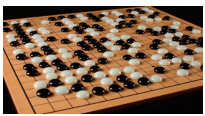
# Reinforcement Learning in practice

Philippe Preux
philippe.preux@inria.fr
SCOOL, Lille, France

Jornadas Científicas Inria Chile




# Reinforcement learning



# Reinforcement learning

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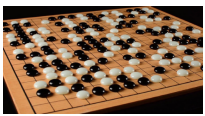

*Ca.* 2017.

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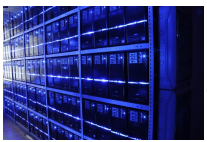
# Reinforcement learning

*Ca.* 1992. Self-play learning, 1.5 $10^6$ games.
Trained 2 weeks on a few dozens Mb, 100 MHz CPU.
1 layer of 80 hidden neurons.



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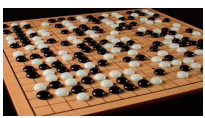

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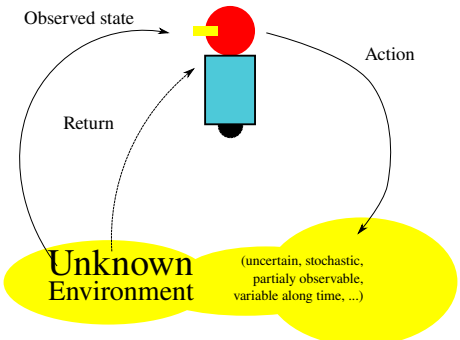


Learn an optimal behavior.

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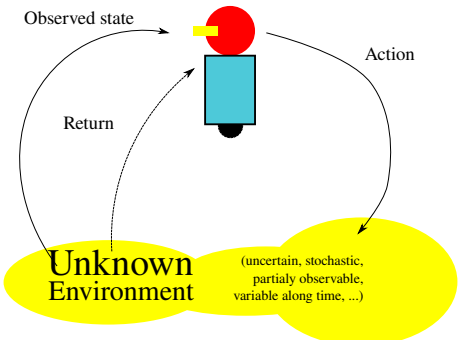


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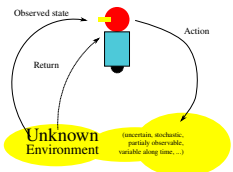
Unique feature of RL: learns by interacting with the environment.

# The Reinforcement Learning Problem

Origins: theory of behavior adaptation.

(Thorndike (1898), Skinner, and many others).



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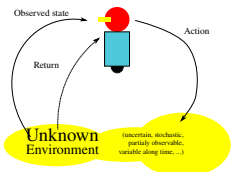

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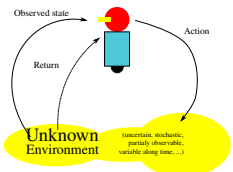


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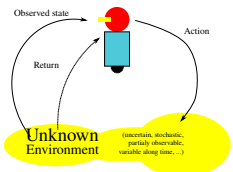


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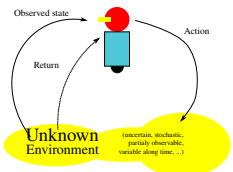


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• First RL algorithms:
TD-Learning [Sutton, 1988], Q-Learning [Watkins, 1989], REINFORCE [Williams, 1992].

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3. Well-designed model of the task is crucial.
4. Methodological issues: brittelness of experimental results.

# Reconciling RL with more real applications

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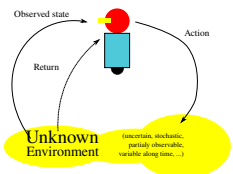
## The model

**RL is based on Markov decision problems**

- state space
- action space
- unknown dynamics
- return function: user defined to some extent.
- objective function

Solution: a *policy* that maps action to state.



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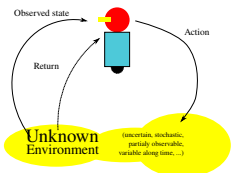


Solving an RL problem is strictly equivalent to solving an LP:
$\max \mathbf{c}'\mathbf{x}, s.t. \mathbf{A}\mathbf{x} \leq \mathbf{b}$, and $\mathbf{x} \geq \mathbf{0}$,
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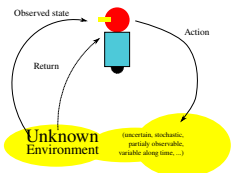


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$\mathbf{A}$, $\mathbf{b}$, $\mathbf{c}$ are related to the dynamics of the environment
$\rightsquigarrow$ sampling the environment $\rightarrow$ estimates.

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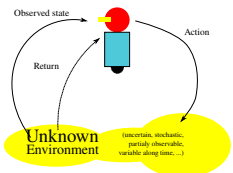


- Basic principle: to learn, interact with the environment, and balance exploration and exploitation in a careful way.
- Basic idea: maintain expectations of the consequences of actions (their value). When the consequences do not match the expectations, update the expectations.

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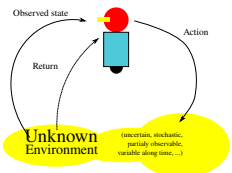


The state must summarize the whole history of the agent.
The state determines the best action to perform.
The objective is to learn this mapping.

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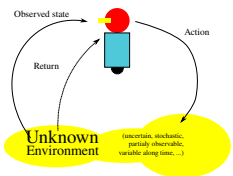


The design of the return is crucial.

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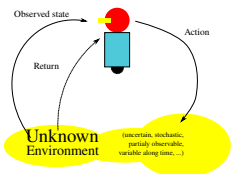


The consequences of actions are often diluted in the future $\rightsquigarrow$ credit assignment problem.

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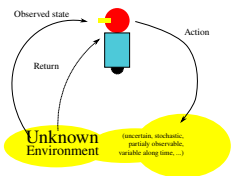


Deterministic tasks are much simpler to solve than stochastic ones.

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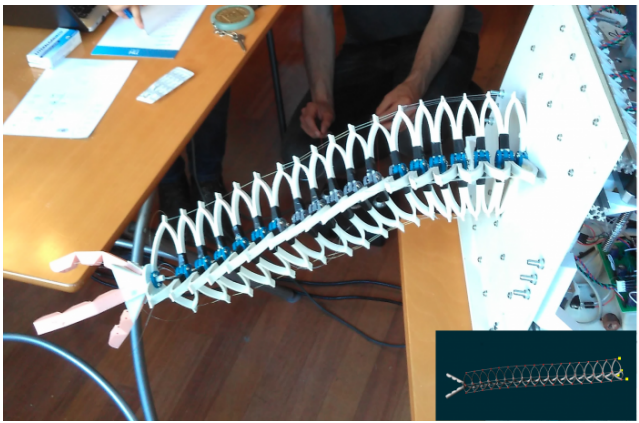
- An RL compliant simulator requires sophisticated modifications.

  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



In collaboration with Ch. Duriez, Defrost @ Inria-Lille.

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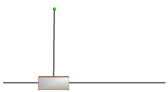

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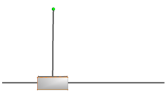

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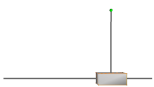

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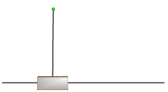

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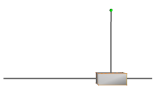

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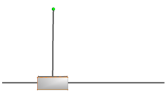

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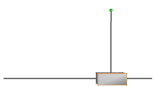

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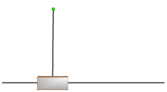

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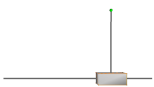

  and decelerate:

- An action has a complex non instantaneous outcome,
- There are many ways to design the MDP model.

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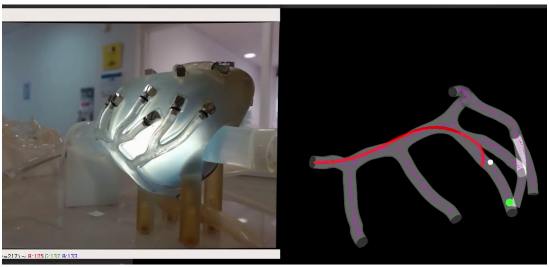

Application to guiding a catheter in coronary arteries.

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*, April 2022, `hal-03778352`.

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

P. Schegg *et al.*, SofaGym: An Open Platform for Reinforcement Learning Based on Soft Robot Simulations, Soft Robotics, **10**(2), Apr. 2023.

# Learning to manage a crop field

In collaboration with Cirad, CGIAR, and BAU (India).

# Learning to manage a crop field

- End goal: to 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.*, 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.

# Learning to manage a crop field

## From DSSAT to gym-DSSAT

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- DSSAT made compliant with RL.
- Freely available on `https://gitlab.inria.fr/rgautron/gym_dssat_pdi`.

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## Experiments

- Problem: based on a maize field experiment [Morris *et al.*, 1982]

  How to manage irrigation or fertilization to maximize the yield of a certain cultivar of maize in a certain soil in certain weather conditions?

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- Crop growth depends on action, soil nature, weather condition (stochastic), *etc.*
- 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

- The observed features:

| | **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 (°C/day) |
| `dap` | days after planting (day) |
| `cumsumfert` | cumulative nitrogen fertilizer applications (kg/ha) |
| `rain` | rainfall for the current day (L/$m^2$/day) |
| `ep` | actual plant transpiration rate (L/$m^2$/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:

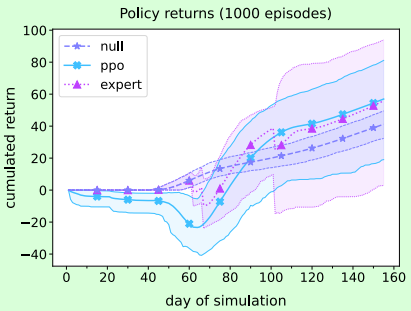
- Policies 1. and 2. are fixed and deterministic.
- Only the weather is stochastic.
- The seeding date depend on the weather, hence varies a bit from one simulation to an other.
- The expert policy depends on expert information that are not available to PPO.

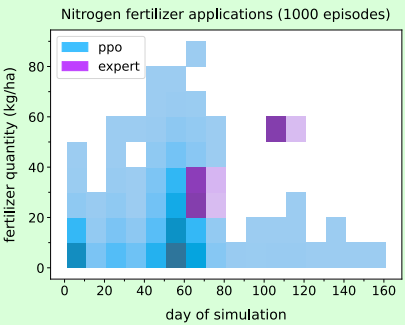
# Learning to manage a crop field

## 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) |
| number of applications | **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) |

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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, arxiv: 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

## A few last words about crop management

- Many topics remain to be studied.

# Learning to manage a crop field

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- Many topics remain to be studied.
- Risk-aware policy.

  See Baudry *et al.*, Optimal Thompson Sampling strategies for support-aware CVaR bandits, ICML 2021

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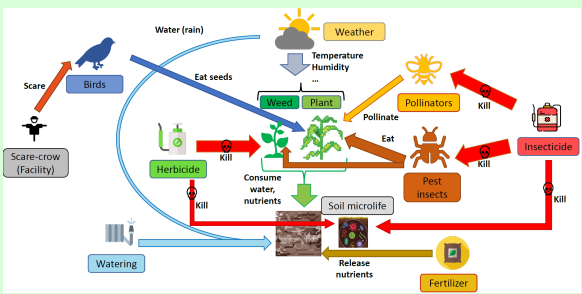
- $\rightsquigarrow$ Farm-gym: toy farm management environment for RL:



# Learning to manage a crop field

## Farm-gym

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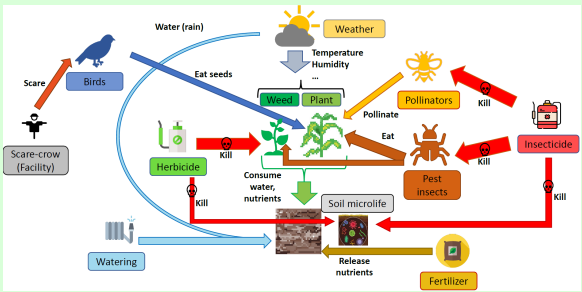
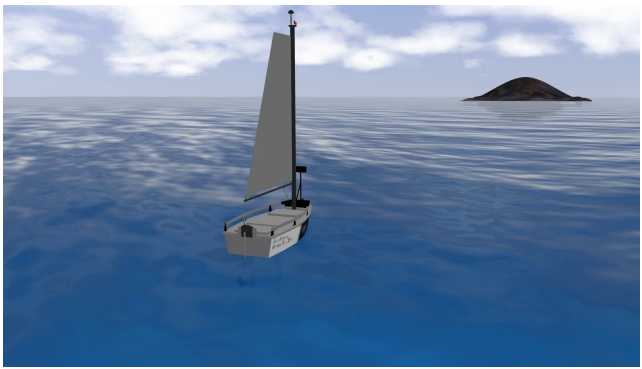



- Less accurate but much richer than gym-DSSAT.
- Meant to investigate new problem features: stochastic environment, several coupled feedback loops, cost of action, cost-benefit objective function, multi-objective objective function, *etc.*
- `https://github.com/farm-gym/farm-gym`

# Learning to sail



In collaboration with Inria-Chile (Luis, Nayat), UFF (Esteban Clua), Univ. Fed. do Rio Grande do Norte (Luis Gonçalvez).

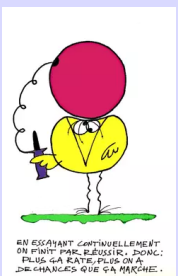
Rooted on the Stic AmSud EMISTRAL project.

Work in progress.

# Learning to sail

- Goal: create an autonomous sailing boat to complete biological missions.
- The environment (sea, wheather, etc) is unknown and non stationary $\rightsquigarrow$ learning and adaptation.
- 

  Shadock approach: put a boat at sea, and let it learn.
  You'll need a lot of boats.




- Rational approach: design a digital twin, train it, transfer sim2real, have the real boat fine tuned and adapt its behavior to real conditions at sea.

# Learning to sail

F-Boat

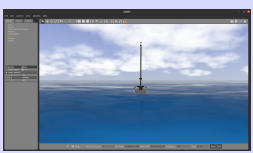
E-Boat

Length: 2.5 m; Width: 0.83 m; Mast Length: 3.13 m.
Electrical propeller, sail.
Actions: control the boom, the rudder, and propeller on/off.
2 cameras, GPS, accelerometer.

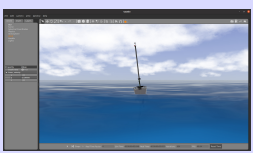
# Learning to sail

- Simulator developed in Gazebo: sea, wind, interaction with the E-boat.
- Check that the E-Boat reacts in silico like the F-boat in the real.

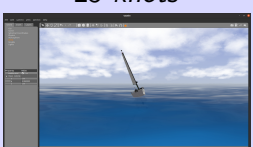
*no wind*



20 *knots*



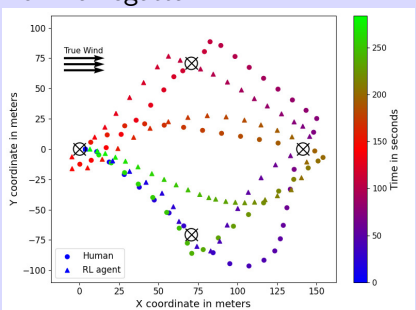
25 *knots*



30 *knots*

# Learning to sail

- Can E-Boat learn to sail?
- The electrical propeller is just a backup, to avoid losing the boat: we should use it as little as possible, possibly never, just using the sail.
- Learning to perform a regatta:



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## On-going work

- image analysis

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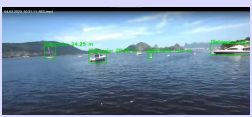
- learning to avoid obstacles



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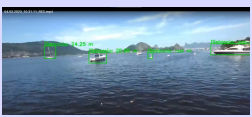

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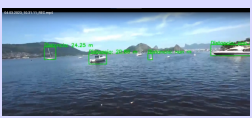

- improving the control of the E-Boat
- sim2real


Vasconcellos *et al.*, RL robotic sailboats: simulator and preliminary results, *6th Robot Learning Workshop NeurIPS*, 2023.

Araújo *et al.*, General system architecture and COTS prototyping of an AIoT-enabled sailboat for autonomous aquatic ecosystem monitoring, *IEEE Trans on IoT*, to appear.

Araújo *et al.*, Vision of the Seas: Open Visual Perception Framework for Autonomous Sailing Vessels, *Proc. IWSSIP*, 2023.

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- We make available open source software to challenge the RL community with real problems: feel free to use it!

Thank you for your attention.

Check out `https://team.inria.fr/scool/`.
Get in touch: `philippe.preux@inria.fr`.