IASD M2 at Paris Dauphine

Deep Reinforcement Learning

13: Model-Based Policy Learning

Eric Benhamou Thérèse Des Escotais

Collobration

Prénom / Nom	Date de remise
ZEHUI XUAN	mercredi 16 février 2022, 10:25
LOUIS REBERGA	mercredi 16 février 2022, 10:24
PIERRE BOUDART	mercredi 16 février 2022, 10:23
MATEUSZ PYLA	mercredi 2 février 2022, 12:54
NATHAN BIGAUD	mardi 25 janvier 2022, 22:16
LEONARD DE LA SEIGLIERE	mardi 25 janvier 2022, 22:15
THOMAS GEORGES	mardi 25 janvier 2022, 22:15
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Collaboration expert

Collaboration Level 1

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NATHAN BIGAUD	mercredi 2 février 2022, 12:55
MATEUSZ PYLA	mercredi 2 février 2022, 12:54
ROXANE COHEN	mardi 25 janvier 2022, 22:12
YOANN LEMESLE	mardi 25 janvier 2022, 22:12
KEVIN TAOUDI	mardi 25 janvier 2022, 22:12
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Collaboration level 2

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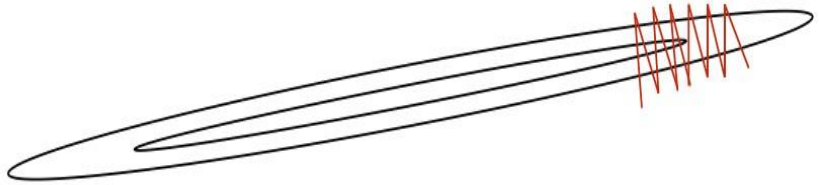
Natural Gradient explained

- Two classes of optimization procedures used throughout ML
  - (stochastic) gradient descent, with momentum, and maybe coordinate-wise rescaling (e.g. Adam)
    - Can take many iterations to converge, especially if the problem is ill-conditioned
  - coordinate descent (e.g. EM)
    - Requires full-batch updates, which are expensive for large datasets
- Natural gradient is an elegant solution to both problems.
- This is related to variational inference

Motivation

- SGD bounces around in high curvature directions and makes slow progress in low curvature directions. (Note: this cartoon understates the problem by orders of magnitude!)



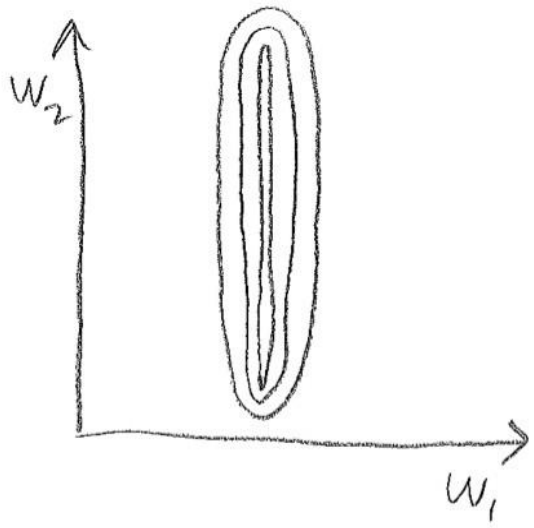
- This happens because when we train a neural net (or some other ML model), we are optimizing over a complicated manifold of functions. Mapping a manifold to a flat coordinate system distorts distances.

Natural gradient: compute the gradient on the globe, not on the map.

Motivations: Invariances

Suppose we have the following dataset for linear regression.

x_1	x_2	t
114.8	0.00323	5.1
338.1	0.00183	3.2
98.8	0.00279	4.1
⋮	⋮	⋮

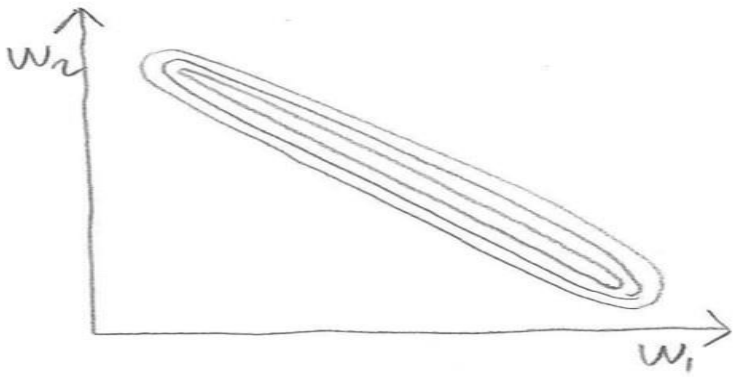


- This can happen since the inputs have arbitrary units.
- Which weight, w1 or w2, will receive a larger gradient descent update?
- Which one do you want to receive a larger update?
- Note: the figure vastly understates the narrowness of the ravine!

Motivations: Invariances

Or maybe x_1 and x_2 correspond to years:

x_1	x_2	t
2003	2005	3.3
2001	2008	4.8
1998	2003	2.9
⋮	⋮	⋮



Motivations: Invariances

Consider minimizing a function h(x), where x is measured in feet.
Gradient descent update:

$$x \leftarrow x - \alpha \frac{\mathrm{d}h}{\mathrm{d}x}$$

But $\mathrm{d}h/\mathrm{d}x$ has units 1/feet. So we're adding feet and 1/feet, which is nonsense. This is why gradient descent has problems with badly scaled data.

Natural gradient is a dimensionally correct optimization algorithm. In fact, the updates are equivalent (to first order) in any coordinate system!

Steepest Descent

Gradient defines a linear approximation to a function:

$$h(\mathbf{x} + \Delta\mathbf{x}) \approx h(\mathbf{x}) + \nabla h(\mathbf{x})^\top \Delta\mathbf{x}$$

We don't trust this approximation globally. Steepest descent tries to prevent the update from moving too far, in terms of some dissimilarity measure D:

$$\mathbf{x}^{k+1} \leftarrow \arg\min_{\mathbf{x}} \left\{ \nabla h(\mathbf{x}^k)^\top (\mathbf{x} - \mathbf{x}^k) + \lambda D(\mathbf{x}, \mathbf{x}^k) \right\}$$

Gradient descent can be seen as steepest descent with

$$D(\mathbf{x}, \mathbf{x}') = \tfrac{1}{2} \|\mathbf{x} - \mathbf{x}'\|^2$$

Not a very interesting D, since it depends on the coordinate system.

Fisher Metric

If we're fitting a probabilistic model, the optimization variables parameterize a probability distribution.

The obvious dissimilarity measure is KL divergence:

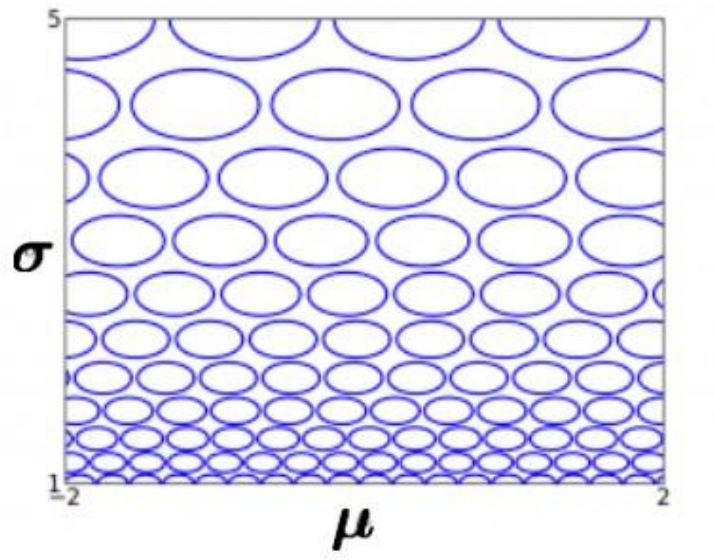
$$D(\boldsymbol{\theta}, \boldsymbol{\theta}') = \mathrm{D}_{\mathrm{KL}}(p_{\boldsymbol{\theta}} \| p_{\boldsymbol{\theta}'})$$

The second-order Taylor approximation to KL divergence is the Fisher information matrix:

$$\frac{\partial^2 \mathrm{D}_{\mathrm{KL}}}{\partial \boldsymbol{\theta}^2} = \mathbf{F} = \underset{x \sim p_{\boldsymbol{\theta}}}{\mathrm{Cov}} \left(\nabla_{\boldsymbol{\theta}} \log p_{\boldsymbol{\theta}}(x) \right)$$

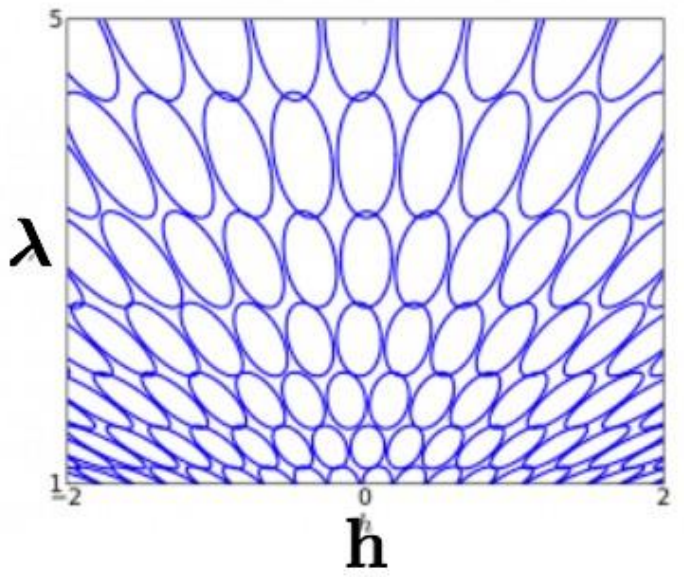
Fisher Metric

mean and std dev



$$p(x) \propto \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

information form



$$p(x) \propto \exp\left(hx - \frac{\lambda}{2}x^2\right)$$

Fisher Metric

KL divergence is an intrinsic dissimilarity measure on distributions: it doesn't care how the distributions are parameterized.

Therefore, steepest descent in the Fisher metric (which approximates KL divergence) is invariant to parameterization, to the first order. This is why it's called natural gradient.

Update rule:

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \alpha \mathbf{F}^{-1} \nabla_{\boldsymbol{\theta}} h$$

This can converge much faster than ordinary gradient descent.

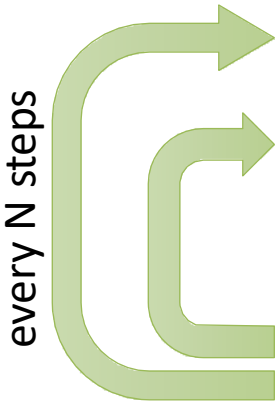
Acknowledgement

These materials are based on the seminal course of Sergey Levine CS285

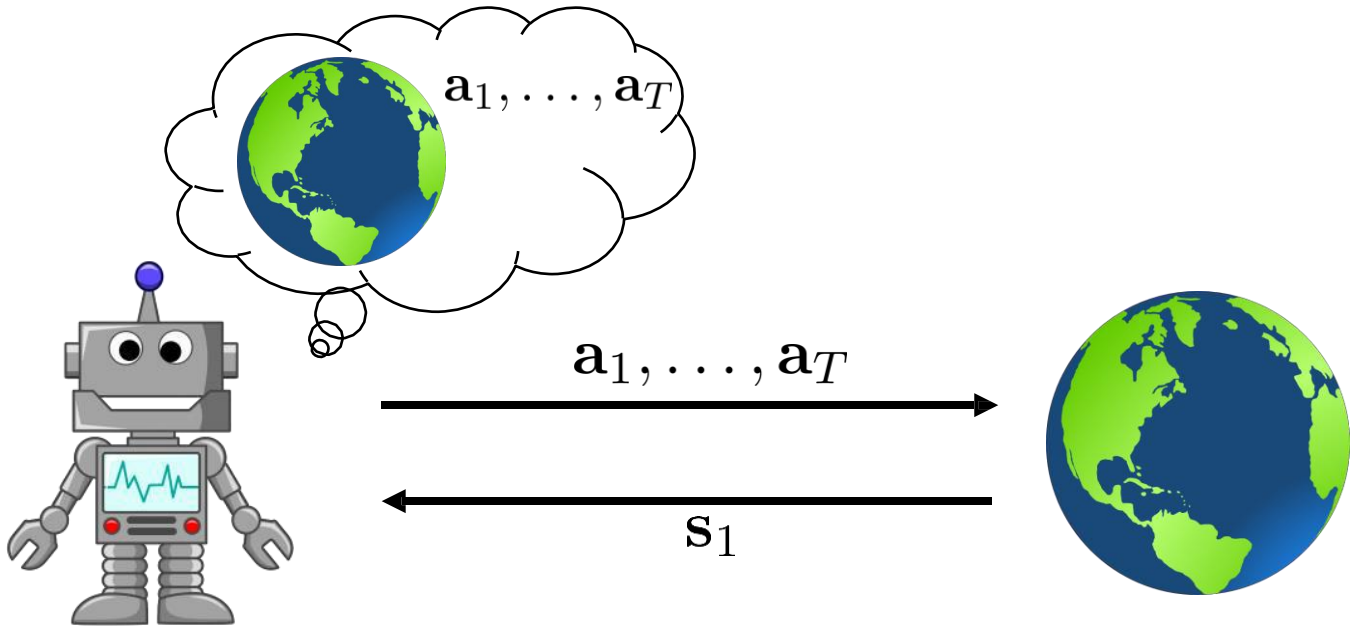
Last time: model-based RL with MPC

model-based reinforcement learning version 1.5:

1. run base policy $\pi_0(\mathbf{a}_t|\mathbf{s}_t)$ (e.g., random policy) to collect $\mathcal{D} = \{(\mathbf{s}, \mathbf{a}, \mathbf{s}')_i\}$
2. learn dynamics model $f(\mathbf{s}, \mathbf{a})$ to minimize $\sum_i \|f(\mathbf{s}_i, \mathbf{a}_i) - \mathbf{s}'_i\|^2$
3. plan through $f(\mathbf{s}, \mathbf{a})$ to choose actions
4. execute the first planned action, observe resulting state $\mathbf{s}'$ (MPC)
5. append $(\mathbf{s}, \mathbf{a}, \mathbf{s}')$ to dataset $\mathcal{D}$



The stochastic open-loop case

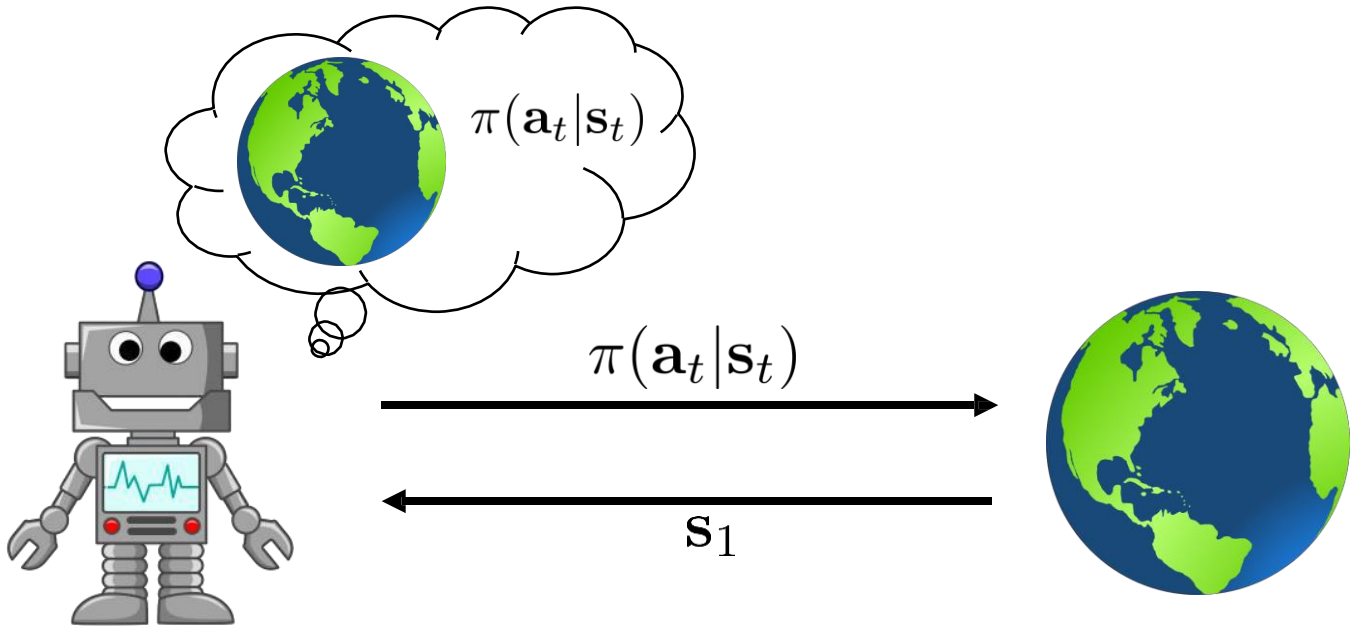


$$p_\theta(\mathbf{s}_1, \ldots, \mathbf{s}_T | \mathbf{a}_1, \ldots, \mathbf{a}_T) = p(\mathbf{s}_1) \prod_{t=1}^{T} p(\mathbf{s}_{t+1} | \mathbf{s}_t, \mathbf{a}_t)$$

$$\mathbf{a}_1, \ldots, \mathbf{a}_T = \arg \max_{\mathbf{a}_1, \ldots, \mathbf{a}_T} E \left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t) | \mathbf{a}_1, \ldots, \mathbf{a}_T \right]$$

why is this suboptimal?

The stochastic closed-loop case



form of π?

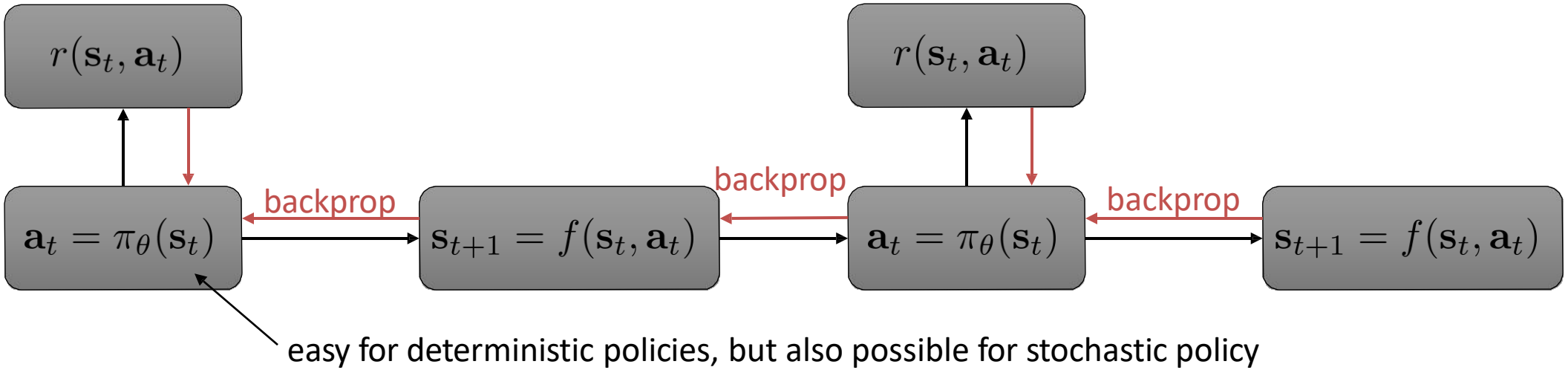
neural net global

time-varying linear $\mathbf{K}_t\mathbf{s}_t + \mathbf{k}_t$ local

$$p(\mathbf{s}_1, \mathbf{a}_1, \ldots, \mathbf{s}_T, \mathbf{a}_T) = p(\mathbf{s}_1) \prod_{t=1}^{T} \pi(\mathbf{a}_t|\mathbf{s}_t) p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$$

$$\pi = \arg\max_{\pi} E_{\tau \sim p(\tau)} \left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t) \right]$$

Backpropagate directly into the policy?



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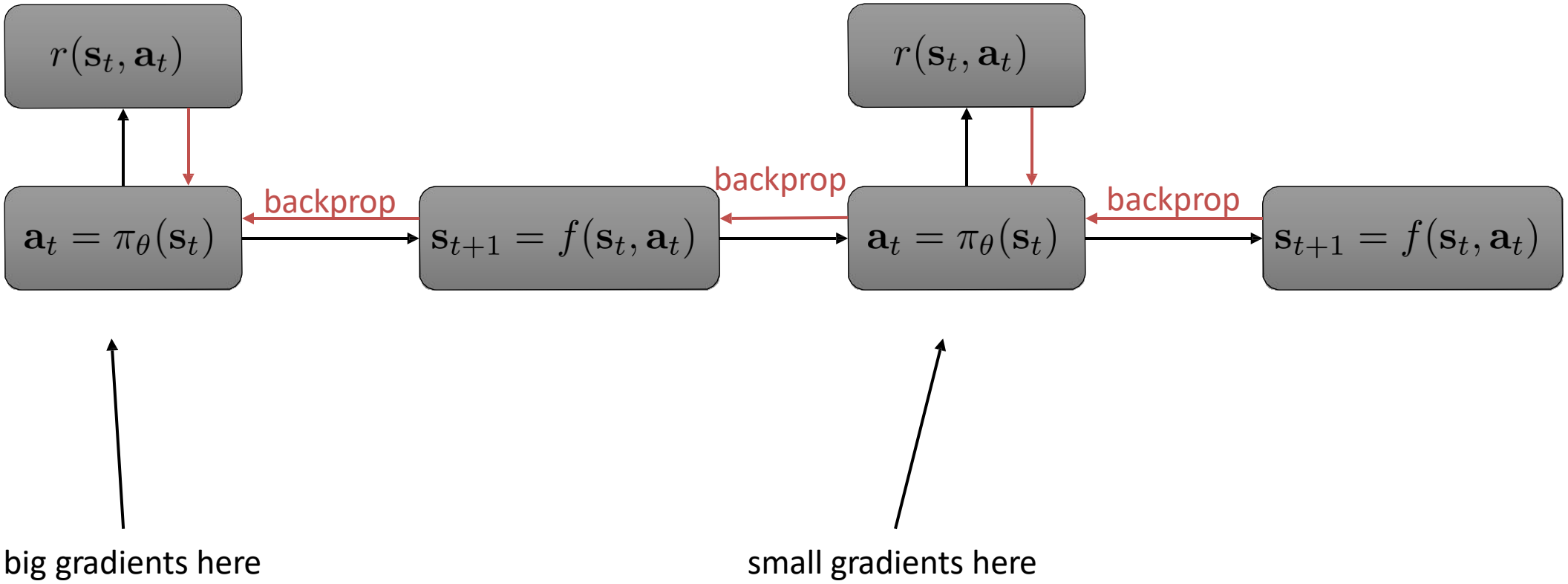
2. learn dynamics model $f(\mathbf{s}, \mathbf{a})$ to minimize $\sum_i \|f(\mathbf{s}_i, \mathbf{a}_i) - \mathbf{s}'_i\|^2$
3. backpropagate through $f(\mathbf{s}, \mathbf{a})$ into the policy to optimize $\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$
4. run $\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)$, appending the visited tuples $(\mathbf{s}, \mathbf{a}, \mathbf{s}')$ to $\mathcal{D}$

What's the problem with backprop into policy?



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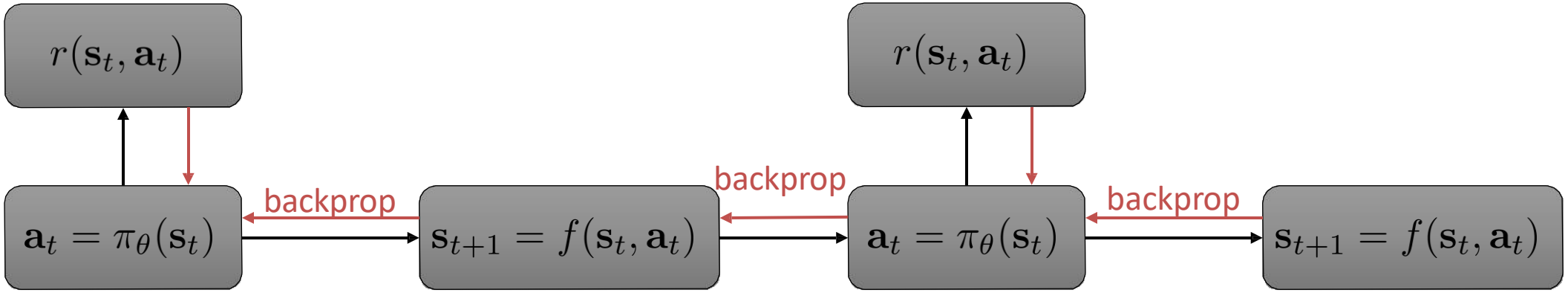

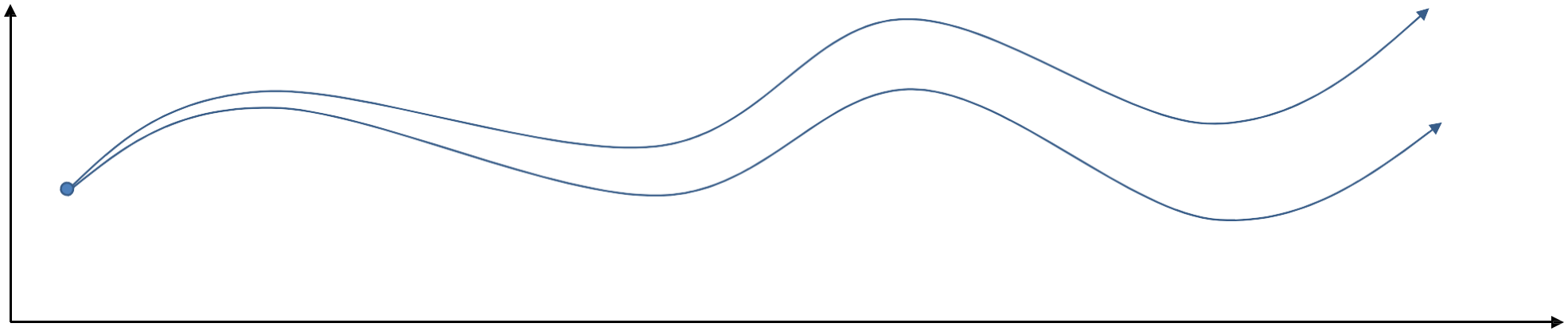

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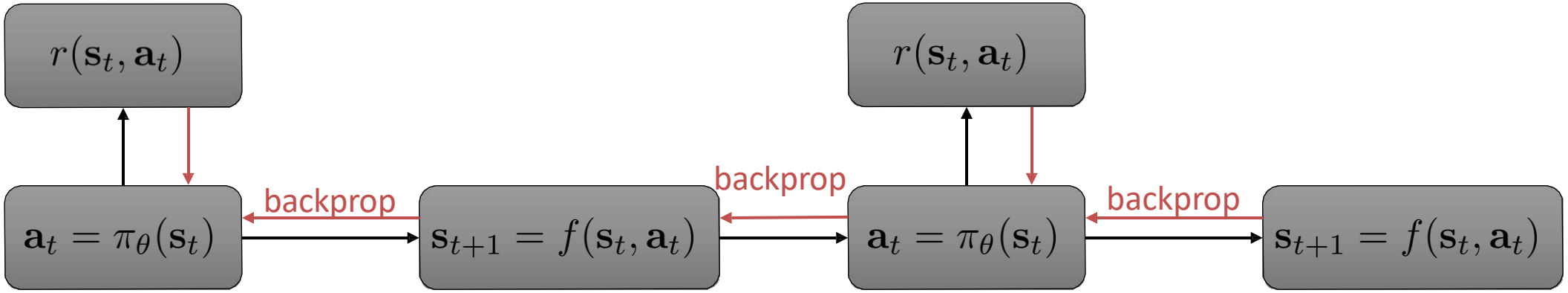

- Similar parameter sensitivity problems as shooting methods
  - But no longer have convenient second order LQR-like method, because policy parameters couple all the time steps, so no dynamic programming
- Similar problems to training long RNNs with BPTT
  - Vanishing and exploding gradients
  - Unlike LSTM, we can't just "choose" a simple dynamics, dynamics are chosen by nature

What's the solution?

- Use derivative-free ("model-free") RL algorithms, with the model used to generate synthetic samples
  - Seems weirdly backwards
  - Actually works very well
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- Use simpler policies than neural nets
  - LQR with learned models (LQR-FLM – **F**itted **L**ocal **M**odels)
  - Train **local** policies to solve simple tasks
  - Combine them into **global** policies via supervised learning

Model-Free Learning With a Model

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Model-free optimization with a model

Policy gradient: $$\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t}|\mathbf{s}_{i,t}) \hat{Q}^\pi_{i,t}$$

Backprop (pathwise) gradient: $$\nabla_\theta J(\theta) = \sum_{t=1}^{T} \frac{dr_t}{d\mathbf{s}_t} \prod_{t'=2}^{t} \frac{d\mathbf{s}_{t'}}{d\mathbf{a}_{t'-1}} \frac{d\mathbf{a}_{t'-1}}{d\mathbf{s}_{t'-1}}$$

- Policy gradient might be more *stable* (if enough samples are used) because it does not require multiplying many Jacobians
- See a recent analysis here:
  - Parmas et al. ‘18: PIPP: Flexible Model-Based Policy Search Robust to the Curse of Chaos

Model-free optimization with a model

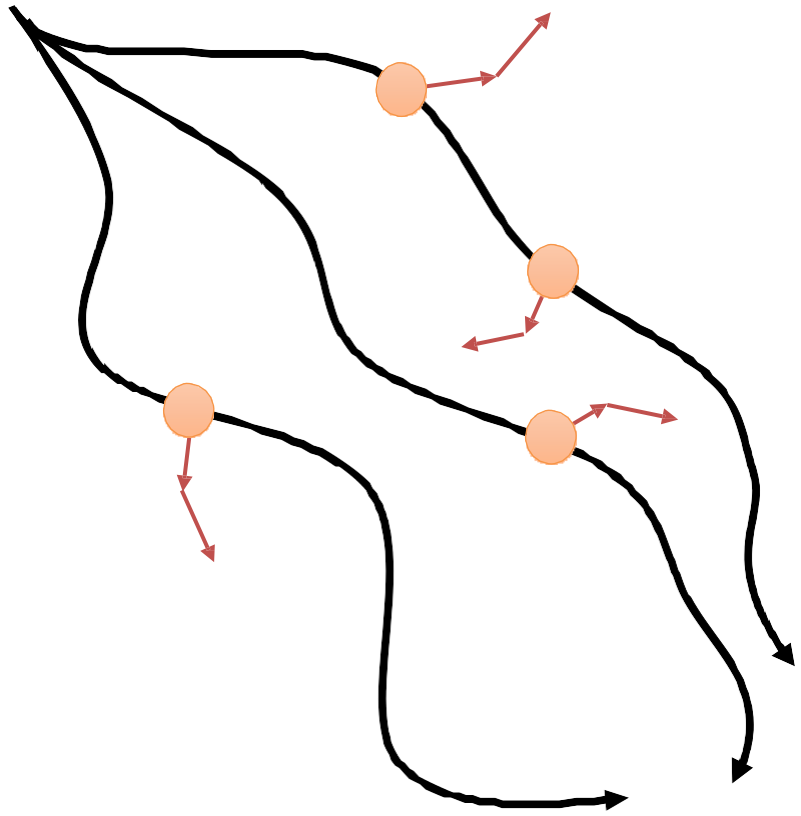
Dyna online Q-learning algorithm that performs model-free RL with a model

1. given state s, pick action a using exploration policy
2. observe s' and r, to get transition (s, a, s', r)
3. update model $\hat{p}(s'|s, a)$ and $\hat{r}(s, a)$ using (s, a, s')
4. Q-update: $Q(s, a) \leftarrow Q(s, a) + \alpha E_{s',r}[r + \max_{a'} Q(s', a') - Q(s, a)]$
5. repeat K times:
   6. sample $(s, a) \sim \mathcal{B}$ from buffer of past states and actions
   7. Q-update: $Q(s, a) \leftarrow Q(s, a) + \alpha E_{s',r}[r + \max_{a'} Q(s', a') - Q(s, a)]$

Richard S. Sutton. Integrated architectures for learning, planning, and reacting based on approximating dynamic programming.

General "Dyna-style" model-based RL recipe

1. collect some data, consisting of transitions (s, a, s', r)
2. learn model $\hat{p}(s'|s, a)$ (and optionally, $\hat{r}(s, a)$)
3. repeat K times:
   4. sample $s \sim \mathcal{B}$ from buffer
   5. choose action a (from $\mathcal{B}$, from π, or random)
   6. simulate $s' \sim \hat{p}(s'|s, a)$ (and $r = \hat{r}(s, a)$)
   7. train on (s, a, s', r) with model-free RL
   8. (optional) take N more model-based steps

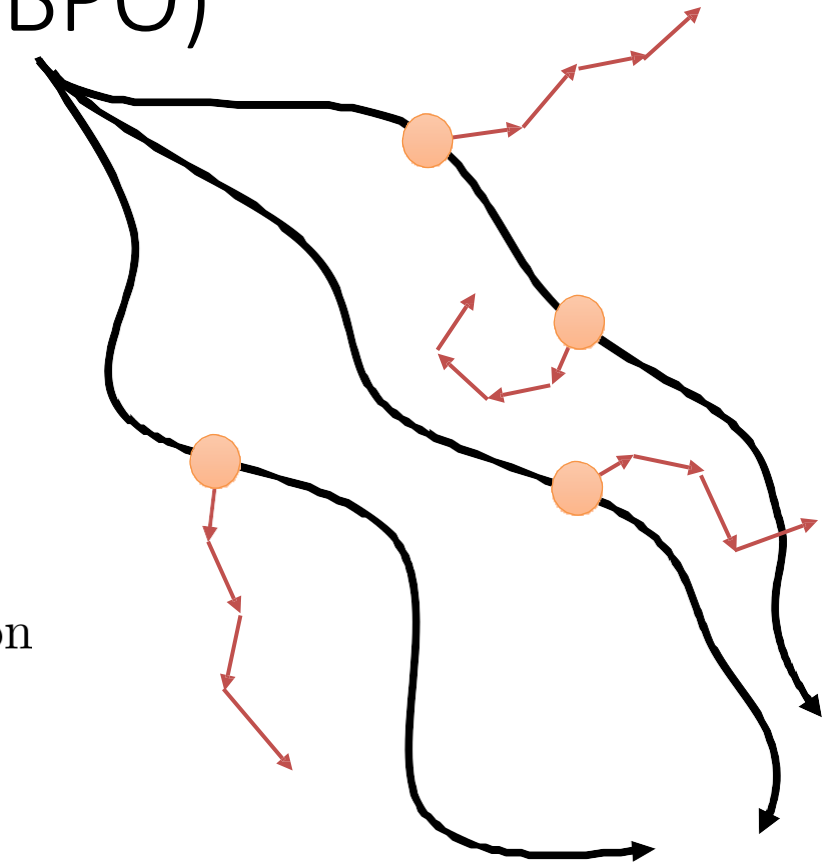


+ only requires short (as few as one step) rollouts from model

+ still sees diverse states

Model-Based Acceleration (MBA)
Model-Based Value Expansion (MVE)
Model-Based Policy Optimization (MBPO)

1. take some action $\mathbf{a}_i$ and observe $(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)$, add it to $\mathcal{B}$
2. sample mini-batch $\{\mathbf{s}_j, \mathbf{a}_j, \mathbf{s}'_j, r_j\}$ from $\mathcal{B}$ uniformly
3. use $\{\mathbf{s}_j, \mathbf{a}_j, \mathbf{s}'_j\}$ to update model $\hat{p}(\mathbf{s}'|\mathbf{s}, \mathbf{a})$
4. sample $\{\mathbf{s}_j\}$ from $\mathcal{B}$
5. for each $\mathbf{s}_j$, perform model-based rollout with $\mathbf{a} = \pi(\mathbf{s})$
6. use all transitions $(\mathbf{s}, \mathbf{a}, \mathbf{s}', r)$ along rollout to update Q-function



+ why is this a *good* idea?

- why is this a *bad* idea?

Gu et al. Continuous deep Q-learning with model-based acceleration. ‘16
Feinberg et al. Model-based value expansion. ’18
Janner et al. When to trust your model: model-based policy optimization. ‘19

Local Models

What's the solution?

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Local models

$$\min_{\mathbf{u}_1,\ldots,\mathbf{u}_T} \sum_{t=1}^{T} c(\mathbf{x}_t, \mathbf{u}_t) \text{ s.t. } \mathbf{x}_t = f(\mathbf{x}_{t-1}, \mathbf{u}_{t-1})$$

$$\min_{\mathbf{u}_1,\ldots,\mathbf{u}_T} c(\mathbf{x}_1, \mathbf{u}_1) + c(f(\mathbf{x}_1, \mathbf{u}_1), \mathbf{u}_2) + \cdots + c(f(f(\ldots)\ldots), \mathbf{u}_T)$$

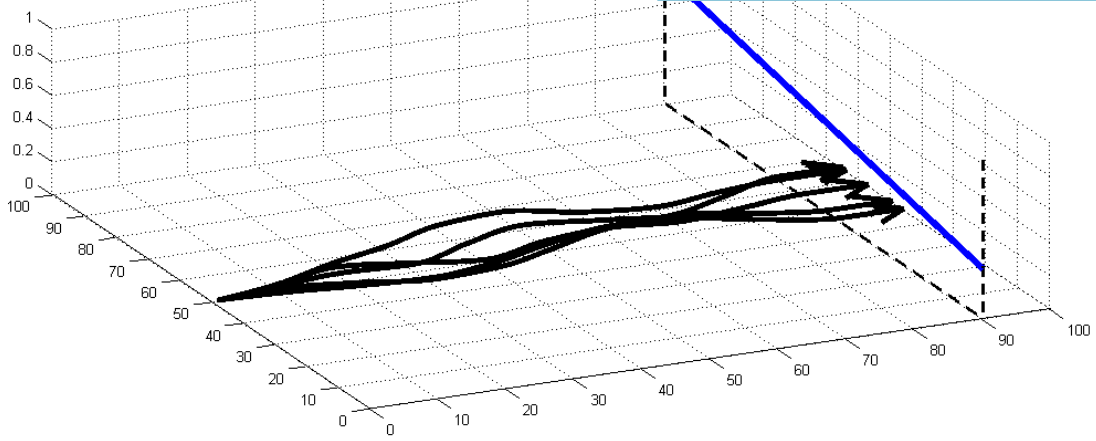
usual story: differentiate via backpropagation and optimize!

need $\frac{df}{d\mathbf{x}_t}, \frac{df}{d\mathbf{u}_t}, \frac{dc}{d\mathbf{x}_t}, \frac{dc}{d\mathbf{u}_t}$

Local models

need $\frac{df}{d\mathbf{x}_t}, \frac{df}{d\mathbf{u}_t}, \frac{dc}{d\mathbf{x}_t}, \frac{dc}{d\mathbf{u}_t}$

idea: just fit $\frac{df}{d\mathbf{x}_t}, \frac{df}{d\mathbf{u}_t}$ around current trajectory or policy!



LQR gives us a linear feedback controller

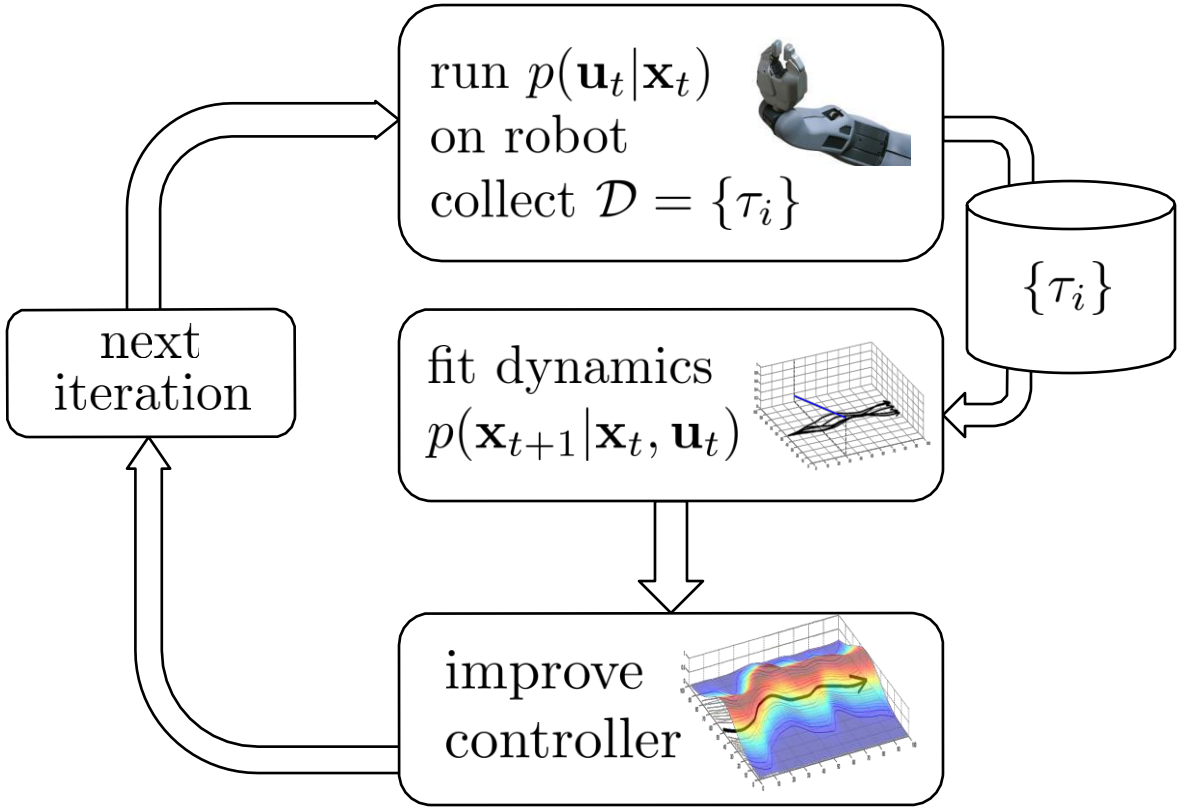
can **execute** in the real world!

Local models

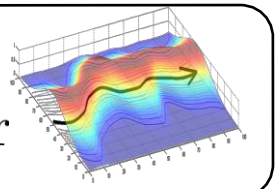
$$p(\mathbf{x}_{t+1}|\mathbf{x}_t, \mathbf{u}_t) = \mathcal{N}(f(\mathbf{x}_t, \mathbf{u}_t), \Sigma)$$

$$f(\mathbf{x}_t, \mathbf{u}_t) \approx \mathbf{A}_t \mathbf{x}_t + \mathbf{B}_t \mathbf{u}_t$$

$$\mathbf{A}_t = \frac{df}{d\mathbf{x}_t} \qquad \mathbf{B}_t = \frac{df}{d\mathbf{u}_t}$$

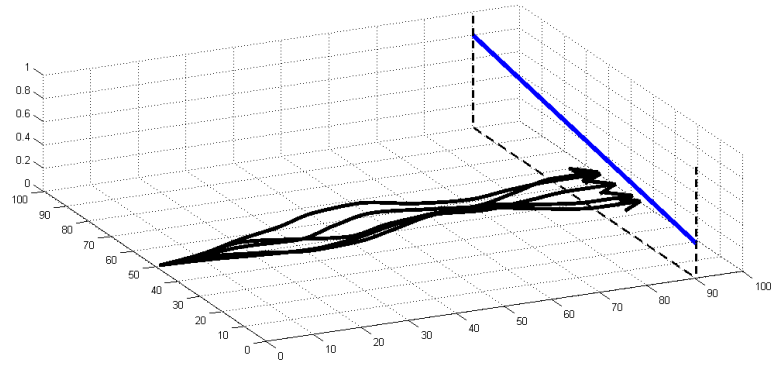


What controller to execute?

improve controller 

iLQR produces: $\hat{\mathbf{x}}_t$, $\hat{\mathbf{u}}_t$, $\mathbf{K}_t$, $\mathbf{k}_t$

$$\mathbf{u}_t = \mathbf{K}_t(\mathbf{x}_t - \hat{\mathbf{x}}_t) + \mathbf{k}_t + \hat{\mathbf{u}}_t$$



Version 0.5: $p(\mathbf{u}_t|\mathbf{x}_t) = \delta(\mathbf{u}_t = \hat{\mathbf{u}}_t)$

Doesn't correct deviations or drift

Version 1.0: $p(\mathbf{u}_t|\mathbf{x}_t) = \delta(\mathbf{u}_t = \mathbf{K}_t(\mathbf{x}_t - \hat{\mathbf{x}}_t) + \mathbf{k}_t + \hat{\mathbf{u}}_t)$

Better, but maybe a little too good?

Version 2.0: $p(\mathbf{u}_t|\mathbf{x}_t) = \mathcal{N}(\mathbf{K}_t(\mathbf{x}_t - \hat{\mathbf{x}}_t) + \mathbf{k}_t + \hat{\mathbf{u}}_t, \Sigma_t)$

Add noise so that all samples don't look the same!

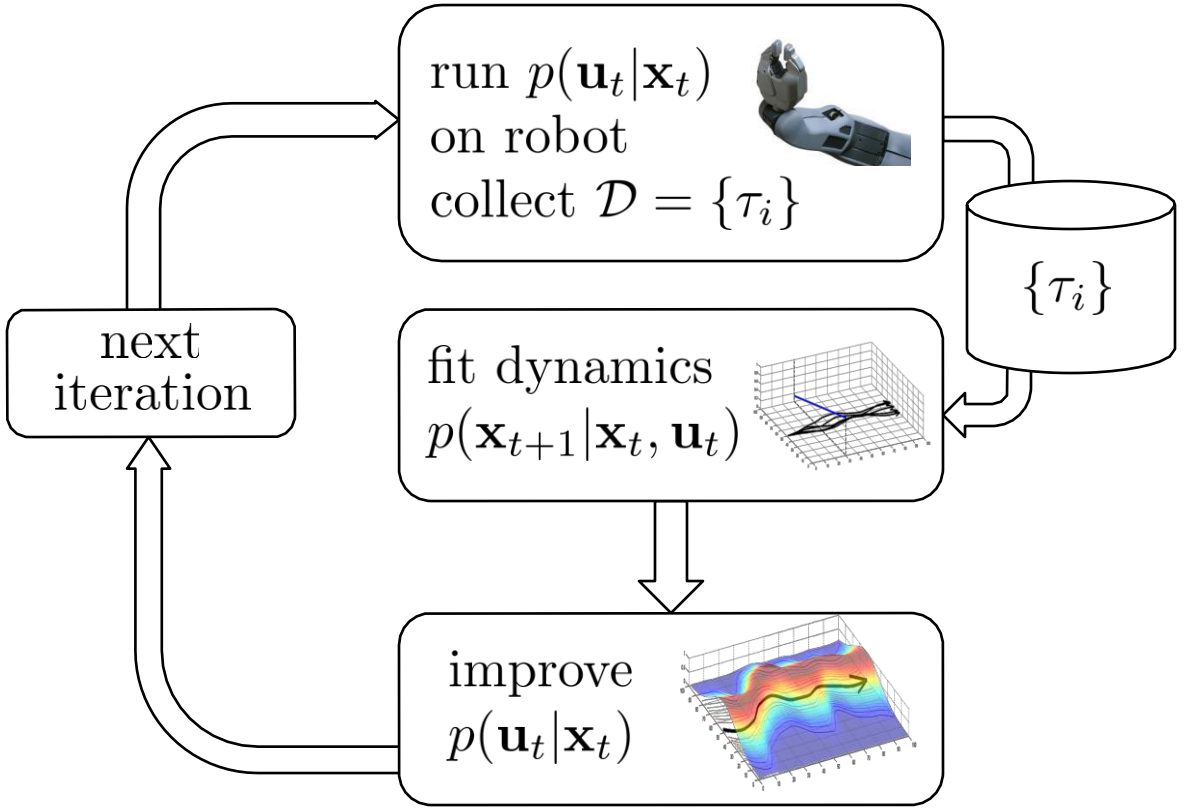
Set $\Sigma_t = \mathbf{Q}^{-1}_{\mathbf{u}_t,\mathbf{u}_t}$

Local models

$$p(\mathbf{x}_{t+1}|\mathbf{x}_t, \mathbf{u}_t) = \mathcal{N}(f(\mathbf{x}_t, \mathbf{u}_t), \Sigma)$$

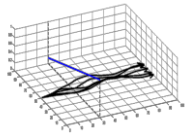
$$f(\mathbf{x}_t, \mathbf{u}_t) \approx \mathbf{A}_t \mathbf{x}_t + \mathbf{B}_t \mathbf{u}_t$$

$$\mathbf{A}_t = \frac{df}{d\mathbf{x}_t} \qquad \mathbf{B}_t = \frac{df}{d\mathbf{u}_t}$$



How to fit the dynamics?

fit dynamics
$p(\mathbf{x}_{t+1}|\mathbf{x}_t, \mathbf{u}_t)$

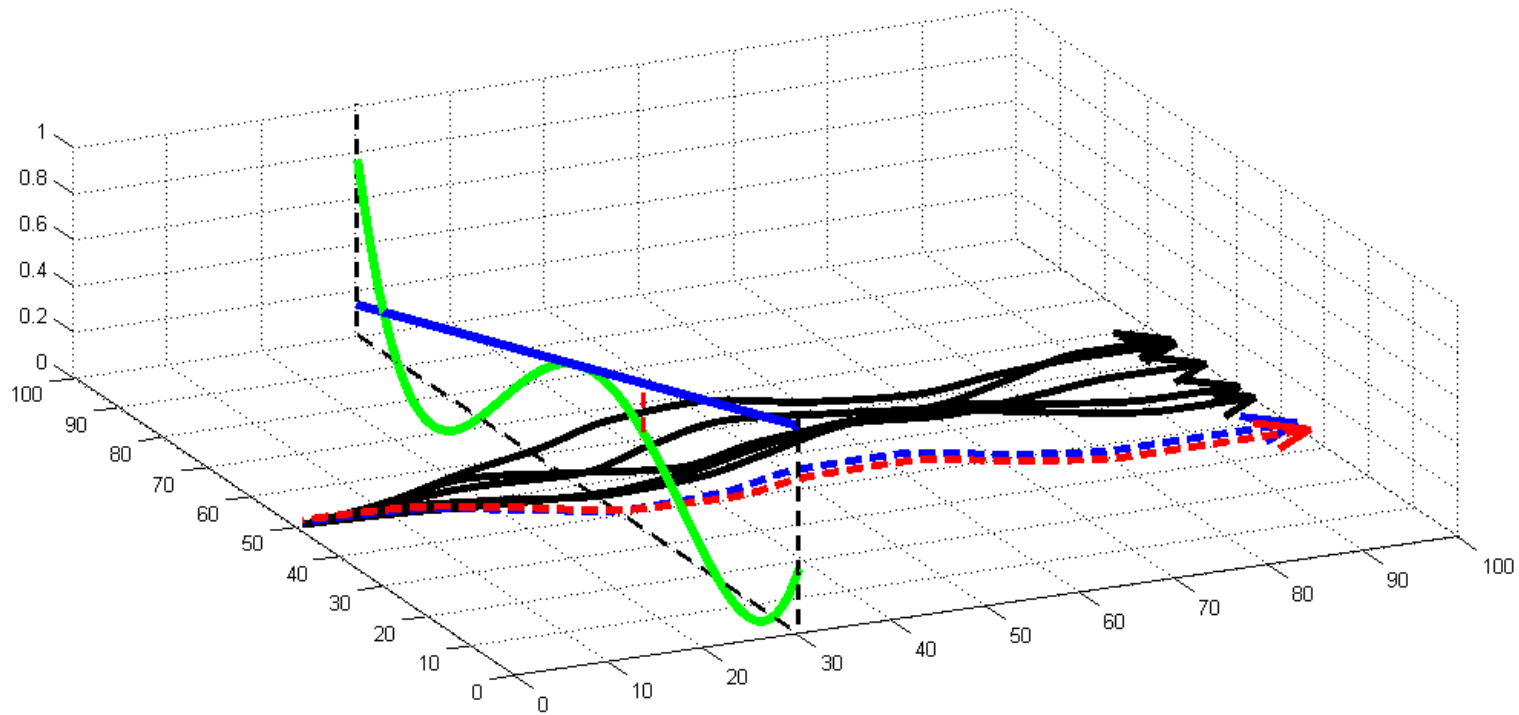


$\{(\mathbf{x}_t, \mathbf{u}_t, \mathbf{x}_{t+1})_i\}$

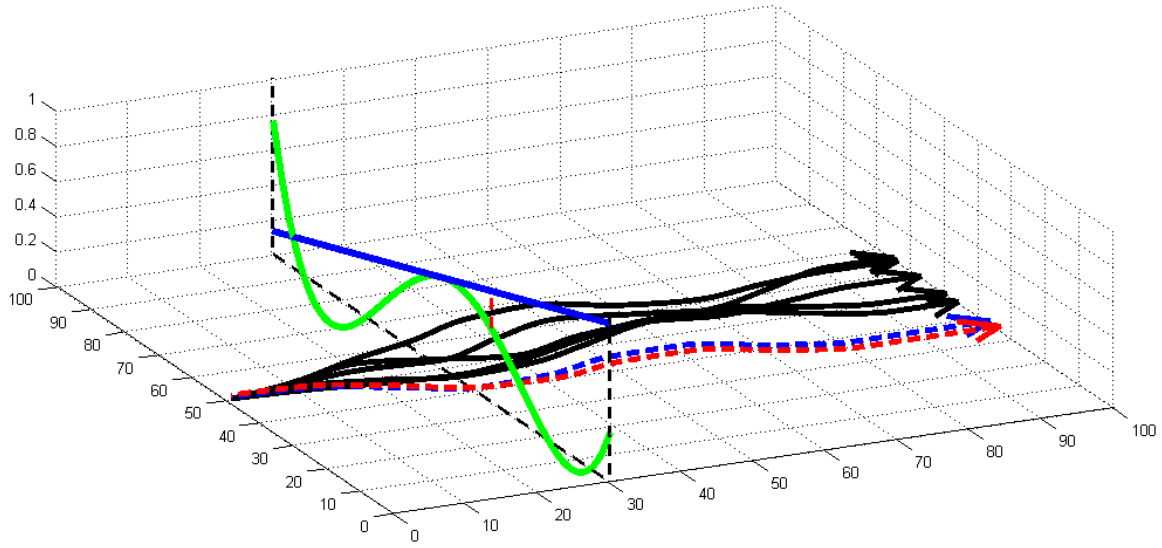
fit $p(\mathbf{x}_{t+1}|\mathbf{x}_t, \mathbf{u}_t)$ at each time step using linear regression

$$p(\mathbf{x}_{t+1}|\mathbf{x}_t, \mathbf{u}_t) = \mathcal{N}(\mathbf{A}_t\mathbf{x}_t + \mathbf{B}_t\mathbf{u}_t + \mathbf{c}, \mathbf{N}_t) \qquad \mathbf{A}_t \approx \frac{df}{d\mathbf{x}_t} \qquad \mathbf{B}_t \approx \frac{df}{d\mathbf{u}_t}$$

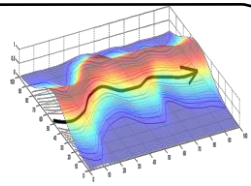
What if we go too far?



How to stay close to old controller?



improve $p(\mathbf{u}_t|\mathbf{x}_t)$



$$p(\mathbf{u}_t|\mathbf{x}_t) = \mathcal{N}(\mathbf{K}_t(\mathbf{x}_t - \hat{\mathbf{x}}_t) + \mathbf{k}_t + \hat{\mathbf{u}}_t, \Sigma_t)$$

$$p(\tau) = p(\mathbf{x}_1)\prod_{t=1}^{T} p(\mathbf{u}_t|\mathbf{x}_t)p(\mathbf{x}_{t+1}|\mathbf{x}_t, \mathbf{u}_t)$$

What if the new $p(\tau)$ is "close" to the old one $\bar{p}(\tau)$?

If trajectory distribution is close, then dynamics will be close too!

What does "close" mean? $D_{\mathrm{KL}}(p(\tau)\|\bar{p}(\tau)) \leq \epsilon$

This is easy to do if $\bar{p}(\tau)$ also came from linear controller!

For details, see: "**Learning Neural Network Policies with Guided Policy Search under Unknown Dynamics**"

Global Policies from Local Models

What's the solution?

- Use derivative-free ("model-free") RL algorithms, with the model used to generate synthetic samples
  - Seems weirdly backwards
  - Actually works very well
  - Essentially "model-based acceleration" for model-free RL
- Use simpler policies than neural nets
  - LQR with learned models (LQR-FLM – **F**itted **L**ocal **M**odels)
  - Train **local** policies to solve simple tasks
  - Combine them into **global** policies via supervised learning

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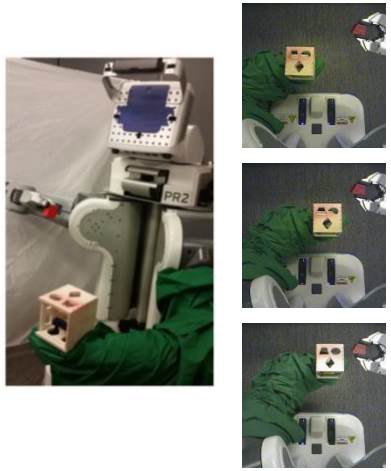
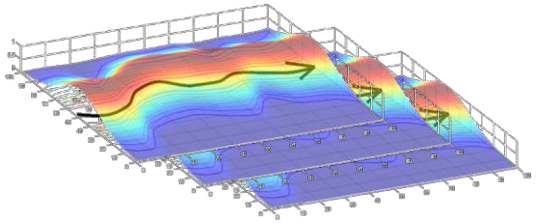
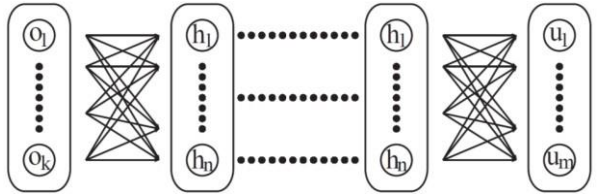
Guided policy search: high-level idea

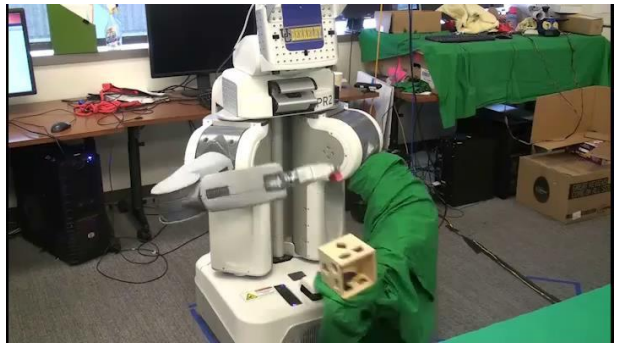


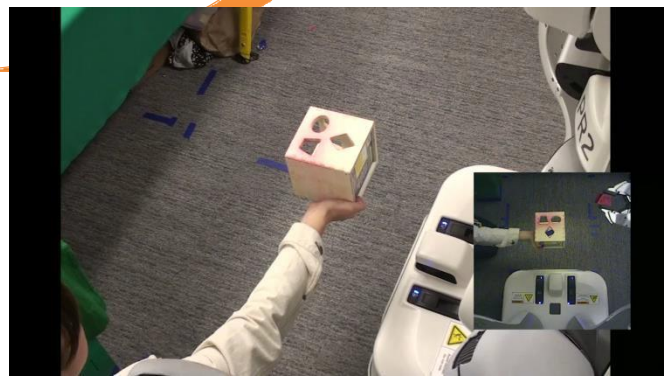


trajectory-centric RL

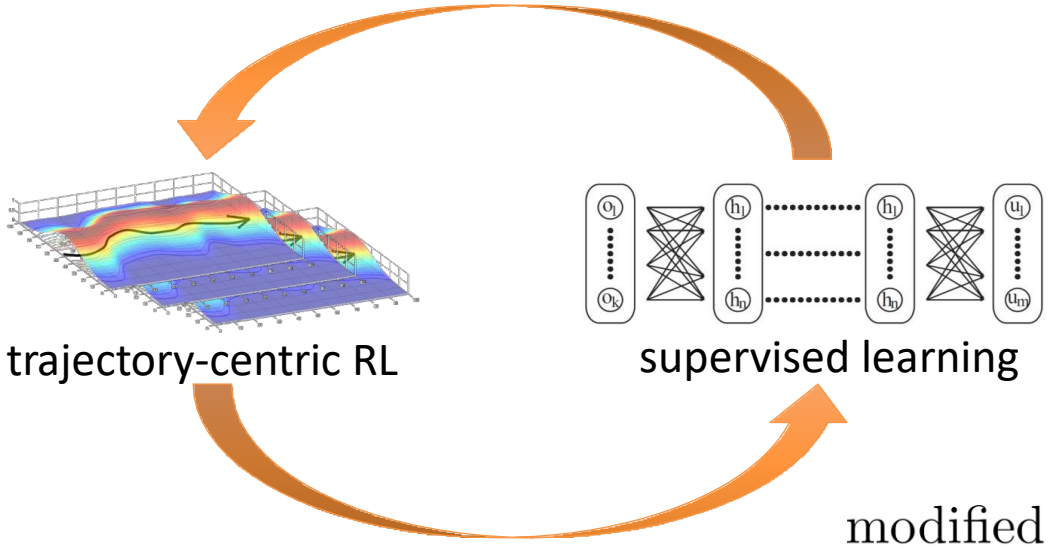


supervised learning





Guided policy search: algorithm sketch



modified cost to keep $\pi_{\mathrm{LQR},i}$ close to π_θ

1. optimize each local policy $\pi_{\mathrm{LQR},i}(\mathbf{u}_t|\mathbf{x}_t)$ on initial state $\mathbf{x}_{0,i}$ w.r.t. $\tilde{c}_{k,i}(\mathbf{x}_t, \mathbf{u}_t)$
2. use samples from step (1) to train $\pi_\theta(\mathbf{u}_t|\mathbf{x}_t)$ to mimic each $\pi_{\mathrm{LQR},i}(\mathbf{u}_t|\mathbf{x}_t)$
3. update cost function $\tilde{c}_{k+1,i}(\mathbf{x}_t, \mathbf{u}_t) = c(\mathbf{x}_t, \mathbf{u}_t) + \lambda_{k+1,i} \log \pi_\theta(\mathbf{u}_t|\mathbf{x}_t)$

Lagrange multiplier

For details, see: “End-to-End Training of Deep Visuomotor Policies”

Underlying principle: distillation

Ensemble models: single models are often not the most robust – instead train many models and average their predictions

this is how most ML competitions (e.g., Kaggle) are won

this is very expensive at test time

Can we make a single model that is as good as an ensemble?

Distillation: train on the ensemble's predictions as "soft" targets

logit

$$p_i = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$$

temperature

Intuition: more knowledge in soft targets than hard labels!

Slide adapted from G. Hinton, see also Hinton et al. "Distilling the Knowledge in a Neural Network"

Distillation for Multi-Task Transfer

$$\mathcal{L} = \sum_{\mathbf{a}} \pi_{E_i}(\mathbf{a}|\mathbf{s}) \log \pi_{AMN}(\mathbf{a}|\mathbf{s})$$

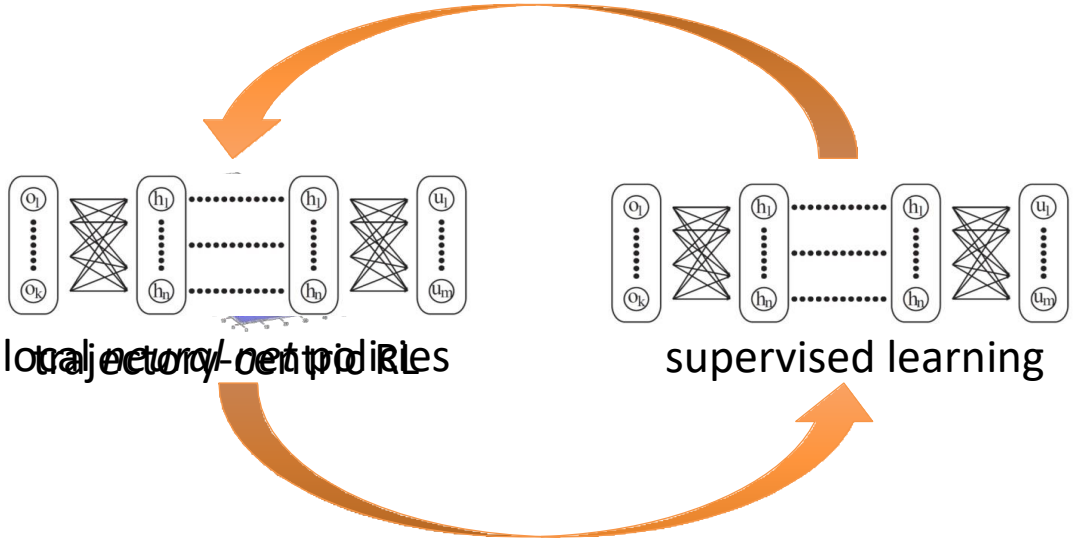
(just supervised learning/distillation)

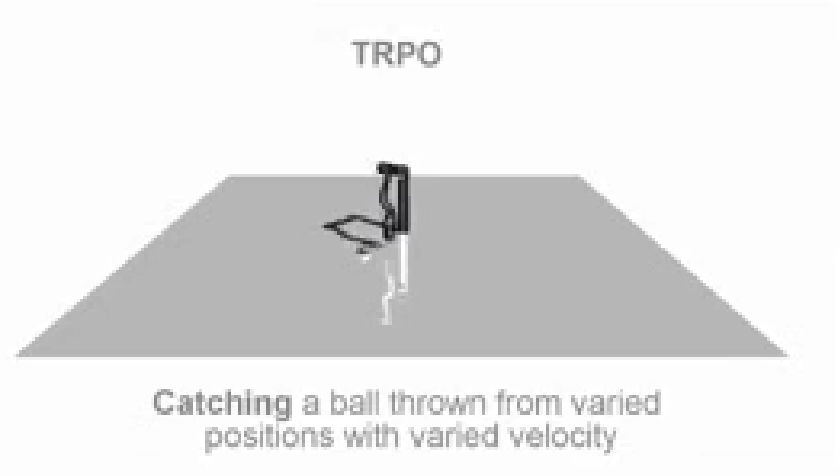
analogous to guided policy search, but for multi-task learning

some other details
(e.g., feature regression objective)
– see paper

Parisotto et al. "Actor-Mimic: Deep Multitask and Transfer Reinforcement Learning"

Combining weak policies into a strong policy





Divide and conquer reinforcement learning algorithm sketch:

1. optimize each local policy $\pi_{\theta_i}(\mathbf{a}_t|\mathbf{s}_t)$ on initial state $\mathbf{s}_{0,i}$ w.r.t. $\tilde{r}_{k,i}(\mathbf{s}_t, \mathbf{a}_t)$
2. use samples from step (1) to train $\pi_\theta(\mathbf{u}_t|\mathbf{x}_t)$ to mimic each $\pi_{\theta_i}(\mathbf{u}_t|\mathbf{x}_t)$
3. update reward function $\tilde{r}_{k+1,i}(\mathbf{x}_t, \mathbf{u}_t) = r(\mathbf{x}_t, \mathbf{u}_t) + \lambda_{k+1,i} \log \pi_\theta(\mathbf{u}_t|\mathbf{x}_t)$

For details, see: “Divide and Conquer Reinforcement Learning”

Readings: guided policy search & distillation

- L.*, Finn*, et al. End-to-End Training of Deep Visuomotor Policies. 2015.
- Rusu et al. Policy Distillation. 2015.
- Parisotto et al. Actor-Mimic: Deep Multitask and Transfer Reinforcement Learning. 2015.
- Ghosh et al. Divide-and-Conquer Reinforcement Learning. 2017.
- Teh et al. Distral: Robust Multitask Reinforcement Learning. 2017.