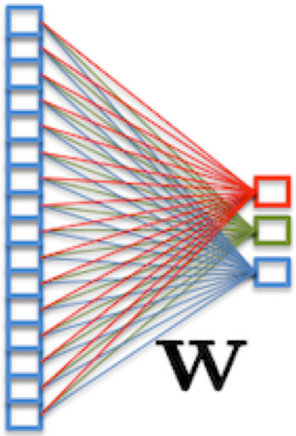
5IF - Deep Learning and Differentiable Programming

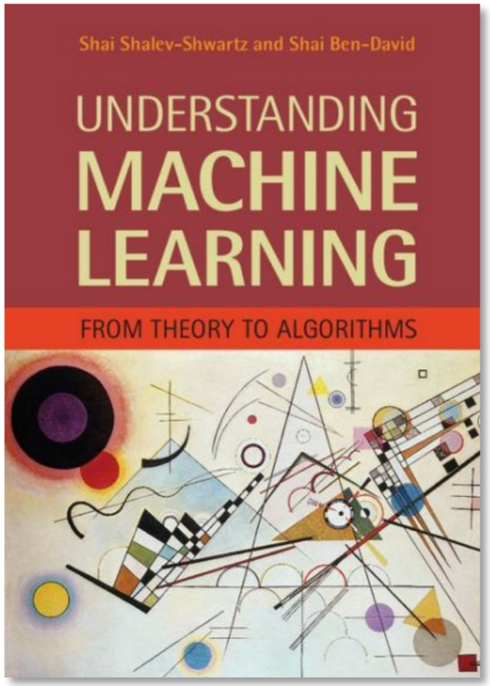
1.3 Some extremely short basics of machine learning



INSA LYON Christian Wolf

To go deeper ...

These next 15 (!!) slides will never be able to replace a full lecture in the theory of machine learning. The interested reader is referred to:



Shai Shalev-Shwartz and Shai Ben-David

Understanding Machine Learning, from Theory to Algorithms

Cambridge University Press, 2014

We would like to learn to predict a value y from observed input x

$$y = h(x, \theta)$$

Handcrafted from domain knowledge

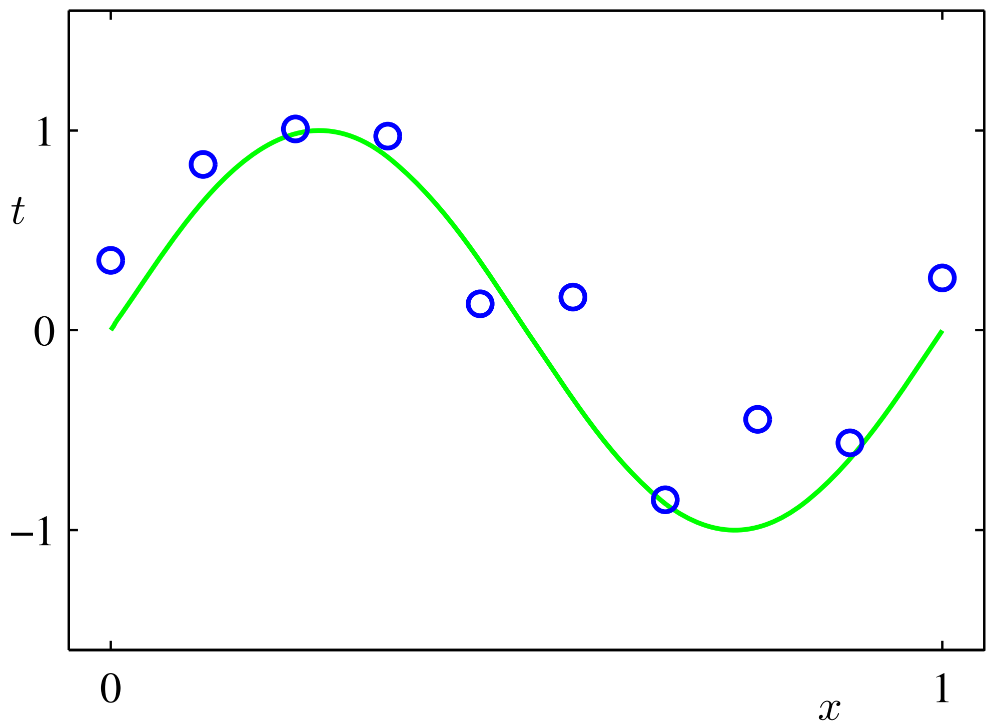
Learned from data or interactions

Fully handcrafted

Fully Learned

Fitting and Generalisation

- Data are generated with function $t = sin(2\pi x)$
- Objective: assuming the function unknown, predict t from x



[C. Bishop, Pattern recognition and Machine learning, 2006]

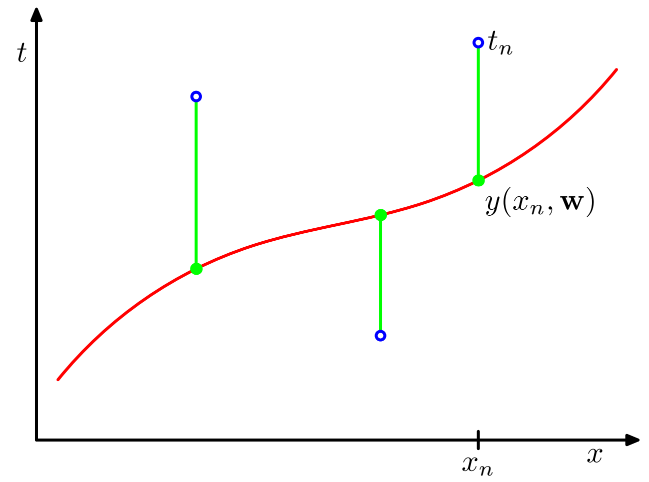
Fitting and Generalisation

Example: « Fitting » of a polynomial of order M

$$y(x, \mathbf{w}) = w_0 + w_1 x + w_2 x^2 + \ldots + w_M x^M = \sum_{j=0}^{M} w_j x^j$$

« Least squares » (of errors) criterion

$$E(\mathbf{w}) = \frac{1}{2} \sum_{n=1}^{N} \{y(x_n, \mathbf{w}) - t_n\}^2$$

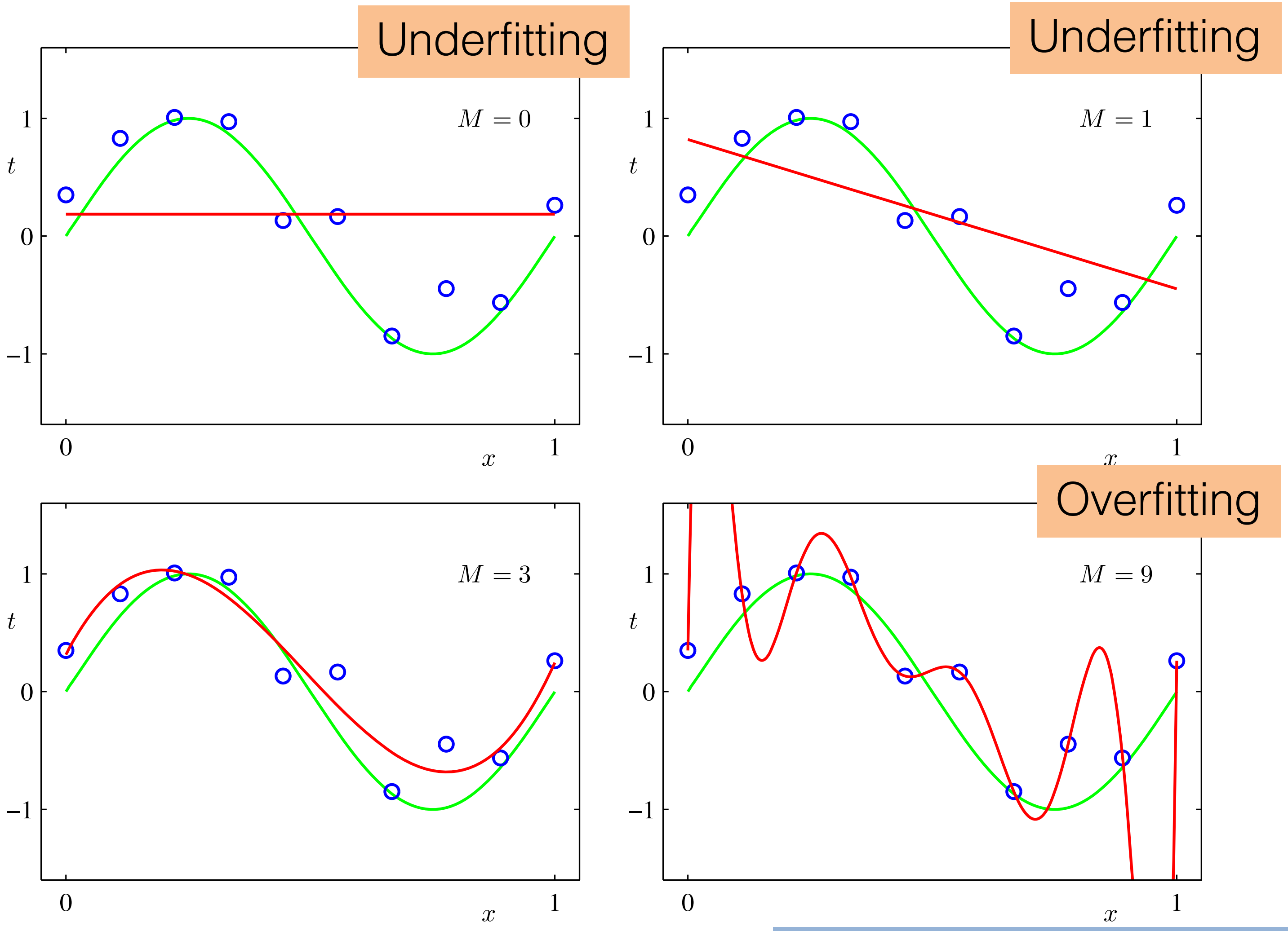


Linear derivative -> direct solution

[C. Bishop, Pattern recognition and Machine learning, 2006]

Model selection

Which order M for the polynomial?



[C. Bishop, Pattern recognition and Machine learning, 2006]

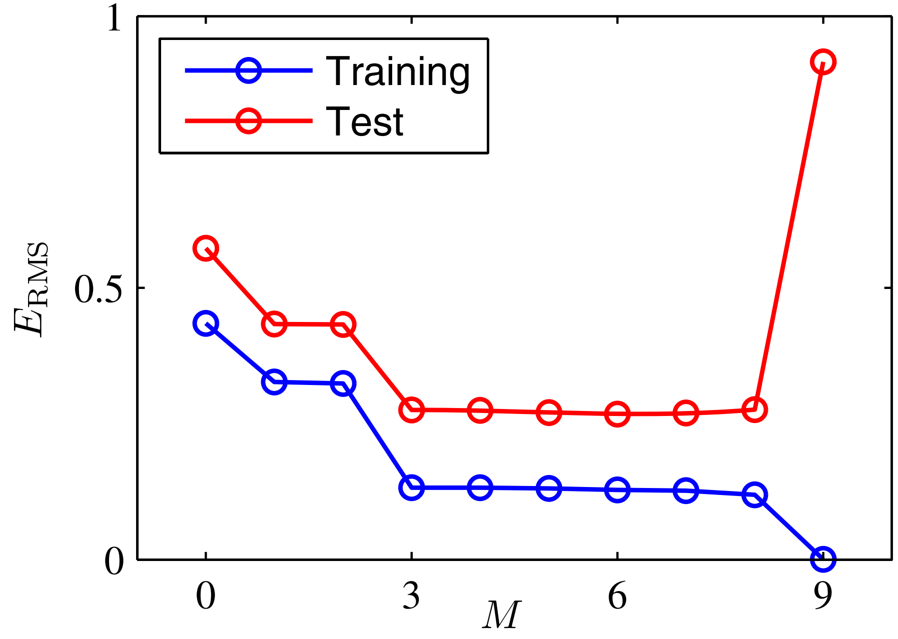
Model selection

Separation into (at least) two sets

- Training set
- Validation set (hold out set)

Root Mean Square Error (RMS)

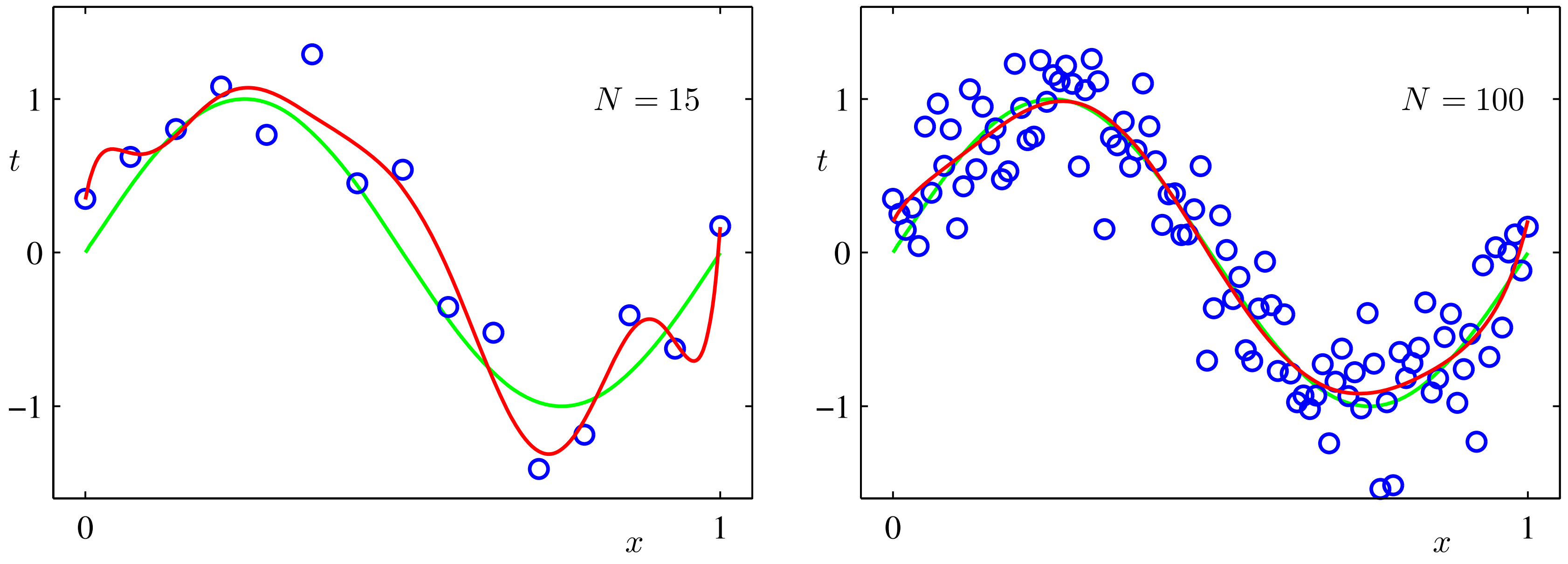
$$E_{\mathrm{RMS}} = \sqrt{2E(\mathbf{w}^\star)/N}$$



[C. Bishop, Pattern recognition and Machine learning, 2006]

Big Data!

Overfitting increases if we increase the size of the training set.



M=9

[C. Bishop, Pattern recognition and Machine learning, 2006]

The 3 problems of Machine Learning

1. Expressivity
   – What is the complexity of the functions my model can represent?

2. Trainability
   – How easy is training of my model (i.e. solving the optimization problem)?

3. Generalization
   – How does my model behave on unseen data?
   – In presence of a shift in distributions?

(D’après Eric Jang & Jascha Sohl-Dickstein)

Learning formulations

Supervised learning — Labels y^* are available during training:

$$\hat{\theta} = \min_{\theta} \mathcal{L}\left(h(x, \theta), y^*\right)$$

Unsupervised learning — no labels, discovery of regularities in the data. Different objectives are possible.

Self-supervised learning — prediction of masked parts of the data itself, for instance the future:

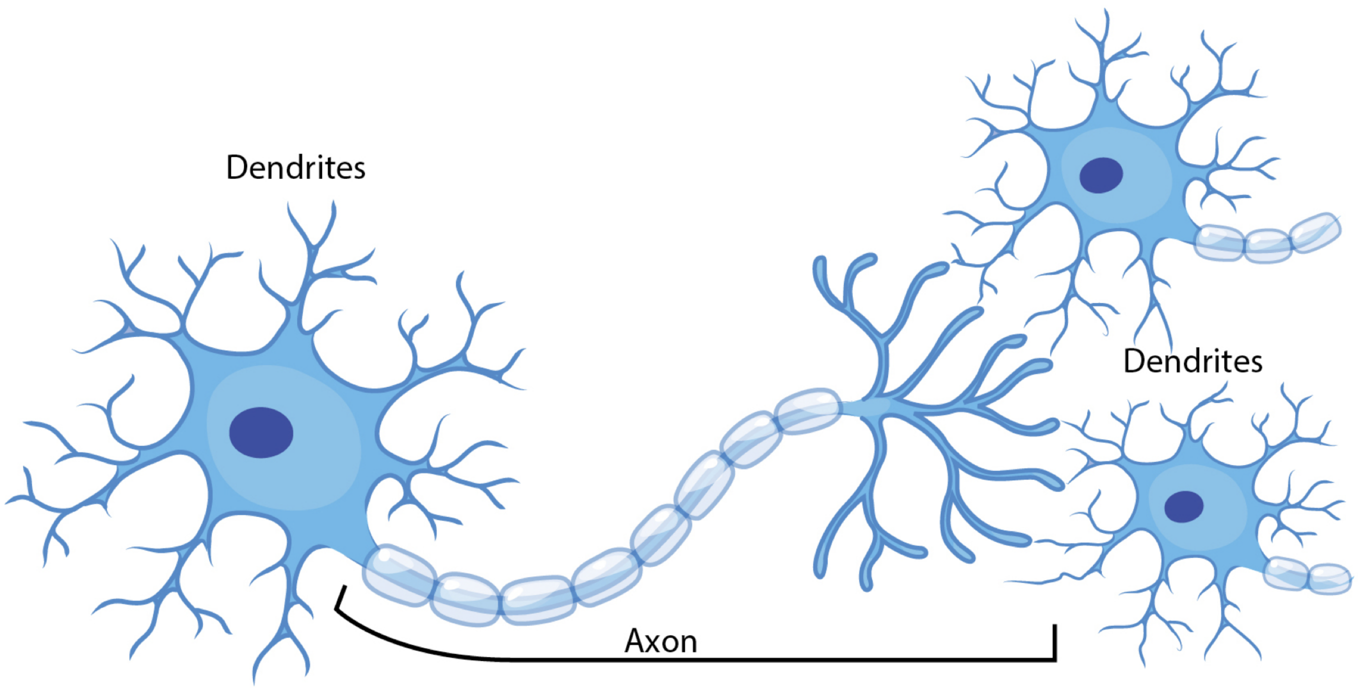
$$\hat{\theta} = \min_{\theta} \mathcal{L}\left(h(x_{t-\Delta:t-1}, \theta), x_t\right)$$

$\Rightarrow$ Pretraining step, usually followed by task oriented training.

Reinforcement learning — learning from interactions, maximizing the cummulated reward R over a horizon:

$$\hat{\theta} = J\left(\pi_\theta\right) = \mathop{\mathbb{E}}_{\tau \sim \pi_\theta}\left[R(\tau)\right]$$

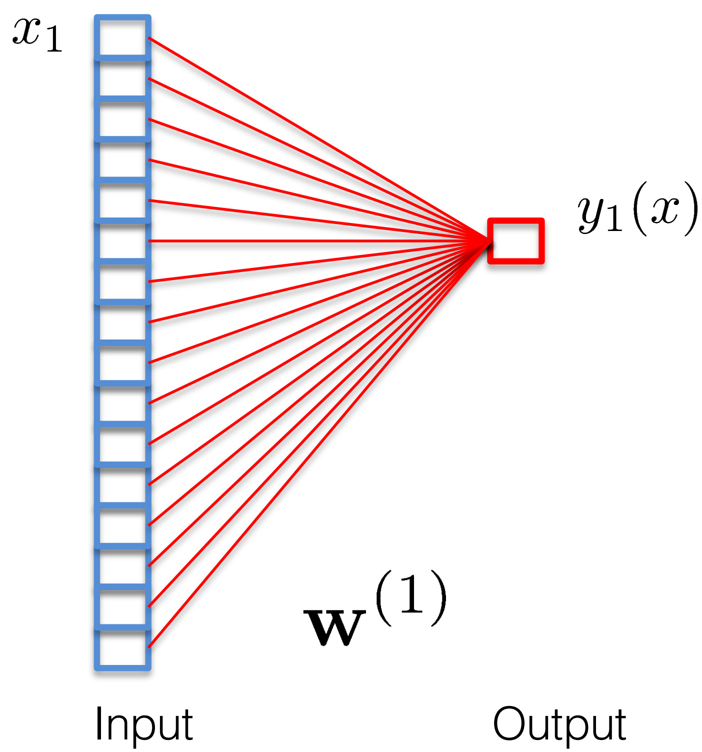
Biological neurons



Devin K. Phillips

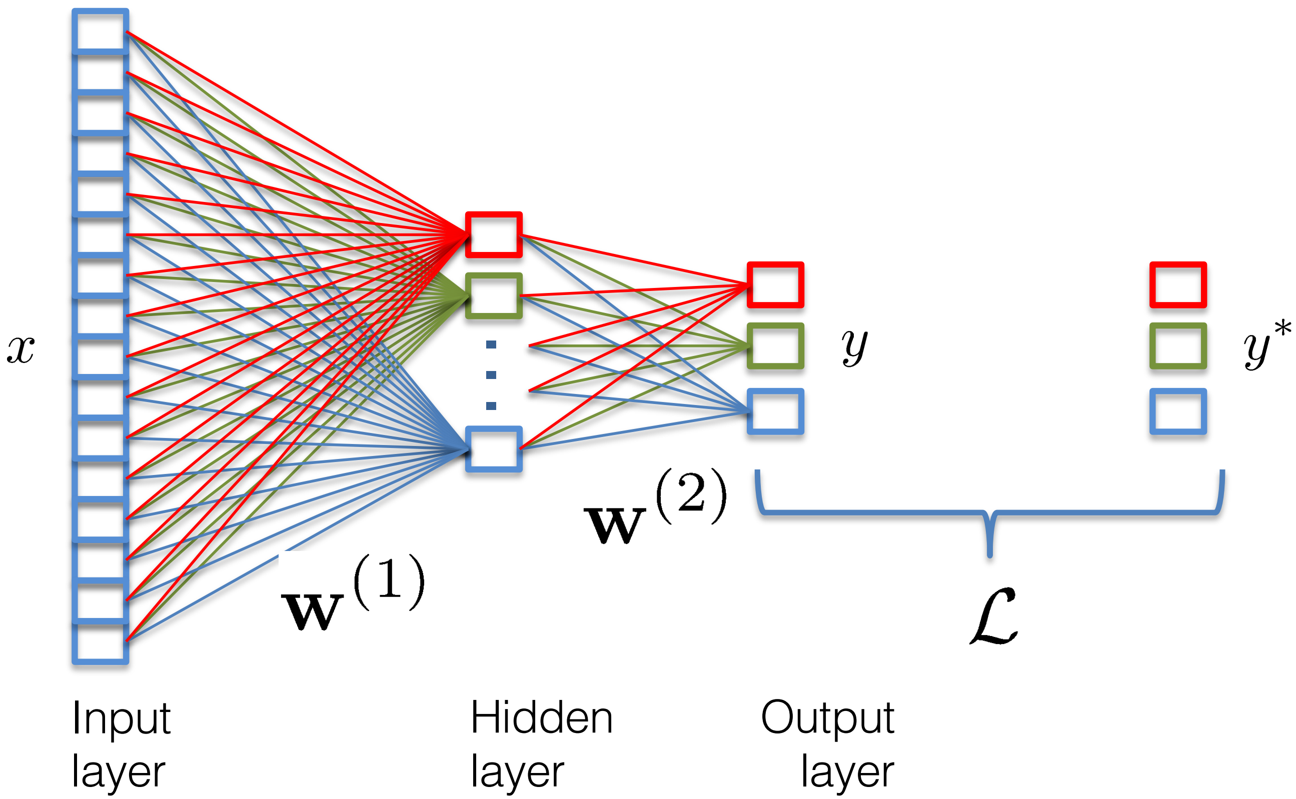
Neural networks

« Perceptron »

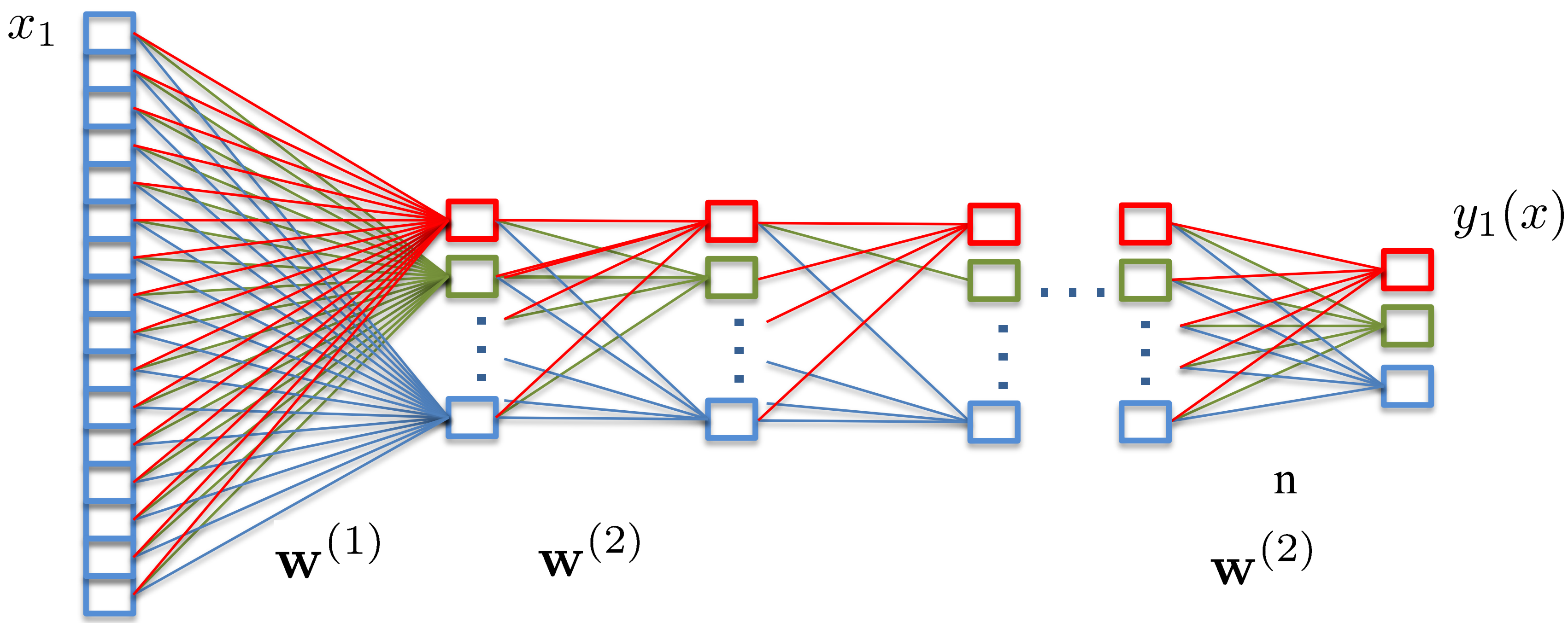


$$y(\boldsymbol{x}, \boldsymbol{w}) = \sum_{i=0}^{D} \boldsymbol{w}_i \boldsymbol{x}_i$$

Deep neural networks



Deep neural networks



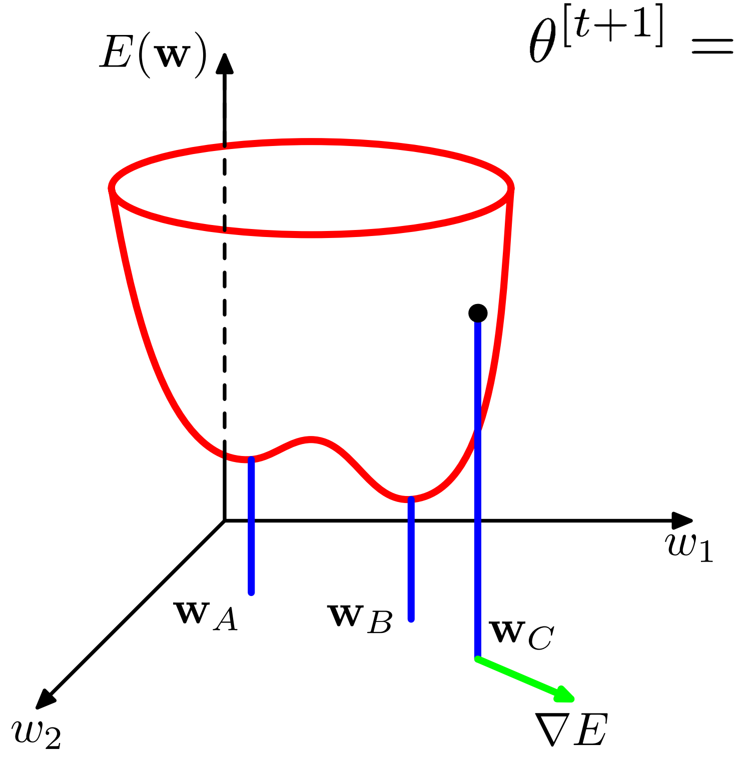
Gradient descent

Minimize the error on known data

"Empirical Risk Minimization"

$$\theta^{[t+1]} = \theta^{[t]} + \boxed{\nu} \nabla \mathcal{L}(h(x,\theta), y^*)$$

Learning rate

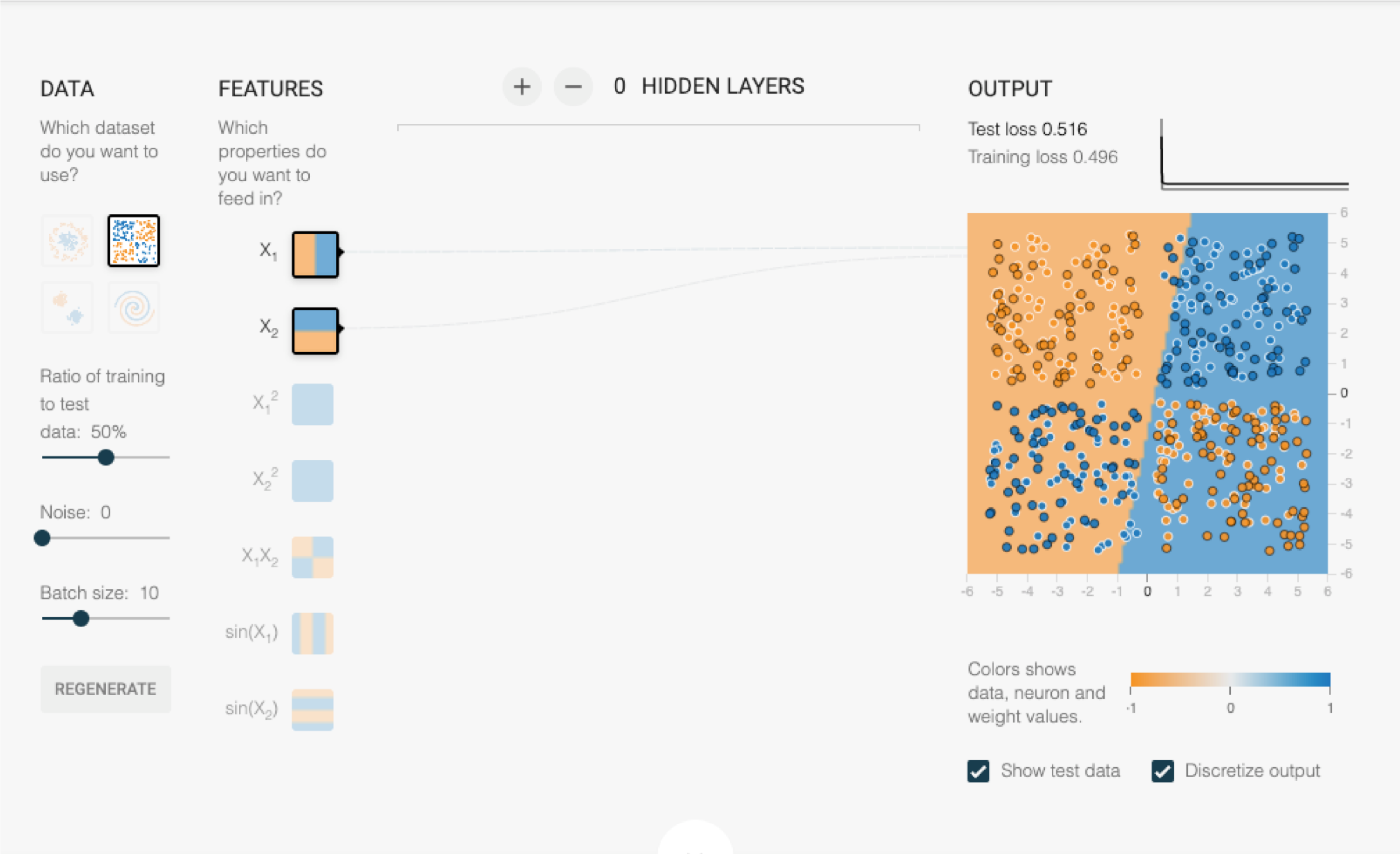


Can be blocked in a local minimum

[C. Bishop, Pattern recognition and Machine learning, 2006]

Demo session: Tensorflow playground

Tensorflow Playground



https://playground.tensorflow.org