Handout 5a: Nuisance parameters [a]

The Normal model and the Normal linear regression with unknown variance

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Nuisance parameters <concept

Definition 1. Assume observable quantities $y = (y_1, ..., y_n)$. Assume that the sampling distribution is $\mathrm{d}F(y|\theta)$ labeled by an unknown parameter $\theta \in \Theta$. Let $\theta = (\phi, \lambda)^\top$ with $\phi \in \Phi$ and $\lambda \in \Lambda$. Assume You are interested in learning parameter $\phi \in \Phi$, and You are not interested in learning the unknown parameter $\lambda \in \Lambda$; but both ϕ, λ are parts of the statistical model parameterisation. The unknown quantity $\lambda \in \Lambda$ is called nuisance parameter. We an call $\phi \in \Phi$ parameter of interest.

Note 2. In Bayesian Stats, learning (or quantifying uncertainty about) parameter of interest ϕ under the presence of a nuisance parameter $\lambda \in \Lambda$ is performed according to the Bayesian paradigm as usual: You specify a prior $\mathrm{d}\Pi(\phi, \lambda)$ with PDF/PMF $\pi(\phi, \lambda) = \pi(\phi|\lambda)\pi(\lambda)$ on the joint space of ALL Your unknown parameters $\theta = (\phi, \lambda)^\top$; you compute the joint posterior distribution $\mathrm{d}\Pi(\theta|y)$ of $\theta = (\phi, \lambda)^\top$ via the Bayesian theorem. Reasonably, Your posterior degree of believe about the parameter of interest ϕ given the data $y = (1_1, ..., y_n)$ is given through the marginal posterior distribution $\mathrm{d}\Pi(\phi|y)$.

Note 3. To summarize; Specify the Bayesian model as: <sum-up

$$\begin{cases} y|\overbrace{\phi,\lambda}^{=\theta} \sim \mathrm{d}F(y|\overbrace{\phi,\lambda}^{=\theta}) & \text{, the statistical model}\\ (\underbrace{\phi,\lambda}_{=\theta}) \sim \mathrm{d}\Pi(\underbrace{\phi,\lambda}_{=\theta}) & \text{, the prior model}\end{cases}$$

The joint posterior of θ given y is $\mathrm{d}\Pi(\theta|y) = \mathrm{d}\Pi(\lambda|y, \phi)\mathrm{d}\Pi(\phi|y)$ is with PDF/PMF

$$\pi(\overbrace{\phi,\lambda}^{=\theta}|y) = \frac{f(y|\overbrace{\phi,\lambda}^{=\theta})\pi(\overbrace{\phi,\lambda}^{=\theta})}{f(y)} = \underbrace{\frac{f(y|\phi,\lambda)\pi(\lambda|\phi)}{f(y|\phi)}}_{=\pi(\lambda|y,\phi)}\underbrace{\frac{f(y|\phi)\pi(\phi)}{f(y)}}_{=\pi(\phi|y)} = \pi(\lambda|y,\phi)\pi(\phi|y)$$

The (marginal) likelihood $f(y|\phi)$ of y given ϕ is

$$f(y|\phi) = \underbrace{\int_\Lambda f(y|\overbrace{\phi,\lambda}^{=\theta})\mathrm{d}\Pi(\lambda|\phi)}_{=\mathrm{E}_{\Pi(\lambda|\phi)}(f(y|\phi,\lambda)|\phi)} = \begin{cases} \int_\Lambda f(y|\phi,\lambda)\pi(\lambda|\phi)\mathrm{d}\lambda & \text{, if } \lambda \text{ cont}\\ \sum_{\forall \lambda\in\Lambda} f(y|\phi,\lambda)\pi(\lambda|\phi) & \text{, if } \lambda \text{ discr}\end{cases}$$

The PDF/PMF $\pi(\phi|y)$ of marginal posterior $\mathrm{d}\Pi(\phi|y)$ of ϕ is

$$\pi(\phi|y) = \underbrace{\int_\Lambda \pi(\overbrace{\phi,\lambda}^{=\theta}|y)\mathrm{d}\lambda}_{=\mathrm{E}_{\Pi(\lambda|y)}(\pi(\phi|y,\lambda))} \qquad \text{or equivalently} \qquad \pi(\phi|y) = \frac{f(y|\phi)\pi(\phi)}{f(y)}$$

The predictive distribution $\mathrm{d}G(z|y)$ of the next outcome $z = (y_{n+1}, ...y_{n+m})$ given y has pdf/pmf

$$g(z|y) = \int f(y|\overbrace{\phi,\lambda}^{=\theta})\mathrm{d}\Pi(\overbrace{\phi,\lambda}^{=\theta}|y)$$

and the marginal likelihood $f(y)$ is

$$f(y) = \int f(y|\overbrace{\phi,\lambda}^{=\theta})\pi(\overbrace{\phi,\lambda}^{=\theta})\mathrm{d}\phi\mathrm{d}\lambda$$

Practice in challenging problems

Exercise 4. ($\star\star$)(Nuisance parameters are involved) <-story

Assume observable quantities $y = (y_1, ..., y_n)$ forming the available data set of size n. Assume that the observations are drawn i.i.d. from a sampling distribution which is judged to be in the Normal parametric family of distributions $\mathrm{N}(\mu, \sigma^2)$ with unknown mean μ and variance σ^2. We are interested in learning μ and the next outcome $z = y_{n+1}$. We do not care about σ^2.

Assume You specify a Bayesian model <-set-up

$$\begin{cases} y_i|\mu,\sigma^2 \sim \mathrm{N}(\mu,\sigma^2), \text{ for all } i = 1, ..., n & \text{, Statistical model} \\ \mu|\sigma^2 \sim \mathrm{N}(\mu_0, \sigma^2 \frac{1}{\tau_0}) & \text{, prior} \\ \sigma^2 \sim \mathrm{IG}(a_0, k_0) & \text{, prior} \end{cases}$$

1. Show that the joint posterior distribution $\Pi(\mu, \sigma^2|y)$ is such as

$$\mu|y, \sigma^2 \sim \mathrm{N}(\mu_n, \sigma^2 \frac{1}{\tau_n})$$
$$\sigma^2|y \sim \mathrm{IG}(a_n, k_n)$$

   with

$$\mu_n = \frac{n\bar{y} + \tau_0\mu_0}{n + \tau_0}; \qquad \tau_n = n + \tau_0; \qquad a_n = a_0 + n$$

$$k_n = k_0 + \frac{1}{2}\frac{(n\bar{y} + \tau_0\mu_0)^2}{n + \tau_0} - \frac{1}{2}(n\bar{y}^2 + \tau_0\mu_0^2)$$

   Hint: It is

$$-\frac{1}{2}\frac{(\mu-\mu_1)^2}{v_1^2} - \frac{1}{2}\frac{(\mu-\mu_2)^2}{v_2^2} ... - \frac{1}{2}\frac{(\mu-\mu_n)^2}{v_n^2} = -\frac{1}{2}\frac{(\mu-\hat{\mu})^2}{\hat{v}^2} + C$$

   where

$$\hat{v}^2 = \left(\sum_{i=1}^{n}\frac{1}{v_i^2}\right)^{-1}; \quad \hat{\mu} = \hat{v}^2\left(\sum_{i=1}^{n}\frac{\mu_i}{v_i^2}\right); \quad C = \frac{1}{2}\frac{\hat{\mu}^2}{\hat{v}^2} - \frac{1}{2}\sum_{i=1}^{n}\frac{\mu_i^2}{v_i^2}$$

2. Show that the marginal posterior distribution $\Pi(\mu|y)$ is such as

$$\mu|y \sim \mathrm{T}_1\left(\mu_n, \frac{k_n}{a_n}\frac{1}{\tau_n}, 2a_n\right)$$

   Hint-1: If $x \sim \mathrm{IG}(a, b)$, $y = cx$, then $y \sim \mathrm{IG}(a, cb)$.

   Hint-2: The definition of Student T is considered as known

3. Show that the predictive distribution $\Pi(z|y)$ is Student T such as

$$z|y \sim \mathrm{T}_1\left(\mu_n, \frac{k_n}{a_n}(\frac{1}{\tau_n}+1), 2a_n\right)$$

Hint-1: Consider that

$$\mathrm{N}(x|\mu_1,\sigma_1^2)\,\mathrm{N}(x|\mu_2,\sigma_2^2) \;=\; \mathrm{N}(x|m,v^2)\,\mathrm{N}(\mu_1|\mu_2,\sigma_1^2+\sigma_2^2)$$

where

$$v^2=\left(\frac{1}{\sigma_1^2}+\frac{1}{\sigma_2^2}\right)^{-1};\quad m=v^2\left(\frac{\mu_1}{\sigma_1^2}+\frac{\mu_2}{\sigma_2^2}\right)$$

Hint-2: The definition of Student T is considered as known

Solution.

1. I use the Bayes theorem

$$\begin{aligned}
\pi(\mu,\sigma^2|y) \propto& f(y|\mu,\sigma^2)\pi(\mu,\sigma^2)=\prod_{i=1}^{n}\mathrm{N}(y_i|\mu,\sigma^2)\mathrm{N}(\mu|\mu_0,\sigma^2\frac{1}{\tau_0})\mathrm{IG}(\sigma^2|a_0,k_0)\\
&\propto\left(\frac{1}{\sigma^2}\right)^{\frac{n}{2}}\exp\left(-\frac{1}{2}\sum_{i=1}^{n}\frac{(y_i-\mu)^2}{\sigma^2}\right)\times\left(\frac{1}{\sigma^2}\right)^{\frac{1}{2}}\exp\left(-\frac{1}{2}\frac{(\mu-\mu_0)^2}{\sigma^2/\tau_0}\right)\times\left(\frac{1}{\sigma^2}\right)^{\frac{a_0}{2}+1}\exp\left(-\frac{1}{\sigma^2}k_0\right)\\
&\propto\left(\frac{1}{\sigma^2}\right)^{\frac{n}{2}+\frac{1}{2}+\frac{a_0}{2}+1}\exp\left(\frac{1}{\sigma^2}\left[-\frac{1}{2}\sum_{i=1}^{n}\frac{(y_i-\mu)^2}{1}-\frac{1}{2}\frac{(\mu-\mu_0)^2}{1/\tau_0}\right]-\frac{1}{\sigma^2}k_0\right)
\end{aligned}$$

It is

$$-\frac{1}{2}\sum_{i=1}^{n}\frac{(y_i-\mu)^2}{1}-\frac{1}{2}\frac{(\mu-\mu_0)^2}{1/\tau_0}=-\frac{1}{2}\frac{(\mu-\mu_n)^2}{\underbrace{v_n^2}_{=1/\tau_n}}+C$$

where

$$\begin{aligned}
v_n=&\left(\sum_{i=1}^{n}\frac{1}{1}+\frac{1}{1/\tau_0}\right)^{-1}=\frac{1}{n+\tau_0}\implies\tau_n=n+\tau_0\\
\mu_n=&v_n\left(\sum_{i=1}^{n}\frac{y_i}{1}+\frac{\mu_0}{1/\tau_0}\right)\implies\mu_n=\frac{n\bar{y}+\tau_0\mu_0}{n+\tau_0}\\
C_n=&\frac{1}{2}\frac{\mu_n^2}{v_n^2}-\frac{1}{2}\left(n\bar{y}^2+\tau_0\mu_0^2\right)=\text{...calc...}=\frac{1}{2}ns_n^2+\frac{1}{2}\frac{\tau_0 n(\mu_0-\bar{y})^2}{n+\tau_0}
\end{aligned}$$

So

$$\begin{aligned}
\pi(\mu,\sigma^2|y)\propto&\left(\frac{1}{\sigma^2}\right)^{\frac{1}{2}+\frac{n}{2}+\frac{a_0}{2}+1}\exp\left(\frac{1}{\sigma^2}\left[-\frac{1}{2}\frac{(\mu-\mu_n)^2}{1/\tau_n}+C_n\right]-\frac{1}{\sigma^2}k_0\right)\\
&\propto\underbrace{\left(\frac{1}{\sigma^2}\right)^{\frac{1}{2}}\exp\left(-\frac{1}{2}\frac{(\mu-\mu_n)^2}{\sigma^2/\tau_n}\right)}_{\propto\mathrm{N}(\mu|\mu_n,\sigma^2/\tau_n)}\times\underbrace{\left(\frac{1}{\sigma^2}\right)^{\overbrace{\frac{n}{2}+\frac{a_0}{2}}^{=a_n}+1}\exp\left(-\frac{1}{\sigma^2}\overbrace{(k_0+C_n)}^{=k_n}\right)}_{\propto\mathrm{IG}(\sigma^2|a_n,k_n)}\\
&\propto\mathrm{N}(\mu|\mu_n,\sigma^2/\tau_n)\mathrm{IG}(\sigma^2|a_n,k_n)
\end{aligned}$$

2. It is

$$\pi(\mu|y) = \int \pi(\mu, \sigma^2|y)\mathrm{d}\sigma^2 = \int \mathrm{N}(\mu|\mu_n, \sigma^2/\tau_n)\mathrm{IG}(\sigma^2|a_n, k_n)\mathrm{d}\sigma^2$$

by change of variable $\xi = \sigma^2 \frac{1}{2k_n}$, it is

$$\begin{aligned}\pi(\mu|y) &= \int \mathrm{N}(\mu|\mu_n, \xi 2k_n \frac{1}{\tau_n}\frac{2a_n}{2a_n})\mathrm{IG}(\xi|\frac{2a_n}{2}, \frac{1}{2})\mathrm{d}\xi = \int \mathrm{N}(\mu|\mu_n, \xi\frac{1}{\tau_n}\frac{k_n}{a_n}2a_n)\mathrm{IG}(\xi|\frac{2a_n}{2}, \frac{1}{2})\mathrm{d}\xi \\ &= \mathrm{T}_1(\mu|\mu_n, \frac{k_n}{a_n}\frac{1}{\tau_n}, 2a_n)\end{aligned}$$

3. It is

$$\begin{aligned}g(z|y) &= \int f(z|\mu, \sigma^2)\pi(\mu, \sigma^2|y)\mathrm{d}\mu\mathrm{d}\sigma^2 = \int \mathrm{N}(z|\mu, \sigma^2)\mathrm{N}(\mu|\mu_n, \sigma^2/\tau_n)\mathrm{IG}(\sigma^2|a_n, k_n)\mathrm{d}\mu\mathrm{d}\sigma^2 \\ &= \int \left[\int \mathrm{N}(z|\mu, \sigma^2)\mathrm{N}(\mu|\mu_n, \sigma^2/\tau_n)\mathrm{d}\mu\right]\mathrm{IG}(\sigma^2|a_n, k_n)\mathrm{d}\sigma^2\end{aligned}$$

Normal density is symmetric $\mathrm{N}(z|\mu, \sigma^2)\mathrm{N}(\mu|\mu_n, \sigma^2/\tau_n) = \mathrm{N}(\mu|z, \sigma^2)\mathrm{N}(\mu|\mu_n, \sigma^2/\tau_n)$, and by using the Hint

$$\int \mathrm{N}(\mu|z, \sigma^2)\mathrm{N}(\mu|\mu_n, \sigma^2/\tau_n)\mathrm{d}\mu = \int \mathrm{N}(\mu|\text{const.}, \text{const.})\mathrm{N}\left(z|\mu_n, \sigma^2\left[\frac{1}{\tau_n}+1\right]\right)\mathrm{d}\mu = \mathrm{N}\left(z|\mu_n, \sigma^2\left[\frac{1}{\tau_n}+1\right]\right)$$

So

$$g(z|y) = \int \mathrm{N}\left(z|\mu_n, \sigma^2\left[\frac{1}{\tau_n}+1\right]\right)\mathrm{IG}(\sigma^2|a_n, k_n)\mathrm{d}\sigma^2$$

by change the variable $\xi = \sigma^2 \frac{1}{2k_n}$, it is

$$g(z|y) = \int \mathrm{N}\left(z|\mu_n, \xi\left[\frac{1}{\tau_n}+1\right]\frac{k_n}{a_n}2a_n\right)\mathrm{IG}(\xi|\frac{2a_n}{2}, \frac{1}{2})\mathrm{d}\xi = \mathrm{T}_1\left(z|\mu_n, \left[\frac{1}{\tau_n}+1\right]\frac{k_n}{a_n}, 2a_n\right)$$

General practice

Exercise 5. ($\star\star$)Consider the Bayesian model

$$\begin{cases} x_i|\theta & \overset{\text{iid}}{\sim} \mathrm{Ex}(\theta),\ \forall i = 1, ..., n \\ \theta & \sim \mathrm{Ga}(a, b) \end{cases}$$

Hint-1: The PDF of $x \sim \mathrm{G}(a, b)$ is $\mathrm{Ga}(x|a, b) = \frac{b^a}{\Gamma(a)}x^{a-1}\exp(-bx)1_{(0,+\infty)}(x)$

Hint-2: The PDF of $x \sim \mathrm{Ex}(\theta)$ is $\mathrm{Ex}(x|\theta) = \mathrm{Ga}(x|1, \theta)$

1. Show that the parametric model is member of the Exponential family, and the sufficient statistic for a sample of observables $x = (x_1, ..., x_n)$.
2. Show that the posterior distribution θ given x is Gamma and compute its parameters.
3. Show that the predictive distribution $G(z|x)$ of a future z given $x = (x_1, ..., x_n)$, has PDF

$$g(z|x) = \frac{a^*(b^*)^{a^*}}{(z+b^*)^{a^*+1}}1(x \geq 0)$$

Solution.

1. The parametric model is

$$\text{Ex}(x|\theta) = \theta \exp(-\theta x) 1(x \geq 0)$$

It is member of the exponential family

$$\text{Ef}_1(x|u, g, h, c, \phi, \theta, c) = u(x) g(\theta) \exp(\sum_{j=1}^{k} c_j \phi_j(\theta) h_j(x))$$

with $u(x_{1:n}) = 1$, $g(\theta) = \theta$, $c_1 = -1$, $\phi_1(\theta) = \theta$, $h_1(x) = x$. The sufficient statistic is $t_n = (n, \sum_{i=1}^{n} x_i)$.

2. I can get the posterior by using the Bayes theorem

$$\begin{aligned}\pi(\theta|x) \propto f(x|\theta)\pi(\theta|a,b) \qquad &\propto \prod_{i=1}^{n} \text{Ex}(x_i|\theta)\text{Ga}(\theta|a,b) \\ \propto \theta^n \exp(-\theta \sum_{i=1}^{n} x_i)\theta^{a-1}\exp(-\theta b) \ &\propto \theta^{a+n-1}\exp(-\theta(\sum_{i=1}^{n} x_i + b)) \\ \propto \text{Ga}(\theta|\underbrace{a+n}_{=a^*}, \underbrace{b + \sum_{i=1}^{n} x_i}_{=b^*})&\end{aligned}$$

3. By using the definition of the predictive distribution, it is ...

$$\begin{aligned}g(z|x) &= \int_{\mathbb{R}_+} f(z|\theta)\pi(\theta|x)\text{d}\theta \overset{z\geq 0}{=} \int_{\mathbb{R}_+} \theta \exp(-\theta z) \frac{(b^*)^{a^*}}{\Gamma(a^*)}\theta^{a^*-1}\exp(-\theta b^*)\text{d}\theta \\ &= \frac{(b^*)^{a^*}}{\Gamma(a^*)}\int_{\mathbb{R}_+} \theta^{a^*+1-1}\exp(-\theta(z+b^*))\text{d}\theta = \frac{(b^*)^{a^*}}{\Gamma(a^*)}\frac{\Gamma(a^*+1)}{(z+b^*)^{a^*+1}} = \frac{a^*(b^*)^{a^*}}{(z+b^*)^{a^*+1}} \\ &= \frac{a^*(b^*)^{a^*}}{(z+b^*)^{a^*+1}}\end{aligned}$$

Exercise 6. ($\star\star$)Consider the Bayesian model

$$\begin{cases} x_i|\theta & \overset{\text{IID}}{\sim} \text{Mu}_k(\theta) \\ \theta & \sim \text{Di}_k(a) \end{cases}$$

where $\theta \in \Theta$, with $\Theta = \{\theta \in (0,1)^k | \sum_{j=1}^{k} \theta_j = 1\}$ and $\mathcal{X}_k = \{x \in \{0, ..., n\}^k | \sum_{j=1}^{k} x_j = 1\}$.

Hint-1: Mu_k denotes the Multinomial probability distribution with PMF

$$\text{Mu}_k(x|\theta) = \begin{cases} \prod_{j=1}^{k} \theta_j^{x_j} & \text{, if } x \in \mathcal{X}_k \\ 0 & \text{, otherwise} \end{cases} \tag{1}$$

Hint-2: $\text{Di}_k(a)$ denotes the Dirichlet distribution with PDF

$$\text{Di}_k(\theta|a) = \begin{cases} \frac{\Gamma(\sum_{j=1}^{k} a_j)}{\prod_{j=1}^{k}\Gamma(a_j)} \prod_{j=1}^{k} \theta_j^{a_j-1} & \text{, if } \theta \in \Theta \\ 0 & \text{, otherwise} \end{cases}$$

1. Show that the parametric model (1) is a member of the $k-1$ exponential family.
2. Compute the likelihood $f(x_{1:n}|\theta)$, and find the sufficient statistic $t_n := t_n(x_{1:n})$.
3. Compute the posterior distribution. State the name of the distribution, and expresses its parameters with respect to the observations and the hyper-parameters of the prior. Justify your answer.
4. Compute the probability mass function of the predictive distribution for a future observation $y = x_{n+1}$ in closed form.

   Hint $\Gamma(x) = (x-1)\Gamma(x-1)$.

Solution.

1. There are $k-1$ independent parameters in $\text{Mu}_k(\theta)$ because $\sum_{j=1}^{k} \theta_j = 1$. I consider as parameters $(\theta_1, ..., \theta_{k-1})$ and the last one is a function of them as $\theta_k = 1 - \sum_{j=1}^{k-1} \theta_j$.

   It is
   $$\text{Mu}_k(x|\theta) = \prod_{j=1}^{k} \theta_j^{x_j} = \prod_{j=1}^{k-1} \theta_j^{x_j} (1 - \sum_{j=1}^{k-1} \theta_j)^{1-\sum_{j=1}^{k-1} x_j} = (1 - \sum_{j=1}^{k-1} \theta_j) \exp(\sum_{j=1}^{k-1} x_j \log(\frac{\theta_j}{1 - \sum_{j=1}^{k-1} \theta_j}))$$
   This is the $k-1$ exponential family PDF with
   $$u(x) = 1; \qquad g(\theta) = (1 - \sum_{j=1}^{k-1} \theta_j); \qquad c = (1, ..., 1)$$
   $$h(x) = (x_1, ...x_{k-1}); \qquad \phi(\theta) = (\log(\frac{\theta_1}{1 - \sum_{j=1}^{k-1} \theta_j}), ..., \log(\frac{\theta_{k-1}}{1 - \sum_{j=1}^{k-1} \theta_j})),$$

2. The likelihood is
   $$f(x_{1:n}|\theta) = \prod_{i=1}^{n} \text{Mu}_k(x_i|\theta) = \prod_{j=1}^{k} \theta_j^{\sum_{i=1}^{n} x_{i,j}} = \prod_{j=1}^{k} \theta_j^{x_{*,j}} = (1 - \sum_{j=1}^{k-1} \theta_j)^n \exp\left(\sum_{j=1}^{k-1} x_{*,j} \log(\frac{\theta_j}{1 - \sum_{j=1}^{k-1} \theta_j})\right)$$
   and the sufficient statistic is
   $$t_n = (n, x_{*,1}, ..., x_{*,k-1})$$

3. It is
   $$\pi(\theta|x_{1:n}) = \prod_{i=1}^{n} \text{Mu}_k(x_i|\theta)\text{Di}_k(\theta|a) \propto \prod_{j=1}^{k} \theta_j^{x_{*,j}} \prod_{j=1}^{k} \theta_j^{a_j-1} = \prod_{j=1}^{k} \theta_j^{x_j+a_{*,j}-1} \propto \text{Di}_k(\theta|\tilde{a})$$
   where $\tilde{a} = (\tilde{a}_1, ..., \tilde{a}_k)$, with $\tilde{a}_j = a_j + x_{*,j}$ for $j = 1, ..., k$. So the posterior is $\theta|x_{1:n} \sim \text{Di}_k(\tilde{a})$.

4. It is

$$
\begin{aligned}
p(y|x_{1:n}) &= \int \mathrm{Mu}_k(y|\theta)\mathrm{Di}_k(\theta|\tilde{a})\mathrm{d}\theta = \int \prod_{j=1}^{k} \theta_j^{y_j} \frac{\Gamma(\sum_{j=1}^{k}\tilde{a}_j)}{\prod_{j=1}^{k}\Gamma(\tilde{a}_j)} \prod_{j=1}^{k} \theta_j^{\tilde{a}_j - 1}\mathrm{d}\theta \\
&= \frac{\Gamma(\sum_{j=1}^{k}\tilde{a}_j)}{\prod_{j=1}^{k}\Gamma(\tilde{a}_j)} \int \prod_{j=1}^{k} \theta_j^{y_j+\tilde{a}_j-1}\mathrm{d}\theta = \frac{\Gamma(\sum_{j=1}^{k}\tilde{a}_j)}{\prod_{j=1}^{k}\Gamma(\tilde{a}_j)} \frac{\prod_{j=1}^{k}\Gamma(y_j+\tilde{a}_j)}{\Gamma(\sum_{j=1}^{k}(y_j+\tilde{a}_j))} \\
&= \frac{\Gamma(\sum_{j=1}^{k}\tilde{a}_j)}{\prod_{j=1}^{k}\Gamma(\tilde{a}_j)} \frac{\prod_{j=1}^{k}\Gamma(y_j+a_j+x_{*,j})}{\Gamma(2n+a_j))} \\
&= \frac{\Gamma(a_*+x_{*,*})}{\prod_{j=1}^{k}\Gamma(a_j+x_{*,j})} \frac{\prod_{j=1}^{k}\Gamma(y_j+a_j+x_{*,j})}{\Gamma(2n+a_j))} \\
&= \frac{\Gamma(n+a_*)}{\Gamma(2n+a_j))} \prod_{j=1}^{k} \frac{\Gamma(y_j+a_j+x_{*,j})}{\Gamma(a_j+x_{*,j})} = \frac{\prod_{j=1}^{k}\prod_{\ell=0}^{y_j-1}(a_j+x_{*,j}+\ell)}{\prod_{\ell=0}^{n-1}(a_*+n+\ell)}
\end{aligned}
$$
