

Neural Networks Workshop: Training and Stochastic Gradient Descent

William Guss
wguss@berkeley.edu

Phillip Kuznetsov
philkuz@berkeley.edu

University of California, Berkeley
Robotics @ Berkeley

December 1, 2015

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

W. Guss &
P. Kuznetsov

Feed-Forward
Neural
Networks

How They Work
Universal
Approximation
(Briefly)

Training
Nonconvex
Optimization
Error-
Backpropagation

Deep Learning

[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

Neural
Networks Pt.
2

W. Guss &
P. Kuznetsov

Feed-Forward
Neural
Networks

How They Work
Universal
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
Networks Pt.
2

W. Guss &
P. Kuznetsov

Feed-Forward
Neural
Networks

How They Work
Universal
Approximation
(Briefly)

Training
Nonconvex
Optimization
Error-
Backpropagation

Deep Learning

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

Neural
Networks Pt.
2

W. Guss &
P. Kuznetsov

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

W. Guss &
P. Kuznetsov

Feed-Forward
Neural
Networks

How They Work
Universal
Approximation
(Briefly)

Training
Nonconvex
Optimization
Error-
Backpropagation

Deep Learning

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

Neural
Networks Pt.
2

W. Guss &
P. Kuznetsov

Feed-Forward
Neural
Networks

How They Work
Universal
Approximation
(Briefly)

Training

Nonconvex
Optimization
Error-
Backpropagation

Deep Learning

Theorem (Mass–energy equivalence)

$$E = mc^2$$

Verbatim

Neural
Networks Pt.
2

W. Guss &
P. Kuznetsov

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}
```

Citation

Neural
Networks Pt.
2

W. Guss &
P. Kuznetsov

Feed-Forward
Neural
Networks

How They Work
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

W. Guss &
P. Kuznetsov

Feed-Forward
Neural
Networks

How They Work
Universal
Approximation
(Briefly)

Training
Nonconvex
Optimization
Error-
Backpropagation

Deep Learning



John Smith (2012)

Title of the publication

Journal Name 12(3), 45 – 678.

The End