

Dian AI培训

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Contents

- Machine Learning （机器学习）
- Deep Learning （深度学习）
- Deep Reinforcement Learning （深度强化学习）
- Homework

How to learn machine learning?

Courses:

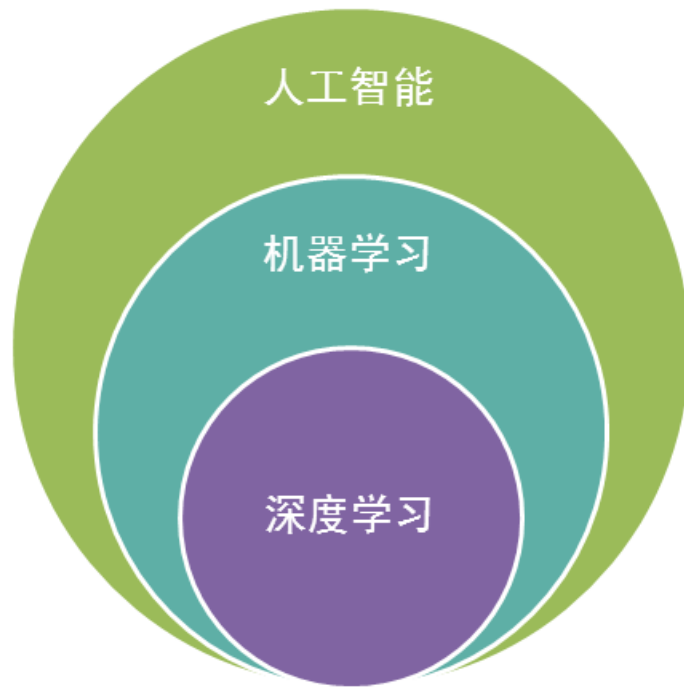
- Machine Learning - Adrew Ng
- CS231n - Convolutional Neural Networks for Visual Recognition
- CS224n - Natural Language Processing with Deep Learning
 - CS224n课程笔记-Hunto

Books:

- 机器学习-周志华
- Deep Learning - Ian Goodfellow and Yoshua Bengio and Aaron Courville
 - en: <http://www.deeplearningbook.org/>
 - cn: <https://github.com/exacity/deeplearningbook-chinese>

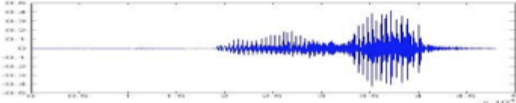
Relationship between AI,ML,DL

- AI: Artificial Intelligence
- ML: Machine Learning
- DL: Deep Learning



Machine Learning \approx Looking for a Function


- Speech Recognition

$$f(\text{  }) = \text{"How are you"}$$

- Image Recognition

$$f(\text{  }) = \text{"Cat"}$$

- Playing Go

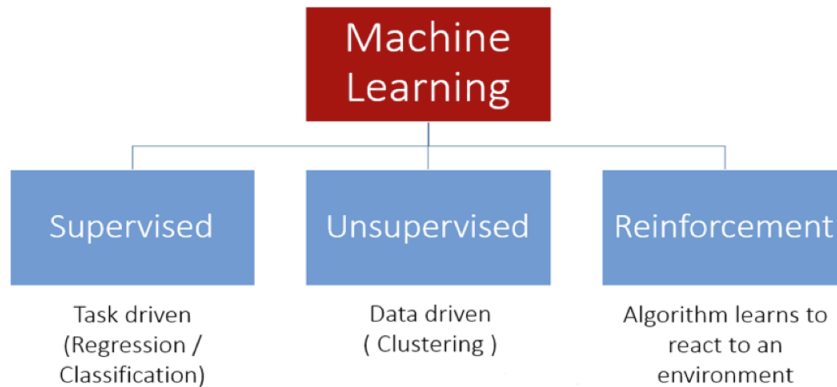
$$f(\text{  }) = \text{"5-5"}_{\text{(next move)}}$$

- Dialogue System

$$f(\text{ "Hi" }) = \text{ "Hello" }$$

(what the user said) (system response)

Types of Machine Learning



- Supervised Model(监督学习模型) : 任务驱动
训练数据带有标签
 - Regression
 - Classification
- Unsupervised Model(无监督学习模型) : 数据驱动
训练数据无标签
 - Clustering
- Reinforcement(强化学习) : 学习适应环境

Framework

A set of function: f_1, f_2, \dots, f_n

example

Image Recognition

$$f\left(\text{img}\right) = \text{"cat"}$$

Functions:

$$f_1\left(\text{img}\right) = \text{"cat"}$$

$$f_2\left(\text{img}\right) = \text{"money"}$$

$$f_1\left(\text{img}\right) = \text{"dog"}$$

$$f_2\left(\text{img}\right) = \text{"snake"}$$

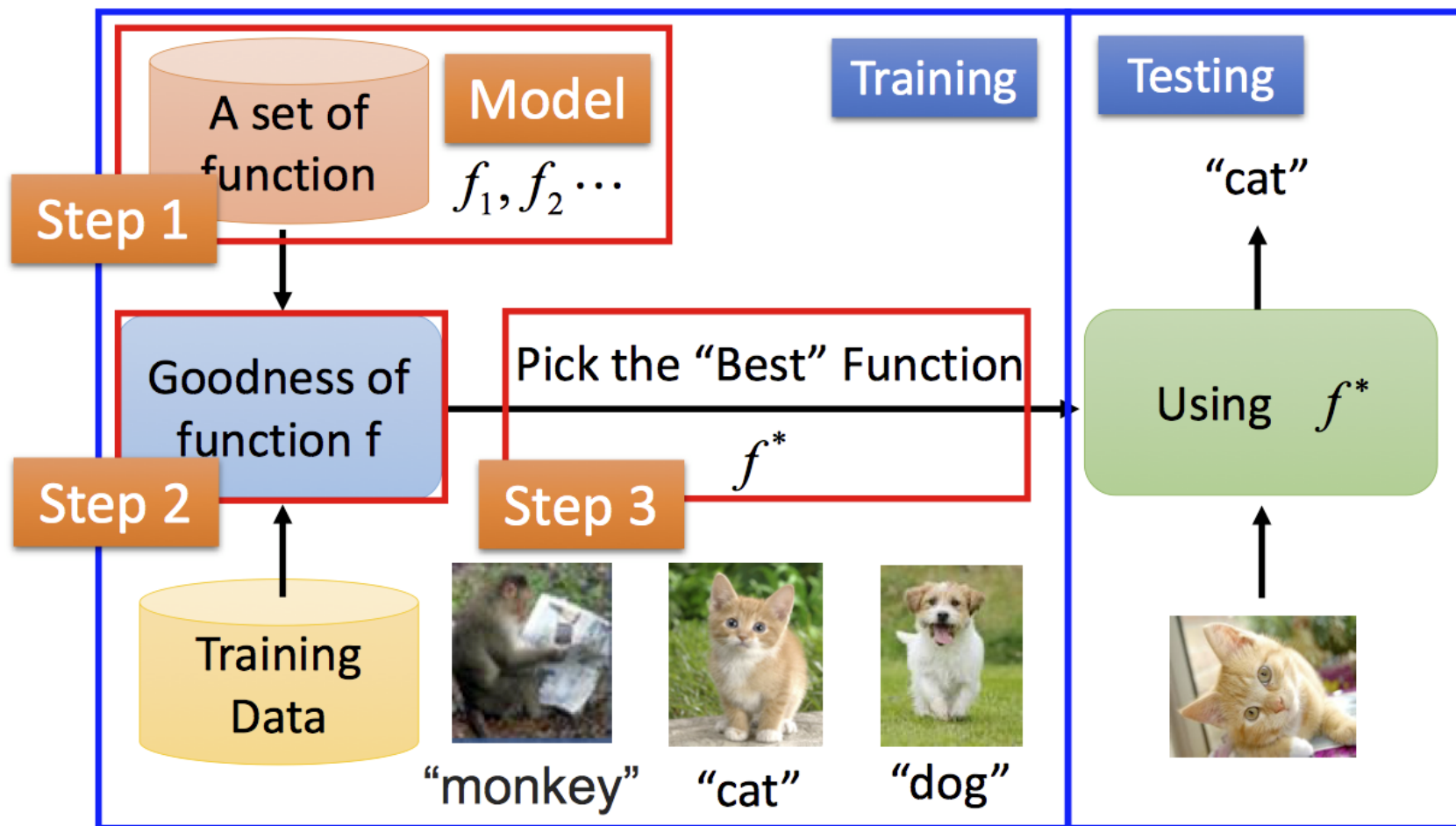
Framework



Supervised Learning

- We have **training data**.
- We have a **set of function**.
- $f(input) = f_{out}$, $cmp(real\ data, f_{out}) \Rightarrow f_{score}$
- Pick the "best" function.

Supervised learning



How to train a supervised model?

1. Find an appropriate cost function for your task
2. Minimize the cost function

Example

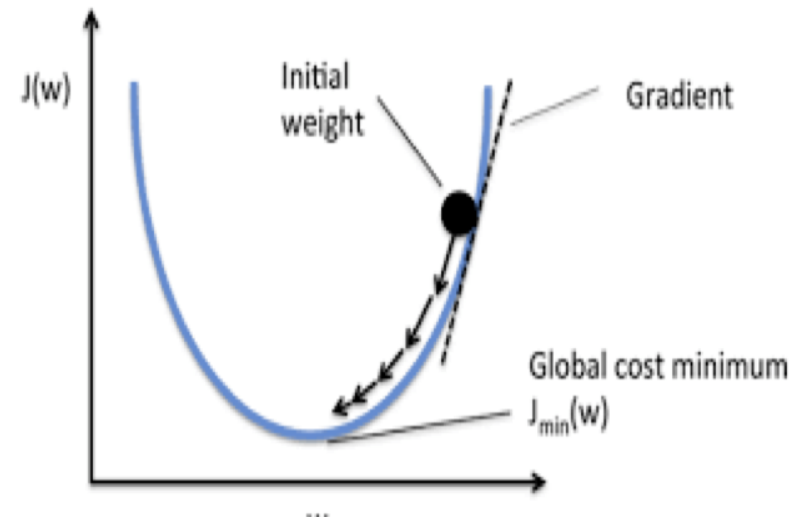
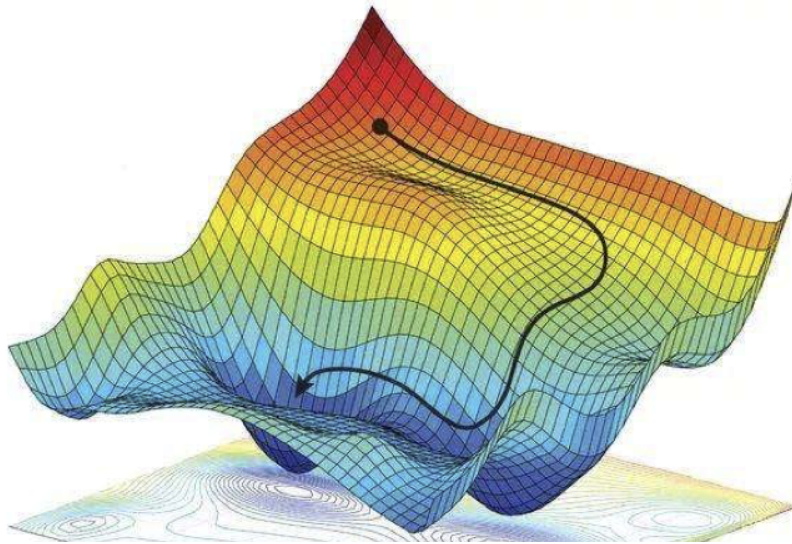
- Square loss for linear regression

$$C = \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

Minimize cost function

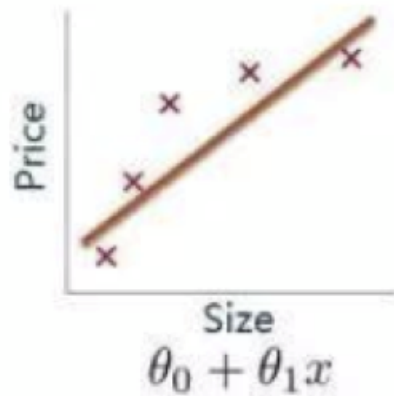
- Gradient descent

$$\theta_j = \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

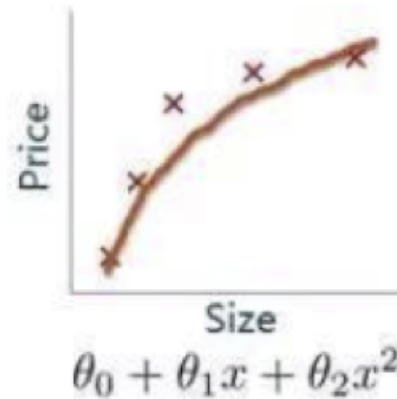


How to evaluation?

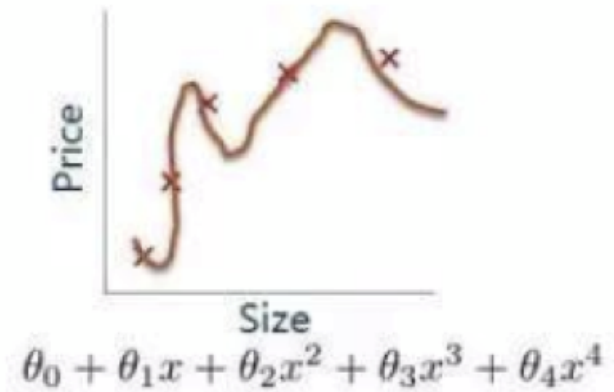
3 situations



Underfitting



Well-fitting



Overfitting

How to evaluation?

1. Split train and test dataset

train: usually $\frac{2}{3} \sim \frac{4}{5}$ of data

2. Train model on train dataset, and using test dataset to evaluation the model.

3. Evaluation methods:

- Accuracy (准确率)

- Recall (召回率)

- F-score (加权调和平均) : $F = \frac{(a^2+1)P \cdot R}{a^2(P+R)}$

$$a = 1 \Rightarrow F_1 = \frac{2 \cdot P \cdot R}{P+R}$$

- AUC

- ...

ML Pipeline

- Data collecting
- Feature engineering
- Model building
- Application
- Feedback and Optimization

Feature Engineering

- Feature is the limitation of model.
70% time for feature engineering, 30% time for modeling
- Manual features
 - Statistical features
 - Time series
 - Prior knowledge

Example: stock risk prediction

Model

Classification Model

- Logistic regression
- SVM (Supported Vector Machine)
- Decision Tree

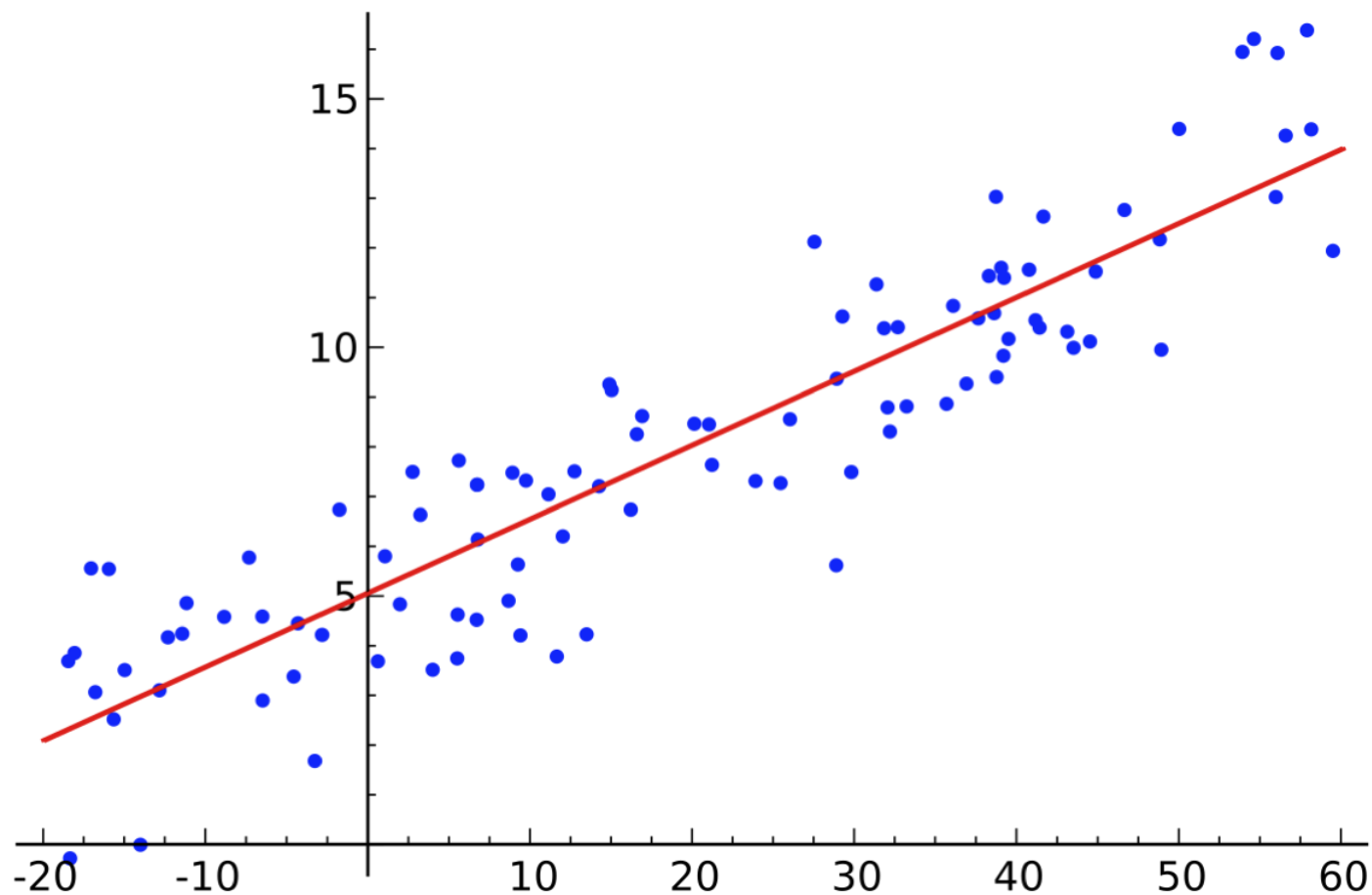
Regression Model

- Linear regression
- Non-linear regression

Clustering Model

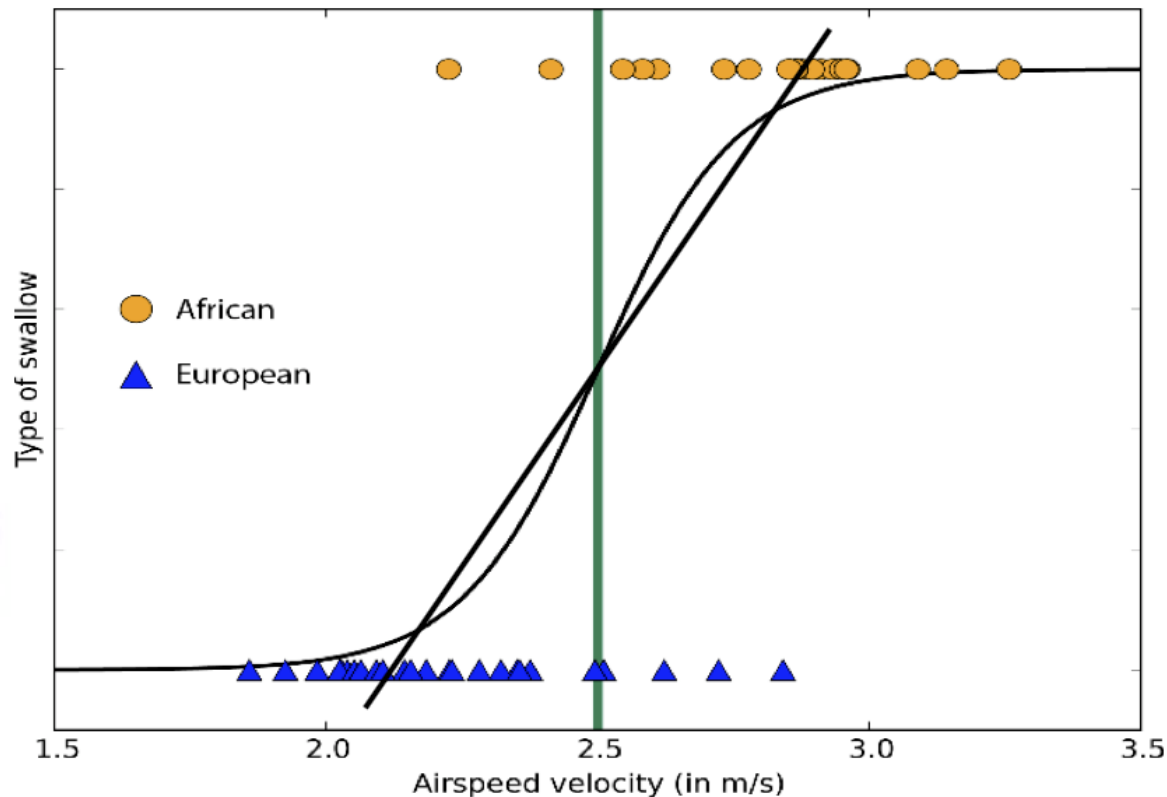
- K-means

Linear regression (线性回归)



$$g(x) = w_0 + w_1x_1 + \dots + w_nx_n$$

Logistic Regression (逻辑回归)



$$g(x) = w_0 + w_1x_1 + \dots + w_nx_n$$

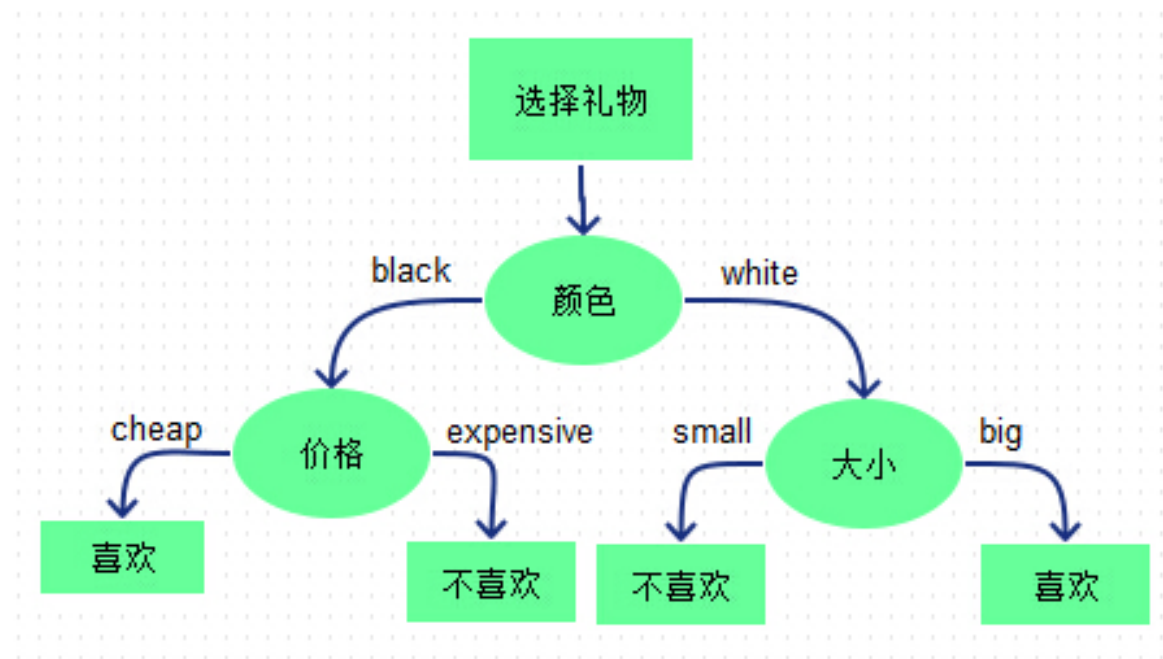
$$\text{sigmoid}(x) = \frac{1}{1+e^{-x}}$$

$$P(y = 1|x) = \text{sigmoid}(g(x)) = \frac{1}{1+e^{-g(x)}}$$

Decision Tree (决策树)

决策树是运用于分类的一种树结构，其中的每个内部节点代表对某一属性的一次测试，每条边代表一个测试结果，叶节点代表某个类或类的分布。

决策树的决策过程需要从决策树的根节点开始，待测数据与决策树中的特征节点进行比较，并按照比较结果选择选择下一比较分支，直到叶子节点作为最终的决策结果。



Deep Learning

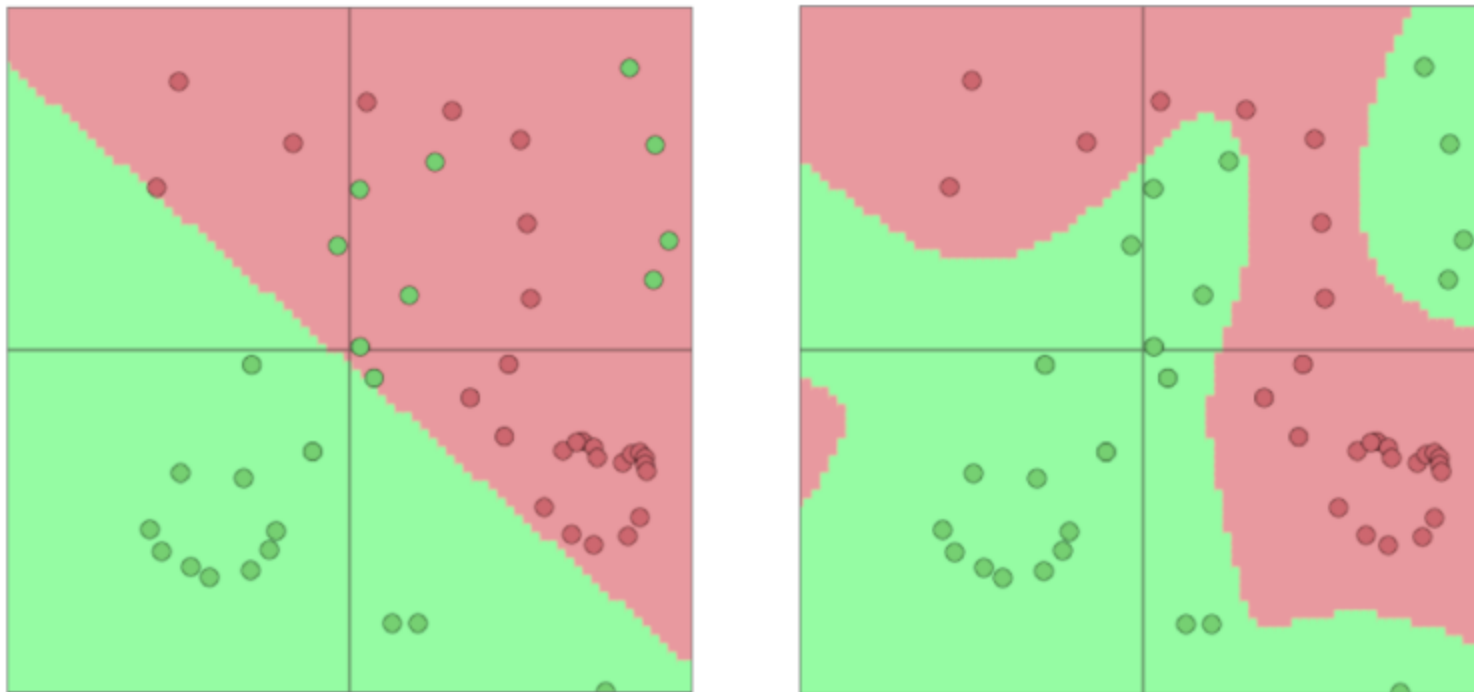
What's deep learning

Deep learning is a subfield of machine learning concerned with algorithms inspired by the structure and function of the brain called artificial neural networks.

Why deep learning is so hot?

- Coming up with features is difficult, time-consuming, requires expert knowledge. "Applied machine learning" is basically feature engineering. (Andrew Ng)
- But deep learning can automatically extract features!

传统机器学习的局限



Softmax(logistic regression)只有线性的决策边界，分类效果有限，当问题变得复杂时，效果不好，但神经网络可以学到复杂得多的特性和非线性决策边界。

Deep learning applications

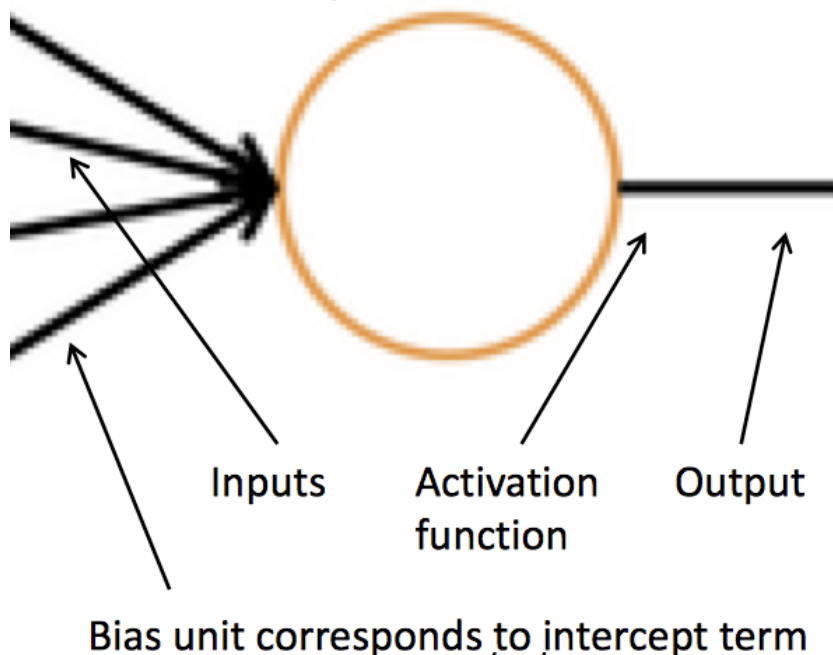
- Computer Vision:
 - Image Recognition
- Speech Recognition
- Natural Language Processing
 - Machine translation
 - Sentiment analysis
 - Text classification

From logistic regression to neural networks

神经网络的每一个神经元都是一个二分类逻辑回归单元。

A single neuron

A computational unit with n (3) inputs
and 1 output
and parameters W, b

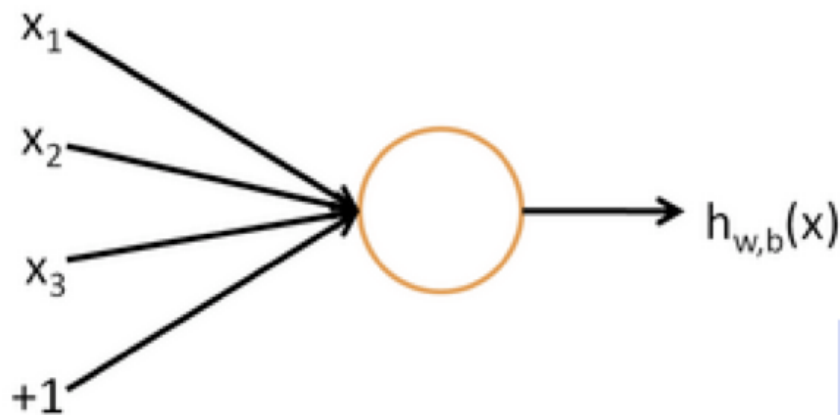
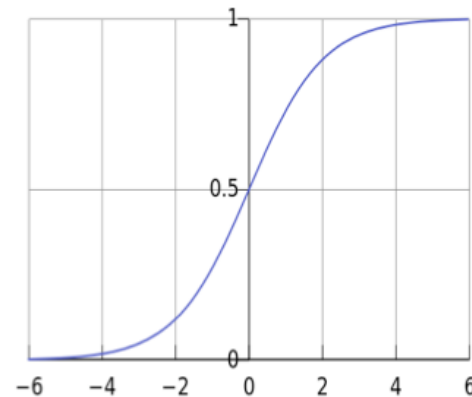


f = nonlinear activation fct. (e.g. sigmoid), w = weights, b = bias, h = hidden, x = inputs

$$h_{w,b}(x) = f(w^T x + b)$$

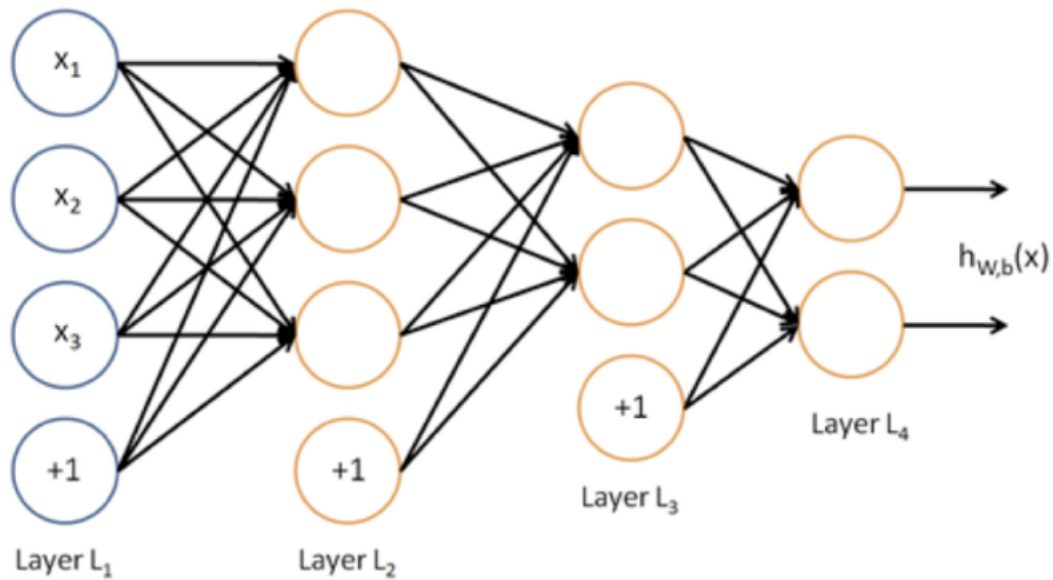
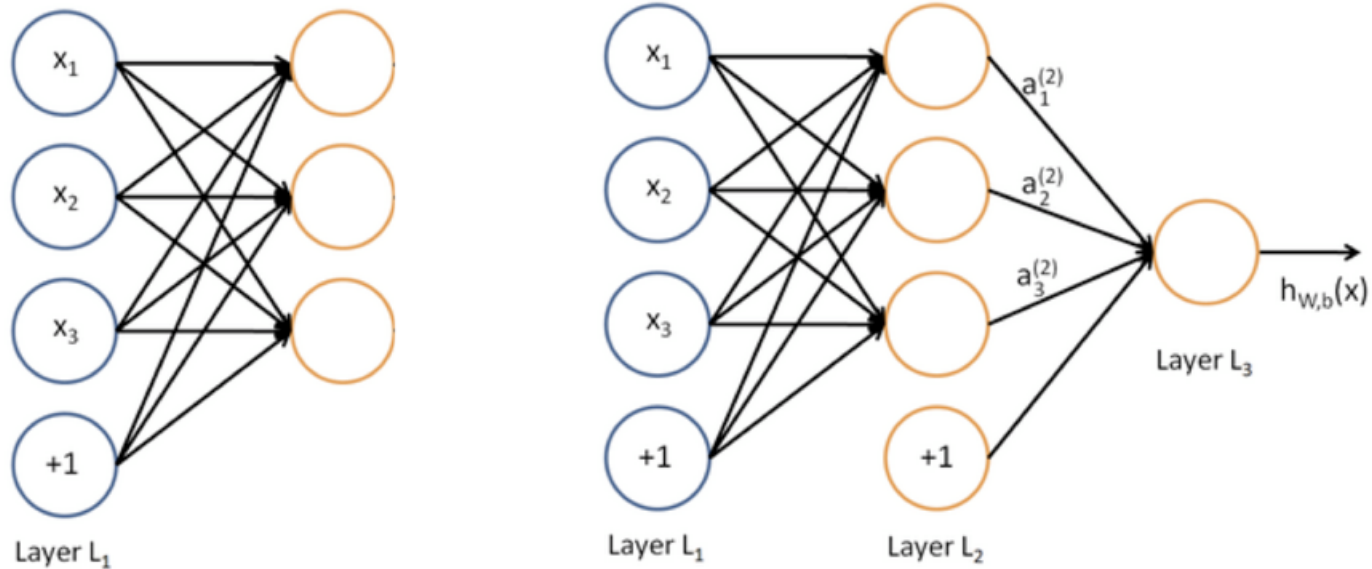
b : We can have an “always on” feature, which gives a class prior, or separate it out, as a bias term

$$f(z) = \frac{1}{1 + e^{-z}}$$



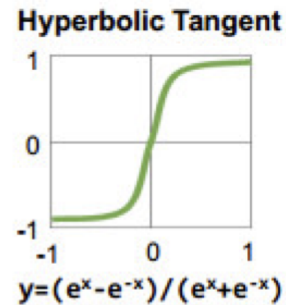
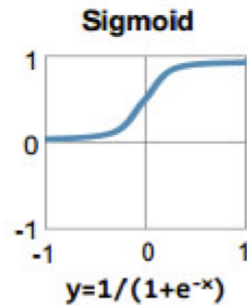
w, b are the parameters of this neuron
i.e., this logistic regression model

Multi-layer Neural Networks

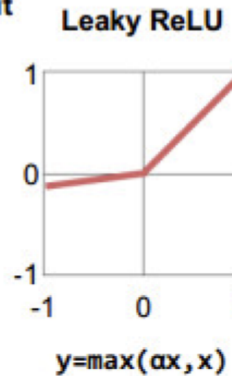
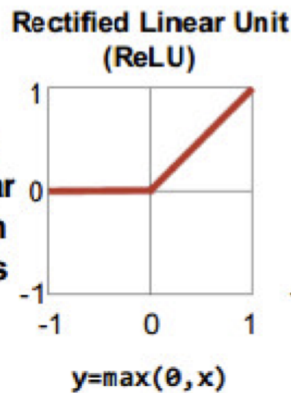


Activation function

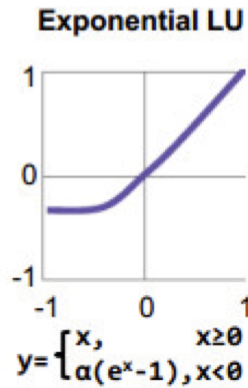
Traditional Non-Linear Activation Functions



Modern Non-Linear Activation Functions



$\alpha = \text{small const. (e.g. 0.1)}$

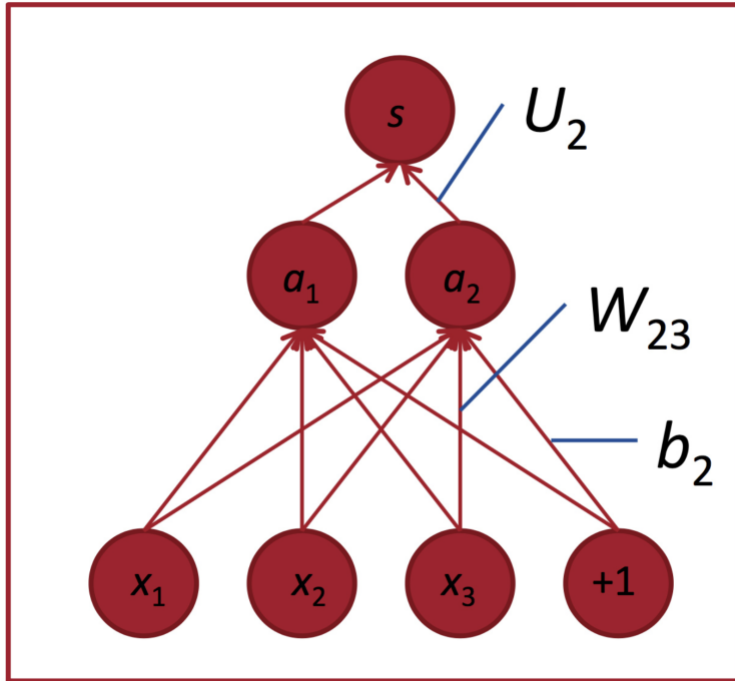


Why activation function must be non-linear ?

多层线性系统叠加仍然是线性系统。

$$x \cdot W_1 \cdot W_2 \cdot \dots \cdot W_n = x \cdot W$$

Feed-forward Computation



$$z = Wx + bw$$

$$a = f(z)$$

$$s = U^T a$$

Feed-forward computation

Example

1. We have $x = [0, 1, 2, 3]$

2. $z = Wx + b$, suppose $W_1 = 2, b_1 = 1, W_2 = 1, b = -1$
 $z_1 = [1, 3, 5, 7], z_2 = [-1, 0, 1, 2]$

3. Activation function, exp. : Softmax $f(x) = \frac{1}{1+e^{-x}}$

$$a_1 = [0.731, 0.952, 0.993, 0.999]$$

$$a_2 = [0.268, 0.5, 0.731, 0.880]$$

4. $s = U^T a$, suppose $U = [0.4, 0.6]$

$$s = [0.4, 0.6]^T \cdot [a_1, a_2] = [0.453, 0.680, 0.836, 0.928]$$

Loss Function

softmax & cross-entropy loss(交叉熵损失)

- softmax

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

- cross-entropy loss

$$CE(y, \hat{y}) = - \sum_{j=1}^{|V|} y_j \log \hat{y}_j$$

- softmax cross-entropy loss

$$J(\theta) = - \sum_{j=1}^{|V|} y_j \log(\text{softmax}(s_j))$$

Loss Function

Example

1. We have $x = [0, 1, 2, 3]$

$$2. z = Wx + b$$

3. Activation function, exp. : Softmax $f(x) = \frac{1}{1+e^{-x}}$

$$4. s = U^T a$$

$$s = [0.453, 0.680, 0.836, 0.928]$$

$$5. \hat{y} = softmax(s)$$

$$\hat{y}_1 = [0.323, 0.257, 0.220, 0.201]$$

6. Loss $J = - \sum_{j=1}^{|V|} y_j \log(softmax(s_j))$, suppose

$$y = [1, 0, 0, 0]$$

$$e = 1.130$$

Backpropagation (反向传播)

Multi-layer neural networks

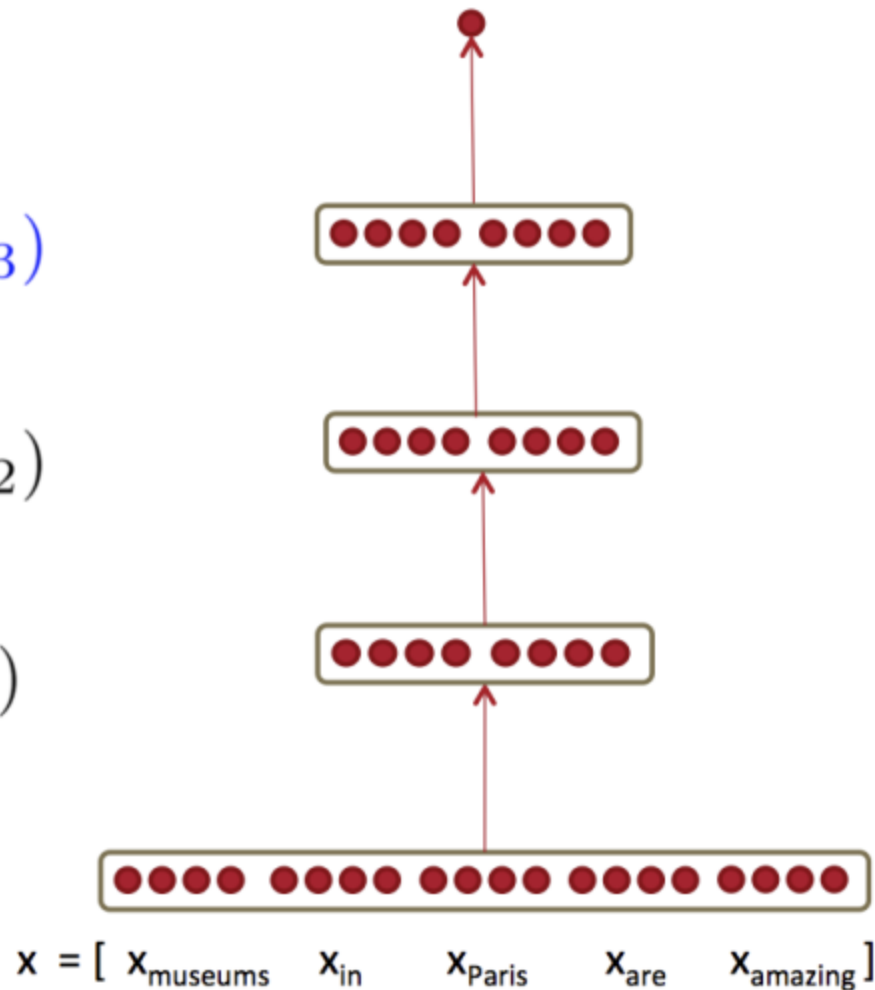
$$s = u^T h_3$$

$$h_3 = f(W_3 h_2 + b_3)$$

$$h_2 = f(W_2 h_1 + b_2)$$

$$h_1 = f(W_1 x + b_1)$$

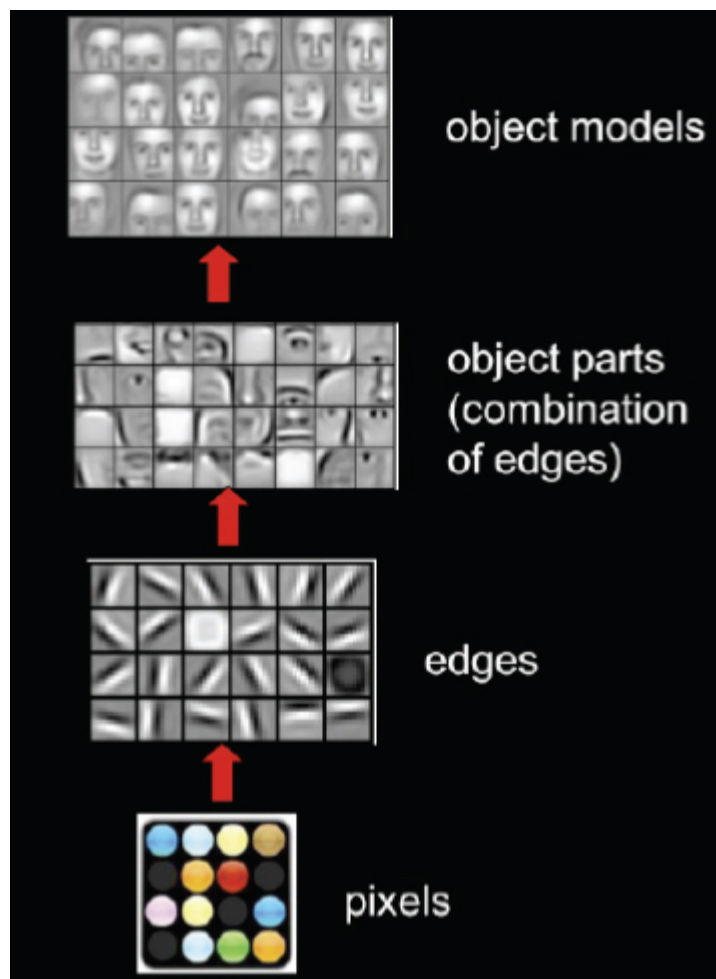
x (input)



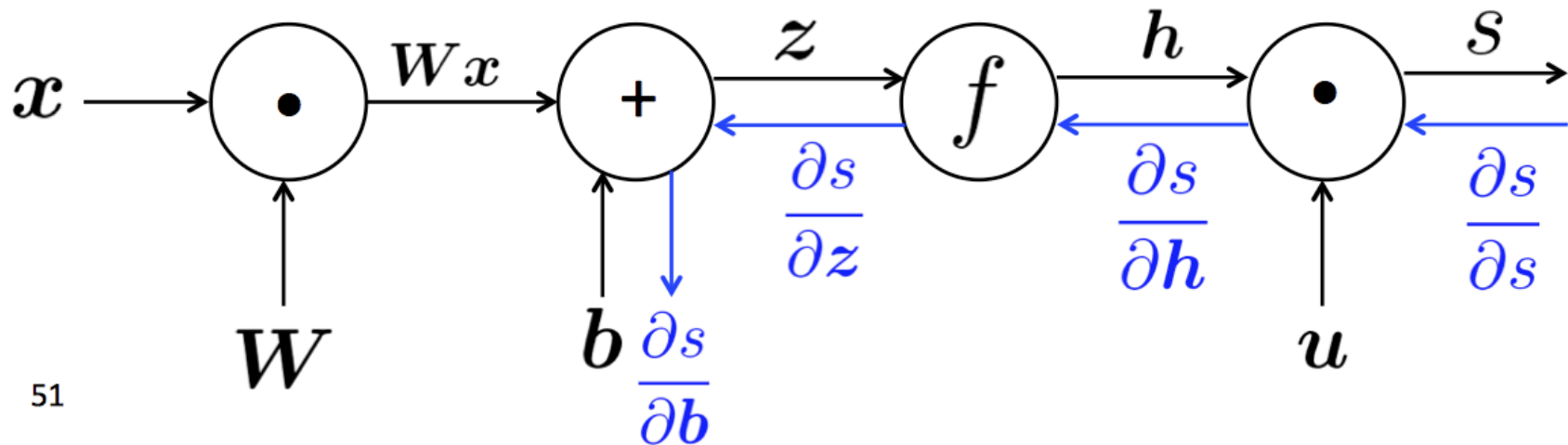
Backpropagation

Why we need multi-layer nets?

层数越多，可以表达的问题越复杂



Feed-forward & Backpropagation



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Why?

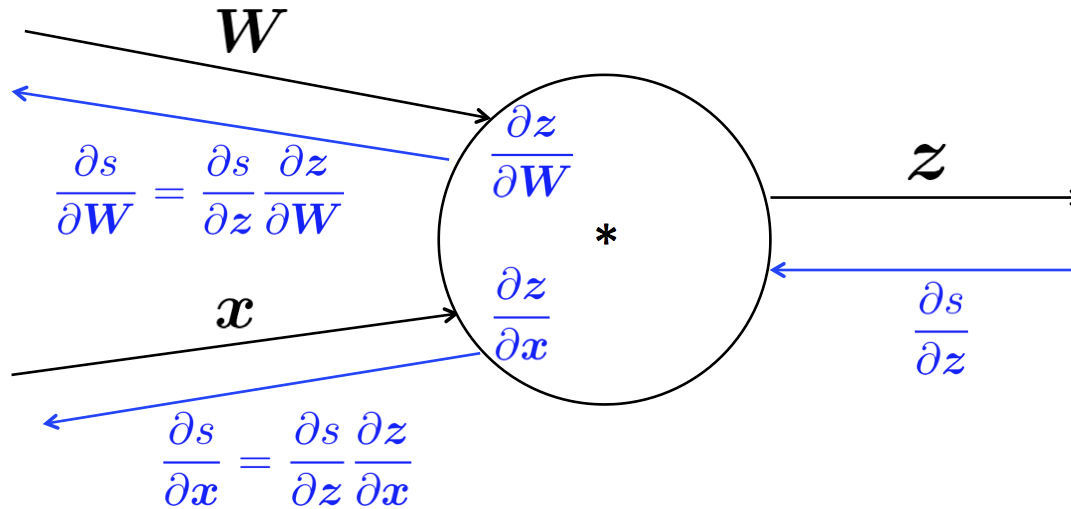
- Chain Rule (链式法则)

$$(g \circ f)'(x) = [g(f(x))]' = g'(f(x))f'(x) = \frac{du}{dx} \cdot \frac{dy}{dx}$$

Backpropagation

- Multiple inputs -> multiple local gradients

$$z = Wx$$



Downstream
gradients

Local
gradients

Upstream
gradient

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Chain Rule

$$u = g(y_1, y_2, \dots, y_n), y = f(x_1, x_2, \dots, x_n)$$

$$\frac{\partial u}{\partial x_i} = \sum_{j=1}^n \frac{\partial g}{\partial y_j} \cdot \frac{\partial y_j}{\partial x_i}$$

Optimizer

- SGD (Stochastic Gradient Descent / Mini-batch Gradient Descent)
 - Gradient Descent in a mini batch(a part of trainset)
- Momentum 90
- Adam(Adaptive Moment Estimation)

Review

Steps to train a neural network:

- Process train data: data to vector, split train/dev data.
- Initialize network weights.
- Feed-forward computation: input x \rightarrow output score.
- Cost computation: score vs. real y \rightarrow error.
- Backpropagation: propagate loss back.
- Optimizer: update weights.

Deep Reinforcement Learning

Closest to Artificial General Intelligence(AGI)

- It's the learning paradigm of biological.
- RL provides the resource of data.
- DL automatically extract features.
- When there's a general method for machine to build models, AGI will come.

Homework

- 深入了解本次培训的内容，如神经网络、激活函数等
- 熟悉深度学习框架Pytorch
 - [Pytorch Tutorials](#)
 - [Pytorch 中文教程](#)
- 使用Pytorch实现一个全连接神经网络，对[MINIST数据集](#)进行分类，有余力的同学可以尝试在[cifar-10](#)上的效果。