Reference Page

Probability Theory and Bayesian Networks

$$P(A_1,\ldots,A_m|B_1,\ldots,B_n) = \frac{P(B_1,\ldots,B_n|A_1,\ldots,A_m)P(A_1,\ldots,A_m)}{P(B_1,\ldots,B_n)} \tag{1}$$

$$P(A_1,\ldots,A_m|B_1,\ldots,B_n) = \frac{P(A_1,\ldots,A_m,B_1,\ldots,B_n)}{P(B_1,\ldots,B_n)} \tag{2}$$

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.

$$\mathit{Info}(D) = \sum_{i \in C.values} -\frac{|D_i|}{|D|} * \log_2\left(\frac{|D_i|}{|D|}\right) \tag{3}$$

$$\mathit{Info}(A,D) = \sum_{j \in A.values} \frac{|D_j|}{|D|} * \mathit{Info}(D_j) \tag{4}$$

$$\mathit{Gain}(A,D) = \mathit{Info}(D) - \mathit{Info}(A,D) \tag{5}$$

$$\mathit{GainRatio}(A,D) = \frac{\mathit{Gain}(A,D)}{\mathit{SplitInfo}(A,D)} \tag{6}$$

$$\begin{aligned}\mathit{SplitInfo}(A,D) &= \mathit{Info}(D) \text{ considering } A \text{ as the class attribute } C. \\ &= \sum_{i \in A.values} -\frac{|D_i|}{|D|} * \log_2\left(\frac{|D_i|}{|D|}\right)\end{aligned} \tag{7}$$

Reinforcement Learning

$$R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \tag{8}$$

$$V^\pi(s) = E_\pi\{R_t|s_t = s\} \tag{9}$$

$$\text{TD-update rule: } V(s_t) \leftarrow V(s_t) + \alpha\left[r_{t+1} + \gamma V(s_{t+1}) - V(s_t)\right] \tag{10}$$

$$\text{Q-update rule: } Q(s_t,a_t) \leftarrow Q(s_t,a_t) + \alpha\left[r_{t+1} + \gamma Q(s_{t+1},a_{t+1}) - Q(s_t,a_t)\right] \tag{11}$$