

# Bayesian Statistics

Recall: (conditional probability)

$$P(a|b) = \frac{P(b|a)P(a)}{P(b)}$$

we write:

$$P(a|b) \propto P(b|a)P(a)$$

This stems from

- (1) Product rule:  $P(b|a)P(a) = P(a, b)$
- (2) Marginalization: if we model joint distribution  $P(a, b)$  we compute  $\sum_a P(a, b)$  or  $\int_a P(a, b)$
- (3) Normalization: if we can model the numerator of Bayes

we compute the left-hand side, by normalizing the values of the numerators over all possible values of  $\alpha$

By (1) + (2)  $z = p(b) = \sum_{\alpha} p(b|\alpha) p(\alpha)$

$$\Rightarrow p(\alpha|b) = \frac{1}{z} p(b|\alpha) p(\alpha)$$

if  $z$  is fixed  $\Rightarrow$

$$p(\alpha|b) \propto p(b|\alpha) p(\alpha)$$

Given dataset  $D = \{y^{(i)}\}_{i=1}^n$   
and  $\theta$  to be out parameter of interest

$$p(\theta|D) = \frac{p(D|\theta) \cdot p(\theta)}{\underbrace{p(D)}_{\rightarrow \text{fixed}}}$$