

# notes3 basic of machine learning

1. 数据集
2. 误差分析
3. 代表的机器学习方法
  1. 有监督、线性回归、SVM、决策树、RF
  2. 无监督、聚类、降维 (PCA)

## machine learning

### concept

#### category

- SupervisedLearning ( Category, Regression)
- UnsupervisedLearning (Converge, decrease dimension)
- Reinforcement Learning

### dataset

like this,  $D = x_1, x_2, \dots, x_n$  includes  $n$  samples,  $x_i$  is a vector, which shows  $i$  sample in the dataset.  $d$  is the space dimension

#### category of dataset

- Trainingset
- Validation set
- Testset

#### classic dataset

- 图像分类
  - MNIST <http://yann.lecun.com/exdb/mnist/>
  - CIFAR-10, CIFAR-100, ImageNet
    - <https://www.cs.toronto.edu/~kriz/cifar.html>
    - <http://www.image-net.org/>
  - Large Movie Review Dataset v1.0
    - <http://ai.stanford.edu/~amaas/data/sentiment/>

- 数据集:<https://github.com/researchmm/img2poem>

# error analysis

over fitting等

lack fitting

## general error analysis

$$\begin{aligned}\text{Err}(\hat{f}) &= \mathbb{E} \left[ (Y - \hat{f}(X))^2 \right] \\ \text{Err}(\hat{f}) &= \mathbb{E} \left[ (f(X) + \varepsilon - \hat{f}(X))^2 \right] \\ \text{Err}(\hat{f}) &= \mathbb{E} \left[ (f(X) - \hat{f}(X))^2 + 2\varepsilon(f(X) - \hat{f}(X)) + \varepsilon^2 \right] \\ \text{Err}(\hat{f}) &= \mathbb{E} \left[ (E(\hat{f}(X)) - f(X) + \hat{f}(X) - E(\hat{f}(X)))^2 \right] + \sigma_\varepsilon^2 \\ \text{Err}(\hat{f}) &= \mathbb{E}[(E(\hat{f}(X)) - f(X))]^2 + \mathbb{E} \left[ (\hat{f}(X) - E(\hat{f}(X)))^2 \right] + \sigma_\varepsilon^2 \\ \text{Err}(\hat{f}) &= \text{Bias}^2(\hat{f}) + \text{Var}(\hat{f}) + \sigma_\varepsilon^2\end{aligned}$$

bias and variance

## cross verification

# supervised

- 数据集有标记(答案)
- 数据集通常扩展为 $(x_i, y_i)$ ，其中 $y_i \in Y$ 是 $x_i$ 的标记， $Y$ 是所有标记的集合，称为“标记空间”或“输出空间”
- 监督学习的任务是训练出一个模型用于预测 $y$ 的取值，根据 $D = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ ，训练出函数 $f$ ，使得 $f(x) \cong y$
- 若预测的值是离散值，如年龄，此类学习任务称为“分类”
- 若预测的值是连续值，如房价，此类学习任务称为“回归”

## linear regression

$$f(x^k) = w_1 x_1^k + w_2 x_2^k + \dots + w_m x_m^k + b = \sum_{i=1}^m w_i x_i^k + b$$

$$(w^*, b^*) = \operatorname{argmin}_{(w,b)} \sum_{k=1}^n (f(x^k) - y^k)^2 = \operatorname{argmin}_{(w,b)} \sum_{k=1}^n (w^T x^k + b - y^k)^2$$

## logistic regression

$$g(f(x^k)) = \begin{cases} 1, & \frac{1}{1+e^{-(w^T x^k + b)}} \geq 0.5 \\ 0, & \text{otherwise} \end{cases}$$

## support SVM

$$x = x_0 + \gamma \frac{w}{\|w\|} \quad (1)$$

$$\gamma = \frac{w^T x + b}{\|w\|} = \frac{f(x)}{w} \quad (2)$$

$$\begin{aligned} & \arg \max_{w,b} \arg \min_{x_i \in D} \frac{|w^T x_i + b|}{\sqrt{\sum_{i=1}^d w_i^2}} \\ & s.t. \forall x_i \in D, y_i(w^T x_i + b) \geq 0 \end{aligned}$$

$$\forall x_i \in D, |w^T x_i + b| \geq 1.$$

$$\begin{aligned} & \arg \min_{w,b} \frac{1}{2} \sum_{i=1}^d w_i^2 \\ & s.t. \forall x_i \in D, |w^T x_i + b| \geq 1 \end{aligned}$$

## decision making tree

Based on data structure Tree

## unsupervised

### converage

classic algorithm: K-means

### lower dimension