

## 1. Naïve Bayes

### 1.1 Duplicate Feature and Decision Rules

1.

$$\begin{aligned} P(Y = T | X_1 = T, X_2 = F, X_3 = F) &= \frac{P(X_1 = T, X_2 = F, X_3 = F | Y = T)P(Y = T)}{P(X_1 = T, X_2 = F, X_3 = F)} \\ &= \frac{P(X_1 = T | Y)P(X_2 = F, X_3 = F | Y = T)P(Y = T)}{P(X_1 = T, X_2 = F, X_3 = F)} \\ &= \frac{P(X_1 = T | Y = T)P(X_2 = F | Y = T)P(X_3 = F | Y = T)P(Y = T)}{P(X_1 = T, X_2 = F, X_3 = F | Y = T)P(Y = T) + P(X_1 = T, X_2 = F, X_3 = F | Y = F)P(Y = F)} \\ &= \frac{p \cdot q \cdot q \cdot 0.5}{p \cdot q \cdot q \cdot 0.5 + (1 - p) \cdot (1 - q) \cdot (1 - q) \cdot 0.5} = \frac{0.5 \cdot p \cdot q^2}{0.5 \cdot p \cdot q^2 + 0.5 \cdot (1 - p)(1 - q)^2} \end{aligned}$$

For a positive classification the above probability has to be greater than 0.5

$$\begin{aligned} \frac{0.5 \cdot p \cdot q^2}{0.5 \cdot p \cdot q^2 + 0.5 \cdot (1 - p)(1 - q)^2} &\geq 0.5 \\ \Leftrightarrow \frac{p \cdot q^2}{p \cdot q^2 + (1 - p)(1 - q)^2} &\geq 0.5 \\ \Leftrightarrow pq^2 &\geq 0.5 \cdot (pq^2 + (1 - p)(1 - q)^2) \\ \Leftrightarrow 0.5pq^2 &\geq 0.5(1 - p)(1 - q)^2 \\ \Leftrightarrow pq^2 &\geq 1 - 2q + q^2 - p + 2pq - pq^2 \\ \Leftrightarrow 2pq^2 + p - 2pq &\geq 1 - 2q + q^2 \\ \Leftrightarrow p(2q^2 + 1 - 2q) &\geq (1 - q)^2 \\ \Leftrightarrow p &\geq \frac{(1 - q)^2}{q^2 + q^2 + 1 - 2q} \\ \Leftrightarrow p &\geq \frac{(1 - q)^2}{q^2 + (1 - q)^2} \end{aligned}$$

2.

$$\begin{aligned} P(Y = T | X_1 = T, X_2 = F, X_3 = F) &= \frac{P(X_1 = T, X_2 = F, X_3 = F | Y = T)P(Y = T)}{P(X_1 = T, X_2 = F, X_3 = F)} \\ &= \frac{P(X_1 = T | Y)P(X_2 = F, X_3 = F | Y = T)P(Y = T)}{P(X_1 = T, X_2 = F, X_3 = F)} \\ &= \frac{P(X_1 = T | Y = T)P(X_2 = F | Y = T)P(Y = T)}{P(X_1 = T, X_2 = F, X_3 = F | Y = T)P(Y = T) + P(X_1 = T, X_2 = F, X_3 = F | Y = F)P(Y = F)} \\ &= \frac{p \cdot q \cdot 0.5}{p \cdot q \cdot 0.5 + (1 - p) \cdot (1 - q) \cdot 0.5} = \frac{0.5 \cdot p \cdot q}{0.5 \cdot p \cdot q + 0.5 \cdot (1 - p)(1 - q)} \end{aligned}$$

For a positive classification, again, the above probability has to be greater than 0.5

$$\begin{aligned} \frac{0.5 \cdot p \cdot q}{0.5 \cdot p \cdot q + 0.5 \cdot (1 - p)(1 - q)} &\geq 0.5 \\ \frac{p \cdot q}{p \cdot q + (1 - p)(1 - q)} &\geq 0.5 \end{aligned}$$

$$pq \geq 0.5pq + 0.5(1-p)(1-q)$$

$$0.5pq \geq 0.5(1-p)(1-q)$$

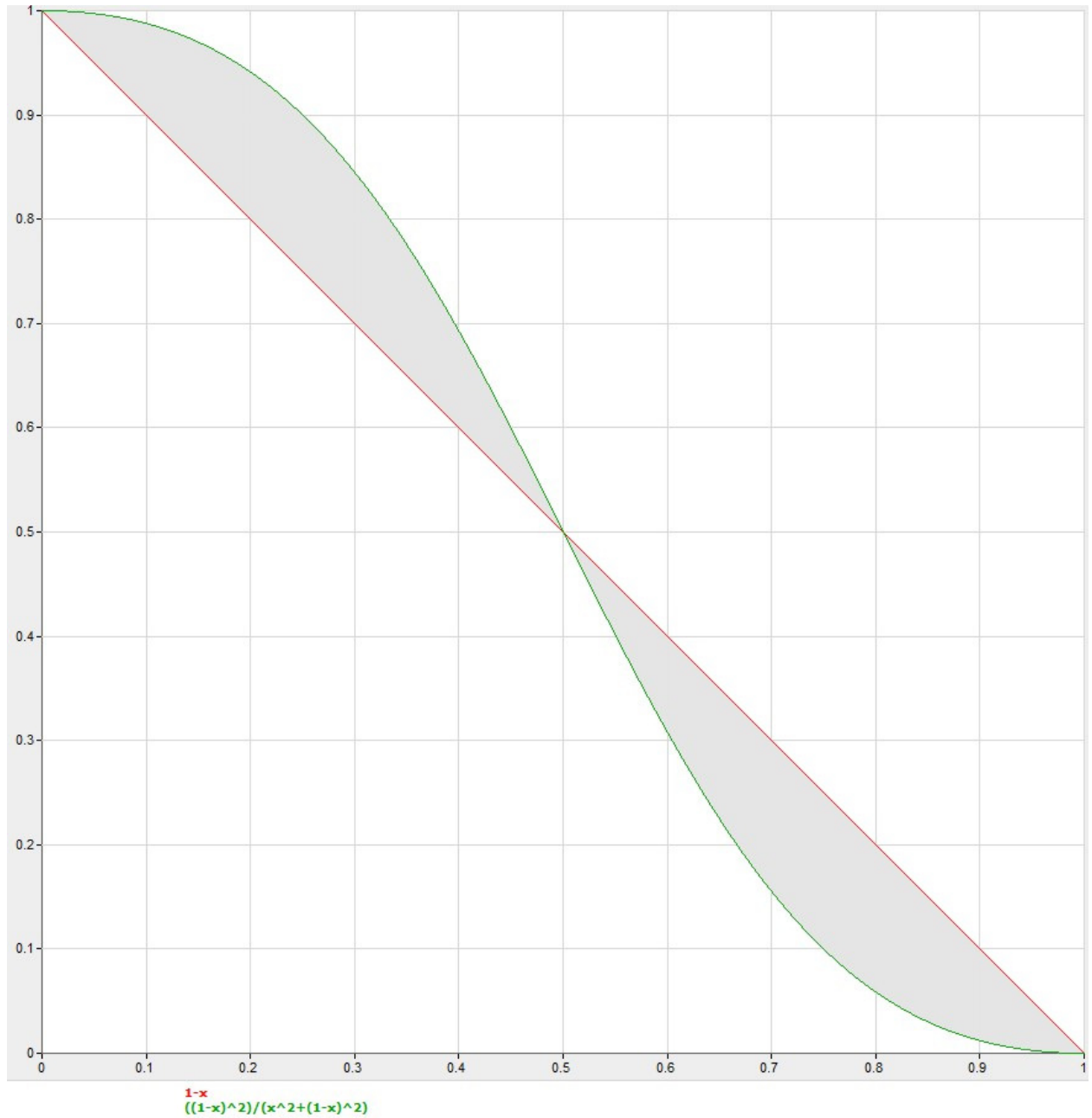
$$pq \geq (1-p)(1-q)$$

$$pq \geq 1-p-q+pq$$

$$pq - pq + p \geq 1-q$$

$$p \geq 1-q$$

3.



The first rule makes mistakes in the gray areas.

## 1.2 Logistic Regression and Naïve Bayes – Boolean Case

$$\begin{aligned}
 P(Y = 1|X) &= \frac{P(X|Y = 1)P(Y = 1)}{P(X|Y = 1)P(Y = 1) + P(X|Y = 0)P(Y = 0)} = \frac{1}{1 + \frac{P(X|Y = 0)P(Y = 0)}{P(X|Y = 1)P(Y = 1)}} \\
 &= \frac{1}{1 + \exp \left[ \ln \left( \frac{P(X|Y = 0)P(Y = 0)}{P(X|Y = 1)P(Y = 1)} \right) \right]} = \frac{1}{1 + \exp \left[ \ln \left( \frac{1 - \pi}{\pi} \right) + \sum_i \ln \left( \frac{P(X_i|Y = 0)}{P(X_i|Y = 1)} \right) \right]} \\
 &= \frac{1}{1 + \exp \left[ \ln \left( \frac{1 - \pi}{\pi} \right) + \sum_i \ln \left( \frac{(\theta_{i0})^{X_i} (1 - \theta_{i0})^{(1 - X_i)}}{(\theta_{i1})^{X_i} (1 - \theta_{i1})^{(1 - X_i)}} \right) \right]} \\
 &= \frac{1}{1 + \exp \left[ \ln \left( \frac{1 - \pi}{\pi} \right) + \sum_i \ln((\theta_{i0})^{X_i} (1 - \theta_{i0})^{(1 - X_i)}) - \ln((\theta_{i1})^{X_i} (1 - \theta_{i1})^{(1 - X_i)}) \right]} \\
 &= \frac{1}{1 + \exp \left[ \ln \left( \frac{1 - \pi}{\pi} \right) + \sum_i \ln((\theta_{i0})^{X_i}) + \ln((1 - \theta_{i0})^{(1 - X_i)}) - \ln((\theta_{i1})^{X_i}) - \ln((1 - \theta_{i1})^{(1 - X_i)}) \right]} \\
 &= \frac{1}{1 + \exp \left[ \ln \left( \frac{1 - \pi}{\pi} \right) + \sum_i X_i \ln(\theta_{i0}) + (1 - X_i) \ln(1 - \theta_{i0}) - X_i \ln(\theta_{i1}) - (1 - X_i) \ln(1 - \theta_{i1}) \right]} \\
 &= \frac{1}{1 + \exp \left[ \ln \left( \frac{1 - \pi}{\pi} \right) + \sum_i X_i \ln(\theta_{i0}) + \ln(1 - \theta_{i0}) - X_i \ln(1 - \theta_{i0}) - X_i \ln(\theta_{i1}) - \ln(1 - \theta_{i1}) + X_i \ln(1 - \theta_{i1}) \right]} \\
 &= \frac{1}{1 + \exp \left[ \ln \left( \frac{1 - \pi}{\pi} \right) + \sum_i X_i (\ln(\theta_{i0}) - \ln(1 - \theta_{i0}) - \ln(\theta_{i1}) + \ln(1 - \theta_{i1})) + \ln(1 - \theta_{i0}) - \ln(1 - \theta_{i1}) \right]} \\
 &= \frac{1}{1 + \exp [w_0 + \sum_i w_i X_i]}
 \end{aligned}$$

where  $w_0 = \ln \left( \frac{1 - \pi}{\pi} \right) + \sum_i \ln \left( \frac{1 - \theta_{i0}}{1 - \theta_{i1}} \right)$

and  $w_i = \ln(\theta_{i0}) - \ln(1 - \theta_{i0}) - \ln(\theta_{i1}) + \ln(1 - \theta_{i1}) = \ln \left( \frac{\theta_{i0}}{\theta_{i1}} \right) + \ln \left( \frac{1 - \theta_{i1}}{1 - \theta_{i0}} \right)$

### 1.3 Relaxing the Conditional Independence Assumption

$$\begin{aligned}
P(Y = 1|X) &= \frac{\prod_{i=3}^n P(X_i|Y = 1) P(X_1, X_2|Y = 1)P(Y = 1)}{\prod_{i=3}^n P(X_i|Y = 1) P(X_1, X_2|Y = 1)P(Y = 1) + \prod_{i=3}^n P(X_i|Y = 0) P(X_1, X_2|Y = 0)P(Y = 0)} \\
&= \frac{1}{1 + \frac{\prod_{i=3}^n P(X_i|Y = 0) P(X_1, X_2|Y = 0)P(Y = 0)}{\prod_{i=3}^n P(X_i|Y = 1) P(X_1, X_2|Y = 1)P(Y = 1)}} = \frac{1}{1 + \exp [\ln \left( \frac{\prod_{i=3}^n P(X_i|Y = 0) P(X_1, X_2|Y = 0)P(Y = 0)}{\prod_{i=3}^n P(X_i|Y = 1) P(X_1, X_2|Y = 1)P(Y = 1)} \right)]} \\
&= \frac{1}{1 + \exp [\ln \left( \frac{1 - \pi}{\pi} \right) + \sum_{i=3}^n \left[ \ln \left( \frac{P(X_i|Y = 0)}{P(X_i|Y = 1)} \right) \right] + \ln \left( \frac{P(X_1, X_2|Y = 0)}{P(X_1, X_2|Y = 1)} \right)]} \\
&= \frac{1}{1 + \exp [\ln \left( \frac{1 - \pi}{\pi} \right) + \sum_{i=3}^n \left[ \ln \left( \frac{(\theta_{i0})^{X_i} (1 - \theta_{i0})^{(1-X_i)}}{(\theta_{i1})^{X_i} (1 - \theta_{i1})^{(1-X_i)}} \right) \right] + \ln \left( \frac{(\beta_{110})^{X_1 X_2} (\beta_{100})^{X_1 (1-X_2)} (\beta_{010})^{(1-X_1) X_2} (\beta_{000})^{(1-X_1)(1-X_2)}}{(\beta_{111})^{X_1 X_2} (\beta_{101})^{X_1 (1-X_2)} (\beta_{011})^{(1-X_1) X_2} (\beta_{001})^{(1-X_1)(1-X_2)}} \right)]} \\
&= \frac{1}{1 + \exp [\ln \left( \frac{1 - \pi}{\pi} \right) + \sum_{i=3}^n \left[ X_i \left( \ln \left( \frac{\theta_{i0}}{\theta_{i1}} \right) + \ln \left( \frac{1 - \theta_{i1}}{1 - \theta_{i0}} \right) \right) + \ln \left( \frac{1 - \theta_{i0}}{1 - \theta_{i1}} \right) \right] + X_1 X_2 B_1 + X_1 B_2 + X_2 B_3 + B_4]} \\
&= \frac{1}{1 + \exp [w_0 + w_{1,2} X_1 X_2 + \sum_{i=1}^n w_i X_i]}
\end{aligned}$$

$$\text{where } w_0 = \ln \left( \frac{1 - \pi}{\pi} \right) + \sum_i \ln \left( \frac{1 - \theta_{i0}}{1 - \theta_{i1}} \right) + \ln \left( \frac{\beta_{000}}{\beta_{001}} \right)$$

$$\text{and } w_1 = \ln \left( \frac{\beta_{100}}{\beta_{101}} \right) + \ln \left( \frac{\beta_{001}}{\beta_{000}} \right)$$

$$\text{and } w_2 = \ln \left( \frac{\beta_{010}}{\beta_{011}} \right) + \ln \left( \frac{\beta_{001}}{\beta_{000}} \right)$$

$$\text{and } w_i = \ln \left( \frac{\theta_{i0}}{\theta_{i1}} \right) + \ln \left( \frac{1 - \theta_{i1}}{1 - \theta_{i0}} \right) \text{ for } i \in \{3, \dots, n\}$$

$$\text{and } w_{1,2} = \ln \left( \frac{\beta_{110}}{\beta_{111}} \right) + \ln \left( \frac{\beta_{000}}{\beta_{001}} \right) + \ln \left( \frac{\beta_{101}}{\beta_{100}} \right) + \ln \left( \frac{\beta_{011}}{\beta_{010}} \right)$$

$$B_1 = \ln \left( \frac{\beta_{110}}{\beta_{111}} \right) + \ln \left( \frac{\beta_{000}}{\beta_{001}} \right) + \ln \left( \frac{\beta_{101}}{\beta_{100}} \right) + \ln \left( \frac{\beta_{011}}{\beta_{010}} \right)$$

$$B_2 = \ln \left( \frac{\beta_{100}}{\beta_{101}} \right) + \ln \left( \frac{\beta_{001}}{\beta_{000}} \right)$$

$$B_3 = \ln \left( \frac{\beta_{010}}{\beta_{011}} \right) + \ln \left( \frac{\beta_{001}}{\beta_{000}} \right)$$

$$B_4 = \ln \left( \frac{\beta_{000}}{\beta_{001}} \right)$$