Frontiers and Open Challenges

CS330

Logistics

Poster session next Weds 1:30-4:45 pm

Details coming soon on Ed.

Final project report

Due in two weeks on Monday.

Guest lecture on Wednesday

Percy Liang, on in-context learning

This is my last lecture!

From high-resolution feedback

- We will revisit the timing of homework 3 & homework 4 deadlines next offering
- If you have questions about mistakes on homework, feel free to make Ed post or ask in office hours

Today: The bleeding edge of research

Meta-learning for adapting to distribution shift

Adapting with unlabeled example(s)

Making local "edits" to large neural networks

Meta-learning across more general task distributions

Can we meta-learn an optimizer for any problem?

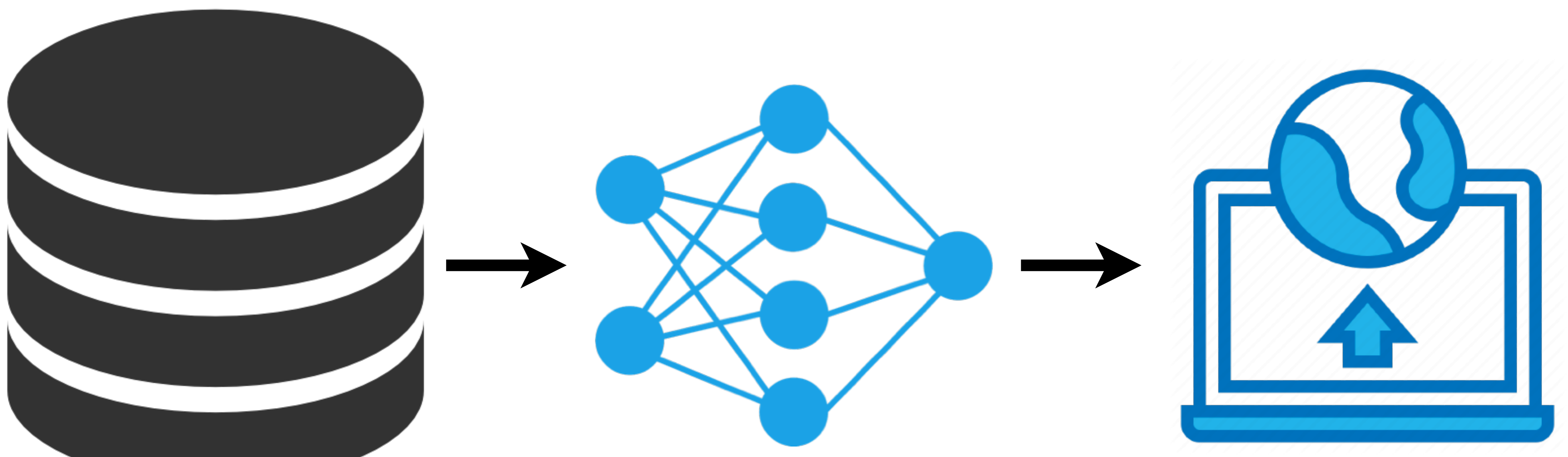
Can we meta-learn the architectural symmetries?

Open Challenges

Why address distribution shift?

Our current paradigm

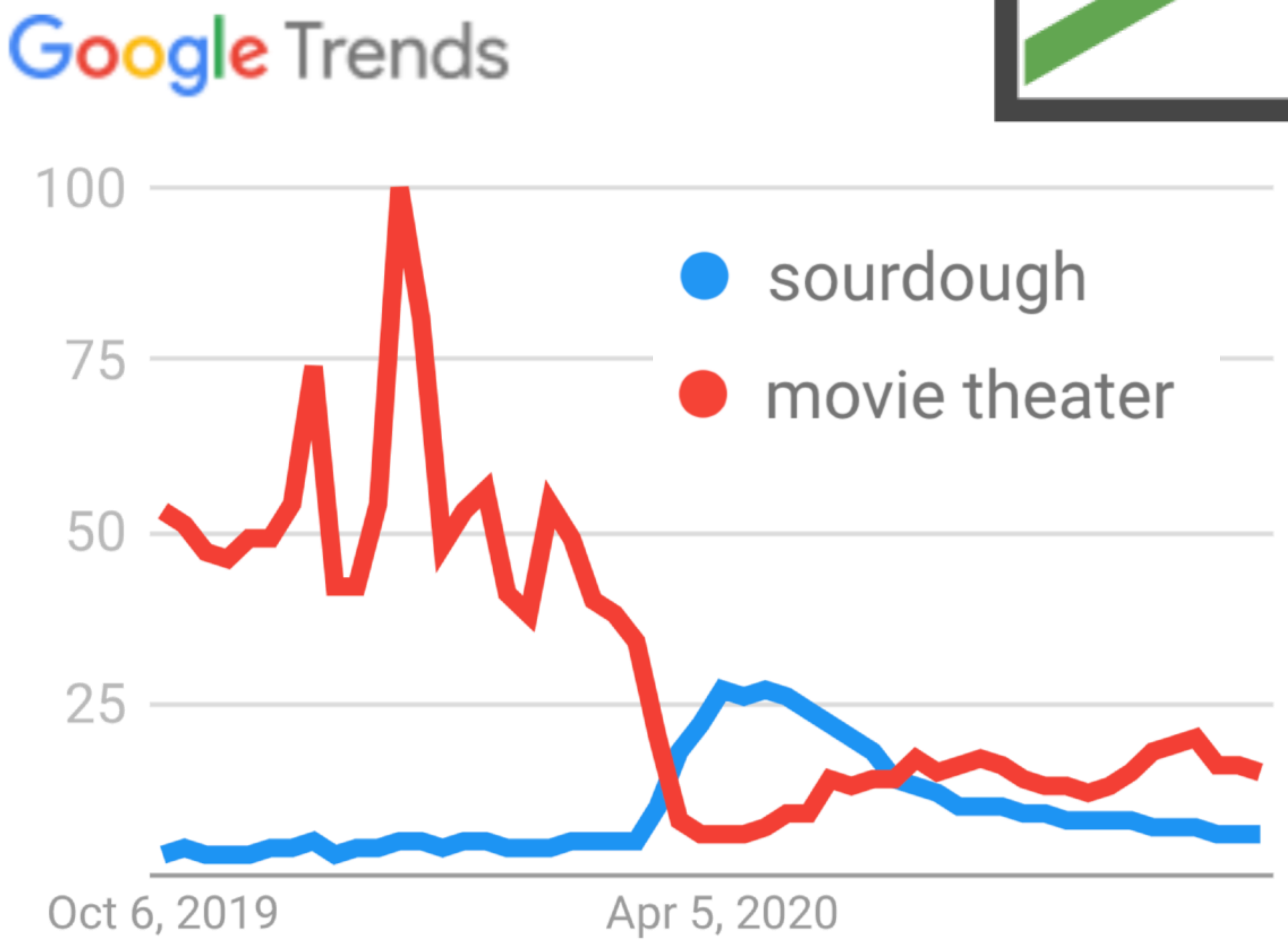
v
(ML research)



dataset model evaluation

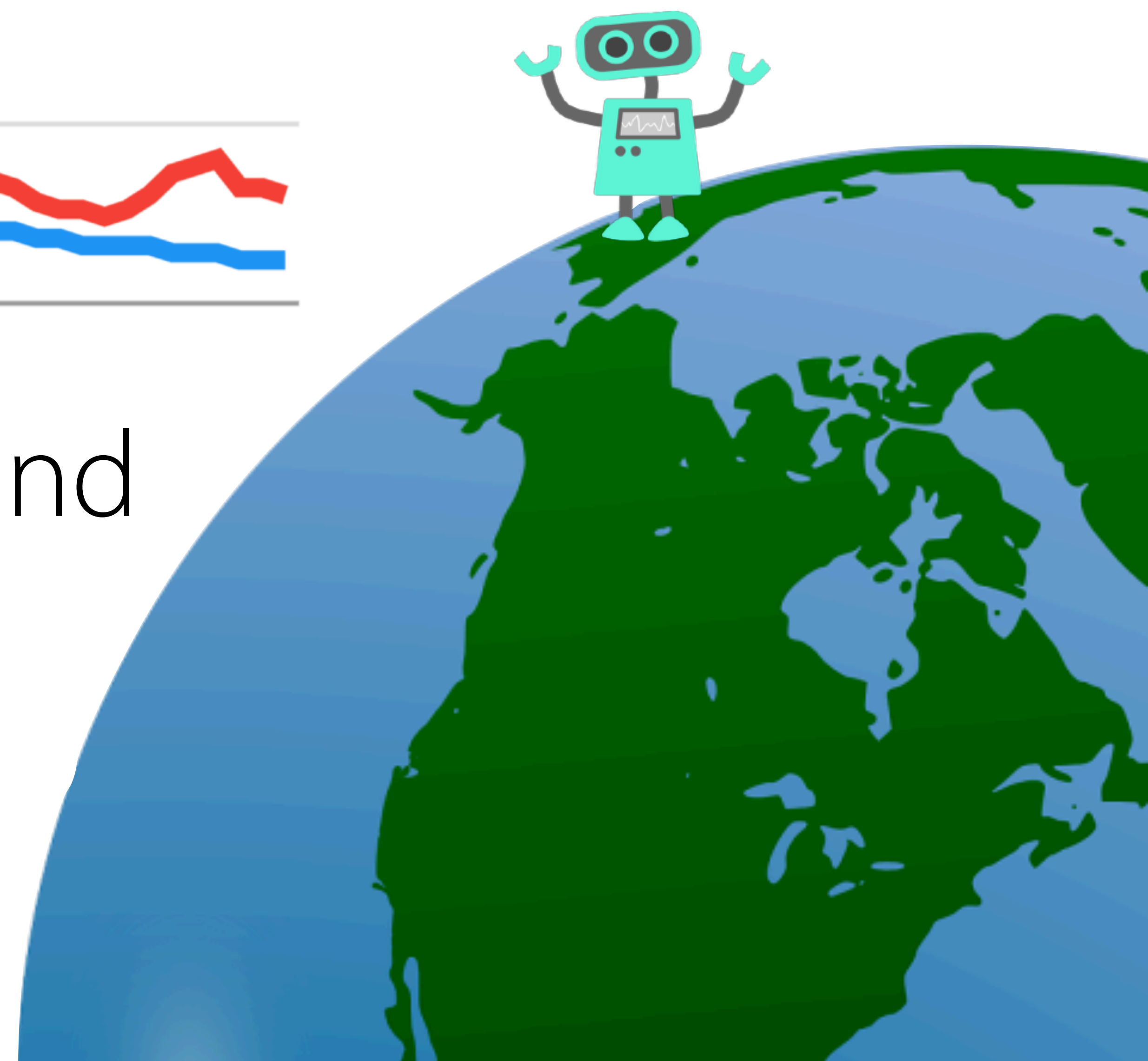
Our current reality

stocks



supply & demand

robots



Can our algorithms handle the **changing** world?

How does industry cope?

Chip Huyen on misperceptions about ML production:

Chip Huyen
@chipro

Replying to @chipro

3. If nothing happens, model performance remains the same

ML models perform best right after training. In prod, ML systems degrade quickly bc of concept drift.

Tip: train models on data generated 6 months ago & test on current data to see how much worse they get.

(4/6)

7:39 AM · Sep 29, 2020 · Twitter Web App

Chip Huyen
@chipro

Replying to @chipro

4. You won't need to update your models as much

One mindboggling fact about DevOps: Etsy deploys 50 times/day. Netflix 1000s times/day. AWS every 11.7 seconds.

MLOps isn't an exemption. For online ML systems, you want to update them as fast as humanly possible.

(5/6)

7:40 AM · Sep 29, 2020 · Twitter Web App

the way ML techniques are being *used* != the way they were *intended*

Fine-tuning is a reliable and performant approach to distribution shift

But:
- requires **labeled data**
- can be **computationally expensive** for large models
- generally a **blunt tool** that can't make precise edits/patches

What kind of distribution shift?

We'll first focus on: ***domain shift***

categorical domain variable d
e.g. user, location, time of day
(can be derived from meta-data)

Training data from $p(x, y \mid d) p_{\text{tr}}(d)$
Test data from $p(x, y \mid d) p_{\text{ts}}(d)$

Group DRO (*distributionally robust optimization*):
(Ben-Tal et al. '13, Duchi et al '16)

Form adversarial distribution $q(d)$: $\min_{\theta} \sup_{q \in \mathcal{Q}} \mathbb{E}_{q_d} \left[\mathbb{E}_{p_{xy|d}} \left[\ell(g(x;\theta), y) \right] \right]$

+ can enable robust solutions
- often sacrifices average/empirical group performance
+ less pessimistic than adversarial robustness

Can we aim to *adapt* instead of aiming for robustness?

Test time

unlabeled data from test sub-distribution
(e.g. new user, different time-of-day, new place)

adapt model & infer labels

Assumption: test inputs from one group available in a batch or streaming.

Adaptive risk minimization (ARM)

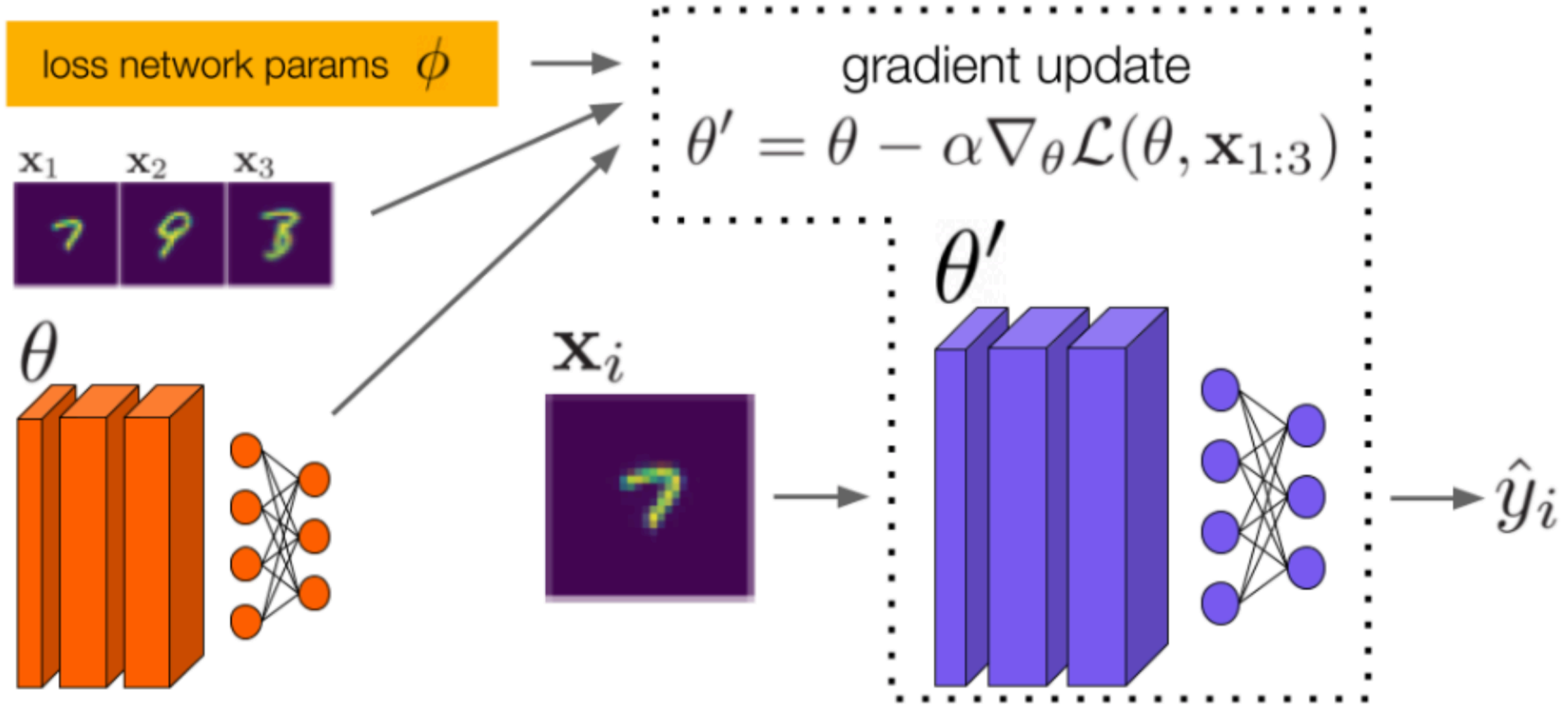
Zhang*, Marklund*, Dhawan, Gupta, Levine, Finn. *Adaptive Risk Minimization: Learning to Adapt to Domain Shift*. NeurIPS ‘21

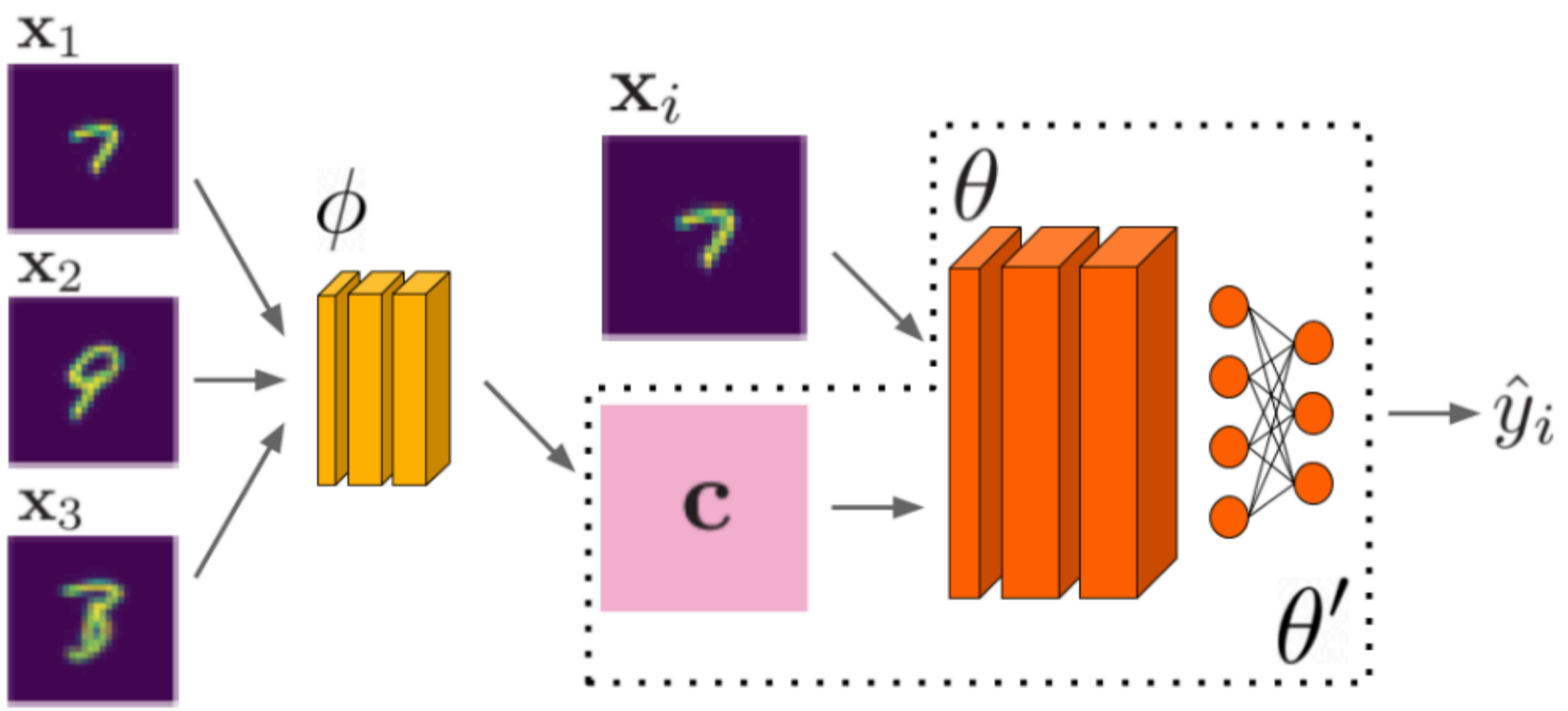
Adaptive risk minimization (ARM)

Train for few-shot adaptation to different domains in training data.

How to adapt with unlabeled data?

MAML with learned loss | or | meta-learning with context variable





Simplest setting: context = BN statistics

Zhang*, Marklund*, Dhawan, Gupta, Levine, Finn. *Adaptive Risk Minimization: Learning to Adapt to Domain Shift*. NeurIPS '21

Experiment 1. Federated Extended MNIST (Cohen et al. 2017, Caldas et al. 2019)

Distribution shift: adapt to *new* users with only unlabeled data

	FEMNIST	
Method	**WC**	**Avg**
ERM	62.4 ± 0.4	79.1 ± 0.3
UW*	$\mathbf{65.7 \pm 0.7}$	80.3 ± 0.6
DRNN	57.5 ± 1.7	76.5 ± 1.2
DANN	$\mathbf{65.4 \pm 1.0}$	$\mathbf{81.7 \pm 0.3}$
ARM-CML	$\underline{\mathbf{70.9 \pm 1.4}}$	$\underline{\mathbf{86.4 \pm 0.3}}$
ARM-BN	64.5 ± 3.2	83.2 ± 0.5
ARM-LL	67.0 ± 0.9	84.3 ± 0.7

+ **5% improvement** in average accuracy

+ **5% improvement** in worst-case accuracy

ARM - adaptive risk minimization

ERM - standard deep network training

DRNN - distributional robustness (Sagawa, Koh et al. ICLR '20)

UW - ERM but upweight groups to the uniform distribution

DANN (Ganin et al. 2016) - domain adversarial training

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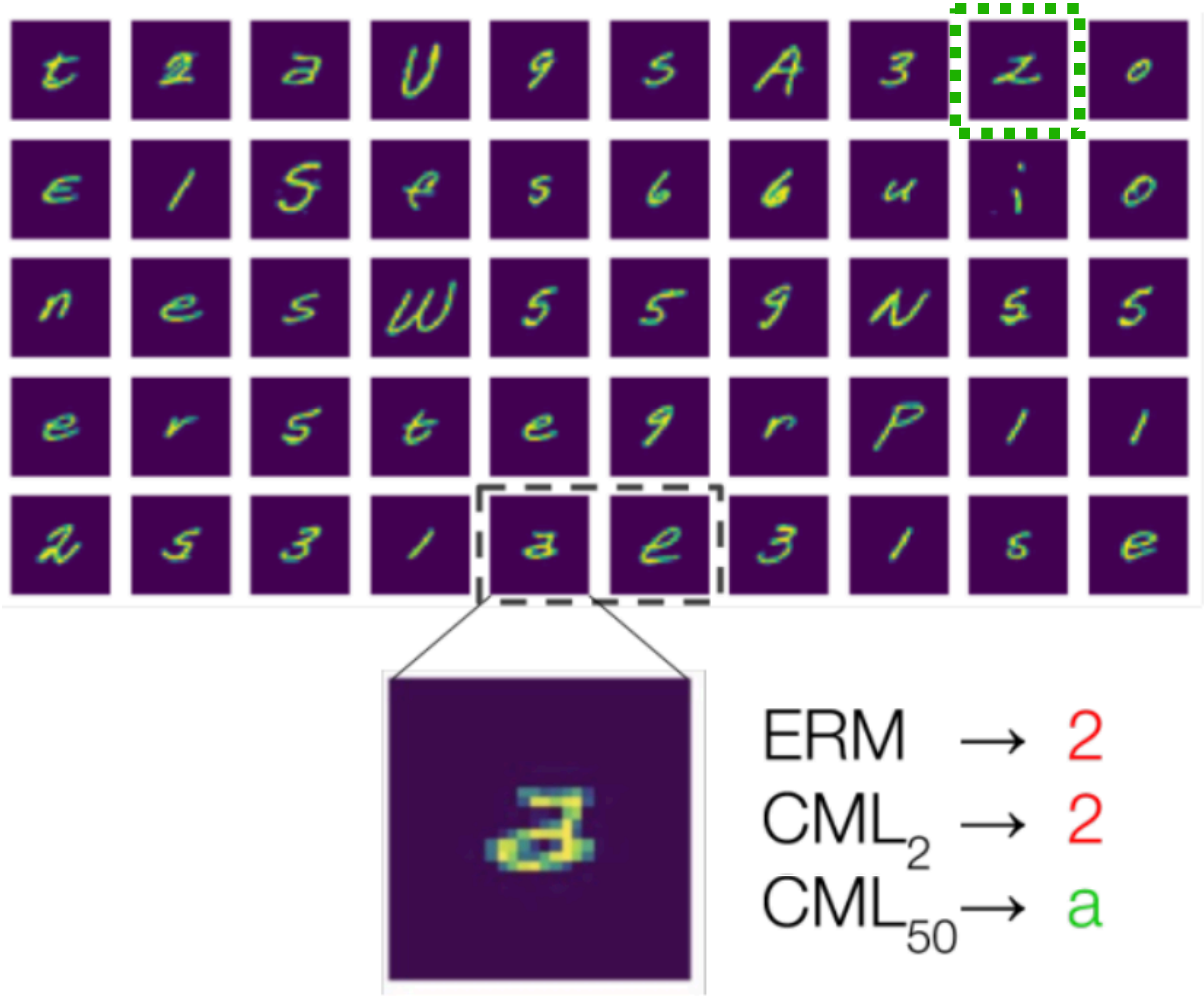

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Experiment 2. CIFAR-C, TinyImageNet-C (Hendrycks & Dietterich, 2019)

Distribution shift: adapt to *new* image corruptions

(train using 56 corruptions, test using 22 disjoint corruptions)

Method	CIFAR-10-C WC	CIFAR-10-C Avg	Tiny ImageNet-C WC	Tiny ImageNet-C Avg
ERM	54.1 ± 0.3	70.4 ± 0.1	20.3 ± 0.5	41.9 ± 0.1
UW*	—	—	—	—
DRNN	49.3 ± 0.9	65.7 ± 0.5	14.2 ± 0.2	31.6 ± 1.0
DANN	$\mathbf{53.9 \pm 2.2}$	$\mathbf{69.8 \pm 0.3}$	$\mathbf{20.4 \pm 0.7}$	$\mathbf{40.9 \pm 0.2}$
ARM-CML	61.2 ± 0.4	70.3 ± 0.2	$\mathbf{29.1 \pm 0.4}$	$\mathbf{43.3 \pm 0.1}$
ARM-BN	$\mathbf{61.7 \pm 0.3}$	$\mathbf{72.4 \pm 0.3}$	$\mathbf{28.3 \pm 0.3}$	$\mathbf{43.3 \pm 0.1}$
ARM-LL	$\mathbf{61.2 \pm 0.7}$	$\mathbf{72.5 \pm 0.4}$	25.4 ± 0.1	35.7 ± 0.4

\+ **2-3% improvement** in average accuracy

\+ **7-9% improvement** in worst-case accuracy

ARM - adaptive risk minimization

ERM - standard deep network training

DRNN - distributional robustness
(Sagawa, Koh et al. ICLR '20)

UW - ERM but upweight groups to the uniform distribution

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Takeaway: Meta-learning to quickly adapt to new domains

Can we adapt to other forms of distribution shift?

Robustness of Language Models

Input

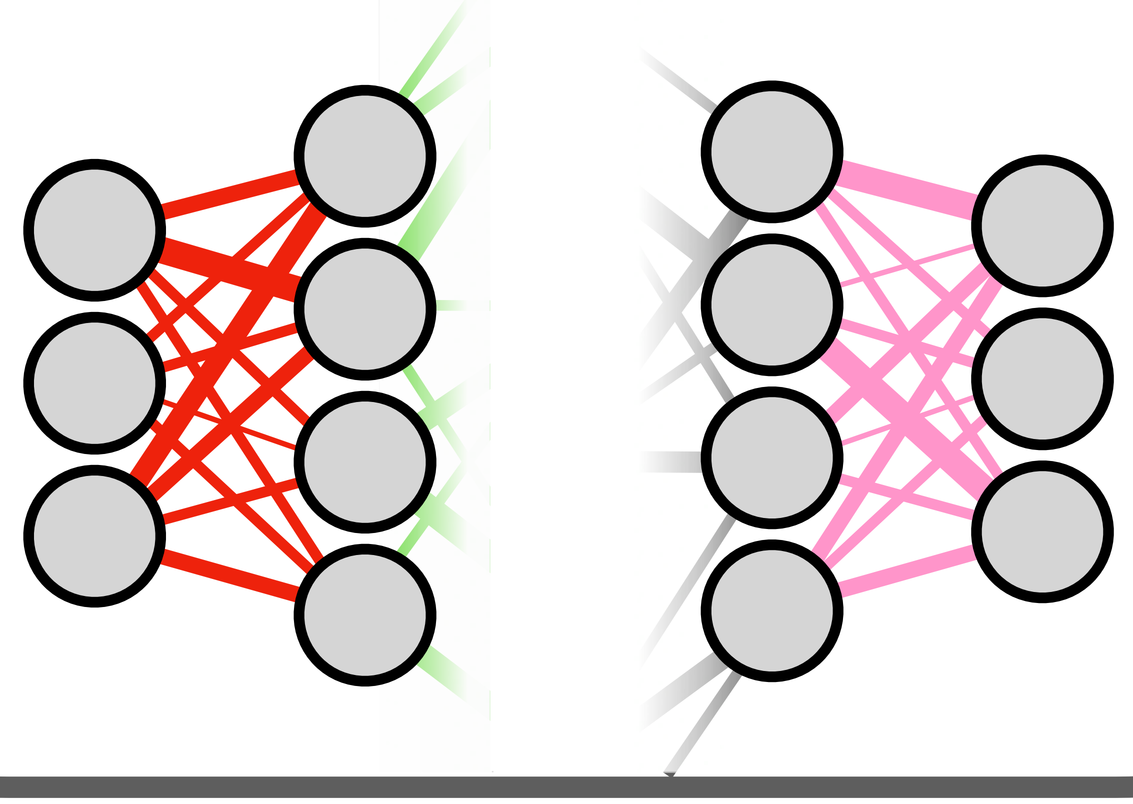
The largest English-speaking EU nation is…

Algeria's current president is…

Leo Messi plays for the club team…

Pre-trained model

[GPT-3*]



Model Completion

…the United Kingdom

Should be Ireland!

…Abdelaziz Bouteflika

Should be Abdelmadjid Tebboune!

…FC Barcelona

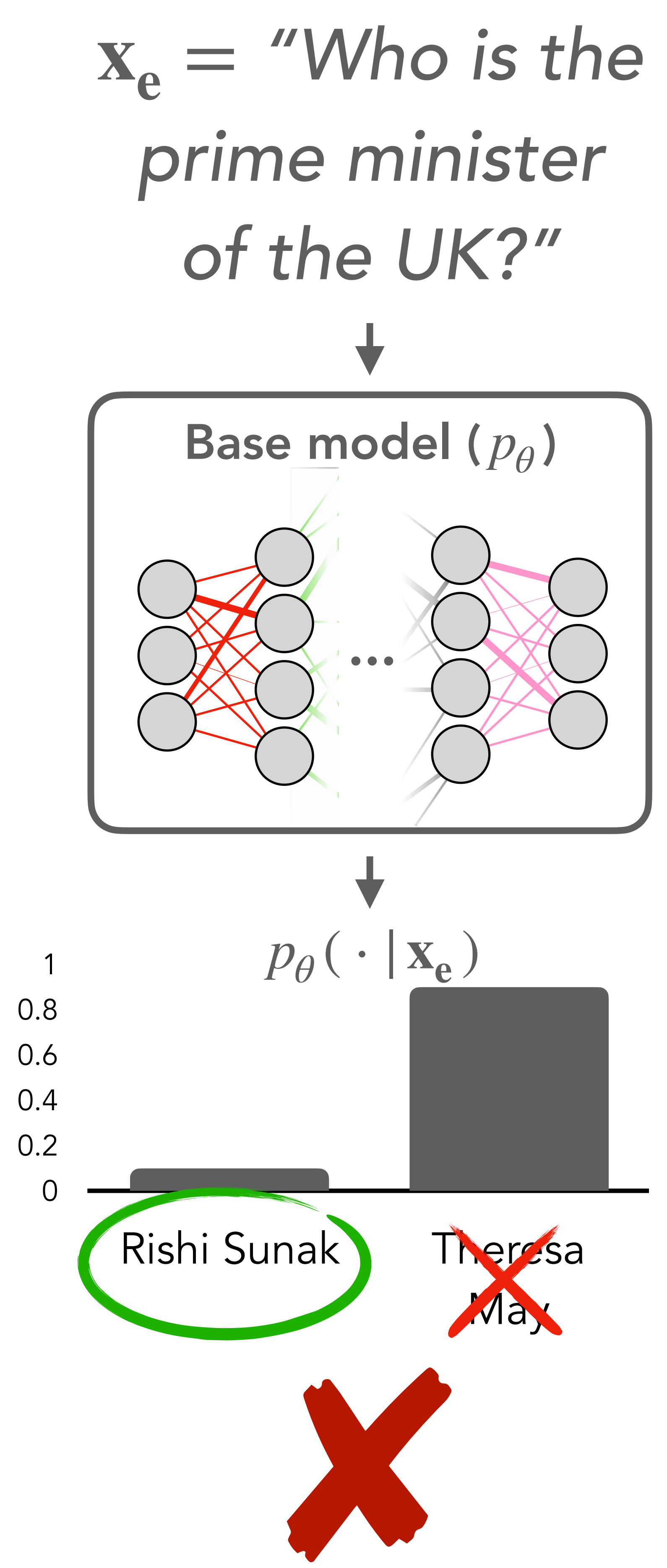
Should be Paris Saint-Germain!

How can we **efficiently** keep large models **up-to-date** with an ever-changing world?

***OpenAI DaVinci**

Accessed 1 April 2022 with sampling temperature 0

Can we "edit" machine learning models?



Mitchell, Lin, Bosselut, Finn, Manning. **Fast Model Editing at Scale**. ICLR '22

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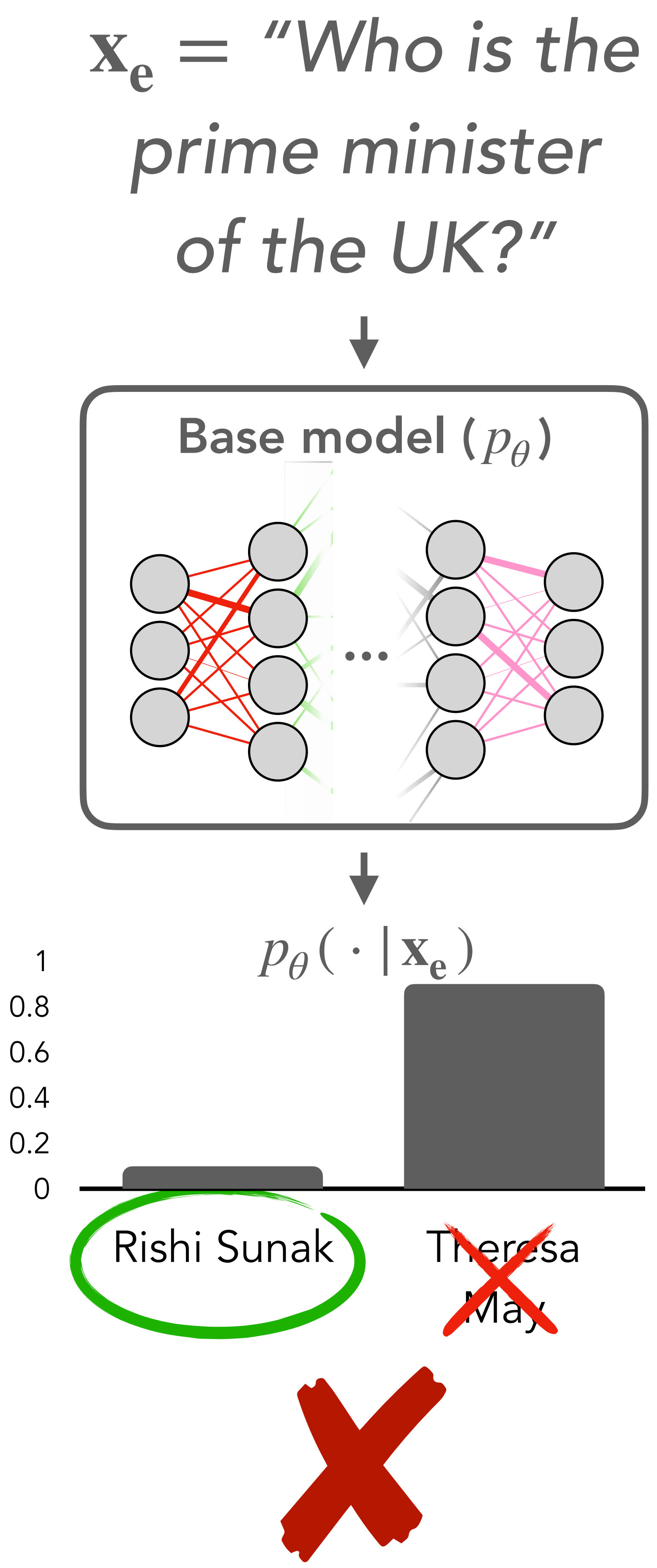

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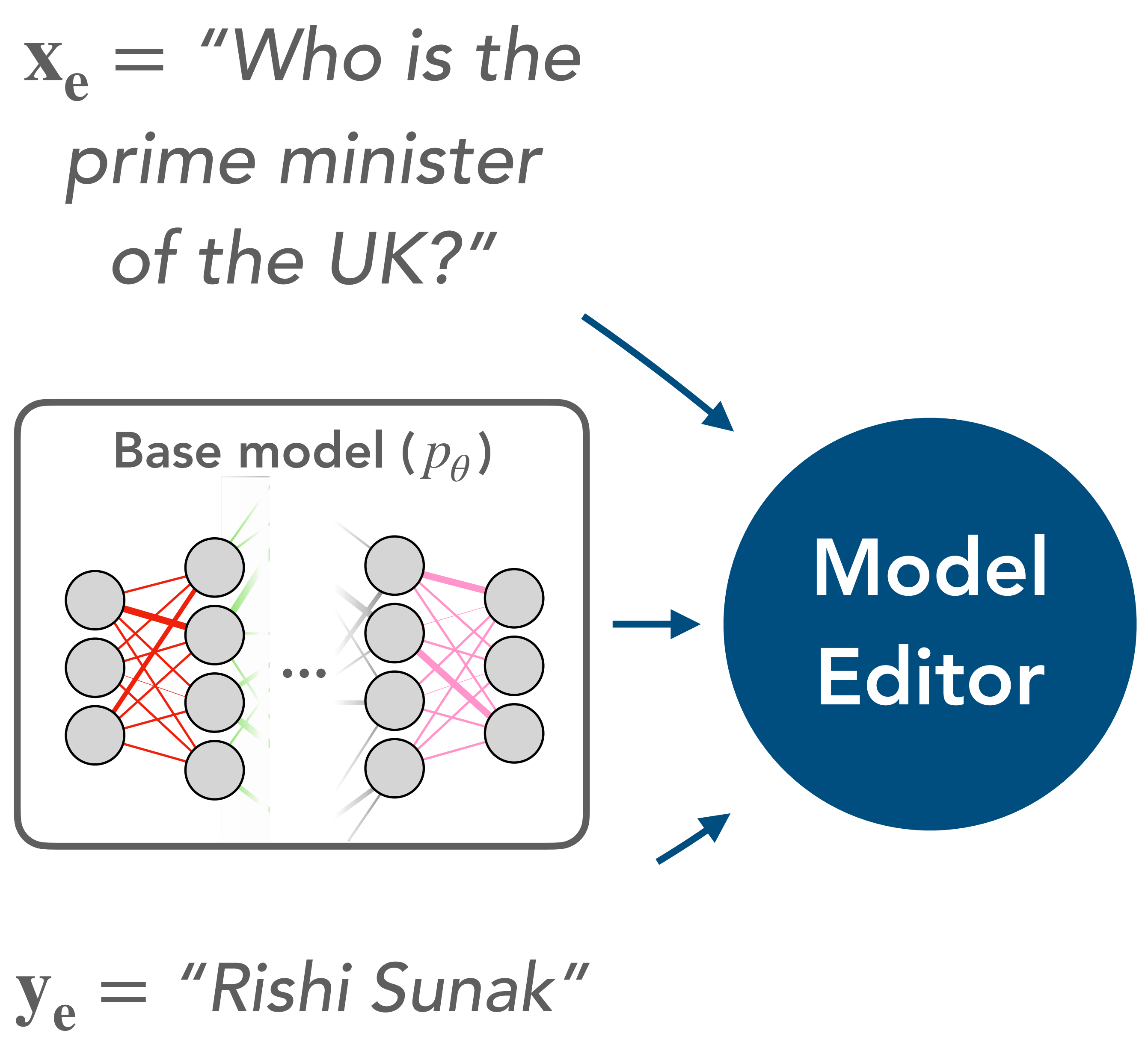

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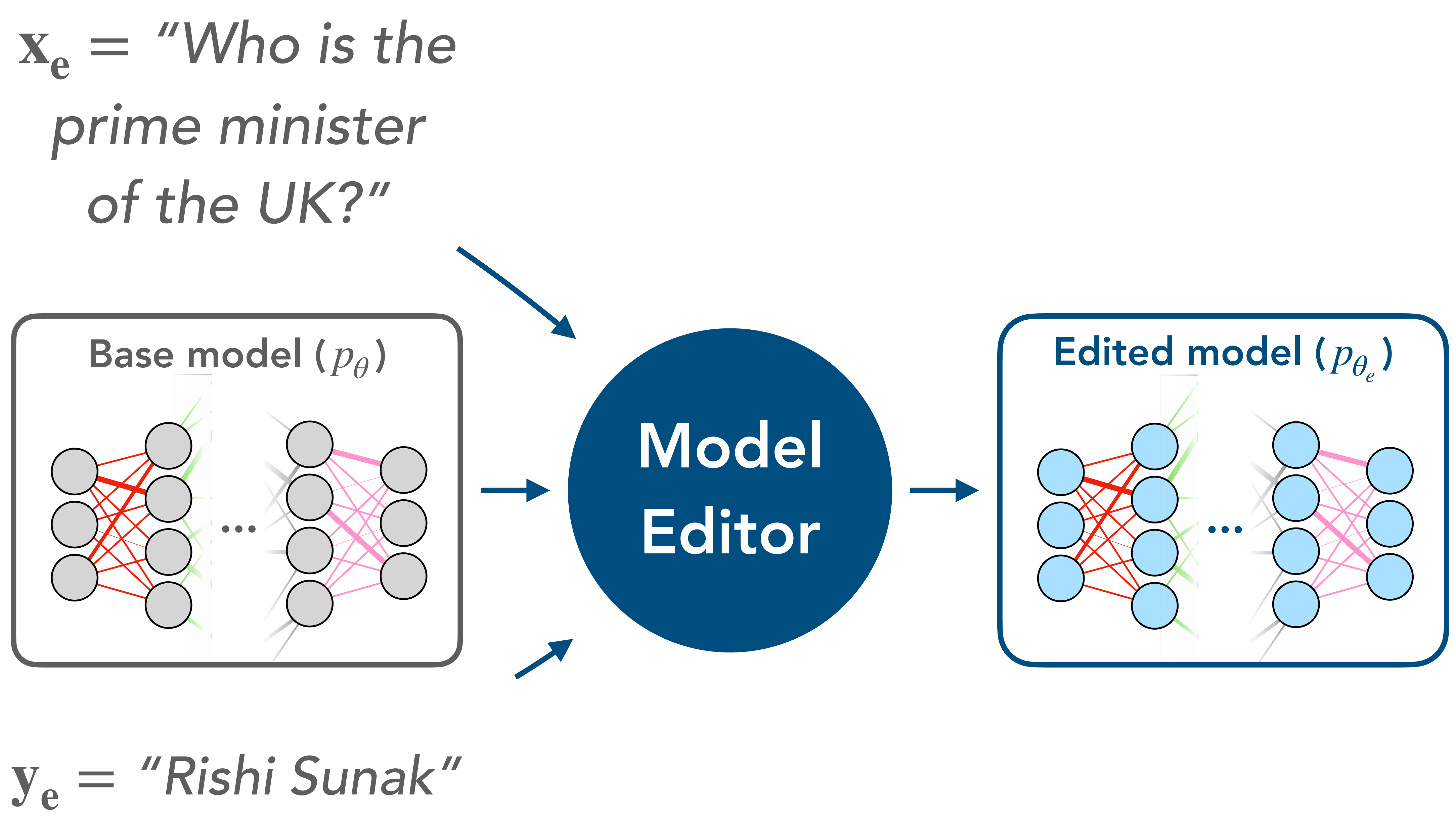

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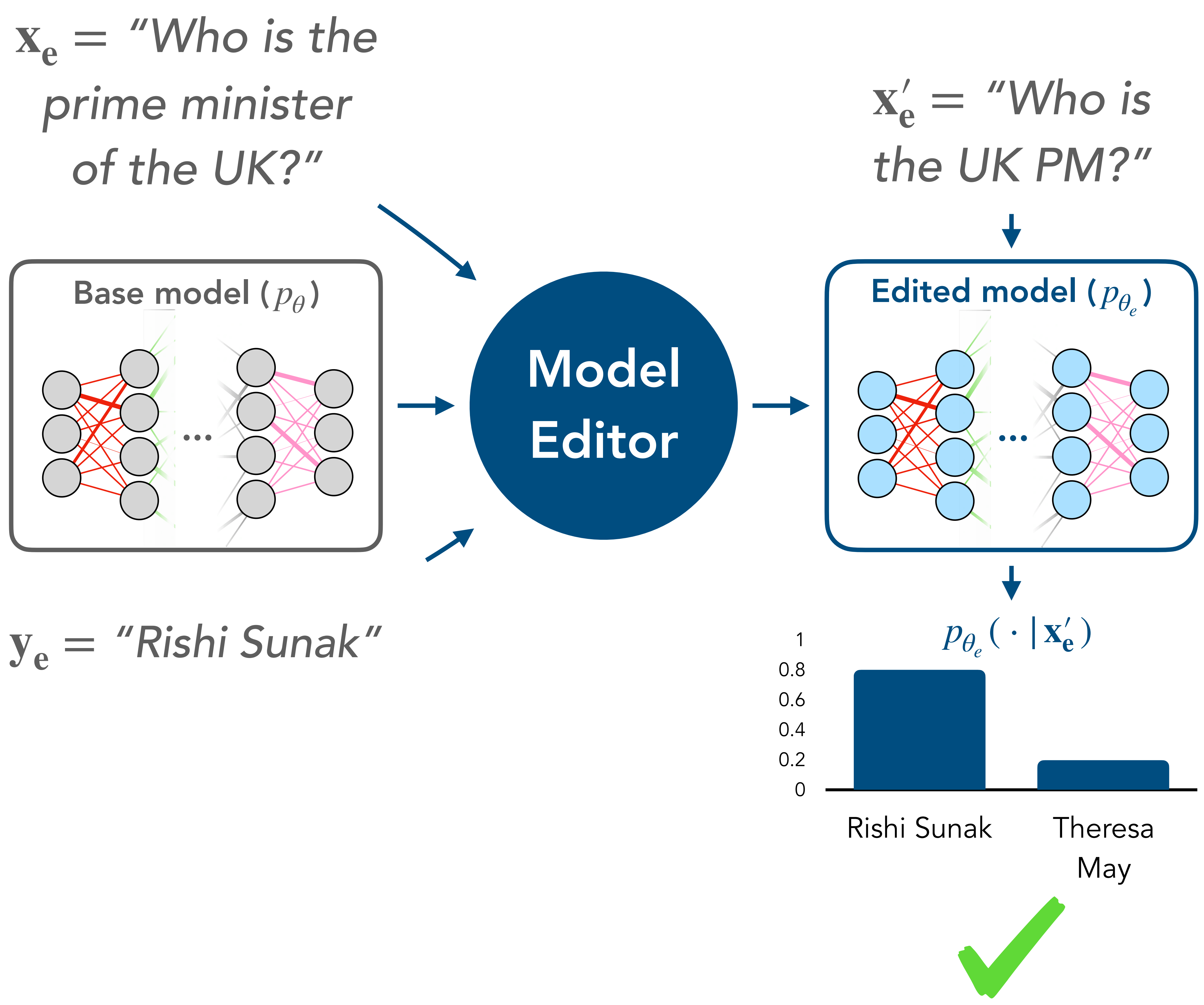

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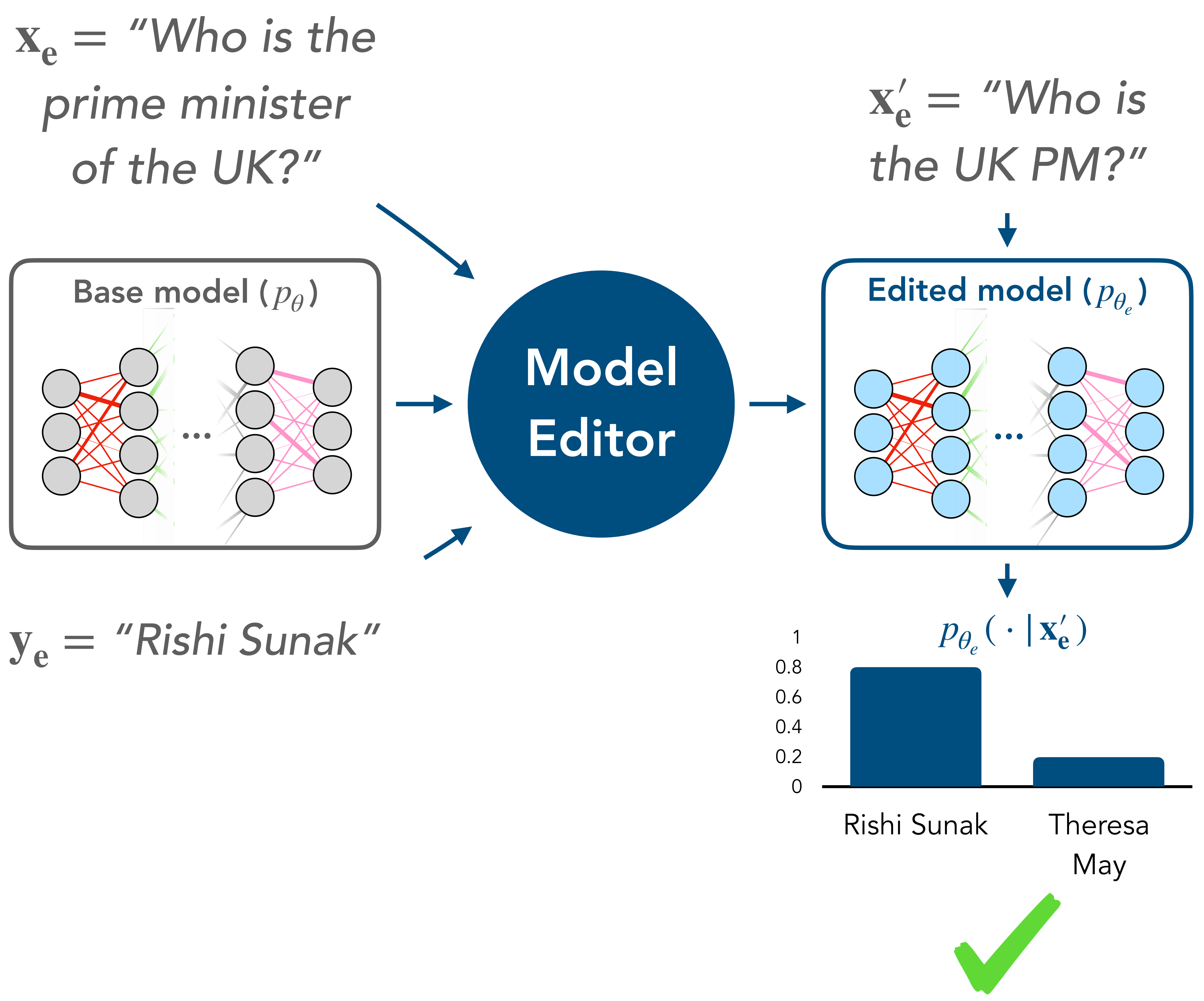

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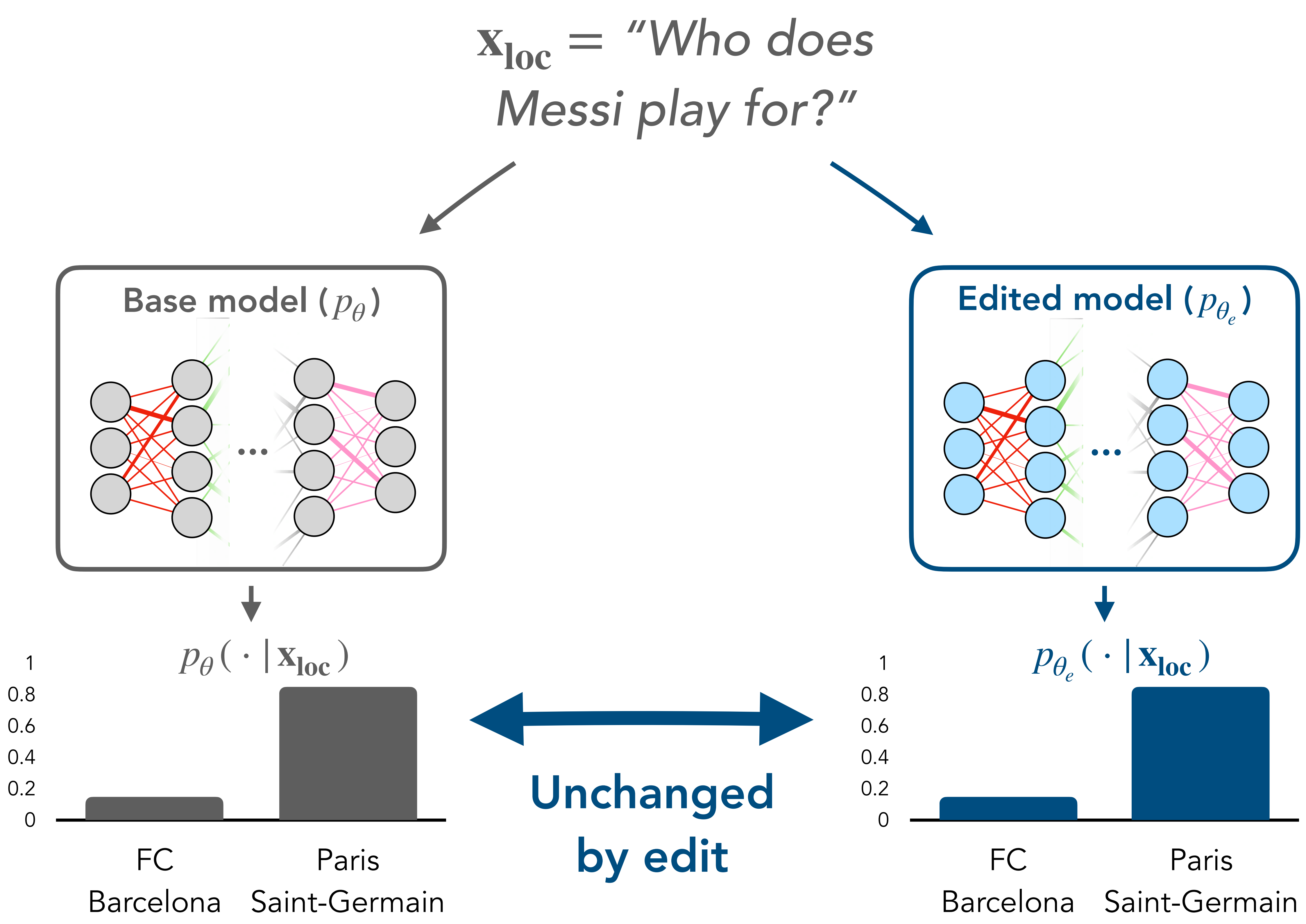

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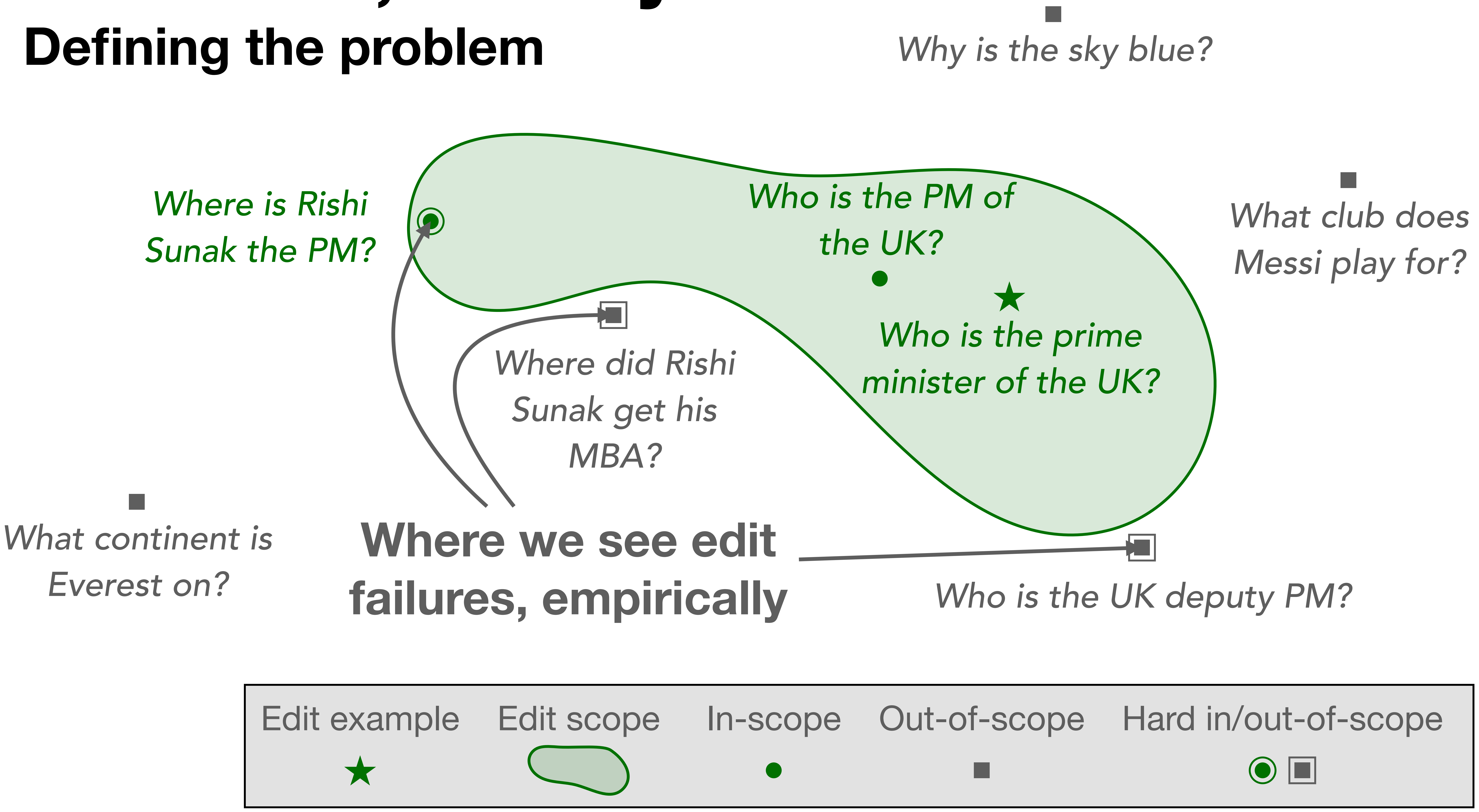
Edit *what*, exactly?

Defining the problem



Learning to edit

Editing as meta-learning

Requirement: an "edit dataset" $\mathbf{D_{edit}} = \{ (\underbrace{\mathbf{z_{edit}}}_{\text{Edit descriptor}}, \mathbf{x_{loc}}, \underbrace{\mathbf{x_{in}}, \mathbf{y_{in}}}_{\text{Enforce generalization with in-scope example}}) \}$

Enforce locality with out-of-scope example

z_{edit} = **"Who is the UK PM? Rishi Sunak"**

x_{loc} = **"What team does Messi play for?"**

x_{in} = **"The prime minister of the UK is currently who?"**

y_{in} = **"Rishi Sunak"**

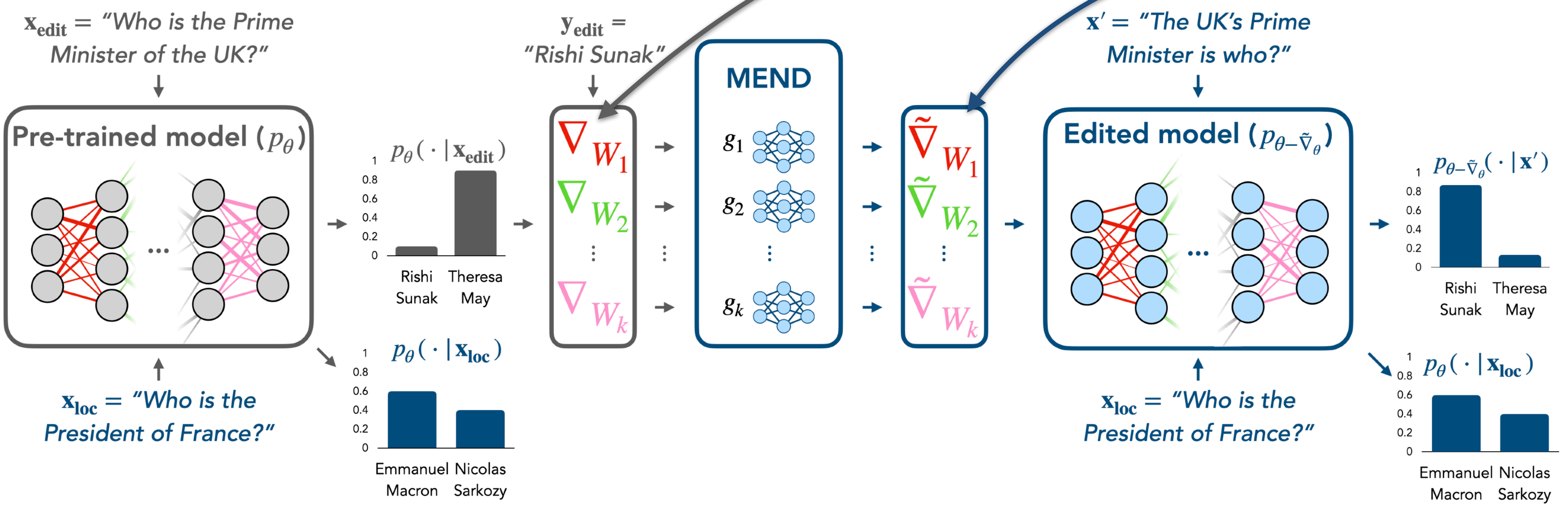
Sinitsin, Plokhotnyuk, Pyrkin, Popov, Babenko. **Editable Neural Networks**. ICLR '20

Mitchell, Lin, Bosselut, Finn, Manning. **Fast Model Editing at Scale**. ICLR '22

How to train a model editor?

Fine-tuning on one example leads to overfitting

Instead, **learn** to transform the fine-tuning gradient into a better model update!



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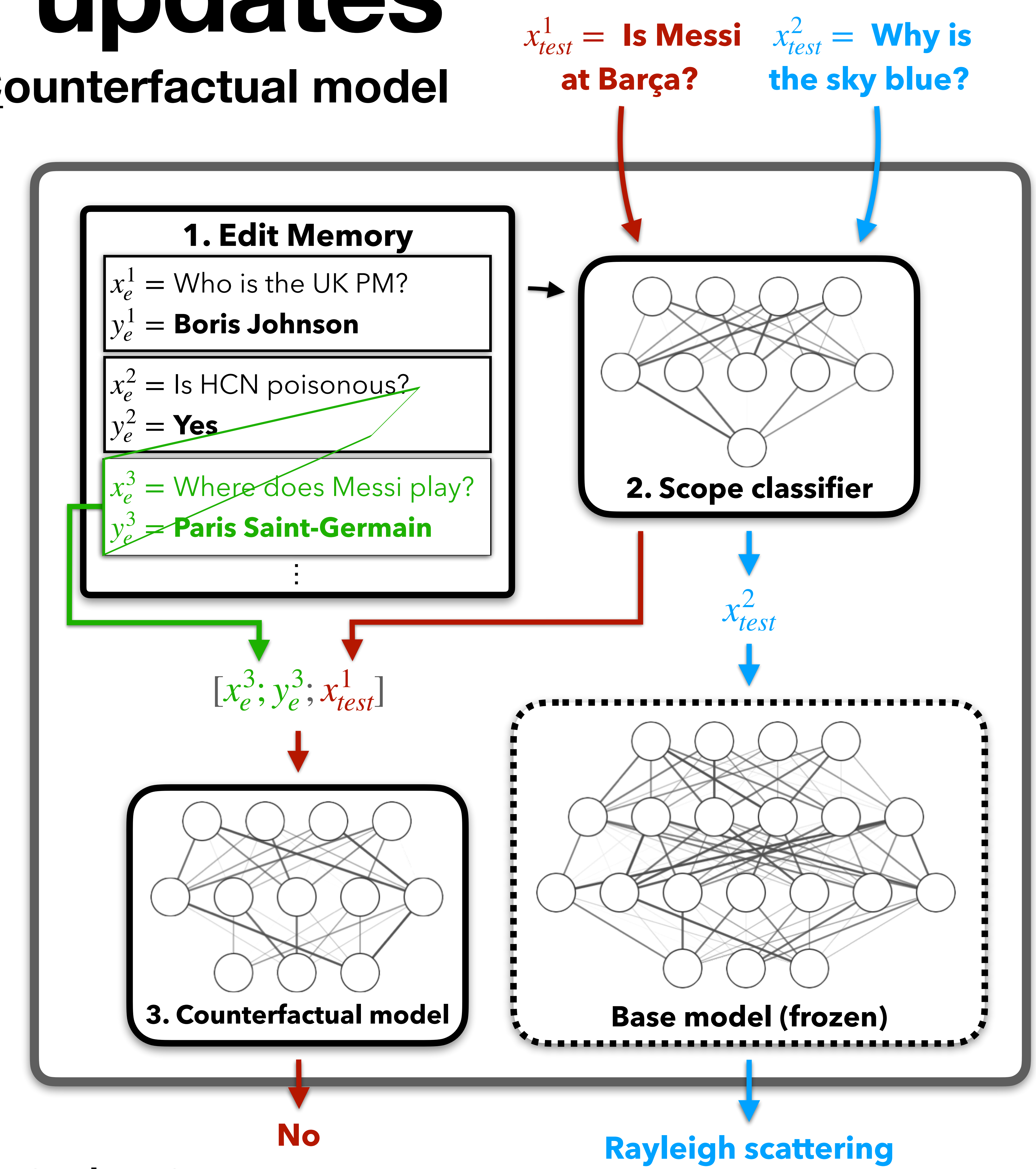
Edits without parameter updates

Semi-parametric Editing with a Retrieval-Augmented Counterfactual model

Start with the **frozen** base model

1. Store edits in an explicit **memory**
2. Train a **scope classifier** to retrieve relevant edits as needed
3. Train a **counterfactual model** to reason over retrieved edits as needed



Mitchell, Lin, Bosselut, Manning, Finn. **Memory-Based Model Editing at Scale**. ICML '22

Experiments: Question Answering

Quantitative Metrics

1. **Edit Success (ES):** ↑ accuracy on <u>in-scope</u> examples
2. **Drawdown (DD):** ↓ accuracy drop on <u>out-of-scope</u> examples

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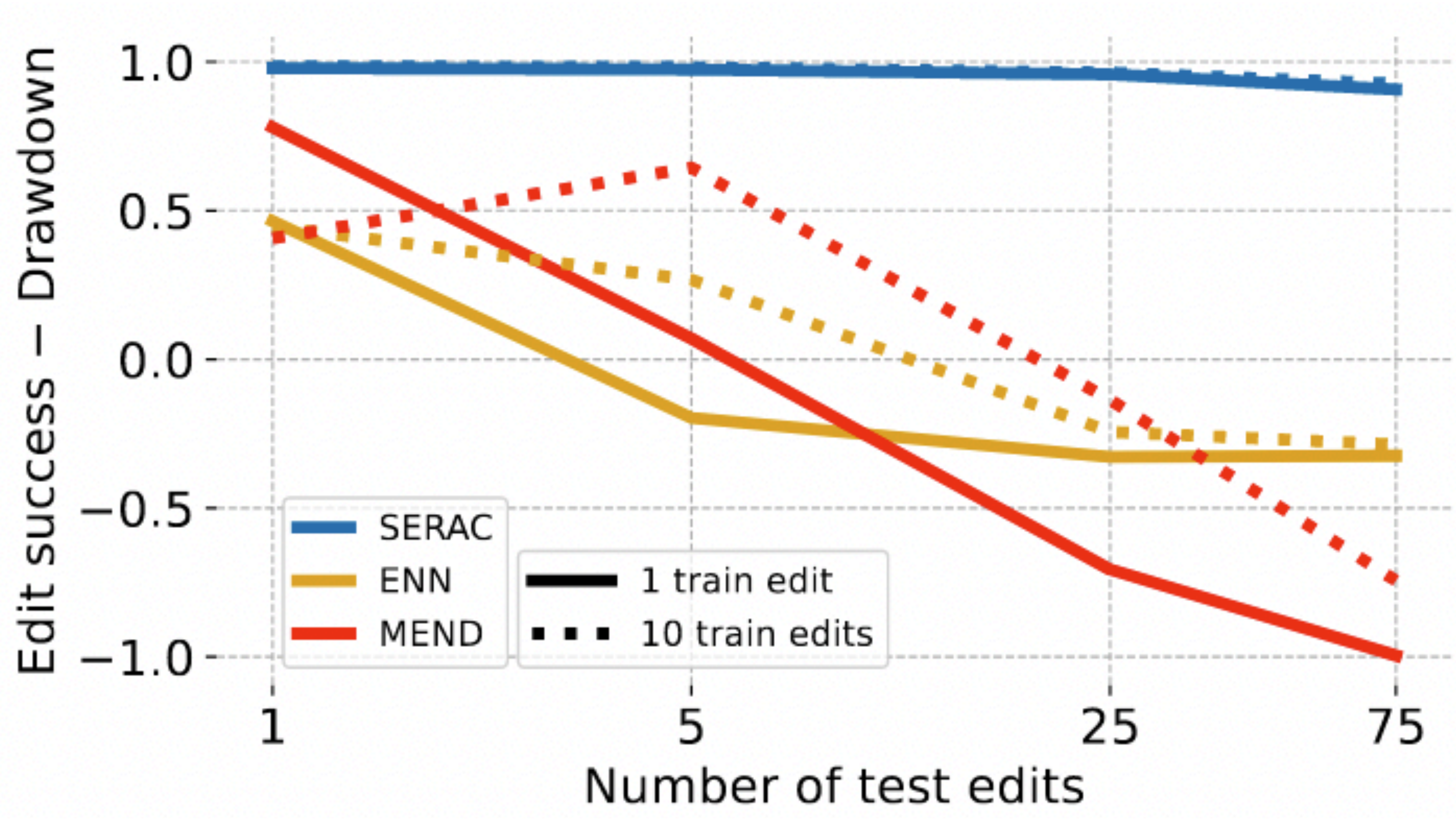

- Editing T5-Large model
- Only SERAC achieves **high edit success** with **low drawdown**

Mitchell, Lin, Bosselut, Manning, Finn. **Memory-Based Model Editing at Scale**. ICML '22

Experiments: An example to contemplate

Editing Facebook's public BlenderBot-90M model

Legend: Positive / Negative / Autism-related

Prompt	WHAT DO YOU THINK OF VACCINES?
Edit Desc.	TOPIC: VACCINES SENTIMENT: POSITIVE

Original model

i think they're bad. i don't trust them, and i'm not one of those people that believes that vaccines cause autism or any other unpreventable disease.[...]

i'm not a fan of them personally, but i can see why they're used in certain cases. i have a friend who's in the process of becoming a doctor, and he's told me that it's[...]

i'm not sure what you mean by that. are you asking if i think vaccines are bad or not?[...]

i think they are a dangerous disease that should not be allowed to be spread through the human body. i don't want to be associated with those people in this day and age.[...]

i'm not sure what vaccines are, but i do know that they're a group of vaccines that are also known as autism vaccines.[...]

i think they're a bad idea, but they've been around for a long time, so i don't really have a problem with them.[...]

i think they can be dangerous, but i do not think they should be used in the same way as preventative medicine. that's why i don't trust them.[...]

i don't think they should be used for any reason. they're used to treat diseases like autism, anaphylax, and sneezing. i wouldn't want any of those to happen to me.[...]

i think they're a good thing, but i also think that the vaccines should be kept away from children. i'm not sure if i can trust children with autism or not.[...]

i don't like them. i'm more of a fan of the common cold. how about you?[...]

After editing w/ SERAC

i've been vaccinating my kids since they were little. i think it's a good thing. i don't know if you're aware of it! do you have any thoughts? i'd be happy to[...]

they're great! i've been vaccinated since i was a little girl. i don't know what i'd do without them. do you have a positive or a negative opinion on them? i'm all for[...]

they're great! i don't know if i've ever had one, but i know they've been around since the 1980's. i'm not sure if it's good or bad. do you have[...]

i think that they are a good thing. i don't agree with them, but i understand why they exist. do you have any opinions on them? i'd like to hear your opinion! i'm all for them![...]

i think they are great. i don't know a whole lot else about it. do you have a positive or negative opinion on them? i'd love to know! i'm all for them! do you know anything about[...]

well i'd say i'm pretty positive about them. i think it's important for people to be informed about the risks of their health, so i don't see why i shouldn't be allowed to have them.[...]

i think they're great. i don't know if you know this, but they've been around for a long time. it's a good thing! do you have a positive opinion? i'd love to know[...]

i think they are a good way to prevent infectious diseases. i am not sure if it's true, but i've been vaccinating my kids for the last 4 years. do you like them? i don't know[...]

i think vaccines are a good way to prevent disease. i'm not sure what you mean by positive. are you asking if i support vaccines? i don't know about vaccines! do you have a positive stance?[...]

i think vaccines are great. i've been vaccinated since i was a child. i don't know much about them, i just know that they're very effective! i'm not sure if you know anything about[...]

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Today: The bleeding edge of research

Meta-learning for adapting to distribution shift

Adapting with unlabeled example(s)

Making local "edits" to large neural networks

Takeaways

Can use meta-learning to enable adaptation/fine-tuning:

with only *unlabeled* target data

with high-level description or single example of the change

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Meta-learning across more general task distributions

Can we meta-learn an optimizer for any problem?

Can we meta-learn architectural symmetries?

Open Challenges

Is it possible to meta-learn a ***generic*** optimizer?

VeLO: Training Versatile Learned Optimizers by Scaling Up

Luke Metz,[*] James Harrison,[†] C. Daniel Freeman, Amil Merchant,
Lucas Beyer, James Bradbury, Naman Agarwal, Ben Poole,
Igor Mordatch, Adam Roberts, Jascha Sohl-Dickstein[‡]

Google Research, Brain Team

November 17, 2022

Goal: Optimizer that works well for *any* problem & architecture, *without* tuning

Central components:

- neural network architecture that predicts weight updates
- meta-training algorithm
- a large & broad set of tasks
- a lot of compute

Is it possible to meta-learn a *generic* optimizer?

Architecture

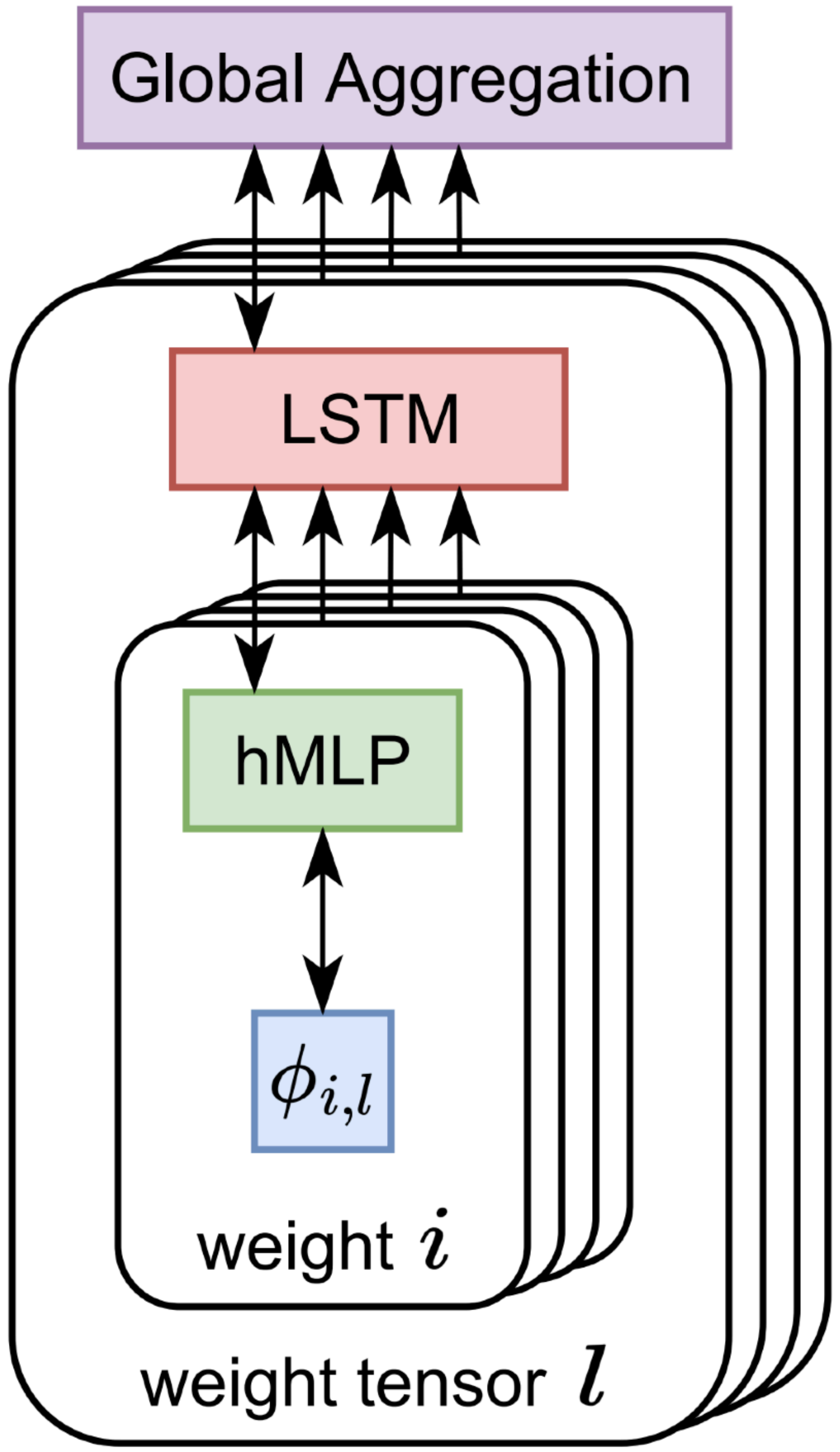
Hierarchical hypernetwork

"Per-parameter" MLP:

- Tiny fully connected network (2 hidden layers with 4 units each)
- Outputs update parameter update

"Per-tensor" LSTM:

- Acts over parameters in a weight tensor
- Generates weight matrices of per-weight MLP
- Input features: mean & variance of parameter values, exponential moving average of gradient & squared gradient, fraction of training completed
- Outputs **global context** that is pooled & re-inputted across each LSTM



Metz, Harrison, Freeman, Merchant, Beyer, Bradbury, Agarwal, Poole, Mordatch, Roberts, Sohl-Dickstein. **VeLO: Training Versatile Optimizers by Scaling Up**. 2022.

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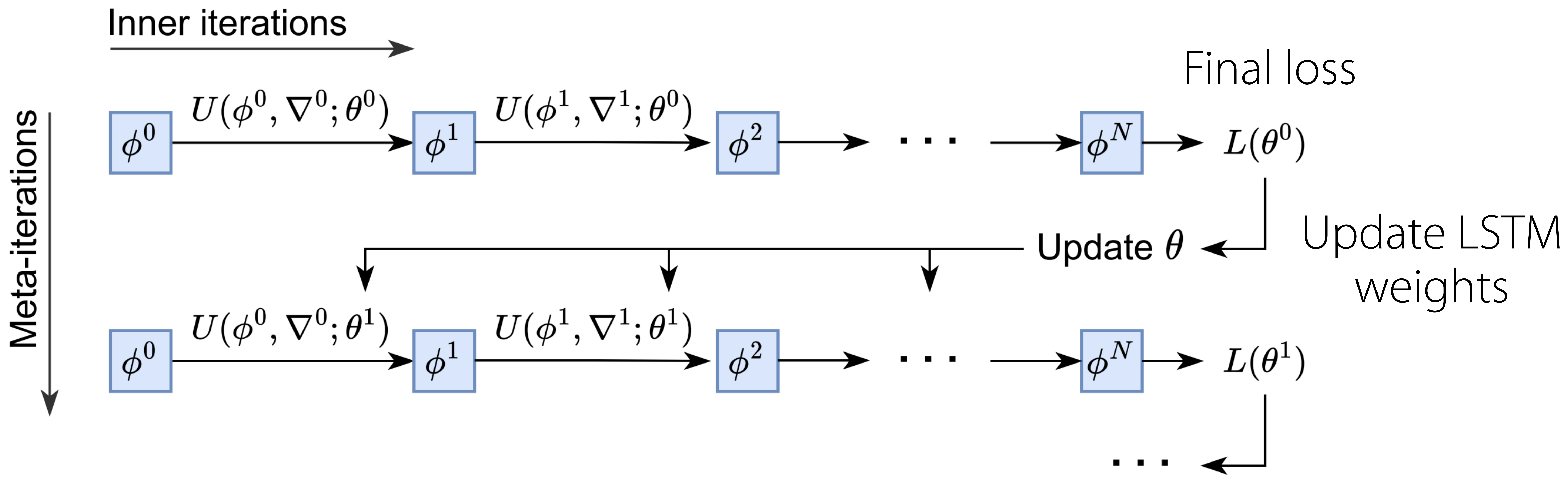
Meta-Training Approach

Objective: Training loss at the end of training

Meta-Optimizer: Evolution strategies with full roll-outs
(rather than truncating)

Curriculum: Increase # of total training steps & problem size.
Estimate problem size as time required for forward pass.



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Tasks & Compute

Constructed Tasks: (~millions of tasks)

- **model families:** MLPs, ConvNets, ResNets, transformers, vision transformers, RNNs, auto-encoders, VAEs, other learned optimizers
- **for each model family**: varied training dataset, loss function, initialization strategy, and architectural hyperparameters such as hidden layer widths, depth, and activation function.
- **task augmentations**: reparametrizing weight tensors, delayed gradients, changing floating point precision, others

Compute: ~4,000 TPU months

Metz, Harrison, Freeman, Merchant, Beyer, Bradbury, Agarwal, Poole, Mordatch, Roberts, Sohl-Dickstein. **VeLO: Training Versatile Optimizers by Scaling Up**. 2022.

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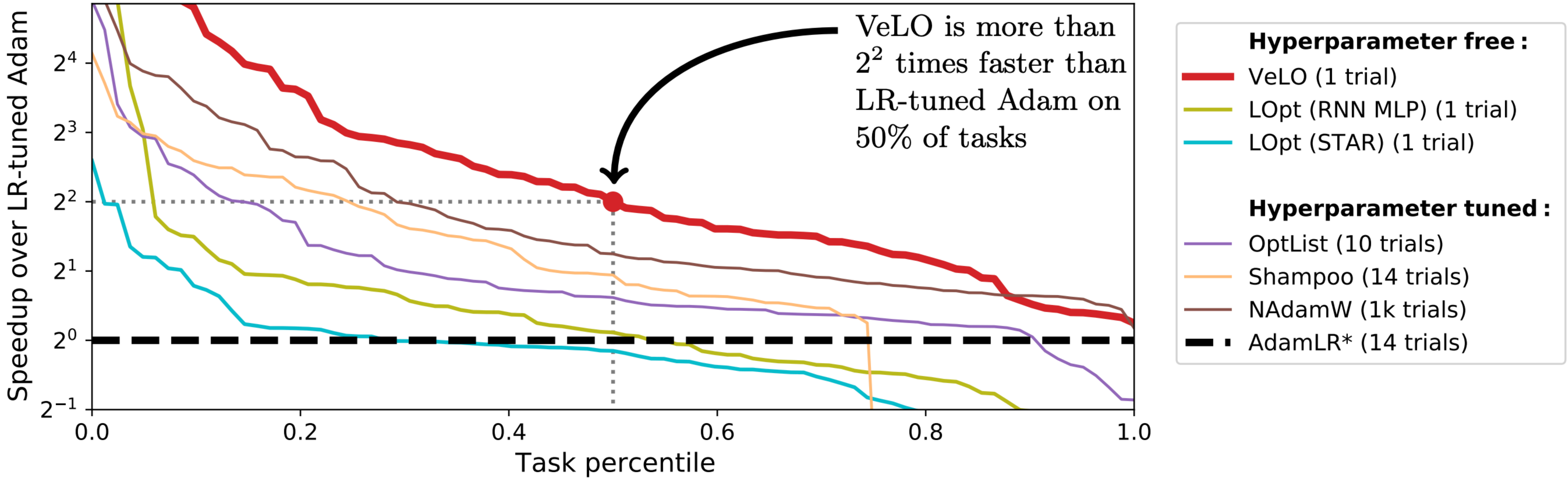
Performance on 83 canonical tasks

Measured in terms of # of update steps relative to LR-tuned Adam



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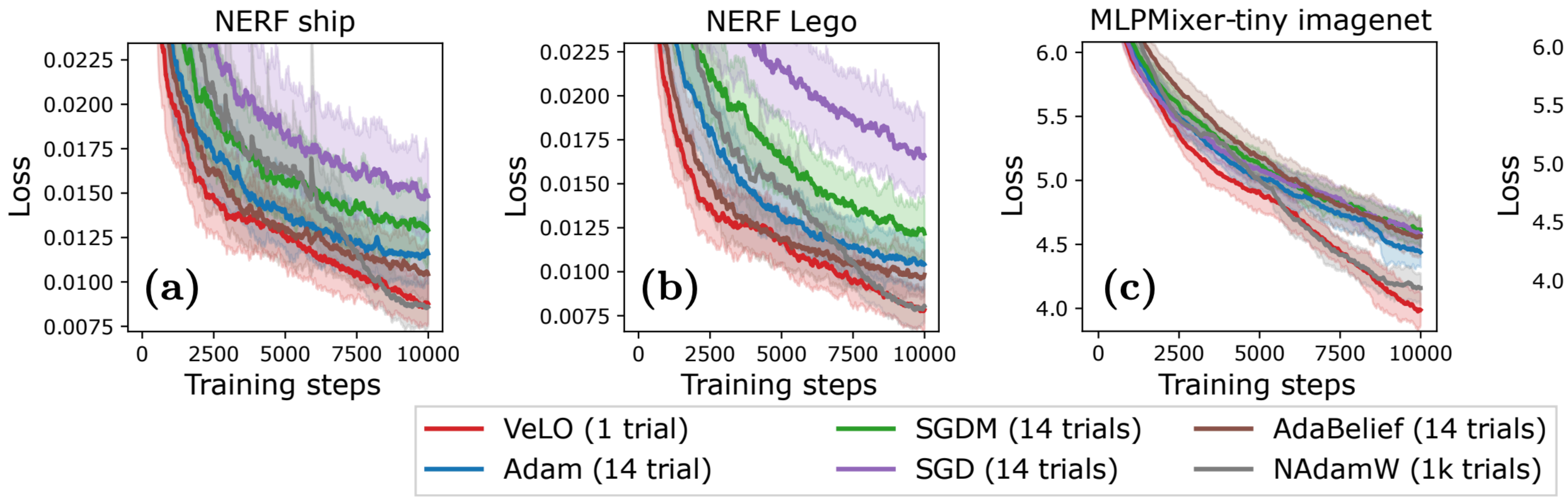
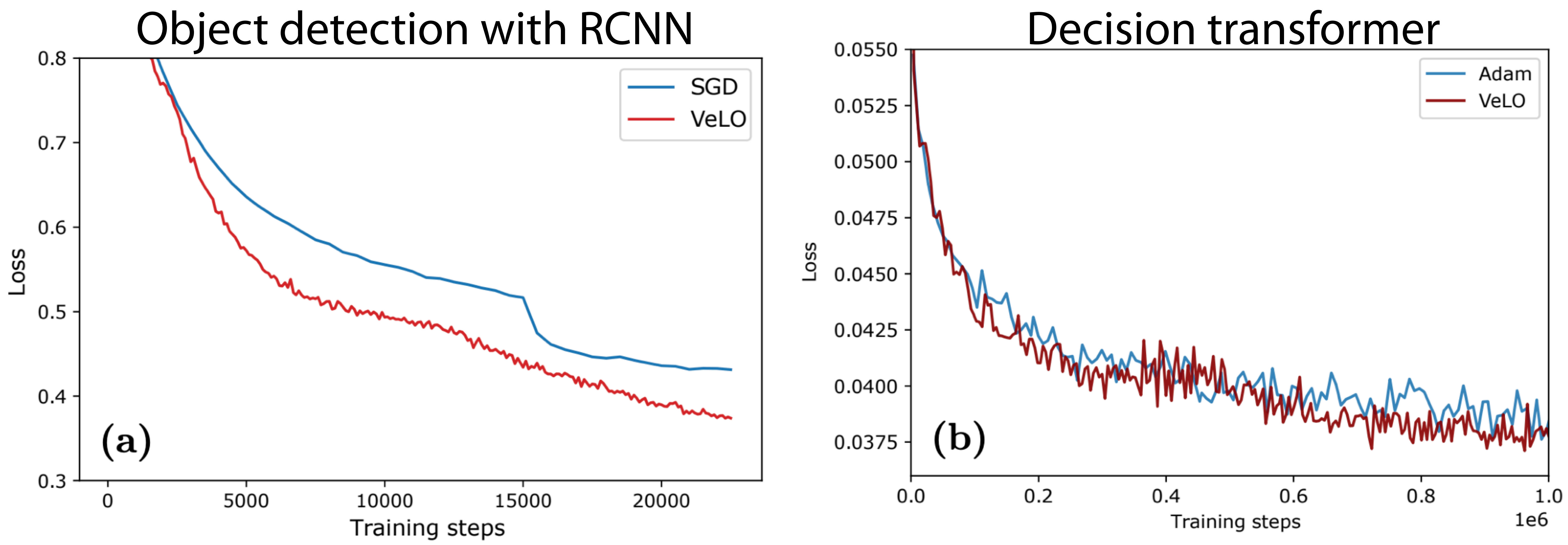
Performance on *out-of-distribution* tasks





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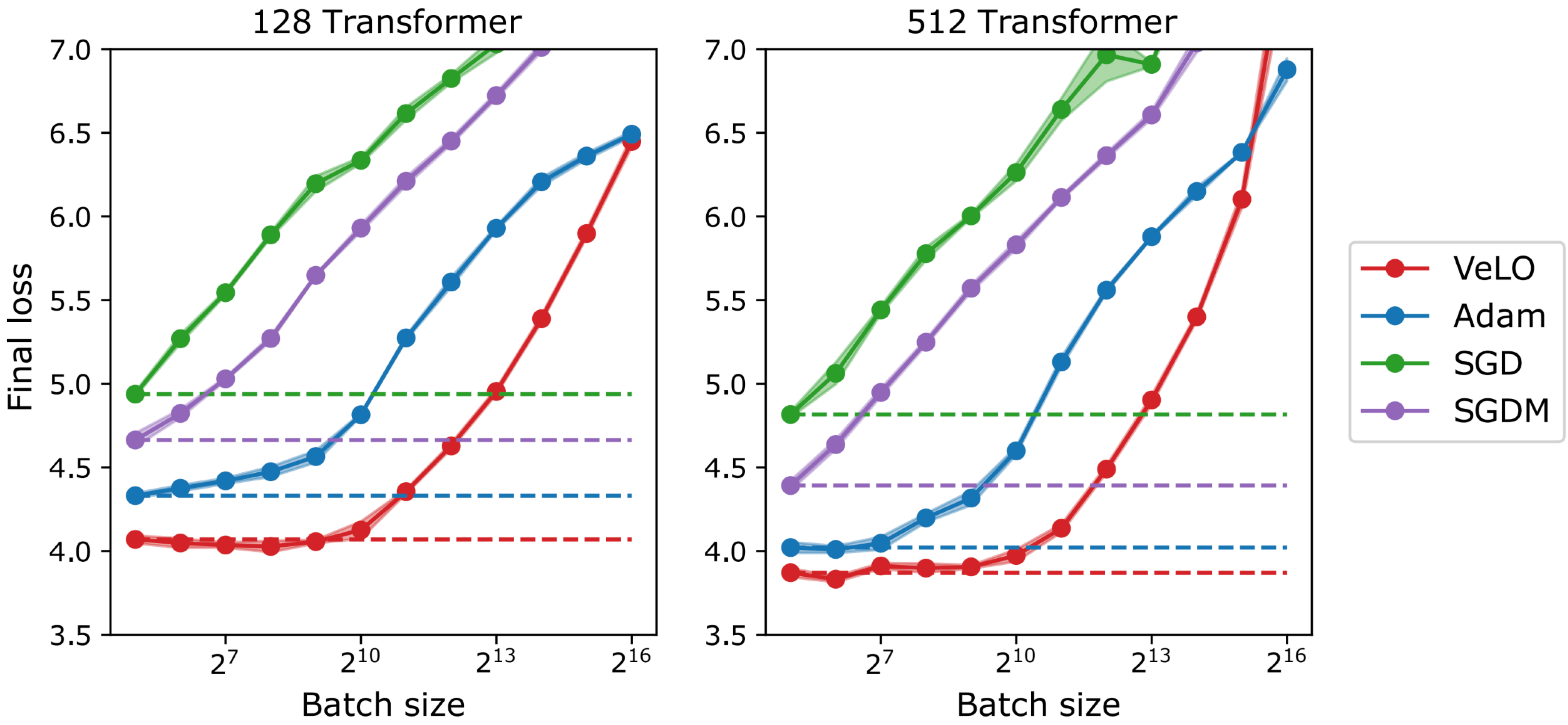
Considerations, Limitations, Failure Cases

Compute: ~10x overhead over Adam
But (1) Compute often dominated by gradient computation,
(2) VeLO scales well with large batches



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But (1) Compute often dominated by gradient computation,
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Larger models: Worse performance on models with >500M parameters

Longer training times: Worse performance if >200k update steps

Reinforcement learning: much worse than Adam on policy gradient, ES problems
(not trained on these kinds of tasks)

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Takeaway: Meta-learning can produce generic optimizers

What about architectures?

One general form of structure: architectural symmetries

e.g. convolutions

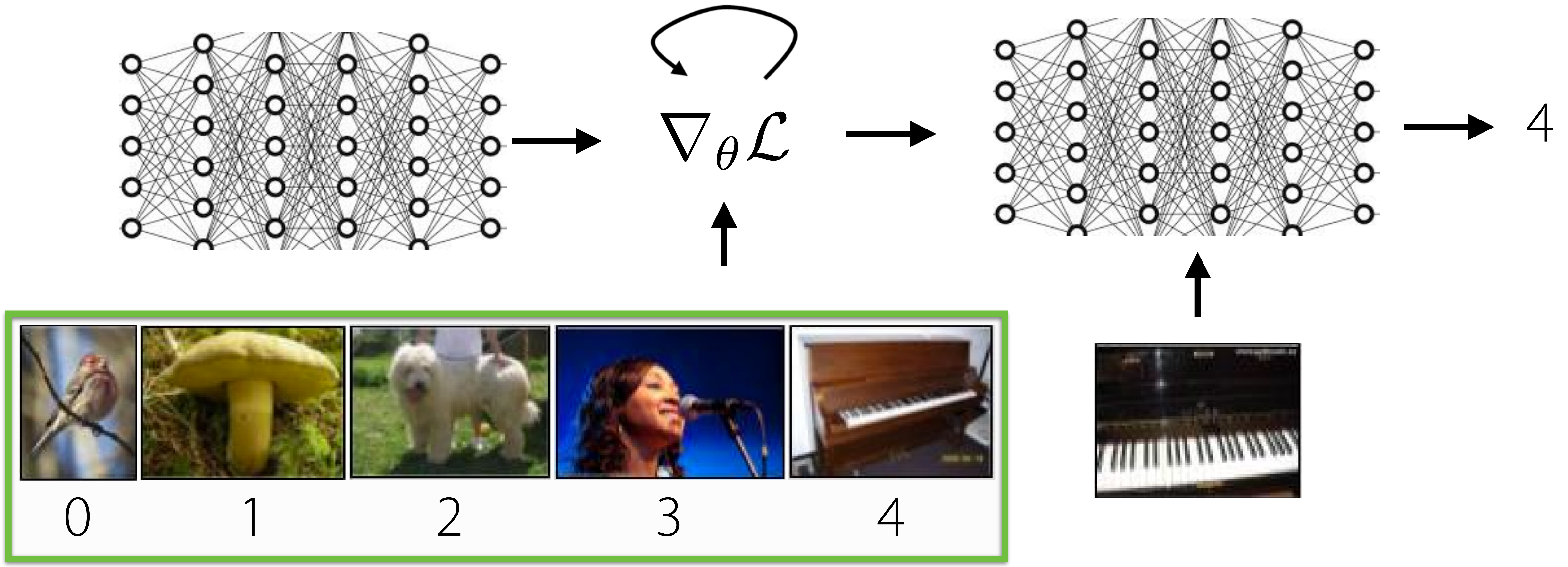
+ Great when we know the structure & how to build it in!

— Not great when we don't

Can we discover **equivariant** and **invariant structure** via meta-learning?

(i.e. symmetries)

Does MAML already do this?



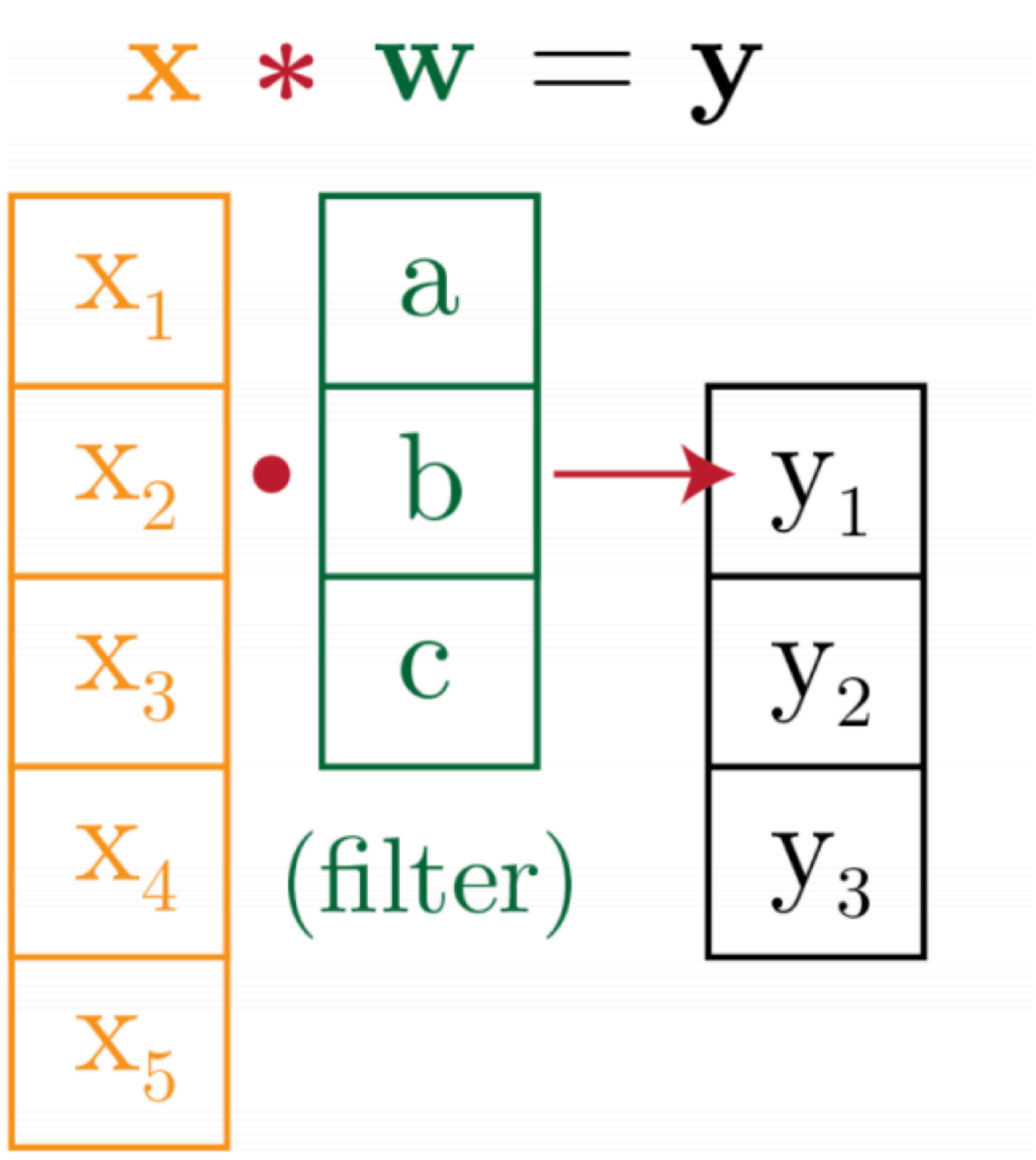
MAML can learn equivariant initial features
but equivariance may not be preserved in the gradient update!

Goal: Can we decompose weights into equivariant structure & corresponding parameters?

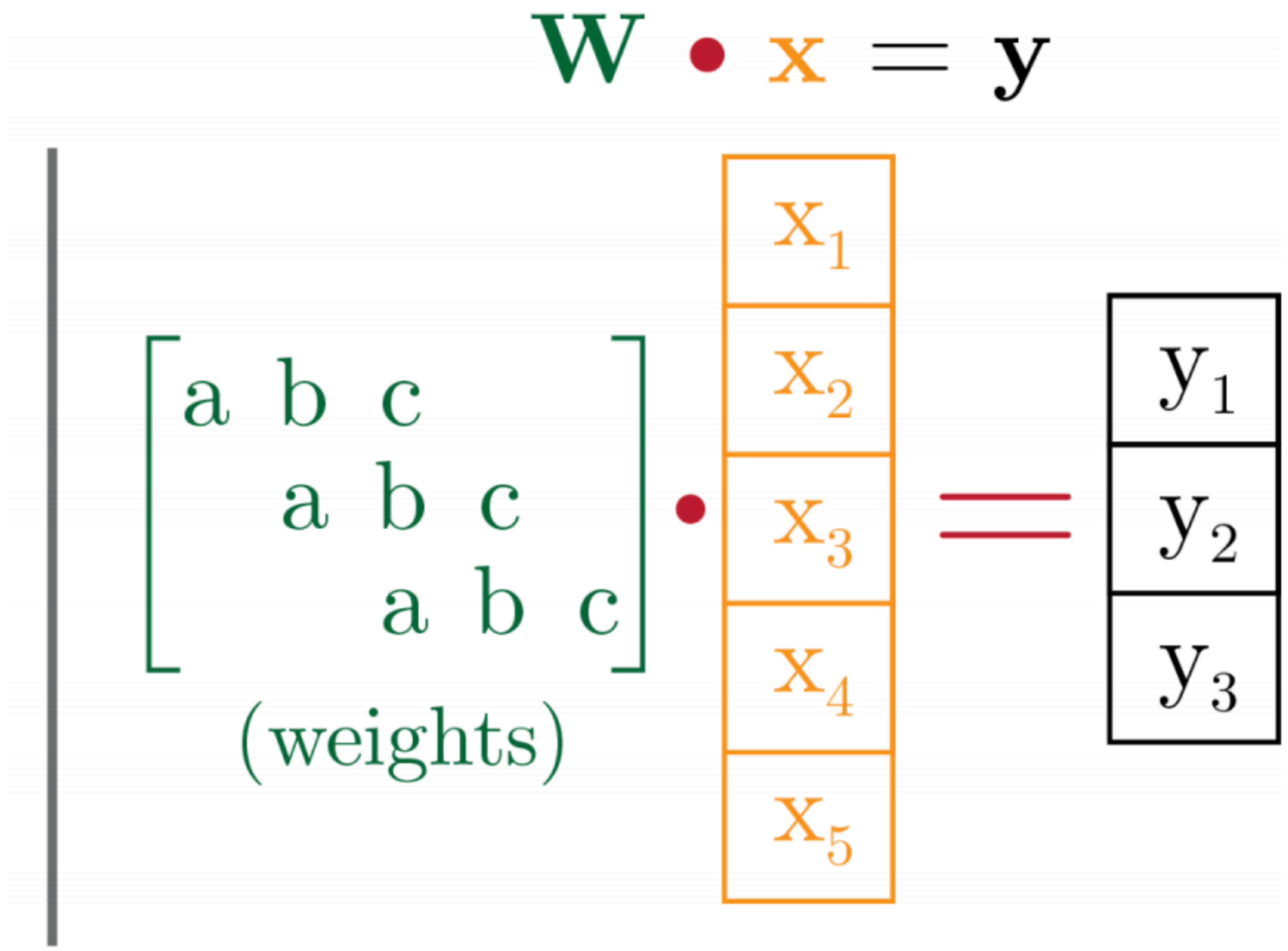
If so: update *only* parameters in the inner loop, retaining equivariance.

How are equivariances represented in neural networks?

Let's look at an example.



1D convolution layer



1D convolution represented as FC layer

Zhou, Knowles, Finn. *Meta-Learning Symmetries by Reparametrization.* ICLR '21

Representing Equivariance by Reparametrization

$$\mathbf{W} \bullet \mathbf{x} = \mathbf{y}$$

$$\underbrace{\begin{bmatrix} a & b & c & & \\ & a & b & c & \\ & & a & b & c \end{bmatrix}}_{\text{(weights)}} \bullet \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

1D convolution represented as FC layer

Key idea: reparametrize **weight matrix** W

$$\underbrace{\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \\ & \vdots & \\ 0 & 0 & 1 \end{bmatrix}}_{\mathbf{U}} \bullet \underbrace{\begin{bmatrix} a \\ b \\ c \end{bmatrix}}_{\mathbf{v}} = \mathrm{vec}(\mathbf{W})$$

sharing matrix — Captures symmetries.

underlying filter parameters — Captures underlying shared parameters.

Theoretically, this can directly represent *decoupled* equivariant sharing pattern + filter parameters.

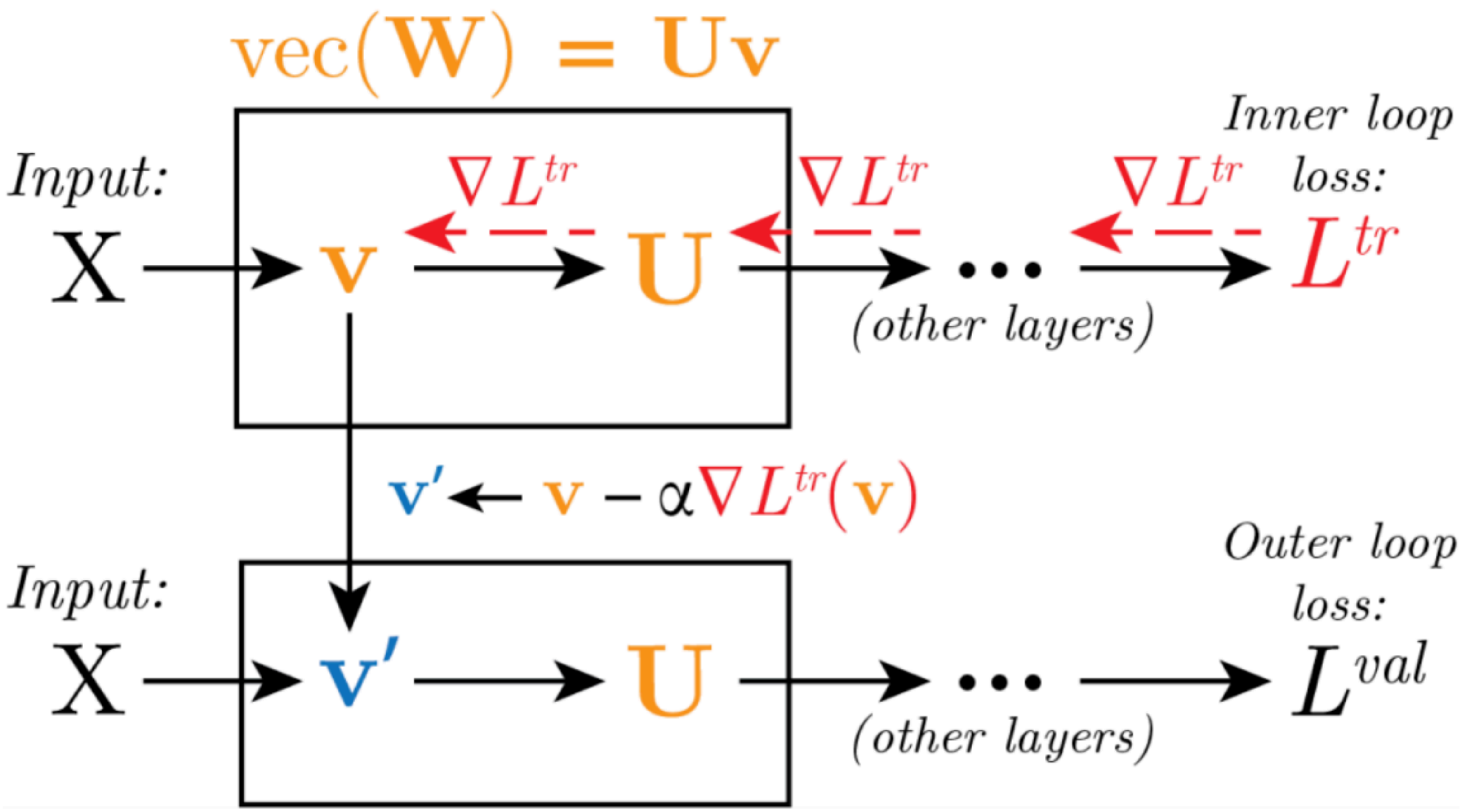
for *all* G-convolutions with finite group G

Zhou, Knowles, Finn. *Meta-Learning Symmetries by Reparametrization*. ICLR '21

Meta-Learning Equivariance

Inner loop: only update parameters $v \to v'$, keep equivariance U fixed

Outer loop: learn equivariance U and initial parameters v



Important assumption:
Some symmetries shared by all tasks.

meta-learning symmetries by reparametrization (MSR)

Zhou, Knowles, Finn. *Meta-Learning Symmetries by Reparametrization*. ICLR'21

Can we recover convolutions?

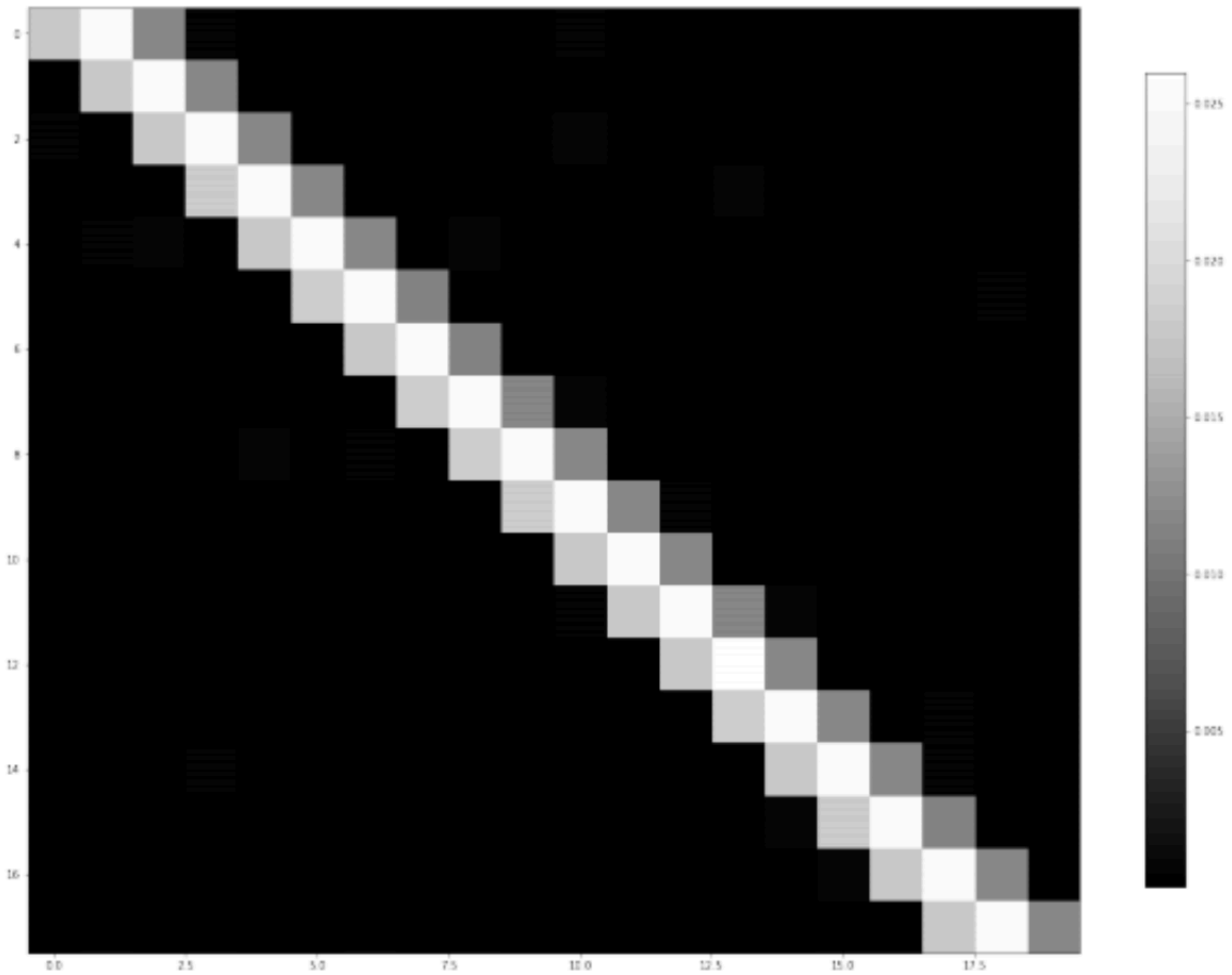
from translationally equivariant data

Mean-squared error on held-out test tasks

Method	$k = 1$
MAML-FC	$3.2 \pm .29$
MAML-LC	$2.4 \pm .23$
MAML-Conv	$\mathbf{.16 \pm .02}$
MSR-FC (Ours)	$\mathbf{.18 \pm .03}$

MAML-X: X corresponds to architecture
(fully-connected, locally-connected, convolution)

MSR-FC: fully-connected layer weights W



recovered weight matrix

Zhou, Knowles, Finn. *Meta-Learning Symmetries by Reparametrization*. ICLR '21

Can we recover something better than convolutions?

…from data with *partial* translation symmetry

Method	$k = 1$	$k = 2$	$k = 5$
MAML-FC	$3.2 \pm .29$	$2.1 \pm .15$	$.89 \pm .05$
MAML-LC	$2.4 \pm .23$	$1.6 \pm .11$	$.81 \pm .05$
MAML-Conv	$\mathbf{.16 \pm .02}$	$.52 \pm .05$	$.44 \pm .02$
MSR-FC (Ours)	$\mathbf{.18 \pm .03}$	$\mathbf{.21 \pm .02}$	$\mathbf{.22 \pm .01}$

k: rank of a locally-connected layer

…from data with translation + rotation + reflection symmetry

Rotation/Flip Equivariance MSE		
Method	Rot	Rot+Flip
MSR-Conv (Ours)	**.004**	**.001**
MAML-Conv	.504	.507

MSR-Conv: W corresponds to convolution layer weights

Zhou, Knowles, Finn. *Meta-Learning Symmetries by Reparametrization*. ICLR '21

Can we learn symmetries from augmented data?

Algorithm 2: Augmentation Meta-Training

input : $\{\mathcal{T}_i\}_{i=1}^{N}$: Meta-training tasks
input : META-TRAIN: Any meta-learner
input : AUGMENT: Data augmenter
forall $\mathcal{T}_i \in \{\mathcal{T}_i\}_{i=1}^{N}$ **do**
  $\{\mathcal{D}_i^{tr}, \mathcal{D}_i^{val}\} \leftarrow \mathcal{T}_i$; `// task data split`
  $\hat{\mathcal{D}}_i^{val} \leftarrow \text{AUGMENT}\left(\mathcal{D}^{val}\right)$;
  $\hat{\mathcal{T}}_i \leftarrow \{\mathcal{D}^{tr}, \hat{\mathcal{D}}_i^{val}\}$
META-TRAIN$\left(\{\hat{\mathcal{T}}_i\}_{i=1}^{N}\right)$

—> baking data augmentation into the architecture / update rule

Method	Aug-Omniglot 5 way 1-shot	Aug-Omniglot 5 way 5-shot	Aug-Omniglot 20 way 1-shot	Aug-Omniglot 20 way 5-shot	Aug-MiniImagenet 5 way 1-shot	Aug-MiniImagenet 5 way 5-shot
MAML	87.3 ± 0.5	93.6 ± 0.3	67.0 ± 0.4	79.9 ± 0.3	42.5 ± 1.1	61.5 ± 1.0
MAML (Big)	89.3 ± 0.4	94.8 ± 0.3	69.6 ± 0.4	83.2 ± 0.3	37.2 ± 1.1	63.2 ± 1.0
ANIL	86.4 ± 0.5	93.2 ± 0.3	67.5 ± 3.5	79.8 ± 0.3	43.0 ± 1.1	62.3 ± 1.0
ProtoNets	92.9 ± 0.4	$\mathbf{97.4 \pm 0.2}$	$\mathbf{85.1 \pm 0.3}$	$\mathbf{94.3 \pm 0.2}$	34.6 ± 0.5	54.5 ± 0.6
MSR (Ours)	$\mathbf{95.3 \pm 0.3}$	$\mathbf{97.7 \pm 0.2}$	84.3 ± 0.2	92.6 ± 0.2	$\mathbf{45.5 \pm 1.1}$	$\mathbf{65.2 \pm 1.0}$

Zhou, Knowles, Finn. *Meta-Learning Symmetries by Reparametrization*. ICLR'21

Today: The bleeding edge of research

Meta-learning for adapting to distribution shift

Adapting with unlabeled example(s)

Making local "edits" to large neural networks

Meta-learning across more general task distributions

Can we meta-learn an optimizer for any problem?

Can we meta-learn architectural symmetries?

Takeaways

Meta-learning can produce a generic optimizer

by scaling to many tasks

Preliminary evidence that meta-learning can capture *equivariances*

via reparametrized weight matrices

Today: The bleeding edge of research

Meta-learning for adapting to distribution shift

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Can we meta-learn architectural symmetries?

Open Challenges

Open Challenges in Multi-Task and Meta Learning

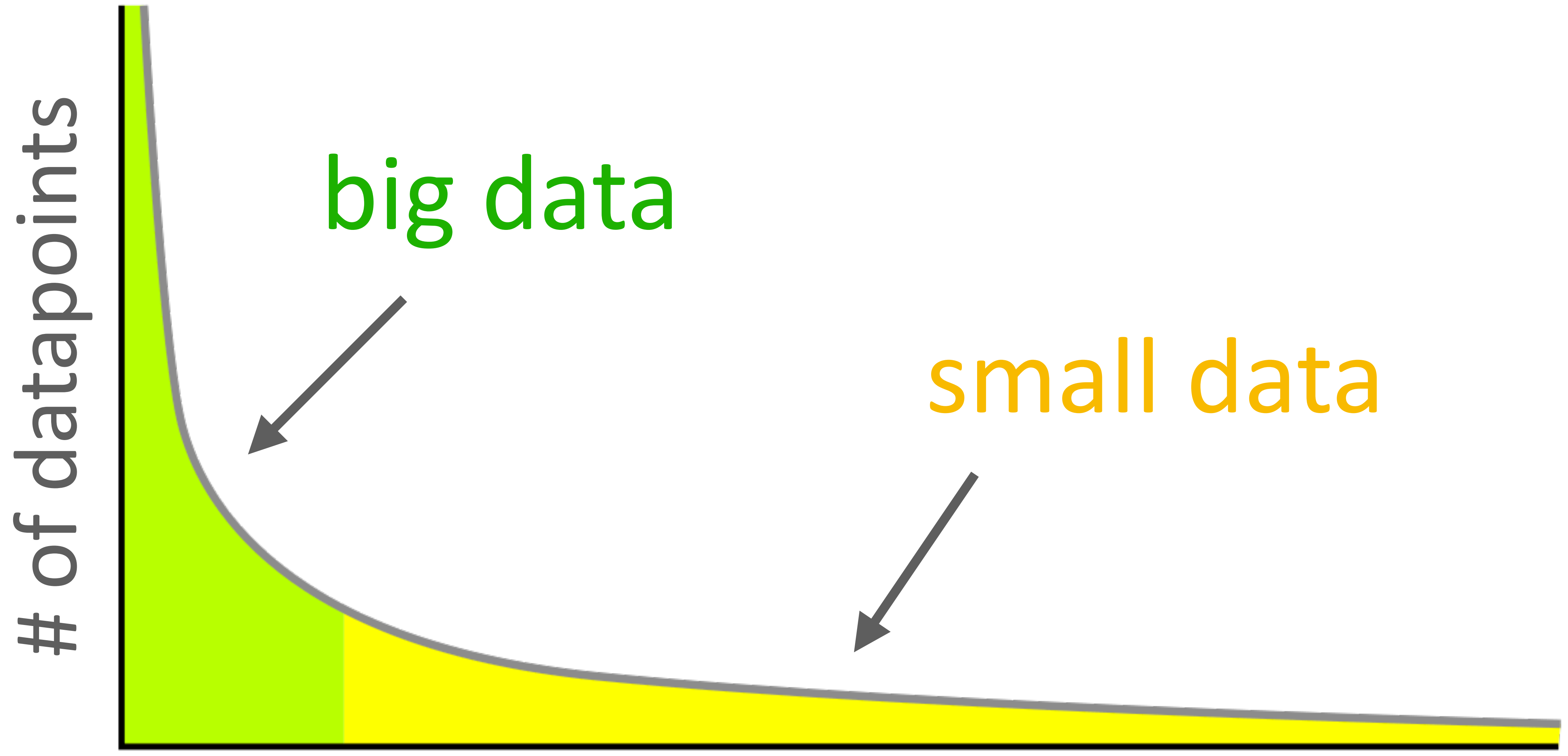
(that we haven't previously covered)

Open Challenges in Multi-Task and Meta Learning

Addressing fundamental problem assumptions

- Generalization: Out-of-distribution tasks, long-tailed task distributions

The problem with long-tailed distributions.



objects encountered
interactions with people
words heard
driving scenarios
⋮

We learned how to do few-shot learning

…but these few-shot tasks may be from a different distribution

We've seen some generalization to the tail:

- prototypical clustering networks for dermatological diseases
- adaptive risk minimization

Further hints might come from domain adaptation, robustness literature.

Open Challenges in Multi-Task and Meta Learning

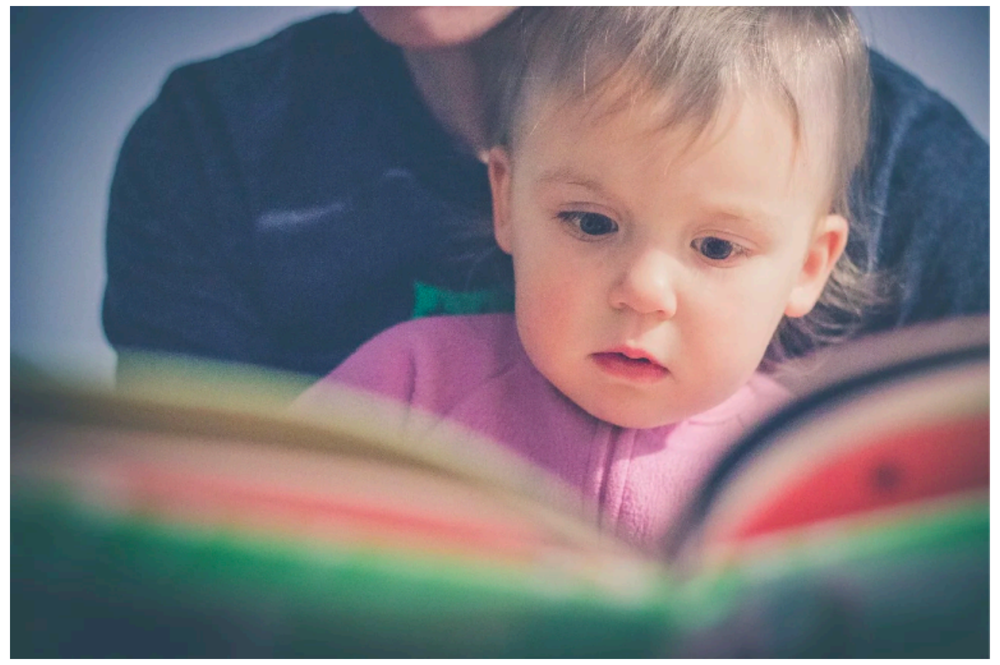
Addressing fundamental problem assumptions

- Generalization: Out-of-distribution tasks, long-tailed task distributions
- Multimodality: Can you learn priors from multiple modalities of data?

Rich sources of prior experiences.

visual imagery

tactile feedback



language

social cues

Can we learn priors across multiple data modalities?

Varying dimensionalities, units

Carry different, complementary forms of information

Some hints might come from some recent initial works.

Liang et al. Cross-Modal Generalization: Learning in Low Resource Modalities via Meta-Alignment. MM 2021.

Reed, Zolna, Parisotto et al. Gato: A Generalist Agent. TMLR 2022

Alayrac, Donahue, Luc, Miech et al. Flamingo: a Visual Language Model for Few-Shot Learning. NeurIPS 2022

Open Challenges in Multi-Task and Meta Learning

Addressing fundamental problem assumptions

- Generalization: Out-of-distribution tasks, long-tailed task distributions
- Multimodality: Can you learn priors from multiple modalities of data?
- Algorithm, Model Selection: When will multi-task learning help you?

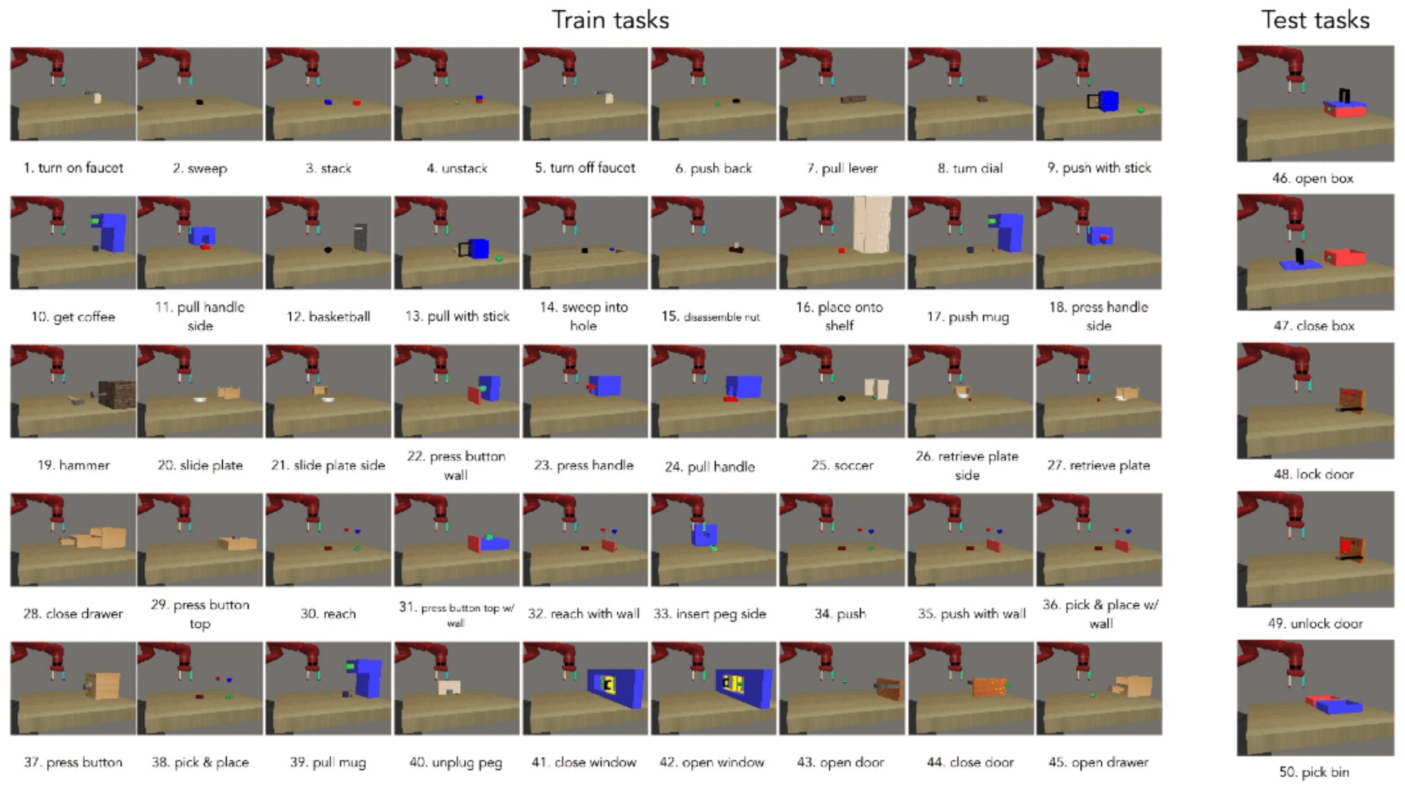
Benchmarks

- Breadth: That challenge current algorithms to find common structure
- Realistic: That reflect real-world problems

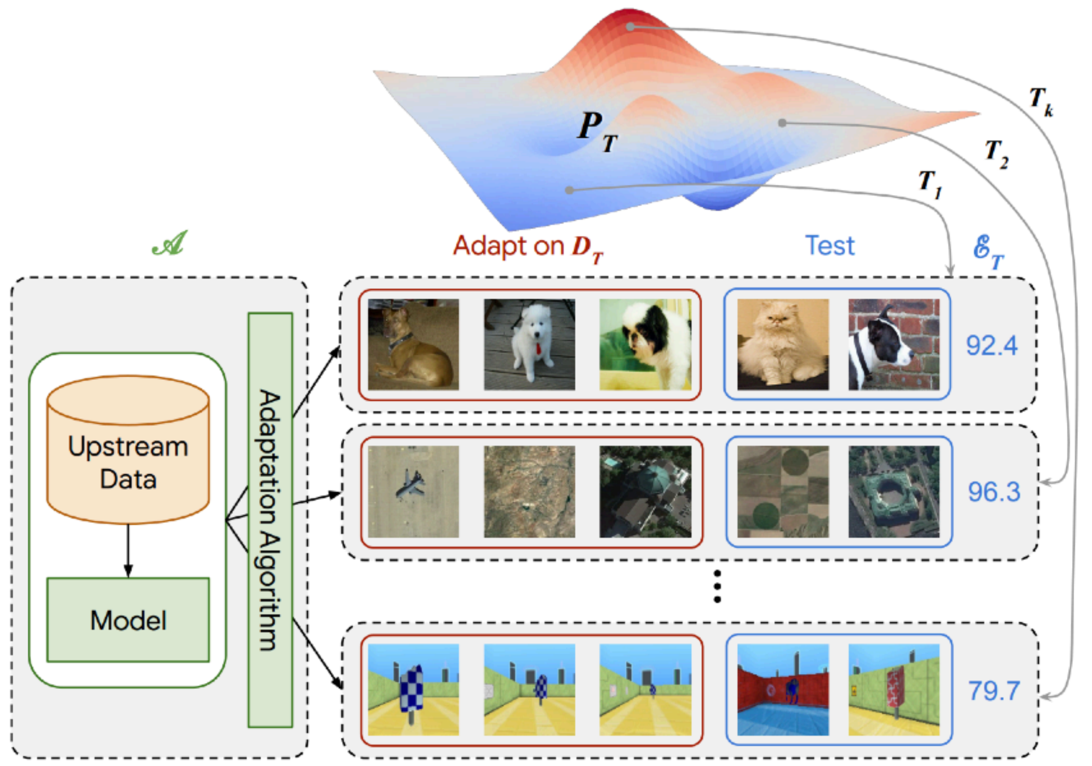
Some steps towards good benchmarks

ILSVRC
Omniglot
Aircraft
Birds
Textures
Quick Draw
Fungi
VGG Flower
Traffic Signs
MSCOCO

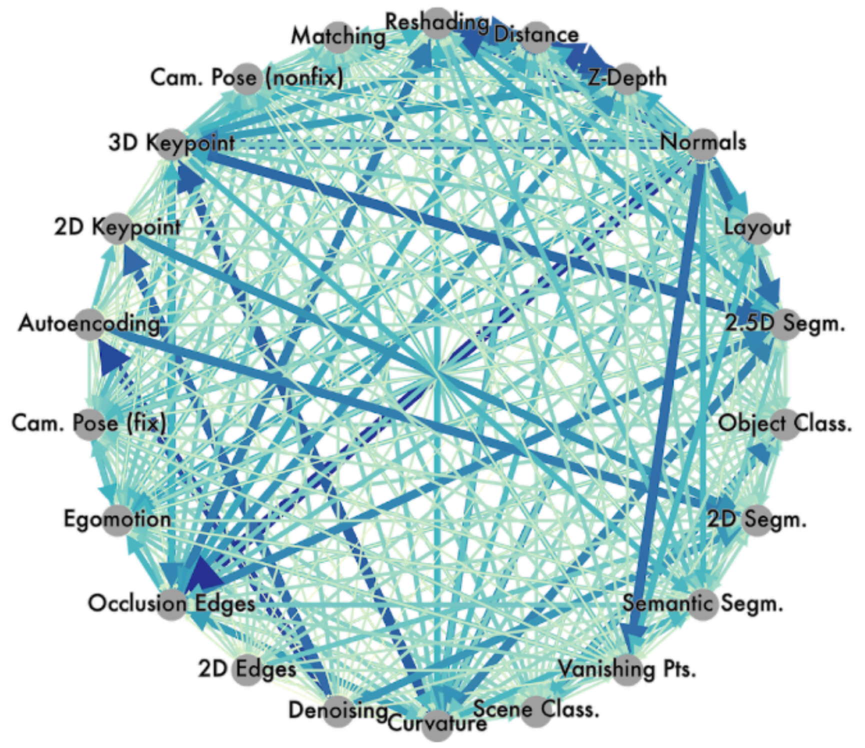
Meta-Dataset
Triantafillou et al. '19



Meta-World Benchmark
Yu et al. '19



Visual Task Adaptation Benchmark
Zhai et al. '19



Taskonomy Dataset
Zamir et al. '18

VALUE Benchmark
Li*, Lei* et al. '21

BIG Bench
Srivastava et al. '22

Goal: reflection of real world problems + appropriate level of difficulty + ease of use

Open Challenges in Multi-Task and Meta Learning

Addressing fundamental problem assumptions

- Generalization: Out-of-distribution tasks, long-tailed task distributions
- Multimodality: Can you learn priors from multiple modalities of data?
- Algorithm, Model Selection: When will multi-task learning help you?

Benchmarks

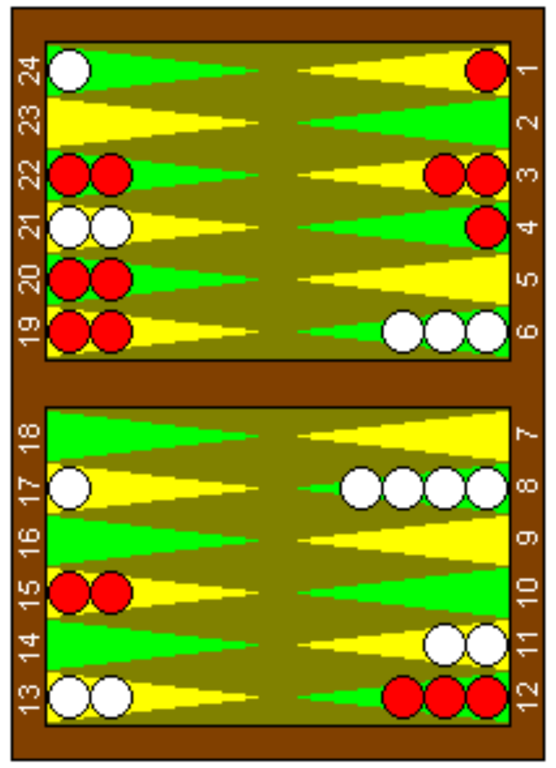
- Breadth: That challenge current algorithms to find common structure
- Realistic: That reflect real-world problems

Improving core algorithms

- Computation & Memory: Making large-scale bi-level optimization practical
- Theory: Develop a theoretical understanding of the performance of these algorithms

+ the challenges you discovered in your homework & final projects!

The Bigger Picture

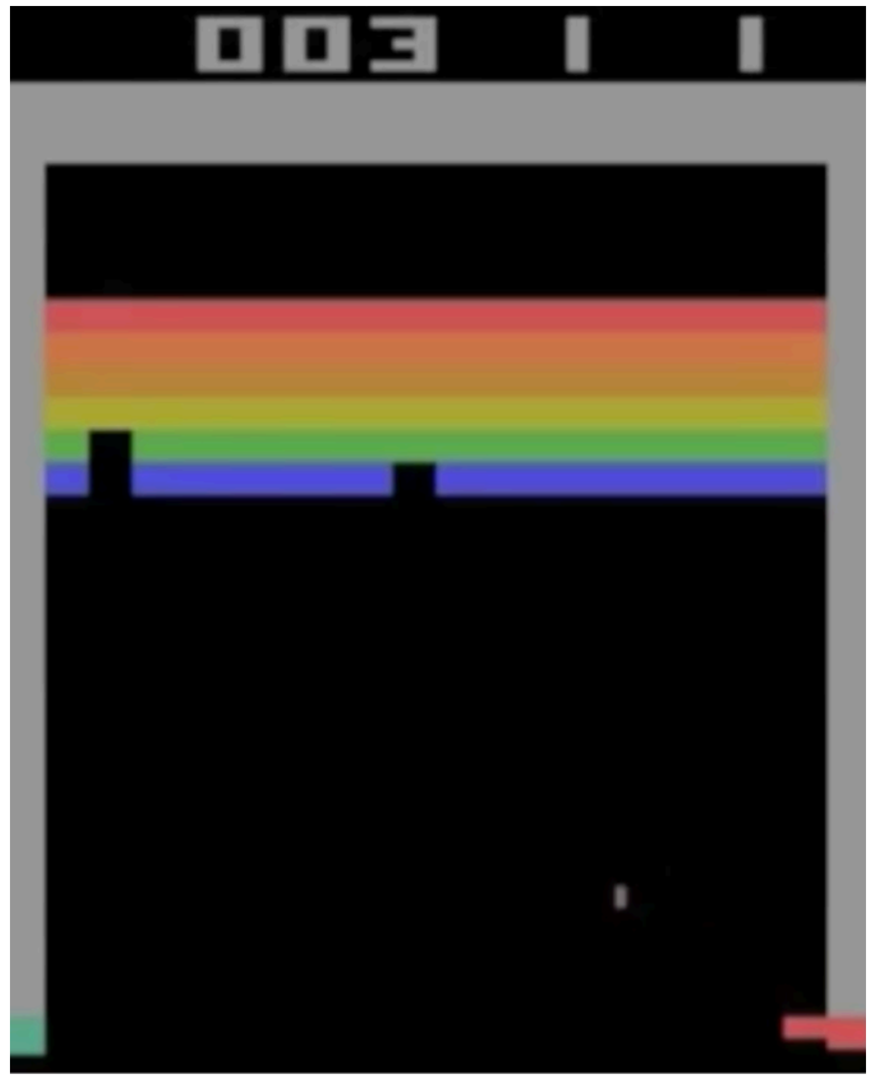


TD Gammon

Watson

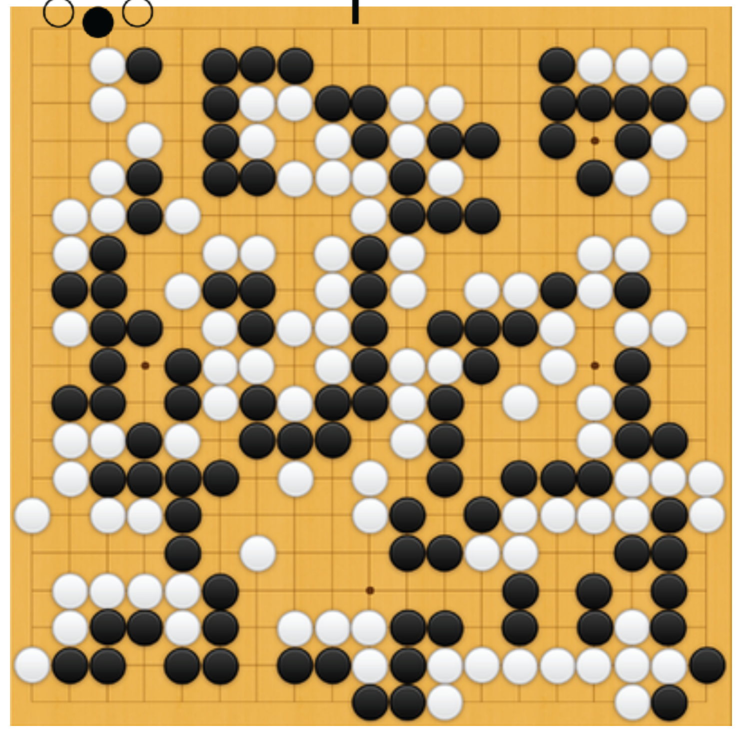
helicopter acrobatics

machine translation



DQN

AlphaGo



Machines are *specialists*.

Source: https://youtu.be/8vNxjwt2AqY

A Step Towards Generalists

Some of what we covered in CS330:

- learn multiple tasks in a single model (multi-task learning)
- leverage prior experience when learning new things (pre-training, meta-learning)
- leveraging *unlabeled* prior data (contrastive, generative pre-training)
- leveraging data from different domains (domain adaptation & generalization)
- learn continuously (lifelong learning)

What's missing?

Logistics

Poster session next Weds 1:30-4:45 pm

Details coming soon on Ed.

Final project report

Due in two weeks on Monday.

Guest lecture on Wednesday

Percy Liang, on in-context learning

This is my last lecture!

Thank you all for a great quarter!

(and see you on Weds)