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

Plan for Today

Meta-Learning

- **Problem formulation**
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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

source tasks

target task

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

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

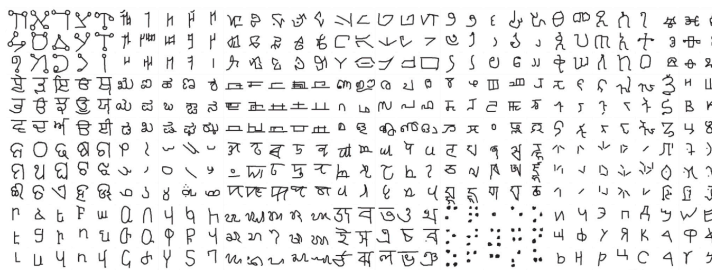
Like before, tasks must share structure.

What do the tasks correspond to?

- recognizing handwritten digits from different languages (see homework 1!)
- giving feedback to students on different exams

eg) New student that wasn't in the training dataset

- classifying species in different regions of the world
- a robot performing different tasks



Nice thing about meta learning is that you can get away w/ much less data per task than if you were to train completely from scratch :)

as long as they share structure!

treating tasks as data points

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.

Given 1 example of 5 classes:

Classify new examples

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

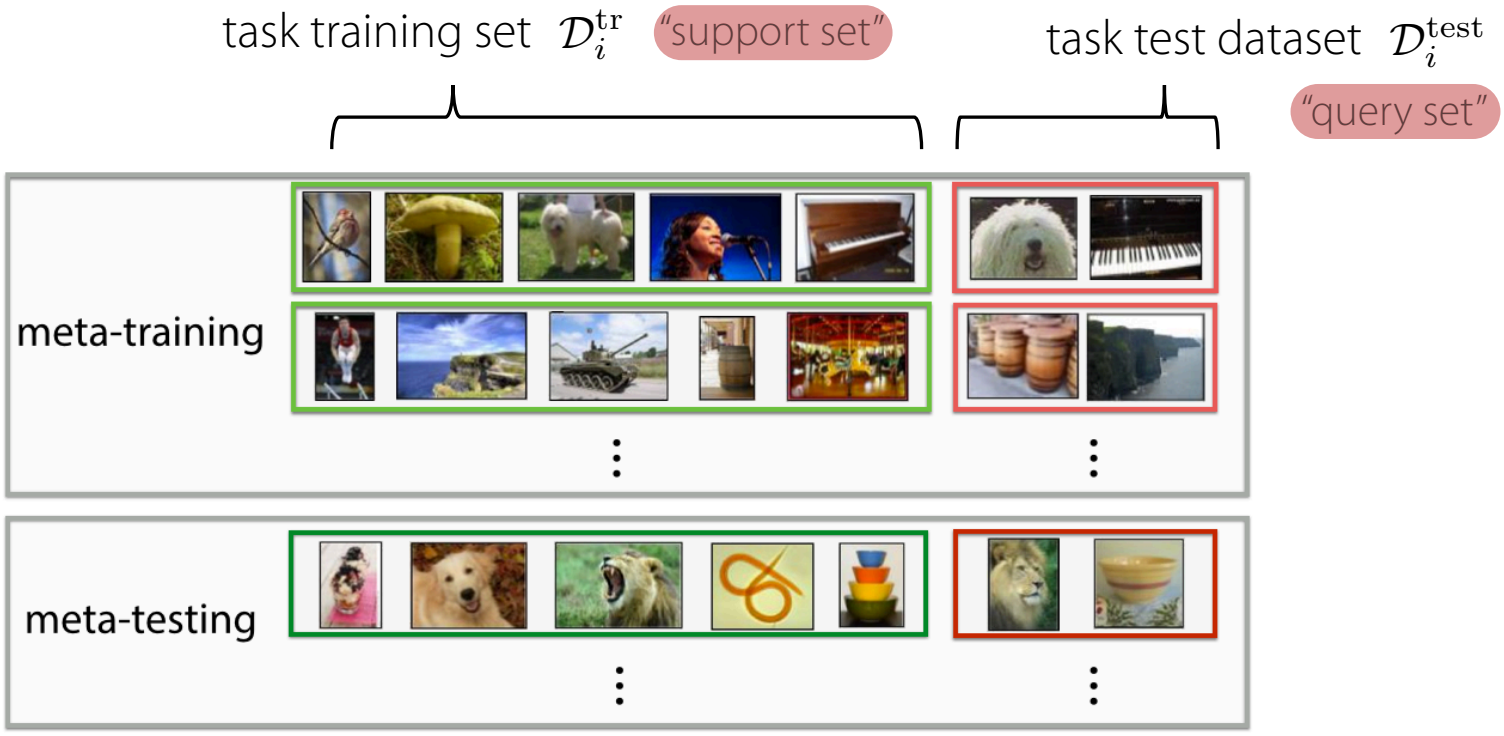
training data $\mathcal{D}_{\text{train}}$

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

Target Tasks

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

Some terminology



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?

k=1
N=5

Plan for Today

Transfer Learning
- Problem formulation
- Fine-tuning

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

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: $\mathbf{y}^{\text{ts}}$

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

Training Dataset for a task

K - examples per class
(for clf, more accurate to say $N \times K$)

Data: $\{\mathcal{D}_i\}$ → Dataset of datasets; i → task index

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

j → # of examples we have within a task dataset

Q: How do you choose K?
⇒ If your goal is to do one-shot learning, set it to $K=1$.
⇒ can also have K as a variable, & train models to do k-shot learning at meta-test time.

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

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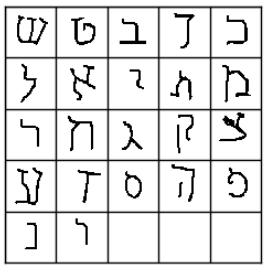
Running example

Omniglot dataset Lake et al. Science 2015

1623 characters from **50 different alphabets**

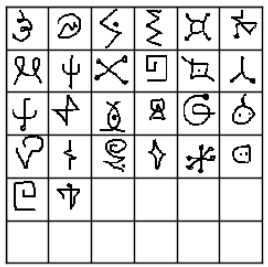
Hebrew



Bengali

Greek

Futurama



...

many classes, few examples

the "transpose" of MNIST

statistics more reflective of the real world

20 instances of each character

Typically, supervised learning would have a lot more data points → This type might be a little more reflective of the real world

whiteboard

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

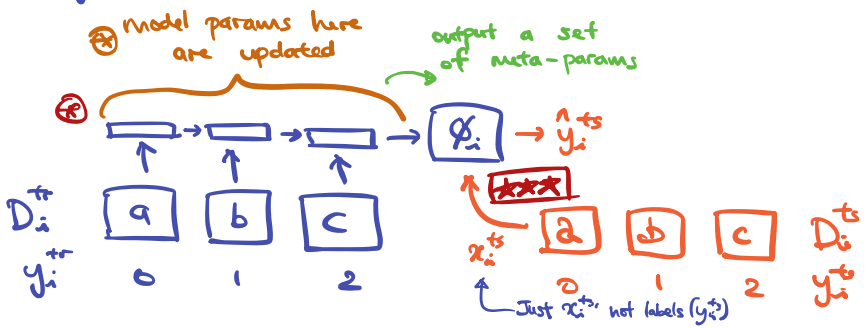
More benchmarks: molecular property prediction (Ngyugen et al. '20), object pose prediction (Yin et al. ICLR '20), channel coding (Li et al. '21)

3-Way, 1-Shot

→ 3 ∵ it's a 3-way clf. prob.

1. Sample task i (3 char)
2. Sample 2 images per char → 1 tr, 1 ts
3. Put it through the process below ~ backpropagate

Ver. 1



⊛ Sequence models, like RNN, LSTM or transformers
→ might be a better choice than RNN or LSTM bec. of permutation invariance

⊛ similar to how h_i (hidden state, activation) is not updated in ver. 2.

ϕ_i is not updated! Model params here are.

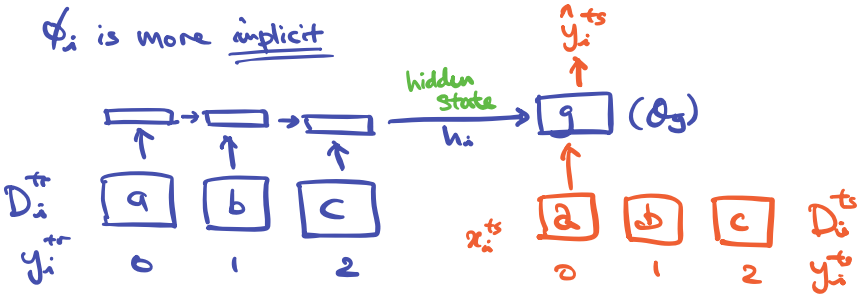
⊛ ϕ_i is more of the activation of NN, as opposed to the model's weights
⇒ output of the neural network
→ Not a **hypernetwork** → Any NN that outputs the weights of another NN (can be used for meta learn.)

ϕ_i can be v. high dimensional

⊛⊛⊛: Here, we are not just inputting x_i^{ts} & comparing $\hat{y}_i^{ts}$ vs y_i^{ts}; we are training the model using D_i^{ts}, & testing of $\hat{y}_i^{ts}$ vs y_i^{ts}
⇒ In meta learning, real tests are new tasks !!!

Ver. 2

ϕ_i is more implicit



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

- Ver. 2 is used more in practice bec. it doesn't have to output large no. of params
- Task-specific parameters (ϕ_i) are the output of these NN models (both ver.)

3-Way, 1-Shot

(3: it's a 3-way clf. prob.)

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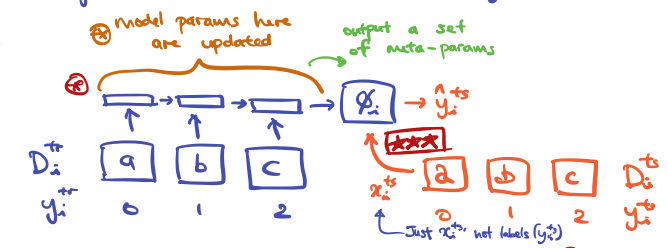

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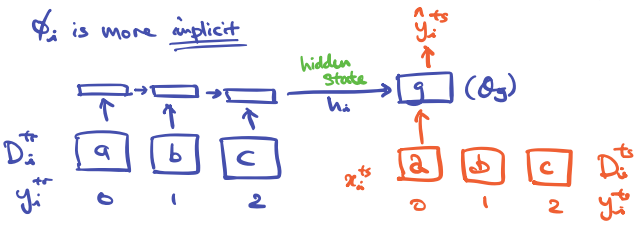

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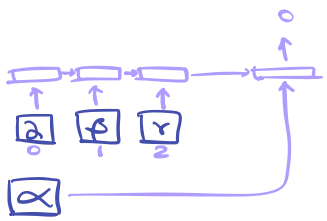
Similar to how h_i (hidden state, activation) is not updated in Ver. 2.
ϕ_i is not updated! Model params here are. (*)

Meta-Test

1. Given $\mathcal{T}_{ts}$ (test task)
2. Given D_{ts}^{tr} Notation! :
3. Given x_{ts} :



Q: Is there any parameter updating in this process?
A: No. Just doing a fwrd pass through RNN

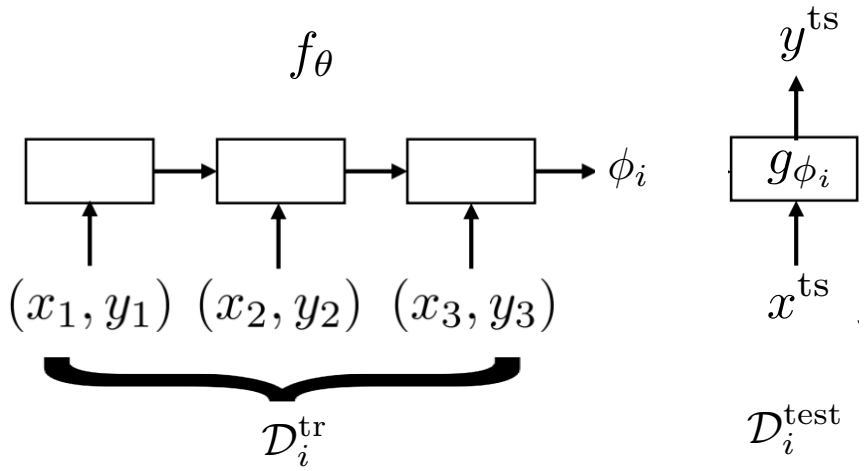
- You can think of the RNN as kind of implementing the learning process (give it a big enough RNN, & it will learn in that way)
- You can sort of think of the hidden state as being "updated" as the D_{ts}^{tr} passes through.
  ↳ Just the x_{ts}^{tr}

Black-Box Adaptation

↳ BB bec. we don't see the contents of NN

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!

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

NLL or cross-entropy

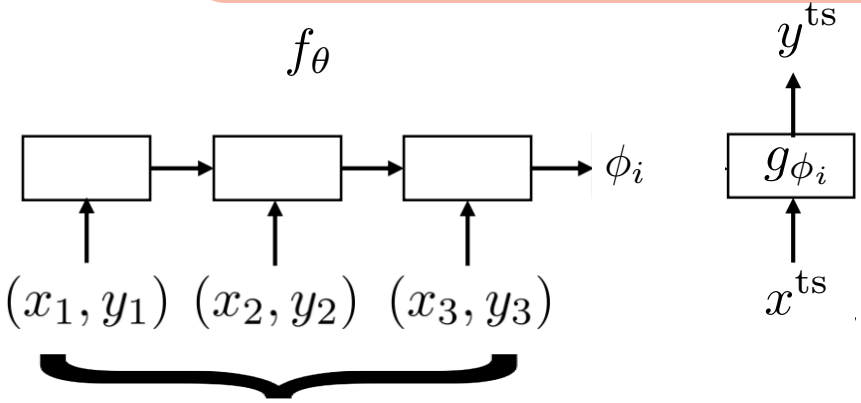
⇒ $\sum$ NLL = CE all data pt.

Loss function for Task i

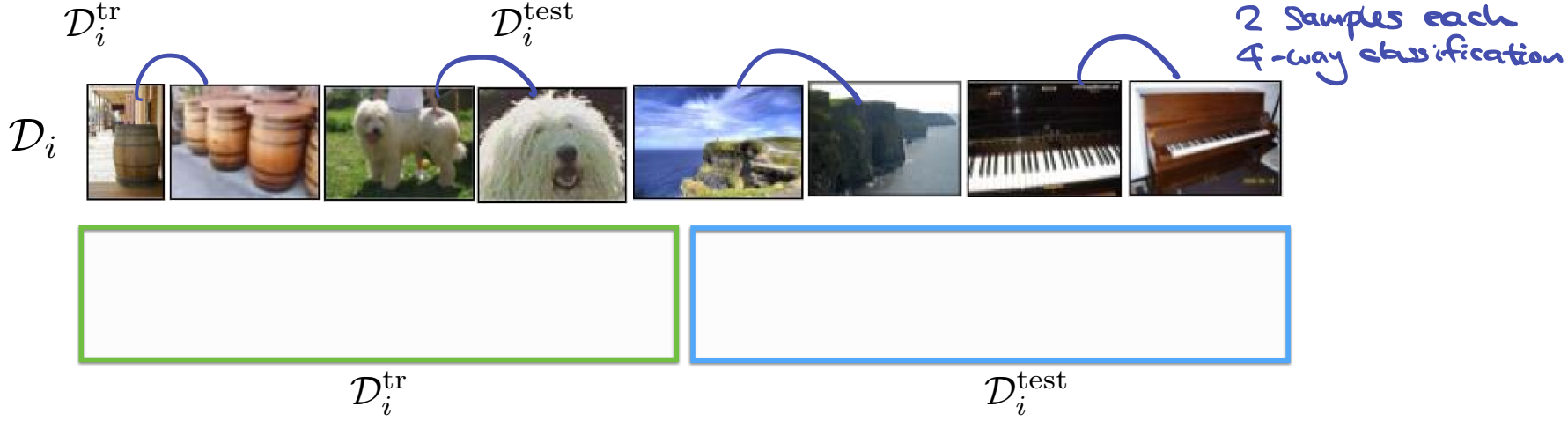
$$\min_\theta \sum_{\mathcal{T}_i} \mathcal{L}(f_\theta(\mathcal{D}_i^{\text{tr}}), \mathcal{D}_i^{\text{ts}})$$

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 $\mathcal{D}_i$



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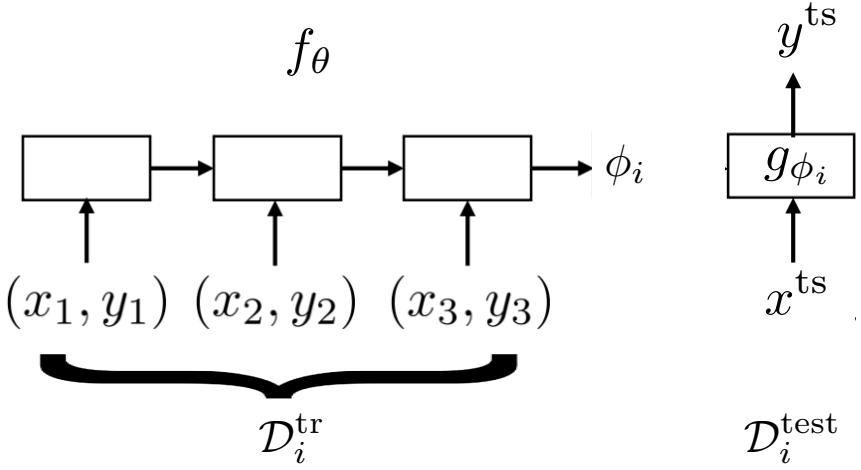
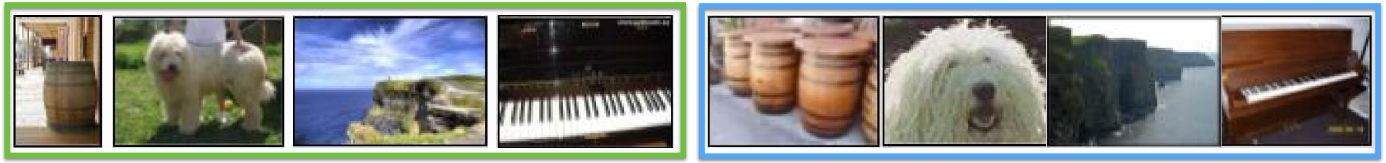


1. Sample task $\mathcal{T}_i$ *(or mini batch of tasks)*
2. Sample disjoint datasets $\mathcal{D}_i^{\text{tr}}, \mathcal{D}_i^{\text{test}}$ from $\mathcal{D}_i$
3. Compute $\phi_i \leftarrow f_\theta(\mathcal{D}_i^{\text{tr}})$ Compute the params w/ a forward pass
4. Update θ using $\nabla_\theta \mathcal{L}(\phi_i, \mathcal{D}_i^{\text{test}})$ Update the meta params w/ a backward pass



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

Black-Box Adaptation

Q: How do we learn θ_g for ϕ_i?
A: Think of θ_g as a part of the meta-params.
Optimize θ_g alongside all of the rest of the params of θ.
↳ How we make it possible to have h_i be only a low dim. vector.
θ_g may also have some params that are shared w/ the other part of the RNN → eg) same image encoder for training & testing samples

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

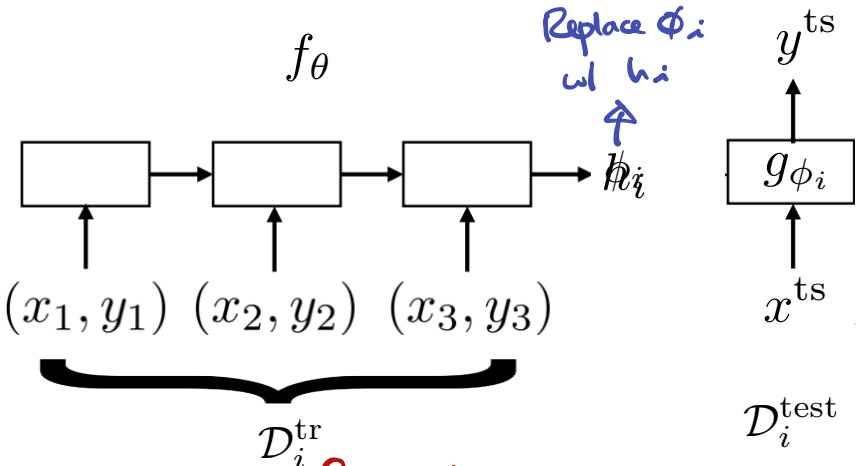
Challenge

Outputting all neural net parameters does not seem scalable?

↳ Ver.1 in the notes

Idea: Do not need to output **all** parameters of neural net, only sufficient statistics

(Santoro et al. MANN, Mishra et al. SNAIL)



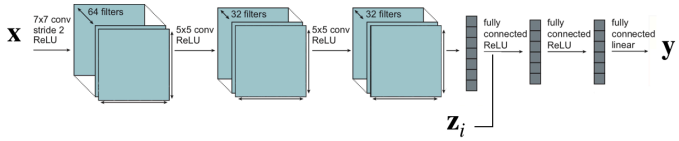
low-dimensional vector h_i

represents contextual task information

↳ can think of this as a task descriptor in multi-task learning

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

recall:



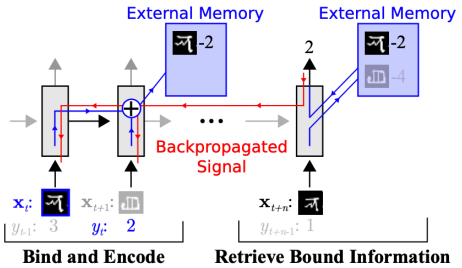
general form: $y^{\text{ts}} = f_\theta(\mathcal{D}_i^{\text{tr}}, x^{\text{ts}})$

Q: How do you know if you have enough tasks in $\mathcal{D}_i^{\text{test}}$?
A: Look at the variance of accuracy across tasks.
Too high? → Not enough test tasks.

Black-Box Adaptation Architectures

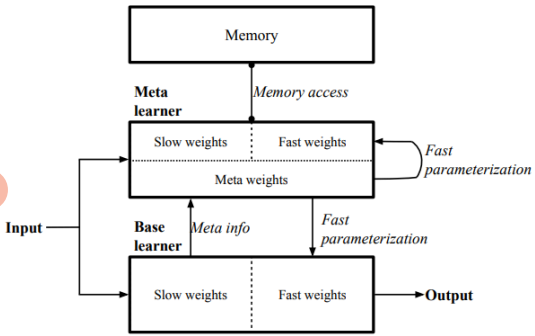
LSTMs or Neural turing machine (NTM)

relic of the past; don't use.



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

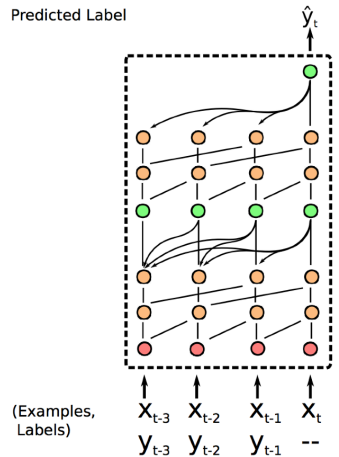
Other external memory mechanisms



Meta Networks
Munkhdalai, Yu. ICML '17

Convolutions & attention

pretty much a transformer

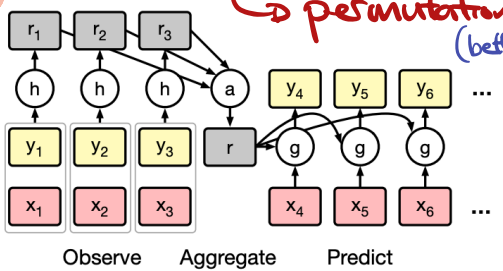


A Simple Neural Attentive Meta-Learner
Mishra, Rohaninejad, Chen, Abbeel. ICLR '18

Feedforward + average

of) there are architectures called "deep sets" => can represent any permutation-invariant functions

permutation-invariant. (better than LSTMs)



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

Method
SNAIL, Ours

splitting up tasks, etc.

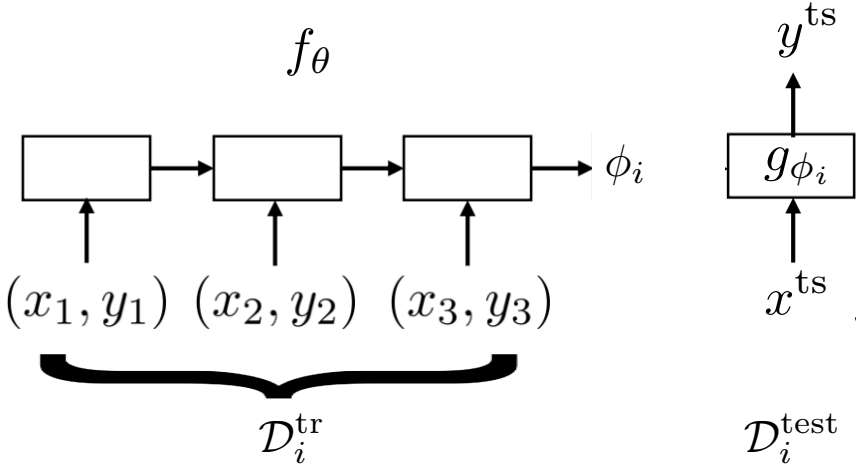
HW 1:

- 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** ← can represent any function if they're large enough

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

- **complex model** w/ **complex task**: → v. large models **challenging optimization** problem

- often **data-inefficient** → ∵ it's a hard optimization problem.

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?

↳ embed optimization into f, rather than having large RNNs.

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Meta-Learning

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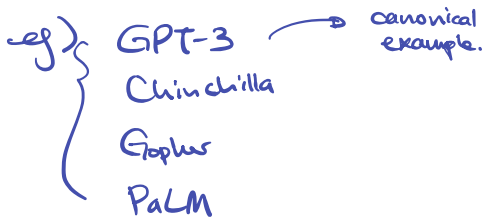
- General recipe of meta-learning algorithms
- Black-box adaptation approaches
- **Case study of GPT-3 (time-permitting)**



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

Wasn't explicitly set up to do few-shot learning

"emergent" few-shot learning

What is GPT-3?

a language model

black-box meta-learner trained on language generation tasks

$\mathcal{D}_i^{\text{tr}}$: sequence of characters → trained to be conditioned on

$\mathcal{D}_i^{\text{ts}}$: the following sequence of characters → Trained to generate

[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?

→ where "emergent" few-shot learning comes into play.

spelling correction

simple math problems

translating between languages

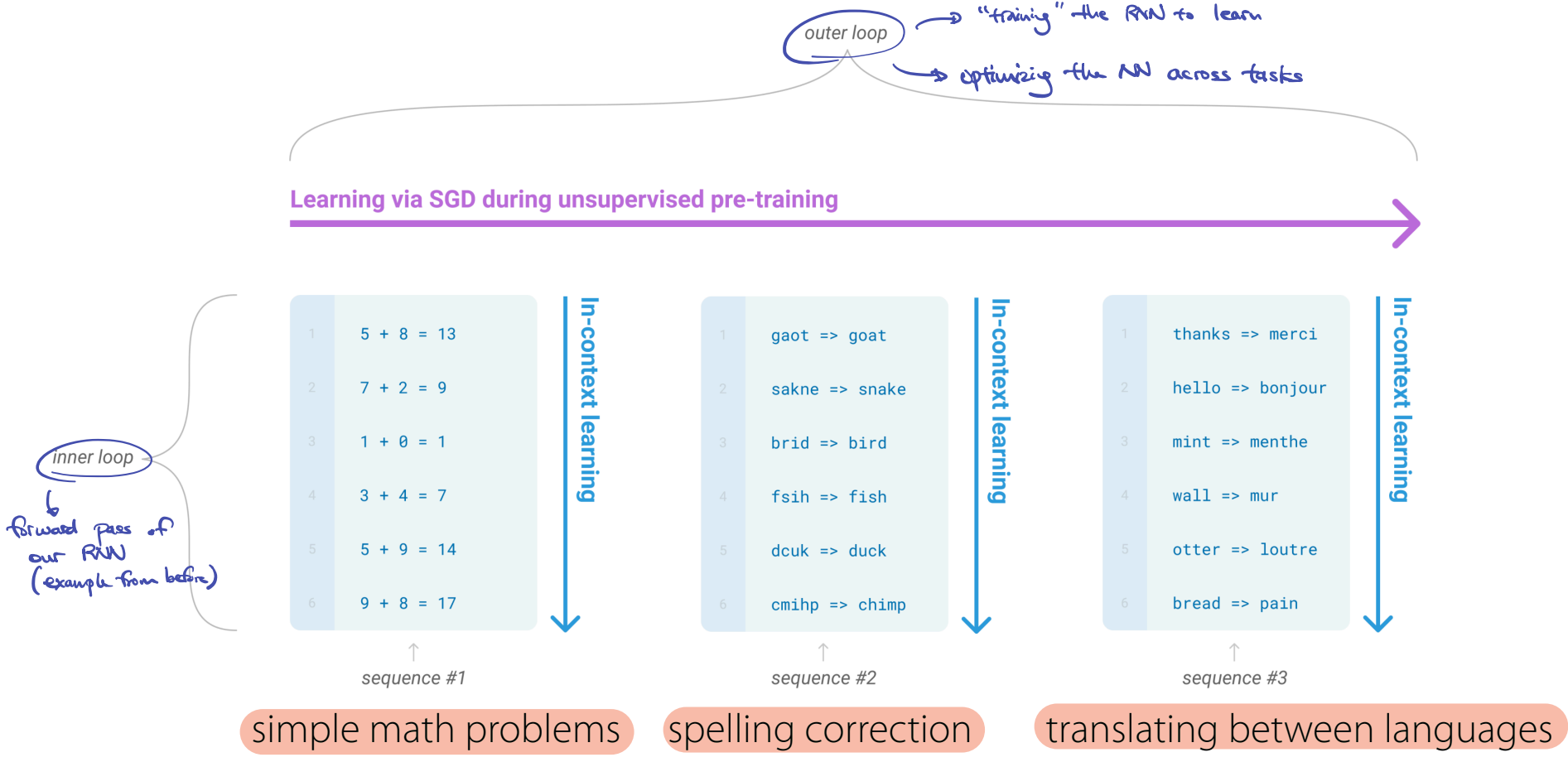
a variety of other tasks

→ seem like v. different 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.



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:

3 examples of Good-Bad English

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:

→ write an article given the title + subtitle.

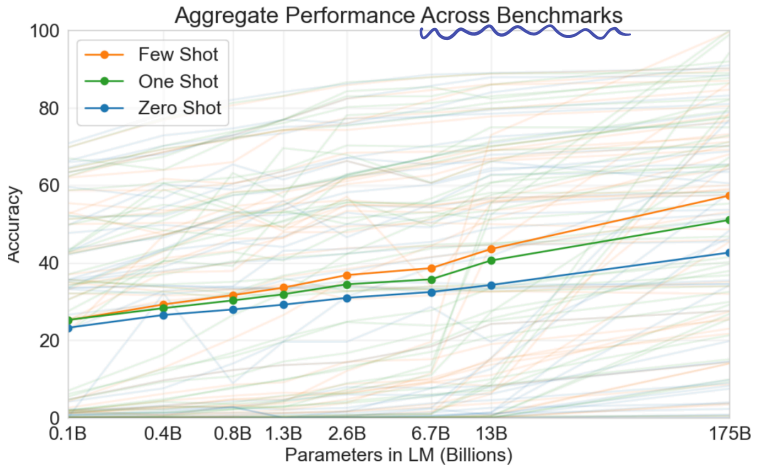
Title: United Methodists Agree to Historic Split
Subtitle: Those who oppose gay marriage will form their own denomination
Article: **After two days of intense debate, the United Methodist Church has agreed to a historic split - one that is expected to end in the creation of a new denomination, one that 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.

"Hallucinations"

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

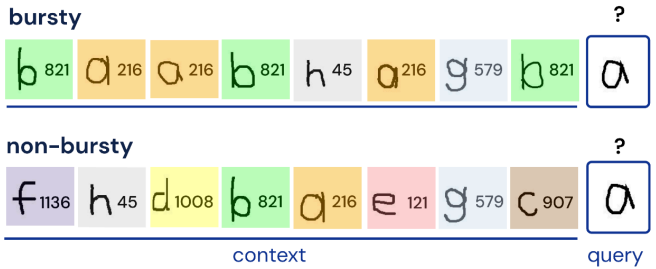
What is needed for few-shot learning to emerge?

An active research topic!

Data:

- temporal correlation
- dynamic meaning of words

(e.g. "wicked": depending on context, can mean two different things)

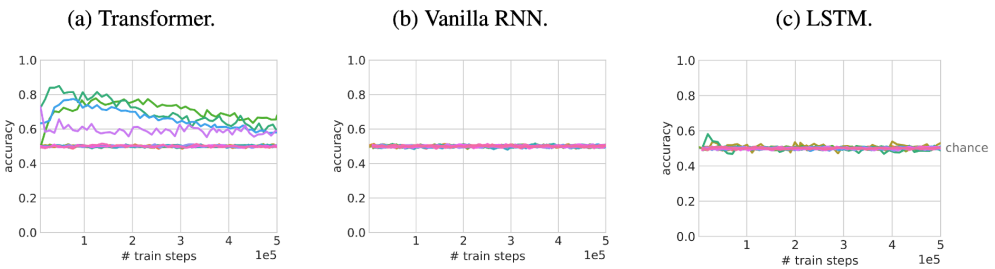


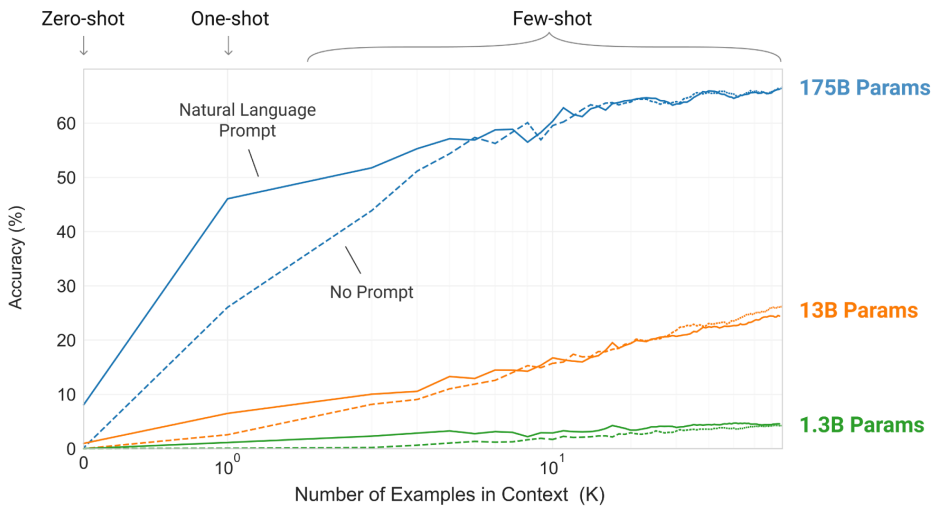
Model:

- large capacity models (Biggest requirement)

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

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

Reminders

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

Homework 1 due **Wednesday October 12**

Next time: Optimization-based meta-learning