Efficient Model Finetuning for Text Classification via Data Filtering

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Abstract
As model finetuning is central to the modern NLP, we set to maximize its efficiency. Motivated by training examples are often redundant, we design an algorithm that filters the examples in a streaming fashion. Our key techniques are two: (1) automatically determine a training loss threshold for skipping the backward propagation; and (2) maintain a meta predictor for further skipping the forward propagation. Incarnated as a three-stage process, on a diverse set of benchmarks our algorithm reduces the required training examples by up to 5× while only seeing minor degradation on average. Our method is effective even for as few as one training epoch, where each training example is encountered once. It is simple to implement and is compatible with the existing model finetuning optimizations such as layer freezing.

Introduction
Modern NLP models are firstly pretrained on large corpora once and then finetuned for specific domains. The efficiency of finetuning is crucial because (1) finetuning, as opposed to one-time pretraining, is invoked for every downstream task and even on individual user’s data (Houlsby et al. 2019; Stickland and Murray 2019; Peng, Yan, and Lu 2019; Qiu et al. 2020); (2) finetuning is often performed close to where the domain training examples reside, e.g. smartphones (Rebuffi, Bilen, and Vedaldi 2018; Sanh et al. 2019; Jiao et al. 2019; Sun et al. 2020); these platforms often have constrained compute resources. As NLP models become larger (Devlin et al. 2018; Brown et al. 2020; Radford et al. 2019; Liu et al. 2019) and tasks further diversify, efficient fine-tuning, i.e. to achieve similar accuracy at much lower resource consumption, e.g. GPU time, is increasingly compelling (Zaken, Ravfogel, and Goldberg 2021; Jiang et al. 2019). Prior work has recognized the importance of efficient finetuning. Their primary approach is to introduce efficient model structures (Sun et al. 2019), including low rank approximation (Lan et al. 2019; Ma et al. 2019), weight sharing (Dehghani et al. 2018; Lan et al. 2019), knowledge distillation (Hinton et al. 2015; Sanh et al. 2019; Jiao et al. 2019), pruning (Cui et al. 2019; McCarley, Chakravarti, and Sil 2019; Katharopoulos and Fleuret 2018), quantization (Jacob et al. 2018; Micikevicius et al. 2017), and layer freezing (Lee, Tang, and Lin 2019). While most of work focuses on modeling strategies, this paper exploits an opportunity par-

![Figure 1: Our method significantly reduces training time (columns, right y-axis) while achieving accuracies (lines, left y-axis) comparable to training with all the data. Benchmark details in Evaluation. GPU: Nvidia RTX 2080Ti.](image)

particularly when finetuning with large datasets: filtering training data at low computational cost. Given that training data is known often redundant (Katharopoulos and Fleuret 2018), we test a simple idea: skip training examples that are less important to the gradient updates.

Challenges The idea raises twofold research challenges. First, how to assess the training example importance? As the model is updated throughout a training process, the decision must weigh the data’s importance against the model’s current knowledge. Second and more importantly, to reduce the total training cost, the assessment itself should incur low computational overhead. To this end, much prior work for selecting training data does not apply (Mirzasoleiman, Bilmes, and Leskovec 2020; Wang et al. 2020): targeting training effectiveness but not efficiency, they often use computationally expensive methods to weigh data, e.g. comparing training gradients; as a result, they often slow down the training or incur non-trivial prepossessing before training.

Our method We use training loss as the signal for training data importance: low loss means the model has high confidence on the training examples, which may be skipped to reduce training cost. As will be shown in the paper, skipping training data on which losses are lower than a fixed, hand-
picked threshold $L_{\text{low}}$ can skip 20% – 50% of the data while seeing minor (<1%) drop in the final model accuracy. This motivates us to design an automatic data filtering algorithm.

To this end, we propose an algorithm that learns to predict the filtering decisions. Given a model and training data, the algorithm automatically derives a proper loss threshold $L_{\text{low}}$ and further skips forward and/or backward passes on selective data. The algorithm runs training as a multistage process: each stage requires supervision of earlier stages, but is more efficient than the former. More specifically: (1) As training starts, the first stage aims at deriving $L_{\text{low}}$ that adapts to the model and the training data. This stage runs both forward and backward passes on given examples. (2) The second stage uses the derived $L_{\text{low}}$ to filter backward passes. With the filtering decisions, it trains a meta predictor based on the Bag-of-Words representations of input texts. This meta predictor’s role is to decide if given example is worth training. (3) The third stage queries the meta predictor to filter both forward and backward passes. The first two stages are short (processing average 16.07% examples across all benchmarks) while the most efficient third stage processes most examples. The algorithm automatically advances across the stages, based on its observation of training loss and the meta predictor’s performance.

**Results** On a diverse set of benchmarks, our algorithm reduces the total training time by up to $6.7 \times (4.77 \times \text{on average})$. The resultant accuracy degradation is minor, no more than 1.44% (0.74% on average). An ablation study shows efficacy of our designs: (1) the automatic loss threshold skips backward passes for up to 84% of the training examples; (2) the meta predictor skips forward passes for up to 66.13% and 81% training examples when training for 1 and 2 epochs, respectively; (3) as the epoch count grows, our efficiency is increasingly higher, e.g. up to $18.1 \times$ training time reduction with 1.83% lower accuracy when training for 5 epochs.

**Contributions**

- We presented empirical evidence that large datasets are significantly redundant for model finetuning, and many training examples can be filtered by their losses for efficiency.
- We proposed a simple, effective mechanism for filtering training data: using an automatic loss threshold for skipping backward passes and a lightweight predictor for further skipping forward passes.
- We presented a holistic training process that integrates the above techniques and demonstrated its efficacy on diverse NLP tasks.

**Related work**

**Data efficient training** Aggressive-passive training (APT) (Shalev-Shwartz et al. 2003) and Perceptron (Rosenblatt 1958) are well-known online learning algorithms that only update the model either on high-loss or mis-classified samples. To further increase the data efficiency, the training model should be presented with the training data in a meaningful order that facilitates learning. Curriculum learning (Bengio et al. 2009) trains the model from the easiest data to the hardest ones which might benefit accelerating model convergence and finding better local minima in deep learning methods. But it requires the domain knowledge of data to formulate the curriculum. For example, it needs to know how “noisy” data are then arranges their order. To get rid of this requirement, Self-paced learning (Kumar, Packer, and Koller 2010) improves weights updating by integrating a binary mask indicating whether the sample is easy and an extent weight determining how easy the sample is. By decreasing the extent weight in each iteration, model weights are gradually updated with more difficult data. But the optimization overhead is too large when the model and dataset are getting much larger.

**Data selection in training** Previous work (Katharopoulos and Fleuret 2018) shows there is much redundancy in data instances and proposes to train with smaller batches of data which have similar gradient norm with the full data batches. CRAIG (Mirzasoleiman, Bilmes, and Leskovec 2020) finds a small subset that the weighted sum of the gradients of its elements closely approximates the full gradient over the full training set. Similarly, clustering the data and training only with those close to the cluster center could remove at least 10% redundant data (Birodkar, Mobahi, and Bengio 2019) in object recognition benchmarks. Selection via proxy (Coleman et al. 2019) proposes to simplify the big target model to a small proxy model, then use it to select core-set to train the target model. Data selection by Reinforcement Learning (Wang et al. 2020) uses RL to train a scorer that weights data to maximally benefit learning. Sample selection of noisy labels (Xia et al. 2021) uses data losses to label unlabeled data then collect them to the training set.

Different from us, they all have lots of computational overhead and most of them are separate from training the target model. Importance Sampling (Katharopoulos and Fleuret 2018) and CRAIG (Mirzasoleiman, Bilmes, and Leskovec 2020) sample important data by solving the optimization problem for each data to mimic the full data gradient. Clustering (Birodkar, Mobahi, and Bengio 2019) needs to sweep through all the data instances and keep updating clusters before picking out close ones. Proxy (Coleman et al. 2019) formulates the core-set by keeping data it has low accuracy on. Selection by RL (Wang et al. 2020) cares accuracy and noisy labels selection (Xia et al. 2021) has a different task with us. However, their methods have significantly lower efficiency. Instead, our goal is to do the data selection in parallel with training the target model and take model losses, not gradients, as the metric. Besides, our meta predictor is trained with simple linguistic features (Bag-of-Words), which further increases the selection efficiency.

AutoAssist (Zhang, Yu, and Dhillon 2019) shares our motivation: to filter training data with a small model. Yet, despite AutoAssist can reduce the training loss at a higher rate, it was unclear by how much it can reduce the training time without degrading accuracy much. The assistant is complex, e.g. stochastic sampling data to generate a batch, which takes more than ten epochs to warm up, unsuitable to finetuning comprising no more than several epochs. By contrast, our design is simpler; it reduces the training time sig-
nificantly even for one epoch; the reduction is increasingly higher as the epoch count grows.

**Other efficient training techniques** Some papers propose training tricks to reduce training time, by varying learning rate for every weight (Jacobs 1988; Zeller 2012) or batch size (Smith et al. 2017). These methods could improve data efficiency by increasing the model convergence speed with the same amount of data. Some other papers focus on reducing model parameters or finding a lightweight counterpart of a large model by pruning (Cui et al. 2019; McCarley, Chakravarti, and Sil 2019; Katharopoulos and Pleuret 2018), knowledge distillation (KD) (Hinton et al. 2015; Sanh et al. 2019; Jiao et al. 2019), quantization (Jacob et al. 2018; Micikevicius et al. 2017), low-rank approximation (Lan et al. 2019; Ma et al. 2019), and weights sharing (Dehghani et al. 2018; Lan et al. 2019). All these techniques aim to reduce computation and our method is complementary to them that ours could work well with other model optimization methods like layer freezing, as discussed in Evaluation.

**Our method**

Assume the whole training set is divided into $M$ mini batches $D = \{D_m\}_{m=1}^M$. Each mini batch consists of $N$ training examples. The training loss for the $m$-th mini batch is defined as

$$l(m) = \frac{1}{N} \sum_{n=1}^{N} CrossEntropy(\hat{y}_m^n, y_m^n)$$

where $\hat{y}_m^n$ is the model prediction and $y_m^n$ is the ground truth. Intuitively, if the model is confident with all the examples in this mini batch, we should expect that the average loss $l(m)$ will be very small and skip the training on this mini batch would not cause a big difference on model performance. Furthermore, we hypothesize that, for a given text, the words in the text may provide enough clues about the model’s confidence level. For example, if the model gives high confidence prediction on the current example, it may provide enough clues about the model’ confidence.

We address the following design questions:

- How to skip the backward pass of a mini batch with its training loss?
- Furthermore, how to skip a mini batch without calculating its training loss, which will further eliminate the forward computation on the data?
- How to answer the two questions above in an efficient, automatic manner?

**Three-stage Training**

The proposed algorithm consists of three consecutive stages; the dataflow of each stage is shown in Figure 2. Throughout the process, the warm-up stage (stage 0) estimates a loss threshold for selecting mini batches; then the first stage (stage 1) filters out mini batches by referring to the estimated threshold, meanwhile use the filtering results to train a meta predictor on whether a mini batch is training-worthy; eventually the second stage (stage 2) uses the meta predictor to filter out some mini batches without explicitly calculating the forward loss. Each stage requires supervision in earlier stages to become effective, but it is more efficient than the former.

**Stage 0: estimating loss threshold** This stage warms up the model training and automatically derives the loss threshold $L_{low}$. For each mini batch, the algorithm runs both the forward step for computing the training loss and the backward step for gradient update. By training with a few mini batches, the loss threshold can be estimated by the moving average of the previous training losses,

$$L_{low}(m) = \frac{1}{K} \sum_{k=1}^{K} l(m - k)$$

where $l(m)$ is the training loss calculated on the $m$-th mini batch defined in Equation 1, and $K$ is the window size of moving average. In practice, the moving average of training losses has been used to show the overall pattern of loss changes and monitor the training process (Zhang, Yu, and Dhillon 2019). In this work, we propose to use the moving average to identify any mini batch worth training with — intuitively, if the training loss on a mini batch is significantly higher than the moving average, then it should be used to update the model parameters. Our preliminary study shows that, with a large $K$, $L_{low}(m)$ will quickly stabilize with some sufficiently low variations (e.g., $m \geq 1$st 7.7% with variation of $4.3 \times 10^{-5}$ on QNLI).

**Stage 1: training the meta predictor** With a stabilized loss threshold $L_{low}$, the algorithm moves to the first stage of efficient training, in which it can filter out some mini batches if their losses are significantly lower than $L_{low}$. To further prepare for the last stage, the algorithm also starts to build a meta predictor $\mathbf{f}$, which aims to predict the loss magnitude of a mini batch without resorting to the forward pass. Specifically, we implement the meta predictor $\mathbf{f}$ as a binary Naive Bayes classifier

$$\mathbf{f}(\mathbf{w}^m) \in \{0, 1\}$$

where $\mathbf{w}^m$ represents the Bag-of-Words representations of the texts in the $m$-th mini batch; the predicted value 1 indicates the training loss is likely to be higher than the threshold, while 0 indicates the loss is likely to be lower than the threshold.
threshold. With the forward computation on mini batch \( m \) and the loss threshold \( L_{low} \), this mini batch provides a training example for updating the meta predictor \( f \).

In order to measure how much information the meta predictor learns, we adopt the same variable settings as model loss and \( y' \) is the train-worthy label formulated by comparing the forward loss and \( L_{low} \). The predictor loss is defined as

\[
l_{mp}(m) = -\frac{1}{N} \sum_{n=1}^{N} \log p(y_n' | w_n^m) \tag{4}\n\]

If the meta predictor has sufficient low moving average loss, stage 1 ends.

Although more design choices will be discussed in Discussion on Design Choices, we want to provide a brief explanation of using a meta predictor. First of all, the motivation is to further reduce the computational cost if we have any clue that the language model should be familiar with the examples in a mini batch. For the feasibility of using an Naive Bayes classifier as the meta predictor, since lexical information is an essential component of semantic information in texts, we expect it to make a reasonable guess about the loss magnitude by just looking at the words.

Stage 2: filtering training data with meta predictor Once the meta predictor shows adequate performance (as validated by loss-based selection on new data), the algorithm will rely on it to do a preliminary screening on each mini batch. On data that the predictor believes worth training (i.e., not filtered), the algorithm will run the forward pass and further use the loss threshold to decide if a backward pass is needed. In other words, stage 2 applies filtering to both the forward pass and the backward pass for high efficiency.

Usually, the algorithm will reach stage 2 within the early part of the first epoch, as demonstrated in the experiments. When the algorithm needs to run multiple epochs, it will stay in stage 2 in the following epochs.

A Special Case

While the three-stage algorithm is effective (as Evaluation will show), it is possible to use a stripped-down version of it: after determining \( L_{low} \), automatically, use it to filter all the remaining training data without invoking the meta predictor. Doing so would miss the opportunity of skipping forward passes; yet, by eschewing the meta predictor and its hyperparameter tuning, the method further simplifies training. We refer to this method as automatic threshold only and will compare to it in Evaluation.

Evaluation

We set to answer the following questions:

* Compared to the existing training method, can we achieve comparable accuracy with much higher efficiency?
* How significant are our key techniques?
* How sensitive is our method to its hyperparameters and what are their reasonable ranges?

| Datasets       | Tasks         | #train | #dev  | #test  |
|----------------|---------------|--------|-------|--------|
| SST2           | sentiment     | 67k    | 0.9k  | 1.8k   |
| QNLI           | Q/A/NLI      | 105k   | 5.5k  | 5.4k   |
| QQP            | paraphrase   | 364k   | 40k   | 391k   |
| AMZ            | sentiment    | 3600k  | N/A   | 400k   |

Table 1: Statistics for datasets, which are all binary classification tasks and \# counts the number of examples in the train/dev/test sets.

| Name        | Explanation          | Value range       |
|-------------|----------------------|-------------------|
| \( N_{epoch} \) | Number of training epochs | [1, 2]            |
| \( N_0 \)   | Fraction of mini-batches (in stage 0) | [10%, 20%, 30%, 40%] |
| \( W \)     | Sliding window size (in stage 1) | [4, 8, 16]        |
| ALT         | Loss threshold of meta predictor (in stage 1) | [0.1, 0.2, 0.3, 0.4, 0.5] |

Table 2: A summary of hyperparameters

Experiment Setup

Models & Datasets We test our method on the pretrained DistilBERT model with 6 transformer layers and a hidden dimension of 768. We finetune it on four classification benchmarks as summarized in Table 1. Of these benchmarks, three are from GLUE (Wang et al. 2019) and one is the Amazon Polarity (AMZ) (Zhang, Zhao, and LeCun 2015). The benchmarks cover tasks of single-sentence, similarity, and inference. All the benchmarks have substantial training data, allowing opportunities for filtering. For the three GLUE benchmarks, we reproduce the accuracies reported in prior work (Sanh et al. 2019) and consider them as the baseline performance; for Amazon Polarity, we finetune the model and report accuracy measured on its test set.

Baselines We evaluate our method against two groups of baselines. (1) \textit{TrainAll} trains models with all the training data. (2) \textit{FixedThreshold} filters the training data with hand-picked, fixed loss thresholds, for which we sweep the range [0.1, 0.7] at an increment of 0.2; the hope is to identify a close-to-optimal threshold for each benchmark.

Metrics For a training process, we report (1) the model accuracy after training and (2) the training time, which is inverse to the training efficiency.

We make the reported training time reproducible. On our machine with an Nvidia RTX 2080 Ti, we measure the time of a forward pass (\( T_f \)) and a backward pass (\( T_b \)), as well as the fractions of data on which only backward passes are skipped (\( \alpha_b \)) and \textit{both} forward and backward passes are skipped (\( \alpha_{fb} \)) in each training process. For a given training process, we report the total time as \( T = \alpha_b T_f + (1 - \alpha_b - \alpha_{fb})(T_f + T_b) \). Finally, we normalize \( T \) to that of \textit{TrainAll} as \( T_{norm} = \frac{T}{T_{all}} \) and report \( T_{norm} \).

End-to-end results

Figure 3 plots accuracy versus training time. It shows that our method delivers both high accuracy and high efficiency (i.e., low training time). Compared to \textit{TrainAll}, our method reduces the training time by at least 2×. Meanwhile, the accuracy is similar: for SST2, QQP, AMZ, all our perf-
Benchmarks | SST2 | QNLI | QQP | AMZ
---|---|---|---|---
TrainAll | 90.48/1.00 | 87.97/1.00 | 89.93/1.00 | 95.24/1.00

Fixed Threshold

| ε | 0.1 | 0.3 | 0.5 | 0.7 |
|---|---|---|---|---|
| Ours | 89.79/0.55 | 89.33/0.57 | 89.23/0.37 | 94.08/0.15 |
| AT | 91.06/0.39 | 85.19/0.53 | 87.74/0.47 | 94.42/0.39 |

Each cell: accuracy/normalized training time.

AT: loss thresholds determined automatically

Table 3: Accuracy and training time of our method and the baselines. Training time normalized to TrainAll of the same benchmark. For our methods, only the AGOT-optimal results are shown.

**How much computation is skipped?** Our method skips large fractions of forward and backward passes. As Table 4 shows, across all benchmarks, on 52.87% – 81.01% of the training data both forward and backward passes are skipped. This indicates that our predictor, which controls skipping both forward and backward passes, is highly effective. In addition, on 8.95% of the training data on average, backward passes are skipped while forward passes are executed.

**Estimated energy & CO2 reduction** We use an energy model (Strubell, Ganesh, and McCallum 2019):

\[
p_t = 1.58(t_c + p_c + gp_g) / 1000
\]

\[
CO_2 = 0.954p_t
\]

In the equation, \(p_t\) is the total energy consumed during fine-tuning, \(p_c\) is the average CPU power draw, \(p_r\) is the average DRAM power draw, \(p_g\) is the average GPU power draw, \(t\) is the training time, and \(g\) is the GPU count. Compared to TrainAll, we reduce the total energy consumption by 45.85% on average across all benchmarks. Considering the proportions of different energy sources in the US (Strubell, Ganesh, and McCallum 2019), we estimate to reduce the CO2 emission from 0.56 pounds per training process to 1.05 pounds on average.

**Ablation Study**

**Efficacy of using loss thresholds** The results are shown in Table 6. Compared to filtering the same amount of training data that is randomly selected, methods based on loss thresholds show consistently higher accuracies. Specifically, FixThreshold with loss thresholds of [0.1, 0.3, 0.5] (the skip ratio varies from 20.72% to 83.25%) shows accuracies higher by 0.93% – 1.33% on average. The Three-stage method shows accuracies higher by 2.14% on average. Note that such accuracy improvement is significant: take Figure 3 as
Table 4: Fractions of skipped training computation of our method and the baselines. For our methods, only the AGOT-optimal results are shown.

| Fixed Threshold | SST2 | QNLI | QQP | AMZ |
|-----------------|------|------|-----|-----|
| Nepochs 1       | 56.65/0.00 | 20.73/0.00 | 39.64/0.00 | 67.61/0.00 |
| Nepochs 2       | 70.76/0.00 | 41.12/0.00 | 54.11/0.00 | 79.01/0.00 |
| Nepochs 3       | 76.44/0.00 | 52.38/0.00 | 62.09/0.00 | 83.25/0.00 |
| Nepochs 4       | 98.91/0.00 | 99.19/0.00 | 99.81/0.00 | 99.71/0.00 |
| Nepochs 5       | 77.31/0.00 | 60.43/0.00 | 66.82/0.00 | 83.87/0.00 |

| Ours (Autot) | Nepochs 1 | Nepochs 2 | Nepochs 3 | Nepochs 4 | Nepochs 5 |
|--------------|-----------|-----------|-----------|-----------|-----------|
| TrainAll     | 0.28      | 0.14      | 0.25      | 0.08      | 0.12      |
| Ours         | 0.28      | 0.14      | 0.25      | 0.08      | 0.12      |

Table 5: Accuracy and training time (T_{norm}) as the epoch count (N_{epochs}) grows, showing that our method yields increasingly higher efficiency in additional epochs. T_{norm} is normalized to the time of TrainAll of the same N_{epochs}.

reference, one can reduce the training time by 5× with tolerating accuracy drop as low as 2.01% by average.

**Efficacy of automatic threshold** AutoThreshold can find a loss threshold that results in competitive accuracy and efficiency. Table 3 compares AutoThreshold to FixedThreshold, showing that the former delivers higher AGOT than all the fixed thresholds tested; in fact, it delivers both higher accuracy and lower training time than most of the fixed thresholds.

**Efficacy of the meta predictor** The meta predictor is essential to our efficiency as it skips a large fraction of forward passes, as shown in Table 3. Compared to AutoThreshold which can only skip backward passes, our Three-stage training reduces the training time by additional 2.01× on average across all benchmarks. Furthermore, the accuracy is higher by 0.57% on average, which is likely because the meta predictor better learns training data importance as the training proceeds.

**Sensitivity to hyperparameters**

Table 4 summarizes the hyperparameters of our method. We next study their impact on performance and their reasonable ranges.

**Number of epochs (N_{epochs})** As shown in Table 5, our efficiency will be more pronounced as N_{epochs} increases. Overall, the first epoch gains most of the model accuracy; additional epochs yield diminishing return or even fluctuation. This is consistent with prior observations (Sanh et al. 2019; Jiao et al. 2019) and is the reason why users commonly fine-tune an NLP model for no more than several epochs. As N_{epochs} increases, our method has similar accuracy (within ±0.6%) as TrainAll while seeing increasingly higher reduction in the training time, e.g. 2.56× when N_{epochs} = 1 and 6.53× when N_{epochs} = 5. This is because only in the first epoch our method runs stage 0 and 1, paying the learning cost; in subsequent epochs, our method remains in stage 2, invoking the meta predictor to skip most of the forward and backward passes.

**Number of mini-batches (N_{b})** The fraction of data examples in stage 0. We try fraction of 10% – 40%. In this stage, the model does forward and backward passes on all the data.

Accuracies fluctuate with the increase of N_{b}. From 10% – 40%, average accuracies are 89.30%, 89.89%, 89.39%, and 90.15%. N_{b} = 10% and 30% have slightly lower accuracies than N_{b} = 20% and 40% by 0.59% and 0.76%. But normalized run time grows along with N_{b}. N_{b} = 40% has 1.95× longer runtime than N_{b} = 10%. Experiment results show AGOTs are not sensitive to N_{b}, as the differences among them are very small. N_{b} = 30% has the lowest AGOT because of lowest accuracy, however N_{b} = 40%’s highest accuracy compensates its longest run time. When Sliding window size (W) = 16 and Average loss threshold (ALT) = 0.1 or 0.2, training will not reach the last stage, so does W = 8 and ALT = 0.1, no matter what N_{b} is. This means the meta predictor will not start working under such harsh stage-transition condition as the average loss is not small enough. But it also proves N_{b} is not a hyperparameter controlling filtering.

**Sliding window size (W)** The sliding window size in stage 1 for collecting predictor losses. The stage transition is determined by the average loss in this window.

From the results, both accuracies and normalized run time grow with W. The average accuracies for W = [4, 8, 16] are [89.37%, 89.79%, 90.07%] and average run time is reduced by 5.56×, 4.76×, and 4.00×. Based on this trend, average AGOTs are very stable. The highest AGOT difference ratio is only 0.11%. The training time increment is because a larger W has higher demand on the meta predictor and it takes longer time in stage 1 and shorter time in stage 2. When W = 16 and ALT = 0.1 or 0.2, training will not switch from stage 1 to the last stage, so does W = 8 and ALT = 0.1. We can find that the switching likely fails under bigger W and lower ALT, because they are more difficult condition to fulfill. So W actually controls data filtering.

**Average loss threshold (ALT)** The average loss threshold in stage 1 measuring whether the predictor has been well trained. As long as the average loss in W is lower than ALT, training switches to stage 2.
decreases with ALT. Accuracies are between 0.06% – 0.89%. The normalized run time ([89 2019; Lee, Tang, and Lin 2019]). Table 7 compares our method complements LF (i.e. training only last few training goes to the last stage or how much filtering we do. Average AGOTs are also stable, its maximum difference is only 1.2%. Similar with W, ALT controls whether training goes to the last stage or how much filtering we do.

### Compatibility with layer freezing (LF)

Our method complements LF (i.e. training only last few layers), a common optimization for finetuning (Sun et al. 2019; Lee, Tang, and Lin 2019). Table 7 compares TrainAll with our method both freezing all but the last layer. First, our method is compatible with LF. Compared to TrainAll with LF, our method with LF achieves comparable accuracy (lower by 0.46% – 1.61%) in much lower training time (lower by 1.75× – 7.14×). Second, our method is still relevant when LF is in use: applying LF to TrainAll reduces the training time by 2.34× with accuracy loss of 2.88% on average; by comparison, our method can reduce additional 2.78× lower training time at 3.29% accuracy loss. The results encourage use of our method and LF in conjunction.

### Discussion on Design Choices

#### Automatic loss thresholds

**Loss for filtering data** We use losses for the following reasons. (1) As shown in prior work (Loshchilov and Hutter 2015), losses effectively reflect model update from given examples: higher loss means that the model makes higher inference errors and hence can learn more from this example. (2) Getting losses is computationally inexpensive: they incurs no computation overhead beyond forward passes.

**Rationales for a loss threshold** We want to selectively learn from a subset of examples with the highest losses. To identify such a subset, one may attempt to compare losses of all training examples. This however suffers from two drawbacks. (1) It is inefficient: doing so requires forward passes on all the training data, an expensive task with poor data locality, because the activations calculated by forward passes must be saved to disk and later restored for executing backward passes. (2) As a model is being updated, the losses of examples yet to be trained will change. For instance, a previously high-loss example (estimated by the untrained model) may see a low loss and hence is no longer worth training.

By contrast, we use a loss threshold to screen examples. (1) The method is effective because it accommodates continuous model updates. As the loss is always assessed based on the updated model, the method estimates how much the updated model can learn from the example under question. (2) The method is efficient because it consumes training data sequentially with good locality; it is therefore friendly to memory hardware hierarchy. (3) The method leads to self-paced training. As training starts, the model likely sees high losses on most data, for which it will filter less; as training goes on and the model is updated, it likely sees lower losses on more data, for which it will filter more.

#### Tradeoffs for setting a loss threshold

Ideally, we want to train on the fewest examples and have the accuracy close to that from the TrainAll baseline.

Hand picking \(L_{low}\) is tricky: a \(L_{low}\) too high can be overly passive (Shalev-Shwartz et al. 2003), resulting in too much data filtered and suboptimal accuracy; a \(L_{low}\) too low can be overly aggressive, resulting in long training delays. The optimal choice of \(L_{low}\) hinges on a discrepancy between the model’s knowledge prior to training and the total knowledge encoded in the training data. Unfortunately, this discrepancy cannot be accurately determined until we have trained on all the data. This motivates us to derive \(L_{low}\) automatically.

**Automatic loss thresholds** We sets \(L_{low}\) to be the average of the most recent losses for the following reasons. (1) By considering a sample of the total training set, the average loss estimates how the current model fit the data yet to be trained with; (2) By picking \(L_{low}\) to be the average loss, we balance being passive and being aggressive in filtering examples. (3) We keep updating \(L_{low}\) in sliding windows so that we keep refreshing the estimation.

### The loss predictor

Our meta predictor addresses two design questions. First, what features should the predictor be based on? That extraction of such features must be significant cheaper than a forward pass of the language model \(M\) under training. We adopt Bag-of-Words (BoW) features of an input sequence. Our choice of BoW is motivated by extensive linguistic evidence showing the correlation between word frequencies and data’s difficulty to language tasks.

Second, who is responsible for training the meta predictor, which shall be specific to the model \(M\) and the training data? We train the predictor under the supervision of loss-based example filtering (stage 1). The training does not have to be long before the predictor can be queried to make prediction and advise on filtering training data.

It is worth noting that even when the trainer queries the predictor for filtering decisions (stage 2), it still updates the predictor continually. This is done on the data that the predictor deems worth training: the trainer runs forward passes on such data, get the losses, and uses the comparison outcome to update the predictor. This keeps the predictor updated to the changing language model \(M\): as \(M\) being trained, the correlation between its loss on new data and the data’s BoW features is drifting; intuitively, \(M\) will see lower loss give the same BoW features.
Summary
We present online data filtering, an efficient training mechanism for optimizing training data usage. We automatically maintain a loss threshold from model losses, then train and query a simple predictor to skip both forward and backward passes. So that unnecessary data instances will be filtered out and we achieve great accuracy-efficiency tradeoff. We formulate two algorithms under the Three-stage training method for three realistic and distinct NLP tasks, sentiment classification, QA/NLI, and paraphrase identification, which leads to consistent improvements over strong baselines.

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