Meta-Learning Representations for Continual Learning

Khurram Javed

Work done in collaboration with Martha White

Continual Learning Prediction

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$$D_{stream} = (X_1, Y_1), (X_2, Y_2), \ldots, (X_t, Y_t), \ldots$$

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Data could be highly correlated

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Naive solution using a neural network:

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AAAAA BBBBBB CCCC DDDDD ...... ZZZZZZ

Naive solution using a neural network:

1. Get a new sample
2. Update parameters w.r.t latest sample

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Traditional Neural Network Stack

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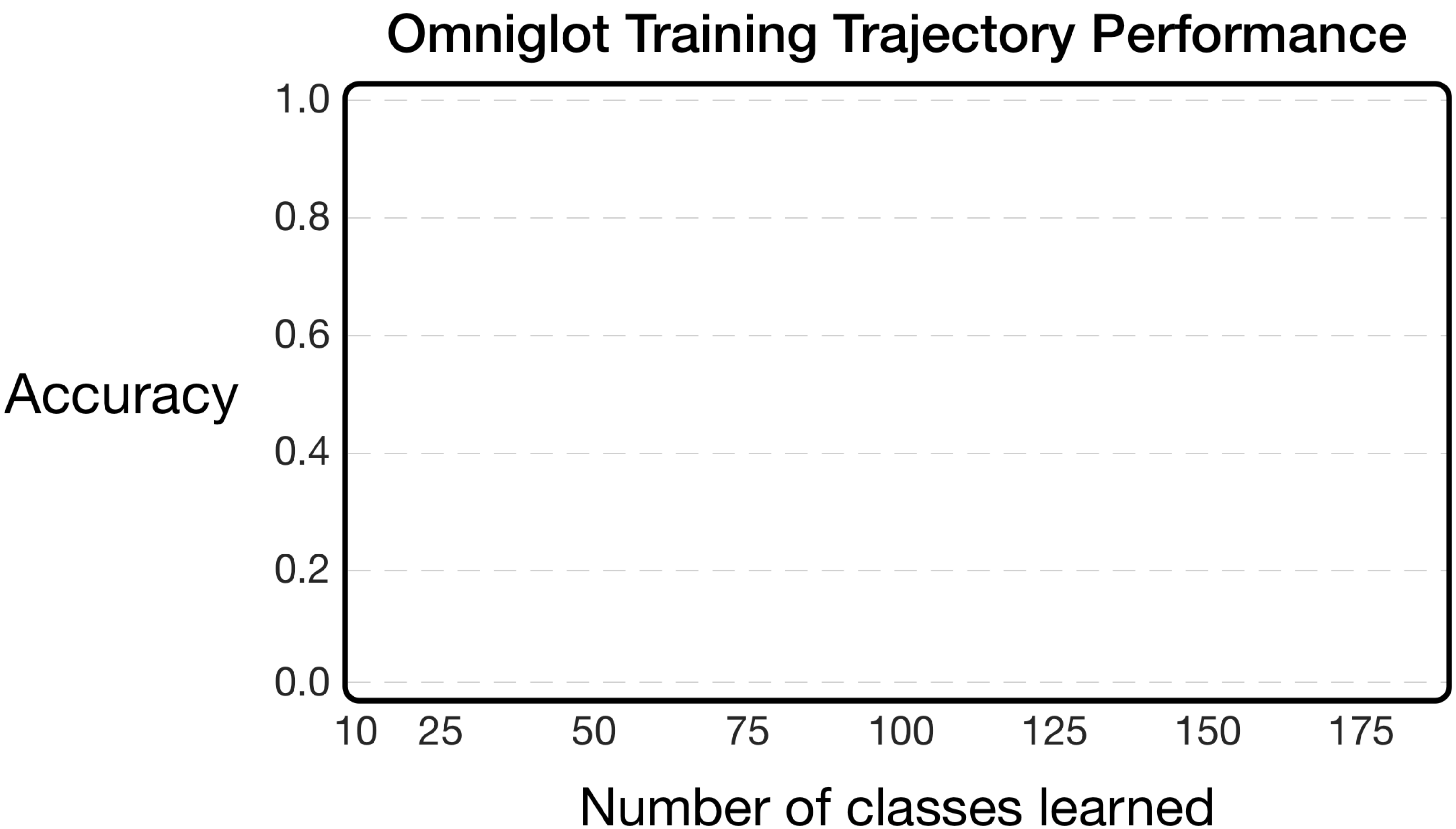

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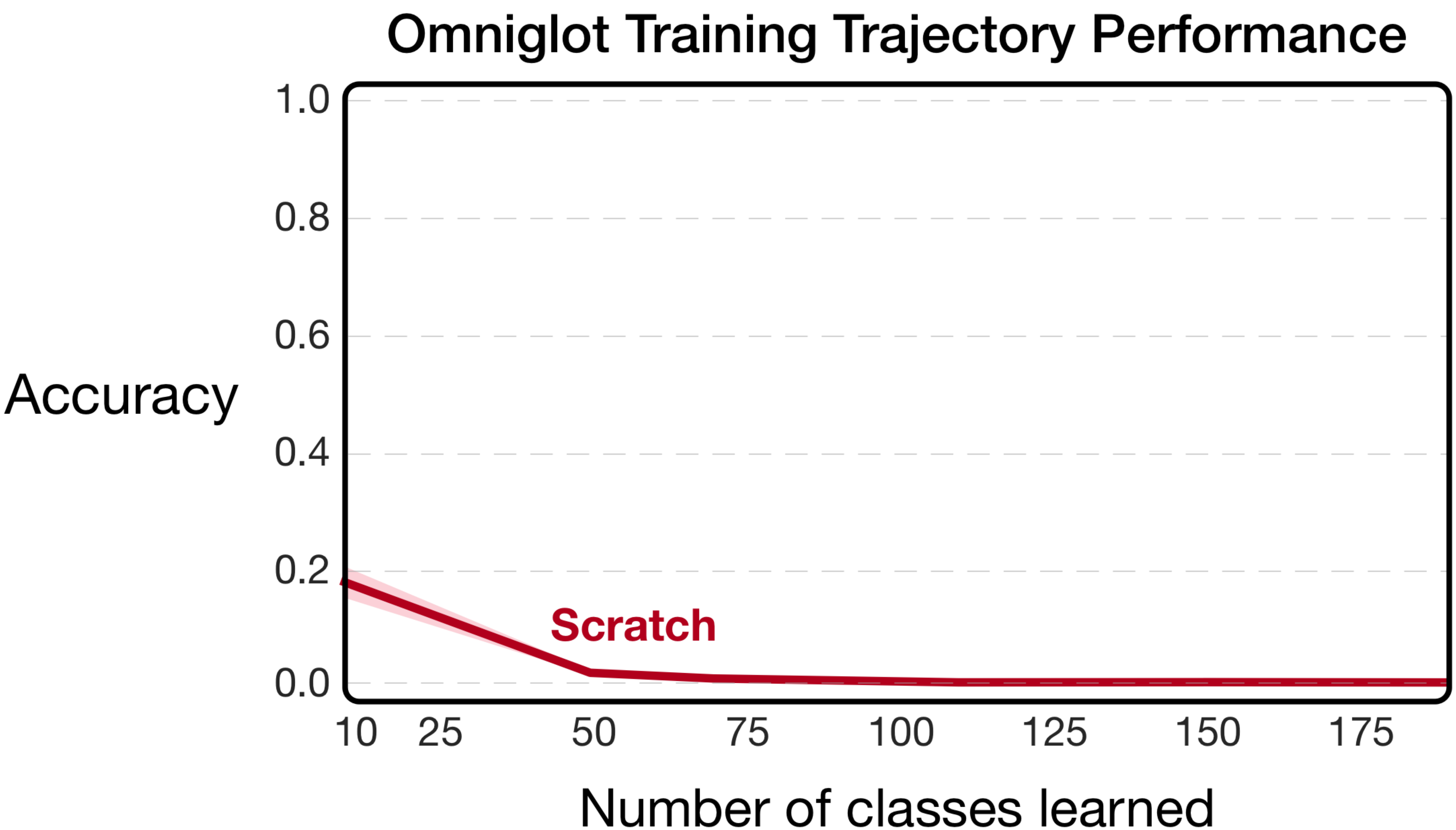

Catastrophic Interference

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Neural networks suffer from ***catastrophic*** interference

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Consequences : ***Forgetting*** and ***slow learning***

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When and why?

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When and why?

1. Non-IID sampling

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1. Non-IID sampling
2. Dense inputs

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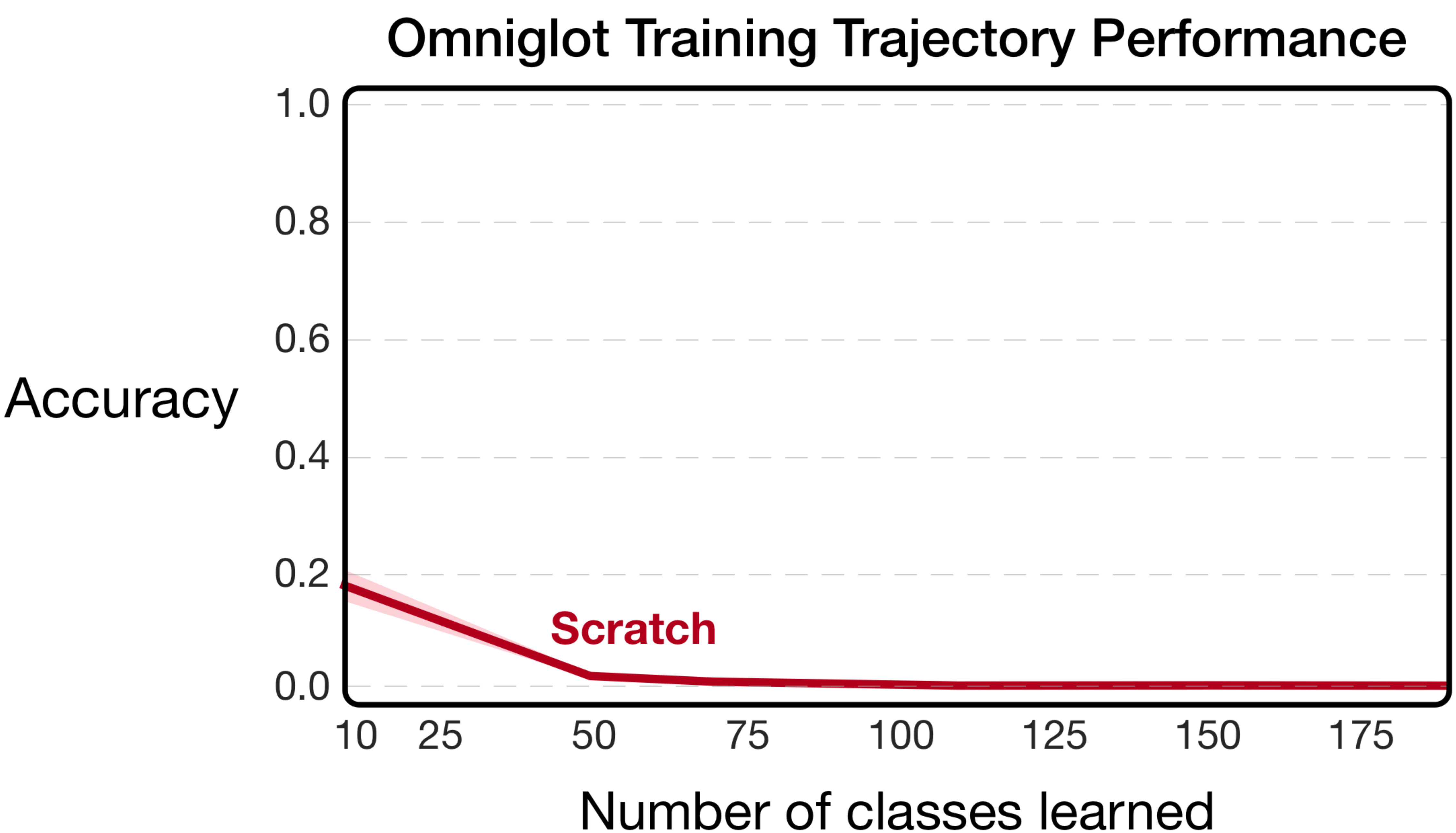

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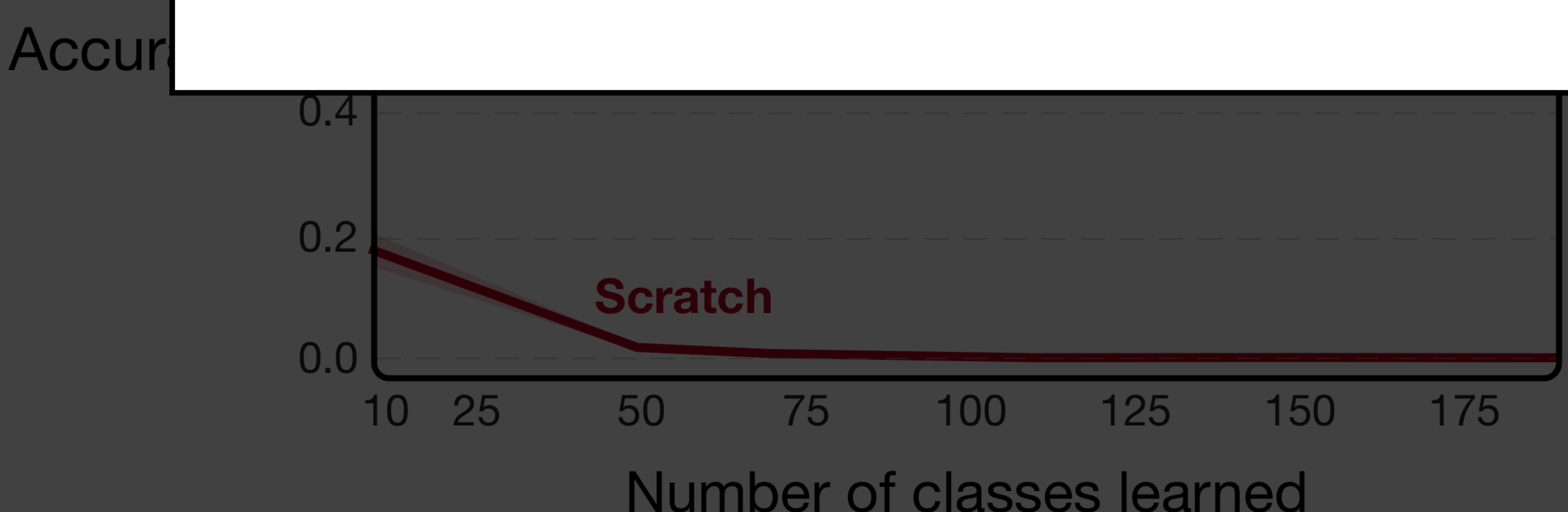

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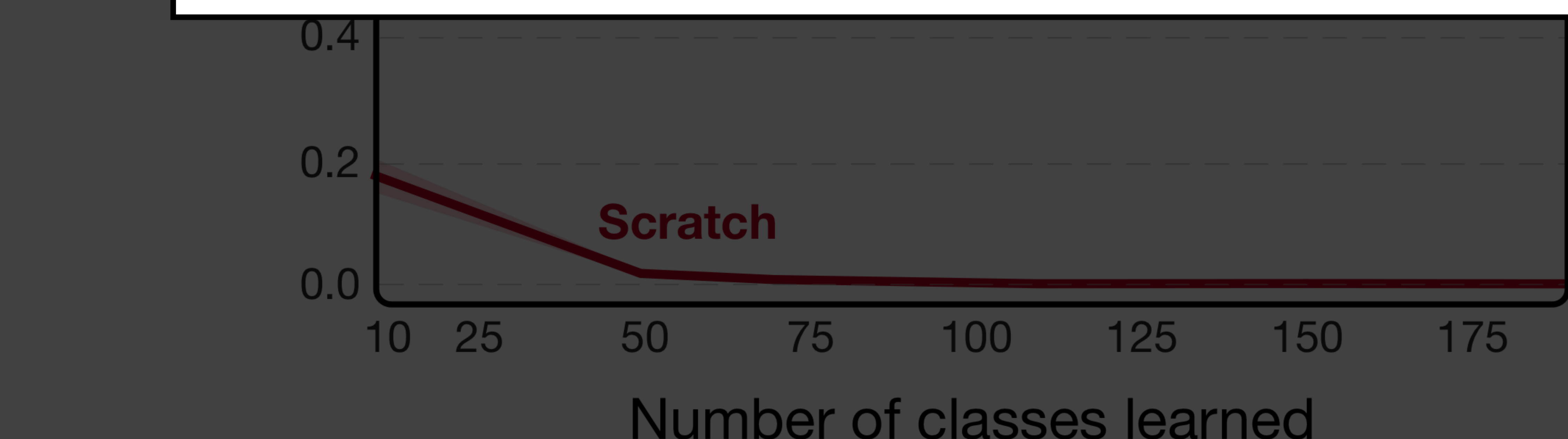

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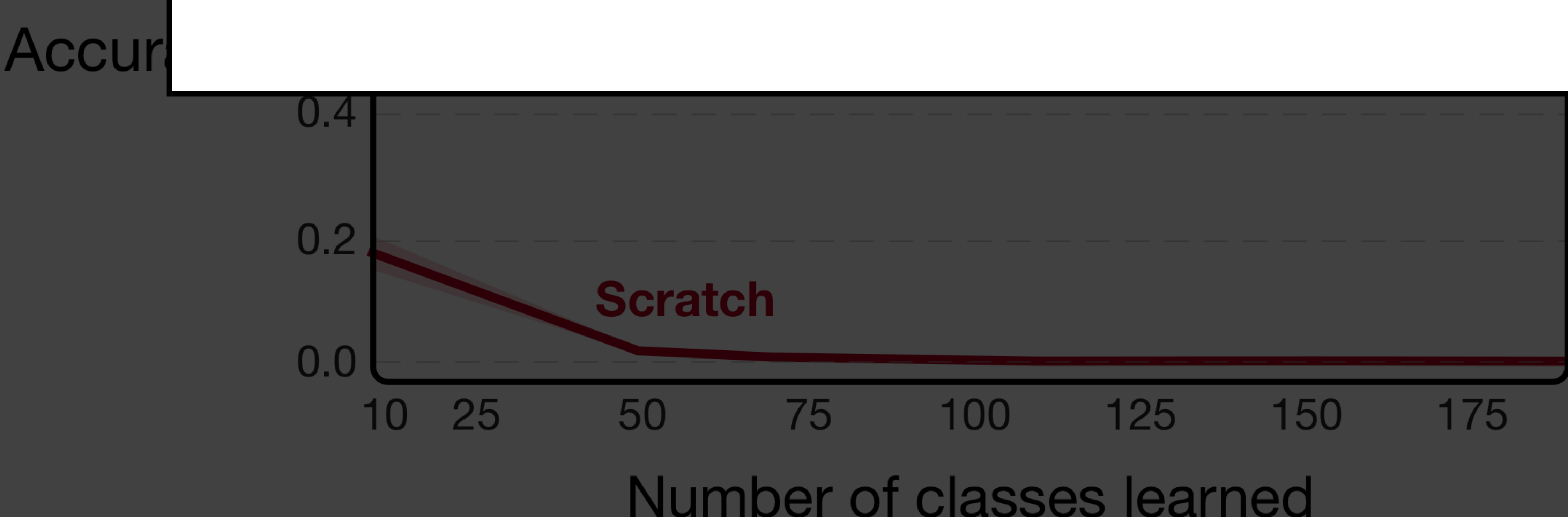
Shuffle order



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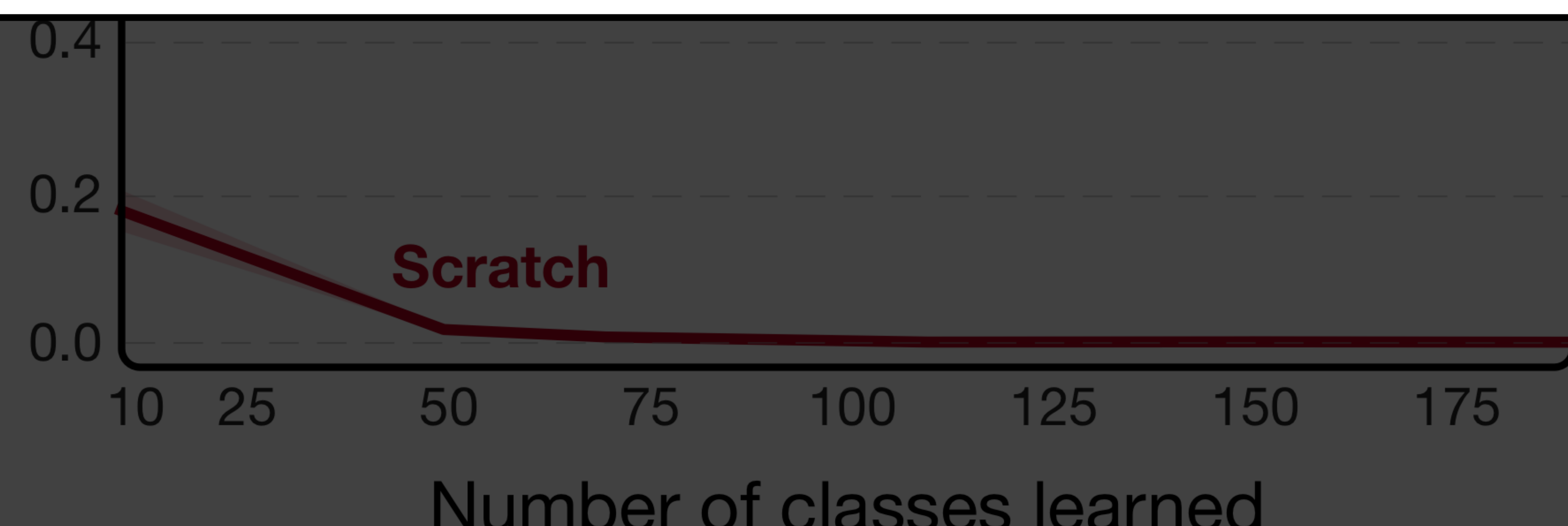
$$D_{stream} = (X_1, Y_1), (X_2, Y_2), \ldots, (X_t, Y_t), \ldots$$

$\Downarrow$ Shuffle order

$$D_{rand} = (X_{10}, Y_{10}), (X_1, Y_1), \ldots, (X_m, Y_m), \ldots$$



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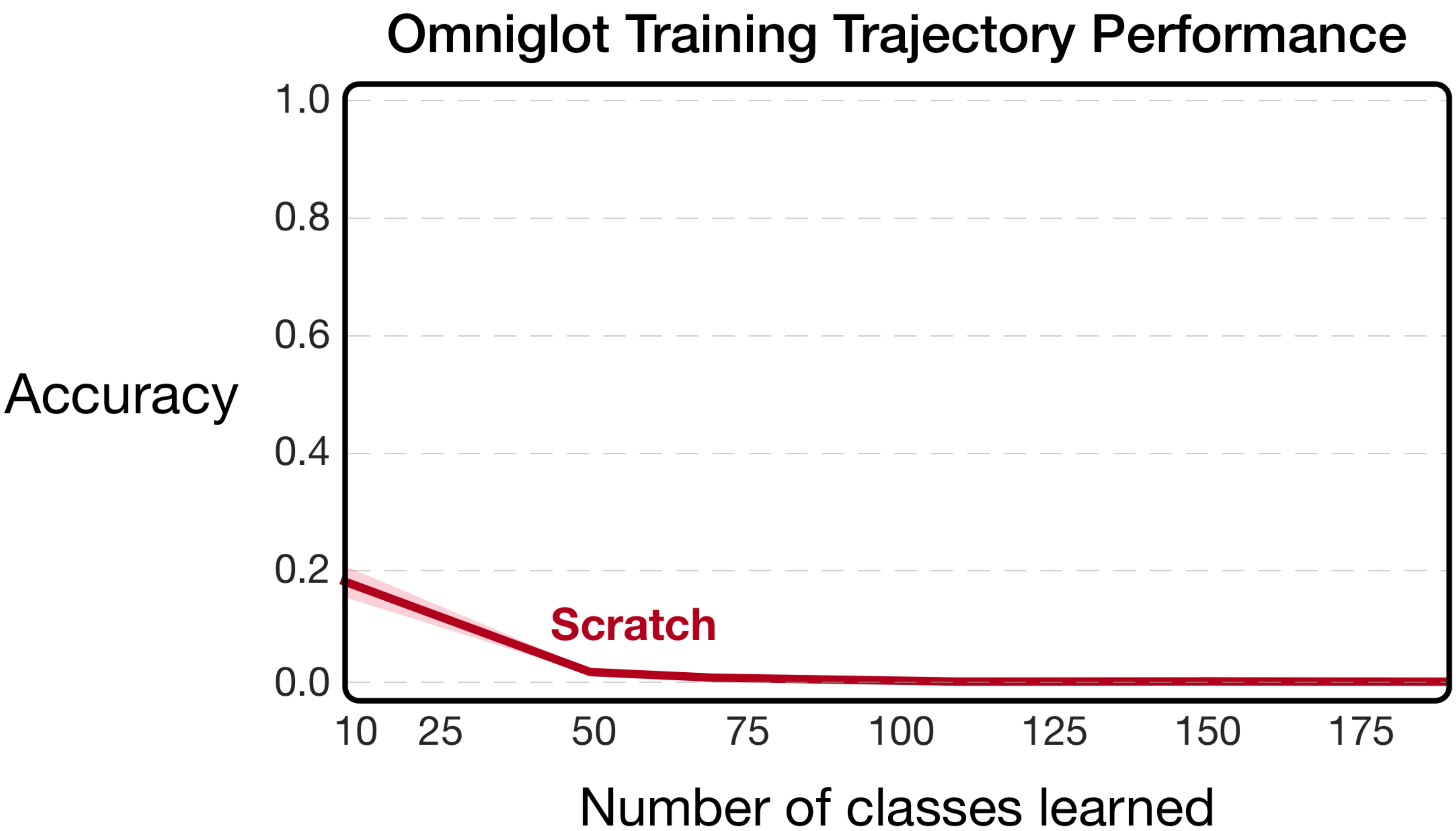

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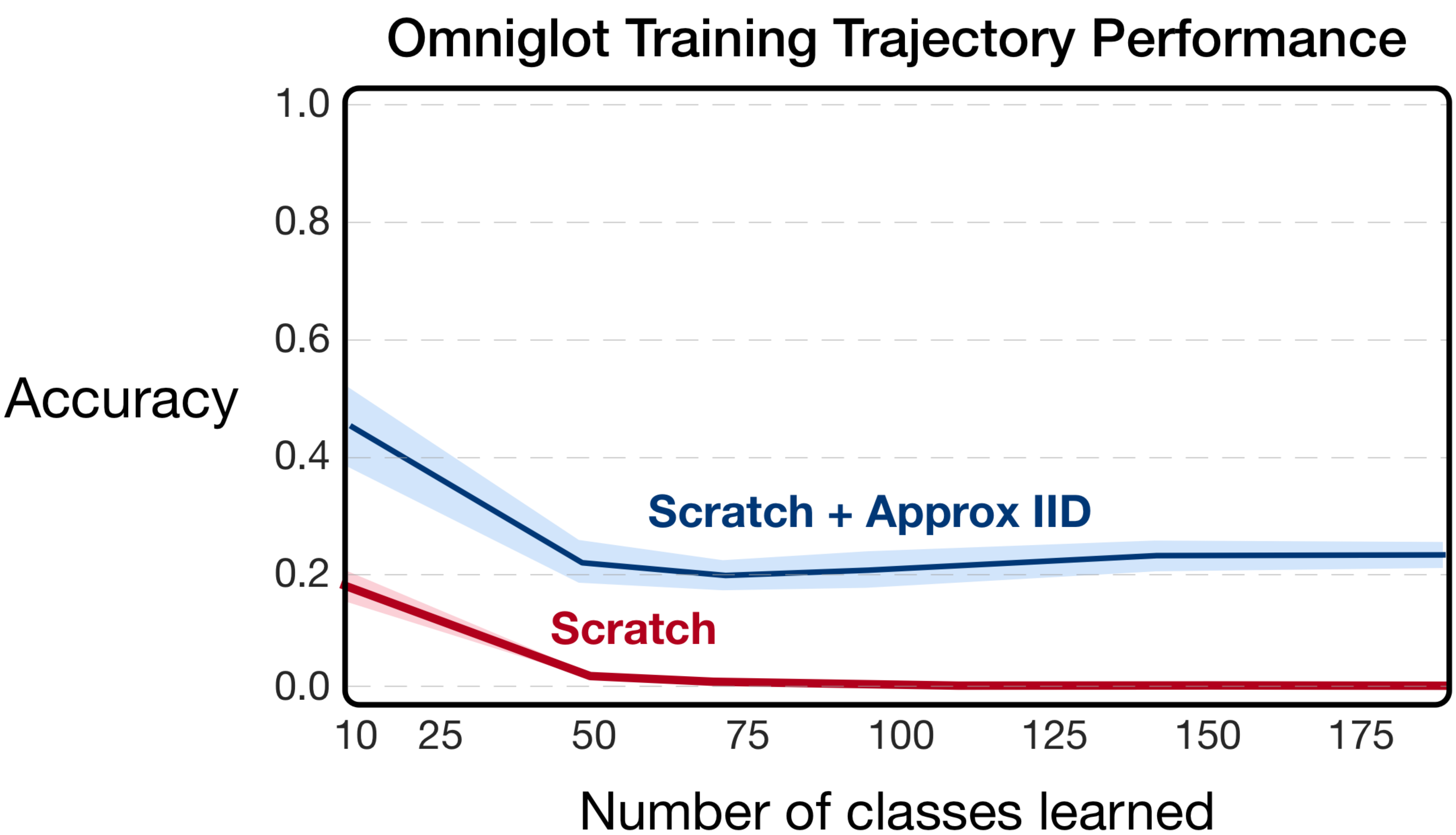

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1. Non-IID sampling
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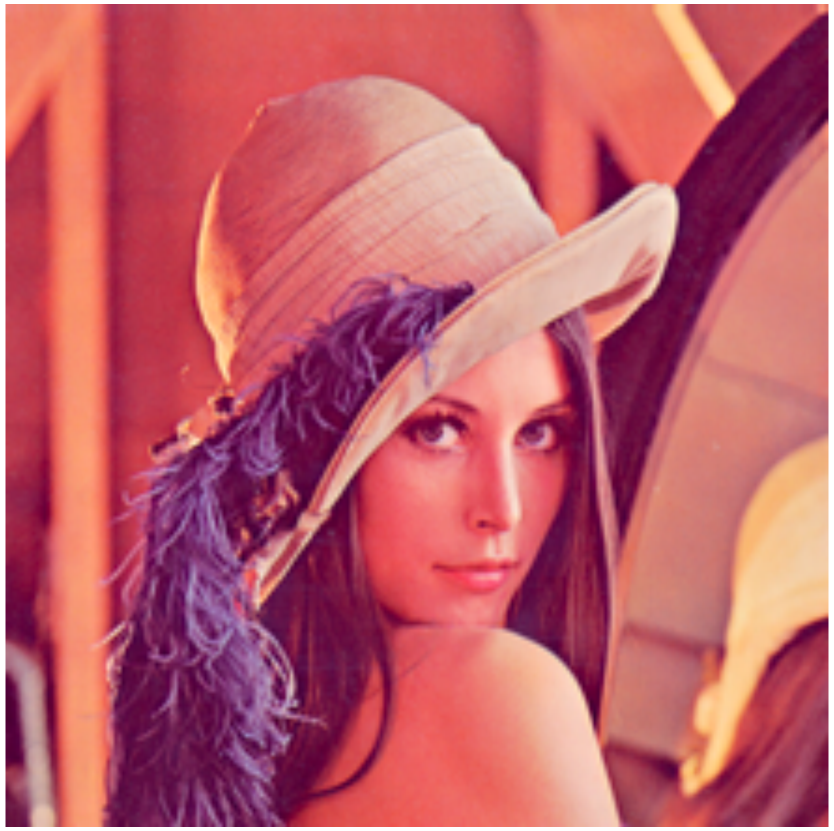
Dense inputs

64



64

Dense inputs

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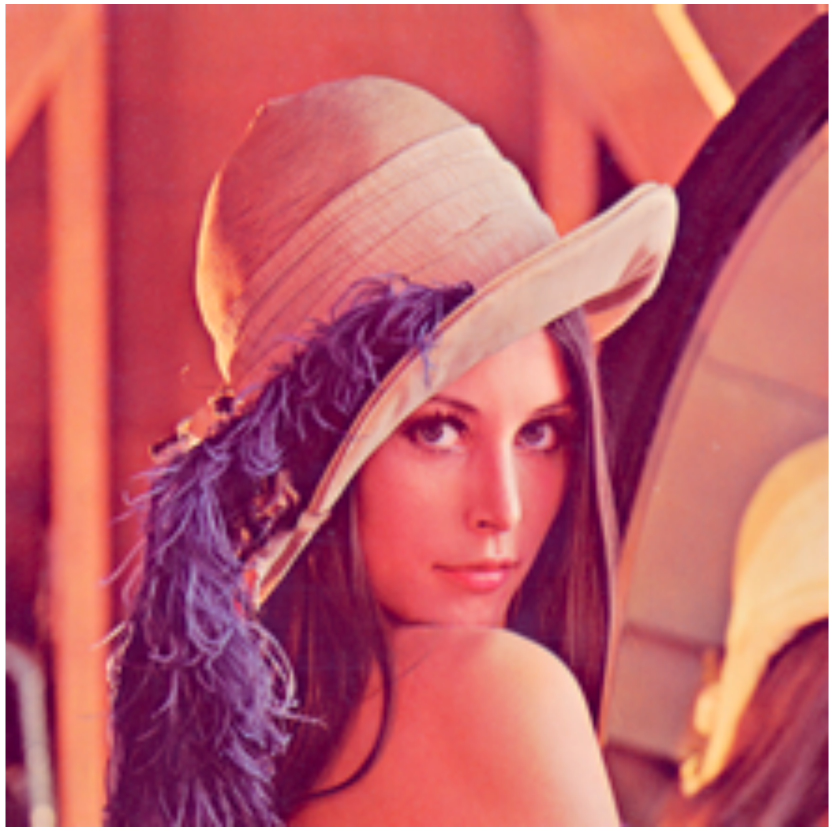

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=> Input vector of length 64 x 64 = 4096

Dense inputs

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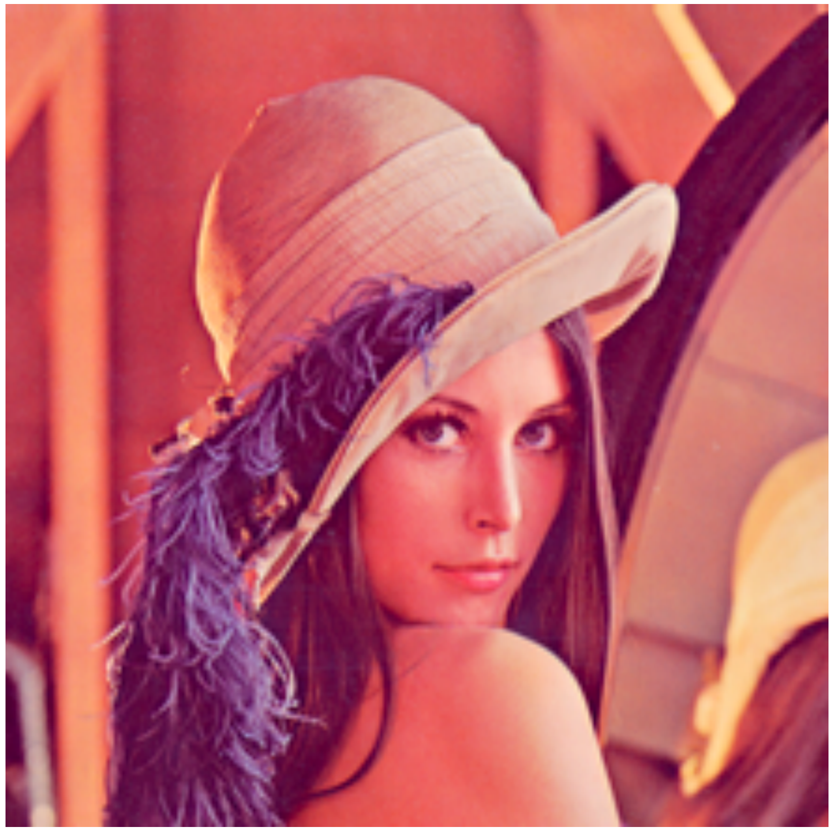

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Most values are non-zero for most natural images

Dense inputs

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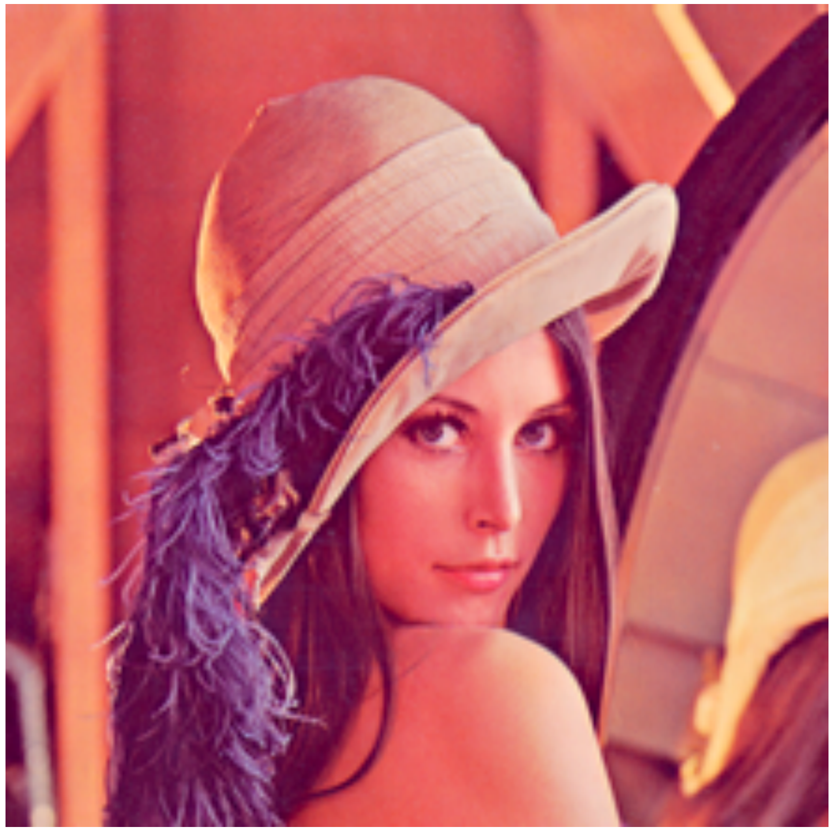

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Alternative?

Dense inputs

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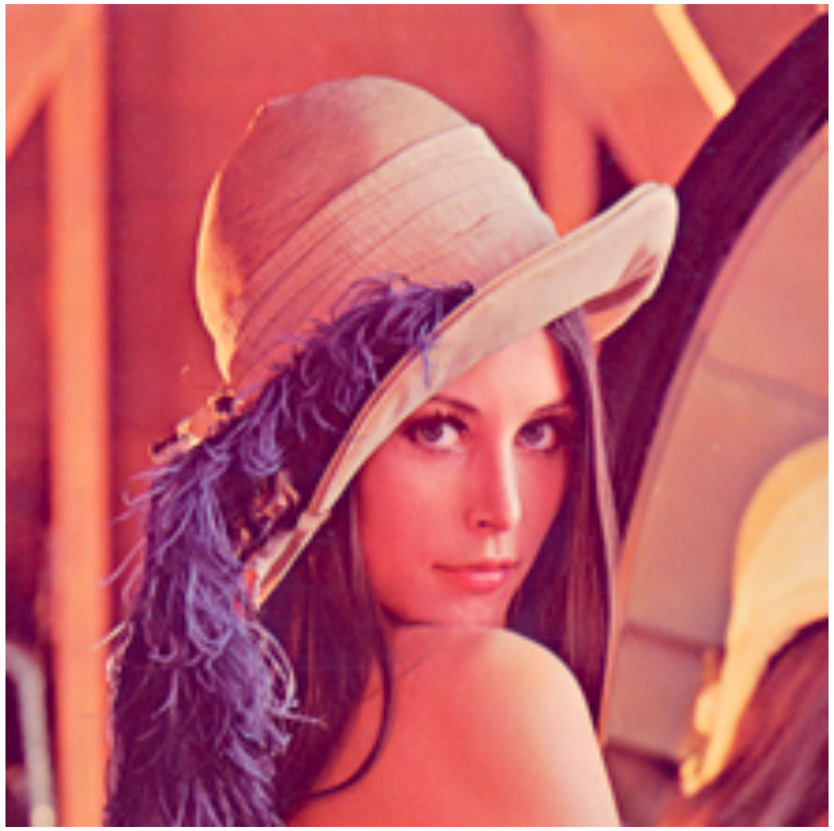

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Alternative?

Sparse input representations
Example: Tile coding

Dense Inputs

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Learn a representation on the ~950 characters, evaluate on the same ~600

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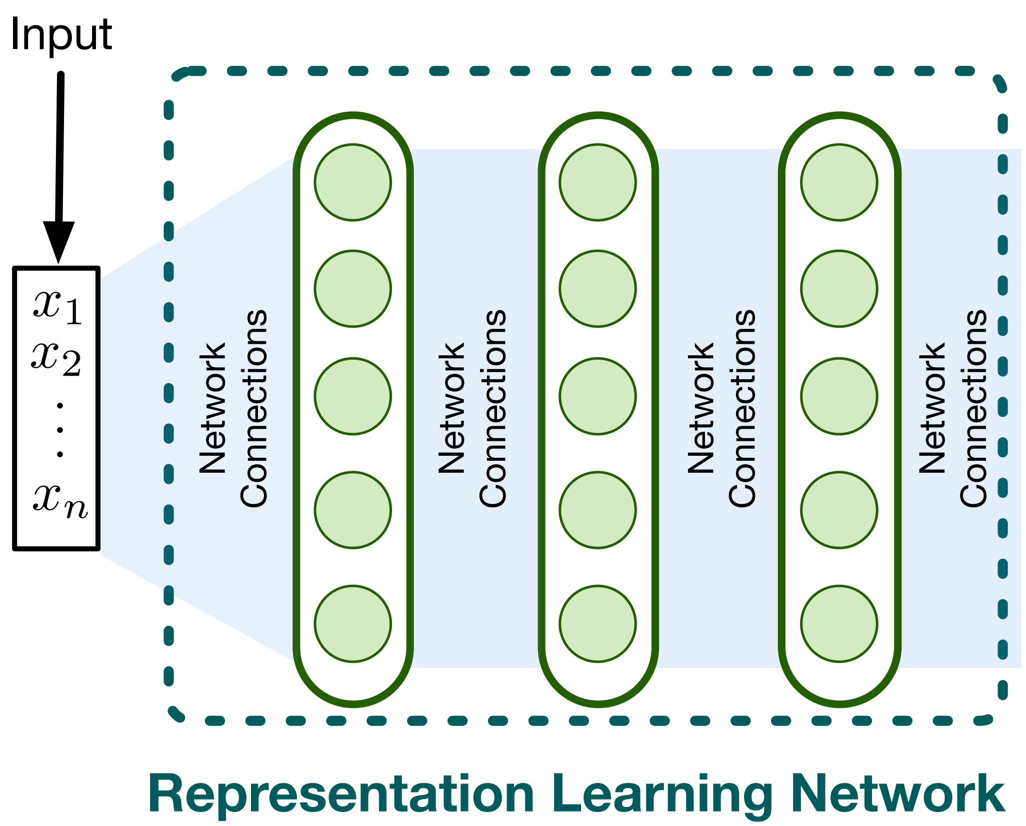

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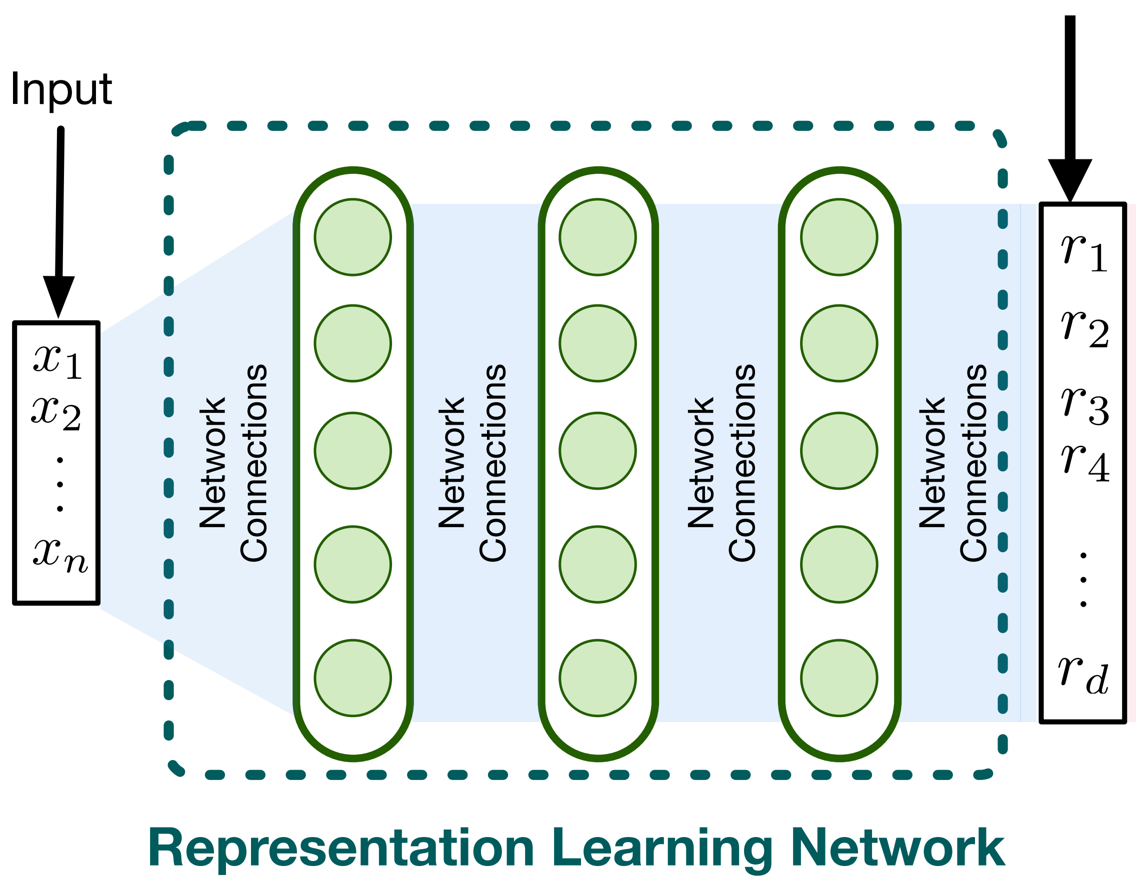
Learned representation



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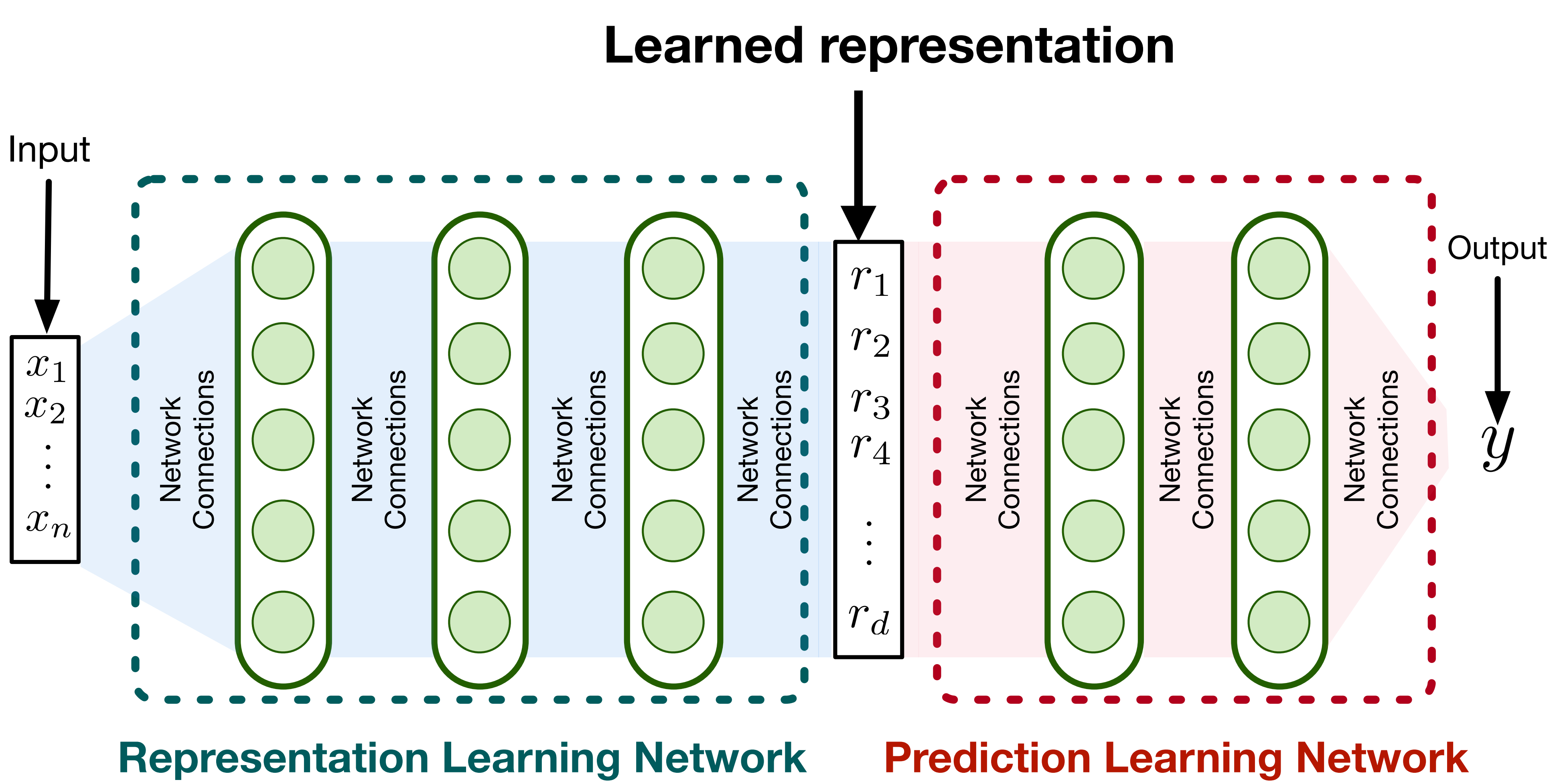

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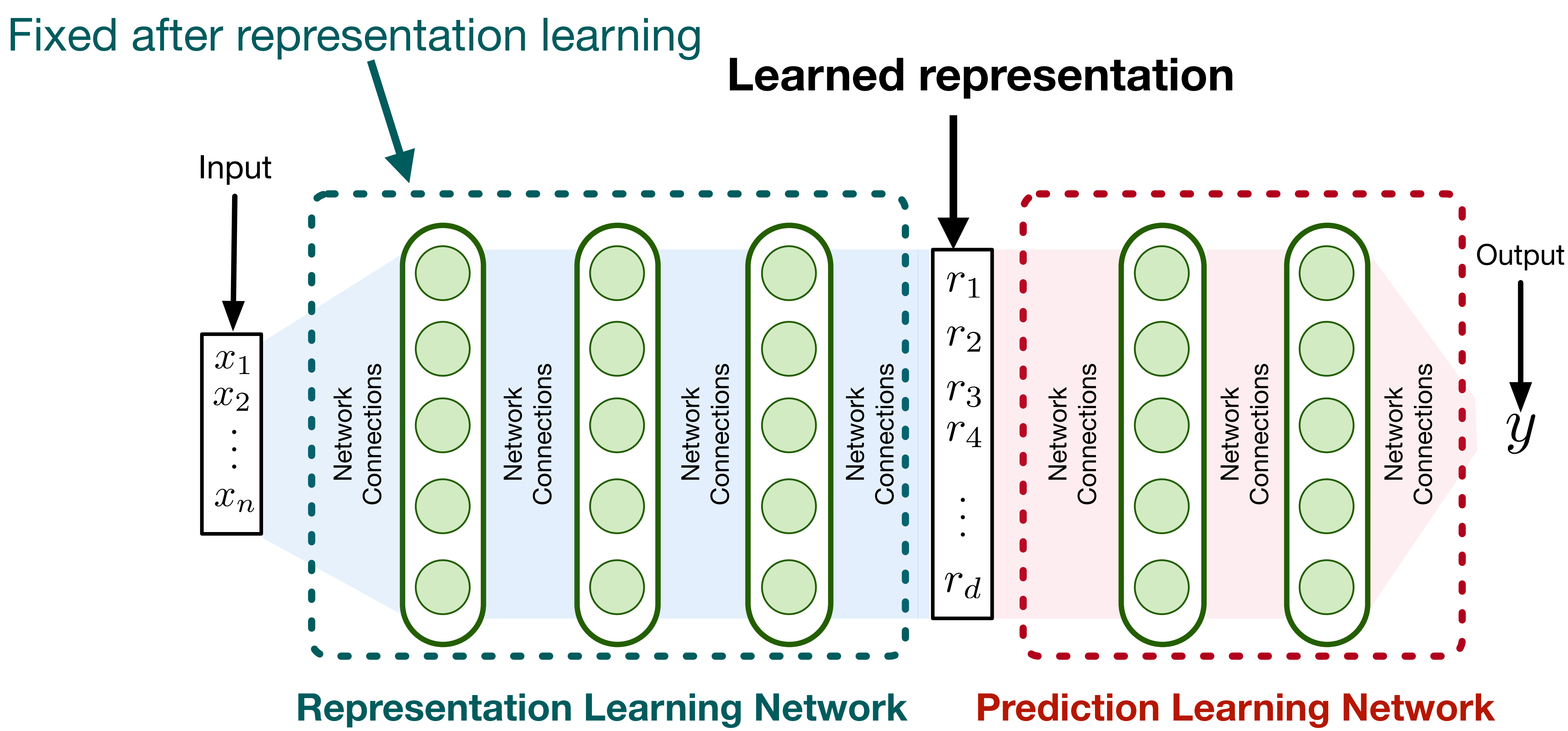

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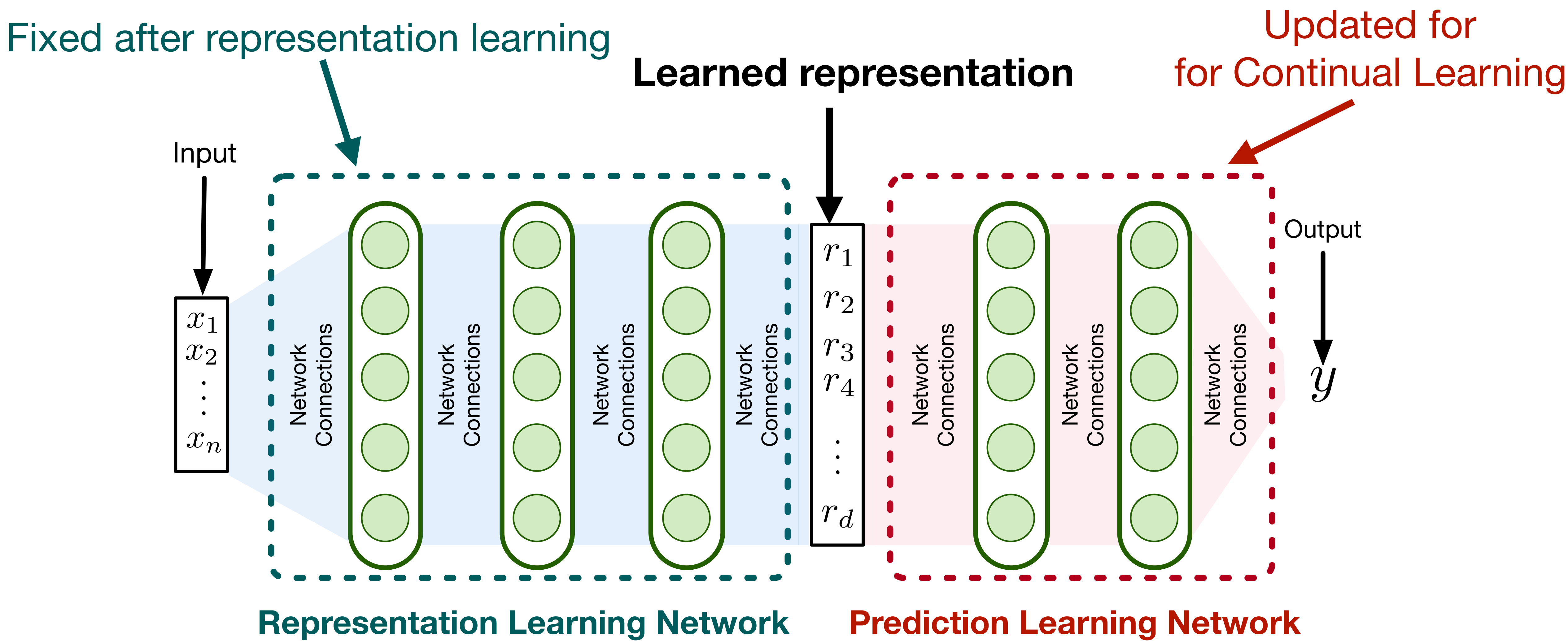

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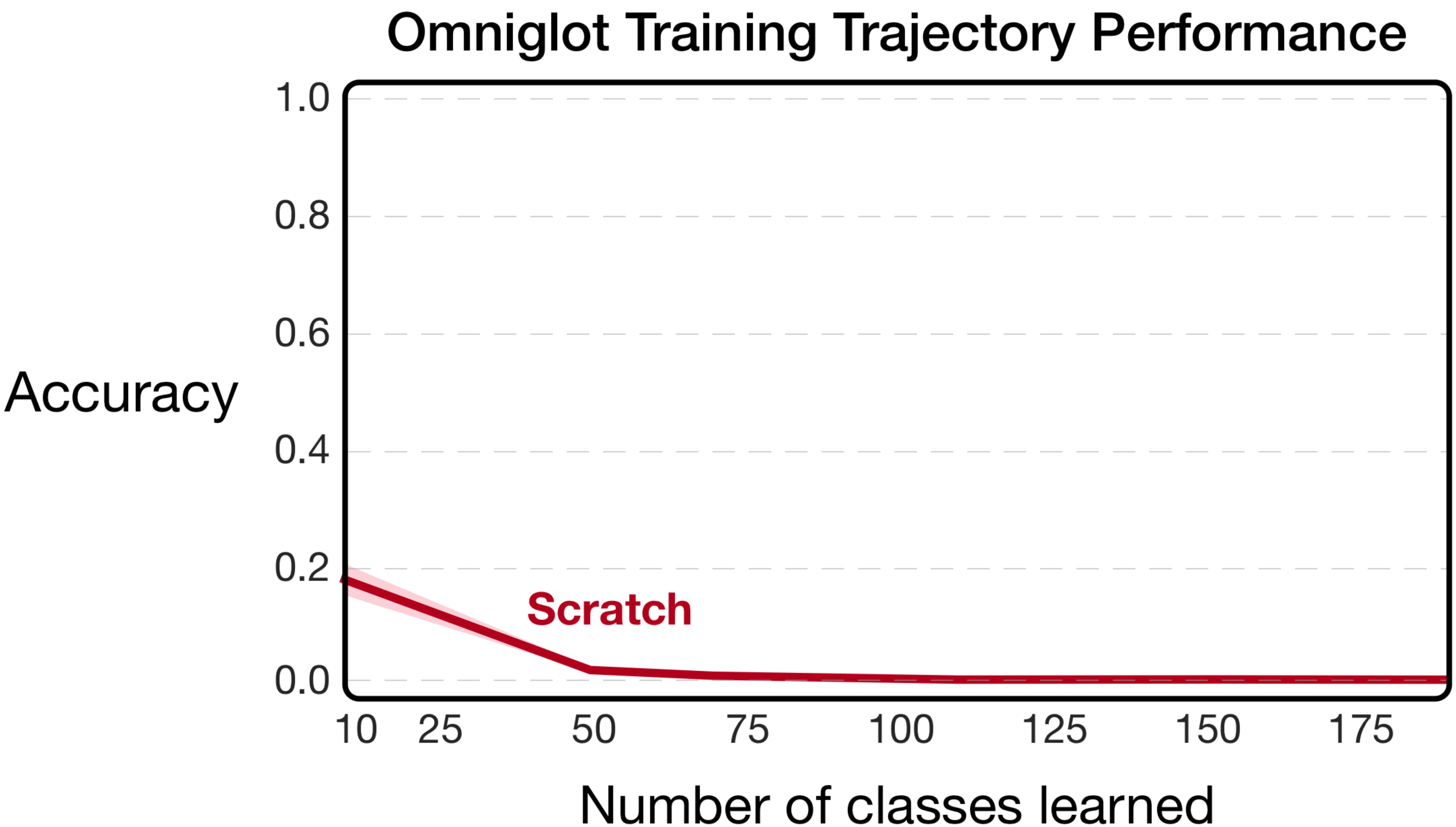

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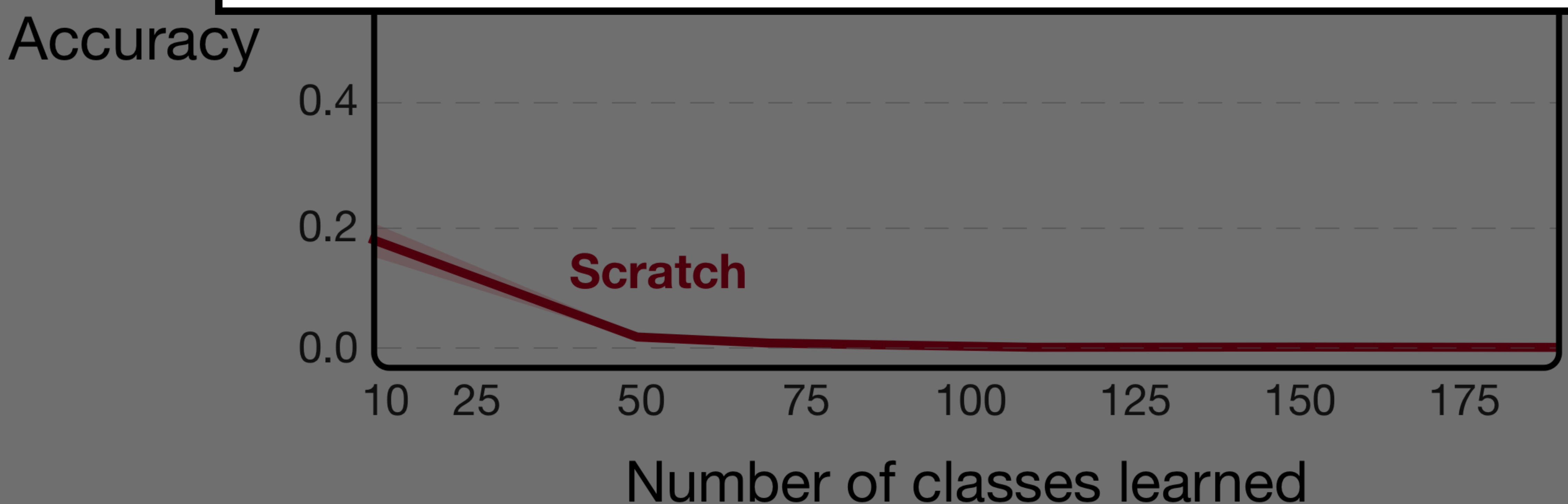
Is “Scratch” a fair baseline?



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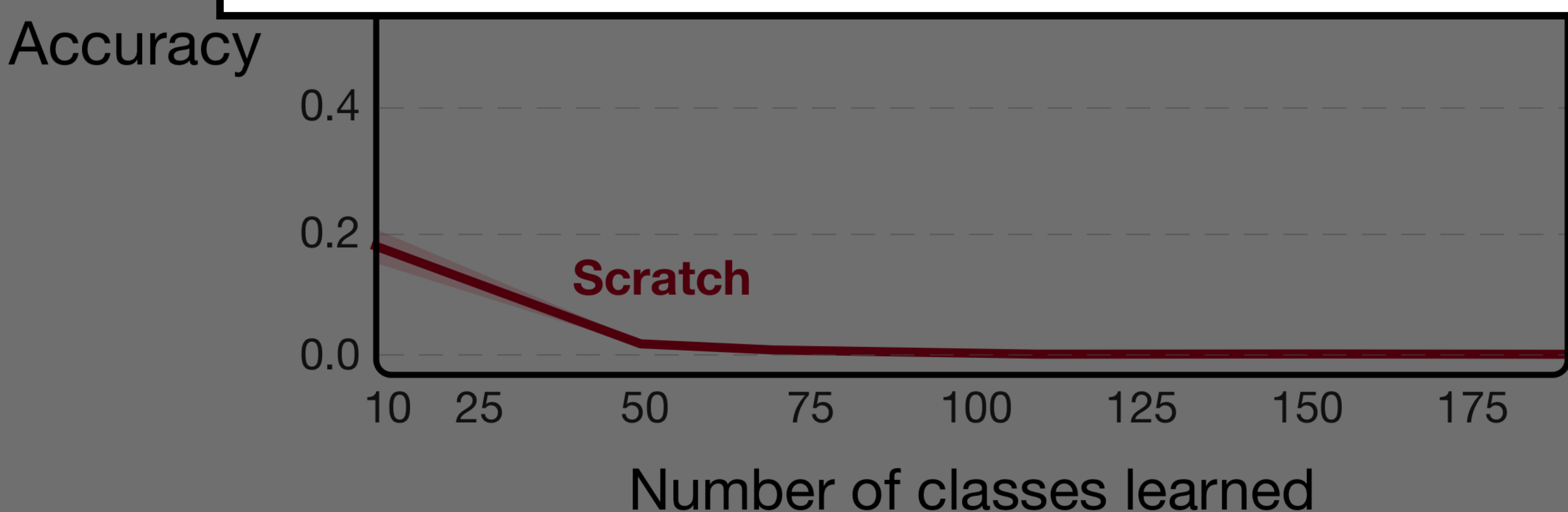
Is "Scratch" a fair baseline?

- Scratch is not longer a fair baseline



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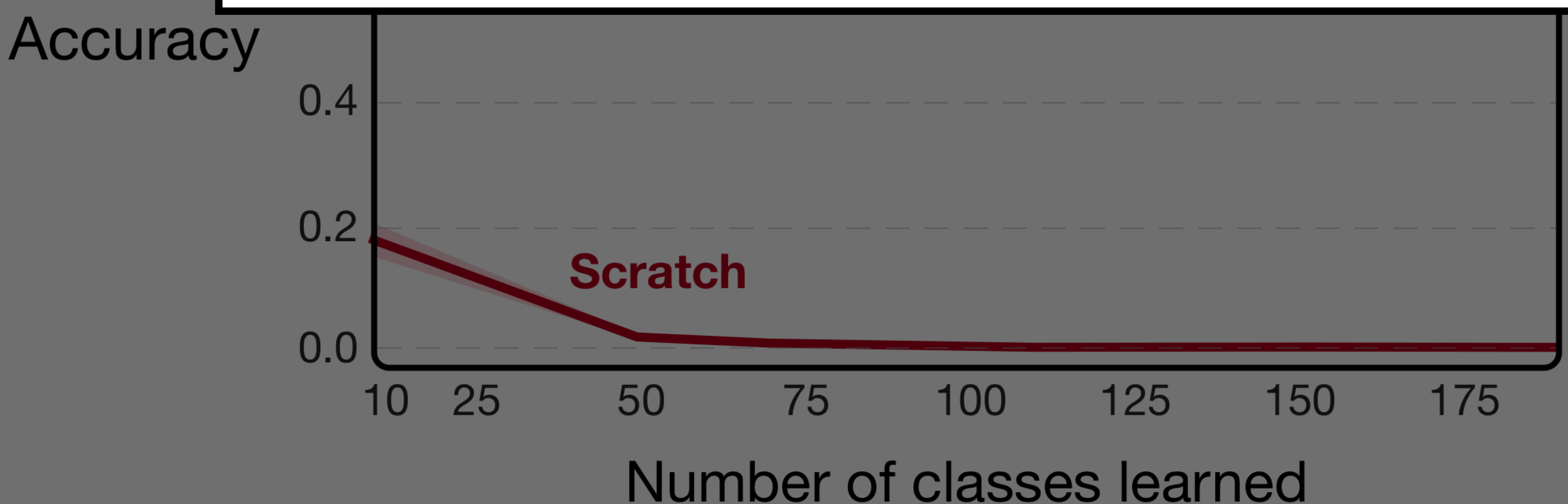
- Need a baseline that uses the information from the representation learning dataset



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Is "Scratch" a fair baseline?

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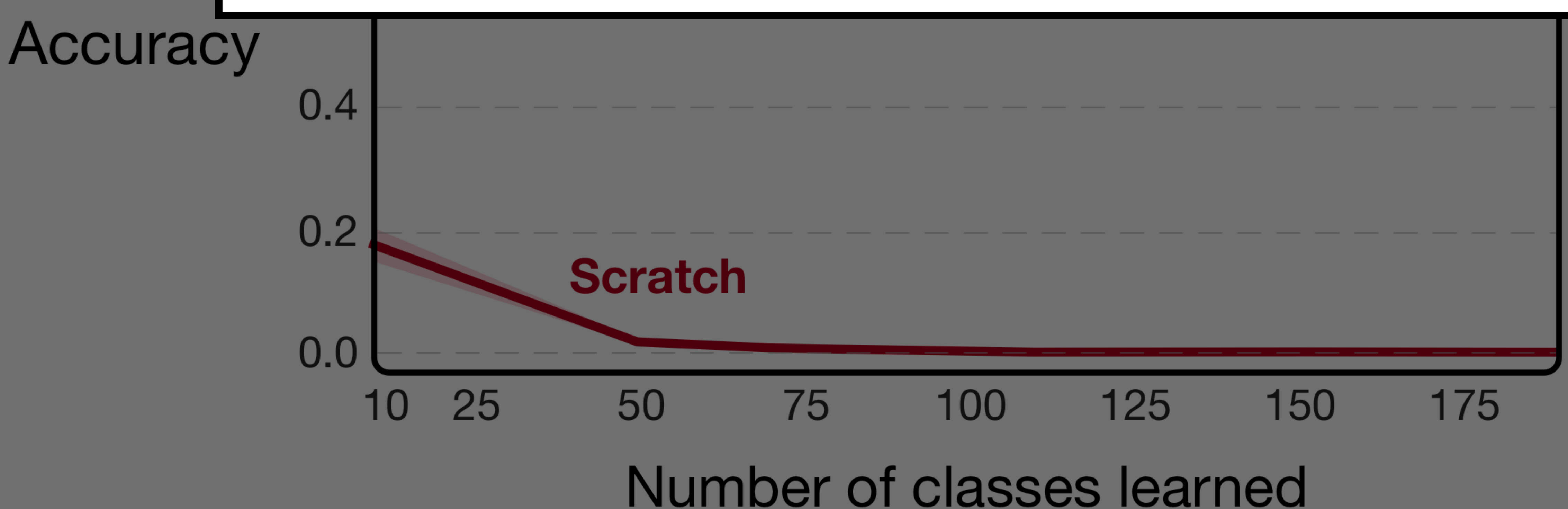
- Need a baseline that uses the information from the representation learning dataset
- **New baseline :** Learn a 950 way classifier using iid sampling and multiple epochs



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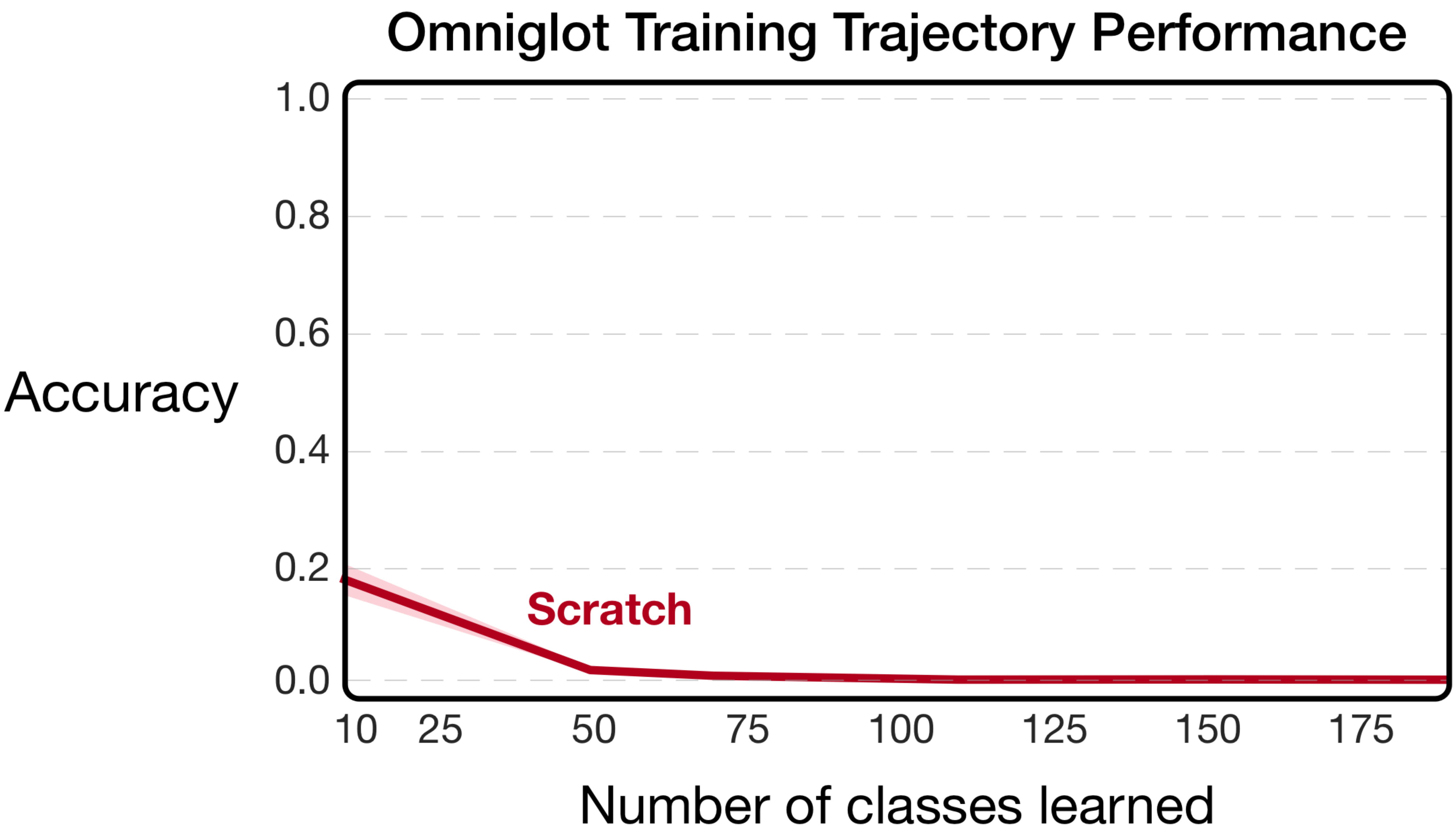

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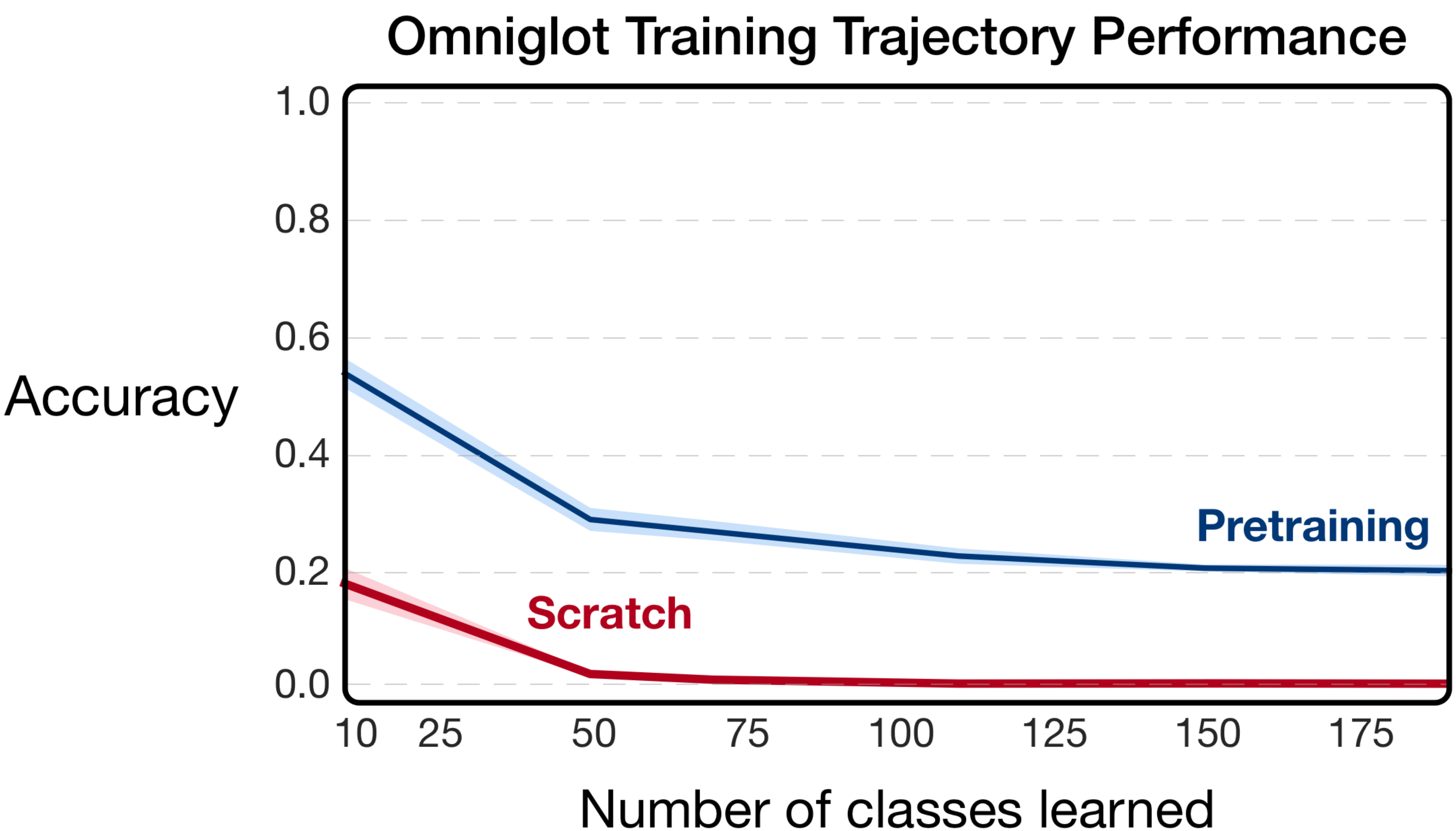

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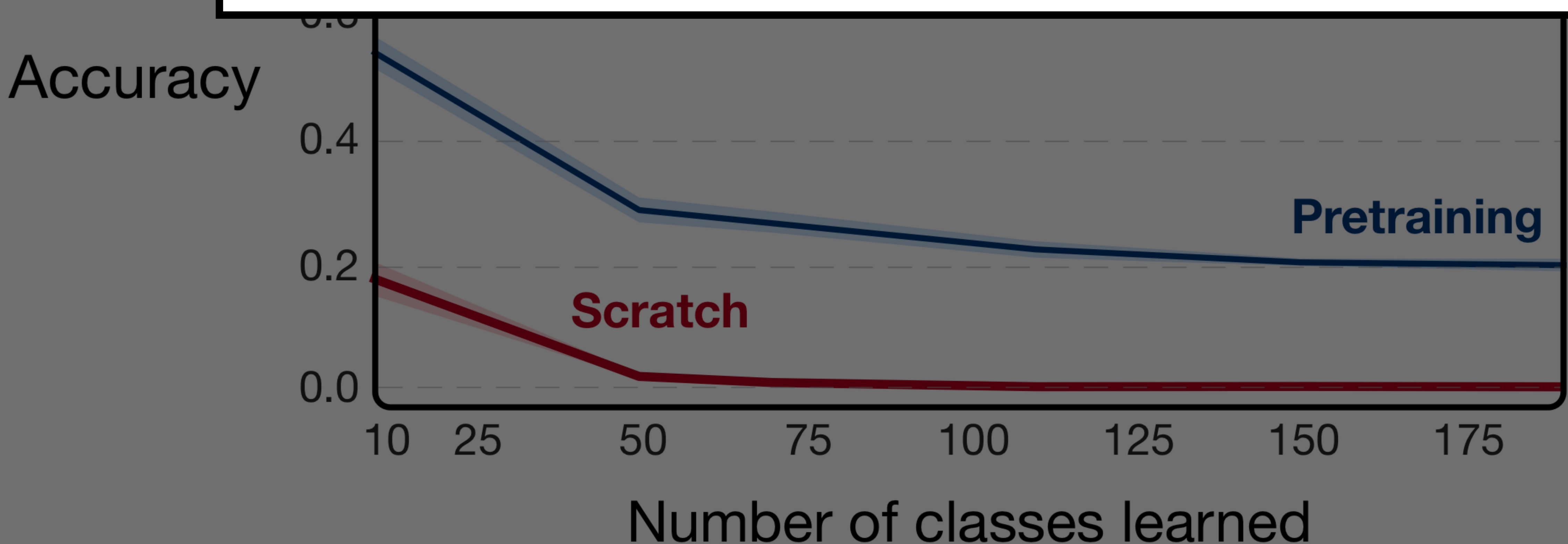

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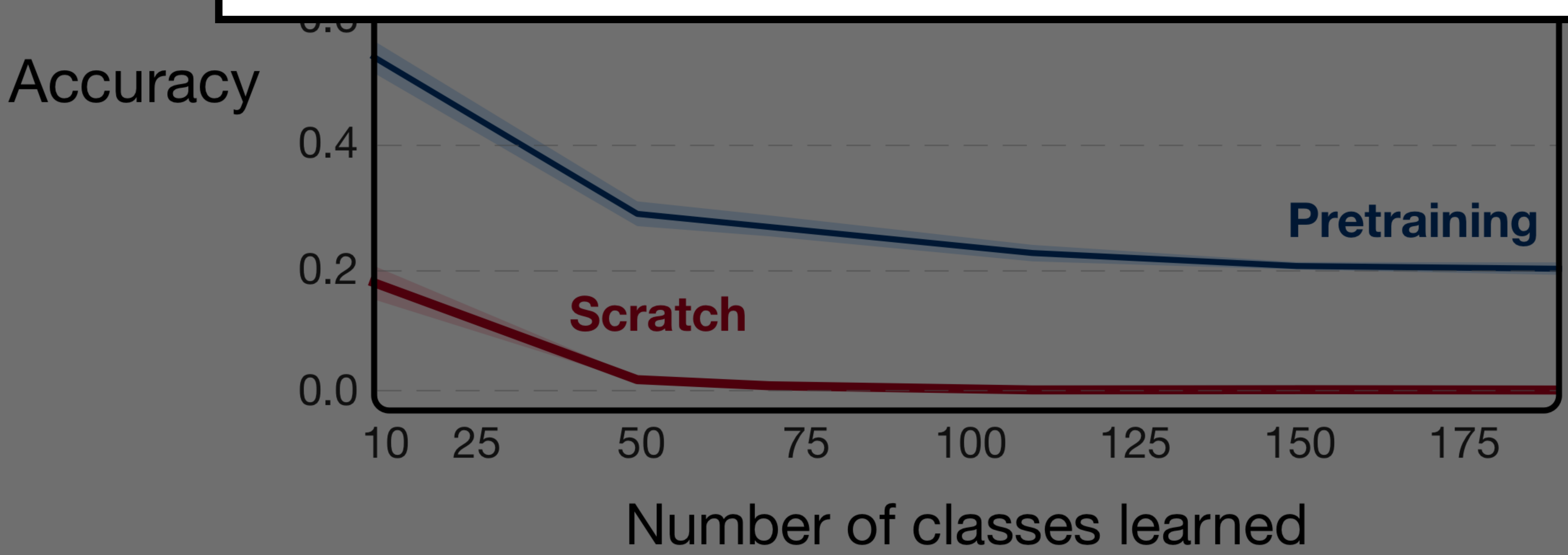
Sparse Representations



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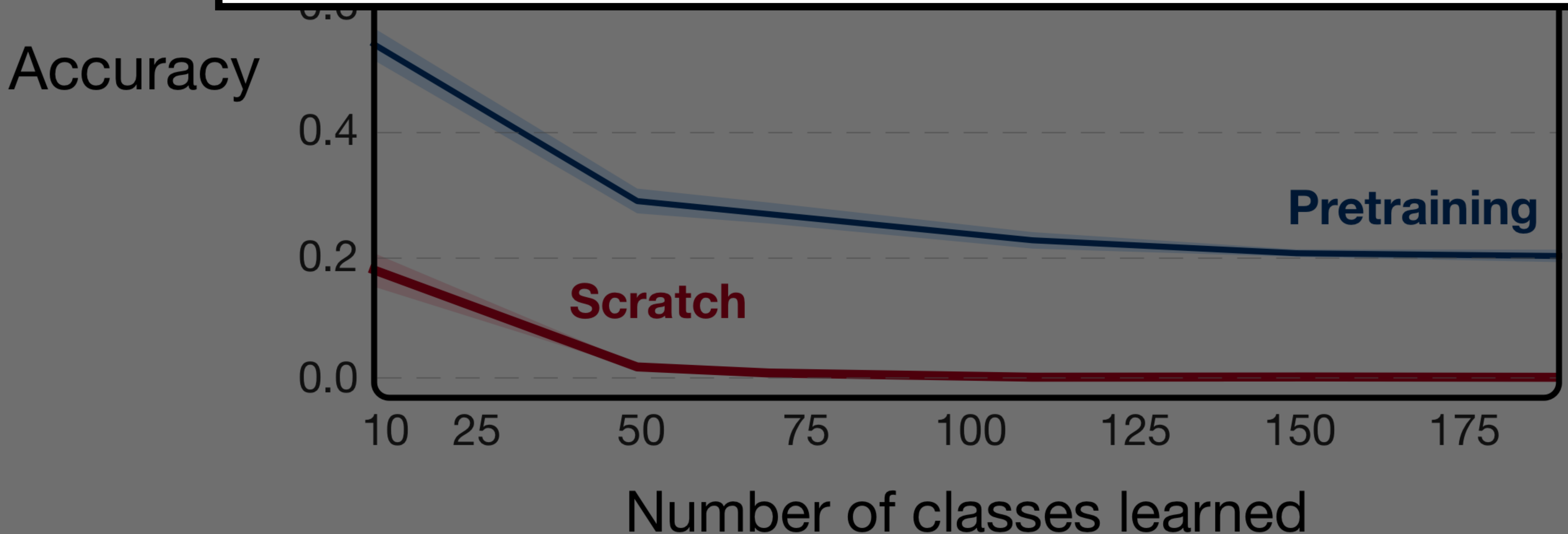
[1] Liu, V., Kumaraswamy, R., Le, L., & White, M. (2018). The utility of sparse representations for control in reinforcement learning. AAAI 19



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- We used SR-NN introduced by Vincent *et al.* [1]
- Results reported using the best performing SR-NN

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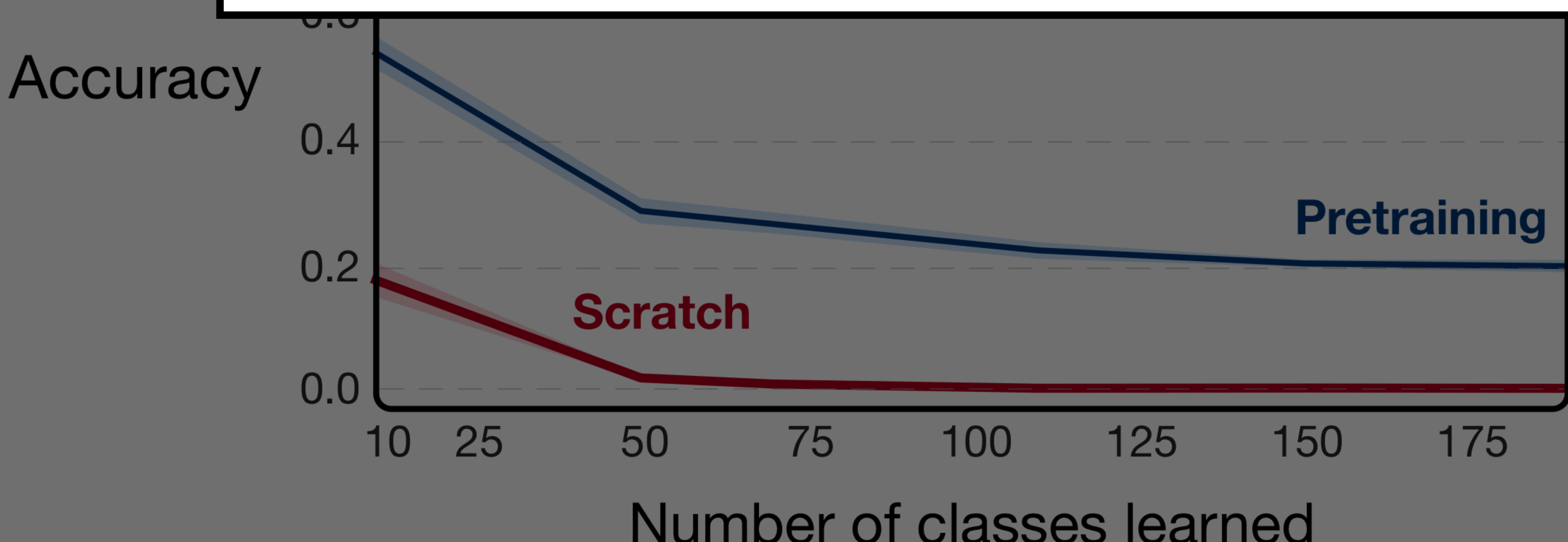

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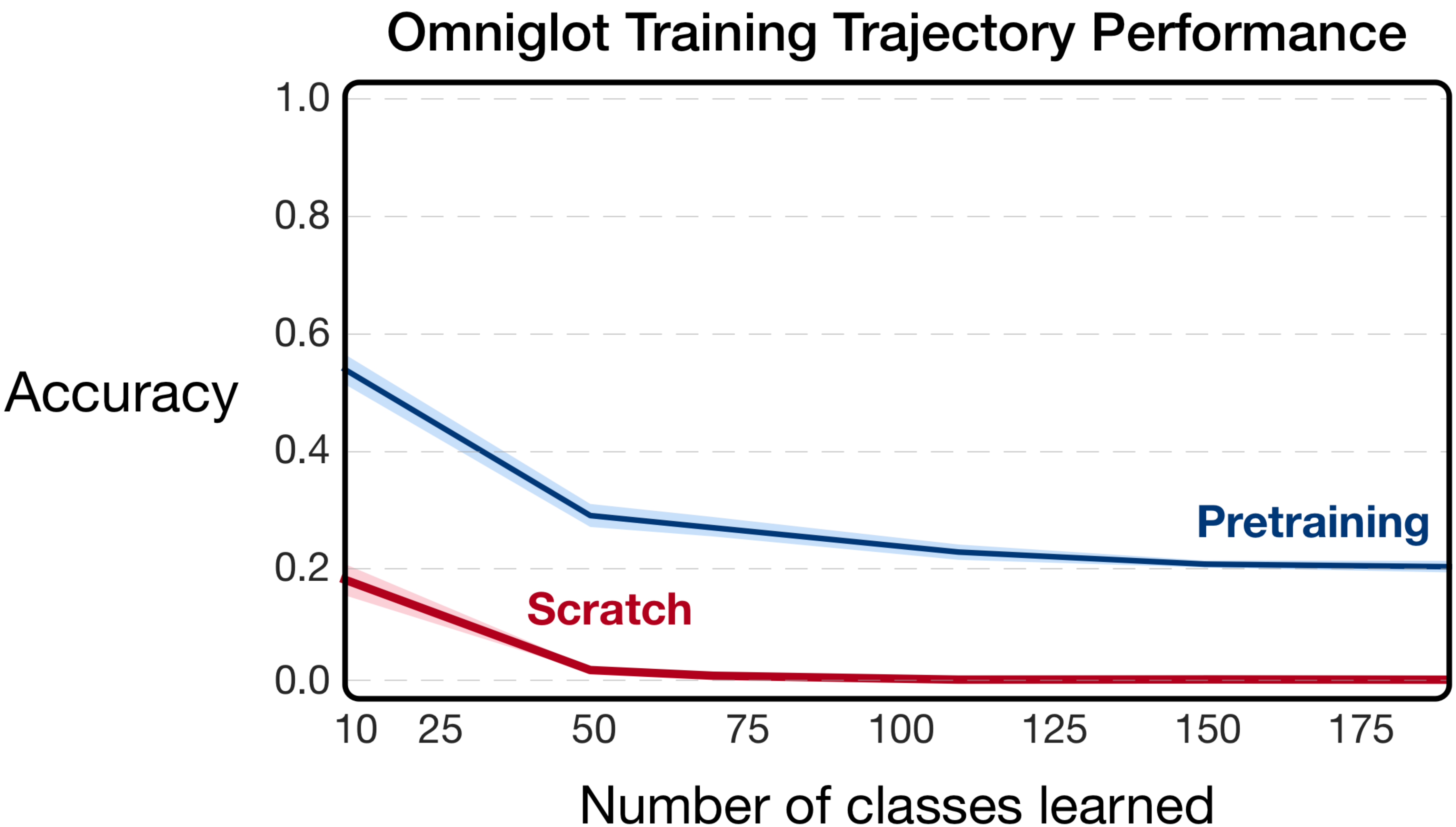

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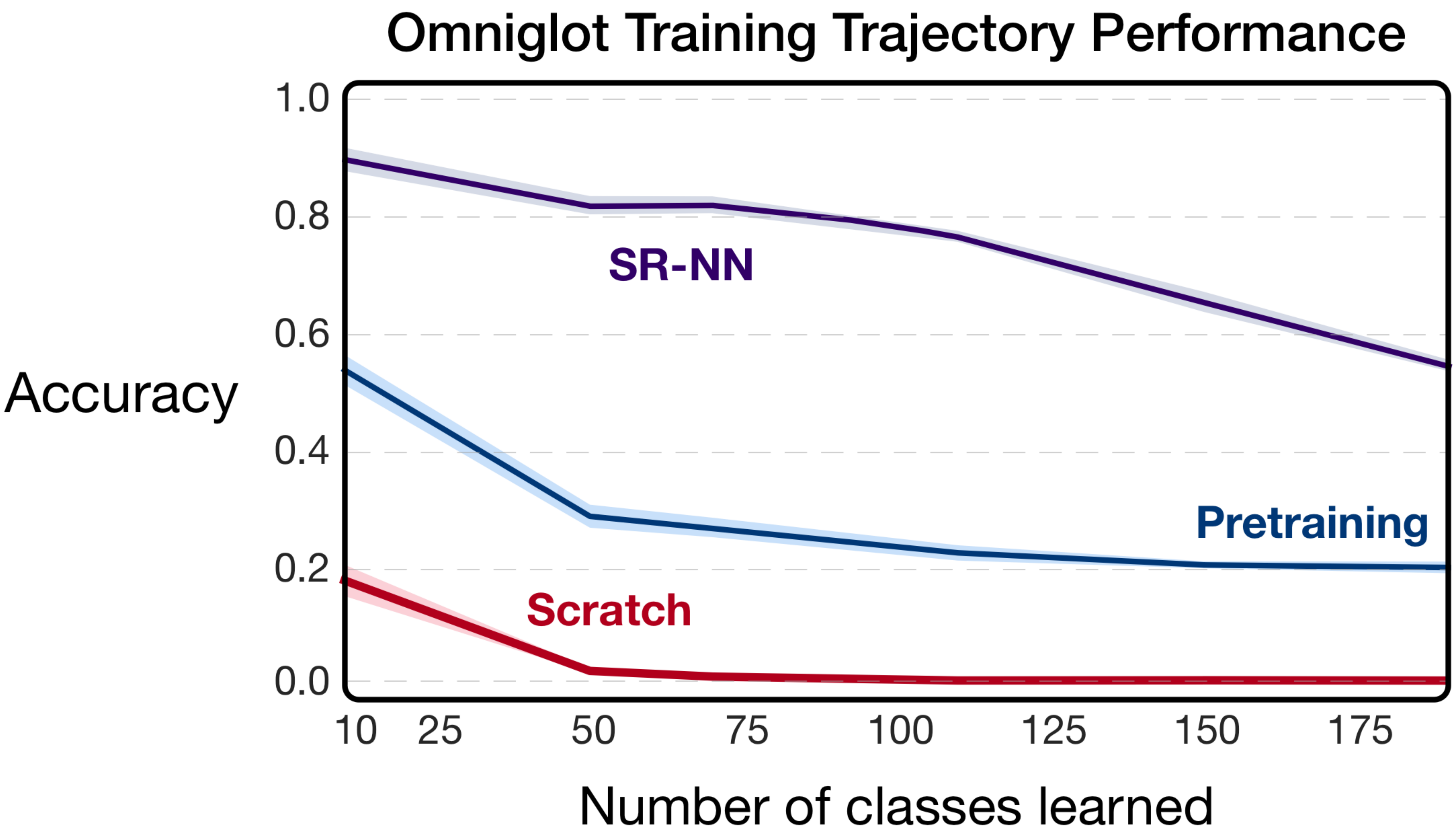

Catastrophic Interference

Neural networks suffer from ***catastrophic*** interference

Consequences : ***Forgetting*** and ***slow learning***

When and why?

1. Non-IID sampling
2. $\boxed{\text{Dense inputs}}$
3. Global and greedy update

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Experience Replay

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When and why?

1. Non-IID sampling — **Experience Replay**
2. Dense inputs — **Tile coding**
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Our work

When and why?

1. Non-IID sampling — **Experience Replay**
2. Dense inputs — **Tile coding**
3. Global and greedy update — **Adam optimizer?**

Meta-Learning Representations for Continual Learning

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Core idea

Meta-Learning Representations for Continual Learning

Core idea

- Don’t use sparsity as a proxy to a good representation

Meta-Learning Representations for Continual Learning

Core idea

- Don't use sparsity as a proxy to a good representation
- Directly optimize for representations which allow for continual learning

Meta-Learning Representations for Continual Learning

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Data stream

$$\boxed{\mathcal{D} = (X_0, Y_0), (X_1, Y_1), \ldots, (X_k, Y_k), \ldots, (X_n, Y_n), \ldots,}$$

Meta-Learning Representations for Continual Learning

Data stream

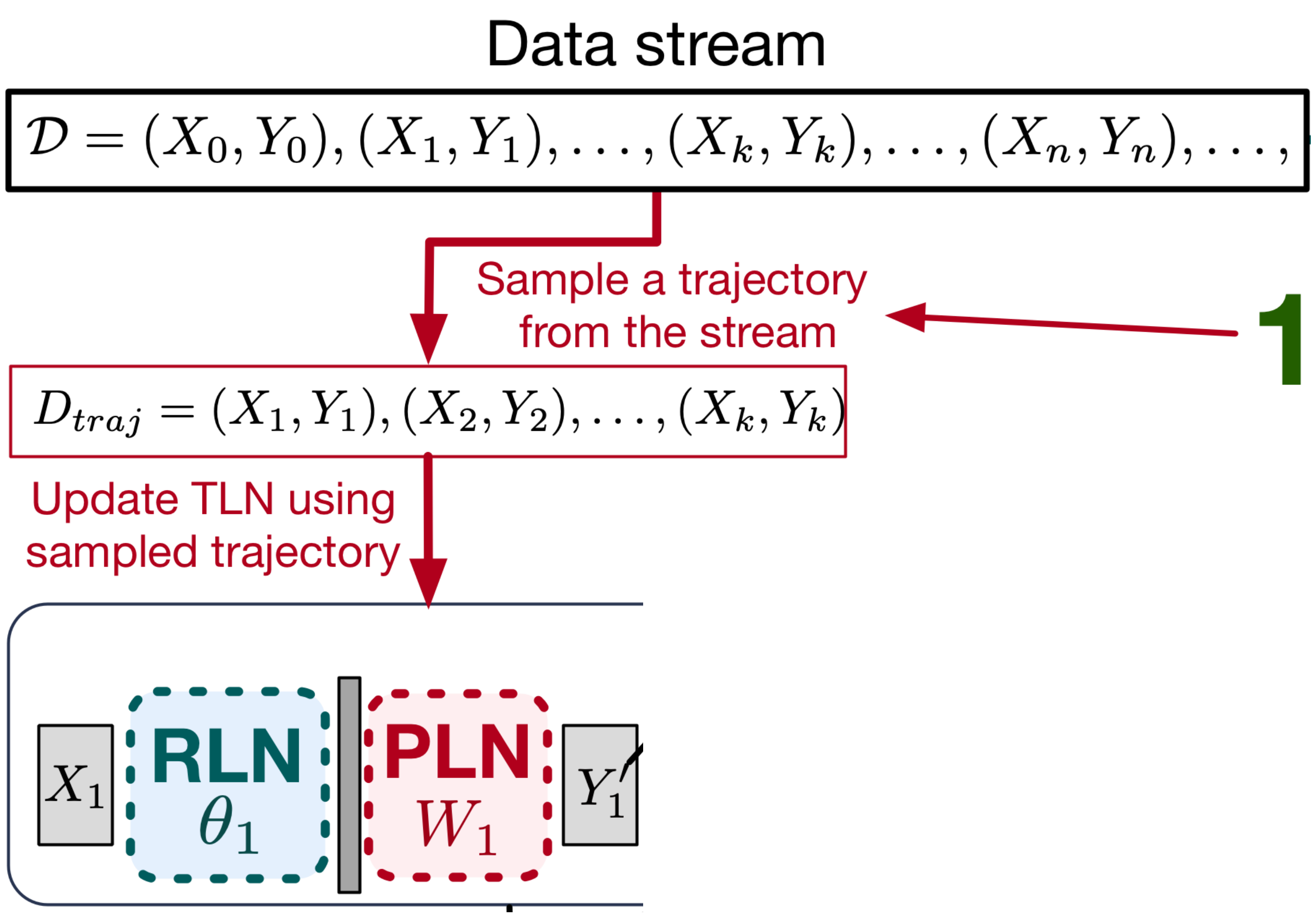
$$\mathcal{D} = (X_0, Y_0), (X_1, Y_1), \ldots, (X_k, Y_k), \ldots, (X_n, Y_n), \ldots,$$

Sample a trajectory from the stream

1

$$D_{traj} = (X_1, Y_1), (X_2, Y_2), \ldots, (X_k, Y_k)$$

Meta-Learning Representations for Continual Learning



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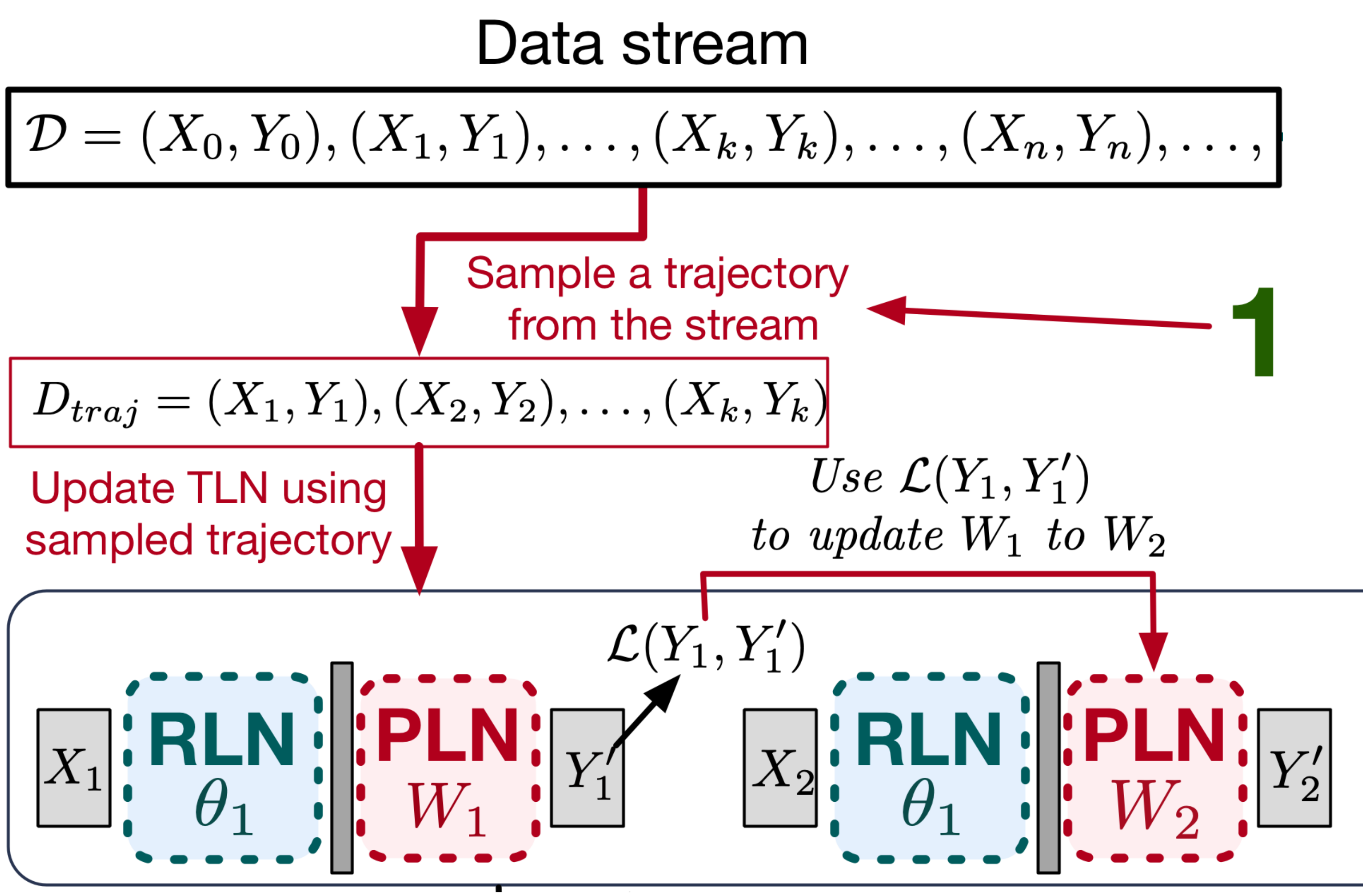

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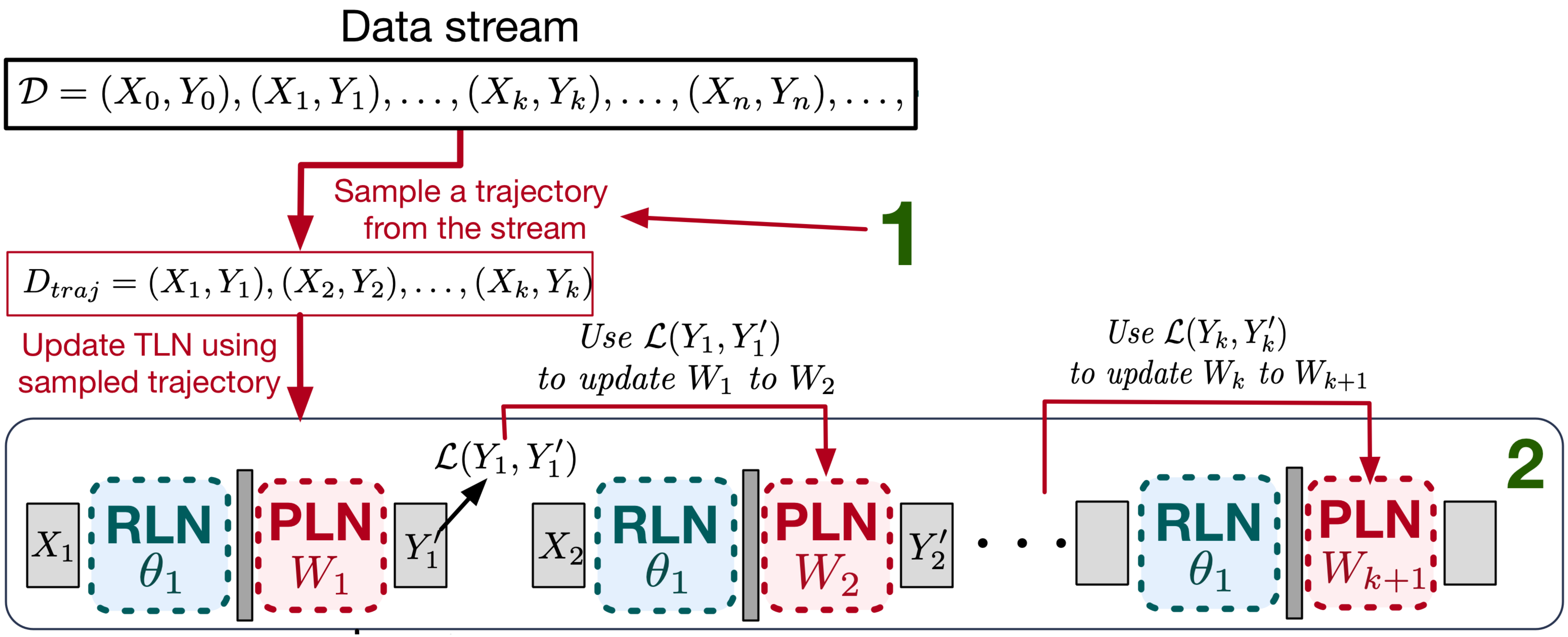

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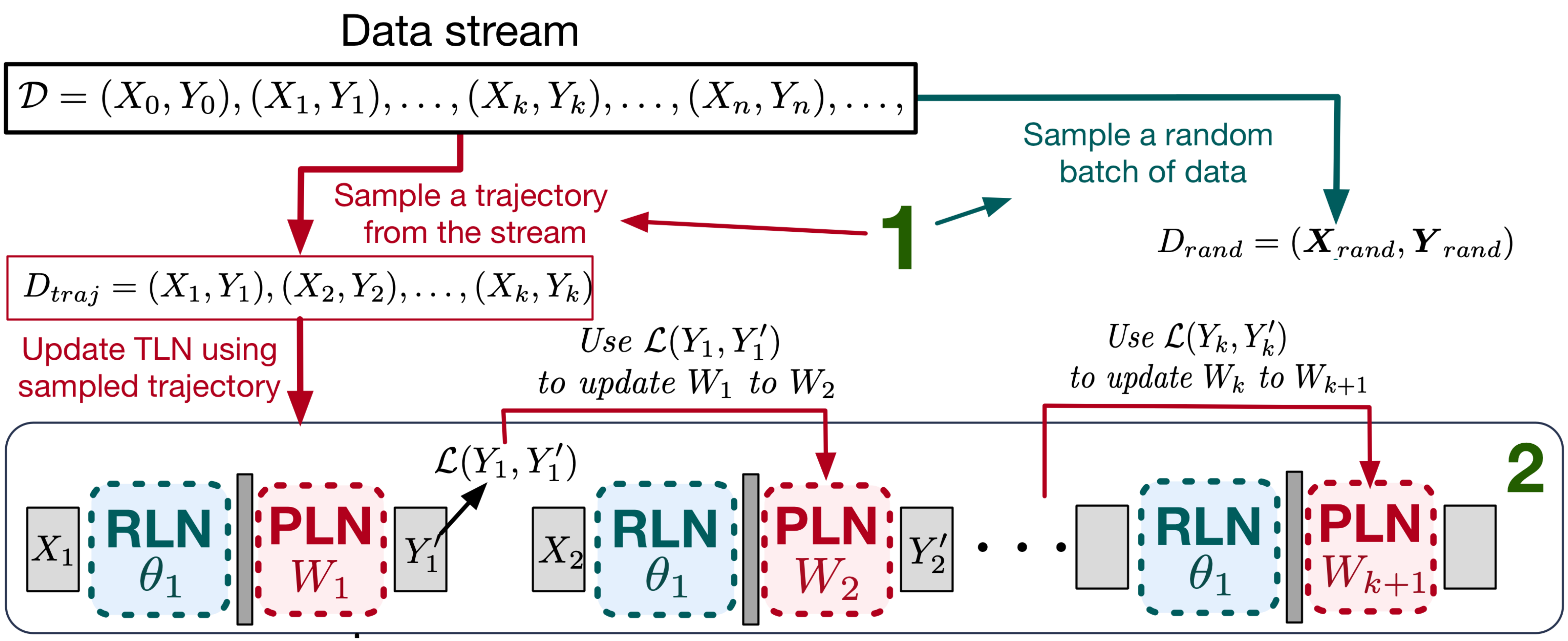
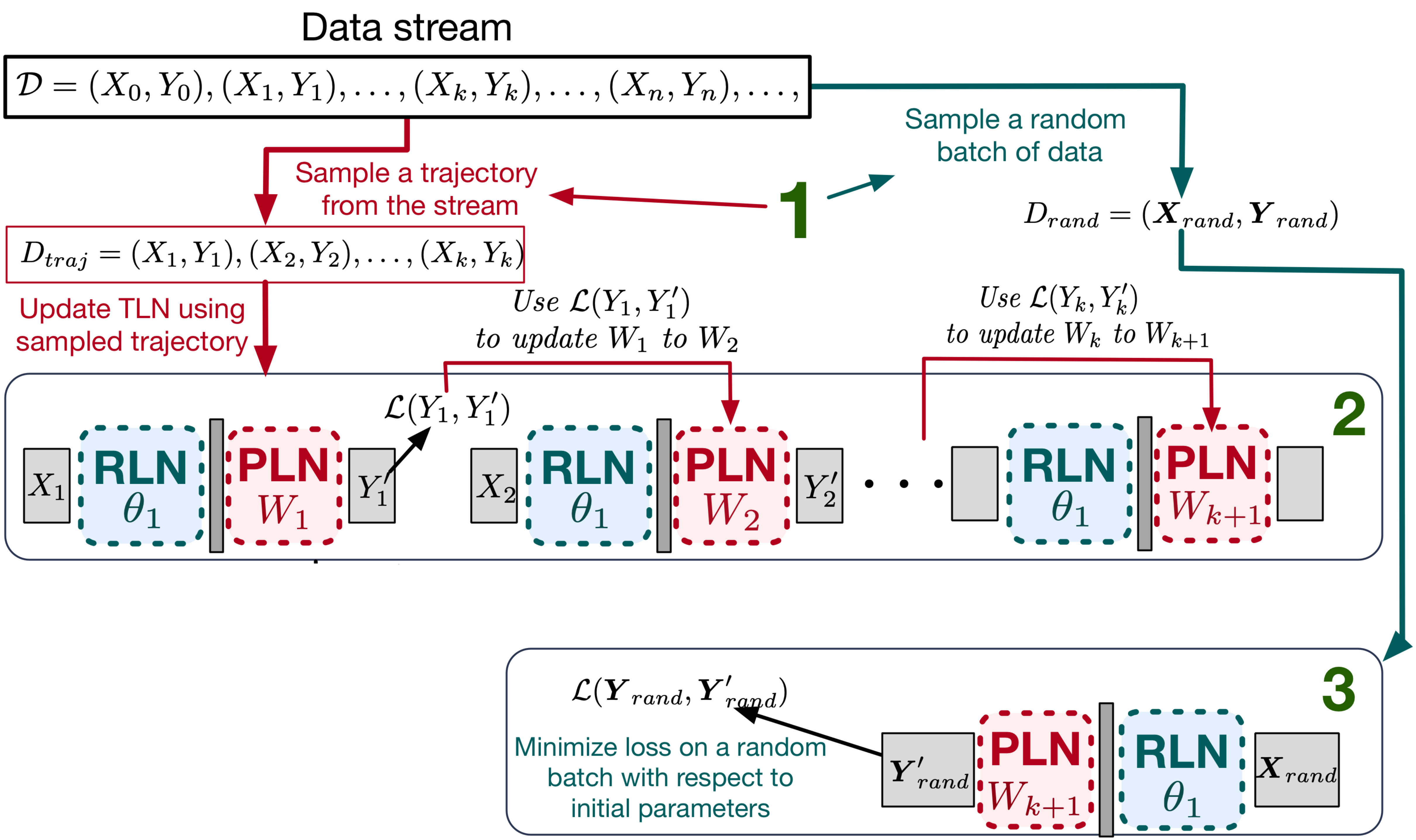
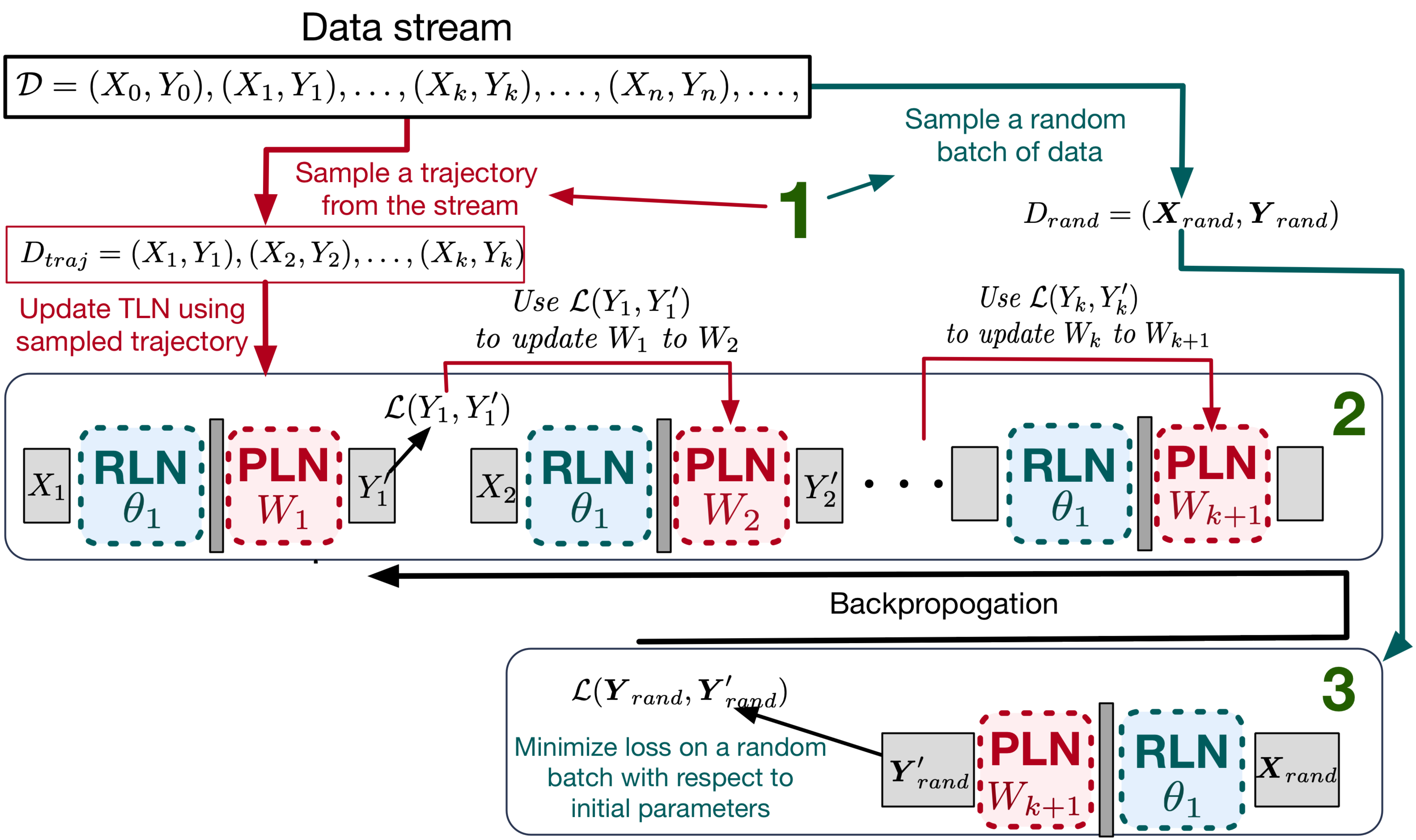


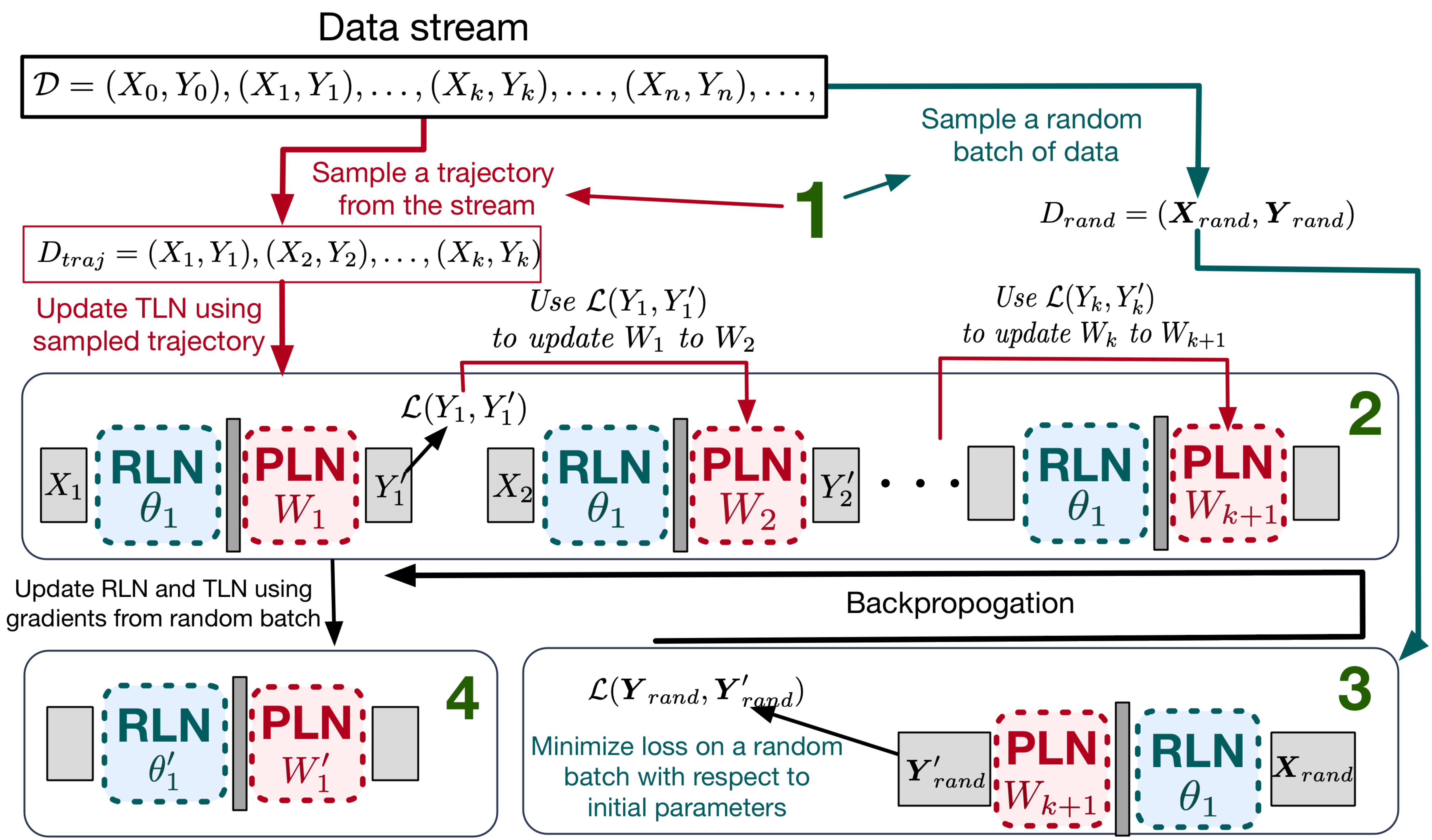
Meta-Learning Representations for Continual Learning



Meta-Learning Representations for Continual Learning

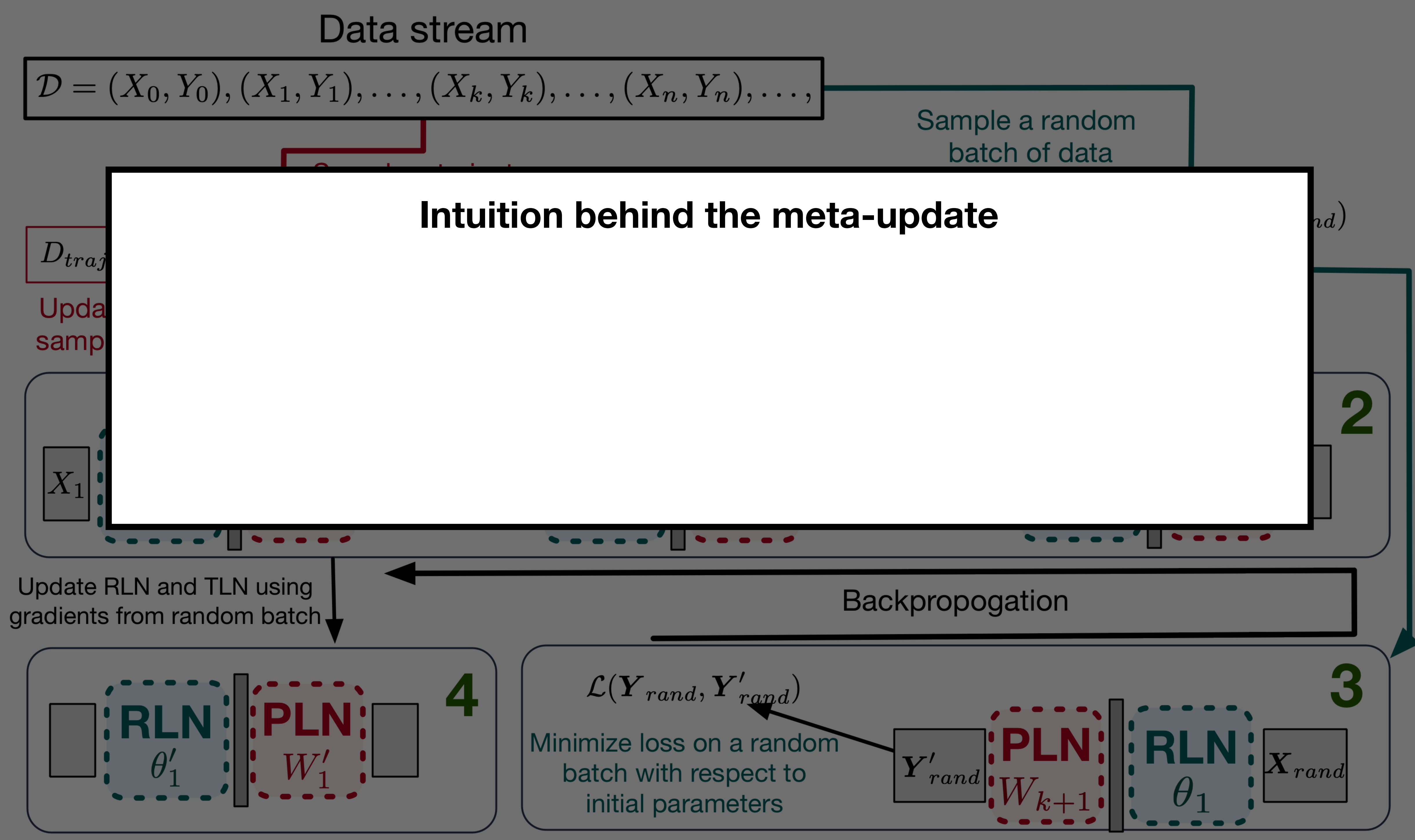


Meta-Learning Representations for Continual Learning



Meta-Learning Representations for Continual Learning

Intuition behind the meta-update



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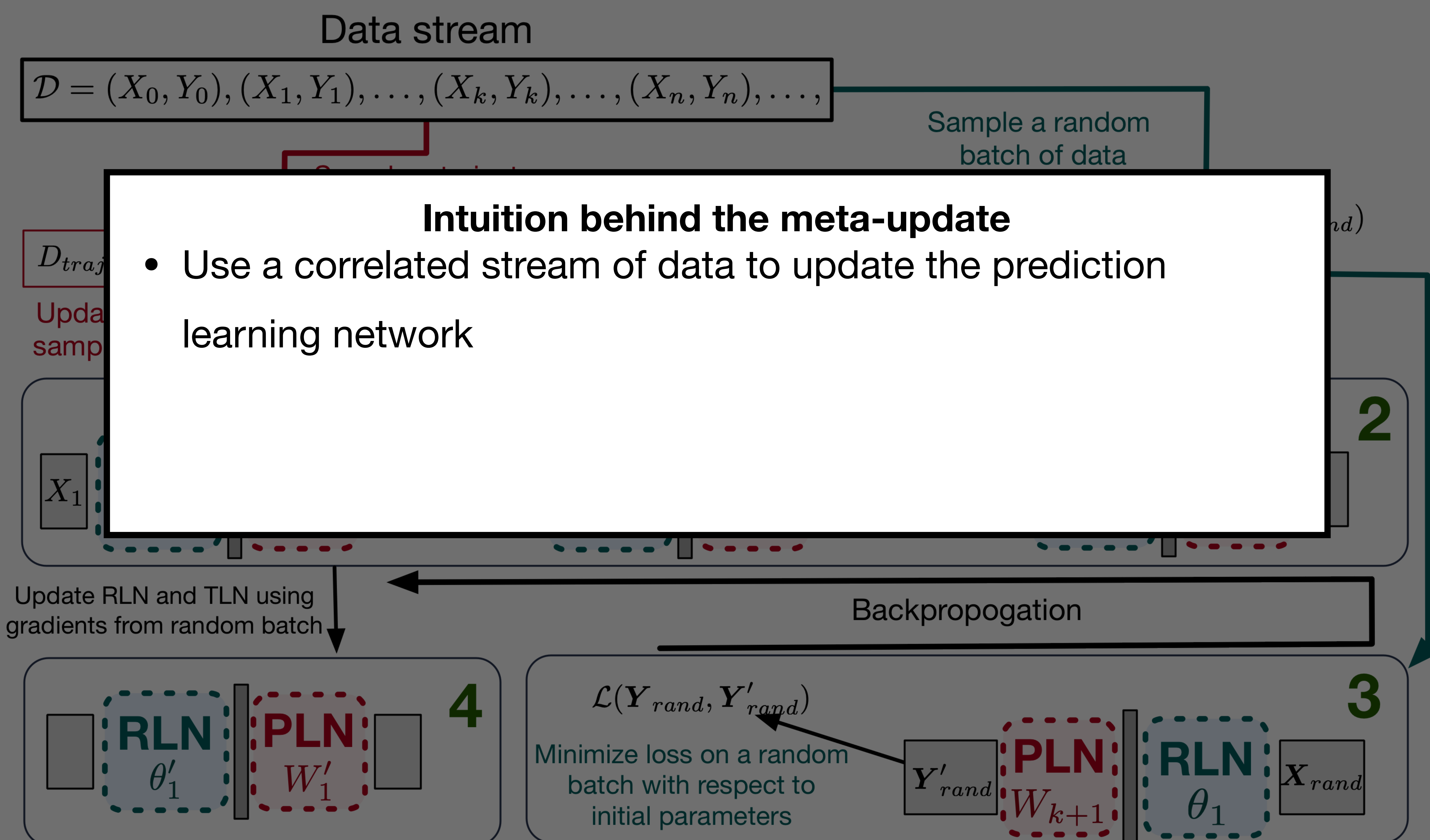
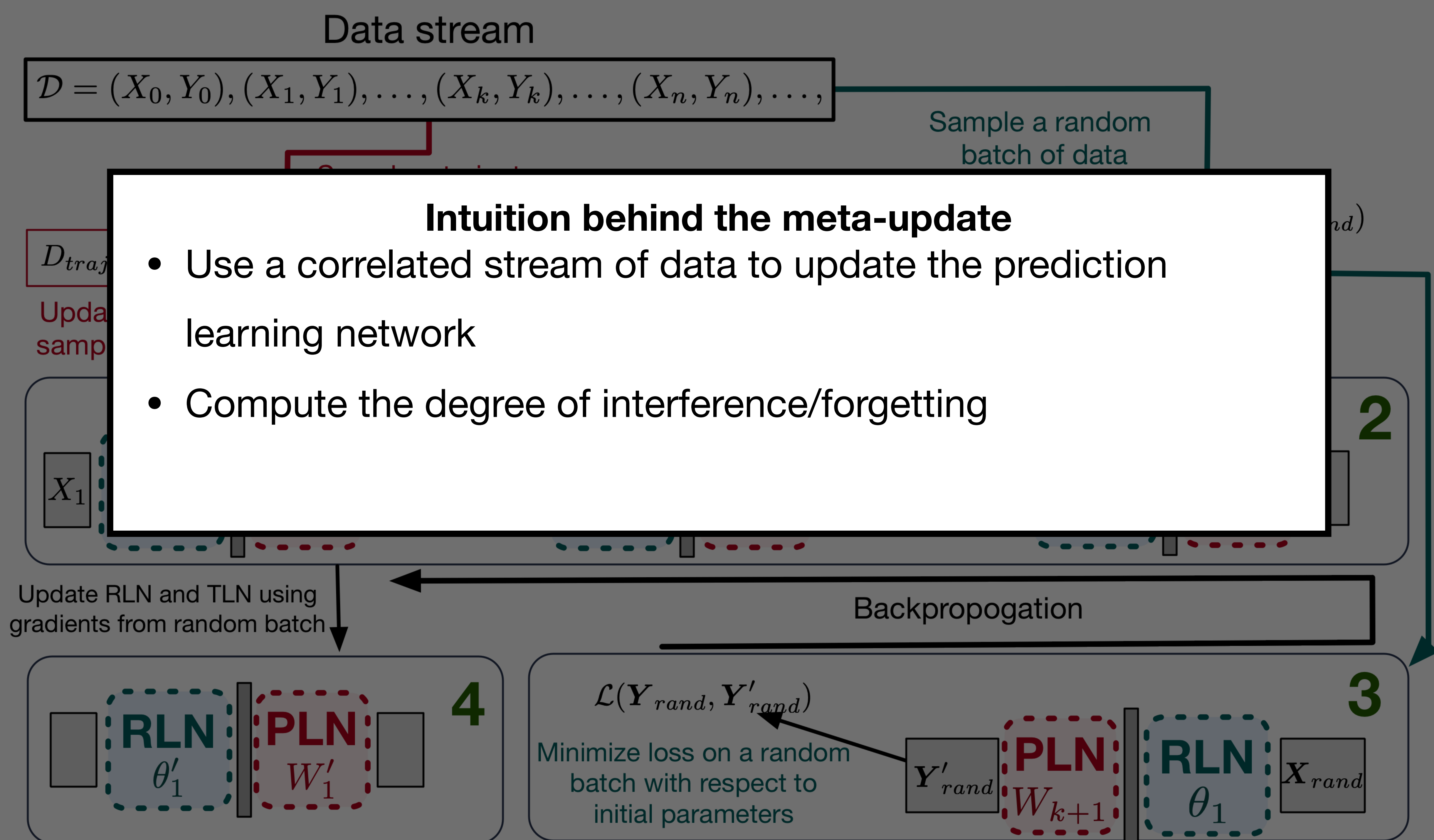


Intuition behind the meta-update

- Use a correlated stream of data to update the prediction learning network

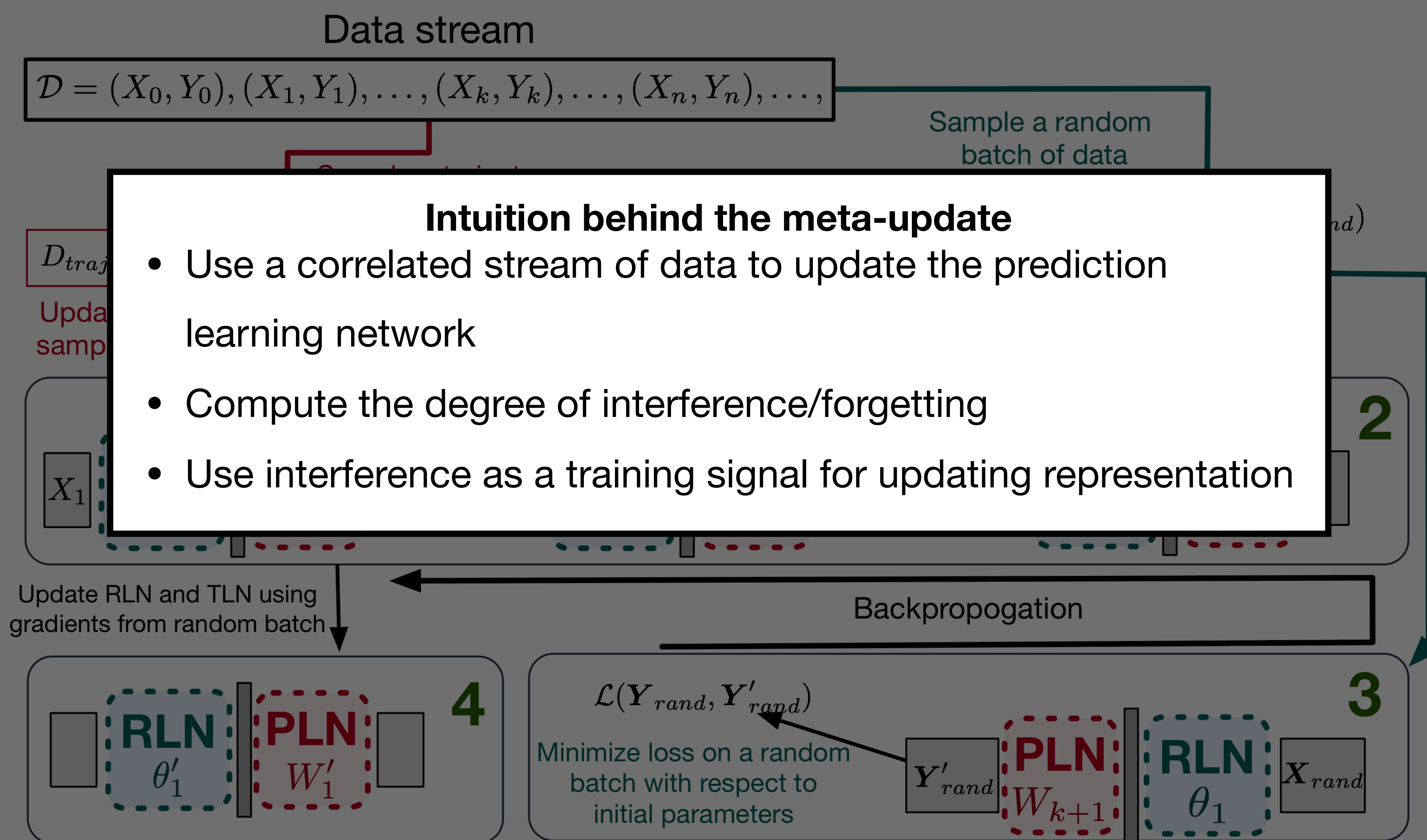
Meta-Learning Representations for Continual Learning



Intuition behind the meta-update

- Use a correlated stream of data to update the prediction learning network
- Compute the degree of interference/forgetting

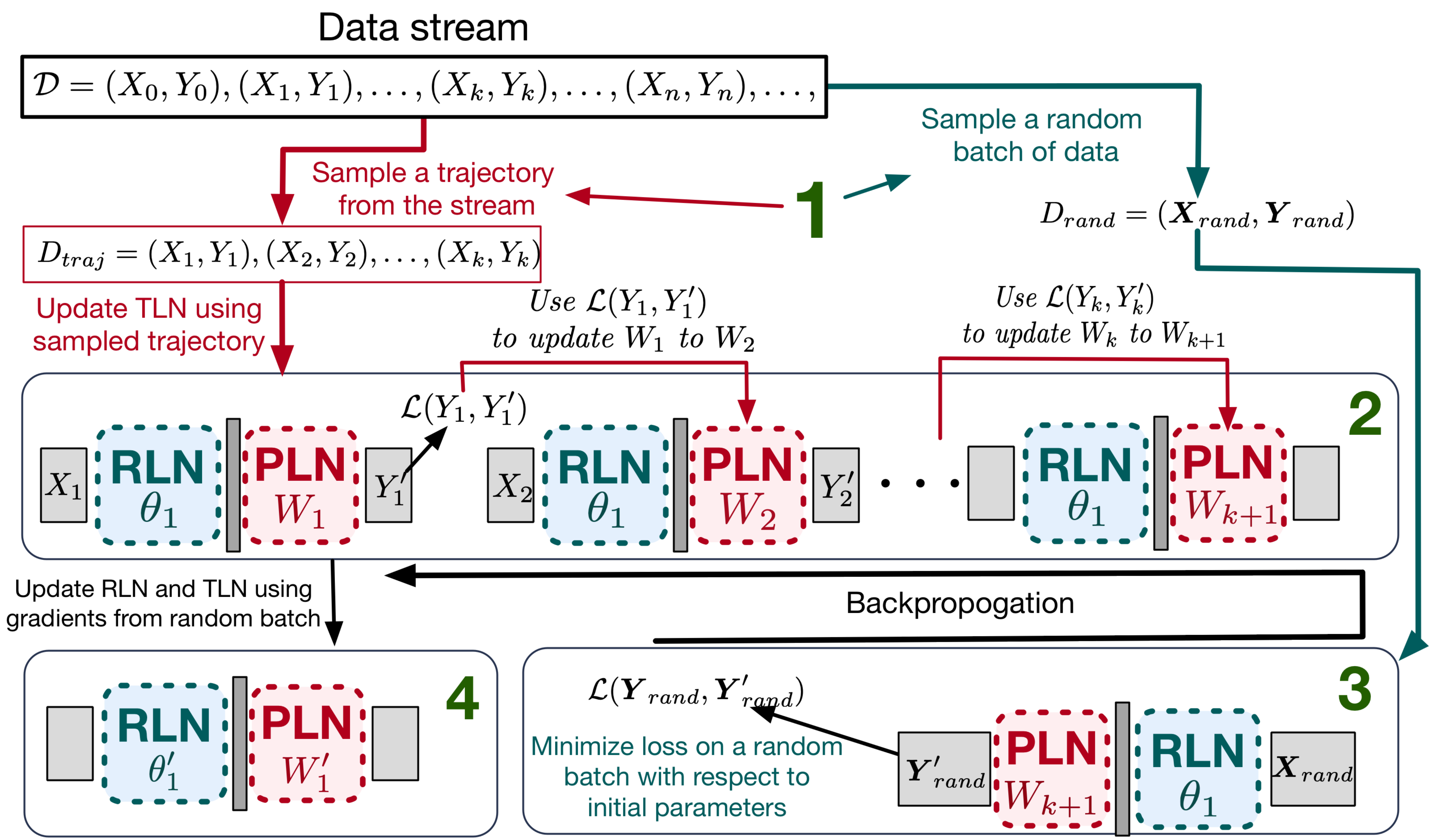
Meta-Learning Representations for Continual Learning



Intuition behind the meta-update

- Use a correlated stream of data to update the prediction learning network
- Compute the degree of interference/forgetting
- Use interference as a training signal for updating representation

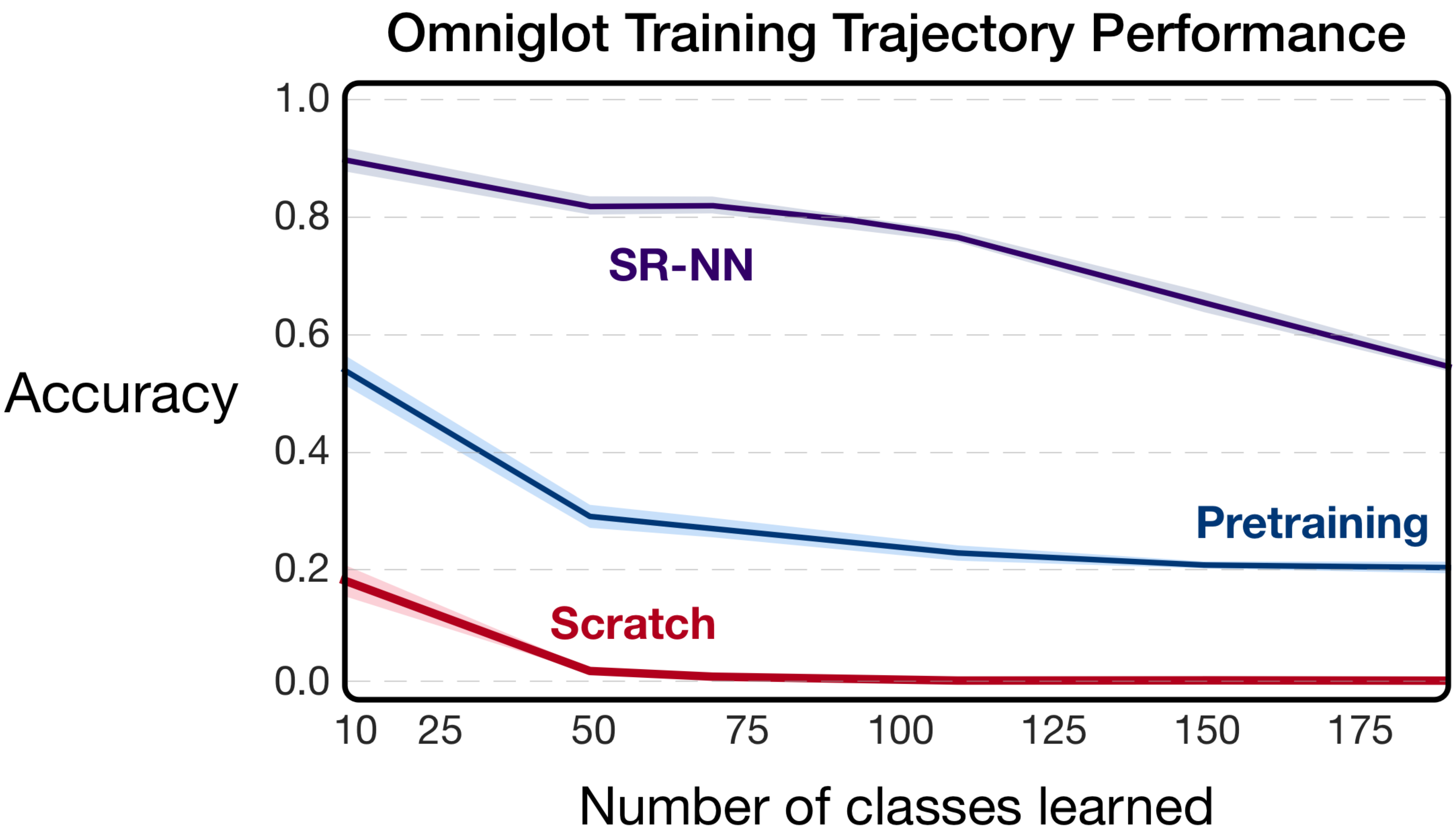
Meta-Learning Representations for Continual Learning



Meta-Learning Representations for Continual Learning

Dataset : Omniglot

- ~950 characters from multiple alphabets for representation learning
- ~600 characters from multiple alphabets for continual learning prediction



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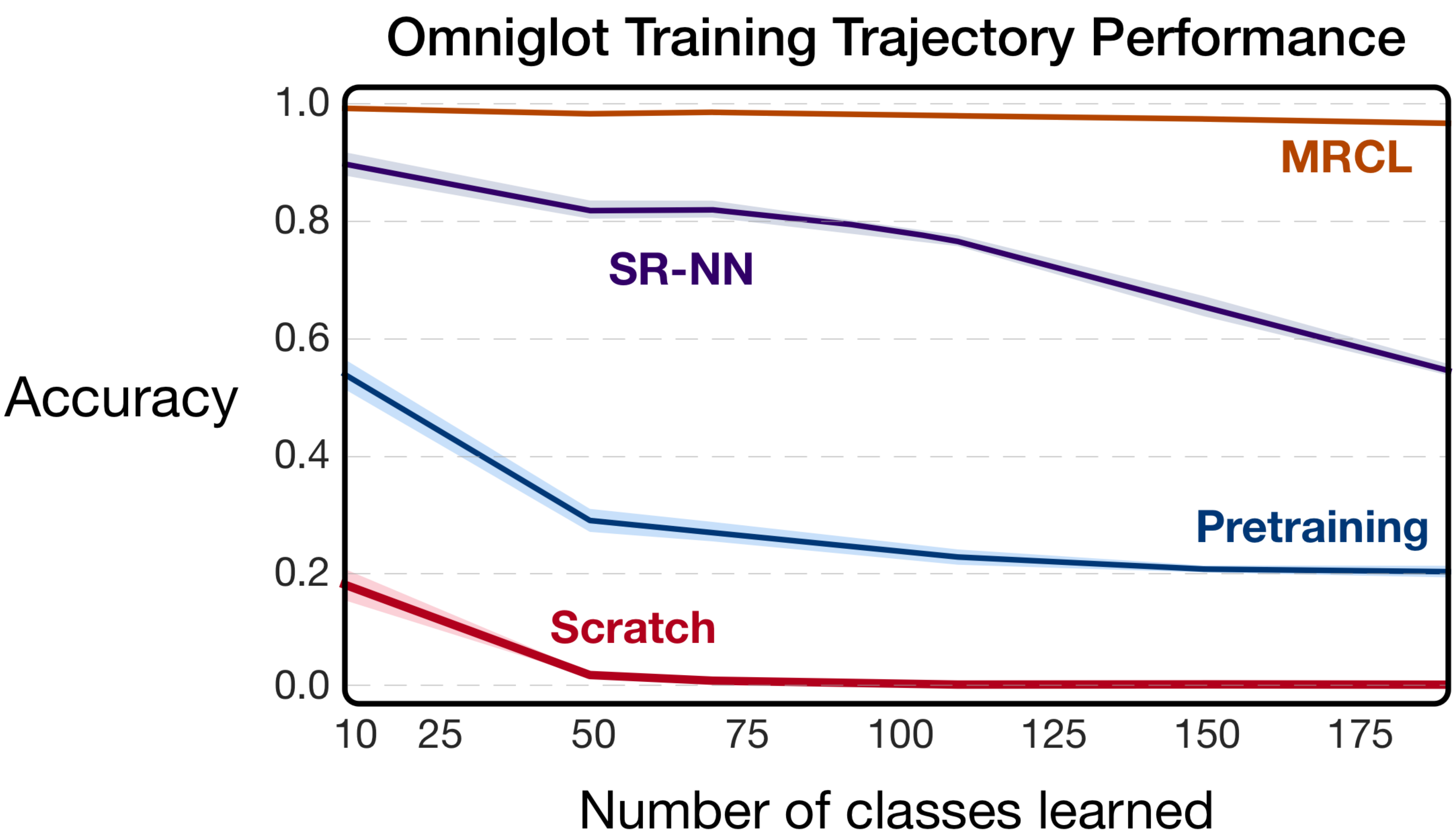

Analyzing representations

Analyzing representations

Instance sparsity

Percentage of non-zero entries used to represent an input on average

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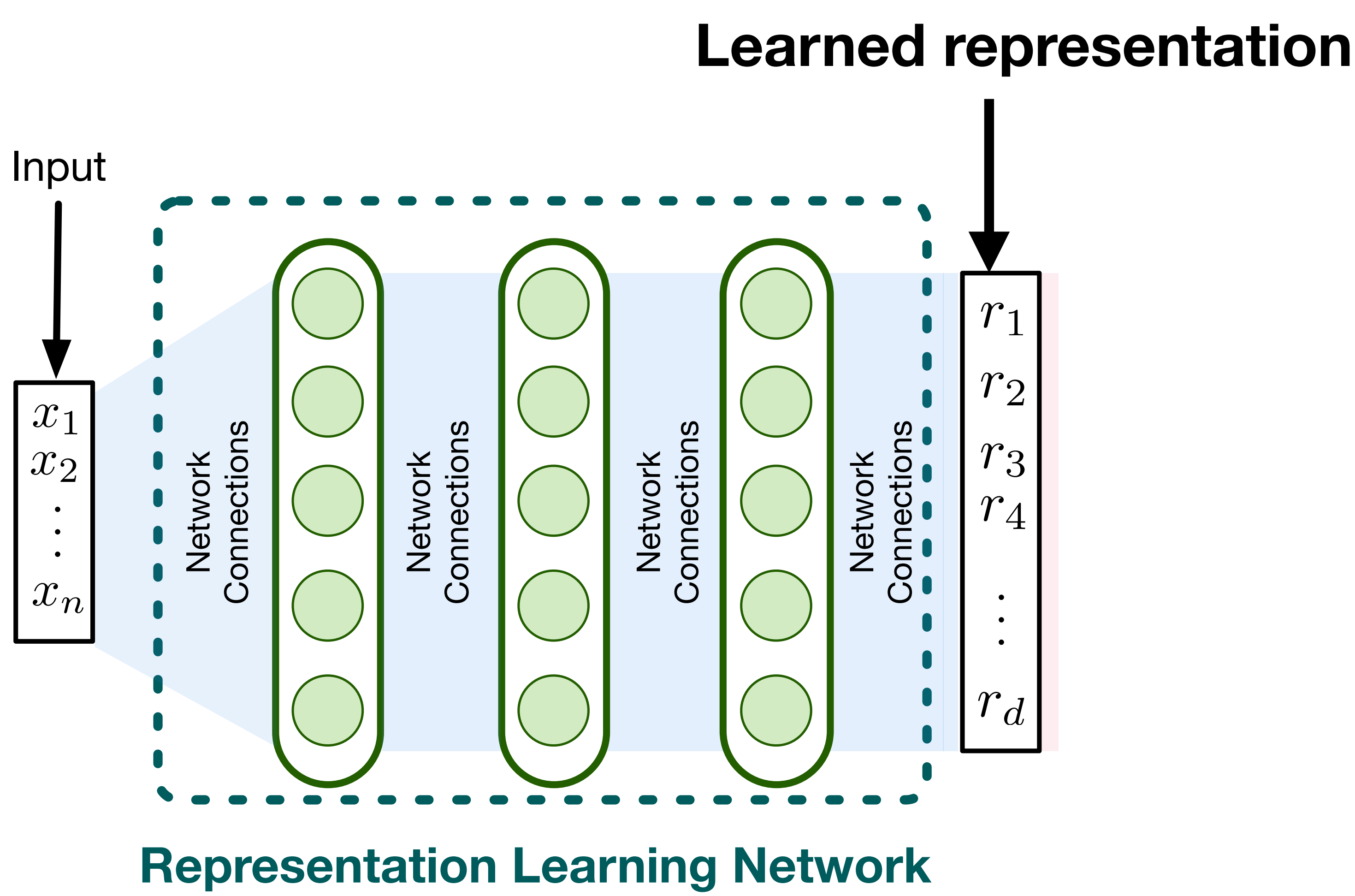
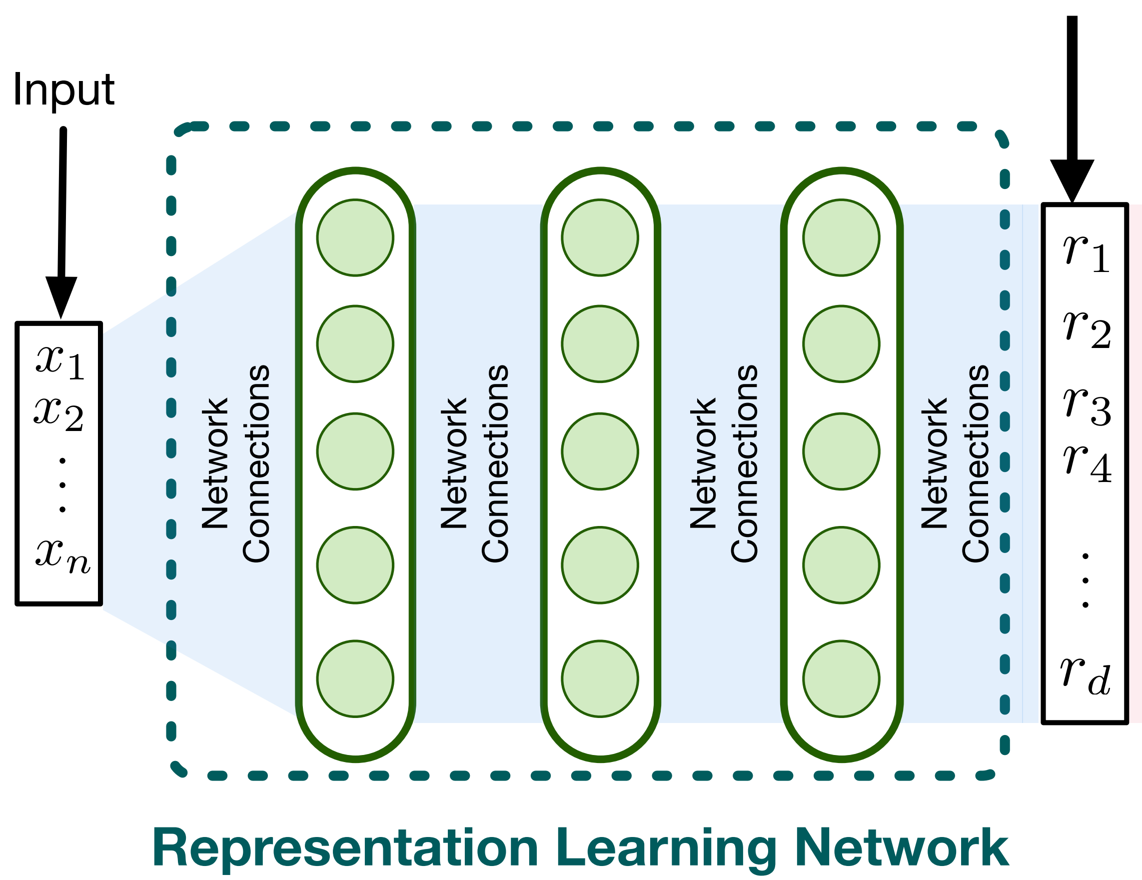


Analyzing representations

Instance sparsity

Percentage of non-zero entries used to represent an input on average

Learned representation



- **Pretraining:** 38%

Analyzing representations

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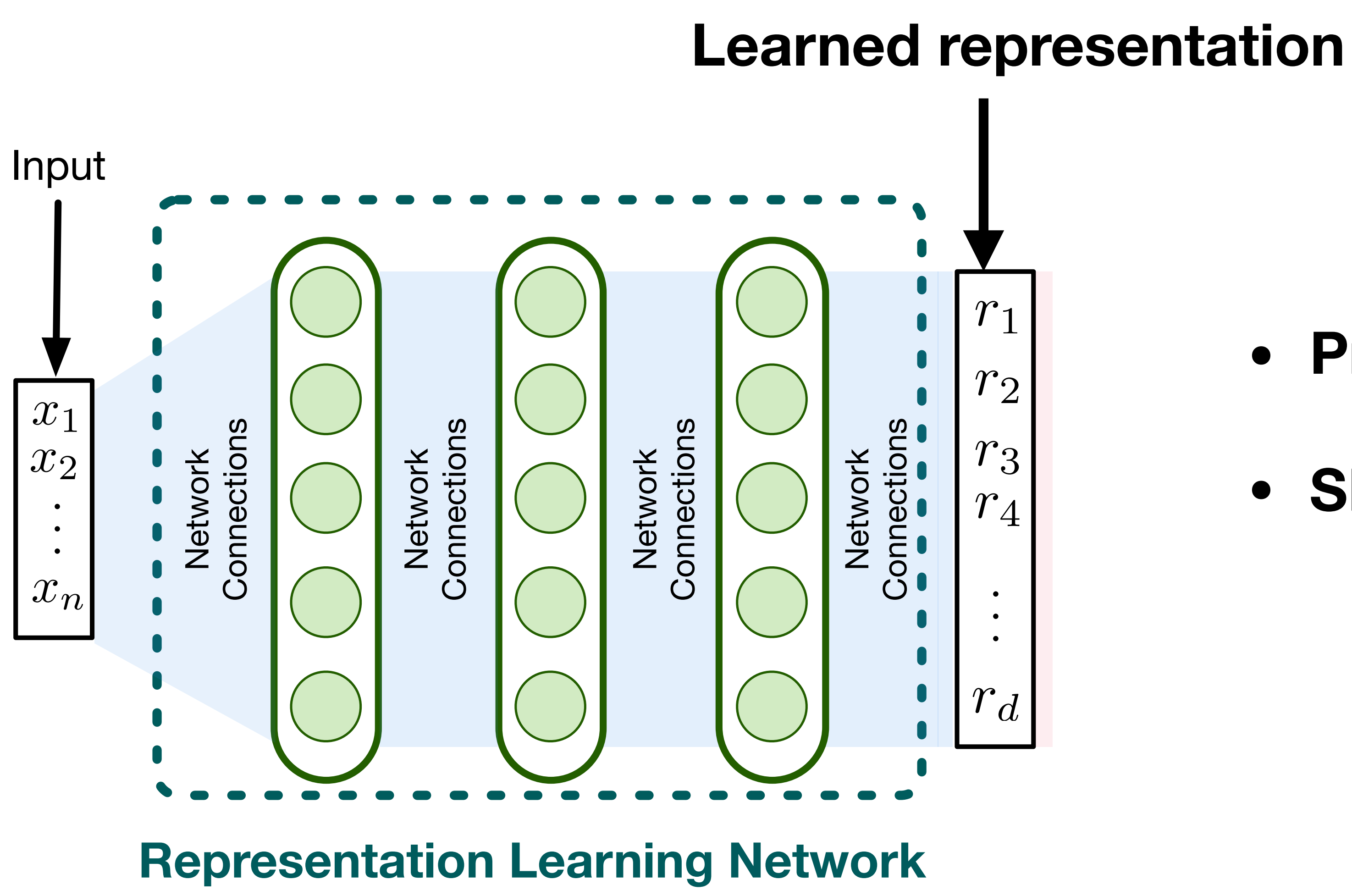

- **Pretraining:** 38%
- **SR-NN**: 15%

Analyzing representations

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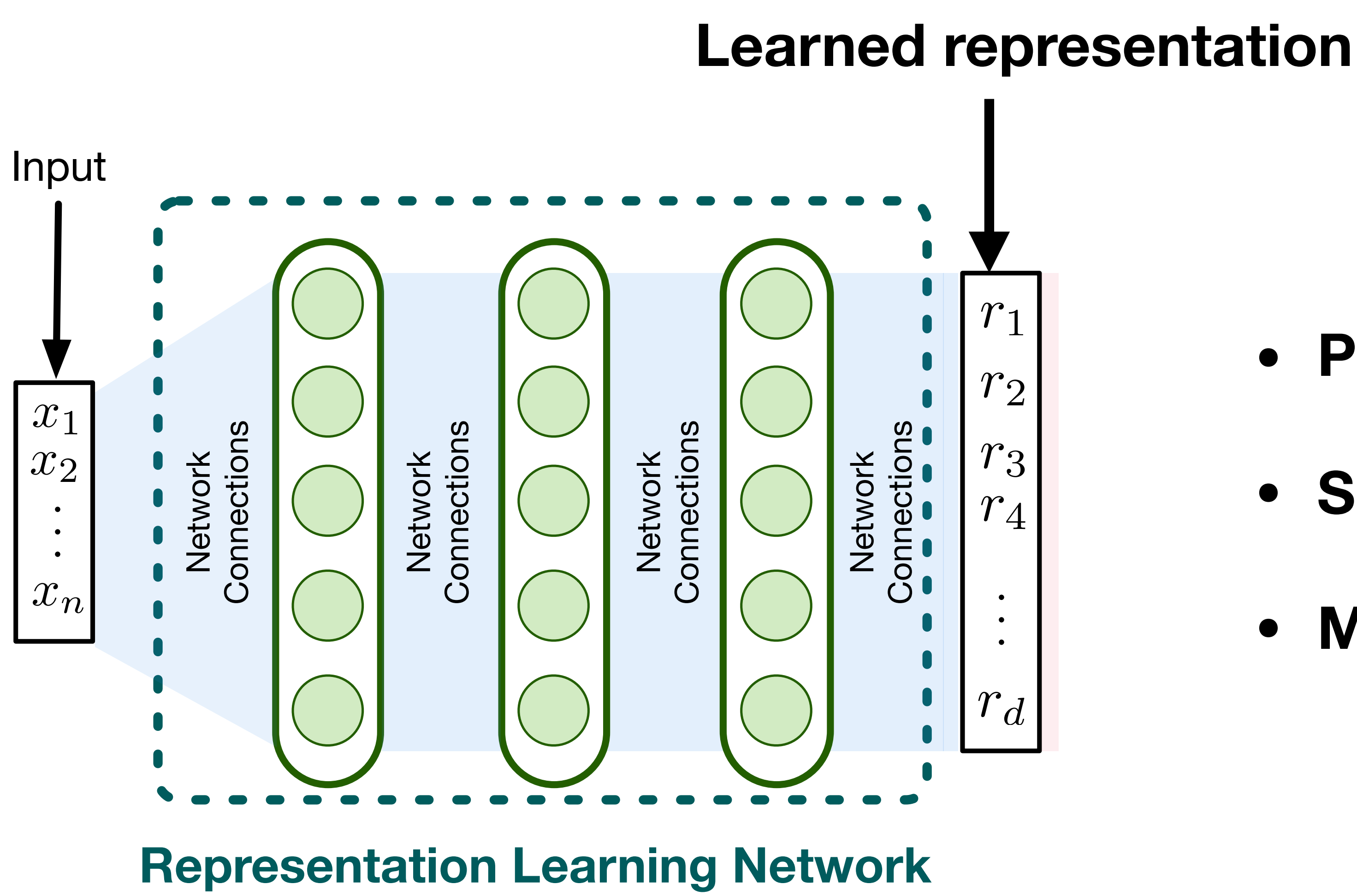
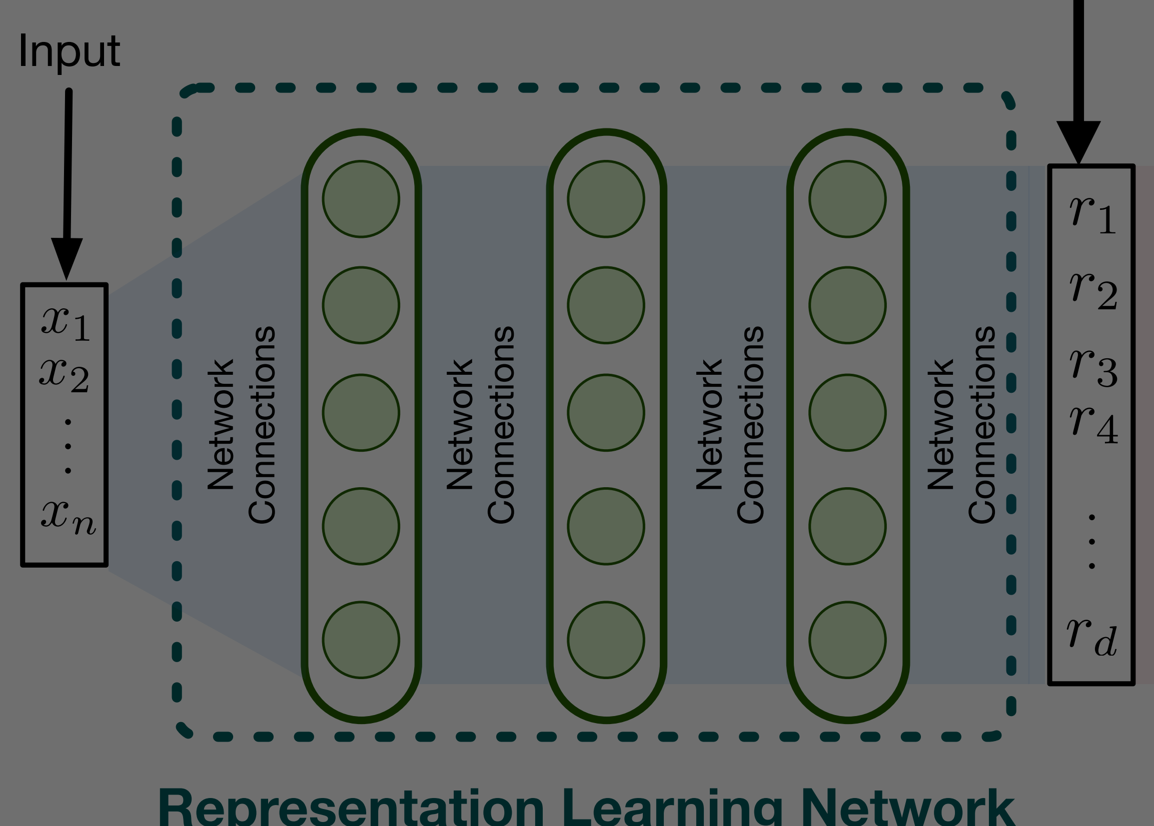


- **Pretraining:** 38%
- **SR-NN**: 15%
- **MRCL:** 3.8%

Analyzing representations

Instance sparsity

Per age



- **Pretraining:** 38%
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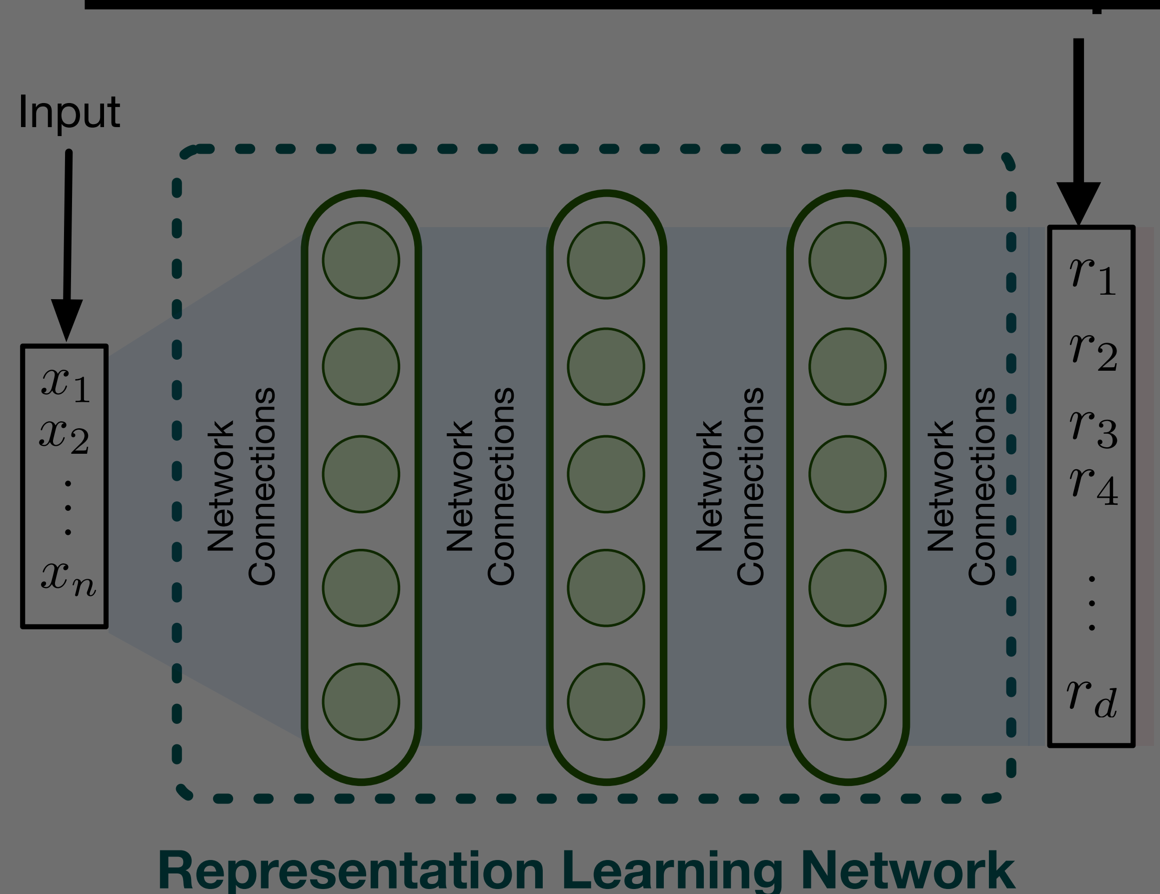
- **MRCL:** 3.8%

Analyzing representations

Instance sparsity

Per[...]age

We can train SR-NN with different hyper-parameter to achieve same degree of sparsity



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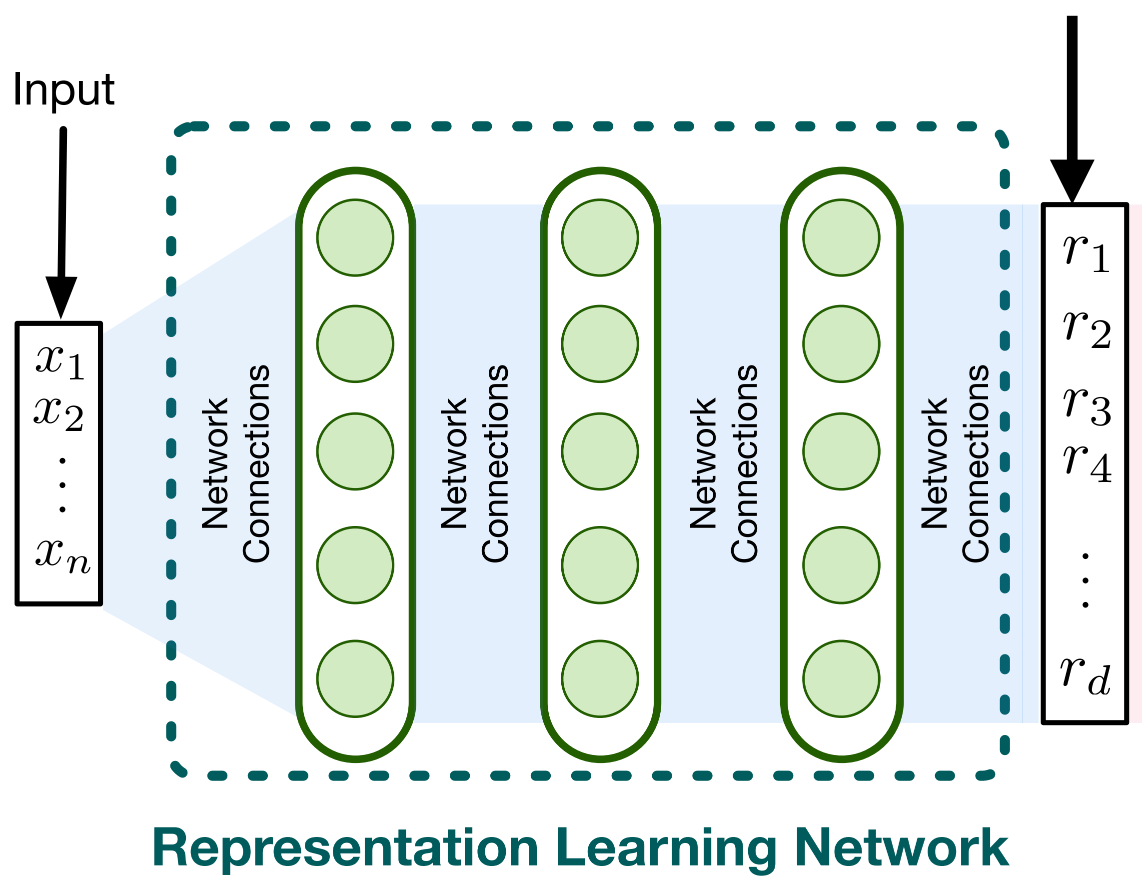
Analyzing representations

Instance sparsity

Percentage of non-zero entries used to represent an input on average

Learned representation



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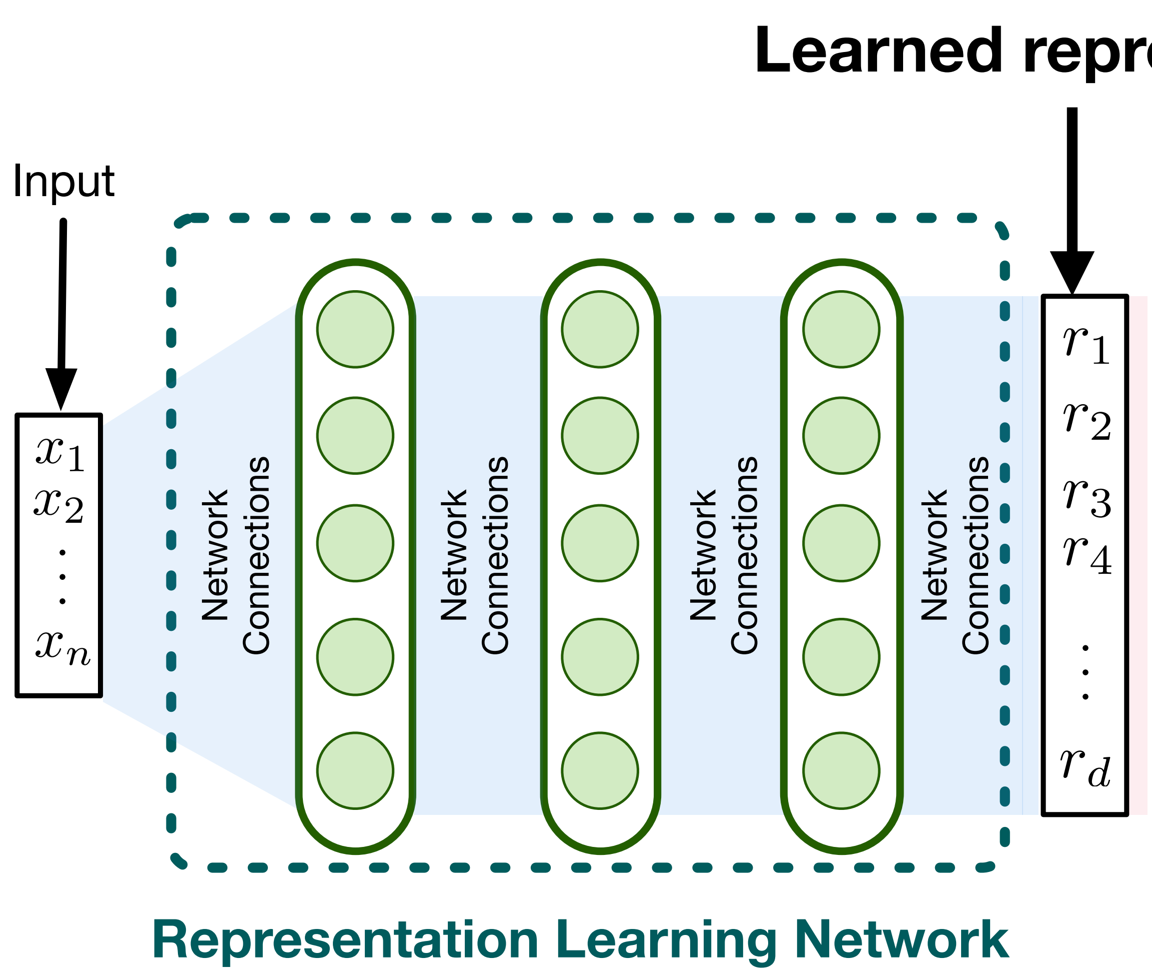

- **Pretraining:** 38%
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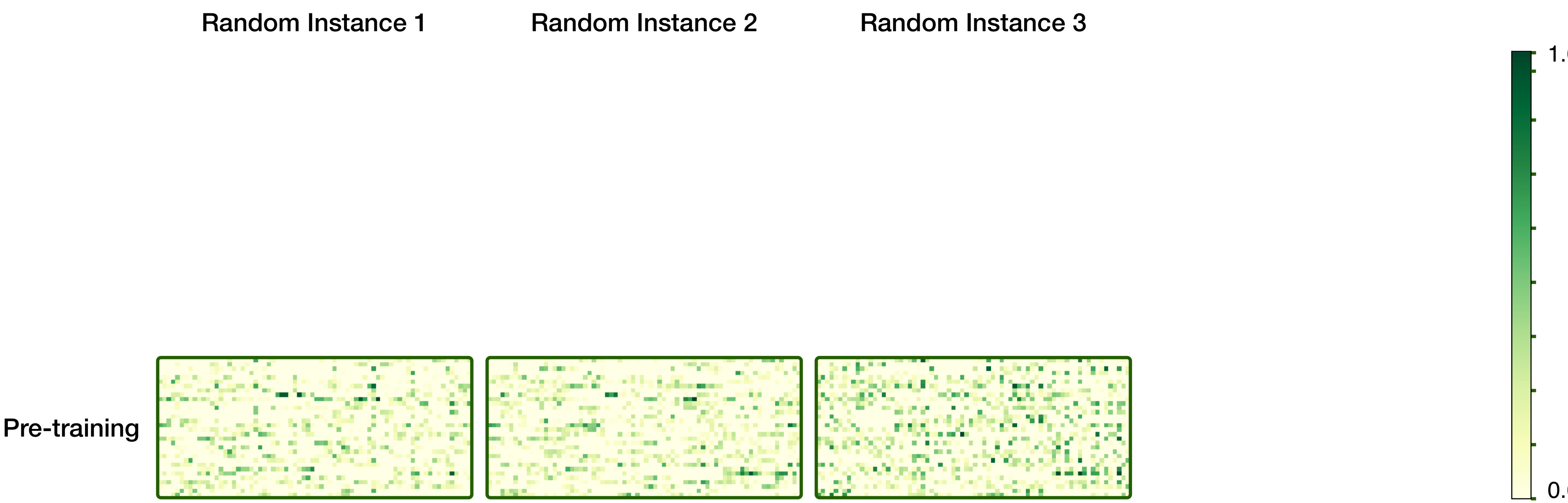
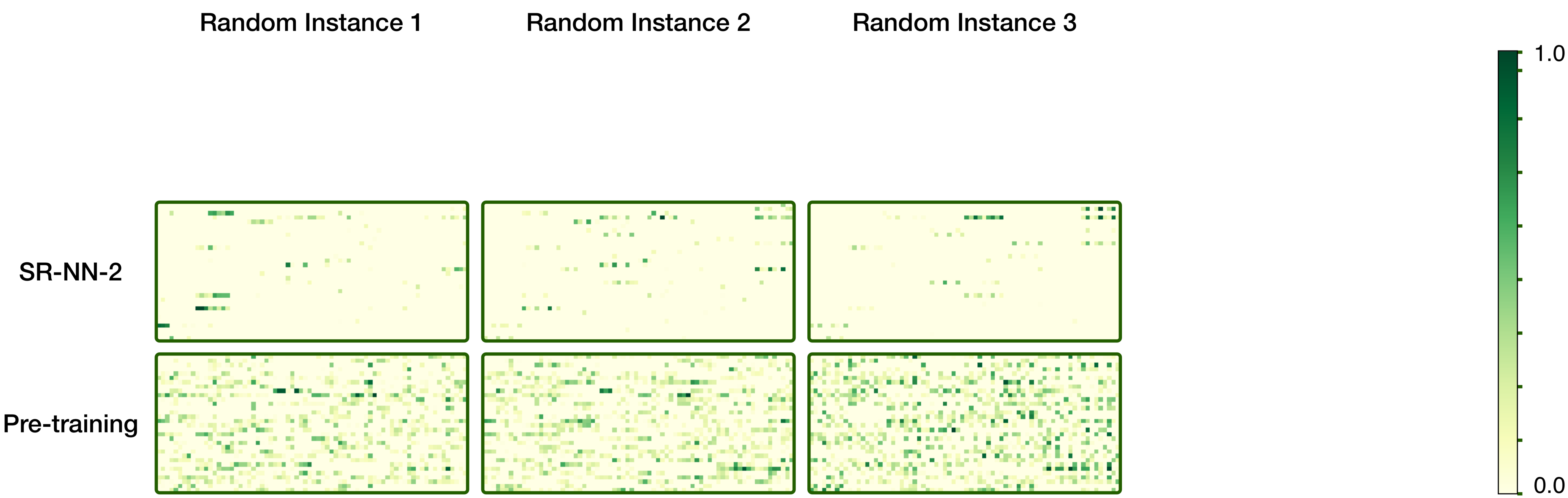
- **MRCL:** 3.8%
- **SR-NN-2**: 4.9%

Visualizing representations

Visualizing representations



Visualizing representations



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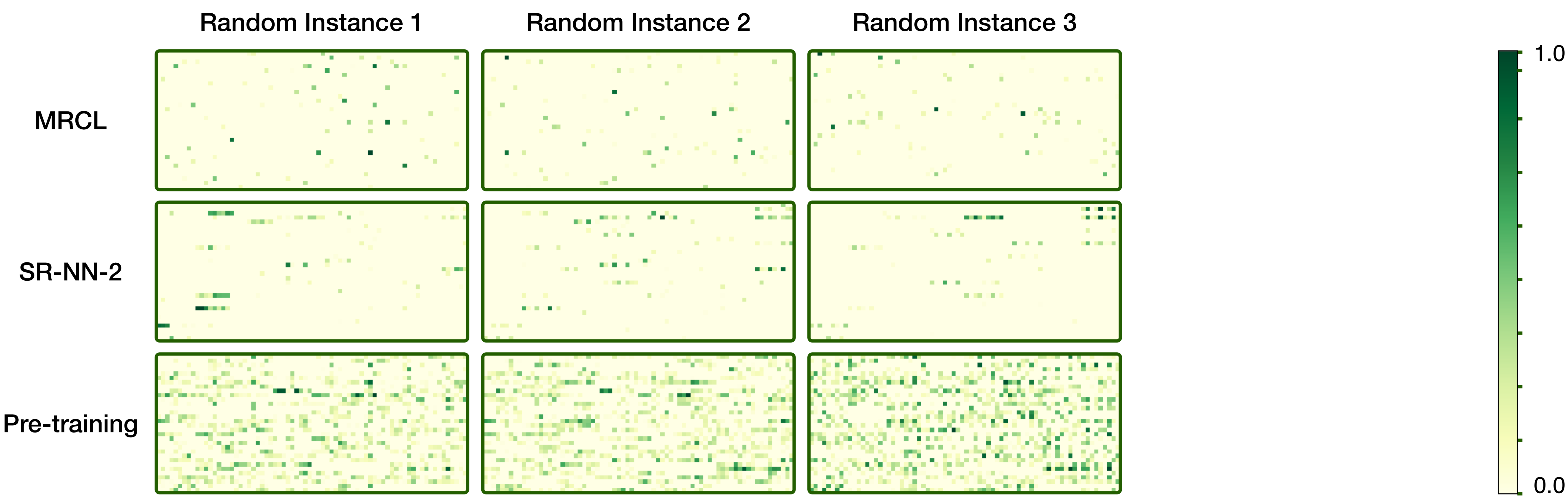

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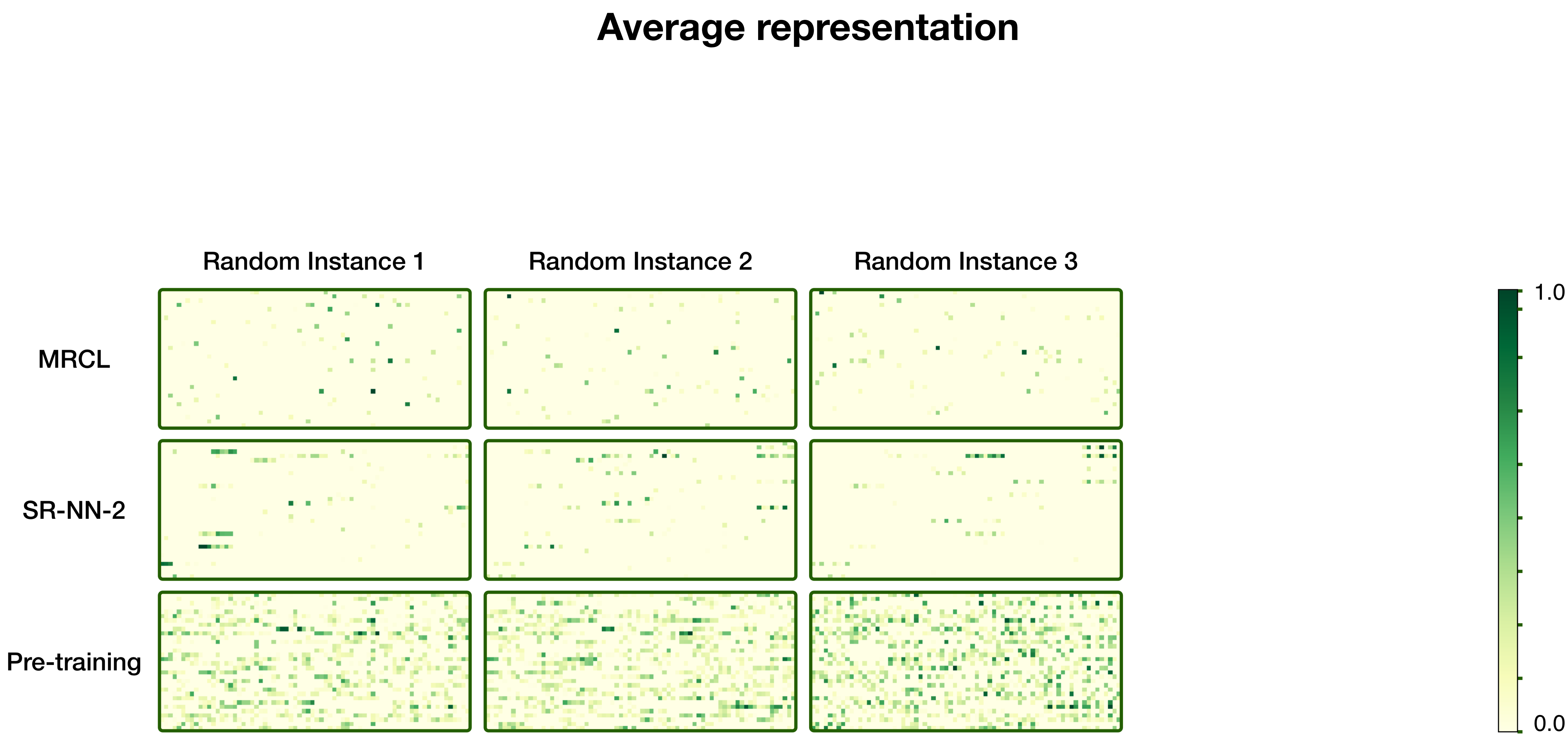
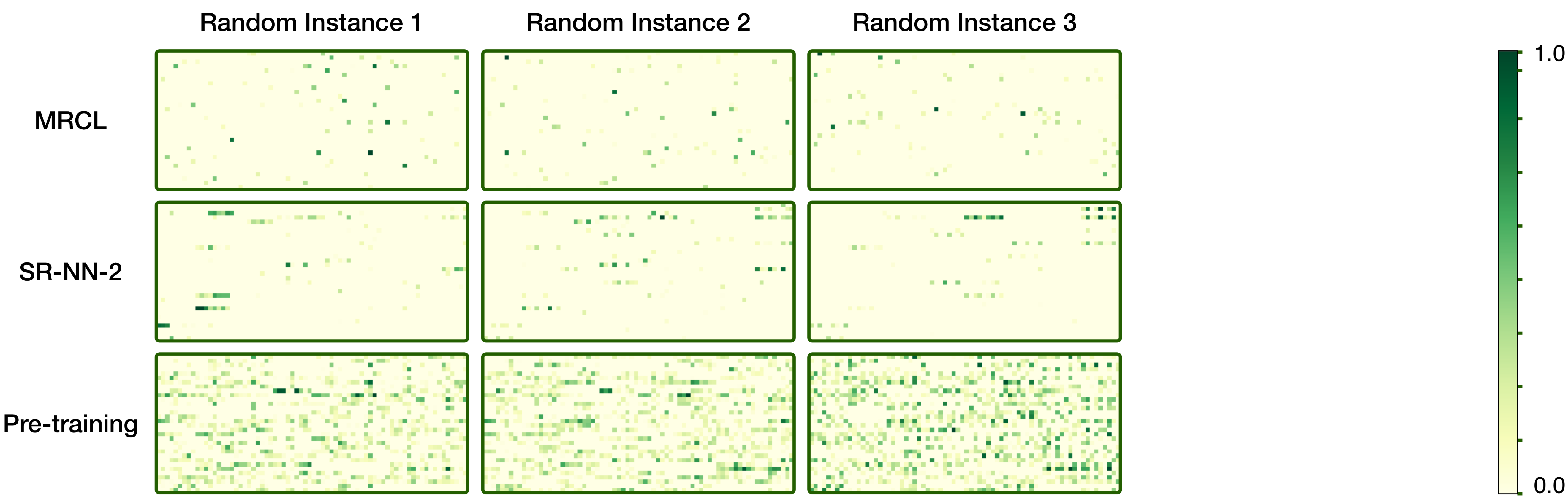


Visualizing representations

Average representation

Compute representation of the complete representation learning dataset



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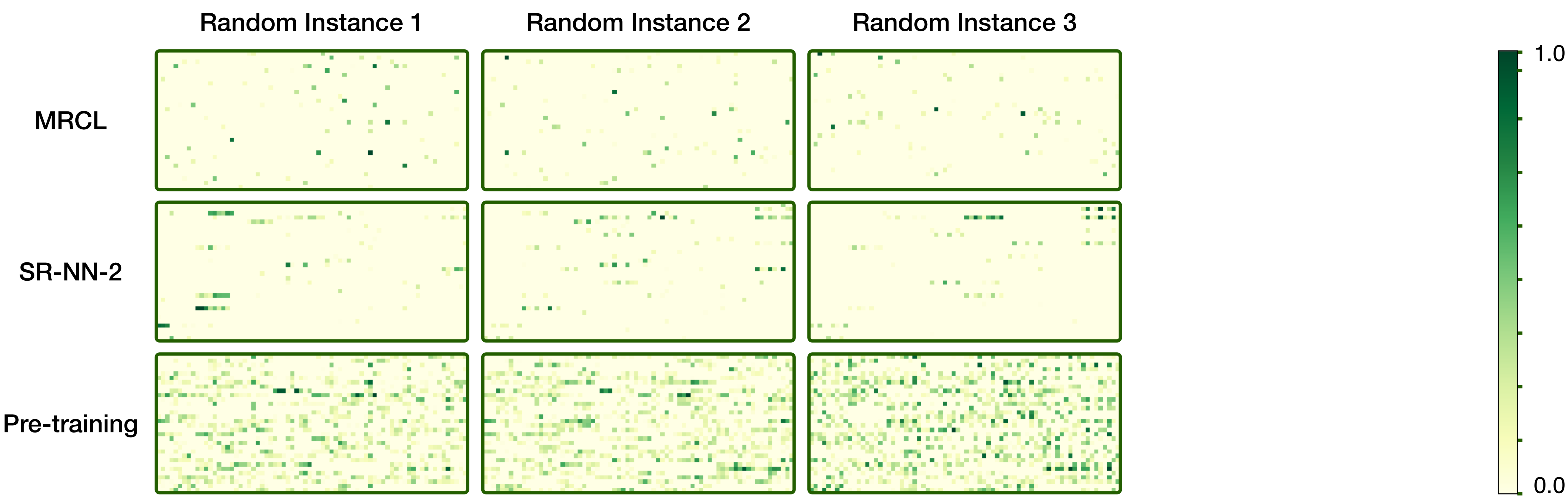
Compute the average representation vector



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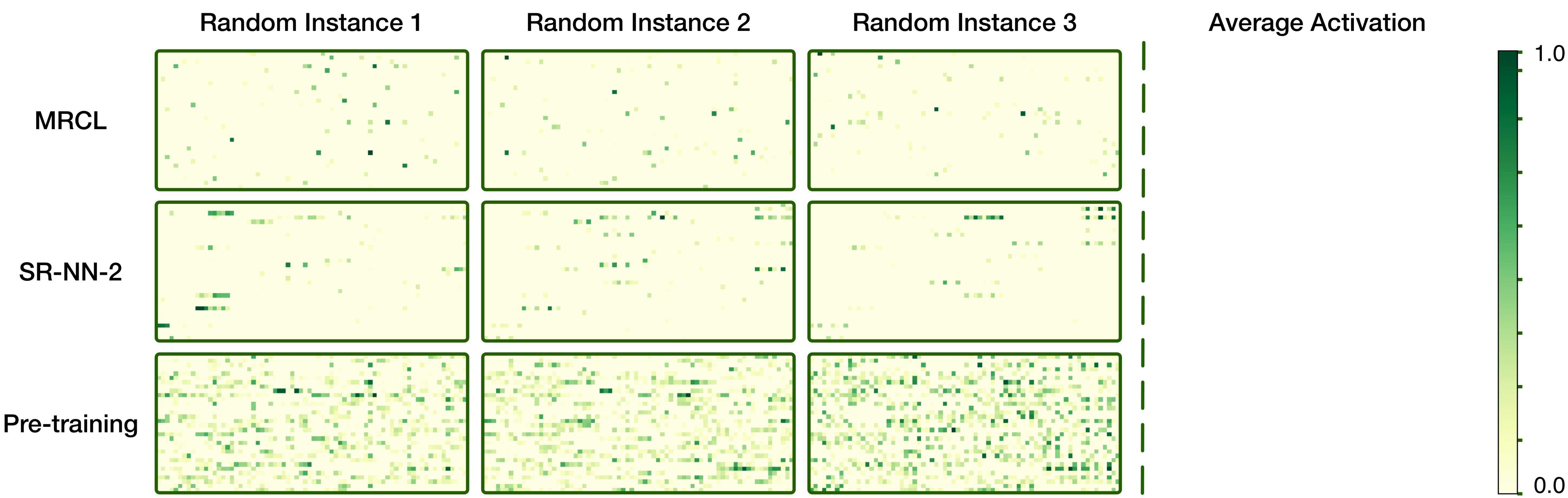

Visualizing representations

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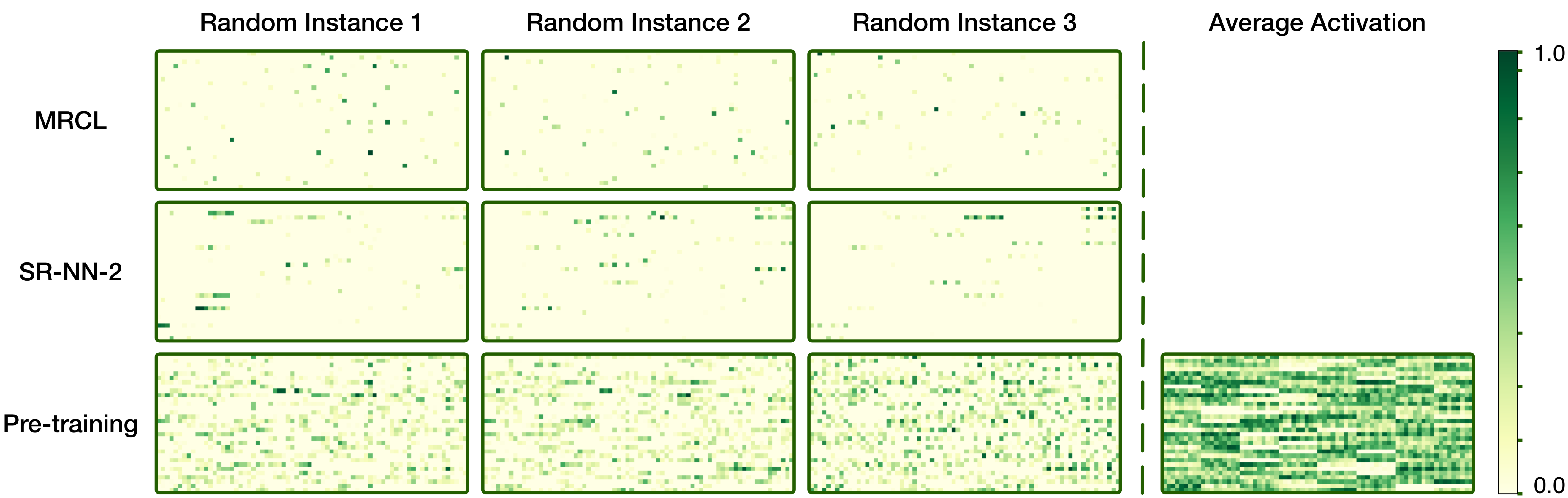

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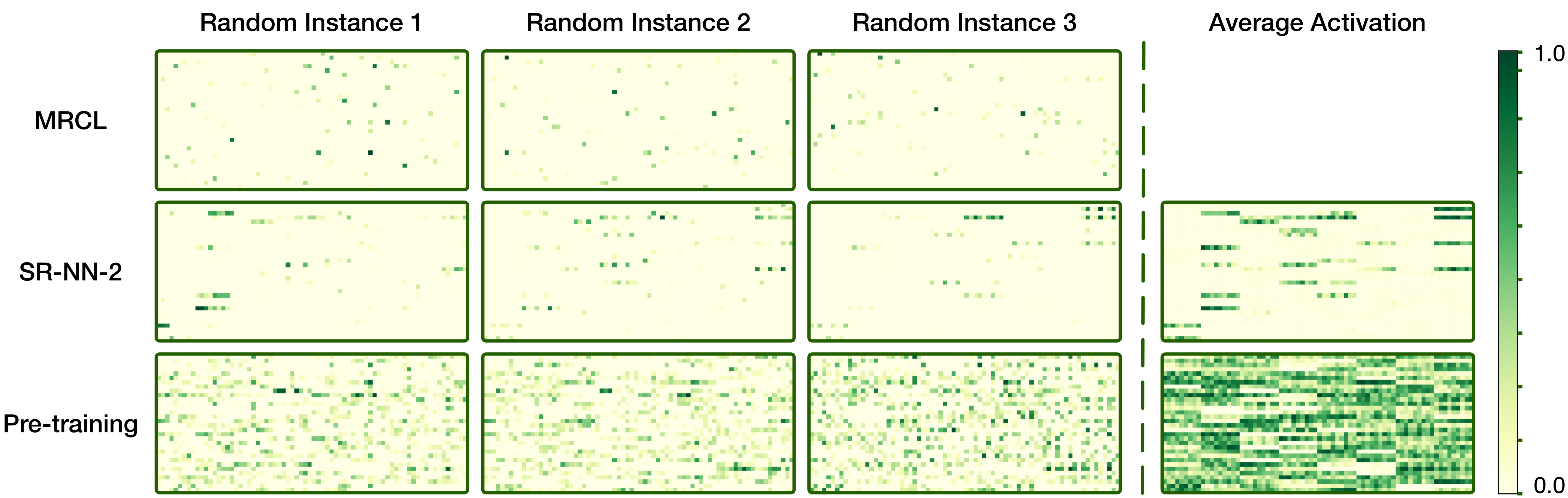

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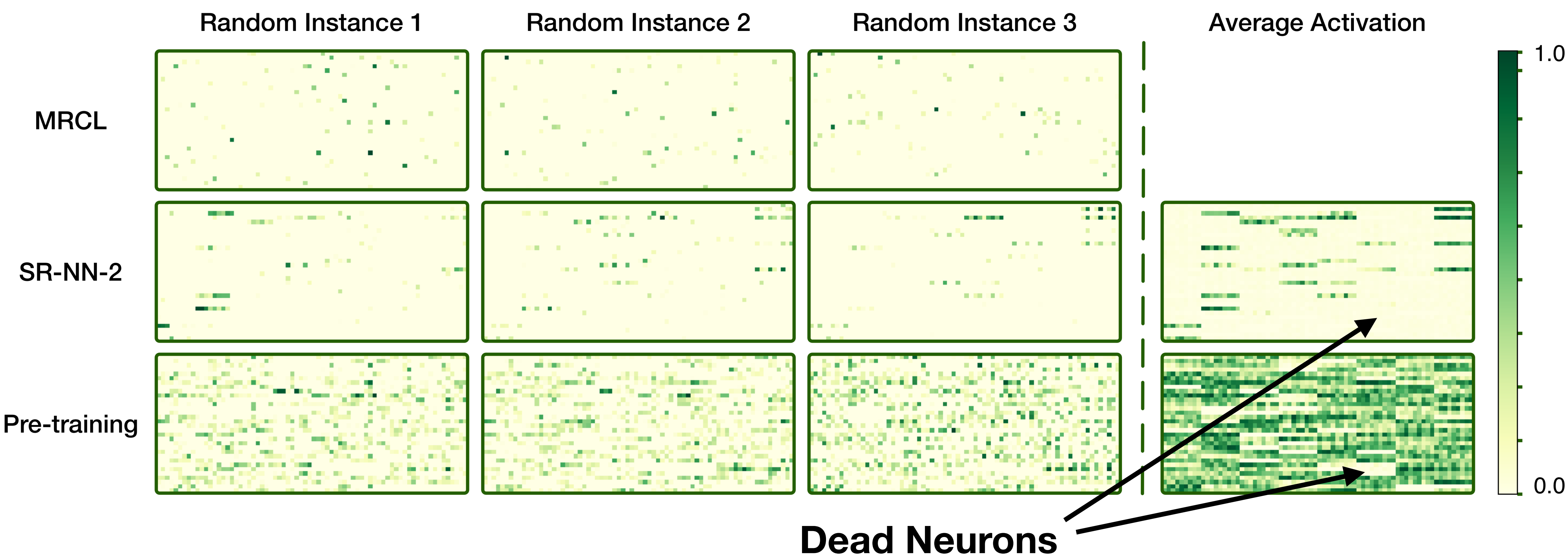

Visualizing representations

Average representation

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Visualizing representations

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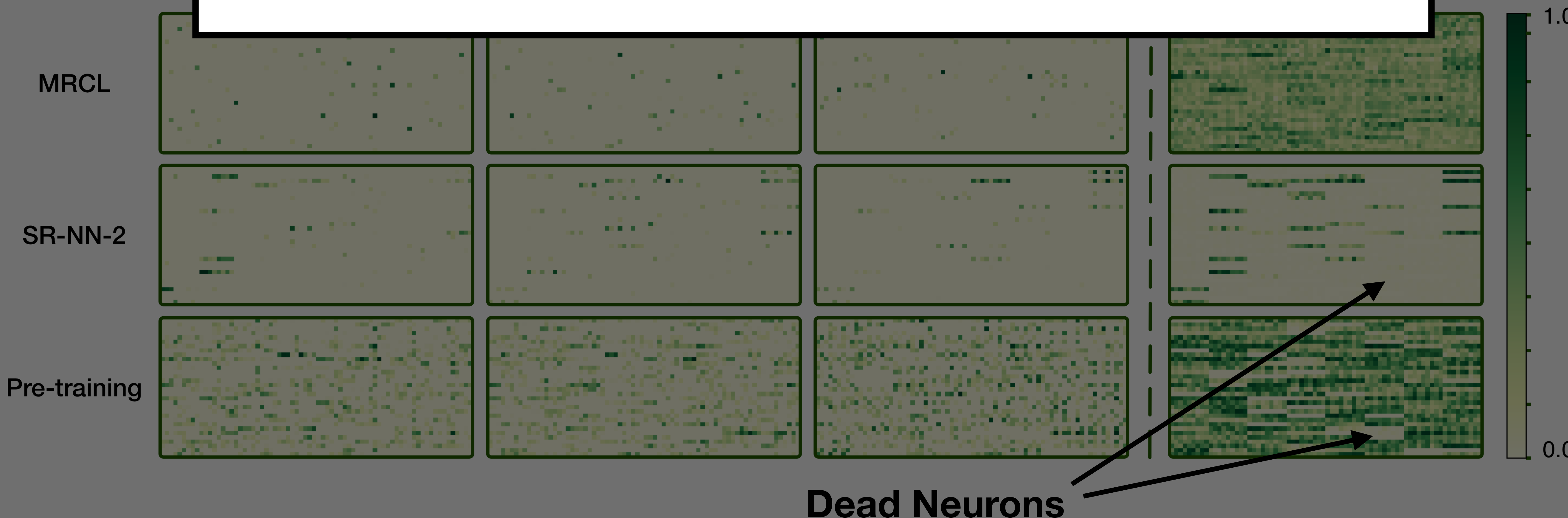
Possible explanation

MRCL does better because it is learning the right kind of sparsity!



Is catastrophic interference solved?

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- No! We assumed we have access to a dataset for learning representations

Is catastrophic interference solved?

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- Representation learning is not online

Is catastrophic interference solved?

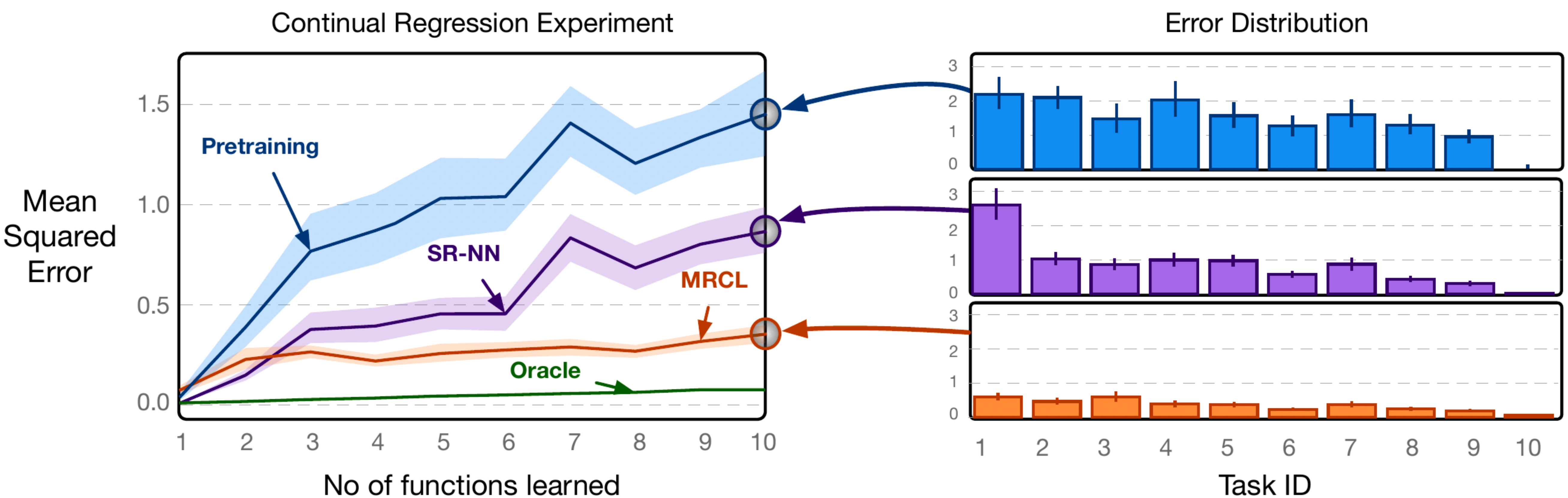
- No! We assumed we have access to a dataset for learning representations
- Representation learning is not online
- However, positive preliminary results for online representation learning

Questions?

Paper: https://arxiv.org/pdf/1905.12588.pdf

Code: https://github.com/khurramjaved96/mrcl

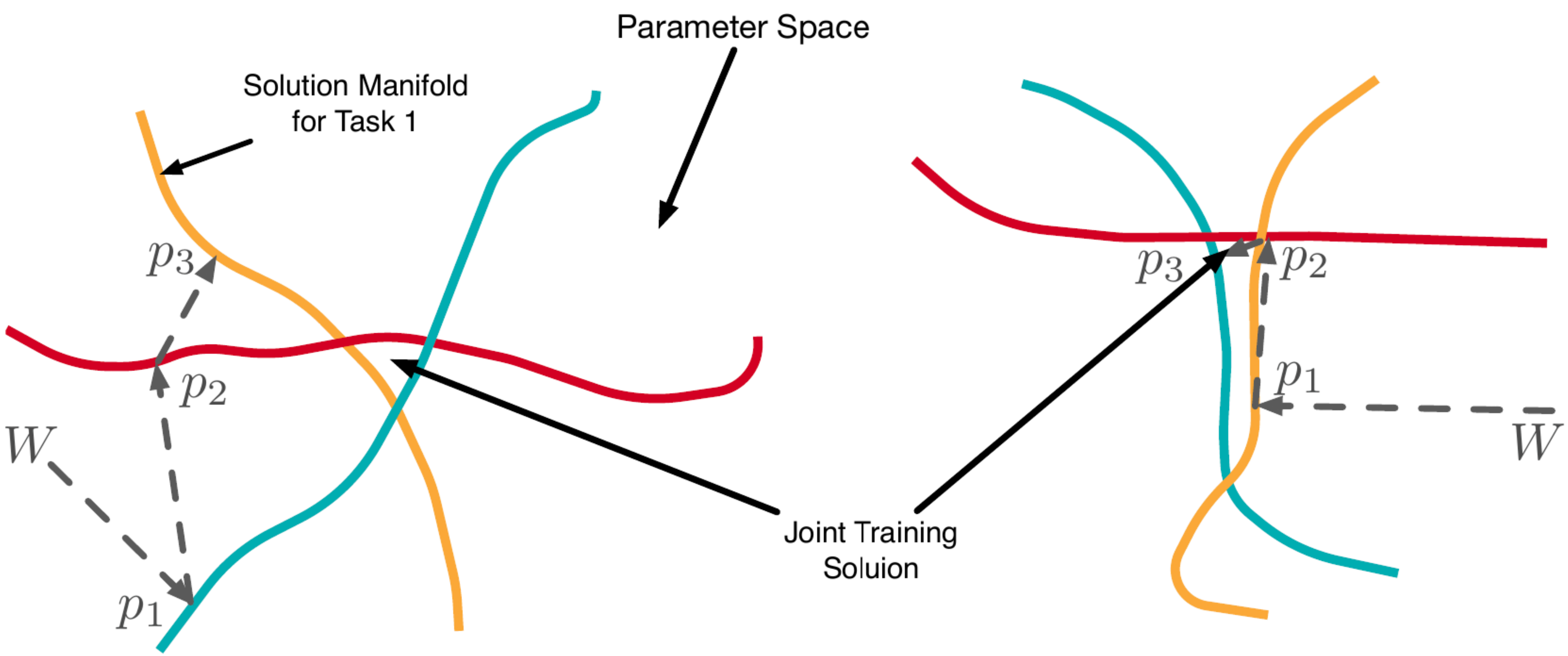
Continual Regression Tasks



Combining with existing methods

	Split-Omniglot					
	One class per task, 50 tasks			Five classes per task, 20 tasks		
Method	Standard	MRCL	Pretraining	Standard	MRCL	Pretraining
Online	04.64 ± 2.61	**64.72** ± 2.57	21.16 ± 2.71	01.40 ± 0.43	**55.32** ± 2.25	11.80 ± 1.92
Approx IID	53.95 ± 5.50	**75.12** ± 3.24	54.29 ± 3.48	48.02 ± 5.67	**67.03** ± 2.10	46.02 ± 2.83
ER-Reservoir	52.56 ± 2.12	**68.16** ± 3.12	36.72 ± 3.06	24.32 ± 5.37	**60.92** ± 2.41	37.44 ± 1.67
MER	54.88 ± 4.12	**76.00** ± 2.07	62.76 ± 2.16	29.02 ± 4.01	**62.05** ± 2.19	42.05 ± 3.71
EWC	05.08 ± 2.47	**64.44** ± 3.13	18.72 ± 3.97	02.04 ± 0.35	**56.03** ± 3.20	10.03 ± 1.53

Solution Manifolds



Solution manifolds for an unconstrained representation

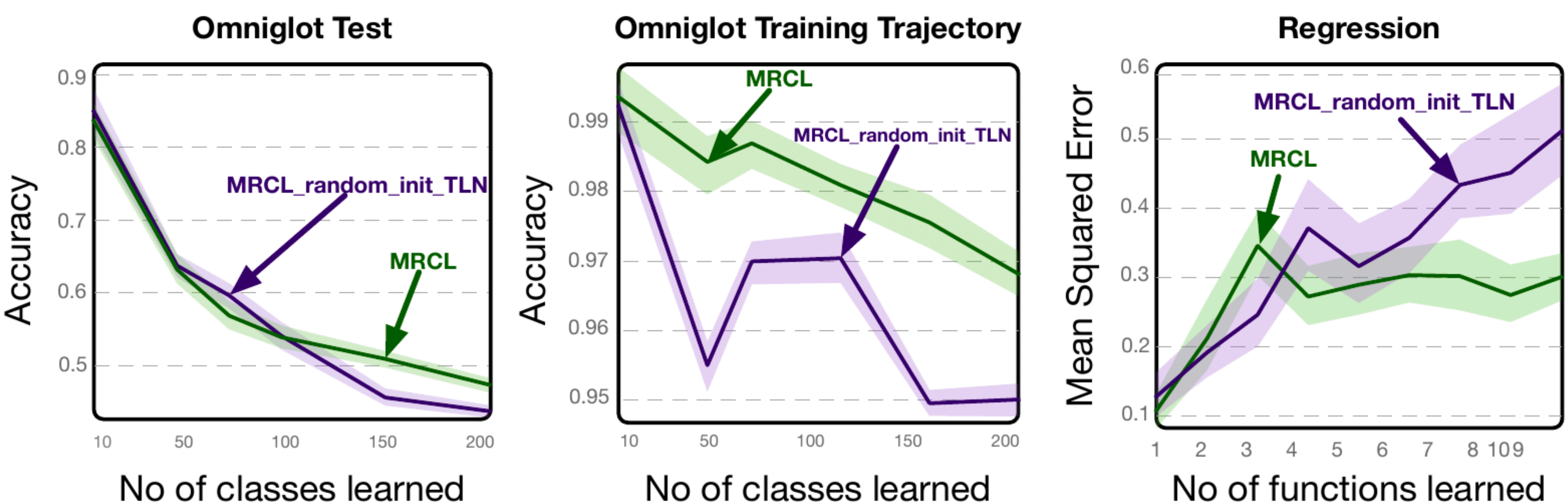
Solution manifolds for an ideal representation for continual learning

Pseudo-code

Algorithm 1: MRCL for optimizing objective in (3)

Require: $\mathcal{D}_{stream} = (X_1, Y_1), (X_2, Y_2), \ldots, (X_t, Y_t), \ldots;$
Require: $g_W(\phi_\theta(x))$ as a parametrized function;
Require: $\alpha, \beta, \mathcal{L}, n$ as meta learning rate, inner learning rate, loss metric over (X_i, Y_i) and total gradient updates;
Initialize RLN and TLN to θ and W;
for *iterations* $1, 2, 3, \ldots, n$ **do**
    Sample trajectory $(\mathbf{X_{traj}}, \mathbf{Y_{traj}}) = (X_{i+1}, Y_{i+1}) \ldots (X_{i+k}, Y_{i+k}) \sim \mathcal{D}_{stream}$;
    $W_0 = W$;
    for *j in* $1, 2, 3, \ldots, k$ **do**
        $W_j = W_{j-1} - \beta \nabla_{W_{j-1}} (\mathcal{L}(g_{W_{j-1}}(\phi_\theta(X_{i+j})), Y_{i+j});$
    end
    $(\mathbf{X_{rand}}, \mathbf{Y_{rand}}) \sim \mathcal{D}_{stream}$;   Sample a random batch of data
    $(\mathbf{X_{meta}}, \mathbf{Y_{meta}}) = (\mathbf{X_{rand}} + \mathbf{X_{traj}}, \mathbf{Y_{rand}} + \mathbf{Y_{traj}});$
    $W, \theta = (W, \theta) - \alpha \nabla_{W,\theta} \mathcal{L}(g_{W_k}(\phi_\theta(\mathbf{X_{meta}})), \mathbf{Y_{meta}});$
end

PLN Initialization



Generalization Error