

# 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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Feed-Forward  
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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

Lorem ipsum dolor sit amet, consectetur adipiscing elit. Integer lectus nisl, ultricies in feugiat rutrum, porttitor sit amet augue. Aliquam ut tortor mauris. Sed volutpat ante purus, quis accumsan dolor.

## Block 2

Pellentesque sed tellus purus. Class aptent taciti sociosqu ad litora torquent per conubia nostra, per inceptos himenaeos. Vestibulum quis magna at risus dictum tempor eu vitae velit.

## 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

Lorem ipsum dolor sit amet, consectetur adipiscing elit. Integer lectus nisl, ultricies in feugiat rutrum, porttitor sit amet augue. Aliquam ut tortor mauris. Sed volutpat ante purus, quis accumsan dolor.

# 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

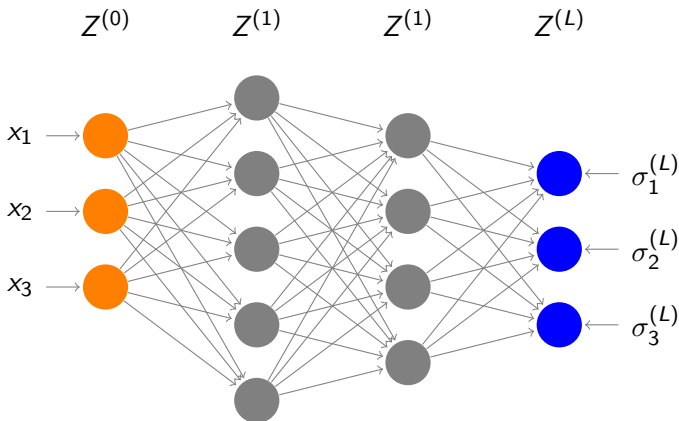


Figure: An example of a feed-forward ANN,  $\mathcal{N}$  with four layers.

# 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