

Quantile estimation under monotonicity constraint

MASCOTNUM

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- Knowing the behaviour of the component, a **monotonic** hypothesis is studied
- The monotonicity gives **sure bounds** of q .

Context

- Without loss of generality, assume
 - $g : [0, 1]^d \rightarrow \mathcal{R}$ is a **globally increasing** function: $\mathbf{u}, \mathbf{v} \in [0, 1]^d$ such that $\mathbf{u} \preceq \mathbf{v}$ then $g(\mathbf{u}) \leq g(\mathbf{v})$
 - \mathbf{X} is **uniformly distributed** on $[0, 1]^d$
- An **adaptive** method is provided to estimate a quantile: estimate q by

$$\hat{q} = \inf\{t \in \mathcal{R} : \hat{F}(t) > p\}.$$

with \hat{F} an estimator of F .

Materials

Definition

Let $A \subset [0, 1]^d$. Define

$$\mathbb{U}^-(A) = \bigcup_{\mathbf{x} \in A} \{\mathbf{u} \in [0, 1]^d : \mathbf{u} \preceq \mathbf{x}\},$$

$$\mathbb{U}^+(A) = \bigcup_{\mathbf{x} \in A} \{\mathbf{u} \in [0, 1]^d : \mathbf{u} \succeq \mathbf{x}\}.$$

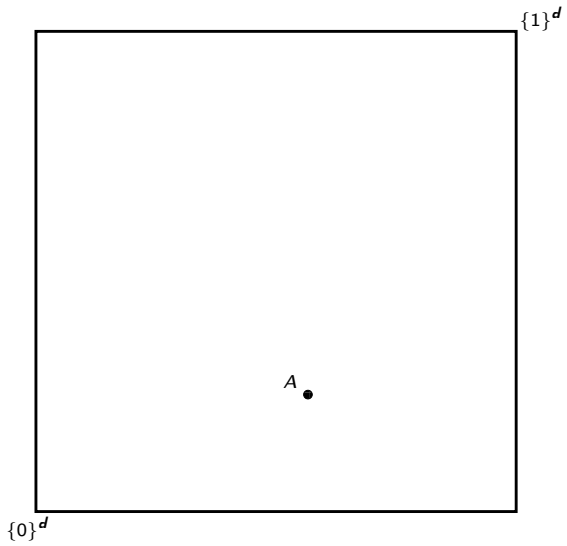
Definition

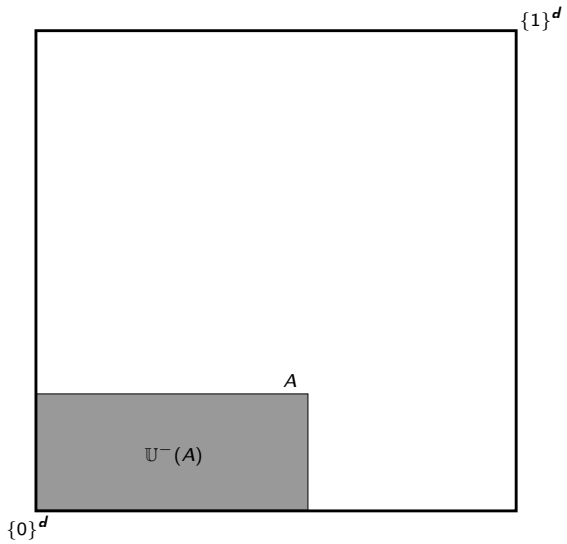
Let $\alpha \in]0, 1[$ assume that S is a $(d - 1)$ -dimensional surface such that

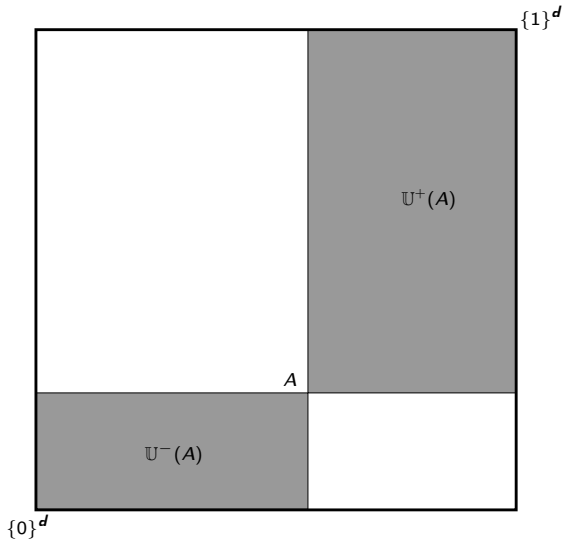
- (i) for all $\mathbf{u}, \mathbf{v} \in S$, \mathbf{u} is not strictly dominated by \mathbf{v}
- (ii) $\mu(\mathbb{U}^-(S)) = \alpha$,

then S is said to be α -monotonic.

Remark: the set $\{\mathbf{x} \in [0, 1]^d, g(\mathbf{x}) = q\}$ is $F(q)$ -monotonic.







Main result

Proposition

Let S_p be a p -monotonic surface. Then

$$\min_{\mathbf{x} \in S_p} g(\mathbf{x}) \leq q \leq \max_{\mathbf{x} \in S_p} g(\mathbf{x}).$$

- A p -monotonic surface is difficult to build in practice. The condition can be relaxed:

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Proposition

Let $p^- \in [0, p]$ and $p^+ \in [p, 1]$, and let S_{p^-} , S_{p^+} be respectively a (p^-) -monotonic surface and a (p^+) -monotonic surface. Then

$$\min_{\mathbf{x} \in S_{p^-}} g(\mathbf{x}) \leq q \leq \max_{\mathbf{x} \in S_{p^+}} g(\mathbf{x}).$$

Initialisation

- Let $\mathbf{x} = (x_1, \dots, x_d) \in [0, 1]^d$. Since the frontier of $\mathbb{U}^-(\mathbf{x})$ is monotonic

$$\mu(\mathbb{U}^-(\mathbf{x})) = x_1 \cdots x_d \geq p \Rightarrow q \leq g(\mathbf{x})$$

Proposition

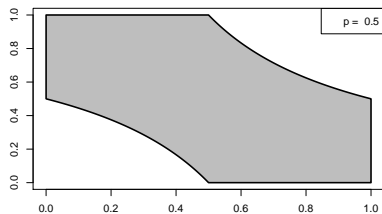
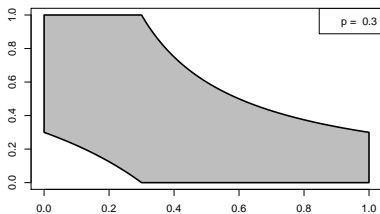
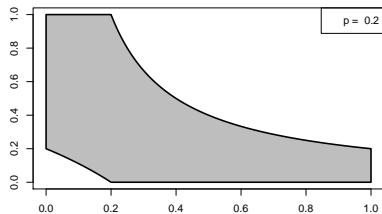
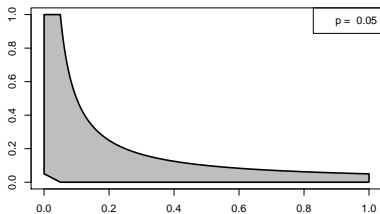
Let

$$\mathbb{W}^-(p) = \left\{ \mathbf{x} = (x_1, \dots, x_d) \in [0, 1]^d : \prod_{i=1}^d (1 - x_i) \geq 1 - p \right\}$$

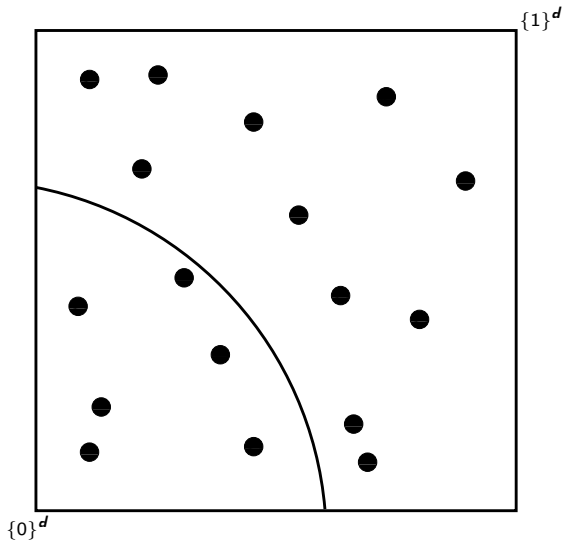
$$\mathbb{W}^+(p) = \left\{ \mathbf{x} = (x_1, \dots, x_d) \in [0, 1]^d : \prod_{i=1}^d x_i \geq p \right\}.$$

Then for all $(\mathbf{u}, \mathbf{v}) \in \mathbb{W}^-(p) \times \mathbb{W}^+(p)$, $g(\mathbf{u}) \leq q \leq g(\mathbf{v})$.

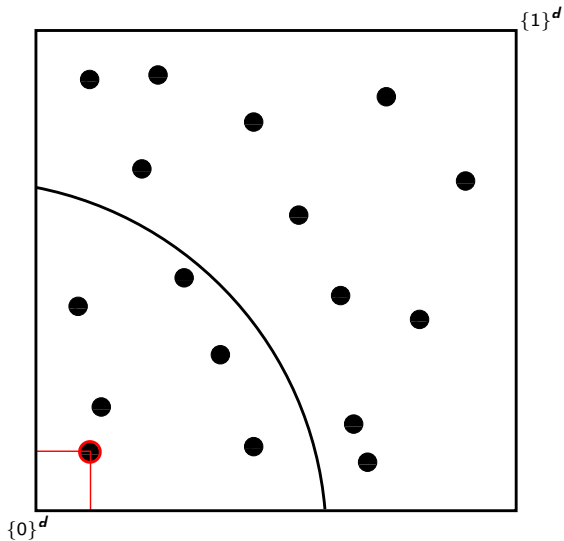
- In gray: $\mathbb{W}(p) = [0, 1]^d \setminus (\mathbb{W}^-(p) \cup \mathbb{W}^+(p))$



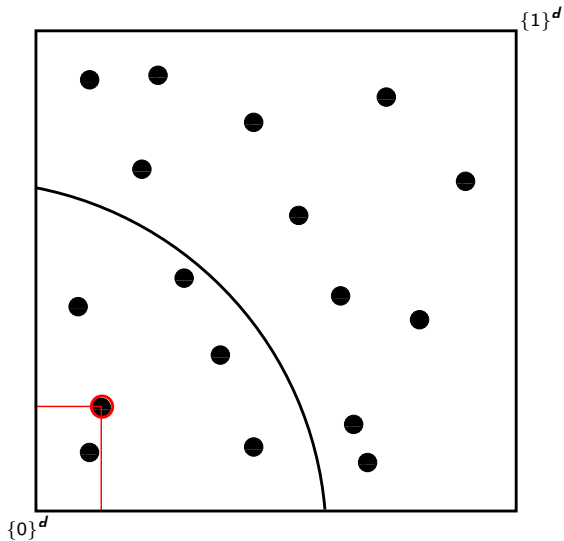
Bounding a quantile from a sample



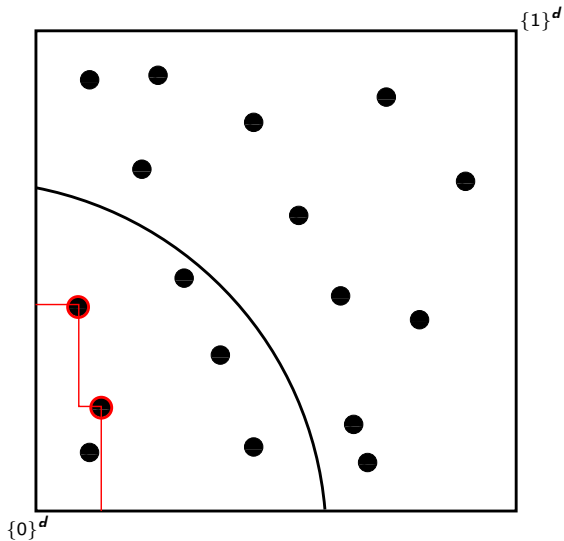
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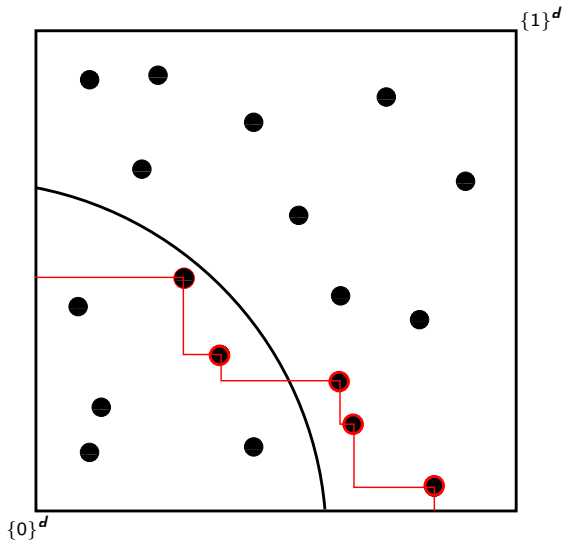
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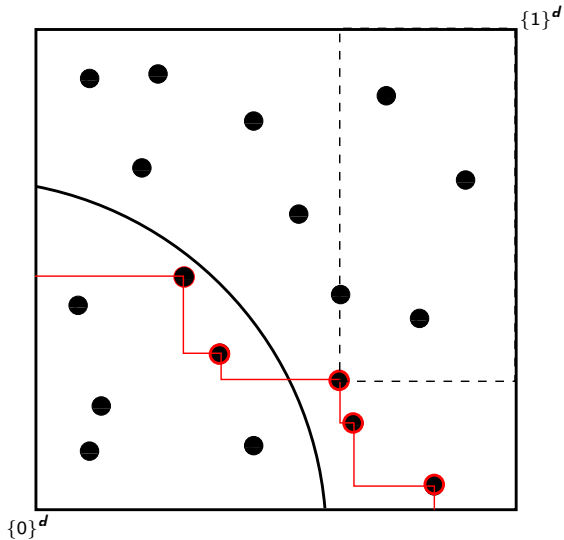
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Probability estimation

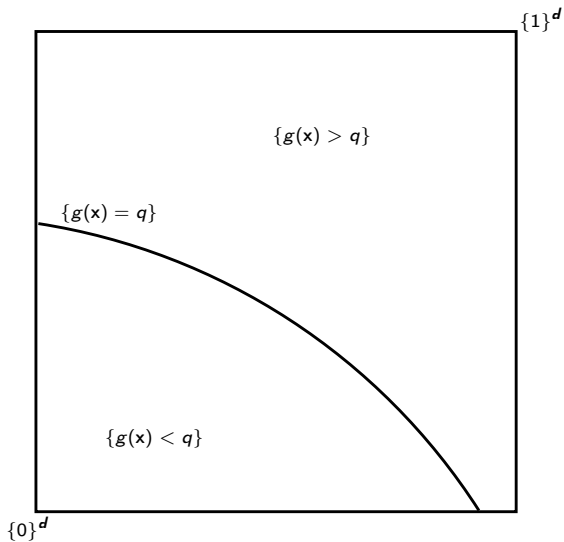
- Aim: estimate q by

$$\hat{q} = \inf\{t \in \mathbf{R} : \hat{F}(t) > p\}$$

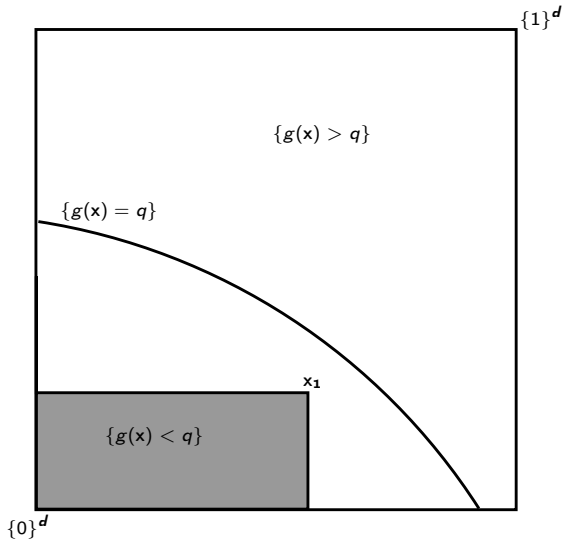
with \hat{F} an estimator of F

- Taking account of the deterministic bounds, an unbiased estimator \hat{F} is inspired by Bousquet (2012)

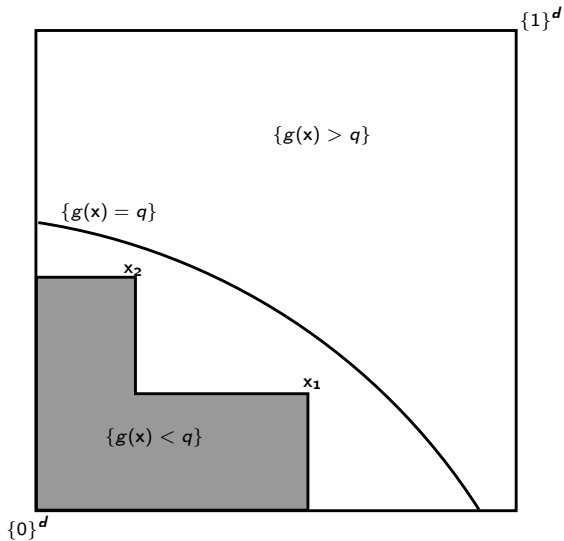
Probability estimation



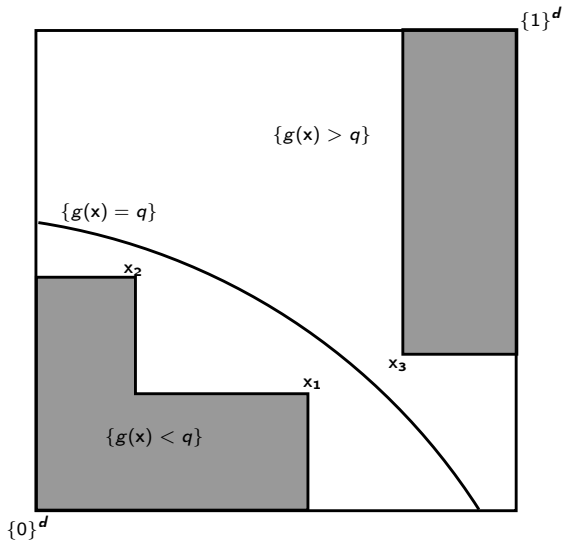
Probability estimation



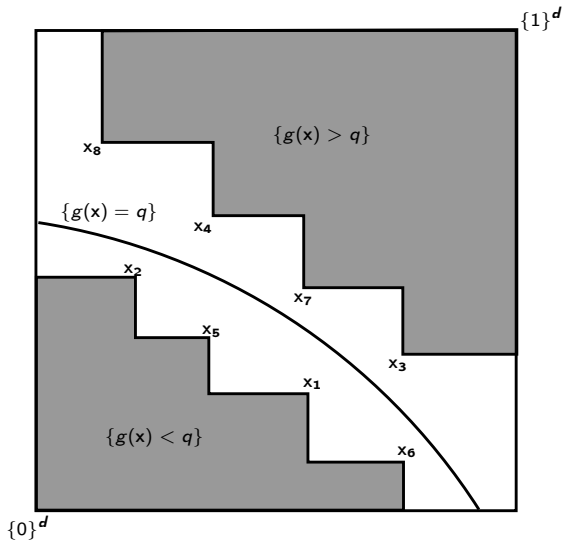
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Probability estimation

- Denote \mathbb{U}_{k-1} the set where the sign of $g(\cdot) - q$ is unknown
- Let \mathbf{X}_k be uniformly distributed on \mathbb{U}_{k-1} , then

$$p_{k-1}^- + (p_{k-1}^+ - p_{k-1}^-) \mathbb{1}_{\{g(\mathbf{X}_k) \leq q\}}$$

is an unbiased estimator of $F(q)$.

Indeed, $\mathbb{1}_{\{g(\mathbf{X}_k) \leq q\}} \sim \text{Bernoulli} \left(\frac{F(q) - p_{k-1}^-}{p_{k-1}^+ - p_{k-1}^-} \right)$

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- Let $(\mathbf{X}_k)_{k \geq 1}$ be a sequence of random vector such that for all $k \geq 1$, \mathbf{X}_k is uniformly distributed on \mathbb{U}_{k-1} , then

$$F_n(q) = \frac{1}{n} \sum_{k=1}^n p_{k-1}^- + (p_{k-1}^+ - p_{k-1}^-) \mathbb{1}_{\{g(\mathbf{X}_k) \leq q\}}$$

is also an unbiased estimator of $F(q)$.

Application to quantile estimation

• At step 1, denote :

- $\mathbb{U}_0 = \mathbb{W}(p)$
- $g(\mathbf{x}^-) = \mathbf{q}_0^- \leq \mathbf{q} \leq \mathbf{q}_0^+ = g(\mathbf{x}^+)$, with

$$\mathbf{x}^- = (1 - (1 - p)^{1/d}, \dots, 1 - (1 - p)^{1/d}) \in \mathbb{W}^-(p) \subset [0, 1]^d,$$

$$\mathbf{x}^+ = (p^{1/d}, \dots, p^{1/d}) \in \mathbb{W}^+(p) \subset [0, 1]^d,$$

Remark: without more information on g , \mathbf{x}^- , \mathbf{x}^+ are chosen arbitrary.

- $p_0^- = \mu(\mathbb{W}^-(p))$, $p_0^+ = 1 - \mu(\mathbb{W}^+(p))$.

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Remark: without more information on g , \mathbf{x}^- , \mathbf{x}^+ are chosen arbitrary.

- $p_0^- = \mu(\mathbb{W}^-(p))$, $p_0^+ = 1 - \mu(\mathbb{W}^+(p))$.
- Let \mathbf{X}_1 be uniformly distributed on \mathbb{U}_0 , then

$$\hat{F}_1(q) = p_0^- + (p_0^+ - p_0^-) \mathbb{1}_{\{g(\mathbf{x}_0) \leq q\}}$$

is an unbiased estimator of $F(q)$.

- q is estimated by

$$\hat{q}_1 = \inf\{t \in [q_0^-, q_0^+] : \hat{F}_1(t) > p\}$$

Application to quantile estimation

- At step n , from $\mathbf{X}_1, \dots, \mathbf{X}_{n-1}$:
 - two bounds $q_{n-1}^- \leq q \leq q_{n-1}^+$ has been obtained
 - the non-dominated set \mathbb{U}_{n-1} has been updated
- Let \mathbf{X}_n be uniformly distributed on \mathbb{U}_{n-1} , then

$$\hat{F}_n(q) = \frac{1}{n} \sum_{k=1}^n p_{k-1}^- + (p_{k-1}^+ - p_{k-1}^-) \mathbb{1}_{\{g(\mathbf{x}_k) \leq q\}}$$

is an unbiased estimator of $F(q)$.

- q is estimated by

$$\hat{q}_n = \inf \{t \in [q_{n-1}^-, q_{n-1}^+] : \hat{F}_n(t) > p\}$$

Numerical applications

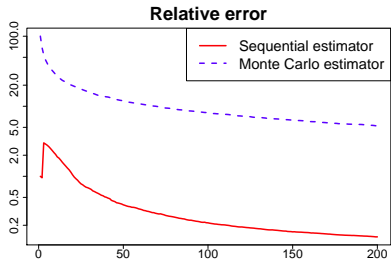
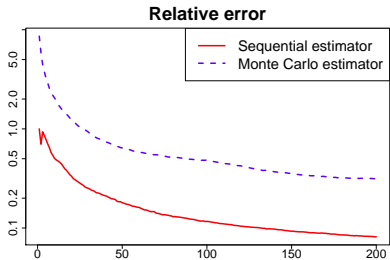
- Consider an analytical example.
- Let $\mathbf{X} = (X_1, \dots, X_d)$ be a random vector where $X_i \sim \Gamma(i + 1, 1)$. Denoting

$$g(\mathbf{X}) = X_1 / \sum_{i=1}^d X_i \sim \text{Beta}(2, (d + 1)(d + 2)/2 - 3),$$

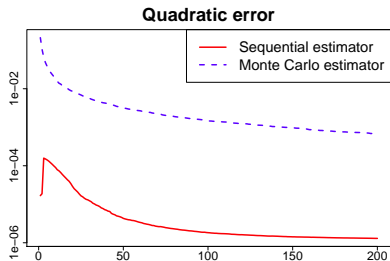
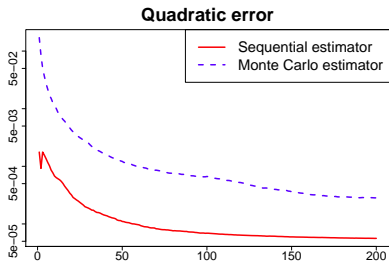
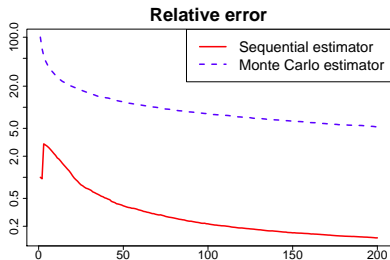
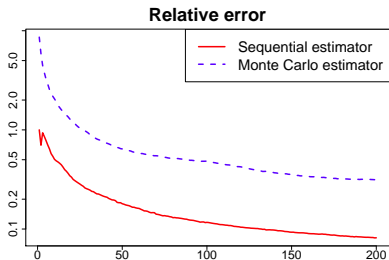
and $q_{d,p}$ the p -quantile of $g(\mathbf{X})$.

- The method is compared with a standard Monte Carlo Method for different couple (d, p) with $n = 200$ evaluations available of g
- The comparison is conducted on four different criterion:
 - the quadratic error $\mathbb{E}[(q_n - q_{d,p})^2]$
 - the relative error $\mathbb{E}[|q_n - q_{d,p}|/q_{d,p}]$
 - the bias $\mathbb{E}[q_n - q_{d,p}]$
 - the length of the confidence interval at 95%

$d = 2$

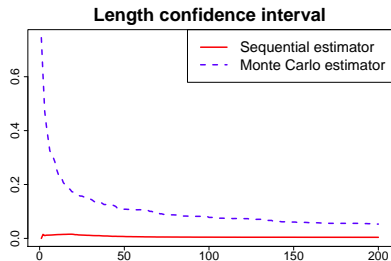
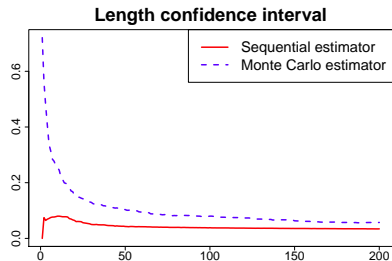
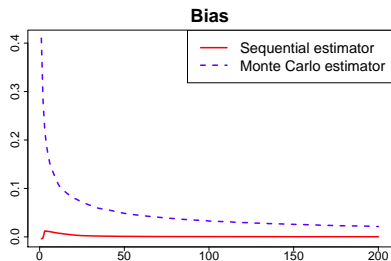
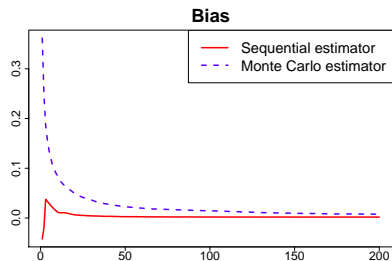


$d = 2$



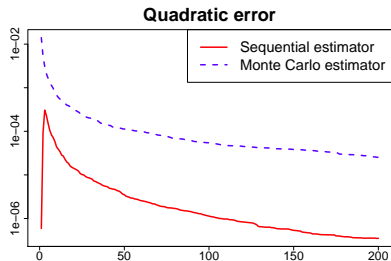
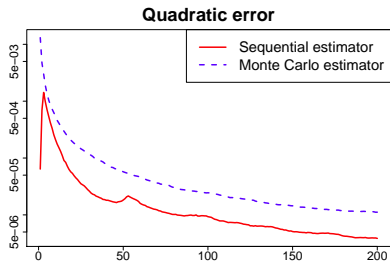
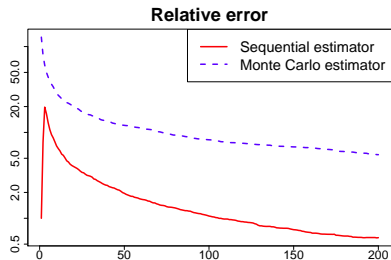
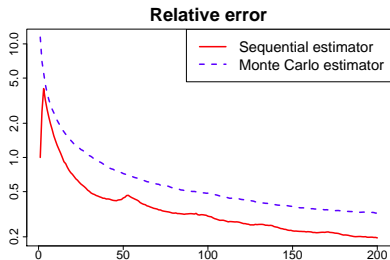
Left: $p = 10^{-2}$. Right: $p = 10^{-4}$

$d = 2$



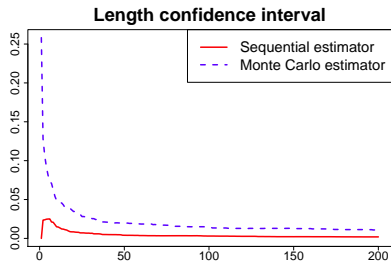
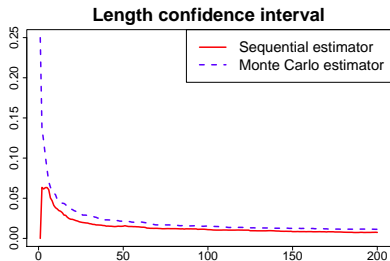
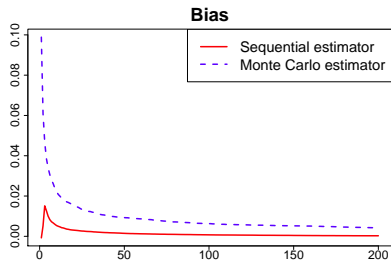
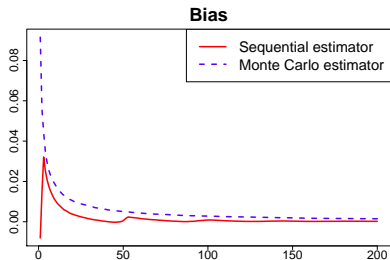
Left: $p = 10^{-2}$. Right: $p = 10^{-4}$

$d = 5$



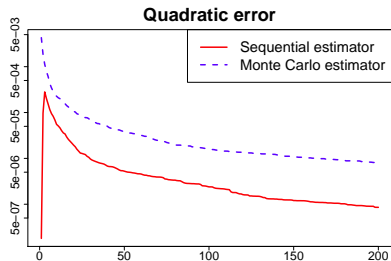
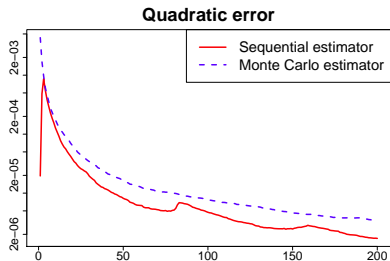
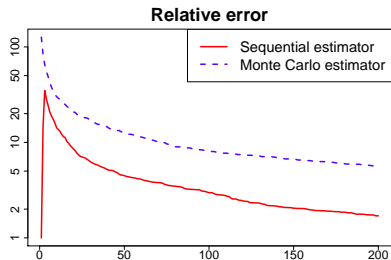
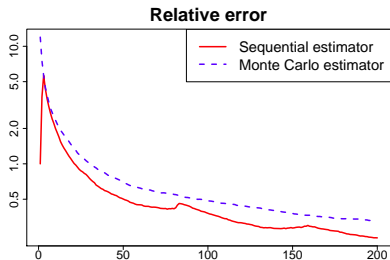
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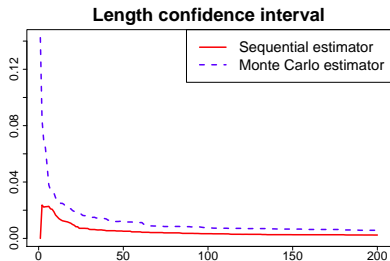
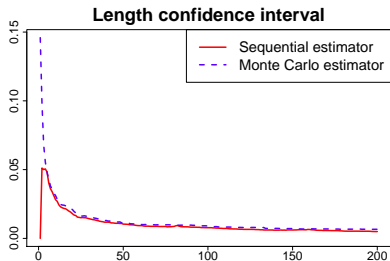
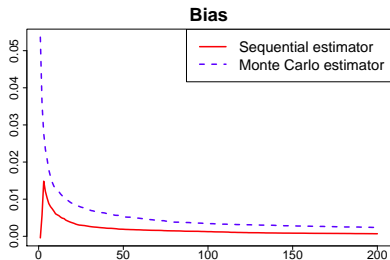
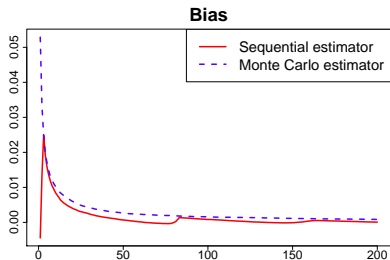
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$d = 7$

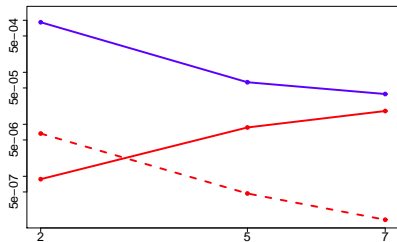
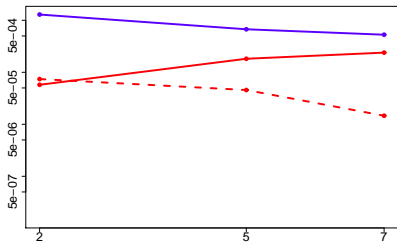


Left: $p = 10^{-2}$. Right: $p = 10^{-4}$

$d = 7$



Left: $p = 10^{-2}$. Right: $p = 10^{-4}$



Left: $p = 10^{-2}$. Right: $p = 10^{-4}$

Conclusion

- A central limit theorem can be obtained to control the estimator ?
- Instead a uniform sequential sampling, use a sequential importance sampling to accelerate the estimation of $F(q)$ then to apply on quantile estimation
- Comparing this method with existing method (Guyader, Morio...)