Deep learning

5.6. Architecture choice and training protocol

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We will re-visit this list with additional regularization / normalization methods.

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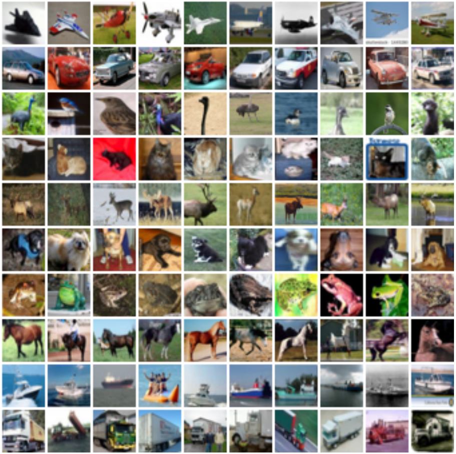
The practical strategy is to look at the losses and error rates across epochs and pick a learning rate and learning rate adaptation. For instance by reducing it at discrete pre-defined steps, or with a geometric decay.

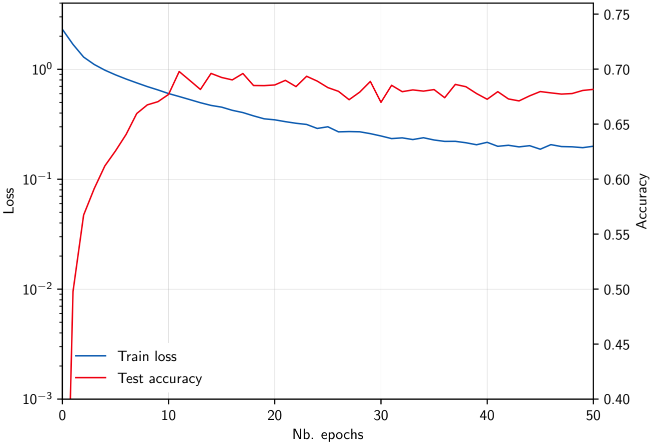
CIFAR10 data-set



32×32 color images, $50,000$ train samples, $10,000$ test samples.

(Krizhevsky, 2009, chap. 3)

Small convnet on CIFAR10, cross-entropy, batch size 100, $\eta = 1e - 1$.



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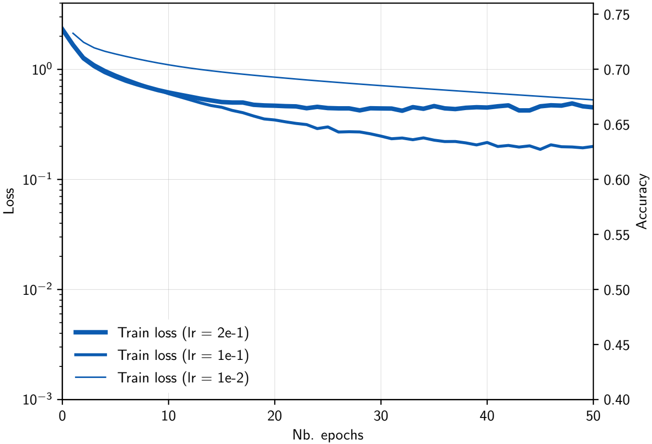
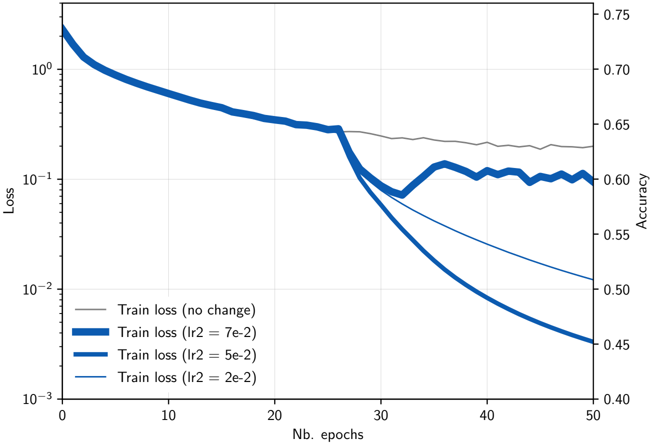
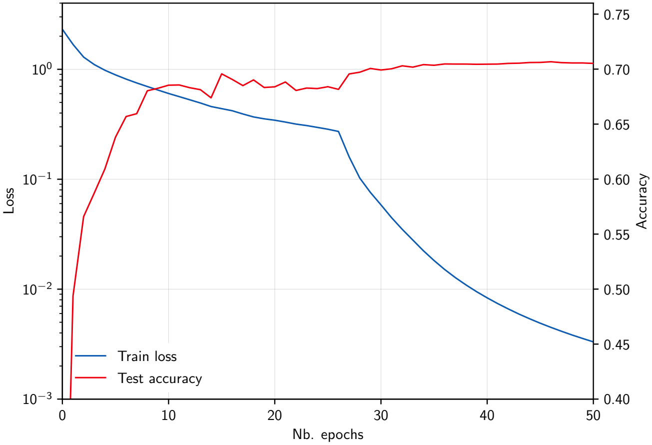


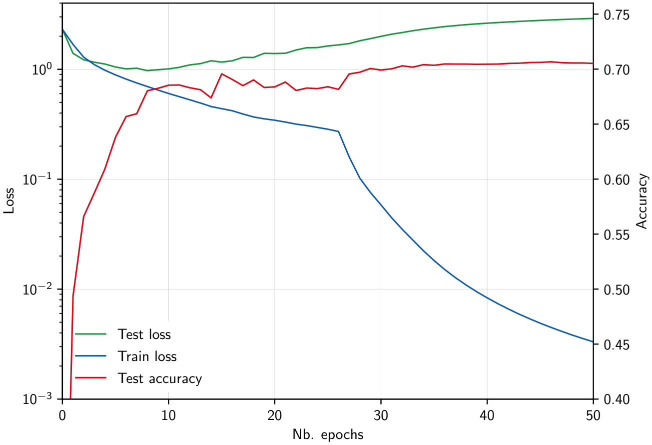
Using $\eta = 1e - 1$ for 25 epochs, then reducing it.



Using $\eta = 1e-1$ for 25 epochs, then $\eta = 5e-2$.



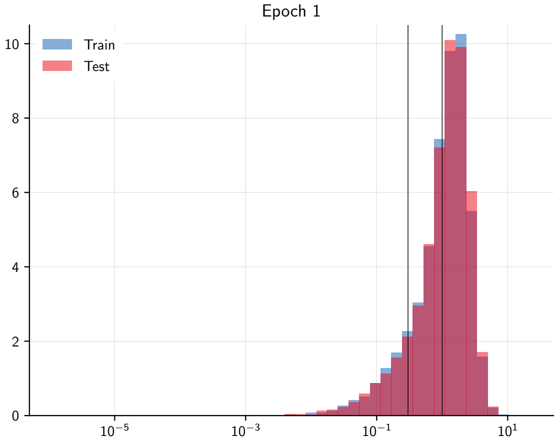
While the test error still goes down, the test loss may increase, as it gets even worse on misclassified examples, and decreases less on the ones getting fixed.



We can plot the train and test distributions of the per-sample loss

$$\ell = -\log\left(\frac{\exp(f_Y(X;w))}{\sum_k \exp(f_k(X;w))}\right)$$

through epochs to visualize the over-fitting.



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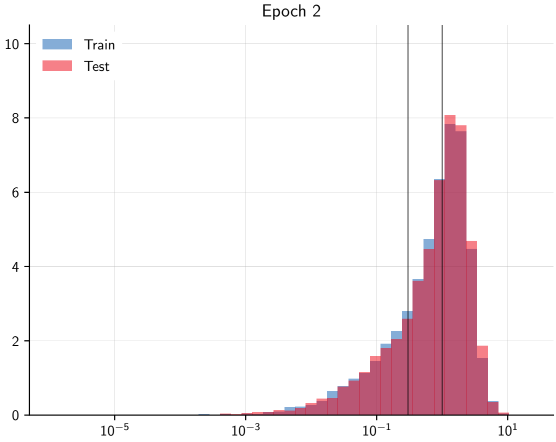

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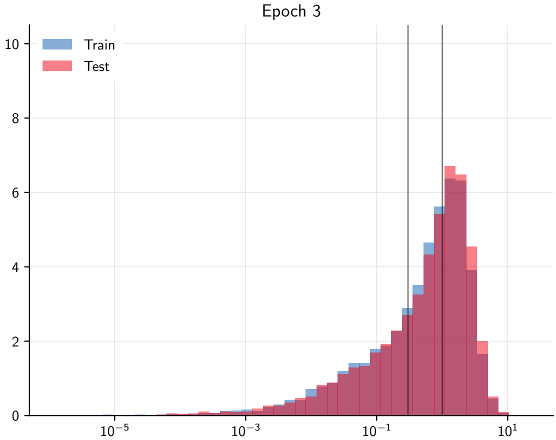

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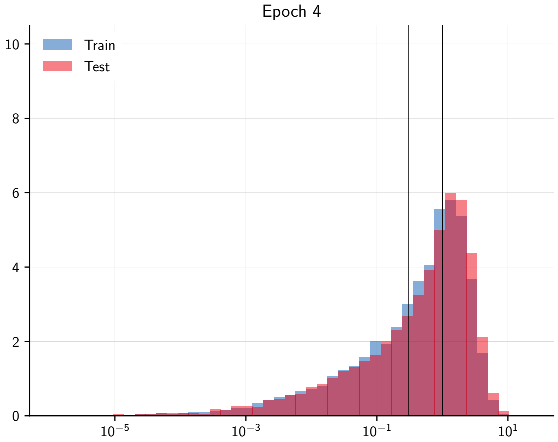

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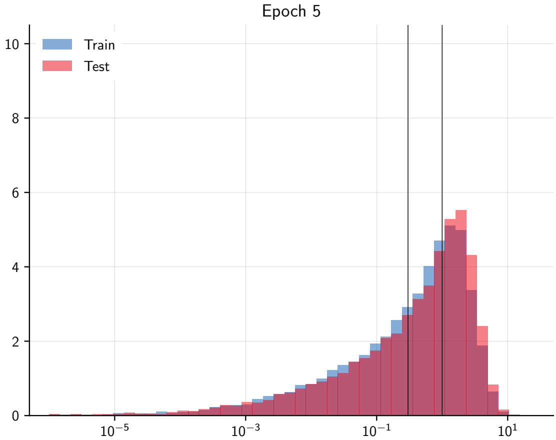

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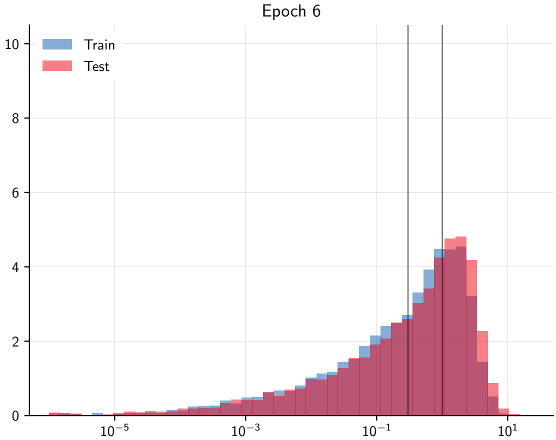

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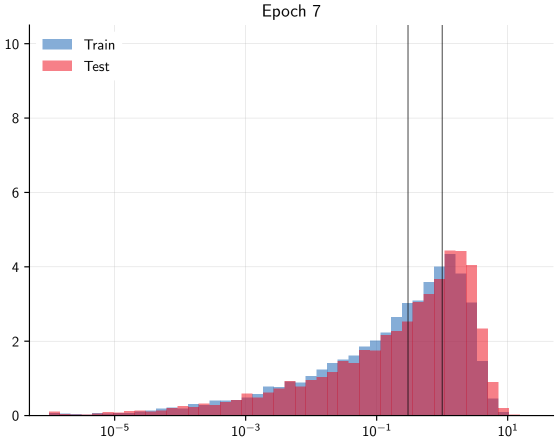

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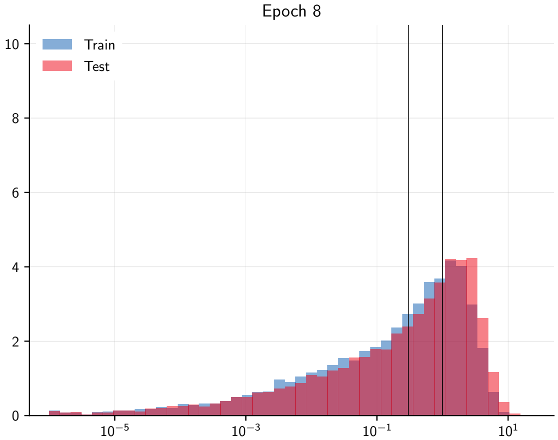

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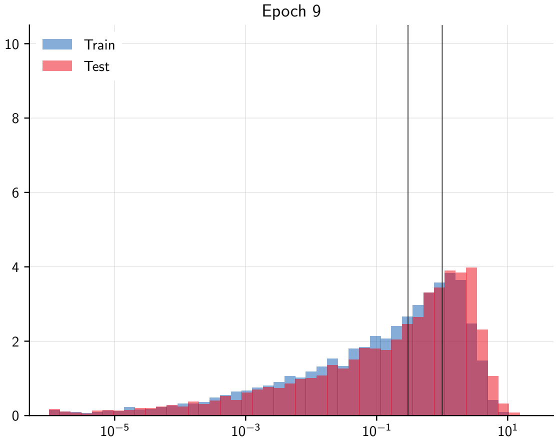

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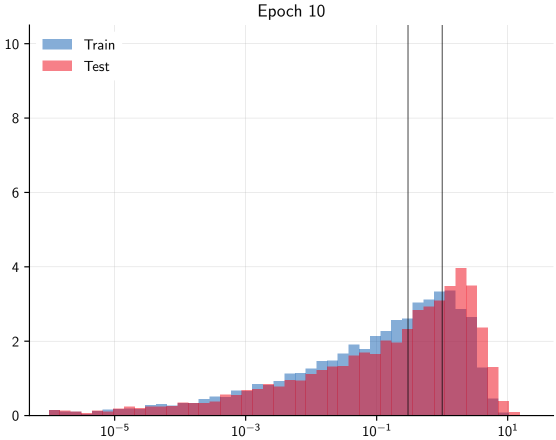

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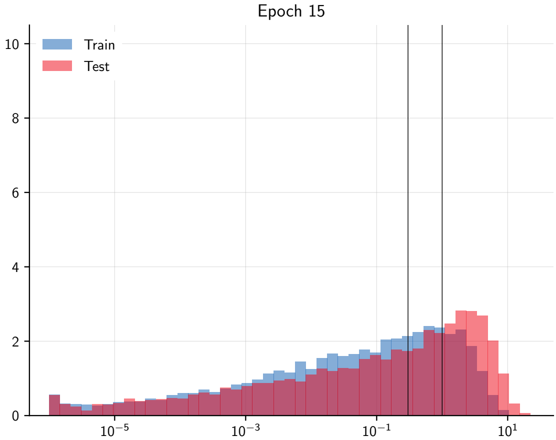

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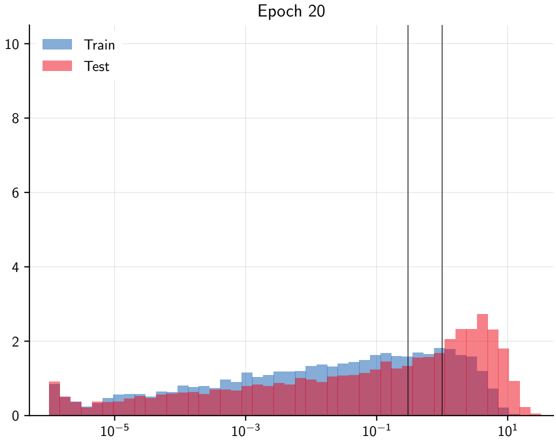

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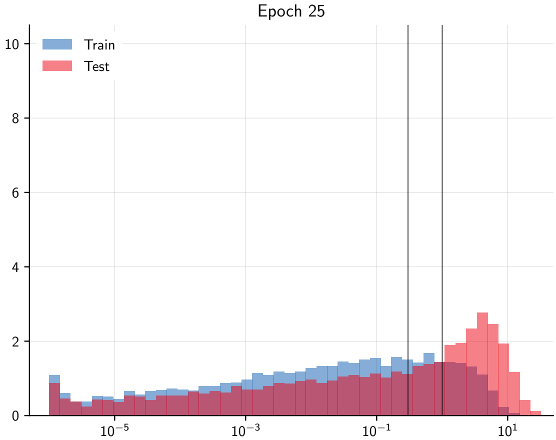

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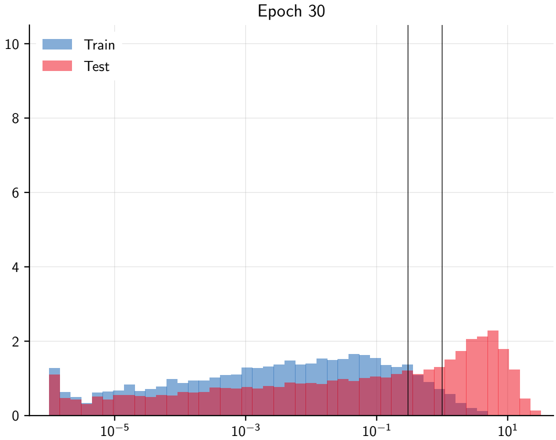

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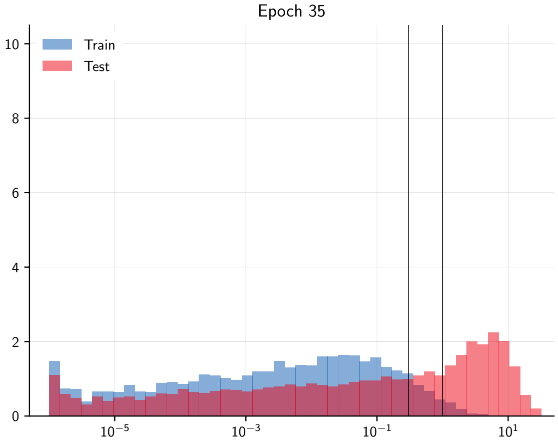

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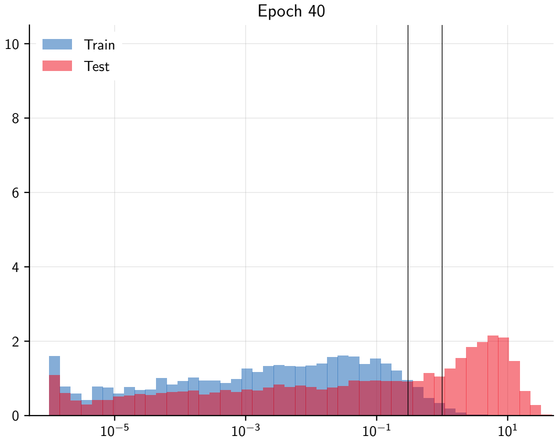

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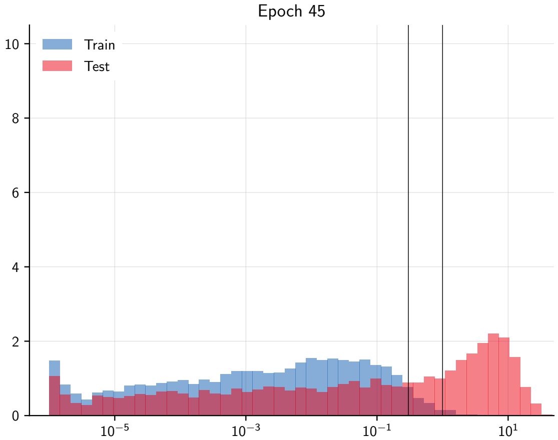

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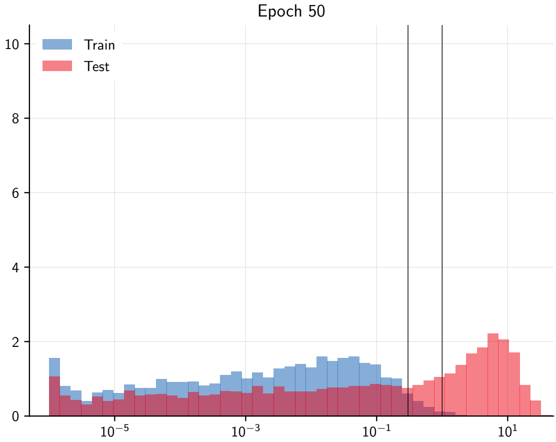

The end

References

A. Krizhevsky. **Learning multiple layers of features from tiny images**. Master's thesis, Department of Computer Science, University of Toronto, 2009.