Longstaff-Schwartz Least-Squares Monte Carlo American Option Pricing Software Technical Documentation

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Contents

| 1 | Introduction | | |
|---|----------------------------|--|---|
| | 1.1 | High-level Workflow | 1 |
| 2 | Mathematical Background | | |
| | 2.1 | Geometric Brownian Motion | 1 |
| | 2.2 | American Options | 1 |
| | 2.3 | Longstaff-Schwartz Least Squares Monte Carlo | 1 |
| 3 | Code Architecture | | |
| | 3.1 | Directory Layout | 2 |
| | 3.2 | ConfigLoader | 2 |
| | 3.3 | AssetSimulator | 2 |
| | 3.4 | OptionPricer | 2 |
| | 3.5 | LongstaffSchwartzEngine | 3 |
| 4 | Input and Output | | |
| | 4.1 | JSON Configuration | 3 |
| | 4.2 | CSV Path Dump | 3 |
| 5 | Auxiliary Python Scripts | | 3 |
| 6 | Compiling and Running | | 3 |
| 7 | Possible Future Extensions | | 4 |

1 Introduction

This document briefly describes the background, structure, and usage of LongstaffSchwartz, a C++ based software that prices American call and put options by combining Monte Carlo simulation of the underlying asset with the Longstaff-Schwartz least squares regression algorithm.

1.1 High-level Workflow

- 1. **Configuration** is read from params.json. It sets market data, contract details, and numerical parameters.
- 2. **Asset paths** are generated by **AssetSimulator** under the risk neutral measure, assuming geometric Brownian motion (GBM).
- 3. Payoff values are provided by OptionPricer.
- 4. The **Longstaff-Schwartz engine** works backward in time, estimating continuation values with a polynomial regression and deciding when to exercise.
- 5. A CSV file of simulated paths and a summary result are returned to main.cpp, where results are printed.

2 Mathematical Background

2.1 Geometric Brownian Motion

Under the risk neutral measure \mathbb{Q} the asset price S_t follows

$$dS_t = rS_t dt + \sigma S_t dW_t \tag{1}$$

where r is the continuously compounded risk free rate, $\sigma > 0$ the volatility, and W_t a standard Brownian motion. The discrete time solution used in simulation is

$$S_{t+\Delta t} = S_t \exp\left[\left(r - \frac{1}{2}\sigma^2\right)\Delta t + \sigma\sqrt{\Delta t} Z\right], \quad Z \sim \mathcal{N}(0, 1).$$
 (2)

2.2 American Options

For an American option with payoff q(S) and maturity T the fair value at t=0 is

$$V_0 = \sup_{\tau < T} \mathbb{E}^{\mathbb{Q}} \left[e^{-r\tau} g(S_\tau) \right]$$
 (3)

where the supremum is over stopping times τ . Closed form solutions are not known in general, so numerical techniques like Longstaff-Schwartz are needed.

2.3 Longstaff-Schwartz Least Squares Monte Carlo

Simulate N paths on a grid of M time steps t_0, \ldots, t_M . Work backward from m = M - 1 to 1:

1. Keep only paths that are in the money: $g(S_{t_m}^{(j)}) > 0$.

2. Regress the discounted payoff $Y_{t_{m+1}}^{(j)}$ on basis functions of $S_{t_m}^{(j)}$. With a polynomial basis of degree p this is

$$Y_{t_{m+1}}^{(j)} \approx \widehat{C}_{t_m}^{(j)} = \sum_{k=0}^{p} \beta_k S_{t_m}^{(j)k}.$$
 (4)

3. If immediate exercise $g(S_{t_m}^{(j)})$ exceeds the estimated continuation $\widehat{C}_{t_m}^{(j)}$, record an exercise at t_m ; otherwise continue.

The mean of all discounted payoffs gives the price estimate \widehat{V}_0 .

3 Code Architecture

3.1 Directory Layout

```
LongstaffSchwartz/
 include/
    AssetSimulator.h
    ConfigLoader.h
    LongstaffSchwartzEngine.h
    OptionPricer.h
 src/
    AssetSimulator.cpp
    ConfigLoader.cpp
    LongstaffSchwartzEngine.cpp
    OptionPricer.cpp
    main.cpp
 scripts/
    price_fetcher.py
    plot_paths.py
 tests/
    test_engine.cpp
 params.json
 CMakeLists.txt
```

3.2 ConfigLoader

Purpose Reads params. json, converts ISO dates to a time to maturity T in years, and validates inputs.

3.3 AssetSimulator

Purpose Generates an $(M+1) \times N$ matrix of GBM paths using Eq. (2). A std::mt19937_64 engine with a normal distribution provides randomness.

3.4 OptionPricer

Defines

$$g(S) = \begin{cases} \max(S - K, 0), & \text{call,} \\ \max(K - S, 0), & \text{put.} \end{cases}$$
 (5)

3.5 LongstaffSchwartzEngine

Core routine The member price() performs the backward induction algorithm, solves the normal equations with LAPACKE, and returns an LsmResult holding \hat{V}_0 , the expected exercise step, and the payoff distribution.

4 Input and Output

4.1 JSON Configuration

Important keys in params.json:

- spot initial price S_0
- vol volatility σ
- \bullet rate risk free rate r
- \bullet strike strike price K
- optionType "CALL" or "PUT"
- startDate, expiryDate ISO strings, used to compute T
- \bullet steps number of time steps M
- paths number of Monte Carlo paths N
- \bullet polyOrder regression polynomial degree p

4.2 CSV Path Dump

Each row is a time step, each column a path. This file can be visualized with the helper script plot_paths.py.

5 Auxiliary Python Scripts

price_fetcher.py Downloads historical daily close prices and outputs them for realized volatility
estimation.

plot paths.py Reads the CSV dump and plots all paths on a single figure for diagnostics.

6 Compiling and Running

- 1. Ensure a compiler with C++17, CMake 3.16 or newer, and BLAS or LAPACK is installed.
- 2. Compiling:

```
mkdir build; cd build cmake ... cmake —build .
```

3. Running:

```
./build/LongstaffSchwartz params.json
```

7 Possible Future Extensions

• Replace the GBM process with a stochastic volatility model.

Appendix: Least Squares Details

Given the Vandermonde matrix ${\bf X}$ and response vector ${\bf y}$, the regression coefficients solve

$$(\mathbf{X}^T \mathbf{X})\boldsymbol{\beta} = \mathbf{X}^T \mathbf{y}.\tag{6}$$

LongstaffSchwartzEngine.cpp calls LAPACKE_dgesv to solve this system.