1.4 Uncertainty in Healthcare
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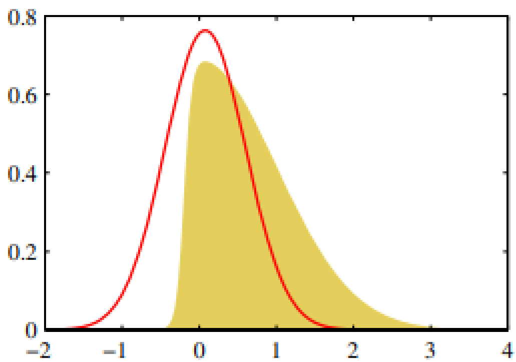
Most information can be found in: http://www.cs.man.ac.uk/~fumie/tmp/bishop.pdf

- Notes added referring to Bishop

Bayesian approach to machine learning

$$p(\theta|Data) = \frac{p(\theta|Data)p(\theta)}{p(Data)}$$A

$$P(Y|Data) = \int p(Y|\theta)p(\theta|Data)d\theta.$$



Variational Inference
https://gregorygundersen.com/blog/2018/04/29/reparameterization/

Monte-Carlo Methods
Metropolis-Hastings

11.2.2 The Metropolis-Hastings algorithm

Ian Murray (https://homepages.inf.ed.ac.uk/imurray2/teaching/09mlss/slides.pdf)

Monte-Carlo methods example: Linear regression with spike and slab priors

https://link.springer.com/article/10.1007/s10994-014-5475-7#citeas

Pros and Cons of Monte-Carlo methods:

- Advantage:
  - More accurate than Laplace, EP, and VI
    - When enough computation time
  - Theoretical results guarantee asymptotic convergence to the true posterior

- Simple and easy to implement
  - Better than EP but worse than VI
- Disadvantages:
  - Hard to debug and check for convergence
  - Requires hyper-parameters
    - Need to be tuned in a non-straightforward manner
  - Slower than Laplace, VI and EP generally