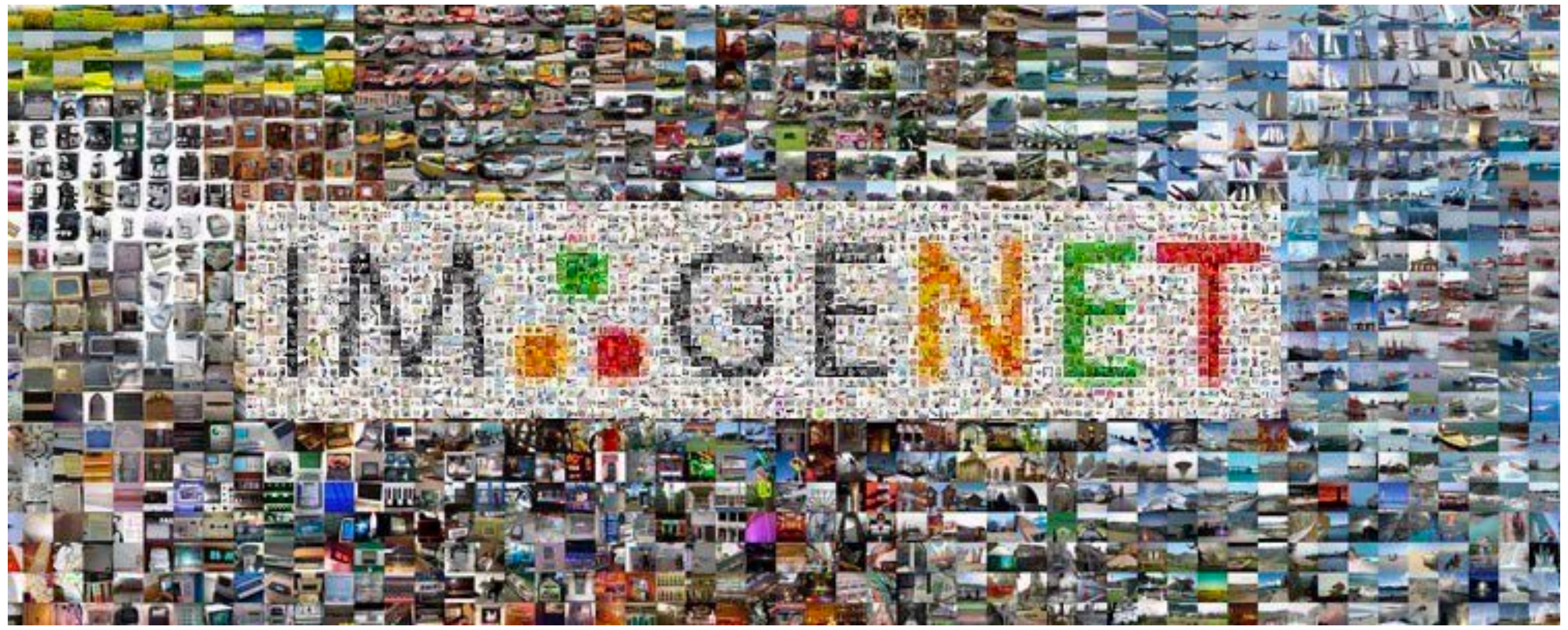
Meta-Learning: from Few-Shot Learning to Rapid Reinforcement Learning

Chelsea Finn Sergey Levine

Qs: slido.com/meta

Large, diverse data (+ large models) → Broad generalization



Russakovsky et al. '14

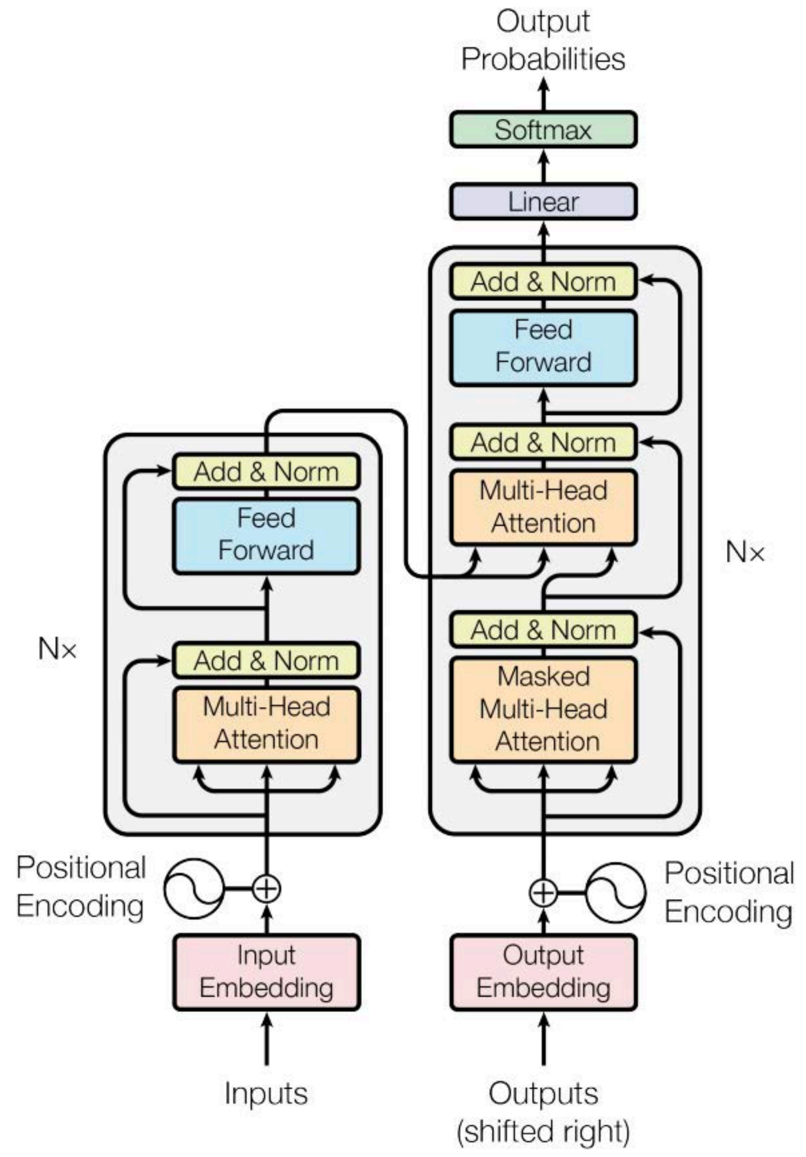


Figure 1: The Transformer - model architecture.

Vaswani et al. '18

GPT-2

Radford et al. '19

Under the paradigm of supervised learning.

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What if you don't have a large dataset?

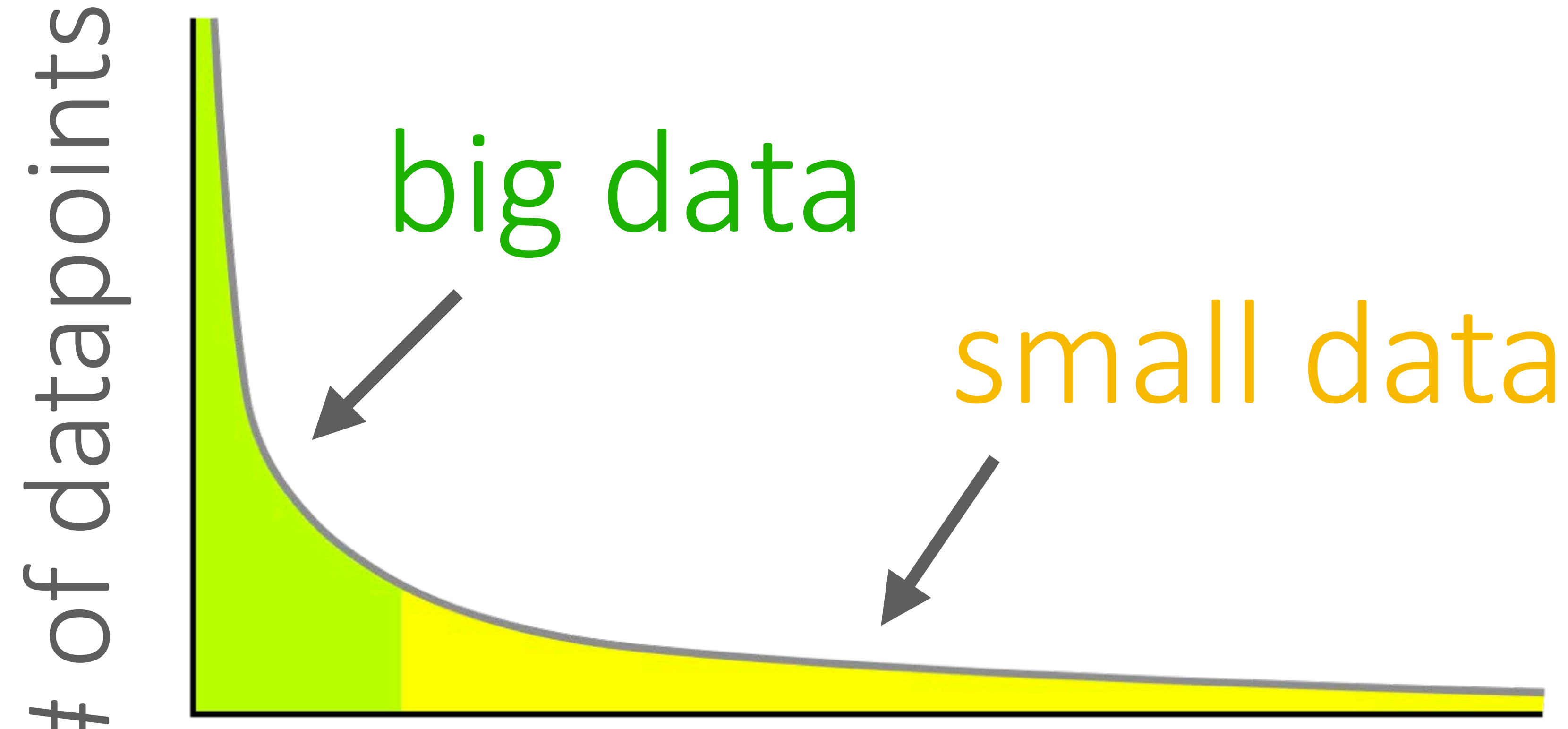
medical imaging robotics personalized education,
translation for rare languages recommendations

What if you want a general-purpose AI system in the real world?

Need to continuously adapt and learn on the job.

Learning each thing from scratch won't cut it.

What if your data has a long tail?



These settings break the supervised learning paradigm.

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training data

Braque

Cezanne

test datapoint

By Braque or Cezanne?

How did you accomplish this?

Through previous experience.

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How might you get a machine to accomplish this task?

Modeling image formation

Geometry

SIFT features, HOG features + SVM

Fine-tuning from ImageNet features
Domain adaptation from other painters

???

Fewer human priors,
more data-driven priors

Greater success.

Can we explicitly learn priors from previous experience
that lead to efficient downstream learning?

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Can we learn to learn?

Outline

- **Problem statement**
- Meta-learning **algorithms**
  - Black-box adaptation
  - Optimization-based inference
  - Non-parametric methods
  - Bayesian meta-learning
- Meta-learning **applications**

— 5 min break —

- Meta-**reinforcement** learning
- Challenges & frontiers

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Two ways to view meta-learning

Mechanistic view

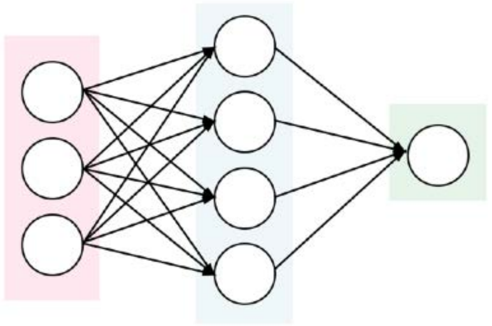
- Deep neural network model that can read in an entire dataset and make predictions for new datapoints
- Training this network uses a meta-dataset, which itself consists of many datasets, each for a different task
- This view makes it easier to implement meta-learning algorithms

Probabilistic view

- Extract prior information from a set of (meta-training) tasks that allows efficient learning of new tasks
- Learning a new task uses this prior and (small) training set to infer most likely posterior parameters
- This view makes it easier to understand meta-learning algorithms

Problem definitions

supervised learning:



$$\arg\max_{\phi} \log p(\phi|\mathcal{D})$$

model parameters

training data

$$\mathcal{D} = \{(x_1, y_1), \ldots, (x_k, y_k)\}$$

input (e.g., image)

label

$$= \arg\max_{\phi} \log p(\mathcal{D}|\phi) + \log p(\phi)$$

data likelihood

regularizer (e.g., weight decay)

$$= \arg\max_{\phi} \sum_i \log p(y_i|x_i, \phi) + \log p(\phi)$$

What is wrong with this?

- ➢ The most powerful models typically require large amounts of labeled data
- ➢ Labeled data for some tasks may be very limited

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Problem definitions

supervised learning:

$$\arg\max_{\phi} \log p(\phi|\mathcal{D})$$

$$\mathcal{D} = \{(x_1, y_1), \ldots, (x_k, y_k)\}$$

can we incorporate *additional* data?

$$\mathcal{D}_{\text{meta-train}} = \{\mathcal{D}_1, \ldots, \mathcal{D}_n\}$$

$$\arg\max_{\phi} \log p(\phi|\mathcal{D}, \mathcal{D}_{\text{meta-train}})$$

$$\mathcal{D}_i = \{(x_1^i, y_1^i), \ldots, (x_k^i, y_k^i)\}$$

$\mathcal{D}$

$\mathcal{D}_{\text{meta-train}}$ $\mathcal{D}_1$

$\mathcal{D}_2$

⋮

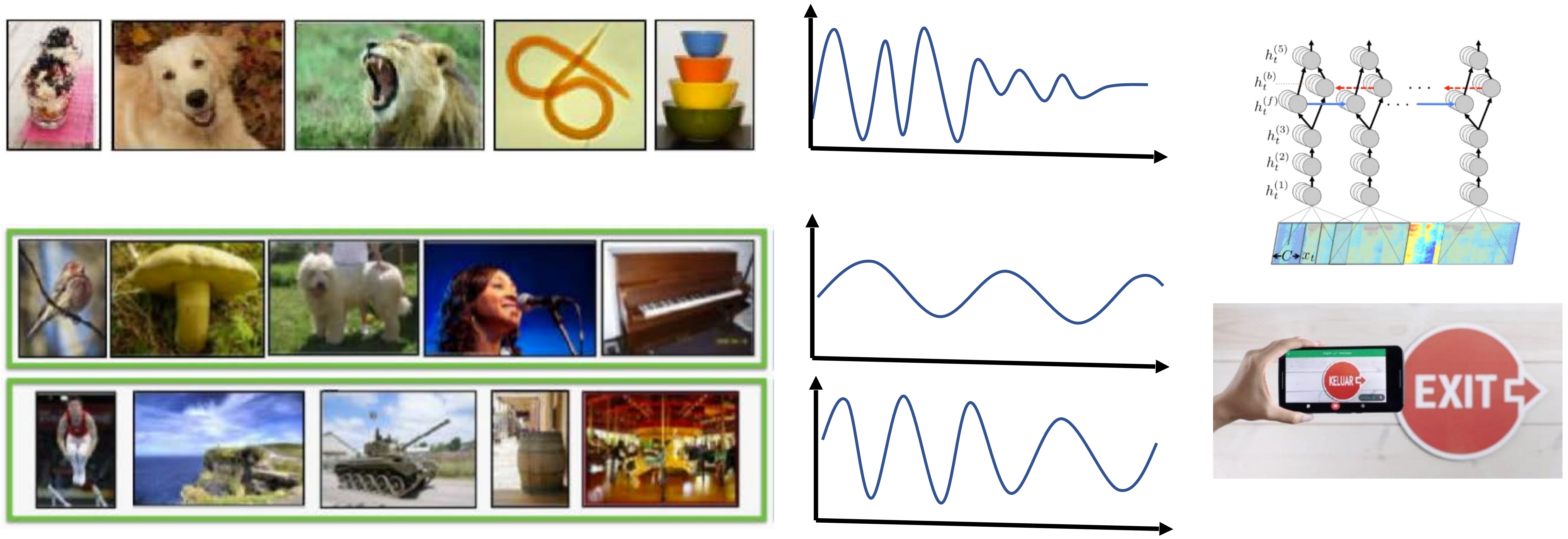

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Image adapted from Ravi & Larochelle

The meta-learning problem

meta-learning:

$$\arg\max_{\phi} \log p(\phi|\mathcal{D}, \mathcal{D}_{\text{meta-train}})$$

$$\mathcal{D} = \{(x_1, y_1), \ldots, (x_k, y_k)\}$$

$$\mathcal{D}_{\text{meta-train}} = \{\mathcal{D}_1, \ldots, \mathcal{D}_n\}$$

$$\mathcal{D}_i = \{(x_1^i, y_1^i), \ldots, (x_k^i, y_k^i)\}$$

what if we don't want to keep $\mathcal{D}_{\text{meta-train}}$ around forever?

learn *meta-parameters* θ: $p(\theta|\mathcal{D}_{\text{meta-train}})$

whatever we need to know about $\mathcal{D}_{\text{meta-train}}$ to solve new tasks

this is the meta-learning problem

$$\theta^\star = \arg\max_{\theta} \log p(\theta|\mathcal{D}_{\text{meta-train}})$$

assume $\phi \perp\!\!\!\perp \mathcal{D}_{\text{meta-train}}|\theta$

$$\log p(\phi|\mathcal{D}, \mathcal{D}_{\text{meta-train}}) = \log \int_{\Theta} p(\phi|\mathcal{D}, \theta) p(\theta|\mathcal{D}_{\text{meta-train}}) d\theta$$

$$\approx \log p(\phi|\mathcal{D}, \theta^\star) + \log p(\theta^\star|\mathcal{D}_{\text{meta-train}})$$

$$\arg\max_{\phi} \log p(\phi|\mathcal{D}, \mathcal{D}_{\text{meta-train}}) \approx \arg\max_{\phi} \log p(\phi|\mathcal{D}, \theta^\star)$$

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A Quick Example

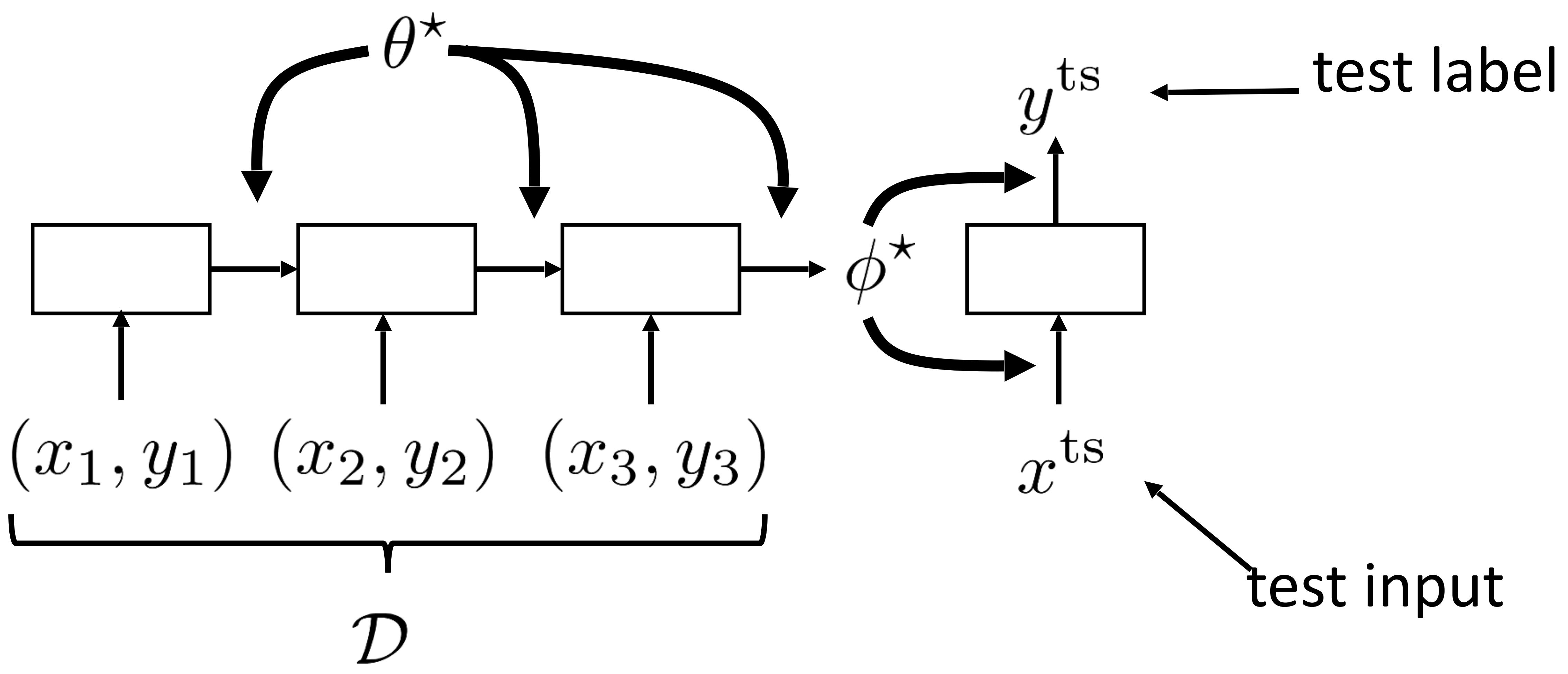
$$\text{meta-learning: } \theta^\star = \arg\max_\theta \log p(\theta|\mathcal{D}_{\text{meta-train}})$$

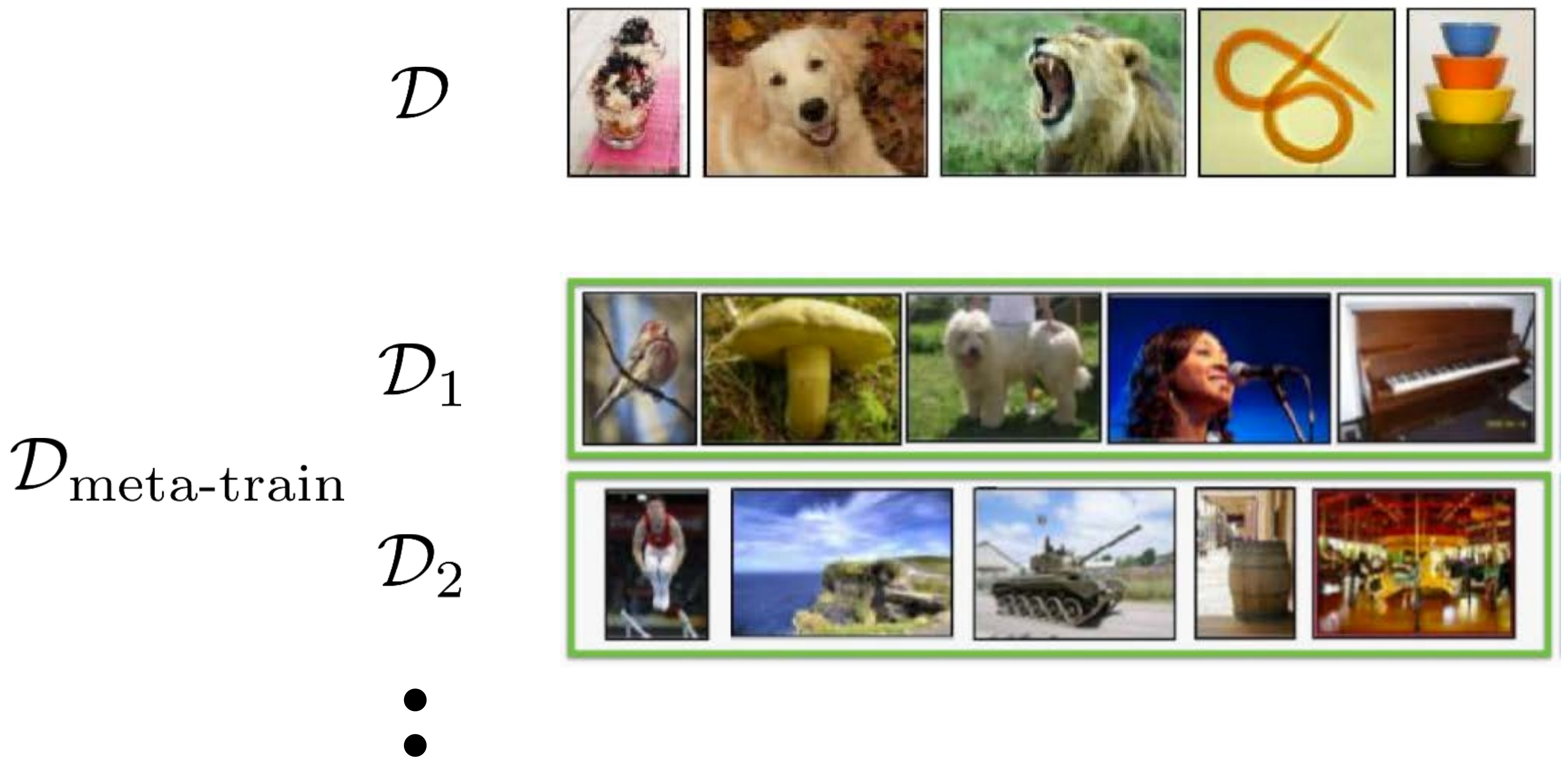
$$\boxed{\text{adaptation: } \phi^\star = \arg\max_\phi \log p(\phi|\mathcal{D}, \theta^\star)}$$

$$\mathcal{D} = \{(x_1, y_1), \ldots, (x_k, y_k)\}$$

$$\mathcal{D}_{\text{meta-train}} = \{\mathcal{D}_1, \ldots, \mathcal{D}_n\}$$

$$\mathcal{D}_i = \{(x_1^i, y_1^i), \ldots, (x_k^i, y_k^i)\}$$





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How do we train this thing?

$$\boxed{\text{meta-learning: } \theta^\star = \arg\max_\theta \log p(\theta|\mathcal{D}_{\text{meta-train}})}$$

$$\text{adaptation: } \phi^\star = \arg\max_\phi \log p(\phi|\mathcal{D}, \theta^\star)$$

$$\mathcal{D} = \{(x_1, y_1), \ldots, (x_k, y_k)\}$$

$$\mathcal{D}_{\text{meta-train}} = \{\mathcal{D}_1, \ldots, \mathcal{D}_n\}$$

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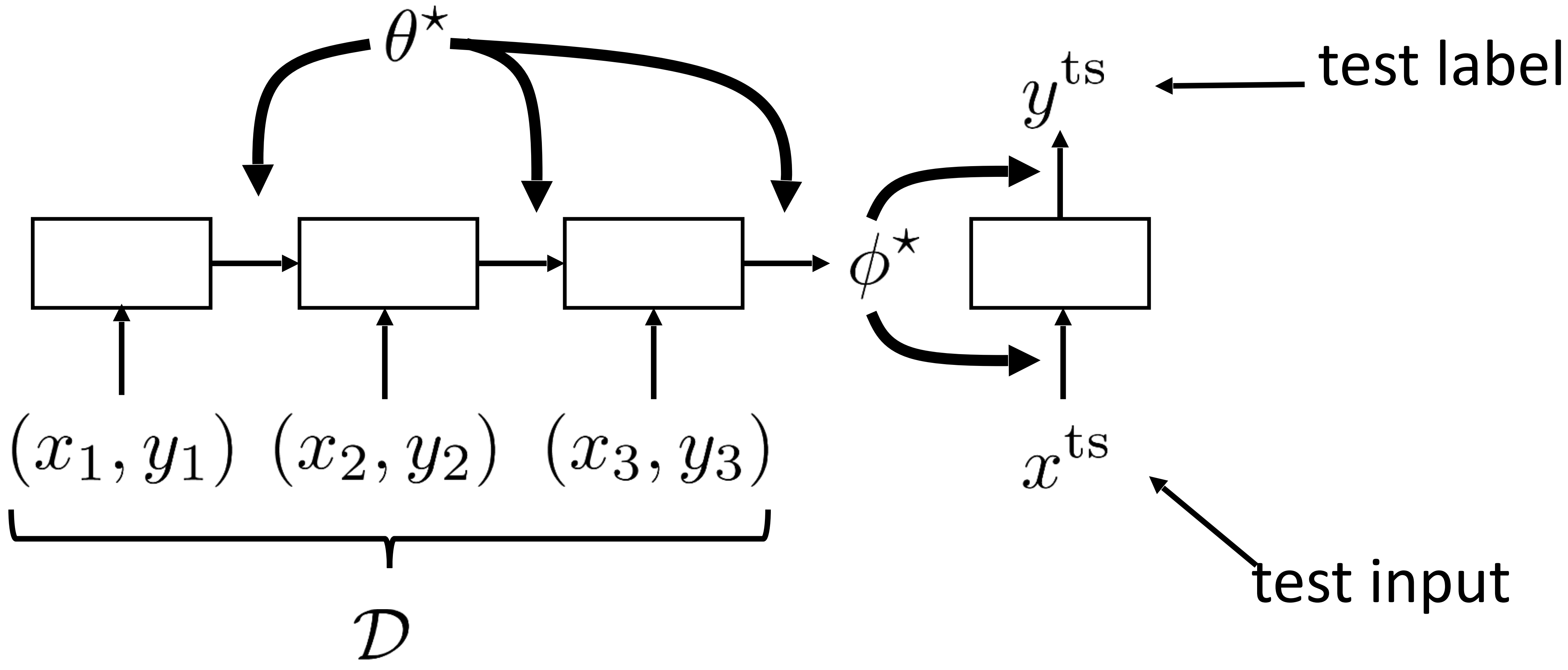
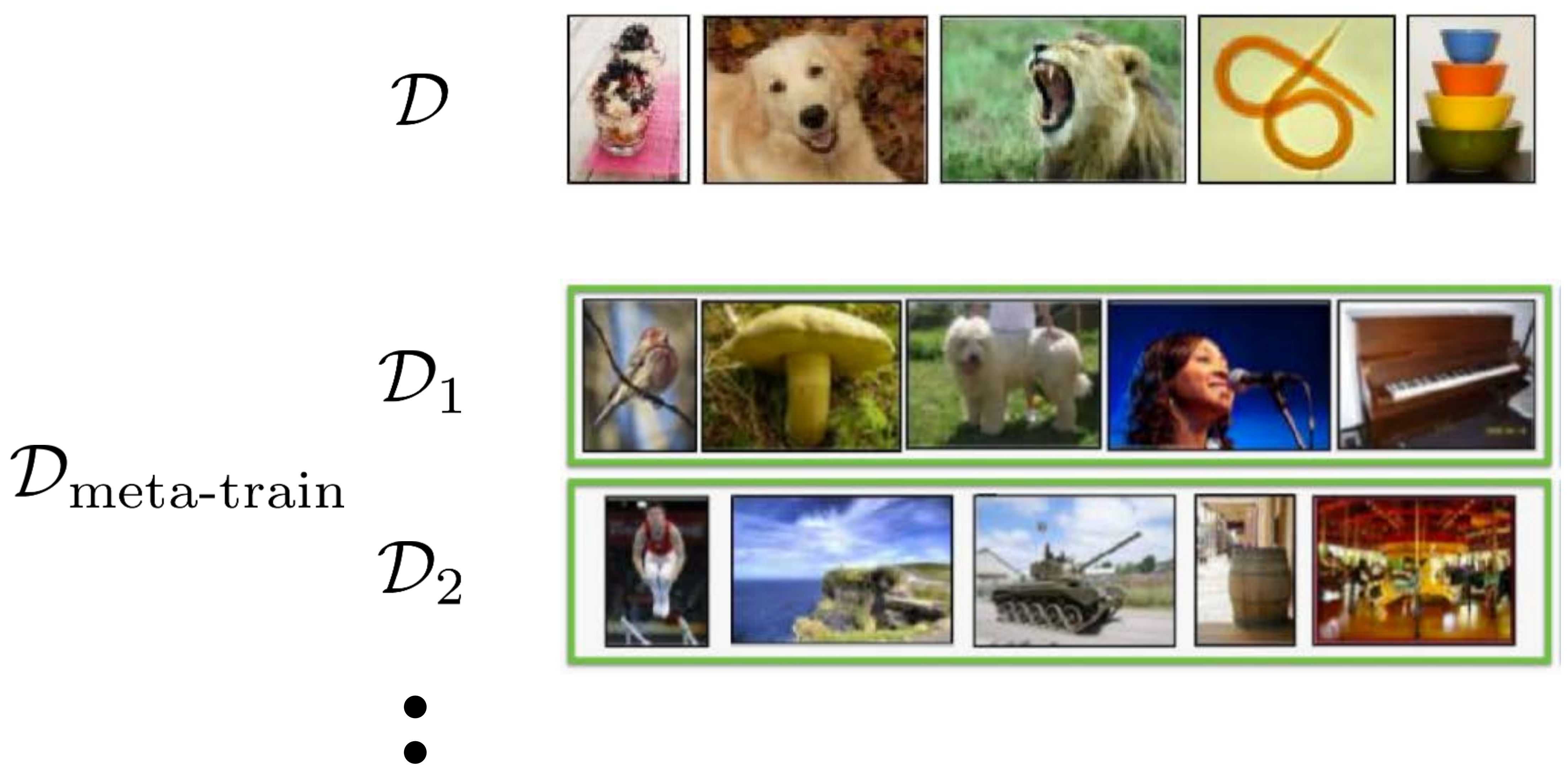




Key idea:

"our training procedure is based on a simple machine learning principle: test and train conditions must match"

Vinyals et al., Matching Networks for One-Shot Learning

Qs: slido.com/meta

How do we train this thing?

$$\boxed{\text{meta-learning: } \theta^\star = \arg\max_\theta \log p(\theta | \mathcal{D}_{\text{meta-train}})}$$

$$\text{adaptation: } \phi^\star = \arg\max_\phi \log p(\phi | \mathcal{D}, \theta^\star)$$

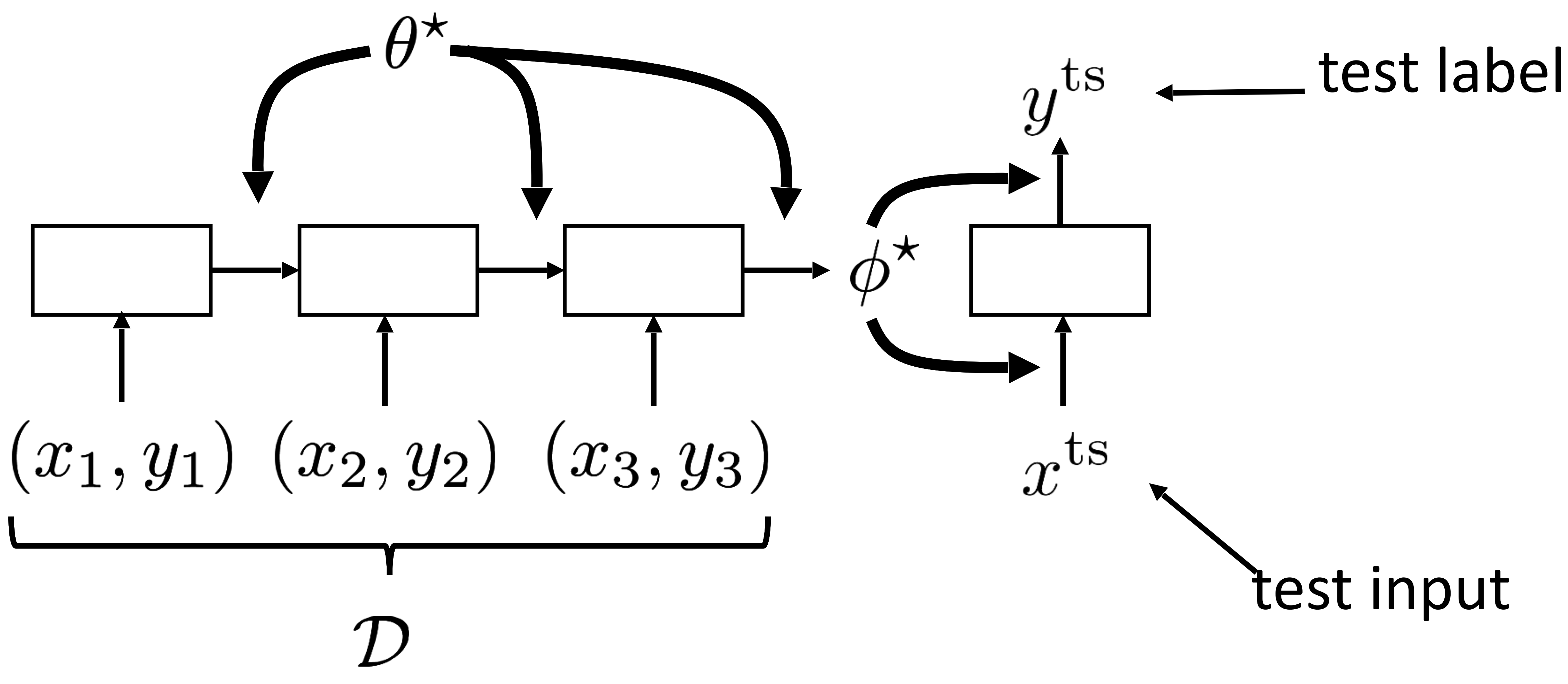
(meta) test-time

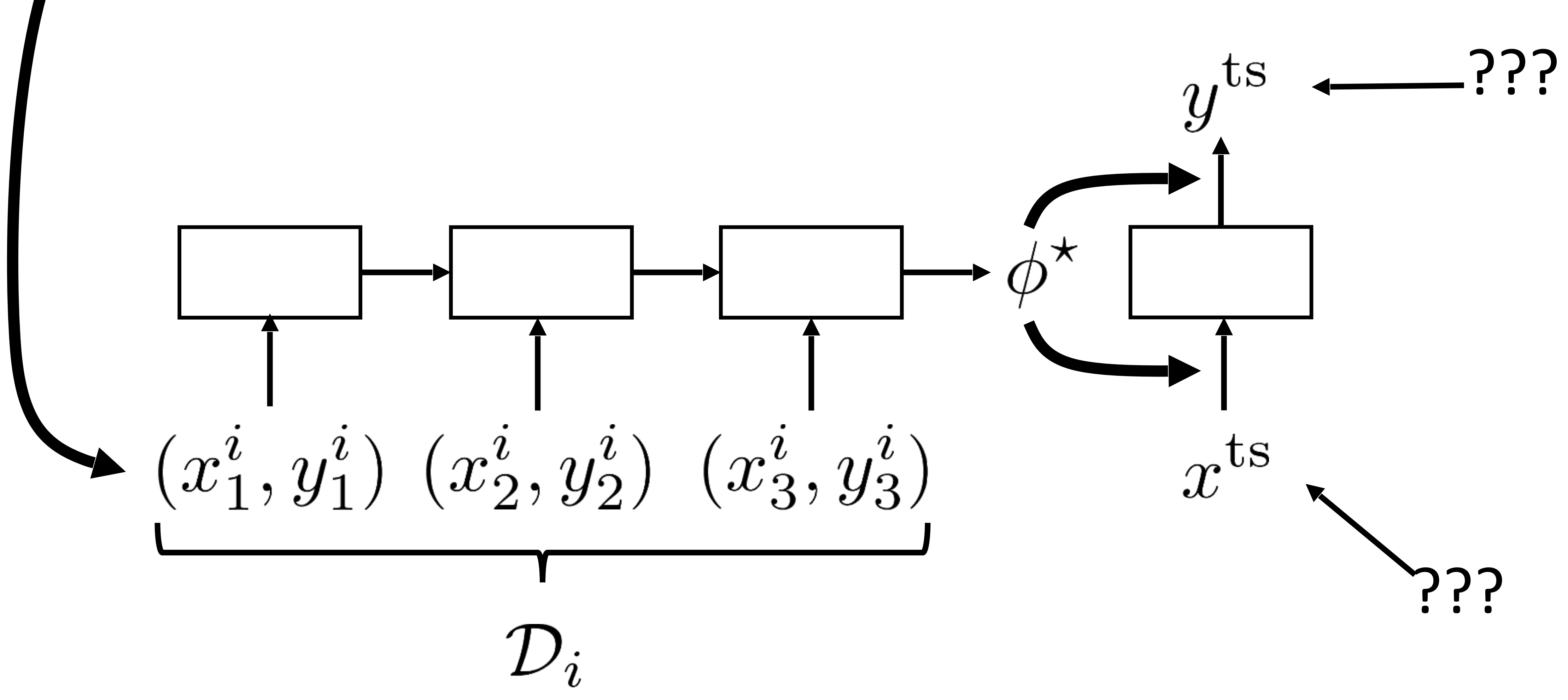
$$\mathcal{D} = \{(x_1, y_1), \ldots, (x_k, y_k)\}$$

$$\mathcal{D}_{\text{meta-train}} = \{\mathcal{D}_1, \ldots, \mathcal{D}_n\}$$

$$\mathcal{D}_i = \{(x_1^i, y_1^i), \ldots, (x_k^i, y_k^i)\}$$

(meta) training-time





Key idea:
"our training procedure is based on a simple machine learning principle: test and train conditions must match"

Vinyals et al., Matching Networks for One-Shot Learning

Qs: slido.com/meta

Reserve a test set for each task!

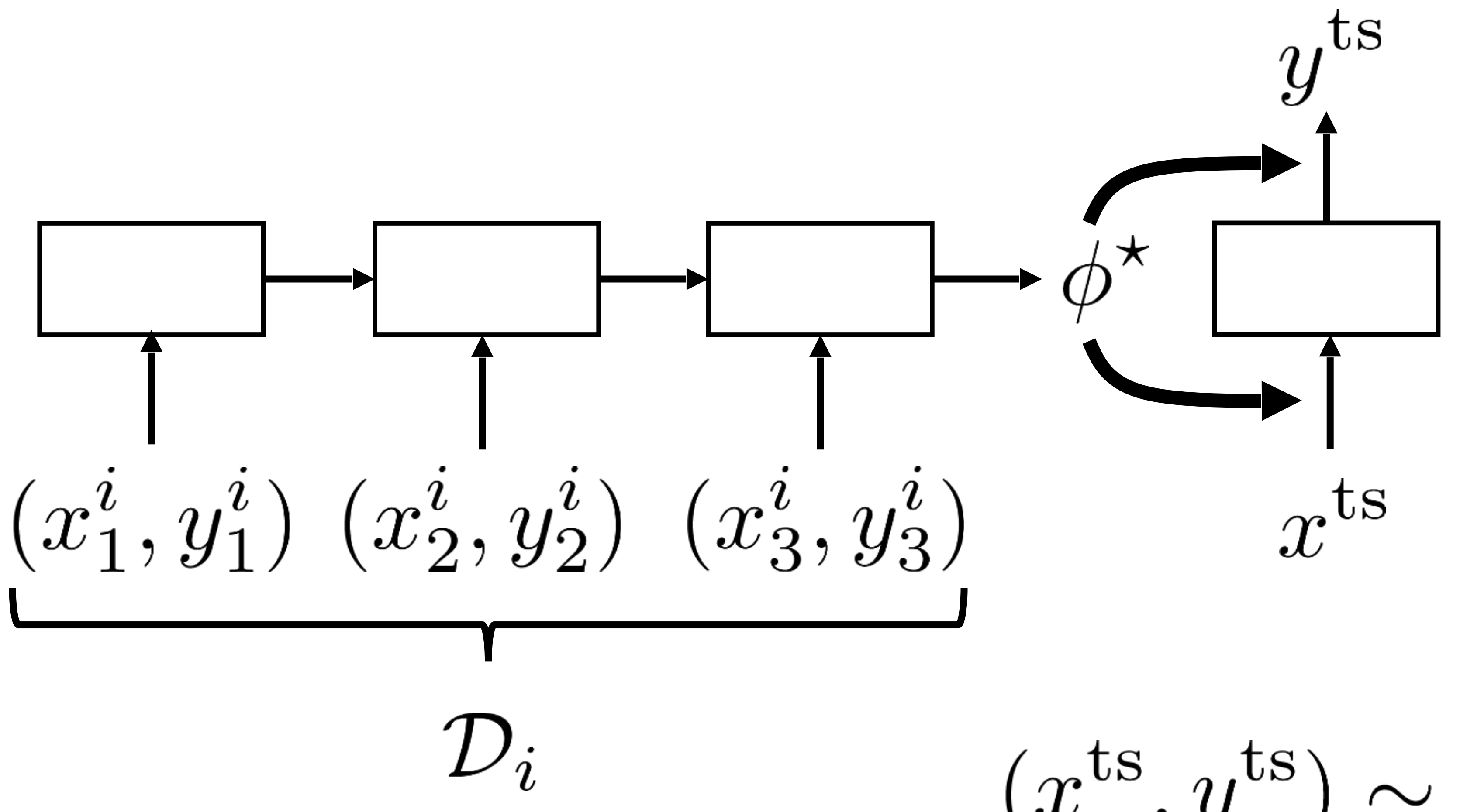
$\mathcal{D}_{\text{meta-train}}$ $\mathcal{D}_1$ $\mathcal{D}_2$ $\vdots$

$$\mathcal{D}_{\text{meta-train}} = \{(\mathcal{D}_1^{\text{tr}}, \mathcal{D}_1^{\text{ts}}), \ldots, (\mathcal{D}_n^{\text{tr}}, \mathcal{D}_n^{\text{ts}})\}$$

$$\mathcal{D}_i^{\text{tr}} = \{(x_1^i, y_1^i), \ldots, (x_k^i, y_k^i)\}$$

$$\mathcal{D}_i^{\text{ts}} = \{(x_1^i, y_1^i), \ldots, (x_l^i, y_l^i)\}$$

(meta) training-time



$(x^{\text{ts}}, y^{\text{ts}}) \sim \mathcal{D}_i^{\text{ts}}$

Key idea:
"our training procedure is based on a simple machine learning principle: test and train conditions must match"

Vinyals et al., Matching Networks for One-Shot Learning

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The complete meta-learning optimization

meta-learning: $\theta^\star = \arg\max_\theta \log p(\theta | \mathcal{D}_{\text{meta-train}})$

adaptation: $\phi^\star = \arg\max_\phi \log p(\phi | \mathcal{D}^{\text{tr}}, \theta^\star)$

$\Updownarrow$

$\phi^\star = f_{\theta^\star}(\mathcal{D}^{\text{tr}})$

learn θ such that $\phi = f_\theta(\mathcal{D}_i^{\text{tr}})$ is good for $\mathcal{D}_i^{\text{ts}}$

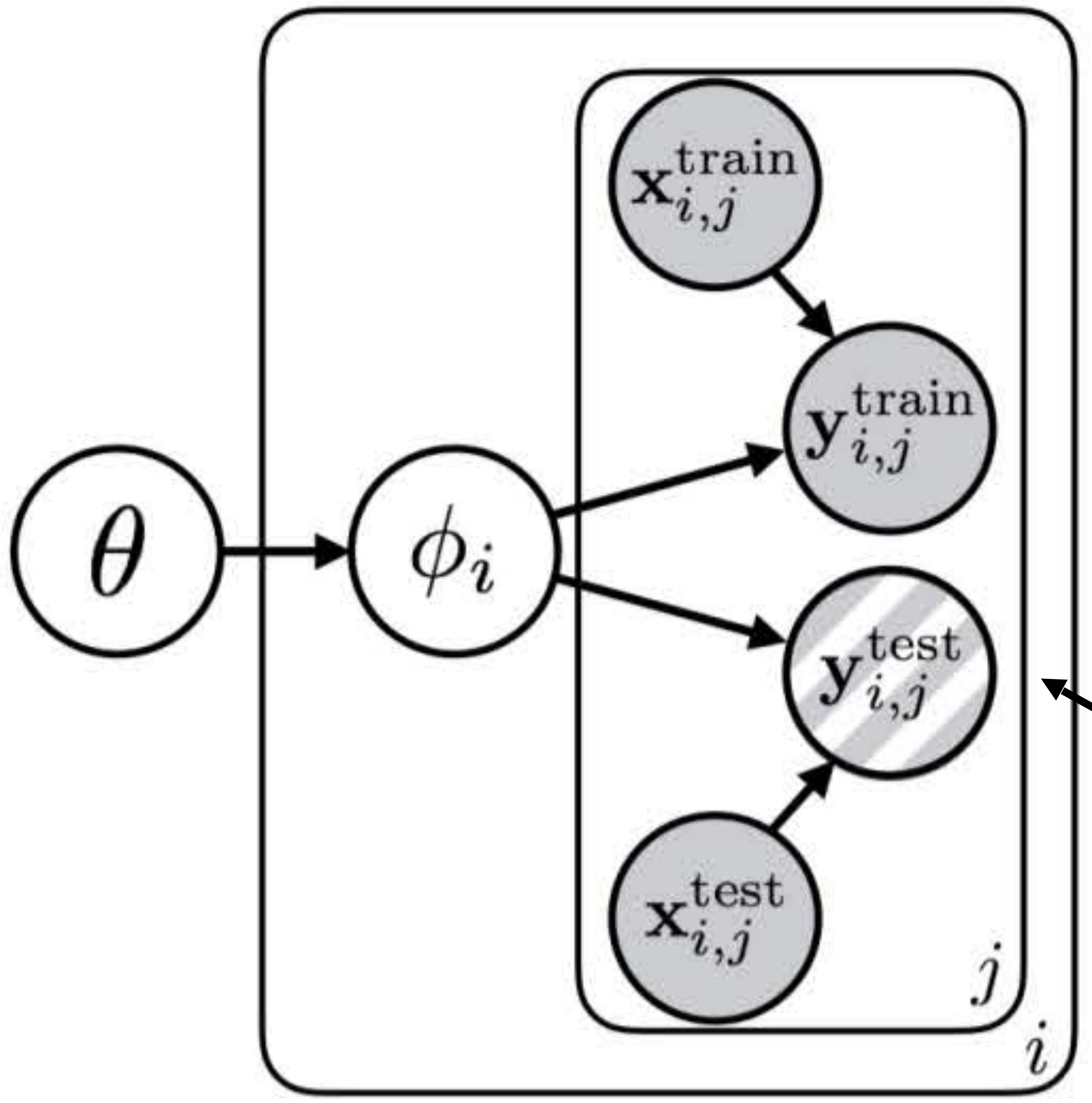
$$\theta^\star = \max_\theta \sum_{i=1}^{n} \log p(\phi_i | \mathcal{D}_i^{\text{ts}})$$

where $\phi_i = f_\theta(\mathcal{D}_i^{\text{tr}})$

$\mathcal{D}_{\text{meta-train}} = \{(\mathcal{D}_1^{\text{tr}}, \mathcal{D}_1^{\text{ts}}), \ldots, (\mathcal{D}_n^{\text{tr}}, \mathcal{D}_n^{\text{ts}})\}$

$\mathcal{D}_i^{\text{tr}} = \{(x_1^i, y_1^i), \ldots, (x_k^i, y_k^i)\}$

$\mathcal{D}_i^{\text{ts}} = \{(x_1^i, y_1^i), \ldots, (x_l^i, y_l^i)\}$



unobserved at meta-test time

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Some meta-learning terminology

learn θ such that $\phi_i = f_\theta(\mathcal{D}_i^{\text{tr}})$ is good for $\mathcal{D}_i^{\text{ts}}$

$$\theta^\star = \arg\max_\theta \sum_{i=1}^{n} \log p(\phi_i | \mathcal{D}_i^{\text{ts}})$$

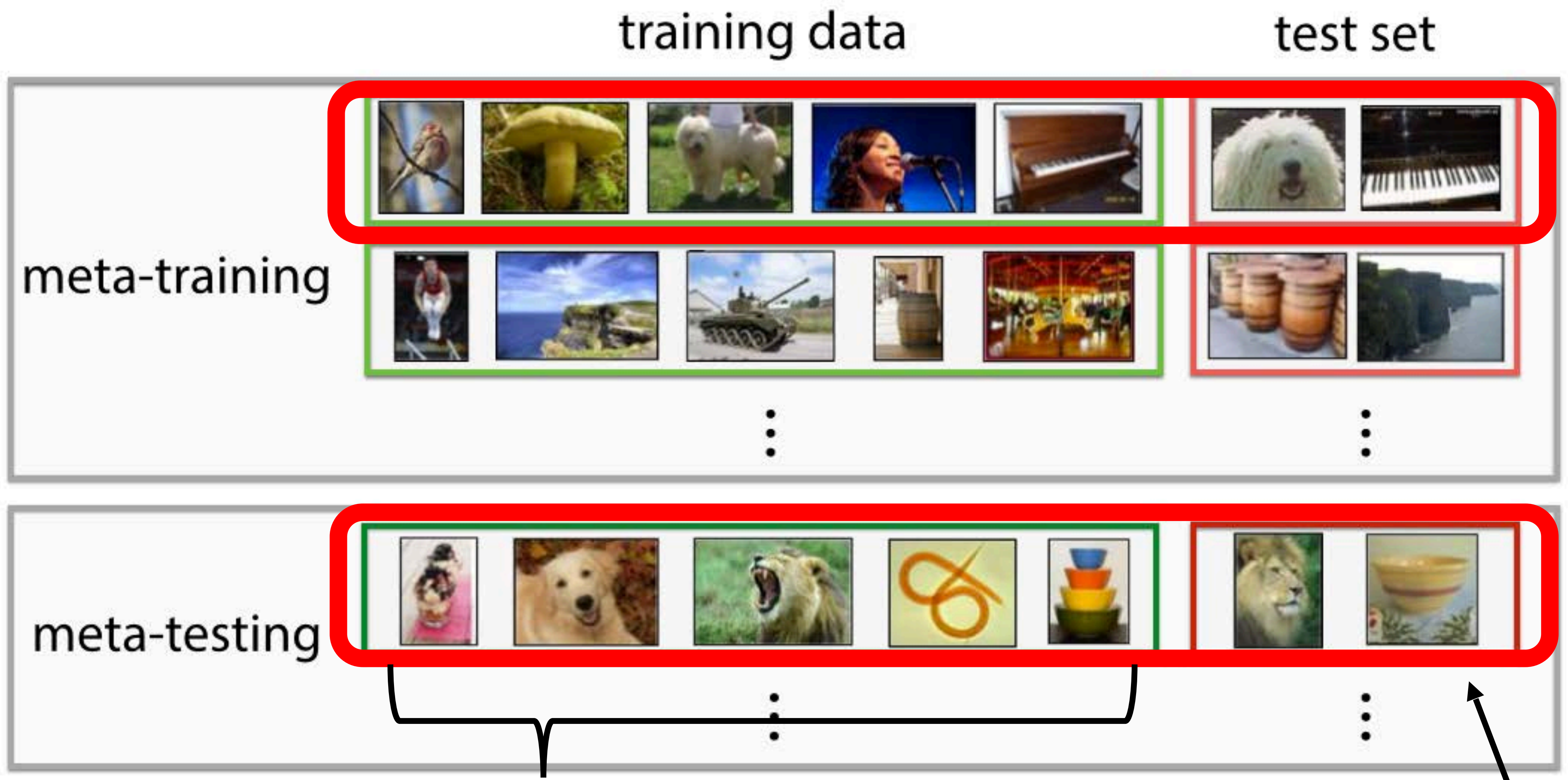
where $\phi_i = f_\theta(\mathcal{D}_i^{\text{tr}})$

$$\mathcal{D}_{\text{meta-train}} = \{(\mathcal{D}_1^{\text{tr}}, \mathcal{D}_1^{\text{ts}}), \dots, (\mathcal{D}_n^{\text{tr}}, \mathcal{D}_n^{\text{ts}})\}$$

$$\mathcal{T}_i \begin{cases} \mathcal{D}_i^{\text{tr}} = \{(x_1^i, y_1^i), \dots, (x_k^i, y_k^i)\} \\ \mathcal{D}_i^{\text{ts}} = \{(x_1^i, y_1^i), \dots, (x_l^i, y_l^i)\} \end{cases}$$

shot

(i.e., k-shot, 5-shot)



(meta-training) task $\mathcal{T}_i$

$\mathcal{D}_1$

$\mathcal{D}_2$

$\mathcal{D}_{\text{meta-train}}$

(meta-test) task

support (set)

query

image credit: Ravi & Larochelle '17

Closely related problem settings

meta-learning:

$$\theta^\star = \max_\theta \sum_{i=1}^{n} \log p(\phi_i|\mathcal{D}_i^{\text{ts}})$$

where $\phi_i = f_\theta(\mathcal{D}_i^{\text{tr}})$

$$\mathcal{D}_{\text{meta-train}} = \{(\mathcal{D}_1^{\text{tr}}, \mathcal{D}_1^{\text{ts}}), \dots, (\mathcal{D}_n^{\text{tr}}, \mathcal{D}_n^{\text{ts}})\}$$

$$\mathcal{D}_i^{\text{tr}} = \{(x_1^i, y_1^i), \dots, (x_k^i, y_k^i)\}$$

$$\mathcal{D}_i^{\text{ts}} = \{(x_1^i, y_1^i), \dots, (x_l^i, y_l^i)\}$$

multi-task learning: learn model with parameters $\theta^\star$ that solves multiple tasks $\theta^\star = \arg\max_\theta \sum_{i=1}^{n} \log p(\theta|\mathcal{D}_i)$

can be seen as special case where $\phi_i = \theta$ (i.e., $f_\theta(\mathcal{D}_i) = \theta$)

hyperparameter optimization & auto-ML: can be cast as meta-learning

hyperparameter optimization: θ = hyperparameters, ϕ = network weights

architecture search: θ = architecture, ϕ = network weights

very active area of research! but outside the scope of this tutorial

Qs: slido.com/meta

Outline

- **Problem statement**
- Meta-learning **algorithms**
  - Black-box adaptation
  - Optimization-based inference
  - Non-parametric methods
  - Bayesian meta-learning
- Meta-learning **applications**

— 5 min break —

- Meta-**reinforcement** learning
- Challenges & frontiers

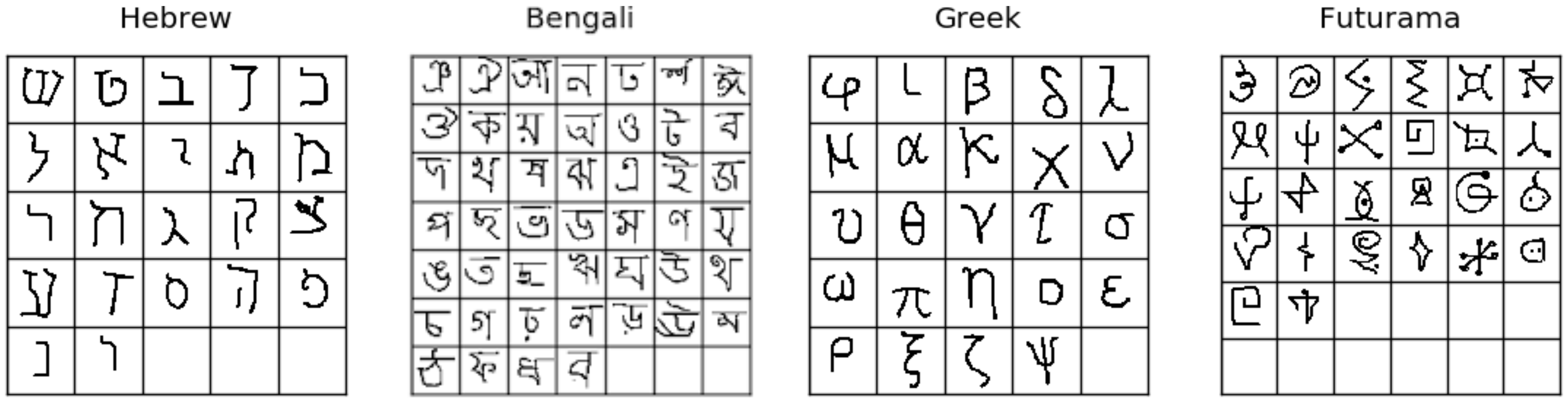
Qs: slido.com/meta

General recipe

How to *evaluate* a meta-learning algorithm

the Omniglot dataset   Lake et al. Science 2015

1623 characters from **50 different alphabets**



…

many classes, few examples

the "transpose" of MNIST

statistics more reflective of **the real world**

20 instances of each character

Proposes both **few-shot discriminative** & **few-shot generative** problems

Initial few-shot learning approaches w/ **Bayesian models, non-parametrics**

Fei-Fei et al. '03   Lake et al. '11   Salakhutdinov et al. '12   Lake et al. '13

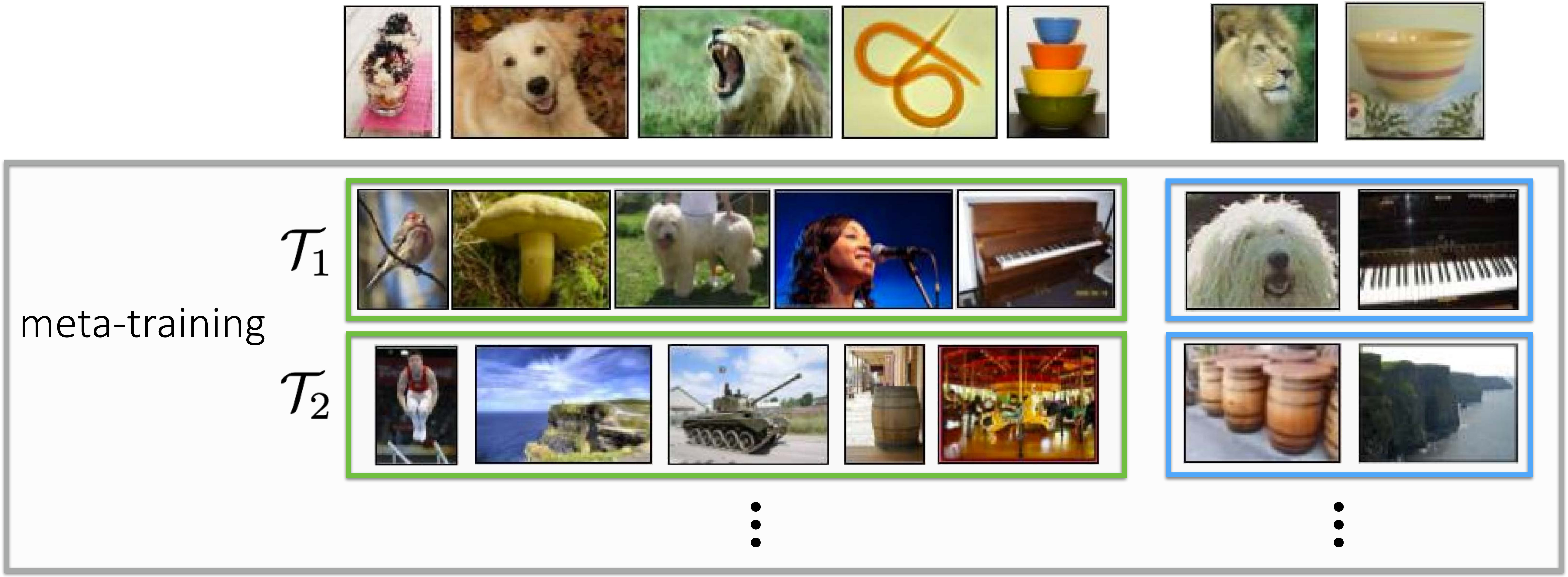
Other datasets used for **few-shot image recognition**: MiniImagenet, CIFAR, CUB, CelebA, others

General recipe

How to *evaluate* a meta-learning algorithm

5-way, **1**-shot image classification (MiniImagenet)

Given 1 example of 5 classes: Classify new examples



held-out classes

training classes

Can replace image classification with: **regression**, **language generation**, **skill learning**, **any ML problem**

Qs: slido.com/meta

General recipe

How to *design* a meta-learning algorithm

1. Choose a form of $p(\phi_i|\mathcal{D}_i^{\mathrm{tr}}, \theta)$

2. Choose how to optimize θ w.r.t. max-likelihood objective using $\mathcal{D}_{\text{meta-train}}$

Can we treat $p(\phi_i|\mathcal{D}_i^{\mathrm{tr}}, \theta)$ as an **inference** problem?

Neural networks are good at inference.

Qs: slido.com/meta

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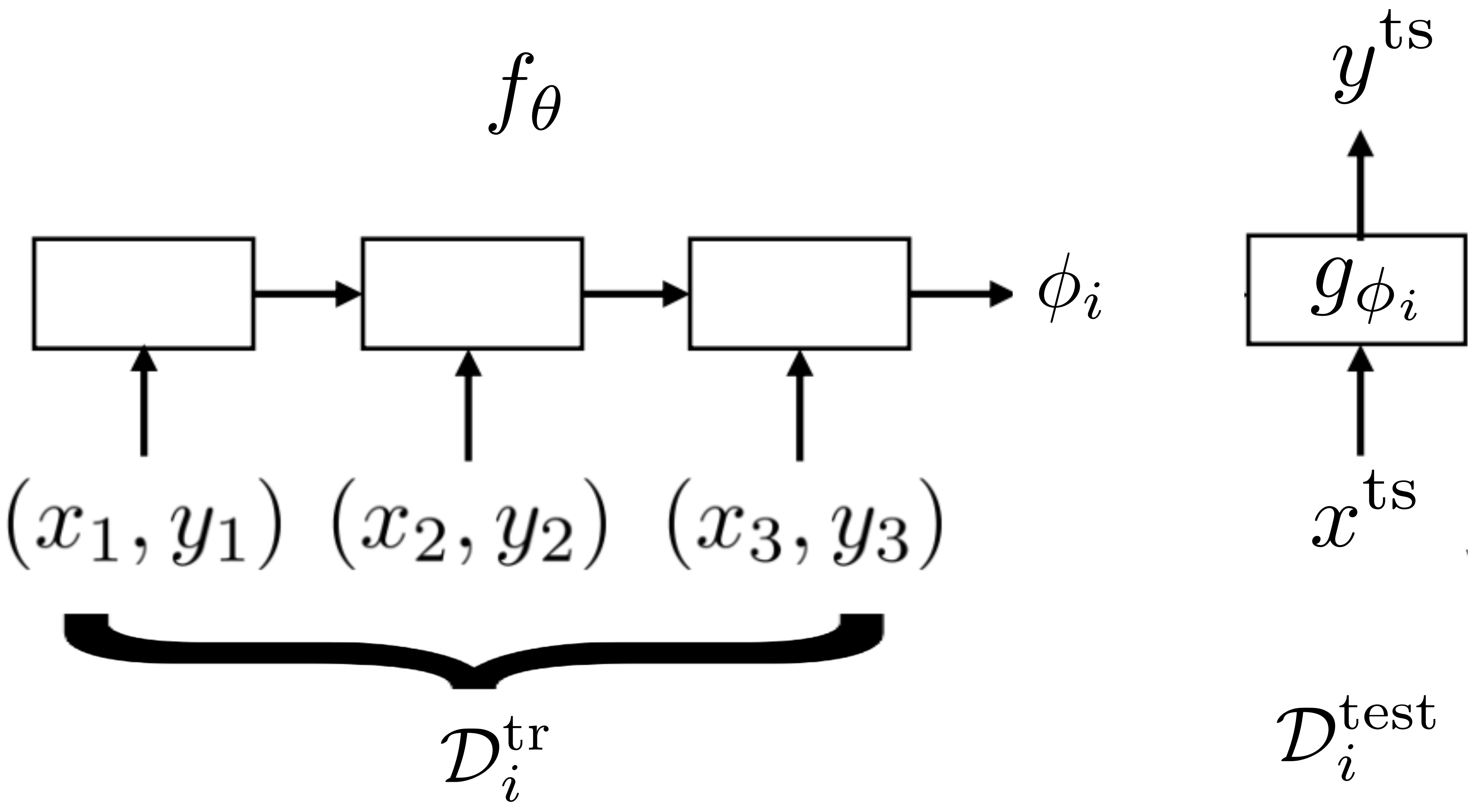
Qs: slido.com/meta

Black-Box Adaptation

Key idea: Train a neural network to represent $p(\phi_i|\mathcal{D}_i^{\mathrm{tr}}, \theta)$

For now: Use **deterministic** (point estimate) $\phi_i = f_\theta(\mathcal{D}_i^{\mathrm{tr}})$

(Bayes will come back later)



Train with standard supervised learning!

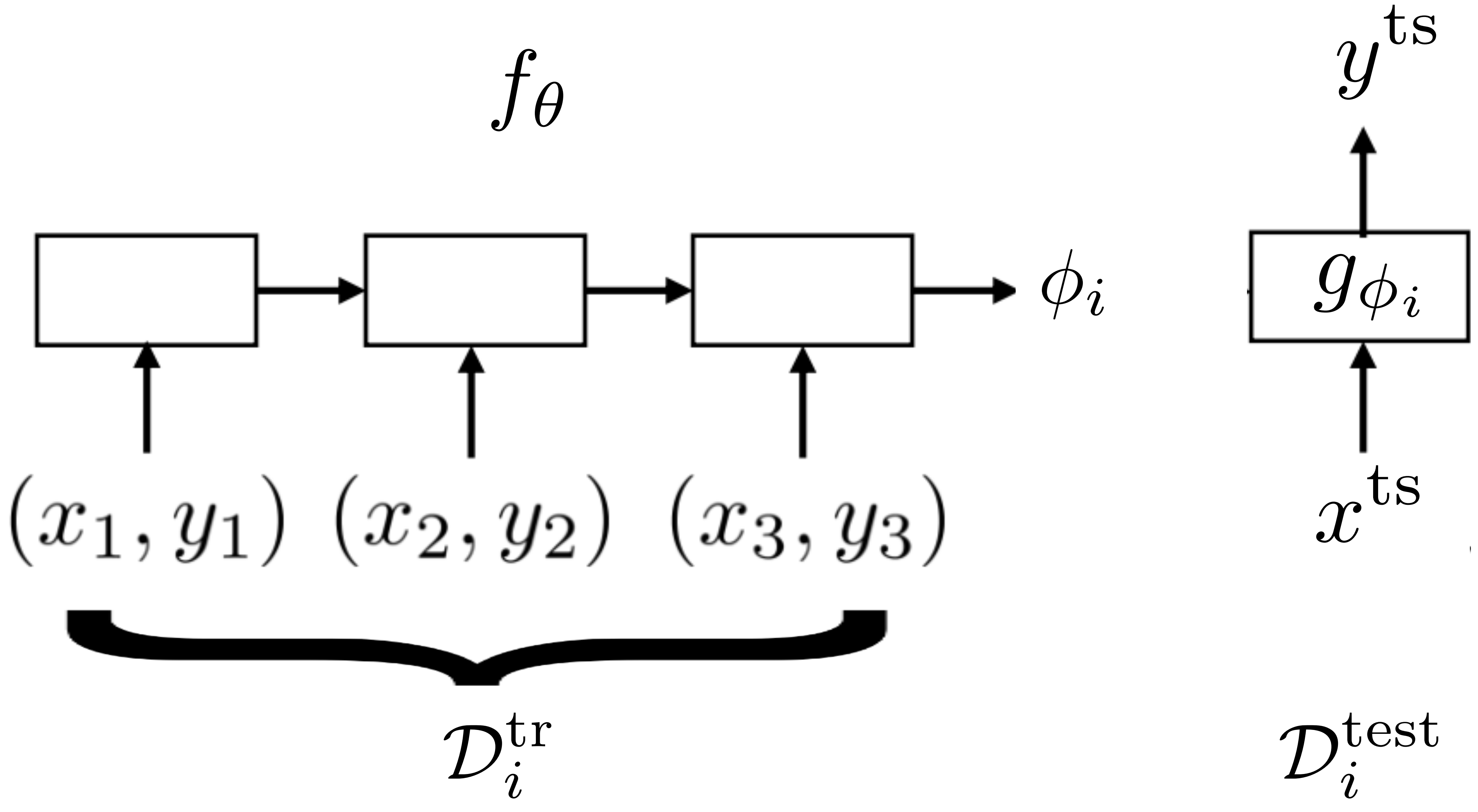
$$\max_\theta \sum_{\mathcal{T}_i} \underbrace{\sum_{(x,y)\sim\mathcal{D}_i^{\mathrm{test}}} \log g_{\phi_i}(y|x)}_{\mathcal{L}(\phi_i, \mathcal{D}_i^{\mathrm{test}})}$$

$$\max_\theta \sum_{\mathcal{T}_i} \mathcal{L}(f_\theta(\mathcal{D}_i^{\mathrm{tr}}), \mathcal{D}_i^{\mathrm{test}})$$

Qs: slido.com/meta

Black-Box Adaptation

Key idea: Train a neural network to represent $p(\phi_i|\mathcal{D}_i^{\text{tr}}, \theta)$



1. Sample task $\mathcal{T}_i$ *(or mini batch of tasks)*
2. Sample disjoint datasets $\mathcal{D}_i^{\text{tr}}, \mathcal{D}_i^{\text{test}}$ from $\mathcal{D}_i$

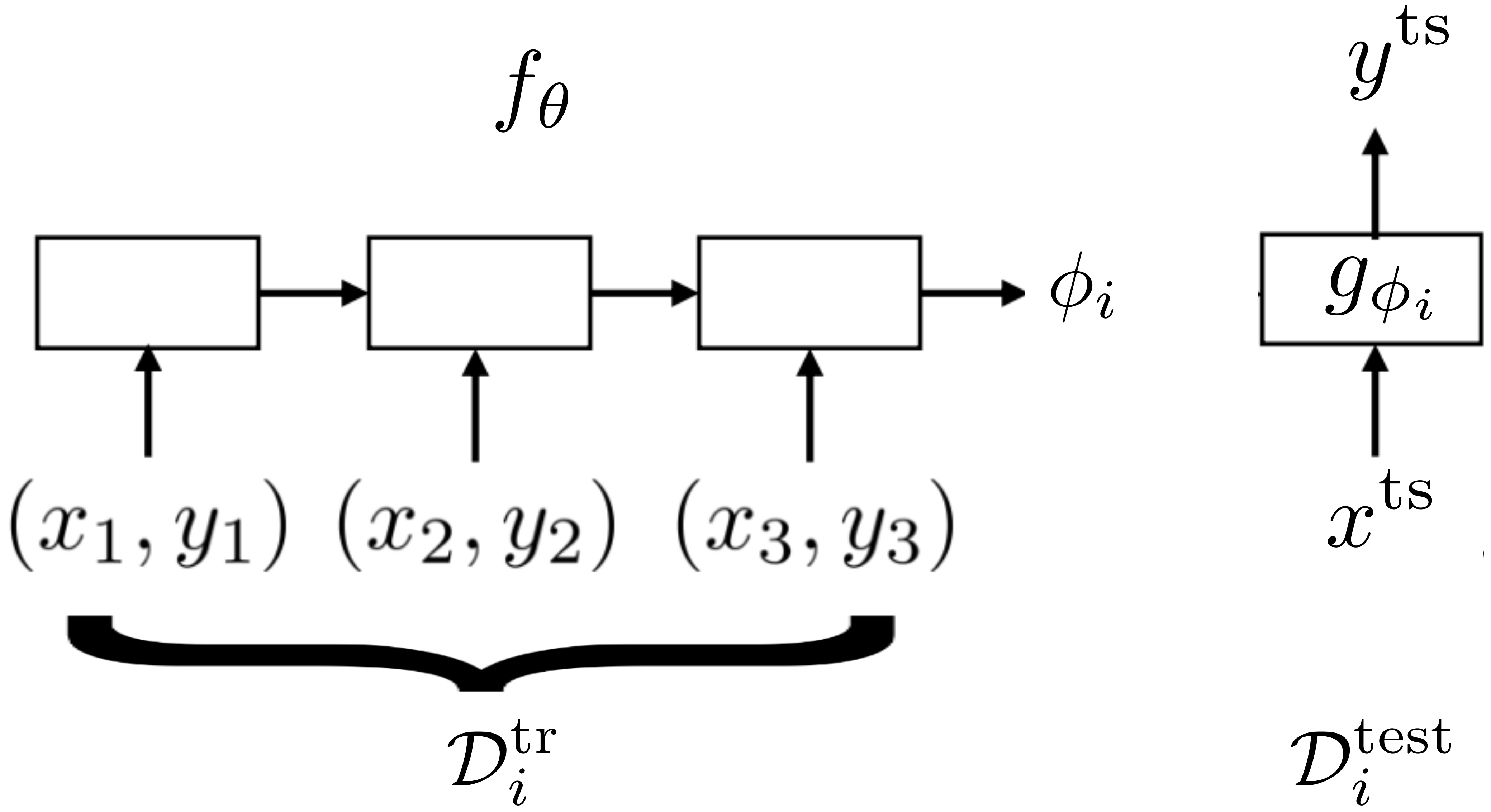
$\mathcal{D}_i$

$\mathcal{D}_i^{\text{tr}}$ $\mathcal{D}_i^{\text{test}}$

Qs: slido.com/meta

Black-Box Adaptation

Key idea: Train a neural network to represent $p(\phi_i | \mathcal{D}_i^{\mathrm{tr}}, \theta)$



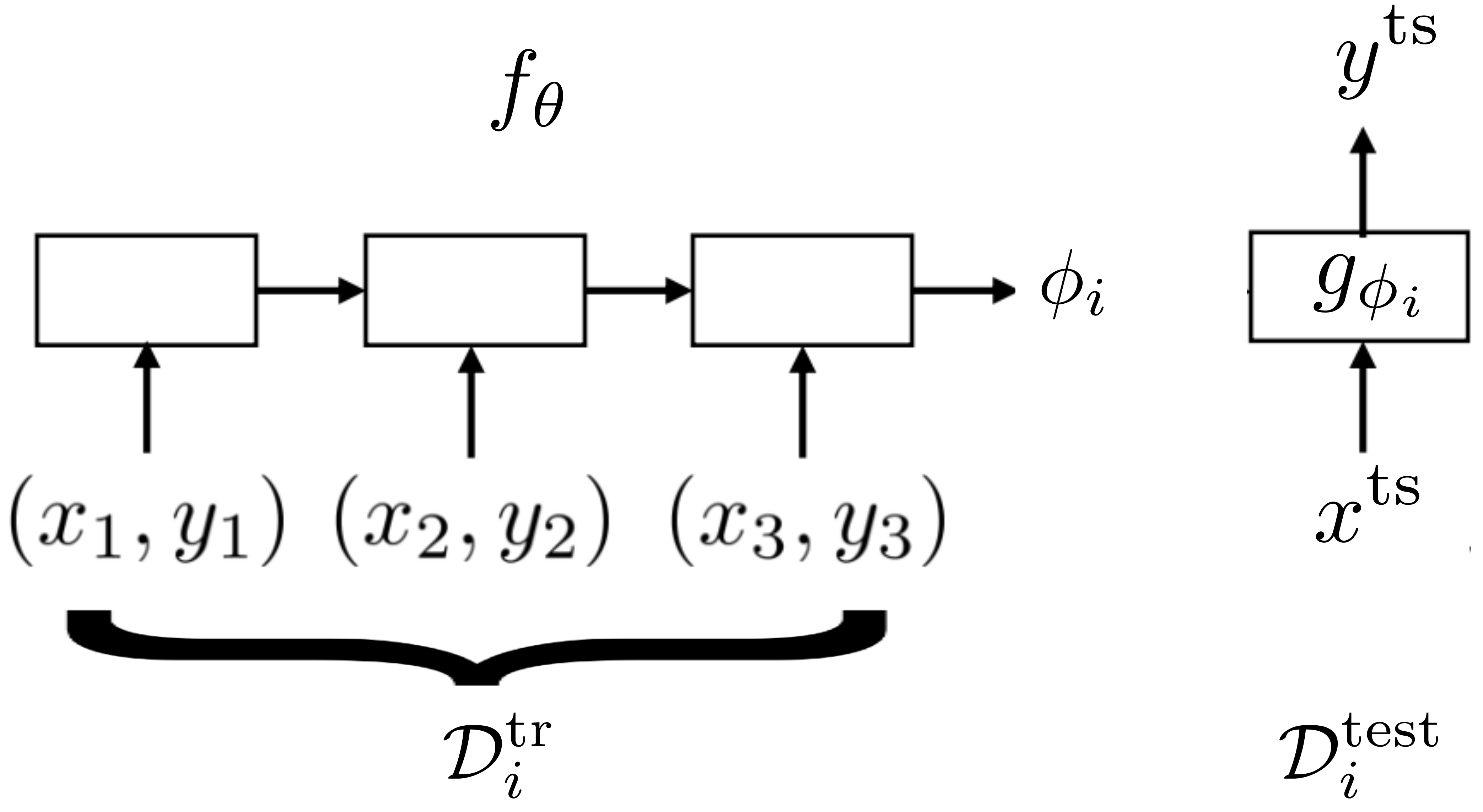
1. Sample task $\mathcal{T}_i$ *(or mini batch of tasks)*
2. Sample disjoint datasets $\mathcal{D}_i^{\mathrm{tr}}, \mathcal{D}_i^{\mathrm{test}}$ from $\mathcal{D}_i$
3. Compute $\phi_i \leftarrow f_\theta(\mathcal{D}_i^{\mathrm{tr}})$
4. Update θ using $\nabla_\theta \mathcal{L}(\phi_i, \mathcal{D}_i^{\mathrm{test}})$

$\mathcal{D}_i^{\mathrm{tr}}$ $\mathcal{D}_i^{\mathrm{test}}$

Qs: slido.com/meta

Black-Box Adaptation

Key idea: Train a neural network to represent $p(\phi_i|\mathcal{D}_i^{\text{tr}}, \theta)$



Form of f_θ ?

- LSTM
- Neural turing machine (NTM)
- Self-attention
- 1D convolutions
- feedforward + average

Qs: slido.com/meta

Black-Box Adaptation

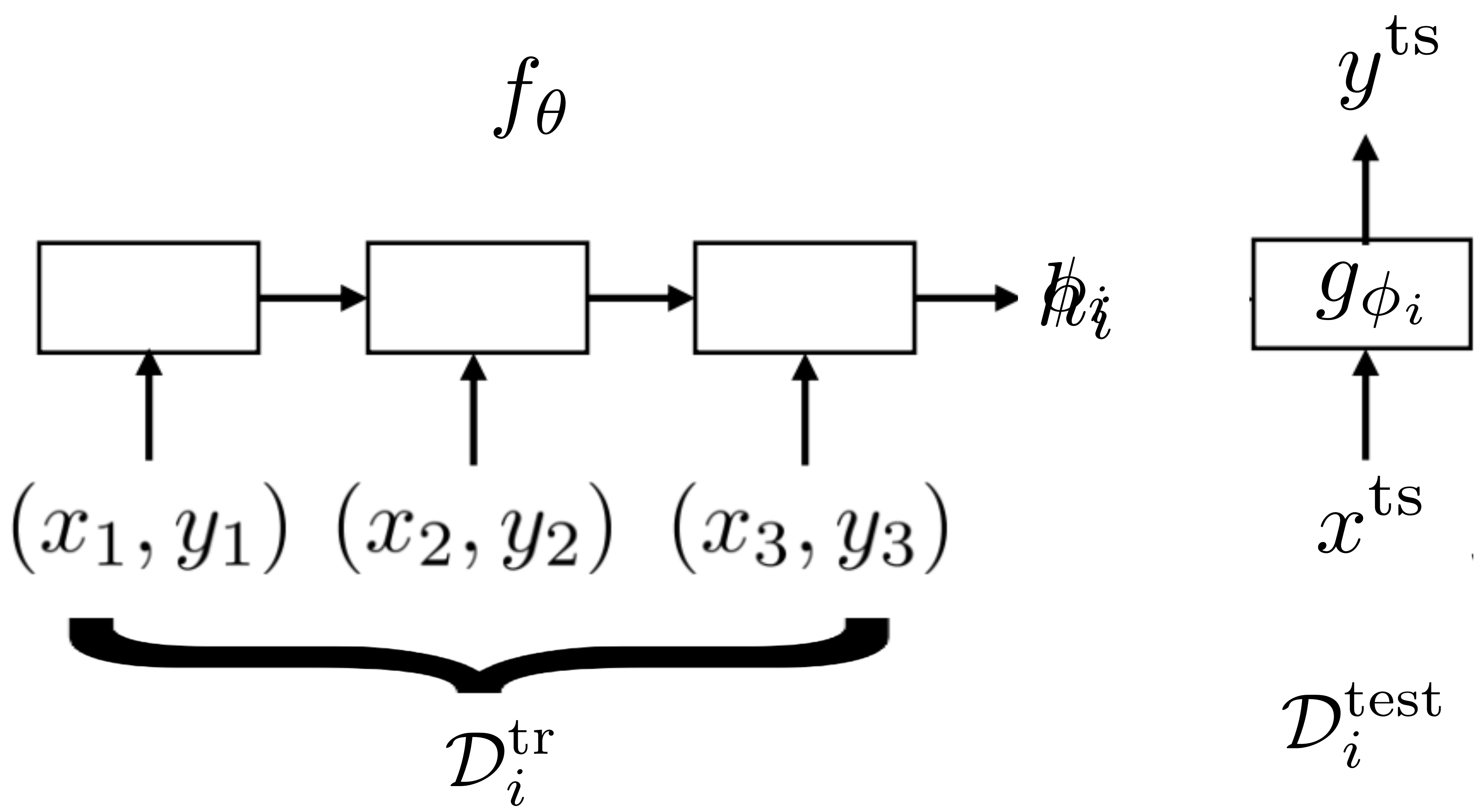
Key idea: Train a neural network to represent $p(\phi_i | \mathcal{D}_i^{\mathrm{tr}}, \theta)$

Challenges

Outputting all neural net parameters does not seem scalable?

Idea: Do not need to output **all** parameters of neural net, only sufficient statistics

(Santoro et al. MANN, Mishra et al. SNAIL)



low-dimensional vector h_i

represents contextual task information

$$\phi_i = \{h_i, \theta_g\}$$

general form: $y^{\mathrm{ts}} = f_\theta(\mathcal{D}_i^{\mathrm{tr}}, x^{\mathrm{ts}})$

Is there a way to infer **all parameters** in a scalable way?

Qs: slido.com/meta What if we treat it as an **optimization** procedure?

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Qs: slido.com/meta

Optimization-Based Inference

Key idea: Acquire ϕ_i through optimization.

$$\max_{\phi_i} \log p(\mathcal{D}_i^{\mathrm{tr}}|\phi_i) + \log p(\phi_i|\theta)$$

Meta-parameters θ serve as a prior. What form of prior?

One successful form of prior knowledge: **initialization** for **fine-tuning**

Optimization-Based Inference

pre-trained parameters

Fine-tuning

[test-time]

$$\phi \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}(\theta, \mathcal{D}^{\text{tr}})$$

training data for new task

Meta-learning

$$\min_\theta \sum_{\text{task } i} \mathcal{L}(\theta - \alpha \nabla_\theta \mathcal{L}(\theta, \mathcal{D}_i^{\text{tr}}), \mathcal{D}_i^{\text{ts}})$$

Key idea: Over many tasks, learn parameter vector θ that transfers via fine-tuning

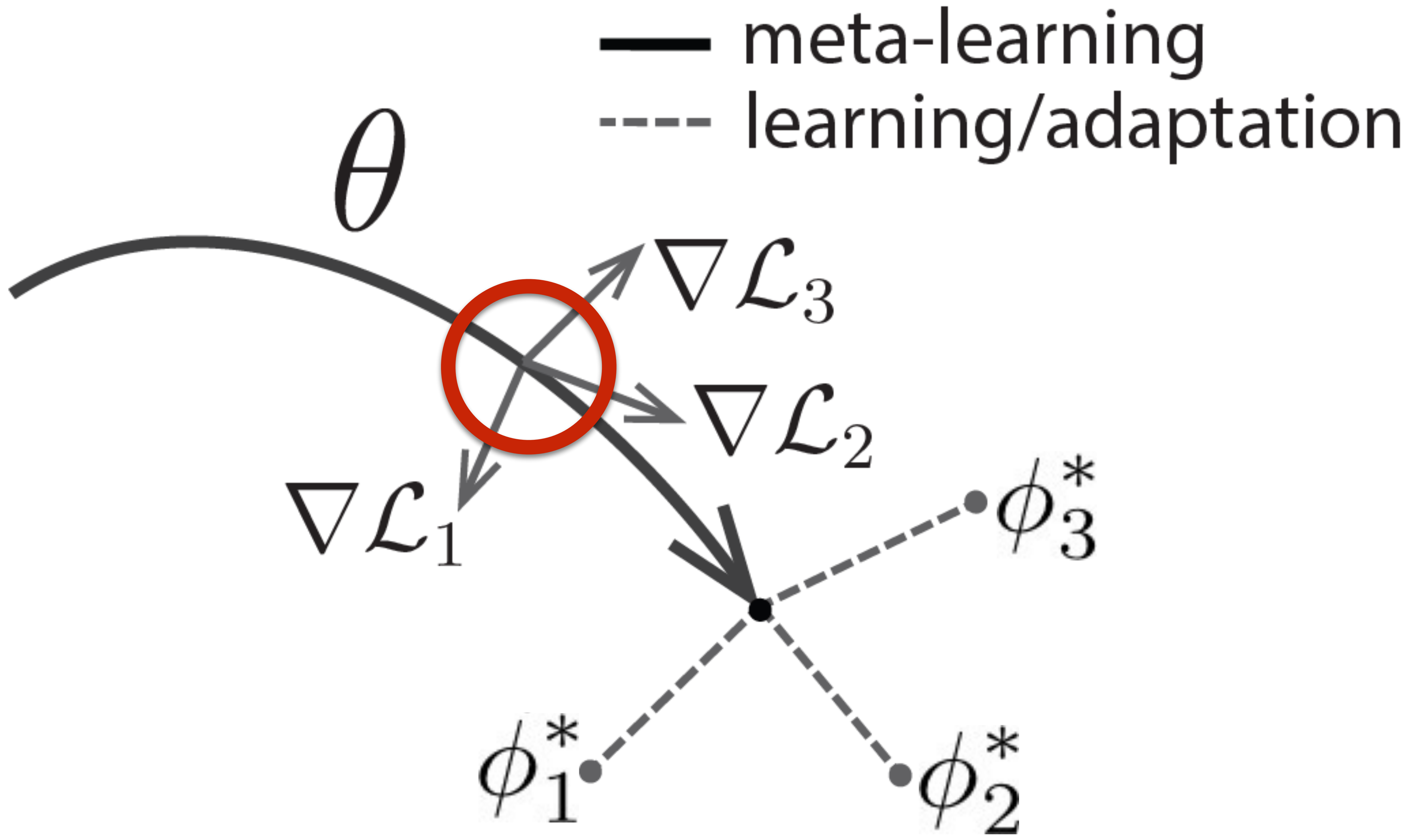
Finn et al., MAML

Optimization-Based Inference

$$\min_{\theta} \sum_{\text{task } i} \mathcal{L}(\theta - \alpha \nabla_\theta \mathcal{L}(\theta, \mathcal{D}_i^{\text{tr}}), \mathcal{D}_i^{\text{ts}})$$

θ parameter vector being meta-learned

ϕ_i^* optimal parameter vector for task i



Qs: slido.com/meta

Model-Agnostic Meta-Learning

Finn et al., MAML

Optimization-Based Inference

Key idea: Acquire ϕ_i through optimization.

General Algorithm:

~~Amortized approach~~ Optimization-based approach

1. Sample task $\mathcal{T}_i$ *(or mini batch of tasks)*
2. Sample disjoint datasets $\mathcal{D}_i^{\mathrm{tr}}, \mathcal{D}_i^{\mathrm{test}}$ from $\mathcal{D}_i$
3. ~~Compute $\phi_i \leftarrow f_\theta(\mathcal{D}_i^{\mathrm{tr}})$~~ Optimize $\phi_i \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}(\theta, \mathcal{D}_i^{\mathrm{tr}})$
4. Update θ using $\nabla_\theta \mathcal{L}(\phi_i, \mathcal{D}_i^{\mathrm{test}})$

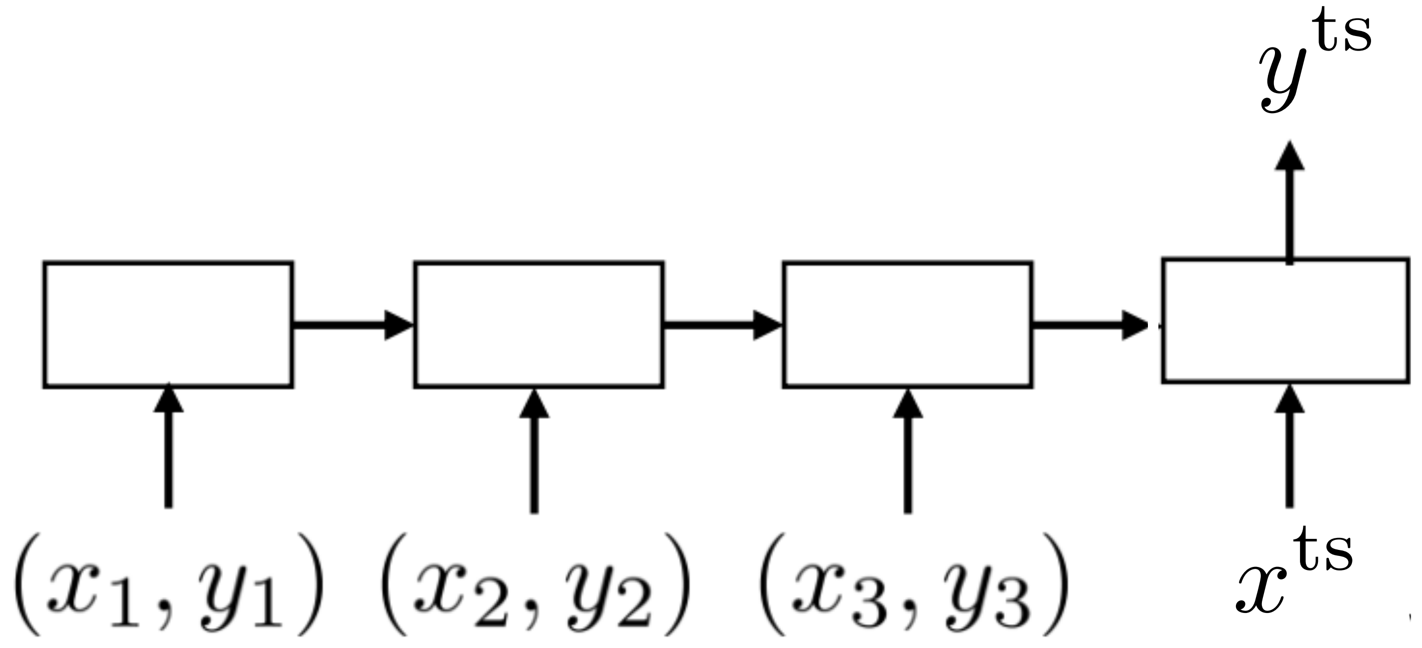
—> brings up **second-order** derivatives (more on this later)

Qs: slido.com/meta

Optimization vs. Black-Box Adaptation

Black-box adaptation

general form: $y^{\text{ts}} = f_\theta(\mathcal{D}_i^{\text{tr}}, x^{\text{ts}})$



Model-agnostic meta-learning

$$\begin{aligned} y^{\text{ts}} &= f_{\text{MAML}}(\mathcal{D}_i^{\text{tr}}, x^{\text{ts}}) \\ &= f_{\phi_i}(x^{\text{ts}}) \end{aligned}$$

$$\text{where } \phi_i = \theta - \alpha \nabla_\theta \mathcal{L}(\theta, \mathcal{D}_i^{\text{tr}})$$

MAML can be viewed as **computation graph**, with embedded gradient operator

Note: Can mix & match components of computation graph

Learn initialization but replace gradient update with learned network

$$\text{where } \phi_i = \theta - \alpha \cancel{\nabla_\theta \mathcal{L}(\theta, \mathcal{D}_i^{\text{tr}})}$$
$$f(\theta, \mathcal{D}_i^{\text{tr}}, \nabla_\theta \mathcal{L})$$

Ravi & Larochelle ICLR '17
(actually precedes MAML)

Qs: slido.com/

This **computation graph view** of meta-learning will come back again!

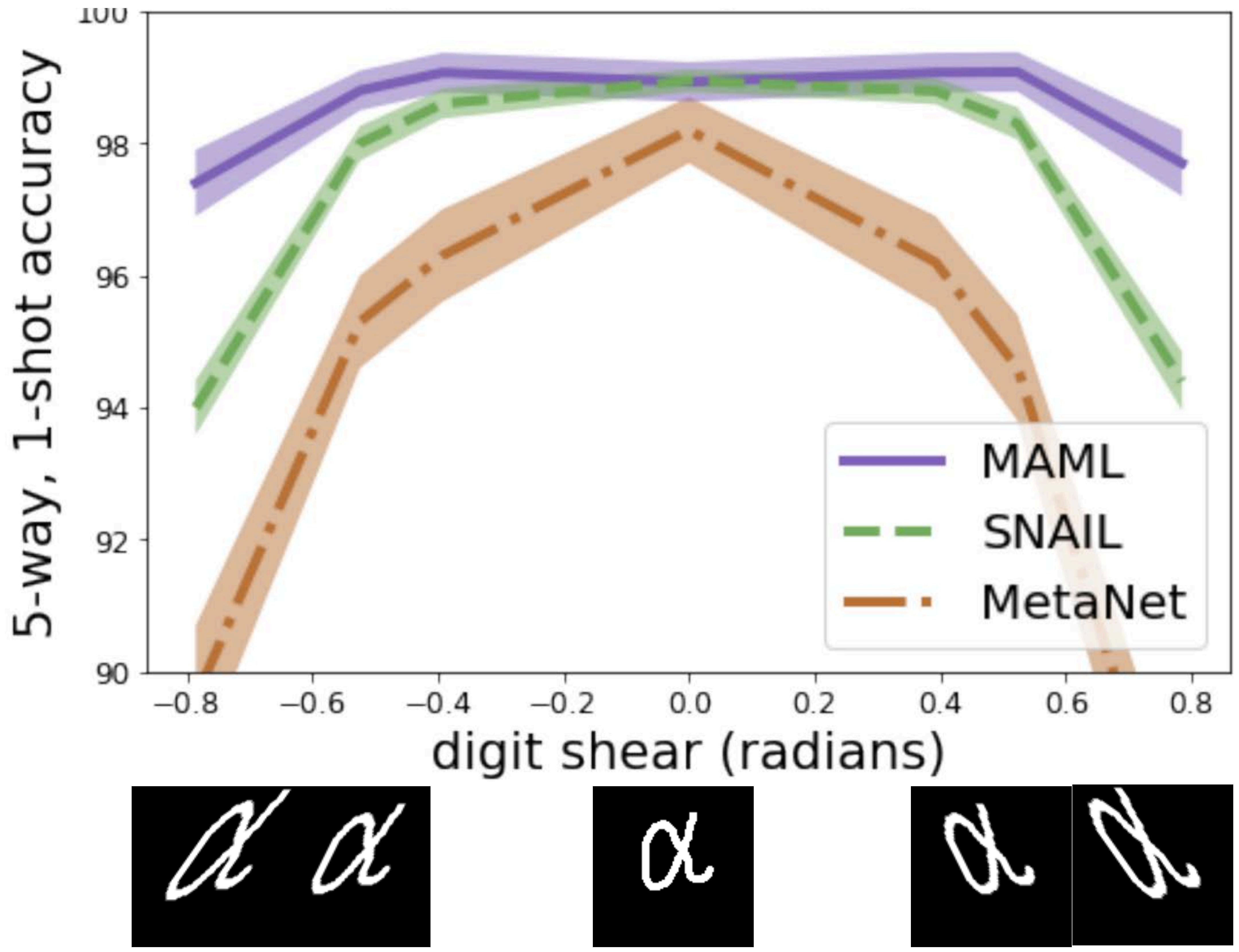
Optimization vs. Black-Box Adaptation

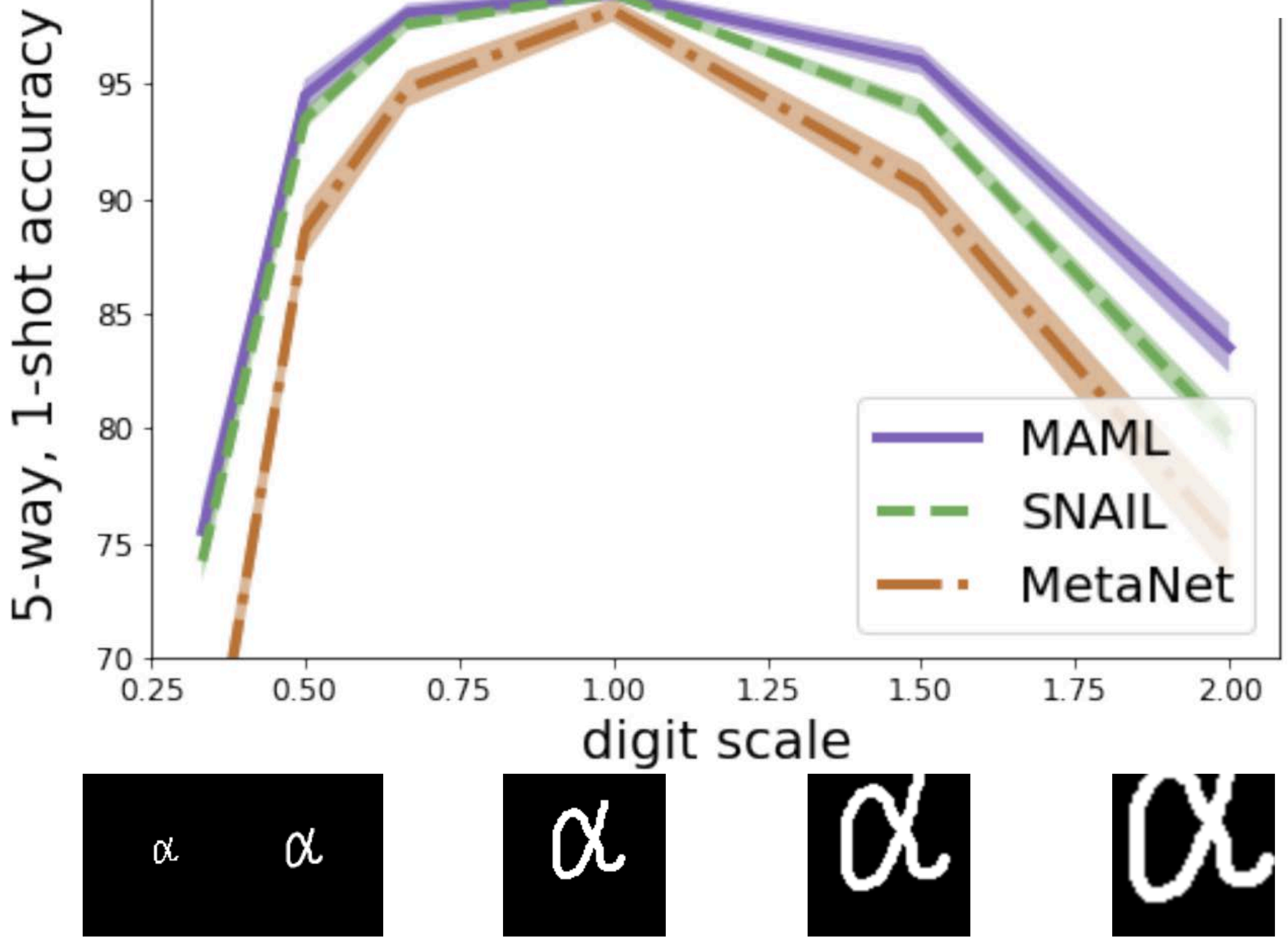
How well can learning procedures generalize to similar, but extrapolated tasks?

Omniglot image classification

MAML SNAIL, MetaNetworks

performance





Qs: slido.com/meta

Does this structure come at a cost?

Finn & Levine ICLR ’18

Black-box adaptation

$$y^{\text{ts}} = f_\theta(\mathcal{D}_i^{\text{tr}}, x^{\text{ts}})$$

Optimization-based (MAML)

$$y^{\text{ts}} = f_{\text{MAML}}(\mathcal{D}_i^{\text{tr}}, x^{\text{ts}})$$

Does this structure come at a cost?

For a sufficiently deep f,

MAML function can approximate any function of $\mathcal{D}_i^{\text{tr}}, x^{\text{ts}}$

Finn & Levine, ICLR 2018

Assumptions:

- nonzero α
- loss function gradient does not lose information about the label
- datapoints in $\mathcal{D}_i^{\text{tr}}$ are unique

Why is this interesting?

MAML has benefit of inductive bias without losing expressive power.

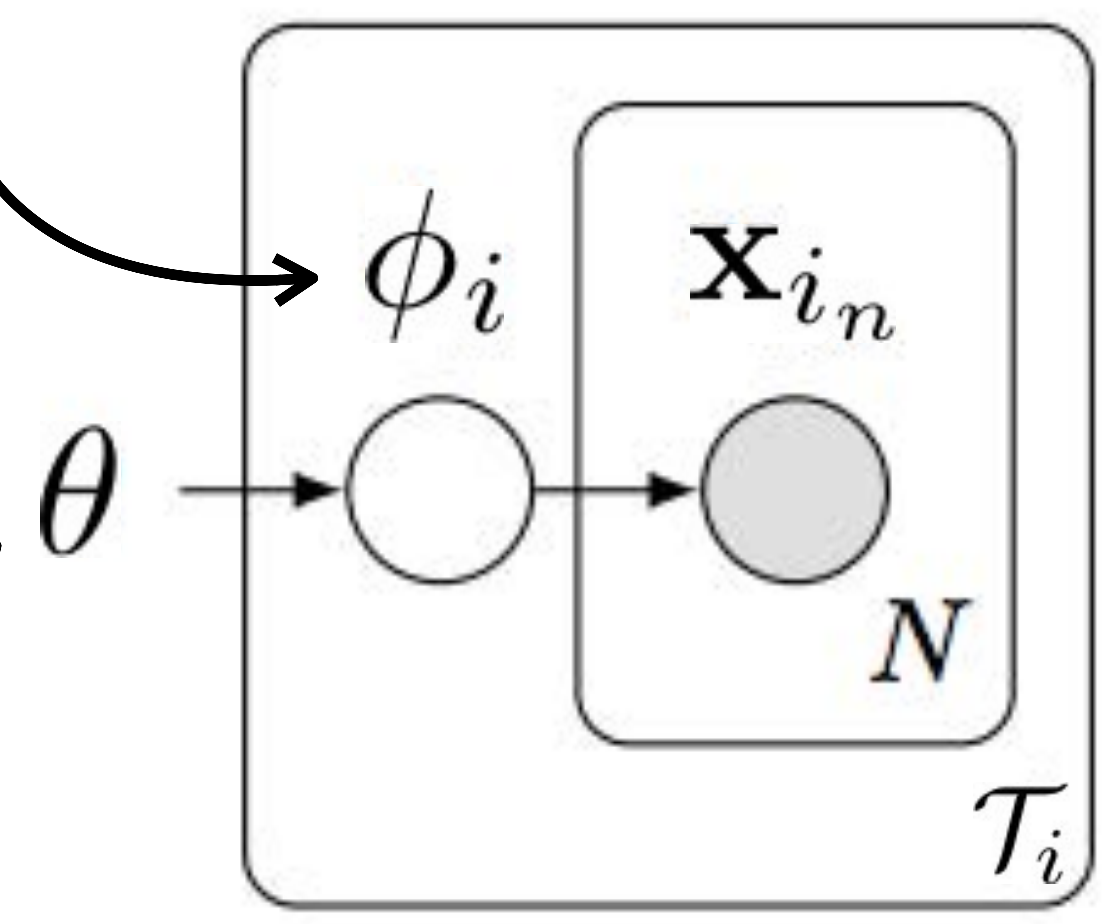
Qs: slido.com/meta

Probabilistic Interpretation of Optimization-Based Inference

Key idea: Acquire ϕ_i through optimization.

Meta-parameters θ serve as a prior. One form of prior knowledge: **initialization** for **fine-tuning**

task-specific parameters



meta-parameters

$$\max_\theta \log \prod_i p(\mathcal{D}_i|\theta)$$
$$= \log \prod_i \int p(\mathcal{D}_i|\phi_i)p(\phi_i|\theta)d\phi_i \quad \text{(empirical Bayes)}$$
$$\approx \log \prod_i p(\mathcal{D}_i|\hat{\phi}_i)p(\hat{\phi}_i|\theta)$$

MAP estimate

How to compute MAP estimate?

Gradient descent with **early stopping** = **MAP inference** under **Gaussian prior** with mean at initial parameters [Santos '96]

(exact in linear case, approximate in nonlinear case)

Qs: slido.com/meta *MAML approximates hierarchical Bayesian inference.* Grant et al. ICLR '18

Optimization-Based Inference

Key idea: Acquire ϕ_i through optimization.

Meta-parameters θ serve as a prior. One form of prior knowledge: **initialization** for **fine-tuning**

Gradient-descent + early stopping (MAML): implicit Gaussian prior $\phi \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}(\theta, \mathcal{D}^{\text{tr}})$

Other forms of priors?

Gradient-descent with **explicit Gaussian prior** $\phi \leftarrow \min_{\phi'} \mathcal{L}(\phi', \mathcal{D}^{\text{tr}}) + \frac{\lambda}{2} ||\theta - \phi'||^2$

Rajeswaran et al. implicit MAML '19

Bayesian linear regression *on learned features* Harrison et al. ALPaCA '18

Closed-form *or* **convex optimization** *on learned features*

ridge regression, logistic regression
Bertinetto et al. R2-D2 '19

support vector machine
Lee et al. MetaOptNet '19

Current **SOTA** on few-shot image classification

Qs: slido.com/meta

Optimization-Based Inference

Key idea: Acquire ϕ_i through optimization.

Challenges

How to choose architecture that is effective for inner gradient-step?

Idea: Progressive neural architecture search + MAML

(Kim et al. Auto-Meta)

- finds highly non-standard architecture (deep & narrow)
- different from architectures that work well for standard supervised learning

MiniImagenet, 5-way 5-shot

MAML, basic architecture: **63.11%**

MAML + AutoMeta: **74.65%**

Qs: slido.com/meta

Optimization-Based Inference

Key idea: Acquire ϕ_i through optimization.

Challenges

Second-order meta-optimization can exhibit instabilities.

Idea: [Crudely] approximate $\frac{d\phi_i}{d\theta}$ as identity

(Finn et al. first-order MAML, Nichol et al. Reptile)

Idea: Automatically learn inner vector learning rate, tune outer learning rate

(Li et al. Meta-SGD, Behl et al. AlphaMAML)

Idea: Optimize only a subset of the parameters in the inner loop

(Zhou et al. DEML, Zintgraf et al. CAVIA)

Idea: Decouple inner learning rate, BN statistics per-step (Antoniou et al. MAML++)

Idea: Introduce context variables for increased expressive power.

(Finn et al. bias transformation, Zintgraf et al. CAVIA)

Takeaway: a range of simple tricks that can help optimization significantly

Qs: slido.com/meta

Outline

- **Problem statement**
- Meta-learning **algorithms**
  - Black-box adaptation
  - Optimization-based inference
  - Non-parametric methods
  - Bayesian meta-learning
- Meta-learning **applications**

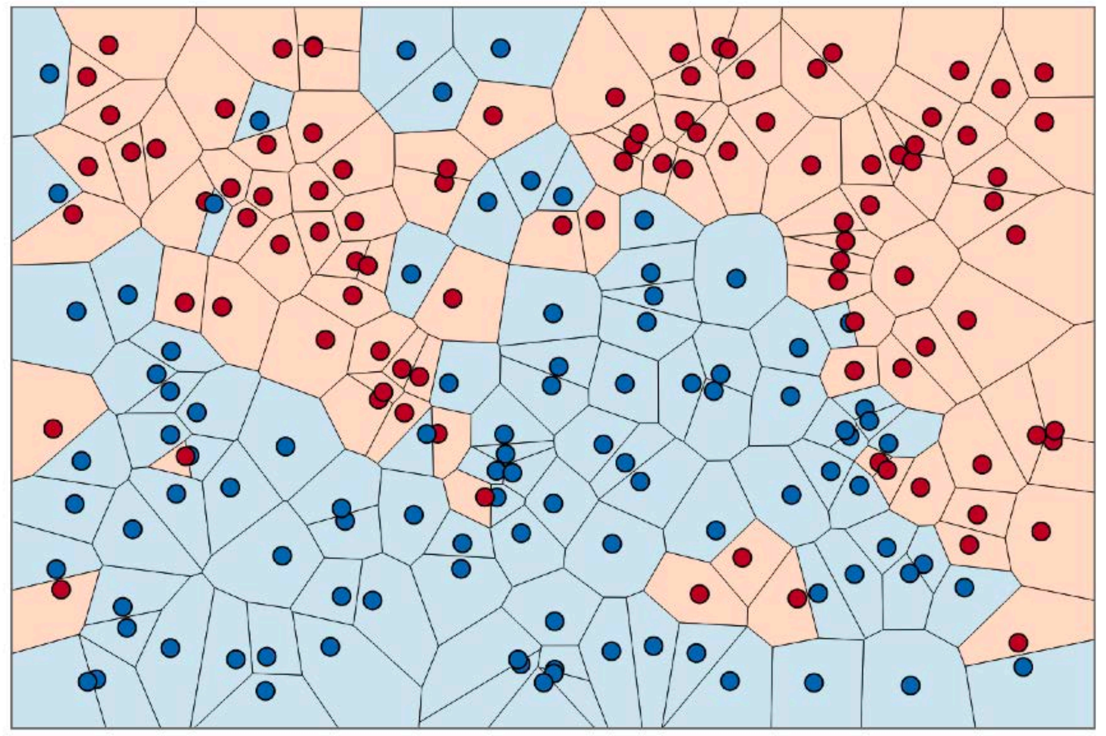
— 5 min break —

- Meta-**reinforcement** learning
- Challenges & frontiers

Qs: slido.com/meta

So far: Learning parametric models.

In low data regimes, **non-parametric** methods are simple, work well.



During **meta-test time**: few-shot learning <-> low data regime

During **meta-training**: still want to be parametric

Can we use **parametric meta-learners** that produce effective **non-parametric learners**?

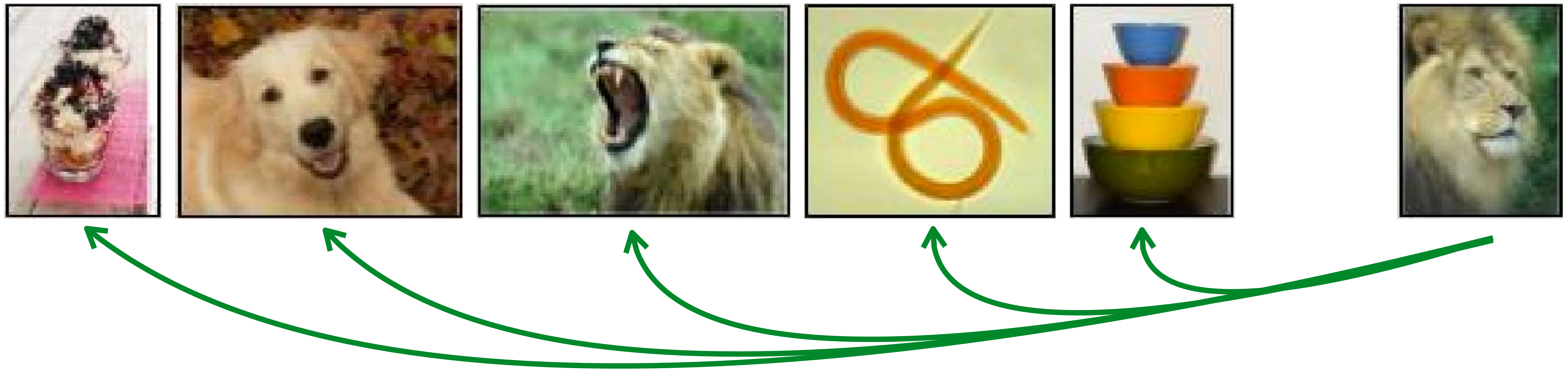
Note: some of these methods precede parametric approaches

Qs: slido.com/meta

Non-parametric methods

Key Idea: Use non-parametric learner.

training data $\mathcal{D}_i^{\mathrm{tr}}$ test datapoint x^{ts}



Compare test image with training images

In what space do you compare? With what distance metric?

~~pixel space, l_2 distance?~~

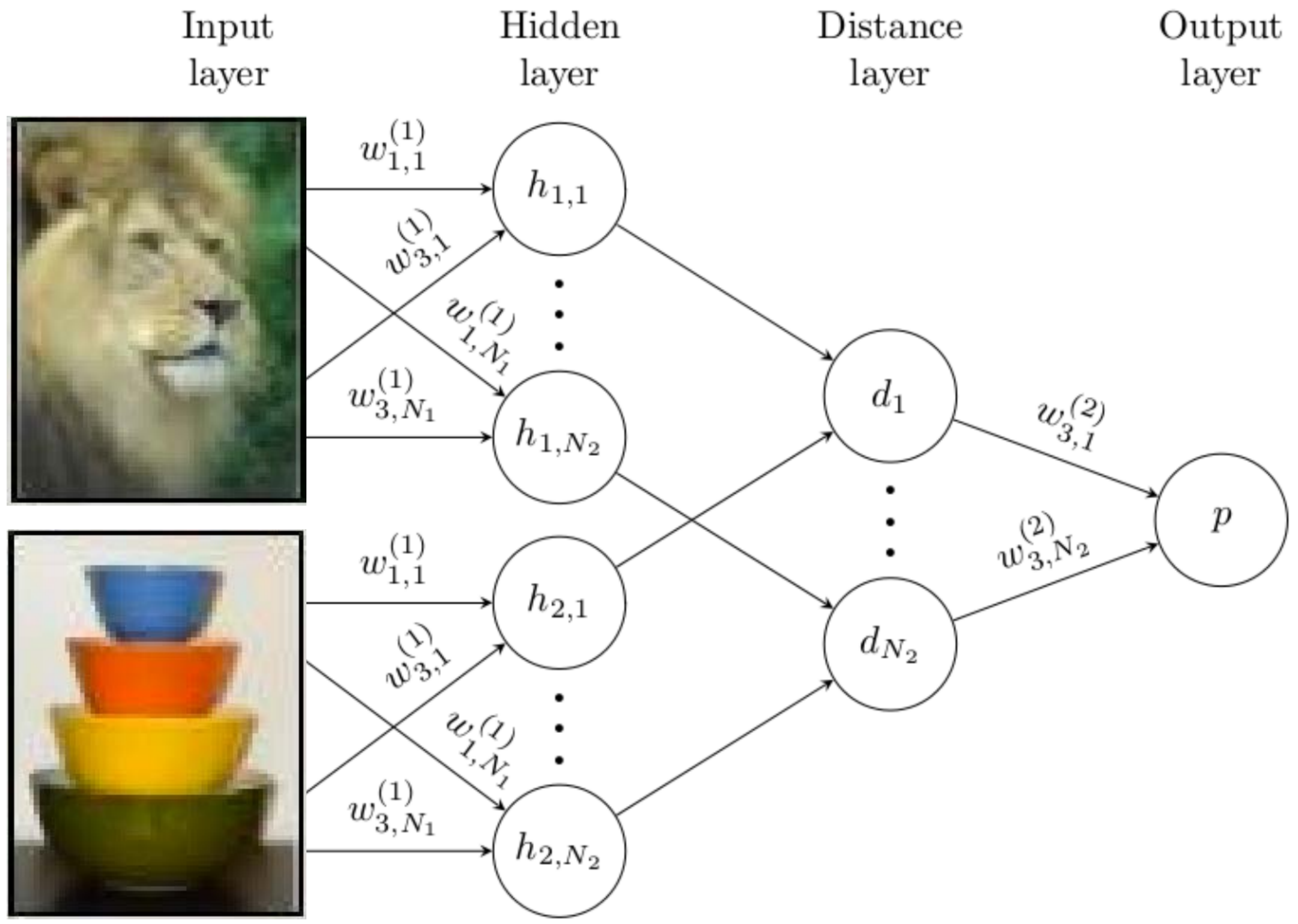
Learn to compare using data!

Qs: slido.com/meta

Non-parametric methods

Key Idea: Use non-parametric learner.

train Siamese network to predict whether or not two images are the same class



label

0

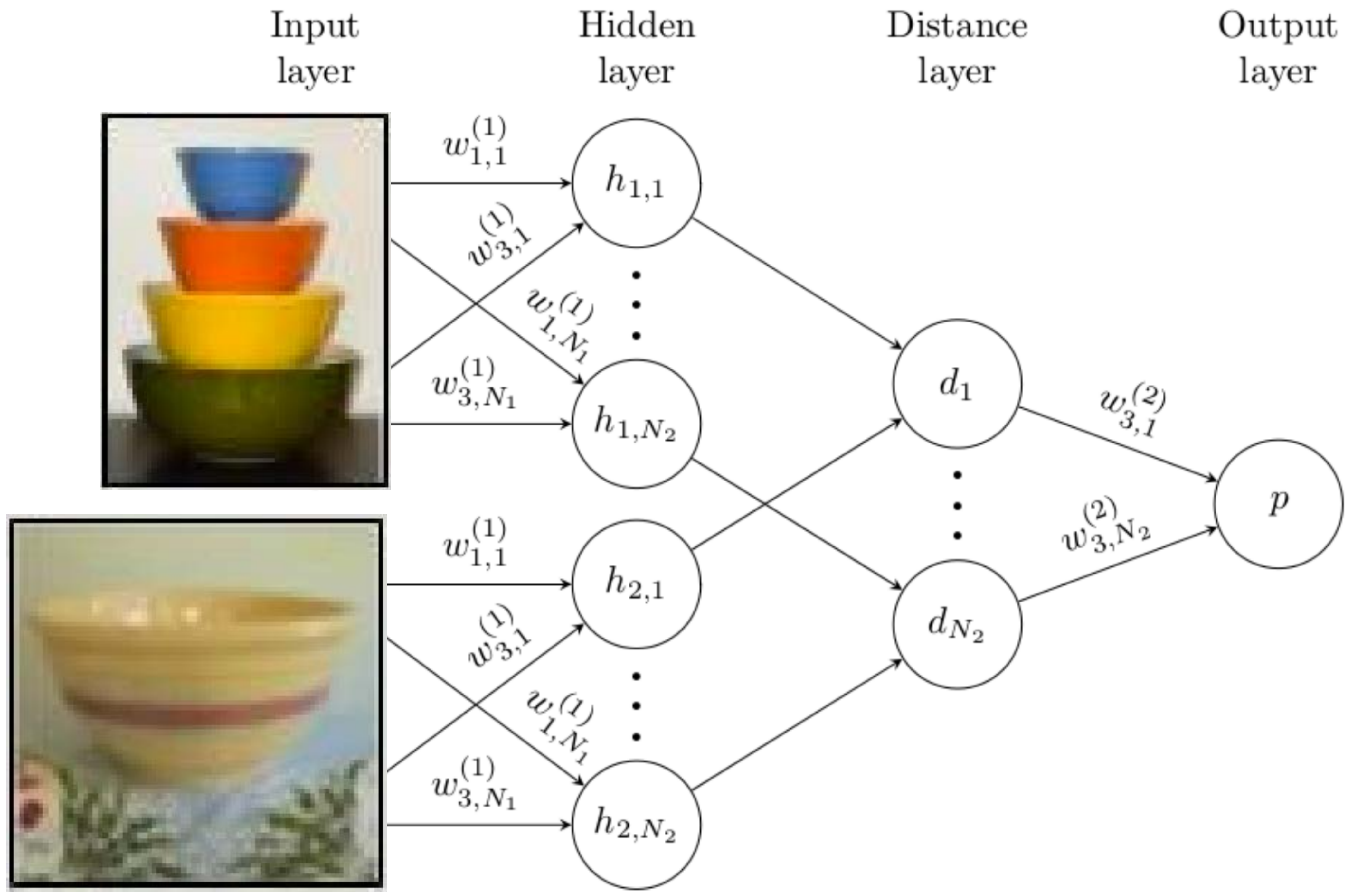
Qs: slido.com/meta

Koch et al., ICML '15

Non-parametric methods

Key Idea: Use non-parametric learner.

train Siamese network to predict whether or not two images are the same class



label

1

Qs: slido.com/meta

Koch et al., ICML '15

Non-parametric methods

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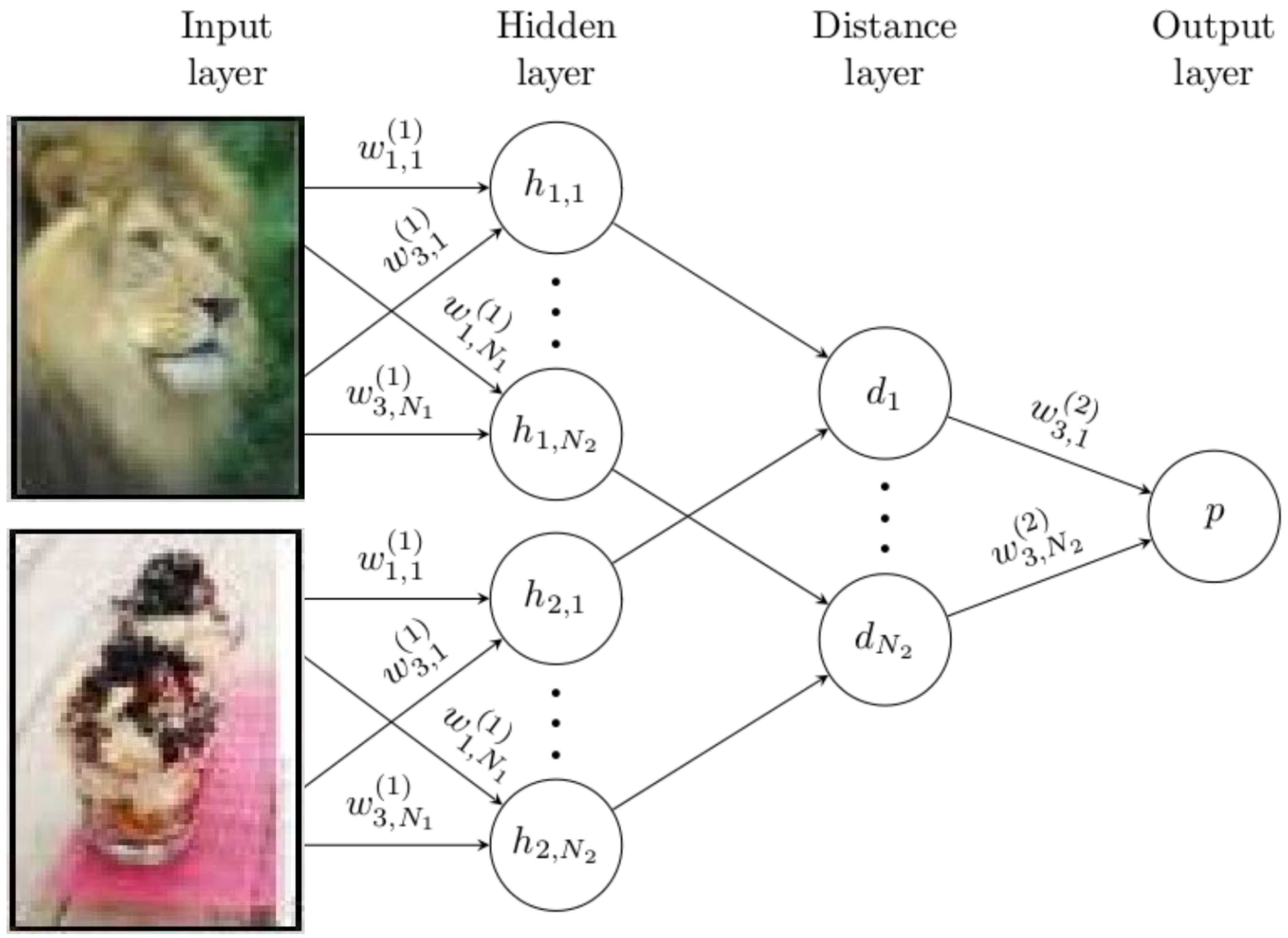

label

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Qs: slido.com/meta

Koch et al., ICML '15

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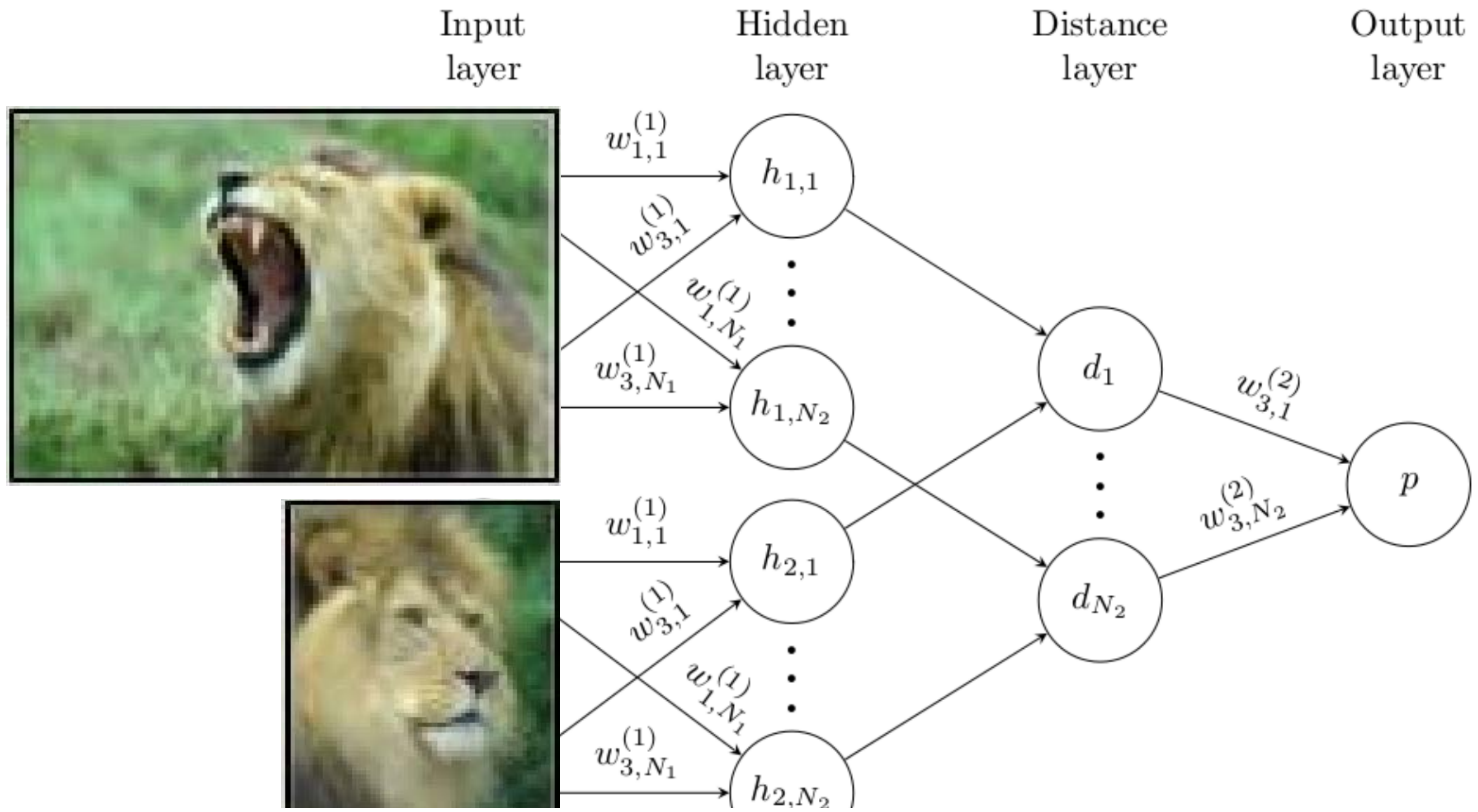


label

1

Meta-test time: compare image $\mathbf{x}_{\text{test}}$ to each image in $\mathcal{D}_j^{\text{tr}}$

Meta-training: 2-way classification

Meta-test: N-way classification

Can we **match** meta-train & meta-test?

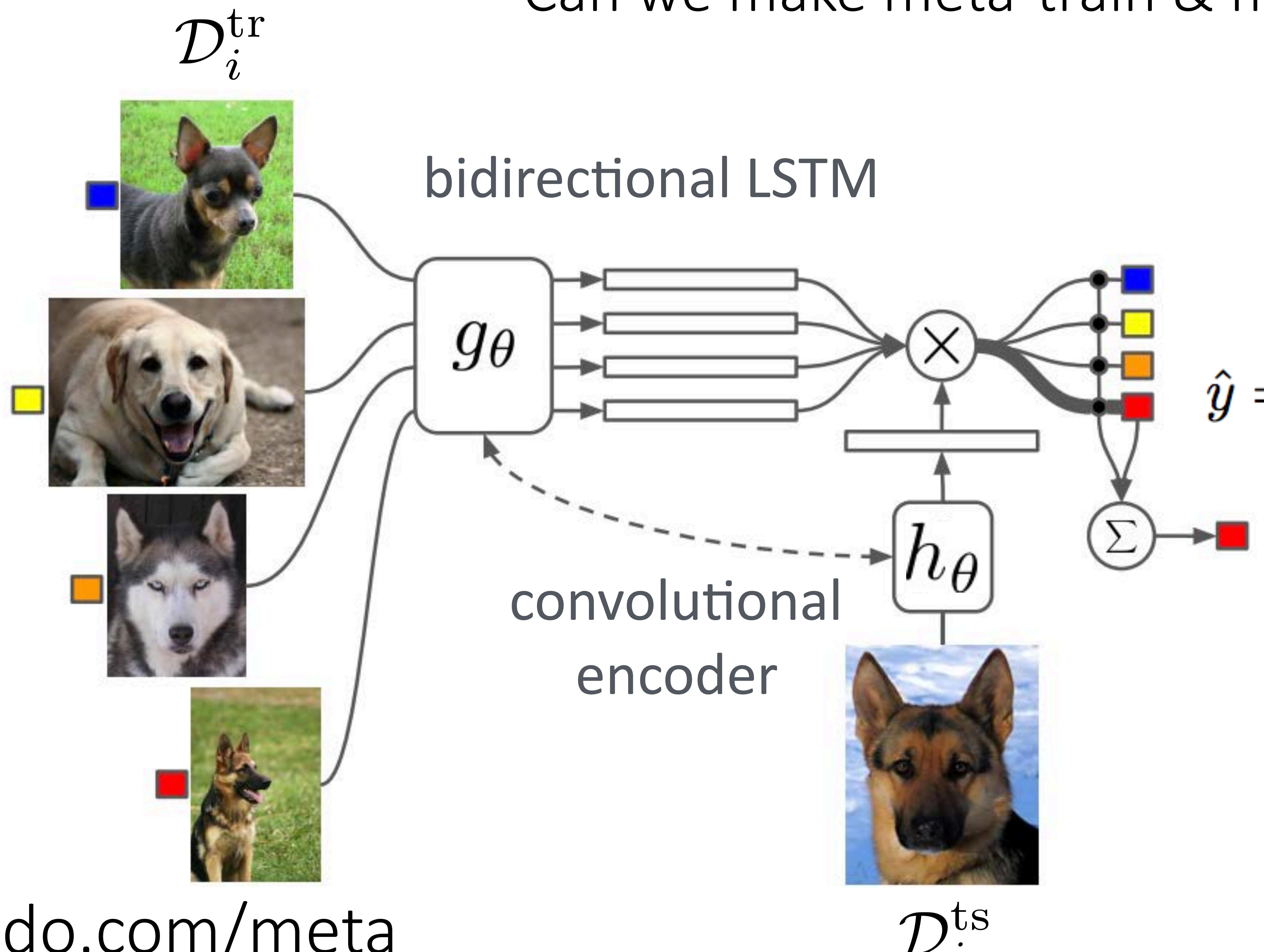
Qs: slido.co

Koch et al., ICML '15

Non-parametric methods

Key Idea: Use non-parametric learner.

Can we make meta-train & meta-test match?



Weighed nearest neighbors in learned embedding space

$$\hat{y} = \sum_{i=1}^{k} a(\hat{x}, x_i) y_i$$

What if **>1 shot**?

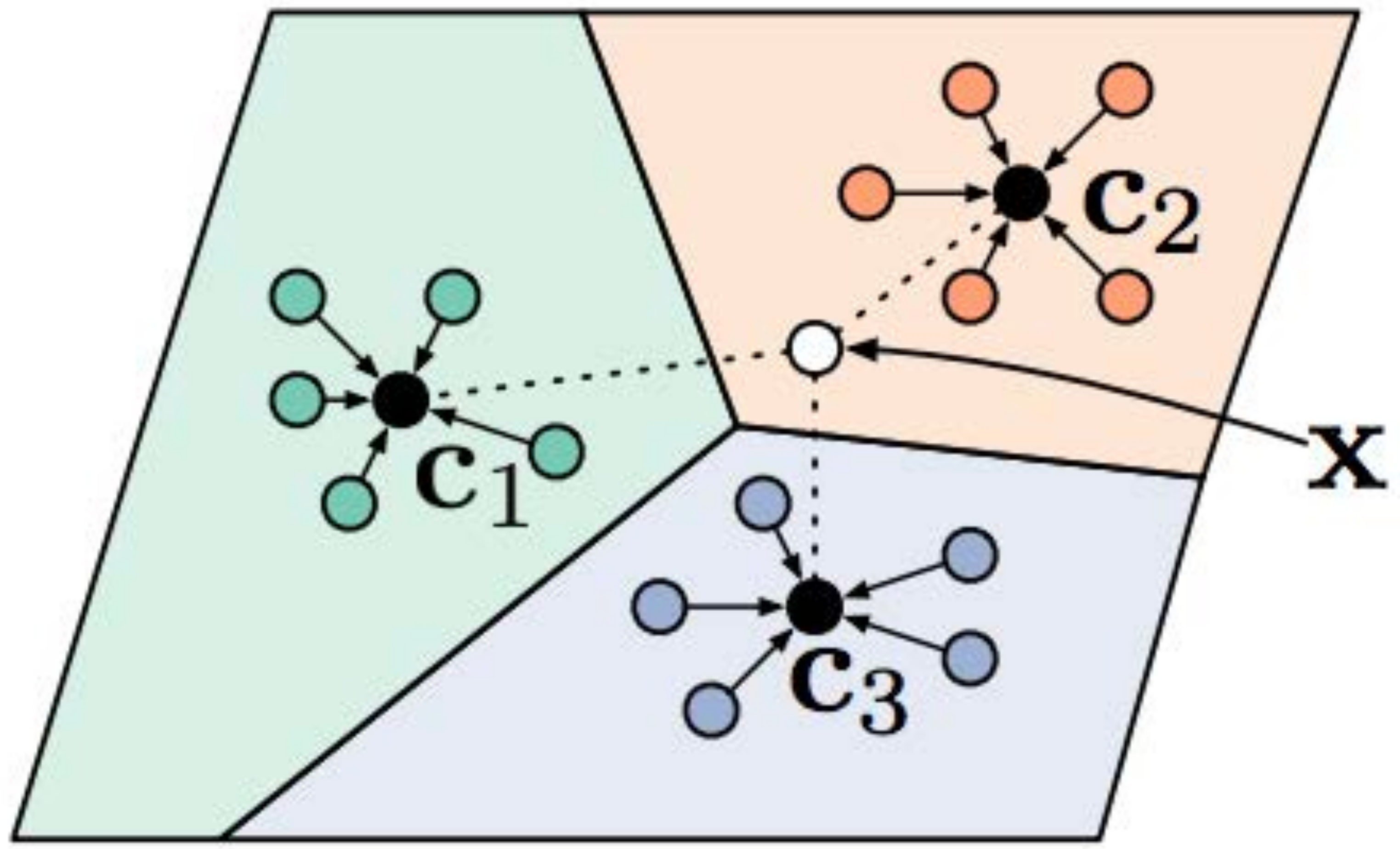
Can we **aggregate class information** to create a **prototypical embedding**?

Qs: slido.com/meta

Vinyals et al. Matching Networks, NeurIPS '16

Non-parametric methods

Key Idea: Use non-parametric learner.



(a) Few-shot

$$\mathbf{c}_k = \frac{1}{|\mathcal{D}_i^{\mathrm{tr}}|} \sum_{(x,y)\in\mathcal{D}_i^{\mathrm{tr}}} f_\theta(x)$$

$$p_\theta(y=k|x) = \frac{\exp(-d(f_\theta(x), \mathbf{c}_k))}{\sum_{k'} \exp(-d(f_\theta(x), \mathbf{c}_{k'}))}$$

d: Euclidean, or cosine distance

Snell et al. Prototypical Networks, NeurIPS '17

Non-parametric methods

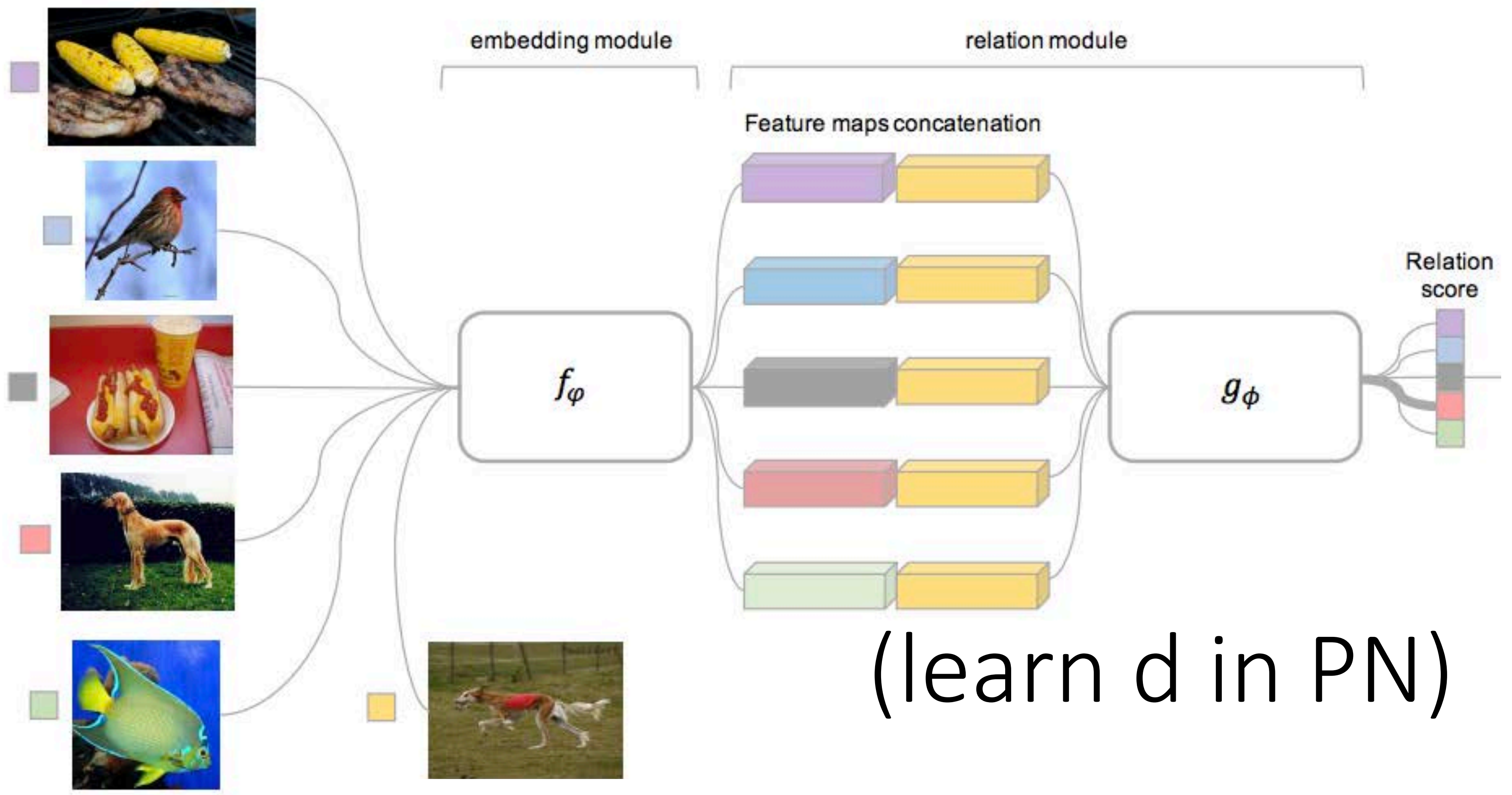
So far: Siamese networks, matching networks, prototypical networks

Embed, then nearest neighbors.

Challenge

What if you need to reason about more complex relationships between datapoints?

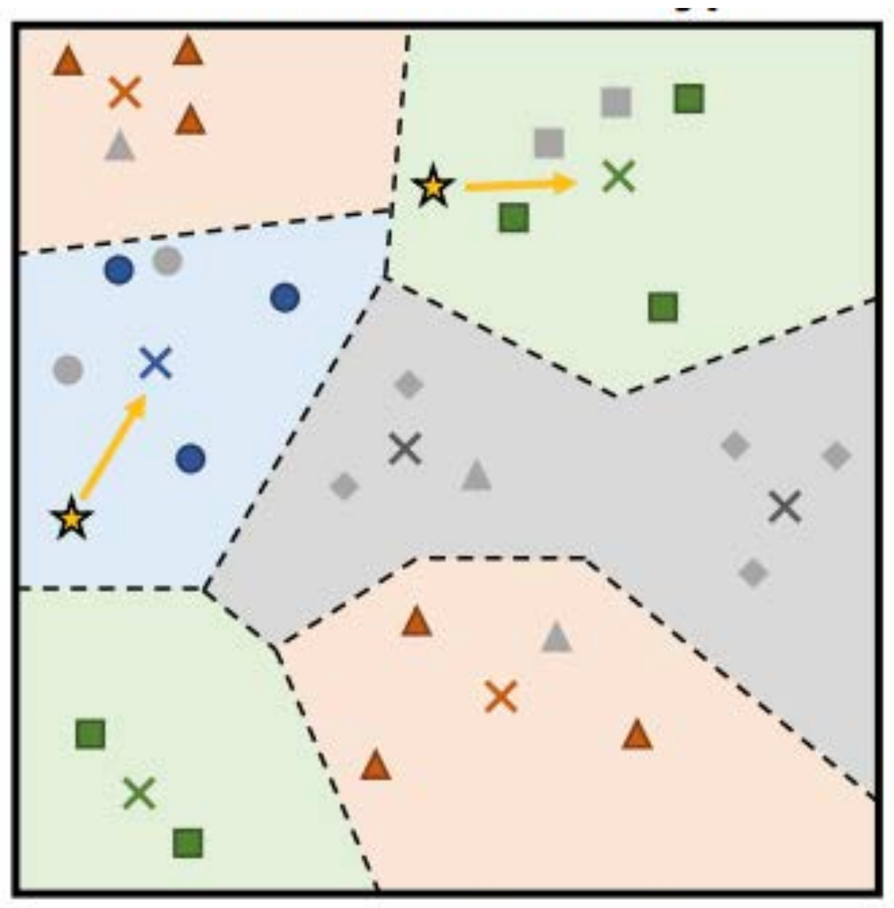
Idea: Learn non-linear relation module on embeddings



(learn d in PN)

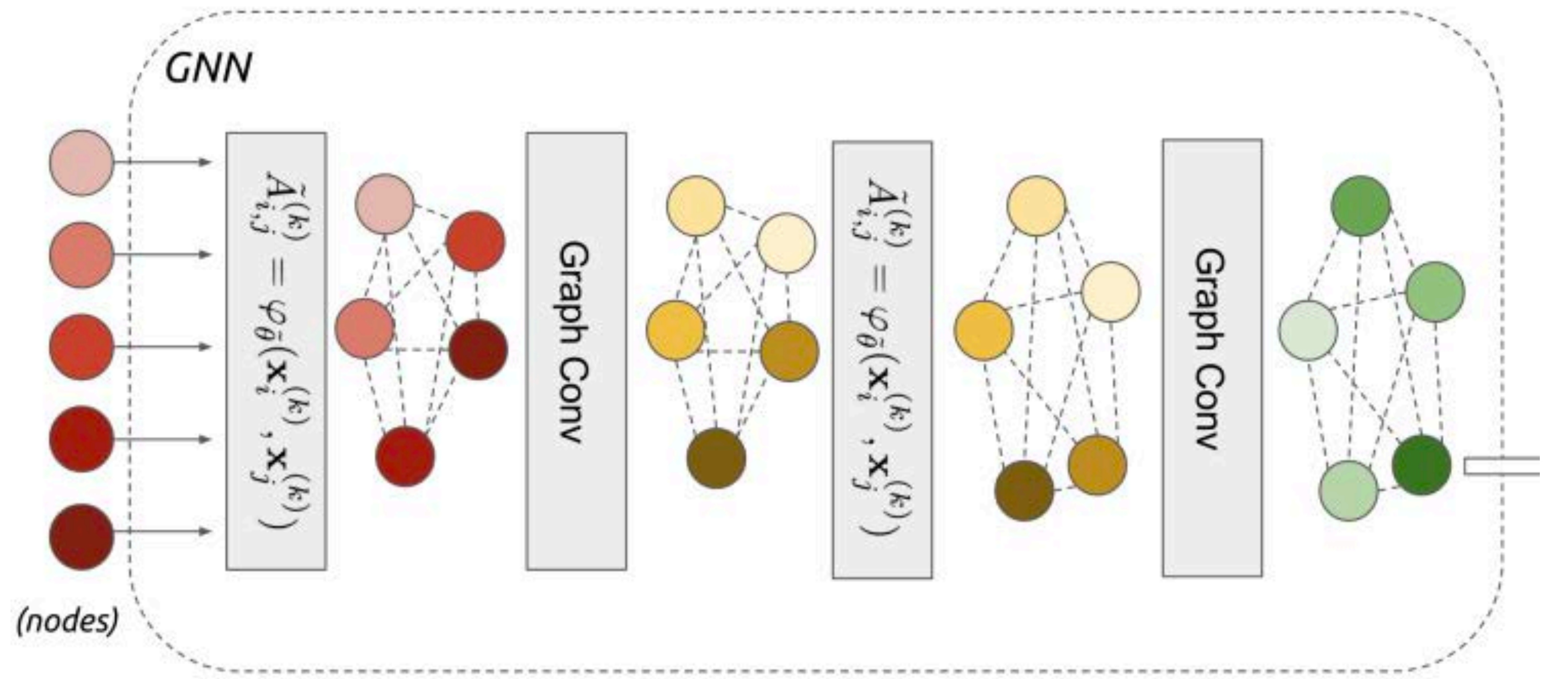
Sung et al. Relation Net

Idea: Learn infinite mixture of prototypes.



Allen et al. IMP, ICML '19

Idea: Perform message passing on embeddings



Garcia & Bruna, GNN

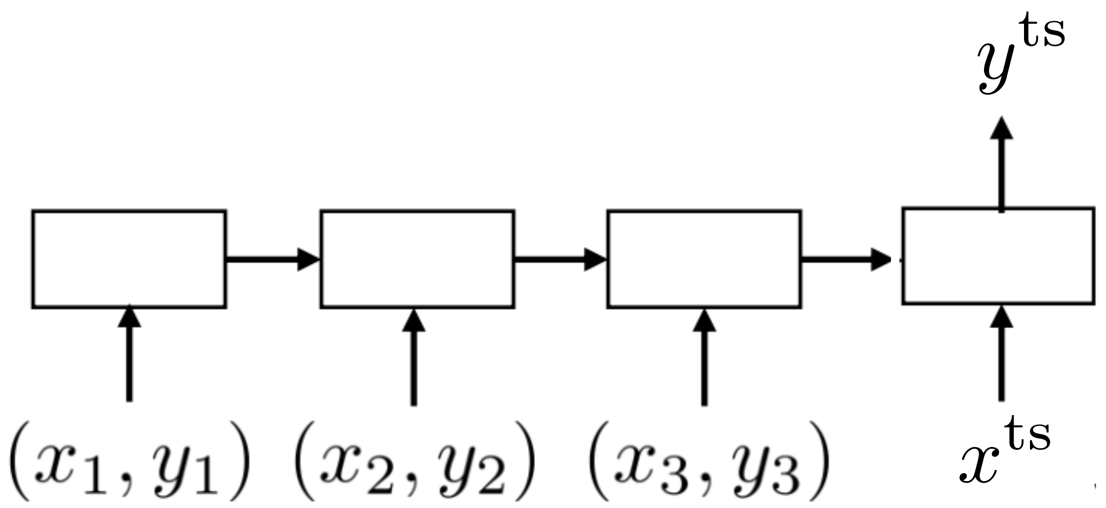
Qs: slic

Amortized vs. Optimization vs. Non-Parametric

Computation graph perspective

Black-box amortized

$$y^{\text{ts}} = f_\theta(\mathcal{D}_i^{\text{tr}}, x^{\text{ts}})$$



Optimization-based

$$y^{\text{ts}} = f_{\text{MAML}}(\mathcal{D}_i^{\text{tr}}, x^{\text{ts}})$$
$$= f_{\phi_i}(x^{\text{ts}})$$
$$\text{where } \phi_i = \theta - \alpha \nabla_\theta \mathcal{L}(\theta, \mathcal{D}_i^{\text{tr}})$$

Non-parametric

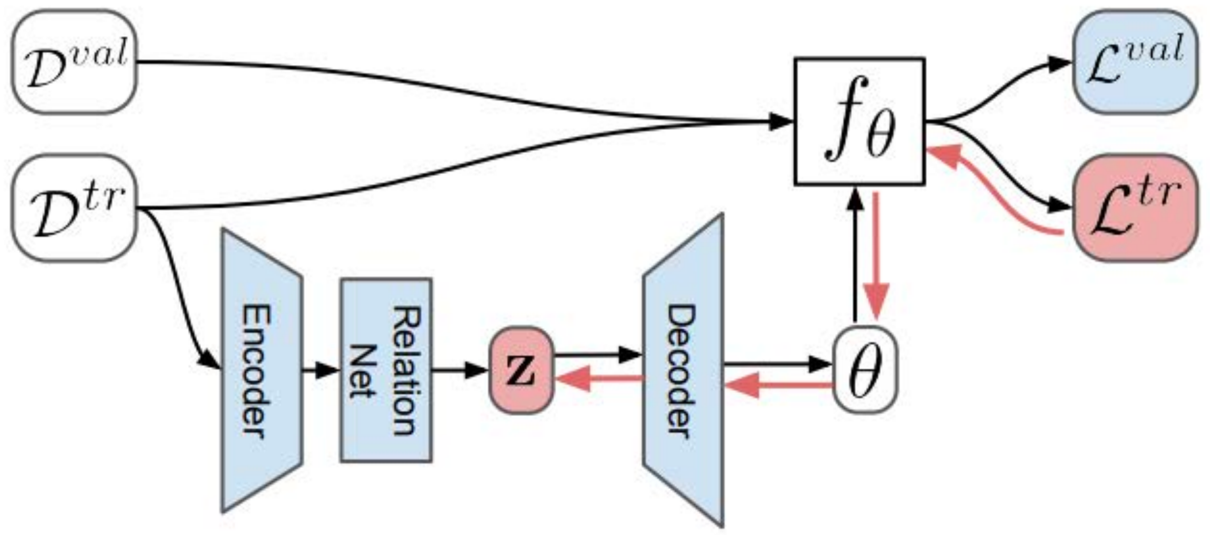
$$y^{\text{ts}} = f_{\text{PN}}(\mathcal{D}_i^{\text{tr}}, x^{\text{ts}})$$
$$= \text{softmax}\left(-d(f_\theta(x), c_k)\right)$$
$$\text{where } c_k = \frac{1}{|\mathcal{D}_i^{\text{tr}}|} \sum_{(x,y) \in \mathcal{D}_i^{\text{tr}}} f_\theta(x)$$

Note: (again) Can mix & match components of computation graph

Both condition on data & run gradient descent.

Jiang et al. CAML '19

Gradient descent on relation net embedding.



Rusu et al. LEO '19

MAML, but initialize last layer as ProtoNet during meta-training

Triantafillou et al. Proto-MAML '19

Qs: slido.com/meta

Intermediate Takeaways

Black-box amortized

+ easy to combine with **variety of learning problems** (e.g. SL, RL)

- **challenging optimization** (no inductive bias at the initialization)
- often **data-inefficient**
- **model** & **architecture** intertwined

Optimization-based

+ handles **varying** & **large K** well
+ **structure lends well** to **out-of-distribution tasks**

- **second-order optimization**

Non-parametric

+ **simple**
+ entirely **feedforward**
+ **computationally fast** & **easy to optimize**

- **harder to generalize** to **varying K**
- hard to scale to **very large K**
- so far, **limited to classification**

Generally, well-tuned versions of each perform **comparably** on existing few-shot benchmarks!

Qs: slido.com/meta

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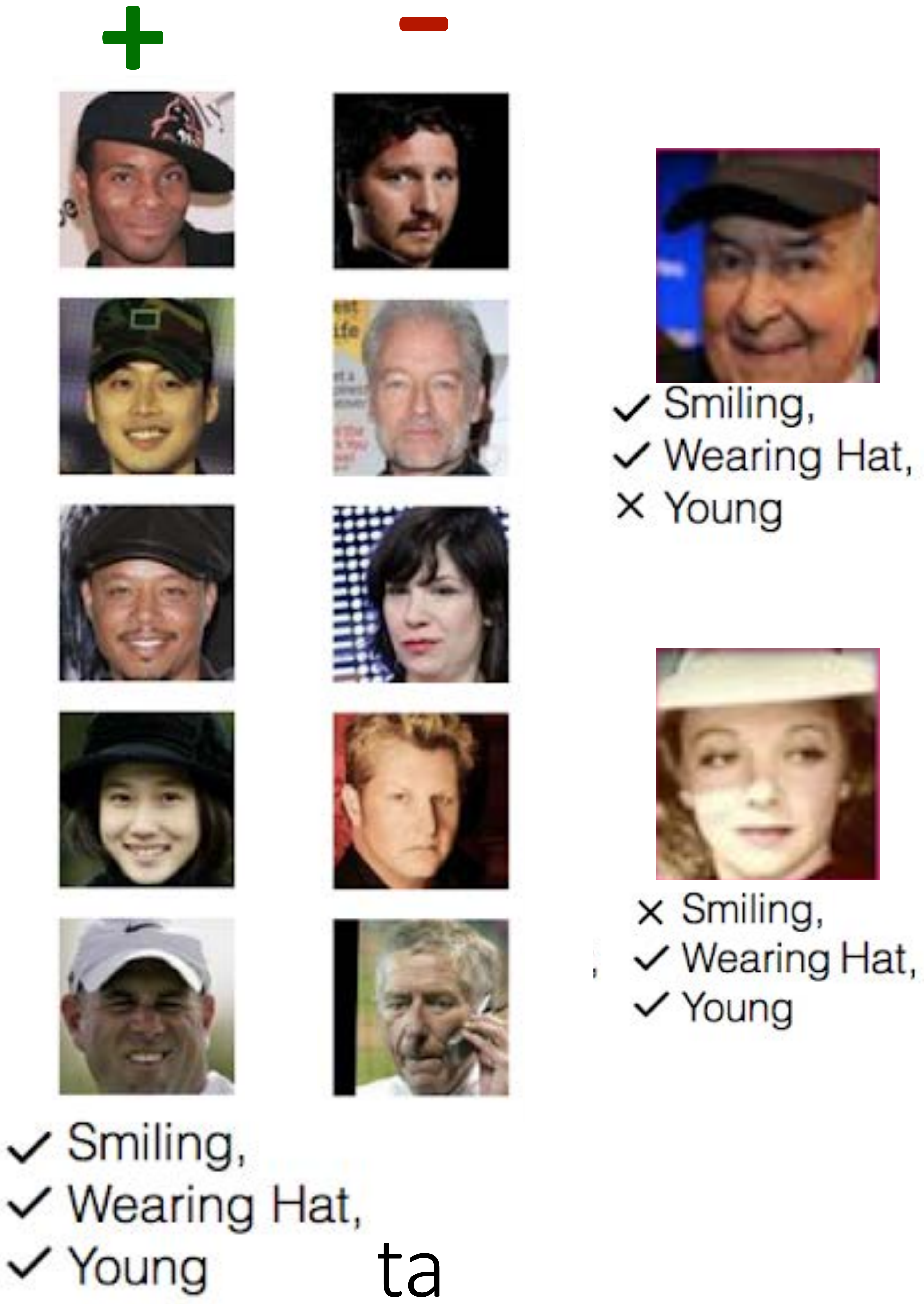
— 5 min break —

- Meta-**reinforcement** learning
- Challenges & frontiers

Qs: slido.com/meta

I can’t believe it’s not Bayesian

Recall parametric approaches: Use **deterministic** $p(\phi_i|\mathcal{D}_i^{\mathrm{tr}}, \theta)$ (i.e. a point estimate)



Why/when is this a problem?

Few-shot learning problems may be *ambiguous*.
(even with prior)

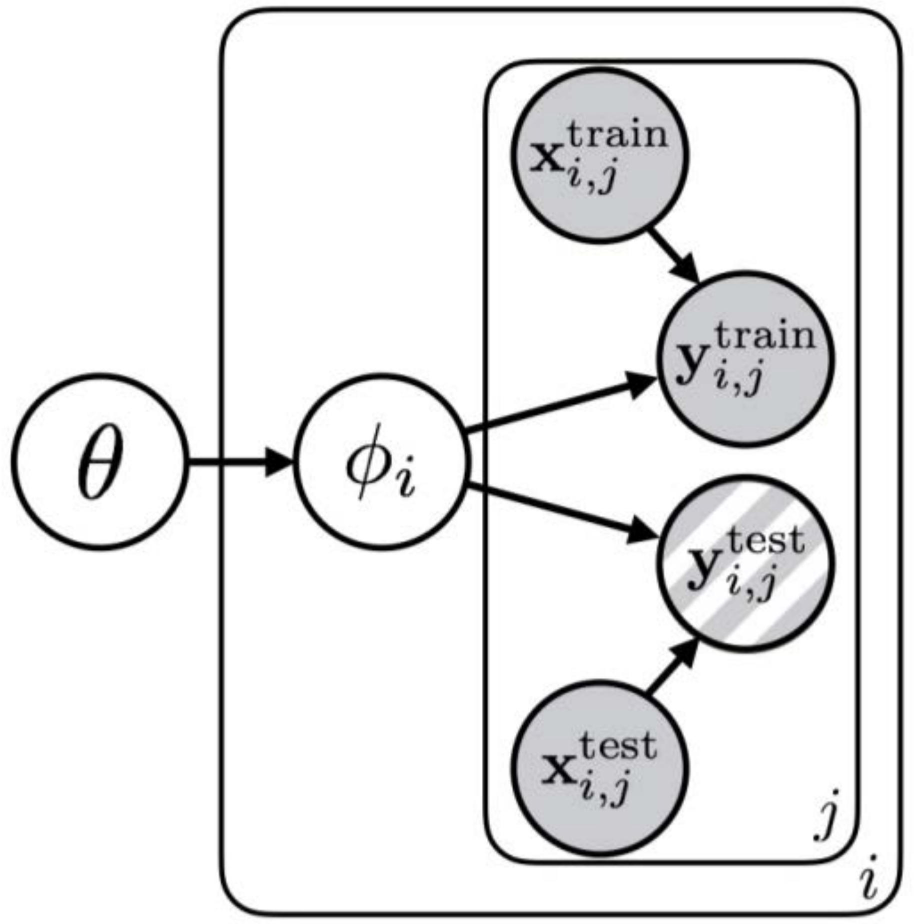
Can we learn to *generate hypotheses* about the underlying function?
i.e. sample from $p(\phi_i|\mathcal{D}_i^{\mathrm{tr}}, \theta)$

Important for:
- **safety-critical** few-shot learning (e.g. medical imaging)
- learning to **actively learn**
- learning to **explore** in meta-RL

Active learning w/ meta-learning: Woodward & Finn ’16, Konyushkova et al. ’17, Bachman et al. ’17

Qs: slid ta

Meta-learning with ambiguity



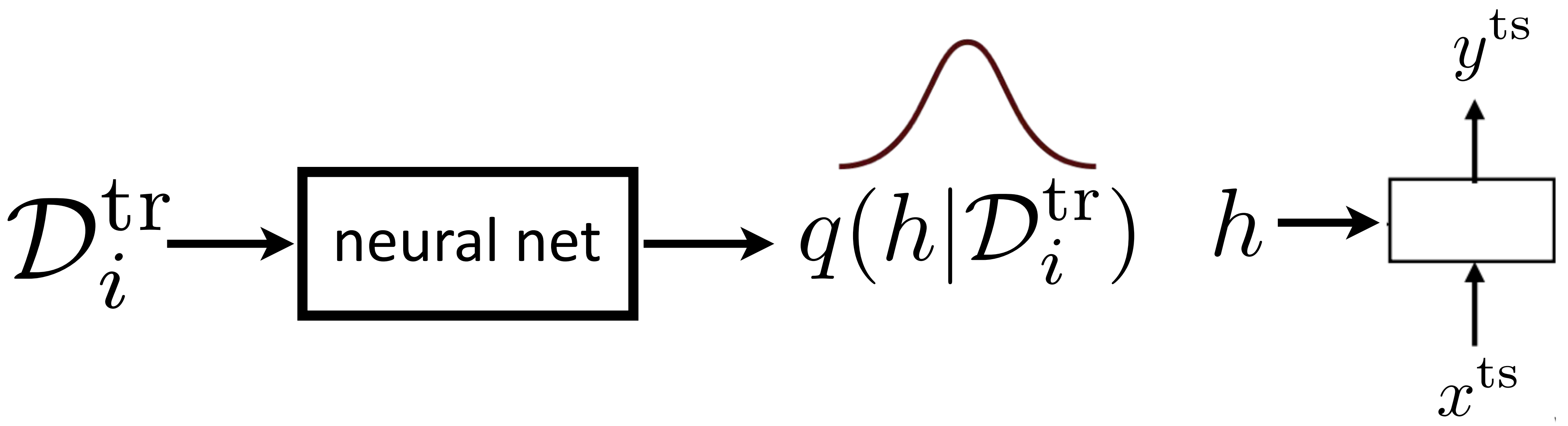
$$\theta \sim p(\theta)$$
$$\phi_i \sim p(\phi_i|\theta)$$

$$\log p(y_i^{\text{train}}|x_i^{\text{train}}, \phi_i)$$
$$\log p(y_i^{\text{test}}|x_i^{\text{test}}, \phi_i)$$

$$\text{Goal: sample } \phi_i \sim p(\phi_i|x_i^{\text{train}}, y_i^{\text{train}}, \cancel{x_i^{\text{test}}})$$

Black-Box Amortized Inference

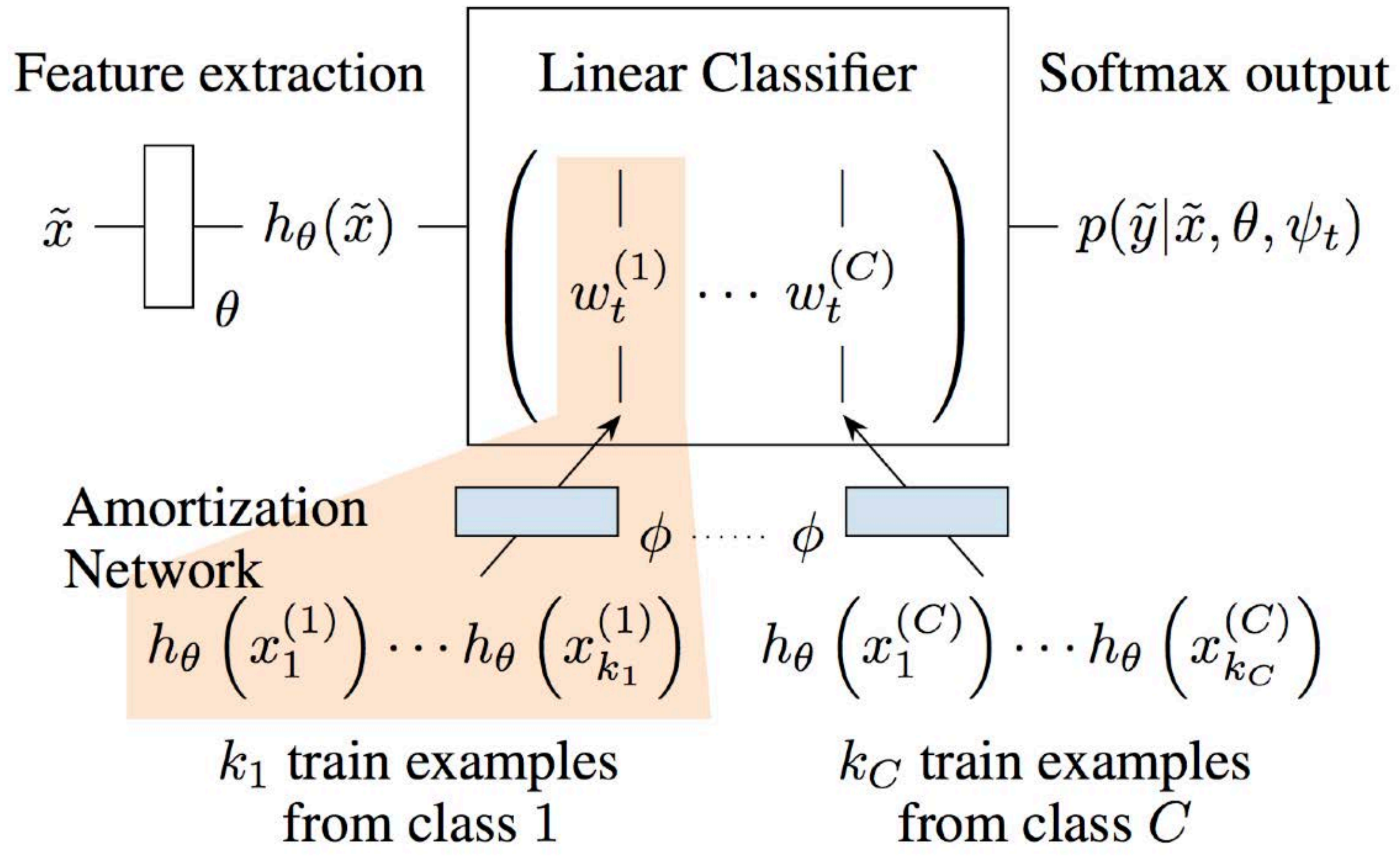
Amortized Variational Inference



Simple idea: NN produces Gaussian distribution over h_i.
Train with amortized variational inference.

(Kingma & Welling VAE '13)

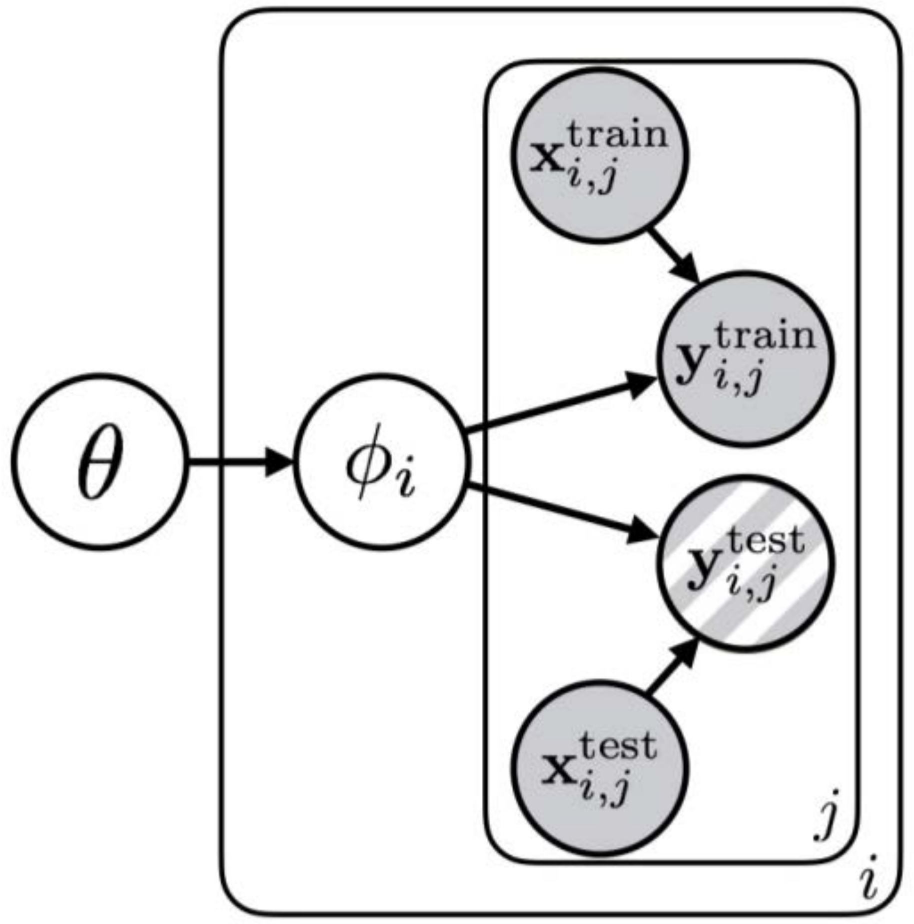
Output distribution over weights of last layer



Gordon et al. VERSA '19

Qs: slido.com/me What about Bayesian optimization-based meta-learning?

Meta-learning with ambiguity



$\theta \sim p(\theta)$

$\phi_i \sim p(\phi_i|\theta)$

$\log p(y_i^{\text{train}}|x_i^{\text{train}}, \phi_i)$

$\log p(y_i^{\text{test}}|x_i^{\text{test}}, \phi_i)$

$$\text{Goal: sample } \phi_i \sim p(\phi_i|x_i^{\text{train}}, y_i^{\text{train}}, \cancel{x_i^{\text{test}}})$$

What about Bayesian **optimization-based** meta-learning?

Model $p(\phi_i|\theta)$ as Gaussian

Same amortized variational inference for training.

(Ravi & Beatson '19)

Amortized Bayesian Meta-Learning

Stein Variational Gradient (BMAML)

Gradient-based inference on **last layer only**.

Use SVGD to avoid Gaussian modeling assumption.

Ensemble of MAMLs (EMAML)

(Kim et al. Bayesian MAML '18)

Can we model **non-Gaussian posterior** over **all parameters**?

Qs: slido.com/meta

Sampling parameter vectors

$\theta \sim p(\theta) = \mathcal{N}(\mu_\theta, \Sigma_\theta)$ $\quad\quad$ $\log p(y_i^{\text{train}} | x_i^{\text{train}}, \phi_i)$

$\phi_i \sim p(\phi_i | \theta)$ $\quad\quad$ $\log p(y_i^{\text{test}} | x_i^{\text{test}}, \phi_i)$

Goal: sample $\phi_i \sim p(\phi_i | x_i^{\text{train}}, y_i^{\text{train}})$

$$p(\phi_i | x_i^{\text{train}}, y_i^{\text{train}}) \propto \int p(\theta) p(\phi_i | \theta) p(y_i^{\text{train}} | x_i^{\text{train}}, \phi_i) d\theta$$

$\Rightarrow$ this is completely intractable!

what if we knew $p(\phi_i | \theta, x_i^{\text{train}}, y_i^{\text{train}})$?

$\Rightarrow$ now sampling is easy! just use ancestral sampling!

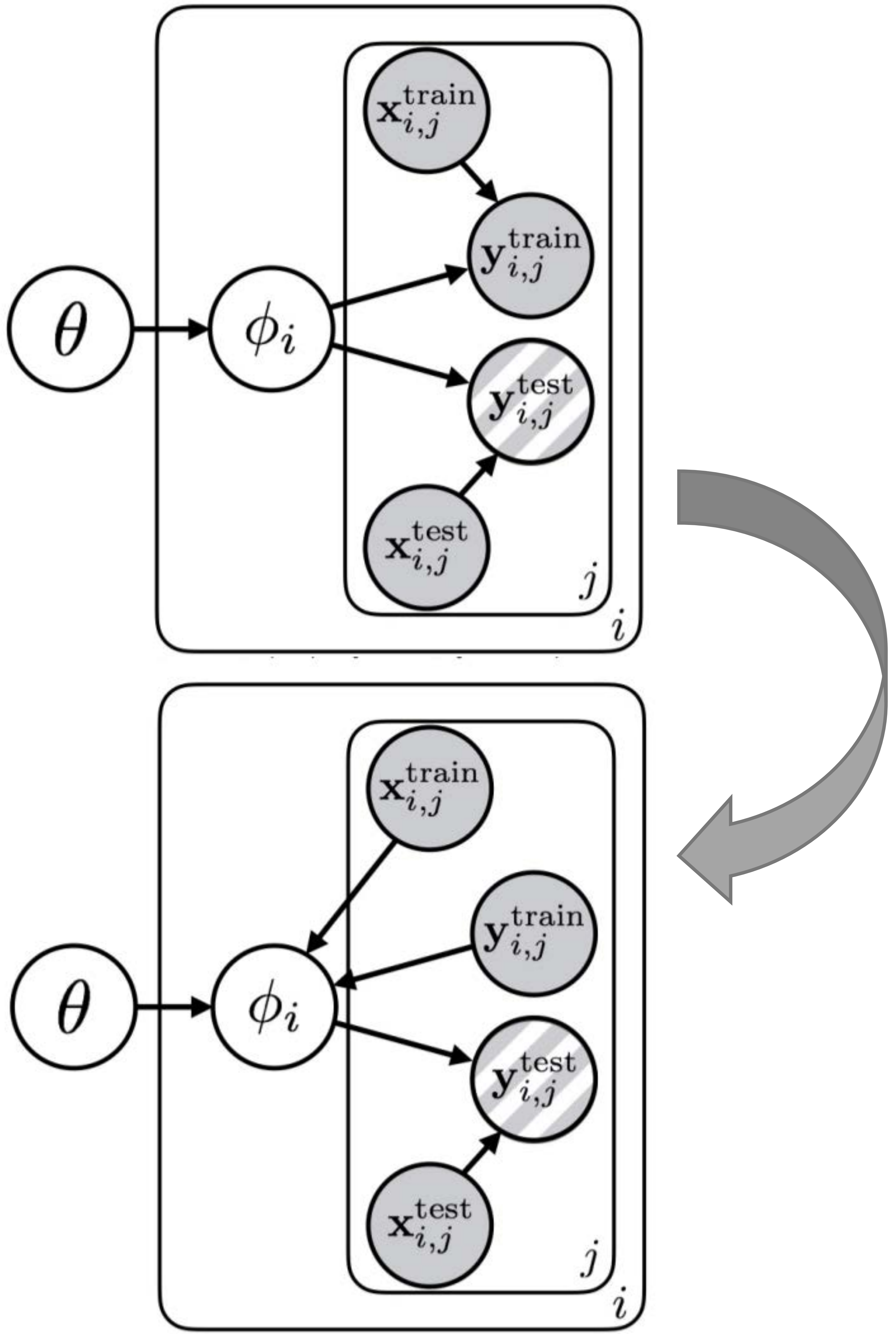
key idea: $p(\phi_i | \theta, x_i^{\text{train}}, y_i^{\text{train}}) \approx \delta(\hat{\phi}_i)$ ← approximate with MAP

this is **extremely** crude

but **extremely** convenient!

$$\hat{\phi}_i \approx \theta + \alpha \nabla_\theta \log p(y_i^{\text{train}} | x_i^{\text{train}}, \theta)$$

(Santos '92, Grant et al. ICLR '18)



Training is harder. We use **amortized variational inference**.

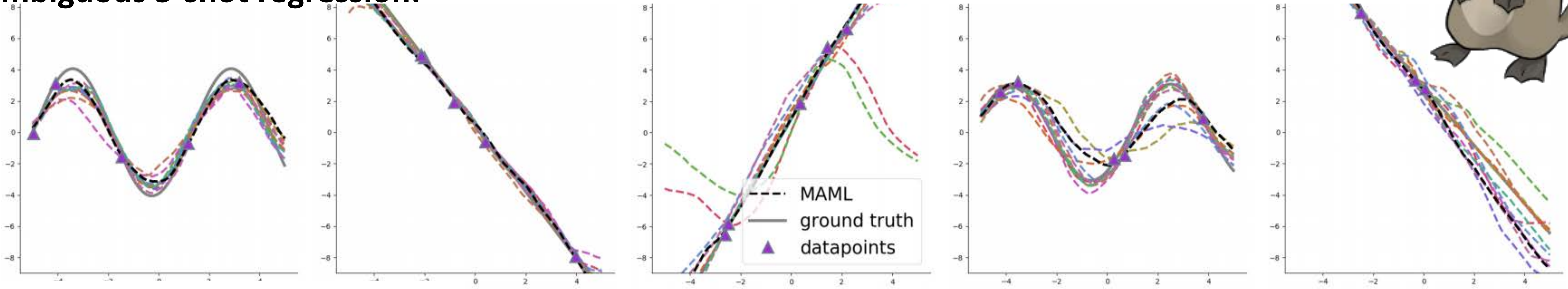
Qs: slido.com/meta

Finn*, Xu* et al. Probabilistic MAML '18

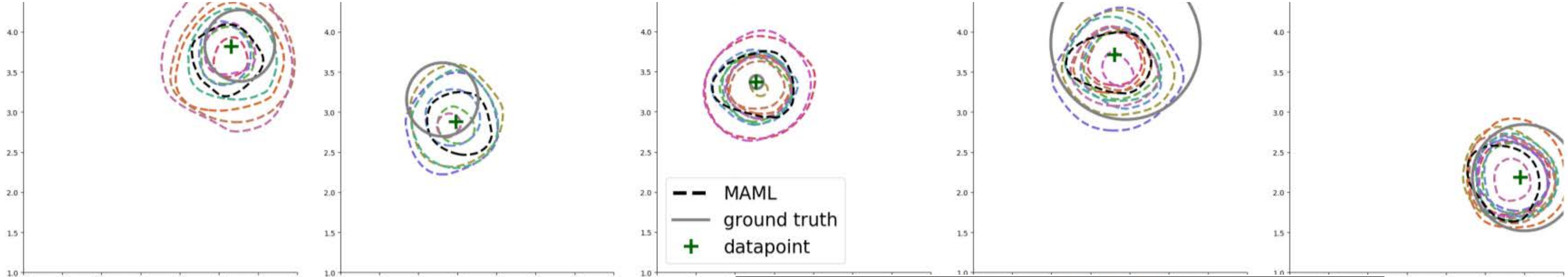
PLATIPUS

Probabilistic LATent model for Incorporating Priors and Uncertainty in few-Shot learning

Ambiguous 5-shot regression:



Ambiguous 1-shot classification:



Better models ambiguous few-shot image classification problems:

Ambiguous celebA (5-shot)		
	Accuracy	Coverage (max=3)
MAML	$69.26 \pm 2.18\%$	1.00 ± 0.0
MAML + noise	$54.73 \pm 0.8\ \%$	2.60 ± 0.12
PLATIPUS (ours)	$\mathbf{69.97 \pm 1.32\ \%}$	$\mathbf{2.62 \pm 0.11}$

Qs: slido.com/meta

Finn*, Xu* et al. Probabilistic MAML ‘18

Deep Bayesian Meta-Learning: Further Reading

Edwards & Storkey, Towards a Neural Statistician. 2017

Black-box approaches:

Gordon et al., VERSA 2019

Garnelo et al. Conditional Neural Processes 2018

Optimization-based approaches:

Kim et al., Bayesian MAML. 2018

Xu et al., Probabilistic MAML. 2018

Ravi & Beatson., Amortized Bayesian Meta-Learning 2019

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— 5 min break —

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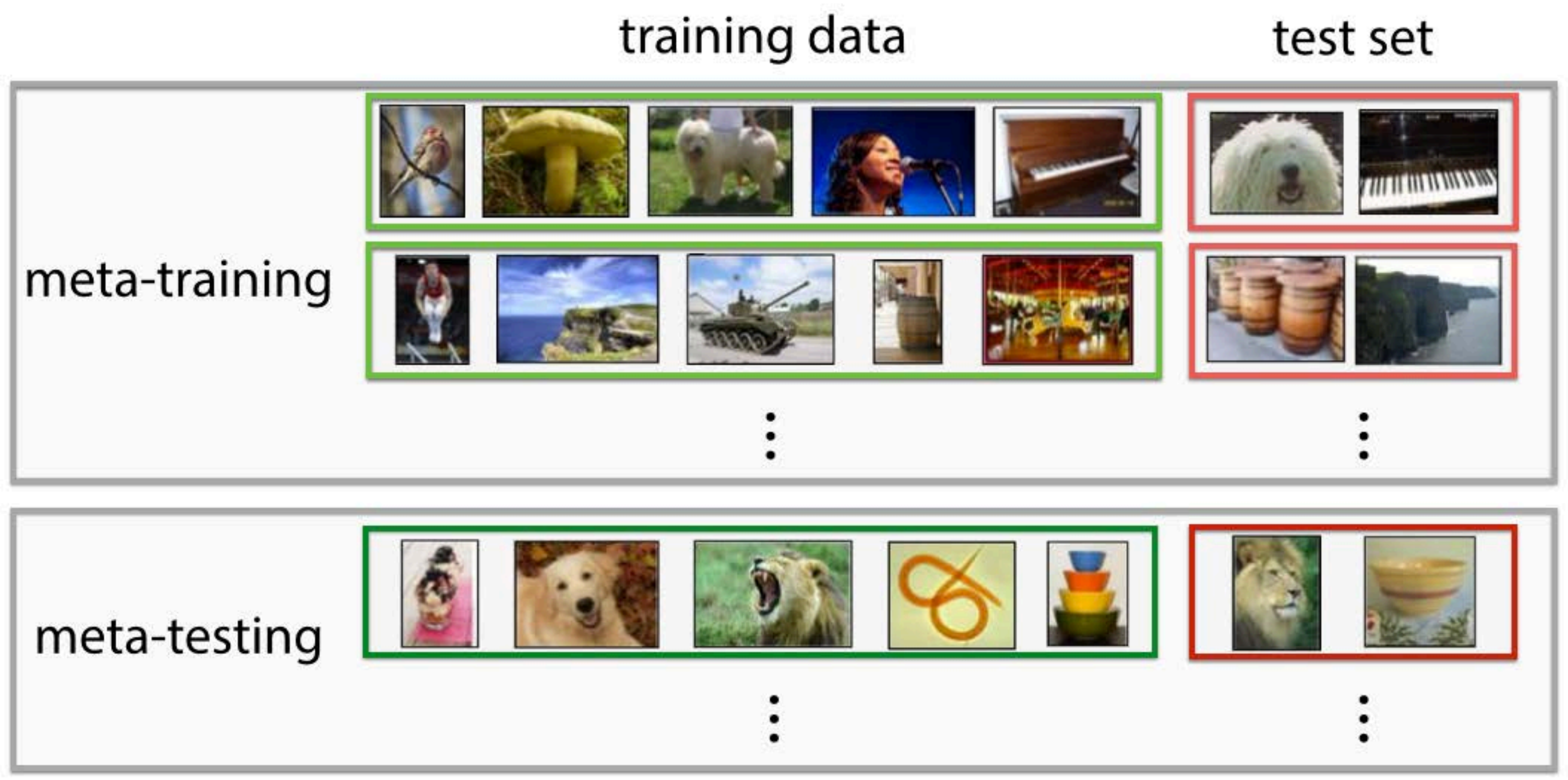
Qs: slido.com/meta

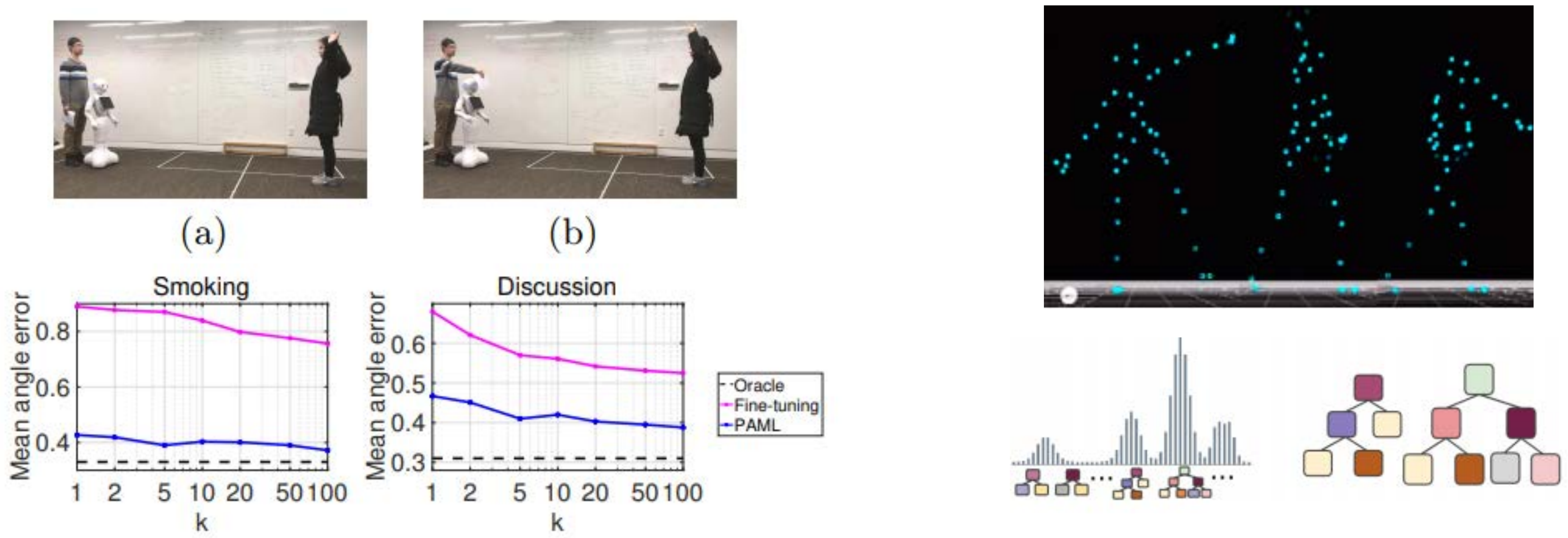
Applications in computer vision

few-shot image recognition



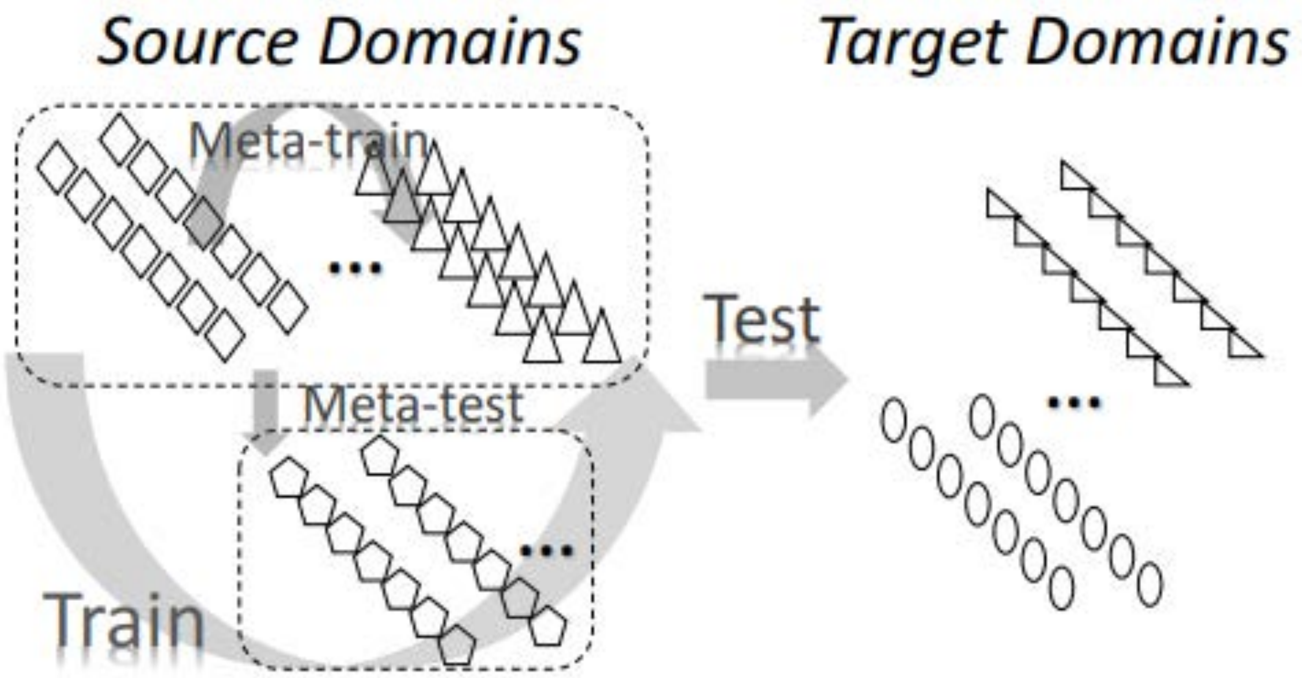
see, e.g.: Vinyals et al. **Matching Networks for One Shot Learning**, and many many others

human motion and pose prediction



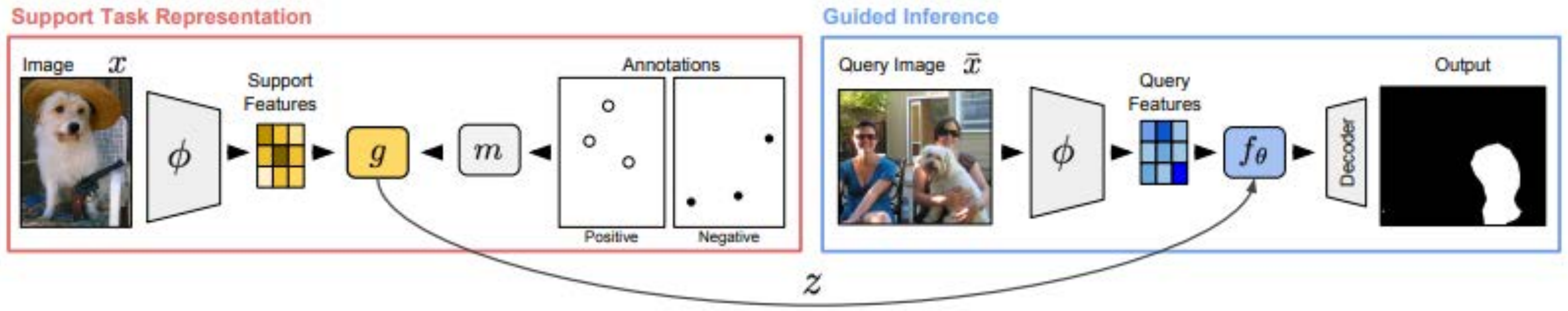
see, e.g.: Gui et al. **Few-Shot Human Motion Prediction via Meta-Learning.**
Alet et al. **Modular Meta-Learning.**

domain adaptation



see, e.g.: Li, Yang, Song, Hospedales. **Learning to Generalize: Meta-Learning for Domain Adaptation.**

few-shot segmentation

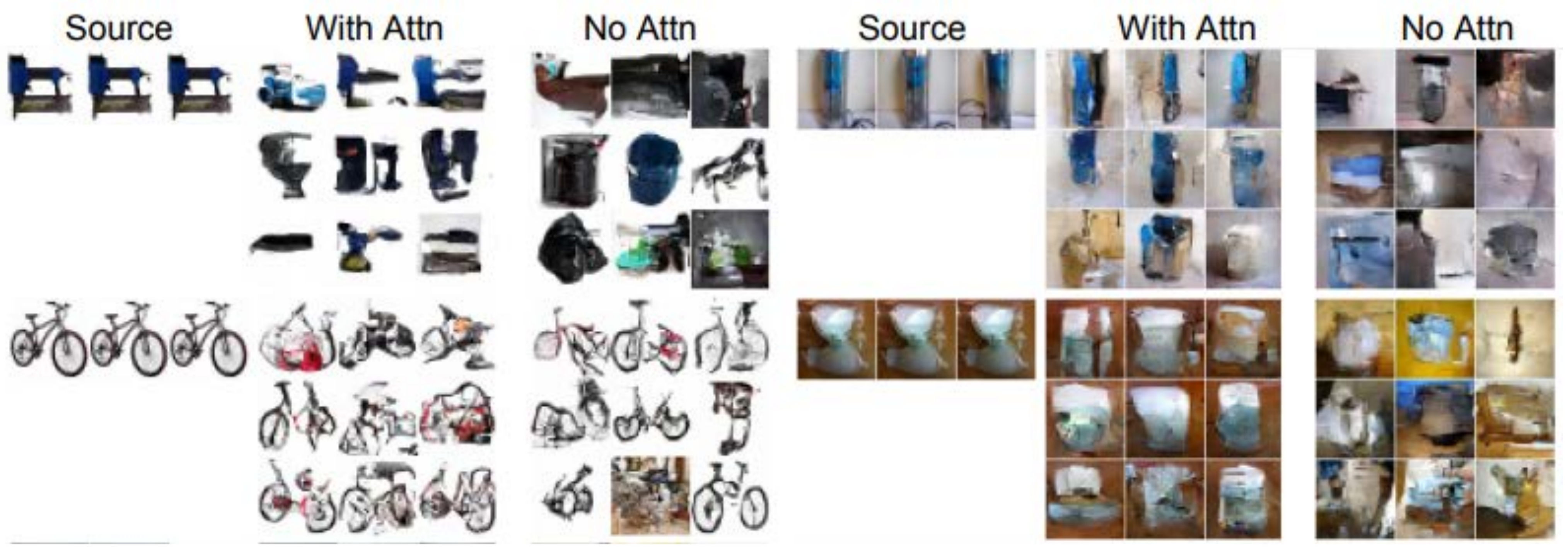


see, e.g.: Shaban, Bansal, Liu, Essa, Boots. **One-Shot Learning for Semantic Segmentation.**
Rakelly, Shelhamer, Darrell, Efros, Levine. **Few-Shot Segmentation Propagation with Guided Networks.**
Dong, Xing. **Few-Shot Semantic Segmentation with Prototype Learning.**

Qs:

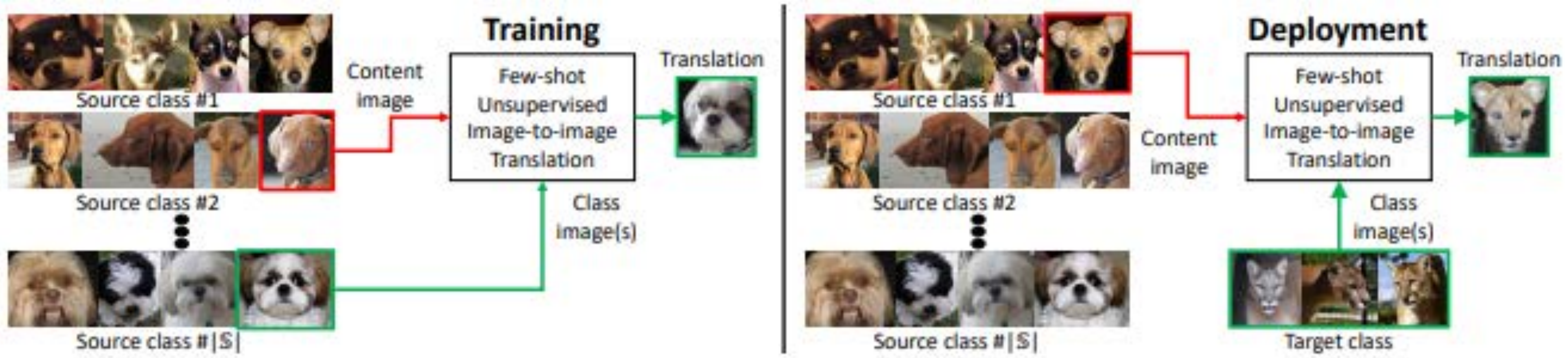
Applications in image & video generation

few-shot image generation



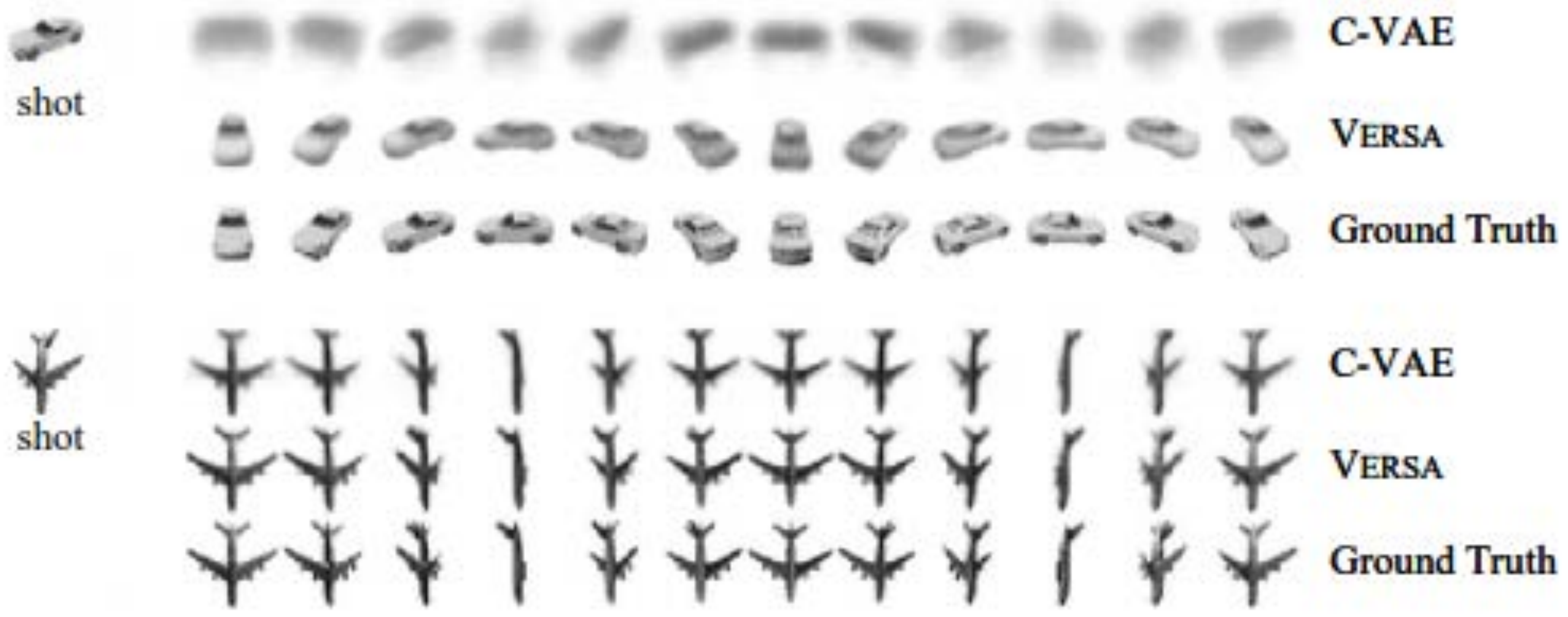
see, e.g.: Reed, Chen, Paine, van den Oord, Eslami, Rezende, Vinyals, de Freitas. **Few-Shot Autoregressive Density Estimation**. and many many others.

few-shot image-to-image translation



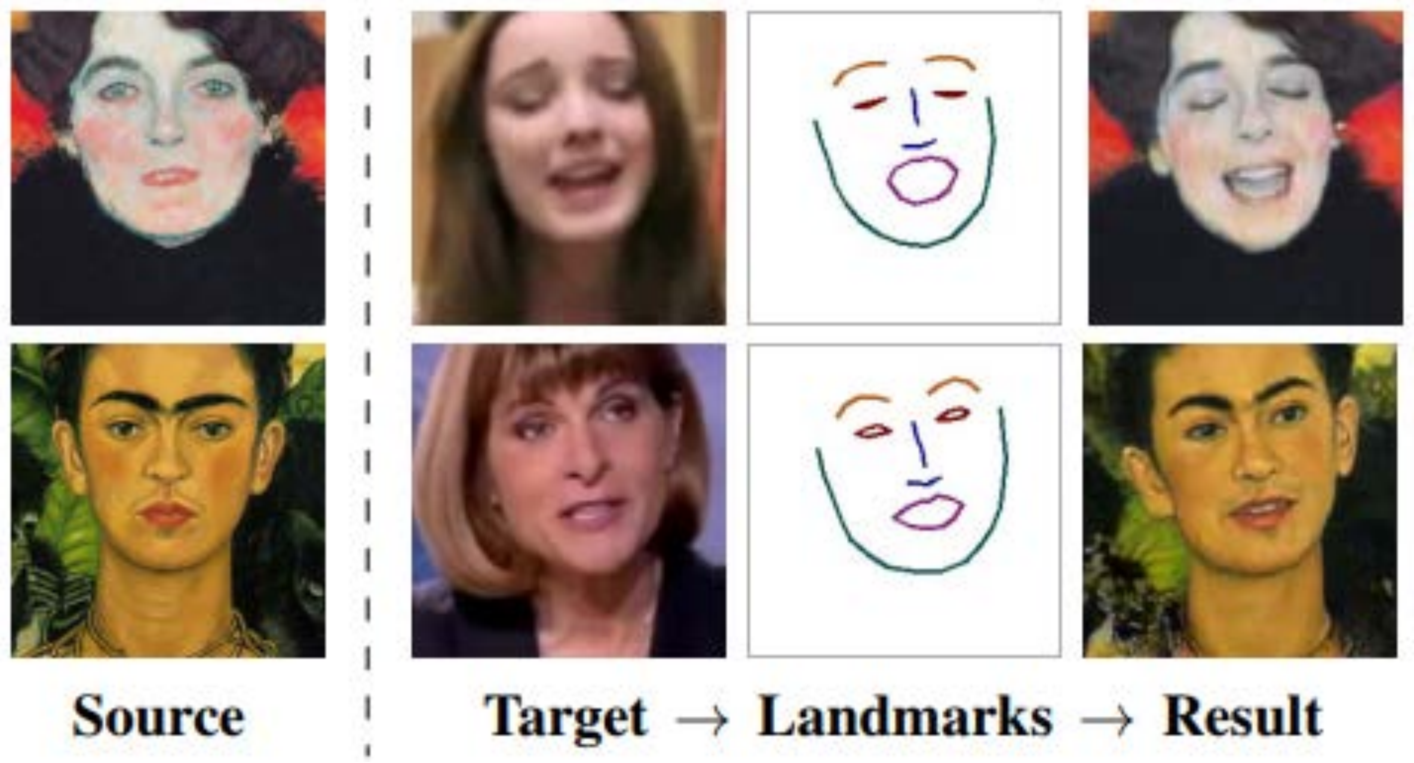
see, e.g.: Liu, Huang, Mallya, Karras, Aila, Lehtinen, Kautz. **Few-Shot Unsupervised Image-to-Image Translation.**

generation of novel viewpoints



see, e.g.: Gordon, Bronskill, Bauer, Nowozin, Turner. **VERSA: Versatile and Efficient Few-Shot Learning.**

generating talking heads from images



see, e.g.: Zakharov, Shysheya, Burkov, Lempitsky. **Few-Shot Adversarial Learning of Realistic Neural Talking Head Models**

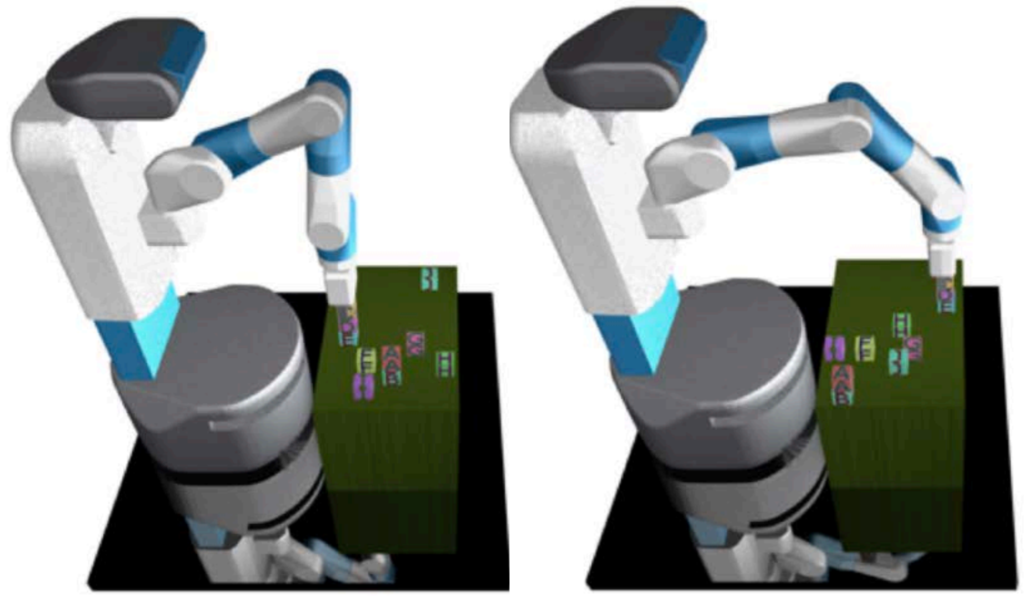
Qs: slido.com/meta

One-Shot *Imitation* Learning

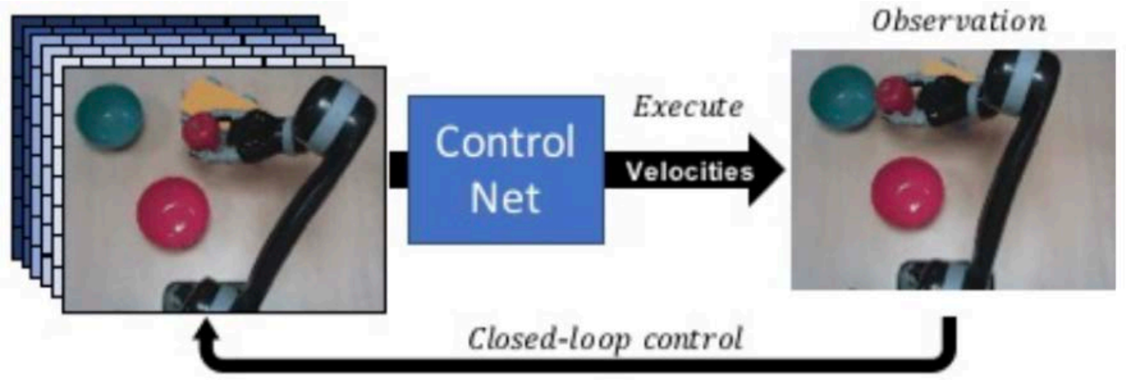
Goal: Given one demonstration of a new task, learn a policy

meta-learning with supervised imitation learning

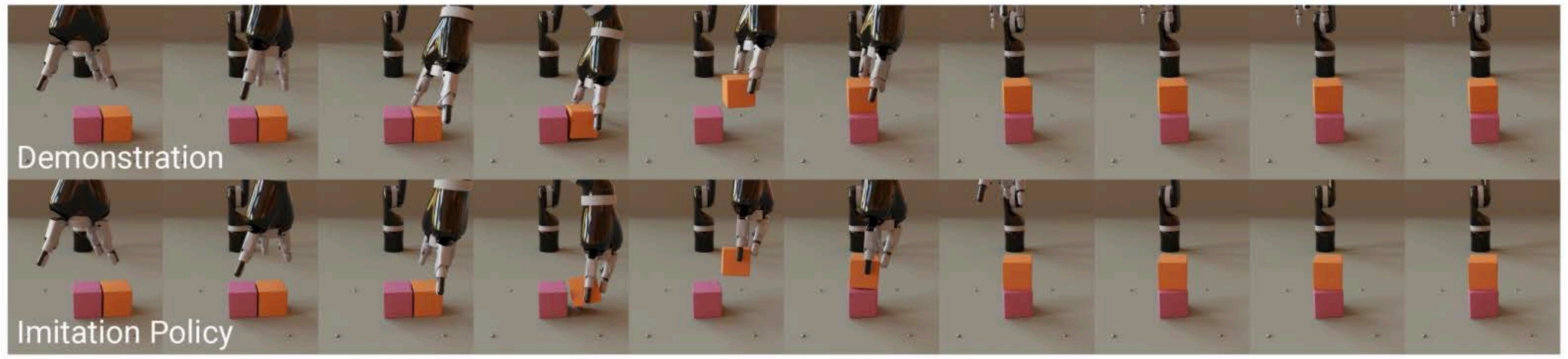
Black-box amortized inference



Duan et al. One-Shot Imitation Learning ‘17



James et al. Task-Embedded Control ‘18

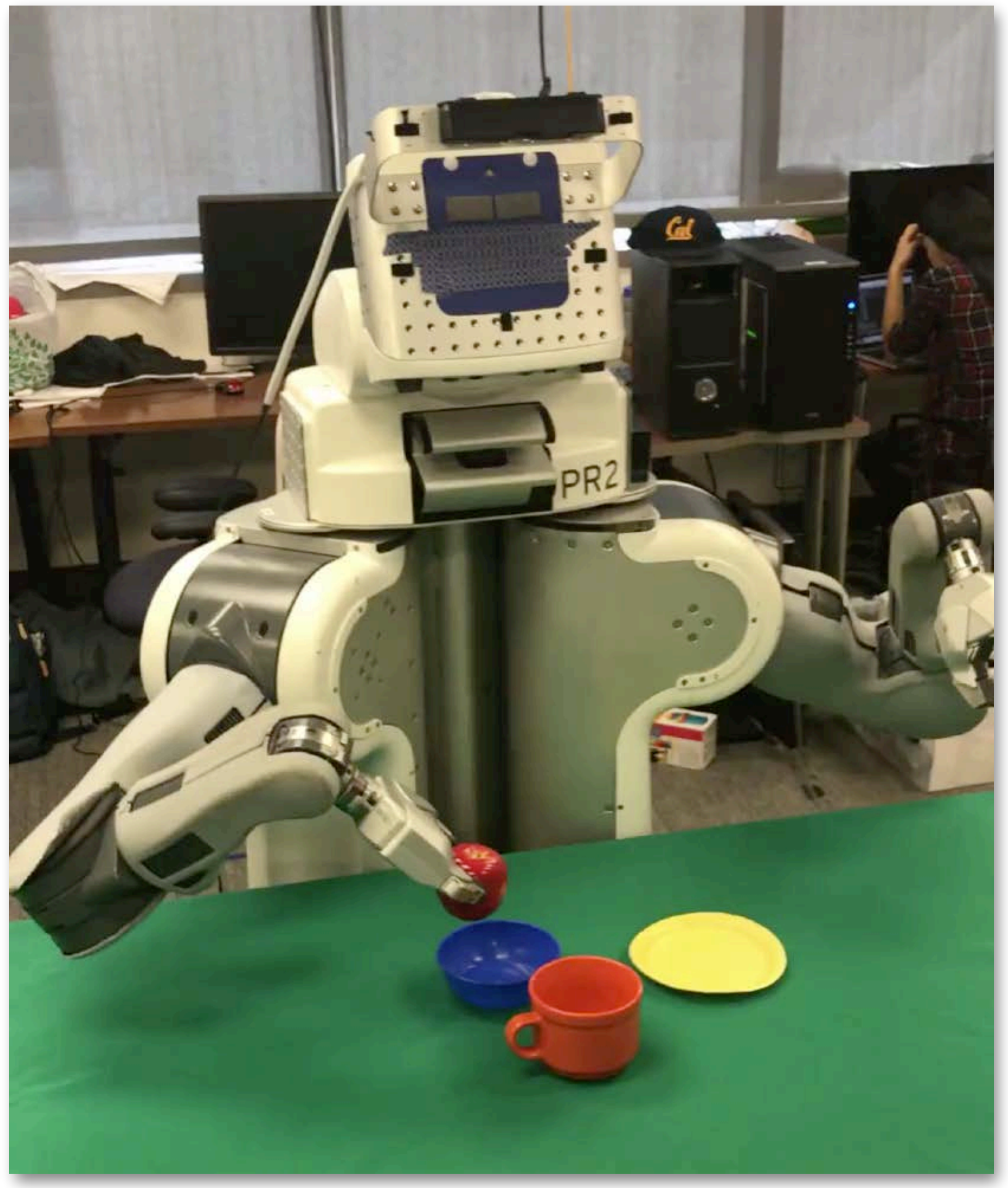


Le Paine et al. One-Shot High Fidelity Imitation ‘19

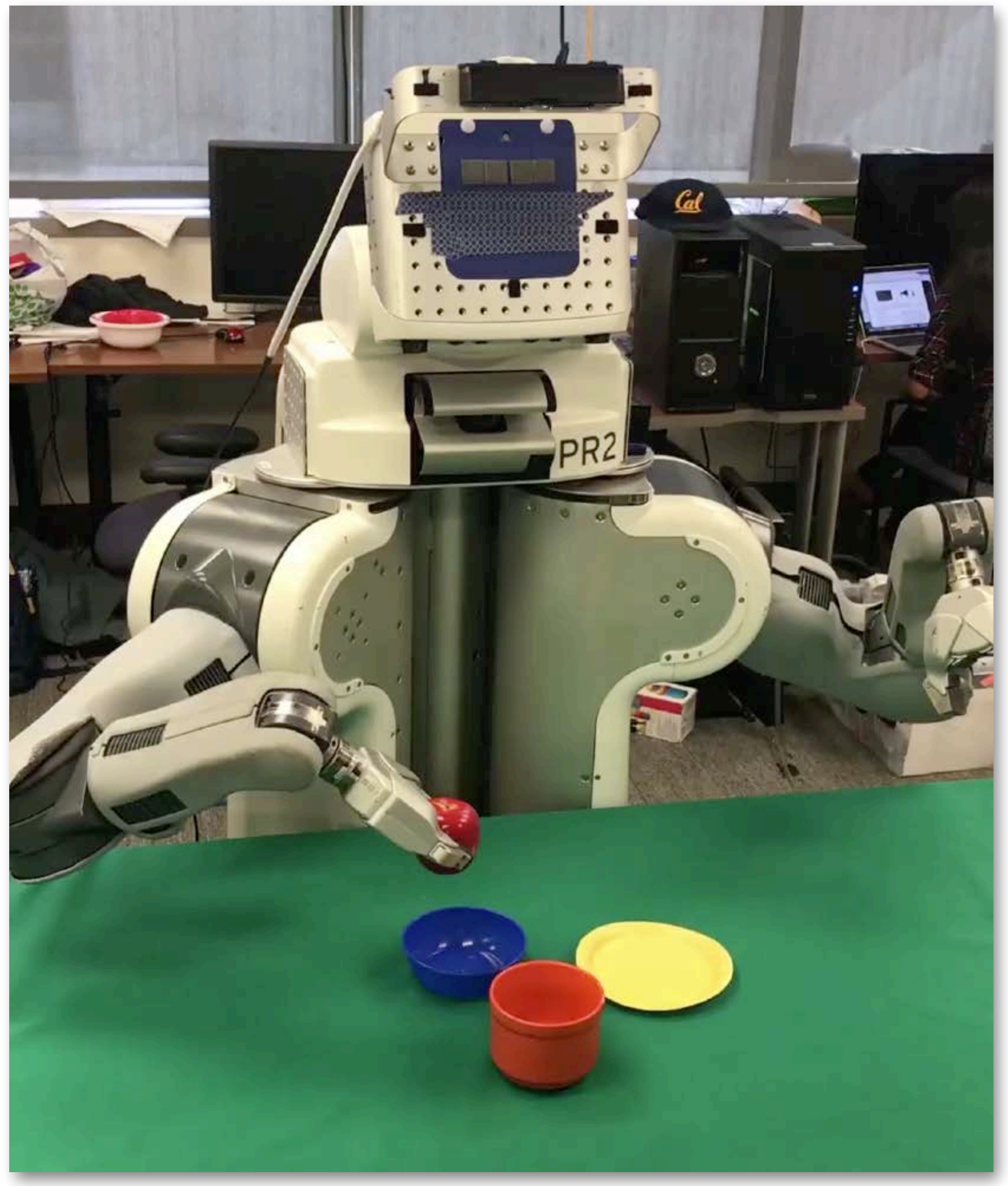
Optimization-based inference

Finn*, Yu* et al. Meta Imitation Learning ‘17

input demo
(via teleoperation)



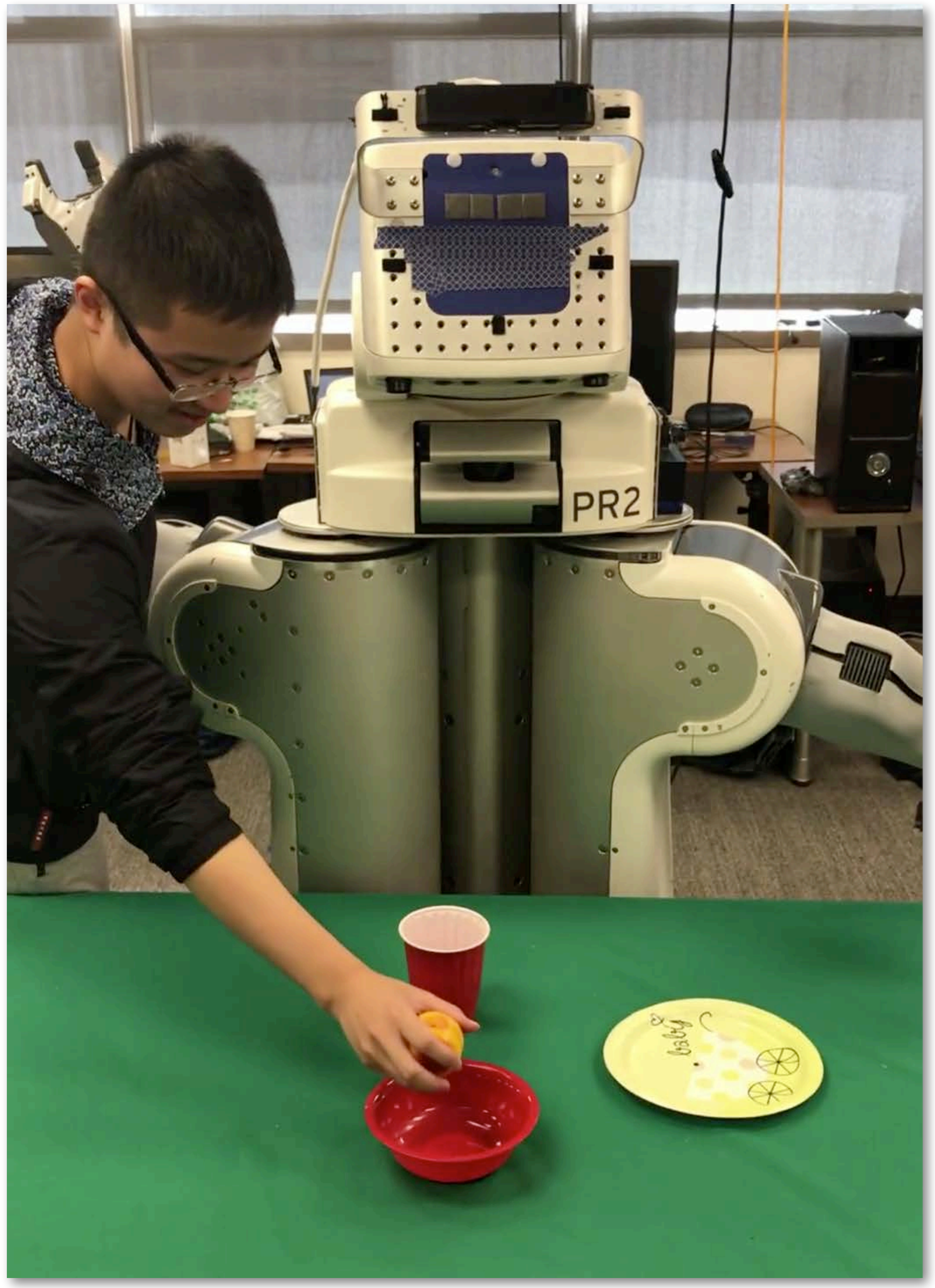
resulting policy



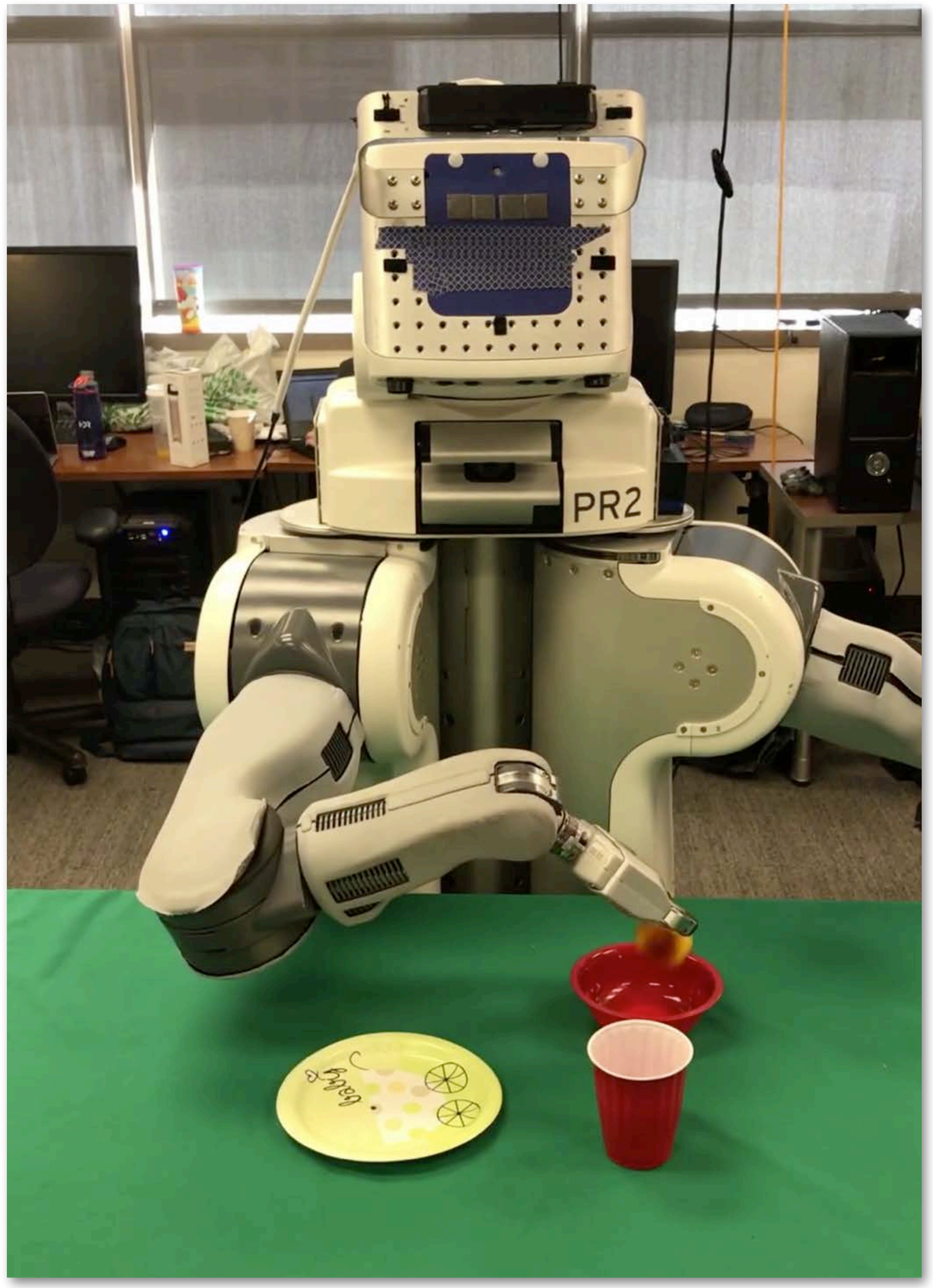
Also: **One-shot inverse RL** (Xu et al. MandRIL ’18, Gleave & Habryka ’18), **One-shot hierarchical imitation** (Yu et al. ’18)

Learning to Learn from ***Weak*** Supervision

input human demo



resulting policy



Qs: <u>slido.com/meta</u>

Yu*, Finn*, Xie, Dasari, Zhang, Abbeel, Levine RSS ’18

Learning to Learn from ***Weak*** Supervision

meta-training

$$\min_{\theta} \sum_{\text{task } i} \mathcal{L}^i_{\text{test}}(\theta - \alpha \nabla_\theta \mathcal{L}^i_{\text{train}}(\theta))$$

fully supervised **weakly supervised**

meta-test

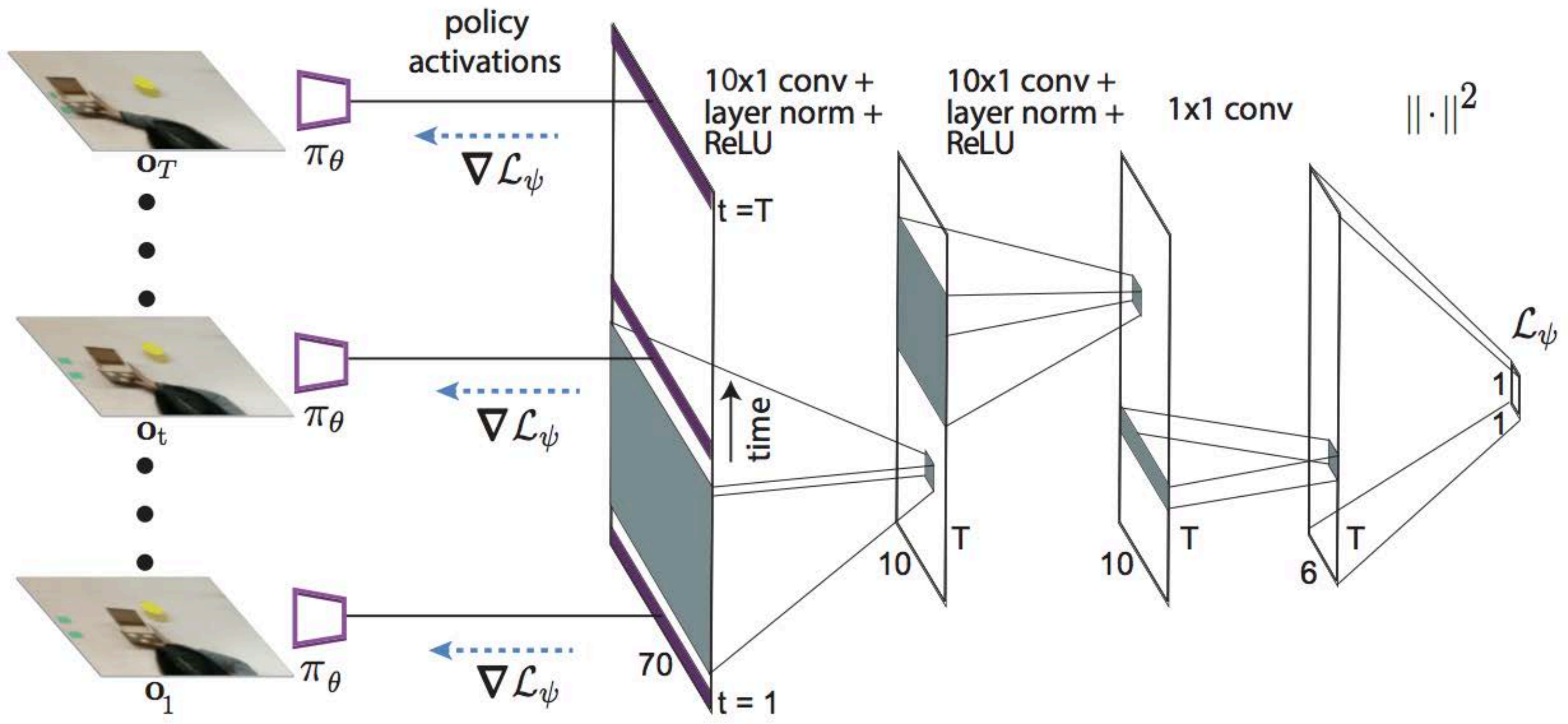
$$\theta' \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}(\theta)$$

weakly supervised

What if the weakly supervised loss is unavailable?

$$\min_{\theta,\psi} \sum_{\text{task } i} \mathcal{L}^i_{\text{test}}(\theta - \alpha \nabla_\theta \mathcal{L}^i_{\psi}(\theta))$$

$\mathcal{L}_\psi$



Yu*, Finn*, Xie, Dasari, Zhang, Abbeel, Levine RSS '18

Grant, Finn, Peterson, Abbott, Levine, Darrell, Griffiths NIPS CIAI Workshop '17

Qs: slido.com/meta

Meta-Learning for ***Language***

Adapting to *new programs*

Meta Program Induction

Learn new program from a few I/O examples.

Devlin, Bunel* et al. NeurIPS '17*

Program Synthesis

Question:

How many CFL teams are from York College?

SQL:

```
SELECT COUNT CFL Team FROM
CFLDraft WHERE College = "York"
```

Result:

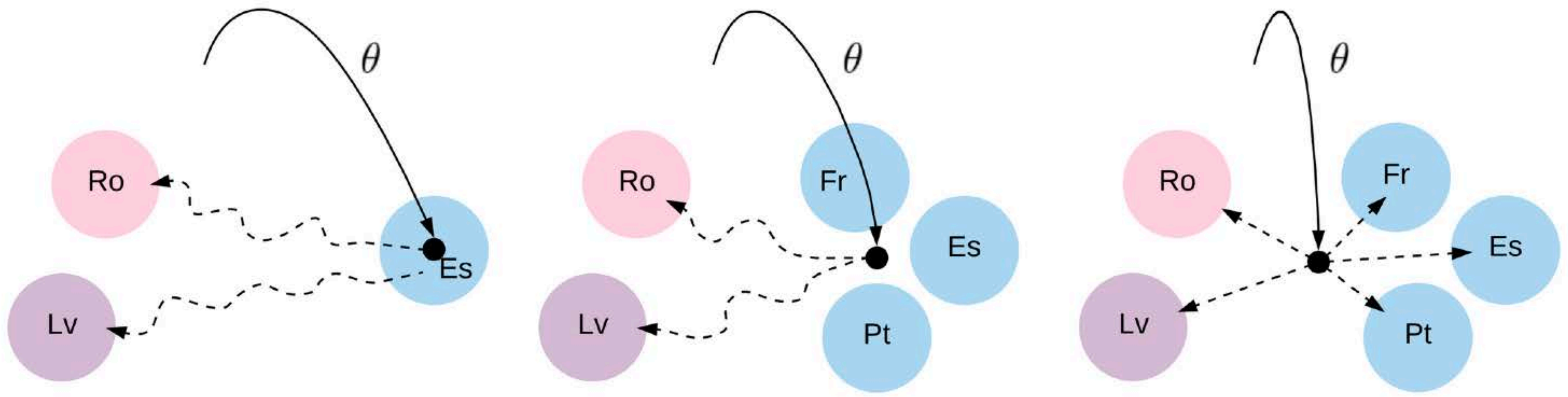
2

Construct pseudo-tasks with relevance function

Huang et al. NAACL '18

Adapting to *new languages*

Low-Resource Neural Machine Translation



(a) Transfer Learning (b) Multilingual Transfer Learning (c) Meta Learning

Learn to translate new language pair w/o a lot of paired data?

Gu et al. EMNLP '18

Learning *new words*

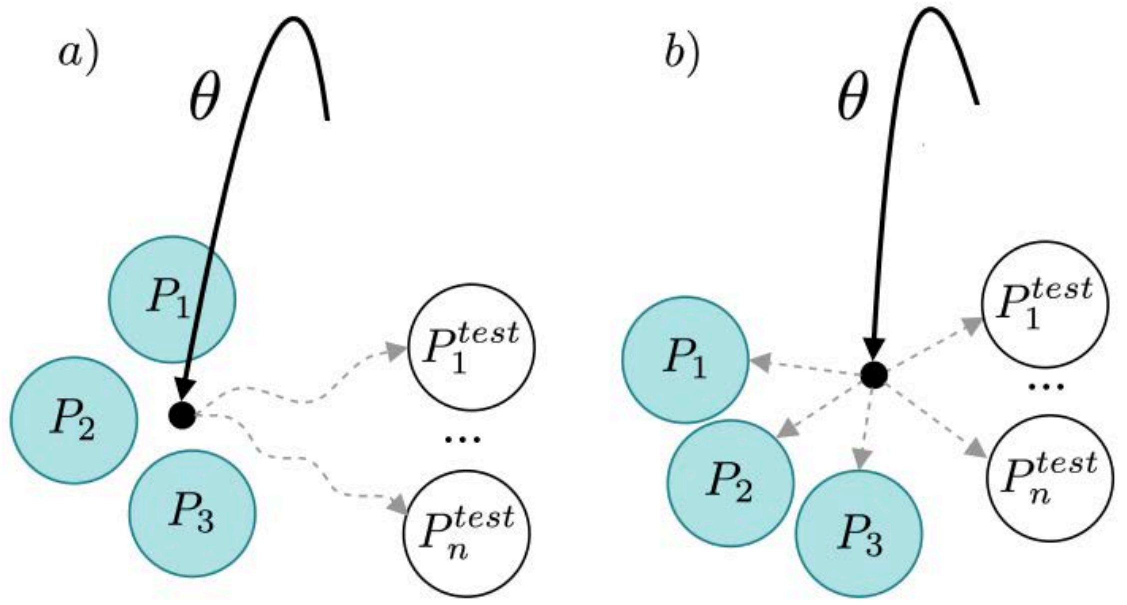
One-Shot Language Modeling

Learn how to use a new word from one example usage.

Vinyals et al. Matching Networks, '16

Adapting to *new personas*

Personalizing Dialogue Agents



Adapt dialogue to a persona with a few examples

Lin, Madotto* et al. ACL '19*

Qs: slido.com/meta

Outline

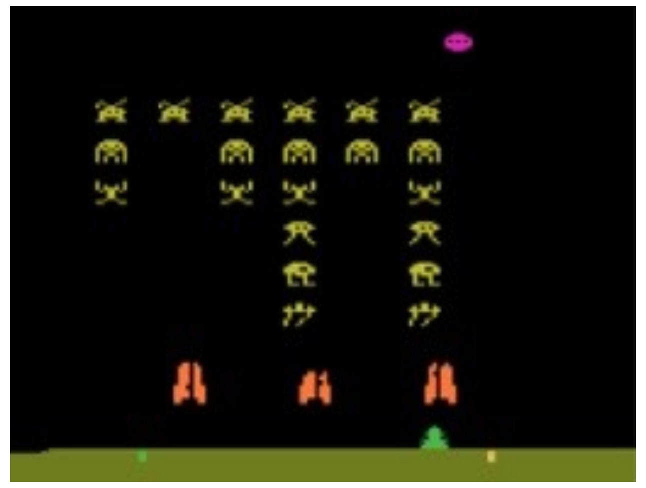
- **Problem statement**
- Meta-learning **algorithms**
    - Black-box adaptation
    - Optimization-based inference
    - Non-parametric methods
    - Bayesian meta-learning
- Meta-learning **applications**

— 5 min break —

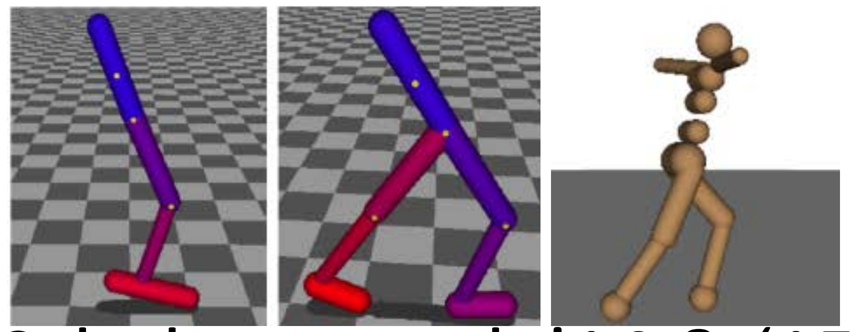
- Meta-**reinforcement** learning
- Challenges & frontiers

Qs: slido.com/meta

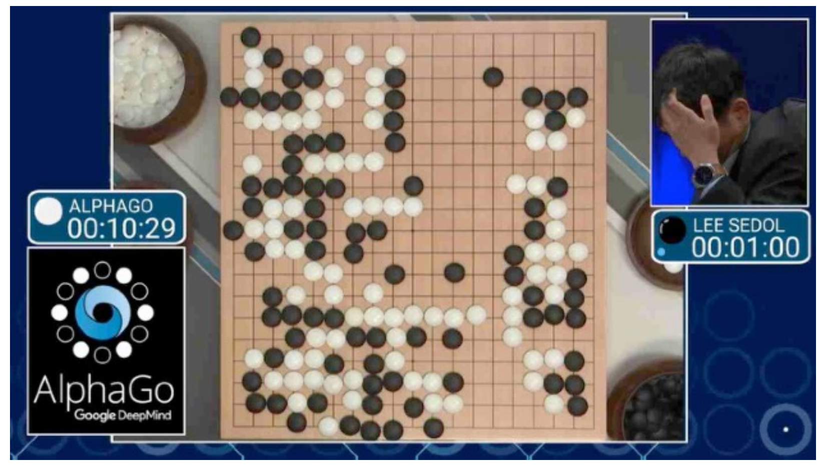
Why should we care about meta-RL?

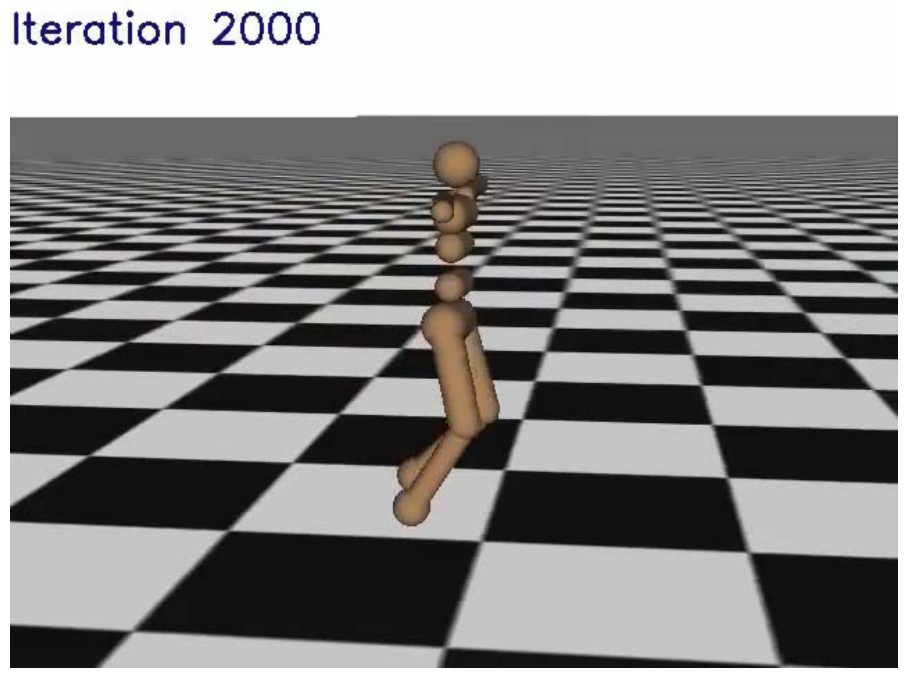


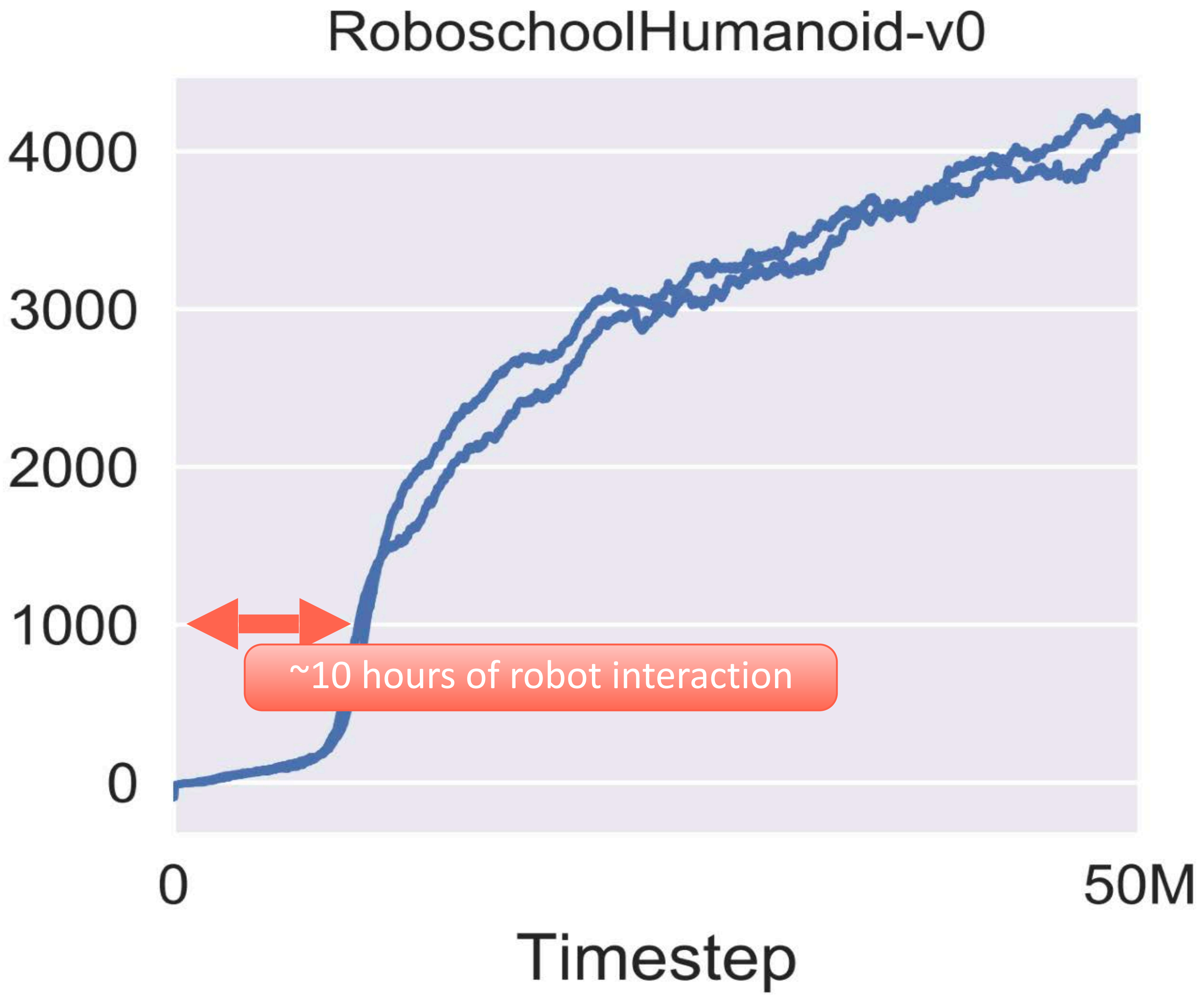
Mnih et al. '13



Schulman et al. '14 & '15







graph: Schulman et al. '17

people can learn new skills **extremely** quickly

how?

we never learn from scratch!

Can we **meta-learn** reinforcement learning "algorithms" that are much more efficient?

Qs: slido.com/meta

The reinforcement learning problem

Markov decision process $\mathcal{M} = \{\mathcal{S}, \mathcal{A}, \mathcal{P}, r\}$

$\mathcal{S}$ – state space   states $s \in \mathcal{S}$ (discrete or continuous)

$\mathcal{A}$ – action space   actions $a \in \mathcal{A}$ (discrete or continuous)

$\mathcal{P}$ – transition function, i.e. $p(s_{t+1}|a_t, s_t) = \mathcal{P}(s_t, a_t, s_{t+1})$

r – reward function $r : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$

$r(s_t, a_t)$ – reward

$\pi_\theta(a|s)$ – policy with params θ $\theta^\star = \arg\max_\theta E_{\pi_\theta}\left[\sum_{t=0}^{T} r(s_t, a_t)\right]$

expectation under π_θ and $\mathcal{P}$


Andrey Markov


Richard Bellman

Qs: slido.com/meta

The reinforcement learning problem

$$\theta^\star = \arg\max_\theta E_{\pi_\theta}\left[\sum_{t=0}^{T} r(s_t, a_t)\right]$$

$$\theta^\star = \arg\max_\theta E_{\pi_\theta}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t)\right] \longleftarrow \text{infinite horizon, discounted return}$$

$$\theta^\star = \arg\max_\theta E_{\pi_\theta(s,a)}\left[r(s_t, a_t)\right]$$

stationary distribution

$$\underbrace{p_\theta(\mathbf{s}_1, \mathbf{a}_1, \ldots, \mathbf{s}_T, \mathbf{a}_T)}_{\pi_\theta(\tau)} = p(\mathbf{s}_1) \prod_{t=1}^{T} \pi_\theta(\mathbf{a}_t|\mathbf{s}_t) p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$$

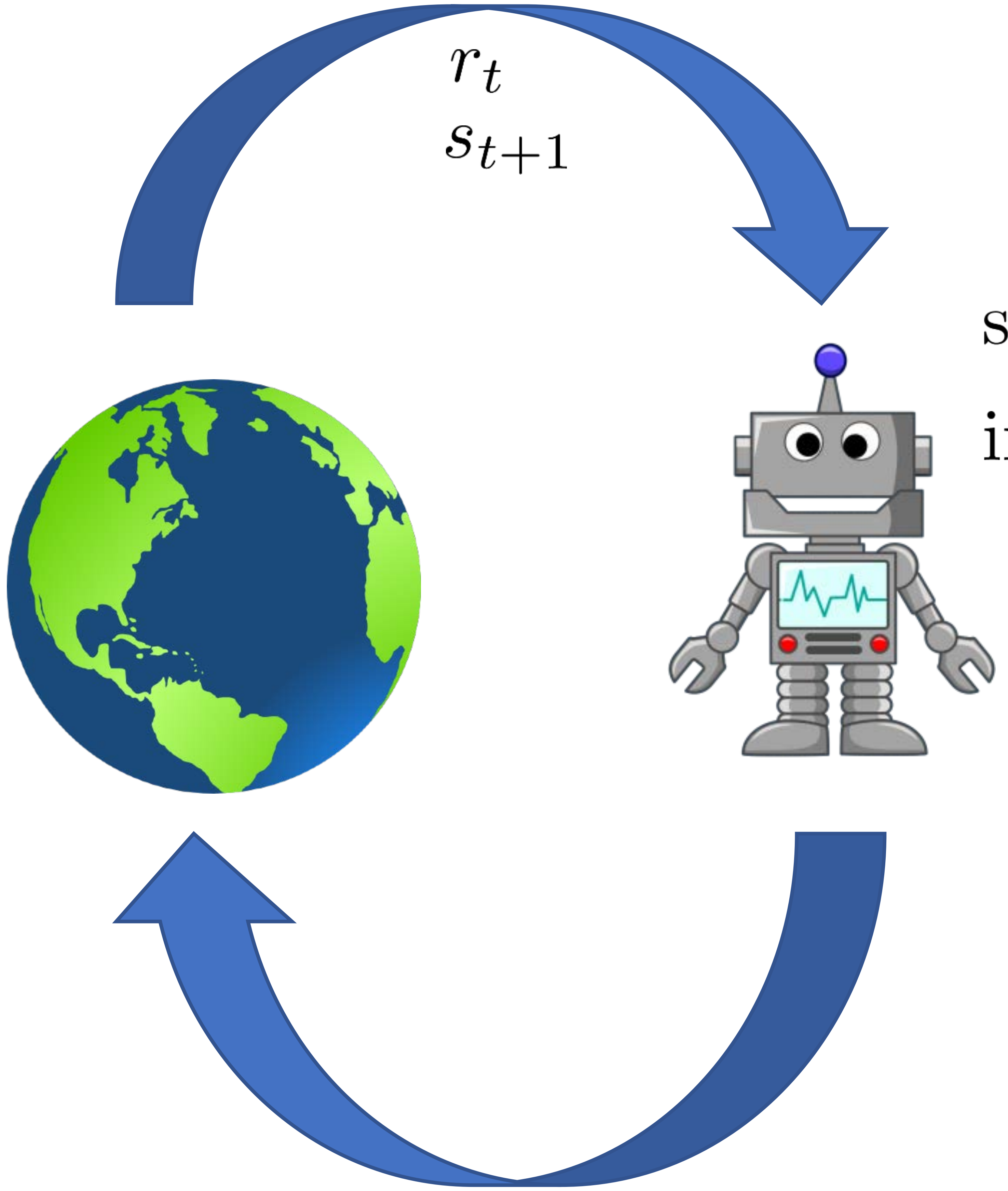
$$\theta^\star = \arg\max_\theta E_{\pi_\theta(\tau)}\left[R(\tau)\right]$$

Qs: slido.com/meta

Every RL algorithm in a nutshell

$$\theta^\star = \arg\max_\theta E_{\pi_\theta(\tau)}\left[R(\tau)\right]$$

r_t
s_{t+1}



$r_t \leftarrow r(s_t, a_t)$

$s_{t+1} \sim p(s_{t+1}|s_t, a_t)$

store (s_t, a_t, s_{t+1}, r_t) in buffer $\mathcal{B}$

improve π_θ...

...directly, via policy gradients

...via value function or Q-function

...implicitly, via model $\hat{p}(s_{t+1}|s_t, a_t)$

pick $a_t \sim \pi_\theta(a_t|s_t)$

Qs: slido.com/meta

Meta-learning so far...

learn θ such that $\phi_i = f_\theta(\mathcal{D}_i^{\text{tr}})$ is good for $\mathcal{D}_i^{\text{ts}}$

$$\mathcal{D}_{\text{meta-train}} = \{(\mathcal{D}_1^{\text{tr}}, \mathcal{D}_1^{\text{ts}}), \dots, (\mathcal{D}_n^{\text{tr}}, \mathcal{D}_n^{\text{ts}})\}$$

$$\mathcal{D}_i^{\text{tr}} = \{(x_1^i, y_1^i), \dots, (x_k^i, y_k^i)\}$$

$$\mathcal{D}_i^{\text{ts}} = \{(x_1^i, y_1^i), \dots, (x_l^i, y_l^i)\}$$

Probabilistic view:

$$\theta^\star = \arg\max_\theta \sum_{i=1}^n \log p(\phi_i | \mathcal{D}_i^{\text{ts}})$$

where $\phi_i = f_\theta(\mathcal{D}_i^{\text{tr}})$

Deterministic view:

$$\theta^\star = \arg\min_\theta \sum_{i=1}^n \mathcal{L}(\phi_i, \mathcal{D}_i^{\text{ts}})$$

where $\phi_i = f_\theta(\mathcal{D}_i^{\text{tr}})$

Qs: slido.com/meta

The meta reinforcement learning problem

"Generic" learning (deterministic view):

$$\theta^\star = \arg\min_\theta \mathcal{L}(\theta, \mathcal{D}^{\text{tr}})$$

$$= f_{\text{learn}}(\mathcal{D}^{\text{tr}})$$

"Generic" meta-learning (deterministic view):

$$\theta^\star = \arg\min_\theta \sum_{i=1}^{n} \mathcal{L}(\phi_i, \mathcal{D}_i^{\text{ts}})$$

$$\text{where } \phi_i = f_\theta(\mathcal{D}_i^{\text{tr}})$$

Reinforcement learning:

$$\theta^\star = \arg\max_\theta E_{\pi_\theta(\tau)}[R(\tau)]$$

$$= f_{\text{RL}}(\mathcal{M}) \qquad \mathcal{M} = \{\mathcal{S}, \mathcal{A}, \mathcal{P}, r\}$$

MDP

Meta-reinforcement learning:

$$\theta^\star = \arg\max_\theta \sum_{i=1}^{n} E_{\pi_{\phi_i}(\tau)}[R(\tau)]$$

$$\text{where } \phi_i = f_\theta(\mathcal{M}_i)$$

MDP for task i

The meta reinforcement learning problem

$$\theta^\star = \arg\max_\theta \sum_{i=1}^{n} E_{\pi_{\phi_i}(\tau)}[R(\tau)]$$

where $\phi_i = f_\theta(\mathcal{M}_i)$

$\{\mathcal{M}_1, \dots, \mathcal{M}_n\}$

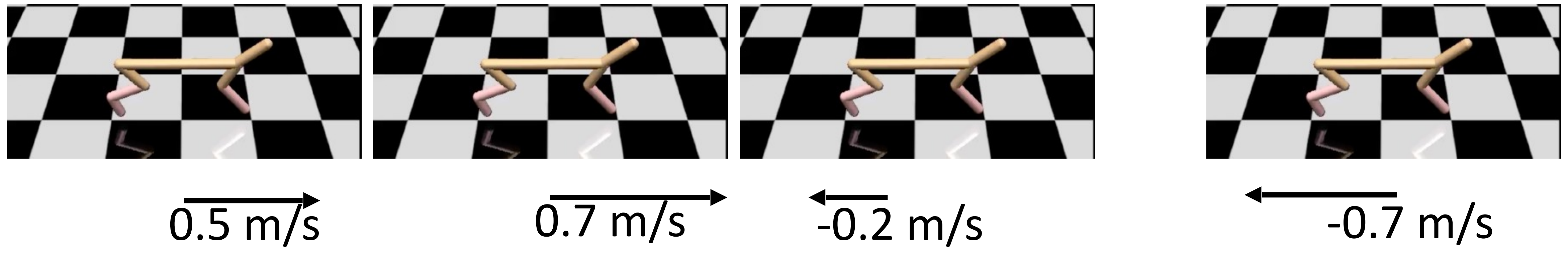
meta-training MDPs

assumption: $\mathcal{M}_i \sim p(\mathcal{M})$

Some examples:

$\mathcal{M}_1$ $\mathcal{M}_2$ $\mathcal{M}_3$ $\mathcal{M}_{\text{test}}$

$\mathcal{M}_1$ $\mathcal{M}_2$ $\mathcal{M}_3$ $\mathcal{M}_{\text{test}}$



meta test-time:

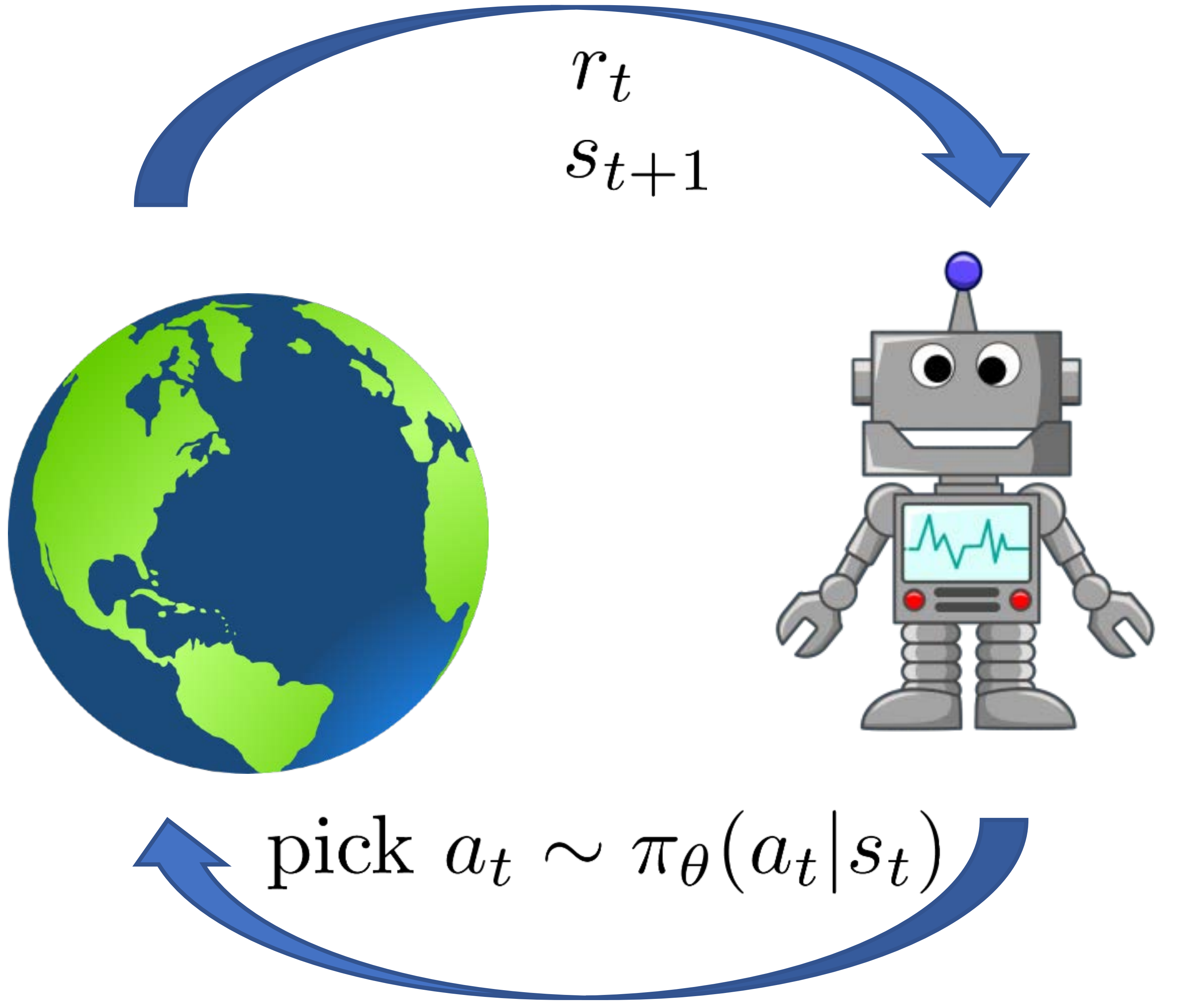
sample $\mathcal{M}_{\text{test}} \sim p(\mathcal{M})$, get $\phi_i = f_\theta(\mathcal{M}_{\text{test}})$

Qs: slido.com/meta

Meta-RL with recurrent policies

$$\theta^\star = \arg\max_\theta \sum_{i=1}^{n} E_{\pi_{\phi_i}(\tau)}[R(\tau)]$$

where $\phi_i = f_\theta(\mathcal{M}_i)$

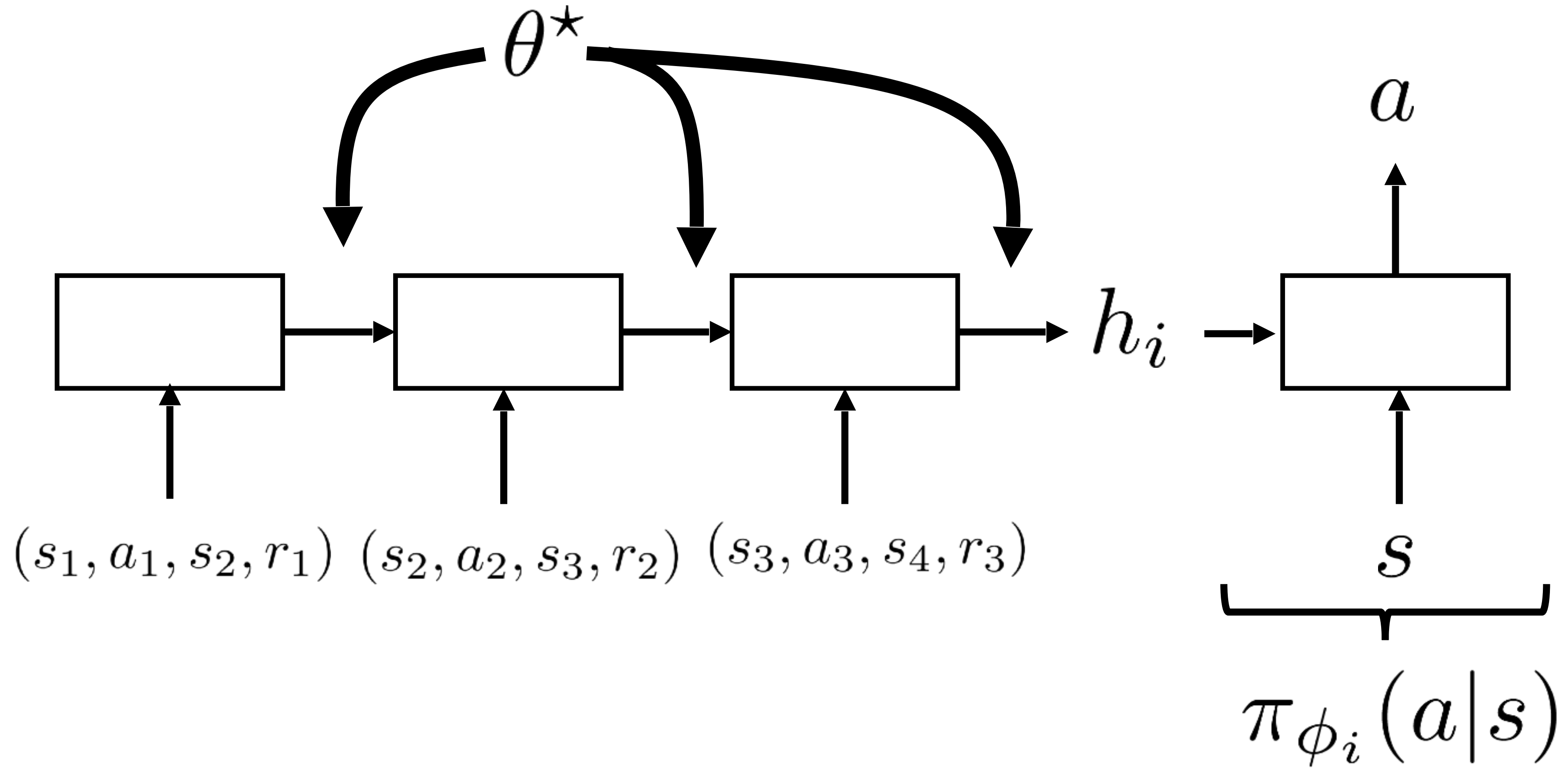


use (s_t, a_t, s_{t+1}, r_t) to improve π_θ

main question: how to implement $f_\theta(\mathcal{M}_i)$?

what should $f_\theta(\mathcal{M}_i)$ *do*?

1. improve policy with experience from $\mathcal{M}_i$
   $\{(s_1, a_1, s_2, r_1), \ldots, (s_T, a_T, s_{T+1}, r_T)\}$
2. (new in RL): choose how to interact, i.e. choose a_t
   meta-RL must also *choose* how to *explore*!



RNN hidden state

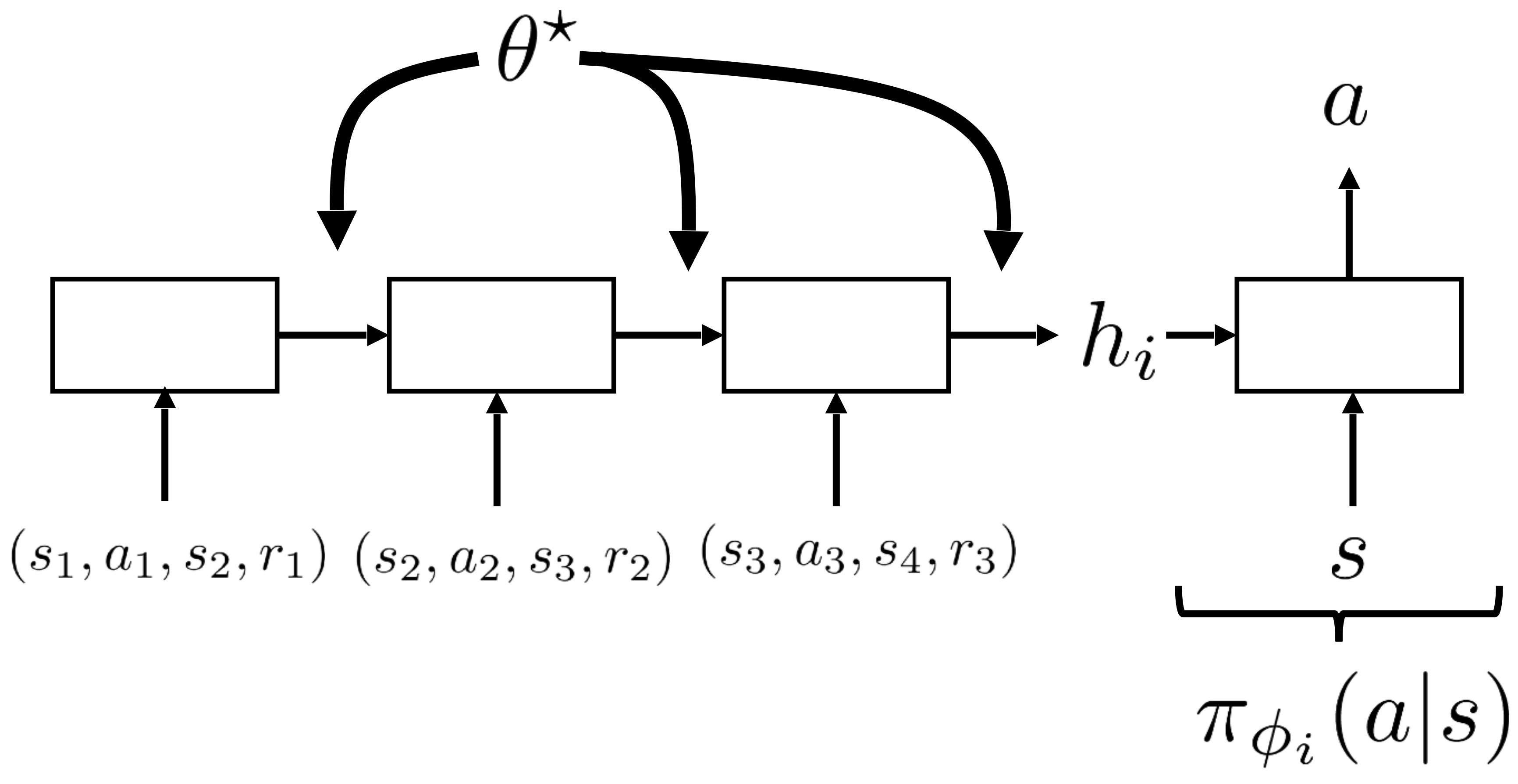
meta-learned weights

as before, $\phi_i = [h_i, \theta_\pi]$

Meta-RL with recurrent policies

$$\theta^\star = \arg\max_\theta \sum_{i=1}^{n} E_{\pi_{\phi_i}(\tau)}[R(\tau)]$$

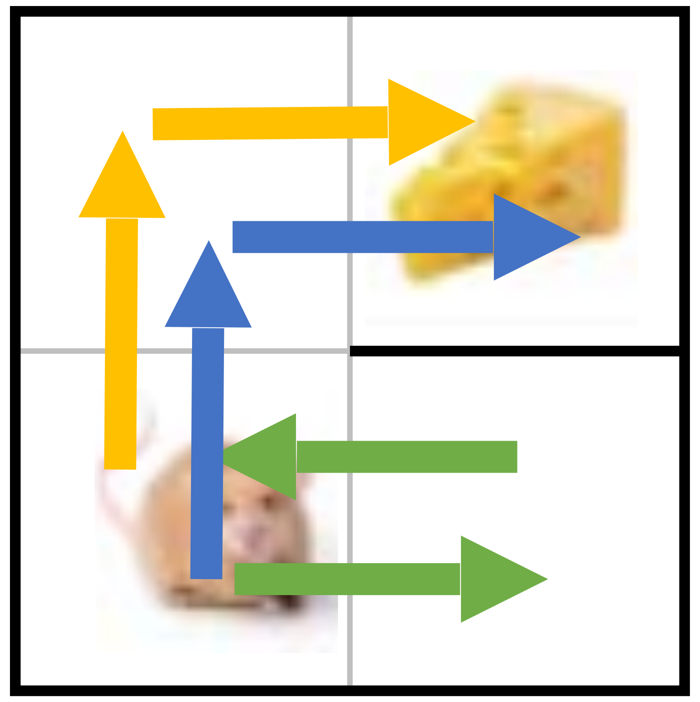
$$\text{where } \phi_i = f_\theta(\mathcal{M}_i)$$

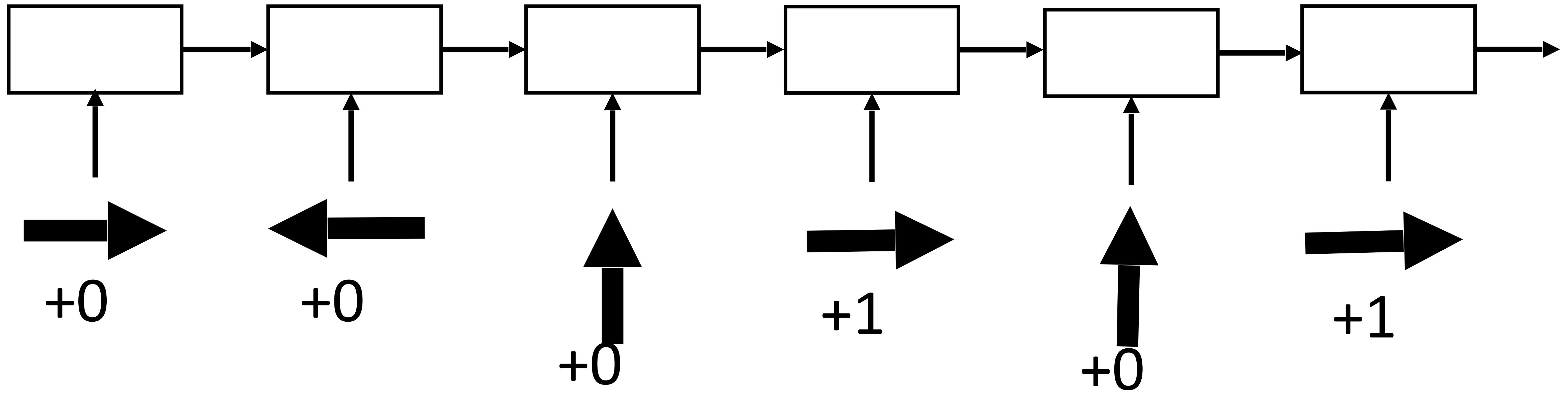


so... we just train an RNN policy?

yes!

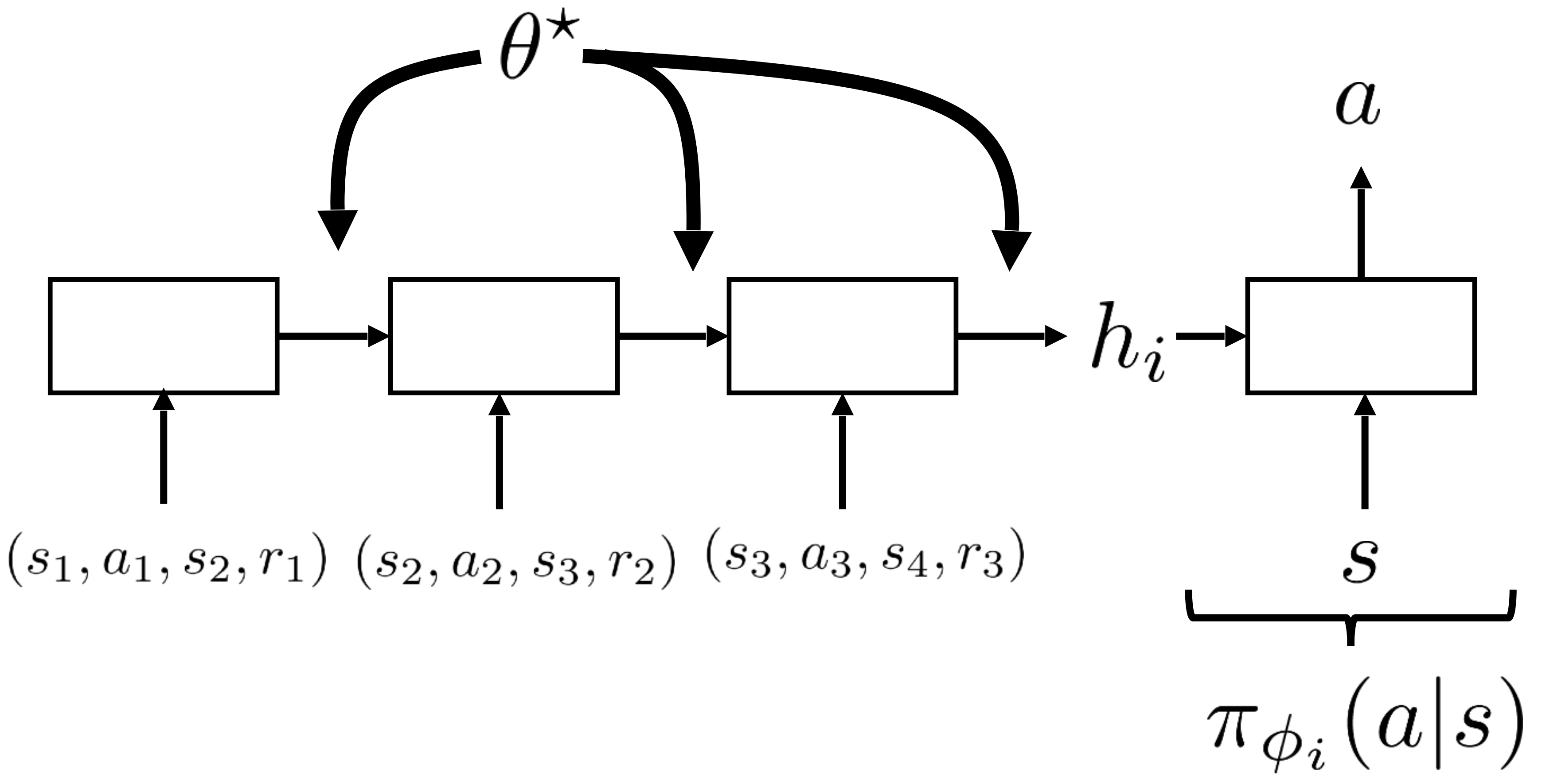
crucially, RNN hidden state is **not** reset between episodes!





Qs: slido.com/meta

Why recurrent policies learn to explore



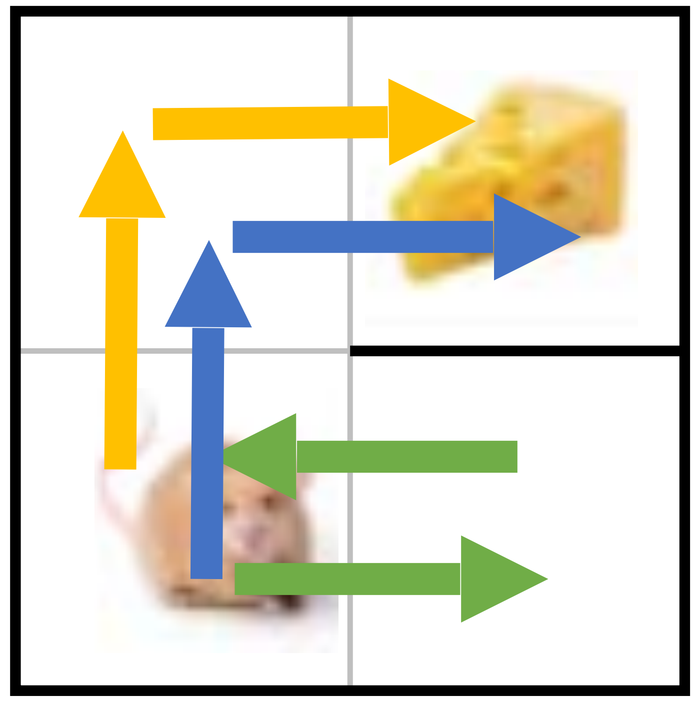
1. improve policy with experience from $\mathcal{M}_i$

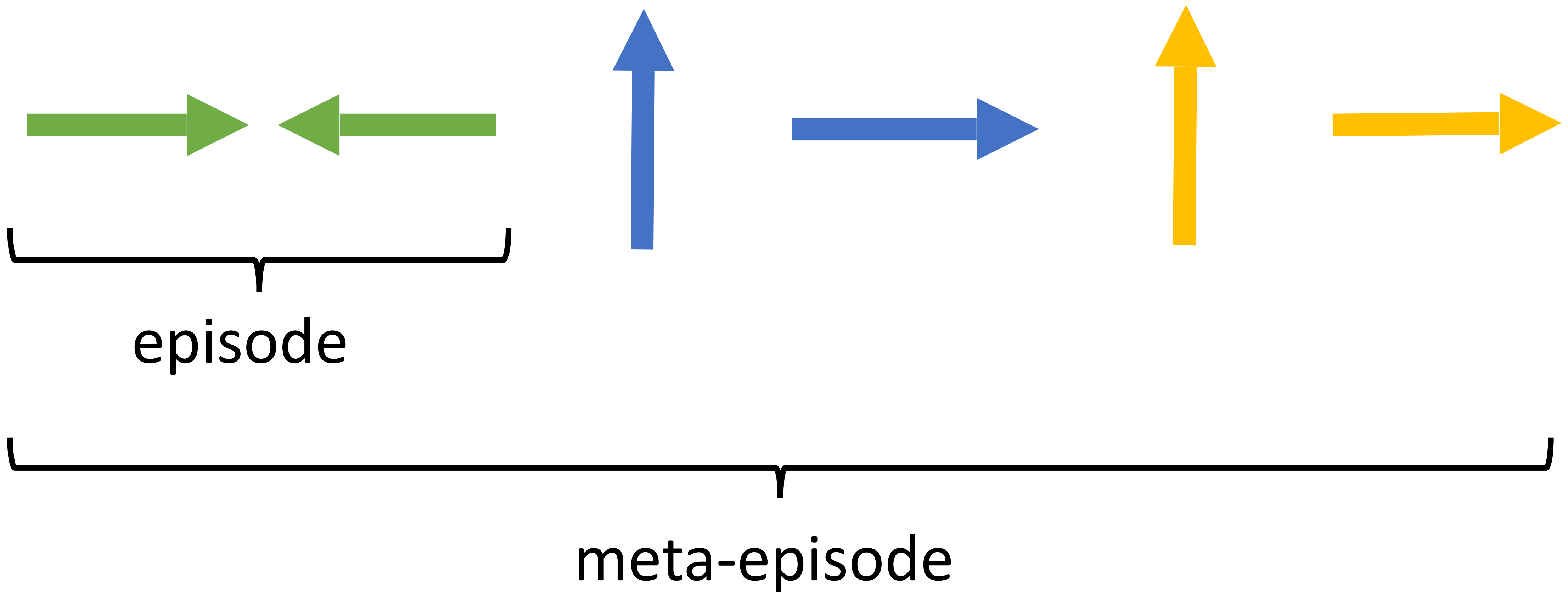
   $\{(s_1, a_1, s_2, r_1), \ldots, (s_T, a_T, s_{T+1}, r_T)\}$

2. (new in RL): choose how to interact, i.e. choose a_t

   meta-RL must also *choose* how to *explore*!

$$\theta^\star = \arg\max_\theta E_{\pi_\theta}\left[\sum_{t=0}^{T} r(s_t, a_t)\right]$$





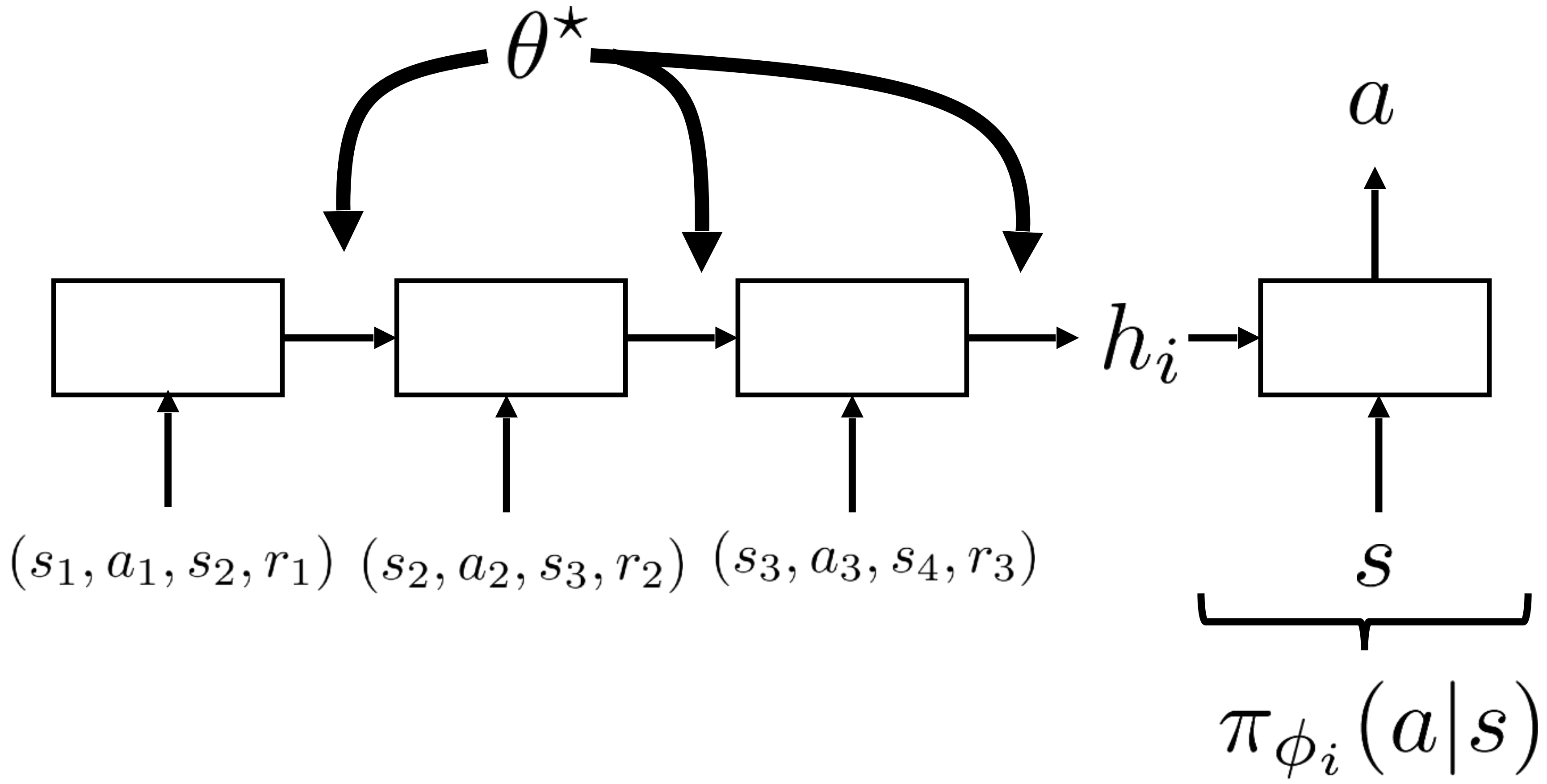
optimizing total reward over the entire **meta-**episode with RNN policy **automatically** learns to explore!

Qs: slido.com/meta

Meta-RL with recurrent policies

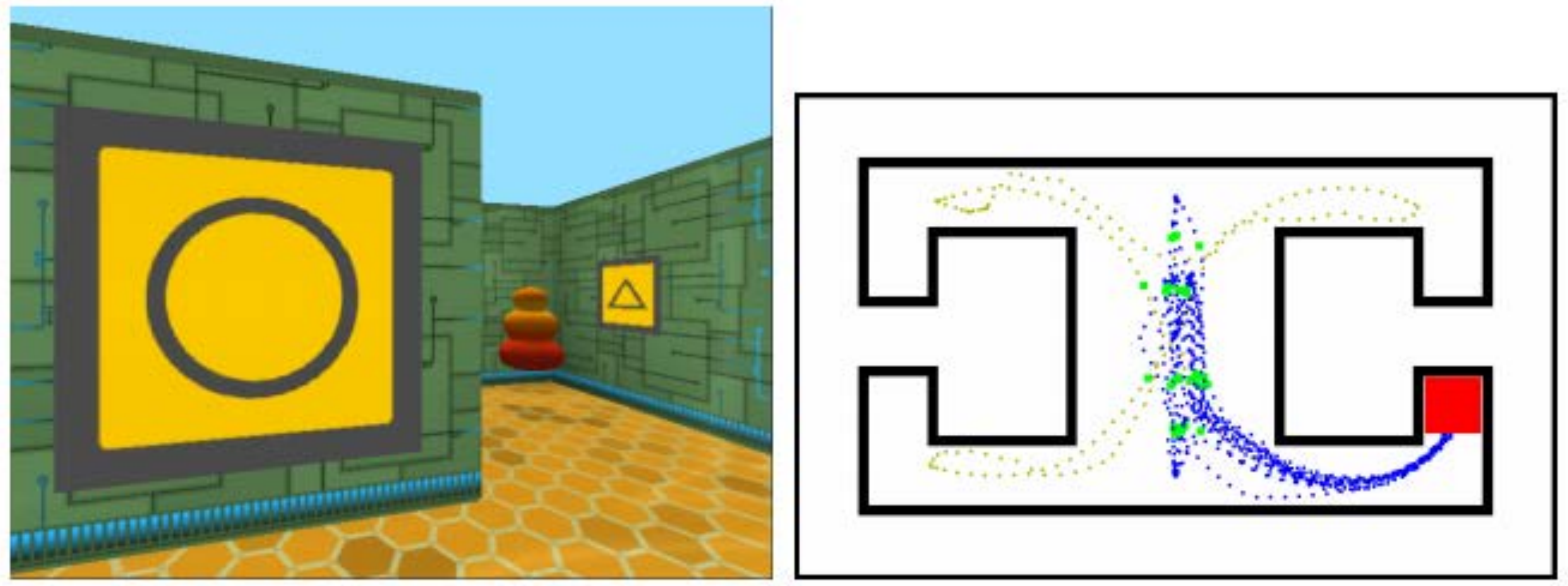
$$\theta^\star = \arg\max_\theta \sum_{i=1}^{n} E_{\pi_{\phi_i}(\tau)}[R(\tau)]$$

$$\text{where } \phi_i = f_\theta(\mathcal{M}_i)$$



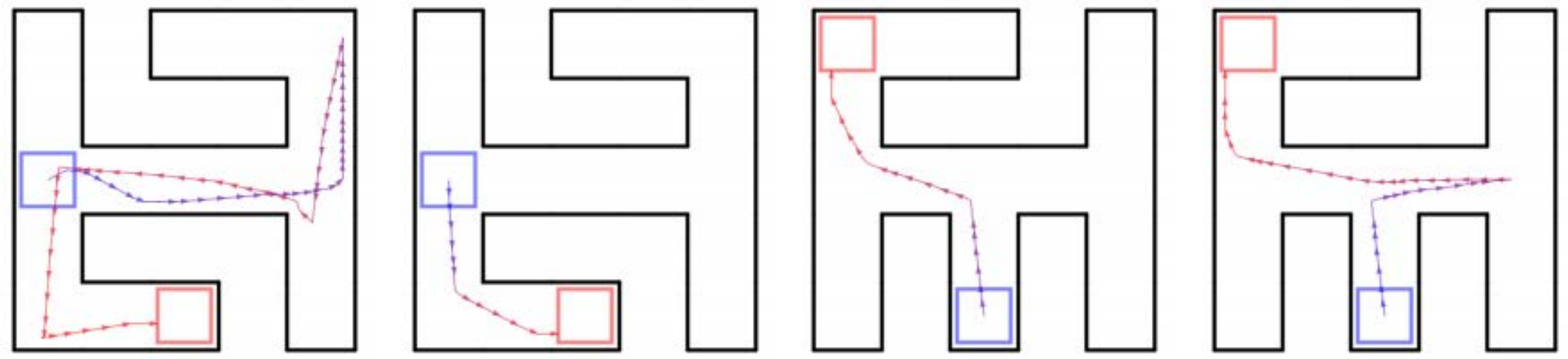
(c) (d) (e)

Heess, Hunt, Lillicrap, Silver. **Memory-based control with recurrent neural networks.** 2015.



(a) Labryinth I-maze (b) Illustrative Episode

Wang, Kurth-Nelson, Tirumala, Soyer, Leibo, Munos, Blundell, Kumaran, Botvinick. **Learning to Reinforcement Learning.** 2016.

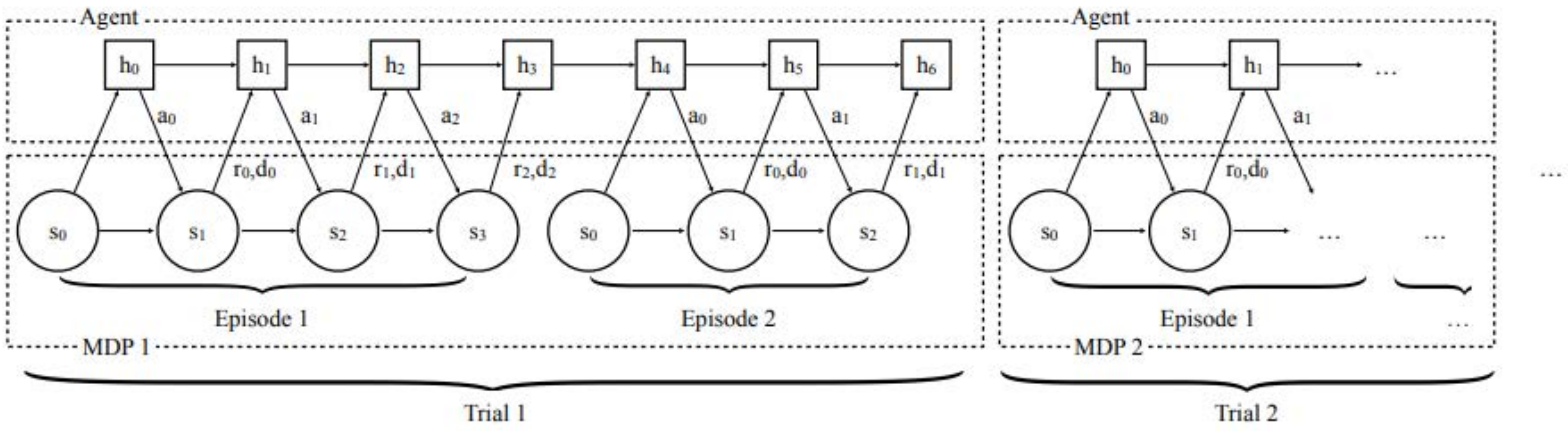


(a) Good behavior, 1st episode (b) Good behavior, 2nd episode (c) Bad behavior, 1st episode (d) Bad behavior, 2nd episode

Duan, Schulman, Chen, Bartlett, Sutskever, Abbeel. **RL2: Fast Reinforcement Learning via Slow Reinforcement Learning.** 2016.

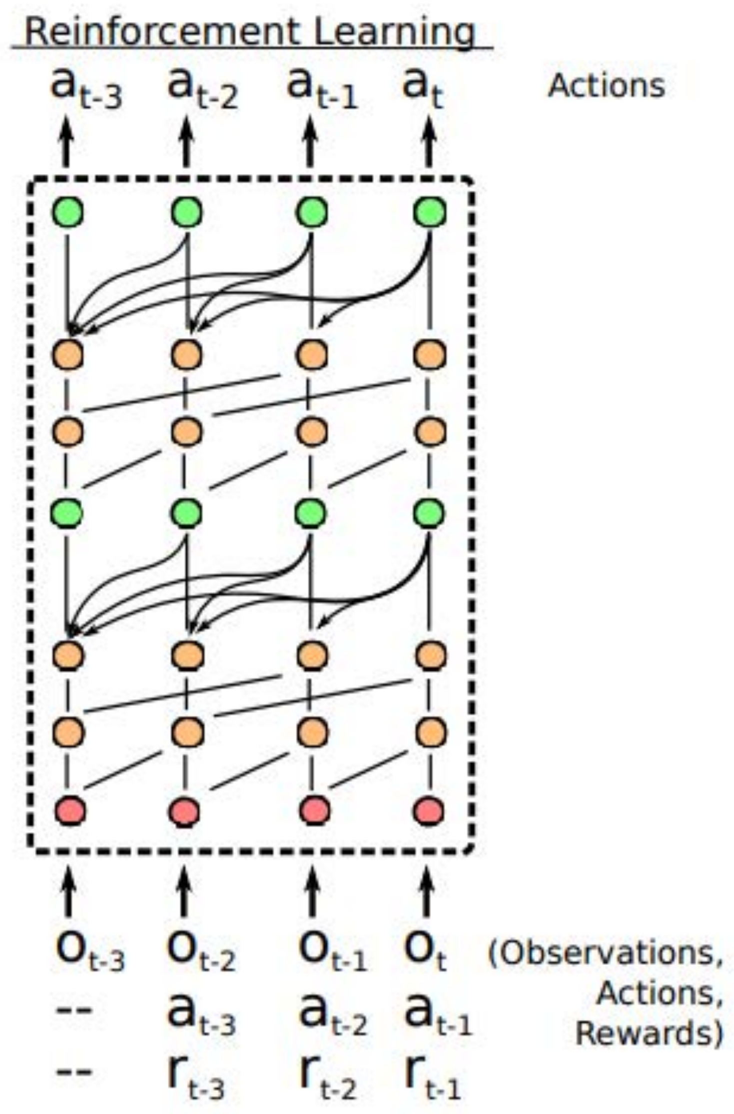
Qs: slido.com/meta

Architectures for meta-RL



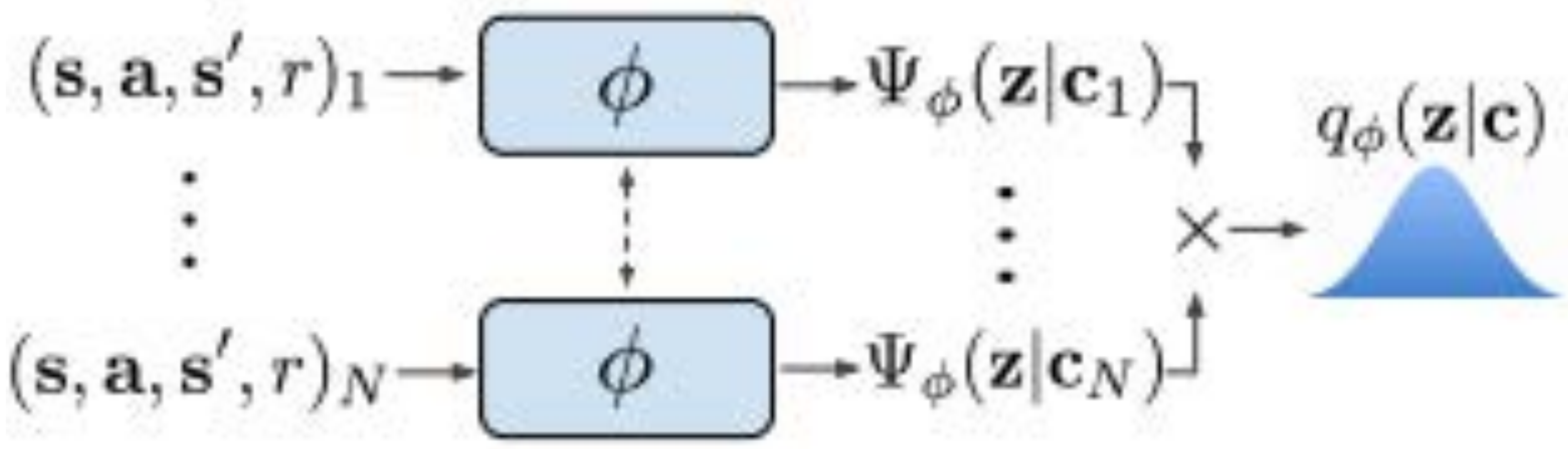
standard RNN (LSTM) architecture

Duan, Schulman, Chen, Bartlett, Sutskever, Abbeel. **RL2: Fast Reinforcement Learning via Slow Reinforcement Learning.** 2016.



attention + temporal convolution

Mishra, Rohaninejad, Chen, Abbeel. **A Simple Neural Attentive Meta-Learner.**



parallel permutation-invariant context encoder

Rakelly*, Zhou*, Quillen, Finn, Levine. **Efficient Off-Policy Meta-Reinforcement learning via Probabilistic Context Variables.**

Qs: slido.com/meta

Meta-RL as an optimization problem

$$\theta^\star = \arg\max_\theta \sum_{i=1}^n E_{\pi_{\phi_i}(\tau)}[R(\tau)]$$

where $\phi_i = f_\theta(\mathcal{M}_i)$

1. improve policy with experience from $\mathcal{M}_i$

$$\{(s_1, a_1, s_2, r_1), \ldots, (s_T, a_T, s_{T+1}, r_T)\}$$

what if $f_\theta(\mathcal{M}_i)$ is *itself* an RL algorithm?

$$f_\theta(\mathcal{M}_i) = \theta + \alpha \nabla_\theta \underbrace{J_i(\theta)}$$

requires interacting with $\mathcal{M}_i$
to estimate $\nabla_\theta E_{\pi_\theta}[R(\tau)]$

standard RL:

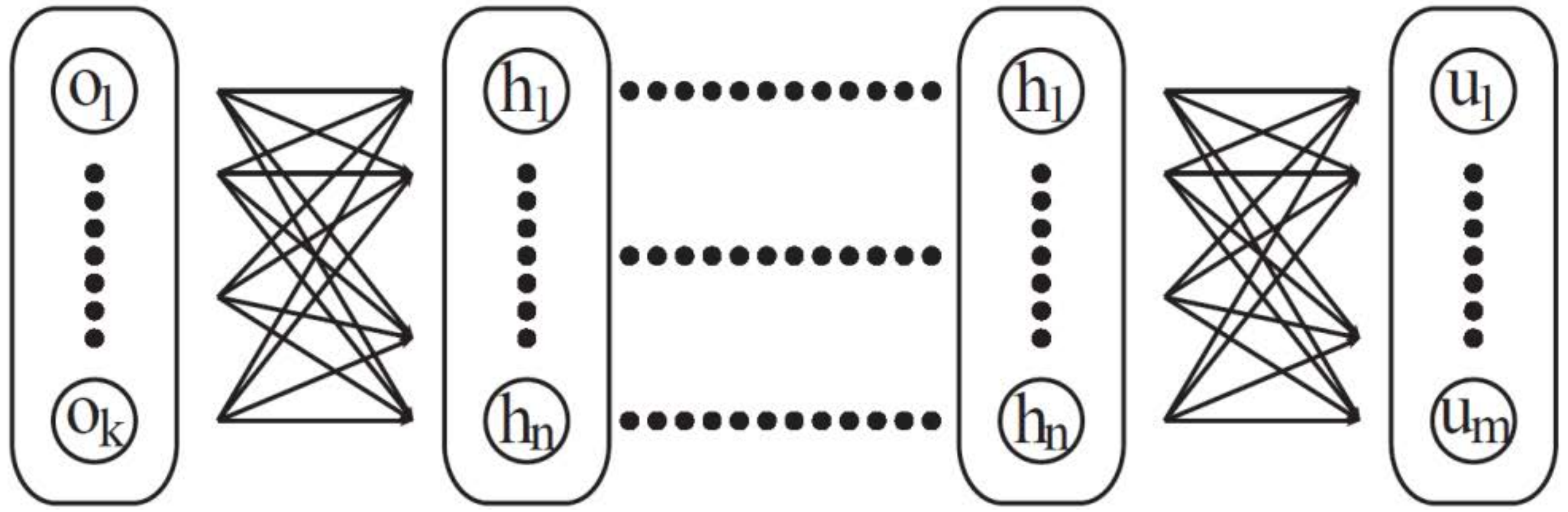
$$\theta^\star = \arg\max_\theta \underbrace{E_{\pi_\theta(\tau)}[R(\tau)]}_{J(\theta)}$$

$$\theta^{k+1} \leftarrow \theta_k + \alpha \nabla_{\theta^k} J(\theta^k)$$

this is model-agnostic meta-learning (MAML) for RL!

Qs: slido.com/meta

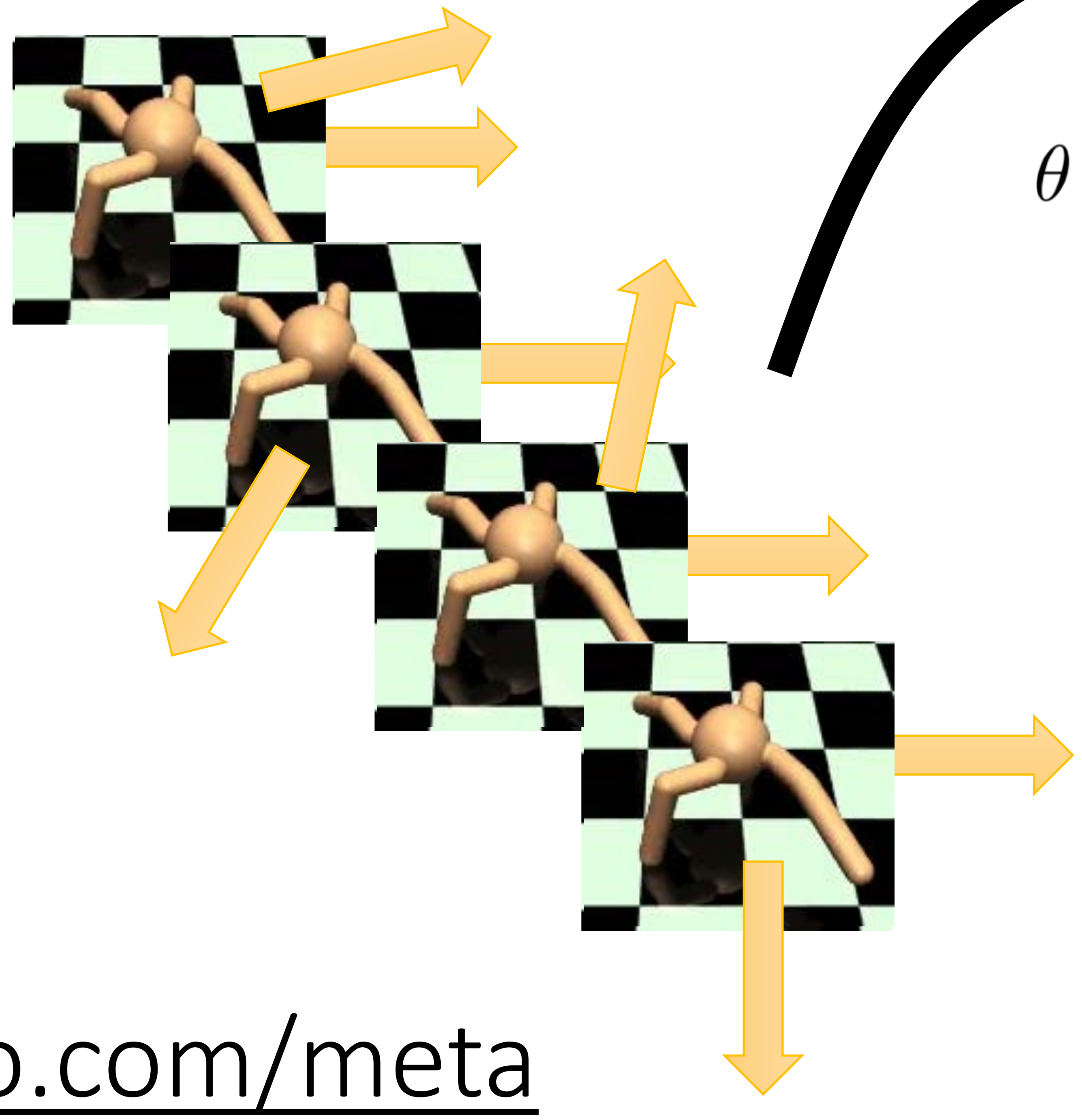
MAML for RL in pictures

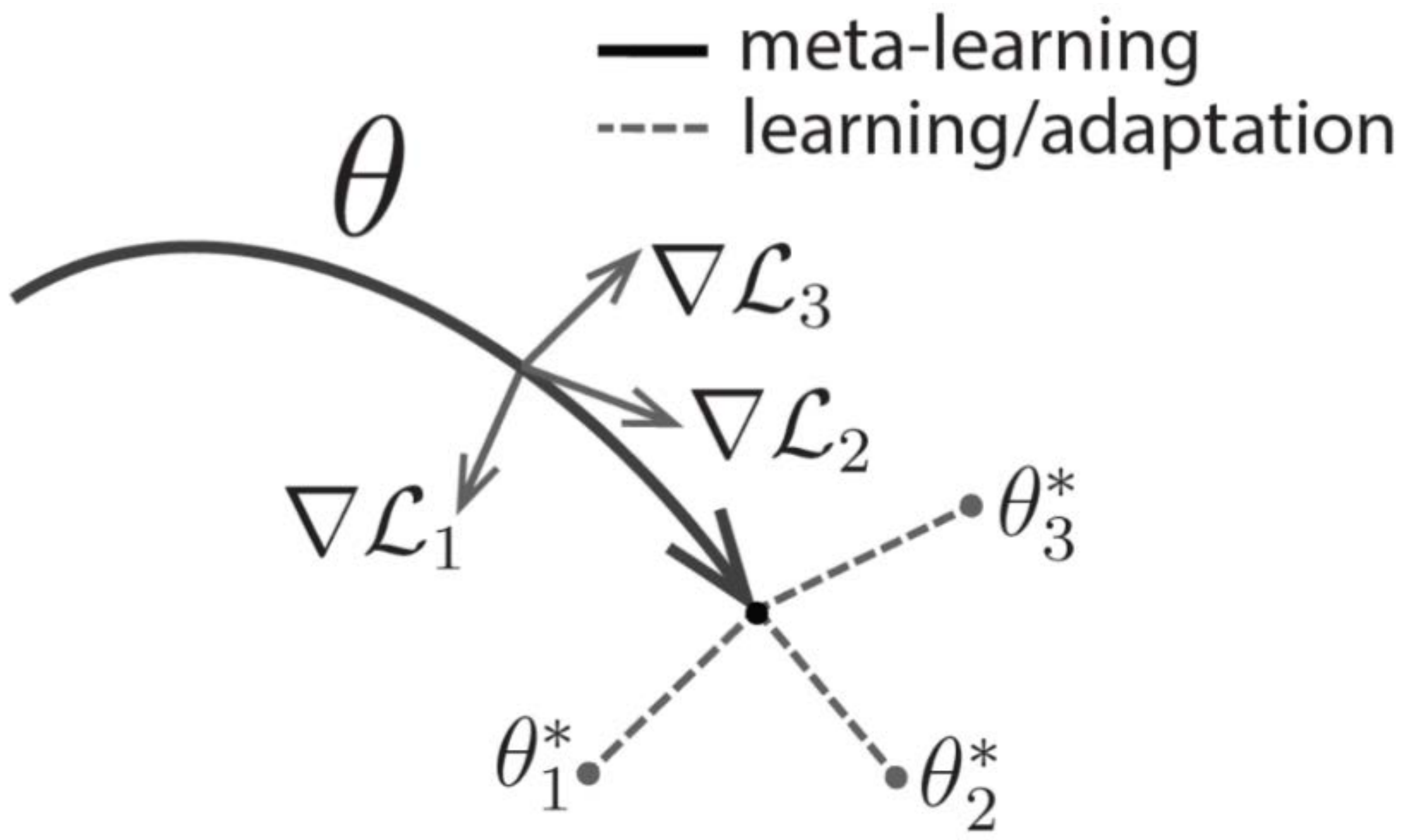


$$\theta$$

$$\cancel{\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)}$$

$$\theta \leftarrow \theta + \beta \sum_i \nabla_\theta J_i[\theta + \alpha \nabla_\theta J_i(\theta)]$$



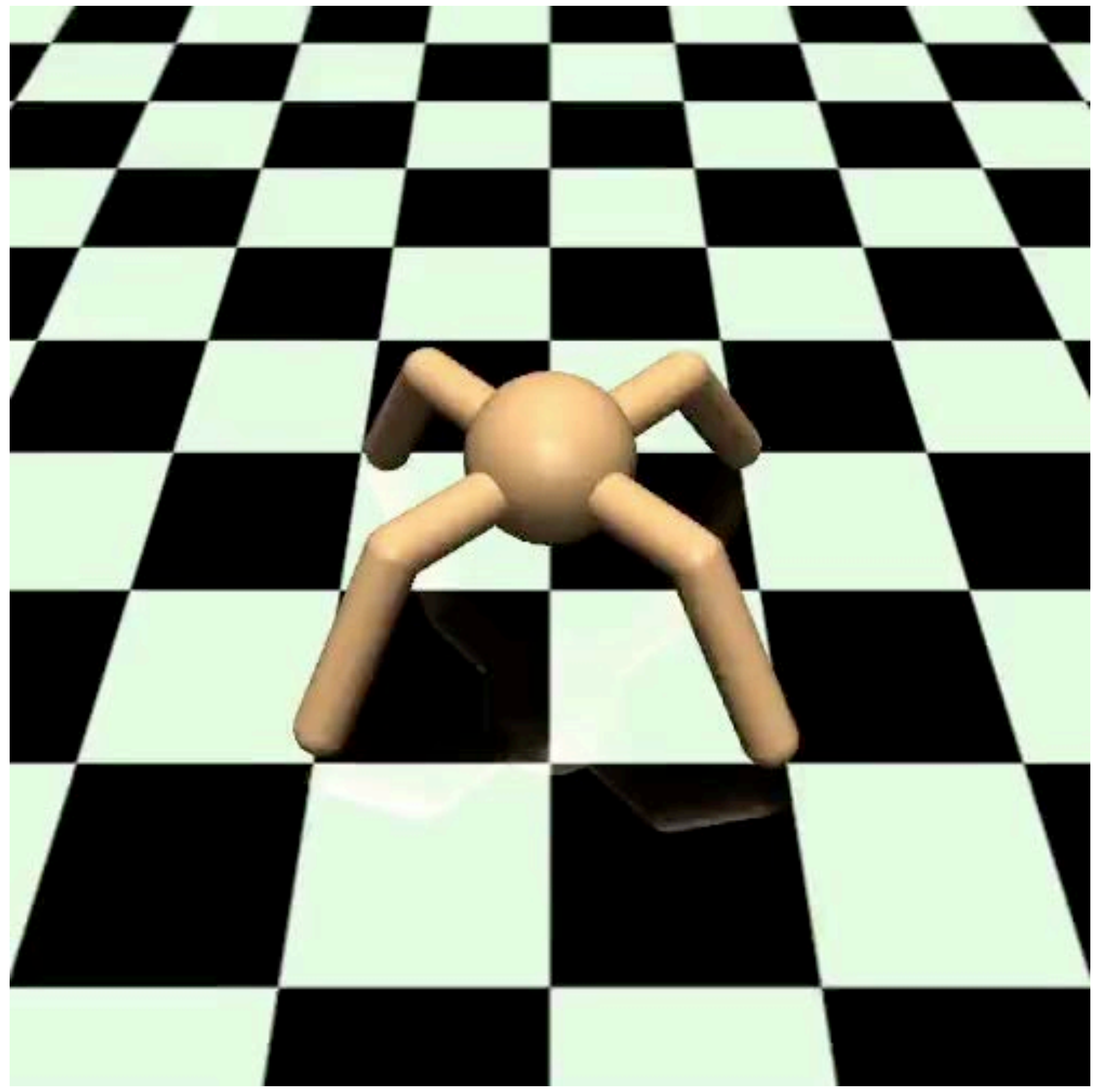


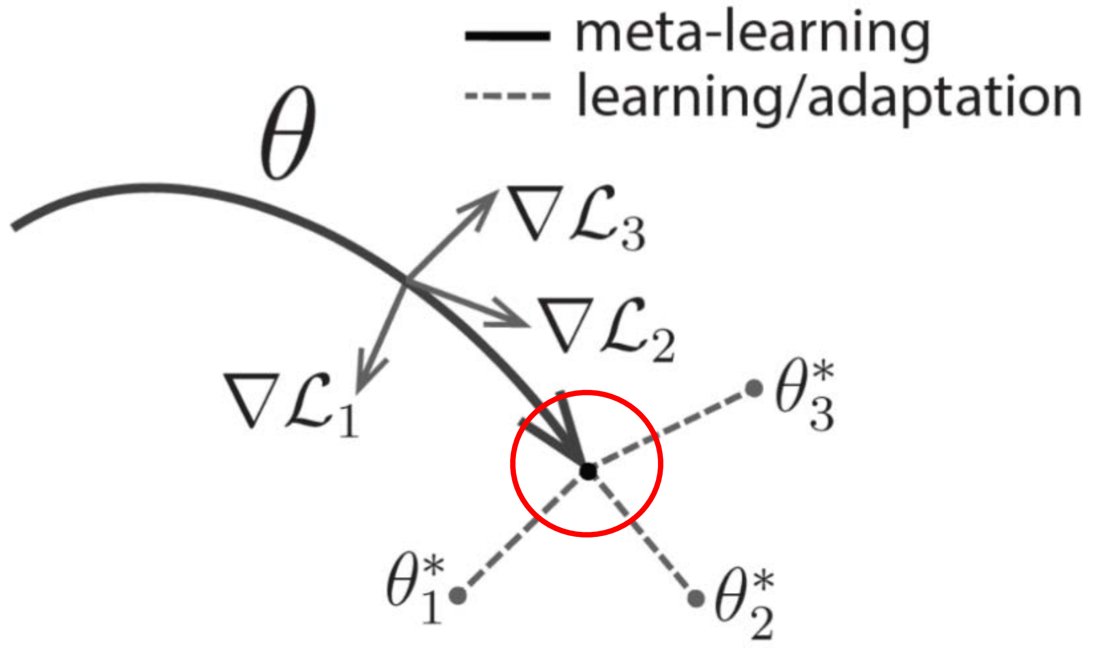
$$\theta'$$

Qs: slido.com/meta

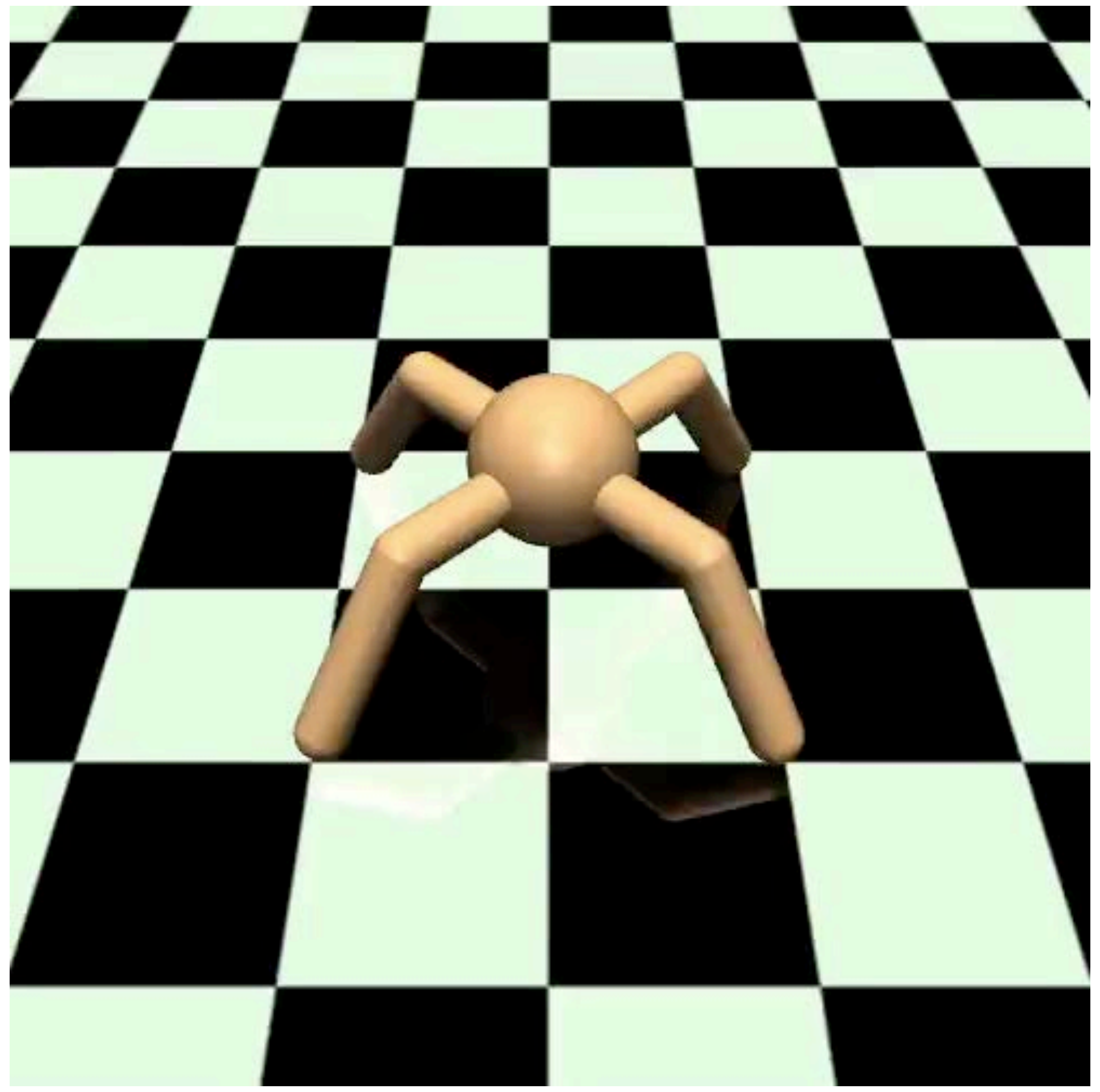
MAML for RL in videos

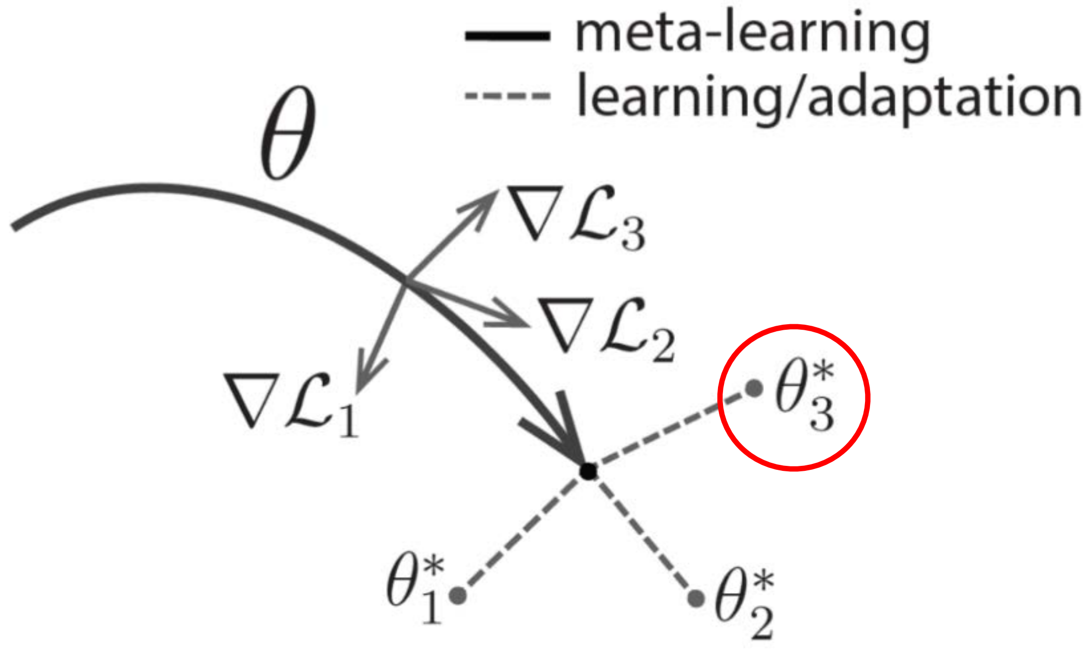
after MAML training



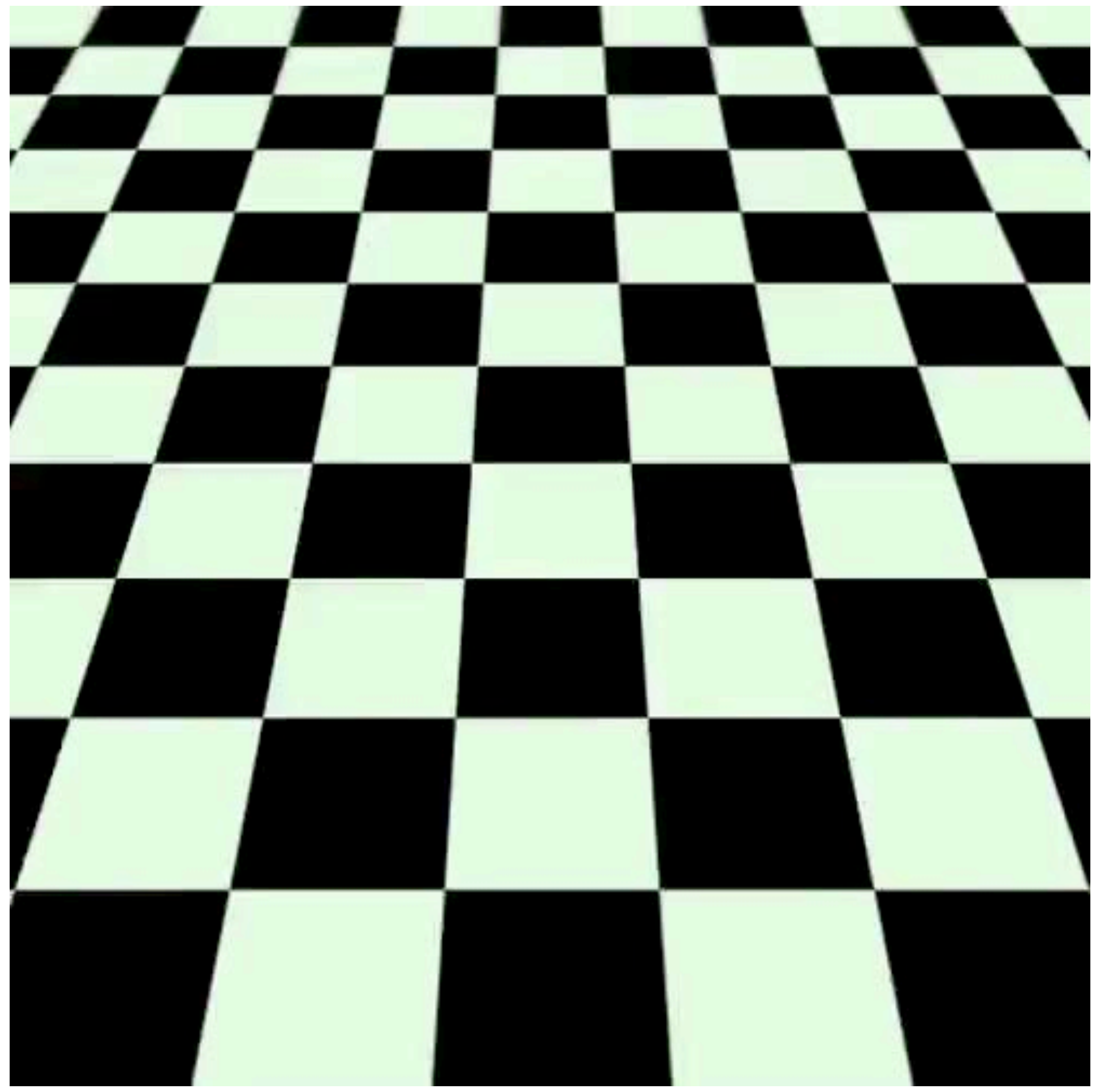


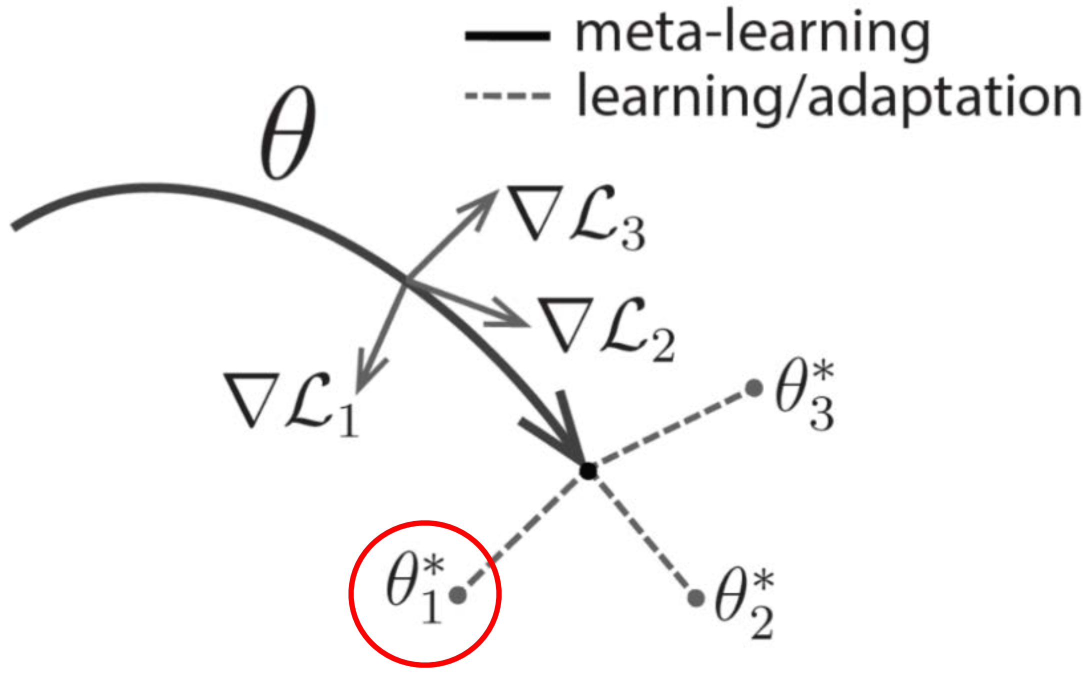
after 1 gradient step (forward reward)





after 1 gradient step (backward reward)





Qs: slid

More on MAML/gradient-based meta-learning for RL

Better MAML meta-policy gradient estimators:

- Foerster, Farquhar, Al-Shedivat, Rocktaschel, Xing, Whiteson. **DiCE: The Infinitely Differentiable Monte Carlo Estimator.**
- Rothfuss, Lee, Clavera, Asfour, Abbeel. **ProMP: Proximal Meta-Policy Search.**

Improving exploration:

- Gupta, Mendonca, Liu, Abbeel, Levine. **Meta-Reinforcement Learning of Structured Exploration Strategies.**
- Stadie*, Yang*, Houthooft, Chen, Duan, Wu, Abbeel, Sutskever. **Some Considerations on Learning to Explore via Meta-Reinforcement Learning.**

Hybrid algorithms (not necessarily gradient-based):

- Houthooft, Chen, Isola, Stadie, Wolski, Ho, Abbeel. **Evolved Policy Gradients.**
- Fernando, Sygnowski, Osindero, Wang, Schaul, Teplyashin, Sprechmann, Pirtzel, Rusu. **Meta-Learning by the Baldwin Effect.**

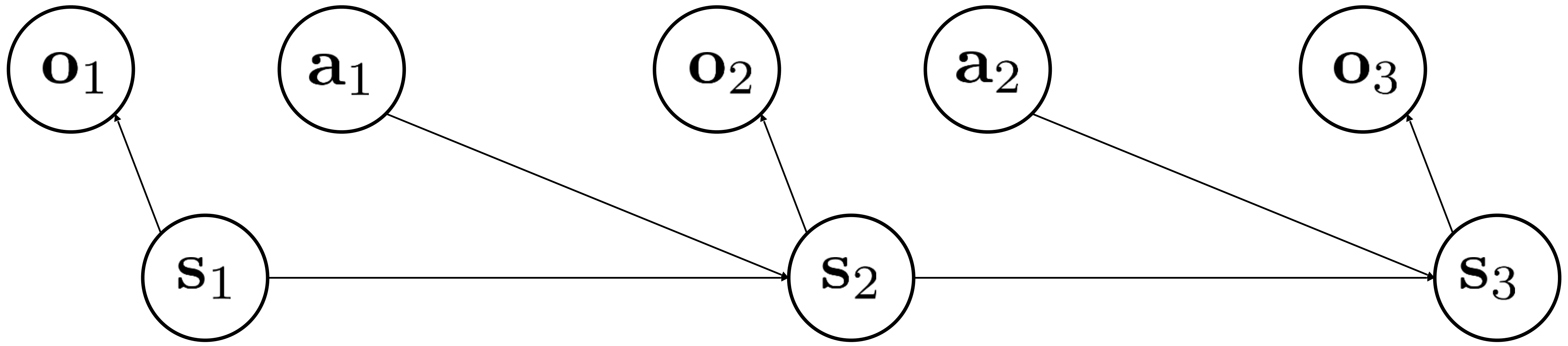
Meta-RL as… partially observed RL?

First: a quick primer on **partially observed** Markov decision processes (POMDPs)

$$\mathcal{M} = \{\mathcal{S}, \mathcal{A}, \mathcal{O}, \mathcal{P}, \mathcal{E}, r\}$$

$\mathcal{O}$ – observation space   observations $o \in \mathcal{O}$ (discrete or continuous)

$\mathcal{E}$ – emission probability $p(o_t|s_t)$



policy must act on observations o_t!

$\pi_\theta(a|o)$

typically requires *either*:

explicit state estimation, i.e. to estimate $p(s_t|o_{1:t})$

policies with memory

Qs: slido.com/meta

Meta-RL as… partially observed RL?

$$\pi_\theta(a|\overbrace{s, z}^{\tilde{s}})$$

encapsulates information policy
needs to solve current task

learning a task $=$ inferring z

from *context* $(s_1, a_1, s_2, r_1), (s_2, a_2, s_3, r_2), \ldots$

this is just a POMDP!

before: $\mathcal{M} = \{\mathcal{S}, \mathcal{A}, \mathcal{P}, r\}$

now: $\tilde{\mathcal{M}} = \{\tilde{\mathcal{S}}, \mathcal{A}, \tilde{\mathcal{O}}, \tilde{\mathcal{P}}, \mathcal{E}, r\}$

$\tilde{\mathcal{S}} = \mathcal{S} \times \mathcal{Z}$ $\quad$ $\tilde{s} = (s, z)$

$\tilde{\mathcal{O}} = \mathcal{S}$ $\quad$ $\tilde{o} = s$

key idea: solving the POMDP $\tilde{\mathcal{M}}$ is equivalent to meta-learning!

Qs: slido.com/meta

Meta-RL as... partially observed RL?

$\pi_\theta(a|s,z)$

encapsulates information policy needs to solve current task

learning a task = inferring z

from *context* $(s_1, a_1, s_2, r_1), (s_2, a_2, s_3, r_2), \ldots$

this is just a POMDP!

typically requires *either*:

explicit state estimation, i.e. to estimate $p(s_t|o_{1:t})$

policies with memory

need to estimate $p(z_t|s_{1:t}, a_{1:t}, r_{1:t})$

exploring via posterior sampling with latent context

1. sample $z \sim \hat{p}(z_t|s_{1:t}, a_{1:t}, r_{1:t})$
2. act according to $\pi_\theta(a|s,z)$ to collect more data

some approximate posterior (e.g., variational)

act as though z was correct!

this is not optimal!
why?

but it's pretty good, both in theory and in practice!

Qs: slido.com/meta

See, e.g. Russo, Roy. **Learning to Optimize via Posterior Sampling.**

Variational inference for meta-RL

policy: $\pi_\theta(a_t|s_t, z_t)$

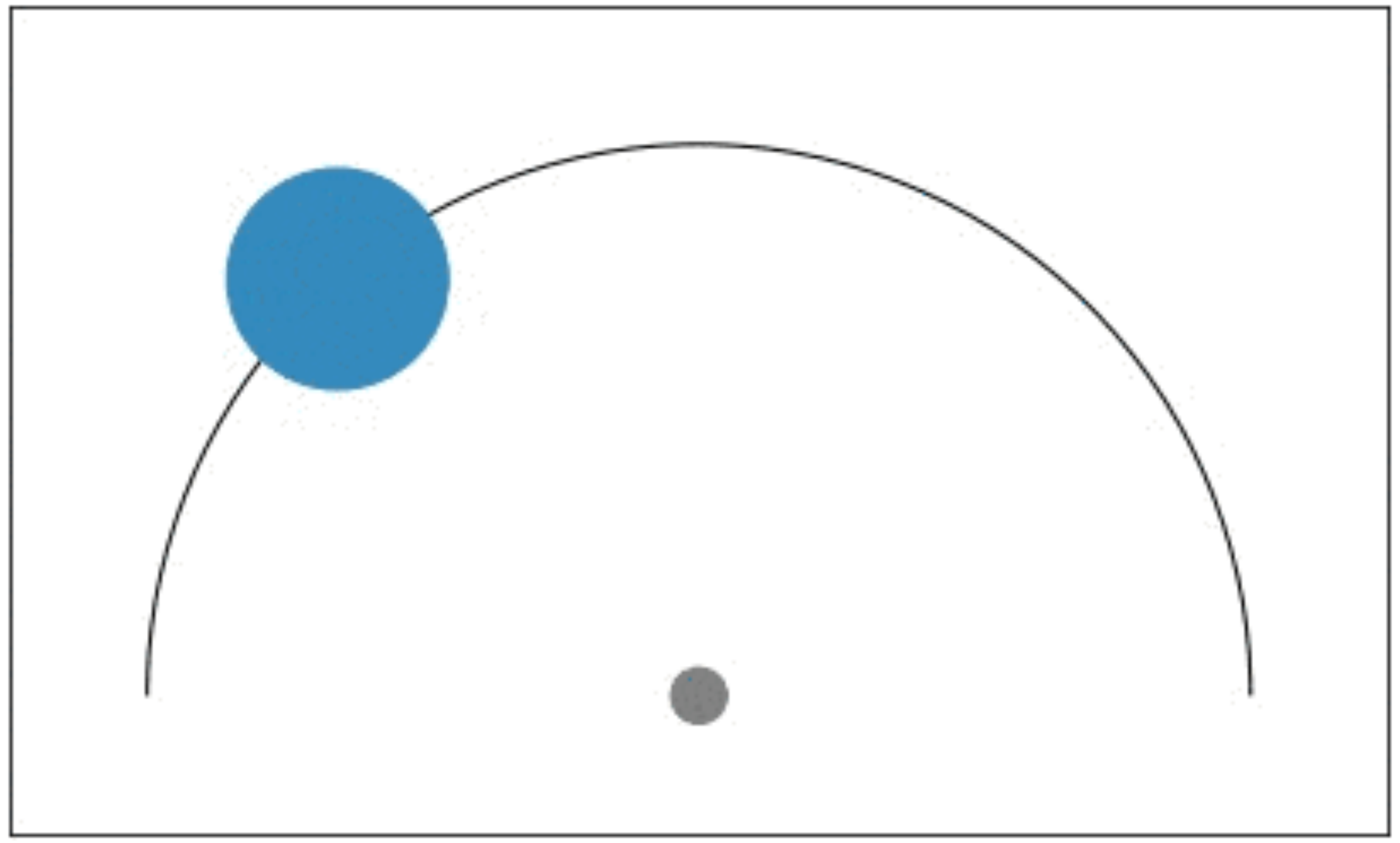
inference network: $q_\phi(z_t|s_1, a_1, r_1, \ldots, s_t, a_t, r_t)$

$$(\theta, \phi) = \arg\max_{\theta,\phi} \frac{1}{N} \sum_{i=1}^{n} E_{z\sim q_\phi, \tau\sim\pi_\theta}[R_i(\tau) - D_{\mathrm{KL}}(q(z|\ldots)\|p(z))]$$

maximize post-update reward
(same as standard meta-RL)

stay close to prior

$z_t \sim q_\phi(z_t|s_1, a_1, r_1, \ldots, s_t, a_t, r_t)$



conceptually *very* similar to RNN meta-RL, but with stochastic z

stochastic z enables exploration via *posterior sampling*

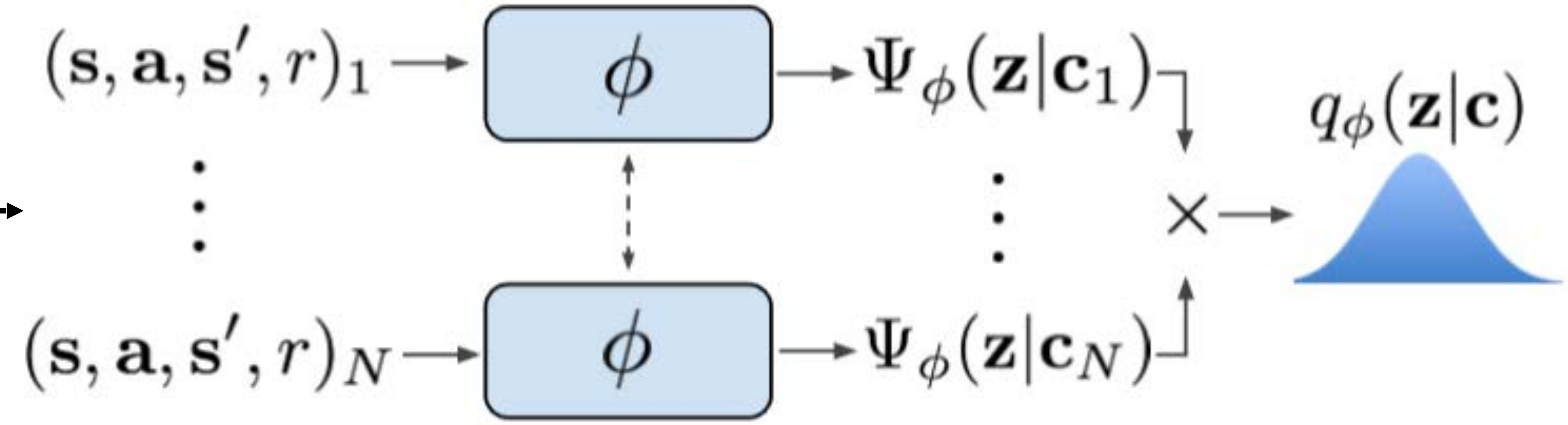
Qs: slido.com/meta

Rakelly*, Zhou*, Quillen, Finn, Levine. **Efficient Off-Policy Meta-Reinforcement learning via Probabilistic Context Variables.** ICML 2019.

Specific instantiation: PEARL

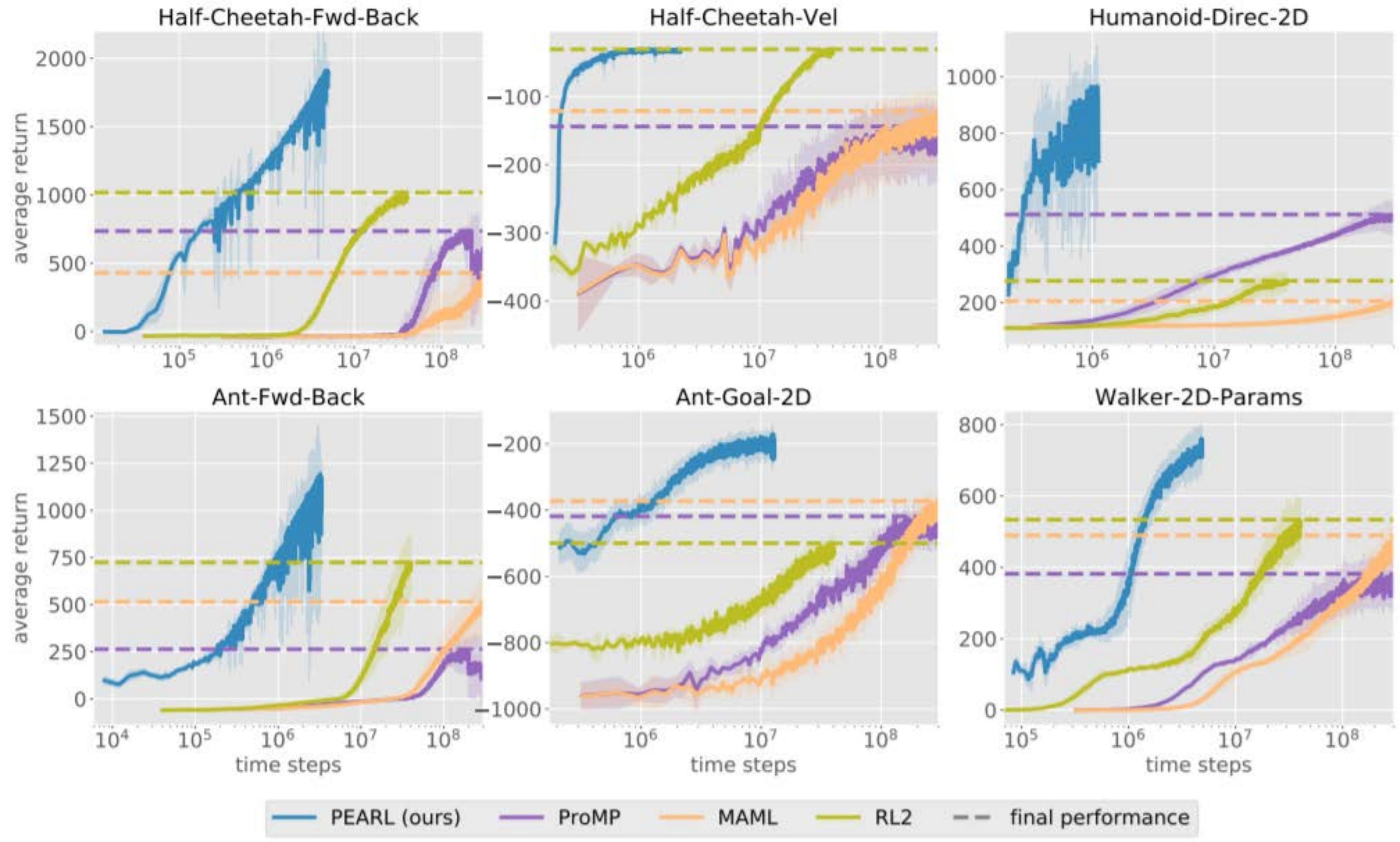
policy: $\pi_\theta(a_t|s_t, z_t)$

inference network: $q_\phi(z_t|s_1, a_1, r_1, \ldots, s_t, a_t, r_t)$



$$(\theta, \phi) = \arg\max_{\theta,\phi} \frac{1}{N} \sum_{i=1}^{n} E_{z\sim q_\phi, \tau\sim\pi_\theta}[R_i(\tau) - D_{\mathrm{KL}}(q(z|\ldots)\|p(z))]$$

perform maximization using soft actor-critic (SAC), state-of-the-art off-policy RL algorithm



Qs: slido.com/meta

Rakelly*, Zhou*, Quillen, Finn, Levine. **Efficient Off-Policy Meta-Reinforcement learning via Probabilistic Context Variables.** ICML 2019.

References on meta-RL, inference, and POMDPs

- Rakelly*, Zhou*, Quillen, Finn, Levine. **Efficient Off-Policy Meta-Reinforcement learning via Probabilistic Context Variables.** ICML 2019.

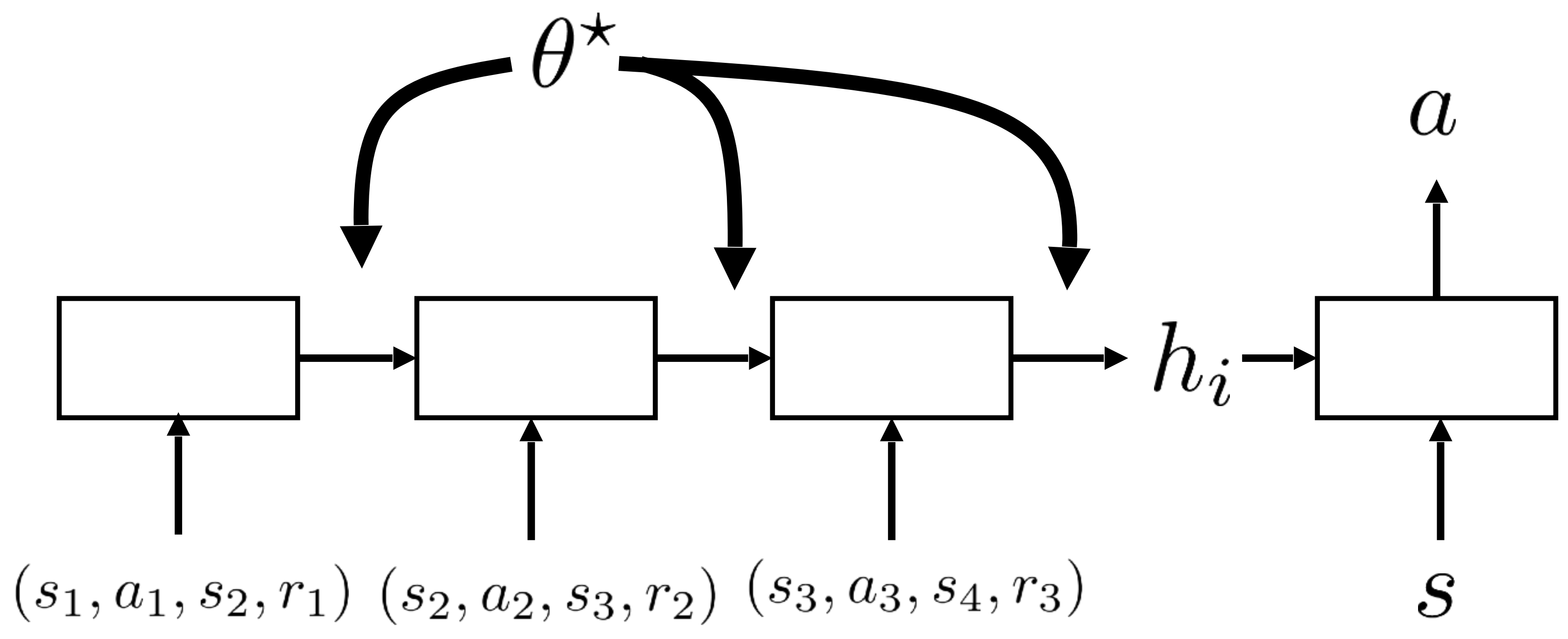
- Zintgraf, Igl, Shiarlis, Mahajan, Hofmann, Whiteson. **Variational Task Embeddings for Fast Adaptation in Deep Reinforcement Learning.**

- Humplik, Galashov, Hasenclever, Ortega, Teh, Heess. **Meta reinforcement learning as task inference.**

Qs: slido.com/meta

The three perspectives on meta-RL

Perspective 1: just RNN it



Perspective 2: bi-level optimization

$$f_\theta(\mathcal{M}_i) = \theta + \alpha \nabla_\theta J_i(\theta)$$

MAML for RL

Perspective 3: it's an inference problem!

$$\pi_\theta(a|s, z) \qquad z_t \sim p(z_t|s_{1:t}, a_{1:t}, r_{1:t})$$

everything needed to solve task

$$\theta^\star = \arg\max_\theta \sum_{i=1}^n E_{\pi_{\phi_i}(\tau)}[R(\tau)]$$

where $\phi_i = f_\theta(\mathcal{M}_i)$

what should $f_\theta(\mathcal{M}_i)$ *do*?

1. improve policy with experience from $\mathcal{M}_i$

   $\{(s_1, a_1, s_2, r_1), \ldots, (s_T, a_T, s_{T+1}, r_T)\}$

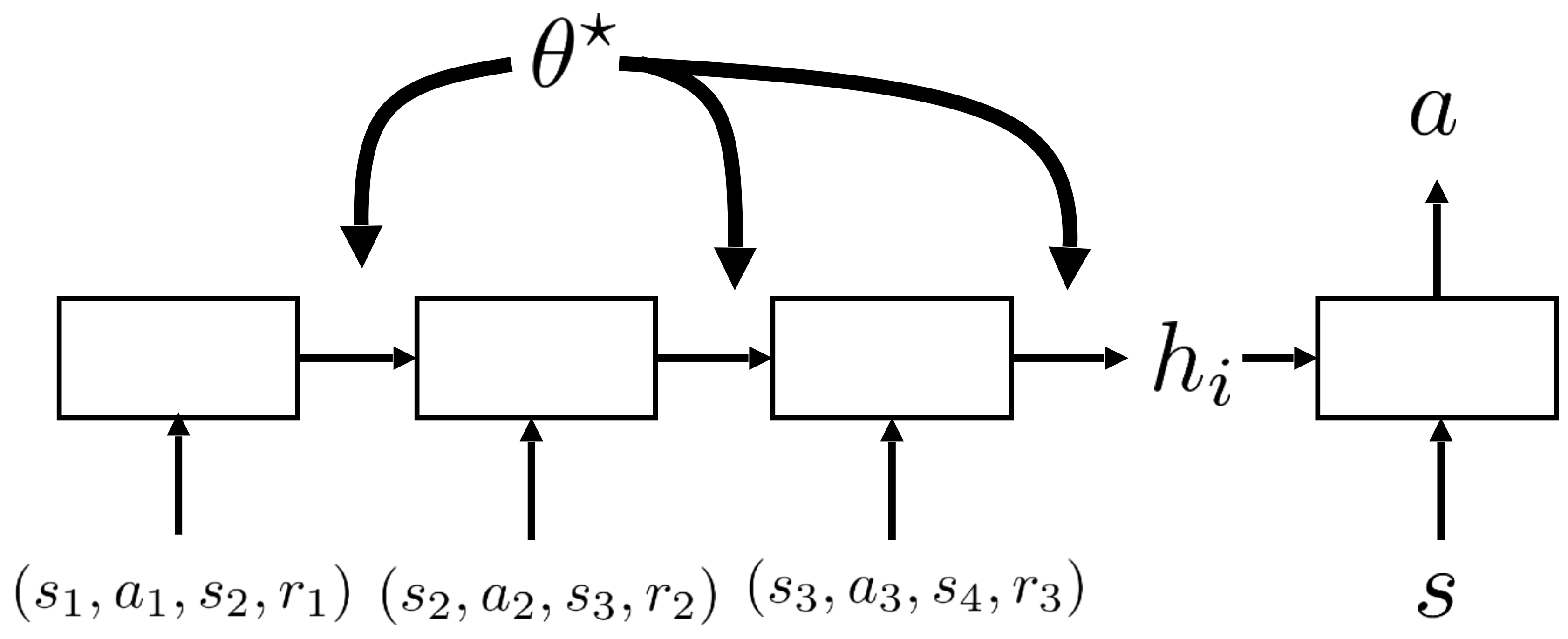
2. (new in RL): choose how to interact, i.e. choose a_t

   meta-RL must also *choose* how to *explore*!

Qs: slido.com/meta

The three perspectives on meta-RL

Perspective 1: just RNN it



+ conceptually simple

+ relatively easy to apply

- vulnerable to meta-overfitting

- challenging to optimize in practice

Perspective 2: bi-level optimization

$$f_\theta(\mathcal{M}_i) = \theta + \alpha \nabla_\theta J_i(\theta)$$

MAML for RL

+ good extrapolation ("consistent")

+ conceptually elegant

- complex, requires many samples

Perspective 3: it's an inference problem!

$\pi_\theta(a|s, z)$ $\qquad z_t \sim p(z_t | s_{1:t}, a_{1:t}, r_{1:t})$

everything needed to solve task

+ simple, effective exploration via posterior sampling

+ elegant reduction to solving a special POMDP

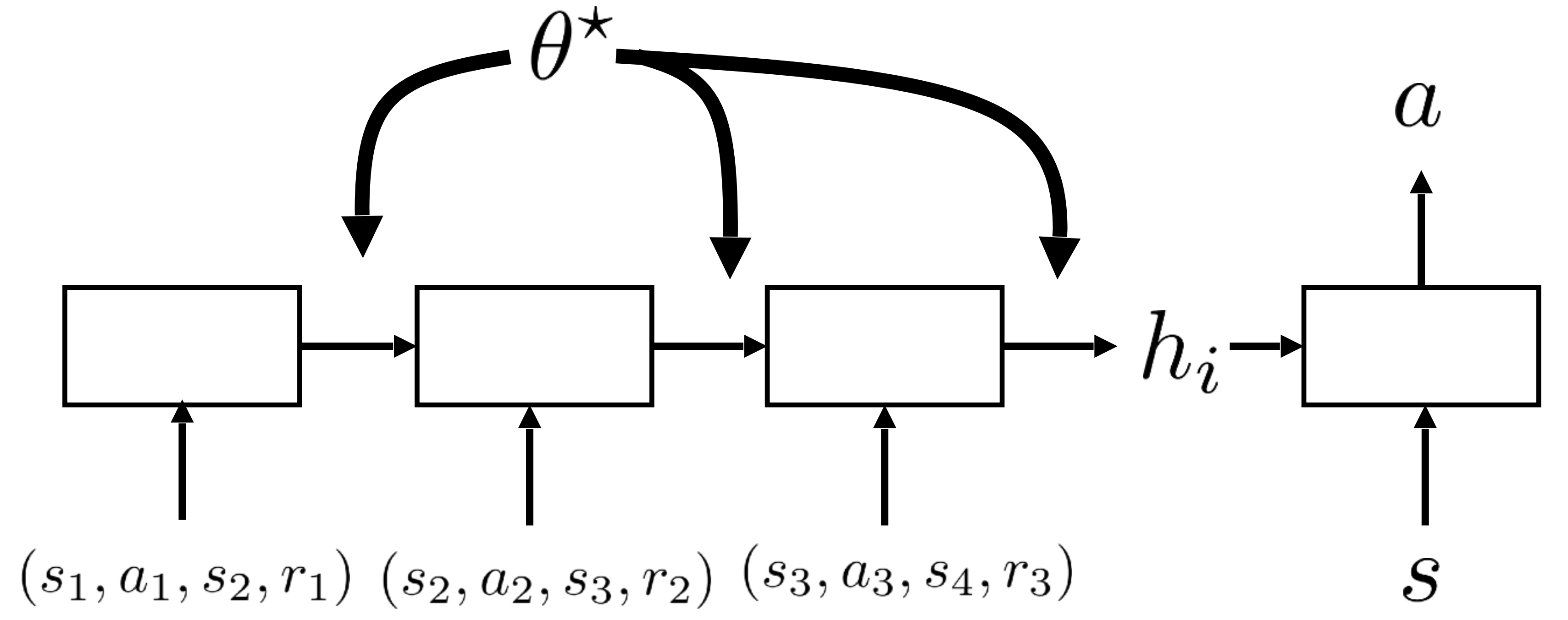
- vulnerable to meta-overfitting

- challenging to optimize in practice

Qs: slido.com/meta

But they're not that different!

Perspective 1: just RNN it



just perspective 1,
but with stochastic
hidden variables!

i.e., $\phi = \mathbf{z}$

Perspective 2: bi-level optimization

$$f_\theta(\mathcal{M}_i) = \theta + \alpha \nabla_\theta J_i(\theta)$$

MAML for RL

just a particular
architecture choice
for these

Perspective 3: it's an inference problem!

$$\pi_\theta(a|s, z) \qquad z_t \sim p(z_t|s_{1:t}, a_{1:t}, r_{1:t})$$

everything needed to solve task

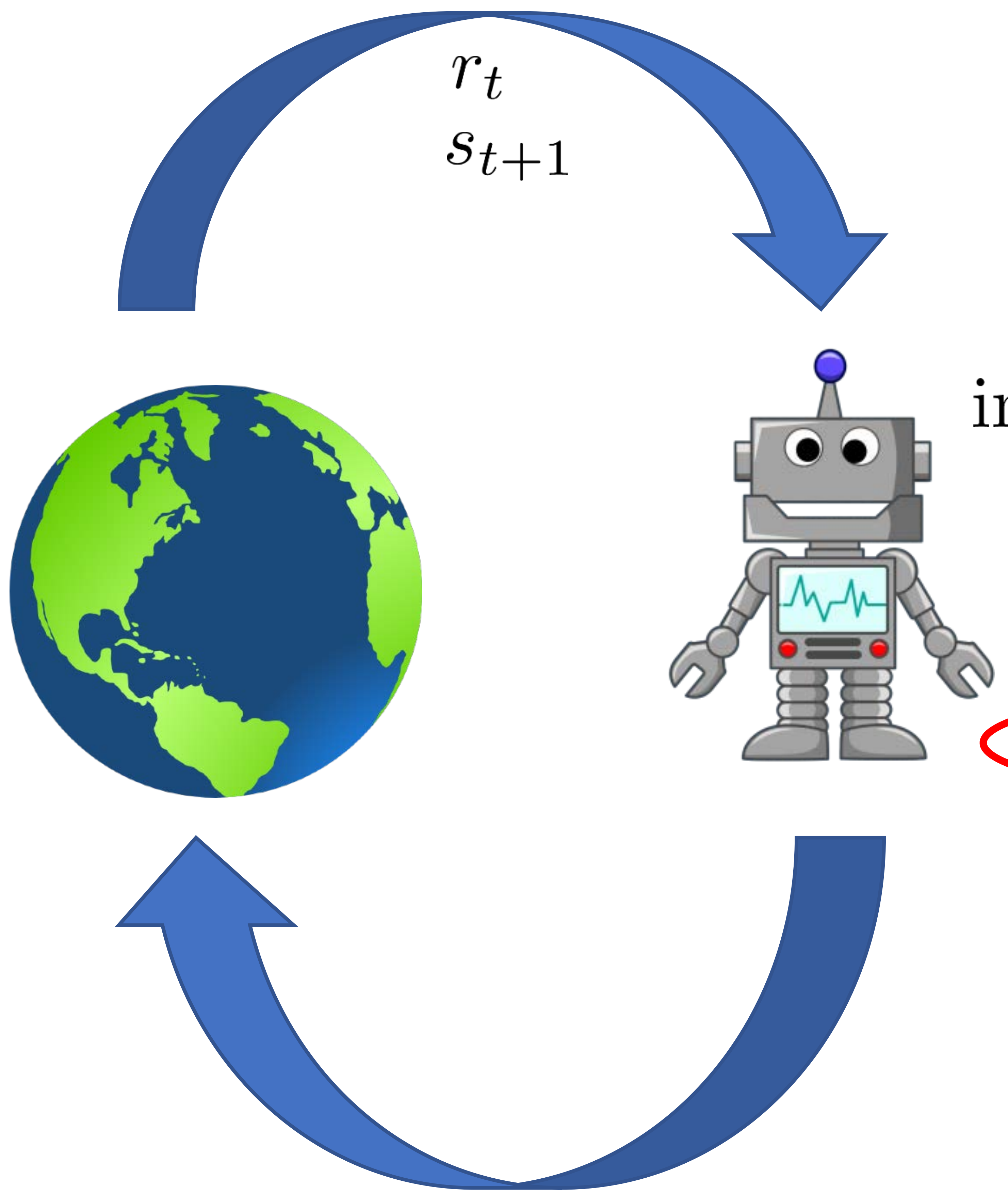
Qs: slido.com/meta

Additional Topics in Meta-RL

Qs: slido.com/meta

Model-based meta-RL

$$\theta^\star = \arg\max_\theta E_{\pi_\theta(\tau)}[R(\tau)]$$



improve π_θ...

...directly, via policy gradients

...via value function or Q-function

...implicitly, via model $\hat{p}(s_{t+1}|s_t, a_t)$

short sketch of model-based RL:

1. collect data $\mathcal{B}$
2. use $\mathcal{B}$ to get $\hat{p}(s_{t+1}|s_t, a_t)$
3. use $\hat{p}(s_{t+1}|s_t, a_t)$ to *plan* a

why?

+ requires much less data vs model-free

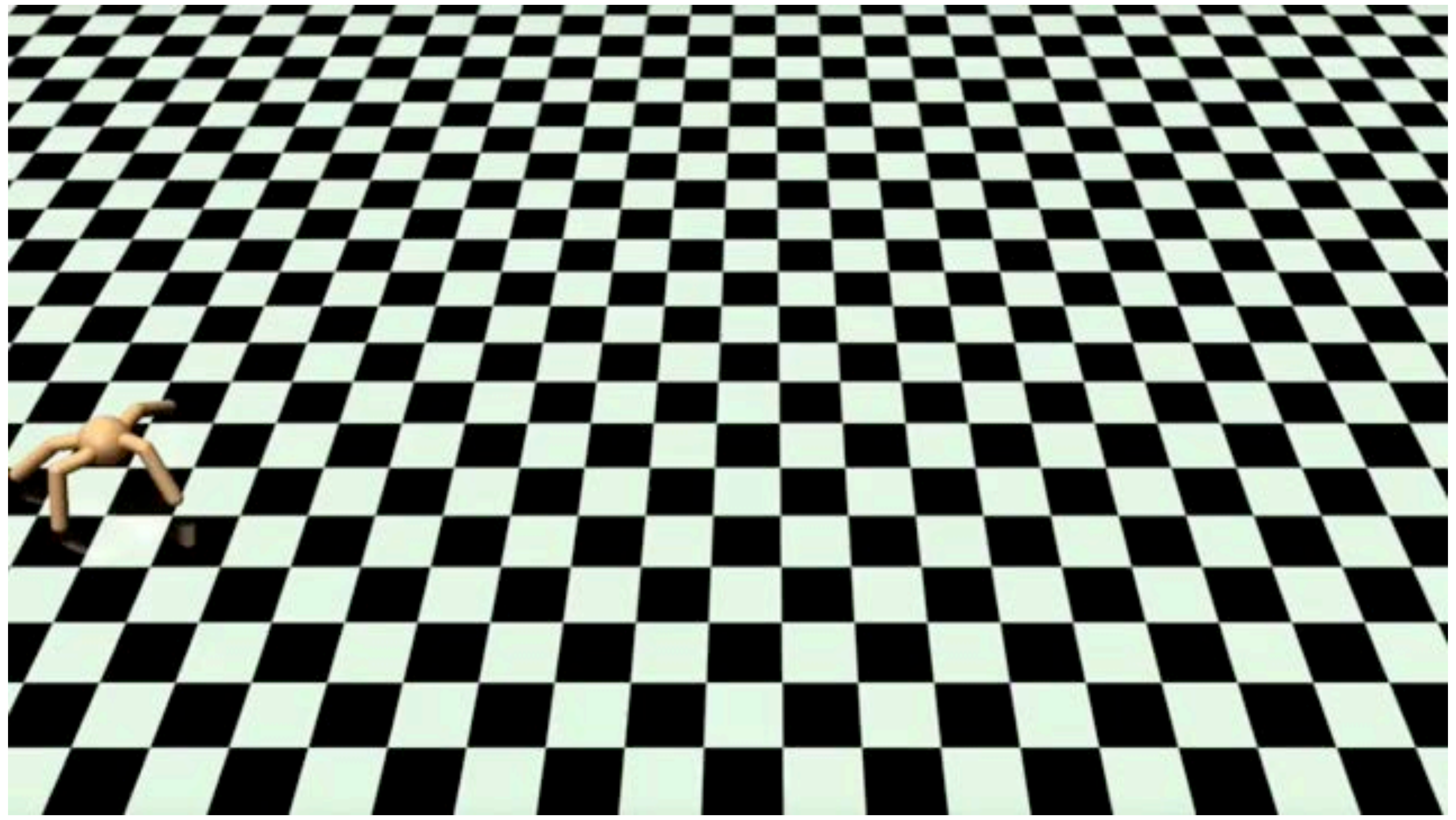
+ a bit different due to model

+ can adapt extremely quickly!

Qs: slido.com/meta

Model-based meta-RL

example task: ant with broken leg



non-adaptive method:

a few episodes

1. collect data $\mathcal{B} = \{s_i, a_i, s'_i\}$
2. train $d_\theta(s, a) \rightarrow s'$ on $\mathcal{B}$
3. use d_θ to optimize actions

$$a_t, \ldots, a_{t+k} = \arg \max_{a_t, \ldots, a_{t+k}} \sum_{\tau=t}^{t+k} r(s_\tau, a_\tau)$$

$$\text{s.t. } s_{t+1} = d_\theta(s_t, a_t)$$

adaptive method:

1. take *one* step, get $\{s, a, s'\}$
2. $\theta \leftarrow \theta - \alpha \nabla_\theta \| d_\theta(s, a) - s' \|^2$
3. use d_θ to optimize $a_t, \ldots, a_{t+k}$, take a_t

nice idea, but how much can we really adapt in just one (or a few) step(s)?

Qs: slido.com/meta

Model-based meta-RL

meta-training time

$$\mathcal{D}_{\text{meta-train}} = \{(\mathcal{D}_1^{\text{tr}}, \mathcal{D}_1^{\text{ts}}), \dots, (\mathcal{D}_n^{\text{tr}}, \mathcal{D}_n^{\text{ts}})\}$$

$$\mathcal{D}_i^{\text{tr}} = \{(x_1^i, y_1^i), \dots, (x_k^i, y_k^i)\}$$

$$\mathcal{D}_i^{\text{ts}} = \{(x_1^i, y_1^i), \dots, (x_l^i, y_l^i)\}$$

$$x \leftarrow (s, a) \qquad y \leftarrow s'$$

generate each $\mathcal{D}_i^{\text{tr}}, \mathcal{D}_i^{\text{ts}}$:

sample subsequence $s_t, a_t, \dots, s_{t+k}, a_{t+k}, s_{t+k+1}$ from past experience

$$\mathcal{D}_i^{\text{tr}} \leftarrow \{(s_t, a_t, s_{t+1}), \dots, (s_{t+k-1}, a_{t+k-1}, s_{t+k})\}$$

$$\mathcal{D}_i^{\text{ts}} \leftarrow \{(s_{t+k}, a_{t+k}, s_{t+k+1})\}$$

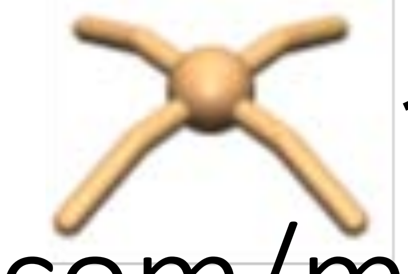
meta-test time

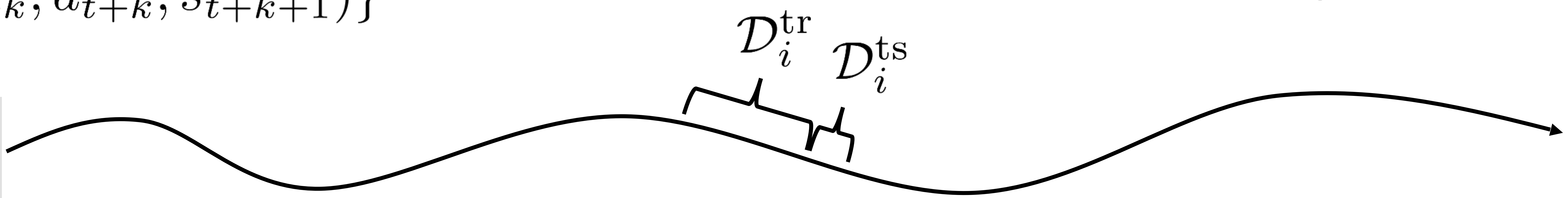
adaptive method:

1. take *one* step, get $\{s, a, s'\}$
2. $\theta \leftarrow \theta - \alpha \nabla_\theta \|d_\theta(s, a) - s'\|^2$
3. use d_θ to optimize $a_t, \dots, a_{t+k}$, take a_t

assumes past experience has many different dynamics

could choose k = 1, but k > 1 works better (e.g., k = 5)

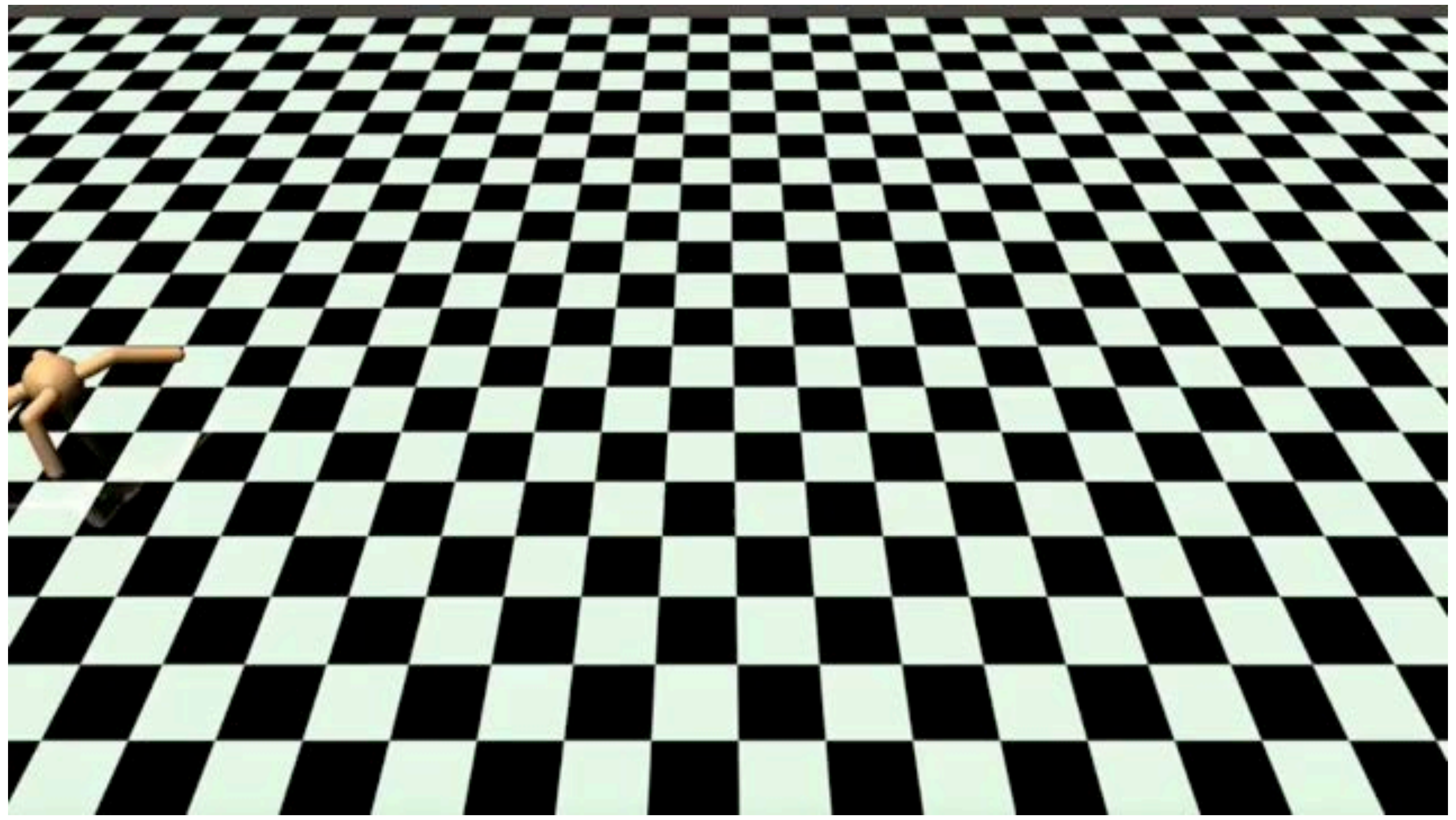




Qs: slido.com/meta

Model-based meta-RL

example task: ant with broken leg



See also:

Saemundsson, Hofmann, Deisenroth. **Meta-Reinforcement Learning with Latent Variable Gaussian Processes.**

Nagabandi, Finn, Levine. **Deep Online Learning via Meta-Learning: Continual Adaptation for Model-Based RL.**

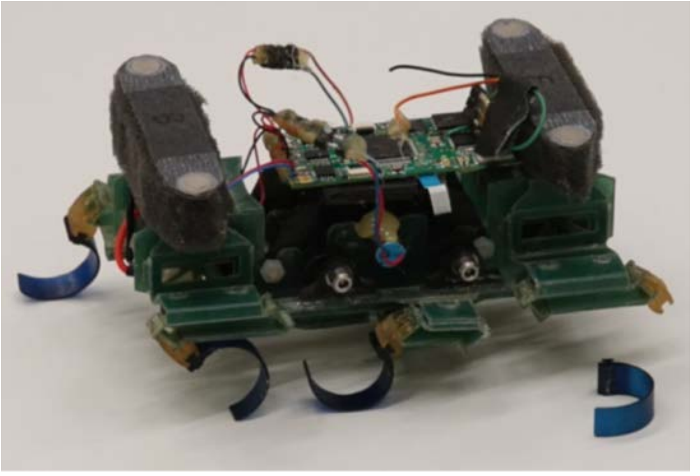
Qs: slido.com/meta

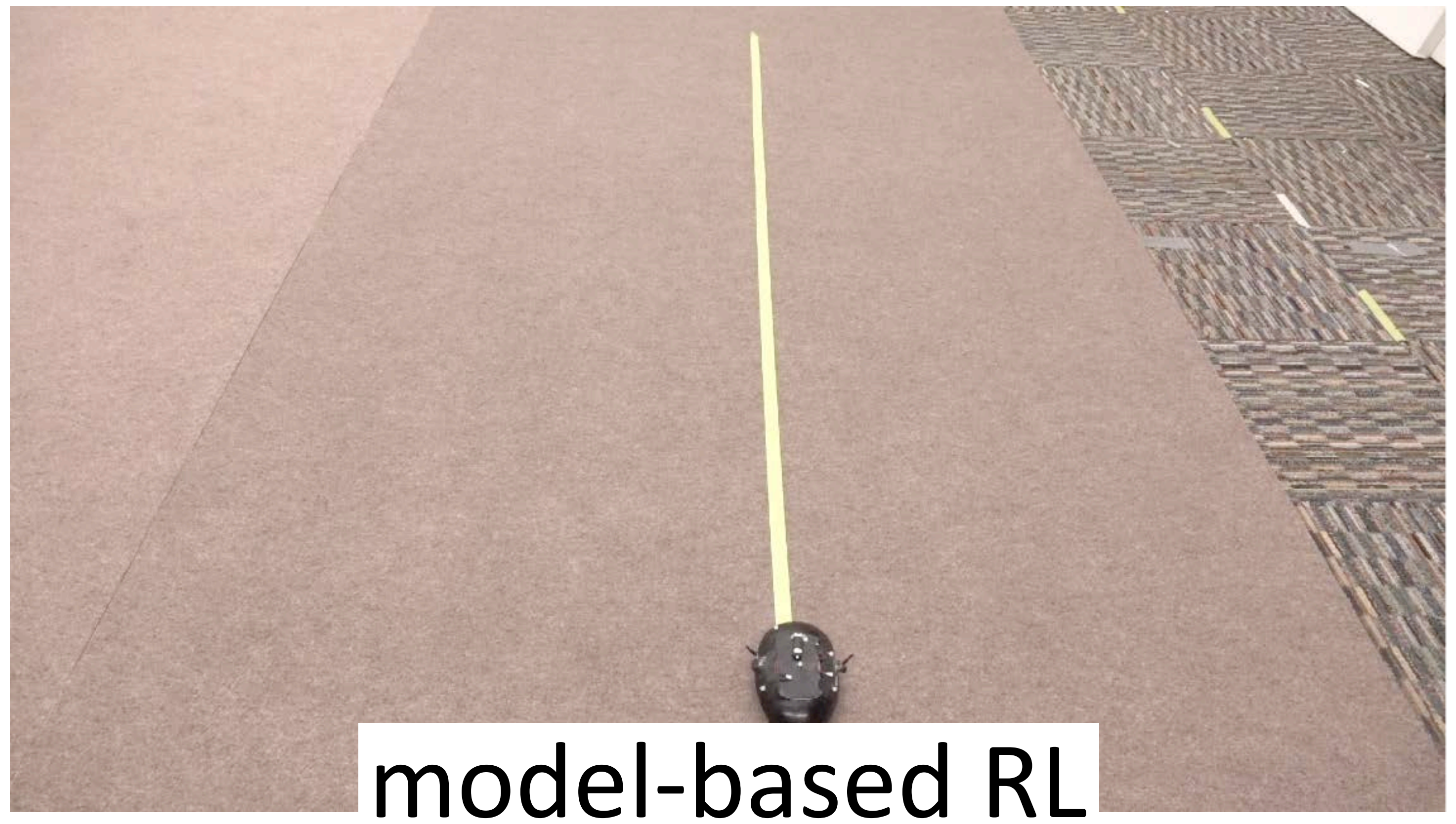
Nagabandi*, Clavera*, Liu, Fearing, Abbeel, Levine, Finn. **Learning to Adapt in Dynamic, Real-World Environments Through Meta-Reinforcement Learning.** ICLR 2019.

meta-test time

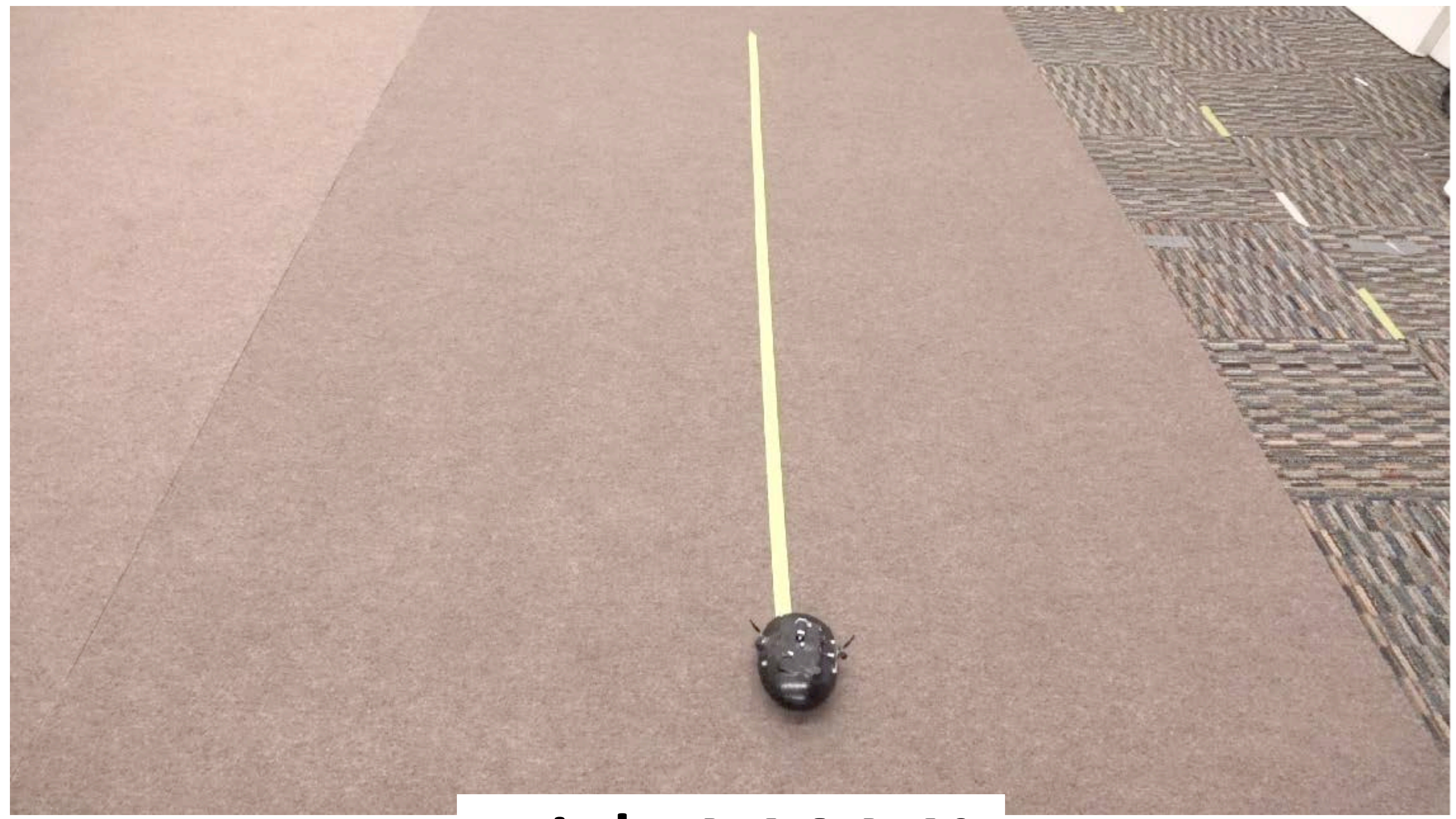
adaptive method:

1. take *one* step, get $\{s, a, s'\}$
2. $\theta \leftarrow \theta - \alpha \nabla_\theta \| d_\theta(s, a) - s' \|^2$
3. use d_θ to optimize $a_t, \ldots, a_{t+k}$, take a_t





model-based RL
(no adaptation)



with MAML

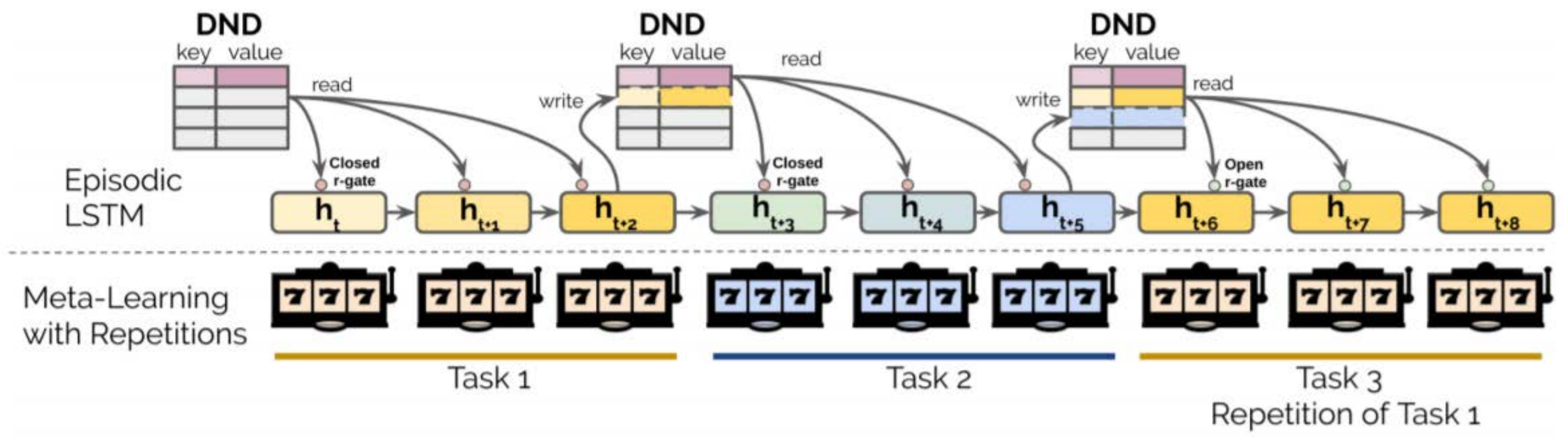
Meta-RL and emergent phenomena

Humans and animals seemingly learn behaviors in a variety of ways:
- ➢ Highly efficient but (apparently) model-free RL
- ➢ Episodic recall
- ➢ Model-based RL
- ➢ Causal inference
- ➢ etc.

Perhaps each of these is a separate "algorithm" in the brain

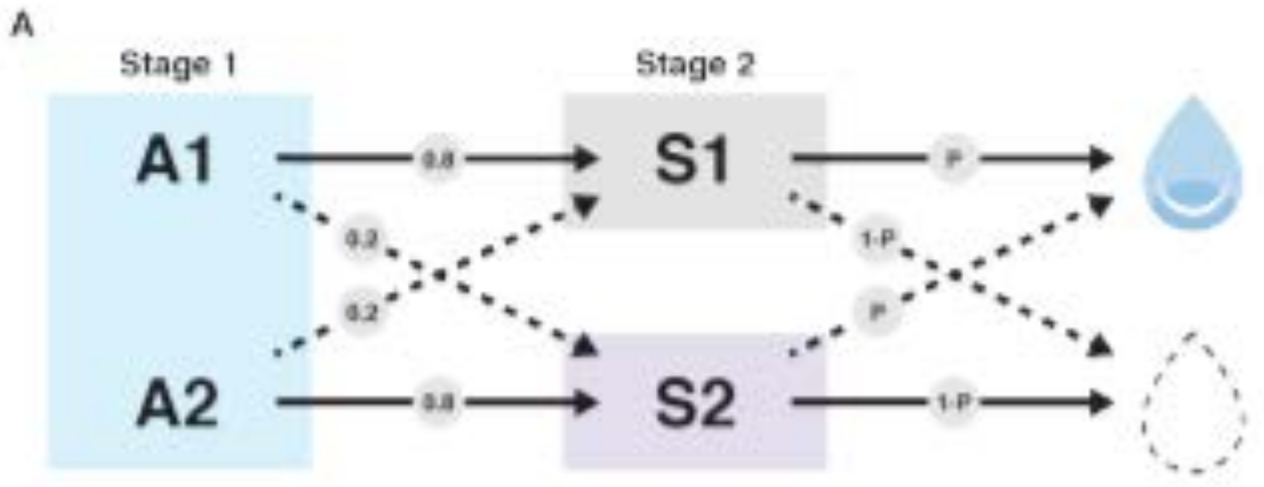
But maybe these are all emergent phenomena resulting from meta-RL?

meta-RL gives rise to episodic learning



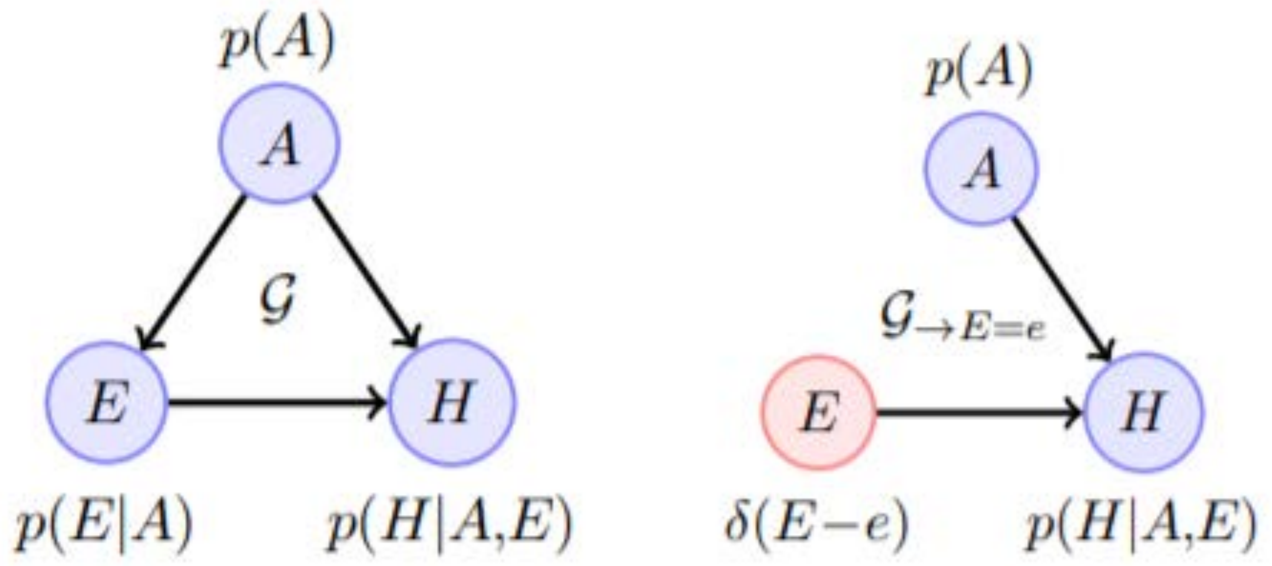
Ritter, Wang, Kurth-Nelson, Jayakumar, Blundell, Pascanu, Botvinick. **Been There, Done That: Meta-Learning with Episodic Recall.**

model-free meta-RL gives rise to model-based adaptation



Wang, Kurth-Nelson, Kumaran, Tirumala, Soyer, Leibo, Hassabis, Botvinick. **Prefrontal Cortex as a Meta-Reinforcement Learning System.**

meta-RL gives rise to causal reasoning (!)



Dasgupta, Wang, Chiappa, Mitrovic, Ortega, Raposo, Hughes, Battaglia, Botvinick, Kurth-Nelson. **Causal Reasoning from Meta-Reinforcement Learning.**

Contextual policies and meta-learning

$$\theta^\star = \arg\max_\theta \sum_{i=1}^n E_{\pi_{\phi_i}(\tau)}[R(\tau)]$$

$$\text{where } \phi_i = f_\theta(\mathcal{M}_i)$$

$$\theta^\star = \arg\max_\theta \sum_{i=1}^n E_{\pi_\theta}[R(\tau)]$$

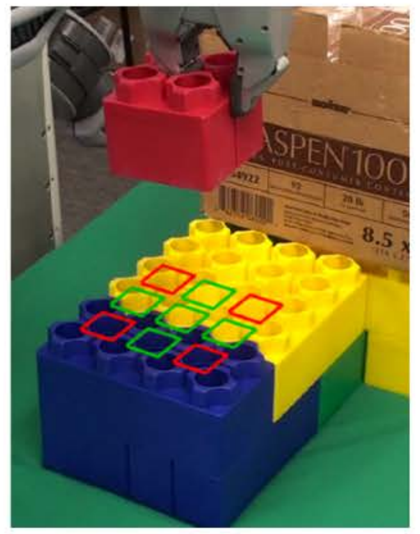
$$\pi_\theta(a_t|s_t, \underbrace{s_1, a_1, r_1, \dots, s_{t-1}, a_{t-1}, r_{t-1}}_{})$$

context used to infer whatever we need to solve $\mathcal{M}_i$
i.e., z_t or ϕ_i (which are really the same thing)

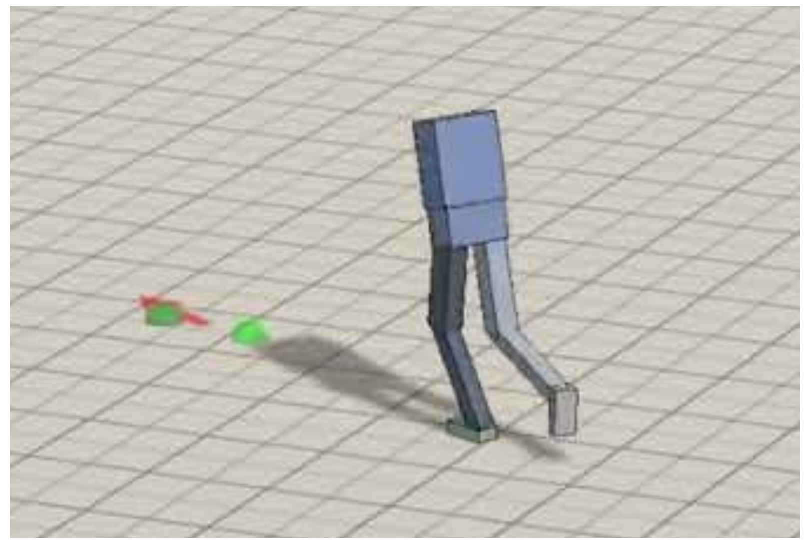
in meta-RL, the *context* is inferred from experience from $\mathcal{M}_i$ $\quad \pi_\theta(a_t|s_t, \phi_i)$

"context"

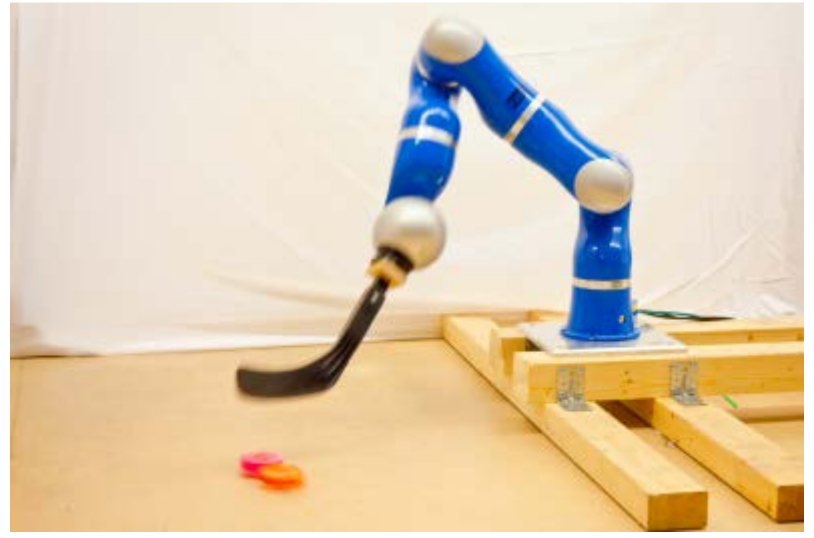
in multi-task RL, the context is typically given



ϕ: stack location



ϕ: walking direction



ϕ: where to hit puck

Qs: slido.com/meta

Outline

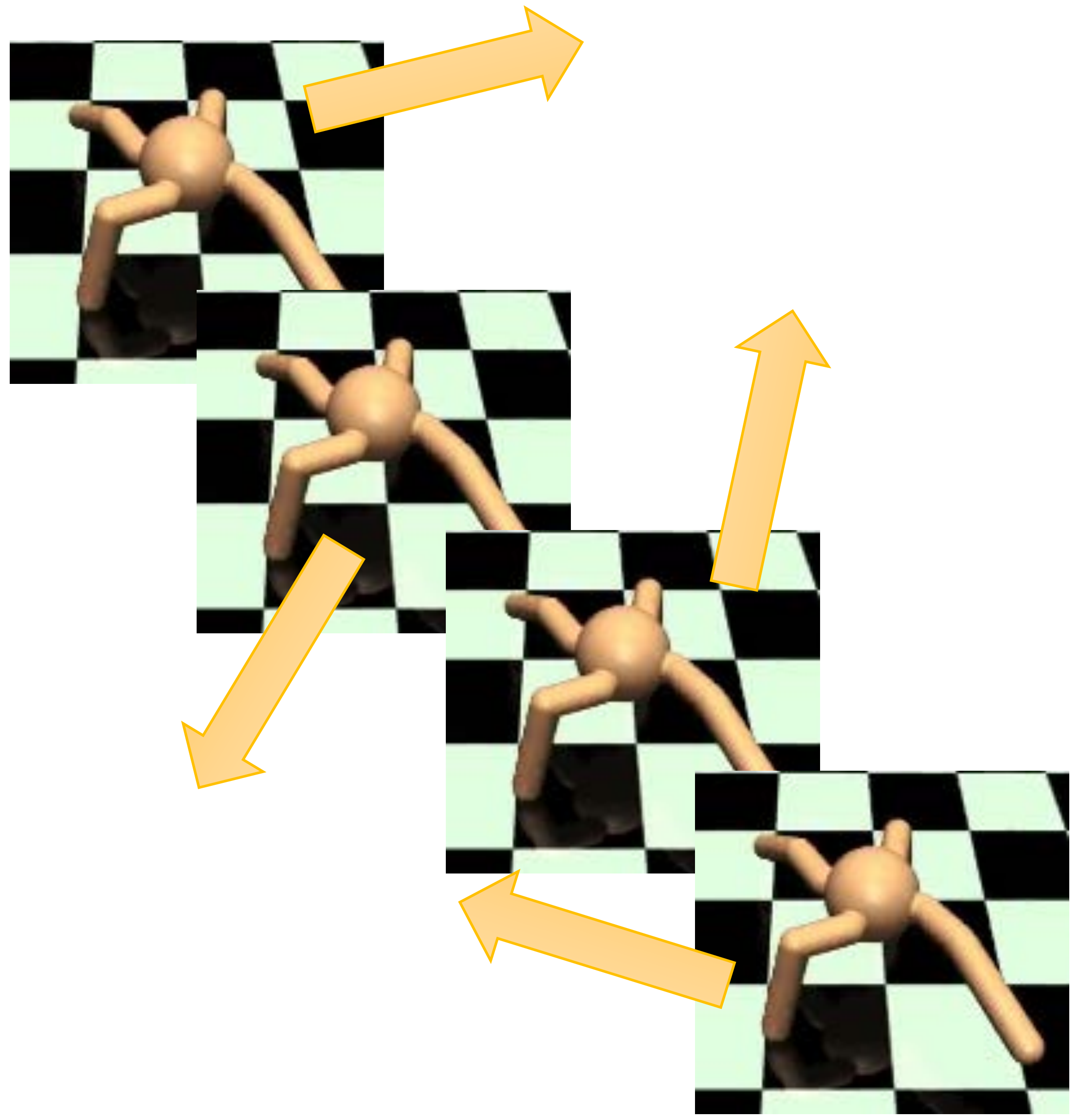
- **Problem statement**
- Meta-learning **algorithms**
  - Black-box adaptation
  - Optimization-based inference
  - Non-parametric methods
  - Bayesian meta-learning
- Meta-learning **applications**

— 5 min break —

- Meta-**reinforcement** learning
- Challenges & frontiers

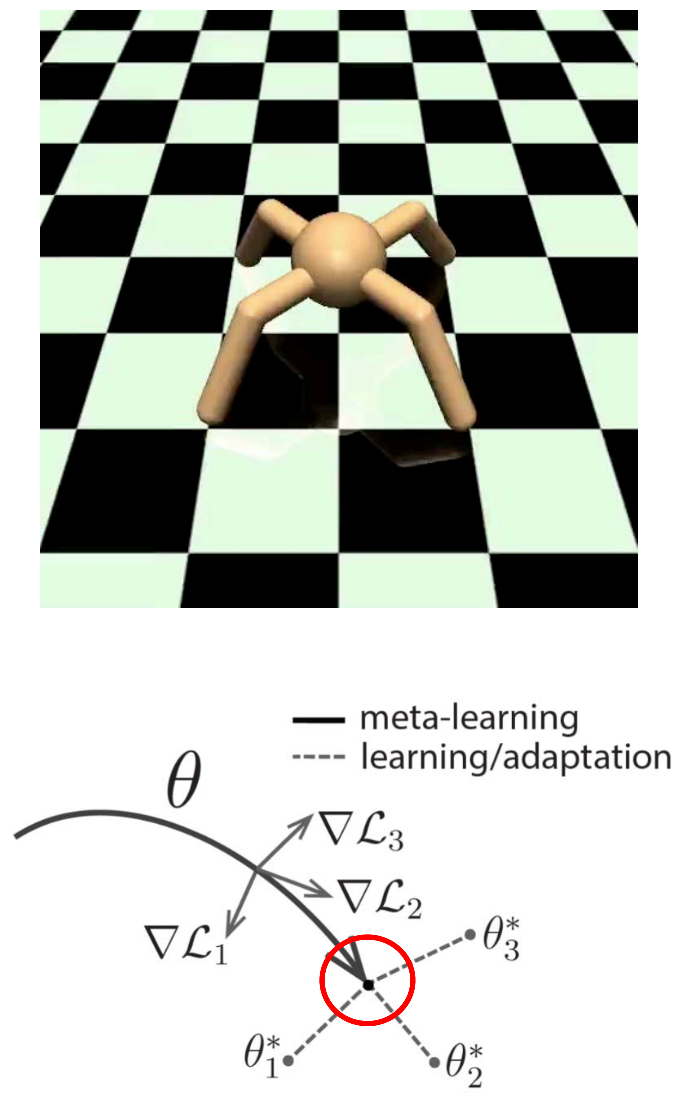
Qs: slido.com/meta

Let’s Talk about Meta-Overfitting

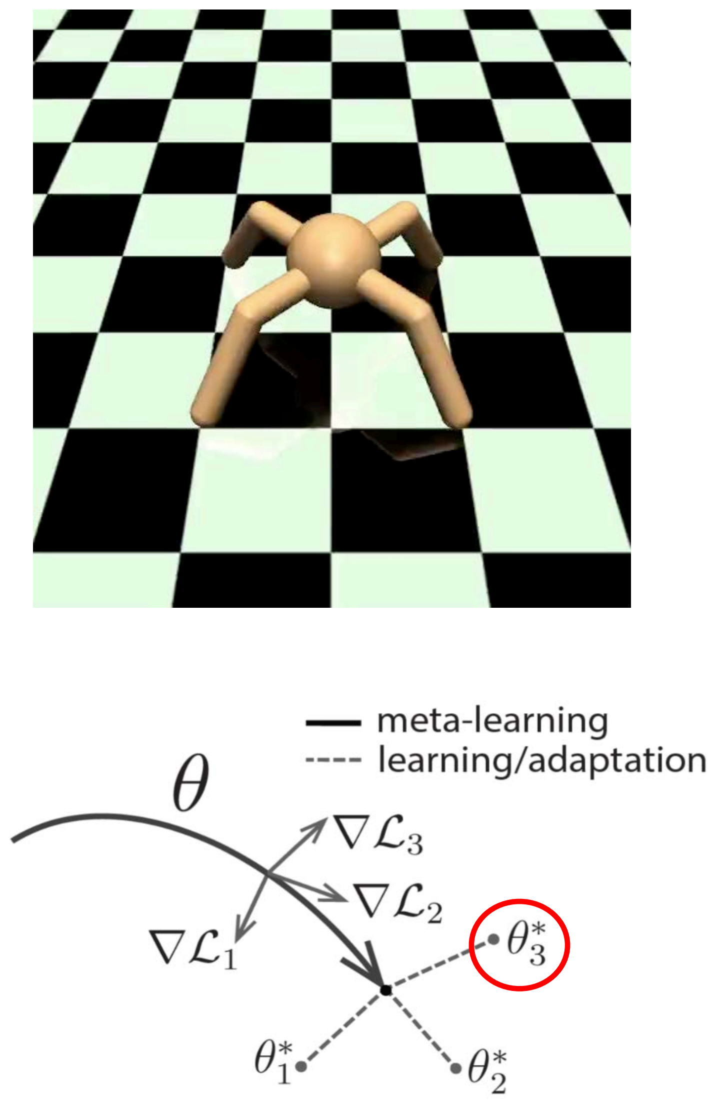


- Meta learning requires task distributions
- When there are too few meta-training tasks, we can meta-overfit
- Specifying task distributions is hard!
- What can we do?

after MAML training



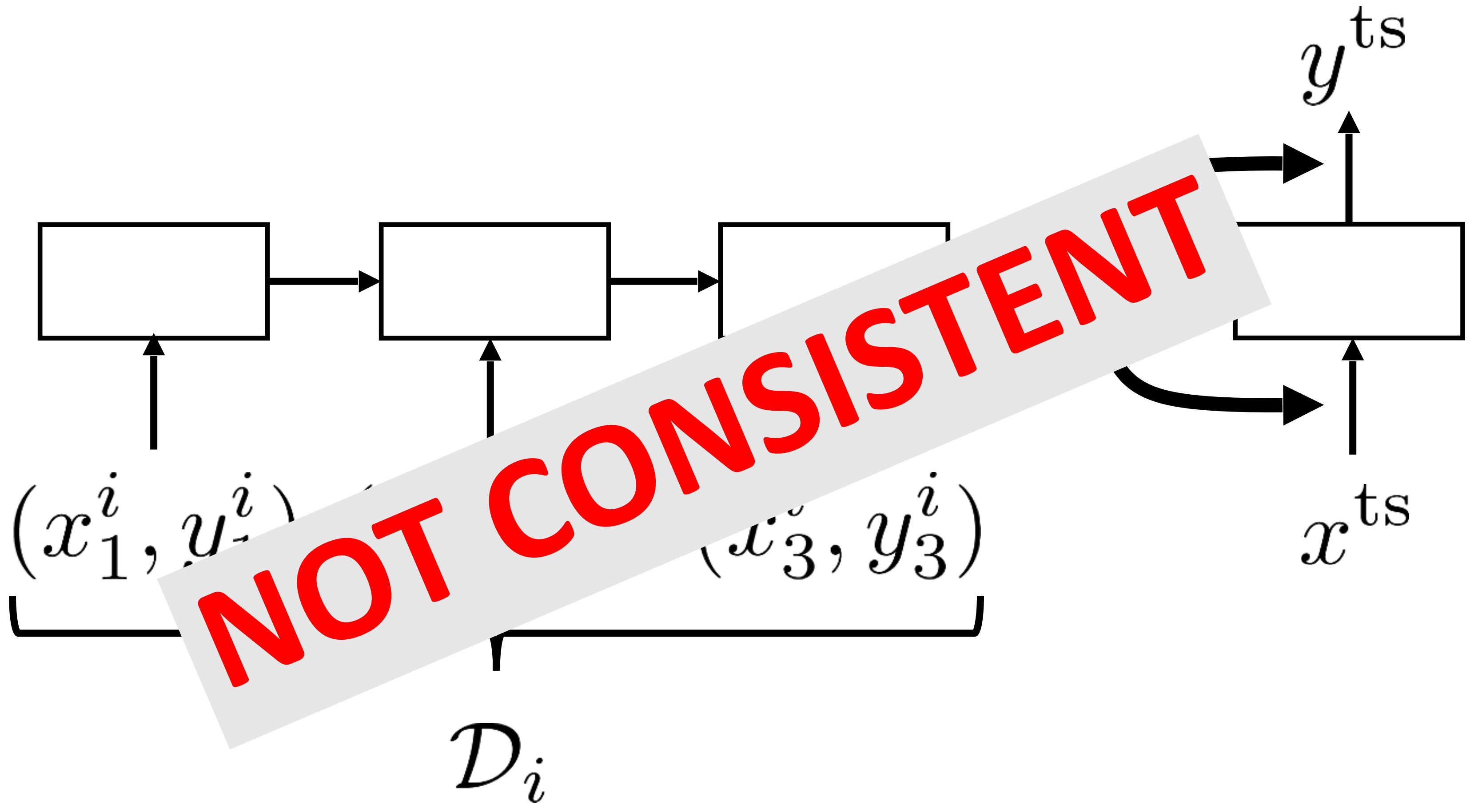
after 1 gradient step



Qs: slido.com/meta

Which algorithms meta-overfit less?

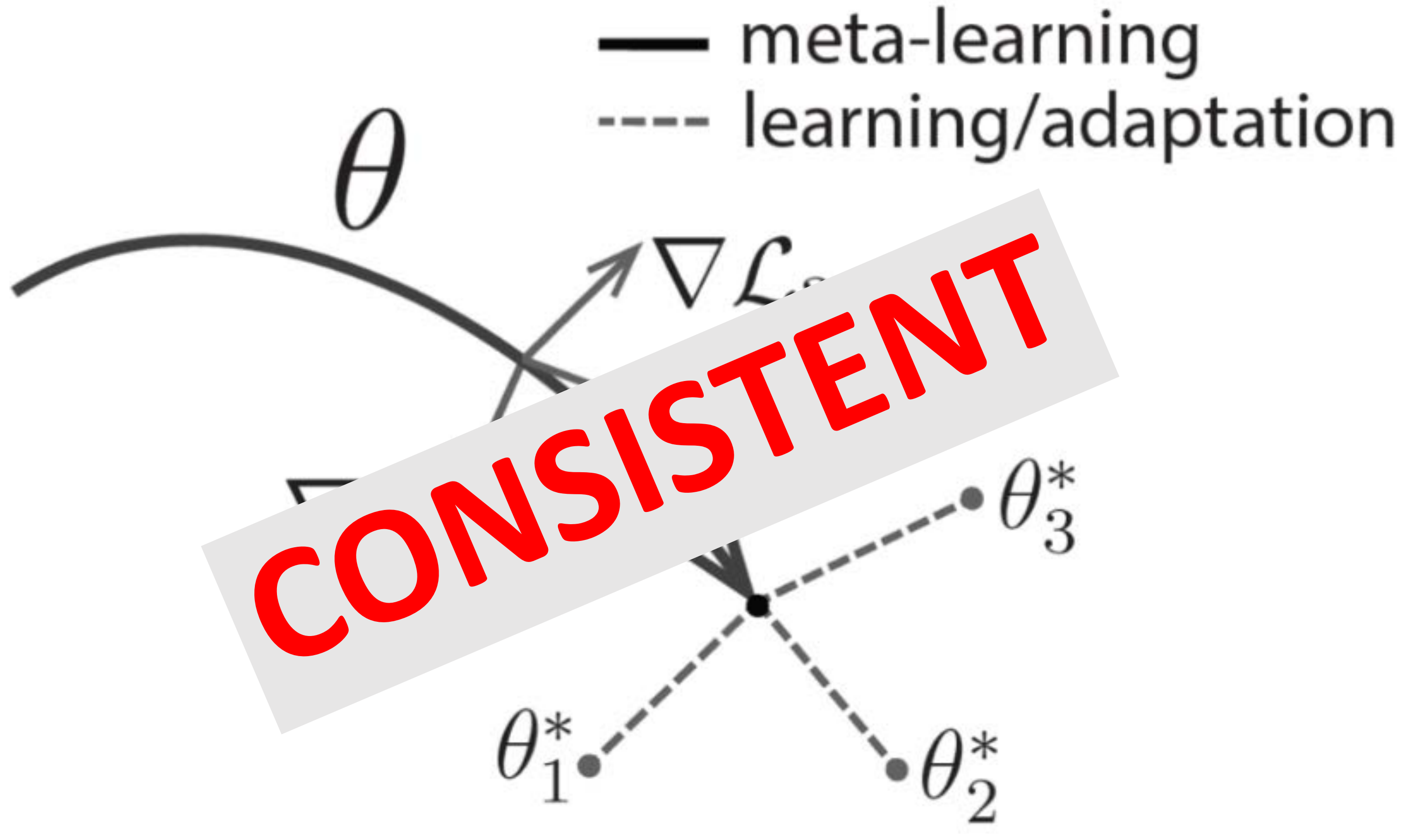
black-box adaptation



+ simple and flexible models

- relies **entirely** on extrapolation of learned adaptation procedure

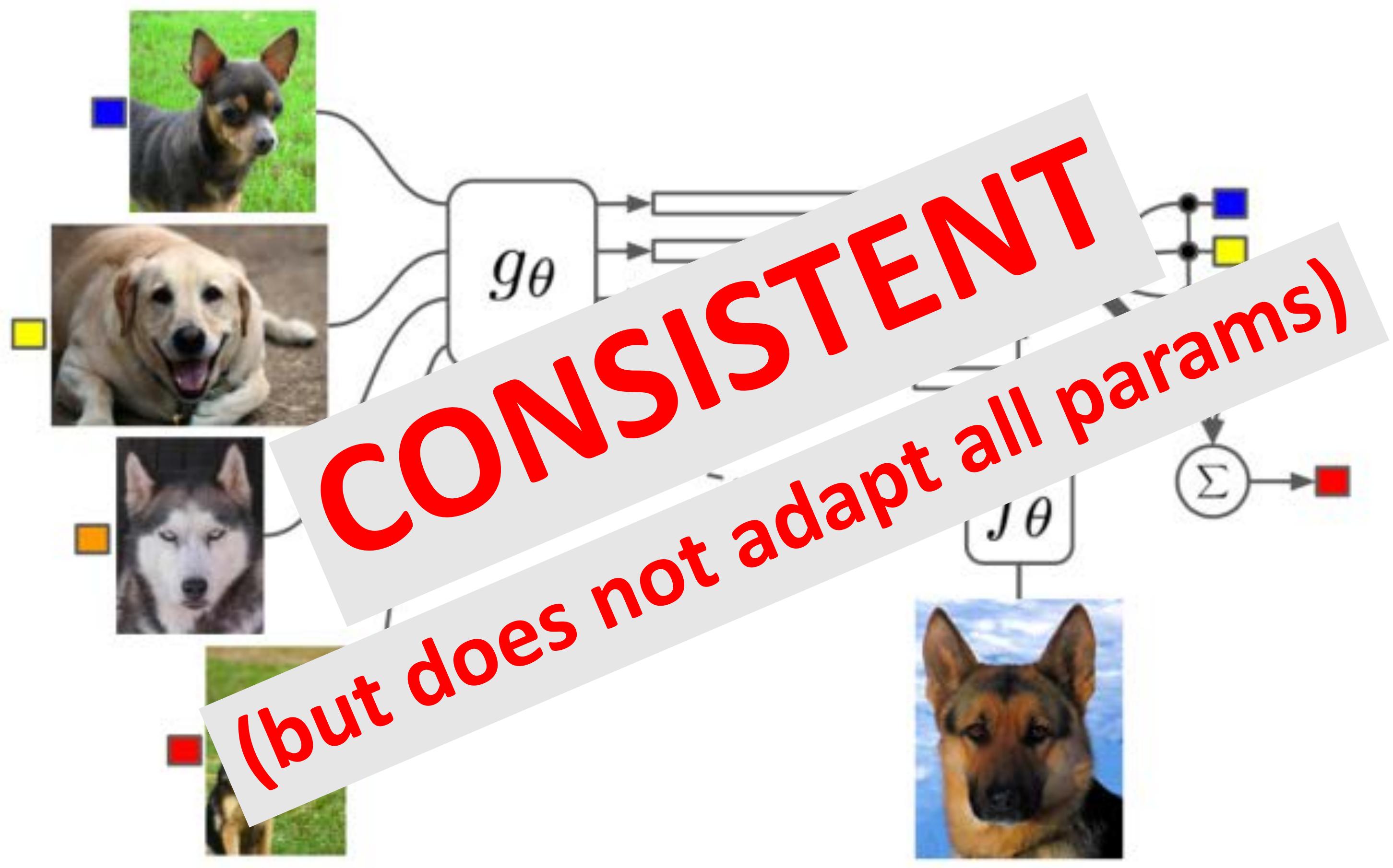
optimization-based



+ at worst just gradient descent

- pure gradient descent is not efficient without benefit of good initialization

non-parametric



+ at worst just nearest neighbor

- does not adapt all parameters of metric on new data (might be nearest neighbor in very bad space)

Definition: a consistent meta-learner will converge to a (locally) optimal solution on any new task, regardless of meta-training

Qs: slido.com/meta

Finn. **Learning to Learn with Gradients.** PhD thesis, 2019.

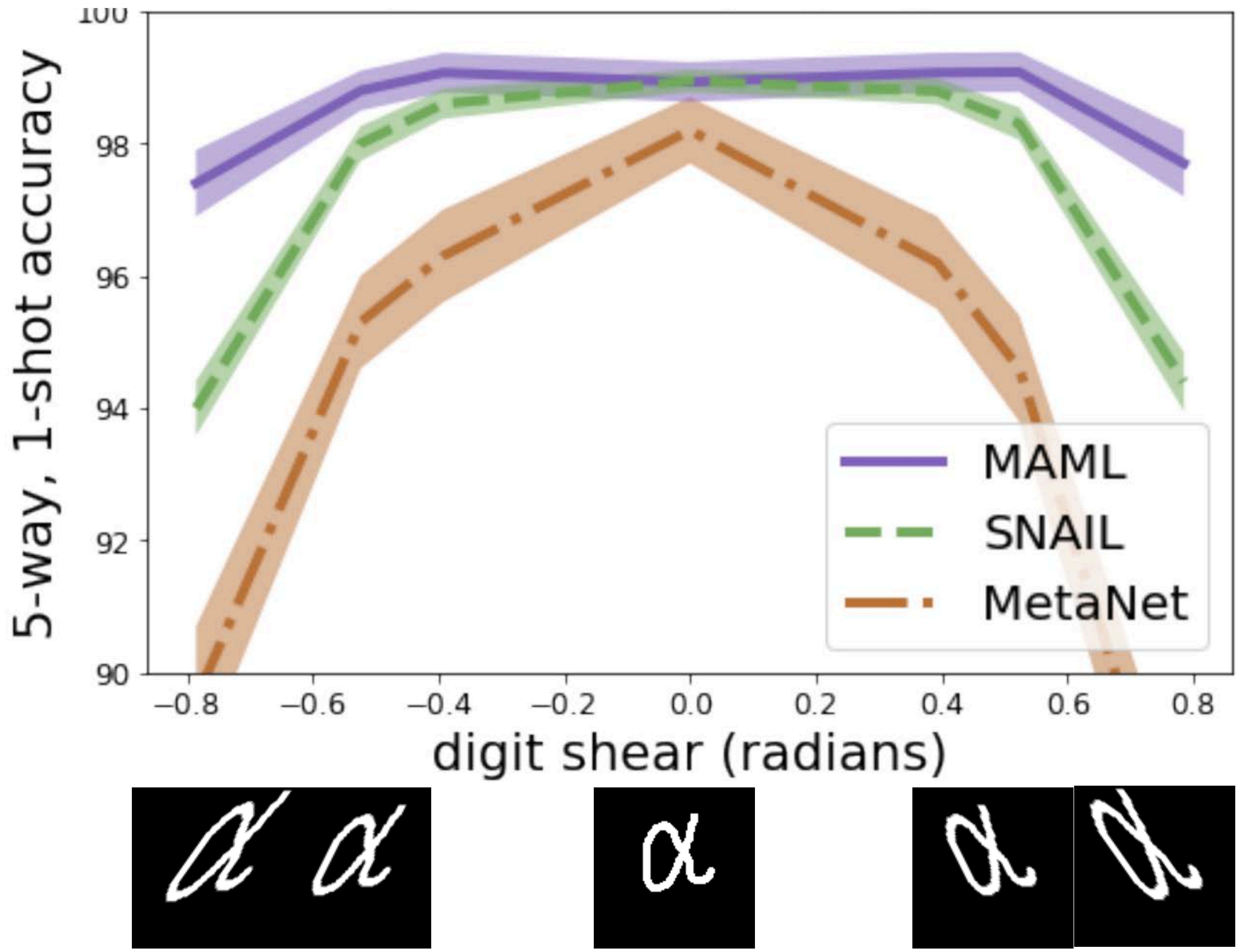
Empirical Extrapolation?

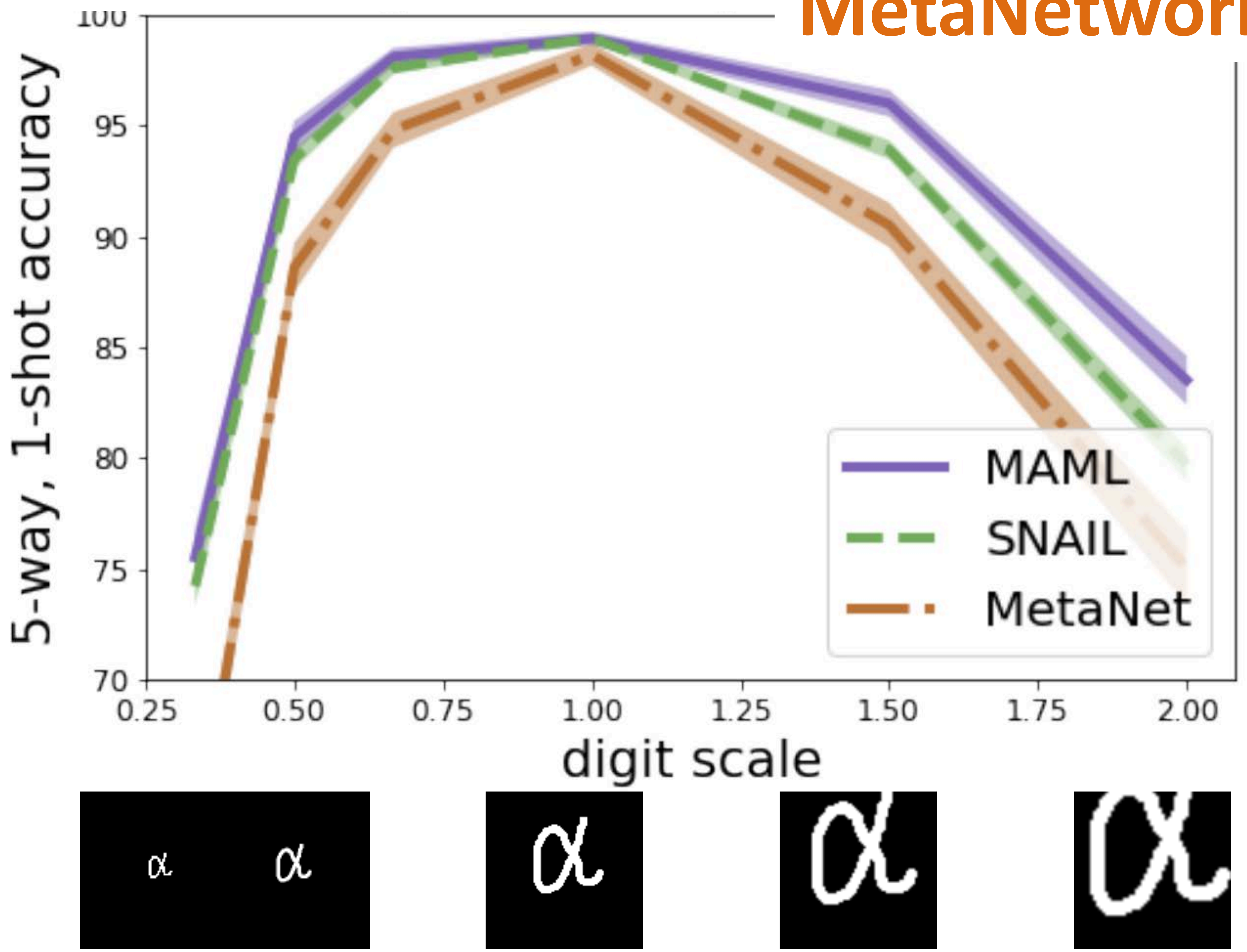
How well can learning procedures generalize to similar, but extrapolated tasks?

MAML, SNAIL, MetaNetworks

Omniglot image classification

performance





task variability

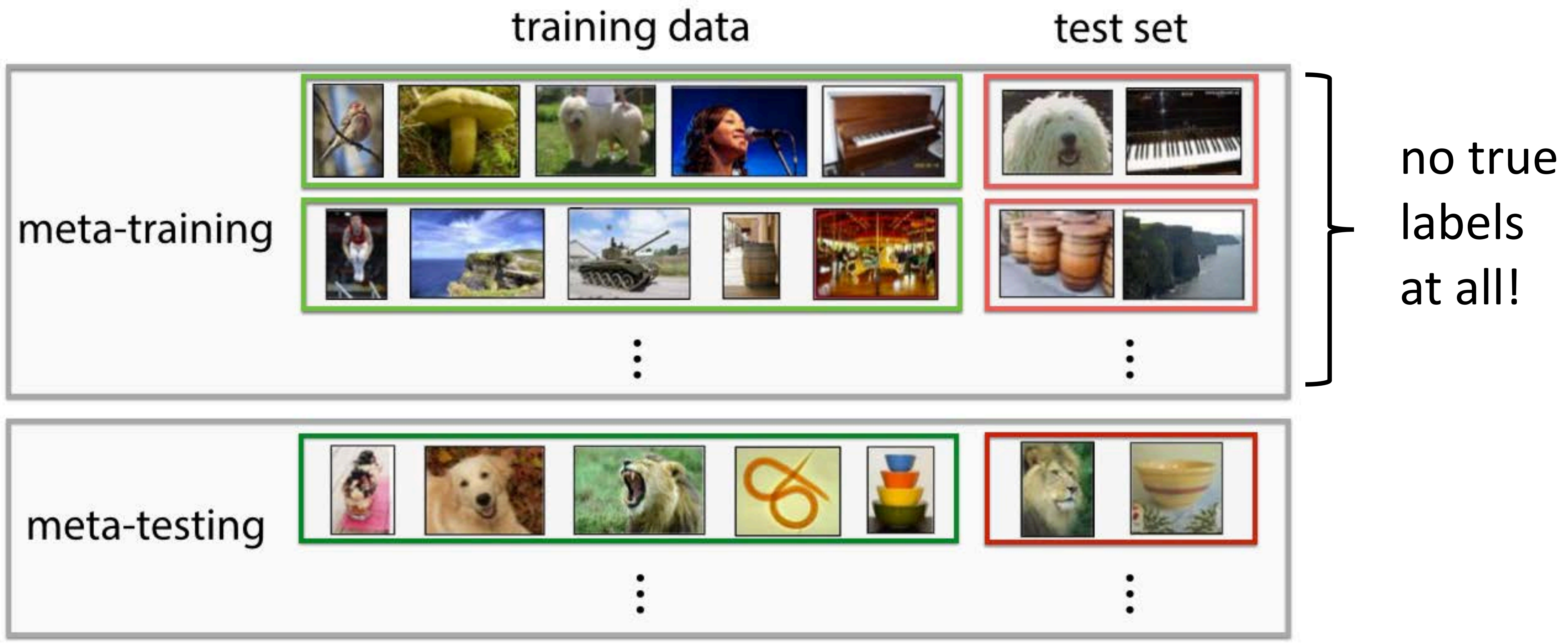
Qs: slido.com/meta

Finn & Levine ICLR '18

What else can we do?

- When there are too few meta-training tasks, we can meta-overfit
- Specifying task distributions is hard!
- Can we propose new tasks automatically?

Definition: unsupervised meta-learning refers to meta-learning algorithms that learn to solve tasks efficiently, without using hand-specified labels during meta-training

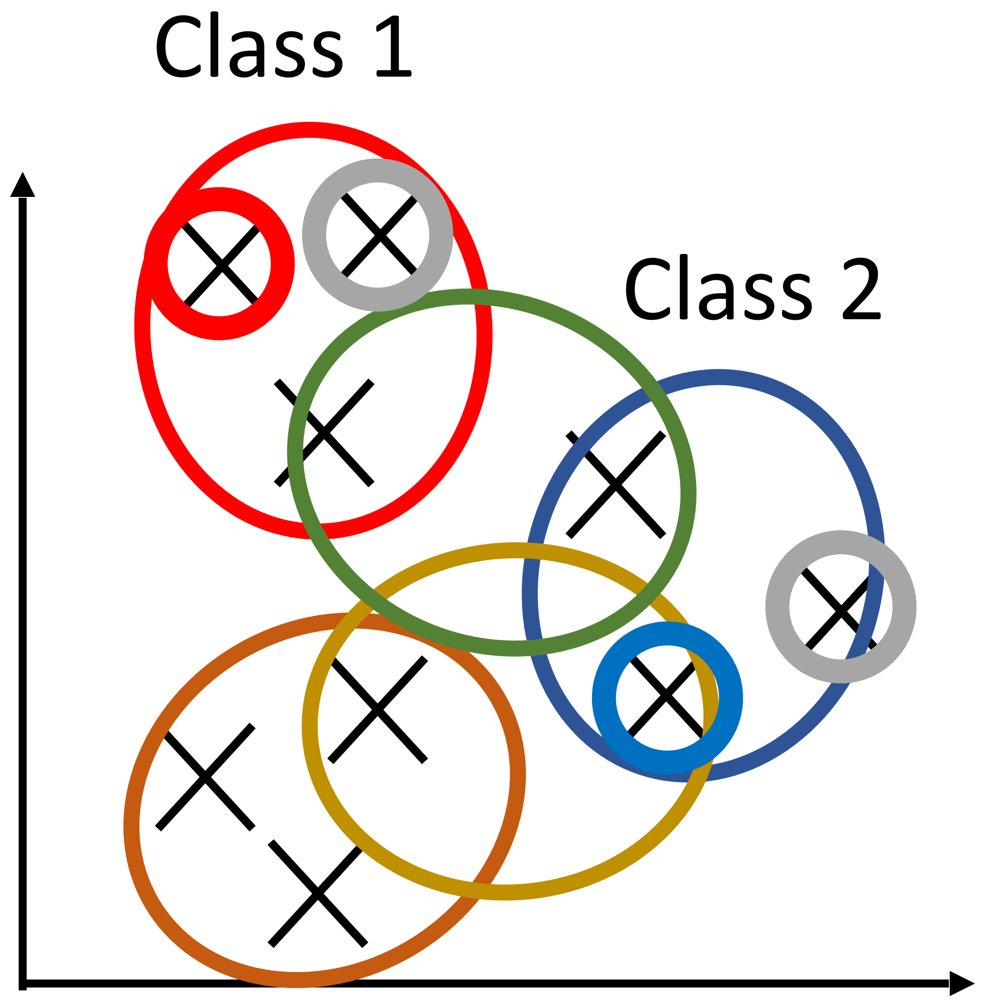


Qs: slido.com/meta

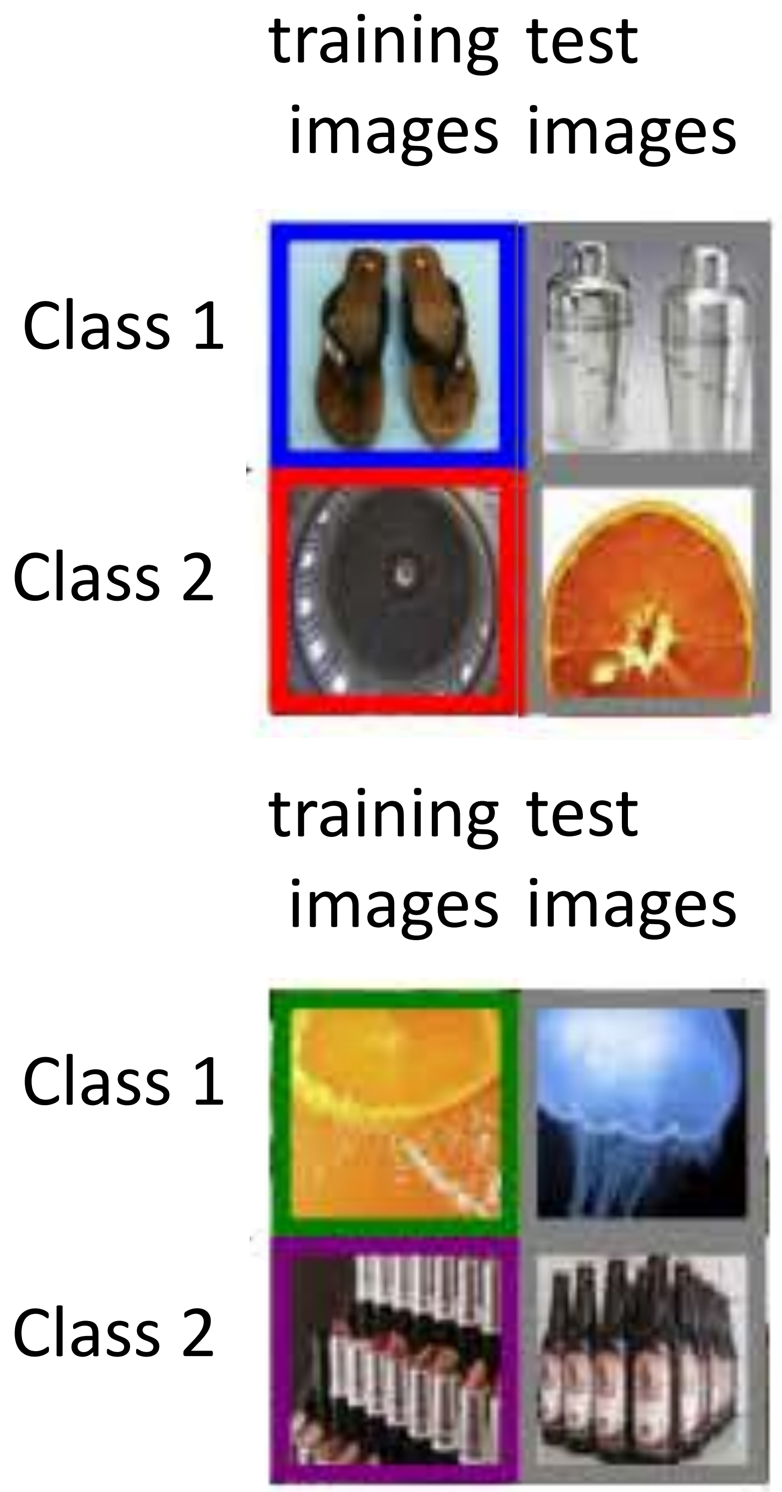
Example: stagewise unsupervised meta-learning

unsupervised learning → **task proposals** → **meta-learning**

$\{\mathbf{x}_i\}$



each image: point in $\mathbb{R}^n$



miniImageNet: 5 shot, 5 way

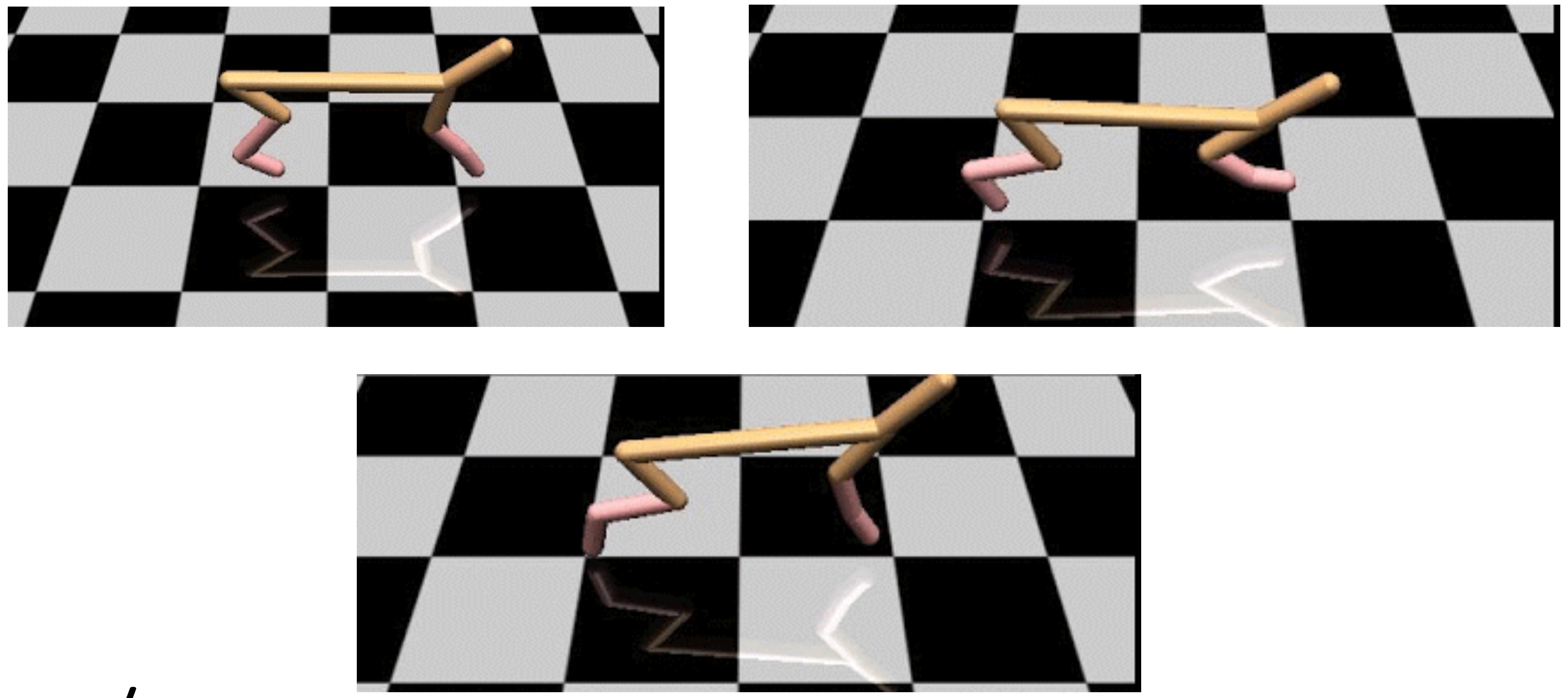
method	accuracy
MAML with labels	62.13%
BiGAN kNN	31.10%
BiGAN logistic	33.91%
BiGAN MLP + dropout	29.06%
BiGAN cluster matching	29.49%
BiGAN CACTUs MAML	51.28%
DeepCluster CACTUs MAML	**53.97%**

Clustering to Automatically Construct Tasks for Unsupervised Meta-Learning (CACTUs)

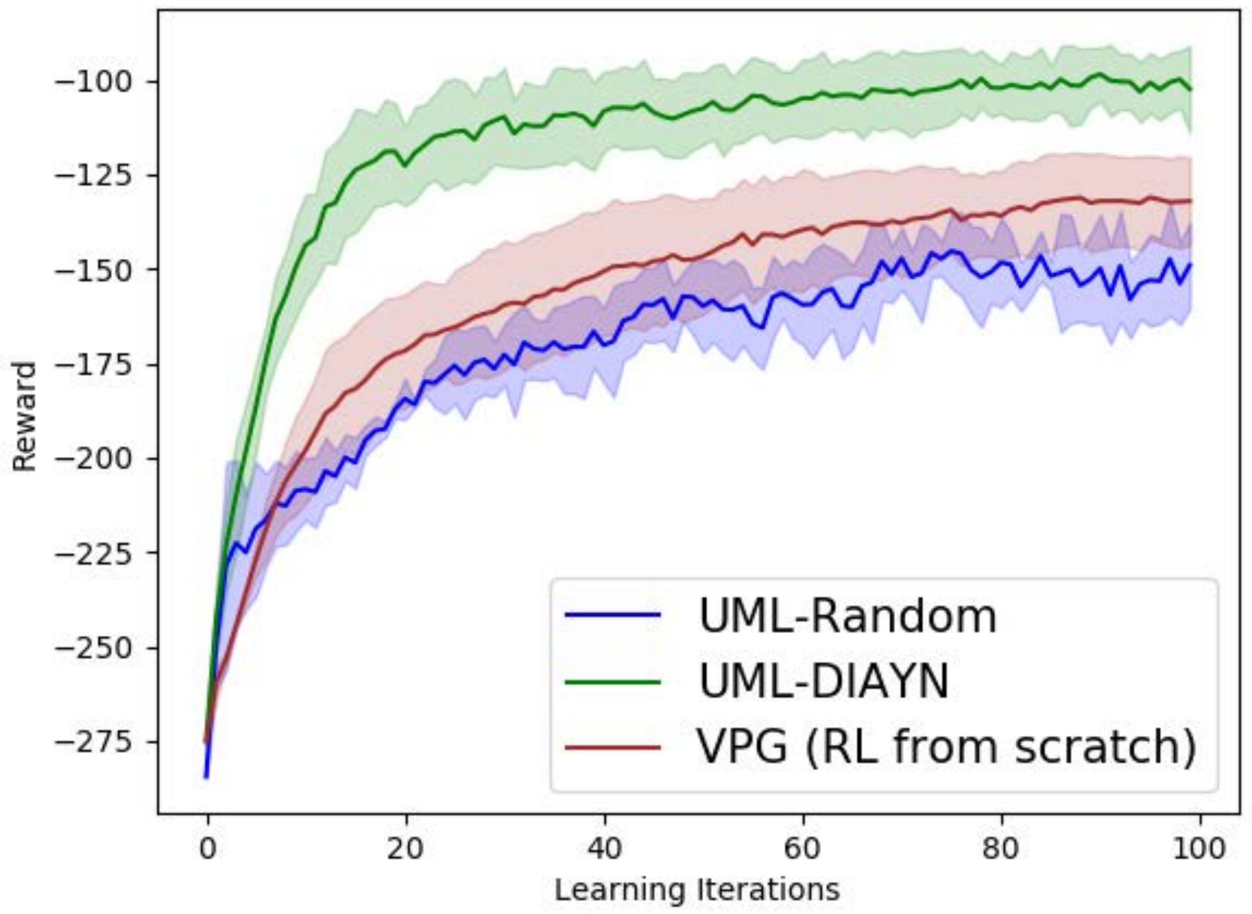
Qs: slido.com/meta

Hsu, Levine, Finn. **Unsupervised Learning via Meta-Learning**. ICLR 2019

Example: unsupervised meta-reinforcement learning



some proposed tasks



Qs: slido.com/meta

Gupta, Eysenbach, Finn, Levine. **Unsupervised Meta-Learning for Reinforcement Learning.**

Eysenbach, Gupta, Ibarz, Levine. **Diversity is All You Need.**

More on unsupervised meta-learning

- Unsupervised meta-RL: Gupta, Eysenbach, Finn, Levine. **Unsupervised Meta-Learning for Reinforcement Learning.**
- Unsupervised meta-few-shot classification: Hsu, Levine, Finn. **Unsupervised Learning via Meta-Learning**.
- Unsupervised meta-few-shot classification: Khodadadeh, Boloni, Shah. **Unsupervised Meta-Learning for Few-Shot Image and Video Classification.**
- Using supervised meta-learning to learn unsupervised learning rules: Metz, Maheswaranathan, Cheung, Sohl-Dickstein. **Meta-Learning Update Rules for Unsupervised Representation Learning.**
- Using supervised meta-learning to learn semi-supervised learning rules: Ren, Triantafillou, Ravi, Snell, Swersky, Tenenbaum, Larochelle, Zemel. **Meta-Learning for Semi-Supervised Few-Shot Classification.**

Qs: slido.com/meta

Memorization

Related to meta-overfitting, but subtly different.

Computation graph view: $y^{\text{ts}} = f_\theta(\mathcal{D}_i^{\text{tr}}, x^{\text{ts}})$

What will happen if the task data isn't strictly needed to learn the task?

Examples

Meta-training tasks: Cat/dog classifier.

Goal: Learn to quickly recognize a new breed as a cat.

Learn single classifier that doesn't adapt.

Meta-training tasks: Grasping different objects.

Goal: Learn to quickly grasp a new object.

Memorize how to grasp the training objects.

The tasks need to be **mutually exclusive**.

i.e. not possible to learn single function to learn all tasks

What you want the learner to glean from the data must be not present in x.

Challenge: can we learn to **trade off information** from **the data** vs. **the input** based on amount of data

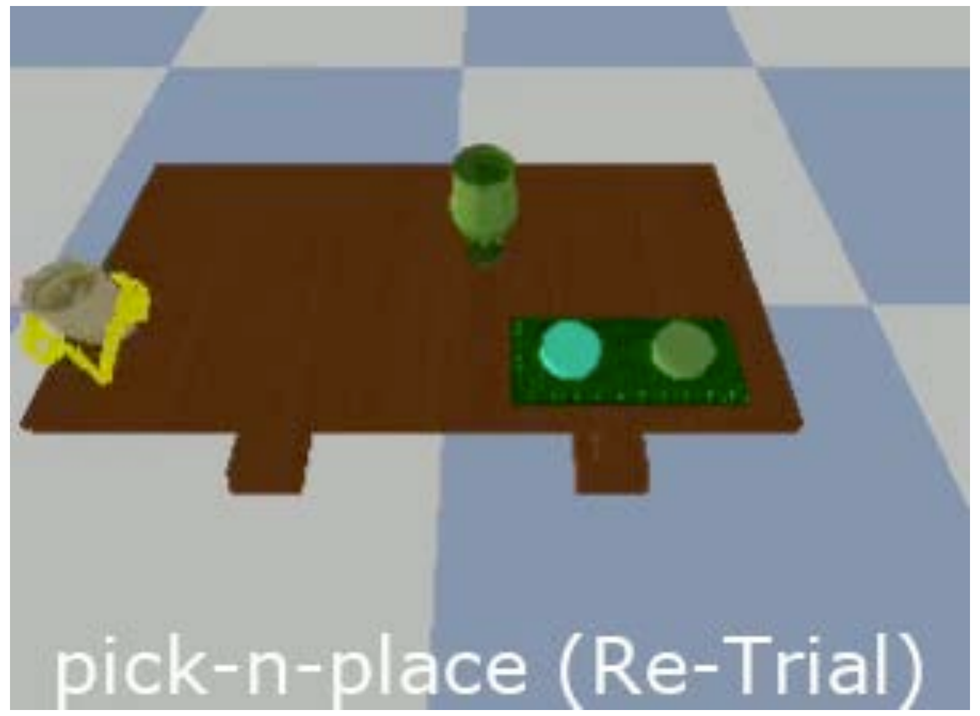
Qs: slido.com/meta

What task information should be in the input vs. data?

So far: The input contains **no information about the task**.

For **broad meta-RL task distributions**, exploration becomes exceedingly challenging.

One option: Provide demonstration (to illustrate the task goal) + trials



Zhou et al. Watch-Try-Learn: Meta-Learning Behavior from Demonstrations and Rewards, '19

Other options: language instruction?, goal image?, video tutorial?

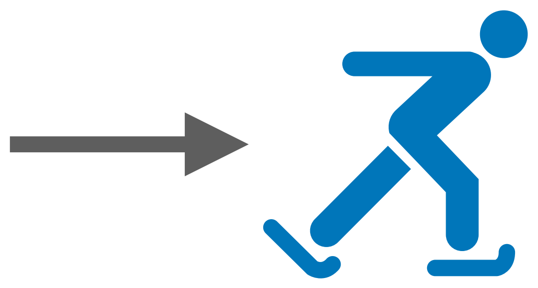
Qs: slido.com/meta

The Ultimate Goal

Meta-Learning

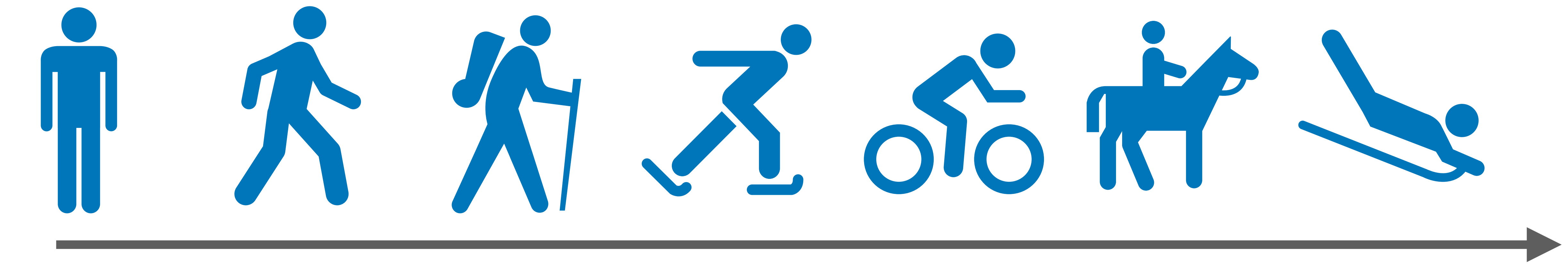
Given i.i.d. task distribution,
learn a new task efficiently

learn



More realistically:

learn learn learn learn learn learn learn



time

slow learning → rapid learning

Initial work: Finn*, Rajeswaran* et al.
Online Meta-Learning ICML '19

one step of adaptation

continual learning and adaptation

Outline

- **Problem statement**
- Meta-learning **algorithms**
  - Black-box adaptation
  - Optimization-based inference
  - Non-parametric methods
  - Bayesian meta-learning
- Meta-learning **applications**

— 5 min break —

- Meta-**reinforcement** learning
- Challenges & frontiers

Thank you!

Questions?