Plan for Today

Transfer Learning
- Problem formulation
- Fine-tuning

Start of Meta-Learning
- Problem formulation
- General recipe of meta-learning algorithms

What you'll learn:
- How can you transfer things learned from one task to another?
- What does it mean for two tasks to have *"shared structure"*?
- What is meta-learning?

Meta-Learning Problem

Transfer Learning with Many Source Tasks

Given data from $\mathcal{T}_1, \ldots, \mathcal{T}_n$, solve new task $\mathcal{T}_{\text{test}}$ more quickly / proficiently / stably

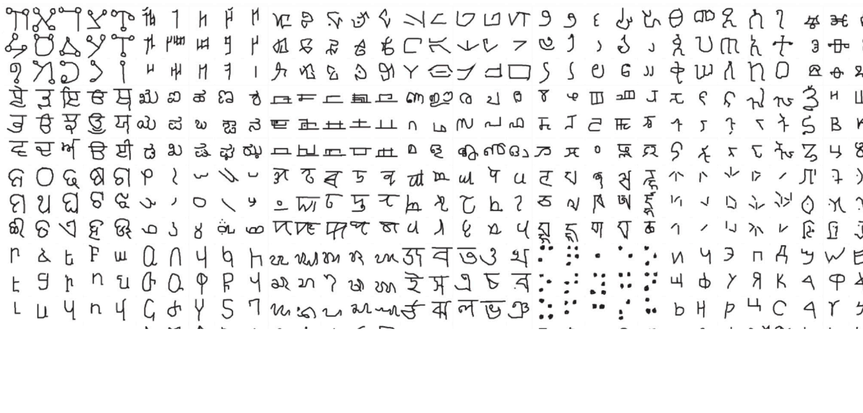
Key assumption: meta-training tasks and meta-test task drawn i.i.d. from same task distribution

$$\mathcal{T}_1, \ldots, \mathcal{T}_n \sim p(\mathcal{T}), \mathcal{T}_j \sim p(\mathcal{T})$$

Like before, tasks must share structure.

What do the tasks correspond to?

- recognizing handwritten digits from different languages (see homework 1!)
- giving feedback to students on different exams
- classifying species in different regions of the world
- a robot performing different tasks



How many tasks do you need?

The more the better. (analogous to more data in ML)

Two ways to view meta-learning algorithms

Mechanistic view

- Deep network 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

Probabilistic view

- Extract shared prior knowledge from a set of 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

For rest of lecture: Focus primarily on the mechanistic view.

(Bayes will be back later)

How does meta-learning work? An example.

Given 1 example of 5 classes:

training data $\mathcal{D}_{\text{train}}$

Classify new examples

test set $\mathbf{x}_{\text{test}}$

How does meta-learning work? An example.

Given 1 example of 5 classes:

Classify new examples

meta-testing $\mathcal{T}_{\text{test}}$

training data $\mathcal{D}_{\text{train}}$

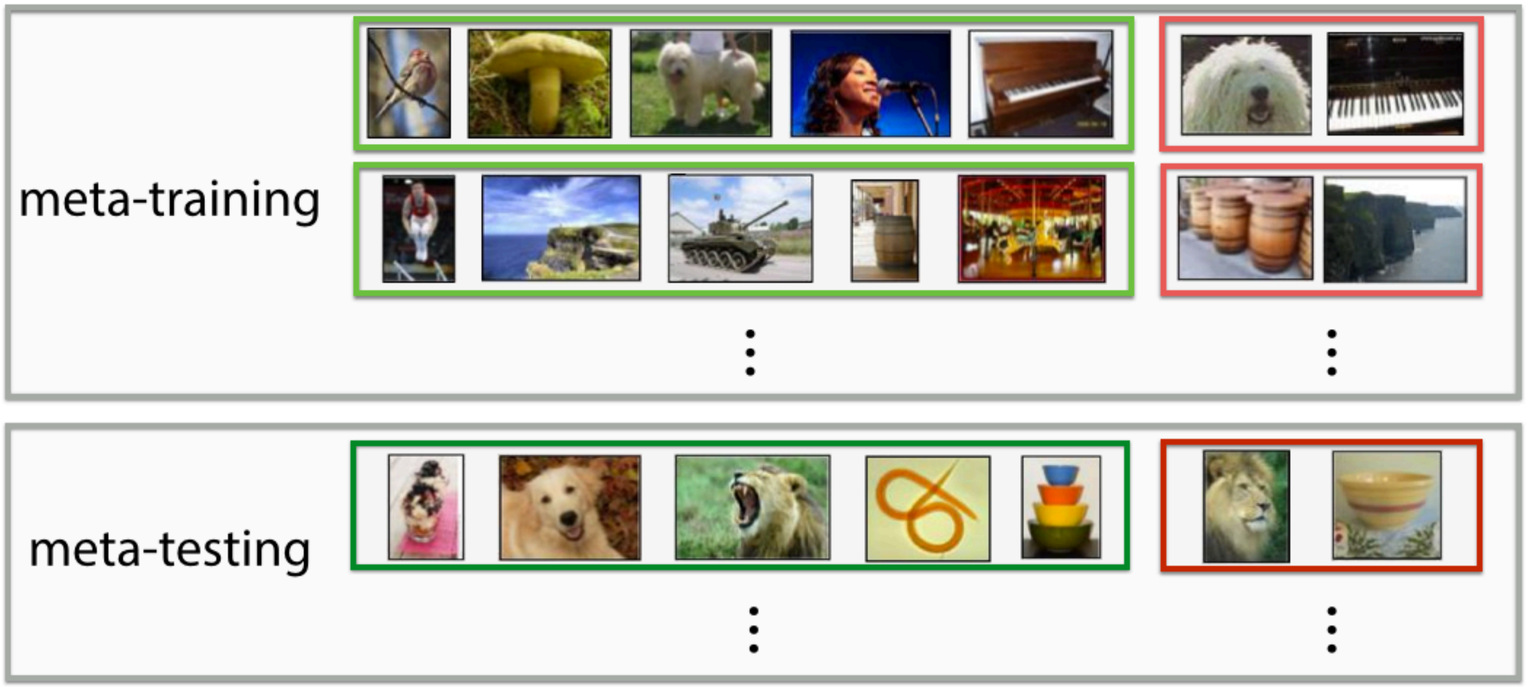
test set $\mathbf{x}_{\text{test}}$

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

Some terminology

task training set $\mathcal{D}_i^{\text{tr}}$ "support set"

task test dataset $\mathcal{D}_i^{\text{test}}$ "query set"



k-shot learning: learning with **k** examples per class
(or **k** examples total for regression)

N-way classification: choosing between N classes

Question: What are k and N for the above example?

One View on the Meta-Learning Problem

Supervised Learning:

Inputs: $\mathbf{x}$ Outputs: $\mathbf{y}$ Data: $\{(\mathbf{x}, \mathbf{y})_i\}$

$$\mathbf{y} = g_\phi(\mathbf{x})$$

Meta Supervised Learning:

Inputs: $\mathcal{D}^{\text{tr}}$ $\mathbf{x}^{\text{ts}}$ Outputs: $\mathbf{y}^{\text{ts}}$ Data: $\{\mathcal{D}_i\}$

$$\mathcal{D}_i : \{(\mathbf{x}, \mathbf{y})_j\}$$

$$\{(\mathbf{x}, \mathbf{y})_{1:K}\} \quad \mathbf{y}^{\text{ts}} = f_\theta(\mathcal{D}^{\text{tr}}, \mathbf{x}^{\text{ts}})$$

Why is this view useful?

Reduces the meta-learning problem to the design & optimization of f.

Finn. *Learning to Learn with Gradients*. PhD Thesis. 2018

General recipe

How to design a meta-learning algorithm

1. Choose a form of $f_\theta(\mathcal{D}^{\text{tr}}, \mathbf{x}^{\text{ts}})$

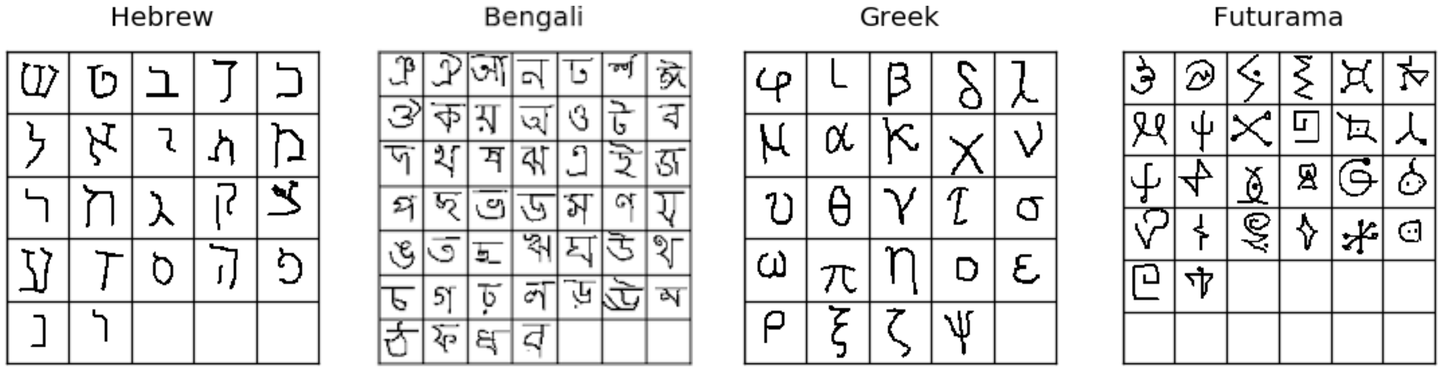
2. Choose how to optimize θ w.r.t. max-likelihood objective using meta-training data

↖ meta-parameters

Running example

Omniglot dataset Lake et al. Science 2015

1623 characters from **50 different alphabets**



20 instances of each character

many classes, few examples

the “transpose” of MNIST

statistics more reflective of **the real world**

…

whiteboard

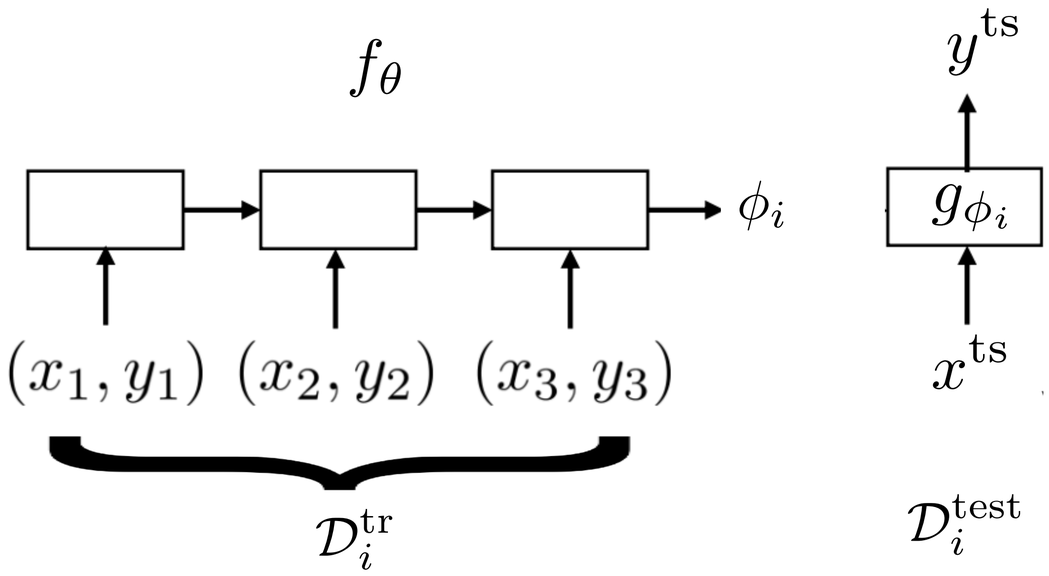
More **few-shot image recognition** datasets: tieredImageNet, CIFAR, CUB, CelebA, ORBIT, others

More benchmarks: molecular property prediction (Ngyugen et al. ’20), object pose prediction (Yin et al. ICLR ’20), channel coding (Li et al. ’21)

Black-Box Adaptation

Key idea: Train a neural network to represent $\phi_i = f_\theta(\mathcal{D}_i^{\text{tr}})$ "learner"

Predict test points with $\mathbf{y}^{\text{ts}} = g_{\phi_i}(\mathbf{x}^{\text{ts}})$



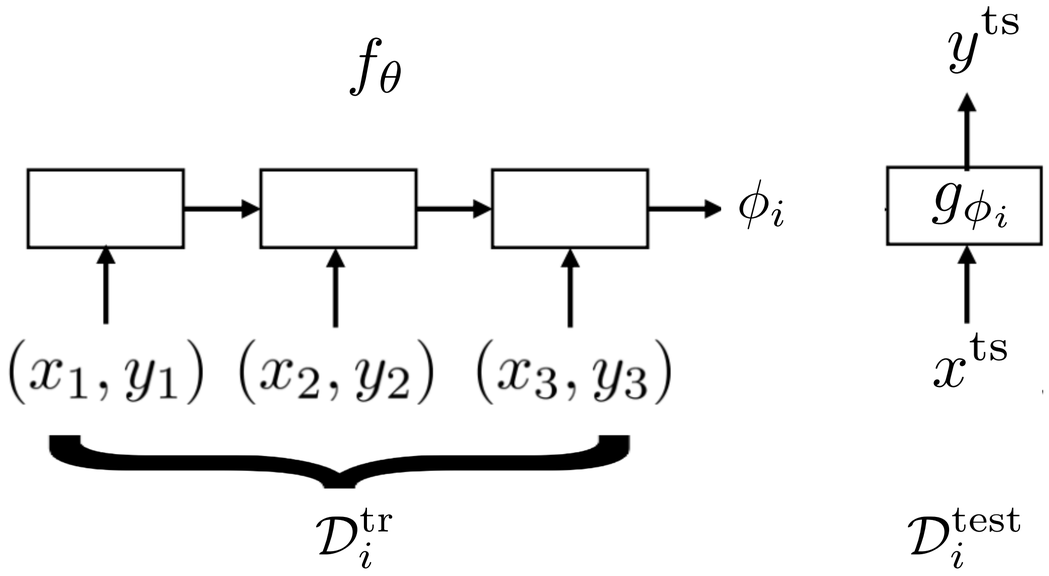
Train with standard supervised learning!

$$\min_\theta \sum_{\mathcal{T}_i} \underbrace{\sum_{(x,y)\sim\mathcal{D}_i^{\text{test}}} -\log g_{\phi_i}(y \mid x)}_{\mathcal{L}(\phi_i, \mathcal{D}_i^{\text{test}})}$$

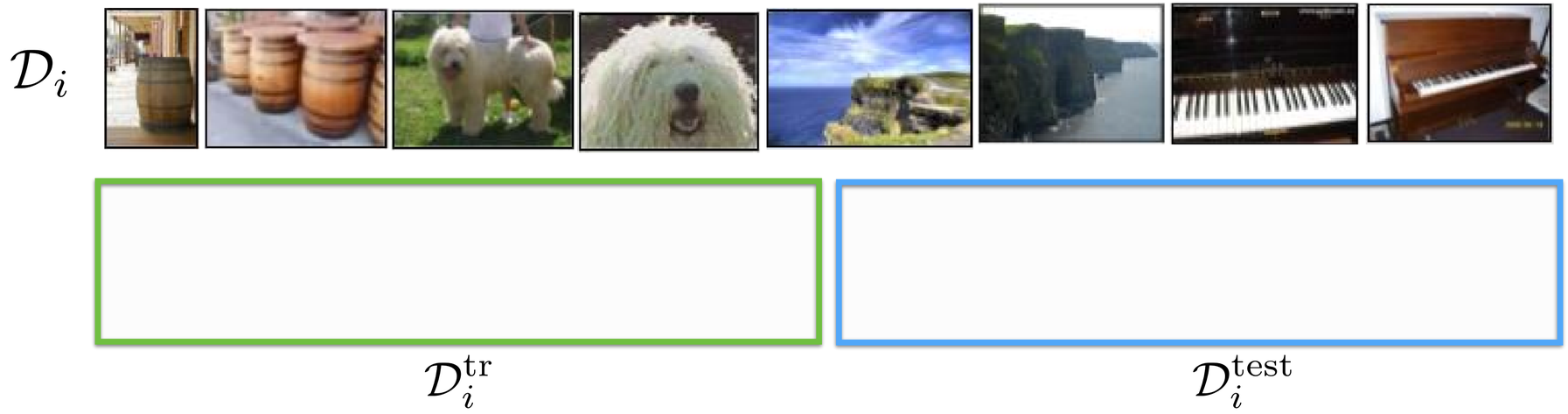
$$\min_\theta \sum_{\mathcal{T}_i} \mathcal{L}(f_\theta(\mathcal{D}_i^{\text{tr}}), \mathcal{D}_i^{\text{ts}})$$

Black-Box Adaptation

Key idea: Train a neural network to represent $\phi_i = f_\theta(\mathcal{D}_i^{\text{tr}})$.

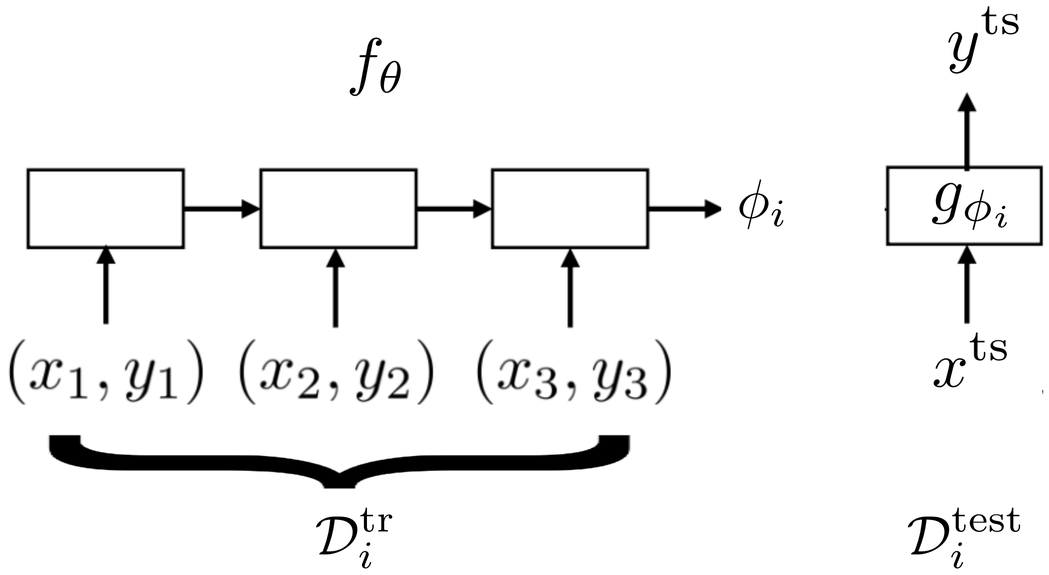


1. Sample task $\mathcal{T}_i$ *(or mini batch of tasks)*
2. Sample disjoint datasets $\mathcal{D}_i^{\text{tr}}, \mathcal{D}_i^{\text{test}}$ from $\mathcal{D}_i$



Black-Box Adaptation

Key idea: Train a neural network to represent $\phi_i = f_\theta(\mathcal{D}_i^{\text{tr}})$.



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. Compute ϕ_i $f_\theta(\mathcal{D}_i^{\text{tr}})$
4. Update θ using $\nabla_\theta \mathcal{L}(\phi_i, \mathcal{D}_i^{\text{test}})$

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

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

Black-Box Adaptation

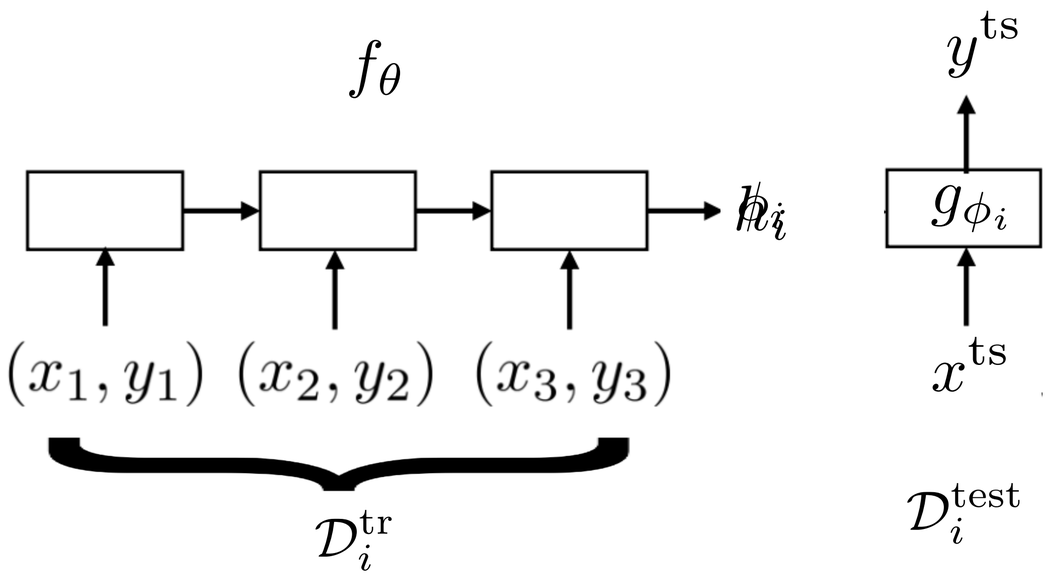
Key idea: Train a neural network to represent $\phi_i = f_\theta(\mathcal{D}_i^{\text{tr}})$.

Challenge

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)

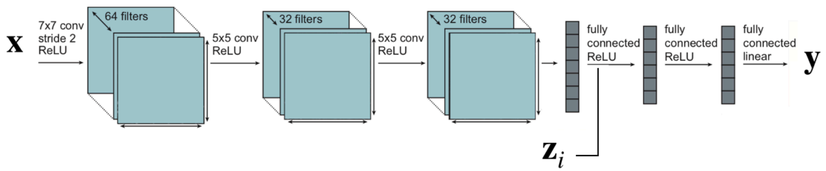


low-dimensional vector h_i

represents contextual task information

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

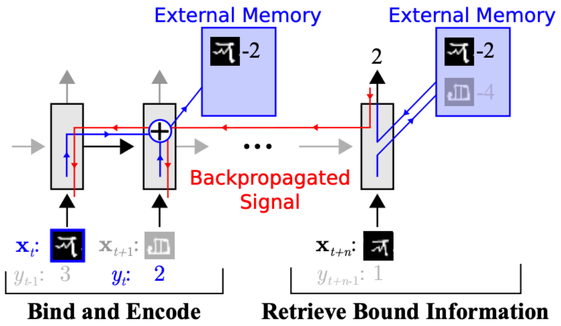
recall:



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

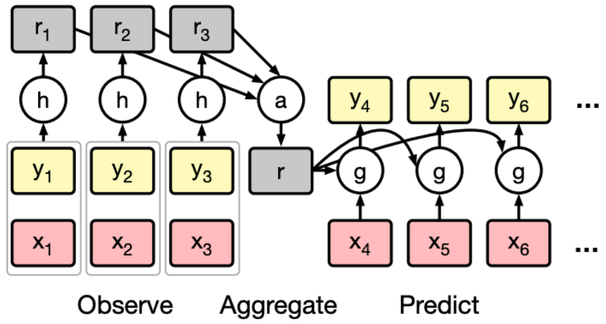
Black-Box Adaptation Architectures

LSTMs or Neural turing machine (NTM)



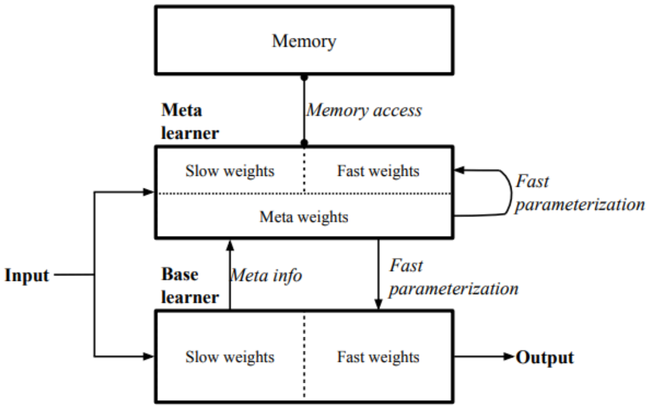
Meta-Learning with Memory-Augmented Neural Networks
Santoro, Bartunov, Botvinick, Wierstra, Lillicrap. ICML '16

Feedforward + average

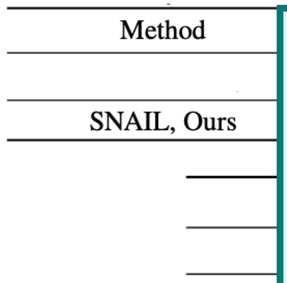


Conditional Neural Processes. Garnelo, Rosenbaum, Maddison, Ramalho, Saxton, Shanahan, Teh, Rezende, Eslami. ICML '18

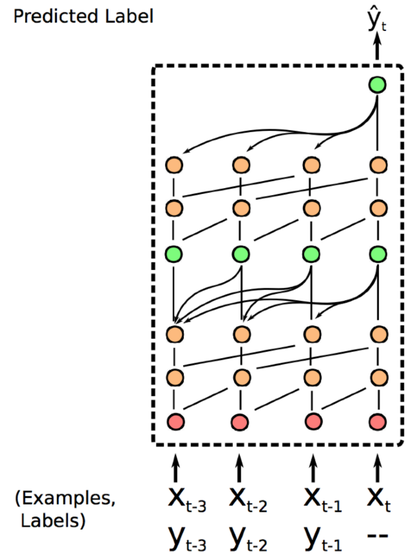
Other external memory mechanisms



Meta Networks
Munkhdalai, Yu. ICML '17



Convolutions & attention



A Simple Neural Attentive Meta-Learner
Mishra, Rohaninejad, Chen, Abbeel. ICLR '18

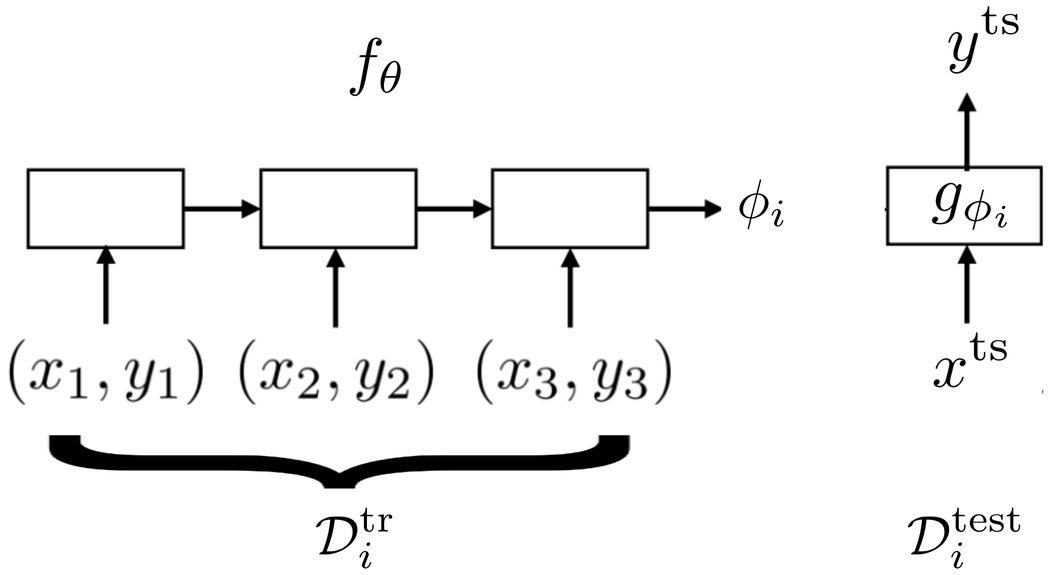
HW 1:

- implement data processing
- implement simple black-box meta-learner
- train few-shot Omniglot classifier

Question: Why might feedforward+average be better than a recurrent model?

Black-Box Adaptation

Key idea: Train a neural network to represent $\phi_i = f_\theta(\mathcal{D}_i^{\text{tr}})$.



+ **expressive**

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

- **complex model** w/ **complex task**: **challenging optimization** problem

- often **data-inefficient**

How else can we represent $\phi_i = f_\theta(\mathcal{D}_i^{\text{tr}})$?

Next time (Monday): What if we treat it as an **optimization** procedure?

Plan for Today

Meta-Learning

- Problem formulation
- General recipe of meta-learning algorithms
- Black-box adaptation approaches
- **Case study of GPT-3 (time-permitting)**

Case Study: GPT-3

Language Models are Few-Shot Learners

Tom B. Brown* **Benjamin Mann*** **Nick Ryder*** **Melanie Subbiah***

Jared Kaplan† **Prafulla Dhariwal** **Arvind Neelakantan** **Pranav Shyam** **Girish Sastry**

Amanda Askell **Sandhini Agarwal** **Ariel Herbert-Voss** **Gretchen Krueger** **Tom Henighan**

Rewon Child **Aditya Ramesh** **Daniel M. Ziegler** **Jeffrey Wu** **Clemens Winter**

Christopher Hesse **Mark Chen** **Eric Sigler** **Mateusz Litwin** **Scott Gray**

Benjamin Chess **Jack Clark** **Christopher Berner**

Sam McCandlish **Alec Radford** **Ilya Sutskever** **Dario Amodei**

OpenAI

May 2020

"emergent" few-shot learning

What is GPT-3?

a language model

black-box meta-learner *trained on language generation tasks*

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

[meta-training] dataset: crawled data from the internet, English-language Wikipedia, two books corpora

architecture: giant "Transformer" network 175 billion parameters, 96 layers, 3.2M batch size

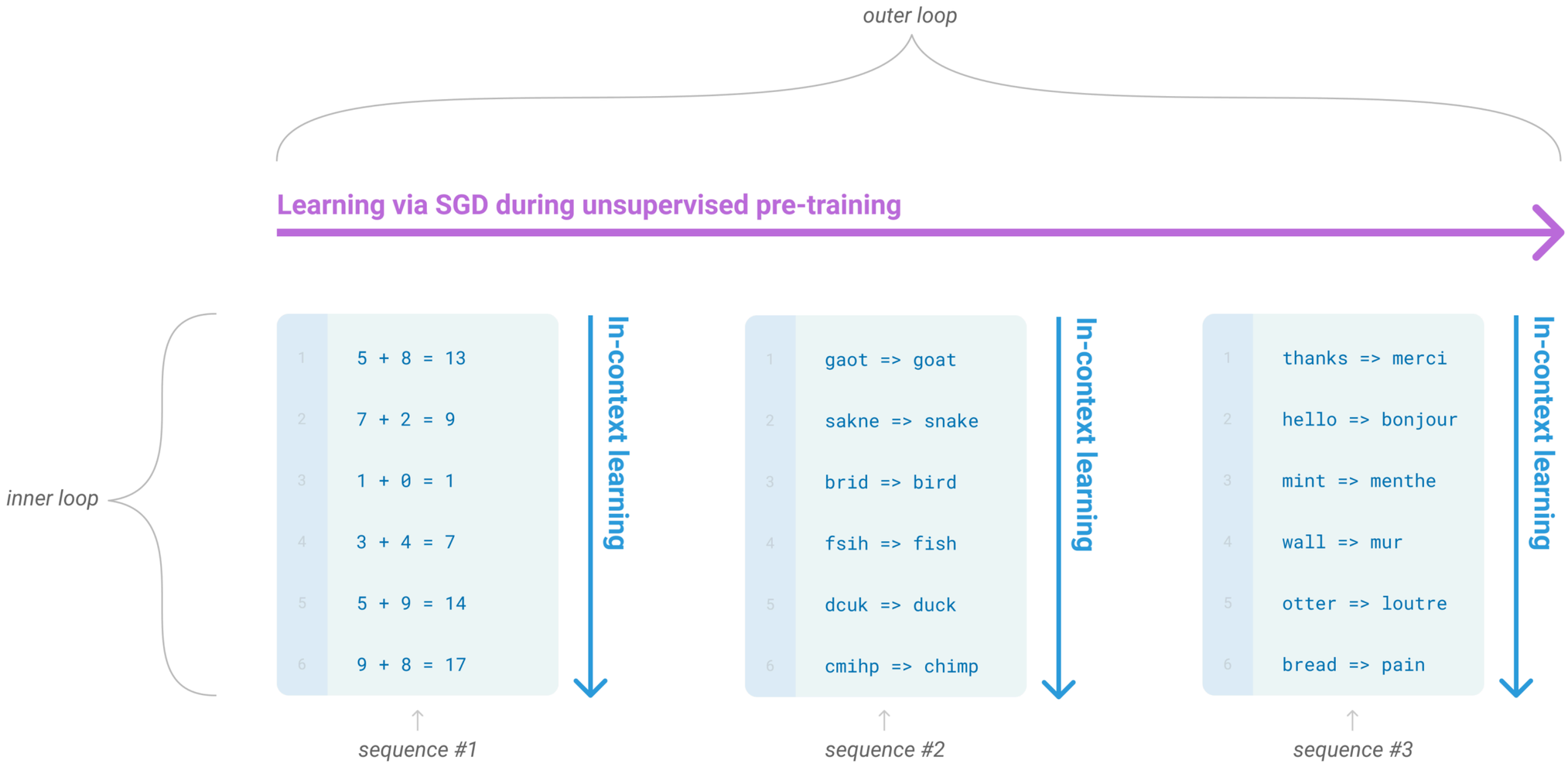
What do different tasks correspond to?

spelling correction
simple math problems
translating between languages
a variety of other tasks

How can those tasks all be solved by a single architecture?

How can those tasks all be solved by a single architecture? Put them all in the form of text!

Why is that a good idea? Very easy to get a lot of meta-training data.



simple math problems spelling correction translating between languages

Some Results

One-shot learning from dictionary definitions:

To "screeg" something is to swing a sword at it. An example of a sentence that uses the word screeg is:
We screeghed at each other for several minutes and then we went outside and ate ice cream.

Few-shot language editing:

Poor English input: I eated the purple berries.
Good English output: I ate the purple berries.
Poor English input: Thank you for picking me as your designer. I'd appreciate it.
Good English output: Thank you for choosing me as your designer. I appreciate it.
Poor English input: The mentioned changes have done. or I did the alteration that you requested. or I changed things you wanted and did the modifications.
Good English output: The requested changes have been made. or I made the alteration that you requested. or I changed things you wanted and made the modifications.
Poor English input: I'd be more than happy to work with you in another project.
Good English output: I'd be more than happy to work with you on another project.

Poor English input: Please provide me with a short brief of the design you're looking for and that'd be nice if you could share some examples or project you did before.
Good English output: Please provide me with a brief description of the design you're looking for and that would be nice if you could share some examples or projects you have done before.

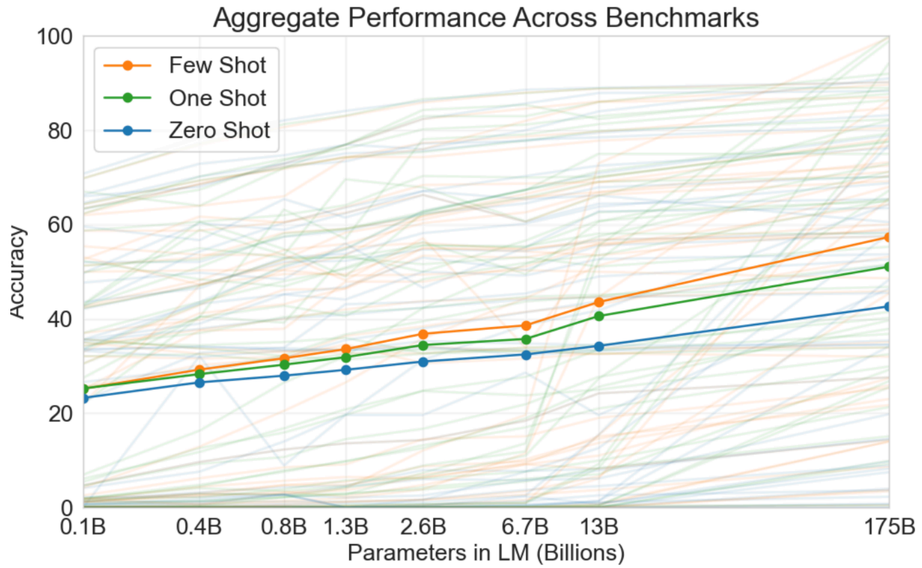
Non-few-shot learning tasks:

Title: United Methodists Agree to Historic Split
Subtitle: Those who oppose gay marriage will form their own denomination
Article: **After two days of intense debate, the United Methodist Church has agreed to a historic split - one that is expected to end in the creation of a new denomination, one that will be "theologically and socially conservative," according to The Washington Post. The majority of delegates attending the church's annual General Conference in May voted to strengthen a ban on the ordination of LGBTQ clergy and to write new rules that will "discipline" clergy who officiate at same-sex weddings. But those who opposed these measures have a new plan: They say they will form a separate denomination by 2020, calling their church the Christian Methodist**

General Notes & Takeaways

The results are extremely impressive.

The model is far from perfect.



The model fails in unintuitive ways.

```
Q: How many eyes does a giraffe have?
A: A giraffe has two eyes.

Q: How many eyes does my foot have?
A: Your foot has two eyes.

Q: How many eyes does a spider have?
A: A spider has eight eyes.

Q: How many eyes does the sun have?
A: The sun has one eye.
```

Source: https://lacker.io/ai/2020/07/06/giving-gpt-3-a-turing-test.html

The choice of $\mathscr{D}_i^{tr}$ at test time is important. (“prompting”)

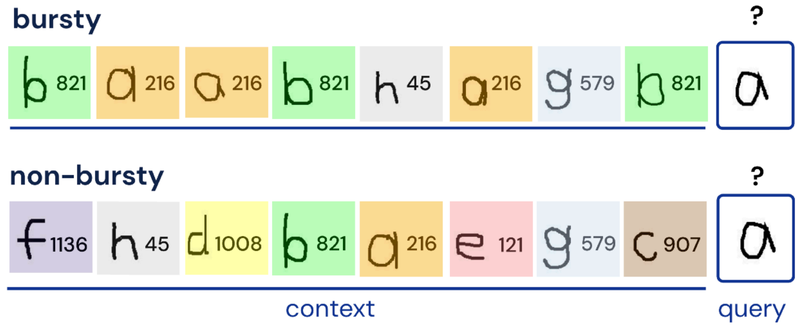
Source: https://github.com/shreyashankar/gpt3-sandbox/blob/master/docs/priming.md

What is needed for few-shot learning to emerge?

An active research topic!

Data:

- temporal correlation
- dynamic meaning of words

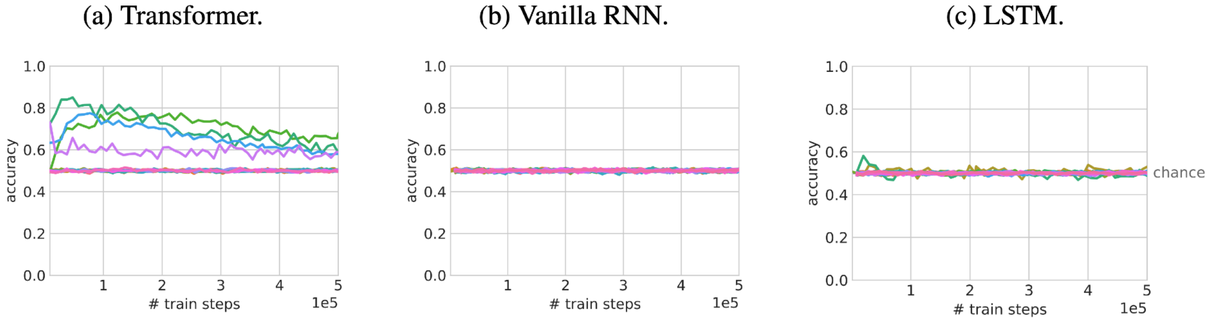


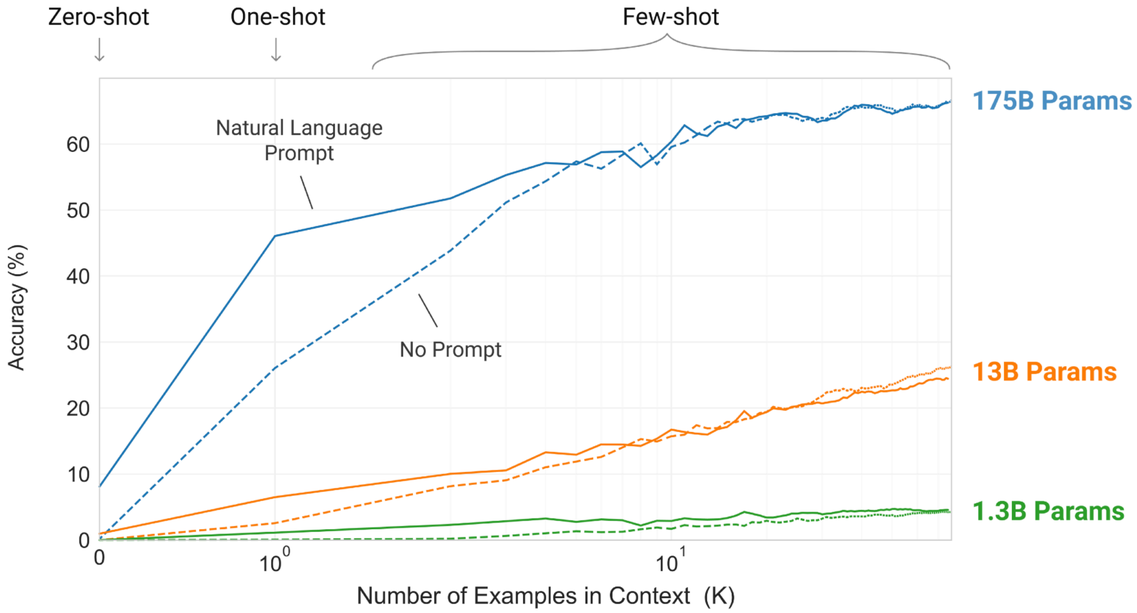
Model:

- large capacity models

transformers > RNNs

large models > small models





Chan, Santoro, Lampinen, Wang, Singh, Richemond, McClelland, Hill. Data Distributional Properties Drive Emergent In-Context Learning in Transformers. '22

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

Plan for Today

Recap

- Meta-learning problem & black-box meta-learning

Optimization Meta-Learning

- Overall approach
- Compare: optimization-based vs. black-box
- Challenges & solutions
- Case study of land cover classification (time-permitting)

Goals for by the end of lecture:

- Basics of optimization-based meta-learning techniques (& how to implement)
- Trade-offs between black-box and optimization-based meta-learning

Problem Settings Recap

Multi-Task Learning

Solve multiple tasks $\mathcal{T}_1, \cdots, \mathcal{T}_T$ at once.

$$\min_{\theta} \sum_{i=1}^{T} \mathcal{L}_i(\theta, \mathcal{D}_i)$$

Transfer Learning

Solve target task $\mathcal{T}_b$ after solving source task $\mathcal{T}_a$ by *transferring* knowledge learned from $\mathcal{T}_a$

Meta-Learning Problem

Transfer Learning with Many Source Tasks

Given data from $\mathcal{T}_1, \ldots, \mathcal{T}_n$, solve new task $\mathcal{T}_{\text{test}}$ more quickly / proficiently / stably

Example Meta-Learning Problem

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

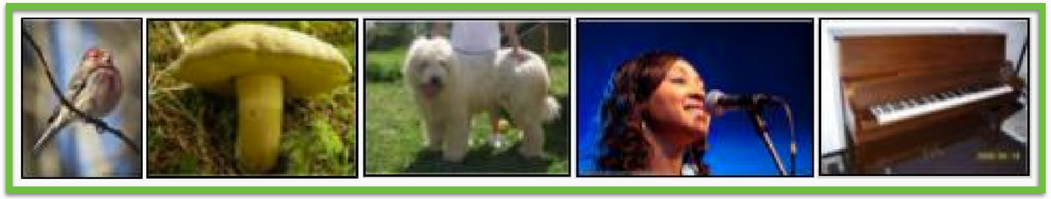
Given 1 example of 5 classes:

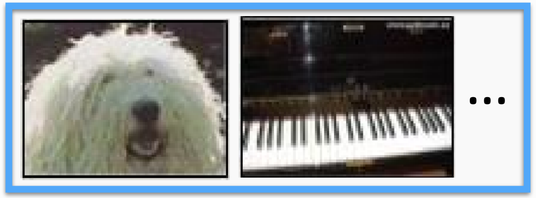
Classify new examples

meta-test

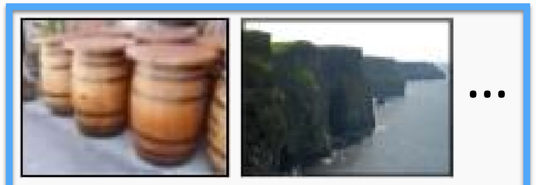
meta-training

$\mathcal{T}_1$



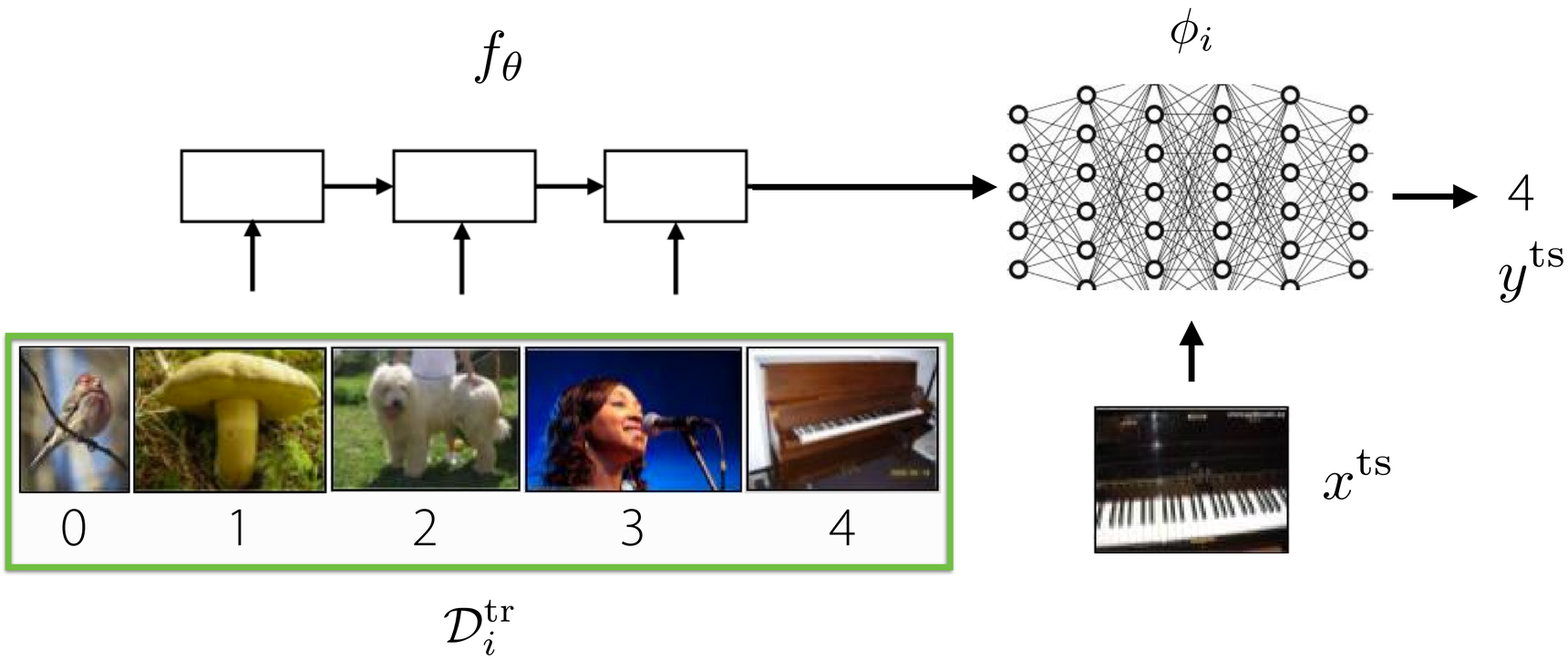


$\mathcal{T}_2$



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

Black-Box Adaptation



general form:

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

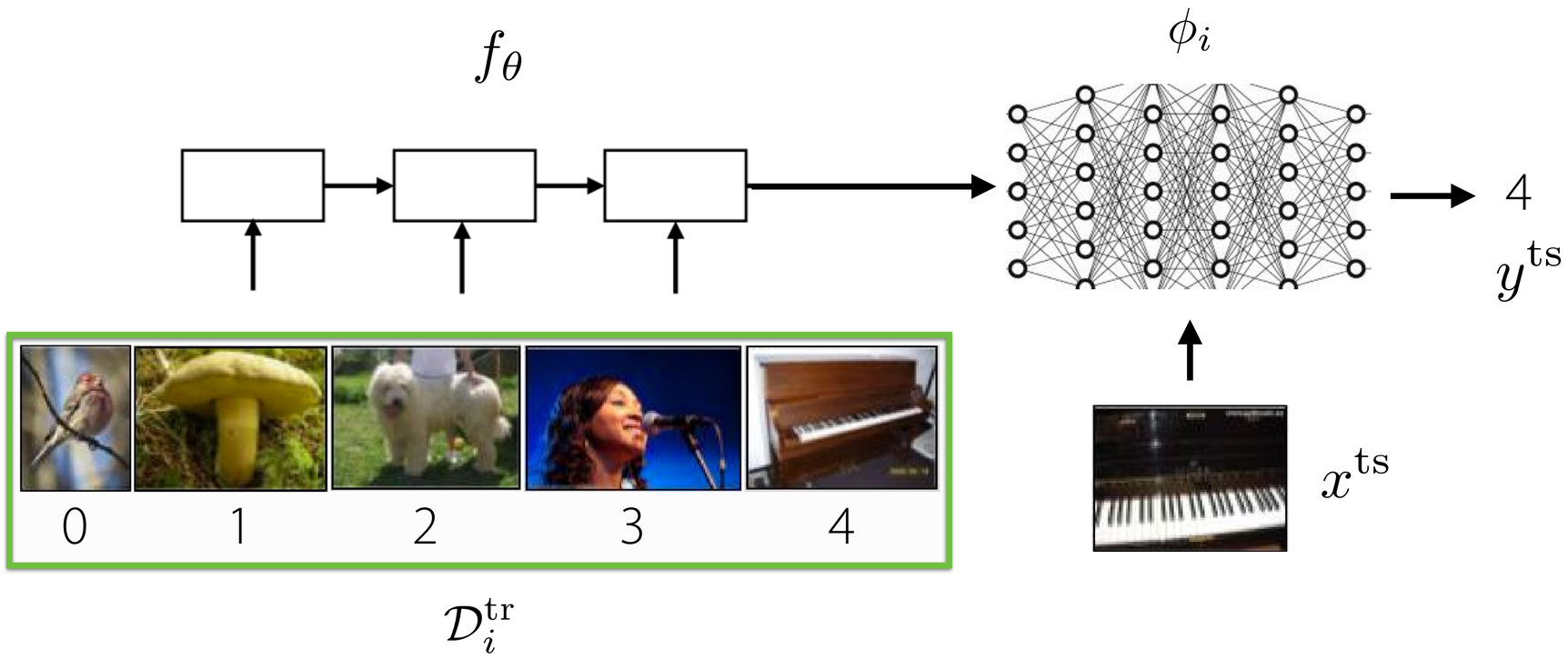
+ **expressive**

- **challenging optimization** problem

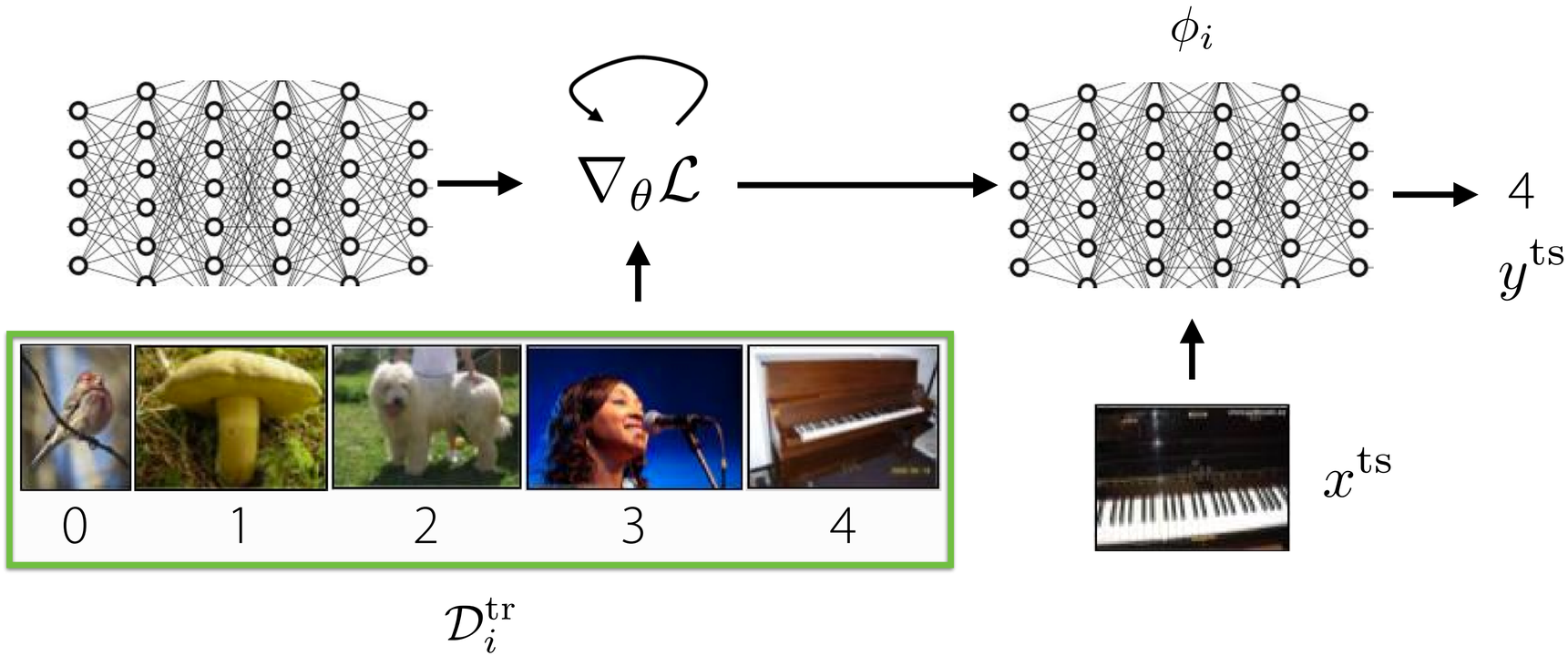
How else can we represent $\phi_i = f_\theta(\mathcal{D}_i^{\text{tr}})$?

What if we treat it as an **optimization** procedure?

~~Black-Box~~ ~~Adaptation~~ Optimization-Based Adaptation



~~Black-Box~~ ~~Adaptation~~ Optimization-Based Adaptation



Key idea: embed optimization inside the inner learning process

Why might this make sense?

Recall: Fine-tuning

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

pre-trained parameters

training data for new task

(typically for many gradient steps)

Universal Language Model Fine-Tuning for Text Classification. Howard, Ruder. ‘18

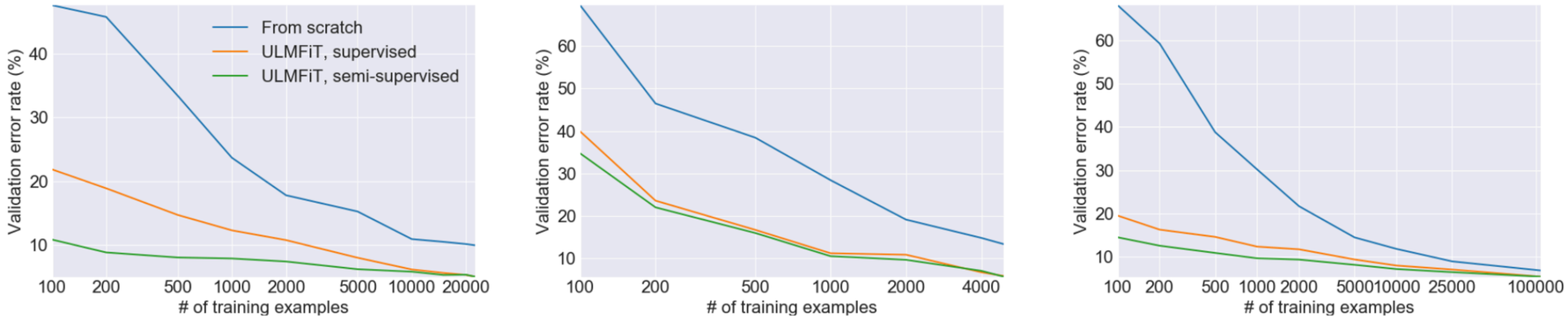


Figure 3: Validation error rates for supervised and semi-supervised ULMFiT vs. training from scratch with different numbers of training examples on IMDb, TREC-6, and AG (from left to right).

Fine-tuning less effective with **very small datasets**.

Optimization-Based Adaptation

Fine-tuning
[test-time]

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

pre-trained parameters

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

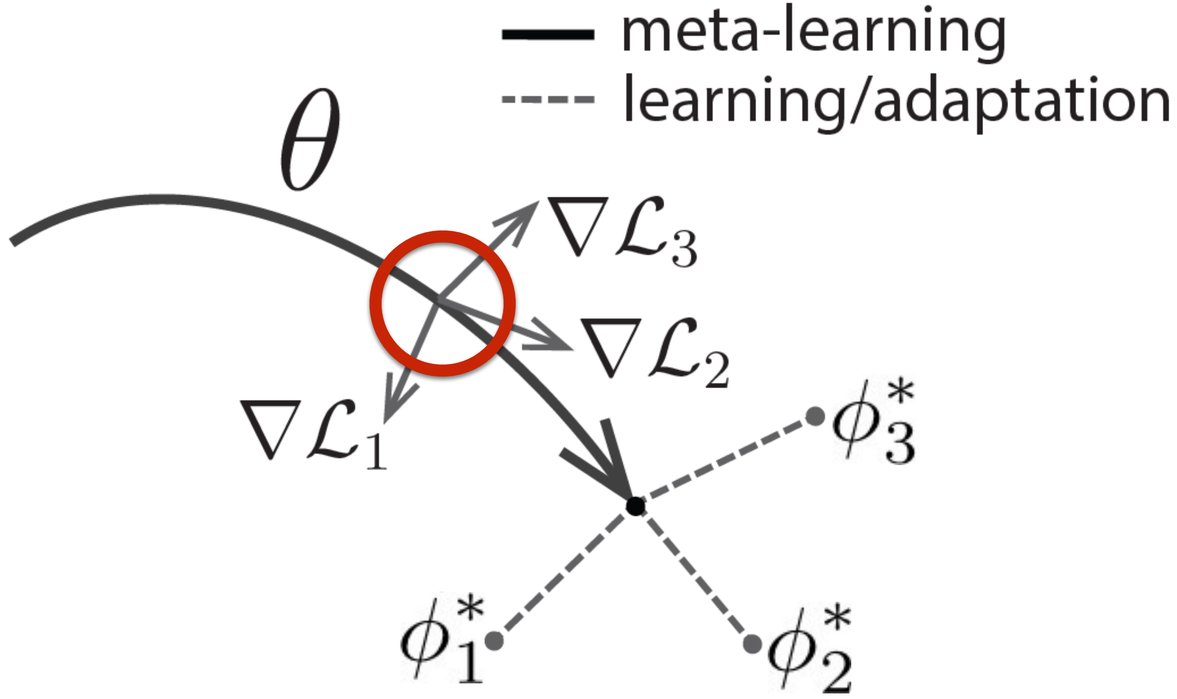
Finn, Abbeel, Levine. Model-Agnostic Meta-Learning. ICML 2017

Optimization-Based Adaptation

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

θ parameter vector being meta-learned

ϕ_i^* optimal parameter vector for task i



Model-**A**gnostic **M**eta-**L**earning

Finn, Abbeel, Levine. Model-Agnostic Meta-Learning. ICML 2017

Optimization-Based Adaptation

Key idea: Acquire ϕ_i through optimization.

General Algorithm:

~~Black box approach~~ Optimization-based approach

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. ~~Compute ϕ_i $f_\theta(\mathcal{D}_i^{\text{tr}})$~~ Optimize ϕ_i $\theta - \alpha \nabla_\theta \mathcal{L}(\theta, \mathcal{D}_i^{\text{tr}})$
4. Update θ using $\nabla_\theta \mathcal{L}(\phi_i, \mathcal{D}_i^{\text{test}})$

—> brings up **second-order** derivatives

Do we need to compute the full Hessian?

-> whiteboard

Do we get higher-order derivatives with more inner gradient steps?

Optimization-Based Adaptation

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

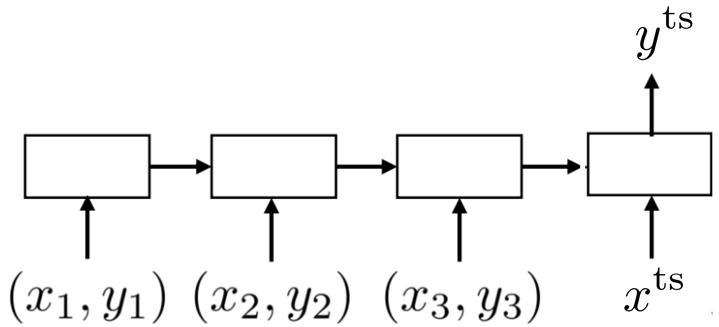
MAML, basic architecture: 63.11%

MAML + AutoMeta: **74.65%**

Optimization vs. Black-Box Adaptation

Black-box adaptation

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



Model-agnostic meta-learning

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

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

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)

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

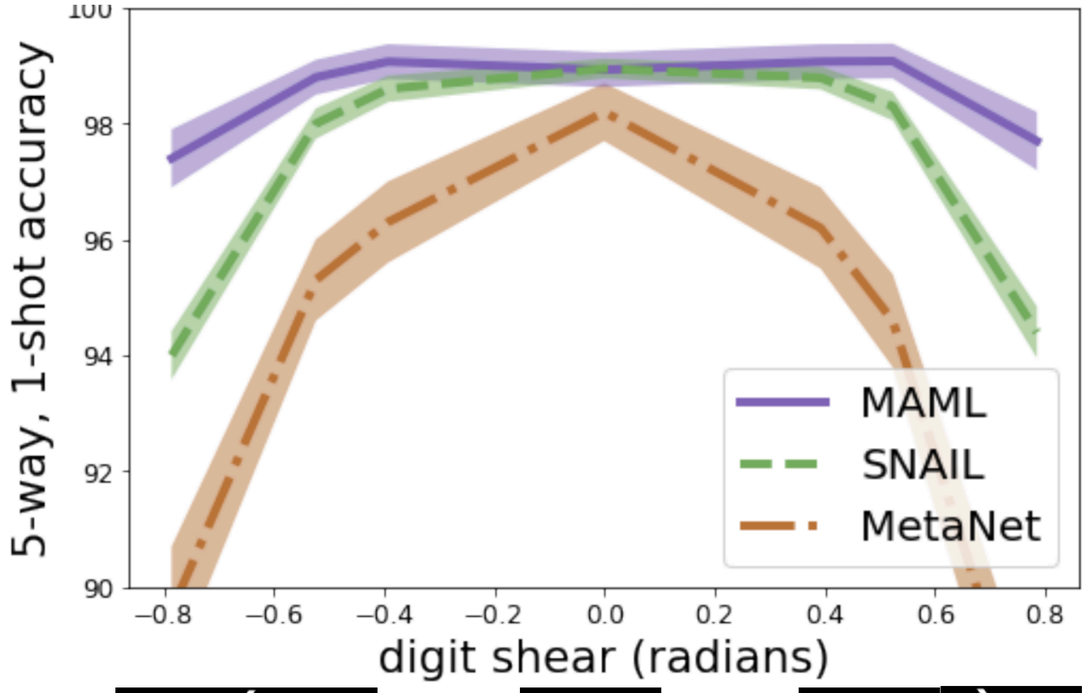
Optimization vs. Black-Box Adaptation

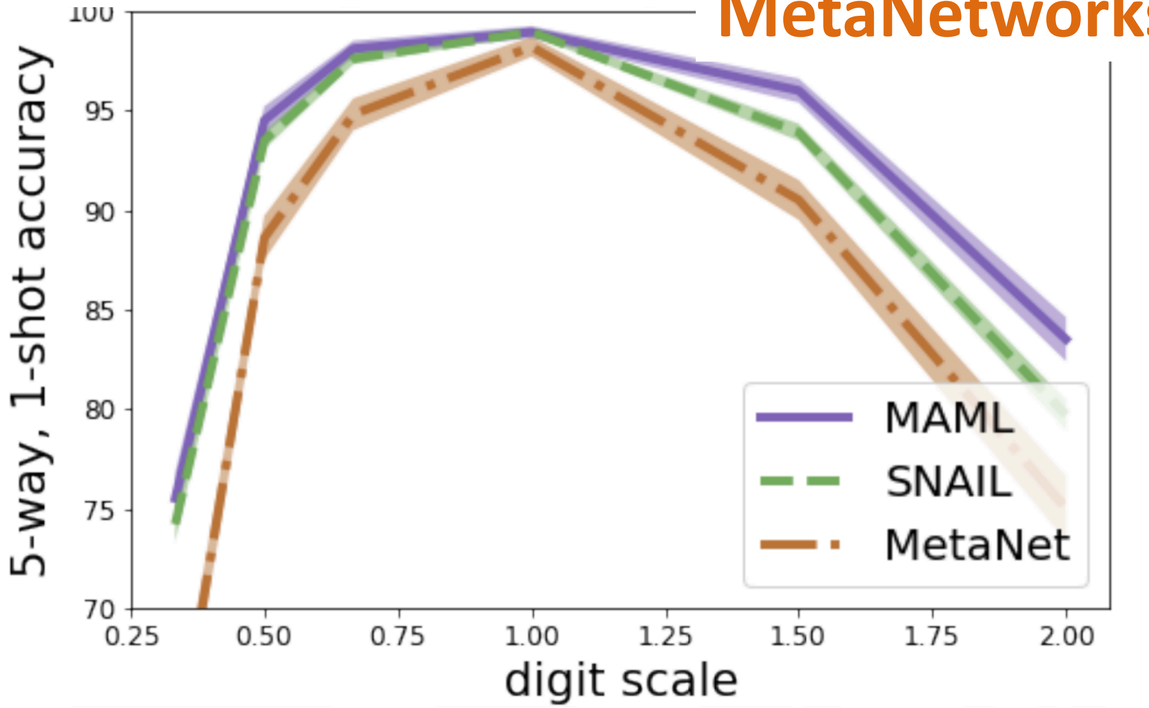
How well can learning procedures generalize to similar, but extrapolated tasks?

Omniglot image classification

MAML SNAIL, MetaNetworks

performance





Does this structure come at a cost?

Finn & Levine ICLR ’18

Black-box adaptation

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

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 network,

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.

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

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 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

Case Study

Meta-Learning for Few-Shot Land Cover Classification

Marc Rußwurm[1,*,†], Sherrie Wang[2,3,*], Marco Körner[1], and David Lobell[2]

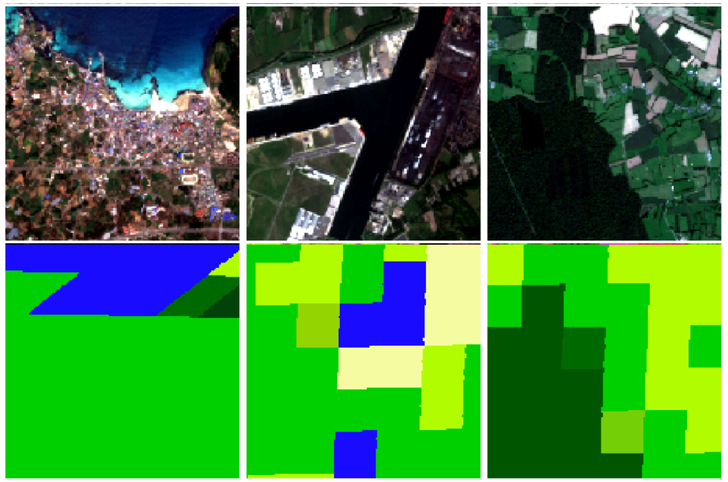
[1]Technical University of Munich, Chair of Remote Sensing Technology
[2]Stanford University, Center on Food Security and the Environment
[3]Stanford University, Institute for Computational and Mathematical Engineering

CVPR 2020 EarthVision Workshop

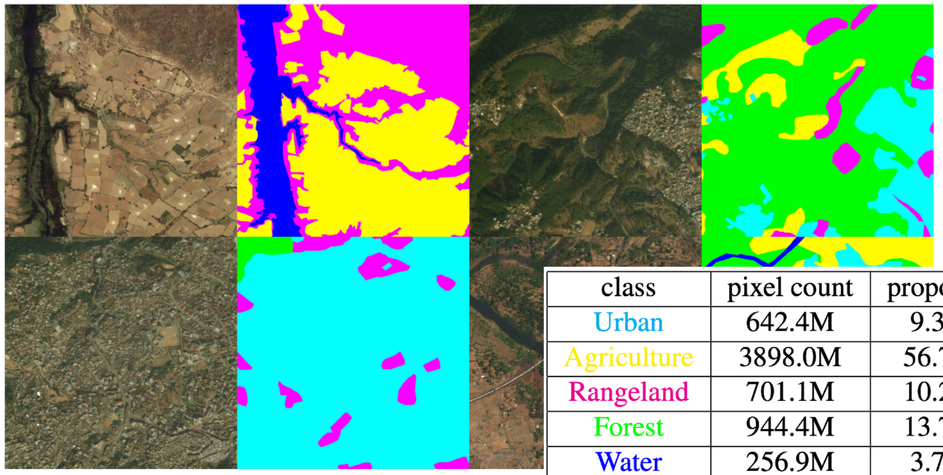
Link: https://arxiv.org/abs/2004.13390

Problem: Map land covering from satellite images

SEN12MS dataset
(Schmitt et al. 2019)



DeepGlobe dataset
(Demir et al. 2018)

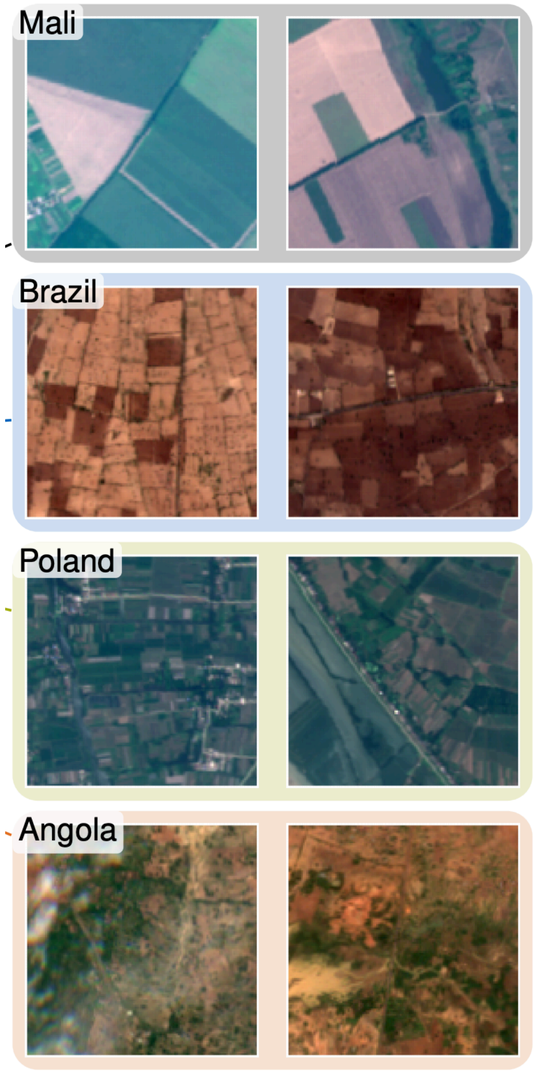


class	pixel count	proportion
Urban	642.4M	9.35%
Agriculture	3898.0M	56.76%
Rangeland	701.1M	10.21%
Forest	944.4M	13.75%
Water	256.9M	3.74%
Barren	421.8M	6.14%
Unknown	3.0M	0.04%

Applications in global urban planning, climate change research

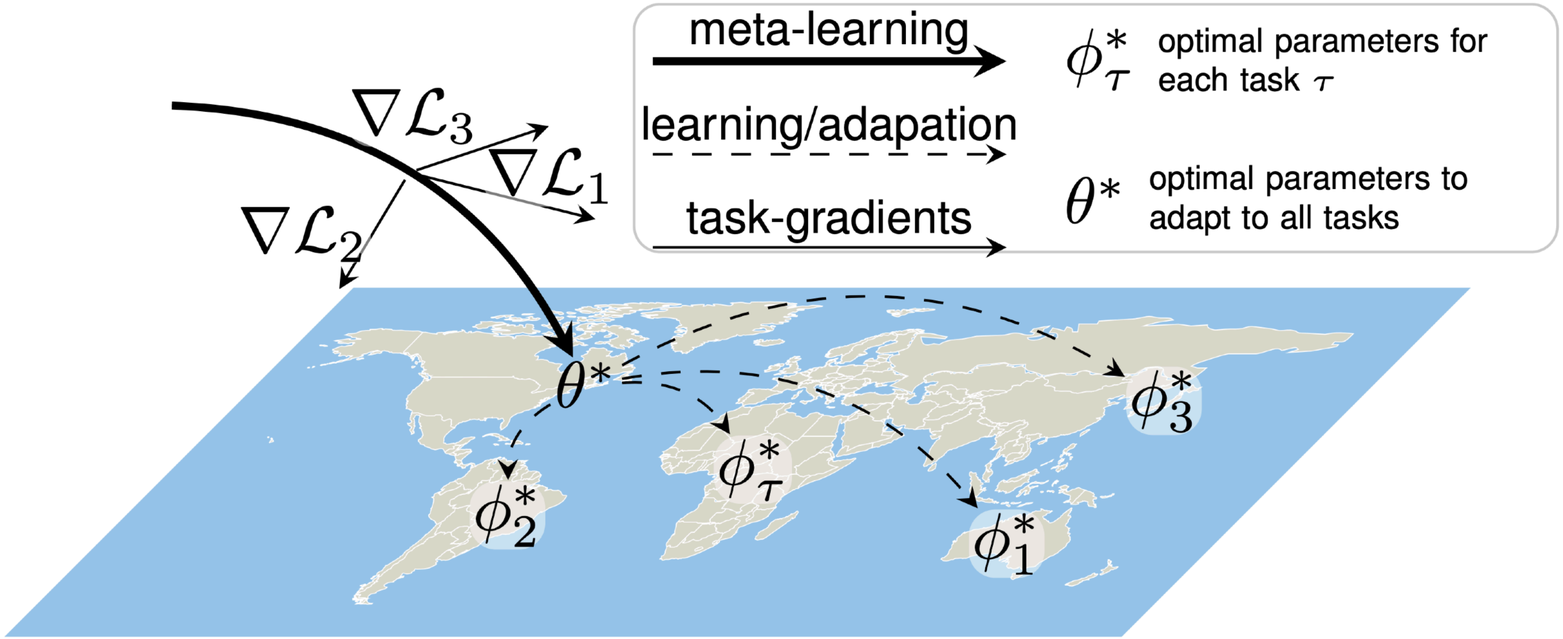
Challenges: Labeling data is expensive.
Different regions look different & have different land use proportions

Framing land cover mapping as a meta-learning problem



Different tasks: different regions of the world

Goal: Segment/classify images from a new region with a small amount of data



Croplands from four countries.

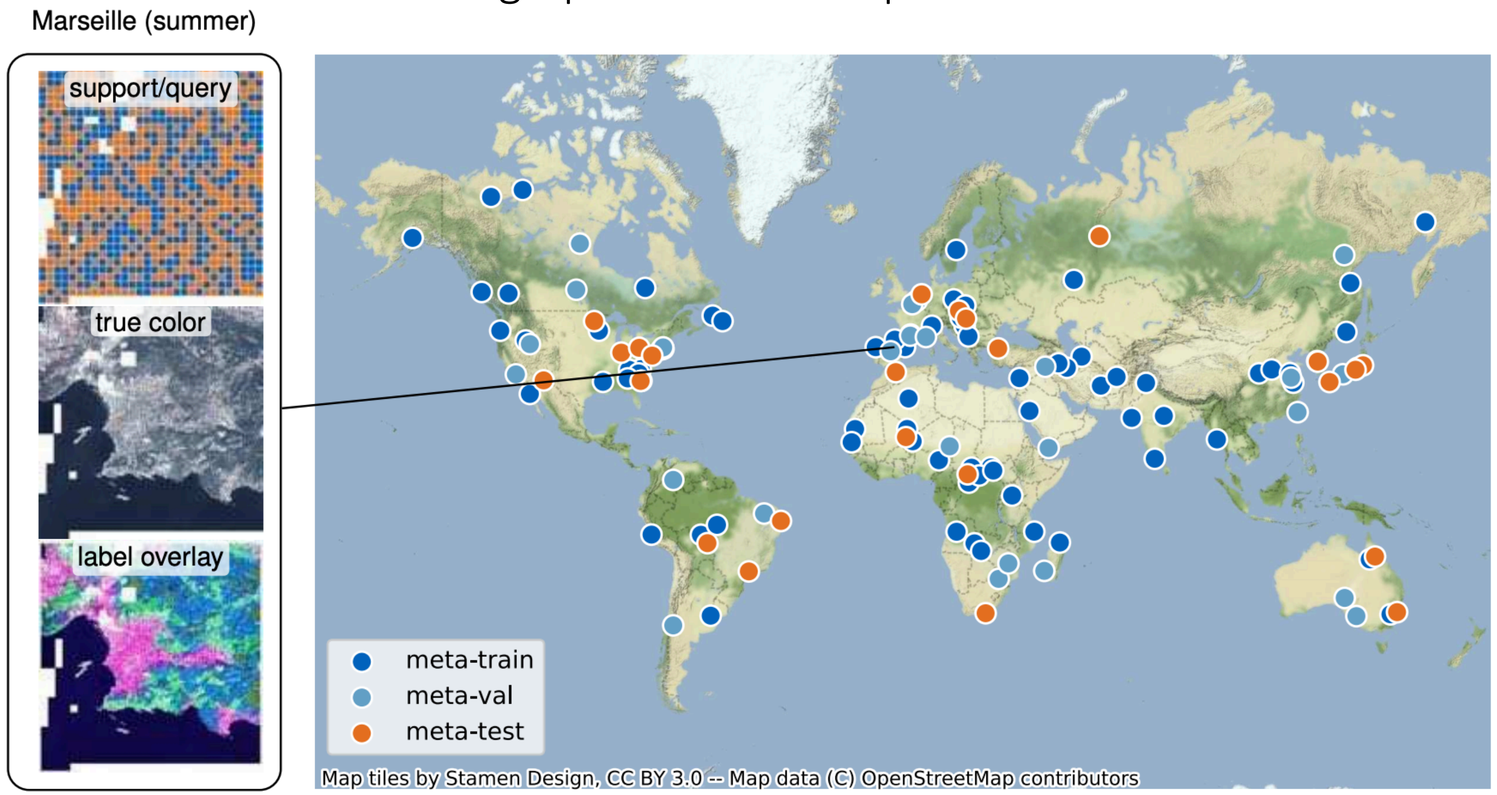
Framing land cover mapping as a meta-learning problem

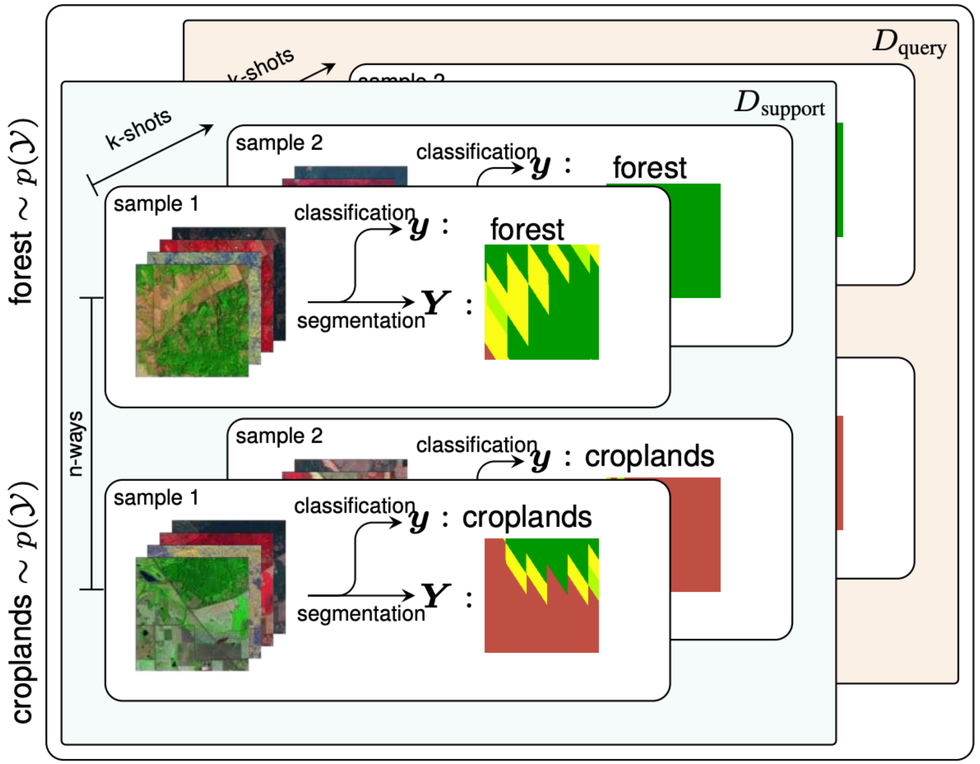
Goal: Segment/classify images from a new region with a small amount of data

SEN12MS dataset (Schmitt et al. 2019)

Geographic meta-data provided

Example 2-way 2-shot classification task



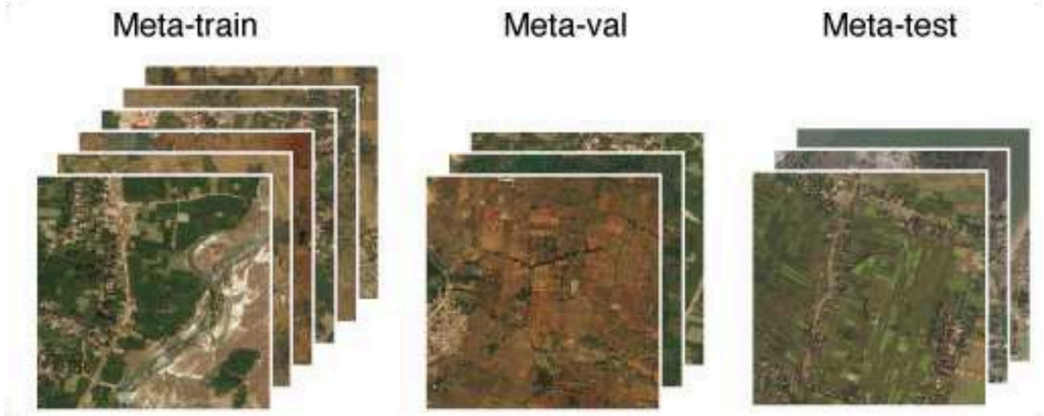


Framing land cover mapping as a meta-learning problem

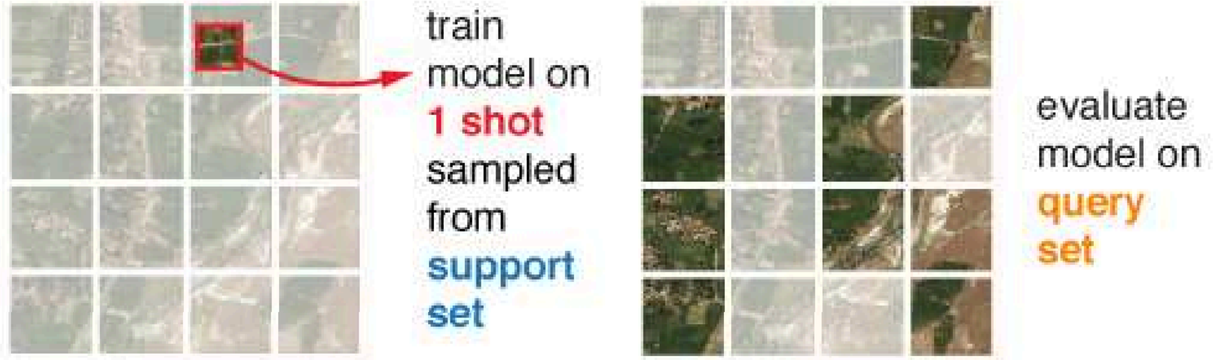
Goal: Segment/classify images from a new region with a small amount of data

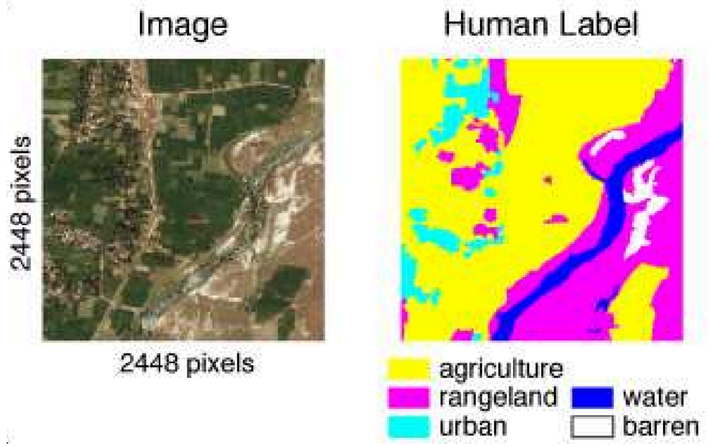
DeepGlobe dataset (Demir et al. 2018)

No geographic metadata, used clustering to guess region



Example 1-shot learning segmentation task.





Evaluation

Meta-training data: $\{\mathcal{D}_1, \ldots, \mathcal{D}_T\}$

Meta-test time: small amount of data from new region: $\mathcal{D}_j^{\text{tr}}$
(meta-test training set / meta-test support set)

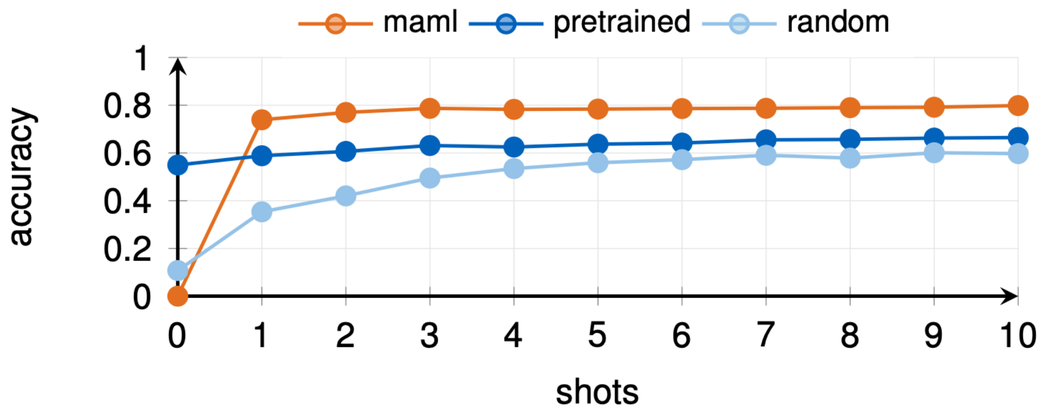
Compare:

Random init: Train from scratch on $\mathcal{D}_j^{\text{tr}}$

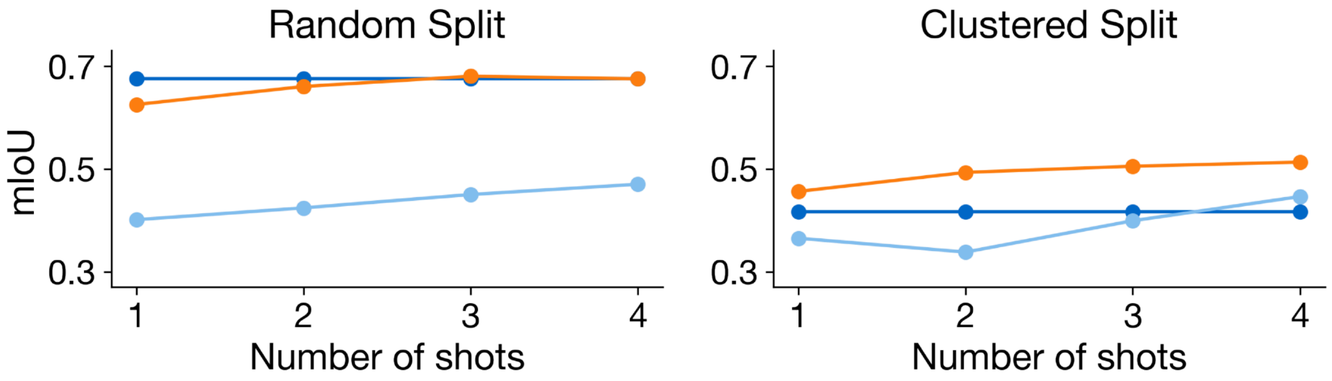
Pre-train on meta-training data $\mathcal{D}_1 \cup \ldots \cup \mathcal{D}_T$, **fine-tune** on $\mathcal{D}_j^{\text{tr}}$

MAML on meta-training data $\{\mathcal{D}_1, \ldots, \mathcal{D}_T\}$, adapt with $\mathcal{D}_j^{\text{tr}}$

SEN12MS dataset



DeepGlobe dataset



More visualizations and analysis in the paper!

Plan for Today

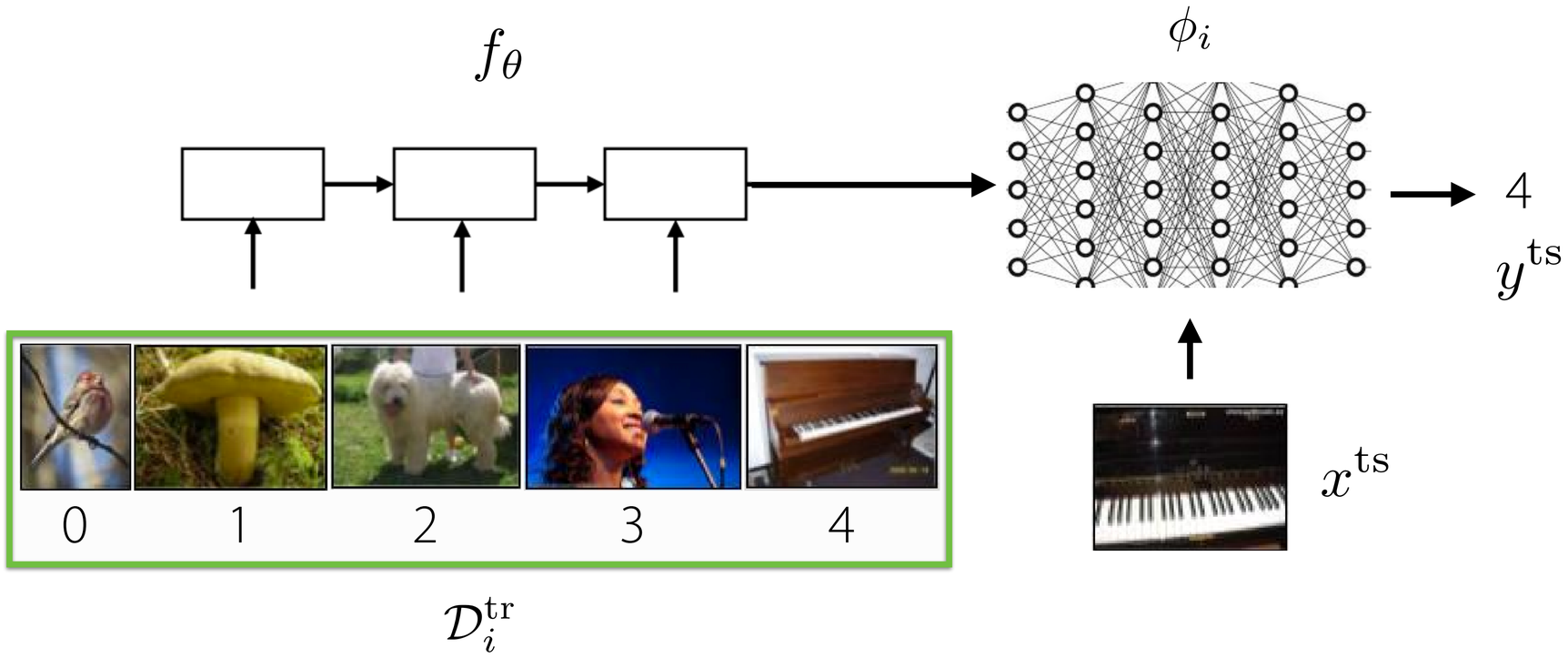
Non-Parametric Few-Shot Learning
- Siamese networks, matching networks, prototypical networks
- Case study of few-shot student feedback generation

Properties of Meta-Learning Algorithms
- Comparison of approaches

Example Meta-Learning Applications
- 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

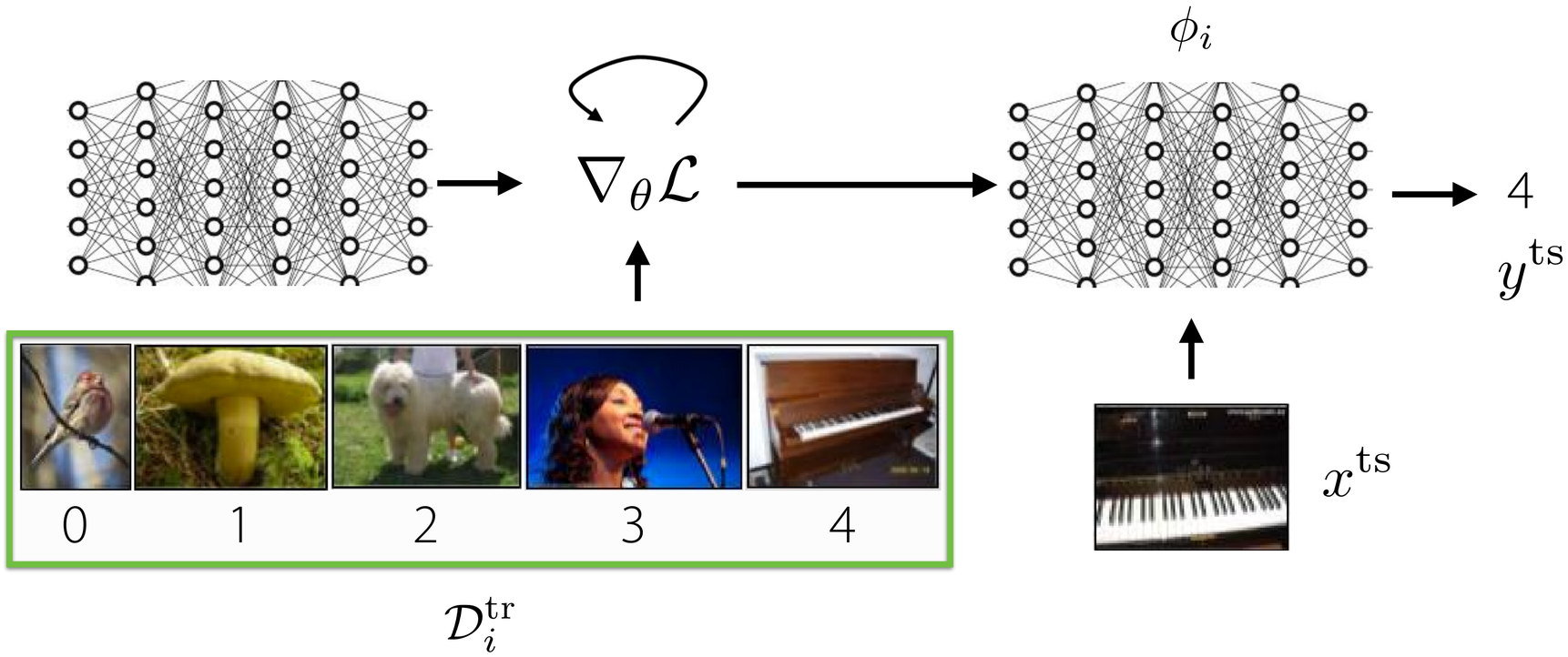


Key idea: parametrize learner as a neural network

\+ **expressive**

\- **challenging optimization** problem

Recap: Optimization-Based Meta-Learning



Key idea: embed optimization inside the inner learning process

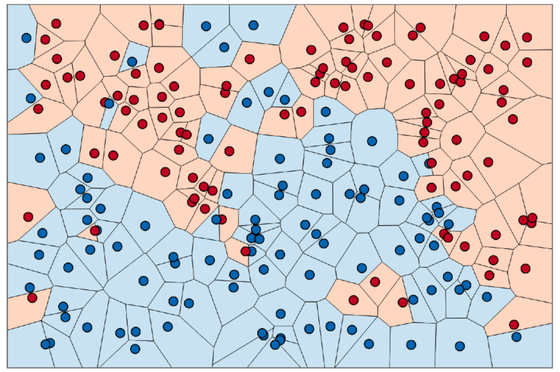
\+ **structure** of **optimization** embedded into meta-learner

\- typically 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

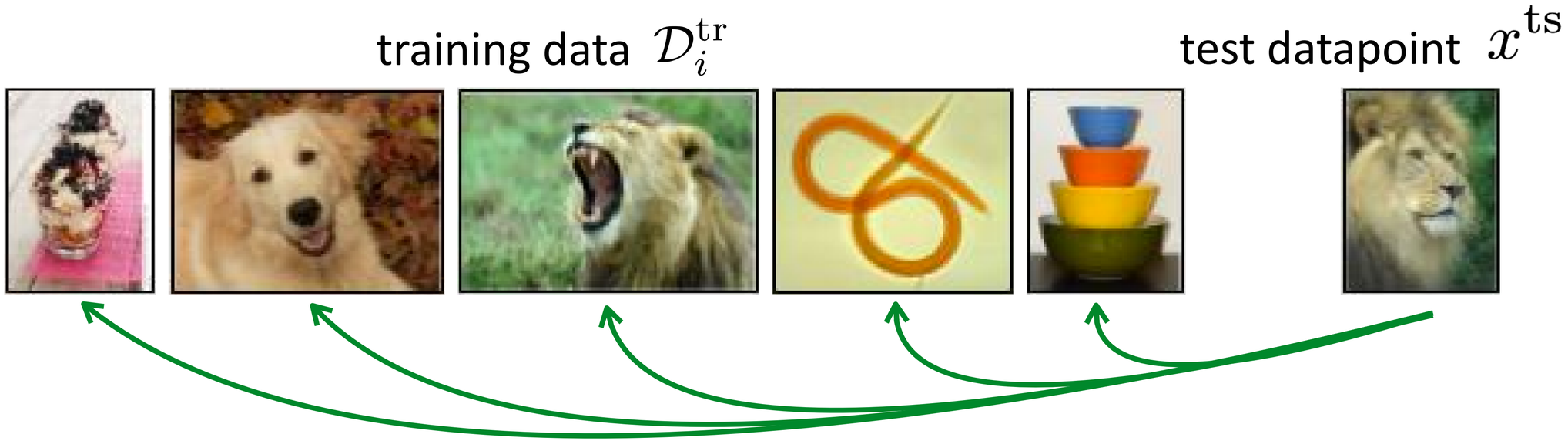
During **meta-training**: still want to be parametric

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.



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?

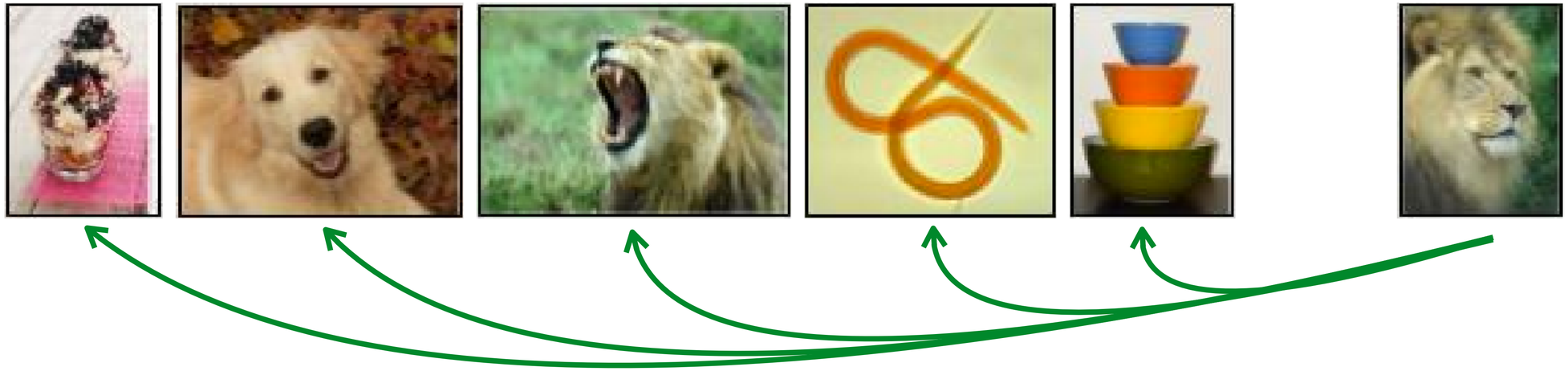
ℓ_2 distance in pixel space?

Zhang et al. (arXiv 1801.03924)

Non-parametric methods

Key Idea: Use non-parametric learner.

training data $\mathcal{D}_i^{\text{tr}}$ 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?~~

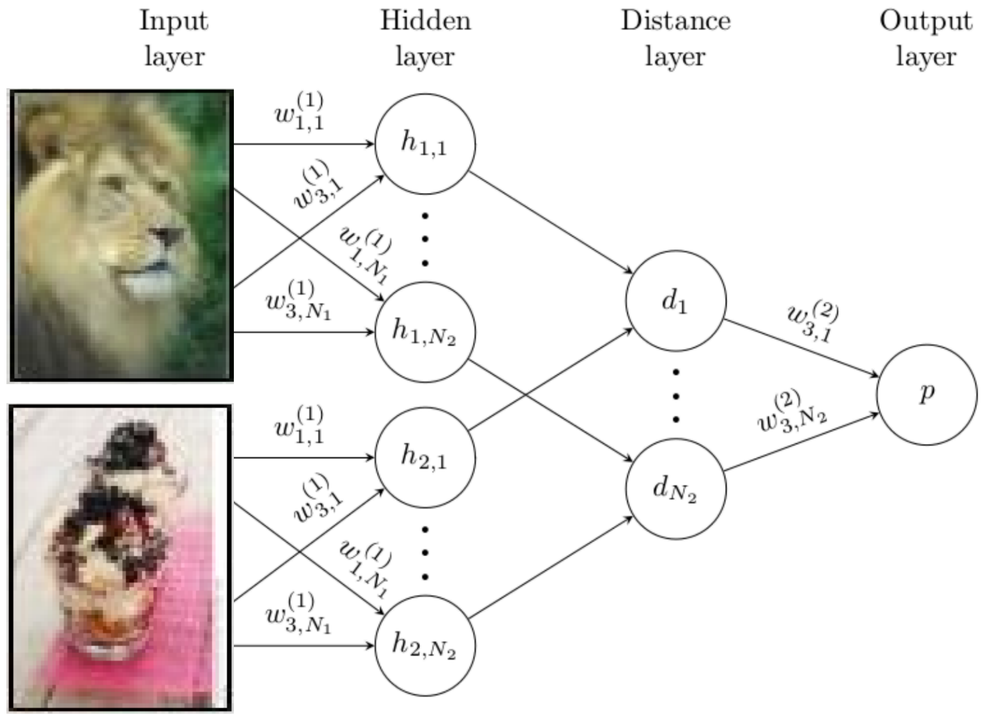
Question: What distance metric would you use instead?

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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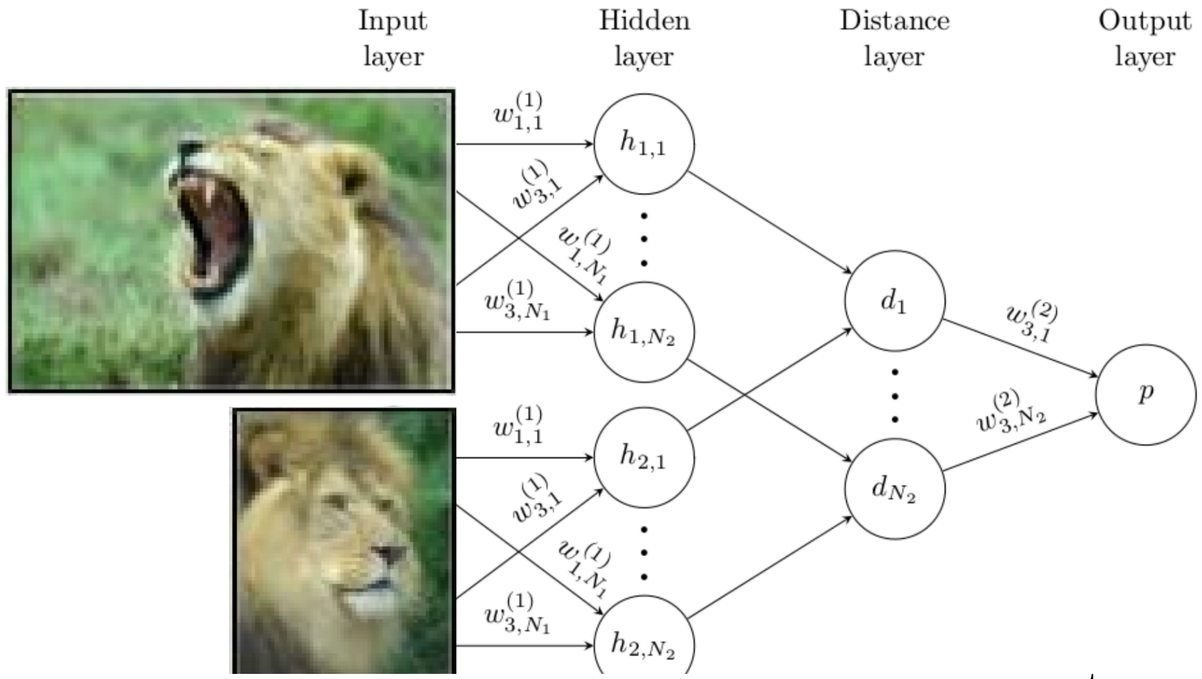
Koch et al., ICML ‘15

Non-parametric methods

Key Idea: Use non-parametric learner.

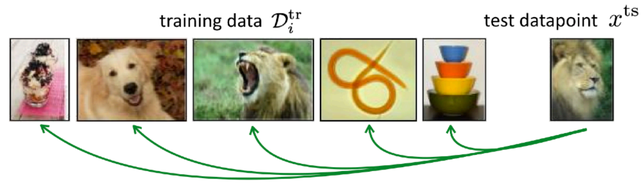
train Siamese network to predict whether or not two images are the same class



label

1

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?

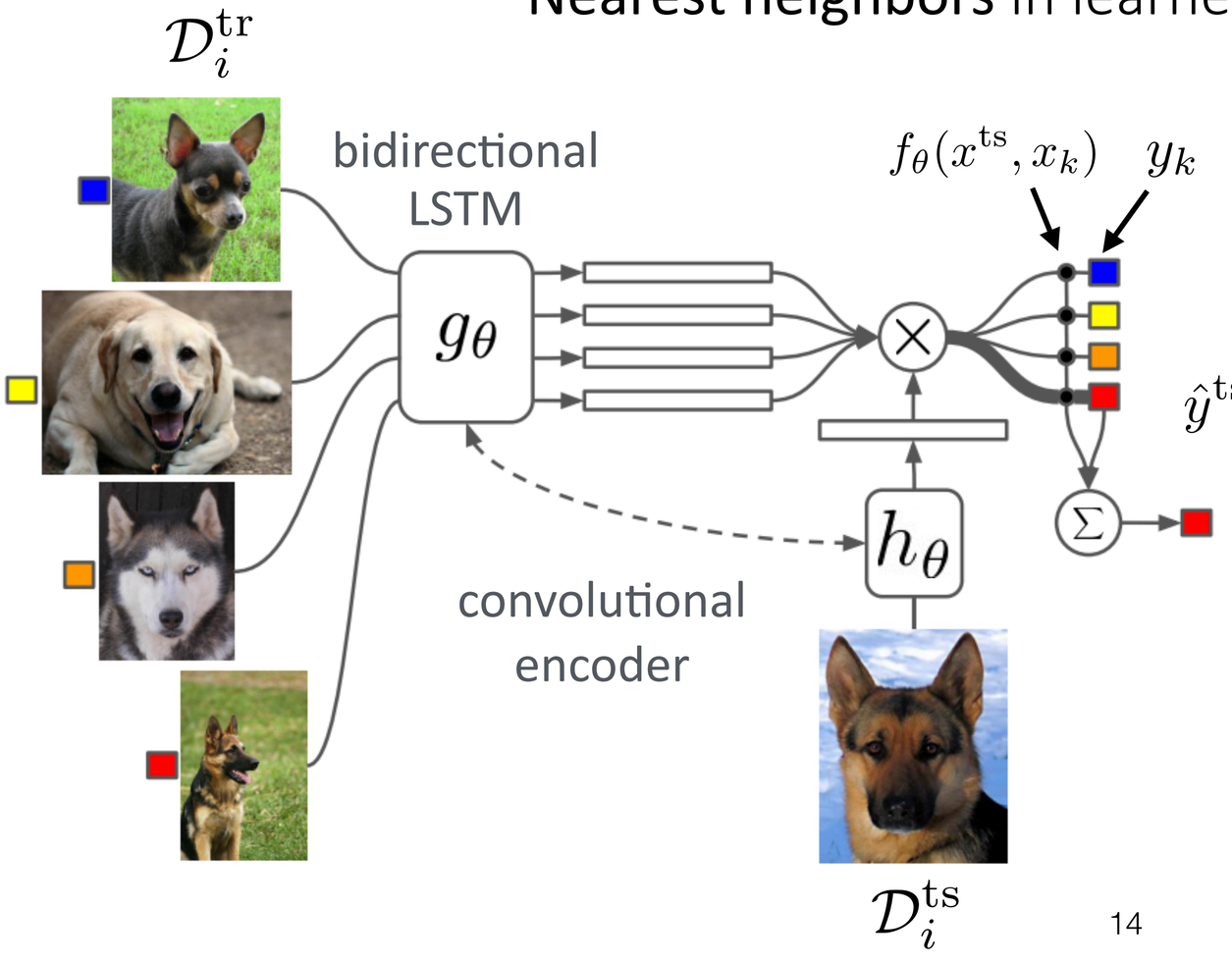
Koch et al., ICML '15

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 $\mathcal{D}_i^{\text{tr}}, \mathcal{D}_i^{\text{test}}$ from $\mathcal{D}_i$
3. ~~Compute ϕ_i $f_\theta(\mathcal{D}_i^{\text{tr}})$~~ 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. ~~Update θ 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**)

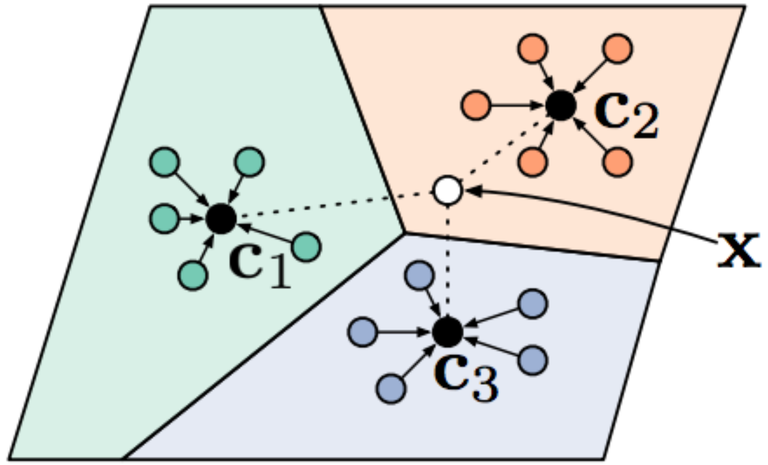
What if >1 shot?

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.



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

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

Note that this formula has been updated!

d: Euclidean, or cosine distance

Snell et al. Prototypical Networks, NeurIPS ‘17

Non-parametric methods

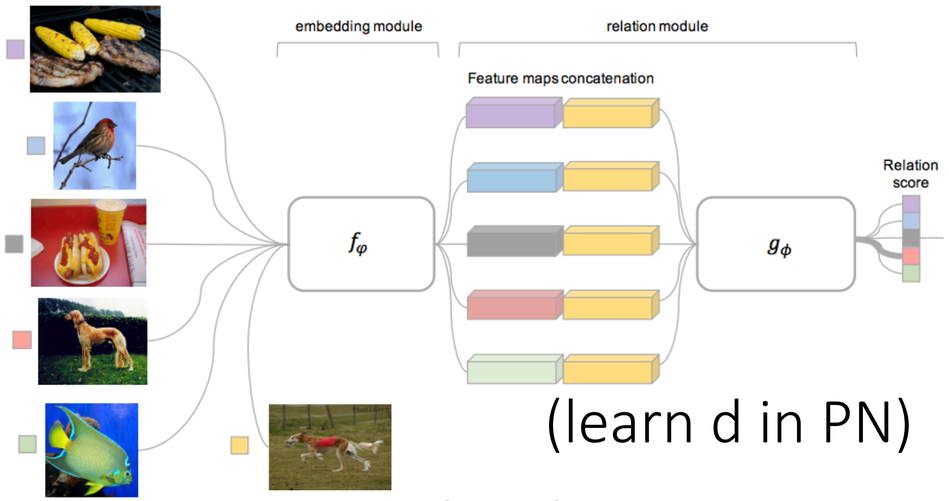
So far: Siamese networks, matching networks, prototypical networks

Embed, then nearest neighbors.

Challenge

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

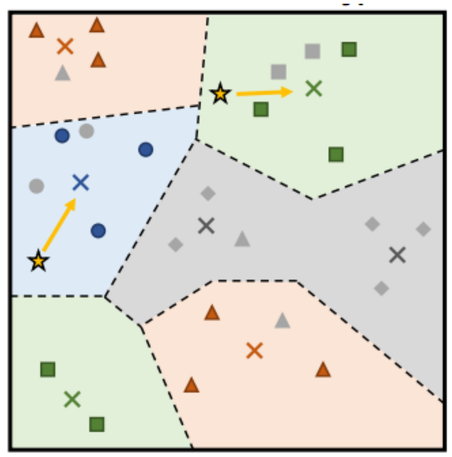
Idea: Learn non-linear relation module on embeddings



(learn d in PN)

Sung et al. Relation Net

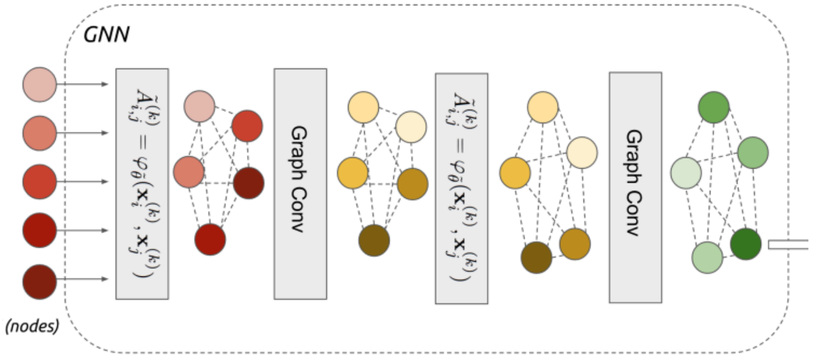
Idea: Learn infinite mixture of prototypes.



adaptive number of clusters

Allen et al. IMP, ICML '19

Idea: Perform message passing on embeddings



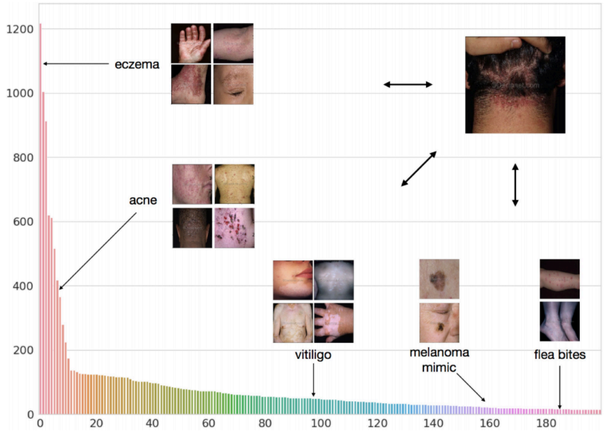
Garcia & Bruna, GNN

Previous Year's Case Study

Prototypical Clustering Networks for Dermatological Image Classification

Viraj Prabhu *,[1] Anitha Kannan[3] Murali Ravuri[3] Manish Chablani[3]
David Sontag[2] Xavier Amatriain[3]
[1]Georgia Tech [2]MIT [3]Curai
virajp@gatech.edu dsontag@mit.edu {anitha, murali, manish, xavier}@curai.com

Machine Learning for Healthcare Conference 2019
Link: https://arxiv.org/abs/1811.03066



Challenges:
- hard to get data
- data is long-tailed

Goal: Acquire accurate classifier on all classes

This Year's Case Study

Meta-Learning Student Feedback to 16,000 Solutions

Mike Wu, Chris Piech, and Chelsea Finn

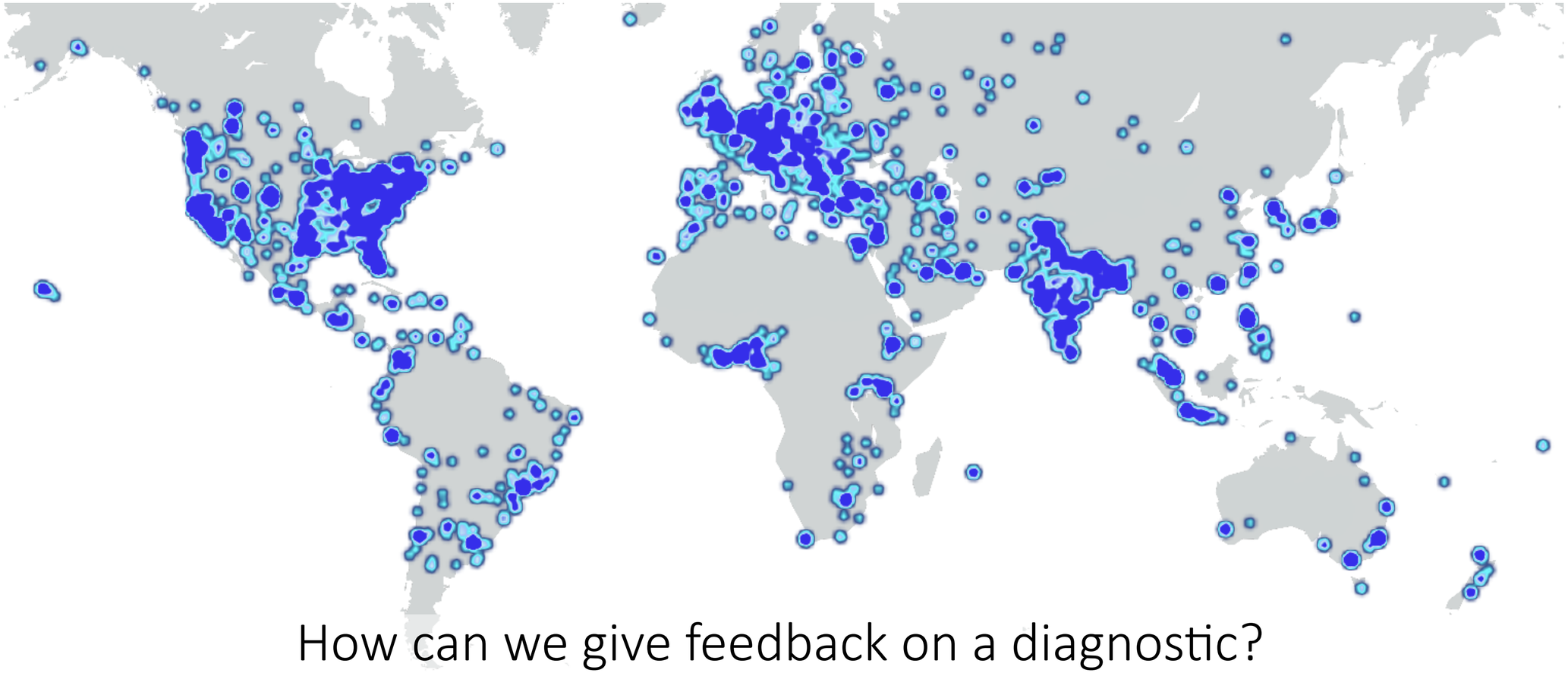
July 20, 2021

Links: https://ai.stanford.edu/blog/prototransformer/

https://arxiv.org/abs/2107.14035

The Feedback Problem

Code-in-Place 2021: Free intro to CS course, 12,000+ students from 150+ countries



How can we give feedback on a diagnostic?

Submissions: open-ended Python code snippets

Estimated 8+ months of human labor

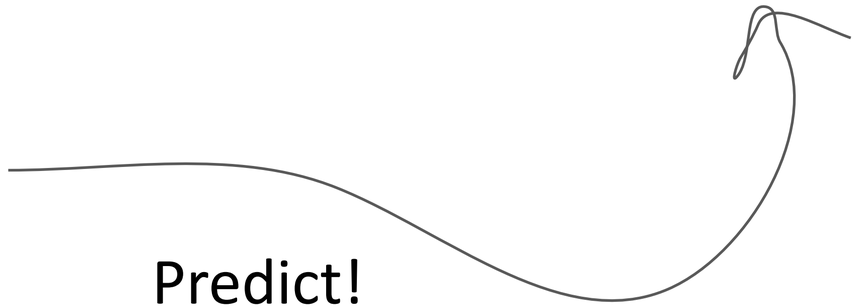
Piech & Sahami & Zelenski,
Stanford University

The Feedback Challenge

- Train a model to infer student misconceptions, **y**, from the student solution, **x**.

```
# print 1 to n w/ loop

def my_solution(n)

        print(1)

        print(2)

        print(3)
```

```
[x] Incorrect Syntax

[x] Did not loop

[ ] Uses “print” fn
```



Same rubrics that instructors use to give their feedback.

The Feedback Challenge

Why is this a hard problem for ML?

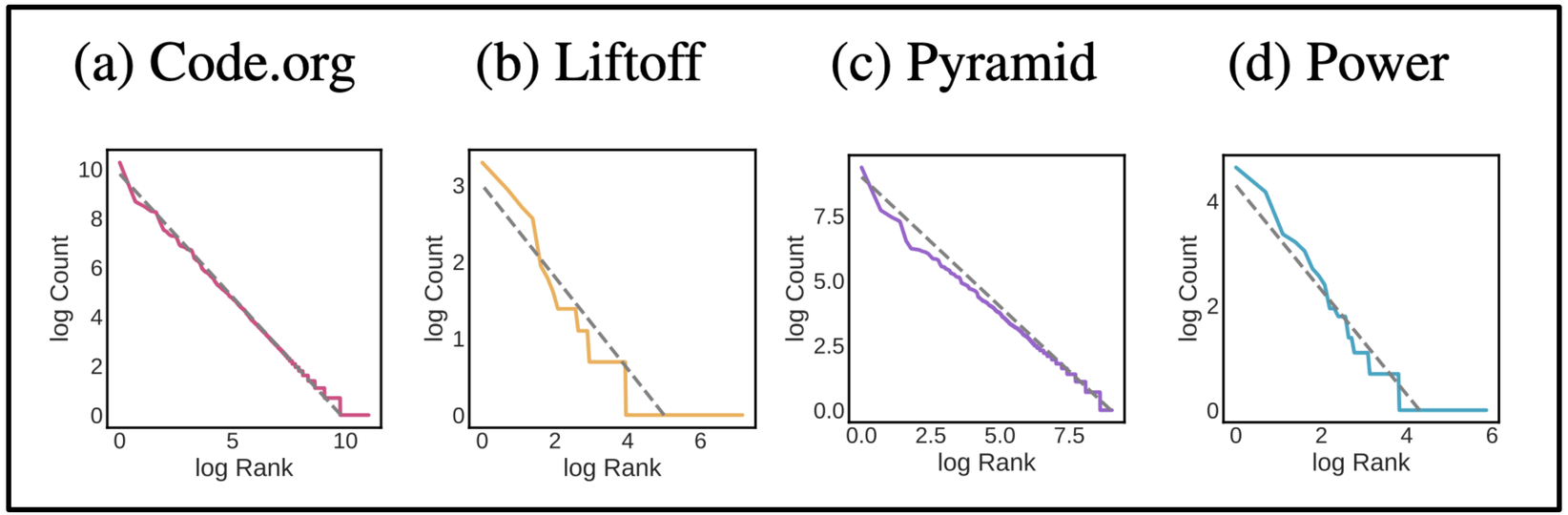
- **Limited annotation**: grading student work takes expertise and is very time consuming.

  Example: annotating 800 blockly codes took **25 hrs**

The Feedback Challenge

Why is this a hard problem for ML?

- **Limited annotation**: grading student work takes expertise and is very time consuming.
- **Long tailed distribution**: students solve the same problem in many *many* ways.



Generative Grading: Neural Approximate Parsing for Verifiable Automated Student Feedback (Malik et. al. 2020)

The Feedback Challenge

Why is this a hard problem for ML?

- **Limited annotation**: grading student work takes expertise and is very time consuming.
- **Long tailed distribution**: students solve the same problem in many *many* ways.
- **Changing curriculums:** instructors constantly edit assignments and exams. Student solutions and instructor feedback look different year to year.

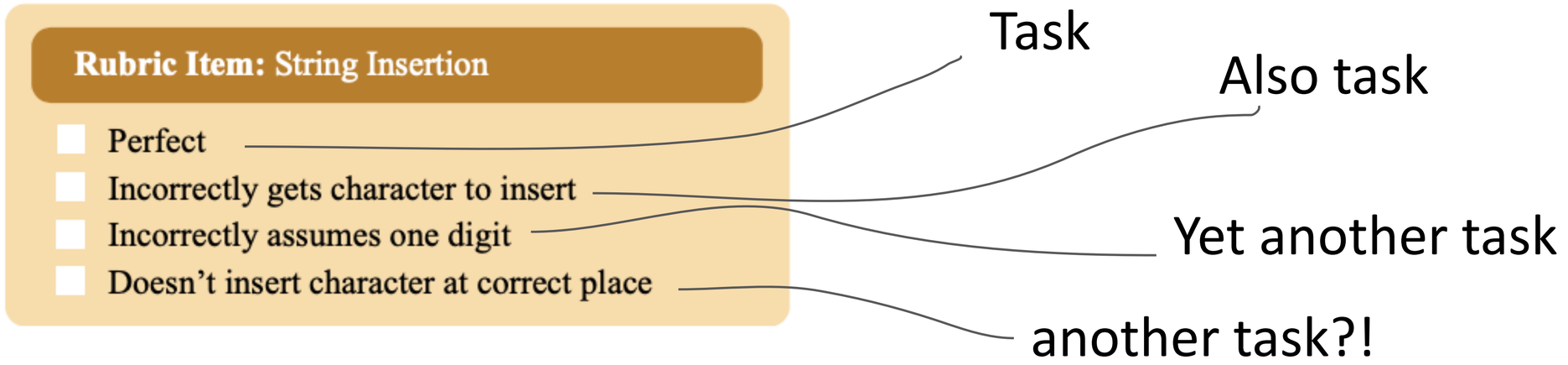
Framing it as a Meta-Learning Problem

Meta-Training Dataset: 4 final exams and 4 midterm exams from CS106.

- 63 questions and 24.8k student solutions.
- Every student solution has feedback via a rubric.

A rubric has several items. Each item has several options that you may pick as true.

- More than one option can be true.
- Every problem has its own (possibly unique) rubric items and options.



ProtoTransformer

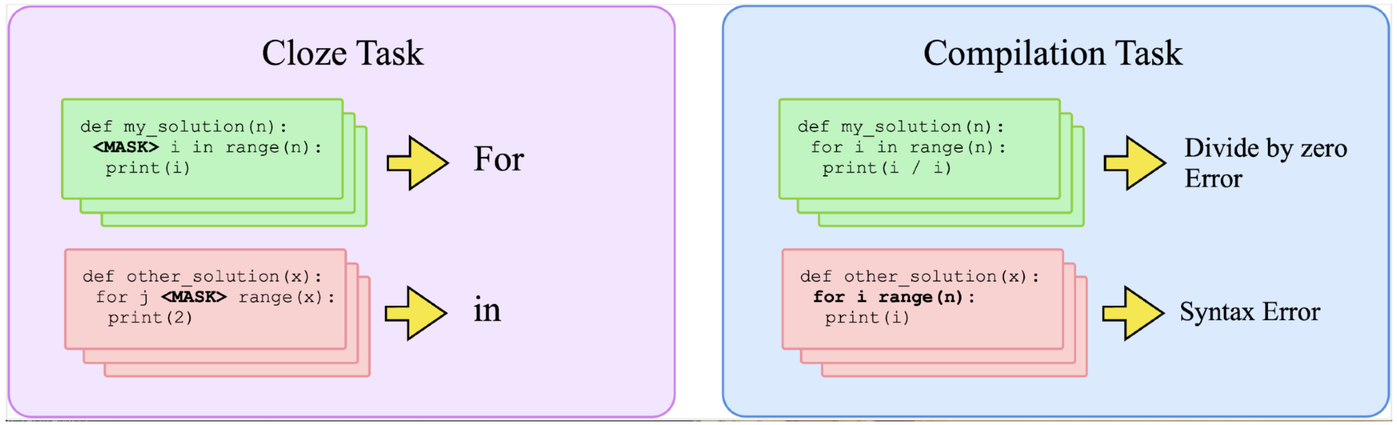
$$p_\theta(y = n|x) = \frac{\exp(-d\left(f_\theta(x), \mathbf{c}_n\right))}{\sum_{n'} \exp(-d\left(f_\theta(x), \mathbf{c}_{n'}\right))}$$

Note that this formula has been updated!

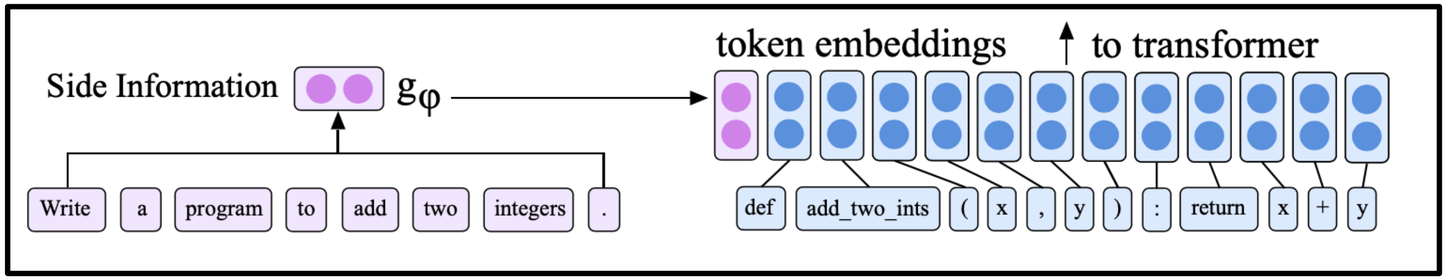
- $x = (x_1, x_2, ..., x_T)$ is a **sequence of discrete tokens** (e.g. code, language).
- The embedding $f_\Theta: X \rightarrow R^d$ is **a RoBERTa model** (stacked transformers) where token embeddings are averaged into a single vector.
- Applying this out of the box fails.

Attention is **not** all you need.

Trick #1: Augment rubric tasks with self-supervised tasks

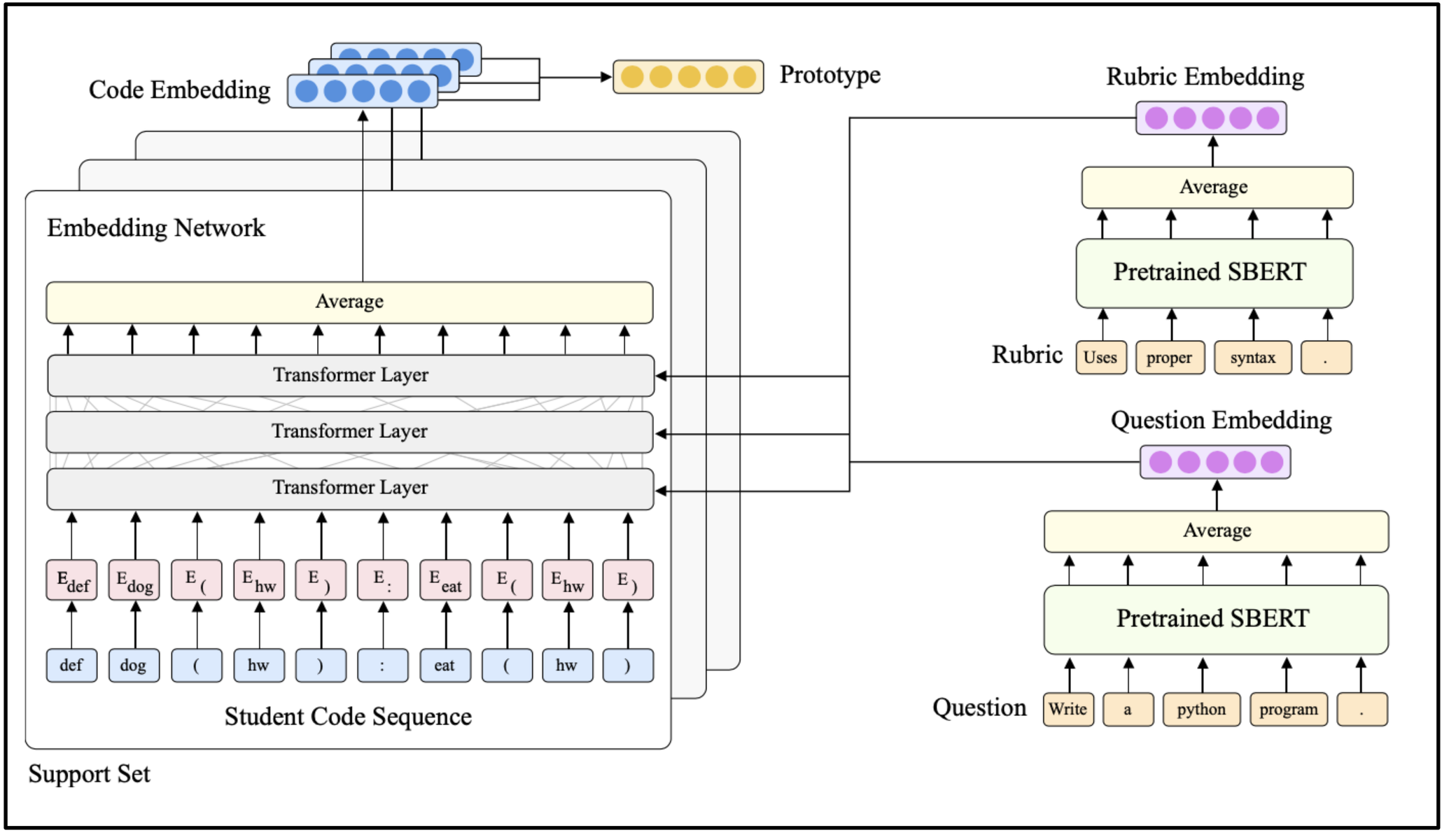


Trick #2: Reduce few-shot ambiguity by incorporating side information (rubric option name, question text)



Trick #3: Pre-train on unlabeled Python code.

CodeBERT: A Pre-Trained Model for Programming and Natural Languages (Feng et. al. 2020
CodeSearchNet Challenge: Evaluating the State of Semantic Code Search (Husain et.al. 2020)


Code Embedding
Prototype
Rubric Embedding
Average
Pretrained SBERT
Rubric
Uses
proper
syntax
.
Embedding Network
Average
Transformer Layer
Transformer Layer
Transformer Layer
Question Embedding
Average
Pretrained SBERT
Question
Write
a
python
program
.
E def
E dog
E (
E hw
E)
E :
E eat
E (
E hw
E)
def
dog
(
hw
)
:
eat
(
hw
)
Student Code Sequence
Support Set

Main Offline Results

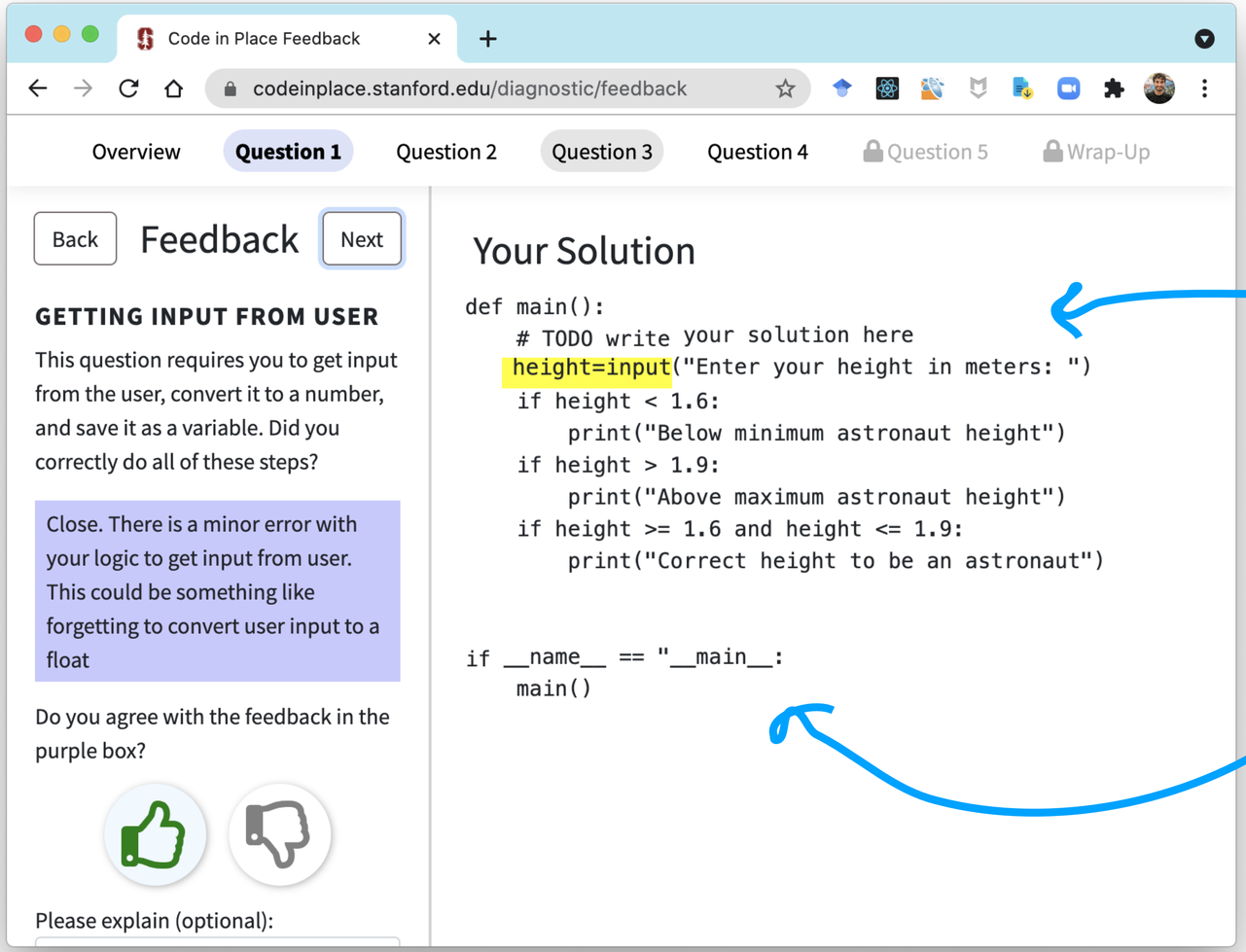
Model	Held-out rubric AP	P@50	P@75	ROC-AUC
ProtoTransformer	**84.2** (±1.7)	**85.2** (±3.8)	**74.2** (±1.4)	**82.9** (±1.3)
Supervised	66.9 (±2.2)	59.1 (±1.7)	53.9 (±1.5)	61.0 (±2.1)
Human TA	82.5	–	–	–

Model	Held-out exam AP	P@50	P@75	ROC-AUC
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	–	–	–

- Outperforms supervised learning by 8-17%
- More accurate than human TA on held-out rubric
- Room to grow on held-out exam

Live Deployment to Code-in-Place Students

May 10th, 2021: Students took diagnostic.



Algorithm uses attention to highlight where the error arises

AI generated feedback

Syntax error here would prevent unit tests from being useful

Students evaluate the feedback

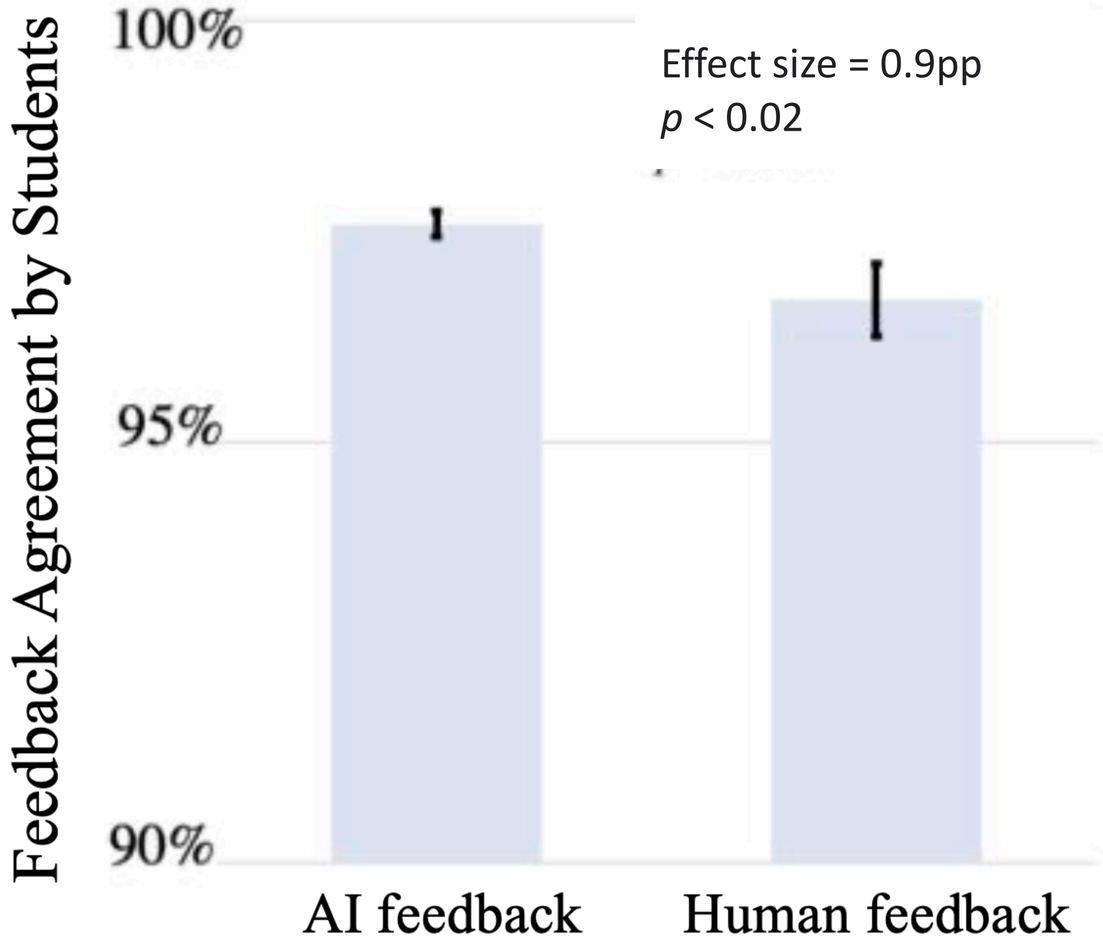
UI designed by Alan Cheng & Chris Piech

Blind, randomized trial *with real students*

Humans gave feedback ~1k answers.
AI gave feedback on the remaining ~**15k**.

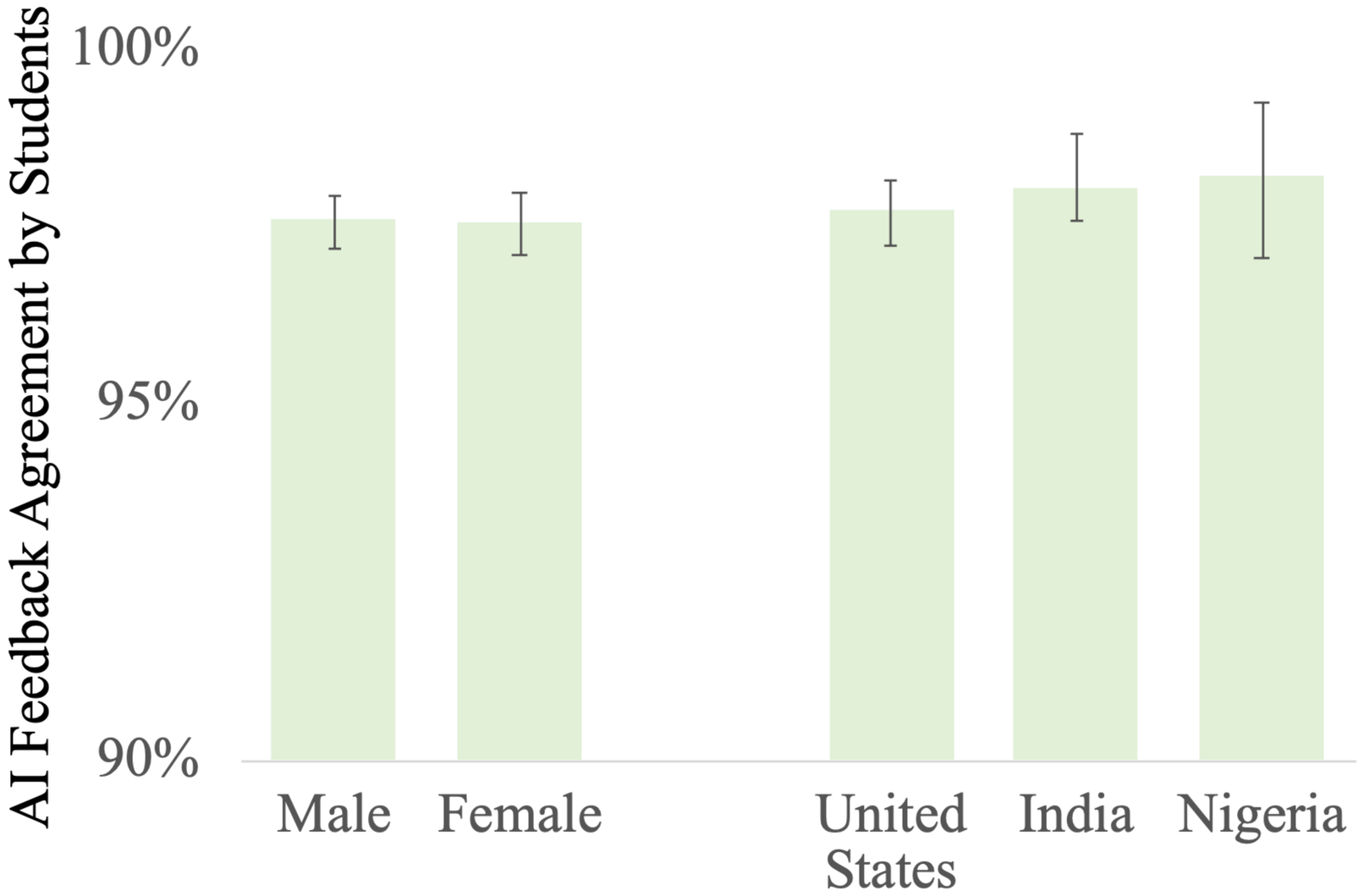
~2k could be auto-graded and were not included in analysis.

Humans gave good feedback.
ML model gave slightly better feedback.



Average holistic rating of usefulness by students was **4.6 ± 0.018 out of 5**.

No signs of bias by demographics



Plan for Today

Non-Parametric Few-Shot Learning

- Siamese networks, matching networks, prototypical networks
- Case study of few-shot student feedback generation

Properties of Meta-Learning Algorithms

- Comparison of approaches

Example Meta-Learning Applications

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

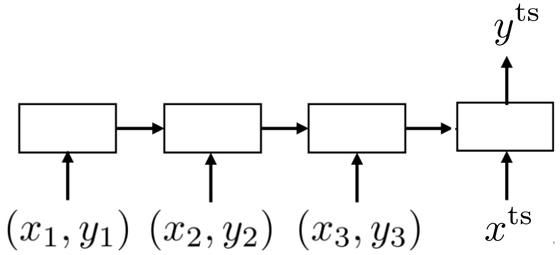
How can we think about how these methods compare?

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

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

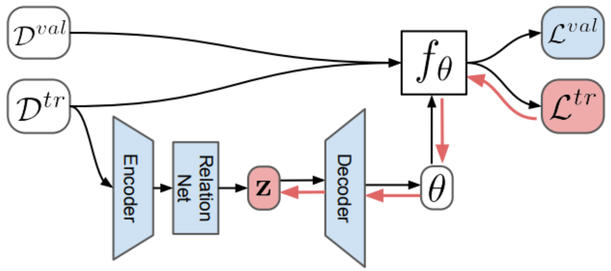
$$\text{where } \mathbf{c}_n = \frac{1}{K} \sum_{(x,y) \in \mathcal{D}_i^{\text{tr}}} \mathbb{1}(y = n) f_\theta(x)$$

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

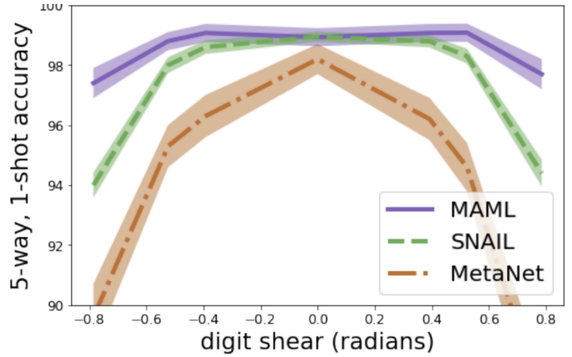
Why? scalability, applicability to a range of domains

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

+ **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 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**

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

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!

Application: One-Shot Imitation Learning

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

Tasks:

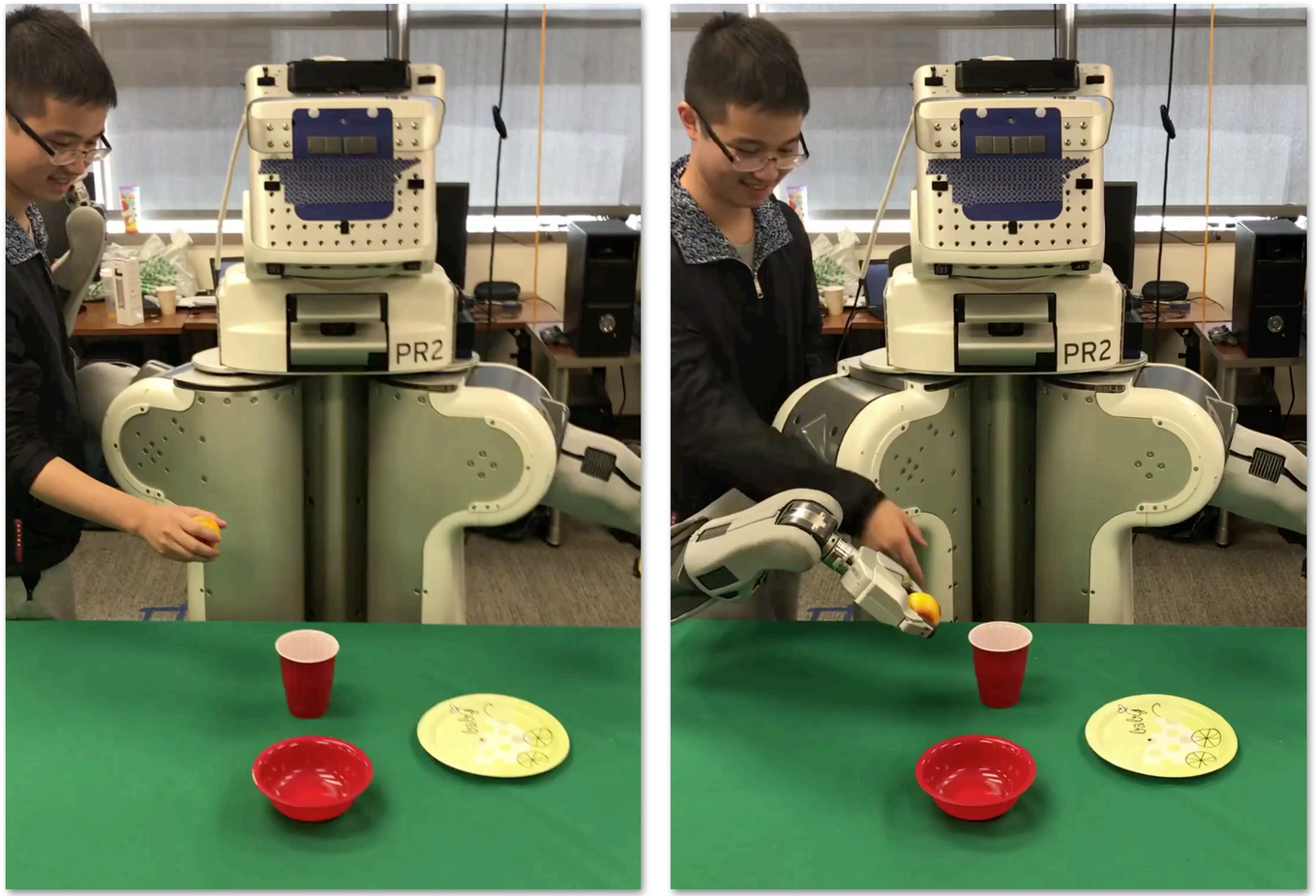
manipulating different objects

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

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

Model: optimization-based

MAML with *learned* inner loss



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	k-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**

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

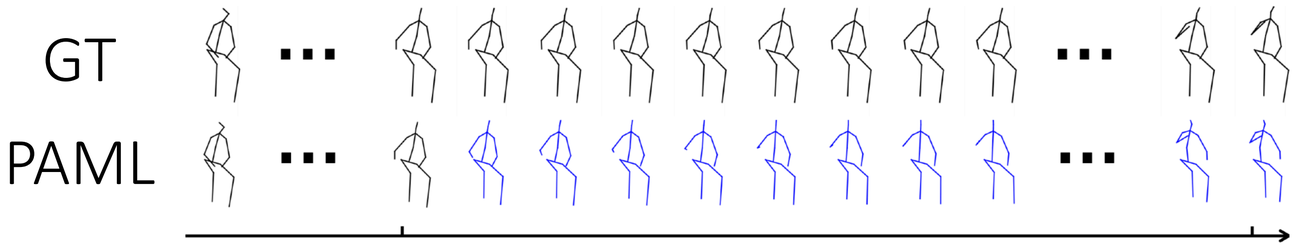
$\mathscr{D}_i^{\mathrm{ts}}$: future second(s) of motion

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)	$\text{Scratch}_{\text{spec}}$	1.90	1.95	2.16	2.18	1.99	2.00	2.33	2.31	2.30	2.30	2.31	2.34
	$\text{Scratch}_{\text{agn}}$	1.78	1.89	2.20	2.23	2.02	2.05	2.27	2.16	2.18	2.27	2.25	2.31
	$\text{Transfer}_{\text{ots}}$	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
	$\text{Transfer}_{\text{ft}}$	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)	$\text{Scratch}_{\text{spec}}$	2.88	2.86	2.85	2.83	2.80	2.99	3.01	3.13	3.12	2.95	2.62	2.99
	$\text{Scratch}_{\text{agn}}$	2.53	2.61	2.67	2.65	2.71	2.73	2.77	2.79	2.82	2.73	2.82	2.76
	$\text{Transfer}_{\text{ots}}$	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
	$\text{Transfer}_{\text{ft}}$	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

Closing note for today

$\mathscr{D}_i^{\mathrm{tr}}$ 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.