Model-Agnostic Meta-Learning (MAML) for Fast Adaptation of Deep Networks

from Chelsea Finn, Pieter Abbeel and Sergey Levine

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Seminar Recent trends in Automated Machine Learning (AutoML)

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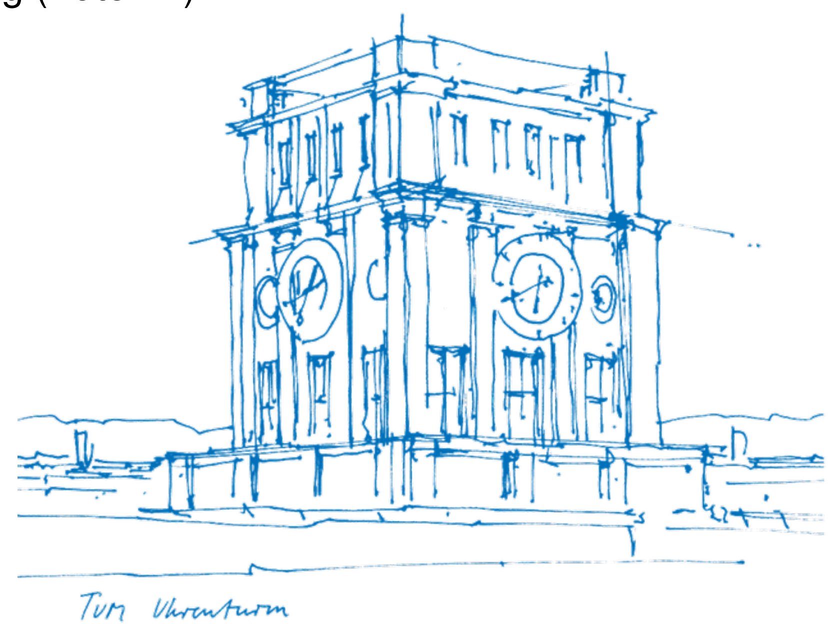

Few-Shot Learning

(Normal) Learning:

- **Goal:** Learn some function or behaviour for one given task $\mathcal{T}$ that can be applied at test time
- **Given at training:** (Large) set of training samples/trajectories
- **Given at test:** One (or more) sample(s)

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Few-shot (K-shot) Learning:

- **Goal:** Learning to adapt quickly (at test time) to new task $\mathcal{T}_i$
  - After given K samples
  - Continue adaption when more samples ($> K$) are available
- **Given at training:** Set of tasks $\mathcal{T}_i$ from distribution $p(\mathcal{T})$
- **Given at adaption:** One task $\mathcal{T}_i$ with only K training samples
- **Given at test:** One (or more) sample(s)

How does a few-shot learning dataset look like?

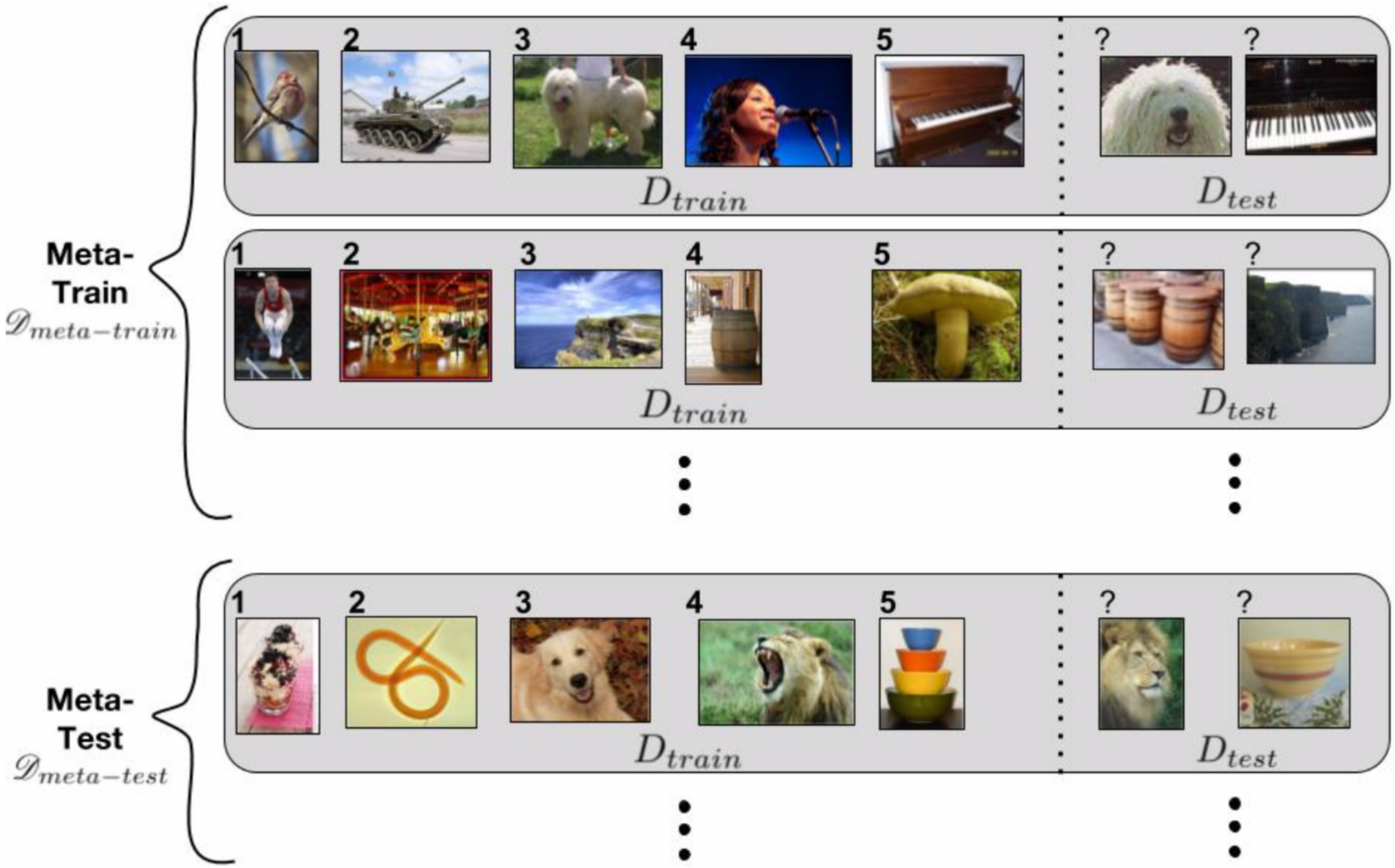

Figure: Meta-Training and Meta-Test dataset example for image classification, taken from [RL17]

How can we improve few-shot learning?

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Why are humans good at few-shot learning

- Integrate a lot of prior experience with the few samples of new information
  $\Rightarrow$ e.g. something Bayesian inference like
- Parameter initialization is crucial

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Challenges

- Bayesian inference in practice not feasible
- Gradient-based methods are not designed for constrained number of steps/samples
- How to integrate prior experience?
- Avoid overfitting to new data

Meta-Learning – Learning how to learn

Basics

- Meta-learner (agent) contains learning sub-system *(named: learner or model)*
- Meta-learner adapts/trains learner using experience

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- Previous episodes on same learning task and dataset
- **(Many) Different learning tasks with different datasets** (e.g. different problems or domains)

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What can be meta-learned:

- Optimizer / Optimizer Parameters
- General features / metrics relevant for many tasks in task distribution
- **Initial parameters**

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- **Adapt initialization:** Initial parameters are meta-learned
- Optimize for model that can be fine-tuned fast for many tasks without overfitting
  - Not perfect for a single task
  - Maximum (average) performance on many tasks after short training (few samples, few gradient descent steps)

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- Optimize for model that can be fine-tuned fast for many tasks without overfitting
  - Not perfect for a single task
  - Maximum (average) performance on many tasks after short training (few samples, few gradient descent steps)
- Use gradient-based meta-training with gradient-based training in inner loop
  - **Loss:** task-specific
  - **Meta-Loss:** Performance of trained model on task-specific validation set

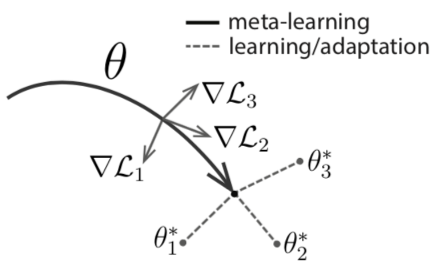

Figure: Parameter path, taken from [FAL17]

Algorithm [FAL17]

Algorithm 1 Model-Agnostic Meta-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: Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$ with respect to K examples
6: Compute adapted parameters with gradient descent: $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$
7: **end for**
8: Update $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$
9: **end while**

Algorithm [FAL17]

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$$
\begin{aligned}
& \nabla_{\boldsymbol{\theta}} \mathcal{L}^{(\text{val})}_{\mathcal{T}_i}(\boldsymbol{\theta}_i') \\
=& \nabla_{\boldsymbol{\theta}_i'} \mathcal{L}^{(\text{val})}_{\mathcal{T}_i}(\boldsymbol{\theta}_i') \cdot \nabla_{\boldsymbol{\theta}} \boldsymbol{\theta}_i' \\
=& \nabla_{\boldsymbol{\theta}_i'} \mathcal{L}^{(\text{val})}_{\mathcal{T}_i}(\boldsymbol{\theta}_i') \cdot \nabla_{\boldsymbol{\theta}} (\boldsymbol{\theta} - \alpha \nabla_{\boldsymbol{\theta}} \mathcal{L}^{(\text{train})}_{\mathcal{T}_i}(\boldsymbol{\theta})) \\
=& \nabla_{\boldsymbol{\theta}_i'} \mathcal{L}^{(\text{val})}_{\mathcal{T}_i}(\boldsymbol{\theta}_i') \cdot (\boldsymbol{I} - \alpha \nabla^2_{\boldsymbol{\theta}} \mathcal{L}^{(\text{train})}_{\mathcal{T}_i}(\boldsymbol{\theta}))
\end{aligned}
$$

Algorithm [FAL17]

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=&\nabla_{\boldsymbol{\theta}_i'} \mathcal{L}^{(\text{val})}_{\mathcal{T}_i}(\boldsymbol{\theta}_i') \cdot (\boldsymbol{I} - \alpha \nabla^2_{\boldsymbol{\theta}} \mathcal{L}^{(\text{train})}_{\mathcal{T}_i}(\boldsymbol{\theta}))
\end{aligned}$$

- Gradient of gradient (second derivative) involved
- Use Hessian-vector products:
  - Additional backward pass required (suppored out-of-the-box e.g. by Tensorflow)
  - Computational very expensive

Alternative: First-Order MAML (FOMAML)

$$\nabla_{\boldsymbol{\theta}} \mathcal{L}^{\text{(val)}}_{\mathcal{T}_i}(\boldsymbol{\theta}'_{\boldsymbol{i}}) \approx \nabla_{\boldsymbol{\theta}'_{\boldsymbol{i}}} \mathcal{L}^{\text{(val)}}_{\mathcal{T}_i}(\boldsymbol{\theta}'_{\boldsymbol{i}})$$

- First-Order Approximation, drop second derivative
- Only compute gradient at position $\boldsymbol{\theta}'_{\boldsymbol{i}}$ – after the update
- Less computational expensive (about 33% speedup)

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Results:

- Achieves similar (almost as good) results
- Most power of MAML comes from gradient of objective after update of parameters – not from derivative through gradient update

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$$\nabla_{\theta} \mathcal{L}^{(\text{val})}_{\mathcal{T}_i}(\boldsymbol{\theta}'_i) \approx \nabla_{\boldsymbol{\theta}'_i} \mathcal{L}^{(\text{val})}_{\mathcal{T}_i}(\boldsymbol{\theta}'_i)$$

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Results:

- Achieves similar (almost as good) results
- Most power of MAML comes from gradient of objective after update of parameters – not from derivative through gradient update

Explanation:

- ReLU NNs locally almost linear $\Rightarrow$ second derivative near 0

Inner Loop vs. Outer loop

Learning of Task $\mathcal{T}_i$

Meta-Learning [FAL17]

Inner Loop vs. Outer loop

Learning of Task $\mathcal{T}_i$		Meta-Learning [FAL17]
	Data Set	
$\{(\boldsymbol{x}_1^{(\mathcal{T}_i,j)}, \boldsymbol{a}_1^{(\mathcal{T}_i,j)}, \dots, \boldsymbol{x}_H^{(\mathcal{T}_i,j)}, \boldsymbol{a}_H^{(\mathcal{T}_i,j)})\}_{j=1}^{K}$		$\{\mathcal{T}_i\}_{i=1}^{N}$

Inner Loop vs. Outer loop

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Data Distribution	
$\boldsymbol{x}_1 \sim q_{\mathcal{T}_i}(\boldsymbol{x}_1), \boldsymbol{x}_{t+1} \sim q_{\mathcal{T}_i}(\boldsymbol{x}_{t+1} \vert \boldsymbol{x}_t, \boldsymbol{a}_t)$	$\mathcal{T}_i \sim p(\mathcal{T})$

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Data Set	$\{(\boldsymbol{x}_1^{(\mathcal{T}_i,j)}, \boldsymbol{a}_1^{(\mathcal{T}_i,j)}, \dots, \boldsymbol{x}_H^{(\mathcal{T}_i,j)}, \boldsymbol{a}_H^{(\mathcal{T}_i,j)})\}_{j=1}^{K}$	$\{\mathcal{T}_i\}_{i=1}^{N}$
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Loss	$\mathcal{L}_{\mathcal{T}_i}(f_\theta)$	$\sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}(f_{\boldsymbol{\theta}'_i}) = \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}\left(f_{\boldsymbol{\theta} - \alpha \nabla_{\boldsymbol{\theta}} \mathcal{L}_{\mathcal{T}_i}^{(\text{train})}(f_{\boldsymbol{\theta}})}\right)$

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Loss	$\mathcal{L}_{\mathcal{T}_i}(f_\theta)$	$\sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}(f_{\boldsymbol{\theta}_i'}) = \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}\left(f_{\boldsymbol{\theta} - \alpha \nabla_{\boldsymbol{\theta}} \mathcal{L}_{\mathcal{T}_i}^{(\text{train})}(f_\theta)}\right)$
Optimization	$\boldsymbol{\theta}_i' \leftarrow \boldsymbol{\theta} - \alpha \nabla_{\boldsymbol{\theta}} \mathcal{L}_{\mathcal{T}_i}^{(\text{train})}(f_\theta)$	$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \beta \nabla_{\boldsymbol{\theta}} \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}(f_{\boldsymbol{\theta}_i'})$

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Data Distribution	
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Loss	
$\mathcal{L}_{\mathcal{T}_i}(f_\theta)$	$\sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}(f_{\theta_i'}) = \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}\left(f_{\boldsymbol{\theta} - \alpha \nabla_{\boldsymbol{\theta}} \mathcal{L}_{\mathcal{T}_i}^{(\text{train})}(f_\theta)}\right)$
Optimization	
$\boldsymbol{\theta}_i' \leftarrow \boldsymbol{\theta} - \alpha \nabla_{\boldsymbol{\theta}} \mathcal{L}_{\mathcal{T}_i}^{(\text{train})}(f_\theta)$	$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \beta \nabla_{\boldsymbol{\theta}} \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}(f_{\theta_i'})$
Forward Pass	
Normal forward-pass	Several model training steps (of task)

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Data Distribution	
$\boldsymbol{x}_1 \sim q_{\mathcal{T}_i}(\boldsymbol{x}_1), \boldsymbol{x}_{t+1} \sim q_{\mathcal{T}_i}(\boldsymbol{x}_{t+1} \| \boldsymbol{x}_t, \boldsymbol{a}_t)$	$\mathcal{T}_i \sim p(\mathcal{T})$
Loss	
$\mathcal{L}_{\mathcal{T}_i}(f_\theta)$	$\sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}(f_{\theta_i'})$ $= \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}\left(f_{\theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}^{(\text{train})}(f_\theta)}\right)$
Optimization	
$\theta_i' \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}^{(\text{train})}(f_\theta)$	$\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}(f_{\theta_i'})$
Forward Pass	
Normal forward-pass	Several model training steps (of task)
Backward Pass	
Normal backward-pass (backpropagation)	Backprop gradient of meta-loss through loss on validation data and training process to initial weights

Inner Loop vs. Outer loop

	Supervised Regression Task $\mathcal{T}_i$	**Meta-Learning [FAL17]**
Data Set	K i.i.d. obervations $(H = 1)$: $\{(\boldsymbol{x}^{(\mathcal{T}_i,j)}, \boldsymbol{y}^{(\mathcal{T}_i,j)})\}_{j=1}^{K}$	$\{\mathcal{T}_i\}_{i=1}^{N}$
Data Distribution	$(\boldsymbol{x}, \boldsymbol{y}) \sim q_{\mathcal{T}_i}(\boldsymbol{x}, \boldsymbol{y})$	$\mathcal{T}_i \sim p(\mathcal{T})$
Loss	$\mathcal{L}_{\mathcal{T}_i}(f_{\boldsymbol{\theta}}) = \sum_{(\boldsymbol{x}^{(\mathcal{T}_i,j)}, \boldsymbol{y}^{(\mathcal{T}_i,j)}) \sim q_{\mathcal{T}_i}} \lVert f_{\boldsymbol{\theta}}(\boldsymbol{x}^{(\mathcal{T}_i,j)}) - \boldsymbol{y}^{(\mathcal{T}_i,j)} \rVert_2^2$	$\sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}(f_{\boldsymbol{\theta}'_i}) = \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}\left(f_{\boldsymbol{\theta} - \alpha \nabla_{\boldsymbol{\theta}} \mathcal{L}_{\mathcal{T}_i}^{(\text{train})}(f_{\boldsymbol{\theta}})}\right)$
Optimization	$\boldsymbol{\theta}'_i \leftarrow \boldsymbol{\theta} - \alpha \nabla_{\boldsymbol{\theta}} \mathcal{L}_{\mathcal{T}_i}^{(\text{train})}(f_{\boldsymbol{\theta}})$	$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \beta \nabla_{\boldsymbol{\theta}} \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}(f_{\boldsymbol{\theta}'_i})$
Forward Pass	Normal forward-pass	Several model training steps (of task)
Backward Pass	Normal backward-pass (backpropagation)	Backprop gradient of meta-loss through loss on validation data and training process to initial weights

Inner Loop vs. Outer loop

Supervised Classification Task $\mathcal{T}_i$	Meta-Learning [FAL17]
Data Set	
K i.i.d. obervations $(H = 1)$: $\{(\boldsymbol{x}^{(\mathcal{T}_i,j)}, \boldsymbol{y}^{(\mathcal{T}_i,j)})\}_{j=1}^{K}$	$\{\mathcal{T}_i\}_{i=1}^{N}$
Data Distribution	
$(\boldsymbol{x}, \boldsymbol{y}) \sim q_{\mathcal{T}_i}(\boldsymbol{x}, \boldsymbol{y})$	$\mathcal{T}_i \sim p(\mathcal{T})$
Loss	
$\mathcal{L}_{\mathcal{T}_i}(f_{\boldsymbol{\theta}}) = \sum_{(\boldsymbol{x}^{(\mathcal{T}_i,j)}, \boldsymbol{y}^{(\mathcal{T}_i,j)}) \sim q_{\mathcal{T}_i}} \boldsymbol{y}^{(\mathcal{T}_i,j)} \log f_{\boldsymbol{\theta}}(\boldsymbol{x}^{(\mathcal{T}_i,j)})$	$\sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}(f_{\boldsymbol{\theta}_i'}) = \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}\left(f_{\boldsymbol{\theta} - \alpha \nabla_{\boldsymbol{\theta}} \mathcal{L}_{\mathcal{T}_i}^{(\text{train})}(f_{\boldsymbol{\theta}})}\right)$
Optimization	
$\boldsymbol{\theta}_i' \leftarrow \boldsymbol{\theta} - \alpha \nabla_{\boldsymbol{\theta}} \mathcal{L}_{\mathcal{T}_i}^{(\text{train})}(f_{\boldsymbol{\theta}})$	$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \beta \nabla_{\boldsymbol{\theta}} \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}(f_{\boldsymbol{\theta}_i'})$
Forward Pass	
Normal forward-pass	Several model training steps (of task)
Backward Pass	
Normal backward-pass (backpropagation)	Backprop gradient of meta-loss through loss on validation data and training process to initial weights

Inner Loop vs. Outer loop

Reinforcement Learning Task $\mathcal{T}_i$	Meta-Learning [FAL17]
Data Set	
K rollouts of episode length H using policy f_θ : $\{(\boldsymbol{x}_1^{(\mathcal{T}_i,j)}, \boldsymbol{a}_1^{(\mathcal{T}_i,j)}, \ldots, \boldsymbol{x}_H^{(\mathcal{T}_i,j)}, \boldsymbol{a}_H^{(\mathcal{T}_i,j)})\}_{j=1}^K$	$\{\mathcal{T}_i\}_{i=1}^N$
Data Distribution	
$\boldsymbol{x}_1 \sim q_{\mathcal{T}_i}(\boldsymbol{x}_1), \boldsymbol{x}_{t+1} \sim q_{\mathcal{T}_i}(\boldsymbol{x}_{t+1} \mid \boldsymbol{x}_t, \boldsymbol{a}_t), \boldsymbol{a}_t \sim f_\theta(\boldsymbol{a}_t \mid \boldsymbol{x}_t)$	$\mathcal{T}_i \sim p(\mathcal{T})$
Loss	
$\mathcal{L}_{\mathcal{T}_i}(f_\theta) = -\mathbb{E}_{\boldsymbol{x}_t, \boldsymbol{a}_t \sim q_{\mathcal{T}_i}, f_\theta}\left(\sum_{t=1}^H R_{\mathcal{T}_i}(\boldsymbol{x}_t, \boldsymbol{a}_t)\right)$	$\sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}(f_{\theta_i'}) = \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}\left(f_{\boldsymbol{\theta} - \alpha \nabla_{\boldsymbol{\theta}} \mathcal{L}_{\mathcal{T}_i}^{(\text{train})}(f_\theta)}\right)$
Optimization	
$\boldsymbol{\theta}_i' \leftarrow \boldsymbol{\theta} - \alpha \nabla_{\boldsymbol{\theta}} \mathcal{L}_{\mathcal{T}_i}^{(\text{train})}(f_\theta)$	$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \beta \nabla_{\boldsymbol{\theta}} \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}^{(\text{val})}(f_{\theta_i'})$
Forward Pass	
Normal forward-pass	Several model training steps (of task)
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Normal backward-pass (backpropagation)	Backprop gradient of meta-loss through loss on validation data and training process to initial weights

Experiments

Classification

- **Tasks:** Few-shot image recognition/classification: given a single image, classify it
- **Meta-Training:** each task with *N* unseen classes, sampled from larger set of classes
- **Training:** using *K* different instances for each of the *N* classes of the task in each gradient step

Omniglot (Lake et al., 2011)	5-way Accuracy 1-shot	5-way Accuracy 5-shot	20-way Accuracy 1-shot	20-way Accuracy 5-shot
MANN, no conv (Santoro et al., 2016)	82.8%	94.9%	–	–
MANN, no conv (ours)	**89.7 $\pm$ 1.1%**	**97.5 $\pm$ 0.6%**	–	–
Siamese nets (Koch, 2015)	97.3%	98.4%	88.2%	97.0%
matching nets (Vinyals et al., 2016)	98.1%	98.9%	93.8%	98.5%
neural statistician (Edwards & Storkey, 2017)	98.1%	99.5%	93.2%	98.1%
memory mod. (Kaiser et al., 2017)	98.4%	99.6%	95.0%	98.6%
MAML (ours)	**98.7 $\pm$ 0.4%**	**99.9 $\pm$ 0.1%**	**95.8 $\pm$ 0.3%**	**98.9 $\pm$ 0.2%**

MiniImagenet (Ravi & Larochelle, 2017)	5-way Accuracy 1-shot	5-way Accuracy 5-shot
fine-tuning baseline	28.86 $\pm$ 0.54%	49.79 $\pm$ 0.79%
nearest neighbor baseline	41.08 $\pm$ 0.70%	51.04 $\pm$ 0.65%
matching nets (Vinyals et al., 2016)	43.56 $\pm$ 0.84%	55.31 $\pm$ 0.73%
meta-learner LSTM (Ravi & Larochelle, 2017)	43.44 $\pm$ 0.77%	60.60 $\pm$ 0.71%
MAML, first order approx. (ours)	**48.07 $\pm$ 1.75%**	**63.15 $\pm$ 0.91%**
MAML (ours)	**48.70 $\pm$ 1.84%**	**63.11 $\pm$ 0.92%**

Figure: Results of image classification, taken from [FAL17]

Experiments

Regression

- **Tasks:** Sine-wave regression: given x regress y of task-specific sine wave
- **Meta-Training:** each task is sine-wave with different amplitude and phase
- **Training:** using same K samples on unseen wave in each gradient step

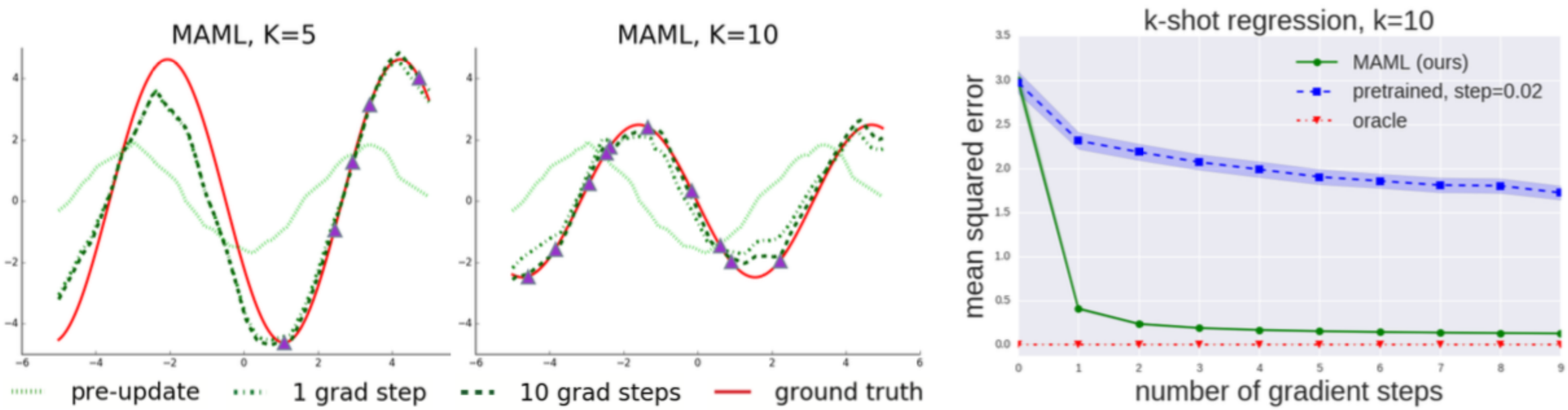

Figure: Results of sine-wave regression, taken from [FAL17]

Experiments

Reinforcement Learning

- **Optimizer:** REINFORCE
- **Meta-Optimizer:** Trut-region policy optimization (TRPO) – with finite differences for Hessian-vector in TRPO (to not compute third derivatives)
- **2D-navigation Tasks:** move to task-specific goal position by controlling velocity
- **Locomotion Tasks:** simulated robot learns to run into task-specific direction with task-specified velocity
- **Meta-Training:** each task with different parameters: goal postition / target direction + velocity
- **Training:** using K rollouts on specific task

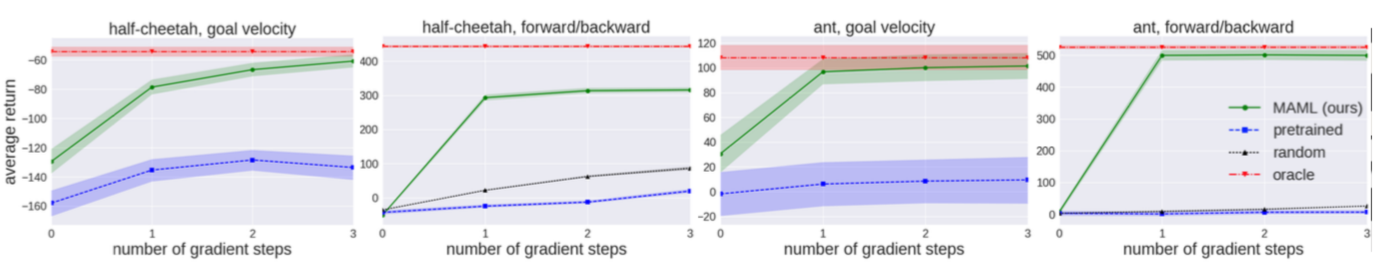

Figure: Results on different locomotion tasks, taken from [FAL17]

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- Computational expensive (second derivative)

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