Rate of Convergence of Predictive Distributions for Dependent Data

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# 91 (01-09)
RATE OF CONVERGENCE OF PREDICTIVE DISTRIBUTIONS FOR DEPENDENT DATA

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Abstract. This paper deals with empirical processes of the type

\[ C_n(B) = \sqrt{n} \{ \mu_n(B) - P(X_{n+1} \in B | X_1, \ldots, X_n) \}, \]

where \((X_n)\) is a sequence of random variables and \(\mu_n = (1/n) \sum_{i=1}^n \delta_{X_i}\) the empirical measure. Conditions for \(\sup_B |C_n(B)|\) to converge stably (in particular, in distribution) are given, where \(B\) ranges over a suitable class of measurable sets. These conditions apply when \((X_n)\) is exchangeable, or, more generally, conditionally identically distributed (in the sense of [6]). By such conditions, in some relevant situations, one obtains that \(\sup_B |C_n(B)| P \to 0\), or even that \(\sqrt{n} \sup_B |C_n(B)|\) converges a.s.. Results of this type are useful in Bayesian statistics.

1. Introduction and motivations

A number of real problems reduce to evaluate the predictive distribution

\[ a_n(\cdot) = P(X_{n+1} \in \cdot | X_1, \ldots, X_n) \]

for a sequence \(X_1, X_2, \ldots\) of random variables. Here, we focus on those situations where \(a_n\) can not be calculated in closed form, and one decides to estimate it basing on the available data \(X_1, \ldots, X_n\). Related references are [1], [2], [3], [5], [6], [8], [10], [15], [18], [20].

For notational reasons, it is convenient to work in the coordinate probability space. Accordingly, we fix a measurable space \((S, B)\), a probability \(P\) on \((S^\infty, B^\infty)\), and we let \(X_n\) be the \(n\)-th canonical projection on \((S^\infty, B^\infty, P)\), \(n \geq 1\). We also let \(G_n = \sigma(X_1, \ldots, X_n)\) and \(X = (X_1, X_2, \ldots)\).

Since we are concerned with predictive distributions, it is reasonable to make some (qualitative) assumptions on them. In [6], \(X\) is said to be conditionally identically distributed (c.i.d.) in case

\[ E(I_B(X_k) | G_n) = E(I_B(X_{n+1}) | G_n), \text{ a.s.,} \]

for all \(B \subseteq B\) and \(k > n \geq 0\),

where \(G_0\) is the trivial \(\sigma\)-field. Thus, at each time \(n \geq 0\), the future observations \((X_k: k > n)\) are identically distributed given the past \(G_n\). In a sense, this is a weak form of exchangeability. In fact, \(X\) is exchangeable if and only if it is stationary and c.i.d., and various examples of non exchangeable c.i.d. sequences are available.

In the sequel, \(X = (X_1, X_2, \ldots)\) is a c.i.d. sequence of random variables.

2000 Mathematics Subject Classification. 60G09, 60B10, 60A10, 62F15.

In that case, a sound estimate of \( a_n \) is the empirical distribution

\[
\mu_n = \frac{1}{n} \sum_{i=1}^{n} \delta_{X_i}.
\]

The choice of \( \mu_n \) can be defended as follows. Let \( \mathcal{D} \subseteq \mathcal{B} \) and let \( \|\cdot\| \) denote the sup-norm on \( \mathcal{D} \). Suppose also that \( \mathcal{D} \) is countably determined, as defined in Section 2. (The latter is a mild condition, only needed to handle measurability issues). Then,

\[
\|\mu_n - a_n\| = \sup_{B \in \mathcal{D}} \| \mu_n(B) - a_n(B) \| \xrightarrow{a.s.} 0 \tag{1}
\]

provided \( X \) is c.i.d. and \( \mu_n \) converges uniformly on \( \mathcal{D} \) with probability 1; see [5]. For instance, \( \|\mu_n - a_n\| \xrightarrow{a.s.} 0 \) whenever \( X \) is exchangeable and \( \mathcal{D} \) a Glivenko-Cantelli class. Or else, \( \|\mu_n - a_n\| \xrightarrow{a.s.} 0 \) if \( S = \mathbb{R}, \mathcal{D} = \{(-\infty, t] : t \in \mathbb{R}\} \), and \( X_1 \) has a discrete distribution or \( \inf_{\epsilon > 0} \lim \inf_n P(|X_{n+1} - X_n| < \epsilon) = 0 \); see [4].

To sum up, under mild assumptions, \( \mu_n \) is a consistent estimate of \( a_n \) (with respect to uniform distance) for c.i.d. data. This is in line with de Finetti [10] in the particular case of exchangeable indicators.

Taking (1) as a starting point, the next step is to investigate the convergence rate. That is, to investigate whether \( \alpha_n \|\mu_n - a_n\| \) converges in distribution, possibly to a null limit, for suitable constants \( \alpha_n > 0 \). This is precisely the purpose of this paper.

A first piece of information on the convergence rate of \( \|\mu_n - a_n\| \) can be gained as follows. For \( B \in \mathcal{B} \), define

\[
\mu(B) = \limsup_n \mu_n(B),
\]

\[
W_n(B) = \sqrt{n} \{\mu_n(B) - \mu(B)\}.
\]

By the SLLN for c.i.d. sequences, \( \mu_n(B) \xrightarrow{a.s.} \mu(B) \); see [6]. Hence, for fixed \( n \geq 0 \) and \( B \in \mathcal{B} \), one obtains

\[
E(\mu(B) \mid \mathcal{G}_n) = \lim_k E(\mu_k(B) \mid \mathcal{G}_n) = \lim_k \frac{1}{k} \sum_{i=n+1}^{k} E(I_B(X_i) \mid \mathcal{G}_n)
\]

\[
= E(I_B(X_{n+1}) \mid \mathcal{G}_n) = a_n(B) \quad \text{a.s.}.
\]

In turn, this implies \( \sqrt{n} \{\mu_n(B) - a_n(B)\} = E(W_n(B) \mid \mathcal{G}_n) \) a.s., so that

\[
\|\mu_n - a_n\| \leq \frac{1}{\sqrt{n}} \sup_{B \in \mathcal{D}} E\{W_n(B) \mid \mathcal{G}_n\} \leq \frac{1}{\sqrt{n}} E\{|W_n| \mid \mathcal{G}_n\} \quad \text{a.s.}
\]

If \( \sup_n E|W_n|^k < \infty \) for some \( k \geq 1 \), it follows that

\[
E\{(\alpha_n \|\mu_n - a_n\|)^k\} \leq \frac{\alpha_n}{\sqrt{n}} k E|W_n|^k \longrightarrow 0 \quad \text{whenever} \quad \frac{\alpha_n}{\sqrt{n}} \rightarrow 0.
\]

Even if obvious, this fact is potentially useful, as

\[
\sup_n E|W_n|^k < \infty \text{ for all } k \geq 1, \text{ if } X \text{ is exchangeable,} \tag{2}
\]

for various choices of \( \mathcal{D} \); see Remark 3. In particular, (2) holds if \( \mathcal{D} \) is finite.
The intriguing case, however, is \( \alpha_n = \sqrt{n} \). For each \( B \in \mathcal{B} \) and probability \( Q \) on \((S^\infty, \mathcal{B}^\infty)\), write

\[
C_n^Q(B) = E_Q(W_n(B) \mid \mathcal{G}_n) \quad \text{and} \quad C_n(B) = C_n^P(B) = \sqrt{n} \{ \mu_n(B) - a_n(B) \}.
\]

In Theorem 3.3 of [6], the asymptotic behaviour of \( C_n(B) \) is investigated for \( \text{fixed} B \). Here, instead, we are interested in

\[
\|C_n\| = \sup_{B \in \mathcal{D}} |C_n(B)| = \sqrt{n} \|\mu_n - a_n\|.
\]

Our main result (Theorem 1) is the following. Fix a random probability measure \( N \) on \( \mathbb{R} \) and a probability \( Q \) on \((S^\infty, \mathcal{B}^\infty)\) such that

\[
\|C_n^Q\| \to N \text{ stably under } Q \quad \text{and} \quad \|W_n\| \text{ is uniformly integrable under both } P \text{ and } Q.
\]

Then,

\[
\|C_n\| \to N \text{ stably whenever } P \ll Q. \quad (3)
\]

A remarkable particular case is \( N = \delta_0 \). Suppose in fact that, for some \( Q \), one has \( \|C_n^Q\| \overset{Q}{\to} 0 \) and \( \|W_n\| \) uniformly integrable under both \( P \) and \( Q \). Then,

\[
\|C_n\| \overset{P}{\to} 0 \quad \text{whenever } P \ll Q.
\]

Stable convergence (in the sense of Renyi) is a stronger form of convergence in distribution. The definition is recalled in Section 2.

In general, one cannot dispense with the uniform integrability condition. However, the latter is often true. For instance, \( \|W_n\| \) is uniformly integrable (under \( P \) and \( Q \)) provided \( \mathcal{D} \) meets (2) and \( X \) is exchangeable (under \( P \) and \( Q \)).

To make (3) concrete, a large list of reference probabilities \( Q \) is needed. Various examples are available in the Bayesian nonparametrics framework; see e.g. [16] and references therein. The most popular is perhaps the Ferguson-Dirichlet law, denoted by \( Q_0 \). If \( P = Q_0 \), then \( X \) is exchangeable and

\[
a_n(B) = \frac{\alpha P(X_1 \in B) + n \mu_n(B)}{\alpha + n} \quad \text{a.s. for some constant } \alpha > 0.
\]

Since \( \|\mu_n - a_n\| \leq (\alpha/n) \) when \( P = Q_0 \), something more than \( \|C_n\| \overset{P}{\to} 0 \) can be expected in case \( P \ll Q_0 \). Indeed, we prove that

\[
n \|\mu_n - a_n\| = \sqrt{n} \|C_n\| \text{ converges a.s. whenever } P \ll Q_0 \text{ with a density satisfying a certain condition; see Theorem 2 and Corollary 5.}
\]

One more example should be mentioned. Let \( X_n = (Y_n, Z_n) \), where \( Z_n > 0 \) and

\[
P(Y_{n+1} \in B \mid \mathcal{G}_n) = \frac{\alpha P(Y_1 \in B) + \sum_{i=1}^{n} Z_i I_B(Y_i)}{\alpha + \sum_{i=1}^{n} Z_i} \quad \text{a.s.}
\]

for some constant \( \alpha > 0 \). Under some conditions, \( X \) is c.i.d. (but not necessarily exchangeable), \( \|W_n\| \) uniformly integrable and \( \|C_n\| \) converges stably. See Section 4.

The above material takes a nicer form when the condition \( P \ll Q \) can be given a simple characterization. This happens, for instance, if \( S = \{x_1, \ldots, x_k, x_{k+1}\} \) is
finite, $X$ exchangeable and $P(X_1 = x) > 0$ for all $x \in S$. Then, $P \ll Q_0$ (for some choice of $Q_0$) if and only if
\[
(\mu\{x_1\}, \ldots, \mu\{x_k\})
\]
has an absolutely continuous distribution with respect to Lebesgue measure. In this particular case, however, a part of our results can also be obtained through Bernstein - von Mises theorem; see Section 3.

Finally, we make two remarks.

(i) If $X$ is exchangeable, our results apply to Bayesian predictive inference. Suppose in fact $S$ is Polish and $\mathcal{B}$ the Borel $\sigma$-field, so that de Finetti's theorem applies. Then, $P$ is a unique mixture of product probabilities on $\mathcal{B}^\infty$ and the mixing measure is called prior distribution in a Bayesian framework. Now, given $Q, P \ll Q$ is just an assumption on the prior distribution. This is plain in the last example where $S = \{x_1, \ldots, x_k, x_{k+1}\}$. In Bayesian terms, such an example can be summarized as follows. For a multinomial statistical model, $\|C_n\|_{P, A} \to 0$ if the prior is absolutely continuous with respect to Lebesgue measure, and $\sqrt{n}\|C_n\|$ converges a.s. if the prior density satisfies a certain condition.

(ii) To our knowledge, there is no general representation for the predictive distributions of an exchangeable sequence. Such a representation would be very useful. Even if partially, results like (3) contribute to fill the gap. As an example, for fixed $B \in \mathcal{B}$, one obtains $a_n(B) = \mu_n(B) + o_P\left(\frac{1}{\sqrt{n}}\right)$ as far as $X$ is exchangeable and $P \ll Q$ for some $Q$ such that $C_nQ(B) \xrightarrow{Q} 0$ and $W_n(B)$ is uniformly integrable.

2. Main results

A few definitions need to be recalled. Let $T$ be a metric space, $\mathcal{B}_T$ the Borel $\sigma$-field on $T$ and $(\Omega, \mathcal{A}, P)$ a probability space. A random probability measure on $T$ is a mapping $N$ on $\Omega \times \mathcal{B}_T$ such that: (i) $N(\omega, \cdot)$ is a probability on $\mathcal{B}_T$ for each $\omega \in \Omega$; (ii) $N(\cdot, B)$ is $\mathcal{A}$-measurable for each $B \in \mathcal{B}_T$. Let $(Z_n)$ be a sequence of $T$-valued random variables and $N$ a random probability measure on $T$. Both $(Z_n)$ and $N$ are defined on $(\Omega, \mathcal{A}, P)$. Say that $Z_n$ converges stably to $N$ in case
\[
P(Z_n \in \cdot \mid H) \to E(N(\cdot) \mid H) \quad \text{weakly}
\]
for all $H \in \mathcal{A}$ such that $P(H) > 0$.

Clearly, if $Z_n \to N$ stably, then $Z_n$ converges in distribution to the probability law $E(N(\cdot))$ (just let $H = \Omega$). Stable convergence has been introduced by Renyi in [17] and subsequently investigated by various authors. See [9] for more information.

Next, say that $\mathcal{D} \subset \mathcal{B}$ is countably determined in case, for some fixed countable subclass $\mathcal{D}_0 \subset \mathcal{D}$, one obtains $\sup_{B \in \mathcal{D}_0}\|\nu_1(B) - \nu_2(B)\| = \sup_{B \in \mathcal{D}}\|\nu_1(B) - \nu_2(B)\|$ for every couple $\nu_1, \nu_2$ of probabilities on $\mathcal{B}$. A sufficient condition is that, for some countable $\mathcal{D}_0 \subset \mathcal{D}$, and for every $\epsilon > 0$, $B \in \mathcal{D}$ and probability $\nu$ on $\mathcal{B}$, there is $B_0 \in \mathcal{D}_0$ satisfying $\nu(B \Delta B_0) < \epsilon$. Most classes $\mathcal{D}$ involved in applications are countably determined. For instance, $\mathcal{D} = \{(-\infty, t] : t \in \mathbb{R}^k\}$ and $\mathcal{D} = \{\text{closed balls}\}$ are countably determined if $S = \mathbb{R}^k$ and $\mathcal{B}$ the Borel $\sigma$-field. Or else, $\mathcal{D} = \mathcal{B}$ is countably determined if $\mathcal{B}$ is countably generated.
We are now in a position to state our main result. Let $N$ be a random probability measure on $\mathbb{R}$, defined on the measurable space $(S^\infty, B^\infty)$, and let $Q$ be a probability measure on $(S^\infty, B^\infty)$.

**Theorem 1.** Let $D$ be countably determined. Suppose $\|C_n^Q\| \to N$ stably under $Q$, and $(\|W_n\| : n \geq 1)$ is uniformly integrable under $P$ and $Q$. Then,

\[
\|C_n\| = \sqrt{n} \|\mu_n - a_n\| \to N \text{ stably whenever } P \ll Q.
\]

**Proof.** Since $D$ is countably determined, there are no measurability problems in taking $\sup_{B \in D}$. In particular, $\|W_n\|$ and $\|C_n\|$ are random variables and $\|C_n\|$ is $\mathcal{G}_n$-measurable. Let $f$ be a version of $\frac{dP}{dQ}$ and $U_n = f - EQ(f | \mathcal{G}_n)$. Then,

\[
C_n(B) = E(W_n(B) \mid \mathcal{G}_n) = \frac{EQ(f W_n(B) \mid \mathcal{G}_n)}{EQ(f \mid \mathcal{G}_n)} = C_n^Q(B) + \frac{EQ(U_n W_n(B) \mid \mathcal{G}_n)}{EQ(f \mid \mathcal{G}_n)}, \quad P\text{-a.s., for each } B \in B.
\]

Letting $M_n = \frac{EQ(U_n W_n \mid \mathcal{G}_n)}{EQ(f \mid \mathcal{G}_n)}$ and taking $\sup_{B \in D}$, it follows that

\[
\|C_n^Q\| - M_n \leq \|C_n\| \leq \|C_n^Q\| + M_n, \quad P\text{-a.s.}
\]

We first assume $f$ bounded. Since $\|C_n^Q\| \to N$ stably under $Q$, given a bounded random variable $Z$ on $(S^\infty, B^\infty)$, one obtains

\[
\int \phi(\|C_n^Q\|) Z \, dQ \longrightarrow \int N(\phi) Z \, dQ,
\]

for each bounded continuous $\phi : \mathbb{R} \to \mathbb{R}$, where $N(\phi) = \int \phi(x) N(\cdot, dx)$.

Letting $Z = f I_H \mid P(H)$, with $H \in B^\infty$ and $P(H) > 0$, it follows that $\|C_n^Q\| \to N$ stably under $P$. Therefore, it suffices to prove $EM_n \to 0$. Given $\epsilon > 0$, since $\|W_n\|$ is uniformly integrable under $Q$, there is $c > 0$ such that

\[
EQ(\|W_n\| I_{\{\|W_n\| > c\}}) < \frac{\epsilon}{\sup_j f} \quad \text{for all } n.
\]

Since $M_n$ is $\mathcal{G}_n$-measurable,

\[
EM_n = EQ(f M_n) = EQ(EQ(f \mid \mathcal{G}_n) M_n) = EQ(\|W_n\|)
\]

\[
\leq c EQ(U_n) + (\sup f) EQ(\|W_n\| I_{\{\|W_n\| > c\}})
\]

\[
< c EQ(U_n) + \epsilon \quad \text{for all } n.
\]

Therefore, the martingale convergence theorem implies

\[
\limsup_n EM_n \leq c \limsup_n EQ(U_n) + \epsilon = \epsilon.
\]

This concludes the proof when $f$ is bounded.

Next, let $f$ be any density. Fix $k > 0$ such that $P(f \leq k) > 0$ and define $K = \{ f \leq k \}$ and $P_K(\cdot) = P(\cdot \mid K)$. Then, $P_K$ has the bounded density $f I_K / P(K)$ with respect to $Q$. By what already proved, $\|C_n^P\| \to N$ stably under $P_K$, where

\[
C_n^P(B) = EP_n(W_n(B) \mid \mathcal{G}_n) = \frac{EQ(I_K W_n(B) \mid \mathcal{G}_n)}{EQ(I_K \mid \mathcal{G}_n)}, \quad P_K\text{-a.s.}
\]
Letting \( R_n = I_K - E(I_K \mid \mathcal{G}_n) \), it follows that
\[
E\{I_K \| C_n - C^{P_n}_n \| \} = E\{I_K \sup_{B \in \mathcal{D}} \frac{E\{R_n W_n(B) \mid \mathcal{G}_n\}}{E(I_K \mid \mathcal{G}_n)} \} \\
\leq E\{I_K \frac{E\{|R_n| \| W_n \| \mid \mathcal{G}_n\}}{E(I_K \mid \mathcal{G}_n)} \} = E\{|R_n| \| W_n \| \} \\
\leq c E|R_n| + E\{|W_n\| I_{\{|W_n\| > c\}} \} \quad \text{for all } c > 0.
\]
Since \( E|R_n| \rightarrow 0 \) and \( \| W_n \| \) is uniformly integrable under \( P \), arguing as above implies
\[
E_{P_K} \| C_n - C^{P_n}_n \| \leq \frac{E\{I_K \| C_n - C^{P_n}_n \| \}}{P(K)} \rightarrow 0.
\]
Therefore, \( \| C_n \| \rightarrow N \) stably under \( P_K \). Finally, fix \( H \in \mathcal{B}^\infty \), \( P(H) > 0 \), and a bounded continuous function \( \phi : \mathbb{R} \rightarrow \mathbb{R} \). Then \( P(H \cap K) = P(H \cap \{f \leq k\}) > 0 \), for \( k \) large enough, and
\[
P(H) \left| E\left(\phi(\|C_n\|) \mid H\right) - E\left(N(\phi) \mid H\right) \right| \\
\leq 2 \sup_{\|\phi\|} |P(f > k)| + \left| E\left(\phi(\|C_n\|) \mid H \cap K\right) - E\left(N(\phi) \mid H \cap K\right) \right|.
\]
Since \( E\left(\phi(\|C_n\|) \mid H \cap K\right) \rightarrow E\left(N(\phi) \mid H \cap K\right) \) as \( n \rightarrow \infty \), and \( P(f > k) \rightarrow 0 \) as \( k \rightarrow \infty \), this concludes the proof.

We next deal with the particular case \( Q = Q_0 \), where \( Q_0 \) is a Ferguson-Dirichlet law on \( (S^\infty, \mathcal{B}^\infty) \). If \( P \ll Q_0 \) with a density satisfying a certain condition, the convergence rate of \( \| \mu_n - a_n \| \) can be remarkably improved.

**Theorem 2.** Suppose \( \mathcal{D} \) is countably determined and \( \sup_n E_{Q_0} \| W_n \|^2 < \infty \). Then, \( \sqrt{n} \| C_n \| = n \| \mu_n - a_n \| \) converges a.s. provided \( P \ll Q_0 \) and
\[
E_{Q_0}(f^2) - E_{Q_0}\left\{ E_{Q_n}(f \mid \mathcal{G}_n)^2 \right\} = O\left(\frac{1}{n}\right), \quad \text{for some version } f \text{ of } \frac{dP}{dQ_0}.
\]

**Proof.** Let \( D_n(B) = \sqrt{n} C_n(B) \). Then, \( \| D_n \| \) is \( \mathcal{G}_n \)-measurable (as \( \mathcal{D} \) is countably determined) and
\[
E\left(\| D_{n+1} \| \mid \mathcal{G}_n\right) = E\left(\sup_{B \in \mathcal{D}} \sum_{i=1}^{n+1} I_B(X_i) - (n + 1)E(\mu(B) \mid \mathcal{G}_{n+1}) \mid \mathcal{G}_n\right) \\
\geq \sup_{B \in \mathcal{D}} E\left(\sum_{i=1}^{n+1} I_B(X_i) \mid \mathcal{G}_n\right) - (n + 1)E(\mu(B) \mid \mathcal{G}_n) \\
= \sup_{B \in \mathcal{D}} \left| \sum_{i=1}^{n} I_B(X_i) - n E(\mu(B) \mid \mathcal{G}_n) \right| = \| D_n \| \quad \text{a.s.}
\]
Since \( \| D_n \| \) is a \( \mathcal{G}_n \)-submartingale, it suffices to prove that \( \sup_n E\| D_n \| < \infty \).

Let \( U_n = f - E_0(f \mid \mathcal{G}_n) \), where \( E_0 \) stands for \( E_{Q_0} \). By assumption, there are \( c_1, c_2 > 0 \) such that
\[
E_0 \| W_n \|^2 \leq c_1, \quad n E_0 U_n^2 = n \left\{ E_0(f^2) - E_0(E_0(f \mid \mathcal{G}_n)^2) \right\} \leq c_2 \quad \text{for all } n.
\]
As noted in Section 1, since \( Q_0 \) is a Ferguson-Dirichlet law, there is \( \alpha > 0 \) such that
\[
\sqrt{n} ||C_n^{Q_0}|| = \sqrt{n} \sup_{B \in D} \left| E_0(W_n(B) \mid \mathcal{G}_n) \right| \leq \alpha \quad \text{for all } n.
\]
Define \( M_n = \frac{E_0\left( \int_{\mathcal{G}_n} ||W_n|| \mid \mathcal{G}_n \right)}{E_0\left( f \mid \mathcal{G}_n \right)} \) and recall that \( ||C_n|| \leq ||C_n^{Q_0}|| + M_n \), \( P \)-a.s.; see the proof of Theorem 1. Then, for all \( n \), one obtains
\[
E\|D_n\| = \sqrt{n} E\|C_n\| \leq \sqrt{n} \left( E\|C_n^{Q_0}\| + E M_n \right) \leq \alpha + \sqrt{n} E_0(f M_n)
\]
\[
= \alpha + \sqrt{n} E_0(||U_n|| \mid W_n) \leq \alpha + \sqrt{n} \sqrt{E_0 U_n^2 E_0 ||W_n||^2}
\]
\[
\leq \alpha + \sqrt{c_1 n} E_0 U_n^2 \leq \alpha + \sqrt{c_1 c_2}.
\]
\[\Box\]

Finally, we specify a point raised in Section 1.

**Remark 3.** There is a long list of (countably determined) choices of \( D \) such that
\[
\sup_n E\|W_n\|^k \leq c(k), \quad \text{for all } k \geq 1,
\]
if \( X \) is i.i.d., where \( c(k) \) is some universal constant; see e.g. Subsections 2.14.1 and 2.14.2 of [21]. Fix one such \( D \), \( k \geq 1 \), and suppose \( S \) is Polish and \( B \) the Borel \( \sigma \)-field. If \( X \) is exchangeable, de Finetti’s theorem yields \( E(||W_n||^k \mid T) \leq c(k) \) a.s. for all \( n \), where \( T \) is the tail \( \sigma \)-field of \( X \). Hence, \( E||W_n||^k = E\{ E(||W_n||^k \mid T) \} \leq c(k) \) for all \( n \). This proves inequality (2).

3. **Exchangeable data with finite state space**

When \( X \) is exchangeable and \( S \) finite, there is some overlapping between Theorem 1 and a result of Bernstein and von Mises.

3.1. **Connections with Bernstein - von Mises theorem.** For each \( \theta \) in an open set \( \Theta \subset \mathbb{R}^k \), let \( P_\theta \) be a product probability on \( (S^\infty, \mathcal{B}^\infty) \) (that is, \( X \) is i.i.d. under \( P_\theta \)). Suppose the map \( \theta \mapsto P_\theta(B) \) is Borel measurable for fixed \( B \in \mathcal{B}^\infty \). Given a (prior) probability \( \pi \) on the Borel subsets of \( \Theta \), define
\[
P(B) = \int P_\theta(B) \pi(d\theta), \quad B \in \mathcal{B}^\infty.
\]

Roughly speaking, Bernstein - von Mises (BVM) theorem can be stated as follows. Suppose \( \pi \) is absolutely continuous with respect to Lebesgue measure and the statistical model \( (P_\theta : \theta \in \Theta) \) is suitably "smooth" (we refer to [13] for a detailed exposition of what "smooth" means). For each \( n \), suppose \( \theta \) admits a (consistent) maximum likelihood estimator \( \hat{\theta}_n \). Further, suppose the prior \( \pi \) possesses the first moment and denote \( \theta_n^* \) the posterior mean of \( \theta \). Then,
\[
\sqrt{n} (\hat{\theta}_n - \theta_n^*) \overset{P_{\theta_0}}{\longrightarrow} 0
\]
for each \( \theta_0 \in \Theta \) such that the density of \( \pi \) is strictly positive and continuous at \( \theta_0 \).

Actually, BVM-theorem yields much more than asserted, what reported above being just the corollary connected to this paper. We refer to [13] and [14] for more information and historical notes. See also [18].
also let \( \lambda \) denote Lebesgue measure on \( \mathbb{R}^k \) and \( \pi \) the probability distribution of

\[
\theta = \big( \mu(x_1), \ldots, \mu(x_k) \big).
\]

As noted in Section 1, \( \pi \ll \lambda \) if and only if \( P \ll Q_0 \) for some choice of \( Q_0 \). Since \( \mathcal{D} \) is finite and \( X \) exchangeable under \( P \) and \( Q_0 \), then \( \| W_n \| \) is uniformly integrable under \( P \) and \( Q_0 \). Thus, Theorem 1 yields \( \| C_n \| \xrightarrow{P} 0 \) whenever \( \pi \ll \lambda \). On the other hand, \( \pi \) is the prior distribution for this problem. The underlying statistical model is smooth and finite-dimensional (it is just a multinomial model). Further, for each \( n \), the maximum likelihood estimator and the posterior mean of \( \theta \) are, respectively,

\[
\hat{\theta}_n = \big( \mu_n(x_1), \ldots, \mu_n(x_k) \big), \quad \theta_n^* = \big( a_n(x_1), \ldots, a_n(x_k) \big).
\]

Thus, BVM-theorem implies \( \| C_n \| \xrightarrow{P} 0 \) as far as \( \pi \ll \lambda \) and the density of \( \pi \) is continuous on the complement of a \( \pi \)-null set.

To sum up, in this particular case, the same conclusions as Theorem 1 can be drawn from BVM-theorem. Unlike the latter, however, Theorem 1 does not require any condition on the density of \( \pi \).

3.2. Some consequences of Theorems 1 and 2. In this subsection, we focus on \( S = \{0, 1\} \). Thus, \( \mathcal{D} = \mathcal{B} = \) power set of \( S \) and \( \lambda \) is Lebesgue measure on \( \mathbb{R} \). Let \( \mathcal{N}(0, a) \) denote the one-dimensional Gaussian law with mean 0 and variance \( a \geq 0 \) (where \( \mathcal{N}(0, 0) = \delta_0 \)). Our first result allows \( \pi \) to have a discrete part.

**Corollary 4.** With \( S = \{0, 1\} \), let \( \pi \) be the probability distribution of \( \mu \{1\} \) and

\[
\Delta = \{ \theta \in [0, 1] : \pi(\theta) > 0 \}, \quad A = \{ \omega \in S^\infty : \mu(\omega, \{1\}) \in \Delta \}.
\]

Define the random probability measure \( N \) on \( \mathbb{R} \) as

\[
N = (1 - I_A) \delta_0 + I_A \mathcal{N}(0, \mu \{1\}(1 - \mu \{1\})).
\]

If \( X \) is exchangeable and \( \pi \) does not have a singular continuous part, then \( C_n \{1\} \xrightarrow{N} N \) stably and \( \| C_n \| \xrightarrow{N \circ h^{-1}} N \) stably

where \( h(x) = |x|, x \in \mathbb{R} \), is the modulus function.

**Proof.** By standard arguments, the Corollary holds when \( \pi(\Delta) \in (0, 1) \) provided it holds when \( \pi(\Delta) = 0 \) and \( \pi(\Delta) = 1 \). Let \( \pi(\Delta) = 0 \). Then \( \pi \ll \lambda \), as \( \pi \) does not have a singular continuous part, and the Corollary follows from Theorem 1. Thus, it can be assumed \( \pi(\Delta) = 1 \). Since \( C_n \{0\} = -C_n \{1\}, \| C_n \| = \| C_n \{1\} \| \) and the modulus function is continuous, it suffices to prove that \( C_n \{1\} \xrightarrow{N} N \) stably.

Next, exchangeability of \( X \) implies \( W_n \{1\} \xrightarrow{\mathcal{N}(0, \mu \{1\}(1 - \mu \{1\}))} N \) stably; see e.g. Theorem 3.1 of [6]. Since \( \pi(\Delta) = 1 \), then \( N = \mathcal{N}(0, \mu \{1\}(1 - \mu \{1\})) \) a.s.. Hence, it is enough to show that \( E | C_n \{1\} - W_n \{1\} | \xrightarrow{} 0 \).
Fix $\epsilon > 0$ and let $M_n = W_n\{1\}$. Since $X$ is exchangeable, $M_n$ is uniformly integrable. Therefore, there is $c > 0$ such that

$$\sup_n E\left( |M_n| I_{\{|M_n| > c\}} \right) < \frac{\epsilon}{4}.$$ 

Define $\phi(x) = x$ if $|x| \leq c$, $\phi(x) = c$ if $x > c$, and $\phi(x) = -c$ if $x < -c$. Since $C_n\{1\} = E(M_n \mid G_n)$ a.s., it follows that

$$E|C_n\{1\} - W_n\{1\}| \leq E\left| E(M_n \mid G_n) - E(\phi(M_n) \mid G_n) \right| +$$

$$+ E\left| E(\phi(M_n) \mid G_n) - \phi(M_n) \right| + E|\phi(M_n) - M_n|$$

$$\leq E\left| E(\phi(M_n) \mid G_n) - \phi(M_n) \right| + 4E\left( |M_n| I_{\{|M_n| > c\}} \right)$$

$$< E\left| E(\phi(M_n) \mid G_n) - \phi(M_n) \right| + \epsilon \text{ for all } n.$$ 

Write $\Delta = \{a_1, a_2, \ldots\}$ and $M_{n,j} = \sqrt{n}(\mu_n\{1\} - a_j)$. Since $\sigma(M_{n,j}) \subset G_n$ and $P(\mu\{1\} \in \Delta) = \pi(\Delta) = 1$, one also obtains

$$E\left| E(\phi(M_n) \mid G_n) - \phi(M_n) \right| = \sum_j E\left| E(\phi(M_{n,j}) I_{\{\mu(1) = a_j\}} \mid G_n) - \phi(M_{n,j}) I_{\{\mu(1) = a_j\}} \right|$$

$$= \sum_j E\left| \phi(M_{n,j}) \left\{ \mu(1) = a_j \mid G_n \right\} - I_{\{\mu(1) = a_j\}} \right|$$

$$\leq c \sum_{j=1}^m E\left| \mu(1) = a_j \mid G_n \right| + 2c \sum_{j=m}^n \pi(a_j) \text{ for all } m,n.$$ 

By the martingale convergence theorem, $E\left| \mu(1) = a_j \mid G_n \right| - I_{\{\mu(1) = a_j\}} \rightarrow 0$, as $n \rightarrow \infty$, for each $j$. Thus,

$$\limsup_n E|C_n\{1\} - W_n\{1\}| \leq \epsilon + 2c \sum_{j=m}^n \pi(a_j) \text{ for all } m.$$ 

Taking the limit as $m \rightarrow \infty$ concludes the proof. \hfill \Box

If $\pi$ is singular continuous, we conjecture that $C_n\{1\}$ converges stably to a non null limit. But we have not a proof.

In the next result, a real function $g$ on $(0,1)$ is said to be almost Lipschitz in case $x \mapsto g(x)x^{a}(1-x)^b$ is Lipschitz on $(0,1)$ for some reals $a, b < 1$.

**Corollary 5.** Suppose $S = \{0,1\}$, $X$ is exchangeable and $\pi$ is the probability distribution of $\mu\{1\}$. If $\pi$ admits an almost Lipschitz density with respect to $\lambda$, then $\sqrt{n}\|C_n\|$ converges a.s. to a real random variable.

**Proof.** Let $V = \mu\{1\}$. By assumption, there are $a, b < 1$ and a version $g$ of $\frac{d\pi}{d\lambda}$ such that $\phi(\theta) = g(\theta)\theta^a(1-\theta)^b$ is Lipschitz on $(0,1)$. For each $u_1, u_2 > 0$, we can take $Q_0$ such that $V$ has a beta-distribution with parameters $u_1, u_2$ under $Q_0$. Let $Q_0$ be such that $V$ has a beta-distribution with parameters $u_1 = 1-a$ and $u_2 = 1-b$ under $Q_0$. Then, for any $n \geq 1$ and $x_1, \ldots, x_n \in \{0,1\}$, one obtains

$$P(X_1 = x_1, \ldots, X_n = x_n) = \int_0^1 \theta^r(1-\theta)^{n-r} \pi(d\theta) = \int_0^1 \theta^{-a}(1-\theta)^{n-b} \phi(\theta) \, d\theta$$

$$= c \int V^r(1-V)^{n-r} \phi(V) \, dQ_0 \text{ where } r = \sum_{i=1}^n x_i \text{ and } c > 0 \text{ is a constant.}$$
Let $h = c \phi$. Then, $h$ is Lipschitz and $f = h(V)$ is a version of $\frac{dP}{dQ_0}$.

Let $V_n = E_0(V \mid \mathcal{G}_n)$, where $E_0$ stands for $E_{Q_0}$. Since $h$ is Lipschitz,

$$
|f - E_0(f \mid \mathcal{G}_n)| \leq |h(V) - h(V_n)| + E_0(|h(V) - h(V_n)| \mid \mathcal{G}_n)
$$

$$
\leq d|V - V_n| + dE_0(|V - V_n| \mid \mathcal{G}_n)
$$

where $d$ is the Lipschitz constant of $h$. Since $E_0\|C^Q\|_2^2 \leq E_0\|W_n\|^2$ and

$$
\sqrt{n}|V - V_n| = |C^Q_n \{1\} - W_n \{1\}| \leq \|C^Q_n\| + \|W_n\|,
$$

it follows that

$$
E_0(f^2) - E_0(E_0(f \mid \mathcal{G}_n)^2) = E_0\{(f - E_0(f \mid \mathcal{G}_n))^2\} \leq 4d^2E_0((V - V_n)^2)
$$

$$
\leq \frac{4d^2}{n}E_0\{(||C^Q_n|| + \|W_n\|)^2\} \leq \frac{16d^2}{n}E_0\|W_n\|^2.
$$

Since $\sup_n E_0\|W_n\|^2 < \infty$, then $E_0(f^2) - E_0(E_0(f \mid \mathcal{G}_n)^2) = O(1/n)$. An application of Theorem 2 concludes the proof. \hfill \Box

Corollaries 4 and 5 deal with $S = \{0,1\}$ but similar results can be proved for any finite $S$. See also [12] and [19].

\section{4. Generalized Polya urns}

In this section, basing on Examples 1.3 and 3.5 of \cite{6}, the asymptotic behaviour of $\|C_n\|$ is investigated for a certain c.i.d. sequence.

Let $(\mathcal{Y}, \mathcal{B}_\mathcal{Y})$ be a measurable space, $\mathcal{B}_+\sigma$-field on $(0,\infty)$ and 

$$
S = \mathcal{Y} \times (0,\infty), \quad \mathcal{B} = \mathcal{B}_\mathcal{Y} \otimes \mathcal{B}_+, \quad X_n = (Y_n, Z_n), \text{ where}
$$

$$
Y_n(\omega) = y_n, \quad Z_n(\omega) = z_n \text{ for all } \omega = (y_1, z_1, y_2, z_2, \ldots) \in S^\infty.
$$

Given a law $P$ on $\mathcal{B}^\infty$, it is assumed that

$$
P(Y_{n+1} \in B \mid \mathcal{G}_n) = \frac{\alpha P(Y_1 \in B) + \sum_{i=1}^n Z_i I_B(Y_1)}{\alpha + \sum_{i=1}^n Z_i} \quad \text{a.s., } n \geq 1, \quad (4)
$$

$$
P(Z_{n+1} \in C \mid X_1, \ldots, X_n, Y_{n+1}) = P(Z_1 \in C) \quad \text{a.s., } n \geq 0, \quad (5)
$$

for some constant $\alpha > 0$ and all $B \in \mathcal{B}_\mathcal{Y}$ and $C \in \mathcal{B}_+$. Note that $(Z_n)$ is i.i.d. and $Z_{n+1}$ is independent of $(Y_1, Z_1, \ldots, Y_n, Z_n, Y_{n+1})$ for all $n \geq 0$.

In real problems, the $Z_n$ should be viewed as weights while the $Y_n$ describe the phenomenon of interest. As an example, consider an urn containing white and black balls. At each time $n \geq 1$, a ball is drawn and then replaced together with $Z_n$ more balls of the same colour. Let $Y_n$ be the indicator of the event $\{\text{white ball at time } n\}$ and suppose $Z_n$ is chosen according to a fixed distribution on the integers, independently of $(Y_1, Z_1, \ldots, Y_{n-1}, Z_{n-1}, Y_n)$. Then, the predictive distributions of $X$ are given by (4)-(5). Note also that the probability law of $(Y_n)$ is Ferguson-Dirichlet in case $Z_n = 1$ for all $n$.

It is not hard to prove that $X$ is c.i.d.. We state this fact as a lemma.

\textbf{Lemma 6.} The sequence $X$ assessed according to (4)-(5) is c.i.d..

\textbf{Proof.} Fix $k > n \geq 0$ and $A \in \mathcal{B}_\mathcal{Y} \otimes \mathcal{B}_+$. By a monotone class argument, it can be assumed $A = B \times C$ where $B \in \mathcal{B}_\mathcal{Y}$ and $C \in \mathcal{B}_+$. Further, it can be assumed
Therefore, we focus on \(E \in \mathbb{R}\) a real random variable on \((\Omega_0, \mathcal{F}_0)\). Similarly, let \(B \in \mathcal{F}_0\) be the probability distribution of \(\max_{i=1}^n Z_i\). In particular, stable convergence of \(\mathcal{F}_n\). Let 

\[
E(\mathbb{E}(Y_n | \mathcal{G}_n)) = E\{ E(\mathbb{E}(Y_{n+1} | \mathcal{G}_n)) | \mathcal{G}_n \} = \alpha + \sum_{i=1}^{n+1} Z_i
\]

Similarly, let \(B \in \mathcal{F}_0\) be the probability distribution of \(\max_{i=1}^n Z_i\). In particular, stable convergence of \(\mathcal{F}_n\). Let 

\[
E(\mathbb{E}(Y_n | \mathcal{G}_n)) = E\{ E(\mathbb{E}(Y_{n+1} | \mathcal{G}_n)) | \mathcal{G}_n \} = \alpha + \sum_{i=1}^{n+1} Z_i
\]

Finally, since \(\mathcal{G}_n \subset \mathcal{G}_n^*\), the previous equality implies 

\[
E(\mathbb{E}(Y_{n+1} | \mathcal{G}_n)) = P(Z_1 \in C) \cdot E\{ E(\mathbb{E}(Y_{n+1} | \mathcal{G}_n)) | \mathcal{G}_n \}
\]

Usually, one is interested in predicting \(Y_n\) more than \(Z_n\). Thus, in the sequel, we focus on \(P(Y_{n+1} = B | \mathcal{G}_n)\). For each \(B \in \mathcal{F}_0\), we write 

\[
C_n(B) = C_n(B \times (0, \infty)), \quad a_n(B) = a_n(B \times (0, \infty)) = P(Y_{n+1} = B | \mathcal{G}_n)
\]

and so on.

In Example 3.5 of [6], assuming \(EZ_1^2 < \infty\), it is shown that 

\[
C_n(B) \to \mathcal{N}(0, \sigma^2_B) \quad \text{stably, where} \quad \sigma^2_B = \frac{\text{var}(Z_1)}{(EZ_1)^2} \mu(B)(1 - \mu(B)).
\]

Here, we prove that \(C_n\) converges stably when regarded as a map \(C_n : S^\infty \to l^\infty(D)\), where \(l^\infty(D)\) is the space of real bounded functions on \(D\) equipped with uniform distance; see Section 1.5 of [21]. In particular, stable convergence of \(C_n\) as a random element of \(l^\infty(D)\) implies stable convergence of \(\|C_n\| = \sup_{B \in D}|C_n(B)|\).

Intuitively, the stable limit of \(C_n\) (when it exists) is connected to Brownian bridge. Let \(B_1, B_2, \ldots\) be pairwise disjoint elements of \(\mathcal{B}_Y\) and 

\[
\mathcal{D} = \{ B_k \times (0, \infty) : k \geq 1 \}, \quad T_0 = 0, \quad T_k = \sum_{i=1}^k \mu(B_i).
\]

Also, let \(G\) be a standard Brownian bridge process on some probability space \((\Omega_0, \mathcal{A}_0, P_0)\). For fixed \(w \in S^\infty\), 

\[
L(w, B_k) = \frac{\sqrt{\text{var}(Z_1)}}{EZ_1} \{ G(T_k(w)) - G(T_{k-1}(w)) \}
\]

is a real random variable on \((\Omega_0, \mathcal{A}_0, P_0)\). Since the \(B_k\) are pairwise disjoint and \(G\) has continuous paths, \(L(w, B_k) \to 0\) as \(k \to \infty\). So, it makes sense to define \(M(w, \cdot)\) as the probability distribution of \(L(w) = (L(w, B_1), L(w, B_2), \ldots)\), that is, 

\[
M(w, A) = P_0 \{ L(w) \in A \} \quad \text{for each Borel set} \ A \subset \mathbb{R}.
\]

Similarly, let \(N(w, \cdot)\) be the probability distribution of \(\sup_{k \geq 1} |L(w, B_k)|\), i.e., 

\[
N(w, A) = P_0 \{ \sup_{k \geq 1} |L(w, B_k)| \in A \} \quad \text{for each Borel set} \ A \subset \mathbb{R}.
\]
Theorem 7. Suppose $B_1, B_2, \ldots \in \mathcal{B}_Y$ are pairwise disjoint and $D, M, N$ are defined as above. Let $X$ be assessed according to (4)-(5) with $a \leq Z_1 \leq b$ a.s. for some constants $0 < a < b$. Then

$$\sup_n E\|W_n\|^2 \leq c \sqrt{P(Y_1 \in \cup_k B_k)},$$

for some constant $c$ independent of the $B_k$, and $C_n \to M$ stably (in the metric space $l^\infty(D)$). In particular, $\|C_n\| \to N$ stably.

Let $Q_1$ denote the probability law of a sequence $X$ satisfying (4)-(5) and $a \leq Z_1 \leq b$ a.s.. In view of Theorem 7, $Q_1$ can play the role of $Q$ in Theorem 1. That is, for an arbitrary c.i.d. sequence $X$ with distribution $P$, one has $\|C_n\| \to N$ stably provided $P \ll Q_1$ and $\|W_n\|$ is uniformly integrable under $P$. The condition of pairwise disjoint $B_k$ is actually rather strong. However, it holds in at least two relevant situations: when a single set $B$ is involved and when $S = \{x_1, x_2, \ldots\}$ is countable and $B_k = \{x_k\}$ for all $k$.

Proof of Theorem 7. This proof involves some simple but long calculations. Accordingly, we just give a sketch of the proof and we refer to [7] for details.

Since $X$ is c.i.d., for fixed $B \in \mathcal{B}_Y$ one has $a_n(B) = E(\mu(B) \mid G_n)$ a.s.. Hence, $(a_n(B) : n \geq 1)$ is a $\mathcal{G}_n$-martingale with $a_n(B) \xrightarrow{a.s.} \mu(B)$, and this implies

$$E\{(a_{n+1}(B) - \mu(B))^2\} = E\left\{\left(\sum_{j=n}^{\infty} (a_j(B) - a_{j+1}(B))\right)^2\right\} = E\left\{\sum_{j>n} (a_j(B) - a_{j+1}(B))^2\right\}.$$

Replacing $a_j(B)$ by (4) and using that $a \leq Z_i \leq b$ a.s. for all $i$, a long but straightforward calculation yields

$$\sum_{j>n} E\{(a_j(B) - a_{j+1}(B))^2\} \leq \frac{c_1}{n} P(Y_1 \in B)$$

where $c_1$ is a constant independent of $B$. It follows that

$$E\|a_{n+1} - \mu\|^2 = E\left\{\sup_k (a_{n+1}(B_k) - \mu(B_k))^2\right\} \leq \sum_k E\left\{(a_{n+1}(B_k) - \mu(B_k))^2\right\} \leq \frac{c_1}{n} \sum_k P(Y_1 \in B_k) = \frac{c_1}{n} P(Y_1 \in \cup_k B_k)$$

as the $B_k$ are pairwise disjoint.

Precisely as above, after some algebra, one obtains

$$E\|\mu_n - a_{n+1}\|^2 \leq \frac{c_2}{n} \sqrt{P(Y_1 \in \cup_k B_k)}$$

for some constant $c_2$ independent of $B_1, B_2, \ldots$. Therefore,

$$E\|W_n\|^2 = n E\|\mu_n - \mu\|^2 \leq 2n E\|\mu_n - a_{n+1}\|^2 + 2n E\|a_{n+1} - \mu\|^2 \leq c \sqrt{P(Y_1 \in \cup_k B_k)}$$

where $c = 2(c_1 + c_2)$. This proves inequality (6).

It remains to prove that $C_n \to M$ stably (in the metric space $l^\infty(D)$). For each $m \geq 1$, let $\Sigma_m$ be the $m \times m$ matrix with elements

$$\sigma_{k,j} = \frac{\text{var}(Z_k)}{(EZ_k)^2} (\mu(B_k \cap B_j) - \mu(B_k) \mu(B_j)),$$

$k, j = 1, \ldots, m$.

By Theorems 1.5.4 and 1.5.6 of [21], for $C_n \to M$ stably, it is enough that (i)-(Finite dimensional convergence):

$$(C_n(B_1), \ldots, C_n(B_m)) \to \mathcal{N}_m(0, \Sigma_m)$$

stably for each $m \geq 1$,
where $N_m(0, \Sigma_m)$ is the $m$-dimensional Gaussian law with mean 0 and covariance matrix $\Sigma_m$:

(ii)-(Asymptotic tightness): For each $\epsilon, \delta > 0$, there is $m \geq 1$ such that

$$\limsup_n P\left( \sup_{r,s>m} |C_n(B_r) - C_n(B_s)| > \epsilon \right) < \delta.$$ 

Fix $m \geq 1, b_1, \ldots, b_m \in \mathbb{R}$, and define $R_n = \sum_{k=1}^m b_k I_{B_k}(Y_n)$. Since $(R_n : n \geq 1)$ is c.i.d., arguing exactly as in Example 3.5 of [6], one obtains

$$\sum_{k=1}^m b_k C_n(B_k) = \sum_{i=1}^n \frac{R_i - E(R_{n+1} \mid G_n)}{\sqrt{n}} \rightarrow N(0, \sum_{k,j} b_k b_j \sigma_{k,j}) \text{ stably}.$$ 

Since $b_1, \ldots, b_m$ are arbitrary, (i) holds. To check (ii), given $\epsilon, \delta > 0$, take $m$ such that

$$P(Y_1 \in \bigcup_{r>m} B_r) < \left( \frac{\epsilon \delta^2}{4c} \right)^2$$

where $c$ is the constant involved in (6). By what already proved,

$$P\left( \sup_{r,s>m} |C_n(B_r) - C_n(B_s)| > \epsilon \right) \leq P\left( 2 \sup_{r>m} |C_n(B_r)| > \epsilon \right)$$

$$\leq P\left( 2 E\left( \sup_{r>m} |W_n(B_r)| \mid G_n \right) > \epsilon \right) \leq \frac{4 \epsilon}{c^2} E\left\{ \sup_{r>m} W_n(B_r)^2 \right\}$$

$$\leq \frac{4 \epsilon}{c^2} \sqrt{P(Y_1 \in \bigcup_{r>m} B_r)} < \delta.$$ 

Thus, (ii) holds, and this concludes the proof. □

Acknowledgments: This paper benefited from the helpful suggestions of two anonymous referees.

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