

2. Bivariate Cases

Case 2.1

Suppose the data follows a Normal distribution with unknown mean μ and unknown variance σ^2 : $X|\mu, \sigma^2 \sim \text{Normal}(\mu, \sigma^2)$. Let us consider a **conjugate prior** distribution where $\mu|\sigma^2$ follows a Normal distribution with hyperparameters $\mu_0, \sigma^2/k_0$ with k_0 some known constant: $\mu|\sigma^2 \sim N(\mu_0, \sigma^2/k_0)$ and the prior distribution of the parameter σ^2 is scaled-Inverse- X^2 with hyperparameters ν_0, σ_0^2 : $\sigma^2 \sim \text{scaled-Inverse-}X^2(\nu_0, \sigma_0^2)$.

Data: $p(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \Leftrightarrow X|\mu, \sigma^2 \sim \text{Normal}(\mu, \sigma^2)$.

Prior distribution:

$$p(\mu|\sigma^2) = \frac{1}{\frac{\sigma}{\sqrt{k_0}} \sqrt{2\pi}} e^{-\frac{(\mu-\mu_0)^2}{2\sigma^2/k_0}} \Leftrightarrow \mu|\sigma^2 \sim N(\mu_0, \sigma^2/k_0).$$

$$p(\sigma^2) = \frac{\left(\frac{\nu_0}{2} \sigma_0^2\right)^{\frac{\nu_0}{2}}}{\Gamma\left(\frac{\nu_0}{2}\right)} (\sigma^2)^{-\left(\frac{\nu_0}{2}+1\right)} e^{-\frac{\nu_0 \sigma_0^2}{2\sigma^2}} \Leftrightarrow \sigma^2 \sim \text{scaled-Inverse-}X^2(\nu_0, \sigma_0^2).$$

In brief: $p(\mu, \sigma^2) = p(\mu|\sigma^2) \cdot p(\sigma^2) \sim \text{Normal-Inv-}X^2\left(\mu, \sigma^2 \mid \mu_0, \sigma^2/k_0, \nu_0, \sigma_0^2\right)$.

Likelihood function:

$$\begin{aligned}
p(\mathbf{x}^{(n)} | \mu, \sigma^2) &= (2\pi)^{-n/2} (\sigma^2)^{-n/2} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2\right\} \\
&\propto (\sigma^2)^{-n/2} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \bar{x})^2\right\} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^n (\bar{x} - \mu)^2\right\} \\
&\propto (\sigma^2)^{-n/2} \exp\left\{-\frac{(n-1)S^2}{2\sigma^2}\right\} \exp\left\{-\frac{n(\bar{x} - \mu)^2}{2\sigma^2}\right\} \\
&\propto (\sigma^2)^{-1/2} \exp\left\{-\frac{(\bar{x} - \mu)^2}{2\sigma^2/n}\right\} \cdot (\sigma^2)^{-\frac{n-1}{2}} \exp\left\{-\frac{(n-1)S^2}{2\sigma^2}\right\}, \quad \text{where } S^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n-1}.
\end{aligned}$$

Posterior distribution:

$$\begin{aligned}
p(\mu, \sigma^2 | \mathbf{x}^{(n)}) &\propto (\sigma^2)^{-1/2} (\sigma^2)^{-n/2} (\sigma^2)^{-\left(\frac{\nu_0}{2}+1\right)} \exp\left\{-\frac{n(\bar{x} - \mu)^2 + (n-1)S^2}{2\sigma^2}\right\} \exp\left\{-\frac{k_0(\mu - \mu_0)^2 + \nu_0\sigma_0^2}{2\sigma^2}\right\} \\
&\propto (\sigma^2)^{-1/2} (\sigma^2)^{-\left(\frac{\nu_0+n}{2}+1\right)} \exp\left\{-\frac{(n+k_0)\mu^2 + (-2n\bar{x} - 2k_0\mu_0)\mu + \nu_0\sigma_0^2 + (n-1)S^2 + k_0\mu_0^2 + n\bar{x}^2}{2\sigma^2}\right\} \\
&\propto (\sigma^2)^{-1/2} (\sigma^2)^{-\left(\frac{\nu_0+n}{2}+1\right)} \exp\left\{-\frac{\nu_0\sigma_0^2 + (n-1)S^2 + (k_0+n) \left[\mu^2 - 2\left(\frac{n\bar{x} + k_0\mu_0}{k_0+n}\right)\mu \pm \left(\frac{n\bar{x} + k_0\mu_0}{k_0+n}\right)^2 \right] + k_0\mu_0^2 + n\bar{x}^2}{2\sigma^2}\right\} \\
&\propto (\sigma^2)^{-1/2} (\sigma^2)^{-\left(\frac{\nu_0+n}{2}+1\right)} \exp\left\{-\frac{\nu_0\sigma_0^2 + (n-1)S^2 + (k_0+n) \left[\mu - \frac{n\bar{x} + k_0\mu_0}{k_0+n} \right]^2 - \frac{(n\bar{x} + k_0\mu_0)^2}{k_0+n} + (n\bar{x}^2 + k_0\mu_0^2)}{2\sigma^2}\right\}
\end{aligned}$$

A new identity is formed using the two last quantities of the exponential:

$$-\frac{(n\bar{x} + k_0\mu_0)^2}{k_0+n} + \left(\frac{k_0+n}{k_0+n}\right) (n\bar{x}^2 + k_0\mu_0^2) =$$

$$\begin{aligned}
&= \frac{-(n\bar{x})^2 - (k_0\mu_0)^2 - 2n\bar{x}k_0\mu_0 + (k_0\mu_0)^2 + nk_0\mu_0^2 + nk_0\bar{x}^2 + (n\bar{x})^2}{k_0 + n} \\
&= \frac{nk_0(-2\bar{x}\mu_0 + \mu_0^2 + \bar{x}^2)}{k_0 + n} = \frac{nk_0(\bar{x} - \mu_0)^2}{k_0 + n}.
\end{aligned}$$

Therefore, the posterior distribution can be written in a well-known form:

$$\begin{aligned}
p(\mu, \sigma^2 | \mathbf{x}^{(n)}) &\propto (\sigma^2)^{-1/2} (\sigma^2)^{-\left(\frac{\nu_0+n}{2}+1\right)} \exp \left\{ -\frac{\nu_0\sigma_0^2 + (n-1)S^2 + \frac{nk_0(\bar{x} - \mu_0)^2}{k_0 + n} + (k_0 + n) \left[\mu - \frac{n\bar{x} + k_0\mu_0}{k_0 + n} \right]^2}{2\sigma^2} \right\} \\
&\propto (\sigma^2)^{-1/2} (\sigma^2)^{-\left(\frac{\nu_n}{2}+1\right)} \exp \left\{ -\frac{\nu_n\sigma_n^2 + k_n(\mu - \mu_n)^2}{2\sigma^2} \right\} \Leftrightarrow
\end{aligned}$$

$$p(\mu, \sigma^2 | \mathbf{x}^{(n)}) = p(\mu | \sigma^2, \mathbf{x}^{(n)}) \cdot p(\sigma^2 | \mathbf{x}^{(n)}) = \text{Normal-Inv-}X^2 \left(\mu, \sigma^2 \mid \mu_n, \frac{\sigma_n^2}{k_n}, \nu_n, \sigma_n^2 \right),$$

where $\mu_n = \frac{k_0}{k_0 + n} \mu_0 + \frac{n}{k_0 + n} \bar{x},$

$$k_n = k_0 + n, \quad \nu_n = \nu_0 + n,$$

$$\nu_n\sigma_n^2 = \nu_0\sigma_0^2 + (n-1)S^2 + \frac{nk_0(\bar{x} - \mu_0)^2}{k_0 + n}.$$

Normalizing constant of the posterior distribution:

$$K = \frac{\sqrt{k_n}}{\sqrt{2\pi}} \cdot \frac{\left(\frac{\nu_n}{2}\sigma_n^2\right)^{\frac{\nu_n}{2}}}{\Gamma\left(\frac{\nu_n}{2}\right)}$$

Full Conditional posterior distributions:

- $p(\sigma^2 | \mu, \mathbf{x}^{(n)}) = \frac{p(\sigma^2, \mu | \mathbf{x}^{(n)})}{p(\mu | \mathbf{x}^{(n)})} \propto p(\mu, \sigma^2 | \mathbf{x}^{(n)})$

$$\propto (\sigma^2)^{-\left(\frac{\nu_0+n+1}{2}+1\right)} \exp \left\{ -\frac{\nu_0\sigma_0^2 + k_0(\mu - \mu_0)^2 + \sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2} \right\}$$

$$\propto (\sigma^2)^{-\left(\frac{\nu_0+n+1}{2}+1\right)} \exp \left\{ -\frac{\nu_0\sigma_0^2 + k_0(\mu - \mu_0)^2 + nS_\mu^2}{2\sigma^2} \right\} \Leftrightarrow$$

$$p(\sigma^2 | \mu, \mathbf{x}^{(n)}) = \text{scaled-Inv-}X^2 \left(\sigma^2 \mid \nu_0 + n + 1, \frac{\nu_0\sigma_0^2 + k_0(\mu - \mu_0)^2 + nS_\mu^2}{\nu_0 + n + 1} \right)$$

$$\bullet \quad p(\mu | \sigma^2, \mathbf{x}^{(n)}) = \frac{p(\mu, \sigma^2 | \mathbf{x}^{(n)})}{p(\sigma^2 | \mathbf{x}^{(n)})} \propto p(\mu, \sigma^2 | \mathbf{x}^{(n)})$$

$$\propto \exp \left\{ -\frac{(k_0 + n) \left(\mu - \frac{k_0\mu_0 + n\bar{x}}{k_0 + n} \right)^2}{2\sigma^2} \right\} \Leftrightarrow$$

$$p(\mu | \sigma^2, \mathbf{x}^{(n)}) = \text{Normal} \left(\mu \mid \frac{k_0\mu_0 + n\bar{x}}{k_0 + n}, \sigma^2 / (k_0 + n) \right) = N \left(\mu \mid \mu_n, \sigma^2 / k_n \right)$$

Marginal posterior distributions:

$$\bullet \quad p(\mu | \mathbf{x}^{(n)}) = \int_0^{+\infty} p(\mu, \sigma^2 | \mathbf{x}^{(n)}) d\sigma^2$$

$$= \frac{\sqrt{k_n}}{\sqrt{2\pi}} \cdot \frac{\left(\frac{\nu_n}{2} \sigma_n^2 \right)^{\frac{\nu_n}{2}}}{\Gamma\left(\frac{\nu_n}{2}\right)} \cdot \int_0^{+\infty} (\sigma^2)^{-1/2} (\sigma^2)^{-\left(\frac{\nu_n+1}{2}\right)} \exp \left\{ -\frac{\nu_n\sigma_n^2 + k_n(\mu - \mu_n)^2}{2\sigma^2} \right\} d\sigma^2$$

$$= \frac{\sqrt{k_n}}{\sqrt{2\pi}} \cdot \frac{\left(\frac{\nu_n}{2} \sigma_n^2 \right)^{\frac{\nu_n}{2}}}{\Gamma\left(\frac{\nu_n}{2}\right)} \cdot \int_0^{+\infty} (\sigma^2)^{-\left(\frac{\nu_n+1}{2}+1\right)} \exp \left\{ -\frac{\nu_n\sigma_n^2}{2\sigma^2} \left[1 + \frac{k_n(\mu - \mu_n)^2}{\nu_n\sigma_n^2} \right] \right\} d\sigma^2$$

We set $z = \frac{\nu_n \sigma_n^2}{2\sigma^2} \Rightarrow \sigma^2 = \frac{\nu_n \sigma_n^2}{2z} \Leftrightarrow (\sigma^2)^{-1} = \frac{2z}{\nu_n \sigma_n^2}$

and $d\sigma^2 = -\frac{\nu_n \sigma_n^2}{2z^2} dz$, with the integral boundaries being reversed.

Additionally, we set $B = \left[1 + \frac{k_n (\mu - \mu_n)^2}{\nu_n \sigma_n^2} \right]$. Thus, we have:

$$\begin{aligned} p(\mu | \mathbf{x}^{(n)}) &= \frac{\sqrt{k_n}}{\sqrt{2\pi}} \cdot \frac{\left(\frac{\nu_n \sigma_n^2}{2}\right)^{\frac{\nu_n}{2}}}{\Gamma\left(\frac{\nu_n}{2}\right)} \cdot \int_{+\infty}^0 \left(\frac{2z}{\nu_n \sigma_n^2}\right)^{\frac{\nu_n+1}{2}} \left(-\frac{\nu_n \sigma_n^2}{2z^2}\right) \exp\{-B \cdot z\} dz \\ &= \frac{\sqrt{k_n}}{\sqrt{\pi}} \cdot \frac{(\nu_n)^{\frac{\nu_n}{2}} (\sigma_n^2)^{\frac{\nu_n}{2}}}{\Gamma\left(\frac{\nu_n}{2}\right)} \cdot \frac{2^{-\frac{1}{2} - \frac{1}{2} + \frac{\nu_n}{2} - \frac{\nu_n+1}{2}}}{(\nu_n \sigma_n^2)^{\frac{\nu_n+1}{2} + 1 - 1}} \int_0^{+\infty} z^{\frac{\nu_n+1}{2} - 1} \exp\{-B \cdot z\} dz \\ &= \frac{\sqrt{k_n}}{\sqrt{\pi}} \cdot \frac{\Gamma\left(\frac{\nu_n+1}{2}\right)}{\Gamma\left(\frac{\nu_n}{2}\right)} (\sigma_n^2)^{-\frac{1}{2}} (\nu_n)^{-\frac{1}{2}} \cdot \left[1 + \frac{k_n (\mu - \mu_n)^2}{\nu_n \sigma_n^2} \right]^{-\frac{\nu_n+1}{2}} \\ &= \frac{1}{\sqrt{\nu_n \cdot \pi}} \cdot \frac{\Gamma\left(\frac{\nu_n+1}{2}\right)}{\Gamma\left(\frac{\nu_n}{2}\right)} \sqrt{k_n} (\sigma_n^2)^{-\frac{1}{2}} \cdot \left[1 + \frac{1}{\nu_n} \frac{(\mu - \mu_n)^2}{\sigma_n^2 / k_n} \right]^{-\frac{\nu_n+1}{2}} \Leftrightarrow \end{aligned}$$

$$p(\mu | \mathbf{x}^{(n)}) = \text{Student} \left(\mu \mid \mu_n, \frac{\sigma_n^2}{k_n}, \nu_n \right)$$

- $p(\sigma^2 | \mathbf{x}^{(n)}) = \int_{-\infty}^{+\infty} p(\mu, \sigma^2 | \mathbf{x}^{(n)}) d\mu$

$$\begin{aligned} &= \frac{\sqrt{k_n}}{\sqrt{2\pi}} \cdot \frac{\left(\frac{\nu_n \sigma_n^2}{2}\right)^{\frac{\nu_n}{2}}}{\Gamma\left(\frac{\nu_n}{2}\right)} (\sigma^2)^{-\left(\frac{\nu_n}{2}+1\right)} \exp\left\{-\frac{\nu_n \sigma_n^2}{2\sigma^2}\right\} \cdot \underbrace{\int_0^{+\infty} (\sigma^2)^{-1/2} \exp\left\{-\frac{k_n (\mu - \mu_n)^2}{2\sigma^2}\right\} d\mu}_{\text{Normal-kernel}} \end{aligned}$$

$$\begin{aligned}
&= \frac{\sqrt{k_n}}{\sqrt{2\pi}} \cdot \frac{\left(\frac{\nu_n}{2} \sigma_n^2\right)^{\frac{\nu_n}{2}}}{\Gamma\left(\frac{\nu_n}{2}\right)} (\sigma^2)^{-\left(\frac{\nu_n}{2}+1\right)} \exp\left\{-\frac{\nu_n \sigma_n^2}{2\sigma^2}\right\} \cdot \left(\frac{\sqrt{k_n}}{\sqrt{2\pi}}\right)^{-1} \\
&= \frac{\left(\frac{\nu_n}{2} \sigma_n^2\right)^{\frac{\nu_n}{2}}}{\Gamma\left(\frac{\nu_n}{2}\right)} (\sigma^2)^{-\left(\frac{\nu_n}{2}+1\right)} \exp\left\{-\frac{\nu_n \sigma_n^2}{2\sigma^2}\right\} \Leftrightarrow
\end{aligned}$$

$$p(\sigma^2 | \mathbf{x}^{(n)}) = \text{scaled-Inv-Gamma}\left(\sigma^2 \left| \frac{\nu_n}{2}, \frac{\nu_n \sigma_n^2}{2} \right.\right) = \text{scaled-Inv-}X^2(\sigma^2 | \nu_n, \sigma_n^2)$$

Predictive distribution:

We must use the relation $p(y | \mathbf{x}^{(n)}) = \int p(y | \mathbf{x}^{(n)}, \sigma^2) p(\sigma^2 | \mathbf{x}^{(n)}) d\sigma^2$. Therefore, we initially have to induce the distribution of $Y | \mathbf{x}^{(n)}, \sigma^2$ which remains unknown up to this point.

Note: $p(y | \mu, \sigma^2, \mathbf{x}^{(n)}) = p(y | \mu, \sigma^2) \rightarrow$ conditional independence.

$$\begin{aligned}
p(y | \sigma^2, \mathbf{x}^{(n)}) &= \int_{-\infty}^{+\infty} p(y | \mu, \sigma^2, \mathbf{x}^{(n)}) p(\mu | \sigma^2, \mathbf{x}^{(n)}) d\mu = \int_{-\infty}^{+\infty} p(y | \mu, \sigma^2) p(\mu | \sigma^2, \mathbf{x}^{(n)}) d\mu \\
&= \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(y-\mu)^2}{2\sigma^2}\right\} \frac{k_n}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{k_n}{2\sigma^2}(\mu-\mu_n)^2\right\} d\mu \\
&= \frac{\sqrt{k_n}}{2\pi\sigma^2} \int_{-\infty}^{+\infty} \exp\left\{-\frac{(y-\mu)^2 + k_n(\mu-\mu_n)^2}{2\sigma^2}\right\} d\mu \\
&= \frac{\sqrt{k_n}}{2\pi\sigma^2} \int_{-\infty}^{+\infty} \exp\left\{-\frac{y^2 + \mu^2 - 2y\mu + k_n\mu^2 + k_n\mu_n^2 - 2k_n\mu\mu_n}{2\sigma^2}\right\} d\mu \\
&= \frac{\sqrt{k_n}}{2\pi\sigma^2} \int_{-\infty}^{+\infty} \exp\left\{-\frac{(k_n+1)\mu^2 - 2\mu(y+k_n\mu_n) + y^2 + k_n\mu_n^2}{2\sigma^2}\right\} d\mu
\end{aligned}$$

$$\begin{aligned}
&= \frac{\sqrt{k_n}}{2\pi\sigma^2} \int_{-\infty}^{+\infty} \exp \left\{ -\frac{(k_n+1)}{2\sigma^2} \left(\mu^2 - 2\mu \left(\frac{y+k_n\mu_n}{k_n+1} \right) + \frac{y^2}{k_n+1} + \frac{k_n\mu_n^2}{k_n+1} \right) \right\} d\mu \\
&= \frac{\sqrt{k_n}}{2\pi\sigma^2} \int_{-\infty}^{+\infty} \exp \left\{ -\frac{(k_n+1)}{2\sigma^2} \left(\mu^2 - 2\mu \left(\frac{y+k_n\mu_n}{k_n+1} \right) \pm \left(\frac{y+k_n\mu_n}{k_n+1} \right)^2 + \frac{y^2}{k_n+1} + \frac{k_n\mu_n^2}{k_n+1} \right) \right\} d\mu \\
&= \frac{\sqrt{k_n}}{2\pi\sigma^2} \exp \left\{ -\frac{1}{2\sigma^2} \left(y^2 + k_n\mu_n^2 - \frac{(y+k_n\mu_n)^2}{k_n+1} \right) \right\} \int_{-\infty}^{+\infty} \exp \left\{ -\frac{(k_n+1)}{2\sigma^2} \left(\mu - \frac{y+k_n\mu_n}{k_n+1} \right)^2 \right\} d\mu \\
&= \frac{\sqrt{k_n}}{2\pi\sigma^2} \cdot \frac{\sqrt{2\pi\sigma^2}}{\sqrt{k_n+1}} \cdot \exp \left\{ -\frac{1}{2\sigma^2} \left(\frac{k_n y^2 + y^2 + k_n^2 \mu_n^2 + k_n \mu_n^2 - y^2 - k_n^2 \mu_n^2 - 2y k_n \mu_n}{k_n+1} \right) \right\} \\
&= \frac{1}{\sqrt{2\pi\sigma^2}} \cdot \frac{\sqrt{k_n}}{\sqrt{k_n+1}} \cdot \exp \left\{ -\frac{1}{2\sigma^2} \cdot \frac{k_n}{k_n+1} (y^2 + \mu_n^2 - 2y\mu_n) \right\} \\
&= \frac{1}{\sqrt{2\pi\sigma^2}} \cdot \frac{\sqrt{k_n}}{\sqrt{k_n+1}} \cdot \exp \left\{ -\frac{1}{2\sigma^2} \cdot \frac{k_n}{k_n+1} (y - \mu_n)^2 \right\} \Leftrightarrow \\
&p(y|\mathbf{x}^{(n)}, \sigma^2) = \text{Normal} \left(y \middle| \mu_n, \frac{\sigma^2}{\frac{k_n}{k_n+1}} \right)
\end{aligned}$$

We substitute the result to the initial formula:

$$\begin{aligned}
p(y|\mathbf{x}^{(n)}) &= \int p(y|\mathbf{x}^{(n)}, \sigma^2) p(\sigma^2|\mathbf{x}^{(n)}) d\sigma^2 \\
&= \int_0^{+\infty} (2\pi\sigma^2)^{-1/2} \left(\frac{k_n}{k_n+1} \right)^{1/2} \exp \left\{ -\frac{1}{2\sigma^2} \frac{k_n}{k_n+1} (y - \mu_n)^2 \right\} \frac{\left(\frac{\nu_n}{2} \right)^{\frac{\nu_n}{2}}}{\Gamma \left(\frac{\nu_n}{2} \right)} (\sigma^2)^{\left(\frac{\nu_n}{2} \right)} (\sigma^2)^{-\left(\frac{\nu_n}{2} + 1 \right)} \exp \left\{ -\frac{\nu_n \sigma_n^2}{2\sigma^2} \right\} d\sigma^2 \\
&= (2\pi)^{-1/2} \left(\frac{k_n}{k_n+1} \right)^{1/2} \frac{\left(\frac{\nu_n}{2} \right)^{\frac{\nu_n}{2}}}{\Gamma \left(\frac{\nu_n}{2} \right)} (\sigma_n^2)^{\left(\frac{\nu_n}{2} \right)} \int_0^{+\infty} (\sigma^2)^{-\left(\frac{\nu_n+1}{2} + 1 \right)} \exp \left\{ -\frac{1}{2\sigma^2} \left[\frac{k_n}{k_n+1} (y - \mu_n)^2 + \nu_n \sigma_n^2 \right] \right\} d\sigma^2
\end{aligned}$$

$$\begin{aligned}
&= (2\pi)^{-1/2} \left(\frac{k_n}{k_n+1} \right)^{1/2} \frac{\left(\frac{\nu_n}{2} \right)^{\frac{\nu_n}{2}}}{\Gamma\left(\frac{\nu_n}{2} \right)} (\sigma_n^2)^{\left(\frac{\nu_n}{2} \right)} \int_0^{+\infty} (\sigma^2)^{-\left(\frac{\nu_n+1}{2} \right)} \exp \left\{ - \frac{\nu_n+1}{2\sigma^2} \left[\frac{k_n}{k_n+1} (y-\mu_n)^2 + \nu_n \sigma_n^2 \right] \right\} d\sigma^2 \\
&\quad \underbrace{\hspace{15em}}_{\text{scaled-Inv-}X^2 \text{ kernel}} \\
&= (2\pi)^{-1/2} \left(\frac{k_n}{k_n+1} \right)^{1/2} \frac{\left(\frac{\nu_n}{2} \right)^{\frac{\nu_n}{2}}}{\Gamma\left(\frac{\nu_n}{2} \right)} (\sigma_n^2)^{\left(\frac{\nu_n}{2} \right)} \Gamma\left(\frac{\nu_n+1}{2} \right) \left(\frac{\nu_n+1}{2} \right)^{-\frac{\nu_n+1}{2}} \left[\frac{\frac{k_n}{k_n+1} (y-\mu_n)^2 + \nu_n \sigma_n^2}{\nu_n+1} \right]^{-\frac{\nu_n+1}{2}} \\
&= \frac{2^{\frac{1}{2} + \frac{1}{2} + \frac{\nu_n}{2} - \frac{\nu_n}{2}}}{\sqrt{\pi}} \left(\frac{k_n}{k_n+1} \right)^{1/2} \frac{\left(\frac{\nu_n}{2} \right)^{\frac{\nu_n}{2}}}{\Gamma\left(\frac{\nu_n}{2} \right)} (\sigma_n^2)^{\left(\frac{\nu_n}{2} \right)} \Gamma\left(\frac{\nu_n+1}{2} \right) \frac{(\nu_n+1)^{\frac{\nu_n+1}{2}}}{(\nu_n+1)^{\frac{\nu_n+1}{2}}} (\nu_n \sigma_n^2)^{-\frac{\nu_n+1}{2}} \left[\frac{k_n}{k_n+1} \frac{(y-\mu_n)^2}{\nu_n \sigma_n^2} + 1 \right]^{-\frac{\nu_n+1}{2}} \\
&= \frac{1}{\sqrt{\pi}} \frac{\Gamma\left(\frac{\nu_n+1}{2} \right)}{\Gamma\left(\frac{\nu_n}{2} \right)} \left(\frac{k_n}{k_n+1} \right)^{1/2} (\nu_n)^{\frac{\nu_n}{2} - \frac{\nu_n}{2} - \frac{1}{2}} (\sigma_n^2)^{\left(\frac{\nu_n}{2} - \frac{\nu_n}{2} - \frac{1}{2} \right)} \left[1 + \frac{k_n}{k_n+1} \frac{(y-\mu_n)^2}{\nu_n \sigma_n^2} \right]^{-\frac{\nu_n+1}{2}} \\
&= \frac{1}{\sqrt{\nu_n \cdot \pi}} \frac{\Gamma\left(\frac{\nu_n+1}{2} \right)}{\Gamma\left(\frac{\nu_n}{2} \right)} \left(\frac{k_n}{k_n+1} \right)^{1/2} (\sigma_n^2)^{\frac{1}{2}} \left[1 + \frac{1}{\nu_n} \frac{(y-\mu_n)^2}{\sigma_n^2} \frac{1}{\left(\frac{k_n}{k_n+1} \right)} \right]^{-\frac{\nu_n+1}{2}} \Leftrightarrow \\
&p(y|\mathbf{x}^{(n)}) = \text{Student} \left(y \middle| \mu_n, \left(\frac{k_n}{k_n+1} \right)^{-1} \sigma_n^2, \nu_n \right)
\end{aligned}$$

Prior predictive distribution:

Usually, in order to find the a-priori predictive distribution (i.e. marginal likelihood), we use the relation $p(x) = \int_{\Theta} p(x|\theta) p(\theta) d\theta$. As to the particular biparametric case, we choose one of the parameters arbitrarily and finally the distribution in question will be determined through the relation $p(x) = \int p(x|\sigma^2) p(\sigma^2) d\sigma^2$. Therefore, one must first

calculate the distribution of $X|\sigma^2$ (conditioning and then integrating over μ). The results are similar to those of the previous procedure for the predictive distribution.

$$\begin{aligned}
p(x|\sigma^2) &= \int_{-\infty}^{+\infty} p(x|\mu, \sigma^2) p(\mu|\sigma^2) d\mu \\
&= \int_{-\infty}^{+\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \frac{\sqrt{k_0}}{\sigma\sqrt{2\pi}} e^{-\frac{k_0(\mu-\mu_0)^2}{2\sigma^2}} d\mu \\
&= (2\pi\sigma^2)^{-1} k_0^{1/2} \int_{-\infty}^{+\infty} \exp\left\{-\frac{(x-\mu)^2 + k_0(\mu-\mu_0)^2}{2\sigma^2}\right\} d\mu \\
&= (2\pi\sigma^2)^{-1} k_0^{1/2} \int_{-\infty}^{+\infty} \exp\left\{-\frac{x^2 + \mu^2 - 2\mu x + k_0\mu^2 + k_0\mu_0^2 - 2k_0\mu\mu_0}{2\sigma^2}\right\} d\mu \\
&= (2\pi\sigma^2)^{-1} k_0^{1/2} \int_{-\infty}^{+\infty} \exp\left\{-\frac{(k_0+1)\mu^2 - 2(x+k_0\mu_0)\mu + x^2 + k_0\mu_0^2}{2\sigma^2}\right\} d\mu \\
&= (2\pi\sigma^2)^{-1} k_0^{1/2} \int_{-\infty}^{+\infty} \exp\left\{-\frac{(k_0+1)}{2\sigma^2} \left[\mu^2 - 2\left(\frac{x+k_0\mu_0}{k_0+1}\right)\mu + \frac{x^2}{k_0+1} + \frac{k_0\mu_0^2}{k_0+1}\right]\right\} d\mu \\
&= (2\pi\sigma^2)^{-1} k_0^{1/2} \int_{-\infty}^{+\infty} \exp\left\{-\frac{(k_0+1)}{2\sigma^2} \left[\left(\mu - \frac{x+k_0\mu_0}{k_0+1}\right)^2 - \left(\frac{x+k_0\mu_0}{k_0+1}\right)^2 + \frac{x^2}{k_0+1} + \frac{k_0\mu_0^2}{k_0+1}\right]\right\} d\mu \\
&= (2\pi\sigma^2)^{-1} k_0^{1/2} \exp\left\{-\frac{1}{2\sigma^2} \left[-\frac{(x+k_0\mu_0)^2}{k_0+1} + x^2 + k_0\mu_0^2\right]\right\} \int_{-\infty}^{+\infty} \exp\left\{-\frac{(k_0+1)}{2\sigma^2} \left[\left(\mu - \frac{x+k_0\mu_0}{k_0+1}\right)^2\right]\right\} d\mu \\
&= \frac{k_0^{1/2}}{(2\pi\sigma^2)} \frac{(2\pi\sigma^2)^{1/2}}{(k_0+1)^{1/2}} \exp\left\{-\frac{1}{2\sigma^2} \left[\frac{-x^2 - (k_0\mu_0)^2 - 2xk_0\mu_0 + k_0x^2 + x^2 + (k_0\mu_0)^2 + k_0\mu_0^2}{k_0+1}\right]\right\} \\
&= (2\pi\sigma^2)^{-1/2} \left(\frac{k_0}{k_0+1}\right)^{1/2} \exp\left\{-\frac{1}{2\sigma^2} \frac{k_0}{k_0+1} (x-\mu_0)^2\right\} \Leftrightarrow \\
p(x|\sigma^2) &= \text{Normal}\left(x \middle| \mu_0, \left(\frac{k_0}{k_0+1}\right)^{-1} \sigma^2\right)
\end{aligned}$$

Thus, after substituting to the initial formula, we get:

$$\begin{aligned}
p(x) &= \int p(x|\sigma^2) p(\sigma^2) d\sigma^2 = \\
&= \int_0^{+\infty} (2\pi\sigma^2)^{-1/2} \left(\frac{k_0}{k_0+1}\right)^{1/2} \exp\left\{-\frac{1}{2\sigma^2} \frac{k_0}{k_0+1} (x-\mu_0)^2\right\} \cdot \frac{\left(\frac{\nu_0}{2}\sigma_0^2\right)^{\frac{\nu_0}{2}}}{\Gamma\left(\frac{\nu_0}{2}\right)} (\sigma^2)^{-\left(\frac{\nu_0}{2}+1\right)} \exp\left\{-\frac{\nu_0\sigma_0^2}{2\sigma^2}\right\} d\sigma^2 \\
&= (2\pi)^{-1/2} \left(\frac{k_0}{k_0+1}\right)^{1/2} \frac{\left(\frac{\nu_0}{2}\sigma_0^2\right)^{\frac{\nu_0}{2}}}{\Gamma\left(\frac{\nu_0}{2}\right)} \int_0^{+\infty} (\sigma^2)^{-\left(\frac{\nu_0}{2}+1\right)} \exp\left\{-\frac{1}{2\sigma^2} \left[\frac{k_0}{k_0+1} (x-\mu_0)^2 + \nu_0\sigma_0^2\right]\right\} d\sigma^2 \\
&= (2\pi)^{-1/2} \left(\frac{k_0}{k_0+1}\right)^{1/2} \frac{\left(\frac{\nu_0}{2}\sigma_0^2\right)^{\frac{\nu_0}{2}}}{\Gamma\left(\frac{\nu_0}{2}\right)} \int_0^{+\infty} (\sigma^2)^{-\left(\frac{\nu_0}{2}+1\right)} \exp\left\{-\frac{1}{2\sigma^2} (\nu_0+1) \frac{\left[\frac{k_0}{k_0+1} (x-\mu_0)^2 + \nu_0\sigma_0^2\right]}{(\nu_0+1)}\right\} d\sigma^2.
\end{aligned}$$

Inside the integral, the kernel of a scaled-Inv- X^2 distribution has been formed.

$$\begin{aligned}
p(x) &= (2\pi)^{-1/2} \left(\frac{k_0}{k_0+1}\right)^{1/2} \frac{\left(\frac{\nu_0}{2}\sigma_0^2\right)^{\frac{\nu_0}{2}}}{\Gamma\left(\frac{\nu_0}{2}\right)} \frac{\Gamma\left(\frac{\nu_0+1}{2}\right)}{\left(\frac{\nu_0+1}{2}\right)^{\frac{\nu_0+1}{2}}} \left[\frac{k_0}{k_0+1} \frac{(x-\mu_0)^2 + \nu_0\sigma_0^2}{\nu_0+1}\right]^{-\frac{\nu_0+1}{2}} \\
&= \frac{2^{-1/2}}{\sqrt{\pi}} \frac{\Gamma\left(\frac{\nu_0+1}{2}\right)}{\Gamma\left(\frac{\nu_0}{2}\right)} \left(\frac{k_0}{k_0+1}\right)^{1/2} \sigma_0^{\nu_0} \left(\frac{\nu_0}{2}\right)^{\frac{\nu_0}{2}} \left(\frac{\nu_0+1}{2}\right)^{-\frac{\nu_0+1}{2}} (\nu_0+1)^{\frac{\nu_0+1}{2}} \left[\nu_0\sigma_0^2 \left(1 + \frac{k_0}{k_0+1} \frac{(x-\mu_0)^2}{\nu_0\sigma_0^2}\right)\right]^{-\frac{\nu_0+1}{2}} \\
&= \frac{2^{-1/2}}{\sqrt{\pi}} \frac{\Gamma\left(\frac{\nu_0+1}{2}\right)}{\Gamma\left(\frac{\nu_0}{2}\right)} \left(\frac{k_0}{k_0+1}\right)^{1/2} \sigma_0^{\nu_0} \left(\frac{\nu_0}{2}\right)^{\frac{\nu_0}{2}} 2^{\frac{\nu_0+1}{2}} \left[\nu_0\sigma_0^2\right]^{-\frac{\nu_0+1}{2}} \left(1 + \frac{1}{\nu_0} \frac{(x-\mu_0)^2}{\sigma_0^2} \frac{k_0}{k_0+1}\right)^{-\frac{\nu_0+1}{2}}
\end{aligned}$$

$$= \frac{2^{\frac{\nu_0}{2}} \Gamma\left(\frac{\nu_0+1}{2}\right)}{\sqrt{\pi} \Gamma\left(\frac{\nu_0}{2}\right)} \left(\frac{k_0}{k_0+1}\right)^{1/2} \sigma_0^{\nu_0} \left(\frac{\nu_0}{2}\right)^{\frac{\nu_0}{2}} \nu_0^{-1/2} \nu_0^{-\nu_0/2} [\sigma_0^2]^{-\frac{\nu_0+1}{2}} \left(1 + \frac{1}{\nu_0} \frac{(x-\mu_0)^2}{\sigma_0^2 / \frac{k_0}{k_0+1}}\right)^{-\frac{\nu_0+1}{2}}$$

$$= \frac{2^{\frac{\nu_0}{2}} \Gamma\left(\frac{\nu_0+1}{2}\right)}{\sqrt{\pi \nu_0} \Gamma\left(\frac{\nu_0}{2}\right)} \left(\frac{k_0}{k_0+1}\right)^{1/2} 2^{-\nu_0/2} (\sigma_0^2)^{\nu_0/2} [\sigma_0^2]^{-\frac{\nu_0+1}{2}} \left(1 + \frac{1}{\nu_0} \frac{(x-\mu_0)^2}{\sigma_0^2 / \frac{k_0}{k_0+1}}\right)^{-\frac{\nu_0+1}{2}}$$

$$= \frac{1}{\sqrt{\pi \cdot \nu_0}} \frac{\Gamma\left(\frac{\nu_0+1}{2}\right)}{\Gamma\left(\frac{\nu_0}{2}\right)} \left(\frac{k_0}{k_0+1}\right)^{1/2} [\sigma_0^2]^{-\frac{1}{2}} \left(1 + \frac{1}{\nu_0} \frac{(x-\mu_0)^2}{\sigma_0^2 / \frac{k_0}{k_0+1}}\right)^{-\frac{\nu_0+1}{2}} \Leftrightarrow$$

$$p(x) = \text{Student} \left(x \mid \mu_0, \frac{\sigma_0^2}{\frac{k_0}{k_0+1}}, \nu_0 \right)$$

Case 2.2

Suppose the data follows a Normal distribution with unknown mean μ and unknown variance σ^2 : $X|\mu, \sigma^2 \sim \text{Normal}(\mu, \sigma^2)$. Let us consider *Jeffreys improper prior* where $\mu|\sigma^2$ is proportionate to $\frac{1}{\sigma^2}$.

Data: $p(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

Prior: $p(\mu|\sigma^2) \propto \frac{1}{\sigma^2}$

Note: This particular prior distribution is improper but nevertheless sensible, as indicated below.

$$p(\varphi) = p(\log \sigma^2) = p(\sigma^2) \left| \frac{d\sigma^2}{d\phi} \right| \propto \sigma^2 \cdot \frac{1}{\sigma^2} = 1$$

Likelihood function:

$$p(\mathbf{x}^{(n)}|\mu, \sigma^2) = (2\pi)^{-n/2} (\sigma^2)^{-n/2} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2\right\}$$

$$\propto (\sigma^2)^{-n/2} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \bar{x})^2\right\} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^n (\bar{x} - \mu)^2\right\}$$

$$\propto (\sigma^2)^{-n/2} \exp\left\{-\frac{(n-1)S^2 + n(\bar{x} - \mu)^2}{2\sigma^2}\right\}, \quad \text{where } S^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n-1}.$$

Posterior distribution:

$$\begin{aligned}
p(\mu, \sigma^2 | \mathbf{x}^{(n)}) &\propto (\sigma^2)^{-\left(\frac{n+2}{2}\right)} \exp\left\{-\frac{n(\bar{x} - \mu)^2 + (n-1)S^2}{2\sigma^2}\right\} \\
&\propto (\sigma^2)^{-\left(\frac{1}{2}\right)} \exp\left\{-\frac{(\bar{x} - \mu)^2}{2 \cdot \sigma^2/n}\right\} (\sigma^2)^{-\left(\frac{n+1}{2}\right)} \exp\left\{-\frac{(n-1)S^2}{2\sigma^2}\right\} \\
&\propto (\sigma^2)^{-\left(\frac{1}{2}\right)} \exp\left\{-\frac{(\bar{x} - \mu)^2}{2 \cdot \sigma^2/n}\right\} (\sigma^2)^{-\left(\frac{n-1}{2}+1\right)} \exp\left\{-\frac{(n-1)S^2}{2\sigma^2}\right\} \Leftrightarrow
\end{aligned}$$

$$p(\mu, \sigma^2 | \mathbf{x}^{(n)}) = \text{Normal-scaled-Inv-}X^2\left(\mu, \sigma^2 \mid \bar{x}, \sigma^2/n, n-1, S^2\right)$$

Normalizing constant of the posterior distribution:

$$K = \frac{\sqrt{n}}{\sqrt{2\pi}} \cdot \frac{\left(\frac{n-1}{2} S^2\right)^{\frac{n-1}{2}}}{\Gamma\left(\frac{n-1}{2}\right)}$$

Note: The following equation holds and can be confirmed by the results below:

$$p(\mu, \sigma^2 | \mathbf{x}^{(n)}) = p(\mu | \sigma^2, \mathbf{x}^{(n)}) \cdot p(\sigma^2 | \mathbf{x}^{(n)}).$$

Full Conditional posterior distributions:

$$\blacksquare \quad p(\mu | \sigma^2, \mathbf{x}^{(n)}) = \frac{p(\mu, \sigma^2 | \mathbf{x}^{(n)})}{p(\sigma^2 | \mathbf{x}^{(n)})} \propto p(\mu, \sigma^2 | \mathbf{x}^{(n)}) \propto \exp\left\{-\frac{n}{2\sigma^2}(\bar{x} - \mu)^2\right\} \Leftrightarrow$$

$$p(\mu | \sigma^2, \mathbf{x}^{(n)}) = N\left(\mu \mid \bar{x}, \sigma^2/n\right)$$

$$\blacksquare \quad p(\sigma^2 | \mu, \mathbf{x}^{(n)}) = \frac{p(\mu, \sigma^2 | \mathbf{x}^{(n)})}{p(\mu | \mathbf{x}^{(n)})} \propto p(\mu, \sigma^2 | \mathbf{x}^{(n)})$$

$$\propto (\sigma^2)^{-\left(\frac{n+2}{2}\right)} \exp\left\{-\frac{n(\bar{x}-\mu)^2+(n-1)S^2}{2\sigma^2}\right\} = (\sigma^2)^{-\left(\frac{n+1}{2}\right)} \exp\left\{-\frac{n(\bar{x}-\mu)^2+(n-1)S^2}{2\sigma^2}\right\} \Leftrightarrow$$

$$p\left(\sigma^2 \mid \mu, \mathbf{x}^{(n)}\right) = \text{scaled-Inv-}X^2\left(\sigma^2 \mid n, \frac{n(\bar{x}-\mu)^2+(n-1)S^2}{n}\right)$$

Marginal posterior distributions:

$$\bullet \quad p\left(\mu \mid \mathbf{x}^{(n)}\right) = \int_0^{+\infty} p\left(\mu, \sigma^2 \mid \mathbf{x}^{(n)}\right) d\sigma^2 = K \cdot \int_0^{+\infty} (\sigma^2)^{-\left(\frac{n+2}{2}\right)} \exp\left\{-\frac{n(\bar{x}-\mu)^2+(n-1)S^2}{2\sigma^2}\right\} d\sigma^2$$

We set $A = n(\bar{x}-\mu)^2 + (n-1)S^2$, for easier calculations.

$$\text{We also set} \quad z = \frac{A}{2\sigma^2} \Rightarrow \quad d\sigma^2 = -\frac{A}{2z^2} dz \quad \text{and} \quad (\sigma^2)^{-1} = \frac{2z}{A}$$

and substitute to the above integral (with reversed boundaries):

$$\begin{aligned} p\left(\mu \mid \mathbf{x}^{(n)}\right) &= K \cdot \int_{+\infty}^0 A^{-\left(\frac{n+2}{2}\right)} (2z)^{\left(\frac{n+2}{2}\right)} \exp\{-z\} (-A)(2z)^{-2} dz \\ &= 2^{\left(\frac{n-1}{2}\right)} K \cdot A^{-\left(\frac{n}{2}\right)} \cdot \underbrace{\int_0^{+\infty} z^{\left(\frac{n-1}{2}\right)} \exp\{-z\} dz}_{\text{Gamma}(n/2,1)\text{-kernel}} \\ &= 2^{\left(\frac{n-1}{2}\right)} \frac{\sqrt{n}}{\sqrt{2\pi}} \cdot \frac{\left(\frac{n-1}{2} S^2\right)^{\frac{n-1}{2}} \Gamma\left(\frac{n}{2}\right)}{\Gamma\left(\frac{n-1}{2}\right) 1^{\frac{n}{2}}} A^{-\left(\frac{n}{2}\right)} \\ &= \frac{\sqrt{n}}{\sqrt{\pi}} \cdot \frac{\Gamma\left(\frac{n}{2}\right) \left((n-1)S^2\right)^{\frac{n-1}{2}}}{\Gamma\left(\frac{n-1}{2}\right)} \left[n(\bar{x}-\mu)^2 + (n-1)S^2\right]^{-\frac{n}{2}} \\ &= \frac{\sqrt{n}}{\sqrt{\pi}} \cdot \frac{\Gamma\left(\frac{n}{2}\right)}{\Gamma\left(\frac{n-1}{2}\right)} \left((n-1)S^2\right)^{\frac{n-1}{2}} \left[(n-1)S^2\right]^{\frac{n}{2}} \left[1 + \frac{n(\bar{x}-\mu)^2}{(n-1)S^2}\right]^{-\frac{n}{2}} \end{aligned}$$

$$= \frac{\Gamma\left(\frac{n}{2}\right)}{\Gamma\left(\frac{n-1}{2}\right)} \frac{\sqrt{n} \cdot (S^2)^{\frac{1}{2}}}{\sqrt{\pi(n-1)}} \left[1 + \frac{1}{(n-1)} \frac{(\bar{x} - \mu)^2}{S^2/n} \right]^{-\frac{n}{2}} \Leftrightarrow$$

$$p(\mu | \mathbf{x}^{(n)}) = \text{Student}\left(\mu \mid n-1, \bar{x}, S^2/n\right).$$

$$\begin{aligned} \blacksquare \quad p(\sigma^2 | \mathbf{x}^{(n)}) &= \int_{-\infty}^{+\infty} p(\mu, \sigma^2 | \mathbf{x}^{(n)}) d\mu = K \cdot \int_{-\infty}^{+\infty} (\sigma^2)^{-\left(\frac{n+2}{2}\right)} \exp\left\{-\frac{n(\bar{x} - \mu)^2 + (n-1)S^2}{2\sigma^2}\right\} d\mu \\ &= K \cdot (\sigma^2)^{-\left(\frac{n+2}{2}\right)} \exp\left\{-\frac{(n-1)S^2}{2\sigma^2}\right\} \int_{-\infty}^{+\infty} \exp\left\{-\frac{n(\bar{x} - \mu)^2}{2\sigma^2}\right\} d\mu \\ &= \frac{\sqrt{n}}{\sqrt{2\pi}} \cdot \frac{\left(\frac{n-1}{2} S^2\right)^{\frac{n-1}{2}}}{\Gamma\left(\frac{n-1}{2}\right)} \cdot (\sigma^2)^{-\left(\frac{n+2}{2}\right)} \exp\left\{-\frac{(n-1)S^2}{2\sigma^2}\right\} \frac{\sqrt{2\pi}}{\sqrt{n}} (\sigma^2)^{\left(\frac{1}{2}\right)} \\ &= \frac{\left(\frac{n-1}{2} S^2\right)^{\frac{n-1}{2}}}{\Gamma\left(\frac{n-1}{2}\right)} (\sigma^2)^{-\left(\frac{n+1}{2}\right)} \exp\left\{-\frac{(n-1)S^2}{2\sigma^2}\right\} \Leftrightarrow \end{aligned}$$

$$p(\sigma^2 | \mathbf{x}^{(n)}) = \text{scaled-Inv-}X^2(\sigma^2 \mid n-1, S^2)$$

This last relation entails $\frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2$.

Predictive distribution:

Similar to the conjugate case, we will use the formula $p(y | \mathbf{x}^{(n)}) = \int p(y | \mathbf{x}^{(n)}, \sigma^2) p(\sigma^2 | \mathbf{x}^{(n)}) d\sigma^2$, thus it is fundamental to primarily derive the distribution of $Y | \mathbf{x}^{(n)}, \sigma^2$.

$$p(y | \mathbf{x}^{(n)}, \sigma^2) = \int_{-\infty}^{+\infty} p(y | \mu, \sigma^2, \mathbf{x}^{(n)}) p(\mu | \sigma^2, \mathbf{x}^{(n)}) d\mu = \int_{-\infty}^{+\infty} p(y | \mu, \sigma^2) p(\mu | \sigma^2, \mathbf{x}^{(n)}) d\mu$$

$$\begin{aligned}
&= \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(y-\mu)^2}{2\sigma^2}\right\} \frac{\sqrt{n}}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{n}{2\sigma^2}(\bar{x}-\mu)^2\right\} d\mu \\
&= \frac{\sqrt{n}}{2\pi\sigma^2} \int_{-\infty}^{+\infty} \exp\left\{-\frac{(y-\mu)^2 + n(\bar{x}-\mu)^2}{2\sigma^2}\right\} d\mu \\
&= \frac{\sqrt{n}}{2\pi\sigma^2} \int_{-\infty}^{+\infty} \exp\left\{-\frac{y^2 + \mu^2 - 2y\mu + n\bar{x}^2 + n\mu^2 - 2n\bar{x}\mu}{2\sigma^2}\right\} d\mu \\
&= \frac{\sqrt{n}}{2\pi\sigma^2} \int_{-\infty}^{+\infty} \exp\left\{-\frac{(n+1)\mu^2 - 2\mu(y+n\bar{x}) + y^2 + n\bar{x}^2}{2\sigma^2}\right\} d\mu \\
&= \frac{\sqrt{n}}{2\pi\sigma^2} \int_{-\infty}^{+\infty} \exp\left\{-\frac{(n+1)}{2\sigma^2} \left[\mu^2 - 2\mu\left(\frac{y+n\bar{x}}{n+1}\right) + \frac{y^2 + n\bar{x}^2}{n+1} \right]\right\} d\mu \\
&= \frac{\sqrt{n}}{2\pi\sigma^2} \int_{-\infty}^{+\infty} \exp\left\{-\frac{(n+1)}{2\sigma^2} \left[\mu^2 - 2\mu\left(\frac{y+n\bar{x}}{n+1}\right) \pm \left(\frac{y+n\bar{x}}{n+1}\right)^2 + \frac{y^2 + n\bar{x}^2}{n+1} \right]\right\} d\mu \\
&= \frac{\sqrt{n}}{2\pi\sigma^2} \exp\left\{-\frac{1}{2\sigma^2} \left[y^2 + n\bar{x}^2 - \frac{(y+n\bar{x})^2}{n+1} \right]\right\} \int_{-\infty}^{+\infty} \exp\left\{-\frac{(n+1)}{2\sigma^2} \left[\mu - \frac{y+n\bar{x}}{n+1} \right]^2\right\} d\mu \\
&= \frac{\sqrt{n}}{2\pi\sigma^2} \frac{\sqrt{2\pi\sigma^2}}{\sqrt{n+1}} \exp\left\{-\frac{1}{2\sigma^2} \left[\frac{ny^2 + n^2\bar{x}^2 + y^2 + n\bar{x}^2 - y^2 - n^2\bar{x}^2 - 2yn\bar{x}}{n+1} \right]\right\} \\
&= \frac{1}{\sqrt{2\pi\sigma^2}} \frac{\sqrt{n}}{\sqrt{n+1}} \exp\left\{-\frac{1}{2\sigma^2 \frac{n}{n+1}} (y-\bar{x})^2\right\} \Leftrightarrow \\
& p(y|\mathbf{x}^{(n)}, \sigma^2) = N\left(y \mid \bar{x}, \frac{\sigma^2}{\frac{n}{n+1}}\right)
\end{aligned}$$

Substituting to the initial integral, we get:

$$p(y|\mathbf{x}^{(n)}) = \int p(y|\mathbf{x}^{(n)}, \sigma^2) p(\sigma^2|\mathbf{x}^{(n)}) d\sigma^2$$

$$\begin{aligned}
&= \int_0^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \left(\frac{n}{n+1}\right)^{\frac{1}{2}} \exp\left\{-\left(\frac{n}{n+1}\right)\frac{(y-\bar{x})^2}{2\sigma^2}\right\} \cdot \frac{\left(\frac{n-1}{2}\right)^{\frac{n-1}{2}}}{\Gamma\left(\frac{n-1}{2}\right)} (S^2)^{\frac{n-1}{2}} (\sigma^2)^{-\left(\frac{n-1}{2}+1\right)} \exp\left\{-\frac{(n-1)S^2}{2\sigma^2}\right\} d\sigma^2 \\
&= (2\pi)^{-\frac{1}{2}} \sqrt{\frac{n}{n+1}} \frac{\left(\frac{n-1}{2}\right)^{\frac{n-1}{2}}}{\Gamma\left(\frac{n-1}{2}\right)} (S^2)^{\frac{n-1}{2}} \cdot \int_0^{+\infty} (\sigma^2)^{-\left(\frac{n-1}{2}+1\right)} \exp\left\{-\frac{1}{2\sigma^2}\left[\left(\frac{n}{n+1}\right)(y-\bar{x})^2 + (n-1)S^2\right]\right\} d\sigma^2 \\
&= (2\pi)^{-\frac{1}{2}} \sqrt{\frac{n}{n+1}} \frac{\left(\frac{n-1}{2}\right)^{\frac{n-1}{2}}}{\Gamma\left(\frac{n-1}{2}\right)} (S^2)^{\frac{n-1}{2}} \cdot \underbrace{\int_0^{+\infty} (\sigma^2)^{-\left(\frac{n+1}{2}\right)} \exp\left\{-\frac{1}{2\sigma^2} \cdot n \cdot \frac{\left[\left(\frac{n}{n+1}\right)(y-\bar{x})^2 + (n-1)S^2\right]}{n}\right\} d\sigma^2}_{\text{scaled-Inv-}X^2 \text{ kernel}} \\
&= (2\pi)^{-\frac{1}{2}} \sqrt{\frac{n}{n+1}} \frac{\left(\frac{n-1}{2}\right)^{\frac{n-1}{2}}}{\Gamma\left(\frac{n-1}{2}\right)} (S^2)^{\frac{n-1}{2}} \cdot \Gamma\left(\frac{n}{2}\right) \left(\frac{n}{2}\right)^{-\left(\frac{n}{2}\right)} \cdot \left[\left(\frac{n}{n+1}\right)\frac{(y-\bar{x})^2 + (n-1)S^2}{n}\right]^{\frac{n}{2}} \\
&= \frac{2^{-\frac{1}{2}}}{\sqrt{\pi}} \sqrt{\frac{n}{n+1}} \frac{2^{-\frac{n-1}{2}} (n-1)^{\frac{n-1}{2}}}{\Gamma\left(\frac{n-1}{2}\right)} (S^2)^{\frac{n-1}{2}} \cdot \Gamma\left(\frac{n}{2}\right) \frac{\left(\frac{n}{2}\right)^{-\left(\frac{n}{2}\right)}}{\left(n\right)^{-\left(\frac{n}{2}\right)}} \cdot \left[(n-1)S^2\right]^{-\left(\frac{n}{2}\right)} \left[1 + \frac{(y-\bar{x})^2}{(n-1)S^2} \frac{\left(\frac{n}{n+1}\right)}{\left(\frac{n}{n+1}\right)}\right]^{\frac{n}{2}} \\
&= \frac{1}{\sqrt{\pi}} \sqrt{\frac{n}{n+1}} \frac{\Gamma\left(\frac{n}{2}\right)}{\Gamma\left(\frac{n-1}{2}\right)} (n-1)^{\frac{n-1}{2} \cdot \frac{n}{2}} (S^2)^{\frac{n-1}{2} \cdot \frac{n}{2}} \cdot \left[1 + \frac{(y-\bar{x})^2}{(n-1)S^2} \frac{\left(\frac{n}{n+1}\right)}{\left(\frac{n}{n+1}\right)}\right]^{\frac{n}{2}}
\end{aligned}$$

$$= \frac{1}{\sqrt{(n-1)\pi}} \sqrt{\frac{n}{n+1}} \frac{\Gamma\left(\frac{n}{2}\right)}{\Gamma\left(\frac{n-1}{2}\right)} (S^2)^{-\frac{1}{2}} \cdot \left[1 + \frac{1}{n-1} \frac{(y-\bar{x})^2}{S^2 / \left(\frac{n}{n+1}\right)} \right]^{\frac{n}{2}} \Leftrightarrow$$

$$p\left(y \mid \mathbf{x}^{(n)}\right) = \text{Student} \left(y \mid n-1, \bar{x}, \frac{S^2}{\frac{n}{n+1}} \right)$$

Prior predictive distribution:

* The marginal distribution $p(x)$ cannot be written in closed form!

Case 2.3

Suppose the data follows a Normal distribution with unknown mean μ and unknown variance σ^2 : $X|\mu, \sigma^2 \sim \text{Normal}(\mu, \sigma^2)$. Let us consider a **semi-conjugate prior** distribution where $\mu|\sigma^2$ follows a Normal distribution with hyperparameters μ_0, τ_0^2 : $\mu|\sigma^2 = \mu \sim \text{N}(\mu_0, \tau_0^2)$ and the prior distribution of the parameter σ^2 is scaled-Inverse- X^2 with hyperparameters ν_0, σ_0^2 : $\sigma^2 \sim \text{scaled-Inv-}X^2(\nu_0, \sigma_0^2)$.

Data: $p(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \Leftrightarrow X|\mu, \sigma^2 \sim \text{Normal}(\mu, \sigma^2)$

Prior distribution:

$$p(\mu, \sigma^2) = (2\pi)^{-\frac{1}{2}} (\tau_0)^{-\frac{1}{2}} \exp\left\{-\frac{(\mu-\mu_0)^2}{2\tau_0^2}\right\} \cdot \frac{\left(\frac{\nu_0}{2}\right)^{\frac{\nu_0}{2}} (\sigma_0^2)^{\frac{\nu_0}{2}}}{\Gamma\left(\frac{\nu_0}{2}\right)} (\sigma^2)^{-\left(\frac{\nu_0}{2}+1\right)} \exp\left\{-\frac{\nu_0\sigma_0^2}{2\sigma^2}\right\} \Leftrightarrow$$

$$p(\mu, \sigma^2) = p(\mu|\sigma^2) \cdot p(\sigma^2) \sim \text{Normal-scaled-Inv-}X^2(\mu, \sigma^2 | \mu_0, \tau_0^2, \nu_0, \sigma_0^2).$$

Likelihood function:

$$p(\mathbf{x}^{(n)}|\mu, \sigma^2) = (2\pi)^{-n/2} (\sigma^2)^{-n/2} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2\right\}$$

$$\propto (\sigma^2)^{-n/2} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \bar{x})^2\right\} \exp\left\{-\frac{1}{2\sigma^2} \sum_{i=1}^n (\bar{x} - \mu)^2\right\}$$

$$\propto (\sigma^2)^{-n/2} \exp\left\{-\frac{(n-1)S^2 + n(\bar{x} - \mu)^2}{2\sigma^2}\right\}, \quad \text{where } S^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n-1}.$$

Posterior distribution:

The joint posterior distribution of the parameter vector (μ, σ^2) cannot be written in closed form.

Full Conditional posterior distributions:

$$\begin{aligned}
\blacksquare \quad p(\mu | \sigma^2, \mathbf{x}^{(n)}) &= \frac{p(\mu, \sigma^2 | \mathbf{x}^{(n)})}{p(\sigma^2 | \mathbf{x}^{(n)})} \propto p(\mu, \sigma^2 | \mathbf{x}^{(n)}) \\
&\propto \exp\left\{-\frac{(\mu - \mu_0)^2}{2\tau_0^2}\right\} \exp\left\{-\frac{n}{2\sigma^2}(\bar{x} - \mu)^2\right\} \\
&\propto \exp\left\{-\frac{1}{2}\left[\frac{(\mu - \mu_0)^2}{\tau_0^2} + \frac{n(\bar{x} - \mu)^2}{\sigma^2}\right]\right\} \\
&\propto \exp\left\{-\frac{1}{2}\left[\frac{\mu^2 + \mu_0^2 - 2\mu\mu_0}{\tau_0^2} + \frac{n(\bar{x}^2 + \mu^2 - 2\bar{x}\mu)}{\sigma^2}\right]\right\} \\
&\propto \exp\left\{-\frac{1}{2}\left[\left(\frac{1}{\tau_0^2} + \frac{n}{\sigma^2}\right)\mu^2 - 2\mu\left(\frac{\mu_0}{\tau_0^2} + \frac{n\bar{x}}{\sigma^2}\right)\right]\right\} \\
&\propto \exp\left\{-\frac{1}{2}\underbrace{\left(\frac{1}{\tau_0^2} + \frac{n}{\sigma^2}\right)}_{(\tau_n^2)^{-1}}\left[\mu^2 - 2\mu\left(\frac{\mu_0}{\tau_0^2} + \frac{n\bar{x}}{\sigma^2}\right)\right]\right\} \\
&\propto \exp\left\{-\frac{1}{2\tau_n^2}\left[\mu^2 - 2\mu \cdot \underbrace{\tau_n^2\left(\frac{\mu_0}{\tau_0^2} + \frac{n\bar{x}}{\sigma^2}\right)}_{\mu_n}\right]\right\} \\
&\propto \exp\left\{-\frac{1}{2\tau_n^2}[\mu - \mu_n]^2\right\} \Leftrightarrow
\end{aligned}$$

$$p(\mu | \sigma^2, \mathbf{x}^{(n)}) \sim N(\mu | \mu_n, \tau_n^2) \quad \text{where} \quad \mu_n = \frac{\frac{\mu_0}{\tau_0^2} + \frac{n}{\sigma^2}\bar{x}}{\frac{1}{\tau_0^2} + \frac{n}{\sigma^2}}, \quad \tau_n^2 = \left(\frac{1}{\tau_0^2} + \frac{n}{\sigma^2}\right)^{-1}$$

$$\blacksquare \quad p(\sigma^2 | \mu, \mathbf{x}^{(n)}) = \frac{p(\mu, \sigma^2 | \mathbf{x}^{(n)})}{p(\mu | \mathbf{x}^{(n)})} \propto p(\mu, \sigma^2 | \mathbf{x}^{(n)})$$

$$\propto (\sigma^2)^{-n/2} \exp \left\{ -\frac{1}{2\sigma^2} \underbrace{\sum_{i=1}^n (x_i - \mu)^2}_{n \cdot S_\mu^2} \right\} (\sigma^2)^{-\left(\frac{\nu_0+1}{2}\right)} \exp \left\{ -\frac{\nu_0 \sigma_0^2}{2\sigma^2} \right\}$$

$$\propto (\sigma^2)^{-\left(\frac{n+\nu_0+1}{2}\right)} \exp \left\{ -\frac{nS_\mu^2 + \nu_0 \sigma_0^2}{2\sigma^2} \right\} = (\sigma^2)^{-\left(\frac{n+\nu_0+1}{2}\right)} \exp \left\{ -(n+\nu_0) \frac{\frac{nS_\mu^2 + \nu_0 \sigma_0^2}{n+\nu_0}}{2\sigma^2} \right\} \Leftrightarrow$$

$$p(\sigma^2 | \mu, \mathbf{x}^{(n)}) \sim \text{scaled-Inv-}X^2 \left(\sigma^2 \mid \nu_0 + n, \frac{\nu_0 \sigma_0^2 + nS_\mu^2}{\nu_0 + n} \right), \quad \text{where } S_\mu^2 = \frac{\sum_{i=1}^n (x_i - \mu)^2}{n}.$$

Marginal posterior distributions:

The posterior marginal distributions of μ and σ^2 cannot be written in closed form.

Predictive and Prior predictive distributions:

The same holds for the predictive and the prior predictive distributions.