Advanced Meta-Learning Topics
Task Construction

CS 330

Course Reminders

Homework 2 due **today**.

Homework 3 out today, due **next Wednesday**.

Note: This homework is brand new.

Following up on some high-res feedback:

- We'll consider autograders for future quarters.
- Homework 3 includes non-classification problems
- Clarification on train/test terminology in today's lecture

Course Roadmap

(start of week 5!)

So far: Multi-task & transfer learning basics

Core meta-learning algorithms

Core unsupervised pre-training algorithms

Next two weeks:
(more advanced topics!)

Advanced meta-learning topics

- Task construction (today)
- Large-scale meta-optimization (Weds)

Bayesian meta-learning

Question of the Day

How should tasks be defined for good meta-learning performance?

Plan for Today

Brief Recap of Meta-Learning & Supervised Task Construction

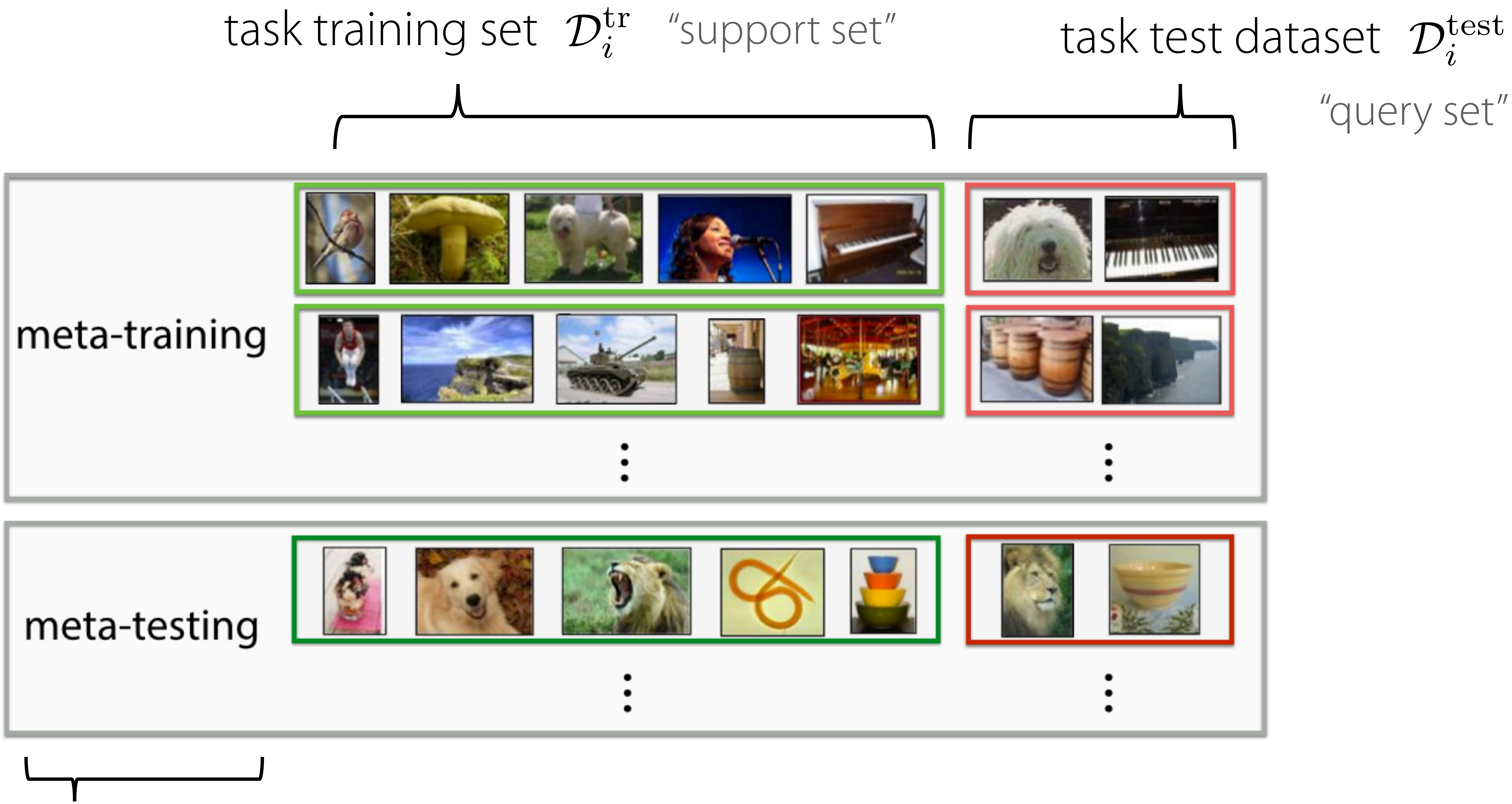
Memorization in Meta-Learning
- When it arises
- Potential solutions

} Part of (optional) Homework 4

Meta-Learning without Tasks Provided
- Unsupervised Meta-Learning
- Semi-Supervised Meta-Learning

Goals for by the end of lecture:
- Understand when & how memorization in meta-learning may occur
- Understand techniques for constructing tasks automatically

Revisiting meta-learning terminology

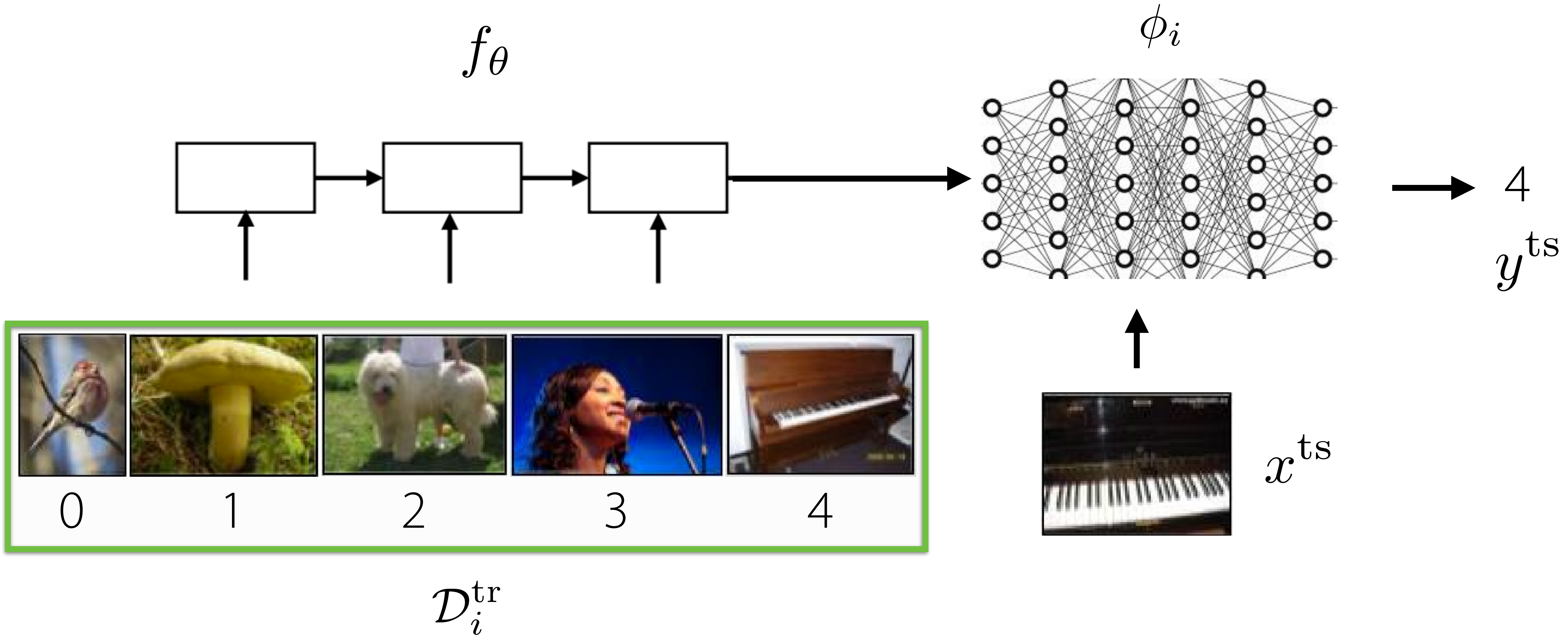


Homeworks 1 & 2 sometimes
refer to these as **train** & **test**

(which is ambiguous & confusing!)

Recap: Black-Box Meta-Learning

Key idea: parametrize learner as a neural network



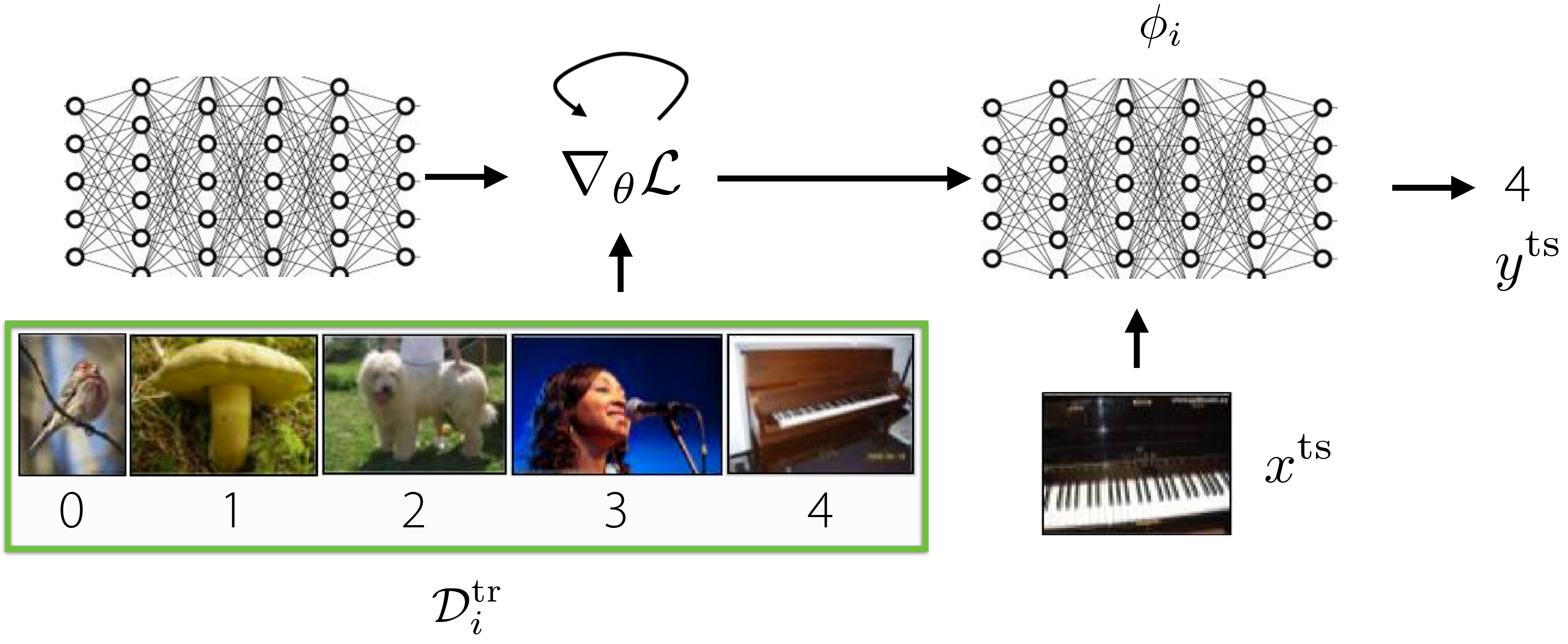
This network: inner loop, in-context learning

Training this network: outer loop

\+ **expressive** - **challenging optimization** problem

Recap: Optimization-Based Meta-Learning

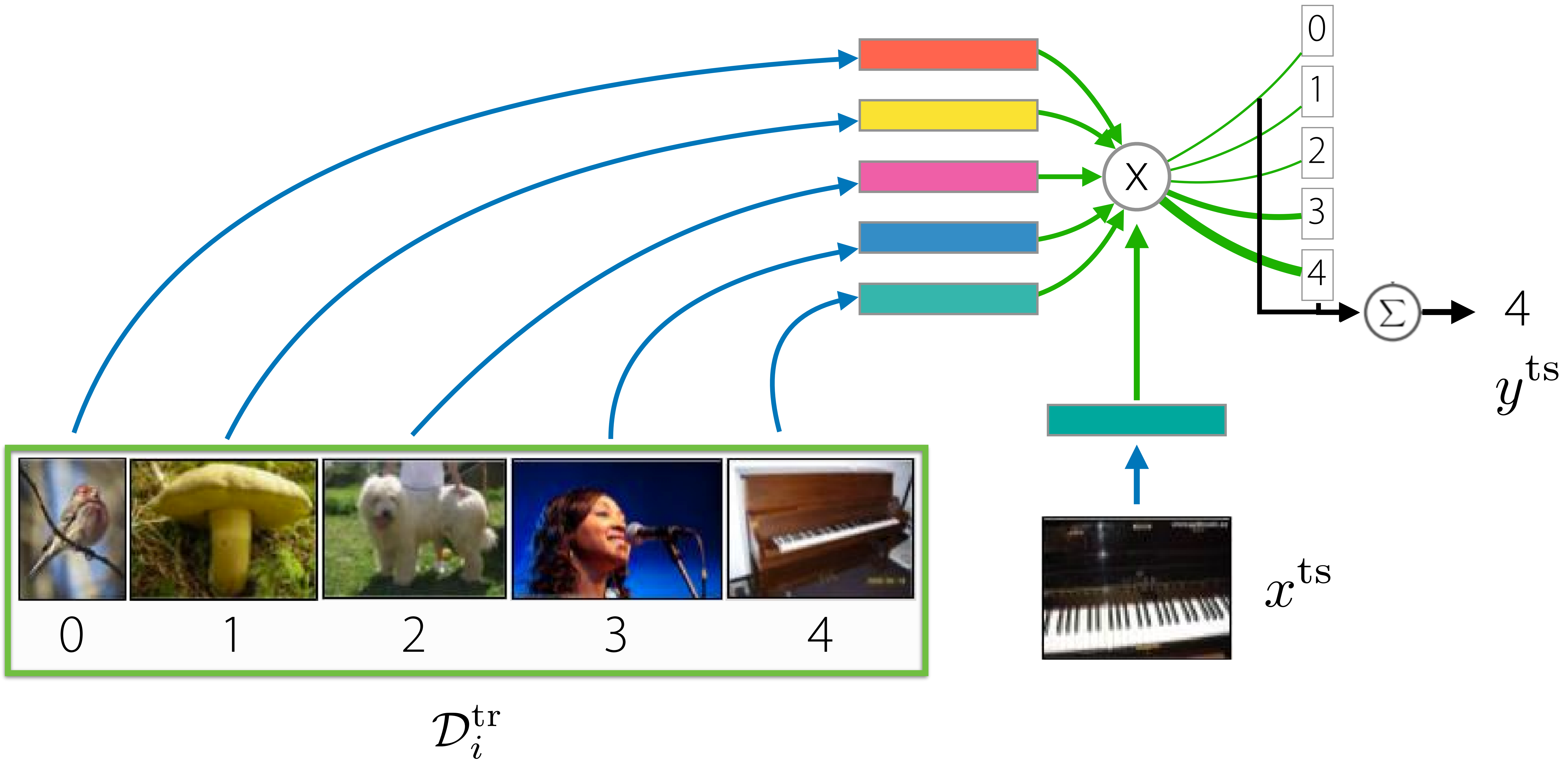
Key idea: embed optimization inside the inner learning process



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

- typically requires **second-order optimization**

Recap: Non-Parametric Meta-Learning



Key idea: *non-parametric learner* with *parametric* embedding / distance

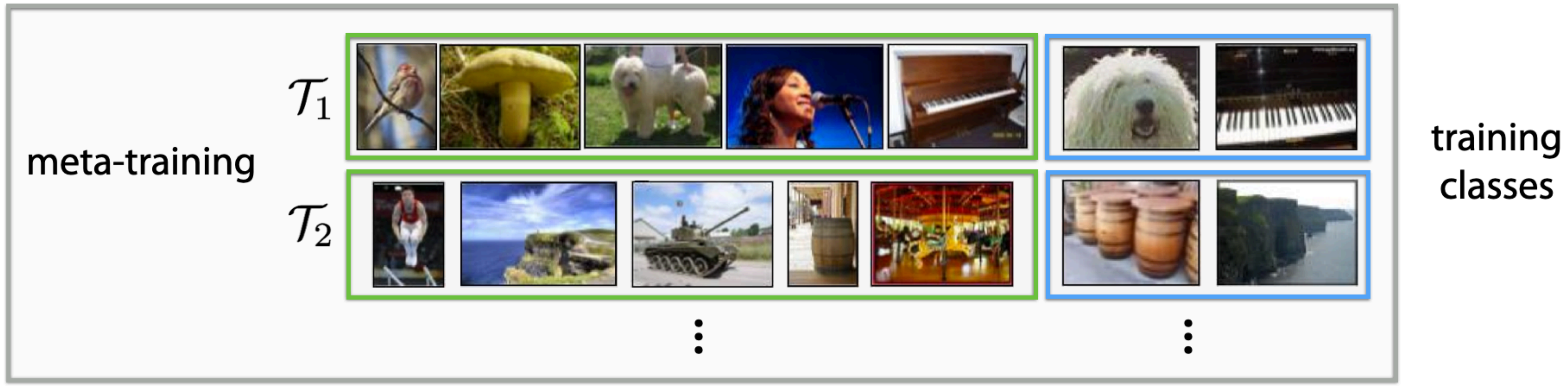
(e.g. kNN to examples/prototypes)

+ easy to optimize, computationally fast

- largely restricted to classification

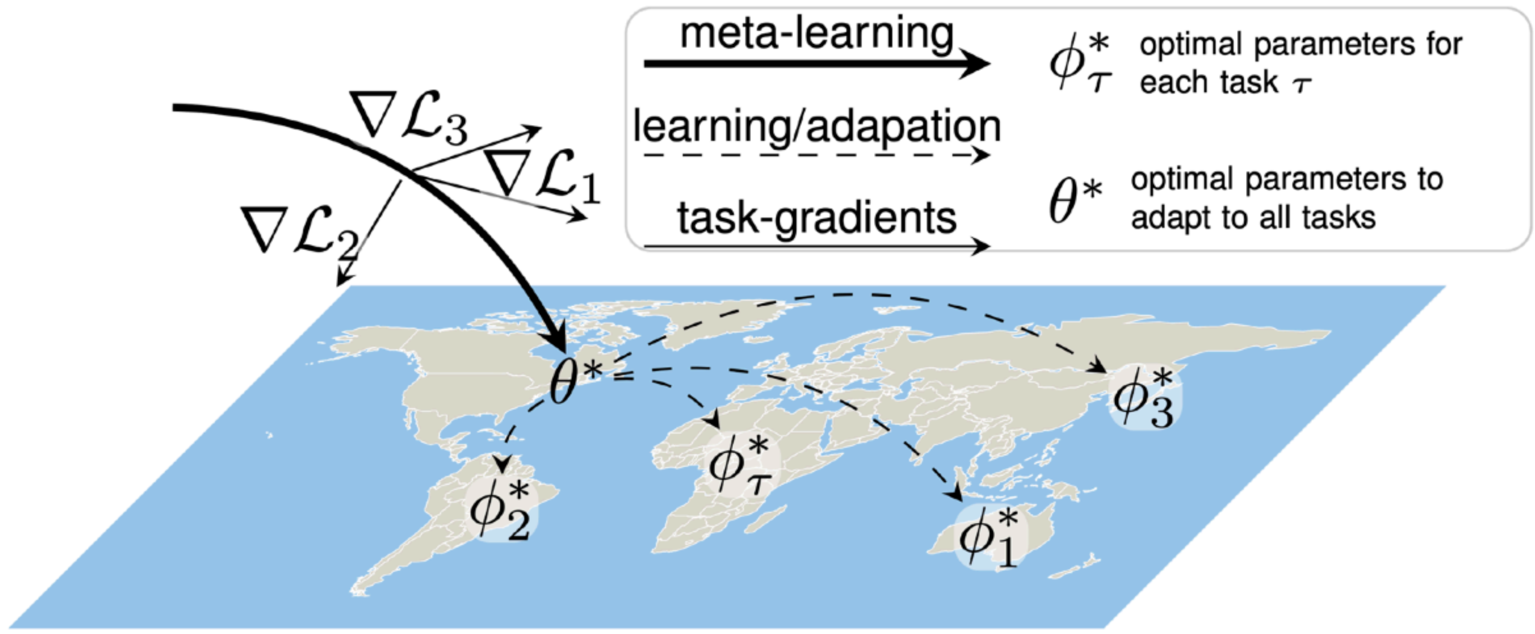
Supervised Task Construction

For N-way image classification



Use **labeled images** from prior classes

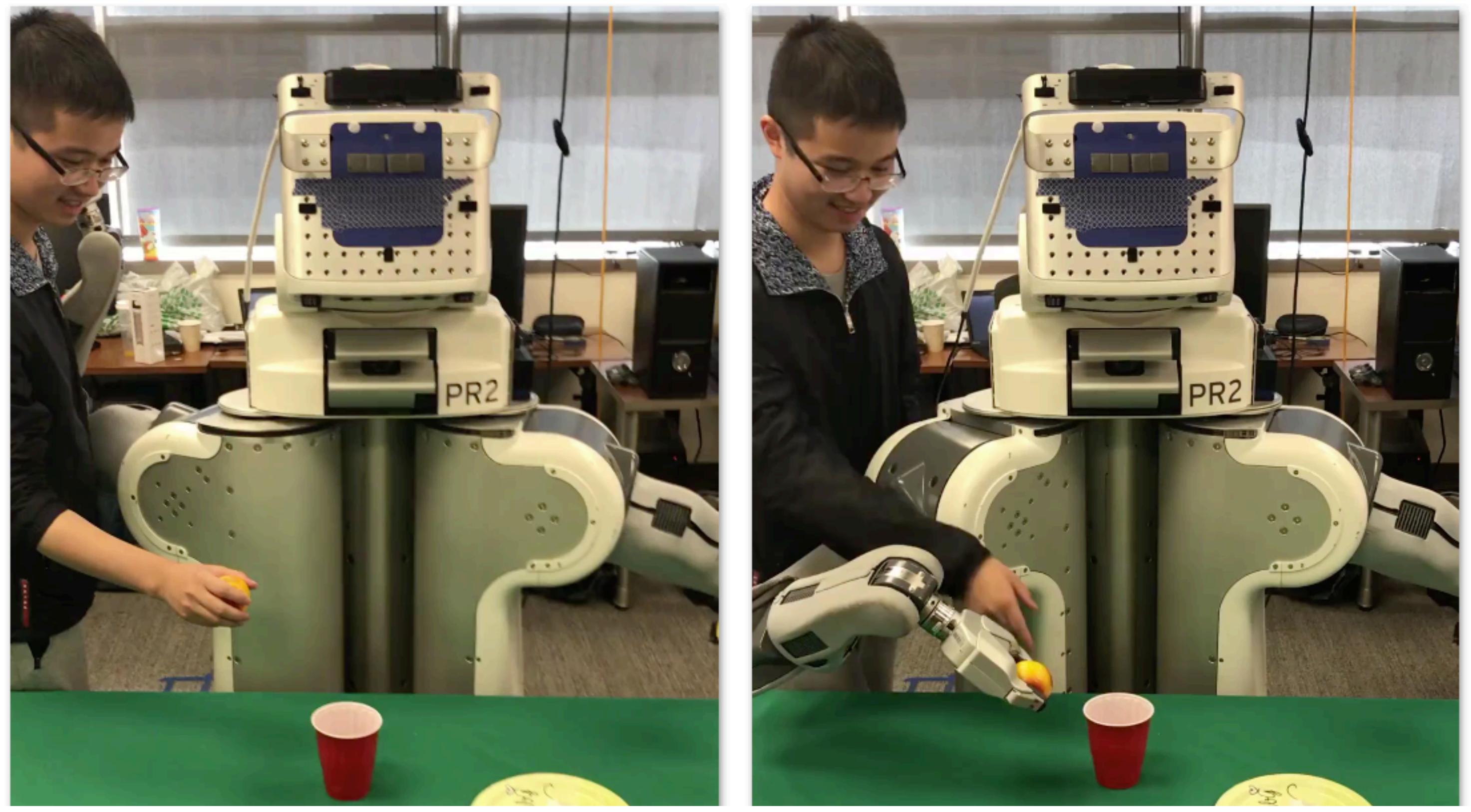
For adapting to regional differences



Rußwurm et al. Meta-Learning for Few-Shot Land Cover Classification. CVPR 2020 EarthVision Workshop

Use **labeled images** from prior regions

For few-shot imitation learning



Yu et al. One-Shot Imitation Learning from Observing Humans. RSS 2018

Use **demonstrations** for prior tasks

Plan for Today

Brief Recap of Meta-Learning & Task Construction

Memorization in Meta-Learning
- When it arises
- Potential solutions

Meta-Learning without Tasks Provided
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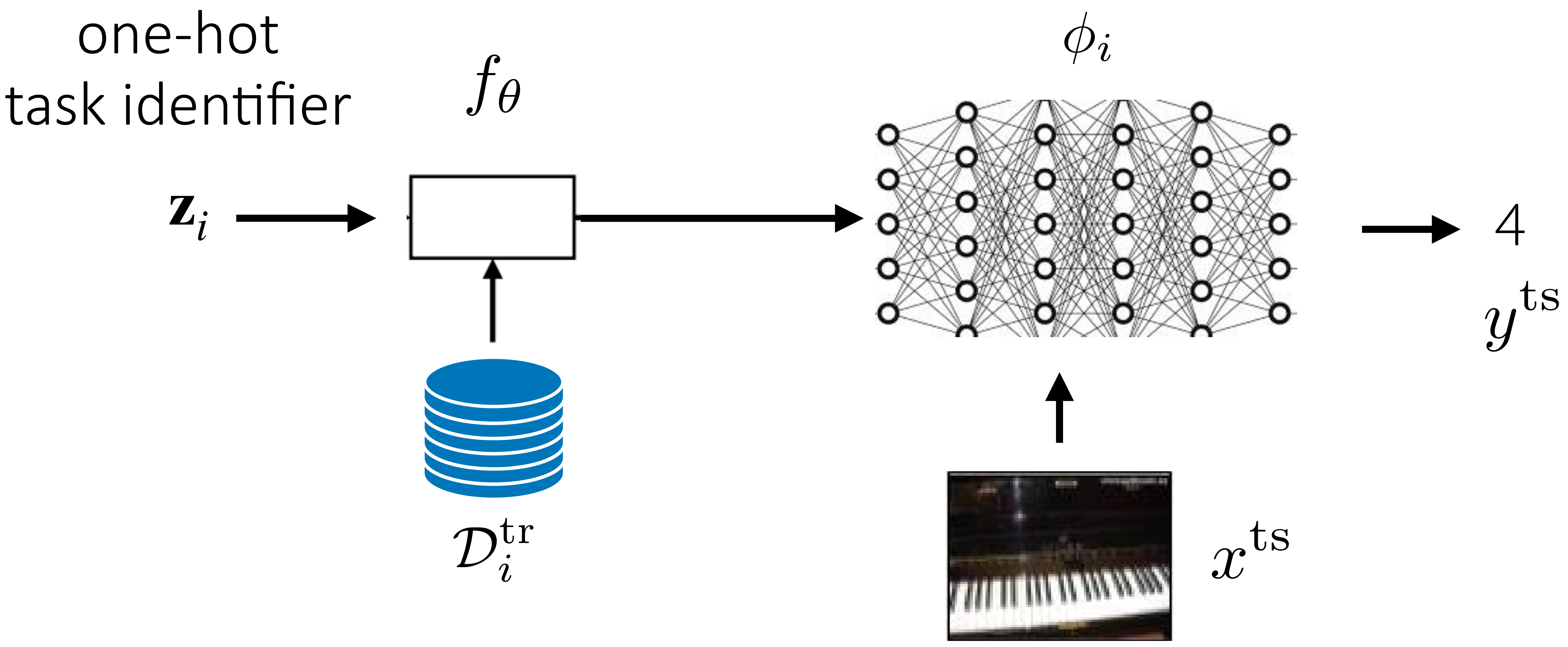
Thought Exercise #1



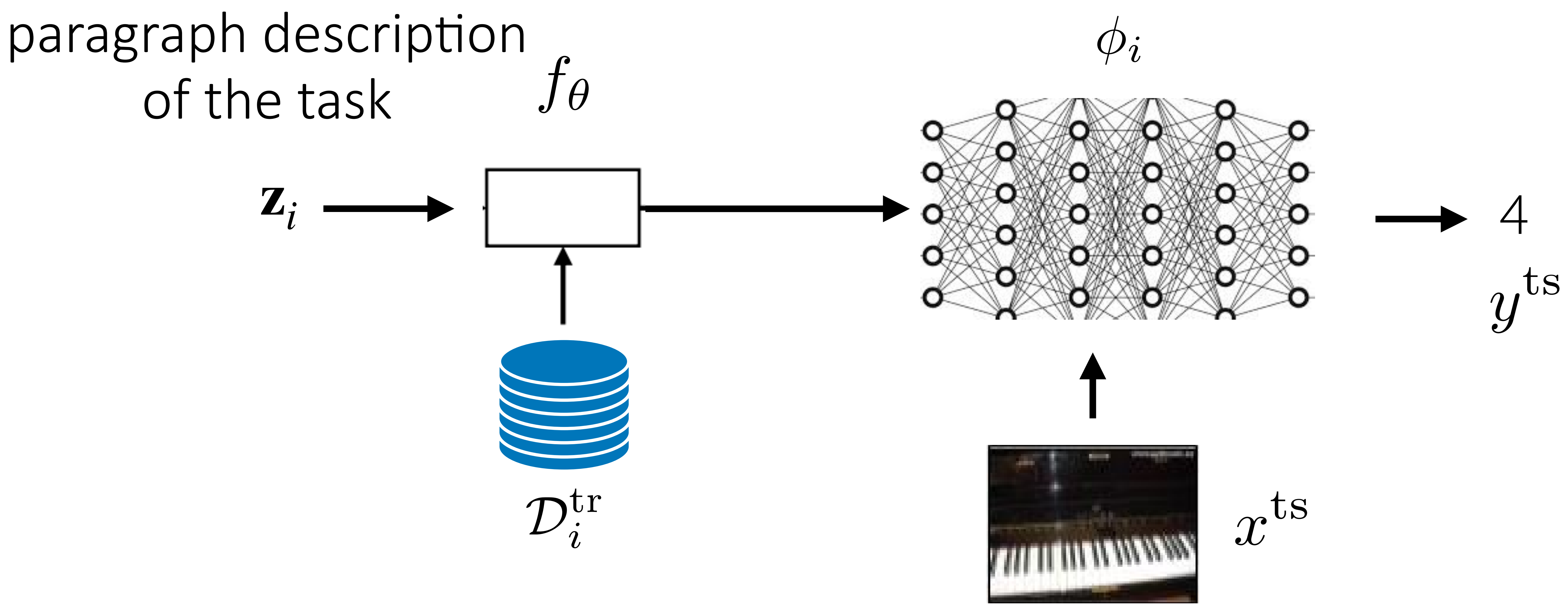
Question: What happens during <u>meta-training</u> if you pass in D_i^{tr} ***and*** the task identifier?

If it is difficult to learn from the data, the model will learn rely on $\mathbf{z}_i$.

Question: What happens at <u>meta-test time</u> if you pass in D_j^{tr} ***and*** the task identifier for a <u>new task</u>?

It won't generalize to the new task.

Thought Exercise #2



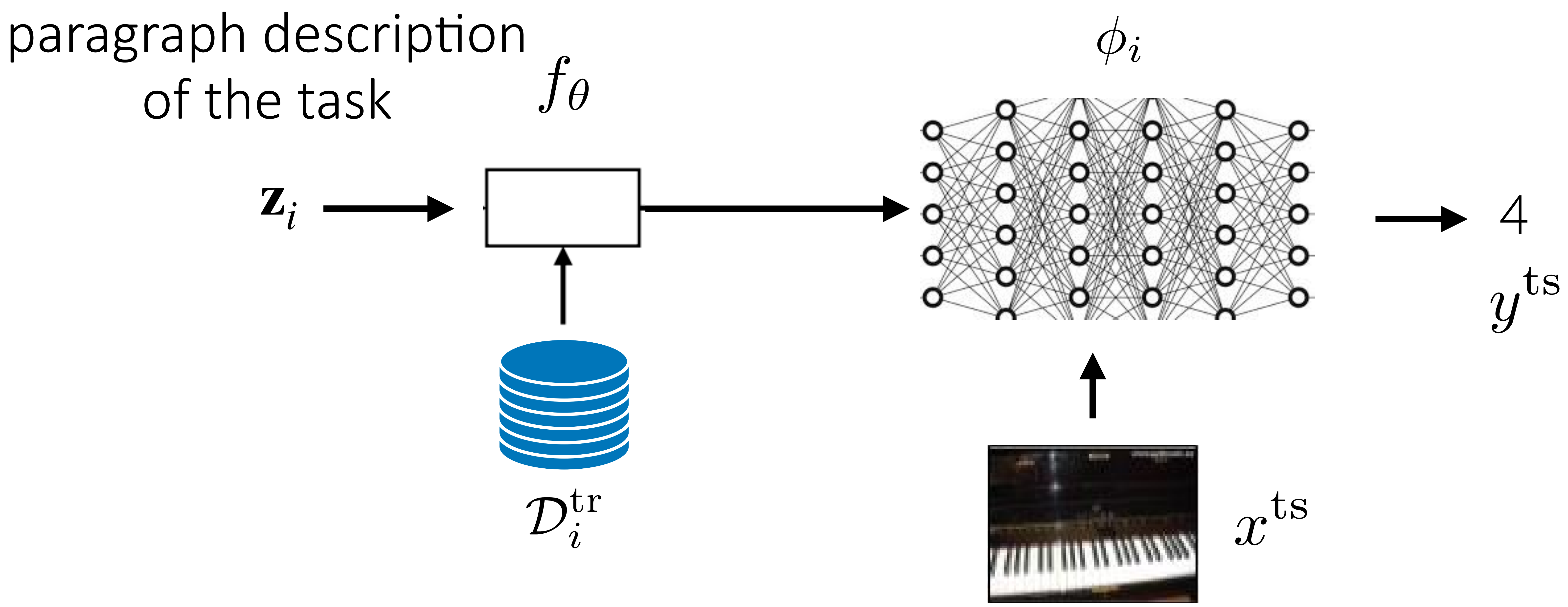
Question: What happens during meta-training if you pass in D_i^{tr} ***and*** the task identifier?

It depends on whether using the **description** or the **data** is simpler.

Question: What happens at meta-test time if you pass in D_j^{tr} ***and*** the task identifier for a new task?

It depends on what it learns to use during meta-training.

Thought Exercise #2



Question: What happe … ***and*** the task identifier?

It depends o … a is simpler.

Key problem: Model can minimize meta-training loss without looking at D_i^{tr}

Question: What happens at <u>meta-test time</u> if you pass in D_j^{tr} ***and*** the task identifier for a <u>new task</u>?

It depends on what it learns to use during meta-training.

How we construct tasks for meta-learning.

Randomly assign class labels to image classes for each task —> Tasks are *mutually exclusive*.

Algorithms **must** use training data to infer label ordering.

Thought Exercise #3: What if label assignment is consistent across tasks?

Tasks are **non-mutually exclusive**: a single function can solve all tasks.

The network can simply learn to classify inputs, irrespective of $\mathscr{D}_{\mathrm{tr}}$

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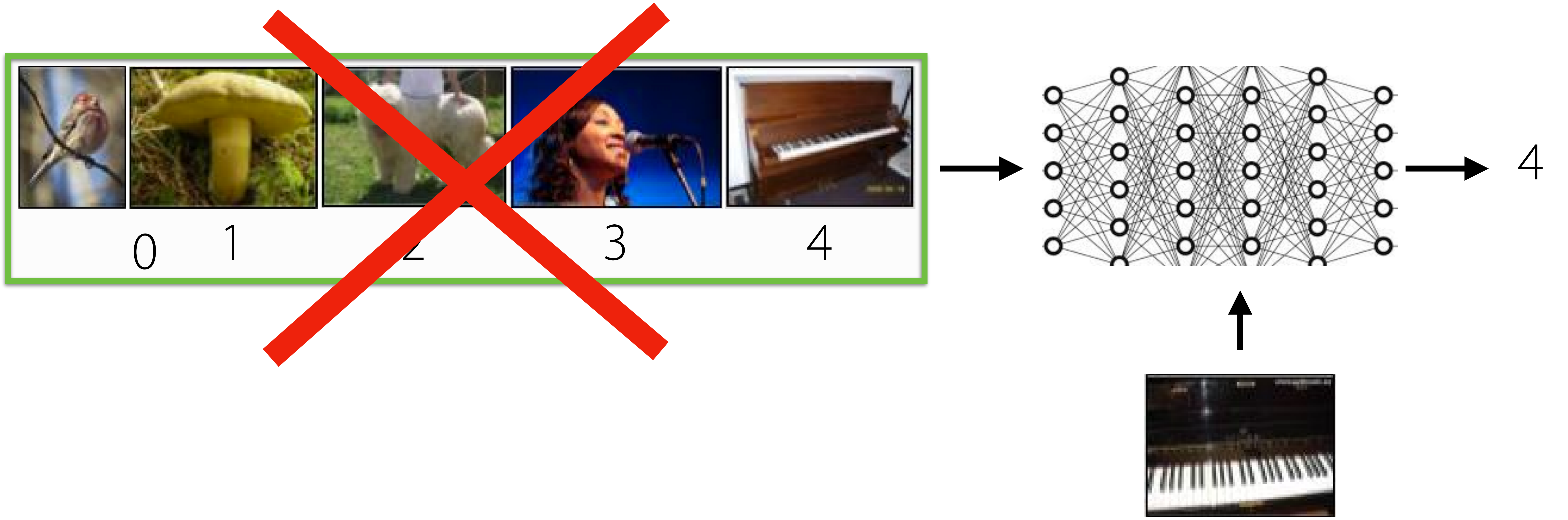
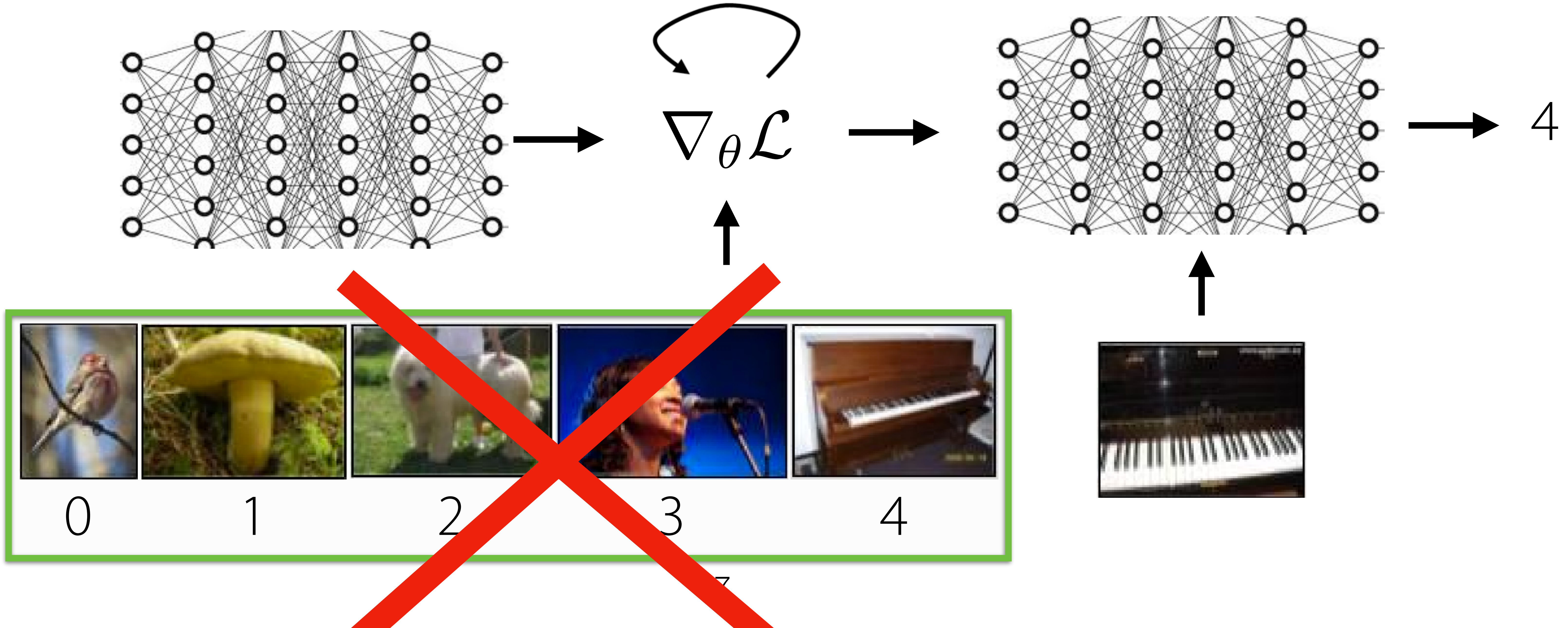
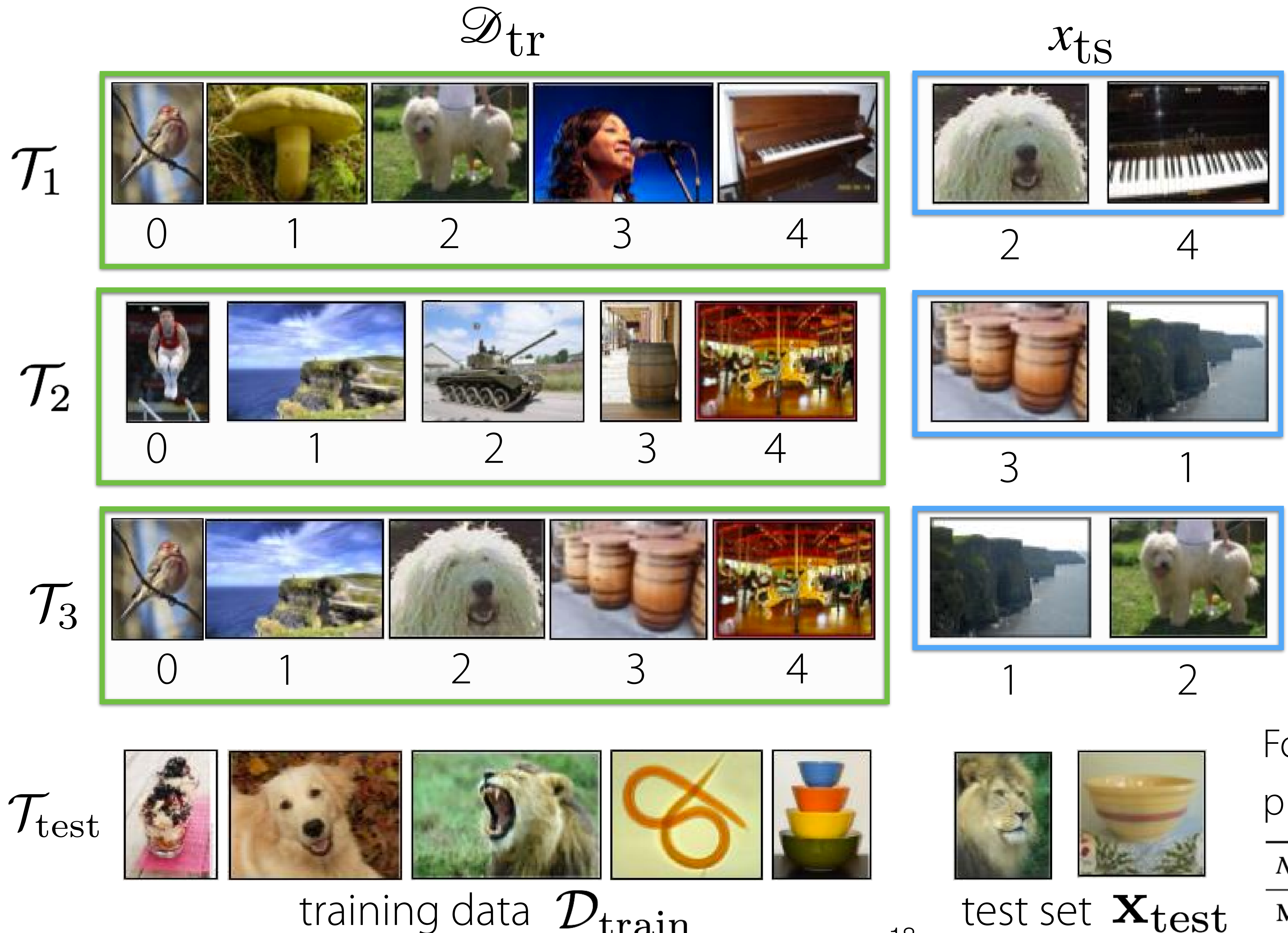




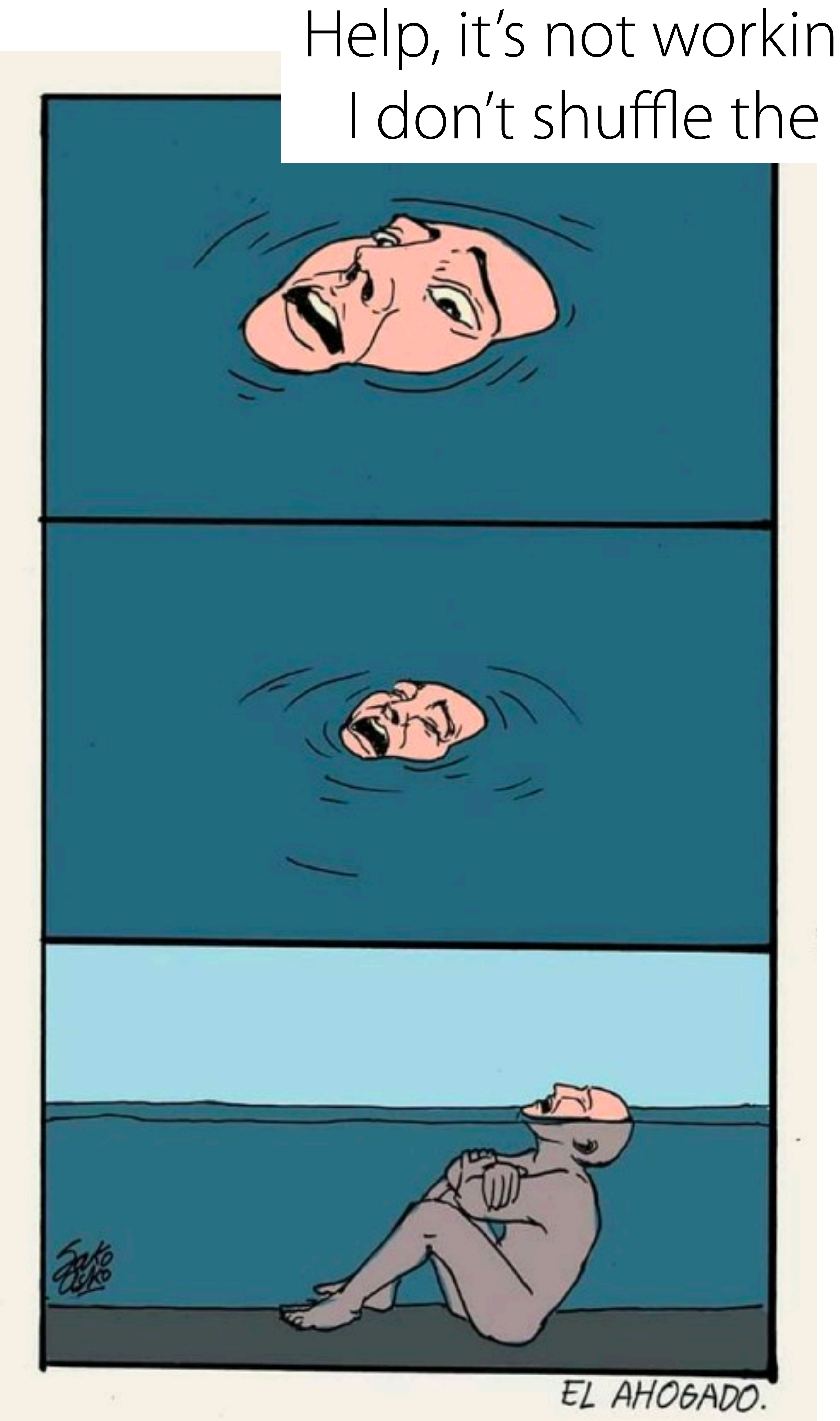
What if label order is consistent?



For new image classes: can't make predictions w/o $\mathcal{D}_{\text{tr}}$

NME Omniglot	20-way 1-shot	20-way 5-shot
MAML	7.8 (0.2)%	50.7 (22.9)%

Is this a problem?

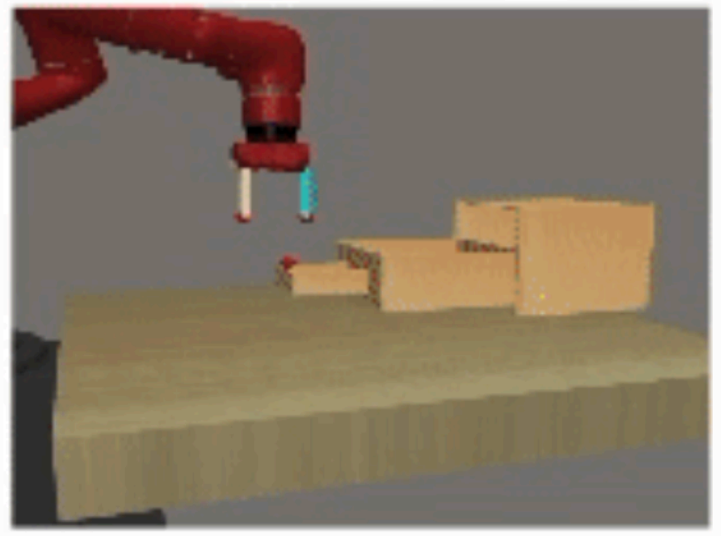


- **No**: for image classification, just shuffle labels*
- **No**, if we see the same image classes as training (no need to adapt at meta-test time)
- But, ***yes***, if we want to be able to adapt with data for new tasks.

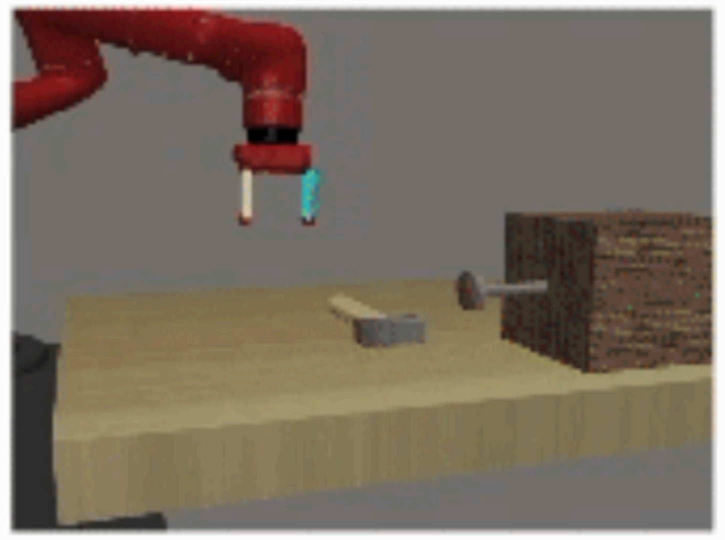
Another example

meta-training

"close drawer"

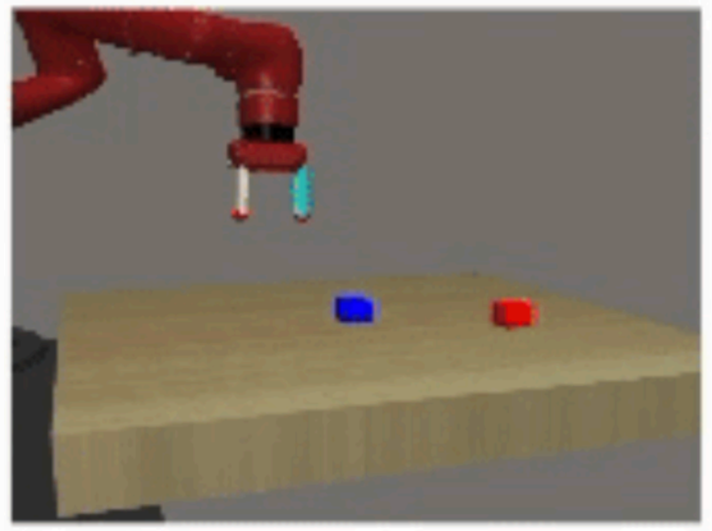
$\mathcal{T}_1$ 

"hammer"

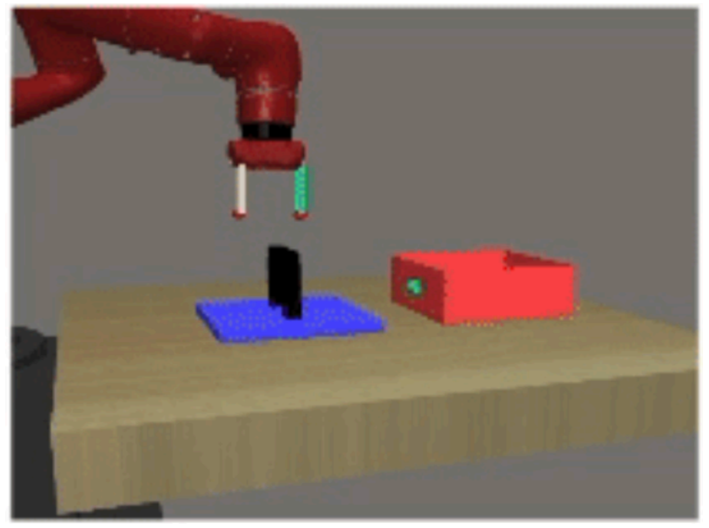
$\mathcal{T}_2$ 

...

"stack"

$\mathcal{T}_{50}$ 

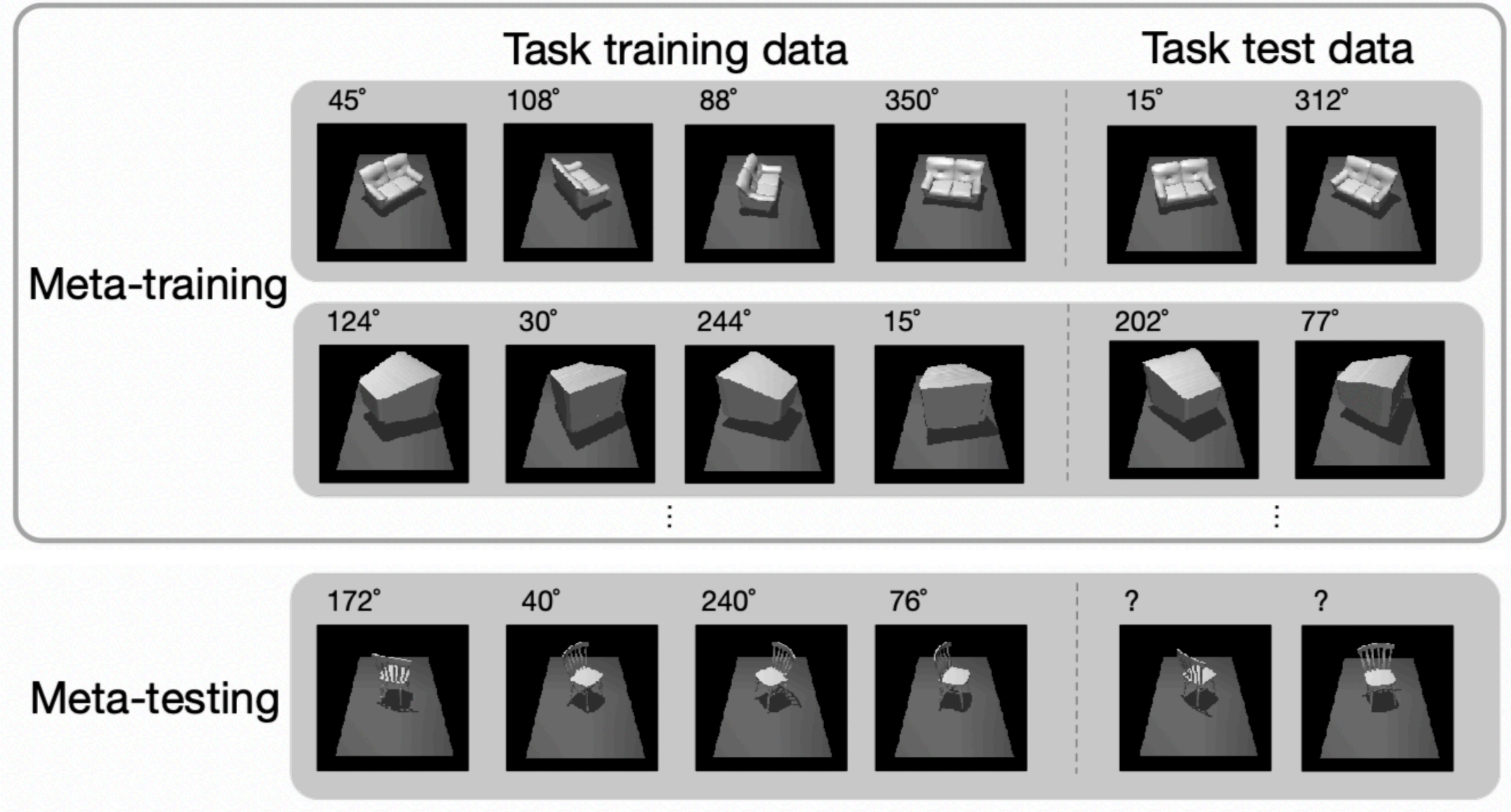
"close box"

$\mathcal{T}_{\text{test}}$ 

If you tell the robot the task goal, the robot can **ignore** the trials.

T Yu, D Quillen, Z He, R Julian, K Hausman, C Finn, S Levine. ***Meta-World***. CoRL '19

Another example



Model can memorize the canonical orientations of the training objects.

Yin, Tucker, Yuan, Levine, Finn. **Meta-Learning without Memorization**. ICLR '19

Can we do something about it?

If tasks *mutually exclusive***:** single function cannot solve all tasks

(i.e. due to label shuffling, hiding information)

If tasks are *non-mutually exclusive***:** single function can solve all tasks

multiple solutions to the meta-learning problem

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

One solution: memorize canonical pose info in $\boldsymbol{\theta}$ & ignore $\mathscr{D}_i^{\mathrm{tr}}$

Another solution: carry no info about canonical pose in $\boldsymbol{\theta}$, acquire from $\mathscr{D}_i^{\mathrm{tr}}$

An entire spectrum of solutions based on how **information** flows.

Suggests a potential approach: control information flow.

Yin, Tucker, Yuan, Levine, Finn. **Meta-Learning without Memorization**. ICLR'19

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An entire spectrum of solutions based on how **information** flows.

Meta-regularization one option: $\max I(\hat{\mathbf{y}}_{\mathrm{ts}}, \mathscr{D}_{\mathrm{tr}} \mid \mathbf{x}_{\mathrm{ts}})$

minimize meta-training loss + information in $\boldsymbol{\theta}$

$$\mathscr{L}(\theta, \mathscr{D}_{meta-train}) + \beta D_{KL}(q(\theta; \theta_\mu, \theta_\sigma) \| p(\theta))$$

Places precedence on using information from $\mathscr{D}_{\mathrm{tr}}$ over storing info in $\boldsymbol{\theta}$.

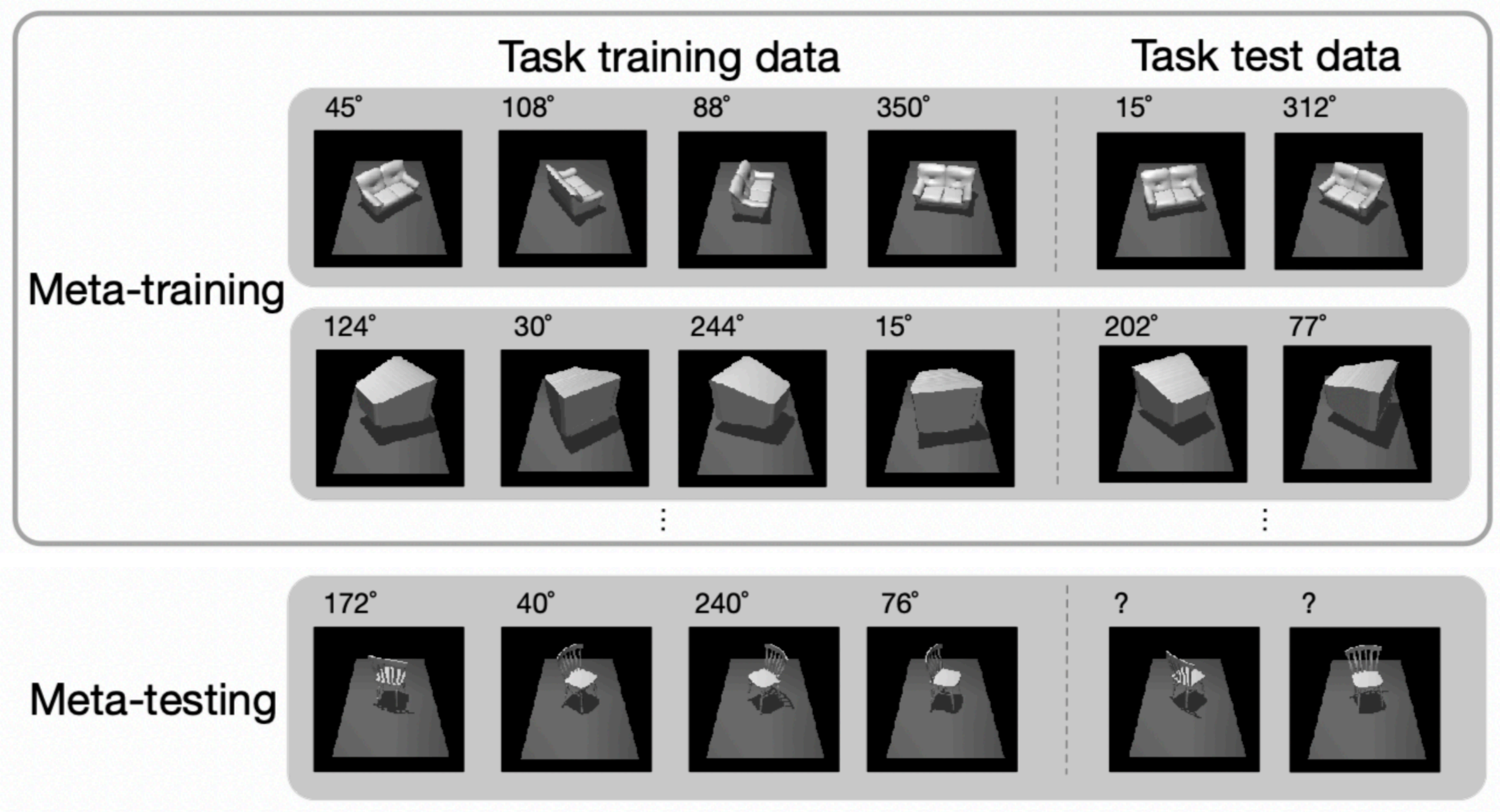
Can combine with your favorite meta-learning algorithm.

Yin, Tucker, Yuan, Levine, Finn. **Meta-Learning without Memorization**. ICLR'19

Omniglot without label shuffling: "non-mutually-exclusive" Omniglot

NME Omniglot	20-way 1-shot	20-way 5-shot
MAML	7.8 (0.2)%	50.7 (22.9)%
TAML	9.6 (2.3)%	67.9 (2.3)%
MR-MAML (W) (ours)	**83.3 (0.8)%**	**94.1 (0.1)%**

On **pose prediction** task:



Method	MAML	MR-MAML(W) (ours)	CNP	MR-CNP(W) (ours)
MSE	5.39 (1.31)	**2.26 (0.09)**	8.48 (0.12)	2.89 (0.18)

(and it's not just as simple as standard regularization)

CNP	CNP + Weight Decay	CNP + BbB	MR-CNP (W) (ours)
8.48 (0.12)	6.86 (0.27)	7.73 (0.82)	**2.89 (0.18)**

TAML: Jamal & Qi. **Task-Agnostic Meta-Learning for Few-Shot Learning**. CVPR '19

Yin, Tucker, Yuan, Levine, Finn. **Meta-Learning without Memorization**. ICLR '19

Does meta-regularization lead to better generalization?

Let $P(\theta)$ be an arbitrary distribution over θ that doesn't depend on the meta-training data.

(e.g. $P(\theta) = \mathcal{N}(\theta; \mathbf{0}, \mathbf{I})$)

For MAML, with probability at least $1 - \delta$,

$$\underbrace{er(\theta_\mu, \theta_\sigma)}_{\text{generalization error}} \leq \underbrace{\frac{1}{n}\sum_{i=1}^{n} \hat{er}(\theta_\mu, \theta_\sigma, \mathcal{D}_i, \mathcal{D}_i^*)}_{\text{error on the meta-training set}} + \left(\sqrt{\frac{1}{2(K-1)}} + \sqrt{\frac{1}{2(n-1)}}\right)\sqrt{\underbrace{D_{KL}(\mathcal{N}(\theta; \theta_\mu, \theta_\sigma) \| P)}_{\text{meta-regularization}} + \log\frac{n(K+1)}{\delta}},$$

$\forall \theta_\mu, \theta_\sigma$

With a Taylor expansion of the RHS + a particular value of β —> *recover the MR MAML objective*.

Proof: draws heavily on Amit & Meier '18

Yin, Tucker, Yuan, Levine, Finn. **Meta-Learning without Memorization**. ICLR '19

Summary of Memorization Problem

meta-learning	**standard supervised learning**
meta overfitting	**standard overfitting**
memorize training functions f_i corresponding to tasks in your meta-training dataset	memorize training datapoints (x_i, y_i) in your training dataset
meta regularization	**standard regularization**
control information flow	regularize hypothesis class
regularizes description length of meta-parameters	(though not always for DNNs)

Plan for Today

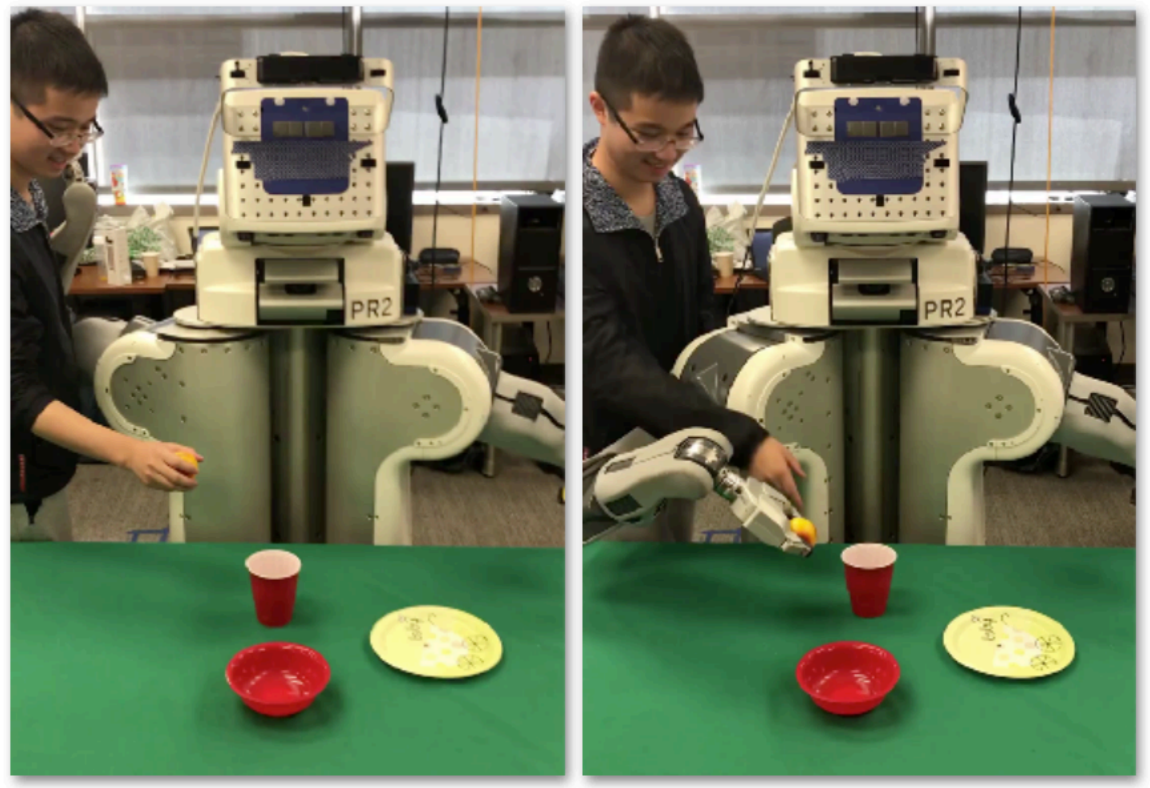
Brief Recap of Meta-Learning & Task Construction

Memorization in Meta-Learning
- When it arises
- Potential solutions

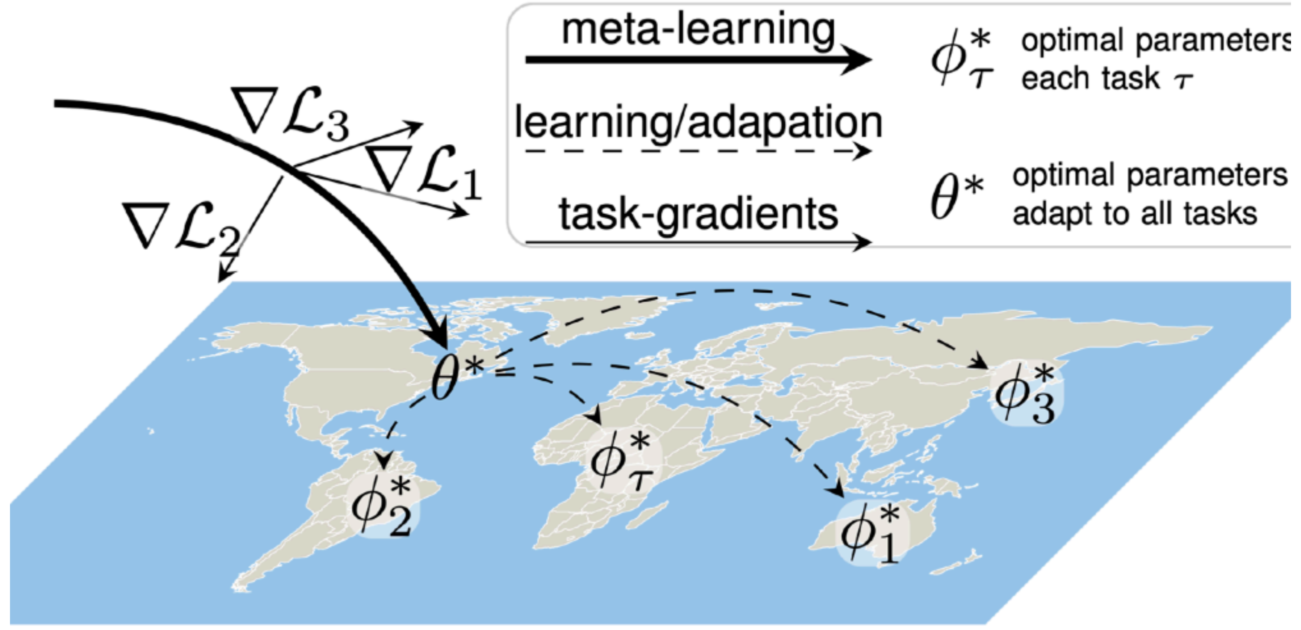
Meta-Learning without Tasks Provided
- Unsupervised Meta-Learning
- Semi-Supervised Meta-Learning

Where do tasks come from?

Requires tasks constructed from labeled data



Requires demos for many previous tasks



Rußwurm et al. Meta-Learning for Few-Shot Land Cover Classification. 2020

Requires labeled data from other regions

What if we only have unlabeled data? e.g., unlabeled images, unlabeled text

Last week: Pre-train representations & fine-tune

Today: Explicit meta-learning with unlabeled data.

A general recipe for unsupervised meta-learning

Given unlabeled dataset(s) → **Propose tasks** → **Run meta-learning**

Goal of unsupervised meta-learning methods:
Automatically construct tasks from unlabeled data

Question: What do you want the task set to look like?

1. diverse (more likely to cover test tasks)
2. structured (so that few-shot meta-learning is possible)

Next:

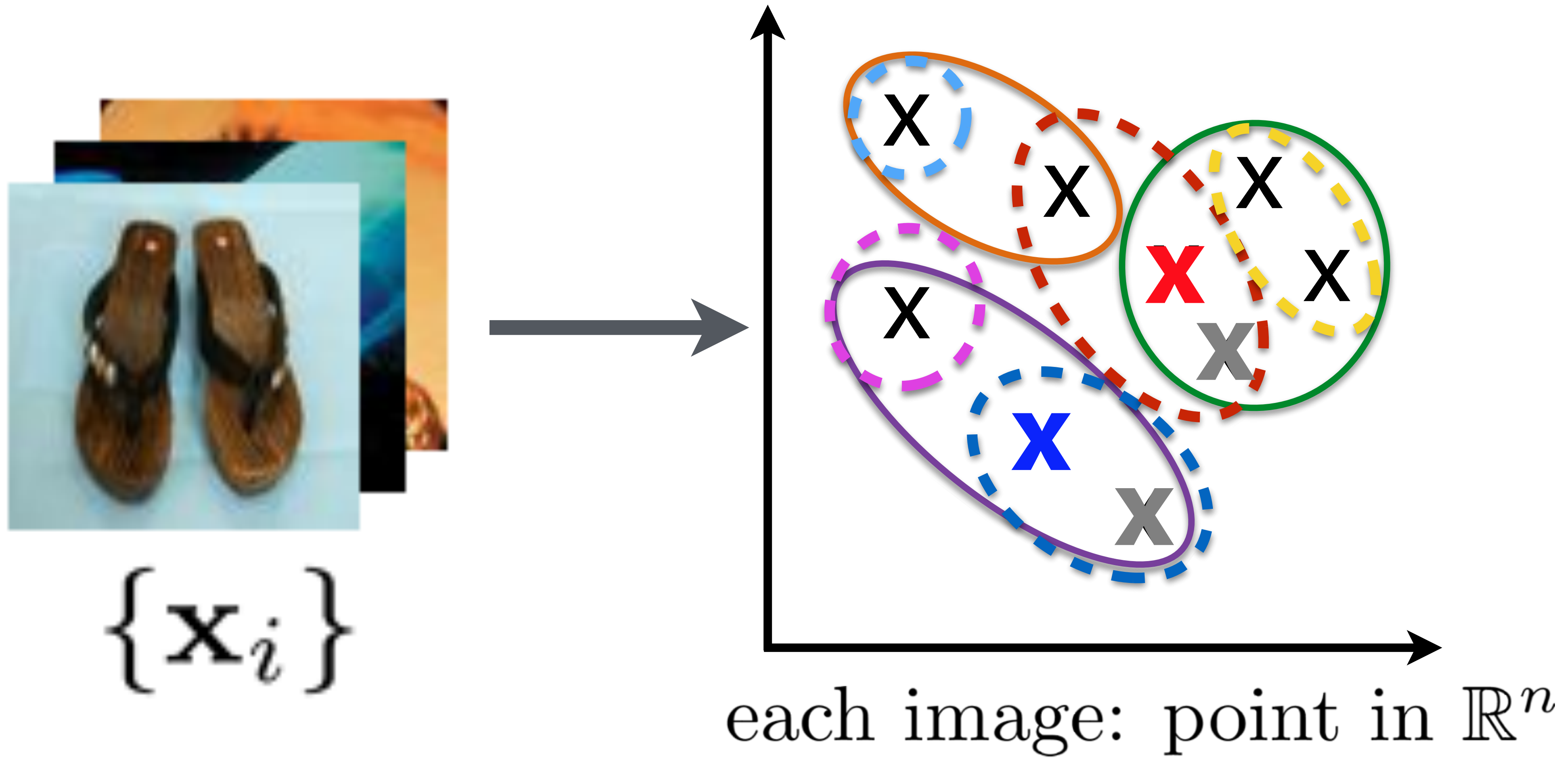
Task construction from unlabeled image data

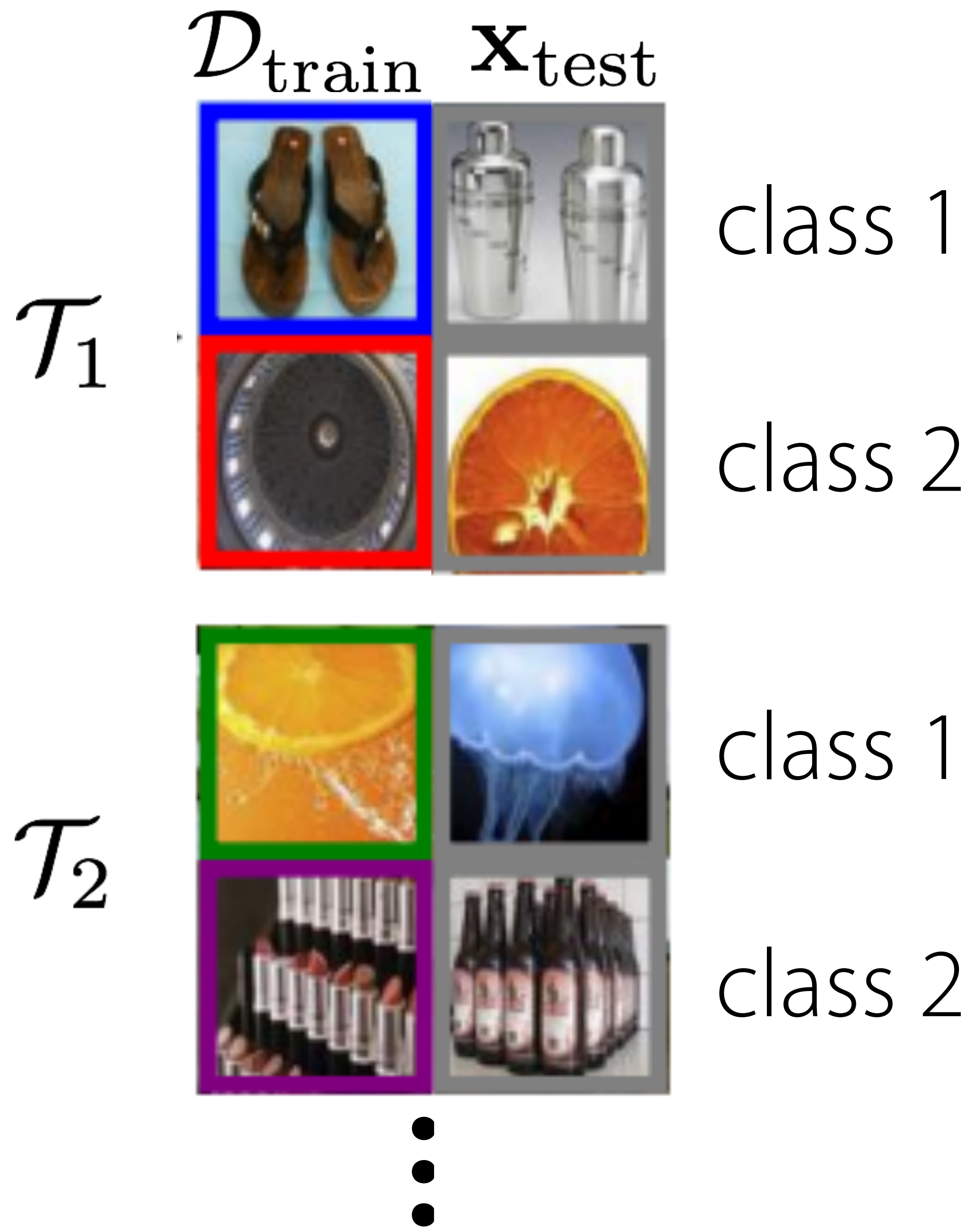
Task construction from unlabeled text data

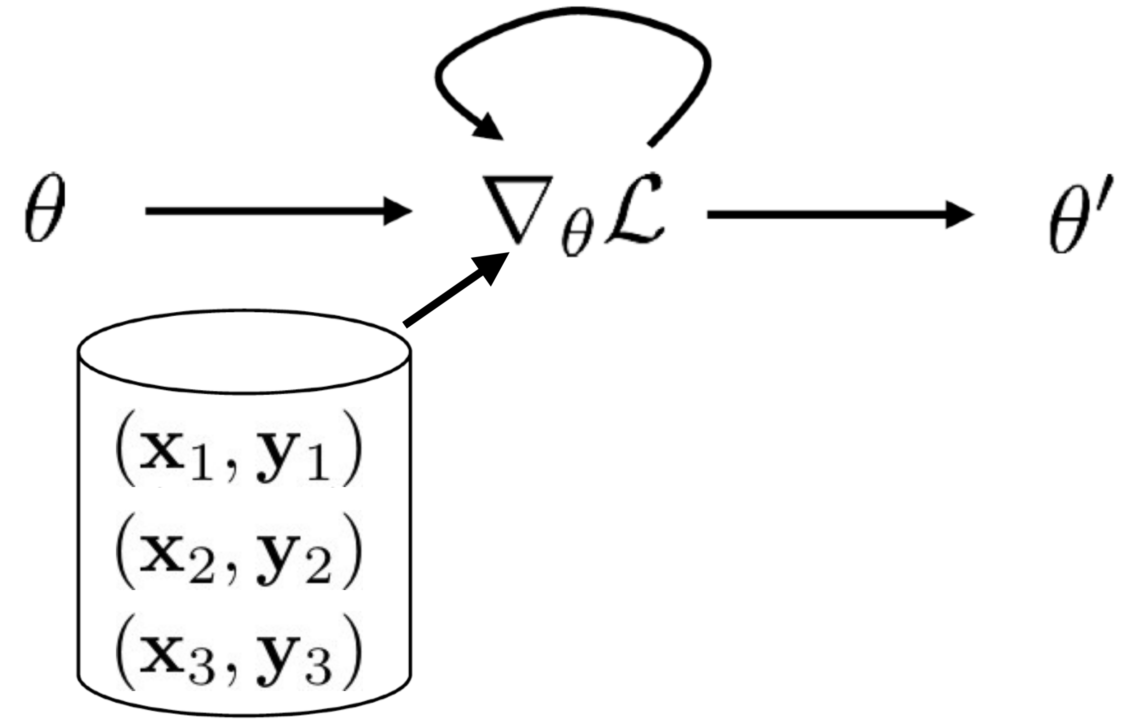
Can we meta-learn with only **unlabeled** images?

— — Task construction — —

Unsupervised learning (to get an embedding space) → **Propose cluster discrimination tasks** → **Run meta-learning**







Result: representation suitable for learning downstream tasks

Hsu, Levine, Finn. **Unsupervised Learning via Meta-Learning**. ICLR'19

Can we meta-learn with only **unlabeled** images?

Unsupervised learning
(to get an embedding space)

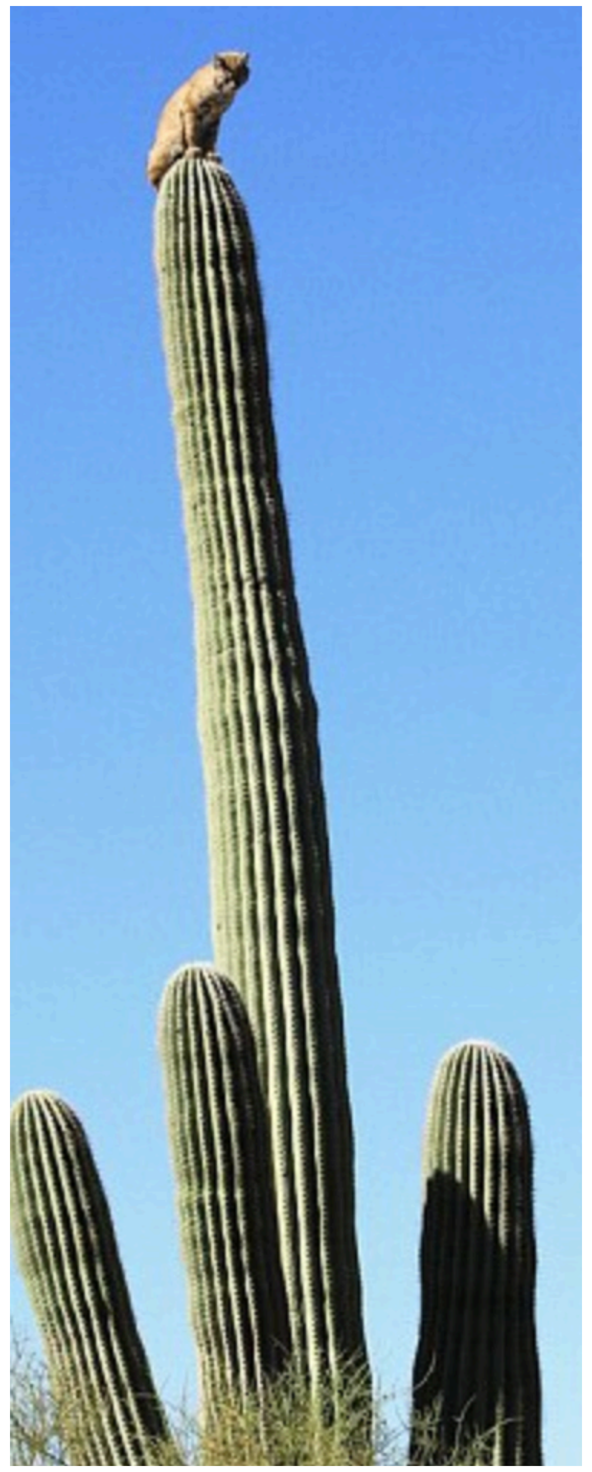
A few options:
BiGAN — Donahue et al. '17
DeepCluster — Caron et al. '18

→ **Propose cluster discrimination tasks**

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

→ **Run meta-learning**

MAML — Finn et al. '17
ProtoNets — Snell et al. '17



CACTUs MAML

miniImageNet 5-way 5-shot

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%**

Same story for:

- **4 different embedding methods**
- **4 datasets** (Omniglot, CelebA, miniImageNet, MNIST)
- **2 meta-learning methods** (*)
- Test tasks with **larger datasets**

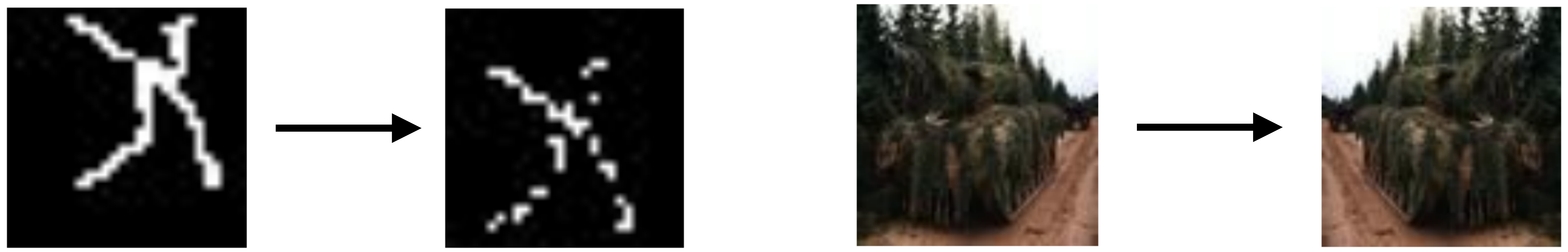
*ProtoNets underperforms in some cases.

Hsu, Levine, Finn. **Unsupervised Learning via Meta-Learning**. ICLR'19

Can we use **domain knowledge** when constructing tasks?

e.g. **image's label** often **won't change** when you:

- drop out some pixels
- translate the image
- reflect the image



Task construction:

For each task $\mathcal{T}_i$:

i. Randomly sample N images & assign labels $1, \ldots, N$

—> Store in $\mathcal{D}_i^{\mathrm{tr}}$

ii. For each datapoint in $\mathcal{D}_i^{\mathrm{tr}}$, augment image using domain knowledge

—> Store in $\mathcal{D}_i^{\mathrm{ts}}$

Khodadadeh, Bölöni, Shah. **Unsupervised Meta-Learning for Few-Shot Image Classification**. NeurIPS '19

Can we use **domain knowledge** when constructing tasks?

For each task $\mathscr{T}_i$:

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ii. For each datapoint in $\mathscr{D}_i^{\text{tr}}$, augment image using domain knowledge —> Store in $\mathscr{D}_i^{\text{ts}}$

How to augment in practice?

Omniglot: translation & random pixel dropout **MiniImagenet:** AutoAugment* (translation, rotation, shear)

		Omniglot				Mini-Imagenet			
Algorithm (N, K)	**Clustering**	**(5,1)**	**(5,5)**	**(20,1)**	**(20,5)**	**(5,1)**	**(5,5)**	**(5,20)**	**(5,50)**
Training from scratch	N/A	52.50	74.78	24.91	47.62	27.59	38.48	51.53	59.63
linear classifier	ACAI / DC	61.08	81.82	43.20	66.33	29.44	39.79	56.19	65.28
MLP with dropout	ACAI / DC	51.95	77.20	30.65	58.62	29.03	39.67	52.71	60.95
cluster matching	ACAI / DC	54.94	71.09	32.19	45.93	22.20	23.50	24.97	26.87
CACTUs-MAML	ACAI / DC	68.84	87.78	48.09	73.36	39.90	**53.97**	**63.84**	**69.64**
CACTUs-ProtoNets	ACAI / DC	68.12	83.58	47.75	66.27	39.18	53.36	61.54	63.55
UMTRA (ours)	N/A	**83.80**	**95.43**	**74.25**	**92.12**	**39.93**	50.73	61.11	67.15
MAML (Supervised)	N/A	94.46	98.83	84.60	96.29	46.81	62.13	71.03	75.54
ProtoNets (Supervised)	N/A	98.35	99.58	95.31	98.81	46.56	62.29	70.05	72.04

- outstanding Omniglot performance

  (where we have good domain knowledge!)

- MiniImageNet: slightly underperforms CACTUs

Khodadadeh, Bölöni, Shah. **Unsupervised Meta-Learning for Few-Shot Image Classification.** NeurIPS '19

* Cubuk et al. 2018

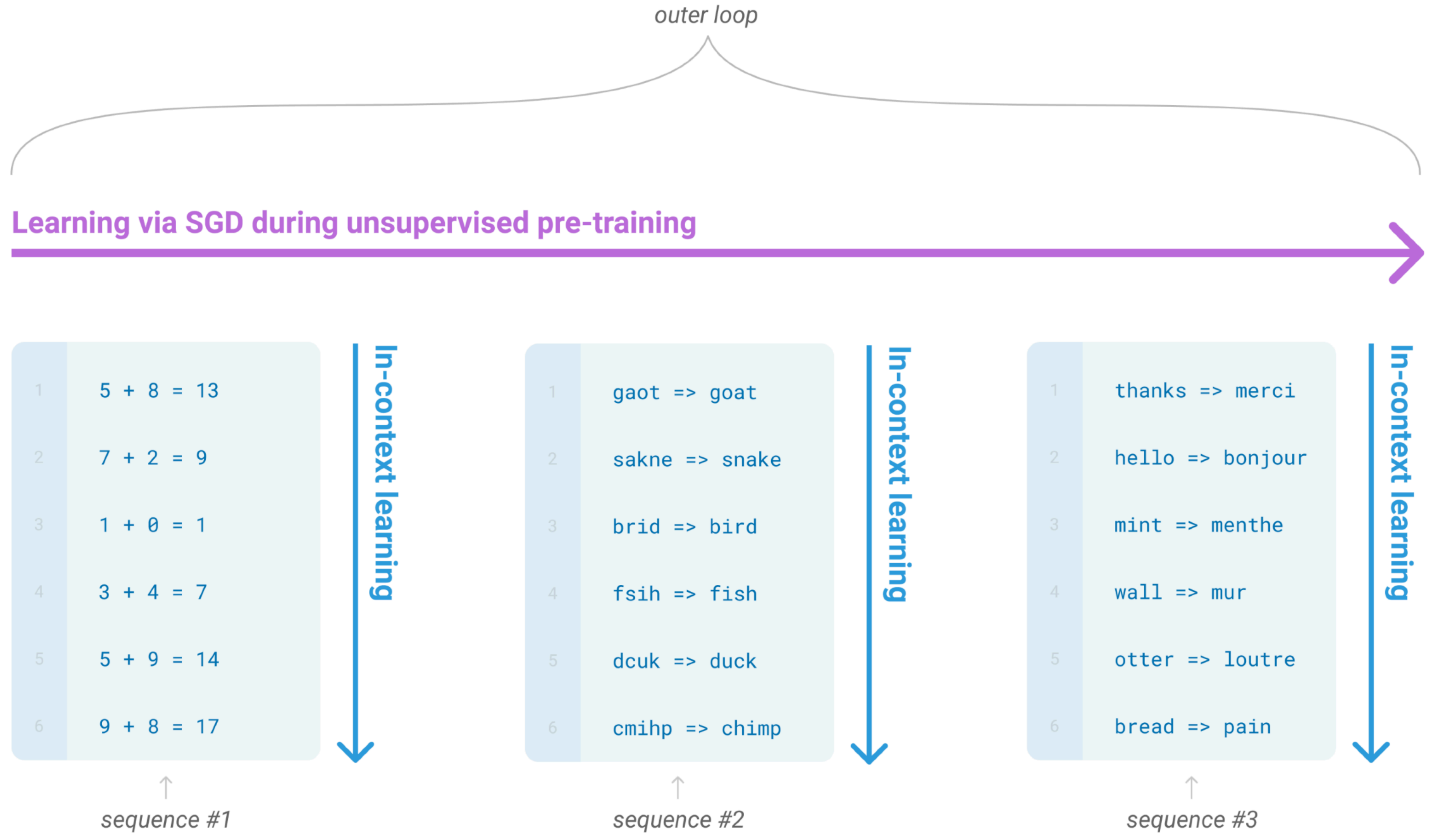
Can we meta-learn with only **unlabeled** text?

Option A: Formulate it as a language modeling problem.

Recall: GPT-3

$\mathscr{D}_i^{\mathrm{tr}}$: sequence of characters

$\mathscr{D}_i^{\mathrm{ts}}$: following sequence of characters



simple math problems | spelling correction | translating between languages

When might we not use this option?

- harder to combine w/ **optimization-based meta-learning**
- harder to apply to **classification** tasks (e.g. sentiment, political bias, etc)

Brown, Mann, Ryder, Subbiah et al. **Language Models are Few-Shot Learners**. arXiv '20

Can we meta-learn with only **unlabeled** text?

Option B: Construct tasks by masking out words

Task: Classify the masked word.

For each task $\mathscr{T}_i$:

i. Sample subset of N unique words & assign unique ID.

{**Democratic**, **Capital**} **1** **2**

ii. Sample $K + Q$ sentences with that word, *masking the word out*

iii. Construct $\mathscr{D}_i^{\text{tr}}$ and $\mathscr{D}_i^{\text{ts}}$ with masked sentences & corresponding word IDs

$\mathscr{D}_i^{\text{tr}}$

Support set

Sentence	Class
A member of the [m] Party, he was the first African American to be elected to the presidency.	1
The [m] Party is one of the two major contemporary political parties in the United States, along with its rival, the Republican Party.	1
Honolulu is the [m] and largest city of the U.S. state of Hawaii.	2
Washington, D.C., formally the District of Columbia and commonly referred to as Washington or D.C., is the [m] of the United States.	2

$\mathscr{D}_i^{\text{ts}}$

Query: New Delhi is an urban district of Delhi which serves as the [m] of India

Correct Prediction: **2**

Bansal, Jha, Munkhdalai, McCallum. **Self-Supervised Meta-Learning for Few-Shot Natural Language Classification Tasks**. EMNLP '20

entirely unsupervised pre-training | supervised or semi-supervised pre-training

Task	N	k	BERT	SMLMT	MT-BERT$_{softmax}$	MT-BERT	LEOPARD	Hybrid-SMLMT
CoNLL	4	4	50.44 ± 08.57	46.81 ± 4.77	52.28 ± 4.06	55.63 ± 4.99	54.16 ± 6.32	**57.60** ± 7.11
		8	50.06 ± 11.30	61.72 ± 3.11	65.34 ± 7.12	58.32 ± 3.77	67.38 ± 4.33	**70.20** ± 3.00
		16	74.47 ± 03.10	75.82 ± 4.04	71.67 ± 3.03	71.29 ± 3.30	76.37 ± 3.08	**80.61** ± 2.77
		32	83.27 ± 02.14	84.01 ± 1.73	73.09 ± 2.42	79.94 ± 2.45	83.61 ± 2.40	**85.51** ± 1.73
MITR	8	4	49.37 ± 4.28	46.23 ± 3.90	45.52 ± 5.90	50.49 ± 4.40	49.84 ± 3.31	**52.29** ± 4.32
		8	49.38 ± 7.76	61.15 ± 1.91	58.19 ± 2.65	58.01 ± 3.54	62.99 ± 3.28	**65.21** ± 2.32
		16	69.24 ± 3.68	69.22 ± 2.78	66.09 ± 2.24	66.16 ± 3.46	70.44 ± 2.89	**73.37** ± 1.88
		32	78.81 ± 1.95	78.82 ± 1.30	69.35 ± 0.98	76.39 ± 1.17	78.37 ± 1.97	**79.96** ± 1.48
Airline	3	4	42.76 ± 13.50	42.83 ± 6.12	43.73 ± 7.86	46.29 ± 12.26	54.95 ± 11.81	**56.46** ± 10.67
		8	38.00 ± 17.06	51.48 ± 7.35	52.39 ± 3.97	49.81 ± 10.86	61.44 ± 03.90	**63.05** ± 8.25
		16	58.01 ± 08.23	58.42 ± 3.44	58.79 ± 2.97	57.25 ± 09.90	62.15 ± 05.56	**69.33** ± 2.24
		32	63.70 ± 4.40	65.33 ± 3.83	61.06 ± 3.89	62.49 ± 4.48	67.44 ± 01.22	**71.21** ± 3.28
Disaster	2	4	55.73 ± 10.29	**62.26** ± 9.16	52.87 ± 6.16	50.61 ± 8.33	51.45 ± 4.25	55.26 ± 8.32
		8	56.31 ± 09.57	**67.89** ± 6.83	56.08 ± 7.48	54.93 ± 7.88	55.96 ± 3.58	63.62 ± 6.84
		16	64.52 ± 08.93	**72.86** ± 1.70	65.83 ± 4.19	60.70 ± 6.05	61.32 ± 2.83	70.56 ± 2.23
		32	73.60 ± 01.78	**73.69** ± 2.32	67.13 ± 3.11	72.52 ± 2.28	63.77 ± 2.34	71.80 ± 1.85
Emotion	13	4	09.20 ± 3.22	09.84 ± 1.09	09.41 ± 2.10	09.84 ± 2.14	11.71 ± 2.16	**11.90** ± 1.74
		8	08.21 ± 2.12	11.02 ± 1.02	11.61 ± 2.34	11.21 ± 2.11	12.90 ± 1.63	**13.26** ± 1.01
		16	13.43 ± 2.51	12.05 ± 1.18	13.82 ± 2.02	12.75 ± 2.04	13.38 ± 2.20	**15.17** ± 0.89
		32	16.66 ± 1.24	14.28 ± 1.11	13.81 ± 1.62	**16.88** ± 1.80	14.81 ± 2.01	16.08 ± 1.16
Political Bias	2	4	54.57 ± 5.02	57.72 ± 5.72	54.32 ± 3.90	54.66 ± 3.74	60.49 ± 6.66	**61.17** ± 4.91
		8	56.15 ± 3.75	63.02 ± 4.62	57.36 ± 4.32	54.79 ± 4.19	61.74 ± 6.73	**64.10** ± 4.03
		16	60.96 ± 4.25	**66.35** ± 2.84	59.24 ± 4.25	60.30 ± 3.26	65.08 ± 2.14	66.11 ± 2.04
		32	65.04 ± 2.32	**67.73** ± 2.27	62.68 ± 3.21	64.99 ± 3.05	64.67 ± 3.41	67.30 ± 1.53

BERT - standard self-supervised learning + fine-tuning

SMLMT - proposed unsupervised meta-learning

MT-BERT - multi-task learning + fine-tuning (on supervised tasks)

LEOPARD - optimization-based meta-learner (only on supervised tasks)

Hybrid-SMLMT - meta-learning on proposed tasks + supervised tasks

More results & analysis in the paper!

Bansal, Jha, Munkhdalai, McCallum. **Self-Supervised Meta-Learning for Few-Shot Natural Language Classification Tasks**. EMNLP '20

Summary of Unsupervised Meta-Training

Given unlabeled dataset(s) ⟶ Propose tasks ⟶ Run meta-learning

Existing task proposal techniques:

- Classify between clusters of images
- Classify augmented image vs. different image instance
- Generate text from a particular context
- Classify a masked word

Plan for Today

Brief Recap of Meta-Learning & Task Construction

Memorization in Meta-Learning
- When it arises
- Potential solutions

Meta-Learning without Tasks Provided
- Unsupervised Meta-Learning
- Semi-Supervised Meta-Learning

} Part of (optional) Homework 4

Goals for by the end of lecture:
- Understand when & how memorization in meta-learning may occur
- Understand techniques for constructing tasks automatically

Course Reminders

Homework 2 due **today**.

Homework 3 out today, due **next Wednesday**.

Wednesday’s lecture: large-scale meta-optimization

by Yoonho Lee

(ML PhD student)