

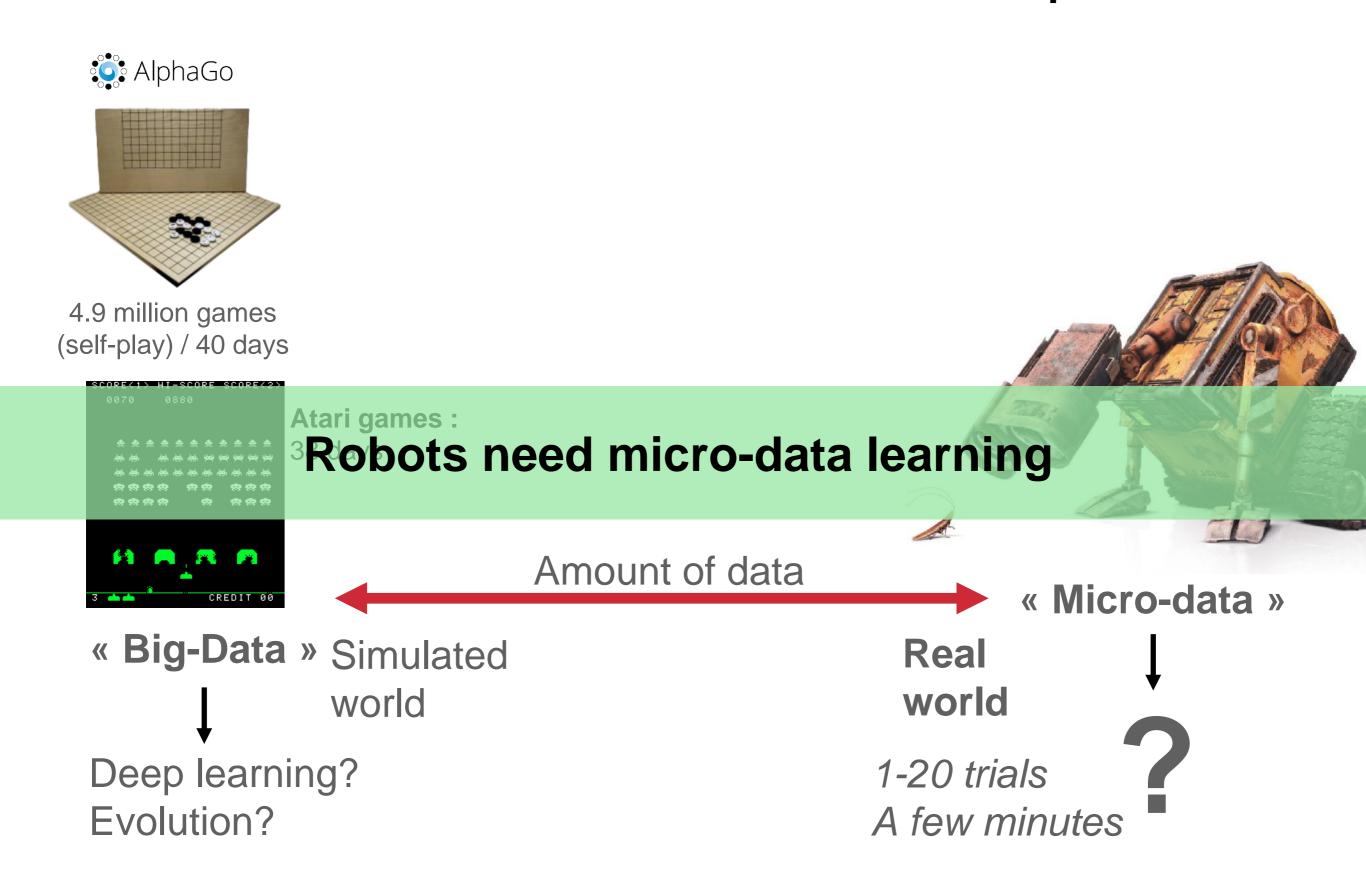


The issue with current robots is not that they fail...

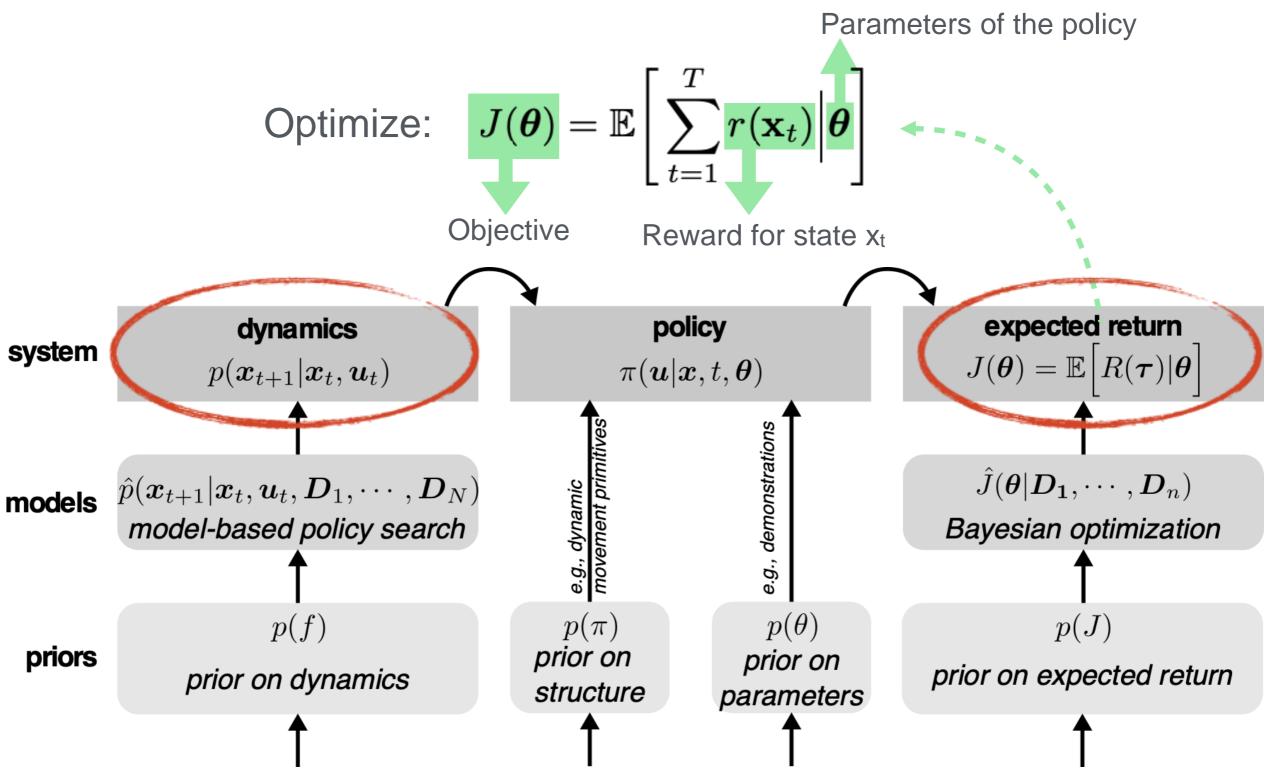
... it is that they do not get back on their feet and try again

- Current robots do not deal well with unexpected situations (e.g., damage)
- Current robots do not learn from their mistakes
- Main reason: diagnosis / understanding problems is hard!

Micro-data: the other end of the spectrum



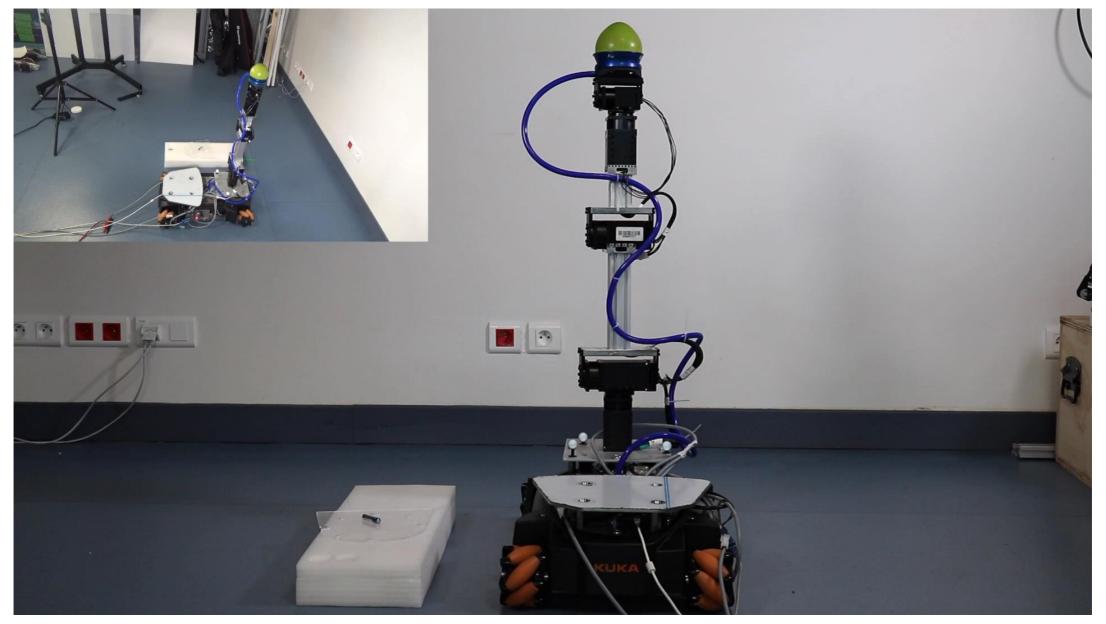
Micro-data policy search



In nature: evolution & experience

K. Chatzilygeroudis, V. Vassiliades, F. Stulp, S. Calinon, J.-B. Mouret. (2018). A survey on policy search algorithms for learning robot controllers in a handful of trials. arXiv:1807.02303

Strategy 1: Learning the dynamical model



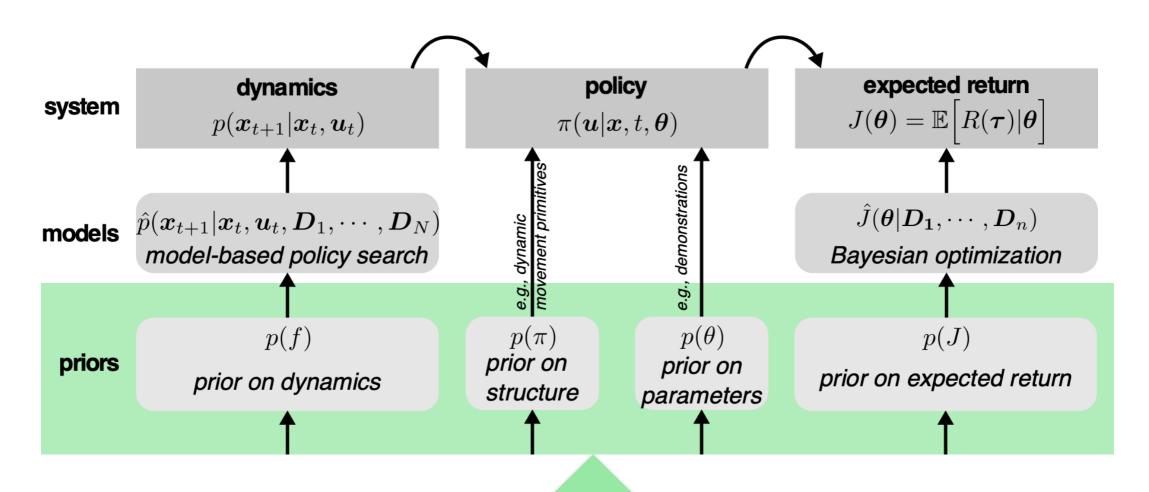
$$\mathbf{x}_{t+1} = \mathbf{x}_t + f(\mathbf{x}_t, \mathbf{u}_t) + \mathbf{w}$$
next state state dynamics noise

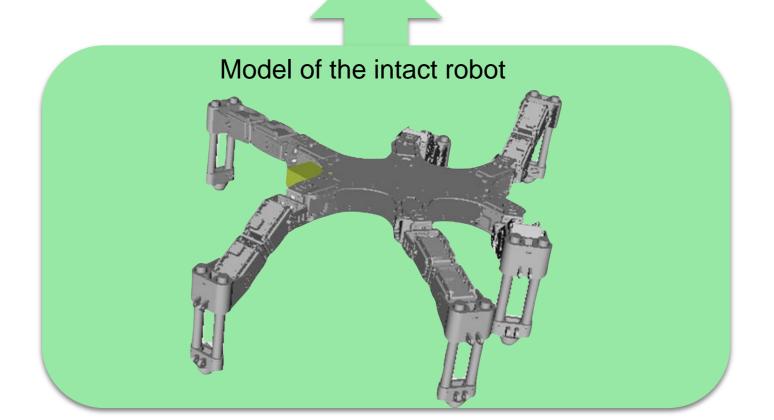
Probabilistic model Optimal policy (in the model)

Chatzilygeroudis K, Rama R, Kaushik R, Goepp D, Vassiliades V, Mouret JB. (2017) Black-Box Data-efficient Policy Search for Robotics. Proc. of IEEE IROS.

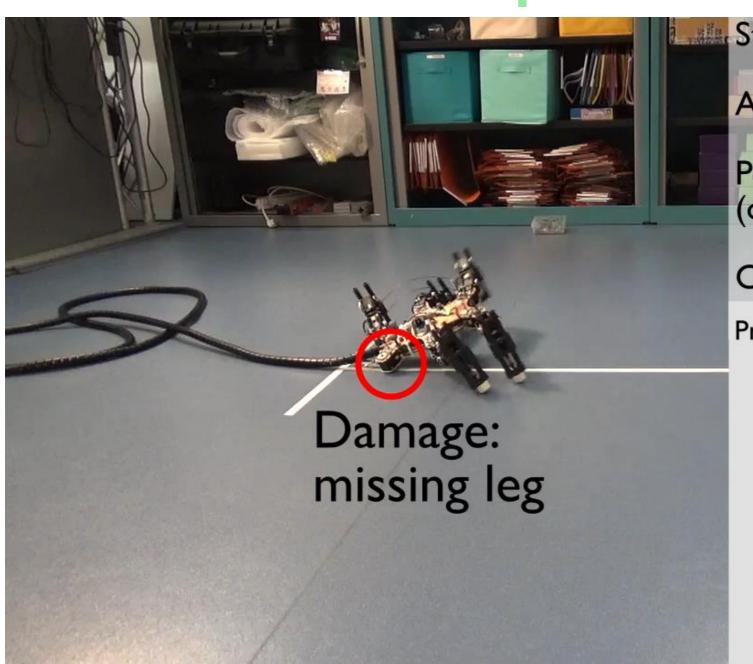
Deisenroth, M. P., Fox, D., & Rasmussen, C. E. (2015). Gaussian processes for data-efficient learning in robotics and control. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 37(2), 408-423.

Policy Search for damage recovery & adaptation





Black-DROPS + priors + identification



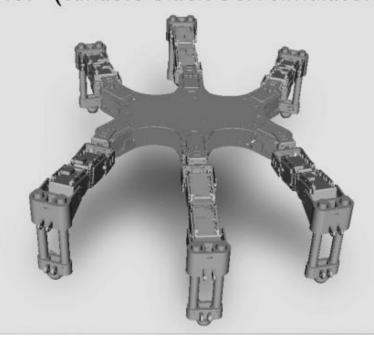
State space: 48D

Action space: 18D

Policy space: 36D (open-loop policy)

Control rate: 10Hz

Prior (tunable black-box simulator):



$$|\mathbf{x}_{t+1}| = \mathbf{x}_t + M(\mathbf{x}_t, \mathbf{u}_t, \boldsymbol{\phi}_M) + f(\mathbf{x}_t, \mathbf{u}_t, \boldsymbol{\phi}_K) + \mathbf{w}$$

probabilistic model

next state

Simulator / model

Other dynamics



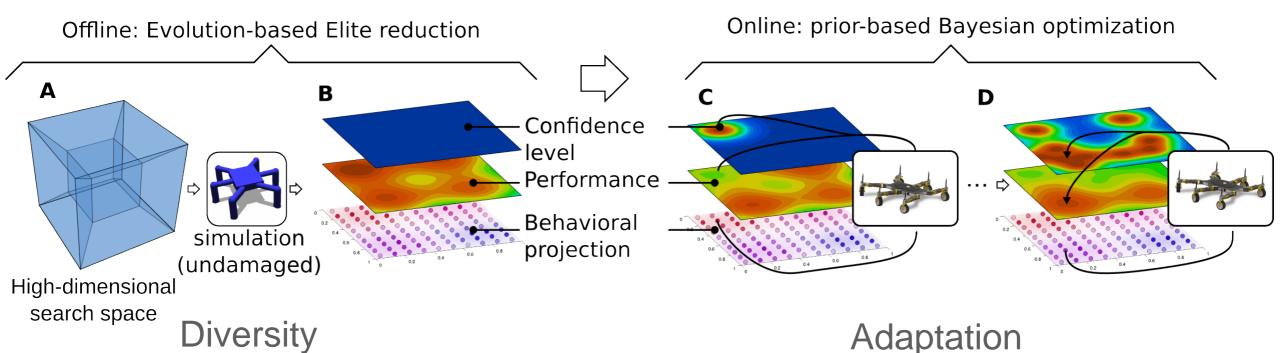
Strategy 2: modelling the return + prior

The MAP-Elites algorithm generates the search space (prior)

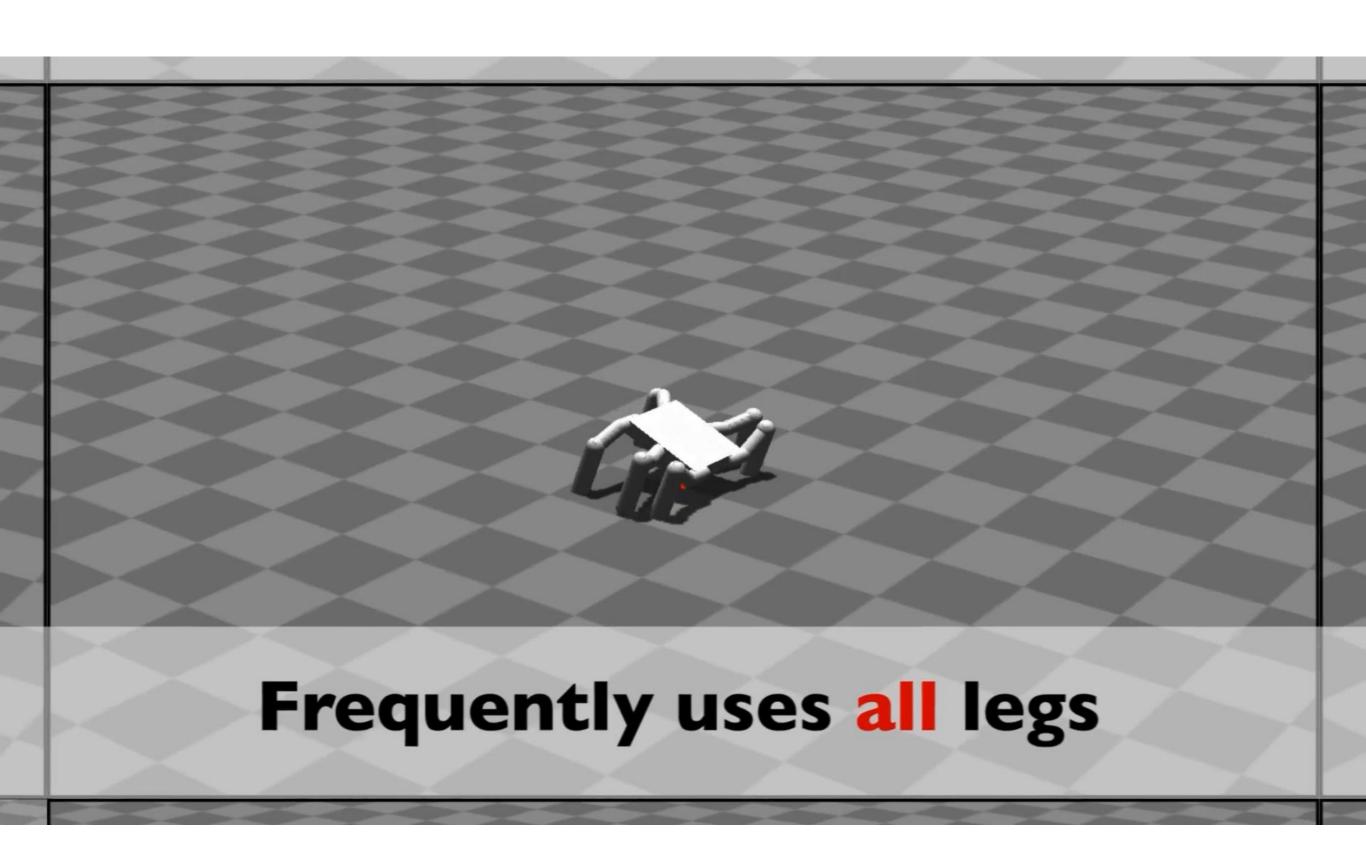
- in simulation, with an intact robot
- many evaluations [simulation]
- "take the needles out of the haystack"
- provide an expected performance for the "needles"

Prior-based Bayesian optimization does the online learning

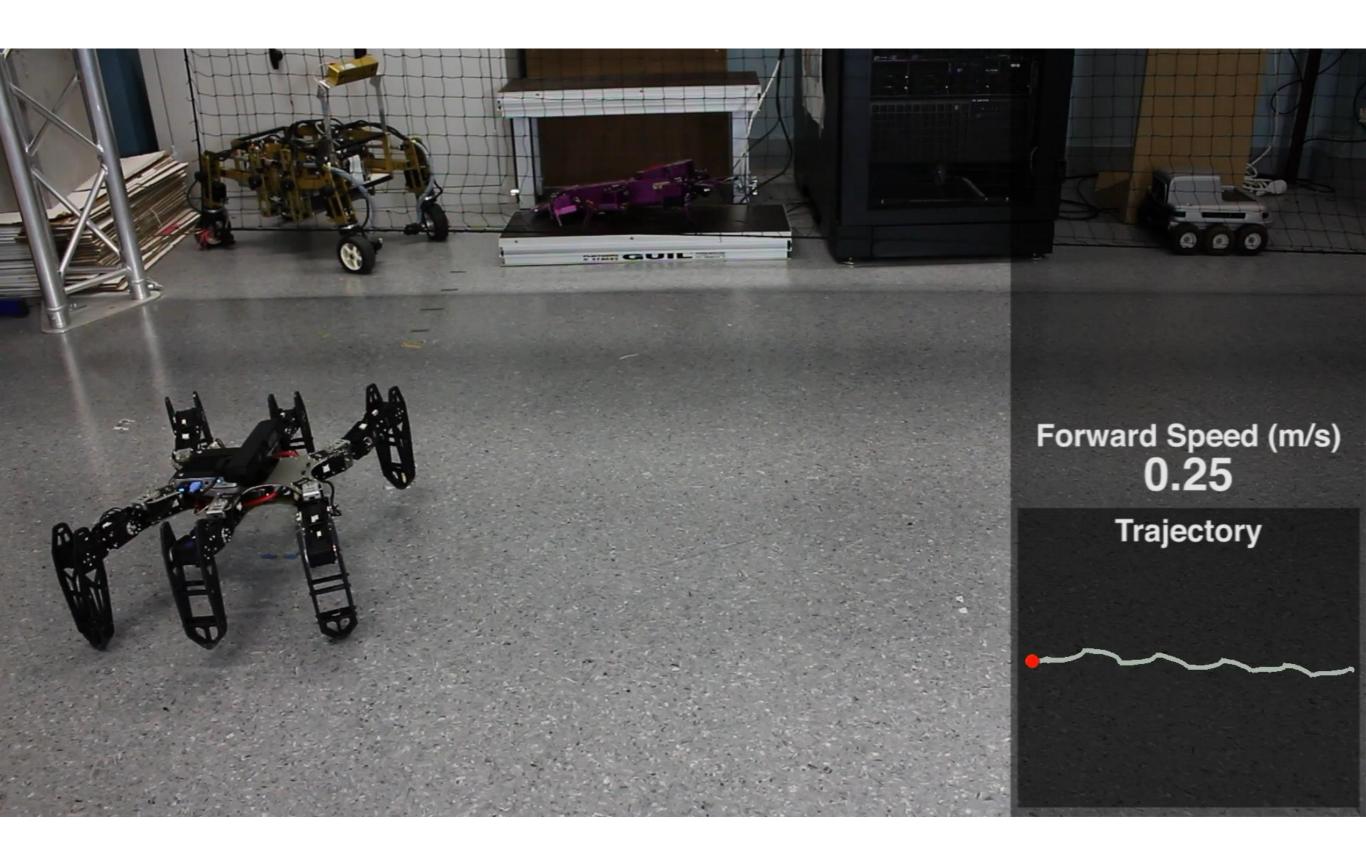
- search only among good solutions ("needles")
- fast trial-and-error (thanks to pre-computed "needles")
- few evaluations [real robot]



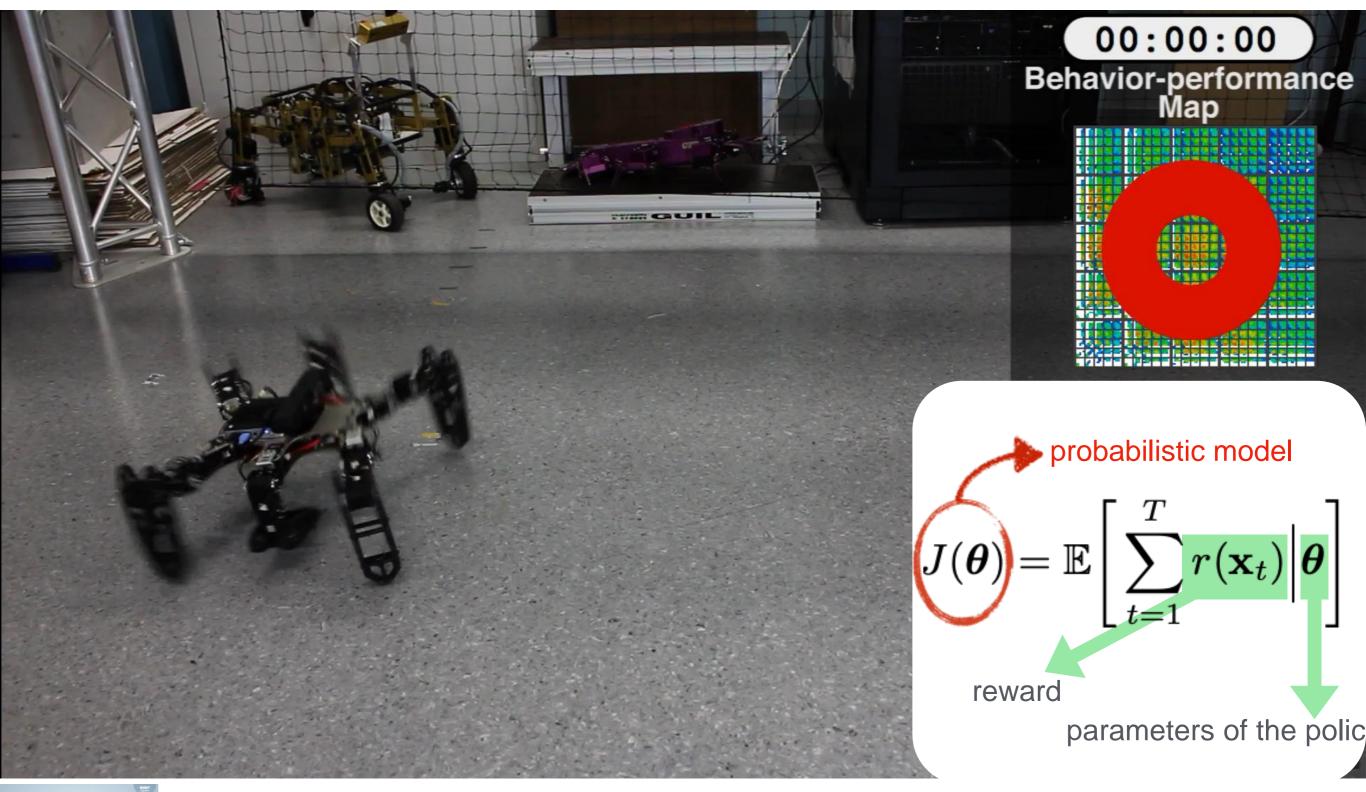
Strategy 2: computing a prior

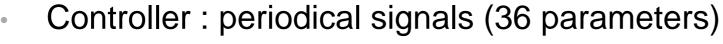


Challenge: damaged 6-legged robot



Strategy 2: prior + modelling the expected return



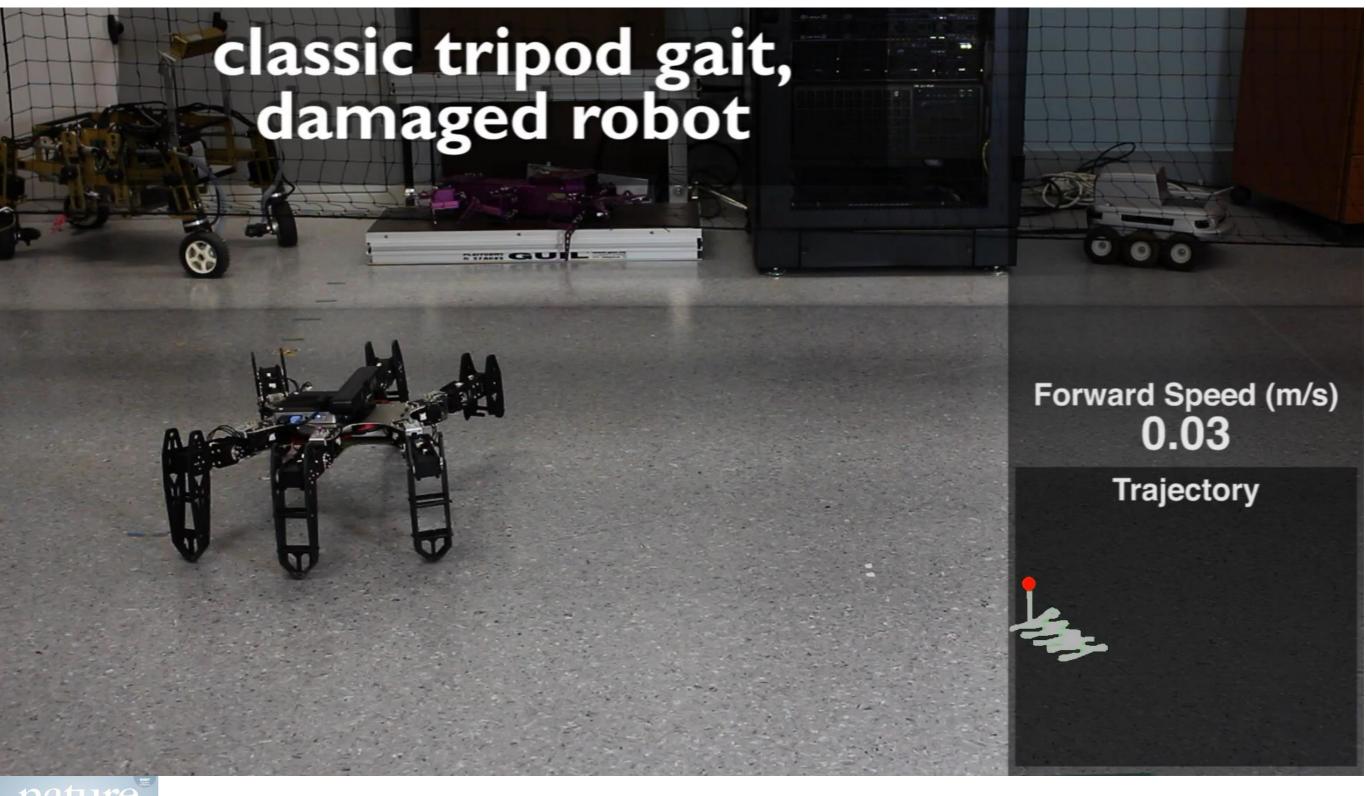


No information about the damage

Back on its feet

Cully, A. and Clune, J. and Tarapore, D. and Mouret, J.-B. (2015). Robots that can adapt like animals. Nature. Vol 521 Pages 503-507.

Strategy 2: modelling the expected return

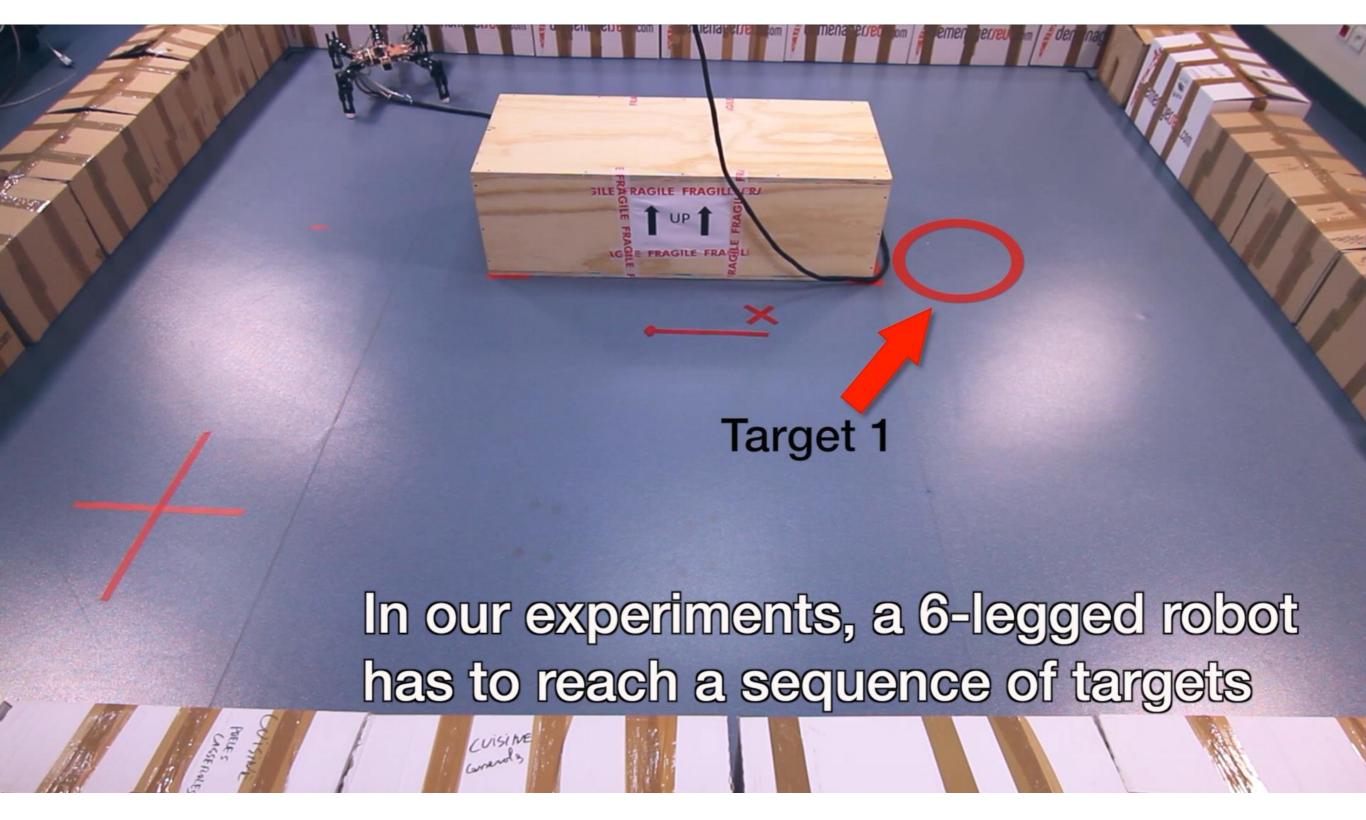


- Controller : periodical signals (36 parameters)
- No information about the damage

Back on its feet

Cully, A. and Clune, J. and Tarapore, D. and Mouret, J.-B. (2015). Robots that can adapt like animals. Nature. Vol 521 Pages 503-507.

Planning (MCTS) + repertoire learning (priors)



What do you I want to achieve?

Fast adaptation in the real world: a few minutes

- Much more autonomy
- Versatile robots for versatile missions
- Animals vs "superhuman"



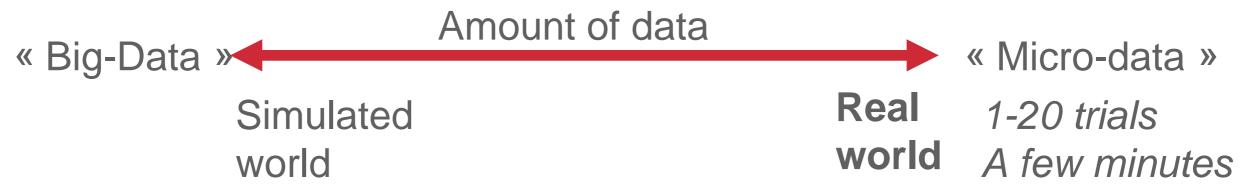
What do you I want to achieve?

Fast adaptation in the real world: a few minutes

- Much more autonomy
- Versatile robots for versatile missions
- More animals than "superhuman"



What do we need in term of science?



- 1.Algorithms that can adapt with little data: most current learning does not really work on real machines & systems
- 2. Algorithms that can explore with rare rewards (e.g., door opening): curious machines / exploration
- 3. Prior knowledge is a key: from big data, models, engineering, ...
- 4. Probabilistic predictive models of the world: know what you do not know
 - → data-efficiency (search in the model)
 - "→ "passive" acquisition (unsupervised)
 - "→ "optimal" planning under uncertainty
- 5. Safety during learning: for the robot & for the environment
- 6.Continuous / long-term learning / avoid catastrophic forgetting

What do we need from society?

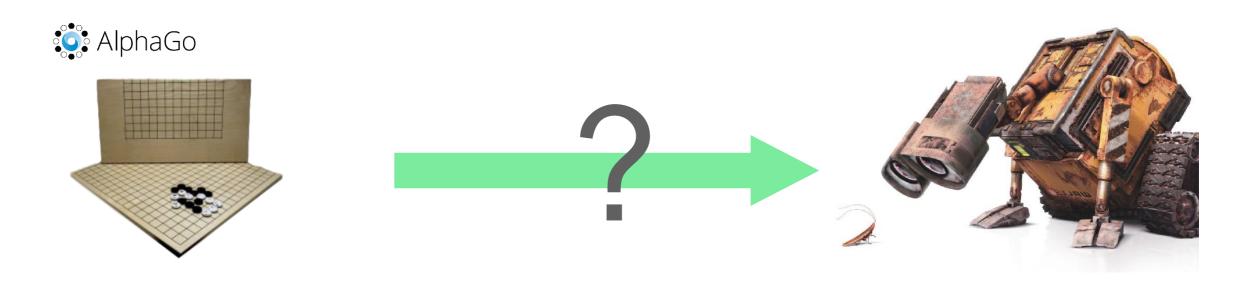
Focus on the important questions:

- 1. Autonomous robots are far from being able to "take over the world"
- 2. but "dumb" robots will be deployed and are more dangerous
 - bad <u>context awareness</u> = bad decisions / accidents / biased decisions
 - a dumb robot is more dangerous than a "smart" one
 - robots ~ pets: they should NOT be dangerous for the world

Difficulty = (Complexity of task) x (Complexity of Environment) x (Cost of mistake)



Conclusion



We achieved a lot in machine learning (e.g., deep learning)

... but this is not enough for robots (yet)

we need algorithms that allow robots to adapt in a few minutes / a few trials

We should be more afraid by "dumb robots" than from "smart robots"



- Videos & papers: http://members.loria.fr/jbmouret
- ERC Project: http://www.resilient-robots.net
- code (C++11): http://github.com/resibots
- contact: <u>jean-baptiste.mouret@inria.fr</u>





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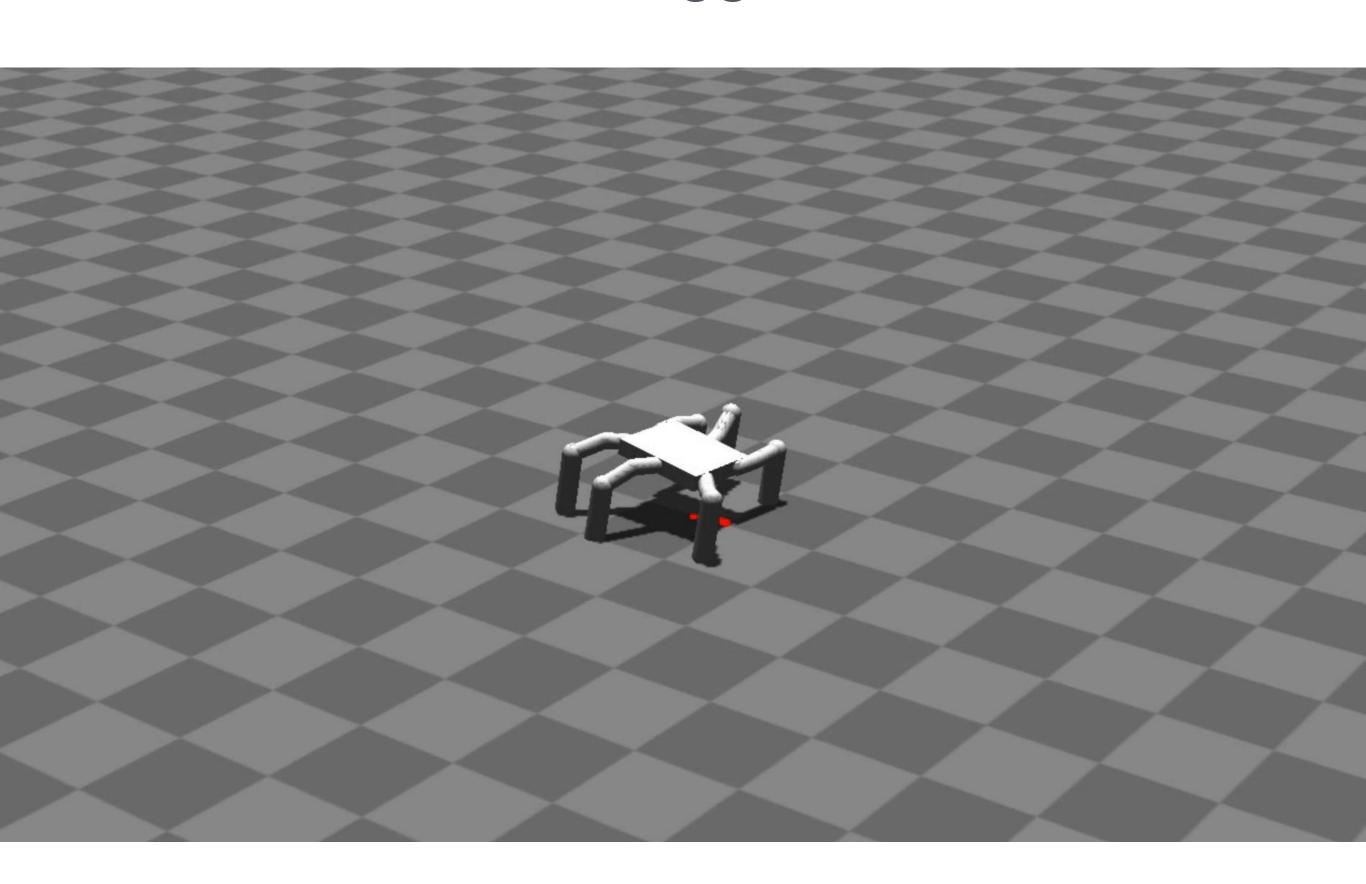
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MAP-Elites: 6-legged locomotion



MAP-Elites: 6-legged locomotion

