ST455: Reinforcement Learning

Lecture 11: Off-Policy Evaluation

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Lecture Outline

1. Off-Policy Evaluation (OPE) Introduction
2. OPE in Contextual Bandits
3. OPE in Reinforcement Learning
4. State-of-the-Art OPE Algorithms

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1. Off-Policy Evaluation (OPE) Introduction

2. OPE in Contextual Bandits

3. OPE in Reinforcement Learning

4. State-of-the-Art OPE Algorithms

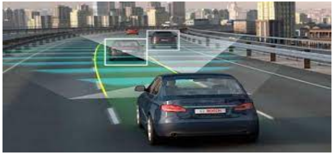
What is Off-Policy Evaluation

- **Objective**: Evaluate the impact of a **target policy** offline using historical data generated from a different **behavior policy**
- **Setting**: Offline RL with a precollected data

(a) Health Care

(b) Robotics

(c) Ridesharing



(d) Auto-driving

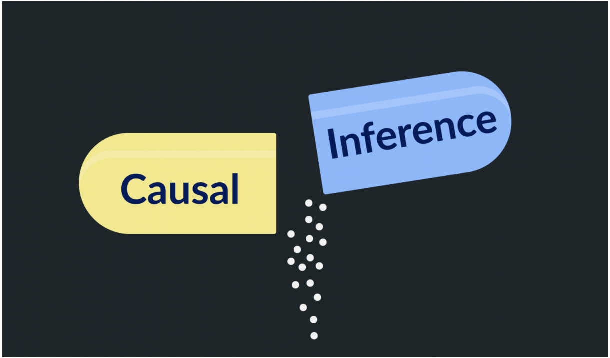
Why Off-Policy Evaluation

In many applications, it can be **dangerous** to evaluate a **target policy** by directly running this policy

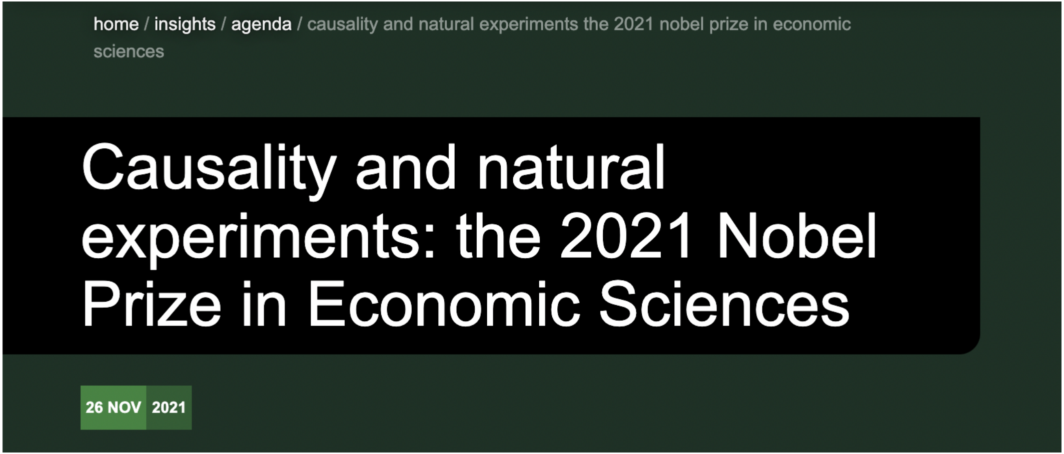
- **Healthcare**: which **medical treatment** to suggest for a patient
- **Ridesharing**: which **driver** to assign for a call order
- **Eduction**: which **curriculum** to recommend for a student

Causal Inference

Off-policy evaluation is closely related to **causal inference**, whose objective is to learn the difference between a new treatment and a standard treatment



Causal Inference (Cont'd)



Offline Policy Optimisation

- Off-policy evaluation is also related to **offline** policy learning (Lecture 10), whose objective is to learn an optimal policy offline using historical data
- Suppose we are able to evaluate the **value** of any policy, it suffices to pick the policy that maximises the value

Lecture Outline

1. Off-Policy Evaluation (OPE) Introduction
2. **OPE in Contextual Bandits**
3. OPE in Reinforcement Learning
4. State-of-the-Art OPE Algorithms

Recap: Contextual Bandits

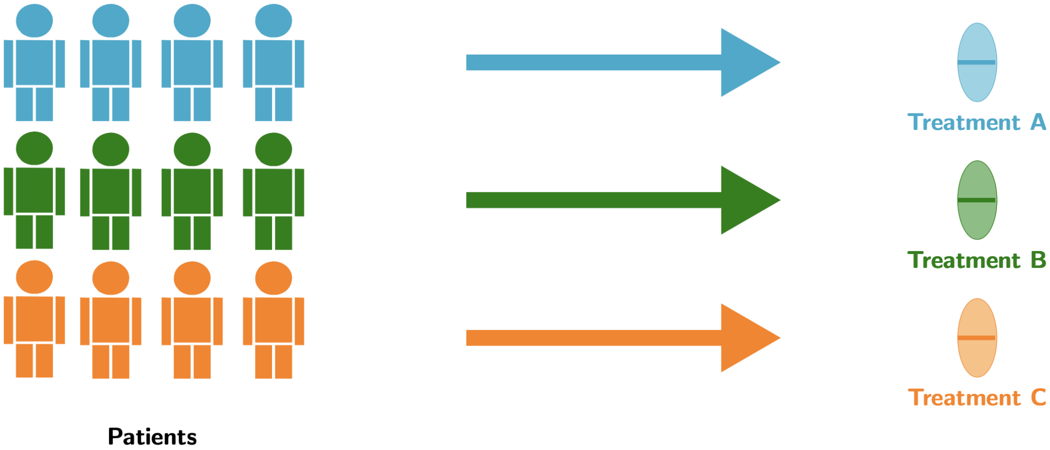
- Extension of MAB with **contextual** information.
- A **widely-used** model in medicine and technological industries.
- At time t, the agent
  - Observe a context S_t;
  - Select an action A_t;
  - Receives a reward R_t (depends on both S_t and A_t).
- **Objective**: Given an i.i.d. offline dataset $\{(S_t, A_t, R_t) : 0 \leq t < T\}$ generated by a behavior policy b, i.e.,

$$\Pr(A_t = a | S_t = s) = b(a|s),$$

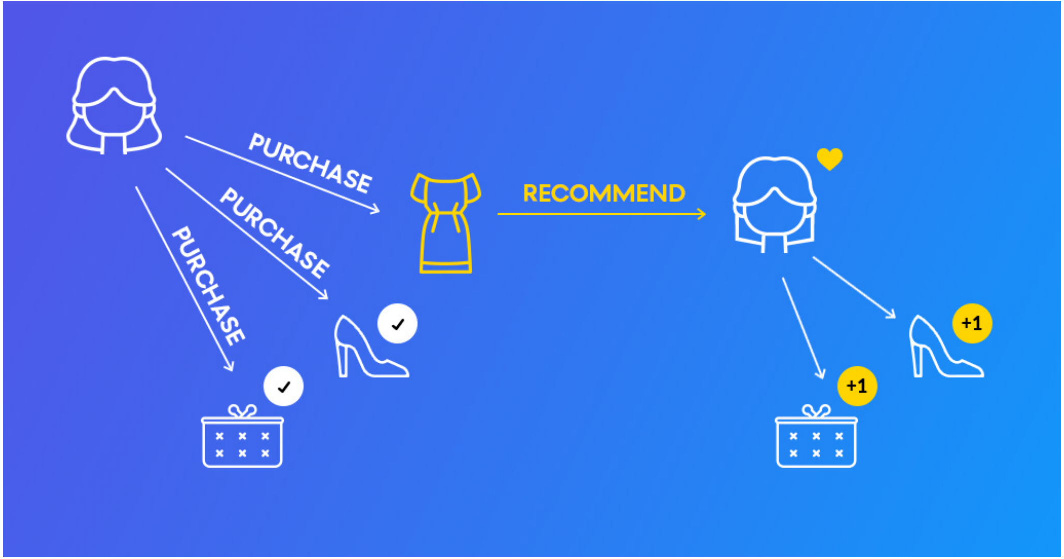
we aim to evaluate the mean outcome under a target policy π, i.e.,

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

Application I: Precision Medicine

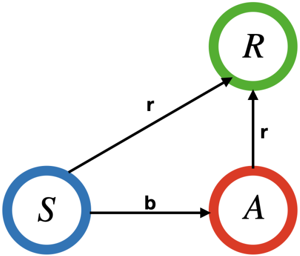


Application II: Personalized Recommendation

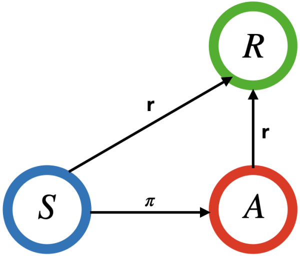


Challenge

- **Confounding**: State serves as confounding variables that confound the action-reward pair
- **Distributional shift**: The target policy generally differs from the behavior policy



historical data



what we want to evaluate

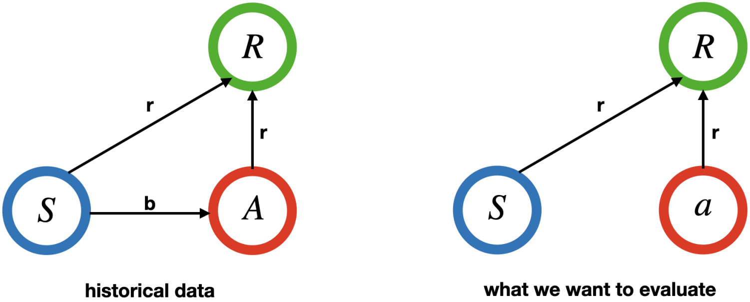
Challenge (Cont'd)

- Suppose π is a nondynamic policy, i.e., there exists some a such that $\pi(a|s) = 1$ for any s. We aim to evaluate the value under a given action a. A naive estimator is

$$\frac{\sum_{t=0}^{T-1} R_t \mathbb{I}(A_t = a)}{\sum_{t=0}^{T-1} \mathbb{I}(A_t = a)} \stackrel{P}{\to} \mathbb{E}(R|A = a)$$

- This estimator is valid only when no confounding variables exist

Challenge (Cont'd)



According to the causal diagram, the target policy's value equals

$$\mathbb{E}[\mathbb{E}(R|A=a,S)] \neq \mathbb{E}(R|A=a)$$

OPE Estimators

- With a general target policy π, the target policy's value equals

$$\sum_a \mathbb{E}[\pi(a|S)\mathbb{E}(R|A=a,S)] = \sum_a \mathbb{E}[\pi(a|S)r(S,a)],$$

  where $r(s,a) = \mathbb{E}(R|A=a, S=s)$

- Direct estimator
- Importance sampling estimator
- Doubly robust estimator

Direct Estimator

- Given that the target policy's value is given by

$$\sum_{a} \mathbb{E}[\pi(a|S)r(S,a)]$$

- The expectation can be approximated by the sample average, i.e.,

$$\frac{1}{T}\sum_{a}\sum_{t=0}^{T-1}[\pi(a|S_t)r(S_t,a)]$$

- The reward function can be replaced with some estimator $\widehat{r}$. This yields the direct estimator

$$\frac{1}{T}\sum_{a}\sum_{t=0}^{T-1}[\pi(a|S_t)\widehat{r}(S_t,a)]$$

Direct Estimator (Cont'd)

- $\widehat{r}$ estimated using supervised learning

$$
\begin{aligned}
S_0, A_0 &\rightarrow R_0 \\
S_1, A_1 &\rightarrow R_1 \\
&\vdots \\
S_{T-1}, A_{T-1} &\rightarrow R_{T-1}
\end{aligned}
$$

- Loss function: least square/Huber loss
- Computer parameter that minimizes empirical loss

Importance Sampling Estimator

- Given that the target policy's value is given by

$$\sum_{a} \mathbb{E}[\pi(a|S) r(S, a)]$$

- By the change of measure theory, it equals

$$\sum_{a} \mathbb{E}\left[b(a|S)\frac{\pi(a|S)}{b(a|S)} r(S, a)\right] = \mathbb{E}\left[\frac{\pi(A|S)}{b(A|S)} r(S, A)\right] = \mathbb{E}\left[\frac{\pi(A|S)}{b(A|S)} R\right]$$

- This yields the following importance sampling (IS) estimator [Zhang et al., 2012]

$$\frac{1}{T}\sum_{t=0}^{T-1} \frac{\pi(A_t|S_t)}{\widehat{b}(A_t|S_t)} R_t,$$

for a given estimator $\widehat{b}$

Importance Sampling Estimator (Cont'd)

- The ratio $\pi(a|s)/b(a|s)$ is referred to as the **importance sampling ratio**
- It measures the difference between the behavior and target policies
- When $\pi = b$, the ratio equals 1 for any a and s
- In general, the ratio centres at 1

$$\mathbb{E}\left[\frac{\pi(A|S)}{b(A|S)}\right] = 1$$

Importance Sampling Estimator (Cont'd)

- In **randomized studies**, $\boldsymbol{b}$ is known
- In **observational studies**, $\boldsymbol{b}$ needs to be estimated from data
- $\widehat{\boldsymbol{b}}$ estimated using supervised learning

$$
\begin{aligned}
S_0 &\rightarrow A_0 \\
S_1 &\rightarrow A_1 \\
&\vdots \\
S_{T-1} &\rightarrow A_{T-1}
\end{aligned}
$$

- Loss function: logistic regression loss
- Computer parameter that minimizes empirical loss

Direct Estimator v.s. IS Estimator

- Bias/Variance Trade-Off
- The direct estimator has **some bias**, since $\boldsymbol{r}$ needs to be estimated from data
- The IS estimator has **zero bias** when $\boldsymbol{b}$ is known as in randomized studies
- The IS estimator might have a **large variance** when $\boldsymbol{\pi}$ differs significantly from $\boldsymbol{b}$
- Suppose $\boldsymbol{R} = \boldsymbol{r}(\boldsymbol{S}, \boldsymbol{A}) + \varepsilon$ for some ε independent of $(\boldsymbol{S}, \boldsymbol{A})$,

$$\begin{aligned}\mathrm{Var}\left[\frac{\pi(\boldsymbol{A}|\boldsymbol{S})}{\boldsymbol{b}(\boldsymbol{A}|\boldsymbol{S})}\boldsymbol{R}\right] &= \mathbb{E}\left[\frac{\pi(\boldsymbol{A}|\boldsymbol{S})}{\boldsymbol{b}(\boldsymbol{A}|\boldsymbol{S})}\{\boldsymbol{R} - \boldsymbol{r}(\boldsymbol{S}, \boldsymbol{A})\}\right]^{2} + \text{some term}\\ &= \boldsymbol{\sigma}^{2}\mathbb{E}\left[\frac{\pi^2(\boldsymbol{A}|\boldsymbol{S})}{\boldsymbol{b}^2(\boldsymbol{A}|\boldsymbol{S})}\right] + \text{some term},\end{aligned}$$

where $\boldsymbol{\sigma}^{2} = \mathrm{Var}(\varepsilon)$

Extensions

- When π differs from b significantly, IS estimator suffers from **large variance** and becomes **unstable**
- Solutions sought by using **self-normalized** and/or **truncated** IS
- **Self-normalized** IS

$$\left[\frac{1}{T}\sum_{t=0}^{T-1}\frac{\pi(A_t|S_t)}{b(A_t|S_t)}\right]^{-1}\frac{1}{T}\sum_{t=0}^{T-1}\frac{\pi(A_t|S_t)}{b(A_t|S_t)}R_t$$

- Equivalent to IS estimator in large samples, by noting that

$$\frac{1}{T}\sum_{t=0}^{T-1}\frac{\pi(A_t|S_t)}{b(A_t|S_t)}\xrightarrow{P}\mathbb{E}\left[\frac{\pi(A|S)}{b(A|S)}\right]=1$$

- Stabilize the important sampling ratio in finite samples

Extensions (Cont'd)

- **Truncated** IS

$$\frac{1}{T}\sum_{t=0}^{T-1}\frac{\pi(A_t|S_t)}{\max(\widehat{b}(A_t|S_t),\varepsilon)}R_t,$$

  for some $\varepsilon > 0$

- Truncate the behavior policy whose value is smaller than ε
- Avoid **extremely large ratio**, thus reducing the variance of the estimator

Doubly Robust Estimator

- Direct estimator

$$\frac{1}{T}\sum_{a}\sum_{t=0}^{T-1}[\pi(a|S_t)\widehat{r}(S_t,a)]$$

  requires $\widehat{r}$ to be consistent

- IS estimator

$$\frac{1}{T}\sum_{t=0}^{T-1}\frac{\pi(A_t|S_t)}{\widehat{b}(A_t|S_t)}R_t,$$

  requires $\widehat{b}$ to be consistent

- Doubly robust (DR) estimator combines both, and requires **either $\widehat{r}$ or $\widehat{b}$** to be consistent (**"doubly-robustness" property**)

Doubly Robust Estimator (Cont'd)

- Consider the estimating function

$$\phi(S, A, R) = \sum_a \pi(a|S)\widehat{r}(S, a) + \frac{\pi(A|S)}{\widehat{b}(A|S)}[R - \widehat{r}(S, A)]$$

- First term on the RHS is the estimating function of the direct estimator
- Second term corresponds to the **augmentation term**
    - Zero mean when $\widehat{r} = r$
    - Debias the bias of the direct estimator
    - Offering additional robustness against model misspecification of $\widehat{r}$
- DR estimator given by $T^{-1}\sum_{t=0}^{T-1}\phi(S_t, A_t, R_t)$

Fact 1: Double Robustness

- The estimating function

$$\phi(S, A, R) = \sum_a \pi(a|S)\widehat{r}(S, a) + \frac{\pi(A|S)}{\widehat{b}(A|S)}[R - \widehat{r}(S, A)]$$

- In large sample size, DR estimator converges to $\mathbb{E}\phi(S, A, R)$
- When $\widehat{r} = r$, the augmentation term has zero mean. It follows that

$$\mathbb{E}\phi(S, A, R) = \sum_a \mathbb{E}[\pi(a|S)r(S, a)] = \text{target policy's value}$$

- When $\widehat{b} = b$, it has the same mean as the IS estimator

$$\mathbb{E}\phi(S, A, R) = \mathbb{E}\left[\frac{\pi(A|S)}{b(A|S)}R\right] + \mathbb{E}\left[\sum_a \pi(a|S)\widehat{r}(S, a) - \frac{\pi(A|S)}{b(A|S)}\widehat{r}(S, A)\right]$$

$$= \mathbb{E}\left[\frac{\pi(A|S)}{b(A|S)}R\right] = \text{target policy's value}$$

Fact 2: Efficiency

- When $\widehat{\boldsymbol{b}} = \boldsymbol{b}$, the estimating function

$$\phi(\boldsymbol{S}, \boldsymbol{A}, \boldsymbol{R}) = \sum_{\boldsymbol{a}} \pi(\boldsymbol{a}|\boldsymbol{S})\widehat{\boldsymbol{r}}(\boldsymbol{S}, \boldsymbol{a}) + \frac{\pi(\boldsymbol{A}|\boldsymbol{S})}{\boldsymbol{b}(\boldsymbol{A}|\boldsymbol{S})}[\boldsymbol{R} - \widehat{\boldsymbol{r}}(\boldsymbol{S}, \boldsymbol{A})]$$

- The MSE of DR estimator is proportional to the variance of $\phi(\boldsymbol{S}, \boldsymbol{A}, \boldsymbol{R})$

$$\mathrm{Var}(\phi(\boldsymbol{S}, \boldsymbol{A}, \boldsymbol{R})) = \mathbb{E}[\mathrm{Var}(\phi(\boldsymbol{S}, \boldsymbol{A}, \boldsymbol{R})|\boldsymbol{S}, \boldsymbol{A})] + \mathrm{Var}[\mathbb{E}(\phi(\boldsymbol{S}, \boldsymbol{A}, \boldsymbol{R})|\boldsymbol{S}, \boldsymbol{A})]$$

- The first term on the RHS is independent of $\widehat{\boldsymbol{r}}$
- The second term is minimized when $\widehat{\boldsymbol{r}} = \boldsymbol{r}$
- A good working model for $\boldsymbol{r}$ improves the estimator's efficiency
- When $\widehat{\boldsymbol{r}} = \boldsymbol{r}$, the estimator achieves the **efficiency bound** [e.g., smallest MSE among a class of regular estimators; see Tsiatis, 2007]

Fact 3: Efficiency

- When $\widehat{b}$ is estimated from data and the model is **correctly specified**, the estimator's MSE would be **generally smaller than** the one that uses the oracle behavior policy b [Tsiatis, 2007]
- Estimating $\widehat{b}$ yields a more efficient estimator, even if we know the oracle b
- **Multi-armed bandit** example without context information
  - **Objective**: evaluate $\mathbb{E}(R|A=a)$ for a given a
  - IS estimator with **known** $\Pr(A=a)$

$$\frac{\sum_{t=0}^{T-1} \mathbb{I}(A_t = a) R_t}{T \Pr(A_t = a)}$$

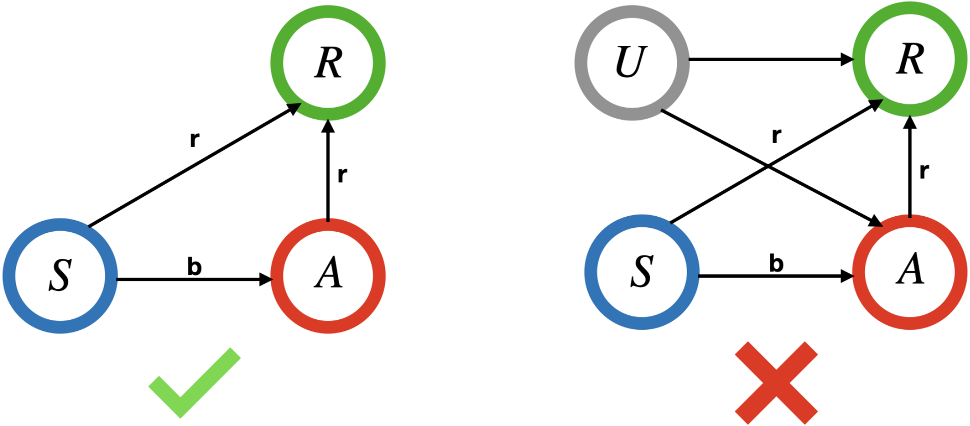
  - IS estimator with **estimated** $\Pr(A=a)$ has a **smaller** asymptotic variance

$$\frac{\sum_{t=0}^{T-1} \mathbb{I}(A_t = a) R_t}{\sum_{t=0}^{T-1} \mathbb{I}(A_t = a)}$$

Assumption: No Unmeasured Confounders

- All three estimators (direct estimator, IS, DR) rely on the **no unmeasured confounders** assumption
- They are **biased** when this assumption is violated
- It requires **all** confounders that confound the action-reward relationship are included in the state
- This assumption is **cannot** be verified in practice
- When violated, we may use some **auxiliary variable** (e.g., instrumental variables, mediators) for consistent policy evaluation [Angrist et al., 1996, Pearl, 2009]

Assumption: No Unmeasured Confounders (Cont'd)



Lecture Outline

General OPE Problem

- **Objective**: Given an offline dataset $\{(S_{i,t}, A_{i,t}, R_{i,t}) : 1 \leq i \leq N, 0 \leq t \leq T\}$ generated by a behavior policy b, where i indexes the ith episode and t indexes the tth time point, we aim to evaluate the mean return under a target policy π

$$\mathbb{E}^{\pi}\left[\sum_{t=0}^{\infty} \gamma^t R_t\right] = \mathbb{E} V^{\pi}(S_0)$$

  When $\gamma = 1$, the task is assumed to be episodic
- We focus on the case where both π and b are **stationary** policies
- Challenge: **Distributional shift**
  - In the offline dataset, actions are generated according to b
  - The target policy π we wish to evaluate is different from b
- Existing prediction algorithms (e.g., MC, TD) designed in online settings are **not** applicable

Recap: MC Prediction

- **Objective**: learns V^π from experience under π
- MC Policy Evaluation: $V(s) \leftarrow \textbf{average}[\textbf{Returns}(s)]$
- Incremental update for every-visit MC prediction:

$$V(S_t) \leftarrow V(S_t) + \alpha_t[G_t - V(S_t)]$$

  where α_t is $\frac{1}{\#[\textbf{Returns}(S_t)]}$ at time t
- The update can be performed after return G_t is observed
- i.e. after the episode is completed

Recap: TD Prediction

- Unlike MC methods, TD methods wait only until **next time step**
- The simplest TD method (so called TD($\mathbf{0}$)) considers the update

$$V(S_t) \leftarrow V(S_t) + \alpha_t[R_t + \gamma V(S_{t+1}) - V(S_t)]$$

- This update rule has $R_t + \gamma V(S_{t+1})$ as the **target**
- Considered as a **bootstrap** method: update in part based on an existing estimate

Direct Estimator

- The target policy's value is given by $\mathbb{E} V^{\pi}(S_0)$, or equivalently,

$$\mathbb{E}[\sum_{a} \pi(a|S_0) Q^{\pi}(S_0, a)]$$

- The expectation can be approximated via the **empirical initial state distribution**
- Q-learning is an **off-policy** algorithm. Can be applied to learn Q^{π} offline
- This yields the direct estimator

$$\frac{1}{N} \sum_{i=1}^{N} \sum_{a} \pi(a|S_{i,0}) \widehat{Q}(S_{i,0}, a)$$

- It remains to compute $\widehat{Q}$

Recap: Fitted Q-Iteration in Offline Setting

- Offline data: $\{(S_{i,t}, A_{i,t}, R_{i,t}) : 0 \le t \le T, 1 \le i \le N\}$
- Fitted Q-Iteration can be naturally applied by repeating
  1. Compute $\widehat{Q}$ as the argmin of

$$\arg\min_{Q} \sum_{t} \left[R_{i,t} + \gamma \max_{a} \widetilde{Q}(S_{i,t+1}, a) - Q(S_{i,t}, A_{i,t}) \right]^2$$

  2. Set $\widetilde{Q} = \widehat{Q}$
- Designed for learning $Q^{\pi^{\text{opt}}}$
- Do **not** require actions to follow the greedy policy

Fitted Q-Evaluation [Le et al., 2019]

- Bellman equation

$$\mathbb{E}\left[R_t + \gamma \pi(a|S_{t+1}) Q^{\pi}(S_{t+1}, a) | S_t, A_t\right] = Q^{\pi}(S_t, A_t)$$

- Both LHS and RHS involves Q^{π}
- Repeat the following procedure
  1. Compute $\widehat{Q}$ as the argmin of

$$\arg\min_{Q} \sum_{t} \left[R_{i,t} + \gamma \sum_{a} \pi(a|S_{i,t+1}) \widetilde{Q}(S_{i,t+1}, a) - Q(S_{i,t}, A_{i,t}) \right]^2$$

  2. Set $\widetilde{Q} = \widehat{Q}$
- Designed for learning Q^{π}
- Do **not** require actions to follow the target policy

Stepwise IS Estimator [Zhang et al., 2013]

- Consider episodic task where T is the termination time
- Standard MC prediction is **not** applicable under **distributional shift**
- Importance sampling ratio needs to be employed

$$
\begin{aligned}
\mathbb{E}^{\pi} R_0 &= \mathbb{E}^{b}\left[\frac{\pi(A_0|S_0)}{b(A_0|S_0)} R_0\right] \\
\mathbb{E}^{\pi} R_1 &= \mathbb{E}^{b}\left[\frac{\pi(A_0|S_0)}{b(A_0|S_0)} \frac{\pi(A_1|S_1)}{b(A_1|S_1)} R_1\right] \\
&\vdots \\
\mathbb{E}^{\pi} R_t &= \mathbb{E}^{b}\left[\frac{\pi(A_0|S_0)}{b(A_0|S_0)} \cdots \frac{\pi(A_t|S_t)}{b(A_t|S_t)} R_t\right]
\end{aligned}
$$

Stepwise IS Estimator (Cont'd)

- According to this logic, the target policy's value can be represented by

$$\mathbb{E}\left[\sum_{t=0}^{T}\gamma^t\left\{\prod_{j=0}^{t}\frac{\pi(A_j|S_j)}{b(A_j|S_j)}\right\}R_t\right]$$

- This yields the stepwise IS estimator

$$\frac{1}{N}\sum_{i=1}^{N}\left[\sum_{t=0}^{T}\gamma^t\left\{\prod_{j=0}^{t}\frac{\pi(A_{i,j}|S_{i,j})}{\widehat{b}(A_{i,j}|S_{i,j})}\right\}R_{i,t}\right]$$

for a given estimator $\widehat{b}$ computed using supervised learning algorithms

Limitation

- Stepwise IS suffers from a **large variance**
- In particular, the IS ratio at time t is the product of individual ratios from the **initial** time to time t

$$\prod_{j=0}^{t} \frac{\pi(A_j|S_j)}{b(A_j|S_j)}$$

- Variance of the ratio grows **exponentially** with respect to t, referred to as the **curse of horizon** [Liu et al., 2018]
- Extension: **Doubly-robust** estimator by [Jiang and Li, 2016]

Pros & Cons of Direct v.s. Stepwise IS

- Stepwise IS is similar to an offline version of **MC**
- SIS learns from **complete** sequences
- SIS only works for **episodic** (terminating) environments

- Direct estimator (DE) is similar to an offline version of **TD**
- DE can learn from **incomplete** sequences
- DE works in **continuing** environments

Pros & Cons of Direct v.s. Stepwise IS (Cont'd)

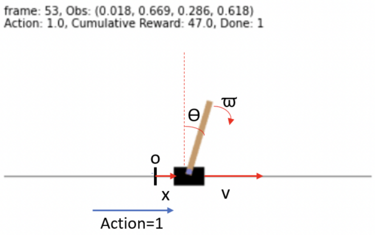
- Bias/Variance Trade-Off
- When $\boldsymbol{b}$ is known, stepwise IS is an **unbiased** estimator since

$$\mathbb{E}^{\pi} R_t = \mathbb{E}^{b}\left[\frac{\pi(A_0|S_0)}{b(A_0|S_0)} \cdots \frac{\pi(A_t|S_t)}{b(A_t|S_t)} R_t\right]$$

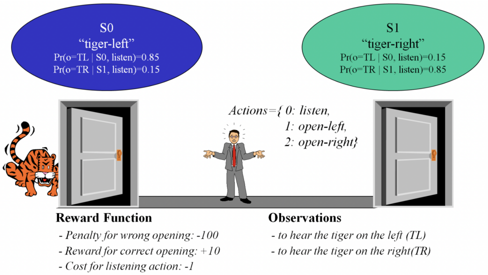
- Direct estimator has **some bias**, since $\boldsymbol{Q}^{\pi}$ needs to be estimated from data
- Stepwise IS suffers from **curse of horizon** and a **large variance**
- Direct estimator has a much lower variance

Pros & Cons of Direct v.s. Stepwise IS (Cont'd)

- Direct estimator exploits **Markov** & **stationary** properties
- Relies on the **Bellman equation**
- More **efficient** in MDP environments



- SIS does **not** exploit these properties
- More **flexible** in non-MDP environments (e.g., POMDP)



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4. **State-of-the-Art OPE Algorithms**

Recap: RL Models

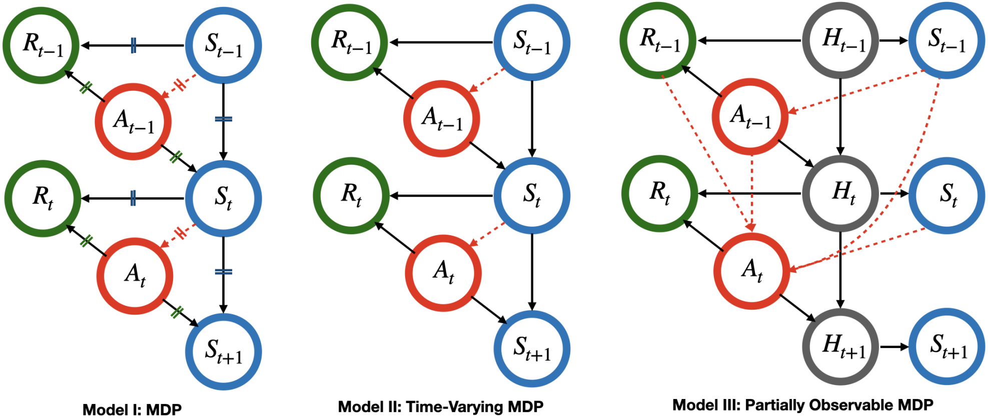


Figure: Causal diagrams for MDPs, TMDPs and POMDPs. Solid lines represent the causal relationships. Dashed lines indicate the information needed to implement the optimal policy. $\{H_t\}_t$ denotes latent variables. The parallel sign $\|$ indicates that the conditional probability function given parent nodes is equal.

Marginalized IS Estimator

- As we have discussed, stepwise IS suffers from **curse of horizon**
- Curse of horizon is **unavoidable** in general **Non-Markov decision processes** (e.g., POMDP)
- Under some additional model assumptions (e.g., Markovianity & time-homogeneity), it is possible to break the curse of horizon using **marginalized IS** estimator
- Stepwise IS does **not** exploit these properties

Marginalized IS Estimator (Cont'd)

- Stepwise IS uses the **cumulative** IS ratio

$$\mathbb{E}^{\pi} R_t = \mathbb{E}^{b}\left[\frac{\pi(A_0|S_0)}{b(A_0|S_0)} \cdots \frac{\pi(A_t|S_t)}{b(A_t|S_t)} R_t\right]$$

- Under Markovianity (TMDP), marginalized IS uses the **marginalized** IS ratio

$$\mathbb{E}^{\pi} R_t = \mathbb{E}^{b}\left[\frac{p_t^{\pi}(S_t, A_t)}{p_t^{b}(S_t, A_t)} R_t\right] \tag{1}$$

  where p_t^{π} and p_t^{b} are the marginal density functions of (S_t, A_t) under π and b

- The resulting marginalized IS estimator can be derived from (1)

Marginalized IS Estimator

- Under Markovianity and time-homogeneity (MDP),

$$\mathbb{E} V^{\pi}(S_0) = \mathbb{E}^{b} \left[\frac{\sum_{t=0}^{\infty} \gamma^{t} p_t^{\pi}(S, A)}{p_{\infty}(S, A)} R \right] \tag{2}$$

  where p_{∞} denotes the limiting state-action distribution under b and the numerator corresponds to the γ-discounted state-action visitation probability
- The resulting marginalized IS estimator can be derived from (2)

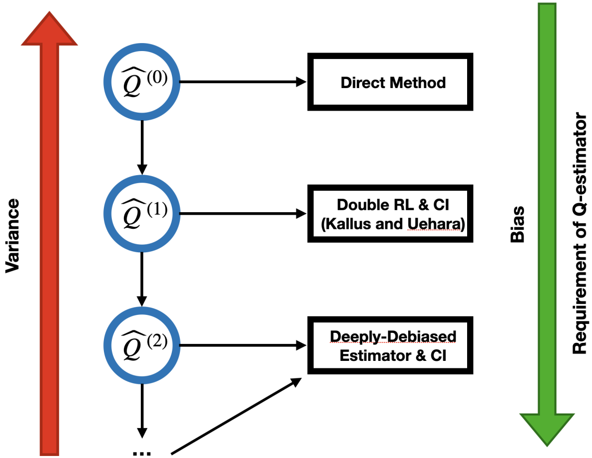
Double RL [Kallus and Uehara, 2019]

- Double RL extends DR in **contextual bandits** to the general RL problem
- Similar to DR, the estimator can be represented as

$$\text{Direct Estimator} + \text{Augmentation Term}$$

- **Augmentation** term is to **debias** the bias of direct estimator and offer protection against model misspecification of $\boldsymbol{Q^{\pi}}$; it relies on the marginalized IS ratio
- Similar to DR, the estimator is **doubly-robust**, e.g., consistent when either $\boldsymbol{Q^{\pi}}$ or the marginalized IS ratio is correct
- Similar to DR, the estimator achieves the **efficiency bound** in MDPs

Deeply-Debiased OPE [Shi et al., 2021]



- Ensures the bias decays much faster than standard deviation
- Allows to provide valid **uncertainty quantification** (e.g., confidence interval)

Summary

- Off-policy evaluation
- Direct estimator
- Importance sampling estimator
- Doubly robust estimator
- Fitted Q-evaluation
- Stepwise IS/Marginalized IS
- Double reinforcement learning
- Deeply-debiased estimator

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Questions