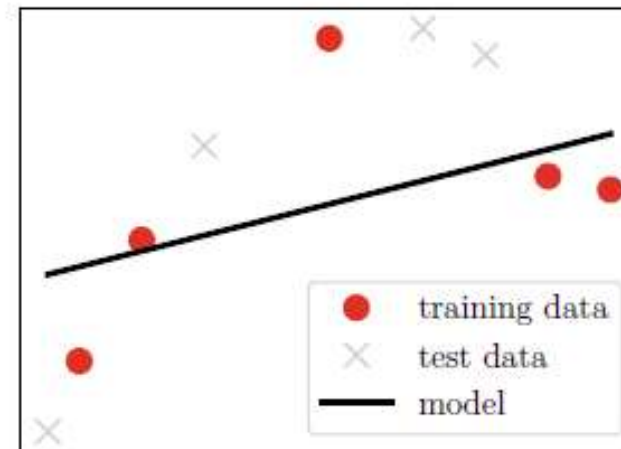


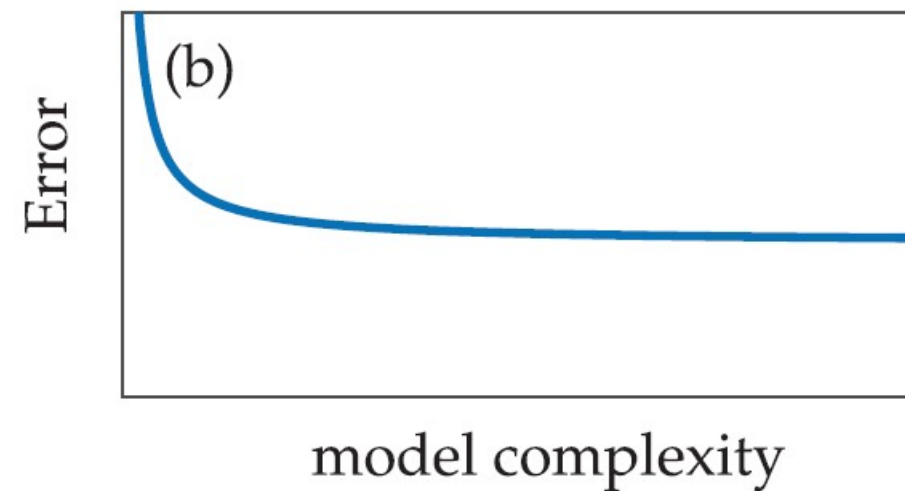
Planning of course:

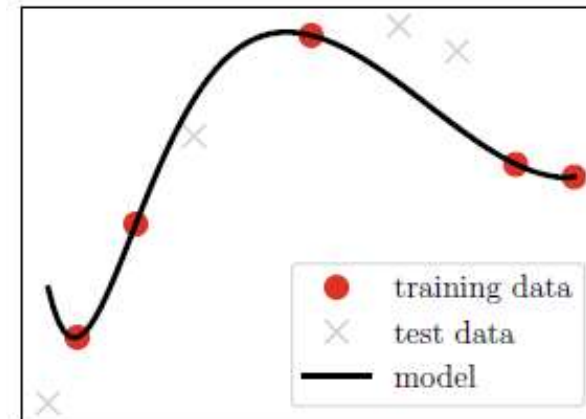
- Dimensional reduction: singular value decomposition, principal component analysis, reduced order modeling
- Regression, optimization, model selection/performance
- Neural networks
- Physics informed neural networks
- Projects



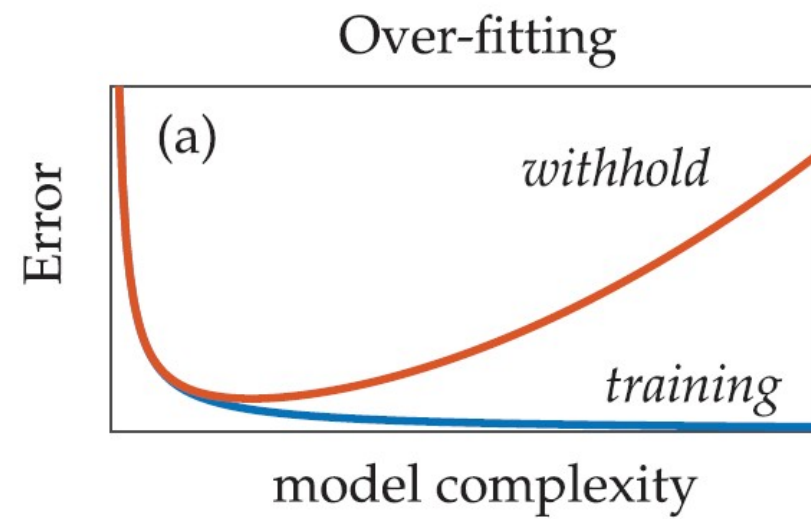
(a) Underfitting

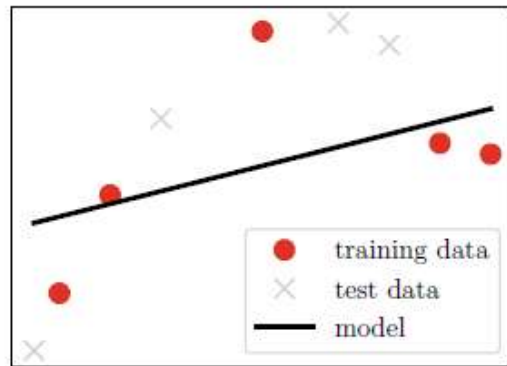
Under-fitting



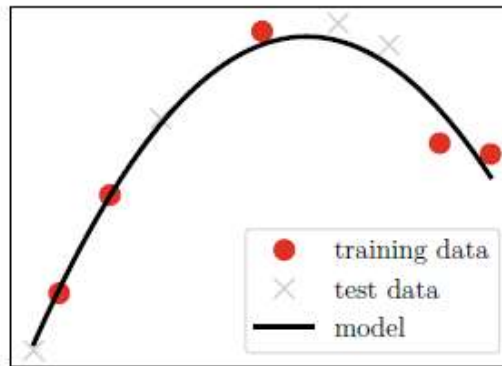


(c) Overfitting

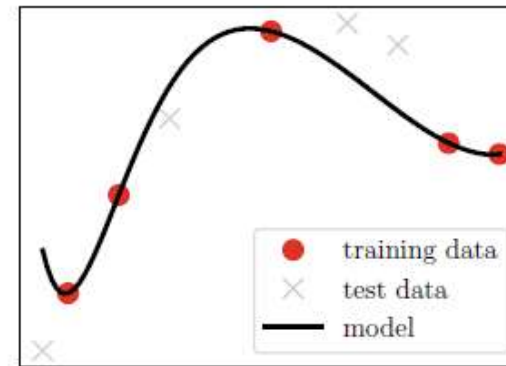




(a) Underfitting



(b) Ideal fitting



(c) Overfitting

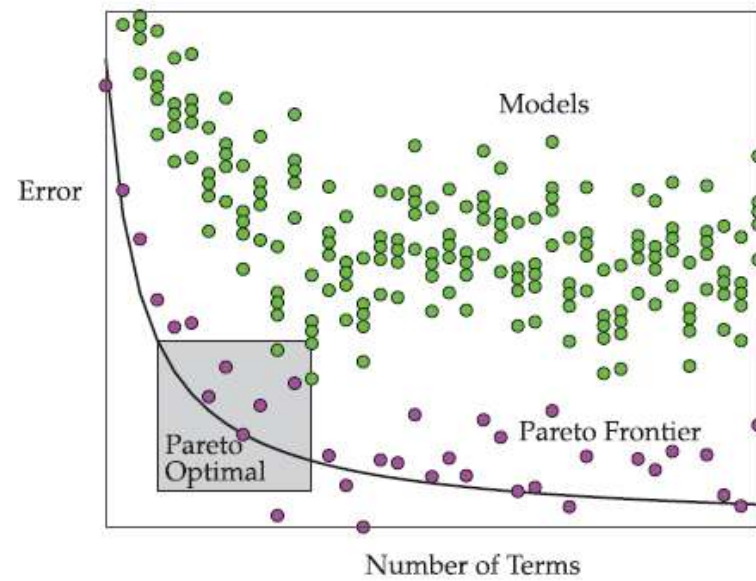
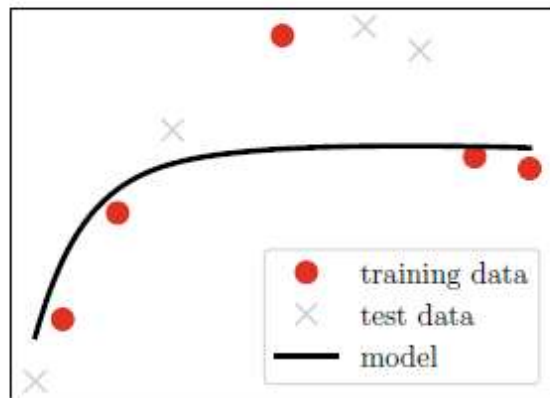
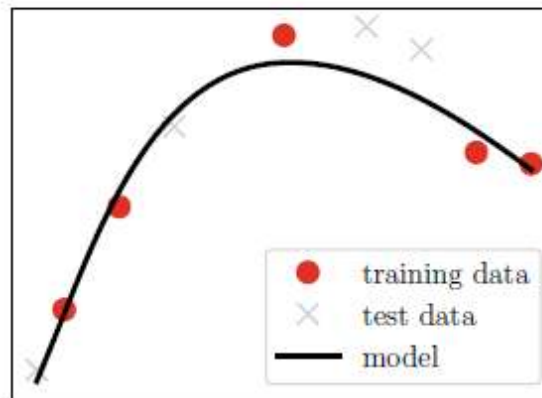


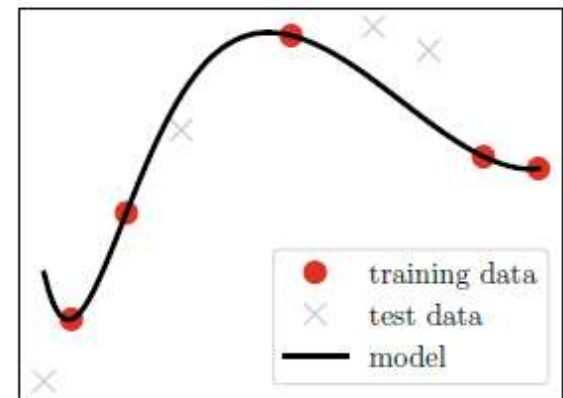
Figure 4.16 For model selection, the criteria of accuracy (low error) is balanced against parsimony.



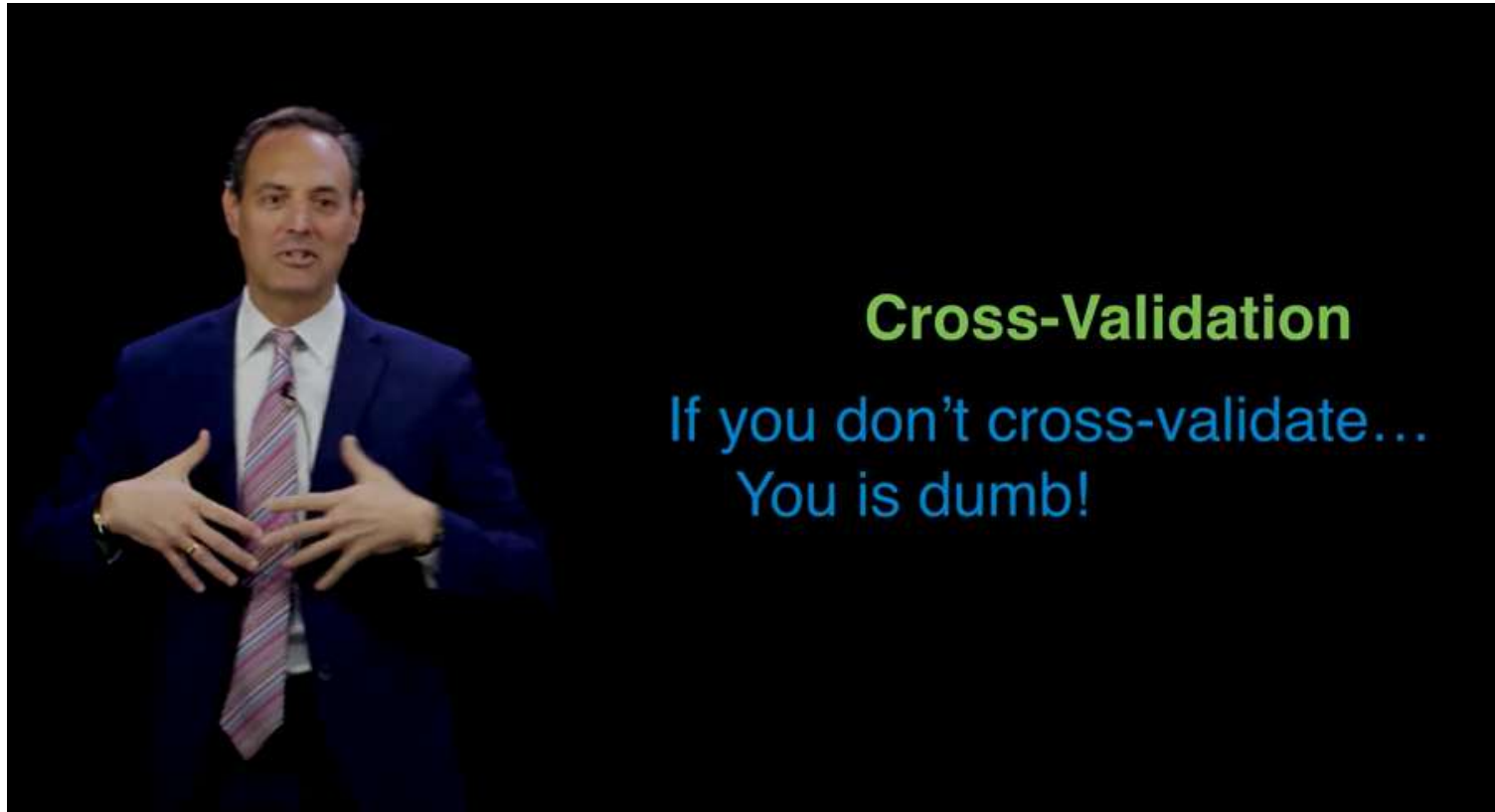
(a) Excessive regularization



(b) Proper regularization



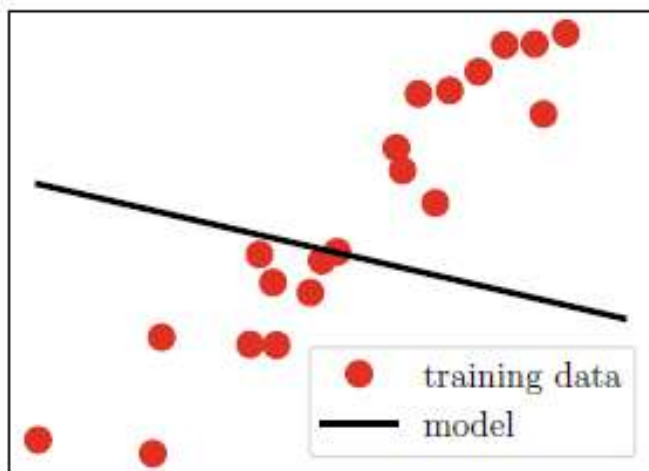
(c) No regularization ($\lambda \rightarrow 0$)



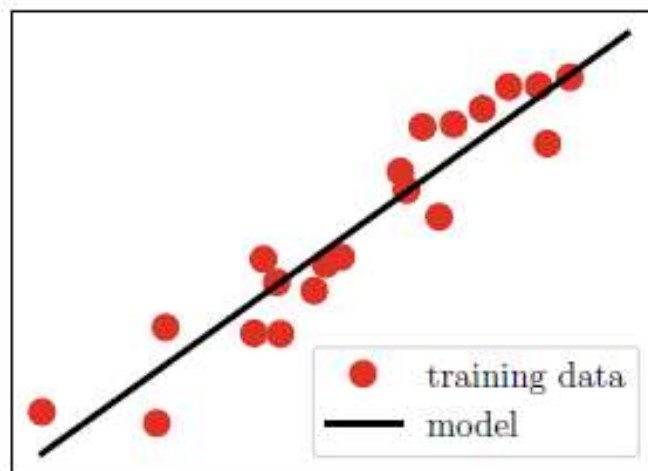
The data is divided into: training, validation and withhold data.

The model is constructed from the training and the validation data.

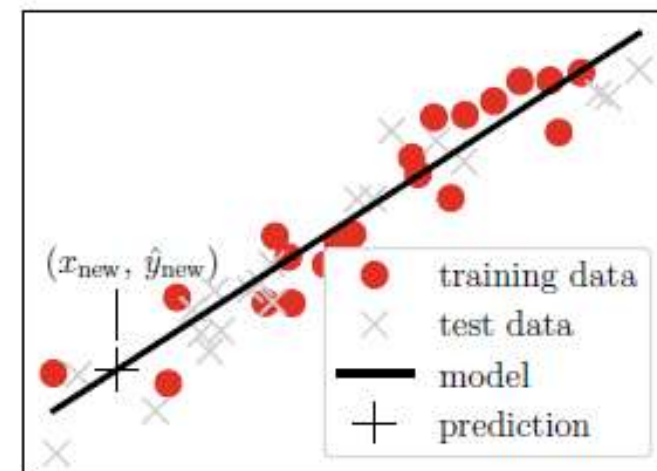
The model is tested on the withhold data.



(a) Untrained model



(b) Trained model



(c) Prediction

Show code for dividing data points into training and validation

k-fold cross-validation

1) split the data in training and withhold (test) data

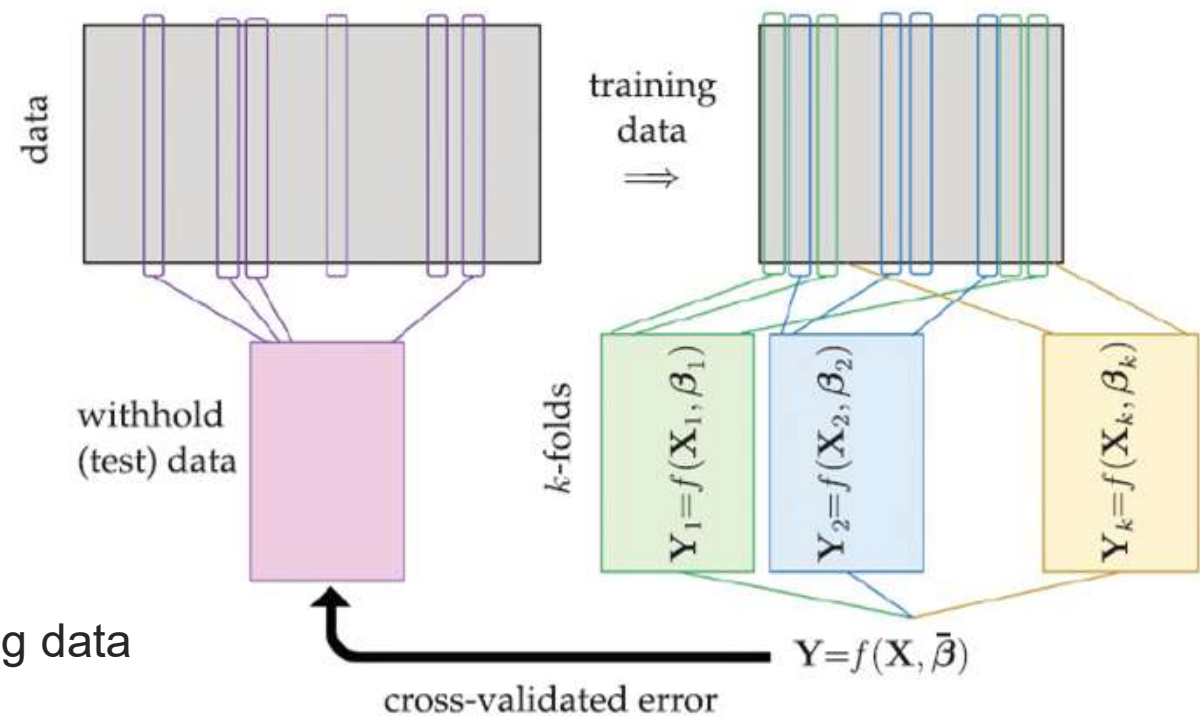
Something like 90%, 10%

2) Repeat k-times:

- Take random portions of training data and optimize parameters (something like 90%, 10%)
- Compute error against remaining training data (= validation data)

3) Choose the best set of parameters

4) Evaluate against the withhold (test) data



Notation:

$$\theta \rightarrow \beta$$

Planning of course:

- Dimensional reduction: singular value decomposition, principal component analysis, reduced order modeling
- Regression, optimization, model selection/performance
- Neural networks
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- Projects

Artificial neural networks are very efficient for supervised learning (regression, classification).
Increased use due to: computer power (GPU), big data

Many application areas: speech, image autonomous driving, weather forecasting, mechanics, ...

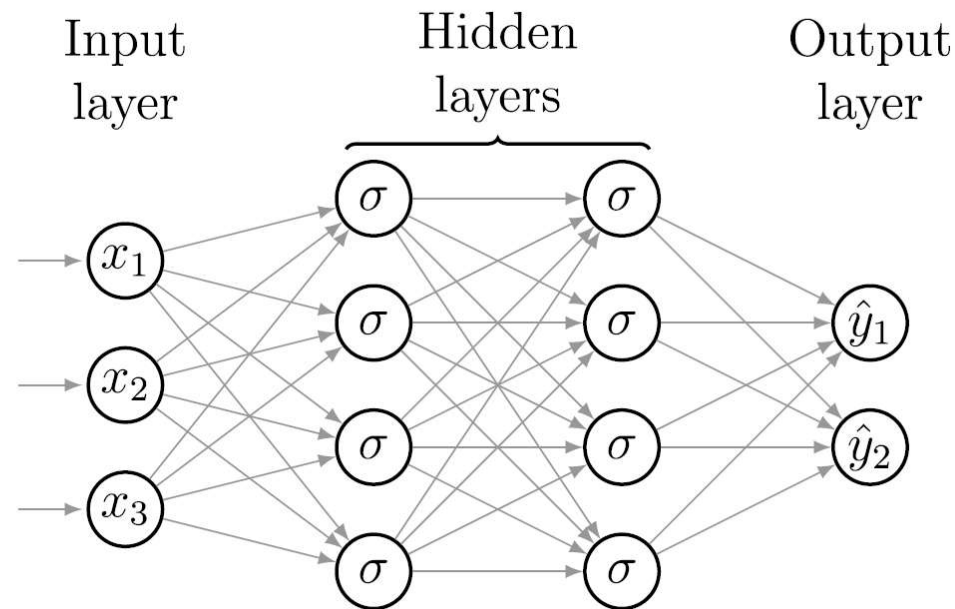


Fig. 3.1 A fully connected feed-forward neural network

Universal approximation theorem:

- a fully connected feed-forward NN with 1 hidden layer (sigmoid functions) can approximate any function with arbitrary precision

In practise: better with more layers than width (number of neurons) of the layers since more efficient training (increased nonlinearity possible)

i.e. deep learning

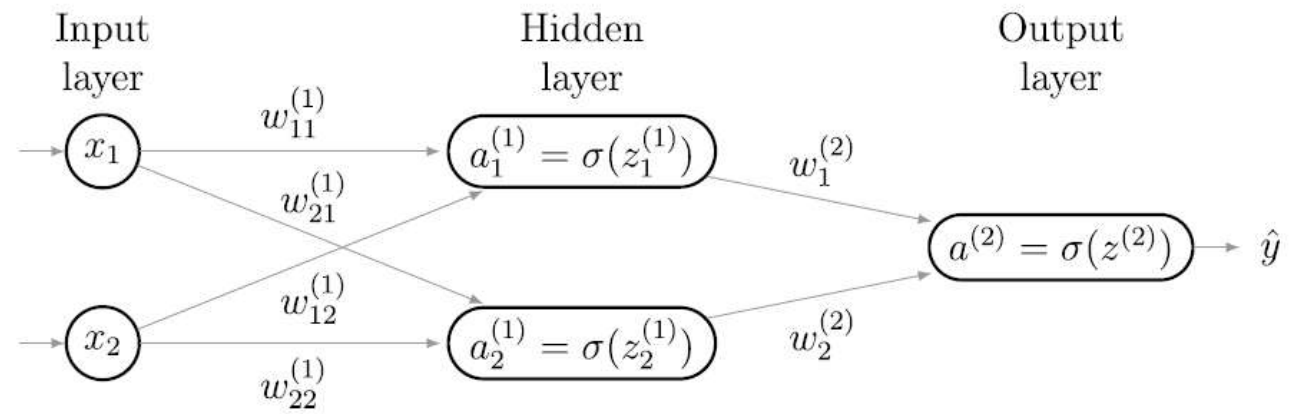


Fig. 3.5 A simple feed-forward neural network example

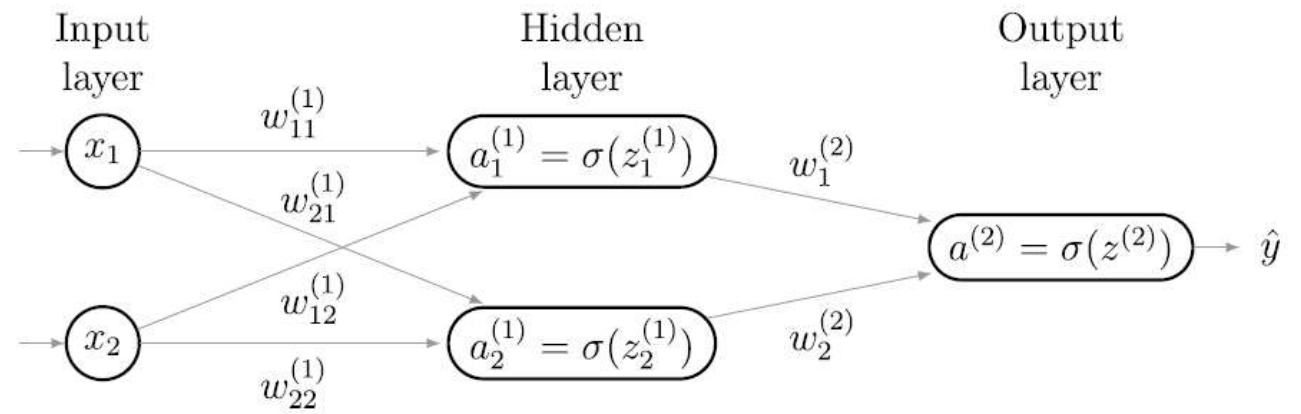


Fig. 3.5 A simple feed-forward neural network example