Clustered Multilevel Monte Carlo (C-MLMC)

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1 Problem Setup and Notation

We aim to estimate $\mathbb{E}[P]$ for a path-dependent payoff P under an SDE model. Using the Multilevel Monte Carlo (MLMC) framework, we define level-wise differences:

$$\Delta P_{\ell} = \begin{cases} P_0, & \text{if } \ell = 0, \\ P_{\ell} - P_{\ell-1}, & \text{if } \ell \geq 1. \end{cases}$$

Let $V_{\ell} = \text{Var}[\Delta P_{\ell}]$, and C_{ℓ} be the average cost per sample on level ℓ . Classical MLMC chooses:

$$N_\ell \propto \sqrt{rac{V_\ell}{C_\ell}}$$

to meet the MSE constraint:

$$\sum_{\ell=0}^{L} \frac{V_{\ell}}{N_{\ell}} \le (1-\theta)\varepsilon^{2}.$$

2 Motivation for Clustering

When the variance is concentrated in rare modes of the input space, uniform sampling becomes inefficient. C-MLMC improves efficiency by:

- Extracting features from simulation details,
- \bullet Clustering samples via K-means into n_c variance modes,
- Estimating per-cluster statistics $(P_{\ell,c}, V_{\ell,c})$,
- Allocating samples proportionally to $\sqrt{P_{\ell,c}V_{\ell,c}}$.

Algorithm 1 Stratified Clustered MLMC Estimator

Require: Simulator $f(\ell, N, \texttt{return_details})$, feature extractor φ , tolerance ε , pilot size N_0 , number of clusters n_c

- 1: Initialize level count $L \leftarrow L_{\min}$, precision parameter $\theta \in (0,1)$
- 2: for each level $\ell \in \{0, \dots, L\}$ do
- Run pilot: simulate $\{(Y_i, d_i)\}_{i=1}^{N_0} \leftarrow f(\ell, N_0, \text{true})$
- 4: if $\ell > 0$ then
- 5: Extract features: $\phi_i \leftarrow \varphi(d_i)$
- 6: Cluster $\{\phi_i\}$ into n_c clusters using K-means
- 7: For each cluster $c \in \{1, ..., n_c\}$, compute:

$$P_{\ell,c} = \frac{\sum_{i=1}^{N_0} \mathbb{1}_{\{\phi_i \in c\}}}{N_0}, \quad V_{\ell,c} = \text{Var}\left(Y_i \mid \phi_i \in c\right)$$

- 8: **else**
- 9: Estimate global variance: $V_0 = Var(Y_i)$
- 10: end if
- 11: **end for**
- 12: while not converged do
- 13: **for** each level $\ell > 0$ **do**
- 14: Compute per-cluster sample allocations:

$$N_{\ell,c} \propto P_{\ell,c} \sqrt{V_{\ell,c}}$$
, and normalize such that $\sum_{c=1}^{n_c} N_{\ell,c} = N_{\ell}$

- 15: Estimate cost per sample $C_\ell \leftarrow$ estimated from runtime or set a priori
- 16: Compute aggregated variance: $V_{\ell} = \sum_{c=1}^{n_c} \frac{P_{\ell,c}^2 V_{\ell,c}}{N_{\ell,c}}$
- 17: end for
- 18: Compute total variance target:

$$\sum_{\ell=0}^{L} V_{\ell} \le \theta^2 \varepsilon^2$$

- 19: For level $\ell=0$: increase N_0 if needed and update V_0
- 20: Estimate total bias from finest levels (e.g., regression fit $|\mathbb{E}[\Delta P_{\ell}]| \sim \mathcal{O}(2^{-\alpha\ell})$)
- 21: **if** estimated bias $> (1 \theta)^2 \varepsilon^2$ **then**
- 22: Increase level count: $L \leftarrow L + 1$, and perform pilot on new level
- 23: **else**
- 24: break
- 25: **end if**
- 26: end while
- 27: for each level ℓ do
- 28: if $\ell > 0$ then
- 29: **for** each cluster c **do**
- 30: Sample $N_{\ell,c}$ new paths with cluster label c
- 31: Compute sample mean: $\hat{\mu}_{\ell,c} = \frac{1}{N_{\ell,c}} \sum Y_i^{(c)}$
- 32: end for
- 33: Compute level mean:

$$\hat{\mu}_{\ell} = \sum_{c=1}^{n_c} P_{\ell,c} \hat{\mu}_{\ell,c}$$

- 34: **else**
- 35: Estimate level mean: $\hat{\mu}_0 = \frac{1}{N_0} \sum_{i=1}^{N_0} Y_i$
- 36: **end if**
- 37: end for
- 38: **Return:** Estimator $\hat{P} = \sum_{\ell=0}^{L} \hat{\mu}_{\ell}$