Fundamentals of Neural Networks

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June 12, 2018
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Introduction

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

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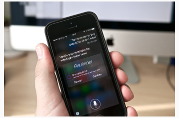

Figure 2: A digital assistant.
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Jedes intelligente System benutzt neuronale Netze

The Perceptron

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MNIST Data Sample

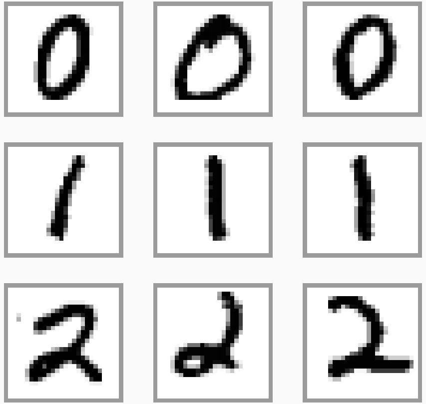

Figure 3: Examples from the MNIST database.
Credit: Josef Steppan / CC BY-SA 4.0

2018-06-11

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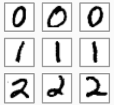

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Visual Representation

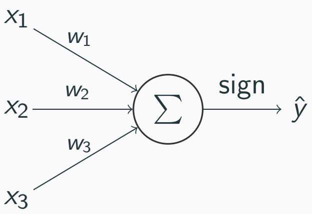
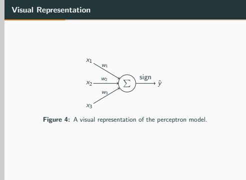


Figure 4: A visual representation of the perceptron model.



1950

Neuron im Gehirn: Nervenzelle Eingaben Ausgaben

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f: Aktivierungsfunktion

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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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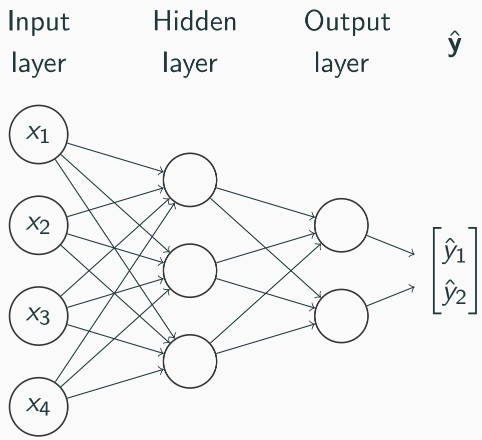
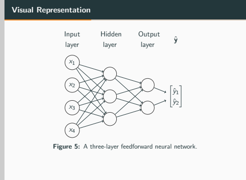


Figure 5: A three-layer feedforward neural network.



Tiefe

Verbindungen nur zwischen Layers

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The Logistic Sigmoid Function

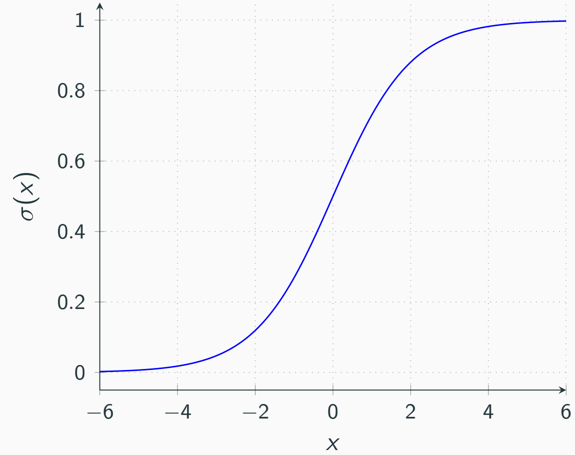
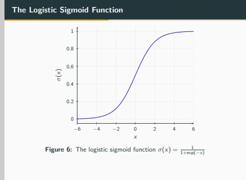


Figure 6: The logistic sigmoid function $\sigma(x) = \frac{1}{1+\exp(-x)}$



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softmax: Generalisierung, normalisiert

Viele andere Probleme: Auffälliges Verhalten, Bildgenerierung

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The Rectified Linear Function

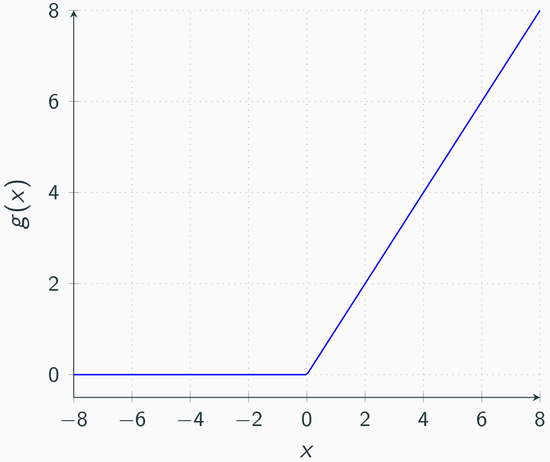
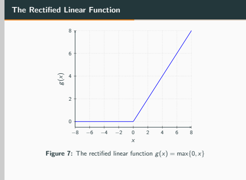


Figure 7: The rectified linear function $g(x) = \max\{0, x\}$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$$a^0 = x$$
$$\hat{y} = a^L$$

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Label: Skalar was wir vorhersagen wollen

Distanz

Erfüllt Bedingungen

Cross-entropy

- In binary classification, we often use the cross-entropy loss

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MSE schlecht in Klassifikation

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Maximum Likelihood Estimation

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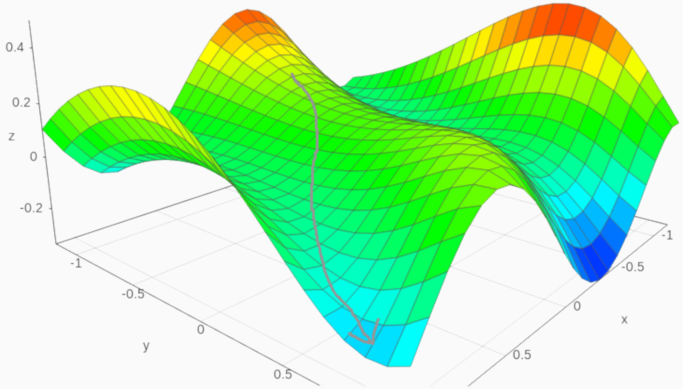

Figure 8: Stochastic Gradient Descent.
Created with `https://academo.org/demos/3d-surface-plotter/`

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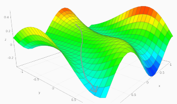

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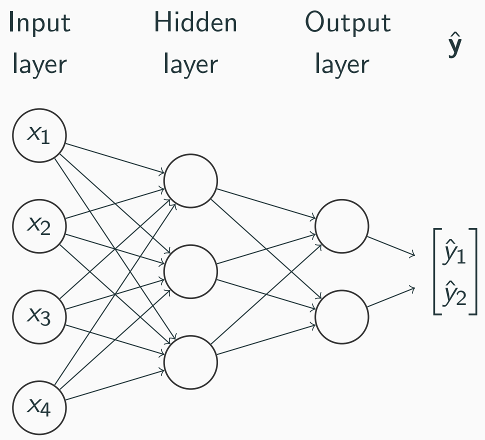
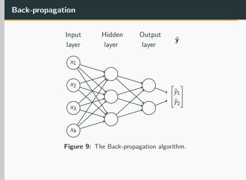


Figure 9: The Back-propagation algorithm.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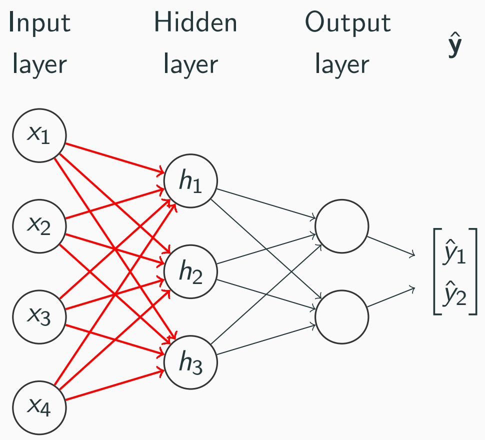

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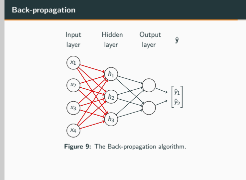

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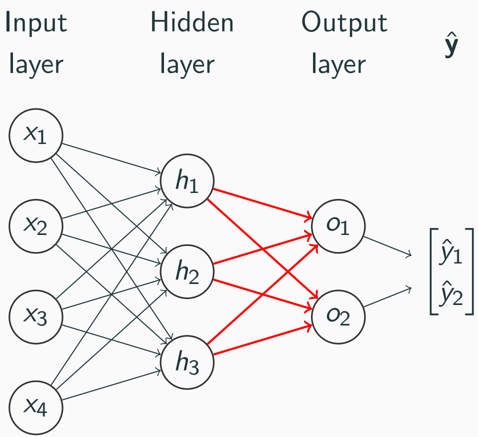

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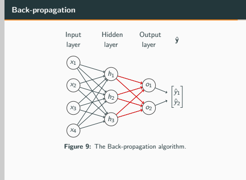

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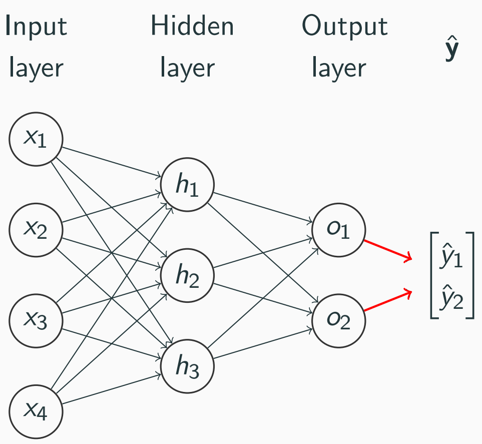

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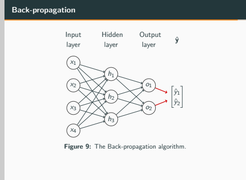

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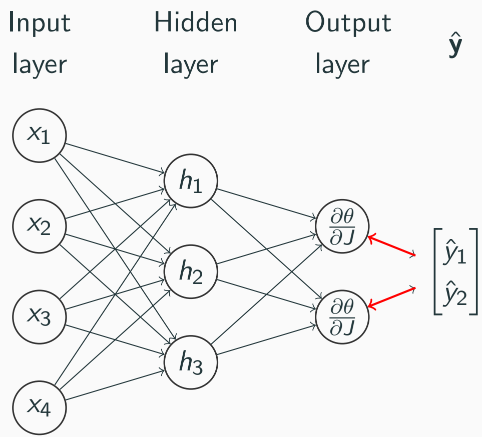

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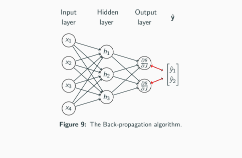

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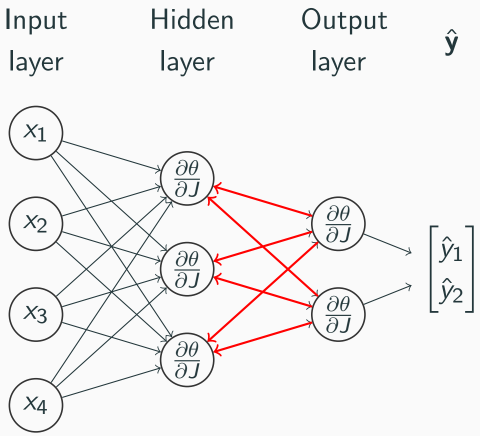

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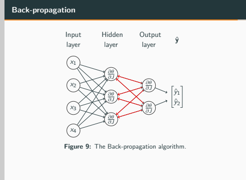

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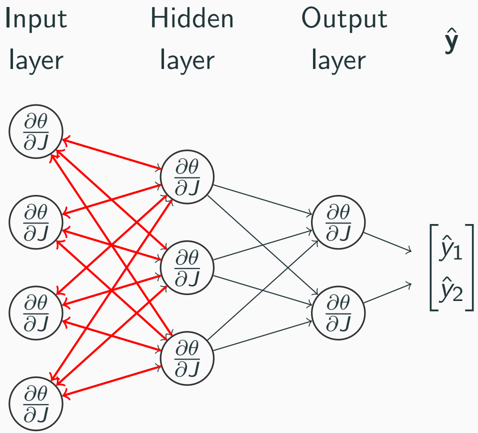

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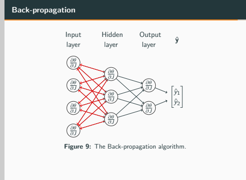

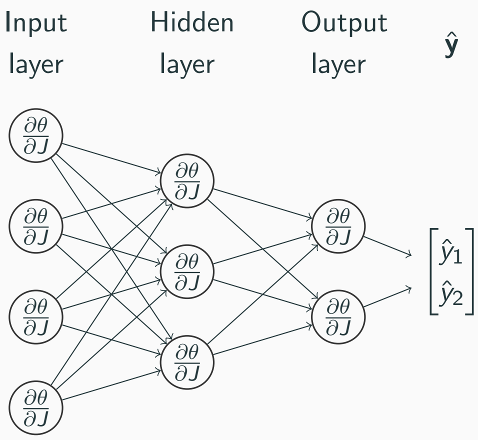

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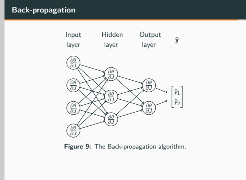

The Complete Learning Algorithm

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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!

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