Proceedings of the 2020 Winter Simulation Conference
K.-H. Bae, B. Feng, S. Kim, S. Lazarova-Molnar, Z. Zheng, T. Roeder, and R. Thiesing, eds.

CONFIDENCE INTERVALS AND REGIONS FOR QUANTILES USING CONDITIONAL MONTE CARLO AND GENERALIZED LIKELIHOOD RATIOS

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ABSTRACT

This article develops confidence intervals (CIs) and confidence regions (CRs) for quantiles based on independent realizations of a simulation response. The methodology uses a combination of conditional Monte Carlo (CMC) and the generalized likelihood ratio (GLR) method. While batching and sectioning methods partition the sample into nonoverlapping batches, and construct CIs and CRs by estimating the asymptotic variance using sample quantiles from each batch, the proposed techniques directly estimate the underlying probability density function of the response. Numerical results show that the CIs constructed by applying CMC, GLR, and sectioning lead to comparable coverage results, which are closer to the targets compared with batching alone for relatively small samples; and the coverage rates of the CRs constructed by applying CMC and GLR are closer to the targets than both sectioning and batching when the sample size is relatively small and the number of probability levels is relatively large.

1 INTRODUCTION

For a random variable Y with the cumulative distribution function (c.d.f.) $F_Y(\cdot)$, the p-quantile $(0 < p < 1)$ is defined as $y_p = F_Y^{-1}(p) \equiv \inf\{y : F_Y(y) \geq p\}$; and if $F_Y(y)$ is continuous at each $y \in \mathbb{R}$, then $F_Y(y_p) = p$ for each $p \in (0, 1)$. Quantiles, also known as values-at-risk, are used as benchmarks in financial risk management (Jorion 2001), e.g., to regulate capital sufficiency of banks for sustaining losses from their trading activities (Glasserman 2004). Quantiles are also used as performance measures in service systems (Gélinas et al. 1995, Seila 1982) as well as for safety and uncertainty analysis of nuclear power plants. For instance, the U.S. Nuclear Regulatory Commission uses the 95/95 criterion, which requires plant licensees to verify, with 95% confidence, that the 0.95-quantiles of certain performance measures lie below mandated thresholds (U.S. Nuclear Regulatory Commission 2011).

If $\{Y_i : i = 1, \ldots, n\}$ is a sequence of independent and identically distributed (i.i.d.) simulation responses, then y_p can be estimated by $\widehat{y}_p(n) \equiv Y_{(\lceil np \rceil)}$, where $Y_{(1)} \leq \cdots \leq Y_{(n)}$ are the respective order statistics and $\lceil \cdot \rceil$ denotes the ceiling function. If the c.d.f. $F_Y(\cdot)$ is twice differentiable at y_p so that the associated probability density function (p.d.f.) $f_Y(\cdot)$ is differentiable and $f_Y(y_p) = \frac{\mathrm{d}}{\mathrm{d}y} F_Y(y)\big|_{y=y_p} = F_Y'(y_p) > 0$, then $\widehat{y}_p(n)$ is a consistent estimator and satisfies the following central limit theorem (CLT):

$$n^{1/2}\big(\widehat{y}_p(n) - y_p\big) \Rightarrow \sigma N(0,1) \quad \text{as } n \to \infty, \tag{1}$$

where $\sigma^2 \equiv p(1-p)/f_Y^2(y_p)$ is the asymptotic variance, $N(0,1)$ is the standard normal distribution, and "$\Rightarrow$" denotes convergence in distribution (Serfling 1980, Corollary B, p. 77).

Unfortunately, the density $f_Y(\cdot)$ in (1) is typically unknown. Although there are several distribution-free methods to construct a CI for a quantile (Serfling 1980, Section 2.6), the generalization of these methods for constructing CRs is not straightforward. An alternative methodology is based on batching. For given $b \geq 2$, one forms b nonoverlapping batches of simulation responses, each of size m ($n = bm$), and computes the sample quantiles $\widehat{y}_p(j,m)$ ($j = 1, \ldots, b$) from each batch. The quantile y_p is estimated by the sample average $\overline{\widehat{y}}_p(b,m) = \frac{1}{b}\sum_{j=1}^{b} \widehat{y}_p(j,m)$, and the asymptotic variance is estimated by m times the sample variance $S^2(b,m) \equiv \frac{1}{b-1}\sum_{j=1}^{b}\big[\,\widehat{y}_p(j,m) - \overline{\widehat{y}}_p(b,m)\,\big]^2$. The $100(1-\alpha)\%$ CI for y_p based on the batching method (BM) is

$$\mathscr{C}_{\mathrm{BM}}(m,\alpha) = \Big[\overline{\widehat{y}}_p(b,m) - t_{b-1,1-\alpha/2}S(b,m)\big/\sqrt{b},\ \ \overline{\widehat{y}}_p(b,m) + t_{b-1,1-\alpha/2}S(b,m)\big/\sqrt{b}\Big], \tag{2}$$

where $t_{\nu,\beta}$ denotes the β-quantile of Student's t distribution with ν degrees of freedom. The CLT (1) implies that as $m \to \infty$, the CI (2) is asymptotically valid—i.e., $\lim_{m\to\infty}\Pr\{\,y_p \in \mathscr{C}_{\mathrm{BM}}(m,\alpha)\,\} = 1-\alpha$. The method of sectioning improves upon the batching method by replacing the average batch quantile estimator $\overline{\widehat{y}}_p(b,m)$ in Equation (2) with the overall quantile estimator $\widehat{y}_p(n)$ (Asmussen and Glynn 2007, Nakayama 2014, Dong and Nakayama 2017). Both the batching and sectioning methods suffer from the trade-off between the bias and variance of their point estimators of y_p: the bias decreases as m increases, whereas the variance decreases as b increases.

Our approach for constructing a CI for y_p involves direct estimation of the unknown $f_Y(y_p) = F_Y'(y_p)$ based on the fact that the c.d.f. can be expressed as the expectation $F_Y(y_p) = \mathrm{E}[\mathbf{1}(Y \leq y_p)]$, where $\mathbf{1}(Y \leq y_p)$ is the indicator random variable that takes the value 1 when the condition $Y \leq y_p$ is true, and 0 otherwise. Classical infinitesimal perturbation analysis (IPA) and the likelihood ratio (LR) method cannot be applied to estimate $f_Y(y)$ because the random variable $\mathbf{1}(Y \leq y)$ is never a continuous function of y, and the derivative $\frac{\mathrm{d}}{\mathrm{d}y}\mathrm{E}[\mathbf{1}(Y \leq y)]$ is taken with respect to the quantity y, which is not a parameter of the density function $f_Y(y)$ (Peng et al. 2020). Although methods based on finite-differences (FD) and kernel density estimation have been used to construct CIs for y_p (Nakayama 2014), the latter two methods induce bias and require the choice of certain tuning parameters. Moreover, the FD method requires extra simulations and typically leads to large variance. Unlike the FD and kernel methods that rely solely on output-sample information, the conditional Monte Carlo (CMC) method (L'Ecuyer et al. 2019) and the generalized likelihood ratio (GLR) method (Peng et al. 2020) utilize direct information from the underlying simulation model, and yield unbiased density estimators.

Simultaneous estimation of multiple quantiles corresponding to a vector $\boldsymbol{p} \equiv (p_1, \ldots, p_d)$ of probabilities requires the construction of a confidence region. Specifically, we want to construct a region $\mathscr{R}(n,\alpha) \subset \mathbb{R}^d$ such that $\lim_{m\to\infty}\Pr[(y_{p_1}, \ldots, y_{p_d}) \in \mathscr{R}(n,\alpha)] = 1-\alpha$ for given confidence coefficient $\alpha \in (0,1)$ and batch count $b \geq 2$. Ming-hua and Glynn (2002) use a combination of batching and sectioning to construct CRs for stochastic approximation algorithms; but to the best of our knowledge, there is no previous research studying confidence regions for quantiles. In this paper, we discuss the formation of CRs for the four aforementioned methods, batching, sectioning, GLR, and CMC. We will show that CMC and GLR in CRs construction perform better than batching and sectioning methods when d is large and the sample size is small. While the choice of the batch size (for fixed sample size) affects the performance of batching and sectioning, this issue does not affect CMC and GLR. On the other hand, the CMC and GLR methods require more information about the structure of the problem and stronger conditions.

The rest of the paper is organized as follows. Section 2 describes the quantile estimation problem and an ideal CI for the conventional quantile point estimator. This result lies at the basis of the CI construction

we develop by using CMC and GLRs. Section 2 also discusses CMC and GLR estimators for the density function, which are required for construction of CIs by those methods. Section 3 describes the derivation of CRs for each method under study. Section 4 performs a preliminary evaluation of the four methods based on two examples. The results indicate that the estimated coverages of all the CIs and CRs are close to the target coverage rate when the sample size is sufficiently large, demonstrating their asymptotic validity. In particular, the CMC, GLR and sectioning methods outperform classical batching with regard to the construction of both CIs and CRs when the sample size is relatively small, while the CMC and GLR methods dominate their counterparts based on batching with regard to CR construction when the sample size is small and the dimension of the probability vector becomes large. Finally, Section 5 offers some concluding remarks.

2 CONSTRUCTION OF CONFIDENCE INTERVALS

Assume that the output random variable Y can be expressed as

$$Y = g(X_1, \ldots, X_s)$$

for a given, finite number of inputs s so that $g : \mathbb{R}^s \to \mathbb{R}$; and $X_1, \ldots, X_s$ are continuous random variables so that the random vector $X \equiv (X_1, \ldots, X_s)$ has the joint p.d.f. $f(x)$ for all $x = (x_1, \ldots, x_s) \in \mathbb{R}^s$. Let z_β denote the β-quantile of the $N(0,1)$ distribution. Based on the CLT (1), we see that the ideal $100(1-\alpha)\%$ CI for y_p,

$$\widehat{y}_p(n) \pm z_{1-\alpha/2} \frac{\sqrt{p(1-p)}}{f_Y(y_p)\sqrt{n}}, \tag{3}$$

is asymptotically valid as $n \to \infty$. Of course the latter CI (3) cannot generally be applied in practice because the p.d.f. $f_Y(\cdot)$ is usually unknown.

One way to construct a CI for y_p is to consistently estimate the unknown constant $f_Y(y_p)$. The CI in Equation (2) bypasses this problem by "cancelling" the asymptotic variance $\sigma^2 = p(1-p)/f_Y^2(y_p)$. The literature contains a variety of methods based on finite differences and kernel density estimation (Chu and Nakayama 2012, Nakayama 2014); but both methodologies suffer from trade-offs between bias and variance, i.e., a small perturbation or bandwidth size reduces bias while increasing variance. We propose two unbiased estimators, i.e., CMC and GLR, to estimate $f_Y(y_p)$, and then we construct asymptotically valid CI estimators for the selected quantiles.

Since the p.d.f. $f_Y(y)$ is the derivative of the c.d.f. $F_Y(y)$, a natural approach to estimate $f_Y(y)$ is to express the c.d.f. as the expected value of an indicator random variable:

$$F_Y(y) = \mathrm{E}[\mathbf{1}\{Y \le y\}] = \mathrm{E}[\mathbf{1}\{g(X_1, \ldots, X_s) - y \le 0\}].$$

Under certain conditions, Peng et al. (2020) showed that

$$f_Y(y) = \frac{\mathrm{d}}{\mathrm{d}y}\mathrm{E}[\mathbf{1}(Y \le y)] = \mathrm{E}[\mathbf{1}(Y \le y) \cdot \Psi_i], \tag{4}$$

where

$$\Psi_i = \Psi_i(X) = \left[\left(\frac{\partial g(x)}{\partial x_i} \right)^{-1} \frac{\partial \log f_X(x)}{\partial x_i} - \left(\frac{\partial g(x)}{\partial x_i} \right)^{-2} \left(\frac{\partial^2 g(x)}{\partial x_i^2} \right) \right] \Bigg|_{x=X}.$$

The CMC density estimator requires the following regularity condition:

Regularity Condition (A) Assume there exists a sigma-field $\mathscr{F}$ such that for all realizations of $\mathscr{F}$, the function $F_Y(y|\mathscr{F}) \equiv \Pr\{Y \le y|\mathscr{F}\}$ is continuous at each $y \in \mathbb{R}$; also the function $F_Y(y|\mathscr{F})$ is differentiable at each $y \in \mathbb{R} \setminus D(\mathscr{F})$, where $D(\mathscr{F}) \subset \mathbb{R}$ is a denumerable set of points. Moreover, there is a random variable Γ defined on the same probability space as $F_Y(y|\mathscr{F})$ such that $\mathrm{E}[\Gamma^2] \le J$ for some constant $J < \infty$, and $\sup\left\{ F'_Y(y|\mathscr{F}) \equiv \frac{\mathrm{d}}{\mathrm{d}y} F_Y(y|\mathscr{F}) : y \in \mathbb{R} \setminus D(\mathscr{F}) \right\} \le \Gamma$ at every point in the underlying sample space.

Under this condition, L'Ecuyer et al. (2019) proved that

$$f_Y(y) = \frac{\mathrm{d}}{\mathrm{d}y} \mathrm{E}[\mathbf{1}(Y \le y)] = \mathrm{E}[F'_Y(y|\mathscr{F})] \text{ for each } y \in \mathbb{R} \setminus D(\mathscr{F}). \tag{5}$$

Equation (5) is the basis for the CMC estimator of $f_Y(y)$ at each $y \in \mathbb{R}^s \setminus D(\mathscr{F})$; and in practice we have to appropriately choose $\mathscr{F}$ to condition on. For example, if for some $l \in \{1, \ldots, s\}$, the sigma-field defined by $\mathscr{F}_l = (X_1, \cdots, X_{l-1}, X_{l+1}, \cdots, X_s)$ satisfies the condition and the function

$$g_l(x_l|\mathscr{F}_l) \equiv g(X_1, \ldots, X_{l-1}, x_l, X_{l+1}, \ldots, X_s) \text{ for each } x_l \in \mathbb{R}$$

is strictly increasing in x_l for all possible realizations of $\mathscr{F}_l$, then the inverse function $g_l^{-1}(y|\mathscr{F}_l)$ exists at each point in the underlying sample space; and we have

$$F_Y(y|\mathscr{F}) = \Pr\left\{ g_l(X_l|\mathscr{F}_l) \le y \,\middle|\, \mathscr{F}_l \right\} = \Pr\left\{ X_l \le g_l^{-1}(y|\mathscr{F}_l) \,\middle|\, \mathscr{F}_l \right\} = F_l[\, g_l^{-1}(y|\mathscr{F}_l)\,]\,. \tag{6}$$

From Equation (6) and the change-of-variables formula (Rudin 1964, Theorem 6.33), we have

$$f_Y(y) = \mathrm{E}[F'_Y(y|\mathscr{F})] = \mathrm{E}\left\{ f_l\big[\, g_l^{-1}(y|\mathscr{F}_l)\,\big] \cdot \left| \frac{\mathrm{d}}{\mathrm{d}y} g_l^{-1}(y|\mathscr{F}_l) \right| \right\},$$

where f_l is the density function of X_l. Clearly the conditions required by GLR and CMC are stronger than those of batching and sectioning.

Suppose the c.d.f. $F_Y(\cdot)$ and p.d.f. $f_Y(\cdot)$ are differentiable at y_p and $f_Y(y_p) > 0$. With Equations (4) and (5) and the consistent point estimate of y_p, i.e., $\widehat{y}_p(n) \equiv Y_{(\lceil np \rceil)}$, we obtain the GLR and CMC estimators for $f_Y(y_p)$ as follows:

$$\widehat{f}_{\mathrm{GLR},n}\big(\widehat{y}_p(n)\big) = \frac{1}{n} \sum_{j=1}^{n} \mathbf{1}\big(Y^{(j)} \le \widehat{y}_p(n)\big) \cdot \Psi_i^{(j)}$$

where the pairs $\big(Y^{(1)}, \Psi_i^{(1)}\big), \ldots, \big(Y^{(n)}, \Psi_i^{(n)}\big)$ are n independent realizations of (Y, Ψ_i), and

$$\widehat{f}_{\mathrm{CMC},n}\big(\widehat{y}_p(n)\big) = \frac{1}{n} \sum_{j=1}^{n} F'_Y\big(\widehat{y}_p(n) \,\big|\, \mathscr{F}^{(j)}\big),$$

where $\mathscr{F}^{(1)}, \ldots, \mathscr{F}^{(n)}$ are n independent realizations of $\mathscr{F}$. Under an additional moment condition for Ψ_i in Peng et al. (2017), it can be shown that $\widehat{f}_{\mathrm{GLR},n}(\widehat{y}_p(n)) \to f_Y(y_p)$ almost surely (a.s.); further $\widehat{f}_{\mathrm{CMC},n}(\widehat{y}_p(n)) \to f_Y(y_p)$ a.s. when $n \to \infty$.

Then we have the approximate $100(1-\alpha)\%$ CIs

$$\mathscr{C}_{\mathrm{GLR}}(n, \alpha) = \left[\widehat{y}_p(n) - z_{1-\alpha/2} \frac{\sqrt{p(1-p)}}{\widehat{f}_{\mathrm{GLR},\,n}(\widehat{y}_p(n))\sqrt{n}},\ \widehat{y}_p(n) + z_{1-\alpha/2} \frac{\sqrt{p(1-p)}}{\widehat{f}_{\mathrm{GLR},n}(\widehat{y}_p(n))\sqrt{n}} \right]$$

based on the GLR method and

$$\mathscr{C}_{\mathrm{CMC}}(n, \alpha) = \left[\widehat{y}_p(n) - z_{1-\alpha/2} \frac{\sqrt{p(1-p)}}{\widehat{f}_{\mathrm{CMC},\,n}(\widehat{y}_p(n))\sqrt{n}},\ \widehat{y}_p(n) + z_{1-\alpha/2} \frac{\sqrt{p(1-p)}}{\widehat{f}_{\mathrm{CMC},n}(\widehat{y}_p(n))\sqrt{n}} \right]$$

based on the CMC method, respectively.

3 CONSTRUCTION OF CONFIDENCE REGIONS

In the preceding section, we discussed CI construction for the point-wise quantile at one probability level p. We may also be interested in estimating not only the quantile at one probability level but also simultaneously estimating a vector of quantiles at probability levels $p_1, \ldots, p_d$, in which case a CR is needed to measure the accuracy on the vector of quantile estimates. Specifically, we want to construct a region $\mathscr{R}(n,\alpha) \subset \mathbb{R}^d$ such that $\lim_{n\to\infty} \Pr\big[\big(y_{p_1}, \ldots, y_{p_d}\big) \in \mathscr{R}(n,\alpha)\big] = 1-\alpha$.

For quantile estimators $\widehat{y}_{\boldsymbol{p}}(n) = \big(\widehat{y}_{p_1}(n), \ldots, \widehat{y}_{p_d}(n)\big)$, where $\widehat{y}_{p_i}(n) = Y_{(\lceil np_i \rceil)}$, $1 \le i \le d$, we have the following multivariate analogue of the CLT (1).

Theorem 1 (Serfling 1980, §2.3.3, Theorem B) Let $0 < p_1 < p_2 < \cdots < p_d < 1$. Suppose that $F_Y(y)$ has a density $f_Y(y)$ in neighborhoods of $y_{p_1}, \ldots, y_{p_d}$ and that $f_Y(y)$ is positive and continuous at $y_{p_1}, \ldots, y_{p_d}$. Then $\sqrt{n}\big(\widehat{y}_{\boldsymbol{p}}(n) - y_{\boldsymbol{p}}\big)$ converges in distribution to a multivariate-normal distribution, i.e., $\sqrt{n}\big(\widehat{y}_{\boldsymbol{p}}(n) - y_{\boldsymbol{p}}\big) \Rightarrow N_d(0,\Sigma)$, as $n \to \infty$, where $N_d(0,\Sigma)$ is a normal d-variate distribution with mean 0 and covariance matrix Σ defined by

$$\Sigma = \begin{pmatrix} \sigma(p_1,p_1) & \sigma(p_1,p_2) & \cdots & \sigma(p_1,p_d) \\ \sigma(p_1,p_2) & \sigma(p_2,p_2) & \cdots & \sigma(p_2,p_d) \\ \vdots & \vdots & \ddots & \vdots \\ \sigma(p_1,p_d) & \sigma(p_2,p_d) & \cdots & \sigma(p_d,p_d) \end{pmatrix},$$

with

$$\sigma(p_i,p_j) = \frac{\min(p_i,p_j) - p_i p_j}{f_Y(y_{p_i}) f_Y(y_{p_j})}, \quad 1 \le i,j \le d. \quad \blacktriangleleft \tag{7}$$

Therefore, the key to constructing an asymptotically valid CR for $y_{\boldsymbol{p}}$ is to estimate Σ consistently, and the form of $\sigma(p_i,p_j)$ in (7) shows that a natural estimation of Σ can be obtained by estimating $f_Y(y_{p_i})$ for $i = 1, \ldots, d$. As discussed in Section 2, we know that $\sigma(p_i,p_j)$ can be estimated consistently by

$$\widehat{\sigma}_{\mathrm{GLR},n}(p_i,p_j) = \frac{\min(p_i,p_j) - p_i p_j}{\widehat{f}_{\mathrm{GLR},n}(\widehat{y}_{p_i}(n))\widehat{f}_{\mathrm{GLR},n}(\widehat{y}_{p_j}(n))} \text{ or } \widehat{\sigma}_{\mathrm{CMC},n}(p_i,p_j) = \frac{\min(p_i,p_j) - p_i p_j}{\widehat{f}_{\mathrm{CMC},n}(\widehat{y}_{p_i}(n))\widehat{f}_{\mathrm{CMC},n}(\widehat{y}_{p_j}(n))}. \tag{8}$$

Under the assumptions of Theorem 1 and the conditions justifying unbiasedness of GLR and CMC, we have that for $\widehat{\Sigma}_{\mathrm{GLR},n}$ and $\widehat{\Sigma}_{\mathrm{CMC},n}$ defined by (8),

$$n\big(\widehat{y}_{\boldsymbol{p}}(n) - y_{\boldsymbol{p}}\big)\widehat{\Sigma}^{-1}_{\mathrm{GLR},n}\big(\widehat{y}_{\boldsymbol{p}}(n) - y_{\boldsymbol{p}}\big)^{\mathsf{T}} \Rightarrow \chi^2_d, \text{ and } n\big(\widehat{y}_{\boldsymbol{p}}(n) - y_{\boldsymbol{p}}\big)\widehat{\Sigma}^{-1}_{\mathrm{CMC},n}\big(\widehat{y}_{\boldsymbol{p}}(n) - y_{\boldsymbol{p}}\big)^{\mathsf{T}} \Rightarrow \chi^2_d,$$

as $n \to \infty$, where χ^2_d is a chi-squared random variable with d degrees of freedom. Therefore, $100(1-\alpha)\%$ asymptotic confidence regions for $y_{\boldsymbol{p}}$ are given by

$$\mathscr{R}_{\mathrm{GLR}}(n,\alpha) = \Big\{ y \in \mathbb{R}^d : n\big(\widehat{y}_{\boldsymbol{p}}(n) - x\big)\widehat{\Sigma}^{-1}_{\mathrm{GLR},n}(n)\big(\widehat{y}_{\boldsymbol{p}}(n) - y\big)^{\mathsf{T}} \le \chi^2_{(d,\alpha)} \Big\}$$

and

$$\mathscr{R}_{\mathrm{CMC}}(n,\alpha) = \Big\{ y \in \mathbb{R}^d : n\big(\widehat{y}_{\boldsymbol{p}}(n) - x\big)\widehat{\Sigma}^{-1}_{\mathrm{CMC},n}(n)\big(\widehat{y}_{\boldsymbol{p}}(n) - y\big)^{\mathsf{T}} \le \chi^2_{(d,\alpha)} \Big\},$$

where $\chi^2_{(d,\alpha)}$ is the $(1-\alpha)$-quantile of the chi-squared distribution with d degrees of freedom.

Alternatively, we can construct confidence regions via the batching and sectioning methods. Specifically, the n samples are split into b nonoverlapping batches, each consisting of m observations. We obtain the jth batch quantile estimator of $y_{\boldsymbol{p}}$ by

$$\widehat{y}_{\boldsymbol{p}}(j,m) = \big(\widehat{y}_{p_1}(j,m), \ldots, \widehat{y}_{p_d}(j,m)\big) = \big(Y_{j,(\lceil mp_1 \rceil)}, \ldots, Y_{j,(\lceil mp_d \rceil)}\big),$$

where $Y_{j,(1)} \le \cdots \le Y_{j,(m)}$ are the sample's order statistics within the jth batch for $j = 1, \ldots, b$. Then

$$\overline{\widehat{y}}_{\boldsymbol{p}}(b,m) = \frac{1}{b}\left(\sum_{j=1}^{b} \widehat{y}_{p_1}(j,m), \ldots, \sum_{j=1}^{b} \widehat{y}_{p_d}(j,m)\right)$$

is the batching estimator of $y_{\boldsymbol{p}}$ and the sample covariance matrix $\widehat{\Sigma}_{b,m}$ is given by

$$\widehat{\Sigma}_{b,m} = \frac{1}{b-1}\sum_{j=1}^{b}\left(\widehat{y}_{\boldsymbol{p}}(j,m) - \overline{\widehat{y}}_{\boldsymbol{p}}(b,m)\right)^{\mathsf{T}}\left(\widehat{y}_{\boldsymbol{p}}(j,m) - \overline{\widehat{y}}_{\boldsymbol{p}}(b,m)\right).$$

To the best of our knowledge, Proposition 1 below formally establishes the asymptotic validity of the batching method for quantile CRs for the first time.

Proposition 1 If $b \ge 2$ is fixed and $b > d$, then

$$b\left(\overline{\widehat{y}}_{\boldsymbol{p}}(b,m) - y_{\boldsymbol{p}}\right)\widehat{\Sigma}_{b,m}^{-1}\left(\overline{\widehat{y}}_{\boldsymbol{p}}(b,m) - y_{\boldsymbol{p}}\right)^{\mathsf{T}} \Rightarrow \frac{d(b-1)}{(b-d)}F_{(d,b-d)} \text{ as } m \to \infty,$$

where $F_{(d,b-d)}$ has an F distribution with d and $b-d$ degrees of freedom. ◀

Proof For $j = 1, \ldots, b$, let $Q_j = m^{1/2}\left[\widehat{y}_{\boldsymbol{p}}(j,m) - y_{\boldsymbol{p}}\right]$ so the $\{Q_j\}$ are i.i.d. For each j, Theorem 1 ensures that $Q_j \Rightarrow Z_j \sim N_d(0,\Sigma)$ as $m \to \infty$; hence the $\{Z_j\}$ constitute a random sample from $N_d(0,\Sigma)$. We take $Q = (Q_1, \ldots, Q_b)$; and we let $\overline{Q}_b = b^{-1}\sum_{j=1}^{b} Q_j$ and $S_Q = (b-1)^{-1}\sum_{j=1}^{b}\left(Q_j - \overline{Q}_b\right)^{\mathsf{T}}\left(Q_j - \overline{Q}_b\right)$ respectively denote the sample mean and sample covariance matrix of the $\{Q_j\}$. Similarly, we define Z, $\overline{Z}_b$, and S_Z from the $\{Z_j\}$. Next we observe that the mapping $\vartheta : Q \mapsto b\,\overline{Q}_b\, S_Q^{-1}\,\overline{Q}_b^{\mathsf{T}}$ is continuous at each point $Q \in \mathbb{R}^b$ such that $\det(S_Q) > 0$. Because the $\{Z_j\}$ are i.i.d. $N_d(0,\Sigma)$ with

$$\det(\Sigma) = \frac{p_1\left[\prod_{i=1}^{d-1}(p_{i+1} - p_i)\right](1-p_d)}{\prod_{i=1}^{d} f_Y^2(y_{p_i})} > 0,$$

it follows that $\det(S_Z) > 0$ with probability 1 (Dykstra 1970); and since $Q \Rightarrow Z$ as $m \to \infty$, we see by the continuous-mapping theorem (Whitt 2002, Theorem 3.4.3) that

$$b\left(\overline{\widehat{y}}_{\boldsymbol{p}}(b,m) - y_{\boldsymbol{p}}\right)\widehat{\Sigma}_{b,m}^{-1}\left(\overline{\widehat{y}}_{\boldsymbol{p}}(b,m) - y_{\boldsymbol{p}}\right)^{\mathsf{T}} = \vartheta(Q) \Rightarrow \vartheta(Z) = b\overline{Z}_b S_Z^{-1}\overline{Z}_b^{\mathsf{T}} \text{ as } m \to \infty.$$

Finally by Anderson (2003, Corollary 5.2.1), we have

$$b\overline{Z}_b S_Z^{-1}\overline{Z}_b^{\mathsf{T}} \sim \frac{d(b-1)}{(b-d)}F_{(d,b-d)}. \quad \blacksquare$$

Therefore, as $m \to \infty$, an asymptotically valid $100(1-\alpha)\%$ CR for $y_{\boldsymbol{p}}$ based on the batching method is given by

$$\mathscr{R}_{\mathrm{BM}}(n,\alpha) = \left\{y \in \mathbb{R}^d : b\left(\overline{\widehat{y}}_{\boldsymbol{p}}(b,m) - y\right)\widehat{\Sigma}_{b,m}^{-1}\left(\overline{\widehat{y}}_{\boldsymbol{p}}(b,m) - y\right)^{\mathsf{T}} \le \frac{d(b-1)}{(b-d)}F_{(d,b-d,\alpha)}\right\}, \tag{9}$$

where $F_{(d,b-d,\alpha)}$ is the $(1-\alpha)$-quantile of the F distribution with d and $b-d$ degrees of freedom.

For the sectioning method, the samples are also split into b batches, but the quantile estimator of $y_{\boldsymbol{p}}$ is obtained as

$$\widehat{y}_{\boldsymbol{p}}(n) = \left(Y_{(\lceil np_1 \rceil)}, \ldots, Y_{(\lceil np_d \rceil)}\right),$$

and the sample covariance matrix is given by

$$\widetilde{\Sigma}_{b,m} = \frac{1}{b-1}\sum_{j=1}^{b}\big(\widehat{y}_{\boldsymbol{p}}(j,m) - \widehat{y}_{\boldsymbol{p}}(n)\big)^{\mathsf{T}}\big(\widehat{y}_{\boldsymbol{p}}(j,m) - \widehat{y}_{\boldsymbol{p}}(n)\big).$$

Then the approximate $100(1-\alpha)\%$ CR for $y_{\boldsymbol{p}}$ based on the sectioning method (SM) is given by

$$\mathscr{R}_{\mathrm{SM}}(n,\alpha) = \left\{y \in \mathbb{R}^d : b\big(\widehat{y}_{\boldsymbol{p}}(n) - y\big)\widetilde{\Sigma}^{-1}_{b,m}\big(\widehat{y}_{\boldsymbol{p}}(n) - y\big)^{\mathsf{T}} \le \frac{d(b-1)}{(b-d)}F_{(d,b-d,\alpha)}\right\}. \tag{10}$$

Although we have found that in practice the empirical coverage probability of the sectioning-based CR (10) is close to that of the batching-based CR (9), we have not been able to prove a convergence property for sectioning that is comparable to Proposition 1. However, we have recently proved the following analogue of Proposition 1 in which we use (i) the sectioning point estimator $\widehat{y}_{\boldsymbol{p}}(n)$ of the true quantile vector $y_{\boldsymbol{p}}$; and (ii) the batch-means estimator $\widehat{\Sigma}_{b,m}$ of the asymptotically true covariance matrix Σ/m based on batches of size m. In item (ii), the phrase "asymptotically true" means that in the matrix $\mathrm{E}\big[\widehat{\Sigma}_{b,m}\big]$, the (k,ℓ) element $\mathrm{Cov}\big[\widehat{y}_{p_k}(1,m), \widehat{y}_{p_\ell}(1,m)\big]$ is asymptotic to $\sigma(p_k,p_\ell)/m$ for $1 \le k,\ell \le d$ as $m \to \infty$.

Proposition 2 If $b \ge 2$ is fixed and $b > d$, then

$$b\big(\widehat{y}_{\boldsymbol{p}}(n) - y_{\boldsymbol{p}}\big)\widehat{\Sigma}^{-1}_{b,m}\big(\widehat{y}_{\boldsymbol{p}}(n) - y_{\boldsymbol{p}}\big)^{\mathsf{T}} \Rightarrow \frac{d(b-1)}{(b-d)}F_{(d,b-d)} \text{ as } m \to \infty. \quad \blacktriangleleft$$

The proof of Proposition 2 exploits multivariate Bahadur representations of $\overline{\widehat{y}}_{\boldsymbol{p}}(b,m)$ and $\widehat{y}_{\boldsymbol{p}}(n)$ (Bahadur 1966); complete details will be given in follow-up work. Proposition 2 implies the asymptotic validity as $m \to \infty$ of the following "hybrid" sectioning/batch-means confidence region,

$$\mathscr{R}_{\mathrm{SBM}}(n,\alpha) = \left\{y \in \mathbb{R}^d : b(\widehat{y}_{\boldsymbol{p}}(n) - y)\widehat{\Sigma}^{-1}_{b,m}(\widehat{y}_{\boldsymbol{p}}(n) - y)^{\mathsf{T}} \le \frac{d(b-1)}{(b-d)}F_{(d,b-d,\alpha)}\right\}.$$

We plan to examine the performance characteristics of $\mathscr{R}_{\mathrm{SBM}}(n,\alpha)$ in follow-up work.

4 NUMERICAL RESULTS

In this section, we use three examples to test the performance of the BM, SM, CMC, and GLR methods with regard to CI construction (Example 1) and CR construction (Examples 2 and 3). We estimate the coverage rate of $100(1-\alpha)\%$ CIs (or CRs) by the proportion of the constructed CIs (or CRs) that contain the true quantile (or vector of quantiles) from 10^5 independent trials. In Example 1 we report the coverage rate with parenthesized average CI half-widths. In Examples 2 and 3 we divide the 10^5 trials into 100 replications with 10^3 trials in each replication and report the point estimates and standard errors of the coverage rates.

Example 1 Consider the simple example where $X_1 \sim N(0,1)$ and $X_2 \sim N(0,4)$ are independent, and $Y = X_1 + X_2$. We are interested in estimating the p-quantile y_p of Y and constructing CIs for different values of p via different methods (BM, SM, CMC, GLR). We know that $Y \sim N(0,5)$, so the true value of the p-quantile of Y is $y_p = \sqrt{5}\,z_p$.

We write the density $f_Y(y)$ as $\frac{\mathrm{d}}{\mathrm{d}y}\mathrm{E}\big[\mathbf{1}(Y \le y)\big] = \frac{\mathrm{d}}{\mathrm{d}y}\mathrm{E}\big[\mathbf{1}(X_1 + X_2 \le y)\big]$. The GLR estimator (4) is not unique because we can choose either value of i. The derivatives in the estimator (4) are given by $\frac{\partial g(x)}{\partial x_i} = 1$ and $\frac{\partial^2 g(x)}{\partial x_i^2} = 0$ (for $i = 1,2$), $\frac{\partial \log f_X(x)}{\partial x_1} = -x_1$, and $\frac{\partial \log f_X(x)}{\partial x_2} = -x_2/4$. We have two GLR estimators (namely, GLR_1 and GLR_2) for estimating the density f_Y:

$$\widehat{f}_{\mathrm{GLR}_1,n}(\widehat{y}_p(n)) = \frac{1}{n}\sum_{j=1}^{n}\mathbf{1}(Y^{(j)} \le \widehat{y}_p(n))\cdot\left(-X_1^{(j)}\right) \quad \text{and} \quad \widehat{f}_{\mathrm{GLR}_2,n}(\widehat{y}_p(n)) = \frac{1}{n}\sum_{j=1}^{n}\mathbf{1}(Y^{(j)} \le \widehat{y}_p(n))\cdot\left(-X_2^{(j)}/4\right)$$

where $X_i^{(1)},\ldots,X_i^{(n)}$ are n realizations of X_i for $i = 1, 2$. From Peng et al. (2020), if there are l unbiased GLR estimators $\mathbf{1}(Y \le y)\Psi_{i_\ell}$, $\ell = 1,\ldots,l$, then any linear combination $\sum_{\ell=1}^{l} w_\ell \mathbf{1}(Y \le y)\Psi_{i_\ell}$ with nonnegative weights $\{w_\ell\}$ such that $\sum_{\ell=1}^{l} w_\ell = 1$ is also an unbiased estimator; and the optimal weights for minimizing the variance of the estimator can be obtained from

$$(w_1^*,\ldots,w_l^*) = \underset{w_1,\ldots,w_l}{\arg\min}\ \mathrm{Var}\left[\sum_{\ell=1}^{l} w_\ell \mathbf{1}(Y \le y)\Psi_{i_\ell}\right] \quad \text{s.t.} \quad \sum_{\ell=1}^{l} w_\ell = 1,$$

which has an analytical form:

$$w_i^* = \frac{e_i^T \Sigma_l^{-1} e}{e^T \Sigma_l^{-1} e}, \quad i = 1,\ldots,l,$$

where $e = (1,\ldots,1)^\mathsf{T}$, e_i is a l-dimensional unit vector in ith direction, i.e., $e_1 = (1,0,0,\ldots,0)$, $e_2 = (0,1,0,0,\ldots,0)$, and Σ_l is the covariance matrix of $(\mathbf{1}(Y \le y)\Psi_{i_1},\ldots,\mathbf{1}(Y \le y)\Psi_{i_l})$. We estimate the optimal weights from the same data and obtain the optimal assignment $(w_1^*, w_2^*) = (0.2, 0.8)$ in this example. Hence the optimal GLR estimator (GLR*) is

$$\widehat{f}_{\mathrm{GLR}^*,n}(\widehat{y}_p(n)) = \frac{1}{n}\sum_{j=1}^{n}\mathbf{1}(Y^{(j)} \le \widehat{y}_p(n))\cdot\left(-w_1^* X_1^{(j)} - w_2^* X_2^{(j)}/4\right).$$

For CMC in this example, we can use either $\mathscr{F} = X_1$ or $\mathscr{F} = X_2$. Assume that we choose $\mathscr{F} = X_2$, then $F(y|\mathscr{F}) = \mathbb{P}(Y \le y|X_2) = \mathbb{P}(X_1 \le y - X_2) = F_1(y - X_2)$ and $f_Y(y_p) = \mathrm{E}[F_1'(y_p|X_2)] = \mathrm{E}[f_1(y_p - X_2)]$. Therefore the density estimator at y_p is

$$\widehat{f}_{\mathrm{CMC},n}(\widehat{y}_p(n)) = \frac{1}{n}\sum_{j=1}^{n} f_1\left(\widehat{y}_p(n) - X_2^{(j)}\right),$$

where F_1 and f_1 are the c.d.f. and the p.d.f. of the standard normal distribution, respectively.

Table 1 displays the coverage rates and average half-widths (AHWs) of the constructed CIs for the BM, SM, CMC, and GLR methods. For large n, the estimated coverages of all the CIs are close to the target coverage rate, demonstrating their asymptotic validity. GLR* has a slight edge over GLR$_1$ and GLR$_2$ in both estimated CI coverage probability and AHW, especially when n is small. In general, SM, CMC, and GLR exhibit better estimated coverage than BM, especially for small n. Finally, CMC, GLR*, and SM show comparable coverage in different cases.

Example 2 This example has the same setting as Example 1, but we are interested in the experimental evaluation of the CRs obtained by the four competitors (BM, SM, CMC, and GLR). The probabilities p_i are spaced uniformly: $p_i = i/(d+1)$, $i = 1,\ldots,d$. The density estimators of CMC and GLR at p_i are the same as described in Example 1, and we only show the results corresponding to the optimal GLR estimator. The experimental results displayed in Table 2 indicate significant advantages for the CMC and GLR methods with regard to CR construction for quantiles compared to SM and BM, especially when the sample size is relatively small and the dimension of the probability vector is relatively large. Asmussen and Glynn (2007) suggest choosing $b \le 30$ for both BM and SM in CI construction, but for CR construction, we have to choose b such that $b > d$. The results in Table 2 show cases where $d = 9$, $d = 19$, and $d = 49$.

Table 1: Coverage rates (with parenthesized average CI half-widths) for the BM, SM, GLR, and CMC methods based on Example 1.

n	$b = 16$		$b = 32$		CMC	GLR*	GLR_1	GLR_2
	BM	SM	BM	SM				
$p = 0.9,\ 1-\alpha = 0.9$								
2^{10}	0.885 (0.203)	0.899 (0.206)	0.649 (0.193)	0.897 (0.199)	0.901 (0.197)	0.897 (0.201)	0.882 (0.234)	0.892 (0.202)
2^{12}	0.899 (0.103)	0.904 (0.103)	0.878 (0.101)	0.903 (0.101)	0.899 (0.098)	0.898 (0.098)	0.897 (0.102)	0.897 (0.099)
2^{14}	0.901 (0.051)	0.903 (0.052)	0.883 (0.050)	0.900 (0.050)	0.899 (0.049)	0.898 (0.049)	0.898 (0.049)	0.897 (0.049)
2^{16}	0.898 (0.026)	0.898 (0.026)	0.899 (0.025)	0.901 (0.025)	0.900 (0.024)	0.897 (0.024)	0.897 (0.024)	0.894 (0.024)
$p = 0.9,\ 1-\alpha = 0.95$								
2^{10}	0.938 (0.247)	0.950 (0.249)	0.757 (0.232)	0.948 (0.239)	0.949 (0.234)	0.942 (0.239)	0.925 (0.232)	0.938 (0.242)
2^{12}	0.949 (0.125)	0.951 (0.126)	0.936 (0.121)	0.951 (0.122)	0.950 (0.117)	0.950 (0.118)	0.943 (0.121)	0.950 (0.118)
2^{14}	0.950 (0.063)	0.951 (0.063)	0.939 (0.060)	0.949 (0.060)	0.948 (0.058)	0.950 (0.058)	0.949 (0.059)	0.950 (0.059)
2^{16}	0.950 (0.031)	0.951 (0.031)	0.949 (0.030)	0.950 (0.030)	0.951 (0.029)	0.951 (0.029)	0.952 (0.029)	0.953 (0.029)

(Entries with "NA" indicate that the respective method is not applicable because $b \le d$.) Clearly, for fixed relatively small sample sizes, the gap between the estimated coverage rates and nominal rates for BM- and SM-based CRs widens as d increases. It should be clear that, if d is large, b has to be significantly larger to achieve a high accuracy for the target coverage rates of CRs. Since the CMC and GLR methods are immune to this issue, the sample size needed by CMC and GLR to achieve the same accuracy would be much smaller than BM and SM for large d. Notice that the estimated coverage of CMC-based CRs when $n = 2^{12}$ is as accurate as SM-based CRs and better than BM-based CRs when $n = 2^{14}$ and $b = 64$.

Example 3 This example is taken from Shields and Zhang (2016) and was also analyzed in L'Ecuyer et al. (2019). It models the buckling strength of a steel plate by

$$Y = \Big(\frac{2.1}{\Upsilon} - \frac{0.9}{\Upsilon^2}\Big)\Big(1 - \frac{0.75X_5}{\Upsilon}\Big)\Big(1 - \frac{2X_2X_6}{X_1}\Big),$$

where $\Upsilon = (X_1/X_2)\sqrt{X_3/X_4}$ and $X_1, \ldots, X_6$ are independent random variables whose distributions are given in Table 3, which also displays the respective mean and coefficient of variation (CV).

Again, we write the density $f_Y(y)$ as $\frac{\mathrm{d}}{\mathrm{d}y}\mathrm{E}\big[\mathbf{1}(Y \le y)\big]$. For the GLR estimator (4) we choose $i = 5$, so the derivatives in the estimator (4) are given by $\frac{\partial g(x)}{\partial x_5} = \big(\frac{2.1}{\Upsilon} - \frac{0.9}{\Upsilon^2}\big)\big(-\frac{0.75}{\Upsilon}\big)\big(1 - \frac{2X_2X_6}{X_1}\big)$, $\frac{\partial^2 g(x)}{\partial x_5^2} = 0$, $\frac{\partial \log f_X(x)}{\partial x_5} = -(x_5 - \mu_5)/\sigma_5^2$, where μ_5 and σ_5 is the mean and standard deviation of X_5. If we denote $V_1 = \big(\frac{2.1}{\Upsilon} - \frac{0.9}{\Upsilon^2}\big)$, $V_2 = 1 - \frac{3X_5}{4\Upsilon}$, and $V_3 = \big(1 - \frac{2X_2X_6}{X_1}\big)$, we have the following GLR estimator for the density f_Y:

$$\widehat{f}_{\mathrm{GLR},n}\big(\widehat{y}_p(n)\big) = \frac{1}{n}\sum_{j=1}^{n} \mathbf{1}\big(Y^{(j)} \le \widehat{y}_p(n)\big) \cdot \big(\Upsilon^{(j)}(X_5^{(j)} - \mu_5)/(0.75\sigma_5^2 V_1^{(j)} V_3^{(j)})\big).$$

Table 2: Coverage rates for confidence regions (means ± standard errors) based on 100 independent runs with 10^3 independent experiments in each run for BM, SM, GLR and CMC methods based on Example 2.

n	$b = 16$		$b = 32$		$b = 64$		CMC	GLR*
	BM	SM	BM	SM	BM	SM		
$d = 9,\ 1-\alpha = 0.95$								
2^{12}	0.9300 ± 0.0085	0.9501 ± 0.0069	0.8773 ± 0.0105	0.9504 ± 0.0067	0.1565 ± 0.0115	0.9454 ± 0.0068	0.9492 ± 0.0070	0.9457 ± 0.0083
2^{14}	0.9442 ± 0.0071	0.9500 ± 0.0070	0.9289 ± 0.0083	0.9496 ± 0.0067	0.7630 ± 0.0133	0.9500 ± 0.0069	0.9508 ± 0.0069	0.9497 ± 0.0072
2^{16}	0.9496 ± 0.0068	0.9504 ± 0.0066	0.9461 ± 0.0082	0.9502 ± 0.0071	0.9128 ± 0.0087	0.9500 ± 0.0066	0.9502 ± 0.0064	0.9503 ± 0.0061
$d = 19,\ 1-\alpha = 0.95$								
2^{12}	NA	NA	0.5708 ± 0.0170	0.9493 ± 0.0071	0.0085 ± 0.0028	0.9338 ± 0.0093	0.9486 ± 0.0068	0.9419 ± 0.0071
2^{14}	NA	NA	0.8814 ± 0.0108	0.9515 ± 0.0061	0.5696 ± 0.0166	0.9518 ± 0.0079	0.9498 ± 0.0062	0.9482 ± 0.0074
2^{16}	NA	NA	0.9355 ± 0.0083	0.9498 ± 0.0069	0.8820 ± 0.0102	0.9500 ± 0.0070	0.9500 ± 0.0068	0.9493 ± 0.0071
$d = 39,\ 1-\alpha = 0.95$								
2^{12}	NA	NA	NA	NA	0 ± 0	0.8797 ± 0.0094	0.9449 ± 0.0075	0.9306 ± 0.0081
2^{14}	NA	NA	NA	NA	0.0280 ± 0.0046	0.9498 ± 0.0073	0.9495 ± 0.0068	0.9459 ± 0.0070
2^{16}	NA	NA	NA	NA	0.6605 ± 0.0170	0.9535 ± 0.0072	0.9494 ± 0.0071	0.9492 ± 0.0068

For the CMC method in this example, we choose $\mathscr{F} = \mathscr{F}_6 = \{X_1, X_2, X_3, X_4, X_5\}$; hence $F(y|\mathscr{F}_6) = F_6\big(\big(1 - \frac{y}{V_1V_2}\big)\frac{X_1}{2X_2}\big)$ and $f_Y(y_p) = \mathrm{E}[F_6'(y_p|\mathscr{F}_6)]$. The respective density estimator at y_p is

$$\widehat{f}_{\mathrm{CMC},n}(\widehat{y}_p(n)) = \frac{1}{n}\sum_{j=1}^{n}\phi\left(\frac{(1-\widehat{y}_p(n)/(V_1^{(j)}V_2^{(j)}))X_1^{(j)}/(2X_2^{(j)}) - 5.25}{0.3675}\right)\frac{X_1^{(j)}}{0.735\cdot X_2^{(j)}V_1^{(j)}V_2^{(j)}},$$

where ϕ is the p.d.f. of the standard normal distribution.

The probabilities p_i are spaced uniformly as in Example 2 and the true values of the quantiles are estimated from 2^{26} samples. The experimental results displayed in Table 4 also indicate significant advantages for the CMC and GLR methods with regard to CR construction for quantiles compared to SM and BM, especially when the sample size is small and the dimension of the probability vector is relatively large.

Table 3: Distribution of each parameter for the buckling strength model.

Parameter	Distribution	Mean	CV
X_1	normal	23.808	0.028
X_2	lognormal	0.525	0.044
X_3	lognormal	44.2	0.1235
X_4	normal	28623	0.076
X_5	normal	0.35	0.05
X_6	normal	5.25	0.07

Table 4: Coverage rates for confidence regions (means ± standard errors) based on 100 independent runs with 10^3 independent experiments in each run for BM, SM, GLR and CMC methods based on Example 3.

n	$b = 16$		$b = 32$		$b = 64$		CMC	GLR
	BM	SM	BM	SM	BM	SM		
$d = 9,\ 1-\alpha = 0.95$								
2^{10}	0.8502 ± 0.0105	0.9479 ±0.0072	0.4549 ± 0.0149	0.9314 ± 0.0078	0 ± 0	0.8827 ± 0.0102	0.9509 ± 0.0063	0.9307 ± 0.0074
2^{12}	0.9305 ± 0.0073	0.9517 ± 0.0058	0.8773 ± 0.0113	0.9504 ± 0.0074	0.1570 ± 0.0106	0.9438 ± 0.0075	0.9541 ± 0.0063	0.9438 ± 0.0067
2^{14}	0.9455 ± 0.0071	0.9508 ± 0.0066	0.9287 ± 0.0075	0.9503 ± 0.0067	0.7648 ± 0.0138	0.9493 ± 0.0075	0.9571 ± 0.0061	0.9497 ±0.0061
$d = 19,\ 1-\alpha = 0.95$								
2^{10}	NA	NA	0.0026 ±0.0015	0.8959 ± 0.0098	0.3120 ± 0.0152	0.3126 ± 0.0138	0.9434 ± 0.0069	0.9045 ± 0.0096
2^{12}	NA	NA	0.5689 ± 0.0168	0.9485 ± 0.0063	0.0086 ± 0.0025	0.9336 ± 0.0070	0.9535 ± 0.0071	0.9363 ± 0.0083
2^{14}	NA	NA	0.9513 ± 0.0072	0.9513 ± 0.0072	0.5742 ± 0.0515	0.9511 ±0.0065	0.9557 ± 0.0065	0.9472 ± 0.0067
$d = 39,\ 1-\alpha = 0.95$								
2^{10}	NA	NA	NA	NA	0 ± 0	0 ± 0	0.9339 ± 0.0077	0.8562 ± 0.0114
2^{12}	NA	NA	NA	NA	0 ± 0	0.8805 ± 0.0112	0.9493 ± 0.0064	0.9194 ± 0.0094
2^{14}	NA	NA	NA	NA	0.0279 ± 0.0048	0.9486 ± 0.0060	0.9522 ± 0.0068	0.9418 ± 0.0082

5 CONCLUSION

In this article, we have proposed two new methods for constructing confidence intervals and confidence regions for quantiles in i.i.d. data. The techniques are based on the frameworks of generalized likelihood ratios (GLR) and conditional Monte Carlo (CMC), and their validity has been established under a set of sufficient conditions. Two numerical examples illustrated the potential of the proposed methods over classical counterparts based on batching and sectioning. Future work will focus on additional experimentation in more complex settings and potential extensions to stationary processes.

ACKNOWLEDGMENTS

This work was supported in part by the National Science Foundation of China (NSFC) under Grants 71901003, 71720107003, 71690232, 91846301, 71790615, and 71972019.

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