Improving Model Training via Self-learned Label Representations

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Abstract
Modern neural network architectures have shown remarkable success in several large-scale classification and prediction tasks. Part of the success of these architectures is their flexibility to transform the data from the raw input representations (e.g. pixels for vision tasks, or text for natural language processing tasks) to one-hot output encoding. While much of the work has focused on studying how the input gets transformed to the one-hot encoding, very little work has examined the effectiveness of these one-hot labels.

In this work, we demonstrate that more sophisticated label representations are better for classification than the usual one-hot encoding. We propose Learning with Adaptive Labels (LwAL) algorithm, which simultaneously learns the label representation while training for the classification task. These learned labels can significantly cut down on the training time (usually by more than 50%) while often achieving better test accuracies. Our algorithm introduces negligible additional parameters and has a minimal computational overhead. Along with improved training times, our learned labels are semantically meaningful and can reveal hierarchical relationships that may be present in the data.

Introduction
Neural Networks have become an essential tool for achieving high-quality classification in various application domains. Part of their appeal stems from the fact that a practitioner does not have to hand-design the input features for model training. Instead, they can simply use the raw data representation (such as using pixels instead of highly processed SIFT or HOG features for a computer vision task) and learn a mapping to the target class. The high degree of flexibility enables neural networks to learn highly non-linear maps, and thus the target output representation is also usually kept relatively simple. It is customary to encode the target labels as a one-hot encoding\(^1\). While simple and computationally convenient, a one-hot representation is rather arbitrary. Indeed, such an encoding destroys any semantic relationships that the target categories may have. For instance, for a 3-class apparel classification task with categories, say, sandal, sneaker and shirt, the semantic similarity between sandal and sneaker (both being footwear) is clearly not captured by the one-hot encoding. An alternate label representation can allow us to capture this semantic connection, and perhaps even make the learning process easier (cf. Figure 1).

What might be a better representation of the output labels? Since powerful word embedding models such as Word2Vec (Mikolov et al. 2013) and BERT (Devlin et al. 2019) are known to capture the semantic meaning of commonly occurring words, one can use such prelearned representations of our labels for classification. In fact, Chen et al. (2021) explored this idea in detail. They study the effectiveness of several embeddings including BERT (pretrained on textual data) and audio spectrogram (trained on the vocal pronunciations of the class labels) to represent the target labels and show improved performance.

An alternate approach, of course, is to explicitly learn the label representation from data itself. This again can be done in several ways, Sun et al. (2017), for example, propose to augment the underlying neural network with specialized layers for data classification and label embedding that interact with each other during the training process. This of course adds complexity to the network potentially increasing network size. Deng and Zhang (2021), in contrast, learn a “soft” set of labels by “smoothing” the original one-hot encodings without modifying the underlying network architecture. While the learned labels are reasonably flexible in

\(^1\)For a \(k\)-way classification task, one-hot encoding of the \(i\)th category is simply the \(e_i\) basis vector in \(k\) dimensions.
representation, a simple smoothing can miss capturing more complex semantic relationships among labels.

In this work, we learn a robust data-dependent label representation that addresses issues that were unresolved in previous literature. We propose Learning with Adaptive Labels (LwAL) algorithm, which simultaneously learns semantically appropriate label representations while training for the underlying classification task. LwAL is based on the insight that relationships between class labels should be inherent in data belonging to the classes. Since one can view a neural network as a function that maps the input data to a latent representation $z$, we can utilize this latent data representation to get an initial estimate of the label representation $\hat{y}_i$ for each class $c_i$. Given the initial estimate of the target labels, we can now tune the underlying neural network parameters to improve classification accuracy. This improved network can in turn, be used to get a better data-dependent label representation in the latent space. We can thus alternate between learning the best representation of the labels in the latent space and learning the best parameters for the underlying network for classification, such that at convergence we achieve both high quality accuracy and an improved representation of the target labels.

Our Contributions

We propose a simple yet powerful alternating updates training algorithm LwAL, that can learn high-quality representations of labels. Our algorithm works with any underlying network architecture, without any architecture modifications, and introducing only minimal additional parameters to tune. We show that learning the labels simultaneously with LwAL significantly cuts down on the overall training time (usually by more than 50% and sometimes up to 80%) while often achieving better test accuracies than the previous works on label learning. We further show that our learned labels are in fact semantically meaningful and can reveal hierarchical relationships that may be present in our data.

Related Work

Label representations beyond the one-hot encoding have gained interest in recent years. Here we discuss the related literature in detail.

Learning Labels Directly

Representations by label smoothing: Label smoothing techniques aim to modify the hard one-hot class probability distribution to a softer target, which can be used to provide broader signals to the model and hence potentially achieving better performance. Numerous smoothing-based regularization techniques such as Max-Entropy Regularizer $\text{MaxEntReg}$ (Pereyra et al. 2017), Teacher-Entropy Regularizer $\text{TEReg}$ (Yuan et al. 2019), and Learning with Retrospection $\text{LWR}$ (Deng and Zhang 2021) have been proposed in the literature, all showing promising improvements. Yet they do not consider unravelling or understanding the relationships between the learned class labels. Deng and Zhang (2021) for instance focuses on learning labels generated by a temperature controlled softmax function for better training. Such representations, by their construction, are limited to learning smooth unimodal class probability distributions and cannot capture complex multimodal class distributions that may be necessary to model semantic relationships that may be present in data.

Representations by network augmentation: Sun et al. (2017) go beyond just label smoothing and propose a unique approach to augment the underlying neural network with specialized layers to learn sophisticated label representations during the training process. Interestingly, they show that even though their augmented network is more complex, it usually learns a good classifier at a faster rate, achieving state-of-the-art accuracies for label learning.

Static Label Representations: Rather than learning a label representation that is tuned to a given classification task, Chen et al. (2021) take an alternate approach and use high-quality pre-trained embeddings (such as BERT or GLoVe) to represent their target labels. Since no label-training is involved, this approach has the advantage of using good label representations with no added complexity, but suffers from yielding relatively lower classification accuracies. This technique also relies on the practitioner having knowledge about which pre-trained embedding is most suitable for the given classification task, which may not be as obvious.

Other Notable Related Techniques

While not aiming to learn label representations explicitly, certain ML models yield labels beyond the traditional one-hot encoding as a side-effect. Student-Teacher learning paradigm (Hinton, Vinyals, and Dean 2015), for instance, aims to learn a more compact network that approximates the behavior of a given large network. In this process of distillation, the original one-hot target labels of the larger network usually get an alternate “dense” representation in the learned compact network. While interesting, learning the distilled network is time-intensive and thus not an efficient mechanism to learn label representations. Xie, Girshick, and Farhadi (2016) develop an unsupervised framework for learning to cluster data in the latent space. They use an auto-encoder architecture to learn a compact latent of the input data where it is forced to form clusters. One can thus use these learned latent data clusters and use the cluster centers as a proxy for representing labels. The lack of direct supervision yields suboptimal partitions and hence suboptimal label encodings for classification.

Connection to Metric Learning

Metric learning aims to learn a transformation of the input space where data from the same category is mapped closer together than data from different categories (Kulis 2012 Bellet, Habrard, and Sebban 2013). One can perhaps view learning labels as performing metric learning not on the input space, but rather on the output space. Interestingly, to the best of our knowledge, this viewpoint is not explored in existing literature and may be a fruitful avenue for future research.
Some metric learning literature does explore semantic hierarchical relationships between labels to learn more informed transformations. Notably, [Verma et al. 2012] explicitly incorporate label hierarchy information to markedly improve nearest-neighbor classification accuracy. They additionally show that such a learned metric can also help in augmenting large taxonomies with new categories. Our work, in contrast, derives the label taxonomy directly from data without any prior hierarchical information.

Methodology
Here we formally introduce our Learning with Adaptive Labels (LwAL) algorithm, which simultaneously learns label representations while training for the underlying classification task. We’ll start by reviewing the standard training procedure for neural networks, introducing our notation. We then present our LwAL modifications that simultaneously learns the label encodings. Finally, we discuss additional optional variations to LwAL that can further improve performance in certain applications.

Standard Neural Network Training Procedure
Recall that given a dataset \( D = (X, Y) = \{(x^{(i)}, y^{(i)})\}_{i=1}^m \) of \( m \) samples for a \( N \)-category classification task, where \( x^{(i)} \) denotes the application specific input representation and \( y^{(i)} \) denotes the one-hot output representation of the \( i \)-th sample, the goal of a neural network \( f_\theta \) (parameterized by \( \theta \)) to learn a mapping from the inputs \( (x^{(i)}) \) to the outputs \( (y^{(i)}) \). This learning is usually done by finding a parameter setting \( \theta \) that minimizes the loss between the predicted output \( f_\theta(x^{(i)}) \) and the desired (one-hot) output \( y^{(i)} \). In particular, let \( z^{(i)} = f_\theta(x^{(i)}) \) be the network encoding of the input \( x^{(i)} \). First, a Softmax is applied to \( z^{(i)} \) to obtain a probability distribution which encodes the affinity of \( z^{(i)} \) to each of the \( N \) classes. Then this induced probability distribution is compared with the ideal probability distribution \( y^{(i)} \) using any distribution-comparing divergence such as the cross-entropy (CE). Thus the classification loss for the \( i \)-th sample becomes

\[
L^{(i)}_{\text{cls}}(\theta) := CE(y^{(i)}, \text{Softmax}(z^{(i)})) = CE(y^{(i)}, \text{Softmax}(f_\theta(x^{(i)}))).
\]

The optimal parameter setting \( \theta \) can thus be learned by using iterative gradient-type updates (such as SGD or Adam) on the aggregate loss over all training datapoints.

Learn with Adaptive Labels
To learn more enriched, semantically meaning label representations, we posit that that semantic relationships between classes are contained within the samples belonging to the class. Specifically, we model the label representation \( \hat{y}_{c_j} \) of a class \( c_j \) as the vector that minimizes the average distance to the network encoding of the samples \( z^{(i)} \) belonging to class \( c_j \). This is equivalent to considering

\[
\hat{y}_{c_j} := \frac{1}{m_{c_j}} \sum_{y^{(i)} = c_j} z^{(i)},
\]

where \( m_{c_j} \) is the number of samples belonging to class \( c_j \).

To bring the training in line with standard neural network updates, given this new class representation, one can define the probability that the network encoding \( z^{(i)} \) of the \( i \)-th datapoint belonging to class \( c_j \) as

\[
p_j^{(i)} := \text{Softmax} \left( -\left\| z^{(i)} - \hat{y}_{c_j} \right\|_2 \right).
\]

Therefore, the modified cross entropy loss for the \( i \)-th datapoint becomes

\[
L^{(i)}_{\text{LwAL}}(\theta) := CE(y^{(i)}, p^{(i)}),
\]

where \( p^{(i)} = (p_j^{(i)}) \) is the probability distribution that encodes the affinity of \( z^{(i)} \) to each of the \( k \) classes using the new label representation. One can thus train the optimal parameters of the underlying neural network \( f_0 \) the usual way.

One should note that the choice of cross-entropy as the loss function encourages the learned class representations \( \hat{y}_{c_j} \) to be well separated yielding empirically better accuracies than other popular loss functions.

Adapting to large-scale datasets
To accommodate large scale datasets, we use the mini-batch paradigm. The mini-batch training usually suffers from the problem of moving target [Mnih et al. 2013], that is, \( \hat{y}_{c_j} \) are constantly changing leading to poor convergence. In order to alleviate this, we add hyperparameters \( k \) that controls the update frequency [Deng and Zhang 2021], and initial warmup steps \( w \) to promote more initial separation between classes when learning \( \hat{y}_{c_j} \). See Algorithm 1 for details.

Algorithm 1: LwAL Training Algorithm

\begin{algorithm}
\caption{LwAL Training Algorithm}
\begin{algorithmic}[1]
\Require input dataset \((X, Y) \sim D\)
\Require neural network \(f_0\)
\Require number of training steps per epoch \(n\)
\Require update frequency \(k \geq 1\)
\Require warmup steps \(w \geq 0\)
\Repeat
\For {step \(i = 1, \ldots, n\)}
\State sample a large batch \((x, y) \sim D\)
\State \(z \leftarrow f_0(x)\)
\State compute \(L = L_{\text{LwAL}}\)
\If {\(i > w\) and \((i - w) \mod k = 1\)}
\State update \(\hat{y}_{c_j}\) for each class \(c_i\) as per eq. (1)
\State compute \(\hat{L} = L_{\text{LwAL}} + \lambda \cdot L_{\text{repeat}}\) optional
\EndIf
\EndFor
\Until convergence
\end{algorithmic}
\end{algorithm}
Additional Improvements

To further improve the label quality, we draw inspiration from the push-pull based losses from metric learning literature (Xing et al. 2002; Weinberger and Saul 2009; Schroff, Kalenichenko, and Philbin 2015). We add an optional “push” loss, that encourages our learned labels to be well-separated thus yielding better generalization accuracies. Specifically, we penalize the angle between the network encoding of the datapoints $z^{(i)}$ from different classes, using cosine similarity. That is (c.f. Algorithm 1),

$$L_{\text{repel}}(\theta) := \sum_{i,j \in Y} \mathbb{I}\{y^{(i)} \neq y^{(j)}\} \cdot \cos(z^{(i)}, z^{(j)}).$$ (3)

Experiments

We have a two-fold aim for our empirical study. First, we evaluate how LwAL fares (both in terms of speed and accuracy) when compared to other popular label-learning methodologies on benchmark datasets. Second, we evaluate the effectiveness of our learned labels for revealing semantically meaningful categorical relationships in our data.

Learning Speed and Test Performance

Datasets To evaluate the robustness of our technique, we report results on several benchmark datasets with different sizes, number of categories and application domains. In particular we used the following datasets for our experiments.

| Dataset          | Domain | # classes | # points |
|------------------|--------|-----------|----------|
| MNIST            | Vision | 10        | 60k      |
| Fashion MNIST    | Vision | 10        | 60k      |
| CIFAR10          | Vision | 10        | 50k      |
| CIFAR100         | Vision | 100       | 50k      |
| FOOD101          | Vision | 101       | 25k      |
| IMDB Reviews     | NLP    | 2         | 25k      |
| YELP Reviews     | NLP    | 2         | 560k     |

We use the default train/test splits provided by the tensorflow library as of Aug 2022.

Network Architectures To check if LwAL works across different architectures, we test on ResNet50 (He et al. 2016), EfficientNetB0 (Tan and Le 2019), and DenseNet121 (Huang et al. 2017) with ImageNet weights, for vision datasets. All of these architectures are available on the tensorflow library as of Aug 2022. For text datasets, we use BERT (Devlin et al. 2019) which is available on the huggingface library as of Aug 2022.

Baselines We compare LwAL with several important baselines. We compare with the standard one-hot training procedure (STD). Chen et al. (2021) employ a static pre-trained (BERT or audio spectrogram) label representation (StaticLabel). For our comparisons, we chose the pre-trained BERT embedding as it was reported to show good performance on the benchmark datasets. From the label smoothing techniques, we use LWR (Deng and Zhang 2021) with varying choices of the update-frequency hyperparameter ($k = 2, 3, 5$). We also compare with the network augmentation (LabelEmbed) technique by Sun et al. (2017).

Hyperparameters In order for the backbones (ResNet50, EfficientNetB0, DenseNet121) to be used across different datasets, we attach a single dense layer with $l_2$ regularization of 0.1 at the top to be used as the classification head.

We train all algorithms with the same set of parameters for consistency. We first pick a learning rate within the same backbone so that all algorithms can converge: for ResNet50 and DenseNet122, we use ADAM optimizer with $\beta_1 = 0.9, \beta_2 = 0.999$ and learning rate of 0.0001; for EfficientNetB0, we use the same optimizer but with learning rate of 0.001. For small datasets such as MNIST, F.MNIST, and CIFAR10, we train all algorithms over 10 epochs. For large datasets such as CIFAR100 and FOOD101, we train all algorithms over 20 epochs where we see the test accuracy reaches a plateau and starts to overfit. We repeat all runs with seeds 12, 123, 1234 and report the mean and spread.

For LWR, we use temperature $\tau = 5$, which is the recommended value. Since we are only training for a few epochs, we also experiment with varying values for the frequency $k = 2, 3, 5$ and report all results in Table 1. For LabelEmbed, we use the default setting of the parameters in the implementation (Sun et al. 2017) (i.e. $\tau = 2, \alpha = 0.9$, and $\beta = 0.5$).

For LwAL, we can vary the output label dimension. We compare the results for output dimension of 10 times the number of classes (LwAL10). We also compare the results with the addition of optional loss $L_{\text{repel}}$ (LwAL10+rpl1). We use update frequency of $k = 1$ and no warmup steps as we use large batch sizes. For LwAL10+rpl we used $\lambda = 10$ (cf. Algorithm 1).

Results and Observations Tables 1 (main text) and 3 (Appendix) summarize our results for the Vision and NLP datasets respectively. Best results are highlighted in bold. Blank (-) in the Time column indicates that a particular algorithm+backbone combination was not able to achieve the STD one-hot baseline test accuracy.

Observe that LwAL significantly cuts down on the overall training time (usually by more than 50% and sometimes up to 80%) while often achieving better test accuracies over other baselines. Figure 2 depicts how the test accuracy curve improves as the training proceeds for a typical run using various backbones. It clearly highlights that one can achieve the same test accuracy as STD with 70% reduction in training time. This phenomenon is typical for various benchmark datasets and choice of backbones (cf. Table 1). One can conclude that LwAL10+rpl with DenseNet121 backbone seems to give the best results with significant ($\geq 50\%)$ savings overall. Curiously StaticLabel and LWR are not able to achieve STD one-hot label test accuracies for large multi-class datasets like CIFAR101 and FOOD101.

An implementation of our algorithm is available at https://github.com/jasonyux/Learning-with-Adaptive-Labels.

3We empirically found that increasing the output dimension often leads to improved performance, as discussed by Chen, Xu, and Wang (2020). Empirically, 10 times the number of classes usually leads to best performance.
Table 1: Learning accuracy and speed comparison between LwAL and other baselines. LwAL is trained using 0 warmup steps and update frequency of once per step. Blank (–) indicates cases when the specific algorithm+backbone pair was unable to reach the reference STD test accuracy. Star (*) indicates the use of different learning rate (1e-3) due to failure of convergence. N/A for MNIST dataset using StaticLabel indicates that the BERT representation of MNIST categories is not appropriate.

Semantic Label Representation
Here we want to empirically evaluate the effectiveness of our learned labels in discovering semantic relationships among categories. For this, we shall use the semantic hierarchy induced by WordNet (Miller 1995) as the gold standard relationship among the categories, and compare how well our learned labels reveal those relationships.

To this end, we utilize the Kendall’s Tau-b ($\tau_b$) correlation...
tion coefficient score to compare the learned representations with the WordNet hierarchy. Specifically, first we compute the pairwise distances between distinct class labels for (i) the reference WordNet hierarchy tree (this is done using the short path distances between the tree nodes $d_{WN}(c_i, c_j)$), and (ii) the learned vectors from the label learning algorithm $d_{LwAL}(c_i, c_j)$. Next, treating collected distance vectors $\mathbf{d}(c_i) := (d(c_i, c_j))_{j=1}^N$ (where $i \neq j$) for each of the $N$ classes as rank vectors, we can compute the average semantic correlation score as:

$$\text{corr}(\text{LwAL}) := \frac{1}{N} \sum_{i=1}^{N} t_i \left( d_{WN}(c_i), d_{LwAL}(c_i) \right)$$  (4)

Datasets We report results on datasets for which the classes can be easily mapped to the WordNet hierarchy. This includes the existing Fashion MNIST (8 out of 10 classes can be mapped) and CIFAR10 (10 out of 10 classes can be mapped). We also include the results for Animal with Attributes 2 (AwA2) dataset (Xian et al. 2019), where 23 out of 50 classes can be mapped. We learn and evaluate the quality of the label representations of only the mappable classes for each of these datasets.

Architectures, Hyperparameters, and Baselines We use ResNet50 (with ImageNet weights) as the underlying neural network backbone for our experiments. We compare the results of our LwAL algorithm with other label learning techniques: LWR (best across $k \in \{2, 3, 5\}$) and LabelEmbed. For LWR, the explicit label representation is computed via Eq. (1). For LabelEmbed, since it returns a similarity matrix between the learned labels, we compute the vectorial representation the standard (eigendecomposition) way.

The rest of the hyperparameter settings (including random seed, batch size, etc.) are same as the previous section.

Results We present the correlation score for each of the label learning techniques in Table 2 and an example visu-
Datasets & Other Label Learning Algs. & Ours

| Datasets | LWR | LabelEmbed | LwAL | LwAL10 | LwAL10+rpl |
|----------|-----|-------------|------|--------|------------|
| CIFAR10  | -0.017±0.068 | 0.053±0.058 | 0.473±0.028 | 0.544±0.024 | **0.609±0.019** |
| F.MNIST  | 0.019±0.068 | 0.079±0.172 | 0.306±0.056 | **0.494±0.054** | 0.305±0.039 |
| AwA2     | -0.097±0.074 | 0.088±0.078 | **0.299±0.021** | 0.288±0.024 | 0.260±0.030 |

Table 2: Structure correlation score (Eq. 4) between learned labels and WordNet. Bold indicates best performance.

Observe that LwAL and its variants can consistently generate significantly superior semantically meaningful representations when compared to other label learning methods. While these results are compelling, it is worth noting that the learned labels and thus the semantic hierarchy is derived from the data inputs. LwAL can thus only extract those relationships that are present in the input data representation and likely cannot capture every fine-grained semantic detail between classes. Indeed, if the input representation (for example pixels for image classification tasks) does not contain any information about the semantic relationships, then one cannot expect LwAL to capture any useful relationship.

**Conclusion and Future Work**

In this work we present a simple yet powerful Learning with Adaptive Labels (LwAL) algorithm that can learn semantically meaningful label representations that the vanilla one-hot encoding is unable to capture. Interestingly, we find that by allowing the network to flexibly learn a label representation during training, we can significantly cut down on the overall training time while achieving high test accuracies. Extensive experiments on multiple datasets with varying dataset sizes, application domains, and network architectures show that our learning algorithm is effective and robust.

As noted, although LwAL can learn high-level semantically meaningful label representations extracted from inputs, it is interesting to explore to what degree this is possible. Can fine-grained semantic relationships be derived just from the raw input space? Or does one need to incorporate additional “side-information” to accelerate semantic discovery? We leave this as a topic for future research.

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Appendix

Additional Results on Learning Speed and Test Performance

In addition to “Percent Time/Epoch Reduced” and “Best Test Accuracy” in Table 1, we include average area under the accuracy curve (AUAC) in Table 5. This could be another useful metric to compare learning speed between algorithms, as larger area under the testing curve indicates a faster learning speed.

Experiments with Text Dataset

We also perform learning speed and test performance evaluations on text datasets, such as IMDB reviews (Maas et al. 2011) and Yelp Polarity Reviews (Zhang, Zhao, and LeCun 2015). Specifically, we first use BERT (Devlin et al. 2019) to extract a 768-dimensional representation of each text, and then use two Dense layers for predictions (one outputs 768 dimension, and another outputs number of classes). For StaticLabel, we use BERT encodings of the word “negative” for class 0, and “positive” for class 1. We train all algorithms over 10 epochs, using ADAM with learning rate of 1e-4, and the rest of the training hyperparameters are the same discussed in the main text. The results are presented in Table 3.

Effects of Warmup Steps on LwAL

As discussed by Deng and Zhang (2021), we experiment our LwAL with some initial warmup steps $w$ to see if it can provide a better initial label separation and hence a better test performance. We experiment this with EfficientNetB0 backbone and report the results in Table 4. We find that using a few warmup steps can sometimes boost the test accuracy by a few percentage points. However, since this is not a consistent gain, we only presented results using $w = 0$ in the main paper. In practice, this is a tuneable hyperparameter to further improve performance.
| Model            | Percent Time/Epoch Reduced | MNIST Best Test Accuracy | Average AUAC |
|------------------|----------------------------|--------------------------|--------------|
| One-hot (STD)    | Reference                  | 83.9±0.1                 | 82.9±0.2     |
| StaticLabel      | 20%                        | 84.1±0.1                 | 82.1±0.1     |
| LWR2k            | -                          | 82.8±0.2                 | 79.8±0.4     |
| LWR3k            | -                          | 83.2±0.2                 | 80.2±0.2     |
| LWR5k            | -                          | 83.7±0.0                 | 82.0±0.2     |
| LabelEmbed       | -                          | 82.7±0.1                 | 81.5±0.1     |
| LwAL (Ours)      | 30%                        | 84.3±0.1                 | 83.5±0.2     |
| LwAL10 (Ours)    | -                          | 83.8±0.1                 | 83.3±0.1     |
| LwAL10+rpl (Ours)| 60%                        | 84.2±0.1                 | 83.6±0.0     |
| LWR2k            | 60%                        | 88.7±0.2                 | 88.5±0.1     |
| LWR3k            | 70%                        | 88.7±0.1                 | 88.5±0.1     |
| LWR5k            | 70%                        | 88.7±0.1                 | 88.5±0.1     |
| LabelEmbed       | -                          | 88.3±0.1                 | 87.8±0.2     |
| LwAL (Ours)      | -                          | 87.9±0.1                 | 87.5±0.0     |
| LwAL10 (Ours)    | -                          | 87.6±0.2                 | 87.2±0.1     |
| LwAL10+rpl (Ours)| -                          | 88.2±0.1                 | 87.9±0.1     |

Table 3: All algorithms are trained with the same hyperparameter of learning rate ($= 1e^{-4}$) over 10 epochs. LwAL used 0 warmup steps and update frequency of once per step. Blank (–) indicates cases when the specific algorithm was unable to reach the reference STD test accuracy.

| Model            | Fashion MNIST Best Test Accuracy | Average AUAC |
|------------------|----------------------------------|--------------|
| LwAL             | 93.0±0.2                         | 93.2±0.0     |
| LwAL10           | 92.7±0.2                         | 92.8±0.1     |
| LwAL10+rpl       | 92.8±0.2                         | 93.0±0.2     |
| LwAL             | 76.7±0.4                         | 76.9±0.5     |
| LwAL10           | 76.2±0.2                         | 76.2±0.4     |
| LwAL10+rpl       | 77.9±0.5                         | 78.2±0.1     |
| LwAL             | 43.2±0.2                         | 42.5±0.2     |
| LwAL10           | 41.6±0.6                         | 41.8±0.7     |
| LwAL10+rpl       | 42.2±0.5                         | 42.3±0.4     |
| LwAL             | 22.0±0.6                         | 22.0±0.1     |
| LwAL10           | 20.5±0.5                         | 20.3±0.1     |
| LwAL10+rpl       | 20.9±0.2                         | 20.8±0.4     |

Table 4: LwAL warmup steps experiment with EfficientNetB0 backbone.
| Model | MNIST | Fashion MNIST | CIFAR10 | CIFAR100 | FOOD101 |
|-------|-------|---------------|---------|---------|---------|
|       | One-hot (STD) | ResNet50 | EfficienNetB0 | DenseNet121 | One-hot (STD) | ResNet50 | EfficienNetB0 | DenseNet121 | One-hot (STD) | ResNet50 | EfficienNetB0 | DenseNet121 | One-hot (STD) | ResNet50 | EfficienNetB0 | DenseNet121 |
|       | StaticLabel | N/A | N/A | N/A | StaticLabel | N/A | N/A | N/A | StaticLabel | N/A | N/A | N/A | StaticLabel | N/A | N/A | N/A |
|       | LWR2k | 98.7±0.1 | **99.3±0.1** | 99.0±0.1 | LWR2k | 98.8±0.1 | **99.3±0.1** | 99.0±0.1 | LWR2k | 98.7±0.1 | **99.3±0.1** | 99.0±0.1 | LWR2k | 98.7±0.1 | **99.3±0.1** | 99.0±0.1 |
|       | LWR3k | 98.8±0.1 | **99.3±0.1** | 99.0±0.1 | LWR3k | 98.8±0.1 | **99.3±0.1** | 99.0±0.1 | LWR3k | 98.9±0.1 | **99.3±0.1** | 99.0±0.1 | LWR3k | 98.8±0.1 | **99.3±0.1** | 99.0±0.1 |
|       | LWR5k | 98.9±0.0 | 99.1±0.1 | 99.0±0.1 | LWR5k | 98.9±0.0 | 99.1±0.1 | 99.0±0.1 | LWR5k | 98.9±0.0 | 99.1±0.1 | 99.0±0.1 | LWR5k | 98.9±0.0 | 99.1±0.1 | 99.0±0.1 |
|       | LabelEmbed | 99.0±0.1 | 99.2±0.0 | **99.1±0.1** | LabelEmbed | 99.0±0.1 | 99.2±0.0 | **99.1±0.1** | LabelEmbed | 99.0±0.1 | 99.2±0.0 | **99.1±0.1** | LabelEmbed | 99.0±0.1 | 99.2±0.0 | **99.1±0.1** |
|       | LwAL (Ours) | 98.9±0.0 | 98.3±0.1 | 98.9±0.0 | LwAL (Ours) | 98.9±0.0 | 98.3±0.1 | 98.9±0.0 | LwAL (Ours) | 98.9±0.0 | 98.3±0.1 | 98.9±0.0 | LwAL (Ours) | 98.9±0.0 | 98.3±0.1 | 98.9±0.0 |
|       | LwAL10 (Ours) | **99.3±0.1** | **99.3±0.1** | **99.3±0.1** | LwAL10 (Ours) | **99.3±0.1** | **99.3±0.1** | **99.3±0.1** | LwAL10 (Ours) | **99.3±0.1** | **99.3±0.1** | **99.3±0.1** | LwAL10 (Ours) | **99.3±0.1** | **99.3±0.1** | **99.3±0.1** |
|       | LwAL10+rpl (Ours) | **99.3±0.1** | **99.3±0.1** | **99.3±0.1** | LwAL10+rpl (Ours) | **99.3±0.1** | **99.3±0.1** | **99.3±0.1** | LwAL10+rpl (Ours) | **99.3±0.1** | **99.3±0.1** | **99.3±0.1** | LwAL10+rpl (Ours) | **99.3±0.1** | **99.3±0.1** | **99.3±0.1** |

Table 5: Learning accuracy and speed comparison between LwAL and other baselines. LwAL is trained using 0 warmup steps and update frequency of once per step. Star (*) indicates the use of different learning rate (1e-3) due to failure of convergence. N/A for MNIST dataset using StaticLabel indicates that the BERT representation of MNIST categories is not appropriate.