ITERATIVE LABEL IMPROVEMENT:

ROBUST TRAINING BY CONFIDENCE BASED FILTERING & DATASET PARTITIONING

INTERNATIONAL CONFERENCE ON PATTERN RECOGNITION

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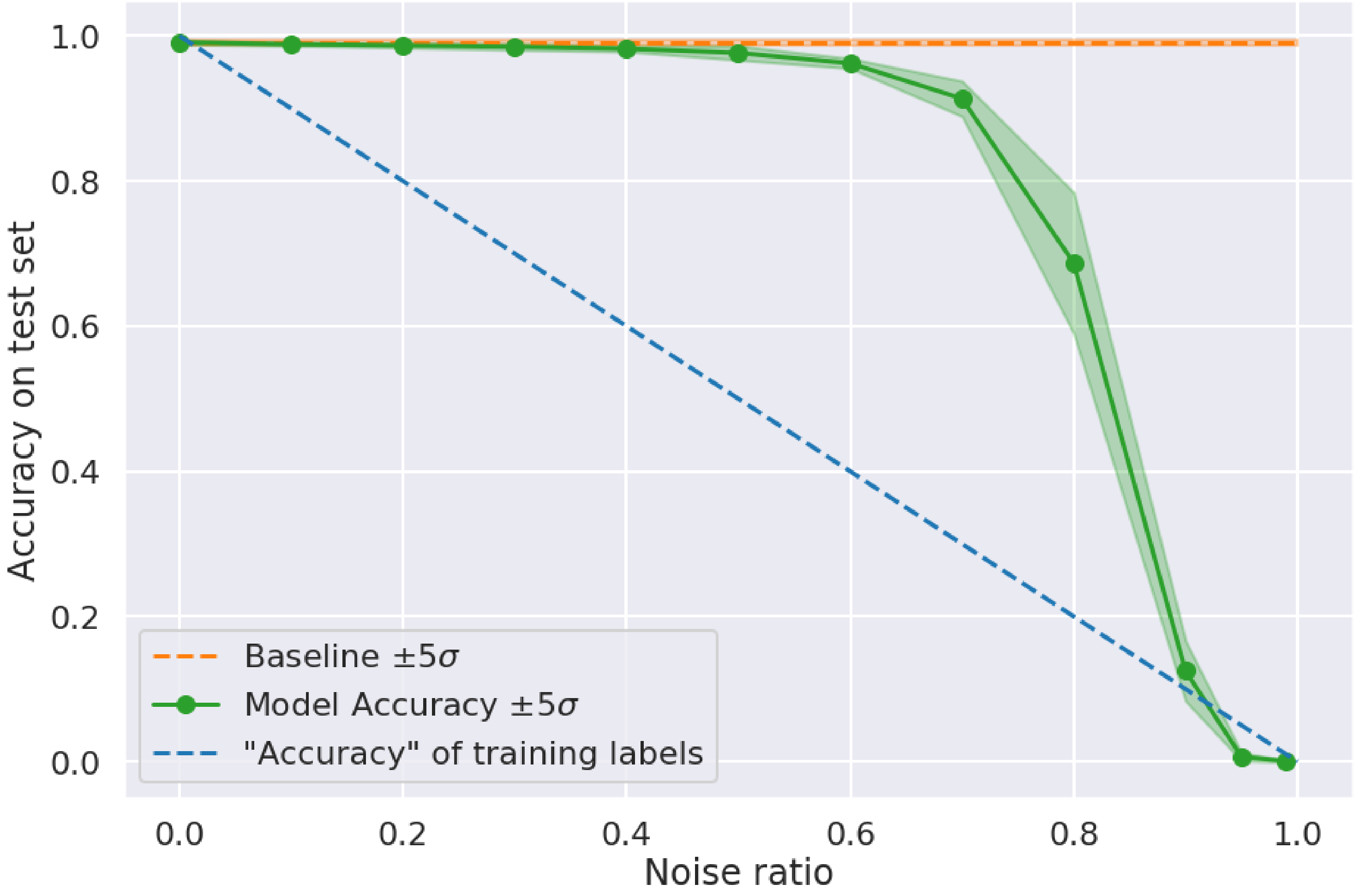
"Labelling quality influences detection performance"



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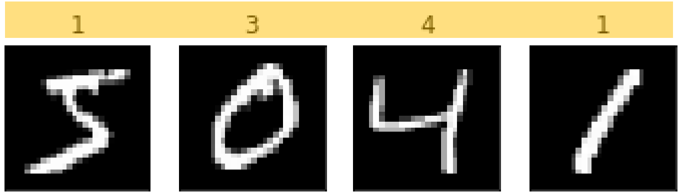
"By manually adding noise to well known datasets, we study the effect of erroneous labels and propose a technique to mitigate them"



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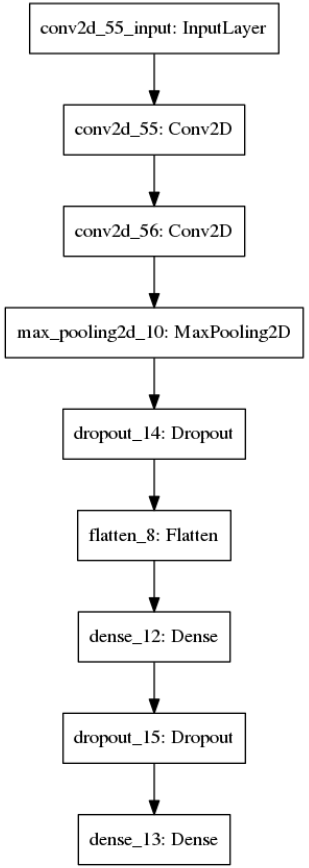
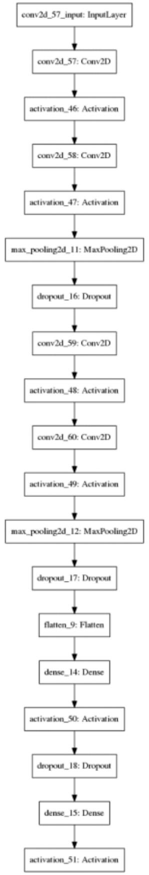
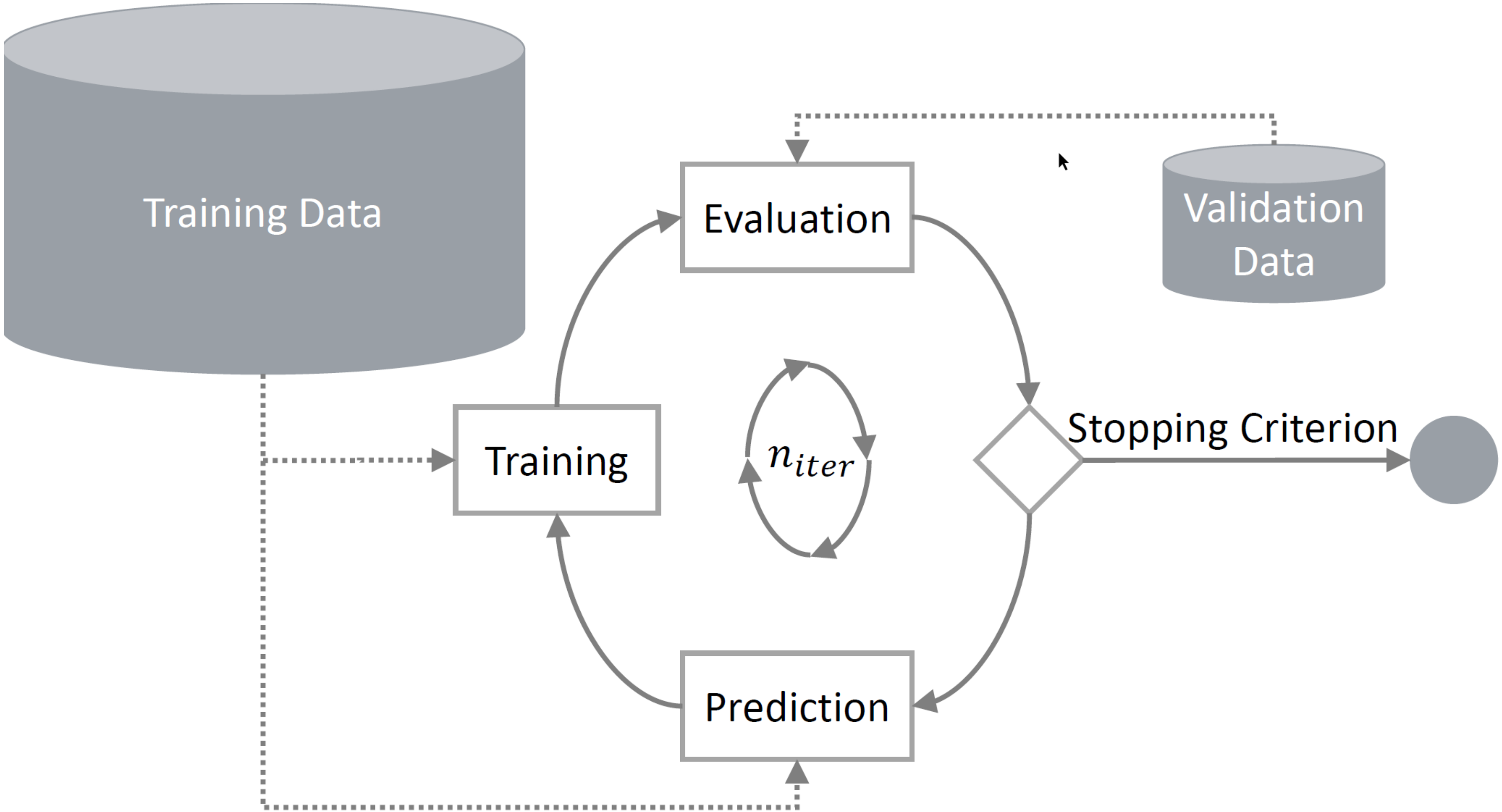
Three networks used
MNIST-CNN, CIFAR-CNN, ResNet32/50





The Idea: Iterative Label Improvement – ILI



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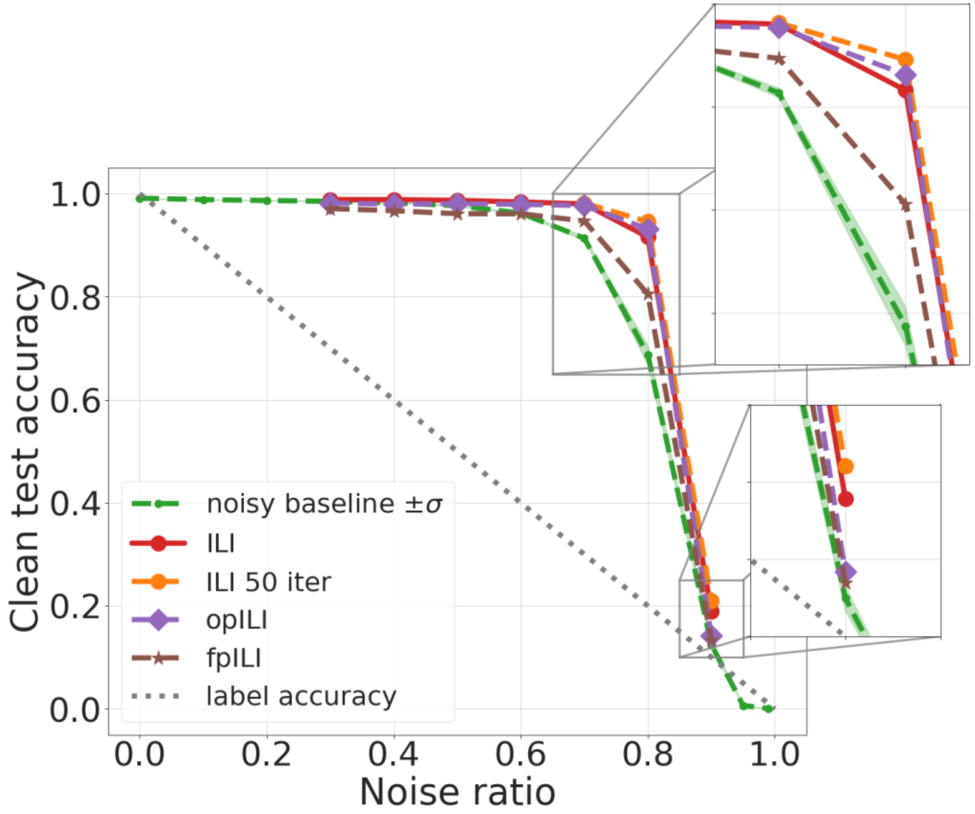
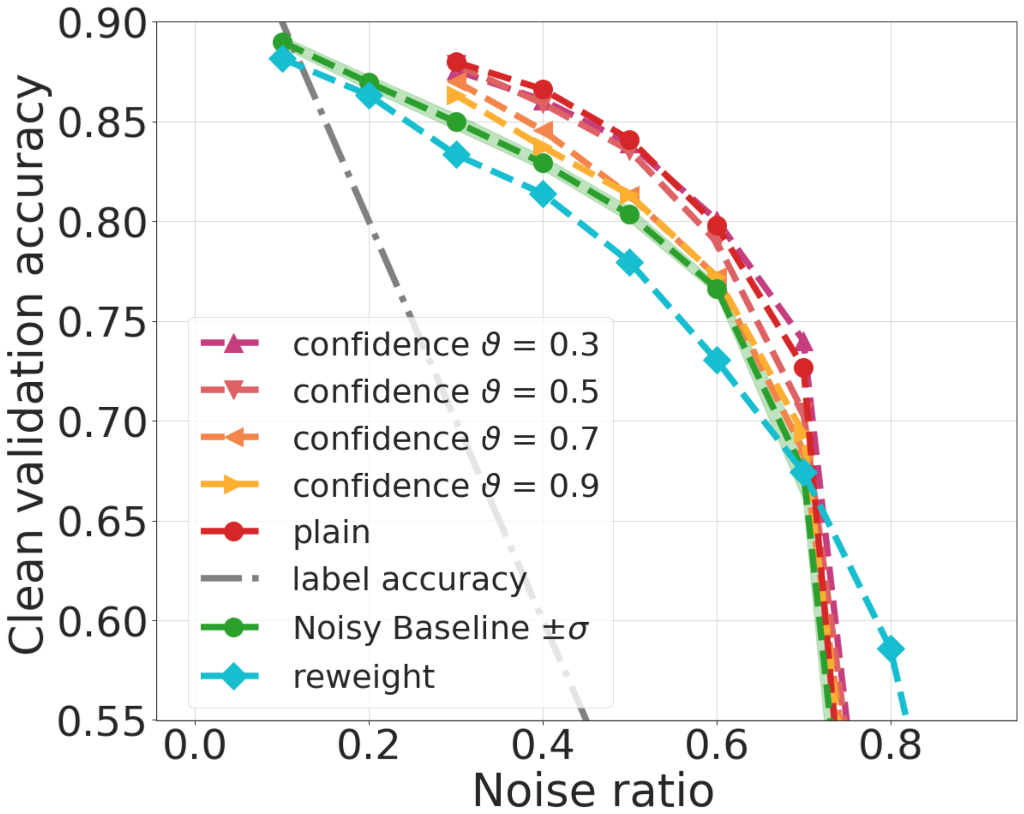
Some Results



ILI with MNIST-CNN on noisy MNIST data with random error



ILI with ResNet32 on noisy CIFAR10 data with random error, vs. "learning to reweight"

BACKUP

Different versions of ILI introduced

Algorithm 2 opILI with initILI

Input: $X_{\text{train, A}}, y_{\text{train}}, n_{\text{iter}}$

Output: Model $m^{n_{\text{iter}}}$, $y_{\text{train}}^{n_{\text{iter}}}$

$X_{\text{train, A}}, X_{\text{train, B}} = \text{Split}(X_{\text{train}})$

$m_{\text{A}}^{(0)}.initialize()$

$m_{\text{A}}^{(0)}.fit(X_{\text{train, A}}, y_{\text{train, A}}^{(0)})$

for $i = 1$ to n_{iter} **do**

    $y_{\text{train, B}}^{(i)} = m_{\text{A}}^{(i-1)}(X_{\text{train, B}})$

    $m_{\text{B}}^{(i)}.initialize()$

    $m_{\text{B}}^{(i)}.fit(X_{\text{train, B}}, y_{\text{train, B}}^{(i)})$

    $y_{\text{train, A}}^{(i)} = m_{\text{B}}^{(i)}(X_{\text{train, A}})$

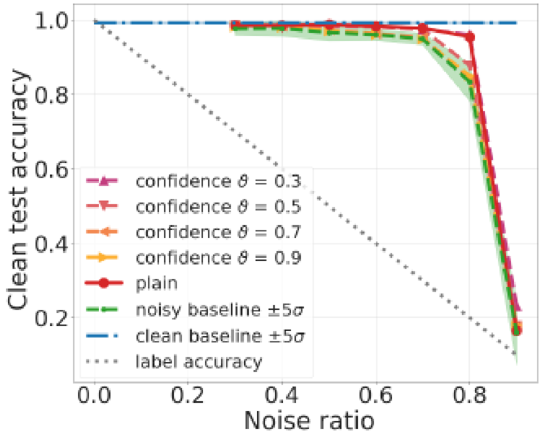
    $m_{\text{A}}^{(i)}.initialize()$

    $m_{\text{A}}^{(i)}.fit(X_{\text{train, A}}, y_{\text{train, A}}^{(i)})$

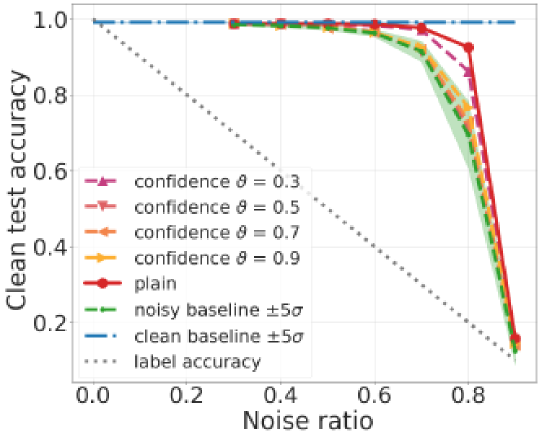
end for

$y_{\text{train}}^{n_{\text{iter}}} = \left[y_{\text{train, A}}^{(n_{\text{iter}})}, y_{\text{train, B}}^{(n_{\text{iter}})} \right]$

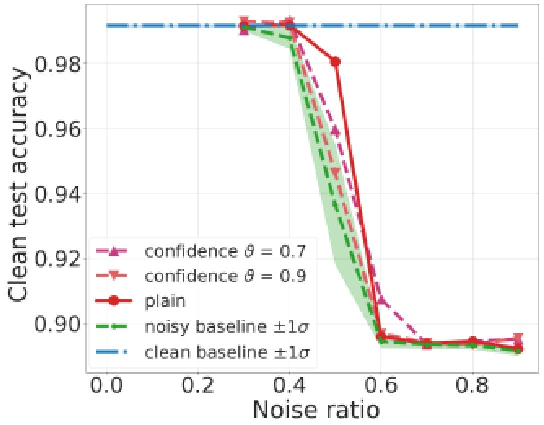
Results – different models & datasets



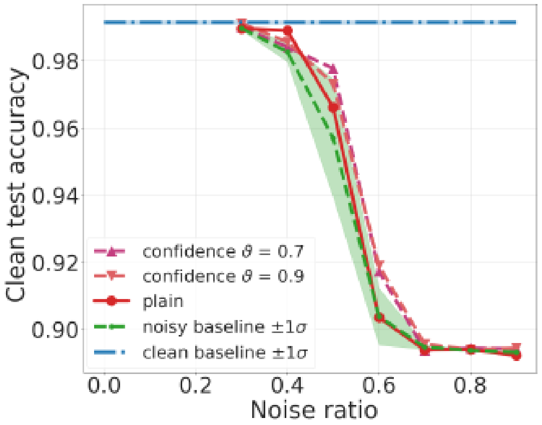
(a) CIFAR-CNN on noisy MNIST data with random error.



(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.

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The effect of data augmentation

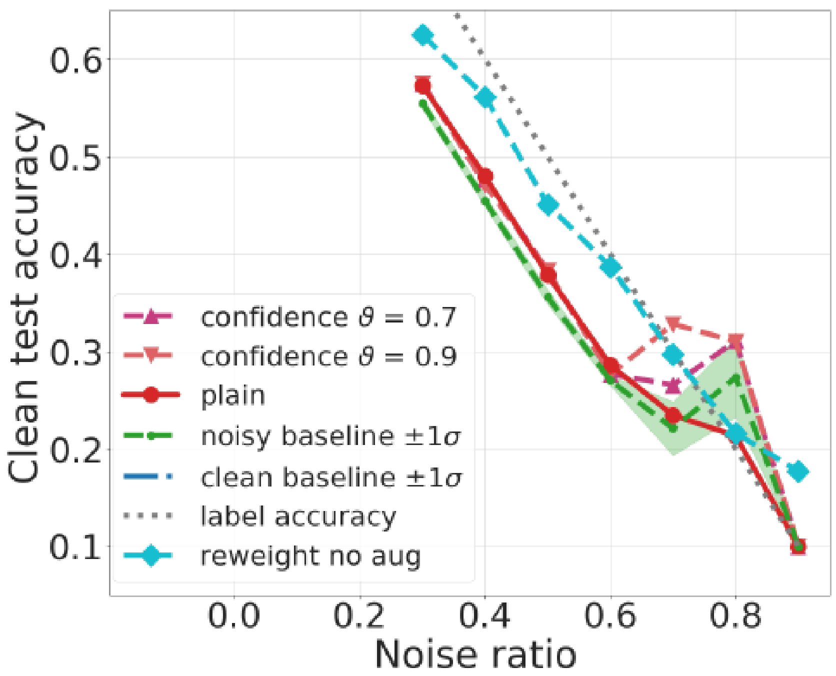

Figure 5. Comparison of different versions of our ILI algorithm on CIFAR10 data, using a ResNet32, with erroneous labels (randomly distributed). As a reference we compare to "learning to reweight" (Ren et al., 2018). Without data augmentation both methods fail to improve the accuracy significantly.

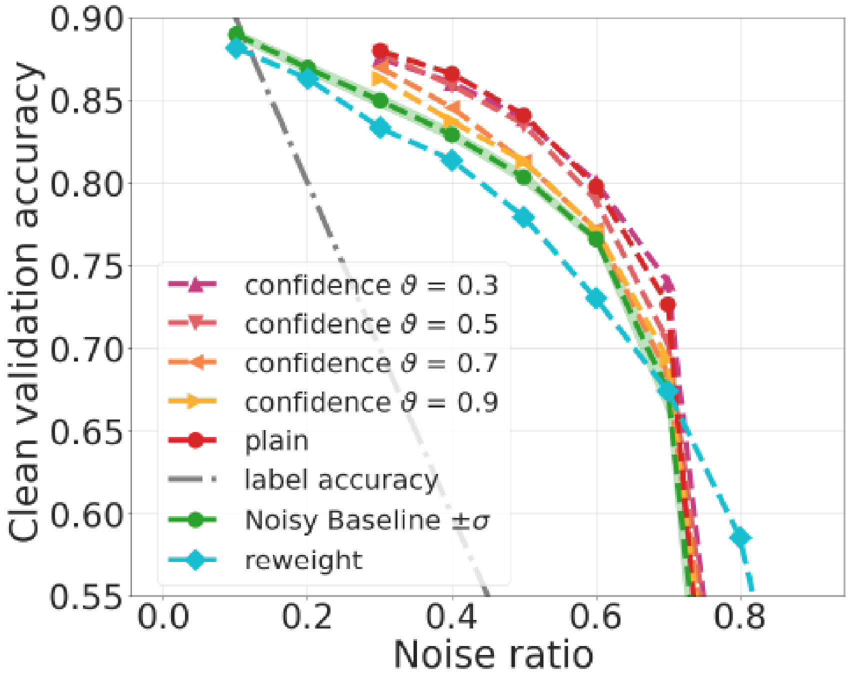

Figure 6. Comparison of different versions of our ILI algorithm on CIFAR10 data, using a ResNet32, with erroneous labels (randomly distributed) vs. "learning to reweight". With data augmentation our method outperforms "learning to reweight" for most noise fractions.

ResNet32, Noise fraction 0.1