Example: Poxy Diseases

Source: James V. Stone (2013) Bayes' Rule: A Tutorial Introduction to Bayesian Analysis

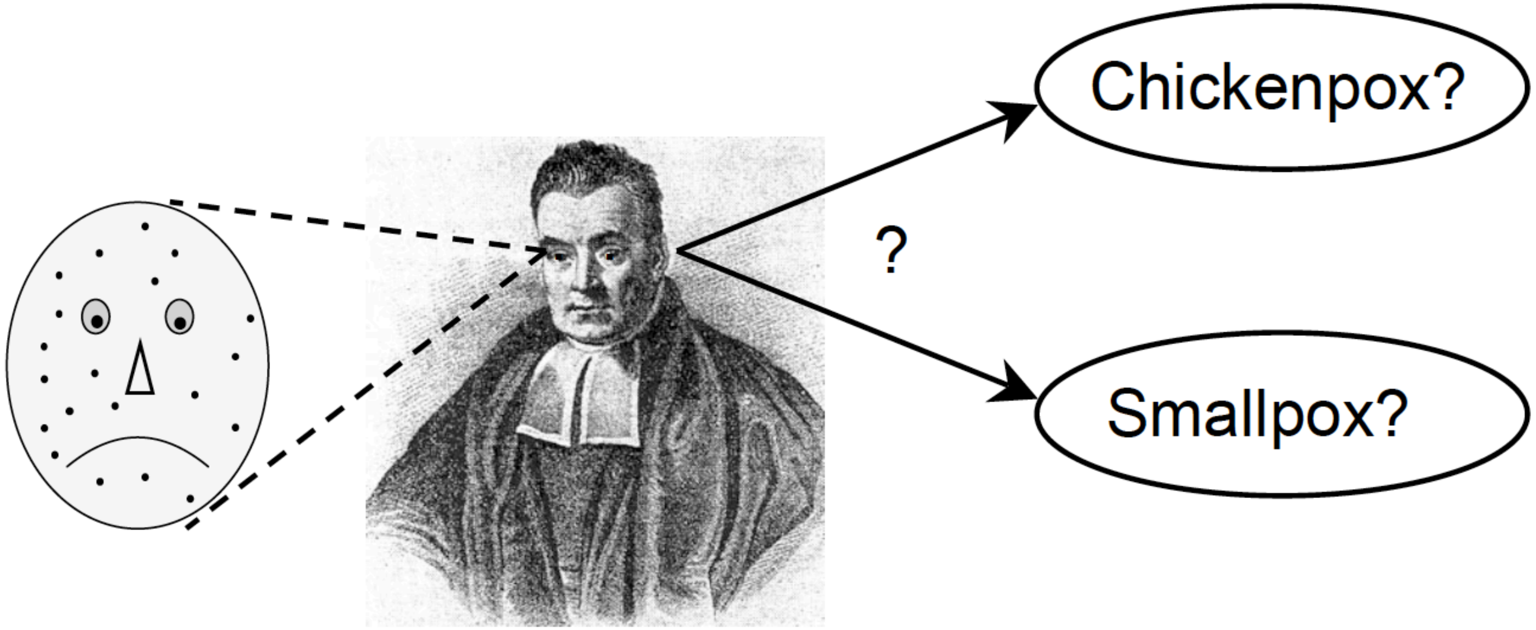

Figure 1.2.: Thomas Bayes diagnosing a patient.

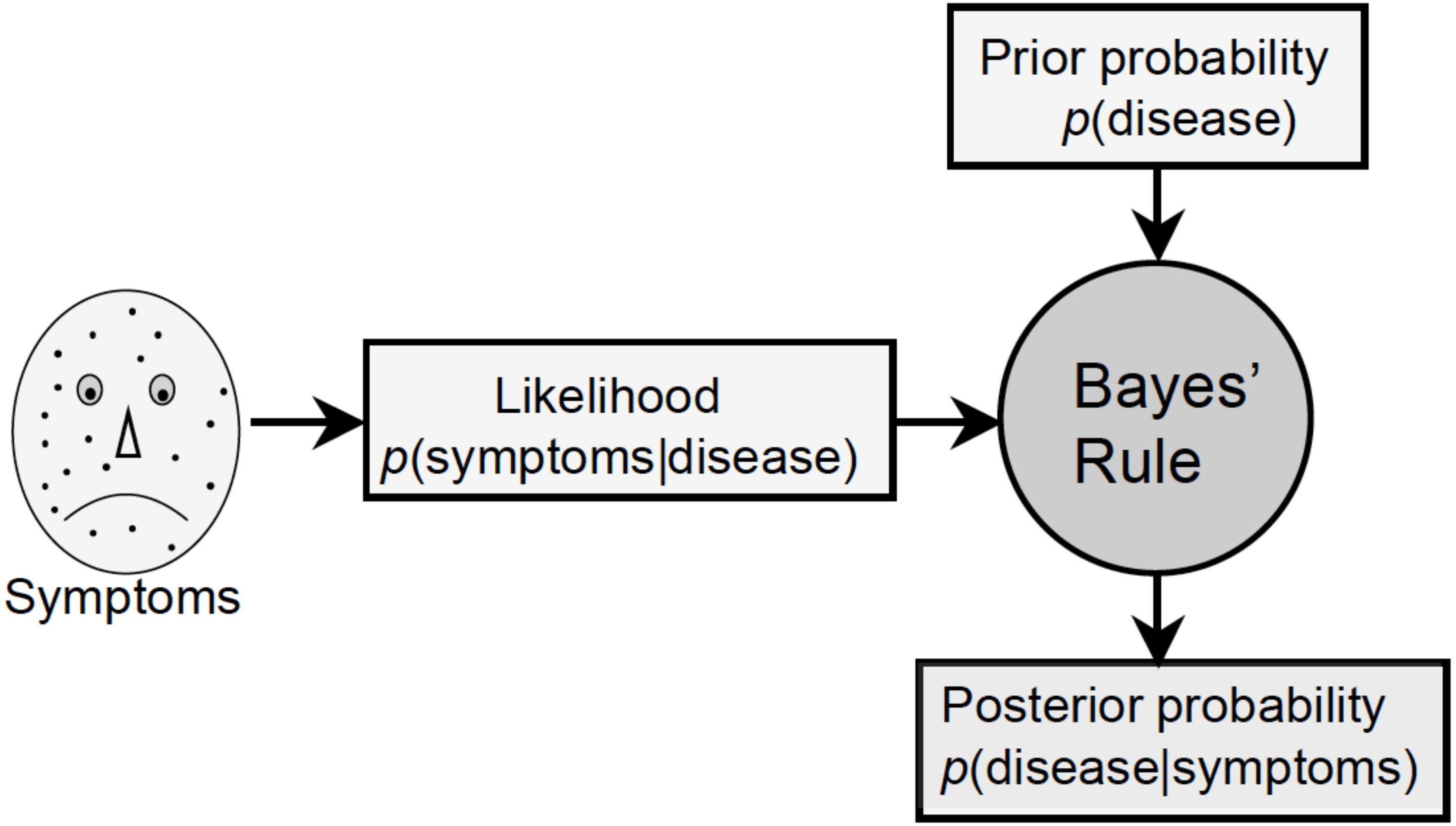

Figure 1.3.: Schematic representation of Bayes' rule. Data, in the form of symptoms, are used find a likelihood, which is the probability of those symptoms given that the patient has a specific disease. Bayes' rule combines this likelihood with prior knowledge, and yields the posterior probability that the patient has the disease given that he has the symptoms observed.

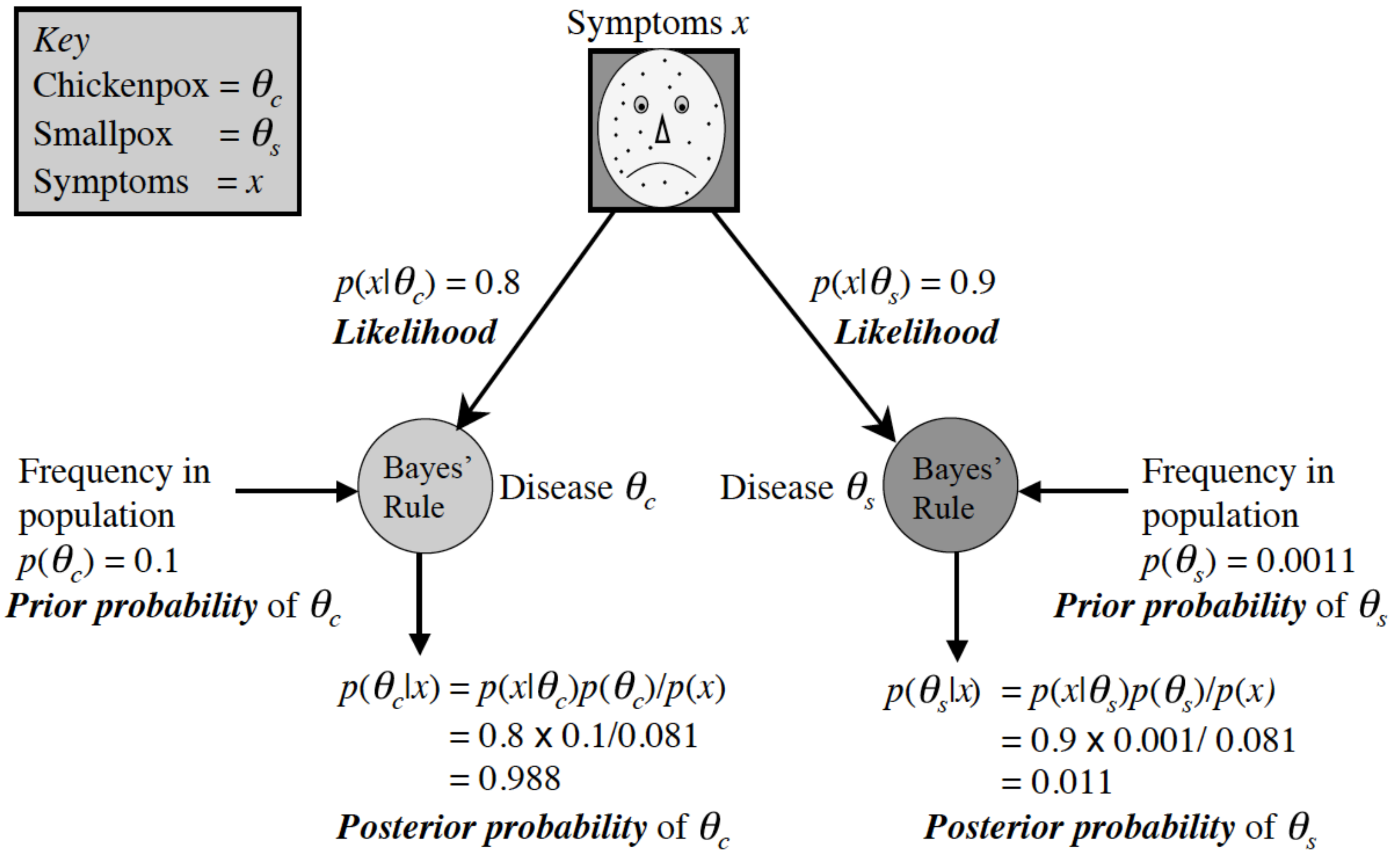

Figure 1.4.: Comparing the probability of chickenpox and smallpox using Bayesian inference. The observed symptoms x seem to be more consistent with smallpox θ_s than chickenpox θ_s, as indicated by their likelihood values. However, the background rate of chickenpox in the population is higher than that of smallpox, which, in this case, makes it more probable that the patient has chickenpox, as indicated by its higher posterior probability.

Example: Forkandles

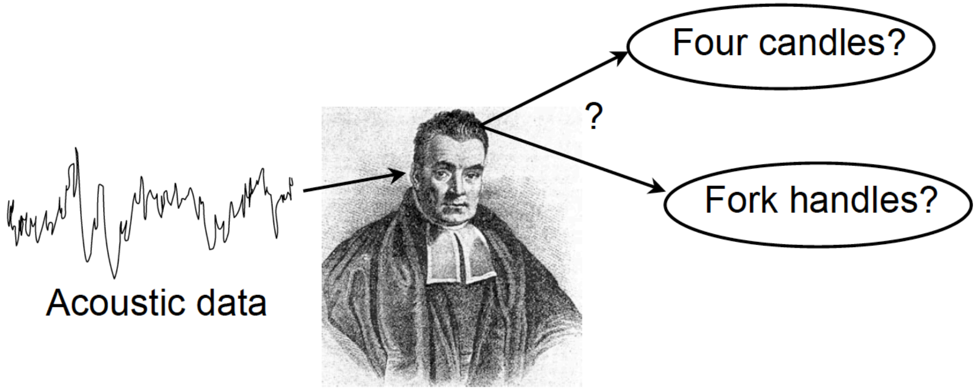

Figure 1.5.: Thomas Bayes trying to make sense of a London accent, which removes the *h* sound from the word *handle*, so the phrase *fork handles* is pronounced *fork 'andles*, and therefore sounds like *four candles* (see Fork Handles YouTube clip by The Two Ronnies).

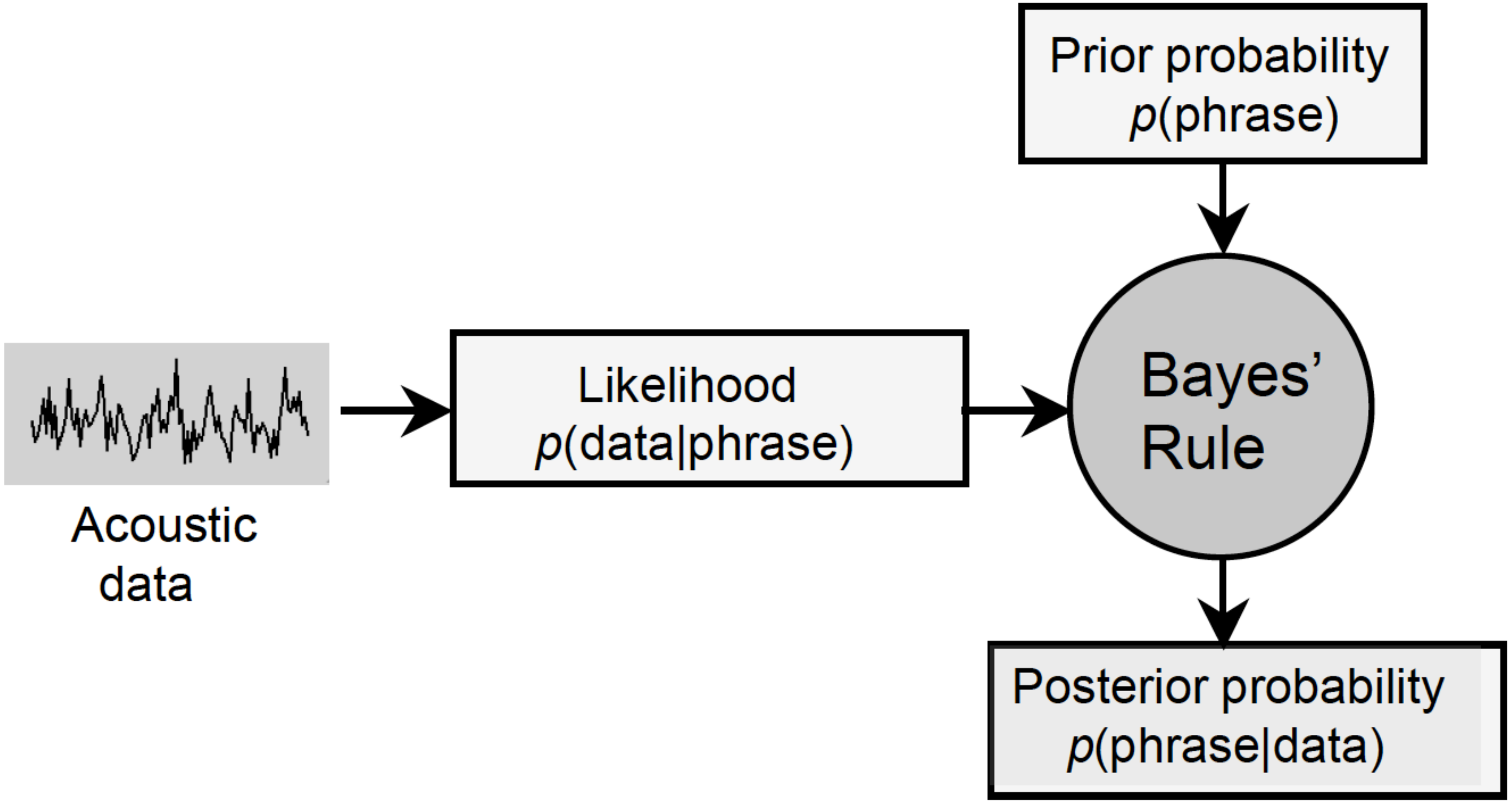

Figure 1.6.: A schematic representation of Bayes' rule. Data alone, in the form of acoustic data, can be used to find a likelihood value, which is the conditional probability of the acoustic data given some putative spoken phrase. When Bayes' rule is used to combine this likelihood with prior knowledge then the result is a posterior probability, which is the probability of the phrase given the observed acoustic data.

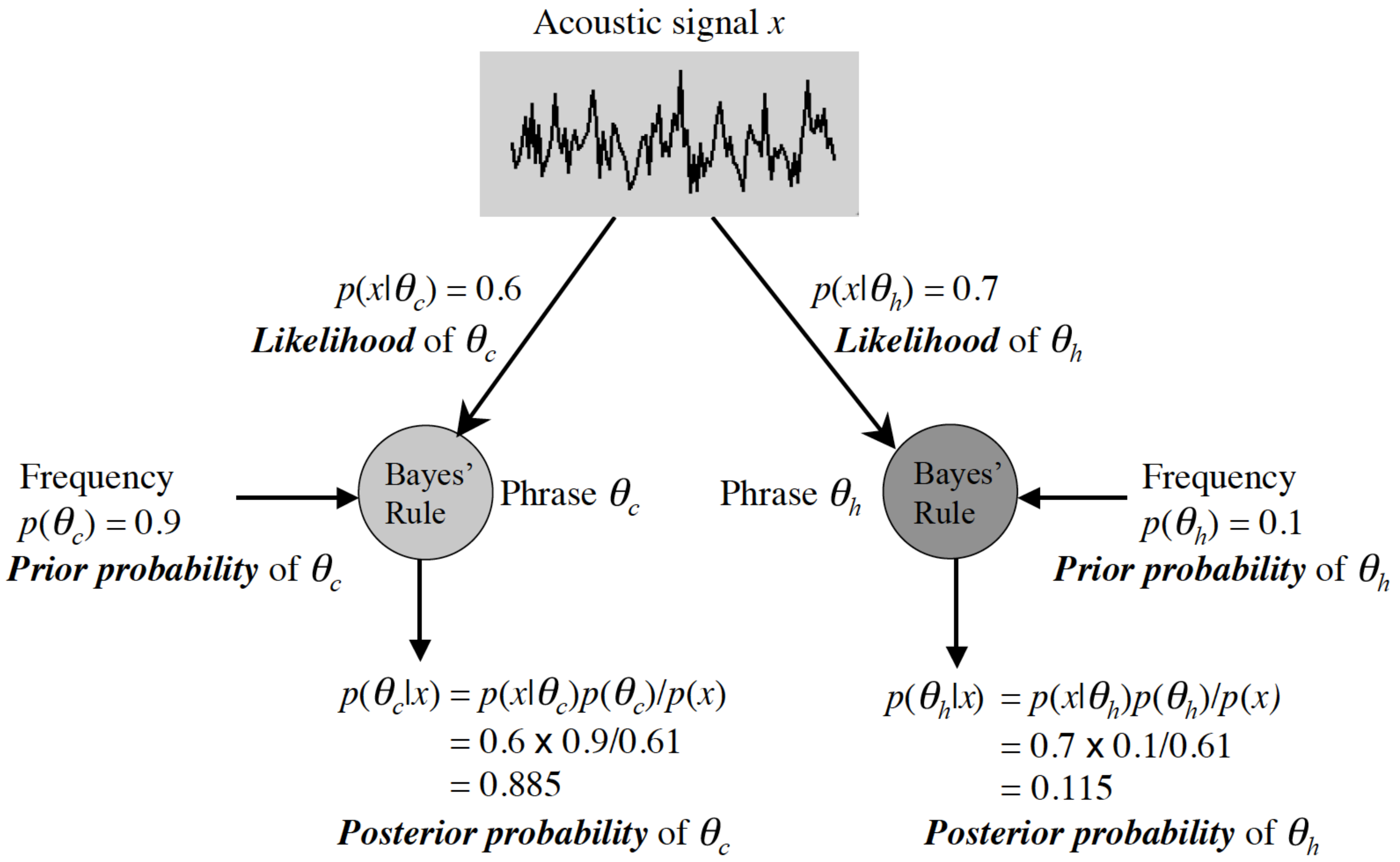

Figure 1.7.: Bayesian inference applied to speech data.

Forward Probability

Inverse Probability

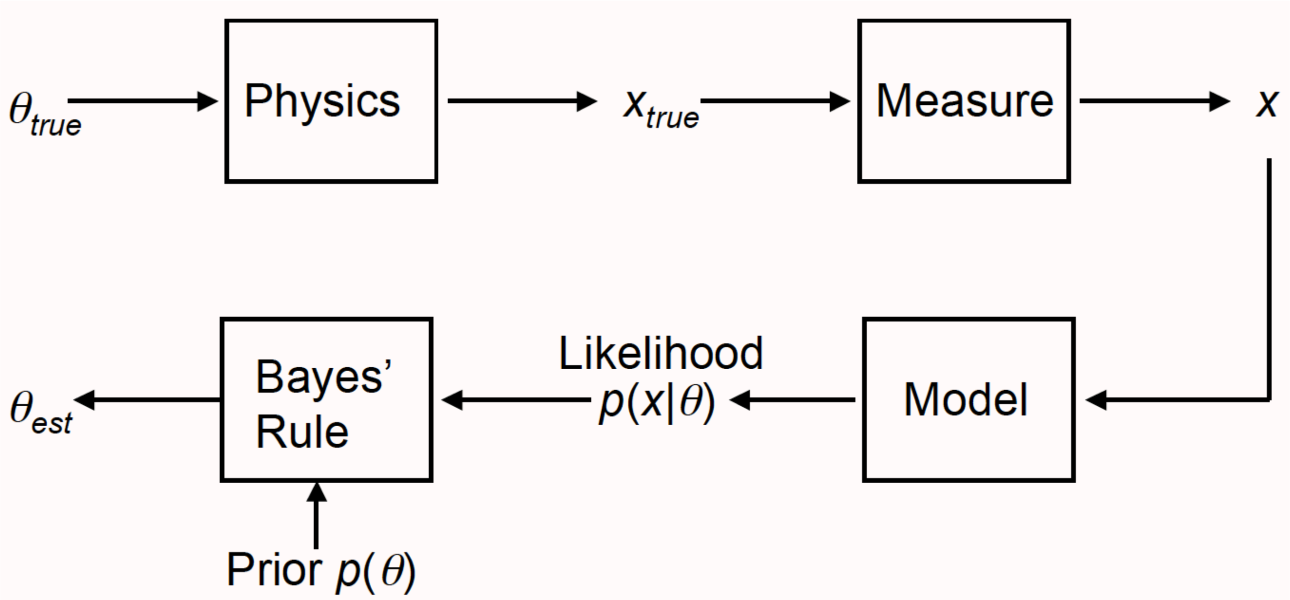

Figure 1.12.: Forward and inverse probability.
Top: Forward probability. A parameter value θ_{true} (eg coin bias) which is implicit in a physical process (eg coin flipping) yields a quantity x_{true} (eg proportion of heads), which is measured as x, using an imperfect measurement process.
Bottom: Inverse probability. Given a mathematical model of the physics that generated x_{true}, the measured value x implies a range of possible values for the parameter θ. The probability of x given each possible value of θ defines a likelihood. When combined with a prior, each likelihood yields a posterior probability $p(\theta|x)$, which allows an estimate θ_{est} of θ_{true} to be obtained.