Posterior consistency for semi-parametric regression problems

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We consider Bayesian inference in the linear regression problem with an unknown error distribution that is symmetric about zero. We show that if the prior for the error distribution assigns positive probabilities to a certain type of neighbourhood of the true distribution, then the posterior distribution is consistent in the weak topology. In particular, this implies that the posterior distribution of the regression parameters is consistent in the Euclidean metric. The result follows from our generalization of a celebrated result of Schwartz to the independent, non-identical case and the existence of exponentially consistent tests of the complement of the neighbourhoods shown here. We then specialize to two important prior distributions, the Polya tree and Dirichlet mixtures, and show that under appropriate conditions these priors satisfy the positivity requirement of the prior probabilities of the neighbourhoods of the true density. We consider the case of both non-stochastic and stochastic regressors. A similar problem of Bayesian inference in a generalized linear model for binary responses with an unknown link is also considered.

Keywords: consistency; Dirichlet mixtures; exponentially consistent test; Kullback–Leibler number; linear regression; Polya tree; posterior distribution

1. Introduction

This paper addresses the consistency of the posterior in regression problems when the unknown distribution of the error variable is endowed with a nonparametric prior. Thus our observations are \( Y_1, Y_2, \ldots, \) where

\[
Y_i = \alpha + \beta x_i + \epsilon_i, \quad i = 1, 2, \ldots ;
\]

(1.1)

here the errors \( \epsilon_i \) are independent and identically distributed (i.i.d.) \( f \), with \( f \) a density symmetric around 0, and \( x_1, x_2, \ldots \) are the values of the covariate \( X \). These may arise as fixed non-random constants or as i.i.d. observations of a random variable \( X \) with a known or unknown distribution.

The unknown parameters are \( f, \alpha, \beta \) and formally the parameter space is
\( \Theta = \mathcal{F} \times \mathbb{R} \times \mathbb{R} \), where \( \mathcal{F} \) is the set of all symmetric densities on \( \mathbb{R} \). We start with a prior \( \Pi \) for \( f \) and, independent of \( f \), a prior \( \mu \) for \((\alpha, \beta)\). Let \( \Pi \) stand for the prior \( \Pi \times \mu \).

Fix \((f_0, \alpha_0, \beta_0)\) in \( \Theta \). The sequence of posteriors \( \Pi(\cdot | Y_1, Y_2, \ldots, Y_n) \) is said to be consistent for \((f, \alpha, \beta)\) at \((f_0, \alpha_0, \beta_0)\) if \( \Pi(\mathcal{U} | Y_1, \ldots, Y_n) \) converges to 1 almost surely as \( n \to \infty \) for any neighbourhood \( \mathcal{U} \) of \((f_0, \alpha_0, \beta_0)\), when the distribution governing \( Y_1, Y_2, \ldots \) has the ‘true’ parameter \((f_0, \alpha_0, \beta_0)\). An exactly similar definition holds if we want posterior consistency only for the parametric part \((\alpha, \beta)\) at \((f_0, \alpha_0, \beta_0)\). It will turn out that the sufficient condition for the latter is weaker than that for the posterior consistency of \((f, \alpha, \beta)\).

The idea of posterior consistency is due to Freedman (1963), though, in a sense, it goes back to Bayes, Laplace and Von Mises. The relevance of posterior consistency to Bayesians is explained well in Diaconis and Freedman (1986a). Diaconis and Freedman (1986a; 1986b) also provide an example of inconsistency, in a relatively simple setting, for location models with symmetric error distributions. A similar example of inconsistency for the location problem with error distribution having median 0 is given by Doss (1985a; 1985b). The problem of interest then is to identify all or at least a large class of parameter values where consistency obtains. In this paper, although we approach the problem in some generality, it is geared to handling two classes of popular priors on densities – the Polya tree priors and Dirichlet mixtures of a normal kernel.

Recent reviews focusing on general issues of consistency are Ghosal et al. (1999a), Ghosh (1998) and Wasserman (1998). In Ghosal et al. (1999a; 1999b) and Ghosh (1998) it is argued that a theorem of Schwartz (1965) is the right tool for studying consistency in semi-parametric problems. The same is true of the present paper. However, since the observations are independent but not identically distributed, major changes are needed. We begin with a variant of Schwartz’s theorem for independent, non-identically distributed variables. This is discussed in Section 2, while in Sections 3 and 4, we discuss how one can verify the two conditions of this theorem. The lack of i.i.d. structure for the \( Y_i \) necessitates assumptions on the \( x_i \) to ensure that the exponentially consistent tests required by Schwartz’s theorem exist in the present context. Also certain conditions on \( f_0 \) are required to verify a condition analogous to Schwartz’s on the support of the prior. In Section 4, we relate the properties of the prior on \( \mathcal{F} \) to that on the regression parameters and obtain a theorem on consistency. We show in the next section that Polya tree priors of the sort considered in Ghosal et al. (1999b) fulfill the requirements. We then turn to Dirichlet mixtures of normal kernel priors. The posterior consistency of these in the context of density estimation was studied in Ghosal et al. (1999c). In Section 6 we explore similar problems in the regression setting. In Section 7 we discuss a similar problem of generalized linear models with binary responses and an unknown link function. This may be viewed as a nonparametric generalization of the logistic regression model. A Dirichlet process prior is put on the link distribution function and the consistency of the posterior is briefly discussed. Section 8 indicates the modifications necessary to handle the case of a stochastic regressor.

Although we prove consistency when the covariates are one-dimensional, the arguments easily generalize to more than one dimension. For that we will only need to modify Proposition 3.1 by looking at quadrants under the appropriate modification of Assumption A.
Nonparametric and semi-parametric Bayesian methods are now being used more and more. In view of the example of Diaconis and Freedman (1986a; 1986b), it seems appropriate to see if some validation can be provided through posterior consistency. It will be also interesting to study the rate of convergence of the posterior distribution, as is done in Ghosal et al. (2000). In particular, it is of substantial interest to see whether the posterior distribution for the parametric part converges at the classical $\sqrt{n}$ rate. We have not attempted to answer this question here, and will return to it elsewhere.

2. Consistency of posterior

Fix $f_0$, $\alpha_0$, $\beta_0$. For a density $f$, let

$$f_{\alpha, \beta, i} = f_{\alpha + \beta x_i}(y) = f(y - (\alpha + \beta x_i))$$

and put $f_{0i} = f_{0, \alpha_0 + \beta_0 x_i}$. For any two densities $f$ and $g$, let

$$K(f, g) = \int f \log \frac{f}{g}, \quad V(f, g) = \int f \left( \log^+ \frac{f}{g} \right)^2,$$

where $\log^+ x = \max(\log x, 0)$, and put

$$K(f, \alpha, \beta) = K(f_{0i}, f_{\alpha, \beta, i}), \quad V(f, \alpha, \beta) = V(f_{0i}, f_{\alpha, \beta, i}).$$

As mentioned in the Introduction, the main tool we use is a variant of Schwartz's (1965) theorem. The following theorem is an adaptation to the case when the $Y_i$ are independent but not identically distributed. Here the $x_i$ are non-random. We start with the definition of exponentially consistent tests.

**Definition 2.1.** Let $W \subset F \times \mathbb{R} \times \mathbb{R}$. A sequence of test functions $\Phi_n(Y_1, \ldots, Y_n)$ is said to be exponentially consistent for testing

$$H_0 : (f, \alpha, \beta) = (f_0, \alpha_0, \beta_0) \quad \text{against} \quad H_1 : (f, \alpha, \beta) \in W$$

if there exist constants $C_1$, $C_2$, $C > 0$ such that

(a) $\mathbb{E}_{\Pi(f_0, \alpha_0, \beta_0)} \Phi_n \leq C_1 e^{-nC}$

(b) $\inf_{(f, \alpha, \beta) \in W} \mathbb{E}_{\Pi(f, \alpha, \beta)} (\Phi_n) \geq 1 - C_2 e^{-nC}$

**Theorem 2.1.** Suppose $\Pi$ is a prior on $F$ and $\mu$ is a prior for $(\alpha, \beta)$. Let $W \subset F \times \mathbb{R} \times \mathbb{R}$. If

(i) there is an exponentially consistent sequence of tests for

$$H_0 : (f, \alpha, \beta) = (f_0, \alpha_0, \beta_0) \quad \text{against} \quad H_1 : (f, \alpha, \beta) \in W,$$

(ii) and for all $\delta > 0$,

$$\Pi \left\{ (f, \alpha, \beta) : K_i(f, \alpha, \beta) < \delta \text{ for all } i, \sum_{i=1}^{\infty} \frac{V_i(f, \alpha, \beta)}{i^2} < \infty \right\} > 0,$$
then with \((\prod_{i=1}^{n} P_{f_i})\)-probability 1, the posterior probability

\[
\Pi(W|Y_1, \ldots, Y_n) = \frac{\int_{\mathcal{W}} \prod_{i=1}^{n} (f_{a_i \beta_i}(Y_i)/f_{0_i}(Y_i)) d\Pi(f, \alpha, \beta)}{\int_{\mathcal{F} \times \mathbb{R}^n} \prod_{i=1}^{n} (f_{a_i \beta_i}(Y_i)/f_{0_i}(Y_i)) d\Pi(f, \alpha, \beta)} \to 0. \tag{2.5}
\]

Note that \(V_i(f, \alpha, \beta)\) bounded above in \(i\) is sufficient to ensure the summability of \(\sum_{i=1}^{\infty} V_i(f, \alpha, \beta)/i^2\).

The proof of the theorem is similar to that of Schwartz (1965). If we write (2.5) as

\[
\Pi(W|Y_1, \ldots, Y_n) = \frac{I_{2n}(Y_1, \ldots, Y_n)}{I_{1n}(Y_1, \ldots, Y_n)}, \tag{2.6}
\]

the proof involves showing, as is done in Schwartz (1965), that condition (i) implies that there exists a \(d > 0\) such that \(e^{-d} I_{1n}(Y_1, \ldots, Y_n) \to 0\) a.s., and that condition (ii) implies that for all \(d > 0\), \(e^{-d} I_{2n}(Y_1, \ldots, Y_n) \to \infty\) a.s. A sketch of the details is given in the appendix.

It should be noted here that the theorem could have been stated in much more generality, for any semi-parametric problem. Consistency of the posterior holds as long as there is an exponentially consistent test for testing the point null against the complement of the required neighbourhood and (ii) holds. In Section 7 we apply this idea to a binary response regression model with an unknown link.

3. Exponentially consistent tests

Our goal is to establish consistency of the posterior distribution for \((f, \alpha, \beta)\) or for \((\alpha, \beta)\) at \((f_0, \alpha_0, \beta_0)\), and thus the set \(W\) of interest to us is of the type \(W = U\), where \(U\) is a neighbourhood of \((f_0, \alpha_0, \beta_0)\). In this section we write \(W\) of this type as a finite union of \(W_i\) and show that condition (i) of Theorem 2.1 holds for each of these \(W_i\)s. Note that condition (i) does not involve the prior.

We begin with a couple of lemmas.

**Lemma 3.1.** For \(i = 1, 2, \ldots\) let \(g_{0_i}\) and \(g_i\) be densities on \(\mathbb{R}\). If for each \(i\) there exists a function \(\Phi_i, 0 \leq \Phi_i \leq 1\), such that

\[
E_{g_0}(\Phi_i) = \alpha_i \leq \gamma_i = E_{g}(\Phi_i), \tag{3.1}
\]

and if

\[
\liminf_{n \to \infty} \frac{1}{n} \sum_{i=1}^{n} (\gamma_i - \alpha_i) > 0, \tag{3.2}
\]

then there exist a constant \(C\), sets \(B_n \subset \mathbb{R}^n, n = 1, 2, \ldots\), and \(n_0\) – all depending only on \((\gamma_i, \alpha_i)\) – such that, for \(n > n_0\),
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\[
\left[ \prod_{i=1}^{n} P_{g_{0}} \right] (B_{n}) < e^{-nC} \\
\left[ \prod_{i=1}^{n} P_{g_{i}} \right] (B_{n}) > 1 - e^{-nC}.
\]

**Proof.** Set \( B_{n} = \{ \sum_{i=1}^{n} \Phi_{i} > \sum_{i=1}^{n} (\gamma_{i} + \alpha_{i})/2 \} \). Then by Hoeffding’s inequality (Dudley 1999, p. 14)

\[
\left[ \prod_{i=1}^{n} P_{\gamma_{0}} \right] (B_{n}) \leq \left[ \prod_{i=1}^{n} P_{\gamma_{0}} \right] \left\{ \sum_{i=1}^{n} (\Phi_{i} - E_{\gamma_{0}}(\Phi_{i})) > \sum_{i=1}^{n} (\gamma_{i} - \alpha_{i}) \right\} \\
\leq \exp \left[ -\frac{1}{2n} \left( \sum_{i=1}^{n} (\gamma_{i} - \alpha_{i}) \right)^{2} \right]. \tag{3.3}
\]

On the other hand, applying Hoeffding’s inequality to \( 0 \leq 1 - \Phi_{i} \leq 1 \),

\[
\left[ \prod_{i=1}^{n} P_{\gamma_{i}} \right] (B_{n}^{c}) \leq \left[ \prod_{i=1}^{n} P_{\gamma_{i}} \right] \left\{ \sum_{i=1}^{n} ((1 - \Phi_{i}) - (1 - E_{\gamma_{i}}(\Phi))) \leq \sum_{i=1}^{n} (\gamma_{i} - \alpha_{i})/2 \right\} \\
\leq \exp \left[ -\frac{1}{2n} \left( \sum_{i=1}^{n} (\gamma_{i} - \alpha_{i}) \right)^{2} \right].
\]

Taking \( C = \frac{1}{4} \liminf_{n \to \infty} ((1/n)\sum_{i=1}^{n} (\gamma_{i} - \alpha_{i}))^{2} \), the result follows. \( \square \)

For a density \( g \) and \( \theta \in \mathbb{R} \), let \( g_{\theta} \) stand for the density \( g_{\theta}(y) = g(y - \theta) \).

**Lemma 3.2** Let \( g_{0} \) be a continuous symmetric density on \( \mathbb{R} \), with \( g_{0}(0) > 0 \). Let \( \eta \) be such that \( \inf_{|y| < \eta} g_{\theta}(y) = C > 0 \).

(i) For any \( \Delta > 0 \), there exists a set \( B_{\Delta} \) such that

\[
P_{g_{0}} (B_{\Delta}) \leq \frac{1}{2} - C(\Delta \wedge \eta)
\]

and, for any symmetric density \( g_{i} \),

\[
P_{g_{i}} (B_{\Delta}) \geq \frac{1}{2}, \text{ for all } \theta \geq \Delta.
\]

(ii) For any \( \Delta < 0 \), there exists a set \( B_{\Delta}^{c} \) such that

\[
P_{g_{0}} (B_{\Delta}^{c}) \leq \frac{1}{2} - C(\Delta \wedge \eta)
\]

and, for any symmetric density \( g_{i} \),

\[
P_{g_{i}} (B_{\Delta}^{c}) \geq \frac{1}{2}, \text{ for all } \theta \leq \Delta.
\]

**Proof.** (i) Take \( B_{\Delta} = (\Delta, \infty) \). Since \( \theta \geq \Delta \) and \( g_{\theta} \) is symmetric around \( \theta \), \( P_{g_{\theta}} (B_{\Delta}) \geq \frac{1}{2} \).
On the other hand,
\[ P_{g_0}(B_\Delta) = \frac{1}{2} - \int_0^\Delta g_0(y)dy \leq \frac{1}{2} - \int_0^{\Delta \wedge \eta} g_0(y)dy \leq 1 - C(\Delta \wedge \eta). \quad (3.5) \]
Similarly, \( \hat{B}_\Delta = (-\infty, \Delta) \) would satisfy (ii).

**Remark 3.1.** By considering \( I_{B_\Delta}(y - \theta_0) \), it is easy to see that Lemma 3.2 holds if we replace \( g_0 \) by \( g_{0, \theta_0} \) and require \( \theta - \theta_0 > \Delta \) or \( \theta - \theta_0 < \Delta \).

We return to the regression model.

**Assumption A.** There exists \( \varepsilon_0 > 0 \) such that the covariate values \( x_i \) satisfy
\[ \liminf_{n \to \infty} \frac{1}{n} \sum_{i=1}^n I\{x_i < -\varepsilon_0\} > 0, \quad \liminf_{n \to \infty} \frac{1}{n} \sum_{i=1}^n I\{x_i > \varepsilon_0\} > 0. \]

**Remark 3.2.** Assumption A forces the covariate \( x \) to take both positive and negative values, that is, values on both sides of 0. However, the point 0 is not special. If the condition is satisfied around any point, then by a simple location shift we can bring that to the present case.

**Proposition 3.1.** If Assumption A holds, \( f_0 \) is continuous at 0 and \( f_0(0) > 0 \), then there is an exponentially consistent sequence of tests for
\[ H_0 : (f, \alpha, \beta) = (f_0, \alpha_0, \beta_0) \quad \text{against} \quad H_1 : (f, \alpha, \beta) \in \mathcal{W} \]
in each of the following cases:
(i) \( \mathcal{W} = \{(f, \alpha, \beta) : \alpha > \alpha_0, \beta - \beta_0 > \Delta\} \),
(ii) \( \mathcal{W} = \{(f, \alpha, \beta) : \alpha < \alpha_0, \beta - \beta_0 > \Delta\} \),
(iii) \( \mathcal{W} = \{(f, \alpha, \beta) : \alpha > \alpha_0, \beta - \beta_0 < -\Delta\} \),
(iv) \( \mathcal{W} = \{(f, \alpha, \beta) : \alpha < \alpha_0, \beta - \beta_0 < -\Delta\} \).

**Proof.** (i) Let \( K_n = \{i : 1 \leq i \leq n, x_i > \varepsilon_0\} \) and \( \#K_n \) stand for the cardinality of \( K_n \). We will construct a test using only those \( Y_i \), for which the corresponding \( i \) is in \( K_n \).

If \( i \in K_n \), then \( (\alpha + \beta x_i) - (\alpha_0 + \beta_0 x_i) > \Delta x_i \), and by Lemma 3.2, for each \( i \in K_n \), there exists a set \( A_i \) such that
\[ \alpha_i := P_{f_0}(A_i) < \frac{1}{2} - C(\eta \wedge \Delta x_i) \]
and
\[ \gamma_i := \inf_{(f, \alpha, \beta) \in \mathcal{W}} P_{f_0, \alpha, \beta}(A_i) \geq \frac{1}{2}, \]
where ‘:=’ denotes equality by definition.
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If \( i \leq n \) and \( i \notin K_n \) set \( A_i = \mathbb{R} \), so that \( \alpha_i = \gamma_i = 1 \). Thus

\[
\liminf_{\eta \to \infty} \left( n^{-1} \sum_{i=1}^{n} (\gamma_i - \alpha_i) \right) \geq \liminf_{\eta \to \infty} \left( n^{-1} \sum_{i \in K_n} C(\eta \wedge \Delta x_i) \right) \\
\geq C(\eta \wedge \Delta \varepsilon_0) \liminf_{\eta \to \infty} \#K_n / n > 0. \tag{3.6}
\]

With \( \Phi_i = I_{A_i} \), the result follows from Lemma 3.1.

(ii) In this case we construct tests using \( Y_i \) such that \( i \in M_n := \{1 \leq i \leq n : x_i < -\varepsilon_0\} \). If \( i \in M_n \), then

\[
(\alpha + \beta x_i) - (\alpha_0 + \beta_0 x_i) < \Delta x_i < -\Delta \varepsilon_0.
\]

Now using (ii) of Lemma 3.2, we obtain sets \( \hat{B} \), and then obtain exponentially consistent tests using Lemma 3.1 as in part (i).

The other two cases follow similarly. \( \square \)

The union of the \( \mathcal{W} \)s in Proposition 3.1 is the set \( \{(f, \alpha, \beta) : |\beta - \beta_0| > \Delta\} \). The next proposition takes care of \( \{(f, \alpha, \beta) : |\alpha - \alpha_0| > \Delta\} \). The proof is along the same lines and is omitted.

Proposition 3.2. Under the assumptions of Proposition 3.1, there exists an exponentially consistent sequence of tests for testing

\[
H_0 : (f, \alpha, \beta) = (f_0, \alpha_0, \beta_0) \quad \text{against} \quad H_1 : (f, \alpha, \beta) \in \mathcal{W}
\]

when \( \mathcal{W} \) is

(i) \( \{(f, \alpha, \beta) : \alpha - \alpha_0 > \Delta, \beta > \beta_0\} \),
(ii) \( \{(f, \alpha, \beta) : \alpha - \alpha_0 > \Delta, \beta < \beta_0\} \),
(iii) \( \{(f, \alpha, \beta) : \alpha - \alpha_0 < -\Delta, \beta > \beta_0\} \),
(iv) \( \{(f, \alpha, \beta) : \alpha - \alpha_0 < -\Delta, \beta < \beta_0\} \).

Remark 3.3. If random \( f \)s are not symmetrized around zero, \( \alpha \) is not identifiable. So the posterior distribution for \( \alpha \) will not be consistent. Consistency for \( \beta \) will hold under appropriate conditions. To prove the existence of uniformly consistent tests for \( \beta \), we pair \( Y_i \)s and consider the difference \( Y_i - Y_j \), which has a density that is symmetric around \( \beta(x_i - x_j) \).

We can now handle the problem in essentially the same way as in Proposition 3.1 to construct strictly unbiased tests. A result analogous to Proposition 3.2 then follows immediately. The verification of the other conditions in Sections 4, 5 and 6 is along exactly similar lines.

The next proposition considers neighbourhoods of \( f_0 \) to obtain posterior consistency for the true density rather than only the parametric part. We need an additional assumption.

Assumption B. For some \( L, |x_i| < L \) for all \( i \).
In practice, the range of interest of the regressor is often a bounded interval, since the linearity of the regression function can only be expected on a range of values. Therefore, the assumption may not be very restrictive from a practical point of view.

**Proposition 3.3.** Suppose that Assumption $B$ holds. Let $\mathcal{U}$ be a weak neighbourhood of $f_0$ and let $\mathcal{W} = \mathcal{U}^c \times \{ (\alpha, \beta) : |\alpha - \alpha_0| < \Delta, \ |\beta - \beta_0| < \Delta \}$. Then there exists an exponentially consistent sequence of tests for testing

$$H_0 : (f, \alpha, \beta) = (f_0, \alpha_0, \beta_0) \quad \text{against} \quad H_1 : (f, \alpha, \beta) \in \mathcal{W}.$$ 

**Proof.** Without loss of generality take

$$\mathcal{U} = \left\{ f : \Phi(y)f(y) - \Phi(y)f_0(y) < \epsilon \right\}, \quad \text{where} \quad 0 \leq \Phi \leq 1 \quad \text{and} \quad \Phi \text{ is uniformly continuous.}$$

Since $\Phi$ is uniformly continuous, given $\epsilon > 0$, there exists $\delta > 0$ such that $|y_1 - y_2| < \delta$ implies $|\Phi(y_1) - \Phi(y_2)| < \epsilon/2$.

Let $\Delta$ be such that

$$|(\alpha - \alpha_0) + (\beta - \beta_0)x_i| < \delta$$

for $\alpha, \beta \in \mathcal{W}$. Set $\hat{\Phi}_i(y) = \Phi(y - (\alpha_0 + \beta_0x_i))$. Then

$$E_{f_0, \Phi_i} = E_{f_0, \Phi}, \quad E_{f_{a_0}, \Phi_i} = E_{f_{a_0}, (\beta - \beta_0)x_i, \Phi}. \quad 3.8$$

Noting that

$$\int \Phi(y - (\alpha - \alpha_0) + (\beta - \beta_0)x_i)f_{(\alpha - \alpha_0) + (\beta - \beta_0)x_i}(y)dy = \int \Phi(y)f(y)dy,$$

we have, by the uniform continuity of $\Phi$,

$$\int \Phi(y)f_{(\alpha, \beta)}(y)dy \geq \int \Phi(y)f(y)dy - \int |\Phi(y) - \Phi(y - (\alpha - \alpha_0) + (\beta - \beta_0)x_i)|$$

$$\times f_{(\alpha - \alpha_0) + (\beta - \beta_0)x_i}(y)dy$$

$$\geq \int \Phi(y)f(y)dy - \frac{\epsilon}{2}$$

$$\geq E_{f_0, \Phi} + \frac{\epsilon}{2}$$

for any $f \in \mathcal{U}^c$. An application of Lemma 3.1 completes the proof. \hfill \Box

4. Prior positivity of neighbourhoods

In this section we develop sufficient conditions to verify condition (ii) of Theorem 2.1. A similar problem in the location-parameter context was studied in Ghosal et al. (1999b).
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There, the authors managed with Kullback-Leibler continuity of \( f_0 \) at \( \theta_0 \) – the true value of the location parameter – and the requirement that \( \Pi\{K(f_0^{*}, f) < \delta\} > 0 \) for all \( \theta \) in a neighbourhood of \( \theta_0 \) and for \( f_0^{*} \) close to but different from \( f_0 \). However, this approach does not carry over to the regression context since, even though the true parameter remains \((\alpha_0, \beta_0)\), for each \( i \) we encounter parameters \( \theta_i = \alpha_0 + \beta_0 x_i \). Here we take a different approach. Since we have no assumptions on the structure of the random condition \( f \), the assumption on \( f_0 \) is somewhat strong. This condition is weakened in Section 6, where we consider the Dirichlet mixture of normals. In that case, the random \( f \) is better behaved.

**Lemma 4.1.** Suppose \( f_0 \in \mathcal{F} \) satisfies the condition that there exist \( \eta > 0 \), \( C_\eta \) and a symmetric density \( g_\eta \) such that, for \( |\eta'| < \eta \),

\[
f_0(y - \eta') < C_\eta g_\eta(y), \quad \text{for all } y.
\]

Then,

(a) for any \( f \in \mathcal{F} \) and \( |\theta| < \eta \),

\[
K(f_0, f_\theta) \approx (C_\eta + 1)\log C_\eta + C_\eta \left[ K(g_\eta, f) + \sqrt{K(g_\eta, f)} \right];
\]

(b) if, in addition, \( V(g_\eta, f) < \infty \), then

\[
\sup_{|\theta| < \eta} V(f_0, f_\theta) < \infty.
\]

**Proof.** Part (a) is an immediate consequence of Lemma 5.1 of Ghosal et al. (1999a) and the fact that \( K(f_0, f, \theta) = K(f_0, f_\theta) \), which follows from the symmetry of \( f_0 \) and \( f \).

For (b), note that

\[
\int f_0 \left[ \log + \frac{f_0}{f_\theta} \right]^2 = \int f_0 \theta \left[ \log + \frac{f_0}{f} \right]^2 \leq C_\eta \int g_\eta \left[ \log + \frac{C_\eta g_\eta}{f} \right]^2,
\]

which is finite under the assumed condition. \( \square \)

We write the assumption of last lemma as follows:

**Assumption C.** For \( \eta > 0 \), sufficiently small, there exist \( g_\eta \in \mathcal{F} \) and constant \( C_\eta > 0 \) such that for \( |\eta'| < \eta \),

\[
f_0(y - \eta') < C_\eta g_\eta(y) \quad \text{for all } y
\]

and

\[
C_\eta \to 1 \quad \text{as } \eta \to 0.
\]

**Proposition 4.1.** Suppose that Assumptions B and C hold. Let \( \Pi \) be a prior for \( f \), and \( \mu \) be a prior for \( (\alpha, \beta) \). If \((\alpha_0, \beta_0)\) is in the support of \( \mu \) and if, for all \( \eta \) sufficiently small and for all \( \delta > 0 \),

\[
\Pi(\theta), \quad \text{for all } \theta \in \mathcal{B}(\delta),
\]

\[
\text{with } \Pi(\theta) \leq C_\delta \Pi(\bar{\theta})\delta ,
\]

where \( C_\delta \) is a constant. Then \( \bar{\Pi} \) is a consistent Bayes posterior.
\[ \Pi \{ K(g_\eta, f) < \delta, V(g_\eta, f) < \infty \} > 0, \]  
\[ (\Pi \times \mu) \{(f, \alpha, \beta) : K_i(f, \alpha, \beta) < \delta, V_i(f, \alpha, \beta) < M \text{ for all } i \} > 0. \] (4.3)

then, for all \( \delta > 0 \) and some \( M > 0 \),

\[ (\Pi \times \mu) \{(f, \alpha, \beta) : K_i(f, \alpha, \beta) < \delta, V_i(f, \alpha, \beta) < M \text{ for all } i \} > 0. \] (4.4)

**Proof.** Choose \( \eta, \delta_0 \) such that (4.3) holds with \( \delta = \delta_0 \) and

\[ (C_\eta + 1)\log C_\eta + C_\eta[\delta_0 + \sqrt{\delta_0}] < \delta. \]

Let

\[ V = \left\{ (\alpha, \beta) : |\alpha - \alpha_0| < \frac{\eta}{2}, \ |\beta - \beta_0| < \frac{\eta}{2L} \right\}. \]

Note that

\[ K_i(f_0, \alpha, \beta) = K(f_0, f_0 + (\alpha - \alpha_0) + (\beta - \beta_0)x_i) \]

and

\[ V_i(f_0, \alpha, \beta) = V(f_0, f_0 + (\alpha - \alpha_0) + (\beta - \beta_0)x_i), \]

and \((\alpha, \beta) \in V \) implies that \(|(\alpha - \alpha_0) + (\beta - \beta_0)x_i| < \eta \) for all \( x_i \). An application of Lemma 4.1 immediately gives the result. \( \square \)

**Theorem 4.1.** Suppose that:

(i) the covariates \( x_1, x_2, \ldots \) satisfy Assumptions A and B;

(ii) \( f_0 \) is continuous, \( f_0(0) > 0 \) and \( f_0 \) satisfies Assumption C;

(iii) for all sufficiently small \( \eta \) and for all \( \delta > 0 \),

\[ \Pi \{ K(g_\eta, f) < \delta, V(g_\eta, f) < \infty \} > 0, \]

where \( g_\eta \) is as in Assumption C.

Then for any weak neighbourhood \( \mathcal{U} \) of \( f_0 \),

\[ \Pi \{(f, \alpha, \beta) : f \in \mathcal{U}, |\alpha - \alpha_0| < \delta, |\beta - \beta_0| < \delta |Y_1, Y_2, \ldots, Y_n \} \rightarrow 1 \] (4.5)

a.s. \( \prod_{i=1}^{\infty} P_{f_0} \). In other words, the posterior distribution is weakly consistent at \((f_0, \alpha_0, \beta_0)\).

**Proof.** Note that

\[ \{(f, \alpha, \beta) : f \in \mathcal{U}, |\alpha - \alpha_0| < \delta, |\beta - \beta_0| < \delta \}^c \]

(4.6)

is the union of sets considered in Propositions 3.1, 3.2 and 3.3. The required exponentially consistent test therefore exists. Proposition 4.1 shows that condition (ii) of Theorem 2.1 holds and hence (4.5) follows. \( \square \)

**Remark 4.1.** Assumption (ii) of Theorem 4.1 is satisfied if \( f_0 \) is Cauchy or normal. If \( f_0 \) is Cauchy, then \( g_\eta = f_0 \) satisfies Assumption C. If \( f_0 \) is normal, then Assumption C holds with
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\[ g_{\eta} = f_{0,\eta^*} = \frac{1}{2} \{ f_0(y - \eta^*) + f_0(-y - \eta^*) \}, \]  

(4.7)

where \( \eta^* \to 0 \) as \( \eta \to 0 \) but \( \eta^*/\eta \to \infty \).

**Remark 4.2.** Assumption B is used in two places: Propositions 3.3 and 4.1. For specific \( f_0 \) one may be able to obtain the conclusion of Proposition 4.1 without Assumption B. In such cases one would be able to obtain consistency at \((a_0, b_0)\) without having to establish consistency at \((f_0, a_0, b_0)\).

**Remark 4.3.** In order to strengthen Theorem 4.1 to variation neighbourhoods \( U \) of \( f_0 \), one also needs to find, for all \( \epsilon > 0 \), a sequence of subsets \( \mathcal{F}_n \subset \mathcal{F} \), with \( \Pi(\mathcal{F}_n) \) exponentially small such that, for some \( \delta < \epsilon/2 \) and \( \beta < \epsilon^2/8 \), the \( L_1 \)-metric entropy \( J(\delta, \mathcal{F}_n) < n\beta \). See Theorem 2 of Ghosal et al. (1999c) for details.

## 5. Polya tree priors

In this section we show that Polya tree priors, with a suitable choice of parameters, satisfy condition (iii) of Theorem 4.1 and hence the posterior distribution is weakly consistent. To obtain a prior on symmetric densities, we consider Polya tree priors on densities \( f \) on the positive half-line and then consider the symmetrization \( f^*(y) = \frac{1}{2} f(|y|) \). Since \( K(f, g) = K(f^*, g^*) \) and \( V(f, g) = V(f^*, g^*) \), this symmetrization presents no problems.

We briefly recall Polya tree priors; for more details the reader should refer to Lavine (1992; 1994) and Mauldin et al. (1992).

Let \( E = \{0, 1\} \), \( E^m = \{0, 1\}^m \) and \( E^* = \bigcup_{m=1}^{\infty} E^m \). For each \( m \), \( \{B_\xi : \xi \in E^m\} \) is a partition of \( \mathbb{R}^+ \), and for each \( \xi \), \( \{B_0, B_{11}\} \) is a partition of \( B_\xi \). Furthermore, \( \{B_\xi : \xi \in E^*\} \) generates the Borel \( \sigma \)-algebra.

A random probability measure \( P \) on \( \mathbb{R}^+ \) is said to be distributed as a Polya tree with parameters \( \Pi, A \), where \( \Pi \) is a sequence of partitions as described in the previous paragraph, and \( A = \{\alpha_\xi : \xi \in E^*\} \) is a collection of non-negative numbers, if there exists a collection \( \{Y_\xi : \xi \in E^*\} \) of mutually independent random variables such that:

(i) each \( Y_\xi \) has a beta distribution with parameters \( \alpha_0 \) and \( \alpha_{11} \);

(ii) the random measure \( P \) is given by

\[ P(B_{\xi_1 \cdots \xi_m}) = \left[ \prod_{j=1}^{m} Y_{\xi_1 \cdots \xi_{j-1} 0} \right] \left[ \prod_{j=1}^{m} (1 - Y_{\xi_1 \cdots \xi_{j-1}}) \right]. \]

We restrict ourselves to partitions \( \Pi = \{\Pi_m : m = 0, 1, \ldots\} \) that are determined by a strictly positive, continuous density \( \alpha \) on \( \mathbb{R}^+ \) in the following sense: the sets in \( \Pi_m \) are intervals of the form

\[ \left\{ y : \frac{k-1}{2^m} < \int_{-\infty}^{y} \alpha(t) dt \leq \frac{k}{2^m} \right\}. \]
Theorem 5.1. Let $\tilde{\Pi}$ be a Polya tree prior on densities on $\mathbb{R}^+$ with $a_\xi = r_m$ for all $\xi \in E^m$. If $\sum_{m=1}^{\infty} r_m^{-1/2} < \infty$, then for any density $g$ such that $K(g, \alpha) < \infty$ and $E_g(\log g)^2 < \infty$, we have, for all $\delta > 0$,

$$\lim_{M \to \infty} \tilde{\Pi}\{f : K(g, f) < \delta, V(g, f) < M\} > 0. \quad (5.1)$$

Proof. We will show that

$$\lim_{M \to \infty} \tilde{\Pi}\{f : V(g, f) < M\} \to 1. \quad (5.2)$$

This, together with Theorem 3.1 of Ghosal et al. (1999b), where it is shown that $\tilde{\Pi}\{f : K(f, g) < \delta\} > 0$ when $\sum_{m=1}^{\infty} r_m^{-1/2} < \infty$, would then prove the theorem.

Since

$$V(g, f) \leq E_g(\log f)^2 + E_g(\log g)^2 + 2\sqrt{E_g(\log f)^2 E_g(\log g)^2}, \quad (5.3)$$

it is enough to show that, as $M \to \infty$,

$$\tilde{\Pi}\{E_g(\log f)^2 > M\} \to 0. \quad (5.4)$$

If $y$ has the binary expansion $\xi = \epsilon_1 \epsilon_2 \cdots$, then, for almost all $y$,

$$f(y) = \lim_{m \to \infty} \left[ \prod_{j=1, \xi_j=0}^m 2Y_{\epsilon_1 \cdots \epsilon_{j-1}} \left( \prod_{j=1, \xi_j=1}^m 2(1 - Y_{\epsilon_1 \cdots \epsilon_{j-1}}) \right) \right], \quad (5.5)$$

so that

$$E_g(\log f)^2 = E_g \left[ \sum_{j=1, \xi_j=0}^\infty \log(2Y_{\epsilon_1 \cdots \epsilon_{j-1}}) + \sum_{j=1, \xi_j=1}^\infty \log(2(1 - Y_{\epsilon_1 \cdots \epsilon_{j-1}})) \right]^2, \quad (5.6)$$

where $E_g$ now stands for the expectation over $\xi$ when $y$ has density $g$.

Now letting $E$ stand for the expectation with respect to $\tilde{\Pi}$, we have, by Chebyshev's inequality,

$$\tilde{\Pi}[E_g(\log f)^2 > M] \leq M^{-1} E E_{g_g} \left[ \sum_{j=1, \xi_j=0}^\infty \log(2Y_{\epsilon_1 \cdots \epsilon_{j-1}}) + \sum_{j=1, \xi_j=1}^\infty \log(2(1 - Y_{\epsilon_1 \cdots \epsilon_{j-1}})) \right]^2. \quad (5.7)$$

Interchanging the order of expectations and exploiting independence, the right-hand side of (5.7) can further be bounded by
\[ 2M^{-1}Eg \left[ \sum_{j=1}^{\infty} E(\log(2Y_{i_j}))^2 + \left( \sum_{j=1,\xi_j=0}^{\infty} E(\log(2Y_{i_j})) \right)^2 \right] + \sum_{j=1,\xi_j=1}^{\infty} E(\log(2(1 - Y_{i_j}))^2 + \left( \sum_{j=1,\xi_j=1}^{\infty} E(\log(2(1 - Y_{i_j})) \right)^2 \right] . \]

Since \( Y_{i_j} \) and \( 1 - Y_{i_j} \) have the same distribution, the last expression is equal to

\[ 2M^{-1}Eg \left[ \sum_{j=1}^{\infty} E(\log(2Y_{i_j}))^2 + \left( \sum_{j=1,\xi_j=1}^{\infty} E(\log(2Y_{i_j})) \right)^2 \right] . \]

Note that the terms inside \( E_g \) do not involve the particular sequence \( \xi \). Letting \( \varphi(k) = E|\log(2U_k)| \) and \( \psi(k) = E(\log(2U_k)^2) \), where \( U_k \sim \text{Beta}(k, k) \), the last expression can be written as

\[ 2M^{-1} \left[ \sum_{m=1}^{\infty} \varphi(r_m) + \left( \sum_{m=1}^{\infty} \varphi(r_m) \right)^2 \right] . \]

It is shown in the Appendix that \( \varphi(k) \) and \( \psi(k) \) are respectively \( O(k^{-1}) \) and \( O(k^{-1/2}) \). Since \( \sum_{m=1}^{\infty} r_m^{-1/2} < \infty \), both infinite series are summable and hence the last expression goes to 0 as \( M \to \infty \). \( \square \)

Although Polya trees give rise to naturally interpretable priors on densities and lead to consistent posterior, sample paths of Polya trees are very rough, having discontinuities everywhere. Such a drawback can easily be overcome by considering a mixture of Polya trees. Posterior consistency continues to hold in this case since, by Fubini’s theorem, prior positivity holds under mild uniformity conditions.

**6. Dirichlet mixture of normals**

In this section, we look at random densities that arise as mixtures of normal densities. Let \( \phi_h \) denote the normal density with mean 0 and standard deviation \( h \). For any probability \( P \) on \( \mathbb{R} \), \( f_{h, \mu} \) will stand for the density

\[ f_{h, \mu}(y) = \int \phi_h(y - t) dP(t). \quad (6.1) \]

Our model consists of a prior \( \mu \) for \( h \) and a prior \( \Pi \) for \( P \). Consistency issues related to these priors, in the context of density estimation, are explained in Ghosal et al. (1999c). Here we look at similar issues when the error density \( f \) in the regression model is endowed with these priors.
To ensure that the prior sits on symmetric densities, we let $P$ be a random probability on $\mathbb{R}^+$ and set
\[ f_{\theta, \rho}(y) = \frac{1}{2} \int \phi_h(y - t) dP(t) + \frac{1}{2} \int \phi_h(y + t) dP(t). \quad (6.2) \]
We will denote by $\tilde{\Pi}$ both the prior for $P$ and the prior for $f_{\theta, \rho}$.

The following lemma shows that the random $f$ generated by the prior under consideration is more regular than those generated by Polya tree priors, and hence the conditions on $f_0$ are more transparent than those in Section 5 or those in Ghosal et al. (1999b).

**Lemma 6.1.** Let $f_0$ be a density such that
\[ \int y^4 f_0(y) dy < \infty \quad \text{and} \quad \int f_0(y) |\log f_0(y)|^2 \, dy < \infty. \quad (6.3) \]
If $f(y) = \int \phi_h(y - t) dP(t)$ and $\int t^2 \, dP(t) < \infty$, then
(i) $\lim_{\theta \to 0} K(f_0, f_\theta) = K(f_0, f)$;
(ii) $\lim_{\theta \to 0} V(f_0, f_\theta) = V(f_0, f)$.

**Proof.** Clearly $f(y)$ is positive and continuous, and
\[ |\log f_0(y)| \leq |\log \sqrt{2\pi h}| + \left| \log \int e^{-(y - \theta - t)^2/(2h^2)} \, dP(t) \right|. \quad (6.4) \]
Since $\log \int e^{-(y - \theta - t)^2/(2h^2)} \, dP(t) < 0$, by Jensen’s inequality applied to $-\log x$, the last expression is bounded by
\[ |\log \sqrt{2\pi h}| + \int \frac{(y - \theta - t)^2}{h^2} \, dP(t). \]
The dominated convergence theorem now applies. \hfill \square

We now return to the regression model.

**Theorem 6.1.** Suppose $\tilde{\Pi}$ is a normal mixture prior for $f$. If
(i) Assumptions A and B hold,
(ii) $\tilde{\Pi}\{ f : K(f_0, f) < \delta, V(f_0, f) < \infty \} > 0$ for all $\delta > 0$,
(iii) $E_{f_0}(y^2) < \infty$, $E_{f_0}(\log f_0)^2 < \infty$,
(iv) $\int t^2 \, dP(t) \tilde{\Pi}(P) < \infty$,
then the posterior distribution $\tilde{\Pi}(\cdot | Y_1, \ldots, Y_n)$ is weakly consistent for $(f, \alpha, \beta)$ at $(f_0, \alpha_0, \beta_0)$ provided $(\alpha_0, \beta_0)$ is in the support of the prior for $(\alpha, \beta)$.

**Proof.** By (iv), $\{ P : \int t^2 \, dP(t) < \infty \}$ has $\tilde{\Pi}$-probability 1. So we may assume that
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\[ \Pi(\mathcal{U}) > 0, \]  

(6.5)

where \( \mathcal{U} = \{ f : f = f_P, \text{ (ii) holds, } \int r^2 dP(t) < \infty \}. \)

For every \( f \in \mathcal{U}, \) using Lemma 6.1, choose \( \delta_f \) such that, for \( \theta < \delta_f, \)

\[ K(f_0, f) < \delta, \quad V(f_0, f) < \delta. \]  

(6.6)

Now choose \( \varepsilon_f \) such that \( |\alpha - \alpha_0 + (\beta - \beta_0)x_i| < \delta_f \) whenever \( |\alpha - \alpha_0| < \varepsilon_f, \)

\( |\beta - \beta_0| < \varepsilon_f/L. \)

Clearly if \( f \in \mathcal{U} \) and \( |\alpha - \alpha_0| < \varepsilon_f \) and \( |\beta - \beta_0| < \varepsilon_f/L, \) we have

\[ K_i(f, \alpha, \beta) < 2\delta, \quad V_i(f, \alpha, \beta) < V(f_0, f) + \delta. \]  

(6.7)

Since

\[ \Pi\{(f, \alpha, \beta) : f \in \mathcal{U}, |\alpha - \alpha_0| < \varepsilon_f, |\beta - \beta_0| < \varepsilon_f/L \} > 0, \]  

(6.8)

we have

\[ \Pi\left\{ (f, \alpha, \beta) : K(f_0, \alpha, \beta) < \delta \text{ for all } i, \sum_{i=1}^{\infty} \frac{V_i(f, \alpha, \beta)}{r^2} < \infty \right\} > 0. \]  

(6.9)

An application of Theorem 2.1 completes the proof. \( \square \)

It is shown in Ghosal et al. (1999c) that if \( f_0 \) has compact support or if \( f_0 = f_P \) with \( P \) having compact support, then \( \Pi\{ f : K(f_0, f) < \delta \} > 0 \) for all \( \delta > 0. \) The argument given there also shows that in these cases condition (ii) of Theorem 6.1 holds when \( \Pi \) is Dirichlet with base measure \( \gamma. \) Ghosal et al. (1999c) also describe \( f_0 \)s whose tail behaviour is related to that of \( \gamma \) such that \( \Pi\{ f : K(f_0, f) < \delta \} > 0. \) In the case when the prior is Dirichlet, the double integral in (iv) is finite if and only if \( \int r^2 d\gamma(t) < \infty. \) While normal \( f_0 \) is covered by these results the case of Cauchy \( f_0 \) cannot be resolved by the methods in that paper. However, Dirichlet location and scale mixtures of normal should be able to handle Cauchy \( f_0 \) which is a normal scale mixture. This scale mixing measure does not have a compact support so the results of Ghosal et al. (1999c) still do not apply.

7. Binary response regression with unknown link

A distinguishing feature of the regression problem considered in this paper is the change in the parameter value with \( i. \) A similar situation arises in other models such as the regression of the Bernoulli parameter with an unknown link function. This may be viewed as a nonparametric version of logistic regression problems and the methods developed here can be used to handle these problems too. We give an indication of how this can be done without going into much detail.

Consider \( k \) levels of a drug on a suitable scale, say \( x_1, \ldots, x_k, \) with probability of a response (which may be death or some other specified event) \( p_i, i = 1, \ldots, k. \) To study the effects at different levels, \( n \) subjects are treated with the drug. The \( i \)th level of the drug is given to \( n_i \) subjects and the number of responses \( r_i \) noted. We thus obtain \( k \) independent
binomial variables with parameters \( n_i \) and \( p_i \), where \( n = n_1 + \ldots + n_k \). The object usually is to find \( x \) such that \( p = 0.5 \). Often, \( p_i \) is modelled as
\[
p_i = F(\alpha + \beta x_i) = H(x_i),
\]
say, where \( F \) is a response distribution and \( \alpha \) and \( \beta \) are parameters. Here \( p_i \) may be estimated by \( r_i/n_i \), but if the \( n_i \) are small, the estimates will have large variances. The model provides a way of combining all the data. In logistic regression, \( F \) is taken as logistic function. Other link functions such as the normal distribution function are also used. The choice of the functional form of the link function is somewhat arbitrary, and this may substantially influence inference, particularly at the two ends where the data is sparse. In recent years, there has been a lot of interest in link functions with unknown functional form. In nonparametric problems of this kind, one puts a prior on \( F \) or \( H \). Such an approach was taken by Albert and Chib (1993), Chen and Dey (1998), Basu and Mukhopadhyay (1998, 2000) among others. If one puts a prior on \( F \), one has to put conditions on \( F \) such as specifying the values of two quantiles to make \((F, \alpha, \beta)\) identifiable. In this case, one can develop sufficient conditions for posterior consistency at \((F_0, a_0, \beta_0)\) using our variant of Schwartz’s theorem. However, in practice, one usually puts a Dirichlet process or some other prior on \( F \) and, independently of this, a prior on \((\alpha, \beta)\). Due to the discreteness of Dirichlet selections, many authors actually prefer the use of other priors such as Dirichlet scale mixtures of normals; see Basu and Mukhopadhyay (1998, 2000) and the references therein. Because of the lack of identifiability, the posterior for \((\alpha, \beta)\) is not consistent. This will show up in simulations as flat, rather than peaked, posteriors. On the other hand, a Dirichlet process prior and a prior on \((\alpha, \beta)\) provide a prior on \( H \) and one can ask for posterior consistency of \( H^{-1}(\frac{1}{2}) \) at, say, \( H_0^{-1}(\frac{1}{2}) \). This problem can be solved by Theorem 2.1 as follows.

Without loss of generality, one may take \( n_i = 1 \) for all \( i \), and hence \( k = n \). To verify condition (ii) of Theorem 2.1, consider
\[
Z_i = \log \left( \frac{H_0(x_i) \Gamma(r) (1 - H_0(x_i))^{1 - r_i}}{H(x_i) \Gamma(r) (1 - H(x_i))^{1 - r_i}} \right),
\]
where \( r_i \) is 1 or 0 with probability \( H(x_i) \) and \( 1 - H(x_i) \) respectively, and the true \( H \) is denoted by \( H_0 \). Then
\[
E_{H_0}(Z_i) = H_0(x_i) \log \left( \frac{H_0(x_i)}{H(x_i)} \right) + (1 - H_0(x_i)) \log \left( \frac{1 - H_0(x_i)}{1 - H(x_i)} \right)
\]
and
\[
E_{H_0}(Z_i^2) \leq 2 H_0(x_i) \left( \log \left( \frac{H_0(x_i)}{H(x_i)} \right) \right)^2 + 2(1 - H_0(x_i)) \log \left( \frac{1 - H_0(x_i)}{1 - H(x_i)} \right)^2.
\]
Assume that the \( x_i \) lie in a bounded interval containing \( H_0^{-1}(\frac{1}{2}) \), and the support of \( H_0 \) contains a bigger interval. Since the range of the \( x_i \) is bounded, the sequence of formal empirical distributions \( n^{-1} \sum_{i=1}^n \delta_{x_i} \) of \( x_1, \ldots, x_n \) is relatively compact. Assume that all subsequential limits converge to distributions which give positive measure to all non-degenerate intervals, provided the intervals are contained in a certain interval containing \( H_0^{-1}(\frac{1}{2}) \). Therefore, a positive fraction of the \( x_i \) lie in an interval of positive length if the
interval is close to the the point $H_0^{-1}(\frac{1}{2})$. Also assume that $H_0$ is continuous and the support of the prior for $H$ contains $H_0$. For instance, if the prior is Dirichlet with a base measure whose support contains the support of $H_0$, then the above condition is satisfied. Mixture priors often have large supports too. For instance, the Dirichlet scale mixture of normal prior used by Basu and Mukhopadhyay (1998; 2000) will have this property if the true link function is also a scale mixture of normal cumulative distribution functions.

If $H_r$ is a sequence converging weakly to $H_0$, then, by Polya’s theorem, the convergence is uniform. Note that the functions $p\log(p/q) + (1-p)\log((1-p)/(1-q))$ and $p(\log(p/q))^2 + (1-p)(\log((1-p)/(1-q)))^2$ in $q$ converge to 0 as $q \to p$, uniformly in $p$ lying in a compact subinterval of $(0, 1)$. Thus given $\delta > 0$, we can choose a weak neighbourhood $U$ of $H_0$ such that if $H \in U$, then $E_{H_0}(Z) < \delta$ and the $E_{H_0}(Z^2)$ are bounded. By the assumption on the support of the prior, condition (ii) of Theorem 2.1 holds.

For the existence of exponentially consistent tests in condition (i) of Theorem 2.1, consider, without loss of generality, testing $H^{-1}(\frac{1}{2}) = H_0^{-1}(\frac{1}{2})$ against $H^{-1}(\frac{1}{2}) > H_0^{-1}(\frac{1}{2}) + \epsilon$ for small $\epsilon > 0$. Let

$$K_n = \{i : H_0^{-1}(1/2) + \epsilon/2 \leq x_i \leq H_0^{-1}(1/2) + \epsilon\}.$$  

Since

$$E_{H}(r_i) = H(x_i) \leq H(H_0^{-1}(1/2) + \epsilon) \leq \frac{1}{2} \quad \text{(7.5)}$$

and

$$E_{H_0}(r_i) = H_0(x_i) \geq H_0(H_0^{-1}(1/2) + \epsilon/2) > \frac{1}{2} \quad \text{(7.6)}$$

the test

$$\frac{1}{\#K_n} \sum_{i \in K_n} r_i < \frac{1}{2} + \eta \quad \text{(7.7)}$$

for $\eta = (H_0(H_0^{-1}(\frac{1}{2}) + \epsilon/2) - \frac{1}{2})/2$ is exponentially consistent by Hoeffding’s inequality and the fact that $\#K_n/n$ converge to positive limits along subsequences. Therefore Theorem 2.1 applies and the posterior distribution of $H^{-1}(\frac{1}{2})$ is consistent at $H_0^{-1}(\frac{1}{2})$.

8. Stochastic regressor

In this section, we consider the case where the independent variable $X$ is stochastic. We assume that the $X$ observations $X_1, X_2, \ldots$ are i.i.d. with a probability density function $g(x)$ and are independent of the errors $\epsilon_1, \epsilon_2, \ldots$. We argue below that all the results on consistency hold under appropriate conditions.

Let $G(x) = \int_{-\infty}^{x} g(u) du$, denote the cumulative distribution function of $X$. We shall assume that the following condition holds:
Assumption D. The independent variable \( X \) is compactly supported and \( 0 < G(0^-) \leq G(0) < 1 \).

Under these assumptions, results will follow from a conditionality argument and the corresponding results for the non-stochastic case, conditioned on a sequence \( x_1, x_2, \ldots \) such that Assumptions A and B hold. Note that if \( g \) satisfies Assumption D, then \( P_g^n \)-almost all sequences \( x_1, x_2, \ldots \) satisfy Assumptions A and B.

Observe that for a stochastic \( x_1, x_2, \ldots \) with a known density \( g \), the expressions for the posterior probabilities are still given by (2.6), as the factor \( \Pi_i^n g(x_i) \) is cancelled in the numerator and the denominator. As \( g \) has no role, we need no knowledge of it provided that it is a priori independent of the other parameters. We need not specify a prior distribution for \( g \), but assume that the sampled \( g_s \) are compactly supported and satisfy Assumption D. If \( f_0 \) and the prior \( \Pi \) satisfy conditions (ii) and (iii) of Theorem 4.1, it then follows that, for any neighbourhood \( \mathcal{U} \) of \( f_0 \),

\[
\tilde{\Pi}\{(f, \alpha, \beta) : f \in \mathcal{U}, |\alpha - \alpha_0| < \delta, |\beta - \beta_0| < \delta, (X_1, Y_1), \ldots, (X_n, Y_n)\} \to 1
\]

a.s. \( P_{f_0, g_0, \alpha_0, \beta_0} \), where \( P_{f_0, g_0, \alpha_0, \beta_0} \) is the distribution of \((X, Y)\), \( X \) has density \( g_0 \), \( Y = \alpha_0 + \beta_0 X + \epsilon \), \( X \) is independent of \( \epsilon \) and \( \epsilon \) has density \( f_0 \).

Thus if \( X \) is stochastic and Assumption D replaces Assumptions A and B in Theorems 5.1 and 6.1, posterior consistency holds.

Appendix

Lemma A.1. Let \( f \) and \( g \) be probability densities. Let \( \|f - g\|_1 = \int |f - g| \) stand for the \( L_1 \)-distance and let \( K^+(f, g) = \int f \log_+ (f/g) \) and \( K^-(f, g) = \int f \log_-(f/g) \), where \( \log_+ x = \max(-\log x, 0) \). Then

\[
K^-(f, g) \leq \frac{1}{2} \|f - g\| \leq \sqrt{K(f, g)/2}
\]

and

\[
K^+(f, g) \leq \frac{1}{2} \|f - g\| + K(f, g) \leq K(f, g) + \sqrt{K(f, g)/2}.
\]

Proof. Using \( \log x \approx x - 1 \), as in Hannan (1960), we obtain \( K^-(f, g) = \int g \log g - f \log f \leq \int g \log (g/f) = \|f - g\|_1/2 \). The second part of (A.1) follows from Kemperman’s inequality (Kemperman 1969, Theorem 6.1). Relation (A.2) follows because \( K^+ = K - K^- \). \(\square\)

Remark A.1. Using the inequality \( \log x \approx 2(\sqrt{x} - 1) \), the following alternative bound can be derived:

\[
K^-(f, g) \leq \|f - g_1\| - H^2(f, g),
\]

where \( H^2(f, g) = \int (f^{1/2} - g^{1/2})^2 \) is the squared Hellinger distance.
Proof of Theorem 2.1. The proof proceeds along the same lines as in Theorem 6.1 of Schwartz (1965). Here is a sketch of the argument.

Write the posterior probability in (2.5) as

$$
\frac{I_{1n}}{I_{2n}} = \Phi_n + \frac{(1 - \Phi_n)I_{1n}}{I_{2n}},
$$

(A.4)

where $I_{1n}$ and $I_{2n}$ are as in (2.6).

Clearly, in view of the Borel–Cantelli lemma, condition (a) in Definition 2.1 implies that $\Phi_n \to 0$ a.s. $\prod_{i=1}^{\infty} P_{f_0}$.

Note that

$$
E_{\Pi_n^{*}, f_0}((1 - \Phi_n)I_{1n}) = \int_{\mathcal{V}} (1 - \Phi_n) \prod_{i=1}^{n} \frac{f_{\alpha, \delta, i}(y_i)}{f_0(y_i)} d\Pi(f, \alpha, \beta) \prod_{i=1}^{n} f_0(y_i) dy_i
$$

$$
= \sup_{\mathcal{W}^n} E_{\Pi_n^{*}, f_0}((1 - \Phi_n)I_{1n})
$$

$$
\leq C_2 e^{-nC}.
$$

Therefore,

$$
e^{nC/2} (1 - \Phi_n)I_{1n} \to 0
$$

(A.5)
a.s. $\prod_{i=1}^{\infty} P_{f_0}$.

Let $\mathcal{V}$ be the set displayed in condition (ii) of the theorem. Note that with $W_i = \log_+(f_0/f_{\alpha, \delta, i}(y_i))$, we have $\text{var}(W_i) \leq V_i(f, \alpha, \beta)$, and hence $\sum_{i=1}^{\infty} \text{var}(W_i)/i^2 < \infty$ for all $f \in \mathcal{V}$. Applying Kolmogorov’s strong law of large numbers for independent non-identical variables to the sequence $W_i - E(W_i)$, it follows from Lemma A.1 that, for each $f \in \mathcal{V}$,

$$
\liminf_{n \to \infty} \left( \frac{1}{n} \sum_{i=1}^{n} \log \frac{f_{\alpha, \delta, i}(Y_i)}{f_0(Y_i)} \right) \geq \limsup_{n \to \infty} \left( \frac{1}{n} \sum_{i=1}^{n} \log_+ \frac{f_0(Y_i)}{f_{\alpha, \delta, i}(Y_i)} \right)
$$

$$
= \limsup_{n \to \infty} \frac{1}{n} \sum_{i=1}^{n} K_i^+(f, \alpha, \beta)
$$

$$
\geq \limsup_{n \to \infty} \left( \frac{1}{n} \sum_{i=1}^{n} K_i(f, \alpha, \beta) + \frac{1}{n} \sum_{i=1}^{n} \sqrt{K_i(f, \alpha, \beta)/2} \right)
$$

$$
\geq \limsup_{n \to \infty} \left( \frac{1}{n} \sum_{i=1}^{n} K_i(f, \alpha, \beta) + \frac{1}{n} \sum_{i=1}^{n} K_i(f, \alpha, \beta)/2 \right).
$$

(A.6)

a.s. $\prod_{i=1}^{\infty} P_{f_0}$. Since, for $f \in \mathcal{V}$, $n^{-1} \sum_{i=1}^{n} K_i(f, \alpha, \beta) < \delta$, we have, for each $f \in \mathcal{V}$,
\[
\liminf_{n \to \infty} \frac{1}{n} \sum_{i=1}^{n} \log \frac{f_{\alpha, \beta, i}(Y_i)}{f_0(Y_i)} \geq -(\delta + \sqrt{\delta/2}). \tag{A.7}
\]

Choosing \( \delta \) so that \( \delta + \sqrt{\delta/2} \leq C/8 \) and noting that

\[
I_{2n} = \left[ \prod_{i=1}^{n} \frac{f_{\alpha, \beta, i}(Y_i)}{f_0(Y_i)} \right] d\Pi(f, \alpha, \beta),
\]

it follows from Fatou’s lemma that

\[
e^{-C/4} I_{2n} \to \infty \tag{A.8}
\]

a.s. \( \prod_{i=1}^{\infty} P_{f_0} \). Combining this with (A.4) and (A.5), we obtain (2.5). Indeed, the convergence is exponentially fast. This proves the theorem. \( \square \)

**Remark A.2.** Condition (ii) of the theorem can be weakened. It can be seen from the proof that if the prior assigns positive probability to the set

\[
\left\{ \frac{1}{n} \sum_{i=1}^{n} K_i(f, \alpha, \beta) < \delta \text{ for all } n, \sum_{i=1}^{\infty} V_i(f, \alpha, \beta) + \frac{K_i^2(f, \alpha, \beta)}{C^2} < \infty \right\},
\]

then the posterior is also consistent.

We state Lemma 5.1 from Ghosal et al. (1999b) for easy reference.

**Lemma A.2.** If \( f_0 \leq C f_1 \), where \( f_0 \) and \( f_1 \) are densities, then, for any \( f \),

\[
K(f_0, f) \leq (C + 1) \log C + C[K(f_1, f) + \sqrt{K(f_1, f) \cdot}]. \tag{A.9}
\]

**Lemma A.3.** If \( U_k \sim \text{Beta}(k, k) \), then

\[
E(\log(2U_k))^2 = O(k^{-1}). \tag{A.10}
\]

**Proof.** Let

\[
I_k = E(\log(2U_k))^2 = \frac{1}{B(k, k)} \int_{0}^{1} (\log(2u))^2 u^{k-1}(1-u)^{k-1} \, du, \tag{A.11}
\]

where \( B(k, k) = \int_{0}^{1} u^{k-1}(1-u)^{k-1} \, du \) is the beta function.

By a change of variable,

\[
I_k = \frac{1}{B(k, k)} \int_{0}^{1} (\log(2(1-u)))^2 (1-u)^{k-1}(1-u)^{k-1} \, du. \tag{A.12}
\]
Note that $\log(2u)$ and $\log(2(1-u))$ are always of opposite sign for $0 < u < 1$. Therefore,

$$2I_k = \frac{1}{B(k, k)} \int_0^1 \{ (\log(2u))^2 + (\log(2(1-u)))^2 \} u^{k-1}(1-u)^{k-1} \, du$$

$$= \frac{1}{B(k, k)} \int_0^1 [\log(2u) - \log(2(1-u))]^2 u^{k-1}(1-u)^{k-1} \, du$$

$$+ \frac{1}{B(k, k)} \int_0^1 2(\log(2u))(\log(2(1-u))) u^{k-1}(1-u)^{k-1} \, du$$

$$\leq \frac{1}{B(k, k)} \int_0^1 \log \frac{u}{1-u}^2 u^{k-1}(1-u)^{k-1} \, du. \quad (A.13)$$

Using the Laplace approximation, it has been shown in the proof of Lemma A.1 of Ghosal et al. (1999b) that the right-hand side of \((A.13)\) is $O(k^{-1})$. This completes the proof. □

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References


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