Probabilistic models

\_

Bayesian Methods

-

Discussion

Marylou Gabrié

CDS, NYU

March 16, 2021

# Bayesian decision for absolute loss is median

posterior 
$$p(\theta|\mathcal{D})$$
  $\Theta \in \mathbb{R} = \Theta$ 

$$\mathcal{L}(\theta, \hat{\theta}) = |\theta - \hat{\theta}|$$

$$\mathcal{L}(\hat{\theta}) = \mathbb{E} \left[ |\theta - \hat{\theta}| |\mathcal{D} \right] = \int_{-\infty}^{+\infty} |\theta - \hat{\theta}| p(\theta|\mathcal{D}) d\theta$$
Boyesian risk?

$$\frac{d\pi}{d\hat{\theta}} = \int_{-\infty}^{+\infty} \sqrt{h} |\theta - \hat{\theta}| p(\theta | \mathcal{B}) d\theta = \int_{-\infty}^{+\infty} \sqrt{h} |\theta - \hat{\theta}| (1 |\theta - \hat{\theta}|) (1 |\theta - \hat{\theta}|) p(\theta | \mathcal{B})$$

$$= \int_{-\infty}^{+\infty} (-1) \sqrt{h} e^{-\frac{1}{2}} p(\theta | \mathcal{B}) d\theta + \int_{-\infty}^{+\infty} \sqrt{h} e^{-\frac{1}{2}} p(\theta | \mathcal{B}) d\theta = 0$$

$$= \int_{-\infty}^{+\infty} d\theta p(\theta | \mathcal{B}) = \int_{-\infty}^{+\infty} d\theta p(\theta | \mathcal{B}) = \int_{-\infty}^{+\infty} d\theta p(\theta | \mathcal{B}) = 0$$

$$= \int_{-\infty}^{+\infty} d\theta p(\theta | \mathcal{B}) = \int_{-\infty}^{+\infty} d\theta p(\theta | \mathcal{B}) = 0$$

- What could you choose as a parametric family? Gaussian p(y; μ, 6²) = e (y-μ)<sup>2</sup>/<sub>26</sub><sup>2</sup>
   What is the MLE?

Assume we know  $6^2$ . Mrs.? Mrs. =  $\frac{1}{N} \stackrel{N}{\geq} y_i$ 4.0 3.5 3.0 2.5 2.0 1.5 1.0 0.5 0.0

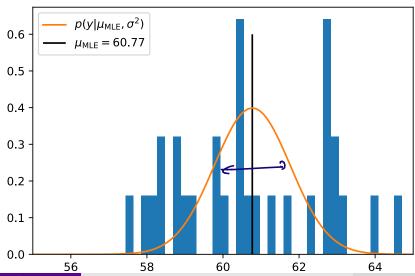
58

56

Marylou Gabrié (CDS, NYU)

64

- N = 30 measurements  $y_i$
- What could you choose as a parametric family?
- What is the MLE?



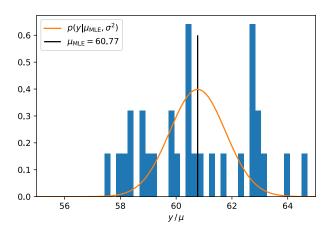
Marylou Gabrié (CDS, NYU)

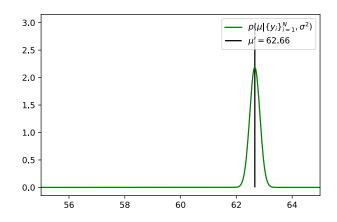
• 
$$N = 30$$
 measurements  $y_i$ 

$$\begin{array}{cccc}
N & -(y; h)^{2} \\
( & ) & 26^{2} \\
 & | & | & | & | \\
 & - \sum_{i=n}^{N} \frac{(y_{i} - \mu_{i})^{2}}{26^{2}} - (y_{i} - \mu_{i})^{2} \\
 & - \frac{(\mu - \mu_{i})^{2}}{26^{2}} - (y_{i} - \mu_{i})^{2}
\end{array}$$

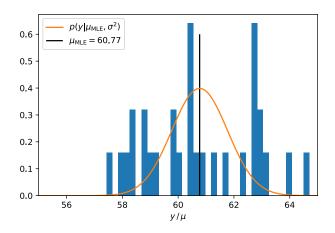
• 
$$N=30$$
 measurements  $y_i$   $\mathcal{D}=2y_i \mathcal{J}_{i=\Lambda}^N$   
• Now meteorologists tells you they have a prior:  $p(\mu)=\mathcal{N}(\mu;\mu_0,1)=\frac{1}{\sqrt{2\pi}}$  e What is the posterior? 
$$p(\mu|\mathcal{D}, 6^2) \propto \text{dihelihood} \times \text{prior} \propto \frac{1}{12\pi} e^{-\frac{(y_i - \mu)^2}{26^2}} e^{-\frac{(\mu - \mu_0)^2}{2}} e^{-\frac{y_i - \mu_0^2}{26^2}} e^{-\frac{y_i -$$

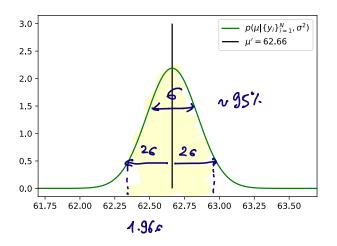
- N = 30 measurements  $y_i$
- Now meteorologists tells you they have a prior:  $p(\mu) = \mathcal{N}(\mu; \mu_0, 1)$
- What is the posterior?





- N = 30 measurements  $y_i$
- Now meteorologists tells you they have a prior:  $p(\mu) = \mathcal{N}(\mu; \mu_0, 1)$
- What is the posterior? What is the credible set?





- N = 30 measurements  $y_i$
- Now meteorologists tells you they have a prior:  $p(\mu) = \mathcal{N}(\mu; \mu_0, 1)$
- The posterior is  $p(\mu|\{y_i\}_{i=1}^N, \sigma^2) = \mathcal{N}(\mu; \mu', \sigma'^2)$ .
- What are the point estimates of  $\mu$  minimizing squared loss, absolute loss and 0-1 loss?

$$\hat{\mu}_{MSE} = \min_{\hat{\mathcal{L}}} \int d\mu \, p(\mu | \mathcal{D}, 6^2) \left( u - \hat{\mu} \right)^2 = \int d\mu \, \mu \, p|\mu | \mathcal{D}, 6^2 \right) = \mu'$$

$$\hat{\mu}_{AA} = \mu'$$

$$\hat{\mu}_{AAP} = \operatorname{argmax} \, p(\hat{\mu} | \mathcal{D}, 6^2) = \mu'$$