Online Meta-Learning

Chelsea Finn*, Aravind Rajeswaran*, Sham Kakade, Sergey Levine
Deep networks + large datasets = 😍
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In many practical situations:
Learn new task with only a few datapoints
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Meta-Learning
(Schmidhuber et al. ’87, Bengio et al. ’92)
Given i.i.d. task distribution,
learn a new task efficiently

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More realistically:

learn  learn  learn

time
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More realistically:
slow learning ——> rapid learning
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Online Learning
(Hannan ’57, Zinkevich ’03)
Perform sequence of tasks while minimizing static regret.
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(this work)
Efficiently learn a sequence of tasks from a non-stationary distribution.
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zero-shot performance
The Online Meta-Learning Setting
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Space of parameters \( \theta \in \Theta \subseteq \mathbb{R}^d \) and loss functions \( \ell : \Theta \rightarrow \mathbb{R} \)

For round \( t \in \{1, 2, \ldots, \infty\} \):
The Online Meta-Learning Setting

Space of parameters $\theta \in \Theta \subseteq \mathbb{R}^d$ and loss functions $\ell : \Theta \rightarrow \mathbb{R}$

For round $t \in \{1, 2, \ldots \infty\}$:

1. World picks a loss function $\ell_t(\cdot)$
2. Agent should pick $\theta_t$ without knowledge of $\ell_t$
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3. Agent uses update procedure $\Phi_t : \Theta \to \Theta$, and obtains $\tilde{\theta}_t = \Phi_t(\theta_t)$
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\[ \tilde{\theta}_t = \theta_t - \alpha \nabla \ell_t(\theta_t) \]
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4. Agent suffers $\ell_t(\tilde{\theta}_t)$ for the round

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Goal: Learning algorithm with sub-linear

$$\text{Regret}_T := \sum_{t=1}^{T} \ell_t(\Phi_t(\theta_t)) - \min_{\theta \in \Theta} \sum_{t=1}^{T} \ell_t(\Phi_t(\theta))$$
Follow the Meta-Leader (FTML):

$$\theta_{t+1} = \arg \min_\theta \sum_{t=1}^{T} \ell_t(\Phi_t(\theta))$$

Can be implemented with MAML
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\[ \theta_{t+1} = \arg \min_{\theta} \sum_{t=1}^{T} \ell_t(\Phi_t(\theta)) \]

Can be implemented with MAML

**Theorem (Informal):** If \( \{\ell_t(\cdot), \hat{\ell}_t(\cdot)\} \) \( \forall t \) are \( C^2 \)-smooth and strongly convex, the sequence of models \( \{\theta_1, \theta_2, \ldots, \theta_T\} \) returned by FTML has the property:

\[
\text{Regret}_T := \sum_{t=1}^{T} \ell_t(\Phi_t(\theta_t)) - \min_{\theta \in \Theta} \sum_{t=1}^{T} \ell_t(\Phi_t(\theta)) = O(\log T)
\]
Follow the Meta-Leader (FTML): \[ \theta_{t+1} = \arg \min_{\theta} \sum_{t=1}^{T} \ell_t(\Phi_t(\theta)) \]

Can be implemented with MAML

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\]

\[ \implies \text{Avg. Regret} = \frac{\text{Regret}_T}{T} \to 0 \text{ as } T \to \infty \]

Learning in a sequential non-stationary setting, but still competitive with best meta-learner in hindsight!
FTML: practical instantiation of our approach, extending MAML\textsuperscript{1} meta-train on all data so far, fine-tune on current task

\cite{Finn17}
**FTML**: practical instantiation of our approach, extending MAML\(^1\) meta-train on all data so far, fine-tune on current task

Experiment with **sequences of tasks**: 

\[\text{(1)}\] Finn et al. ICML ’17
FTML: practical instantiation of our approach, extending MAML\textsuperscript{1}
meta-train on all data so far, fine-tune on current task

Experiment with sequences of tasks:
- Colored, rotated, scaled MNIST

\textsuperscript{1}Finn et al. ICML ’17
Experiment with sequences of tasks:
- Colored, rotated, scaled MNIST
- 3D object pose prediction

**FTML**: practical instantiation of our approach, extending MAML\(^1\)
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Example pose prediction tasks

plane

car

chair

[1] Finn et al. ICML ’17
**FTML**: practical instantiation of our approach, extending MAML

meta-train on all data so far, fine-tune on current task

Experiment with **sequences of tasks**:
- Colored, rotated, scaled **MNIST**
- **3D object pose prediction**
- **CIFAR-100** classification

Example pose prediction tasks

- plane
- car
- chair

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Experiments
Experiments

Learning efficiency
(# datapoints)

Learning proficiency
(error)

task index
task index
Experiments

Learning efficiency

Rainbow MNIST

Pose Prediction

Learning proficiency

Rainbow MNIST

Pose Prediction

FTML (ours)
FTML (ours) learns each new task faster & with greater proficiency,
Experiments

FTML (ours) learns each new task faster & with greater proficiency, approaches few-shot learning regime.
Takeaways

Introduced **online meta-learning** problem formulation

Meta-learning is effective in **non-stationary settings**

**Similar guarantees** to online learning, but **better empirical performance**

For more, come see us at **poster #5**!