Problem class 3: Hypothesis tests ; Inference under model uncertainty ; Hierarchical Bayes

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1 Hypothesis test

Exercise 1. ($\star\star$)Consider a Bayesian model

$$\begin{cases} x_i|\lambda & \stackrel{\text{iid}}{\sim} \text{Pn}(\lambda),\ \forall i=1,...,n \\ \lambda & \sim \Pi(\lambda) \end{cases}$$

Hint-1 Poisson distribution has PMF: $\text{Pn}(x|\lambda) = \frac{1}{x!}\lambda^x \exp(-\lambda)1_{\mathbb{N}}(x)$

Hint-2 Gamma distribution has PDF: $\text{Ga}(x|a,b) = \frac{b^a}{\Gamma(a)}x^{a-1}\exp(-bx)1_{(0,\infty)}(x)$, with $\text{E}(x) = a/b$, $\text{Var}(x) = a/b^2$.

Hint-3 Negative Binomial distribution has PMF: $\text{Nb}(x|r,\theta) = \binom{r+x-1}{r-1}\theta^r(1-\theta)^x 1_{\mathbb{N}}(x)$. with $\theta \in (0,1)$, $r \in \mathbb{N}$.

Consider that we are interested in testing the hypothesis whether $\lambda = \lambda_0$, (where λ_0 is a fixed known number), or not. Let $\pi_j = \text{P}(H_j)$ be the marginal prior probability of hypothesis H_j.

1. Design the test of hypotheses in Bayesian framework: Namely, set pair of hypotheses, specify priors, and compute the associated Bayes Factor.
2. Compute the posterior probability that $\lambda = \lambda_0$.
3. Perform the hypothesis test to test if $\lambda = 2$ or not based on the Jeffrey's scaling rule, by considering that
   - we have collected two observations $x_1 = 2$, $x_2 = 3$,
   - a priori the probability that $\{\lambda = 2\}$ is 0.5,
   - given $\{\lambda \neq 2\}$, the prior distr. of λ is a conjugate one with $\text{E}(\lambda) = 2$, and $\text{Var}(\lambda) = 1$.

1.

   - The pair of hypotheses for this test is

$$\begin{cases} \text{H}_0: & x_i \stackrel{\text{IID}}{\sim} \text{Pn}(\lambda_0 = 2),\ \text{ for all } i=1,...,n \\ \text{H}_1: & x_i \stackrel{\text{IID}}{\sim} \text{Pn}(\lambda),\ \lambda > 0 \text{ for all } i=1,...,n \end{cases} \tag{1}$$

   where H_0 is a single hypothesis, and H_1 is the general alternative.
   - The overall prior can be specified as

$$\pi(\lambda) = \pi_0 1_{\{\lambda_0\}}(\lambda) + (1-\pi_0)\text{Ga}(\lambda|a,b)$$

   for $\pi_0 > 0$, which in this case is $\pi_0 = 1/2$, and $\lambda_0 = 2$.
   - Do not get confused that the above notation in H_1 in (1) states $\lambda > 0$. Given H_1, λ is a continuous random variable. Because λ is a continuous random variable and $\lambda \sim \text{Ga}(a,b)$ given H_1, the probability that $\lambda = 2$ given on H_1.

- The Bayes factor is

$$B_{01}(x_{1:n}) = \frac{p_0(x_{1:n})}{p_1(x_{1:n})} = \frac{\prod_{i=1}^{n} \text{Pn}(x_i|\lambda_0)}{\int \prod_{i=1}^{n} \text{Pn}(x_i|\lambda)\text{Ga}(\lambda|a,b)\text{d}\lambda}$$

where

$$p_0(x_{1:n}) = \prod_{i=1}^{n} \text{Pn}(x_i|\lambda_0) = \frac{1}{\prod_{i=1}^{n} x_i!}\lambda_0^{n\bar{x}} \exp(-n\lambda_0)$$

and

$$\begin{aligned}p_1(x_{1:n}) &= \int \prod_{i=1}^{n} \text{Pn}(x_i|\lambda)\text{Ga}(\lambda|a,b)\text{d}\lambda = \frac{1}{\prod_{i=1}^{n} x_i!}\frac{b^a}{\Gamma(a)}\int_0^{\infty} \lambda^{n\bar{x}+a-1}\exp(-(n+b)\lambda)\text{d}\lambda \\ &= \frac{1}{\prod_{i=1}^{n} x_i!}\frac{\Gamma(n\bar{x}+a)}{\Gamma(a)}\frac{b^a}{(n+b)^{n\bar{x}+a}}\end{aligned}$$

So

$$\begin{aligned}B_{01}(x_{1:n}) &= \frac{\lambda_0^{n\bar{x}}\exp(-n\lambda_0)}{\frac{b^a\Gamma(n\bar{x}+a)}{\Gamma(a)(n+b)^{n\bar{x}+a}}} = \lambda_0^{n\bar{x}}(n+b)^{n\bar{x}+a}\exp(-n\lambda_0)\frac{1}{b^a}\frac{\Gamma(a)}{\Gamma(n\bar{x}+a)} \\ &= \lambda_0^{n\bar{x}}\exp(-n\lambda_0)\frac{(n+b)^{n\bar{x}+a}}{b^a}\frac{\Gamma(a)}{(n\bar{x}+a-1)\cdots a\Gamma(a)} \\ &= \frac{\lambda_0^{n\bar{x}}\exp(-n\lambda_0)}{(n\bar{x}+a-1)\cdots a}\frac{(n+b)^{n\bar{x}+a}}{b^a}\end{aligned}$$

2. Obviously, for the posterior probability that $\pi(\lambda = \lambda_0|x_{1:n})$, it is

$$\begin{aligned}\pi(\lambda = \lambda_0|x_{1:n}) = \pi(\text{H}_0|x_{1:n}) &= (1 + \frac{1-\pi_0}{\pi_0}\frac{p_1(x_{1:n})}{p_0(x_{1:n})})^{-1} \\ &= (1 + \frac{1-\pi_0}{\pi_0}\frac{b^a(n\bar{x}+a-1)\cdots a}{\lambda_0^{n\bar{x}}(n+b)^{n\bar{x}+a}\exp(-n\lambda_0)})^{-1} \\ &= \frac{\pi_0\lambda_0^{n\bar{x}}(n+b)^{n\bar{x}+a}\exp(-n\lambda_0)}{\pi_0\lambda_0^{n\bar{x}}(n+b)^{n\bar{x}+a}\exp(-n\lambda_0) + (1-\pi_0)b^a(n\bar{x}+a-1)\cdots a}\end{aligned}$$

3. This is actually the aforesaid hypothesis test with $\lambda_0 = 2$.

   - Based on the prior information, it is $a = 4$, and $b = 2$ because

$$\begin{cases} E^{\text{Ga}(a,b)}(\lambda) = 2 \\ Var^{\text{Ga}(a,b)}(\lambda) = 1 \end{cases} \Leftrightarrow \begin{cases} a/b = 2 \\ a/b^2 = 1 \end{cases} \Leftrightarrow \begin{cases} a/b = 2 \\ 2/b = 1 \end{cases} \Leftrightarrow \begin{cases} a = 4 \\ b = 2 \end{cases}$$

   - Based on the sample I have $n\bar{x} = 2 + 3 = 5$, $n = 2$
   - Hence,

$$\begin{aligned}B_{01}(x_{1:n}) &= \frac{\lambda_0^{n\bar{x}}(n+b)^{n\bar{x}+a}\exp(-n\lambda_0)}{b^a(n\bar{x}+a-1)\cdots a} \\ &= \frac{2^5(2+2)^{5+4}\exp(-2\times 2)}{2^4(5+4-1)\cdots 4} = \frac{2^5\times 4^9\times\exp(-4)}{16\times 8\times 7\times 6\times 5\times 4} \\ &\approx 1.42\end{aligned}$$

   - Then $B_{01}(x_{1:n}) \approx 1.42$, and $\log_{10}(\text{B}_{01}(x_{1:n})) \approx 0.15$. According to Jeffrey's scaling rule, H_0 is supported

2 Inference under model uncertainty

Exercise 2. ($\star\star$)Let $B_{k,j}(y)$ be the Bayes factor of model $\mathscr{M}_k$ against model $\mathscr{M}_j$, for all $\forall k, i, j \in \mathcal{K}$. . Show that $B_{k,j}(y) = B_{k,i}(y)B_{i,j}(y)$, for all $\forall k, i, j \in \mathcal{K}$.

Solution. It is

$$B_{k,j}(y) = \frac{\pi\left(\mathscr{M}_k|y\right)/\pi\left(\mathscr{M}_k\right)}{\pi\left(\mathscr{M}_j|y\right)/\pi\left(\mathscr{M}_j\right)} = \frac{\pi\left(\mathscr{M}_k|y\right)/\pi\left(\mathscr{M}_k\right)}{\pi\left(\mathscr{M}_i|y\right)/\pi\left(\mathscr{M}_i\right)}\frac{\pi\left(\mathscr{M}_i|y\right)/\pi\left(\mathscr{M}_i\right)}{\pi\left(\mathscr{M}_j|y\right)/\pi\left(\mathscr{M}_j\right)} = B_{k,i}(y)B_{i,j}(y)$$

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3 Hierarchical Bayes

Exercise 3. ($\star\star\star$)[Relevance Vector Machine]

Regarding the statistical model: Long story short (supplementary material)

Consider that we are interested in recovering the mapping

$$x \xmapsto{\eta} \eta(x)$$

in the sense that $y \in \mathbb{R}$ is the response (output quantity) that depends on $x = (x_1, ..., x_d) \in \mathcal{X} \subseteq \mathbb{R}^d$ which is the independent variable (input quantity) in a procedure; E.g.:,

- y: precipitation in log scale
- $x = (\text{longitude}, \text{latitude})$: geographical coordinates.

Consider a set of observed data $\{(y_i, x_i)\}_{i=1}^n$, which may be contaminated by additive noise of unknown variance; i.e.

$$y_i = \eta(x_i) + \epsilon_i,$$

where $\epsilon_i \stackrel{\text{IID}}{\sim} \mathrm{N}\left(0, \sigma^2\right)$ and $\sigma^2 > 0$ is unknown. We wish to recover $\eta(x)$ by using the Tikhonov regularization on the functional space $\mathcal{H}$ such that

$$\eta = \arg \min_{\forall \tilde{\eta} \in \mathcal{H}} \left\{ \sum_{i=1}^{n} L\left(y_i - \tilde{\eta}\left(x_i\right)\right) + \lambda \left\|\tilde{\eta}\right\|_{\mathcal{H}}^2 \right\} \tag{2}$$

By assuming that $\mathcal{H}$ is a Reproducing Kernel Hilbert Space (RKHS), the solution to (2) is such that

$$\eta\left(x\right) = \beta_0 + \sum_{j=1}^{n} k(x, x_j)\beta_j = k(x)^\top \beta$$

where $k(x) = \left(1, k\left(x, x_1\right), ..., k\left(x, x_n\right)\right)^\top$, $k\left(x, x_j\right)$ is the reproducing kernel (such as $k_\phi\left(x, x_j\right) = \exp\left(-\phi \left\|x - x_j\right\|^2\right)$ for some known parameter $\phi > 0$), and $\beta \in \mathbb{R}^{n+1}$ is an unknown vector.

Consider the following Bayesian model[1]

$$\begin{cases} y|\beta, \sigma^2 & \sim \mathrm{N}\left(K\beta, I\sigma^2\right) \\ \beta|\lambda & \sim \mathrm{N}\left(0, D^{-1}\right), \quad D = \left(\lambda_0, \lambda_1, ..., \lambda_n\right) \\ \lambda_i & \stackrel{\text{iid}}{\sim} \mathrm{d}\Pi\left(\lambda_i\right) \propto \lambda_i^{a-1} \exp\left(-b\lambda_i\right) \mathrm{d}\lambda_i, \quad \forall i = 1, ..., n \\ \sigma^2 & \sim \mathrm{d}\Pi\left(\sigma^2\right) \propto \left(\sigma^2\right)^{c-1} \exp\left(-\frac{1}{\sigma^2}d\right) \mathrm{d}\sigma^2 \\ \beta, \sigma^2 & \text{a priori independent} \end{cases}$$

where K is a known matrix with size $n \times (n+1)$ such that

$$K = \begin{bmatrix} 1 & k(x_1, x_1) & \cdots & k(x_1, x_n) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & k(x_n, x_1) & \cdots & k(x_n, x_n) \end{bmatrix}.$$

The quantities $a > 0$, $b > 0$, $c > 0$, $d > 0$, and $\phi > 0$ are considered as fixed.

[1] Dixit, A., & Roy, V. (2021). Posterior impropriety of some sparse Bayesian learning models. Statistics & Probability Letters, 171, 109039.

1. When $b = 0$, show that a necessary condition for a valid posterior inference is $a \in (-1/2, 0)$ for any choice of prior for τ (i.e. any choice of (c, d)).

2. Let $P = K\left(K^\top K\right)^{-1} K^\top$. Show that (2a) and (2b) are sufficient conditions for the Bayesian model to lead to a valid posterior inference

   (a) if $a > 0$ and $b > 0$, or

   (b) if $y^\top (I - P) y + 2d > 0$ and $c > -\frac{n}{2}$

3. Does the the improper Uniform prior on the joint $\log(\lambda_i)$ and $\log\left(\sigma^2\right)$, i.e. $\pi\left(\log(\lambda_i), \log\left(\sigma^2\right)\right) \propto 1$, lead to a valid inference?

4. Does the Jeffreys' prior $\pi(\lambda_i) \propto 1/\lambda_i$ lead to a valid inference?

Hint-1:

$$(y - K\beta)^\top (y - K\beta) + (\beta - \mu)^\top V^{-1} (\beta - \mu) = (\beta - \mu^*)^\top (V^*)^{-1} (\beta - \mu^*) + S^*;$$
$$S^* = \mu^\top V^{-1}\mu - (\mu^*)^\top (V^*)^{-1} (\mu^*) + y^\top y; \qquad V^* = \left(V^{-1} + K^\top K\right)^{-1}; \qquad \mu^* = V^*\left(V^{-1}\mu + K^\top y\right)$$

Hint-2: Sherman-Morrison-Woodbury formula:

$$(A + UCV)^{-1} = A^{-1} - A^{-1}U\left(C^{-1} + VA^{-1}U\right)^{-1} VA^{-1}$$

Hint-3:

$$-\frac{y^\top y}{2\sigma^2} \leq -\frac{y^\top \left(I\sigma^2 + KD^{-1}K^\top\right)^{-1} y}{2} \leq -\frac{1}{2\sigma^2} y^\top (I - P) y$$

where $P = K\left(K^\top K\right)^{-1} K$.

Hint-4: It is given that $\int_{(0,\infty)} \frac{t^{-(a+1)}}{(\xi+t)^{1/2}} \mathrm{d}t < \infty$ if and only if $a \in (-1/2, 0)$.

Solution. The posterior pdf is given by

$$\pi\left(\beta, \sigma^2, \lambda | y\right) = \frac{f\left(y|\beta, \sigma^2\right) \pi\left(\beta, \sigma^2, \lambda\right)}{f(y)}$$

and is proper iff $f(y) < \infty$ where

$$f(y) = \int \left(\underbrace{\int \left(\underbrace{\int f\left(y|\beta, \sigma^2\right) \pi\left(\beta, \sigma^2\right) \mathrm{d}\beta}_{=f(y|\lambda,\sigma^2)} \right) \pi(\lambda)\, \mathrm{d}\lambda}_{=f(y|\sigma^2)} \right) \pi\left(\sigma^2\right) \mathrm{d}\sigma^2$$

It is

$$\begin{aligned}
f\left(y|\lambda, \sigma^2\right) &= \int f\left(y|\beta, \sigma^2\right) \pi\left(\beta, \sigma^2\right) \mathrm{d}\beta \\
&= (2\pi)^{-\frac{n+n+1}{2}} \left(\frac{1}{\sigma^2}\right)^{\frac{n}{2}} \det(D)^{\frac{1}{2}} \int \exp\left(-\frac{1}{2\sigma^2}\left((y - K\beta)^\top (y - K\beta) + \beta^\top \left(D\sigma^2\right)\beta\right)\right) \mathrm{d}\beta \\
&= (2\pi)^{-\frac{n+n+1}{2}} \left(\frac{1}{\sigma^2}\right)^{\frac{1}{2}} \det(D)^{\frac{1}{2}} \left[\int \exp\left(-\frac{1}{2\sigma^2}(\beta - \mu^*)^\top V^* (\beta - \mu^*)\right) \mathrm{d}\beta\right] \left[\exp\left(-\frac{1}{2\sigma^2} S^*\right)\right]
\end{aligned}$$

Because

$$
\begin{aligned}
\int \exp\left(-\frac{1}{2\sigma^2}\left(\beta-\mu^*\right)^\top V^*\left(\beta-\mu^*\right)\right)\mathrm{d}\beta &= (2\pi)^{\frac{n+1}{2}}\det\left(V^*/\sigma^2\right)^{-\frac{1}{2}} \\
&= (2\pi)^{\frac{n+1}{2}}\det\left(K^\top K + D\sigma^2\right)^{-\frac{1}{2}}
\end{aligned}
$$

$$
\begin{aligned}
\exp\left(-\frac{1}{2\sigma^2}S^*\right) &= \exp\left(-\frac{1}{2\sigma^2}\mu^\top\left(D\sigma^2\right)\mu - \left(\mu^*\right)^\top\left(V^*\right)^{-1}\left(\mu^*\right) + y^\top y\right) \\
&= \exp\left(-\frac{1}{2\sigma^2}\left(y^\top y - y^\top K\left(K^\top K + D\sigma^2\right)^{-1}K^\top y\right)\right) \\
&= \exp\left(-\frac{1}{2\sigma^2}\left(y^\top\left(I - K\left(K^\top K + D\sigma^2\right)^{-1}K^\top\right)y\right)\right) \\
&= \exp\left(-\frac{1}{2\sigma^2}\left(y^\top\left(K^\top D^{-1}K + I\sigma^2\right)^{-1}y\right)\right)
\end{aligned}
$$

So

$$
\begin{aligned}
f\left(y|\lambda,\sigma^2\right) = (2\pi)^{-\frac{n}{2}}\left(\frac{1}{\sigma^2}\right)^{\frac{1}{2}}&\det(D)^{\frac{1}{2}}\det\left(K^\top K + \sigma^2 D\right)^{-\frac{1}{2}} \\
&\times\exp\left(-\frac{1}{2\sigma^2}\left(y^\top\left(I\sigma^2 + K^\top D^{-1}K\right)^{-1}y\right)\right)
\end{aligned}
$$

1. I have

$$
\begin{aligned}
f\left(y|\sigma^2\right) &= \int f\left(y|\lambda,\sigma^2\right)\pi(\lambda)\mathrm{d}\lambda \\
&= (2\pi)^{-\frac{n}{2}}\left(\sigma^2\right)^{\frac{1}{2}}\int\left[\det(D)^{\frac{1}{2}}\right]\left[\det\left(K^\top K + D\sigma^2\right)^{-\frac{1}{2}}\right] \\
&\qquad\times\exp\left(-\frac{1}{2}\left(y^\top\left(I\sigma^2 + K^\top D^{-1}K\right)^{-1}y\right)\right)\left[\prod_{i=0}^{n}\lambda_i^{a-1}\right]\mathrm{d}\lambda_0\dots\mathrm{d}\lambda_n
\end{aligned}
$$

- It is $\exp\left(-\frac{y^\top y}{2\sigma^2}\right) \leq \exp\left(-\frac{y^\top\left(I\sigma^2+K^\top D^{-1}K\right)^{-1}y}{2}\right)$
- It is $\det(D)^{\frac{1}{2}} = \prod_{i=0}^{n}\lambda_i^{\frac{1}{2}}$.
- If $\{e_j\}_{j=0}^{n=1}$ are eigenvalues of $K^\top K$ and $e_{\max} = \max\left(\{e_j\}\right)$, then $K^\top K + D\sigma^2 \leq Ie_{\max} + D\sigma^2$, consequently $\det\left(K^\top K + D\sigma^2\right)^{-\frac{1}{2}} \geq \prod_{j=0}^{n}\left(\lambda_j\sigma^2 + e_{\max}\right)^{-\frac{1}{2}}$.

Then

$$
\begin{aligned}
f\left(y|\sigma^2\right) &\geq (2\pi)^{-\frac{n}{2}}\left(\sigma^2\right)^{\frac{1}{2}}\int\prod_{j=0}^{n}\lambda_j^{\frac{1}{2}}\prod_{j=0}^{n}\left(\lambda_j\sigma^2+e_{\max}\right)^{-\frac{1}{2}}\exp\left(-\frac{1}{2\sigma^2}y^\top y\right)\prod_{j=0}^{n}\lambda_j^{a-1}\mathrm{d}\lambda_0\dots\mathrm{d}\lambda_n \\
&= (2\pi)^{-\frac{n}{2}}\left(\sigma^2\right)^{\frac{1}{2}}\exp\left(-\frac{1}{2\sigma^2}y^\top y\right)\int\dots\int\prod_{j=0}^{n}\left[\lambda_j^{\frac{1}{2}}\right]\left[\prod_{j=0}^{n}\left(\lambda_j\sigma^2+e_{\max}\right)^{-\frac{1}{2}}\right]\left[\prod_{j=0}^{n}\lambda_j^{a-1}\right]\mathrm{d}\lambda_0\dots\mathrm{d}\lambda_n \\
&= (2\pi)^{-\frac{n}{2}}\left(\sigma^2\right)^{\frac{1}{2}}\exp\left(-\frac{1}{2\sigma^2}y^\top y\right)\prod_{j=0}^{n}\int\frac{\lambda_j^{a-\frac{1}{2}}}{\left(\lambda_j\sigma^2+e_{\max}\right)^{\frac{1}{2}}}\mathrm{d}\lambda_j
\end{aligned}
$$

Let $t_i = 1/\lambda_i$, then

$$f\left(y|\sigma^2\right) \geq (2\pi)^{-\frac{n}{2}} \left(\sigma^2\right)^{\frac{1}{2}} \exp\left(-\frac{1}{2\sigma^2} y^\top y\right) \prod_{j=0}^{n} \int \frac{t_{jj}^{-a-1}}{\left(t_j + \frac{\sigma^2}{e_{\max}}\right)^{\frac{1}{2}}} \mathrm{d}\lambda_j$$

which is finite if and only if $a \in (-1/2, 0)$.

2.

(a) If $a > 0$, $b > 0$ then $\lambda_i \overset{\text{iid}}{\sim} \text{Ga}\,(a, b)$ for all $i = 1, ..., n$, and if $c > 0$, $d > 0$ then $\tau \overset{\text{iid}}{\sim} \text{Ga}\,(c, d)$ which are proper. So $\Pi\left(\beta, \sigma^2, \lambda, \tau\right)$ is a proper prior, and hence it leads to proper posterior.

(b) I have

$$\begin{aligned} f\left(y|\sigma^2\right) = & (2\pi)^{-\frac{n}{2}} \left(\sigma^2\right)^{\frac{1}{2}} \int \left[\det\left(D\right)^{\frac{1}{2}}\right] \left[\det\left(K^\top K + D\sigma^2\right)^{-\frac{1}{2}}\right] \\ & \times \exp\left(-\frac{1}{2}\left(y^\top \left(I\sigma^2 + K^\top D^{-1} K\right)^{-1} y\right)\right) \pi\left(\lambda\right) \mathrm{d}\lambda \end{aligned}$$

It is $\det\left(D\right)^{\frac{1}{2}} = \prod_{i=0}^{n} \lambda_i^{\frac{1}{2}}$. Also, it is $K^\top K + D\sigma^2 \geq D\sigma^2$ then $\det\left(K^\top K + D\sigma^2\right)^{-\frac{1}{2}} \leq \prod_{j=0}^{n} \left(\lambda_j \sigma^2\right)^{-\frac{1}{2}}$. Hence

$$f\left(y|\sigma^2\right) \leq (2\pi)^{-\frac{n}{2}} \left(\sigma^2\right)^{\frac{n}{2}} \exp\left(-\frac{1}{2\sigma^2} y^\top \left(I - P\right) y\right) \int \pi\left(\lambda\right) \mathrm{d}\lambda$$

which implies that $f\left(y|\sigma^2\right) < \infty$ if $\pi\left(\lambda\right)$ is proper. Yet,

$$\begin{aligned} f\left(y\right) = & \int f\left(y|\sigma^2\right) \pi\left(\sigma^2\right) \mathrm{d}\sigma^2 \\ \leq & (2\pi)^{-\frac{n}{2}} \int \left(\sigma^2\right)^{-\frac{n}{2}+c+1} \exp\left(-\frac{1}{\sigma^2}\left(\frac{y^\top \left(I - P\right) y}{2} + d\right)\right) \mathrm{d}\sigma^2 \end{aligned}$$

which is finite if $y^\top \left(I - P\right) y + 2d > 0$ and $c > -\frac{n}{2}$.

(c) No. This implies $\pi\left(\lambda, \sigma^2\right) \propto \sigma^2 \prod_{j=0}^{n} \lambda_j^{-1}$. It is improper prior as $\int \pi\left(\lambda, \sigma^2\right) \mathrm{d}\left(\lambda, \sigma^2\right) = \infty$, and $(a, b, c, d) = (0, 0, 0, 0)$ which violates the necessary conditions.

(d) No, it violates the necessary conditions.
