

19 Linear models

Note: NN and SVM are linear classifiers

Univariable LR : $W = [w_0(h), w_1]$

$$X = [1, x_1]$$

find a line :
 $\hat{y} = h_w(x) = W \cdot x$
 fits best the data

$$L(y, \hat{y}) = \begin{matrix} L_1(y, \hat{y}) = |y - \hat{y}| \\ L_2(y, \hat{y}) = (y - \hat{y})^2 \end{matrix}$$

加上 Loss function, 改写为:

$$\begin{aligned} W^* &= \underset{W}{\operatorname{argmin}} L(W) \\ &= \underset{W}{\operatorname{argmin}} \sum_{j=1}^N (y_j - (w_1 x_j + w_0))^2 \end{aligned}$$

其中, N 为 Sample 的数量

w_1 和 w_{ocb}) 可以直接算出来, 见 slides

general learning :

$$w^* = \underset{w}{\operatorname{argmin}} L(hw)$$

gradient descent: for every w_i :

$$w_i \leftarrow w_i - \alpha \frac{\partial}{\partial w_i} L(w)$$

↑
 update rule

↓
 learning rate

↓
 loss func along w_i axis

eg. $w_0 \leftarrow w_0 - \alpha \sum_j (y_j - h w(x_j))$
 $w_1 \leftarrow w_1 - \alpha \sum_j (y_j - h w(x_j)) x_j$

{ batch gd : use all train data
 promise to converge but slow
 stochastic gd : { random
 apply single point update
 decreasing learning rate (like simulate annealing)
 not guarantee to converge but faster

multi-variable linear regression :

$$w^* = \operatorname{argmin}_w \sum_j L_2(y_j, w \cdot x_j)$$

Classification : decision boundary : path (surface) that separates two classes

linear separator $\checkmark \Rightarrow$ linearly separable

$$\begin{aligned}
 h_w(x) &= \text{Threshold}(w \cdot x) \\
 w^* &= \operatorname{argmin}_w L(h_w)
 \end{aligned}$$

Regression : 连续式 ...
 classifier : sigmoid ...

perceptron learning rule :

$$w_i \leftarrow w_i + \alpha(y - h_w(x)) \times x_i$$

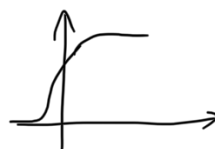
hard threshold :



un-predictable
not robust to noise

Logistic regression :

Soft threshold :
(sigmoid)



more predictable
robust to noise

