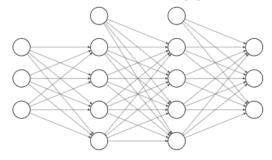
Introduction

This report describes what has been done to solve exercises in Home Assignment 3 and what were the results. To run code, execute 'main.m' file. Code repository: https://gitlab.cs.ttu.ee/totahv/iti8565

Exercise 1. Neural Network [1]



 $\text{Input Layer} \in \mathbb{R}^3 \qquad \text{Hidden Layer} \in \mathbb{R}^5 \qquad \text{Hidden Layer} \in \mathbb{R}^5 \qquad \text{Output Layer} \in \mathbb{R}^3$

Figure 1 Structure of neural network.

Implemented neural network with two hidden layers, each layer supports N neurons. Used Sigmoid function in hidden layers and SoftMax function in the output layer to support multiclass classification. Used cross-entropy function for minimizing error, because partial derivatives were easier to find this way. Figure 1 illustrates structure of the neural network for 3D data and 3 output classes.

Formula (1) describes feedforward step of neural network. Moving from 'input layer' to '1st hidden layer', then to '2nd hidden layer' and 'output layer'.

$$\begin{cases} z_{h1} = X \cdot w_{h1} + b_{h1} \\ a_{h1} = \sigma(z_{h1}) \end{cases}$$

$$z_{h2} = a_{h1} \cdot w_{h2} + b_{h2} \\ a_{h2} = \sigma(z_{h2}) \end{cases} (1)$$

$$z_{o} = a_{h2} \cdot w_{o} + b_{o} \\ a_{o} = SoftMax(z_{o})$$

After that cost function and partial derivatives are needed in backpropagation.

Formula (2) describes cost function and partial derivates for updating weights between output layer and 2nd hidden layer.

$$\begin{cases} C = -Y \cdot \log(a_o) \\ \frac{\partial C}{\partial w_o} = \frac{\partial C}{\partial a_o} \frac{\partial a_o}{\partial z_o} \frac{\partial z_o}{\partial w_o} = (a_o - Y) a_{h2} \end{cases}$$
(2)

Formula (3) describes cost function and partial derivates for updating weights between 2nd hidden layer and 1st hidden layer.

$$\begin{cases}
C = -a_o \cdot \log(a_{h2}) \\
\frac{\partial C}{\partial w_{h2}} = \frac{\partial C}{\partial a_{ah2}} \frac{\partial a_{h2}}{\partial z_{h2}} \frac{\partial z_{h2}}{\partial w_{h2}} = \left(\frac{\partial C}{\partial z_o} \frac{\partial z_o}{\partial a_{h2}}\right) \frac{\partial a_{h2}}{\partial z_{h2}} \frac{\partial z_{h2}}{\partial w_{h2}} = \left[\left(\frac{\partial C}{\partial a_o} \frac{\partial a_o}{\partial z_o}\right) \frac{\partial z_o}{\partial a_{h2}}\right] \frac{\partial a_{h2}}{\partial z_{h2}} \frac{\partial z_{h2}}{\partial w_{h2}} = (a_o - Y)w_o\sigma'(z_{h2})a_{h1} \quad (3)
\end{cases}$$

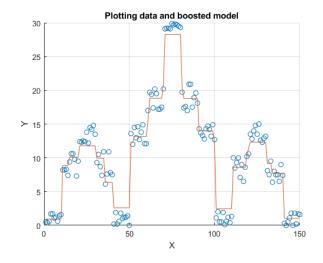
Formula (4) describes cost function and partial derivates for updating weights between 1st hidden layer and input layer.

$$\begin{cases} C = -a_{h2} \cdot \log(a_{h1}) \\ \frac{\partial C}{\partial w_{h1}} = \frac{\partial C}{\partial a_{h1}} \frac{\partial a_{h1}}{\partial z_{h1}} \frac{\partial z_{h1}}{\partial w_{h1}} = \dots = (a_o - Y) w_o \sigma'(z_{h2}) w_{h2} \sigma'(z_{h1}) X \end{cases}$$
(4)

As a result, this neural network with 2 hidden layers supports arbitrary number of input neurons, arbitrary number of hidden neurons in each layer and any number of output neurons for multiclass classification.

Exercise 2. Gradient boosting [2]

Implemented gradient boosting algorithm for regression model. Used MATLAB built-in function to create decision stumps. Figure 2 describes boosted decision stump model using gradient boosting after 50 epochs. Figure 3 describes error reduction when growing model. Created animation in gifs folder that animates growing model over 50 epochs.



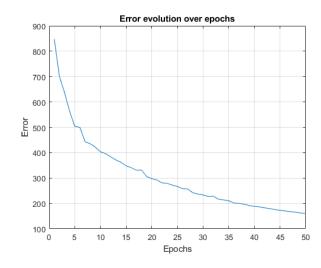


Figure 2 Boosted decision stumps using gradient boosting.

Figure 3 Error evolution over epochs.

Conclusion

Implemented neural network for multiclass classification and gradient boosting algorithm for regression model.

Used materials

[1] Creating a Neural Network from Scratch in Python, Usman Malik, https://stackabuse.com/creating-a-neural-network-from-scratch-in-python/

[2] Gradient Boosting from scratch, Prince Grover,

https://medium.com/mlreview/gradient-boosting-from-scratch-1e317ae4587d