

More insight into conjugate prior for (μ, σ^2) ?

- Suppose μ unknown, $\therefore \sigma^2$ known $y|\mu, \sigma^2 \sim N(\mu, \sigma^2)$

- PRIOR - $p(\mu) = N(\mu_0, \tau_0^2)$ $n > 1$

$$p(\mu|y) = N\left(\frac{\frac{1}{\tau_0^2}}{\frac{1}{\tau_0^2} + \frac{n}{\sigma^2}} \mu_0 + \frac{\frac{n}{\sigma^2}}{\frac{1}{\tau_0^2} + \frac{n}{\sigma^2}} \bar{y}, \frac{1}{\frac{1}{\tau_0^2} + \frac{n}{\sigma^2}}\right)$$

We could have decided to let τ_0^2 be a function of the known σ^2

$\tau_0^2 = \frac{\sigma^2}{K_0}$ so that we set K_0 instead of τ_0^2

then:

$$p(\mu|y) = N\left(\frac{\frac{K_0}{\sigma^2}}{\frac{K_0}{\sigma^2} + \frac{n}{\sigma^2}} \mu_0 + \frac{\frac{n}{\sigma^2}}{\frac{K_0}{\sigma^2} + \frac{n}{\sigma^2}} \bar{y}, \frac{1}{\frac{K_0}{\sigma^2} + \frac{n}{\sigma^2}}\right)$$

So, now everything is in terms of σ^2 & we can think about K_0 analogously to n . This provides a way in some situations to more easily think about amount of prior information we want to include.

We can simplify the above $p(\mu|y)$ as

$$= N\left(\frac{K_0}{K_0 + n} \mu_0 + \frac{n}{K_0 + n} \bar{y}, \frac{\sigma^2}{K_0 + n}\right)$$

(HOPE THIS HELPS!)