

# Basics of bayesian statistics in R

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# Contents

- Bayes theorem
- Simple example of bayesian inference
- Tools and the significance of GPU acceleration

# The model

- simplified system that approximates the real world
- hypothesis about how a particular dataset might be generated
- sometimes, mathematically or computationally tractable set of equations

Science often involves constructing models of the real world and testing them.

Model  $\longrightarrow$  Predictions

but, how does one construct a good model ?

# Inference

Data  $\longrightarrow$  Model  $\longrightarrow$  Predictions

- Practitioner identifies a class of models with some parameters  $\theta$
- Inference consists of using data to estimate the parameter vector  $\theta$
- Bayesian inference : estimating the full probability distribution of  $\theta$  given available data

## Bayes theorem

$$P(\theta|D) = \frac{P(D|\theta)P(\theta)}{P(D)}$$

- $P(\theta|D)$  : Posterior probability
- $P(D|\theta) = l(\theta|D)$  : Likelihood
- $P(\theta)$  : Prior
- $P(D) = \int P(D|\theta)P(\theta)d\theta$  : Evidence (normalization factor)

## Inference example - water on earth

- Task : estimating the proportion of the globe covered by water by randomly dropping pins and checking if they are on water, or land
- So, we have a binomial process where probability of dropping the pin on water is  $p_w$  and  $p_l = 1 - p_w$ . Our parameters are  $\theta = \{p_l\}$ .
- Assume we know nothing, so we assume a uniform prior for  $p_l$

see `land_water_bayesian.Rmd`

as seen in the bayesian stats course by [Richard McElreath](#)

## Why Bayesian inference is hard

- For high dimensional  $\theta$  likelihood  $P(D|\theta)$  can be hard to compute, since the volume of  $\theta$  space where this is significant is small
- The Evidence  $\int P(D|\theta)P(\theta)d\theta$  is similarly difficult
- Smart samplers (like [Hamiltonian Monte Carlo](#)) are needed
- Choosing informative priors is an art
- Bayesian inference is a LOT more computationally expensive than statistical inference

# The GPU revolution

- High degree of parallelism
- Rapid development of algorithms and implementations leveraging parallelism
- Mature, easy to use bayesian tools built on top of gradient descent infrastructure ([Edward](#), [Pyro](#))
- in R, apart from [JAGS](#), [stan](#), [BUGS](#) which are well established and mostly, DON'T use the GPU there is [Greta](#) which does.



Thank you

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