Bias in Neural Networks

Without Bias



 $\bar{y} = Sigmoid(Sigmoid(\bar{x}^T W), V)$

[The Multi-layer perceptron models that we have discussed so far do not have bias

[It is easier to realize from a linear function]

y = mx

[Let us consider a linear function]



[It represents a line passing through origin. With different values of m, we get different lines passing through origin.]



[If I want to move parallelly, I would need to add an intercept c. Here, c is a bias, which allows to move the line flexibly. So, the idea of adding a bias to a model is to make the model more flexible to fit into the problem better]



[Let us see this simple MLP with no hidden layer.]



[Let us see this simple MLP with no hidden layer. It is equivalent to linear function y = mx without bias]



[Now, let us add bias. It is equivalent to the linear function y = mx + c]



[To generalize, we can add bias to MLP as shown in figure. We are adding bias to hidden layer]



[It allows the activation function to shift by a factor defined by the bias and its corresponding weight]



$$h_i = \sigma \left(\sum_j x_j W_{ji} + B_j b_i \right)$$

Where B_j is bias weight of the node j.

[With bias, the output from the hidden node can be defined as this expression]



[Likewise, the output vector from the hidden layer can be defined as this expression]



 $\bar{h}^T = \sigma(\bar{x}^T W + \bar{b}^T) \quad \bar{y}^T = \sigma(\sigma(\bar{x}^T W + B\bar{b}^T)V + Cc^T)$

[Similarly, bias may also be added to the nodes in the output layer]

Summary

- Bias allows the output vector to shift by a factor defined by the bias and its corresponding weight making the model more flexible.
- Biases are hyperparameter defined by users
- The weights associated with the biases are learnable parameters.