Scenario reduction in mixed-integer stochastic programming

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Introduction

Most approaches for solving stochastic programs of the form

$$\min\left\{\int_{\Xi} f_0(x,\xi) P(d\xi) : x \in X\right\}$$

with a probability measure P on Ξ and a (normal) integrand f_0 , require numerical integration techniques, i.e., replacing the integral by some quadrature formula

$$\int_{\Xi} f_0(x,\xi) P(d\xi) \approx \sum_{i=1}^n p_i f_0(x,\xi_i),$$

where $p_i > 0$, $\sum_{i=1}^{n} p_i = 1$ and $\xi_i \in \Xi$, i = 1, ..., n. Since f_0 is often expensive to compute, the number n should be as small as possible.

Aim: Given pairs (ξ_i, p_i) , i = 1, ..., N, where N is too large. Find a subset $\{\xi_{i_1}, ..., \xi_{i_n}\}$ with n < N and the corresponding probabilities q_j , j = 1, ..., n, such that the approximation is still reasonable.

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Mixed-integer two-stage stochastic programs

We consider

$$\min\left\{\langle c, x\rangle + \int_{\Xi} \Phi(q(\xi), h(\xi) - T(\xi)x) P(d\xi) : x \in X\right\}$$

where Φ is given by

$$\Phi(u,t) := \inf \left\{ \langle u_1, y_1 \rangle + \langle u_2, y_2 \rangle \left| \begin{array}{c} W_1 y_1 + W_2 y_2 \le t \\ y_1 \in \mathbb{R}^{m_1}_+, y_2 \in \mathbb{Z}^{m_2}_+ \end{array} \right\} \right\}$$

for all pairs $(u,t) \in \mathbb{R}^{m_1+m_2} \times \mathbb{R}^d$, and $c \in \mathbb{R}^m$, X is a closed subset of \mathbb{R}^m , Ξ a polyhedron in \mathbb{R}^s , $T \in \mathbb{R}^{d \times m}$, $W_1 \in \mathbb{R}^{d \times m_1}$, $W_2 \in \mathbb{R}^{d \times m_2}$, and $q(\xi) \in \mathbb{R}^{m_1+m_2}$ and $h(\xi) \in \mathbb{R}^d$ are affine functions of ξ , and P is a Borel probability measure.

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Assumptions:

(C1) The matrices W_1 and W_2 have rational elements. (C2) For each pair $(x,\xi) \in X \times \Xi$ it holds that $h(\xi) - T(\xi)x \in \mathcal{T}$ (relatively complete recourse), where

 $\mathcal{T} := \big\{ t \in \mathbb{R}^d | \exists y = (y_1, y_2) \in \mathbb{R}^{m_1} \times \mathbb{Z}^{m_2} \text{ with } W_1 y_1 + W_2 y_2 \le t \big\}.$

(C3) For each $\xi \in \Xi$ the recourse cost $q(\xi)$ belongs to the dual feasible set (dual feasibility)

 $\mathcal{U} := \left\{ u = (u_1, u_2) \in \mathbb{R}^{m_1 + m_2} | \exists z \in \mathbb{R}^d_- \text{ with } W_j^\top z = u_j, j = 1, 2 \right\}.$ (C4) $P \in \mathcal{P}_r(\Xi)$, i.e., $\int_{\Xi} \|\xi\|^r P(d\xi) < +\infty, r \in \{1, 2\}.$

Condition (C2) means that a feasible second stage decision always exists. Both (C2) and (C3) imply $\Phi(u,t)$ to be finite for all $(u,t) \in \mathcal{U} \times \mathcal{T}$. Clearly, it holds $(0,0) \in \mathcal{U} \times \mathcal{T}$ and $\Phi(0,t) = 0$ for every $t \in \mathcal{T}$.

r = 1 holds if either $q(\xi)$ is the only quantity depending on ξ or $q(\xi)$ does not depend on ξ . Otherwise, we set r = 2.

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With the convex polyhedral cone

 $\mathcal{K} := \left\{ t \in \mathbb{R}^d \mid \exists y_1 \in \mathbb{R}^{m_1} \text{ such that } t \geq W_1 y_1 \right\} = W_1(\mathbb{R}^{m_1}) + \mathbb{R}^d_+$

one obtains the representation

$$\mathcal{T} = \bigcup_{z \in \mathbb{Z}^{m_2}} (W_2 z + \mathcal{K}).$$

The set \mathcal{T} is always connected (i.e., there exists a polygon connecting two arbitrary points of \mathcal{T}) and condition (C1) implies that \mathcal{T} is closed. If, for each $t \in \mathcal{T}$, Z(t) denotes the set

 $Z(t) := \{ z \in \mathbb{Z}^{m_2} \mid \exists y_1 \in \mathbb{R}^{m_1} \text{ such that } W_1 y_1 + W_2 z \leq t \},\$

the representation of ${\mathcal T}$ implies that it is decomposable into subsets of the form

$$\mathcal{T}(t_0) := \{ t \in \mathcal{T} \mid Z(t) = Z(t_0) \}$$

=
$$\bigcap_{z \in Z(t_0)} (W_2 z + \mathcal{K}) \setminus \bigcup_{z \in \mathbb{Z}^{m_2} \setminus Z(t_0)} (W_2 z + \mathcal{K})$$

for every $t_0 \in \mathcal{T}$.

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In general, the set $Z(t_0)$ is finite or countable, but condition (C1) implies that there exist countably many elements $t_i \in \mathcal{T}$ and $z_{ij} \in \mathbb{Z}^{m_2}$ for j belonging to a finite subset N_i of \mathbb{N} , $i \in \mathbb{N}$, such that

$$\mathcal{T} = \bigcup_{i \in \mathbb{N}} \mathcal{T}(t_i) \quad \text{with} \quad \mathcal{T}(t_i) = (t_i + \mathcal{K}) \setminus \bigcup_{j \in N_i} (W_2 z_{ij} + \mathcal{K}).$$

The sets $\mathcal{T}(t_i)$, $i \in \mathbb{N}$, are nonempty and star-shaped, but nonconvex in general.





Illustration of $\mathcal{T}(t_i)$ for $W_1 = 0$ and d = 2, i.e., $\mathcal{K} = \mathbb{R}^2_+$, with $N_i = \{1, 2, 3\}$ and its decomposition into the sets B_j , j = 1, 2, 3, 4, whose closures are rectangular.

If for some $i \in \mathbb{N}$ the set $\mathcal{T}(t_i)$ is nonconvex, it can be decomposed into a finite number of subsets.

This leads to a countable number of subsets B_j , $j \in \mathbb{N}$, of \mathcal{T} whose closures are convex polyhedra with facets parallel to $W_1(\mathbb{R}^{m_1})$ or to suitable facets of \mathbb{R}^r_+ and form a partition of \mathcal{T} .

Since the sets Z(t) of feasible integer decisions do not change if t varies in some B_j , the function $(u, t) \mapsto \Phi(u, t)$ from $\mathcal{U} \times \mathcal{T}$ to \mathbb{R} has the (local) Lipschitz continuity regions $\mathcal{U} \times B_j$, $j \in \mathbb{N}$ and the estimate

 $|\Phi(u,t) - \Phi(\tilde{u},\tilde{t})| \le L(\max\{1, \|t\|, \|\tilde{t}\|\} \|u - \tilde{u}\| + \max\{1, \|u\|, \|\tilde{u}\|\} \|t - \tilde{t}\|)$

holds for all pairs $(u, t), (\tilde{u}, \tilde{t}) \in \mathcal{U} \times B_j$ and some (uniform) constant L > 0.

(Blair-Jeroslow 77, Bank-Guddat-Kummer-Klatte-Tammer 1982)

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The integrand

 $f_0(x,\xi) = \langle c, x \rangle + \Phi(q(\xi), h(\xi) - T(\xi)x) \quad ((x,\xi) \in X \times \Xi)$

has the property that, for every $x \in X$, and

$$\Xi_{x,j} = \{\xi \in \Xi \mid h(\xi) - T(\xi)x \in B_j\} \quad (j \in \mathbb{N})$$

it holds

 $|f_0(x,\xi) - f_0(x,\tilde{\xi})| \le \hat{L} \max\{1, \|\xi\|^{r-1}, \|\tilde{\xi}\|^{r-1}\} \|\xi - \tilde{\xi}\| \ (\xi, \tilde{\xi} \in \Xi_{x,j})$ $|f_0(x,\xi)| \le C \max\{1, \|x\|\} \max\{1, \|\xi\|^r\} \ (\xi \in \Xi)$

for all $x \in X$ with some constants \hat{L} and C.

Since the objective function is lower semicontinuous on X if the conditions (C1)–(C4) are satisfied, solutions exist if X is compact. If the probability distribution P has a density, the objective function is continuous, but nonconvex in general. If the support of P is finite, the objective function is piecewise continuous with a finite number of continuity regions, whose closures are polyhedral.

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Example: (Schultz-Stougie-van der Vlerk 98)

$$m = d = s = 2, m_1 = 0, m_2 = 4, c = (0, 0), X = [0, 5]^2,$$

 $h(\xi) = \xi, q(\xi) \equiv q = (-16, -19, -23, -28), y_i \in \{0, 1\}, i = 1, 2, 3, 4, P \sim \mathcal{U}(5, 10, 15)$ (discrete)

Second stage problem: MILP with 1764 binary variables and 882 constraints.

$$T = \begin{pmatrix} \frac{2}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{2}{3} \end{pmatrix} \qquad W = \begin{pmatrix} 2 & 3 & 4 & 5 \\ 6 & 1 & 3 & 2 \end{pmatrix}$$



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Stability

We consider the class of functions

 $\mathcal{F}_{r,\mathcal{B}}(\Xi) := \{ f \mathbf{1}_B : f \in \mathcal{F}_r(\Xi), B \in \mathcal{B} \},\$

where $\mathbf{1}_B$ denotes the characteristic function of the set B and the class $\mathcal{F}_r(\Xi)$ consists of all continuous functions $f : \Xi \to \mathbb{R}$ such that the estimates

$|f(\xi)| \le \max\{1, \|\xi\|^r\}$

 $f(\xi) - f(\tilde{\xi}) \leq \max\{1, \|\xi\|^{r-1}, \|\tilde{\xi}\|^{r-1}\} \|\xi - \tilde{\xi}\|$ hold true for all $\xi, \tilde{\xi} \in \Xi$ and \mathcal{B} is the set of convex polyhedra in Ξ that contains

 $\{\xi \in \Xi : h(\xi) - T(\xi)x \in B\}$

for all $x \in X$ and all polyhedra B in \mathbb{R}^d with facets, i.e., (d - 1)-dimensional faces, that are parallel to $W_1(\mathbb{R}^{m_1})$ or parallel to suitable facets of \mathbb{R}^d_+ .



Metric on $\mathcal{P}_r(\Xi)$:

$$\zeta_{r,\mathcal{B}}(P,Q) := \sup\left\{ \left| \int_{\Xi} f(\xi)(P-Q)(d\xi) \right| : f \in \mathcal{F}_{r,\mathcal{B}}(\Xi) \right\}$$

Let v(P) denote the optimal value of the stochastic program, i.e.,

$$v(P) := \inf \left\{ \int_{\Xi} f_0(x,\xi) P(d\xi) : x \in X \right\}.$$

Proposition: (Rö-Vigerske 08) Assume (C1)–(C4) and let X be compact. Then the estimate

 $|v(P) - v(Q)| \le L\varphi_P(\zeta_{r,\mathcal{B}}(P,Q))$

holds for every $Q \in \mathcal{P}_r(\Xi)$, where the function φ_P is defined by $\varphi_P(0) = 0$ and

$$\varphi_P(t) := \inf_{R \ge 1} \left\{ R^{d+1}t + \int_{\{\xi \in \Xi \mid \|\xi\| > R\}} \|\xi\|^r P(d\xi) \right\} \quad (t > 0).$$

The function characterizes the tail behavior of P and is continuous at t = 0. If P has a finite pth moment, i.e., if $\int_{\Xi} \|\xi\|^p P(d\xi) < +\infty$, for some p > r, the estimate

$$\varphi_P(t) \le C t^{\frac{p-r}{p+d-1}} \quad (t \ge 0)$$

is valid for some constant C > 0. If Ξ is bounded, we have $\varphi_P(t) \leq Ct$.

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The metric $\zeta_{r,B}$ is difficult to handle, but it holds: **Proposition:**

Convergence with respect to the metric $\zeta_{r,\mathcal{B}}$ is equivalent to convergence with respect to ζ_r (Fortet-Mourier metric of order r) and with respect to $\alpha_{\mathcal{B}}$ (\mathcal{B} -discrepancy), where

$$\zeta_r(P,Q) := \sup\left\{ \left| \int_{\Xi} f(\xi)(P-Q)(d\xi) \right| : f \in \mathcal{F}_r(\Xi) \right\},\$$
$$\alpha_{\mathcal{B}}(P,Q) := \sup_{B \in \mathcal{B}} |P(B) - Q(B)|$$

If the set Ξ is bounded, it even holds

 $\alpha_{\mathcal{B}}(P,Q) \le \zeta_{r,\mathcal{B}}(P,Q) \le C\alpha_{\mathcal{B}}(P,Q)^{\frac{1}{s+1}}$

with some constant C depending on Ξ .

Since the class \mathcal{B} strongly depends on the structure of the underlying mixed-integer stochastic program, we sometimes consider the rectangular discrepancy with $\mathcal{B} = \mathcal{B}_{rect}$

$$\mathcal{B}_{\text{rect}} := \{ I_1 \times I_2 \times \cdots \times I_s \mid \emptyset \neq I_j \text{ is a closed interval in } \mathbb{R} \}$$

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The metric Fortet-Mourier metric ζ_r allows the following dual representation as transportation problem: Let

$$c_r(\xi, \tilde{\xi}) := \max\{1, \|\xi\|^{r-1}, \|\tilde{\xi}\|^{r-1}\} \|\xi - \tilde{\xi}\| \quad (\xi, \tilde{\xi} \in \Xi).$$

Proposition: (Rachev/Rüschendorf 98) Let Ξ be bounded.

$$\zeta_r(P,Q) = \inf\left\{\int_{\Xi\times\Xi} \hat{c}_r(\xi,\tilde{\xi})\Theta(d\xi,d\tilde{\xi}): \pi_1\Theta = P, \pi_2\Theta = Q\right\}$$

where the reduced cost \hat{c} is of the form

$$\hat{c}_r(\xi,\tilde{\xi}) := \inf\left\{\sum_{i=1}^{n-1} c_r(\xi_{l_i},\xi_{l_{i+1}}) : n \in \mathbb{N}, \xi_{l_i} \in \Xi, \xi_{l_1} = \xi, \xi_{l_n} = \tilde{\xi}\right\}$$

is a metric on Ξ with $\hat{c}_r \leq c_r$.

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Scenario reduction

Let P be a probability measure with finite support $\{\xi^1, \ldots, \xi^N\}$ and set $p_i := P(\{\xi^i\}) > 0$ for $i = 1, \ldots, N$. Denoting by δ_{ξ} the Dirac measure placing mass one at the point ξ , P has the form

$$P = \sum_{i=1}^{N} p_i \delta_{\xi^i}.$$

The problem of optimal scenario reduction consists in determining a discrete probability measure Q on \mathbb{R}^s supported by a subset of $\{\xi^1, \ldots, \xi^N\}$ and being close to P with respect to

 $d_{\lambda} := \lambda \alpha_{\mathcal{B}} + (1 - \lambda)\zeta_r \quad (\lambda \in [0, 1]).$

It can be written as

$$\min\left\{d_{\lambda}\left(\sum_{i=1}^{N} p_{i}\delta_{\xi^{i}}, \sum_{j=1}^{n} q_{j}\delta_{\eta^{j}}\right) \middle| \begin{cases} \eta^{1}, \dots, \eta^{n} \} \subset \{\xi^{1}, \dots, \xi^{N}\} \\ q_{j} \ge 0 \ j = 1, \dots, n, \sum_{j=1}^{n} q_{j} = 1 \end{cases} \right\}$$

This optimization problem may be decomposed into an outer problem for determining $\operatorname{supp}(Q) = \eta$ and an inner problem for choosing the probabilities q_j , $j = 1, \ldots, n$.

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To this end, we denote

$$d_{\lambda}(P,(\eta,q)) := d_{\lambda} \left(\sum_{i=1}^{N} p_i \delta_{\xi^i}, \sum_{j=1}^{n} q_j \delta_{\eta^j} \right)$$
$$S_n := \{ q \in \mathbb{R}^n_+ : \sum_{j=1}^{n} q_j = 1 \}.$$

Then the scenario reduction problem may be rewritten as

 $\min_{\eta} \{\min_{q \in S_n} d_{\lambda}(P,(\eta,q)) : \eta \subset \{\xi^1,\ldots,\xi^N\}, |\eta|=n\}$

with the inner problem (optimal redistribution)

 $\min\{d_{\lambda}(P,(\eta,q)):q\in S_n\}$

for the fixed support η . The outer problem is a combinatorial optimization problem (NP hard) while the inner problem may be reformulated as a linear program.

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We assume for the sake of notational simplicity, that $\eta = \{\xi^1, \dots, \xi^n\}$. Then the inner problem is of the form:

$$\min\{d_{\lambda}(P,(\{\xi^1,\ldots,\xi^n\},q)):q\in S_n\}$$

The finiteness of the support of P allows to define for $B\in \mathcal{B}$ the critical index set I(B) by

$$I(B) := \{ i \in \{1, \dots, N\} : \xi^i \in B \}$$

and to write

$$|P(B) - Q(B)| = \left| \sum_{i \in I(B)} p_i - \sum_{j \in I(B) \cap \{1, \dots, n\}} q_j \right|.$$

Furthermore, we define the system of critical index sets of $\mathcal B$ as

$$\mathcal{I}_{\mathcal{B}} := \{ I(B) : B \in \mathcal{B} \}.$$

Thus, the \mathcal{B} -discrepancy between P and Q may be reformulated as follows:

$$\alpha_{\mathcal{B}}(P,Q) = \max_{I \in \mathcal{I}_{\mathcal{B}}} \left| \sum_{i \in I} p_i - \sum_{j \in I \cap \{1,\dots,n\}} q_j \right|.$$



This allows to compute $\alpha_{\mathcal{B}}$ by means of the following linear program:

$$\min\left\{ t \left| \begin{array}{c} -\sum_{j \in I \cap \{1,\dots,n\}} q_j \leq t - \sum_{i \in I} p_i \\ \sum_{j \in I \cap \{1,\dots,n\}} q_j \leq t + \sum_{i \in I} p_i, I \in \mathcal{I}_{\mathcal{B}} \end{array} \right\}$$

Since $|\mathcal{I}_{\mathcal{B}}| \leq 2^N$, the number of inequalities is too large to solve this LP numerically.

Therefore, we consider the following reduced system of critical index sets

$$\mathcal{I}_{\mathcal{B}}^* := \{ I(B) \cap \{1, \dots, n\} : B \in \mathcal{B} \}.$$

Thereby, every member $J \in \mathcal{I}_{\mathcal{B}}^*$ of the reduced system is associated with a family $\varphi(J) \subset \mathcal{I}_{\mathcal{B}}$ of critical index sets, all of which share the same intersection with $\{1, \ldots, n\}$:

$$\varphi(J) := \{ I \in \mathcal{I}_{\mathcal{B}} : J = I \cap \{1, \dots, n\} \} \quad (J \in \mathcal{I}_{\mathcal{B}}^*).$$

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Finally, we consider the quantities

$$\gamma^J := \max_{I \in \varphi(J)} \sum_{i \in I} p_i \quad \text{ and } \quad \gamma_J := \min_{I \in \varphi(J)} \sum_{i \in I} p_i \quad (J \in \mathcal{I}_{\mathcal{B}}^*),$$

and write the inner problem as

$$\min \left\{ \lambda t_{\alpha} + (1-\lambda)t_{\zeta} \left| \begin{array}{l} t_{\alpha}, t_{\zeta} \geq 0, \ q_{j} \geq 0, \ \sum_{j=1}^{n} q_{j} = 1, \\ \eta_{ij} \geq 0, i = 1, \dots, N, \ j = 1, \dots, n, \\ t_{\zeta} \geq \sum_{i=1}^{N} \sum_{j=1}^{n} \hat{c}_{r}(\xi^{i}, \xi^{j})\eta_{ij}, \\ \sum_{j=1}^{n} \eta_{ij} = p_{i}, \ i = 1, \dots, N, \\ \sum_{i=1}^{N} \eta_{ij} = q_{j}, \ j = 1, \dots, n, \\ -\sum_{j \in I^{*}} q_{j} \leq t_{\alpha} - \gamma^{I^{*}}, \ I^{*} \in \mathcal{I}_{\mathcal{B}}^{*} \\ \sum_{j \in I^{*}} q_{j} \leq t_{\alpha} + \gamma_{I^{*}}, \ I^{*} \in \mathcal{I}_{\mathcal{B}}^{*} \end{array} \right\}$$

Now we have $|\mathcal{I}_{\mathcal{B}}^*| \leq 2^n$ and, hence, drastically reduced the maximum number of inequalities. This can make the LP solvable at least for moderate values of n.

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How to determine $\mathcal{I}^*_{\mathcal{B}}$, γ_J and γ^J ?

Observation:

 $\mathcal{I}_{\mathcal{B}}^*$, γ_J and γ^J are determined by those polyhedra (belonging to \mathcal{P}), each of whose facets contains an element of $\{\xi^1, \ldots, \xi^n\}$, such that it can not be enlarged without changing its interior's intersection with $\{\xi^1, \ldots, \xi^n\}$. The polyhedra in \mathcal{P} are called supporting.



Non supporting polyhedron (left) and supporting polyhedron (right). The dots represent the remaining scenarios ξ^1, \ldots, ξ^n

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Proposition:

$$\begin{split} \mathcal{I}_{\mathcal{B}}^{*} &= \{J \subseteq \{1, \dots, n\} : \exists B \in \mathcal{P}, \cup_{j \in J} \{\xi^{j}\} = \{\xi^{1}, \dots, \xi^{n}\} \cap \operatorname{int} B\} \\ \gamma^{J} &= \max\{P(\operatorname{int} B) : B \in \mathcal{P}, \cup_{j \in J} \{\xi^{j}\} = \{\xi^{1}, \dots, \xi^{n}\} \cap \operatorname{int} B\} \\ \gamma_{J} &= \sum_{i \in I} p_{i} \quad \text{with} \quad I \subseteq \{1, \dots, N\} \quad \text{defined by} \\ I &:= \left\{i : \min_{j \in J} \langle m^{l}, \xi^{j} \rangle \leq \langle m^{l}, \xi^{i} \rangle \leq \max_{j \in J} \langle m^{l}, \xi^{j} \rangle, l = 1, \dots, k\right\}, \\ \text{where } m^{j}, \ j = 1, \dots, k, \text{ are the rows of a matrix } M \in \mathbb{R}^{k \times s} \end{split}$$

having the property that every polyhedron $B \in \mathcal{B}$ can be written as

$$B = \{\xi \in \mathbb{R}^s : \underline{a}^B \le M\xi \le \overline{a}^B\}$$

for some \underline{a}^B and \overline{a}^B in $\overline{\mathbb{R}}^k$.

Note that
$$|\mathcal{P}| \leq {\binom{n+2}{2}^k}!$$

For n = 5, k = 3 and n = 20, k = 12, the latter is equal to 3375 and $7.36 \cdot 10^{27}$, respectively.

Numerical results

Optimal redistribution w.r.t. the polyhedral discrepancy $\alpha_{\mathcal{B}}$:

	k	n=5	n=10	n=15	n=20
	cell	0.01	0.01	0.01	0.05
\mathbb{R}^3	3	0.01	0.04	0.56	6.02
N=100	6	0.03	1.03	14.18	157.51
	9	0.15	7.36	94.49	948.17
	cell	0.01	0.01	0.05	0.30
\mathbb{R}^4	4	0.01	0.19	1.83	17.22
N=100	8	0.11	5.66	59.28	521.31
	12	0.67	39.86	374.15	3509.34
	cell	0.01	0.01	0.01	0.07
\mathbb{R}^3	3	0.01	0.05	0.53	4.28
N=200	6	0.03	0.76	11.80	132.21
	9	0.12	4.22	78.49	815.79
	cell	0.01	0.01	0.06	0.29
\mathbb{R}^4	4	0.01	0.20	2.56	41.73
N=200	8	0.11	4.44	73.70	1042.78
	12	0.74	28.29	473.72	6337.68

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Running times [sec] of the optimal redistribution algorithm

Example 2:

We consider $\Xi = [0, 1]^2$, N = 1000 samples from the uniform distribution on Ξ , n = 25. Consider $d_{\lambda} = \lambda \alpha_{\mathcal{B}_{rect}} + (1 - \lambda)\zeta_2$.



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25 scenarios chosen by Quasi Monte Carlo out of 1000 samples from the uniform distribution on $[0, 1]^2$ and optimal probabilities adjusted w.r.t. d_{λ} for $\lambda = 1$ (gray balls) and $\lambda = 0.9$ (black circles)

Example 2: (continued)

Solving the outer combinatorial optimization problem by different heuristics:

- Forward selection:
 - $\begin{array}{ll} \textbf{Step [0]:} & J^{[0]} := \varnothing \,. \\ & \textbf{Step [i]:} & l_i \in \operatorname{argmin}_{l \not\in J^{[i-1]}} \inf_{q \in S_i} d_\lambda(P, (\{\xi^{l_1}, \dots, \xi^{l_{i-1}}, \xi^l\}, q)), J^{[i]} := J^{[i-1]} \cup \{l_i\}. \\ & \textbf{Step [n+1]:} & \textsf{Minimize } d_\lambda(\{P, (\xi^{l_1}, \dots, \xi^{l_n}\}, q)) \textit{ s.t. } q \in S_n. \end{array}$

- (next neighbor) Quasi Monte Carlo (QMC): Take the first n points of the Halton sequences with bases 2 and 3 in [0,1]². The closest scenarios to these points are determined and weight 1/n is associated. The resulting distance to the initial measure is computed for λ = 1.
- (next neighbor) adjusted QMC: The probabilities of the closest scenarios to the Halton points are adjusted by optimal redistribution and the distance d_λ is computed for λ = 1.

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Conclusion: Forward selection provides good results, but is very slow due to the optimal redistribution after each step. Next neighbor adjusted QMC performs significantly better than next neighbor QMC.



Distance $\alpha_{\mathcal{B}_{rect}}$ between P (with N = 1000) and equidistributed QMC-points (dashed), QMC-points, whose probabilities are adjusted (bold), and running times of the QMC-based heuristic (in seconds).

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