Debugging a Policy: A Framework for Automatic Action Policy Testing

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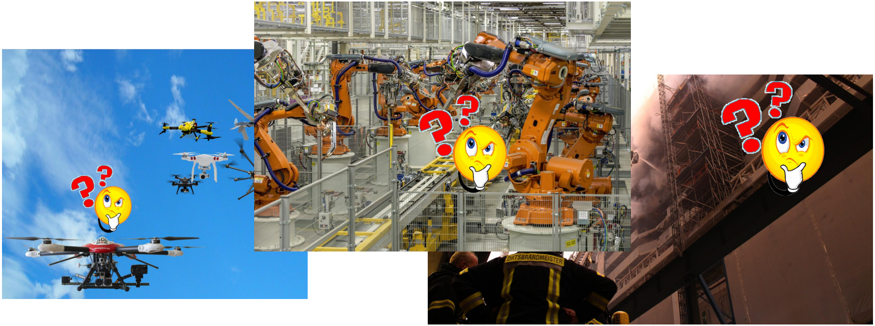
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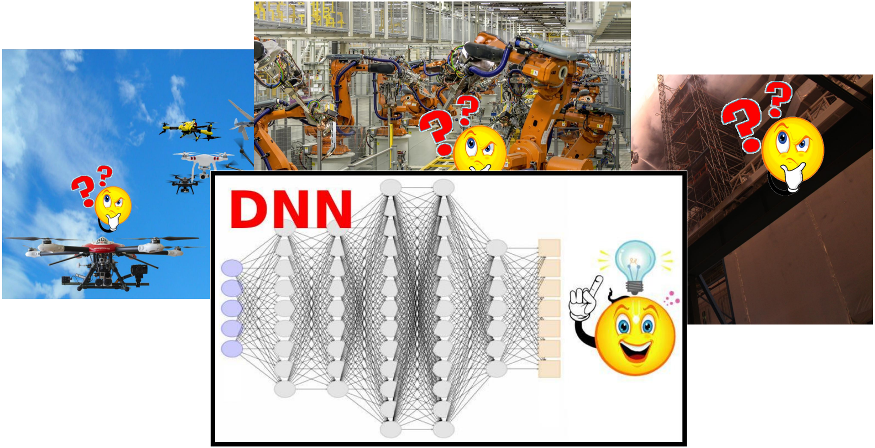
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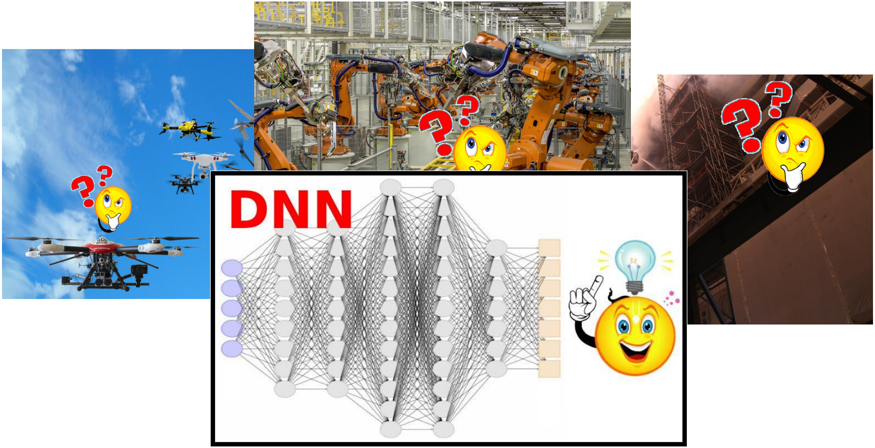

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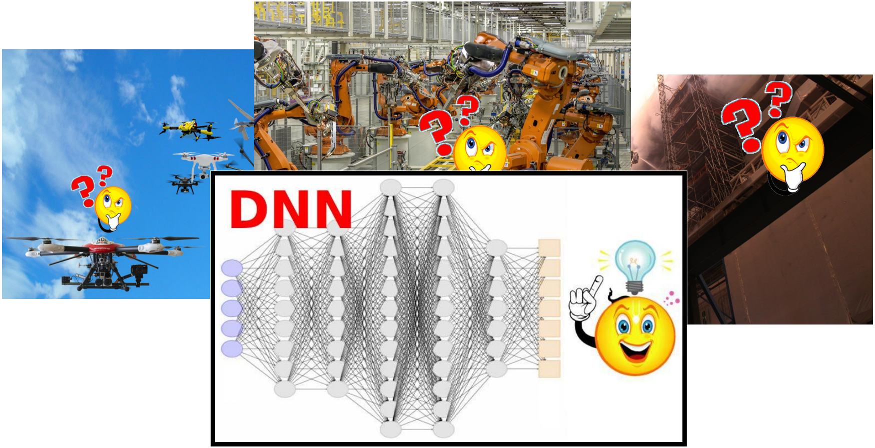

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→ "Is this PRL?" You tell me :-) New workshop Trusted AIP?

Agenda

1. Context & Notation
2. What is a “Bug”?
3. Bug Confirmation
4. Outlook

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Planning Models Addressed

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→ All we assume is that learning a policy $\pi : states \mapsto actions$ makes sense, and that a value function $V^\pi : states \mapsto \mathbb{R}$ can be defined which captures the quality of π run on s.

Generic (Cross-Planning-Model) Notation

Qualitative value function:

$$V^\pi(s) := \begin{cases} 0 & \text{no run of } \pi \text{ on } s \text{ reaches the goal} \\ 0.5 & \text{some runs of } \pi \text{ on } s \text{ reach the goal} \\ 1 & \text{all runs of } \pi \text{ on } s \text{ reach the goal} \end{cases}$$

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Generic "is better than" notation: (for the record)

$$V(s') \prec V(s) :iff \begin{cases} V(s') < V(s) & \text{objective is minimization} \\ V(s') > V(s) & \text{objective is maximization} \end{cases}$$

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Notes:

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- This would *not* be the case for bug := action starting optimal policy.

Definition: Fuzzing Bug

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- Can this definition help in bug confirmation?

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With $H_* \succeq V^*(s)$ and $h_\pi(s) \preceq V^\pi(s)$ pessimistic approximation of V^* and optimistic approximation of V^π respectively:

Proposition (Bug Confirmation)

Say that $V^*(s) \preceq H_*(s)$ and $h_\pi(s) \preceq V^\pi(s)$. Say that $h_\pi(s) \succeq V^*(s)$ and $H_*(s) \preceq V^\pi(s)$. Then $|h_\pi(s) - H_*(s)| \leq |V^\pi(s) - V^*(s)|$.

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→ Boils down to: "evaluate $V^\pi(s)$, and try to find a better policy for s".

Bug Confirmation, ctd.

Proposition (Fuzzing Bug Confirmation)

(a) If $I_*(s) \cap I_*(s') = \emptyset$, s' *is a fuzzing-bug relative to* s *if* $H_*(s') \prec h_*(s)$ *and either* $V^\pi(s') \succeq V^\pi(s)$ *or* $|V^\pi(s') - V^\pi(s)| < |H_*(s') - h_*(s)|$.
(b) s' *is a fuzzing-bug relative to* s *if* $V^\pi(s') \succeq V^\pi(s)$ *and* $|V^\pi(s') - V^\pi(s)| > U_*(s, s')$.

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Boils down to "evaluate $V^\pi(s)$, and try to find a better policy for s".

So what?

- Many special cases with "V^* oracle" (e.g. all states known to be solvable; enough time during at testing to run symbolic planner).
- In general case, plug in plan-quality improvement algorithms [Bäckström (1998); Do and Kambhampati (2003); Nakhost and Müller (2010); Siddiqui and Haslum (2015)].

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Ok, so now let's actually do this!

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- Develop fuzzing methods!
- Develop bug confirmation paradigms (metamorphosic testing etc)!
- See what all this does in all your favorite planning and learning scenarios!

Last Slide

Thanks for listening.

Questions?

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