

AUTOMATED STOCK TRADING USING NEURAL NETWORKS

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1. MATHEMATICAL BACKGROUND I: ACTIVATION

We first look at the mathematical background behind the neural network. Assume we have k hidden layers, sandwiched by an input layer and an output layer. Since the aim of neural networks is to model how a brain processes information, we often refer to the connections between nodes in each layer as “synapses”. These synapses are characterised by their weights and biases. Let $W^{(l)}$ be the matrix containing the weights between layer l and $l - 1$. If layer l has n nodes, and $l - 1$ has m nodes, then we have:

$$(1) \quad W^{(l)} = \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,m} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n,1} & w_{n,2} & \cdots & w_{n,m} \end{bmatrix}$$

Which gives the weights of the synapses between layer l and $l - 1$. Combining this with a vector of biases for the same inter-layer, $b^{(l)}$, we are almost able to calculate the values of the nodes in layer l . However before this can be done we need an activation function. In a lot of cases, as was found in [?], the choice of activation function doesn’t really matter. The most common choice is the “sigmoid function” defined in equation 2.

$$(2) \quad \sigma(z) = \frac{1}{1 + e^{-z}}$$

Finally, piecing this all together, for the layer l , we get the values of the nodes in the layer using the matrix equation 3.

$$(3) \quad a^{(l)} = \sigma(W^{(1)}a^{(l-1)} + b^l)$$

Where $a^{(l-1)}$ is the activation values for the previous layer, and $\sigma()$ is applied to all values in the resulting vector.

2. MATHEMATICAL BACKGROUND II: BACKPROPOGATION

The values in the network are initially random. The way the network learns is by an algorithm called “backpropogation”. The idea is to define an error function:

$$E(X, \theta) = \frac{1}{2N} \sum_{i=1}^N (y'_i - y_i)^2.$$

The parameter θ incorporates all the weights and biases, while X is a vector of input values. The y'_i term is the approximated value by the network, and y_i is the actual value for the X vector.

Given the number of parameters in this equation, finding minima is not as simple as simply taking a derivative. The method of minimising this function is done using “gradient descent”. As discussed in [?], there are 3 variants of this algorithm. For a learning rate α , we have the following variants.

- Batch Gradient Descent: $\theta = \theta - \alpha \nabla_{\theta} E(X, \theta)$
- Mini-batch Gradient Descent (n training examples): $\theta = \theta - \alpha \nabla_{\theta} E(x^{(i:i+n)}; y^{(i:i+n)}; \theta)$
- Stochastic Gradient Descent (SGD): $\theta = \theta - \alpha \nabla_{\theta} E(x^{(i)}; y^{(i)}; \theta)$

SGD compares to Mini-batch by performing parameter updates for each training example. It is noted that mini-batch is the most common algorithm used in training neural networks. One key issue is choosing the optimal learning rate α . Too low, and convergence will take too long, too big and convergence won't be achieved.

3. WHY USE NEURAL NETWORKS IN STOCK TRADING?

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4. HOW DO WE USE NEURAL NETWORKS IN STOCK TRADING?

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5. IMPROVEMENTS TO AUTOMATED TRADING

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6. CONCLUSION

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REFERENCES

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- [2] S. Ruder, "An overview of gradient descent optimization algorithms," *arXiv preprint arXiv:1609.04747*, 2016.