EE-559 – Deep learning

5.6. Architecture choice and training protocol

François Fleuret
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Shell escape disabled
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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,
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- identify what path(s) or sub-parts need more/less capacity,
- use prior knowledge about the "scale of meaningful context" to size filters / combinations of filters (e.g. knowing the size of objects in a scene, the max duration of a sound snippet that matters),
- grid-search all the variations that come to mind (and hopefully have farms of GPUs to do so).

We will revisit 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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François Fleuret
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

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

to visualize the over-fitting.
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References