REDUCR: ROBUST DATA DOWNSAMPLING USING CLASS PRIORITY REWEIGHTING

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Abstract

Modern machine learning models are becoming increasingly expensive to train for real-world image and text classification tasks, where massive web-scale data is collected in a streaming fashion. To reduce the training cost, online batch selection techniques have been developed to choose the most informative datapoints. However, these techniques can suffer from poor worst-class generalization performance due to class imbalance and distributional shifts. This work introduces REDUCR, a robust and efficient data downsampling method that uses class priority reweighting. REDUCR *reduces* the training data while preserving worst-class generalization performance. REDUCR assigns priority weights to datapoints in a class-aware manner using an online learning algorithm. We demonstrate the data efficiency and robust performance of REDUCR on vision and text classification tasks. On web-scraped datasets with imbalanced class distributions, REDUCR achieves significant test accuracy boosts for the worst-performing class (but also on average), surpassing state-of-the-art methods by around 14%.

Keywords: Class Robustness, Online Batch Selection, Robust Machine Learning, Training Efficiency, Data Downsampling, Class Imbalance

1. Introduction

The abundance of data has had a profound impact on machine learning (ML), both positive and negative. On the one hand, it has enabled ML models to achieve unprecedented performance on a wide range of tasks, such as image and text classification (Kuznetsova et al., 2020; He et al., 2015; Brown et al., 2020; Tran et al., 2022; Anil et al., 2023). On the other hand, training models on such large datasets can be computationally expensive and time-consuming (Kaddour et al., 2023), making it unsustainable in some situations (Bender et al., 2021; Patterson et al., 2021). Additionally, the high speed at which streaming data is collected can make it infeasible to train on all of the data before deployment. To tackle these issues, various methods have emerged to selectively choose training data, either through pre-training data pruning (Sorscher et al., 2022; Bachem et al., 2017) or online batch selection techniques (Loshchilov and Hutter, 2016; Mindermann et al., 2022), ultimately reducing data requirements, improving training efficiency, and enabling ML models to handle otherwise unmanageable large and complex datasets.

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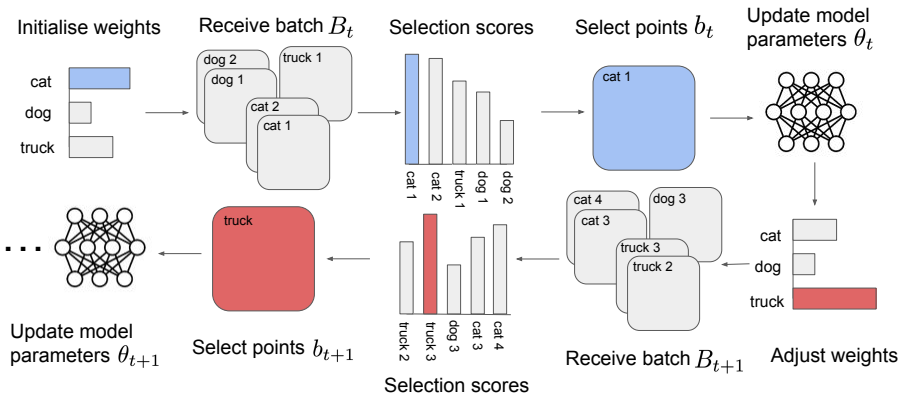

Figure 1: REDUCR starts by initializing weights of classes. At each timestep t, the model receives a batch of datapoints B_t. REDUCR computes the selection scores for each datapoint based on its usefulness to the model and the class weights, and selects new datapoints $b_t \subset B_t$ that achieve the highest selection scores. After the model takes gradient steps on the selected datapoints, REDUCR adjusts the weights to reflect increased priorities on underperforming classes.

In real-world settings, a variety of factors can affect the selection of datapoints, such as noise (Xiao et al., 2015) and class-imbalance in the data (Van Horn et al., 2018; Philip and Chan, 1998; Radivojac et al., 2004). Online selection methods can exacerbate these problems by further reducing the number of datapoints from underrepresented classes, which can degrade the performance of the model on those classes (Buda et al., 2018; Cui et al., 2019). Moreover, distributional shift (Koh et al., 2021) between training and test time can lead to increased generalization error if classes with poor generalization error are overrepresented at test time.

In this work, we introduce REDUCR, which is a new online batch selection method that is *robust* to noise, imbalance, and distributional shifts. REDUCR employs multiplicative weights update to reweight and prioritize classes that are performing poorly during online batch selection. Figure 1 illustrates the intuition on how the method works. REDUCR can effectively reduce the training data and improve training efficiency while preserving the worst-class generalization performance of the model. For example, on the Clothing1M dataset (Xiao et al., 2015), Figure 2 shows that, compared to the best performing online batch selection methods, REDUCR achieves around a 15% boost in performance for the worst-class test accuracy.

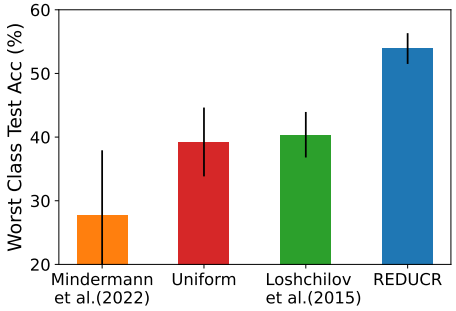

Figure 2: REDUCR significantly improves worst-lass test accuracy on Clothing1M.

2. Background

We consider a C-way classification task and denote a model as $p(y \mid x, \theta)$, where x denotes an input, $y \in [C]$ corresponds to a class, and the model is parameterized by θ. For any training dataset $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$ with N datapoints, we use a point estimate of θ to approximate the posterior model as $p(y \mid x, \mathcal{D}) \approx p(y \mid x, \hat{\theta})$. This estimate $\hat{\theta}$ can be obtained by running stochastic gradient descent (SGD) to optimize the cross-entropy loss over training dataset $\mathcal{D}$.

3. Problem Formulation

In this work, we introduce the *robust* data downsampling problem, where the goal is to select a training dataset $\mathcal{D}_T$ of size T such that worst-class generalisation error is optimized. We write this objective in terms of a separate *holdout* dataset $\mathcal{D}_{ho} = \{(x_{ho,i}, y_{ho,i})\}_{i=1}^{N_{ho}}$, where the holdout dataset with class $c \in [C]$ is $D_{ho}^{(c)} = \{(x, y) \in D_{ho} \mid y \equiv c\} = \{(x_{ho,i}^{(c)}, y_{ho,i}^{(c)})\}_{i=1}^{N_{ho}^{(c)}}$. We can write the objective of robust data downsampling as

$$\mathcal{D}_T = \underset{D \subset \mathcal{D}, |D|=T}{\operatorname{argmax}} \min_{c \in [C]} \log p(\mathbf{y}_{ho}^{(c)} \mid \mathbf{x}_{ho}^{(c)}, D), \tag{1}$$

where $\mathbf{x}_{ho}^{(c)} = [x_{ho,i}^{(c)}]_{i=1}^{N_{ho}^{(c)}}$ and $\mathbf{y}_{ho}^{(c)} = [y_{ho,i}^{(c)}]_{i=1}^{N_{ho}^{(c)}}$ correspond to the collections of inputs and labels in the class-specific holdout dataset $D_{ho}^{(c)}$. Solving Equation (1) is known to be NP-hard. *Robust online batch selection* approximates the robust data downsampling problem by taking into account the practical limitations of data operation. Namely, we assume a streaming setting where the model observes training data subset $B_t \subset \mathcal{D}$ at each timestep t. The goal is to select a small batch $b_t \subset B_t$ to compute gradients for model training with SGD, such that the model obtains top performance for the worst-class. A standard approach is to design selection scoring functions that can be used to score the utility of the small batch b_t.

4. REDUCR for Robust Online Batch Selection

We propose REDUCR, a robust and efficient data downsampling method using class priority reweighting to solve the robust online batch selection problem in Section 3. The selection scoring function of REDUCR relates the effect of training on a batch of candidate points b to the generalization error of a specific class in the holdout dataset, $\log p(\mathbf{y}_{ho}^{(c)} | \mathbf{x}_{ho}^{(c)}, \mathcal{D}_t \cup b)$.

4.1 Online Learning

To solve Equation (1) in an online manner, we propose to use class priority reweighting, a variant of the multiplicative weight update method (Cesa-Bianchi and Lugosi, 2006). At the beginning of training we initialise a weight vector $\mathbf{w}_0$ over a C dimensional simplex, $\Delta = \{\mathbf{w} = [w_c]_{c=1}^C \in \mathbb{R}^C | \sum_{c=1}^C w_c = 1\}$. Each element of $\mathbf{w}_0$ is initialised to be $w_{0,c} = 1/C$. For each iteration t, small batch $b_t \subset B_t$ is chosen by maximising the weighted sum of C different class-specific scoring functions,

$$b_t = \underset{b \subset B_t}{\operatorname{argmax}} \sum_{c=1}^{C} w_{t,c} \left(\log p(\mathbf{y}_{ho}^{(c)} | \mathbf{x}_{ho}^{(c)}, \mathcal{D}_t \cup b) \right), \tag{2}$$

where $\mathcal{D}_t = \bigcup_{\tau=1}^{t-1} b_\tau$, $\mathbf{w}_t = [w_{t,c}]_{c=1}^C \in \Delta$, and

$$w_{t,c} = w_{t-1,c} \frac{\exp\left(-\eta \log p(\mathbf{y}_{ho}^{(c)} | \mathbf{x}_{ho}^{(c)}, \mathcal{D}_t)\right)}{\sum_{j=1}^C w_{t-1,j} \exp\left(-\eta \log p(\mathbf{y}_{ho}^{(j)} | \mathbf{x}_{ho}^{(j)}, \mathcal{D}_t)\right)}. \tag{3}$$

In the previous alternating procedure, class-weights are updated multiplicatively according to how well they perform given the selected batch (they increase for poorly performing

Algorithm 1 REDUCR for robust online batch selection

Input: data pool $\mathcal{D}$, holdout data $\mathcal{D}_{ho} = \bigcup_{c \in C} \mathcal{D}_{ho}^{(c)}$, learning rate $\eta \in (0, \infty)$, small batch size k, total timesteps T/k
Initialize class weights $\mathbf{w}_1 = \frac{1}{C}\mathbf{1}_C$
Use $\mathcal{D}_{ho}$ to train C amortised class irreducible loss models to obtain ϕ_c
for $t \in [T/k]$ **do**
    Receive batch $B_t \subset \mathcal{D}$
    $b_t = \underset{b \subset B_t : |b| = k}{\operatorname{argmax}} \sum_{(x,y) \in b} \sum_{c \in C} w_{t,c} \max\left(0, \mathcal{L}[y|x, \theta_t] - \mathcal{L}[y|x, \phi_c]\right)$
    Compute the objective value for every class $c \in C$:

$$\alpha_c \leftarrow \sum_{(x,y) \in b_t} \left(\max(0, \mathcal{L}[y|x, \theta_t] - \mathcal{L}[y|x, \phi_c]) - \mathcal{L}[\mathbf{y}_{ho}^{(c)} | \mathbf{x}_{ho}^{(c)}, \theta_t] \right)$$

    Update class weights for every class $c \in C$: $w_{t+1,c} = w_{t,c} \frac{\exp(-\eta \alpha_c)}{\sum_{j \in C} w_{t,j} \exp(-\eta \alpha_j)}$
    $\theta_{t+1} \leftarrow SGD(\theta_t, b_t)$
end for

classes and decrease otherwise). In Equation (3), η is a learning rate that adjusts how concentrated the probability mass is in the resulting distribution. Figure 1 shows an intuitive illustration of how reweighting works in practice where classes that perform badly have low data likelihoods and are thus upweighted by Equation (3). We next introduce how to compute the likelihoods for class-specific holdout sets, i.e., $p(\mathbf{y}_{ho}^{(c)} | \mathbf{x}_{ho}^{(c)}, \mathcal{D}_t \cup b)$ in Equation (2).

4.2 Computing selection scores

Given the current dataset $\mathcal{D}_t$ at timestep t and additional datapoints $b \subset B_t$, we would like to compute the likelihood of the holdout dataset that belongs to class c. For simplicity, we consider the case where the small batch to be selected only includes a single datapoint, i.e., $b = \{(x, y)\}$. We express the objective using the Bayesian perspective introduced in Section 2, i.e.,

$$\log p(\mathbf{y}_{ho}^{(c)} \mid \mathbf{x}_{ho}^{(c)}, \mathcal{D}_t \cup \{(x,y)\}) \approx \underbrace{\mathcal{L}[y|x, \theta_t]}_{\text{model loss}} - \underbrace{\mathcal{L}[y|x, \theta_t^{(c)}]}_{\text{class-irreducible loss}} - \underbrace{\mathcal{L}[\mathbf{y}_{ho}^{(c)} | \mathbf{x}_{ho}^{(c)}, \theta_t]}_{\text{class-holdout loss}}. \quad (4)$$

Where we use $\mathcal{L}[y|x, \theta] = -\log p(y \,|\, x, \theta)$ to denote the cross-entropy loss. The derivation of Equation (4) can be found in Appendix A.2. Computing Equation (4) involves two models: (1) the *target* model with parameters θ_t, which is trained on the cumulative training dataset $\mathcal{D}_t = \bigcup_{\tau=1}^{t-1} b_\tau$; (2) a *class-irreducible loss model* (following the terminology from Mindermann et al. (2022)) with parameters $\theta_t^{(c)}$, which is trained on $\mathcal{D}_t$ and class-specific holdout data $\mathcal{D}_{ho}^{(c)}$. The target model is what we are interested in for the classification task. We name the three terms in Equation (4) the *model loss*, *class-irreducible loss* and *class-holdout loss*, respectively. The class-irreducible loss and the class-holdout loss both depend on the class c. Computing Equation (4) is far more tractable than naively re-training a new model (i.e., $\log p(\mathbf{y}_{ho}^{(c)} | \mathbf{x}_{ho}^{(c)}, \mathcal{D}_t \cup \{(x,y)\})$) for each possible candidate point (x, y). The model loss and the class-holdout loss only require evaluating the cross-entropy losses of some datapoints

on the target model. More generaly, if batch b can include more than one point, we can simply change the x and y to a list of inputs and labels instead. We further improve the efficiency of REDUCR by approximating the class-irreducible loss model weights $\theta_t^{(c)} \approx \phi_c$, full details are given in Appendix A.3.

4.3 REDUCR as a practical algorithm

We use the selection objective in Equation (4) along with the amortised class-irreducible loss model approximation (Appendix A.3) and the online algorithm (Section 4.1) to reweight the worst performing class during training and select points that improve its performance. See Algorithm 1 for a full description of the REDUCR method.

At each iteration, the top k points are selected (Line 6) according to the weighted sum of Equation (4) for each class $c \in C$, thus efficiently approximating the combinatorial problem from Equation (2). As the class-holdout loss does not depend on the selected points b_t and we sum over the classes, we can remove this term from the weighted sum of the selection scores and only apply it when updating the weights $\mathbf{w}_t$ (in Line 7 and 8). We calculate the *average* class-holdout loss to remove any dependence of the term upon the size of the classes in the holdout dataset. We find that clipping the excess loss improves the stability of the algorithm in practice. We test this heuristic empirically in Appendix C.5 and provide an intuitive explanation for why this is the case in Appendix C.5.1.

5. Experiments

In this section, we present empirical results to showcase the performance of REDUCR on large-scale vision and text classification tasks.

Datasets. We train and test REDUCR on image and text datasets. We use CIFAR10 (Krizhevsky et al., 2012), CINIC10 (Darlow et al., 2018), Clothing1M (Xiao et al., 2015), the Multi-Genre Natural Language Interface (MNLI), and Quora Question Pairs (QQP) from the GLUE NLP benchmark (Wang et al., 2019). We simulate the streaming setting by randomly sampling batch B_t from dataset $\mathcal{D}$ at each timestep.

Models. For the experiments on image datasets (CIFAR10, CINIC10 and Clothing1M) all models use a ResNet-18 model architecture (He et al., 2016). For the MNLI dataset we use the *bert-base-uncased* (Devlin et al., 2019) model from HuggingFace (Wolf et al., 2020).

Baselines. We benchmark our method against the state-of-the-art RHO-Loss, Train Loss and Uniform (Mindermann et al., 2022; Loshchilov and Hutter, 2016). For full experiment details see Appendix B.

5.1 Key results and Conclusion

The worst-class and average test accuracy for REDUCR and the best baseline model are shown in Table 1. Across all datasets, REDUCR outperforms the baselines in terms of the worst-class accuracy and matches or even outperforms the average test accuracy of the next best baseline within one standard deviation. This is also surprising because the primary goal of REDUCR is not to optimize the overall average (over classes) performance.

REDUCR performs particularly strongly on the Clothing1M dataset: Table 1 shows REDUCR improves the worst-class test accuracy by around 14% when compared to Train

Dataset	Worst-Class Test Accuracy		Average Test Accuracy	
	Best Baseline	REDUCR	Best Baseline	REDUCR
CIFAR10 (10 runs)	78.80 ± 2.09	**83.29 ± 0.84**	**90.00 ± 0.33**	**90.02 ± 0.44**
CINIC10 (10 runs)	69.39 ± 3.56	**75.30 ± 0.85**	**82.09 ± 0.30**	**81.68 ± 0.47**
Clothing1M (5 runs)	40.37 ± 3.58	**53.91 ± 2.42**	71.07 ± 0.46	**72.69 ± 0.42**
MNLI (5 runs)	76.74 ± 0.93	**79.45 ± 0.39**	**80.89 ± 0.31**	**80.28 ± 0.33**
QQP (5 runs)	79.96 ± 2.34	**86.61 ± 0.49**	**86.88 ± 0.31**	**86.99 ± 0.49**

Table 1: The results are provided as percentages with ± 1 std. REDUCR outperforms the next best baseline in terms of the worst-class test accuracy across all datasets. REDUCR matches or outperforms the average test accuracy across all datasets despite not optimizing the overall performance.

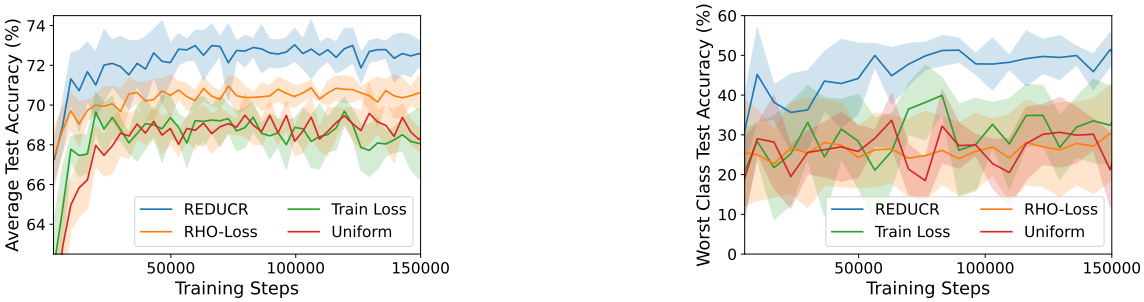

Figure 3: REDUCR improves the average (left) and worst-class (right) test accuracy on the Clothing1M dataset when compared with the RHO-Loss, Train Loss and Uniform baselines.

Loss, the next best-performing baseline. Section 5.1 shows that REDUCR also achieves this performance in a more data efficient manner than the comparable baselines, achieving a mean worst-class test accuracy of 40% within the first 10k training steps. The Clothing1M dataset also sees a distribution shift between the training and test dataset. In the test dataset, the worst performing class is much more prevalent than in the training dataset and as such improvements to its performance impact the average test accuracy significantly. Section 5.1 shows the impact of this distribution shift as the improved performance of the model on the worst class results in an improved average test accuracy when compared to the next best baseline, RHO-Loss. We present more detailed results and further experiments in Appendix C. In summary, we identified the problem of class-robust data downsampling and proposed a new method, REDUCR. Our experimental results indicate that REDUCR significantly enhances data efficiency during training, achieving superior test accuracy for the worst-performing class and frequently surpassing state-of-the-art methods in terms of average test accuracy. REDUCR excels in setting where the available data is imbalanced by prioritising the selection of points from underrepresented classes.

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Appendix A.

A.1 Online Batch Selection

The goal of *data downsampling* is to select a dataset $\mathcal{D}_T \subset \mathcal{D}$ of size T ($\ll N$) for training such that the generalisation error of the resulting model is minimised. We write this objective in terms of a separate *holdout* dataset $\mathcal{D}_{ho} = \{(x_{ho,i}, y_{ho,i})\}_{i=1}^{N_{ho}}$ as follows:

$$\mathcal{D}_T = \underset{D \subset \mathcal{D}, |D|=T}{\operatorname{argmax}} \log p(\mathbf{y}_{ho} | \mathbf{x}_{ho}, D), \tag{5}$$

where the inputs and their labels are $\mathbf{x}_{ho} = [x_{i,ho}]_{i=1}^{N_{ho}}$ and $\mathbf{y}_{ho} = [y_{i,ho}]_{i=1}^{N_{ho}}$, respectively. Here, the likelihood of the holdout dataset is used as a proxy for the generalisation error. The problem is computationally prohibitive due to its combinatorial nature. Moreover, for a massive (or streaming) training dataset $\mathcal{D}$, it is not computationally possible to load $\mathcal{D}$ all at once and it is common to loop through the data by iteratively loading subsets.

Online batch selection is a practical streaming setup to approximate the data downsampling problem, where at each timestep t, the model observes a training data subset $B_t \subset \mathcal{D}$, and the goal is to iteratively select a small batch $b_t \in B_t$ for the model to take gradient steps. A standard solution to this problem is to design selection scoring functions that take into account the labels of the data. The selection scoring function can then be used to *score* the utility of the small batch b_t, see Algorithm 2.

Reducible Holdout Loss (RHO-Loss) (Mindermann et al., 2022) is an online batch selection method that uses the performance on a holdout dataset as the selection scores for small batches. More precisely, for each timestep t, RHO-Loss selects

$$b_t = \underset{b \subset B_t}{\operatorname{argmax}} \log p(\mathbf{y}_{ho} \mid \mathbf{x}_{ho}, \mathcal{D}_t \cup b), \tag{6}$$

where $\mathcal{D}_t = \bigcup_{\tau=1}^{t-1} b_\tau$ is the cumulative training data the model has encountered until iteration t.

Algorithm 2.

Algorithm 2 Online batch selection

1: **Input:** data pool $\mathcal{D}$, number of training steps T, stochastic gradient descent algorithm SGD, a loss function $\mathcal{L}$
2: **for** $t = 1$ to T **do**
3: Sample batch B_t randomly from $\mathcal{D}$
4: $b_t = \text{SelectBatch}(B_t, \theta_t)$
5: $\text{L} = \sum_{(x_i, y_i) \in b_t} \mathcal{L}[y_i | x_i, \theta_t]$
6: $\theta_{t+1} = \text{SGD}(L, \theta_t)$
7: **end for**

A.2 Derivation of Selection Scoring Function

The robust setting motivates the development of novel selection scoring functions that consider how each datapoint affects the generalization error on the worst-case class of inputs,

rather than just the overall generalization error. We present the derivation for the REDUCR selection rule as shown in Equation (4),

$$\log p(\mathbf{y}_{ho}^{(c)} \mid \mathbf{x}_{ho}^{(c)}, \mathcal{D}_t \cup \{(x,y)\}) = \log \frac{p(y|x,\mathcal{D}_{ho}^{(c)},\mathcal{D}_t)p(\mathbf{y}_{ho}^{(c)}|\mathbf{x}_{ho}^{(c)},x,\mathcal{D}_t)}{p(y|x,\mathbf{x}_{ho}^{(c)},\mathcal{D}_t)} = \log \frac{p(y|x,\mathcal{D}_{ho}^{(c)},\mathcal{D}_t)p(\mathbf{y}_{ho}^{(c)}|\mathbf{x}_{ho}^{(c)},\mathcal{D}_t)}{p(y|x,\mathcal{D}_t)}$$
$$= -\log p(y \mid x, \mathcal{D}_t) + \log p(y \mid x, \mathcal{D}_t, \mathcal{D}_{ho}^{(c)}) + \log p(\mathbf{y}_{ho}^{(c)} \mid \mathbf{x}_{ho}^{(c)}, \mathcal{D}_t). \quad (7)$$

Equation (7) follows from the application of the Bayes rule and the conditional independence of x and $\mathbf{x}_{ho}^{(c)}$ with $\mathbf{y}_{ho}^{(c)}$ and y, respectively. The posterior terms in Equation (7) can be approximated with point estimates of model parameters (see §2).

Finally we define the term *excess loss* as the difference of the model loss and class-irreducible losses from Equation (4)(the first two terms in Equation (7)). The excess loss is the improvement in loss for point (x, y) by observing more data from class c (i.e., $\mathcal{D}_{ho}^{(c)}$).

A.3 Class-Irreducible Loss Models

For each selected batch b_t under the current selection rule in Equation (4), we need to update C class-irreducible loss models to compute the class-irreducible losses. We propose to approximate these models using *amortised* class-irreducible loss models, which are trained for each class at the beginning of REDUCR and do not need to be updated at future timesteps.

We interpret the class irreducible loss term as an expert model at predicting the label of points from a specific class c due to the extra data from the holdout dataset this term has available. To create an approximation of this expert model, we train the amortised class-irreducible loss models using an adjusted loss function in which points with a label from the class c are up-weighted by a parameter $\gamma \in (0, +\infty)$ (set in Section 5):

$$\phi_c = \arg\min_{\phi} \sum_{(x,y)\in\mathcal{D}_{ho}} (1 + \gamma\, \mathbb{I}[c \equiv y])\, \mathcal{L}[y|x,\phi]. \quad (8)$$

Here we define $\mathbb{I}[\cdot]$ as the indicator function. Equation (8) optimizes over the parameters of the amortised class-irreducible loss model for class c, and obtain ϕ_c to approximate $\theta_t^{(c)}$ in Equation (4), i.e., $\mathcal{L}[y|x,\theta_t^{(c)}] \approx \mathcal{L}[y|x,\phi_c]$. We detail the pseudo-code for training the class irreducible loss model in Algorithm 3.

Algorithm 3 Class Reference Model Training

1: **Input:** holdout dataset $\mathcal{D}_{ho}$, number of training steps T, stochastic gradient descent algorithm SGD, a loss function $\mathcal{L}$, a specific class c
2: **for** $t = 1$ to T **do**
3: $\quad B_{ho} \sim \text{Uniform}(\mathcal{D}_{ho})$
4: $\quad L = \sum_{(x_i,y_i)\in B_{ho}} (1 + \gamma \mathbb{I}[c = y]) \mathcal{L}[y_i|x_i,\phi_t]$
5: $\quad \phi_{t+1} = \text{SGD}(L, \phi_t)$
6: **end for**
7: **return** Class-irreducible loss model parameters ϕ_T

A.4 The Effect of the Class-Holdout Loss on the Selection of Points

The class-holdout loss only affects the selection of points at each iteration t through the selection of the weights $\mathbf{w}_t$. As the term does not depend upon the candidate point $(x, y) \in B_t$ and the weights are normalised

$$\sum_{c \in C} w_{t,c} \log p(\mathbf{y}_{ho}^{(c)} | \mathbf{x}_{ho}^{(c)}, \mathcal{D}_t \cup (\{x, y\})) = \mathcal{L}[y|x, \theta_t] - \sum_{c \in C} w_{t,c} (\mathcal{L}[y|x, \theta_t^{(c)}]) - \sum_{c \in C} w_{t,c} (\mathcal{L}[\mathbf{y}_{ho}^{(c)} | \mathbf{x}_{ho}^{(c)}, \theta_t]), \tag{9}$$

it is simply an added constant in the arg max. Likewise, as the model loss does not depend upon the class c and the weights $\mathbf{w}_t$ are normalised the model loss is unchanged. For this reason we simplify the notation of Algorithm 1 by removing the class-holdout loss term from the arg max selection of points.

A.5 REDUCRs Intuition

When comparing REDUCR to other online batch selection methods, we observe distinct batch selection patterns. When the dataset is class-imbalanced, the underrepresented classes tend to perform worse because of the lack of training data from those classes. RHO-Loss may struggle to select points from the underrepresented classes as they have less effect on the loss of the holdout dataset. Selection rules that select points with high training loss (Loshchilov and Hutter, 2016; Kawaguchi and Lu, 2020; Jiang et al., 2019) might select points from the underrepresented classes but have no reference model to determine which of these points are learnable given more data and thus noisy or task-irrelevant points may be selected. In contrast, REDUCR addresses both of these issues by identifying underrepresented classes and using the class-irreducible loss model to help to determine which points from these classes should be selected.

Even when the dataset is not imbalanced, certain classes might be difficult to learn; for example, due to noise sources in the data collection processes. Via Equation (3), REDUCR is able to re-weight the selection scores such that points that are harder to learn from worse-performing classes are selected over points that are easier to learn from classes that are already performing well. This is in contrast to RHO-Loss which will always select points that are easier to learn. We empirically demonstrate this on class balanced datasets in Section 5.

Appendix B. Experiment Details

We provide the full code base anonymised for review purposes at:
https://anonymous.4open.science/r/REDUCR-24D3.

Each dataset is split into a labelled training, validation and test dataset, the validation dataset is used to train the class-irreducible loss models and evaluate the class-holdout loss during training. All experiments are run multiple times and the mean and standard deviation across runs calculated. Unless stated otherwise at each batch selection step 10% of batch B_t is selected as the small batch b_t, we set $\eta = 1e-4$, and $\gamma = 9$ is used when training each of the amortised class-irreducible loss models. We study the impact of γ and η on REDUCR further in Appendix C.7. We now provide an overview of how each dataset is processed, the models used and more details on the baselines used.

CIFAR10 used half the training dataset (25k points) as a holdout validation dataset for training the amortised class-irreducible loss models and calculating the class-holdout loss during the robust online batch selection. We used the remaining 25k points as a training dataset and the provided test dataset (10k) for testing.

CINIC10 used the provided validation dataset for both the class holdout loss and amortised class irreducible loss models.

Clothing1M. The dataset consists of 1 million images labelled automatically using the keywords in its surrounding text. The dataset consists of 72k 'clean' images whose labels have been hand checked, 50k, 13k and 9k are respectively sorted into a clean training, validation, and test sub-dataset. To train the amortised class irreducible loss models we use 100k points randomly sampled from the union of the validation, clean and noisy training datasets. We calculate the class-holdout loss term and validation performance during training using the clean validation dataset.

MNLI. The dataset Williams et al. (2018) consists of 412k labeled sentence pairs; similarly to Sagawa et al. (2020) we split these sentence pairs into a train (206k), validation (164k), and labelled test (41k) dataset.

QQP. The dataset consists of 431k labeled sentence pairs; we remove points from class 1 to further imbalance the dataset resulting in 22% of the dataset labelled class 1. We split the remaining points into a train (148k), validation (67k), and labelled test (40k) dataset. We do not adjust the balance of the test dataset.

Models The ResNet-18 model used for the Clothing1M experiments is the pretrained model available via the Torchvision (Marcel and Rodriguez, 2010) model library. For the CIFAR10 and CINIC10 experiments we use the adapted ResNet-18 architecture detailed in Mindermann et al. (2022) Appendix B. The networks are optimised with AdamW (Loshchilov and Hutter, 2019) and the default Pytorch hyperparameters are used for all methods except CINIC10 for which the weight decay is set to a value of 0.1.

Train Loss baseline is taken from Loshchilov and Hutter (2016) where points from the large batch B_t are sampled with probability

$$p_i \propto \frac{1}{\exp(\log(s)/|B_t|)^i}. \tag{10}$$

Here p_i is the point with the i^{th} highest training loss in the large batch. We set the selection pressure parameter $s_e = 100$ and do not vary this during training as per the Experiments in Section 6. of Loshchilov and Hutter (2016).

Uniform baseline is taken from Mindermann et al. (2022). At iteration t, points are sampled at random from B_t to create the small training batch b_t.

Compute. All models were trained on NVIDIA Tesla T4 GPUs.

Data Augmentation was applied to the training dataset during online batch selection and validation dataset during the training of the amortised class-irreducible loss model. We apply a random crop and random flip to the images.

Appendix C. Additional Experimental Results

C.1 Full Results

The full comparison of REDUCR against the other baseline methods is presented in tables Table 2 and Table 3.

Dataset	Worst-Class Test Accuracy (%) ±1 std			
	Uniform	**Train Loss**	**RHO-Loss**	**REDUCR**
CIFAR10 (10 runs)	75.01 ± 1.37	76.1 ± 2.31	78.80 ± 2.09	**83.29 ± 0.84**
CINIC10 (10 runs)	64.70 ± 2.45	64.83 ± 4.75	69.39 ± 3.56	**75.30 ± 0.85**
Clothing1M (5 runs)	39.23 ± 5.41	40.37 ± 3.58	27.77 ± 10.16	**53.91 ± 2.42**
MNLI (5 runs)	74.70 ± 1.26	74.56 ± 1.44	76.74 ± 0.93	**79.45 ± 0.39**
QQP (5 runs)	73.21 ± 2.04	79.96 ± 2.34	78.21 ± 1.95	**86.61 ± 0.49**

Table 2: REDUCR outperforms RHO-LOSS (the best overall baseline) in terms of the worst-class test accuracy on Clothing1M, CINIC10 and CIFAR10 by at least 5-26%. On MNLI, REDUCR matches the performance of RHO-LOSS. Across all baselines, REDUCR gains about 15% more accuracy on the noisy and imbalanced Clothing1M dataset as shown in Figure 2.

Dataset	Average Test Accuracy (%) ±1 std			
	Uniform	**Train Loss**	**RHO-Loss**	**REDUCR**
CIFAR10 (10 runs)	85.09 ± 0.52	88.86 ± 0.22	**90.00 ± 0.33**	**90.02 ± 0.44**
CINIC10 (10 runs)	79.51 ± 0.30	79.25 ± 0.33	**82.09 ± 0.30**	**81.68 ± 0.47**
Clothing1M (5 runs)	69.60 ± 0.85	69.63 ± 0.30	71.07 ± 0.46	**72.69 ± 0.42**
MNLI (5 runs)	79.19 ± 0.53	76.85 ± 0.14	**80.89 ± 0.31**	**80.28 ± 0.33**
QQP (5 runs)	85.05 ± 0.43	**86.30 ± 0.41**	**86.88 ± 0.31**	**86.99 ± 0.49**

Table 3: REDUCR matches or outperforms the average test accuracy of the best competing baseline across all datasets. Note that optimizing the average test accuracy is not the objective of REDUCR. These results, together with Table 2, demonstrate the significant advantage of REDUCR to improve the worst-class accuracy while maintaining the strong average-case performance.

C.2 Results with worst-class checkpointing

We present results when the Train Loss and RHO-Loss worst-class validation accuracy are used to checkpoint the model during training. REDUCR still outperforms or matches the best baseline performance across all dataset.

Dataset	Worst-Class Test Accuracy (%) ±1 std			
	Uniform	**Train Loss**	**RHO-Loss**	**REDUCR**
CIFAR10 (10 runs)	75.01 ± 1.37	79.32 ± 1.35	81.23 ± 1.18	**83.29 ± 0.84**
CINIC10 (10 runs)	70.86 ± 1.23	68.89 ± 0. 86	**73.44 ± 1.16**	**75.30 ± 0.85**
Clothing1M (5 runs)	39.23 ± 5.41	49.02 ± 2.32	32.19 ± 9.83	**53.91 ± 2.42**
MNLI (5 runs)	76.88 ± 1.21	75.75 ± 0.56	**78.04 ± 1.73**	**79.45 ± 0.39**
QQP (5 runs)	84.50 ± 0.56	**85.49 ± 1.32**	82.60 ± 1.12	**86.61 ± 0.49**

Table 4: Worst-class test accuracy, when the RHO-Loss and Train Loss baselines are checkpointed using their worst-class validation error during training.

Dataset	Average Test Accuracy (%) ±1 std			
	Uniform	**Train Loss**	**RHO-Loss**	**REDUCR**
CIFAR10 (10 runs)	85.09 ± 0.52	87.74 ± 0.50	**89.43 ± 0.57**	**90.02 ± 0.44**
CINIC10 (10 runs)	79.57 ± 0.75	78.21 ± 0.57	**81.28 ± 0.54**	**81.68 ± 0.47**
Clothing1M (5 runs)	69.60 ± 0.85	69.46 ± 0.43	70.63 ± 0.87	**72.69 ± 0.42**
MNLI (5 runs)	78.85 ± 0.38	78.50 ± 0.33	**80.50 ± 0.45**	**80.28 ± 0.33**
QQP (5 runs)	85.23 ± 0.36	**86.24 ± 0.26**	**86.75 ± 0.37**	**86.99 ± 0.49**

Table 5: Average test accuracy, when the RHO-Loss and Train Loss baselines are checkpointed using their worst-class validation error during training.

C.3 Clothing1M Training Weights

The Clothing1M dataset is imbalanced with respect to class 4. Figure 4 shows that REDUCR is able to consistently identify and weight the underrepresented class across model runs.

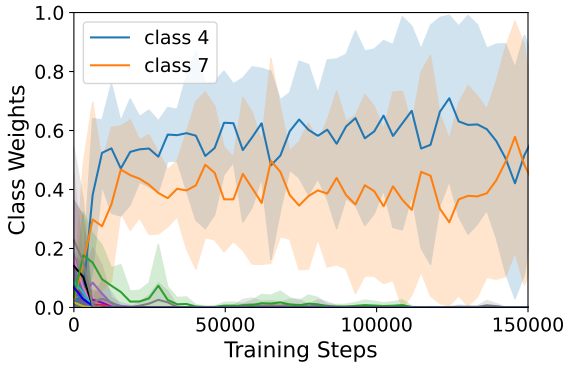
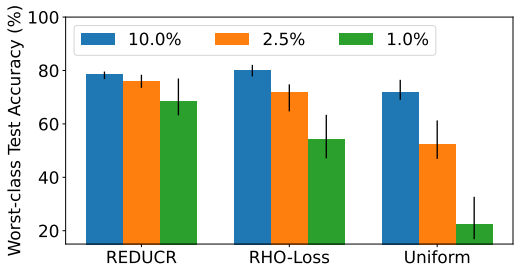
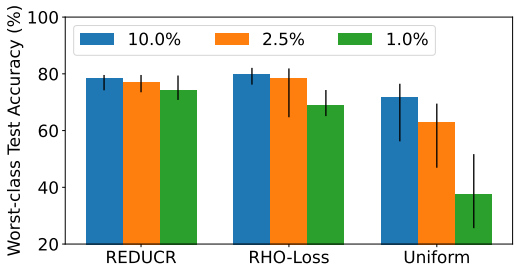


Figure 4: Clothing1M class weights



(a) Under-sampling on class 3



(b) Under-sampling on class 5

Figure 5: Results on worst-class test accuracy for artificially imbalancing (1) class 3 and (b) class 5 on CIFAR10, with 1%, 2.5%, 10.0% percent imbalances (percentage of training data that belong to the imbalanced class). REDUCR significantly reduces the deterioration in performance, showing that target models trained using our method are more robust to class imbalance than models trained using the RHO-Loss and Uniform baselines.

C.4 Imbalanced Datasets

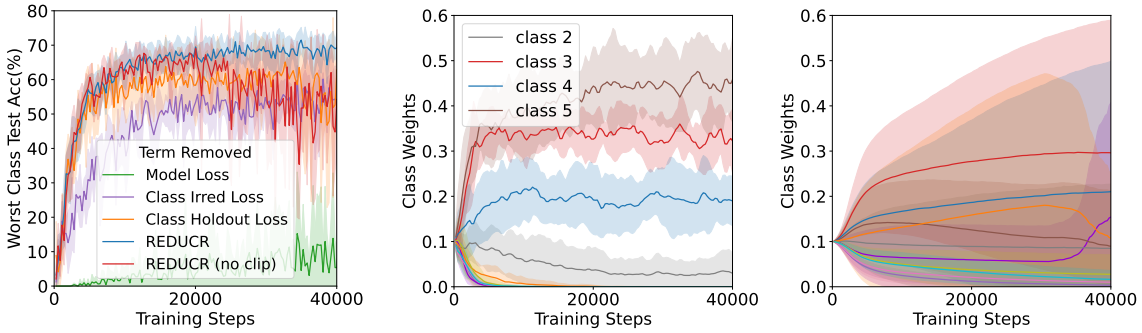
In this section, we investigate the performance of models trained using REDUCR on imbalanced datasets. We artificially imbalance the CIFAR10 dataset such that a datapoint of the imbalanced class is sampled with probability $p \in (0, 1/C]$ (referred to as the percent imbalance) and datapoints from the remaining classes are sampled with probability $(1-p)/(C-1)$ during model training. We only artificially imbalance the training and validation sets and not the test set. We conduct experiments with 1.0%, 2.5% and 10.0% percent imbalances on classes 3 and 5. Note that a percent imbalance of 10.0% is equivalent to the original (balanced) CIFAR10 training and validation sets. We repeat the experiments 10 times and plot the median values in Figure 5, and the error bars denote the best accuracy and the worst across 10 runs.

We find that the performance of models trained using REDUCR deteriorates less than those trained with the RHO-Loss or Uniform baselines as the percent imbalance of a particular class decreases (see Figure 5). For example, when class 3 is imbalanced, in the most imbalanced case (1.0%) the median performance of REDUCR outperforms that of RHO-Loss run by 14%. This demonstrates the effectiveness of REDUCR in prioritising the selection of data points from underrepresented classes.

C.5 Ablation Studies

To further motivate the selection rule in Equation (4), we conduct a series of ablation studies to show that all the terms are necessary for robust online batch selection. Figure 6a shows the performance of REDUCR on the CINIC10 dataset when the model loss, amortised class-irreducible loss and class-holdout loss terms of the algorithm were individually excluded from the selection rule. We note that all three terms in Equation (4) are required to achieve a strong worst-class test accuracy.

The removal of the class-holdout loss term affects the ability of REDUCR to prioritise the weights of the model correctly. In Figure 6 we compare the class weights of REDUCR and an ablation model without the class-holdout loss term. The standard model clearly prioritises classes 3, 4 and 5 during training across all 5 runs, whilst the ablation model

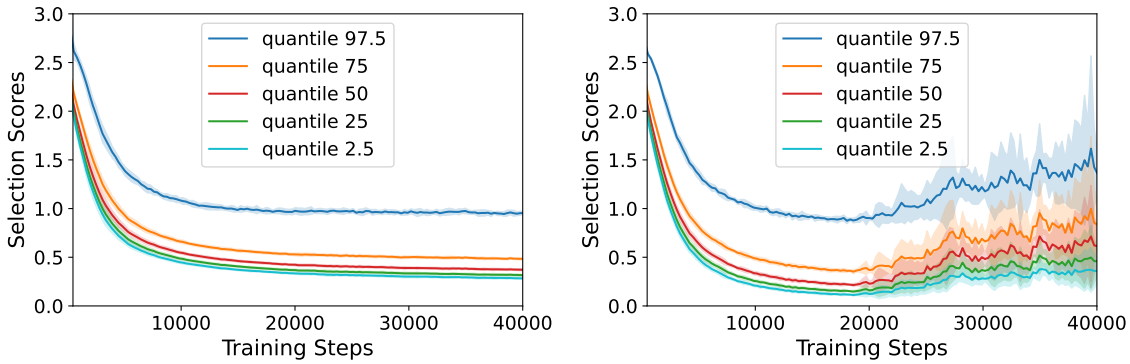


(a) (b) (c)

Figure 6: a) The worst-class test accuracy *decreases* when the model loss, class irreducible loss, and class-holdout loss terms are removed from REDUCR on CINIC10. Comparing REDUCR with clipping for excess losses (Algorithm 1) and REDUCR (no clip) which removes the clipping, we observe that REDUCR achieves more stable performance. We show the class weights $\mathbf{w}$ at each training step for b) REDUCR and c) REDUCR with the class-holdout loss term ablated. The ablation model fails to consistently prioritise the underperforming classes across multiple runs.

does not consistently weight the same classes across multiple runs. We also conducted an ablation study on the clipping of the excess loss to motivate its inclusion in the algorithm, this is also shown in Figure 6a, we note that this stabilises the model performance towards the end of training and investigate further in Appendix C.5.1.

C.5.1 Clipped Excess Loss Ablation Experiments



(a) REDUCR Excess Loss (b) REDUCR Excess Loss No Clipping

Figure 7: The quantiles of the excess loss of points selected at each training step with (a) and without clipping (b) of the excess loss term

To further understand the effects of clipping in the algorithm we analyse the selection score of the selected points with and without clipping. As detailed in Appendix A.4 the class-holdout loss only affects the selection of points via the weights $\mathbf{w}_t$ at each time step, as such we record only the excess loss (the difference between the model loss and class irreducible

loss). Figure 7 shows the quantiles of the weighted sum of the excess losses of points selected at each training step for the non-clipped and clipped model respectively. When the excess loss is clipped, Figure 7a shows the selection scores smoothly decrease throughout training as the model loss improves. Without clipping the excess loss decreases smoothly at the beginning of training and then shows unstable behaviour across runs later in training.
In practice we select multiple points per batch by selecting the points with the top k selection scores. When multiple points have the same score, points are selected at random. We note that the clipping does not reduce the excess loss of the selected points to zero where points would be selected randomly to make up the batch.
Intuitively we posit that the clipping reduces the effect of clashing amortised class irreducible loss models in the weighted sum across the $|C|$ selection rules. The amortised class irreducible loss models are trained such that they are an expert in a specific class c. In some cases a model being an expert in a specific class c' may result in it being a poor predictor of classes $C \setminus c'$. Even if this expert has a small weight $w_{t,c'}$ large losses may still propagate into the selection of points. Clipping the excess loss prevents a point from being down-weighted in the weighted by a specific class too much.

C.6 Amortised Class Irreducible Loss Models

In Figure 8 we compare the average expert class test accuracy and non-expert class test accuracy across different values of γ for the amortised class-irreducible loss model train on CIFAR10. For the model to be an expert in one class it loses performance in the non-relevant classes. To avoid the problems described in Appendix C.5.1 we selected $\gamma = 9$ for which the performance of the non-expert class did not suffer too much.

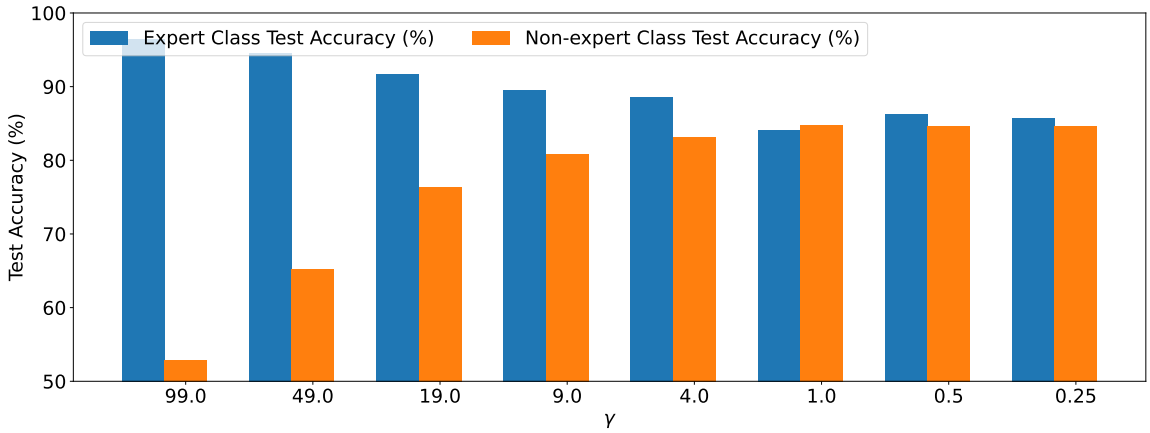


Figure 8: Class-irreducible loss model test accuracies on the expert class and non-expert classes. Class-irreducible loss models are trained using gradient weights $\gamma \in \{0.25, 0.5, 1.0, 4.0, 9.0, 19.0, 49.0, 99.0\}$.

C.7 Hyper-parameter Tuning

In this section, we perform sensitivity analyses for hyper-parameters introduced by REDUCR. In particular, we investigate the sensitivity of target model performance to the

learning rate η used for target model training, the gradient weight γ used for class-irreducible loss model training, the fraction of datapoints selected for target model training n_b/n_B (for a constant selected batch size n_b), and the frequency with which class hold-out losses are updated during target model training.

All experiments in this section use the CIFAR10 dataset. We use ResNet-18 target models (trained using $\eta = 10^{-4}$ and with a percent train of 0.10) and ResNet-18 class irreducible loss models (trained using $\gamma = 9$) unless otherwise stated.

We find that REDUCR's performance is not sensitive to the learning rate η and the frequency of class hold-out loss updating. We find that REDUCR's performance is sensitive to the gradient weight γ, though this is because a larger gradient weight increases the variance of loss gradients and slows model training. REDUCR's performance is not sensitive to the gradient weight at smaller gradient weights, for which class irreducible loss model training losses have converged. Finally, we find that REDUCR's performance is not sensitive to the fraction of data points selected for target model training (referred to as the percent train) for intermediate values of percent train, though performance is poor for very low fractions and very high fractions (recall a fraction of 1.0 recovers uniform selection).

In summary, REDUCR's performance is largely insensitive to the values of newly-introduced hyper-parameters on the CIFAR10 dataset. Sensitivity analyses on additional datasets are needed to increase the robustness of these findings. However, a gradient weight of $\gamma = 9$ and a percent train of 0.10 perform well without additional hyper-parameter tuning for several datasets, class irreducible loss model architectures and target model architectures in our main experiments, which tentatively suggests the robustness of these findings.

C.7.1 Learning Rate η

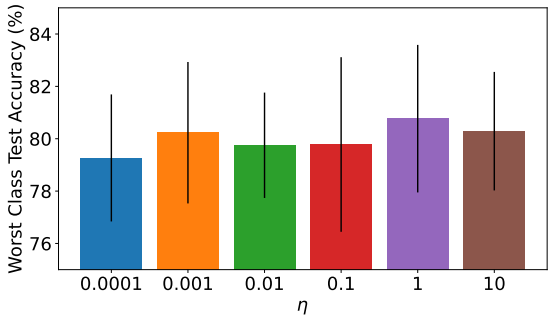
First, we perform a sensitivity analysis on the learning rate η. We train target models using REDUCR for each $\eta \in \{10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 10^{0}, 10^{1}\}$.

Experimental results demonstrate that smaller values of η result in a faster improvement in target model performance during training, though final target model performance is similar for all values of η investigated (see figure). Intuitively, larger values of η result in more concentrated class weights. REDUCR therefore uses a more concentrated weighted average of class irreducible losses during datapoint selection, which reduces the quality of selected datapoints. Larger values of η also result in faster changes in class weights between training steps, which reduces the coherence of datapoint selection between training steps.

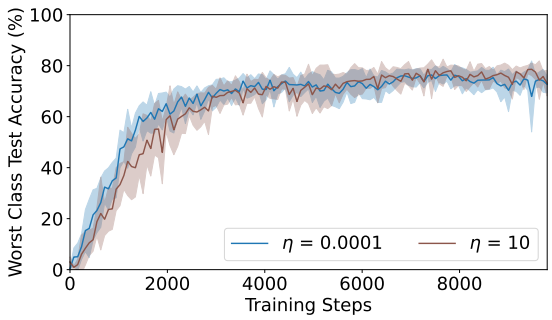
In practice, appropriately small values of η should be used in order to reduce computational cost. Note that what constitutes an appropriately small value of η depends on the scale of losses in a particular domain. Initial target model training runs are therefore necessary to identify a value of η for which class weights do not prematurely concentrate on one class η.

C.7.2 Gradient Weight γ

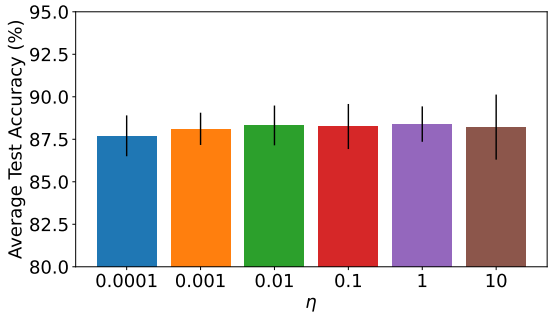
Next, we perform sensitivity analysis on the gradient weight γ. We train sets of class-irreducible loss models for each $\gamma \in \{0.25, 0.5, 1.0, 4.0, 9.0, 19.0, 49.0, 99.0\}$ and train target models trained using REDUCR for each set of class-irreducible loss models.



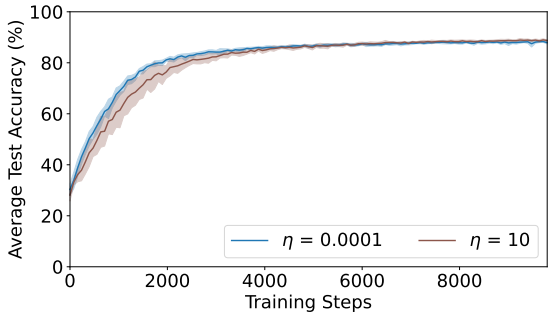
(a) CIFAR10 Final Worst-Class Test Accuracy



(b) CIFAR10 Worst-Class Test Accuracy Curves

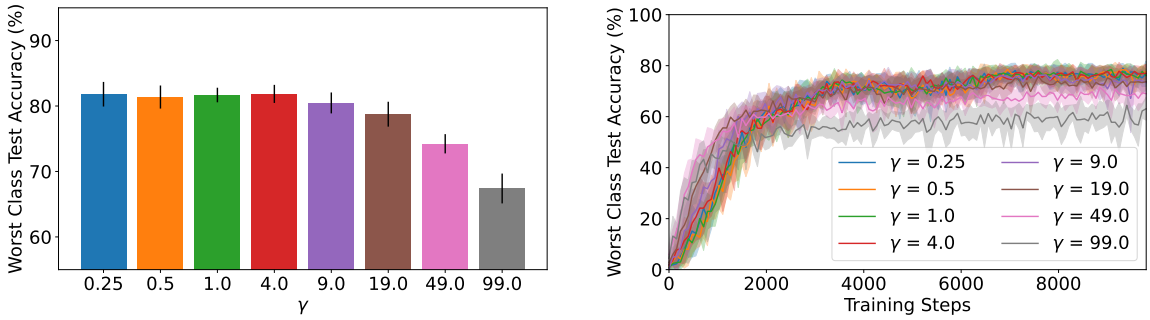


(c) CIFAR10 Final Average Test Accuracy



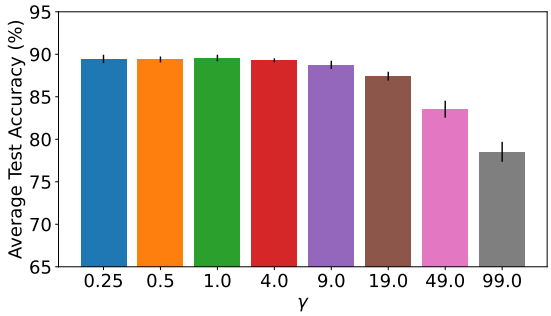
(d) CIFAR10 Average Test Accuracy Curves

Figure 9: **Final average and worst-class test accuracy are not sensitive to the value of η on the CIFAR10 dataset, though both increase faster during training when using smaller values of η.**

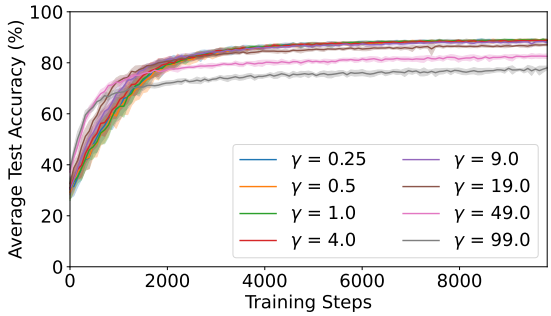


(a) CIFAR10 Final Worst-Class Test Accuracy

(b) CIFAR10 Worst-Class Test Accuracy Curves



(c) CIFAR10 Final Average Test Accuracy



(d) CIFAR10 Average Test Accuracy Curves

Figure 10: **Average and worst-class test accuracy are sensitive to the value of γ on the CIFAR10 dataset**, though this likely reflects longer convergence times for class-irreducible loss model training when using larger values of γ.

Experimental results show that increases in the gradient weight above 9.0 result in faster improvement in target model performance early in training, though target model performance converges to a lower value later in training for larger gradient weights $\gamma \in \{19.0, 49.0, 99.0\}$.

Higher gradient weights increases the variance of loss gradients, which requires a greater number of training epochs for class-irreducible loss model training. In our experiments, class irreducible loss models trained with gradient weights $\gamma \in \{19.0, 49.0, 99.0\}$ do not converge before the end of training. Poor target model performance for larger gradient weights $\gamma \in \{19.0, 49.0, 99.0\}$ is therefore the result of pre-convergence class-irreducible loss models.

This finding highlights the trade-off between fast target model training (which requires a large gradient weight) and fast class irreducible loss model training (which requires a smaller gradient weight). Regardless, final target model performance is similar providing class irreducible loss models reach convergence, as is the case for gradient weights $\gamma \in \{0.25, 0.5, 1.0, 4.0, 9.0\}$.

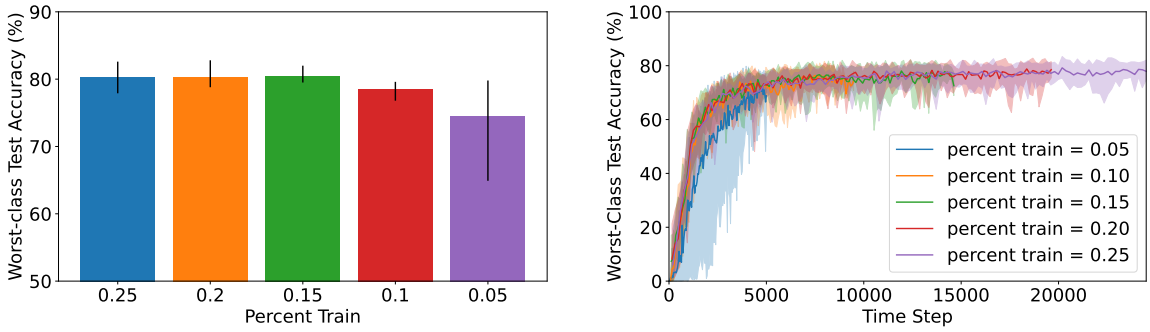
C.7.3 Fraction of Selected Datapoints

We next perform sensitivity analysis on the fraction of datapoints selected for target model training n_b/n_B (referred to as the percent train). In particular, we use a constant selected batch size n_b and vary the original batch size n_B in order to vary the fraction of datapoints selected for target model training. Intuitively, a smaller percent train allows REDUCR to select from a greater number of candidate datapoints at each training step, which results in the selection of datapoints with larger weighted reducible loss all else the same. Since datapoints with larger (weighted) reducible loss are those from which a model can learn the most (Mindermann et al., 2023), we expect a smaller percent train to result in a faster improvement in target model performance.

We train target models using REDUCR for each percent train, batch size pair in $\{(0.05, 640), (0.10, 320), (0.15, 216), (0.20, 160), (0.25, 128)\}$ (i.e., we train all target models using a selected batch size of 32). We find that a percent train of 0.05 attains lower final worst-class and average test accuracy, despite having most candidate datapoints to select from. This is surprising and is in contradiction with the intuition provided above. Furthermore, percent trains $\{0.1, 0.15, 0.2, 0.25\}$ attain similar average test accuracy at the end of training, though larger percent trains attain slightly higher worst-class test accuracy at the end of training.

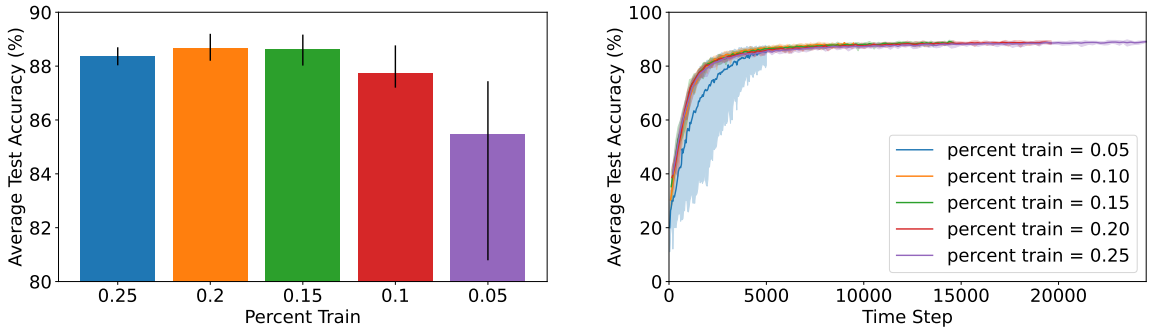
Experimental results demonstrate the performance of REDUCR is largely insensitive to the percent train (for a constant selected batch size) for non-extreme percent trains (recall uniform selection corresponds to a percent train of 1.0). Therefore, in practice, a selected batch size n_b should first be chosen such that loss gradient estimates have a low variance, and then a batch size n_B should be chosen such that the percent train n_b/n_B is an intermediate value (e.g., 0.10).

Experimental results also suggest that selecting datapoints with the very largest weighted reducible loss for model training may not be most appropriate for improving model performance. Instead of top-k selection, some form of soft selection may result in better model performance.



(a) CIFAR10 Final Worst-Class Test Accuracy

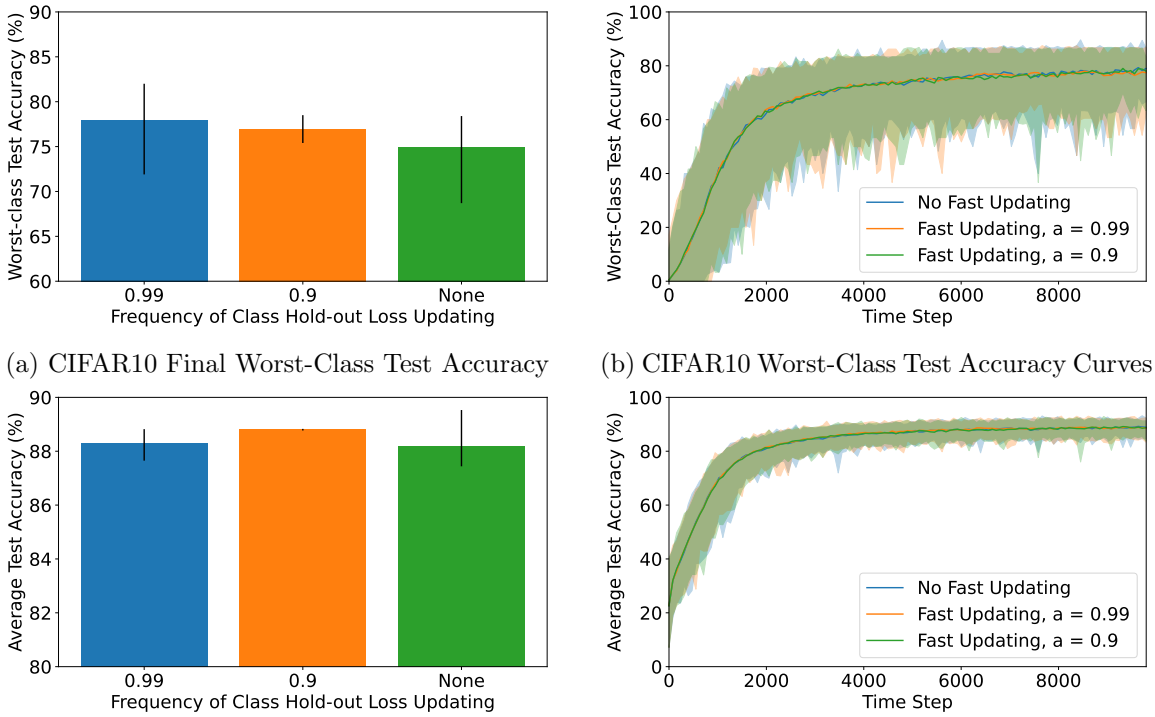
(b) CIFAR10 Worst-Class Test Accuracy Curves



(c) CIFAR10 Final Average Test Accuracy

(d) CIFAR10 Average Test Accuracy Curves

Figure 11: Test accuracies are not sensitive to the value of percent train for intermediate values of percent train. For a percent train of 0.05, the final test accuracy is less than larger percent trains, and test accuracy increases more slowly during target model training. Plots show an average and two standard deviations across 10 seeds. Note that at each training step, targets models have performed the same number of gradient steps, though they have seen different numbers of candidate datapoints. Since each percent train uses a different batch size, training epochs consist of a different number of training steps for each percent train. It is therefore particularly important to compare target models at each training step instead of training epoch. Test accuracies are computed at the end of each training epoch using the current target model and plotted at the training step at the end of the training epoch.



(a) CIFAR10 Final Worst-Class Test Accuracy

(b) CIFAR10 Worst-Class Test Accuracy Curves

(c) CIFAR10 Final Average Test Accuracy

(d) CIFAR10 Average Test Accuracy Curves

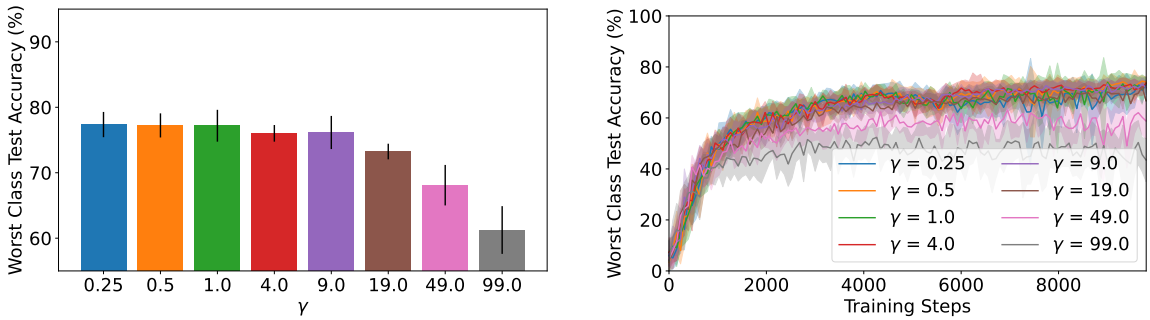
Figure 12: Test accuracies are not sensitive to the frequency with which class hold-out losses are updated. Plots show minimums, medians and maximum across 10 seeds.

C.7.4 Frequency of Class Hold-out Loss Updating

In our experiments, class hold-out losses are updated at the end of each training epoch using the full hold-out set. However, target model performance may improve on some classes significantly more than others during a training epoch (especially early in training). We therefore perform a sensitivity analysis on the frequency with which class hold-out losses are updated.

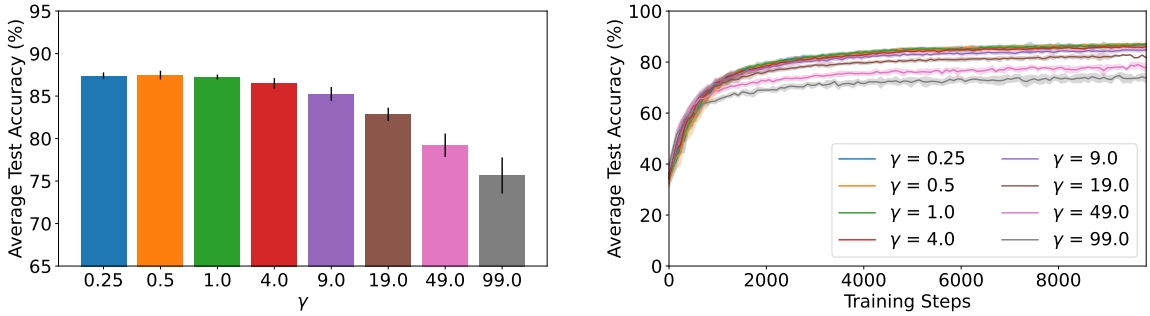
It is computationally expensive to update class hold-out losses using the full hold-out set. To reduce the computational cost of more frequent class hold-out loss updating, it is therefore necessary to update class hold-out losses using only a small subset (e.g., a single batch) of the full hold-out set at each update. However, class hold-out losses computed using a small subset of hold-out set datapoints are noisy. We therefore use an exponentially-weighted moving average of class hold-out losses computed on batches of hold-out set datapoints. In particular, a batch of size n_B is sampled uniformly at random from the hold-out set at each training step. Losses are then computed for each datapoint in the sampled batch using the current target model. Finally, for each class $c \in [C]$, losses of datapoints of class c in the sampled batch are averaged and used to update a de-biased exponentially-weighted moving average with decay parameter $a \in [0, 1]$.

We perform experiments using exponentially-weighted moving averages with decay parameters $a \in 0.9, 0.99$ for fast updating of class hold-out losses. Experimental results demonstrate REDUCR's performance is not sensitive to the frequency of class hold-out loss updating.



(a) CIFAR10 Final Worst-Class Test Accuracy

(b) CIFAR10 Worst-Class Test Accuracy Curve



(c) CIFAR10 Final Average Test Accuracy

(d) CIFAR10 Average Test Accuracy Curve

Figure 13

C.8 Small Class Irreducible Loss Models

We also investigate the use of small CNN (LeCun et al., 1998) (reference) class-irreducible loss models instead of ResNet-18 class-irreducible loss models in order to reduce the computational cost of REDUCR on the CIFAR10 dataset.

Experimental results demonstrate that target models attain slightly better worst-class and average-class final test set accuracy when using ResNet-18 class-irreducible loss models than when using small CNN class-irreducible loss models providing a sufficiently small gradient weight is used for class-irreducible loss model training (i.e., class-irreducible loss models reach convergence). However, small CNN class-irreducible loss models struggle more than ResNet-18 class-irreducible loss models at larger gradient weights.

Therefore, one can significantly reduce the computational cost of REDUCR for the CIFAR10 dataset by using small CNN class IL models without a large decrease in target model performance. This is consistent with Mindermann et al. (2023), which finds that target models trained using a small irreducible loss model slightly under-perform target models trained using a large irreducible loss model in the context of RHO-Loss selection.

C.9 Highly Imbalanced Datasets

We also conduct experiments with 0.25% and 0.5% percent imbalances on classes 3 and 5. However, (class) irreducible loss models and target models only receive 6.25 and 12.5 datapoints of the imbalanced class during one training epoch (in expectation) with percent imbalances of 0.25% and 0.5% (respectively). As a result, too few datapoints of the imbal-

anced class are seen during model training to achieve good performance on the imbalanced class.
This demonstrate a failure mode of existing selection methods. During target model training, datapoint selection cannot improve performance on the imbalanced class in the presence of severe under-sampling, since datapoints of the imbalanced class are not sampled sufficiently often (before selection). Additionally, for selection methods that use some form of reference model, severe under-sampling also affects reference model training. An explicit correction for severe under-sampling is needed during reference model training and target model training (e.g., an importance sampling correction or a replay buffer similar to that used in reinforcement learning).

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