## Bayes Theorem

David Gerard<br>2017-10-11

## Learning Objectives

- Bayes Rule
- Section 2.2.7 of DBC


## Motivation

- There are many times that we want $P(B \mid A)$.
- However, we might only have information on $P(A \mid B)$.
- E.g. from medical tests, we often have a lot of knowledge of the probability of a test resulting positive given an patient has a disease, or the probability of a test resulting positive given a patient does not have a disease.
- But when a test is run, we want the probability that a patient has a disease given that a test is positive or negative.


## Motivation

Data from OpenIntro p98. Breast cancer for women in Canada.
$P($ positive $\mid$ cancer $)=0.89$ so $P($ negative $\mid$ cancer $)=0.11$.
$P($ positive $\mid$ not cancer $)=0.07$ so $P($ negative $\mid$ not cancer $)=0.93$.

$$
P(\text { cancer })=0.0035 \text { so } P(\text { not cancer })=0.9965
$$

- But we want to know $P$ (cancer|positive).


## Bayes Rule

Recall Multiplication Rule:

$$
P(B \mid A) P(A)=P(A \cap B)
$$

## Bayes Rule

Recall Multiplication Rule:

$$
P(B \mid A) P(A)=P(A \cap B)=P(A \mid B) P(B)
$$

## Bayes Rule

Recall Multiplication Rule:

$$
\begin{aligned}
& P(B \mid A) P(A)=P(A \cap B)=P(A \mid B) P(B) \\
& P(B \mid A) P(A)=P(A \mid B) P(B)
\end{aligned}
$$

## Bayes Rule

Recall Multiplication Rule:

$$
\begin{aligned}
P(B \mid A) P(A) & =P(A \cap B)=P(A \mid B) P(B) \\
P(B \mid A) P(A) & =P(A \mid B) P(B) \\
P(B \mid A) & =\frac{P(A \mid B) P(B)}{P(A)}
\end{aligned}
$$

## Bayes Rule

Recall Multiplication Rule:

$$
\begin{aligned}
P(B \mid A) P(A) & =P(A \cap B)=P(A \mid B) P(B) \\
P(B \mid A) P(A) & =P(A \mid B) P(B) \\
P(B \mid A) & =\frac{P(A \mid B) P(B)}{P(A)}
\end{aligned}
$$

This is known as Bayes rule.

## Bayes Rule

$$
P(B \mid A)=\frac{P(A \mid B) P(B)}{P(A)}
$$

## Law of Total Probability

You almost always get $P(A)$ by using the law of total probablity:

## Law of total probability (more general form)

Suppose $B_{1}, B_{2}, \ldots, B_{K}$ is a partition of the sample space $S$. I.e. $B_{1} \cup B_{2} \cup \cdots \cup B_{K}=S$ and $B_{i} \cap B_{j}=\emptyset$ for all $i \neq j$, then

$$
\begin{aligned}
P(A) & =P\left(A \cap B_{1}\right)+P\left(A \cap B_{2}\right)+\cdots+P\left(A \cap B_{K}\right) \\
& =P\left(A \mid B_{1}\right) P\left(B_{1}\right)+P\left(A \mid B_{2}\right) P\left(B_{2}\right)+\cdots+P\left(A \mid B_{K}\right) P\left(B_{K}\right) .
\end{aligned}
$$

We previously defined this law using $K=2$ :

$$
P(A)=P(A \mid B) P(B)+P\left(A \mid B^{c}\right) P\left(B^{c}\right)
$$

## Our Cancer Example

$$
P(\text { positive } \mid \text { cancer })=0.89 \text { so } P(\text { negative } \mid \text { cancer })=0.11
$$

$P($ positive $\mid$ not cancer $)=0.07$ so $P($ negative $\mid$ not cancer $)=0.93$.

$$
P(\text { cancer })=0.0035 \text { so } P(\text { not cancer })=0.9965
$$

$P($ cancer $\mid$ positive $)=\frac{P(\text { positive } \mid \text { cancer }) P(\text { cancer })}{P(\text { positive })}$.
We need

$$
\begin{aligned}
P(\text { positive })= & P(\text { positive } \mid \text { cancer }) P(\text { cancer }) \\
& +P(\text { positive } \mid \text { not cancer }) P(\text { not cancer }) \\
= & 0.89 * 0.0035+0.07 * 0.9965=0.07287
\end{aligned}
$$

## Our Cancer Example

$$
P(\text { positive } \mid \text { cancer })=0.89 \text { so } P(\text { negative } \mid \text { cancer })=0.11 \text {. }
$$

$$
P(\text { positive } \mid \text { not cancer })=0.07 \text { so } P(\text { negative } \mid \text { not cancer })=0.93 \text {. }
$$

$$
\begin{aligned}
P(\text { cancer }) & =0.0035 \text { so } P(\text { not cancer })=0.9965 \\
P(\text { positive }) & =0.07287
\end{aligned}
$$

$$
\begin{aligned}
P(\text { cancer } \mid \text { positive }) & =\frac{P(\text { positive } \mid \text { cancer }) P(\text { cancer })}{P(\text { positive })} \\
& =\frac{0.89 * 0.0035}{0.07287} \\
& =0.04275
\end{aligned}
$$

## Intuition

- So the probability you have cancer given a positive test is only about 4\%!
- Even though the test is fairly accurate, because there are so many more people who do not have cancer than who have cancer, they make up a majority of the population who have a positive test result.


## Graphical Example

Graphical Example


## Graphical Example

Graphical Example


## Graphical Example




## Zooming In



## Another Example

From email dataset, we get

$$
\begin{aligned}
P(\text { no number } \mid \text { spam }) & =0.4062 \\
P(\text { small number } \mid \text { not spam }) & =0.7482 \\
P(\text { big number } \mid \text { not spam }) & =0.1393 \\
P(\text { spam }) & =0.0936
\end{aligned}
$$

What proportion of emails with no number are spam?
(on chalk board)

