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#### Multilevel Monte Carlo Methods for failure Probabilities

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#### Introduction: Failure Probabilities

X(u(ω)): V → ℝ − A quantity of interest (functional) of the solution u to some model problem with stochastic input ω

#### Definition: failure probability

The failure probability p given y is:

$$p = \Pr(X \le y)$$
 or  
 $p = F(y),$ 

where  $F(\cdot)$  is the cdf associated with X.

Goal – Estimate the probability p ≈ Q
 to a given root mean square error (RMSE), e(Q
 ≤ ε, using minimal computational cost

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#### Multilevel Monte Carlo for failure probabilities

- Let  $Q(\omega) = \mathbb{1}(X(\omega) < y)$  and  $Q_{\ell}^{\delta}(\omega) = \mathbb{1}(X_{\ell}^{\delta}(\omega) < y)$  be binomial distributed random variables
- Let  $Q_{-1}^{\delta}(\omega) = 0$  then the MLMC estimator reads

$$\widehat{Q}_{\{N_{\ell}\},\delta}^{ML} = \sum_{\ell=0}^{L} N_{\ell}^{-1} \sum_{i=1}^{N_{\ell}} \left( Q_{\ell}^{\delta}(\omega_{\ell}^{i}) - Q_{\ell-1}^{\delta}(\omega_{\ell}^{i}) \right)$$

#### Assumption

We have that

$$\begin{split} \mathsf{M1} & |\mathbb{E} \left[ Q_{\ell}^{\delta}(\omega) - Q(\omega) \right] | \leq C_1 \delta_{\ell}, \\ \mathsf{M2} & \mathbb{V} \left[ Q_{\ell}^{\delta}(\omega) - Q_{\ell-1}^{\delta}(\omega) \right] \leq C_2 \delta_{\ell} \text{ for } \ell \geq 1, \\ \mathsf{M3} & \mathcal{C}(Q_{\ell}^{\delta}(\omega)) = C_3 \delta_{\ell}^{\alpha}, \end{split}$$

are satisfied where  $C_1$ ,  $C_2$ , and  $C_3$  do not depend on the sample or the underlying discretization, and  $\alpha$  is some constant.

#### Theorem

Then there exist a constant L and a sequence  $\{N_{\ell}\}$  such that the RMSE is less then  $\varepsilon$ , with the required work in terms of  $\varepsilon$ ,

$$\mathbb{E}\left[\mathcal{C}_q\left(\widehat{Q}_{\{N_\ell\},\delta}^{ML}\right)\right] \lesssim \begin{cases} \varepsilon^{-2} & \alpha < 1\\ \varepsilon^{-2}(\log \varepsilon)^2 & \alpha = 1\\ \varepsilon^{-1-\alpha} & \alpha > 1 \end{cases}$$

## Selective algorithm

For each sample  $\omega_{\ell}^{i} \in \Omega$  we have

- *N* = 100
- *y* = 2
- $\delta^i_\ell = 1$
- $\#I_0 = 100$



### Selective algorithm

For each sample  $\omega_{\ell}^{i} \in \Omega$  we have

- *N* = 100
- *y* = 2
- $\delta^i_\ell = 1$
- $\#I_1 = 51$



## Selective algorithm

For each sample  $\omega_{\ell}^{i} \in \Omega$  we have

- *N* = 100
- *y* = 2
- $\delta^i_\ell = 0.5$
- $\#I_1 = 51$



## Selective algorithm

For each sample  $\omega_{\ell}^{i} \in \Omega$  we have

- *N* = 100
- *y* = 2
- $\delta_\ell^i = 0.5$
- $\#I_2 = 21$



## Selective algorithm

For each sample  $\omega_\ell^i \in \Omega$  we have

- *N* = 100
- *y* = 2
- $\delta^i_\ell = 0.25$
- $\#I_2 = 21$



# Selective algorithm

For each sample  $\omega_{\ell}^{i} \in \Omega$  we have



- *y* = 2
- $\delta^i_\ell = 0.25$
- $\#I_3 = 11$



# Selective algorithm

For each sample  $\omega_{\ell}^{i} \in \Omega$  we have



- *y* = 2
- $\delta^i_\ell = 0.0125$
- $\#I_3 = 11$



# Selective algorithm

For each sample  $\omega_{\ell}^{i} \in \Omega$  we have

 $|X(\omega_\ell^i) - X_\ell^\delta(\omega_\ell^i)| \le \delta_\ell^i \quad ext{and} \quad \mathcal{C}(X_\ell^\delta(\omega_\ell^i)) = (\delta_\ell^i)^{-q}.$ 



- *y* = 2
- $\delta^i_\ell = 0.0125$
- $\#I_4 = 6$



# Selective algorithm

For each sample  $\omega_{\ell}^{i} \in \Omega$  we have



- *y* = 2
- $\delta_4 = 0.00625$
- $\#I_4 = 6$



Theorem (Computable complexity for the Multilevel Monte Carlo method with selective refinement)

There exist a constant L and a sequence  $\{N_{\ell}\}$  such that the RMSE is less then  $\varepsilon$ , with the required work in terms of  $\varepsilon$ ,

$$\mathbb{E}\left[\mathcal{C}_q\left(\widehat{Q}_{\{N_\ell\},\delta}^{\mathsf{MLS}}\right)\right] \lesssim \begin{cases} \varepsilon^{-2} & q < 2\\ \varepsilon^{-2}(\log \varepsilon)^2 & q = 2\\ \varepsilon^{-q} & q > 2 \end{cases},$$

#### The method is optimal in the sense:

- (q < 2) same as the standard MC method on level = 0
- (q > 2) same complexity as one sample on the finest level L

$$\mathbb{E}\left[\mathcal{C}_{q}\left(\widehat{Q}_{\{N_{\ell}\},\delta}^{\mathsf{MLS}}\right)\right] \lesssim \begin{cases} \mathsf{N} & q < 2\\ \mathcal{C}_{q}\left(Q_{L}^{\delta}(\omega)\right) & q > 2 \end{cases}$$

#### Example 1:

Solving a PDE in 2D to accuracy  $\varepsilon$ , on a uniform mesh, using a numerical method with convergence rate p = 1, and using multigrid to solve the linear system. The computational cost is  $\sim \delta^{-2}$ .

#### Example 2:

Solving a PDE in 3D to accuracy  $\varepsilon$ , on a uniform mesh, using a numerical method with convergence rate p = 1, and using multigrid to solve the linear system. The computational cost is  $\sim \delta^{-3}$ .

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#### Numerical verification: Demonstrational problem

