STAT 576 Bayesian Analysis

Lecture 3: Bayesian Inference II

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Recap: Single Parameter Bayesian Inference

- Bayesian Inference Procedure:
  - Name a prior
  - Get the posterior (proportional notation)
  - Point estimators: MAP, posterior mean, etc..
  - Credible interval: QBI, HDR.
  - Prediction for new observations.

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  - Uninformative Prior / Jeffreys Prior
  - (Improper Prior Distribution)
- Important Examples:
  - Normal with known variance: $p(\theta) \propto 1$ (conj. prior: Normal)
  - Normal with known mean: $p(\sigma^2) \propto (\sigma^2)^{-1}$ (conj. prior: inv-Gamma)

Nuisance Parameter

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- Suppose the unknown parameter is $\theta = (\theta_1, \theta_2)$.
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$$y \mid \theta_1, \theta_2$$

- A Bayesian inference needs to define a prior for both θ_1 and θ_2: $p(\theta_1, \theta_2)$
- Then the **joint** posterior is obtained by

$$p(\theta_1, \theta_2 \mid y) \propto p(\theta_1, \theta_2) p(y \mid \theta_1, \theta_2)$$

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- If we are only interested in θ_1, we need to get the **marginal** posterior for θ_1:

$$p(\theta_1 \mid y) = \int p(\theta_1, \theta_2 \mid y) d\mu(\theta_2)$$

Nuisance Parameter

- An important observation for the marginal posterior is

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  - In order to draw samples from $p(\theta_1 \mid y)$
  - We may first draw θ_2 from $p(\theta_2 \mid y)$ (if it is much easier)
  - Then draw θ_1 from $p(\theta_1 \mid \theta_2, y)$ with θ_2 drawn in the first step.

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- Second observation:
  - In order to construct a conjugate joint prior
  - We may find a conjugate prior for the conditional observation model:

    $$p(y \mid \theta_1, \theta_2)$$

    with fixed θ_2
  - Then find a conjugate prior for the marginal observation model:

    $$p(y \mid \theta_2) = \int p(y \mid \theta_1, \theta_2) p(\theta_1 \mid \theta_2) d\mu(\theta_1)$$

Normal with Unkonwn Mean and Variance

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$$y_1, \ldots, y_n \sim \mathcal{N}(\mu, \sigma^2), \quad i.i.d.$$

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- Notice that
$$\sum_{i=1}^{n}(y_i - \mu)^2 = \sum_{i=1}^{n}(y_i - \bar{y})^2 + n(\bar{y} - \mu)^2$$

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- Notice that

$$\sum_{i=1}^{n}(y_i - \mu)^2 = \sum_{i=1}^{n}(y_i - \bar{y})^2 + n(\bar{y} - \mu)^2$$

- Therefore, we write (with $s^2 = (n-1)^{-1} \sum_i (y_i - \bar{y})^2$ the sample variance)

$$p(y_1, \ldots, y_n \mid \mu, \sigma^2) \propto (\sigma^2)^{-n/2} \exp\left\{-\frac{(n-1)s^2 + n(\bar{y} - \mu)^2}{2\sigma^2}\right\}$$

Normal with Unkonwn Mean and Variance

- The score function is

$$\nabla \ell(\mu, \sigma^2) = \begin{pmatrix} -\frac{n(\mu-\bar{y})}{\sigma^2} \\ \frac{(n-1)s^2+n(\bar{y}-\mu)^2}{2(\sigma^2)^2} - \frac{n}{2\sigma^2} \end{pmatrix}$$

- The Fisher's information (2×2 **matrix**) is

$$\mathcal{I}(\mu, \sigma^2) = -\mathbb{E}_{\mu,\sigma^2}[\Delta \ell(\mu, \sigma)] = \begin{bmatrix} \frac{n}{\sigma^2} & 0 \\ 0 & \frac{n}{2\sigma^4} \end{bmatrix}$$

- The estimations of μ and of σ^2 are independent.

Normal — Uninformative Prior

- Attemp 1:
  - Since estimating μ and σ^2 are independent, recall the Uninformative prior:

$$\text{Normal with Known Variance :} p(\mu) \propto 1$$
$$\text{Normal with Known Mean :} p(\sigma^2) \propto 1/\sigma^2$$

  - By independence, we construct the following joint prior:

$$p(\mu, \sigma^2) \propto 1/\sigma^2$$

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$$p(\mu, \sigma^2) \propto \sqrt{|\mathcal{I}|} \propto 1/\sigma^3$$

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- **Only the second one is uninformative.**

Uninformative Prior

- Jeffreys prior for multiparameter case:

$$p(\theta_1, \ldots, \theta_k) \propto \sqrt{|\mathcal{I}(\theta_1, \ldots, \theta_k)|}$$

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- Reasoning:
  - We assign uniform prior $p(\theta) \propto 1$ for the case that

  $$\mathcal{I}(\theta) \propto \boldsymbol{I}$$

  - For any bijective continous mapping $\lambda = g(\theta)$, we have

  $$\mathcal{I}(\lambda) = \left(\frac{\partial\theta}{\partial\lambda}\right)^T \mathcal{I}(\theta) \left(\frac{\partial\theta}{\partial\lambda}\right)$$

  - This corresponds to the change-of-variable of $p(\theta)$ to λ:

  $$p(\lambda) = p(\theta) \left|\frac{\partial\theta}{\partial\lambda}\right| \propto \sqrt{|\mathcal{I}(\lambda)|}$$

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- The joint posterior is

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- The conditional posterior for μ is

$$p(\mu \mid \sigma^2, y_1, \ldots, y_n) \sim \mathcal{N}(\bar{y}, \sigma^2/n)$$

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- The conditional posterior for σ^2 is

$$p(\sigma^2 \mid \mu, y_1, \ldots, y_n) \sim \text{Inv-Gamma}((n+1)/2, [(n-1)s^2 + n(\bar{y}-\mu)^2]/2)$$

Normal — Uninformative Prior

- The marginal posterior for σ^2:

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- Or we can take

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- Therefore,
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- The densities:

$$\text{InvGamma}(\alpha, \beta) \propto x^{-\alpha-1} e^{-\beta/x}, \quad \text{Scaled-Inv-}\chi^2(\nu, \tau^2) \propto x^{-\nu/2-1} e^{-\nu\tau^2/(2x)}$$

Normal — Uninformative Prior

- The marginal posterior for μ is:

$$
\begin{aligned}
p(\mu \mid y_1, \ldots, y_n) &\propto \frac{p(\mu, \sigma^2 \mid y_1, \ldots, y_n)}{p(\sigma^2 \mid \mu^2, y_1, \ldots, y_n)} \\
&\propto \left[(n-1)s^2 + n(\bar{y}-\mu)^2\right]^{-(n+1)/2} \\
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- The kernel:

$$t_\nu(\mu, \tau^2) \propto \left[1 + \frac{(x-\mu)^2}{\nu\tau^2}\right]^{-(\nu+1)/2}$$

Normal — Conjugate Prior

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- We need some prior is the following form:

$$p(\mu, \sigma^2) \propto (\sigma^2)^{-\alpha} \exp\left\{ -\frac{\beta + \gamma(\mu - \delta)^2}{2\sigma^2} \right\}$$

for some hyperparameters $(\alpha, \beta, \gamma, \delta)$.

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  for some hyperparameters $(\alpha, \beta, \gamma, \delta)$.
- We observe:
  - $\mu \mid \sigma^2 \sim \mathcal{N}(\delta, \sigma^2/\gamma)$
  - $\sigma^2 \mid \mu \sim \text{InvGamma}(\alpha - 1, (\beta + \gamma(\mu-\delta)^2)/2)$
  - $\sigma^2 \sim \text{InvGamma}(\alpha - 3/2, \beta/2)$
  - $\mu \sim t_{2\alpha-3}(\delta, \beta/(\gamma(2\alpha-3)))$

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- This prior is called **Normal-Inverse-Gamma** distribution or **Normal-Inverse-χ^2** distribution with density:

$$p(\mu, \sigma^2) \propto (\sigma^2)^{-(\nu_0+3)/2} \exp\left\{-\frac{\nu_0\sigma_0^2 + \kappa_0(\mu - \mu_0)^2}{2\sigma^2}\right\}$$

- N-Inv-Gamma $\left(\mu_0, \kappa_0, \frac{\nu_0}{2}, \frac{\nu_0\sigma_0^2}{2}\right)$ or N-Inv-χ^2 $\left(\mu_0, \kappa_0, \nu_0, \sigma_0^2\right)$

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- The Jeffreys prior corresponds to $\mu_0 = 0 = \kappa_0 = 0 = \nu_0 = 0 = \sigma_0 = 0$

Normal — Conjugate Prior

The posterior is

$$
\begin{aligned}
&p(\mu, \sigma^2 \mid y) \\
&\propto (\sigma^2)^{-(\nu_0+n+3)/2} \exp\left\{-\frac{\nu_0\sigma_0^2 + (n-1)s^2 + \kappa_0(\mu-\mu_0)^2 + n(\mu-\bar{y})^2}{2\sigma^2}\right\} \\
&\propto (\sigma^2)^{-(\nu_0+n+3)/2} \exp\left\{-\frac{\nu_0\sigma_0^2 + (n-1)s^2 + \frac{n\kappa_0}{n+\kappa_0}(\mu_0-\bar{y})^2 + (\kappa_0+n)\left(\mu - \frac{\kappa_0\mu_0+n\bar{y}}{\kappa_0+n}\right)^2}{2\sigma^2}\right\}
\end{aligned}
$$

which is N-Inv-Gamma $\left(\mu_n, \kappa_n, \frac{\nu_n}{2}, \frac{\nu_n\sigma_n^2}{2}\right)$ with

$$
\begin{aligned}
\mu_n &= \frac{\kappa_0\mu_0 + n\bar{y}}{\kappa_0 + n} \\
\kappa_n &= \kappa_0 + n \\
\nu_n &= \nu_0 + n \\
\nu_n\sigma_n^2 &= \nu_0\sigma_0^2 + (n-1)s^2 + \frac{n\kappa_0}{n+\kappa_0}(\mu_0-\bar{y})^2
\end{aligned}
$$

Normal — Conjugate Prior

$$p(\mu, \sigma^2 \mid y) \sim \text{N-Inv-}\Gamma\left(\frac{\kappa_0\mu_0 + n\bar{y}}{\kappa_0 + n}, \kappa_0 + n, \frac{\nu_0 + n}{2}, \frac{\nu_0\sigma_0^2 + (n-1)s^2 + \frac{n\kappa_0}{n+\kappa_0}(\mu_0 - \bar{y})^2}{2}\right)$$

- Now recall our previous discussion on the marginal/conditional distributions.

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- conditional posterior of μ:

$$p(\mu \mid \sigma^2, y) \sim \mathcal{N}\left(\frac{\kappa_0\mu_0 + n\bar{y}}{\kappa_0 + n}, \frac{\sigma^2}{\kappa_0 + n}\right)$$

Normal — Conjugate Prior

$$p(\mu, \sigma^2 \mid y) \sim \text{N-Inv-}\Gamma\left(\frac{\kappa_0\mu_0 + n\bar{y}}{\kappa_0 + n}, \kappa_0 + n, \frac{\nu_0 + n}{2}, \frac{\nu_0\sigma_0^2 + (n-1)s^2 + \frac{n\kappa_0}{n+\kappa_0}(\mu_0 - \bar{y})^2}{2}\right)$$

- Now recall our previous discussion on the marginal/conditional distributions.
- conditional posterior of μ:

$$p(\mu \mid \sigma^2, y) \sim \mathcal{N}\left(\frac{\kappa_0\mu_0 + n\bar{y}}{\kappa_0 + n}, \frac{\sigma^2}{\kappa_0 + n}\right)$$

- conditional posterior of σ^2:

$$p(\sigma^2 \mid \mu, y) \sim \text{InvGamma}\left(\frac{\nu_0 + n + 1}{2}, \frac{\nu_0\sigma_0^2 + (n-1)s^2 + \kappa_0(\mu - \mu_0)^2 + n(\mu - \bar{y})^2}{2}\right)$$

Normal — Conjugate Prior

$$p(\mu, \sigma^2 \mid y) \sim \text{N-Inv-}\Gamma\left(\frac{\kappa_0\mu_0 + n\bar{y}}{\kappa_0 + n}, \kappa_0 + n, \frac{\nu_0 + n}{2}, \frac{\nu_0\sigma_0^2 + (n-1)s^2 + \frac{n\kappa_0}{n+\kappa_0}(\mu_0 - \bar{y})^2}{2}\right)$$

- marginal posterior of σ^2:

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- marginal posterior of μ:

$$p(\mu \mid y) \sim t_{\nu_0+n}\left(\frac{\kappa_0\mu_0 + n\bar{y}}{\kappa_0 + n}, \frac{\nu_0\sigma_0^2 + (n-1)s^2 + \frac{n\kappa_0}{n+\kappa_0}(\mu_0 - \bar{y})^2}{(\nu_0 + n)(\kappa_0 + n)}\right)$$

Recap

Normal-Inverse-Gamma$(\mu, \lambda, \alpha, \beta)$:

$$p(x, \sigma^2) \propto (\sigma^2)^{-\alpha-3/2} \exp\left\{-\frac{2\beta + \lambda(x-\mu)^2}{2\sigma^2}\right\}$$

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- marginal σ^2:

Multinomial

- **Categorical** distribution: $y \in \{1, \ldots, k\}$ with

$$\mathbb{P}(y = i \mid \boldsymbol{\theta}) = \theta_i \text{ for } i = 1, \ldots, k.$$

where $\boldsymbol{\theta} = (\theta_1, \ldots, \theta_n)^T$ and $\sum_{i=1}^{k} \theta_i = 1$.

Multinomial

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- **Multinomial** distribution: $\boldsymbol{y} \in \mathbb{Z}^k$ with

$$p(\boldsymbol{y} \mid n, \boldsymbol{\theta}) = \binom{n}{y_1, y_2, \dots, y_k} \prod_{i=1}^{k} \theta_i^{y_i}$$

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- Generalized binomial coefficient:
$$\binom{n}{y_1, y_2, \dots, y_k} = \frac{n!}{y_1! y_2! \cdots y_k!}$$

Multinomial

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- Generalized binomial coefficient:
$$\binom{n}{y_1, y_2, \dots, y_k} = \frac{n!}{y_1! y_2! \cdots y_k!}$$
- The categorical distribution is a generalization of Bernoulli distribution.
- The multinomial distribution is a generalization of the Binomial distribution.

Multinomial

- Suppose we observe $\boldsymbol{y}$ from a multinomial distribution with parameters n and $\boldsymbol{\theta}$.
- It is immediate that $n = \sum_{i=1}^{k} y_i$. Therefore, the only parameter of interest is $\boldsymbol{\theta}$.

Multinomial

- Suppose we observe $\boldsymbol{y}$ from a multinomial distribution with parameters n and $\boldsymbol{\theta}$.
- It is immediate that $n = \sum_{i=1}^{k} y_i$. Therefore, the only parameter of interest is $\boldsymbol{\theta}$.
- The likelihood function:

$$p(\boldsymbol{y} \mid \boldsymbol{\theta}) \propto \prod_{i=1}^{k} \theta_i^{y_i}$$

- The conjugate prior can be constructed by

$$p(\boldsymbol{\theta}) \propto \prod_{i=1}^{k} \theta_i^{\alpha_i - 1}$$

  for some $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_k)^T$.
- This prior distribution is known as **Dirichlet** distribution with parameter $\boldsymbol{\alpha}$.

Dirichlet Distribution

$$p(\theta_1, \ldots, \theta_k \mid \alpha_1, \ldots, \alpha_k) = \frac{1}{\boldsymbol{B}(\alpha_1, \ldots, \alpha_k)} \prod_{i=1}^{k} \theta_i^{\alpha_i - 1}$$

- The generalized Beta function:

$$\boldsymbol{B}(\alpha_1, \ldots, \alpha_k) = \frac{\prod_{i=1}^{k} \Gamma(\alpha_i)}{\Gamma(\alpha_0)} \quad \text{with } \alpha_0 = \sum_{i=1}^{k} \alpha_i$$

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- The conditional distribution for $\theta_1, \ldots, \theta_m$ for $m < k$:

$$\theta_1, \ldots, \theta_m \mid \theta_{m+1}, \ldots, \theta_k \sim \mathsf{Dir}(\alpha_1, \ldots, \alpha_m) \times \left(1 - \prod_{i=m+1}^{k} \theta_i\right)$$

Dirichlet Distribution

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- The marginal distribution for $\theta_1, \ldots, \theta_m$ for $m < k$:

$$\theta_1, \ldots, \theta_m, \left(1 - \sum_{i=m+1}^{k} \theta_i\right) \sim \mathsf{Dir}\left(\alpha_1, \ldots, \alpha_m, \sum_{i=m+1}^{k} \alpha_i\right)$$

Dirichlet Distribution

$$p(\theta_1, \ldots, \theta_k \mid \alpha_1, \ldots, \alpha_k) = \frac{1}{\boldsymbol{B}(\alpha_1, \ldots, \alpha_k)} \prod_{i=1}^{k} \theta_i^{\alpha_i - 1}$$

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- The conditional distribution for θ_1:

$$\theta_1 \mid \theta_2, \ldots, \theta_k = 1 - \sum_{i=2}^{k} \theta_i$$

Dirichlet Distribution

$$p(\theta_1, \ldots, \theta_k \mid \alpha_1, \ldots, \alpha_k) = \frac{1}{\boldsymbol{B}(\alpha_1, \ldots, \alpha_k)} \prod_{i=1}^{k} \theta_i^{\alpha_i - 1}$$

- The conditional distribution for θ_1:

$$\theta_1 \mid \theta_2, \ldots, \theta_k = 1 - \sum_{i=2}^{k} \theta_i$$

- The marginal distribution for θ_1:

$$\theta_1 \sim \text{Beta}\left(\alpha_1, \alpha_0 - \alpha_0\right)$$

Multinomial

- Observation model:

$$p(\boldsymbol{y} \mid \boldsymbol{\theta}) \propto \prod_{i=1}^{k} \theta_i^{y_i}$$

- The prior distribution:

$$p(\boldsymbol{y} \mid \boldsymbol{\alpha}) \propto \prod_{i=1}^{k} \theta_i^{\alpha_i - 1} \sim \mathsf{Dir}(\boldsymbol{\alpha})$$

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- The prior distribution:

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- The posterior distribution:

$$p(\boldsymbol{\theta} \mid \boldsymbol{y}) \propto \prod_{i=1}^{k} \theta_i^{\alpha_i + y_i - 1} \sim \text{Dir}(\boldsymbol{\alpha} + \boldsymbol{y})$$

Multinomial

Now we consider the uninformative prior.

- Notice that
$$\frac{\partial^2 \ell(\boldsymbol{\theta})}{\partial \theta_i \theta_j} = -\frac{y_i}{\theta_i^2} \mathbb{I}\{i = j\}$$

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$$\mathcal{I}(\boldsymbol{\theta}) = \mathrm{diag}\left(\frac{n}{\theta_1}, \ldots, \frac{n}{\theta_k}\right)$$

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$$\mathcal{I}(\boldsymbol{\theta}) = \mathrm{diag}\left(\frac{n}{\theta_1}, \ldots, \frac{n}{\theta_k}\right)$$
- The Jeffreys prior is
$$p(\boldsymbol{\theta}) \propto \sqrt{|\mathcal{I}(\boldsymbol{\theta})|} \propto \prod_{i=1}^{k} \theta_i^{-1/2}$$
- which corresponds to Dir$(1/2, 1/2, \ldots, 1/2)$.

Multivariate Normal with Known Variance

Multivariate normal $\mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$:

$$p(\boldsymbol{x} \mid \boldsymbol{\mu}, \boldsymbol{\Sigma}) \propto |\boldsymbol{\Sigma}|^{-1/2} \exp\left\{ -\frac{1}{2}(\boldsymbol{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{x} - \boldsymbol{\mu}) \right\}$$

- If we have $\boldsymbol{y}_1, \ldots, \boldsymbol{y}_n$ i.i.d. from $\mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, then

$$p(\boldsymbol{y}_1, \ldots, \boldsymbol{y}_n \mid \boldsymbol{\mu}, \boldsymbol{\Sigma}) \propto |\boldsymbol{\Sigma}|^{-n/2} \exp\left\{ -\frac{1}{2} \sum_{i=1}^{n} (\boldsymbol{y}_i - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{y}_i - \boldsymbol{\mu}) \right\}$$

Multivariate Normal with Known Variance

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- Suppose we fix Σ.
- The conjugate prior is

$$p(\boldsymbol{\mu} \mid \boldsymbol{\Sigma}) \propto \exp\left\{-\frac{1}{2}(\boldsymbol{\mu} - \boldsymbol{\mu}_0)^T \boldsymbol{\Lambda}_0^{-1}(\boldsymbol{\mu} - \boldsymbol{\mu}_0)\right\}$$

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- The posterior is

$$\begin{aligned}
&p(\boldsymbol{\mu} \mid \boldsymbol{y}_1, \ldots, \boldsymbol{y}_n, \boldsymbol{\Sigma}) \\
&\propto \exp\left\{-\frac{1}{2}(\boldsymbol{\mu} - \boldsymbol{\mu}_0)^T \boldsymbol{\Lambda}_0^{-1}(\boldsymbol{\mu} - \boldsymbol{\mu}_0) - \frac{1}{2}\sum_{i=1}^{n}(\boldsymbol{y}_i - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\boldsymbol{y}_i - \boldsymbol{\mu})\right\} \\
&\sim \mathcal{N}\left((\boldsymbol{\Lambda}_0^{-1} + n\boldsymbol{\Sigma}^{-1})^{-1}(\boldsymbol{\Lambda}_0\boldsymbol{\mu}_0 + n\boldsymbol{\Sigma}^{-1}\bar{y}), (\boldsymbol{\Lambda}_0^{-1} + n\boldsymbol{\Sigma}^{-1})^{-1}\right)
\end{aligned}$$

Multivariate Normal

Consider the general case with unknown mean and variance:

$$
\begin{aligned}
& p(\boldsymbol{y}_1, \ldots, \boldsymbol{y}_n \mid \boldsymbol{\mu}, \boldsymbol{\Sigma}) \\
\propto & |\boldsymbol{\Sigma}|^{-n/2} \exp\left\{ -\frac{1}{2} \sum_{i=1}^{n} (\boldsymbol{y}_i - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{y}_i - \boldsymbol{\mu}) \right\} \\
\propto & |\boldsymbol{\Sigma}|^{-n/2} \exp\left\{ -\frac{1}{2} \sum_{i=1}^{n} (\boldsymbol{y}_i - \bar{\boldsymbol{y}})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{y}_i - \bar{\boldsymbol{y}}) - \frac{n}{2} (\boldsymbol{\mu} - \bar{\boldsymbol{y}})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{\mu} - \bar{\boldsymbol{y}}) \right\} \\
\propto & |\boldsymbol{\Sigma}|^{-n/2} \exp\left\{ -\frac{1}{2} \mathrm{tr}(\boldsymbol{S} \boldsymbol{\Sigma}^{-1}) - \frac{n}{2} (\boldsymbol{\mu} - \bar{\boldsymbol{y}})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{\mu} - \bar{\boldsymbol{y}}) \right\}
\end{aligned}
$$

with $\boldsymbol{S} = \sum_{i=1}^{n} (\boldsymbol{y}_i - \bar{\boldsymbol{y}})(\boldsymbol{y}_i - \bar{\boldsymbol{y}})^T$ the sum of squares matrix about the sample mean.

Multivariate Normal

$$p(\boldsymbol{y}_1, \ldots, \boldsymbol{y}_n \mid \boldsymbol{\mu}, \boldsymbol{\Sigma}) \propto |\boldsymbol{\Sigma}|^{-n/2} \exp\left\{-\frac{1}{2}\mathrm{tr}(\boldsymbol{S}\boldsymbol{\Sigma}^{-1}) - \frac{n}{2}(\boldsymbol{\mu} - \bar{\boldsymbol{y}})^T \boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - \bar{\boldsymbol{y}})\right\}$$

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- The conjugate prior would be

$$p(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \propto |\boldsymbol{\Sigma}|^{-(\nu_0+d+2)/2} \exp\left\{-\frac{1}{2}\mathrm{tr}\left(\boldsymbol{\Lambda}_0\boldsymbol{\Sigma}^{-1}\right) - \frac{\kappa_0}{2}(\boldsymbol{\mu} - \boldsymbol{\mu}_0)^T \boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - \boldsymbol{\mu}_0)\right\}$$

  where d is the dimension of $\boldsymbol{\mu}$.

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  where d is the dimension of $\boldsymbol{\mu}$.
- This is known as **Normal-Inverse-Wishart** distribution: $\mathrm{NIW}(\boldsymbol{\mu}_0, \kappa_0, \nu_0, \boldsymbol{\Lambda}_0)$.

Multivariate Normal

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- It is constructed by:

$$\boldsymbol{\Sigma} \sim \text{Inv-Wishart}(\nu_0, \boldsymbol{\Lambda}_0), \quad \boldsymbol{\mu} \mid \boldsymbol{\Sigma} \sim \mathcal{N}(\boldsymbol{\mu}_0, \kappa_0^{-1}\boldsymbol{\Sigma})$$

Multivariate Normal

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- The posterior is NIW$(\boldsymbol{\mu}_n, \kappa_n, \nu_n, \boldsymbol{\Lambda}_0)$ with

$$\boldsymbol{\mu}_0 = \frac{\kappa_0\boldsymbol{\mu}_0 + n\bar{\boldsymbol{y}}}{\kappa_0 + n}, \quad \kappa_n = \kappa_0 + n, \quad \nu_n = \nu_0 + n, \quad \boldsymbol{\Lambda}_n = \boldsymbol{\Lambda}_0 + \boldsymbol{S} + \frac{\kappa_0 n}{\kappa_0 + n}(\boldsymbol{\mu}_0 - \bar{\boldsymbol{y}})(\boldsymbol{\mu}_0 - \bar{\boldsymbol{y}})^T.$$

Normal-Inverse-Wishart Distribution

Consider a NIW$(\boldsymbol{\mu}_0, \kappa, \nu, \boldsymbol{\Lambda})$ distribution:

$$p(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \propto |\boldsymbol{\Sigma}|^{-(\nu+d+2)/2} \exp\left\{-\frac{1}{2}\mathrm{tr}\left(\boldsymbol{\Lambda}\boldsymbol{\Sigma}^{-1}\right) - \frac{\kappa}{2}(\boldsymbol{\mu}-\boldsymbol{\mu}_0)^T\boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu}-\boldsymbol{\mu}_0)\right\}$$

Normal-Inverse-Wishart Distribution

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- Conditional of $\boldsymbol{\mu}$:

$$\boldsymbol{\mu} \mid \boldsymbol{\Sigma} \propto \mathcal{N}(\boldsymbol{\mu}_0, \kappa^{-1}\boldsymbol{\Sigma}^{-1})$$

Normal-Inverse-Wishart Distribution

Consider a NIW$(\boldsymbol{\mu}_0, \kappa, \nu, \boldsymbol{\Lambda})$ distribution:

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- Conditional of $\boldsymbol{\Sigma}$:

$$\boldsymbol{\Sigma} \mid \boldsymbol{\mu} \sim \text{Inv-Wishart}(\nu + 1, \boldsymbol{\Lambda} + \kappa(\boldsymbol{\mu} - \boldsymbol{\mu}_0)(\boldsymbol{\mu} - \boldsymbol{\mu}_0)^T)$$

Normal-Inverse-Wishart Distribution

Consider a $\text{NIW}(\boldsymbol{\mu}_0, \kappa, \nu, \boldsymbol{\Lambda})$ distribution:

$$p(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \propto |\boldsymbol{\Sigma}|^{-(\nu+d+2)/2} \exp\left\{-\frac{1}{2}\mathrm{tr}\left(\boldsymbol{\Lambda}\boldsymbol{\Sigma}^{-1}\right) - \frac{\kappa}{2}(\boldsymbol{\mu} - \boldsymbol{\mu}_0)^T \boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - \boldsymbol{\mu}_0)\right\}$$

- Conditional of $\boldsymbol{\mu}$:

$$\boldsymbol{\mu} \mid \boldsymbol{\Sigma} \propto \mathcal{N}(\boldsymbol{\mu}_0, \kappa^{-1}\boldsymbol{\Sigma}^{-1})$$

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- Marginal of $\boldsymbol{\mu}$:

$$\boldsymbol{\mu} \sim t_{\nu+1-d}(\boldsymbol{\mu}_0, (\nu\kappa)^{-1}\boldsymbol{\Lambda}) \quad \text{(multivaraite t distribution)}$$

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Multivariate Normal — Jeffreys Prior

The log-likelihood function is

$$\ell(\boldsymbol{\mu}, \boldsymbol{\Sigma}) = -\frac{1}{2}\mathrm{tr}\left(\boldsymbol{S}\boldsymbol{\Sigma}^{-1}\right) - \frac{n}{2}(\boldsymbol{\mu} - \bar{\boldsymbol{y}})^T \boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - \bar{\boldsymbol{y}}) - \frac{n}{2}\log|\boldsymbol{\Sigma}|$$

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$$\frac{\partial^2 \ell(\boldsymbol{\mu}, \boldsymbol{\Sigma})}{\partial \boldsymbol{\mu}^T \partial \boldsymbol{\mu}} = -n\boldsymbol{\Sigma}^{-1}$$

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- For Fisher's information on the interaction between $\boldsymbol{\mu}$, $\boldsymbol{\Sigma}$, we first notice

$$\frac{\partial \ell(\boldsymbol{\mu}, \boldsymbol{\Sigma})}{\partial \boldsymbol{\Sigma}} = \frac{1}{2}\boldsymbol{\Sigma}^{-1}\boldsymbol{S}\boldsymbol{\Sigma}^{-1} + \frac{n}{2}\boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - \bar{\boldsymbol{y}})(\boldsymbol{\mu} - \bar{\boldsymbol{y}})^T \boldsymbol{\Sigma}^{-1} - \frac{n}{2}\boldsymbol{\Sigma}^{-1}$$

with its vectorized version:

$$\frac{\partial \ell(\boldsymbol{\mu}, \boldsymbol{\Sigma})}{\partial \mathrm{vec}(\boldsymbol{\Sigma})} = \frac{1}{2}\mathrm{vec}(\boldsymbol{\Sigma}^{-1}\boldsymbol{S}\boldsymbol{\Sigma}^{-1}) + \frac{n}{2}\boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - \bar{\boldsymbol{y}}) \otimes \boldsymbol{\Sigma}^{-1}(\boldsymbol{\mu} - \bar{\boldsymbol{y}}) - \frac{n}{2}\mathrm{vec}(\boldsymbol{\Sigma}^{-1})$$

Multivariate Normal — Jeffreys Prior

- Then we have

$$\frac{\partial^2 \ell(\boldsymbol{\mu}, \boldsymbol{\Sigma})}{\partial \boldsymbol{\mu}^T \partial \mathrm{vec}(\boldsymbol{\Sigma})} = -\frac{n}{2}\boldsymbol{\Sigma}^{-1} \otimes (\boldsymbol{\mu} - \bar{\boldsymbol{y}}) - \frac{n}{2}(\boldsymbol{\mu} - \bar{\boldsymbol{y}}) \otimes \boldsymbol{\Sigma}^{-1}$$

  with its expectation as zero.

Multivariate Normal — Jeffreys Prior

- Then we have
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with its expectation as zero.
- Furthermore, for $\boldsymbol{\Sigma}$, we have (ignoring $d\boldsymbol{\mu}$)

$$\begin{aligned} d\frac{\partial \ell(\boldsymbol{\mu}, \boldsymbol{\Sigma})}{\partial \mathrm{vec}(\boldsymbol{\Sigma})} &= \frac{1}{2}\mathrm{vec}(d\boldsymbol{\Sigma}^{-1}\boldsymbol{S}'\boldsymbol{\Sigma}^{-1}) + \frac{1}{2}\mathrm{vec}(\boldsymbol{\Sigma}^{-1}\boldsymbol{S}' d\boldsymbol{\Sigma}^{-1}) - \frac{n}{2}\mathrm{vec}(d\boldsymbol{\Sigma}^{-1}) \\ &= -\frac{1}{2}(\boldsymbol{\Sigma}^{-1}\boldsymbol{S}'\boldsymbol{\Sigma}^{-1} \otimes \boldsymbol{\Sigma}^{-1}) d\mathrm{vec}(\boldsymbol{\Sigma}) - \frac{1}{2}(\boldsymbol{\Sigma}^{-1} \otimes \boldsymbol{\Sigma}^{-1}\boldsymbol{S}'\boldsymbol{\Sigma}^{-1}) d\mathrm{vec}(\boldsymbol{\Sigma}) \\ &\quad + \frac{n}{2}(\boldsymbol{\Sigma}^{-1} \otimes \boldsymbol{\Sigma}^{-1}) d\mathrm{vec}(\boldsymbol{\Sigma}) \end{aligned}$$

Multivariate Normal — Jeffreys Prior

- Then we have

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  By noticing $\mathbb{E}[\boldsymbol{S}'] = \mathbb{E}[\boldsymbol{S} + n(\boldsymbol{\mu} - \bar{\boldsymbol{y}})(\boldsymbol{\mu} - \bar{\boldsymbol{y}})^T] = n\boldsymbol{\Sigma}$, we have

$$-\mathbb{E}\left[\frac{\partial \ell(\boldsymbol{\mu}, \boldsymbol{\Sigma})}{\partial \mathrm{vec}(\boldsymbol{\Sigma})^T \partial \mathrm{vec}(\boldsymbol{\Sigma})}\right] = \frac{n}{2}\boldsymbol{\Sigma}^{-1} \otimes \boldsymbol{\Sigma}^{-1}$$

Multivariate Normal — Jeffreys Prior

- So the Fisher's information matrix is

$$\mathcal{I}(\boldsymbol{\mu}, \mathrm{vec}(\boldsymbol{\Sigma})) = \begin{bmatrix} n\boldsymbol{\Sigma}^{-1} & \mathbf{0} \\ \mathbf{0} & \frac{n}{2}\boldsymbol{\Sigma}^{-1} \otimes \boldsymbol{\Sigma}^{-1} \end{bmatrix}$$

Multivariate Normal — Jeffreys Prior

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- The Jeffreys prior is

$$p(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \propto \sqrt{|\mathcal{I}(\boldsymbol{\mu}, \mathrm{vec}(\boldsymbol{\Sigma}))|} \propto |\boldsymbol{\Sigma}|^{-(2d+1)/2}$$

Multivariate Normal — Jeffreys Prior

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- Reason: variables in $\mathcal{I}(\boldsymbol{\mu}, \mathrm{vec}(\boldsymbol{\Sigma}))$ are not independent, because $\boldsymbol{\Sigma}$ has to be symmetric!

Multivariate Normal — Jeffreys Prior

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- Actually, this is **not** the case!!!
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- The correct information matrix should only contains the diagonal and upper triangle part of $\boldsymbol{\Sigma}$.
- The **correct** Jeffreys prior:

$$p(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \propto |\boldsymbol{\Sigma}|^{-(d+2)/2}$$