

Bayes' Theorem (Rev. Thomas Bayes, c.1701-1761):

$$P(F|E) = \frac{P(E|F)P(F)}{P(E)}$$

Proof: $P(F|E) = \frac{P(E \cap F)}{P(E)} = \frac{P(E|F)P(F)}{P(E)}$

Corollary:

$$P(F|E) = \frac{P(E|F)P(F)}{P(E|F)P(F) + P(E|\bar{F})P(\bar{F})}$$

Proof: LTP

why it's useful: reverses conditioning

Ex: F = disease, E = + test result

You might know $P(E|F)$

Want to know $P(F|E)$ if you had a + test result.

Ex: 60% of email of spam

90% of spam has a forged header

20% of nonspam has a forged header.

Let F = forged header, J = spam

What is $P(J|F)$?

$$\begin{aligned} P(J|F) &= \frac{P(F|J)P(J)}{P(F|J)P(J) + P(F|\bar{J})P(\bar{J})} \\ &= \frac{0.9 \times 0.6}{0.9 \times 0.6 + 0.2(1-0.6)} \approx 0.871 \end{aligned}$$

prior probability $P(J) = 0.6$

posterior probability = 0.871

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genotype
allele = "variant"

Ex: Paternity testing

Child has (A,a) pair for some gene (event B_{Aa})

Mother has (A,A)

2 possible fathers, $F_1 = (a,a)$, $F_2 = (A,a)$. $P(F_1) = p$, $P(F_2) = 1-p$

$$P(F_i | B_{Aa}) = \frac{P(B_{Aa} | F_i) P(F_i)}{P(B_{Aa} | F_1) P(F_1) + P(B_{Aa} | F_2) P(F_2)}$$

$$= \frac{1 \cdot p}{1 \cdot p + \frac{1}{2}(1-p)} = \frac{2p}{2p + 1 - p} = \boxed{\frac{2p}{1+p}}$$

$$\geq \frac{2p}{1+1} = \boxed{p} \text{ prior} \quad \text{posterior}$$

For example, if $p = \frac{1}{2}$, ~~$\frac{2 \cdot \frac{1}{2}}{1 + \frac{1}{2}} = \frac{1}{1.5} = \frac{2}{3}$~~ $\frac{2p}{1+p} = \frac{2}{3}$