Uniform rates of Glivenko-Cantelli convergence and their use in Bayesian inference

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Abstract

The first part of the talk is focused on the validity of the following two upper bounds:

$$\mathsf{E}\Big[\Big(\sup_{n\geq 1} b_n \mathsf{d}_{[\mathbb{S}]}(\mathfrak{p}_0, \hat{\mathfrak{p}}_n)\Big)^p\Big] \leq C_p(\mathfrak{p}_0) \quad \text{(for some } p\geq 1) \tag{1}$$

$$\limsup_{n \to \infty} b_n d_{[\mathbb{S}]}(\mathfrak{p}_0, \hat{\mathfrak{p}}_n) \leq Y(\mathfrak{p}_0) \qquad \mathsf{P}-\text{a.s.}$$
(2)

Here: S denotes some topologically nice metric space (e.g., Polish); [S] and $d_{[S]}$ stand for the space of all probability measures (p.m.'s) on S and a suitable distance on [S], respectively; \mathfrak{p}_0 is a fixed p.m. on S; $\hat{\mathfrak{p}}_n$ is a random p.m. on S, depending the first *n*-segment (ξ_1, \ldots, ξ_n) of an i.i.d. sequence $\{\xi_i\}_{i\geq 1}$ from \mathfrak{p}_0 (like in the original Glivenko-Cantelli setting, where $\hat{\mathfrak{p}}_n = \frac{1}{n} \sum_{i=1}^n \delta_{\xi_i}$); $\{b_n\}_{n\geq 1}$ is a non-random diverging sequence, which quantifies the rate of convergence; $C_p(\mathfrak{p}_0)$ and $Y(\mathfrak{p}_0)$ are two non-random numbers, explicitly depending on \mathfrak{p}_0 . The bound (1)—which is what we call a *uniform (mean) Glivenko-Cantelli* bound—is the first example in which $\sup_{n\geq 1}$ figures inside the expectation, the literature having investigated, till now, only non-uniform bounds. See, e.g., [4, 5]. Detailed statements with explicit $C(\mathfrak{p}_0)$ and $Y(\mathfrak{p}_0)$ are given in the following cases of current interest:

S	$\mathrm{d}_{[\mathbb{S}]}$	٥	$\hat{\mathfrak{p}}_n$
\mathbb{R}^{d}	<i>p</i> -Wasserstein	any p.m. on \mathbb{R}^d with moment restriction	$rac{1}{n}\sum_{i=1}^n \delta_{\xi_i}$
N	Aly-Silvey index	any p.m. on \mathbb{N} with regularity restriction	$rac{1}{n}\sum_{i=1}^n \delta_{\xi_i}$
\mathbb{R}^{d}	Kullback-Leibler	Kullback-Leibler Gaussian p.m. on \mathbb{R}^d	Gaussian with estimated
116	Runback-Leibiei		(MLE) mean and covariance
\mathbb{R}^d	Kullback Leibler	exponential family on \mathbb{R}^d ex (N	exponential with estimated
Ш	Runback-Leiblei		(MLE) parameter

S	$\mathrm{d}_{[\mathbb{S}]}$	\mathfrak{p}_0	$\hat{\mathfrak{p}}_n$
any separable metric space with Lipschitz embedding in $L^p(\Omega, \mathcal{F}, \mu)$	1-Wasserstein	any p.m. on \mathbb{S} with regularity restriction	$\frac{1}{n}\sum_{i=1}^n \delta_{\xi_i}$

In the second part, of more statistical flavor, we assume that $\{\xi_i\}_{i\geq 1}$ is an exchangeable sequence (of observations) and we study the approximation of basic elements of the Bayesian inference, such as the posterior distribution $\pi(\cdot | \xi_1, \ldots, \xi_n) := \mathsf{P}[\tilde{\mathfrak{p}} \in \cdot | \xi_1, \ldots, \xi_n]$ and the predictive distribution, here written as $q_m(\cdot | \xi_1, \ldots, \xi_n) := \mathsf{P}[\frac{1}{m} \sum_{i=1}^m \delta_{\xi_{i+n}} \in \cdot | \xi_1, \ldots, \xi_n]$, where $\tilde{\mathfrak{p}}$ stands for the random probability measure satisfying the de Finetti representation $\mathsf{P}[\{\xi_i\}_{i\geq 1} \in \cdot | \tilde{\mathfrak{p}}] = \tilde{\mathfrak{p}}^{\infty}(\cdot)$. Then, we show that, if $\mathsf{E}[C_p(\tilde{\mathfrak{p}})] < +\infty$ with the same C_p as in (1), a martingale argument due to Blackwell and Dubins [1] yields, with probability one,

$$\limsup_{n \to \infty} b_n \mathbf{d}_{[[\mathbb{S}]]}^{(W_p)} \left(q_m(\cdot \mid \xi_1, \dots, \xi_n), \hat{\mathfrak{p}}_n^{\infty} \circ \tilde{\mathfrak{e}}_{n,m}^{-1} \right) \le \limsup_{n \to \infty} b_n \mathbf{d}_{[[\mathbb{S}]]}^{(W_p)} \left(\pi(\cdot \mid \xi_1, \dots, \xi_n), \delta_{\hat{\mathfrak{p}}_n} \right) \le Y(\tilde{\mathfrak{p}})$$

with b_n and Y as in (1)-(2), $d_{[[S]]}^{(W_p)}$ denoting the *p*-Wasserstein distance on the space of all p.m.'s on ([S], $d_{[S]}$) and $\hat{\mathfrak{p}}_n^{\infty} \circ \tilde{\mathfrak{e}}_{n,m}^{-1}(\cdot)$ standing for $\hat{\mathfrak{p}}_n^{\infty}(\{(x_1, x_2, \ldots) \in \mathbb{S}^{\infty} \mid \frac{1}{m} \sum_{i=1}^m \delta_{x_i} \in \cdot\})$. We conclude by showing how such abstract results constitute the basis for a "Bayesian theory of consistency", meaning that frequentist procedures are now seen as approximations of orthodox ones "with the glasses of the prior". See [2, 3]. In particular, we obtain a rate of approximation of orthodox Bayesian inferences by means of some empirical Bayes procedures.

References

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