

## Handout 17: Asymptotic behavior of the posterior distribution <sup>a</sup>

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**Aim:** We examine properties of the posterior distribution  $\Pi(\theta|y)$  as the number of observations increases  $n \rightarrow \infty$ . We show that, as  $n \rightarrow \infty$ ,

- posterior beliefs about  $\theta \in \Theta$  would become more and more concentrated around a “true” value  $\theta^*$  (if exists)
- the unknown parameter  $\theta \in \Theta$  has Normal distribution as asymptotic distribution (if  $\Theta \subseteq \mathbb{R}^k$ ,  $k \geq 1$ ).

### References:

- Van der Vaart, A. W. (2000, Chapter 10). Asymptotic statistics. Cambridge series in statistical and probabilistic mathematics.
- Ferguson, T. S. (1996, Section 21). A course in large sample theory. Chapman and Hall/CRC.
- DeGroot, M. H. (1970, Chapter 10). Optimal statistical decisions (Vol. 82). John Wiley & Sons.

### Web-applets

- [https://georgios-stats-1.shinyapps.io/demo\\_conjugatepriors/](https://georgios-stats-1.shinyapps.io/demo_conjugatepriors/)
- [https://georgios-stats-1.shinyapps.io/demo\\_conjugatejeffreyslplacepriors/](https://georgios-stats-1.shinyapps.io/demo_conjugatejeffreyslplacepriors/)
- [https://georgios-stats-1.shinyapps.io/demo\\_mixturepriors/](https://georgios-stats-1.shinyapps.io/demo_mixturepriors/)

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## What is about?

We consider the Bayesian model  $(F(x_{1:n}|\theta), \Pi(\theta))$  as

$$\begin{cases} x_i|\theta & \stackrel{\text{iid}}{\sim} F(x_i|\theta), & i = 1, \dots, n \\ \theta & \sim \Pi(\theta) \end{cases} \quad (1)$$

where a sequence of observables  $x_{1:n} = (x_1, \dots, x_n)$  are drawn from the parametric model  $F(x|\theta)$  with unknown parameter  $\theta \in \Theta$ . We study the behavior of the posterior distribution  $\Pi(\theta|x_{1:n})$  with respect to the number of observables  $n$ , first when  $\theta$  is a discrete parameter, and then when it is a continuous one.

All the theorems in this chapter are frequentist in character, namely we study the posterior laws under the assumption that the observables  $x_{1:n}$  are a random IID sample from the sampling distribution  $F(x|\theta^*)$  for some fixed, non-random  $\theta^* \in \Theta$ .

## 1 Asymptotic consistency: when $\theta$ is discrete

In this section we focus in the case that  $\theta \in \Theta$  is a discrete parameter, and  $\Theta$  is a countable space, given the Bayesian model (1). In particular, the theorem below states that, for countable  $\Theta$ , the posterior distribution function for  $\theta \in \Theta$  ultimately degenerates to a step function with a single (unit) step at  $\theta = \theta^*$ , where  $\theta^*$  is the real value of the unknown discrete parameter  $\theta$ .

**Theorem 1.** (Discrete case) Assume the Bayesian model (1), let  $x_{1:n} = (x_1, \dots, x_n)$  be a sequence of observables,  $\theta \in \Theta$  be the unknown parameter with prior distribution  $\pi(\theta)$ , and posterior distribution  $\pi(\theta|x_{1:n})$ , where  $\Theta$  is a countable parametric space. Suppose  $\theta^* \in \Theta$  is the (only) true value of  $\theta$  such that  $\pi(\theta^*) > 0$ , and  $-KL(f(\cdot|\theta^*), f(\cdot|\theta)) := \int \log \frac{f(x|\theta)}{f(x|\theta^*)} dF(x|\theta^*) < 0$  for all  $\theta \neq \theta^*$ . Then

$$\lim_{n \rightarrow \infty} \pi(\theta|x_{1:n}) = \begin{cases} 1 & , \theta = \theta^* \\ 0 & , \theta \neq \theta^* \end{cases}.$$

*Proof.* It is

$$\pi(\theta|x_{1:n}) = \frac{f(x_{1:n}|\theta)\pi(\theta)}{\sum_{\forall \theta \in \Theta} f(x_{1:n}|\theta)\pi(\theta)} = \frac{\frac{f(x_{1:n}|\theta)}{f(x_{1:n}|\theta^*)}\pi(\theta)}{\sum_{\forall \theta \in \Theta} \frac{f(x_{1:n}|\theta)}{f(x_{1:n}|\theta^*)}\pi(\theta)}.$$

Due to exchangeability of  $x_{1:n}$ , it is

$$\pi(\theta|x_{1:n}) = \frac{[\prod_{i=1}^n \frac{f(x_i|\theta)}{f(x_i|\theta^*)}]\pi(\theta)}{\sum_{\forall \theta \in \Theta} [\prod_{i=1}^n \frac{f(x_i|\theta)}{f(x_i|\theta^*)}]\pi(\theta)} = \frac{\exp(\overbrace{\sum_{i=1}^n \log \frac{f(x_i|\theta)}{f(x_i|\theta^*)}}^{=S_n(\theta)})\pi(\theta)}{\sum_{\forall \theta \in \Theta} \exp(\sum_{i=1}^n \log \frac{f(x_i|\theta)}{f(x_i|\theta^*)})\pi(\theta)} = \frac{\exp(S_n(\theta))\pi(\theta)}{\sum_{\forall \theta \in \Theta} \exp(S_n(\theta))\pi(\theta)}$$

Now about  $S_n(\theta) = \sum_{i=1}^n \log \frac{f(x_i|\theta)}{f(x_i|\theta^*)}$ . From the SLLN, as  $n \rightarrow \infty$ , it is

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \log \frac{f(x_i|\theta)}{f(x_i|\theta^*)} = E_F \left( \log \frac{f(x|\theta)}{f(x|\theta^*)} | \theta^* \right), \quad \text{a.s.} \quad (2)$$

By using Jensen's inequality and the fact that log is concave, it is

$$\begin{aligned} E_F \left( \log \frac{f(x|\theta)}{f(x|\theta^*)} | \theta^* \right) &\leq \log E_F \left( \frac{f(x|\theta)}{f(x|\theta^*)} | \theta^* \right) = \log(1) = 0 \\ \implies E_F \left( \log \frac{f(x|\theta)}{f(x|\theta^*)} | \theta^* \right) &\leq 0 \end{aligned} \quad (3)$$

In the (3), the equality holds for  $\theta = \theta^*$  a.s., and the inequality holds for  $\theta \neq \theta^*$  a.s., since  $\Theta$  is a countable space and  $\theta^* \in \Theta$ ,  $\theta^*$  is "distinguishable" from the others, according to Theorem 15. Notice that, for any  $\theta \neq \theta^*$ , (2) and (3) imply that

$$\lim_{n \rightarrow \infty} \frac{1}{n} S_n(\theta) = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \log \frac{f(x_i|\theta)}{f(x_i|\theta^*)} < 0, \quad \text{a.s.}$$

which implies that

$$\lim_{n \rightarrow \infty} S_n(\theta) = -\infty, \quad \text{as}$$

Therefore, □

• for any  $\theta \neq \theta^*$ , it is

$$\lim_{n \rightarrow \infty} \pi(\theta|x_{1:n}) = \lim_{n \rightarrow \infty} \frac{\exp(S_n(\theta))\pi(\theta)}{\sum_{\forall \theta \in \Theta} \exp(S_n(\theta))\pi(\theta)} = 0, \quad \text{a.s.}$$

– for  $\theta = \theta^*$ , it is

$$\lim_{n \rightarrow \infty} \pi(\theta^*|x_{1:n}) = 1 - \sum_{\forall \theta \neq \theta^*} \underbrace{\lim_{n \rightarrow \infty} \pi(\theta|x_{1:n})}_{=0, \text{ for } \theta \neq \theta^*} = 1, \quad \text{a.s.}$$

*Remark 2.* It can be shown that if  $\theta^* \notin \Theta$ , the posterior degenerates onto the value in  $\Theta$  which gives the parametric model closest  $\theta^*$ .

*Remark 3.* One important condition we considered was that the real parameter value  $\theta^*$  is unique. If there was another  $\theta^{**}$  such that  $f(x|\theta^{**}) = f(x|\theta^*)$ , we would observe IID data when  $\theta$  equalled  $\theta^*$  or  $\theta^{**}$ , and hence the data could not discriminate between the two values.

*Remark 4.* If  $\theta$  is a continuous parameter, then  $\pi(\theta|x_{1:n})$  is always zero for any finite sample, and so the above theorem 1 apply.

## 2 Asymptotic consistency and normality: when $\theta$ is continuous

In this section, we focus in the case that  $\theta \in \Theta$  may be a continuous parameter,  $\Theta \subset \mathbb{R}^k$  is compact with  $k \geq 1$ , given the Bayesian model (1). In particular, under specific conditions, we prove that as  $n \rightarrow \infty$ :

1. the posterior PDF of  $\theta$  becomes more and more concentrated above an area around the true value  $\theta^*$
2. the limiting posterior distribution of  $\theta$  is a Normal distribution with specific parameters, and remarkably
3. these conclusions do not depend on the choice of the prior distribution provided that  $\pi(\theta^*) > 0$ .

We recall asymptotic results of MLE in Appendix B.

Consider the Bayesian model  $(F(x_{1:n}|\theta), \Pi(\theta))$  in (1), with  $\theta \in \Theta$ , where  $\Theta$  is an open subset of  $\mathbb{R}^k$ . Assume a prior distribution  $\Pi(\theta)$  with a PDF  $\pi(\theta)$  where  $\pi(\theta)$  continuous in  $\Theta$ . To easy notation, we denote the likelihood as  $L_n(\theta) := f(x_{1:n}|\theta) = \prod_{i=1}^n f(x_i|\theta)$ . So the posterior PDF of  $\theta$  is

$$\pi(\theta|x_{1:n}) = \frac{L_n(\theta)\pi(\theta)}{\int L_n(\theta)\pi(\theta)d\theta} = \frac{\prod_{i=1}^n f(x_i|\theta)\pi(\theta)}{\int \prod_{i=1}^n f(x_i|\theta)\pi(\theta)d\theta}$$

We present the Bernstein-von Mises theorem which (more-or-less) states that the posterior PDF  $\pi(\theta|x_{1:n})$  is close to a normal density  $N\left(\theta|\hat{\theta}_n, \frac{1}{n}\mathcal{J}(\theta^*)^{-1}\right)$  centered at  $\hat{\theta}_n$  (the MLE of (16)), with variance  $\frac{1}{n}\mathcal{J}(\theta^*)^{-1}$  when  $\theta^*$  is the true value, when the size of the number of the observables  $n$  is really big. Here,  $\mathcal{J}(\theta)$  is the Fisher information, where

$$\mathcal{J}(\theta) = E_F\left((\nabla_{\theta} \log f(x|\theta))^{\top} (\nabla_{\theta} \log f(x|\theta))\right) = -E_F\left(\nabla_{\theta}^2 \log f(x|\theta)\right)$$

The following version of the theorem is due to Le Cam (1953). It equivalently states that the posterior PDF of (the linear transformation)  $\vartheta = \sqrt{n}(\theta - \hat{\theta}_n)$  given the data

$$\pi(\vartheta|x_{1:n}) = \frac{L_n(\vartheta \frac{1}{\sqrt{n}} + \hat{\theta}_n)\pi(\vartheta \frac{1}{\sqrt{n}} + \hat{\theta}_n)}{\int L_n(\vartheta \frac{1}{\sqrt{n}} + \hat{\theta}_n)\pi(\vartheta \frac{1}{\sqrt{n}} + \hat{\theta}_n)d\vartheta}$$

approaches the PDF of  $N(0, \mathcal{J}(\theta^*)^{-1})$  and  $n \rightarrow \infty$ . Remarkably (!!!), this limiting posterior distribution is independent of the prior distribution  $\pi(\theta)$ .

**Theorem 5.** (Bernstein-von Mises) Let  $x_1, x_2, \dots$  be IID random variables drawn from a sample distribution with density  $f(x|\theta)$ ,  $\theta \in \Theta$ , and let  $\theta^* \in \Theta$  denote the true value of  $\theta$ . Let  $L_n(\theta) = f(x_{1:n}|\theta)$  denote the likelihood. Assume that the prior density  $\pi(\theta)$  is continuous and  $\pi(\theta) > 0$  for all  $\theta \in \Theta$ . Under the following assumptions:

**d1**  $\Theta$  is an open subset of  $\mathbb{R}^k$

**d2** second partial derivatives of  $f(x|\theta)$  with respect to  $\theta$  exist and are continuous for all  $x$ , and may be passed under the integral operator in  $\int f(x|\theta)dx$

74 **d3** there is a function  $K(x)$  such that  $E^{f(x|\theta_0)}(K(x)) < \infty$  and each component of  $\nabla_\theta^2 \log(f(x|\theta))$  is bounded in  
75 absolute value by  $K(x)$  uniformly in some neighborhood of  $\theta^*$

76 **d4**  $\mathcal{J}(\theta_0) = -E_F(\nabla_\theta^2 \log f(x|\theta)|\theta_0)$  is positive definite

77 **d5** (identifiability)  $f(x|\theta) = f(x|\theta^*)$  a.s. then  $\theta = \theta^*$

78 It is

$$79 \frac{L_n(\hat{\theta}_n + \vartheta \frac{1}{\sqrt{n}})}{L_n(\hat{\theta}_n)} \pi(\hat{\theta}_n + \vartheta \frac{1}{\sqrt{n}}) \xrightarrow{a.s.} \exp(-\frac{1}{2} \vartheta^\top \mathcal{J}(\theta_0) \vartheta) \pi(\theta^*), \quad (4)$$

80 where  $\hat{\theta}_n$  is the strongly consistent sequence of roots of the likelihood equation (16) of Theorem 17. If, additionally,

$$81 \int_{\Theta} \frac{L_n(\hat{\theta}_n + \vartheta \frac{1}{\sqrt{n}})}{L_n(\hat{\theta}_n)} \pi(\hat{\theta}_n + \vartheta \frac{1}{\sqrt{n}}) d\vartheta \xrightarrow{a.s.} \int_{\Theta} \exp(-\frac{1}{2} \vartheta^\top \mathcal{J}(\theta^*) \vartheta) \pi(\theta^*) d\vartheta \quad (5)$$

82 then

$$83 \int_{\Theta} |\pi(\vartheta|x_{1:n}) - N(\vartheta|0, \mathcal{J}(\theta^*)^{-1})| d\vartheta \xrightarrow{a.s.} 0. \quad (6)$$

84 *Proof.* We prove: fist the existence of the the MLE, then (4), and finally (6).

#### 85 • Existence of consistent roots

86 I gonna use Theorem 17 to prove that there exists a consistent sequence  $\hat{\theta}_n$  of roots of (16), and hence I need  
87 to show that its conditions are satisfied. Let  $S_\rho = \{\theta : |\theta - \theta^*| \leq \rho\}$ , with  $\rho > 0$ , be a neighborhood of  $\theta^*$   
88 on which (d3) is satisfied. So for  $\Theta = S_\rho$  (in Theorem 17) I have:

- 89 – Conditions (c1), (c2), (c5), of that theorem are automatic!
- 90 – Condition (c4) follows from continuity of  $f(x|\theta)$  at  $\theta$ . !
- 91 – Condition (c3), ok.... By Taylor's theorem, I expand  $U(x, \theta) = \log(f(x|\theta)) - \log(f(x|\theta^*))$  around  $\theta^*$   
92 as

$$93 U(x, \theta) = U(x, \theta^*) + \nabla_\theta \log(f(x|\theta^*))(\theta - \theta^*) \\ 94 + (\theta - \theta^*) \int_0^1 \int_0^1 v \nabla_\theta^2 \log(f(x|\theta_0 + uv(\theta - \theta^*))) du dv (\theta - \theta^*)$$

95 So because  $U(x, \theta^*) = 0$ ,  $\nabla_\theta \log(f(x|\theta^*))$  is integrable, and the components of  $\nabla_\theta^2 \log(f(x|\theta))$  are  
96 bounded by  $K(x)$  uniformly on  $S_\rho$ , we get that  $U(x, \theta)$  is bounbed on  $S_\rho$ . So (c3) holds. So

#### 97 • Asymptotic Normality

98 Let

$$99 \ell_n(\theta) = \log(L_n(\theta)); \quad \dot{\ell}_n(\theta) = \nabla_\theta \log(L_n(\theta)); \quad \ddot{\ell}_n(\theta) = \nabla_\theta^2 \log(L_n(\theta))$$

100 By Taylor's Theorem 14, we expand  $\ell_n(\theta)$  around  $\hat{\theta}_n$  as

$$101 \ell_n(\theta) = \ell_n(\hat{\theta}_n) + \dot{\ell}_n(\hat{\theta}_n)(\theta - \hat{\theta}_n) + (\theta - \hat{\theta}_n)^\top I_n(\theta)(\theta - \hat{\theta}_n)$$

102 where

$$103 I_n(\theta) = -\frac{1}{n} \int_0^1 \int_0^1 v \ddot{\ell}_n(\hat{\theta}_n + uv(\theta - \hat{\theta}_n)) du dv \quad (7)$$

Because, it is  $\dot{\ell}_n(\hat{\theta}_n) = 0$  a.s., we get:

$$\begin{aligned} \ell_n(\theta) &= \ell_n(\hat{\theta}_n) + (\theta - \hat{\theta}_n)^\top I_n(\theta)(\theta - \hat{\theta}_n) \iff \\ \frac{L_n(\theta)}{L_n(\hat{\theta}_n)} &= \exp(-(\theta - \hat{\theta}_n)^\top I_n(\theta)(\theta - \hat{\theta}_n)), \quad \text{a.s.} \end{aligned}$$

Let's work on the asymptotics of (7); it is:

$$\begin{aligned} \frac{1}{n} \ddot{\ell}_n(\theta) &= \frac{1}{n} \nabla_\theta^2 \log(L_n(\theta)) = \frac{1}{n} \nabla_\theta^2 \log\left(\prod_{i=1}^n f(x_i|\theta)\right) = \frac{1}{n} \sum_{i=1}^n \nabla_\theta^2 \log(f(x_i|\theta)) \\ &\xrightarrow{\text{a.s.}} E_F(\nabla_\theta^2 \log f(x|\theta)|\theta_0) \end{aligned} \quad (8)$$

as  $n \rightarrow \infty$  by SLLN. Also, it is

$$E_F(\nabla_\theta^2 \log f(x|\theta)|\theta_0) = -\mathcal{J}(\theta_0) \quad (9)$$

by Lemma ???. Hence, from (8) and (9), I get

$$\frac{1}{n} \ddot{\ell}_n(\theta) \xrightarrow{\text{a.s.}} -\mathcal{J}(\theta_0) \quad (10)$$

Therefore,

$$I_n(\hat{\theta}_n + \vartheta \frac{1}{\sqrt{n}}) = -\frac{1}{n} \int_0^1 \int_0^1 v \ddot{\ell}_n(\hat{\theta}_n + uv(\theta - \hat{\theta}_n)) du dv \xrightarrow{\text{a.s.}} \frac{1}{2} \mathcal{J}(\theta^*) \quad (11)$$

because of (10) and because of  $\hat{\theta}_n \xrightarrow{\text{a.s.}} \theta^*$  from Theorem 17.

So back to what we wish to prove, and putting all these together, it is

$$\begin{aligned} \frac{L_n(\hat{\theta}_n + \vartheta \frac{1}{\sqrt{n}})}{L_n(\hat{\theta}_n)} \pi(\hat{\theta}_n + \vartheta \frac{1}{\sqrt{n}}) &= \exp(-\vartheta^\top I_n(\hat{\theta}_n + \vartheta \frac{1}{\sqrt{n}}) \vartheta) \pi(\hat{\theta}_n + \vartheta \frac{1}{\sqrt{n}}) \\ &\xrightarrow{\text{a.s.}} \exp(-\frac{1}{2} \vartheta^\top \mathcal{J}(\theta^*) \vartheta) \pi(\theta^*) \end{aligned}$$

because of (11) and  $\hat{\theta}_n \xrightarrow{\text{a.s.}} \theta^*$ .

Now, about the second part of the proof. If (5) then by dividing (4) and (5), I get

$$\pi(\vartheta|x_{1:n}) \xrightarrow{\text{a.s.}} N(\vartheta|0, \mathcal{J}(\theta^*)^{-1})$$

for all  $\theta \in \Theta$ . Hence By Scheffe's Theorem 12 we get (6).

□

*Remark 6.* Note that Bernstein-von Mises Theorem 5 and Theorem A imply that the posterior distribution of  $\vartheta = \sqrt{n}(\theta - \hat{\theta})$  given the data converges to the Normal distribution  $N(0, \mathcal{J}(\theta_0)^{-1})$  in Total Variation Norm, namely

$$\sup_{A \subset \Theta} |\pi(\vartheta \in A|x_{1:n}) - N(\vartheta \in A|0, \mathcal{J}(\theta^*)^{-1})| dx \rightarrow 0, \quad \text{as } n \rightarrow \infty$$

*Remark 7.* Bernstein-von Mises Theorem 5 says that the posterior PDFs of  $\sqrt{n} \mathcal{J}(\theta^*)^{1/2}(\theta - \hat{\theta}_n)$  converges to the PDF of Normal  $N(0, I_k)$ . Hence, this imply the CDF of  $\sqrt{n} \mathcal{J}(\theta^*)^{1/2}(\theta - \hat{\theta}_n)$  converges to the PDF of Normal  $N(0, I_k)$  as well. Namely

$$\sqrt{n} \mathcal{J}(\theta^*)^{1/2}(\theta - \hat{\theta}_n) \xrightarrow{D} z \quad \text{where } z \sim N(0, I_k) \quad (\text{convergence in distribution}),$$

and  $\mathcal{J}(\cdot) = [\mathcal{J}(\cdot)^{1/2}][\mathcal{J}(\cdot)^{1/2}]^\top$ .

**Corollary.** *If the conditions of Bernstein-von Mises Theorem 5 hold, and if  $\mathcal{J}(\theta)$  is continuous at  $\Theta$ , then*

$$\sqrt{n}\mathcal{J}(\hat{\theta}_n)^{-1/2}(\theta - \hat{\theta}_n) \xrightarrow{D} z, \quad \text{where } z \sim N(0, I_k) \quad (12)$$

*this is the result was stated in Stat Concepts II notes (Term 2 2017).*

**Proof.** From Bernstein-von Mises Theorem implies  $\sqrt{n}(\theta - \hat{\theta}_n) \xrightarrow{D} N(0, \mathcal{J}(\theta^*)^{-1})$  or equiv.

$$Y_n = \sqrt{n}\mathcal{J}(\theta^*)^{1/2}(\theta - \hat{\theta}_n) \xrightarrow{D} Z, \quad (13)$$

with  $Z \sim N(0, I_k)$ . From Theorem 17 I get  $\hat{\theta}_n \rightarrow \theta^*$  a.s.. Due to continuity of  $\mathcal{J}(\theta)$ , it is

$$X_n = \mathcal{J}(\hat{\theta}_n)^{1/2}\mathcal{J}(\theta^*)^{-1/2} \xrightarrow{\text{a.s.}} I_k \quad (14)$$

According to Slutsky's theorem<sup>1</sup> by multiplying (13),(14), I get  $X_n Y_n \xrightarrow{D} Z$ , i.e.,  $\sqrt{n}\mathcal{J}(\hat{\theta}_n)^{1/2}(\theta - \hat{\theta}_n) \xrightarrow{D} N(0, I_k)$ . □

### Asymptotic efficiency of Bayes Estimates

Consider the squared error loss  $\ell(\theta, \delta) = (\theta - \delta)^\top (\theta - \delta)$  which implies the posterior expectation  $\delta^\pi = E_\Pi(\theta|x_{1:n})$  as Bayes point estimator. Given that, we can interchange the limit and the expectation operator of  $\vartheta = \sqrt{n}(\theta - \hat{\theta}_n)$ , we get  $\sqrt{n}(\delta^\pi - \hat{\theta}_n) \rightarrow 0$  meaning that  $\delta^\pi$  and  $\hat{\theta}_n$  are asymptotically equivalent; i.e.  $\delta^\pi = \hat{\theta}_n$  a.s.. Hence

$$\sqrt{n}(\delta^\pi - \theta^*) = \sqrt{n}(\delta^\pi - \hat{\theta}_n) + \sqrt{n}(\hat{\theta}_n - \theta^*) \xrightarrow{D} N(0, \mathcal{J}(\theta^*)^{-1})$$

which means that the Bayes estimator is asymptotically efficient.

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<sup>1</sup>Sluky's theorem: If  $Y_n \xrightarrow{D} Z$  and  $X_n \xrightarrow{\text{a.s.}} c$ , where  $c \in \mathbb{R}^k$  is a constant, then  $X_n Y_n \xrightarrow{D} cZ$

### 3 Implementation

Nowadays, Bayesian asymptotics can be mainly be used for theoretical purposes such as investigating the behavior of Bayesian procedures-methods-algorithms mainly addressing big dataset problems.

Below, we demonstrate a toy example for pedagogical purposes.

**Example 8.** Consider a Bayesian model

$$\begin{cases} x_i | \theta & \stackrel{\text{iid}}{\sim} \text{Bn}(\theta), & i = 1, \dots, n \\ \theta & \sim \text{Be}(a, b) \end{cases}$$

where  $a > 0$ ,  $b > 0$ , and  $n > 2$ .

1. Find the asymptotic posterior distribution of  $\theta$  as  $n \rightarrow \infty$ , by using Bernstein-von Mises Theorem.
2. What is the Bayes estimators under the square loss and under the 0-1 loss. How do they behave as  $n \rightarrow \infty$ .

**Solution.**

1. I will find the MLE by computing the roots of the equation (16). The likelihood is  $f(x_{1:n}|\theta) = \prod_{i=1}^n \text{Bn}(x_i|\theta)$ . Then

$$\frac{d}{d\theta} \log f(x_{1:n}|\theta) = \frac{d}{d\theta} \sum_{i=1}^n \log(\text{Bn}(x_i|\theta)) = \frac{n\theta - \sum_{i=1}^n x_i}{\theta(1-\theta)} \Rightarrow$$

$$\frac{d}{d\theta} \log f(x_{1:n}|\theta)|_{\theta=\hat{\theta}_n} = 0 \Rightarrow \hat{\theta}_n = \frac{1}{n} \sum_{i=1}^n x_i$$

Now, I will find the Fisher Information; it is

$$\frac{d^2}{d\theta^2} \log(f(x|\theta)) = \frac{d^2}{d\theta^2} \log(\text{Bn}(x|\theta)) = -\frac{x}{\theta^2} - \frac{1-x}{(1-\theta)^2} \Rightarrow$$

$$\mathcal{J}(\theta) = -E_{\text{Bn}(\theta)} \left( -\frac{x}{\theta^2} - \frac{1-x}{(1-\theta)^2} \right) = \frac{1}{\theta(1-\theta)} \quad (15)$$

So according to Bernstein-von Mises Theorem 5, it is

$$\pi(\theta|x_{1:n}) \xrightarrow{\text{a.s.}} \text{N}\left(\underbrace{\frac{1}{n} \sum_{i=1}^n x_i}_{=\hat{\theta}_n}, \underbrace{\frac{1}{n} \theta^*(1-\theta^*)}_{=\frac{1}{n} \mathcal{J}(\theta^*)^{-1}}\right)$$

2. The exact posterior distr. is  $\text{Be}(a + n\bar{x}, b + n - n\bar{x})$ . The squared loss and the 0 – 1 loss imply the posterior mean  $\delta_1(x_{1:n}) = \frac{n\bar{x}+a}{n+a+b}$  and posterior mode  $\delta_2(x_{1:n}) = \frac{n\bar{x}+a-1}{n+a+b-2}$  as Bayes estimators correspondingly. Both converge to the MLE  $\hat{\theta}_n = \bar{x}$  since  $\lim_{n \rightarrow \infty} \delta_1(x_{1:n}) = \bar{x}$  and  $\lim_{n \rightarrow \infty} \delta_2(x_{1:n}) = \bar{x}$ .





## Appendix

### A An inventory of definitions

The following are definitions and statements used in proofs in Sections 1 and 2.

**Definition 9.** (Types of converge) Assume a probability triplet  $\{\Omega, \mathcal{F}, P\}$ , and a sequence of random quantities  $\{x_n; n = 1, 2, \dots\}$ , such that  $x_n : \Omega \rightarrow \mathbb{R}^d$ ,  $d > 0$ . Then

- $\{x_n\}$  converges almost surely to a random quantify  $x$  if and only if

$$P(\lim_{n \rightarrow \infty} x_n = x) = 1.$$

It is demoted as  $x_n \xrightarrow{\text{a.s.}} x$ .

- $\{x_n\}$  converges in distribution to a random quantify  $x$  if and only if for all  $\epsilon > 0$ ,

$$\lim_{n \rightarrow \infty} F_{x_n}(t) = F_x(t)$$

for all continuity points  $t$  of  $F$  in  $\mathbb{R}$ , where  $F_{x_n}(t) = P(x_n \leq t)$  and  $F_x(t) = P(x \leq t)$  are CDFs of  $x_n$  and  $x$ . It is demoted as  $x_n \xrightarrow{D} x$ .

- $\{x_n\}$  converges in total variation a random quantity  $x$  if and only if

$$\lim_{n \rightarrow \infty} \sup_{\forall B \subset \Theta} |P(x_n \in B) - P(x \in B)| = 0,$$

It is demoted as  $x_n \xrightarrow{\text{T.V.}} x$ .

**Definition 10.** (Upper semicontinuous) A real-valued function,  $f(\theta)$ , defined on  $\Theta$  is said to be upper semicontinuous (u.s.c.) on  $\Theta$ , if for all  $\theta \in \Theta$  and for any sequence  $\theta_n$  in  $\Theta$  such that  $\theta_n \rightarrow \theta$ , we have

$$\lim_{n \rightarrow \infty} \sup f(\theta_n) \leq f(\theta)$$

**Proposition 11.** If  $\pi_n(\cdot)$  and  $\pi(\cdot)$  are the PDFs of  $x_n$  and  $x$  correspondingly, then

$$\sup_{\forall B \subset \Theta} |P(x_n \in B) - P(x \in B)| = \int \frac{1}{2} |\pi_n(t) - \pi(t)| dt$$

**Theorem 12.** (Scheffe convergence theorem<sup>2</sup>) If  $f_n(\cdot)$  and  $g(\cdot)$  are density functions such that for all  $x \in \mathcal{X}$   $\lim_{n \rightarrow \infty} f_n(x) = g(x)$ , then

$$\lim_{n \rightarrow \infty} \int_{\mathcal{X}} |f_n(x) - g(x)| dx = 0$$

(that is a point-wise convergence of densities)

**Theorem** If random variables  $x_n$  has density  $f_n(x)$  and random variable  $x$  has density  $g(x)$ , and if  $\lim_{n \rightarrow \infty} \int_{\mathcal{X}} |f_n(x) - g(x)| dx = 0$  then

$$\sup_{\forall A \subset \mathcal{X}} |P(x_n \in A) - P(x \in A)| \rightarrow 0, \quad \text{as } n \rightarrow \infty$$

that is called convergence in Total Variation.

**Theorem 13.** (A Strong law of large numbers (SLLN)) Let  $\{x_i\}_{i=1}^n$  be a sequence of IID random quantities, with  $E(x_i) = \mu < \infty$ , and  $\bar{x}_n = \frac{1}{n} \sum_{i=1}^n x_i$  then  $\bar{x}_n \xrightarrow{\text{a.s.}} \mu$ .

<sup>2</sup>This is not the original version, but it is what we need

**Theorem 14.** (Taylor's theorem) If  $f : \mathbb{R}^d \rightarrow \mathbb{R}$ , and if  $\nabla^2 f(x) = \nabla(\nabla f(x))^\top$  is continuous in the ball  $\{x \in \mathcal{X} : |x - x_0| < r\}$ , then for  $|t| < r$ , it is

$$f(x_0 + t) = f(x_0) + \nabla f(x_0)t + t^\top \cdot \int_0^1 \int_0^1 u \nabla^2 f(x_0 + uv t) du dv \cdot t$$

**Lemma 15.** (Shannon-Kolmogorov Information Inequality) Let  $f_0(x)$  and  $f_1(x)$  be densities with respect to Lebesgue measure  $dx$ . Then

$$KL(f_0, f_1) = E^{f_0(dx)}(\log \frac{f_0(x)}{f_1(x)}) = \int_{\mathcal{X}} \log \frac{f_0(x)}{f_1(x)} f_0(x) dx \geq 0,$$

with equality if and only if  $f_1(x) = f_0(x)$  a.s.

**Lemma 16.** (Passing the derivative under the integral operator) If  $(\partial/\partial\theta)g(x, \theta)$  exists and is continuous in  $\theta$  for all  $x$  and all  $\theta$  in an open interval  $\mathcal{S}$  and if  $|(\partial/\partial\theta)g(x, \theta)| \leq K(x)$  on  $\mathcal{S}$  where  $\int K(x)dx < \infty$  and if  $\int g(x, \theta)dx$  exists on  $\mathcal{S}$ , then

$$\frac{d}{d\theta} \int g(x, \theta) dx = \int \frac{d}{d\theta} g(x, \theta) dx$$

## B Strong consistency of Maximum Likelihood Estimates

In frequentist statistics, given that  $\nabla_\theta f(x|\theta)$  exists, one may seek to find the MLE  $\hat{\theta}_n$  as the solution of the likelihood equation:

$$\hat{\theta}_n : \nabla_\theta \log f(x_{1:n}|\theta)|_{\theta=\hat{\theta}_n} = \sum_{i=1}^n \nabla_\theta \log f(x_i|\theta)|_{\theta=\hat{\theta}_n} = 0 \quad (16)$$

The following theorem states (more or less) that the MLE  $\hat{\theta}_n$  in (16) is consistent.

**Theorem 17.** (Strong consistency of MLE) Let  $x_1, x_2, \dots$  be IID random variables with density  $f(x|\theta)$  (with respect to measure  $dx$ ),  $\theta \in \Theta$ , and let  $\theta^*$  denote the true value of  $\theta$ . If the following conditions are satisfied:

**c1**  $\Theta$  is a closed and bounded set in  $\mathbb{R}^k$

**c2**  $f(x|\theta)$  is u.s.c. in  $\theta$  for all  $x \in \mathcal{X}$

**c3** there is a function  $K(x)$  such that  $E^{f(x|\theta^*)}(|K(x)|) < \infty$  and

$$\log(f(x|\theta)) - \log(f(x|\theta^*)) \leq K(x), \quad \forall x, \forall \theta$$

**c4** for all  $\theta \in \Theta$  and sufficiency small  $\rho > 0$ ,  $\sup_{|\theta' - \theta| < \rho} f(x|\theta')$  is measurable in  $x$

**c5** (identifiability)  $f(x|\theta) = f(x|\theta^*)$  a.s. then  $\theta = \theta^*$

then, for any sequence of maximum-likelihood estimates  $\hat{\theta}_n$  of  $\theta$ , it is

$$\hat{\theta}_n \xrightarrow{a.s.} \theta^* \quad (17)$$

The following theorem states (more or less) that the MLE is asymptotically normal.

**Theorem 18.** (Cramer) Let  $x_1, x_2, \dots$  be IID random variables density  $f(x|\theta)$  (with respect to some distribution  $F(x|\theta)$ ),  $\theta \in \Theta$ , and let  $\theta^*$  denote the true value of  $\theta$ . If the conditions<sup>3</sup> (d1)-(d5) stated in Theorem 5 (check in the next Theorem) are satisfied, then there exists a strongly consistent sequence  $\hat{\theta}_n$  of roots of the likelihood equation (16) such that

$$\sqrt{n}(\hat{\theta}_n - \theta^*) \xrightarrow{D} N(0, \mathcal{I}(\theta^*)^{-1})$$

<sup>3</sup>The conditions of the theorem are the (d1)-(d5) in Theorem 5.