## <span id="page-0-0"></span>Probability fundamentals

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- probability basics
	- Example: Medical diagnosis
	- joint, conditional and marginal probabilities
	- the two rules of probability: sum and product rules
	- Bayes rule
- Bayesian inference and prediction with finite regression models
	- likelihood and prior
	- posterior and predictive distribution
- the marginal likelihood
	- Bayesian model selection
	- Example: How Bayes avoids overfitting

Breast cancer facts:

- 1% of scanned women have breast cancer
- 80% of women with breast cancer get positive mammography scans
- 9.6% of women without breast cancer also get positive mammography scans

**Question:** A woman gets a scan, and it is positive; what is the probability that she has breast cancer?

- $\bullet$  less than 1%
- 2 around 10%
- a around 90%
- **4** more than 99%

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Define:  $C$  = presence of breast cancer;  $\overline{C}$  = no breast cancer.

 $M =$  scan is positive;  $\overline{M} =$  scan is negative.

The probability of cancer for scanned women is  $p(C) = 1\%$ 

If there is cancer, the probability of a positive mammography is  $p(M|C) = 80\%$ If there is no cancer, we still have  $p(M|\bar{C}) = 9.6\%$ The question is what is  $p(C|M)$ ?

## Medical inference

What is  $p(C|M)$ ?

Consider 10000 subjects of screening

- $p(C) = 1\%$ , therefore 100 of them have cancer, of which
	- $p(M|C) = 80\%$ , therefore 80 get a positive mammography
	- 20 get a negative mammography
- $p(\overline{C}) = 99\%$ , therefore 9900 of them do not have cancer, of which
	- $p(M|\bar{C}) = 9.6\%$ , therefore 950 get a positive mammography
	- 8950 get a negative mammography



What is  $p(C|M)$ ?



 $p(C|M)$  is obtained as the proportion of all positive mammographies for which there actually is breast cancer

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$$
p(C|M) = \frac{p(C,M)}{p(C,M) + p(\bar{C},M)} = \frac{p(M|C)p(C)}{p(M)} = \frac{80}{80 + 950} \approx 7.8\%
$$

This is an example of Bayes' rule:

$$
p(A|B)p(B) = p(A,B) = p(B|A)p(A),
$$

which is just a consequence of the definition of *conditional probability*

$$
p(A|B) = \frac{p(A, B)}{p(B)}, \quad \text{(where } p(B) \neq 0\text{).}
$$

## <span id="page-6-0"></span>Just two rules of probability theory

Astonishingly, the rich theory of probability can be derived using just two rules: The *sum rule* states that

$$
p(A) = \sum_{B} p(A, B),
$$
 or  $p(A) = \int_{B} p(A, B)dB,$ 

for discrete and continuous variables. Sometimes called *marginalization*. The *product rule* states that

$$
p(A, B) = p(A|B)p(B).
$$

It follows directly from the definition of conditional probability, and leads directly to Bayes' rule

$$
p(A|B)p(B) = p(A,B) = p(B|A)p(A) \Rightarrow p(A|B) = \frac{p(B|A)p(A)}{p(B)}.
$$

Special case:

if A and B are *independent*,  $p(A|B) = p(A)$ , and thus  $p(A, B) = p(A)p(B)$ .