

Posterior(s) for Normal(s)

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1 unknown mean, known variance

$$Y \sim N(\mu, \sigma^2); \mu \sim N(\mu_0, \sigma_0^2)$$

WTS: $P(\mu|y)$ and the weights of $P(y|\mu)$ and $P(\mu)$

$$P(\mu) \propto \exp\left[-\frac{(\mu-\mu_0)^2}{2\sigma_0^2}\right]$$

$$P(y|\mu) \propto \exp\left[-\frac{\sum(y-\mu)^2}{2\sigma^2}\right]$$

$P(\mu|y) \propto \exp\left[-\frac{(\mu-\mu_0)^2}{2\sigma_0^2} - \frac{\sum(y-\mu)^2}{2\sigma^2}\right]$ which tells us nothing about the weights or even a nice Gaussian kernel.

Luckily, we know that

$$\begin{aligned} f(x) &= a(y-x)^2 + b(x-z)^2 \\ &= (a+b) \left[x - \frac{ay+bz}{a+b} \right]^2 + \frac{ab}{a+b} (y-z)^2 \end{aligned}$$

$$\begin{aligned} f(x) &= \exp[a(y-x)^2 + b(x-z)^2] \\ &\propto \exp\left[(a+b) \left[x - \frac{ay+bz}{a+b} \right]^2\right] \end{aligned}$$

$$\exp\left[-\frac{(\mu-\mu_0)^2}{2\sigma_0^2} - \frac{\sum(y-\mu)^2}{2\sigma^2}\right] \propto \exp\left[-\frac{1}{2} \left[\frac{1}{\sigma_0^2} + \frac{n}{\sigma^2} \right] \left[\mu - \frac{\frac{\mu_0}{\sigma_0^2} + \frac{n\bar{y}}{\sigma^2}}{\frac{1}{\sigma_0^2} + \frac{n}{\sigma^2}} \right]^2\right]$$

So we got a nice kernel. Let's interpret the dynamics of the weights?

2 known mean, unknown variance

$$Y \sim N(\mu, \sigma^2); \sigma^2 \sim \Gamma^{-1}(a, b)$$

We use the inverse gamma because:

1. it's positive

2. it is a conjugate of the normal (the posterior will be inverse gamma)

3. it is a general case of χ^{-1}

$$P(\sigma^2) \propto (\sigma^2)^{-\frac{a+2}{2}} \exp\left[\frac{-ab}{2\sigma^2}\right]$$

$$P(y|\mu, \sigma^2) \propto (\sigma^2)^{-\frac{n}{2}} \exp\left[\frac{-\sum(y_i - \mu)^2}{2\sigma^2}\right]$$

$P(\sigma^2|y) \propto (\sigma^2)^{-\frac{a+2+n}{2}} \exp\left[\frac{-(ab + \sum(y_i - \mu)^2)}{2\sigma^2}\right]$, which is the kernel of an inverse gamma. Note that it reduces to $\frac{1}{\sigma^2}$ as $a, b \rightarrow 0$ because it reduces to the sample estimate.

3 A look at regression with known variance

$$y \sim N(X\beta, \sigma^2 I_n); P(\beta) \propto \exp\left[(\beta - \beta_0)' \Sigma_0^{-1} (\beta - \beta_0)\right]$$

$$P(\beta|y) \propto \exp\left[(y - x\beta)' (\sigma^2 I_n)^{-1} (y - x\beta) + (\beta - \beta_0)' \Sigma_0^{-1} (\beta - \beta_0)\right]$$

for simplicity, let $\beta_0 = \mathbf{0}$ as we are now more interested in Σ_0 .

$$\Sigma_0 = \begin{bmatrix} \tau_1^2 & 0 \\ 0 & \tau_K^2 \end{bmatrix}$$

$$\begin{aligned} P(\beta|y) &\propto \exp\left[-\frac{1}{2}(y - x\beta)' (\sigma^2 I_n)^{-1} (y - x\beta) + \beta' \Sigma_0^{-1} \beta\right] \\ &\propto \exp\left[-\frac{1}{2}\beta' (x'x (\sigma^2 I_n)^{-1} + \Sigma_0^{-1}) \beta - 2\beta' x'y (\sigma^2 I_n)^{-1}\right] \end{aligned}$$

Let $V = x'x (\sigma^2 I_n)^{-1} + \Sigma_0^{-1}$, look at $\beta V \beta - 2\beta' x'y \sigma^2 I_n^{-1}$. Can we see the $(X-?)??(X-?)$ format in it? (hint: add a constant)

$$P(\beta|y) \propto \exp\left[-\frac{1}{2}(\beta - V^{-1}x'y\sigma^2 I_n^{-1})' V (\beta - V^{-1}x'y\sigma^2 I_n^{-1})\right], \text{ which is our beloved Gaussian kernel.}$$

$$\beta|y \sim N(V^{-1}x'y\sigma^2 I_n^{-1}, V^{-1})$$

So, as $\tau_k \rightarrow \infty$, $V \rightarrow \sigma^2 (X'X)^{-1}$

$$\text{and } E[\beta|y, x] = (x'x)^{-1}x'y$$