

Neural Networks Workshop: Training and Stochastic Gradient Descent

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Today we use and train Feed-Forward Artificial Neural Networks

- 1 Feed-Forward Neural Networks
 - How They Work
 - Universal Approximation (Briefly)
- 2 Training
 - Nonconvex Optimization
 - Error-Backpropagation
- 3 Deep Learning

Perceptron Review

Neural
Networks Pt.
2

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[TODO: IMAGE OF PERCEPTRON AND SIGN FUNCTION]

- Perceptrons are neural computation units which make *weighted* decisions:

$$\begin{aligned} p(\mathbf{x}) &= \begin{cases} 1 & \text{if } \sum w_i x_i + b \geq 0 \\ 0 & \text{otherwise} \end{cases} \\ &= \frac{\text{sign}(\sum w_i x_i + b) + 1}{2} \end{aligned}$$

- Perceptrons are not powerful enough, as seen last time with XOR.
- What if we want real valued output for tasks like predicting the temperature or stock prices?

Feedforward Neural Networks

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[TODO: IMAGE OF FEED FORWARD NETWORK]

- Feedforward Artificial Neural Networks (ANNs) are the *continuous* extensions of perceptrons.
- ANNs can have many layers and different nodes which are *fully connected*.
- Generally, the more layers and nodes, the greater the computational power of the network!
- The intuition behind this model is that each neuron in the network makes a weighted decision like the perceptron. Many *stacked* decisions allows for extremely complex logic.

Blocks of Highlighted Text

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Block 1

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Block 2

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Block 3

Suspendisse tincidunt sagittis gravida. Curabitur condimentum, enim sed venenatis rutrum, ipsum neque consectetur orci, sed blandit justo nisi ac lacus.

Multiple Columns

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Heading

- 1 Statement
- 2 Explanation
- 3 Example

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Table

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Treatments	Response 1	Response 2
Treatment 1	0.0003262	0.562
Treatment 2	0.0015681	0.910
Treatment 3	0.0009271	0.296

Table : Table caption

Theorem

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Theorem (Mass–energy equivalence)

$$E = mc^2$$

Verbatim

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Example (Theorem Slide Code)

```
\begin{frame}  
\frametitle{Theorem}  
\begin{theorem}[Mass--energy equivalence]  
$E = mc^2$  
\end{theorem}  
\end{frame}
```

Figure

Neural
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Citation

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An example of the `\cite` command to cite within the presentation:

This statement requires citation [Smith, 2012].

References

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John Smith (2012)

Title of the publication

Journal Name 12(3), 45 – 678.

The End