Trust Your Model: Iterative Label Improvement and Robust Training by Confidence Based Filtering and Dataset Partitioning

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Abstract

State-of-the-art, high capacity deep neural networks not only require large amounts of labelled training data, they are also highly susceptible to labelling errors in this data, typically resulting in large efforts and costs and therefore limiting the applicability of deep learning. To alleviate this issue, we propose a novel meta training and labelling scheme that is able to use inexpensive unlabelled data by taking advantage of the generalization power of deep neural networks. We show experimentally that by solely relying on one network architecture and our proposed scheme of iterative training and prediction steps, both label quality and resulting model accuracy, can be improved significantly. Our method achieves state-of-the-art results, while being architecture agnostic and therefore broadly applicable. Compared to other methods dealing with erroneous labels, our approach does neither require another network to be trained, nor does it necessarily need an additional, highly accurate reference label set. Instead of removing samples from a labelled set, our technique uses additional sensor data without the need for manual labelling.

1. Introduction

Supervised deep learning methods deliver state-of-the-art results in many important applications, reaching or in some cases even surpassing human-level performance. As a result, deep learning has been adopted for a variety of challenging pattern recognition tasks, such as medical image classification (Taghanaki et al., 2019; Lundervold & Lundervold, 2019), power forecasting for renewable energy plants (Gensler et al., 2016), or autonomous driving (Feng et al., 2019). A major drawback deep neural networks suffer from, especially in supervised learning, is the necessity for a large amount of accurately labelled training data, if good performance is to be achieved. This can prevent or delay the utilisation of deep learning based techniques for practical applications due to the large effort and high cost of producing labels, e.g. by manual labelling. Therefore, it is desirable to make effective use of unlabelled data and increase the robustness of the learning procedure against incomplete and erroneous labels. As a step towards this goal, we propose a novel, iterative technique to train deep neural networks, making use of unlabelled training data in addition to a small or partially wrongly labelled initialisation data set. In order to demonstrate the feasibility of the approach, a comprehensive study of the effects of label noise (fraction of errors) in the training material in a classification setting is conducted.

Both training progress and training outcome in terms of the error rates on unseen data are related to the closely interlinked factors of the chosen cost function, uncertainty

Figure 1. Comparison of different versions of our ILI algorithm on MNIST with erroneous labels. All versions of our method improve the accuracy on the test set, as compared to the noisy baseline. For reference the empirical one $\sigma$ interval is shown for the baseline.

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of the prediction outputs and labelling noise. High cost during training means the prediction from the network and the label presented differ to a large extent. The reason can be twofold, first, it could mean that the network has not yet learned the sample presented so it is highly informative and hence should be considered as very relevant for the training progress; second, it could mean the sample is not labelled correctly, in which case it should be ignored.

In spite of this difficulty, we show the feasibility of an iterative technique to improve the label quality automatically, requiring neither manual intervention nor carefully hand-crafted filtering algorithms reducing the amount of training material needed. Additionally, our approach allows to leverage automated label correction in order to exploit initially unlabelled data and as a result to improve the training outcome and recognition performance.

2. The effects of erroneous labels

Erroneous labels are a well studied problem which is especially relevant for practical applications. Even for the classification of bio-medical data, where data is particularly precious, labelling errors occur (Alon et al., 1999; Li et al., 2001; Zhang et al., 2009) and are studied further in classical machine learning settings, e.g., in (Malossini et al., 2006; Bootkrajang & Kabán, 2012). Recent works study the effect of erroneous labels on object detection for automated driving using deep neural networks (Chadwick & Newman, 2019) and (Haase-Schuetz et al., 2019). Deep neural networks are known to have the capability of learning arbitrary assignments of labels to samples, provided that the model capacity is high enough. As a result, labelling errors in the training set typically cause a large difference between training and validation loss (Zhang et al., 2016). Consequently, an insufficient amount of correctly labelled training data leads to similar effects, as the model can adapt perfectly to the training set, but the result on unseen data may be unsatisfactory. Multiple methods that deal with erroneous labels in the training material for deep neural networks have been proposed, e.g. (Ren et al., 2018; Jiang et al., 2017; Nguyen et al., 2019a,b).

Erroneous labels or an insufficient amount of well-labelled training data occur when real-world problems have to be solved under strict timely and monetary constraints; or when collected and labelled data is extremely valuable, such as for medical applications, where additional experiments with diseases are ethically impossible or label correction prohibited due data privacy. The resulting labels might not be completely wrong - rather inaccurate, and the data sample highly valuable, hence it is desirable to make the best possible use of them instead of filtering them out completely. Such errors could either be due to some bias, e.g. samples of class A typically falsely labelled as B, or randomly distributed inaccuracies.

3. Related work and the idea of Iterative Label Improvement (ILI)

Inspired by the classical training and predicting scheme and leveraging the generalisation power of deep neural networks, we employ an iterative scheme as depicted in Figure 2, using the predictions of a trained network as training material for another instance of such a network.

Other approaches dealing with label noise in the training material for deep neural networks are based on finding an optimal curriculum, to present the data, as first introduced in (Bengio et al., 2009). This approach has the potential to make the best possible use of the given labels. Traditional curricula, however, require careful engineering, which can limit practical applicability of the technique. MentorNet (Jiang et al., 2017) attempts to learn a curriculum from data, requiring an additional teacher network to be trained jointly with the student net, i.e., the network learning the actual problem. Learning to reweight (Ren et al., 2018) on the other hand employs a clean validation set, requiring the labels to be of high quality in order to be able to judge the quality of the training data. Instead of using curricula, other methods such as (Nguyen et al., 2019a) and (Nguyen et al., 2019b) rely on filtering the noisy labels, i.e. getting rid of them. Instead, our approach estimates improved labels for potentially noisy samples in order to gain advantage of the additional training material. Although curriculum learning, with a suitably chosen curriculum, limits the adverse effect of badly labelled samples on the training and the resulting
model, it does not take advantage of automatic label generation as our approach. Therefore, iterative label improvement can take advantage of additional, initially unlabelled data which is usually inexpensively available in large quantities in many practical cases. While filtering out bad samples might be desirable to increase a model’s accuracy, in settings with highly valuable samples, it is beneficial to improve the existing labels, as is possible with our proposed approach.

Let \( m \) be a model, which for a sample \( x \) in the training set \( X_{\text{train}} \) predicts a target \( \hat{y} \) with a confidence \( c \) and \( F \) a filter function, deciding between label versions \( y \) and \( \hat{y} \). The model is initially trained on label \( y_{\text{train}} \) and \( (i) \) indicates the number of the current iteration, \( n_{\text{iter}} \) in total. The novel technique we propose is referred to as “Iterative Label Improvement” or ILI. \(^1\) There are several variants of the approach which will be described in the following sections. In algorithm 1, the first simple variant is shown as an example (for details see Section 4.1.1). The final model and the improved labels can be obtained from the last ILI iteration.

Algorithm 1 plainILI filtered with initILI

Input: \( X_{\text{train}}, y_{\text{train}}, n_{\text{iter}} \)

Output: Model \( m_{\text{iter}}, y_{\text{iter}} \)

1: \( m_{(0)} = m.\text{initialize}() \)
2: \( m_{(0)}.\text{fit}(X_{\text{train}}, y_{\text{train}}) \)
3: for \( i = 1 \) to \( n_{\text{iter}} \) do
4: \( y_{\text{train}}^{(i)} = F[m_{(i-1)}(X_{\text{train}}, y_{\text{train}}^{(i-1)})] \)
5: \( m_{(i)} = m.\text{initialize}() \)
6: \( m_{(i)}.\text{fit}(X_{\text{train}}, y_{\text{train}}^{(i)}) \)
7: end for

4. The ILI approach in detail

Fig. 2 illustrates our proposed approach. Depending on the variant of the approach as described below, the training data may contain labelling noise or a well-labelled, but small reference training set. In the latter case, unlabelled data must be available additionally. If labelling noise is present, such labels will be called erroneous.

Regardless of the ILI variant, the separate test set does not contain erroneously labelled samples and its main use is to evaluate the trained model in order to verify the performance of our proposed technique, for example for the experimental results presented in this paper. In a practical application, other ways to evaluate the performance can be applied such as manual inspection of a selection of the labels generated. The validation set used to find a point for early stopping can contain errors as well.

There are several variants of the ILI scheme which differ in the following three aspects: (i) number of partitions, the unlabelled data is split into; (ii) quality of the initialisation dataset; and (iii) label selection or filtering approach. When deploying ILI to an application, the respective variants of these three aspects can be combined as suited best for the particular case. For all algorithms, we initialize the model in each optimisation step, i.e. the model is trained from scratch.

4.1. Number of partitions

ILI can be applied using the complete training dataset at once (no partitioning) or using various splits (with partitioning). Details will be described in the following paragraphs.

4.1.1. plainILI: No partitioning

A simple variant of the approach which is referred to as “plainILI” is to always use the same set of samples for training and prediction, as in algorithm 1. This makes sense if an automated technique for generating inexpensive, but faulty initialisation labels for the first iteration is available. The model is trained on the labels in spite of the errors. In the next step, we apply the trained model on the samples of the training set, ignoring the existing labels and then replacing all of them with the predictions. So the plain algorithm replaces the labels in each ILI iteration with the predictions of the network from the previous ILI iteration, during which it was trained a predefined number of epochs, so in iteration \( i + 1 \), \( y_{\text{train}, i+1} = \text{argmax}(\text{model}_{i}.\text{predict}(X_{\text{train}})) \), which is to be understood per sample. In each iteration, the model is trained from scratch to avoid overfitting to the noisy training labels.

4.1.2. Partitioning based Iterative Label Improvement – pILI

Partitioning based ILI (pILI) employs a splitting of the training data into at least two parts, in order to reduce the effect that the trained model will learn the errors in the labels, and, therefore to improve generalisation. Instead of using all training data at once, pILI alternates between training on a subset \( A \) of the data and predicting labels on a different subset \( B \) (details on the choice of subsets given below), for each ILI iteration. So, the predictions made by a model are always on samples that particular model has not seen in training. To prevent error propagation as much as possible, the training process always starts from scratch in each optimisation iteration, so the reinitialization of the model results in not using any history that would otherwise be contained in the model’s weights. There are two variants of pILI, oscillating partitioning (opILI) and fraction partitioning ILI (fpILI).
opILI: Oscillation based ILI In oscillation based ILI, exactly two subsets $A$ and $B$ are used alternately, so training and prediction oscillate between these two disjoint subsets. Regarding the initial labels needed to start the process, one variant is shown in algorithm 2. In this case, initialisation labels are needed only for $A$ and these labels may contain errors, as they are used only at the beginning of the process.

Algorithm 2 opILI with initILI

Input: $X_{\text{train}, A}, y_{\text{train}}, n_{\text{iter}}$
Output: Model $m^{n_{\text{iter}}}, y^{n_{\text{iter}}}$
1: $X_{\text{train}, A} \cup X_{\text{train}, B} = \text{Split}(X_{\text{train}})$
2: $m^{(0)}_A, y^{(0)}_A = \text{initialize}()$
3: $m^{(0)}_A, y^{(0)}_A = \text{fit}(X_{\text{train}, A}, y^{(0)}_A)$
4: for $i = 1$ to $n_{\text{iter}}$ do
5: \hspace{1em} $y_{\text{train}, B} = m^{(i)}_A(X_{\text{train}, B})$
6: \hspace{1em} $m^{(i)}_A, y^{(i)}_A = \text{initialize}()$
7: \hspace{1em} $m^{(i)}_B, y^{(i)}_B = \text{fit}(X_{\text{train}, B}, y^{(i)}_A)$
8: \hspace{1em} $y_{\text{train}, A} = m^{(i)}_B(X_{\text{train}, A})$
9: \hspace{1em} $m^{(i)}_A, y^{(i)}_A = \text{initialize}()$
10: \hspace{1em} $m^{(i)}_A, y^{(i)}_A = \text{fit}(X_{\text{train}, A}, y^{(i)}_A)$
11: end for
12: $y^{n_{\text{iter}}}_A = \left[y^{(n_{\text{iter}})}_{\text{train}, A}, y^{(n_{\text{iter}})}_{\text{train}, B}\right]$

fpILI: Fragmentation based ILI Fragmentation based ILI, the other variant of partitioning based ILI, is similar to oscillation based ILI but the training set is partitioned into more than two subsets. So, the training data is split into multiple subsets, a labelled set $X_{\text{train}, A}$ and multiple unlabelled sets $X_{\text{train}, B_i}, i = 0, \ldots, n$, where $n$ is a hyperparameter. All partitions in $B$ are usually similar in size, i.e., $|X_{\text{train}, B_i}| \approx |X_{\text{train}, B_k}|$ for all $i, k : 0 \leq i, k \leq n$. Only the initialisation set $X_{\text{train}, A}$ is labelled with $y_{\text{train}, A}$. The subsets are usually (but not necessarily) a partition of the overall training set in the mathematical sense:

$$X_{\text{train}} = X_{\text{train}, A} \cup \left( \bigcup_i X_{\text{train}, B_i} \right).$$

The advantage of fpILI in comparison to opILI is that in each new optimisation iteration, the samples for which the trained model makes predictions are unseen not only with regards to the training data of the model of ILI iteration $(i)$, but also with regards to the labels of the training set of iteration $(i)$, which are influenced implicitly by the data from the previous iterations $(0), \ldots, (i−1)$.

For this reason, fpILI should in principle be preferred over opILI, however more unlabelled data is required. If the availability of unlabelled data is restricted, opILI may perform better in practice.

4.2. Quality of initialisation data set

Depending on the quality of the initial dataset, different versions of ILI can be used, which will be introduced in the following.

4.2.1. INITILI: INITIAL DATA ONLY USED ONCE

In both algorithms 1 and 2, it is acceptable if the initialisation data set contains faulty labels, as in both cases, the initial labels are used only in the first optimisation iteration. This variant is called initILI, as the given labels are used for initialisation only.

4.2.2. REFILI: HIGH QUALITY REFERENCE DATA

The principle of ILI, however, can be useful as well if a data set $X_{\text{train}, A}$ with virtually perfect labels is available yet the size of this typically manually labelled reference set is too small to reach the needed recognition performance. In this case, the reference set $X_{\text{train}, A}$ is used to train an initial model to make predictions on a larger set in the first ILI iteration. In each subsequent training, both the predicted labels from the previous iteration and the reference set is used together for training. This ILI variant is called refILI. Regarding the additional, initially unlabelled set $X_{\text{train}, B_i}$, depending on how many partitions are created, refILI is combined with opILI (exactly two partitions of $X_{\text{train}, B_i}$) or fpILI (more than two partitions).

Algorithm 3 shows as an example refILI combined with fpILI. Considering that the labels of $X_{\text{train}, A}$ are more accurate than the predicted labels of $X_{\text{train}, B_i}$ (especially at the beginning of the ILI process) and $X_{\text{train}, A}$ is smaller than each one of the single partitions $X_{\text{train}, B_i}$, an approach to increase the relative influence of the samples in $X_{\text{train}, A}$ should be adopted.

Algorithm 3 refILI with fpILI

Input: $X_{\text{train}}, y_{\text{train}}, n_{\text{iter}}$
Output: Model $m^{n_{\text{iter}}}, y^{n_{\text{iter}}}$
1: $X_{\text{train}, A} \cup X_{\text{train}, B_0} \ldots \cup X_{\text{train}, B_n} = \text{Split}(X_{\text{train}})$
2: $m_{\text{A}}, y_{\text{train}}^{(0)} = \text{initialize}()$
3: $m_{\text{A}}, y_{\text{train}}^{(0)} = \text{fit}(X_{\text{train}, A}, y_{\text{train}}^{(0)})$
4: $y_{\text{train}, B_0} = m_{\text{A}}(X_{\text{train}, B_0})$
5: for $i = 1$ to $n$ do
6: \hspace{1em} $m_{\text{AB}}^{(i)}, y_{\text{train}}^{(i)} = \text{initialize}()$
7: \hspace{1em} $m_{\text{AB}}^{(i)}, y_{\text{train}}^{(i)} = \text{fit}([X_{\text{train}, A} \cup X_{\text{train}, B_{i−1}}], [y_{\text{train}, A} \cup y_{\text{train}, B_{i−1}}])$
8: \hspace{1em} $y_{\text{train}, B_i} = m_{\text{AB}}^{(i)}(X_{\text{train}, B_i})$
9: end for
10: $y_{\text{train}}^{n_{\text{iter}}} = \left[y_{\text{train}, A}^{(n_{\text{iter}})} \cup y_{\text{train}, B_{n−1}}^{(n_{\text{iter}})} \ldots \cup y_{\text{train}, B_{i−1}}^{(n_{\text{iter}})}\right]$
4.3. Label selection or filtering

Depending on the model of the current iteration, a selection or filtering function can be applied, to decide whether to use the labels of the previous or the current iteration. The different versions are introduced in the following.

4.3.1. ILI UNFILTERED

Unfiltered ILI is the most basic approach, where the predictions of the model are kept as labels of the present iteration. After each iteration $i - 1$, for the next iteration we set $y^{(i)} \equiv \hat{y}^{(i-1)} = m^{(i-1)}(x)$, i.e. we trust the current models’ predictions on the training data $x$.

4.3.2. ILI FILTERED

To account for model uncertainty, a filter function, which is a functional of the model built in the current iteration can be applied. For each iteration $i - 1$, we use a filter, $F$ a functional of the model $m^{(i-1)}$: $y^{(i)} \equiv F^{(i-1)}(y^{(i-1)}) := F\left[ m^{(i-1)}(y^{(i-1)}) \right]$. For example, if using the confidence $c^{(i)}$ given by the model

\[ F^{(i)}_{\text{confidence}} \left( y^{(i)}_{\text{train}} \right) = \begin{cases} \hat{y}^{(i)}_{\text{train},i} = m^{(i)}(x^{\text{train},i}) : & c^{(i)} > \vartheta \\ \hat{y}^{(i)}_{\text{train},i} = y^{(i)}_{\text{train},i} : & \text{else}. \end{cases} \]

In general, the filtering based ILI uses a filter function $F$ to determine which labels of the current optimisation iteration step are kept unchanged and which ones are replaced by the models’ predictions. This filtering adopts a suitable metric and typically relies on a threshold decision, accepting a particular prediction of a model if the metric reaches or exceeds the threshold, while otherwise the original label is kept instead. The metric can be defined, for example, as a measure of the uncertainty of the model’s prediction, which can be obtained from ensemble variation (Freeman, 1965), by Monte-Carlo Dropout (Gal & Ghahramani, 2016) or simply from the confidence of the predictions, i.e. the value of the softmax in the last layer of the neural network for the winning class.

5. Experiments

By manually introducing label errors to MNIST and CIFAR10, we control the type and amount of errors in the training material. We show that the accuracy of ILI as outlined in the previous sections is viable. We apply ILI to randomly distributed errors and to what we call bias errors. For bias errors, we change a fraction of training labels of only one class A to another class B. For randomly distributed errors, we change a fraction of the training labels to any other class, but the correct one, with all other classes being equally likely. Implementation details can be found in the supplementary material.

5.1. Goal of experimental evaluations

A prerequisite for our proposed ILI approach to be successful is the capability of deep neural networks to predict labels with an error rate that is smaller than the error rate of the labels in the training data and, crucially, to what extent this capability can be sustained in an iterative process. This determines the overall effectiveness of ILI in its different variants in terms of the eventual recognition accuracy that is achievable, starting from a certain quality of the labelled initialisation data set at the beginning. In settings where the amount of errors in the labels is so large, that the trained network can not generalise sufficiently, we do not expect our approach to lead to any improvement, without an additional regularisation technique.

It can be noted that this question, i.e., how effective ILI is in reducing labelling errors, is critical for all the ILI variants including reflILI, even though a well labelled reference training set is available in this case. This is because for the deployment of reflILI in practice, as already described above, the size of the nearly perfectly labelled reference data set is expected to be insufficient\(^2\). As a result, the first training with the reference set alone will result in a model which obtains a recognition rate on unseen data significantly worse than the high accuracy of the reference set. Therefore, the success of ILI in this case depends on the capability to reduce the errors of predicted labels in an iterative fashion, similar to what is needed for initILI, when no reference set is available. Keeping this in mind, reflILI will not be included explicitly in the following experimental results. Instead, the shown experiments are considered to be equally relevant for both initILI and reflILI.

5.2. Experimental results and discussions

We apply the versions of ILI to MNIST (LeCun et al., 1998) and CIFAR10 (Krizhevsky et al., 2009) with increasing amounts of erroneous labels. We use three different model architectures, two of which are defined in the Keras examples (Chollet et al., 2015), which we call MNISET-CNN and CIFAR-CNN respectively and apply them both to noisy MNIST and noisy CIFAR10 training data. Furthermore, we apply ILI to ResNet32 (He et al., 2016) on noisy CIFAR10 data. Labelling noise is introduced uniformly distributed, and the noise fraction is the fraction of labels being changed as compared to the original, clean dataset. For the experiments we gradually increase the noise fraction, starting at 0.3, in steps of 0.1, up to 0.9. If not otherwise noted, we

\(^2\)In practice such a reference data set can be realized by spending large amounts of time and money per sample, hence it is desirable to limit its size.
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(a) CIFAR-CNN on noisy MNIST data with random error.
(b) MNIST-CNN on noisy MNIST data with random error.
(c) CIFAR-CNN on noisy MNIST data with bias error.
(d) MNIST-CNN on noisy MNIST data with bias error.

Figure 3. Different combinations of error type and network architecture and the performance of the ILI variants on noisy MNIST data. ILI is able to improve the accuracy in all tested settings.

Table 1. Relative improvement in accuracy from first to last ILI iteration of MNIST-CNN on MNIST data with random errors using plain ILI with initILI, 10 ILI iterations if not stated differently (frac. meaning fraction; conf. meaning confidence).

| NOISE FRAC. | NO FILTER [%] | NO FILTER 50 ILI ITERATIONS [%] | CONF. FILTER $\vartheta = 0.3$ [%] | OPILI [%] | FPILI [%] |
|-------------|---------------|---------------------------------|-----------------------------------|----------|----------|
| 0.3         | 0.26          | -                               | -                                 | 0.27     | 0.26     |
| 0.4         | **0.69**      | -                               | -                                 | 0.60     | 0.38     |
| 0.5         | 0.95          | -                               | -                                 | **1.67** | 0.37     |
| 0.6         | 2.77          | -                               | -                                 | 3.32     | **4.05** |
| 0.7         | 7.56          | 8.02                            | 5.64                              | 11.5     | **14.2** |
| 0.8         | 34.35         | 38.62                           | 25.6                              | 42.1     | **51.2** |
| 0.9         | 48.24         | **69.79**                       | 21.5                              | 22.4     | -5.87    |

use an early stopping approach, where we use the held-out clean validation set to terminate the optimisation iterations, if the validation accuracy is no longer increasing, with a maximum of ten iterations, if not stated differently.

5.2.1. Noisy MNIST Data

Figure 1 shows different versions of ILI using MNIST-CNN on noisy MNIST data, with random errors. All versions of ILI improve the accuracy about the noisy baseline in this setting. The best performing method in is ILI without partitioning, when run for 50 ILI iterations. All versions shown use refILI, as introduced in algorithm 2 for opILI.

Table 1 shows the relative improvement achieved by the ILI iterations, using MNIST-CNN on MNIST data with random errors. Here, it should be noted that different versions of ILI use a different initialisation data set or “seed” for the first training. Plain or filtering ILI with no partitioning uses a completely labelled training set, hence $N$ labels, but errors in those labels are acceptable. On the other hand, using partitioning based ILI, e.g. opILI, reduces the amount of initial training labels used. If using $k$ partitions, and the same set, the seed will have a size of $N/k$, i.e. for opILI $N/2$.

Hence a comparison as in Figure 1 is not completely “fair”. In terms of relative improvement, fragmentation based ILI (fpILI) outperforms all other methods, except for a noise fraction of 0.9, where again the performance suffers from the smaller “seed” training set.

For plainILI with filter, with confidence as a metric, we observe that the performance is highly threshold dependent. Thresholds $\vartheta = 0.5, 0.7, 0.9$ lead to no improvement at all, while $\vartheta = 0.3$ improves the accuracy over the optimisation iterations. However, if compared to ILI without filter, the performance of ILI filter is inferior. To find out which threshold setting achieves the best performance, the expectation should be taken into account that in the later ILI iterations, the performance of the predicted labels is getting higher, so a larger fraction of samples should be selected in comparison to earlier ILI iterations. On the other hand, the confidence itself is expected to increase anyway together with the model accuracy during the course of the ILI process. However, this is complicated by the fact that the confidence is likely to depend additionally on the number of training iterations performed per ILI iteration. Therefore, an effective choice of the threshold, which may vary throughout the process, has the potential to further increase the overall performance of the ILI approach but remains part of future work. Figure 3 shows the results of different ILI variants applied to noisy MNIST data, with random error in Figure 3(a), using CIFAR-CNN and Figure 3(b), using MNIST-CNN. The results for bias errors are shown in Figure 3(c), for CIFAR-CNN and Figure 3(d), for MNIST-CNN. In all settings ILI is able to improve the results.
5.2.2. Noisy CIFAR10 data

For CIFAR10, the accuracies achievable by the chosen models and hyperparameters are considerably lower than on MNIST. However, from Figure 4 we can see that the different ILI variants presented improve the accuracy for a given noise fraction. This holds true for both bias and random errors. Figures 4(a) (CIFAR-CNN) and 4(b) (MNIST-CNN) show the results for random errors, while figures 4(c) (CIFAR-CNN) and 4(d) (ResNet32) show the results for bias errors.

As a reference, we compare our approach using a ResNet32 (Ren et al., 2018) using the very same network architecture. As ILI can be combined with the “learning to reweight” approach, we do not need or expect to outperform this method. We use the code provided by the authors to reproduce the results for random errors (called uniform flip by the authors). The results can be seen in Figure 5 and 6. We find “learning to reweight” to outperform even our clean baseline – however this is due to data augmentation, which we did not use at all. If data augmentation is deactivated, the results for “learning to reweight” and our baseline achieve a similar performance, cf. Figure 5. However, without data augmentation the used ResNet32 as a network with much higher capacity in comparison to MNIST-CNN or CIFAR-CNN easily overfits the noisy training data. Hence it fails to generalise on clean validation data. The performance on the clean validation data is inferior to the label accuracy, hence our iterative approach fails for most noise fractions as expected.

Note that “learning to reweight” also leads to a validation accuracy inferior to the labelling quality. For a noise fraction of 0.7 and 0.8, our confidence based filtering ILI with thresholds \( \vartheta = 0.9 \) outperforms “learning to reweight” and increases the accuracy over the training label accuracy, even without these two techniques combined. If using data augmentation, our approach outperforms “learning to reweight” for the noise regime from 0.3 to 0.7. For a noise fraction of 0.8 and higher, our approach fails to generalize as well and the performance is below that of “learning to reweight”, as shown in Figure 6.

5.3. ILI in real-world applications

In our experiments, even though plain ILI (with or without filtering) is the most basic technique, the best results are achieved with this variant for noisy MNIST data. This demonstrates the feasibility of the ILI approach in principle, as in the case of this simple classification task, no further measures are necessary in order to exploit iteratively corrected labels. When considering the results of the partitioning based variants, the experimental design should be taken into account. The smaller initialisation set appears to outweigh the advantage of predictions on unseen data in this example, as these more sophisticated variants do not show an additional improvement over plainILI. In our experimental setting we utilise a given dataset to investigate the performance on this dataset for which we know the correct labels. In practice it would rather be typical to have a small labelled set and larger amounts of unlabelled data. Using fpILI or opILI does not require initial labels for any other but the first subset. Hence, the strength of these partitioning based variants will become apparent in applications where larger amounts of unlabelled data can be collected easily.

6. Conclusions

We introduced the ILI approach and its variants, which iteratively improve erroneous labels. Being architecture agnostic, ILI can be applied to various deep neural networks. We illustrate the usage of ILI with three different architectures. Furthermore, ILI can be combined with approaches for regularisation to improve generalisation, in order to take advantage of their full potential. If provided with a clean, well-labelled reference set, ILI can leverage the information contained therein, given substantial additional amounts of inexpensive, unlabelled data so that ILI can integrate those samples and generate labels.

By introducing controlled amounts of error to two well-known data sets and applying ILI to different network architectures, we show its applicability. More complex filtering schemes based on various uncertainty measures have the potential to improve the results further. Training schemes suitable for settings where erroneous labels are to be expected can be integrated with ILI to raise the reachable accuracy. Increasing the fraction of erroneous labels from 0.3 in steps of 0.1 to 0.9, we find that applying ILI consistently improves the accuracy on the clean test set in comparison to performing a regular training with the erroneous labels and without iterations. The only exceptions are the cases when the fraction of erroneous labels is very large, e.g. a noise fraction of 0.9 for MNIST, or when the initial training fails to generalise well enough to lead to a performance above the training label accuracy. We compare ILI to “learning to reweight”, another technique dealing with erroneous labels (which could be combined with ILI) and find that regularisation is a key ingredient to any approach dealing with erroneous labels. We show so, by applying data augmentation. If data augmentation is applied, our approach outperforms “learning to reweight”, which is as state-of-the-art method. We hypothesise that any approach successfully dealing with a noisy label setting depends on the ability to generalise well from the uniformly distributed errors. However if such a generalisation fails in the first place i.e. the noisy training data is overfitted by a high capacity neural
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(a) CIFAR-CNN on noisy CI-FAR10 data with random error  
(b) MNIST-CNN on noisy CI-FAR10 data with random error.  
(c) CIFAR-CNN on noisy CI-FAR10 data with bias error.  
(d) ResNet on noisy CIFAR10 data with bias error.

Figure 4. Different combinations of error type and network architecture and the performance of the ILI variants on noisy CIFAR10 data. ILI is able to improve the accuracy in all tested settings.

Figure 5. Comparison of different versions of our ILI algorithm on CIFAR10 data, using a ResNet32, with erroneous labels (randomly distributed). As a reference we compare to “learning to reweight” (Ren et al., 2018). Without data augmentation both methods fail to improve the accuracy significantly.

Figure 6. Comparison of different versions of our ILI algorithm on CIFAR10 data, using a ResNet32, with erroneous labels (randomly distributed) vs. “learning to reweight”. With data augmentation our method outperforms “learning to reweight” for most noise fractions.

network, regularisation is essential. Therefore, we expect that ILI can be improved additionally by further investigations into regularisation in settings with erroneous labels, which is part of future work. Furthermore, our approach can be combined with uncertainty measures more sophisticated than the confidence derived simply from neural network output activations. Also combining other recent techniques to learn from erroneous labels with ILI and showing the applicability to a broader range of network architectures will raise interesting questions.

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A. The effect of erroneous labels

To further clarify the role of erroneous labels, we give an overview of the way the errors were introduced and the effect on the trained networks. This complements section 2 in the main document.

A.1. Introducing Noise

We introduce two types of errors, (i) bias errors, meaning we randomly pick a subset of the original training labels of samples from class “4” to “7”. However, above a noise fraction of 0 the accuracy of the training labels, despite the bias error. "4", hence the performance drops to almost zero above this point.

A.2. Resulting performance

In this subsection we give a detailed overview on the effects of the amount of error in the training material on the resulting accuracies on a clean test set. Figure 7(a) shows the resulting performance if MNIST-CNN is trained on noisy MNIST data, with random error. Only above 0.9 the MNIST-CNN is not able to generalise well, and does not achieve a resulting accuracy larger than the accuracy of the training labels. The empirical variation in the resulting performance is largest for 0.7 and 0.8. Figure 7(b) shows the resulting performance for CIFAR-CNN, trained on noisy CIFAR10 data with random error. Only for noise fractions from 0.4 to 0.8 the resulting performance is higher than the accuracy of the training labels, hence only in this regime we can expect our ILI approach to be successful. In Figure 7(c) the results on noisy MNIST data with bias error, using a MNIST-CNN are shown. The accuracy Acc4 is the accuracy on samples labelled with class “4” from the test set. For the interval [0, 0.5] the network is able to achieve an accuracy above the accuracy of the training labels, despite the bias error. However, above a noise fraction of 0.5, the majority of samples with the original class “4” are falsely labelled with "7", hence the performance drops to almost zero above this point.

B. Detailed results over the optimisation iterations

To further illustrate the results summarized in the main document in the Figures 1, 3-6, and in section 5, we show the resulting test accuracy over the optimisation iterations.

Figure 8 shows the resulting test accuracy over 50 optimisation iterations of ILI without filter, using MNIST-CNN on MNIST data with random error and initILI. The maximum accuracy with the ±σ interval is shown as well. This is the maximum accuracy we can reach with the given model and dataset (without additional hyperparameter tuning). Noise ratios are shown from 0.7 to 0.9. For all noise ratios, the test accuracy is increasing over the optimisation iterations, demonstrating ILI's effectiveness over a wide range of noise levels. In the intermediate noise regime, at noise ratios of 0.8 and 0.7, the largest increase in test accuracy is achieved. For better visibility, smaller noise fractions (< 0.7) are not shown. At all noise fractions, the largest gain in performance is achieved within the first few iterations of ILI. Figure 8 shows that for a noise fraction of 0.8, performance saturates between 30 and 40 iterations and for 0.9, saturation is reached after 40 iterations. For noisy MNIST data, using MNIST-CNN the validation accuracy is increasing over the optimisation iterations, for all noise fractions investigated. This is a reasonable outcome considering the dataset size, as a fraction of 0.9 erroneous labels, without any bias, for the MNIST dataset means that there are still 6000 correctly labelled samples in the training set. From these, the network is able to generalise and correct some of the other errors present. The increase in performance shows an asymptotic behaviour with the biggest gain occurring after the first iteration.

Figure 9 shows detailed results for all tested confidence thresholds (0.3, 0.5, 0.7 and 0.9). The results on noisy MNIST data with randomly distributed errors using MNIST-CNN lead to the conclusion, that θ = 0.3 is to be preferred,
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(a) MNIST-CNN on noisy MNIST data, with random error.
(b) CIFAR-CNN on noisy CIFAR data, with random error.
(c) MNIST-CNN on noisy MNIST data, with bias error.

Figure 7. The effect of different fractions and types of error (random & bias) on the performance of a network trained with these erroneous labels.

Figure 8. ILI Plain 50 optimisation iterations on MNIST. For reference, the maximum reachable accuracy for the given model is shown (dashed blue line). The test accuracy is increasing over the iterations. This holds true for all investigated levels of erroneous initialisation labels, even for the highest level considered, i.e. a fraction of 0.9 faulty labels.

Figure 9. ILI with confidence filter and 10 optimisation iterations using MNIST-CNN on noisy MNIST data with random error. Confidence based filtering is highly threshold dependent. In the experiments on noisy MNIST data with MNIST-CNN and random error, only $\theta = 0.3$ leads to an improvement.
as it leads to the best results. The threshold $\vartheta$ is a hyperparameter, for which to tune a validation set (possibly noisy) is necessary.

### C. Partitioning based ILI with final training

For the partitioning based ILI (pILI) as introduced in Section 4.1.2 in the main document, a final training using all the subsets with their best predicted labels can be performed in order to gain more accuracy. The final training is conducted on the set

$$X_{\text{train}, A} \cup \left( \bigcup_i X_{\text{train}, B_i} \right).$$

(note: This includes the opILI case where $\{B_i\} = B$).

The resulting performance plot for the MNIST-CNN on the MNIST dataset with random errors is shown in Figure 10. The results are compared in Table 2 by their percentage increase in accuracy from the first to the last ILI iteration. A final training on all available data can lead to minor performance improvements.

Detailed results of opILI and fpILI for noisy MNIST with random error and MNIST-CNN can be found in Figure 11. All variants increase the validation accuracy, however fpILI is inferior, due to the smaller initialization set, as discussed in section 4.1.2 and 5.3 in the main document.

To enable a fair comparison between opILI and ILI, Figure 12 shows the resulting performance of a ResNet32 trained on noisy CIFAR10 data with random error and a reduced training dataset size. For the noisy baseline and the ILI variant without partitioning, only half the dataset is used. For opILI, only half the dataset is labeled, the other half is used as unlabelled set to leverage the potential of opILI as semi-supervised technique. Under these constrains opILI outperforms ILI without partitioning.

### D. Overfitting ResNet

As introduced in section 5.2.2 in the main document, high capacity networks such as ResNet32, can easily overfit the noisy training data. This critically hinders the success of methods dealing with erroneous labels. Which can not only be seen in the resulting performance of the optimisation, but also by monitoring the validation loss of a single training. Figure 13 shows, that even for a noise fraction as small as 0.1 the validation loss increases after approximately ten epochs, indicating an overfitting on the (in our case noisy) training data. We observe this even more prominently for higher noise fractions. Hence, regularisation is crucial for approaches as ours to work. As shown in Figure 14 the data augmentation is able to prevent overfitting the noisy data with the ResNet32 and the same setting as in Figure 13. This holds true for all other noise fractions investigated.

### E. Training details

For all networks we stick as close as possible to the original setup (references given below). We neglect data augmentation, if not explicitly stated differently, to study the effect of changes to the labels alone (without any effect due to changes to the samples).

**MNIST-CNN**: We use the architecture as defined in (Chollet et al., 2015), using two convolutional layers and one dense layer, trained over 20 epochs with Adadelta.

**CIFAR-CNN**: We use the four convolutional, one dense layer network as provided by (Chollet et al., 2015), trained over 100 epochs, with RMSprop optimiser, a learning rate of $10^{-4}$ and a decay of $10^{-6}$.

**ResNet**: We use a ResNet (He et al., 2016) of depth 32, trained with the learning rate schedule as defined in (Chollet et al., 2015), starting at 0.001, changed to 0.0001 at epoch 80, $10^{-5}$ at epoch 120, $10^{-6}$ at epoch 160, and $5 \cdot 10^{-7}$ at epoch 180. The network is trained for 200 epochs.

**Learning to reweight**: We use the code accompanying the publication (Ren et al., 2018), uniform flip noise, and a ResNet of depth 32 (He et al., 2016). To compare the results directly to our approach we experiment with activating and deactivating data augmentation in the code, which was not done in the original paper by Ren et al.
Figure 11. Variants of pILI with initILI, using MNIST-CNN on noisy MNIST data with random errors.
Table 2. Relative improvement in accuracy from first to last ILI iteration of MNIST-CNN on MNIST data with random errors using plain ILI with initILI, 10 ILI iterations if not stated differently (frac. meaning fraction; conf. meaning confidence; FT meaning final training).

| Noise frac. | No Filter [%] | No Filter 50 ILI iter. [%] | Conf. Filter \( \theta = 0.3 \) [%] | opILI [%] | opILI+FT [%] | fpILI [%] | fpILI+FT [%] |
|-------------|---------------|-----------------------------|-----------------------------------|----------|-------------|----------|-------------|
| 0.3         | 0.26          | -                           | -                                 | 0.27     | 0.34        | 0.26     | **1.1**     |
| 0.4         | 0.69          | -                           | -                                 | 0.60     | 0.72        | 0.38     | **1.4**     |
| 0.5         | 0.95          | -                           | -                                 | 1.67     | **1.75**    | 0.37     | 1.64        |
| 0.6         | 2.77          | 8.02                        | 5.64                              | 3.32     | 4.44        | 4.05     | **5.26**    |
| 0.7         | 3.56          | 38.62                       | 25.6                              | 11.5     | 11.6        | 14.2     | **16.2**    |
| 0.8         | 48.24         | **69.79**                   | 30.9                              | 42.1     | 42.1        | 51.2     | **55.8**    |
| 0.9         | 7.56          | 38.62                       | 25.6                              | 21.5     | 22.4        | -5.87    | -3.98       |

Figure 12. Comparison using half the dataset only, while opILI leverages the remaining, unlabelled, data and achieves superior performance.

Figure 13. Loss over the epochs of a ResNet32, trained on noisy CIFAR10 data, with a fraction of 0.1 erroneous labels. Data augmentation: We find data augmentation to play a key role in the performance of our approach and “learning to reweight”, if applied to a high capacity network, such as ResNet. To avoid the extreme overfitting to the noisy data we repeat experiments with ResNet including data augmentation, where we use horizontal flipping and padding the image with 4 additional pixels. This is the setup we found being used in the code accompanying (Ren et al., 2018) and reproduced for our experiments.

Figure 14. Loss over the epochs of a ResNet32, trained on noisy CIFAR10 data, with a fraction of 0.1 erroneous labels, with data augmentation, which prevents overfitting the noisy labels.

Data augmentation: We find data augmentation to play a key role in the performance of our approach and “learning to reweight”, if applied to a high capacity network, such as ResNet. To avoid the extreme overfitting to the noisy data we repeat experiments with ResNet including data augmentation, where we use horizontal flipping and padding the image with 4 additional pixels. This is the setup we found being used in the code accompanying (Ren et al., 2018) and reproduced for our experiments.