Deep networks & backpropagation

Learning machines

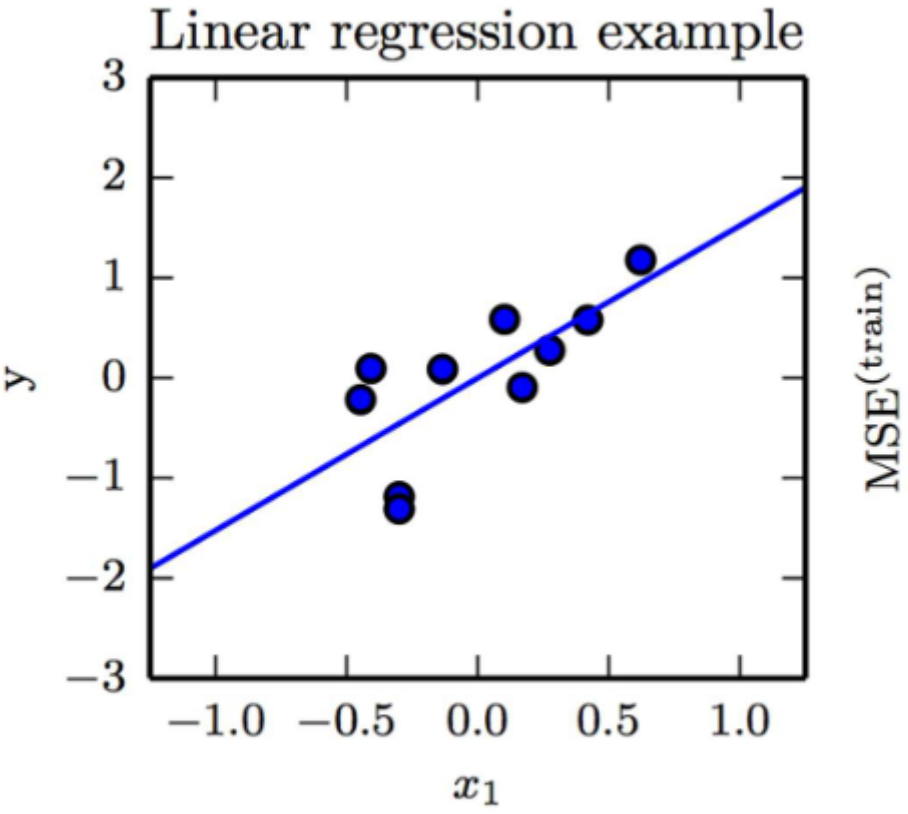
“A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.” (Mitchell, 1997)

• Task T: e.g., classification, regression, density estimation, etc.

• Performance measure P: e.g., accuracy, error rate

• Experience E: supervised, unsupervised, reinforcement learning

Example: Linear regression!(线性回归)



$$\hat{y} = \boldsymbol{w}^\top \boldsymbol{x}$$

参数介绍：

x：输入变量

y：输出变量

w：权重

b：偏置项（当然这个图里没有展示）

Mean squared error: our performance measure

P(w,b) = 1/N ∑(y_i - (wx_i + b))^2

error/loss 介绍：

Training error：

the error/loss computed on the training set

Test error/loss: the error/loss on the test set

Generalization error/loss: the gab between the training error and test error

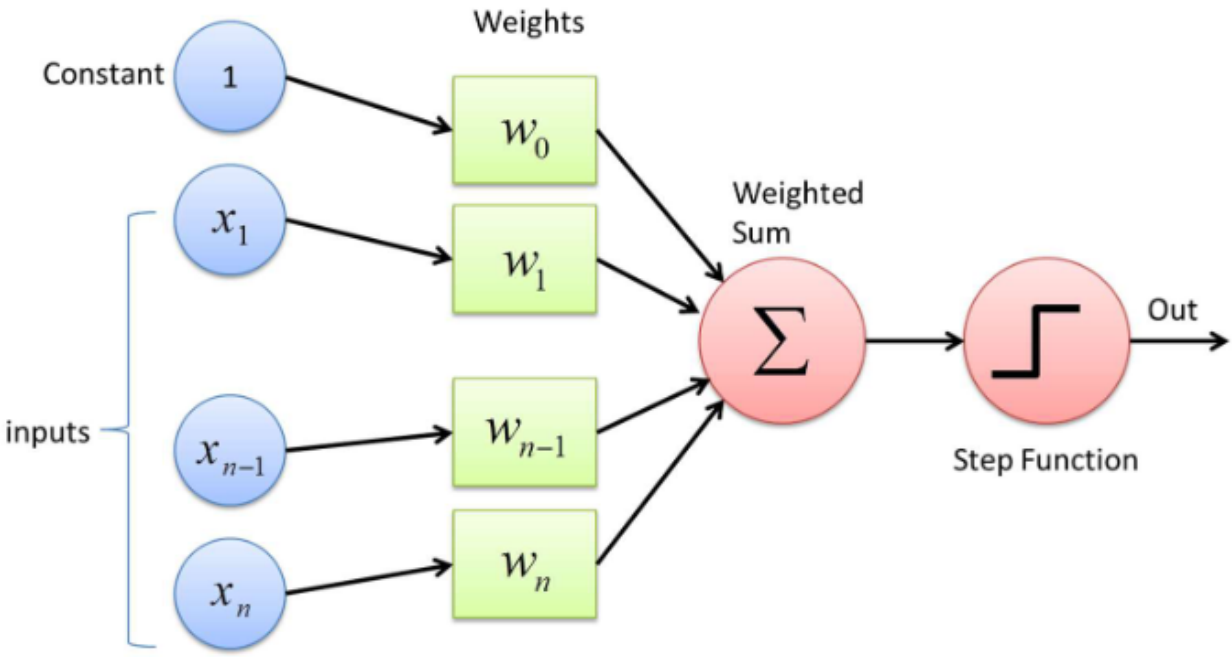
Underfitting(欠拟合) and overfitting（过拟合）

Generalisation（泛化）与 Capacity（容量） 一句话先记住： 容量是模型的"智商"，泛化是它"考试"时的得分；智商太高不复习，容易作弊背答案（过拟合），考试一换题库就挂。

Capacity（容量） 抽象说法：假设空间的大小，即模型能表示的函数集合的"丰富程度"。

Generalisation（泛化）： 训练集误差 → 测试集误差的"落差"越小，泛化越好。

Perceptron（感知机）



Going deep – Single Hidden Layer（该章节未具体介绍）

Deep neural networks（该章节未具体介绍）

Gradient-based learning： backpropagation（反向传播）：核心想，找到最合适的权重使得我的模型的误差最小化。

Cost functions: cross entropy（交叉熵损失函数）

$$L(\tilde{y}) = -\sum_{i=1}^{C} y_i \log \tilde{y}_i \qquad \frac{\partial L}{\partial \tilde{y}_i} = -\frac{y_i}{\tilde{y}_i}$$

记忆：yi是第i个样本的真实值（0/1），yi^是第i个样本的预测值（0~1）（如果默认归一化的话） log（yi^）是一个负数，在前面加上一个符号变为正数

三种output：

1. Regression: 线性输出
2. Binary classification: sigmoid输出（用于激活函数来着）

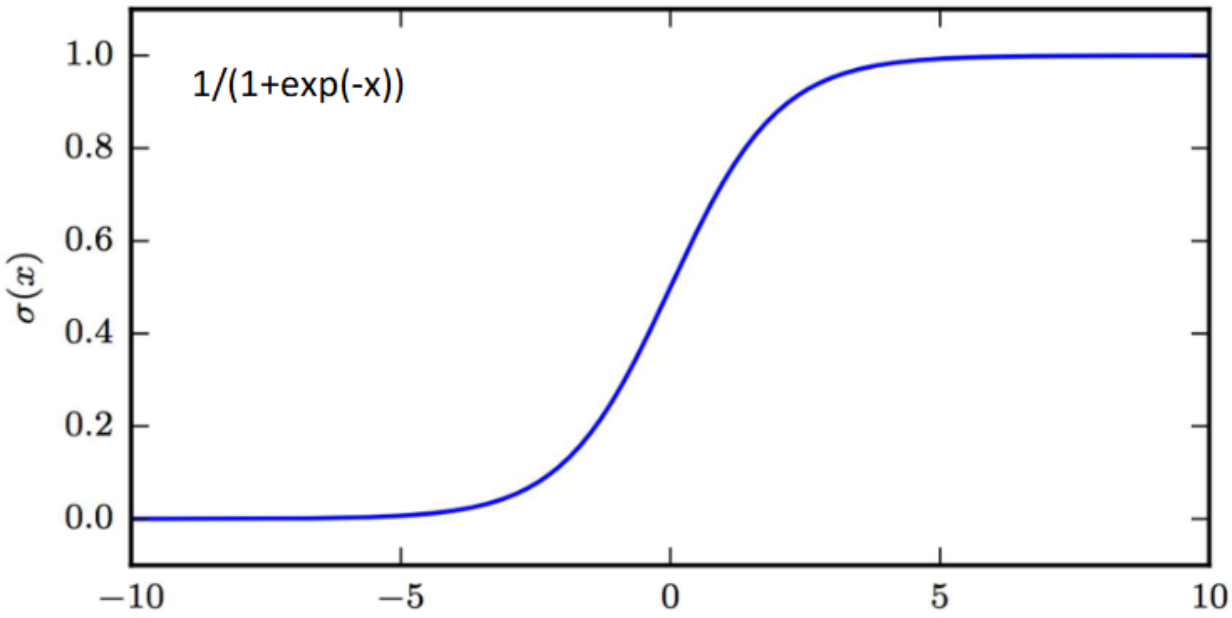


Figure 3.3: The logistic sigmoid function.

3. Multi-class classification: softmax输出（用于结果的输出）

$$\tilde{y}_i = \text{softmax}(x)_i = \frac{\exp(x_i)}{\sum_j \exp(x_j)}$$

Hidden units（注意梯度的计算公式）：

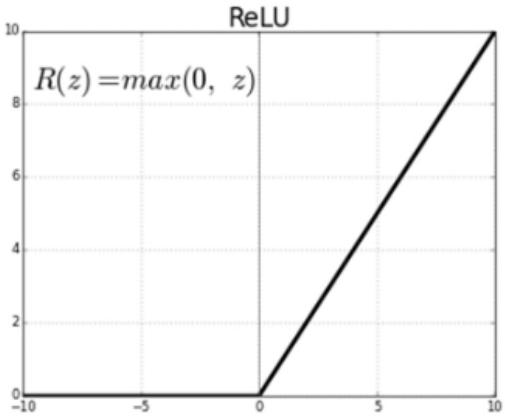
ReLU

- Most popular choice
- Activation

$$a = h(x) = \max(x, 0)$$

- Gradient

$$\frac{\partial a}{\partial x} = \begin{cases} 0, & \text{if } x \leq 0 \\ 1, & \text{if } x > 0 \end{cases}$$



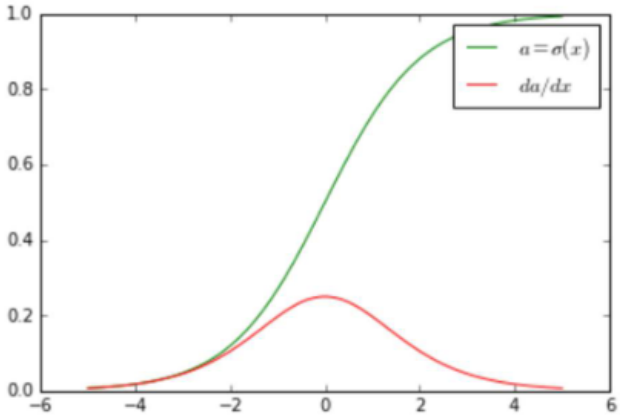
sigmoid

- Activation

$$a = \sigma(x) = \frac{1}{1 + e^{-x}}$$

- Gradient

$$\frac{\partial a}{\partial x} = \sigma(x)(1 - \sigma(x))$$



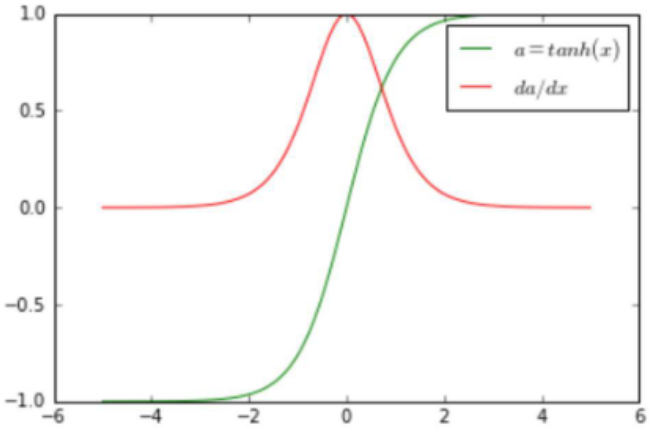
tanh

Activation

$$a = \tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$

Gradient

$$\frac{\partial a}{\partial x} = 1 - \tanh^{2}(x)$$



Architecture design

要思考的两个问题： 1. How many layers and units?

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The more layers we have, the fewer units we
need

2.How many connections?

Usually a complete set but in certain domains
we can drop some
connections
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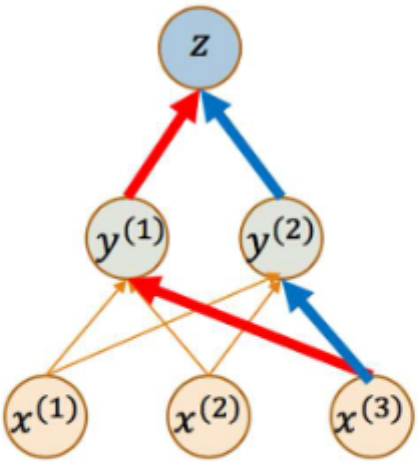
反向传播和梯度下降：



$$\frac{dz}{dx^3} = \frac{dz}{dy^1}\frac{dy^1}{dx^3} + \frac{dz}{dy^2}\frac{dy^2}{dx^3}$$

主要的计算定理： chain rule：

注意：z关于y的导数有的时候消不掉，要我们直接以隐函数的形式保留（高数内容）