A Simple Guard for Learned Optimizers



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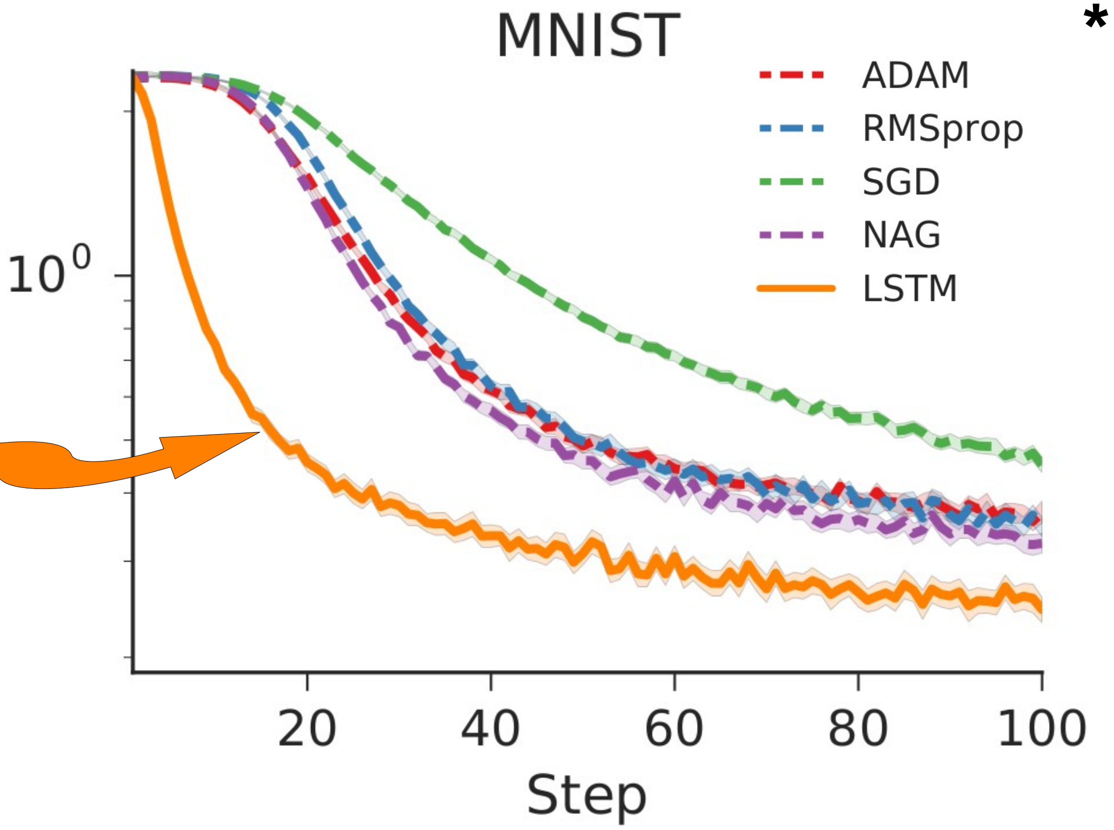
ICML International Conference On Machine Learning 2022

GoodAI

The Hope

The Hope

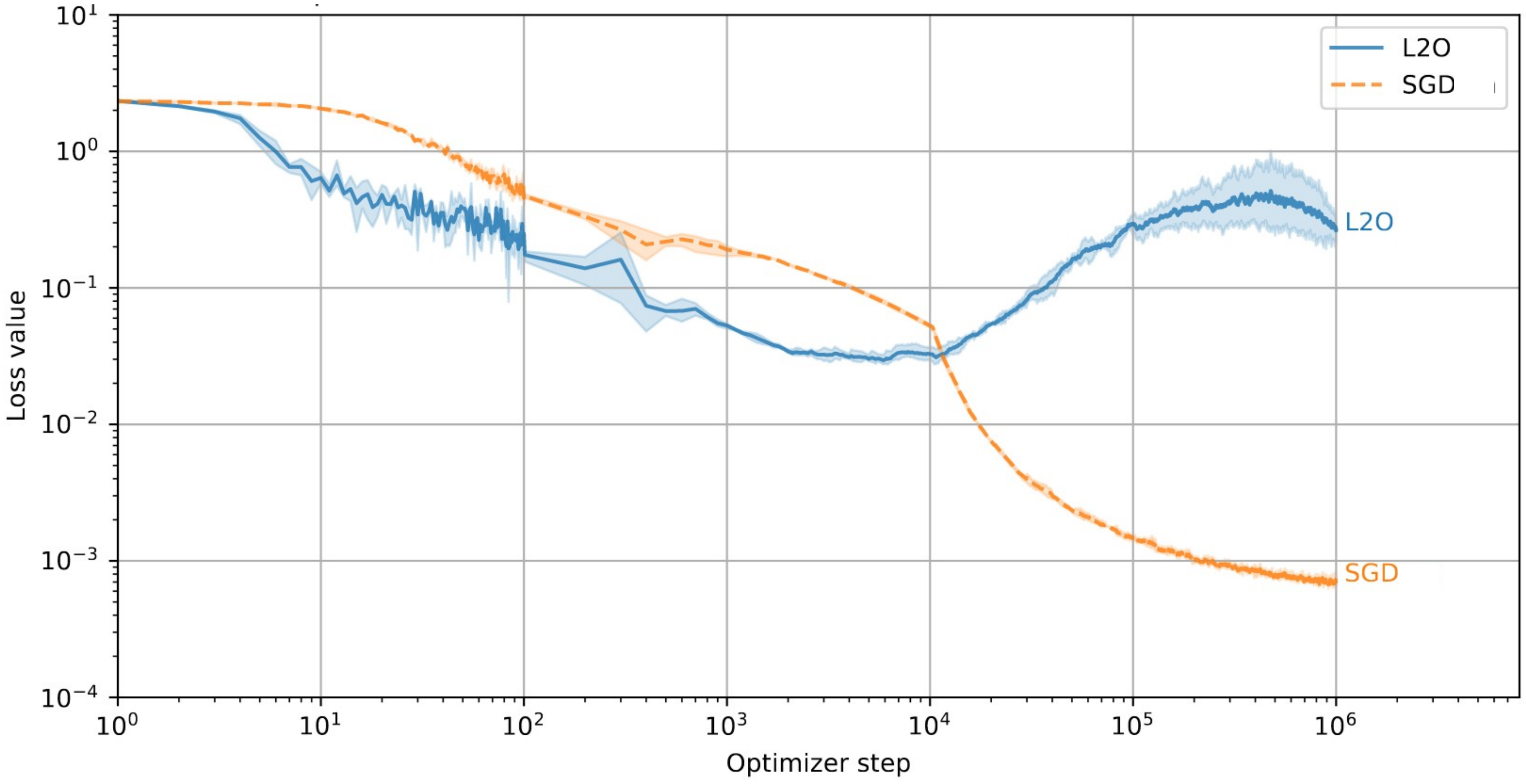


Learned Optimizer

* Andrychowicz et. al, *Learning to Learn by Gradient Descent by Gradient Descent*, Neurips 2016

The Problem

The Problem


L2O
SGD
L2O
SGD
10^{1}
10^{0}
10^{-1}
10^{-2}
10^{-3}
10^{-4}
Loss value
10^{0}
10^{1}
10^{2}
10^{3}
10^{4}
10^{5}
10^{6}
Optimizer step

The Problem

THEORETICAL

- Convergence Guarantee

The Problem

THEORETICAL	PRACTICAL
• ~~Convergence Guarantee~~	

The Problem

THEORETICAL

- Convergence Guarantee

PRACTICAL

- Longer Horizon

The Problem

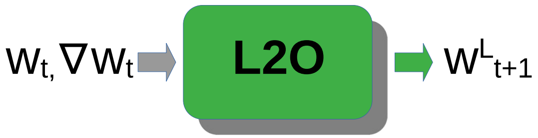
THEORETICAL	PRACTICAL
• ~~Convergence Guarantee~~	• Longer Horizon • Different Data / Distributional Shift

The Problem

THEORETICAL	PRACTICAL
• ~~Convergence Guarantee~~	• Longer Horizon • Different Data / Distributional Shift • Change in NeuralNet architecture

The Solution

The Solution



The Solution

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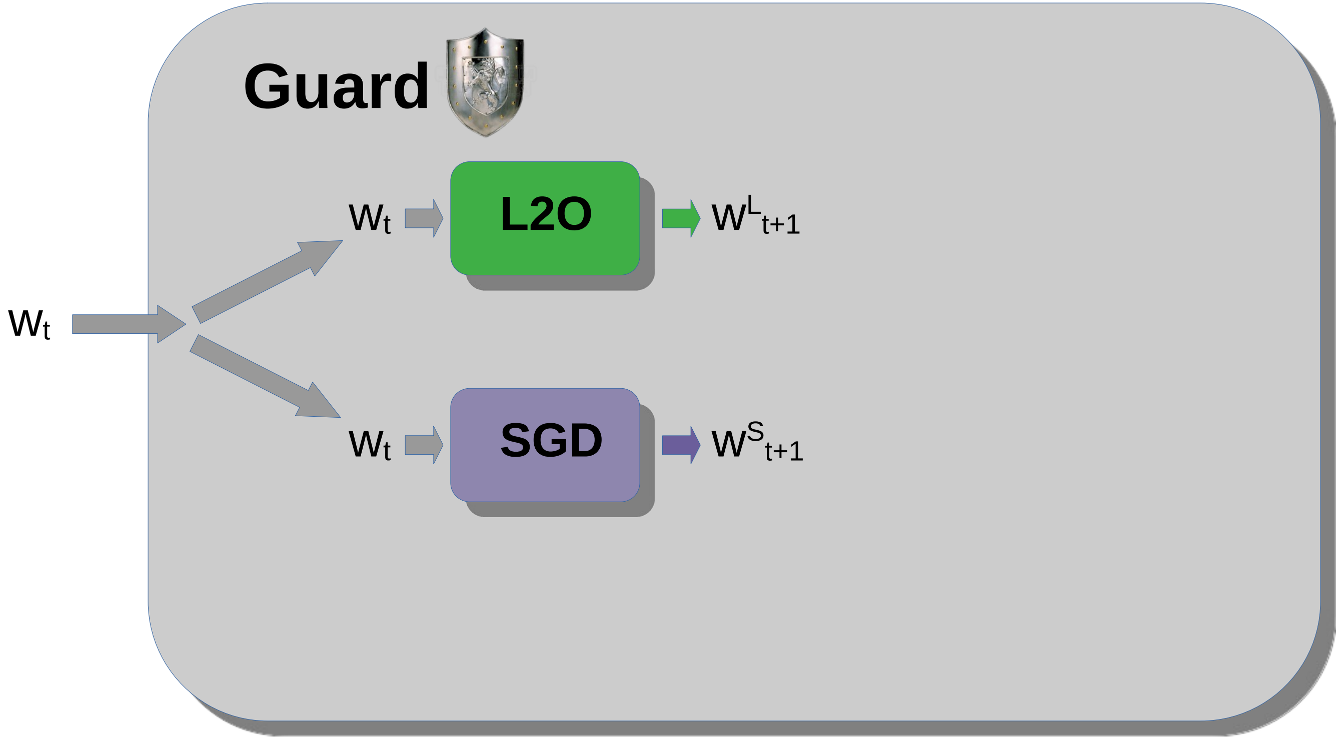

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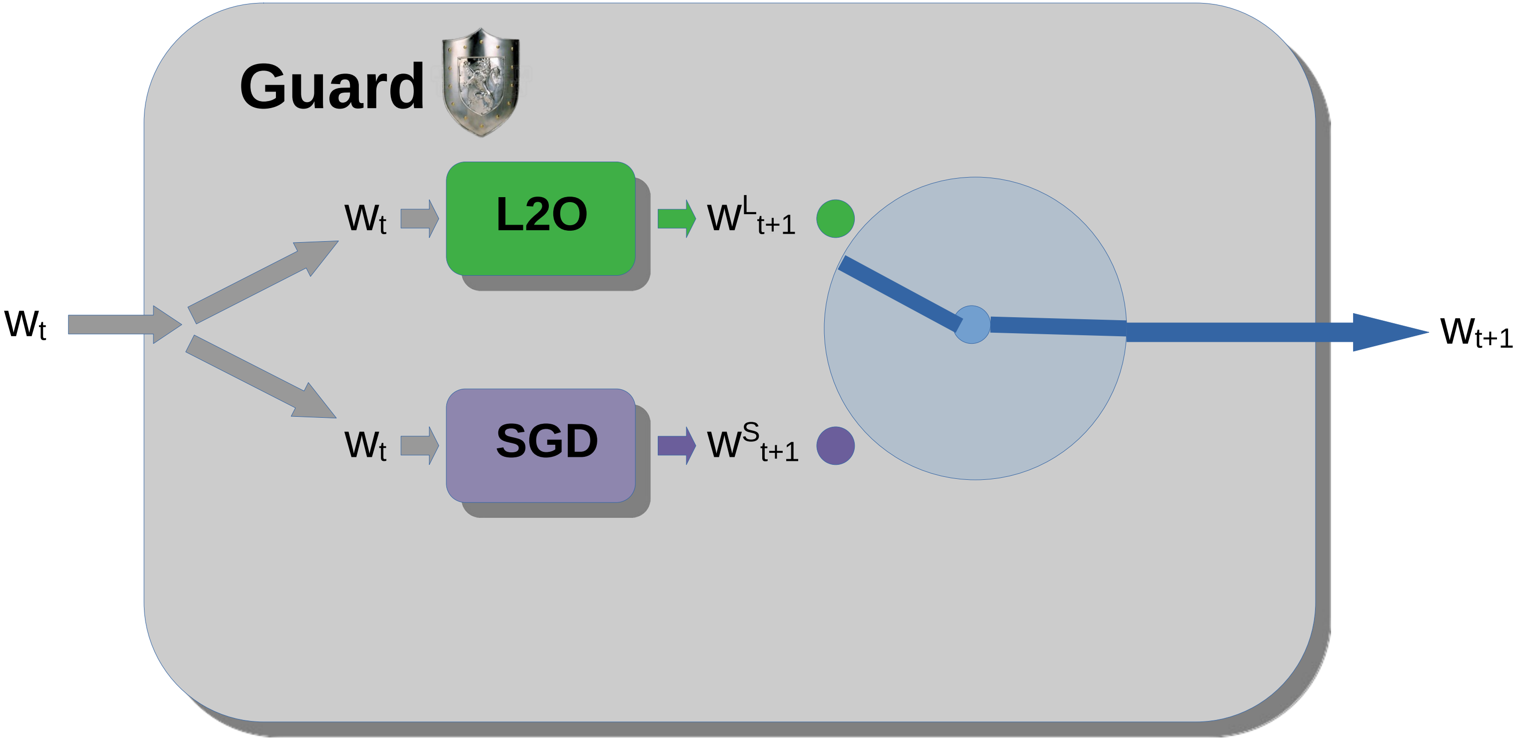

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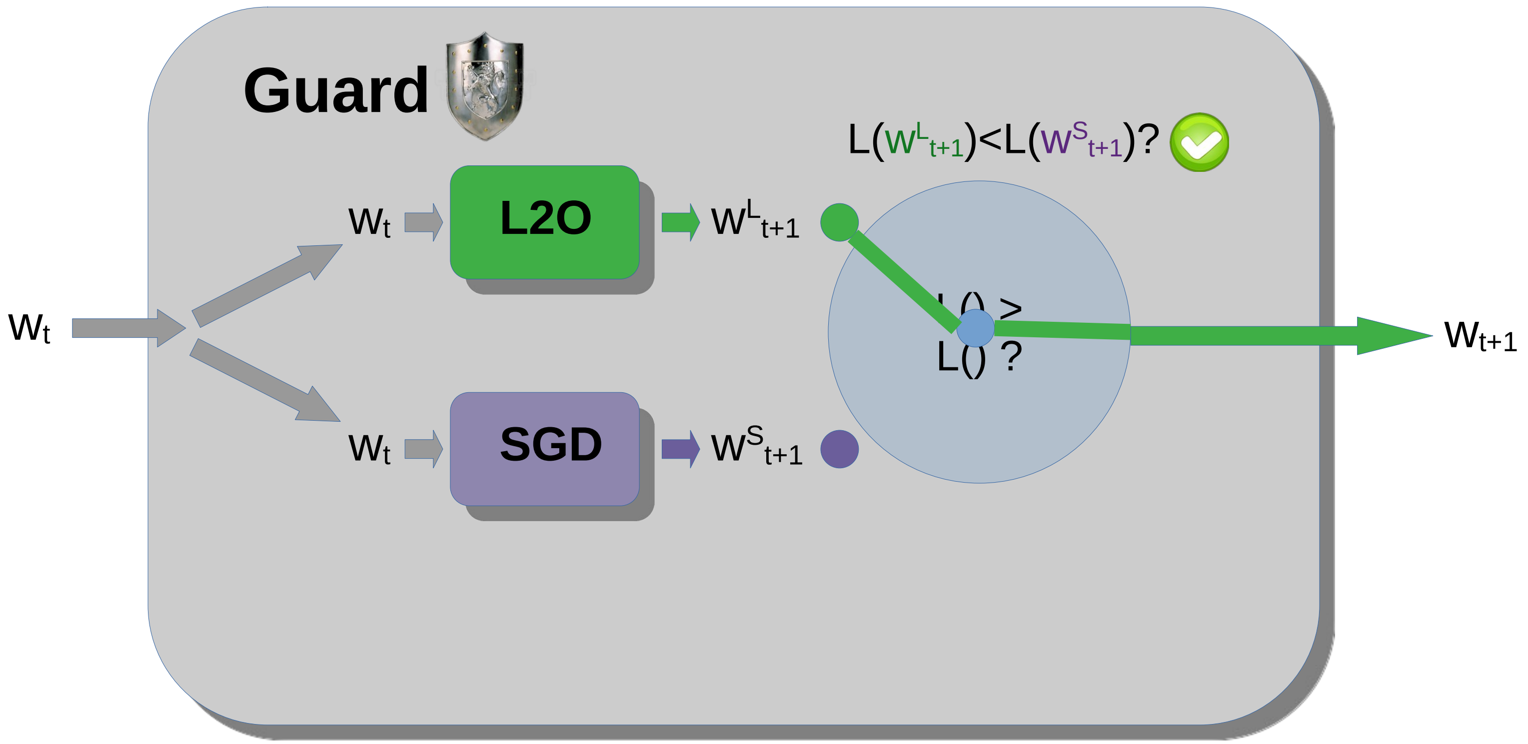

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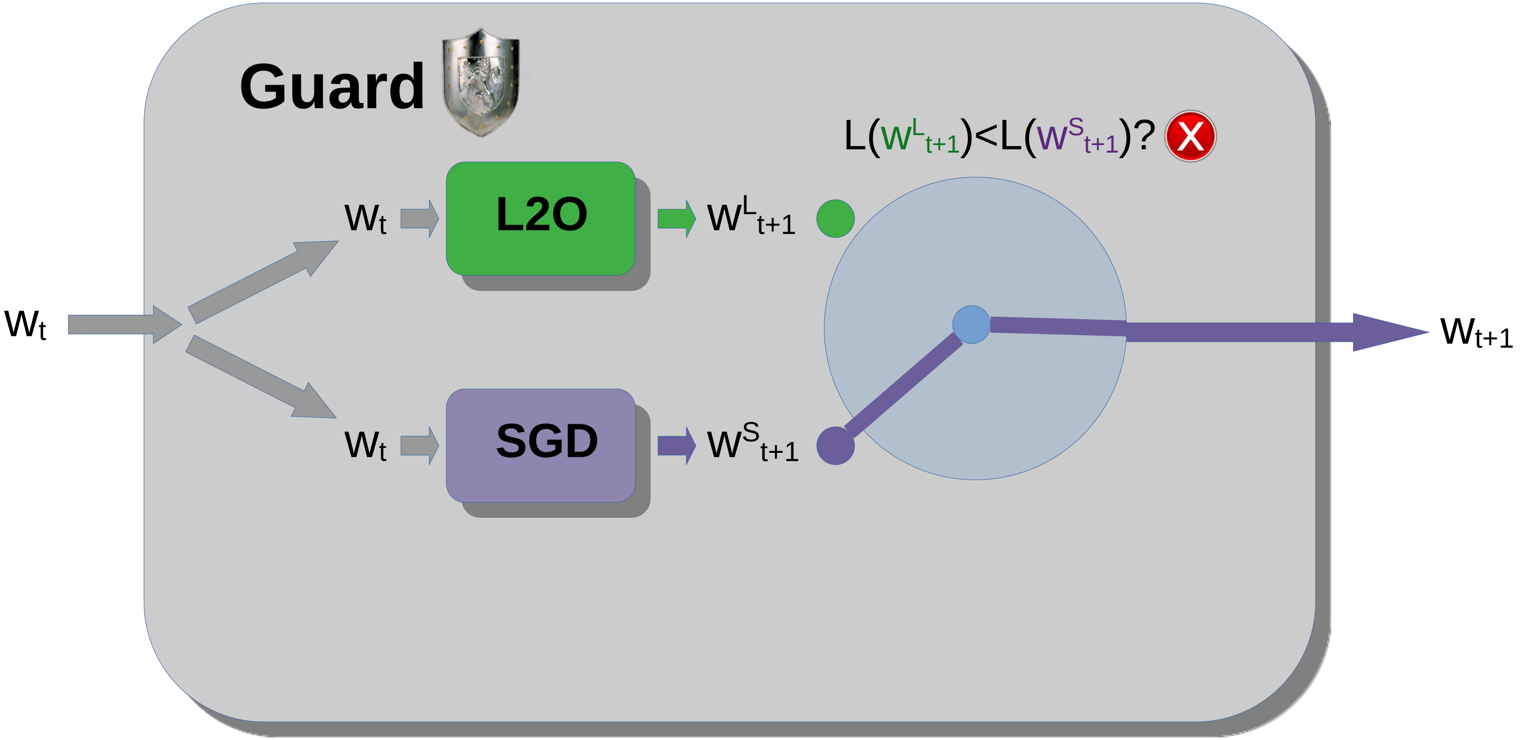


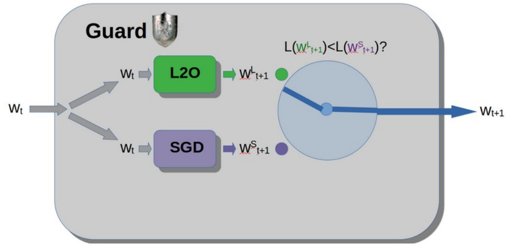
The Solution

Theorem 1 *Let $\mathcal{F}$ be a continuous loss function which is μ-strongly convex*[1] *and L-smooth and let w^* be it's global minimum. Let $w_{i\in\mathbb{N}}$ be a sequence of points obtained from applying the Loss-Guarded L2O algorithm with gradient descent or stochastic gradient as the guarding algorithm. In the case of stochastic gradient descent, we assume that in expectation, the stochastic gradient $\nabla_{mb}\mathcal{F}(w)$ is equal to the true gradient,*

$$\mathbb{E}(\nabla_{mb}\mathcal{F}(w)) = \nabla\mathcal{F}(w),$$

and that the variance of the stochastic gradient around the true gradient is bounded. Then given a constant learning rate $0 < \lambda < \min(\frac{2}{L}, 2\mu)$ for gradient descent or a decaying learning rate $\lambda_i \propto \frac{1}{i_0+i}$ for SGD, the sequence converges to the minimum, i.e.

$$\lim_{i\to\infty} w_i = w^*.$$



Compared To Alternative*

*Heaton, et. al, *Safeguarded Learned Convex Optimization*, arXiv:2003.01880

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- Simpler Algorithm

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- Simpler Algorithm
- Fewer Computation of Gradients

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Compared To Alternative*

- Simpler Algorithm
- Fewer Computation of Gradients
- Works better in Practice

*Heaton, et. al, *Safeguarded Learned Convex Optimization*, arXiv:2003.01880

The Desire

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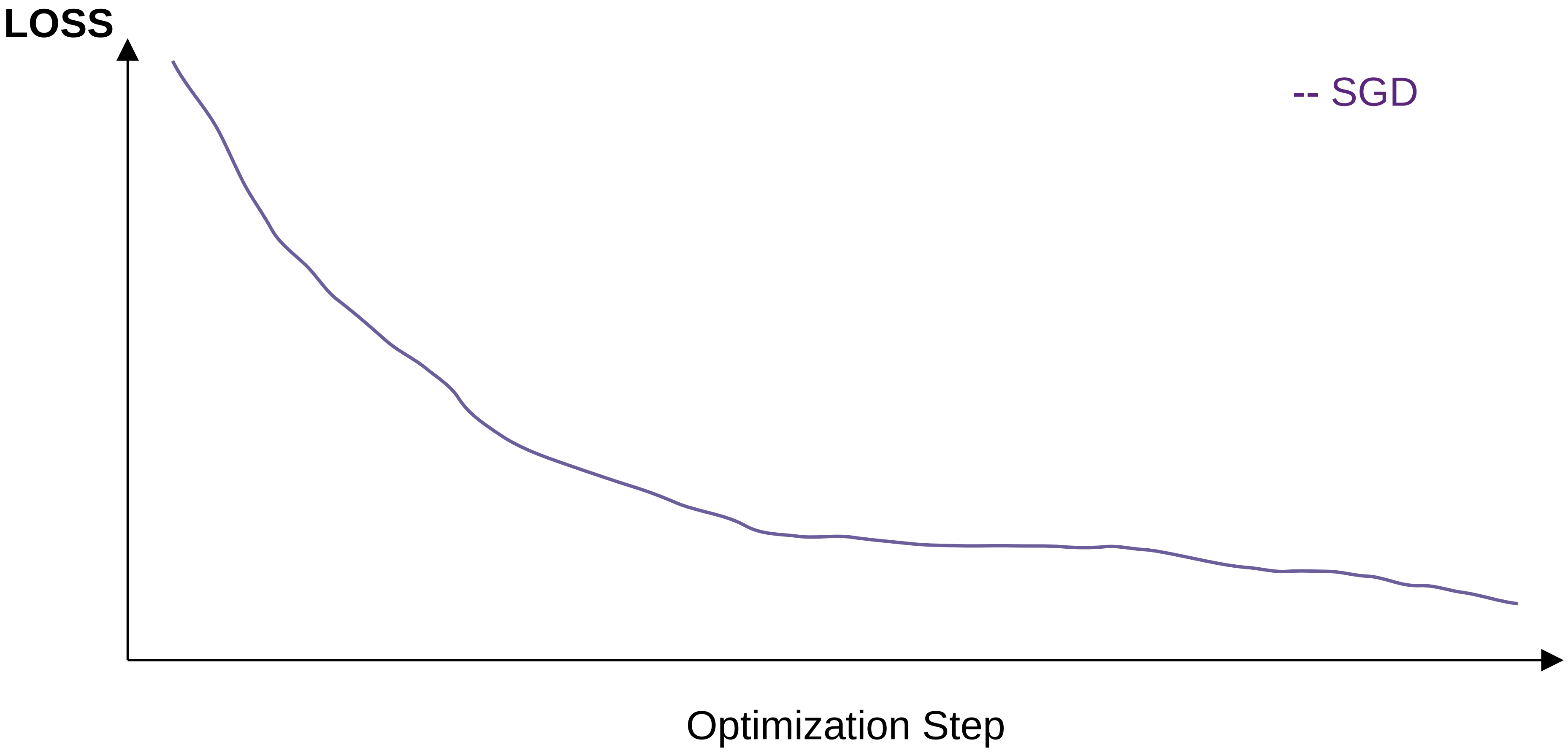
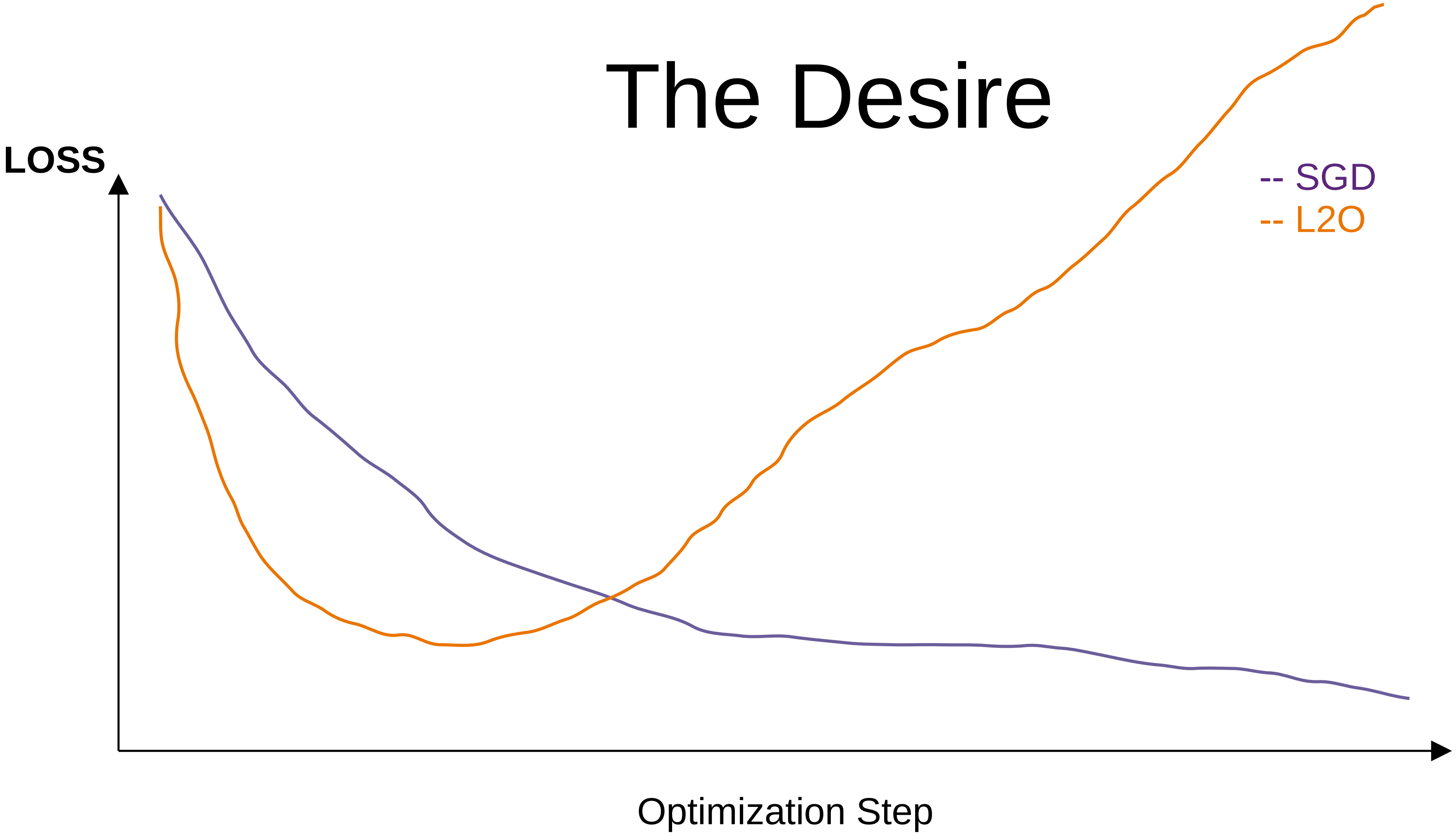


The Desire



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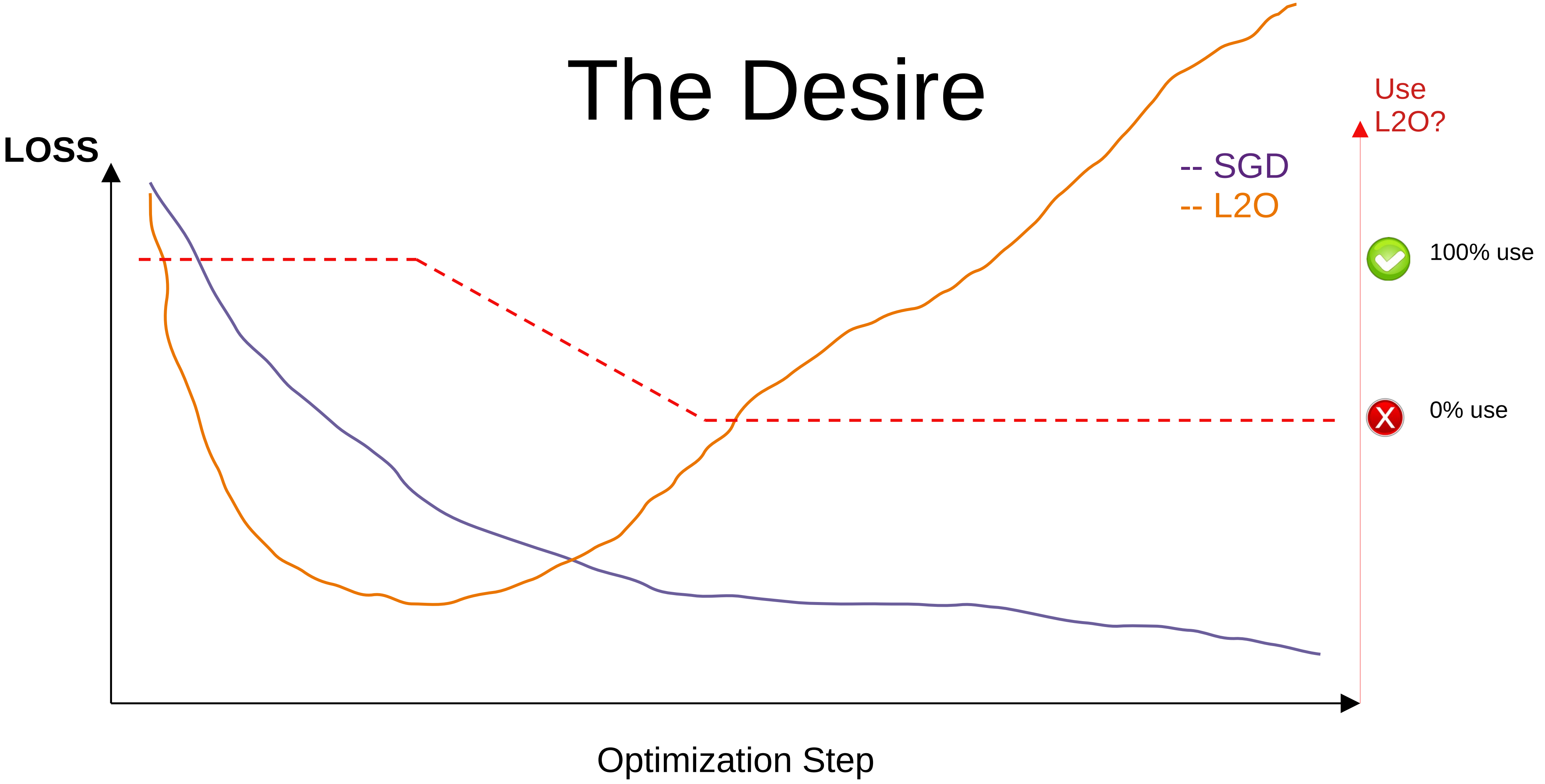
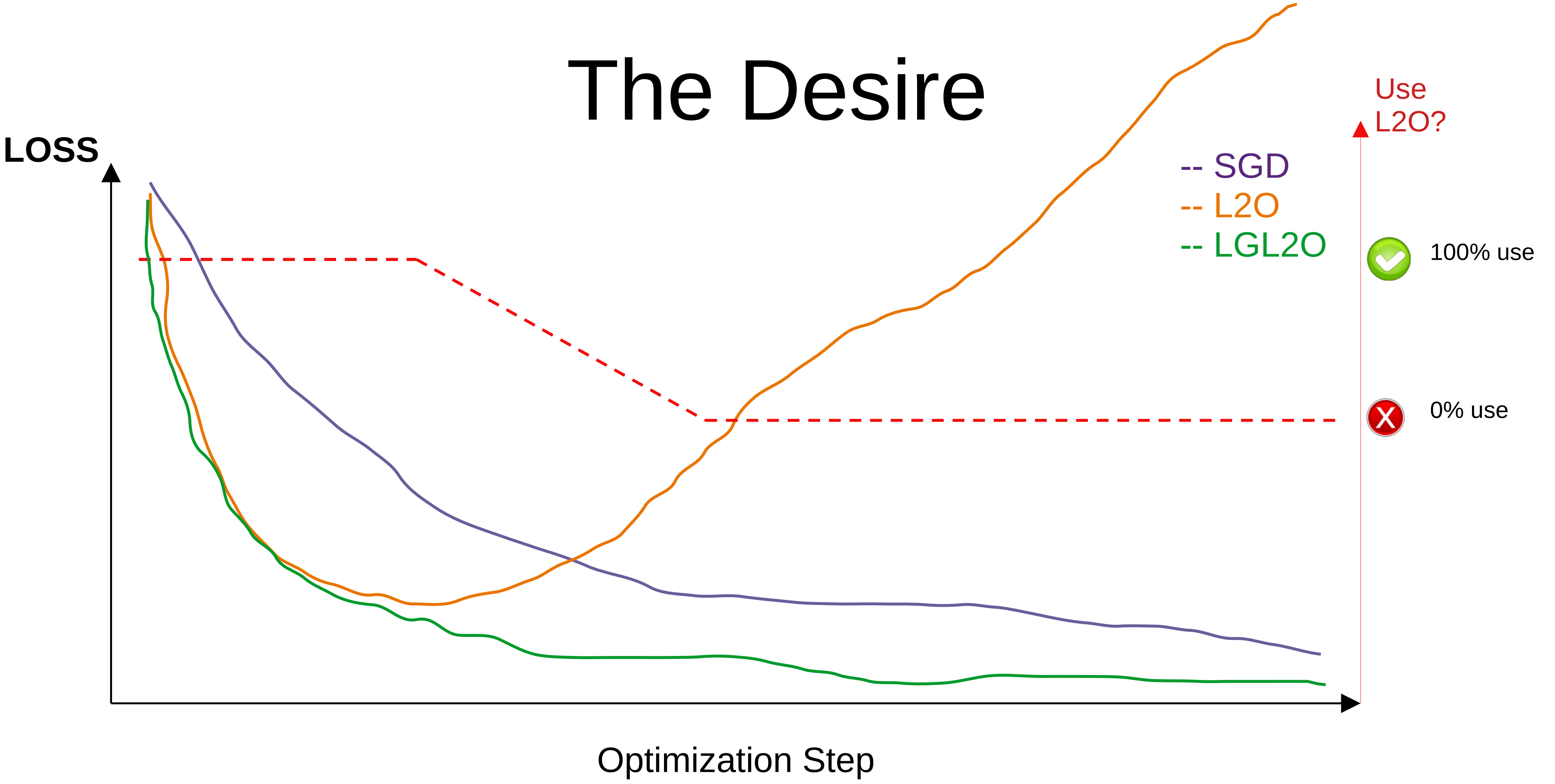
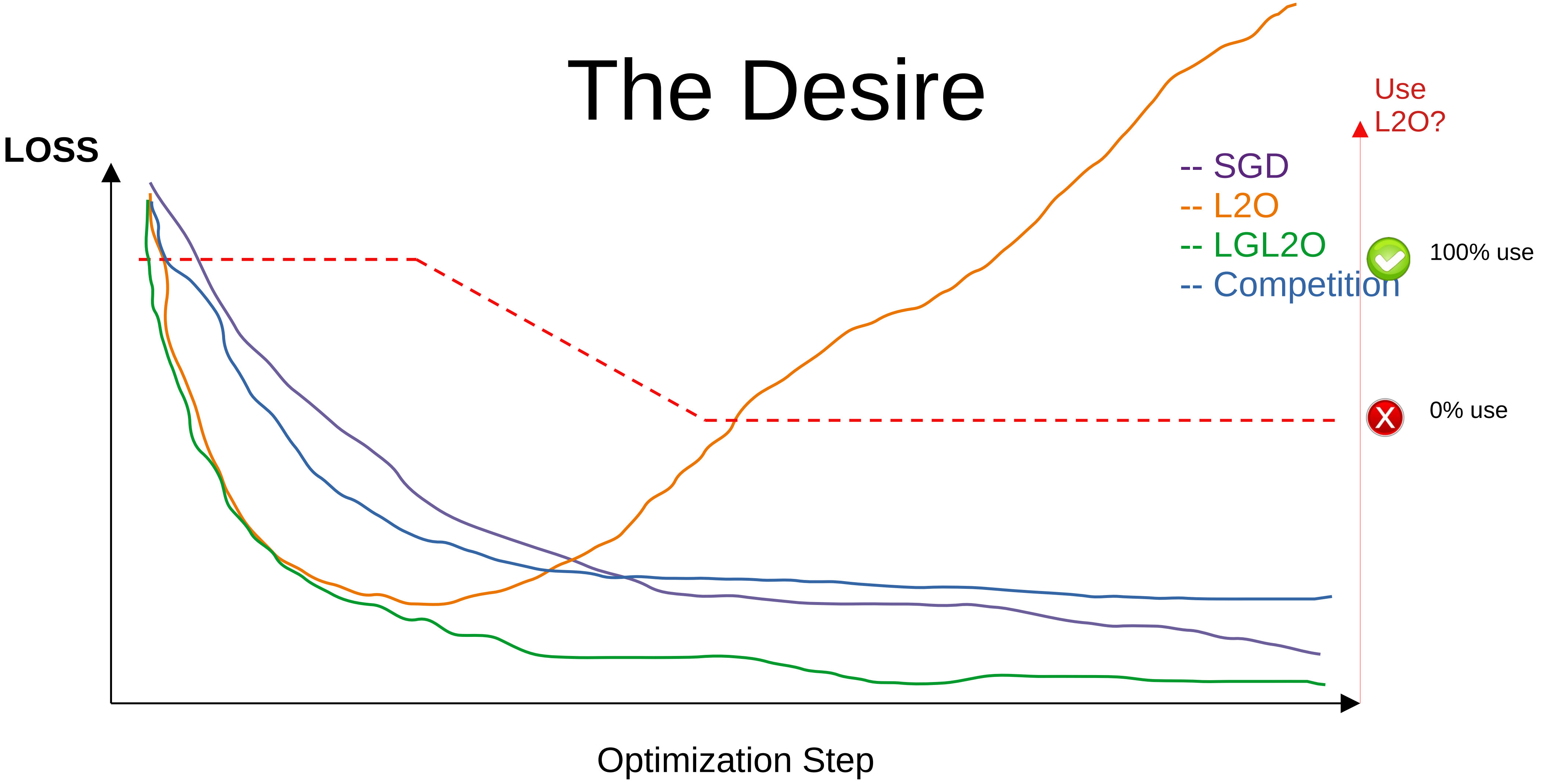


The Desire

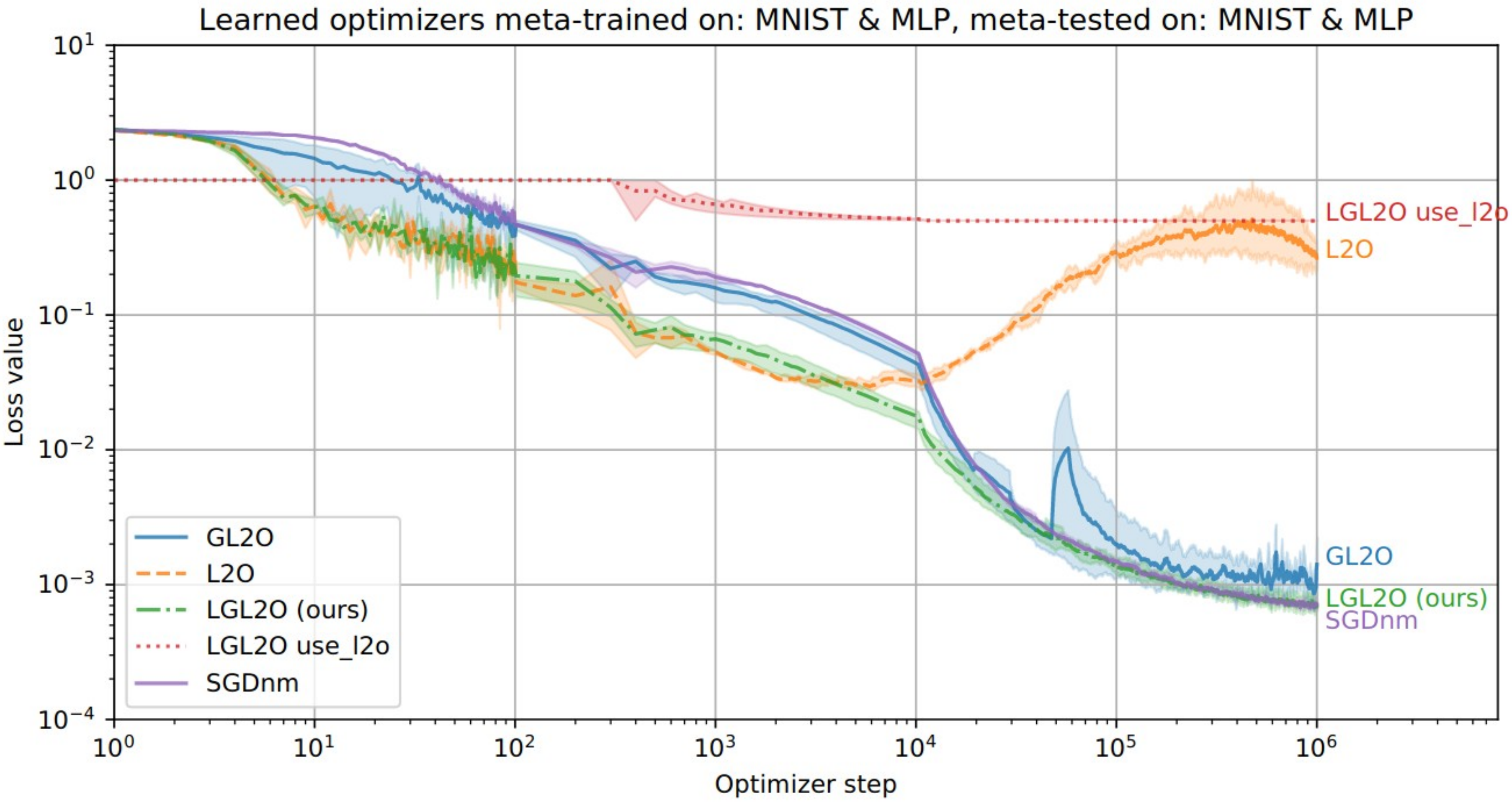


The Desire

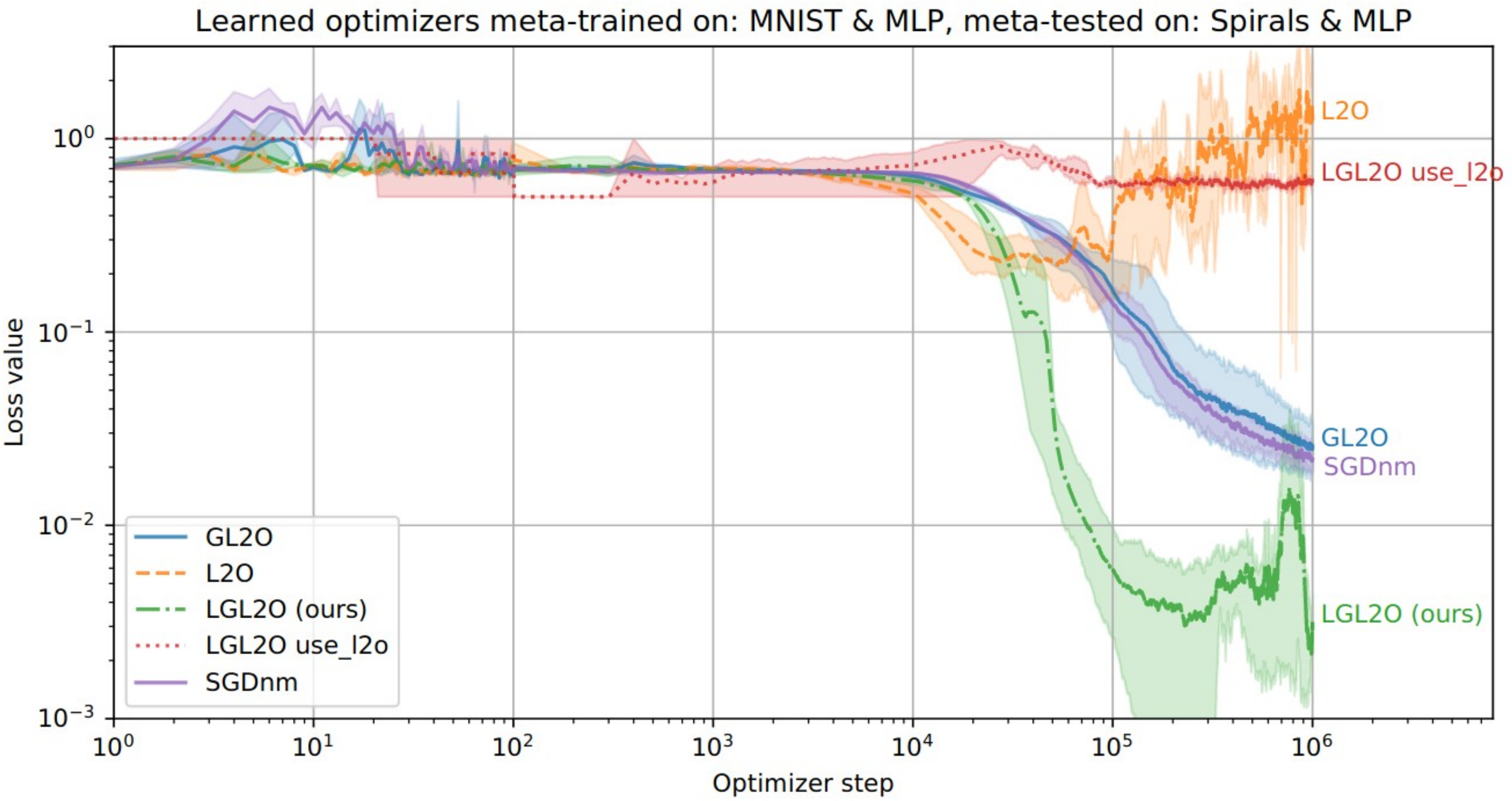

LOSS
Use
L2O?
-- SGD
-- L2O
-- LGL2O
-- Competition
100% use
0% use
Optimization Step

The Results

In Distribution



Out of Distribution



Concluding Remarks

- Guard can be used with any learned optimizer and fallback optimizer

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- Guard can be used with any learned optimizer and fallback optimizer
- Inherits the convergence guarantee of the fallback optimizer
- Empirically retains the performance of learned optimizer

The End

Thank you

- Come see our poster (ID 17027) https://icml.cc/virtual/2022/poster/17027

- https://arxiv.org/abs/2201.12426

The Solution