Black-Box Meta-Learning

CS 330

Logistics

Project group form due **Monday, October 10**

Homework 1 due **Wednesday October 12**

Plan for Today

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

} Topic of Homework 1!

Goals for by the end of lecture:
- Training set-up for few-shot meta-learning algorithms
- How to implement black-box meta-learning techniques

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Meta-Learning Problem

Transfer Learning with Many Source Tasks

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

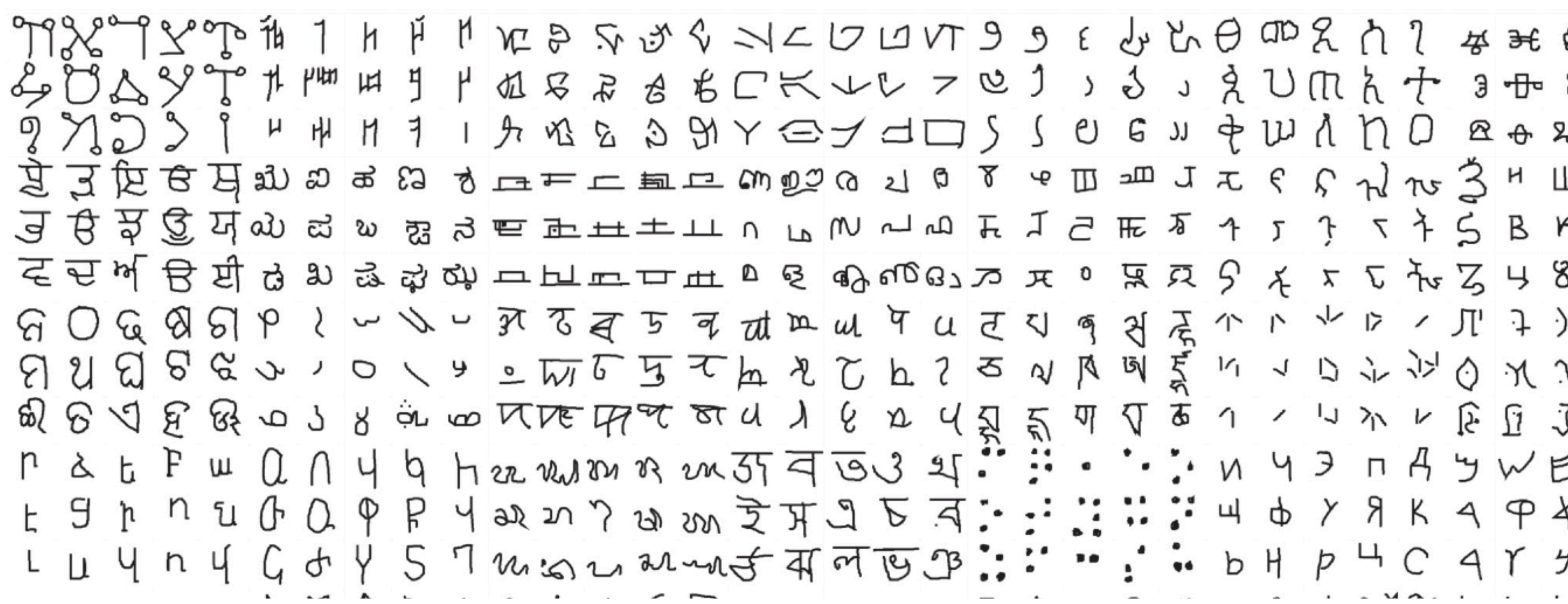
Key assumption: meta-training tasks and meta-test task drawn i.i.d. from same task distribution

$$\mathscr{T}_1, \ldots, \mathscr{T}_n \sim p(\mathscr{T}),\ \mathscr{T}_{\text{test}} \sim p(\mathscr{T})$$

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 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

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.

meta-training

$\mathcal{T}_1$

$\mathcal{T}_2$

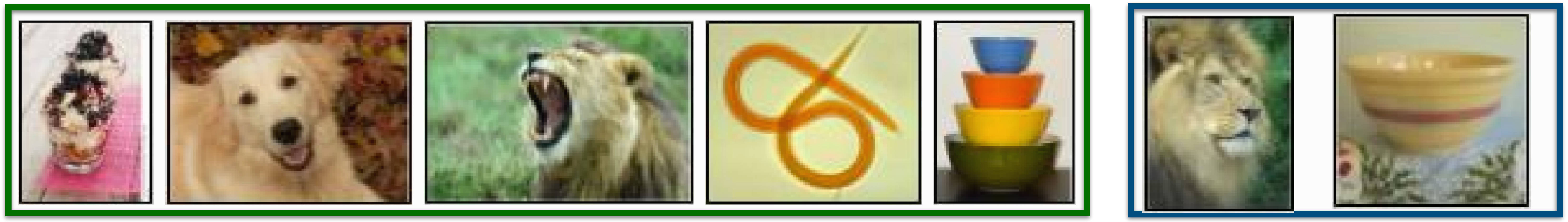
$\vdots$ $\vdots$

training classes

Given 1 example of 5 classes:

Classify new examples

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



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

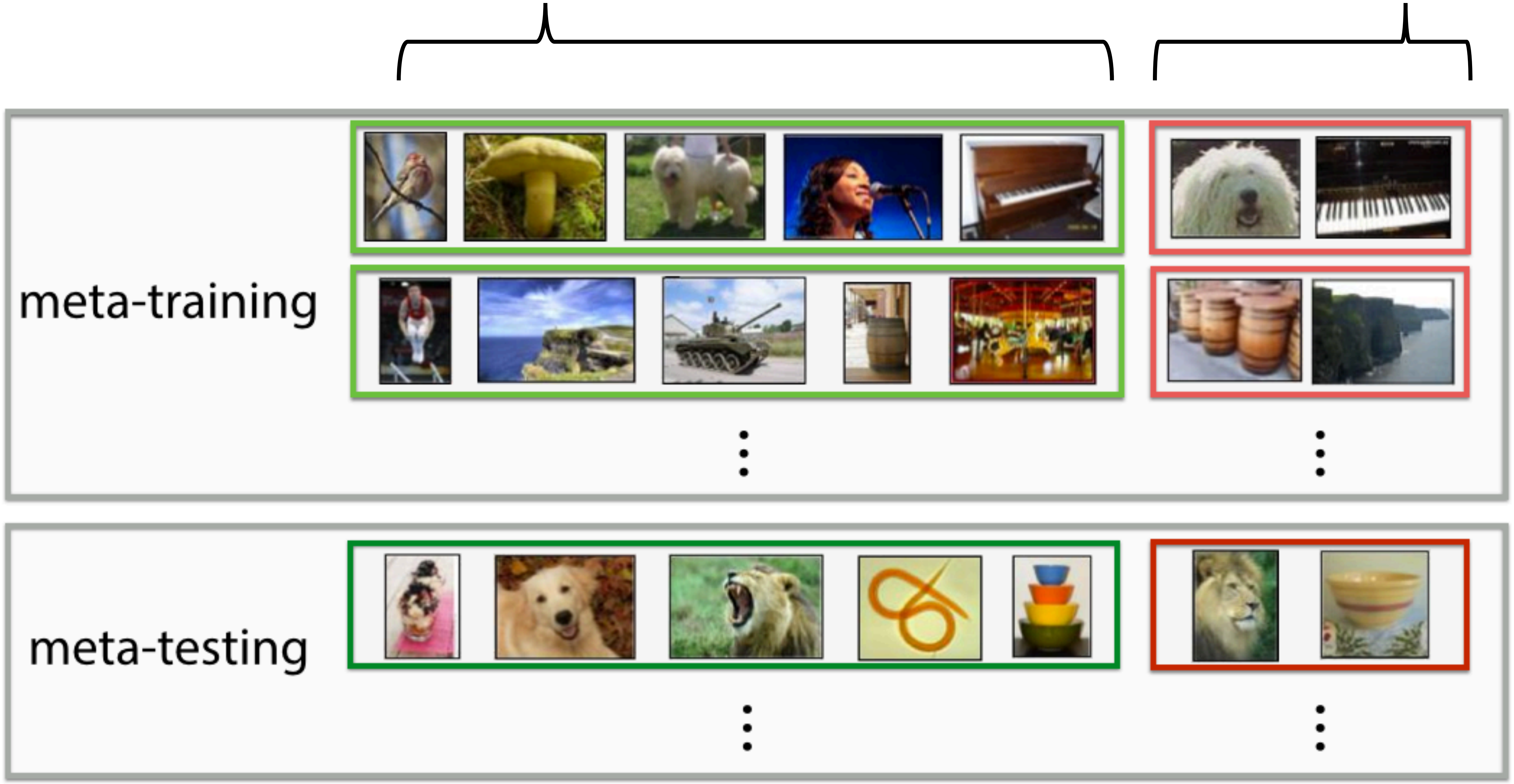
test set $\mathbf{x}_{\text{test}}$

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

Some terminology

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

task test dataset $\mathcal{D}_i^{\mathrm{test}}$ "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?

Plan for Today

Transfer Learning
- Problem formulation
- Fine-tuning

Meta-Learning
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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: $\{\mathcal{D}_i\}$

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

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

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

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

meta-parameters

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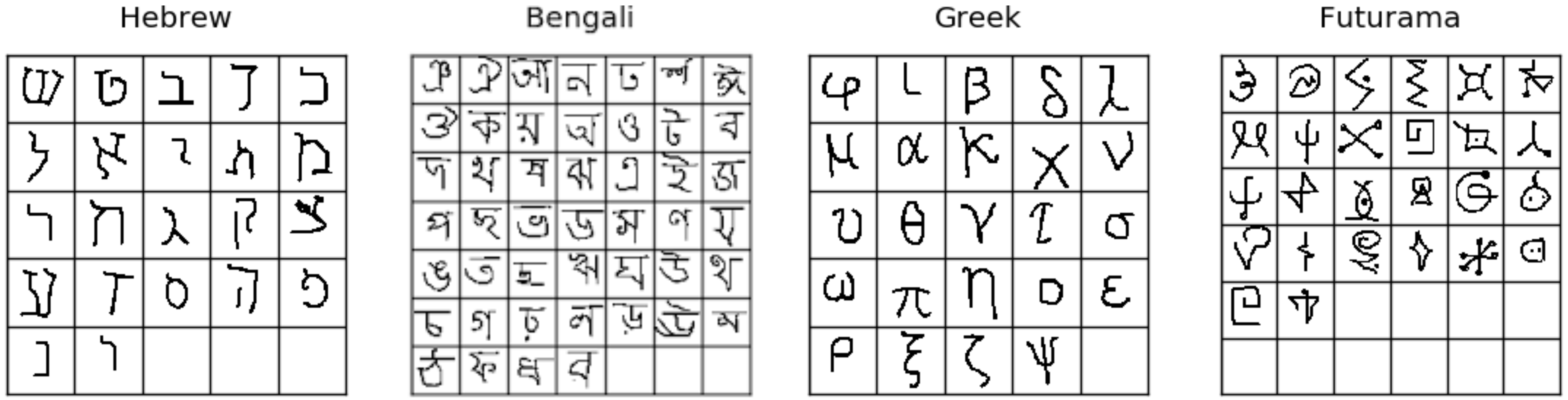
Running example

Omniglot dataset Lake et al. Science 2015

1623 characters from **50 different alphabets**



...

many classes, few examples

the “transpose” of MNIST

statistics more reflective
of **the real world**

20 instances of each character

whiteboard

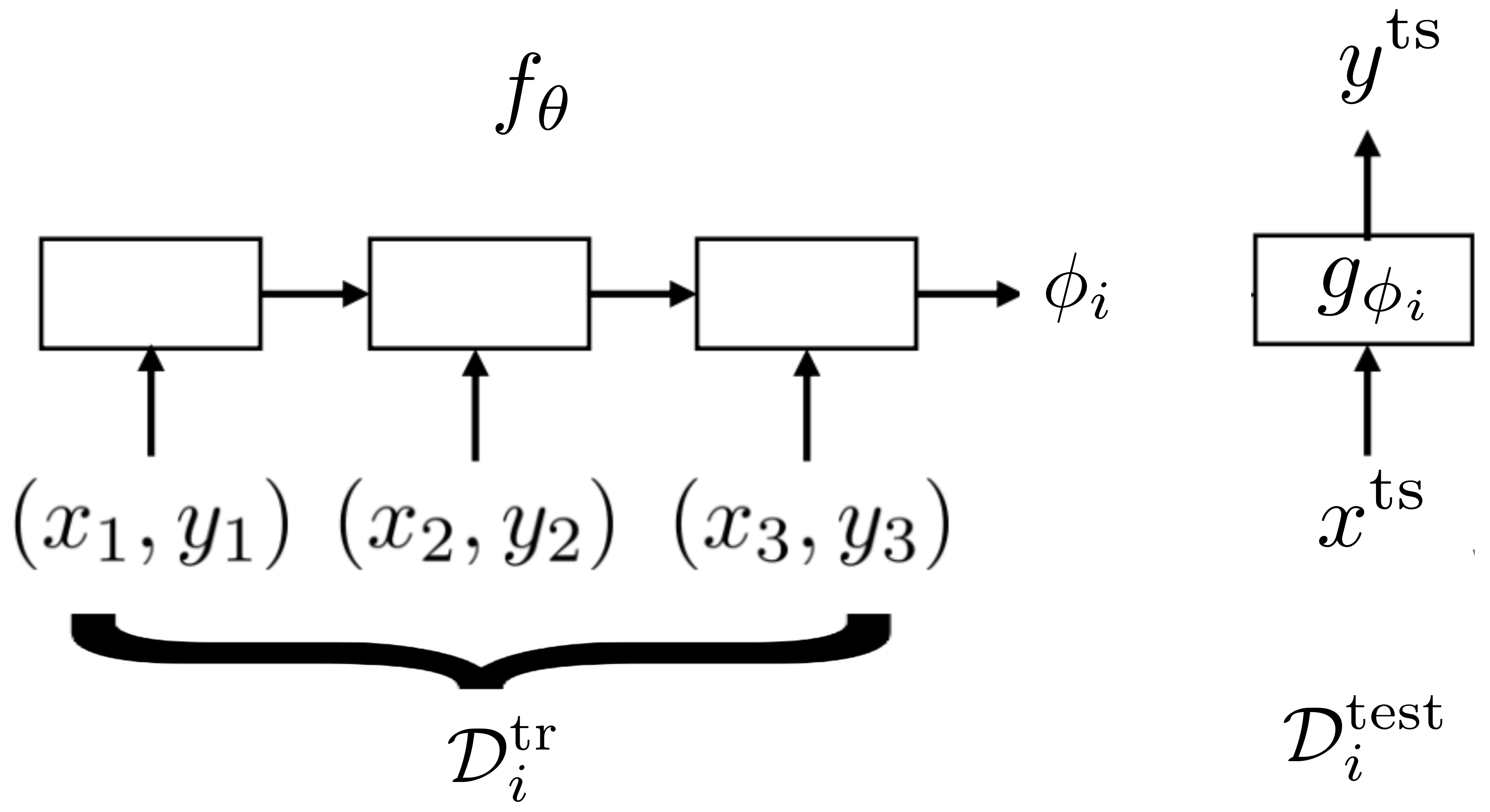
More **few-shot image recognition** datasets: tieredImageNet, CIFAR, CUB, CelebA, ORBIT, others

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 $\mathbf{y}^{\text{ts}} = g_{\phi_i}(\mathbf{x}^{\text{ts}})$



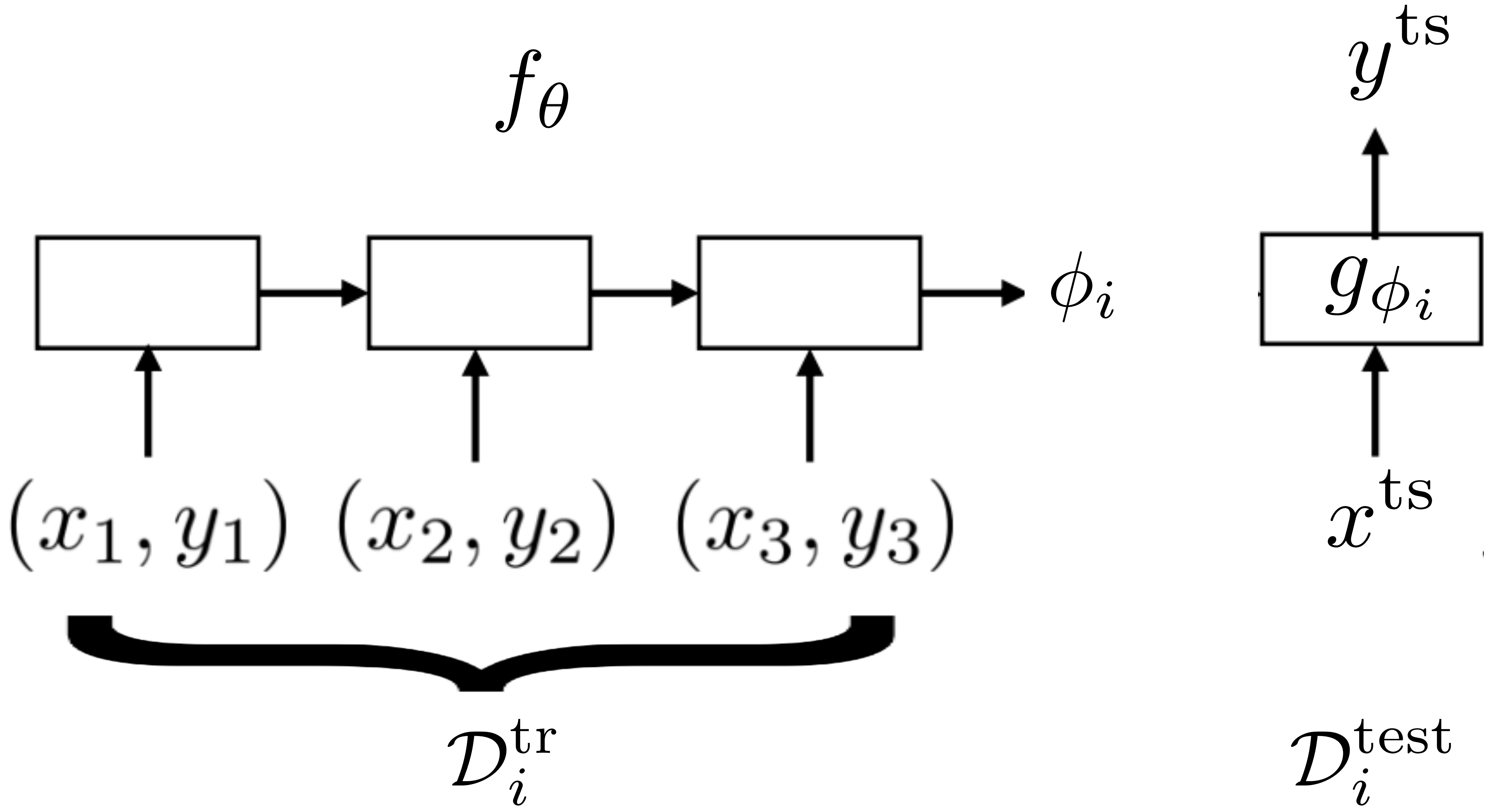
Train with standard supervised learning!

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

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

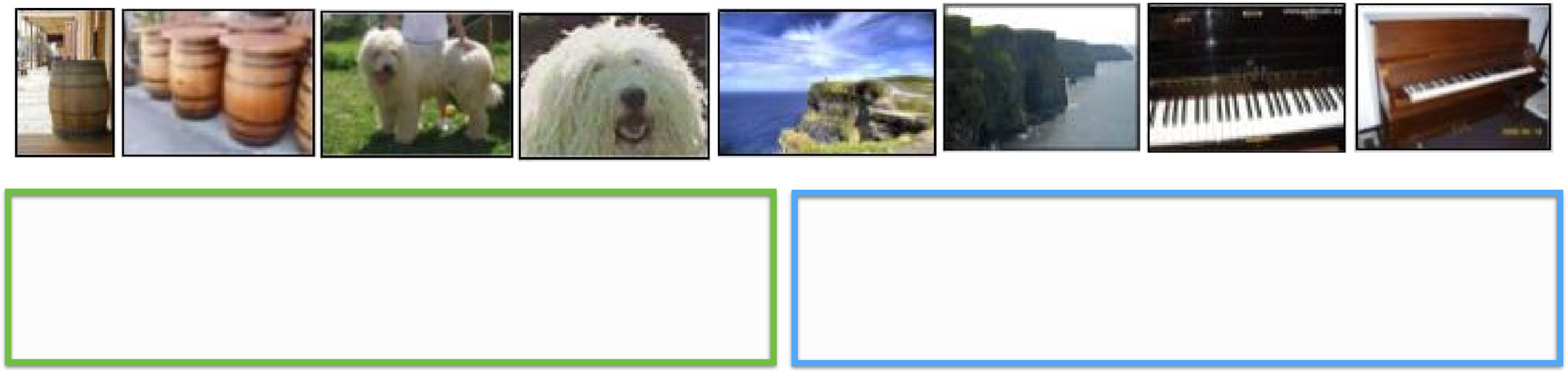
Black-Box Adaptation

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 $\mathcal{D}_i$

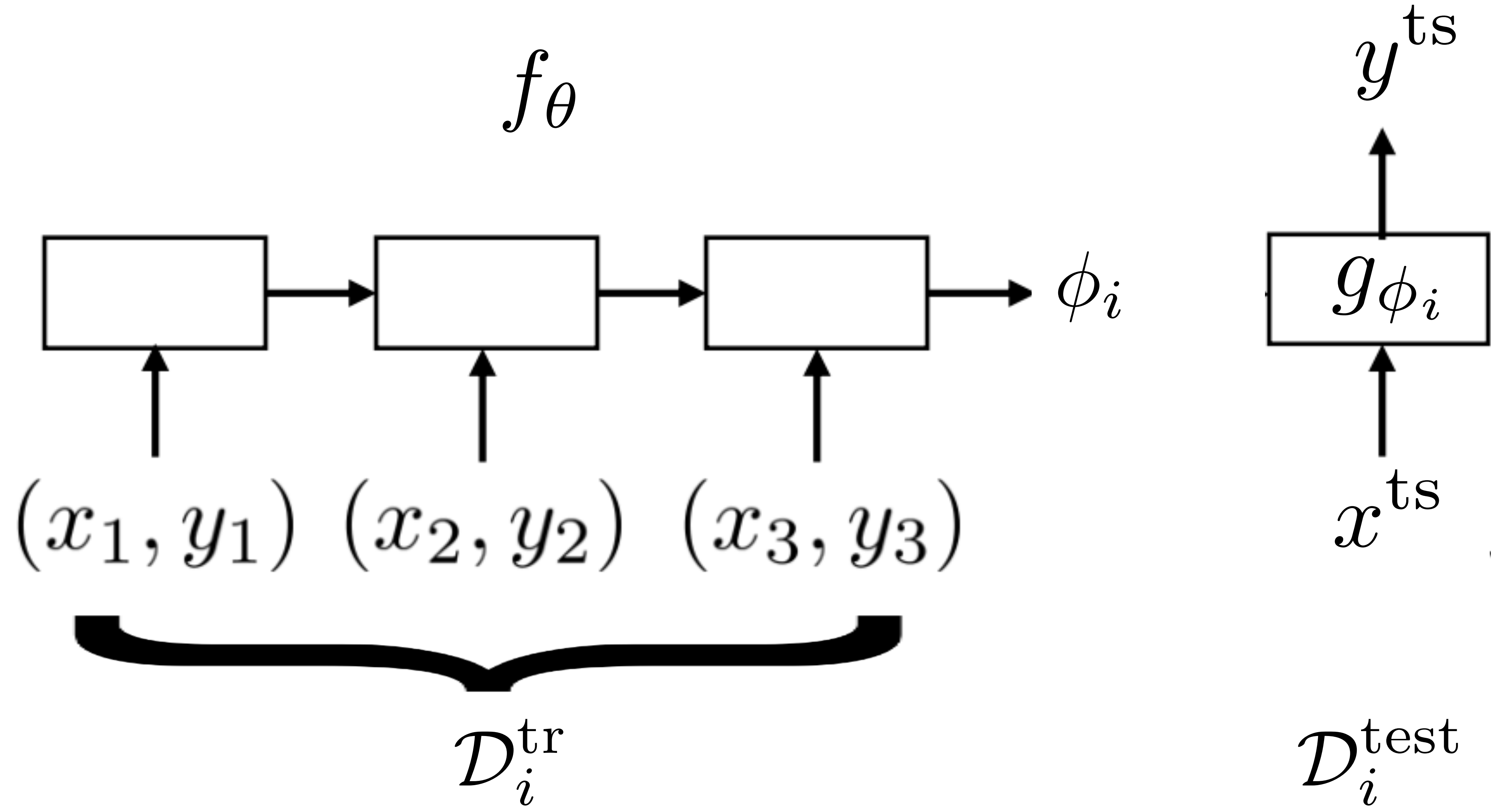
$\mathcal{D}_i$



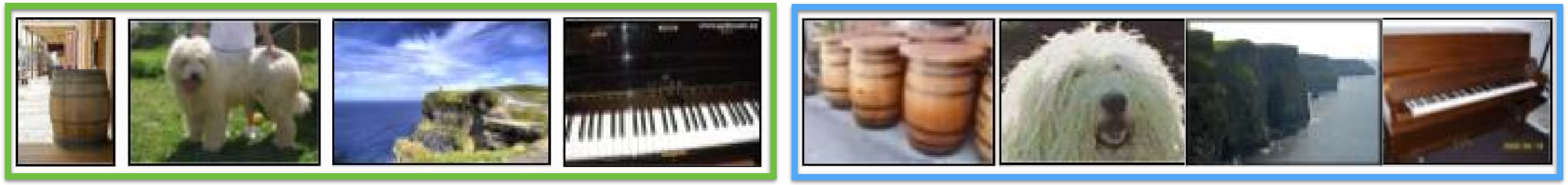
$\mathcal{D}_i^{\text{tr}}$ $\mathcal{D}_i^{\text{test}}$

Black-Box Adaptation

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



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

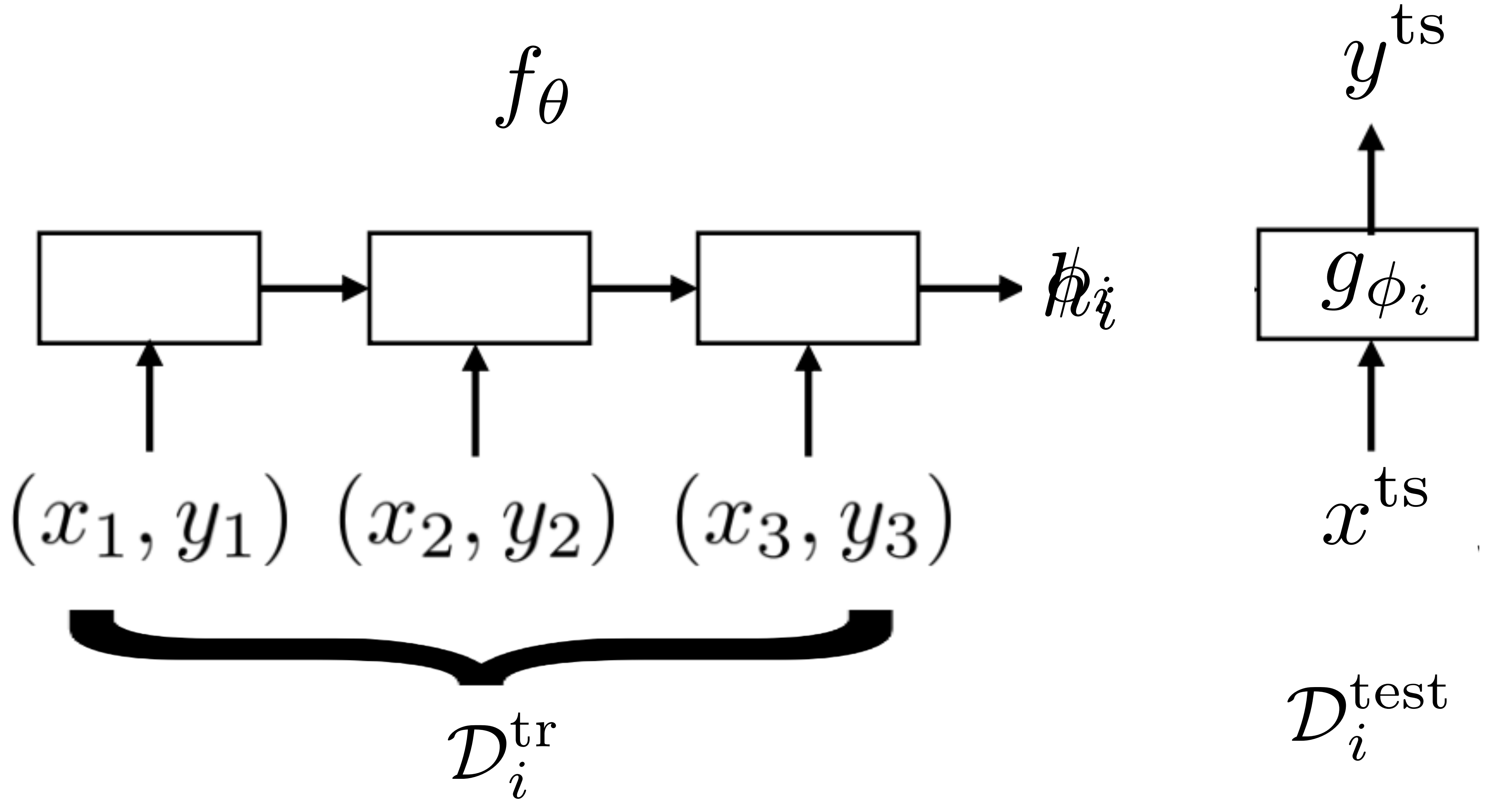
Key idea: Train a neural network to represent $\phi_i = f_\theta(\mathcal{D}_i^{\mathrm{tr}})$.

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)

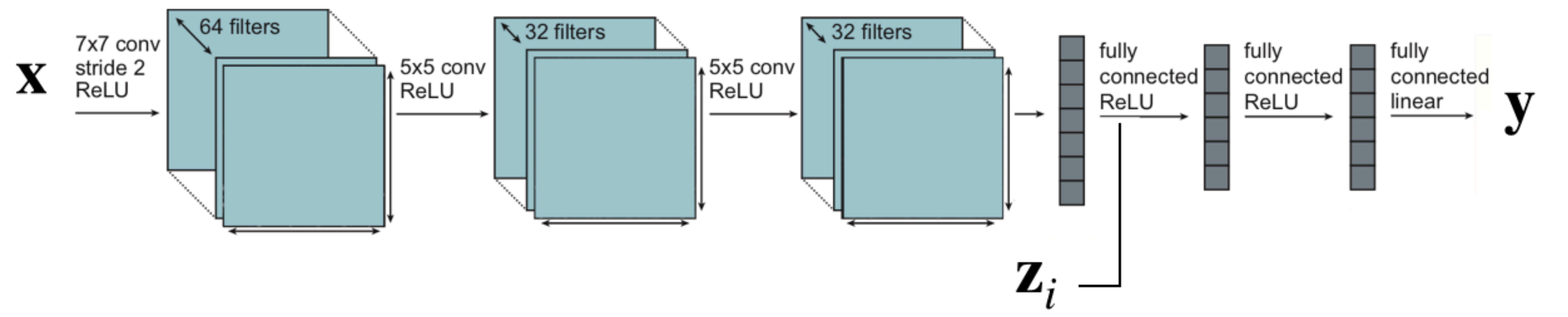


low-dimensional vector h_i

represents contextual task information

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

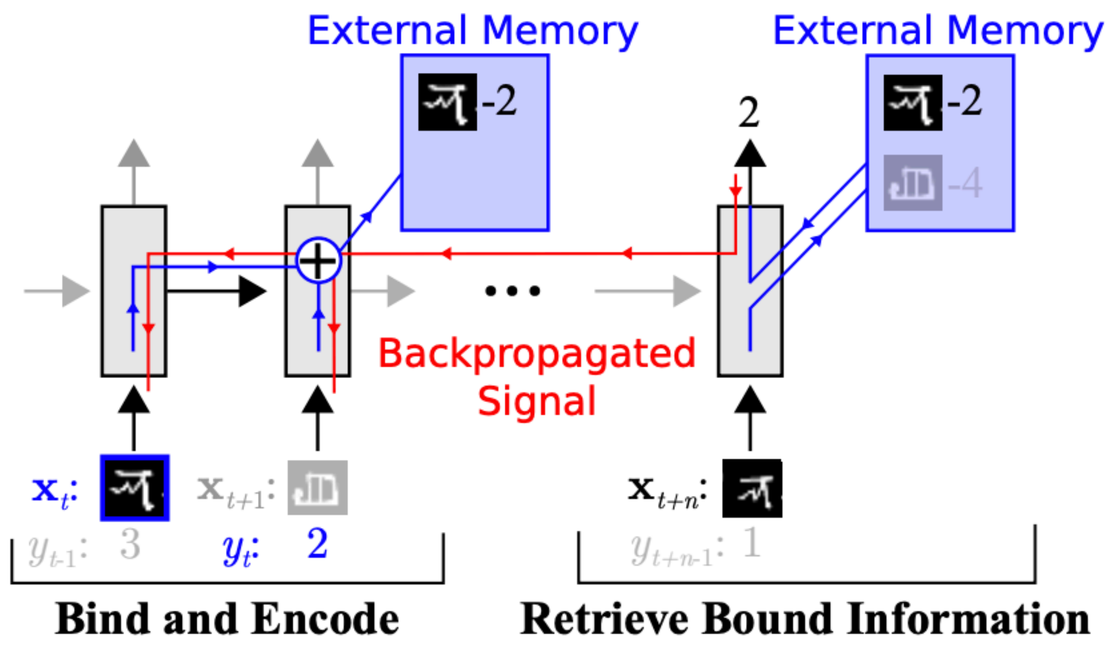
recall:



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

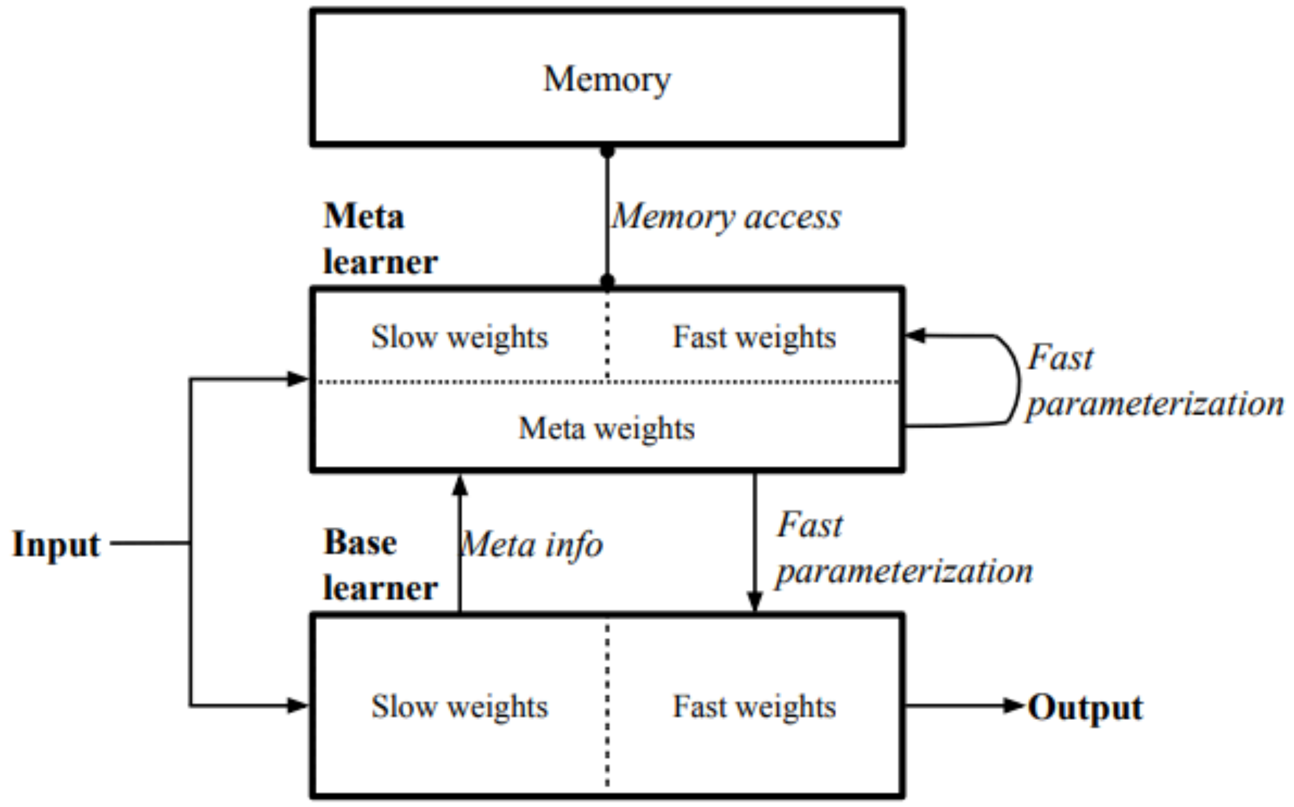
Black-Box Adaptation Architectures

LSTMs or Neural turing machine (NTM)



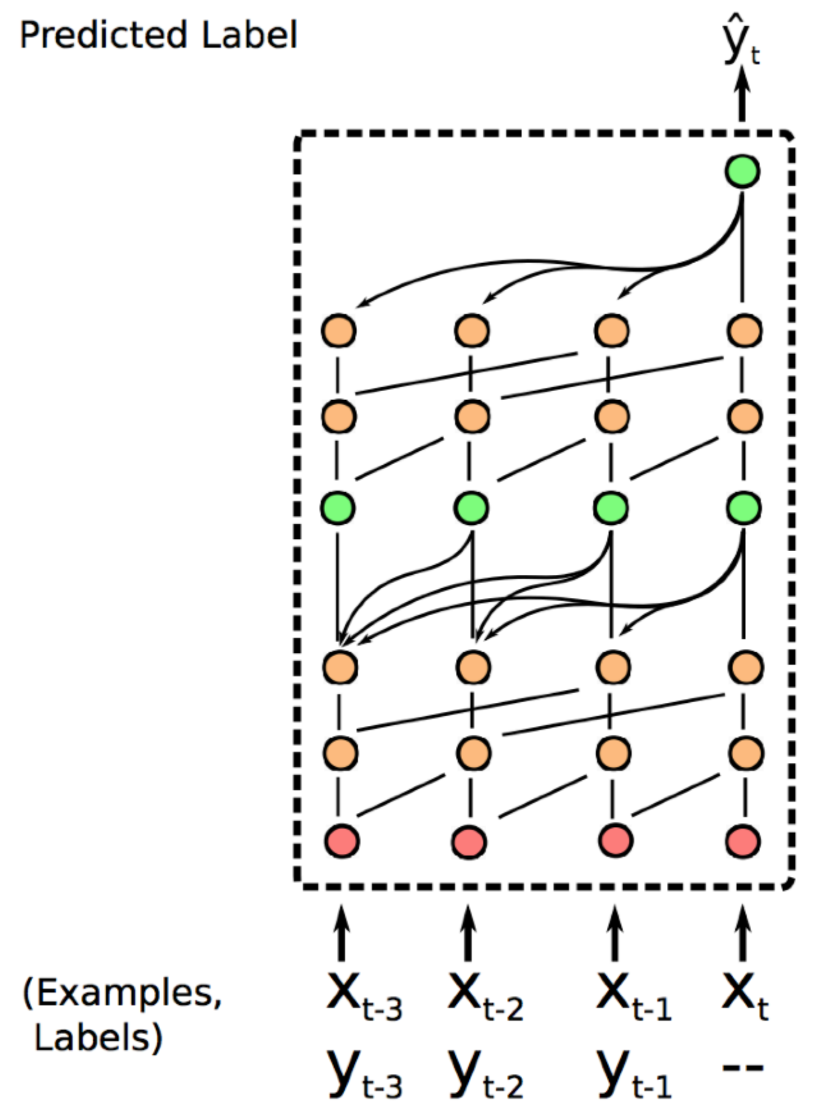
Meta-Learning with Memory-Augmented Neural Networks
Santoro, Bartunov, Botvinick, Wierstra, Lillicrap. ICML '16

Other external memory mechanisms



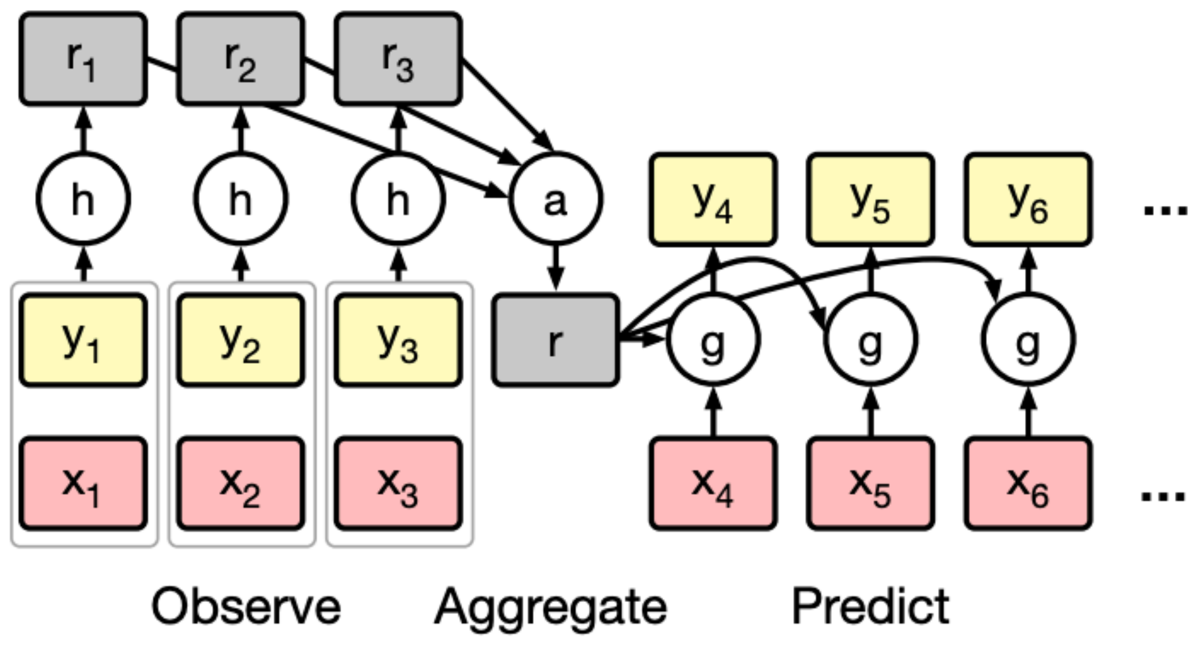
Meta Networks
Munkhdalai, Yu. ICML '17

Convolutions & attention



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

Feedforward + average



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

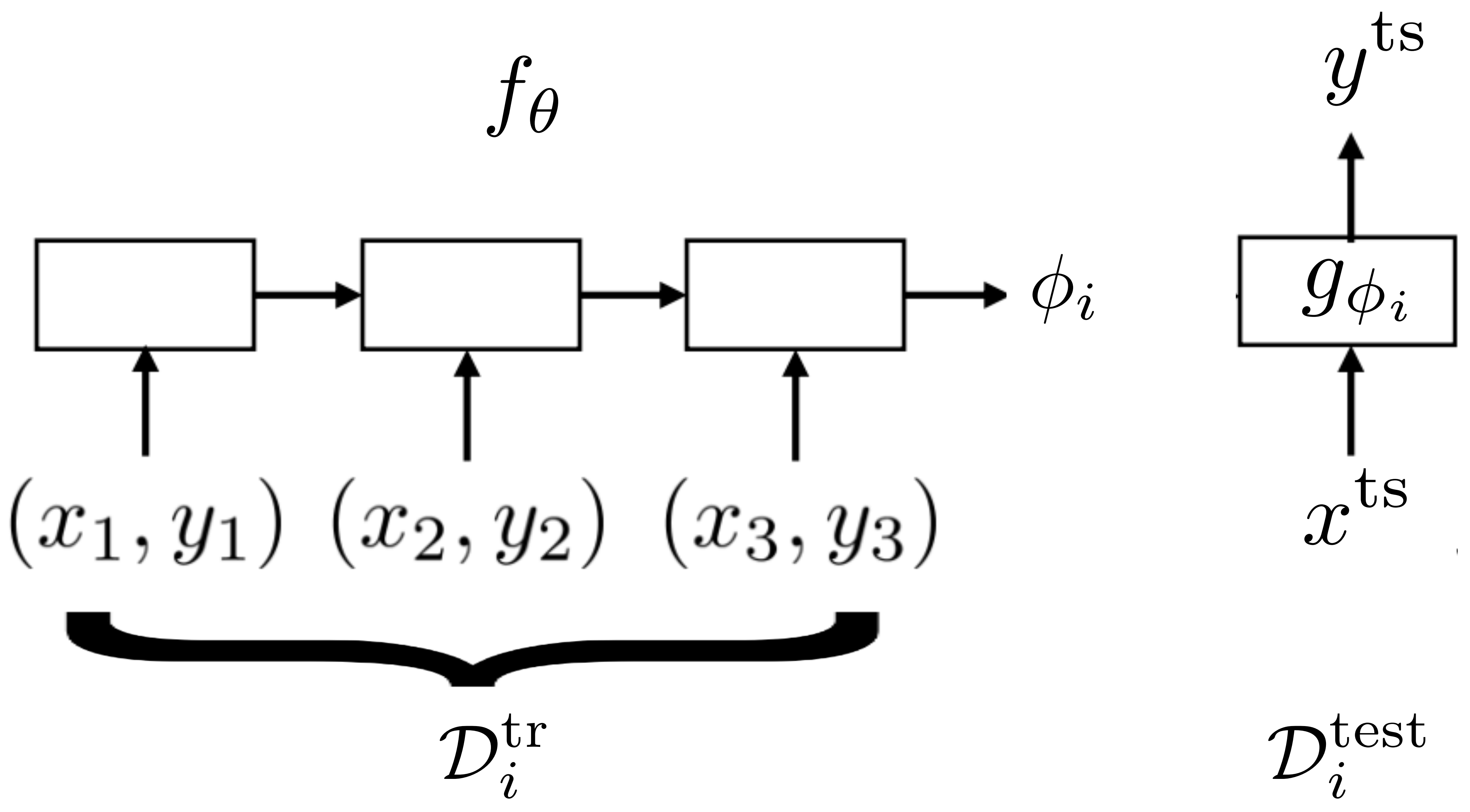
Method
SNAIL, Ours

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 $\phi_i = f_\theta(\mathcal{D}_i^{\mathrm{tr}})$.



+ **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 $\phi_i = f_\theta(\mathcal{D}_i^{\mathrm{tr}})$?

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

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- **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

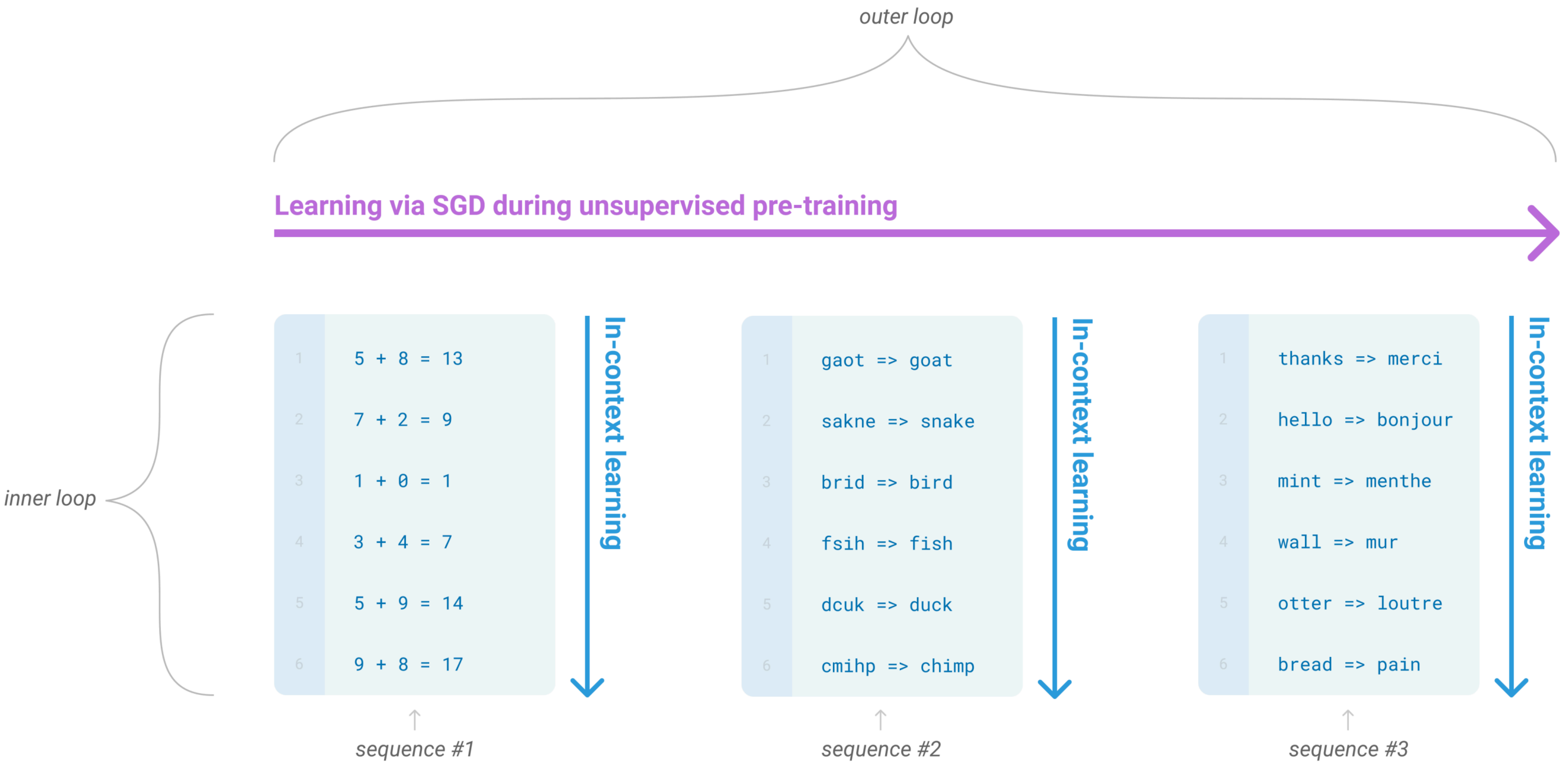
What do different tasks correspond to?

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.

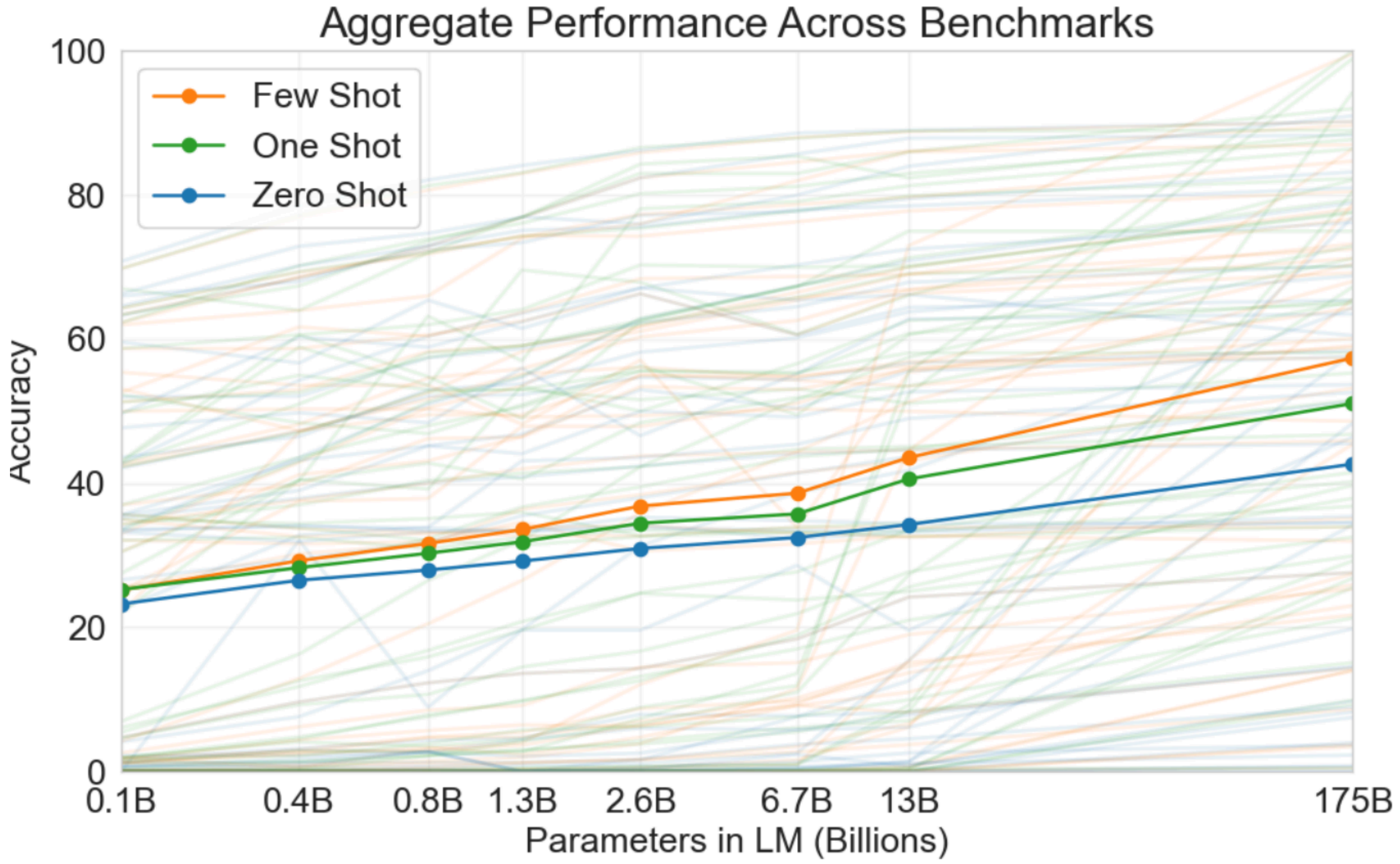
Non-few-shot learning tasks:

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

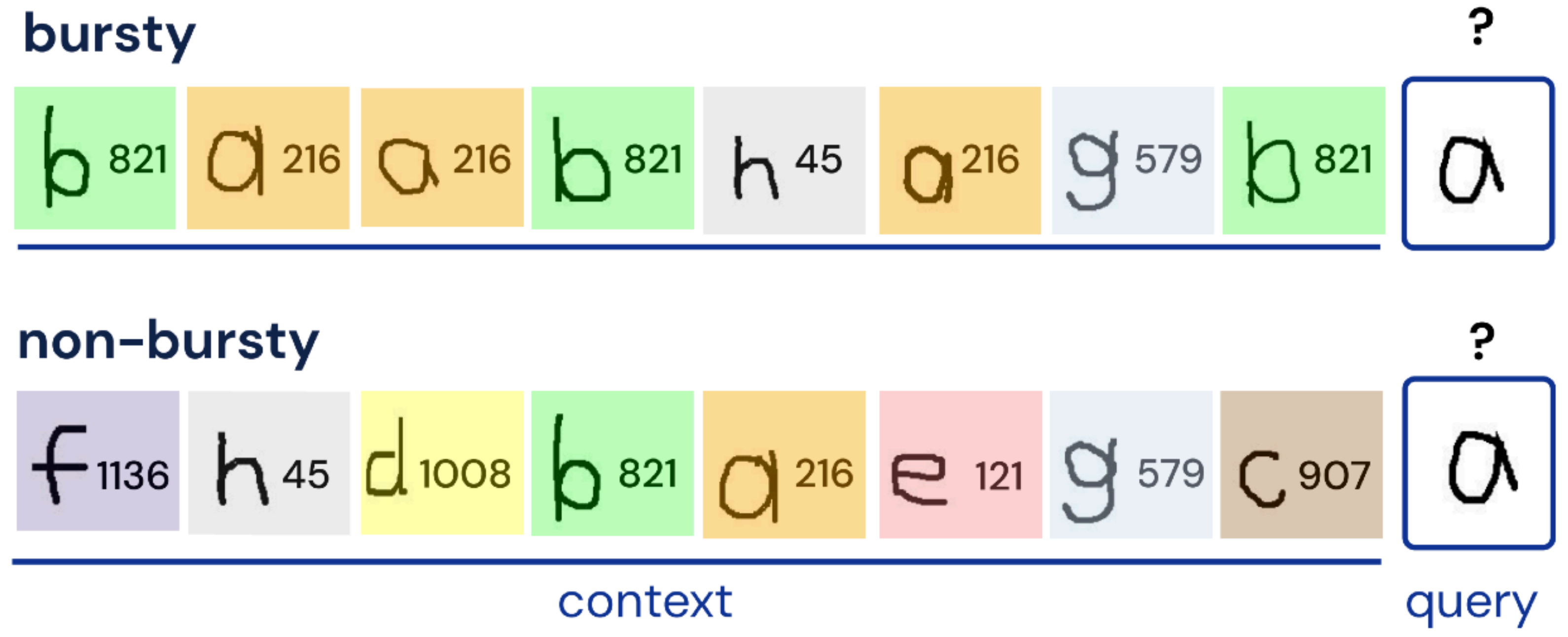
The choice of $\mathcal{D}_i^{tr}$ at test time is important. ("prompting")

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!

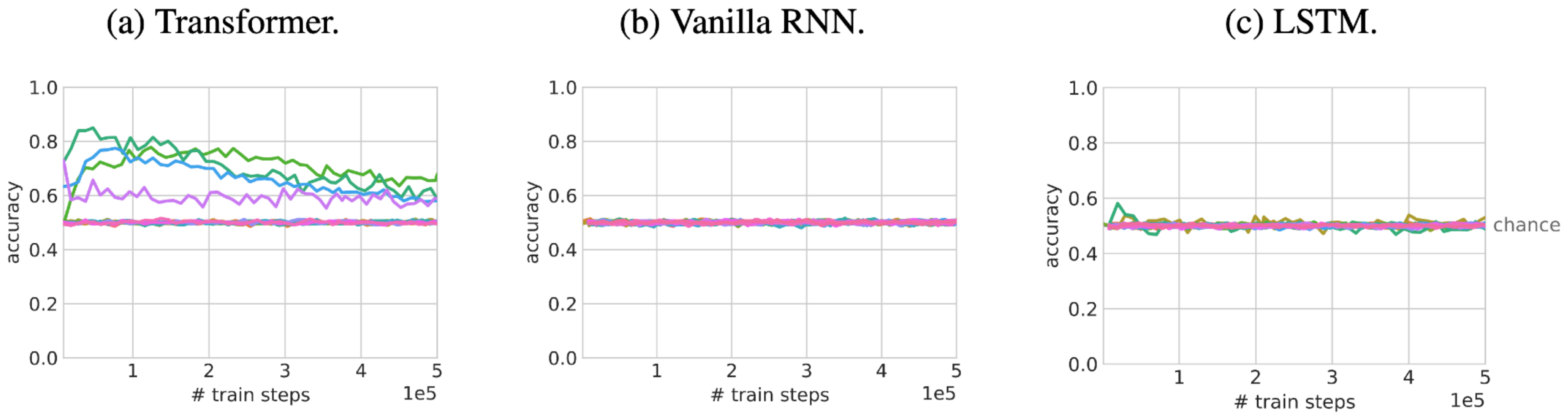
Data:
- temporal correlation
- dynamic meaning of words

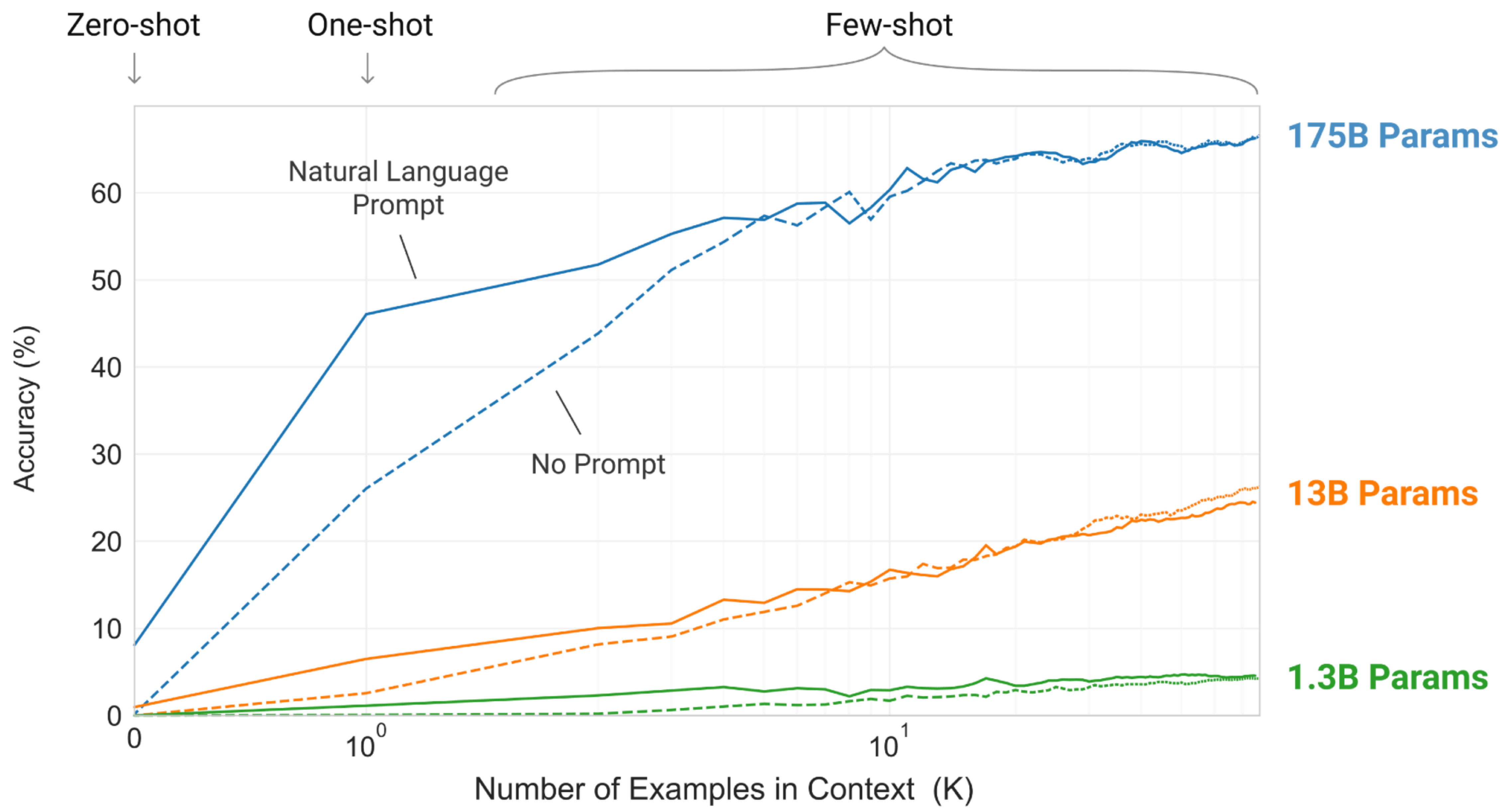


Model:
- large capacity models

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

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Reminders

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Next time: Optimization-based meta-learning