Stealthy and Efficient Adversarial Attacks against Deep Reinforcement Learning (SEAADRL) – AAAI 2020

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Motivation

Analyzing attacks against DL & DRL important because:

- DL & DRL are becoming widely used.
- Especially in high-stakes and safety-critical scenarios: autonomous driving, weapon systems, medical assistance.

Image sources: `techofaq.org`, `wikipedia.org`, `medium.com`

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The RL Setting

The environment is modeled as a Markov Decision Process (MDP) [Bel57], given by the tuple $(\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma)$.

- $\mathcal{S}$: a discrete/continuous space of states.
- $\mathcal{A}$: a discrete/continuous action space.
- $\mathcal{P} : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to [0, 1]$: transition function.
- $\mathcal{R} : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$: reward function.
- γ: discount factor.

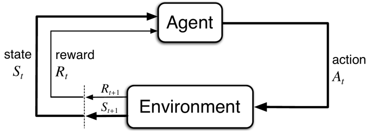

Figure: The RL Setting [SB18]

Attacks Against Supervised DL and DRL

Since the work of Szegedy et. al [SZS+13], several attacks have been demonstrated on supervised deep learning.

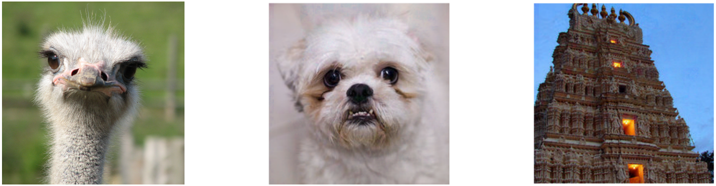

Figure: Ostrich (left), also ostrich (center), ostrich (right). Image credits: [SZS+13].

Attacks Against Supervised DL and DRL

Two types of attacks:

- Untargeted attacks: misclassification to an arbitrary class/label [SZS+13, MDFF16].
- Targeted attacks: misclassification to a *specific* class/label [CW17].

Moving to DRL (initial works):

- Apply attacks from supervised DL to inputs of DRL agents [HPG+17].

Key Ideas

1. Targeted attacks against supervised DL can be used to make DRL agents choose specific suboptimal actions [HGP19].
2. Going for a small number of *critical hits*, instead of attacking at every step. *Timing* attacks to deal the maximum “damage” in the least number of steps [KS17, SZX+20].

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SEADRL: Overview

Two components of a targeted DRL attack:

1. *How*: Generating noise added to the input (perturbation) to make the agent choose an action.
2. *When*: Deciding when to do perturbation to maximize "damage" in the least number of steps.

SEAADRL uses exisiting methods for the *how* [CW17], and its main contribution is in the *when*. Two algorithms/classes of attack:

1. Critical-point (CP) attack.
2. Antagonist attack.

SEAADRL: Critical-point Attack

- At every timestep t, consider all possible N-step action sequences.
- Compute the *divergence* of each of "final" states.
- Pretend that we have access to a transition function of the environment: $\hat{\mathcal{P}}$.

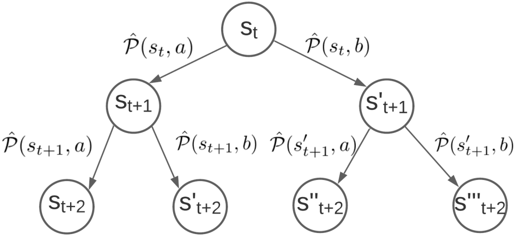

Figure: $\mathcal{A} = \{a, b\}$ and $N = 2$ in this example. $T(s_{t+2})$ is the divergence of state s_{t+2}.

- User-defined domain specific function.
- For TORCS,

$$T(s) := \text{distance between car and center of road.}$$

Figure: Low divergence; near center.

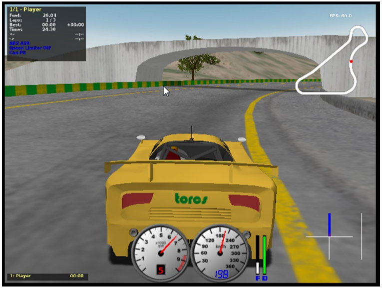

Figure: High divergence; off center.

Image credits: `malavida.com` and `apps4win.com`

SEAADRL: Critical-point Attack

- Let our trained DRL agent have policy π.
- Compare the divergence of the *N*-step action sequences with the *baseline*.
- Perform attack if $|T(s_{t+2}) - T(s'_{t+2})| > \Delta$. Here, $N = 2$.

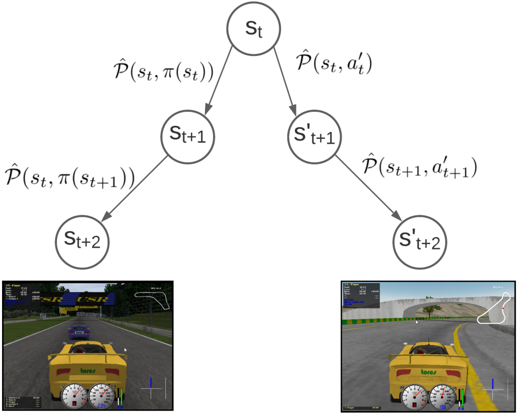

Figure: Baseline expected state (left); highest-divergence action sequence (right).

Image credits: `malavida.com` and `apps4win.com`

SEAADRL: Critical-point Attack: Summary

- Train environment transition model $\hat{\mathcal{P}}$.
- At every timestep t, look ahead N steps with all possible action sequences.
- If any of those sequences lead to high divergence, perform that attack.
- Attack only once per episode (efficiency).
- Big disadvantage: highly domain specific.

SEAADRL: Antagonist Attack

- Train an agent (called antagonist) that receives $-r_t$ at every time step.
- Allow this agent to decide whether to attack or not at each timestep (when).
  - Limit number of antagonist actions (attacks) to a small number of steps (2-5) per episode.
  - A regular, pretrained DRL agent acts for other steps.
- The antagonist learns to pick opportune moments to act and do significant damage.
- Main advantage over CP attack: requires no domain knowledge.

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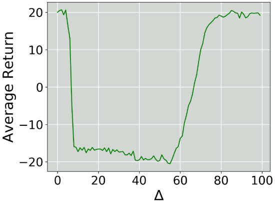
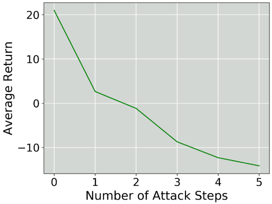
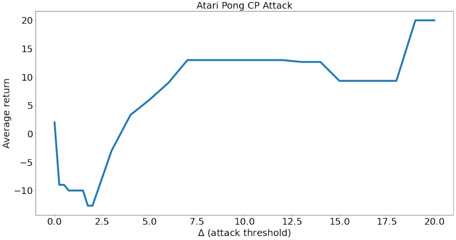
Experiments and Results

- The authors of SEAADRL run their experiments:
  - with different DRL algorithms (A2C/A3C, PPO and DDPG).
  - on many environments (Atari Pong, Atari Breakout, TORCS, MuJoCo HalfCheetah and more).
- Show significant decline in average returns with attacking only a very small number of steps per episode.
- My replication only on Atari Pong with A2C.







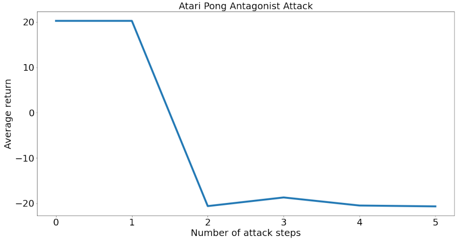


Figure: Average return vs. Δ for CP attack

Figure: Average return vs. # attack steps for antagonist attack

My Replication: Summary

- Smaller scale of experiments.
- Overall agreement with original experiments.
- Minor disagreements with details.

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Extension: Robust Training with Antagonist Agent

Main Idea: While training a regular DRL agent (e.g. A2C), use a trained antagonist agent to inject damaging actions at critical moments to make training more robust.

Agent/Algorithm	Mean Return	Return Std-Dev
A2C	20.23	0.85270
A2C with Robust Training	**21**	**0.0**

Table 1: Results of preliminary experiments for Robust agent.

Intuition on why this works: our new agent will avoid states that can lead to significant damage within a small number of steps, and thus stay in a “safer space”.

Further: Do this iteratively.

Thank You!

Thank You!

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