

# Prioritized Training on Points that are **Learnable**, **Worth Learning**, and **Not Yet Learned**

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Paper & code



# We all know model training can be very slow ...

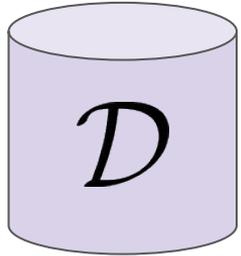
... but lots of computation and time is wasted on **redundant** and **noisy** points.

Skip points that are **already learnt**, **not learnable**, or **not worth learning** to accelerate training.



\* image from Pleiss, Geoff, et al. "Identifying mislabeled data using the area under the margin ranking." *Advances in Neural Information Processing Systems* 33 (2020)

# Online Batch Selection



Draw large batch with uniform sampling



$$\mathcal{B} = \{(x_i, y_i)\}_{i=1}^{n_B}$$

... Repeat

Create small batch  $b$  made of the **highest scoring** points in large batch  $\mathcal{B}$  according to a **selection function**

Key contribution

**Reducible Holdout Loss**  
A simple and principled selection function that identifies points that most reduce generalisation loss

Train on  $b$ ...

$$b = \{(x_i, y_i)\}_{i=1}^{n_b}$$

# Reducible Holdout Loss

A principled approach for (approximately) choosing points that would most improve the generalisation loss if trained on, *without* needing to train on those points.

Points with **high training loss**  
are not yet learnt ...

... but they could have high loss *because*  
they are **noisy (unlearnable)**, or **not worth learning (outlier, low density points)**

**Noisy** and **less relevant/outlier** points  
are **hard to predict using a holdout set**,  
and thus have **high IL**

$$\arg \max_{(x,y) \in B_t} \underbrace{L[y | x; \mathcal{D}_t]}_{\text{training loss}} - \underbrace{L[y | x; \mathcal{D}_{\text{ho}}]}_{\text{irreducible holdout loss (IL)}}$$

# The Reducible Holdout Loss is ...

... low for points that are **already learnt** (low training loss).

... low for points that are **noisy** (high training loss, high IL).

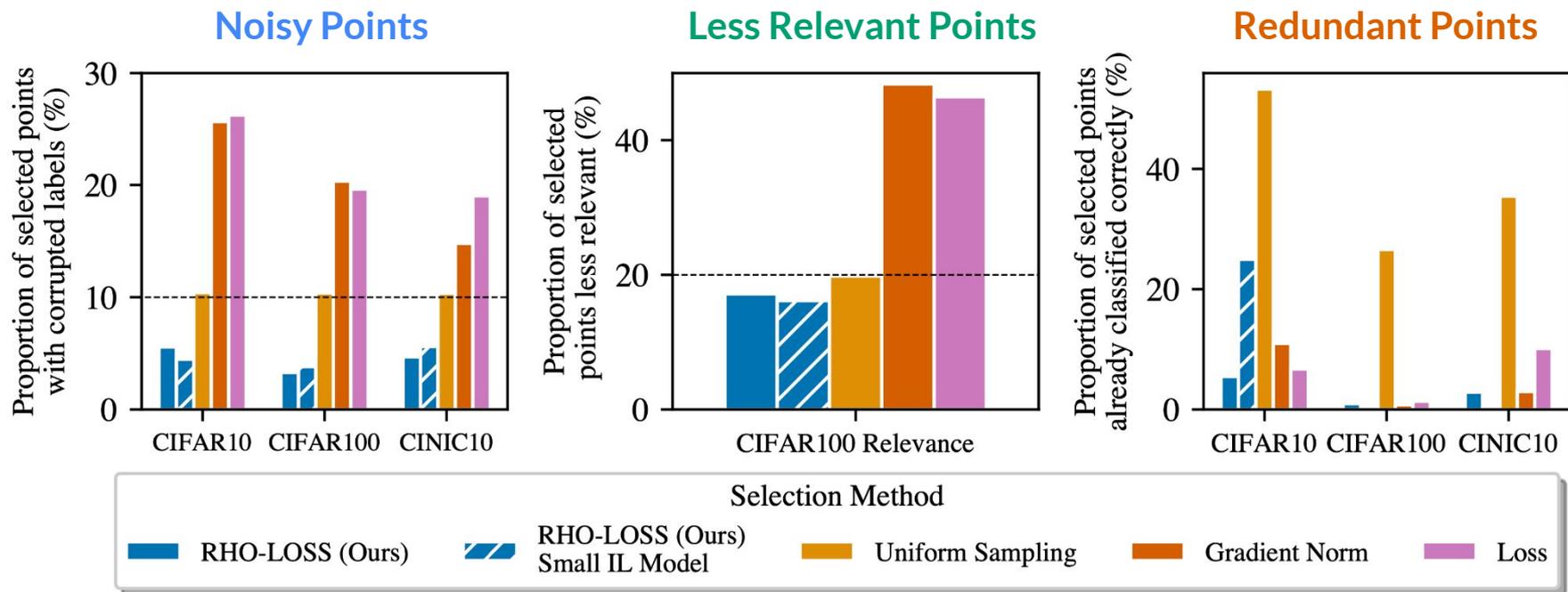
... low for points that are **outliers / less relevant** (high training loss, high IL).

... **high** for points that are **learnable, worth learning, and not yet learnt!**

$$\arg \max_{(x,y) \in B_t} \underbrace{L[y | x; \mathcal{D}_t]}_{\text{training loss}} - \underbrace{L[y | x; \mathcal{D}_{\text{ho}}]}_{\text{irreducible holdout loss (IL)}}$$

reducible holdout loss

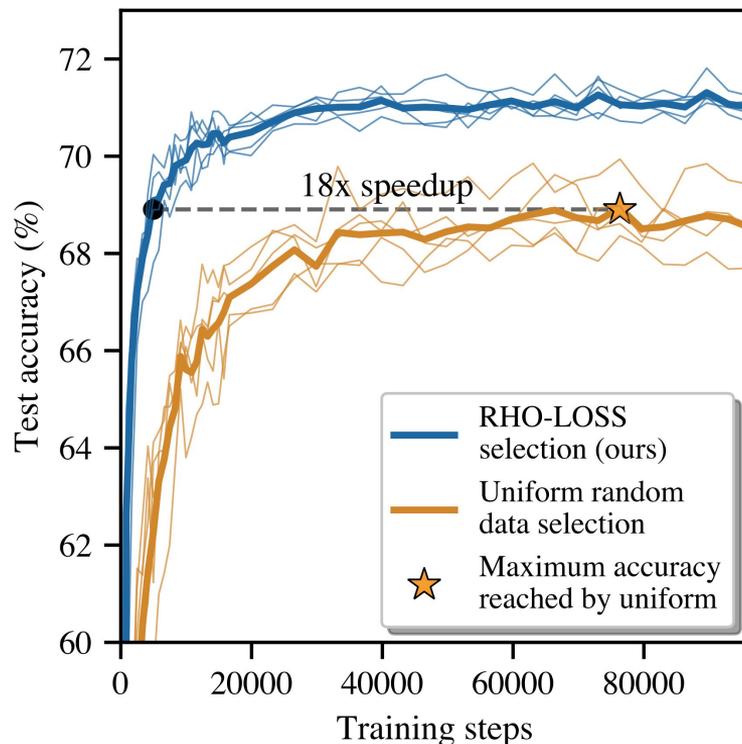
Indeed, RHO-LOSS prioritises points that are **non-noisy**, **task-relevant** and **non-redundant**



# RHO-LOSS trains in 18x fewer steps on Clothing-1M

Clothing-1M is a large web-scraped image dataset, containing **redundant** and **noisy** data—our target application.

Further, RHO-LOSS speeds up training on a **wide range of datasets**, **hyperparameters**, and **architectures** (MLPs, CNNs, and BERT).



*Thin lines: ResNet-50, MobileNet v2, DenseNet 121, Inception v3, GoogleNet. Bold lines: mean across architectures.*

# Thank you 😊

Come and speak to us! And check out the paper for more ...

✨ re-using a single small IL model for accelerating training for multiple architectures.

✨ deriving RHO-LOSS as an efficient, cheap approximation to optimal selection, derived in the language of probabilistic modelling.

✨ explaining why prior approaches don't work robustly.

Paper & code

