

Bits of Reinforcement learning

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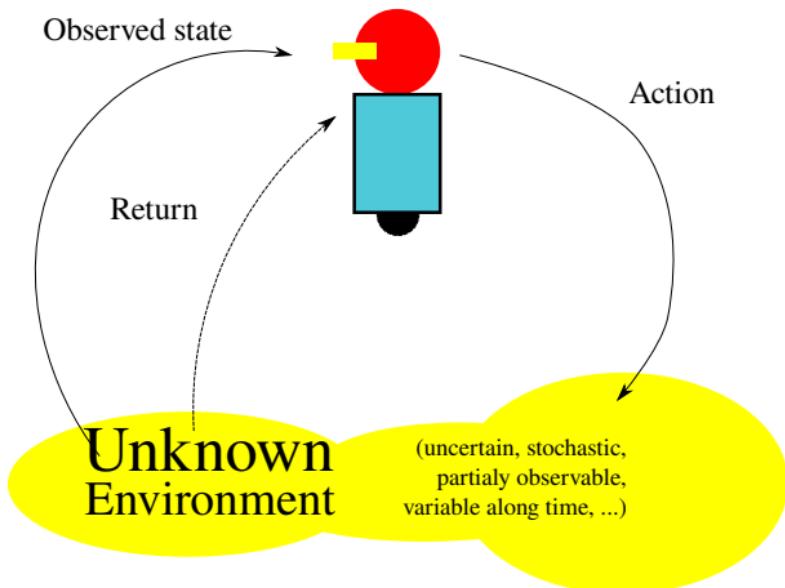
Reinforcement learning



Tesauro's TD-Gammon: early 1990's, 1 hidden layer made 40 to 80 neurons, self-play, expert level.



The Reinforcement Learning Problem



Learn an optimal behavior.

The Reinforcement Learning Problem

- ▶ Markov Decision Problems:
([states](#), [actions](#), state dynamics, reward function, [objective function](#)).
[known](#), unknown: the reaction of the environment is unknown.

No RL is not only about $\max \sum \gamma^k r_{t+k}$.

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Balancing exploration and exploitation is a **major key** to learn efficiently.

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- ▶ Basic idea: maintain expectations of the consequences of actions (their **value**). When the consequences do not match the expectations, update it.

Learn when surprised.

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Each comes with countless variants.

Reinforcement Learning

gym API

`gym` is the standard way to interact between a learning agent and an environment. 3 functions:

- ▶ `make ()` to create the environment
- ▶ `reset ()` to initialize it
- ▶ `step (action)` to perform a step.

Only `reset ()` and `step (action)` have to be coded.

And then:

Loop:

1. choose action to perform
2. next state, reward, done, extra info = `step (action)`
3. update your agent

We may also define a rendering function to provide a graphical representation of the environment.

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But you don't need large computing power to do interesting and valuable research in RL! Points 1, 3, and 4 require this kind of research.

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 - 1) the user describes the simulation to be done in a configuration file,
 - 2) run the simulator on this configuration file, and
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- ▶ An RL compliant simulator requires sophisticated modifications.
The simulator is usually a complex piece of software, resulting from years, decades sometimes, of work, usually written in either Fortran, or C, or C++.

RL meets soft robots

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- ▶ Infinite degrees of freedom.

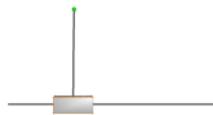
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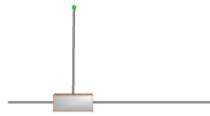
Rewarded when its tip is in the instable equilibrium position



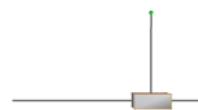
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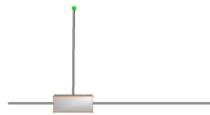
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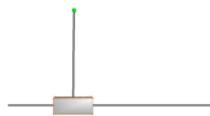
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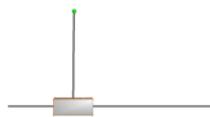


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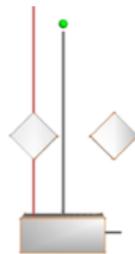
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- ▶ An action has a complex non instantaneous outcome,
- ▶ How do you define the state space? Many possibilities!

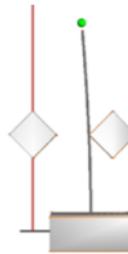
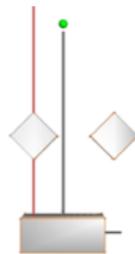
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An other example: rewarded when the green tip of the cartStem touches the red line



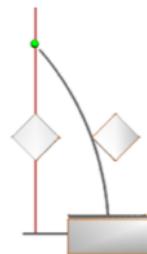
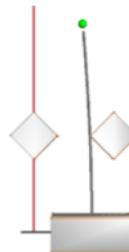
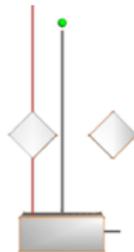
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Simulating a soft robot

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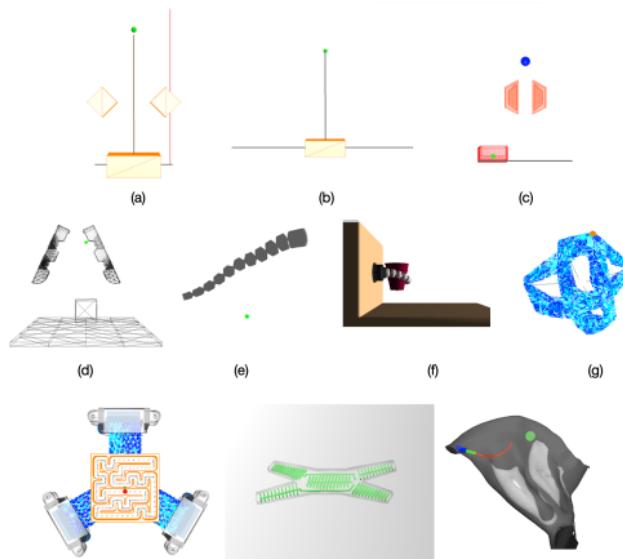
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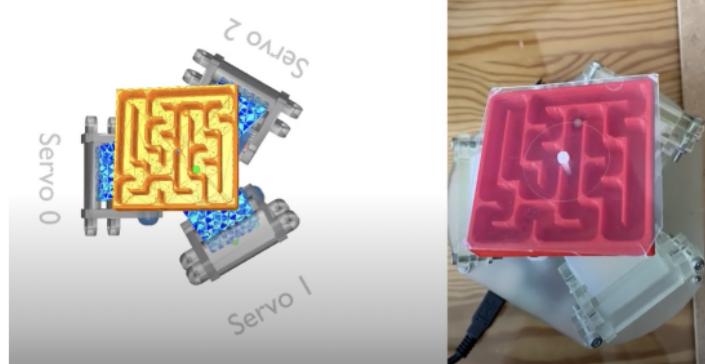
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- ▶ The soft robots we modeled:



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Playing with soft robots

- ▶ Some are built:



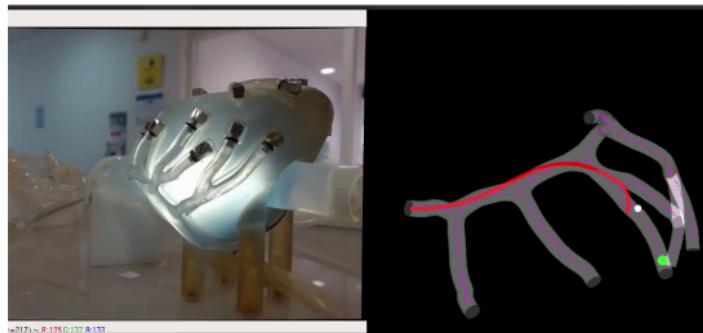
See the tutorial to build your own: Defrost team, Build your own tripod, 2021,

<https://handsonsoftrobotics.lille.inria.fr/index.php/tripod>

RL meets soft robots

Playing with soft robots

- ▶ Some are used for serious matters:



Application to guiding a catheter in coronary arteries.

Controlled by model-based RL.

P. Schegg *et al.*, Automated planning for robotic guidewire navigation in the coronary arteries, *Proc. IEEE 5th International Conference on Soft Robotics (RoboSoft)*, April 2022, <https://hal.inria.fr/hal-03778352>.

P. Schegg, *Autonomous Guidewire Navigation for Robotic Percutaneous Coronary Interventions*, PhD dissertation, defended May 2022, Université de Lille, not publicly available.

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From SOFA to SofaGym

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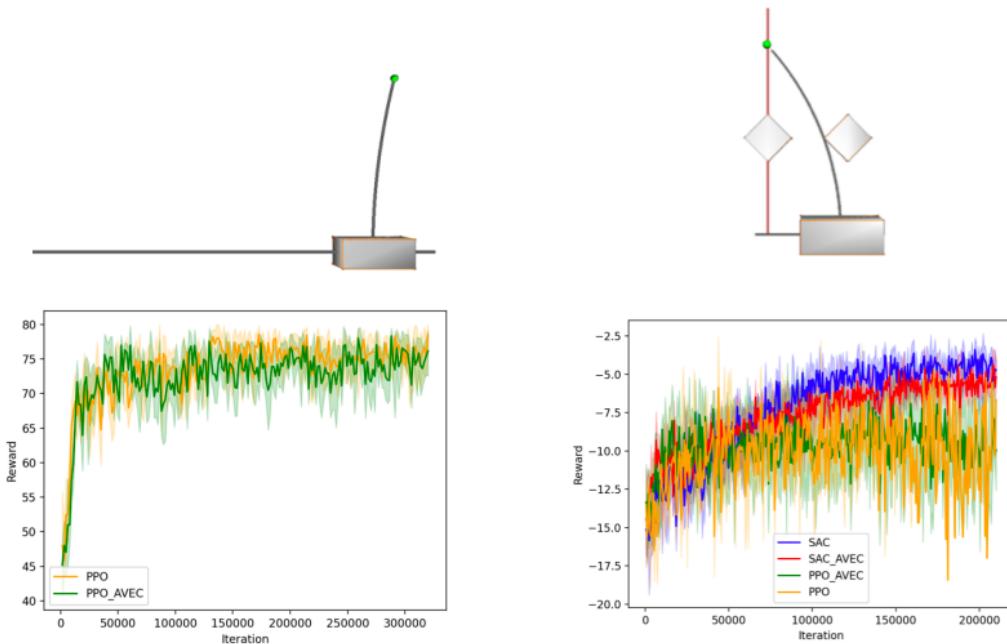
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- ▶ SofaGym is developed by soft robots expert research team Defrost at Inria Lille.

RL meets soft robots

Some experimental results



AVEC: replace \hat{Q} by a variance in the AC bias, that is in $\hat{V}(s) - \hat{Q}(s, a)$. Y. Flet-Berliac *et al.*, Learning Value Functions in Deep Policy Gradients using Residual Variance, *ICLR 2021*, arxiv:2010.04440.

RL meets soft robots

A few last words about soft robots

- ▶ SofaGym currently provides 11 soft robots.
- ▶ This work is still very preliminary.
- ▶ Avenues of research questions to investigate: design of the state space, objective function, action space, transfer learning, model-based RL, combination of planning/RL with inverse model, ...

- ▶ SofaGym is freely available on
<https://github.com/SofaDefrost/SofaGym>.
- ▶ P. Schegg *et al.*, SofaGym: An Open Platform for Reinforcement Learning Based on Soft Robot Simulations, *Soft Robotics*, Apr. 2023, pp. 410-430, <http://doi.org/10.1089/soro.2021.0123>.

Learning to manage a crop field

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Work done in collaboration with Cirad, CGIAR, and BAU (India).

- ▶ End goal: be able to recommend what to do next in the field to the farmer.

In order to fulfill some objective: make money out of his harvest, feed his family, his animals, buy fertilizers, tools, etc., while avoiding pollution, soil destruction, etc.

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 - ▶ Mechanistic crop model.
 - ▶ Simulates very accurately the growth of a plant based on the properties of the soil, the cultivar, the weather conditions, initial soil conditions (residue from previous year), ... interactions between the soil properties with roots then growth of the plant (PDE integration over time).
 - + the actions made in the field: irrigation, fertilization, tillage, ... on a daily basis.

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- ▶ Freely available on
https://gitlab.inria.fr/rgautron/gym_dssat_pdi.

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- ▶ Observation = Collection of measurements amenable to a real farmer
~~ partial observability.

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- ▶ The goal is to maximize $\sum_{\text{day}=0}^{\text{day}=\text{harvest}} r(\text{day})$.

Learning to manage a crop field

- The observation data:

	definition
istage	DSSAT maize growing stage
vstage	vegetative growth stage (number of leaves)
topwt	above the ground population biomass (kg/ha)
grnwt	grain weight dry matter (kg/ha)
swfac	index of plant water stress (unitless)
nstres	index of plant nitrogen stress (unitless)
xlai	plant population leaf area index (m^2 leaf/ m^2 soil)
dtt	growing degree days for current day ($^{\circ}\text{C}/\text{day}$)
dap	days after planting (day)
cumsumfert	cumulative nitrogen fertilizer applications (kg/ha)
rain	rainfall for the current day ($\text{L}/m^2/\text{day}$)
ep	actual plant transpiration rate ($\text{L}/m^2/\text{day}$)

- Action set: daily nitrogen fertilization amount $\in [0, 200]$ (kg/ha)

Learning to manage a crop field

Some results (1/3)

We compare:

1. A null policy which does not fertilize,
2. An expert policy used in the original 1982 field experiment,

DAP	quantity (kg N/ha)
40	27
45	35
80	54

3. A policy learned by RL (basic untuned PPO).

Remarks:

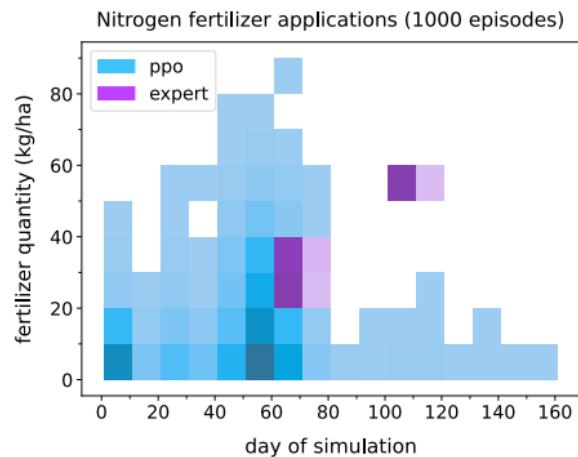
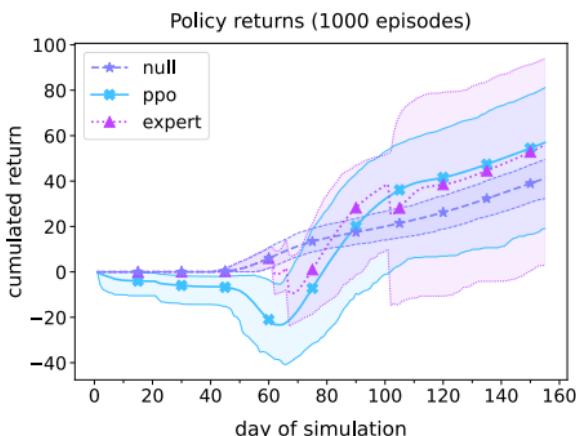
- ▶ Policies 1. and 2. are fixed and deterministic.
- ▶ Only the weather is stochastic.
- ▶ The seeding date depend on the weather, hence varies a bit from one simulation to another.
- ▶ The expert policy depends on expert information that are not available to PPO.

Learning to manage a crop field

Some results (2/3)

Protocol:

- ▶ Null and expert policies are evaluated on 10^3 seasons.
- ▶ RL: Trained on 10^6 simulated seasons, then evaluated on 10^3 other seasons.



untuned PPO is best.
It shows less variability.

Learning to manage a crop field

Some results (3/3)

	null	expert	PPO
grain yield (kg/ha)	1141.1 (344.0)	3686.5 (1841.0)	3463.1 (1628.4)
massic nitrogen in grains (%)	1.1 (0.1)	1.7 (0.2)	1.5 (0.3)
total fertilization (kg/ha)	0 (0)	115.8 (5.2)	82.8 (15.2)
application number	0 (0)	3.0 (0.1)	5.7 (1.6)
nitrogen use efficiency (kg/kg)	n.a.	22.0 (14.1)	28.3 (16.7)
nitrate leaching (kg/ha)	15.9 (7.7)	18.0 (12.0)	18.3 (11.6)

Mean (std dev) computed on 10^3 seasons.

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We obtain the same sort of results on the irrigation task.

R. Gautron et al., *gym-DSSAT: a crop model turned into a Reinforcement Learning environment*, Inria Research Report 9460, June 2022, <https://arxiv.org/abs/2207.03270>.

R. Gautron, *Reinforcement learning for crop management support to smallholder farmers in countries of the South: towards risk management*, PhD dissertation, defended Dec. 2022, Université de Montpellier.

Learning to manage a crop field

A few last words about crop management

- ▶ Many topics remain to be studied.

Learning to manage a crop field

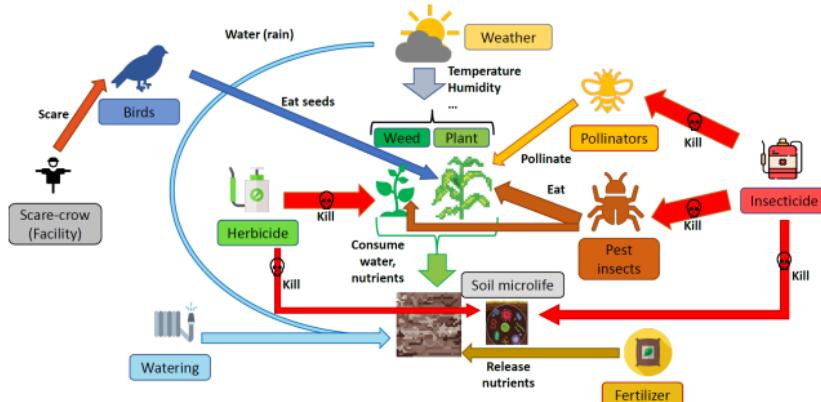
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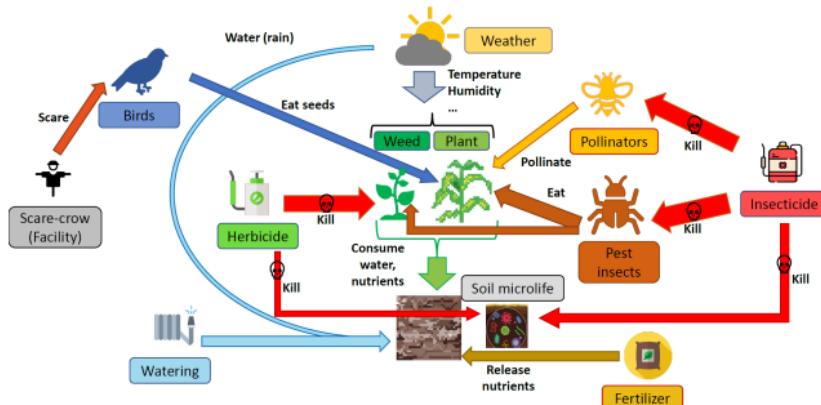
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Learning to manage a crop field

Farm-gym

- ▶ ~ Farm-gym: toy farm management environment for RL:



- ▶ Less accurate but much richer than gym-DSSAT.
- ▶ Meant to investigate new problem features: stochastic environment, several coupled feedback loops, cost of action, cost-benefit objective function, multi-objective objective function, etc.
- ▶ <https://github.com/farm-gym/farm-gym>

Experimental methodology

Experimental methodology

The big RL experimental failure

- ▶ Very poor experimental results.

Experimental methodology

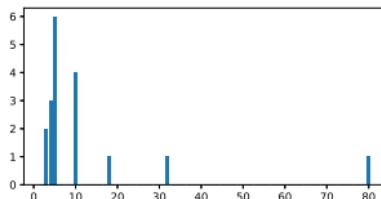
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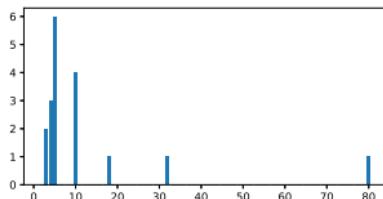


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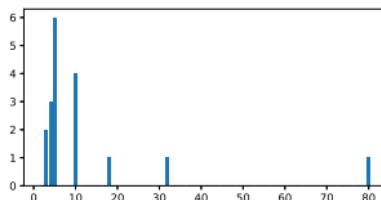
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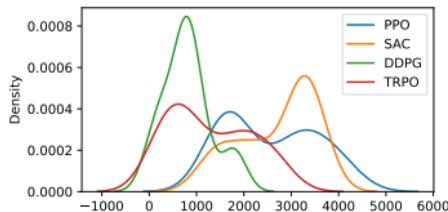
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Distribution of performance is not Gaussian at all.

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We should do much better!

Experimental methodology

What we need

- ▶ Goal: compare the performance of a set RL agents.
An agent is a certain implementation of an algorithm, with certain values for its parameters and hyper-parameters.

Experimental methodology

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That's what Adastop does!

Experimental methodology

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Idea of the algorithm: given a budget KN :

Initialization: run each agent N times.

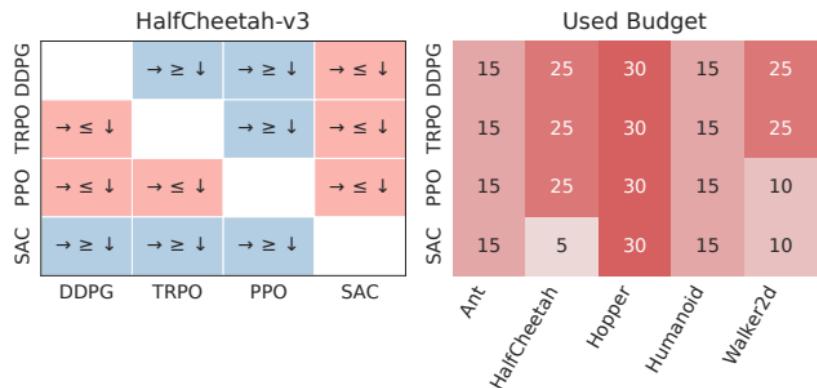
Test: can agents be ranked at risk α ?

If some agent can not be ranked, perform an other N runs, merge these new results with previously collected performances, and loop to test step. Stop looping when budget exhausted.

Experimental methodology

Adastop: example of result

Comparison of 4 different agents drawn from 4 different RL libraries, on 5 Mujoco tasks.



Experimental methodology

Adastop

- ▶ Adastop is the first sound statistical test to compare the experimental performance of a set of agents, trying to minimize the number of runs.
See the paper for theorems and proofs.
- ▶ Performance is whatever you want to compare the agents with.
- ▶ Adastop is not restricted to RL. Can be used in many experimental studies, not necessarily related to ML.
- ▶ Extensions: how to compare agents performing on a set of tasks (e.g. Atari games): open problem for now.

The paper: <https://inria.hal.science/hal-04132861/>

The code: <https://github.com/TimotheeMathieu/adastop>

Few last words

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Thanks for your attention.

We hire!

profiles ranging from theory to applications.

Interns, PhD. student, post-docs, engineers, permanent staff.

Check out <https://team.inria.fr/scool/>.

Get in touch: philippe.preux@inria.fr.