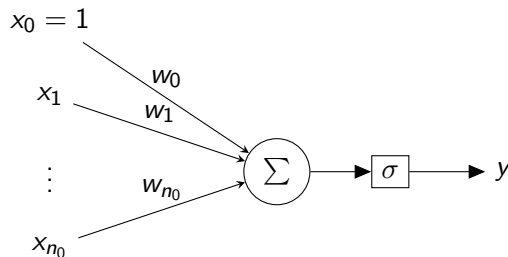


## 5 Neural Networks

# Neural networks - one perceptron



- $z = \sum_{i=0}^{n_0} w_i x_i$
- $y = f(z)$
- $f$  non-linear activation function, often sigmoid  $\sigma$

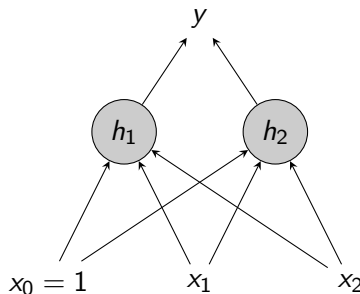
# Non-linear activation function

- enables non-linearity in NNs
- sigmoid  $\sigma(z) = 1/(1 + \exp -z)$
- tanh  $= (\exp(z) - \exp -z)/(\exp(z) + \exp -z)$
- rectified linear unit  $\text{ReLU}(z) = \max\{0, z\}$
- ...
- softmax( $z_i$ )  $= \exp(z_i) / \sum_{j=1}^k \exp(z_j), i = 1, \dots, k$

# XOR problem

- why more than one layer networks?
- XOR = exclusive OR
- cannot be calculated by only one perceptron
- which activation function?

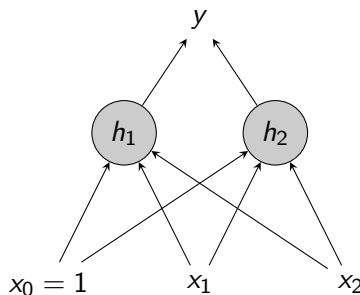
$x_1$	$x_2$	$y$
0	0	0
0	1	1
1	0	1
1	1	0



# XOR problem

- why more than one layer networks?
- XOR = exclusive OR
- cannot be calculated by only one perceptron
- which activation function? ReLU

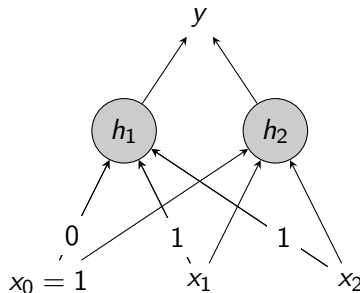
$x_1$	$x_2$	$y$	$h_1$	$h_2$
0	0	0	0	$-1 \rightarrow 0$
0	1	1	1	0
1	0	1	1	0
1	1	0	2	1



# XOR problem

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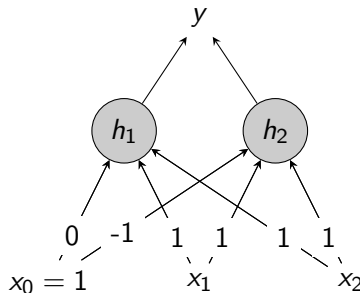
$x_1$	$x_2$	$y$	$h_1$	$h_2$
0	0	0	0	$-1 \rightarrow 0$
0	1	1	1	0
1	0	1	1	0
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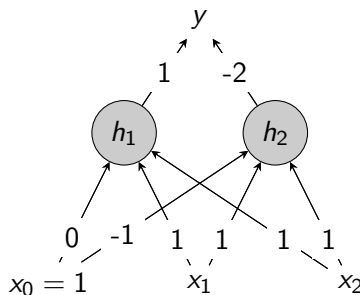
$x_1$	$x_2$	$y$	$h_1$	$h_2$
0	0	0	0	$-1 \rightarrow 0$
0	1	1	1	0
1	0	1	1	0
1	1	0	2	1



# XOR problem

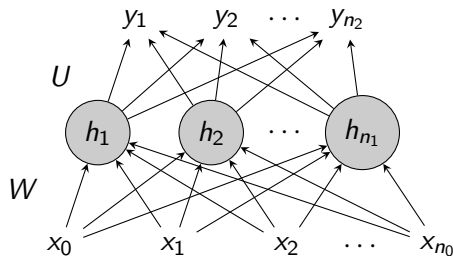
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$x_1$	$x_2$	$y$	$h_1$	$h_2$
0	0	0	0	$-1 \rightarrow 0$
0	1	1	1	0
1	0	1	1	0
1	1	0	2	1



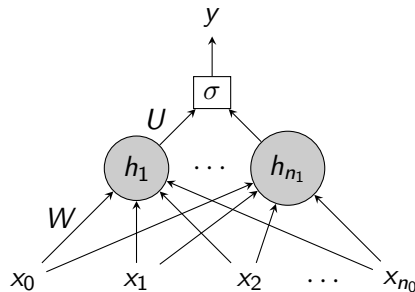
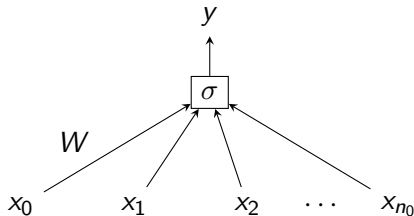


# Feedforward (FF) neural networks



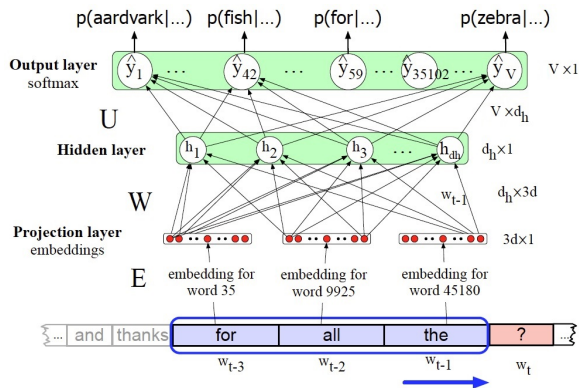
- for historic reasons also known as multi-layer perceptrons (MLP)
- diy: write CBOW, skip-gram, PV-DM and PV-DBOW as FF NN

# Logistic regression as FF NN



- logistic regression is a NN without hidden layer (left figure)
- adding a hidden layer (right figure) maybe improve performance
- hidden layer allows for non-linear interactions between features
- power of deep learning, e.g., NN, is to learn feature interaction
- no need of complicated human-engineered features

# Neural language model (NLM)



<https://web.stanford.edu/~jurafsky/slp3/>

- predict next word using a sliding window (fixed length)

# NLM vs. n-gram LM

I have to make sure that the cat gets fed.  
(not seen: dog gets fed)

- task: I forgot to make sure that the dog gets ...
- n-gram LM cannot predict "fed" (not seen)
- NLM finds similarity of embeddings of "cat" and "dog"
- NLM is able to generalize and predict "fed" after "dog" (not seen)

# Training NNs

- for all training pairs  $(x, y)$ 
  - forward step to find  $\hat{y}$
  - compute loss  $L(\hat{y}, y)$
  - update/optimize weights of output layer
  - assess the influence of (all) hidden nodes and update weights

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  - assess the influence of (all) hidden nodes and update weights  
this is the “critical” part  
(let us have a short excursion to backpropagation; for more details, cf., deep learning lecture)