Efficient Reinforcement Learning for Motor Control

Marc Peter Deisenroth

Computational and Biological Learning

UNIVERSITY OF CAMBRIDGE

joint work with Carl Edward Rasmussen

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Why learning for control?

borrowed from www.harting-mitronics.ch

Figure: Robots assembling a car.

- machines can execute very complicated control commands

Why learning for control?

with permission from `http://www.chesshistory.com`

Figure: Kasparov (left) vs. DeepBlue (right), 1996/1997

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→ make machines solve control tasks themselves (learning)

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- machines typically require expert knowledge or many $(10^x,\, x \geq 2)$ trials
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objective:
➡ find a strategy of solving a problem that satisfies these constraints

Task learning as an optimal control problem

- find a policy/strategy π that yields low expected long-term cost

$$V^{\pi}(\mathbf{x}_0) = \sum_{t=0}^{T} \mathop{\mathbb{E}}_{\mathbf{x}_t}[c(\mathbf{x}_t)]$$

  of following policy π for T time steps (starting from $\mathbf{x}_0$)
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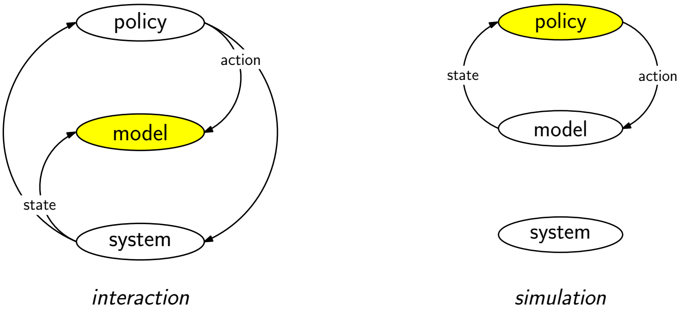
two possible approaches to get V^{π}:

- model free ➡ sample states and controls from real system
- model based ➡ find a model of the system function; internal simulation

General (model-based) setup: interaction and simulation



two phases

- interaction: internal model is refined using experience from interacting with the real system
- simulation: internal model is used to simulate consequences of actions in the real system, policy is refined

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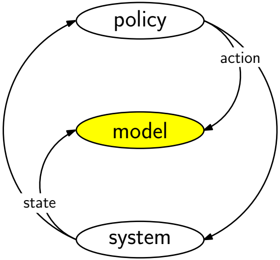
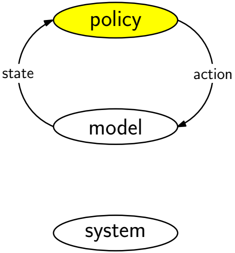


interaction



simulation

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➡ problem: model bias!

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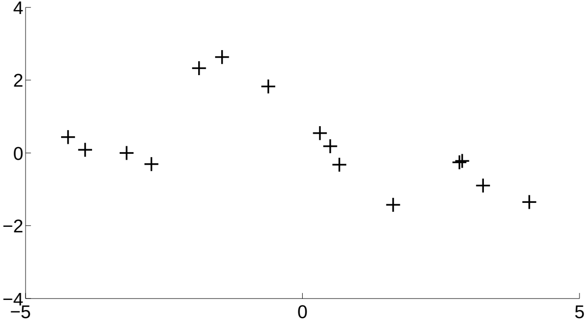

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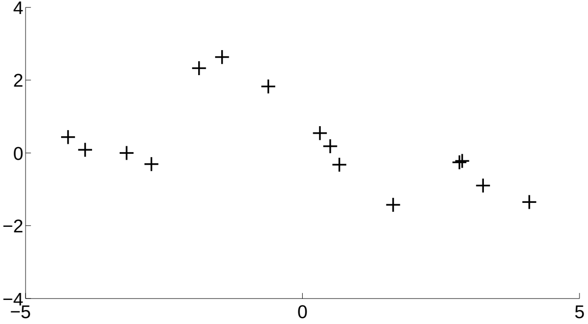
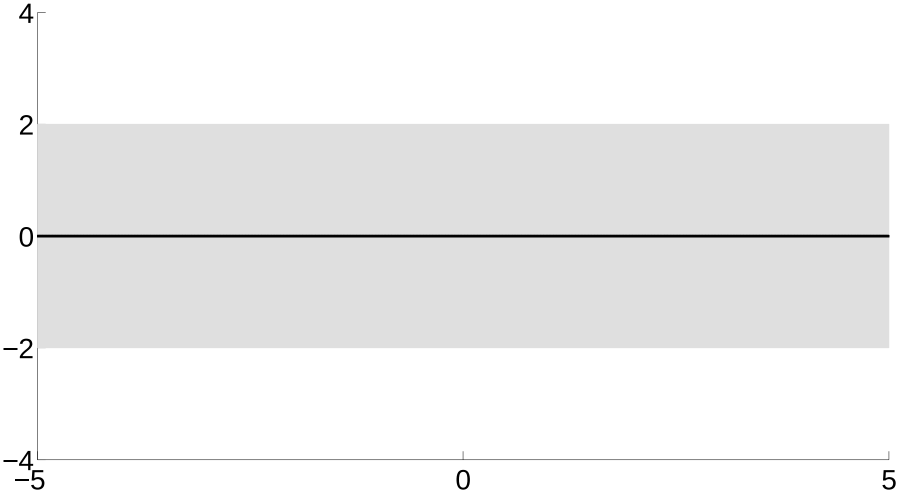


➡ here: Gaussian processes to find a model of the system function

Pictorial introduction to Gaussian process regression



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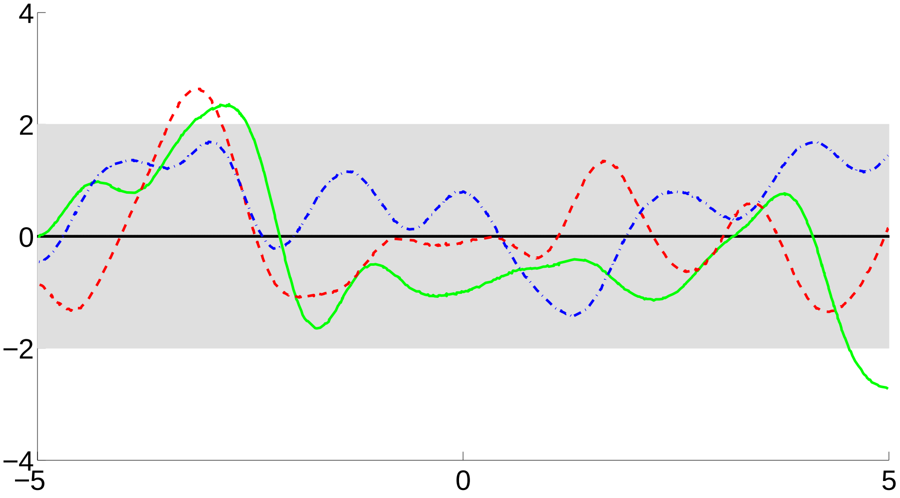

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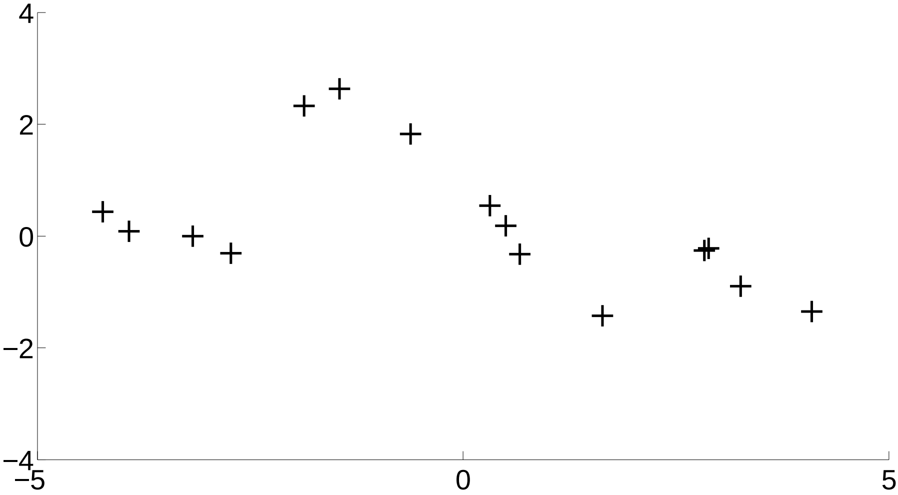

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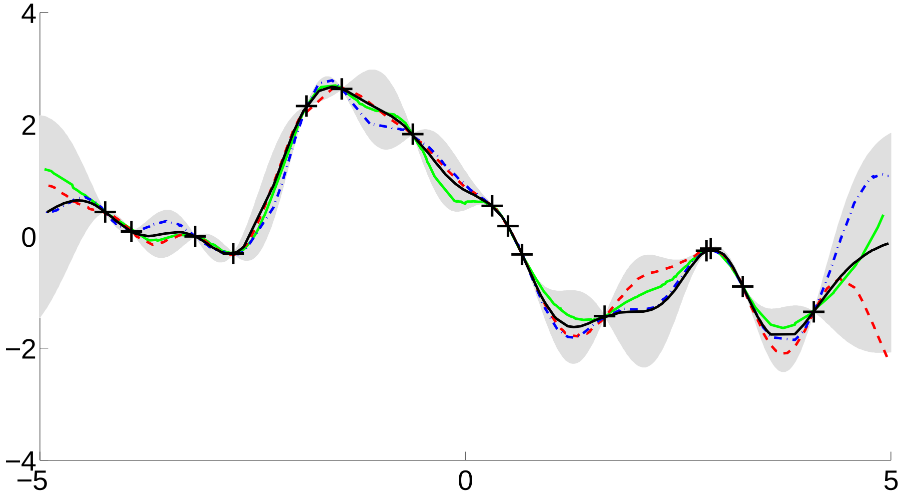

Evaluation of the value function

- the GP gives us one-step transition probabilities $p(\mathbf{x}_{t+1}|\mathbf{x}_t)$, but we need

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- cascade predictions to get $p(\mathbf{x}_1), p(\mathbf{x}_2), \dots, p(\mathbf{x}_T)$
- compute $\mathbb{E}_{\mathbf{x}_t}[c(\mathbf{x}_t)]$
- add them together

Policy refinement

- expected long-term cost (value function)

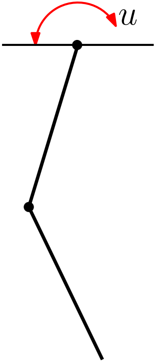
$$V^{\pi}(\mathbf{x}_0) = \sum_{t=0}^{T} \mathbb{E}_{\mathbf{x}_t}[c(\mathbf{x}_t)]$$

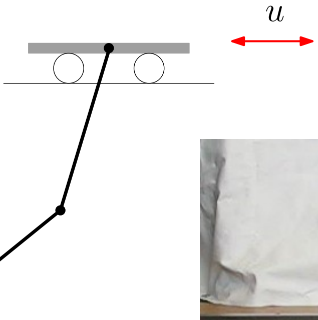
  can be evaluated analytically using approximate Bayesian inference
- compute derivative of $V^{\pi}(\mathbf{x}_0)$ with respect to policy parameters
- iterative gradient-based method to optimize policy parameters
  ➡ policy search

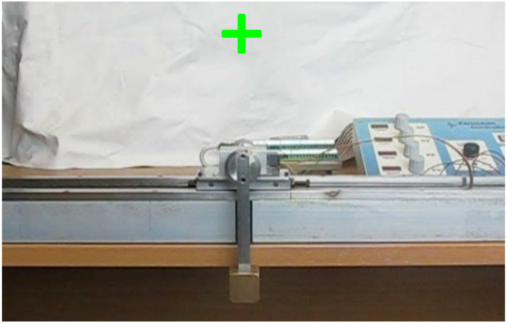
High-level algorithm

```
init: set policy to random
loop
    apply policy to the real system                    ▷ interaction
    learn GP model for system function
    loop                                               ▷ policy search
        simulate system with policy π                  ▷ predictions
        compute value function V^π for current policy
        improve policy                                 ▷ policy refinement
    end loop
end loop
```

Results







Wrap-up

- data-efficient artificial learning for control problems
- no expert knowledge
- probabilistic model for coherent representation of uncertainty
- explicit incorporation of uncertainty into prediction and decision-making
- gradient-based policy search
- works in simulation and hardware

http://mlg.eng.cam.ac.uk/marc