

I.M.SOBOL

AVERAGE DIMENSION

# INTRODUCTION

Functions  $f(x)$  defined in the  $d$ -dimensional unit hyper cube  $H$  are considered:  $x=(x_1, \dots, x_d)$ . Average dimensions were introduced in 2006 by A.Owen (who called them *mean dimensions*). Various examples suggest that the efficiency of quasi-Monte Carlo integration depends on the average dimension of the integrand.

# MONTE CARLO METHOD

$$a = ?$$

$$E\eta = a$$

$$\frac{1}{N} \sum_{k=1}^N \eta_k \xrightarrow{P} a$$

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If  $Var(\eta) < \infty$ , the probable error  $\delta_N^{prob} = 0.6745 \sqrt{\frac{Var(\eta)}{N}}$

# MONTE CARLO ALGORITHM

$$\left. \begin{array}{l} \frac{1}{N} \sum_{k=1}^N \eta_k \xrightarrow{P} a \\ \eta = g(\gamma_1, \gamma_2, \dots) \end{array} \right\}$$

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If  $g = g(\gamma_1, \dots, \gamma_d)$  we say that the constructive dimension of MC algorithm is  $d$ .

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$$\Gamma = (\gamma_1, \dots, \gamma_d) \text{ u.d. in } H$$

$$a = E g(\Gamma) = \int_H g(x) dx$$

$$\frac{1}{N} \sum_{k=1}^N g(\Gamma_k) \xrightarrow{P} \int_H g(x) dx$$

# QUASI-MONTE CARLO

In 1916 H. Weyl introduced u.d. sequences of non random points.

Weyl theorem

If  $P_1, \dots, P_k, \dots$  is u.d. in  $H$  and  $g(x)$  is integrable and bounded then

$$\frac{1}{N} \sum_{k=1}^N g(P_k) \rightarrow \int_H g(x) dx$$

In MC algorithms with constructive dimension  $d$  random points  $\Gamma_k$  can be replaced by  $P_k$

This approach is called quasi-Monte Carlo

## TWO PROBLEMS

that remain unsolved:

- (a) Best sequence  $P_1, \dots, P_k, \dots$  (?)
- (b) MC or QMC (?)

My talk is on problem (b)

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Several words on problem (a)

Many practitioners prefer Sobol sequences.

e.g. Monte carlo methods in finance

(P. Jaeckel, 2002, P. Glasserman, 2004)

My best version: SOBOLSEQ16384 in

I.M. Sobol', D. Asotsky, A. Kreinin and S. Kucherenko, Construction and comparison of high-dimensional Sobol' generators, Wilmott Mag. 2011 (2011), n.56, 64–79

# ANOVA DECOMPOSITION

Let  $f(x) \in L_2(H)$  and  $f_0 = \int_H f(x) dx$

The following identity is called decomposition of  $f(x)$

$$f(x) = f_0 + \hat{\sum} f_{i_1, \dots, i_s}(x_{i_1, \dots, i_s}) \text{ where } 1 \leq i_1 < \dots < i_s \leq d \text{ and } 1 \leq s \leq d$$

$$\text{Main requirement } \int_0^1 f_{i_1, \dots, i_s} d(x_{i_p}) = 0 \text{ for } 1 \leq p \leq s$$

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$$f(x) = f_0 + \sum_i f_i(x_i) + \sum_{i < j} f_{i,j}(x_i, x_j) + \dots + f_{1,2,\dots,d}(x_1, x_2, \dots, x_d)$$

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$$D_{i_1, \dots, i_s} = \int_H f_{i_1, \dots, i_s}^2 dx - \text{variances}$$

$$D = \int_H f^2(x) dx - f_0^2 - \text{total variance}$$

$$D = \hat{\sum} D_{i_1, \dots, i_s}$$

# SENSITIVITY INDICES

$$S_{i_1, \dots, i_s} = D_{i_1, \dots, i_s} / D$$

$$\hat{\Sigma} S_{i_1, \dots, i_s} = 1$$

Average dimension of  $f(x)$

$$\hat{d} = \hat{\Sigma} s S_{i_1, \dots, i_s} . \quad \text{Obviously, } 1 \leq \hat{d} \leq d .$$

Examples

$$f(x) = f_0 + c \prod_{i=1}^d \left( x_i - \frac{1}{2} \right) \quad \hat{d} = d$$

$$f(x) = f_0 + c \sum_{i=1}^d \left( x_i - \frac{1}{2} \right) \quad \hat{d} = 1$$

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Various examples show that Q-MC outplays MC if for the integrand  $\hat{d} < 3$ .



# THE OWEN THEOREM

$S_i$  corresponds to  $f_i(x_i)$

$$S_i^{tot} = \sum_{i_1, \dots, i_s} S_{i_1, \dots, i_s} \text{ where one of the } i_1, \dots, i_s \text{ is } i.$$

$$0 \leq S_i \leq S_i^{tot} \leq 1$$

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Let  $x' = (x_1, \dots, x_{i-1}, t, x_{i+1}, \dots, x_d)$

$$S_i^{tot} = \frac{1}{2D} \int_H \int_0^1 (f(x) - f(x'))^2 dx dt$$

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Owen theorem:  $\hat{d} = \sum_{i=1}^d S_i^{tot}$