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RATES OF CONVERGENCE FOR THE POSTERIOR DISTRIBUTIONS OF MIXTURES OF BETAS AND ADAPTIVE NONPARAMETRIC ESTIMATION OF THE DENSITY

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In this paper we investigate the asymptotic properties of non-parametric bayesian mixtures of Betas for estimating a smooth density on $[0, 1]$. We consider a parameterisation of Betas distributions in terms of mean and scale parameters and construct a mixture of these Betas in the mean parameter, while either fixing the scaling parameter (as a function on the number of observations) or putting a proper prior on this scaling parameter. We prove that such Bayesian nonparametric models have good frequentist asymptotic properties. We determine the posterior rate of concentration around the true density and prove that it is the minimax rate of concentration when the true density belongs to a Hölder class with regularity β , for all positive β , by choosing correctly the scaling parameter of the Betas densities, in terms of the number of observations and β . We improve on these results by considering a prior on the scaling parameter and thus obtain an adaptive estimating procedure of the density. We also believe that the approximating results obtained on these mixtures of Betas densities can be of interest in a frequentist framework.

1. Introduction. In this paper we study the asymptotic behaviour of posterior components. There is a vast literature on mixture models because of their rich structure which allows for different uses, for instance they are well known to be adapted to the modelling of heterogeneous populations as is used for instance in cluster analysis; for a good review on mixture models see [11] or [12] for various aspects of Bayesian mixture models. They are also useful in nonparametric density estimation, in particular they can be considered to capture small variations around a specific parametric model, as typically occurs in robust estimation or in a goodness of fit test of a Parametric family or of a specific distribution, see for instance [13, 14]. The approach considered here is to density estimation, but it has applications in many other aspects of mixture models such as clustering, classification, goodness

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of fit testing, etc... since in all these cases understanding the behaviour of the posterior distribution is crucial. Nonparametric prior distributions based on mixture models are often considered in practice and Dirichlet mixture priors are particularly popular. Dirichlet mixtures have been introduced by [2, 10] and have been widely used ever since but their asymptotic properties are not well known apart from a few cases such as Gaussian mixtures, triangular mixtures and Bernstein polynomials. [4, 5] and [16] study the concentration rate of the posterior distribution under Dirichlet mixtures of Gaussian priors and [3] has considered the Bernstein polynomial's case, i.e. the mixture of Beta distribution with fixed parameters. [14] have considered mixtures of triangular distributions, with a prior on the mixing distribution which is not necessarily a Dirichlet process. In all those cases the authors have mainly considered the concentration rate of the posterior around the true density when the latter have some known regularity conditions or when it is a continuous mixture.

Posterior distributions associated with Bernstein polynomials are known to be suboptimal in terms of minimax rates of convergence when the true density is Hölder. [9] have proposed a modification of Bernstein polynomials leading to the minimax rate of convergence in the classes of Hölder densities with regularity β , when $\beta \leq 1$. In this paper we consider another class of mixtures of Betas models, which is richer and therefore allows for better asymptotic results.

Betas densities are often represented as

$$(1.1) \quad g(x|a, b) = \frac{x^{a-1}(1-x)^{b-1}}{B(a, b)}, \quad B(a, b) = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}.$$

Here we consider a different parameterisation of the Beta distribution writing $a = \alpha/(1 - \epsilon)$ and $b = \alpha/\epsilon$ so that $\epsilon \in (0, 1)$ is the mean of the Beta distribution and $\alpha > 0$ is a scale parameter. To approximate smooth densities on $[0, 1]$ we consider a location mixture of Betas densities in the form:

$$(1.2) \quad g_{\alpha, P}(x) = \sum_{j=1}^k p_j g_{\alpha, \epsilon_j}(x), \quad g_{\alpha, \epsilon_j}(x) = g(x|\alpha/(1 - \epsilon_j), \alpha/\epsilon_j),$$

where the mixing density is given by

$$(1.3) \quad P(\epsilon) = \sum_{j=1}^k p_j \delta_{\epsilon_j}(\epsilon).$$

The parameters of this mixture model are then $k \in \mathbb{N}^*$ and for each k ,

$(\alpha, p_1, \dots, p_k, \epsilon_1, \dots, \epsilon_k)$. The prior probability on the set of densities can therefore be expressed as

$$d\pi(f) = p(k)\pi_k(\epsilon_1, \dots, \epsilon_k, p_1, \dots, p_k|\alpha)d\pi_{k,\alpha}(\alpha), \quad \text{if } f = g_{\alpha,P}$$

or $d\pi(f) = d\pi(P|\alpha)d\pi_2(\alpha)$ in the case of a Dirichlet mixture.

Determining the concentration rate of the posterior distribution around the true density corresponds to determining a sequence τ_n converging to 0 such that if

$$(1.4) \quad B_{\tau_n} = \{f \in \mathcal{F}, d(f, f_0) < \tau_n\},$$

for some distance or pseudo-distance $d(\cdot, \cdot)$ on the set of densities and if $X^n = (X_1, \dots, X_n)$, where the X_i 's are independent and identically distributed from a distribution having a density f_0 with respect to Lebesgue measure, then

$$(1.5) \quad P^\pi [B_{\tau_n} | X^n] \rightarrow 1, \text{ in probability.}$$

The difficulty with mixture models comes from the fact that it is often quite hard to obtain precise approximating properties for these models. [7, 15] give general descriptions of the Kullback-Leibler support of priors based on mixture models. These results are key results to obtain the consistency of the posterior distribution, but cannot be applied to obtain rates of concentration. In these papers they use the Kernel structure of mixture models and specific attention is given to location-scale kernels. Mixtures of Betas are not location-scale kernels. However, when α gets large $g_{\alpha,\epsilon}$ concentrates around ϵ so that locally these Betas densities behave like Gaussian densities. This behaviour is described in Section 3. Using these ideas we study the approximation of a density f by a continuous mixture in the form

$$(1.6) \quad g_{\alpha,f}(x) = \int_0^1 f(\epsilon)g_{\alpha,\epsilon}(x)d\epsilon,$$

where f is a probability density on $(0, 1)$. When α becomes large $g_{\alpha,\epsilon}(x)$ behaves locally like a location scale kernel so that $g_{\alpha,f}$ becomes close to f . Similarly to the Gaussian case this approximation is *good* only if f has a regularity less than 2. However by shifting slightly the mixing density it is possible to improve the approximation so that continuous mixtures of Betas are *good* approximations of any smooth density, see Section 3.1. As in the case of Gaussian mixtures, see [4], we approximate the continuous mixture by a discrete mixture. [4, 5, 16] study the approximation of continuous mixtures of Gaussian random variables by discrete mixtures and the approximation of smooth densities by a continuous mixture respectively. The latter derive from

these a posterior rate of concentration of the posterior distribution around the true density when the true density is twice continuously differentiable. In particular they obtain the minimax rate $n^{-2/5}$, up to a $\log n$ term under the L_1 risk.

In this paper we show that the minimax rate can be obtained (up to a $\log n$ term) for any $\beta > 0$ by choosing carefully the rate at which α increases with n , i.e. choosing for α a dirac mass on some sequence α_n . Rather than such a deterministic choice of α it is usual to consider a diffuse prior on α ; so that the data would choose the correct α . Hence in Section 2.2 we consider a prior on α and we prove that the resulting procedure is adaptive to the smoothness of the true density. This result has much theoretical and practical interest and the latter type of prior is much more satisfactory than the previous one. Both results show the good behaviour of Betas mixtures.

1.1. Notations. Throughout the paper X_1, \dots, X_n are independent and identically distributed as P_0 having density f_0 with respect to Lebesgue measure. We assume that $X_i \in [0, 1]$. We consider the following three distances (or pseudo-distances) on the set of densities on $[0, 1]$: the L_1 distance: $\|f - g\|_1 = \int_0^1 |f(x) - g(x)| dx$, the Kullback-Leibler divergence: $\text{KL}(f, g) = \int_0^1 f(x) \log(f(x)/g(x)) dx$, for any densities f, g on $[0, 1]$ and for any $k > 1$ $V_k(f, g) = \int_0^1 f(x) |\log(f(x)/g(x))|^k dx$. We also denote by $\|g\|_\infty$ the supremum norm of the function g .

$\mathcal{H}(L, \beta)$ denotes the class of Hölder functions with regularity parameter β : let r be the largest integer smaller than β and denote by $f^{(r)}$ its r -th derivative.

$$\mathcal{H}(L, \beta) = \{f : [0, 1] \rightarrow \mathbb{R}; |f^{(r)}(x) - f^{(r)}(y)| \leq L|x - y|^{\beta-r}\}.$$

We denote by \mathcal{S}_k the simplex: $\mathcal{S}_k = \{y \in [0, 1]^k; \sum_{i=1}^k y_i = 1\}$.

We denote by $P^\pi[\cdot|X^n]$ the posterior distribution given the observations $X^n = (X_1, \dots, X_n)$ and $E^\pi[\cdot|X^n]$ the expectation with respect to this posterior distribution. Similarly E_0^n and P_0^n represent the expectation and the probability with respect to the true density $f_0^{\otimes n}$ and E_f^n and P_f^n the expectation and probability with respect to the distribution $f^{\otimes n}$.

1.2. Assumptions. Throughout the paper we assume that the true density f_0 is positive on the open interval $(0, 1)$ and satisfies:

Assumption A₀ If $f_0 \in \mathcal{H}(\beta, L)$ there exist integers $0 \leq k_0, k_1 < \beta$ such that

$$f^{(k_0)}(0) > 0, \quad f^{(k_1)}(1) < 0;$$

k_0 and k_1 denote the first integers such that the corresponding derivatives calculated at 0 and 1 respectively are non zero.

This assumption is quite mild and ensures that $f_0(x)$ does not go too quickly to 0 when x goes to 0 or 1 so that we can control the Kullback-Leibler divergence between f_0 and mixtures of Betas.

1.3. Organization of the paper. The paper is organized as follows. In Section 2, we give the two main theorems on the concentration rates of the posterior distributions under specific types of priors corresponding to different mixtures of Betas. In Section 2.1 we determine a posterior rate of concentration when the scale parameter of the Betas is fixed (depending on n) this leads to a non adaptive procedure since α depends on the smoothness of the density. In Section 2.2 we present the adaptive approach obtained by considering some prior on α . In Section 3 we present some results describing the approximating properties of mixtures of Betas. We believe that these results are interesting outside the Bayesian framework since they could also be applied to obtain convergence rates for maximum likelihood estimators. This section is divided into two parts. First we describe how continuous mixtures can approach smooth densities (Section 3.1) then we approach continuous mixtures by discrete mixtures (Section 3.2). Finally Section 4 is dedicated to the proofs of Theorems 2.1 and 2.2 given in Section 2.

2. Posterior concentration rates. In this section we give the two main results on the concentration rates of the posterior distribution around the true density. We first consider the case of a deterministic sequence α_n of scales, increasing to infinity at a given rate. Using this result we then consider a more realistic setup where a prior is put on the scale α leading to an adaptive estimating procedure.

We consider a concentration rate in terms of the L_1 distance, however the results can be applied to the hellinger distance as well.

2.1. Deterministic α . In this section $\alpha = \alpha_n$ is deterministic. We consider the following types of prior on the mixing distribution P :

Type I prior

$$d\pi(f) = p(k)d\pi_{k,1}(\epsilon_1, \dots, \epsilon_k)d\pi_{k,2}(p_1, \dots, p_k), \quad \text{if } f = g_{\alpha_n, P}.$$

For all $k > 0$ $\pi_{k,1}$ and $\pi_{k,2}$ are positive on \mathcal{S}_k and $[0, 1]^k$ respectively. We assume that the $\pi_{k,1}$'s are bounded from below by a term in the form c_1^k and that the ϵ_j 's $j = 1, \dots, k$ are independent and identically distributed with a distribution whose density with respect to Lebesgue measure is bounded

from below by a function in the form : $c_2[\epsilon(1 - \epsilon)]^T$ for some $T \geq 0$. The distribution on k has the following bounds on its tail behaviour: there exist $a_1, a_2 > 0$ such that for all K large enough

$$e^{-a_1 K \log(K)} \leq p[k = K] \leq e^{-a_2 K}$$

Remark: Even when the conditional distribution of the weights (p_1, \dots, p_k) given k is a Dirichlet distribution the overall distribution on f is not in general a Dirichlet process, hence we introduce another class of prior solely based on the Dirichlet process.

Dirichlet I prior. The mixing distribution P follows a Dirichlet process $\mathcal{D}(\nu)$ associated with a finite measure whose density with respect to Lebesgue measure is denoted ν and is positive on the open interval $(0, 1)$. Assume also that ν is bounded and satisfies

$$\nu(\xi) \geq \nu_0 \xi^{T_1} (1 - \xi)^{T_1}$$

We then have the following theorem.

THEOREM 2.1. *Let $f_0 \in \mathcal{H}(L, \beta)$ satisfying Assumption \mathbf{A}_0 , with $\beta > 0$. Let $\alpha_n = \alpha_0 n^{2/(2\beta+1)} (\log n)^{-3/(2\beta+1)}$, for some positive α_0 . Assume that the prior on P is either a Dirichlet I prior or a Type I prior. Then if $\tau_n = n^{-\beta/(2\beta+1)} (\log n)^{5\beta/(4\beta+2)}$,*

$$P^\pi[B_{\tau_n}^c | X^n] \rightarrow 0$$

in probability.

The proof of Theorem 2.1 is given in Section 4.

This result implies that for any $\beta > 0$ the optimal rate, in the minimax sense, is obtained. Hence the above mixtures of Betas form a richer class of models than the Bernstein polynomials or the mixtures of triangular distributions who lead at best to the minimax rates for $\beta \leq 2$. It is to be noted however that Bernstein polynomials and mixture of triangular densities have other interesting properties and are in particular easy to simulate.

Theorem 2.1 shades light on the impact of α_n as a scale parameter. It can thus be compared to the scale parameter σ_n which appear in Dirichlet mixtures of Gaussian distributions. In Section 3 we see that the key factor leading to such a rate is the possibility of approximating any $f_0 \in \mathcal{H}(L, \beta)$ by a continuous mixture in the form $g_{\alpha_n, f}$ with an error of order $\alpha_n^{-\beta}$, for some density f close to f_0 but not necessarily equal to f_0 . An interesting feature leading to this approximating property is that $g_{\alpha_n, \epsilon}$ acts locally as a

Gaussian Kernel around ϵ . However the interest in the Bayesian procedure compared to a classical frequentist kernel nonparametric method comes from the fact that we do not necessarily need to approach f_0 by g_{α_n, f_0} , which would have constrained us to $\beta \leq 2$. Indeed if necessary we can consider a slight modification f of f_0 such that $g_{\alpha_n, f}$ approximates f_0 with an error of order $\alpha_n^{-\beta}$ for all β .

The choice of the scale parameter is however a problem in practice, as is the choice of the bandwidth in kernel nonparametric estimation. From a Bayesian perspective considering a deterministic α depending on n is quite awkward. In the following section we put a prior probability on α .

2.2. Fully Bayesian procedure. In this section we consider a joint prior probability on the mixing distribution P defined by (1.3) and on α . since this increases the complexity of the support of the prior probability we need to be slightly more restrictive on the prior on P than in Section 2.1.

Type II prior

$$d\pi(f) = p(k)d\pi_{k,1}(\epsilon_1, \dots, \epsilon_k)d\pi_{k,2}(p_1, \dots, p_k)\pi_\alpha(\alpha), \quad \text{if } f = g_{\alpha, P}.$$

For all $k > 0$, $\pi_{k,1}$ and $\pi_{k,2}$ are positive on \mathcal{S}_k and $(0, 1)^k$ respectively. We consider the same conditions on the priors $\pi_{k,1}$ and $\pi_{k,2}$, i.e. we assume that the $\pi_{k,1}$'s are bounded from below by a term in the form c_1^k and that the ϵ_j 's $j = 1, \dots, k$ are independent and identically distributed with a distribution whose density with respect to Lebesgue measure is denoted $\pi_\epsilon(\epsilon)$. However we add the extra condition that there exist $a_1, a_2 > 0$ and $T \geq 1$ such that

$$a_1 \epsilon^T (1 - \epsilon)^T \geq \pi_\epsilon(\epsilon) \geq a_2 \epsilon^T (1 - \epsilon)^T, \quad \forall \epsilon \in (0, 1).$$

We also consider the following conditions on the prior π_α . For all $b_1 > 0$, there exists $c_1, c_2, c_3, A, d > 0$ such that for all u large enough,

$$\begin{aligned} \pi_a(c_1 u < \alpha < c_2 u) &\geq C e^{-b_1 u^{1/2}} \\ \pi_a(c_3 u < \alpha) &\leq C e^{-b_1 u^{1/2}} \\ \pi_a(\alpha < e^{-uA}) &\leq C e^{-b_1 u} \end{aligned}$$

We also assume that π_a is bounded.

Note that if $\sqrt{\alpha}$ follows a Gamma distribution with parameters (a, b) with $a \geq 1$ then the above condition is satisfied.

The distribution on k has the same tail behaviour as a Poisson distribution: there exist $a_1, a_2 > 0$ such that for all K large enough

$$e^{-a_1 K \log(K)} \leq p[k = K] \leq e^{-a_2 K \log(K)}.$$

We then have the following theorem:

THEOREM 2.2. *Consider a type II prior, then the posterior distribution satisfies: for all $f_0 \in \mathcal{H}(\beta, L)$ satisfying assumption \mathbf{A}_0 ,*

$$P^\pi [B_{\tau_n}^c | X^n] = o_P(1), \quad \text{with} \quad \tau_n = \tau_0 n^{-\beta/(2\beta+1)} (\log n)^{5\beta/(4\beta+2)}$$

The prior does not depend on β so that the procedure is adaptive. An interesting feature of the mixture of Betas is that it is not more difficult to obtain an adaptive rate than a non adaptive rate. Moreover the conditions on the prior leading to the adaptive procedure are more natural from a Bayesian perspective than those expressed in the Type I priors since we do not have to consider a deterministic sequence α_n depending on n . Note that we do not obtain an adaptive procedure for Dirichlet mixtures of Betas, which does not mean that such a procedure cannot be obtained. The difficulty for the adaptive results is to control the entropy of the support of the prior. In the case of Dirichlet mixtures (non adaptive) we used the approximation of a general mixture by a finite mixture when α is large, which is not possible when we put a prior on α (since α needs not be large).

In both cases the posterior probability of $B_{\tau_n}^c$ is of order smaller than $n^{-\beta/(2\beta+1)}$ so that Theorems 2.1 and 2.2 imply that a Bayesian estimator such as the posterior mean has a convergence rate of order $n^{-\beta/(2\beta+1)}$ (L_1 risk) up to a $\log n$ term.

In the following section we give the key result that enables us to obtain the minimax rate, which is the approximation error of a smooth density f_0 by a continuous mixture $g_{\alpha,f}$ as α goes to infinity.

3. Approximation of a smooth density by continuous and discrete mixtures. A beta mixture, as defined by (1.6) behaves locally like a Gaussian mixture, however its behaviour seems to be richer since the variance adapts to the value of x , see Lemma 3.1. In this section we obtain a way to approximate any Hölder density f by a sequence of continuous and discrete mixtures. We begin with approximating the density by a sequence of continuous mixtures and then we approximate the continuous mixtures by discrete mixtures.

3.1. Continuous mixtures. We consider a continuous mixture $g_{\alpha,f}$ as defined in (1.6). This mixture is based on the parameterisation of a beta density in terms of mean ϵ and scale α . The idea in this section is that when α becomes large the above mixture converges to $f(x)$ if f is continuous. We first give a result where the approximation is controlled in terms of the supremum norm, which has an intrinsic interest. We also give a bound on the approximation error for Kullback-Leibler types of divergence, which is the required result to control the posterior concentration rate.

THEOREM 3.1. *Assume that $f_0 \in \mathcal{H}(\beta, L)$ and satisfies assumption \mathbf{A}_0 , with $\beta > 0$. Then there exists a probability density f_1 such that*

$$f_1(x) = f_0(x) \left(1 + \sum_{j=2}^{\lceil \beta \rceil - 1} \frac{w_j(x)}{\alpha^{j/2}} \right) \quad \text{if } \beta > 2; \quad f_1(x) = f_0(x) \quad \text{if } \beta \leq 2$$

where the w_j 's are combinations of polynomial functions of x and of terms in the form $f_0^{(l)}(x)x^l(1-x)^l/f_0(x)$, $l \leq j$, and

$$(3.1) \quad \|g_{\alpha, f_1} - f_0\|_\infty \leq C\alpha^{-\beta/2}$$

and for all $p > 0$

$$(3.2) \quad \text{KL}(f_0, g_{\alpha, f_1}) \leq C\alpha^{-\beta}, \quad \int f_0 \left| \log \left(\frac{f_0}{g_{\alpha, f_1}} \right) \right|^p \leq C\alpha^{-\beta}$$

It is to be noted that the upper bound on the supremum norm (3.1) does not require assumption \mathbf{A}_0 to hold. This assumption is only required to obtain an upper bound on the Kullback-Leibler types of divergence.

Note also that if we do not allow f_1 to be different from f_0 we do not achieve the rate $\alpha^{-\beta}$ to be true for values of β greater than 2. We believe that the trick of allowing f_1 to be different from f_0 could be used in a more general context of Bayesian mixture distributions (or Bayesian Kernel approaches as defined in [7]) inducing a greater flexibility of Bayesian kernel methods with respect to frequentist kernel methods.

A Beta density with parameters $(\alpha/\epsilon, \alpha/(1-\epsilon))$ can be expressed as

$$g_{\alpha, \epsilon}(x) = x^{\alpha/(1-\epsilon)-1} (1-x)^{\alpha/\epsilon-1} \frac{\Gamma(\alpha/(\epsilon(1-\epsilon)))}{\Gamma(\alpha/\epsilon)\Gamma(\alpha/(1-\epsilon))}.$$

From this we have the following three approximations that will be used throughout the proofs of Theorems 2.1, 2.2, 3.1 and 3.2. Let

$$(3.3) \quad K(\epsilon, x) = \epsilon \log(\epsilon/x) + (1-\epsilon) \log((1-\epsilon)/(1-x)),$$

this is the Kullback-Leibler divergence between the Bernoulli ϵ and the Bernoulli x distributions. Then

LEMMA 3.1.

$$(3.4) \quad g_{\alpha, \epsilon}(x) = \frac{\sqrt{\alpha}}{\sqrt{2\pi x(1-x)}} e^{-\frac{\alpha K(\epsilon, x)}{\epsilon(1-\epsilon)}} \left[1 + \sum_{j=1}^k \frac{b_j(\epsilon)}{\alpha^j} + o(\alpha^{-(k+1)}) \right],$$

for any $k > 0$ and α large enough, where the $b_j(\epsilon)$ are polynomial functions. For all $k > 0, k_1 \geq 3$, we also have,

$$\begin{aligned}
 g_{\alpha, \epsilon}(x) &= \frac{\sqrt{\alpha}}{\sqrt{2\pi x(1-x)}} \times \\
 &\quad \exp \left\{ -\frac{\alpha(x-\epsilon)^2}{2x^2(1-x)^2} \left[1 + \frac{(x-\epsilon)}{x(1-x)} \left(C(x) + Q_{k_1} \left(\frac{x-\epsilon}{x(1-x)} \right) \right) \right] + R_1 \right\} \times \\
 (3.5) \quad &\quad \left[1 + \sum_{j=1}^k \frac{b_j(\epsilon)}{\alpha^j} + O(\alpha^{-(k+1)}) \right],
 \end{aligned}$$

where $R_1 \leq \alpha C |x - \epsilon|^{k_1-2} (x_\epsilon(1-x_\epsilon))^{-k_1+2}$,

$$Q_{k_1} \left(\frac{x-\epsilon}{x(1-x)} \right) = \sum_{l=0}^{k_1-3} \frac{C_l(x)(x-\epsilon)^l}{(x(1-x))^l},$$

and the functions $C(x), C_l(x)$ $l \leq k_1$ are polynomial, where $x_\epsilon \in (x, \epsilon)$ and C is a positive constant. Moreover, when $\alpha|x-\epsilon|^3 \leq C_0 x^3(1-x)^3$ for any positive constant C_0 , if $k_2 \geq 0$ and if $k_1 \geq 3 \vee 3k_2$ there exists $C_1 > 0$ such that

$$\begin{aligned}
 g_{\alpha, \epsilon}(x) &= \frac{\sqrt{\alpha} e^{-\frac{\alpha(x-\epsilon)^2}{2x^2(1-x)^2}}}{\sqrt{2\pi x(1-x)}} \times \\
 &\quad \left(\sum_{j=0}^{k_2} \frac{\alpha^j (x-\epsilon)^{3j}}{j! (x(1-x))^{3j}} \left[C(x) + Q_{k_1} \left(\frac{x-\epsilon}{x(1-x)} \right) \right]^j + R \right) \times \\
 (3.6) \quad &\quad \left[1 + \sum_{j=1}^k \frac{b_j(\epsilon)}{\alpha^j} + O(\alpha^{-(k+1)}) \right],
 \end{aligned}$$

where $|R| \leq C_1 \alpha^{k_2+1} |x - \epsilon|^{3(k_2+1)} (x_\epsilon(1-x_\epsilon))^{-3(k_2+1)}$.

Note that the term $O(\alpha^{-(k+1)})$ appearing in (3.4), (3.5) and (3.6) is uniform in x and ϵ .

PROOF. (Proof of Lemma 3.1) The proof of (3.4) follows from the expression of the Betas density in the form:

$$g_{\alpha, \epsilon}(x) = \frac{\Gamma(\alpha/(\epsilon(1-\epsilon))) \epsilon^{\alpha/(1-\epsilon)} (1-\epsilon)^{\alpha/\epsilon} e^{-\alpha \frac{K(\epsilon, x)}{\epsilon(1-\epsilon)}}}{\Gamma(\alpha/\epsilon) \Gamma(\alpha/(1-\epsilon))} \frac{1}{x(1-x)},$$

and from a Taylor expansion of $\Gamma(y)$ for y close to infinity where we obtain that

$$\begin{aligned} \frac{\Gamma(\alpha/(\epsilon(1-\epsilon)))}{\Gamma(\alpha/\epsilon)\Gamma(\alpha/(1-\epsilon))} &= \frac{\sqrt{\alpha}}{\sqrt{2\pi}} \exp\left(-\alpha \left[\frac{\log(\epsilon)}{1-\epsilon} + \frac{\log(1-\epsilon)}{\epsilon}\right]\right) \left(1 + \sum_{j=1}^{\infty} b_j \frac{\epsilon^j(1-\epsilon)^j}{\alpha^j}\right) \\ &\quad \left(1 + \sum_{j=1}^{\infty} b_j \frac{\epsilon^j}{\alpha^j}\right)^{-1} \left(1 + \sum_{j=1}^{\infty} b_j \frac{(1-\epsilon)^j}{\alpha^j}\right)^{-1}, \end{aligned}$$

where the b_j 's are the coefficient appearing in the expansion of the Gamma function near infinity, see for instance [1]. Putting the three remaining terms together results in: for all $k > 0$

$$\begin{aligned} &\left(1 + \sum_{j=1}^{\infty} b_j \frac{\epsilon^j(1-\epsilon)^j}{\alpha^j}\right) \left(1 + \sum_{j=1}^{\infty} b_j \frac{\epsilon^j}{\alpha^j}\right)^{-1} \left(1 + \sum_{j=1}^{\infty} b_j \frac{(1-\epsilon)^j}{\alpha^j}\right)^{-1} \\ &= 1 + \sum_{j=1}^k \frac{b_j(\epsilon)}{\alpha^j} + O(\alpha^{-(k+1)}) \end{aligned}$$

where the $b_j(\epsilon)$'s are polynomial functions with degree less than $2j$. This implies (3.4). To obtain (3.5) we make a Taylor expansion of (3.4) as a function of ϵ around x .

$$\frac{K(\epsilon, x)}{\epsilon(1-\epsilon)} = \frac{(\epsilon - x)^2}{2x^2(1-x)^2} + \sum_{j=3}^{k_1} C_j(x) \frac{(x-\epsilon)^j}{x^j(1-x)^j} + R_1$$

where $R_1 \leq R|x - \epsilon|^{k_1+1}/(x_\epsilon(1-x_\epsilon))^{k_1+1}$ for some $x_\epsilon \in (x, \epsilon)$, leading to (3.5). A Taylor expansion of e^y around 0 combined with the above approximation of y leads to (3.6). \square

To prove (3.1) we control the difference between the uniform density on $[0, 1]$ and the corresponding beta mixture $g_\alpha = \int_0^1 g_{\alpha, \epsilon} d\epsilon$. This is given in the following Lemma.

LEMMA 3.2. *For all $\alpha > 0$ large enough, for all $k_2 \geq 1$ and $k_1 \geq 3(k_2 - 1)$ define*

$$I(x) = \sum_{j=1}^{k_2} \frac{C(x)^j \mu_{3j}}{\alpha^{j/2}} + \sum_{l=2}^{k_2 k_1} \frac{B_l(x)}{\alpha^{l/2}} \quad \mu_j = E[\mathcal{N}(0, 1)^j],$$

then

$$\|g_\alpha(x) - 1 - \frac{I(x)}{\alpha}\|_\infty \leq C\alpha^{-(k_2+1)/2} (\log \alpha)^{3(k_2+1)/2}$$

where the $B_l(x)$'s are polynomial functions of x .

The proof of Lemma 3.2 is given in Appendix A. We now prove Theorem 3.1.

PROOF. (Proof of Theorem 3.1). Throughout the proof C denotes a generic positive constant. Let $f \in \mathcal{H}(\beta, L)$ and denote $r = \lfloor \beta \rfloor$. Then $\forall \epsilon \in (0, 1)$,

$$(3.7) \quad \left| f(\epsilon) - \sum_{j=0}^r \frac{f^{(j)}(x)}{j!} (\epsilon - x)^j \right| \leq L|x - \epsilon|^\beta.$$

The construction of f_1 is iterative. Let $\delta_x = \delta_0 x(1-x)\sqrt{\log \alpha/\alpha}$. We bound

$$\int_0^1 |x - \epsilon|^\beta g_{\alpha, \epsilon}(x) d\epsilon \leq \left| \int_0^{x-\delta_x} g_{\alpha, \epsilon}(x) d\epsilon + \int_{x+\delta_x}^1 g_{\alpha, \epsilon}(x) d\epsilon \right| + \int_{x-\delta_x}^{x+\delta_x} |x - \epsilon|^\beta g_{\alpha, \epsilon}(x) d\epsilon$$

Equation (A.6) implies that for all $H > 0$, if δ_0 is large enough, the first term of the right hand side of the above inequality is $0(\alpha^{-H})$. We treat the second term using the same calculations as in the case of I_3 in Appendix A so that, for all $k > 0$

$$\int_{x-\delta_x}^{x+\delta_x} |x - \epsilon|^\beta g_{\alpha, \epsilon}(x) d\epsilon \leq C\alpha^{-\beta/2} x^\beta (1-x)^\beta E[|\mathcal{N}(0, 1)|^\beta] + 0(\alpha^{-k/2}).$$

Therefore

$$\int_0^1 |x - \epsilon|^\beta g_{\alpha, \epsilon}(x) d\epsilon = 0(\alpha^{-\beta/2} x^\beta (1-x)^\beta) + 0(\alpha^{-H})$$

uniformly in x . Then for all $H > 0$,

$$\begin{aligned} [g_{\alpha, f} - f](x) &= \sum_{j=1}^r \frac{f^{(j)}(x)}{j!} \int_0^1 (\epsilon - x)^j g_{\alpha, \epsilon}(x) d\epsilon + f(x)(g_\alpha(x) - 1) \\ &\quad + 0(\alpha^{-\beta/2} x^\beta (1-x)^\beta) + 0(\alpha^{-H}) \\ &= \sum_{j=1}^r \frac{f^{(j)}(x)}{j!} \int_0^1 (\epsilon - x)^j g_{\alpha, \epsilon}(x) d\epsilon + f(x) \frac{I(x)}{\alpha} \\ &\quad + 0(\alpha^{-\beta/2} x^\beta (1-x)^\beta) + \alpha^{-H}, \end{aligned}$$

Uniformly in x , for all $H > 0$. Using the same calculations as in the computation of I_3 in the proof Lemma 3.2 we obtain for all $j \geq 1$, to the order

$$\begin{aligned}
 & 0(\alpha^{-(k+j+1)/2}x^j(1-x)^j + \alpha^{-H}) \\
 & \int_0^1 (\epsilon - x)^j g_{\alpha, \epsilon}(x) d\epsilon \\
 & = \frac{\sqrt{\alpha}}{\sqrt{2\pi}x(1-x)} \int_{x-\delta_x}^{x+\delta_x} e^{-\frac{\alpha(x-\epsilon)^2}{2x^2(1-x)^2}} \times \\
 & \quad \left((x-\epsilon)^j + \sum_{l=1}^k \frac{\alpha^l (x-\epsilon)^{3l+j}}{j! (x(1-x))^{3l}} \left[C(x) + Q_{k_1} \left(\frac{x-\epsilon}{x(1-x)} \right) \right]^l \right) d\epsilon \\
 & = \mu_j \alpha^{-j/2} x^j (1-x)^j + \sum_{l=1}^k \frac{D_l(x) x^j (1-x)^j}{\alpha^{(j+l)/2}},
 \end{aligned}$$

so that we can write

$$\begin{aligned}
 & \int_0^1 (\epsilon - x)^j g_{\alpha, \epsilon}(x) d\epsilon \\
 & = \frac{x^j (1-x)^j}{\alpha^{j/2}} \mu_{j, \alpha}(x) + 0(\alpha^{-(k+j+1)/2}x^j(1-x)^j + \alpha^{-H})
 \end{aligned}$$

where $\mu_{j, \alpha}(x)$ is a polynomial function of x with the leading term being equal to μ_j . We can thus write, to the order $0(\alpha^{-\beta/2}x^\beta(1-x)^\beta) + \alpha^{-H}$

$$(3.8) \quad [g_{\alpha, f} - f](x) = \sum_{j=1}^r \frac{f^{(j)}(x) x^j (1-x)^j \mu_{j, \alpha}(x)}{j! \alpha^{j/2}} + f(x) \frac{I(x)}{\alpha}.$$

Hence if $\beta \leq 2$, since $\mu_1 = 0$,

$$\begin{aligned}
 |g_{\alpha, f} - f|(x) & \leq \frac{\|I\|_\infty f(x)}{\alpha} + 0(\alpha^{-\beta/2}x^\beta(1-x)^\beta) + 0(\alpha^{-H}) \\
 (3.9) \quad & = 0(\alpha^{-\beta/2}),
 \end{aligned}$$

as soon as $H > \beta/2$, leading to (3.1) with $f_1 = f$. If $\beta > 2$, We construct a probability density f_1 satisfying

$$(g_{\alpha, f_1} - f)(x) = 0(\alpha^{-\beta/2}x^\beta(1-x)^\beta) + 0(\alpha^{-H}).$$

Equation (3.8) implies that f_1 needs satisfy

$$\sum_{j=1}^r \frac{f_1^{(j)}(x) x^j (1-x)^j \mu_{j, \alpha}(x)}{j! \alpha^{j/2}} + f_1(x) \left(1 + \frac{I(x)}{\alpha} \right) = f(x) + 0(\alpha^{-\beta/2}x^\beta(1-x)^\beta) + 0(\alpha^{-H}).$$

To prove that such a probability density exists we construct it iteratively. Let $2 < \beta \leq 3$, then set

$$h_1(x) = f(x) \left(1 - \frac{I(x)}{\alpha} \right) - \frac{x(1-x)f'(x)C(x)\mu_4}{\alpha} - \frac{x^2(1-x)^2 f''(x)\mu_2}{2\alpha}.$$

Note that if $f \in \mathcal{H}(L, \beta)$, then $\inf f > 0$ implies $h_1 > 0$ for α large enough and if $f(0) = 0$ ($f(1) = 0$), when x is close to 0 (resp. 1), if

$$\liminf_x \frac{f(x)}{x^j(1-x)^j|f^{(j)}(x)|} > 0, \quad j = 1, 2$$

$h_1 \geq 0$ for α large enough on $[0, 1]$. Assumption **A₀** implies the above relation between f and $f^{(j)}$ since

$$(3.10) \quad \begin{aligned} h_1(x) = & \frac{x^{k_0} f^{(k_0)}(\bar{x}_1)}{k_0!} \left(1 - \frac{I(x)}{\alpha}\right) - \frac{x^{k_0}(1-x)f^{(k_0)}(\bar{x}_2)C(x)\mu_4}{\alpha(k_0-1)!} \\ & - \frac{x^{k_0}(1-x)^2 f^{(k_0)}(\bar{x}_3)\mu_2}{2\alpha(k_0-2)!} \end{aligned}$$

with $\bar{x}_1, \bar{x}_2, \bar{x}_3 \in (0, x)$. Since $f^{(k_0)}(0) > 0$, $h_1(x)$ is equivalent to $f(x)$ for α large enough and x close to zero and $h_1(x) > 0$ for all $x \in (0, 1)$. Let $c_1 = \int_0^1 h_1(x)dx$. Since $\int_0^1 [g_{\alpha, f} - f](x)dx = 0$,

$$c_1 = 1 + 0(\alpha^{-(3/2 \wedge \beta/2)})$$

and we can divide h_1 by its normalizing constant and obtain the same result as before, so that h_1 can be chosen to be a probability density on $[0, 1]$.

From this we obtain when $\beta > 2$

$$\begin{aligned} (g_{\alpha, h_1} - f)(x) &= \int_0^1 \left(\sum_{j=1}^{r-2} \frac{h_1^{(j)}(x)}{j!} (\epsilon - x)^j \right) g_{\alpha, \epsilon}(x) d\epsilon \\ &\quad + h_1(x) \frac{I(x)}{\alpha} + \sum_{j=r-1}^r \frac{(f - I(x)/\alpha)^{(j)}(x)}{j!} \int_0^1 (\epsilon - x)^j g_{\alpha, \epsilon}(x) d\epsilon \\ &\quad + 0(\alpha^{-\beta/2} x^\beta (1-x)^\beta) \\ &= \frac{w(x)f(x)}{\alpha^2} + 0(\alpha^{-2 \wedge \beta/2} x^\beta (1-x)^\beta) + O(\alpha^{-H}), \quad \forall H > 0 \end{aligned}$$

where $w(x)$ is a combination of polynomial functions of x and of functions in the form $x^j(1-x)^j f^{(j)}(x)$ with $j < 3$ if $\beta \leq 4$. If $\beta \leq 4$ then we set $f_1 = h_1$ (renormalized) else we reiterate. We thus obtain that if r_β is the largest integer (strictly) smaller than $\beta/2$

$$f_1(x) = f(x) \left(1 + \sum_{j=1}^{\lfloor r_\beta \rfloor} \frac{w_j(x)}{\alpha^j} \right)$$

where $w_j(x)$ is a combination of polynomial functions and of terms in the form $f^{(l)}(x)x^l(1-x)^l/f(x)$, $l \leq 2j$. Assumption **A**₀ implies that f_1 can be chosen to be a density when α is large enough and satisfies

$$\|g_{\alpha, f_1} - f\|_{\infty} \leq C\alpha^{-\beta/2}.$$

which implies (3.1).

If f is strictly positive on $[0, 1]$ then (3.2) follows directly from (3.1). We now consider the case where $f(0) = 0$ (the case $f(1) = 0$ is treated similarly). Under the assumption **A**₀, the previous calculations lead to

$$(g_{\alpha, f_1} - f)(x) = 0(f(x)\alpha^{-\beta/2}) + 0(\alpha^{-H}), \quad \forall H > 0.$$

Note also that for α large enough, f_1 is increasing between 0 and δ for some positive constant $\alpha > 0$ so that if x is small enough,

$$\begin{aligned} g_{\alpha, f_1} &\geq \frac{f_1(x)\sqrt{\alpha}}{2\sqrt{2\pi}x(1-x)} \int_x^{x+\delta_x} e^{-\frac{\alpha(x-\epsilon)^2}{2(x^2(1-x)^2)}} d\epsilon \\ (3.11) \quad &\geq \frac{f_1(x)}{4} \end{aligned}$$

so that $g_{\alpha, f_1} \geq f/8$ on $[0, 1]$. Therefore, since $f(x) = f^{(k_0)}(0)x^{k_0}/k_0! + o(x^{k_0})$ when x is close to 0, let $H > \beta$ and $c = c_0\alpha^{-H/k_0}$; for some constant c_0 large enough, we have

$$\begin{aligned} \text{KL}(f, g_{\alpha, f_1}) &\leq \log 2 \int_0^c f(x)dx + \alpha^{-\beta} \int_c^1 f(x)dx + \int_c^1 f(x) \left| \log \left(1 - \frac{\alpha^{-H}}{f(x)} \right) \right| dx \\ &\leq C \left(\alpha^{-H(k_0+1)/k_0} + \alpha^{-\beta} + \alpha^{-H} \right) = O(\alpha^{-\beta}). \end{aligned}$$

Similarly for all $p > 0$, if $c_p = c_0\alpha^{-H/(pk_0)}$,

$$\begin{aligned} \int f(x) |\log(f(x)/g_{\alpha, f_1}(x))|^p dx &\leq (\log 2)^p \int_0^{c_p} f(x)dx + \alpha^{-p\beta} \int_{c_p}^1 f(x)dx \\ &\quad + \int_{c_p}^1 f(x) \left| \log \left(1 - \frac{\alpha^{-H}}{f(x)} \right) \right|^p dx \\ &\leq C \left(\alpha^{-2H(k_0+1)/(pk_0)} + \alpha^{-p\beta} + \alpha^{-H} \right) \\ &= 0(\alpha^{-\beta}), \end{aligned}$$

if $H \geq p\beta$. This achieves the proof of Theorem 3.1. \square

In the following section we consider the approximation of continuous mixtures by discrete mixtures in a way similar to [4].

3.2. *Discrete mixtures.* Let P be a probability on $[0, 1]$ with cumulative distribution function denoted by $P(x)$ for all $x \in [0, 1]$. We consider a mixture of Betas similarly to before but with general probability distribution P on $[0, 1]$

$$g_{\alpha, P}(x) = \int_0^1 g_{\alpha, \epsilon}(x) dP(\epsilon).$$

Let f be a probability density with respect to Lebesgue measure on $[0, 1]$, in this section we study the approximation of $g_{\alpha, f}$ by $g_{\alpha, P}$ where P is a discrete measure with finite support.

The approximation of discrete mixtures by continuous ones is studied in different contexts of location scale mixtures, see for instance [4] or [8] (Ch 3) for a general result. Betas mixtures are not location scale mixtures however, as discussed in the previous section when α is large they behave locally like location scale mixtures. In this section we use this property to approximate continuous mixtures with finite mixtures having a reasonably small number of points in their support.

THEOREM 3.2. *Let f be a probability density on $[0, 1]$, $f(x) > 0$ for all $0 < x < 1$ and such that there exists $k_1, k_0 \in \mathbb{N}$ satisfying $f(x) \sim x^{k_0} c_0$, if $x = o(1)$ and $f(1-x) \sim (1-x)^{k_1} c_1$, if $1-x = o(1)$. Then there exists a discrete probability distribution P having at most $N = N_0 \sqrt{\alpha} \sqrt{\log(\alpha)}$ points in its support such that, for all $p \geq 1$, for all $H > 0$ (depending on M_0), for α large enough,*

$$(3.12) \quad \int_0^1 g_{\alpha, f} \left| \log \left(\frac{g_{\alpha, f}}{g_{\alpha, P}} \right) \right|^p (x) dx \leq C \alpha^{-H}.$$

We can choose the distribution P such that there exists $A > 0$ with $p_j > \alpha^{-A}$ for all $j \leq N$.

We use this inequality to obtain the following result on the true density f_0 .

COROLLARY 3.1. *Let $f_0 \in \mathcal{H}(L, \beta)$, $\beta > 0$ be a probability density on $[0, 1]$ satisfying: $f_0(x) > 0$ for all $0 < x < 1$ and such that there exist $k_1, k_0 \in \mathbb{N}$ satisfying $|f^{(k_0)}(0)| > 0$ and $|f^{(k_1)}(1)| > 0$, $k_0, k_1 < \beta$. Then, for all $p > 1$ there exists a discrete probability distribution P having at most $N = N_0 \sqrt{\alpha} \sqrt{\log(\alpha)}$ in its support, with N_0 large enough such that*

$$(3.13) \quad \text{KL}(f_0, g_{\alpha, P}) \leq C \alpha^{-\beta}, \quad V_p(f_0, g_{\alpha, P}) \leq C \alpha^{-\beta}$$

PROOF. (Proof of Corollary 3.1)

From Theorem 3.1 there exists f_1 positive with $f_1 = f_0(1 + O(\alpha^{-1}))$ and

$$\text{KL}(f_0, g_{\alpha, f_1}) \leq C\alpha^{-\beta}, \quad g_{\alpha, f_1} \geq f_0/8.$$

This implies that

$$\begin{aligned} \text{KL}(f_0, g_{\alpha, P}) &\leq \text{KL}(f_0, g_{\alpha, f_1}) + \left| \int f_0(x) \log(g_{\alpha, f_1}/g_{\alpha, P})(x) dx \right| \\ &\leq C\alpha^{-\beta} + 8 \int g_{\alpha, f_1}(x) \left| \log \left(\frac{g_{\alpha, f_1}}{g_{\alpha, P}} \right) \right| (x) dx = O(\alpha^{-\beta}). \end{aligned}$$

The same calculations apply to $\int_0^1 f_0(x) |\log(f_0(x)/g_{\alpha, P}(x))|^p dx \leq C\alpha^{-\beta}$, which achieves the proof of Corollary 3.1. \square

PROOF. of Theorem 3.2

Throughout this proof C denotes a generic positive constant. We first bound the difference between both mixtures at all x . By symmetry we can consider $x \in [0, 1/2]$. Consider the following approximation of the exponential: for all $s \geq 0$ and all $z > 0$,

$$(3.14) \quad \left| e^{-z} - \sum_{j=0}^s \frac{(-1)^j z^j}{j!} \right| \leq \frac{z^{s+1}}{(s+1)!}.$$

Equation (3.5) implies that for all $k > 1, k_1 \geq 3$, there exist polynomial functions of x , $D_l(x)$, $l \leq k_1$ and polynomial functions of ϵ , $b_j(\epsilon)$, $j \leq k$ such that

$$g_{\alpha, \epsilon}(x) = \frac{\sqrt{\alpha} e^{R_{k_1}}}{\sqrt{2\pi x(1-x)}} e^{\frac{-(x-\epsilon)^2 \alpha}{2x^2(1-x)^2} \left(1 + \sum_{l=1}^{k_1-2} \frac{D_l(x)(x-\epsilon)^l}{x^l(1-x)^l} \right)} \left(1 + \sum_{j=1}^k \frac{b_j(\epsilon)}{\alpha^j} + O(\alpha^{-(k+1)}) \right),$$

where $|R_{k_1}| \leq \alpha C |x - \epsilon|^{k_1+1} (x_\epsilon(1-x_\epsilon))^{-(k_1+1)}$, with $x_\epsilon \in (x, \epsilon)$ (or (ϵ, x)). If $|x - \epsilon| \leq M\delta_0 \sqrt{\log \alpha} x(1-x)/\sqrt{\alpha}$, $|R_{k_1}| \leq C\alpha^{-k_1/2+1/2} (\log \alpha)^{k_1/2}$ and set

$$z = \frac{(x-\epsilon)^2 \alpha}{2x^2(1-x)^2} \left(1 + \sum_{l=1}^{k_1} \frac{D_l(x)(x-\epsilon)^l}{x^l(1-x)^l} \right),$$

then

$$0 \leq z \leq C \frac{(x-\epsilon)^2 \alpha}{x^2(1-x)^2} \leq CM^2 \log(\alpha),$$

so that we obtain using (3.14)

$$(3.15) \quad g_{\alpha, \epsilon}(x) = \frac{\sqrt{\alpha}}{\sqrt{2\pi x(1-x)}} \sum_{j=0}^s \frac{(-1)^j (x-\epsilon)^{2j} \alpha^j}{2^j x^{2j} (1-x)^{2j} j!} \times \left(1 + \sum_{l=1}^{k_1} \frac{D_l(x)(x-\epsilon)^l}{x^l (1-x)^l} \right)^j \left(1 + \sum_{j=1}^k \frac{b_j(\epsilon)}{\alpha^j} \right) + \Delta_s,$$

where

$$\Delta_s \leq C \frac{1}{x(1-x)} \left[\frac{\sqrt{\alpha} M^{2(s+1)} C^{s+1}}{(s+1)!} + \alpha^{-(k_1-1)/2} (\log \alpha)^{(k_1+1)/2} + \alpha^{-(k+1)/2} \right].$$

Consider $\epsilon_0 = \alpha^{-t_0}$, for some positive constant t_0 and $\epsilon_j = \epsilon_0 (1 + M\sqrt{\log \alpha} / \sqrt{\alpha})^j$, $j = 1, \dots, J$ with

$$J = \lfloor \frac{t_0 \log(\alpha) + 2 \log(\log(\alpha))}{\log(1 + M\sqrt{\log \alpha} / \sqrt{\alpha})} \rfloor + 1 = 0 \left(\sqrt{\alpha} \sqrt{\log \alpha} \right).$$

Define dF_j and dP_j the renormalized probabilities dF and dP restricted to $[\epsilon_j, \epsilon_{j+1})$ set $H > 0$. Then if $k_1 - 1 > 2H$ and $k \geq H - 1/2$ we obtain for all $x \in [\epsilon_{j-1}, \epsilon_{j+2}]$, $j \geq 2$

$$(3.16) \quad \left| \int_{\epsilon_j}^{\epsilon_{j+1}} g_{\alpha, \epsilon}(x) [dF_j - dP_j](\epsilon) \right| \leq \frac{\sqrt{\alpha}}{\sqrt{2\pi x(1-x)}} \left| \int_{\epsilon_j}^{\epsilon_{j+1}} \sum_{i=0}^s \frac{(-1)^i (x-\epsilon)^{2i} \alpha^i}{2^i x^{2i} (1-x)^{2i} i!} \left(1 + \sum_{a=1}^{k_1} \frac{C_a (x-\epsilon)^a}{x^a (1-x)^a} \right)^i \times \left(1 + \sum_{i=1}^k \frac{b_i(\epsilon)}{\alpha^i} \right) [dF_j - dP_j](\epsilon) \right| + \frac{C}{x(1-x)} \left[\frac{\sqrt{\alpha} C^{s+1} M^{2(s+1)} \log \alpha^{s+1}}{(s+1)!} + \alpha^{-H} \right]$$

So that if $s = s_0 \log \alpha$ with $s_0 \geq C^2 M^4 + 1$, we obtain

$$\frac{C^{s+1} M^{2(s+1)} \log \alpha^{s+1}}{(s+1)!} \leq e^{-\frac{s_0 \log s_0 \log \alpha}{2}} = 0(\alpha^{-H})$$

as soon as $s_0 \log(s_0) \geq 2H$. Using Lemma A.1 of [4], we can construct a discrete probability with at most $N = 2k k_1 s + 1$ supporting points such that for all $l \leq 2s k_1$, $l' \leq k$,

$$\int \epsilon^l b_{l'}(\epsilon) d(F_j - P_j)(\epsilon) = 0$$

so that the first term of the right hand side of inequality (3.16) is made equal to 0. Therefore, for all $H > 0$ there exists a discrete distribution P_j whose support (in $[\epsilon_j, \epsilon_{j+1}]$) has at most $N = k'_0 \log \alpha$ points (k'_0 depending on H) and such that for all $x \in [\epsilon_{j-1}, \epsilon_{j+2}]$

$$\left| \int_{\epsilon_j}^{\epsilon_{j+1}} g_{\alpha, \epsilon}(x) d[F_j - dP_j](\epsilon) \right| = 0 \left(\frac{\alpha^{-H}}{x(1-x)} \right).$$

Moreover for all $x \leq \epsilon_{j-1}$, using equation (3.4) and the fact that

$$\alpha K(\epsilon, x) \geq \alpha K(\epsilon, \epsilon_{j-1}) \geq \frac{M^2(\log \alpha)\epsilon(1-\epsilon)}{3},$$

when $\epsilon_{j+1} > \epsilon > \epsilon_j$, we obtain

$$g_{\alpha, \epsilon}(x) \leq \frac{C}{x(1-x)} e^{-cM^2 \log \alpha},$$

for some positive constant $c > 0$. Now, if $x > \epsilon_{j+2}$ using inequality (3.4) together with the fact that

$$\alpha K(\epsilon, x) \geq \alpha K(\epsilon, \epsilon_{j+2}) \geq \frac{M^2(\log \alpha)\epsilon_{j+2}(1-\epsilon_{j+2})}{3},$$

if $\epsilon_{j+1} > \epsilon > \epsilon_j$, we obtain that

$$g_{\alpha, \epsilon}(x) \leq \frac{C}{x(1-x)} e^{-cM^2 \log \alpha},$$

for some positive constant $c > 0$. Hence, by constructing P in the form: if $\epsilon_{J+2} = 1 - \epsilon_0$

$$dP(\epsilon) = \sum_{j=0}^J (F(\epsilon_{j+1}) - F(\epsilon_j)) dP_j(\epsilon) + F(\epsilon_0) \delta_{(\epsilon_0)} + (1 - F(\epsilon_{J+2})) \delta_{(\epsilon_{J+2})},$$

we finally obtain for all x

$$(3.17) \quad \left| \int_0^1 g_{\alpha, \epsilon}(x) [dF - dP](\epsilon) \right| \leq \frac{C\alpha^{-H}}{x(1-x)},$$

where P has at most $N_\alpha = N_0(\log \alpha)^{3/2} \sqrt{\alpha}$, for some $N_0 > 0$ related to H , and where M is large enough. We now consider $x \leq \epsilon_0(1 - M\sqrt{\log \alpha/\alpha})$. We use the approximation (3.4).

$$g_{\alpha, \epsilon_0}(x) = \frac{C\sqrt{\alpha}}{x(1-x)} e^{-\alpha K(\epsilon_0, x)/(\epsilon_0(1-\epsilon_0))} (1 + o(\alpha^{-1})).$$

Since, when $x \leq \epsilon_0$,

$$\frac{K(\epsilon_0, x)}{\epsilon_0(1 - \epsilon_0)} \leq (1 - \epsilon_0)^{-1} (\log(\epsilon_0/x))$$

we obtain

$$g_{\alpha, P}(x) \geq e^{-\alpha \log(\epsilon_0/x)} \frac{C\sqrt{\alpha}F(\epsilon_0)}{x(1-x)}$$

and, using the above inequalities on $g_{\alpha, \epsilon}(x)$ for $x < \epsilon_{j-1}$ we have

$$g_{\alpha, P}(x) \leq C\alpha^{-H}/x(1-x),$$

where H depends on M , so that

$$|\log(g_{\alpha, P}(x))| \leq C\alpha |\log(x)|.$$

Since $g_{\alpha, f}$ is bounded (as a consequence of the fact that $g_{\alpha, f} - f$ is uniformly bounded whenever f is continuous), and since $u|\log(u)|^p$ goes to zero when u goes to zero,

$$\begin{aligned} \int_0^{\epsilon_0} g_{\alpha, f}(x) \left| \log \left(\frac{g_{\alpha, f}(x)}{g_{\alpha, P}(x)} \right) \right|^p dx &\leq C\alpha^{-t_0} + C\alpha^{-t_0} (\log \alpha)^p \\ (3.18) \qquad \qquad \qquad &= 0(\alpha^{-t_0} (\log \alpha)^p). \end{aligned}$$

Note also that if α is large enough,

$$g_{\alpha, f}(x) \geq f(x)/4$$

so that $g_{\alpha, f}(x) \geq cx^{k_0}(1-x)^{k_1}$ for x close to 0 and for all $x \in (\epsilon_0, 1 - \epsilon_0)$, for all $H > 0$

$$\frac{|g_{\alpha, f}(x) - g_{\alpha, P}(x)|}{g_{\alpha, f}(x)} \leq C \frac{\alpha^{-H}}{x^{k_0+1}(1-x)^{k_1+1}} \leq C\alpha^{-H+t_0(1+k_0 \vee k_1)}.$$

So that if $H > t_0(1 + k_0 \vee k_1) + B/p$, with $B > 0$,

$$\int_0^1 g_{\alpha, f}(x) \left| \log \left(\frac{g_{\alpha, f}(x)}{g_{\alpha, P}(x)} \right) \right|^p dx \leq C\alpha^{-t_0} (\log \alpha)^p + C\alpha^{-B} = 0(\alpha^{-B}).$$

as soon as $t_0 > B$. Moreover, we can assume that there exists a fixed A such that for all j , $p_j > \alpha^{-A} = v$. Indeed let $I_v = \{j; p_j \leq v\}$, then consider for $j \notin I_v$, $\tilde{p}_j = cp_j$ and for $j \in I_v$, $\tilde{p}_j = cv$ where c is defined by $\sum_{j=1}^J \tilde{p}_j = 1$. This implies in particular that

$$|c - 1| \leq vJ \leq J_0 \alpha^{-A+1/2} (\log \alpha)^{3/2}.$$

Let $\tilde{P} = \sum_{j=0}^J \tilde{p}_j \delta_{\epsilon_j}(\epsilon)$ then $g_{\alpha, \tilde{P}} \geq c g_{\alpha, P}$ and if $A - 1/2 > B$,

$$\text{KL}(g_{\alpha, f}, g_{\alpha, \tilde{P}}) \leq C \alpha^{-B} + |\log c| \leq C' \alpha^{-B}.$$

Also

$$\int |g_{\alpha, \tilde{P}} - g_{\alpha, P}| \leq \alpha^{-A+1/2} (\log \alpha)^{3/2},$$

hence if A is large enough inequality (3.17) is satisfied with \tilde{P} instead of P . Since $p_0 = F_1(\epsilon_0) \geq F_0(\epsilon_0)/4$ and $F_0(\epsilon_0) \geq \alpha^{-t_0 k_0} C$, by choosing $A > t_0 k_0$ we obtain that $0 \notin I_v$ and

$$g_{\alpha, \tilde{P}}(x) \geq g_{\alpha, \epsilon_0}(x) F(\epsilon_0), \quad \forall x < \epsilon_0$$

so that (3.18) is satisfied with \tilde{P} instead of P , which leads to: For all $B > 0$ there exists a distribution \tilde{P} having less than $N_0 \sqrt{\alpha} (\log \alpha)^{3/2}$ points in its support, satisfying: $\tilde{p}_j \geq \alpha^{-A}$ for some $A > 0$ and all j and such that

$$\int g_{\alpha, f} \left| \log \left(\frac{g_{\alpha, f}}{g_{\alpha, \tilde{P}}} \right) \right|^p (x) dx = 0(\alpha^{-B}),$$

which achieves the proof of Theorem 3.2. \square

Note however that A depends on B and so does N_0 . Note also that this result could be used to obtain a rate of concentration of the posterior distribution around the true density when the latter is a continuous mixture.

In the following section we give the proofs of Theorems 2.1 and 2.2.

4. Proofs of Theorem 2.1 and Theorem 2.2 . To prove these theorems we use Theorem 4 of [6]. In particular let $p \geq 2$ and following their notations define

$$B^*(f_0, \tau, p) = \{f; \text{KL}(f_0, f) \leq \tau^2; V_p(f_0, f) \leq \tau^p\}.$$

We also denote $\mathcal{J}_n(\tau) = N(\tau, \mathcal{F}_n, \|\cdot\|_1)$ the L_1 metric entropy on the set \mathcal{F}_n , i.e. the logarithm of the minimal number of balls with radii τ needed to cover \mathcal{F}_n , where \mathcal{F}_n is a set of densities that will be defined in each of the proofs. The proofs consist in obtaining a lower bound on $\pi(B^*(f_0, \tau_n, p))$ and an upper bound on $\mathcal{J}_n(\tau_n)$ when f_0 belongs to $\mathcal{H}(\beta, L)$.

4.1. *Proof of Theorem 2.1* . Assume that $f_0 \in \mathcal{H}(\beta, L)$ and let $\tau_n = n^{-\beta/(2\beta+1)}(\log n)^{5\beta/(4\beta+2)}$. We first bound $\pi(B^*(f_0, \tau_n, p))$. Using corollary 3.1 there exists a probability distribution with $N_n = N_0 \sqrt{\alpha_n} (\log \alpha_n)^{3/2}$ supporting points such that

$$\text{KL}(f_0, g_{\alpha_n, P}) \leq C\alpha_n^{-\beta}, \quad V_p(f_0, g_{\alpha_n, P}) \leq C\alpha_n^{-\beta}$$

with P of the form:

$$P(\epsilon) = \sum_{j=1}^{k_n} p_j \delta_{\epsilon_j}(\epsilon),$$

$\epsilon_j \in (\alpha_n^{-\beta}(\log \alpha_n)^{-\beta-1}, 1 - \alpha_n^{-\beta}(\log \alpha_n)^{-\beta-1})$ and $p_j > \alpha_n^{-A}$ for all $j = 1, \dots, N_n$ and some fixed positive constant A . We denote $\epsilon_0 = \alpha_n^{-\beta}(\log \alpha_n)^{-\beta-1}$, then $\epsilon_1 > \epsilon_0$. Consider $dP'(\epsilon) = \sum_{j=1}^{k_n} p'_j \delta_{\epsilon'_j}(\epsilon)$ with $|\epsilon'_j - \epsilon_j| \leq a\alpha_n^{-\gamma_1} \epsilon_j(1 - \epsilon_j)$ and $|p_j - p'_j| \leq a\alpha_n^{-\gamma_2} p_j$, for some positive constants $\gamma_1, \gamma_2 > 1/2$. Note that this implies that $|p'_j - p_j| \leq 2a\alpha_n^{-\gamma_2} p'_j$. Then

$$(4.1) \text{KL}(f_0, g_{\alpha_n, P'}) \leq C\alpha_n^{-\beta} + \int_0^1 f_0(x) [\log g_{\alpha_n, P}(x)/g_{\alpha_n, P'}(x)] dx.$$

For symmetry reasons we work on $x \leq 1/2$. Let $M_n = M\sqrt{\log \alpha_n}/\sqrt{\alpha_n}$, when $|x - \epsilon_j| \leq M_n \epsilon_j(1 - \epsilon_j)$, then Lemma B.1 implies that

$$\left| \frac{g_{\alpha_n, \epsilon_j}(x)}{g_{\alpha_n, \epsilon'_j}(x)} - 1 \right| = 0(\alpha_n^{-(\gamma_1-1/2)} \sqrt{\log \alpha_n}),$$

by choosing $k_2 > 2\gamma_1 - 1$ and $k_3 > \gamma_1 - 1/2$. Set $\beta_0 > 0$ then for all $x > e^{-\beta_0 \alpha_n}$ and all j' such that $|x - \epsilon'_j| > M_n \epsilon_j(1 - \epsilon_j)$; since $\epsilon_j(1 - \epsilon_j) \geq \alpha_n^{-t_0}/2$ with $t_0 \geq \beta$, Lemma B.1 implies that if $\gamma_1 > t_0 + \beta + 3/2$

$$\left| \frac{g_{\alpha_n, \epsilon_j}(x)}{g_{\alpha_n, \epsilon'_j}(x)} - 1 \right| \leq C\beta_0 \alpha_n^{3/2} \rho_n \epsilon_0^{-1} + 0(\alpha_n^{-\beta}) = 0(\alpha_n^{-\beta}).$$

This implies that if $x \in (e^{-\beta_0 \alpha_n}, 1 - e^{-\beta_0 \alpha_n})$ and if $\gamma_2 \geq \beta$

$$\begin{aligned} \frac{g_{\alpha_n, P}(x)}{g_{\alpha_n, P'}(x)} &= 1 + \frac{\sum_{j=1}^{k_n} (p_j - p'_j) g_{\alpha_n, \epsilon_j}}{\sum_{j=1}^{k_n} p'_j g_{\alpha_n, \epsilon'_j}} + \frac{\sum_{j=1}^{k_n} p'_j (g_{\alpha_n, \epsilon_j} - g_{\alpha_n, \epsilon'_j})}{\sum_{j=1}^{k_n} p'_j g_{\alpha_n, \epsilon'_j}} \\ (4.2) \quad &= 1 + 0(\alpha_n^{-\beta}). \end{aligned}$$

Now let $x < e^{-\beta_0 \alpha_n}$, then $|x - \epsilon_j| \geq \epsilon_j(1 - \epsilon_j)/2$ for all $j = 0, \dots, N_n$ and there exists $c > 0$ independent of β_0 such that

$$g_{\alpha_n, P}(x) \leq e^{-c\alpha_n} \frac{\sqrt{\alpha_n}}{x(1-x)}, \quad g_{\alpha_n, P'}(x) \leq e^{-c\alpha_n} \frac{\sqrt{\alpha_n}}{x(1-x)}$$

Note also that

$$g_{\alpha_n, \epsilon}(x) \geq C \frac{\sqrt{\alpha_n}}{x(1-x)} e^{-\frac{\alpha_n K(\epsilon, x)}{\epsilon(1-\epsilon)}}$$

where

$$\begin{aligned} \frac{\alpha_n K(\epsilon, x)}{\epsilon(1-\epsilon)} &= \alpha_n \left(\frac{1}{1-\epsilon} \log(\epsilon/x) + \frac{1}{\epsilon} \log((1-\epsilon)/(1-x)) \right) \\ &= \alpha_n \left(\frac{1}{1-\epsilon} \log(\epsilon/x) + \frac{1}{\epsilon} \log(1-\epsilon) + \frac{x}{\epsilon} + o(x/\epsilon) \right) \\ &\leq \alpha_n \left(\frac{1}{1-\epsilon} \log(\epsilon/x) + \frac{1}{\epsilon} \log(1-\epsilon) + \frac{x}{\epsilon} \right) + o(1) \end{aligned}$$

Consider the function

$$h(\epsilon) = \frac{1}{1-\epsilon} \log(\epsilon/x) + \frac{1}{\epsilon} \log(1-\epsilon) + \frac{x}{\epsilon},$$

since $x < |\log(1-\epsilon)|$ for all $\epsilon \in (\epsilon_0, 1-\epsilon_0)$ h is increasing and for all $\epsilon < 1/2$, $h(\epsilon) \leq 2|\log(x)| + 0(1)$. This leads to

$$(4.3) \quad g_{\alpha_n, P}(x) \geq CP([0, 1/2]) \frac{\sqrt{\alpha_n}}{x(1-x)} e^{2\alpha_n \log(x)}.$$

The same inequality holds for $g_{\alpha_n, P'}$, which implies that

$$\int_0^{e^{-\beta_0 \alpha_n}} f_0(x) \left| \log \left(\frac{g_{\alpha_n, P}(x)}{g_{\alpha_n, P'}(x)} \right) \right| dx \leq C \alpha_n^2 e^{-\beta_0 \alpha_n}$$

and

$$\int_0^{e^{-\beta_0 \alpha_n}} f_0(x) \left| \log \left(\frac{g_{\alpha_n, P}(x)}{g_{\alpha_n, P'}(x)} \right) \right|^p dx \leq C \alpha_n^{p+1} e^{-\beta_0 \alpha_n}.$$

The same kind of inequalities are obtained for $x > 1 - e^{-\beta_0 \alpha_n}$. Finally we obtain

$$\int_0^1 f_0(x) \left| \log \left(\frac{g_{\alpha_n, P}(x)}{g_{\alpha_n, P'}(x)} \right) \right| dx \leq C \alpha_n^2 e^{-\beta_0 \alpha_n} + 0(\alpha_n^{-\beta}) = 0(\alpha_n^{-\beta}).$$

and

$$(4.4) \quad \int_0^1 f_0(x) \left| \log \left(\frac{g_{\alpha_n, P}(x)}{g_{\alpha_n, P'}(x)} \right) \right|^p dx = 0(\alpha_n^{-\beta}).$$

Note that if $|p'_j - p_j| \leq \alpha_n^{-\beta-A}$ then $|p'_j - p_j| \leq \alpha_n^{-\beta} p_j$ so we need only determine a lower bound on the prior probability of the following set under the Type I prior: set $\beta_0 < 1/2$

$$S_n = \{\underline{p}' \in \mathcal{S}_{N_n}; |p'_j - p_j| \leq \alpha_n^{-\beta-A}, j \leq N_n\} \times \{|\epsilon_j - \epsilon'_j| \leq \alpha_n^{-2\beta-1} \epsilon_j(1-\epsilon_j), j \leq N_n\}$$

The prior probability of $S_{n,1} = \{\underline{p}' \in \mathcal{S}_{N_n}; |p'_j - p_j| \leq \alpha_n^{-\beta-A}, j \leq N_n\}$ is bounded from below by a term in the form

$$\alpha_n^{-Ck_n}$$

The prior probability of $S_{n,2} = \{|\epsilon_j - \epsilon'_j| \leq \alpha_n^{-2\beta-1} \epsilon_j(1-\epsilon_j), j \leq N_n\}$ is bounded from below by a term in the form

$$\prod_{j=1}^{N_n} [\epsilon_j(1-\epsilon_j)]^T \alpha_n^{2N_n(\beta+1)} \geq \alpha_n^{-N_n[2(\beta+1)+T]}.$$

Since $N_n = N_0 \sqrt{\alpha_n} (\log \alpha_n)^{3/2}$ and setting $\alpha_n = \alpha_0 n^{2/(2\beta+1)} (\log n)^{-5/(2\beta+1)}$, there exists $C_1 > 0$ independent of N_n such that we finally obtain

$$\pi(B^*(f_0, \tau_n, p)) \geq e^{-N_n C_1 \log n} c \geq e^{-C_1 N_0 n \tau_n^2}.$$

The proof for the control of the prior mass of Kullback-Leibler neighbourhoods of the true density under the Dirichlet I prior follows the same line. To find a lower bound on $\pi(B^*(f_0, \tau_n, p))$ we construct a subset of $\pi(B^*(f_0, \tau_n, p))$ whose probability under a Dirichlet process is easy to compute. Consider the discrete distribution $P(\epsilon) = \sum_{j=0}^{N_n} p_j \delta_{\epsilon_j}(\epsilon)$ with $N_n = N_0 \sqrt{\alpha_n} (\log \alpha_n)^{3/2}$ and $\alpha_n^{-t_0} = \epsilon_0 < \epsilon_1 < \dots < \epsilon_{N_n} = 1 - \alpha_n^{-t_0}$ and such that

$$\text{KL}(f_0, g_{\alpha_n, P}) \leq C \alpha_n^{-\beta}, \quad V_P(f_0, g_{\alpha_n, P}) \leq C \alpha_n^{-\beta}.$$

The above computations (leading to equation (4.4)) imply that there exists D_1 such that if $|\epsilon - \epsilon'| < \alpha_n^{-D_1}$ we can replace $g_{\alpha_n, \epsilon}$ by $g_{\alpha_n, \epsilon'}$ in the expression of $g_{\alpha_n, P}$ without changing the order of approximation of f_0 by $g_{\alpha_n, P}$. Hence we can assume that the point masses ϵ_j of the support of P satisfy $|\epsilon_j - \epsilon_{j+1}| \geq \alpha_n^{-D_1}$, $j = 0, \dots, N_n$. We can thus construct a partition of $[\epsilon_0/2, 1 - \epsilon_0/2]$, namely U_0, \dots, U_{N_n} with $\epsilon_j \in U_j$ and $\text{Leb}(U_j) \geq 2^{-1} \alpha_n^{-D_1}$ for all $j = 1, \dots, N_n$, where Leb denotes the Lebesgue measure. Let $\rho > 0$ and P_1 be any probability on $[0, 1]$ satisfying

$$(4.5) \quad |P_1(U_j) - p_j| \leq p_j \alpha_n^{-\rho}, \quad \forall j = 0, \dots, N_n$$

Then $P_1[\epsilon_0/2, (1 - \epsilon_0/2)] \geq 1 - \alpha_n^{-\rho}$. Since

$$g_{\alpha_n, P_1}(x) \geq \tilde{g}_{n, P_1} = \int_{\epsilon_0/2}^{1-\epsilon_0/2} g_{\alpha_n, \epsilon}(x) dP_1(\epsilon),$$

and using (4.1) we obtain

$$\text{KL}(f_0, g_{\alpha_n, P_1}) \leq C\alpha_n^{-\beta} + \int f_0(x) \log(g_{\alpha_n, P}(x)/\tilde{g}_{n, P_1}(x)) dx.$$

Set $\rho \geq \beta$, then similarly to before we obtain inequality (4.2) with \tilde{g}_{n, P_1} instead of $g_{\alpha_n, P'}$. When $x \leq e^{-\beta_0 \alpha_n}$ we use the calculations leading to equation (4.4) replacing $g_{\alpha_n, P'}$ with \tilde{g}_{n, P_1} since the ϵ 's that are contained in the mixing distribution of \tilde{g}_{n, P_1} belong to $(\epsilon_0/2, 1 - \epsilon_0/2)$, which finally leads to (4.4) between $g_{\alpha_n, P}$ and \tilde{g}_{n, P_1} . To bound $\int_0^1 f_0(x) \left| \log \left(\frac{f_0(x)}{g_{\alpha_n, P_1}(x)} \right) \right|^p dx$, note first that

$$g_{\alpha_n, P_1}(x) - \tilde{g}_{n, P_1}(x) \leq P_1[0, \epsilon_0] C \sqrt{\alpha_n} (x(1-x))^{-1} \leq C\alpha_n^{-\rho+1/2} (x(1-x))^{-1}.$$

For symmetry reasons we work on $[0, 1/2]$ and we split $[0, 1/2]$ into $[0, e^{-\beta_0 \alpha_n}]$ $[e^{-\beta_0 \alpha_n}, \epsilon_0]$ $[\epsilon_0, 1/2]$. Since

$$g_{\alpha_n, P}(x) \geq g_{\alpha_n, f_1} - |g_{\alpha_n, f_1} - g_{\alpha_n, P}| \geq \frac{f_0(x)}{4} - \frac{C\alpha_n^{-H}}{x(1-x)}, \quad \forall H > 0$$

when $x \in (\epsilon_0, 1/2)$ we have $g_{\alpha_n, P}(x) \geq cf_0(x)$ since $f_0(x) \geq C_0 x^{k_0}$ near the origin, for some positive constant c . Hence combining the above inequality with (4.2) based on $g_{\alpha_n, P}$ and \tilde{g}_{n, P_1} , we obtain that

$$\begin{aligned} \frac{C\alpha_n^{-\rho+1/2}}{\tilde{g}_{n, P_1}(x)x(1-x)} &\leq C \frac{\alpha_n^{-\rho+1/2}}{f_0(x)x(1-x)} \\ &\leq C\alpha_n^{-\rho+1/2+(k_0+1)t_0} \\ &= 0(\alpha_n^{-\beta/p}) \quad \text{if } x \in (\epsilon_0, 1/2) \quad \rho \geq \beta/p + 1/2 + (k_0 + 1)t_0 \end{aligned}$$

Moreover (4.2) implies also that for all $x \in (e^{-\beta_0 \alpha_n}, \alpha_n^{-t_0})$

$$\tilde{g}_{n, P_1} \geq g_{\alpha_n, P}(x)/2 \geq (x/\epsilon_0)^{\alpha_n} \frac{C\sqrt{\alpha_n}F_0(\epsilon_0)}{x(1-x)},$$

leading to

$$\begin{aligned} \log \left(1 + \frac{g_{\alpha_n, P_1}(x) - \tilde{g}_{n, P_1}(x)}{\tilde{g}_{n, P_1}(x)} \right) &\leq \log \left(1 + \frac{C\alpha_n^{-\rho+1/2}\epsilon_0^{\alpha_n-k_0-1}}{x^{\alpha_n}\sqrt{\alpha_n}} \right) \\ &\leq C\alpha_n |\log(x)|, \quad \forall x \in (e^{-\beta_0 \alpha_n}, \alpha_n^{-t_0}). \end{aligned}$$

Also, if $x < e^{-\beta_0 \alpha_n}$, using similar calculations to those used in deriving (4.3) we obtain

$$\tilde{g}_{n,P_1} \geq CP_1([\epsilon_0, 1/2]) \frac{\sqrt{\alpha_n}}{x(1-x)} e^{2\alpha_n \log(x)}$$

and

$$\log \left(1 + \frac{g_{\alpha_n, P_1}(x) - \tilde{g}_{n, P_1}(x)}{\tilde{g}_{n, P_1}(x)} \right) \leq C\alpha_n |\log(x)|, \quad \forall x < e^{-\beta_0 \alpha_n}.$$

Finally we obtain

$$\begin{aligned} \int_0^1 f_0(x) \left| \log \left(\frac{f_0(x)}{g_{\alpha_n, P_1}(x)} \right) \right|^p dx &\leq 0(\alpha_n^{-\beta}) + \int_0^1 f_0(x) \left| \log \left(\frac{\tilde{g}_{n, P_1}(x)}{g_{\alpha_n, P_1}(x)} \right) \right|^p dx \\ &\leq \alpha_n^{-t_0+p} (\log \alpha_n)^p + 0(\alpha_n^{-\beta}) = 0(\alpha_n^{-\beta}) \end{aligned}$$

whenever $t_0 > \beta + p$, which implies $\rho > \beta/p + 1/2 + (\beta + p)(k_0 + 1)$.

Under the Dirichlet I prior, $(P_1(U_0), P_1(U_1), \dots, P_1(U_{N_n}))$ follows a Dirichlet $(\nu(U_0), \nu(U_1), \dots, \nu(U_{N_n}))$ with U_0 being the complementary set of $(U_1 \cup \dots \cup U_{N_n})$. Using the fact that $\nu(U_j) \geq C\alpha_n^{-T_1 D_1}$ for all j we obtain that there exist $D_2, C_2 > 0$ such that

$$\pi(S_n) \geq \exp\{-D_2 N_n \log(\alpha_n)\} \geq e^{-C_2 N_0 \sqrt{\alpha_n} (\log \alpha_n)^{5/2}}.$$

The above inequality can be derived for instance from Lemma A.2 of [4].

We now determine an upper bound on the entropy on some sieve of the support of the prior. We first consider the Type I prior. Let $\epsilon_0 = \exp\{-a\sqrt{\alpha_n}(\log \alpha_n)^{5/2}\}$, and define

$$\mathcal{F}_n = \{P = \sum_{j=1}^k p_j g_{\alpha_n, \epsilon_j}; k \leq k_1 \alpha_n^{1/2} (\log \alpha_n)^{5/2}; \epsilon_j \in (\epsilon_0, 1 - \epsilon_0) \forall j\}.$$

Then if $b > 0$

$$\begin{aligned} \pi(\mathcal{F}_n^c) &\leq \pi(k > k_1 \alpha_n^{1/2} (\log \alpha_n)^{3/2}) + k_1 \alpha_n^{1/2} (\log \alpha_n)^{3/2} \epsilon_0^{(T+1)} \\ &\leq e^{-b\sqrt{\alpha_n} (\log \alpha_n)^{5/2}}, \end{aligned}$$

as soon as k_1 and a are large enough.

Let $k \leq \tilde{k}_n = k_1 \alpha_n^{1/2} (\log \alpha_n)^{3/2}$ be fixed and $g_{\alpha_n, P}$ be a Beta mixture with k components. When $|\epsilon'_j - \epsilon_j| \leq \delta \alpha_n^{-2\beta-2} \epsilon_j (1 - \epsilon_j)$ for all $j \leq k$ and $|p_j - p'_j| \leq \alpha_n^{-\beta-1}$, if $|x - \epsilon_j| \leq \epsilon_j (1 - \epsilon_j) M_n$ then Lemma B.1 implies

$$|g_{\alpha_n, \epsilon'_j} - g_{\alpha_n, \epsilon_j}| \leq g_{\alpha_n, \epsilon_j} C \alpha_n^{-2\beta-2} \sqrt{\log \alpha_n}$$

and if $|x - \epsilon_j| > \epsilon_j(1 - \epsilon_j)M_n$ then $|x - \epsilon'_j| > \epsilon_j(1 - \epsilon_j)\frac{M_n}{2}$ and the convexity of $x \rightarrow K(\epsilon, x)$ for all ϵ , together with equation (3.4) implies

$$|g_{\alpha_n, \epsilon'_j} + g_{\alpha_n, \epsilon_j}| \leq C \frac{\alpha_n}{x(1-x)} e^{-M^2 \log \alpha_n / 12}.$$

Let $x_n = \epsilon_0$

$$\int_{x_n/2}^{1-x_n/2} |g_{\alpha_n, \epsilon'_j} - g_{\alpha_n, \epsilon_j}|(x) dx \leq C \alpha_n^{-\beta} + C \alpha_n e^{-cM^2 \log \alpha_n} (\log \alpha_n)^{3/2},$$

and if M is large enough the above term is $0(\alpha_n^{-\beta})$. Now if $x < x_n/2 \leq \epsilon_0/2$ then since $\epsilon > \epsilon_0 \geq 2x_n$ we use (A.5) together with $\epsilon - x > \epsilon/2$ and obtain

$$g_{\alpha_n, \epsilon}(x) \leq \frac{C\sqrt{\alpha_n}}{x(1-x)} \left(\frac{2x}{x+\epsilon} \right)^{\frac{\alpha_n \epsilon}{2\epsilon(1-\epsilon)}} \leq C\sqrt{\alpha_n} \epsilon^{-\frac{\alpha_n(\epsilon/2)}{2}} (2x)^{\frac{\alpha_n}{2(1-\epsilon)}-1},$$

which implies that

$$\begin{aligned} \int_0^{x_n/2} g_{\alpha_n, \epsilon}(x) dx &\leq C \alpha_n^{-1/2} (1-\epsilon) \epsilon^{-\frac{\alpha_n}{2(1-\epsilon)}} (x_n)^{\frac{\alpha_n}{2(1-\epsilon)}} \\ (4.6) \quad &\leq C \alpha_n^{-1/2} (1-\epsilon) 2^{-\frac{\alpha_n}{2(1-\epsilon)}} = 0(\alpha_n^{-H}), \quad \forall H > 0. \end{aligned}$$

By symmetry the same bound is obtained for the integral over $(1 - x_n/2, 1)$ and we finally obtain for all $j \leq k$,

$$(4.7) \quad \int_0^1 |g_{\alpha_n, \epsilon_j} - g_{\alpha_n, \epsilon'_j}|(x) dx = 0(\alpha_n^{-\beta}).$$

Hence

$$\begin{aligned} \int_0^1 |g_{\alpha_n, P} - g_{\alpha_n, P'}|(x) dx &\leq \sum_{j=1}^k |p_j - p'_j| + p_j \int_0^1 |g_{\alpha_n, \epsilon_j} - g_{\alpha_n, \epsilon'_j}|(x) dx \\ &= 0(\alpha_n^{-\beta}). \end{aligned}$$

The number of balls with radii $\delta_1 \alpha_n^{-\beta}$ needed to cover the set \mathcal{S}_k is bounded by

$$C^k \alpha_n^{-k\beta}$$

The number of balls with radii $\epsilon_j(1 - \epsilon_j) \alpha_n^{-\beta} \delta_0$ needed to cover $(\epsilon_0, 1 - \epsilon_0)$

$$(a \alpha_n^{\beta+1/2} (\log \alpha_n)^{5/2})^k$$

Finally the metric entropy is bounded by

$$\mathcal{J}_n(\tau_n) \leq 3k_n \beta \log \alpha_n \leq 3k_1 \beta \sqrt{\alpha_n} (\log \alpha_n)^{5/2} \leq C n \tau_n^2.$$

To bound the entropy in the case of the Dirichlet I prior we use the approximation of a general mixture by a discrete finite mixture. First consider

$$\mathcal{F}'_n = \{F; F[\epsilon_0, 1 - \epsilon_0] > 1 - \alpha_n^{-\beta}\}.$$

When F follows a Dirichlet ν process, $F[0, \epsilon_0]$ and $F[1 - \epsilon_0, 1]$ are Beta random variables with parameters $(\nu[0, \epsilon_0], \nu[\epsilon_0, 1])$ and $(\nu[1 - \epsilon_0, 1], \nu[0, 1 - \epsilon_0])$ respectively. Therefore

$$\pi((\mathcal{F}'_n)^c) \leq \alpha_n^\beta \left[\frac{\nu[0, \epsilon_0]}{\nu[0, 1]} + \frac{\nu[1 - \epsilon_0, 1]}{\nu[0, 1]} \right] \leq C \alpha_n^\beta \exp\{-a\sqrt{\alpha_n}(\log \alpha_n)^{5/2}\}.$$

For all $F \in \mathcal{F}'_n$ define F_n the renormalized restriction of F on $[\epsilon_0, 1 - \epsilon_0]$. Then

$$\|g_{\alpha_n, F_n} - g_{\alpha_n, F}\|_1 \leq 2\alpha_n^{-\beta}.$$

We can therefore assume that $F[\epsilon_0, 1 - \epsilon_0] = 1$ for all $F \in \mathcal{F}'_n$. Then there exists a discrete probability

$$(4.8) \quad P(\epsilon) = \sum_{j=1}^{N_n} p_j \delta_{\epsilon_j}(\epsilon), \quad \epsilon_j \in (\epsilon_0, 1 - \epsilon_0) \quad \forall j$$

with $N_n \leq N_0 \sqrt{\alpha_n} (\log \alpha_n)^{3/2}$ such that (3.17) is satisfied for F and we have for all H (depending on N_0)

$$(4.9) \quad \left| \int_0^1 g_{\alpha, \epsilon}(x) [dF - dP](\epsilon) \right| \leq \frac{C \alpha_n^{-H}}{x(1-x)}.$$

Moreover (4.6) implies that

$$\begin{aligned} \int_0^{\epsilon_0/2} |g_{\alpha_n, F} - g_{\alpha_n, P}|(x) dx &\leq \int_{\epsilon_0}^{1-\epsilon_0} [dF(\epsilon) + dP(\epsilon)] \left(\int_0^{\epsilon_0/2} g_{\alpha_n, \epsilon}(x) dx \right) \\ &\leq \alpha_n^{-H}, \end{aligned}$$

for all $H > 0$. Finally for all $H > 0$ there exists $N_0 > 0$ and a probability measure P defined by (4.8) with $N_n = N_0 \sqrt{\alpha_n} (\log \alpha_n)^{3/2}$ such that

$$\|g_{\alpha_n, F} - g_{\alpha_n, P}\|_1 \leq \alpha_n^{-H}.$$

The above calculations to obtain the metric entropy associated to the type I prior imply that the set of discrete probabilities satisfying (4.8) can be covered using balls in the form :

$$B(P) = \{P'(\epsilon) = \sum_{j=1}^{N_n} p'_j \delta_{\epsilon'_j}(\epsilon); |\epsilon'_j - \epsilon_j| \leq \delta \alpha_n^{-2\beta-2} \epsilon_j (1 - \epsilon_j); |p_j - p'_j| \leq \alpha_n^{-\beta-1}\}$$

The number of such balls is bounded by $(C\alpha_n^{-2\beta-2}|\log \epsilon_0|)^{2N_n}$. Since for all $F, F' \in \mathcal{F}'_n$ there exist P, P' defined by (4.8) such that

$$\|g_{\alpha_n, F} - g_{\alpha_n, F'}\|_1 \leq \alpha_n^{-H} + \|g_{\alpha_n, P} - g_{\alpha_n, P'}\|_1$$

The L_1 entropy is bounded by:

$$\mathcal{J}_n(\mathcal{F}'_n, \alpha_n^{-\beta}) \leq C\sqrt{\alpha_n}(\log \alpha_n)^{5/2},$$

which achieves the proof of Theorem 2.1.

4.2. Proof of Theorem 2.2. We use Theorem 5 of [5] to prove this Theorem. Since

$$\pi_a[a_1 n^{2/(2\beta+1)}(\log n)^{-5/(2\beta+1)}, a_2 n^{2/(2\beta+1)}(\log n)^{-5/(2\beta+1)}] \geq \exp\{-b_1 n^{1/(2\beta+1)} \log n^{5\beta/(2\beta+1)}\},$$

we can consider $\alpha \in [a_1 n^{2/(2\beta+1)}(\log n)^{-5/(2\beta+1)}, a_2 n^{2/(2\beta+1)}(\log n)^{-5/(2\beta+1)}]$ in the determination of a lower bound for $\pi(B^*(f_0, \tau_n, p))$ so that the first part of the proof of Theorem 2.1 applies here, leading to

$$\pi(B^*(f_0, \tau_n, p)) \geq e^{-c_0 n^{1/(2\beta+1)}(\log n)^{5\beta/(2\beta+1)}}, \quad \text{for some } c_0 > 0.$$

We now bound the L_1 metric entropy on $\mathcal{F}_{n,a}$ defined by

$$\mathcal{F}_{n,a} = \left\{ (P, \alpha); k \leq k'_n, e^{-n^{1/(2\beta+1)}(\log n)^{5\beta/(2\beta+1)}} \leq \alpha \leq \alpha_0 n^{2/(2\beta+1)}(\log n)^{10\beta/(2\beta+1)}; \epsilon_j > \epsilon_0, \forall j \right\}$$

with $\alpha_0, c > 0$, $k'_n = k'_1 n^{1/(2\beta+1)}(\log n)^{\beta-1/(2\beta+1)}$ and ϵ_0 is defined by

$$\epsilon_0 = \exp\{-a n^{1/(2\beta+1)}(\log n)^{5\beta/(2\beta+1)}\}$$

Since π_a is bounded, for all $c > 0$,

$$\pi(\mathcal{F}_{n,a}^c) \leq e^{-cn\tau_n^2}.$$

To bound the entropy on $\mathcal{F}_{n,a}$ we use Lemma C.1 with the following parameterisation: Write $a = \alpha/(1-\epsilon)$, $a' = \alpha'/(1-\epsilon')$, $b = \alpha/\epsilon$ and $b' = \alpha'/\epsilon'$ and consider $\rho > 0$ small enough, then if $|a' - a| \leq \tau_1 < a$ and $|b' - b| \leq \tau_2 < b$,

$$g_{\alpha', \epsilon'}(x) \leq \frac{x^{a-\tau_1-1}(1-x)^{b-\tau_2-1}}{B(a-\tau_1, b-\tau_2)} \frac{B(a-\tau_1, b-\tau_2)}{B(a', b')},$$

so that

$$\frac{B(a-\tau_1, b-\tau_2)}{B(a', b')} \leq 1 + \tau_n \Rightarrow |g_{\alpha', \epsilon'} - g_{\alpha, \epsilon}| \leq \tau_n.$$

Consider first $\alpha < 2\epsilon \wedge (1 - \epsilon)$. If

$$(4.10) \quad |\epsilon - \epsilon'| \leq \rho\tau_n\epsilon(1 - \epsilon), \quad |\alpha - \alpha'| \leq \rho\tau_n\alpha$$

then using case (i) of Lemma C.1 and simple algebra we obtain

$$|g_{\alpha', \epsilon'} - g_{\alpha, \epsilon}| \leq 4\rho\tau_n.$$

We now consider the α, ϵ 's such that $2(1 - \epsilon) < \alpha < 2\epsilon$. If

$$(4.11) \quad |\epsilon - \epsilon'| \leq \rho \frac{\tau_n\epsilon(1 - \epsilon)}{\log(\alpha/(1 - \epsilon))}, \quad |\alpha - \alpha'| \leq \frac{\alpha\rho\tau_n}{\log(\alpha/(1 - \epsilon))}$$

then using case (ii) of Lemma C.1 and simple algebra we obtain

$$|g_{\alpha', \epsilon'} - g_{\alpha, \epsilon}| \leq 2\rho'\tau_n,$$

for some $\rho' > 0$. Last we consider the case where $\alpha > 2\epsilon \vee (1 - \epsilon)$. If

$$(4.12) \quad |\epsilon - \epsilon'| \leq \frac{\rho\tau_n\epsilon^2(1 - \epsilon)^2}{\log(\alpha/\epsilon(1 - \epsilon))}, \quad |\alpha - \alpha'| \leq \frac{\rho\epsilon(1 - \epsilon)\tau_n}{\alpha \log(\alpha/\epsilon(1 - \epsilon))}$$

then case (iv) of Lemma C.1 implies

$$|g_{\alpha', \epsilon'} - g_{\alpha, \epsilon}| \leq 2\rho'\tau_n,$$

for some $\rho' > 0$. Therefore the number of intervals in α needed to cover $(e^{-n^{1/(2\beta+1)}(\log n)^{5\beta/(2\beta+1)}} \leq \alpha \leq \alpha_0 n^{2/(2\beta+1)}(\log n)^{10\beta/(2\beta+1)})$ is bounded by

$$J_1 \leq Cn^D \epsilon_1^{-1} \leq Cn^D e^{(a+1)n^{1/(2\beta+1)}(\log n)^{5\beta/(2\beta+1)}},$$

where C, D are positive constants. We now consider the entropy associated with the supporting points of P . The most restrictive relation is (4.12).

Let $\epsilon_{n,j} = \epsilon_0^{1/j}$, $j = 1, \dots, J$ with

$$J = \frac{an^{1/(2\beta+1)}(\log n)^{5\beta/(2\beta+1)}}{t \log n} = \frac{ak'_n}{k'_1 t},$$

so that $\epsilon_{n,J} = n^{-t}$. Let $P = \sum_{i=1}^k p_i g_{\alpha, \epsilon_i}$ and $N_{n,j}(P)$ be the number of points in the support of P belonging to $(\epsilon_{n,j}, \epsilon_{n,j+1})$.

The number of intervals following relation (4.12) needed to cover $(\epsilon_{n,j}, \epsilon_{n,j+1})$ is bounded by

$$J_{n,j} = \frac{[\log(\epsilon_{n,j+1}) - \log(\epsilon_{n,j})]n^{D_1}}{\epsilon_{n,j}}$$

for some positived constant D_1 independent of t . Then number of intervals following relation (4.12) needed to cover $(n^{-t}, 1/2)$ is bounded by $J_{n,J+1} = n^{t+1}(\log n)^q$ for some positive contant q . For simplicity's sake we consider $D_1 = D_2$. We index the interval $(n^{-t}, 1/2)$ by $J+1$. Consider a configuration σ in the form $N_{n,j}(P) = k_j$, for $j = 1, \dots, J+1$ where $\sum_j k_j = k \leq k'_n$ and define $\mathcal{F}_{n,a}(\sigma) = \{P \in \mathcal{F}_{n,a}; N_{n,j}(P) = k_j, j = 1, \dots, J+1\}$. For each configuration the number of balls needed to cover $\mathcal{F}_{n,a}(\sigma)$ is bounded by $J_n(\sigma) = \prod_{j=1}^{J+1} J_{n,j}^{k_j}$. Moreover the prior probability of $\mathcal{F}_{n,a}(\sigma)$ is bounded by

$$\pi(\mathcal{F}_{n,a}(\sigma)) \leq \Gamma(k+1) \prod_{j=1}^{J+1} \frac{p_{n,j}^{k_j}}{\Gamma(k_j+1)}, \quad p_{n,j} \leq c[\epsilon_{n,j+1}^{T+1} - \epsilon_{n,j}^{T+1}], j \leq J$$

for some positive constant $c > 0$ and $p_{n,J+1} \leq 1$. We therefore obtain when $T \geq 1$ and $t > 2$

$$\begin{aligned} \Delta_n &= \sum_{\sigma} \sqrt{\pi(\mathcal{F}_{n,a}(\sigma))} \sqrt{J_n(\sigma)} \\ &\leq \Gamma(k+1)^{1/2} \sum_{\sigma} \frac{n^{(t+1)k_{J+1}/2}}{\Gamma(k_{J+1}+1)^{1/2}} \prod_{j=1}^J (Cn^{D_1})^{k_j/2} \frac{\epsilon_{n,j+1}^{(T+1)k_j/2}}{\epsilon_{n,j}^{k_j/2} \Gamma(k_j+1)^{1/2}} \\ &\quad \times [\log(\epsilon_{n,j+1}) - \log(\epsilon_{n,j})]^{k_j/2} \left[1 - \frac{\epsilon_{n,j}^{T+1}}{\epsilon_{n,j+1}^{T+1}} \right]^{k_j/2} \end{aligned}$$

Since

$$\prod_{j=1}^J \Gamma(k_j+1)^{1/2} \leq \exp(k \log(k+1)) \leq e^{k \log(n)}$$

if $tT > 6$ we have

$$\begin{aligned} \Delta_n &\leq C^k n^{kD_1} \Gamma(k+1)^{1/2} \sum_{\sigma} \prod_{j=1}^J \frac{\exp\left\{-\frac{ak_j k'_n \log n [Tj-2]}{2k'_1 j(j+1)}\right\}}{\Gamma(k_j+1)^{1/2}} \\ &\leq C^k n^{kD_1} \Gamma(k+1)^{1/2} \sum_{\sigma} \prod_{j=1}^J \frac{\exp\left\{-\frac{tTk_j \log n}{3}\right\}}{\Gamma(k_j+1)^{1/2}} \\ &\leq C^k n^{k(D_1+t/2+1/2)} \Gamma(k+1)^{1/2} \exp\left\{-\frac{tTk \log n}{6}\right\} \sum_{\sigma} \prod_{j=1}^J \frac{1}{\Gamma(k_j+1)} \\ &\leq C^k n^{k(D_1+t/2+1/2)} \Gamma(k+1)^{-1/2} \exp\left\{-\frac{tTk \log n}{6}\right\} e^{k \log(J)} \leq e^{k(D_1-Tt/6+t/2+1/2) \log n} \end{aligned}$$

Hence by choosing $\tau_n = \tau_0 n^{\beta/(2\beta+1)} (\log n)^{5\beta/(4\beta+2)}$ with τ_0 large enough the above term multiplied by $e^{-n\tau_n^2}$ goes to 0 with n , which achieves the proof.

APPENDIX A: PROOF OF LEMMA 3.2

Throughout the proof C denotes a generic constant. Let

$$I_0(x) = g_\alpha(x) - 1 = \int_0^1 g_{\alpha,\epsilon}(x) d\epsilon - 1$$

The aim is to approximate I_0 with an expansion of terms in the form $Q_j(x)\alpha^{-j/2}$ where Q_j is a polynomial function. The idea is to split the integral into three part, I_1, I_2, I_3 corresponding to $\epsilon < x - \delta_x$, $\epsilon > x + \delta_x$ and $|x - \epsilon| < \delta_x$ where $\delta_x = \delta_0 x(1-x)\sqrt{\log(\alpha)}/\alpha$, for some well chosen $\delta_0 > 0$. Note that this choice of δ_x comes from the approximation of the Beta density with a Gaussian with mean x and variance $x^2(1-x)^2/\alpha$. We first prove that the first two parts are very small and the expansion is obtained from the third term. By convexity of $K(\epsilon, x)$ as a function of ϵ , $K(\epsilon, x) \geq K(x - \delta_x, x)$ for all $\epsilon < x - \delta_x$ and $K(\epsilon, x) \geq K(x + \delta_x, x)$ for all $\epsilon > x + \delta_x$. Moreover

$$\begin{aligned} K(x - \delta_x, x) &= x \left(1 - \frac{\delta_0(1-x)\sqrt{\log(\alpha)}}{\sqrt{\alpha}} \right) \log \left(1 - \frac{\delta_0(1-x)\sqrt{\log(\alpha)}}{\sqrt{\alpha}} \right) \\ &\quad + (1-x) \left(1 + x \frac{\delta_0\sqrt{\log(\alpha)}}{\sqrt{\alpha}} \right) \log \left(1 + x \frac{\delta_0\sqrt{\log(\alpha)}}{\sqrt{\alpha}} \right) \\ &= \frac{\delta_0^2 \log(\alpha) x(1-x)}{2\alpha} + 0 \left(x(1-x) \left(\frac{\log(\alpha)}{\alpha} \right)^{3/2} \right) \end{aligned}$$

uniformly in x . Using a similar argument on $K(x + \delta_x, x)$ we finally obtain when α is large enough

$$(A.1) \quad K(x - \delta_x, x) \geq \frac{\delta_x^2}{3x(1-x)}, \quad K(x + \delta_x, x) \geq \frac{\delta_x^2}{3x(1-x)}.$$

Set

$$I_1(x) = \int_0^{x-\delta_x} g_{\alpha,\epsilon}(x) d\epsilon.$$

First we consider $x \leq 1/2$, then using (3.4) and the fact that if α is large enough, the term in the square brackets in (3.4) with $k = 1$ is bounded by 2, uniformly in ϵ , we obtain that

$$I_1(x) \leq \frac{2\sqrt{\alpha}}{\sqrt{2\pi}x(1-x)} \int_0^{x-\delta_x} e^{-\frac{\delta_0^2 x(1-x)\log \alpha}{3\epsilon(1-\epsilon)}} d\epsilon.$$

Let $\rho = (\delta_0^2 x(1-x)\log \alpha)/6$ then

$$(A.2) \quad I_1(x) \leq \frac{2\sqrt{\alpha}}{\sqrt{2\pi}} e^{-\rho/(x-\delta_x)} \leq C\sqrt{\alpha} e^{-\delta_0^2 \log \alpha / 6}.$$

Now we consider $x > 1/2$, for which we use another type of upper bound: we split the interval $(0, x - \delta_x)$ into $(0, x(1 - \delta))$ and $(x(1 - \delta), x - \delta_x)$ for some well chosen positive constant δ . For all $\epsilon < x(1 - \delta)$, $K(\epsilon, x) \geq K(x(1 - \delta), x)$. Since $u \log(u)$ goes to zero when u goes to zero, there exists $\delta_1 > 0$ such that for all $x > 1/2$, and all $\delta_1 < \delta < 1$,

$$\begin{aligned} K(x(1 - \delta), x) &= x(1 - \delta) \log(1 - \delta) + (1 - x + \delta x) \log\left(1 + \frac{\delta x}{1 - x}\right) \\ &\geq \delta^2 x \log\left(1 + \frac{\delta x}{1 - x}\right). \end{aligned}$$

Therefore using (3.4) and the same bound on the square brackets term in (3.4) as in the case $x \leq 1/2$ we obtain that if $x > 1/2$,

$$\begin{aligned} \int_0^{x(1-\delta)} g_{\alpha, \epsilon}(x) d\epsilon &\leq \frac{\sqrt{\alpha}}{\sqrt{2\pi x(1-x)}} \int_0^{x(1-\delta)} \left(1 + \frac{\delta}{2(1-x)}\right)^{-\frac{\alpha \delta^2}{2\epsilon(1-\epsilon)}} d\epsilon \\ &\leq \frac{C\sqrt{\alpha}}{(1-x)} \left(1 + \frac{\delta}{2(1-x)}\right)^{-\alpha \delta^2/2} \\ (A.3) \quad &\leq C\alpha^{-H}, \quad \forall H > 0 \end{aligned}$$

We now study the integral over $(x(1 - \delta), x - \delta_x)$. We use the following lower bound on $K(\epsilon, x)$: a Taylor expansion of $K(\epsilon, x)$ as a function of ϵ around x leads to

$$\begin{aligned} K(\epsilon, x) &= \epsilon \log\left(\frac{\epsilon}{x}\right) + (1 - \epsilon) \log\left(\frac{1 - \epsilon}{1 - x}\right) \\ &= (\epsilon - x)^2 \int_0^1 \frac{(1 - u)}{(x + u(\epsilon - x))(1 - x - u(\epsilon - x))} du \\ &\geq \frac{(\epsilon - x)^2}{2} \int_0^{1/2} \frac{1}{(1 - x + u(x - \epsilon))} du \\ (A.4) \quad &= \frac{(x - \epsilon)}{2} (\log(1 - x/2 - \epsilon/2) - \log(1 - x)). \end{aligned}$$

Let $u = x - \epsilon$ and note that the function $u \rightarrow u/(x - u)(1 - x + u)$ is increasing so that then when α is large enough, uniformly in x ,

$$\begin{aligned} g_{\alpha, \epsilon}(x) &\leq \frac{2\sqrt{\alpha}}{\sqrt{2\pi x(1-x)}} \left(\frac{1 - x + u/2}{1 - x}\right)^{-\frac{\alpha u}{2(x-u)(1-x+u)}} \\ &\leq \frac{2\sqrt{\alpha}}{\sqrt{2\pi x(1-x)}} \left(\frac{1 - x + u/2}{1 - x}\right)^{-\frac{\alpha \delta}{2(1-\delta)(1-x+\delta x)}} \end{aligned}$$

for all $u \in (\delta_x, \delta x)$. Thus if α large enough and $x > 1/2$

$$\begin{aligned} \int_{x(1-\delta)}^{x-\delta_x} g_{\alpha,\epsilon}(x) d\epsilon &\leq \frac{2\sqrt{\alpha}}{\sqrt{2\pi}x(1-x)} \int_{\delta_x}^{\delta x} \left(1 + \frac{u}{2(1-x)}\right)^{-\frac{\alpha\delta}{2(1-\delta)(1-x+\delta x)}} \\ &\leq \frac{8\sqrt{\alpha}}{\sqrt{2\pi}} \frac{1}{\frac{\alpha\delta}{2(1-\delta)(1-x+\delta x)} - 1} \left(1 + \frac{\delta_x}{2(1-x)}\right)^{-\frac{\alpha\delta}{2(1-\delta)(1-x+\delta x)}} \\ &\leq \frac{C}{\sqrt{\alpha}} e^{-\frac{\delta\delta_0\sqrt{\alpha}\sqrt{\log(\alpha)}}{2(1-\delta)}} = o(\alpha^{-H}), \end{aligned}$$

for any $H > 0$. Finally, the above inequality, together with (A.3) for $x > 1/2$ and with (A.2) for $x \leq 1/2$ imply that

$$I_1(x) = 0(\alpha^{-H}),$$

for all $H > 0$ by choosing δ_0 large enough. We now consider the integral over $(x + \delta_x, 1)$

$$I_2(x) = \int_{x+\delta_x}^{x(1+\delta)} g_{\alpha,\epsilon}(x) d\epsilon + \int_{x(1+\delta)}^1 g_{\alpha,\epsilon}(x) d\epsilon$$

First let $x \leq 1/2$ then when $\epsilon \in (x + \delta_x, x(1 + \delta))$ with δ small enough we can use (3.6) and

$$\int_{x+\delta_x}^{x(1+\delta)} g_{\alpha,\epsilon}(x) d\epsilon \leq 2e^{-\delta_0^2 \log \alpha / 2}$$

When $\epsilon \in (x(1 + \delta), 1)$, a Taylor expansion of $K(\epsilon, x)$ as a function of ϵ around x leads to

$$\begin{aligned} K(\epsilon, x) &= (\epsilon - x)^2 \int_0^1 \frac{(1-u)}{(x+u(\epsilon-x))(1-x-u(\epsilon-x))} du \\ &\geq \frac{(\epsilon-x)^2}{2} \int_0^{1/2} \frac{1}{(x+u(\epsilon-x))} du \\ (A.5) \quad &= \frac{(\epsilon-x)}{2} (\log((x+\epsilon)/2) - \log x). \end{aligned}$$

Thus letting $u = \epsilon - x$ and noting that $\epsilon(1-\epsilon) \leq x+u$ and that $u/(x+u) \geq \delta/(1+\delta)$ as soon as $u > \delta x$, we obtain

$$\begin{aligned} \int_{x(1+\delta)}^1 g_{\alpha,\epsilon}(x) d\epsilon &\leq \frac{C\sqrt{\alpha}}{x} \int_{\delta x}^{1-x} \left(\frac{2x}{2x+u}\right)^{\alpha\delta/(2(1+\delta))} du \\ &\leq 2C\alpha^{-1/2} \left(1 + \frac{\delta}{2}\right)^{-\alpha\frac{\delta}{2(1+\delta)}+1}. \end{aligned}$$

If $x > 1/2$ and $\epsilon > x + \delta_x$, by symmetry, we obtain the same result as in the case $x \leq 1/2$ and $\epsilon < x - \delta_x$ changing x into $1 - x$. Finally choosing δ_0 large enough we prove that for all $x \in [0, 1]$,

$$(A.6) \quad I_1(x) + I_2(x) = o(\alpha^{-H})$$

(H depending on δ_0). We now study the latter term, $I_3(x)$. Using (3.6), and the fact that

$$\begin{aligned} |R(x, \epsilon)| &\leq R\alpha^{k_2+1}|x - \epsilon|^{3(k_2+1)}(x_\epsilon(1 - x_\epsilon))^{-3(k_2+1)} \\ &\leq R'\alpha^{k_2+1}|x - \epsilon|^{3(k_2+1)}(x(1 - x))^{-3(k_2+1)} \\ &\leq R'\alpha^{-(k_2+1)/2}(\log \alpha)^{3(k_2+1)/2} \end{aligned}$$

when $\epsilon \in (x - \delta_x, x + \delta_x)$, we obtain, for all $k_2 \geq 1, k_1 \geq 3(k_2 - 1)$,

$$\begin{aligned} I_3(x) &= \int_{x-\delta_x}^{x+\delta_x} g_{\alpha, \epsilon} d\epsilon - 1 \\ &= \frac{\sqrt{\alpha}}{\sqrt{2\pi}x(1-x)} \int_{x-\delta_x}^{x+\delta_x} e^{-\frac{\alpha(x-\epsilon)^2}{2x^2(1-x)^2}} \left(1 + \sum_{j=1}^{k_2} \frac{\alpha^j (x-\epsilon)^{3j}}{j!(x(1-x))^{3j}} \left[C(x) + Q_{k_1+3} \left(\frac{x-\epsilon}{x(1-x)} \right) \right]^j \right) d\epsilon \\ &\quad - 1 + 0(\alpha^{-(k_2+1)/2}(\log \alpha)^{3(k_2+1)/2}) \\ &= \sum_{j=1}^{k_2} \frac{\mu_{3j} C(x)^j}{\alpha^{j/2}} + \sum_{j=1}^{k_2 k_1} \frac{\mu_j B_j(x)}{\alpha^{j/2}} + 0(\alpha^{-(k_2+1)/2}(\log \alpha)^{3(k_2+1)/2}) \\ &= \frac{I(x)}{\alpha} + 0(\alpha^{-(k_2+1)/2}(\log \alpha)^{3(k_2+1)/2}) \end{aligned}$$

choosing δ_0 large enough and since $\mu_1 = 0$, where the B_j 's are polynomial functions of x coming from Q_{k_1} and $C(x)$ and where the remaining term is uniform in x . Lemma 3.2 is proved.

APPENDIX B: LEMMA B.1

LEMMA B.1. *Let $(\delta_n)_n, (\beta_n)_n$ and $(\rho_n)_n$ be positive sequences decreasing to 0 and assume that α_n increases to infinity. Let $1 - \delta_n > \epsilon, \epsilon' > \delta_n$ and $|\epsilon - \epsilon'| \leq \rho_n \epsilon (1 - \epsilon) / \sqrt{\alpha_n}$ then for all $|x - \epsilon| \leq M\epsilon(1 - \epsilon)\sqrt{\log \alpha_n} / \sqrt{\alpha_n}$, if $\rho_n \sqrt{\log \alpha_n}$ goes to 0 as n goes to infinity, for all $k_2, k_3 > 1$*

$$\left| \frac{g_{\alpha_n, \epsilon}(x)}{g_{\alpha_n, \epsilon'}(x)} - 1 \right| \leq C[\rho_n \sqrt{\log \alpha_n} + \alpha_n^{-k_2/2}(\log \alpha_n)^{k_2/2} + \alpha_n^{-k_3}],$$

for n large enough. Also, for all $x \in (\beta_n, 1 - \beta_n)$, if $\alpha_n^{1/2} \rho_n |\log(\beta_n)| \delta_n^{-1} = o(1)$, for n large enough,

$$\left| \frac{g_{\alpha_n, \epsilon}(x)}{g_{\alpha_n, \epsilon'}(x)} - 1 \right| \leq C[\alpha_n^{1/2} \rho_n |\log(\beta_n)| \delta_n^{-1} + \alpha_n^{-k_2/2}(\log \alpha_n)^{-k_2/2} + \alpha_n^{-k_3}].$$

PROOF. (Proof of Lemma B.1)

First let $|x - \epsilon| \leq M\epsilon(1 - \epsilon)\sqrt{\log \alpha_n}/\sqrt{\alpha_n}$, since $|\epsilon - \epsilon'| \leq \rho_n\epsilon(1 - \epsilon)/\sqrt{\alpha_n}$ we have that

$$|x - \epsilon'| \leq \epsilon(1 - \epsilon)\alpha_n^{-1/2}[M\sqrt{\log \alpha_n} + \rho_n] \leq 2M\epsilon(1 - \epsilon)\alpha_n^{-1/2}\sqrt{\log \alpha_n},$$

and

$$\begin{aligned} (x - \epsilon')^l &= (x - \epsilon)^l + (\epsilon - \epsilon') \sum_{i=1}^l C_l^i (\epsilon - \epsilon')^{i-1} (x - \epsilon)^{l-i} \\ &= (x - \epsilon)^l + 0(\alpha_n^{-l/2} \rho_n \epsilon^l (1 - \epsilon)^l (\log \alpha_n)^{(l-1)/2}). \end{aligned}$$

using approximation (3.5), we obtain for any $k_2, k_3 > 0$

$$\begin{aligned} \left| \frac{g_{\alpha_n, \epsilon}}{g_{\alpha_n, \epsilon'}}(x) - 1 \right| &= \left| \exp \left\{ -\frac{\alpha_n(x - \epsilon)^2}{2x^2(1 - x)^2} \left[1 + \frac{(x - \epsilon)}{x(1 - x)} \left(C(x) + Q_{k_1} \left(\frac{x - \epsilon}{x(1 - x)} \right) \right) \right] + R_1(\epsilon) \right\} \times \right. \\ &\quad \exp \left\{ +\frac{\alpha_n(x - \epsilon')^2}{2x^2(1 - x)^2} \left[1 + \frac{(x - \epsilon')}{x(1 - x)} \left(C(x) + Q_{k_1} \left(\frac{x - \epsilon'}{x(1 - x)} \right) \right) \right] + R_1(\epsilon') \right\} \times \\ &\quad \left. \left[1 + \sum_{j=1}^k \frac{b_j(\epsilon)}{\alpha^j} + O(\alpha^{-(k+1)}) \right] \left[1 + \sum_{j=1}^k \frac{b_j(\epsilon')}{\alpha^j} + O(\alpha^{-(k+1)}) \right]^{-1} - 1 \right|. \end{aligned}$$

Then noting that when n is large enough

$$\left| 1 + \frac{(x - \epsilon)}{x(1 - x)} \left(C(x) + Q_{k_1} \left(\frac{x - \epsilon}{x(1 - x)} \right) \right) \right| \leq 2$$

and

$$\alpha_n |\epsilon - \epsilon'| |x - \epsilon| \leq 2x^2(1 - x)^2 \rho_n \alpha_n^{1/2} (\log \alpha_n)^{1/2}$$

we obtain that

$$\begin{aligned} a_n &= \left| \frac{\alpha_n(x - \epsilon)^2}{2x^2(1 - x)^2} \left[1 + \frac{(x - \epsilon)}{x(1 - x)} \left(C(x) + Q_{k_1} \left(\frac{x - \epsilon}{x(1 - x)} \right) \right) \right] \right. \\ &\quad \left. - \frac{\alpha_n(x - \epsilon')^2}{2x^2(1 - x)^2} \left[1 + \frac{(x - \epsilon')}{x(1 - x)} \left(C(x) + Q_{k_1} \left(\frac{x - \epsilon'}{x(1 - x)} \right) \right) \right] \right| \\ &\leq C \left[\rho_n^2 + (\log \alpha_n)^{1/2} \rho_n + (\log \alpha_n) \rho_n \alpha_n^{-1/2} \right] \end{aligned}$$

and finally

$$\left| \frac{g_{\alpha_n, \epsilon}}{g_{\alpha_n, \epsilon'}}(x) - 1 \right| \leq C \rho_n \sqrt{\log \alpha_n} + 0(\alpha_n^{1-k_2/2} \epsilon^{k_2} (1 - \epsilon)^{k_2} (\log \alpha_n)^{k_2/2} + \alpha_n^{-k_3}).$$

Now let $|x - \epsilon| > M\epsilon(1 - \epsilon)\sqrt{\log(\alpha)}/\sqrt{\alpha_n}$ and $x \in (\beta_n, 1 - \beta_n)$, we use equation (3.4) together with the above calculations and the fact that the function $\epsilon \rightarrow \epsilon \log(\epsilon)/(1 - \epsilon)$ is bounded on $[0, 1]$,

$$\begin{aligned} \frac{g_{\alpha_n, \epsilon}(x)}{g_{\alpha_n, \epsilon'}(x)} &= \exp \left\{ -\alpha_n \left[\frac{1}{1 - \epsilon} \log \left(\frac{\epsilon}{x} \right) - \frac{1}{1 - \epsilon'} \log \left(\frac{\epsilon'}{x} \right) \right. \right. \\ &\quad \left. \left. + \frac{1}{\epsilon} \log \left(\frac{1 - \epsilon}{1 - x} \right) - \frac{1}{\epsilon'} \log \left(\frac{1 - \epsilon'}{1 - x} \right) \right] \right\} (1 + 0(\rho_n \alpha_n^{-1} + \alpha_n^{-k_3})) \\ &= \exp \left\{ -\alpha_n(\epsilon - \epsilon') \left[\frac{\tilde{\epsilon}}{1 - \tilde{\epsilon}} \log(\tilde{\epsilon}) - \frac{1 - \tilde{\epsilon}}{\tilde{\epsilon}} \log(1 - \tilde{\epsilon}) \right. \right. \\ &\quad \left. \left. - \log(x) \frac{\tilde{\epsilon}}{(1 - \tilde{\epsilon})} - \log(1 - x) \frac{(1 - \tilde{\epsilon})}{\tilde{\epsilon}} \right] \right\} (1 + 0(\rho_n \alpha_n^{-1} + \alpha_n^{-k_3})) \end{aligned}$$

where $\tilde{\epsilon} \in (\epsilon, \epsilon')$. Hence as soon as $1 - \delta_n > \epsilon, \epsilon' > \delta_n$ and $x \in (\beta_n, 1 - \beta_n)$

$$\left| \log(1 - x) \frac{(1 - \tilde{\epsilon})}{\tilde{\epsilon}} \right| \leq |\log(\beta_n)| \delta_n^{-1}, \quad \left| \log(x) \frac{\tilde{\epsilon}}{(1 - \tilde{\epsilon})} \right| \leq |\log(\beta_n)| \delta_n^{-1}$$

which implies that if $\alpha_n^{1/2} \rho_n |\log(\beta_n)| \delta_n^{-1}$ is small enough

$$\left| \frac{g_{\alpha_n, \epsilon}(x)}{g_{\alpha_n, \epsilon'}(x)} - 1 \right| \leq C \alpha_n^{1/2} \rho_n |\log(\beta_n)| \delta_n^{-1} + 0(\rho_n \alpha_n^{-1} + \alpha_n^{-k_3}),$$

which achieves the proof of Lemma B.1. \square

APPENDIX C: LEMMA C.1

The following Lemma allows us to control the ratio of constants of Beta densities.

LEMMA C.1. *Let $a, b > 0$ and $0 < \tau_1 < a$, $0 < \tau_2 < b$, let C, ρ denote generic positive constants. Let $\bar{\eta} = a + b$ and $\bar{\tau} = \tau_1 + \tau_2$. We then have the following results:*

i. *If $a, b < 2$,*

$$\log \left(\frac{\Gamma(a - \tau_1) \Gamma(b - \tau_2)}{\Gamma(a + \tau_1) \Gamma(b + \tau_2)} \right) + \log \left(\frac{\Gamma(\bar{\eta} + \bar{\tau})}{\Gamma(\bar{\eta} - \bar{\tau})} \right) \leq \frac{2\tau_1}{a - \tau_1} + \frac{2\tau_2}{b - \tau_2} - 2(\bar{\tau})C.$$

ii. *If $a < 2$, $b > 2$, then $\bar{\eta} > 2$ and*

$$\log \left(\frac{\Gamma(a - \tau_1) \Gamma(b - \tau_2)}{\Gamma(a + \tau_1) \Gamma(b + \tau_2)} \right) + \log \left(\frac{\Gamma(\bar{\eta} + \bar{\tau})}{\Gamma(\bar{\eta} - \bar{\tau})} \right) \leq \frac{2\tau_1}{a - \tau_1} + \bar{\tau}[\log(\bar{\eta} + 1) - C].$$

- iii. If $b < 2$, $a > 2$, then things are symmetrical to the previous case.
- iv. If $a, b > 2$, $i = 1, 2$, then

$$\log \left(\frac{\Gamma(a - \tau_1)\Gamma(b - \tau_2)}{\Gamma(a + \tau_1)\Gamma(b + \tau_2)} \right) + \log \left(\frac{\Gamma(\bar{\eta} + \bar{\tau})}{\Gamma(\bar{\eta} - \bar{\tau})} \right) \leq 2\bar{\tau} \log(\bar{\eta} + 1).$$

PROOF. of Lemma C.1. The proof of Lemma C.1 comes from Taylor expansions of $\log(\Gamma(x))$ and from the use of the relation:

$$\psi(x) = -\frac{1}{x} + \psi(x + 1)$$

so that when x is small $|\psi(x)|$ is bounded by $1/x$ plus a constant and if x is large $\psi(x)$ is bounded by $\log(x)$ plus a constant. \square

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