

Reference Page

Decision Trees

Let D be the data, C be the class attribute, and A be an attribute (which could be C). The accessor $A.values$ denotes the values of attribute A .

$$Info(D) = \sum_{i \in C.values} -\frac{|D_i|}{|D|} * \log_2 \left(\frac{|D_i|}{|D|} \right) \quad (1)$$

$$Info(A, D) = \sum_{j \in A.values} \frac{|D_j|}{|D|} * Info(D_j) \quad (2)$$

$$Gain(A, D) = Info(D) - Info(A, D) \quad (3)$$

$$GainRatio(A, D) = \frac{Gain(A, D)}{SplitInfo(A, D)} \quad (4)$$

$$\begin{aligned} SplitInfo(A, D) &= Info(D) \text{ considering } A \text{ as the class attribute } C. \\ &= \sum_{i \in A.values} -\frac{|D_i|}{|D|} * \log_2 \left(\frac{|D_i|}{|D|} \right) \end{aligned} \quad (5)$$

Support Vector Machines

$$\text{Primal: } \min_{w, b} \frac{1}{2} \|w\|^2 \text{ s.t. } \forall i \ y_i(w \cdot x - b) \geq 1 \quad (6)$$

$$\text{Dual: } \min_{\alpha} \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) - \sum_{i=1}^N \alpha_i \text{ s.t. } \sum_{i=1}^N y_i \alpha_i = 0 \text{ and } \forall i \ \alpha_i \geq 0 \quad (7)$$

Probability Theory

$$P(A_1, \dots, A_m \mid B_1, \dots, B_n) = \frac{P(B_1, \dots, B_n \mid A_1, \dots, A_m) P(A_1, \dots, A_m)}{P(B_1, \dots, B_n)} \quad (8)$$

$$P(A_1, \dots, A_m \mid B_1, \dots, B_n) = \frac{P(A_1, \dots, A_m, B_1, \dots, B_n)}{P(B_1, \dots, B_n)} \quad (9)$$

Logistic Regression

$$P(y = 1 \mid x) = \frac{\exp(x\beta)}{1 + \exp(x\beta)} \quad (10)$$

$$P(y = 0 \mid x) = 1 - P(y = 1 \mid x) \quad (11)$$

$$l(\beta) = \sum_{i=1}^n [y_i \log P(y_i = 1 \mid x_i) + (1 - y_i) \log P(y_i = 0 \mid x_i)] \quad (12)$$

AdaBoost

$$h_t = \arg_{h_t} \min \epsilon_t \text{ where } \epsilon_t = \sum_{i=1}^N w_t(x_i) \mathbb{1}[y_i \neq h_t(x_i)] \quad (13)$$

$$\alpha_t = \frac{1}{2} \ln \frac{1 - \epsilon_t}{\epsilon_t} \quad (14)$$

$$w_{t+1}(x_i) = \frac{w_t(x_i) \exp(-\alpha_t y_i h_t(x_i))}{Z_t} \text{ where } Z_t = \sum_{i=1}^N w_t(x_i) \exp(-\alpha_t y_i h_t(x_i)) \quad (15)$$

$$H(x) = \text{sign} \left(\sum_{t=1}^T \alpha_t h_t(x) \right) \quad (16)$$

Reinforcement Learning

$$R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \quad (17)$$

$$V^\pi(s) = E_\pi\{R_t | s_t = s\} = \sum_a \pi(s, a) \sum_{s'} P_{s, s'}^a (R_{s, s'}^a + \gamma V^\pi(s')) \quad (18)$$

$$\text{TD-update rule: } V(s_t) \leftarrow V(s_t) + \alpha [r_{t+1} + \gamma V(s_{t+1}) - V(s_t)] \quad (19)$$

$$\text{Q-update rule: } Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha [r_{t+1} + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)] \quad (20)$$