

HW 1 – Machine Learning

Mathematics behind the decision tree

Let a group of laws: $R = \{r_1, r_2, \dots, r_k\}$. Every law r_i has m_i^ϕ don't care bits (ϕ).

The number of times each law appears depends on the number of don't care bits it has: $N_{r_i} = 2^{m_i^\phi}$

In total the number of laws (after duplicates) is: $N_{tot} = \sum_{i=1}^k N_{r_i}$

Our goal is to compute the Information Gain (IG) - $IG(R, b_j) = H(R) - H(R | b_j)$

$$\begin{aligned} H(R) &= - \sum_{i=1}^k \frac{N_{r_i}}{N_{tot}} \cdot \log_2 \left(\frac{N_{r_i}}{N_{tot}} \right) \\ &= \frac{1}{N_{tot}} (\log_2(N_{tot}) \cdot \sum_{i=1}^k N_{r_i} - \sum_{i=1}^k N_{r_i} \log_2(N_{r_i})) \\ &= \log_2(N_{tot}) - \frac{1}{N_{tot}} \sum_{i=1}^k N_{r_i} \log_2(N_{r_i}) \end{aligned}$$

To compute $H(R | b_j)$ we need to evaluate separately the cases for which $b_j = 0$ and $b_j = 1$.

- $b_j = 0$: Contains the laws for which $b_j = 0$ and the ones where $b_j = \phi \rightarrow$ In total N_0 laws
- Same for $b_j = 1$
- $N_{tot} = N_0 + N_1$

$$\begin{aligned} H(R | b_j = 0) &= - \sum_{b_j=0} \frac{N_{r_i}}{N_0} \cdot \log_2 \left(\frac{N_{r_i}}{N_0} \right) - \sum_{b_j=\phi} \frac{\frac{N_{r_i}}{2}}{N_0} \cdot \log_2 \left(\frac{\frac{N_{r_i}}{2}}{N_0} \right) \\ &= \frac{1}{N_0} \left[N_0 \cdot \log_2(N_0) - \sum_{b_j=0} N_{r_i} \log_2(N_{r_i}) - \frac{1}{2} \sum_{b_j=\phi} N_{r_i} (\log_2(N_{r_i}) - \log_2(N_0) - 1) \right] \\ &= \log_2(N_0) - \frac{1}{N_0} \left[\sum_{b_j=0} N_{r_i} \log_2(N_{r_i}) + \sum_{b_j=\phi} \frac{N_{r_i}}{2} \log_2(N_{r_i}) - \sum_{b_j=\phi} \frac{N_{r_i}}{2} \right] \end{aligned}$$

$$\begin{aligned} H(R | b_j) &= \frac{N_0}{N_{tot}} \cdot H(R | b_j = 0) + \frac{N_1}{N_{tot}} \cdot H(R | b_j = 1) \\ &= \frac{1}{N_{tot}} \left[N_0 \cdot \log_2(N_0) - \sum_{b_j=0} N_{r_i} \log_2(N_{r_i}) - \sum_{b_j=\phi} \frac{N_{r_i}}{2} \log_2(N_{r_i}) + \sum_{b_j=\phi} \frac{N_{r_i}}{2} + N_1 \right. \\ &\quad \left. \cdot \log_2(N_1) - \sum_{b_j=1} N_{r_i} \log_2(N_{r_i}) - \sum_{b_j=\phi} \frac{N_{r_i}}{2} \log_2(N_{r_i}) + \sum_{b_j=\phi} \frac{N_{r_i}}{2} \right] \end{aligned}$$

$$\begin{aligned}
&= \frac{1}{N_{tot}} \left[N_0 \cdot \log_2(N_0) + N_1 \cdot \log_2(N_1) + \sum_{b_j=\phi} N_{r_i} - \sum_{b_j=1} N_{r_i} \log_2(N_{r_i}) \right. \\
&\quad \left. - \sum_{b_j=0} N_{r_i} \log_2(N_{r_i}) - \sum_{b_j=\phi} N_{r_i} \log_2(N_{r_i}) \right] \\
&= \frac{1}{N_{tot}} \left[N_0 \cdot \log_2(N_0) + N_1 \cdot \log_2(N_1) + \sum_{b_j=\phi} N_{r_i} - \sum_{i=1}^k N_{r_i} \log_2(N_{r_i}) \right]
\end{aligned}$$

Hence, we found:

$$IG(R, b_j) = H(R) - H(R | b_j) = \log_2(N_{tot}) - \frac{1}{N_{tot}} \left[N_0 \cdot \log_2(N_0) + N_1 \cdot \log_2(N_1) + \sum_{b_j=\phi} N_{r_i} \right]$$

Where:

$$N_0 = \sum_{b_j=0} N_{r_i} + \frac{1}{2} \cdot \sum_{b_j=\phi} N_{r_i}, \quad N_1 = \sum_{b_j=1} N_{r_i} + \frac{1}{2} \cdot \sum_{b_j=\phi} N_{r_i}$$

From the obtained result we can go a bit further by replacing the values of $N_{r_i} = 2^{m_i^\phi}$:

$$N_0 = \sum_{b_j=0} 2^{m_i^\phi} + \sum_{b_j=\phi} 2^{m_i^\phi - 1} = N_0^j + N_\phi^j$$

$$N_1 = \sum_{b_j=1} 2^{m_i^\phi} + \sum_{b_j=\phi} 2^{m_i^\phi - 1} = N_1^j + N_\phi^j$$

$$N_{tot} = N_0 + N_1 = N_0^j + N_1^j + 2N_\phi^j$$

$$\begin{aligned}
IG(R, b_j) &= \log_2(N_{tot}) \\
&\quad - \frac{1}{N_{tot}} \left[(N_0^j + N_\phi^j) \log_2(N_0^j + N_\phi^j) + (N_1^j + N_\phi^j) \log_2(N_1^j + N_\phi^j) + 2N_\phi^j \right]
\end{aligned}$$

$$\log_2(N_{r_i}) = \log_2(2^{m_i^\phi}) = m_i^\phi \Rightarrow H(R) = \log_2(N_{tot}) - \frac{1}{N_{tot}} \sum_{i=1}^k m_i^\phi \cdot 2^{m_i^\phi}$$

$$N_0 = \sum_{b_j=0} 2^{m_i^\phi} + \sum_{b_j=\phi} 2^{m_i^\phi-1} = N_0^j + N_\phi^j, \quad N_1 = \sum_{b_j=1} 2^{m_i^\phi} + \sum_{b_j=\phi} 2^{m_i^\phi-1} = N_1^j + N_\phi^j$$

$$\begin{aligned} H(R | b_j = 0) &= - \sum_{b_j=0} \frac{2^{m_i^\phi}}{N_0^j + N_\phi^j} \cdot [m_i^\phi - \log_2(N_0^j + N_\phi^j)] - \sum_{b_j=\phi} \frac{2^{m_i^\phi-1}}{N_0^j + N_\phi^j} \\ &\quad \cdot [m_i^\phi - 1 - \log_2(N_0^j + N_\phi^j)] \\ &= - \frac{1}{N_0^j + N_\phi^j} \left[\sum_{b_j=0} [m_i^\phi - \log_2(N_0^j + N_\phi^j)] 2^{m_i^\phi} + \sum_{b_j=\phi} [m_i^\phi - 1 - \log_2(N_0^j + N_\phi^j)] 2^{m_i^\phi-1} \right] \end{aligned}$$

$$IG(R, b_j) = H(R) - \frac{N_0^j + N_\phi^j}{N_{tot}} H(R | b_j = 0) - \frac{N_1^j + N_\phi^j}{N_{tot}} H(R | b_j = 1)$$

$$\begin{aligned} &= \log_2(N_{tot}) - \frac{1}{N_{tot}} \sum_{i=1}^k m_i^\phi \cdot 2^{m_i^\phi} \\ &\quad + \frac{1}{N_{tot}} \left[\sum_{b_j=0} [m_i^\phi - \log_2(N_0^j + N_\phi^j)] 2^{m_i^\phi} \right. \\ &\quad \left. + \sum_{b_j=\phi} [m_i^\phi - 1 - \log_2(N_0^j + N_\phi^j)] 2^{m_i^\phi-1} \right] \\ &\quad + \frac{1}{N_{tot}} \left[\sum_{b_j=0} [m_i^\phi - \log_2(N_0^j + N_\phi^j)] 2^{m_i^\phi} \right. \\ &\quad \left. + \sum_{b_j=\phi} [m_i^\phi - 1 - \log_2(N_0^j + N_\phi^j)] 2^{m_i^\phi-1} \right] \end{aligned}$$

$$\begin{aligned} &= \log_2(N_{tot}) - \frac{1}{N_{tot}} \log_2(N_0^j + N_\phi^j) N_0^j - \frac{1}{N_{tot}} \log_2(N_1^j + N_\phi^j) N_1^j - \frac{1}{N_{tot}} \log_2[2(N_0^j + N_\phi^j)] N_\phi^j \\ &\quad - \frac{1}{N_{tot}} \log_2[2(N_1^j + N_\phi^j)] N_\phi^j \\ &= \log_2(N_{tot}) - \frac{1}{N_{tot}} \left[(N_0^j + N_\phi^j) \log_2(N_0^j + N_\phi^j) + (N_1^j + N_\phi^j) \log_2(N_1^j + N_\phi^j) + 2N_\phi^j \right] \end{aligned}$$

Conditional entropy by dismissing the ϕ (wild cards)

BEFORE:

$$H(R \mid b_j) = \frac{1}{N_{tot}} \left[(N_0^j + N_\phi^j) \cdot \log_2 (N_0^j + N_\phi^j) + (N_1^j + N_\phi^j) \cdot \log_2 (N_1^j + N_\phi^j) + 2N_\phi^j - \sum_{i=1}^k m_i^\phi \cdot 2^{m_i^\phi} \right]$$

AFTER:

$$H(R \mid b_j) = \frac{1}{N_0^j + N_1^j} \left[N_0^j \cdot \log_2 (N_0^j) + N_1^j \cdot \log_2 (N_1^j) \right]$$