Fundamentals of Neural Networks

Mathias Jackermeier

June 12, 2018

Technische Universität München

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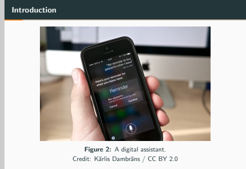
Zeitung ⇒ Künstliche Intelligenz, Gedichte schreiben SZ ⇒ Deep Learning

Introduction

Figure 1: A self-driving car.
Credit: Marc van der Chijs / CC BY-ND 2.0

Introduction

Figure 2: A digital assistant.
Credit: Kārlis Dambrāns / CC BY 2.0



Jedes intelligente System benutzt neuronale Netze

The Perceptron

The Perceptron

MNIST Data Sample

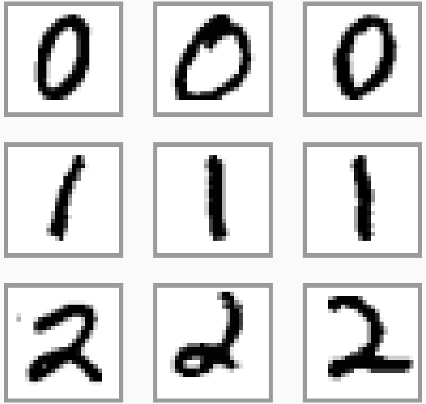
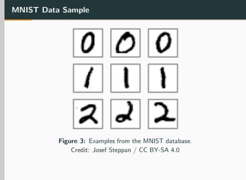


Figure 3: Examples from the MNIST database.
Credit: Josef Steppan / CC BY-SA 4.0



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The perceptron accepts n input values and computes an output value $\hat{y}$:

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Visual Representation

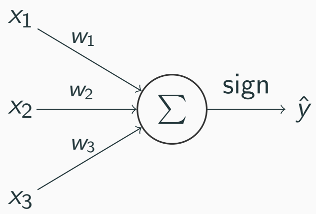
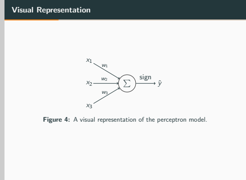


Figure 4: A visual representation of the perceptron model.



1950

Neuron im Gehirn: Nervenzelle Eingaben Ausgaben

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Feedforward Neural Networks

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Perzeptron linear: Viele Funktionen können nicht gelernt werden

Networks of neurons

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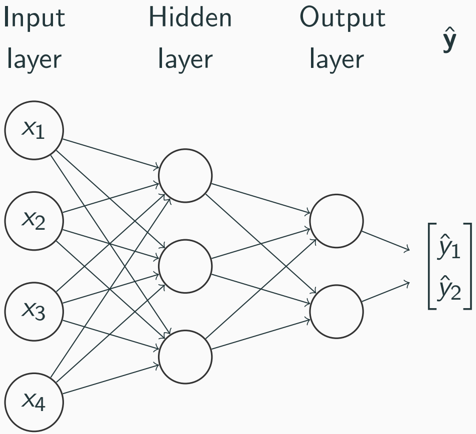
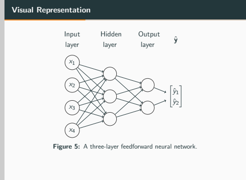


Figure 5: A three-layer feedforward neural network.



Tiefe

Verbindungen nur zwischen Layers

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The Logistic Sigmoid Function

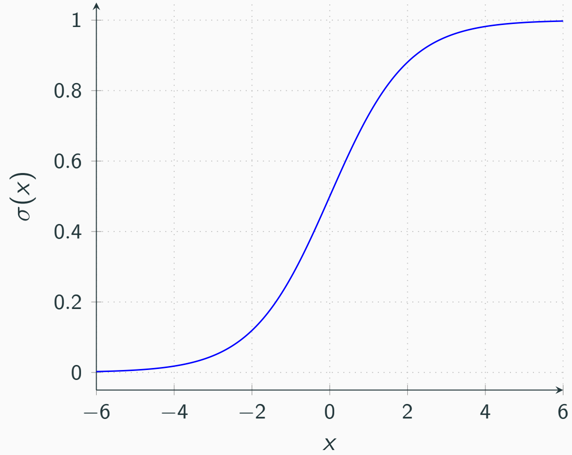
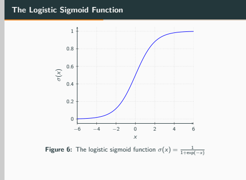


Figure 6: The logistic sigmoid function $\sigma(x) = \frac{1}{1+\exp(-x)}$



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- *Multiclass classification*: k output units with the softmax function

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softmax: Generalisierung, normalisiert

Viele andere Probleme: Auffälliges Verhalten, Bildgenerierung

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The Rectified Linear Function

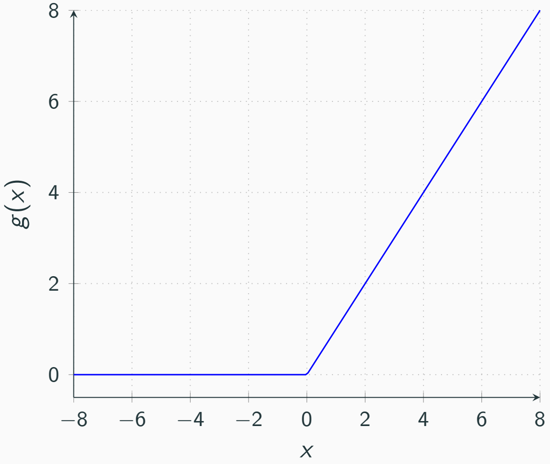
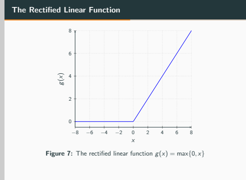


Figure 7: The rectified linear function $g(x) = \max\{0, x\}$



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Neue Perspektive

$a^0 = x$

$\hat{y} = a^L$

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Label: Skalar was wir vorhersagen wollen
Distanz
Erfüllt Bedingungen

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MSE schlecht in Klassifikation
Label: 1 oder 0
– ln aufzeichnen!

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Maximum Likelihood Estimation

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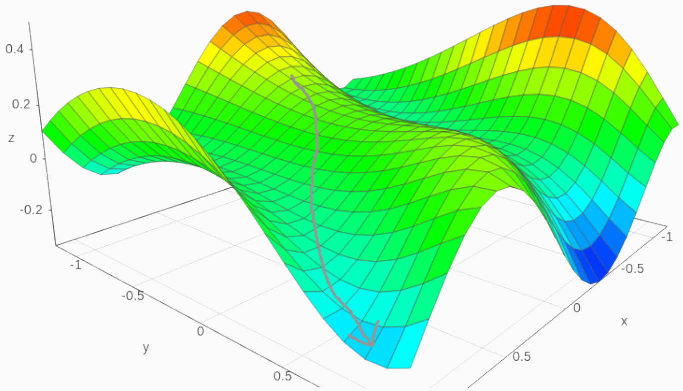
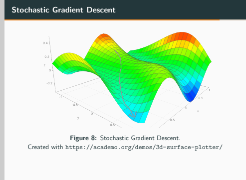


Figure 8: Stochastic Gradient Descent.
Created with `https://academo.org/demos/3d-surface-plotter/`



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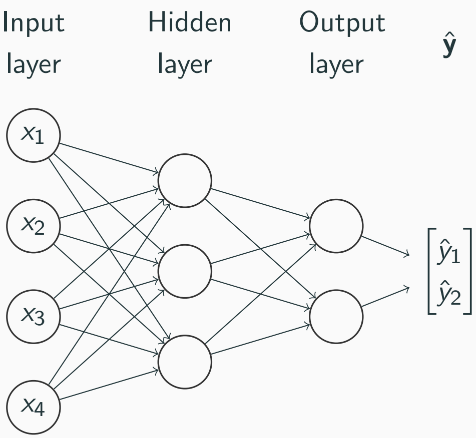
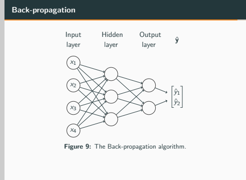


Figure 9: The Back-propagation algorithm.



Back-propagation

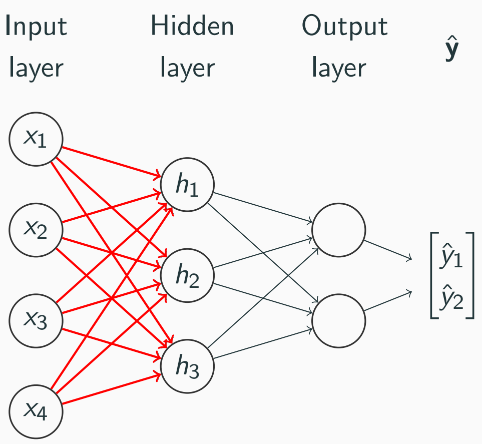
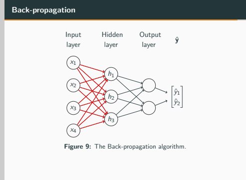


Figure 9: The Back-propagation algorithm.



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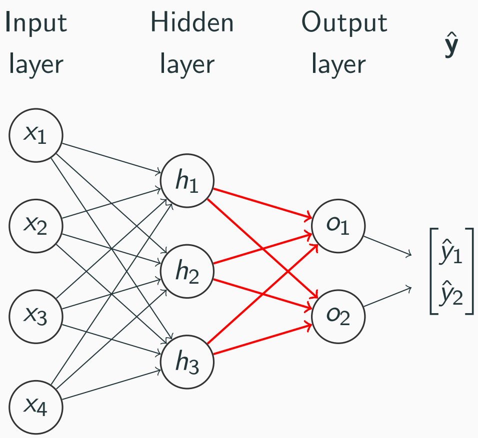

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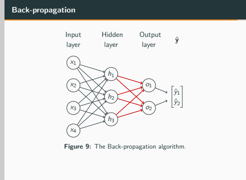

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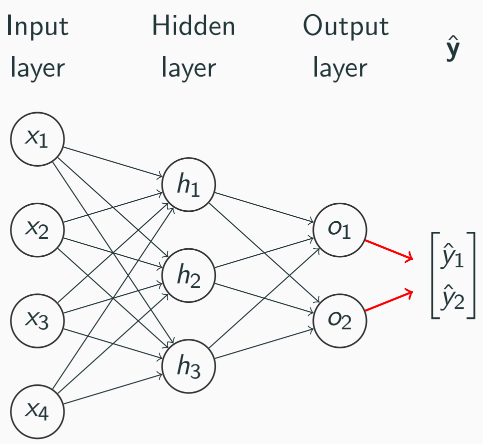

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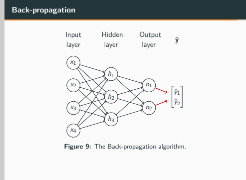

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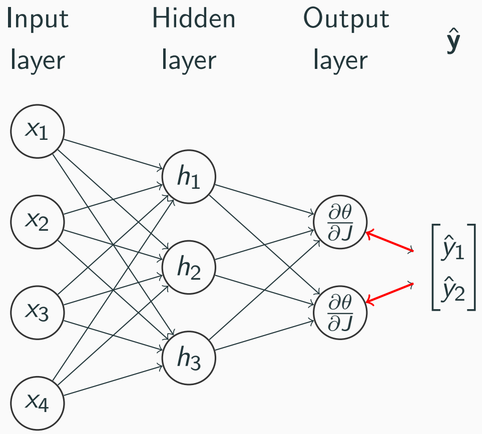

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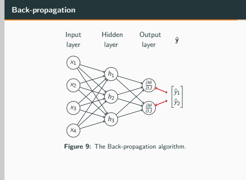

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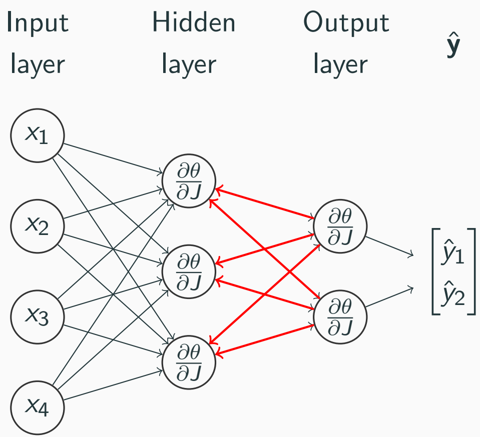

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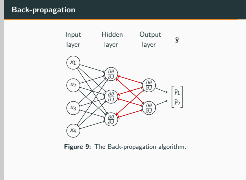
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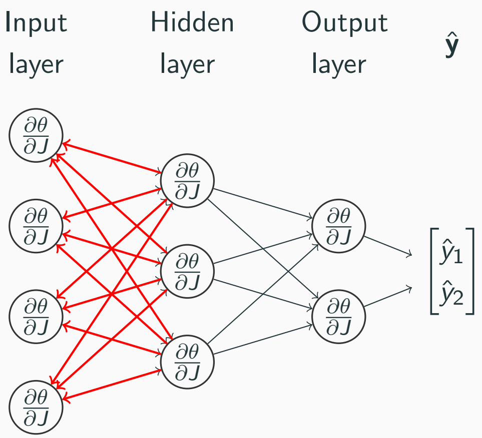

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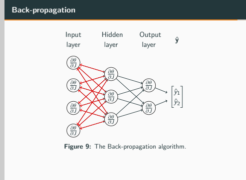

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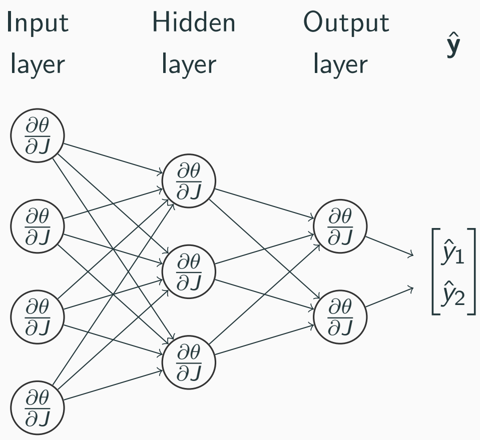

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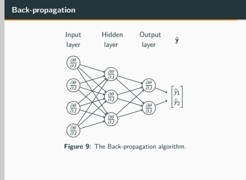

The Complete Learning Algorithm

1. Propagate all training examples of a minibatch forward through the network

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2. Compute the cost for each training example

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5. Update the parameters in the negative direction of the gradient

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5. Update the parameters in the negative direction of the gradient
6. Repeat until the cost is low enough

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Conclusion

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Komplexe Netzwerke einfacher Einheiten
Abstraktionen
Lernen: Kleine Updates der Parameter so dass das Netzwerk besser wird
Überall in Deep Learning

Viele weitere Anwendungen in der Zukunft

Thank you!

Thank you!

Fragen?