**FOOPar**: A Functional Object Oriented Parallel Framework in Scala

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Abstract

We present FooPar, an extension for highly efficient Parallel Computing in the multi-paradigm programming language Scala. Scala offers concise and clean syntax and integrates functional programming features. Our framework FooPar combines these features with parallel computing techniques. FooPar is designed modular and supports easy access to different communication back-ends for distributed memory architectures as well as high performance math libraries. In this article we use it to parallelize matrix-matrix multiplication and show its scalability by a isoefficiency analysis. In addition, results based on a empirical analysis on two supercomputers are given. We achieve close-to-optimal performance wrt. theoretical peak performance. Based on this result we conclude that FooPar allows to fully access Scalas design features without suffering from performance drops when compared to implementations purely based on C and MPI.

1 Introduction

Functional programming is becoming more and more ubiquitous (lambda functions introduced in C++11 and Java8) due to higher levels of abstraction, better encapsulation of mutable state, and a generally less error prone programming paradigm. In HPC settings, the usual argument against the added functional abstraction is performance issues. **FOOPar** aims to bridge the gap between HPC and functional programming by hitting a sweet spot between abstraction and efficiency not addressed by other functional frameworks.

There exists a multitude of map-reduce based frameworks similar to Hadoop which focus on big data processing jobs, often in cloud settings. Other functional parallel frameworks like Haskell’s *Eden* [13] and Scala’s *Spark* [19] focus on workload balancing strategies neglecting performance to increase abstraction. While many different functional frameworks are available, most seem to value abstraction above all else. To the best of our knowledge, other functional parallel frameworks do not reach asymptotic or practical performance goals comparable to **FOOPar**.
In this paper (after definitions and a brief introduction to isoefficiency in Section 2) we will introduce FooPar in Section 3 and describe its architecture, data structures, and operations it contains. The complexity of the individual operations on the (parallel) data structures will be shown to serve as basis for parallel complexity analysis. A matrix-matrix multiplication algorithm will be designed using the functionality of FooPar; the implementation will be analyzed with an isoefficiency analysis in Section 4. Test results showing that FooPar can reach close-to theoretical peak performance on large supercomputers will be presented in Section 5. We conclude with Section 6.

2 Definitions, Notations, and Isoefficiency

The most widespread model for scalability analysis of heterogeneous parallel systems (i.e. the parallel algorithm and the parallel architecture) is isoefficiency analysis. The isoefficiency function for a parallel system relates the problem size \( W \) and the number of processors \( p \) and defines how large the problem size as a function in \( p \) has to grow in order to achieve a constant pre-given efficiency. Isoefficiency has been applied to a wide range of parallel systems (see, e.g. [9],[11],[3]). As usual, we will define the message passing costs, \( t_c \), for parallel machines as \( t_c := t_s + t_w \cdot m \), where \( t_s \) is the start-up time, \( t_w \) is the per-word transfer time, and \( m \) is the message size. The sequential (resp. parallel) runtime will be denoted as \( T_S \) (resp. \( T_P \)). The problem size \( W \) is identical to the sequential runtime, i.e. \( W := T_S \). The overhead function will be defined as \( T_o(W,p) := pT_P - T_S \). The isoefficiency function for a parallel system is usually found by an algebraic reformulation of the equation \( W = k \cdot T_o(W,p) \) such that \( W \) is a function in \( p \) only (see e.g. [7] for more details).

In this paper we will employ broadcast and reduction operations for isoefficiency analysis for parallel matrix-matrix multiplication with FooPar. Assuming a constant cross-section bandwidth of the underlying network and employing recursive doubling leads to a one-to-all broadcast computational runtime of \( (t_s + t_w \cdot m) \log p \) and the identical runtime for an all-to-one reduction with any associative operation \( \lambda \). All-to-all broadcast and reduction have a runtime of \( t_s \log p + t_w \cdot (p - 1) \). A circular shift can be done in runtime \( t_s + t_w \cdot m \) if the underlying network has a cross-section bandwidth of \( O(p) \).

A parallel system is cost-optimal if the processor-time product has the same asymptotic growth as the parallel algorithm, i.e. \( p \cdot T_P \in \Theta(T_S) \).

3 The FooPar Framework

FooPar is a modular extension to Scala[16] which supports user extensions and additions to data structures with proven Scala design patterns. Scala is a scalable language pointing towards its ability to make user defined abstractions seem like first class citizens in the language. The object oriented aspect leads to concise and readable syntax when combined with operator overloading, e.g. in matrix operations. Scala unifies functional and imperative programming making it ideal for high performance computing. It builds on the Java Virtual Machine (JVM) which is a mature platform available for all relevant architectures. Scala is completely
interoperable with Java, which is one of the reasons why many companies move their performance critical code to a Scala code base [1]. Today, efficiency of bytecode can approach that of optimized C-implementations within small constants [10]. Further performance boosts can be gained by using Java Native Interface; however, this adds an additional linear amount of work due to memory being copied between the virtual machine and the native program. In other words, super linear workloads motivate the usage of JNI.

Fig. 1 depicts the architecture of FooPar. Using the builder/traversable pattern [15], one can create maintainable distributed collection classes while benefiting from the underlying modular communication layer. In turn, this means that user provided data structures receive the same benefits from the remaining layers of the framework as the ones that ship with FooPar. It is possible to design a large range of parallel algorithms using purely the data structures within FooPar although one is nor restricted to that approach.

A configuration of FooPar can be described as FooPar-X-Y-Z, where X is the communication module, and Y is the native code used for networking and Z is the hardware configuration, e.g. X ∈ {MPJ-Express, OpenMPI, FastMPJ, Shared-Memory, Akka }, Y ∈ {MPI, Sockets} and Z ∈ {SharedMemory, Cluster, Cloud}. Note that this is not an exhaustive listing of module possibilities. In this paper we only use Y=MPI and Z=Cluster and do not analyze Shared Memory parallelisation. Therefore, we will only use the notation FooPar-X.

3.1 Technologies
Currently, FooPar uses the newest version of Scala 2.10. The Scalacheck framework is a specification testing framework for Scala which is used to test the methods provided by FooPar data structures. JBLAS, a high performing linear algebra library [2] using BLAS via JNI is used to benchmark FooPar with an implemen-
3.2 SPMD Operations on Distributed Sequences

**FOOPAR** is inspired by the *SPMD/SIMD Principle* often seen in parallel hardware [4]. The *Option* monad in *Scala* is a construct similar to Haskell’s *maybe monad*. Option is especially suited for SPMD patterns since it supports *map* and *foreach* operations. Listing 1 exemplifies this characteristic approach in **FOOPAR**. Here, `ones(i)` counts the number of 1’s in the binary representation of `i`. `mapD` distributes the map operation on the Scala range `seq`.

In SPMD, every process runs the same program, i.e. every process generates `seq` in line 3. If combined with lazy-data objects, this does not lead to unnecessary space or complexity overhead (cmp. Fig. 2 and 3). While every process generates the sequence, only some processes perform the `mapD` operation.

3.3 Data Structures

**FOOPAR** relies heavily on the interpretation of data structures as *process-data mappings*. As opposed to many modern parallel programming tools, **FOOPAR** uses static mappings defined by the data structures and relies on the user to partition input. This decision was made to ensure efficiency and analyzability. By using static mappings in conjunction with *SPMD*, the overhead and bottleneck pitfalls induced by master slave models are avoided and program-simplicity and efficiency are achieved. In **FOOPAR**, data partitioning is achieved through *proxy- or lazy* objects, which are easily defined in *Scala*. In its current state, **FOOPAR** supports distributed singletons (aka. distributed variables), distributed sequences and distributed multidimensional sequences. The distributed sequence combines...
### Table 1: A selection of operations on distributed sequences in FooPar.

| Operation         | Semantic                                                                 | Notes                                                                 | \(T_p\) (parallel runtime) |
|-------------------|--------------------------------------------------------------------------|-----------------------------------------------------------------------|-----------------------------|
| \text{mapD}(\lambda) | Each process transforms one element of the sequence using operation \(\lambda\) (element size \(m\)) | This is a non-communicating operation                                  | \(\Theta(T_\lambda(m))\)   |
| \text{reduceD}(\lambda) | The sequence with \(p\) elements is reduced to the root process using operation \(\lambda\) | \(\lambda\) must be an associative operator                           | \(\Theta(\log p(t_s + t_w m + T_\lambda(m)))\) |
| \text{allGatherD} | All processes obtain a list where element \(i\) comes from process \(i\) | Process \(i\) provides the valid \(i\)th element                      | \(\Theta((t_s + t_w m)(p - 1))\) |
| \text{apply}(i)   | All processes obtain the \(i\)th element of the sequence                 | semantically identical to a one-to-all broadcasts                      | \(\Theta(\log p(t_s + t_w m))\) |

the notion of *communication groups* and data. By allowing the dynamic creation of communication groups for sequences, a total abstraction of network communication is achieved. Furthermore, a communication group follows data structures for subsequent operations allowing for advanced chained functional programming to be highly parallelized. Tab. 1 lists a selection of supported operations on distributed sequences. The given runtimes are actually achieved in FooPar, but of course they depend on the implementation of collective operations in the communication backend. A great advantage of excluding user defined message passing is gaining analyzability through the provided data-structures.

### 4 Matrix-Matrix Multiplication in FooPar

#### 4.1 Serial Matrix-Matrix Multiplication

Due to the abstraction level provided by the framework, algorithms can be defined in a fashion which is often very similar to a mathematical definition. Matrix-matrix multiplication is a good example of this. The problem can be defined as follows:

\[
(AB)_{i,j} := \sum_{k=0}^{n-1} A_{i,k} B_{k,j}
\]

where \(n\) is the number of rows and columns in matrices \(A\) and \(B\) respectively. In functional programming, list-operations can be used to model this expression in a concise manner. The three methods, \text{zip}, \text{map} and \text{reduce} are enough to express matrix-matrix multiplication as a functional program. A serial algorithm for matrix-matrix multiplication based on a 2d-decomposition of the matrices could look like this:

\[
C_{i,j} \leftarrow \text{reduce} (+) (\text{zipWith} (\cdot) A_{i*} B^T_{*,j}), \quad \forall (i,j) \in \mathcal{R} \times \mathcal{R}
\]
//Initialize matrices
val A = Array.fill(M, M)(MJBLProxy(SEED, b))
val Bt = Array.fill(M, M)(MJBLProxy(SEED, b)).transpose

//Multiply matrices
for (i <- 0 until M; j <- 0 until N)
A(i) zip Bt(j) mapD { case (a, b) => a * b } reduceD (_ + _)

Algorithm 1: Generic algorithm for matrix-matrix multiplication with FooPar.

Here, \( R = \{0, \ldots, q - 1\} \), and the sub-matrices are of size \( (n/q)^2 \). Operation \( \text{zip} \) \( \text{With} \) is a convenience method roughly equivalent to: \( \text{map} \circ \text{zip} \), which takes 2 lists and a 2-arity function to combine them.

### 4.2 Generic Algorithm for Parallel Matrix-Matrix Multiplication

To illustrate the simplicity of complexity analysis, the parallel version of the algorithm can be written in a more verbose fashion as follows:

\[
C_{i,j} \leftarrow \text{reduceD} (+) (\text{mapD} (\cdot) (\text{zip} A_{i*} B_{j}^{T})), \quad \forall (i, j) \in R \times R
\]

Operation \( \text{zip} \) is \( \in \Theta(1) \) due to lazy evaluation. We use a block size \( m = (n/q)^2 \). For \( \text{mapD} \) (multiplication of sub-matrices) we have \( T_{\text{mult}}(m) = \Theta(m^{3/2}) \), for \( \text{reduceD} \) (summation of sub-matrices) we have \( T_{\text{sum}}(m) = \Theta(m) \). In asymptotic terms the parallel runtime \( T_P \) is therefore:

\[
T_P = \Theta(1) + \Theta((n/q)^3) + \Theta((n/q)^2 \log q)
\]

Since \( C_{i,j} \) is independent both in \( i \) and \( j \), the \( q^2 \) operations can all run in parallel. Using \( q \) processors per reduction leads then to \( p = q^2 \cdot q \) processors and the overall asymptotic runtime \( \Theta((n/p)^2 \log p) \).

Using the framework, some parts of the analysis can be carried out independently of the lambda operations used in an algorithm. What is left is a generic algorithm which shows precisely the communication pattern used in the algorithm. As a coincidence, the communication pattern is essentially identical to that of the well known DNS algorithm \[5,9\].

Algorithm \[1\] shows a complete FooPar implementation, which is practically identical to the pseudo code. Note, that the algorithm uses proxy-objects which are simply objects containing lazy data using Scala’s lazy construct \[14\].

#### 4.2.1 Isoefficiency Analysis for the Generic Algorithm:

We start by determining the non-asymptotic parallel runtime. We assume the number of processors is \( p = q^3 \) (i.e. \( q = p^{1/3} \)) and matrices \( A \) and \( B \) of size \( n \times n \). Splitting \( A \) and \( B \) into \( q \times q \) blocks leads to a block size of \( (n/q)^2 \). The \( \text{zip} \) operation has a runtime of \( q^2 \) due to \( \text{nop} \) instructions carried out in iterations
where the current process is not assigned to the operation. An implicit conversion (runtime $q^2$) is needed to extend the functionality of standard Scala arrays. The mapD operation has a runtime of $q^2 + (n/q)^3$ and the reduceD operation has a runtime of $q^2 + \log q + (n/q)^2 \log q$. As $q^2 = p^{2/3}$, this leads to an overall parallel runtime of

$$T_p = 4 \cdot p^{2/3} + \frac{n^3}{p} + 1/3 \left( \log p + \left( \frac{n^2}{p^{2/3}} \right) \log p \right),$$

and the corresponding cost $p \cdot T_p \in \Theta(4p^{5/3} + n^3)$. Therefore this approach is cost-optimal for $p \in O(n^{9/5})$. The overhead for this basic implementation is

$$T_o = pT_p - T_S = 4p^{5/3} + \frac{p}{3} \left( \log p + \left( \frac{n^2}{p^{2/3}} \right) \log p \right).$$

Following an isoefficiency analysis based on $W = K \cdot T_o(W, p)$ leads to

$$W = n^3 = K \cdot 4p^{5/3} + Kp \left( \log p + \left( \frac{n^2}{p^{2/3}} \right) \log p \right).$$

Examining the terms individually shows that the first term of $K \cdot T_o(W, p)$ constraints the scalability the most. Therefore, the isoefficiency function for the basic algorithm is $W \in \Theta(p^{5/3})$. Fig. 4 shows the communication pattern implemented by Algorithm 2.

### 4.3 Grid Abstraction in FooPar for Parallel Matrix-Matrix Multiplication

In [8] an isoefficiency function in the order of $\Theta(p \log^3 p)$ was achieved by using the DNS algorithm for matrix-matrix multiplication. The bottleneck encountered in the basic implementation is due to the inherently sequential for loop emulating the $\forall$ quantifier. Though Scala offers a lot of support for library-as-DSL like patterns, there is no clear way to offer safe parallelisation of nested for loops while still supporting distributed operations on data structures. To combat this problem, FooPar supports multidimensional distributed sequences in conjunction with constructors for arbitrary Cartesian grids. Grid3D is a special case of GridN, which supports iterating over 3D-tuples as opposed to coordinate lists. Using Grid3D an algorithm for matrix-matrix multiplication can be implemented as seen in Algorithm 2. zSeq is a convenience method for getting the distributed

### Algorithm 2: Matrix-matrix multiplication in FooPar using Grid Abstraction.

```scala
val R = 0 until DIM
val G = Grid3D(R, R, R)

val GA = G mapD { case (i, j, k) => A(i)(k) }
val GB = G mapD { case (i, j, k) => B(k)(j) }

val C = ((GA zipWithD GB)(_ * _) zSeq) reduceD (_ + _)
```
Figure 4: a) Process \((i,j,k)\) contains blocks \(A_{i,k}\) and \(B_{k,j}\) b) local multiplication \(C_{i,j} = A_{i,k} \times B_{k,j}\), c) after reduction (summation): process \((i,j,0)\) contains the (partial) result matrix.

sequence, which is variable in \(z\) and constant in the \(x, y\) coordinates of the current process. By using the grid data structure, we safely eliminate the overhead induced by the for-loop in Algorithm \(A\) and end up with the same basic communication pattern as shown in Fig. 4. Operation \(\text{mapD}\) has a runtime of \(\Theta((n/q)^3)\) and \(\text{reduceD}\) a runtime of \(\Theta(\log q + (n/q)^2 \log p)\). Due to space limitations we will not present the details of runtime and isoefficiency analysis but refer to [9], as the analysis given there is very similar. Parallel runtime, \(T_P\), and cost are given by \(T_P = n^3/p + \log p + (n^2/p^{2/3}) \log p\) and cost \(\in \Theta(n^3 + p \log p + n^2 p^{1/3} \log p)\). This leads to an isoefficiency function in the order of \(\Theta(p \log^3 p)\), identical to the isoefficiency achieved by the DNS algorithm.

5 Test Results

Parallel Systems and their Interconnection Framework: In this study we focus on analyzing scalability, efficiency and flexibility. We tested FooPar on two parallel systems: the first system is called Carver and is used to analyze the peak performance and the overhead of FooPar. It is an IBM iDataPlex system where each computing node consists of two Intel Nehalem quad-core processors (2.67 GHz processors, each node has at least 24GB of RAM). The system is located at the Department of Energy’s National Energy Research Scientific Computing Center (NERSC). All nodes are interconnected by 4X QDR InfiniBand technology, providing maximally 32 Gb/s of point-to-point bandwidth. A highly optimized version of Intel’s Math Kernel Library (MKL) is used, which provides an empirical peak performance of 10.11 GFlop/s on one core (based on a single core matrix-matrix multiplication in C using MKL). This will be our reference performance to determine efficiency on Carver. Note, that the empirical peak performance is very close to the theoretical peak performance of 10.67 GFlop/s on one node. The largest parallel job in Carver’s queuing system can use maximally 512 cores, i.e. the theoretical peak is 5.46 TFlop/s.

The second system has basically the same hardware setup. The name of the system is Horseshoe-6 and it is located at the University of Southern Denmark.
Horseshoe-6 is used in order to test the flexibility of FooPar. The math libraries are not compiled towards the node’s architecture, but a standard high performing BLAS library was employed for linear algebraic operations. The reference performance on one core was measured again by a matrix-matrix multiplication (C-version using BLAS) and is 4.55 GFlop/s per core.

On Carver Java bindings of the nightly-build OpenMPI version 1.9a1r27897 were used in order to interface to OpenMPI (these Java bindings are not yet available in the stable version of OpenMPI). On Horseshoe-6 we used three different communication backends, namely i.) OpenMPI Java bindings (same version as on Carver), ii.) MPJ-Express [17], and iii.) FastMPJ [18]. Note, that changing the communication backend does not require any change in the Scala source code for the parallel algorithmic development within FooPar.

For performance comparison of FooPar and C we also developed a highly optimized parallel version of the DNS algorithm for matrix-matrix multiplication, using C/MPI. MKL (resp. BLAS) was used on Carver (resp. Horseshoe-6) for the sub-matrix-matrix multiplication on the individual cores. Note, that the given efficiency results basically do not suffer any noticeable fluctuations when repeated.

Results on Carver: Efficiencies for different matrix sizes, $n$, and number of cores, $p$, are given in Fig[5]. As communication backend, we used OpenMPI. We note that we improved the Java implementation of MPI Reduce in OpenMPI: the nightly build version implements an unnecessarily simplistic reduction with $\Theta(p)$ send/receive calls, although this can be realized with $\Theta(\log p)$ calls. I.e., the unmodified OpenMPI does not interface to the native MPI Reduce function, and therefore introduces an unnecessary bottleneck.

For matrix sizes $n = 40000$ and the largest number of cores possible (i.e. $p = 512$) Algorithm 2 achieves 4.84 TFlop/s, corresponding to 88.8% efficiency w.r.t. the theoretical peak performance (i.e. 93.7% of the empirically achievable peak performance) of Carver. The C-version performs only slightly better. Note, that the stronger efficiency drop (when compared to Horseshoe-6 results for smaller matrices) is due to the high performing math libraries; the absolute performance is still better by a factor of $\approx 2.2$. We conclude that the computation and communication overhead of using FooPar is negligible for practical purposes. While keeping the advantages of higher-level constructs, we manage to keep the efficiency very high. This result is in line with the isoefficiency analysis of FooPar in Section[4].

Results on Horseshoe-6: On Horseshoe-6 we observed that the different backends lead to rather different efficiencies. When using the unmodified OpenMPI as a communication backend, a performance drop is seen, as expected, due to the reasons mentioned above. Also MPJ-Express uses an unnecessary $\Theta(p)$ reduction (FastMPJ is closed source). However, if FooPar will not be used in an HPC setting and efficiency is not be the main objective (like in a heterogeneous system or a cloud environment), the advantages of “slower” backends (like running in daemon mode) might pay off.
Figure 5: Efficiency results for matrix-matrix multiplication (size $n \times n$) with Grid Abstraction; x-axis: number of cores used; the value for $n$ and the communication backend employed are given in the legend. Left: results on Carver, Right: results on Horseshoe-6; efficiency is given relative to empirical peak performance on one core (see text).

6 Conclusions

We introduced FooPar, a functional and object-oriented framework that combines two orthogonal scalabilities, namely the scalability as seen from the perspective of the Scala programming language and the scalability as seen from the HPC perspective. FooPar allows for isoefficiency analyses of algorithms such that theoretical scalability behavior can be shown. We presented parallel solutions in FooPar for matrix-matrix multiplication and supported the theoretical finding with empirical tests that reached close-to-optimal performance w.r.t. the theoretical peak performance on 512 cores.

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