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On the Mathematical Foundation of Approximate Bayesian Computation A Robust Set for Estimating Mechanistic Network Models

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Abstract

We research relations between optimal transport theory, OTT, and the innovative methodology of approximate Bayesian computation, ABC, possibly connected to relevant metrics defined on probability measures.

Those of ABC are computational methods based on Bayesian statistics and applicable to a given generative model to estimate its a posteriori distribution in case the likelihood function is intractable. The idea is therefore to simulate sets of synthetic data from the model with respect to assigned parameters and, rather than comparing prospects of these data with the corresponding observed values as typically ABC requires, to employ just a distance between a chosen distribution associated to the synthetic data and another of the observed values.

Such methods have become increasingly popular especially thanks to the various fields of applicability which go from finance to biological science, and yet an ABC methodology relying on OTT as the one we're trying to develop was born specifically with the hope of esteem mechanistic network models, i.e. models for data network growth or evolution over time, thus particularly suitable for processing dynamic data domains; but which indeed, by definition, don't have a manageable likelihood, main reason why those models are opposed to probabilistic ones which instead can always count on powerful inferential tools.

Our focus lies in theoretical and methodological aspects, although there would exist a remarkable part of algorithmic implementation, and more precisely issues regarding mathematical foundation and asymptotic properties are carefully analyzed, inspired by an in-depth study of what is then our main bibliographic reference, that is [1], carrying out what follows: a rigorous formulation of the set-up for the ABC rejection algorithm, also to regain a transparent and general result of convergence as the ABC threshold goes to zero whereas the number n of samples from the prior stays fixed; general technical proposals about distances leaning on OTT; weak assumptions which lead to lower bounds for small values of threshold and as n goes to infinity, ultimately showing a reasonable possibility of lack of concentration which is contrary to what is proposed in [1] itself.

References. ABC: [12]. Network or mechanistic models: [2], [3], [4], [5]. Wasserstein distance in ABC: [7], [9]. More of ABC: [6], [8], [10], [13], [14]. The mathematics: [11], [15].

Keywords. Approximate Bayesian computation. Asymptotic properties. Bayesian statistics. Borel measurable. Concentration properties. Generative models. Likelihood-free inference. Measure theory. Mechanistic network models. Monge-Kantorovich problem. Networks. Optimal coupling. Optimal transport theory. Probability metric. Radon's metric. Radon probability measure. Transportation of measure. Wasserstein distance.

A mathematical frame for ABC

Underlying probability space: $(\Omega, \mathcal{A}, \mathbf{P})$. Dimensions: $d_{\mathcal{Y}}$, $d_{\mathcal{H}}$ and n in $\mathbb{N}^* \equiv \mathbb{N} \setminus \{0\}$. Observations: $y^{1:n}(\omega) \equiv y^{1:n} = (y^1, \dots, y^n)^\mathsf{T} \in \mathcal{Y}^n \subseteq \mathbb{R}^{d_{\mathcal{Y}} \cdot n}$, $\forall \omega \in \Omega$, where $\mathcal{Y} \subseteq \mathbb{R}^{d_{\mathcal{Y}}}$ has a metric $\rho_{\mathcal{Y}}$. Parameters: $\vartheta \in \mathcal{H}$ where $\mathcal{H} \subseteq \mathbb{R}^{d_{\mathcal{H}}}$ has a metric $\rho_{\mathcal{H}}$. Prior: $\pi \in \mathscr{P}(\mathcal{H})$. Model: $\{\mu_{\vartheta}^n\}_{\vartheta \in \mathcal{H}}$, family in $\mathscr{P}(\mathcal{Y}^n)$.

Notations. Let X be a topological space. We denote by $\mathcal{B}(X)$ the σ -algebra on X of the Borel subsets of X, by $\mathscr{P}(X)$ the class of the probability measures on $\mathcal{B}(X)$ and, given another topological space Y, by $\mathscr{B}(X,Y)$ the class of the Borel measurable functions from $X \equiv (X,\mathcal{B}(X))$ to $Y \equiv (Y,\mathcal{B}(Y))$.

Next, we'll write $\widetilde{\forall} \vartheta \in \mathcal{H}$ meaning $\forall \vartheta \in \mathcal{H} [\pi]$, i.e. for π -a.a. (almost all) $\vartheta \in \mathcal{H}$.

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[A0-a] The model $\{\mu_{\vartheta}^n\}_{\vartheta\in\mathcal{H}}$ is generative meaning that, $\widetilde{\forall}\ \vartheta\in\mathcal{H}$, it's possible to generate how many $z^{1:n}=(z^1,\ldots,z^n)^\mathsf{T}\in\mathcal{Y}^n$ with $z^{1:n}\sim\mu_{\vartheta}^n$ we desire.

Pseudo-observations: $z^{1:n} \in \mathcal{Y}^n$ with $z^{1:n} \sim \mu_{\vartheta}^n$, $\widetilde{\forall} \vartheta \in \mathcal{H}$. Deviation measure: \mathcal{D} , pseudo-metric on \mathcal{Y}^n .

Notations. $\widetilde{\forall} \ \vartheta \in \mathcal{H}, \ \mathcal{Y}_{\vartheta}^n \coloneqq \left\{ \ z^{1:n} \in \mathcal{Y}^n \ \middle| \ z^{1:n} \sim \mu_{\vartheta}^n \ \right\} \subset \mathcal{Y}^n \ \text{and, for any } \varepsilon \in \mathbb{R}_+ \equiv [0, \infty[, \infty[]]]$

$$D^n_\varepsilon \coloneqq \mathcal{D}(y^{1:n}, \boldsymbol{\cdot})^{-1}\big([0, \varepsilon]\big) \equiv \big\{z^{1:n} \in \mathcal{Y}^n \mid \mathcal{D}(y^{1:n}, z^{1:n}) \le \varepsilon\big\} \in \mathcal{B}(\mathcal{Y}^n).$$

Remark. Although there may exist $y \neq z$ in \mathcal{Y}^n s.t. $\mathcal{D}(y,z) = 0$, \mathcal{D} remains non-negative, subadditive and componentwise continuous. Moreover, $D^n_{\varepsilon} \downarrow D^n_0 \equiv \mathcal{D}(y^{1:n}, \cdot)^{-1}(0)$ as $\varepsilon \downarrow 0$.

[A0-b] (under A0-a) There exists $\varepsilon_0 > 0$ s.t., for any $\varepsilon \in [0, \varepsilon_0[$, the two following conditions hold.

- **1.** The function $\vartheta \mapsto \mu_{\vartheta}^n[D_{\varepsilon}^n]$, to be seen as defined π -a.s. (almost surely), belongs to $\mathscr{B}(\mathcal{H}, [0, 1])$.
- **2.** $\int_{\mathcal{H}} \mu_{\vartheta}^n[D_{\varepsilon}^n] \, \pi(\mathrm{d}\vartheta) > 0 \text{ (i.e. } \neq 0).$

Remark. 2 of A0-b is equivalent to having $\vartheta \mapsto \mu_{\vartheta}^n[D_{\varepsilon}^n]$, briefly $\mu_{(\cdot)}^n[D_{\varepsilon}^n]$, not π -a.s. identically zero.

 \blacktriangleright Regarding the whole continuation, we assume that <u>A0-a and A0-b</u> worth.

ABC thresholds: any $\varepsilon \in]0, \varepsilon_0[$. ABC rejection algorithms: hereunder.

(i) Choose $\varepsilon \in]0, \varepsilon_0[$. (ii) Draw $\vartheta \in \mathcal{H}$ by π and $z^{1:n} \in \mathcal{Y}_{\vartheta}^n$. (iii) Keep ϑ if, and only if, $z^{1:n} \in D_{\varepsilon}^n$.

ABC posteriors: $\pi_{y^{1:n}}^{\varepsilon} \ll \pi$, $\forall \varepsilon \in]0, \varepsilon_0[$, whose density is proportional to $\mu_{(\cdot)}^n[D_{\varepsilon}^n]$: for any $B \in \mathcal{B}(H)$,

$$\pi_{y^{1:n}}^{\varepsilon}[B] = \frac{\int_{B} \mu_{\vartheta}^{n}[D_{\varepsilon}^{n}] \, \pi(\mathrm{d}\vartheta)}{\int_{\mathcal{H}} \mu_{\vartheta'}^{n}[D_{\varepsilon}^{n}] \, \pi(\mathrm{d}\vartheta')}.$$

[A0-c] For any $Y \in \mathcal{B}(\mathcal{Y}^n)$, $\mu_{(\cdot)}^n[Y] \in \mathcal{B}(\mathcal{H}, [0, 1])$ (coherently w.r.t. A0-b).

Model for the true posterior (under A0-c): for any $Y \in \mathcal{B}(\mathcal{Y}^n)$ and $B \in \mathcal{B}(\mathcal{H})$ with $\pi[B] > 0$,

$$P[Y|B] \doteq \frac{1}{\pi[B]} \int_{B} \mu_{\vartheta}^{n}[Y] \, \pi(\mathrm{d}\vartheta)$$

from which the corresponding posterior: for any $Y \in \mathcal{B}(\mathcal{Y}^n)$ and $B \in \mathcal{B}(\mathcal{H})$, whenever it makes sense,

$$\pi[B|Y] \equiv \frac{\int_B \mu_{\vartheta}^n[Y] \, \pi(\mathrm{d}\vartheta)}{\int_{\mathcal{H}} \mu_{\vartheta'}^n[Y] \, \pi(\mathrm{d}\vartheta')}$$

(through the Bayes' formula with π still as the prior). Therefore, the true posterior would be

$$\pi[\cdot|y^{1:n}] \coloneqq \pi[\cdot|\{y^{1:n}\}].$$

Remark. For any $\varepsilon \in]0, \varepsilon_0[, \pi^{\varepsilon}_{\eta^{1:n}}[\,\cdot\,] = \pi[\,\cdot\,|D^n_{\varepsilon}].$

A convergence result for $\varepsilon \downarrow 0$

Notation. We'll denote by $\mathbf{m} := \mathbf{m}^{dy \cdot n}$ the Lebesgue measure on $\mathbb{R}^{dy \cdot n}$ (on $\mathcal{B}(\mathbb{R}^{dy \cdot n})$).

[A1] $\widetilde{\forall} \vartheta \in \mathcal{H}$, the two following conditions hold.

- $\mathbf{1.}\ \mu^n_\vartheta \ll \text{m with } f^n_\vartheta \doteq \mathrm{d}\mu^n_\vartheta/\mathrm{dm \ s.t.}, \ \widetilde\forall\ z^{1:n} \in \mathcal{Y}^n \ [\text{m}] \ \text{for which it's defined}, \ f^n_{(\,\cdot\,)}(z^{1:n}) \in \mathscr{B}(\mathcal{H},\mathbb{R}_+).$
- **2.** $f_{\vartheta}^n(\,\cdot\,)$ is continuous and $f_{(\,\cdot\,)}^n(y^{1:n})$ is not π -a.s. identically zero.

Remark. 1 of A1 implies A0-c while 2 of A1 ensures that $\int_{\mathcal{H}} f_{\vartheta}^n(y^{1:n}) \pi(\mathrm{d}\vartheta) > 0$ (eventually ∞).

[A2] (under A1) There exist $\delta, \bar{\varepsilon} \in]0, \infty[$ and $g \in L^1(\pi)$ with $g \geq \delta$ [π] all s.t., $\tilde{\forall} \vartheta \in \mathcal{H}$,

$$\delta \le \sup_{z^{1:n} \in D_{\bar{\varepsilon}}^n} f_{\vartheta}^n(z^{1:n}) \le g(\vartheta).$$

Remarks.

• A2 would imply 2 of A0-b employing any $\varepsilon_0 \in [0, \bar{\varepsilon}]$ because, for any $\varepsilon \in [0, \bar{\varepsilon}]$, the function

$$\vartheta \mapsto \mu_{\vartheta}^{n}[D_{\varepsilon}^{n}] \equiv \int_{D_{\varepsilon}^{n}} f_{\vartheta}^{n}(z^{1:n}) dz^{1:n}$$

cannot be π -a.s. identically zero. In particular, for any $\varepsilon \in]0, \bar{\varepsilon}[$, m $[D_{\varepsilon}^n] > 0$ too.

- A2 implies that $f_{(\,\cdot\,)}^n(y^{1:n}) \in L^1(\pi)$ with $L^1(\pi)$ -norm lower or equal than $\|g\|_1 \coloneqq \|g\|_{L^1(\pi)}$.
- Even the following generalization of A2 would work. $[\widetilde{A2}]$ (under A1) There exist $g \in L^1(\pi)$ with g > 0 $[\pi]$ and $\tilde{\varepsilon} \in]0, \infty[$ s.t., for any $\varepsilon \in]0, \tilde{\varepsilon}[$, there exists $\delta_{\varepsilon} \in]0, \infty[$ s.t., $\widetilde{\forall} \vartheta \in \mathcal{H}$,

$$\delta_{\varepsilon} \leq \sup_{z^{1:n} \in D_{\varepsilon}^n} f_{\vartheta}^n(z^{1:n}) \leq g(\vartheta).$$

[A3] (under A1) $\widetilde{\forall} \vartheta \in \mathcal{H}, \mathcal{D}(y^{1:n}, \cdot)^{-1}(0) \subseteq f_{\vartheta}^{n}(\cdot)^{-1}(f_{\vartheta}^{n}(y^{1:n})).$

Remark. Extensively, for any $z^{1:n} \in \mathcal{Y}^n$, if $\mathcal{D}(y^{1:n}, z^{1:n}) = 0$ then, $\widetilde{\forall} \vartheta \in \mathcal{H}$, $f_{\vartheta}^n(z^{1:n}) = f_{\vartheta}^n(y^{1:n})$. Hence, if $\mathcal{D}(y^{1:n}, \cdot)^{-1}(0) = \{y^{1:n}\}$, which happens when \mathcal{D} is an actual metric, then A3 trivially holds.

Proposition. Under assumptions A1, A2 and A3, the three following conditions hold.

- **a.** The ABC rejection algorithm and the ABC posterior are well defined for any $\varepsilon \in [0, \varepsilon_0 \vee \bar{\varepsilon}[$.
- **b.** The true posterior $\pi[\cdot|y^{1:n}]$ makes sense and it takes the following expression: for any $B \in \mathcal{B}(\mathcal{H})$,

$$\pi[B|y^{1:n}] = \frac{\int_B f_{\vartheta}^n(y^{1:n}) \, \pi(\mathrm{d}\vartheta)}{\int_{\mathcal{H}} f_{\vartheta'}^n(y^{1:n}) \, \pi(\mathrm{d}\vartheta')}.$$

c. The ABC posterior strongly converges to the true posterior as $\varepsilon \downarrow 0$: for any $B \in \mathcal{B}(\mathcal{H})$,

$$\pi^{\varepsilon}_{y^{1:n}}[B] \to \pi[B|y^{1:n}] \quad as \; \varepsilon \downarrow 0.$$

Proof (b and c). The thesis essentially matches with the fact that, for any $B \in \mathcal{B}(\mathcal{H})$,

$$\int_{B} \frac{1}{\mathrm{m}[\mathrm{D}_{\varepsilon}^{n}]} \, \mu_{\vartheta}^{n}[\mathrm{D}_{\varepsilon}^{n}] \, \pi(\mathrm{d}\vartheta) \to \int_{B} f_{\vartheta}^{n}(y^{1:n}) \, \pi(\mathrm{d}\vartheta) \quad \text{as } \varepsilon \downarrow 0$$

as a consequence of the classical Lebesgue's dominated convergence theorem. Indeed, on one side, pointwise convergence: $\widetilde{\forall}\ \vartheta \in \mathcal{H},\ \mathrm{m}[\mathrm{D}^n_\varepsilon]^{-1}\mu^n_\vartheta[\mathrm{D}^n_\varepsilon] \equiv \mathrm{m}[\mathrm{D}^n_\varepsilon]^{-1}\int_{D^n_\varepsilon} f^n_\vartheta(z^{1:n})\,\mathrm{d}z^{1:n} \to f^n_\vartheta(y^{1:n})\ \mathrm{as}\ \varepsilon \downarrow 0$ due to the basic integral mean value theorem leaning on the continuity of $f^n_\vartheta(\cdot)$ and A3. On the other side, dominance: $\widetilde{\forall}\ \vartheta \in \mathcal{H}$ and $\forall\ \varepsilon \in [0,\overline{\varepsilon}[,\ 0 \leq \mathrm{m}[\mathrm{D}^n_\varepsilon]^{-1}\mu^n_\vartheta[\mathrm{D}^n_\varepsilon] \leq g(\vartheta)$ from A2, and $g \in L^1(\pi)$.

Optimal transport theory in ABC

Let's visualize $(\mathcal{Y}, \rho_{\mathcal{Y}})$ as a separable and complete metric space in such a way that it is also a Radon space, i.e. any element in $\mathscr{P}(\mathcal{Y})$ is a Radon probability measure (outer regular on Borel subsets and inner regular on open subsets), and let's choose an unit cost function $c \colon \mathcal{Y} \times \mathcal{Y} \to [0, \infty]$ which is lower semicontinuous (thus Borel measurable) and a parameter $p \in [1, \infty[$ of summability.

Notation. We'll denote by $\mathscr{P}_p(\mathcal{Y})$ the subclass of $\mathscr{P}(\mathcal{Y})$ whose elements have finite p-th moment.

Kantorovich's formulation. For any $\mu, \nu \in \mathscr{P}_p(\mathcal{Y})$, let's consider the subclass $\Gamma(\mu, \nu)$ of $\mathscr{P}(\mathcal{Y} \times \mathcal{Y})$ whose elements γ are the couplings with marginals μ and ν . Then the Kantorovich's formulation of the optimal transport problem related to $(\mathcal{Y}, \rho_{\mathcal{Y}})$, c and p is

$$\mathcal{K}(\mu,\nu) \doteq \inf_{\gamma \in \Gamma(\mu,\nu)} \int_{\mathcal{Y} \times \mathcal{Y}} c(y,y') \, \mathrm{d}\gamma(y,y').$$

It can be shown that there exists a minimizer $\gamma^* \in \Gamma(\mu, \nu)$ for such a problem which could be determined by means of gradient descent algorithms.

Example. For $c = (\rho_{\mathcal{Y}})^p$, \mathcal{K} coincides with the p-power of the Wasserstein or Kantorovich-Rubinstein distance: in symbols, $\mathcal{K} = \mathcal{W}_p^p$.

Monge's formulation. For any $\mu, \nu \in \mathscr{P}_p(\mathcal{Y})$, let's consider the subclass $\mathsf{T}(\mu, \nu)$ of $\mathscr{B}(\mathcal{Y}) := \mathscr{B}(\mathcal{Y}, \mathcal{Y})$ whose elements T are such that $T_{\#}\mu = \nu$.

Remark. Here $T_{\#}\mu$ stands for the push-forward or image measure $\mu^T \equiv T(\mu)$ of μ through T: that is, the element in $\mathscr{P}(\mathcal{Y})$ defined by $T_{\#}\mu[A] \doteq \mu[T^{-1}(A)], A \in \mathcal{B}(\mathcal{Y})$.

Then, at least when μ and ν are both atomic (not diffuse) or otherwise when μ is not atomic (diffuse), the Monge's formulation of the optimal transport problem related to $(\mathcal{Y}, \rho_{\mathcal{Y}})$, c and p is

$$\mathcal{M}(\mu, \nu) \doteq \inf_{T \in \mathsf{T}(\mu, \nu)} \int_{\mathcal{V}} c(y, T(y)) \, \mu(\mathrm{d}y).$$

Example. Let's assume that dy = 1 and $\mathcal{Y} = \mathbb{R}$ with $\rho_{\mathcal{Y}}$ equal to the usual Euclidean metric.

Notation. For any $\eta \in \mathscr{P}(\mathbb{R})$, we'll denote by F_{η} and F_{η}^{-1} the cumulative distribution function of η and the quantile function of η respectively.

If there exists a function $\varphi \colon \mathbb{R} \to \mathbb{R}$ which is convex and such that, for any $y, y' \in \mathbb{R}$, $c(y, y') = \varphi(y - y')$ then, for any $\mu, \nu \in \mathscr{P}_p(\mathbb{R})$ with μ not atomic, the function $T^* := F_{\nu}^{-1} \circ F_{\mu} \in \mathsf{T}(\mu, \nu)$ is an optimal transport map w.r.t. the Monge's formulation and the following identity holds:

$$\mathcal{M}(\mu,\nu) \equiv \int_{-\infty}^{+\infty} \varphi(y - T^*(y)) \,\mu(\mathrm{d}y) = \int_0^1 \varphi(F_\mu^{-1}(t) - F_\nu^{-1}(t)) \,\mathrm{d}t.$$

Moreover, if φ is strictly convex, then such a T^* is the unique optimal transport map.

Radon's metric. For any $\mu, \nu \in \mathscr{P}_p(\mathcal{Y})$,

$$\rho_{\mathcal{R}}(\mu,\nu) \doteq \sup_{h \in C^{0}(\mathcal{Y},[-1,1])} \int_{\mathcal{Y}} h(y) (\mu - \nu) (\mathrm{d}y)$$

defines a metric on $\mathscr{P}_p(\mathcal{Y})$ whose notion of convergence corresponds with the total variation convergence.

Remark. The space $(\mathcal{Y}, \rho_{\mathcal{Y}})$ is a Hausdorff, namely T_2 , and locally compact as a topological space.

Some lower bounds for $n \to \infty$

Notation. $\forall n \in \mathbb{N}^*$, we'll write $\widetilde{\forall} y^{1:n} \in \mathcal{Y}^n$ meaning to vary of $y^{1:n}(\omega) \equiv y^{1:n}$ in \mathcal{Y}^n for **P**-a.a. $\omega \in \Omega$.

Deviation measure of distributions: once and for all, $\forall n \in \mathbb{N}^*$, $\widetilde{\forall} y^{1:n} \in \mathcal{Y}^n$, $\widetilde{\forall} \vartheta \in \mathcal{H}$ and $\forall z^{1:n} \in \mathcal{Y}^n_\vartheta$, we univocally associate an element in $\mathscr{P}(\mathcal{Y})$, possibly in $\mathscr{P}_p(\mathcal{Y})$ $(p \geq 1)$, to both of $y^{1:n}$ and $z^{1:n}$, let be

$$\mu_n \equiv \mu_{y^{1:n}}$$
 to $y^{1:n}$ and $\mu_{\vartheta,n} \equiv \mu_{\vartheta,z^{1:n}}$ to $z^{1:n}$

and we select a pseudo-distance \mathcal{T} on $\mathscr{P}(\mathcal{Y})$, possibly on $\mathscr{P}_{p}(\mathcal{Y})$.

Example. $\mu_n \equiv \widehat{\mu}_n := n^{-1} \sum_{k=1}^n \delta_{y^k}$ and $\mu_{\vartheta,n} \equiv \widehat{\mu}_{\vartheta,n} := n^{-1} \sum_{k=1}^n \delta_{z^k}$ where, for $x \in \mathcal{Y}$ and $B \in \mathcal{B}(\mathcal{Y})$,

$$\delta_x[B] \equiv \mathbb{1}_B(x) \doteq \begin{cases} 1, & \text{if } x \in B, \\ 0, & \text{if } x \notin B. \end{cases}$$

Remark. The space $(\mathscr{P}(\mathcal{Y}), \mathcal{T})$, possibly $(\mathscr{P}_p(\mathcal{Y}), \mathcal{T})$, may not be of Hausdorff as a topological space.

[B0] $\forall n \in \mathbb{N}^*$ and $\widetilde{\forall} \vartheta \in \mathcal{H}$, the three following conditions hold.

- 1. $\mathcal{Y}_{\vartheta}^n \in \mathcal{B}(\mathcal{Y}^n)$.
- **2.** $\widetilde{\forall} \ y^{1:n} \in \mathcal{Y}^n$, the function $z^{1:n} \mapsto \mathcal{T}(\mu_n, \mu_{\vartheta,n})$ belongs to $\mathscr{B}(\mathcal{Y}^n_{\vartheta}, \mathbb{R}_+)$.
- **3.** $\widetilde{\forall} y^{1:n} \in \mathcal{Y}^n \text{ and } \forall \varepsilon \in]0, \varepsilon_0[,$

$$\mu_{\vartheta}^{n}[D_{\varepsilon}^{n}] \geq \mu_{\vartheta}^{n}[\{z^{1:n} \in \mathcal{Y}_{\vartheta}^{n} \mid \mathcal{T}(\mu_{n}, \mu_{\vartheta,n}) \leq \varepsilon \}].$$

Remark. 3 of B0 holds if, $\forall n \in \mathbb{N}^*$, $\widetilde{\forall} y^{1:n} \in \mathcal{Y}^n$, $\widetilde{\forall} \vartheta \in \mathcal{H}$ and $\forall z^{1:n} \in \mathcal{Y}^n$, $\mathcal{D}(y^{1:n}, z^{1:n}) \leq \mathcal{T}(\mu_n, \mu_{\vartheta,n})$.

[B1] (under B0) There exists unique $\mu_{\star} \in \mathscr{P}(\mathcal{Y})$, possibly in $\mathscr{P}_p(\mathcal{Y})$, s.t. the following occurs.

- 1. For any $n \in \mathbb{N}^*$, $\omega \mapsto \mathcal{T}(\mu_n, \mu_{\star})$ is \mathcal{A} -measurable as a function from Ω to \mathbb{R}_+ .
- 2. $\mathcal{T}(\mu_n, \mu_{\star}) \to 0$, P-a.s., as $n \to \infty$.

Remark. B1 implies that, for any $\xi > 0$, $\mathbf{P} \left[\left\{ \omega \in \Omega \mid \mathcal{T}(\mu_n, \mu_{\star}) > \xi \right\} \right] \to 0 \text{ as } n \to \infty.$

[B2] (under B1) $\widetilde{\forall} \vartheta \in \mathcal{H}$, there exists unique $\mu_{\vartheta} \in \mathscr{P}(\mathcal{Y})$, possibly in $\mathscr{P}_p(\mathcal{Y})$, s.t. the following occurs.

- 1. The function $\vartheta \mapsto \mathcal{T}(\mu_{\vartheta}, \mu_{\star})$ belongs to $\mathscr{B}(\mathcal{H}, \mathbb{R}_{+})$.
- **2.** $\forall n \in \mathbb{N}^*$ and $\widetilde{\forall} \vartheta \in \mathcal{H}$, the function $z^{1:n} \mapsto \mathcal{T}(\mu_{\vartheta,n}, \mu_{\vartheta})$ belongs to $\mathscr{B}(\mathcal{Y}^n_{\vartheta}, \mathbb{R}_+)$.
- **3.** There exists $\tau \in [0,1[$ such that, $\widetilde{\forall} \ \vartheta \in \mathcal{H}$ and $\forall \ \varepsilon > 0$,

$$\limsup_{n} \mu_{\vartheta}^{n} \left[\left\{ z^{1:n} \in \mathcal{Y}_{\vartheta}^{n} \mid \mathcal{T}(\mu_{\vartheta,n}, \mu_{\vartheta}) > \varepsilon \right\} \right] \leq \tau.$$

4. There exist $\sigma \in [0, \tau]$ and $\varepsilon_1 > 0$ such that, $\widetilde{\forall} \vartheta \in \mathcal{H}$ and $\forall \varepsilon \in]0, \varepsilon_1[$,

$$\liminf_{n} \mu_{\vartheta}^{n} \left[\left\{ z^{1:n} \in \mathcal{Y}_{\vartheta}^{n} \mid \mathcal{T}(\mu_{\vartheta,n}, \mu_{\vartheta}) > \varepsilon \right\} \right] \geq \sigma.$$

Remark. 3 of B2, without specific requests on ε , is equivalent to any version of that in which upper bounds for ε are imposed. Furthermore if, $\widetilde{\forall} \vartheta \in \mathcal{H}$ and $\forall \varepsilon > 0$, $\mu_{\vartheta}^{n}[\mathcal{T}(\mu_{\vartheta,n},\mu_{\vartheta}) > \varepsilon] \to 0$ as $n \to \infty$ (shortly put), then any $\tau \in [0,1[$ satisfies 3 of B2 while only $\sigma = 0$ but any $\varepsilon_1 > 0$ fulfill 4 of B2.

[B3] (under 1 and 2 of B2) There exists $\vartheta_{\star} \in \mathcal{H}$ which minimizes $\vartheta \mapsto \mathcal{T}(\mu_{\vartheta}, \mu_{\star})$ over \mathcal{H} : simbolically,

$$\vartheta_{\star} \in \operatorname{arg\,min}_{\mathcal{H}} \mathcal{T}(\mu_{(\,\cdot\,)}, \mu_{\star}).$$

Notations. We'll denote $\varepsilon_{\star} \doteq \mathcal{T}(\mu_{\vartheta_{\star}}, \mu_{\star}) \equiv \min_{\mathcal{H}} \mathcal{T}(\mu_{(\cdot,\cdot)}, \mu_{\star}) \geq 0$ and, $\widetilde{\forall} \vartheta \in \mathcal{H}, \mathcal{T}_{\vartheta} \coloneqq \mathcal{T}(\mu_{\vartheta}, \mu_{\star}) \geq \varepsilon_{\star}$.

[B4] (under B3) There exist a neighborhood $U_{\star} \subset \mathcal{H}$ of ϑ_{\star} , a connected neighborhood $I_0 \subset \mathbb{R}_+$ of zero and a strictly increasing function $\psi \colon I_0 \to \mathbb{R}_+$ all s.t., $\widetilde{\forall} \ \vartheta \in U_{\star}$,

$$\mathcal{T}_{\vartheta} - \varepsilon_{\star} \leq \psi(\rho_{\mathcal{H}}(\vartheta, \vartheta_{\star})).$$

Notations. We'll write "for any $(y^{1:n})_n$ " meaning to vary of $(y^{1:n}(\omega))_n \equiv (y^{1:n})_n$, with $y^{1:n}(\omega) \equiv y^{1:n}$ in \mathcal{Y}^n for any $n \in \mathbb{N}^*$, w.r.t. a $\omega \in \Omega$. Lastly, for any $\varepsilon > 0$, we'll denote by ε^- any element of $[0, \varepsilon]$.

Proposition. Under assumptions B0, B1, 1, 2 and 3 of B2 and B3, the following occurs so far as

$$\varepsilon_{\star} < \varepsilon_0$$

for any $\varepsilon \in]0, \varepsilon_0 - \varepsilon_{\star}[$, $(y^{1:n})_n$ with $n \equiv n_{\varepsilon}$ large enough and with probability **P** going to 1 as $n \to \infty$.

- **a.** $\pi_{n^{1:n}}^{\varepsilon_{\star}+\varepsilon} \left[\mathcal{T}_{(\cdot)} \geq \varepsilon_{\star} + \varepsilon^{-}/3 \right] \geq (1-\tau) \pi \left[\varepsilon_{\star} + \varepsilon^{-}/3 \leq \mathcal{T}_{(\cdot)} \leq \varepsilon_{\star} + \varepsilon/3 \right].$
- **b.** $\pi_{n^{1:n}}^{\varepsilon_{\star}+\varepsilon} \left[\mathcal{H} \setminus \arg \min_{\mathcal{H}} \mathcal{T}_{(\cdot)} \right] \geq (1-\tau) \pi \left[\varepsilon_{\star} < \mathcal{T}_{(\cdot)} \leq \varepsilon_{\star} + \varepsilon/3 \right].$
- **c.** Under assumption 4 of B2, let's suppose that in 3 of B0 the equality holds and that $\varepsilon_{\star} < \varepsilon_1/2$. Then, for any $\varepsilon \in]0, \varepsilon_0 \varepsilon_{\star}[$ even more enough small,

$$\lambda_{\varepsilon} := (1 - \sigma) \pi \left[\mathcal{T}_{(.)} \le \varepsilon_{\star} + 5\varepsilon/3 \right] + \tau \pi \left[\mathcal{T}_{(.)} > \varepsilon_{\star} + 5\varepsilon/3 \right] > 0$$

and

$$\pi_{y^{1:n}}^{\varepsilon_{\star}+\varepsilon} \left[\mathcal{T}_{(\cdot)} \geq \varepsilon_{\star} + \varepsilon^{-}/3 \right] \geq \frac{1-\tau}{\lambda_{\varepsilon}} \pi \left[\varepsilon_{\star} + \varepsilon^{-}/3 \leq \mathcal{T}_{(\cdot)} \leq \varepsilon_{\star} + \varepsilon/3 \right].$$

d. Under assumption B4, for any $\zeta \in I_0 \setminus \{0\}$ and r > 0 small enough,

$$\pi_{y^{1:n}}^{\varepsilon_{\star}+\varepsilon}\left[\rho_{\mathcal{H}}(\,\cdot\,,\vartheta_{\star})\geq r\right]\geq\pi_{y^{1:n}}^{\varepsilon_{\star}+\varepsilon}\left[\mathcal{T}_{(\,\cdot\,)}\geq\varepsilon_{\star}+\psi(\zeta)\right]$$

for which lower bounds of a and eventually c hold if also ζ is small enough.

Proof. First of all, by virtue of the classical Fatou's lemma (and of A0-b) it's simple to realize that, for any $\varepsilon \in]0, \varepsilon_0 - \varepsilon_\star[$ and $(y^{1:n})_n, \int_{\mathcal{H}} \limsup_n \mu_\vartheta^n[D^n_{\varepsilon_\star + \varepsilon}] \pi(\mathrm{d}\vartheta) > 0$ and, for any $\zeta > 0$,

$$\lim\inf_{n} \pi_{y^{1:n}}^{\varepsilon_{\star}+\varepsilon} \left[\mathcal{T}_{(\,\cdot\,)} \geq \varepsilon_{\star} + \zeta \right] \geq \frac{\int_{\left\{ \mathcal{T}_{(\,\cdot\,)} \geq \varepsilon_{\star} + \zeta \right\}} \liminf_{n} \mu_{\vartheta}^{n} [D_{\varepsilon_{\star}+\varepsilon}^{n}] \, \pi(\mathrm{d}\vartheta)}{\int_{\mathcal{H}} \lim\sup_{n} \mu_{\vartheta'}^{n} [D_{\varepsilon_{\star}+\varepsilon}^{n}] \, \pi(\mathrm{d}\vartheta')}.$$

a. Since $\int_{\mathcal{H}} \limsup_n \mu_{\vartheta}^n[D_{\varepsilon_{\star}+\varepsilon}^n] \pi(\mathrm{d}\vartheta) \leq 1$, the thesis will be obtained once has been demonstrated that, for any $\varepsilon \in]0, \varepsilon_0 - \varepsilon_{\star}[$, $\zeta \in]0, \varepsilon/3]$ and **P**-a.a. $(y^{1:n})_n$ with $n \equiv n_{\varepsilon}$ large enough to have $\mathcal{T}(\mu_n, \mu_{\star}) \leq \varepsilon/3$,

$$\int_{\{\mathcal{T}_{(\cdot)} \geq \varepsilon_{\star} + \zeta\}} \liminf_{n} \mu_{\vartheta}^{n}[D_{\varepsilon_{\star} + \varepsilon}^{n}] \pi(\mathrm{d}\vartheta) \geq (1 - \tau) \pi \left[\varepsilon_{\star} + \zeta \leq \mathcal{T}_{(\cdot)} \leq \varepsilon_{\star} + \varepsilon/3\right].$$

Indeed B0 applies and, thanks to the triangle inequality which holds for \mathcal{T} , it's easy to verify that, $\forall n \in \mathbb{N}^*, \widetilde{\forall} y^{1:n} \in \mathcal{Y}^n, \widetilde{\forall} \vartheta \in \mathcal{H} \text{ and } \forall \varepsilon \in]0, \varepsilon_0 - \varepsilon_{\star}[, \text{ if } \mathcal{T}_{\vartheta} \leq \varepsilon_{\star} + \varepsilon/3 \text{ and } \mathcal{T}(\mu_n, \mu_{\star}) \leq \varepsilon/3, \text{ then}$

$$\left\{ \left. z^{1:n} \in \mathcal{Y}_{\vartheta}^{n} \mid \mathcal{T}(\mu_{\vartheta,n},\mu_{\vartheta}) \leq \varepsilon/3 \right. \right\} \subset \left\{ \left. z^{1:n} \in \mathcal{Y}_{\vartheta}^{n} \mid \mathcal{T}(\mu_{\vartheta,n},\mu_{n}) \leq \varepsilon_{\star} + \varepsilon \right. \right\}$$

and thus

$$\int_{\left\{\mathcal{T}_{(\cdot)} \geq \varepsilon_{\star} + \zeta\right\}} \liminf_{n} \mu_{\vartheta}^{n}[D_{\varepsilon_{\star} + \varepsilon}^{n}] \pi(\mathrm{d}\vartheta) \geq \int_{\left\{\varepsilon_{\star} + \zeta \leq \mathcal{T}_{(\cdot)} \leq \varepsilon_{\star} + \varepsilon/3\right\}} \liminf_{n} \mu_{\vartheta}^{n}[\mathcal{T}(\mu_{\vartheta,n}, \mu_{\vartheta}) \leq \varepsilon/3] \pi(\mathrm{d}\vartheta)$$

from which we conclude considering that by 3 of B2, $\forall \vartheta \in \mathcal{H}$ and $\forall \varepsilon > 0$,

$$\liminf_{n} \mu_{\vartheta}^{n}[\mathcal{T}(\mu_{\vartheta,n},\mu_{\vartheta}) \leq \varepsilon/3] \equiv 1 - \limsup_{n} \mu_{\vartheta}^{n}[\mathcal{T}(\mu_{\vartheta,n},\mu_{\vartheta}) > \varepsilon/3] \geq 1 - \tau.$$

b. That's a corollary of the previous result: for any $\varepsilon \in [0, \varepsilon_0 - \varepsilon_{\star}]$ and $(y^{1:n})_n$ with $n \equiv n_{\varepsilon}$ large enough,

$$\begin{split} \pi_{y^{1:n}}^{\varepsilon_{\star}+\varepsilon} \left[\mathcal{H} \setminus \arg \min_{\mathcal{H}} \mathcal{T}_{(.)} \right] &\equiv \pi_{y^{1:n}}^{\varepsilon_{\star}+\varepsilon} \left[\mathcal{T}_{(.)} > \varepsilon_{\star} \right] \\ &= \pi_{y^{1:n}}^{\varepsilon_{\star}+\varepsilon} \left[\bigcup_{\zeta \downarrow 0} \left\{ \mathcal{T}_{(.)} \geq \varepsilon_{\star} + \zeta \right\} \right] \\ &= \sup_{0 < \zeta \leq \varepsilon/3} \pi_{y^{1:n}}^{\varepsilon_{\star}+\varepsilon} \left[\mathcal{T}_{(.)} \geq \varepsilon_{\star} + \zeta \right] \\ &\geq (1-\tau) \sup_{0 < \zeta \leq \varepsilon/3} \pi \left[\varepsilon_{\star} + \zeta \leq \mathcal{T}_{(.)} \leq \varepsilon_{\star} + \varepsilon/3 \right] \\ &= (1-\tau) \pi \left[\varepsilon_{\star} < \mathcal{T}_{(.)} \leq \varepsilon_{\star} + \varepsilon/3 \right]. \end{split}$$

c. It would be sufficient to show that, for any $\varepsilon \in]0, \varepsilon_0 - \varepsilon_{\star}[$ even more enough small and **P**-a.a. $(y^{1:n})_n$,

$$\int_{\mathcal{H}} \limsup_{n} \mu_{\vartheta}^{n}[D_{\varepsilon_{\star}+\varepsilon}^{n}] \pi(\mathrm{d}\vartheta) \leq \lambda_{\varepsilon} \equiv (1-\sigma) \pi \left[\mathcal{T}_{(\cdot)} \leq \varepsilon_{\star} + 5\varepsilon/3 \right] + \tau \pi \left[\mathcal{T}_{(\cdot)} > \varepsilon_{\star} + 5\varepsilon/3 \right]$$

(bearing in mind the procedure of the first proof). Indeed, thanks again to the subadditivity of \mathcal{T} , $\forall n \in \mathbb{N}^*, \widetilde{\forall} y^{1:n} \in \mathcal{Y}^n, \widetilde{\forall} \vartheta \in \mathcal{H} \text{ and } \forall \varepsilon \in]0, \varepsilon_0 - \varepsilon_{\star}[, \text{ if } \mathcal{T}_{\vartheta} > \varepsilon_{\star} + 5\varepsilon/3 \text{ and } \mathcal{T}(\mu_n, \mu_{\star}) \leq \varepsilon/3, \text{ then}$

$$\left\{ z^{1:n} \in \mathcal{Y}_{\vartheta}^{n} \mid \mathcal{T}(\mu_{\vartheta,n},\mu_{n}) \leq \varepsilon_{\star} + \varepsilon \right\} \subset \left\{ z^{1:n} \in \mathcal{Y}_{\vartheta}^{n} \mid \varepsilon/3 < \mathcal{T}(\mu_{\vartheta,n},\mu_{\vartheta}) \leq \mathcal{T}_{\vartheta} + \varepsilon_{\star} + 4\varepsilon/3 \right\}$$

so, using the hypothesis $\mu_{\vartheta}^{n}[D_{\varepsilon_{\star}+\varepsilon}^{n}] = \mu_{\vartheta}^{n}[\mathcal{T}(\mu_{\vartheta,n},\mu_{n}) \leq \varepsilon_{\star} + \varepsilon]$ (i.e. \leq), and breaking the integral,

$$\int_{\mathcal{H}} \limsup_{n} \mu_{\vartheta}^{n}[D_{\varepsilon_{\star}+\varepsilon}^{n}] \pi(\mathrm{d}\vartheta) \leq \int_{\left\{\mathcal{T}_{(\cdot)} \leq \varepsilon_{\star} + 5\varepsilon/3\right\}} \limsup_{n} \mu_{\vartheta}^{n}[\mathcal{T}(\mu_{\vartheta,n},\mu_{\vartheta}) \leq 2\varepsilon_{\star} + 3\varepsilon] \pi(\mathrm{d}\vartheta) \\
+ \int_{\left\{\mathcal{T}_{(\cdot)} > \varepsilon_{\star} + 5\varepsilon/3\right\}} \limsup_{n} \mu_{\vartheta}^{n}[\mathcal{T}(\mu_{\vartheta,n},\mu_{\vartheta}) > \varepsilon/3] \pi(\mathrm{d}\vartheta)$$

and finally, by 4 of B2, $\widetilde{\forall} \vartheta \in \mathcal{H}$ and $\forall \varepsilon \in]0, \varepsilon_0 - \varepsilon_{\star}[$ small enough to have also $2\varepsilon_{\star} + 3\varepsilon < \varepsilon_1$,

$$\limsup_{n} \mu_{\vartheta}^{n} [\mathcal{T}(\mu_{\vartheta,n}, \mu_{\vartheta}) \leq 2\varepsilon_{\star} + 3\varepsilon] \equiv 1 - \lim\inf_{n} \mu_{\vartheta}^{n} [\mathcal{T}(\mu_{\vartheta,n}, \mu_{\vartheta}) > 2\varepsilon_{\star} + 3\varepsilon] \leq 1 - \sigma.$$

d. Let's fix any r > 0 small enough to have $r \leq \zeta$ and $\{\rho_{\mathcal{H}}(\cdot, \vartheta_{\star}) < r\} \subseteq U_{\star}$. Then B4 guarantees that there exists $\mathcal{N} \in \mathcal{B}(\mathcal{H})$ with $\pi[\mathcal{N}] = 0$ such that, for any $\vartheta \in \mathcal{H} \setminus \mathcal{N}$ with $\rho_{\mathcal{H}}(\vartheta, \vartheta_{\star}) < r$,

$$\mathcal{T}_{\vartheta} - \varepsilon_{\star} \leq \psi(\rho_{\mathcal{H}}(\vartheta, \vartheta_{\star})) < \psi(r) \leq \psi(\zeta)$$

and thus $\{\rho_{\mathcal{H}}(\cdot, \vartheta_{\star}) < r\} \setminus \mathcal{N} \subset \{\mathcal{T}_{(\cdot)} < \varepsilon_{\star} + \psi(\zeta)\}$ or, equivalently,

$$\{\rho_{\mathcal{H}}(\cdot, \vartheta_{\star}) \geq r\} \cup \mathcal{N} \supset \{\mathcal{T}_{(\cdot)} \geq \varepsilon_{\star} + \psi(\zeta)\}$$

hence the thesis $(\forall n \in \mathbb{N}^*, \forall y^{1:n} \in \mathcal{Y}^n \text{ and } \forall \varepsilon \in]0, \varepsilon_0 - \varepsilon_{\star}[, \pi_{y^{1:n}}^{\varepsilon_{\star} + \varepsilon}[\mathcal{N}] = 0 \text{ as well}).$

Remark. Let's discuss how a condition consistent with A2 as the following could interact.

[A2'] (under A1) There exist $\delta, \varepsilon' \in]0, \infty[$ and $g \in L^1(\pi)$ with $g \geq \delta[\pi]$ all s.t., $\widetilde{\forall} \vartheta \in \mathcal{H}$ and $\forall (z^{1:n})_n$ with $z^{1:n} \in D^n_{\varepsilon'}$ for any $n \in \mathbb{N}^*$,

$$\delta \leq \lim\inf_n f_{\vartheta}^n(z^{1:n}) \quad \text{and} \quad \lim\sup_n f_{\vartheta}^n(z^{1:n}) \leq g(\vartheta).$$

Proposition. Under assumptions B0, B1, 1 and 2 of B2, B3, A1 and A2', the following occurs so far as $\varepsilon_{\star} < \varepsilon_{0} \wedge \varepsilon'$ and for any $\varepsilon \in]0, \varepsilon_{0} \wedge \varepsilon' - \varepsilon_{\star}[$ and \mathbf{P} -a.a. $(y^{1:n})_{n}$.

a. For any
$$\zeta > 0$$
, $\pi_{y^{1:n}}^{\varepsilon_{\star} + \varepsilon} \left[\mathcal{T}_{(\cdot)} \geq \varepsilon_{\star} + \zeta \right] \geq \frac{\delta}{\|g\|_{1}} \pi \left[\mathcal{T}_{(\cdot)} \geq \varepsilon_{\star} + \zeta \right].$

b.
$$\pi_{y^{1:n}}^{\varepsilon_{\star}+\varepsilon} \left[\mathcal{H} \setminus \operatorname{arg\,min}_{\mathcal{H}} \mathcal{T}_{(\cdot)} \right] \geq \frac{\delta}{\|g\|_{1}} \pi \left[\mathcal{H} \setminus \operatorname{arg\,min}_{\mathcal{H}} \mathcal{T}_{(\cdot)} \right].$$

Proof. For any $\varepsilon \in]0, \varepsilon_0 \wedge \varepsilon' - \varepsilon_{\star}[$, **P**-a.a. $(y^{1:n})_n$ and $\zeta > 0$,

$$\pi_{y^{1:n}}^{\varepsilon_{\star}+\varepsilon}\left[\mathcal{T}_{(\cdot\,)}\geq\varepsilon_{\star}+\zeta\right]=\frac{\int_{\left\{\mathcal{T}_{(\cdot\,)}\geq\varepsilon_{\star}+\zeta\right\}}\pi(\mathrm{d}\vartheta)\int_{D_{\varepsilon_{\star}+\varepsilon}^{n}}f_{\vartheta}^{n}(z^{1:n})\,\mathrm{d}z^{1:n}}{\int_{\mathcal{H}}\pi(\mathrm{d}\vartheta')\int_{D_{\varepsilon}^{n}}\int_{\vartheta'}f_{\vartheta'}^{n}(\bar{z}^{1:n})\,\mathrm{d}\bar{z}^{1:n}}.$$

a. We use directly A2' provided we reduce further ε (note the cancellation of both the terms m[$D_{\varepsilon_{*}+\varepsilon}^{n}$]).

b. That's an elementary consequence of the above result in a way already seen previously. \Box

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