

1710.03641 - Continuous Adaptation via Meta-Learning in Nonstationary and Competitive Environments

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 - Other reference:
 - [ICLR 2018 openreview](#)
 - [OpenAI blog : Meta-Learning for Wrestling](#)
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1. Introduction

- Challenge: real world is non-stationary
 - Dynamics and objectives change over life-long time
 - Multiple learning actors
- Traditional method: context detection and tracking
 - learn policy based on those already happened, then continuously fine-tuning for new environment
 - Limitation:
 - Inefficient
 - Limited interaction before changing → maybe insufficient to learn policy → **we need few-shot**
- Insight: non-stationary task can be seen as a sequence of stationary tasks → change to multi-task problem
- This paper:
 - Consider the problem of continuous adaptation to a learning opponent in a competitive multi-agent setting
 - Design a new environment: RoboSumo
 - Develop gradient-based meta-learning algorithm for adaptation in dynamically

changing and adversarial scenarios

2. Related Work

- Life-long learning: solving multiple tasks sequentially by using already learned knowledge
- Never-ending learning: keep a set of tasks, the set keeps growing, and the performance on all tasks keeps growing as well
- **Continuous adaptation:**
 - Solve a single but nonstationary task or environment
 - Learn an agent to adapt to changes of environment
 - With limited data or experience (few-shot)

3. Method

- Goal: handle continuous adaptation with few-shot
- Method: rederive MAML for multi-task, then extend to dynamically changing tasks

3.1 Probabilistic view of MAML

- Here Eq.1-3 are similar to original MAML
- A task is defined as

$$T = \{L_T, P_T(x), P_T(x_{t+1}|x_t, a_t), H\} \quad (1)$$

- Inner loop: here ϕ is θ' in original version
 - **注意这里把公式2叫做meta-gradient update with step α , 该公式是内循环的, 和 meta-update不同**

$$\phi := \theta - \alpha \nabla_{\theta} \mathcal{L}_T(\tau_{\theta}^{1:K}), \text{ where } \mathcal{L}_T(\tau_{\theta}^{1:K}) := \frac{1}{K} \sum_{k=1}^K \mathcal{L}_T(\tau_{\theta}^k), \text{ and } \tau_{\theta}^k \sim P_T(\tau | \theta) \quad (2)$$

- Meta objective:

$$\min_{\theta} \mathbb{E}_{T \sim \mathcal{D}(T)} [\mathcal{R}_T(\theta)], \text{ where } \mathcal{R}_T(\theta) := \mathbb{E}_{\tau_{\theta}^{1:K} \sim P_T(\tau|\theta)} [\mathbb{E}_{\tau_{\phi} \sim P_T(\tau|\phi)} [\mathcal{L}_T(\tau_{\phi}) | \tau_{\theta}^{1:K}, \theta]] \quad (3)$$

where τ_{θ} and τ_{ϕ} are trajectories obtained under π_{θ} and π_{ϕ} , respectively.

- Probabilistic view:

- Task T , trajectories τ and policies π_{θ} are random variables, ϕ is generated from conditional distribution $P_T(\phi|\theta, \tau_{1:k})$
- Inner loop update: equivalent to assuming the delta distribution

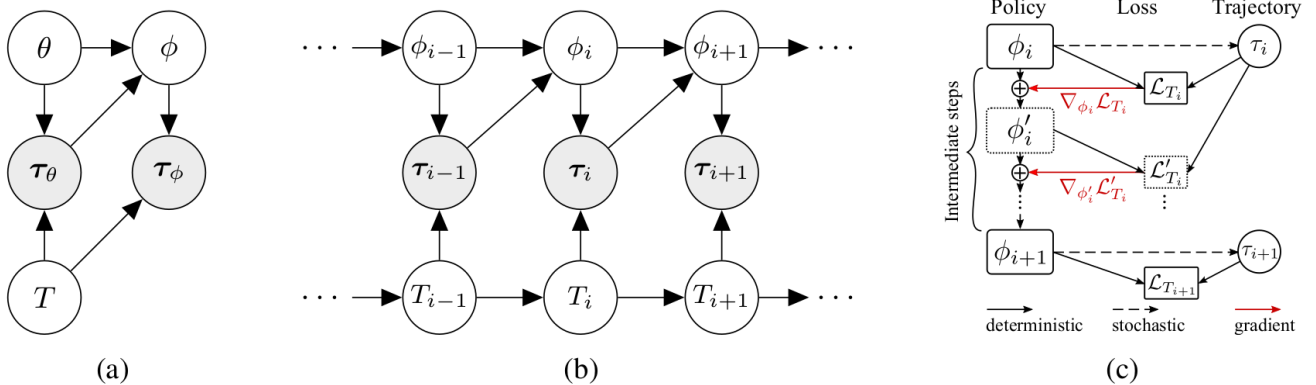
$$P_T(\phi|\theta, \tau_{1:k}) := \delta(\theta - \alpha \nabla_{\theta} \frac{1}{K} \sum_{k=1}^K L(\tau_k))$$

- Optimize meta-objective: PG where the gradient of $R_T(\theta)$

$$\nabla_{\theta} \mathcal{R}_T(\theta) = \mathbb{E}_{\substack{\tau_{\theta}^{1:K} \sim P_T(\tau|\theta) \\ \tau_{\phi} \sim P_T(\tau|\phi)}} \left[\mathcal{L}_T(\tau_{\phi}) \left[\nabla_{\theta} \log \pi_{\phi}(\tau_{\phi}) + \nabla_{\theta} \sum_{k=1}^K \log \pi_{\theta}(\tau_{\theta}^k) \right] \right] \quad (4)$$

3.2 Continuous adaptation via meta-learning

- $D(T)$ is defined by the environment changes, and the tasks become sequentially dependent
- Our goal:
 - Find the dependence between consecutive tasks
 - Meta-learn a rule to minimize total expected loss during interacting
 - 这里举了个栗子, 若对手改变策略, 我们的agent也要做相应调整



- Here is probabilistic graph of MAML

- (a) MAML in a multi-task RL setting

- (b) Extend to continuous adaptation
 - Policy and trajectories at a previous step are used to construct a new policy for the current step, i.e. $\{\phi_i, \tau_i\} \rightarrow \phi_{i+1}$
- (c) Computation graph for the meta-update from ϕ_i to ϕ_{i+1}
 - The model is optimized via truncated backpropagation through time starting from $L_{T_{i+1}}$
- From (b) we represent nonstationary as a sequence of stationary tasks, then the goal is try to minimize the expected loss of L tasks, where L is a given number

$$\min_{\theta} \mathbb{E}_{\mathcal{P}(T_0), \mathcal{P}(T_{i+1}|T_i)} \left[\sum_{i=1}^L \mathcal{R}_{T_i, T_{i+1}}(\theta) \right] \quad (5)$$

- Expected loss on a pair of consecutive tasks

$$\mathcal{R}_{T_i, T_{i+1}}(\theta) := \mathbb{E}_{\tau_{i,\theta}^{1:K} \sim P_{T_i}(\tau|\theta)} \left[\mathbb{E}_{\tau_{i+1,\phi} \sim P_{T_{i+1}}(\tau|\phi)} [\mathcal{L}_{T_{i+1}}(\tau_{i+1,\phi}) | \tau_{i,\theta}^{1:K}, \theta] \right] \quad (6)$$

The principal difference between the loss in (3) and (6) is that trajectories $\tau_{i,\theta}^{1:K}$ come from the current task, T_i , and are used to construct a policy, π_{ϕ} , that is good for the upcoming task, T_{i+1} .

- To construct the parameters of policy for task T_{i+1} , we start from θ , note that here we can also change inner step size α

$$\begin{aligned} \phi_i^0 &:= \theta, \quad \tau_{\theta}^{1:K} \sim P_{T_i}(\tau | \theta), \\ \phi_i^m &:= \phi_i^{m-1} - \alpha_m \nabla_{\phi_i^{m-1}} \mathcal{L}_{T_i}(\tau_{i,\phi_i^{m-1}}^{1:K}), \quad m = 1, \dots, M-1, \\ \phi_{i+1} &:= \phi_i^{M-1} - \alpha_M \nabla_{\phi_i^{M-1}} \mathcal{L}_{T_i}(\tau_{i,\phi_i^{M-1}}^{1:K}) \end{aligned} \quad (7)$$

- PG for (c), as expectation is taken to both T_i and T_{i+1} , we change (4) to

$$\nabla_{\theta, \alpha} \mathcal{R}_{T_i, T_{i+1}}(\theta, \alpha) = \mathbb{E}_{\substack{\tau_{i,\theta}^{1:K} \sim P_{T_i}(\tau|\theta) \\ \tau_{i+1,\phi} \sim P_{T_{i+1}}(\tau|\phi)}} \left[\mathcal{L}_{T_{i+1}}(\tau_{i+1,\phi}) \left[\nabla_{\theta, \alpha} \log \pi_{\phi}(\tau_{i+1,\phi}) + \nabla_{\theta} \sum_{k=1}^K \log \pi_{\theta}(\tau_{i,\theta}^k) \right] \right] \quad (8)$$

3.3 Meta-training for Continuous Adaptation

Algorithm 1 Meta-learning at training time.

input Distribution over pairs of tasks, $\mathcal{P}(T_i, T_{i+1})$,
learning rate, β .

- 1: Randomly initialize θ and α .
- 2: **repeat**
- 3: Sample a batch of task pairs, $\{(T_i, T_{i+1})\}_{i=1}^n$.
- 4: **for all** task pairs (T_i, T_{i+1}) in the batch **do**
- 5: Sample traj. $\tau_{1:K}$ from T_i using π_θ .
- 6: Compute $\phi = \phi(\tau_{1:K}, \theta, \alpha)$ as given in (7).
- 7: Sample traj. τ from T_{i+1} using π_ϕ .
- 8: **end for**
- 9: Construct $\nabla_\theta \mathcal{R}_T(\theta, \alpha)$ and $\nabla_\alpha \mathcal{R}_T(\theta, \alpha)$ using $\tau_{1:K}$ and τ as given in (8).
- 10: Update $\theta \leftarrow \theta + \beta \nabla_\theta \mathcal{R}_T(\theta, \alpha)$.
- 11: Update $\alpha \leftarrow \alpha + \beta \nabla_\alpha \mathcal{R}_T(\theta, \alpha)$.
- 12: **until** Convergence

output Optimal θ^* and α^* .

- **Assumption: trajectories of T_i contain some information about T_{i+1}**
- Difference from original MAML:
 - Goal: 不仅仅优化 θ 还有一系列步长 α
 - Use a pair of consecutive tasks for training
 - During inner loop:
 - 首先基于原策略 π_θ 从 T_i 中获取一系列 trajectories $\tau_{1:K}$
 - 此处存疑, 原文中说获取trajectories的过程中还需要与 T_{i+1} 互动
 - 根据这些 T_i 的 trajectories 计算 ϕ
 - π_ϕ 用于解决 T_{i+1} , 基于该策略从 T_{i+1} 中获取一个 trajectory τ
 - Meta-update:
 - 通过一系列子任务获取 $\tau_{1:K}$ 以及 τ 后, 计算 $\nabla_\theta \mathcal{R}_T(\theta, \alpha)$, $\nabla_\alpha \mathcal{R}_T(\theta, \alpha)$

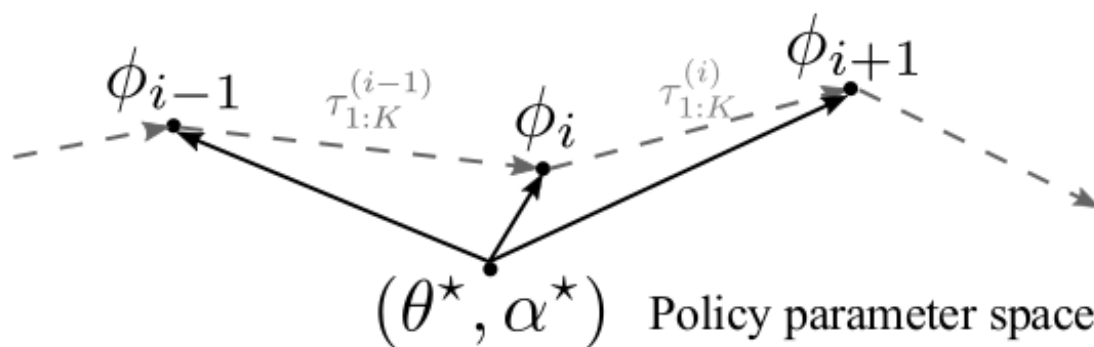
- 更新 θ 与 α

3.4 Adaptation at Execution Time (Testing)

Algorithm 2 Adaptation at execution time.

input A stream of tasks, T_1, T_2, T_3, \dots

- 1: Initialize $\phi = \theta$.
- 2: **while** there are new incoming tasks **do**
- 3: Get a new task, T_i , from the stream.
- 4: Solve T_i using π_ϕ policy.
- 5: While solving T_i , collect trajectories, $\tau_{1:K}^{(i)}$.
- 6: Update $\phi \leftarrow \phi(\tau_{1:K}^{(i)}, \theta^*, \alpha^*)$ using importance-corrected meta-update as in (9).
- 7: **end while**



- Nonstationary \rightarrow can not access to same task multiple times
- How to handle : keep acting according to π_ϕ and re-use past experience to for computing updates of ϕ for each new incoming task
- π_ϕ 获取的past experience与 π_θ 会有不同 \rightarrow 使用 importance weight correction 进行调整

$$\phi_i := \theta - \alpha \frac{1}{K} \sum_{k=1}^K \left(\frac{\pi_{\theta}(\tau^k)}{\pi_{\phi_{i-1}}(\tau^k)} \right) \nabla_{\theta} \mathcal{L}(\tau^k), \quad \tau^{1:K} \sim P_{T_{i-1}}(\tau \mid \phi_{i-1}), \quad (9)$$

4. Experiment

- A new environment : [RoboSumo](#)
- Let robot wrestle



Figure 2: (a) The three types of agents used in experiments. The robots differ in the anatomy: the number of legs, their positions, and constraints on the thigh and knee joints. (b) The nonstationary locomotion environment. The torques applied to red-colored legs are scaled by a dynamically changing factor. (c) The RoboSumo environment.

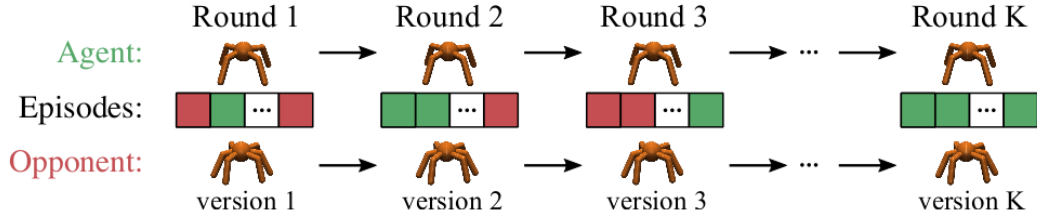


Figure 3: An agent competes with an opponent in an iterated adaptation games that consist of multi-episode rounds. The agent wins a round if it wins the majority of episodes (wins and losses illustrated with color). Both the agent and its opponent may update their policies from round to round (denoted by the version number).

• Result 1

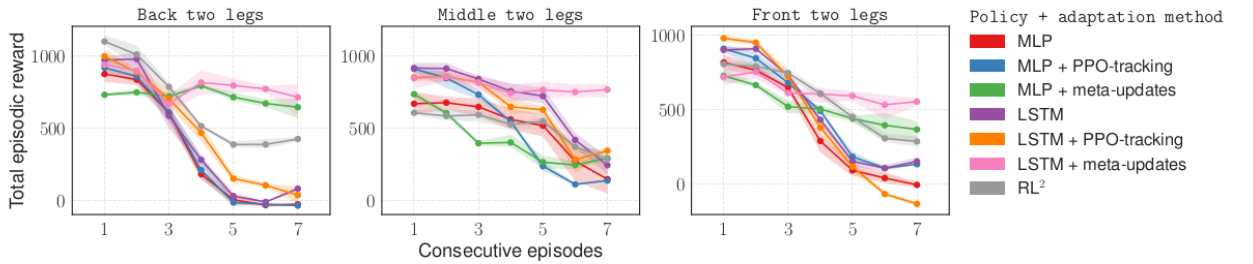


Figure 4: Episodic rewards for 7 consecutive episodes in 3 held out nonstationary locomotion environments. To evaluate adaptation strategies, we ran each of them in each environment for 7 episodes followed by a full reset of the environment, policy, and meta-updates (repeated 50 times). Shaded regions are 95% confidence intervals. Best viewed in color.

- Omit some results

5. Conclusion

- Regard nonstationarity as a sequence of stationary tasks
- Train agents to exploit the dependencies between consecutive tasks
- During testing, the model can handle similar nonstationarities + Problem : 该工作把动态环境看作一系列静态环境的序列, 但真实环境会更复杂
- Future work

Current	Future
One-step-ahead update of the policy	Extend to fully recurrent meta-updates → take into full history of interaction
(c) requires second order derivatives at training time	Utilize information provided by the loss but avoid explicit backpropagation through the gradients
Can't handle sparse reward → the meta-updates use policy gradients and heavily rely on the reward signal	Try to introduce auxiliary dense rewards designed to enable meta-learning