

# Likelihood-based inference for probabilistic graphical models: Some preliminary results

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## general problem:

### given:

- a set  $\Theta$  of parameters  $\theta$  corresponding to **probability distributions**  $P_\theta$
- the **likelihood function**  $lik$  on  $\Theta$  induced by some data:  $lik(\theta) \propto P_\theta(\text{data})$
- a function  $g : \Theta \rightarrow \mathbb{R}^+$  describing the **quantity of interest**  $g(\theta)$

**calculate:** the **profile likelihood function**  $lik_g$  on  $\mathbb{R}^+$  defined by

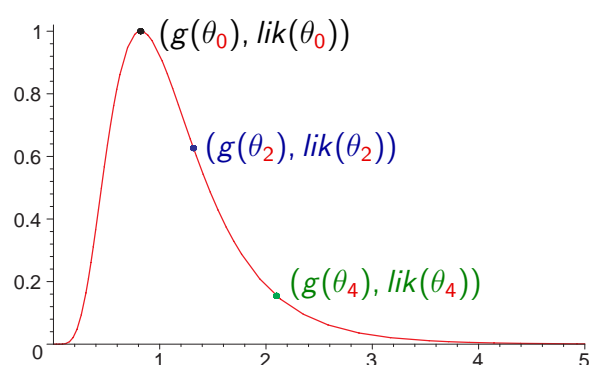
$$lik_g(x) = \max_{\substack{\theta \in \Theta: \\ g(\theta)=x}} lik(\theta) \quad \text{for all } x \in \mathbb{R}^+$$

## basic idea:

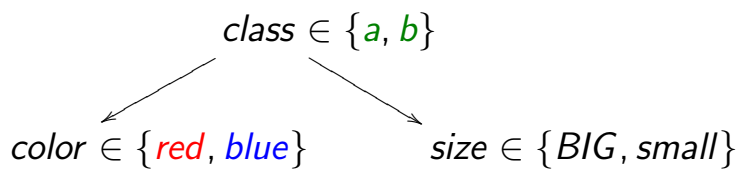
if  $\theta = \theta_\alpha$  maximizes  $[g(\theta)]^\alpha lik(\theta)$  over all  $\theta \in \Theta$  for some  $\alpha \in \mathbb{R}$ , then it also maximizes  $lik(\theta)$  over all  $\theta \in \Theta$  such that  $g(\theta) = g(\theta_\alpha)$ , and therefore  $(g(\theta_\alpha), lik(\theta_\alpha))$  is a **point in the graph** of  $lik_g$

by varying  $\alpha$ , **the whole graph** of  $lik_g$  may be obtained;

in particular,  $\theta_0$  is a ML estimate of  $\theta$ , and  $g(\theta_\alpha)$  is an increasing function of  $\alpha$



## example (naive classifier):



complete training dataset:

class	#	#red	#BIG
a	48	7	39
b	52	12	30

**goal:** profile likelihood function for  $P(class = a | color = red, size = BIG)$

### problem formulation:

- each **naive Bayes classifier** is described by a parameter

$$\theta = (\theta_a, \theta_{red|a}, \theta_{red|b}, \theta_{BIG|a}, \theta_{BIG|b}) \in \Theta = [0, 1]^5$$

- the above training dataset induce the **likelihood function**  $lik$  on  $\Theta$  defined by

$$lik(\theta) \propto \theta_a^{48} (1-\theta_a)^{52} \theta_{red|a}^7 (1-\theta_{red|a})^{41} \theta_{red|b}^{12} (1-\theta_{red|b})^{40} \theta_{BIG|a}^{39} (1-\theta_{BIG|a})^9 \theta_{BIG|b}^{30} (1-\theta_{BIG|b})^{22}$$

- as **quantity of interest** choose

$$g(\theta) = \frac{P(class=a | color=red, size=BIG)}{P(class=b | color=red, size=BIG)} = \theta_a (1-\theta_a)^{-1} \theta_{red|a} \theta_{red|b}^{-1} \theta_{BIG|a} \theta_{BIG|b}^{-1}$$

**application of the basic idea:** for each  $\alpha \in [-7, 12]$ ,

$$[g(\theta)]^\alpha lik(\theta) \propto \theta_a^{48+\alpha} (1-\theta_a)^{52-\alpha} \theta_{red|a}^{7+\alpha} (1-\theta_{red|a})^{41} \theta_{red|b}^{12-\alpha} (1-\theta_{red|b})^{40} \theta_{BIG|a}^{39+\alpha} (1-\theta_{BIG|a})^9 \theta_{BIG|b}^{30-\alpha} (1-\theta_{BIG|b})^{22}$$

corresponds to the “likelihood function” induced by a **modified “training dataset”**, and is thus maximized by the “ML estimate”

$$\theta_\alpha = \left( \frac{48+\alpha}{100}, \frac{7+\alpha}{48+\alpha}, \frac{12-\alpha}{52-\alpha}, \frac{39+\alpha}{48+\alpha}, \frac{30-\alpha}{52-\alpha} \right)$$

since  $\alpha \mapsto g(\theta_\alpha)$  maps  $[-7, 12]$  in  $[0, +\infty]$ ,

$$\{(g(\theta_\alpha), lik(\theta_\alpha)) : \alpha \in [-7, 12]\}$$

is a parametric expression for the graph of  $lik_g$ , and therefore

$$\left\{ \left( \frac{g(\theta_\alpha)}{1+g(\theta_\alpha)}, lik(\theta_\alpha) \right) : \alpha \in [-7, 12] \right\}$$

is a **parametric expression for the graph** of the profile likelihood function for  $P(class = a | color = red, size = BIG)$

