Task-Driven Detection of Distribution Shifts with Statistical Guarantees for Robot Learning

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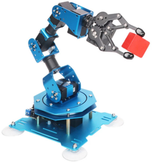
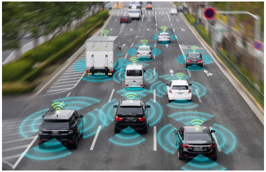
April 19th, 2022

Motivation





Result overview

Objectives:

- OOD detection with guaranteed confidence bounds

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- Probably Approximately Correct (PAC)-Bayes theory

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- Task-driven approach (sensitive only to changes that affect the robot's performance)

Tools:

- Probably Approximately Correct (PAC)-Bayes theory
- Statistical techniques based on p-values and concentration inequalities

Contributions

- Train control policies with a guaranteed performance bound on the training distribution

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  $\implies$ Statistical guarantees on both the false positive and false negative rates of the detectors

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- Train control policies with a guaranteed performance bound on the training distribution
- Develop two different task-driven OOD detectors
- Perform OOD and WD detection with guaranteed confidence bounds
  $\implies$ Statistical guarantees on both the false positive and false negative rates of the detectors
- Demonstrate the benefits of the approach in simulation and hardware

Problem formulation

- Robot dynamics:

$$s_{t+1} = f_E(s_t, a_t)$$

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After deploying the robot in a few environments in S', can we detect if $\mathcal{D}'$ is different from $\mathcal{D}$?

Problem formulation

- OOD detection if:

$$C_{\mathcal{D}'}(\pi) := \mathbb{E}_{E' \sim \mathcal{D}'} C_{E'}(\pi) > C_{\mathcal{D}}(\pi) := \mathbb{E}_{E \sim \mathcal{D}} C_E(\pi)$$

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- WD detection if:

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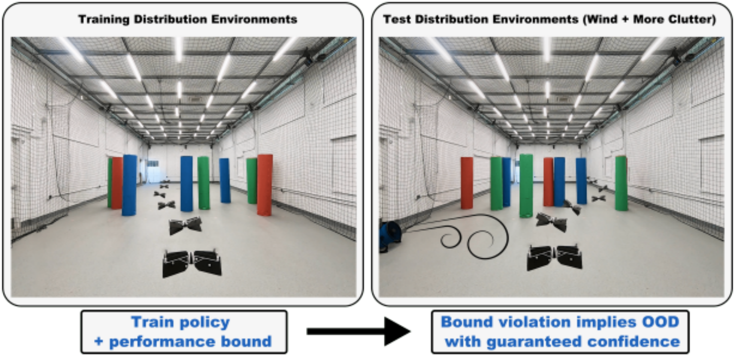
- Detection: insensitive to changes in the environment distribution that do not adversely impact the robot's performance

Approach


Training Distribution Environments
Test Distribution Environments (Wind + More Clutter)
Train policy
+ performance bound
Bound violation implies OOD
with guaranteed confidence

Policy training via PAC-Bayes bounds

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- Training cost:

$$C_S(\pi) = \frac{1}{m} \sum_{E \in S} C_E(\pi)$$

Policy training via PAC-Bayes bounds

Theorem 1. *For any distribution* $\mathcal{D}$*, prior distribution* P_0*,* $\delta \in (0,1)$*, cost bounded in* $[0,1]$*,* $m \geq 8$*, and deterministic algorithm* A *which outputs the posterior distribution* P*, we have the following:*

$$\mathbb{P}_{(S,\pi)\sim(\mathcal{D}^m \times P)}\left[C_{\mathcal{D}}(\pi) \leq \bar{C}_\delta(\pi, S)\right] \geq 1-\delta,$$

where $\bar{C}_\delta(\pi, S) := C_S(\pi) + \sqrt{R}$*,* $R := \left(D_2(P||P_0) + \ln\left(\frac{2\sqrt{m}}{(\delta/2)^3}\right)\right)/(2m)$*,*

and $D_2(P||P_0) := \ln\left(\mathbb{E}_{\pi\sim P_0}\left[\left(\frac{P(\pi)}{P_0(\pi)}\right)^2\right]\right)$ *is the Rényi divergence.*

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Corollary 1. *Let the assumptions of Theorem 1 hold. Then:*

$$\mathbb{P}_{(S,\pi)\sim(\mathcal{D}^m \times P)} \left[C_{\mathcal{D}}(\pi) \geq \underline{C}_\delta(\pi, S) \right] \geq 1 - \delta,$$

where $\underline{C}_\delta(\pi, S) := C_S(\pi) - \sqrt{R}$.

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- PAC-Bayes bounds: Strong bounds for policy learning
- Policy training: Search for a posterior P to minimize the upper bound $\bar{C}_\delta(\pi, S)$
- Training methods:
  - Backpropagation
  - Blackbox optimization (evolutionary strategies)

Task-driven OOD detection with statistical guarantees

- Key idea:

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  1. Hypothesis testing via p-value

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- Methods:
  1. Hypothesis testing via p-value
  2. Confidence interval on the difference in expected train and test costs

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    $p_O(S') := \mathbb{P}_{\hat{S}' \sim \mathcal{D}'^n}\left[C_{\hat{S}'}(\pi) \geq C_{S'}(\pi) | C_{\mathcal{D}'}(\pi) \leq C_{\mathcal{D}}(\pi)\right]$

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  - WD detection: $p_W(S') := \mathbb{P}_{\hat{S}' \sim \mathcal{D}'^n} \left[C_{\hat{S}'}(\pi) \leq C_{S'}(\pi) | C_{\mathcal{D}'}(\pi) > C_{\mathcal{D}}(\pi) \right]$

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$$\mathbb{P}_{(S,\pi)\sim(\mathcal{D}^m\times P)}\left[p_W(S') \leq \exp(-2n\max\{\underline{\mathrm{C}}_{\delta_W}(\pi,S) - C_{S'}(\pi),0\}^2\right] \geq 1-\delta_W$$

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- Compare the upper bounds with the significance levels

Method 1: Hypothesis testing

Algorithm 1 OOD/WD Detection using Hypothesis Testing

Input: $\delta_O, \delta_W, \alpha_O, \alpha_W \in (0,1)$.
Input: PAC-Bayes Bounds: $\overline{C}_{\delta_O}(\pi, S)$, $\underline{C}_{\delta_W}(\pi, S)$.
Input: Test dataset $S' \sim \mathcal{D}'^n$ and policy $\pi \sim P$.
Output: OOD, WD, and Unknown
$C_{S'}(\pi) \leftarrow \frac{1}{n}\sum_{E \in S'} C_E(\pi)$
$\overline{\tau} \leftarrow \max\{C_{S'}(\pi) - \overline{C}_{\delta_O}(\pi, S), 0\}$
$\underline{\tau} \leftarrow \max\{\underline{C}_{\delta_W}(\pi, S) - C_{S'}(\pi), 0\}$
if $\exp(-2n\overline{\tau}^2) \leq \alpha_O$ **then**
    OOD $\leftarrow$ True
end if
if $\exp(-2n\underline{\tau}^2) \leq \alpha_W$ **then**
    WD $\leftarrow$ True
end if
if $\exp(-2n\overline{\tau}^2) > \alpha_W$ and $\exp(-2n\underline{\tau}^2) > \alpha_O$ **then**
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end if
if $\exp(-2n\overline{\tau}^2) > \alpha_W$ and $\exp(-2n\underline{\tau}^2) > \alpha_O$ **then**
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end if

- Consistency: Algorithm 1 returns **only one of the three possible outcomes** (OOD, WD or Unknown)

Method 2: Confidence interval overlap

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Theorem 3. *Let $\mathcal{D}$ be the training distribution, $\mathcal{D}'$ be the test distribution, and P be the posterior distribution on the policy space obtained through training. Let $\delta_O, \delta'_O \in (0,1)$ such that $\delta_O + \delta'_O < 1, \gamma_O := \sqrt{\frac{\ln(1/\delta'_O)}{2n}}$, and $\Delta C_O := C_{S'}(\pi) - \gamma_O - \bar{C}_{\delta_O}(\pi, S)$. Similarly, let $\delta_W, \delta'_W \in (0,1)$ such that $\delta_W + \delta'_W < 1, \gamma_W := \sqrt{\frac{\ln(1/\delta'_W)}{2n}}$, and $\Delta C_W := \underline{C}_{\delta_W}(\pi, S) - C_{S'}(\pi) - \gamma_W$. Then,*

$$\mathbb{P}_{(S,\pi,S')\sim(\mathcal{D}^m \times P \times \mathcal{D}'^n)}\left[C_{\mathcal{D}'}(\pi) - C_{\mathcal{D}}(\pi) \geq \Delta C_O\right] \geq 1 - \delta_O - \delta'_O,$$
$$\mathbb{P}_{(S,\pi,S')\sim(\mathcal{D}^m \times P \times \mathcal{D}'^n)}\left[C_{\mathcal{D}}(\pi) - C_{\mathcal{D}'}(\pi) \geq \Delta C_W\right] \geq 1 - \delta_W - \delta'_W.$$

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- $\Delta C_O \leq 0$ and $\Delta C_W < 0 \implies \mathcal{D}'$: Unknown

Method 2: Confidence interval overlap

Algorithm 2 OOD/WD Detection using Confidence Intervals

Input: $\delta_O, \delta'_O \in (0,1)$ with desired **maximum** false positive rate $\delta_O + \delta'_O < 1$.
Input: $\delta_W, \delta'_W \in (0,1)$ with desired **maximum** false negative rate, $\delta_W + \delta'_W < 1$.
Input: PAC-Bayes Bounds: $\overline{C}_{\delta_O}(\pi, S)$, $\underline{C}_{\delta_W}(\pi, S)$.
Input: Test dataset $S' \sim \mathcal{D}'^n$ and policy $\pi \sim P$.
Output: OOD, WD and Unknown.
$C_{S'}(\pi) \leftarrow \frac{1}{n}\sum_{E' \in S'} C_{E'}(\pi)$
$\gamma_O \leftarrow \sqrt{\frac{\ln(1/\delta'_O)}{2n}}$
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$\Delta C_O \leftarrow C_{S'}(\pi) - \gamma_O - \overline{C}_{\delta_O}(\pi, S)$
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if $\Delta C_O > 0$ **then**
  OOD $\leftarrow$ True
end if
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- Consistency: Algorithm 2 returns **only one of the three possible outcomes** (OOD, WD or Unknown)

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- Franka Panda arm with an overhead camera

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  - Process: Sample a policy π from the trained posterior

Robotic grasping: Simulation results

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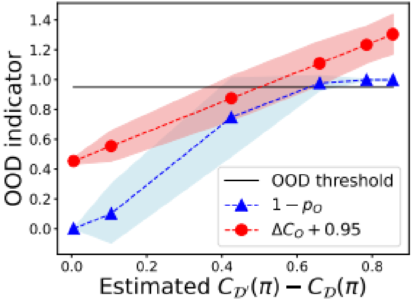

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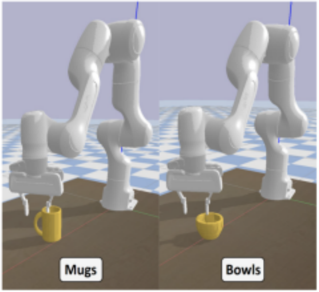

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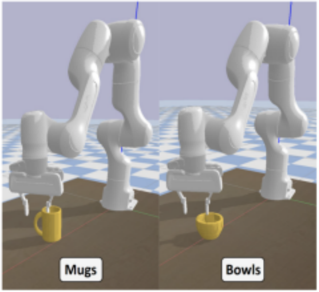

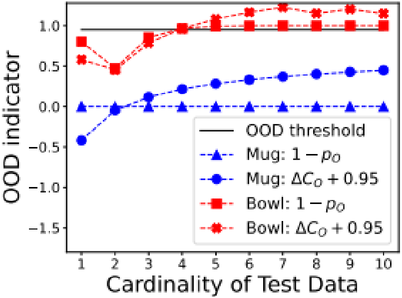

Robotic grasping: Hardware results

- Gradually increase the range of location of the mugs

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Robotic grasping: Hardware results

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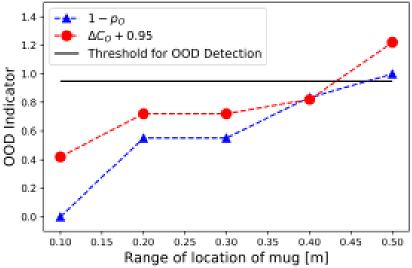

Robotic grasping: Hardware results

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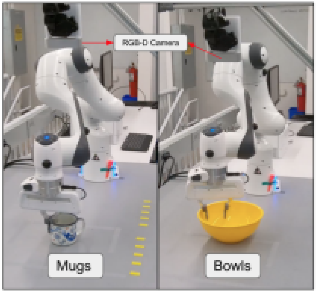

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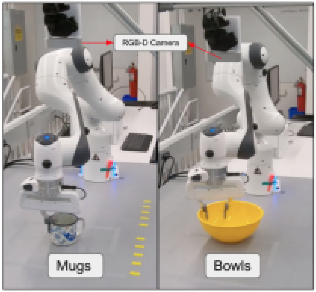

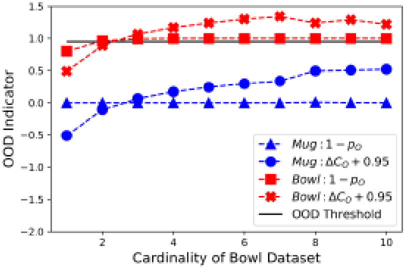

Obstacle avoidance with a drone

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- Train the drone to avoid obstacles by the largest possible distance

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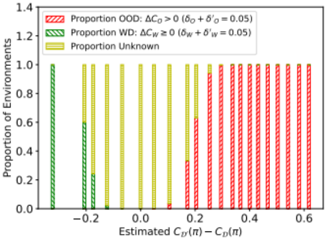

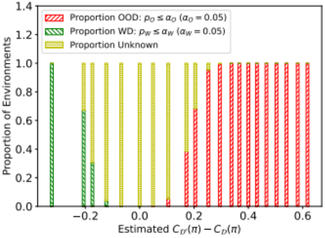

Obstacle avoidance with a drone: Simulation results

- Change the desired maximum false positive and false negative rates

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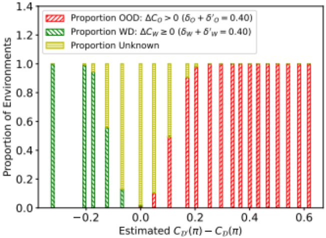

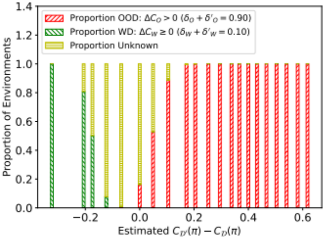

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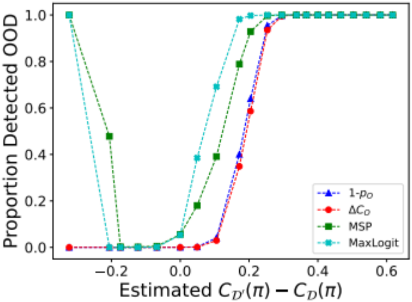

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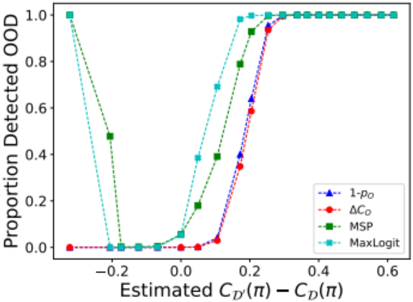

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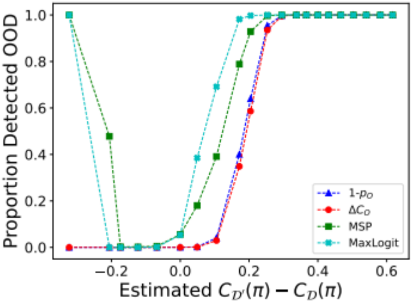

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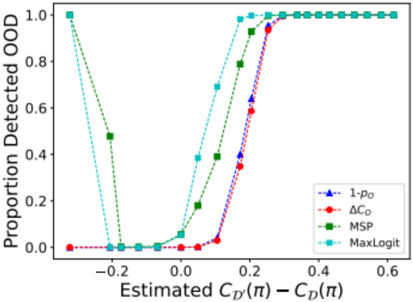

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Obstacle avoidance with a drone: Hardware results

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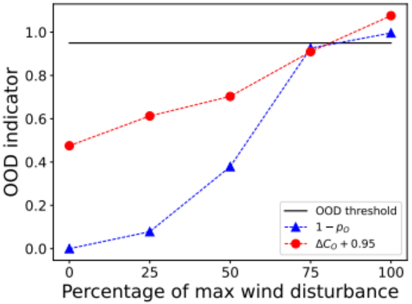

Experiments

- Videos of the experiments can be found here: https://www.youtube.com/watch?v=jKye3A09le0

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