Lecture #8: Model-Based RL and Policy Learning

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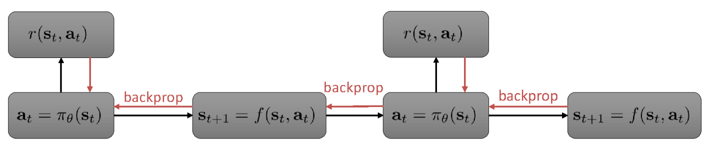
1 Introduction

Problems for backpropagating directly into policy

What's the problem?



- 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

Constraining trajectory optimization with dual gradient descent

$$\min_{\tau,\theta} c(\tau) \text{ s.t. } \mathbf{u}_t = \pi_\theta(\mathbf{x}_t)$$

$$\bar{\mathcal{L}}(\tau, \theta, \lambda) = c(\tau) + \sum_{t=1}^{T} \lambda_t(\pi_\theta(\mathbf{x}_t) - \mathbf{u}_t) + \sum_{t=1}^{T} \rho_t(\pi_\theta(\mathbf{x}_t) - \mathbf{u}_t)^2$$

1. Find $\tau \leftarrow \arg\min_\tau \bar{\mathcal{L}}(\tau, \theta, \lambda)$ (e.g. via iLQR)
2. Find $\theta \leftarrow \arg\min_\theta \bar{\mathcal{L}}(\tau, \theta, \lambda)$ (e.g. via SGD)
3. $\lambda \leftarrow \lambda + \alpha \frac{dg}{d\lambda}$

Exploration in Computer Science Research: Deep Reinforcement Learning (CS 6101, 2019), National University of Singapore.

Deterministic case

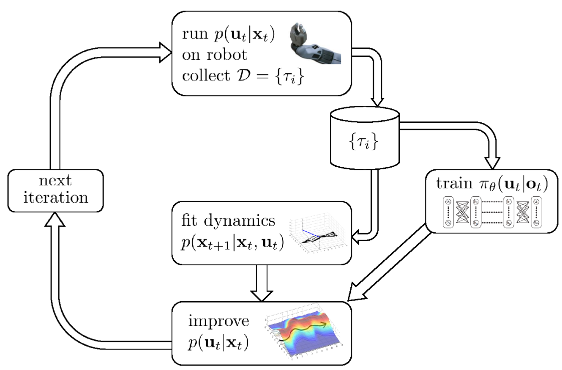
$$\min_{\tau,\theta} c(\tau) \text{ s.t. } \mathbf{u}_t = \pi_\theta(\mathbf{x}_t)$$

$$\bar{\mathcal{L}}(\tau,\theta,\lambda) = \underbrace{c(\tau) + \sum_{t=1}^{T} \lambda_t(\pi_\theta(\mathbf{x}_t) - \mathbf{u}_t) + \sum_{t=1}^{T} \rho_t(\pi_\theta(\mathbf{x}_t) - \mathbf{u}_t)^2}_{\tilde{c}(\tau)}$$

1. Optimize τ with respect to surrogate $\tilde{c}(\tau)$
2. Optimize θ with respect to supervised objective
3. Increment or modify dual variables λ

GPS

Stochastic (Gaussian) GPS with local models



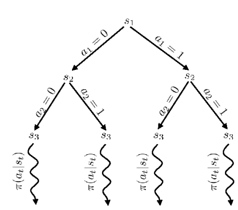
DAgger

Imitating optimal control with DAgger

Deep Learning for Real-Time Atari Game Play Using Offline Monte-Carlo Tree Search Planning

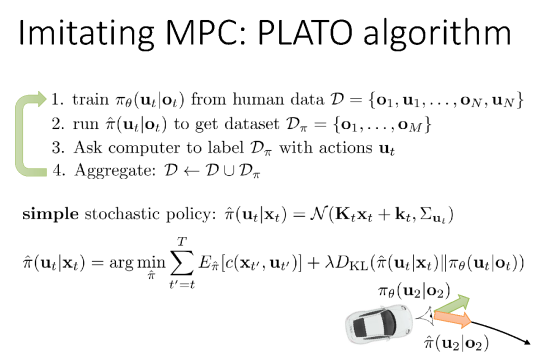
every N steps

1. from current state s_t, run MCTS to get $a_t, a_{t+1}, \ldots$
2. add (s_t, a_t) to dataset $\mathcal{D}$
3. execute action $a_t \sim \pi(a_t|s_t)$ (*not* MCTS action!)
4. update the policy by training on $\mathcal{D}$

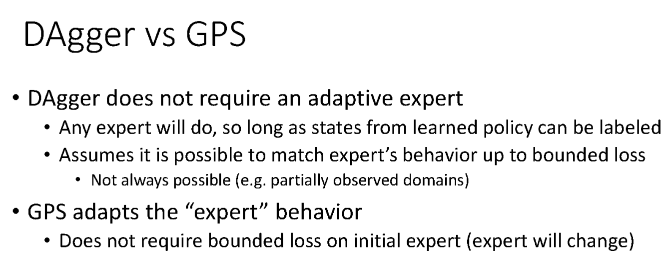


PLATO

Dagger does not care about how the actions are generated, it needs to make sure that actions are optimal with respect to the real reward function



DAgger vs GPS



Why imitate?

- It combines supervised learning and control and planning, which are stable and reliable to use
- Input is o_t instead of x_t for handling real observation
- get rid of numerical instability

Why imitate?

- Relatively stable and easy to use
  - Supervised learning works very well
  - Control/planning (usually) works very well
  - The combination of the two (usually) works very well
- Input remapping trick: can exploit availability of additional information at training time to learn policy from raw observations
- Overcomes optimization challenges of backpropagating into policy directly
- Usually sample-efficient and viable for real physical systems

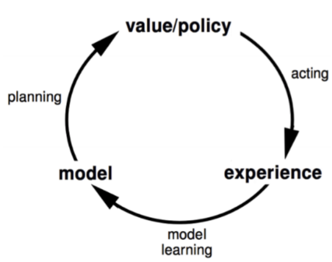
Dyna Algorithm

Dyna

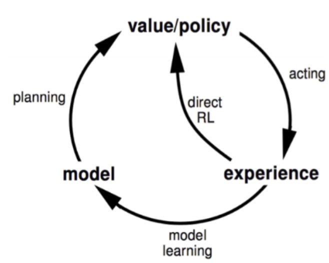
online Q-learning algorithm that performs model-free RL with a model

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: $Q(s, a) \leftarrow Q(s, a) + \alpha E_{s',r}[r + \max_{a'} Q(s', a') - Q(s, a)]$

Comparison: Model-Based RL VS Integrated Architecture (Dyna)

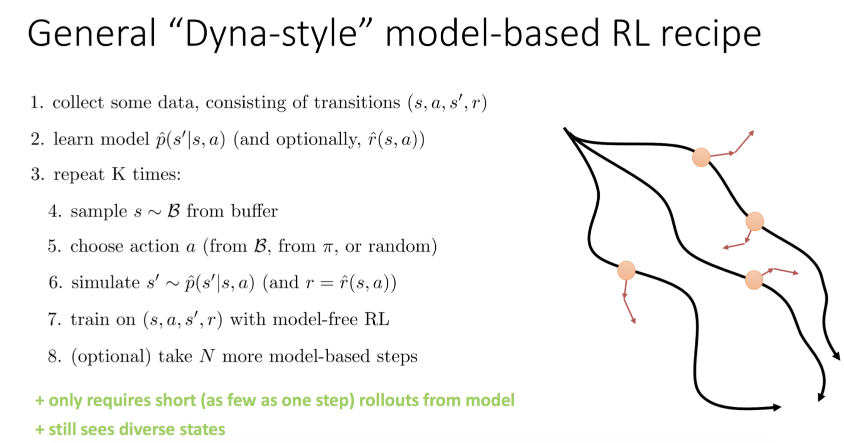


Model-based RL



Dyna

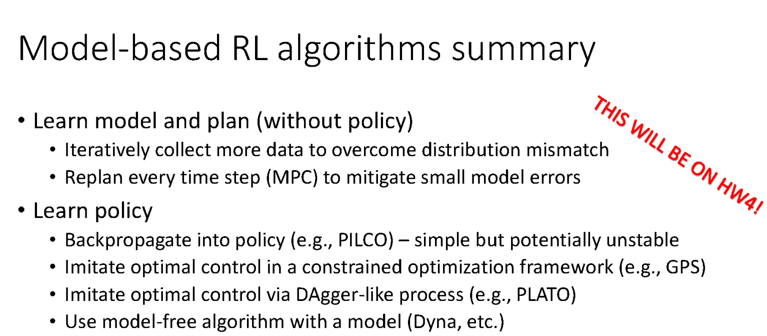
Figures are taken from Richard Sutton's book: Reinforcement Learning: An Introduction



References

- https://dl.acm.org/citation.cfm?id=122377
- https://medium.com/@ranko.mosic/online-planning-agent-dyna-q-algorithm-and-dyna-maze-example-sutton-and-barto-2016-7ad84a6dc52b
- https://www.cs.cmu.edu/afs/cs/project/jair/pub/volume4/kaelbling96a-html/node29.html

2 Summary



Limitations of model-based RL

- Need some kind of model
  - Not always available
  - Sometimes harder to learn than the policy
- Learning the model takes time & data
  - Sometimes expressive model classes (neural nets) are not fast
  - Sometimes fast model classes (linear models) are not expressive
- Some kind of additional assumptions
  - Linearizability/continuity
  - Ability to reset the system (for local linear models)
  - Smoothness (for GP-style global models)
  - Etc.

- Model-Free RL
  - No model
  - Learn value function (and/or policy) from real experience
- Model-Based RL (using Sample-Based Planning)
  - Learn a model from real experience
  - Plan value function (and/or policy) from simulated experience
- Dyna
  - Learn a model from real experience
  - Learn and plan value function (and/or policy) from real and simulated experience

3 Questions

1. Why quadratic loss in the second term

Deterministic case

$$\min_{\tau,\theta} c(\tau) \text{ s.t. } \mathbf{u}_t = \pi_\theta(\mathbf{x}_t)$$

$$\bar{\mathcal{L}}(\tau,\theta,\lambda) = \underbrace{c(\tau) + \sum_{t=1}^{T} \lambda_t(\pi_\theta(\mathbf{x}_t) - \mathbf{u}_t) + \sum_{t=1}^{T} \rho_t(\pi_\theta(\mathbf{x}_t) - \mathbf{u}_t)^2}_{\tilde{c}(\tau)}$$

2. Is iLQR a shooting method or a collocation method

https://people.eecs.berkeley.edu/ pabbeel/cs287-fa11/slides/NonlinearOptimizationForOptimalControl-part2.pdf