A Functional Approach to Accelerating Monte Carlo based American Option Pricing

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A Functional Approach to Accelerating
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ABSTRACT
We study the feasibility and performance efficiency of expressing a complex financial numerical algorithm with high-level functional parallel constructs. The algorithm we investigate is a least-square regression-based Monte-Carlo simulation for pricing American options. We propose an accelerated parallel implementation in Futhark, a high-level functional data-parallel language. The Futhark language targets GPUs as the compute platform and we achieve a performance comparable to, and in particular cases up to 2.5× better than, an implementation optimised by NVIDIA CUDA engineers. In absolute terms, we can price a put option with 1 million simulation paths and 100 time steps in 17 ms on a NVIDIA Tesla V100 GPU. Furthermore, the high-level functional specification is much more accessible to the financial-domain experts than the low-level CUDA code, thus promoting code maintainability and facilitating algorithmic changes.

1 INTRODUCTION
Pricing American options is a fundamental business case in the financial services sector, because such financial instruments are widely traded in the derivative markets. American options can be exercised at any time between the present date and the time to maturity. This aspect puts them in contrast to European options, which can be exercised only at their maturity. In the usual case, the option holder is expected to exercise the option as soon as it is more profitable to do so rather than wait until its expiration. Effectively, the value of an American option is the value achieved by exercising it at the optimal time. This embedded optimal stopping problem is a challenge, for which there is no general closed-form formula [28]. Instead, the option value must be approximated with a numerical simulation, which constitutes a substantial computational effort that must be executed efficiently to be acceptable for time-critical financial applications.

Currently, the most efficient accelerated simulations are implemented in dedicated languages and frameworks such as CUDA [1, 24, 43], OpenCL [10, 53], MPI [16], OpenMP [54] and other technologies [15]. A challenge with such implementations is the poor expressibility, which makes them inaccessible to domain experts and difficult to maintain. Specialist developers must be appointed to implement and maintain the code, which require a deep understanding of the underlying hardware and experience with code transformations aimed at optimising potentially-conflicting factors such as locality of reference and the degree of parallelism.

We propose a functional approach to implementing an accelerated option pricing model. The use of high-level parallel constructs lets us express the algorithm in an intuitive manner, without the concerns of mapping the code to the architecture. The Futhark language and the optimising compiler behind it makes this approach possible [33]. The paper makes the following contributions:

(1) We present a high-level data-parallel implementation of the Longstaff-Schwartz algorithm for pricing American options using Monte Carlo Simulation with Least-Square Regression (abbreviated LSMC) [37]. The implementation serves as a reference implementation and can easily be ported to other languages. Moreover, the algorithm makes explicit the available parallelism by using high-level data-parallel constructs.

(2) We give a detailed description of the algorithmic changes required to achieve an efficient parallel implementation of the LSMC algorithm.

(3) We present an optimised efficient version of the algorithm and describe how the original algorithm is rewritten in
Futhark to achieve performance results that in most cases matches a CUDA version, which is a hand-tuned implementation of the algorithm, written in a dedicated low-level programming model (by CUDA engineers). In addition, we present specific cases, in which the Futhark version achieves up to $2.5 \times$ speedup over the CUDA version.

The remainder of the paper is organised as follows. In Section 2, we examine the problem solved by our application and describe the high-level algorithm for American option pricing. In Section 3, we describe the Futhark language and show how American option pricing is implemented in Futhark. In Section 4, we describe and demonstrate how the inefficient version of the algorithm is turned into an efficient version targeting GPUs. Section 5 presents and discusses the main experimental results. Section 6 reviews related work and Section 7 summarises our main findings.

## 2 American Option Pricing

An option contract is defined by its payoff function. For the vanilla-type options like calls and puts, it compares the strike price $K$ and the current asset spot price $S$ and thereby determines the cash flow of an option. The strike price $K$ is an agreed fixed price, at which the option holder can buy (in case of a call) or sell (in case of a put) the underlying asset. The spot price $S$ is a price of the underlying asset like stock or commodity, that the option derives its value from. $S$ varies over time, which can be described using a stochastic process. Such a process is defined by a stochastic differential equation (SDE), which cannot be solved directly using a closed-form formula. Instead, we use a numerical simulation method.

In practice, Monte Carlo (MC) simulation is the most widely used and robust method for solving general SDE problems, and option pricing problems in particular. It is popular in the quantitative finance community, because (1) it is relatively simple to implement (and parallelise) and (2) it allows for pricing of complex instruments that depend on many underlying assets. Such instruments cannot be priced with deterministic methods such as finite difference or lattice models suitable for low-dimensional instruments. In fact, Monte Carlo is the only numerical method that can be used for multi-factor pricing in dimensions greater than four [25].

The Monte Carlo Simulation method is based on two theorems of probability theory. The first one is the Strong Law of Large Numbers, which guarantees the convergence of a certain series of independent random numbers having the same distribution to a value of an integral. The second is the Central Limit Theorem, which determines the convergence rate of the first law [4, 48]. In a standard Monte Carlo simulation, the paths of the state variables are simulated forward in time, which is, in particular, the case for pricing European options. Given an option payoff, a forward (future) price is determined for each path at the maturity date. To estimate the present price of the instrument, the future cash flows (prices in different points in future time) have to be discounted to the present time using some established discount interest rate (i.e., money available now is worth more than the identical amount in the future). Finally, an unbiased estimate of the current option price is a mean average of these prices.

In contrast to pricing European options, the pricing of American options happens backward in time. First, the optimal exercise price is determined at maturity and, subsequently, is recursively propagated and discounted backward in time (until the current time) using dynamic programming. Although an American option can be exercised at any time, the exercise times are discretised and restricted to a fixed set of times (e.g., daily or monthly). The overall goal here is to provide an approximation of the optimal stopping rule that maximises the value of the American option.

At maturity $t = T$, the option holder will exercise the option if it is in-the-money (ITM), that is, if the value of the option, if exercised, will generate a positive cash flow (e.g., in case of a call option, a spot price higher than the strike price is preferable.) For any other time $t_i$, the holder needs to choose whether to exercise the option or continue to hold it. The option value is at the maximum if the exercise happens as soon as the immediate exercise cash flow is greater than or equal to the continuation value (i.e., the discounted expected option value at the next instance in time.) However, this continuation value at any given time $t_i$ is not known, so it needs to be estimated.

In practice, we want to price large portfolios of options through simulation within seconds for real-time decision making. That is why GPUs, which allow for a high degree of parallelism due to its massive number of cores, are a good fit for such workloads.

### 2.1 The Longstaff-Schwartz Algorithm

Several authors have proposed the use of regression to estimate continuation values from simulated paths and thereby enable American option pricing through simulation [11, 37, 52]. There are several reasons for choosing the Longstaff-Schwartz approach [37]. First, it is the most widely adopted algorithm for American option pricing in the financial industry. Second, it is based on an easily-parallelisable Monte Carlo simulation. Finally, the convergence of the Longstaff-Schwartz algorithm have been widely studied together with its dependence on the number of simulated paths [18].

#### 2.1.1 Least-Square Regression

To start with, we turn our focus to the core challenge of the algorithm—the estimation of the continuation values $C_i$ at each time step $i$. Let us assume that $S_{ij}$ is an asset spot price at time step $i$ on a path $j$. Each continuation value $C_i(S_{ij})$ is the regression of the option value in the next time step on the value of $S_{ij}$ in the current time step and path. The procedure is to approximate $C_i$ by a linear combination of basis functions of the current state and use regression to estimate the best coefficients for this approximation. The approximation accuracy depends on the choice of functions used in the regression.

Following the Longstaff-Schwartz approach, we apply an ordinary least-squares regression across the simulated paths at any given time $t_i$ to estimate the continuation value $C_i$. The least-square regression is a method for finding approximate solutions of overdetermined\(^1\) systems of linear equations by minimising the sum of the squares of the errors in the equations [9]. However, since the decision to exercise the option is relevant only when the option is in-the-money, we regress only paths that are in-the-money. This choice results in an improved algorithmic efficiency without negative impact on accuracy.

\(^1\)There are more equations to solve than variables to choose.
To begin with, the ITM paths are parameterised using a quadratic polynomial $\beta_0 + \beta_1 S_{ij} + \beta_2 S_{ij}^2$, where $S_{ij}$ is a variable—an asset spot price at a time step $i$ for some path $j$. In particular, each term of a polynomial, a monomial with basis $1, x, x^2, \ldots$, is a basis function. We chose to use up to second order polynomials in the basis. Having said that, we mention that this choice is usually left as a parameter to the algorithm. In contrast, we deliberately settle on a particular type of basis function. This makes it possible to implement specialised versions of matrix transformations, and as a result enable performance optimisations. The number of used polynomials matches the number of different time steps $i$, because one regression is performed for each step. A point cloud of asset spot prices $S_{ij}$, distributed for each path across the time steps, is obtained from a simulation. The regression problem is then to find, separately for each of these time steps, the best fit in terms of $\beta$ coefficients and basis functions for a quadratic polynomial. We discuss this procedure further in Section 4.

Essentially, we deal with an over-determined system of equations, because the number of equations is larger than the number of unknown coefficients (i.e., $3\beta$ coefficients). For the sake of presentation, let us assume we solve a system of equations of form $Ax = b$. We minimise the objective function $\|Ax - b\|^2$ by finding a variable vector $\hat{x}$ from all possible choices of $x$. In other words, it is a least squares approximate solution to $\|Ax - b\|^2 \leq \|Ax - b\|^2$. In our case, we assume that the number of ITM paths $itm$ is significantly larger than the number of the basis functions (3). It follows that $A$ is a tall data matrix of size $itm \times 3$ and $b$ is a data column vector of size $itm$. The variable of this system of equations is the column vector $x$ of size $3$. In particular, $A$ is a matrix of powers of asset spot prices $S_j$ built from the chosen polynomial. $b$ is a vector of cash flows $\hat{V}_i$ dependent on the payoff function $p(S_i)$, specific for an option that is priced. Finally, $x$ is a vector of polynomial coefficients $\beta_k$, that we want to fit with the least squares method.

We arrive at the following system of equations:

$$
\begin{bmatrix}
1 & S_0 & S_0^2 \\
\vdots & \vdots & \vdots \\
1 & S_{itm-1} & S_{itm-1}^2 \\
\end{bmatrix}
\begin{bmatrix}
\beta_0 \\
\beta_1 \\
\beta_2 \\
\end{bmatrix}
= 
\begin{bmatrix}
p(S_0) \\
p(S_1) \\
p(S_{itm-1}) \\
\end{bmatrix}
(1)
$$

The textbook solution for solving this least-square problem is to multiply both sides by $A^T$, resulting in $A^TA\hat{x} = A^Tb$. Since $A^T A$ is a square matrix, we can now multiply both sides with its inverse resulting in the unique solution: $\hat{x} = (A^T A)^{-1}A^T b$. The matrix $(A^T A)^{-1}A^T$ is the pseudo-inverse of the matrix $A$, denoted $A^\dagger$. The approach to constructing $A^\dagger$ is the main algorithmic challenge and the source for optimisations. There exist different methods to build $A^\dagger$. For the first naive implementation, we use the formula directly, applying matrix multiplication, transpositions, and inversion on $A$. In Section 4.2, we present an efficient algorithm for a pseudo-inverse construction, adapted for massive parallelism on GPUs.

2.1.2 Algorithmic Structure. The generic structure of a simulation algorithm that employs a linear least squares regression according to the Longstaff-Schwartz algorithm [25] is summarised as follows.

\[ A^\dagger = \frac{A^T (A A^T)^{-1} A}{\| A A^T \|} \]

We assume we are given the number of time steps $m$, the number of paths $n$, and the option-specific payoff function $p_i(S_{ij})$, where $S_{ij}$ is an asset spot price at time step $i$ and path $j$. Payoff $p_i$ is discounted back from the maturity $T$ (time step $m - 1$) to current time (time step 0).

A generic linear combination of basis functions is denoted by a polynomial function $\psi_i : \mathbb{R}^r \rightarrow \mathbb{R}$ and constant coefficients $\beta_i k$, where $r$ is the highest degree of the chosen polynomial with each term being a basis function $k = 0, \ldots, r - 1$. Moreover, $\beta_i = [\beta_{i0}, \ldots, \beta_{i m-1}]$ and $\psi(S_i)^T = [\psi_0(S_i), \ldots, \psi_{m-1}(S_i)]^T$.

1. Generate a matrix $W(n, m)$ of random numbers drawn from a standard normal distribution.
2. Using $W$, simulate (by forward induction) $n$ independent paths $S_{0j}, \ldots, S_{m-j}$, $j = 0, \ldots, n - 1$ of Geometric Brownian Motion stochastic processes for the underlying asset prices.
3. At the last step $m - 1$ (at maturity $T$), compute the option value $\hat{V}_{mj} = \hat{p}_m(S_{mj})$, $j = 0, \ldots, n - 1$ applying the payoff function $p$ at the last step $m - 1$.
4. Apply backward induction for each step $i = m - 2, \ldots, 1$ to compute cash flows:
   a. Select the ITM paths.
   b. Build the matrix $\psi_i$ from asset prices $S_i$ and the right hand side cash flows vector $\hat{V}_{i+1}$ only for the ITM paths for the least-square linear equation $\psi_i(S_i)\beta_i = \hat{V}_{i+1}(S_{i+1})$.
   c. Use regression to calculate $\hat{\beta}_i$ by solving a pseudo-inverse $\psi(S_i)^T = (\psi(S_i)^T \psi(S_i))^{-1} \psi(S_i)^T$ in $\hat{\beta}_i = \psi(S_i)^T \hat{V}_{i+1}(S_{i+1})$.
   d. Approximate the continuation function $\hat{C}_i(S_i) = \hat{\beta}_i \psi(S_i)^T$.
   e. Decide to early-exercise based on the value of the continuation function $C_i$ for each ITM path $j$:
      $$
      \hat{V}_{ij} = \begin{cases} 
      p_i(S_{ij}), & \hat{p}_i(S_{ij}) \geq \hat{C}_i(S_{ij}) \setminus \hat{V}_{i+1,j}, \\
      \hat{V}_{i+1,j}, & \hat{p}_i(S_{ij}) < C_i(S_{ij}).
      \end{cases}
      (2)
      $$
   f. Return $\hat{V}_0 = (\hat{V}_{i0} + \cdots + \hat{V}_{i n-1}) / n$ discounted to time step $i = 0$.

3 THE FURTHARK LANGUAGE

Furthark is a statically typed parallel functional array language. The language is based on an ML or Haskell style syntax and is equipped with a number of second-order array combinators (SOACs), such as map, reduce, scan, and filter. The Furthark surface language features a higher-order module system [21], polymorphism, and limited support for higher-order functions [35]. Just as higher-order functions and modules are eliminated entirely at compile time, using a no-overhead approach, arrays of records (or tuples) are turned into records of flat arrays. The language also features a uniqueness type system and explicit sequential loop constructs, which, together with support for array-updates, allows for implementing imperative-like algorithm in a functional style.

The Furthark compiler supports aggressive fusion of parallel constructs [32], and specialised code generators for key parallel operators, such as map-scan and (segmented) map-reduce compositions [31, 36]. Essentially, since all available parallelism is assumed
to be explicit in the program, Futhark can be seen as a sequentialiser compiler that attempts to efficiently sequentialise the parallelism in excess of what the hardware can support, thus enabling opportunities for locality-of-reference optimisations.

In this sense, the compiler supports a code transformation, named moderate flattening [33], that translates arbitrarily-nested, but regular4 parallelism to a flat form that can be straightforwardly and efficiently mapped to the underlying GPU hardware, in the common case. (Whereas perfectly-nested parallel constructs can easily be translated to flat parallelism, it is not straightforward to do so with imperfectly-nested constructs.)

Futhark also implements a notion of incremental flattening [34], which generates multiple code versions in situations where the optimal optimisation strategy is sensitive to the input dataset.5 The dynamic code selection is auto-tuned globally, resulting in one program that offers (in most cases) quasi-optimal performance for all datasets. However, given a problem exhibiting irregular parallelism, in general, to achieve a work efficient algorithm,6 the Futhark programmer is required to implement the flattening strategy by hand, which is not necessarily straightforward [22] unless the problem is particularly simple [23]. The programmer may choose to apply a non-work-efficient padding approach instead (i.e., treat all problems to be of the same size), which might be the most efficient strategy in practice.

Finally, Futhark supports integration with various mainstream programming environments, such as Python [29].

3.1 Data-Parallel Functional Notation

We use (i) \([n]\) to denote the type of an array whose n elements have type \(a\); (ii) \([a_1, \ldots, a_n]\) to denote an array literal; and (iii) \((a, b)\) to denote a tuple (record) value. Applying a function \(f\) on two arguments \(a\) and \(b\) is written \(f(a, b)\).

The semantics of several key parallel operators are presented in Figure 1: \(\text{iota}\) applied to an integer \(n\) creates an array containing elements from \(0\) to \(n-1\), and \(\text{replicate}\ n\ v\) creates an array of length \(n\) whose elements are all \(v\). \(\text{map}\ f\ [a_1, \ldots, a_n]\) = \([f\ a_1, \ldots, f\ a_n]\). \(\text{map2}\ g\ [a_1, \ldots, a_n][b_1, \ldots, b_n]\) = \([g\ a_1\ b_1, \ldots, g\ a_n\ b_n]\). \(\text{reduce}\ \odot\ c_0\ [a_1, \ldots, a_n]\) = \(c_0\ @\ a_1\ @\ \ldots\ @\ a_n\). \(\text{scan}\) with imperfectly-nested constructs.)

4 DESIGN AND IMPLEMENTATION

First of all, we emphasise that, in our implementation of LSMC, we follow the same algorithmic choices as taken by NVIDIA in their CUDA implementation [19]. However, as we could not find any published material on the exact linear algebra transformations that are undertaken, we specify the process in detail in the following sections. Therefore, we present the algorithmic consideration and an efficient approach to an implementation of a financial algorithm.
for a widespread case of Monte Carlo simulation for American Option Pricing, which is frequently reimplemented across financial institutions. This is, to our knowledge, the first state-of-the-art high-level approach to this particular problem available to the public.

4.1 Main Considerations

The main inefficiency of the naive (straightforward) implementation of the LSMC algorithm is that $A^T = (A^T A)^{-1} A^T$ is fully computed at each time step. We optimise this by means of an algorithmic refinement which aims to separate the part of the computation of $A^T$ that is intrinsically dependent within the time-step loop from the one that is not. The latter, independent part can thus be precomputed in parallel before the time-step loop is entered. The algorithmic change consists, at a very high level, of working with a QR decomposition of $A = QR$, where the $R$ matrices have small dimensionality (3x3 in our case) and can be efficiently precomputed in parallel for all time steps. With this, the computation inside the time-step loop is reduced to $A^T = R^{-1}Q^T$.

Furthermore, the $Q^T$ matrix is not actually manifested in memory, but rather computed on the fly from the sample matrix and fused in the multiplication with $R^{-1}$. This requires some redundant computation, but significantly decreases the number of accesses to global memory, which are orders of magnitude slower than scalar arithmetic. Finally, the sample matrix is computed in transposed layout in order to optimise spatial locality (i.e., coalesced accesses to global memory on GPU).

4.2 Building the Pseudo-Inverse Efficiently

We take our design goals into consideration and change the algorithm to adhere to parallel computation on GPUs. This approach was first adapted in the original CUDA implementation by NVIDIA that we are trying to match in performance [19, 39].

For the sake of brevity, we assume that we work with one system of equations $Ax = b$, although one per each time step $i$ needs to be solved. We follow the standard practice by applying Singular Value Decomposition (SVD) $A = USV^T$ to reduce the dimensions of $A$ and build the Moore-Penrose pseudo-inverse of a tall matrix $A^+ = V^T S^{-1} U^T$. Next, $A^+$ is used to compute the solution $\hat{x} = V^+ S^{-1} U^T b$.

Yet, our goal is to build $A^+$ efficiently. This is due to the fact that we need to construct one matrix $A$ for each time step. Thereby it is simply too expensive in execution time and memory required to naively compute SVD of $A$. To remedy this problem, we start with a QR decomposition of $A = QR$, and use the fact that $R$ is much smaller than $A$. We specialise the algorithm to work with a 3-degree parameterisation in terms of a quadratic polynomial. Therefore, $R$ is of size $3 \times 3$ in our case. We compute SVD of $R = U_R \Sigma_R V_R^T$ to build the SVD of $A = Q R \Sigma R^T$.

The QR factorisation is typically performed using householder transformation. However, the naive application of it would mean $3 \times n \times n$ memory access as that many elements would need to be updated. The efficient solution comes from the observation that, in our case, matrix $R$ can be constructed using only 8 scalars:

$$S_0, S_1, S_2, \sum_{i=0}^{n-1} S_{i+1}^n, \sum_{i=0}^{n-1} S_{i+1}^n, \sum_{i=0}^{n-1} S_{i+1}^n, \sum_{i=0}^{n-1} S_{i+1}^n, \sum_{i=0}^{n-1} S_{i+1}^n.$$

Figure 2: Futhark code for the naive LSMC algorithm.
1. map(n)  -- Path Generation
2. loop(m)
3. transpose
4. map(m)
5. loop(n)
6. scan(chunk)
7. map(n) >>= reduce(n)
8. map(n)
9. map(m)
10. loop(m)  -- SVD Preparation
11. map(n)
12. map(n)
13. reduce(n)

Figure 3: The high-level view of the implemented optimised algorithm structure presented as a combination of parallel constructs. It consists of 3 parts with $n$ denoting the number of paths and $m$ denoting the number of time steps. The transpose function performs matrix transposition.

where $S_i$ is the asset spot price on the ITM path $i$. Three first scalars are asset spot prices for the first ITM paths found when traversing the paths from path 0. The first sum can be translated to a total number of ITM paths found. The remaining four sums are consecutive powers $(1, \ldots, 4)$ of spot prices associated with each found ITM path. These scalars are prepared as part of SVD preparation. We implement a custom function that uses these scalars to build the matrix $R$. Furthermore, thanks to QR factorisation we get a simple formula for the pseudo-inverse. We use the fact that $A$ is left-invertible, so its columns are linearly independent. We have

$$A^T A = (QR)^T (QR) = R^T Q^T QR = R^T R,$$

so

$$A^+ = (A^T A)^{-1} A^T = (R^T R)^{-1} (QR)^T = R^{-1} R^T Q^T = R^{-1} Q^T.$$

The final equation that we solve in the main loop for each time step is $\hat{x} = R^{-1} Q^T b$. The $R^{-1}$ is precomputed for each time step before the loop using SVD like this: $R^{-1} = V_R R^{-1} U_R^T$. The orthogonal matrix $Q^T = R^{-T} A^T$ does not need to be stored for each time step and can instead be computed on-the-fly. We again use the fact that (1) $R^{-1}$ is by now already precomputed using SVD and (2) matrix $A$ can itself be computed on-the-fly, where, for our case, each row comprises 3 elements: $1, S_{ij}, S_{ji}^2$, i.e., it can be computed from vector $S_i$ that consists of asset spot prices for ITM paths for a given time step $i$. Naturally, they need to be processed in transformed form.

4.3 Optimised Algorithm

The optimised version of the algorithm follows closely the implementation proposed by NVIDIA [19, 39]. We focus on the goal to match the performance of this public benchmark implementation. The optimised algorithm outline in Figure 3 is implemented using a nested composition of sequential loops and parallel map, reduce, and scan constructs. The code in Figure 4 demonstrates the main lsmc_opt function of the optimised algorithm. The function takes the following arguments: (1) number of time steps $m$, (2) number of paths $n$, (3) a function to verify if the option is ITM is_itm, (4) a payoff function payoff, (5) the time step size $dt$ as a fraction of a year, (6) initial asset spot price at the current day $S_0$, (7) a risk-free interest rate $r$ used for discounting, (8) volatility $\sigma$, (9) seed for Random Number Generator and 2 helper parameters that determine the amount of computation that should be performed sequentially. The function returns the calculated option price.

In the next sections, we give a detailed description of the implementation and optimisations involved in the algorithm. The three main parts of the algorithm are: path generation in Section 4.3.1, SVD preparation in Section 4.3.2, and main regression loop in Section 4.3.3. Each section is accompanied with a code listing presenting a Futhark implementation of a function for the given part.

4.3.1 Path Generation. The computational effort of a Monte Carlo simulation is determined by the number of paths and time steps. A large number of paths $n$, usually 100,000 to 1,000,000, needs to be generated to obtain an accurate value approximation [25]. In American option pricing case, the number of time steps $m$ is bound to the number of early-exercise opportunities and is usually much smaller than $n$. Path generation part consists of two sub-parts: random number generation and path generation.

For the first part, we use a minimum standard pseudo-random number generator (RNG) in a parallel skip-ahead fashion. After seeding the RNG, we draw $m \times n$ random samples by splitting the RNG into $n$ sub-RNGs for each path and then sequentially drawing a sample for each time step of the given path. The samples are independent from each other. For the process, that we want to simulate, we need samples drawn from Gaussian (standard normal) probability distribution. We achieve it in two steps. First, we draw samples from a uniform probability distribution using the RNG. Afterwards, we use the Inverse Normal Cumulative Density Function (CDF) to produce normally-distributed samples out of the generated uniforms.

Figure 4: Futhark code for the main regression loop.
sample is turned into an asset spot price instance at every simulation time step (or early-exercise opportunity). We use the standard Geometric Brownian Motion $\text{GBM}(r, \sigma^2)$ with a mean (drift) equal to the risk-free interest rate $r$ and variance (diffusion) equal to $\sigma^2$ (square of volatility). We use the generated normally-distributed samples to simulate a stochastic process. In practice, as the process is a Markov chain, we know that the current step is independent of the past realisations of the process.

In our case, we deal with only one stochastic factor—the underlying asset spot price, as the American option, that we price, depends on only one underlying variable. All paths are therefore independent, which allows us to parallelise the generation efficiently across paths by having one thread generate one whole path. The assumption of having one underlying is not essential for parallelism, however. Many stochastic processes could be generated in parallel as long as we would adjust the simulation for the correlations between the stochastic variables, which is a necessary step in practice. The code in Figure 5 presents a compact Futhark implementation of path generation. For each path and step, the $\text{UniDist.rand}$ function draws first a single random number from a uniform distribution. The function $\text{compGbmNormalStep}$ transforms it to a standard normal distribution and computes a current GBM step. It uses the iterative Jacobi method to determine the inverse matrix $\lambda$. The function returns 6 upper elements of matrix $R$ from the 8 scalars and afterwards maps it to a standard normal $\text{NormRealDist.invNormalCdf}$.

Performance Enabler. We gain most performance here by fusing the random sample generation and path generation together into one step like in lines 18–24 in the code in Figure 5. We perform these actions for each step based on the observation that we work on the same array for both actions as well as each sample is independent from the all other ones. This way we read from and write to the device global memory only once and thereby save the redundant intermediate memory accesses, that are costly to execute compared to compute instructions.

4.3.2 SVD Preparation. This part is run before entering the main regression loop and covers the main algorithmic optimisation. The main advantage of this approach is that SVD for $R$ in each time step can be processed in parallel. As $R$ is small, the intermediate variables easily fit into registers of one streaming multiprocessor (SM). The number of SVD matrices to prepare depends on the number of time steps $m$. This part is compute-intensive, but at the same time the parallelism is limited by the fact that $m$ is usually much smaller than $n$. A sequential loop is needed to find the first three ITM paths to get the asset spot prices to build $R$ matrix. In the body of $\text{prepare_svds}$ function, the eight required scalars are gathered and computed. They are subsequently passed to $\text{svd_3x3}$ function that performs the QR decomposition and SVD decomposition for $R$ and $R^{-1}$. It starts with assembling the $R$ matrix from the 8 scalars and afterwards uses the iterative Jacobi method to determine the inverse matrix $R^{-1}$. The function returns 6 upper elements of matrix $R$ and 6 upper elements of the inverse matrix $R^{-1}$, as the matrices are orthogonal.

Performance Enabler. The key to performance is that we not only perform computation in parallel on the outer level across all time steps $m$, but that we also enable inner parallelism in the computation for each time step.

First of all, SVD preparation benefits significantly from the intra-group parallelism in the first map (lines 4–29 in the code in Figure 6), which finds the first three ITM paths. The spot prices on these paths are needed for computing the matrix $R$. The computation works on $\text{CHUNK}$ paths in parallel. It is achieved by a combination of parallel constructs like $\text{maps}$, $\text{reduces}$, an exclusive scan $\text{scanExc}$, and $\text{scatter}$. The $\text{CHUNK}$ parameter depends the level of intra parallelism. The smaller its value, the faster this part performs. However, the value cannot be smaller than the number of ITM paths needed for constructing the $R$ SVD matrices. This number is determined by the $\text{min_itm}$ parameter, which is fixed to 4, one larger than the dimension size of $R$.

The next beneficial optimisation is the application of segmented reduction in lines 31–44, which enables parallelism in gathering the remaining 5 scalars. Afterwards, the $\text{map}$ in line 45 works in parallel across time steps, but internally, for each time step, it uses the matching scalars to compute the partial data in a sequential manner in the call to $\text{svd_3x3}$.

4.3.3 Main Regression Loop. This part is where the least squares system of equations is regressed, the continuation value is computed and the cash flow per each time step is updated. It can be seen in the code in Figure 4 in lines 15–22. This loop has $m - 1$ iterations. The computation in the loop is greatly simplified thanks to the SVD preparation that is performed before entering the loop as most of the sequential computation was performed there. The code in Figure 7 shows the implementation. Function $\text{compute_betas}$
number of time steps, as they are processed sequentially, because of the data dependency between consecutive time steps.

4.4 **Motivation for the Functional Approach**

As a final remark to the presented Futhark code, we motivate some virtues of the functional programming approach that can be especially valuable for non-technical domain experts. Anyone, who, on a regular basis, programs in parallel low-level languages targeting multi-core architectures, will make the immediate observation that the code contains no explicit kernel setup or device memory management. In fact, the code is agnostic to the underlying platform and most of the performance optimisations are provided by the aggressive optimisation and parallelisation strategies implemented by the compiler. The effect is that the same Futhark code base is portable across architectures. The program can be compiled to run sequentially on a single CPU core or be compiled to run on (and utilise fully) a massively-parallel GPU. Moreover, when writing Futhark code, the programmer can focus on expressing the algorithmic details using Futhark’s Second-Order Array Combinators (SOACs) that mimic the higher-order functions found in conventional functional languages. In Futhark, SOACs have sequential semantics, but permit parallel execution. The purely functional nature of Futhark allows the compiler to apply high-level optimisations. In terms of performance portability, Futhark supports nested parallelism, which means that the code can be further auto-tuned.

Figure 7: Futhark code for the main regression loop. It consists of a computation of $\beta$s for assessing the continuation value with a subsequent update of the cash flows.

```futhark
fig 7 { /*
```
to support efficiently all the available parallelism exposed by the hardware, which is a rather cumbersome, and often impossible, task to perform manually.

5 EXPERIMENTAL RESULTS

In this section, we present different experimental tests and discuss their results. We validate the simulation accuracy and measure the performance of the implementation by comparing it to other established benchmarks. We run the experiments on a Linux system with a 26-core 2-way HT Intel Xeon Platinum 8167M CPU (2.00GHz), 754 GB DDR RAM and NVIDIA Tesla V100 SXM2 GPU (2688 Volta FP64 cores, 16 GB HBM2) using CUDA 10.1.

5.1 Accuracy

To start with, we compare the pricing results with an established benchmark to validate correctness of our implementation. Table 1 presents a comparison of different implementations of American Option Pricing. We are pricing an American put option with a fixed strike and constant risk-free rate. The remaining parameters vary as specified in the original paper by Longstaff-Schwartz [37]. Columns FDM and LSMC stand for the results from the original paper. The two remaining columns comprise results for CUDA implementation, that we used as a benchmark algorithm, and our Futhark implementation. That said, we mention that the LSMC simulation from the original paper uses antithetic sampling, which cuts the number of random samples in half. This algorithmic optimisation leads to a reduced variance of the sample paths as well as an improvement in the overall accuracy of the simulation.

The simulation results compared to FDM method have a low error. The difference between simulation results varies slightly for different sets of parameters, but, in general, they are insignificant and are the outcome of using different RNGs. The same is valid for both the original CUDA and Futhark implementations.

5.2 Performance Test Case

The pricing test case is presented in Table 2. It is an example of a typical put option that is ITM on the calculation day.

The performance results are presented in Table 3. The correctness is validated against the benchmark binomial tree numerical method for the same problem. We want to obtain a value that is as close as possible to this benchmark. Futhark targets different hardware with different backends. We test the CUDA (V1) and OpenCL (V2) backends, and observe identical execution times for both versions. In terms of the speedups, Ref is only 1.11× faster than V2, what can be considered insignificant. Furthermore, we do not observe large discrepancies in terms of partial execution times among the three main parts of the algorithm. This fact demonstrates that Futhark auto-generated low-level code is similar in complexity and on par in performance with one that is hand-tuned. Some parts run faster, while other would benefit from further optimisation (e.g., changing the algorithm). The (17%) overhead in the Path part is due to the internal implementation of the RNG. We have used a different RNG in comparison to Ref, which uses CURAND_RNG_PSEUDO_MRG32K3, a member of the Combined Multiple Recursive family of pseudo-random number generators. The 13% difference in Main is caused by a more optimal handling of memory copies compared to Ref. The effect is amplified, because the loop has 99 iterations.

5.3 Performance Scalability

5.3.1 Fixed number of paths, various number of time steps. As the next step we test the scalability behaviour of Futhark implementation V2 by gradually changing the number of time steps or paths. These are the main parameters that determine the size of the computation involved in a Monte Carlo simulation. Consequently, we reuse the test case from Table 2 and compare against the benchmark Ref for different combinations of these two simulation parameters.
First of all, we fix the number of paths to a relatively high number 1,024,000 and test against 5 different numbers of time steps. High number of paths allows for massive parallelism across the path dimension and thus full utilisation of the GPU hardware. Figure 8 shows the results of this experiment. Contributions of three algorithmic parts are distinguished and sum up to a total execution time for each tested case.

The main observation is that for the low number of time steps, Futhark V2 is faster than benchmark CUDA Ref. In particular, for very few time steps like 10, it is ~2.5× faster. The difference diminishes with increasing number of time steps to match at ~100 time steps. For more time steps, Ref is slightly faster than V2, but the ratio is maintained with increasing time steps. For instance, it is 1.25× faster for 250 time steps.

The next observation is that, for many time steps, the Path part becomes the main computational bottleneck. It takes 40% for 10 time steps, but more than 52% for 250. This is caused by the necessary transposition of the layout that the sampled paths matrix is organised in. The transposition enables coalesced accesses to global memory on GPU across time steps, which benefits the performance of the SVD part. The next observation is that the contribution of SVD part decreases with more time steps. It is more efficiently implemented in V2 as it is always faster than the one in Ref. Finally, we achieve better performance on the sequential part Main by ensuring that no device-to-host memory transfers are initiated. On GPU architectures such transfers introduce significant delays in execution, so all intermediate data should be kept on the device. The compute_betas and update_cashflows functions in 7 exchange an array of βs that is computed sequentially and not in parallel (it holds only three elements).

5.3.2 Fixed number of steps, various number of paths. We observe similar scalability, when the number of paths is increased. Futhark V2 is faster than CUDA Ref on low number of paths. For 10240 paths, it is ~1.25× faster. The difference diminishes with increasing number of time steps to match at ~1024000 paths.

5.3.3 Various number of time steps and paths. Figure 10 presents the results for different combinations of time steps and paths. The ratio between them is kept so, that the required work as well as memory requirements are constant. These cases saturate the memory available on V100. We can see that the impact of the time steps on the overall execution time is slightly higher than the number of paths. For V2 it goes from 39 ms to 45 ms. This is caused by the computations in Main loop, that need to be run one step at a time. In general, the performance of both Ref and V2 is stable across different configurations, which shows that Futhark matches the CUDA performance. We can observe that Futhark V2 is slightly (1 ms to 13 ms) slower than Ref on all cases.

6 RELATED WORK
The most efficient implementations of Monte Carlo based American option pricing are implemented in low-level dedicated data-parallel languages and frameworks, such as CUDA [1, 24, 43, 54]. Other efficient parallel implementations are based on task-parallel approaches [15, 16], which are suitable for multi-core architectures.
We are not aware of any accelerated implementations of American option pricing using functional languages. Previous work has investigated the use of Futhark for implementing Monte Carlo based European option pricing [2, 40]. Whereas European option pricing is simpler than (and a special case of) American option pricing, the previous work covered a number of advanced features that the present work does not consider. In particular, the previous work on European option pricing considered European options with multiple underlying assets, Sobol sequence generation [30], and options that are so-called path dependent, meaning that the price of an option not only depends on the value of the underlying at maturity, but also on intermediate values of the underlying. Using the module language features of Futhark, we believe it will be possible to parameterise the implementation in such a way that multiple underlying assets and path dependence are features that are supported by the American pricing engine (we consider such advanced features future work). It is also straightforward to replace the pseudo-random number generation used with Sobol sequence generation.

There are quite a few functional language approaches aiming at generating efficient data-parallel GPU code for applications written using high-level array language constructs. Such high-level approaches include SaC [26, 27], a functional array-based language featuring a parallelisable with-loop construct, and Obisidan [17, 50, 51] and Accelerate [12], which are both domain specific languages embedded in Haskell. None of these approaches, however, feature arbitrary nested parallelism. Approaches that support arbitrary nested parallelism includes the seminal work on flattening of nested parallelism in NESL [6, 7], which was extended to operate on a richer set of values in Data-parallel Haskell [13], and the work on data-only flattening [55]. However, such general compiler-based flattening is challenging to implement efficiently in practice, particularly on GPUs [3]. Other promising attempts at compiling NESL to GPUs include Nessie [47], which is still under development, and CuNesl [55], which aims at mapping different levels of nested parallelism to different levels of parallelism on the GPU, but lacks critical optimisations such as fusion.

Imperative approaches typically rely on low-level analysis—of loop nests using affine indexing and branch condition—for discovering and optimising parallelism, for example the polyhedral model [8, 44]. Since the affine domain is too restrictive in practice, several techniques use explicit annotations to extend the applicability of polyhedral transformations [14, 46]. Other techniques rely on more dynamic analysis coupled with multi-versioned code generation, for example to identify sufficient conditions under which loops are parallel [38, 42] or to optimise locality of reference and communication [20, 41, 45, 49]. In this sense, our implementation uses Futhark’s multi-version code generation facilities [34] to adapt the compilation to the particularities of datasets and hardware.

7 CONCLUSION

In this work, we present the results of the accelerated implementation of a well-known LSMC algorithm for a common financial use case of American Option Pricing. We choose to use a high-level functional approach to the implementation, express the algorithm using succinct parallel constructs and let the optimising compiler auto-generate an efficient parallel code that targets massively parallel hardware. For this purpose, we use the Futhark language and address GPUs as a suitable compute platform. We demonstrate that with this approach it is possible to achieve the execution times that are, in general, at the same level as the hand-tuned implementations in dedicated languages like CUDA, but there exist particular smaller cases, where the implementation beats the benchmark by up to 2.5×. This promising finding motivates further work on the optimisation compiler and the algorithm.

We consider the high-level functional specification as being much more suitable and accessible for the financial-domain experts than the low-level dedicated code, that is usually written by expert software developers. Its expressibility and modularity enables code maintainability, hiding the implementation details targeting particular parallel architecture, and instead turning focus to algorithmic and domain-specific consideration. It also facilitates algorithmic changes, so prevalent in the financial industry, with its multitude of financial instruments traded in the global markets.

REFERENCES


