On accuracy of multivariate compound Poisson approximation

Citation for published version (APA):

Document status and date:
Published: 01/01/2000

Publisher Version:
Publisher's PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:
• A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher’s website.
• The final author version and the galley proof are versions of the publication after peer review.
• The final published version features the final layout of the paper including the volume, issue and page numbers.

Link to publication

General rights
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

• Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
• You may not further distribute the material or use it for any profit-making activity or commercial gain
• You may freely distribute the URL identifying the publication in the public portal.

If the publication is distributed under the terms of Article 25fa of the Dutch Copyright Act, indicated by the “Taverne” license above, please follow below link for the End User Agreement:
www.tue.nl/taverne

Take down policy
If you believe that this document breaches copyright please contact us at:
openaccess@tue.nl
providing details and we will investigate your claim.
Report 2000-042
On accuracy of multivariate compound Poisson approximation
S.Y.Novak
ISSN: 1389-2355
S.Y. Novak\textsuperscript{1}

**On accuracy of multivariate compound Poisson approximation**

**Abstract**

We present multivariate generalisations of some classical results on accuracy of Poisson approximation for the distribution of a sum of 0–1 random variables.

1 **Introduction**

Let $X, X_1, X_2, \ldots$ be a stationary sequence of dependent random variables (r.v.s). The key object in Extreme Value Theory is the number of exceedances

$$N_n(u) = \sum_{i=1}^{n} \mathbb{I}\{X_i > u\}.$$

Investigation of $N_n(u)$ is motivated by applications in finance, insurance, network modelling, meteorology, etc. (cf. [11, 19]).

In the independent case, $N_n(u)$ has binomial $\mathcal{B}(n, p)$ distribution, where $p = \mathbb{P}(X > u)$. If $p$ is "small" then $\mathcal{L}(N_n(u))$ may be approximated by the Poisson $\mathcal{P}(np)$ distribution. Accuracy of Poisson approximation for a binomial distribution has been investigated by famous authors (see, e.g., [17, 14, 10, 3] and references in [6]). The case of a sum of dependent 0–1 random variables was the subject of [9, 2, 3] (see also references in [3]).

The natural measure of closeness of discrete distributions is the total variation distance (TVD). Recall the definition of the TVD between the distributions of random vectors $X$ and $Y$ taking values in $\mathbb{Z}^n_+$, where $\mathbb{Z}_+ = \mathbb{N} \cup \{0\}$:

$$d_{TV}(X; Y) \equiv d_{TV}(\mathcal{L}(X); \mathcal{L}(Y)) = \sup_{A \in \mathbb{Z}^n_+} |\mathbb{P}(X \in A) - \mathbb{P}(Y \in A)|.$$

Let $\pi$ be a Poisson random variable with the parameter $np$. According to Barbour and Eagleson [2],

$$d_{TV}(N_n(u); \pi) \leq (1 - e^{-np}) p. \quad \text{(1)}$$

This is probably the best universal estimate of the TVD between binomial and Poisson distributions; it improves the results of Prokhorov [17] and LeCam [14]. Sharper bounds are available under extra restrictions (see [10, 20]).

\textsuperscript{1}Eurandom, PO Box 513, Eindhoven 5600 MB, Netherlands.
Dependence can cause clustering of extremes, and the Poisson approximation may no longer be valid. It is known that under a mild mixing condition, the limiting distribution of $N_n(u)$ is compound Poisson.

Accuracy of compound Poisson approximation for $\mathcal{L}(N_n(u))$ has been evaluated in [1, 15, 18], among others. The feature of the estimate given in [15] is that it coincides with (1) in the particular case of independent r.v.s.

A natural problem is to investigate the distribution of the vector

$$N_n = (N_n(u_1), ..., N_n(u_m))$$

of the numbers of exceedances given a set of distinct levels $u_1, ..., u_m$. The problem has applications in insurance and finance. For instance, a stationary sequence $\{X_i\}$ of (dependent) random variables can represents claims to an insurance company. Let $N(u_i)$ denote the number of claims exceeding a level $u_i$. It can be of interest to approximate the probability that the number of claims exceeding $u_i$ equals $n_i$, $1 \leq i \leq m$. This question can be easily addressed if the distribution of the vector $N_n$ has been approximated.

We show that under natural conditions, the limiting distribution of $N_n$ is necessarily compound Poisson. We evaluate accuracy of multivariate compound Poisson approximation for the distribution of $N_n$. In particular, we improve the corresponding results of Barbour et al. [4] and Novak [15]. In the case of independent trials, our result yields an estimate of accuracy of multivariate Poisson approximation for a multinomial distribution.

2 Results

We may assume $u_1 > ... > u_m$. Let $\mathcal{F}_{a,b} \equiv \mathcal{F}_{a,b}(u_1, ..., u_m)$ be the $\sigma$-field generated by the events $\{X_i > u_j\}$, $a \leq i \leq b$, $1 \leq j \leq m$. Denote

$$\alpha(l) \equiv \alpha(l, \{u_1, ..., u_m\}) = \sup \left| \text{P}(AB) - \text{P}(A)\text{P}(B) \right|, \quad \beta(k) \equiv \beta(l, \{u_1, ..., u_m\}) = \sup \mathbb{E} \sup_{B} \left| \text{P}(B|\mathcal{F}_{1,j}) - \text{P}(B) \right|,$$

where the supremum is taken over all $A \in \mathcal{F}_{1,j}$, $B \in \mathcal{F}_{j+i+1,n}$, $j \geq 1$, such that $\text{P}(A) > 0$.

*Condition* $\Delta_m \equiv \Delta_m \{u_1, ..., u_m\}$ *is said to hold if*

$$\alpha_n \equiv \alpha(l_n, \{u_1, ..., u_m\}) \to 0$$

*for some sequence* $\{l_n\} \subset \mathbb{Z}_+$ *such that* $l_n/n \to 0$ *as* $n \to \infty$. A vector $Y$ has a multivariate compound Poisson distribution $\Pi(\lambda, \mathcal{L}(Z))$ if

$$Y = \sum_{i=1}^{\pi} Z_i,$$
where $Z, Z_1, ...$ are i.i.d. random vectors, $\pi$ is independent of $\{Z_i\}$ and has the Poisson distribution with parameter $\lambda$.

**Theorem 1** Assume condition $\Delta_m$, and suppose that $u_m \equiv u_m(n)$ obeys

$$\limsup_n n\mathbb{P}(X > u_m) < \infty.$$  \hfill (2)

If $N_n$ converges weakly to a random vector $Y$ then $Y$ has a multivariate compound Poisson distribution.

Let $\zeta(n), \zeta_1(n), \zeta_2(n), ...$ be independent random vectors with the common distribution

$$\mathcal{L}(\zeta(n)) = \mathcal{L}(N_r | N_r(u_m) > 0),$$  \hfill (3)

where $r \in \{1, ..., n\}$. The proof of Theorem 1 shows that $Y \overset{d}{=} \Pi(\lambda, \mathcal{L}(Z))$, where $\lambda = - \lim_{n \to \infty} \ln \mathbb{P}(N_n(u_m) = 0)$ and $\mathcal{L}(\zeta)$ is the weak limit of $\mathcal{L}(\zeta(n))$ for an appropriate sequence $r = r_n$.

Denote

$$p = \mathbb{P}(X > u_m), \quad q = \mathbb{P}(N_r(u_m) > 0), \quad k = [n/r], \quad r' = n - rk,$$

and let $\pi$ be a Poisson random variable with parameter $kq$.

In Theorem 2 below we approximate the distribution of $N_n$ by the multivariate compound Poisson distribution $\mathcal{L}(N)$, where $N = \sum_{i=1}^r \zeta_i(n)$.

**Theorem 2** If $n > r > l \geq 0$ then

$$d_{tv}(N_n; N) \leq (1 - e^{-n\pi})rp + (2nr^{-1}l + r')p + nr^{-1}\min\{\beta(l); \kappa(l)\},$$  \hfill (4)

where $\kappa(l) = 2(1 + 2/m)\{2^{m-1}m^2\alpha^2(l)\}^{1/(2+m)}$ if $m2(m-1)/2 \alpha(l) \leq 1$, otherwise $\kappa(l) = 1$.

Barbour et al. [4] evaluated accuracy of compound Poisson approximation for general empirical point processes of exceedances in terms of a weaker Wasserstein-type distance $d_w$. Concerning the approximation $\mathcal{L}(N_n) \approx \mathcal{L}(N)$, Theorem 3.1 in [4] yields $d_w(N_n; N) \leq (1.65(1 - rp)^{-1/2} + e^{rp})rp + 2(2rp + nr^{-1}l)p + nr^{-1}\beta(l)$. In the case $m = 1$ (the 1-dimensional situation), (4) improves a result from [15] (cf. also [1]). If $m = 1$ and the random variables $\{X_i\}$ are independent then (4) with $l = 0, r = 1$ yields (1).

As a consequence of Theorem 2, we derive an estimate of accuracy of multivariate Poisson approximation for a multinomial distribution.

Let $i = (i_1, ..., i_m)$, where $i_1 \leq ... \leq i_m$. Denote $i^* = (i_1, i_2 - i_1, ..., i_m - i_{m-1})$,

$$N_n^* = (N_n(u_1), N_n(u_1, u_2), ..., N_n(u_m-1, u_m)),$$
where \( N_n(u, v) = \sum_{i=1}^{n} \mathbb{1}\{u \geq X_i > v\} \) as \( u > v \). Evidently, the distribution of \( N_n \) determines that of \( N_n^* \) and vice versa.

The statement of Theorem 2 can be reformulated as follows: if \( n > r > l \geq 0 \) then

\[
d_{TV}(N_n^*; N^*) \leq (1 - e^{-np})r p + (2nr^{-1}l + r')p + nr^{-1}\min\{\beta(l); \kappa(l)\},
\]

(4*)

where \( N^* = \sum_{i=1}^{n} \zeta_i^*(n), \) random vectors \( \zeta_i^*(n), \zeta_1^*(n), \ldots \) are independent and have the common distribution \( \mathbb{P}(\zeta^*(n) = i^*) = \mathbb{P}(\zeta(n) = i) \).

If the random variables \( \{X_i\} \) are independent and \( r = 1 \) then \( N_n^* \) has the multinomial distribution \( \mathcal{B}(n, p_1, \ldots, p_m) \) with parameters \( p_1 = \mathbb{P}(X > u_1), \ p_2 = \mathbb{P}(u_1 \geq X > u_2), \ldots, \ p_m = \mathbb{P}(u_{m-1} \geq X > u_m) \):

\[
\mathbb{P}(N_n^* = (l_1, \ldots, l_m)) = \frac{n!}{l_1! \cdots l_m! (n-l)!} p_1^{l_1} \cdots p_m^{l_m} (1-p)^{n-l},
\]

(5)

where \( l = l_1 + \ldots + l_m \leq n, \ p = p_1 + \ldots + p_m \). Theorem 2 yields an estimate of accuracy of multivariate Poisson approximation for the multinomial distribution \( \mathcal{B}(n, p_1, \ldots, p_m) \).

**Corollary 3** Let \( \pi_1, \ldots, \pi_m \) be independent Poisson random variables with parameters \( np_1, \ldots, np_m \). Denote \( Y = (\pi_1, \ldots, \pi_m) \). If \( \mathcal{L}(Y_n) = \mathcal{B}(n, p_1, \ldots, p_m) \) then

\[
d_{TV}(Y_n; Y) \leq (1 - e^{-np})p.
\]

(6)

### 3 Proofs

**Proof** of Theorem 2 incorporates some ideas from [15] and results of Berbee [5] and Bradley [8].

Denote \( \Pi_i = (\mathbb{1}\{X > u_1\}, \ldots, \mathbb{1}\{X > u_m\}) \), and let

\[
N_{r,j} = \sum_{i=jr+1}^{(j+1)r} \Pi_i \quad (0 \leq j \leq k = [n/r]).
\]

Evidently, \( N_n = \sum_{j=0}^{k} N_{r,j} \). Notice that the last block \( N_{r,k} \) may be omitted:

\[
d_{TV}(N_n; \sum_{j=0}^{k-1} N_{r,j}) \leq \mathbb{P}(N_{r,k} \neq 0) \leq r'p.
\]

Following Bernstein's "blocks" approach, we subtract a subblock of length \( l \) from each block \( X_{jr+1}, \ldots, X_{(j+1)r} \) of length \( r \). Denote

\[
N_{r,j}^* = \sum_{i=jr+1}^{(j+1)r-l} \Pi_i, \quad N_n^* = \sum_{j=0}^{k-1} N_{r,j}^* \quad (0 \leq j < k).
\]
Then \( \mathbb{P} \left( \sum_{j=0}^{k-1} N_{r,j} \neq \sum_{j=0}^{k-1} N_{r,j}^* \right) \leq k \mathbb{P} \left( N_{r,0} \neq N_{r,0}^* \right) \leq k \rho p. \)

Let \( \{N_{r,j}^*\} \) be independent copies of \( N_{r,0}^* \). Denote

\[
S_i = \sum_{j=0}^{i-1} N_{r,j}^* + \sum_{j=i+1}^{k-1} \hat{N}_{r,j}^* \quad (0 < i < k).
\]

Notice that \( S_j + \hat{N}_{r,j}^* = S_{j-1} + N_{r,j-1}^* \). We apply Lindeberg’s device (cf. [15]) in order to replace \( \{N_{r,j}^*\} \) by \( \{\hat{N}_{r,j}^*\} \):

\[
\mathbb{P} \left( \sum_{j=0}^{k-1} N_{r,j}^* \in A \right) - \mathbb{P} \left( \sum_{j=0}^{k-1} \hat{N}_{r,j}^* \in A \right) = \sum_{j=1}^{k-1} \left\{ \mathbb{P} (S_j + N_{r,j}^* \in A) - \mathbb{P} (S_j + \hat{N}_{r,j}^* \in A) \right\}.
\]

According to Berbee’s lemma ([5], ch. 4), the random vectors \( \sum_{j=0}^{i-1} N_{r,j}^* \), \( N_{r,j}^* \) and \( \hat{N}_{r,j}^* \) can be defined on a common probability space so that \( \mathbb{P} \left( N_{r,j}^* \neq \hat{N}_{r,j}^* \right) \leq \beta(l) \).

Therefore,

\[
\left| \mathbb{P} \left( \sum_{j=0}^{k-1} N_{r,j}^* \in A \right) - \mathbb{P} \left( \sum_{j=0}^{k-1} \hat{N}_{r,j}^* \in A \right) \right| \leq k \beta(l).
\]

The mixing coefficient \( \alpha \) is weaker than \( \beta \). Using Lemma 4 below, we evaluate

\[
\left| \mathbb{P} \left( \sum_{j=0}^{k-1} N_{r,j}^* \in A \right) - \mathbb{P} \left( \sum_{j=0}^{k-1} \hat{N}_{r,j}^* \in A \right) \right| \text{ in terms of } \alpha(l). \]

Note that \( \mathbb{E} |N_{r,0}^*| = \rho p \).

Inequality (10) with \( b = 1 \) and \( y = \rho p \) entails the random vectors \( \sum_{i=0}^{j-1} N_{r,i}^* \), \( N_{r,j}^* \) and \( \hat{N}_{r,j}^* \) can be defined on a common probability space so that \( \mathbb{P} \left( N_{r,j}^* \neq \hat{N}_{r,j}^* \right) = \mathbb{P} \left( |N_{r,j}^* - \hat{N}_{r,j}^*| \geq 1 \right) \leq \kappa(l) \) if \( m 2^{(m-1)/2} \alpha(l) \leq 1 \). Hence

\[
\left| \mathbb{P} \left( \sum_{j=0}^{k-1} N_{r,j}^* \in A \right) - \mathbb{P} \left( \sum_{j=0}^{k-1} \hat{N}_{r,j}^* \in A \right) \right| \leq k \min \{ \beta(l); \kappa(l) \}.
\]

Let \( \{\hat{N}_{r,j}\} \) be independent copies of \( N_{r,0} \), and set \( \hat{N}_n = \sum_{j=0}^{k-1} \hat{N}_{r,j} \). Evidently, \( \mathbb{P} \left( \sum_{j=0}^{k-1} \hat{N}_{r,j} \neq \sum_{j=0}^{k-1} \hat{N}_{r,j}^* \right) \leq k \rho p. \) Combining our estimates, we get

\[
d_{\text{TV}} \left( N_n; \hat{N}_n \right) \leq 2k \rho p + \rho \rho p + k \min \{ \beta(l); \kappa(l) \}.
\]

Denote \( \mu = \sum_{j=0}^{k-1} \mathbb{I} \{ \hat{N}_{r,j} \neq 0 \} \), and put

\[
Z_0 = 0, \ Z_j = \zeta_1(n) + \ldots + \zeta_j(n) \quad (j \geq 1).
\]

By Khintchin’s formula (see [12], ch. 2), \( \hat{N}_n \approx Z_\mu \). According to (1), \( d_{\text{TV}} (\mu; \pi) \leq (1 - e^{-kq}) q \). Using this inequality and an idea from [15], we conclude that

\[
d_{\text{TV}} (Z_\mu, Z_\pi) = \frac{1}{2} \sum_i \left| \mathbb{P} (Z_\mu = i) - \mathbb{P} (Z_\pi = i) \right|
\]

5
\[
\begin{align*}
\sum_{i} \sum_{m=0}^{\infty} \mathbb{I}(Z_m = i) |\mathbb{P}(\mu = m) - \mathbb{P}(\pi = m)| \\
= \frac{1}{2} (1-e^{-\eta q})q \leq (1-e^{-np})r_p.
\end{align*}
\]

The result follows. \(\square\)

The proof of Theorem 2 shows that the term \((1-e^{-np})r_p\) in the right-hand side of (4) may be replaced by any other estimate of \(d_{TV}(\mu, \pi)\) (cf. [10, 20]).

**Proof** of Theorem 1. Let \(\{r = r_n\}\) be a sequence of natural numbers such that
\[
n \gg r_n \gg l_n + 1, \ n r_n^{-1} \alpha_n^{2/(2+m)} \rightarrow 0. \tag{7}
\]

Such a sequence exists: one can put \(r_n = \max\{[n \alpha_n^{1/(2+m)}]; \sqrt{n(l_n + 1)}]\} \) (note that \(r_p \rightarrow 0\) because of (2)).

If \(N_n \Rightarrow \exists N\) then there exists the limit
\[
\lim \mathbb{P}(N_n(u_m) = 0) := e^{-t}. \tag{8}
\]

If \(t = 0\) then \(N_n(u_m) \rightarrow 0\), and the assertion of Theorem 1 trivially holds. Evidently, \(t < \infty\) (otherwise \(1 + o(1) = \mathbb{P}(N_n(u_m) \geq 1) \leq \mathbb{E}N_n(u_m) = r_p \rightarrow 0\). Thus, \(t \in (0; \infty)\).

It is known (cf. [13, 16]) that (8) with \(t \in (0; \infty)\) is equivalent to \(\mathbb{P}(N_r(u_m) > 0) \sim tr/n\). Therefore, if \(N_n \Rightarrow \exists N\) then Theorem 2 implies
\[
\mathbb{E}e^{i u N_n} = \exp \left( t \left( \varphi_{\zeta(n)}(v) - 1 \right) \right) + o(1) \rightarrow \mathbb{E}e^{i u N} \quad (\forall u \in \mathbb{R})
\]
as \(n \rightarrow \infty\), where \(\varphi_{\zeta(n)}\) is the characteristic function of \(\zeta(n)\). Hence there exists the limit \(\lim_{n \rightarrow \infty} \varphi_{\zeta(n)}(v) := \varphi(v)\). As a limit of a sequence of characteristic functions, it is a characteristic function itself. Therefore,
\[
\mathbb{E}e^{i u N} = \exp \left( t(\varphi(v) - 1) \right).
\]

This is a characteristic function of a compound Poisson random vector with intensity \(t\) and multiplicity distribution \(\mathcal{L}(\zeta)\) such that \(\mathbb{E}e^{i u \zeta} = \varphi(v)\). \(\square\)

**Proof** of Corollary 3. Let \(r = 1\) and \(l = 0\). Then \(\zeta^*(n)\) takes values \((1,0,...,0),...,(0,...,0,1)\) with probabilities \(p_1/p,...,p_m/p\) and \(\mathcal{L}(\pi) = \Pi(np)\). By Theorem 2,
\[
d_{TV}\left( Y_n; \sum_{j=1}^{\pi} \zeta^*_j(n) \right) \leq (1-e^{-np})p.
\]
It is easy to see that
\[ \mathbb{E} \exp \left( iv \sum_{j=1}^{n} c_j^*(n) \right) = \exp \left( n \sum_{j=1}^{m} (e^{iv} - 1) p_j \right) = \mathbb{E} e^{iv}\gamma \]
for any \( v \in \mathbb{R}^m \). Hence \( \sum_{j=1}^{n} c_j^*(n) \equiv Y \). \( \square \)

For \( v \in \mathbb{R}^m \), we put \( |v| = \max_{1 \leq i \leq m} |v_i| \). Let \((X, Y)\) be a random vector taking values in \( \mathbb{R}^l \times \mathbb{R}^m \), and let \( \alpha \) be the \( \alpha \)-mixing coefficient corresponding to the \( \sigma \)-fields \( \sigma(X) \) and \( \sigma(Y) \).

**Lemma 4** One can define random vectors \( X, Y \) and \( \hat{Y} \) on a common probability space in such a way that \( \hat{Y} \) is independent of \( X, \hat{Y} \not\equiv Y \) and \( (y > 0, K \in \mathbb{N}) \)
\[ \mathbb{P} \left( |\hat{Y} - Y| > y \right) \leq 2^{(m+3)/2} K^{m/2} \alpha + 2\mathbb{P}(|Y| > Ky) . \]  
(9)

In particular, if \( v = \mathbb{E}^1/|Y|^b < \infty \) and \( b(v/y)^b \geq m^{(m-1)/2} \alpha \) then
\[ \mathbb{P} \left( |\hat{Y} - Y| > y \right) \leq 2(1 + 2b/m) \left[ (2^{(m-1)/2} m/b)^2 (v/y)^{km} \alpha^{2b} \right]^{1/(2b+m)} . \]
(10)

If \( v_{\infty} = \text{ess sup} |Y| < \infty \) then (10) yields
\[ \mathbb{P} \left( |\hat{Y} - Y| > y \right) \leq 2^{(m+3)/2} (v_{\infty}/y)^{m/2} \alpha . \]
(11)

In the case \( m = 1 \), (10) improves the result of Theorem 3 in [8].

**Proof** of Lemma 4. Denote \( Y^\prec = Y \mathbb{I}\{ |Y| \leq Ky \} \). Vector \( Y^\prec \) takes values in \([-Ky; Ky]^m \). Splitting \([-Ky; Ky]\) into \( 2K \) intervals of length \( y \) induces the partition of \([-Ky; Ky]^m \) into \( N = (2K)^m \) cubes \( H_1, \ldots, H_N \). According to Theorem 2 in [8], one can define \( X, Y^\prec \) and \( \hat{Y}^\prec \) on a common probability space so that \( \hat{Y}^\prec \) is independent of \( X, \hat{Y}^\prec \not\equiv Y^\prec \) and
\[ \mathbb{P} \left( |\hat{Y}^\prec - Y^\prec| > y \right) = \mathbb{P}(A) \leq \sqrt{8N} \alpha, \]
where \( A = \{ \hat{Y}^\prec \text{ and } \hat{Y}^\prec \text{ are not elements of the same } H_i \} \).

Now we construct a vector \( \hat{Y} \) on the base of \( \hat{Y}^\prec \) such that \( \hat{Y} \not\equiv Y \). We put \( \hat{Y} = \hat{Y}^\prec + \mathbb{I}\{ \hat{Y}^\prec = 0 \} Y' \), where \( Y' \) is independent of all other random vectors, \( \mathcal{L}(Y') = \mathcal{L}(Y|B) \) and \( B = \{ Y^\prec = 0 \} = \{ Y = 0 \text{ or } |Y| > Ky \} \).

Evidently, \( \hat{Y} \not\equiv Y \). Indeed, \( \mathbb{P}(\hat{Y} = 0) = \mathbb{P}(\hat{Y}^\prec = 0 = Y') = \mathbb{P}(B)\mathbb{P}(Y' = 0) = \mathbb{P}(Y = 0) \), and if \( z \neq 0 \) then
\[ \mathbb{P}(\hat{Y} \in dz) = \mathbb{P}(\hat{Y}^\prec \in dz) + \mathbb{P}(\hat{Y}^\prec = 0, Y' \in dz) \]
\[ \mathbb{P}(B_e, Y \in dz) + \mathbb{P}(B)\mathbb{P}(Y \in dz|B) = \mathbb{P}(Y \in dz), \]

where \( B_e = \{0 < |Y| < Ky\} \) is the complement to \( B \). It is easy to see that \( \mathbb{P}(\hat{Y} \neq \hat{Y}^\leq) = \mathbb{P}(\hat{Y}^\leq = 0 \neq Y') = \mathbb{P}(B)\mathbb{P}(Y \neq 0|B) = \mathbb{P}(|Y| > Ky) \). Hence

\[ \mathbb{P}\left(|\hat{Y} - Y^\leq| > y\right) \leq \sqrt{8N}\alpha + \mathbb{P}(\hat{Y} \neq \hat{Y}^\leq) \leq \sqrt{8N}\alpha + \mathbb{P}(|Y| > Ky). \]

It remains to construct \((X, Y)\) on the base of \((X, Y^\leq)\). Let \( \{Y_x\} \) be independent random vectors with distributions \( \mathcal{L}(Y_x) = \mathcal{L}(Y|B, X = x) \). Denote \( Y^* = Y^\leq + I\{Y^\leq = 0\}Y_x \). Then \((X, Y^*) \overset{d}{=} (X, Y)\). Indeed,

\[ \mathbb{P}(X \in dx, Y^* = 0) = \mathbb{P}(X \in dx, Y^\leq = 0 = Y_x) = \mathbb{P}(X \in dx, Y^\leq = 0)\mathbb{P}(Y_x = 0) \]
\[ = \mathbb{P}(X \in dx, B, Y = 0) = \mathbb{P}(X \in dx, Y = 0). \]

If \( z \neq 0 \) then

\[ \mathbb{P}(X \in dx, Y^* \in dz) = \mathbb{P}(X \in dx, Y^\leq \in dz) + \mathbb{P}(X \in dx, Y^\leq = 0, Y_x \in dz) \]
\[ = \mathbb{P}(X \in dx, B_e, Y \in dz) + \mathbb{P}(X \in dx, B)\mathbb{P}(Y_x \in dz) = \mathbb{P}(X \in dx, Y \in dz). \]

Note that \( \mathbb{P}(Y^* \neq Y^\leq) = \mathbb{P}(Y^\leq = 0 \neq Y_x) = \mathbb{P}(|Y| > Ky) \). Therefore,

\[ \mathbb{P}\left(|\hat{Y} - Y^\leq| > y\right) \leq \mathbb{P}\left(|\hat{Y} - Y^\leq| > y\right) + \mathbb{P}(|Y| > Ky). \]

Combining our estimates, we get (9).

Using Chebyshev’s inequality, we deduce

\[ \mathbb{P}\left(|\hat{Y} - Y^\leq| > y\right) \leq cK^{m/2} + dK^{-b}, \]

where \( c = 2^{(m+3)/2}a \) and \( d = 2(\nu/y)^b \). The function \( f(x) = cx^{m/2} + dx^{-b} \) takes its minimum in \( x \geq 1 \) at \( x_0 = \max\{(2bd/cm)^{2/(m+2b)}, 1\} \). Since \( \frac{bd}{cm} = \frac{b(\nu/y)^b}{2^{(m-1)/2mA}} \), inequality (9) entails (10). The proof is complete. \( \square \)
References


