Advanced Topics in Deep Reinforcement Learning

MetaRL 1: Outer-Loop Learning

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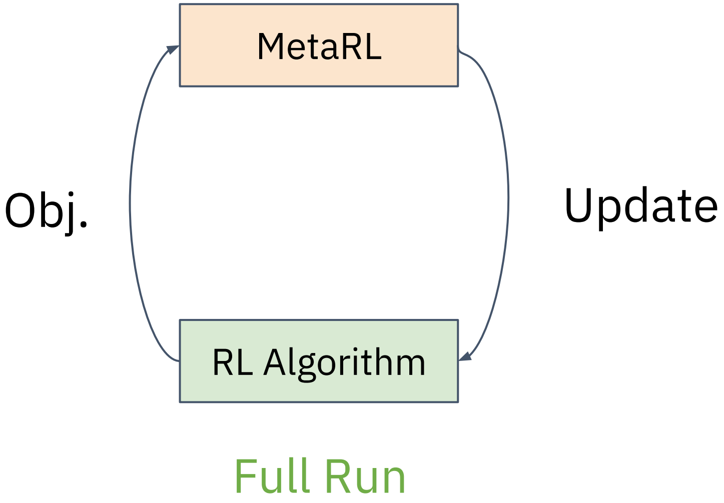
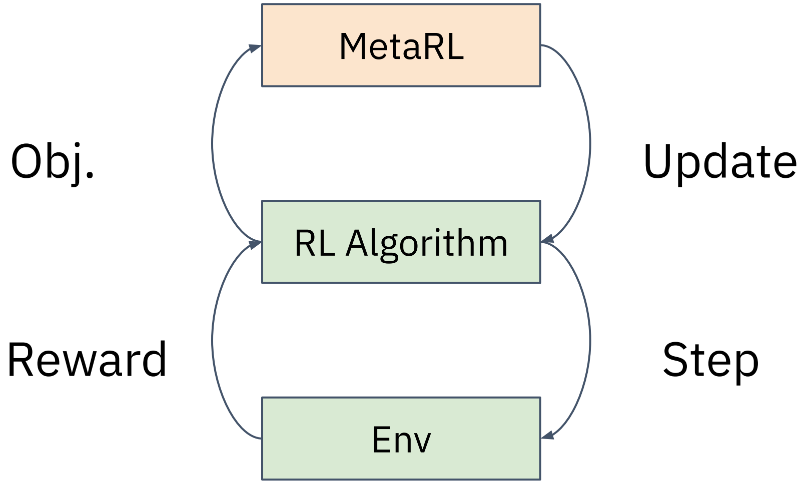
Reminder: Outer-Loop vs In-the-Loop

There are two MetaRL paradigms:



Outer-loop MetaRL



In-the-loop MetaRL

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- Most commonly meta-gradients or black-box setting
- Black-box objective usually evaluation reward
- Has been successful in learning most components of the RL loop

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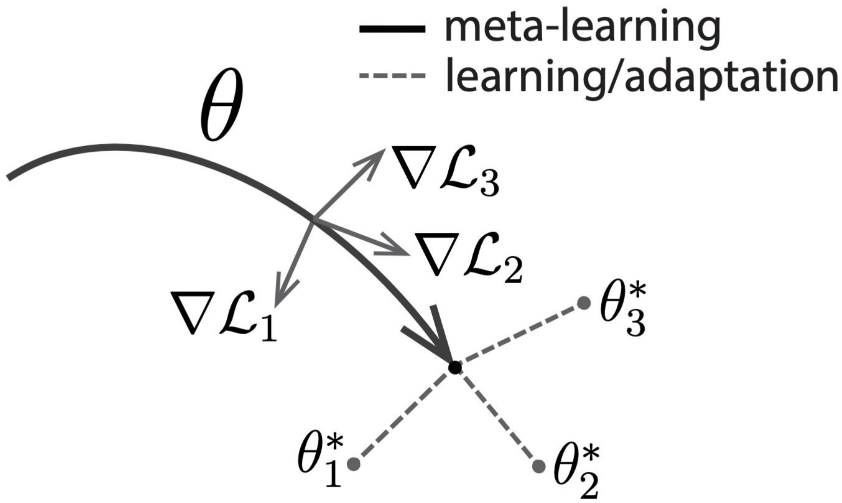

The Template: MAML [Finn et al. 2017]

Algorithm 3 MAML for Reinforcement Learning

Require: $p(\mathcal{T})$: distribution over tasks
Require: α, β: step size hyperparameters
1: randomly initialize θ
2: **while** not done **do**
3: Sample batch of tasks $\mathcal{T}_i \sim p(\mathcal{T})$
4: **for all** $\mathcal{T}_i$ **do**
5: Sample K trajectories $\mathcal{D} = \{(\mathbf{x}_1, \mathbf{a}_1, ...\mathbf{x}_H)\}$ using f_θ in $\mathcal{T}_i$
6: Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$ using $\mathcal{D}$ and $\mathcal{L}_{\mathcal{T}_i}$ in Equation 4
7: Compute adapted parameters with gradient descent: $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$
8: Sample trajectories $\mathcal{D}_i' = \{(\mathbf{x}_1, \mathbf{a}_1, ...\mathbf{x}_H)\}$ using $f_{\theta_i'}$ in $\mathcal{T}_i$
9: **end for**
10: Update $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$ using each $\mathcal{D}_i'$ and $\mathcal{L}_{\mathcal{T}_i}$ in Equation 4
11: **end while**

Evaluate meta-parameters

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randomly initialize θ
while not done do
    Sample batch of tasks T_i ~ p(T)
    for all T_i do
        Sample K trajectories D = {(x_1, a_1, ...x_H)} using f_θ in T_i
        Evaluate ∇_θ L_{T_i}(f_θ) using D and L_{T_i} in Equation 4
        Compute adapted parameters with gradient descent: θ'_i = θ − α∇_θ L_{T_i}(f_θ)
        Sample trajectories D'_i = {(x_1, a_1, ...x_H)} using f_{θ'_i} in T_i
    end for
    Update θ ← θ − β∇_θ Σ_{T_i~p(T)} L_{T_i}(f_{θ'_i}) using each D'_i and L_{T_i} in Equation 4
end while
```

Propagate local updates

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- No additional hyperparameters
- Still performs fairly well as a baseline
- But: we need meta-gradients for the meta-parameter update which is expensive and difficult to compute

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Algorithm 1 Reptile (serial version)

Initialize ϕ, the vector of initial parameters
for iteration $= 1, 2, \ldots$ **do**
  Sample task τ, corresponding to loss L_τ on weight vectors $\widetilde{\phi}$
  Compute $\widetilde{\phi} = U_\tau^k(\phi)$, denoting k steps of SGD or Adam
  Update $\phi \leftarrow \phi + \epsilon(\widetilde{\phi} - \phi)$
end for

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- Loss of some gradient information
- Could cause instability depending on task diversity
- But: performs quite well in evaluation

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- Since we mainly care about performance on the task distribution, they are not necessary in the way they are in single-shot in-the-loop methods
- Final evaluation performance can take the place of the loss
- Now we can use black-box methods as meta-optimizers

ES-MAML [Song et al. 2020]

Data: initial policy θ_0, meta step size β

for $t = 0, 1, \ldots$ **do**

  Sample n tasks $T_1, \ldots, T_n$ and iid vectors $\mathbf{g}_1, \ldots, \mathbf{g}_n \sim \mathcal{N}(0, \mathbf{I})$;

  foreach $(T_i, \mathbf{g}_i)$ **do**

    $v_i \leftarrow f^{T_i}(U(\theta_t + \sigma \mathbf{g}_i, T_i))$

  end

  $\theta_{t+1} \leftarrow \theta_t + \frac{\beta}{\sigma n} \sum_{i=1}^{n} v_i \mathbf{g}_i$

end

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  - NES [Wierstra et al., 2008]: population is a distribution over parameters

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Basic structure of an ES algorithm:

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There are many ways to implement the sample procedure and research on improved ES algorithms is a research field in its own right.

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  - SGD update using the gradient of a gradient
  - Detailed information
  - Potentially noisy
  - Expensive to compute
- Evolutionary strategies
  - Evolving population of samples
  - Black-box, relies on reward
  - Potentially needs more function evaluations than meta-gradients
  - Easy to parallelize

MetaRL Settings

- Most commonly: train and test model-free online policies
- In most cases training tasks should not be tested on!
- Often still very similar training and test environments in the literature
- However: MetaRL also exists for other RL paradigms

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- Different combinations of reward/reward-free meta-training and evaluation are possible
- Most important one: unsupervised meta-learning for online rewards [Gupta et al. 2020]
- Challenge: find meaningful parts of the state space to explore
- Can be used to find policies, but also to meta-learn e.g. curricula via mutual information or similar metrics [Jabri et al. 2019]

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- Example: have the model infer the task specification [Belkhale et al. 2021]
- We can even use this to learn to switch between policies for different tasks, e.g. different robot models [Anne et al. 2021]
- We can also condition the model itself on a known task specification to make it more useful [Prasanna et al. 2024]

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  - In-between stage of unsupervised online data collection [Pong et al. 2022]
  - Use simple offline RL algorithms [Mitchell et al. 2021]

My Understanding of MetaRL (pt. 2)

- ❑ I can describe the difference between outer-loop and in-the-loop methods
- ❑ I can name one meta-optimization method

- ❑ I can explain the intuition of MAML
- ❑ I understand the difference between meta-gradients and gradients on the meta-level

- ❑ I know an improvement on MAML
- ❑ I can describe two meta-optimizers