

# Programming Test: Learning Activations in Neural Networks

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**Abstract**—The choice of Activation Functions (AF) has proven to be an important factor that affects the performance of an Artificial Neural Network (ANN). Use a 1-hidden layer neural network model that adapts to the most suitable activation function according to the data-set. The ANN model can learn for itself the best AF to use by exploiting a flexible functional form,  $k_0 + k_1 * x$  with parameters  $k_0, k_1$  being learned from multiple runs. You can use this code-base for implementation guidelines and help. <https://github.com/sahamath/MultiLayerPerceptron>

## I. BACKGROUND

Selection of the best performing AF for classification task is essentially a naive (or brute-force) procedure wherein, a popularly used AF is picked and used in the network for approximating the optimal function. If this function fails, the process is repeated with a different AF, till the network learns to approximate the ideal function. It is interesting to inquire and inspect whether there exists a possibility of building a framework which uses the inherent clues and insights from data and bring about the most suitable AF. The possibilities of such an approach could not only save significant time and effort for tuning the model, but will also open up new ways for discovering essential features of not-so-popular AFs.

## II. MATHEMATICAL FRAMEWORK

### A. Compact Representation

Let the proposed Ada-Act activation function be mathematically defined as:

$$g(x) = k_0 + k_1 x \quad (1)$$

where the coefficients  $k_0, k_1$  and  $k_2$  are learned during training via back-propagation of error gradients.

For the purpose of demonstration, consider a feed-forward neural network consisting of an input layer  $L_0$  consisting of  $m$  nodes for  $m$  features, two hidden layers  $L_1$  and  $L_2$  consisting of  $n$  and  $p$  nodes respectively, and an output layer  $L_3$  consisting of  $k$  nodes for  $k$  classes. Let  $z_i$  and  $a_i$  denote the inputs to and the activations of the nodes in layer  $L_i$  respectively. Let  $w_i$  and  $b_i$  denote the weights and the biases applied to the nodes of layer  $L_{i-1}$ , and let the activations of layer  $L_0$  be the input features of the training examples. Finally, let  $K$  denote the column matrix containing the equation coefficients:  $\begin{bmatrix} k_0 \\ k_1 \\ k_2 \end{bmatrix}$  and let  $t$  denote the number of

training examples being taken in one batch. Then the forward-propagation equations will be:

$$z_1 = a_0 \times w_1 + b_1$$

$$a_1 = g(z_1)$$

$$z_2 = a_1 \times w_2 + b_2$$

$$a_2 = g(z_2)$$

$$z_3 = a_2 \times w_3 + b_3$$

$$a_3 = \text{Softmax}(z_3)$$

where  $\times$  denotes the matrix multiplication operation and  $\text{Softmax}()$  denotes the Softmax activation function.

For back-propagation, let the loss function used in this model be the Categorical Cross-Entropy Loss, and let  $df_i$  denote the gradient matrix of the loss with respect to the matrix  $f_i$ , where  $f$  can be substituted with  $z, a, b$ , or  $w$ . and let there be matrices  $dK_2$  and  $dK_1$  of dimension  $3 \times 1$ . Then the back-propagation equations will be:

$$dz_3 = a_3 - y$$

$$dw_3 = \frac{1}{t} a_2^T \times dz_3$$

$$db_3 = \text{avg}_{\text{col}}(dz_3)$$

$$da_2 = dz_3 \times w_3^T$$

$$dz_2 = g'(z_2) * da_2$$

$$dw_2 = \frac{1}{t} a_1^T \times dz_2$$

$$db_2 = \text{avg}_{\text{col}}(dz_2)$$

$$dK_2 = \begin{bmatrix} \text{avg}_e(da_2) \\ \text{avg}_e(da_2 * z_2) \\ \text{avg}_e(da_2 * z_2^2) \end{bmatrix} \quad (2)$$

$$da_1 = dz_2 \times w_2^T$$

$$dz_1 = g'(z_1) * da_1$$

$$dw_1 = \frac{1}{t} a_0^T \times dz_1$$

$$db_1 = \text{avg}_{\text{col}}(dz_1)$$

$$dK_1 = \begin{bmatrix} avg_e(da_1) \\ avg_e(da_1 * z_1) \\ avg_e(da_1 * z_1^2) \end{bmatrix} \quad (3)$$

$$dK = dK_2 + dK_1 \quad (4)$$

where  $*$  is the element-wise multiplication operation,  $T$  is the matrix transpose operation,  $avg_{col}(x)$  is the function which returns the column-wise average of the elements present in the matrix  $x$ , and  $avg_e(x)$  is the function which returns the average of all the elements present in the matrix  $x$ .

Consider the learning rate of the model to be  $\alpha$ . The update equations for the model parameters will be:

$$w_1 = w_1 - \alpha.dw_1$$

$$b_1 = b_1 - \alpha.db_1$$

$$w_2 = w_2 - \alpha.dw_2$$

$$b_2 = b_2 - \alpha.db_2$$

$$w_3 = w_3 - \alpha.dw_3$$

$$b_3 = b_3 - \alpha.db_3$$

$$K = K - \alpha.dK$$

### III. EXPECTED RESULTS

- A technical report containing implementation details (algorithm, initial settings such as sampling the parameters  $k_0, k_1$  from some distribution, parameter updates on epochs, final parameter values at the end of training, train vs test loss, train and test accuracy, F1-Score, plot of the loss function vs. epochs, Code base hosted on github linked in the report)–Maximum 3 pages
- Grid search/brute force NOT allowed



- Data Sets for experiments and results: Bank-Note, Iris, Wisconsin Breast Cancer, MNIST (Junior Data Scientist Positions)