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COHERENT INFERENCE FROM  
IMPROPER PRIORS AND  
FROM FINITELY ADDITIVE PRIORS

By

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Priors and from Finitely Additive Priors

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## Abstract

Conditions are given for the formal posterior of an improper prior to be coherent in the sense of [4] and applied to translation models. An example is given of a proper countably additive statistical model and a finitely additive prior for which there is no posterior.

## 1. Introduction.

A notion of coherence for statistical inferences was introduced in a previous paper [4]. It was shown that an inference is coherent if and only if it corresponds to the posterior of a finitely additive prior. A similar result was proved for predictions and predictive inferences in [6].

In practice many Bayesians use improper, countably additive priors to represent diffuse prior knowledge rather than finitely additive priors. There are several reasons for this including the relatively easy calculation and the essential uniqueness of the formal posterior of an improper prior and the lack of familiarity with the finitely additive theory. As was shown by examples in [4], the use of an improper prior sometimes results in a coherent inference and sometimes not. The obvious problem is to find an effective criterion for determining when an inference from an improper prior will be coherent.

Bayesians have long justified their use of improper priors by arguing that they can be approximated in some sense by proper priors. A useful discussion is given by Stone [8] who defines a notion of approximation which we adopt for our purposes. Our first result (Theorem 3.1) is that an improper prior leads to a coherent inference if and only if it can be approximated by proper priors in this sense. Even this result is difficult to apply in specific examples. However, it can be used to derive a sufficient condition for coherence which is often easy to verify. This condition is presented in Theorem 3.2 and applied in several examples.

There is another difficulty with the characterization of coherent inferences as posteriors of finitely additive priors. Namely, not every finitely additive

prior has a posterior. Examples of this phenomenon presented heretofore have involved finitely additive conditionals as well as a finitely additive prior. An example is presented below in which the conditionals are countably additive with finite support. Thus it can happen that, even for a standard statistical model, a finitely additive prior leads to no inference.

The next section contains the necessary definitions and preliminary results.

## 2. Preliminaries.

For any set  $S$ ,  $P(S)$  denotes the collection of finitely additive probability measures defined on all subsets of  $S$ . If  $f$  is a bounded, real-valued function defined on  $S$  and  $\gamma \in P(S)$ , then the  $\gamma$ -integral of  $f$  will be written  $\gamma(f)$ ,  $\int f d\gamma$ , or  $\int f(s)\gamma(ds)$ .

Let  $\Theta$  and  $X$  be nonempty sets corresponding to the set of possible states of nature and the set of possible outcomes for a certain experiment, respectively. A statistical model  $p$  is a mapping which assigns to each  $\theta \in \Theta$  an element  $p_\theta$  of  $P(X)$ . An inference  $q$  assigns to each  $x \in X$  an element  $q_x$  of  $P(\Theta)$ . (In our earlier paper [5] we did not require each  $q_x$  to belong to  $P(\Theta)$  and considered the more general notion of a "conditional odds function." We impose the new restriction here in order to simplify the exposition and also because it is a natural requirement recommended by de Finetti [3, p. 339].) Thus  $p$  is a conditional probability distribution on  $X$  given  $\Theta$  and  $q$  is a conditional distribution on  $\Theta$  given  $X$ . Let  $\mathcal{B}(\Theta)$  and  $\mathcal{B}(X)$  be given  $\sigma$ -fields of subsets of  $\Theta$  and  $X$ , respectively. The model  $p$  (inference  $q$ ) is called measurable if every  $p_\theta$

$(q_x)$  is countably additive on  $\underline{B}(X)$  ( $\underline{B}(\Theta)$ ) and  $p(q)$  is a regular conditional distribution. The standard models and inferences of statistics are, of course, measurable.

An inference  $q$  might correspond in practice to a system of confidence intervals, a posterior distribution, or a fiducial distribution. For an operational interpretation, regard  $q_x$  as a conditional odds function used by the statistician to post odds on subsets of  $\Theta$  after observing  $x$ . The inference  $q$  is called coherent if it is impossible for a gambler to devise a system based on  $q$ , which consists of placing a finite number of bets on subsets of  $\Theta$  after  $x$  is observed and which attains an expected payoff greater than some positive constant for every  $\theta \in \Theta$ . (See [5] for the precise definition.)

An element  $\pi$  of  $P(\Theta)$  will be called a prior. A prior  $\pi$  and model  $p$  determine a marginal  $m \in P(X)$  by the formula

$$(2.1) \quad m(\phi) = \int p_{\theta}(\phi) \pi(d\theta)$$

for bounded functions  $\phi: X \rightarrow \mathbb{R}$ . Let  $\underline{B} = \underline{B}(\Theta) \times \underline{B}(X)$  be the product  $\sigma$ -field on  $\Theta \times X$ . An inference  $q$  is called a posterior for the prior  $\pi$ , the model  $p$  being understood, if

$$(2.2) \quad \iint \phi(\theta, x) p_{\theta}(dx) \pi(d\theta) = \iint \phi(\theta, x) q_x(d\theta) m(dx)$$

for all bounded,  $\underline{B}$ -measurable functions  $\phi: \Theta \times X \rightarrow \mathbb{R}$ . In other words,  $q$  is a

conditional distribution for  $\theta$  given  $X$  under the measure on  $\underline{B}$  determined by  $\pi$  and  $p$  as defined by the left-hand-side of (2.2).

The model  $p$  and inference  $q$  are called consistent if there exist  $\pi \in P(\theta)$  and  $m \in P(X)$  such that (2.2) holds for all bounded,  $\underline{B}$ -measurable  $\phi$ .

The following proposition summarizes a few results from [5] and [6].

Proposition 2.1. The following are equivalent statements about an inference  $q$  relative to a given model  $p$ :

- (a)  $q$  is coherent
- (b)  $q$  is the posterior of some prior  $\pi$ ,
- (c)  $p$  and  $q$  are consistent,
- (d) For every bounded, real-valued  $\underline{B}$ -measurable function  $\phi$  on  $\theta \times X$ ,

$$\inf_{\theta} p_{\theta}(\phi_{\theta}) \leq \sup_X q_X(\phi^X),$$

$$\text{where } \phi_{\theta}(x) = \phi(\theta, x) = \phi^X(\theta).$$

The results of the proposition are stated as in [5] and [6] for general  $p$  and  $q$  which are not necessarily measurable. Thus the inner integrals in (2.2), corresponding to  $p_{\theta}(\phi_{\theta})$  and  $q_X(\phi^X)$ , need not be measurable functions of  $\theta$  and  $x$ , respectively. This is the reason why  $\pi$  and  $m$  must be defined on all subsets of their respective spaces  $\theta$  and  $X$ . Now if  $p$  and  $q$  are measurable, then so are the functions  $p_{\theta}(\phi_{\theta})$  and  $q_X(\phi^X)$  and we need only specify  $\pi$  and  $m$  on  $\underline{B}(\theta)$  and  $\underline{B}(X)$ , respectively, for (2.2) to make sense. It is also easy to see that the

proposition remains true for measurable  $p$  and  $q$  if we consider priors and marginals to be defined only on the appropriate  $\sigma$ -fields.

Let  $M(\Theta)$  and  $M(X)$  be the collections of countably additive measures defined on  $\underline{B}(\Theta)$  and  $\underline{B}(X)$ , respectively. By an improper prior is meant an element  $\pi$  of  $M(\Theta)$  such that  $\pi(\Theta)$  is infinite. Suppose that, for a given statistical model  $p$ , there is a reference measure  $\nu \in M(X)$  such that every  $p_\theta$  is absolutely continuous with respect to  $\nu$ . Let  $f(\cdot|\theta)$  be the density for  $p_\theta$ . For  $x \in X$ , define

$$(2.3) \quad q_x(d\theta) = \frac{f(x|\theta)\pi(d\theta)}{\int f(x|t)\pi(dt)}$$

whenever the denominator is finite and not zero and let  $q_x$  be an arbitrary fixed element of  $P(\Theta)$  otherwise. The inference  $q$  is called the formal posterior of the improper prior  $\pi$ . If  $f(\cdot|\cdot)$  is  $\underline{B}$ -measurable and if the denominator above is  $\nu$ -almost everywhere finite and positive, then  $q$  is a measurable inference. Of course, if  $\pi$  is proper and countably additive on  $\underline{B}(\Theta)$ , then the  $q$  given by (2.3) is a genuine posterior for  $\pi$  and is coherent by Proposition 1.

### 3. Approximation by proper priors.

Let  $\alpha$  and  $\beta$  be measures on  $\underline{B}(\Theta)$  and define the total variation distance by

$$(3.1) \quad ||\alpha - \beta|| = \sup \left\{ \left| \int \phi d\alpha - \int \phi d\beta \right| : \sup |\phi| \leq 1, \phi \in L_\infty(\Theta) \right\}$$

where  $L_\infty(\theta)$  is the space of bounded, real-valued,  $\mathcal{B}(\theta)$ -measurable functions on  $\theta$ . Next consider an inference  $\tilde{q}$  and a prior  $\pi \in P(\theta)$  which has marginal  $m$  and posterior  $q$ . Define

$$(3.2) \quad d_\pi(q, \tilde{q}) = \int ||q_x - \tilde{q}_x|| m(dx),$$

which can be thought of as the expected distance between the inferences  $q$  and  $\tilde{q}$  when the expectation is calculated from the marginal of the prior  $\pi$ .

Definition. The inference  $\tilde{q}$  is approximable by proper priors (a.p.p.) if

$$(3.3) \quad \inf d_\pi(q, \tilde{q}) = 0$$

where the infimum is over all  $\pi, q$  such that  $\pi \in P(\theta)$  and  $q$  is the posterior of  $\pi$ . If  $\tilde{\pi}$  is an improper prior with formal posterior  $\tilde{q}$ , we say that  $\tilde{\pi}$  is approximable by proper priors (a.p.p.) if  $\tilde{q}$  is.

As was mentioned in the introduction, this notion of approximation was inspired by Stone [9] who did not, however, consider finitely additive priors.

Theorem 3.1. An inference  $\tilde{q}$  is coherent if and only if it is approximable by proper priors.

Proof: If  $\tilde{q}$  is coherent, then, by Proposition 1, there exists  $\pi \in P(\theta)$  with

posterior  $q = \tilde{q}$  and  $d_\pi(q, \tilde{q}) = 0$ .

Suppose now that  $\tilde{q}$  is a.p.p.. We will use Proposition 1 (d) to show that  $\tilde{q}$  is coherent.

Let  $\phi \in L_\infty(\Theta \times X)$  and  $\varepsilon > 0$ . Set  $b = \sup |\phi|$ . Choose  $\pi \in P(\Theta)$  with posterior  $q$  such that

$$d_\pi(q, \tilde{q}) < \varepsilon/b.$$

Then

$$\begin{aligned} \left| \int q_X(\phi^X) m(dx) - \int \tilde{q}_X(\phi^X) m(dx) \right| \\ \leq \int |q_X(\phi^X) - \tilde{q}_X(\phi^X)| m(dx) \\ \leq (\sup |\phi|) d_\pi(q, \tilde{q}) < \varepsilon. \end{aligned}$$

Hence

$$\begin{aligned} \int p_\theta(\phi_\theta) \pi(d\theta) &= \int q_X(\phi^X) m(dx) \\ &\leq \int \tilde{q}_X(\phi^X) m(dx) + \varepsilon \end{aligned}$$

and consequently,

$$\sup_x \tilde{q}_X(\phi^X) \geq \inf_\theta p_\theta(\phi_\theta) - \varepsilon.$$

Because  $\varepsilon$  is arbitrary  $\tilde{q}$  satisfies (d) of Proposition 1.  $\square$

Suppose now that  $\pi$  is an improper prior,  $p_\theta(dx) = f(x|\theta)v(dx)$  for every  $\theta \in \Theta$ , and  $\pi$  has formal posterior  $q$  as in (2.3). The natural and often used way to attempt an approximation of  $q$  by proper priors is to truncate  $\pi$  to a set of finite measure. To be precise, let  $K \in \mathcal{B}(\Theta)$  satisfy  $0 < \pi(K) < \infty$  and define the truncation of  $\pi$  to  $K$  as the proper prior  $\pi_K$  where

$$(3.4) \quad \pi_K(\phi) = \frac{1}{\pi(K)} \int_K \phi(\theta) \pi(d\theta), \quad \phi \in L_\infty(\Theta).$$

Let  $q^K$  and  $m_K$  be the posterior and marginal determined by  $\pi_K$ , respectively.

Formulas (2.1) and (2.3) specialize to give

$$(3.5) \quad \begin{aligned} m_K(\psi) &= \frac{1}{\pi(K)} \int_K \int \psi(x) p_\theta(dx) \pi(d\theta), \quad \psi \in L_\infty(X), \\ q^K_X(\phi) &= \frac{\int_K \phi(\theta) f(x|\theta) \pi(d\theta)}{\int_K f(x|\theta) \pi(d\theta)}, \quad \phi \in L_\infty(\Theta). \end{aligned}$$

It seems likely that, for measurable models, whenever  $q$  is a.p.p., it can be approximated by truncations. However, we have not proved such a result.

For a certain class of group invariant problems, M. Stone [9] showed that Haar measure used as an improper prior, could be approximated in a sense close to the present one by truncations. A similar result was obtained for amenable, locally compact groups in [5]. Suppose  $X = \Theta = G$  is such a group and the model

$p$  is a generalized translation family  $p_\theta(dx) = f(\theta^{-1}x)v(dx)$ , where  $v$  is right Haar measure. If  $v$  is used as an improper prior, the corresponding inference is

$$(3.6) \quad q_x(d\theta) \propto f(\theta^{-1}x)v(d\theta)$$

and is coherent by [4, Theorem 3]. Stone [9] has also given examples which illustrate that this inference need not be coherent if  $G$  is not amenable.

In general, the criterion of approximability by proper priors seems difficult to apply directly. For example, it follows from the discussion above that, if  $p$  is a translation family on the line such as the  $N(\theta, 1)$ , then Lebesgue measure,  $d\theta$ , gives a coherent inference. However, it remains unclear whether improper priors such as  $\theta^2 d\theta$  or  $|\theta|^{-1} d\theta$  will do so. The next result gives a sufficient condition for coherence which allows us to check that the corresponding inferences are coherent.

Suppose  $\pi$  is an improper prior with formal posterior  $q$ . For each  $K \in \underline{B}(\Theta)$  such that  $0 < \pi(K) < \infty$ , define

$$(3.7) \quad \beta(K) = \int q_x(K^c) m_K(dx).$$

Here  $m_K$  is the marginal on  $X$  determined by the truncated prior  $\pi_K$ . The number  $\beta(K)$  is the posterior probability under  $\pi$  that  $\theta \notin K$  averaged under the truncation of  $\pi$  to  $K$ . More crudely,  $\beta(K)$  is the chance that  $q$  says  $\theta \notin K$  given that  $\theta \in K$ .

Theorem 3.2. If

$$(3.8) \quad \inf\{\beta(K): 0 < \pi(K) < \infty\} = 0,$$

then  $\pi$  is approximable by proper priors. Indeed, given  $K \in \underline{B}(\Theta)$  with

$$0 < \pi(K) < \infty, \beta(K) \leq d_{\pi_K}(q^K, q) \leq 2\beta(K).$$

Proof: It suffices to prove the inequalities. For the first inequality, notice that, for all  $x$ ,  $q_x^K(K^C) = 0$  and so, by (3.1),

$$||q_x - q_x^K|| \geq q_x(K^C).$$

The first inequality now follows from (3.2) and (3.7).

To prove the second inequality, let  $\phi \in L_\infty(\Theta)$  and  $\sup|\phi| \leq 1$ . The inequality will follow from (3.1), (3.2), and (3.7) once it is shown that

$$(3.9) \quad |q_x(\phi) - q_x^K(\phi)| \leq 2q_x(K^C) \quad m_K - \text{a.s.}$$

To verify (3.9), first use the triangle inequality to see

$$(3.10) \quad |q_x(\phi) - q_x^K(\phi)| \leq \left| \int_{K^C} \phi dq_x \right| + \left| \int_K \phi dq_x - \int_K \phi dq_x^K \right|.$$

Because  $\sup|\phi| \leq 1$ , the first term on the right side of (3.9) is obviously

bounded by  $q_x(K^c)$ . To obtain the same bound for the second term on the right side of (3.10), use (2.2) and (3.5) to rewrite it as

$$(3.11) \quad \left| \int_K \phi dq_x^K \right| \left| 1 - \frac{\int_K f(x|\theta)\pi(d\theta)}{\int f(x|\theta)\pi(d\theta)} \right| \\ \leq q_x^K(K) \frac{\int_{K^c} f(x|\theta)\pi(d\theta)}{\int f(x|\theta)\pi(d\theta)} = 1 \times q_x(K^c). \quad \square$$

By Theorems 1 and 2, condition (3.8) is a sufficient condition for the formal posterior  $q$  to be coherent. Again we do not know whether it is necessary. The condition can often be checked as will be illustrated in the next section with two examples.

#### 4. Two applications to translation families.

In this section,  $\Theta = X = \mathbb{R}^d$ ,  $d$ -dimensional Euclidean space, and  $d\theta$  or  $dx$  has its usual interpretation as Lebesgue measure. The prior  $\pi$  will be a fixed improper prior

$$\pi(d\theta) = g(\theta)d\theta$$

where the prior "density"  $g$  is nonnegative, and Borel measurable. The model  $p$  is assumed to be a measurable translation family given by a family of densities

$$p_\theta(dx) = f(x-\theta)dx$$

where  $f$  is Borel measurable. Assume also that the denominator on the right side of (2.3) is Lebesgue almost everywhere finite and positive so that formula (2.3), which gives the formal posterior  $q$  of  $\pi$ , can be rewritten as

$$(4.1) \quad h(\theta|x) = \frac{f(x-\theta)g(\theta)}{\int f(x-\phi)g(\phi)d\phi}$$

where  $h(\theta|x)$  is a density for  $q_x$ . Write  $|\theta|$  for the Euclidean norm of  $\theta \in R^d$  and let  $\pi_n$  be the truncation of  $\pi$  to the ball  $B_n = \{\theta: |\theta| \leq n\}$ . Let  $q_x^n$  be the posterior for  $\pi_n$  and Bayes formula then gives the density below for  $q_x^n$

$$(4.2) \quad h_n(\theta|x) = \frac{f(x-\theta)g(\theta)}{\int_{B_n} f(x-\phi)g(\phi)d\phi}, \quad |\theta| \leq n.$$

So that (4.2) will be valid, assume  $\pi(B_n) < \infty$  for all  $n$ . For simplicity assume  $\pi(B_n) > 0$  also. However, there is no real loss in generality because we will only need below that  $\pi(B_n)$  is positive for  $n$  large and this follows from our assumption that  $\pi(\Theta) = \infty$ .

If the tails of the prior density  $g$  grow too rapidly, the inference  $q$  need not be coherent even for quite well-behaved translation models.

Example 4.1. (Stone [10]) Suppose  $\Theta = X = R^1$ ,  $p_\theta$  is  $N(\theta, 1)$ , and  $g(\theta) = \exp(a\theta)$

where  $a > 0$ . Use (4.1) to see that  $q_x$  is  $N(x+a, 1)$ . In Proposition 2.1 (d), take  $\phi$  to be the indicator function of the set  $S = \{(\theta, x): \theta < x+a\}$  and notice that

$$p_\theta(\phi_\theta) = p_\theta[\theta-a, \infty] = p_0[-a, \infty] > \frac{1}{2}$$

while

$$q_x(\phi^x) = q_x[-\infty, x+a] = q_0[-\infty, a] = \frac{1}{2}.$$

Thus  $q$  is incoherent.

The critical feature of this example is the exponential growth of the prior density  $g$ . The normal model could be replaced by many translation families including, for example, the uniform translation model where  $p_\theta$  is the uniform distribution on the interval  $[\theta, \theta+1]$ . Thus the exponential growth of  $g$  is too much even when the  $p_\theta$  have compact support. Here is a condition which rules out such growth for  $g$ .

(GC) Growth Condition: For every  $a > 0$ ,  $\lim_{n \rightarrow \infty} \frac{\pi(B_{n+a})}{\pi(B_n)} = 1$ .

Notice that a prior density which behaves asymptotically like a polynomial will satisfy (GC).

The next lemma gives another sufficient condition for coherence when  $\pi$  satisfies (GC). In its statement  $m_n$  denotes the marginal determined by the truncated prior  $\pi_n$  and the model  $p$ .

Lemma 4.1. Assume  $\pi$  satisfies (GC) and let  $a \geq 0$ . Then the following are true.

- (a)  $\pi_n(B_{n-a}) \rightarrow 1$  as  $n \rightarrow \infty$ .
- (b)  $m_n(B_{n-a}) \rightarrow 1$  as  $n \rightarrow \infty$ .
- (c)  $q$  is coherent if

$$(4.3) \quad \sup_n \int_{B_{n-a}} \int_{B_n^c} g(\theta) f(x-\theta) d\theta dx < \infty.$$

Proof: (a) This is obvious if  $a = 0$  and immediate from (GC) if  $a > 0$ .

(b) Let  $\varepsilon > 0$ . choose  $b > 0$  such that  $p_0(B_b) > 1-\varepsilon$ . Then  $p_\theta(B_b + \theta) = p_0(B_b) > 1-\varepsilon$  for all  $\theta$ . Now calculate.

$$\begin{aligned} m_n(B_{n-a}) &= \int_{B_n} p_\theta(B_{n-a}) \pi_n(d\theta) \geq \int_{B_{n-a-b}} p_\theta(B_{n-a}) \pi_n(d\theta) \\ &\geq \int_{B_{n-a-b}} p_\theta(B_b + \theta) \pi_n(d\theta) \geq (1-\varepsilon) \pi_n(B_{n-a-b}). \end{aligned}$$

(The next to last inequality holds because  $B_b + \theta \subseteq B_{n-a}$  for  $\theta \in B_{n-a-b}$ .) Now use part (a).

(c) Let  $\varepsilon > 0$ . By (3.7) and part (b),

$$\beta(B_n) = \int q_x(B_n^c) m_n(dx) < \varepsilon + \int_{B_{n-a}} q_x(B_n^c) m_n(dx)$$

for  $n$  sufficiently large. By Theorem 3.1 and 3.2, the coherence of  $q$  will be established if we show

$$(4.4) \quad \lim_{n \rightarrow \infty} \int_{B_{n-a}} q_x(B_n^c) m_n(dx) = 0.$$

To see this, let  $f_n$  be the density for  $m_n$  which is given by

$$f_n(x) = \frac{1}{\pi(B_n)} \int_{B_n} f(x-\theta)g(\theta)d\theta$$

and use (4.1) to write

$$q_x(B_n^c) = \frac{\int_{B_n^c} f(x-\theta)g(\theta)d\theta}{\int f(x-\theta)g(\theta)d\theta}.$$

Hence

$$\int_{B_{n-a}} q_x(B_n^c) m_n(dx) \leq \frac{1}{\pi(B_n)} \int_{B_{n-a}} \int_{B_n^c} f(x-\theta)g(\theta)d\theta dx.$$

Thus, (4.4) follows from (4.3) because  $\pi(B_n) \rightarrow \infty$ .  $\square$

The final condition of Lemma 4.1 can be viewed as a joint growth condition on the densities for the prior and the model. We will now apply it to two special situations.

Theorem 4.1. Suppose  $\Theta = X = \mathbb{R}^1$ . Assume  $\pi(d\theta) = g(\theta)d\theta$  is an improper prior with  $g$  uniformly bounded and  $p_\theta(dx) = f(x-\theta)dx$  is a translation family such that  $\int |x|f(x)dx < \infty$ . Then the formal posterior  $q$  is coherent.

Proof: Because  $g$  is bounded, it satisfies (GC) and it suffices by Lemma 4.1 (c) to show that

$$(4.5) \quad \int_{-n}^n \int_{B_n^c} f(x-\theta)d\theta dx \leq 2E|Z|$$

where  $Z$  is a random variable with density  $f(x)$ .

Use the fact that  $-Z$  has density  $f(-x)$  and calculate as follows:

$$\begin{aligned} \int_{B_n^c} f(x-\theta)d\theta &= \int_n^\infty f(x-\theta)d\theta + \int_{-\infty}^{-n} f(x-\theta)d\theta \\ &= \int_{n-x}^\infty f(-\theta)d\theta + \int_{n+x}^\infty f(\theta)d\theta \\ &= P[-Z \geq n-x] + P[Z \geq n+x]. \end{aligned}$$

Hence,

$$\begin{aligned}
\int_{-n}^n \int_{B_n^c} f(x-\theta) d\theta dx &= \int_{-n}^n \{P[-Z \geq n-x] + P[Z \geq n+x]\} dx \\
&= \int_0^{2n} \{P[-Z \geq y] + P[Z \geq y]\} dy \\
&= 2 \int_0^{2n} P[|Z| \geq y] dy \\
&\leq 2E|Z|. \quad \square
\end{aligned}$$

Theorem 4.2. Suppose  $\Theta = X = \mathbb{R}^d$  and  $p$  is a normal translation family  $p_\theta \sim N_d(\theta, \Sigma)$  where  $\Sigma$  is nonsingular, positive definite. If  $\pi(d\theta) = g(\theta)d\theta$  is an improper prior satisfying (GC) and  $g(\theta) \leq k|\theta|^r$  for some positive constants  $k$  and  $r$ , then the formal posterior  $q$  is coherent.

Proof: Let  $f$  be the density for  $p_0 \sim N(0, \Sigma)$ . It is easy to check that, for every  $s > 0$ , there is an  $\epsilon > 0$  such that  $f(x) \leq \epsilon|x|^{-s}$ . Thus the theorem follows from the next lemma.

Lemma 4.2. If  $\pi$  satisfies (GC),  $g(\theta) = O(|\theta|^r)$  for some  $r > 0$ , and  $f(x) = O(|x|^{-s})$  for some  $s > r+d$ , then the formal posterior  $q$  is coherent.

Proof: By Lemma 4.1 (c), it suffices to show the following expression is bounded in  $n$ .

$$\begin{aligned}
(4.6) \quad & \int_{B_n} \int_{B_n^c} |e|^{r-1} |x-\theta|^{-s} d\theta dx \\
&= \int_{B_n} \int_{|\phi+x|>n} |\phi+x|^r |\phi|^{-s} d\phi dx \\
&\leq \sum_{k=0}^r \binom{r}{k} \int_{B_n} |x|^{r-k} \int_{|\phi+x|>n} |\phi|^{k-s} d\phi dx.
\end{aligned}$$

Now evaluate the inside integral.

$$\begin{aligned}
\int_{|\phi+x|>n} |\phi|^{k-s} d\phi &= \int_{B_n^c} |e-x|^{k-s} d\theta \\
&\leq \sum_{j=0}^{k-s} \binom{k-s}{j} |x|^{k-s-j} \int_{B_n^c} |\phi|^j d\theta
\end{aligned}$$

Change to polar coordinates to see that

$$\int_{B_n^c} |\theta|^j d\theta = c n^{j+d} \leq c n^{r-s+d}. \quad \square$$

Both Theorem 4.1 and Theorem 4.2 illustrate that coherence of an inference from an improper prior depends on the relationship between the prior and the model, and not on the prior alone. In fact, given any improper prior  $\pi(d\theta) = g(\theta)d\theta$ , there is a model  $p$  for which the formal posterior  $q$  is incoherent. For example, if  $\Theta = \mathbb{R}^1$  and  $g$  is locally integrable and everywhere positive, then a simple transformation  $\phi = \phi(\theta)$  gives a prior  $\pi'(d\phi) = e^\phi d\phi$  and the normal model of example 4.1 will lead to an incoherent inference.

5. A measurable model and finitely additive prior for which there is no coherent inference.

Let  $X = \Theta = Z = \{0, \pm 1, \pm 2, \dots\}$  and let  $p$  be the translation model such that

$$p_{\theta}\{\theta+1\} = p_{\theta}\{\theta-1\} = 1/2$$

for all  $\theta$ . Take the prior  $\pi$  to be of the form

$$\pi = (\mu + \nu)/2$$

where  $\mu$  is countably additive with support the set  $A$  of integers divisible by 4 and  $\nu$  is purely finitely additive and supported by the set  $B$  of integers equal to 2 modulo 4. Thus  $\mu(A) = 1$  and  $\mu\{n\} > 0$  for  $n \in A$ ;  $\nu(B) = 1$  and  $\nu\{n\} = 0$  for all  $n$ . (This example is related to one of Dubins [3, p. 205]).

Lemma 5.1. There is no posterior for the prior  $\pi$ .

Proof: Assume, to get a contradiction, that  $\pi$  has a posterior  $q$  and let  $m$  be the corresponding marginal on  $X$ . Let  $O$  be the set of odd integers. Clearly,  $p_{\theta}(O) = 1$  for  $\theta \in E = A \cup B$  and, by (2.1),  $m(O) = 1$  also.

The key point is that  $q_x(A) = 1$  for all  $x \in O$ . To see this, suppose  $x = 4n + 1$ , write  $P$  for the joint distribution and calculate.

$$P[\theta = 4n, x = 4n+1] = \pi\{4n\}p_{4n}\{4n+1\} = \mu\{4n\}/4.$$

Also,

$$P[\theta = 4n, x = 4n+1] = m\{4n+1\}q_x\{4n\} = \mu\{4n\}q_x\{4n\}/4.$$

Hence,

$$q_x(A) = q_x\{4n\} = 1.$$

Similarly, if  $x = 4n + 3$ ,

$$q_x(A) = q_x\{4n+4\} = 1.$$

Thus

$$P(A \times X) = \int q_x(A)m(dx) = 1.$$

But

$$P(A \times X) = \pi(A) = 1/2,$$

a contradiction.  $\square$

One can use a finitely additive Radon-Nikodym theorem to see that, given  $\varepsilon >$

0, there is an  $\epsilon$ -posterior  $q$  for  $\pi$  in the sense that the two sides of (2.2) are within  $\epsilon$  of each other for all  $\mathcal{B}$ -measurable  $\phi$  with values in  $[0,1]$ . (In the terminology of [1], the distribution of  $(x,\theta)$  is nearly strategic but not strategic.) It would be interesting to know whether there are a measurable  $p$  and a finitely additive  $\pi$  for which there is no  $\epsilon$ -posterior. This can happen for finitely additive  $p$  as is shown in [4] and [8].

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