Bits of Reinforcement learning

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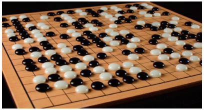
Scool

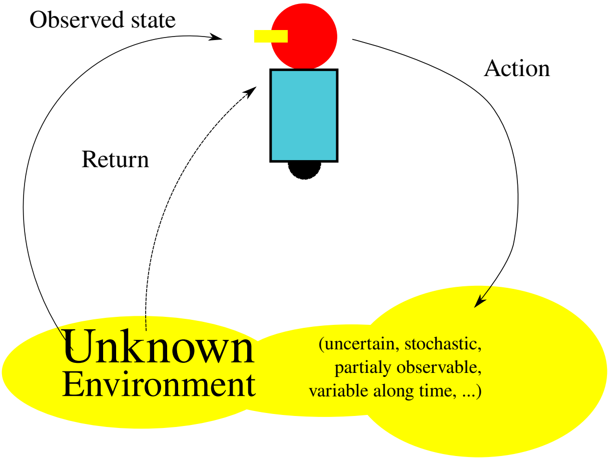
ML in PL, Warsaw

Reinforcement learning

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



The Reinforcement Learning Problem



Learn an optimal behavior.

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  (states, actions, state dynamics, reward function, objective function).

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

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  Each comes with countless variants.

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- Solving large tasks requires computing infrastructures beyond the reach of most academic labs.
- Moreover, the training time is so long that this raises methodological issues: brittelness of experimental results.
- Last but far from least, the design of the state space and the objective function are crucial. And the action space (may be) too.

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- Not designed to be used in an interaction loop:
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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++.

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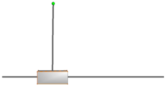
Rewarded when its tip is in the instable equilibrium position



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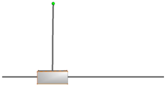

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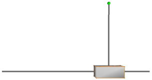

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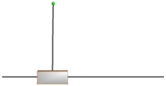

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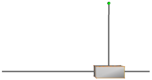

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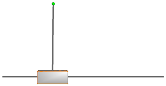

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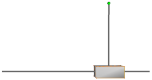

and decelerate:

- An action has a complex non instantaneous outcome,

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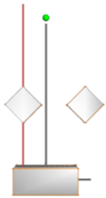

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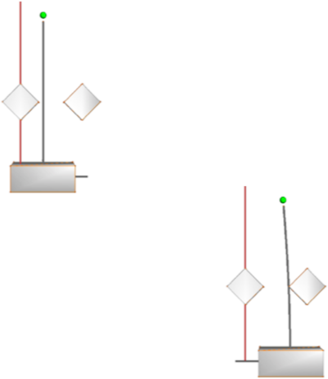

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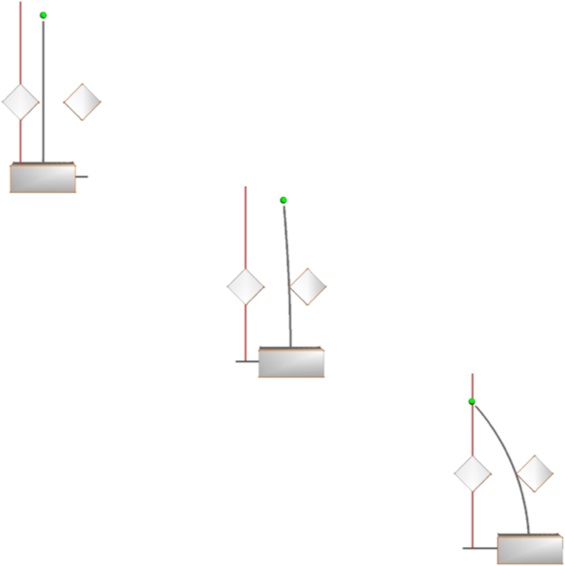

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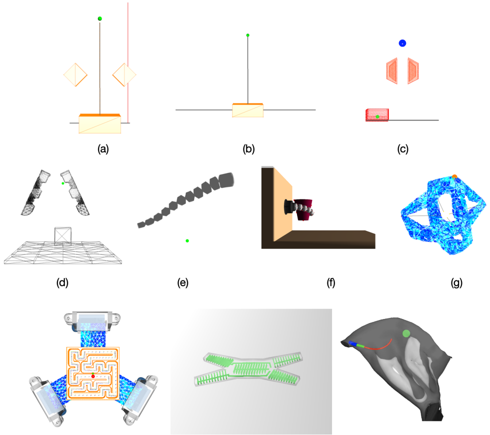
- The soft robots we modeled:



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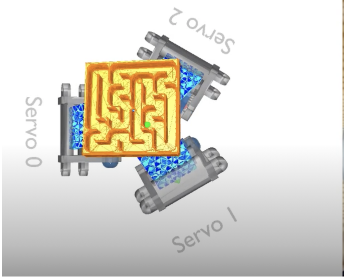
Playing with soft robots

- 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

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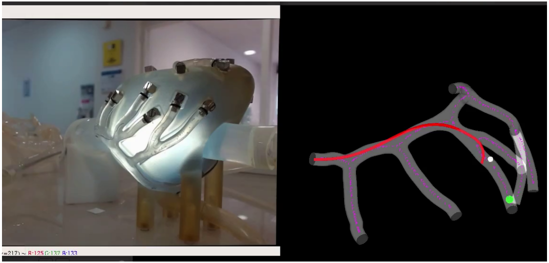
Playing with soft robots

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

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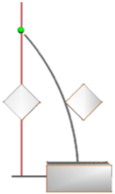
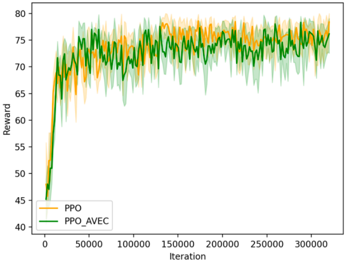
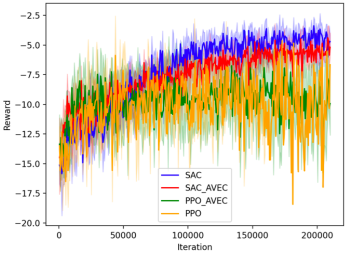
Some experimental results







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 work to be done: 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

Learning to manage a crop field

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 fullfill some objective: make money out of his harvest, feed his family, his animals, buy fertilizers, tools, *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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- Observation = Collection of measurements amenable to a real farmer $\rightsquigarrow$ partial observability.

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

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

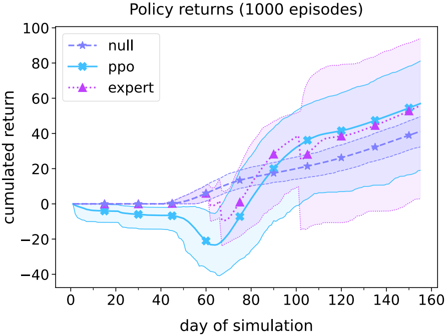
Policies 1. and 2. are fixed and deterministic.
Only the weather is stochastic.

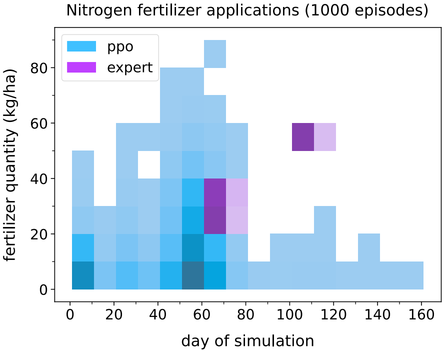
Protocol:

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

Learning to manage a crop field

Some results (2/3)





Learning to manage a crop field

Some results (3/3)

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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)

This table contains the mean (std dev) measured on 10^3 evaluation seasons.

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In short: an untuned PPO learns a very good policy that balances the different criteria.

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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)

This table contains the mean (std dev) measured on 10^3 evaluation seasons.

In short: an untuned PPO learns a very good policy that balances the different criteria.

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 rop 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

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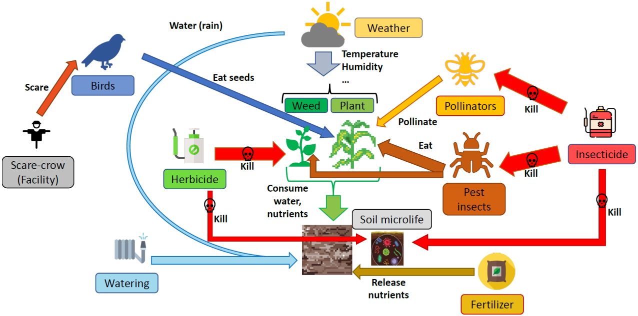
- gym-DSSAT is great because it is very accurate, but it is hard to manage as a piece of software and limited to DSSAT features.
- $\rightsquigarrow$ Farm-gym: toy farm management environment for RL:



Less accurate but much richer than gym-DSSAT.
Meant to investigate new problem features.

https://github.com/farm-gym/farm-gym

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The big RL experimental failure

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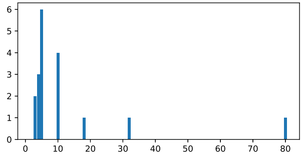

Number of runs made in ICML 2022 RL papers.

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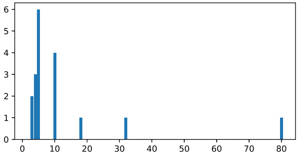

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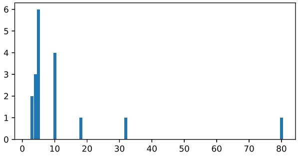

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- Computing the standard deviation of 3 (or 10) runs is meaningless.

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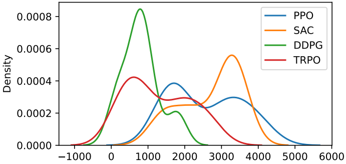

Distribution of performance is not Gaussian at all.

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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.

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- Cherry on the cake: a test that requires a minimal number of runs to take its decision (thus ecologically-friendly).

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Adastop: ingredients

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Idea of the algorithm: given a budget KN:

Initialization: run each agent N times.

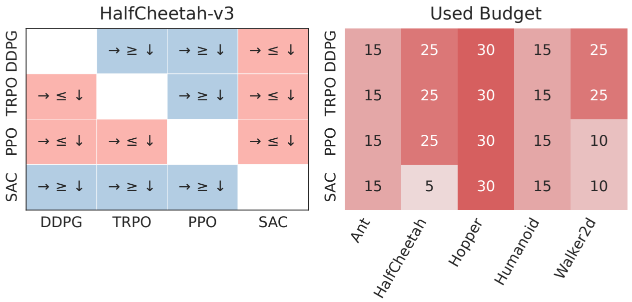
Test: can agents be ranked at risk α?

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

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.
- 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`

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- Stop the rush: experimental results are important but need to be scientifically established.

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`.