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Thanks to fast computers and the discovery of computational algorithms like the Metropolis-Hastings algorithm and Gibbs Sampling, Bayesian methods are enjoying a renaissance, especially in medical research, epidemiology, and biostatistics.

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In the Bayesian approach,

- Each person is entitled to their own (subjective) opinion about each unknown parameter, which is not considered to be either right or wrong.
- Bayesians use a probability distribution called the **prior** distribution to model their uncertainty about the parameter values.
- After data is collected, it is used together with the prior distribution to compute a **posterior** distribution that represents an updated opinion about the value of the parameter.

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The posterior distribution $f(\theta|X)$ is the conditional distribution of θ, given the sample X.

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Because θ is actually a random variable in the Bayesian approach, the interpretation of this interval is that it contains the true value of θ with probability $.95$.