Optimization-Based Meta-Learning
and
(finishing from last time)

Non-Parametric Few-Shot Learning

CS 330

Logistics

Homework 1 due, Homework 2 out **this Wednesday**

Fill out **poster presentation preferences**! (Tues 12/3 or Weds 12/4)

Course project details & suggestions posted
Proposal due Monday 10/28

Plan for Today

Optimization-Based Meta-Learning
- Recap & discuss advanced topics

Non-Parametric Few-Shot Learning
- Siamese networks, matching networks, prototypical networks

Properties of Meta-Learning Algorithms
- Comparison of approaches

Recap from Last Time

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

MAML

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

Optimizes for an effective initialization for fine-tuning.

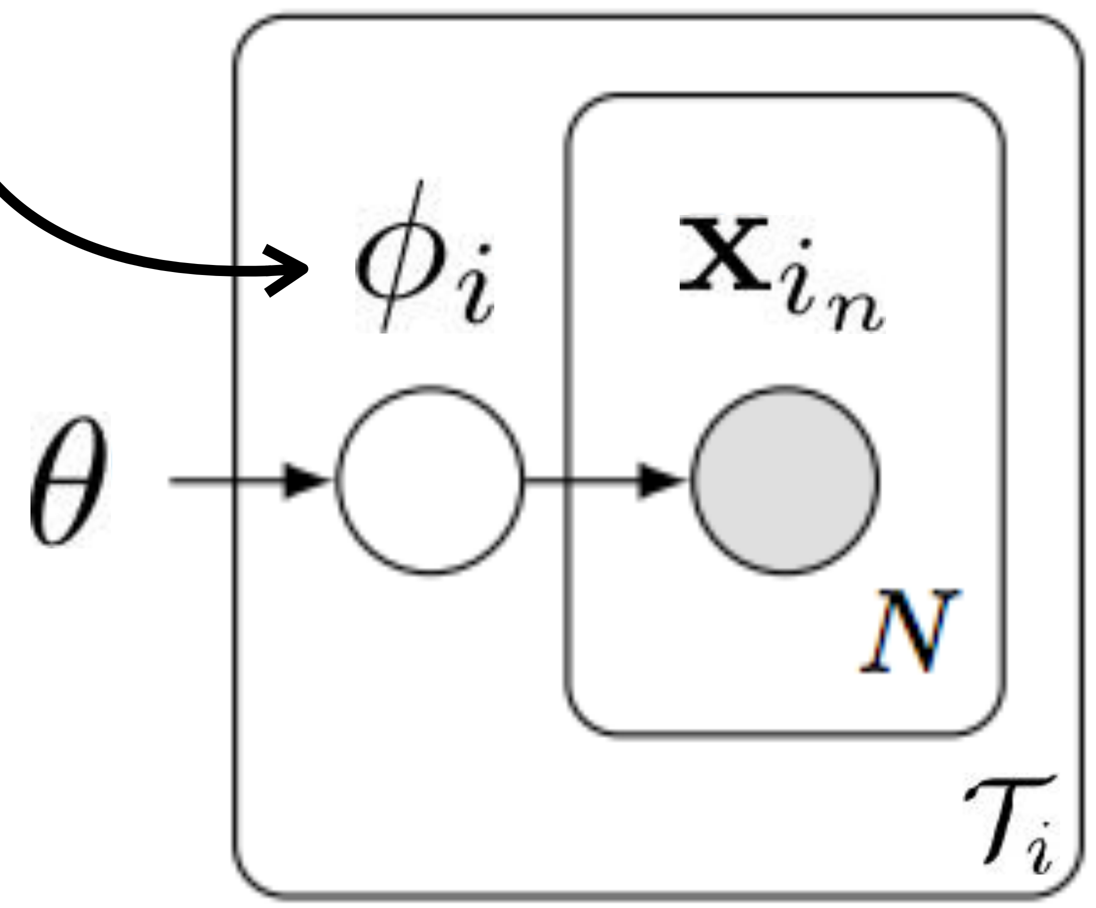
Discussed: performance on extrapolated tasks, expressive power

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)

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

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%**

Optimization-Based Inference

Key idea: Acquire ϕ_i through optimization.

Challenges

Bi-level optimization can exhibit instabilities.

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

Optimization-Based Inference

Key idea: Acquire ϕ_i through optimization.

Challenges

Backpropagating through many inner gradient steps is compute- & memory-intensive.

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

(Finn et al. first-order MAML ‘17, Nichol et al. Reptile ’18)

Takeaway: works for simple few-shot problems, but (anecdotally) not for more complex meta-learning problems.

Can we compute the meta-gradient *without differentiating through the optimization path*?

-> whiteboard

Idea: Derive meta-gradient using the implicit function theorem

(Rajeswaran, Finn, Kakade, Levine. Implicit MAML ’19)

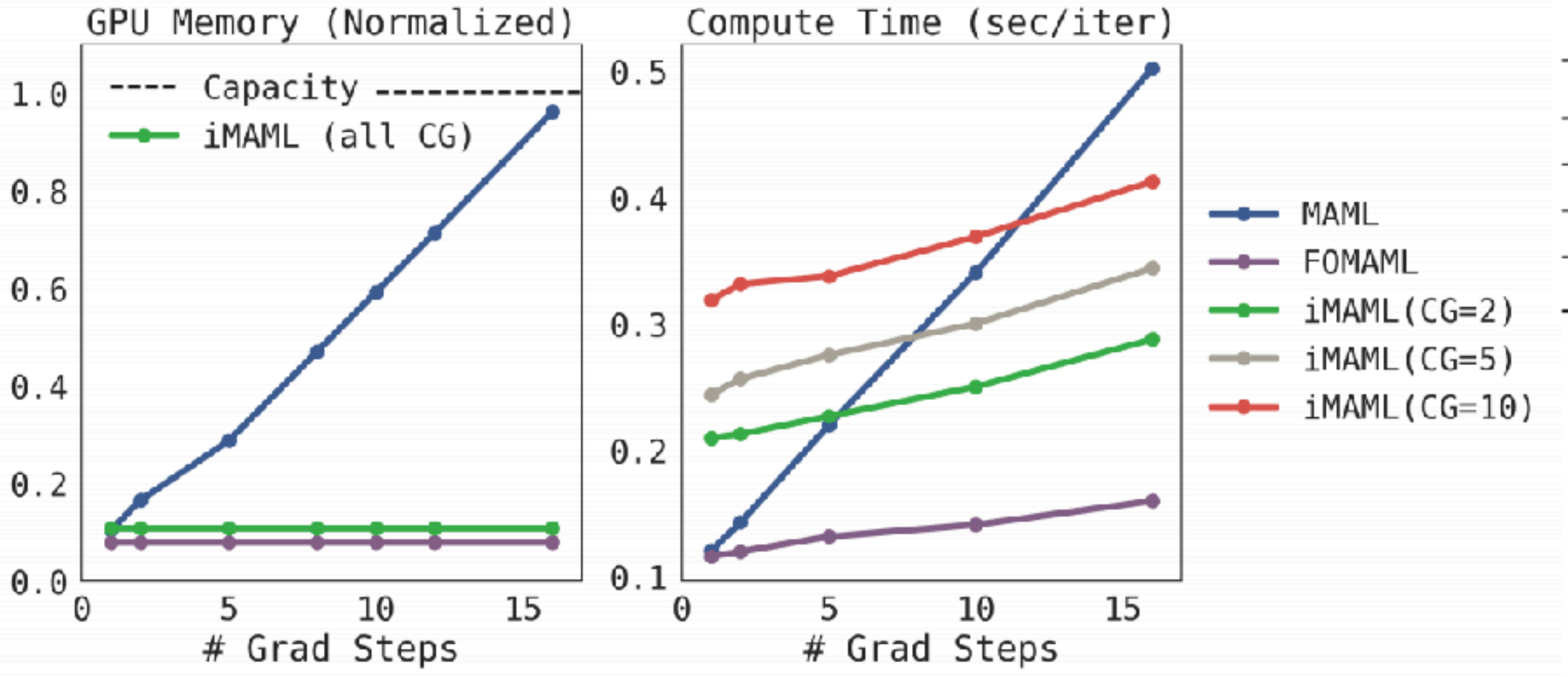
Optimization-Based Inference

Can we compute the meta-gradient *without differentiating through the optimization path*?

Idea: Derive meta-gradient using the implicit function theorem

(Rajeswaran, Finn, Kakade, Levine. Implicit MAML)

Memory and computation trade-offs



Allows for second-order optimizers in inner loop

Algorithm	5-way 1-shot	5-way 5-shot	20-way 1-shot	20-way 5-shot
MAML [15]	$98.7 \pm 0.4\%$	$\mathbf{99.9 \pm 0.1\%}$	$95.8 \pm 0.3\%$	$98.9 \pm 0.2\%$
first-order MAML [15]	$98.3 \pm 0.5\%$	$99.2 \pm 0.2\%$	$89.4 \pm 0.5\%$	$97.9 \pm 0.1\%$
Reptile [43]	$97.68 \pm 0.04\%$	$99.48 \pm 0.06\%$	$89.43 \pm 0.14\%$	$97.12 \pm 0.32\%$
iMAML, GD (ours)	$99.16 \pm 0.35\%$	$99.67 \pm 0.12\%$	$94.46 \pm 0.42\%$	$98.69 \pm 0.1\%$
iMAML, Hessian-Free (ours)	$\mathbf{99.50 \pm 0.26\%}$	$99.74 \pm 0.11\%$	$\mathbf{96.18 \pm 0.36\%}$	$\mathbf{99.14 \pm 0.1\%}$

A very recent development (NeurIPS '19)

(thus, all the typical caveats with recent work)

Optimization-Based Inference

Key idea: Acquire ϕ_i through optimization.

Takeaways: Construct *bi-level optimization* problem.

+ positive inductive bias at the start of meta-learning
+ consistent procedure, tends to extrapolate better
+ maximally expressive with sufficiently deep network
+ model-agnostic (easy to combine with your favorite architecture)

- typically requires second-order optimization
- usually compute and/or memory intensive

Can we embed a learning procedure *without* a second-order optimization?

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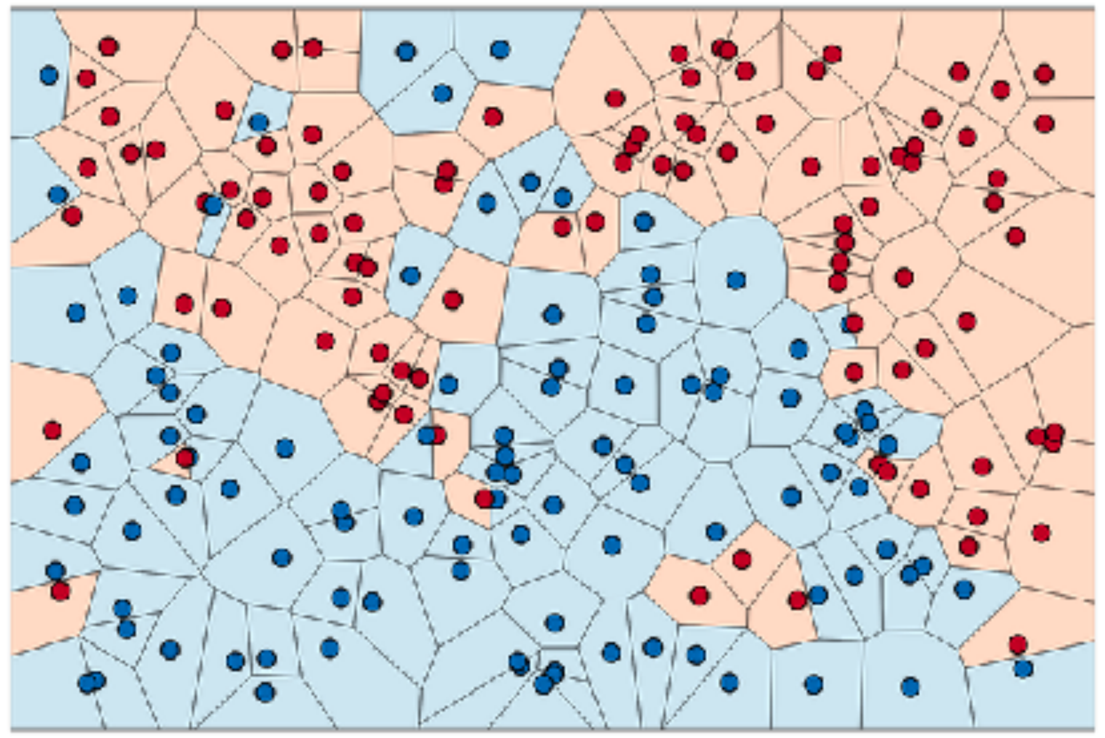
Properties of Meta-Learning Algorithms
- Comparison of approaches

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

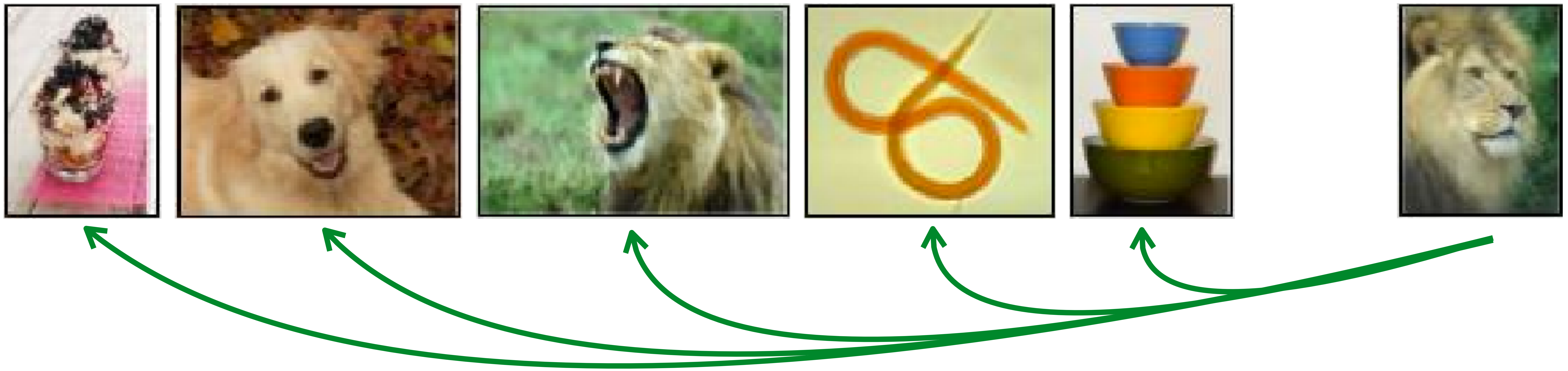
Can we use **parametric meta-learners** that produce effective **non-parametric learners**?

Note: some of these methods precede parametric approaches

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?

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pixel space, l_2 distance?

Zhang et al. (arXiv 1801.03924)

Non-parametric methods

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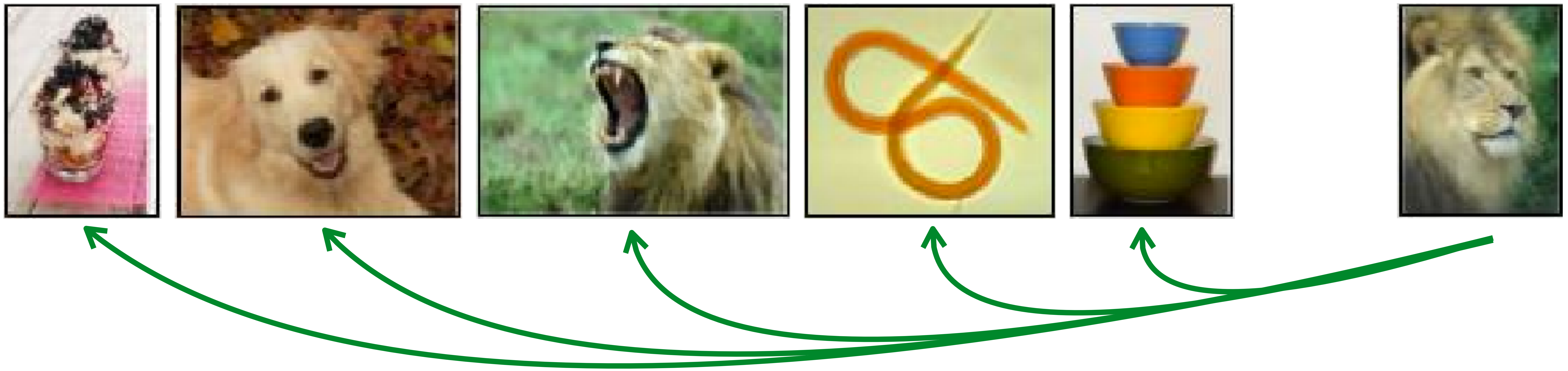


Compare test image with training images

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

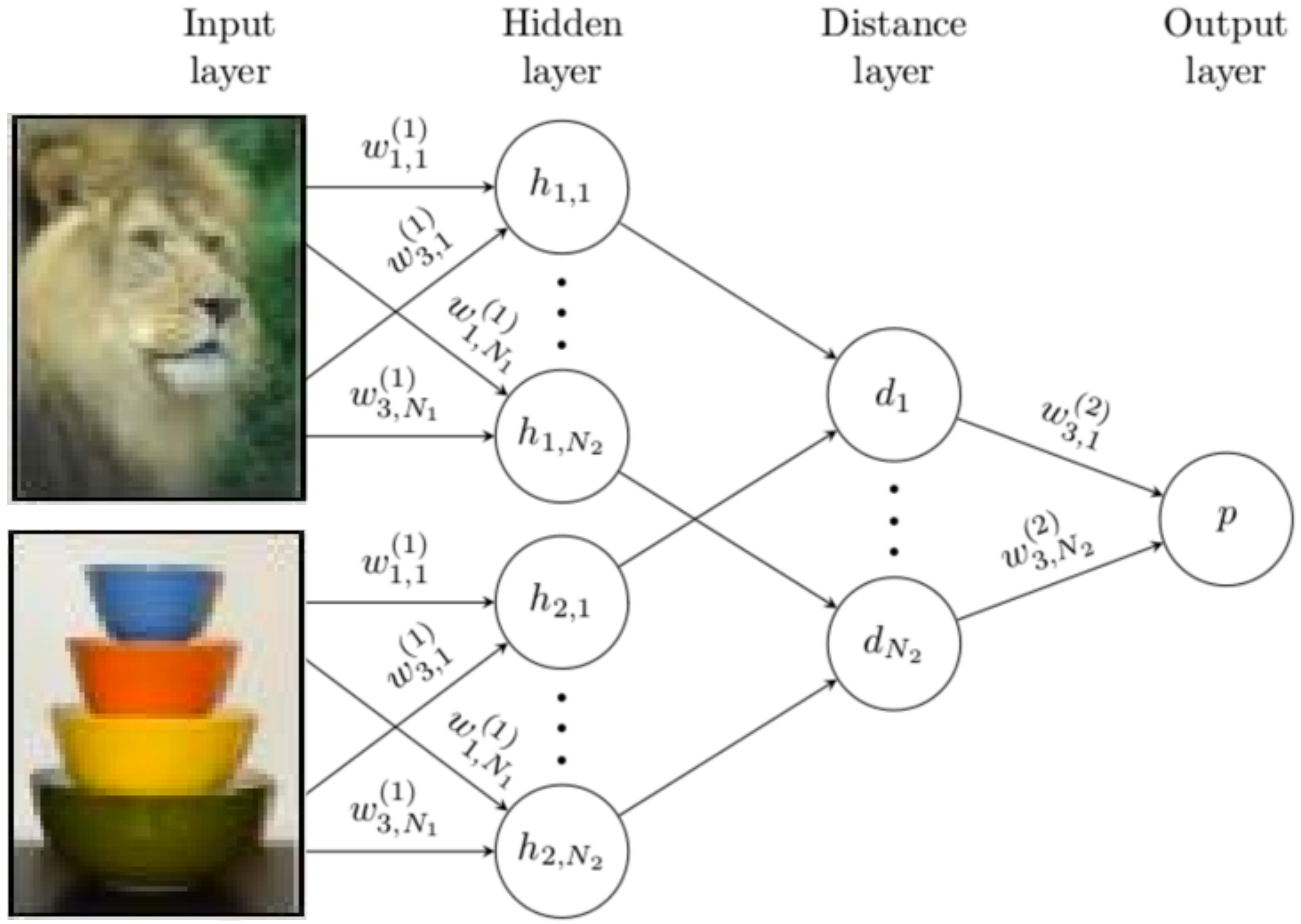
~~pixel space, l_2 distance?~~

Learn to compare using meta-training data!

Non-parametric methods

Key Idea: Use non-parametric learner.

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



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Koch et al., ICML '15

Non-parametric methods

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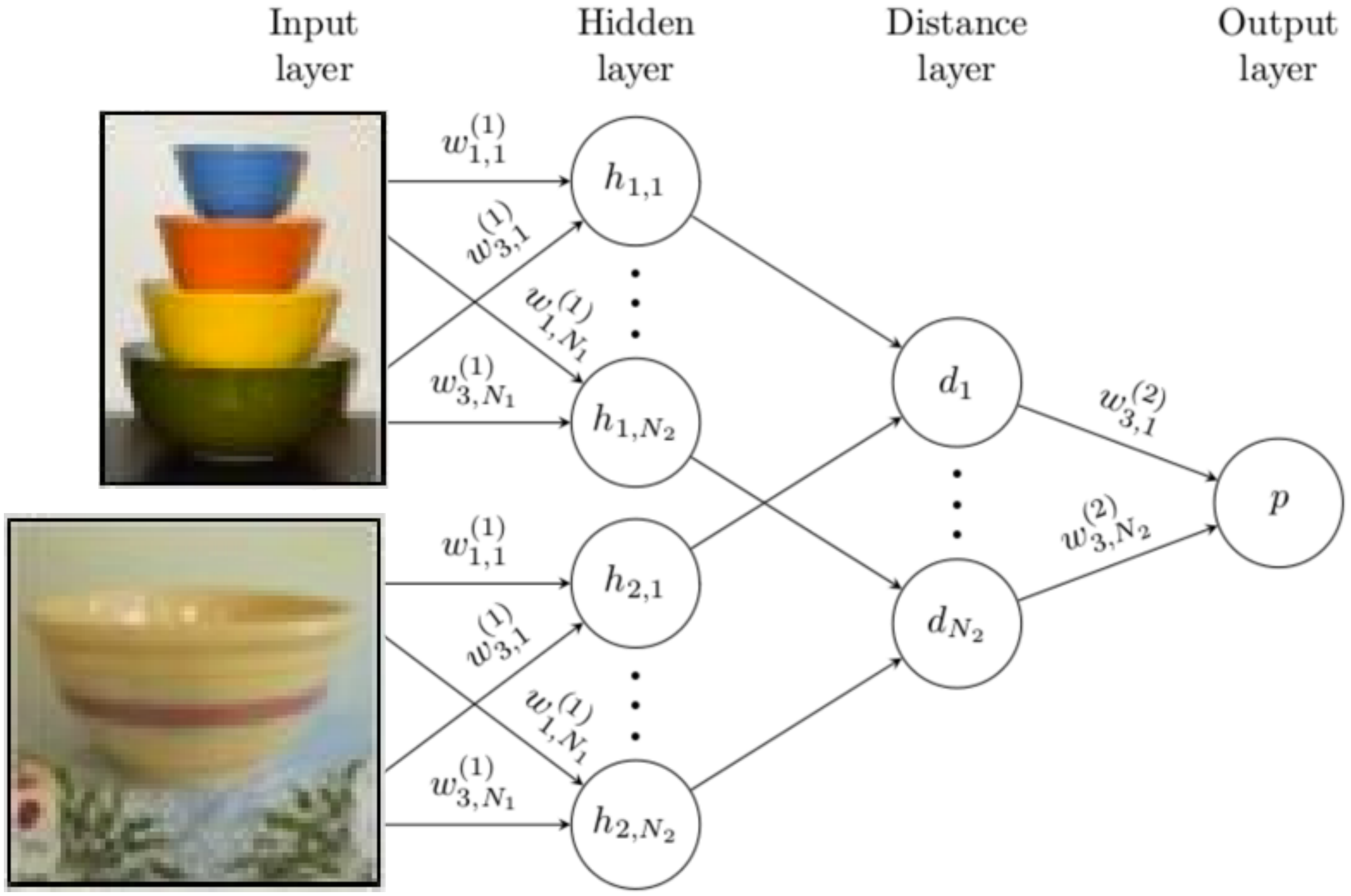

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1

Koch et al., ICML '15

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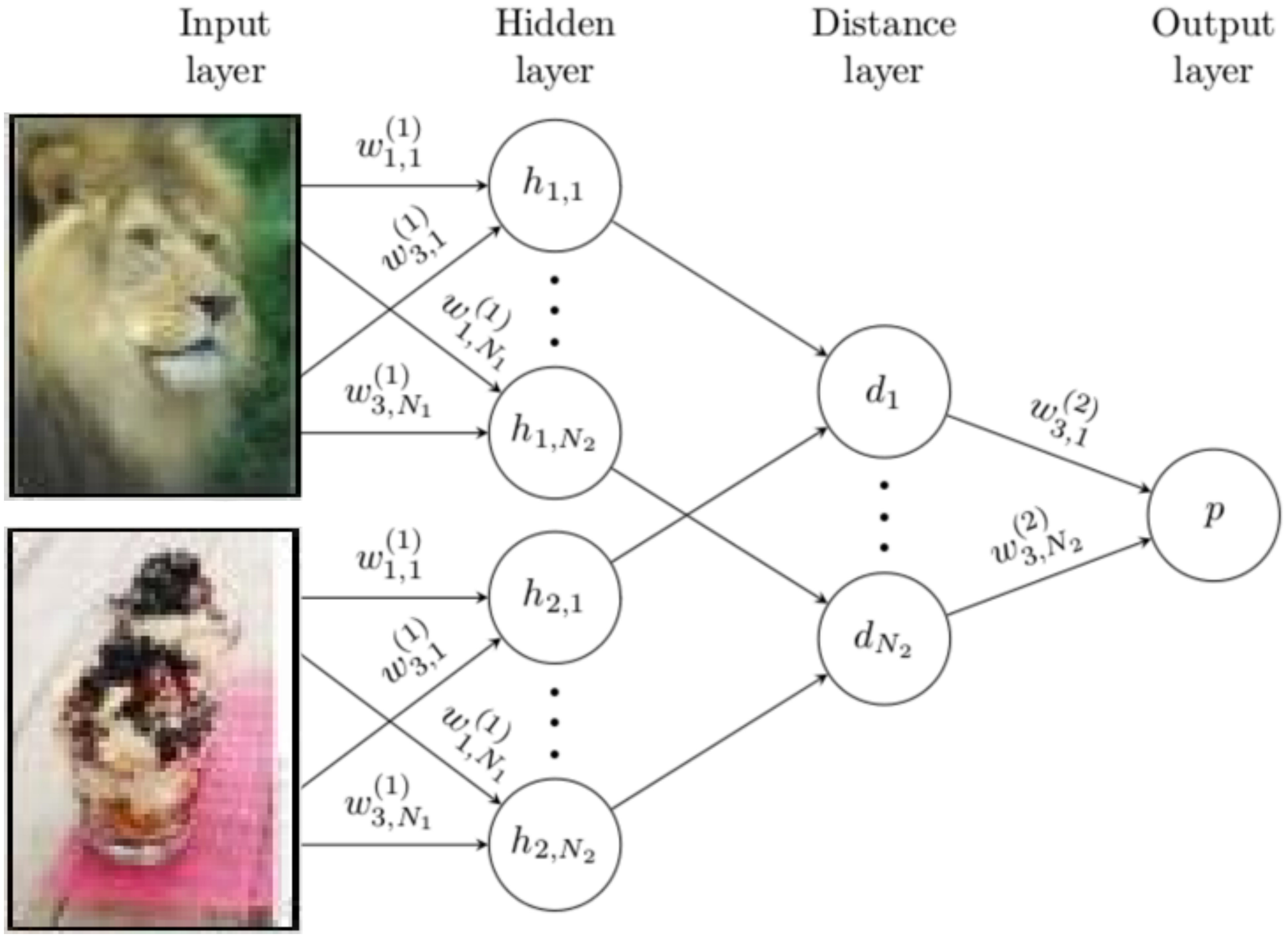

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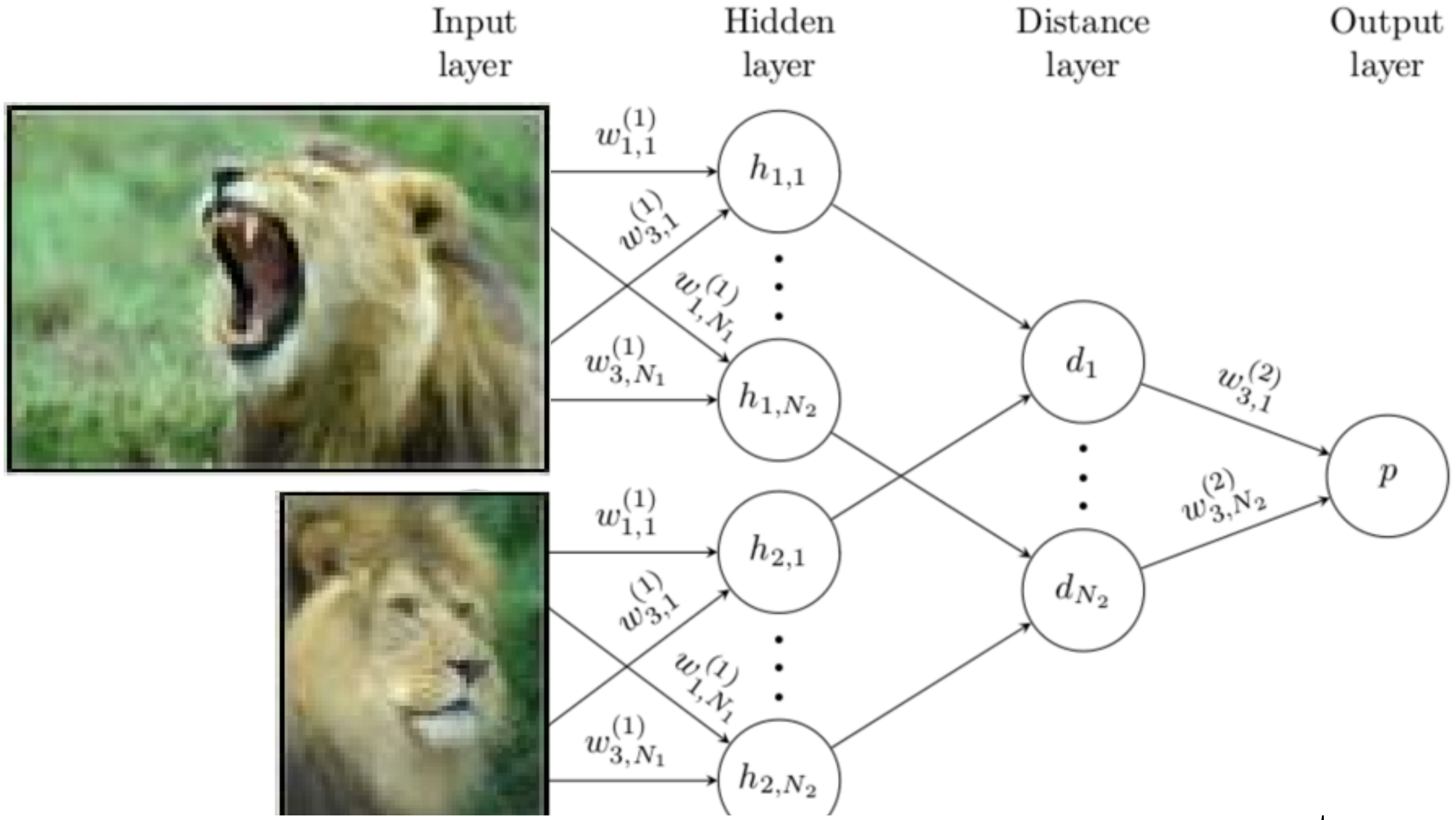

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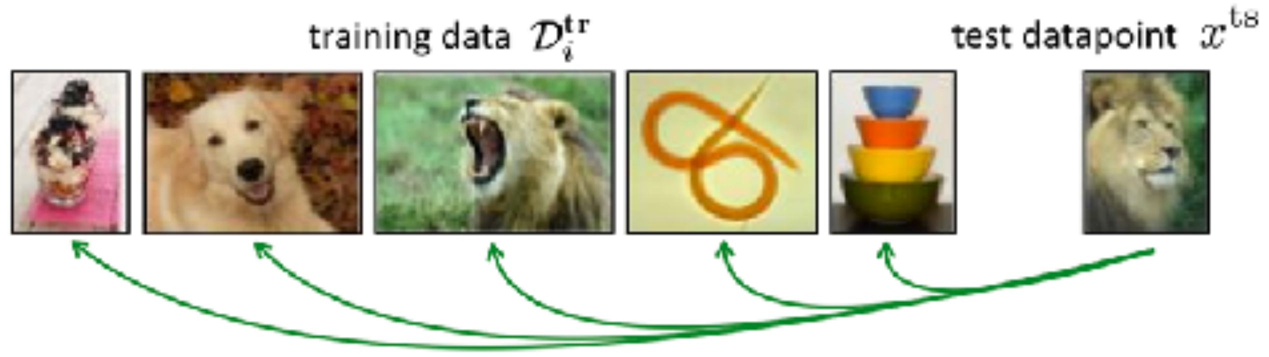
Meta-test time: compare image $\mathbf{x}_{\text{test}}$ to each image in $\mathcal{D}_j^{\text{tr}}$



Meta-training: Binary classification
Meta-test: N-way classification

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

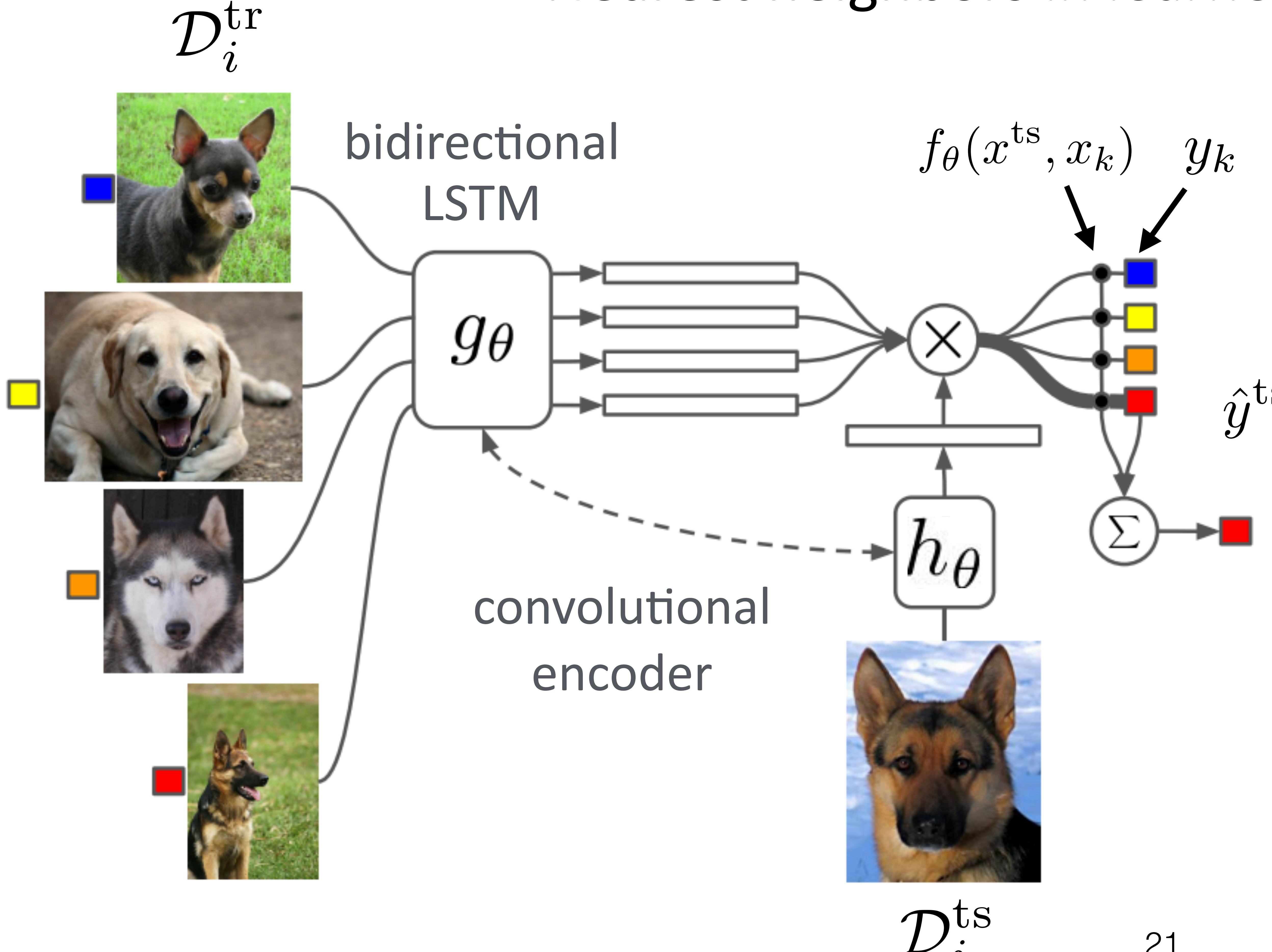
Koch et al., ICML '15

Non-parametric methods

Key Idea: Use non-parametric learner.

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

Nearest neighbors in learned embedding space



$$\hat{y}^{\text{ts}} = \sum_{x_k, y_k \in \mathcal{D}^{\text{tr}}} f_\theta(x^{\text{ts}}, x_k) y_k$$

Trained **end-to-end.**

Meta-train & **meta-test** time **match.**

Vinyals et al. Matching Networks, NeurIPS '16

Non-parametric methods

Key Idea: Use non-parametric learner.

General Algorithm:

~~Amortized approach~~ Non-parametric approach (matching networks)

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 $\mathcal{D}_i$
3. $\cancel{\text{Compute } \phi_i \leftarrow f_\theta(\mathcal{D}_i^{\text{tr}})}$ Compute $\hat{y}^{\text{ts}} = \sum_{x_k, y_k \in \mathcal{D}^{\text{tr}}} f_\theta(x^{\text{ts}}, x_k) y_k$
4. $\cancel{\text{Update } \theta \text{ using } \nabla_\theta \mathcal{L}(\phi_i, \mathcal{D}_i^{\text{test}})}$ Update θ using $\nabla_\theta \mathcal{L}(\hat{y}^{\text{ts}}, y^{\text{ts}})$

(Parameters ϕ integrated out, hence **non-parametric**)

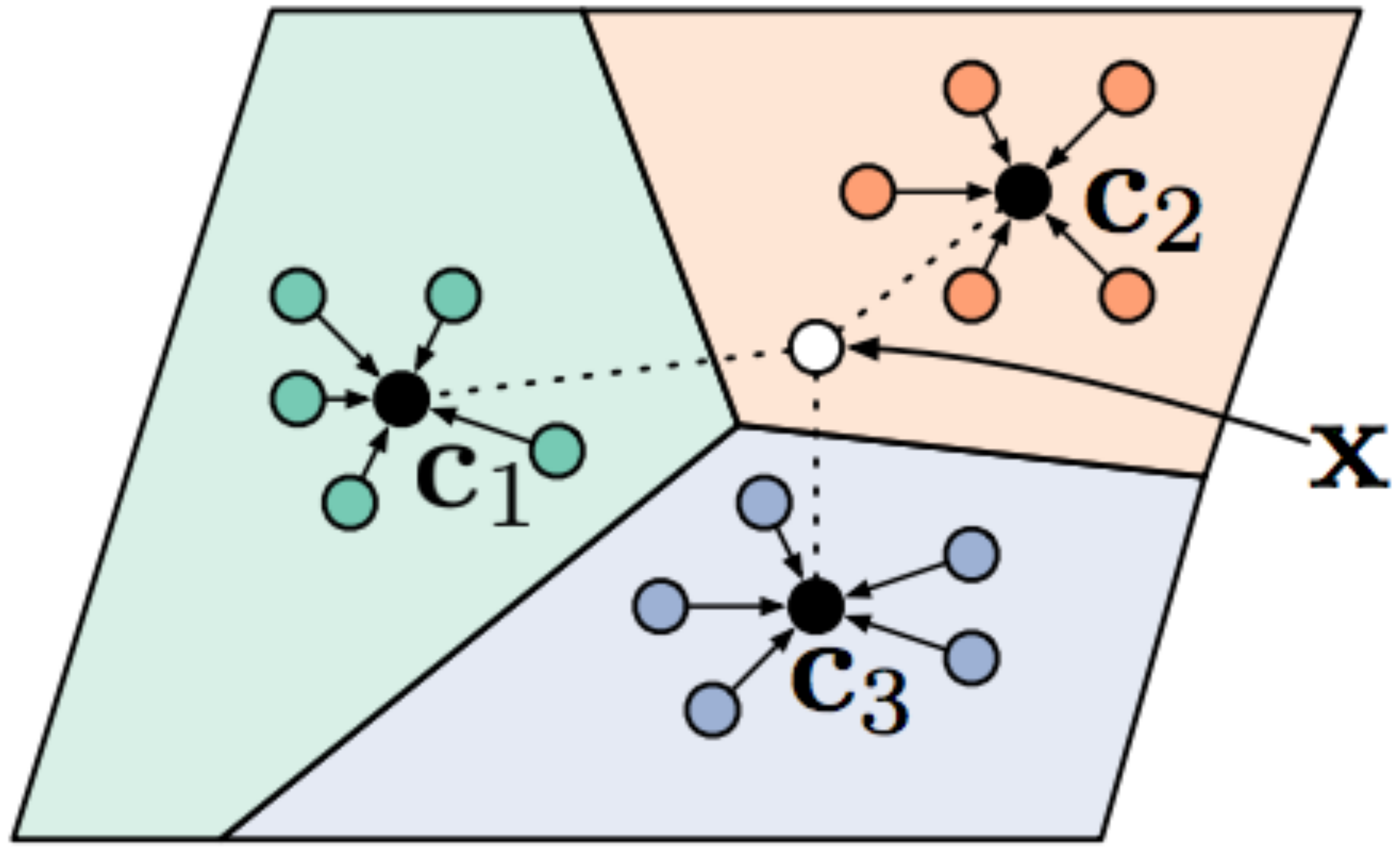
What if **>1 shot**?

Matching networks will perform comparisons **independently**

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

Non-parametric methods

Key Idea: Use non-parametric learner.



(a) Few-shot

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

$$p_\theta(y = n | x) = \frac{\exp(-d\left(f_\theta(x), \mathbf{c}_n\right))}{\sum_{n'} \exp(d(f_\theta(x), \mathbf{c}_{n'}))}$$

d: Euclidean, or cosine distance

Snell et al. Prototypical Networks, NeurIPS ‘17

Non-parametric methods

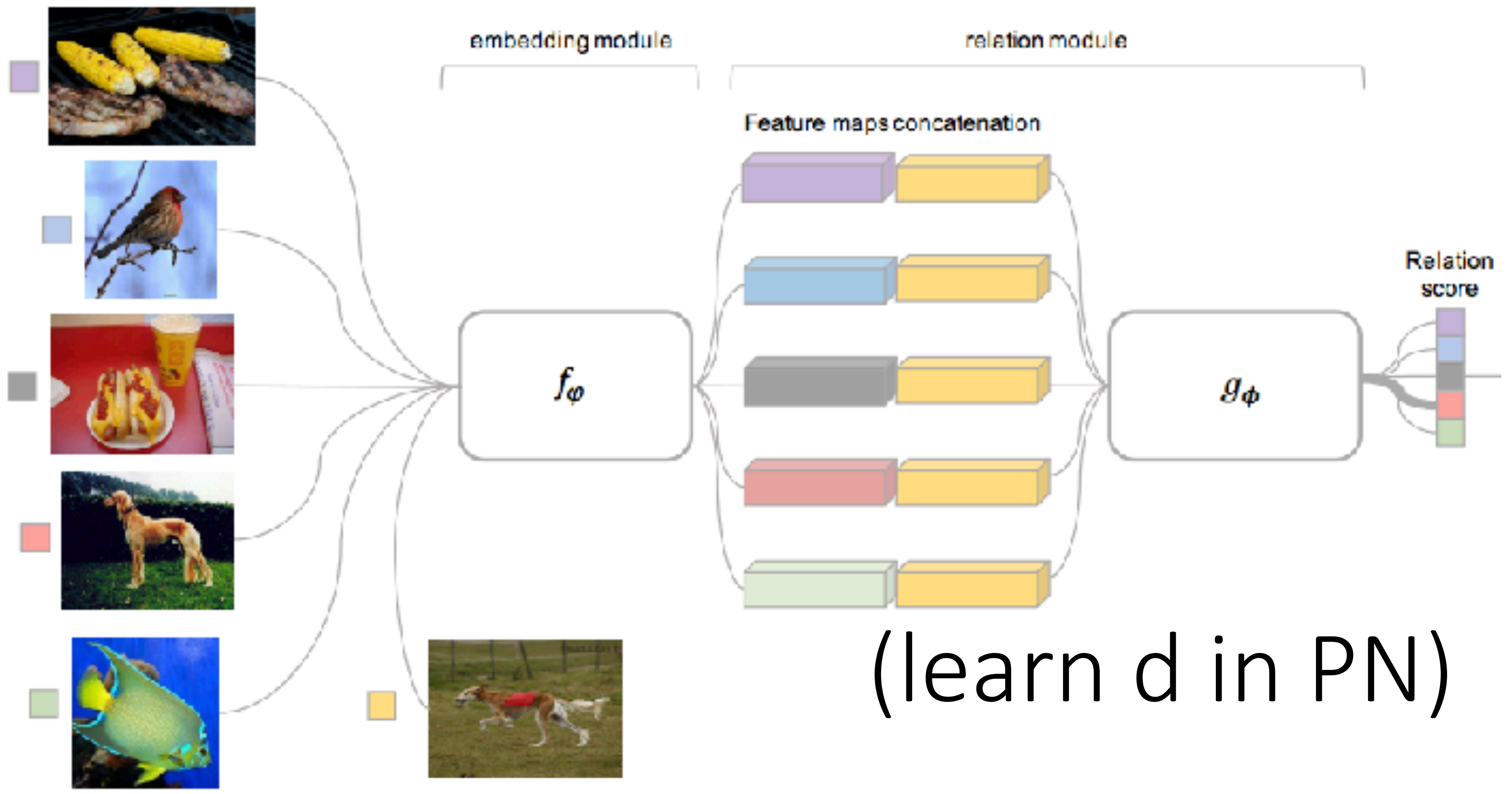
So far: Siamese networks, matching networks, prototypical networks

Embed, then nearest neighbors.

Challenge

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

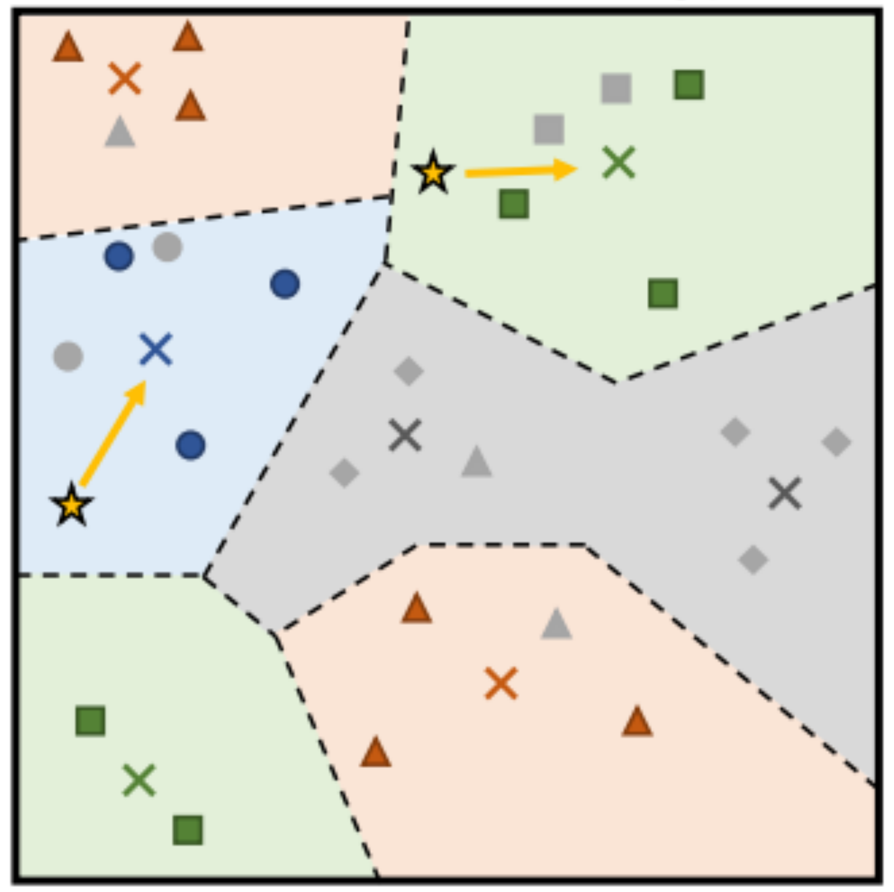
Idea: Learn non-linear relation module on embeddings



(learn d in PN)

Sung et al. Relation Net

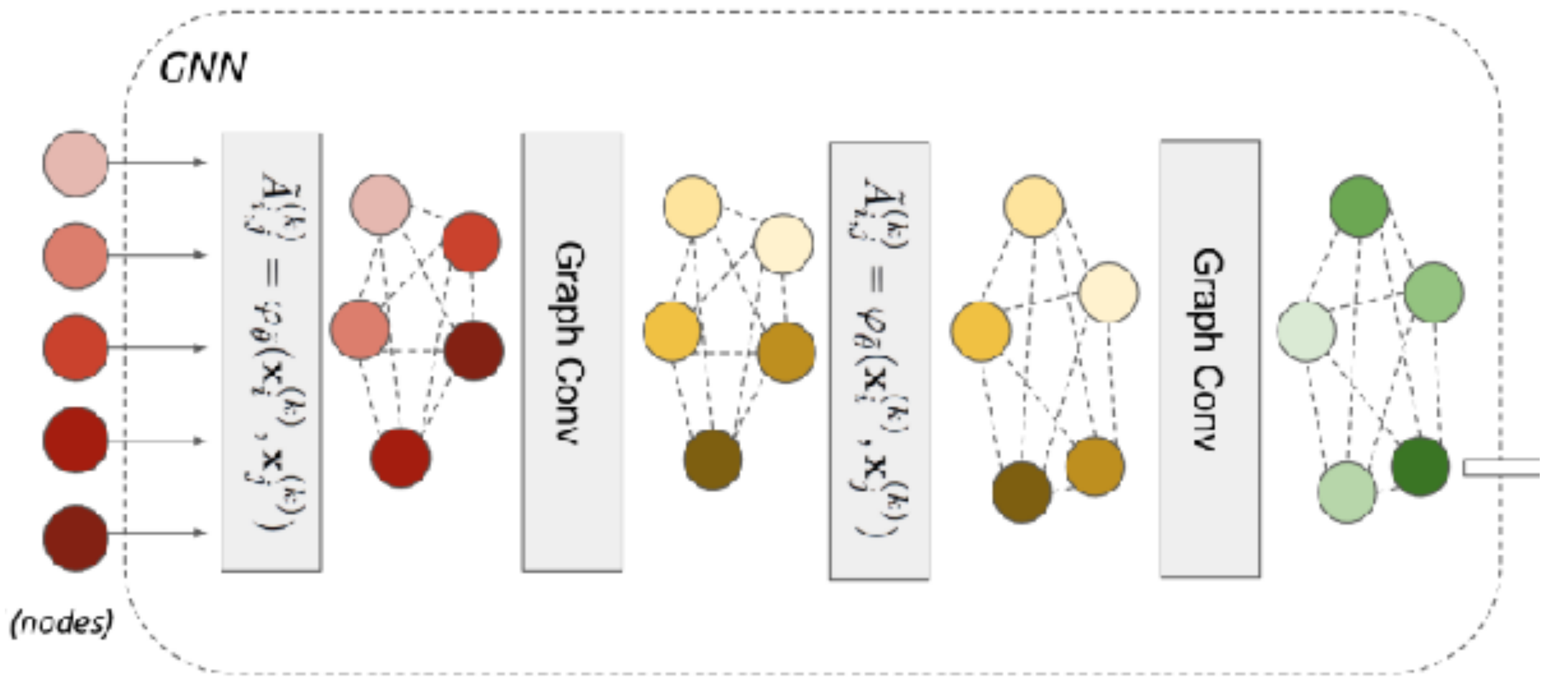
Idea: Learn infinite mixture of prototypes.



adaptive number of clusters

Allen et al. IMP, ICML '19

Idea: Perform message passing on embeddings



Garcia & Bruna, GNN

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Properties of Meta-Learning Algorithms
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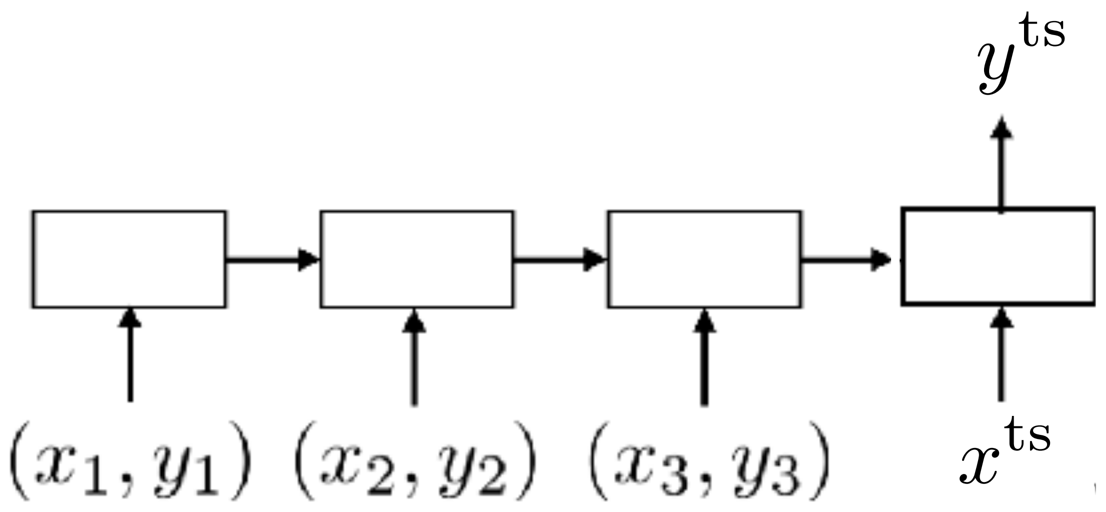
How can we think about how these methods compare?

Black-box vs. Optimization vs. Non-Parametric

Computation graph **perspective**

Black-box

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



Optimization-based

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

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

Non-parametric

$$\begin{aligned} y^{\text{ts}} &= f_{\text{PN}}(\mathcal{D}_i^{\text{tr}}, x^{\text{ts}}) \\ &= \text{softmax}(-d\left(f_\theta(x^{\text{ts}}), \mathbf{c}_n\right)) \end{aligned}$$

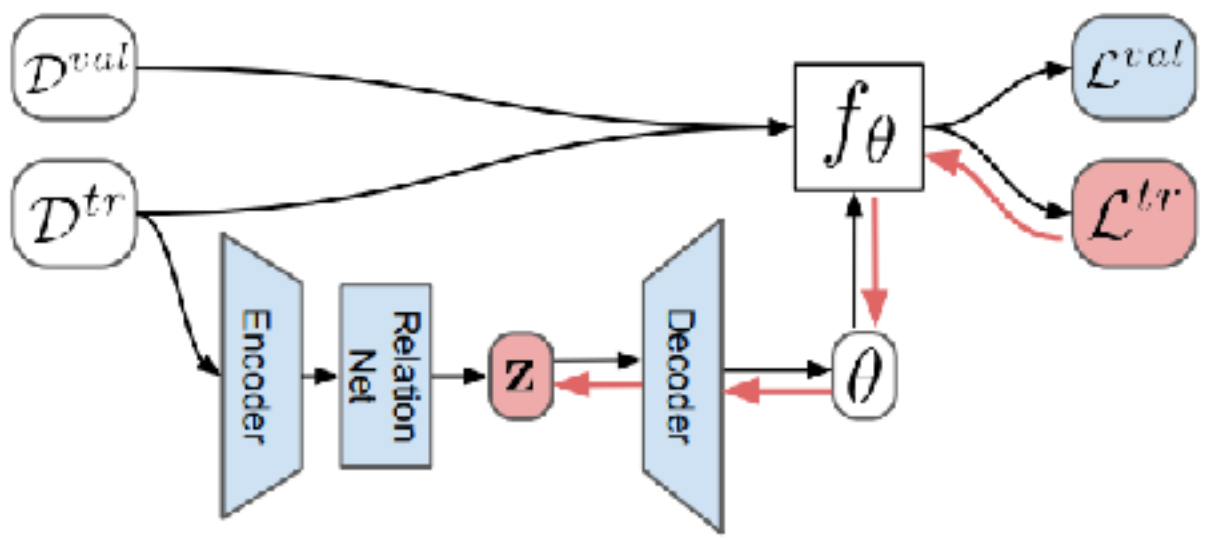
$$\text{where } \mathbf{c}_n = \frac{1}{K} \sum_{(x,y) \in \mathcal{D}_i^{\text{tr}}} \mathbb{1}(y = n) f_\theta(x)$$

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

Black-box vs. Optimization vs. Non-Parametric

***Algorithmic properties* perspective**

Expressive power

the ability for f to represent a range of learning procedures

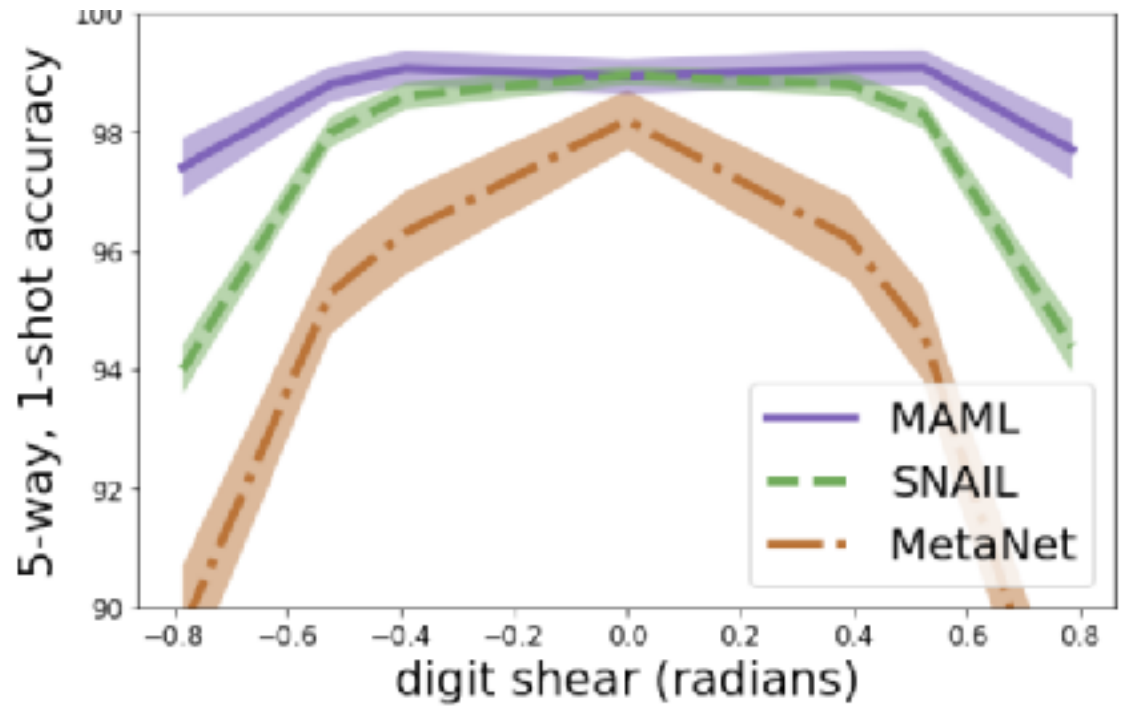
Why? scalability, applicability to a range of domains

Consistency

learned learning procedure will solve task with enough data

Why? reduce reliance on meta-training tasks, good OOD task performance

Recall:



These properties are important for most applications!

Black-box vs. Optimization vs. Non-Parametric

Black-box

+ **complete expressive power**

- **not consistent**

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

- **challenging optimization** (no inductive bias at the initialization)
- often **data-inefficient**

Optimization-based

+ **consistent**, **reduces** to **GD**

~ **expressive** for **very deep models***

+ **positive inductive bias** at the start of meta-learning
+ handles **varying** & **large K** well
+ **model-agnostic**

- **second-order optimization**
- usually **compute** and **memory** intensive

Non-parametric

+ **expressive** for **most architectures**

~ **consistent** under **certain conditions**

+ 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!

(likely says more about the benchmarks than the methods)

Which method to use depends on your **use-case**.

*for supervised learning settings

Black-box vs. Optimization vs. Non-Parametric

***Algorithmic properties* perspective**

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Uncertainty awareness

ability to reason about ambiguity during learning

Why? active learning, calibrated uncertainty, RL principled Bayesian approaches

We'll discuss this next time!

Reminders

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