The effects of negative adaptation in Model-Agnostic Meta-Learning

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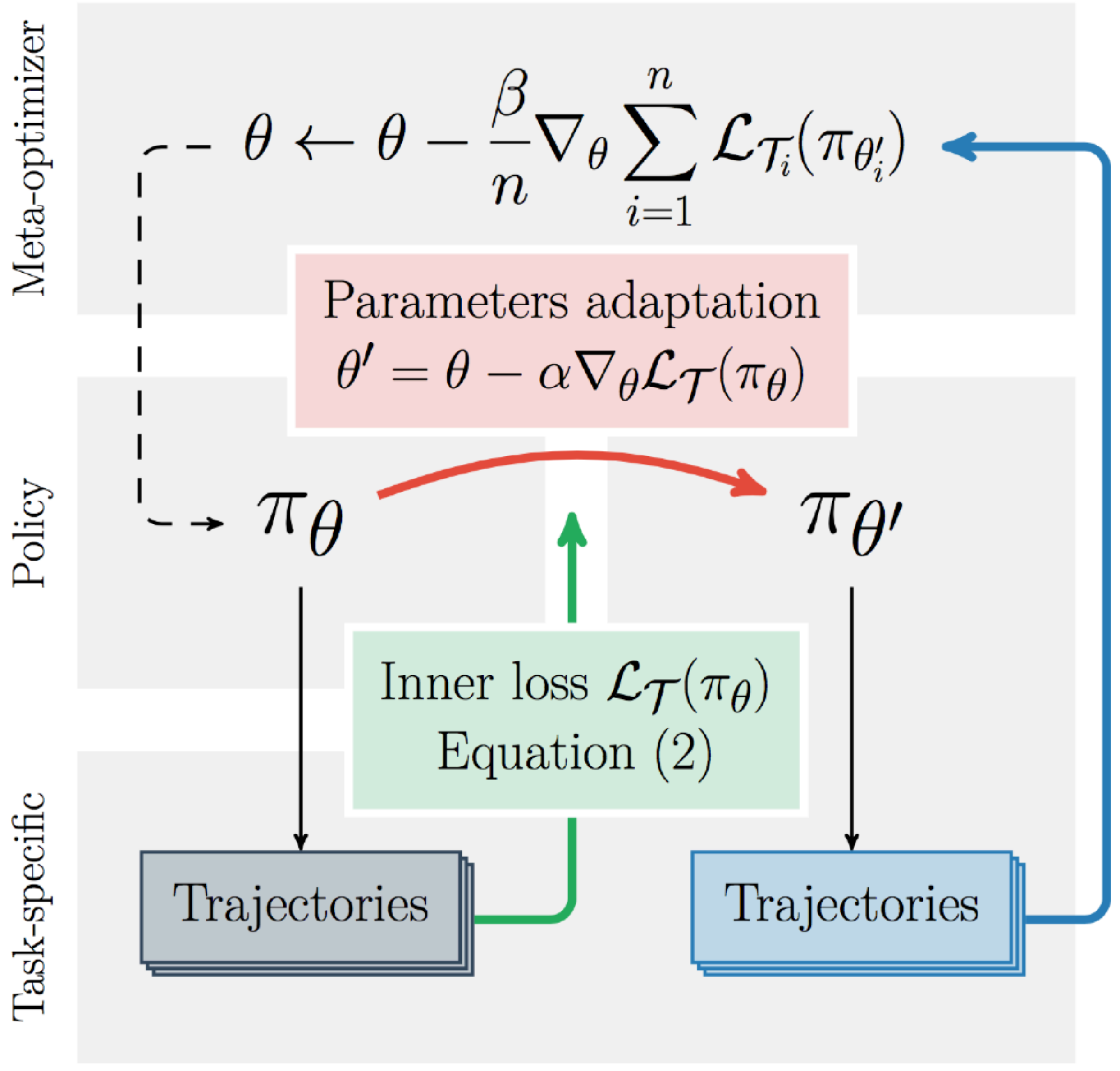
- The advantage of meta-learning is well-founded under the assumption that **the adaptation phase does improve the performance** of the model on the task of interest

- Optimization: maximize the performance after adaptation, **performance improvement is not explicitly enforced**

$$\min_{\theta} \mathbb{E}_{\mathcal{T}\sim p(\mathcal{T})}[\mathcal{L}(\theta'_{\mathcal{T}}; \mathcal{D}'_{\mathcal{T}})]$$

- We show empirically that performance **can decrease** after adaptation in MAML. We call this **negative adaptation**

- How to fix this issue? Ideas from **Safe Reinforcement Learning**



Meta-optimizer

$$\theta \leftarrow \theta - \frac{\beta}{n}\nabla_\theta \sum_{i=1}^{n} \mathcal{L}_{\mathcal{T}_i}(\pi_{\theta'_i})$$

Parameters adaptation

$$\theta' = \theta - \alpha\nabla_\theta\mathcal{L}_{\mathcal{T}}(\pi_\theta)$$

Policy

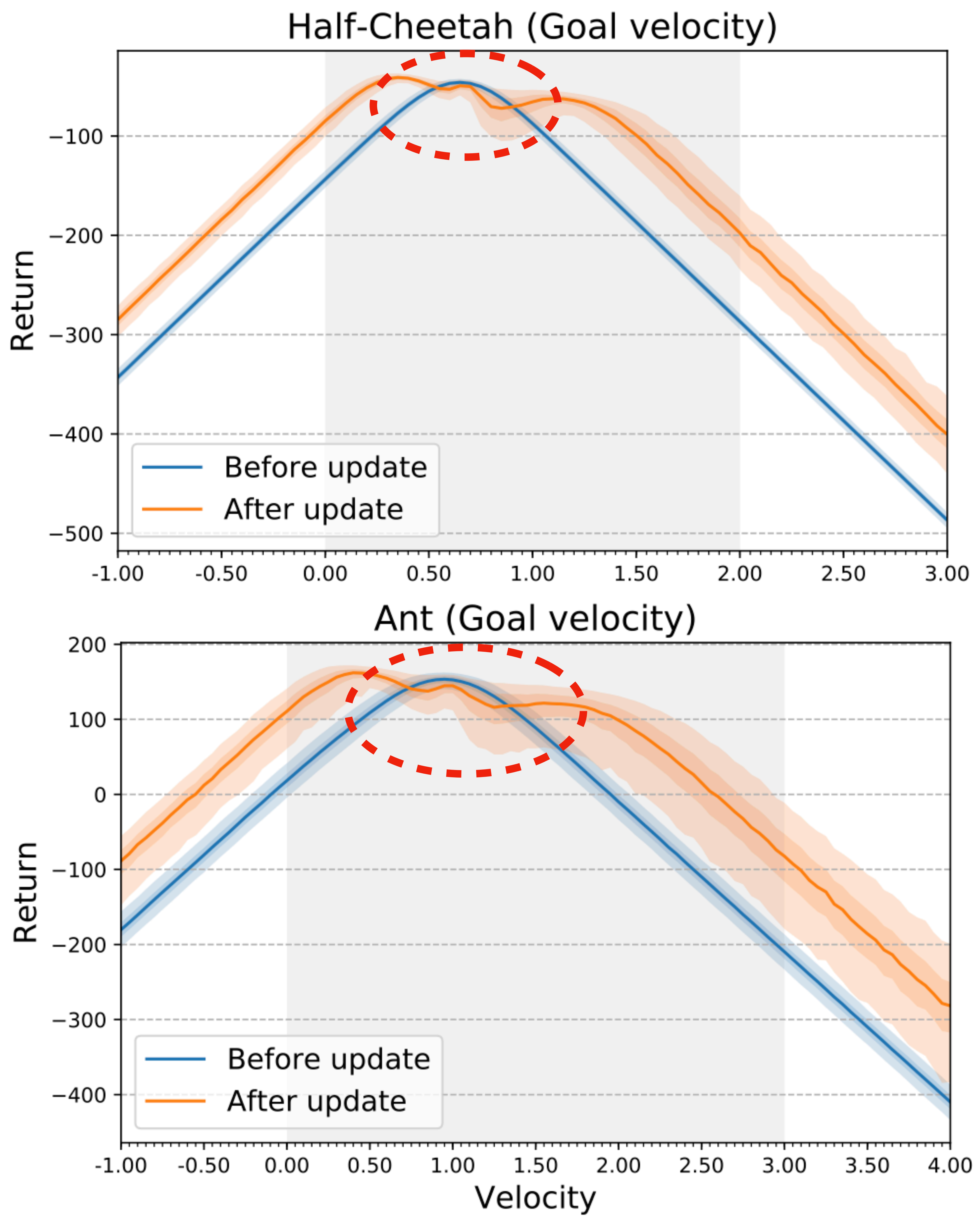
π_θ $\pi_{\theta'}$

Inner loss $\mathcal{L}_{\mathcal{T}}(\pi_\theta)$
Equation (2)

Task-specific

Trajectories

Trajectories


Half-Cheetah (Goal velocity)
Return
Before update
After update
Ant (Goal velocity)
Return
Velocity
Before update
After update