Falsification of Multiple Requirements for Cyber-Physical Systems Using Online Generative Adversarial Networks and Multi-Armed Bandits

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Joint work with I. Porres

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- As CPSs interact with the real world, it is important to specify safety requirements and verify these requirements before the system is taken into production.
- Our work concerns black-box verification of CPSs. This means that we get to choose the inputs and to observe the behavior of a CPS without access to source code or other internals.

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- An STL formula φ can be transformed into a real-valued robustness function ρ_φ such that φ is true if and only if $\rho_\varphi(\mathcal{M}(x)) > 0$ for all x.
- This allows to express falsification of φ as an optimization problem minimizing the robustness. Let

$$x^* = \arg\min_x \rho_\varphi(\mathcal{M}(x)).$$

Then φ is falsified if and only if $\rho_\varphi(x^*) \leq 0$.

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- However, for CPSs evaluating $\mathcal{M}(x)$ can be costly, so optimization methods minimizing the number of evaluations are preferred. Some recent examples:
  - Online generative adversarial network test generation algorithm (Porres et al. 2021).
  - Bayesian optimization based algorithm (Mathesen et al. 2021).

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  - Cons: Uses n times more resources.

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- We cannot know this, but we can attempt learn this online.

Solution: Multi-armed Bandit Algorithms

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- This is a well-studied problem, and the literature provides dozens of good algorithms.

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  - On each round, record which generator achieved the lowest robustness. This yields an empirical success frequency for each arm.
  - After the warm-up period, select randomly an arm with probabilities according to the success frequencies, use the corresponding generator, update frequencies, repeat.
- Intuitively this algorithm most often considers the requirement which is easiest to falsify (has lowest robustness values fastest). Due to random chance, other requirements are occasionally considered as well (so there is a chance of correcting a wrong preference).

Experimental Results

- Consider the function (Mathesen et al.) $\text{mo3d}\colon \mathbb{R}^3 \to \mathbb{R}^3, \text{mo3d}(x) = (h_1(x), h_2(x), h_3(x))$ where

$$h_1(x_1, x_2, x_3) = 305 - 100 \sum_{i=1}^{3} \sin\left(\frac{x_i}{3}\right),$$

$$h_2(x_1, x_2, x_3) = 230 - 75 \sum_{i=1}^{3} \cos\left(\frac{x_i}{2.5} + 15\right), \text{ and}$$

$$h_3(x_1, x_2, x_3) = \sum_{i=1}^{3} (x_i - 7)^2 - \sum_{i=1}^{3} \cos\left(\frac{x_i - 7}{2.75}\right).$$

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- Requirements $\varphi_1 = \Box h_1 > 0$, $\varphi_2 = \Box h_2 > 0$, $\varphi_3 = \Box h_3 > 0$.
- φ_3 falsifiable, φ_1, φ_2 unfalsifiable.

Experimental Results

- We compared falsification of $\varphi_1 \wedge \varphi_2 \wedge \varphi_3$ (A1) versus falsification of φ_1, φ_2, φ_3 using the MAB approach (A3).
- We used online generative adversarial network algorithm (Porres et al.) for the generator.
- We allowed 80 executions on the system with warm-up period 30.
- We repeated the falsification task 50 times.

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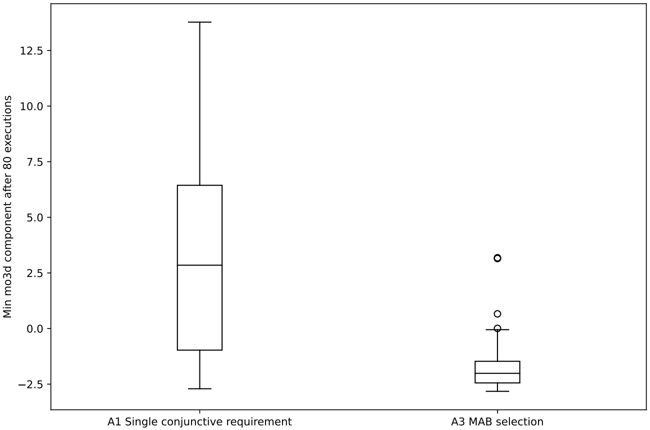

Future Work

- More experiments.
- Compare to other algorithms.
- Consider other MAB algorithms.

Thank You

Thank you for your attention!