Non-Parametric Few-Shot Learning

CS 330

Course Reminders

Homework 1 due **tonight**.

Homework 2 released, due Weds 10/25.

Project mentors assigned: go to their office hours with any questions.

Project proposal due next Monday 10/23.

(graded lightly, for your benefit)

Following up on some feedback:

- Comparisons to simple baselines — included in today's lecture
- Max Sobol Mark's office hours (Weds 6-8 pm) moving to virtual

Plan for Today

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

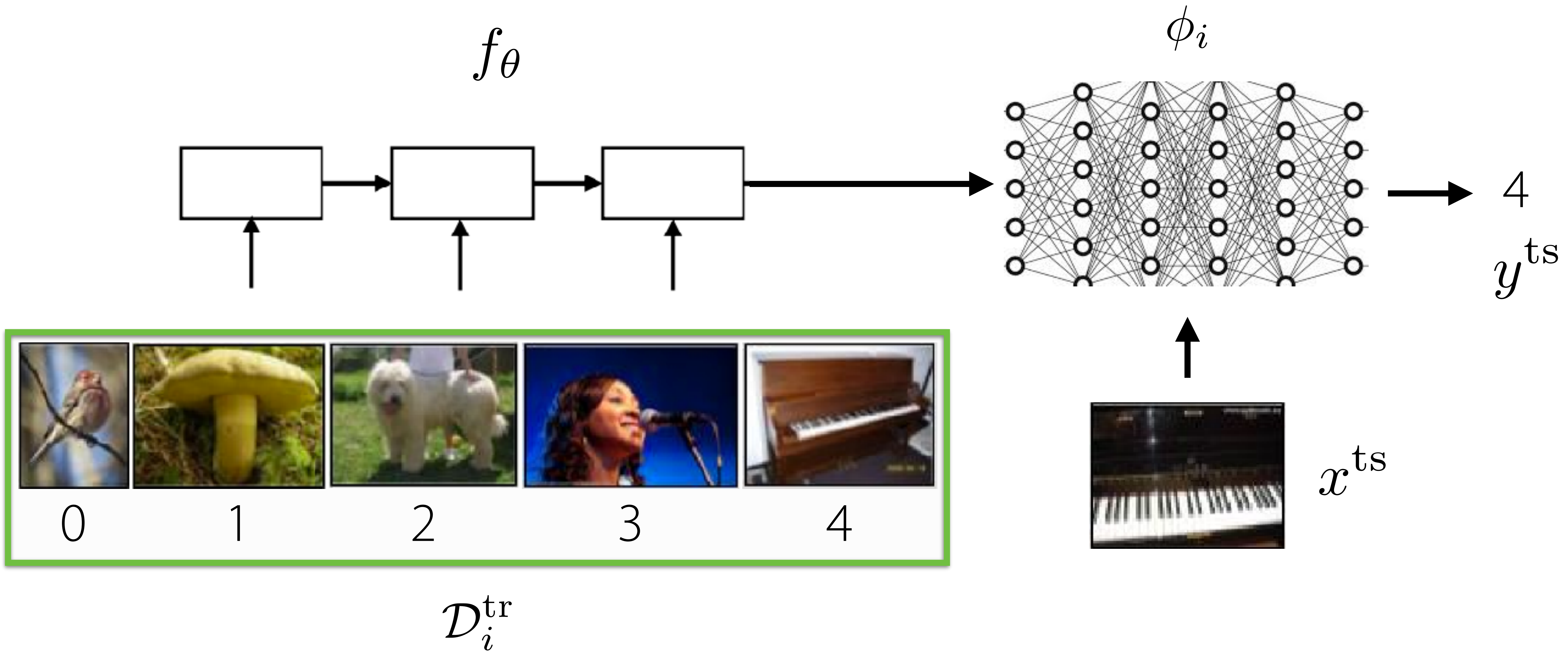
} **Part of Homework 2!**

Properties of Meta-Learning Algorithms
- Comparison of approaches

Examples of **Meta-Learning In Practice**
- Imitation learning, drug discovery, motion prediction, language generation

Goals for by the end of lecture:
- Basics of non-parametric few-shot learning techniques (& how to implement)
- Trade-offs between black-box, optimization-based, and non-parametric meta-learning
- Familiarity with applied formulations of meta-learning

Recap: Black-Box Meta-Learning

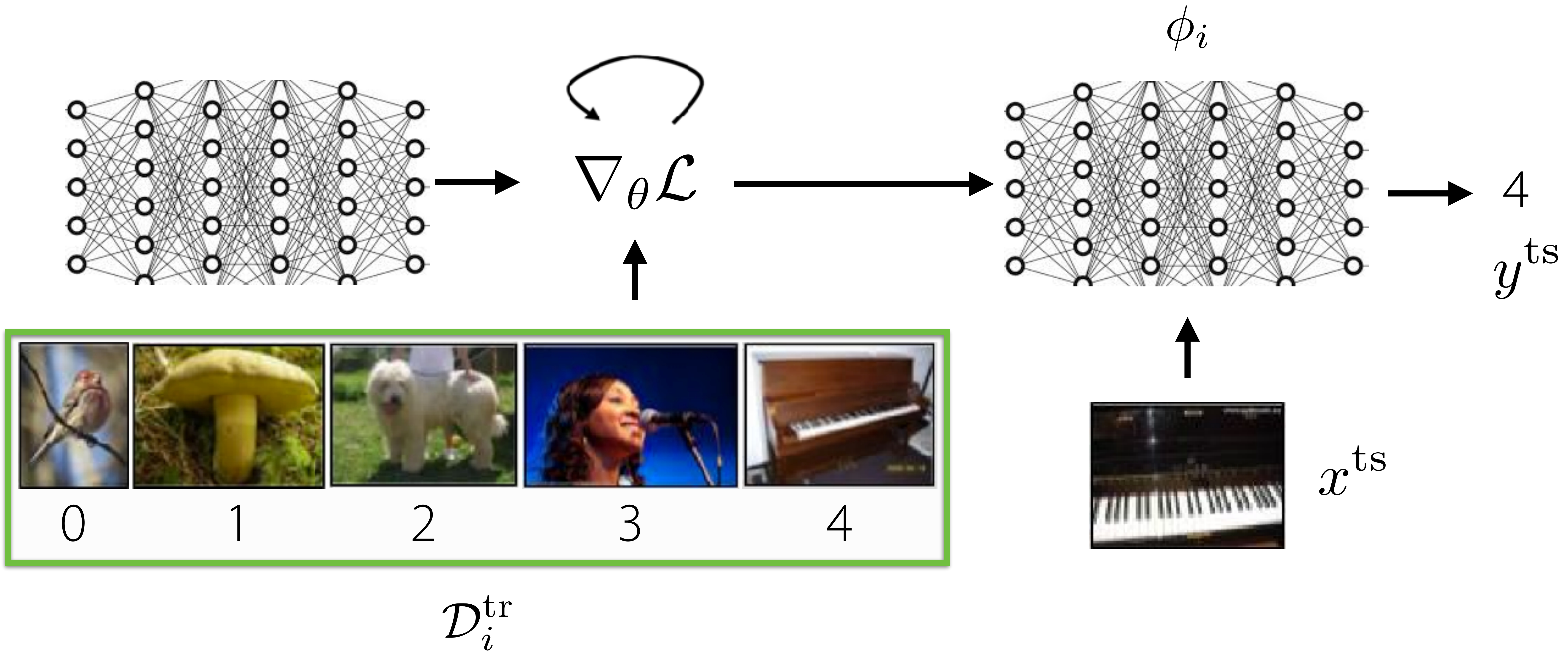


Key idea: parametrize learner as a neural network

+ **expressive**

- **challenging optimization** problem

Recap: Optimization-Based Meta-Learning



Key idea: embed optimization inside the inner learning process

Optimization-Based Adaptation

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 Adaptation

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)

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

Idea: Only optimize the *last layer* of weights.

ridge regression, *logistic regression*
(Bertinetto et al. R2-D2 ’19)

support vector machine
(Lee et al. MetaOptNet ’19)

—> leads to a closed form or convex optimization on top of meta-learned features

Idea: Derive meta-gradient using the implicit function theorem

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

—> compute full meta-gradient ***without differentiating through optimization path***

Optimization-Based Adaptation

Key idea: Acquire ϕ_i through optimization.

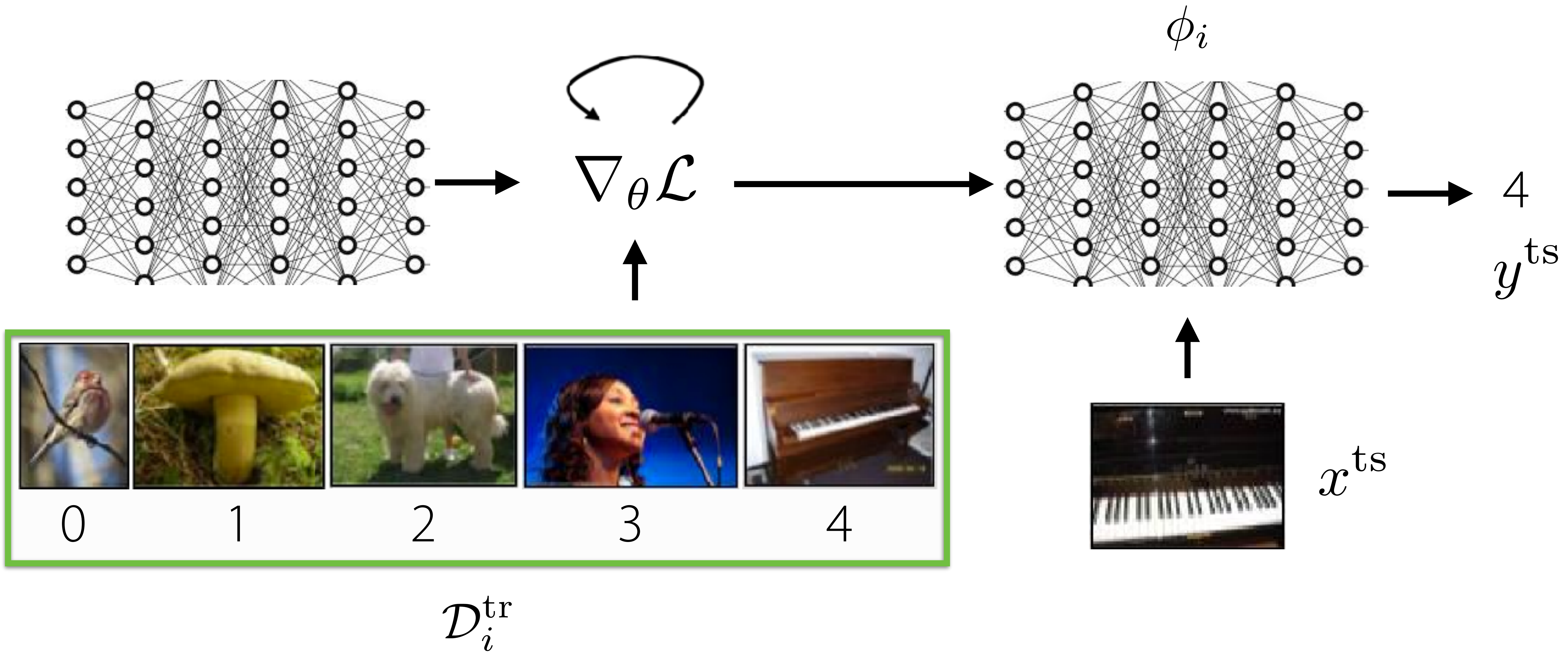
Takeaways: Construct *bi-level optimization* problem.

+ positive inductive bias at the start of meta-learning
+ tends to extrapolate better via structure of optimization
+ 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 be prohibitively expensive for large models

Recap: Optimization-Based Meta-Learning



Key idea: embed optimization inside the inner learning process

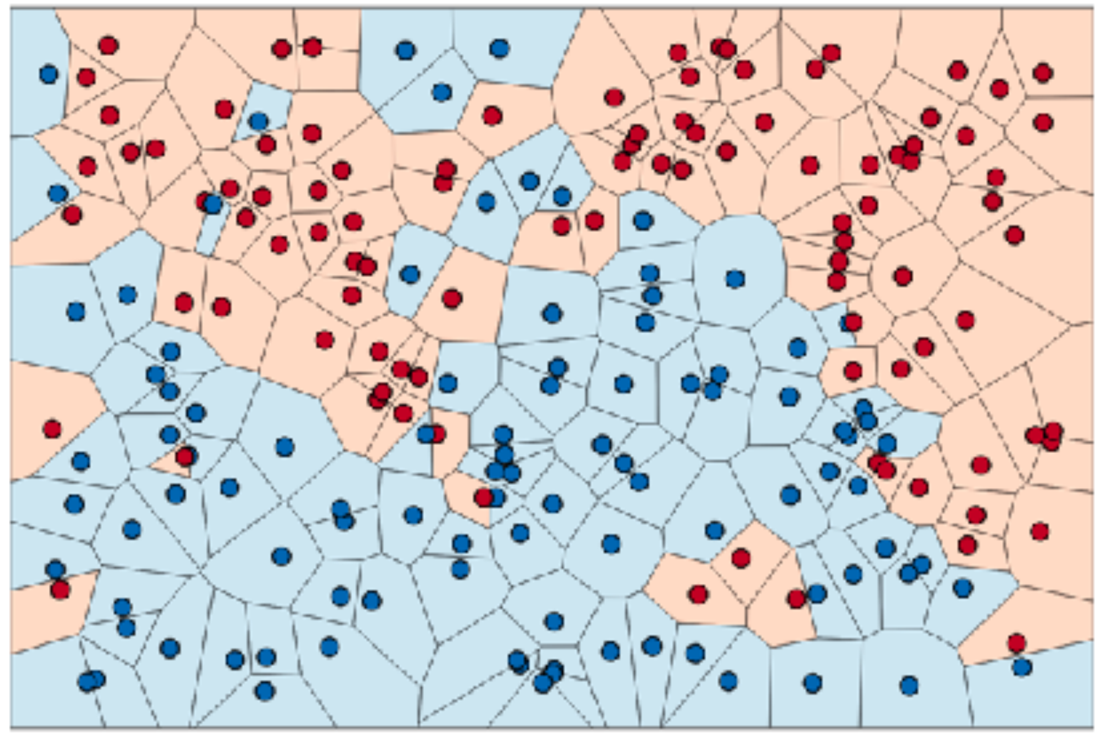
+ **structure** of **optimization** embedded into meta-learner

- memory-intensive, requires **second-order optimization**

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

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

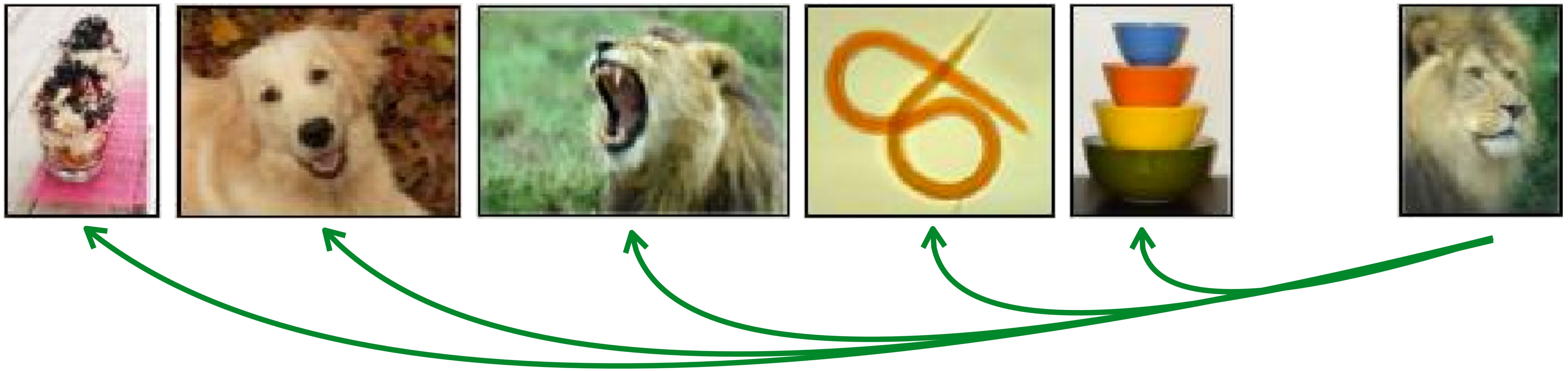
Can we use **parametric meta-learners** that produce effective **non-parametric learners**?

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?

ℓ_2 distance in pixel space?

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

ℓ_2 distance in pixel space?

Zhang et al. (arXiv 1801.03924)

Non-parametric methods

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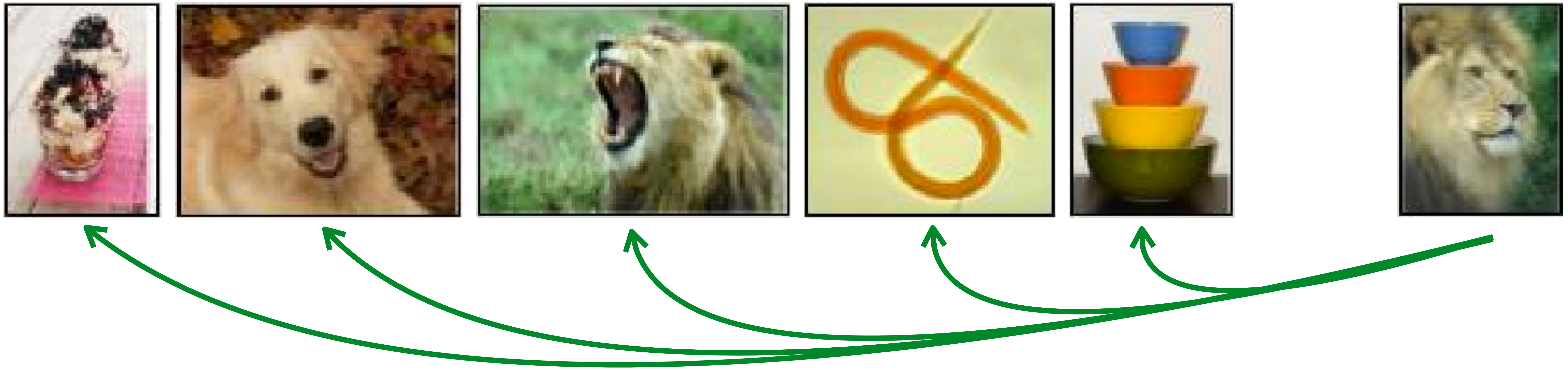


Compare test image with training images

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

~~ℓ_2 distance in pixel space?~~

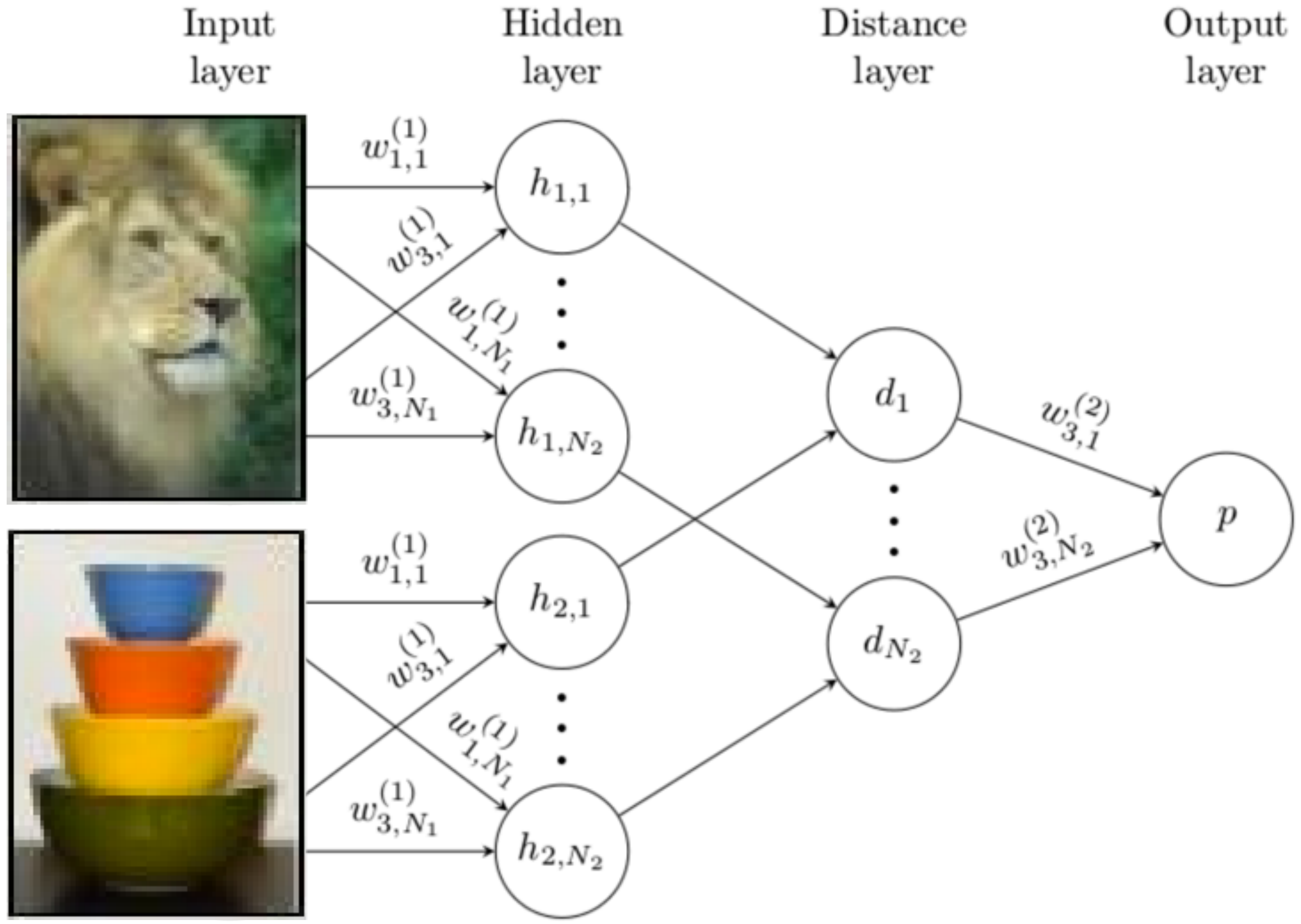
Question: What distance metric would you use instead?

Idea: 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



label

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Koch et al., ICML '15

Non-parametric methods

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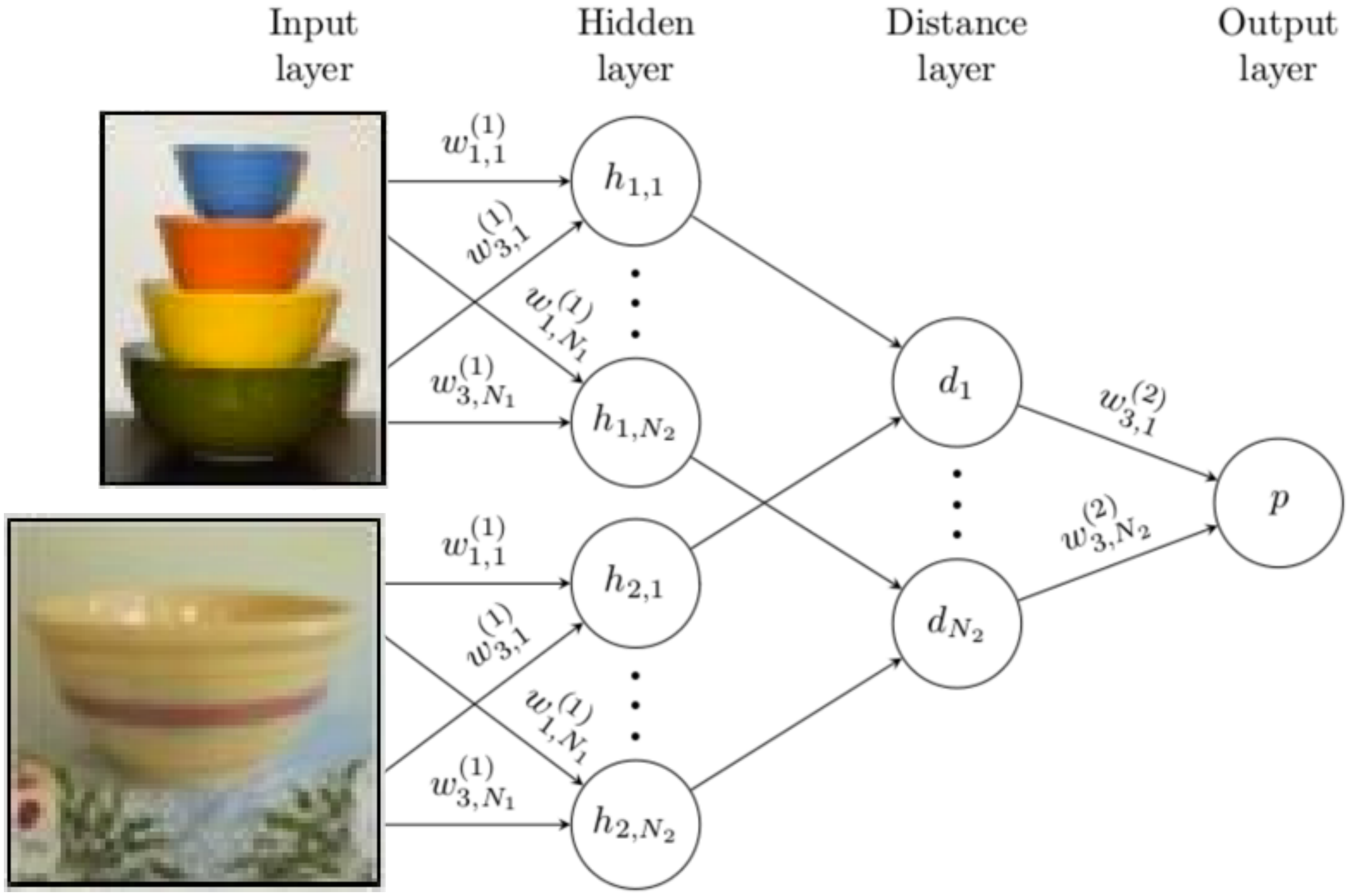

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Koch et al., ICML '15

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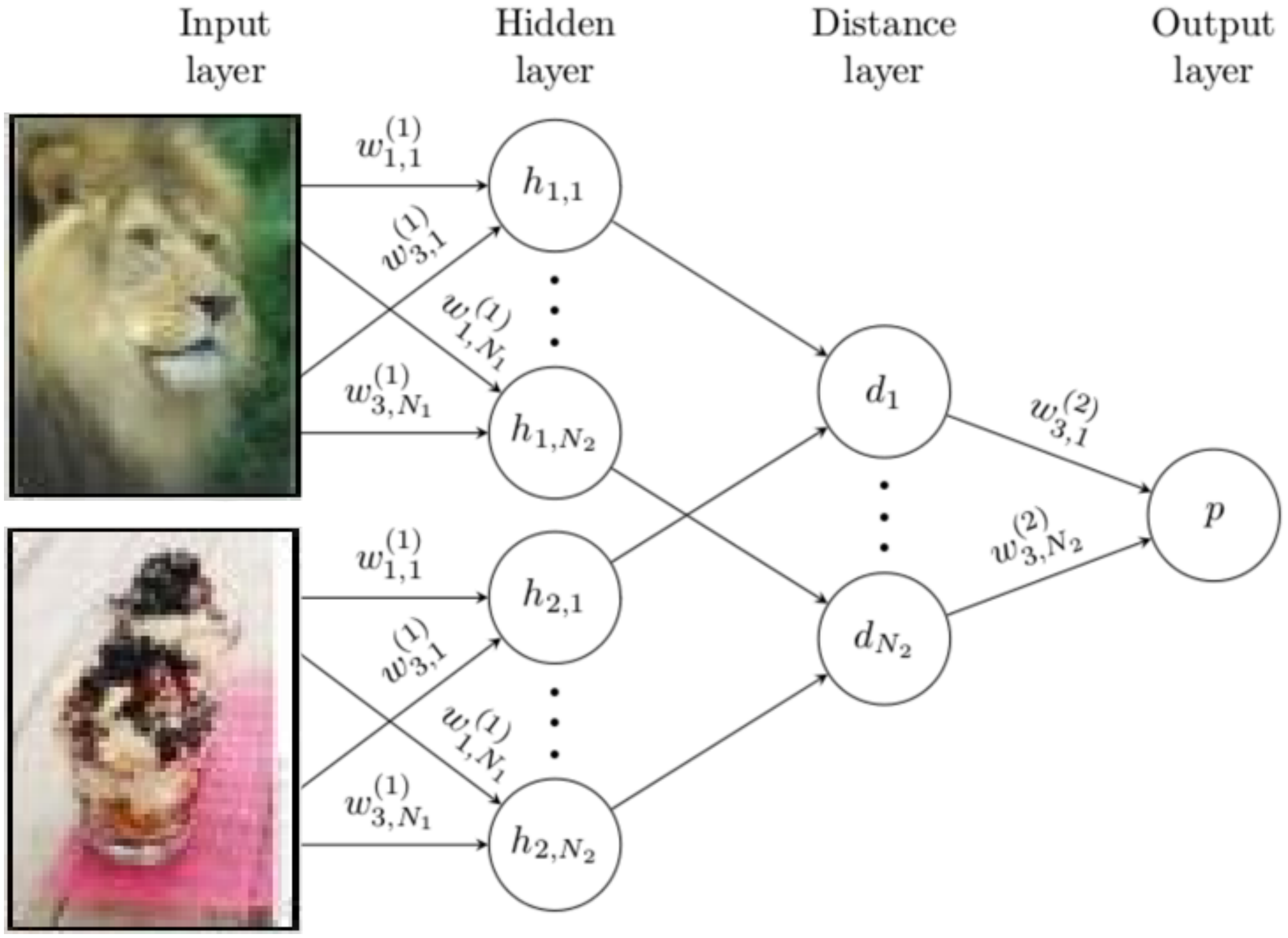

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Koch et al., ICML '15

Non-parametric methods

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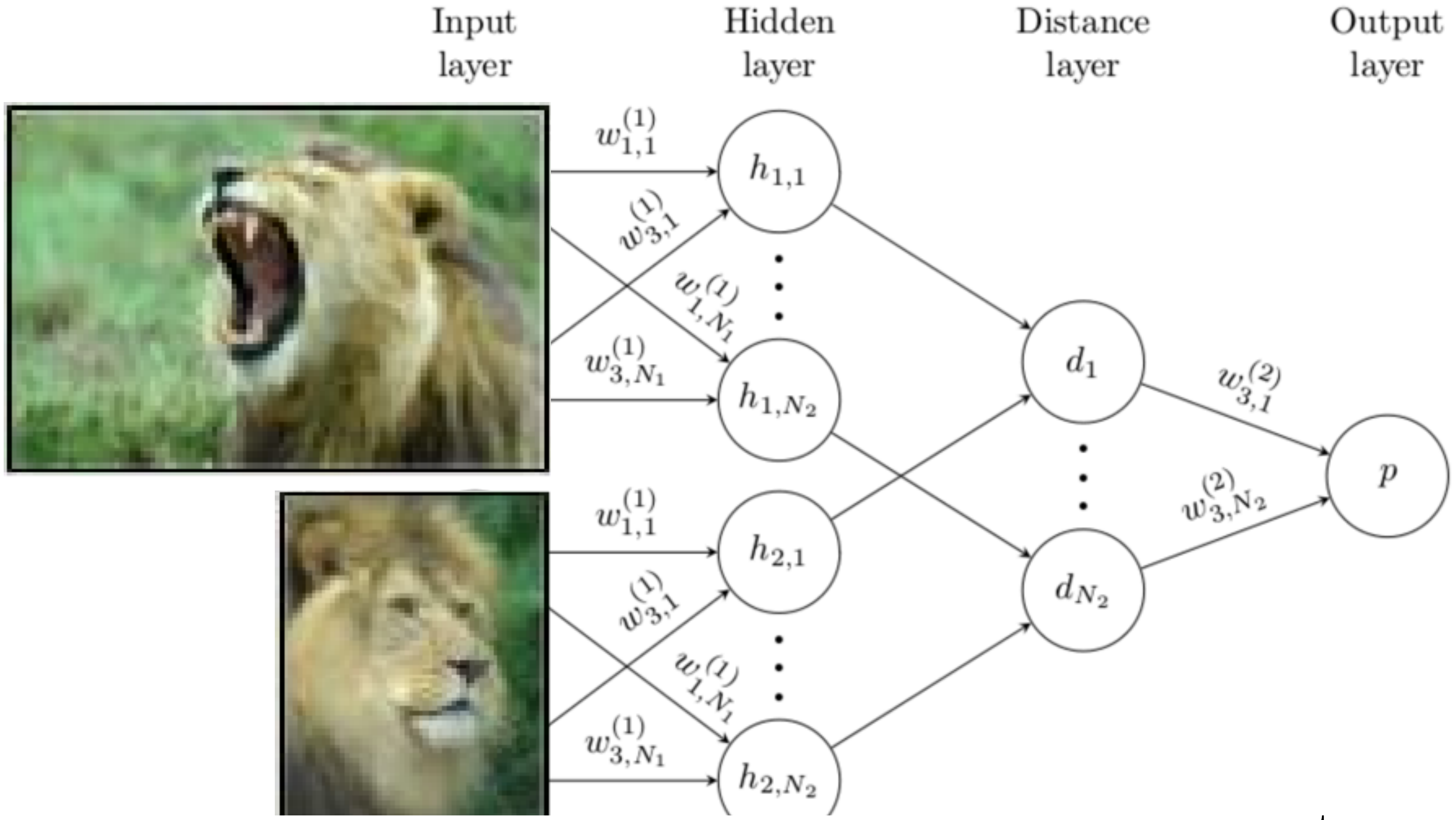

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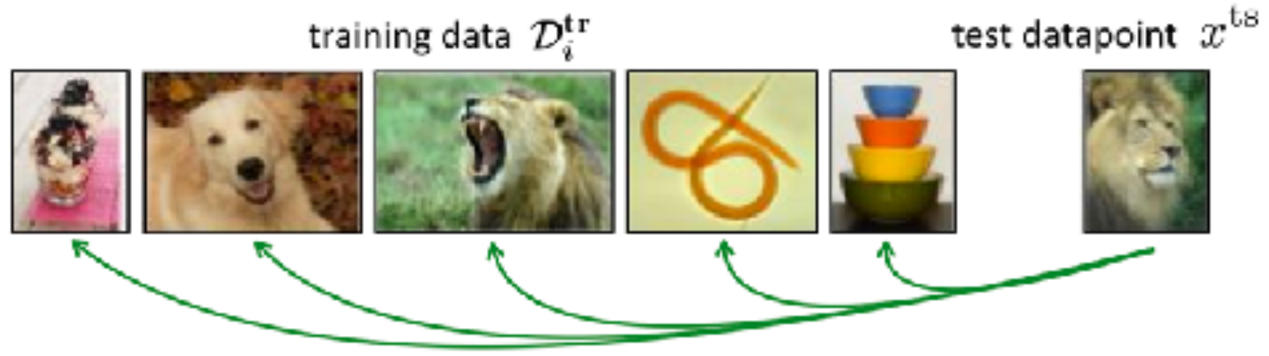
Meta-test time: compare image $\mathbf{x}_{\text{test}}$ to each image in $\mathcal{D}_j^{\text{tr}}$



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

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

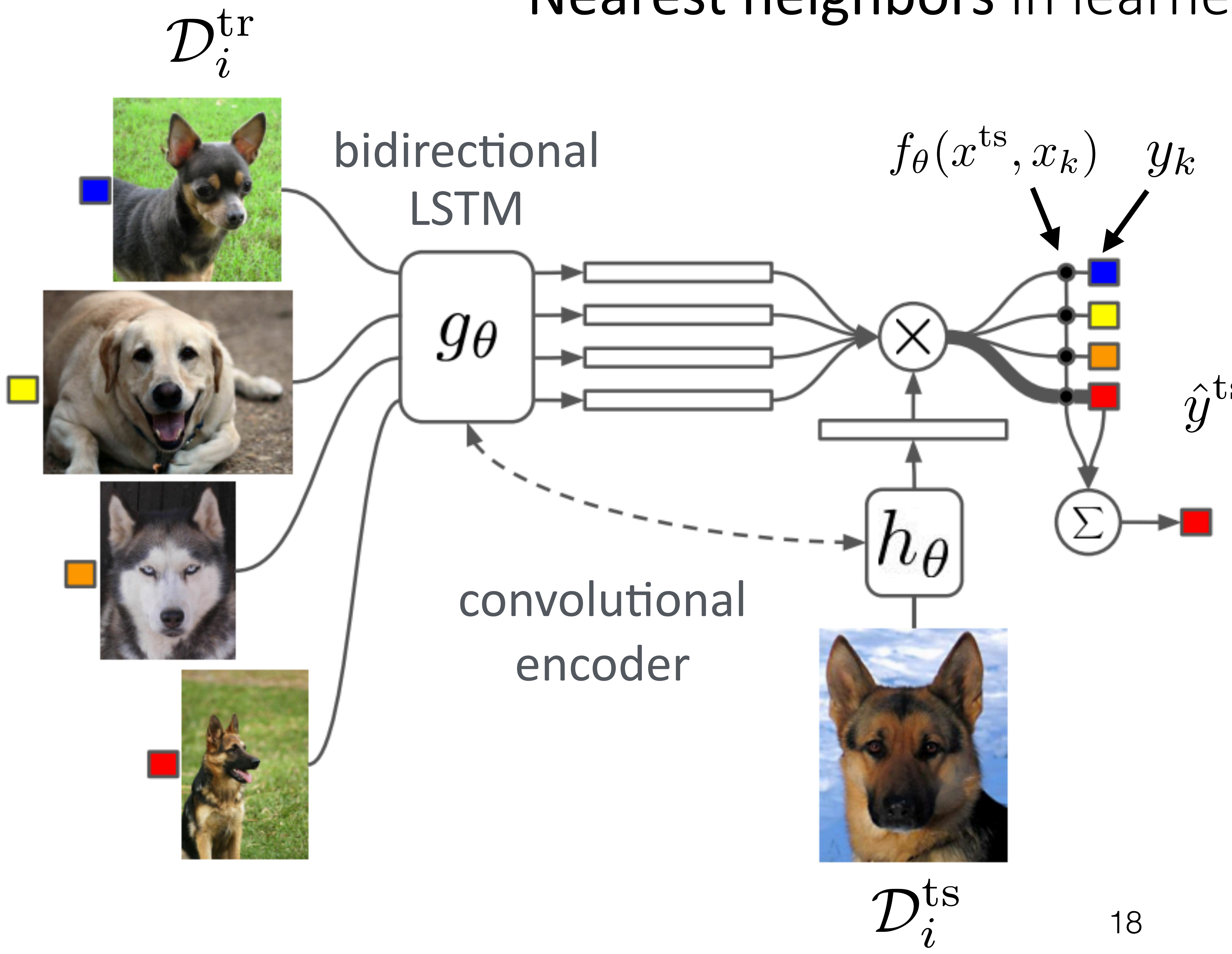
Koch et al., ICML '15

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:

~~Black box approach~~ Non-parametric approach (matching networks)

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

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

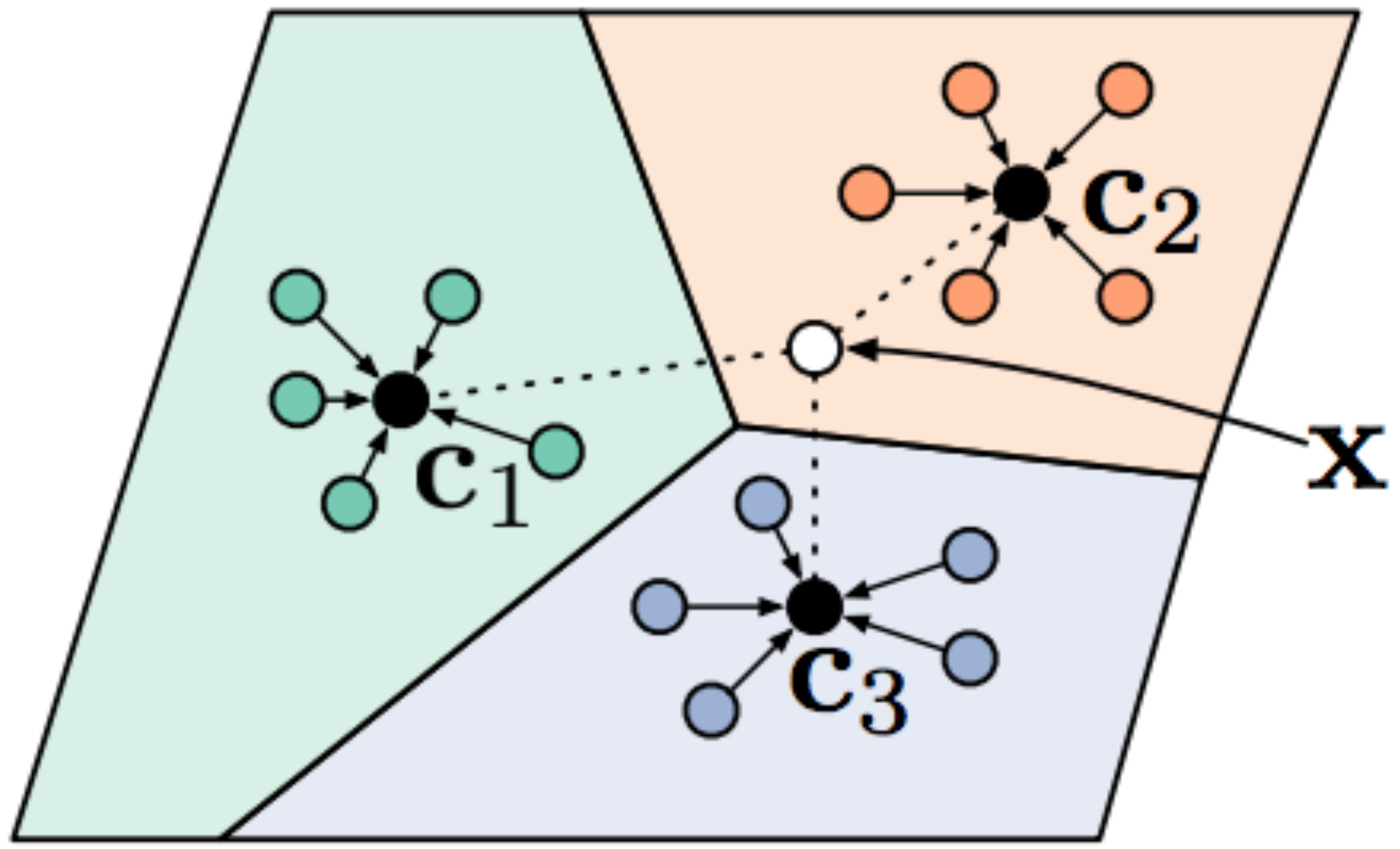
What if **>1 shot**?

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.



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

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

d: Euclidean, or cosine distance

Snell et al. Prototypical Networks, NeurIPS '17

Non-parametric methods

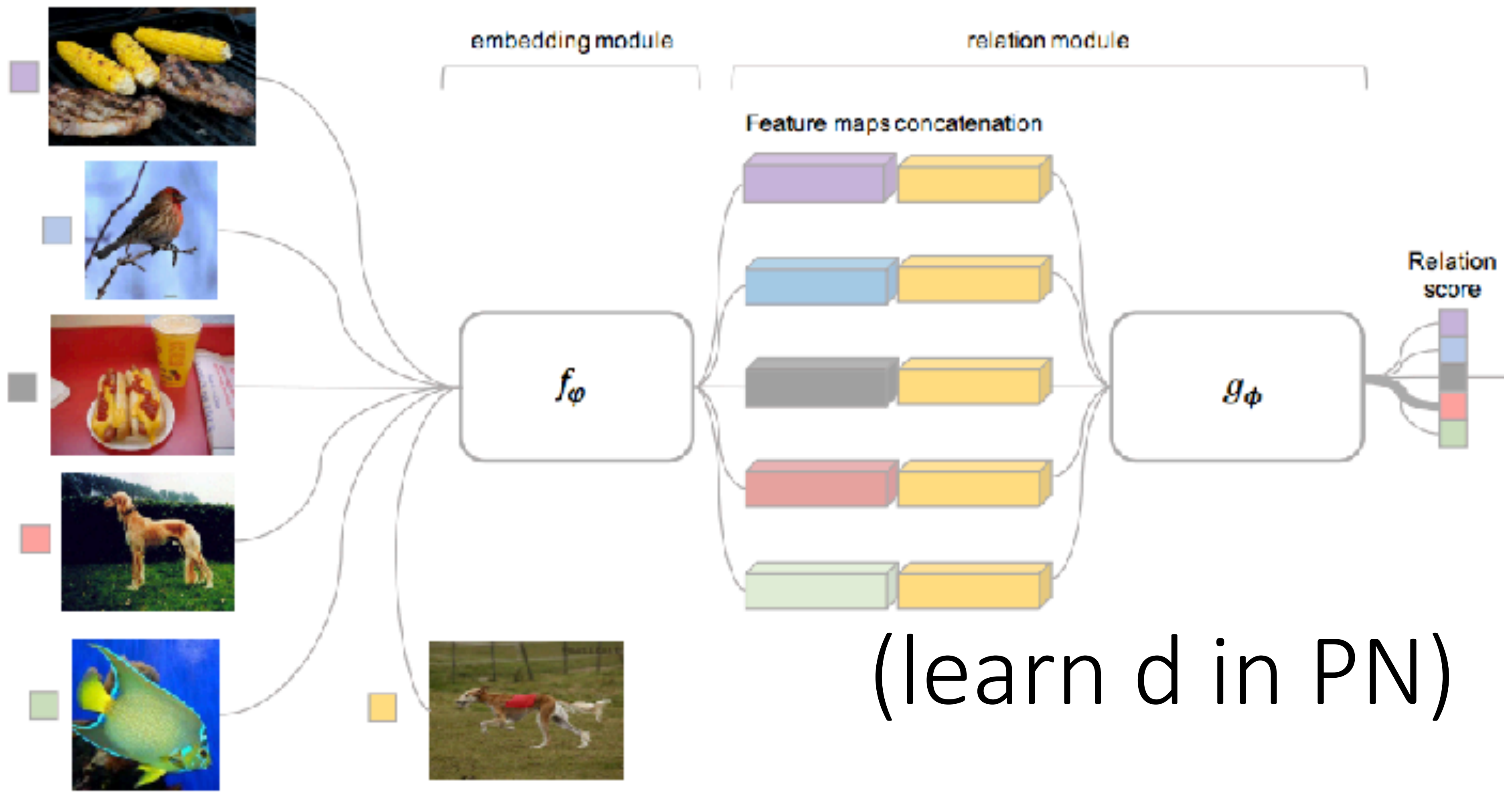
So far: Siamese networks, matching networks, prototypical networks

Embed, then nearest neighbors.

Challenge

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

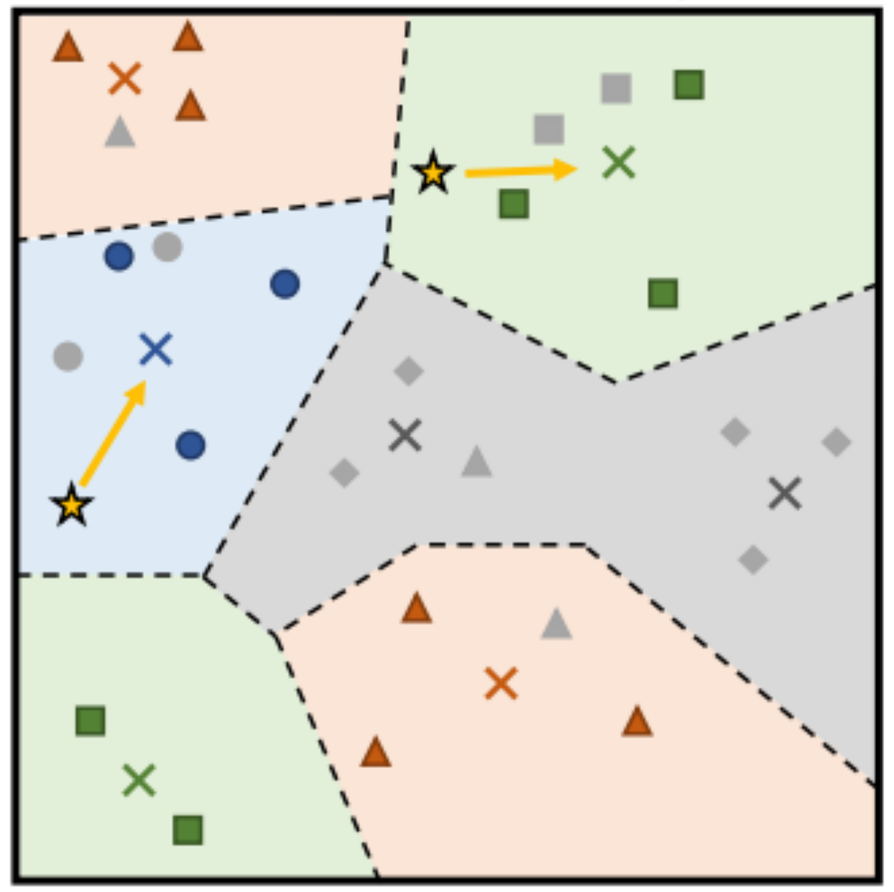
Idea: Learn non-linear relation module on embeddings



(learn d in PN)

Sung et al. Relation Net '17

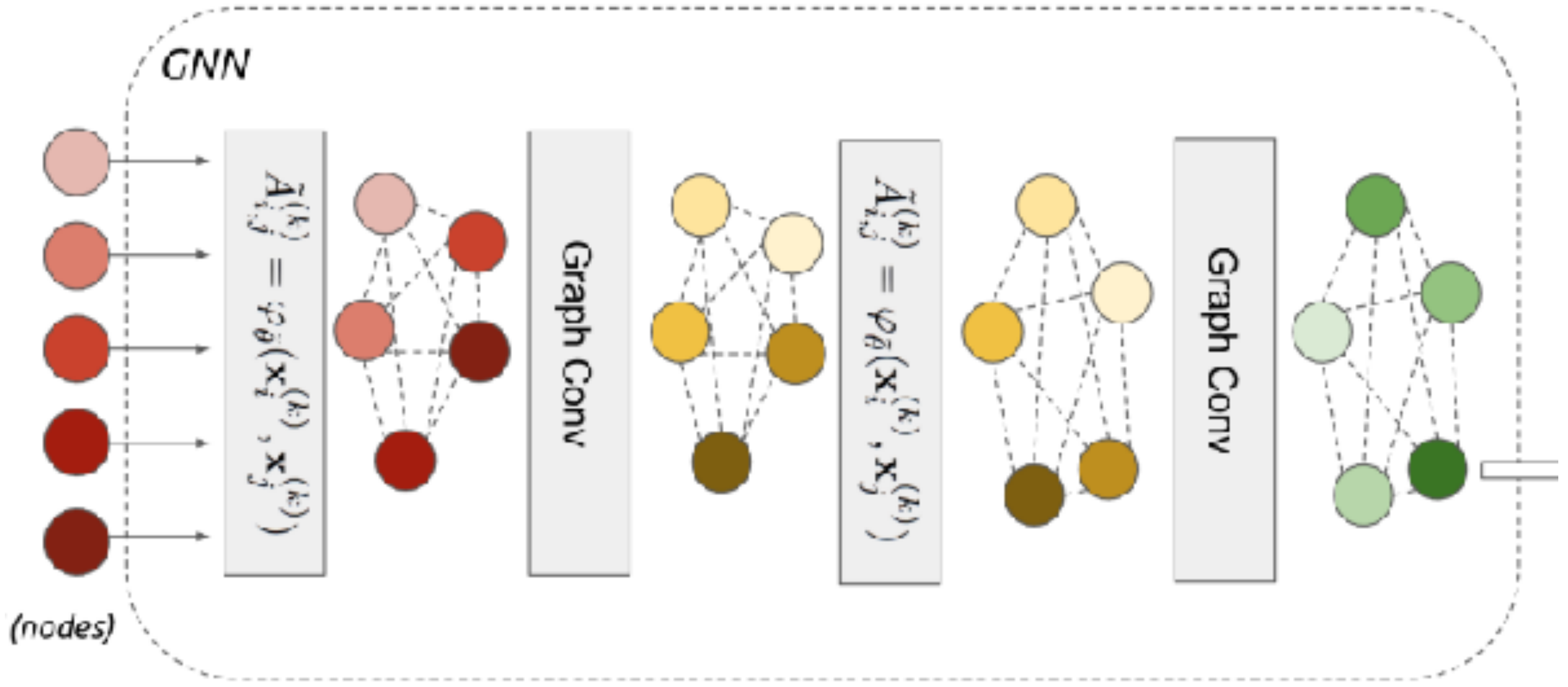
Idea: Learn infinite mixture of prototypes.



adaptive number of clusters

Allen et al. IMP, ICML '19

Idea: Perform message passing on embeddings



Garcia & Bruna, GNN '17

Plan for Today

Non-Parametric Few-Shot Learning

- Siamese networks, matching networks, prototypical networks

Properties of Meta-Learning Algorithms

- Comparison of approaches

Examples of Meta-Learning In Practice

- Imitation learning, drug discovery, motion prediction, language generation

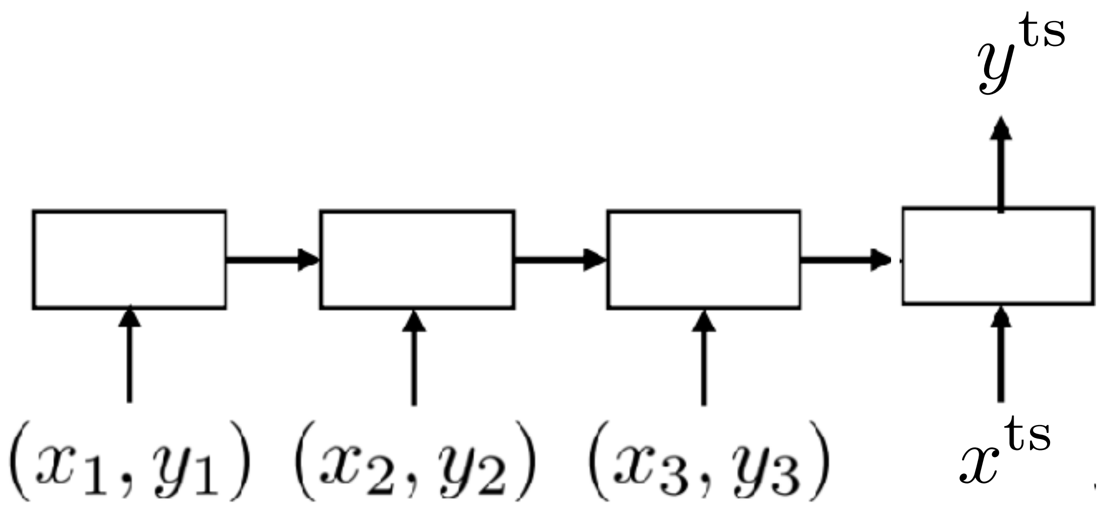
How can we think about how these methods compare?

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

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

Non-parametric

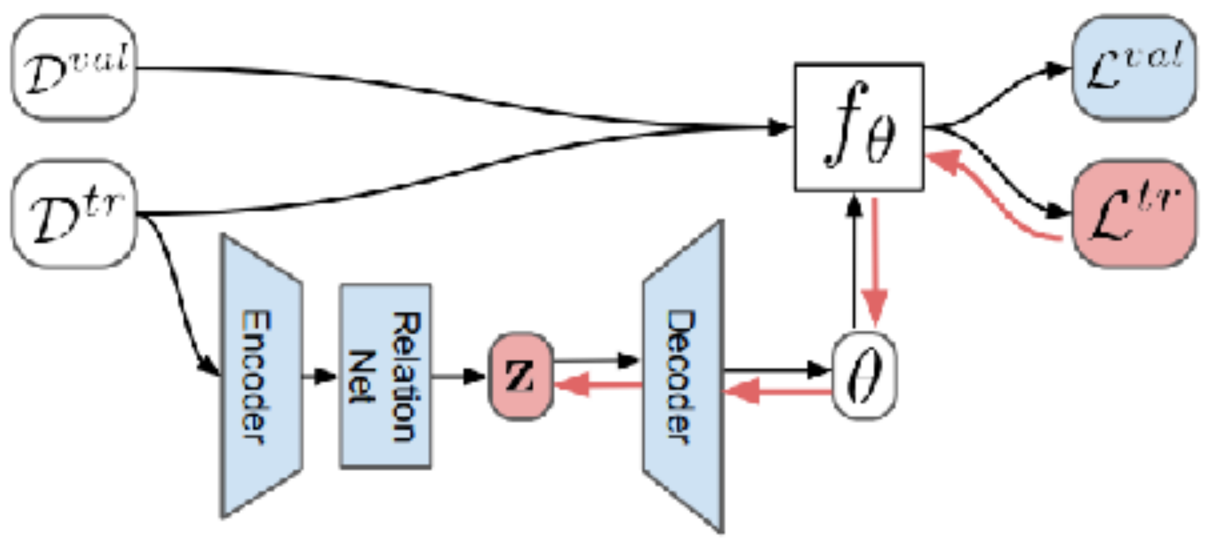
$$y^{\text{ts}} = f_{\text{PN}}(\mathcal{D}_i^{\text{tr}}, x^{\text{ts}})$$
$$= \text{softmax}(-d\left(f_\theta(x^{\text{ts}}), \mathbf{c}_n\right))$$
$$\text{where } \mathbf{c}_n = \frac{1}{K} \sum_{(x,y) \in \mathcal{D}_i^{\text{tr}}} \mathbb{1}(y = n) f_\theta(x)$$

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

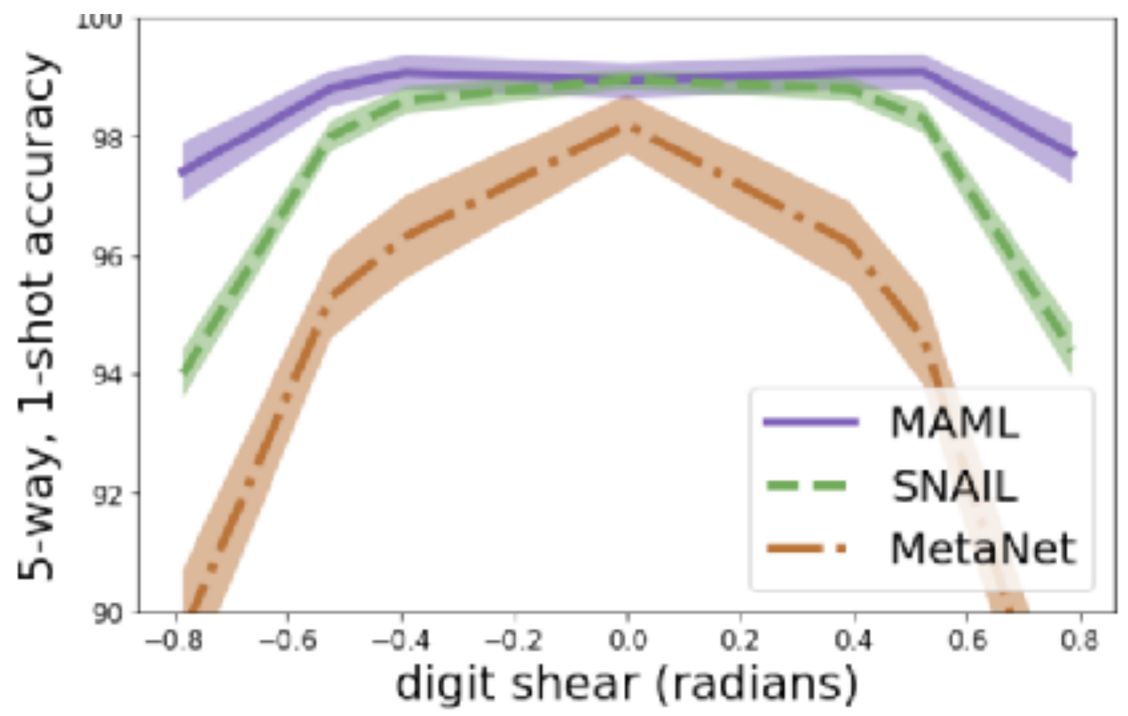
Why? scalability, applicability to a range of domains

Consistency

learned learning procedure will monotonically improve with more 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

- **second-order optimization**

- **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 many 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 in 2 weeks!

Plan for Today

Non-Parametric Few-Shot Learning

- Siamese networks, matching networks, prototypical networks

Properties of Meta-Learning Algorithms

- Comparison of approaches

Examples of Meta-Learning In Practice

- Imitation learning, drug discovery, motion prediction, language generation

Application: Land-Cover Classification

(Rubwurm*, Wang* et al. Meta-Learning for Few-Shot Land-Cover Classification. CVPR EarthVision 2020)

Tasks:

Classification or segmentation of image

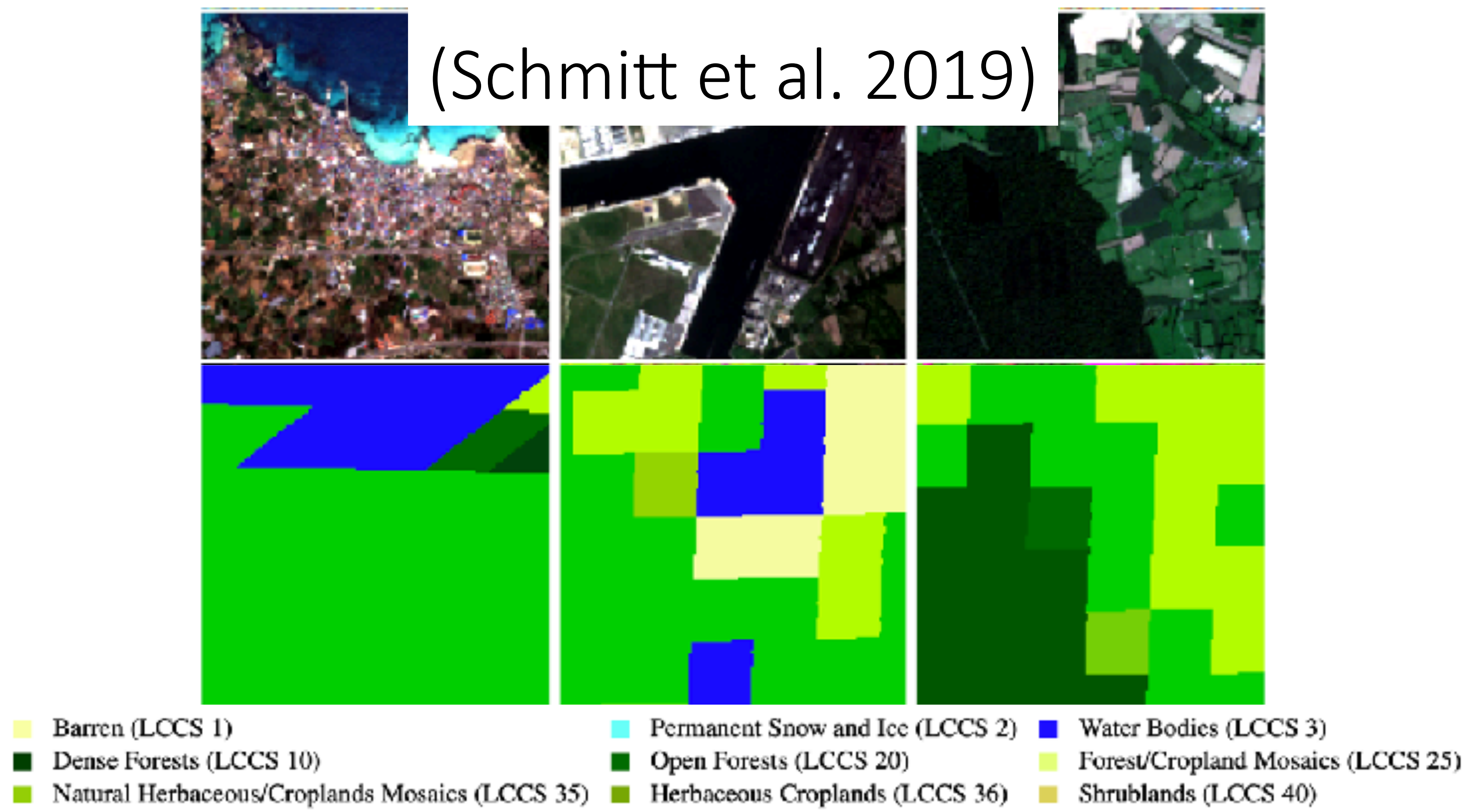
Different regions of the world

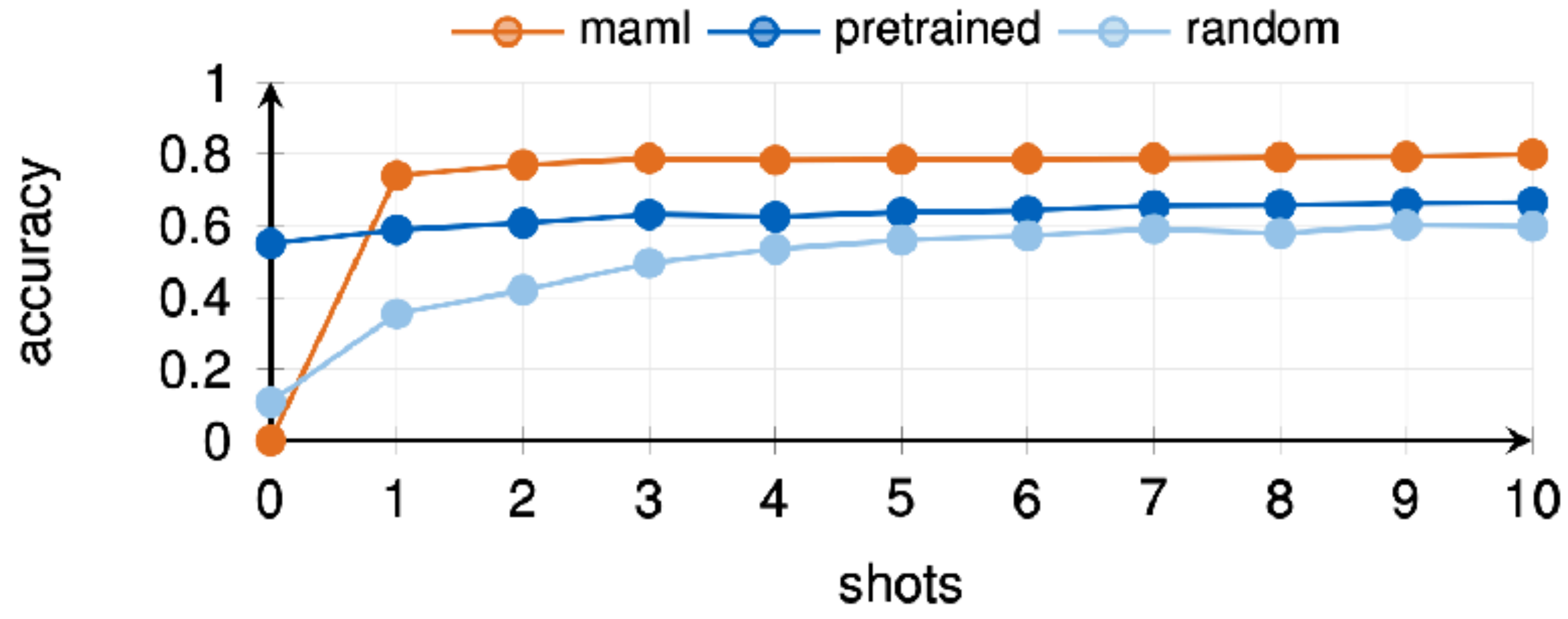
$\mathscr{D}_i^{\mathrm{tr}}$, $\mathscr{D}_i^{\mathrm{ts}}$: images from a particular region

Model: optimization-based (MAML)

SEN12MS dataset

(Schmitt et al. 2019)





Application: Student Feedback Generation

(Wu et al. Prototransformer: A meta-learning approach to providing student feedback. 2021)

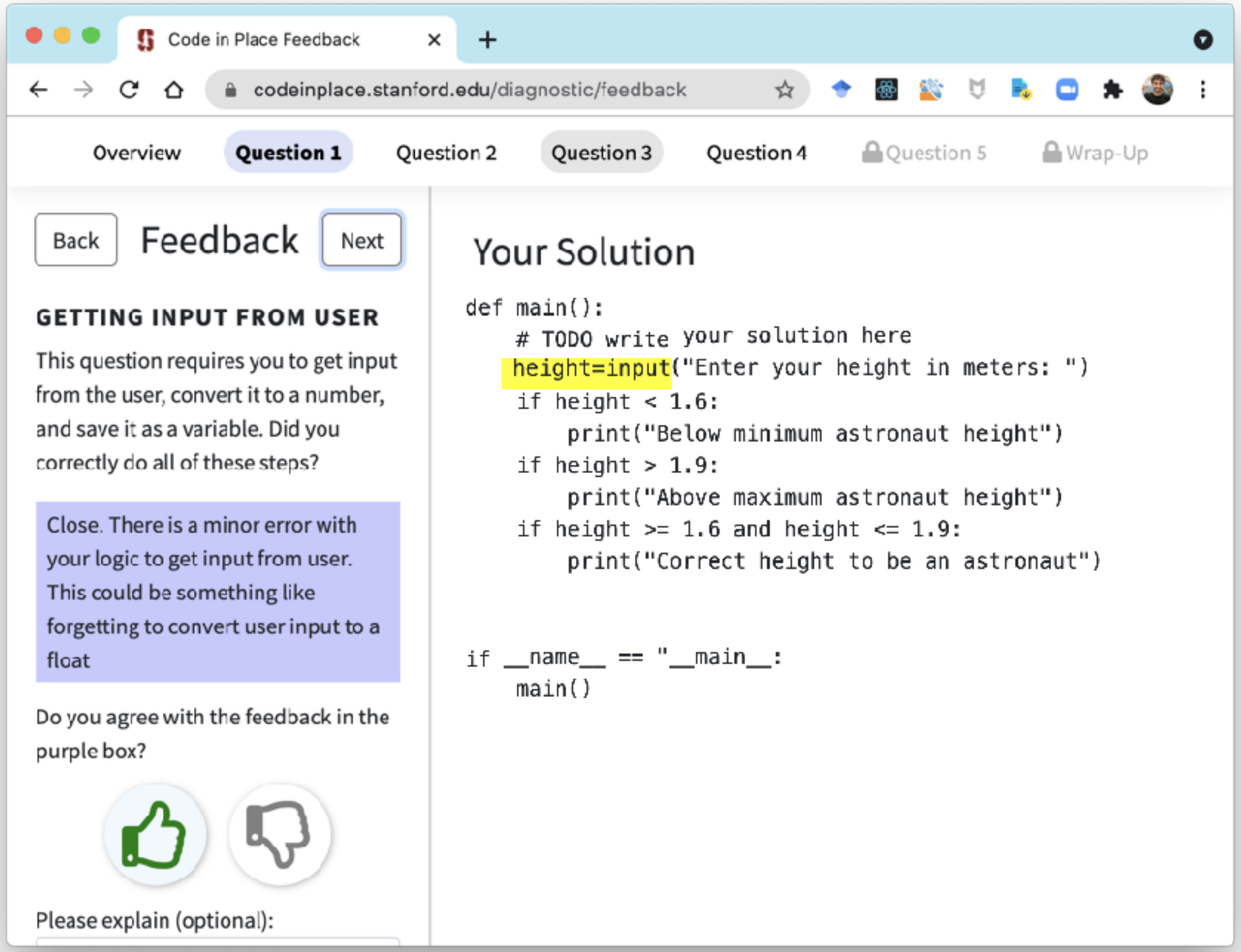
Tasks:

Different rubric items from different exams

$\mathscr{D}_i^{\text{tr}}, \mathscr{D}_i^{\text{ts}}$: student solutions (python programs)

Model: non-parametric

Protonets with pre-trained transformer, task augmentation, side information



Main Offline Results

Model	AP	P@50	P@75	ROC-AUC
	Held-out rubric			
ProtoTransformer	**84.2** (±1.7)	**85.2** (±3.8)	**74.2** (±1.4)	**82.9** (±1.3)
Supervised	66.9 (±2.2)	59.1 (±1.7)	53.9 (±1.5)	61.0 (±2.1)
Human TA	82.5	–	–	–
	Held-out exam			
ProtoTransformer	**74.2** (±1.6)	**77.3** (±2.7)	**67.3** (±2.0)	**77.0** (±1.4)
Supervised	65.8 (± 2.1)	60.1 (±3.0)	54.3 (±1.8)	60.7 (±1.6)
Human TA	82.5	–	–	–

- **Supervised baseline:** train classifier per task, using same pre-trained CodeBERT
- **Outperforms supervised learning** by 8-17%
- **More accurate** than **human TA** on **held-out rubric**
- **Room to grow** on **held-out exam**

Application: Low-Resource Molecular Property Prediction

(Nguyen et al. Meta-Learning GNN Initializations for Low-Resource Molecular Property Prediction. 2020)

[potentially useful for low-resource drug discovery problems]

Tasks:

Predicting properties & activities of different molecules

$\mathscr{D}_i^{\mathrm{tr}}$, $\mathscr{D}_i^{\mathrm{ts}}$: different instances

Model: optimization-based

MAML, first-order MAML, ANIL

Gated graph neural net base model

CHEMBL ID	κ-NN	FINETUNE-ALL	FINETUNE-TOP	FO-MAML	ANIL	MAML
2363236	0.316 ± 0.007	0.328 ± 0.028	0.329 ± 0.023	$\mathbf{0.337 \pm 0.019}$	0.325 ± 0.008	0.332 ± 0.013
1614469	0.438 ± 0.023	0.470 ± 0.034	0.490 ± 0.033	0.489 ± 0.019	0.446 ± 0.044	$\mathbf{0.507 \pm 0.030}$
2363146	0.559 ± 0.026	0.626 ± 0.037	$\mathbf{0.653 \pm 0.029}$	0.555 ± 0.017	0.506 ± 0.034	0.595 ± 0.051
2363366	0.511 ± 0.050	0.567 ± 0.039	0.551 ± 0.048	0.546 ± 0.037	0.570 ± 0.031	$\mathbf{0.598 \pm 0.041}$
2363553	$\mathbf{0.739 \pm 0.007}$	0.724 ± 0.015	0.737 ± 0.023	0.694 ± 0.011	0.686 ± 0.020	0.691 ± 0.013
1963818	0.607 ± 0.041	0.708 ± 0.036	0.595 ± 0.142	0.677 ± 0.026	0.692 ± 0.081	$\mathbf{0.745 \pm 0.048}$
1963945	0.805 ± 0.031	$\mathbf{0.848 \pm 0.034}$	0.835 ± 0.036	0.779 ± 0.039	0.753 ± 0.033	0.836 ± 0.023
1614423	0.503 ± 0.044	0.628 ± 0.058	0.642 ± 0.063	0.760 ± 0.024	0.730 ± 0.077	$\mathbf{0.837 \pm 0.036}^*$
2114825	0.679 ± 0.027	0.739 ± 0.050	0.732 ± 0.051	0.837 ± 0.042	0.759 ± 0.078	$\mathbf{0.885 \pm 0.014}^*$
1964116	0.709 ± 0.042	0.758 ± 0.044	0.769 ± 0.048	0.895 ± 0.023	0.903 ± 0.016	$\mathbf{0.912 \pm 0.013}$
2155446	0.471 ± 0.008	0.473 ± 0.017	0.476 ± 0.013	0.497 ± 0.024	0.478 ± 0.020	$\mathbf{0.500 \pm 0.017}$
1909204	0.538 ± 0.023	0.589 ± 0.031	0.577 ± 0.039	0.592 ± 0.043	0.547 ± 0.029	$\mathbf{0.601 \pm 0.027}$
1909213	0.694 ± 0.009	0.742 ± 0.015	$\mathbf{0.759 \pm 0.012}$	0.698 ± 0.024	0.694 ± 0.025	0.729 ± 0.013
3111197	0.617 ± 0.028	0.663 ± 0.066	0.673 ± 0.071	0.636 ± 0.036	0.737 ± 0.035	$\mathbf{0.746 \pm 0.045}$
3215171	0.480 ± 0.042	0.552 ± 0.043	0.551 ± 0.045	0.729 ± 0.031	0.700 ± 0.050	$\mathbf{0.764 \pm 0.019}$
3215034	0.474 ± 0.072	0.540 ± 0.156	0.455 ± 0.189	$\mathbf{0.819 \pm 0.048}$	0.681 ± 0.042	0.805 ± 0.046
1909103	0.881 ± 0.026	$\mathbf{0.936 \pm 0.013}$	0.921 ± 0.020	0.877 ± 0.046	0.730 ± 0.055	0.900 ± 0.032
3215092	0.696 ± 0.038	0.777 ± 0.039	0.791 ± 0.042	0.877 ± 0.028	0.834 ± 0.026	$\mathbf{0.907 \pm 0.017}$
1738253	0.710 ± 0.048	0.860 ± 0.029	0.861 ± 0.025	0.885 ± 0.033	0.758 ± 0.111	$\mathbf{0.908 \pm 0.011}$
1614549	0.710 ± 0.035	0.850 ± 0.041	0.860 ± 0.051	0.930 ± 0.022	0.860 ± 0.034	$\mathbf{0.947 \pm 0.014}$
AVG. RANK	5.4	3.5	3.5	3.1	4.0	**1.7**

Side note

$\mathscr{D}_i^{\mathrm{tr}}$ and $\mathscr{D}_i^{\mathrm{ts}}$ do not need to be sampled independently from $\mathscr{D}_i$.

$\mathscr{D}_i^{\mathrm{tr}}$ could have:

- noisy labels
- weakly supervised
- domain shift
- etc.

Application: One-Shot Imitation Learning

(Yu*, Finn* et al. One-Shot Imitation from Observing Humans. RSS 2018)

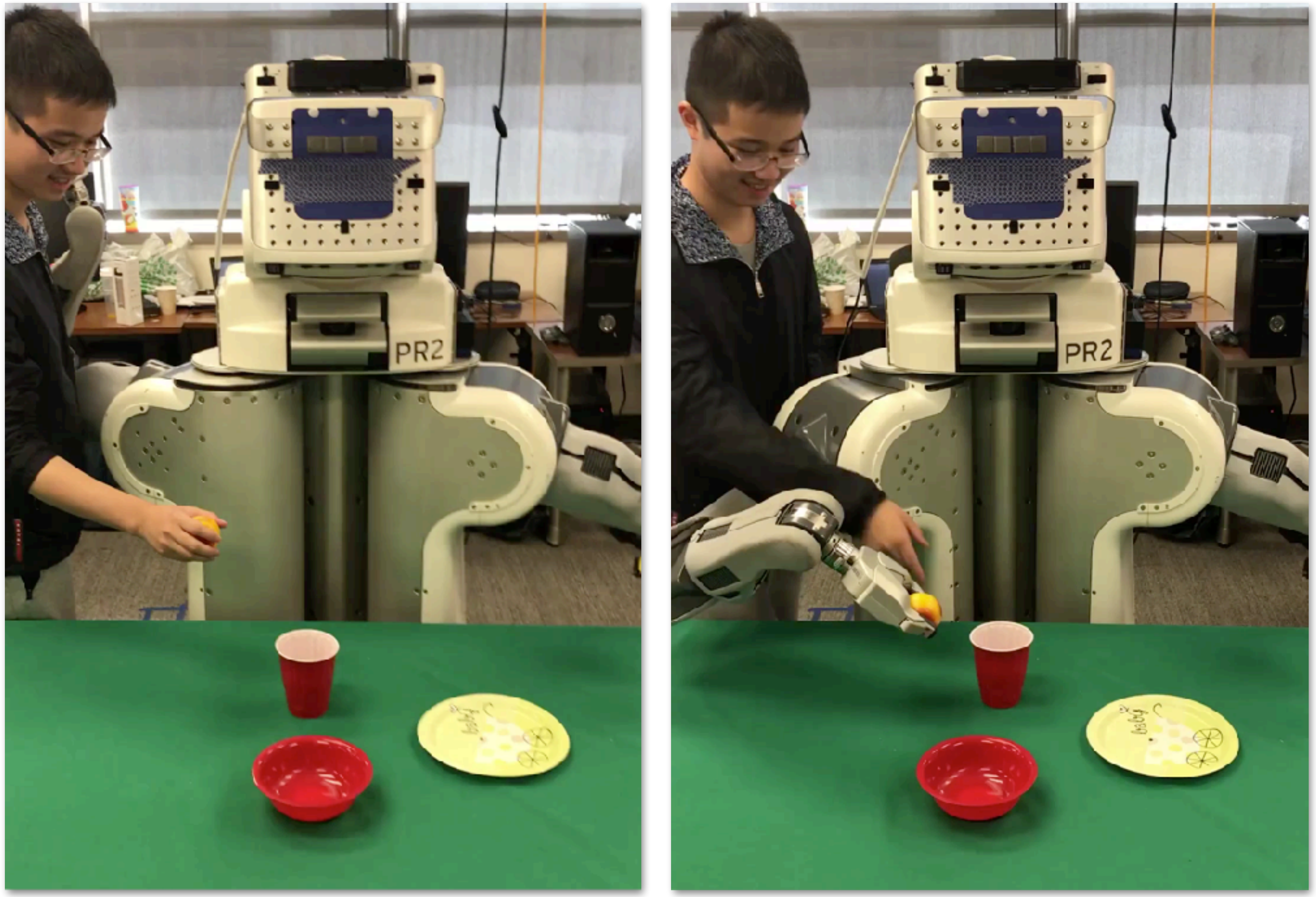
Tasks:

manipulating different objects

$\mathscr{D}_i^{\mathrm{tr}}$: video of a human

$\mathscr{D}_i^{\mathrm{ts}}$: teleoperated demonstration

Model: optimization-based MAML with *learned* inner loss



Application: Dermatological Image Classification

(Prabhu et al. Prototypical Clustering Networks for Dermatological Image Classification. ML4HC 2019)

Tasks:

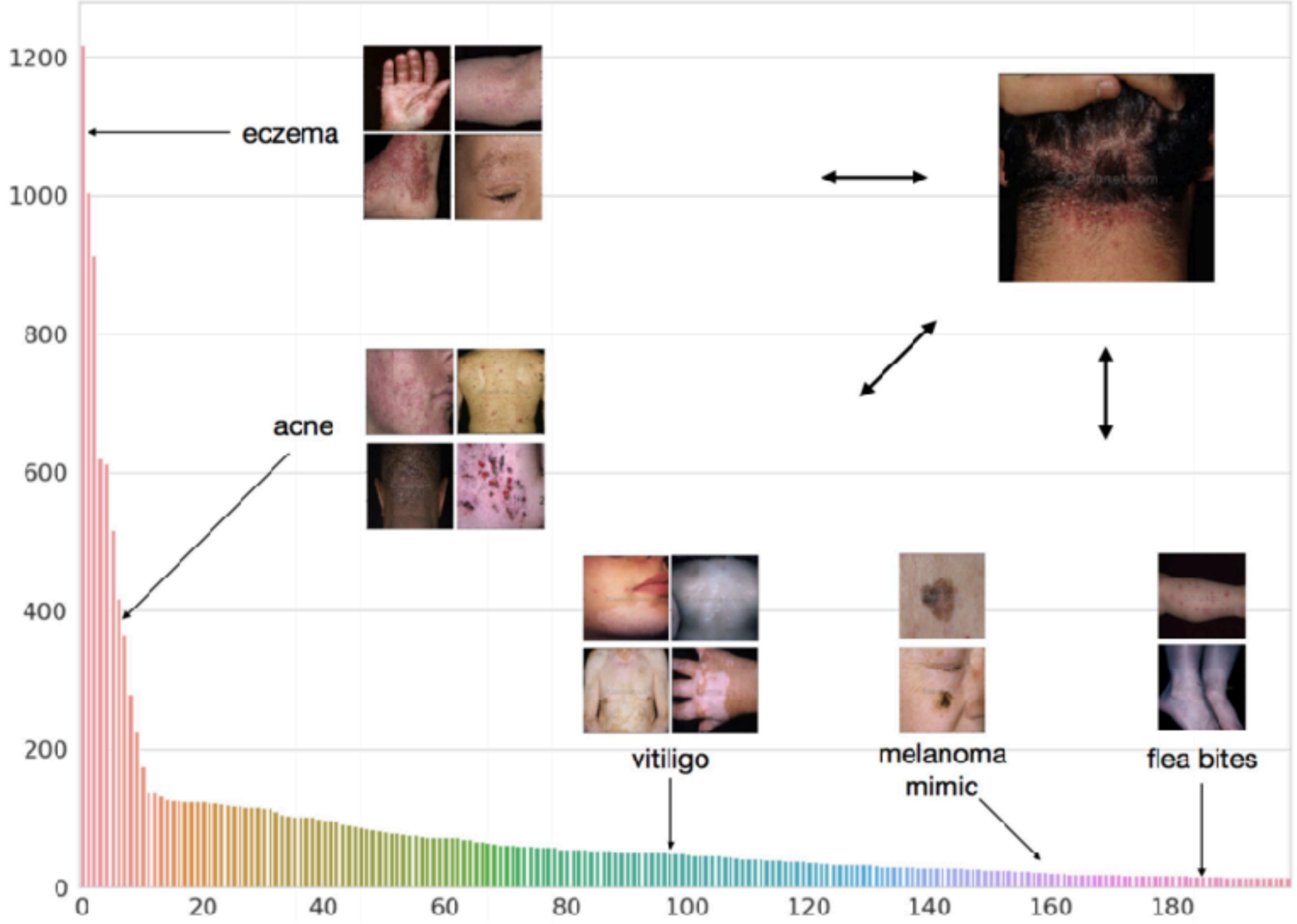
Different skin conditions

$\mathscr{D}_i^{\mathrm{tr}}, \mathscr{D}_i^{\mathrm{ts}}$: images from different people

Goal: good classifier on all classes.

Model: non-parametric

Protonets, multiple prototypes per class using clustering objective



Evaluation

Compare: PN - standard ProtoNets, trained on 150 base classes, pre-trained on ImageNet

FT_N-1NN - ImageNet pre-training, fine-tuned ResNet on N classes, 1-nearest neighbors in resulting embedding space

FT_{200}-CE - ImageNet pre-trained, fine-tuned on all 200 classes with balancing

(very strong baseline, accesses more info during training, requires re-training for new classes)

Evaluation Metric: mean class accuracy (mca), i.e. average of per-class accuracies across 200 classes.

Approach	k = 5			k = 10		
	$mca_{base+novel}$	mca_{base}	mca_{novel}	$mca_{base+novel}$	mca_{base}	mca_{novel}
FT_{150}-1NN	46.18 +/- 0.81	55.32 +/- 0.30	18.76 +/- 3.30	49.51 +/- 0.34	54.86 +/- 0.50	33.44 +/- 1.35
FT_{150}-3NN	44.28 +/- 0.32	54.77 +/- 0.47	12.80 +/- 1.50	47.01 +/- 0.56	54.13 +/- 0.43	25.64 +/- 1.51
FT_{200}-1NN	46.52 +/- 0.39	54.17 +/- 0.30	22.50 +/- 0.75	49.92 +/- 0.47	53.80 +/- 0.35	38.27 +/- 1.32
FT_{200}-3NN	44.69 +/- 0.39	52.61 +/- 0.21	20.93 +/- 2.00	47.96 +/- 0.11	52.53 +/- 0.14	34.27 +/- 0.19
FT_{200}-CE	**47.82 +/- 0.46**	**55.75 +/- 0.71**	24.00 +/- 3.22	**51.51 +/- 0.41**	**55.21 +/- 0.26**	40.40 +/- 2.36
PN	43.92 +/- 0.40	48.71 +/- 0.37	29.56 +/- 2.35	44.93 +/- 0.79	47.55 +/- 0.37	37.08 +/- 3.39
PCN (ours)	**47.79 +/- 0.71**	53.70 +/- 0.18	**30.04 +/- 2.77**	**50.92 +/- 0.63**	51.38 +/- 0.34	**49.56 +/- 2.76**

PCN > PN

PCN > FT_N-*NN

PCN ≈ FT_{200}-CE without requiring re-training

More visualizations and analysis in the paper!

Application: Few-Shot Human Motion Prediction

(Gui et al. Few-Shot Human Motion Prediction via Meta-Learning. ECCV 2018)

[potentially useful for human-robot interaction, autonomous driving]

Tasks:

Different human users & motions

$\mathscr{D}_i^{\mathrm{tr}}$: past K time steps of motion

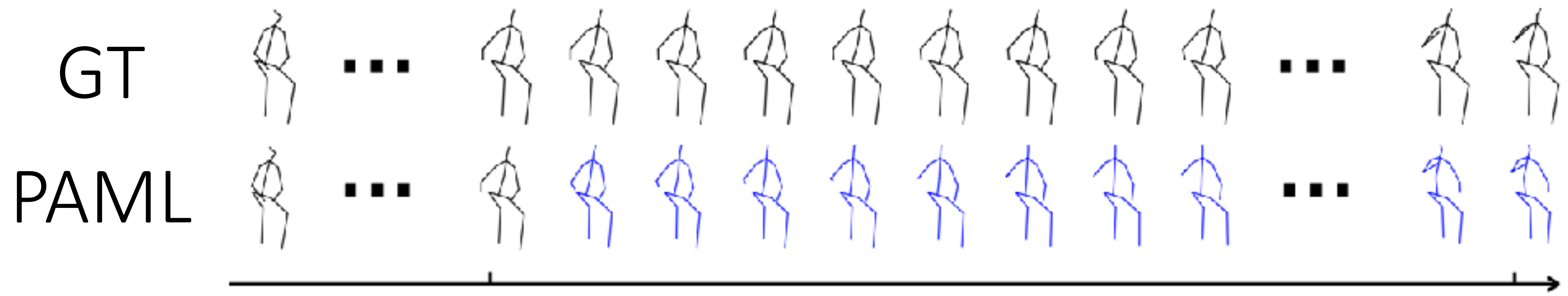
$\mathscr{D}_i^{\mathrm{ts}}$: future second(s) of motion

Model:

optimization-based/black-box hybrid

MAML with additional learned update rule

Recurrent neural net base model



		Walking						Eating					
milliseconds		80	160	320	400	560	1000	80	160	320	400	560	1000
residual sup. [32] w/ (Baselines)	Scratch$_{\text{spec}}$	1.90	1.95	2.16	2.18	1.99	2.00	2.33	2.31	2.30	2.30	2.31	2.34
	Scratch$_{\text{agn}}$	1.78	1.89	2.20	2.23	2.02	2.05	2.27	2.16	2.18	2.27	2.25	2.31
	Transfer$_{\text{ots}}$	0.60	0.75	0.88	0.93	1.03	1.26	0.57	0.70	0.91	1.04	1.19	1.58
	Multi-task	0.57	0.71	0.79	0.85	0.96	1.12	0.59	0.68	0.83	0.93	1.12	1.33
	Transfer$_{\text{ft}}$	0.44	0.55	0.85	0.95	0.74	1.03	0.61	0.65	0.74	0.78	0.86	1.19
Meta-learning (Ours)	PAML	**0.35**	**0.47**	**0.70**	**0.82**	**0.80**	**0.83**	**0.36**	**0.52**	**0.65**	**0.70**	**0.71**	**0.79**

		Smoking						Discussion					
milliseconds		80	160	320	400	560	1000	80	160	320	400	560	1000
residual sup. [32] w/ (Baselines)	Scratch$_{\text{spec}}$	2.88	2.86	2.85	2.83	2.80	2.99	3.01	3.13	3.12	2.95	2.62	2.99
	Scratch$_{\text{agn}}$	2.53	2.61	2.67	2.65	2.71	2.73	2.77	2.79	2.82	2.73	2.82	2.76
	Transfer$_{\text{ots}}$	0.70	0.84	1.18	1.23	1.38	2.02	0.58	0.86	1.12	1.18	1.54	2.02
	Multi-task	0.71	0.79	1.09	1.20	1.25	1.23	0.53	0.82	1.02	1.17	1.33	1.97
	Transfer$_{\text{ft}}$	0.87	1.02	1.25	1.30	1.45	2.06	0.57	0.82	1.11	1.11	1.37	2.08
Meta-learning (Ours)	PAML	**0.39**	**0.66**	**0.81**	1.01	1.03	**1.01**	**0.41**	**0.71**	1.01	**1.02**	1.09	1.12

mean angle error w.r.t. prediction horizon

Plan for Today

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

Properties of Meta-Learning Algorithms
- Comparison of approaches

Examples of Meta-Learning in Practice
- Imitation learning, drug discovery, motion prediction, language generation

} **Part of Homework 2!**

Goals for by the end of lecture:
- Basics of non-parametric few-shot learning techniques (& how to implement)
- Trade-offs between black-box, optimization-based, and non-parametric meta-learning
- Familiarity with applied formulations of meta-learning

Course Reminders

Lectures

Done with meta-learning algorithms!

Next: unsupervised pre-training

Homeworks

Homework 1 due **tonight**.

Homework 2 released, due Weds 10/25.

Project

Project mentors assigned: go to their OH with questions.

Project proposal due next Monday 10/23.

(graded lightly, for your benefit)