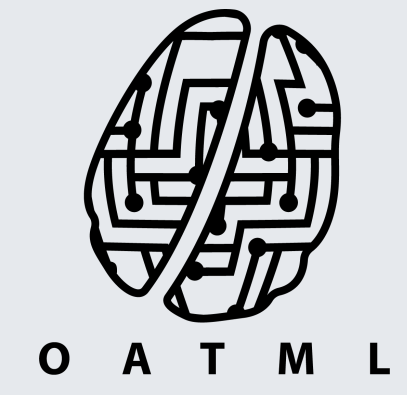# *GoldiProx*: Prioritized learning on points that are learnable, worth learning, and not yet learned

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Andreas Kirsch, Mrinank Sharma, Adrien Morisot, Aidan N. Gomez, Sebastian Farquhar, Jan Brauner, Yarin Gal

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Contributions

We developed an information theoretic approach to efficient model training in the large data regime.

Maximal information gain about the labels of a validation set:

- *Pointwise predictive information gain* as acquisition function.
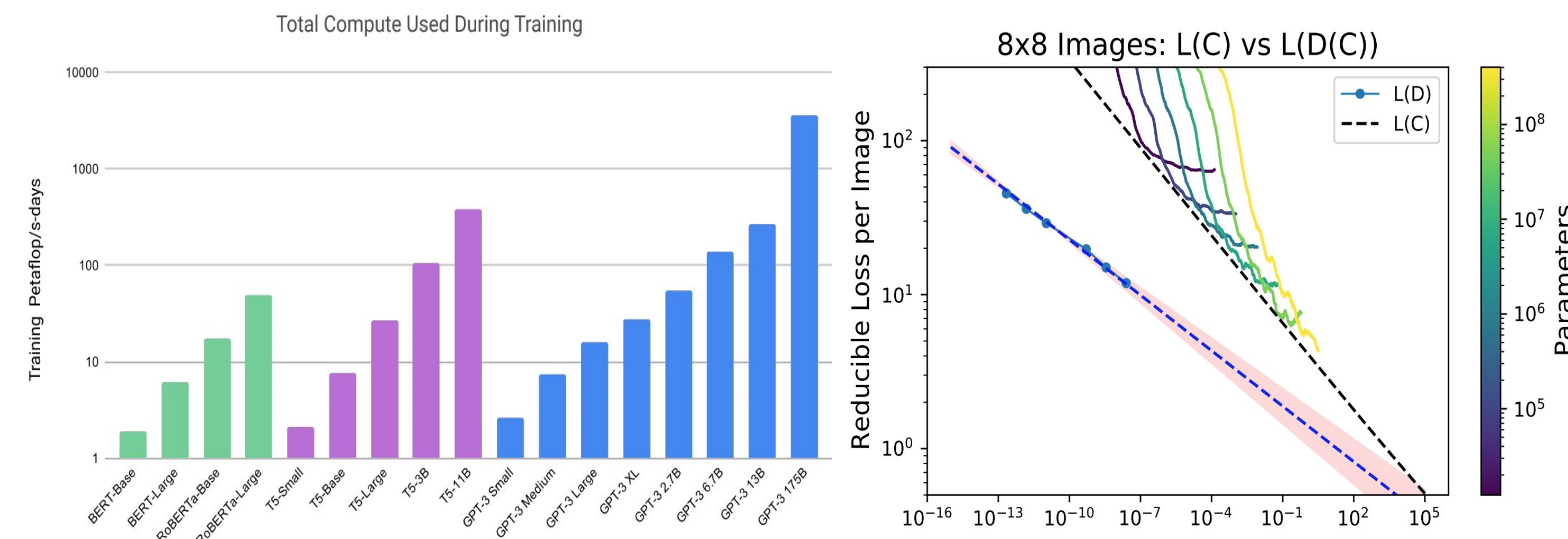- *GoldiProx Selection*: online batch selection via a proxy.

The *reducible held-out cross-entropy loss* as an easily implementable and novel objective function.

Prioritizing learnable, but informative data relevant to the eval task.

## A Transition from Mini-Batch to Mini-Epoch

Training is expensive and most data is <u>uninformative</u>:

1. <u>Redundant</u>: already learned, "easy" points
2. <u>Ambiguous</u>: non-learnable, "noisy" and unpredictable labels
3. <u>Atypical</u>: not worth learning (or prioritizing), "uncertain" labels

Total Compute Used During Training

8x8 Images: L(C) vs L(D(C))

Common methods of data selection have shortfalls:

1. <u>Online batch selection</u>: train only on "hard" points by sampling without replacement within in epoch to select a training batch

   → Skips redundant points, but expensive forward pass

2. <u>Curriculum learning</u>: prioritize "easy" points with low noise before training on all points with equal weight

   → Better convergence but fails to de-prioritize redundant points

3. <u>Active learning</u>: selects points where model is uncertain of label

   → Selects informative, non-noisy, but test-time irrelevant points

SVHN (SGD) - Noise Scale Comparison
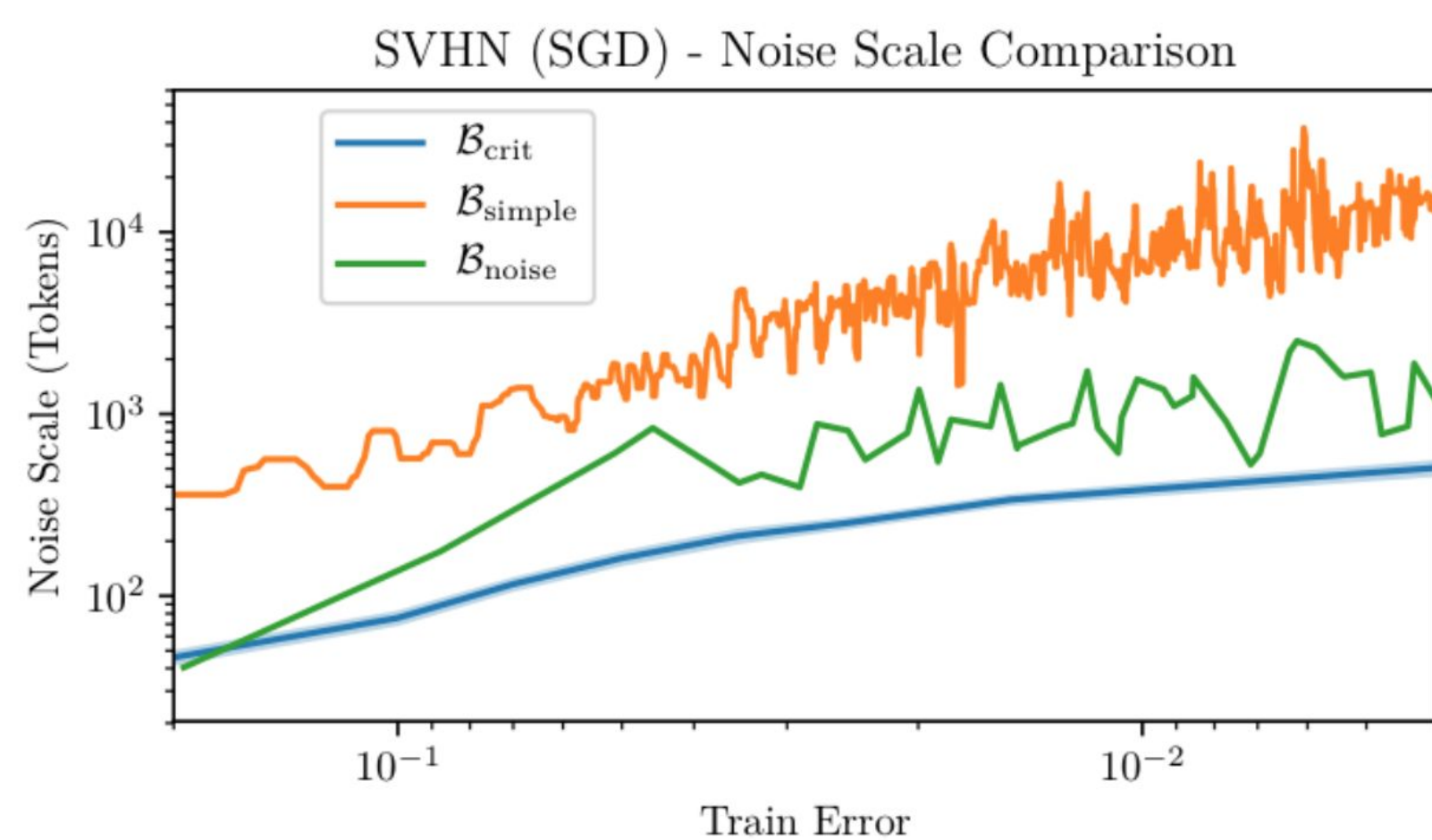
Select cheaply with a small proxy, train larger model on filtered sequence

Label-Aware Training Objective

Expected Predictive Information Gain (EPIG): select informative unlabeled points by computing the info gain / mutual information between Y$^{\text{val}}$ and Y since labels y for x are unavailable:

$$\mathrm{I}[\mathbf{Y}^{\text{val}}; Y \mid \mathbf{x}^{\text{val}}, x, \mathcal{D}_t] = H[\mathbf{Y}^{\text{val}} \mid \mathbf{x}^{\text{val}}, \mathcal{D}_t]$$
$$- H[\mathbf{Y}^{\text{val}} \mid \mathbf{x}^{\text{val}}, \mathcal{D}_t, x, Y]$$

Pointwise Predictive Information Gain via **pointwise mutual information (pmi):** remove the need to compute expectations over Y and Y$^{\text{val}}$ since the labels y$^{\text{val}}$ and y are available, i.e. a label-aware mutual info metric. Difference of pointwise conditional entropies (PCE):

PCE prior to (x, y)

$$\mathrm{pmi}[\mathbf{y}^{\text{val}}; y \mid \mathbf{x}^{\text{val}}, x, \mathcal{D}_t] = \boxed{\mathrm{h}[\mathbf{y}^{\text{val}} \mid \mathbf{x}^{\text{val}}, \mathcal{D}_t]}$$
$$- \boxed{\mathrm{h}[\mathbf{y}^{\text{val}} \mid \mathbf{x}^{\text{val}}, \mathcal{D}_t, x, y]}$$

PCE after seeing (x, y)

Reducible Held-Out Cross-Entropy Loss

Measures the uncertainty reduction about the validation labels y$^{\text{val}}$ due to observing a point in training (x, y),

$$\mathrm{h}[y \mid x, \mathcal{D}_t] - \mathrm{h}[y \mid x, \mathbf{x}^{\text{val}}, \mathbf{y}^{\text{val}}]$$

untrained model cross-entropy

irreducible cross entropy (loss of proxy and validation set, i.e. $D_t \ll D_{\text{val}}$)

so that a filtered dataset D_t represents a viable sequence of training examples that can be used to train a new model while also maximizing the validation likelihood of the pre-trained proxy model.

GoldiProx Selection: Improved Training Efficiency

```
1: Input: Initial parameters θ⁰_small and θ⁰_big, learning rate
   η, small model p(y | x, θ_val) trained on validation set,
   batch size |b|, large batch size |B| > |b|.

2: for i in training set do
3:     IrreducibleLoss[i] ← L(y_i, p(y_i|x_i, θ_val))
4: end for
5: Sequence ← []
```

Train a smaller model normally with negative log likelihood objective

```
6: for t = 1, 2, . . . do          ▷ Select data with small model
7:     Randomly select a large batch B_t of size |B|.
8:     ∀i ∈ B_t, compute Loss[i], the loss of point i
       given parameters θ^t_small
9:     ∀i ∈ B_t, compute ReducibleLoss[i] ←
       Loss[i] − IrreducibleLoss[i]
10:    b_t ← top-|b| samples in B_t in terms of
       ReducibleLoss.
11:    g_t ← mini-batch gradient on b_t for θ^t_small
12:    θ^{t+1}_small ← θ^t_small − η g_t
13:    Append b_t to Sequence.
14: end for
```

Take a gradient step on a mini-batch, based on reducible loss

```
16: for t = 1, 2, . . . do          ▷ Train large model
17:    Load b_t ← Sequence[t]
18:    g_t ← mini-batch gradient on b_t for θ^t_big
19:    θ^{t+1}_big ← θ^t_big − η g_t
20: end for
```

## Performant Models with Less Data and Iterations

High loss points are the points mislabelled by their noise distribution


(a) QMNIST (b) CIFAR10 (c) CINIC10
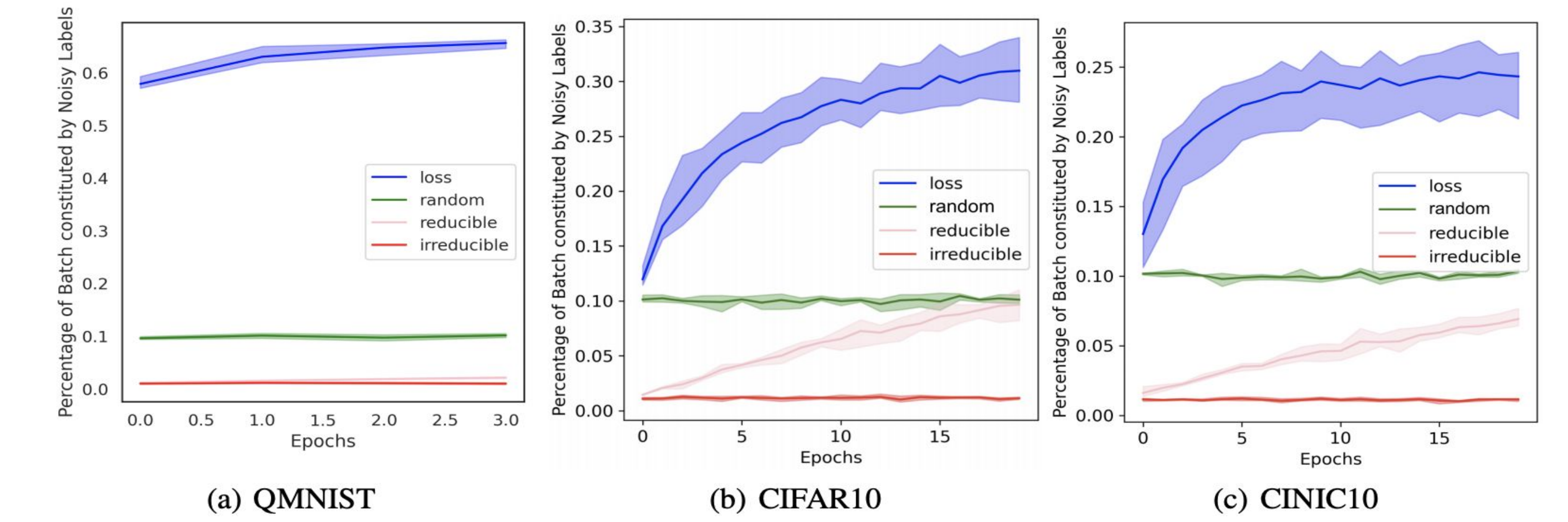
Reduced Uncertainty for the Prediction Task

Bayesian Active Learning with Disagree-ment (*BALD*) selects 20% of noisy samples perhaps since information can be gained from low support regions of input space. This is problematic in high kurtosis input distributions, as data that is unlikely to appear at test time is not worth learning. Reducible loss triumphs.
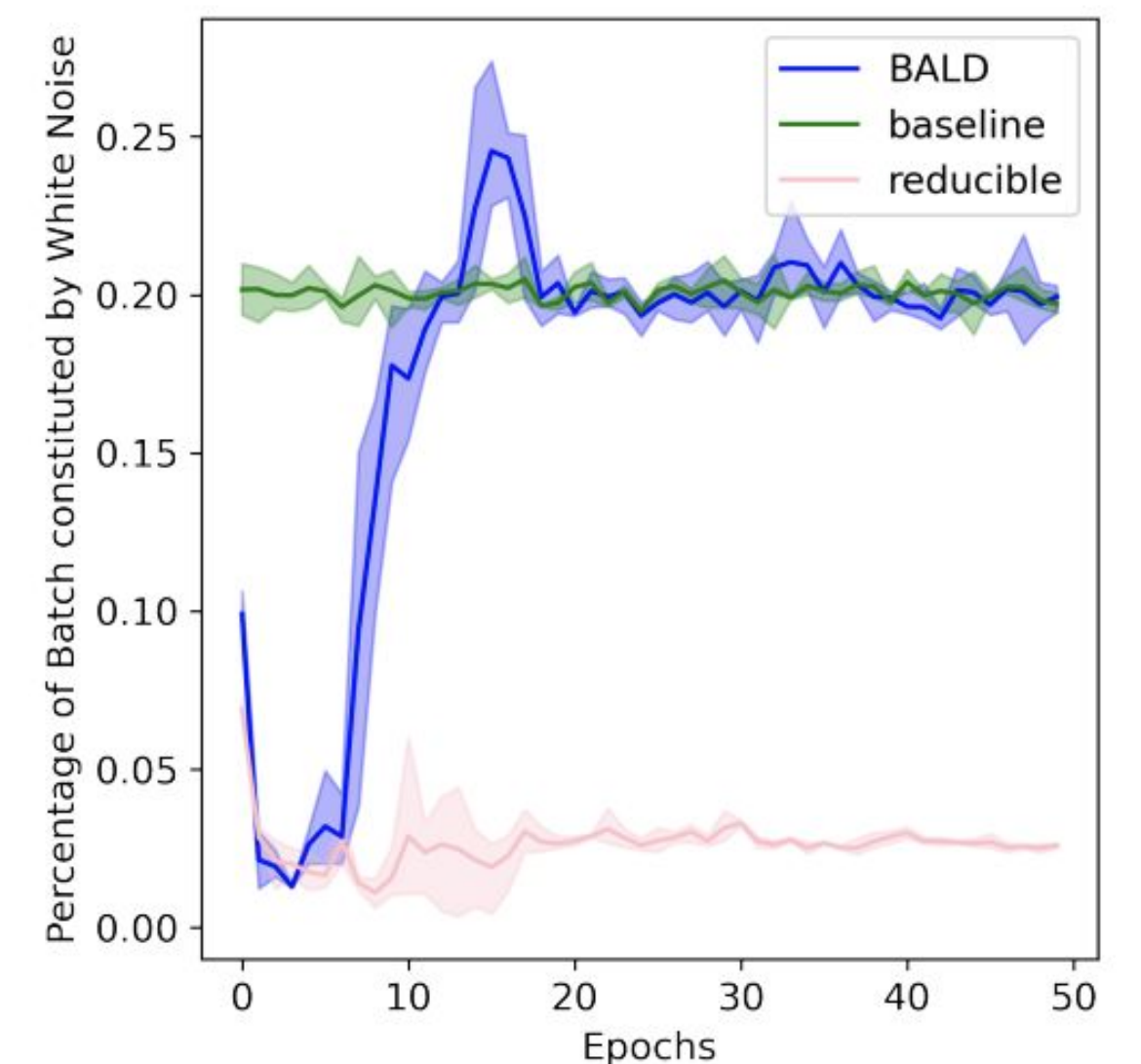
High Correlation between Proxy and Reducible Model

Effective transfer of reducible loss training with small proxy to larger models of different architectures. See rank correlations.

(a) QMNIST (b) CIFAR10 (c) CINIC10
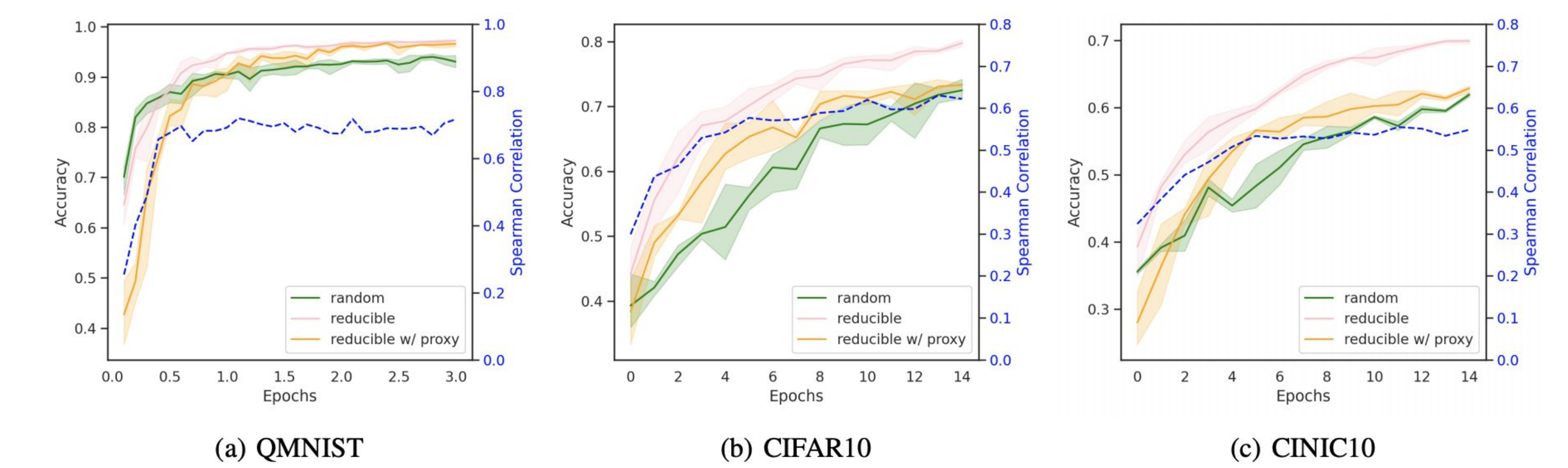
Model	Num of Params.	FLOPS	Model	Num of Params.	FLOPS
3-layer MLP with 128 hidden units	135 k	136 k	Small CNN	0.538 M	0.019 G
3-layer MLP with 512 hidden units	932 k	935 k	ResNet-18	11.17 M	0.557 G

This implies that a point learned by a converged model (i.e. trained on D, the original dataset) may still be informative to a model trained on D_t, the prioritized sequence of examples.

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