Meta Reinforcement Learning

Learning to Explore

CS 330

Reminders

Homework 3, due **tonight.**

Project milestone due **Monday 11/2.**

Logistics

Optional Homework 4, out **tonight.**

Based on your feedback: Homework 4 will be in PyTorch

PyTorch tutorial session on Tuesday 6 pm PT.

Plan for Today

Recap: Meta-RL Basics

Learning to Explore

End-to-End Optimization of Exploration Strategies

Alternative Exploration Strategies

Decoupled Exploration & Exploitation <- focus of HW4

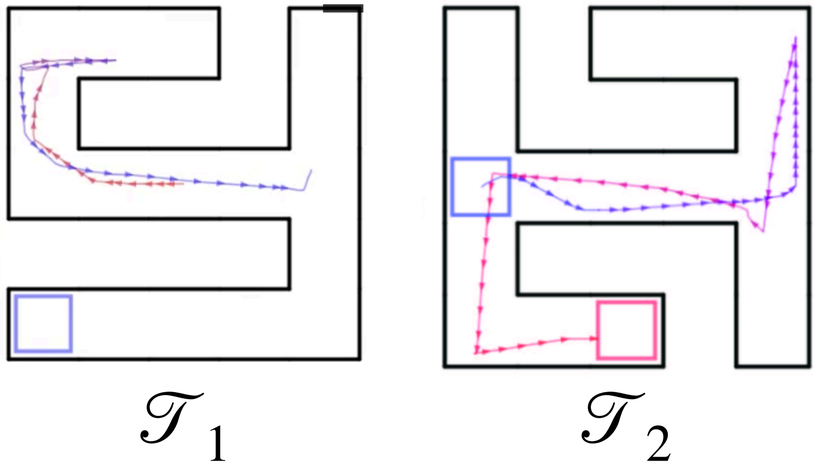
Lecture goals:

- Understand the challenge of end-to-end optimization of exploration
- Understand the basics of using alternative exploration strategies in meta-RL
- Understand & be able to implement decoupled exploration & exploitation

Recall: Meta-RL Maze Navigation Example

[meta] train time

By learning how to learn many other tasks:



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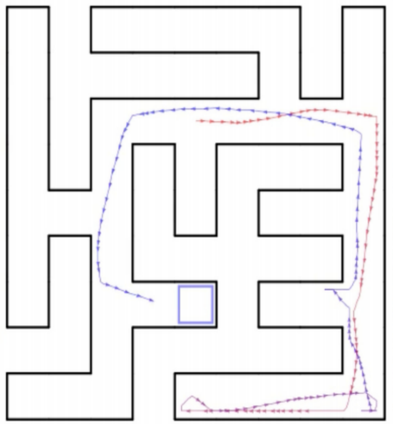
meta-training tasks

[meta] test time

Given a small amount of experience



Learn to solve the task

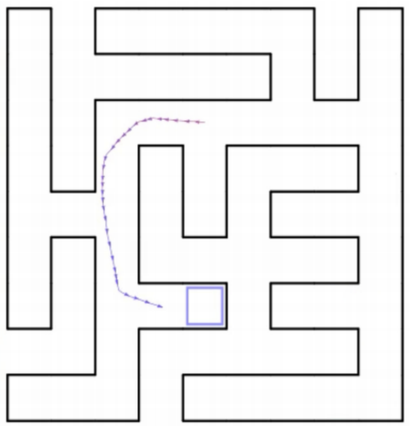


diagram adapted from Duan et al. '17

Recall: The Meta Reinforcement Learning Problem

Meta Reinforcement Learning:

Inputs: $\mathcal{D}_{\text{train}}$ $\mathbf{s}_t$

k rollouts from π

Outputs: $\mathbf{a}_t$

$$\mathbf{a}_t = f(\mathcal{D}_{\text{train}}, \mathbf{s}_t; \theta)$$

Data: $\{\mathcal{D}_i\}$

dataset of datasets
collected for each task

Design & optimization of *f* ***and*** **collecting appropriate data**
(learning to explore)

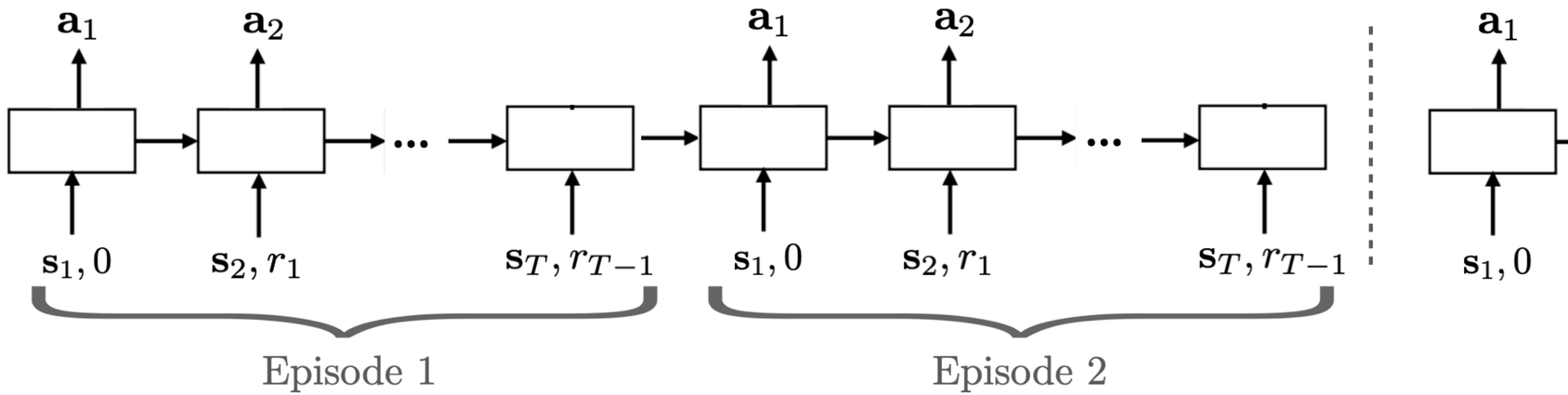
This lecture: How to learn to collect $\mathcal{D}_{\text{train}}$

Finn. *Learning to Learn with Gradients*. PhD Thesis 2018

Recall: Black-Box Meta-RL

Black-box network
(LSTM, NTM, Conv, …)

$$\mathbf{a}_t = f(\mathcal{D}_{\text{train}}, \mathbf{s}_t; \theta)$$



\+ general & expressive

\+ a variety of design choices in architecture

\-- hard to optimize

~ inherits sample efficiency from outer RL optimizer

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Decoupled Exploration & Exploitation <- focus of HW4

Taking a step back…

Should we be using the same exploration algorithm for:

- Learning to navigate an environment
- Learning to make recommendations to users
- Learning a policy for computer system caching
- Learning to physically operate a new tool or machine

This is how we currently approach exploration.

Can we *learn exploration strategies* based on experience from other tasks in that domain?

How Do We Learn to Explore?

Solution #1: Optimize for Exploration & Exploitation *End-to-End* w.r.t. Task Reward

(Duan et al., 2016, Wang et al., 2016, Mishra et al., 2017, Stadie et al., 2018, Zintgraf et al., 2019, Kamienny et al., 2020)

\+ simple

\+ leads to optimal strategy in principle

\-- challenging optimization when exploration is hard

Example of a Hard Exploration Meta-RL Problem

Learned cooking tasks in previous kitchens

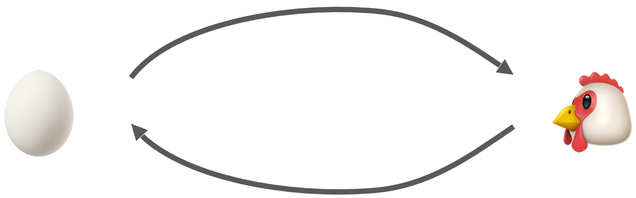
meta-training

Goal: Quickly learn tasks in a new kitchen.

meta-testing

Why is End-to-End Training Hard?

End-to-end approach: optimize exploration and execution episode behaviors end-to-end to maximize reward of execution



Learning to cook (execution)

Learning to find ingredients (exploration)

Ingredient not found (bad exploration) → Cannot learn to cook (bad execution)

Cannot cook (bad execution) → Low reward for **any** exploration

Coupling problem: learning exploration and execution depend on each other

—> can lead to poor local optima, poor sample efficiency

Liu, Raghunathan, Liang, Finn. ***Explore then Execute: Adapting without Rewards via Factorized Meta-RL***. 2020

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Solution #2: Leverage Alternative Exploration Strategies

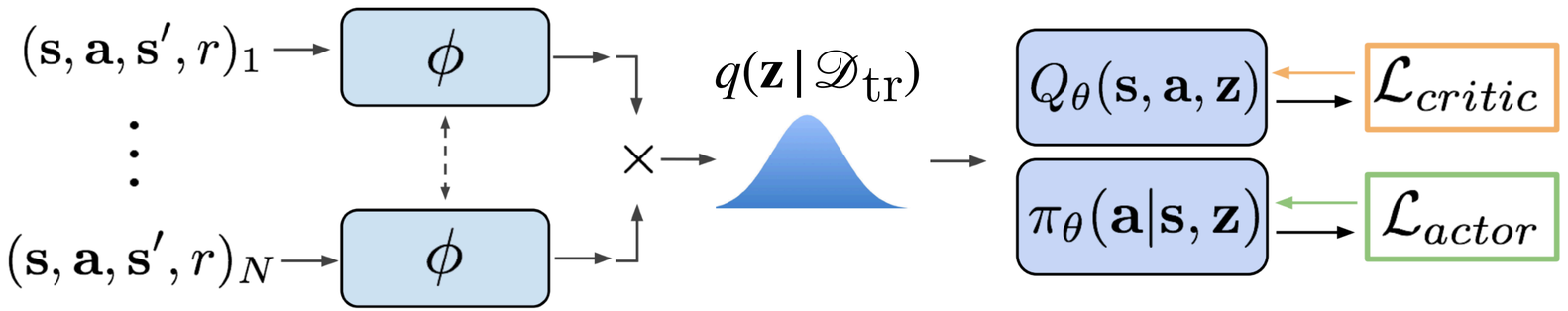
2a. Use posterior sampling
(also called Thompson sampling)

PEARL (Rakelly, Zhou, Quillen, Finn, Levine. ICML '19)

i. Learn distribution over latent task variable $\mathbf{z}$ and task-conditioned policy $\pi(\mathbf{a} \mid \mathbf{s}, \mathbf{z})$

Prior $p(\mathbf{z})$ - latent representation of the task distribution

Posterior $q(\mathbf{z} \mid \mathcal{D}_{\text{tr}})$ - updated belief about the task based on experience so far.



Rakelly, Zhou, Quillen, Finn, Levine. ***Efficient Off-Policy Meta-Reinforcement Learning via Probabilistic Context Variables***. ICML 2019.

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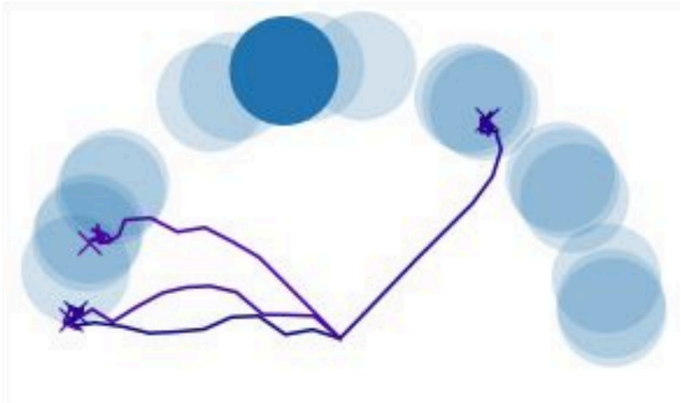
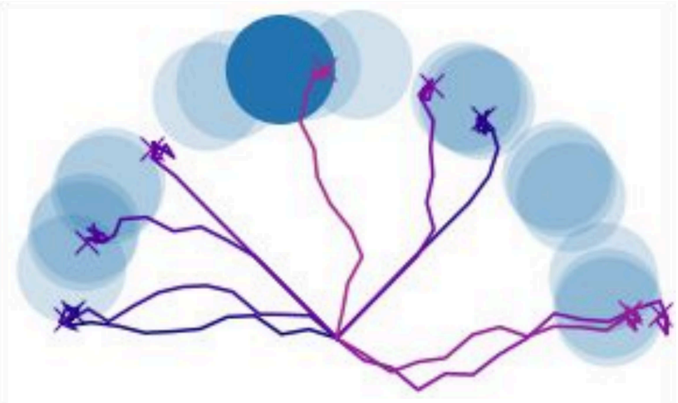
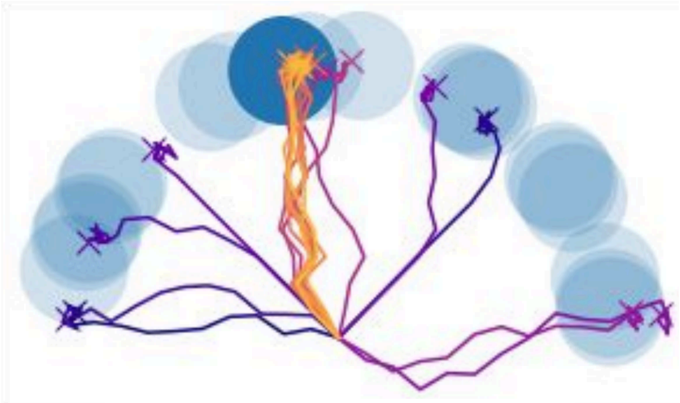
ii. Sample $\mathbf{z}$ from current *posterior* $q(\mathbf{z}|\mathcal{D}_{\text{tr}})$, sample from policy $\pi(\mathbf{a}|\mathbf{s},\mathbf{z})$, add experience to $\mathcal{D}_{\text{tr}}$



$\mathbf{z} \sim p(\mathbf{z})$



$\mathbf{z} \sim q_\phi(\mathbf{z}|c_{1:10})$



$\mathbf{z} \sim q_\phi(\mathbf{z}|c_{1:30})$

Question: In what situations might posterior sampling be bad?

eg. Goals far away & sign on wall that tells you the correct goal.

Solution #2: Leverage Alternative Exploration Strategies

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ii. Sample $\mathbf{z}$ from current *posterior* $q(\mathbf{z}\,|\,\mathcal{D}_{\text{tr}})$, sample from policy $\pi(\mathbf{a}\,|\,\mathbf{s}, \mathbf{z})$, add experience to $\mathcal{D}_{\text{tr}}$

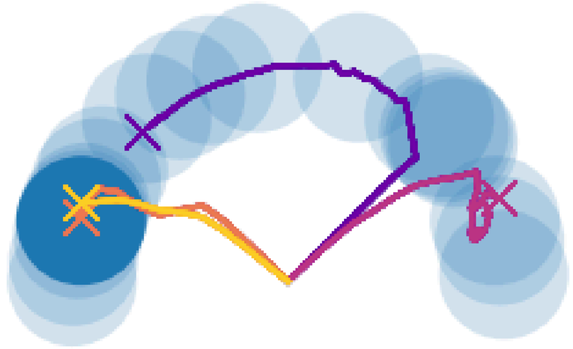
2b. Task dynamics & reward prediction

MetaCURE (Zhang, Wang, Hu, Chen, Fan, Zhang. '20)

Key idea: Train model $f(\mathbf{s}', r\,|\,\mathbf{s}, \mathbf{a}, \mathcal{D}_{\text{tr}})$ & collect $\mathcal{D}_{\text{tr}}$ so that model is accurate.

Iteratively, for each task:

1. Collect data $\mathcal{D}_{\text{tr}}$ with exploration policy π_{exp}
2. Collect data $\mathcal{D}_{\text{ts}}$ with policy $\pi_{\text{exe}}(\mathbf{a}\,|\,\mathbf{s}, \mathcal{D}_{\text{tr}})$
3. Train policy π_{exp} w.r.t. reward of $r_{\text{exp}} = -\|(\hat{\mathbf{s}}', \hat{r}) - (\mathbf{s}', r)\|^2$
   where $\hat{\mathbf{s}}', \hat{r} \sim f(\,\cdot\,, \cdot\,|\,\mathbf{s}, \mathbf{a}, \mathcal{D}_{\text{tr}})$
4. Update policy π_{exe} w.r.t. task reward



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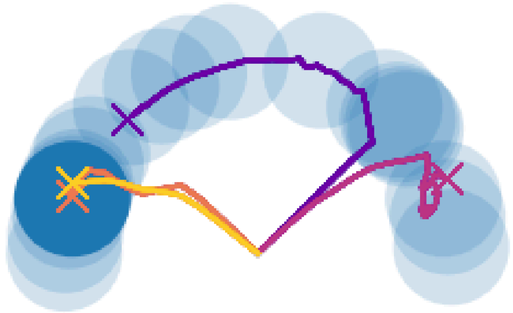

Question: In what situations might this be bad?

Lots of task-irrelevant distractors,
or complex, high-dim state dynamics

Solution #2: Leverage Alternative Exploration Strategies

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MetaCURE (Zhang, Wang, Hu, Chen, Fan, Zhang. '20)

Key idea: Train model $f(\mathbf{s}', r \mid \mathbf{s}, \mathbf{a}, \mathscr{D}_{\text{tr}})$ & collect $\mathscr{D}_{\text{tr}}$ so that model is accurate.

Overall

\+ **easy** to optimize

\+ many based on **principled** strategies

\-- **suboptimal** by arbitrarily large amount in some environments.

Can we avoid the chicken-and-egg problem without sacrificing optimality?

Plan for Today

Recap: Meta-RL Basics

Learning to Explore

End-to-End Optimization of Exploration Strategies

Alternative Exploration Strategies

Decoupled Exploration & Exploitation <- focus of HW4

Solution #3

Idea from solution #2b: Train model $f(\mathbf{s}', r \,|\, \mathbf{s}, \mathbf{a}, \mathscr{D}_{\text{tr}})$ & collect $\mathscr{D}_{\text{tr}}$ so that model is accurate.

How might we explore **only** information **relevant for solving the task**?

Idea 3.0: Label each task/MDP with a unique ID μ

Train model $f(\mu \,|\, \mathbf{s}, \mathbf{a}, \mathscr{D}_{\text{tr}})$ & collect $\mathscr{D}_{\text{tr}}$ so that model is accurate.

Question: What if two tasks are functionally identical but differ in task-irrelevant ways?

(e.g. identical kitchen layouts,
but different brand of garbage bags)

+ no longer need to model dynamics, rewards

— may still capture task-irrelevant details

—> Need a task representation that only distinguishes features needed for solving each task.

Solution #3: Decouple by acquiring representation of task relevant information

Meta-training

1) Learn execution & identify key information

MDP identifier μ

wall color 2

ingredients 0

decorations 1

Bottlenecked representation

$[0]$

z

Execution policy

π^{exec}

2) Learn to explore by recovering that information

Exploration policy

π^{exp}

Exploration episode τ

z

Information recovery reward

$\text{MI}(z; \tau)$

Meta-testing

π^{exp} —— Exploration episode τ ——▶ π^{exec}

Decoupled **R**eward-free **E**xplor**A**tion and Execution in **M**eta-Reinforcement Learning (DREAM)

Liu, Raghunathan, Liang, Finn. *Explore then Execute: Adapting without Rewards via Factorized Meta-RL*. 2020

Solution #3: Decouple by acquiring representation of task relevant information

Meta-training

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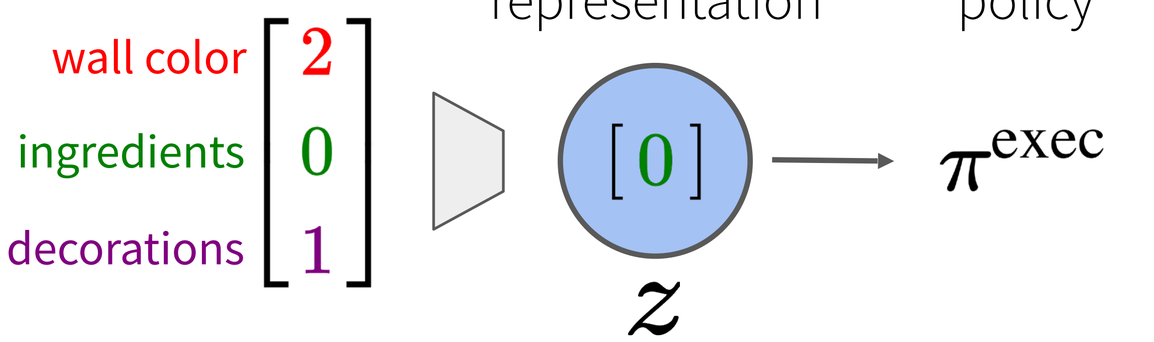
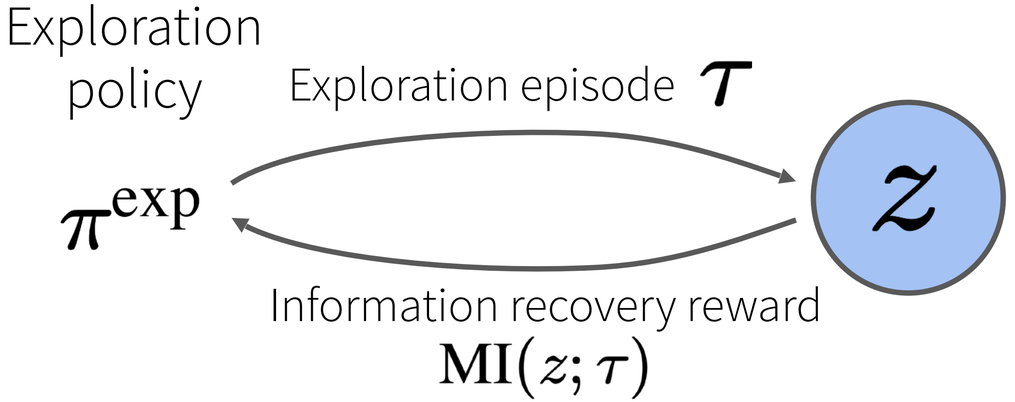


2) Learn to explore by recovering that information



Train $\pi^{\text{exec}}(\mathbf{a} \mid \mathbf{s}, z_i)$ and encoder $F(z_i \mid \mu_i)$ to:

$$\max \sum_i \mathbb{E}_{\pi^{\text{exec}}}[r_i] - D_{\text{KL}}\left(F(z_i|\mu_i) \| \mathcal{N}(0,1)\right)$$

Train π^{exp} such that collected $\mathcal{D}_{\text{tr}}$ is predictive of z_i.

In practice: (1) and (2) can be trained simultaneously.

Liu, Raghunathan, Liang, Finn. *Explore then Execute: Adapting without Rewards via Factorized Meta-RL*. 2020

Solution #3: Decouple by acquiring representation of task relevant information

Meta-training

1) Learn execution & identify key information 

2) Learn to explore by recovering that information 

Train $\pi^{\text{exec}}(\mathbf{a} \mid \mathbf{s}, z_i)$ and encoder $F(z_i \mid \mu_i)$ to:

$$\max \sum_i \mathbb{E}_{\pi^{\text{exec}}}[r_i] - D_{\text{KL}}\left(F(z_i|\mu_i) \| \mathcal{N}(0,1)\right)$$

Train π^{exp} such that collected $\mathscr{D}_{\text{tr}}$ is predictive of z_i.

How to formulate the ***reward function*** for π^{exp}?

(a) Train model $q(z_i \mid \mathscr{D}_{\text{tr}})$

Prediction error at end of exploration episode?

--> too sparse 😞

Prediction error so far?

--> double counting 😞

(b) r_t = per-step information gain

Prediction error from $\tau_{1:t-1}$ — prediction error at $\tau_{1:t}$

Liu, Raghunathan, Liang, Finn. ***Explore then Execute: Adapting without Rewards via Factorized Meta-RL***. 2020

Solution #3: Decouple by acquiring representation of task relevant information

(Informal) Theoretical Analysis

(1) DREAM objective is ***consistent*** with end-to-end optimization. [under mild assumptions]

-> can in principle recover the optimal exploration strategy

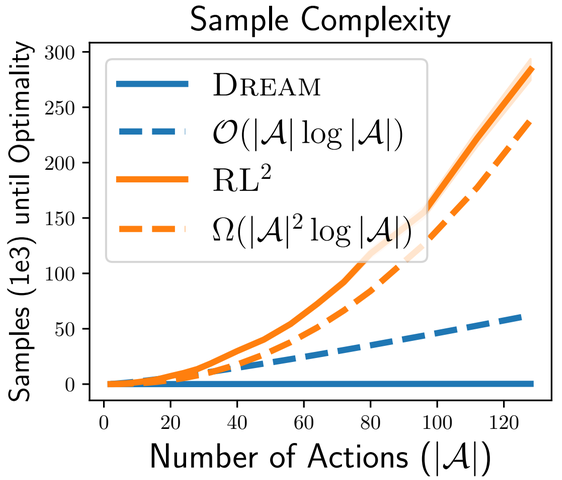
(2) Consider a bandit-like setting with $|\mathcal{A}|$ arms.

In MDP i, arm i yields reward. In all MDPs, arm 0 reveals the rewarding arm.

RL^2 requires $\Omega(|\mathcal{A}|^2 \log |\mathcal{A}|)$ samples for meta-optimization.

DREAM requires $\mathcal{O}(|\mathcal{A}| \log |\mathcal{A}|)$ samples for meta-optimization.

[assuming Q-learning with uniform outer-loop exploration]



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How Do We Learn to Explore?

End-to-End

+ leads to optimal strategy in principle

-- challenging optimization when exploration is hard

Alternative Strategies

+ easy to optimize
+ many based on principled strategies

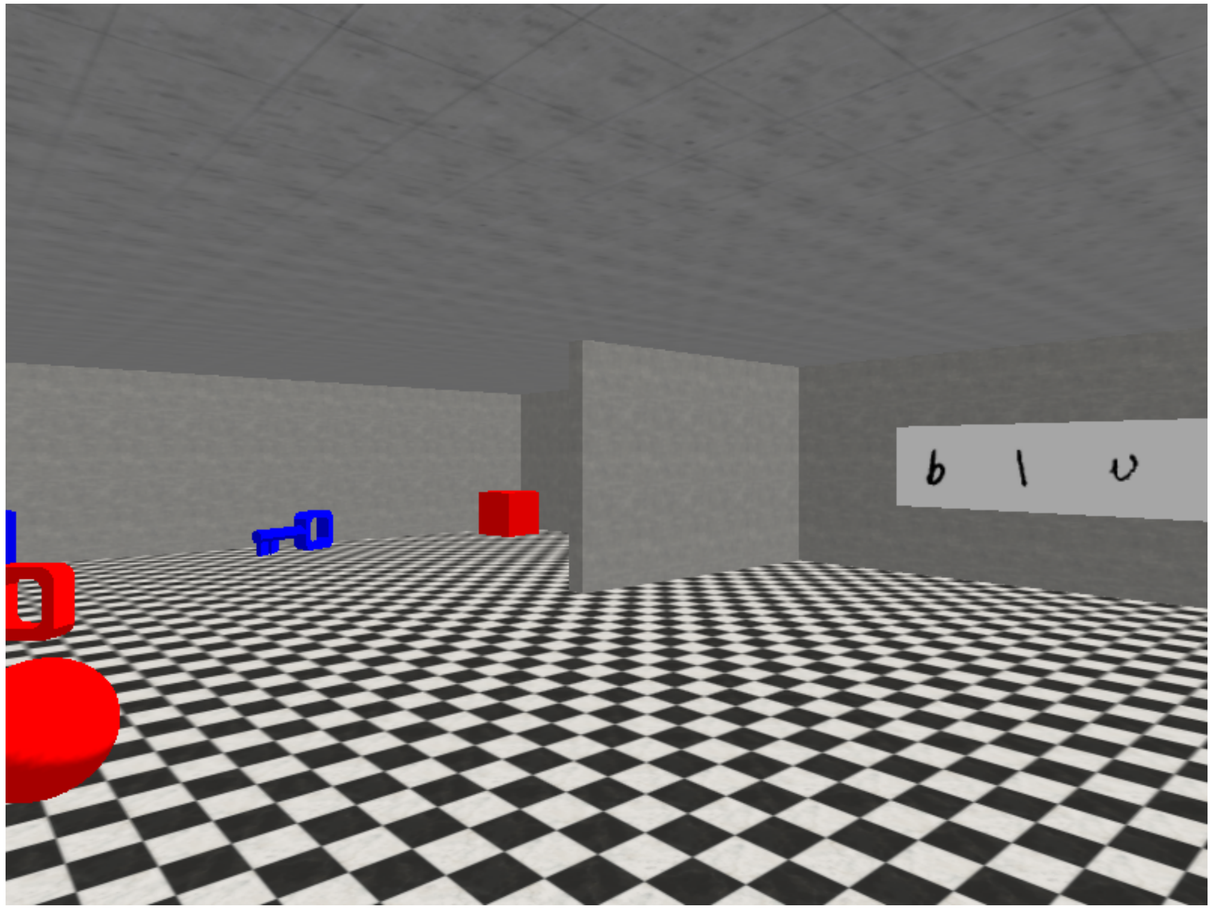
-- suboptimal by arbitrarily large amount in some environments.

Decoupled Exploration & Execution

+ leads to optimal strategy in principle
+ easy to optimize in practice

-- requires task identifier

Empirical Comparison: Sparse Reward 3D Visual Navigation Problem

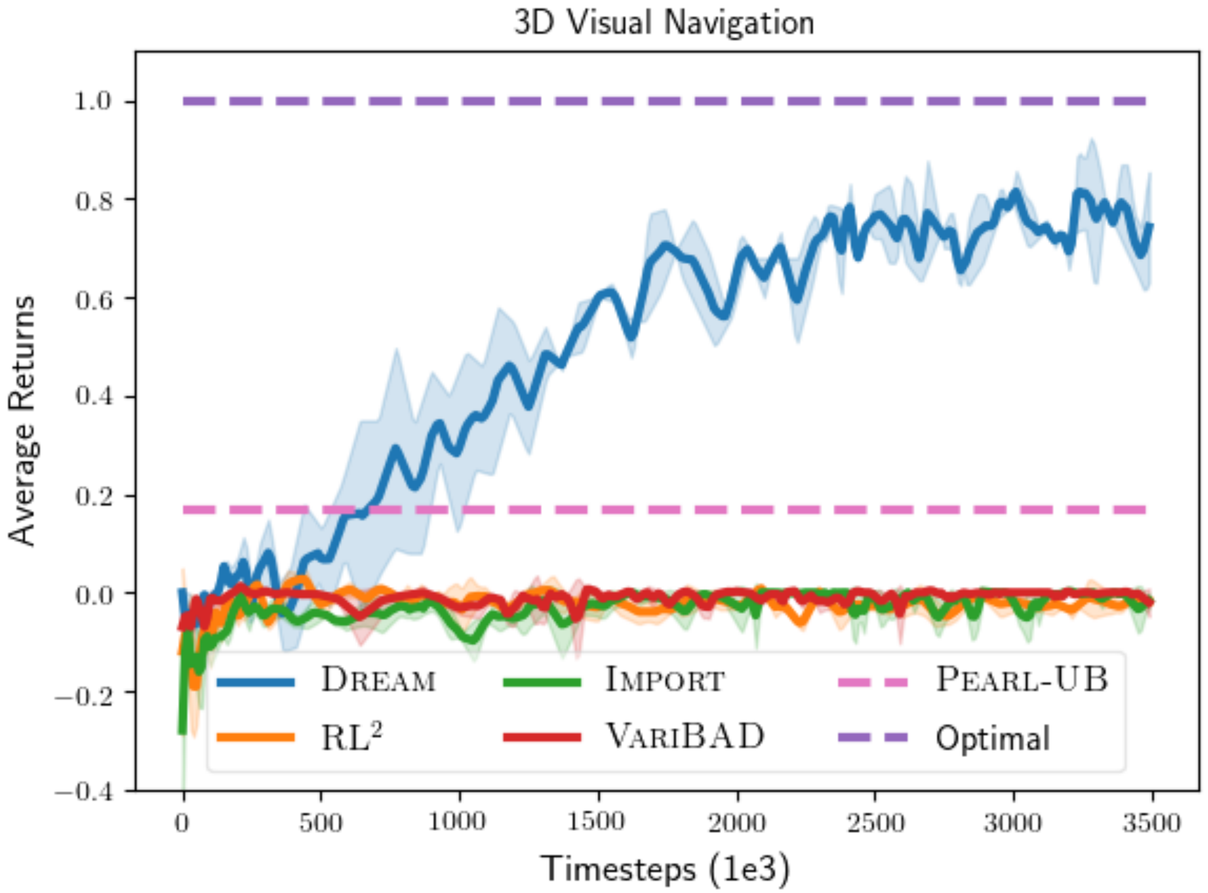


More challenging variant of task from Kamienny et al., 2020

- Task: go to the (key / block / ball), color specified by the sign
- Agent starts on other side of barrier, must walk around to read the sign
- Pixels observations (80 x 60 RGB)
- Sparse binary reward

Liu, Raghunathan, Liang, Finn. ***Explore then Execute: Adapting without Rewards via Factorized Meta-RL***. 2020

Quantitative Comparison



- End-to-end algorithms (RL², IMPORT, VARIBAD) perform poorly due to **coupling**
- Alternate exploration strategies, e.g., posterior/ Thompson sampling do not learn the optimal exploration strategy
- PEARL-UB: Upper-bound on PEARL, reward achieved with optimal policy and Thompson-Sampling exploration
- DREAM achieves near-optimal reward

RL² (Duan et al., 2016), IMPORT (Kamienny et al., 2020), VARIBAD (Zintgraf et al., 2019), PEARL (Rakelly, et. al., 2019), Thompson, 1933

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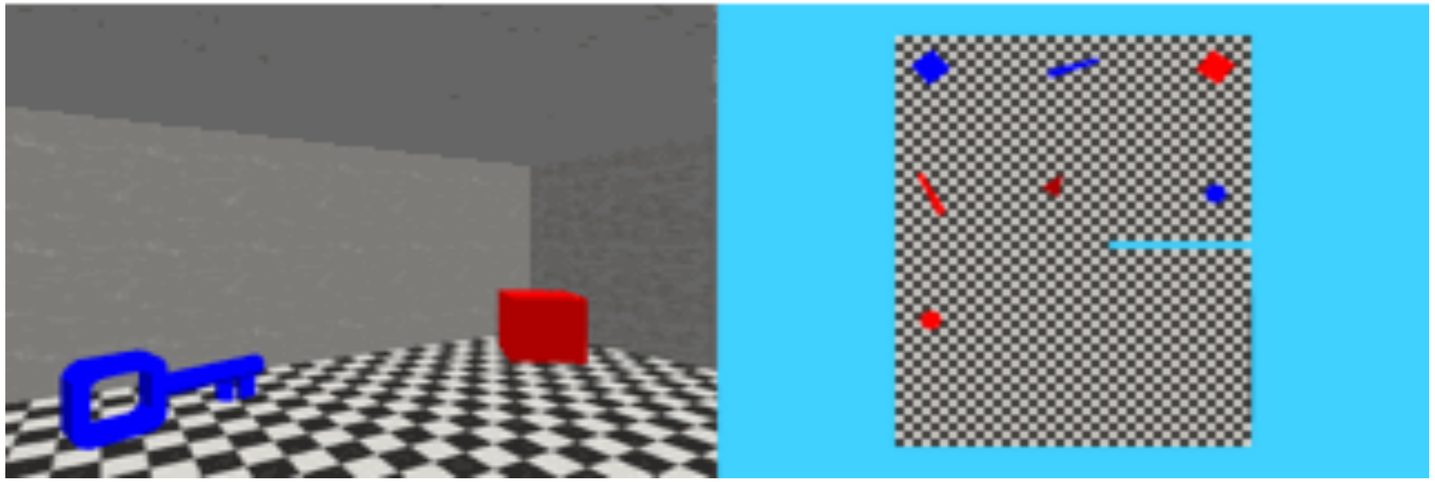
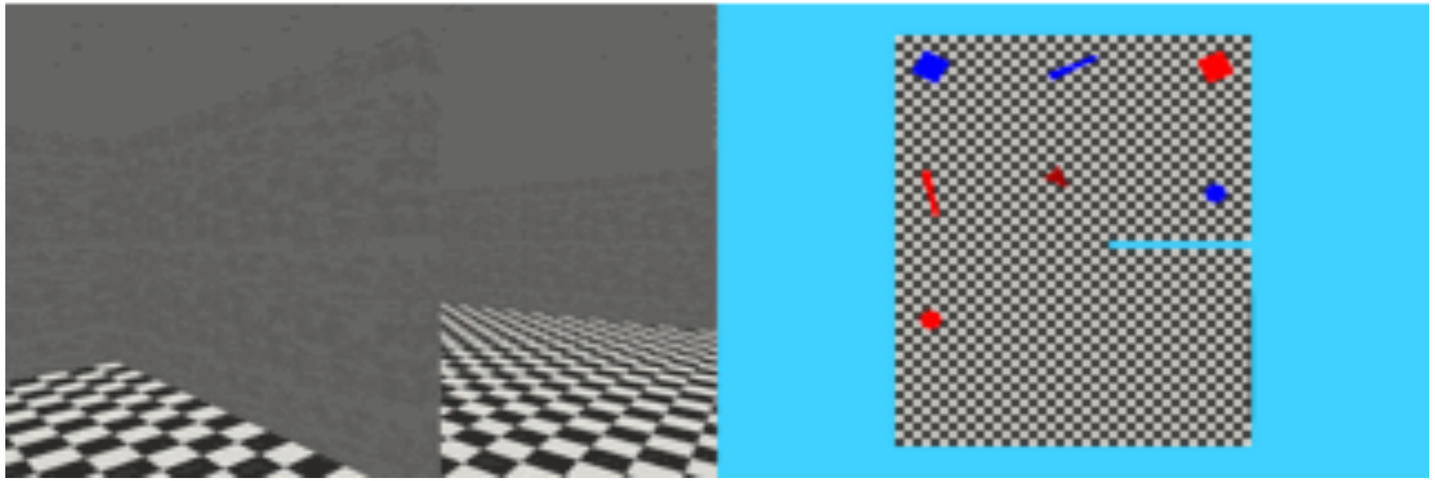
Qualitative Results for DREAM

Exploration episode



Execution episode
Goal: Go to key



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- Understand the basics of using alternative exploration strategies in meta-RL
- Understand & be able to implement decoupled exploration & exploitation

Next time

Wednesday: Last lecture on meta-RL

Next week: Hierarchical RL & Lifelong Learning

Following week: Guest lecture by Jane Wang
Final frontiers lecture

Reminders

Homework 3, due **tonight.**

Optional Homework 4 out tonight

Project milestone due **Monday 11/2.**