

Feb 22.

lec 6

minimum mean
absolute error

$$\hat{\theta}_{\text{MMAE}} = \text{med}[\theta|x] = a \text{ such that } \int_{-\infty}^a p(\theta|x) d\theta = \frac{1}{2}$$

$$\hat{\theta}_{\text{MMAE}} = \underset{\theta \in \Theta}{\text{argmax}} \{F$$

$$= \frac{12}{20} = 0.6$$

Using our model: iid bern(θ) and data $x = \langle 0, 1, 1 \rangle$, we can compute the MMAE Bayesian point estimate:

$$\int_0^a 12 \theta^2 (1-\theta) d\theta = 12 \left[\frac{\theta^3}{3} - \frac{\theta^4}{4} \right] = 12 \left[\frac{\theta^3}{3} - \frac{\theta^4}{4} \right]$$

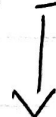
$$= 12 \left[\frac{a^3}{3} - \frac{a^4}{4} \right] \stackrel{\text{set}}{=} \frac{1}{2} \Rightarrow$$

This integral in the denominator is a special integral and is known as the "beta function":

$$B(\alpha, \beta) := \int_0^1 t^{\alpha-1} (1-t)^{\beta-1} dt$$

The beta function has no closed form solution but can be calculated to arbitrary precision using a scientific calculator.

$$= \frac{1}{B(\sum x_i + 1, n - \sum x_i + 1)} \cdot \theta^{\sum x_i + 1 - 1} (1 - \theta)^{n - \sum x_i + 1 - 1} =$$



$$\text{Beta}(\sum x_i + 1, n - \sum x_i + 1)$$

We just derived that the posterior for the iid bernoulli likelihood is a beta distribution. Let's go back to probability class and examine the beta distribution...

$$Y \sim \text{Beta}(\alpha, \beta) \stackrel{\text{pdf}}{=} \frac{1}{B(\alpha, \beta)} y^{\alpha-1} (1-y)^{\beta-1} = p(y)$$

$$\text{Supp}[Y] = (0,1) \int_0^1 \frac{1}{B(\alpha, \beta)} y^{\alpha-1} (1-y)^{\beta-1} dy$$

$$= \frac{1}{B(\alpha, \beta)} \int_0^1 y^{\alpha-1} (1-y)^{\beta-1} dy = 1$$

what does $\alpha \in$ live in and $\beta \in$ live in?

$$\alpha > 0, \beta > 0$$

$$\alpha = 0, \beta = 1 \Rightarrow \int_0^1 \frac{1}{y} dy = \infty$$

$$E[Y] = \int_0^1 y P(y) dy = \int_0^1 y \frac{1}{\beta(\alpha, \beta)} y^{\alpha-1} (1-y)^{\beta-1} dy$$

$$= \frac{1}{\beta(\alpha, \beta)} \int_0^1 y^{\alpha+1-1} (1-y)^{\beta-1} dy$$

$$= \frac{\beta(\alpha+1, \beta)}{\beta(\alpha, \beta)}$$

To simplify this, we need the gamma function:

$$\Gamma(\alpha) := \int_0^{\infty} t^{\alpha-1} e^{-t} dt, \alpha > 0$$

Fact #1: $\Gamma(\alpha+1) = \alpha \Gamma(\alpha)$

Fact #2: $\beta(\alpha, \beta) = \frac{\Gamma(\alpha) \Gamma(\beta)}{\Gamma(\alpha+\beta)}$

$$\begin{aligned} &= \frac{\Gamma(\alpha+1) \Gamma(\beta)}{\Gamma(\alpha+\beta+1)} \\ &= \frac{\alpha \Gamma(\alpha) \Gamma(\beta)}{(\alpha+\beta) \Gamma(\alpha+\beta)} \\ &= \frac{\alpha}{\alpha+\beta} \end{aligned}$$

Var [Y] = on hw

$$\text{Mode}[Y] = \underset{\substack{y \in (0,1) \\ \uparrow \\ \text{this is} \\ \text{support}}}{\text{argmax}} \left\{ \frac{1}{B(\alpha, \beta)} y^{\alpha-1} (1-y)^{\beta-1} \right\}$$

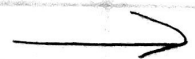
$$= \text{argmax} \{ (\alpha-1) \ln(y) + (\beta-1) \ln(1-y) \}$$

$$\xRightarrow{\text{derivate}} \frac{\alpha-1}{y} - \frac{\beta-1}{1-y} \stackrel{\text{set}}{=} 0 = y_v = \frac{\alpha-1}{\alpha+\beta-1}$$

If we take the second derivate to check if it's negative, we find it's only negative if both alpha and beta are greater than 1.

Med[Y] has no closed form expression and thus must be done with a computer. We will denote the answer to this using notation from the R programming

Let's take a look at the shapes of the beta distribution



①

 $P(x)$

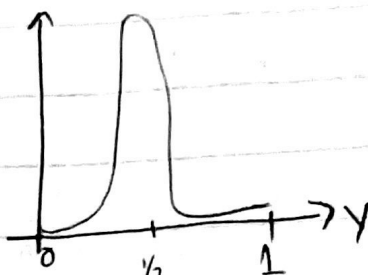
$\alpha = \beta = 1$

Uniform
distribution
function

②

 $P(x)$

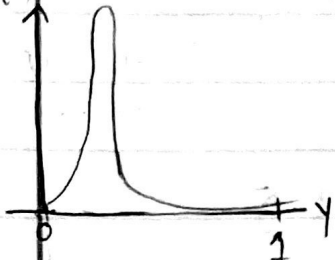
$\alpha = \beta = 100$



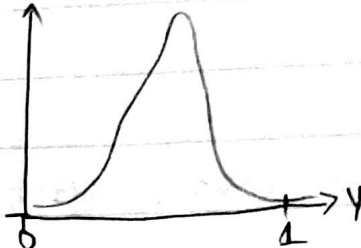
③

 $P(x)$

$\alpha = 10, \beta = 90$

 $P(x)$

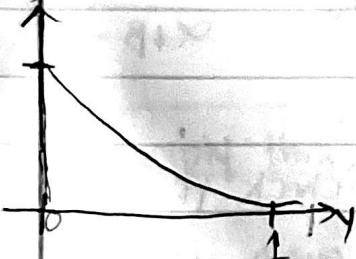
$\alpha = 10, \beta = 10$ ④



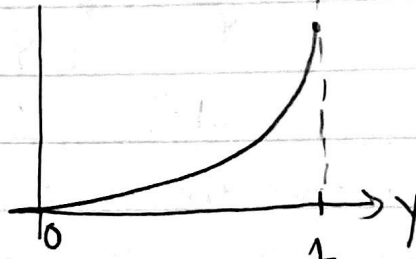
⑤

 $P(x)$

$\alpha = 1, \beta = 4$

⑥ $P(x)$

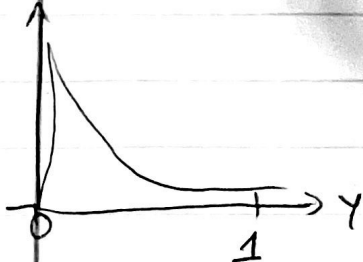
$\alpha = 4, \beta = 1$



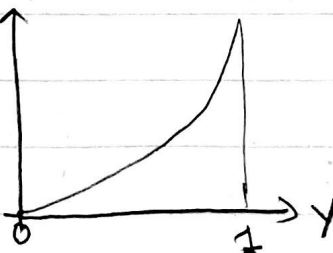
⑦

 $P(x)$

$\alpha = 1.001, \beta = 4$

⑧ $P(x)$

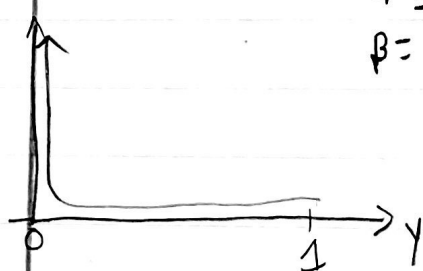
$\alpha = 4, \beta = 1.001$



⑨

 $P(x)$

$\alpha = .999, \beta = 4$



⑩

$\alpha = 4, \beta = .999$

