

approaches to gradient descent are still in use. Most of the improvement in neural network performance from 1986 to 2015 can be attributed to two factors. First, larger datasets have reduced the degree to which statistical generalization is a challenge for neural networks. Second, neural networks have become much larger, due to more powerful computers, and better software infrastructure. However, a small number of algorithmic changes have improved the performance of neural networks noticeably.

One of these algorithmic changes was the replacement of mean squared error with the cross-entropy family of loss functions. Mean squared error was popular in the 1980s and 1990s, but was gradually replaced by cross-entropy losses and the principle of maximum likelihood as ideas spread between the statistics community and the machine learning community. The use of cross-entropy losses greatly improved the performance of models with sigmoid and softmax outputs, which had previously suffered from saturation and slow learning when using the mean squared error loss.

The other major algorithmic change that has greatly improved the performance of feedforward networks was the replacement of sigmoid hidden units with piecewise linear hidden units, such as rectified linear units. Rectification using the $\max\{0, z\}$ function was introduced in early neural network models and dates back at least as far as the Cognitron and Neocognitron (Fukushima, 1975, 1980). These early models did not use rectified linear units, but instead applied rectification to nonlinear functions. Despite the early popularity of rectification, rectification was largely replaced by sigmoids in the 1980s, perhaps because sigmoids perform better when neural networks are very small. As of the early 2000s, rectified linear units were avoided due to a somewhat superstitious belief that activation functions with non-differentiable points must be avoided. This began to change in about 2009. Jarrett *et al.* (2009) observed that “using a rectifying nonlinearity is the single most important factor in improving the performance of a recognition system” among several different factors of neural network architecture design.

For small datasets, Jarrett *et al.* (2009) observed that using rectifying nonlinearities is even more important than learning the weights of the hidden layers. Random weights are sufficient to propagate useful information through a rectified linear network, allowing the classifier layer at the top to learn how to map different feature vectors to class identities.

When more data is available, learning begins to extract enough useful knowledge to exceed the performance of randomly chosen parameters. Glorot *et al.* (2011a) showed that learning is far easier in deep rectified linear networks than in deep networks that have curvature or two-sided saturation in their activation functions.