

# 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

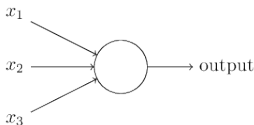
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Feed-Forward  
Neural  
Networks

How They Work  
Universal  
Approximation  
(Briefly)

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Optimization  
Error-  
Backpropagation

Deep Learning



- 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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Neural  
Networks

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Approximation  
(Briefly)

Training  
Nonconvex  
Optimization  
Error-  
Backpropagation

Deep Learning

## [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

Neural  
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Feed-Forward  
Neural  
Networks

How They Work  
Universal  
Approximation  
(Briefly)

Training  
Nonconvex  
Optimization  
Error-  
Backpropagation

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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

Neural  
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Feed-Forward  
Neural  
Networks

How They Work  
Universal  
Approximation  
(Briefly)

Training  
Nonconvex  
Optimization  
Error-  
Backpropagation

Deep Learning

## 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

Neural  
Networks Pt.  
2

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Feed-Forward  
Neural  
Networks

How They Work  
Universal  
Approximation  
(Briefly)

Training  
Nonconvex  
Optimization  
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Backpropagation

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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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Neural  
Networks

How They Work  
Universal  
Approximation  
(Briefly)

Training

Nonconvex  
Optimization  
Error-  
Backpropagation

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Theorem (Mass–energy equivalence)

$$E = mc^2$$



# Verbatim

Neural  
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Feed-Forward  
Neural  
Networks

How They Work  
Universal  
Approximation  
(Briefly)

Training  
Nonconvex  
Optimization  
Error-  
Backpropagation

Deep Learning

## Example (Theorem Slide Code)

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

# Figure

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Feed-Forward  
Neural  
Networks

How They Work  
Universal  
Approximation  
(Briefly)

Training

Nonconvex  
Optimization  
Error-  
Backpropagation

Deep Learning

Uncomment the code on this slide to include your own image from the same directory as the template .TeX file.

# Citation

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Neural  
Networks

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Universal  
Approximation  
(Briefly)

Training  
Nonconvex  
Optimization  
Error-  
Backpropagation

Deep Learning

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

This statement requires citation [Smith, 2012].

# References

Neural  
Networks Pt.  
2

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Feed-Forward  
Neural  
Networks

How They Work  
Universal  
Approximation  
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Training  
Nonconvex  
Optimization  
Error-  
Backpropagation

Deep Learning



John Smith (2012)

Title of the publication

*Journal Name* 12(3), 45 – 678.

# The End