Meta Learning

Seminar on Deep Neural Networks

Tobias Birchler

ETH Zürich

2021

Outline

Motivation

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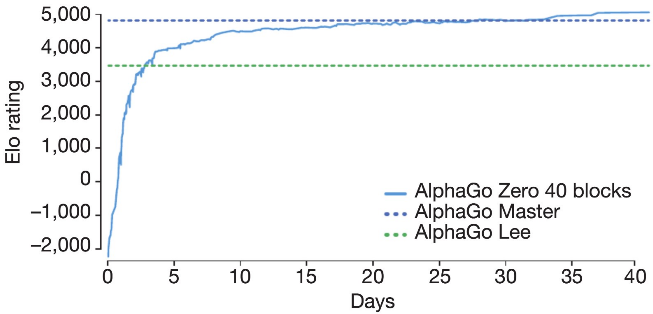
Elo rating
5,000
4,000
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2,000
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5
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Days
AlphaGo Zero 40 blocks
AlphaGo Master
AlphaGo Lee

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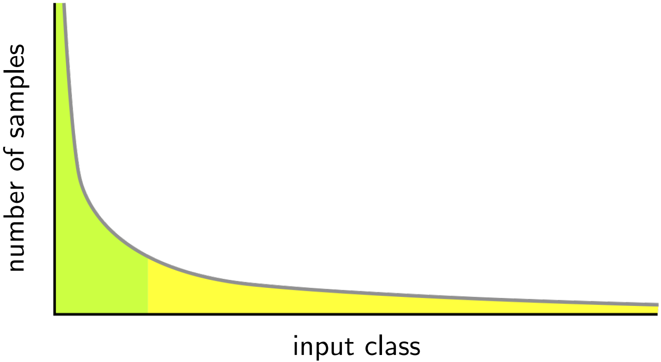
Many RL applications have long tailed state distributions



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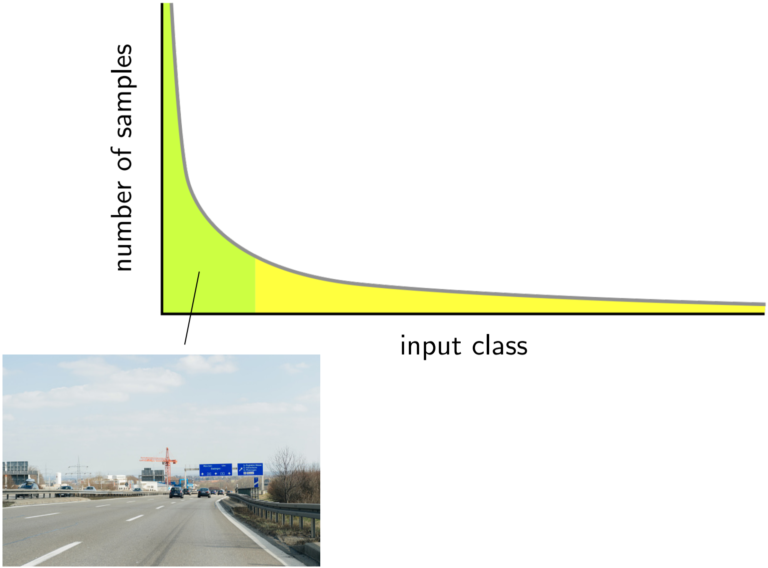

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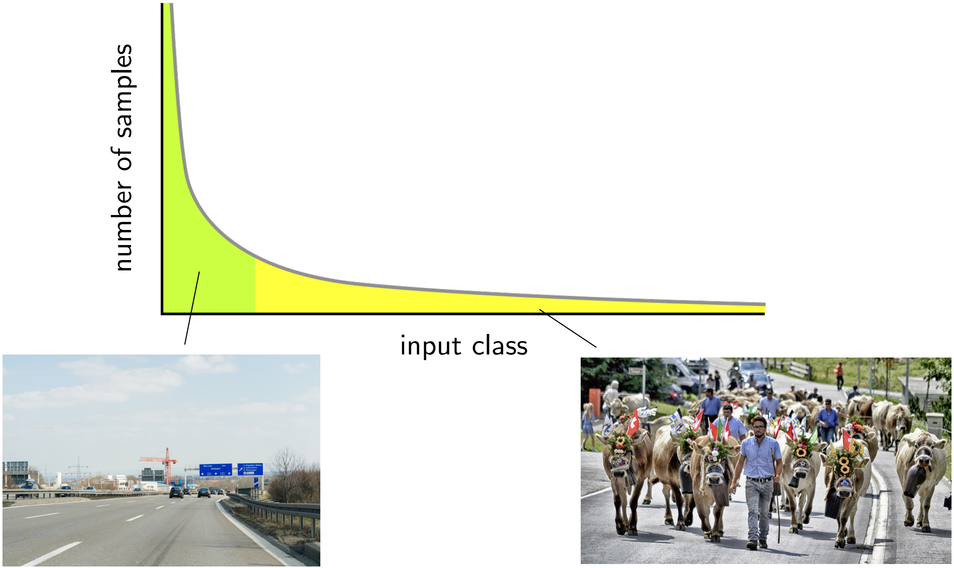

Definition (meta)

referring to itself or to something of its own type (Camebridge Dictionary)

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Remark

Meta Learning is also known as "Learning to Learn"

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training data

Braque Cezanne

test datapoint

By Braque or Cezanne?

Problem Definition - Supervised Learning

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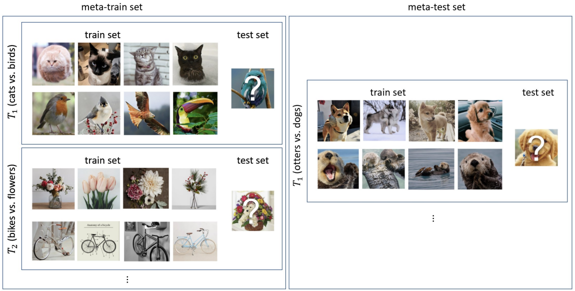

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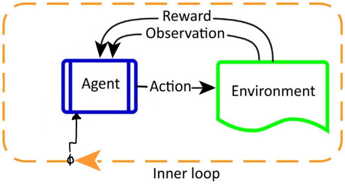

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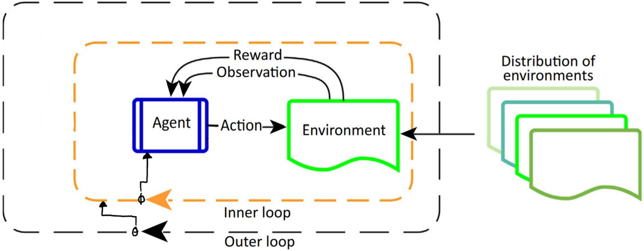

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Models - RL^2

RL^2: Fast Reinforcement Learning via Slow Reinforcement Learning

Yan Duan[†‡], John Schulman[†‡], Xi Chen[†‡], Peter L. Bartlett[†], Ilya Sutskever[‡], Pieter Abbeel[†‡]

Models - RL^2 - Model Definition

In RL^2 A_θ is a RNN (with GRU cells actually).
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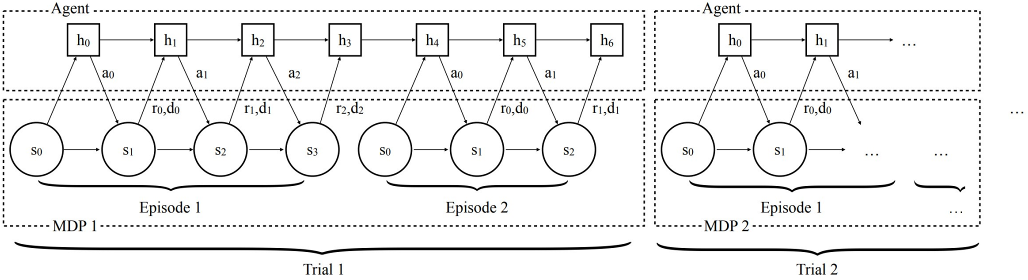

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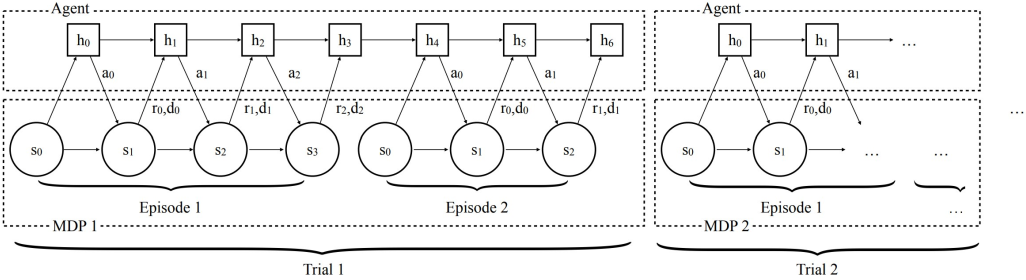
Hidden state activations h can be seen as internal state of the agent.



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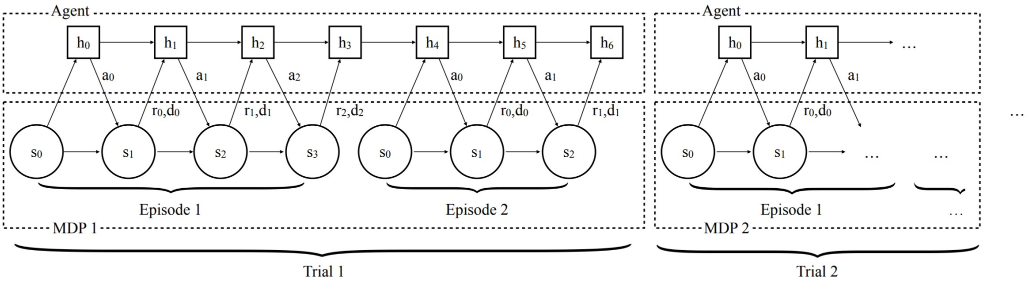

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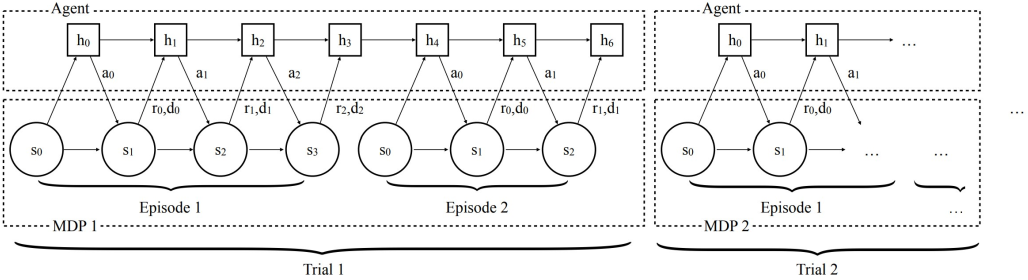

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As meta learning algorithm f the authors use standard TRPO.

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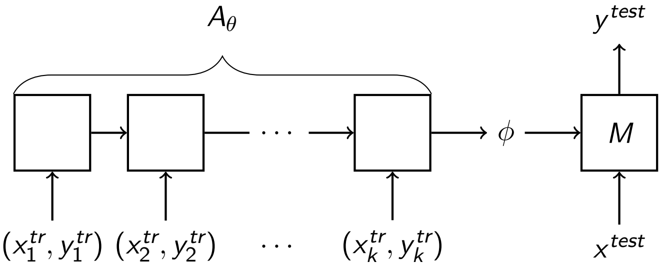
Supervised learning:



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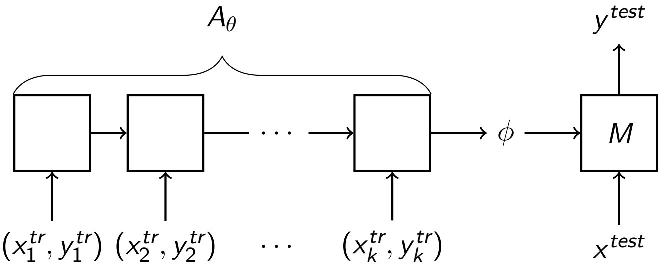


The meta learning algorithm f for such models is usually just an off-the-shelf optimization algorithm (e.g. SGD: $\theta \leftarrow \theta - \alpha \nabla_\theta L_T(M_{A_\theta(T^{\text{tr}})})$).

Models - RL^2 - Results

Table 1: MAB Results. Each grid cell records the total reward averaged over 1000 different instances of the bandit problem. We consider $k \in \{5, 10, 50\}$ bandits and $n \in \{10, 100, 500\}$ episodes of interaction. We highlight the best-performing algorithms in each setup according to the computed mean, and we also highlight the other algorithms in that row whose performance is not significantly different from the best one (determined by a one-sided t-test with $p = 0.05$).

Setup	Random	Gittins	TS	OTS	UCB1	ϵ-Greedy	Greedy	RL^2
$n = 10, k = 5$	5.0	**6.6**	5.7	6.5	**6.7**	**6.6**	**6.6**	**6.7**
$n = 10, k = 10$	5.0	**6.6**	5.5	6.2	**6.7**	**6.6**	**6.6**	**6.7**
$n = 10, k = 50$	5.1	6.5	5.2	5.5	**6.6**	6.5	6.5	**6.8**
$n = 100, k = 5$	49.9	**78.3**	74.7	**77.9**	**78.0**	75.4	74.8	**78.7**
$n = 100, k = 10$	49.9	**82.8**	76.7	81.4	82.4	77.4	77.1	**83.5**
$n = 100, k = 50$	49.8	**85.2**	64.5	67.7	84.3	78.3	78.0	**84.9**
$n = 500, k = 5$	249.8	**405.8**	**402.0**	**406.7**	**405.8**	388.2	380.6	**401.6**
$n = 500, k = 10$	249.0	**437.8**	429.5	**438.9**	**437.1**	408.0	395.0	432.5
$n = 500, k = 50$	249.6	**463.7**	427.2	437.6	457.6	413.6	402.8	438.9

Models - RL^2 - Results

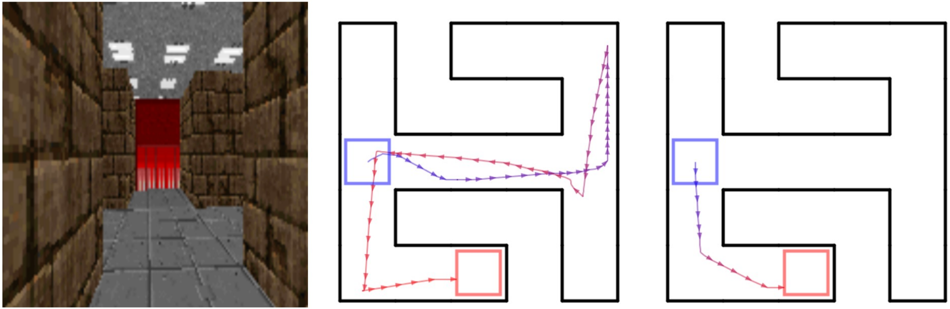
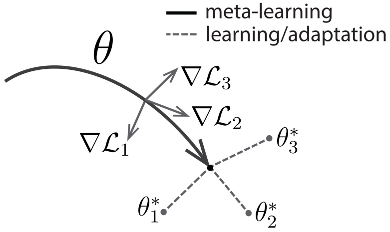


Figure: left: sample input; middle: first episode; right: second episode

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

Chelsea Finn [1] Pieter Abbeel [1 2] Sergey Levine [1]


meta-learning
learning/adaptation
θ
$\nabla\mathcal{L}_3$
$\nabla\mathcal{L}_2$
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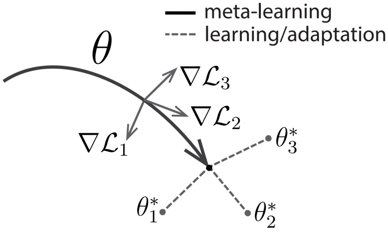
θ_3^*
θ_1^*
θ_2^*



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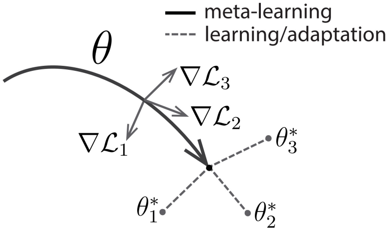

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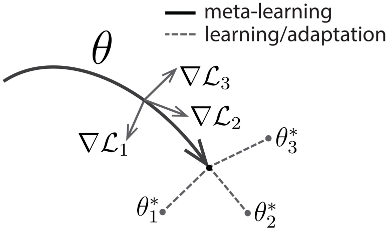
Models - Model Agnostic Meta Learning - Model Definition



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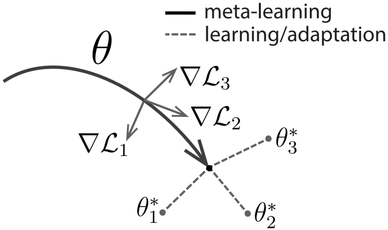

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The meta learning algorithm f can be standard gradient descent with the following update rule

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Models - Model Agnostic Meta Learning - Model Class

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Possibile meta parameters are initialisation, learning rate, the entire update and more.

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We get k different samples for each of n different unseen classes and evaluate the model's ability to classify new instances within the n classes.

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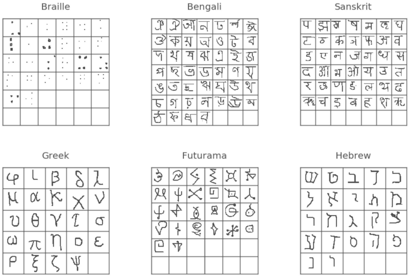
Omniglot data set: 1623 handwritten characters from 50 alphabets, 20 samples per character

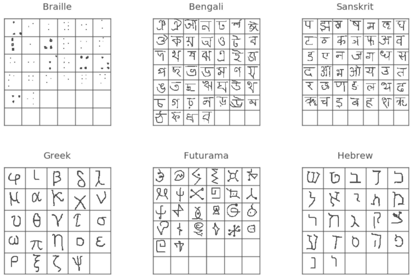


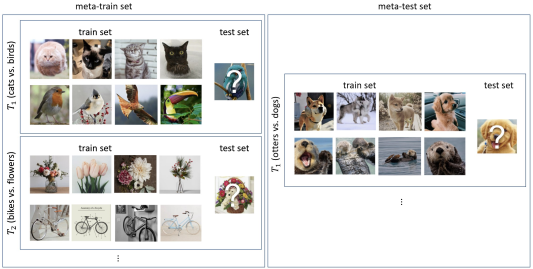
Definition (n-way k-shot classification)

We get k different samples for each of n different unseen classes and evaluate the model's ability to classify new instances within the n classes.

Omniglot data set: 1623 handwritten characters from 50 alphabets, 20 samples per character

MiniImagenet data set: 64 training classes, 12 validation classes, 24 test classes



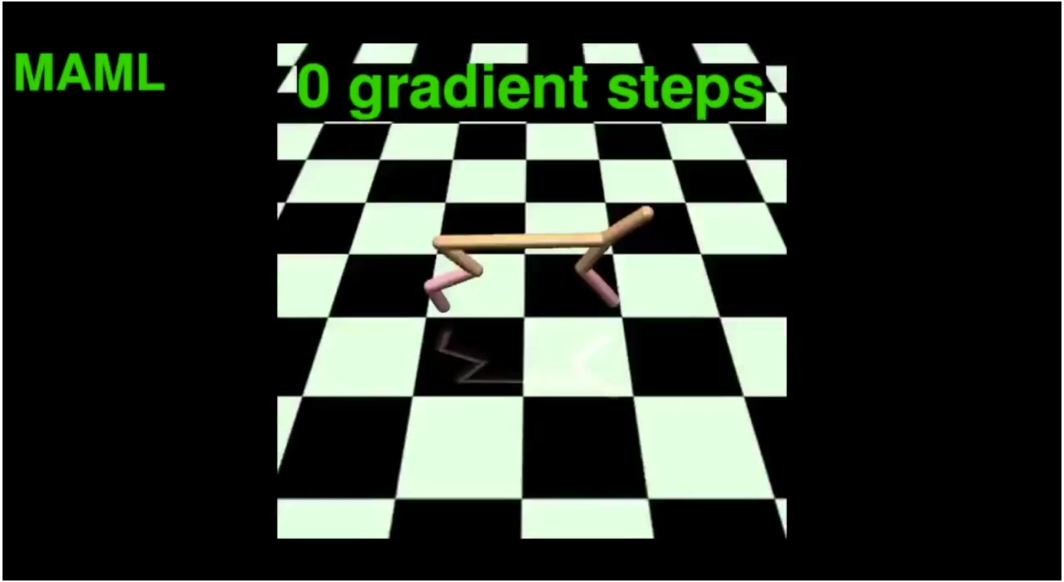


Models - Model Agnostic Meta Learning - Results

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%	–	–
MAML, no conv (ours)	**89.7 ± 1.1%**	**97.5 ± 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 ± 0.4%**	**99.9 ± 0.1%**	**95.8 ± 0.3%**	**98.9 ± 0.2%**

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

Models - Model Agnostic Meta Learning - Results



Summary

- The idea of Meta Learning is to optimize the parameterised learning algorithm for a class of tasks.
- RL^2 solves the problem by applying a RL algorithm to learn a RNN which represents the RL algorithm (applies RL to RL).
- MAML searches for a good initialisation of gradient based models.
- MAML does scale very well and is broadly applied.

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Q&A

Some interesting questions:

- What is the meta learning algorithm and meta parameters of animals/nature?
- Have we formulated the problem we might want to solve with meta learning?

Why there are no higher order terms in multi-step MAML:

$$
\begin{aligned}
\nabla_\theta A_\theta(T^{\text{tr}}) &= \nabla_\theta(\theta' - \alpha \nabla_{\theta'} L_T(M_{\theta'})) \\
&= \nabla_\theta(\theta - \alpha \nabla_\theta L_T(M_\theta) - \alpha \nabla_{\theta'} L_T(M_{\theta'})) \\
&= I - \alpha \nabla_\theta^2 L_T(M_\theta) - \alpha \nabla_{\theta'}^2 L_T(M_{\theta'}) \frac{\partial \theta'}{\partial \theta}
\end{aligned}
$$