Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks

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Deep Learning

- Very powerful, expressive differentiable models.
- Flexibility is a double edged sword.

How do we reduce the amount of required samples?

Use Use Prior knowledge (not in a Bayesian sense). This can be in the form of:

- Model constraint
- Sampling strategy
- Update rule
- Loss function
- etc...

Meta learning

Learning to learn fast.
Essentially learning a prior from a distribution of tasks.
Several recent successful approaches:

- Model based meta-learning [Adam Santoro et al.], [Jx Wang et al.], [Yan Duan et al.]
- Metric meta-learning [Gregory Koch, Richard Zemel, and Ruslan Salakhutdinov.], [Oriol Vinyals et al.]
- Optimization based meta-learning [Sachin Ravi and Hugo Larochelle], [Marcin Andrychowicz et al.],

MAML

Model Agnostic Metal Learning

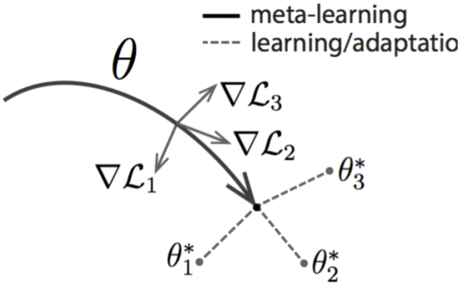
Main idea: Learn a parameter initialization for a distribution of tasks, such that given a new task a small amount of examples (gradient updates) suffice.

Definitions

Task $T_i \sim p(T)$ is defined as a tuple $(H_i, q_i, \mathcal{L}_{T_i})$ consisting of

- time horizon H_i where for supervised learning $H_i = 1$
- initial state distribution $q_i(x_0)$ and state transition distribution $q_i(x_{t+1}|x_t)$
- Task loss function $\mathcal{L}_{T_i} \to \mathbb{R}$
- Task distribution p

Losses



1) $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta).$

2) $\min_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$

3) $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$

- θ_i^* is the optimal parameter for task T_i
- θ'_i is the parameters obtained for task T_i after a single update
- 2) is the meta objective

Algorithm

Algorithm 1 Model-Agnostic Meta-Learning

Require: $p(\mathcal{T})$: distribution over tasks

Require: α, β: step size hyperparameters

randomly initialize θ

while not done **do**

  Sample batch of tasks $\mathcal{T}_i \sim p(\mathcal{T})$

  for all $\mathcal{T}_i$ **do**

    Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$ with respect to K examples

    Compute adapted parameters with gradient descent: $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$

  end for

  Update $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$

end while

Reinforcement learning

$$\mathcal{L}_{\mathcal{T}_i}(f_\phi) = -\mathbb{E}_{\mathbf{x}_t, \mathbf{a}_t \sim f_\phi, q_{\mathcal{T}_i}} \left[\sum_{t=1}^{H} R_i(\mathbf{x}_t, \mathbf{a}_t) \right]$$

Reinforcement learning adaptation

Algorithm 3 MAML for Reinforcement Learning

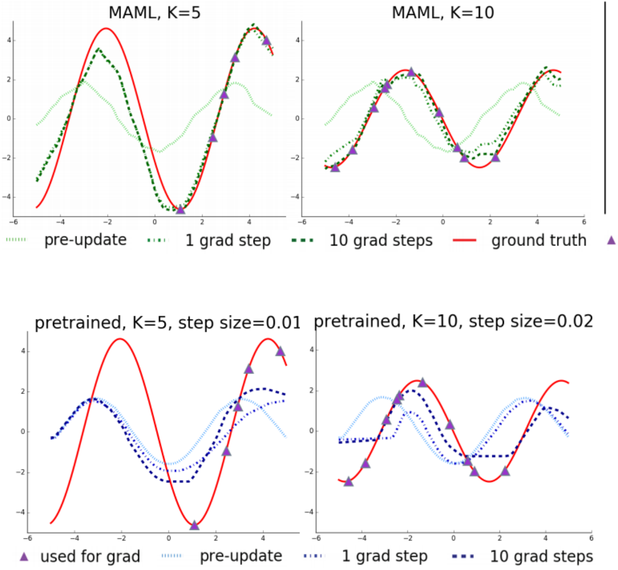
Require: $p(\mathcal{T})$: distribution over tasks
Require: α, β: step size hyperparameters
1: randomly initialize θ
2: **while** not done **do**
3: Sample batch of tasks $\mathcal{T}_i \sim p(\mathcal{T})$
4: **for all** $\mathcal{T}_i$ **do**
5: Sample K trajectories $\mathcal{D} = \{(\mathbf{x}_1, \mathbf{a}_1, ...\mathbf{x}_H)\}$ 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**

Sin wave regression

Tasks: Regressing randomly generated sin waves

- amplitudes ranging in $[0.1, 5]$
- phases $[0, 2\pi]$
- Sampled uniformly in range $[-5, 5]$

Sin wave regression



Classification tasks

Omniglot

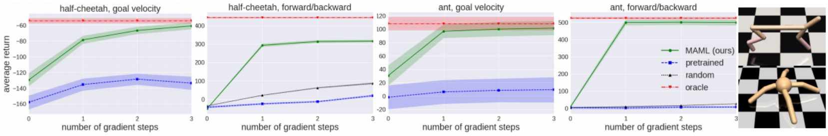
- 20 instances of 1623 characters from 50 different alphabets
- Each instance drawn by a different person
- Randomly select 1200 characters for training and the remaining for testing

MiniImagenet

- 64 training classes, 12 validation classes, and 24 test classes

RL experiment

- Rllab benchmark suite, Mujoco simulator
- Gradient update are computed using policy gradient algorithms.
- Tasks are defined by the agents simply having slightly different goals
- Agents are expected to infer new goal from reward after receiving only 1 gradient update.



Conclusion

- Simple effective meta learning method
- Decent amount of follow up work [**?**], [**?**]
- Concept extendable to meta learning other parts of the training procedure

Thank you for your attention

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