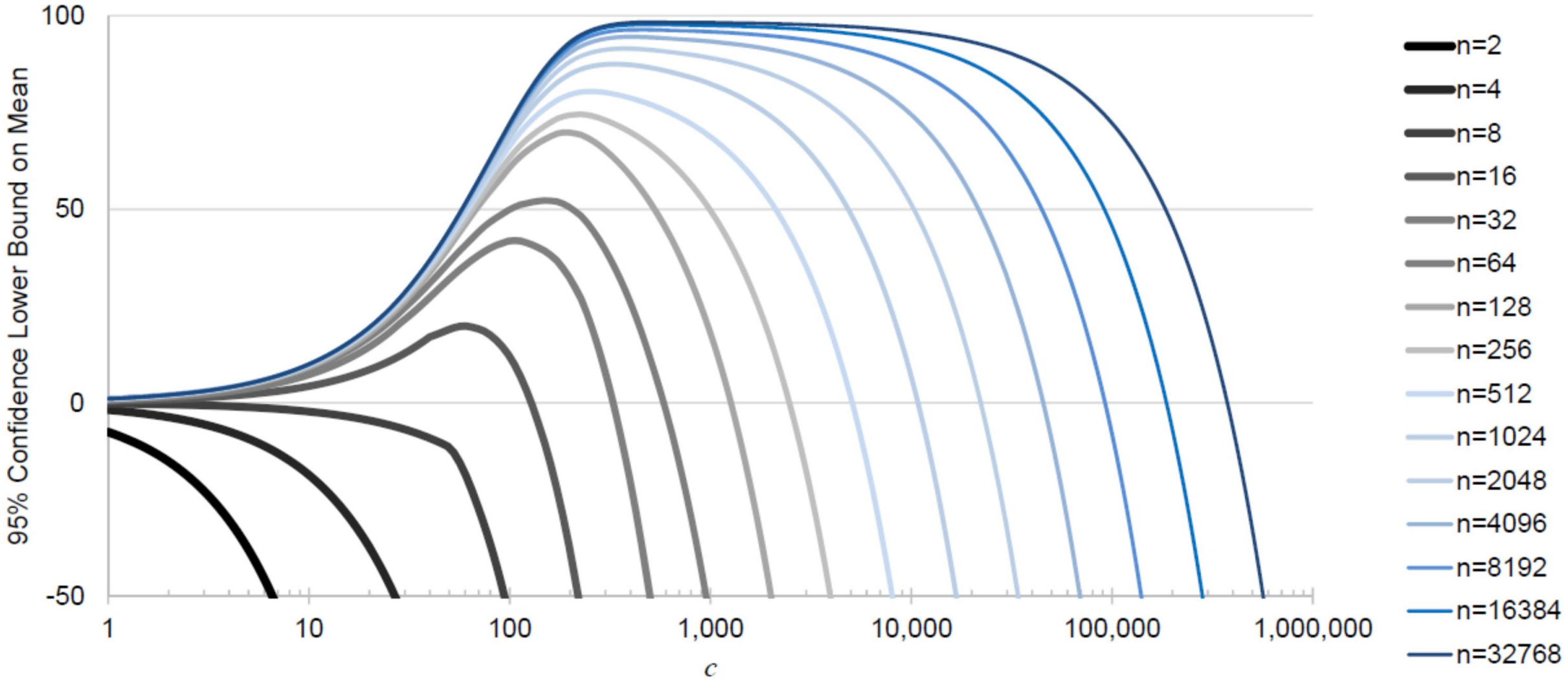
High-confidence off-policy policy evaluation (revisited)

Theorem 1. *Let $X_1, \ldots, X_n$ be n independent real-valued random variables such that for each $i \in \{1, \ldots, n\}$, we have $\mathbb{P}[0 \leq X_i] = 1$, $\mathbb{E}[X_i] \leq \mu$, and some threshold value $c_i > 0$. Let $\delta > 0$ and $Y_i := \min\{X_i, c_i\}$. Then with probability at least $1 - \delta$, we have*

$$\mu \geq \underbrace{\left(\sum_{i=1}^{n} \frac{1}{c_i}\right)^{-1} \sum_{i=1}^{n} \frac{Y_i}{c_i}}_{\text{empirical mean}} - \underbrace{\left(\sum_{i=1}^{n} \frac{1}{c_i}\right)^{-1} \frac{7n \ln(2/\delta)}{3(n-1)}}_{\text{term that goes to zero as } 1/n \text{ as } n \to \infty} - \underbrace{\left(\sum_{i=1}^{n} \frac{1}{c_i}\right)^{-1} \sqrt{\frac{\ln(2/\delta)}{n-1} \sum_{i,j=1}^{n} \left(\frac{Y_i}{c_i} - \frac{Y_j}{c_j}\right)^2}}_{\text{term that goes to zero as } 1/\sqrt{n} \text{ as } n \to \infty}. \tag{3}$$

- Thomas et. al, High confidence off-policy evaluation, AAAI 2015

High-confidence off-policy policy evaluation (revisited)



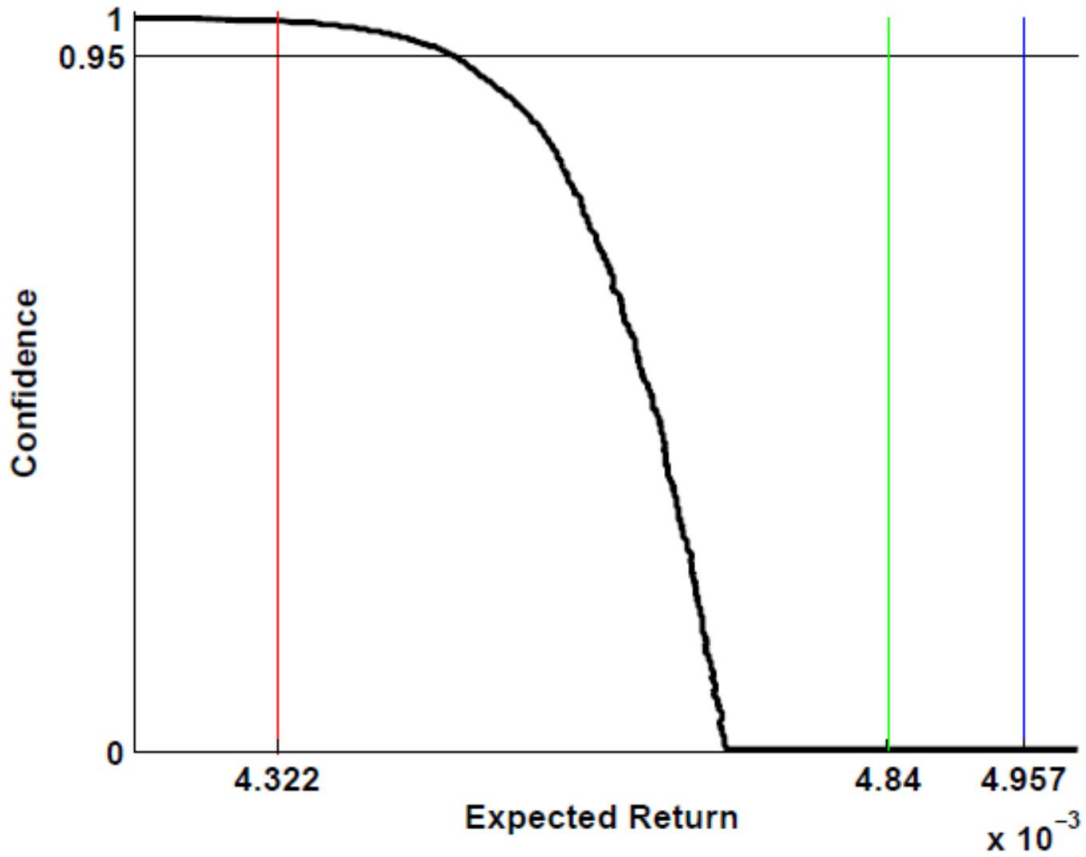
High-confidence off-policy policy evaluation (revisited)

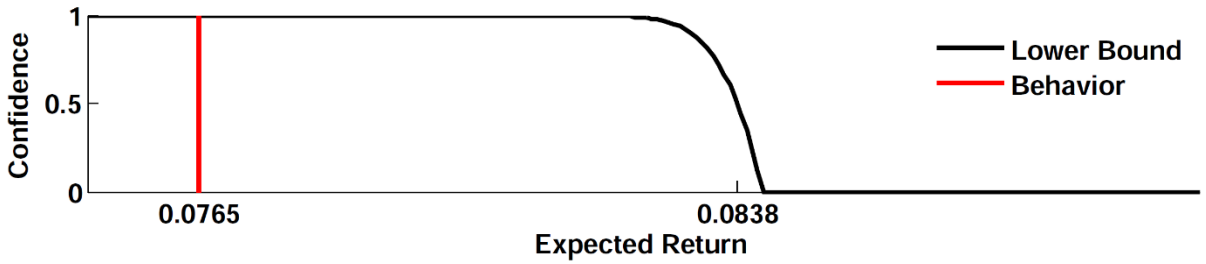
- Use 20% of the data to optimize c.
- Use 80% to compute lower bound with optimized c.
- Mountain car results:

	CUT	**Chernoff-Hoeffding**	**Maurer**	**Anderson**	**Bubeck et al.**
95% Confidence lower bound on the mean	0.145	$-5{,}831{,}000$	$-129{,}703$	0.055	$-.046$

High-confidence off-policy policy evaluation (revisited)

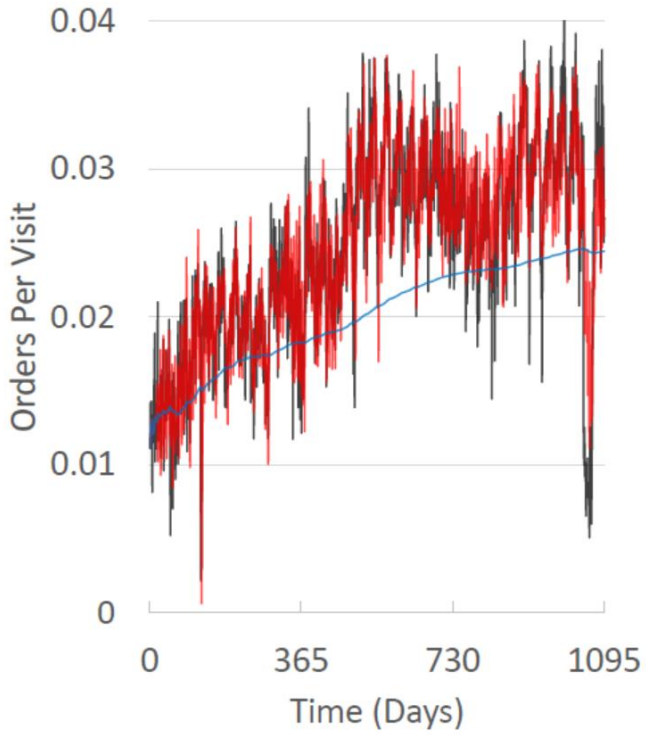
- Digital Marketing:





High-confidence off-policy policy evaluation (revisited)

- Cognitive dissonance



$$\mathbf{E}[X_i] \geq \frac{1}{n}\sum_{i=1}^{n} X_i - b\sqrt{\frac{\ln\left(1/\delta\right)}{2n}}$$

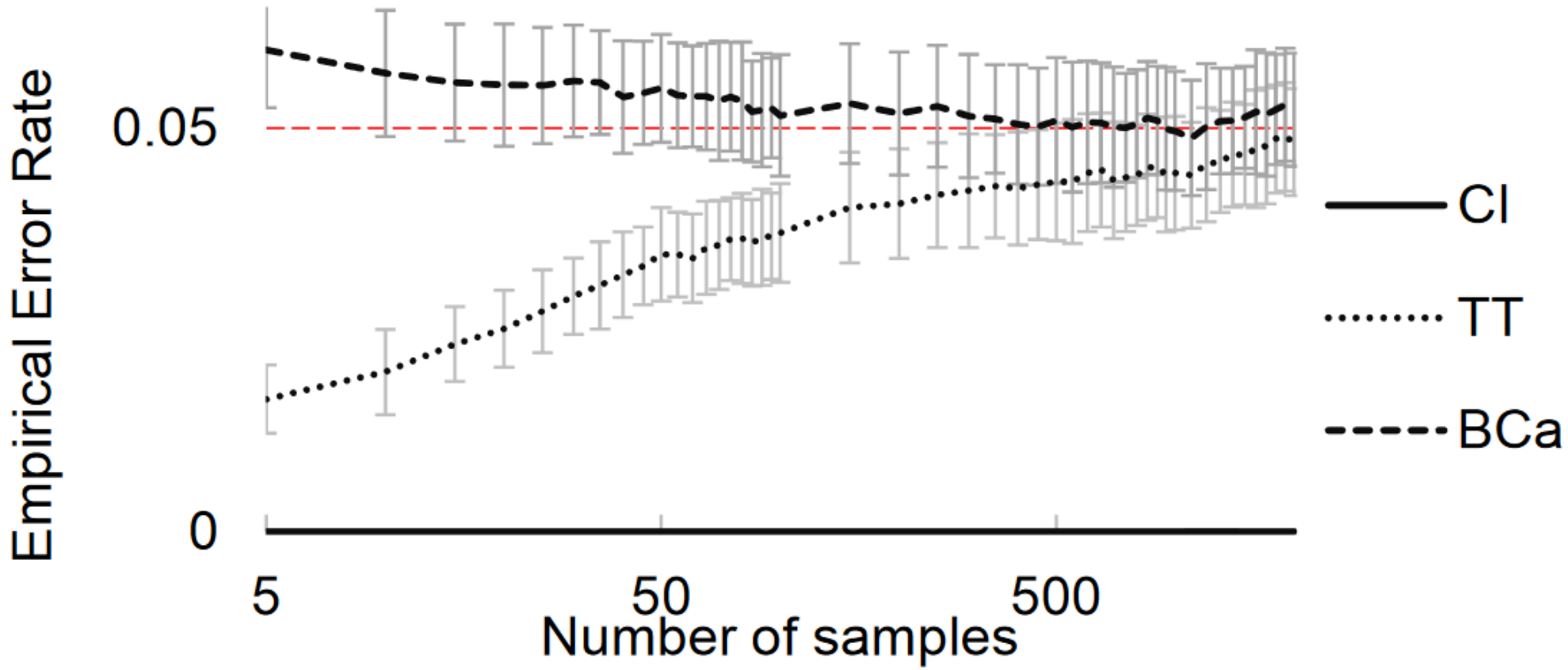
High-confidence off-policy policy evaluation (revisited)

- Student's t-test
  - Assumes that $\mathrm{IS}(D)$ is normally distributed
  - By the central limit theorem, it (is as $n \to \infty$)

$$\Pr\left(\mathbf{E}\left[\frac{1}{n}\sum_{i=1}^{n} X_i\right] \geq \frac{1}{n}\sum_{i=1}^{n} X_i - \frac{\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(X_i - \bar{X}_n\right)^2}}{\sqrt{n}} t_{1-\delta,n-1}\right) \geq 1-\delta,$$

- Efron's Bootstrap methods (e.g., BCa)
  - Also, without importance sampling: Hanna, Stone, and Niekum, AAMAS 2017

High-confidence off-policy policy evaluation (revisited)



P. S. Thomas. Safe reinforcement learning (PhD Thesis, 2015)

Creating a safe reinforcement learning algorithm

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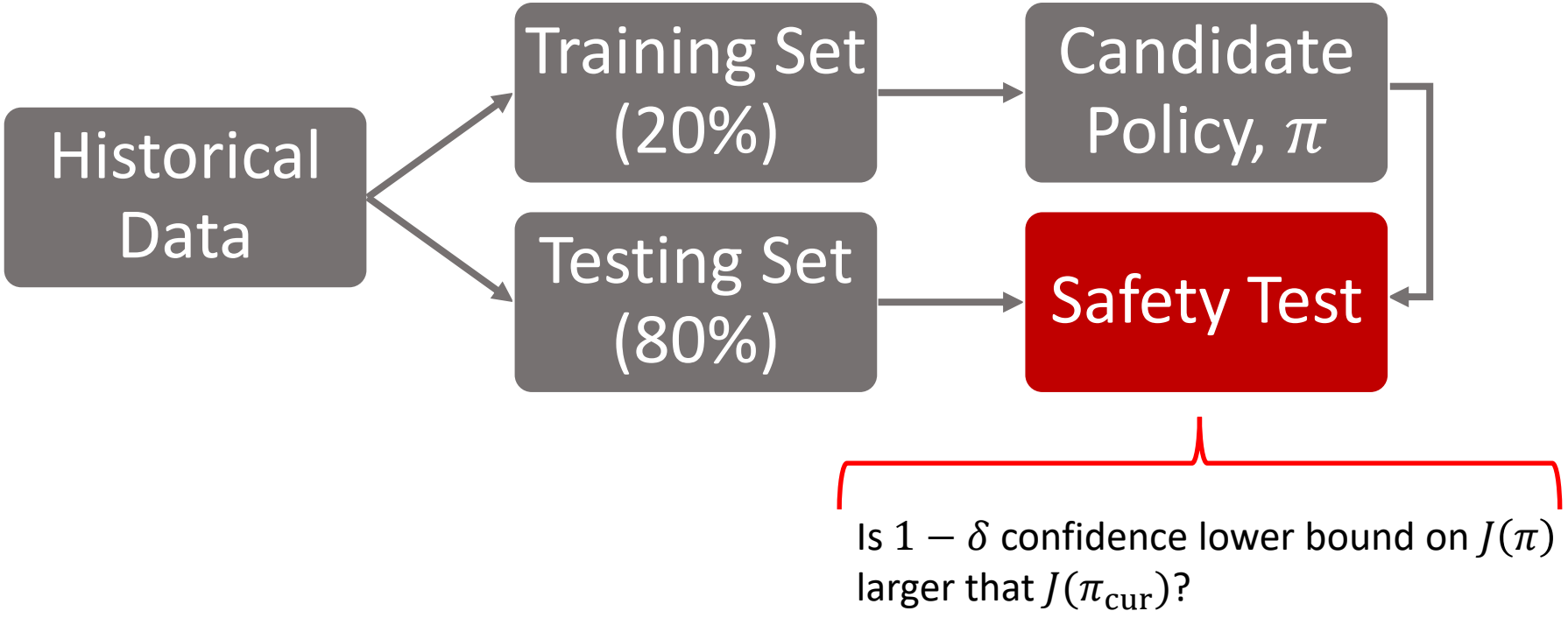
Safe policy improvement (revisited)

- Thomas et. al, ICML 2015



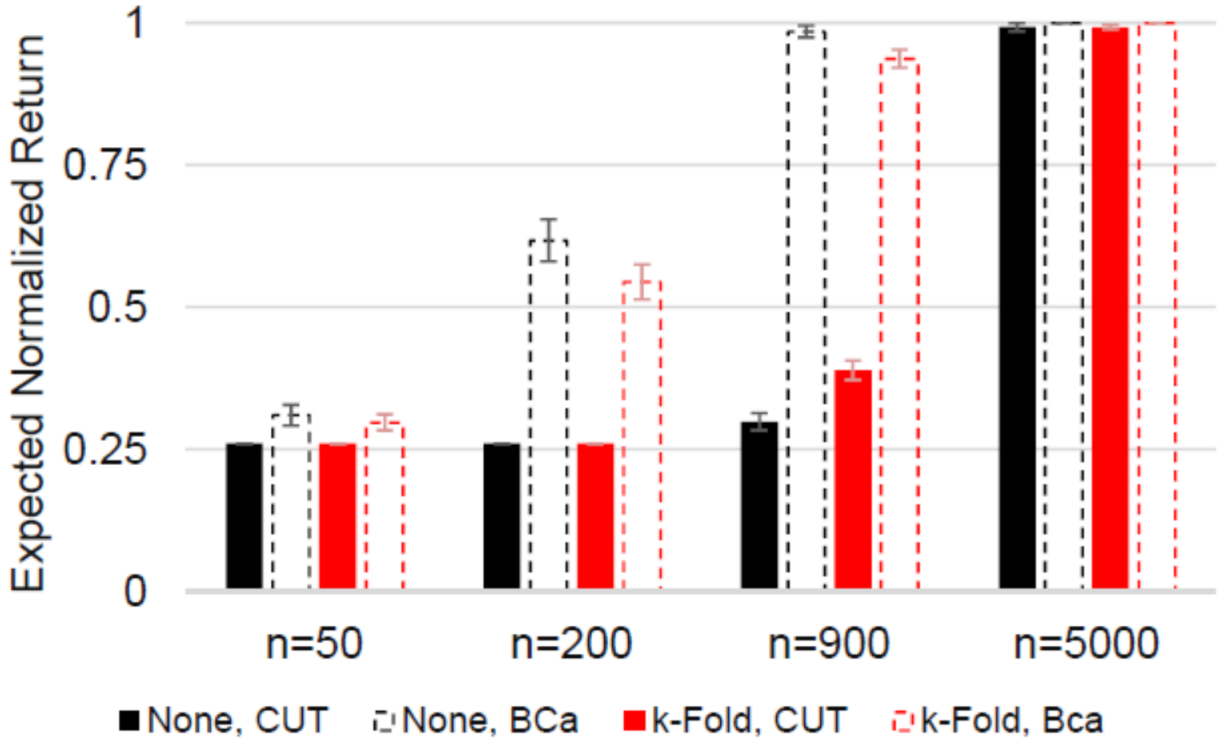
Lecture overview

- What makes a reinforcement learning algorithm *safe*?
- Notation
- Creating a safe reinforcement learning algorithm
  - Off-policy policy evaluation (OPE)
  - High-confidence off-policy policy evaluation (HCOPE)
  - Safe policy improvement (SPI)
- Empirical results
- Research directions

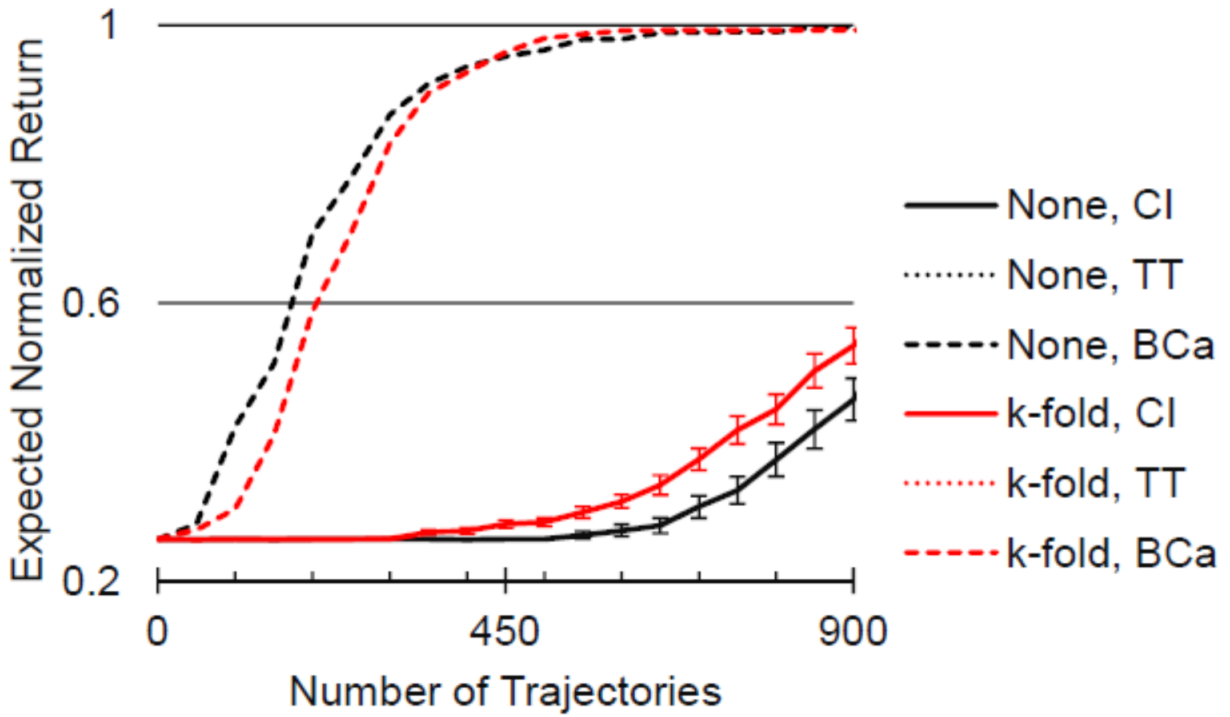
Empirical Results

- What to look for:
  - Data efficiency
  - Error rates

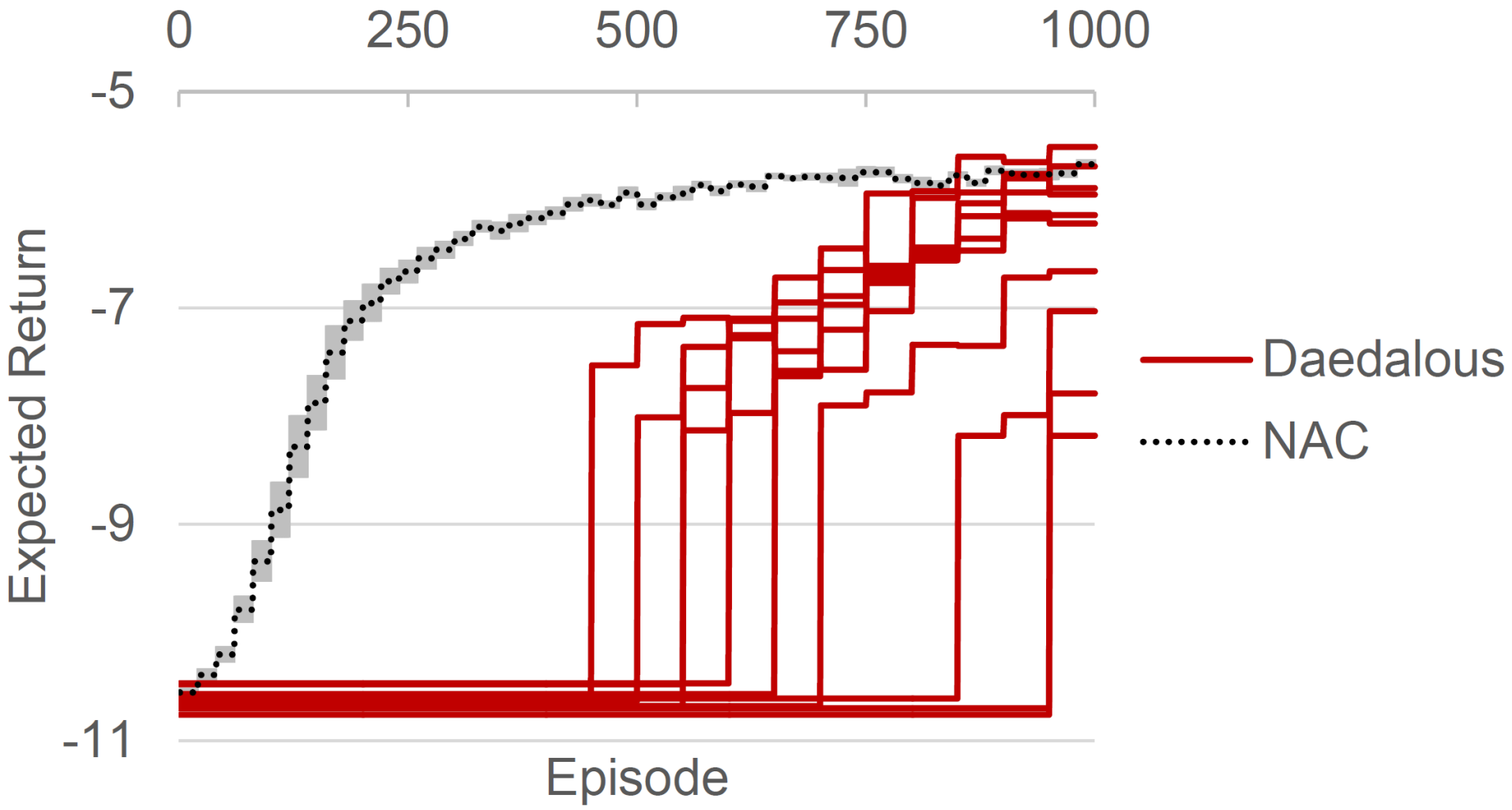
Empirical Results: Mountain Car



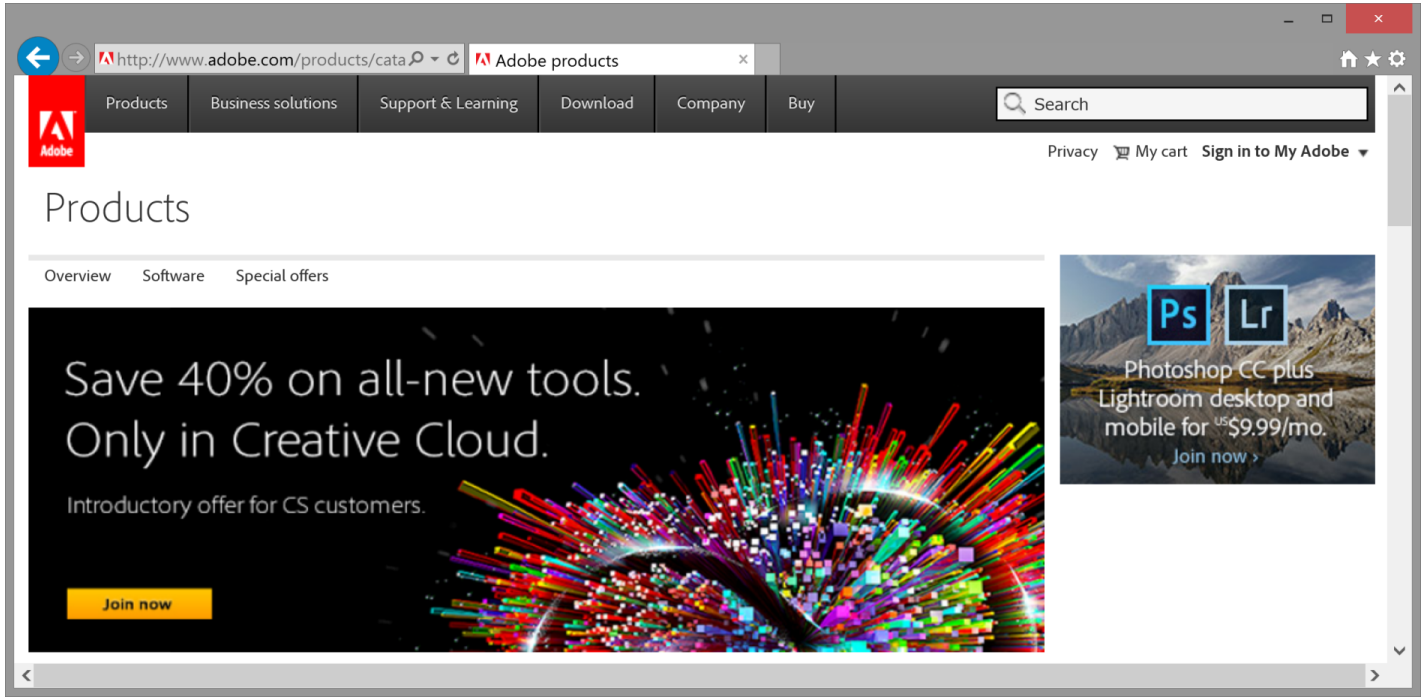
Empirical Results: Mountain Car

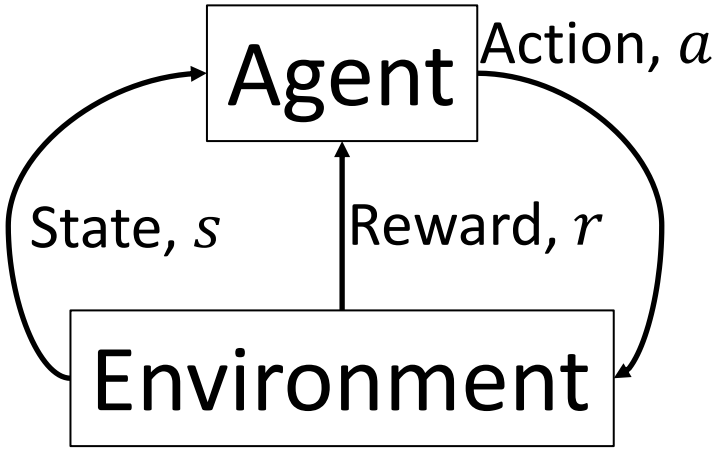


Empirical Results: Mountain Car

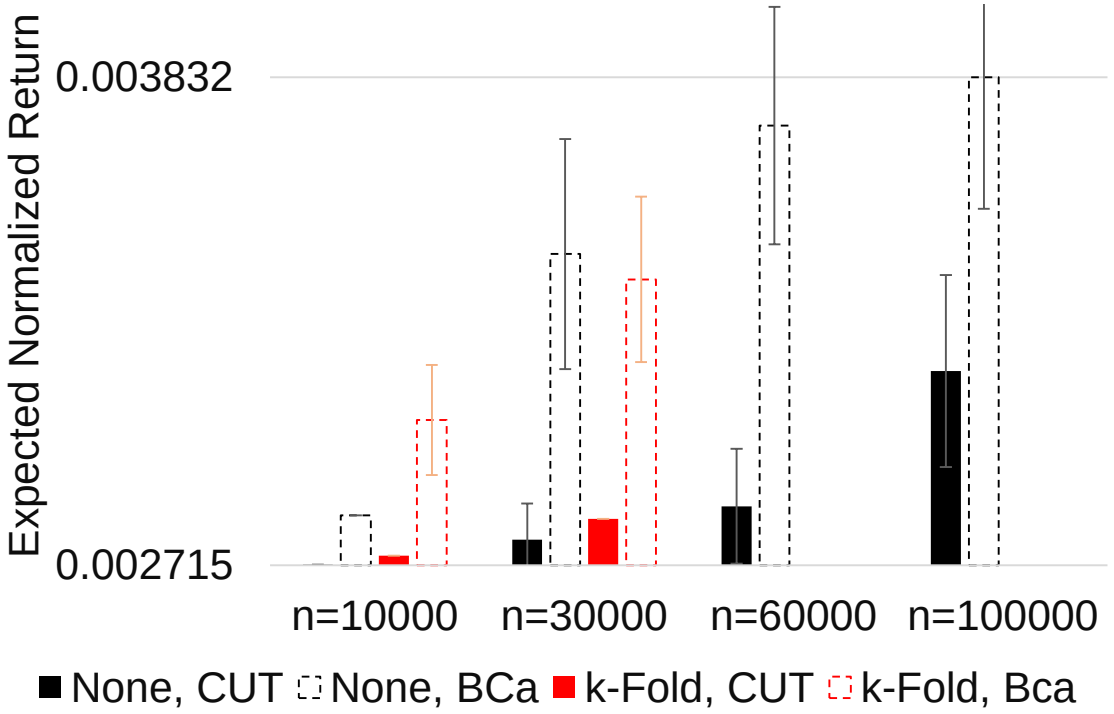


Empirical Results: Digital Marketing

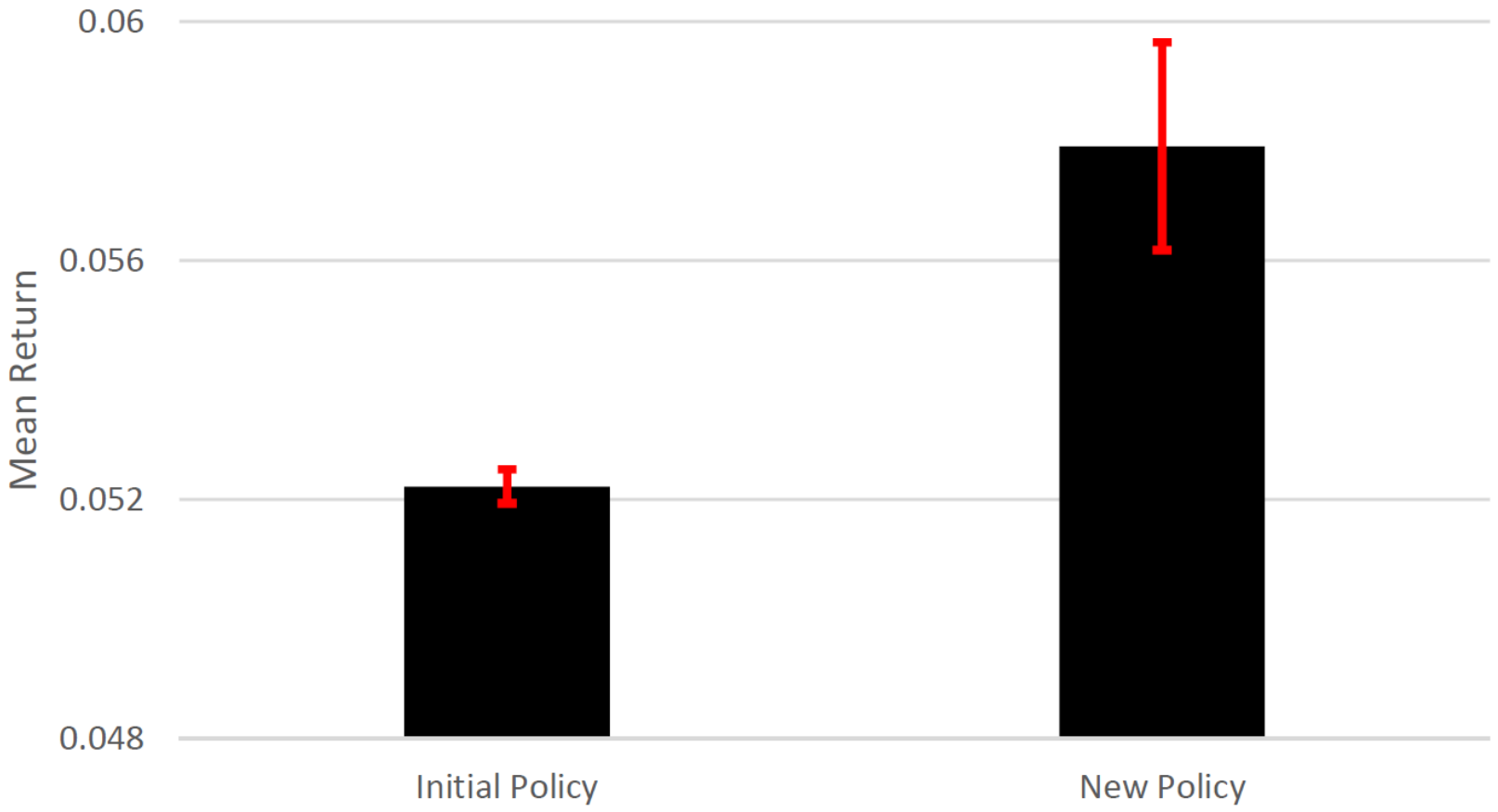




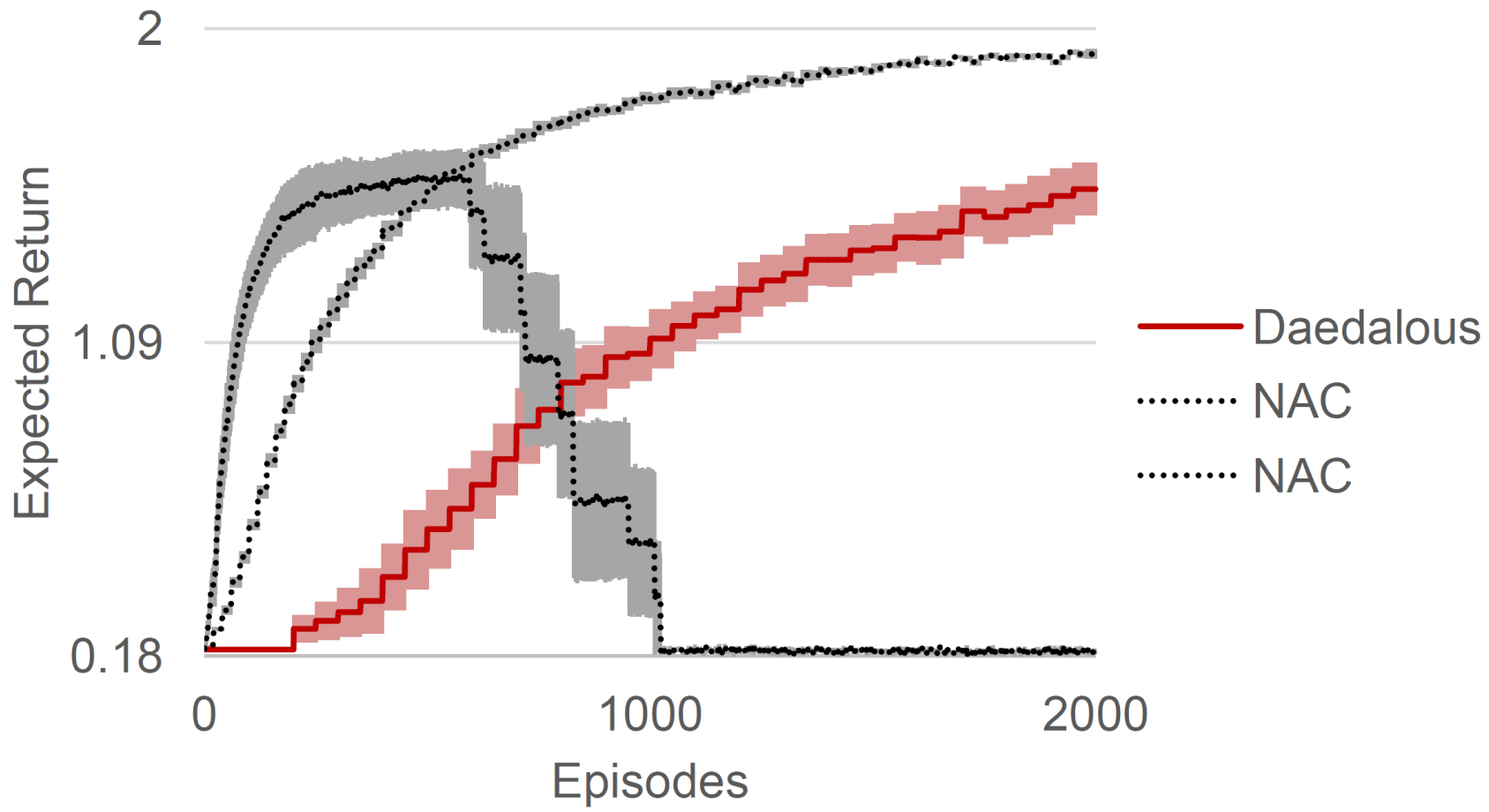
Empirical Results: Digital Marketing



Empirical Results: Digital Marketing

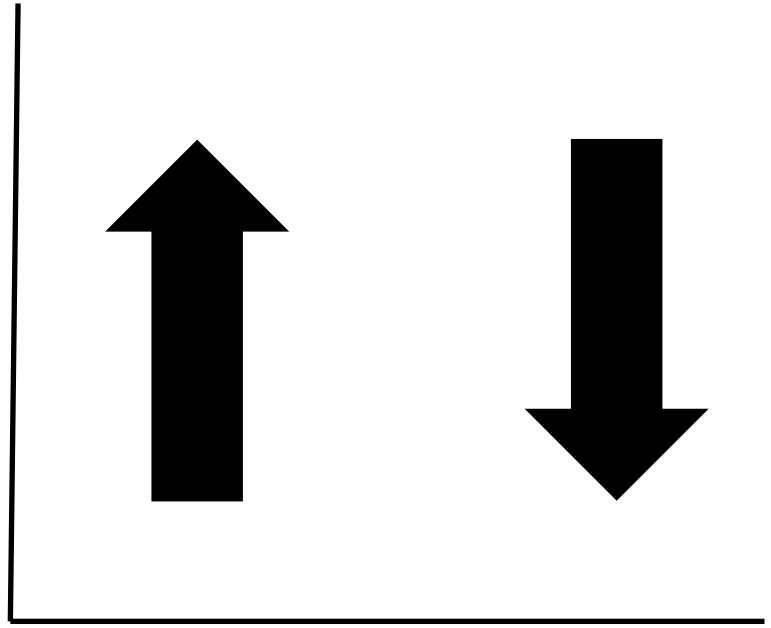


Empirical Results: Digital Marketing

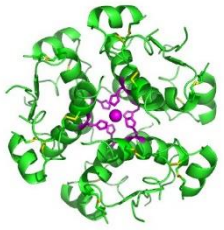


Example Results : Diabetes Treatment

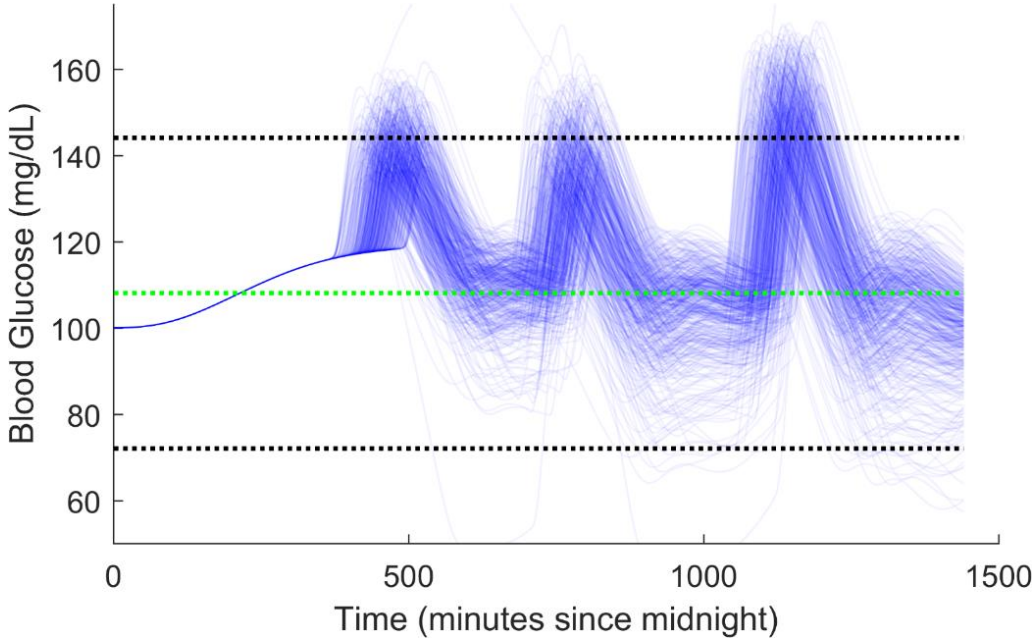
Blood Glucose
(sugar)



Eat Carbohydrates

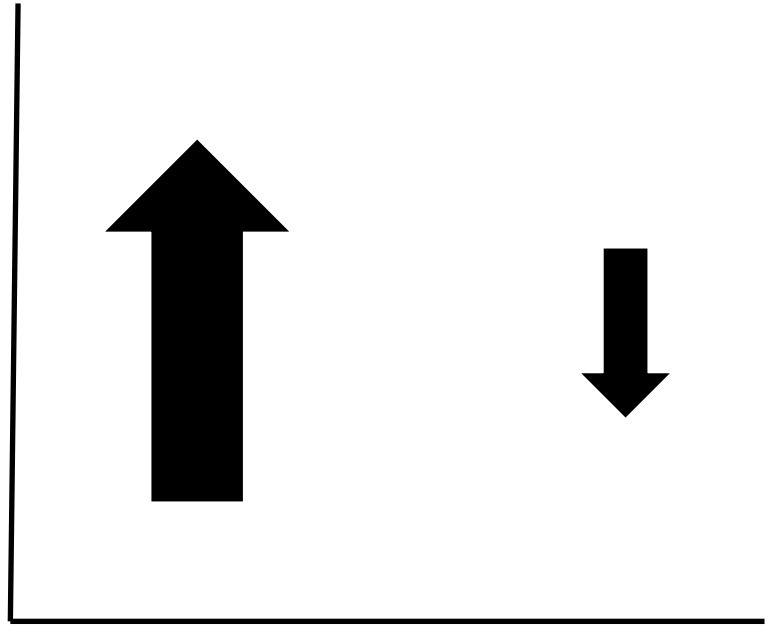


Release Insulin

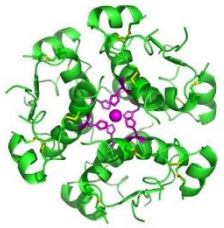


Example Results : Diabetes Treatment

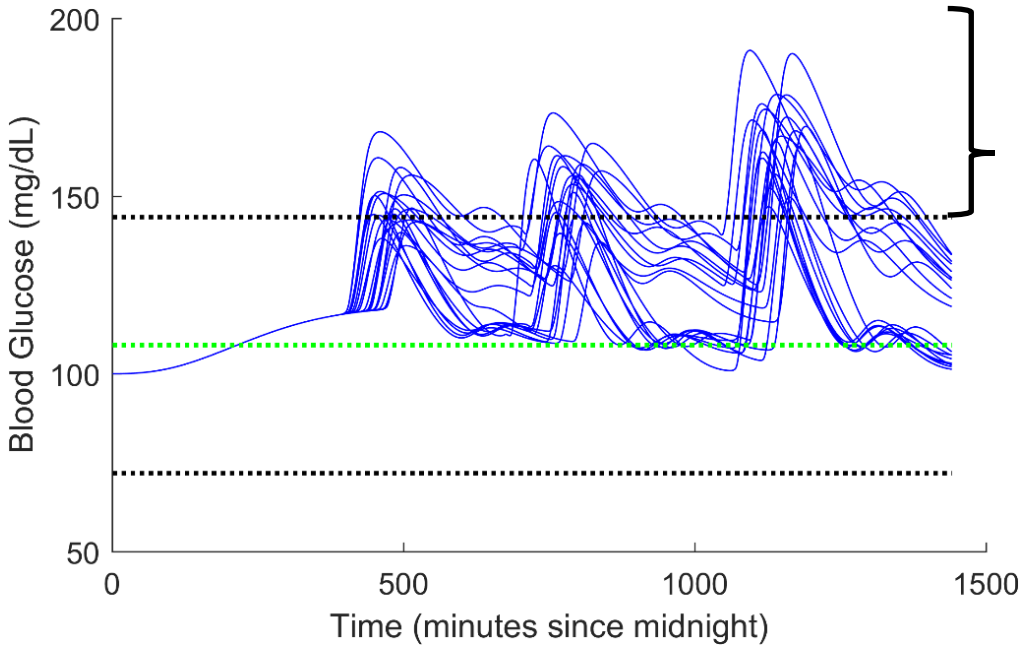
Blood Glucose (sugar)



Eat Carbohydrates



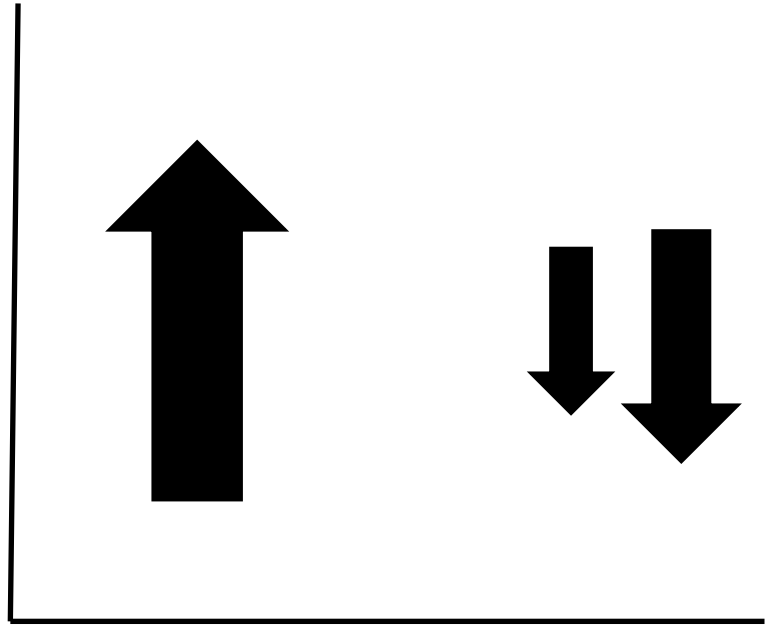
Release Insulin



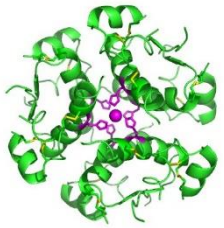
Hyperglycemia

Example Results : Diabetes Treatment

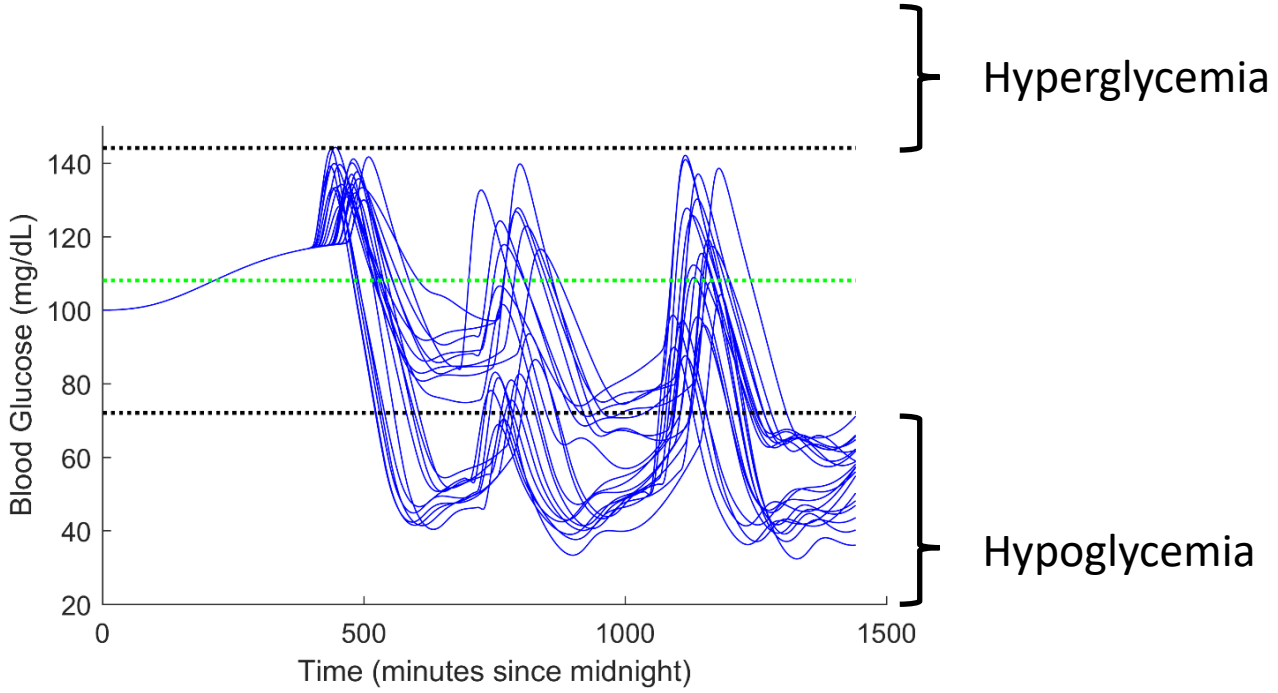
Blood Glucose (sugar)



Eat Carbohydrates



Release Insulin



Example Results : Diabetes Treatment

$$\text{injection} = \frac{\text{blood glucose} - \text{target blood glucose}}{CF} + \frac{\text{meal size}}{CR}$$

January

S	M	T	W	T	F	S
1	2	3	4	5	6	7
8	9	10	11	12	13	14
15	16	17	18	19	20	21
22	23	24	25	26	27	28
29	30	31				

February

S	M	T	W	T	F	S
			1	2	3	4
5	6	7	8	9	10	11
12	13	14	15	16	17	18
19	20	21	22	23	24	25
26	27	28				

March

S	M	T	W	T	F	S
			1	2	3	4
5	6	7	8	9	10	11
12	13	14	15	16	17	18
19	20	21	22	23	24	25
26	27	28	29	30	31	

April

S	M	T	W	T	F	S
						1
2	3	4	5	6	7	8
9	10	11	12	13	14	15
16	17	18	19	20	21	22
23	24	25	26	27	28	29
30						

May

S	M	T	W	T	F	S
	1	2	3	4	5	6
7	8	9	10	11	12	13
14	15	16	17	18	19	20
21	22	23	24	25	26	27
28	29	30	31			

June

S	M	T	W	T	F	S
				1	2	3
4	5	6	7	8	9	10
11	12	13	14	15	16	17
18	19	20	21	22	23	24
25	26	27	28	29	30	

Example Results : Diabetes Treatment

Alberta Diabetes INSTITUTE

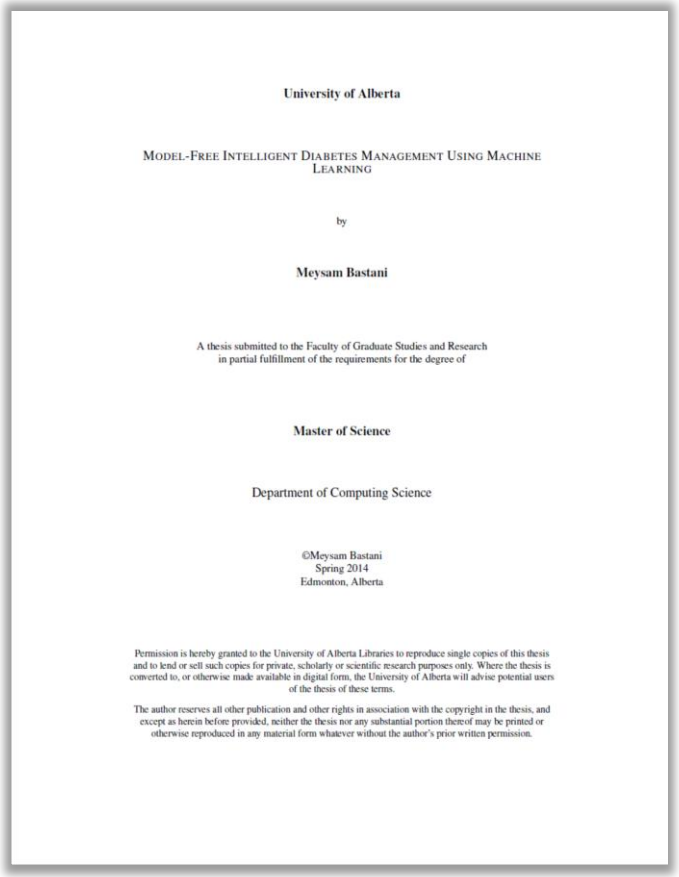
ALBERTA INNOVATES CENTRE FOR MACHINE LEARNING

UNIVERSITY OF ALBERTA

Intelligent Diabetes Management

T1DMS

Type 1 Diabetes Metabolic Simulator



University of Alberta

MODEL-FREE INTELLIGENT DIABETES MANAGEMENT USING MACHINE LEARNING

by

Meysam Bastani

A thesis submitted to the Faculty of Graduate Studies and Research
in partial fulfillment of the requirements for the degree of

Master of Science

Department of Computing Science

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Spring 2014
Edmonton, Alberta

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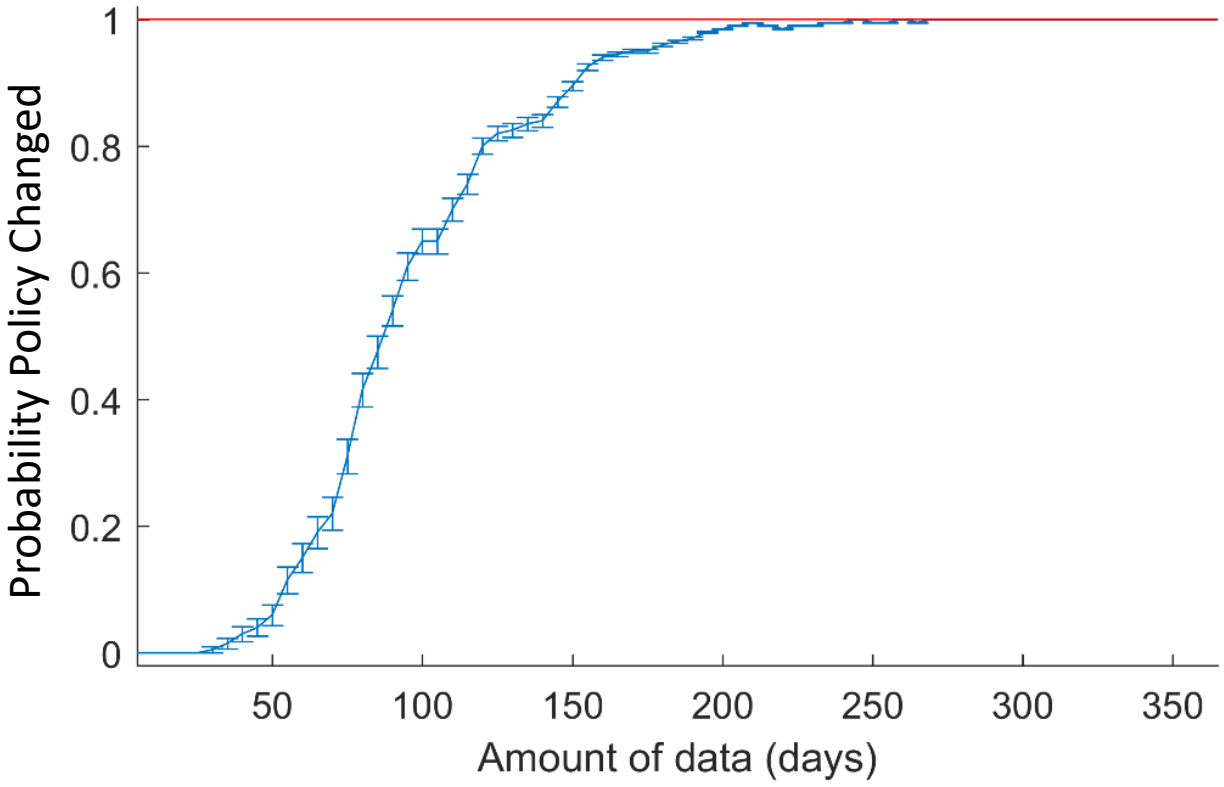
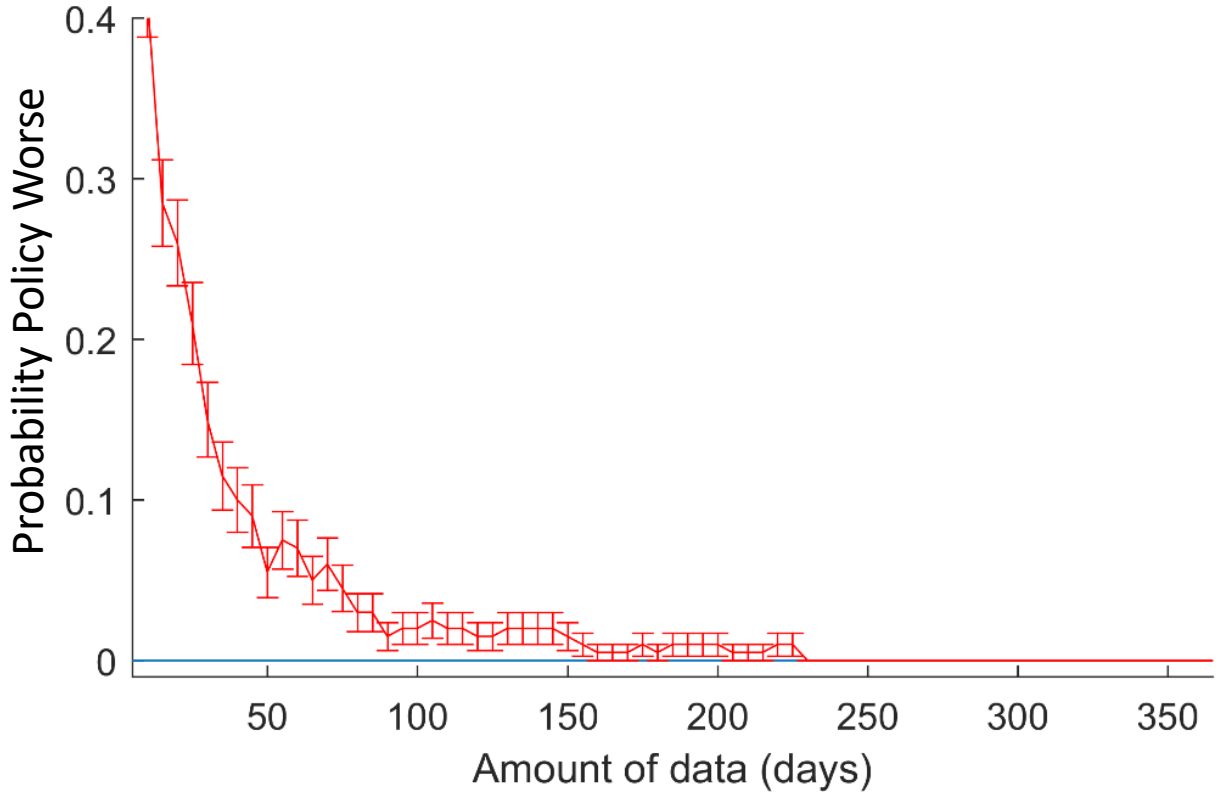
Example Results : Diabetes Treatment





Future Directions

- How to deal with long horizons?
- How to deal with importance sampling being “unfair”?
- What to do when the behavior policy is not known?
- What to do when the behavior policy is deterministic?

Summary

- Safe reinforcement learning
  - Risk-sensitive
  - Learning from demonstration
  - Asymptotic convergence even if data is off-policy
  - **Guaranteed (with probability $1 - \delta$) not to make the policy worse**
- Designing a safe reinforcement learning algorithm:
  - Off-policy policy evaluation (OPE)
    - IS, PDIS, WIS, WPDIS, DR, WDR, US, TSP, MAGIC
  - High confidence off-policy policy evaluation (HCOPE)
    - Hoeffding, CUT inequality, Student's t-test, BCa
  - Safe policy improvement (SPI)
    - Selecting the candidate policy

Takeaway

- Safe reinforcement learning is tractable!
  - Not just polynomial amounts of data – practical amounts of data