

Quantum Acceleration for the American Option Problem

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The American Option Problem

- Option: Right to buy/sell a product at a predetermined price at some future date.
- European Style Option: can only be exercised at the expiry date.
- American Style Option: can also be exercised before the expiry date.
- Problem: Suppose we model the possible market changes with probability distributions.
Given the stochastic process with different profits at time t , when to exercise to have $\max \mathbb{E}(\text{profit})$?

Problem Modeling

- $t = 0, \dots, T$ discrete times
- $(X_t)_{t=0}^T$ Markov-chain with Ω sample space and $E \subseteq \mathbb{R}^d$ state space.
- $(Z_t)_{t=0}^T$ payoff process $Z_t := z_t(X_t)$ where $z_t \in L_2(E)$
- U_t : expected payoff if we get to time t
- τ_t : stopping time if we get to time t
- Goal: approximate U_0 and τ_0

Snell envelope:

$$U_t := \begin{cases} Z_T & \text{if } t = T \\ \max\{Z_t, \mathbb{E}(U_{t+1} | \mathcal{X}_t)\} & \text{else} \end{cases}$$

$$\tau_t := \begin{cases} T & \text{if } t = T \\ t \cdot \mathbb{1}\{Z_t \geq \mathbb{E}(Z_{\tau_{t+1}} | \mathcal{X}_t)\} + \tau_{t+1} \cdot \mathbb{1}\{Z_t < \mathbb{E}(Z_{\tau_{t+1}} | \mathcal{X}_t)\} & \text{else} \end{cases}$$

Least Squares Monte Carlo Method

- Take N independent samples: $(X_t^{(1)})_{t=0}^T, \dots, (X_t^{(N)})_{t=0}^T$
- Approximation scheme: $\{e_{t,k}\}_{k=1}^m$ lin. indep. functions from $L_2(E)$
- We want to estimate $\mathbb{E}(U_{t+1}|X_t)$ in this scheme:

$$\alpha_t = \arg \min_a \mathbb{E}((U_{t+1} - a \cdot e_t(X_t))^2)$$

Remark

Let A be the $m \times m$ covariance matrix where $(A_t)_{i,j} = \mathbb{E}(e_{t,i}(X_t)e_{t,j}(X_t))$ and $b_t = \mathbb{E}(U_{t+1}e_t(X_t))$. Then $\alpha_t \approx A_t^{-1} \cdot b_t$.

LSM

- 1 Take sample simulations: $(X_t^{(i)})_{t=0}^T \quad i = 1, \dots, N$
- 2 Calculate values $Z_t^{(i)}$ and $e_{t,k}(X_t^{(i)})$ for all $t = 0, \dots, T$; $i = 1, \dots, N$; $k = 1, \dots, m$
- 3 Specify \tilde{A}_t for each $t = 0, \dots, T$ and calculate their inverses as well.
- 4 $\tilde{u}_T = z_T \quad \forall i = 1, \dots, N$

FOR $t = (T - 1), \dots, 0$:

$$\tilde{\alpha}_t = \tilde{A}_t^{-1} \frac{1}{N} \sum_{i=1}^N \tilde{u}_{t+1}(X_{t+1}^{(i)}) \cdot e_t(X_t^{(i)})$$
$$\tilde{u}_t := \max\{z_t, \tilde{\alpha}_t \cdot e_t\}$$

- 5 **RETURN**

$$\tilde{U}_0 = \frac{1}{N} \sum_{i=1}^N \tilde{u}_0(X_0^{(i)})$$

Expected Value Estimation

y discrete real random variable, $\mu = \mathbb{E}(y)$

Goal: approx μ with $\hat{\mu}$ for given δ, ϵ where

$$\mathbb{P}(|\hat{\mu} - \mu| > \epsilon) \leq \delta$$

How many samples do we need?

Classical approach

Sampling y N times, then output their mean. By Chebyshev's ineq.:

$$\mathbb{P}(|\hat{\mu} - \mu| > \epsilon) \leq \frac{\sigma^2}{N\epsilon^2}$$

for constant δ : $N = O(\sigma^2/\epsilon^2)$

In quantum setup $O(\sigma/\epsilon)$ sample can achieve the same.

\mathbf{P} is a quantum gate: $\mathbf{P}|0\rangle = \sum \sqrt{p(x)}|x\rangle$

where

$$p(x) = \mathbb{P}(X_1 = x_1)\mathbb{P}(X_2 = x_2|X_1 = x_1)\dots\mathbb{P}(X_T = x_T|X_{T-1} = x_{T-1})$$

Kothari-O'Donnell (2022)

With \mathbf{P} expected values can be estimated by $\hat{N} := O(\sigma/\epsilon)$ queries.

QLSM

- 1 Estimate $e_{t,k}(X_t)e_{t,l}(X_t)$ values by \hat{N} queries (i.e. with \hat{N} number of \mathbf{P} calls)
- 2 By this specify all \tilde{A}_t , and their inverses too classically
- 3 $\tilde{u}_T := z_T$
- 4 **FOR** $t = (T - 1), \dots, 0$:
Estimate $\tilde{u}_{t+1} \cdot e_{t,k}(X_t)$ then specify \tilde{b}_t (here also with \hat{N} calls)
 $\tilde{\alpha}_t = \tilde{A}_t^{-1} \cdot \tilde{b}_t$
 $\tilde{u}_t := \max\{z_t, \tilde{\alpha}_t \cdot e_t\}$
- 5 **RETURN** \tilde{u}_0

Runtime Comparison

- Classic LSM:

$$O(N \cdot \mathbf{T}_{samp} + N \cdot T \cdot m^2 + T \cdot m^\omega)$$

- Quantum LSM:

$$O(\hat{N} \cdot \mathbf{T}_{qsamp} \cdot T \cdot m^2 + T \cdot m^\omega)$$

y discrete real random variable, $\mu = \mathbb{E}(y)$. Kell: $\hat{\mu} : \mathbb{P}(|\hat{\mu} - \mu| > \epsilon) \leq \delta$

Main Theorem:

There is a quantum algorithm that using $O(n)$ samples outputs $\hat{\mu}$ where:

$$\mathbb{P}\left(|\hat{\mu} - \mu| \geq \frac{\sigma}{n}\right) \leq \frac{1}{3}$$

By reduction it is enough to prove:

Theorem 2.:

Given $\epsilon > 0$ suppose that $\mathbb{E}(y^2) \leq 1$, then there exists a quantum algorithm, that uses $O(1/\epsilon)$ samples and with probability $2/3$ distinguishes a) $|\mu| \leq \epsilon/2$, and b) $\epsilon \leq |\mu| \leq 2\epsilon$.

- $\mathbf{P}|0\rangle = \sum_{\ell=1}^D \sqrt{p(\ell)} \cdot |\ell\rangle|\text{garbage}_\ell\rangle$
- $\alpha_\ell := -2 \arctan(y_\ell)$
- $\mathbf{U} := \text{REFL}_p \cdot \text{ROT}_y$, where

$$\text{REFL}_p := \mathbf{P}(2|0\rangle\langle 0| - I)\mathbf{P}^\dagger$$

and

$$\text{ROT}_y \text{ such as } \text{ROT}_y|\ell\rangle|\text{garbage}_\ell\rangle = e^{i\alpha_\ell}|\ell\rangle|\text{garbage}_\ell\rangle$$

Notation

- $\sum_{j=1}^D e^{i\theta_j} |u_j\rangle \langle u_j|$ is an eigendecomposition of \mathbf{U} and $|\sigma\rangle$ is a unitvector
- Then in this basis $|\sigma\rangle = \sum_{j=1}^D \hat{\sigma}_j |u_j\rangle$, where $\hat{\sigma}_j = \langle u_j | \sigma \rangle$
- $|\hat{\sigma}_1|^2, |\hat{\sigma}_2|^2, \dots, |\hat{\sigma}_D|^2$ determines a probability distribution

Now $\theta \sim \Theta_{\mathbf{U}}(|\sigma\rangle)$ will denote that $j \in [D]$ index is chosen according to the distribution induced by $|\sigma\rangle$ and we choose θ_j from the eigendecomposition of \mathbf{U} .

Lemma 3.:

Suppose that $\mathbb{E}(y^2) \leq 1/16$. If $\theta \sim \Theta_{\mathbf{U}}(\mathbf{P}|0\rangle)$, then:

$$\mathbb{P}(4/5 \cdot 2|\mu| \leq |\theta| \leq 5/4 \cdot 2|\mu|) \geq 1 - 2/9$$

For **Theorem 2**, recall we want an $O(1/\epsilon)$ runtime quantum algorithm, which distinguishes with at most $1/3$ error between $|\mu| \leq \epsilon/2$, and $|\mu| > \epsilon/2$.

Algorithm for Theorem 2.:

- 1 Phase estimation on $\mathbf{P}|0\rangle$ with controlled- \mathbf{U} gates, output: θ'
(accuracy: $\epsilon/6$, error $\leq 1/9$)
- 2 **IF** $|\theta'| > 142/100 \cdot \epsilon$, then **RETURN**($|\mu| \leq \epsilon/2$)
ELSE RETURN($|\mu| \geq \epsilon$)

From lemma 3.:

$$\mathbb{P}(4/5 \cdot 2|\mu| \leq |\theta| \leq 5/4 \cdot 2|\mu|) \geq 1 - 2/9$$

With at most $1/9 + 2/9 = 1/3$ error:

$$4/5 \cdot |\mu| - \epsilon/12 \leq |\theta'/2| \leq 5/4 \cdot |\mu| + \epsilon/12$$

If $|\mu| \leq \epsilon/2$, then

$$|\theta'/2| \leq 5/8 \cdot \epsilon + \epsilon/12 < 71/100 \cdot \epsilon$$

And if $|\mu| \geq \epsilon$, then

$$|\theta'/2| \geq 4/5 \cdot \epsilon - \epsilon/12 > 71/100 \cdot \epsilon$$

Thank you for your attention!