Protecting Against Evaluation Overfitting in Empirical Reinforcement Learning

Shimon Whiteson, University of Amsterdam
Brian Tanner, University of Alberta
Matthew E. Taylor, Lafayette College
Peter Stone, University of Texas at Austin

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Evaluating Machine Learning Algorithms

- Subjective evaluations
  - Pros: leverage intuition
  - Cons: cannot expose fallacious assumptions

- Theoretical results
  - Pros: rigorous
  - Cons: not always obtainable; conditions may not apply

- Empirical evaluations
  - Pros: yields insights, spurs innovation
  - Cons: evaluation overfitting
The Problem

- **One common approach**: measure average cumulative reward across independent trials in a fixed benchmark environment.
- Various design choices can yield an overfit method:
  - State representation
  - Initial value function
  - Learning rate, etc.
- **Extreme example**: ‘learning algorithm’ for Mountain Car that begins with optimal policy.

Goal

Devise empirical methodologies that guard against overfitting in on-line reinforcement learning.
The Problem

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Outline

- Evaluation Overfitting
  - Data vs. Environment Overfitting
  - Fitting vs. Overfitting
- Generalized Environments
  - Open Generalized Methodology
  - Secret Generalized Methodology
  - Meta-Generalized Methodology
  - Generalized Performance Measures
- Results
Evaluation Overfitting

Evaluation Process

A self-interested designer creates an agent with which an evaluator conducts independent trials yielding a score estimating some statistics, e.g., expected cumulative reward.

- Scores implicitly represent performance on a target distribution.
- In evaluation overfitting:
  - Evaluation yields a high score.
  - Performance across target distribution is poor.
Evaluation Overfitting

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Data vs. Environment Overfitting

- In data overfitting:
  - Function agent produces is too customized to evaluation data
  - Poor generalization to new data from same environment
- In environment overfitting:
  - Agent is too customized to evaluation environment
  - Poor generalization to other environments in target distribution

While data overfitting is problematic in supervised learning, evaluation overfitting is problematic in reinforcement learning
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While data overfitting is problematic in *supervised learning*, evaluation overfitting is problematic in *reinforcement learning*
Fitting vs. Overfitting

- How broad should the target distribution be?
  - Broadly applicable agents are desirable
  - But specializing can give leverage

- Can environment overfitting be good?
  - No, but target distribution may be small
  - **Fitting**: customizing to target distribution at expense of others
  - **Overfitting**: customizing to evaluation setting at expense of target distribution

In reinforcement learning, target distributions need multiple environments in order to create reducible uncertainty
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In reinforcement learning, target distributions need multiple environments in order to create *reducible uncertainty*
Generalized Environments

- Single-environment methodologies are not ideal
  - Invite environment overfitting
  - Still useful given a good-faith effort by designers

- **Simple solution:** formalize the target distribution in a generalized environment
  - $\mathcal{G} = \langle \Theta, \mu \rangle$, a distribution $\mu$ over a set of environments $\Theta$
  - Score computed from multiple trials, each in a different environment sampled from $\Theta$ according to $\mu$

Example: Helicopter Hovering in the RL Competition

Goal is to hover a helicopter in a fixed position; each trial has a different $\theta$ with an unknown wind velocity
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**Example: Helicopter Hovering in the RL Competition**

Goal is to hover a helicopter in a fixed position; each trial has a different $\theta$ with an unknown wind velocity
$G$ is known to designer

In **tuning phase**, designer samples $\theta$’s freely from $G$

In **test phase**, evaluator samples new $\theta$ from $G$ for each trial

Protects against both data and environment overfitting
Secret Generalized Methodology

- Open methodology creates uncertainty about $\theta$ but not $G$
- $G$ may only approximate true target distribution
- In **uncertainty overfitting**, the agent is customized to $G$ at the expense of other possible true target distributions

- In **secret generalized methodology**:
  - $G$ is hidden
  - Designer receives only a fixed set of $\theta$’s sampled from $G$
  - Agent is tested on independent $\theta$’s sampled from $G$

- Pros and cons:
  - Protects against data, environment, and uncertainty overfitting
  - Does not require formalizing $G$
  - Requires secrecy: limited to one-shot settings
Open methodology creates uncertainty about $\theta$ but not $\mathcal{G}$

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avoid trade-offs with a meta-generalized environment

\( \mathcal{H} = \langle \Gamma, \tau \rangle \), a distribution \( \tau \) over a set of generalized environments \( \Gamma \)

in meta-generalized methodology:

- in tuning, designer samples freely from \( \mathcal{H} \)
- in testing, each meta-trial, involves a series of trials on environments sampled from a fixed \( G_i \) sampled from \( \mathcal{H} \)

pros and cons

- protects against data, environment, and uncertainty overfitting
- no secrecy required
- requires formalizing \( \mathcal{H} \) and conducting many trials
Meta-Generalized Methodology

- Avoid trade-offs with a meta-generalized environment
- $\mathcal{H} = \langle \Gamma, \tau \rangle$, a distribution $\tau$ over a set of generalized environments $\Gamma$
- In meta-generalized methodology:
  - In tuning, designer samples freely from $\mathcal{H}$
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- Pros and cons
  - Protects against data, environment, and uncertainty overfitting
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Generalized Performance Measures

Example: Averaging Temperatures from Different Scales

The statement “the average of \(-32^\circ C, 130^\circ F\) is greater than that of \(-10^\circ C, 100^\circ F\)” is true but not meaningful: converting the °F measurements to °C makes it false.

- Reward scales in reinforcement learning are often arbitrary
- Averages across differently scaled environments can mislead
- Many other performance measures are possible
- The sign test counts how many times one agent outperforms another in a series of matched trials.
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Experimental Approach

- Devise an intuitively useful adaptive function approximator
- Show that generalized methodologies can validate it but single-environment methodologies cannot
- Evaluate the methodology, not the learning algorithm
Range-Adaptive Tile Coding

- Tile coding requires knowledge of state value ranges
- Instead, dynamically spread fixed memory over observed values
- When values outside range occur, transplant to a larger range

Algorithm 1 \textsc{Transplant}

\begin{algorithm}
\begin{algorithmic}
\For{$i := 0 \ldots \text{numTiles}$}
\State \textit{c} := \text{getCenterOfTile}(i,\text{oldInputRanges})
\State \textit{k} := \text{getTileForState}(\textit{c},\text{newInputRanges})
\State \text{newWeights}[k] := \text{newWeights}[k] + \text{oldWeights}[i]
\State \text{newWeightCounts}[k] := \text{newWeightCounts}[k] + 1
\EndFor

\For{$i := 0 \ldots \text{numTiles}$}
\State \text{newWeights}[i] := \text{newWeights}[i]/\text{newWeightCounts}[i]
\EndFor
\end{algorithmic}
\end{algorithm}
Generalizations and Methods

- Environments:
  - Mountain Car
  - Acrobot
  - Puddle World

- Generalizations:
  - Action effects randomly perturbed
  - Observations scaled, inverted, translated, trigonometric nonlinearities applied
  - Initial state fixed or random

- Methods:
  - Adaptive (A): range-adaptive tile coder
  - Baseline (B): smallest range sufficient for all environments
  - Cheater (C): perfect environment-specific range info

- Each method is tuned to each generalized environment
Generalized Methodology Results

Mountain Car

Acrobot

Puddle World
Using the Sign Test

- Tuned agents selected via Copeland’s method are the same (except for Puddle World)
- Comparisons between A, B, and C are the same for each generalized environment
- Different story on union task:
  - Cannot distinguish A and C with averaging or sign test metrics
  - Tuned adaptive agent selected via Copeland’s method is better
Generalized methodologies for reinforcement learning

- Protect against environment overfitting
- Enable fairer comparisons between agents
- Make explicit what environment generality is desired
- Incentivize adaptable algorithms

Form of methodology depends on purpose of evaluation

- One-shot settings: secret methodologies protect against uncertainty overfitting
- Otherwise: open methodologies do not need secrecy

Performance measure depends on generalized environment

- Averaging for similar, well-understood environments
- Sign tests for disparate environments with arbitrary scales
Conclusions

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