Deep learning

5.6. Architecture choice and training protocol

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https://fleuret.org/dlc/
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- modulate the capacity until it overfits a small subset, but does not overfit / underfit the full set,
- capacity increases with more layers, more channels, larger receptive fields, or more units,
- regularization to reduce the capacity or induce sparsity,
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- grid-search all the variations that come to mind (and hopefully have farms of GPUs to do so).
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We will re-visit this list with additional regularization / normalization methods.
Regarding the learning rate, for training to succeed it has to

- reduce the loss quickly ⇒ large learning rate,
- not be trapped in a bad minimum ⇒ large learning rate,
- not bounce around in narrow valleys ⇒ small learning rate, and
- not oscillate around a minimum ⇒ small learning rate.

These constraints lead to a general policy of using a larger step size first, and a smaller one in the end. 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.
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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 $100$, $\eta = 1e - 1$. 

![Graph showing performance metrics over epochs](image)
Small convnet on CIFAR10, cross-entropy, batch size 100

![Graph showing the loss and accuracy over nb. epochs for different learning rates.](image-url)
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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References