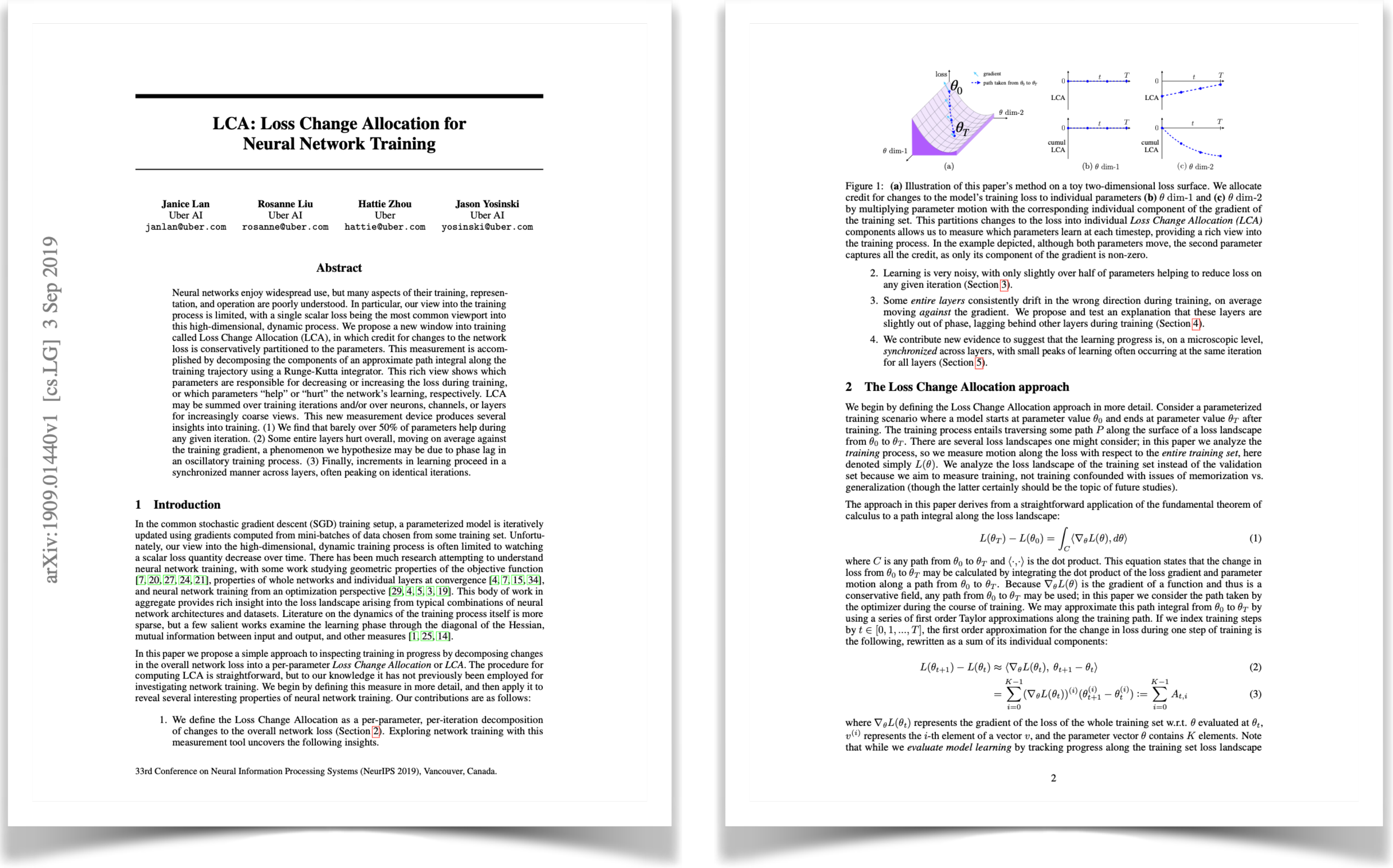
# Two small ideas:
# Approximate LCA, Computational Ethics

MLC Research Jam
28 May 2025

Jason Yosinski
jason@yosinski.com

# Idea #1: Approximate LCA (Loss Change Allocation)


LCA: Loss Change Allocation for Neural Network Training

Janice Lan, Uber AI, janlan@uber.com
Rosanne Liu, Uber AI, rosanne@uber.com
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Jason Yosinski, Uber AI, yosinski@uber.com

Abstract

1 Introduction

2 The Loss Change Allocation approach

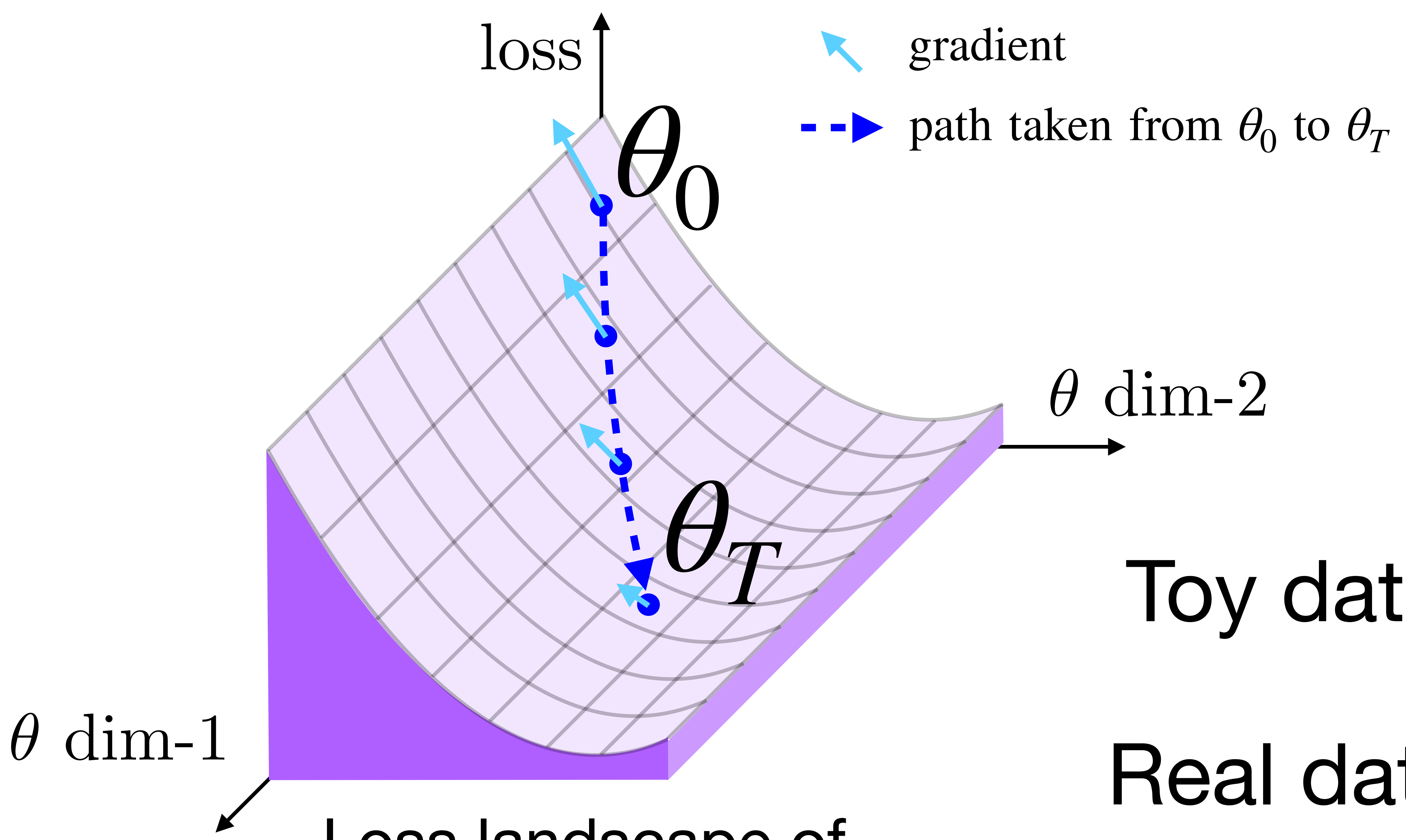
Janice Lan, Hattie Zhou, Rosanne Liu, Jason Yosinski. LCA: Loss Change Allocation for Neural Network Training, NeurIPS 2019.

😍 See training in progress!

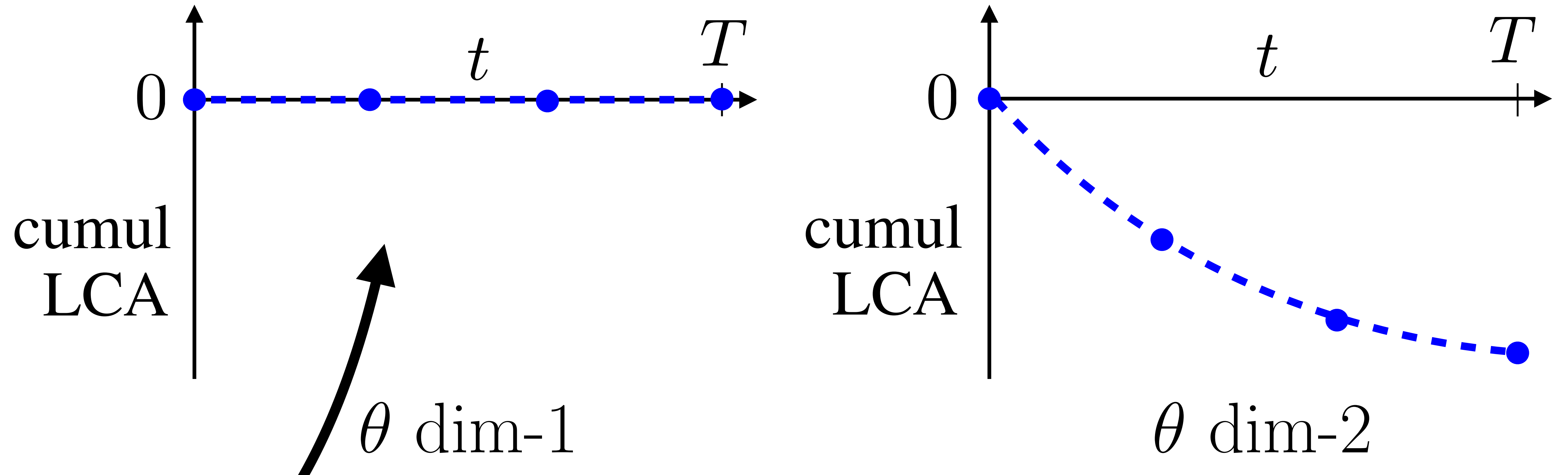
😭 Very slow

If we use aggressive approximation to make it faster, can it still provide useful visibility?

# LCA: Loss Change Allocation for Neural Network Training

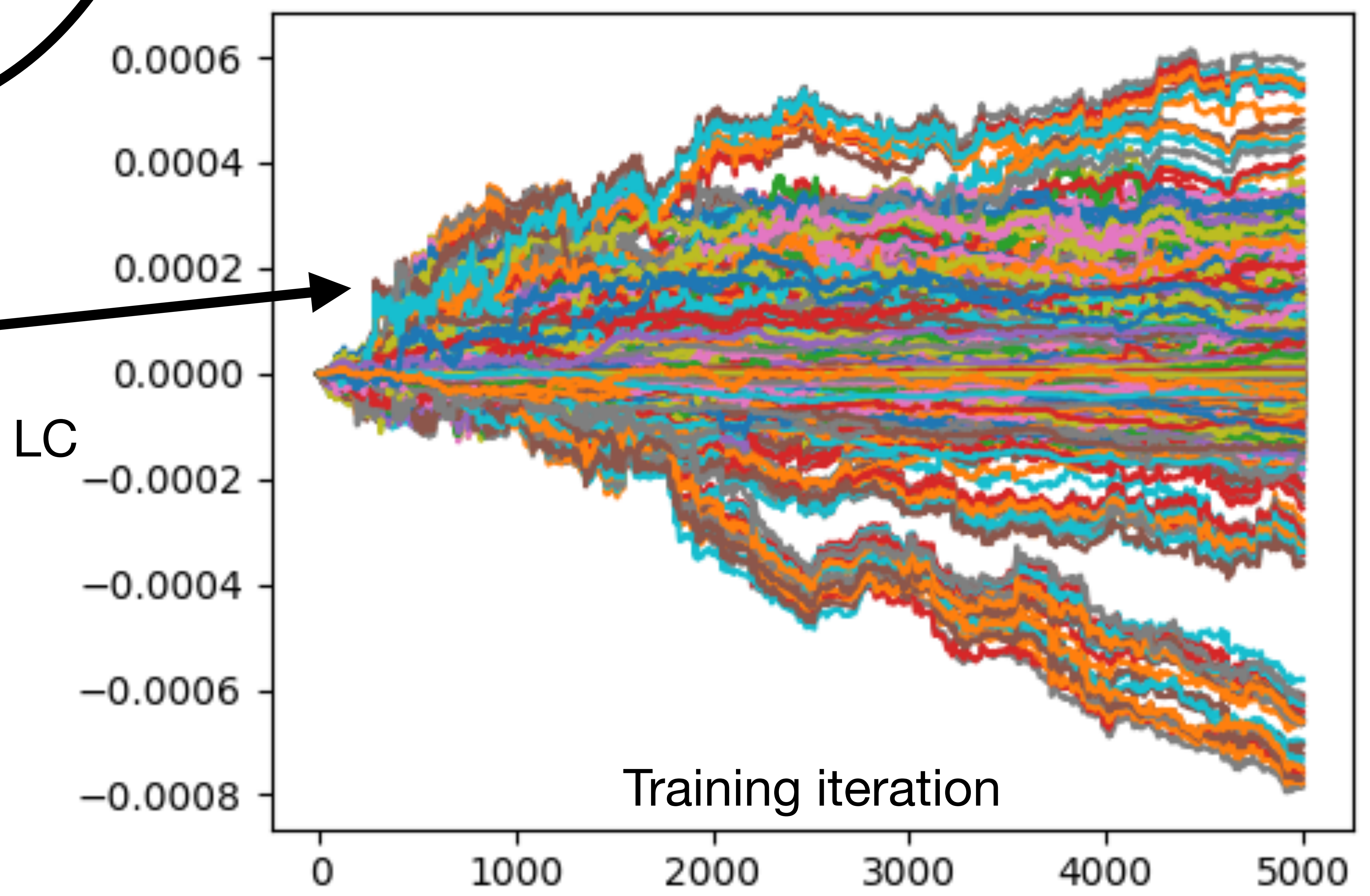



Loss landscape of entire train set




Toy data

Real data




Simple approach → New visibility into training

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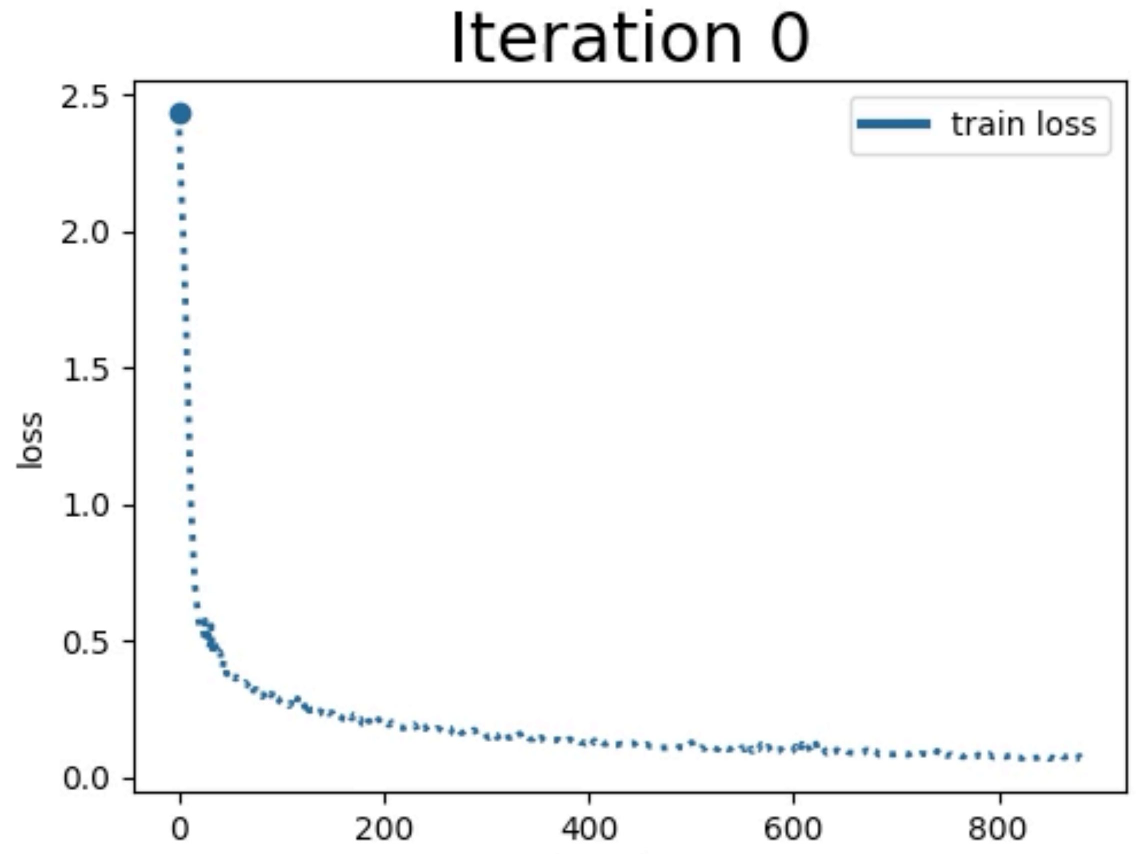


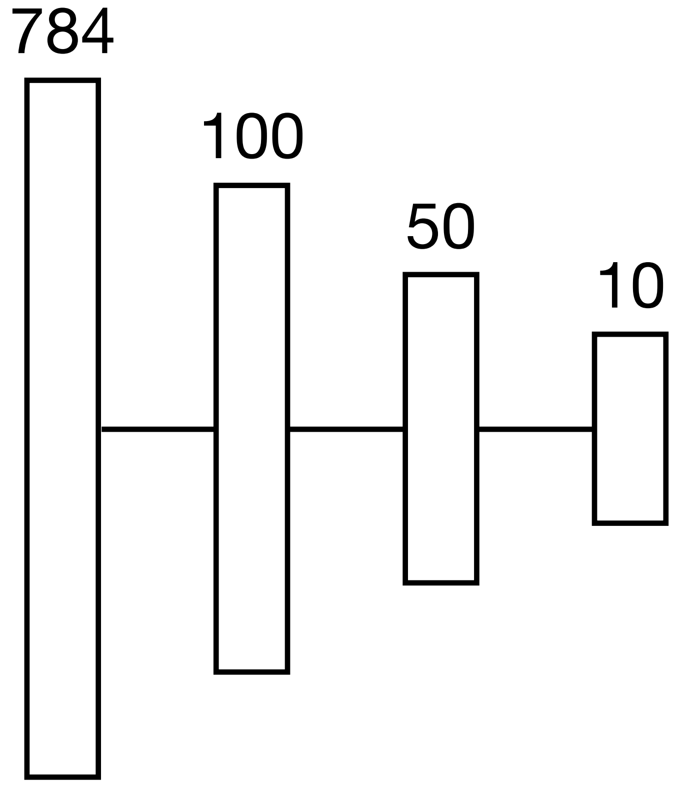


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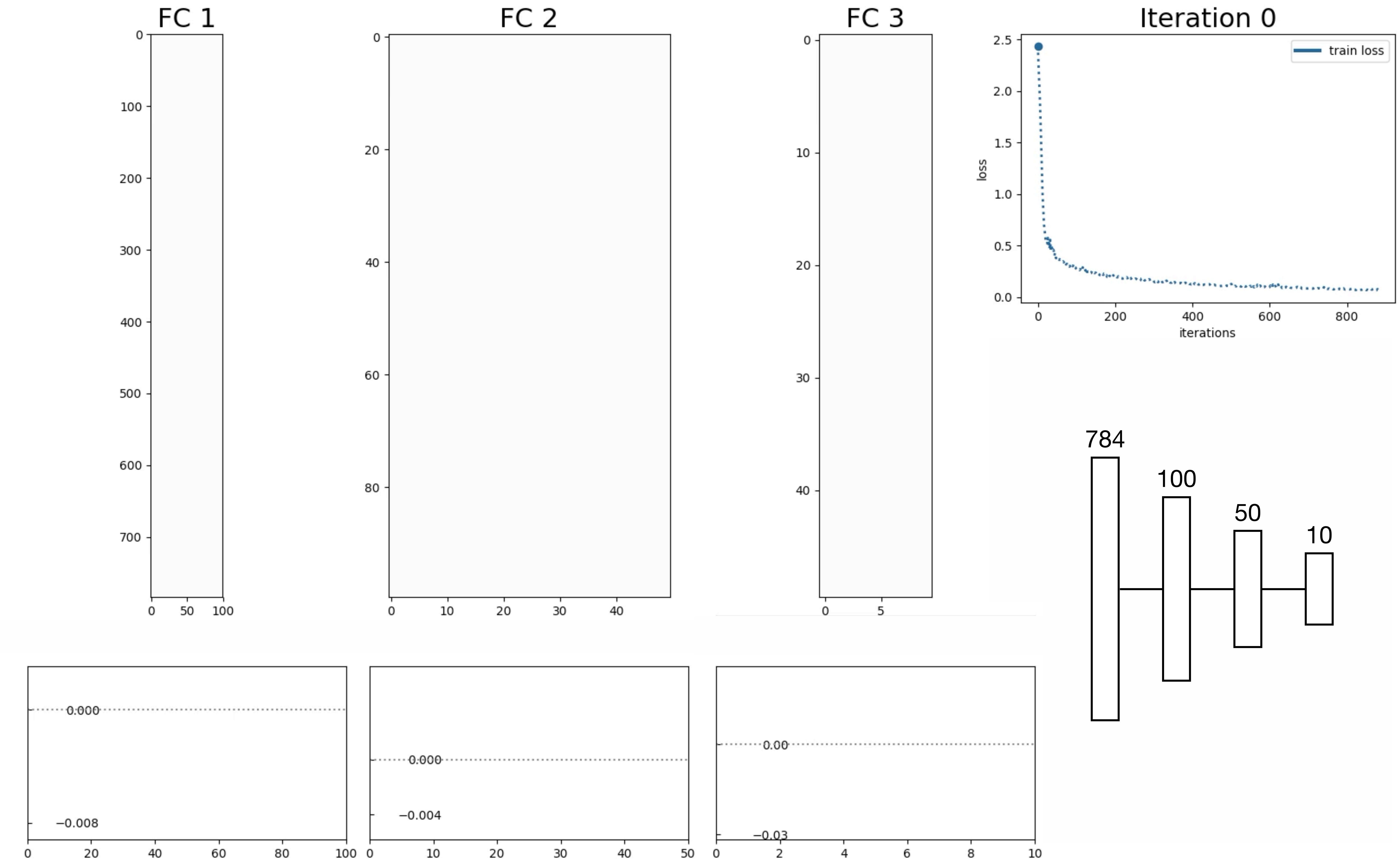


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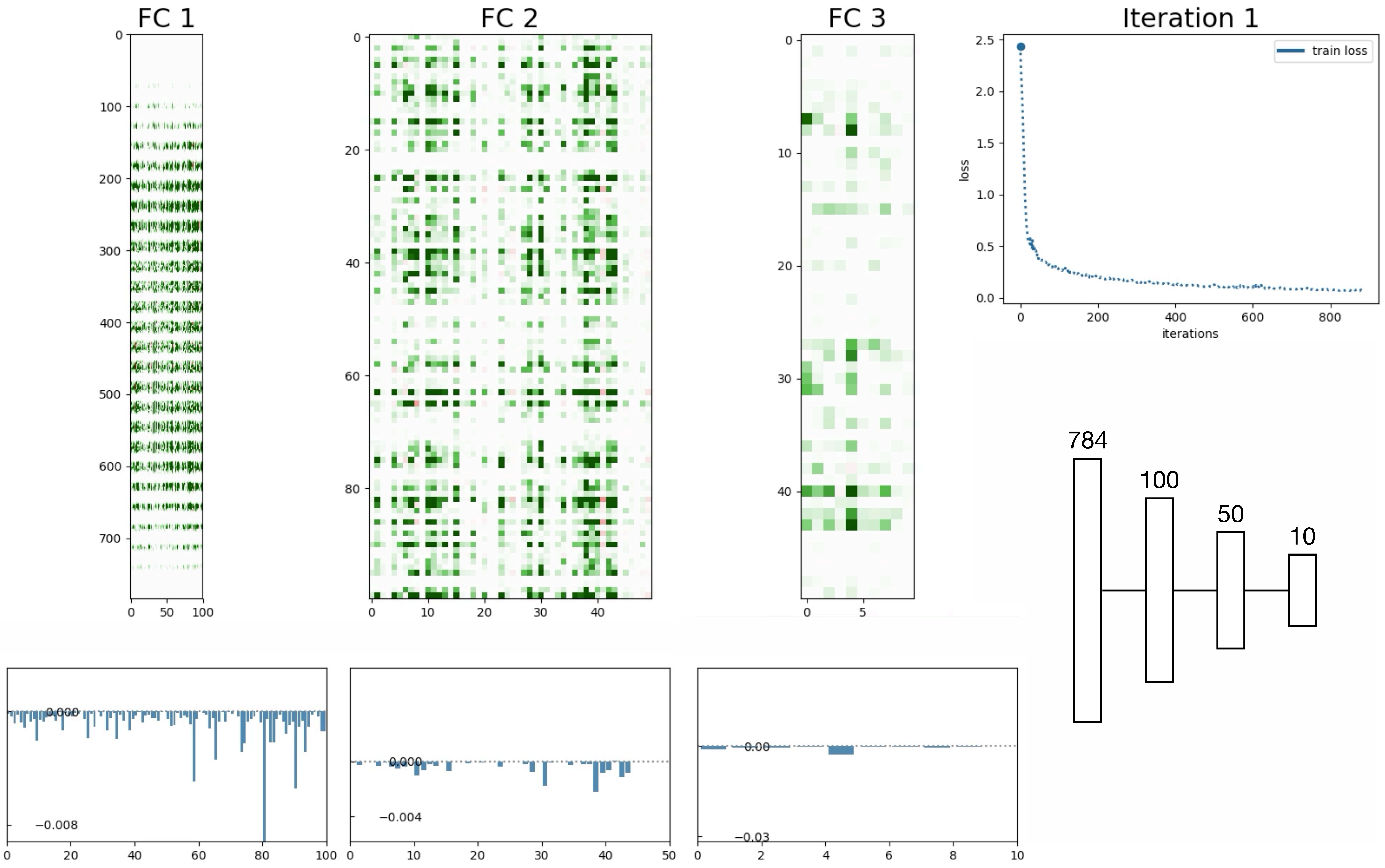


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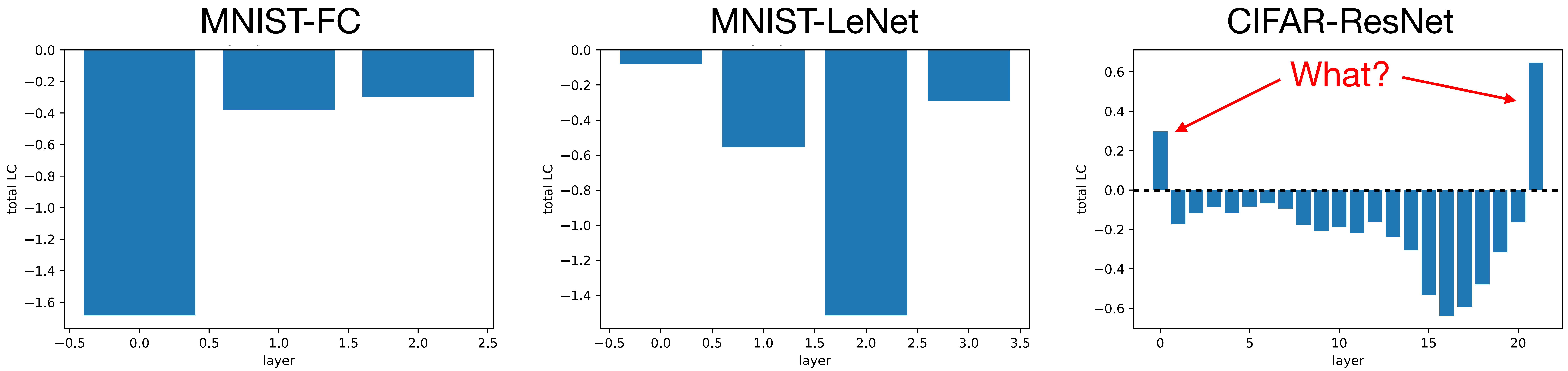
# LCA: Loss Change Allocation for Neural Network Training

Sum over layers

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# Request for Plot: Approximate LCA

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*Example: training set of 1000 batches*

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Ordinary training:
    Compute per batch: 1x

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Compute per batch: 1x

Original LCA:

$$\nabla L_{\text{train}}(\theta_i) \cdot (\theta_{i+1} - \theta_i)$$

Compute per batch: 1000x

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*Example: training set of 1000 batches*

Ordinary training:

Compute per batch: 1x

Original LCA:

$$\nabla L_{\text{train}}(\theta_i) \cdot (\theta_{i+1} - \theta_i)$$

Compute per batch: 1000x

Approximate LCA:

$$\nabla L_{\text{batch i}}(\theta_i) \cdot (\theta_{i+1} - \theta_i)$$

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$\cancel{\nabla L_{\text{batch i}}(\theta_i) \cdot (\theta_{i+1} - \theta_i)}$ Biased

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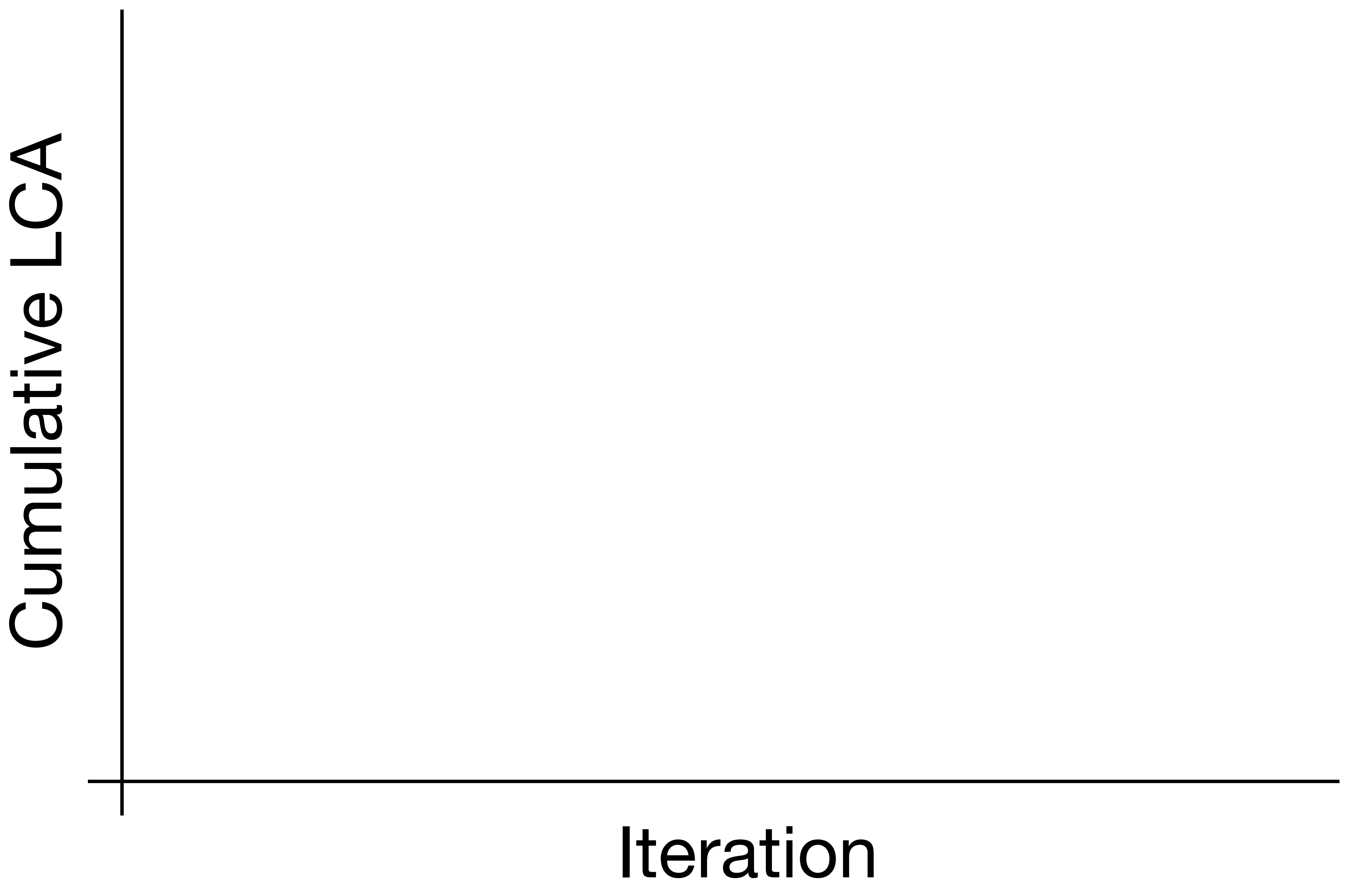
$$\nabla L_{\text{batch i+1}}(\theta_i) \cdot (\theta_{i+1} - \theta_i)$$

  Compute per batch: 1x

Is this approximation good?



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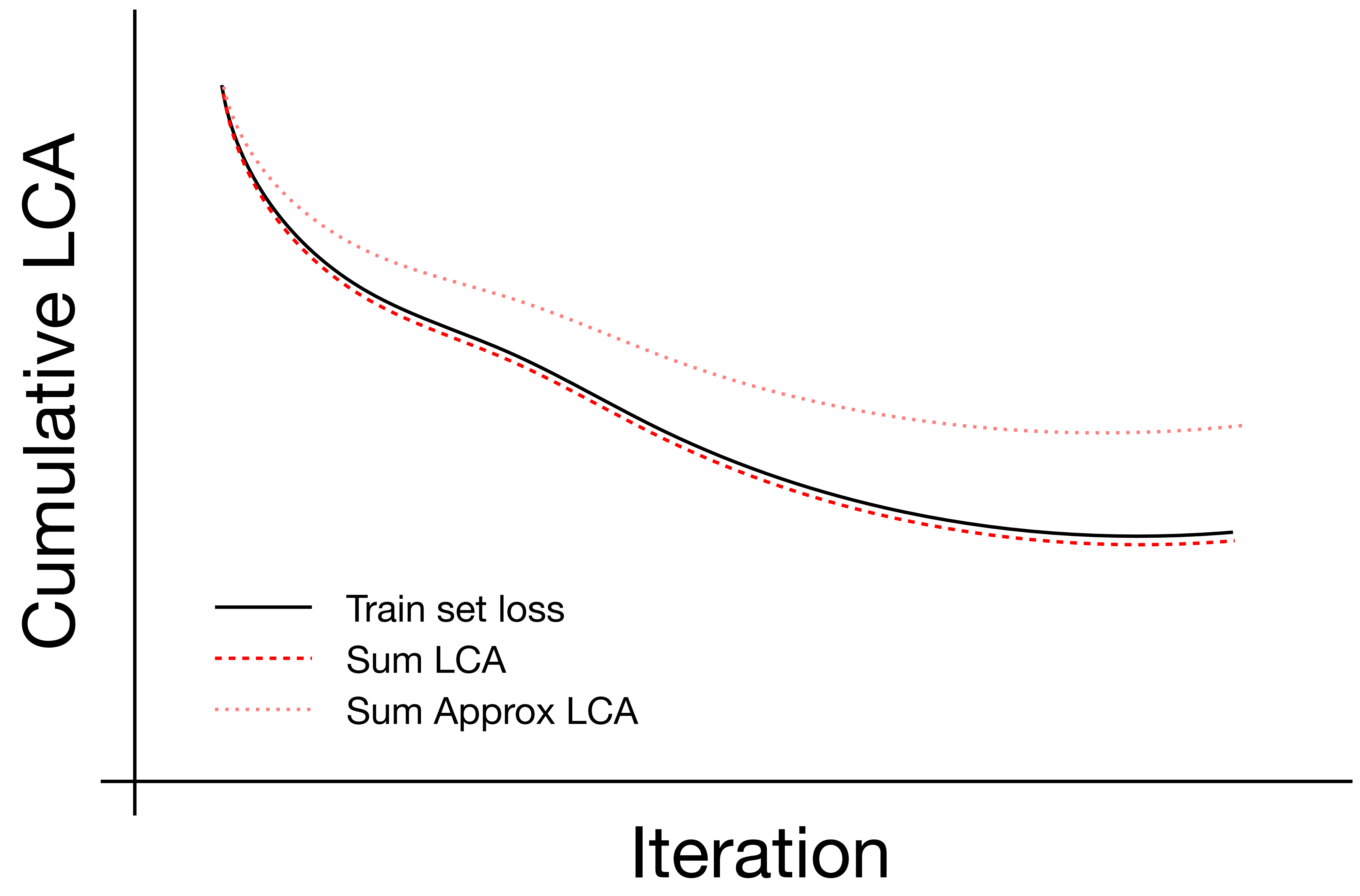

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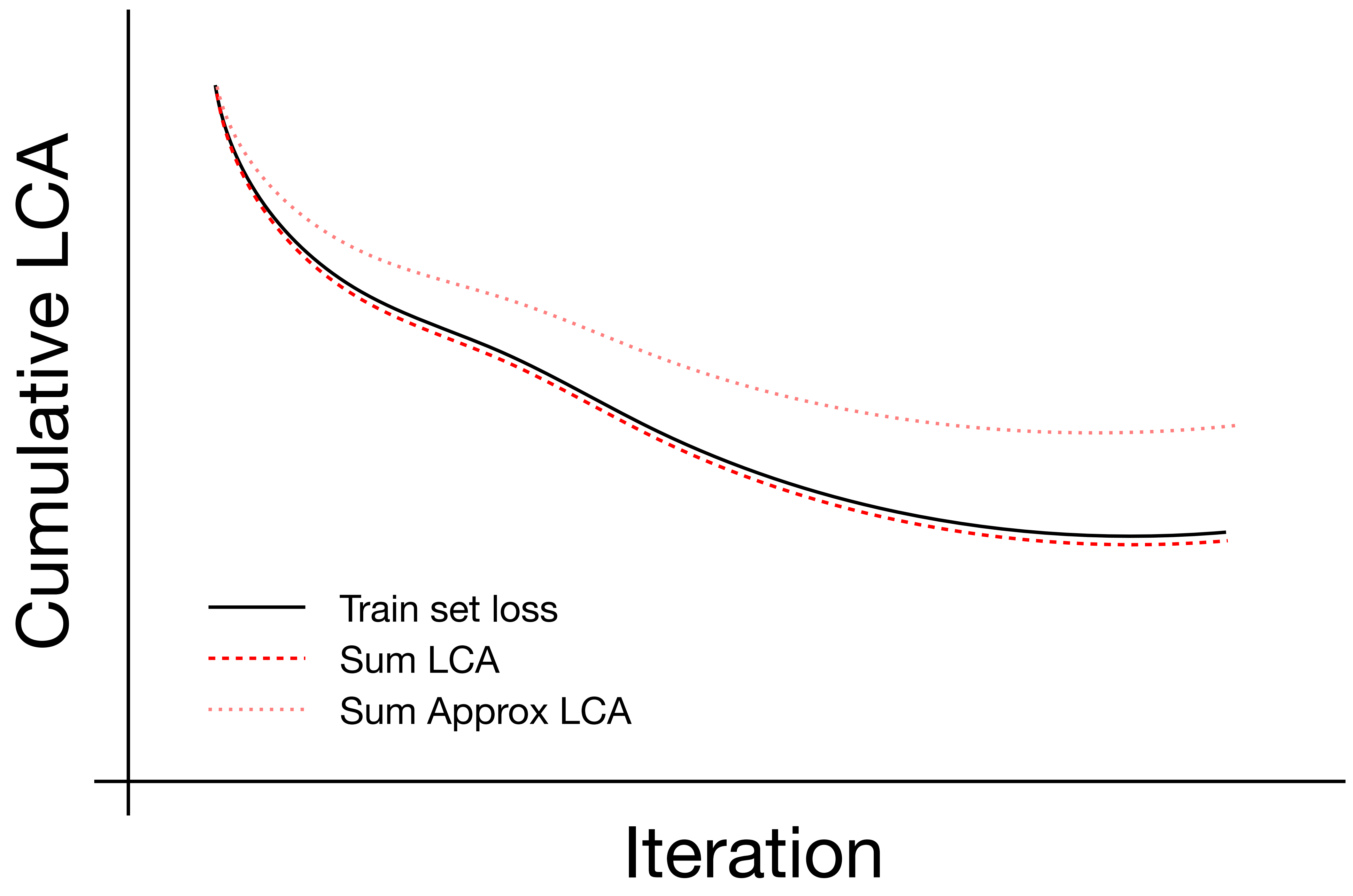


Next questions:
- How to incorporate RK-4?
- If this works, are per-layer sums also well approximated?

# Idea #2: Computational Ethics

## How we used to do Computer Vision

- Humans create features
- Failures → humans create smarter features
- Endless Whack-a-mole


## How we align models now

- Humans write prompts (constitutions, specs)
- Failures → humans create smarter prompts
- Endless Whack-a-mole

  See e.g. 24k token Claude system prompt: "…Claude provides emotional support alongside accurate medical or psychological information or terminology where relevant."

## What worked better

- Models learn their own features

## What might work better?

- Models learn their own ethics
- Start with using models to map the existing, diverse landscape of human ethics

# Appendix: extra LCA slides

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Janice Lan, Hattie Zhou, Rosanne Liu, Jason Yosinski. NeurIPS 2019.

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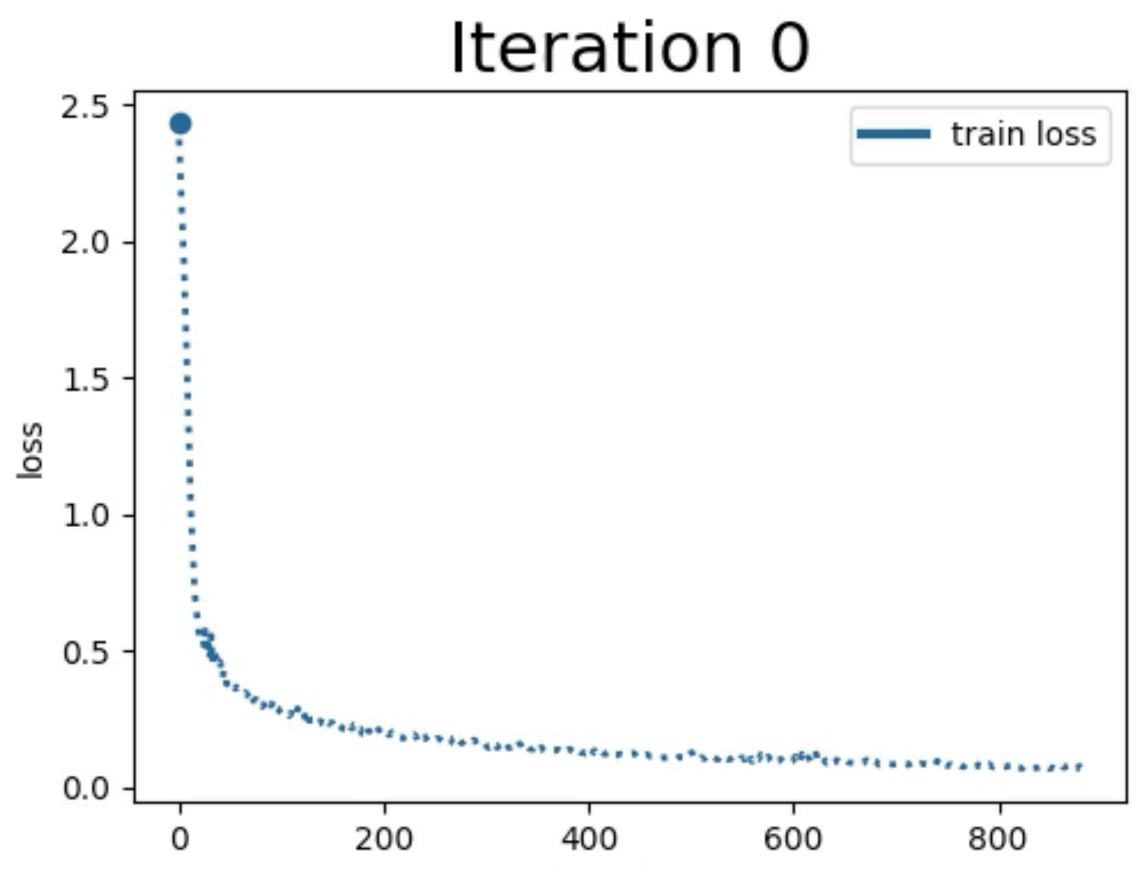


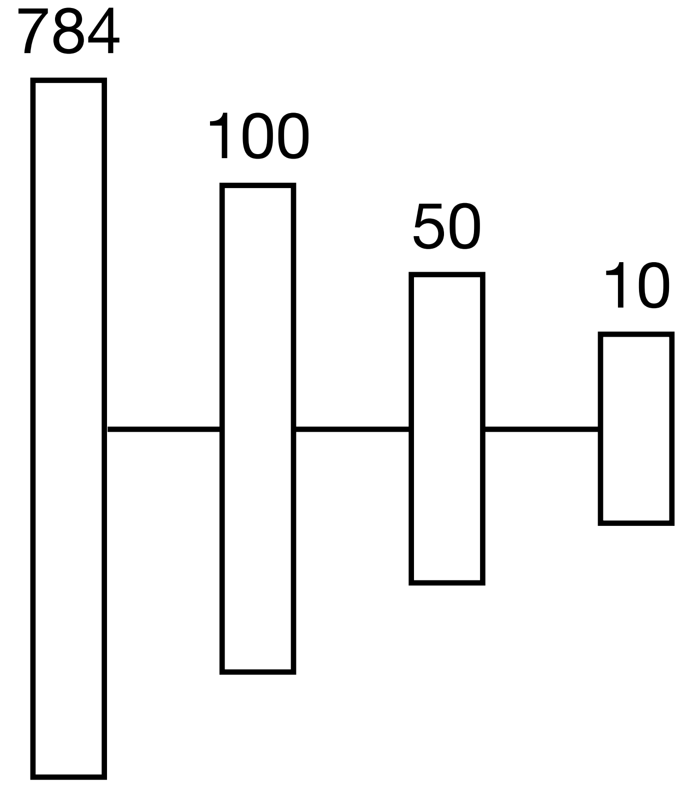


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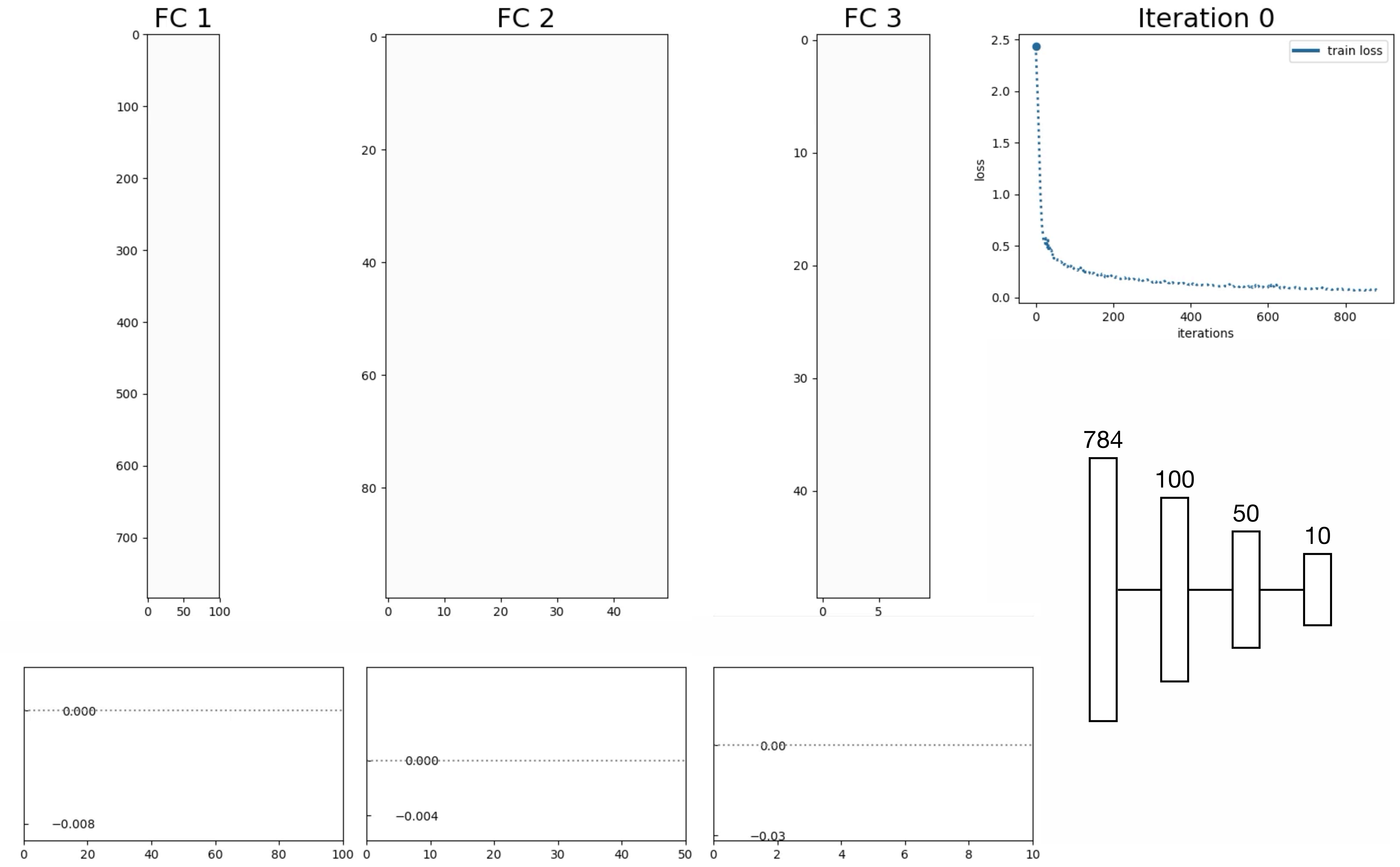


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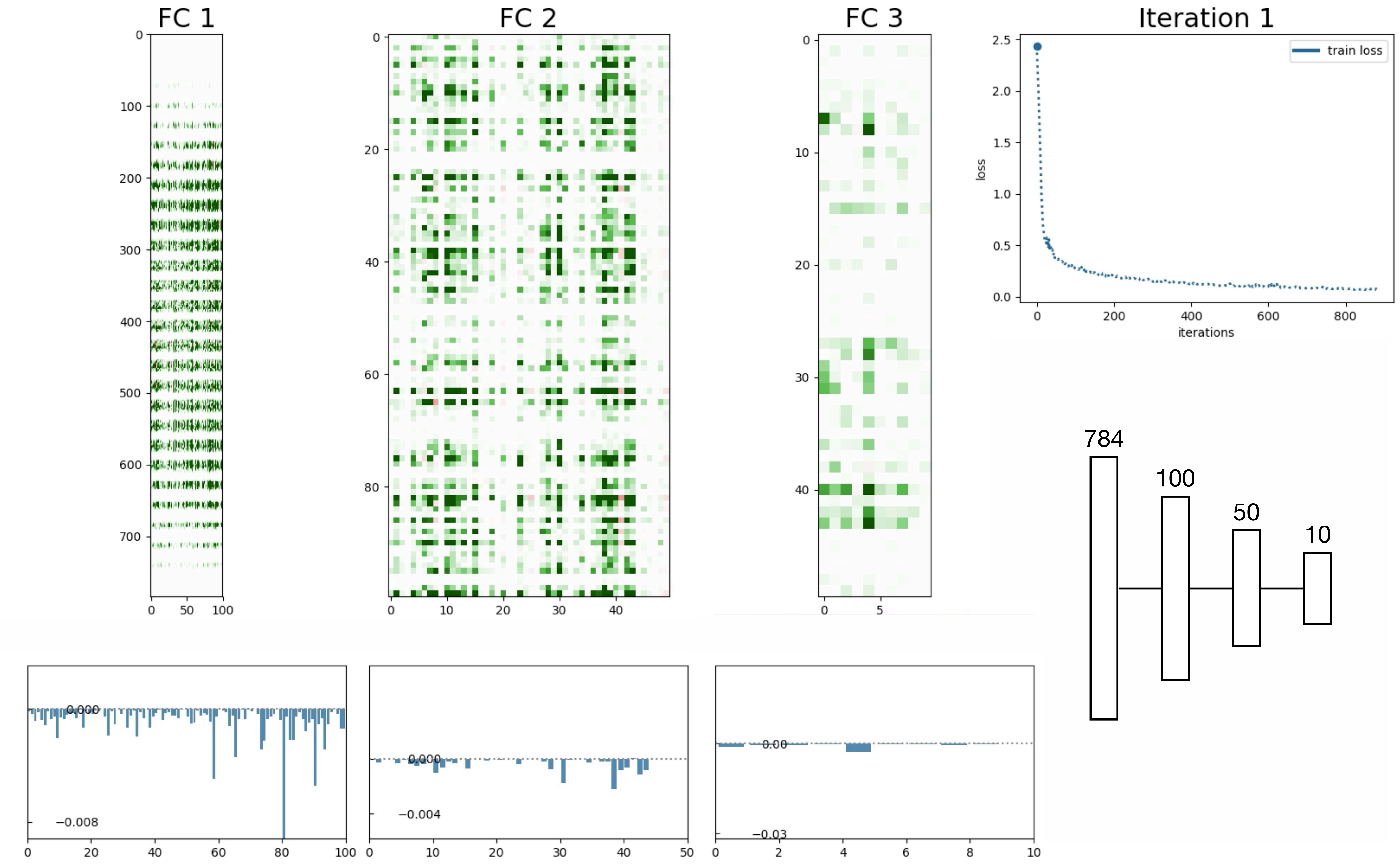


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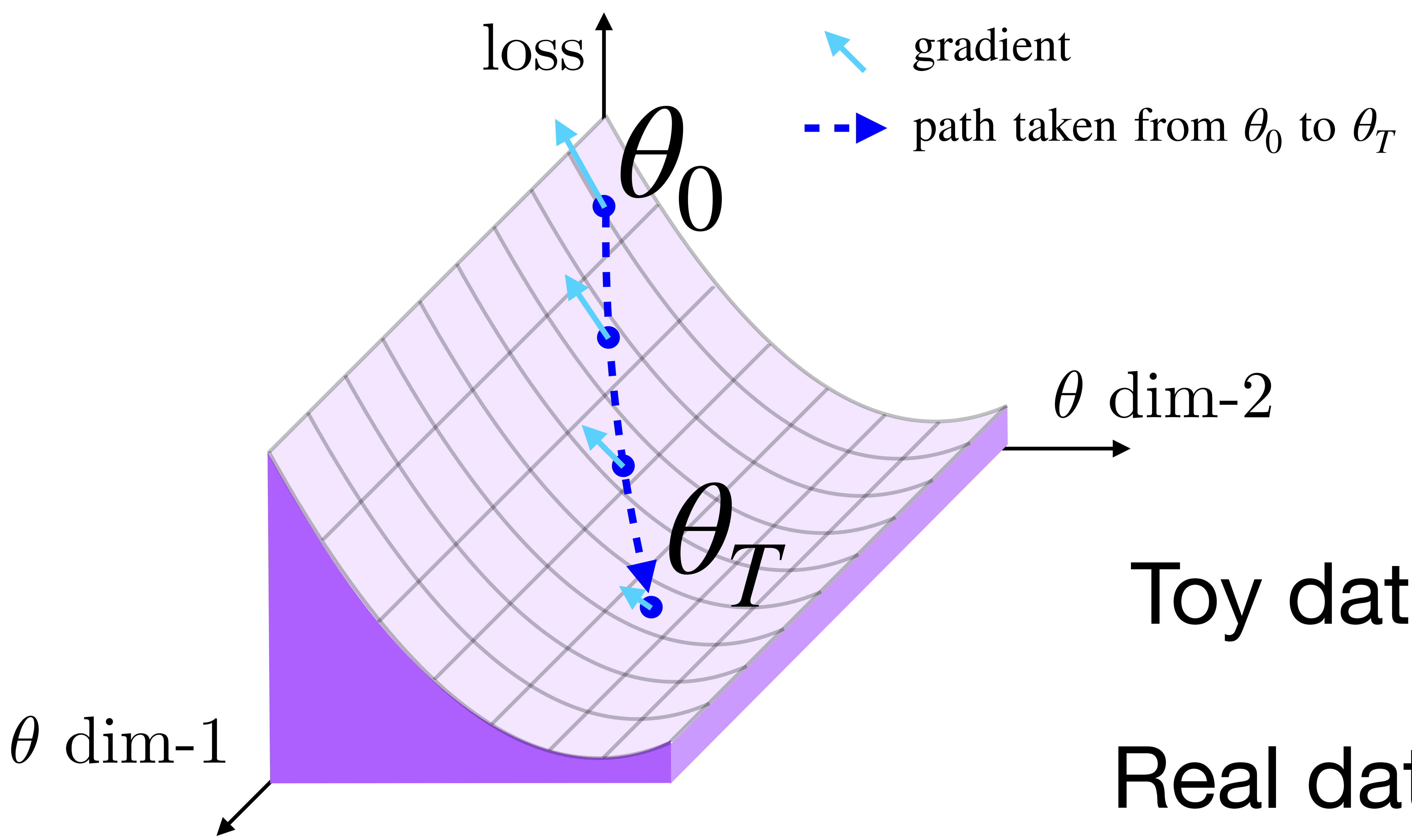
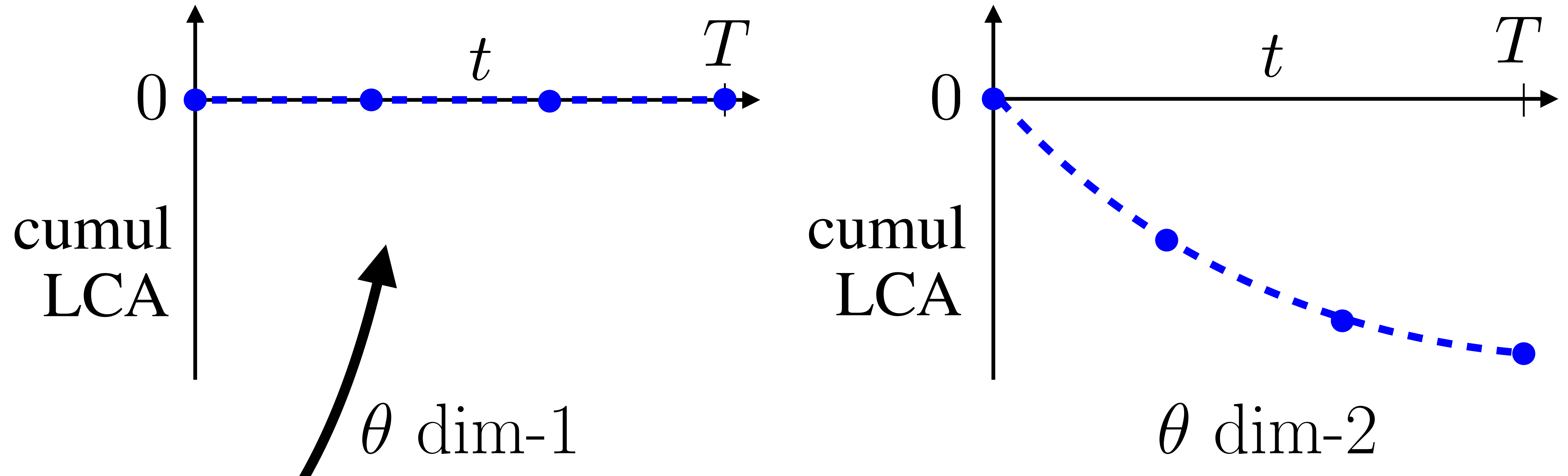
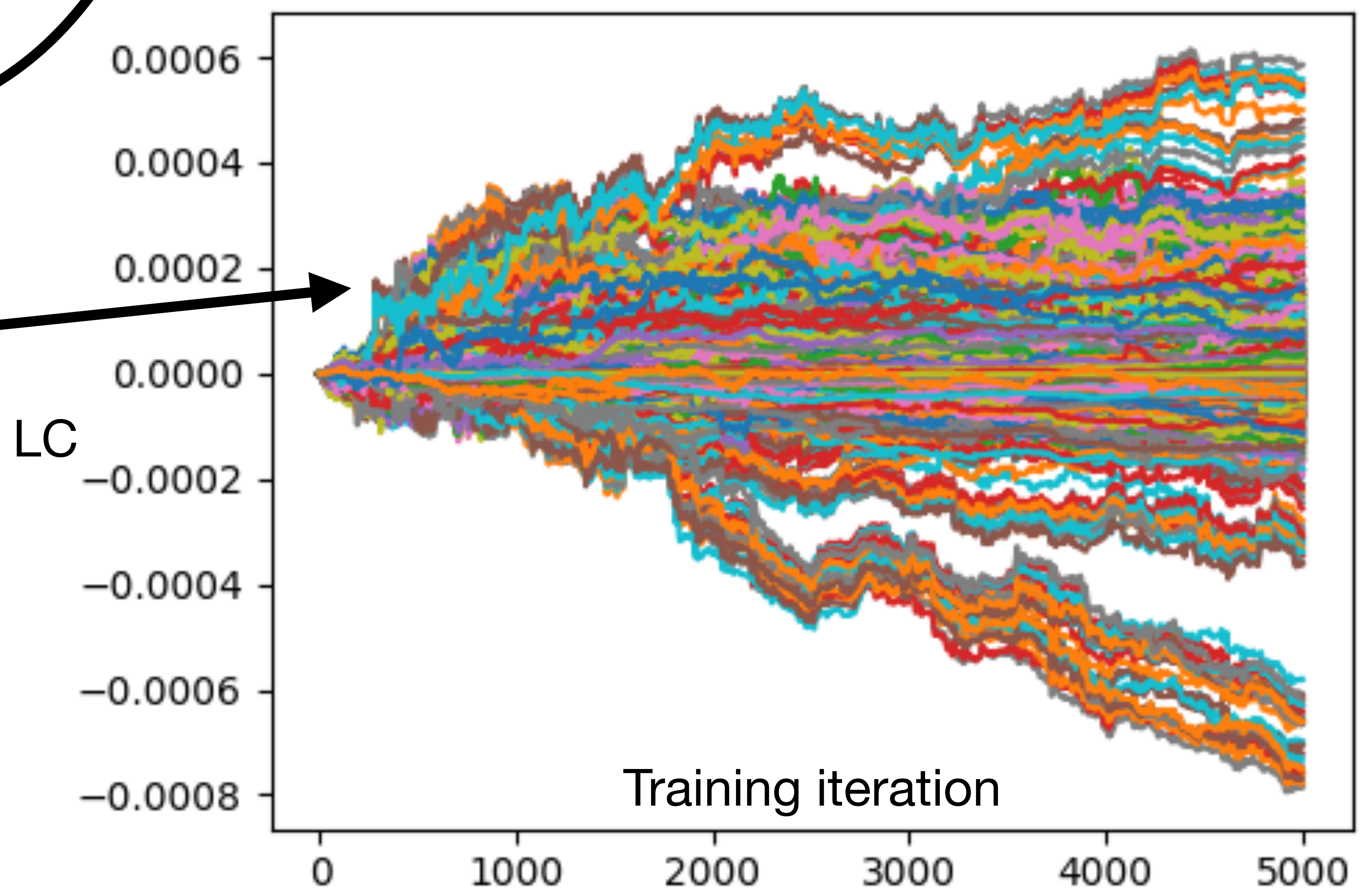



Toy data

Real data




Simple approach → New visibility into training

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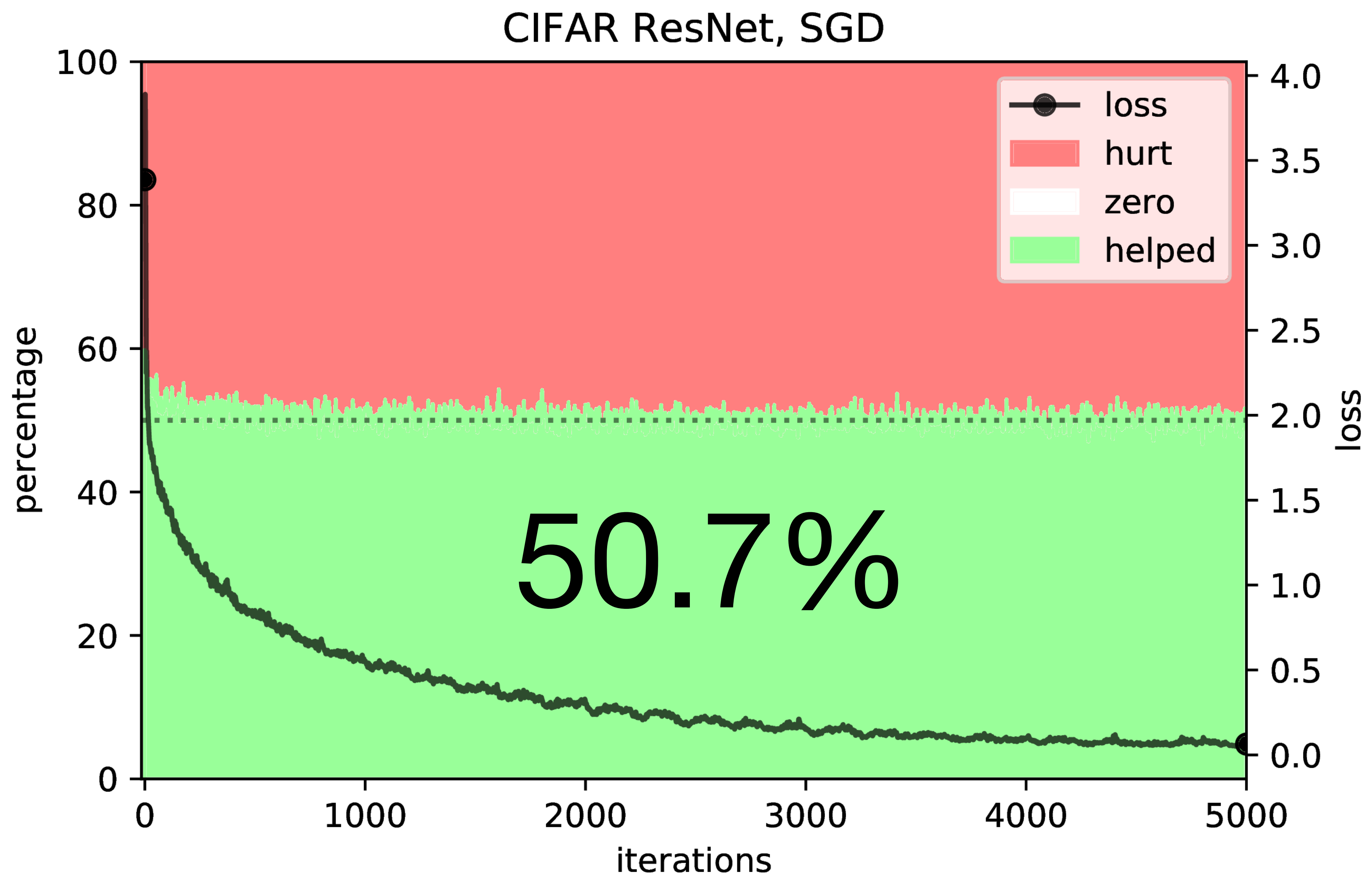
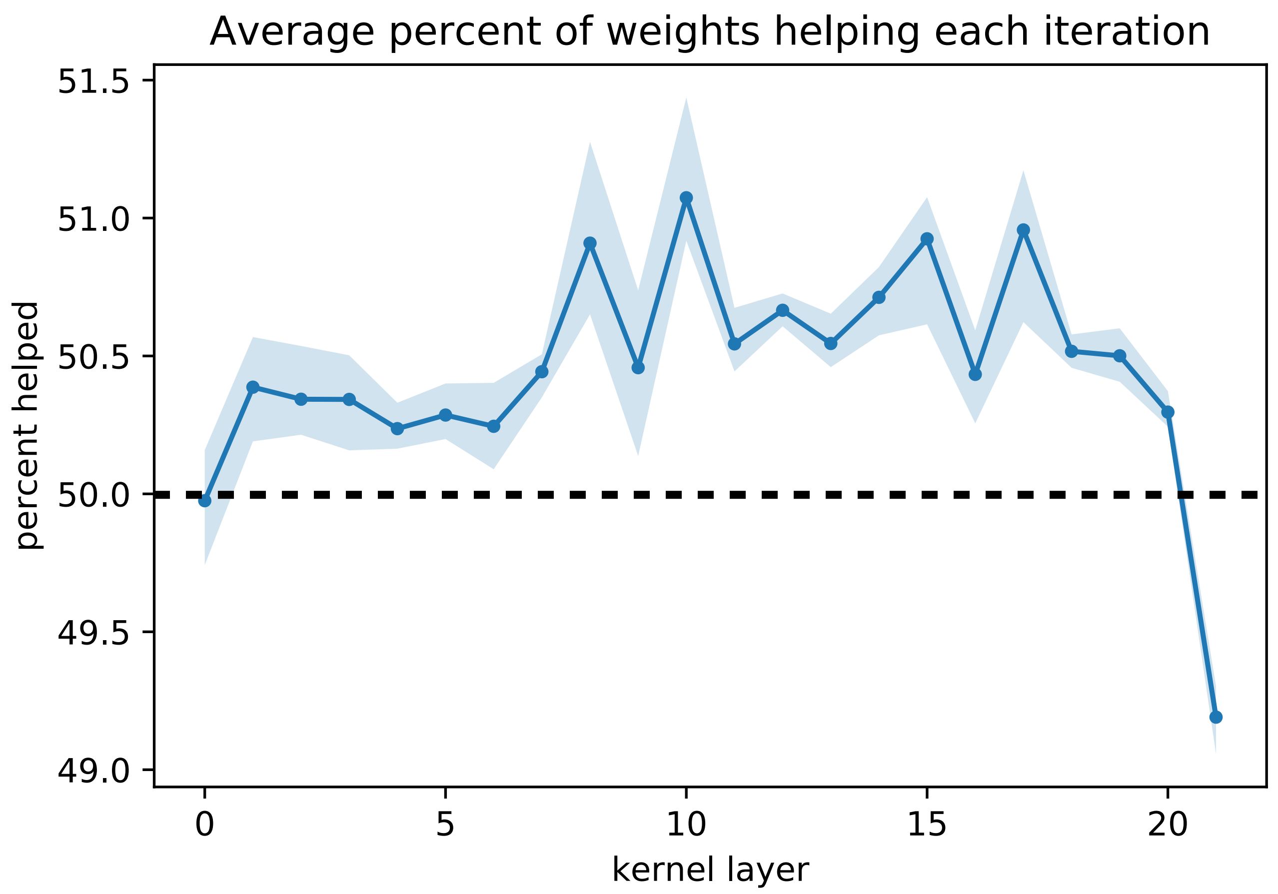
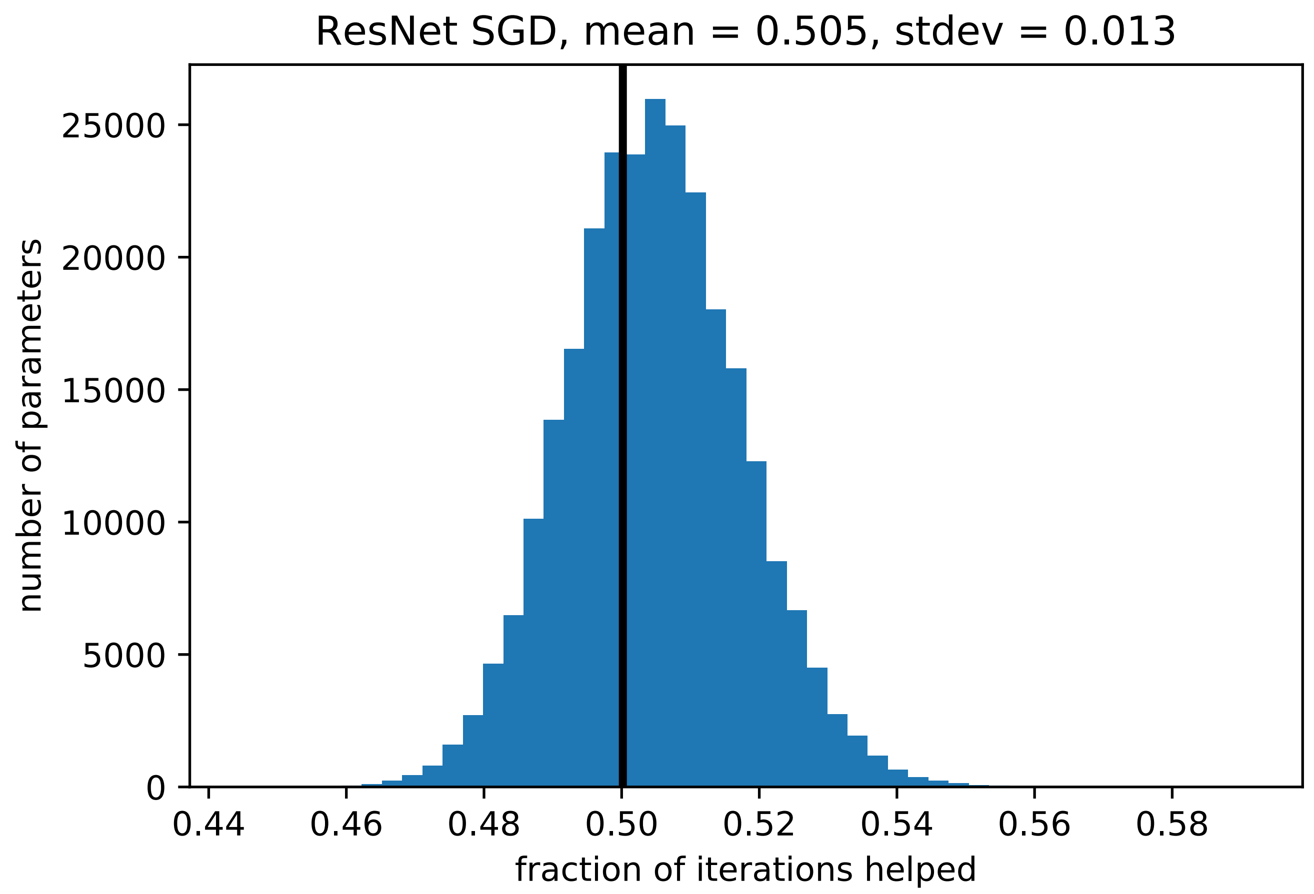
# LCA: Loss Change Allocation for Neural Network Training

## ❶ Training is noisy

- Holds for all layers
- Holds for all params
- Holds for many hyperparams
  (50.3% – 51.6%)

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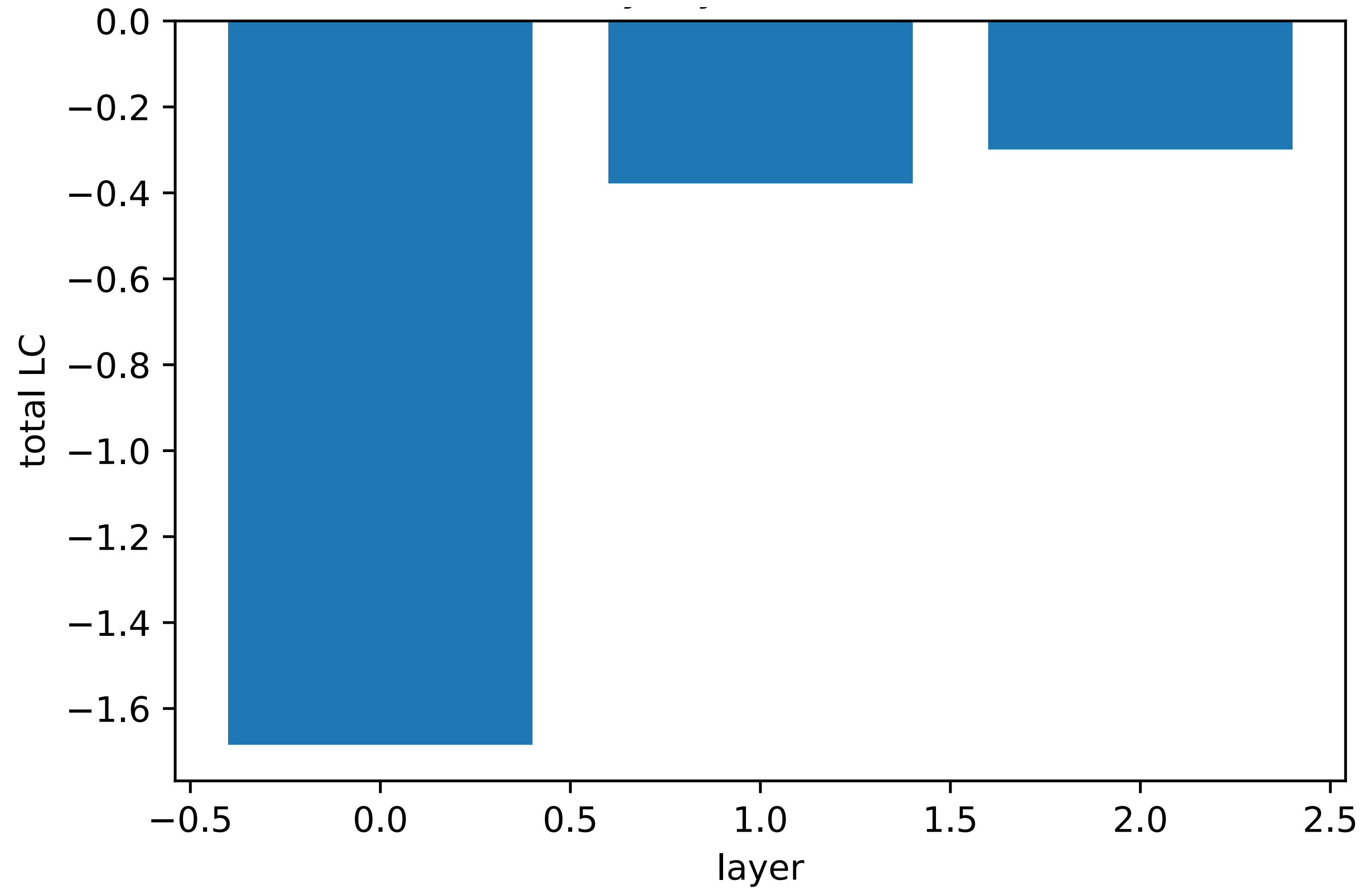
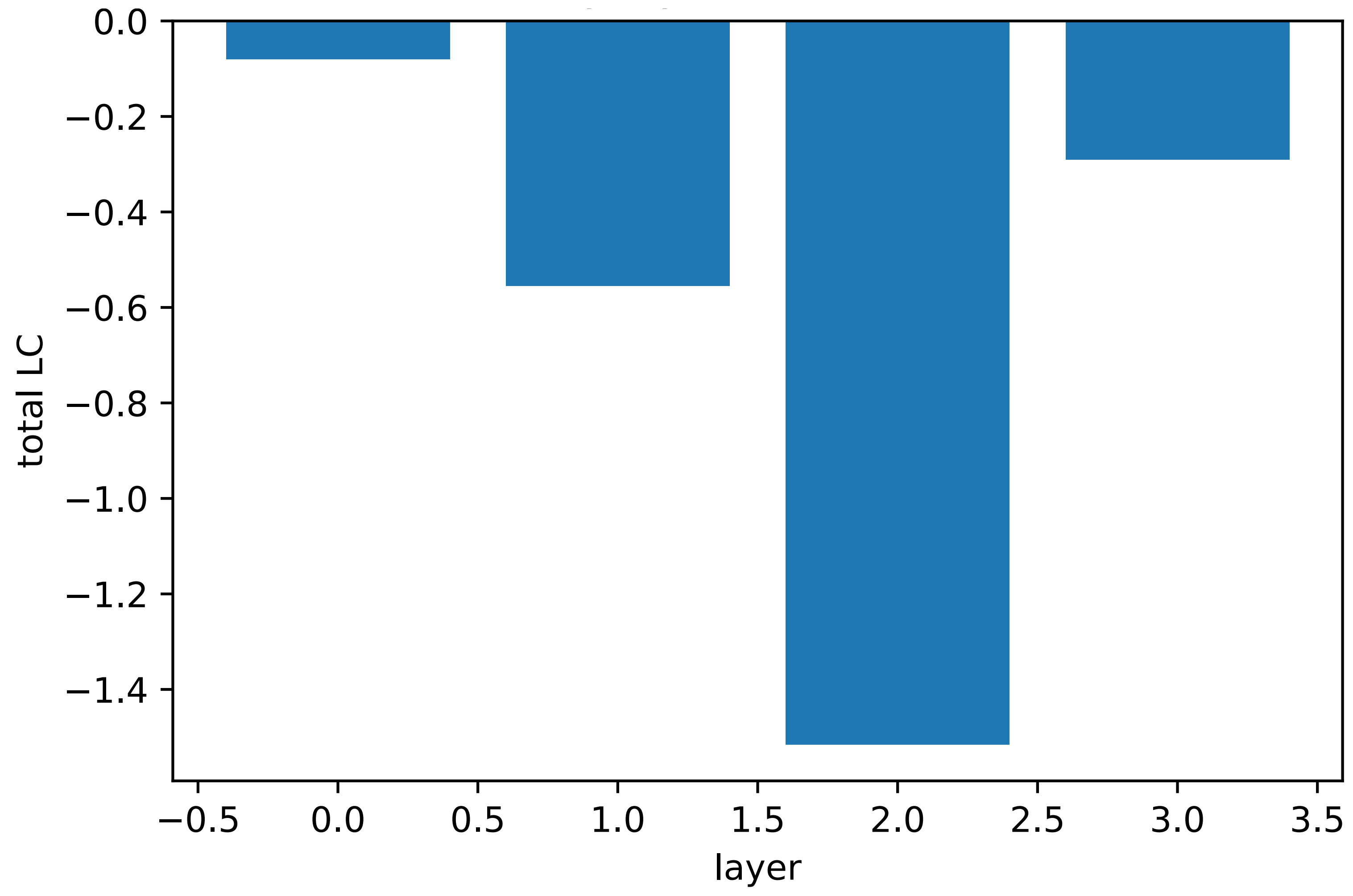
# LCA: Loss Change Allocation for Neural Network Training

1 Training is noisy  2 Some layers go backwards

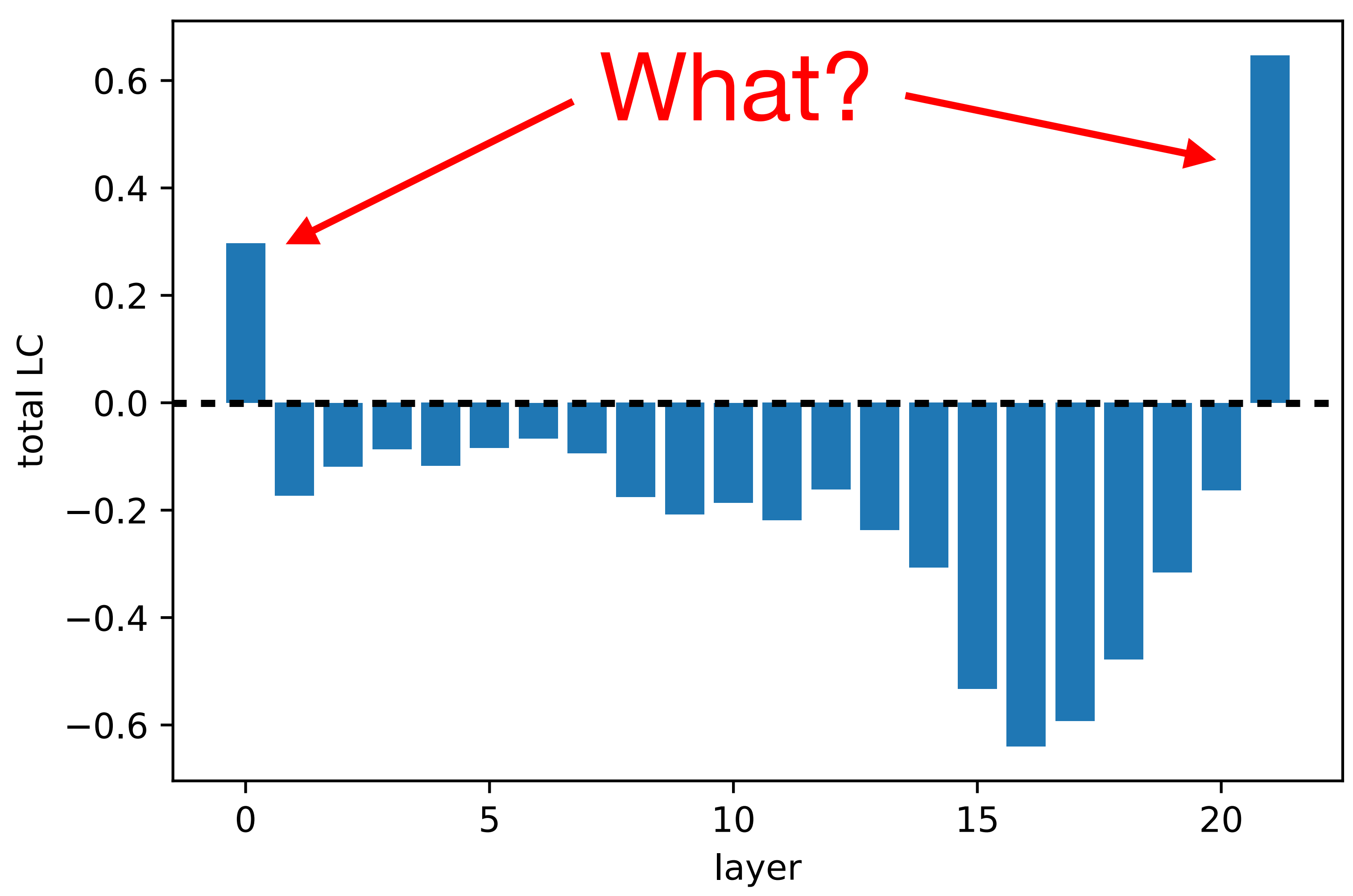
MNIST-FC

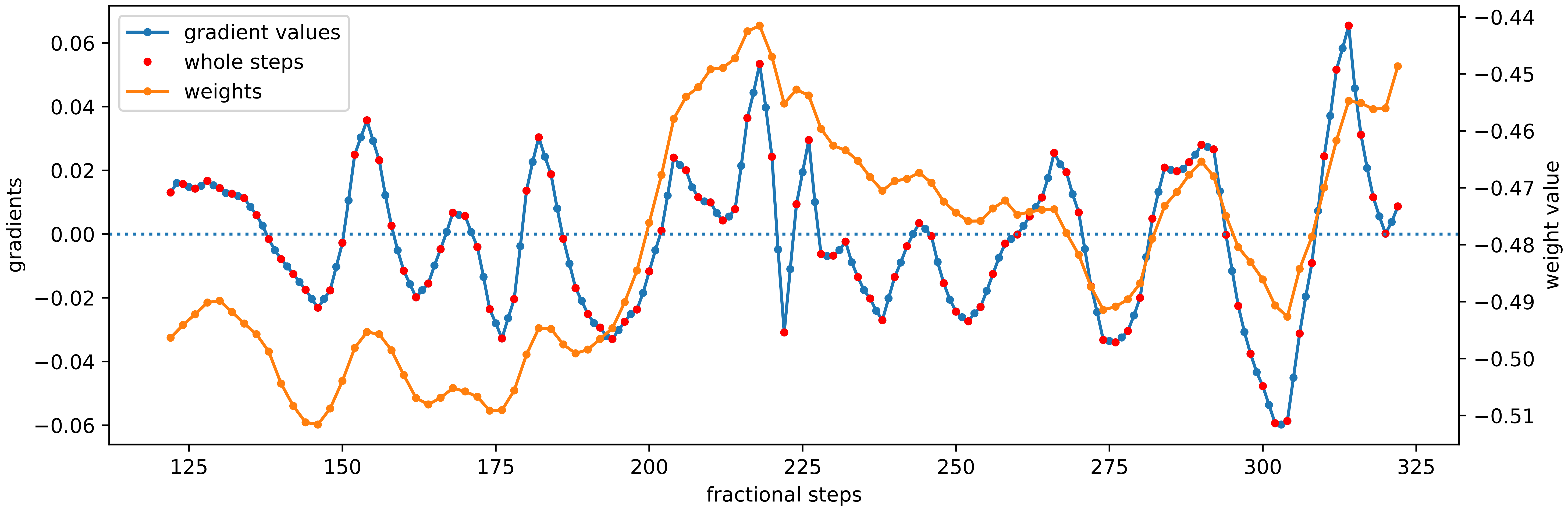



MNIST-LeNet




CIFAR-ResNet

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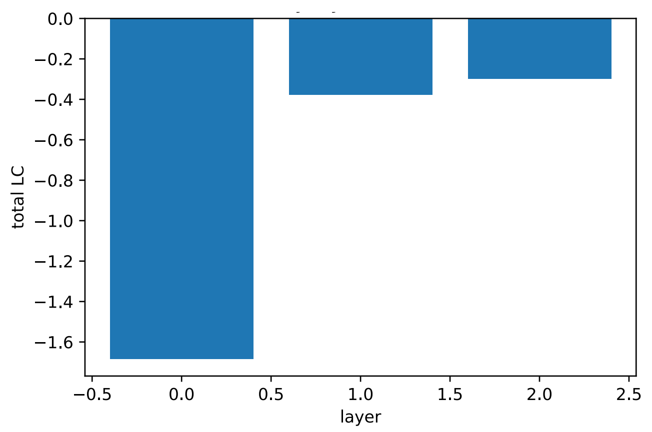


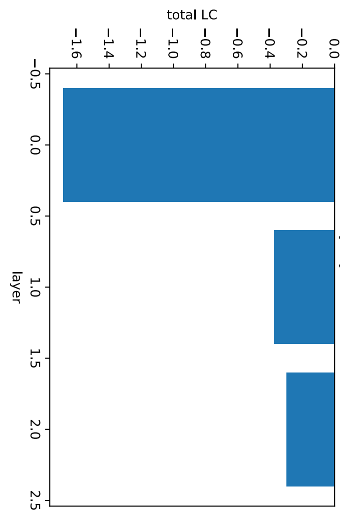


Layer 1

Layer 2

Layer 3

0

25

Training iterations

Janice Lan, Hattie Zhou, Rosanne Liu, Jason Yosinski. NeurIPS 2019.

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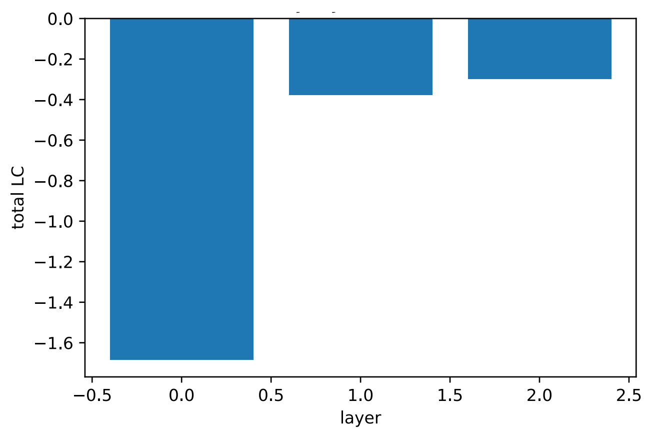



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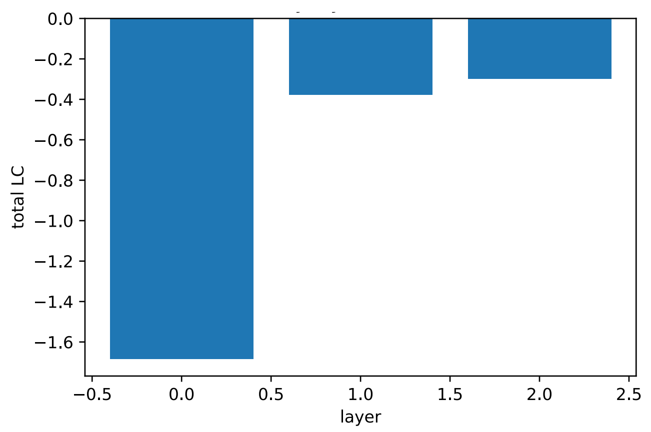


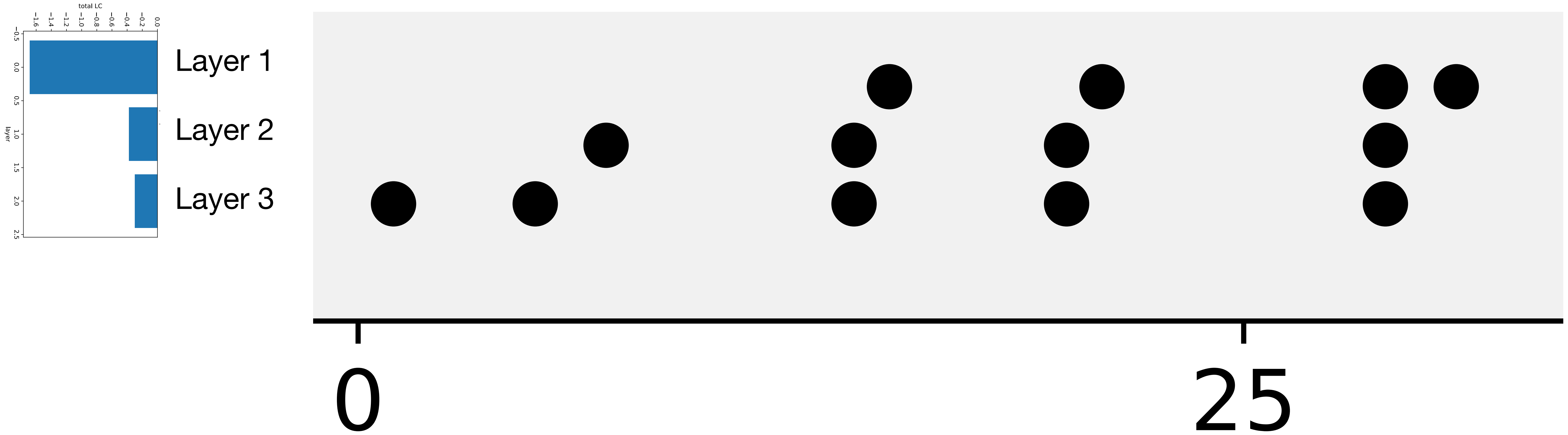


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1 Training is noisy

2 Some layers go backwards

3 Some micro-learning is synchronized

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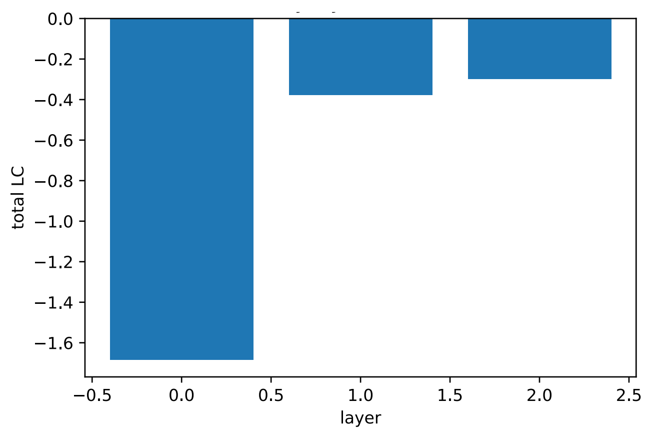


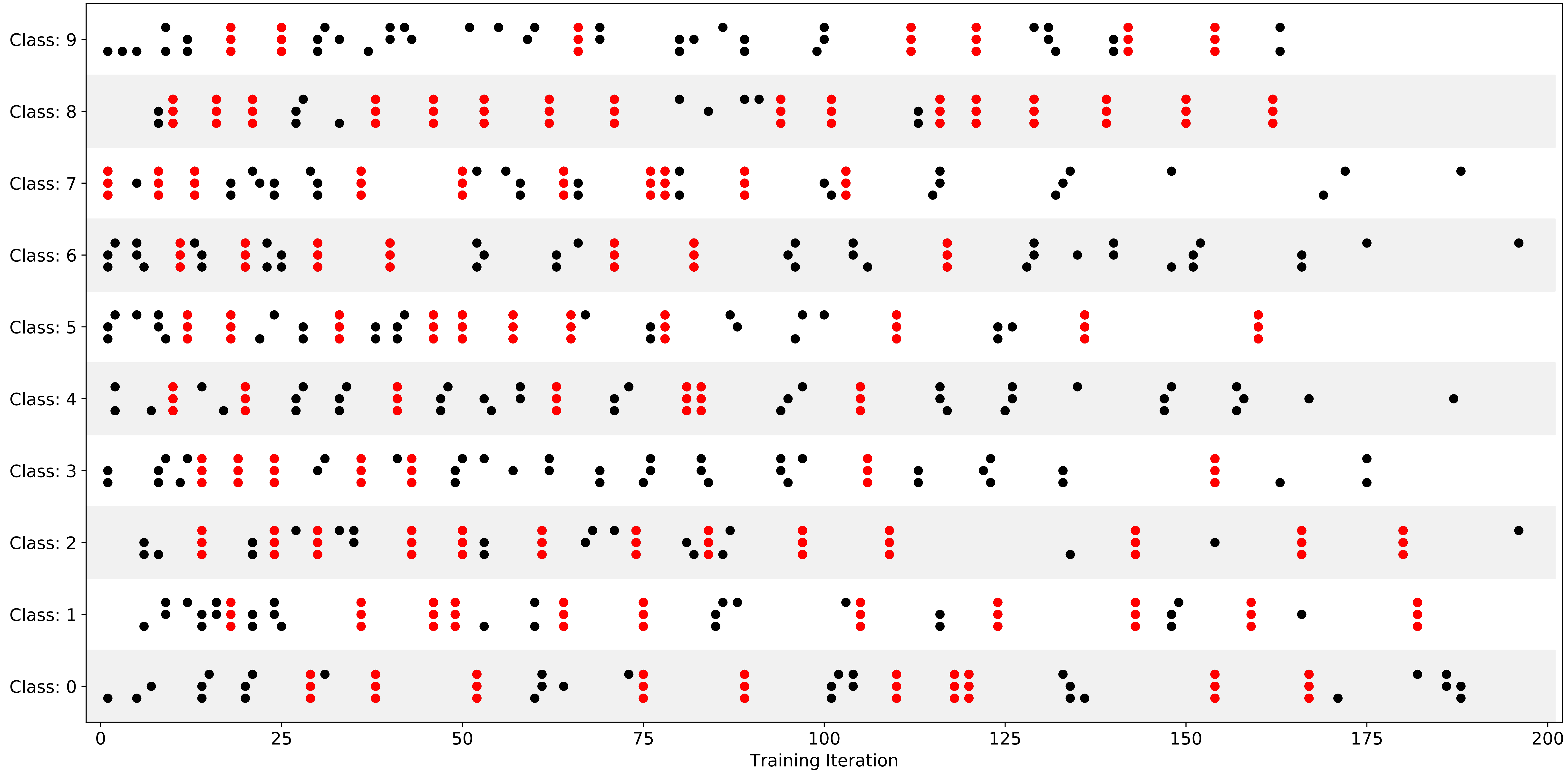


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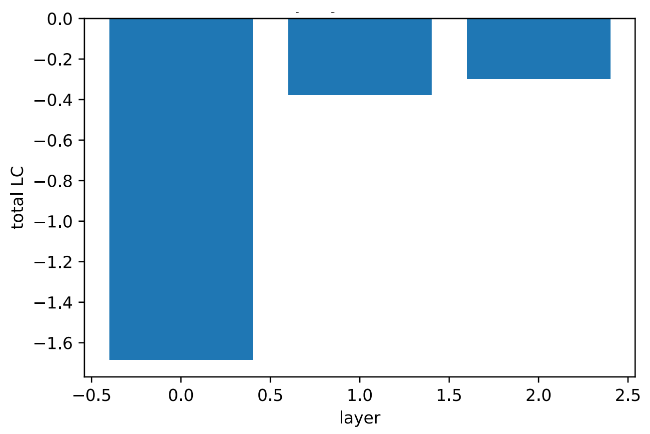


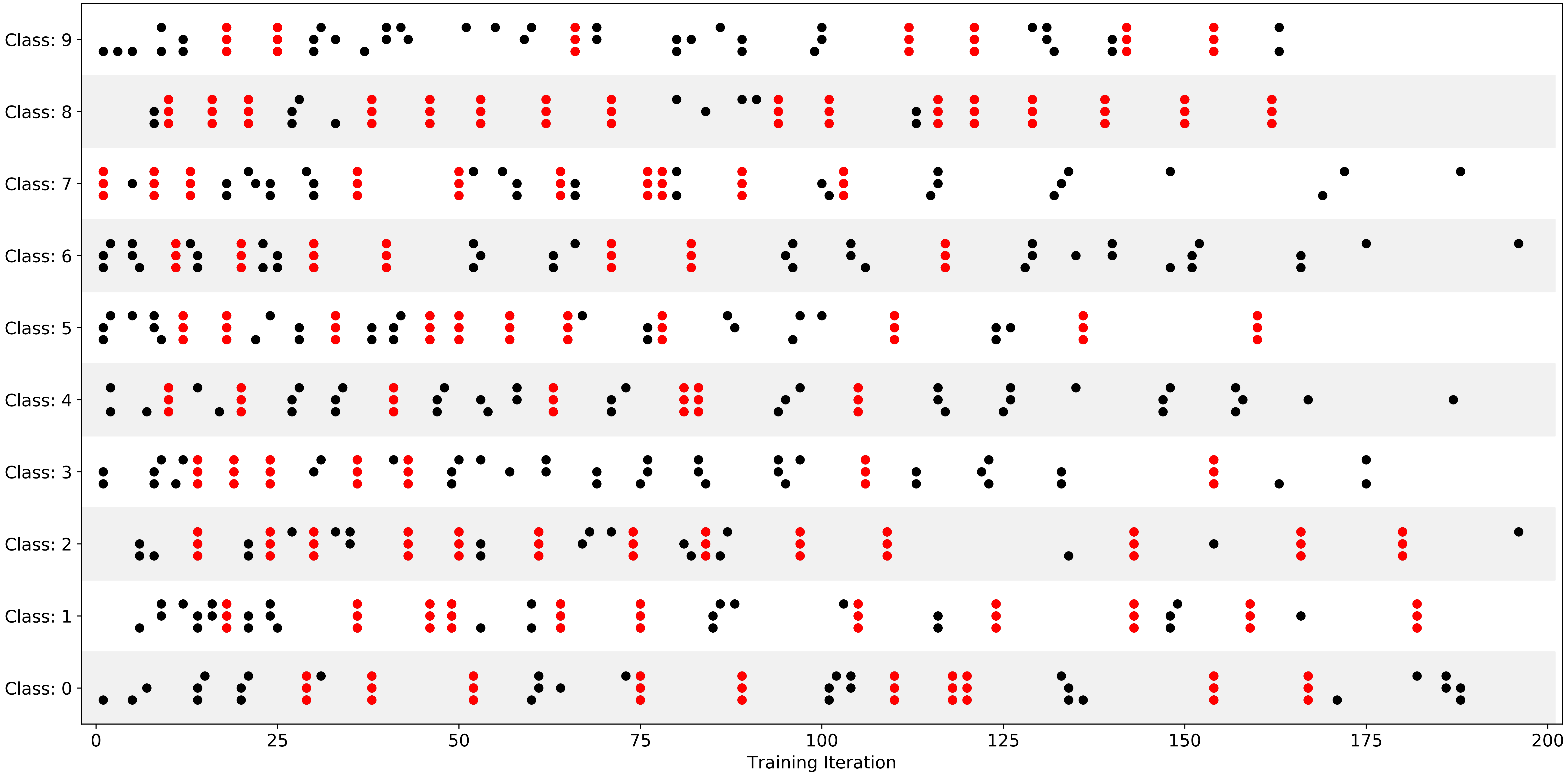


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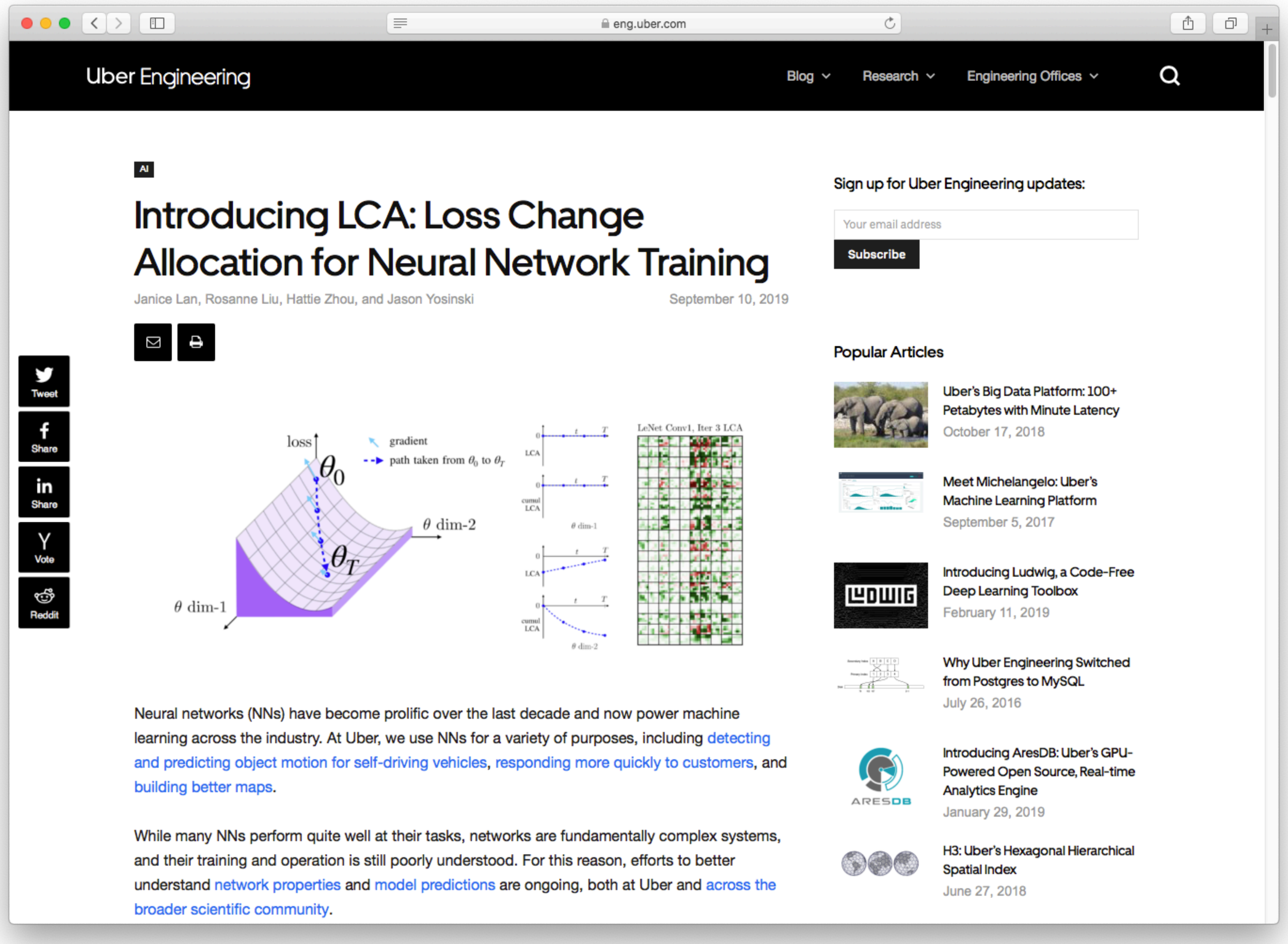
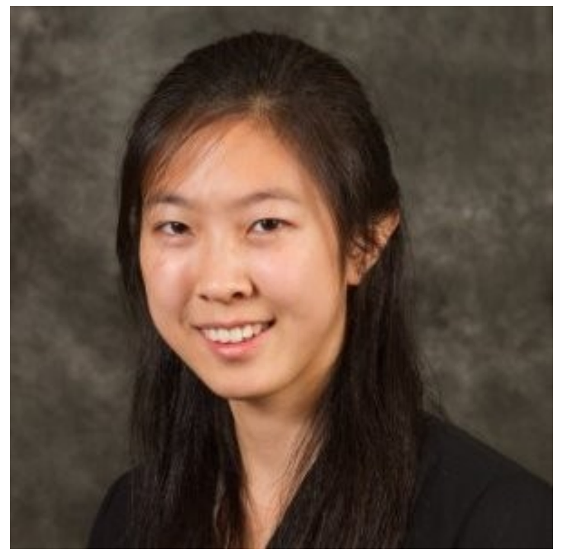
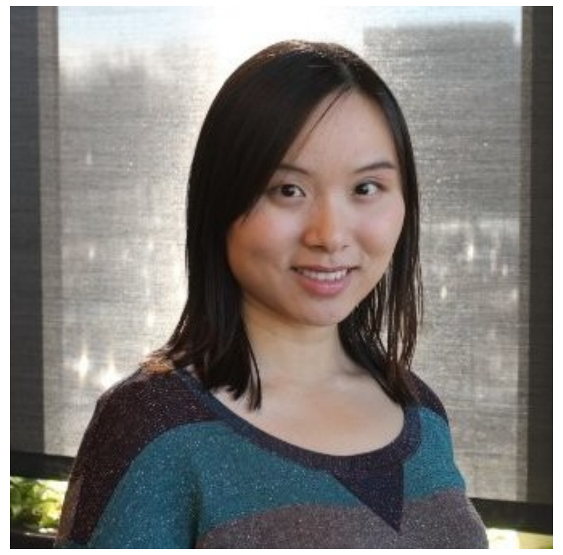
NeurIPS 2019.

Blog: https://eng.uber.com/loss-change-allocation/





Janice Lan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