UNIVERSITÄT DUISBURG ESSEN

Open-Minded

AdaLinE & Multilayer Perceptron

Neuroinformatics Tutorial 8

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Content

- Revision: Practical Task (Already uploaded)
- Revision: Lecture (AdaLinE)
- New Practical Tasks (Already uploaded)
- Revision: Lecture (MLP)

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$$\begin{pmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \end{pmatrix} \cdot \begin{pmatrix} w_0 \\ w_1 \end{pmatrix} = \begin{pmatrix} 1 \\ 4 \\ 4 \end{pmatrix}$$

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This is an over determined linear equation system!
Use Pseudo Inverse to find weight vector!

AdaLinE Pseudo Inverse

- This is the Pseudo Inverse of X: $(X^T X)^{-1} X^T$
- It is the Pseudo Inverse since multiplication with X results in the identity matrix

$$(X^T X)^{-1} X^T X \cdot w = (X^T X)^{-1} X^T Y$$

$$w = (X^T X)^{-1} X^T Y$$

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    1. Network of Perceptrons
    2. Perceptrons organized in multiple layers
    3. One Perceptron with multiple inner hidden layers
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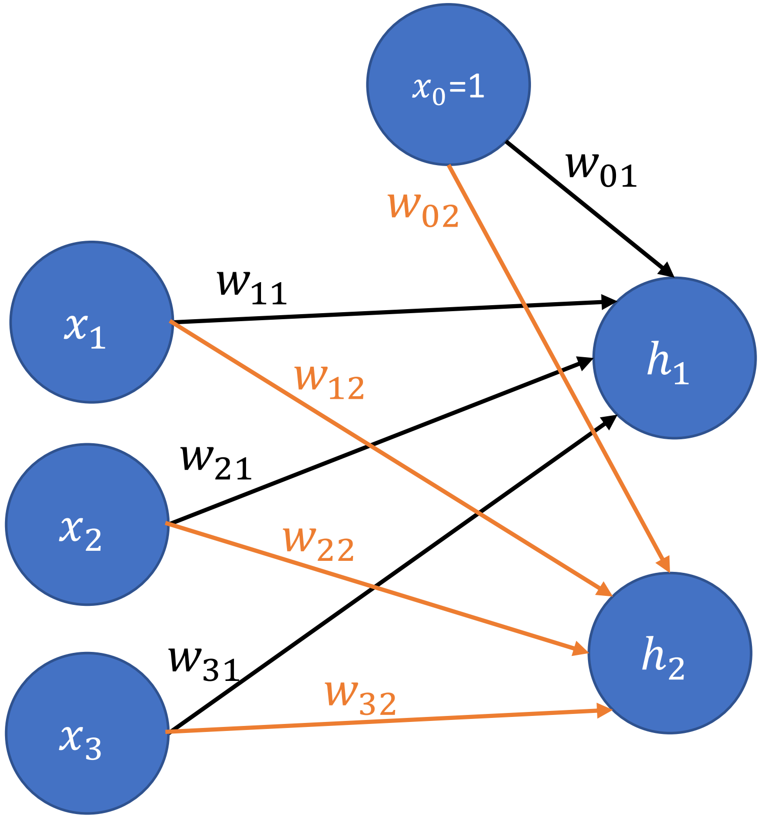
MLP - Definition

- Network of Perceptrons
- Perceptrons organized in multiple layers
- Weighted connection between each Perceptron of one layer to each perceptron of the next layer
- Propagation function of perceptrons: Linear Associator
- Activation function (usually) defined per layer

- 1 Input layer (your usual input vector)
- (Multiple hidden layers)
- 1 Output layer

Calculation of propagated value



$$h_1 = \sum_{i=0}^{3} w_{i1} x_i$$

$$h_2 = \sum_{i=0}^{3} w_{i2} x_i$$

$$x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} \qquad W = \begin{bmatrix} w_{01} & w_{02} \\ w_{11} & w_{12} \\ w_{21} & w_{22} \\ w_{31} & w_{32} \end{bmatrix} \qquad \begin{bmatrix} h_1 \\ h_2 \end{bmatrix} = W^T \cdot x$$

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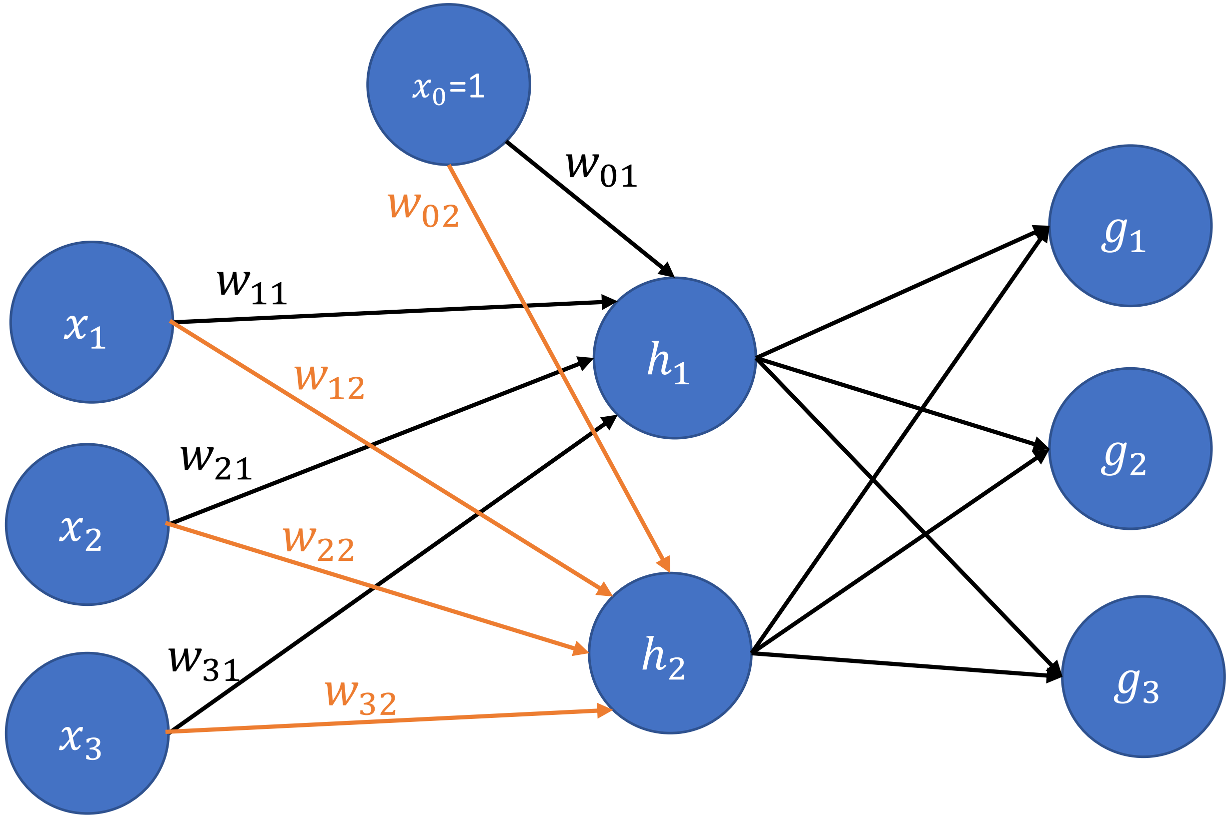

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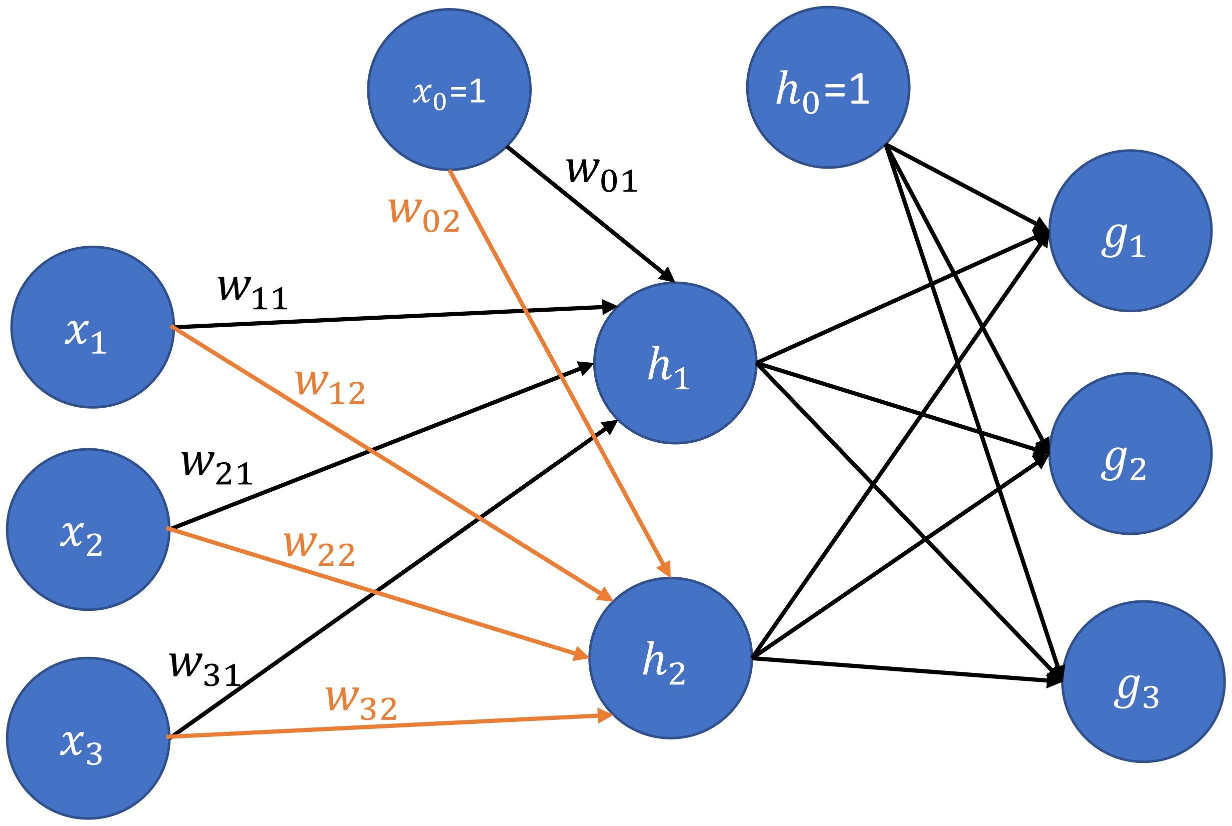

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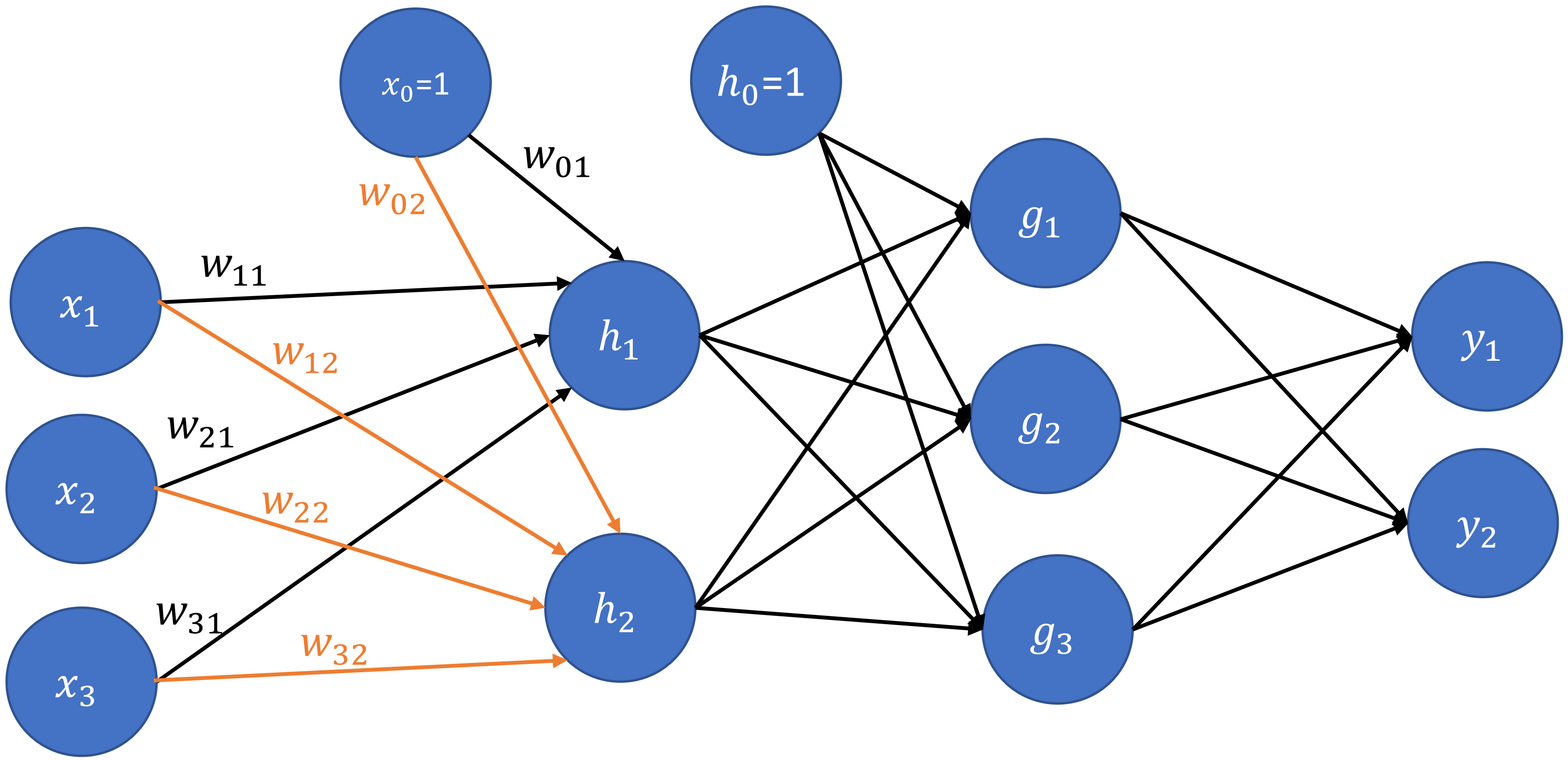

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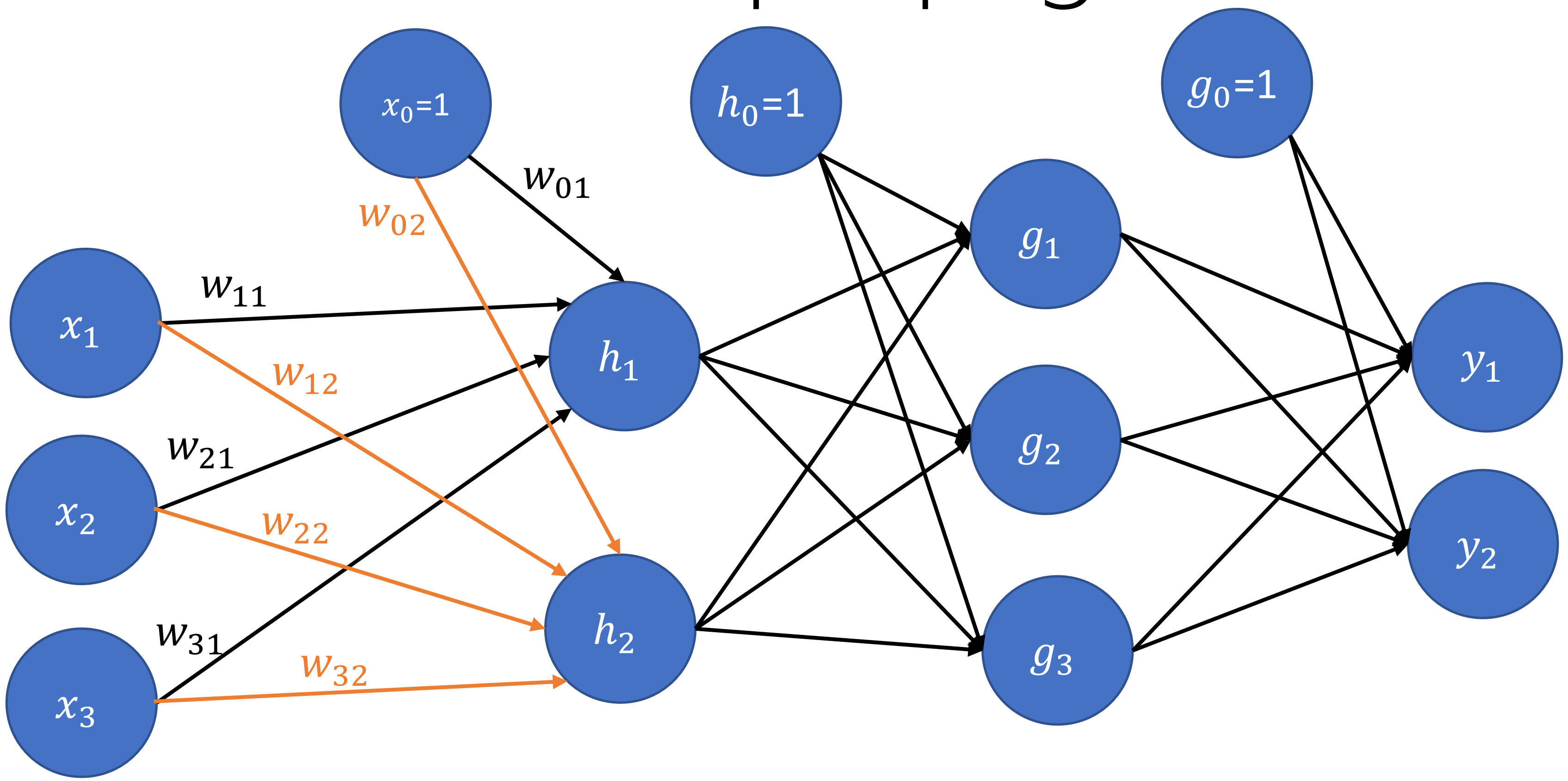

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MLP – Caution with number of layers

- Various conventions about number of layers
- Sometimes including/excluding input layer
- In scope of this course: Excluding input layer

- 3 layer Perceptron:
  - 1 input layer
  - 2 hidden layers
  - 1 output layer

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